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.

IDENTIFY PROBLEM WITHIN THE COMPANY

IDEATE A DATA ANALYTICS PROJECT ADDRESSING THE PROBLEM

YOU ARE HERE

WRITE MEMO PITCHING THE IDEA TO **CHIEF ANALYTICS OFFICER**

JUN 16

IDEA APPROVED. WRITE A PROJECT **PROPOSAL** TO **CAO**

THE PROPOSAL IS APPROVED

STORYBOARD PROJECT & RESULTS FOR **CHIEF MARKETING OFFICER**

DEVELOP **INFOGRAPHIC** OF PROJECT & RESULTS FOR **CONSUMERS**

PRESENT PROJECT & RESULTS TO **CHIEF EXECUTIVE OFFICER** SHOWING VALUE OF ONGOING ANALYTICS

CONDUCT DATA ANALYSIS

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.

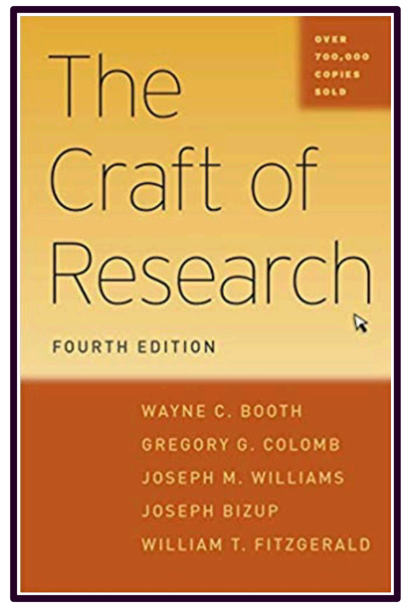
Who is your audience?

What's your purpose for communicating?

tl;dr

“TL;DR.” “TL;DR.” wikipedia.com. N.p., 1 Feb. 2019. Web. 1 Feb. 2019.

Readings



Revising style: telling your story clearly

Booth and co-authors

The 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.

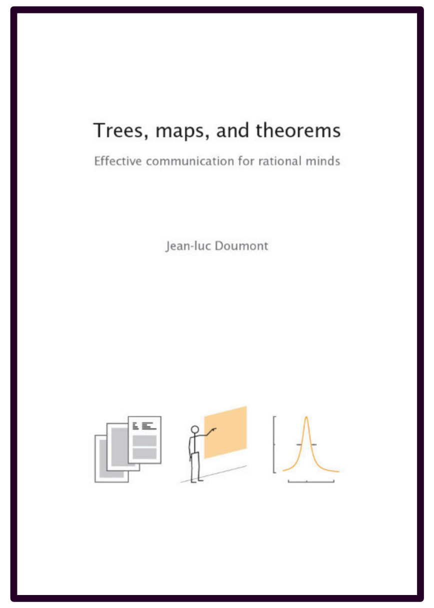
Make your central characters the subjects of those verbs; keep those subjects short, concrete, and specific.

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.

Booth, Wayne C et al. *The Craft of Research*. Fourth. University of Chicago Press, 2016. Print.



Trees, maps, theorems

Doumont

Author, audience, and purpose

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.

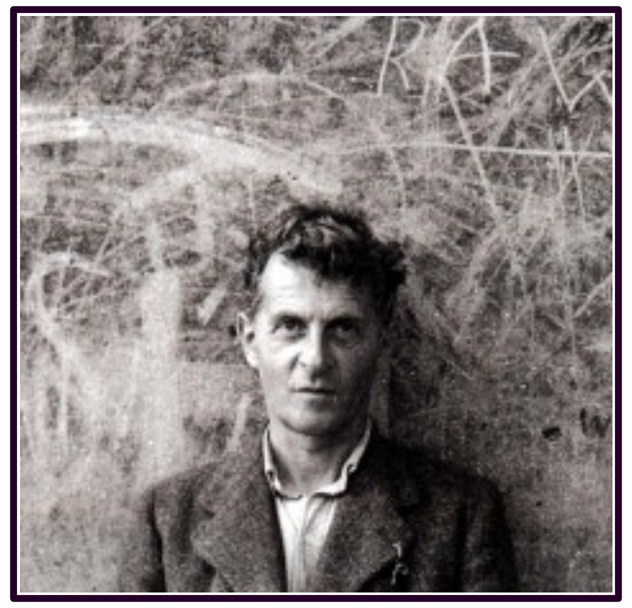
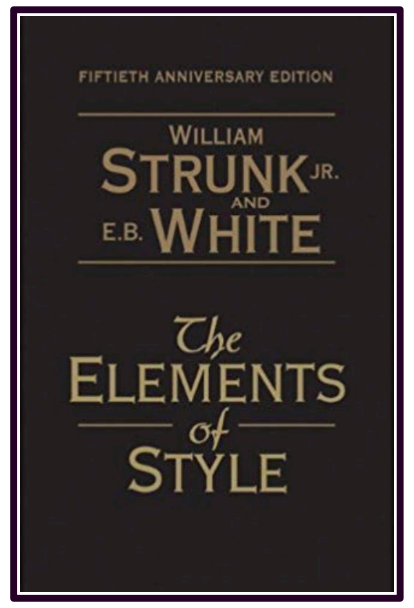
Messages, not just information

