Storytelling With Data

Principles of persuasion and brief proposals

Scott Spencer | Columbia University

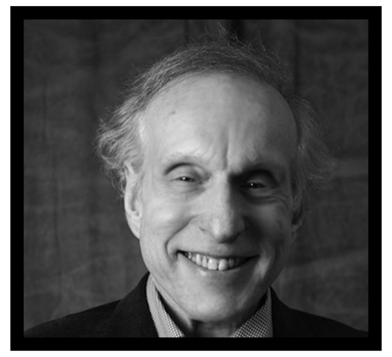
Conceptual project timeline

What is persuasion?

Persuading as teaching, not boxing

~~I'm right, your wrong!~~

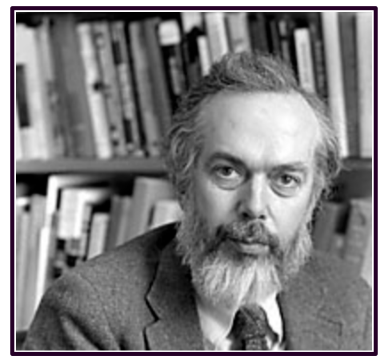
Persuading can be "moving people step by step to a solution, helping them appreciate why the advocated position solves the problem best."



Perloff, Richard

Is persuasion *appropriate* in data science?

The purpose of statistics is to organize a useful argument from quantitative evidence, using a form of principled rhetoric ... that conveys an interesting and credible point.



Abelson, Robert

More than 70% of researchers have tried and failed to reproduce another scientist's experiments, and more than half have failed to reproduce their own experiments.

Baker, Monya

More specifically, we propose to refer to *transparent statistics* as a *philosophy of statistical reporting whose purpose is to advance scientific knowledge rather than to persuade*. Although transparent statistics recognizes that rhetoric plays a major role in scientific writing [1], it dictates that when persuasion is at odds with the dissemination of clear and complete knowledge, the latter should prevail.

[1] Robert P Abelson. 2012. *Statistics as principled argument*. Psychology Press.

Special interest Group on Transparent Statistics Guidelines

Consider this paradox: statistics is the science of uncertainty and variation, but data-based claims in the scientific literature tend to be stated deterministically (e.g. "We have discovered ... the effect of X on Y is ... hypothesis H is rejected").

Is statistical communication about exploration and discovery of the unexpected, or is it about making a persuasive, data-based case to back up an argument?

Gelman, Andrew

The answer to this question is necessarily each at different times, and sometimes both at the same time.

Just as you write in part in order to figure out what you are trying to say, so you do statistics not just to learn from data but also to learn what you can learn from data, and to decide how to gather future data to help resolve key uncertainties.

Traditional advice on statistics and ethics focuses on professional integrity, accountability, and responsibility to collaborators and research subjects.

All these are important, but when considering ethics, statisticians must also wrestle with fundamental dilemmas regarding the analysis and communication of uncertainty and variation.

Gelman, Andrew

How do we change beliefs, enable change?

establish credibility

combine evidence with story, metaphor

find common ground

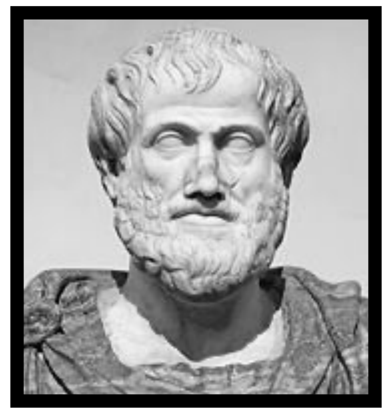
connect emotionally

Conger, Jay

Let’s go back more than 2000 years earlier . . .

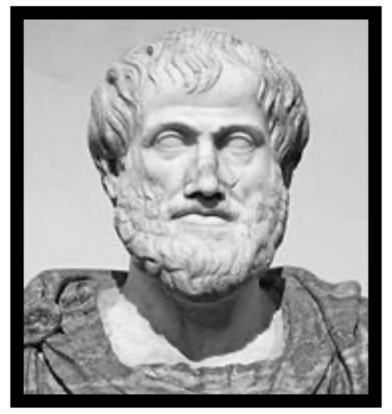
Kairos, pathos, ethos, logos

Consider appropriateness of timing and setting. Can the entity act upon the insights from your data analytics project, for example? What affect may acting at another time or place mean for the audience?



Aristotle

Arguments should be based on building common ground between author and audience. Common ground may emerge from shared emotions, values, beliefs, ideologies, or anything else of substance.



Aristotle

When you provide someone with new data, they

quickly accept evidence that confirms their preconceived notions (what are known as prior beliefs) and

assess counter evidence with a critical eye.

Focusing on what you and your audience have in common, rather than what you disagree about, enables change.

Sharot, Tali

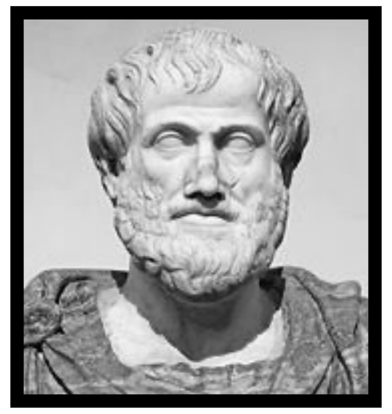
Factors for changing beliefs

old belief • confidence in old belief

new belief • confidence in new belief

Sharot, Tali

Arguments relying on the knowledge, experience, credibility, integrity, or trustworthiness of the speaker — ethos — may emerge from the character of the advocate or from the character of another within the argument, or from the sources used in the argument.

