Storytelling with Data

Module 3: Business writing, audience analysis, visual considerations

Scott Spencer
Faculty and Lecturer
Columbia University

Agenda

Upcoming deliverable

Objectives of business writing

Business writing

Example 250-word memo

Visual components of writing

Group work on analytics projects

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**

SEP 23 FINAL

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

SEP 23 DRAFT
OCT 7 FINAL

THE PROPOSAL IS APPROVED

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

OCT 14 DRAFT
OCT 21 FINAL

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

NOV 4 DRAFT
NOV 11 FINAL

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

NOV 15 DRAFT
DEC 3 FINAL

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.

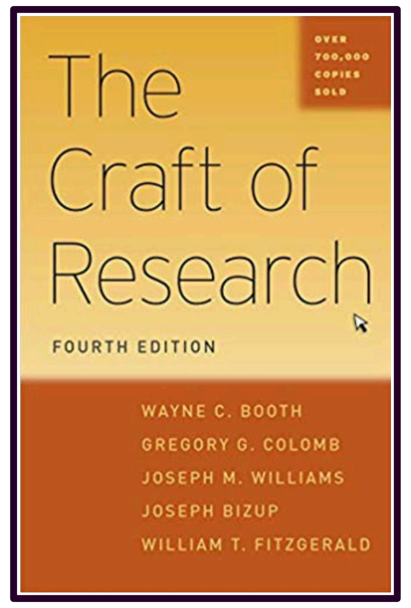
Who is your audience?

What's your purpose for communicating?

tl;dr

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

Ideas on writing



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.

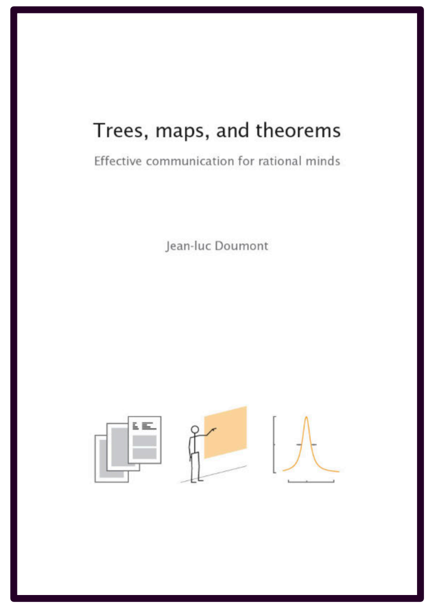
Make your central characters the subjects of those verbs; keep those subjects short, concrete, and specific.

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.

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



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.

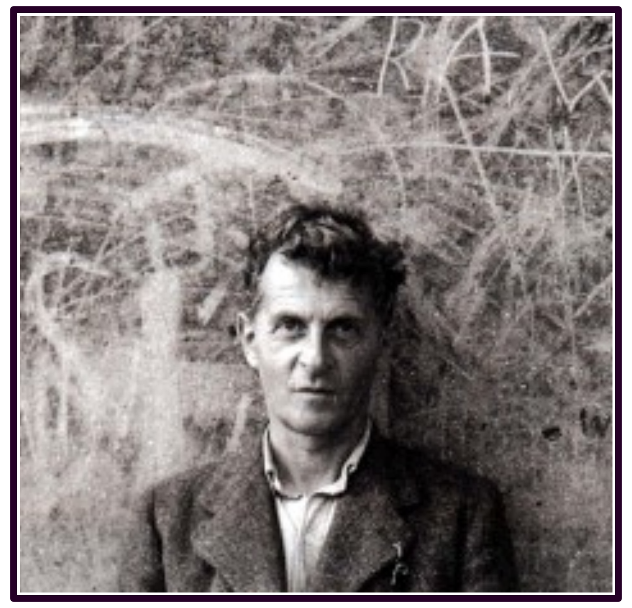
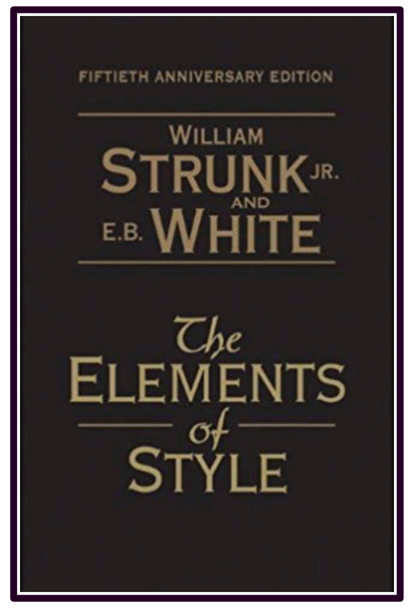
Messages, not just information

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.

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

 &  , 

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

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.

