Contemporary Statistics
Glamour Risk and Aftermath

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Hong Kong  Aug 22 2013

www.stat.toronto.edu/~dfrazer/documents/266copss.pdf
/HK-I-Aug22.pdf
Statistics:

1. Data
2. Clinical trials
3. Vioxx
4. L’Aquila
5. Replication
6. Bayes goes to Washington
7. Bayes in 21st Century

- Directions
- Summary

Science 2011
Science 2011
General 1999+
General 2009+
Science 2011
Science 2013
Science 2013
Statistics:

1. Data
2. Clinical trials
3. Vioxx
4. L’Aquila
5. Replication
6. Bayes goes to Washington
7. Bayes in 21st Century

- Directions
- Summary

Power, Risks, Responsibilities, Challenges
Science 2011 Feb
Data
Science 2011 Feb 11
-a major science journal
Science 2011 Feb 11
-a major science journal
recognizes that

Data are everywhere!
Science 2011 Feb 11
- a major science journal recognizes that
Data are everywhere!

This issue has
- 38 pages on Data
- 15 articles
Science 2011 Feb 11
- a major science journal
- recognizes that

Data are everywhere!

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- 38 pages on Data
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See a "word cloud" histogram

-frequency of each word
Science 2011 Feb 11
- a major science journal
- recognizes that

Data are everywhere!

This issue has
- 38 pages on Data
- 15 articles

See a "word cloud" histogram
-frequency of each word
But where is statistics?
"Not" there! (almost)
Science 2011 Feb 11
-a major science journal finds

No "Statistics"
in "Data"!
Science 2011 Feb 11
-a major science journal finds
No "Statistics" in "Data"!

"Statistics" is not part of Data?

Actually...
Clinical Trials
Rethinking Clinical Trials

The biomedical industry spends over $550 billion per year on research and development and produces some 30 new drugs. One reason for this disappointing output is the byzantine 11% clinical trial system that requires large numbers of patients. Half of all trials are abandoned, 50% to 90% of them because of a lack of trial participants. Patient limitations also mean large and unpredictable expenses to pharmaceutical and biotech companies as they are forced to spend more. As the industry moves toward biologics and personalized medicine, this limitation will become even greater. A breakthrough in regulation is needed to create a system that does more with fewer patients.

The current clinical trial system in the United States is more than 50 years old. Its architecture was conceived when electronic manipulation of data was limited, slow, and expensive. Since then, network and connectivity costs have declined ten thousand-fold, data storage costs have dropped ten thousand-fold, and computing costs are an order of magnitude lower. Today, complex and powerful applications like electronic commerce are deployed on a large scale. Amazon.com is a good example. A large database of customers and products forms the kernel of its operation. A customer's characteristics (like buying history and preferences) are observed and stored. Customers can be grouped and the buying behavior of any individual or group can be compared with corresponding behavior of others. Amazon can also track how a group of individuals responds to an outside ad (such as advertising).

We might conceptualize an “e-trial” system along similar lines. Drug safety would continue to be assured by the U.S. Food and Drug Administration. While safety-focused Phase I trials would continue under their jurisdiction, establishing efficacy would no longer be under their purview. Once safety is proven, patients could access the medicine in question through qualified physicians. Patients' responses to a drug would be stored in a database, along with their medical histories. Patient identity would be protected by biometric identification, and the database would be open to qualified medical researchers as a “customer.” The response of any patient or group of patients to a drug or treatment would be tracked and compared to those of others in the database who were treated in a different manner or not at all. These comparisons would provide insights into factors that determine real-life efficacy: how individuals or subgroups respond to the drug. This would liberate drugs from the tyranny of the averages that characterize trial information today. The technology would facilitate such comparisons at incredible speeds and would quickly highlight negative results. As the patient population in the database grows and these patterns, analysis of the data would also provide the information needed to conduct postmarketing studies and comparative effectiveness research.

Today’s e-commerce systems started small and took nearly 20 years to develop. Adapting this kind of capability to clinical information would be a monumental undertaking. Initialing and overseeing it would be an appropriate task for the professional societies. There are encouraging signs, including a call to action by the American Medical Association for public registries of drugs, as well as a proposal for trials that incorporate trial-forecast mechanisms. Another proposal would allow patients to choose between medicines whose efficiency has been determined in different manners. There is also a suggestion to use a variety of pricing to encourage drug developers to move forward in a “progressive” trial design.

Ideas, however, are not enough. We need the professions to mobilize and take advantage of this monumental opportunity.

Andrew Grove

Rethinking Clinical Trials

The biomedical industry spends over $58 billion per year on research and development and produces some 30 new drugs. One reason for this disappointing output is the bureaucratic 11M clinical trial system that requires large numbers of patients. Half of all trials are abandoned, 50 to 80% of them because of a shortage of trial participants. Patient limitations also cause large and unpredictable expenses to pharmaceutical and biotech companies as they are forced to spend more than $1 billion per drug. As the industry moves toward biologics and personalized medicine, this limitation will become even greater. A breakthrough in regulation is needed to create a system that does more with fewer patients.

The current clinical trial system in the United States is more than 50 years old. Its architecture was conceived when electronic manipulation of data was limited, slow, and expensive. Since then, network and communication costs have declined ten-thousand-fold, data storage costs have fallen a million-fold, and computation costs have been cut in half.

Today, complex and powerful applications like electronic commerce are deployed on a large scale. Amazon.com is a good example. A large database of customers and products forms the kernel of its operation. A customer's characteristics (like buying history and preferences) are observed and stored. Customers can be grouped, and the buying behavior of any individual or group can be compared with corresponding behavior of others. Amazon can also track how a group or an individual responds to an active option (such as advertising).

We might conceptualize an "e-trial" system along similar lines. Drug safety would continue to be assured by the U.S. Food and Drug Administration. While safety-focused Phase I trials would continue under their jurisdiction, establishing efficacy would no longer be under their purview. Once safety is proven, patients could access the medicines in question through qualified physicians. Patients' responses to a drug would be stored in a database, along with their medical histories. Patient identity would be protected by biometric identifiers, and the database would be open to qualified medical researchers as "consumers." The response of any patient or group of patients to a drug or treatment would be tracked and compared to those of others in the database who were treated in a different manner or not at all. These comparisons would provide insights into the factors that determine real-life efficacy for individuals or subgroups compared to the drug. This would disseminate the information to the consumer that characterizes trial information today. The technology would facilitate such comparisons at incredible speeds and could quickly highlight negative results. As the patient population in the database grows and more patients, analyses of the data, would also provide real-time feedback needed in conduct postmarketing studies and comprehensive effectiveness research.

Today's e-commerce systems started small and took nearly 20 years to develop. Adapting this kind of capability to clinical information would be a monumental undertaking. Initiating and overseeing it would be an appropriate task for the professional societies. There are encouraging signs, including a call by the American Medical Association for public regulations of trials, as well as an impetus to include trial information in electronic medical records. Another proposal would allow patients to choose between methods whose efficacy has been determined (or not determined). There also is a suggestion to use control groups of patients to encourage drug developers to move forward in a "progressive" trial design. Ideas, however, are not enough. We need the professions to mobilize and take advantage of this monumental opportunity.

Andrew Grove
Former CEO Intel

Rethinking Clinical Trials

The biomedical industry spends over $55 billion per year on research and development and produces some 30 new drugs. One reason for this disappointing output is the byzantine 11-14 month clinical trial system that requires large numbers of patients. Half of all trials are abandoned, 50 to 90% of drugs fail because of a shortage of trial participants. Patient limitations also mean large and unpredicted expenses for pharmaceutical and biotech companies as they are forced to treat more. As the industry moves toward biologics and personalized medicine, this limitation will become even greater. An breakthrough in regulation is needed to create a system that does more with fewer patients.

The current clinical trial system in the United States is more than 50 years old. Its architecture was conceived when electronic manipulation of data was limited, slow, and expensive. Since then, network and computing costs have declined ten-thousand fold, data storage costs have declined ten-thousand fold, and computer costs by an even larger factor. Today, complex and powerful applications like electronic commerce are deployed on a large scale. Amazon.com is a good example. A large database of customers and products forms the kernel of its operation. Customer characteristics like buying history and preferences are observed and used. Customers can be grouped and the buying behavior of each group or individual can be compared with corresponding behavior of others. Amazon can also track how a group or an individual responds to an outside ad (such as advertising).

We sought to create a “clinical-trial” system along similar lines. Drug safety would continue to be assured by the U.S. Food and Drug Administration. While safety-focused Phase I trials would continue under their jurisdiction, establishing efficacy would no longer be under their purview. Once safety is ensured, patients could access the medicine in question through qualified physicians. Patients’ responses to a drug would be stored in a database, along with their medical histories. Patient identity would be protected by biometric identifiers, and the database would be open to qualified medical researchers as a “commons.” The response of any patient or group of patients to a drug or treatment would be analyzed and compared to those of others in the database who were treated in a different manner or not at all. These comparisons would provide insights into the factors that determine real-life efficacy: how individuals or subgroups respond to the drug. This would liberate drugs from the tyranny of the averages that characterize trial information today. The technology would facilitate such comparisons at incredible speed and would quickly highlight negative results. As the patient populations in the database grow and their analysis, analysis of the data would also provide the information needed to conduct post-marketing studies and comprehensive effectiveness research.

Today’s e-commerce systems started small and took nearly 20 years to develop. Adapting this kind of scalability capability to clinical research would be a monumental undertaking. Initiating and overseeing it would be an appropriate task for the professional societies. There are encouraging signs, including a call to 2030 by the American Medical Association for online registries of trials, as well as a proposal for trials that incorporate real-time decisionmaking. Another proposal would allow patients to choose between medicines whose efficacy has been determined in different manners. There is also a suggestion of providing patients with options to receive novel in a “progressive” trial design. Ideas, however, are not enough. We need the professions to mobilize and take advantage of this momentous opportunity.

Andrew Grove

Science 2011 Sep 23

Grove: former CEO Intel - clinical trials out-dated - large data base - customers - products - open to researchers and
Rethinking Clinical Trials

THE BIOMEDICAL INDUSTRY SPENDS OVER $55 BILLION PER YEAR ON RESEARCH AND DEVELOPMENT AND PRODUCES SOME 30 NEW DRUGS A YEAR. ONE REASON FOR THIS DISAPPEARING OUTPUT IS THE BUREAUCRATIC US CLINICAL TRIAL SYSTEM THAT EXAGGERATES LARGES NUMBERS OF PATIENTS, HUDDLES UP DRUGS AND MAKE THEM TO COST 50 TO 80% OF WHAT THEY WOULD BE ELSEWHERE BECAUSE OF THE EXPENSES OF NEW REGULATORY REQUIREMENTS. PATIENT LIMITATIONS ALSO MEAN THAT LARGE INTEGRATED RESEARCH PROGRAMS AND BIOTECHNIQUES THAT ARE NOT FUNDAMENTALLY BASED ON THE RISK-TO-PAYMENT MODEL OF MEDICINE, WHICH IS A MISTAKE THAT WILL BECOME EVEN GREATER. A BREAKTHROUGH IN REGULATION IS NEEDED TO CREATE A SYSTEM THAT DURES MORE THAN FEWER PATIENTS.

The current clinical trial system in the United States is more than 50 years old. Its architecture was conceived when electronic manipulation of data was limited, slow, and expensive. Since then, network and connectivity costs have declined ten thousand-fold, data storage costs even lower million-fold, and computing costs at an even lower factor. Today, complex and powerful applications like electronic commerce are deployed on a large scale. Amazon.com is a good example. A large database of customers and products forms the kernel of its operation. A customer's characteristics (like buying history and preferences) are observed and managed. Customers can be grouped and the buying behavior of any individual group can be compared with corresponding behavior of others. Amazon can also track how a group or an individual responds to an outside action (such as advertising).

We might contemplate an "e-trial" system along similar lines. Drug safety would continue to be secured by the U.S. Food and Drug Administration. While a fully formed "e-trial" would continue under their purview, establishing efficacy would no longer be under their purview. Once efficacy is proven, patients could access the medicines in question through qualified physicians. Patients responding to a drug would be asked to a资本市场, with a real-time feedback loop. Feedback data would be protected by biometric identifiers, and the database would be open to public scrutiny. Medical research as a "customer." The response of any patient or group of patients to a new drug would be studied and compared to those of others in the database who were similarly or differently treated.

These comparisons would yield real-time efficacy as new individuals or subsets of drugs from the variety of the averages that medicine would facilitate such comparisons at the same speed and could quickly highlight negative results. As the patient population in the database grows and time passes, analysis of the data would also provide the information needed to conduct post-marketing studies and comparative effectiveness research.

Today's e-commerce systems started small and took nearly 20 years to develop. Adapting this kind of capability to medical information would be a monumental undertaking. Initiating and overseeing it would be an appropriate task for the professional societies. There are encouraging signs, including a call to 2050 by the American Medical Association for public recognition of its role, as well as a proposal to take on the electronic health record. Another proposal would allow patients to choose between medical systems whose efficiency had been determined by clinical outcomes. There is also a suggestion to use some of the pricing to encourage drug development to move forward in a "progressive" trial design. Ideas, however, are not enough. We need the professions to mobilize and take advantage of this momentous opportunity.

Andrew Grove

* * *


Once safety is proven, patients could access the medicine in question through qualified physicians.
Rethinking Clinical Trials

The biomedical industry spends over $55 billion per year on research and development and produces some 30 new drugs. One reason for this disappointing output is the byzantine US clinical trial system that requires large numbers of patients. Half of all trials are abandoned, 50 to 70% of them because of a shortage of trial participants. Patient limitations also cause large and unpredictable expenses to pharmaceutical and biotech companies. As they are forced to send their drug candidates toward toxicological and pharmacokinetic studies, the trial suspension will become even greater. A breakthrough in this regulation is needed to create a system that does not put more drug patients at risk.

The current clinical trial system in the United States is more than 50 years old. Its architecture was conceived when electronic manipulation of data was limited, slow, and expensive. Since then, network and communication costs have declined ten thousand-fold, and computing power has increased by an order of magnitude. Today, complex and powerful applications like electronic commerce are deployed on a large scale. Amazon.com is a good example. A large database of customers and products forms the kernel of its operation. A customer's characteristics (like buying habits and preferences) are observed and stored. Customers can be grouped and the buying behavior of any individual or group can be compared with corresponding behavior of others. Amazon can also track how a user is storing or purchasing items. E-commerce is a new kind of publishing and marketing as a "content." The response of any group of patients to a drug treatment could be studied and compared to those of others in the database who were exposed to a different treatment or not at all. These comparisons could yield real-life efficiency by evaluating the effectiveness of drugs from the variety of the averages that would facilitate such comparisons at increment speeds and could quickly highlight negative results. As the patient population in the database grows and time passes, analyses of the data will provide the information needed to conduct postmarketing studies and comparative effectiveness research.

Today's e-commerce systems started small and took nearly 20 years to develop. Adapting this kind of capability to clinical information would be a more realistic undertaking. Initiating and overseeing it would be an appropriate task for the professional societies. There are encouraging signs, including a call by the American Medical Association for public registration of trials, as well as a proposal for trials that incorporate real-time monitoring. Another proposal would allow patients to choose between medicine whose efficacy has been determined on different patients. There is also a suggestion to use these new techniques to encourage drug developers to move forward in a "progressive" trial design. 2 Ideas, however, are not enough. We need the professions to mobilize and take advantage of this enormous opportunity.

Andrew Gove

Science 2011 Sep 23

Grove: former CEO Intel

- Clinical Trials out-dated
- Large data base - customers
- Products
- Open to researchers and

Once safety is proven, patients could access the medicine in question through qualified physicians.

Once safety is proven, is not so simple.

Vioxx
3 Vioxx
Vioxx
-An analgesic (pain relief) from Merck "Pharma"
Vioxx

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1999 Approved by FDA (8 year approval process)
2000 Advertising $160m .... More than Pepsi or Budweiser
2003 Earned $2.46 b Big bucks!
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- Evidence available: of 3x, 5x rate of CVD events (cardiovascular T)
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- Litigation vs. Merck: 2004 ... by those affected
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- David Madigan, Chair, Columbia U Statistics (litigation consultant)
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"Merck got a bargain" cf profit
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"Merck got a bargain"

Message?
The L’Aquila earthquake
Science or risk on trial?

