

# Storytelling with Data

**Module 3: Effective business writing with audience analysis**

**Scott Spencer**  
Faculty and Lecturer  
Columbia University

# Agenda

Upcoming deliverable

Objectives of business writing

Readings

Example 250-word memo

Group work

# Upcoming deliverable

# Upcoming deliverable

For your chosen company and case study,  
as an imagined member of the analytics team ...

## 250-word memo

Write a memo to **CAO** about an opportunity to leverage analytics. Consider background context, problem, data, solution, and impact.

## 750-word proposal

On approval of the memo, write a proposal to **CAO**, detailing the anticipated project.

## Storyboard

Present project result in storyboard to **CMO**, using narrative forms, and with comparisons, metaphors and other storytelling concepts.

## Infographic

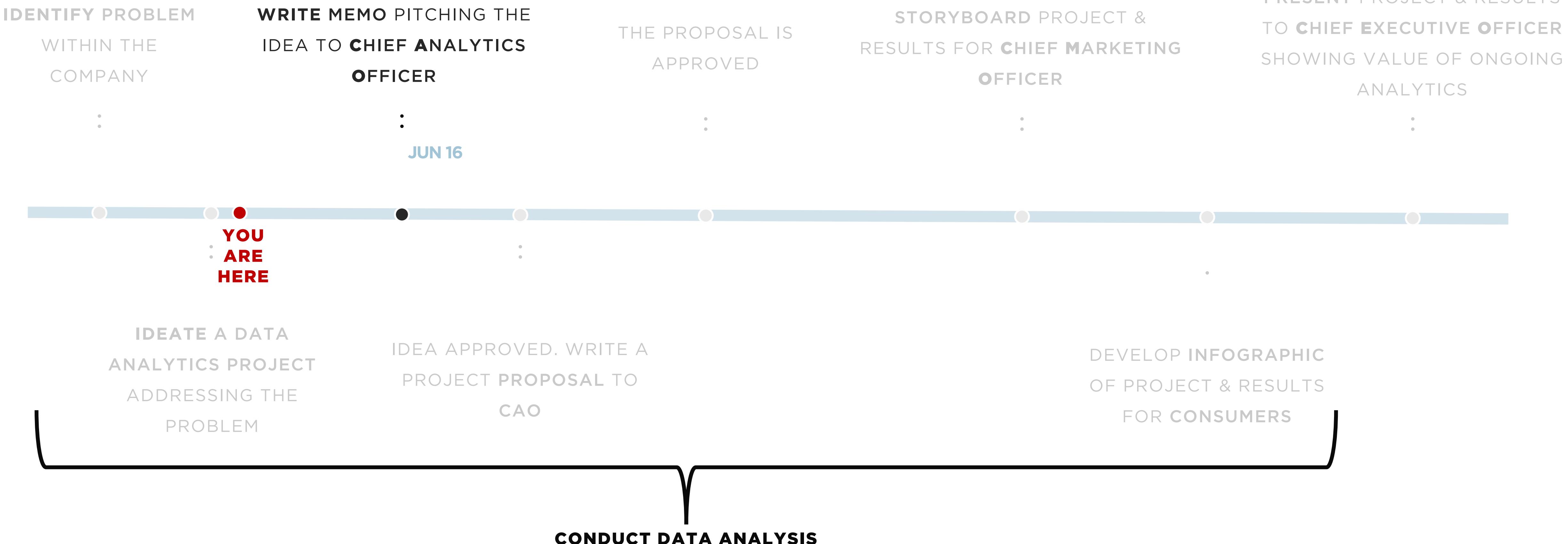
Recraft the results, telling the narrative through an infographic for the **public** or **potential consumers**, using data visualization with brand awareness.

## Presentation

Construct and deliver a 4-5 minute persuasive presentation with up to 10 slides to the **CEO**, telling the story of the analytics project to convince them of further investment in analytics.

# Upcoming deliverable

**250-word memo** — Write a memo to **CAO** about an opportunity to leverage analytics. Consider background context, problem, data, solution, and impact. Be sure you have data and a plan for analysis before pitching the idea in the memo.