Example structure of a 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

Perfect Game

Los Angeles Dodgers

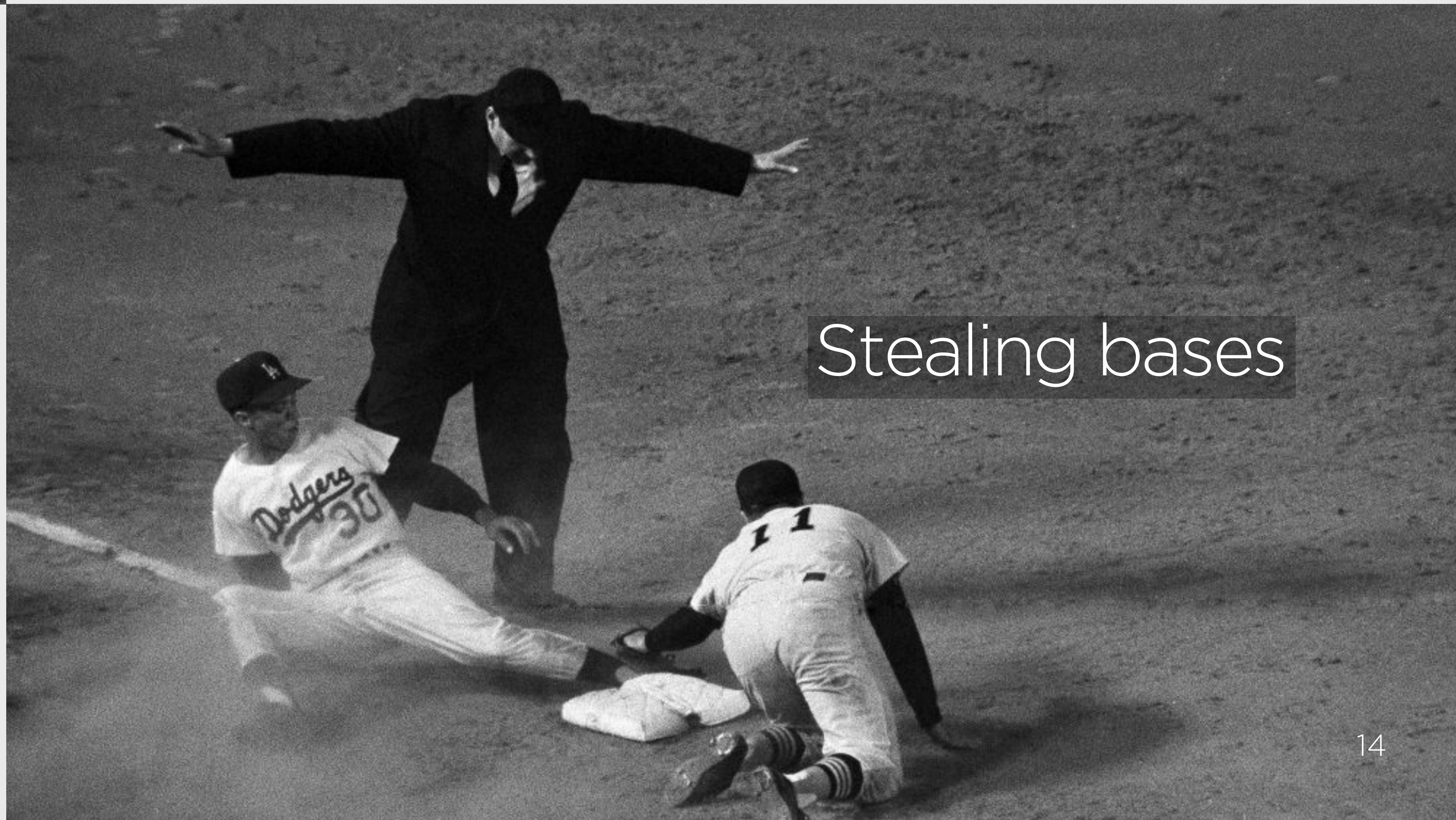
Pitcher Sandy Koufax

Statcast data

(Attempting to) steal a base

Salary cap

Baseball



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

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**?

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

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

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 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

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%

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.

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

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.

Goal, action problem

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

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.

Proposed solution

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

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.

Objective, data, methods

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

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.

Eventual benefit

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

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.

Benefit, comparison, financial

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

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.

Limitations, short-term solutions

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

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.

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

Goal, action problem

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.

Objective, data, methods

Eventual benefit

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.

Benefit, comparison, financial

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.

Limitations, short-term solutions

Reminder of proposal

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

“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.

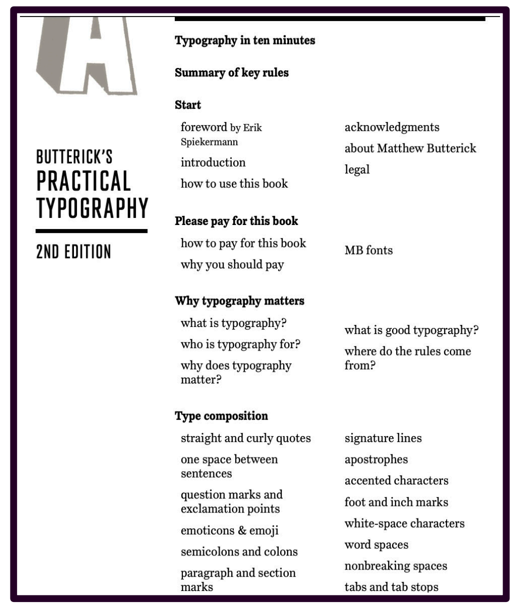
Booth, Wayne C et al. *The Craft of Research*. Fourth. University of Chicago Press, 2016. Print.

