Storytelling With Data

Principles of persuasion and brief proposals

Scott Spencer | Columbia University

Conceptual project timeline



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What is persuasion?

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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

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Is persuasion appropriate in data science?

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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

Is persuasion *appropriate* in data science?

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?

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The Necessary Art of Persuasion

establish credibility

find common ground



Conger, Jay

combine evidence with story, metaphor

connect emotionally

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

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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



Kairos, pathos, ethos, logos

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

assess counter evidence with a critical eye.



- quickly accept evidence that confirms their preconceived notions (what are known as prior beliefs) and
- Focusing on what you and your audience have in common, rather than what you disagree about, enables change.



Factors for changing beliefs



Sharot, Tali

old belief • confidence in **old** belief

new belief • confidence in **new** belief

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Kairos, pathos, ethos, logos

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 solution

common ground



Aristotle

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meaning



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



Abelson, Robert

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meaning?





meaning?



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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



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



Abelson, Robert





Magnitude of effects -

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



Abelson, Robert

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.



Magnitude of effects dichotomous tests

```
set.seed(9)
y < - rnorm(n = 1000)
x < - rnorm(n = 1000),
fit <- lm(y \sim x)
```

Call: $lm(formula = y \sim x)$ 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



Magnitude of effects dichotomous tests

$\boldsymbol{P}(\boldsymbol{H}|\boldsymbol{D}) = \frac{\boldsymbol{P}(\boldsymbol{D}|\boldsymbol{H})\boldsymbol{P}(\boldsymbol{H})}{\boldsymbol{P}(\boldsymbol{D}|\boldsymbol{H})\boldsymbol{P}(\boldsymbol{H}) + \boldsymbol{P}(\boldsymbol{D}|\boldsymbol{\neg}\boldsymbol{H})\boldsymbol{P}(\boldsymbol{\neg}\boldsymbol{H})}$

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

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

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.

standards of comparison



Magnitude of effects | difference between means

NHST			
effective	p = .0003	Pill 1	-•-
non-significant (ineffective?)	p = .056	Pill 2	
effective	p = .048	Pill 3	
effective	p = .012	Pill 4	



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.





Andrews, R.J.

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

Magnitude of effects Articulation of results -Generality of effects

Interestingness of argument Credibility of argument



Abelson, Robert

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).



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



Abelson, Robert

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



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



Abelson, Robert

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.



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



Abelson, Robert

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



story, analogy, metaphor, syllogism, enthymeme

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

solution

target domain >

The thing you are trying to explain

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Kövecses, Zoltán. Lakoff, George.

story, analogy, metaphor, syllogism, enthymeme

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

solution

story, analogy, metaphor, syllogism, enthymeme

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.

solution

story, analogy, metaphor, syllogism, enthymeme

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.

. . .





Andrews, R.J.

solution

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

brief proposals

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

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

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?

1 Our current analyses do not optimize expected wins

Seven terabytes of uncompressed data generated per game overshadow the lack of situational data needed for decision-making that maximizes expected utility. Consider that pitchers, on average, only face10 percent of major league batters regardless of game state; the reverse is true, too. Or when deciding whether a base runner should attempt to steal against a specific pitcher and catcher in a state of play, say, we are lucky to have any data. Common analyses and heuristics for these situations are inadequate: they not only overfit the data (if any exist), but also offer no manner of estimating changes in probabilities for maximizing *expected* utility (winning the game).

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:



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:



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.

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

PROPOSAL FOR EXPLORING GAME DECISIONS INFORMED BY EXPECTATIONS OF JOINT PROBABILITY DISTRIBUTIONS 3

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

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.

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 Characters
- Paragraphs
- Sentences

Averages

- Sentences per Paragraph Words per Sentence
- Characters per Word

Readability

Flesch Reading Ease Flesch-Kincaid Grade Level **Passive Sentences**



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

PROPOSAL FOR EXPLORING GAME DECISIONS INFORMED BY EXPECTATIONS OF JO

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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

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Seven terabytes of uncompressed data generated per game overshadow the lack of situational data needed for decision-making that maximizes expected utility. Consider that pitchers, on average, only face10 percent of major league batters regardless of game state; the reverse is true, too. Or when deciding whether a base runner should attempt to steal against a specific pitcher and catcher in a state of play, say, we are lucky to have any data. Common analyses and heuristics for these situations are inadequate: they not only overfit the data (if any exist), but also offer no manner of estimating changes in probabilities for maximizing *expected* utility (winning the game).

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



Layout to improve understanding and credibility

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

Average line length: 84 characters wit Butterick recommended 45-90

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

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Leading (line sponsider that Butterick recommendation)		pacing): 145% of font size ended: 120-145% of font size
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t enable us to our objectives r et al. 2017).		
enefit ain, the deci-		



Layout to improve understanding and credibility





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Graphics are paragraphs about data.



Tufte, Edward

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



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

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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



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projects

workshopping your proposal

Exercise: 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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