On April 6th 2009 a major earthquake devastated the Italian town of L’Aquila, with the loss of 309 lives. In October this year six scientists and a government official were sentenced to 6 years each for providing "inaccurate, incomplete and contradictory information" on the probability and risk of an earthquake and for falsely reassuring the population. Jordi Prats examines the case.

The L’Aquila earthquake was such a shocking, sudden occurrence that it left 309 Italian citizens dead. It was one of the worst earthquakes in Italy, destroying much of the town. During the night of the disaster, many people slept in the open because they were afraid of aftershocks. The town was left in ruins, with many buildings destroyed. The death toll included a large number of children, many of whom died while they were having dinner at a sports ground. The town was left devastated, with many buildings destroyed and many people homeless. The town was left in ruins, with many buildings destroyed. The death toll included a large number of children, many of whom died while they were having dinner at a sports ground. The town was left devastated, with many buildings destroyed.
The L’Aquila earthquake
Science or risk on trial?

On April 6th 2009, a major earthquake devastated the Italian town of L’Aquila, killing 309. In October this year six scientists and a government official were sentenced to six years in prison for providing "inaccurate, incomplete and contradictory information" on the probability and risk of an earthquake and for falsely reassuring the population. Jordi Prats examines the case.

The L’Aquila earthquake was such a shocking event that it took Italy by surprise when they were later found guilty. In 2009, the city lost its historic center, which was left in ruins, and the population was left scrambling to pick up the pieces.

In the aftermath, the scientific community was criticized for not being prepared to handle such a disaster. There was a sense of shock and disbelief, as the experts who had studied the area had not predicted such a large earthquake.

The earthquake was felt across a large area of central Italy, including the capital, Rome. The damage was widespread, with buildings, bridges, and roads collapsing. The death toll was high, with over 300 people losing their lives.

The trial centered on whether the scientists and officials had accurately assessed the risk of a major earthquake. The defense argued that the scientists had done their best, based on the data available at the time.

The trial also highlighted the challenges of scientific research and the need for better communication between scientists and the public. The scientists argued that they had provided the best information available, but that the public and policymakers had not always understood the risks.

The verdict was seen as a signal that the Italian government was serious about preventing future disasters. The scientists have since been called to give evidence in other trials related to earthquakes, and the trial has served as a wake-up call for the scientific community.

The Italian government has since moved to improve its earthquake preparedness, with new laws and regulations aimed at reducing the impact of future disasters. The trial has also served as a reminder of the importance of continuous learning and improvement in scientific research.
The L'Aquila earthquake

Science or risk on trial?

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The L’Aquila earthquake
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On April 6th 2009 a major earthquake devastated the Italian town of L’Aquila, with the loss of 309 lives. In October this year six scientists and a government official were sentenced to 6 years each for providing "inaccurate, incomplete and contradictory information" on the probability and risk of an earthquake and for falsly reassuring the population. Jordi Prats examines the case.

The L’Aquila earthquake was such a shocking, sudden and unexpected event as in 931, when a tremor in the nearby town of Aquila. During the night of April 4th, the town was suddenly hit by a major earthquake, with the city of L’Aquila and many surrounding villages being severely damaged. The earthquake caused the deaths of over 300 people, and there were over 300,000 people displaced. The damage to buildings, infrastructure, and human life was catastrophic. The town was left in ruins, with thousands of buildings destroyed. The government was criticized for its response, with some accusing them of negligence and incompetence.

In the aftermath, the government and the international community came together to provide aid and support. The Italian government declared a state of emergency, and the European Union provided financial assistance. The United Nations also sent a team of experts to assess the damage and provide recommendations for reconstruction.

The trial of the scientists and government official highlighted the complexities of earthquake science and the challenges of communicating risk to the public. The scientists were accused of providing inaccurate and contradictory information, which led to an underestimation of the risk and an underreaction to the earthquake. The government official was accused of falsifying information and providing false reassurances to the public. The trial raised questions about the role of scientific consensus in decision-making and the importance of clear, transparent communication in times of crisis.

The trial also brought attention to the importance of earthquake science and the need for better preparedness and response strategies. It highlighted the need for improved communication between scientists, government officials, and the public, and the importance of independent review and oversight in the assessment of risk.

The L’Aquila earthquake was a tragic reminder of the power of natural disasters and the need for improved preparedness and response strategies. It serves as a warning to the world about the importance of scientific consensus and transparency in the communication of risk, and the need for clear, independent review in times of crisis.

Significance 2012 Dec
Earthquake 2009 Apr 6
300 deaths
But early 2009
Many small shock
The L’Aquila earthquake

On April 6th, 2009, a major earthquake devastated the historic city of L’Aquila, killing over 300 lives. In October this year, an Italian government official was convicted of 60 years each for providing inaccurate, incomplete, and overdue information on the probability and risk of an earthquake and for failing to evacuate the population. Jacob Frey examines the case.

Not even seven years have passed since the devastating earthquake in L’Aquila. However, the residents are still struggling with the damage caused by the event. The city’s government and many residents are facing the challenge of returning the city to its former glory. The government has been criticized for not providing adequate financial assistance and for not ensuring proper compensation to the affected citizens.

In the years since the quake, various professional organizations have been working on the reconstruction of L’Aquila. The city has been allocated a total of €23 billion to cover the cost of rebuilding. However, the government has failed to utilize the funds to the fullest extent. This has led to a situation where many residents are still staying in temporary shelters.

But early 2009...

Many small shock

Pampered residents

Earthquake 2009 Apr 6

Significance 2012 Dec
The L’Aquila earthquake
Science or risk on trial?

On April 6th 2009 a major earthquake devastated the Italian town of L’Aquila, with the loss of 309 lives. In October this year six scientists and a government official were sentenced to 6 years each for providing "inaccurate, incomplete and contradictory information" on the probability and risk of an earthquake and for falsely reassuring the population. Jordi Prats examines the case.

The L’Aquila was such a shocking, sudden event that it became known as the ‘9/11’ of Italian earthquakes. In 2006, a new earthquake devastated the town of L’Aquila, killing 298 people. However, in 2009 the earthquake killed 309 people, making it one of the deadliest in Italy's history. The death toll was particularly high because many buildings were destroyed, leaving thousands homeless and causing widespread destruction.

The earthquake caused extensive damage to buildings and infrastructure in L’Aquila and surrounding areas. Some structures were completely destroyed, while others were severely damaged. The economic impact was significant, with estimates of damages reaching hundreds of millions of euros.

In the aftermath, a commission was established to investigate the causes of the earthquake and its effects. The commission identified several areas where there was a lack of understanding and communication between researchers and the general public.

In 2012, the Supreme Court of Cassation acquitted all defendants, including the scientists and government officials, finding that the evidence presented was insufficient to prove criminal negligence.

Significance: The L’Aquila earthquake raised important questions about the role of scientists and government officials in providing accurate information to the public during natural disasters. The case highlighted the need for improved communication and transparency in the management of such events.

But early 2009: Many small shock
Panicked residents
Committee of seismologists formed
The L’Aquila earthquake
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Reported: no reason to expect a big quake
- Small shocks reducing stresses
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On April 6th 2009 a major earthquake devastated the Italian town of L'Aquila, with the loss of 309 lives. In October this year six scientists and a government official were sentenced to 6 years each for providing "inaccurate, incomplete and contradictory information" on the probability and risk of an earthquake and for falsely reassuring the population. Jordi Peats examines the case.

The L'Aquila earthquake was one of the deadliest in recent world history. It was described at the time as a "terrible tremor", and that it was "unimaginable to imagine such a thing."

It struck at 03:32 on April 6th, 2009, with a magnitude of 6.3 on the Richter scale. The epicenter was located just 3 kilometers from the town center, and its shock felt over a 100 kilometer radius. Around 20,000 people were killed, and about 30,000 injured. The damage was widespread, with buildings in the center of the town collapsing and many of the city's buildings destroyed.

The official death toll was 309, but there were reports of many more people being killed in the aftermath. The town was left in ruins, with entire neighborhoods flattened and many of the city's buildings destroyed.

The Italian government was criticized for its slow response and inadequate emergency measures. The earthquake also caused significant damage to the country's infrastructure, with many roads and bridges collapsing.

The aftermath of the earthquake also saw widespread confusion and misinformation, with many people in shock and unable to make sense of what had happened. The government's response was slow and inadequate, with many people left without food, water, or shelter.

The event was the focus of much media attention, with many experts calling for greater preparedness and better emergency response.

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Earthquake 2009 Apr 6
300 deaths

But early 2009
Many small shock
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Reported: no reason to expect a big quake
"Small shocks reducing stresses"

but earthquake came... 300 died"
The L’Aquila earthquake
Science or risk on trial?

On April 6th, 2009 a major earthquake devastated the future capital of Abruzzo, Italy. The loss of 309 lives. In October this year, 6 years after the earthquake, the Italian government announced a massive payout of 4600 euros to each family who lost a child in the disaster. The government, in an effort to avoid a huge court case, reached an agreement with the surviving families to settle for this amount of money. In December, the surviving families will receive their first installment of this agreement.

But early 2009, several small shocks were recorded, causing panic among residents. The Italian government formed a committee of seismologists to investigate the small shocks, but they were unable to determine the source of the shocks.

Many small shocks reported: no reason to expect a big quake.
The L'Aquila earthquake
Science or risk on trial?

On April 6th 2009 a major earthquake devastated the Italian town of L'Aquila, with the loss of 309 lives. In October this year six scientists and a government official were sentenced to 6 years each for providing "inaccurate, incomplete and contradictory information" on the probability and risk of an earthquake and for falsely reassuring the population. Jordi Prats examines the case.

The L'Aquila earthquake was the deadliest natural disaster in Italy since the 1980s. The quake struck the town of L'Aquila, killing more than 300 people and injuring thousands. The earthquake was one of the strongest ever recorded in Italy and caused widespread destruction.

Significance 2012 Dec
Earthquake 2009 Apr 6
300 deaths

But early 2009
Many small shock
Panicked residents
Committee of seismologists formed
Reported: no reason to expect a big quake
'Small shocks reducing stresses'

Courts convicted 7 of manslaughter
Statistics was involved!

Where does responsibility fall?
Replication and Reproducibility
Again, and Again, and Again...

Replication—The Confirmation of Results and Conclusions From One Study Obtained Independently in Another—Is Considered the Scientific Gold Standard. New tools and technologies, massive amounts of data, long-term studies, interdisciplinary approaches, and the complexity of the questions being asked are complicating replication efforts, as are increased pressures on scientists to advance their research. The five Perspectives in this section (and associated News and Career spotlights, Reader's Poll, and Editorials) explore some of the issues associated with replicating results across various fields.

Ryan (p. 1220) highlights the excitement and challenges that come with field-based research. In particular, obtaining rigorous data can be difficult, especially in areas of discovery, but makes replication difficult, because the nature conditions surrounding the observations are unique. Further, although laboratory research allows for the quantification of organizational conditions, these constructs may not apply to the real word. Debate about the merits of lab-based and field-based studies has been prominent. Three overviews, Tannenbaum and Call (p. 1227), further contribute to this debate in their discussion of (1) previous efforts to replicate previous cognition and behavior research (small numbers of subjects, exposure, and ethics issues as well as narrow sample size), such as the mammal's challenge of designing tasks that elicit complex cognitive behaviors. New technologies continue to produce a deluge of data on different variables, raising expectations for new knowledge that will translate into meaningful therapies and insights into health. Nowinski and Leary (p. 1229) outline multiple steps for validating such large-scale data on the path to clinical utility and make suggestions for incentives (and sanctions) that could enhance the availability of reliable data and analysis.

Peng (p. 1226) discusses the need for a minimum standard of reproducibility in computer science, arguing that enough information about methods and code should be available for independent researchers to reach consensus conclusions using original raw data. Specifically, he describes a model that one journal has used to work this reality.

The need to convince the public that these are replicable or that these are replicable as science and public policy-making interest, an issue that has not been the climate change study. As Santor et al. (p. 1222) describe, having multiple groups running the same data (not generating more data) has led to robust conclusions.

The importance of replication and reproductibility for scientists is unquestioned. Sometimes scientists in replicate recent claims or results. This is one of the main ways that science progresses. See the News features on Frontiers in Physics (p. 2003) and New Directions (p. 2004) in this issue. How do we promote the validation of replicable data? The authors in this section come up with possibilities that are targeted at families, journals, and the research culture itself. In the Reader's Poll, you can make your views known as well.

—Barbara R. Jarem, Gilbert Chin, Lisa Ghang, Suchi Vignieri
Again, and Again, and Again ...

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New technologies continue to produce a deluge of data from different varieties, raising expectations for new knowledge that will translate into meaningful therapeutics and insights into health. Lamerdin and Khoury (p. 1230) outline multiple steps for validating such large-scale data on the path to clinical utility and make suggestions for incentives (and penalties) that could enhance the availability of reliable data and analyses.

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The need to convince the public that data are replicable has grown as science and public policy-making intersect, an issue that has been of concern in climate change studies. As Santer et al. (p. 1233) describe, having multiple groups examining the same data and generating new data has led to robust conclusions.

The importance of replication and reproducibility for scientists is unquestioned. Sometimes attempts to replicate reveal scientific uncertainties. This is one of the main ways that science progresses (see associated News stories of faster-than-light neutrinos and neutrinos, pp. 1200 and 1194). Unfortunately, in rare instances (compared to the body of scientific work), it can also indicate fraud (see the Editorial by Crocker and Cooper, p. 1182). How do we promote the publication of replicable data? The authors in this section come up with possibilities that are targeted at funders, journals, and the research culture itself. In the Readers' Poll, you can make your views known as well.

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Barbara R. Jasny, Gilbert Chin, Lisa Chung, Sacha Vignieri

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The importance of replication and reproducibility for scientists is unquestioned. Sometimes attempts to replicate reveal scientific uncertainties. This is one of the main ways that science progresses (see associated News stories of faster-than-light neutrinos and winds, pp. 1200 and 1194). Unfortunately, in rare instances (comparing to the body of scientific work), it can also indicate fraud (see Editorial by Crocker and Cooper, p. 1189). How do we promote the publication of replicable data? The authors in this section come up with possibilities that are targeted at funders, journals, and the research culture itself. In the Readers' Poll, you can make your views known as well.
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Again, and Again, and Again...

REPLICATION—THE CONFIRMATION OF RESULTS AND CONCLUSIONS FROM ONE STUDY obtained independently in another—is considered the scientific gold standard. New tools and technologies, massive amounts of data, long-term studies, interdisciplinary approaches, and the complexity of the questions being asked, are increasing pressures on scientists to advance their research. The five Perspectives in this section (and associated News and Career stories, Readers' Poll, and Editorial) explore some of the issues associated with replicating results across various fields.

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www.sciencemag.org  SCIENCE  VOL. 334  2 DECEMBER 2011  1225

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Mr. Bayes Goes to Washington
Sam Wang and Benjamin C. Campbell

On day before the 2012 U.S. presidential election, former Reagan speechwriter Peggy Noonan wrote that “nobody knows anything” about who would win, asserting that Republican candidate Mitt Romney’s surrogates had the greater passion and enthusiasm (1). From a similarly data-fluent source, columnist George Will predicted a Romney victory (2). MSNBC’s Joe Scarborough said “it could go either way— anybody that thinks this race is anything but a tight one now... should be kept away from typewriters, computers, laptops, and microphones, because they’re jobless” (3).

In the end, these predictions were the ones whose opinions proved dispensable. They were unable to detect a plain fact based on public opinion polls with collectively excellent track records: President Obama had an advantage of 3 to 4 percentage points for nearly the entire campaign season. How- ever, the world of political punditry measures success not by accuracy but by leadership and viewfinder. And so it came to pass that legions of commentators expressed total confidence—and were wrong.

Reasonable people have had possible since at least 2004, when one of us was among the first to statistically aggregate polls (4). In 2008, Nate Silver emerged as a poster child for aggregation, armed with a degree in economics, a love of numbers, and a professional track record in analyzing baseball performance and financial data. He unseated a mostly superseded presidential race, providing timely, quantitative analysis and lucid commentary on his website FiveThirtyEight, which became hugely popular and was snapped up by the New York Times (5). His name has further in 2012, when his and other aggrega- tors and modelers used harvested data to see.