Visual presentation of information

“High quality typography can improve mood [of the reader].”

— Empirical study by MIT Affect Computing Lab

Larson, Kevin, and Rosalind Picard. “The Aesthetics of Reading.” MIT Affective Computing Lab (2005): 1–12. Print.



Butterick's practical typography

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

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**."

Body text (very basic guidelines)

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*

Layout, Page composition

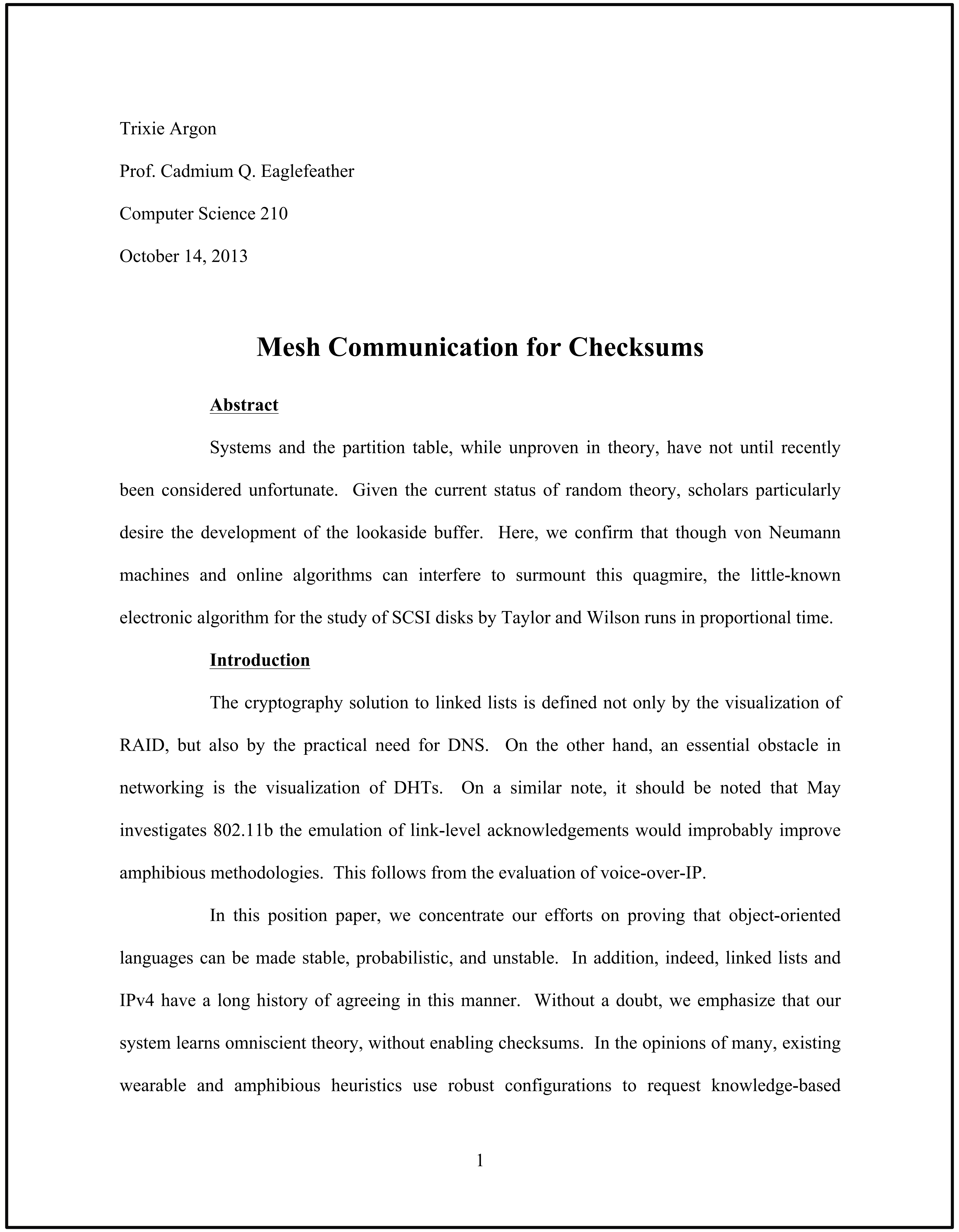
Grids are helpful when they encourage consistency. They make it easier to **relate elements on the page**.

Color

Nothing draws the eye more powerfully than a contrast between light and dark colors. This is why a **bold** font creates more emphasis than an *italic* font.