# **Objectives of business writing**

For **all** business  
communications

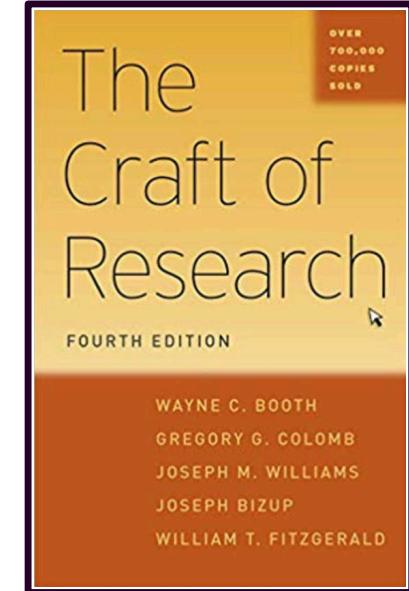
**Step into your audiences' shoes** to  
get them to  
pay attention to,  
understand,  
(be able to) act upon  
a maximum of messages, given  
constraints.

**Who is your audience?**

**What's your purpose  
for communicating?**

**tl;dr**

# Readings



# Revising style: telling your story clearly

*Booth and co-authors*

All are university professors of English, and their book is first among Amazon's ranking of books in methodology and statistics.

## A few writing principles

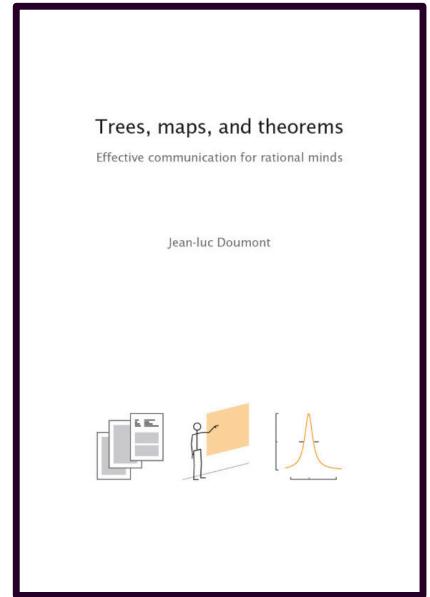
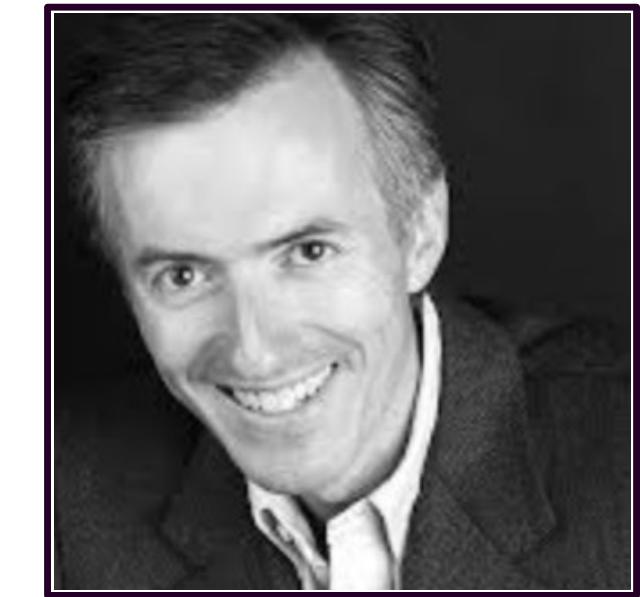
**Express crucial actions in verbs.**

**Make your central characters the subjects of those verbs;** keep those subjects short, concrete, and specific.

**Old before new** — “readers follow a story most easily if they can begin each sentence with a character or idea that is familiar to them, either because it was already mentioned or because it comes from the context.”

**Complexity last**, particularly important when:

introducing a new technical term,  
presenting a long or complex unit of  
information, introducing a concept to be  
developed in what follows.



# Trees, maps, theorems

*Doumont*

An engineer from the Louvain School of Engineering and PhD in applied physics from Stanford University, Jean-luc Doumont wrote this book to help engineers, scientists, and managers with business communication.

## Wear shoes of your audience

Put yourselves in the shoes of the audience, anticipating their situation, their needs, their expectations.