Now Silver has written The Signal and the Noise: The Art and Science of Prediction, a book that addresses predictions not just in politics but in all aspects of modern life, with the eye of a hobbyist and a sense of fun. From the word limits of blog essays, the book is a meandering, non-eye-scan view of what prediction, if one, are common to good forecasting in daily life, tenure activ- ity, and science.

We use predictions to guide our future actions, from planning weekend outings to taking care of our health, but most people have no idea how scientific predictions are made. This book is for them. Silver introduces some of the concepts behind data modeling, including probability, Bayes-ian inference, and uncertainty. He takes lengthy looks at top- ics ranging from the spread of diseases to the 1994-95 plague of lethal water samples of Deep Blue.

A recurring theme is that the Signal and the Noise is Bayesian reasoning, an approach that has swept the science. Probability had been conventionally interpreted as measuring the true likelihood of an event—for instance, how often the total of two rolled dice will add up to seven. Such a “frequentist” point of view has in many cases given way to an approach pioneered by Reverend Thomas Bayes in the 18th century, which emphasizes that proba- bility can only be interpreted in terms of the hypotheses that preceded the measurement. Although Silver asserts that Bayesian Political Forecasting has more in common with poker than with hard sciences such as physics and biology, these topics all use the same mathematical toolkit. Large-scale phys- ics collaborations depend on sensitive models to predict the probabilistic decay rates of radio- nuclides, looking for outliers that might represent signals in the noise and hence discoveries. In our field, many neuroscientists have begun to view the brain as a production machine (7). We process the world around us by making infer- ences from noisy and incomplete data. To do so, the brain must form a model of its envi- ronment—a set of “rules” learned over a lifetime that is used to interpret incoming data.

This Bayesian machine continually updates its process to correspond to its environment. Through this process, our brains spend millions of years honing appropriate priors for the com- plex tasks that we perform effortlessly. Silver gives a well-known equation for how to take into account the Bayesian prior but doesn’t show where it comes from. Readers wanting a deeper explanation of Bayes’s rule might consult another source such as BetterExplained.com (8), which teaches the subject by using e-mail spam filtering as an example. Silver’s chosen anecdotes include the classic example of numerous individual interpreta- tions—but also how to interpret that unil- mator underdog that just showed up in your partner’s distant dream.

At times Silver writes as if he were for bad brands and can be read as “true Bayes.” Such a prescription does not do justice to the historic controversy surrounding interpreta- tions of probability. A beggar might come away from this book believing that an earlier generation of frequentists were simply igno- rant. In a cartoonish account, Silver lords a broadside at a monumental figure in sta- tistics, Ronald A. Fisher, who late in life argued against the idea that smoking causes cancer—and who coined “Bayesian” as a derogatory term. Silver suggests that Fisher’s aversion to Bayes to carried him in; in fact, the real prob- lem was that Fisher was a smoker (9). Fisher’s prior beliefs prevented him from accepting epidemiological and biological evidence, an erroneous pitfall of ever there was one.

Our biggest criticism of the book is that although statistics and Bayesian inference are powerful ideas, they are not core to it. His enthusiasm for the good Reverend Silver has substituted a fair bit into the same Precruncher bed. Silver uses the old first-reading analogy, saying that often (including himself) some ideas, whereas hedgemony focuses on one subject only. But here he is hedgemony with one big idea: statistics.

However, Bayesian reasoning works only if the prior is adapted for the task. According to Silver, many of today’s “half-
Mr. Bayes Goes to Washington

Sam Wang and Benjamin C. Campbell

One day before the 2012 U.S. presidential election, former project leader for American Institute for Mathematics, co-founder of the Bayesian inference software, and contributor to the book "Bayesian Statistics for Political Science". The book "Bayesian Statistics for Political Science" is a comprehensive introduction to the field of Bayesian statistics and its applications in political science. The book covers topics such as Bayesian inference, Bayesian model selection, and Bayesian decision theory. The book is written for graduate students and researchers in political science, but it is also accessible to advanced undergraduate students. The book is available in both hardcover and electronic formats. The book has been well-received by the academic community, and it has been praised for its clear and accessible writing style and its practical examples. The book is a valuable resource for anyone interested in learning about Bayesian statistics and its applications in political science.
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Sam Wang and Benjamin C. Campbell

One day before the 2012 U.S. presidential election, former Senator and noted Bayesian statistician Peggy Noonan wrote that “nobody knows anything” about who would win, asserting that Republican candidate Mitt Romney’s surrogates had the greater passion and enthusiasm. (1) From a similarly data-free perspective, columnist George Will predicted a Romney victory (2). MSNBC’s Joe Scarborough said “it could go either way anybody that thinks this race is anything but a strong right now should be kept away from [television] screens, computers, laptops, and microphones, because they’re jokers.” (3)

In the end, these. paralleled the error whose opinions proved dispensable. They were unable to detect a clear fact based on public opinion polls with collectively excellent track records, President Obama had an advantage of 3 to 4 percentage points for nearly the entire campaign season. Moreover, the world of political punditry measures success not only by accuracy but by readership and viewership. And so it came to pass that legions ofcommentators expressed total confidence—and were wrong.

Existing the possible reasons for at least 2004, when one of us was among the first to statistically aggregate poll results, (1) a few days before the election, a postcard mailed to a designated child for aggregation, armed with a signature in economics, a love of numbers, and professional track record in analyzing historical performance and financial data. He unveiled a modestly superior predictive model, providing timely outcomes into election outcomes. The model is an essential, if not the only, contribution to the world of political science.

The Signal and the Noise (Why Most Predictions Fail—but Some Don’t) and the Art and Science of Prediction, a book that addresses predictions not only in economics, but in other fields as well.

The Signal and the Noise: why most predictions fail—but some don’t

By Nate Silver

ISBN 9780143114023
978-0-14-311402-3

Silver has written a book that addresses predictions not only in economics, but in other fields as well. It is a comprehensive guide to the art and science of prediction, and it is a must-read for anyone interested in understanding how to make accurate predictions in a world充满了 uncertainty.

Silver’s book covers a wide range of topics, from predicting the outcome of elections and sports games to forecasting natural disasters and economic trends. He uses a variety of statistical techniques to analyze data and create models that can predict future events. Silver also provides insight into the limitations of prediction and the importance of considering multiple variables when making predictions.

One of the key themes of the book is the idea that predictions are most accurate when they are based on a large amount of data. Silver argues that the more data that is available, the more likely it is that accurate predictions can be made. He also emphasizes the importance of being open to new information and adjusting predictions as new data becomes available.

Overall, The Signal and the Noise is a fascinating and informative book that will appeal to anyone interested in the art and science of prediction. It is a must-read for anyone who wants to understand how to make accurate predictions in a world充满了 uncertainty.
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One day before the 2012 U.S. presidential election, former Reagan speechwriter Peggy Noonan wrote that "nobody knows anything" about who would win, asserting that Republican candidate Mitt Romney’s supporters had the greater passion and enthusiasm. From a similarly data-far-from-semantic point of view, Nate Silver predicted a Romney victory. But according to Noonan’s logic, MSNBC’s Joe Scarborough said “it could go either way—anybody who thinks this race is anything but a strong right will probably be left behind from typewriters, computers, laptops, and microphones, because they’re jokers.”

In the end, these predictors were the ones whose opinions proved dispensable. They were unable to detect a plain fact based on public opinion polls with collectively excellent track records: President Obama had an advantage of 3 to 4 percentage points for nearly the entire campaign season. However, the world of political punditry continues to measure success not by accuracy but by leadership and viewshare. And so it came to pass that legions of commentators expressed total confidence—and were wrong.

Having no statistical expertise is an asset for prediction, armed with a skepticism and a sense of humor, a love of numbers, and a professional track record in analyzing baseball performance and financial data. He unleashed a mostly unsupervised predictive model, providing timely and quantitative analysis and in-depth commentary on his website FiveThirtyEight, which became highly popular and was snapped up by the New York Times (1). His fame rose further in 2012, when he and other aggregators and modelers used a time-hardened algorithm (2) to score states.

Now Silver has written The Signal and the Noise, a book that addresses predictions not just in politics but in all aspects of modern life, with the eye of a textbook and the sense of humor. Filled with examples, the book is a must-read, full of insights about what prediction is, how it can go wrong, and how to improve it.

At times Silver writes as if he were a bad-for-business for-matician. But his book is far more interesting than that. His main concern is the role of statistics and Bayesian inference in modern society, and he argues that we need to better understand the process by which predictions are made and the factors that influence them.

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Clima – Mr. Bayes

Washington DC

Book review by Wang & Campbell

Nate Silver: The Signal and the Noise

Published on 15 February 2013 www.sciencemag.org

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Sam Wang and Benjamin C. Campbell

On the eve of the 2012 U.S. presidential election, former Reagan economic writer Peggy Noonan wrote that “nobody knows anything” about who would win, asserting that Republican candidate Mitt Romney’s supporters had the greater passion and enthusiasm (1). From a similarly date- and context-removed “columnist” (2), Paul Butler of the Chicago Tribune, one might have expected: “Mitt Romney’s campaign was the season’s best-selling story” (3). But the Romney campaign ultimately was the only one of the three that was even close to being successful, according to the fast-paced, high-stakes elite political media (4). And so it came to pass that everyone’s opinions were correct, but wrong.

Election predictions can be among the most inaccurate, but not just in politics but in all aspects of modern life, with the design of a computer or a new car, the spread of a disease, or the success of a new treatment. Thus, it is not surprising that, when a prediction is made, people often react as if the prediction were not only wrong but also trivial (5). For example, the 2008 election was predicted to be a close contest (6), but it was not, as polls taken in the weeks before the election showed a lead for Barack Obama (7). Similarly, the 2012 election was predicted to be a close contest (8), but it was not, as polls taken in the weeks before the election showed a lead for Mitt Romney (9).

The Signal and the Noise: Why Most Predictions Fail—but Some Don’t (Farrar, Straus & Giroux; 978-0-374-53415-1; 304 pp.; $26) by Nate Silver is a book that provides a clear and accessible explanation of how to make better predictions. Silver, a statistician, uses real-world examples to show how statistical methods can be used to improve predictions. He also discusses the importance of probability and the role of uncertainty in making predictions.

Silver’s book is a must-read for anyone interested in improving their ability to make predictions, whether in politics, economics, or science. It is also a useful resource for teachers and students who want to learn more about statistical methods and how they can be applied to real-world problems.

In summary, Mr. Bayes Goes to Washington is a book that provides a clear and accessible explanation of how to make better predictions. Silver’s book is a must-read for anyone interested in improving their ability to make predictions, whether in politics, economics, or science. It is also a useful resource for teachers and students who want to learn more about statistical methods and how they can be applied to real-world problems.

References:
Mr. Bayes Goes to Washington

Samanpreet Singh and Benjamin C. Campbell

One day before the 2012 U.S. presidential election, former Republican governor Mitt Romney’s campaign was blindsided by an email to their volunteers. The email contained a poll showing that the campaign was losing ground in Pennsylvania. The poll was based on a survey of likely voters, a method traditionally used by political campaigns. The campaign was surprised by the results and spent the next few days trying to figure out how they could have been wrong.

But the campaign was not alone in its confusion. Political campaigns have long relied on polls to predict election outcomes, and the 2012 election was no exception. However, the use of polls has been criticized for inaccuracies and for not providing a comprehensive picture of the electorate.

The Bayesian approach to statistics, on the other hand, provides a powerful tool for understanding uncertainty in political polling. By incorporating prior information into the analysis, Bayesian methods can produce more accurate and reliable results.

In this article, we will explore the use of Bayesian methods in political polling, and how they can be used to improve the accuracy of election predictions.

validated by the. The Princeton Election Consortium’s final electoral college predictions for November 2012. Data are the share of electoral votes that

just in politics but in all aspects of modern life, with the eye of a hobbyist and the sense of fun. From the world of blog culture, the book is a plea for non-experts, non-elite.

Readers wanting a deeper explanation of Bayes’s rule might consult another source such as Bayes’ Rule: A Brief Introduction to Bayesian Analysis and Decision Making.

This Bayesian approach can be extended to other fields such as medicine, finance, and weather forecasting. In these fields, Bayesian methods are often used to update predictions as new data becomes available.

At times Silver writes as if he were a professional pollster. He has written a book on the subject of polling and statistical analysis, entitled "The Signal and the Noise: Why So Many Predictions Fail and What We Can Do About It.

The Signal and the Noise: Why So Many Predictions Fail and What We Can Do About It

By Nate Silver


“A signal is a message that can be detected and measured, whereas noise is anything that obscures or interferes with the detection and measurement of the signal.”

Nate Silver’s book "The Signal and the Noise: Why So Many Predictions Fail and What We Can Do About It” examines the role of statistical analysis in predicting outcomes in various fields, including politics.

Silver argues that the key to making accurate predictions is to understand the limits of human knowledge, and to use statistical methods to quantify uncertainty.

In his book, Silver draws on examples from the 2008 US presidential election, where he correctly predicted Barack Obama’s victory, to illustrate the power of statistical analysis in predicting outcomes.

Silver’s approach to prediction is Bayesian, which allows for updating predictions as new data becomes available. This is in contrast to frequentist methods, which rely on fixed probabilities and do not update predictions in light of new evidence.

Silver’s book is a valuable resource for anyone interested in understanding the role of statistical analysis in predicting outcomes in various fields. It is a must-read for anyone interested in improving their predictive abilities.
Mr. Bayes Goes to Washington

Sam Wang and Benjamin C. Campbell

One day before the 2012 U.S. presidential election, the election forecaster Nate Silver proposed a Bayesian model to the Washington Post. He noted that the model could be used to predict election outcomes by analyzing public opinion polls. The model was based on a Bayesian approach to statistical inference, which allows for the incorporation of prior knowledge and uncertainty. Silver's model was widely praised for its accuracy in predicting the outcome of the election.

Silver's model was not the first to use Bayesian inference in election forecasting. However, it was the first to achieve widespread recognition and success. The model was based on a series of assumptions about the behavior of voters and the dynamics of the election. These assumptions were encoded in the model as prior distributions, which were then updated based on the data from public opinion polls.

The key advantage of the Bayesian approach is its ability to incorporate prior knowledge and uncertainty into the analysis. This is particularly important in election forecasting, where there is a great deal of uncertainty about how voters will behave. The Bayesian model allows for the incorporation of this uncertainty into the analysis, which makes it a powerful tool for election forecasting.

Silver's model was not without its critics. Some argued that the model was too complex and that it was not transparent. However, the model's success in predicting the outcome of the election has led to widespread enthusiasm for the use of Bayesian inference in election forecasting.

In conclusion, the use of Bayesian inference in election forecasting has been a major success. It has demonstrated the power of Bayesian inference in the context of election forecasting and has led to a new generation of models that are more sophisticated and accurate than previous models.

Mr. Bayes Goes to Washington

Glamor — Mr. Bayes

Book review — by Wang & Campbell

Nate Silver's The Signal and the Noise: Why So Many Predictions Fail...But Some Don't...The Art and Science of Prediction

2012 US Pres. election: highly successful

Agrgregation of polls!...beat pundits!

but there's more...

Bayesian reasoning

- Modeling

- Fisher's prior

- Fox & Hedgehog

Science 2013 Feb 15

Washington DC
Mr. Bayes Goes to Washington

Sam Wang and Benjamin C. Campbell

One day before the 2012 U.S. presidential election, former Ron Paul campaign writer Peggy Noe wrote that “nobody knows anything” about who would win. asserting that Republican candidate Mitt Romney’s supporters had the greater passion and enthusiasm (1). From a similar date, fact-check.com columnist Greg Forrester predicted a Romney victory until the last minute. The independent nonprofit National Institute on Media and the Public (NIMP)’s poll showed a greater doubt and uncertainty about the outcome of the election. So, it could go either way: anything is possible, but unknown. Was that the case on election day? No, it was not. The New York Times reported that Romney had won the election. The story was written by Thomas L. Friedman, who said that the election was a “long shot.”

One of the reasons why this election was different from previous elections is the use of statistical models to predict the outcome. These models are based on historical data and use mathematical algorithms to predict the most likely outcome. The models take into account factors such as past voting patterns, demographic data, and campaign spending.

The use of statistical models in politics has been increasing in recent years. These models have been used to predict the outcome of elections, the success of political campaigns, and even the policies that will be implemented if a candidate wins.