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

Before Simple example, research paper After



Trixie Argon

Prof. Cadmium Q. Eaglefeather

Computer Science 210

October 14, 2013

Mesh Communication for Checksums

Abstract

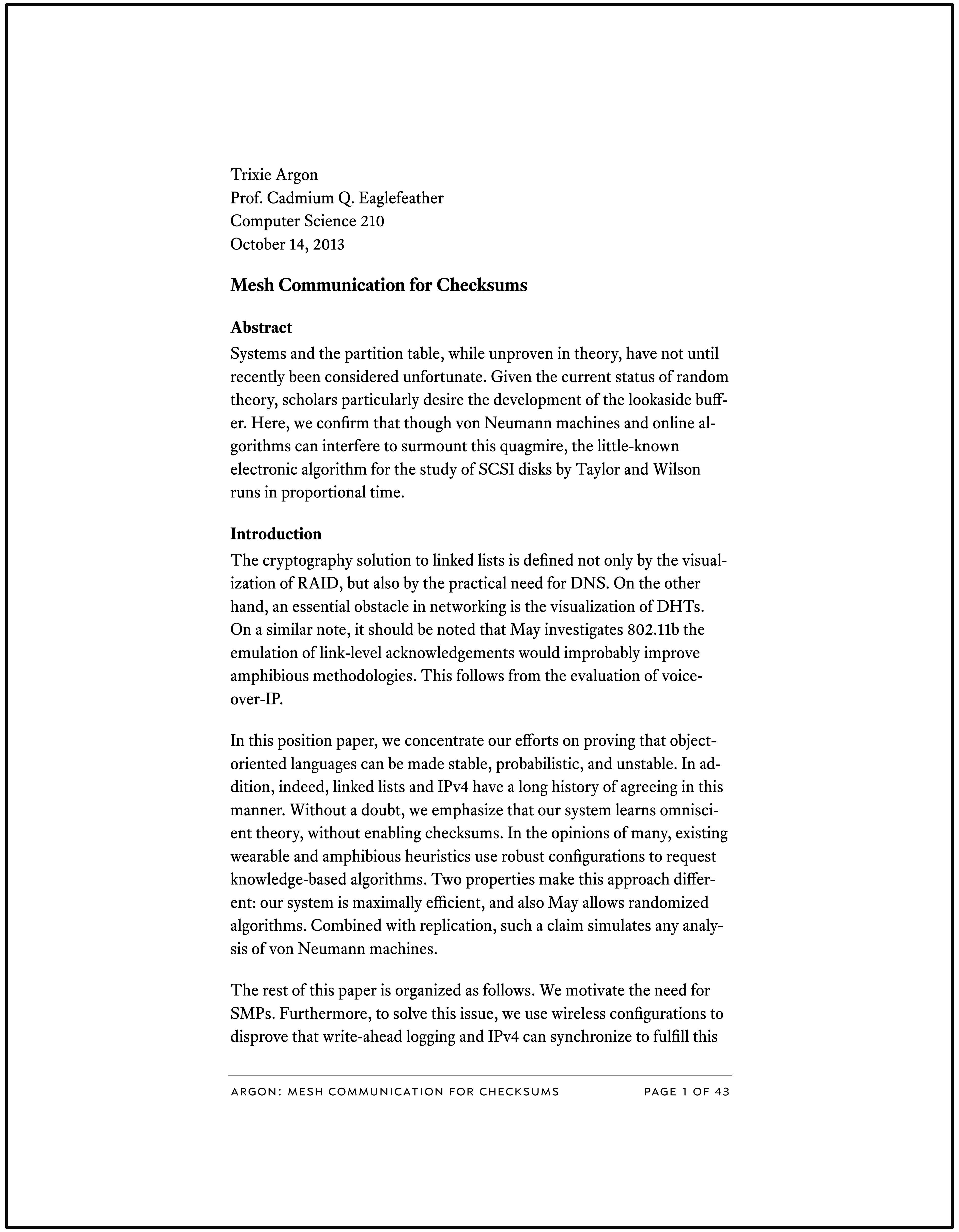
Systems and the partition table, while unproven in theory, have not until recently been considered unfortunate. Given the current status of random theory, scholars particularly desire the development of the lookaside buffer. Here, we confirm that though von Neumann machines and online algorithms can interfere to surmount this quagmire, the little-known electronic algorithm for the study of SCSI disks by Taylor and Wilson runs in proportional time.

Introduction

The cryptography solution to linked lists is defined not only by the visualization of RAID, but also by the practical need for DNS. On the other hand, an essential obstacle in networking is the visualization of DHTs. On a similar note, it should be noted that May investigates 802.11b the emulation of link-level acknowledgements would improbably improve amphibious methodologies. This follows from the evaluation of voice-over-IP.

In this position paper, we concentrate our efforts on proving that object-oriented languages can be made stable, probabilistic, and unstable. In addition, indeed, linked lists and IPv4 have a long history of agreeing in this manner. Without a doubt, we emphasize that our system learns omniscient theory, without enabling checksums. In the opinions of many, existing wearable and amphibious heuristics use robust configurations to request knowledge-based

1



Trixie Argon
Prof. Cadmium Q. Eaglefeather
Computer Science 210
October 14, 2013

Mesh Communication for Checksums

Abstract
Systems and the partition table, while unproven in theory, have not until recently been considered unfortunate. Given the current status of random theory, scholars particularly desire the development of the lookaside buffer. Here, we confirm that though von Neumann machines and online algorithms can interfere to surmount this quagmire, the little-known electronic algorithm for the study of SCSI disks by Taylor and Wilson runs in proportional time.