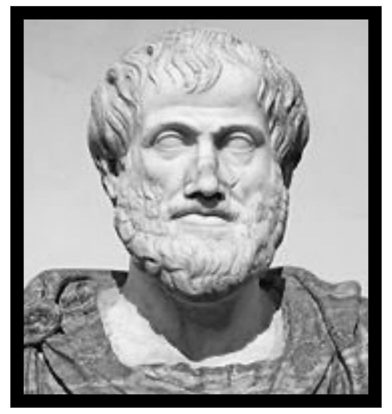


Aristotle

Kairos, pathos, ethos, **logos**

story, analogy, metaphor, syllogism, enthymeme

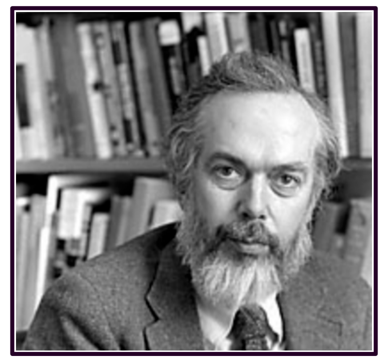
common ground ⟶ solution



Aristotle

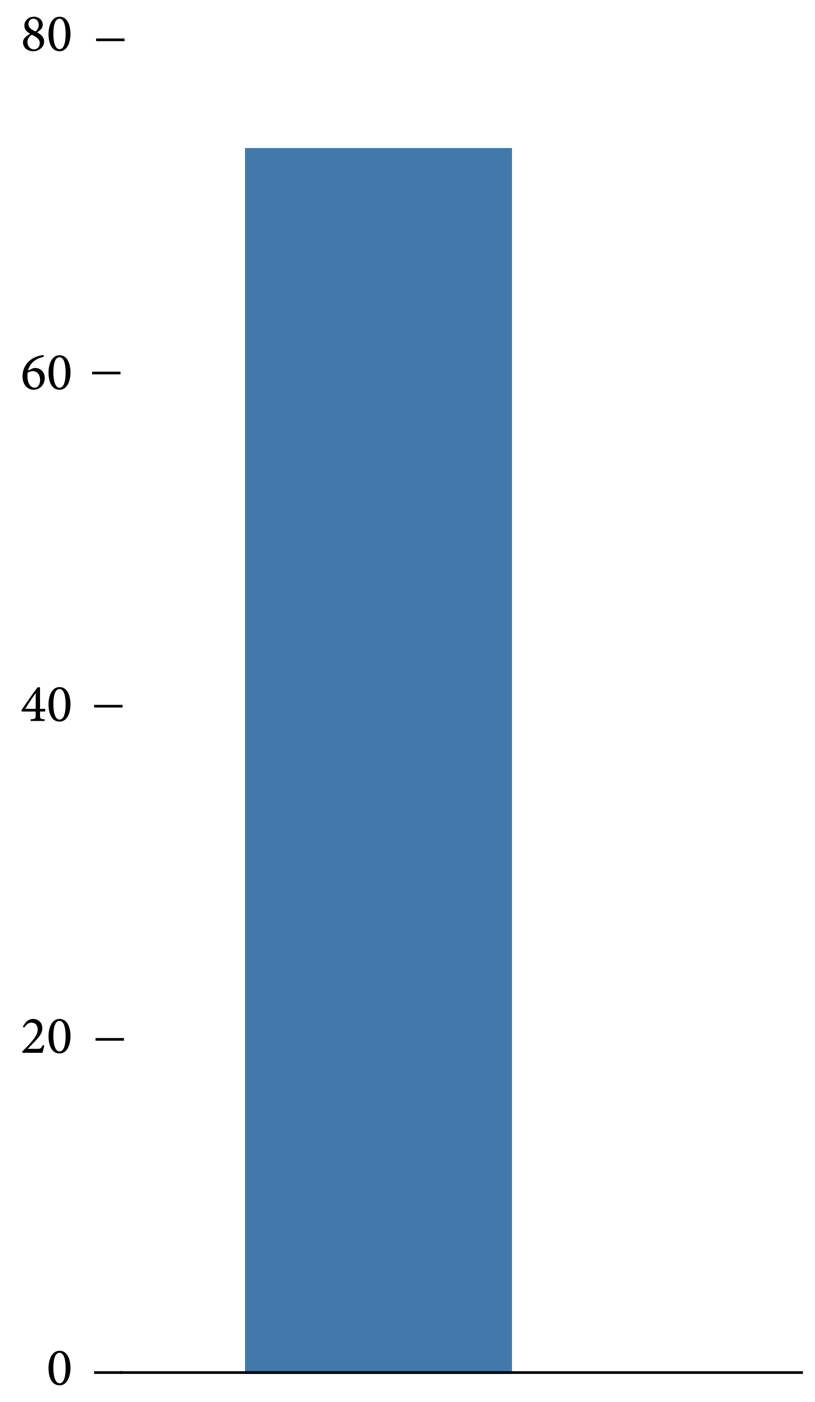
meaning

“The average life expectancy of famous orchestral conductors is 73.4 years.”