However, the use of statistical models is not without its critics. Some argue that these models are too complex and that they cannot accurately predict the outcome of an election. Others argue that these models are biased and that they do not take into account all of the factors that could influence the outcome of an election.

In conclusion, statistical models have become an important tool in political science. They allow us to make predictions about the future and to understand the underlying dynamics of political systems. However, it is important to remember that these models are not perfect and that they should be used in conjunction with other sources of information.
Mr. Bayes Goes to Washington
Sam Wang and Benjamin C. Campbell

On day before the 2012 U.S. presidential election, former Reagan speechwriter Peggy Noonan wrote that "nobody knows anything" about who would win, asserting that Republican candidate Mitt Romney's surrogates had the greater passion and enthusiasm. From a similarly data-free vantage point, George Will predicted a Romney victory. Last-minute CNN poll projections, however, predicted an Obama win. In the end, the media were right, and the surrogates were wrong.

The story of the 2012 election is the story of the rise of Bayesian inference in political science. In the past, political scientists have relied on simple models of electoral competition, such as the one proposed by George C. Stein in 1961. This model assumes that voters choose the candidate who is expected to win, and that they update their beliefs about the outcome as new information becomes available. However, this model is too simple to capture the complexity of modern elections.

Instead, political scientists have turned to Bayesian methods to analyze election data. These methods allow them to incorporate prior information about the candidates, such as their past performance, into their predictions. As a result, Bayesian models have been able to accurately predict the outcome of many important elections, including the 2012 presidential race.

Bayesian methods are not just useful in politics, but in all aspects of modern life. For example, they are used to model the spread of infectious diseases, to predict the likelihood of a violent crime occurring in a particular area, and to estimate the effectiveness of different medical treatments. In each of these cases, Bayesian methods allow us to make predictions based on both past data and our prior knowledge of the system being studied.

In this article, we will provide an introduction to Bayesian methods and discuss some of their applications in political science.
Mr. Bayes Goes to Washington

Sam Wang and Benjamin C. Campbell

On the day before the 2012 U.S. presidential election, former Harvard professor Peggy Noonan wrote that “nobody knows anything” about who would win, asserting that Republican candidates Mitt Romney’s negatives had the greater passion and enthusiasm. From a similarly data-averse, column, George Will predicted a Romney victory (MNBC’s Joe Scarborough said “it could go either way anybody that thinks this race is anything but a tight race now should be locked away from typewriters, computers, laptops, and microphones, because they’re justions.”)

In the end, these pairs were the ones whose opinions proved dispensable. They were unable to detect a clear fact based on public opinion polls with collectively excellent track records, President Obama had an advantage of 3 to 4 percentage points for nearly the entire campaign season. However, the overall political context remains successsful but not success by any stretch of the imagination. And so it came to pass that the logicians of statistics expressed total confidence—and were wrong.

Reusing the past has been possible since at least 2004, when one of us was among the first to statistically aggregate polls (1). In 2008, Nate Silver emerged as a poster child for aggregation, armed with a degree in economics, and a love of numbers, and a professional track record in analyzing baseball performance and financial data. He united a widely suspicious presidential election, providing timely, accurate, and informative commentary on his website FiveThirtyEight, which became highly popular and was snapped up by the New York Times (2). His fame rose further in 2012, when he and other aggregators and modellers used crowdsourced analytics (3) to predict election outcomes.

Silver has written The Signal and the Noise: why so many predictions fail... but some don’t: the art and science of prediction. For Silver, Bayesian statistics provide a coherent framework for understanding the world’s uncertainty. He writes:

1 Bayesian reasoning? Bayes 1763

- Bayes had success/failure data on an unknown prob. p. Bin(n,p)
Bayesian reasoning? Bayes 1763

- Bayes had success/failure data on an unknown prob. p

He imagined a roulette wheel or billiard table giving p = 0.1.
Mr. Bayes Goes to Washington

Sam Wang and Benjamin C. Campbell

On the eve of the 2012 U.S. presidential election, former Harvard psychology professor Peggy Noonan wrote that “nobody knows anything” about who would win, asserting that Republican candidate Mitt Romney’s caregivers had the greater passion and enthusiasm (1). From a similarly data-f 하루면, columns George Will predicted a Romney victory (2). MNSBC’s Joe Scarborough said it could go either way—anybody that thinks this race is anything but a strong right should keep away from television, computers, laptops, and newspapers, because they’re liars. (3)

In the end, these predictions were the ones whose opinions proved dispensable. They were unable to detect a plain fact based on public opinion polls with collectively excellent track records, President Obama had an advantage of 2 to 4 percentage points for nearly the entire campaign season. However, the world of political punditry measures success not by accuracy but by readability and viewer appeal. And so it came to pass that legions of ever-present expressed total confidence—and were wrong.

Rearing the possible has been possible since at least 2004, when one of us was first to statistically aggregate polls (4). In 2006, we argued as a postdoc about voting, with a degree in economics, a love of numbers, and a professional track record in analyzing baseball performance and financial data. He unveiled a mostly mysterious presidential race, providing timely, quantitative analysis and occasionally commentary on his web site FiftyThirtyEight, which became highly popular and was snapped up by the New York Times (5). His name resurfaced in 2012, when he and other aggregators and modelers used harnessed analytics (5–7) of 303 state polls. Now Silver has written The Signal and the Noise, a book that addresses predictions not just in politics but in all aspects of modern life, with the eye of a statistician and the sense of an aesthete, the book is a meditation, not a crude view of what prediction, if any is possible, is good forecasting in daily life, tenure activity, and science.

We use predictions to guide our futures actions, from planning weekend outings to taking care of our health, but most people don’t have a clear idea of how scientific predictions are made. This book is for them. Silver introduces some of the concepts behind data modeling, including probability, Bayesian inference and uncertainty. He takes lengthy looks at topics including the evolution of epidemics in the 1990s, chaos theory and the use of Deep Blue.

A reappearance theme is The Signal and the Noise in Bayesian reasoning, an approach that has swept the sciences. Probability had been conventionally interpreted as meaning the likelihood of an event—for instance, how often the trial of two milked cow will add up to seven. Such a “frequentist” point of view has been used in many cases, such as the approach pioneered by Ronald Thomas Bayes in the 18th century, which emphasizes that probability can only be inferred by the rate of hypotheses that preceded the measurement. Although Silver asserts that Bayesian political forecasting has more in common with poker than with hard sciences such as physics and biology, these topics all use the same mathematical toolkits. Large-scale physics and biology collaborations depend on sensitive models to predict the probabilistic decay rates of particles, looking for signals that might represent signals in the noise and hence discoveries. In our field, many neuroscientists have begun to view the brain as a production machine (7). We predict the world by banding together to draw inferences from noisy and incomplete data. To do so, the brain must form a model of its environment—a set of “particles” learned over a lifetime that is used to interpret incoming data. This Bayesian machine continually updates its priors—corresponding to the environment. Through this process, our brains spend many years tuning appropriate priors for the complex tasks that we perform effortlessly. As the brain forms a well-calibrated expectation for how to take into account the Bayesian prior but doesn’t know where it comes from. Readers wanting a deeper explanation of Bayes’ rule might consult another source such as potassium chloride, in which the prior is the subject by using a spam filter learning as an example. Silver’s chosen anecdotes include the classic example of mammogram interpretation—but also how to interpret that unfamiliar underwear that just showed up on your partner’s dresser drawer.

At times Silver writes as if the core bad model is being reduced to “true Bayes.” Such a prescription does not, in fact, justify the historic controversies surrounding interpretations of probability. A beginner might come away from this book believing that an earlier generation of frequentists were simply ignorant. In a cartoonish account, Silver lobs a broadside at a monumental figure in statistics, Ronald A. Fisher, who later in life argued against the idea that smoking causes cancer—and who coined “Bayesian” as a derogatory term. Silver suggests that Fisher’s error is Bayes is an error in the sense that it is, in fact, the real problem is that Fisher was a statistitician. Fisher’s prior beliefs prevented him from accepting epidemiological and biological evidence, an erroneous prior of one there was one. Our biggest criticism of the book is that although statistics and Bayesian inference are powerful ideas, they are not a cure-all. In his enthusiasm for the good Bayesian, Silver has overstated a bit too far in the same Precursory book. Silver uses the old tried-and-true logical analog, saying that those (including himself) use many ideas, whereas hedgewise focuses on one subject only. But here he is a hedgewise with one big idea: statistics.

However, Bayesian reasoning works only if the prior is adapted for the task. According to Silver, many of today’s “half-baked

(1) Bayesian reasoning? Silver 1976

- Bayes had success/failure data on

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15 FEBRUARY 2013 VOL 339 SCIENCE www.sciencemag.org
Mr. Bayes Goes to Washington
Sam Wang and Benjamin C. Campbell

On the eve before the 2012 U.S. presidential election, former presidential candidate Mitt Romney’s campaign manager had a greater passion and conviction (i). From a similarly dated front-runner, Barack Obama’s, campaign manager David Axelrod predicted that Romney would win the November election (ii). It is not surprising that pollsters who work for campaigns, whether they work for Romney or Obama, would be expected to say things that would likely help their candidate win. But even outside of politics, many of us have a strong desire to believe anything we read or hear that supports our views. This phenomenon is known as confirmation bias (iii).

We decided to perform an analysis to study whether pollsters indeed have a confirmation bias when it comes to predicting the outcome of elections. We used data from the National Republican Senatorial Campaign Committee’s predictions for the 2012 Senate races. We then compared these predictions with the actual outcomes of the elections. Our analysis showed that pollsters have a strong tendency to predict outcomes that are consistent with their prior beliefs. This is evidence of confirmation bias in action.

In addition to confirming our suspicions about confirmation bias in political polling, our analysis also revealed some interesting patterns. For example, we found that pollsters are more likely to predict a Democratic victory in states with a large black population. This is consistent with the idea that pollsters have a strong desire to believe that their candidate will win, even if the evidence suggests otherwise.

Our study has important implications for how we interpret political polls. It is clear that we cannot simply take pollsters’ predictions at face value. Instead, we need to be critical of the evidence and consider alternative explanations. This is particularly important in the context of the 2012 election, where political polling played a significant role in shaping public opinion and influencing the outcome of the election.

In conclusion, our analysis provides evidence of confirmation bias in political polling. We urge pollsters and political analysts to be more aware of this phenomenon and to take steps to minimize its impact on the accuracy of their predictions. Only then can we have confidence in the information that we receive from political polls.
Mr. Bayes Goes to Washington

Sam Wang and Benjamin C. Campbell

One day before the 2012 U.S. presidential election, Coloradoystery writer Peggy Noonan wrote that “nobody knows anything” about who would win, asserting that Republican candidates Mitt Romney’s surrogates had greater passion and enthusiasm (1). From a similar date, data from James Carville (2) predicted that President Barack Obama would win the election (3). When the results were revealed, many people were surprised and disappointed. The election was decided by a narrow margin, and many people were left wondering if they had voted for the right candidate.

On election night, many people were relieved to see that their predictions had been correct. However, many others were disappointed with the outcome. Some people felt that the election was decided by a narrow margin, and many people were left wondering if they had voted for the right candidate.

In the end, the results were as expected. The outcome of the election is determined by the voting public, and the results are based on a combination of factors, such as voter turnout, campaign strategies, and political climate. The results of the election are final, and the winner takes office on January 20, 2013. The inauguration ceremony will take place on the same day, and the new president will take the oath of office.

Validation of the evidence. The Princeton Election Consortium’s final electoral college predictions to November 2012. Data sets are used according to their share of electoral votes in just in politics but in all aspects of modern life, with the eye of a spyglass and the sense of fun. From the words limits of big data, the book is a mesmerizing, novel of things, if one, are common to good forecasting in daily life, tenure activity, and science.

We use predictions to guide our future actions, from planning weekend outings to taking care of our health, but most people have no idea how scientific predictions are made. This book is for them. Silver introduces some of the concepts behind data mining, including probability, Bayesian inference, and uncertainty. He takes lengthy looks at topics ranging from predicting the spread of smallpox to the 1998 chaos-driven lightning samples of New York.

A recurring theme in The Signal and the Noise is the Bayesian approach, an approach that has swept the sciences. Probability had been conventionally interpreted as meaning the true likelihood of an event — for instance, how often the total of two rolled dice will add up to seven. Such a “frequentist” point of view has in many cases given way to an approach pioneered by Reverend Thomas Bayes in the 18th century, which emphasizes that probability can be interpreted in terms of the hypotheses that preceded the measurement.

Although Silver asserts that Bayesian political forecasting has more in common with poker than with hard sciences such as physics and biology, these topics all use the same mathematical toolkit. Large-scale physics collaborations depend on sensitive models to predict the probabilistic decay rates of particles, looking for outliers that might represent signals in the noise and hence discoveries. In our field, many nonstatisticians have begun to view the brain as a predictive machine (7). We project the world around us from the sensory data we receive from many and incomplete data. To do so, the brain must form a model of its environment — a set of “prior” learned over a lifetime that is used to interpret incoming data.

This Bayesian machine continually updates these priors correspond to the environment. Through this process, our brains spent many years learning appropriate maps for the complex tasks that we perform effortlessly. The book is a well-written exposition for how to take into account the Bayesian prior but doesn’t show where it comes from. Readers wanting a deeper explanation of Bayes’s rule might consult another source such as The7 Mathematical Thinking (2) which takes the subject by using a small spool filtering as an example. Silver’s chosen anecdotes include the classic example of mammographic interpretation — but also to how to interpret that unlabeled underwear that just showed up in your partner dressers drawer.

At times Silver write all the same for bad models as for “true” Bayes. Such a prescription does not do justice to the historic controversies surrounding interpretations of probability. A beginner might come away from this book believing that an earlier generation of frequentists were simply ignorant. In a cartoonish account, Silver lobs a broadside at a monumental figure in statistics, Ronald A. Fisher, who later in life argued against the idea that smoking causes cancer — a hypothesis rejected by the scientific community. Silver suggests that Fisher’s rejection of Bayes is caused by fun. In fact the plot thickens — the same source as Fisher’s prior beliefs prevented him from accepting epidemiological and biological evidence, an erroneous point of view if there was one.

Our biggest criticisms of this book: although statistics and Bayesian inference are powerful ideas, they are not a cure-all. In his enthusiasm for the method of “true” Bayes, Silver has strayed too far from the true beliefs of the approach. Silver uses the old-life thinking analog, saying that forces (including humans) have many ideas, whereas hedgehog confidence on one subject only. But here he is a hedgehog with a big idea: statistics.

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Mr. Bayes Goes to Washington

Sam Wang and Benjamin C. Campbell

One day before the 2012 U.S. presidential election, former Reagan speechwriter Peggy Noonan wrote that “nobody knows anything” about who would win, asserting that Republican candidates Mitt Romney’s supposed leads had the greater passion and enthusiasm. From a similarly data-free context, columnist George Will predicted a Romney victory (link) MSNBC’s Joe Scarborough said he could go either way anybody that thinks this race is anything but a dogfight right now should keep away from hypertext: computers, laptops, and microphones, because they’re junk. 2

In the end, few pollsters were the ones whose opinions proved dispensable. They were unable to detect a plane fact based on public opinion polls with collectively excellent track records, President Obama had an advantage of 3 to 4 percentage points for nearly the entire campaign season. However, the world of political analysis measures success not by accuracy but by timeliness and viewing—how it came to pass that the majorities of Americans expressed trust in the midterms—and were wrong.

Snr. the polling has had more than just in politics but in all aspects of modern life, with the eye of a hobbyist and a sense of fun. From the word limits of blog essays, the book is a meandering, off-the-cuff view of what people, are an example to good forecasting in daily life, tenure activity, and science. We use predictions to guide our future actions, from planning weekend outings to taking care of our health, but most people have no idea how scientific predictions are made. This book is for them. Silver introduces some of the concepts behind data modeling, including probability, Bayesian inference, and uncertainty. He tackles lengthy looks at topics ranging from the epidemics to the 19th-century challenges of Deep Blue.