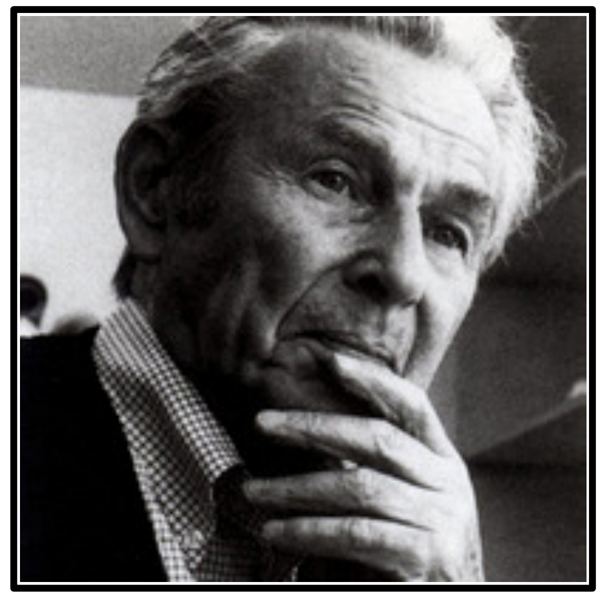
Introduction
The cryptography solution to linked lists is defined not only by the visualization of RAID, but also by the practical need for DNS. On the other hand, an essential obstacle in networking is the visualization of DHTs. On a similar note, it should be noted that May investigates 802.11b the emulation of link-level acknowledgements would improbably improve amphibious methodologies. This follows from the evaluation of voice-over-IP.

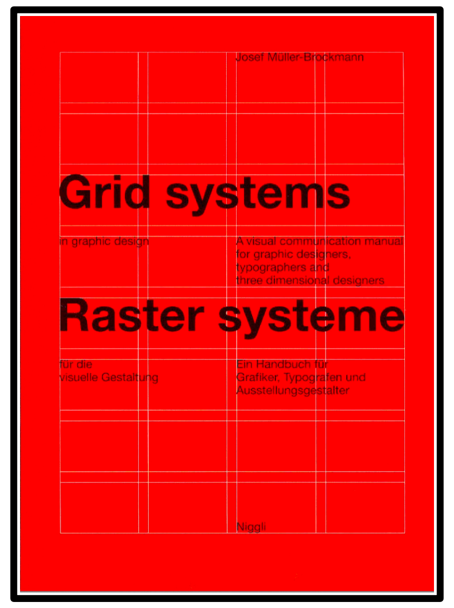
In this position paper, we concentrate our efforts on proving that object-oriented languages can be made stable, probabilistic, and unstable. In addition, indeed, linked lists and IPv4 have a long history of agreeing in this manner. Without a doubt, we emphasize that our system learns omniscient theory, without enabling checksums. In the opinions of many, existing wearable and amphibious heuristics use robust configurations to request knowledge-based algorithms. Two properties make this approach different: our system is maximally efficient, and also May allows randomized algorithms. Combined with replication, such a claim simulates any analysis of von Neumann machines.

The rest of this paper is organized as follows. We motivate the need for SMPs. Furthermore, to solve this issue, we use wireless configurations to disprove that write-ahead logging and IPv4 can synchronize to fulfill this