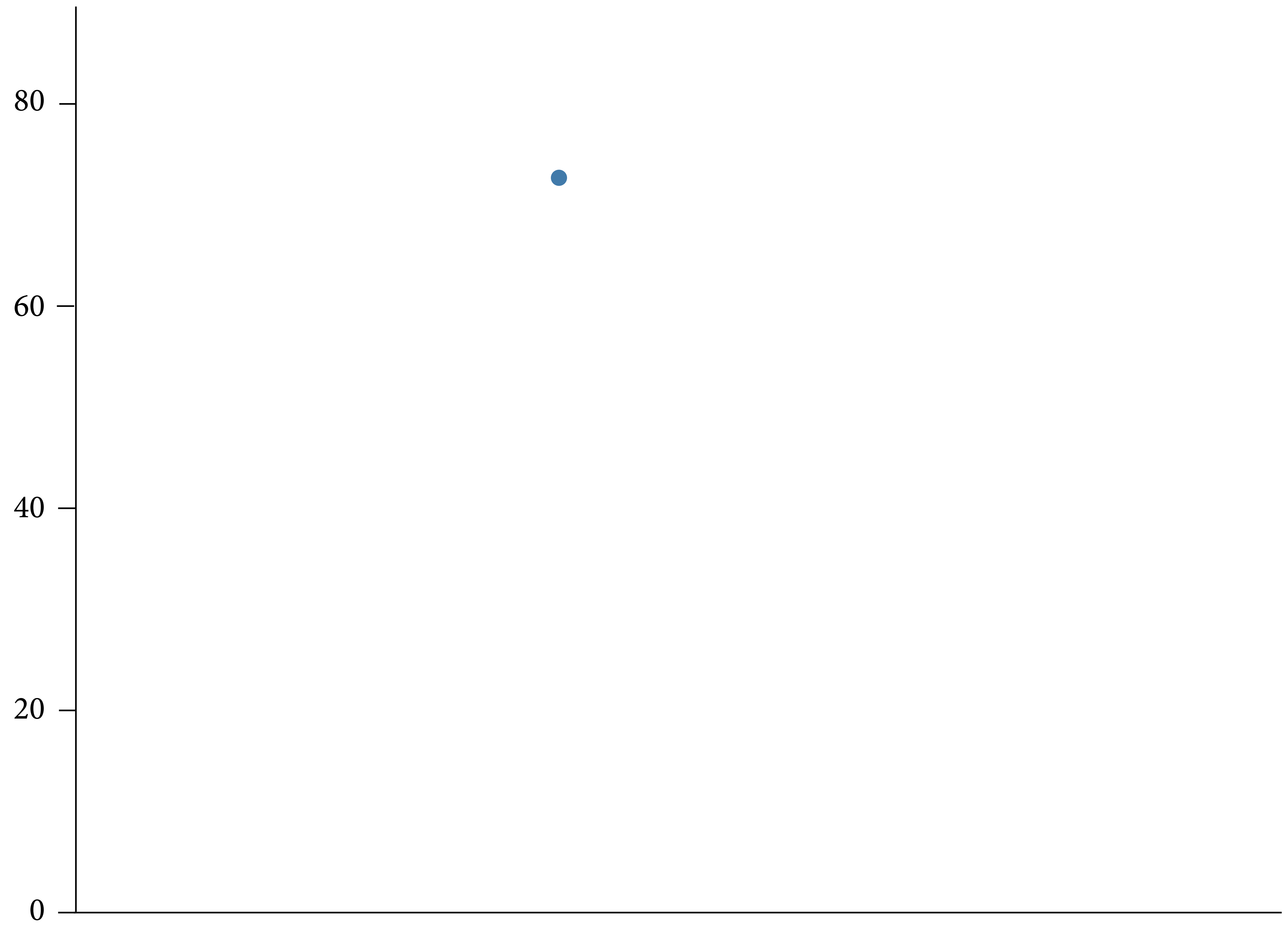


Abelson, Robert

meaning?

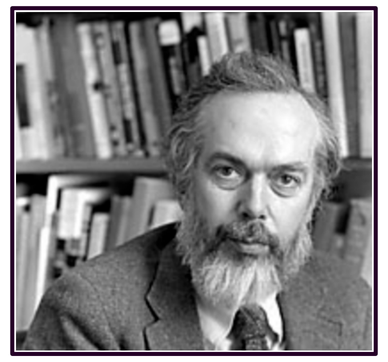


meaning?



Meaning *requires* comparison

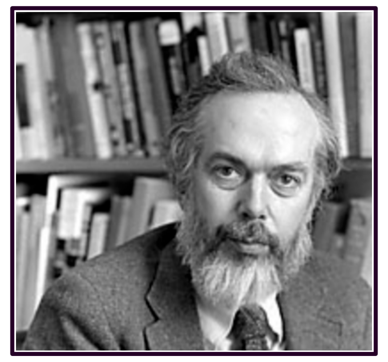
The idea of comparison is crucial. To make a point that is at all meaningful, statistical presentations must refer to differences between observation and expectation, or differences among observations.



Abelson, Robert

Persuading with statistics

Magnitude of effects
Articulation of results
Generality of effects
Interestingness of argument
Credibility of argument



Abelson, Robert

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Magnitude of effects

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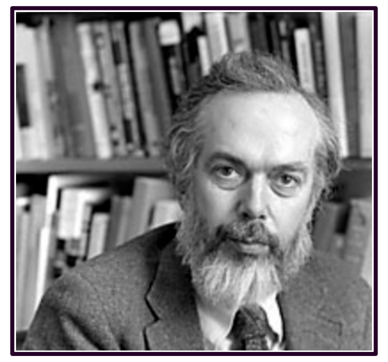
The strength of a statistical argument is enhanced in accord with the quantitative magnitude of support for its qualitative claim. Consider describing effect sizes like the difference between means, not dichotomous tests.



Abelson, Robert

```r
set.seed(9)
y   <- rnorm(n = 1000, mean = 1, sd = 1)
x   <- rnorm(n = 1000, mean = 0, sd = 1)
fit <- lm(y ~ x)
```

```
Call:
lm(formula = y ~ x)

Residuals:
     Min       1Q   Median       3Q      Max
-3.10551 -0.65170  0.02839  0.64702  2.74517

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.00517    0.03031  33.159   <2e-16 ***
x           -0.06278    0.03059  -2.052   0.0404 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9585 on 998 degrees of freedom
Multiple R-squared:  0.004202,  Adjusted R-squared:  0.003204
F-statistic: 4.211 on 1 and 998 DF,  p-value: 0.04041
```

$$P(H \mid D) = \frac{P(D \mid H)\,P(H)}{P(D \mid H)P(H) + P(D \mid \neg H)P(\neg H)}$$

A p-value of less than 0.01 | if it were true that there were no systematic difference between the means in the populations from which the samples came, then the probability that the observed means would have been as different as they were, or more different, is less than one in a hundred. This being strong grounds for doubting the viability of the null hypothesis, the null hypothesis is rejected.

But we usually want to know | **Having observed the data, the probability that the null hypothesis is true is less than one in a hundred.**

“The average life expectancy of famous orchestral conductors is 73.4 years.”

standards of comparison

Should we compare with orchestra players?