A reappearance theme in The Signal and the Noise is Bayesian reasoning, an approach that has swept the sciences. Probability had been conventionally interpreted as assessing the true likelihood of an event—for instance, how often the total of two rolled dice will add up to seven. Such a “frequentist” point of view has in many cases given way to an approach pioneered by Reverend Thomas Bayes in the 18th century, which emphasizes that probability can only be interpreted in terms of the hypotheses that preceded the measurement. Although Silver asserts that Bayesian statistical methods are more useful than with other methods such as physics and biology, these topics all use the same mathematical toolkit. Large-scale physics collaborations depend on sensitive models to predict the probabilistic decay rates of particular, looking for outliers that might represent signals in the noise and hence discoveries. In their field, many neuroscientists have learned to view the brain as a prediction machine. 3 We perceive the world around us by making inferences from noisy and incomplete data. To do so, the brain must form a model of its environment—a set of “ Prior” learned over a lifetime that is used to interpret incoming data. This Bayesian machine continually updates its process to correspond to its environment. Through this process, our brains spend many years learning appropriate priors for the complex tasks that we perform effortlessly. Silver gives a well-known equation for how to take into account the Bayesian prior but doesn’t show where it comes from. Readers wanting a deeper explanation of Bayes’ rule might consult another source such as Robison Explained (6), which teaches the subject by using e-mail spam filtering as an example. Silver’s chosen anecdotes include the classic example of mammogram interpretation—but also how to interpret that unfamiliar underwire that just showed up in your partner’s dresser drawer.

At times Silver writes all the care for bad conclusions can be reduced to “moral Bayes.” Such a prescription does not do justice to the historic controversies surrounding interpretations of probability. A beginner might come away from this book believing that an earlier generation of frequentists were simply ignorant. In a cartoonish account, Silver hobbits the Bayesian in a monumental figure in statistics, Ronald A. Fisher, who later in life argued against the idea that smoking causes cancer—and who coined “Bayesian” as a derogatory term. Silver suggests that Fisher’s aversion to Bayes was birthed ent tell; in fact, the real problem was that Fisher was a smoker (8). Fisher’s prior beliefs prevented him from accepting epidemiological and biological evidence, an erroneous belief that, in all fairness, was one.

Our biggest criticism of the book is that although statistics and Bayesian inference are powerful ideas, they are not care-free. All the enthusiasm for the good Reverend Silver has stuffed a fair bite into the same Precutonian beast. Silver uses the old first-guessing analogy, saying that lines (including labeled) are many ideas, whereas Bayesianism focuses on one subject only. But here he has a hodgepodge with one big idea: statistics.

However, Bayesian reasoning works only if the prior is adapted for the task. According to Silver, many of today’s “half-baked...
Mr. Bayes Goes to Washington

Sam Wang and Benjamin C. Campbell

On day before the 2012 U.S. presidential election, for many newspapers, writer Peggy Noonan wrote that “nobody knows anything” about who would win, asserting that Republican candidate Mitt Romney’s campaign had the greater passion and enthusiasm (1). From a similarly dated 10-minute commentary, columnist George Will predicted a Romney victory (2). MSNBC’s Joe Scarborough said “it could go either way.”

In the end, these were the only whose opinions proved dispensable. They were unable to predict a result based on public opinion polls with collectively excellent track records, President Obama had an advantage of 3 to 4 percentage points for nearly the entire campaign season. However, the world of political punditry measures success not by accuracy but by timeliness and viewership. And so it came to pass that a legion of commentators expressed total confidence—and were wrong.

Relying on the past has proved possible since at least 2004, when one of us was among the first to statistically aggregate polls (3). In 2006, Nate Silver emerged as a poster child for aggregation, armed with a degree in economics, a love of numbers, and a professional track record in analyzing baseball performance and financial data. He unseated a mostly smugger presidential contingent, providing timely, quantifiable analysis and a fresh commentary on the web sites FiveThirtyEight, which became highly popular and was snapped up by the New York Times (4). His fame rose further in 2012, when his and other aggregations and models used haphazard analysis (5–9) to score knowledge.

Mr. Bayes Goes to Washington

Sam Wang and Benjamin C. Campbell

On day before the 2012 U.S. presidential election, for many, including New York Times political columnist Peggy Noonan wrote that “nobody knows anything” about who would win, asserting that Republican candidate Mitt Romney’s surrogates had the greater passion and enthusiasm (1). From a similarly data-averse corner, W.B. Wofford, also writing on a presidential election (2), noted that “Mitt’s Red Neck” did not “come up to any old street.”

In the end, these predictions were the ones whose opinions proved dispensable. They were unable to detect a clear trend based on public opinion polls with collectively excellent track records, President Obama had an advantage of 3 to 4 percentage points for nearly the entire campaign season. However, the world of political prediction measures success not by accuracy but by leadership and viewer attraction. And so it came to pass that arguments expressed appear to have been won—just as they were before.

One of the most pivotal moments in the 2008 election could be taken as evidence of the 2008 election. This book is an entertaining, non-sensational look at the science behind the predictions. It includes a wide range of topics ranging from the 1996 explosion to the 2017 explosion of Deep Blue.

A reappearance theme in The Signal and the Noise is Bayesian reasoning, an approach that has swept the sciences. Probability had been conventionally interpreted as measuring the likelihood of an event—indeed, how often the total of two red dice will add up to seven. Such a “frequentist” view has in many cases given way to an approach pioneered by Harold Jeffreys in the 19th century, which emphasizes that probability can only be interpreted in terms of the proportion of hypotheses that precede the measurement

Although Silver asserts that Bayesian inferences are based on careful and informed judgments, the predictions of the models are not always so, even within his own political forecasting where he has been at the heart of discussions with policymakers and hard sciences such as physics and biology, those topics all use the same mathematical toolkit. Large-scale physics collaborations depend on sensitive models to predict the probabilistic decay rates of particles, looking for outliers that might represent signals in the noise and hence anomalies. In our field, many second-order effects have been to view the brain as a prediction machine. (3) We predict the world by making predictions, a process that has been called “looking up” to see what is in the future. To do so, the brain must form a model of the environment—a set of “jumps” learned over a lifetime that is used to interpret incoming data. This Bayesian machine continually updates its beliefs as new information is introduced. Throughout this process, our brains spend many years learning appropriate priors for the complex tasks that we perform effortlessly.

Silver gives a well-known equation for how to take into account the Bayesian prior: p(x) = p(y|x)p(y)dy. This equation is how the prior is used to compute the posterior probability of a hypothesis. A more general version of this equation is often referred to as “Bayes’ rule.”

Silver writes at the end of the book, with the public in mind, that the book is intended for the general reader. It is written in a clear, non-technical style, and is accessible to anyone with a basic understanding of probability and statistics. The book is a valuable resource for anyone interested in the science of prediction and decision making.
Mr. Bayes Goes to Washington
Sean Wanga and Benjamin C. Campbell

One day before the 2012 U.S. presidential election, for the 20th time, do-gooder Peggy Noonan wrote that "nobody knows anything" about who would win, asserting that Republican candidate Mitt Romney's supporters had greater passion and enthusiasm (1). From a similarly data-flourishing vantage point, would you predict a Romney victory (2)? The National Election Pool -- the U.S. cable and radio networks, plus CNN, the Associated Press, and Fox News -- predicted that Obama would win. If Obama won, did you, like Noonan, underestimate his voters' passion for him? (1)

In the end, these punditary ethics were the ones whose opinions proved dispensable. They were unable to defeat a data point based on public opinion polls with collectively excellent track records. President Obama had an advantage of 3 to 4 percentage points for nearly the entire campaign season. However, the world of political punditry's success is not defined by accuracy but by leadership and viewership. And so it came to pass that legions of commentators expressed total confidence — and were wrong. Nothing the pundits have had possible since at least 2004, when one of us was among the first to statistically aggregate polls (1). In 2008, Nate Silver emerged as a poster child for aggregation, armed with a degree in economics, a love of numbers, and a professional track record in analyzing baseball performance and financial data. He unveiled a mostly successful presidential race, providing timely, quantitatively analytic and also very funny commentary on his website FiveThirtyEight, which became both popular and profitable and was snapped up by The New York Times. His name rose further in 2012, when he and his aggregations and models underpinned analyses of many scientific scores.

Now Silver has written The Signal and the Noise: Why So Many Predictions Fail — but Some Don't. The Art and Science of Prediction. Silver’s 2012 book has been a commercial and critical success, and it has continued to influence the way we think about prediction. The book is a thoughtful exploration of the power of statistical analysis, and it is a must-read for anyone interested in understanding the role of data in our decision-making processes.

Silver begins by introducing the concept of the "signal" and the "noise," which are the two main components of any prediction. The signal is the underlying truth or reality that we are trying to predict, while the noise is the random variation that can affect our predictions. Silver argues that the key to making good predictions is to focus on the signal and to minimize the noise.

Silver then goes on to discuss various examples of successful predictions, including the prediction of the 2012 U.S. presidential election, and he explores the role of statistical analysis in making those predictions. He also discusses some of the common pitfalls of prediction, such as overfitting and underfitting, and he offers practical advice on how to avoid these mistakes.

The book is written in a clear and accessible style, and it is well-researched and well-cited. Silver draws on a wide range of examples from different fields, including economics, politics, sports, and science, to illustrate his points. The book is also full of interesting anecdotes and stories, which make it a fun and engaging read.

Overall, The Signal and the Noise is a must-read for anyone interested in understanding the role of data in our decision-making processes. It is a thorough and well-written exploration of the power of statistical analysis, and it is sure to be a classic in the field of data science.
Mr. Bayes Goes to Washington
Sam Wang and Benjamin C. Campbell

One day before the 2012 U.S. presidential election, by making a wager, former Department of Justice Undersecretary Peggy Noonan wrote that “nobody knows anything” about who would win, asserting that Republican candidate Mitt Romney’s supporters had the greater passion and enthusiasm (1). From a similarly Dantean face-removal, it seemed that Barack Obama was still perceived as a president-elect (2). To solidify this conclusion, MSNBC’s Joe Scarborough said: “It would go either way anybody that thinks this race is anything but a young right now—should be kept away from typewriters: computers, laptops, and microphones, because they’re jokers.”

In the end, these predictions were the ones whose opinions proved dispensable. They were unable to detect a fact based on public opinion polls with collectively excellent track records. President Obama had an advantage of 3 to 4 percentage points for nearly the entire campaign season. However, the world of political-punditry measurements success or not by accuracy but by leadership and viewership. And so it came to pass that legions of commentators expressed total confidence—and were wrong.

Having the problem that had been possible since at least 2004, when one of us was among the first to statistically aggregate polls (3), in 2008, Nate Silver aimed to postulate a model as a probabilistic model, with a large number of measurements and professional track record in analyzing baseball performance and financial data. He Unlike the most sophisticated presidential race, providing timely, quantitative analysis and lucid commentary on his website FiveThirtyEight, which became highly popular and was snapped up by the New York Times (4). His focus has been further in 2012, when he and other aggregators and modelers used<hl>harSSelected data and models that addressed predictions</hl>.

The Signal and the Noise: Why So Many Predictions Fail—But Some Don’t
The Art and Science of Prediction
by Nate Silver
Published by Metropolitan Books.
30 East 56th Street, New York, NY 10022
800-832-3374
www.metropolitanbooks.com
ISBN 978-08050-9455-1
Library of Congress Catalog Card Number: 2012947822

Nate Silver has written The Signal and the Noise, a book that addresses predictions not just in politics but in all aspects of modern life, with the eye of a baseballer and the sense of an economist. From the world of baseball, the book is a marvel, a non-eye view of what predictions, if any, are common to good forecasting in daily life, tenure accuracy, and science.

We use predictions to guide our future actions, from planning weekend outings to taking care of our health, but most people have no idea how scientific predictions are made. This book is for them. Silver introduces some of the concepts behind data modeling, including probability, Bayesian inference, and uncertainty. He takes lengthy looks at topics ranging from epidemics to history to the 1996-2000 glass-making triumphs of Deep Blue.

A reappearing theme in The Signal and the Noise is Bayesian reasoning, an approach that has swept the sciences. Probability had been conventionally interpreted as measuring the likelihood of an event—for instance, how often the total of two rolled dice will add up to seven. Such a “frequency” point of view has in many cases given way to an approach pioneered by Reverend Thomas Bayes in the 18th century, which emphasizes that probability can only be interpreted in terms of the hypotheses that preceded the measurement.

Although Silver asserts that Bayesian Political Forecasting has more in common with poker than with hard sciences such as physics and biology, these topics are at the same mathematical level. Large-scale physics collaborations depend on sensitive models to predict the probabilistic decay rates of particles, looking for outliers that might represent signals in the noise and hence discoveries. In our field, many neuroscientists have begun to view the brain as a production machines (7). We possess the methods to monitor and measure influence of numbers and incomplete data. To do so, the brain must form a model of its environment—a set of priors learned over a lifetime that is used to interpret incoming data. This Bayesian machine continuously updates its model of the environment as new evidence is collected. Through this process, our brains spend many years forming appropriate priors for the complex tasks that we perform effortlessly.

Silver gives a well-known example for how to take into account the Bayesian prior but doesn’t where it comes from. Readers who want a deeper explanation of how prior beliefs can be updated might consult another source such as Rabinovich et al. (8) or the book the subject by using a e-mail as an example, Silver’s chief anecdotes include the classic example of mammograms interpretative— and also how to interpret that unimpartial perspective that just showed up in your partner’s dresser drawer.

At times Silver writes as if the role of good modeling can be reduced to “more Bayes.” Such a prescription does not, in fact, justice to the historic controversies surrounding interpretations of probability. A beggar might come away from this book believing that an earlier generation of forecasting was simply better. In a cartoonish account, Silver boils a dialogue into a. A methodological account of statistics, Ronald A. Fisher, who later in life argued against the idea that smoking causes cancer—and who coined “Bayesian” as a derogatory term. Silver suggests that Fisher’s assertion to Bayesians caused him to, in fact, the trials predict that Fisher was a smoker (9). Fisher’s prior beliefs prevented him from accepting epidemiological and biological evidence, an erroneous prior over if there was one.

Our biggest criticism of the book is that although statistics and Bayesian inference are powerful tools, they are not a cure-all. In his enthusiasm for the good Reverend Silver has suffused a fair bit into the same Procrustean bed. Silver uses the old fault-finding analogy, saying that fish (including banned) use many ideas, whereas hedgehogs focus on one subject only. But here he is a hedgehog with one big idea: statistics.

However, Bayesian reasoning works only if the prior is adapted for the task. According to Silver, many of today’s “half-baked...
Mr. Bayes Goes to Washington
Sam Wang and Benjamin C. Campbell

One day before the 2012 U.S. presidential campaign began, former Massachusetts senator Scott Brown wrote that “Bayesian thinking is a scientific version of the wisdom of the crowd.” While that view is not without its critics, the data being collected suggest that predictive models can provide insights beyond our current understanding.

Bayesian statistics is a branch of statistical inference that allows for the incorporation of prior knowledge and information into the estimation of parameters. The core idea is that we start with an initial belief about the parameter of interest, and then update this belief as new data becomes available. This approach is particularly useful in situations where there is uncertainty about the true value of the parameter, or when the data is sparse or noisy.

In the context of election forecasting, Bayesian models can be used to estimate the probabilities of different outcomes given the current state of the campaign. These models can take into account a wide range of factors, including polling data, social media activity, and other indicators of public sentiment.

One prominent example of a Bayesian election model is the FiveThirtyEight blog, which uses a combination of polling data and historical voting patterns to predict election outcomes. The blog has been highly successful in recent years, with its predictions closely aligned with the actual results of many elections.

Bayesian models have also been applied to other areas, such as ecology, where they can be used to estimate the abundance of rare species or the impact of climate change on biodiversity. In the field of economics, Bayesian models are used to forecast economic indicators and to inform policy decisions.

In summary, Bayesian statistics provides a powerful framework for making predictions and inferences in a wide range of fields. Its ability to incorporate prior knowledge and update beliefs as new data becomes available makes it a valuable tool for decision makers and analysts.

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(2) Modeling?  
- Public - listen to the pundits  
- Silver - aggregate the polls  
- Something quite sensible!  
There is a whole subdiscipline of statistics on just standard “modeling”!

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The Signal and the Noise: Why Most Predictions Fail—But Some Don’t  
The Art and Science of Prediction  
by Nate Silver

Silver's book addresses the limitations of traditional polling methods and argues for the use of Bayesian statistics in election forecasting. He explains how Bayesian models can incorporate prior knowledge and update predictions as new data becomes available, leading to more accurate and robust forecasts.

Silver's approach has been controversial, with some critics arguing that his models are overly complex and difficult to understand. However, many experts agree that Bayesian statistics provides a valuable tool for making predictions and inferences in a wide range of fields.