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.

Doumont, Jean-Luc. *Trees, Maps, and Theorems*. Principiæ, 2009. Print.

 &  , 

The elements of style

Strunk & White

The authors

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

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.

Mimic examples, be concise, don't overstate

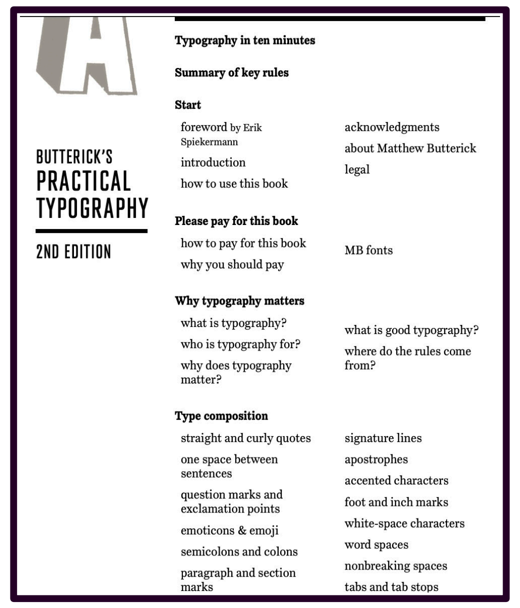
Leading by example, this tiny book provides dos and don'ts with examples of each. Re-read.

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.

Strunk, William, and E B White. *The Elements of Style*. Fiftieth Anniversary. Pearson Longman, 2009. Print.



BUTTERICK'S PRACTICAL TYPOGRAPHY
2ND EDITION

Butterick's practical typography

Matthew Butterick

The author

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

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.**"

Very basic guidelines, body text

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.

Butterick, Matthew. "Butterick's Practical Typography." practicaltypography.com. N.p., 2018. Web. 8 Sept. 2018.