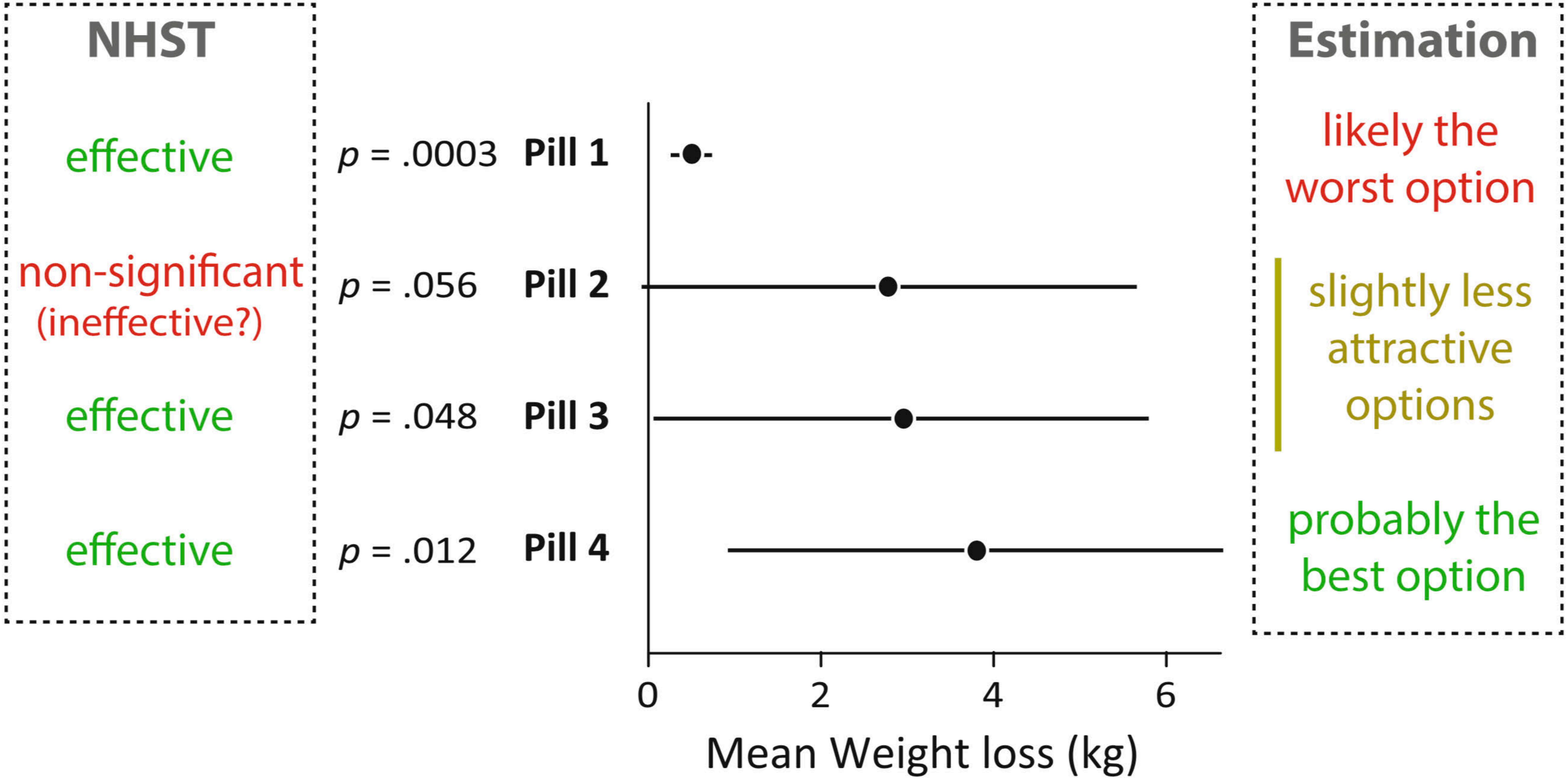
With non-famous conductors?

With the public?

With other males in the United States, whose average life expectancy was 68.5 at the time of the study reported by Abelson?

With other males who have already reached the age of 32, the average age of appointment to a first conducting post, almost all of whom are male? This group’s average life expectancy was 72.0.

Magnitude of effects | difference between means



Dragicevic, Pierre

Languages of numeric comparison | *additive, multiplicative, graphical*

The Apollo program crew had **one more** astronaut than Project Gemini. Apollo's Saturn V rocket had about **seventeen times more** thrust than the Gemini-Titan II.

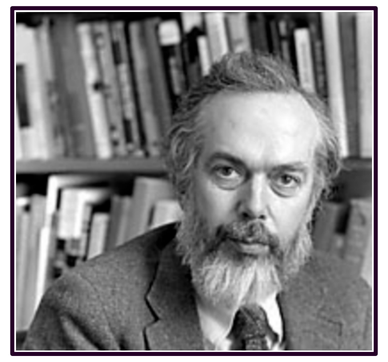
"Seventeen times more"
"1,700 percent more"
"33 versus 1.9"

Andrews, R.J.

Persuading with statistics

Magnitude of effects
Articulation of results →
Generality of effects
Interestingness of argument
Credibility of argument

The degree of comprehensible detail in which conclusions are phrased. This is a form of specificity. We want to honestly describe and frame our results to maximize clarity (minimizing exceptions or limitations to the result) and parsimony (focusing on consistent, connected claims).



Abelson, Robert

Persuading with statistics

Magnitude of effects
Articulation of results
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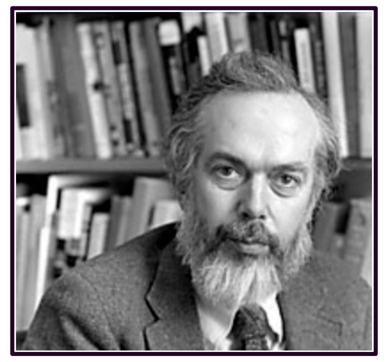
This is the breadth of applicability of the conclusions. Over what context can the results be replicated?



Abelson, Robert

Persuading with statistics

Magnitude of effects
Articulation of results
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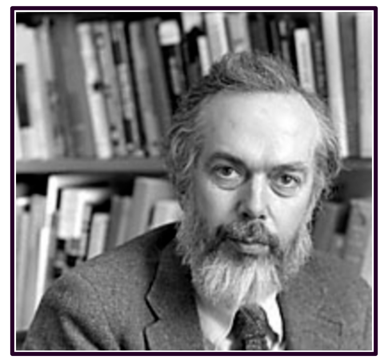
Interestingness of argument →
Credibility of argument

For a statistical story to be theoretically interesting, it must have the potential, through empirical analysis, to change what people believe about an important issue.