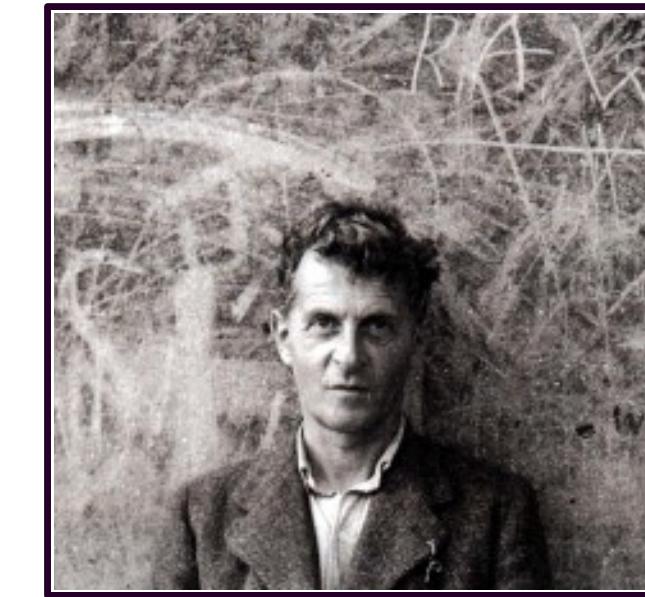
Structure the story along their line of reasoning, recognizing the constraints they might bring: their familiarity with the topic, their mastery of the language, the time they can free for us.

## Messages, not just information

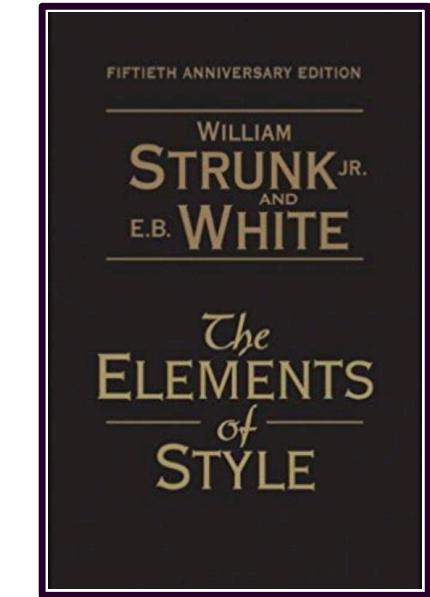
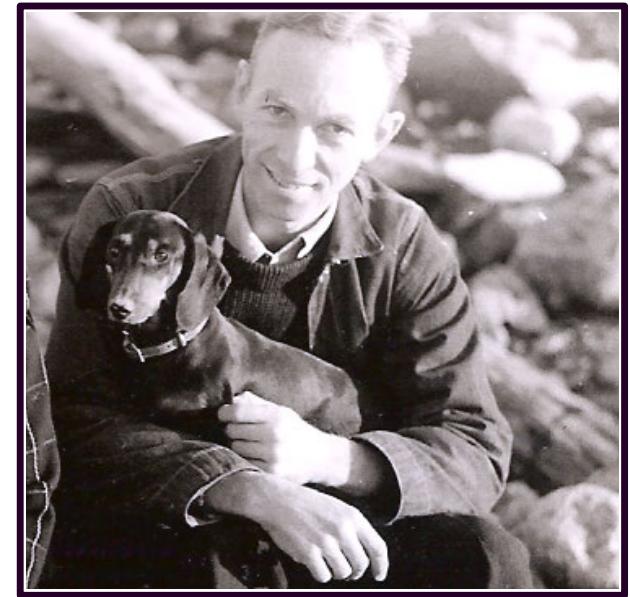
A message differs from raw information in that it interprets the information for a specific audience and for a specific purpose.

## Organization, messages first

Get the audience interested. Once you have their attention, tell your main message. Last, support this message, tell how you got there.



&



# The elements of style

## *Strunk & White*

William Strunk Jr. was an English professor at Cornell University; E. B. White was his student. White wrote for *The New Yorker* — perhaps the best edited magazine — for sixty years, and won a Pulitzer for his writing.

### Why read S&W, by Richard Ford

**Mimic examples,  
be concise,  
don't overstate**

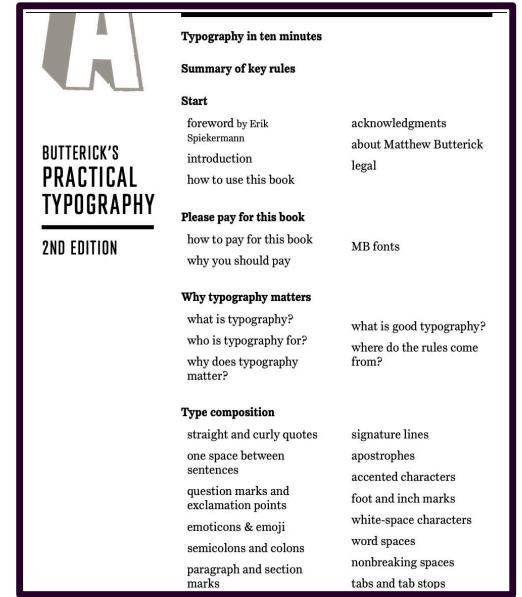
S&W doesn't really teach you how to write, it just tantalizingly reminds you that there's an orderly way to go about it, that clarity's ever your ideal, but — really — it's all going to be up to you.