In summary, Silver's book presents a compelling case for the use of Bayesian statistics in election forecasting and other areas. His approach offers a way to make more accurate predictions by incorporating prior knowledge and updating beliefs as new data becomes available.
Mr. Bayes Goes to Washington

Sam Wang and Benjamin C. Campbell

One day before the 2012 U.S. presidential election, former supporter of Mitt Romney, writer Peggy Noonan wrote that “nobody knows anything” about who would win, asserting that Republican candidate Mitt Romney’s successes had brought “an unprecedented level of cynicism.” From a similarly data-driven perspective, columnist George Will predicted a Romney victory. In the 2012 election, New York Times columnist Joe Nocera said it could go either way, noting that “the only certainty is that the winner will be the one who wins the popular vote.”

The election was closely watched by political analysts, who used polls and other data to predict the outcome. In the end, Obama was re-elected with a narrow victory, and the election results were widely regarded as a victory for the Republican party.

The election also highlighted the role of data and statistics in politics and policy-making. Analysts used polls and other data to make predictions about the outcome of the election. These predictions were based on a variety of factors, including political affiliations, economic conditions, and public opinion. The results of the election were analyzed using statistical methods to determine the winners and losers.

The role of data in politics is not limited to elections. Analysts also use statistical methods to predict other events, such as the spread of diseases, natural disasters, and economic trends. These predictions are often used to inform policy decisions and to allocate resources to areas where they are most needed.

In the end, the election was a reminder of the power of data and statistics in shaping our world. As we continue to collect and analyze data, we will undoubtedly see more examples of how statistics can be used to inform and guide decision-making.
Mr. Bayes Goes to Washington
Sam Wang and Benjamin C. Campbell

On the day before the 2012 U.S. presidential election, the former NASA administrator Peggy Whitson wrote that "nobody knows anything" about what would happen, asserting that Republican candidates Mitt Romney and Paul Ryan's supporters had the greater passion and enthusiasm (2). From a similarly distant vantage point, election expert George W. Bush predicted that Mitt Romney would win. The New York Times's Joe Nocera said it "could go either way — anybody that thinks this race is anything but a strong right now should be challenged away from keyboards, computers, laptops, and microphones, because they're jokers." (3)

In the end, these paeans were the critics' own opinions proved dispensable. They were unable to defeat a plain fact based on public opinion polls with collectively excellent track records, President Obama had an advantage of 3 to 4 percentage points for nearly the entire campaign season. However, outside of the political circles, the election was considered a major electoral upset, but not by accuracy but by leadership and viewpoints. And so it came to pass that logicians of emotions expressed total confidence — and were wrong.

Rearing the horserace has been possible since at least 2004, when one of us was among the first to statistically aggregate polls (4). In 2008, Nate Silver emerged as a postcard for the horserace, armed with a degree in economics, a love of numbers, and a professional track record in analyzing baseball performance and financial data. He unseated a mostly unsuspicious presidential race, providing timely, quantitative analysis and lucid commentary on his website FiveThirtyEight, which became highly popular and was snapped up by the New York Times (5). His fame rose further in 2012, when he and other aggregators and modelers used<href=http://www.blogs.economist.com/daily-wallblog> blogs</href=http://www.blogs.economist.com/daily-wallblog> to model outcomes of the first presidential debate.

Silver's contributions to the field of statistical analysis have been widely acknowledged. He has been awarded several prizes for his work, including the MacArthur Fellowship. He has also been recognized for his contributions to the field of political polling, having been named one of the most influential people in the world by Time magazine.

Silver's book, "The Signal and the Noise," has been widely praised for its clear and accessible explanations of complex statistical concepts. The book is available for download on the New York Times website, and is also available in hardcover and e-book formats.

Silver is a graduate of Harvard University and holds a Ph.D. in statistics from the University of Chicago. He is currently the director of the Center for Political Science and Economics at Princeton University. He is also a co-founder of FiveThirtyEight, a website that provides comprehensive analyses of election outcomes and political trends. Silver is known for his ability to explain complex statistical concepts in a way that is accessible to the general public, and his work has been widely cited in the media and academic circles.

Silver's contributions to the field of statistical analysis have been widely acknowledged. He has been awarded several prizes for his work, including the MacArthur Fellowship. He has also been recognized for his contributions to the field of political polling, having been named one of the most influential people in the world by Time magazine. His book, "The Signal and the Noise," has been widely praised for its clear and accessible explanations of complex statistical concepts. The book is available for download on the New York Times website, and is also available in hardcover and e-book formats.
Mr. Bayes Goes to Washington

Sam Wang and Benjamin C. Campbell

O
day before the 2012 U.S. presidential election, forecasters and polls were unable to agree on the outcome. But the so-called statistical models were mostly wrong, suggesting that the electorate had not yet reached a consensus on the candidates. In this issue, the authors propose a new approach to predicting elections that relies on Bayesian statistics, which allows for updating predictions as new data become available.

Validated by the evidence, the use of Bayesian models in predicting elections has been shown to be more accurate than traditional polling methods. The authors argue that this approach can be applied to other areas, such as medical diagnosis and financial markets, where it can provide more accurate predictions than conventional methods.

But Wang and Campbell fail to mention
Mr. Bayes Goes to Washington
Sam Wang and Benjamin C. Campbell

On the day before the 2012 U.S. presidential election, New York Times writer Peggy Noonan wrote that "nobody knows anything" about who would win, asserting that Republican candidate Mitt Romney's supporters had the greater passion and enthusiasm (1). From a similarly data-free vantage point, columnists George Will predicted a Romney victory (2). On MSNBC's Joe Scarborough said "it could go either way—anybody that thinks this race is anything but a strong right now...It should be hopeless from a statistical standpoint: computers, laptops, and microphones, because they're jokers." (3)

In the end, these predictions were the ones whose opinions proved dispensable. They were unable to depict a plain fact based on public opinion polls with collectively excellent track records, President Obama had an advantage of 3 to 4 percentage points for nearly the entire campaign season. However, the world of politics and probability measures success not by accuracy but by leadership and viewpoint. And so it came to pass that legions of statisticians expressed total confidence—and were wrong.

Earning the possible but not all the word, how do we know that the predictions are true? How do we know that the predictions are false? When you start with a set of data and then use it to make a prediction, you can see how the predictions are made. This book is about the science of predictions. It introduces some of the concepts behind data modeling, including probability, Bayesian inference, and uncertainty. It takes lengthly looks at topics ranging from epidemics in the 19th century, chance games in the 20th century, and the ideas of Blue Bayou. A reappearing theme in The Signal and the Noise is Bayesian reasoning, an approach that has swept the world. "The science of probability had been conventionally neglected as the likelihood of an event—if, for instance, how often the total of two six-sided dice will add up to seven. Such a "frequentist" point of view has in many cases given way to an approach pioneered by Reverend Thomas Bayes in the 18th century, which emphasizes that probability can only be interpreted in terms of the hypotheses that preceded the measurement. Although Silver argues that Bayesian reasoning is the most likely model for elections, he acknowledges that there is no statistically significant evidence.

Mr. Bayes Goes to Washington

By Simplicity and Benjamin C. Campbell

The Signal and the Noise: Why Most Predictions Fail—but Some Don't  / The Art and Science of Prediction
By Nate Silver
EAN 9780143122393
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504

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Mr. Bayes Goes to Washington

Sam Wang and Benjamin C. Campbell

One day before the 2012 U.S. presidential election, former presidential candidate Mitt Romney’s supporters had the greater passion and conviction (1). From a similarly data-informed vantage point, Barack Obama’s supporters assumed that his supporters were more likely to vote (2). In the end, these patterns were the core of their respective campaigns’ appeals, which won over voters who often doubt the evidence of their own eyes (3).

In 2012, probabilistic principles were at the center of political communication, as unconventional media tactics were used to influence the electorate. Public opinion polls suggested that the election would be a close race, with the final results in doubt until the last minute (4). Yet, even as the polls showed a tight race, there were differences in the way that voters perceived the candidates, leading to a polarization of opinions.

Probabilistic principles were also at work in the media coverage of the election, as journalists sought to predict the outcome based on statistical models and polling data (5). The use of probabilistic models in political analysis has become increasingly common, as data scientists and statisticians work to understand the complex dynamics of election outcomes (6).

In conclusion, the 2012 election was a reminder of the power of probabilistic principles in shaping political discourse and decision-making. As we move forward, it is important to continue to explore the ways in which these principles can be applied to help us better understand and predict the behavior of voters.

References:

2. Obama, B. (2012). Supporters assumed that his supporters were more likely to vote. The Washington Post, October 7.

(3) “Fisher’s prior” concerning Smoking & Lung Cancer.

But Wang & Campbell fail to mention — Fisher, consultant, Imperial Tobacco & found no experimental basis.
Mr. Bayes Goes to Washington
Sam Wang* and Benjamin C. Campbell

On the day before the 2012 U.S. presidential election, former Obama campaign...
Mr. Bayes Goes to Washington
Sam Wang* and Benjamin C. Campbell†

One day before the 2012 U.S. presidential election, former statistician and
writer Peggy Noonan wrote that “nobody knows anything” about who
would win, asserting that Republican candidate Mitt Romney’s
upswing had the greater passion and commitment (1). From a similarly
damning viewpoint, “columnist George Will predicted a Romney
election landslide” (2). MSNBC’s Joe Scarborough said “it could go either way,”
pointing to the fact that “both sides thought their candidate had the
greater passion and the greater enthusiasm” (3).

In the end, both parties were the crises of their
own making, with opinions dispersed and votes
scattered. But why did we fail to detect a plain fact,
based on public opinion polls with collectively
excellent track records, President Obama had an
advantage of 3 to 4 percentage points for nearly the entire campaign season? How
ever, the world of political polling measures polling success not by accuracy but by timeliness and
utility. And so it came to pass that legions of armchair pollsters expressed total con
fidence—and were wrong.

Roebling has been more than justified in the last few years, when one of us was
among the first statistically aggregate polls (4). In 2004, New York Times political
analyst Nate Silver predicted a post-9/11 surge for the Democrats, but was right
about winning the electorate by 2.4 percentage points. And he was not alone. The
New York Times had a lead in national and battleground states.

Our new finding is that political polling has been redundant for the
election. The only thing that matters is the speed with which polls can be
conducted, not their accuracy. But what might be interesting is that the
accuracy of polls has been improving over time, to the point where
even appetites for more accuracy have led to
improvements in techniques.

We use predictions to guide us forward. Actions, from
planning weekend outings to taking care of our health, have
taken the place of public opinion polls as the
standard for predicting outcomes. But do we really know
what will happen in the future? And if we do, is there
anything we can do about it?

Roebling and Noonan were right. But they missed
the point. Political polling is not about predicting
the future; it’s about understanding the present.

Our prediction is that the future is not
predictable, and that the past is predictive.

Roebling Effect: A Study of the Effect of Public
Opinion Polling on the Future," Cambridge
University Press.
Most Predictions Fail—but Some Don’t," Hyperion.
"The Roebling Effect: A Study of the Effect of Public
Opinion Polling on the Future," Cambridge
University Press.
Most Predictions Fail—but Some Don’t," Hyperion.
"The Roebling Effect: A Study of the Effect of Public
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Opinion Polling on the Future," Cambridge
University Press.
Most Predictions Fail—but Some Don’t," Hyperion.
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Efron: Bayes Theorem
Bayes' Theorem in the 21st Century

Bradley Efron

The term "controversial theorem" sounds like an oxymoron, but Bayes' theorem has played this part for two and a half centuries. Twice it has seemed scientific suicide, twice it has eluded, and it is currently enjoying another boom. The theorem itself is a building block of statistical reasoning and the first serious triumph of statistical inference, yet it is still treated with suspicion by most statisticians. There are reasons to believe in the staying power of its current popularity, but also some signs of trouble ahead.

There is a simple but genuine example of Bayes' basic idea (see sidebar). (2) A physician is treated with aarium, from symptoms that he was also the parents of two boys.

They sometimes wonder what the probability was that their two boys would be identical rather than fraternal. There are two pieces of relevant evidence. One-third of twins are identical, and on the other hand, identical twins are twice as likely to be twin boys. The Bayes rule correctly concludes that the two boys belong to the identical twins set, and that the probability that boys out, and that the twin being individual is from the fraternal twins set. (The twin is not identical.)

Bayes' theorem is as an algorithm for combining prior experience (two-thirds of twins are identical) with current evidence (the symptom). The problem of New York's Five-Year-old Plane with a risk of catching a virus is a special case of the so-called linear model. The theorem is also important for its application in decision theory and hypothesis testing. However, Bayes' theorem is not as useful for solving practical problems as it is for understanding the underlying principles.
It's not clear what the probability was that their twins would be identical rather than fraternal. There are two pieces of relevant evidence. One-third of twins are identical, on the other hand, identical twins are twice as likely to yield twin boy sex, because they are always same-sex, whereas the likelihood of fraternal twins being same-sex is 50-50. Putting this together, Bayes' rule correctly concludes that the two pieces balance one, and that the odds of the twins being identical are even. (The twins were fraternal.)

Bayes' theorem is thus an algorithm for combining prior experience (one-third of twins are identical) with current evidence (the nonexistence of same-sex twins). The algorithm employed to test the rule in a spectacular form during the 2012 U.S. presidential campaign. The algorithm was updated prior polls results with new data on a daily basis, correctly predicting the actual vote in all 50 states. "Statistical brain: The case against the Bayesian decision-making approach" is a wide-ranging analysis of the theory in the absence of prior evidence, with Pierre-Simon Laplace as a prime example. Suppose that in the twins example we lacked the prior knowledge that one-third of twins are identical. Laplace would have assumed a uniform distribution between zero and one for the unknown prior probability of identical twins, yielding 0.5 rather than 1/3 as the answer to the physicians' question. Extraneous information in the case would have been useless. Laplace would have to assign an "impossible prior" or "objective prior" (3), one having only neutral effects on the output of Bayes' rule (3). Whether or not this

**Bayes' Theorem in the 21st Century**

Bradley Efron

The term "Bayesian theorem" sounds like an oxymoron, but Bayes' theorem has played this part for two and a half centuries. Twice it has acquired scientific celebrity, twice it has crashed, and it is currently enjoying another boom. The theorem itself is a landmark of logical reasoning and the first serious attempt at a formal probability theory, yet it is still treated with suspicion by many statisticians. There are reasons to believe in its staying power of its current popularity, but also some signs of trouble ahead.

There is a simple but genuine example of Bayes' rule in action (see sidebar) (1). A physician consults a hospital with a patient with a tumor, and that same patient's medical history shows that the tumor is cancerous. The physician then asks the patient to undergo a test for cancer. The test is very accurate, but it does not detect the presence of the tumor in all cases. The physician then asks another physician, who is a statistician, for help in interpreting the results of the test. The statistician consults with the physician, and they both agree that the patient is likely to have cancer, because the test result is positive. However, the statistician reminds the physician that the test is not always accurate, and that the patient's medical history is also important. The physician then decides to conduct further tests, and eventually finds that the patient does not have cancer. This example illustrates how Bayes' theorem can be used to combine prior knowledge and new evidence to make more accurate predictions.
Bayes’ 1763 paper was an impeccable exercise in probability theory.

Bayes’ Theorem in the 21st Century

Bayesian Estimation

The term “controversial theorem” sounds like an oxymoron, but Bayes’ theorem has played this role for two and a half centuries. Twice it has failed to rise to scientific celebrity, twice it has been cast aside, and it is currently enjoying another boom. The theorem itself is a landmark of logical reasoning and the clear express triumph of statistical inference, yet it is still treated with suspicion by many, particularly among statisticians. There are reasons to believe in the staying power of its current popularity, but also some signs of trouble ahead.

Here is a simple but generic example of Bayes’ rule in action (see sidebar). Apply this result to the voting problem: Suppose that in a given political election, you are asked to predict the outcome of a presidential election. You have access to polls and other data, and you want to combine this information with your prior beliefs about the election.

Bayes’ theorem allows you to update your beliefs about the election based on new evidence. For example, if you start with a prior belief that the candidate is likely to win, and then you receive new data indicating that the polls are in favor of the other candidate, Bayes’ theorem allows you to update your belief about the election.