Abelson, Robert

Persuading with statistics

Magnitude of effects
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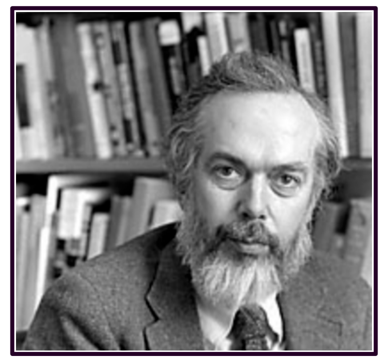
Refers to the believability of a research claim, and requires both methodological soundness and theoretical coherence.



Abelson, Robert

Human body
Animals
Plants
Buildings and constructions
Machines and tools
Games and Sport
Money
Cooking and food
Heat and cold
Light and darkness
Movement and direction

source domain > target domain

The thing you are trying to explain

Ing & collaborators

To bring [Rembrandt] back, we distilled the artistic DNA from his work and used it to create *The Next Rembrandt*. . . . To create new artwork using data from Rembrandt's paintings, we had to maximize the data pool from which to pull information. . . . We created a height map using two different algorithms that found texture patterns of canvas surfaces and layers of paint. That information was transformed into height data, allowing us to mimic the brushstrokes used by Rembrandt.

Ing & collaborators

How do we think about the albums we love? A lonely microphone in a smoky recording studio? A needle's press into hot wax? A rotating can of magnetic tape? A button that clicks before the first note drops? No!

The mechanical ephemera of music's recording, storage, and playback may cue nostalgia, but they are not where the magic lies. The magic is in the music. The magic is in the information that the apparatuses capture, preserve, and make accessible. It is the same with all information.

Andrews, R.J.

When you envision data, do not get stuck in encoding and storage. Instead, try to see the music.

...

Looking at tables of any substantial size is a little like looking at the grooves of a record with a magnifying glass. You can see the data but you will not hear the music.

...

Then, we can see data for what it is, whispers from a past world waiting for its music to be heard again.

Andrews, R.J.

brief proposals

How does the example proposal structure compare with the example memo?

Proposal for exploring game decisions informed by expectations of joint probability distributions

To: Scott Powers, Senior Baseball Analyst, Los Angeles Dodgers
From: Scott Spencer, Faculty and Lecturer, Columbia University

14 February 2019

Our game decisions based on current modeling do not maximize spend per win. We witnessed the mid-market Astros use analytics to overtake us in the 2017 World Series (Luhnow 2018ab). Our efforts also do not maximize expected wins. But we can. To do so, we need to jointly model probabilities of all game events and base decisions on *expectations* of those distributions. With adequate computing emerging, we can be first using the probabilistic programming language Stan and parallel processing. To demonstrate the concept, consider a probability model for decisions to steal second base, below, which suggests teams are too conservative, leaving wins unclaimed. This model allows us to ask, for example—*should Sanchez steal against Sabathia? Or against Pineda?*

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Accurately quantifying probabilities, and changes thereof, in a given context enable us to answer counterfactuals, from which we can build strategies that maximize our objectives (Parmigiani 2002). This approach is possible at scale using Stan (Carpenter et al. 2017). It's time to jointly model probabilities of all events.

2 Modeling probabilities for steal success illustrates a broader benefit

To see the potential of implementing probability models, let's consider, again, the decision to steal bases, given a specific counterfactual:

> In a game against New York Yankees, should Milwaukee Brewers's Lorenzo Cain attempt to steal second base with no one else on base and two outs before the seventh inning, against Gary Sanchez as catcher and Michael Pineda as pitcher? What if against Sanchez and CC Sabathia as pitcher?

More specifically, how can we know the *expectation* that Cain's attempt in each situation increases the probability of expected runs that inning and by how much? Using Stan, I've coded a generative model that along with play outcomes considers various information (runner foot-speed, catcher pop-time) and player characteristics, like pitcher handedness. With the model, we have an answer that also shows the uncertainty. Given 2017 data, this model suggests Cain should steal against Pineda, not Sabathia:

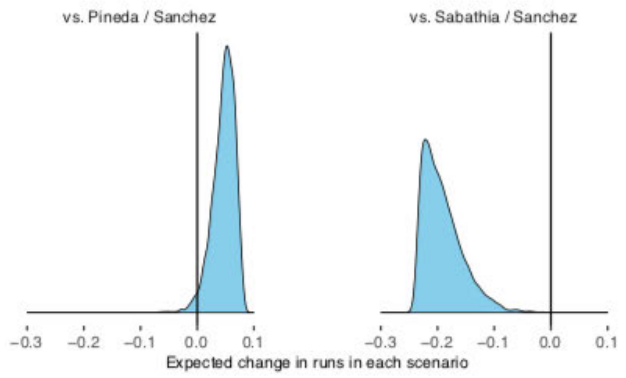

Figure 1. Of the two scenarios, Cain should only attempt to steal against the Sanchez–Pineda duo.

Notably, we get these expectations without multiple trials of either scenario. More generally, this model suggests that on average team managers are too conservative, leaving runs unrealized:

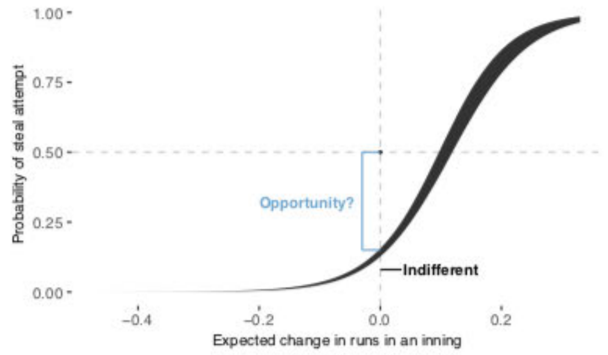

Figure 2. When the change in expected runs is zero, managers should be indifferent to attempted steals, saying go half the time.

The **black band** represents the range of variation across managers' decisions. At the intersection of **indifference**, managers tend to say steal only **10 percent** of the time, leaving opportunity.

The above is but one example of a more general approach that weighs probabilities of all possible outcomes to maximize expected utility. With broad implementation—jointly modeling the conditional probabilities of all relevant events—we can optimize decisions.