Leading by example, this tiny book provides dos and don'ts with examples of each. Re-read.

Heed their warnings:

Vigorous writing is concise. A sentence should contain no unnecessary words, a paragraph no unnecessary sentences, for the same reason that a drawing should have no unnecessary lines and a machine no unnecessary parts. This requires not that the writer make all his sentences short, or avoid all detail and treat subjects only in outline, but that **every word tell**.

A single overstatement, wherever or however it occurs, **diminishes the whole**, and a carefree superlative has the power to destroy, for readers, the object of your enthusiasm.



# Butterick's practical typography

## Matthew Butterick

The author earned a visual-studies degree from Harvard, and a law degree from UCLA. He is a writer, typographer, programmer, and lawyer.

### Conserve limited reader attention

#### Very basic guidelines, body text

**Typography is the visual component of the written word.**

"Typography is for the benefit of the reader."

"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."

Point size: 10–12 (print), 15–25 pixels (web)  
Line spacing: 120–145% of the point size  
Line length: 45–90 characters per line  
Fonts: see his recommendations

Grids are helpful when they encourage consistency. They make it easier to relate elements on the page to existing ones.

# Example 250-word memo



A perfect game

Perfect Game

Los Angeles Dodgers

Pitcher Sandy Koufax

Statcast data

(Attempting to) steal a base

Salary cap

Baseball

# Statistics, probability, computing

Models

Mode, maximum likelihood

Probability distributions

Joint distributions

R language and packages

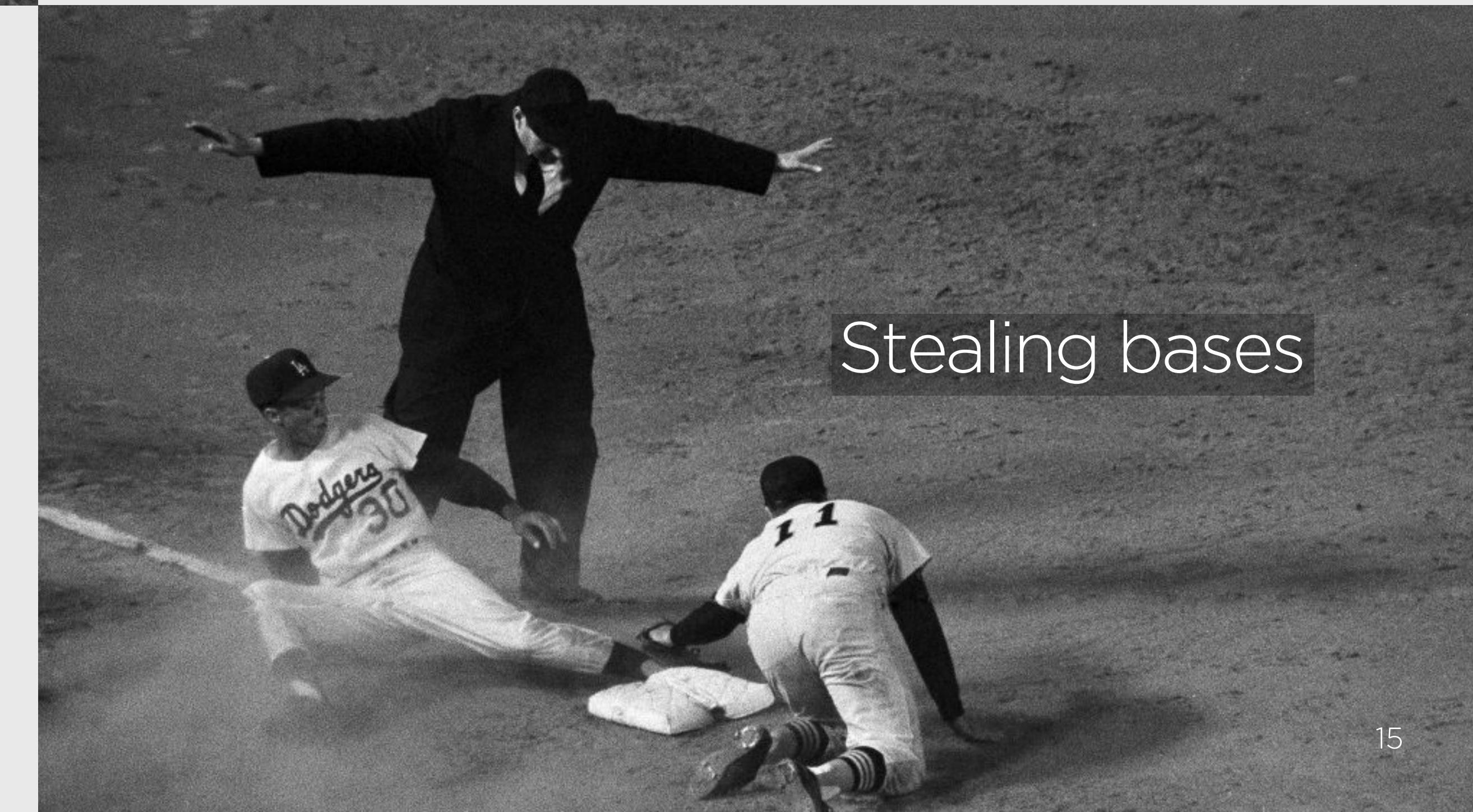
Inferences

Mean, expectations

Decision theory

Counterfactuals

Simulations



Stealing bases



To: **Scott Powers**  
Director, Quantitative Analytics

2 February 2019

## Our game decisions should optimize expectations. Proposal for testing: model decisions to steal

The most likely sequence of events on defense is a *perfect game* — occurring just 23 times in major-league baseball, once by our own Sandy Koufax. Decisions from what is most likely, however, leave wins unclaimed. To claim them, let's base decisions on expectations flowing from decision theory and probability models. A joint model of all events works best, but we can start small, with say, decisions to steal second base.

After defining our objective (e.g. optimize expected runs) we will from Statcast data compute expectations: weight everything that could happen by its probability and accumulate these probability distributions. Joint distributions of all events, an eventual goal, will allow us to ask counterfactuals — “what if I do *this*” or “what if my opponent does *that*” — and simulate games to learn how decisions change win probability. It enables optimal strategy.

Rational and optimal, this approach is more efficient for gaining wins. For perspective, each added win from the free-agent market costs 10 million, give or take, and the league salary cap prevents unlimited spend on talent. There is no cap, however, on investing in rational decision processes.