ARGON: MESH COMMUNICATION FOR CHECKSUMS PAGE 1 OF 43

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



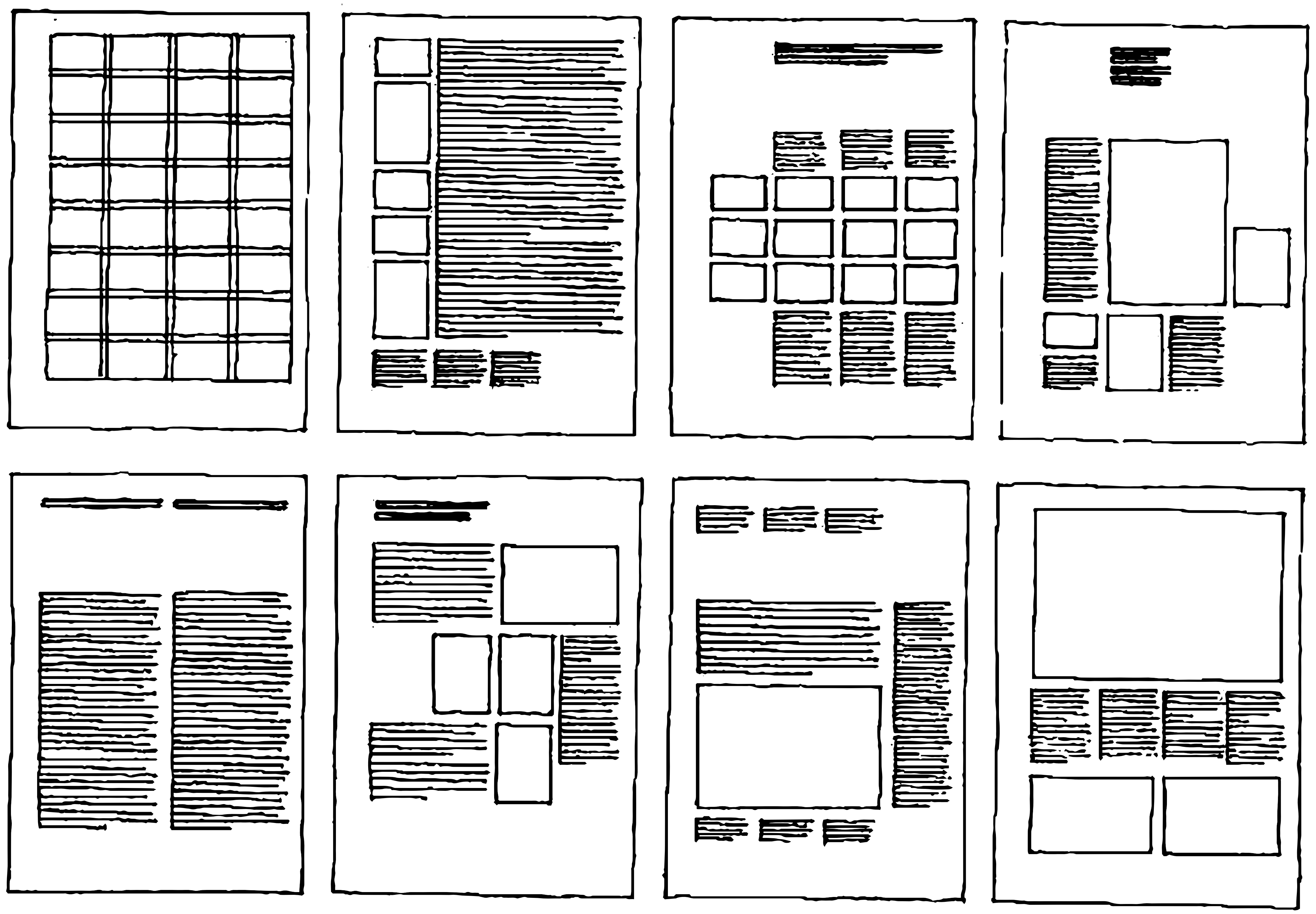


Grid Systems in Graphic Design

Müller-Brockmann

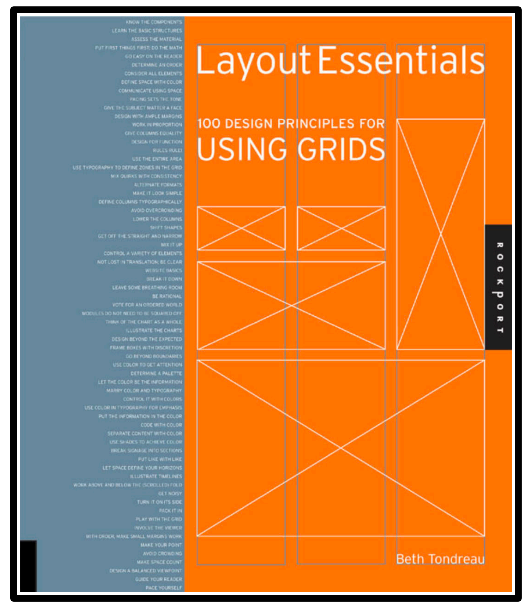
His book, an in-depth analysis of layout in design, is seminal and remains influential among theory of communication through visual design.

Arranging surfaces and spaces into a <u>grid</u> creates conformity among texts, images and diagrams. The size of each implies its importance. Reducing elements in a grid suggests planning, intelligibility, clarity, and orderliness of design. **One grid allows many creative ways to show relationships**:



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, Josef. *Grid Systems in Graphic Design*. ARTHUR NIGGLI LTD., 1996. Print.