Example 250-word memo

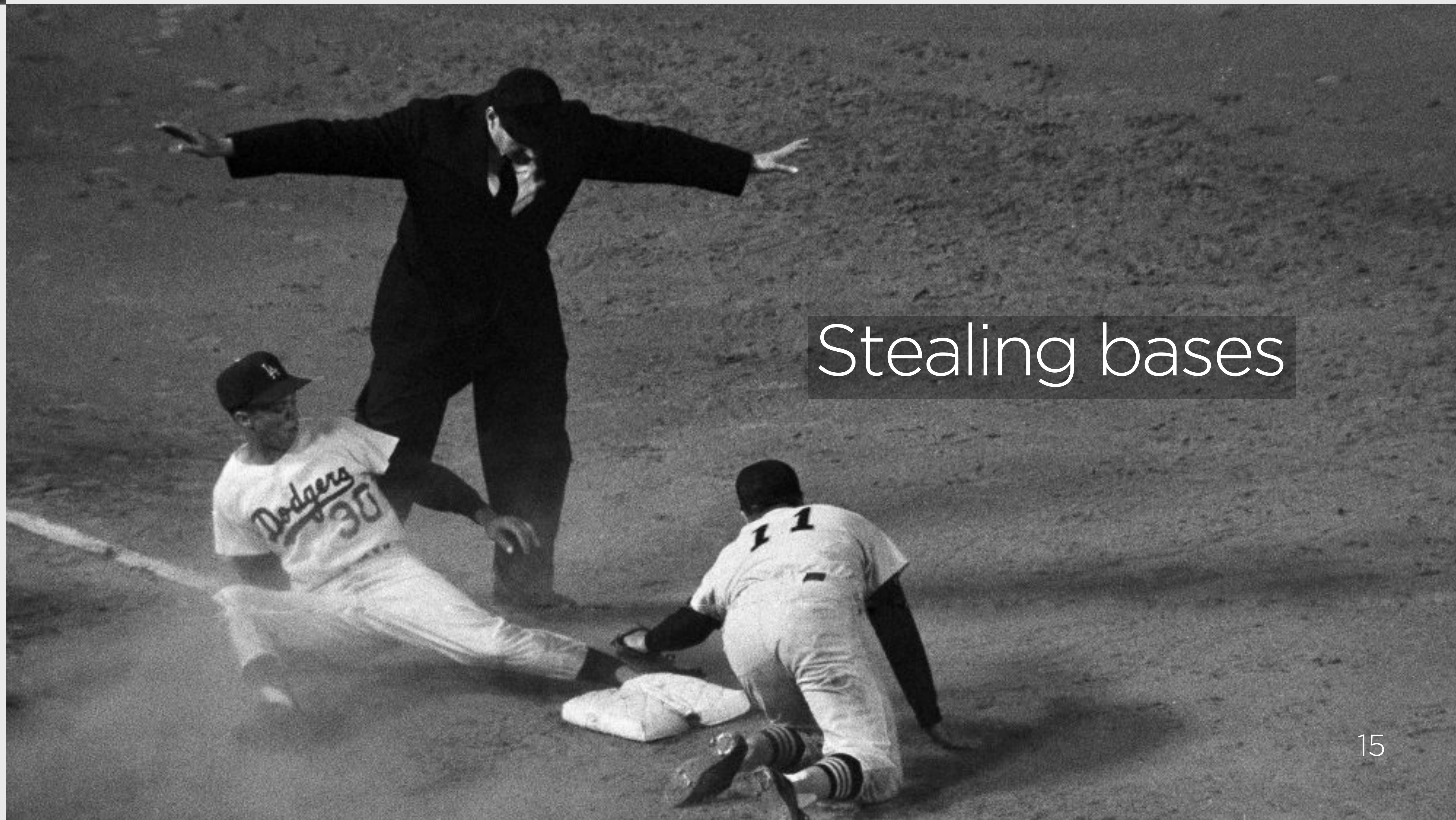
Statistics, probability, computing

- Models
- Mode, maximum likelihood
- Probability distributions
- Joint distributions
- R language and packages

- Inferences
- Mean, expectations
- Decision theory
- Counterfactuals
- Simulations

Baseball

- Perfect Game
- Los Angeles Dodgers
- Pitcher Sandy Koufax
- Statcast data
- (Attempting to) steal a base
- Salary cap



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

2 February 2019

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

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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

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**?

Caldeira, Joao et al. "Improving Traffic Safety Through Video Analysis: Pulse Lab Jakarta." dssg.uchicago.edu. N.p., 2018. Web. 2 Feb. 2019.
ING et al. "The Next Rembrandt." 5 Apr. 2016. Web. https://www.nextrembrandt.com

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

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Message first, context

Main body word count, 250

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Readability Statistics

Counts	
Words	250
Characters	1,357
Paragraphs	4
Sentences	14
Averages	
Sentences per Paragraph	3.5
Words per Sentence	17.8
Characters per Word	5.2
Readability	
Flesch Reading Ease	43.5
Flesch-Kincaid Grade Level	11.6
Passive Sentences	0%

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Context, orient the audience

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Goal, action problem

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Proposed solution

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Objective, data, methods

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Eventual benefit

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Benefit, comparison, financial

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Limitations, short-term solutions

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Reminder of proposal

Sincerely,
Scott Spencer

Audience background

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

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

2 February 2019

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

Message first, context

Context, orient the audience

Proposed solution

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"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

Goodman, Richard. *The Soul of Creative Writing*. Routledge, 2008. Print.
Williams, Joseph M. *Style: Toward Clarity and Grace*. University of Chicago Press, 1990. Print.
Booth, Wayne C et al. *The Craft of Research*. Fourth. University of Chicago Press, 2016. Print.

Questions: tools for revising your memo

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.

Strunk, William, and E B White. *The Elements of Style*. Fiftieth Anniversary. Pearson Longman, 2009. Print.

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Group work

Group help on case studies, memo

Get together in groups, work with your peers to get and give helpful feedback to refine your ideas for your choice of company, 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

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

The minimum

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!