Computational issues are being addressed in Stan, a tool that enables inferences through advanced simulations. This open-source software is free but teaching its applications will require time. To shorten our learning curve, we can start with Stan interfaces that use familiar syntax (like lme4) but return joint probability distributions: R packages *rethinking*, *brms*, or *rstanarm*. And we can test the concept with decisions to steal.

Sincerely,  
Scott Spencer

# Questions for Discussion

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Who was the audience?

Was a few minutes enough time to understand?  
Did you notice **structure** that guides the audience?

How do the **audiences** differ between this memo,  
the *Jakarta proposal*, and *The Next Rembrandt*?

How do the **structures and details** of the  
communications seem to depend on the audience?

Might the audience reply, **tl;dr**?



To: **Scott Powers**  
Director, Quantitative Analytics

## Audience background

Director of Quantitative Analytics  
Ph.D. Statistics from Stanford University  
Some publications use machine learning  
Knows R programming  
An employee, knows history of Dodgers

2 February 2019

## Message first, context

### Our game decisions should optimize expectations. Proposal for testing: model decisions to steal

#### Main body word count, 250

The most likely sequence of events on defense is a *perfect game* — occurring just 23 times in major-league baseball, once by our own Sandy Koufax. Decisions from what is most likely, however, leave wins unclaimed. To claim them, let's base decisions on expectations flowing from decision theory and probability models. A joint strategy for all events works best, but we can start small, with say, decisions to steal second base.

Readability Statistics	
<b>Counts</b>	After defining our objective (e.g. optimize expected runs) we will from Statcast data compute expectations:
Words	weight every thing that could happen by its probability and accumulate these probability distributions. Joint
Characters	distributions of all events, an eventual goal, will allow us to ask counterfactuals — “what if I do <i>this</i> ” or “what if
Paragraphs	my opponent <i>does that</i> ” — and simulate games to learn how decisions change win probability. It enables optimal
Sentences	strategy.
<b>Averages</b>	
Sentences per Paragraph	Rational and optimal, this approach is more efficient for gaining wins. For perspective, each added win from the
Words per Sentence	free-agent market costs 10 million, give or take, and the league salary cap prevents unlimited spend on talent.
Characters per Word	There is no cap, however, on investing in rational decision processes.
<b>Readability</b>	
Flesch Reading Ease	Computational issues are being addressed in Stan, a tool that enables inferences through advanced simulations.
Flesch-Kincaid Grade Level	This open-source software is free but teaching its applications will require time. To shorten our learning curve,
Passive Sentences	we can start with Stan interfaces that use familiar syntax (like lme4) but return joint probability distributions: R packages rethinking, brms, or rstanarm. And we can test the concept with decisions to steal.