3 For value, compare an investment to free-agent costs

A fully-realized model will require significant effort from a team with deep experience in baseball, generative modeling, and Stan. To get the talent, we should compare cost to acquiring expected wins from free-agents. Each win above a *replacement-level* player costs about 10 million per year (Swartz 2017). As with free-agent value over replacement player, game-time decisions informed from more accurate probabilities should add wins over a season. The scope of what we can answer, moreover, goes beyond in-game strategy (player acquisitions, salary arbitration). More immediately, however, we can begin to implement this approach for specific events, with a scope closer to the example above, being mindful that information learnt are conditional upon unmodeled context.

4 For accuracy, compare model results to betting market odds

Measuring performance of a fully-realized model may seem tricky: *we only see the outcome of our decisions.* But we can, say, compare the accuracy of our estimates against the betting market where interested investors are trying to forecast game outcomes.

5 Conclusion

The mid-market Astros show teams can do more with information. Millions in additional revenue—and more wins—await discovery through a joint, probability model of all events from which we can maximize conditional expectations. Let's discuss how to draw the talent for a title worth our spend.

6 References

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Readability Statistics

Counts	
Words	720
Characters	3,997
Paragraphs	16
Sentences	35
Averages	
Sentences per Paragraph	4.3
Words per Sentence	18.1
Characters per Word	5.3
Readability	
Flesch Reading Ease	33.2
Flesch-Kincaid Grade Level	13
Passive Sentences	0%

Messaging—We want **messages first**, not just information. **Details follow**.

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Accurately quantifying probabilities, and changes thereof, in a given context enable us to answer counterfactuals, from which we can build strategies that maximize our objectives (Parmigiani 2002). This approach is possible at scale using Stan (Carpenter et al. 2017). It's time to jointly model probabilities of all events.

2 Modeling probabilities for steal success illustrates a broader benefit

To see the potential of implementing probability models, let's consider, again, the decision to steal bases, given a specific counterfactual:

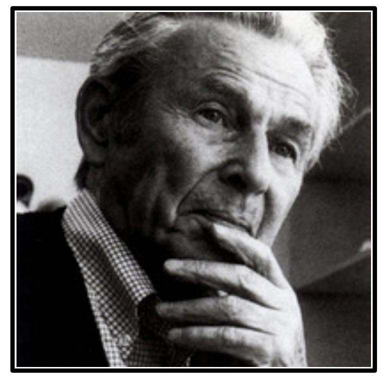
Typography is *for the audience*

Most readers are looking for reasons to stop reading. . . . Readers have other demands on their time. . . . The goal of most professional writing is persuasion, and attention is a prerequisite for persuasion. Good typography can help your reader devote less attention to the mechanics of reading and more attention to your message.

Butterick, Matthew

Layout to improve understanding and credibility

Orderliness adds credibility to the information and induces confidence. Information presented with clear and logically set out titles, subtitles, texts, illustrations and captions will not only be read more quickly and easily but the information will also be better understood.



Müller-Brockmann

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Average line length: 84 characters with spaces
Butterick recommended 45-90

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Leading (line spacing): 145% of font size
Butterick recommended: 120-145% of font size

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Layout to improve understanding and credibility

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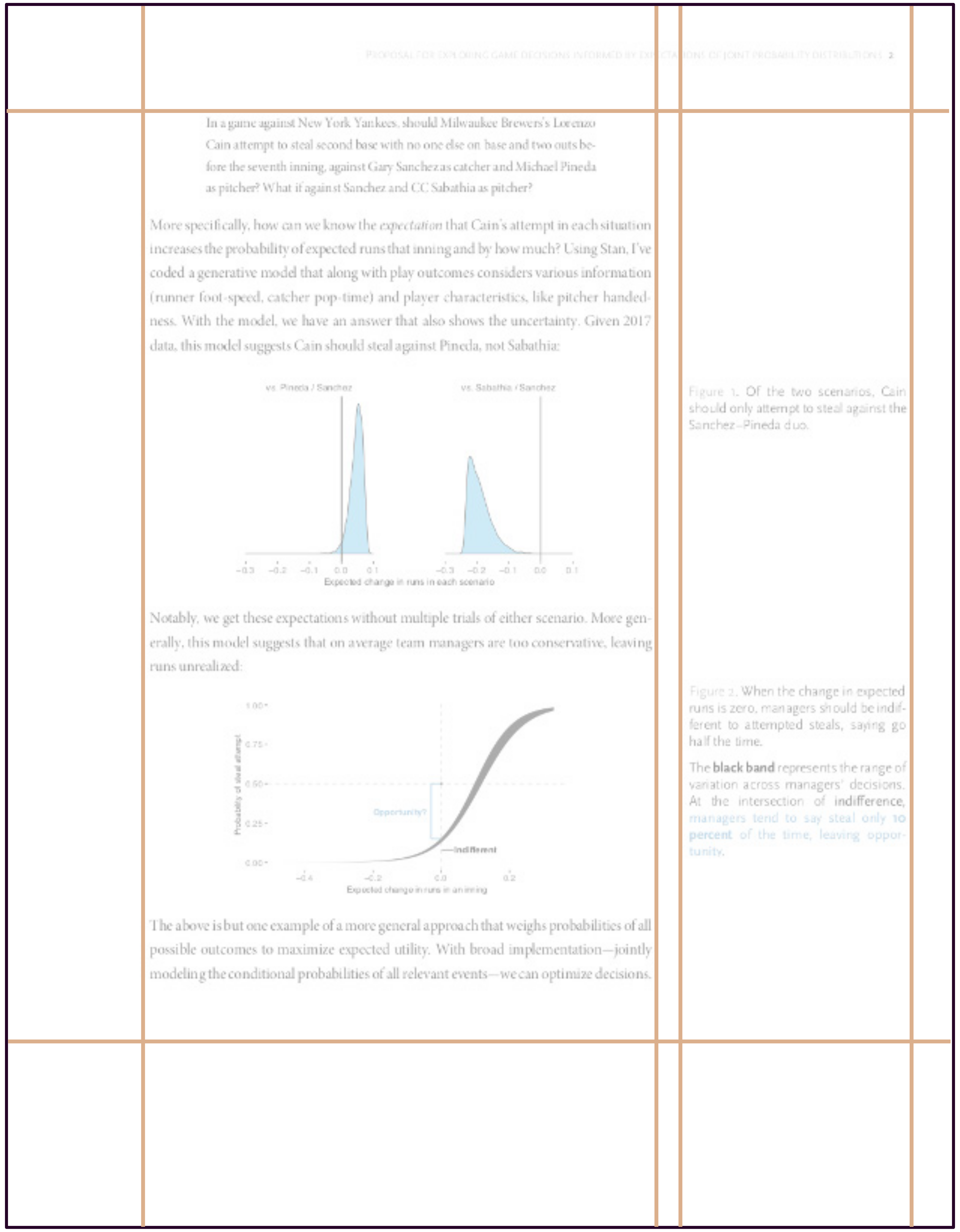
To see the potential of implementing probability models, let's consider, again, the decision to steal bases, given a specific counterfactual:



PROPOSAL FOR EXPLORING GAME DECISIONS INFORMED BY EXPECTATIONS OF JOINT PROBABILITY DISTRIBUTIONS 2

In a game against New York Yankees, should Milwaukee Brewers's Lorenzo Cain attempt to steal second base with no one else on base and two outs before the seventh inning, against Gary Sanchez as catcher and Michael Pineda as pitcher? What if against Sanchez and CC Sabathia as pitcher?

More specifically, how can we know the *expectation* that Cain's attempt in each situation increases the probability of expected runs that inning and by how much? Using Stan, I've coded a generative model that along with play outcomes considers various information (runner foot-speed, catcher pop-time) and player characteristics, like pitcher handedness. With the model, we have an answer that also shows the uncertainty. Given 2017 data, this model suggests Cain should steal against Pineda, not Sabathia:

Figure 1. Of the two scenarios, Cain should only attempt to steal against the Sanchez–Pineda duo.

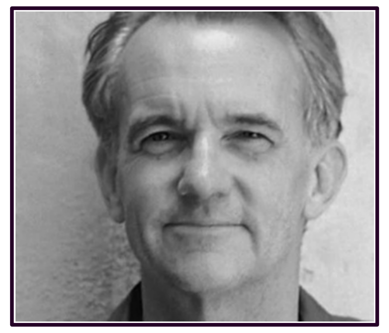
Notably, we get these expectations without multiple trials of either scenario. More generally, this model suggests that on average team managers are too conservative, leaving runs unrealized:

Figure 2. When the change in expected runs is zero, managers should be indifferent to attempted steals, saying go half the time.

The **black band** represents the range of variation across managers' decisions. At the intersection of indifference, managers tend to say steal only 10 percent of the time, leaving opportunity.

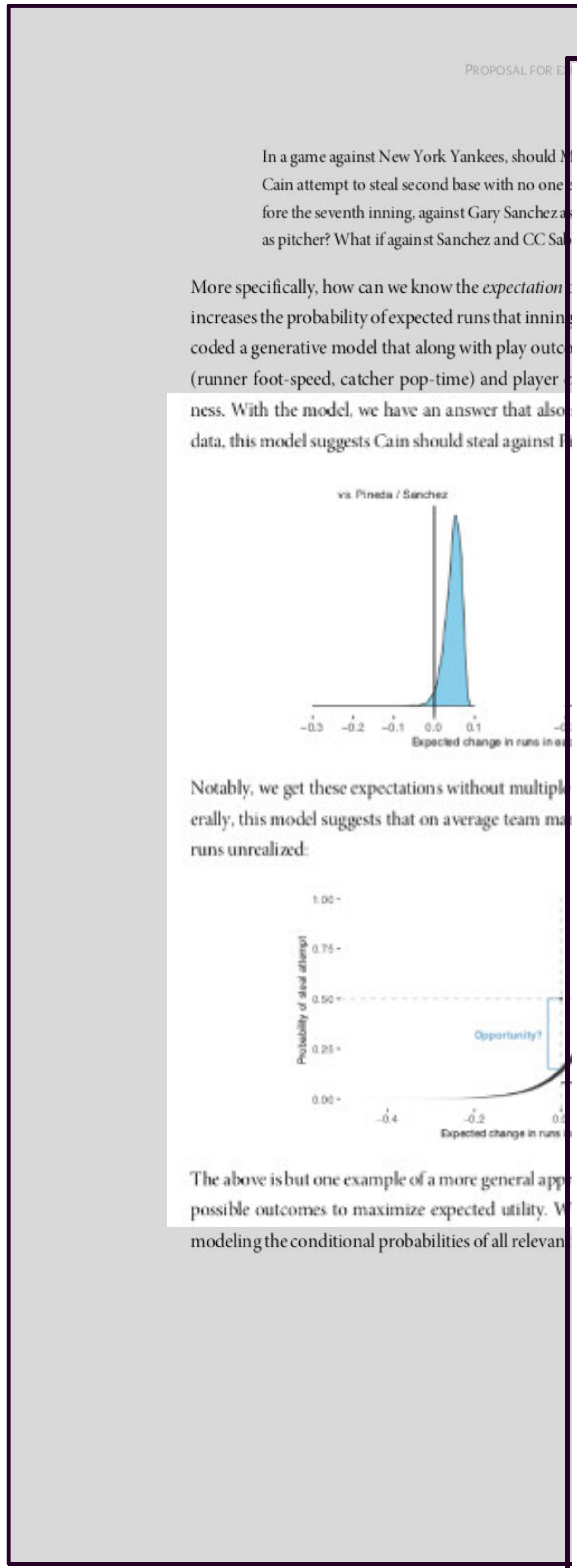
The above is but one example of a more general approach that weighs probabilities of all possible outcomes to maximize expected utility. With broad implementation—jointly modeling the conditional probabilities of all relevant events—we can optimize decisions.

Graphics are paragraphs about data.



Tufte, Edward

Graphics as paragraphs; annotation, *linking* words to data in graphics.