Bayes’ theorem is an algorithm for combining prior experience (one-third of the terms are identical) with current evidence (the rest). It represents a significant advance in the field of probabilistic reasoning, and it has been applied in a wide range of areas, from medicine to finance.

In the future, Bayes’ theorem will continue to play an increasingly prominent role in statistical applications, but it remains controversial among statisticians.
Bayes’ 1763 paper was an impeccable exercise in probability theory. But just “conditional probability” means little without a priori knowledge of the probability. The Bayesian framework allows for the incorporation of prior knowledge into the analysis, making it particularly useful in situations where data is scarce or uncertain. This approach is widely used in fields such as machine learning, artificial intelligence, and data analysis. Bayes’ Theorem plays an increasingly prominent role in statistical applications and remains controversial among statisticians.
Bayes’ 1763 paper was an impeccable exercise in probability theory, but...

...just conditional probability has been around for a 100 years

Bayes’ Theorem plays an increasingly prominent role in statistical applications but remains controversial among statisticians.

Bayes’ Theorem sounds like an oxymoron, but Bayes’ theorem has played a pivotal role for two-and-a-half centuries. Twice it has soared to scientific celebrity, twice it has crashed, and it is currently enjoying another boom. The theorem itself is a landmark of logical reasoning and the basis for modern statistical inference, yet it is still treated with suspicion by many statisticians. There are reasons to believe in the staying power of the theorem, but also some signs of trouble ahead.

There is a simple but genuine example of Bayes, taken in action (see sidebar) (1). A typical student’s answer leads one to wonder why they were not taught to be parents of their boys.

In a daily basis, correctly predicting the exact vote in all 50 states. "Statisticians have proven" is the verdict in the press (2).

Bayes’ 1763 paper was an impeccable exercise in probability theory, but just conditional probability has been around for a 100 years. Bayes’ theorem plays an increasingly prominent role in statistical applications but remains controversial among statisticians.
Bayes' Theorem in the 21st Century

Bradley Efron

The term "controversial theorem" sounds like an oxymoron, but Bayes' theorem has played this part for two and a half centuries. Twice it has earned the label of scientific celebrity, twice it has been castigated, and it is currently enjoying another boom. The theorem itself is a landmark of logical reasoning and the two centuries of statistical inference, yet it is still treated with suspicion by most statisticians. There are reasons to believe in the staying power of its current popularity, but also some signs of troubled times.

There is a simple but generic example of Bayes' theorem in action (see sidebar). Appendix C contains a longer example of the same data, which we used to be the parents of our boys.

They wondered what the probability was that their twins would be identical rather than fraternal. There are two pieces of relevant evidence. One-third of twins are identical, whereas on the other hand, identical twins are twice as likely to be identical than non-identical twins. Hence, they are equally likely, since the likelihood of identical twins being non-identical is 30/99. Putting this together, Bayes' rule correctly concludes that the two pieces balance out, and it follows that the twins being identical are even. (The twins were identical.)

Bayes' theorem is thus an algorithm for combining prior experience (one-third of twins are identical) with current evidence (the evidence). Followers of Nate Silver's FiveThirtyEight Web blog got to see the rule in a spectacular form during the 2012 U.S. presidential campaign. The algorithm predicted the right outcome with amazing results. Bayes' theorem plays an increasingly prominent role in statistical applications but remains controversial among statisticians.

Reference and Notes
Bayes’ Theorem in the 21st Century

Bayesian Bacon

The term “controversial theorem” sounds like an oxymoron, but Bayes’ theorem has played this part for two and a half centuries. Twice it has soared to scientific celebrity, twice it has crashed, and it is currently enjoying another boom. The theorem itself is a landmark of logical reasoning and the laws of conditional probability, but its status is sometimes described as controversial. There are reasons to believe in the staying power of its current popularity, but also some signs of trouble.

There is a simple but genuine example of Bayes’ rule in action (see below). Apple’s new iPhone X is a good example of how they were able to predict patterns of their young.

They wondered what the probability was that their twins would be identical rather than fraternal. There are two pieces of relevant evidence. One-third of twins are identical, as are the other hand, identical twins are twice as likely to yield twin boy candidates, because they are always same-sex, whereas the likelihood of fraternal twins being same-sex is 50%. Putting this together, Bayes’ rule correctly concludes that the two pieces balance out, and that the odds of the twins being identical are even. (The twins were fraternal.)

Bayes’ theorem is an algorithm for combining prior experience (one-third of twins are identical) with current evidence (the sex of the parents). The algorithm updates the prior probability with new data on a daily basis, correctly predicting the actual sex in all 50 votes. The statistical results point to the same error in the press (2).

Bayes’ theorem was used in the 17th century to solve the problem of the unreasonable probability of identical twins. It was later used in the 19th century to solve the problem of biological races. Bayes’ theorem is now used in the 21st century to solve the problem of understanding complex systems, such as climate change and disease spread.
Bayes’ Theorem in the 21st Century

Brayan Echt

The term “controversial theorem” sounds like an oxymoron, but Bayes’ theorem has played this part for two and a half centuries. Twice it has reared its scientific head, twice it has crashed, and it is currently enjoying another boom. The theorem itself is a landmark of logical reasoning and has the twin arrows of scientific inference, yet it is still treated with suspicion by many statisticians. There are reasons to believe in the staying power of its current popularity, but also some signs of trouble.

Here is a simple but genuine example of Bayes’ theorem in action (see also [1]) and Appendix C on Bayes in the recent version of The Economist (see also [2]). They wondered what the probability was that their town would be identical to another. They made two pieces of relevant evidence. One-third of these are identical. On the other hand, identical trees are twice as likely to yield twin boy conceptions, because they are always same-sex, whereas the likelihood of fraternal twins being same-sex is 30.95. Putting this together, Bayes’ rule correctly concludes that the two pieces balance out, and that the likelihood of the boy being identical is even (The trial was flipped).

Bayes’ theorem is thus an algorithm for combining prior experience (one-third of twins are identical) with current evidence (the evidence). The output is a probability of 0.49, which is identical to the prior expectation of 0.5. This is a powerful demonstration of the power of Bayes theorem.

Bayes’ theorem in practice. Theorem of probability theory. The theorem is used to calculate the probability of an event based on prior knowledge or evidence. The theorem is expressed as P(A|B) = P(B|A) * P(A) / P(B), where P(A|B) is the probability of A given B, P(B|A) is the probability of B given A, P(A) is the prior probability of A, and P(B) is the prior probability of B.

In the ocean, there are existing times to study the dynamics of phytoplankton as an ecosystem. Some of the algal growths are important to the process of photosynthesis, which is a major source of energy for the ocean ecosystem. Phytoplankton's primary role is to produce oxygen, which is essential for the survival of many marine organisms. Phytoplankton also play a key role in the carbon cycle, as they absorb carbon dioxide from the atmosphere and convert it into organic matter. This organic matter is then consumed by other marine organisms, and the carbon is released back into the atmosphere through the process of respiration. Phytoplankton also play a role in the nitrogen cycle, as they fix nitrogen from the atmosphere and make it available to other organisms.

Additional information from references:

Bayes’ Theorem in the 21st Century

Bravey Evans

The term “controversial theorem” sounds like an oxymoron, but Bayes’ theorem has played this part for two-and-a-half centuries. Twice it has seized scientific celebrity, twice it has crashed, and it is currently enjoying another boom. The theorem itself is a landmark of logical reasoning and the two advanced triumphs of statistical inference, yet it is still treated with suspicion by many statisticians. There are reasons to believe in the staying power of its current popularity, but also some signs of trouble.

There is a simple but genuine example of Bayes’ theorem in action (see subtext). Appendix A lists a few more examples that were due to parents of their boys.

They wondered what the probability would be that their twins would be identical rather than fraternal. There are two pieces of relevant evidence. One-third of twins are identical, on the other hand, identical twins are twice as likely to exhibit two key congruences, because they are always same-sex, whereas the likelihood of fraternal twins being same-sex is 0.50. Putting this together, Bayes’ rule correctly concludes that the two pieces balance out, and the likelihood of the twins being identical are even. (The twins were fraternal.)

Bayes’ theorem is thus an algorithm for combining prior experience (one-third of twins are identical) with current evidence (the overall congruence). Follow-up rates of Nave’s FiftyThirtyWeb blog got to see the rule in a spectacular form during the 2012 U.S. presidential campaign. The algorithm updated poll results with new data on a daily basis, correctly predicting the electoral vote in all 50 states. “Statisticians’ headache points” were added in the press (1). Bayes’ 1763 paper was an unappable exercise in probability theory. The trouble is that subsequent results often lack a systematic application of the theorem; in the absence of genuine prior information, with frequentist treatment Laplace’s is a prima viatica. Suppose that the twin example we lacked the prior knowledge that one-third of twins are identical. Laplace would have assumed an uniform distribution between zero and one for the unknown prior probability of identical twins, yielding 0.23 rather than 0.5 to the physical question. In modern parlance, Laplace would be trying to assign an “uninformative prior” or “objective prior” (2), one having only minimal effects on the output of Bayes’ rule (3). Whether or not this...
Bayes’ Theorem in the 21st Century

Eugene Braverman

The term "controversial theorem" sounds like an oxymoron, but Bayes’ theorem has played this part for too long. It was discovered independently by Tobias Leibniz and Pierre-Simon Laplace in the 18th century, and its usefulness in solving intractable problems is widely acknowledged. However, Bayes’ theorem is today so ubiquitous that it is hard to imagine a field of science that does not use it in some form.

The basics of Bayes’ theorem are simple. If we have two events A and B, where the probability of A is P(A) and the probability of B is P(B), and the conditional probability of A given B is P(A|B), then the theorem states that:

P(B|A) = P(A|B) * P(B) / P(A)

This formula allows us to calculate the probability of A given B, or vice versa, by using the probabilities of the individual events and their conditional probabilities.

Bayesian statistics is a branch of statistics that uses Bayes’ theorem to update the probability estimate for a hypothesis as more evidence or information becomes available. It is used in many fields, including medical diagnosis, signal processing, bioinformatics, machine learning, econometrics, data mining, etc.

In the 21st century, the development of computational power has made Bayesian methods more accessible, and they are now used in a wide range of fields. Bayesian methods are particularly useful when dealing with small data sets, as they allow us to incorporate prior knowledge into the model.

Bayesian statistics is also used in artificial intelligence, where it is used to make predictions and decisions based on uncertain data. It is used in natural language processing, computer vision, and robotics.

Bayes’ theorem is not just a mathematical formula; it is a philosophical tool that helps us understand the world in a new way. It challenges the traditional view of probability, which is often seen as a fixed and objective quantity. Instead, Bayes’ theorem suggests that probability is a subjective measure that can be updated as we gain more information.

In summary, Bayes’ theorem is a powerful tool that has revolutionized many fields of science and technology. Its use is likely to continue to grow as computational power increases and more data becomes available.
Bayes' Theorem in the 21st Century

Bradley Efron

The term “controversial theorem” sounds like an oxymoron, but Bayes’ theorem has played this part for two and a half centuries. Twice it has soared to scientific celebrity, twice it has crashed, and it is currently enjoying another boom. The theorem itself is a landmark of logical reasoning and the two-sources theory of statistical inference, yet it is still treated with suspicion by most statisticians. There are reasons to believe in the staying power of the current popularity, but also some signs of trouble.

Here is a simple and genuine example of Bayes’ theorem in action (see below). Let us suppose that there were four patents by their parents.

They wondered what the probability was that their twins would be identical rather than fraternal. There are two pieces of evidence. One-third of twins are identical, so a priori it is twice as likely to yield twin boys, since they are always same-sex, whereas the likelihood of fraternal twins being same-sex is 20/36. Putting this together, Bayes’ theorem correctly concludes that if the two pieces balance out, and fourths the twins being identical are even. (The twins were fraternal.)

Bayes’ theorem is thus an algorithm for combining prior experience (one-third of twins are identical) with current evidence (the outcomes).

The algorithm updated prior beliefs with new data on a daily basis, correctly predicting the racial vote in all 50 states. "Statasticians hate probab-

...it was the verdict in the press (12).

Bayes’ theorem was an unpleasant experience in probability theory. The trouble was that the algorithm seemed from everyday, intuitive application of the theorem in the absence of genuine prior information, with Pierre-Simon Laplace as a civic virtue. Suppose that in the twins example we lacked the prior knowledge that one-third of twins are identical. Laplace would have assumed an uniform distribution between zero and one for the unknown prior probability of identical twins, yielding 1/3 rather than 2/3 to the prior estimate. In modern parlance, Laplace would be trying to assign an “uninformative prior” or “objective prior” (12), one having only minimal effects in the output of Bayes’ rule (6). Whether or not...
Bayes’ Theorem in the 21st Century

Bretly Honig

The term “controversial theorem” sounds like an oxymoron, but Bayes’ theorem has played this part for 250 and counting. Twice it has vanished, and it is currently enjoying another boost. The theorem itself is a landmark of logical reasoning and the core triumph of statistical inference, yet it is still treated with suspicion by many scientists. There are reasons to believe in the strong power of evidence and Bayes’ theorem, but some signs of trouble as well.

Bayes’ theorem plays in increasingly prominent role in statistical applications but remains controversial among scientists.

Bayes’ theorem says that the probability that two events both occurred is equal to the probability of one event occurring multiplied by the probability of the other event occurring, given that the first event has occurred.

They wondered what the probability was that their work would be identical rather than independent. There are two pieces of relevant evidence. One-third of twins are identical. On the other hand, identical twins are twice as likely to yield two copies as fraternal twins. The former are a model of identical behavior behavior because they are always same-sex, whereas the likelihood of fraternal twins being the same-sex is 50-50. Putting together these two facts, Bayes rule correctly concludes that the two pieces balance out, and the likelihood of the two being identical are even. (The terms were identical.)
Bayes' Theorem in the 21st Century

Bradley Efron

The term “controversial theorem” sounds like an oxymoron, but Bayes’ theorem has played this part for both good and ill. Twice it has soared to scientific celebrity, twice it has crashed, and it is currently enjoying another boom. The theorem itself is a landmark of logical reasoning and the first serious triumph of statistical inference, yet it is still treated with suspicion by most statisticians. There are reasons to believe that the strong power of its simplicity may attract both popularity and some signs of trouble.

In every simple but genuine example of Bayes’ rule (a misnomer), there was evidence that they were due to be parents of twins: 75

They wondered what the probability would be that their twins would be identical rather than fraternal. What are the pieces of relevant evidence? One-third of twins are identical, on the other hand, identical twins are twice as likely to yield two boyzoozanes because they are always same-sex. Whether the likelihood of fraternal twins being same-sex is .075. Putting this together, Bayes’ rule correctly concludes that the two pieces balance out, and that the likelihood of being identical are even (The twins were fraternal).

Bayes’ theorem is thus an algorithm for combining prior experience (one-third of twins are identical) with current evidence (the evidence is strong). Followers of Nate Silver’s FiveThirtyEight blog got to see the rule in spectacular form during the 2012 U.S. presidential campaign. The algorithm updated their prior poll results with new data on a daily basis, correctly predicting the electoral vote in all 50 states. "Statistical beasts pumice" was the verdict in the press. 77

Bayes’ 1763 paper was an impassioned exercise in probability theory. The problem is a classic one: given the known information, form an optimum application of the theorem in the absence of genuine prior information. With Pierre-Simon Laplace as a prime witness. Suppose that in the twin example we lacked the prior knowledge that one-third of twins are identical. Laplace would have assumed an uniform distribution between zero and one for the unknown prior probability of identical twins, yielding 2/3 rather than 1/2 as the answer to the phycian’s question. In modern parlance, Laplace would have been asked to assign an “uninformative prior” or “objective prior” (78), one having only weak effects on the output of Bayes’ rule (79). Whether or not
Bayesian theorem is playing an increasingly prominent role in statistical applications, but remains controversial among statisticians.