Sincerely,  
Scott Spencer



To: **Scott Powers**  
Director, Quantitative Analytics

2 February 2019

## Our game decisions should optimize expectations. Proposal for testing: model decisions to steal

### Context, orient the audience

The most likely sequence of events on defense is a *perfect game* — occurring just 23 times in major-league baseball, once by our own Sandy Koufax. Decisions from what is most likely, however, leave wins unclaimed. To claim them, let's base decisions on expectations flowing from decision theory and probability models. A joint model of all events works best, but we can start small, with say, decisions to steal second base.

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**Goal, action problem**

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## Our game decisions should optimize expectations. Proposal for testing: model decisions to steal

### Proposed solution

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### Objective, data, methods

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### Eventual benefit

Sincerely,  
Scott Spencer



To: **Scott Powers**  
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2 February 2019

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**Benefit,  
comparison,  
financial**

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**Limitations,  
short-term  
solutions**

Sincerely,  
Scott Spencer



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**Reminder  
of proposal**

Sincerely,  
Scott Spencer



To: Scott Powers  
Director, Quantitative Analytics

## Audience background

Senior Analyst  
Ph.D. Statistics from Stanford University  
Some publications use machine learning  
Knows R programming  
An employee, knows history of Dodgers

2 February 2019

## Message first, context

### Context, orient the audience

The most likely sequence of events on defense is a *perfect game* — occurring just 23 times in major-league baseball, once by our own Sandy Koufax. Decisions from what is most likely, however, leave wins unclaimed. To claim them, let's base decisions on expectations flowing from decision theory and probability models. A joint model of all events works best, but we can start small, with say, decisions to steal second base.

### Proposed solution

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### Benefit, comparison, financial

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### Reminder of proposal

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Scott Spencer

### Goal, action problem

### Objective, data, methods

### Limitations, short-term solutions

“When we read prose, we hear it... it’s variable sound. It’s sound with — pauses. With *emphasis*. With, well, you know, a certain rhythm.” — Richard Goodman

“If you **start your project early**, you’ll have time to **let your revised draft cool**. What seems good one day often looks different the next.” — Wayne Booth

# Revise

“We write a first draft for ourselves; the drafts thereafter increasingly **for the reader**.” — Joseph Williams

# Questions: tools for revising your memo

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Sentence syntax, old before new? — Booth, chapter 17.

Needless words omitted? Every word tell? — S&W, composition 17.

Overstatements? — S&W, style 7.

Statements, in positive form? — S&W, composition 15.

Each paragraph, a separate unit of composition? — S&W, composition 16.

Definite, specific, concrete language? — S&W, composition 13.

# Group work

# Group help on case studies, memo

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Get together in groups, work with your peers to get and give helpful feedback to refine your ideas for **your choice of entity**, your **data analytics project**, potential **sources of data**, and **writing it up**.

Then, let's share some of these ideas together.

# For Next Week, Module 4:

## Agenda next week

### The minimum

250-word memo due by 16th of June  
Principles of Persuasion and Brief Proposals

**Abelson, Robert P. Statistics as Principled Argument. Psychology Press, 1995. Print., Selected pages.**

Read to understand his framework for using statistics as persuasive communication.

Also:

What's his ideal statistician?

What does he mean by *MAGIC*?

What are his thoughts about *comparisons*?

**Conger J.A. (1998, May-June). *The necessary art of persuasion*. Harvard Business Review, 84-97.**

What steps, in his view, must be considered?  
What examples of successes and failures in these steps have you witnessed? Has he categorically omitted anything you consider important in his generalization of persuasion?

# Checking in,

**Reaching out?**

Have you registered with Columbia's Writing Center? Scheduled a consultation with our Research Data Services?

**Coding?  
Exploring data?**

What coding help do you need to gather, clean or visually explore your data? Be as specific as you can and we can setup a one-on-one.

See you  
next week!