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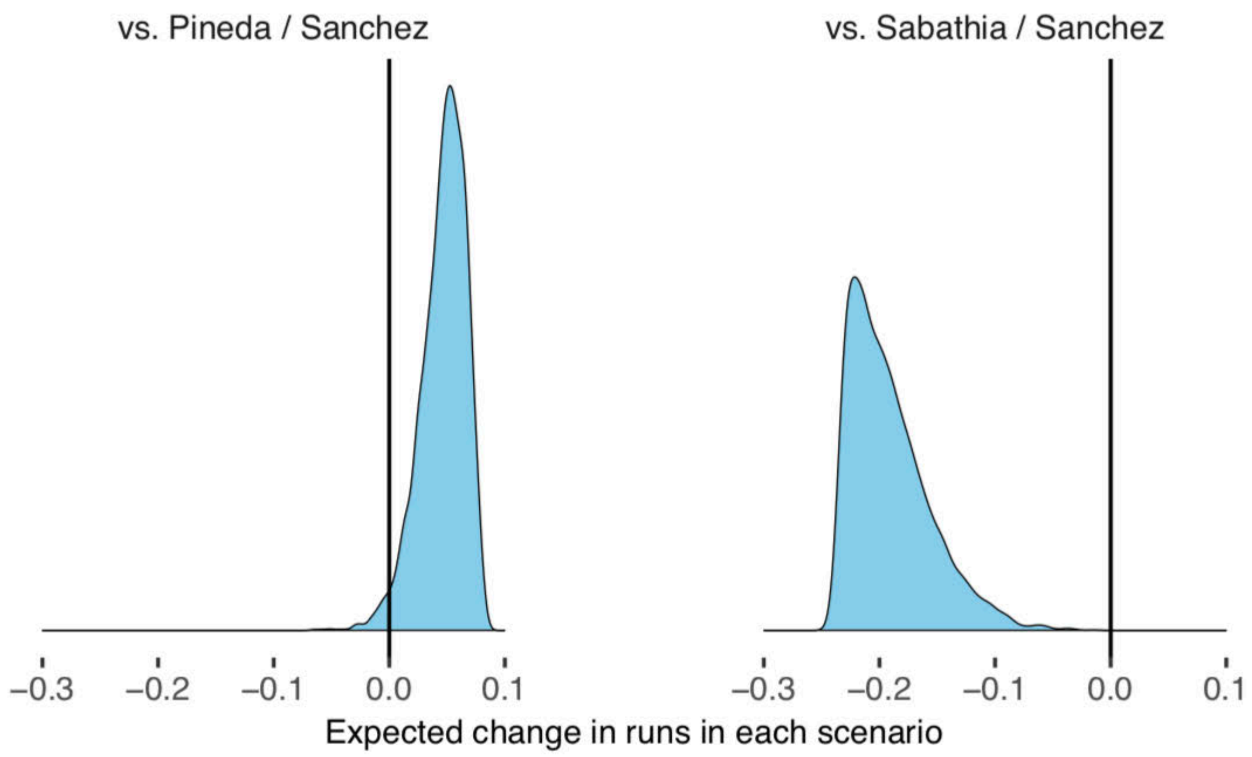

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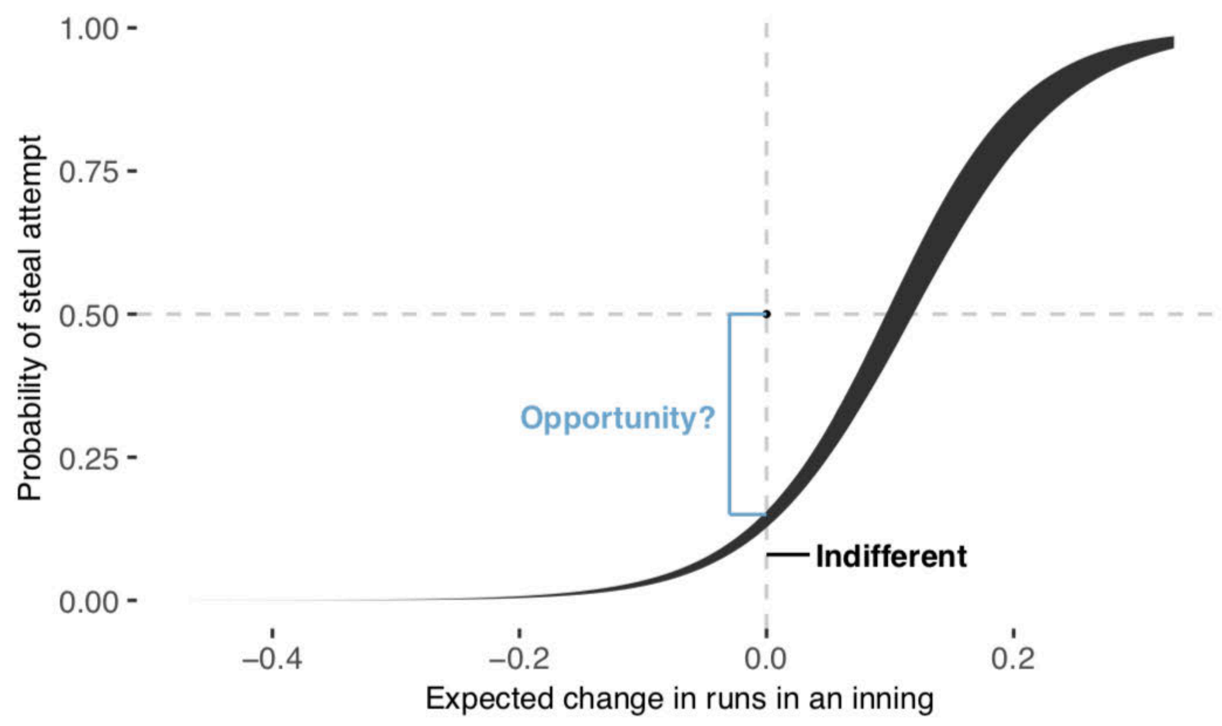

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The above is but one example of a more general approach that weighs probabilities of all possible outcomes to maximize expected utility. With broad implementation—jointly

projects

Exercise: workshopping your proposal

Pair up with a new colleague. Work through your plan to begin analyzing the data you have found. Explain your steps. **Be specific**. The colleague listening should consider the plan from the perspective of the head of analytics, but work together as a colleague. **Formulate questions** about the feasibility of the project and, together, work through a way to address those questions.

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