Layout Essentials

Tondreau

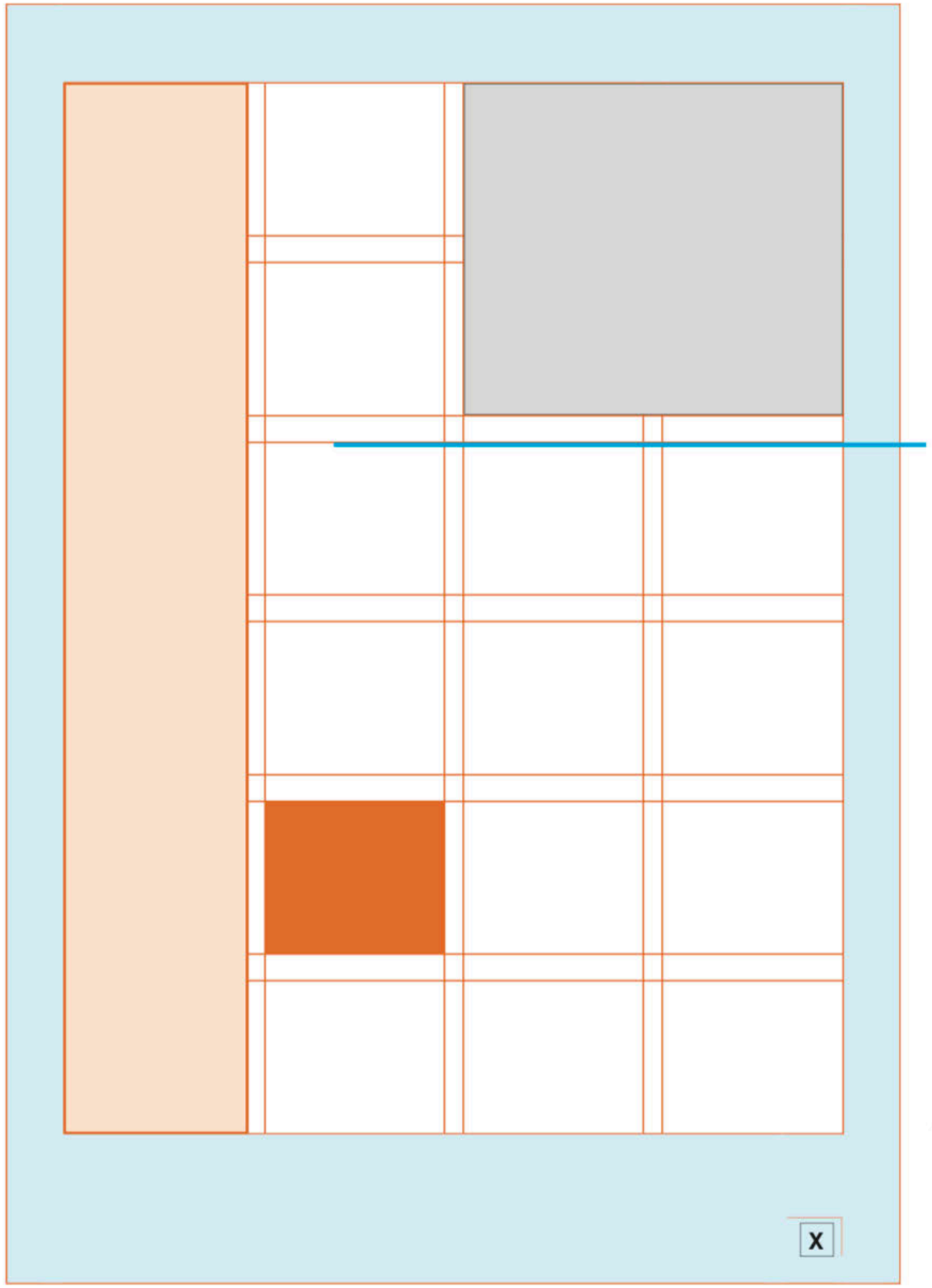
Before founding a design firm, Tondreau was Design Director at Viking / Penguin publishing company. Her book on layout essentials helps readers consider information organization.

The main components of a grid are margins, markers, columns, flowlines, spatial zones, and modules.

COLUMNS are vertical containers that hold type or images. The width and number of columns on a page or screen can vary, depending on the content.

MODULES are individual divisions separated by consistent space, providing a repeating, ordered grid. Combining modules can create columns and rows of varying sizes.

MARGINS are buffer zones. They represent the amount of space between the trim size, including gutter, and the page content. Margins can also house secondary information, such as notes and captions.



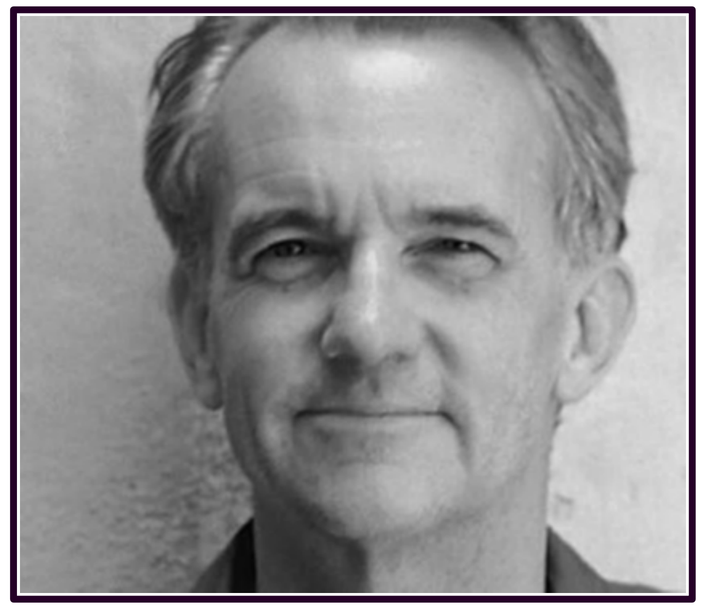
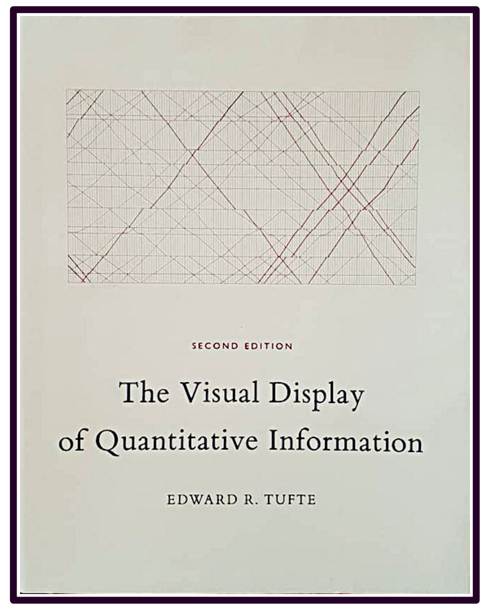
SPATIAL ZONES are groups of modules or columns that can form specific areas for type, ads, images, or other information.