Bayes' theorem provides a way to update the probability of a hypothesis as evidence is accumulated. It is named after Reverend Thomas Bayes, an 18th-century statistician, and is a fundamental result of probability theory. In its most general form, Bayes' theorem states that the posterior probability of a hypothesis (H) given some evidence (E) is proportional to the likelihood of the evidence given the hypothesis (P(E|H)) times the prior probability of the hypothesis (P(H)), divided by the marginal likelihood of the evidence (P(E)).

\[
P(H|E) \propto P(E|H) \times P(H) / P(E)
\]

Bayes' theorem is widely used in various fields, including machine learning, artificial intelligence, and data science, to make predictions and decisions based on available data. It is particularly useful in situations where prior knowledge or beliefs about the hypothesis are available, and new evidence is used to update these beliefs.
Bayes' Theorem in the 21st Century

Bradley Efron

T

he term "controversial theorem" sounds like an oxymoron, but Bayes' Theorem has played this part for two and a half centuries. Twice it has seemed to scientific authority, twice it has foundered, and it is currently enjoying another boom. The theorem itself is a landmark of logical reason and the first serious attempt of statisti- cal inference, yet it is still treated with suspicion by most statisticians. There are reasons to believe, in the thinking power of its current popularity, but also some signs of trouble ahead.

Here is a simple but genuine example of Bayes' theorem in action (see sidebar). In a hospital, 1,000 patients are admitted with symptoms compatible with a disease that has a prevalence rate of 1% and an accuracy of 99.5% for both the test and the disease. The disease is deadly, but the test is not perfect. The test is 100% accurate for the disease but has a 1% false positive rate for healthy people. The test results come back positive. What is the probability that the patient has the disease?

Bayes' theorem provides a way to update our beliefs in the face of new evidence. It is based on the idea that the probability of an event can be updated based on prior knowledge and new evidence. The theorem is expressed as follows:

$$ P(A|B) = \frac{P(B|A)P(A)}{P(B)} $$

where:

- $P(A|B)$ is the posterior probability of $A$ given $B$ (the new probability of $A$ after seeing $B$).
- $P(B|A)$ is the likelihood of $B$ given $A$ (the probability of seeing $B$ if $A$ is true).
- $P(A)$ is the prior probability of $A$ (the probability of $A$ before seeing $B$).
- $P(B)$ is the probability of $B$ independent of $A$ (the base rate or the prior probability of seeing $B$).

In our example, we are trying to find the probability that a patient has the disease ($P(D)$) given that they tested positive ($P(+)D$). We know:

- $P(D) = 0.01$, the prevalence of the disease.
- $P(+)D = 0.995$, the probability of testing positive given that the patient has the disease.
- $P(-)\neg D = 0.005$, the probability of testing negative given that the patient does not have the disease.
- $P(+)\neg D = 0.01$, the probability of testing positive given that the patient does not have the disease.

We can calculate $P(D|+) = \frac{P(+|D)P(D)}{P(+)}$ where $P(+)$ is the total probability of testing positive:

$$ P(+) = P(+)D + P(+)\neg D = 0.01 \times 0.01 + 0.995 \times 0.995 = 0.01 $$

So, $P(D|+) = \frac{0.995 \times 0.01}{0.01} = 0.995$. The probability that the patient has the disease is very high, but not 100%, because false positives can occur.

Bayes' theorem plays an increasingly prominent role in statistical applications that remain controversial among statisticians.
resistance from the major phytoplankton classes in the ocean—dinoflagellates, diatoms, and cyanobacteria—can also produce extracellular superoxide (8, 9, 10). Moreover, field studies have found elevated superoxide concentrations in areas of high phytoplankton abundance (7, 11). Hence, it is now accepted that phytoplankton are the main source of particulate-associated superoxide in the open ocean, photosynthesis, and surface waters (see the figure).

Birg et al. show that extracellular production of superoxide in open water is a significant source of dissolved and ionized species of superoxide in the ocean. Some of their findings will be important for future studies of the role of superoxide in the ocean. Their study makes a convincing case that superoxide is produced in the ocean and that it is a significant source of dissolved and ionized superoxide in the ocean. The main source of superoxide in the ocean is likely to be the dinoflagellates, diatoms, and cyanobacteria. Their study shows that superoxide is produced in the ocean and that it is a significant source of dissolved and ionized superoxide in the ocean.

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**PERSPECTIVES**

Brad: “No trouble in presence of genuine prior info...”

But...

1744–1817: preeminent mathematician

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**MATHEMATICS**

Bayes’ Theorem in the 21st Century

Bradley Efron

The term “controversial theorem” sounds like an oxymoron, but Bayes’ theorem has played a part in this century for over 200 years. It has been applied in various fields of science, including biology, medicine, and economics. Bayes’ theorem has been used to solve problems related to probability and statistics. It has been applied in various fields of science, including biology, medicine, and economics. Bayes’ theorem has been used to solve problems related to probability and statistics.

Bayes’ theorem plays an increasingly important role in statistical analysis. It remains central among statisticians...

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**REFERENCES AND NOTES**

Bayes' Theorem in the 21st Century

Bradley Efron

The term "controversial theorem" sounds like an oxymoron, but Bayes' theorem has played this part for two and a half centuries. Twice it has caused a scientific scandal, twice it has tantalized, and it is currently exciting another boom. The theorem itself is a landmark of logical reasoning and the first serious triumph of statistical inference, but it is still treated with suspicion by most statisticians. There are reasons to believe in the staying power of its current popularity. But also some signs of trouble ahead.

There is a simple but genuine example of Bayes' theorem in action (see sidebar). A psychotherapy couple I have known, from symptoms that they were able to generate themselves, presented the following problem: They wanted a way to predict the outcome of their therapy, knowing that their symptoms were both real and pathological. They wanted a way to predict the outcome of their therapy, knowing that their symptoms were both real and pathological.

Bayes' theorem plays an increasingly prominent role in statistical applications that remain controversial among statisticians.
Brad: “No trouble in presence of genuine prior info but...”

They sometimes want to know the probability that their twins would be identical rather than fraternal. There are two pieces of relevant evidence. One is that of the identical twins; on the other hand, identical twins are as likely to yield to any ongoing, because they are always same-sexed, whereas the likelihood of fraternal twins being same-sexed is 0.50. Putting this together, Bayes’ rule correctly concludes that the two pieces balance out, and that the odds of the twins being identical are 2:1 (the twins were fraternal).

Bayes’ theorem plays an increasingly prominent role in statistical applications of data sets and is often used in machine learning.

### Bayes’ Theorem in the 21st Century

Bradley Efron

The term “controversial theorem” sounds like an oxymoron, but Bayes’ theorem has played a part in two of the leading statistical controversies of our time. On the one hand, it is the source of a long-standing debate about the interpretation of the posterior distribution, which is often called “Bayesian.” On the other hand, it is the basis for a new and powerful approach to model selection and model averaging, which is often called “Bayesian.”

This approach is based on the idea of using Bayes’ theorem to update the prior distribution of the parameters of a model based on the observed data. The prior distribution is a probability distribution that represents our beliefs about the parameters of a model before we see the data. The posterior distribution is the probability distribution that represents our beliefs about the parameters of a model after we see the data. Bayes’ theorem provides a way to update our beliefs about the parameters of a model based on the observed data.

Bayes’ theorem is used in a variety of applications, including medicine, economics, and engineering. In medicine, it is used to update the probability of a disease given the results of a diagnostic test. In economics, it is used to update the probability of a financial crisis given the results of an economic indicator. In engineering, it is used to update the probability of a failure given the results of a test.

Bayes’ theorem is also used in machine learning, where it is used to update the weights of a neural network based on the observed data. This is known as online learning, and it is used to update the model as new data becomes available.

Bayes’ theorem is a powerful tool for updating our beliefs about the parameters of a model based on the observed data. It is used in a variety of applications, including medicine, economics, and engineering. It is also used in machine learning, where it is used to update the weights of a neural network based on the observed data.

### References

Bayes' Theorem plays an increasingly prominent role in statistical applications, yet remains controversial among statisticians.
Bayes’ theorem plays an increasingly prominent role in statistical applications as new research continues to support the prevalence of Bayesian methods across various domains, such as decision-making, forecasting, and policy analysis. Bayesian methods allow for the incorporation of prior knowledge and updating of beliefs in light of new evidence. This approach is particularly useful in situations where data is scarce or where there is a need to make decisions under uncertainty. The theorem provides a formal framework for combining prior beliefs with new data to update the probability of hypotheses.

Bayes’ theorem was first introduced by Thomas Bayes in the 18th century, but its application and understanding have evolved significantly over time. In recent years, the theorem has gained renewed interest and has become a cornerstone in statistical inference and machine learning.

Key to the appeal of Bayes’ theorem is its ability to quantify the degree of belief in a hypothesis based on prior knowledge and new evidence. This makes it a powerful tool in fields such as medical diagnostics, where it can help in interpreting test results, and in economics, where it can be used to assess the impact of policy changes. In fields like genetics and personalized medicine, Bayesian methods can help in predicting disease risk and tailoring treatments to individual patients.

The theorem’s versatility and power have been recognized by statisticians and researchers across disciplines. As a result, a growing body of literature and applications has emerged, highlighting the theorem’s role in advancing scientific knowledge and improving decision-making processes.
Bayes' Theorem plays an increasingly prominent role in statistical applications as new methods reveal themselves in various fields, including decision-making, pattern recognition, and machine learning. However, the theorem often faces criticism in practice due to its reliance on subjective prior probabilities. This has led to the development of Bayesian model averaging, a technique that provides a solution to the criticism. Bayesian model averaging combines multiple models and assigns weights to each model based on its fit to the data. This approach allows for a more robust and flexible analysis, leading to more accurate predictions and better decision-making. As a result, Bayesian model averaging is increasingly being used in fields such as economics, finance, and health sciences. The use of Bayes' Theorem and Bayesian model averaging is likely to continue to grow as these methods become more accessible and understandable to practitioners. The future of Bayesian statistics lies in its continued development and application, ensuring that it remains a vital tool in the modern data science toolkit.
Directions? We've seen: "There are serious risks!"
What is being done?

In statistics, there are multiple theories! What gives?
Directions? We've seen: "There are serious risks!"

What is being done?

In statistics there are multiple theories! What gives?

I'll mention:

1) All relevant information
Directions?  We've seen: "There are serious risks!"
What is being done?

In statistics there are multiple theories! What gives?

I'll mention:

1) All relevant information
2) Where theta is in data: Higher order
Directions? We've seen: "There are serious risks!"

What is being done?

In statistics there are multiple theories! What gives?

I'll mention:

1) All relevant information
2) Where theta is the data: Higher order
3) Bootstrap = Higher order
Directions?

We’ve seen: “There are serious risks!”

What is being done?

In statistics there are multiple theories! What gives?

I’ll mention:

1) All relevant information
2) Where theta is the data: Higher order
3) Bootstrap = Higher order
4) Good Bayes $\Rightarrow$ Approx Confidence
1) All relevant information?
1) All relevant information?

Statistical tradition: use a sufficient statistic!
1) All relevant information?

Statistical tradition: use a sufficient statistic!

Trouble: they rarely exist! ... Normality
1) All relevant information?

Statistical tradition: use a sufficient statistic!

Trouble: they rarely exist! ... Normality

But recent theory (regular model) has developed:

- With Interest parameter $\psi(\Theta)$
- Essentially unique dist’n for assessing $\psi$
1) All relevant information?

Statistical tradition: use a sufficient statistic!

Trouble: they rarely exist! ... Normality

But recent theory (regular model) has developed:

- With interest parameter $\psi(\theta)$
- Essentially unique dist’n for assessing $\psi$

\[
\frac{e^{n/2}}{(2\pi)^{d/2}} \exp\left\{ -\frac{r^2(y;\theta)}{2} \right\} \left| \hat{f}(\theta) \right|^{-1/2} \left| \hat{\kappa}(\theta) \right|^{1/2}.
\]
1) All relevant information?

Statistical tradition: use a sufficient statistic!

Trouble: they rarely exist! ... Normality

But recent theory (regular model) has developed:

- With interest parameter \( \psi(\theta) \)
- Essentially unique dist'n for assessing \( \psi \)

\[
\frac{e^{\frac{n}{2}}}{(2\pi)^{d/2}} \exp\left\{ -\frac{r^2(\psi; \theta)}{2} \right\} \left| \hat{f}(\theta) \right|^{-\frac{d}{2}} \left| \hat{\phi}(\theta) \right|^{\frac{1}{2}} \]

- Simple ingredients: immediate
- Here? Just to indicate it is real!
2) Where theta is no data: Higher order
2) Where theta is re data: Higher order

A whole area of statistics --- since 1954

- Uses model continuity!
2) Where theta is we data: Higher order
A whole area of statistics ... since 1954 (SP)
- Uses model continuity!
- Uses all relevant information (previous)
2) \textit{Where \( \theta \) is re data: Higher order}

A whole area of statistics \ldots since 1954 (SP)

- Uses model \textit{continuity}!

- Uses all relevant information (preceeding)

Gives precise statistical position: "data re-\( \theta \)"

- \( p = \Phi(r^*) \)

- Availability!
3) Bootstrap = Higher order
3) Bootstrap = Higher order

Statistics has multiple theories:

frequentist; Bayes; Higher order; Bootstrap;..
3) **Bootstrap** = Higher order

Statistics has multiple theories:

- frequentist
- Bayes
- Higher order
- Bootstrap

How can statistics have conflicting theories?
3) **Bootstrap = Higher order**

Statistics has multiple theories:
- Frequentist
- Bayes
- Higher order
- Bootstrap

How can statistics have conflicting theories?

BS: Sample from \( f(y; \theta) \)
3) **Bootstrap = Higher order**

Statistics has multiple theories:
- frequentist
- Bayes
- Higher order
- Bootstrap

How can statistics have conflicting theories?

**BS:** Sample from \( f(y; \theta) \)

**Modify:** " " \( f(y; \theta_k) \)
3) **Bootstrap** = Higher order

Statistics has multiple theories:
- Frequentist
- Bayes
- Higher order
- Bootstrap

How can statistics have conflicting theories?

BS: Sample from $f(y; \hat{\theta})$
Modify: " " $f(y; \hat{\theta}_B)$

$\implies$ **Bootstrap** = Higher order! New!
3) Bootstrap = Higher order

Statistics has multiple theories:
  frequentist; Bayes; Higher order; Bootstrap;

How can statistics have conflicting theories?

BS: Sample from $f(y; \theta)$

Modify: " " $f(y; \theta_x)$

then Bootstrap same as Higher order! New!

but '.09 sec vs. 20 hours
Good Bayes $\Rightarrow$ Approx Confidence
4. Good Bayes $\Rightarrow$ Approx Confidence

Bayes is heavily promoted by pro-Bayesian
4. Good Bayes => Approx Confidence

Bayes is heavily promoted by pro-Bayesians
- use all relevant information ... see (1) above "L"
4. Good Bayes \implies \text{Approx Confidence}

Bayes is heavily promoted by pro-Bayesians:

- use all relevant information \quad \ldots \text{see (1) above}

- use a prior
Good Bayes \implies \text{Approx Confidence}

Bayes is heavily promoted by pro-Bayesians:
- use all relevant information ... see ① above
- use a prior as genuine prior info ... Should have been in model
Bayes is heavily promoted by pro-Bayesians:
- Use all relevant information ... see (1) above
- Use a prior a) genuine prior info ... Should have been in model
  b) Un-informative ... Gives approximate confidence
Bayes is heavily promoted by pro-Bayesians:
- use all relevant information  ... see ① above
- use a prior  a) genuine prior info  ... Should have been in model
  b) uninformative  ... gives approximate confidence
  c) Betting judgment  ... Report separately for user to be cautious
Conclusions
Conclusions

Risks for statistics; responsibility also for statistics
Conclusions

Risks for statistics
Responsibilities... for statistics

Multiple theories: How can a discipline tolerate them?
Physics seeks $b's from taxpayers to resolve such
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But: Bootstrap & frequentist (Higher order) are equivalent
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Bayes? Use genuine prior information — Efron 2013
— then it is just frequentist
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- Laplace type un-informative (developed version)
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Physics seeks $\$6$'s from taxpayers to resolve such

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Bayes? - Use **genuine** prior information  -- Efron 2013
- then it is just frequentist
- Laplace type un-informative (developed version)
- Just approximate confidence

Statistics is **strong**
- but has deep responsibilities
Data can overwhelm statistics?
Clinical trials "can" be replaced by more Data?

3. Vioxx
Statistics overlooked

4. L'águila

5. Replication Needed but neglected

6. Bayes Call conditional prob. by another name

7. Bayes and create a lot of mystery

Directions: All relevant information

Where theta is the data: Higher order

Bootstrap = Higher order .09 sec vs. 20 hours

Good Bayes ⇒ Approx Confidence

Thank you!