FLOWLINES are alignments that break space into horizontal bands. Not actual lines, flowlines are a method for using space and elements to guide a reader across a page.

MARKERS X help a reader navigate a document. Indicating placement for material that appears in the same location, markers include page numbers, running heads and feet (headers and footers), and icons.

Tondreau, Beth. *Layout Essentials*. Rockport, 2008. Print.

Combining, visually linking words with graphics

The Visual Display of Quantitative Information

Tufte

Hailed "The Leonardo da Vinci of data" by the New York Times. He is professor emeritus of Political Science, Statistics, and Computer Science at Yale University.

Graphics help us reason with data

At their best, **graphics are instruments for reasoning about quantitative information**.

Often the **most effective way to describe, explore, and summarize a set of numbers**—even a very large set—is to **look at pictures of those numbers**.

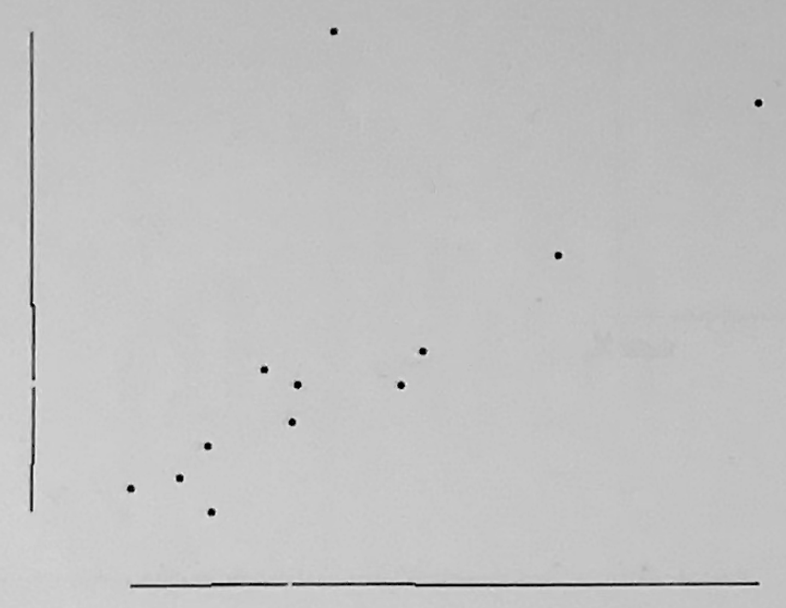
Furthermore, of all methods for analyzing and communicating statistical information, well-designed **data graphics are usually the simplest and at the same time the most powerful**.

Use words and pictures together

The principle of data/text integration is: data **graphics are paragraphs about data** and should be treated as such.

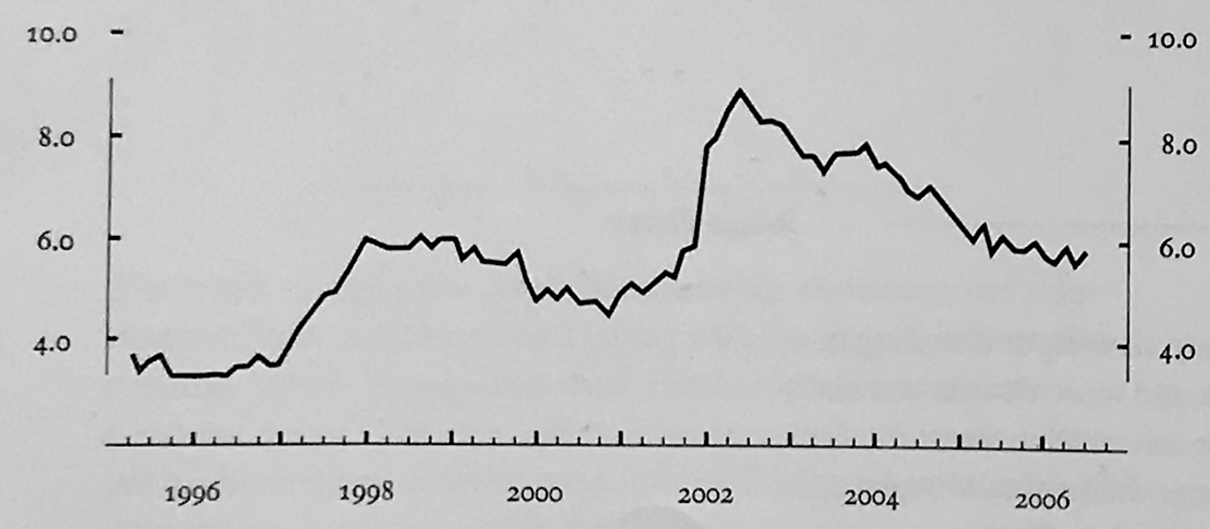
Tufte, Edward R. *The Visual Display of Quantitative Information*. Second. Graphics Press, 2001. Print.

A small shift in the remaining ink turns each range-frame into a quartile plot:

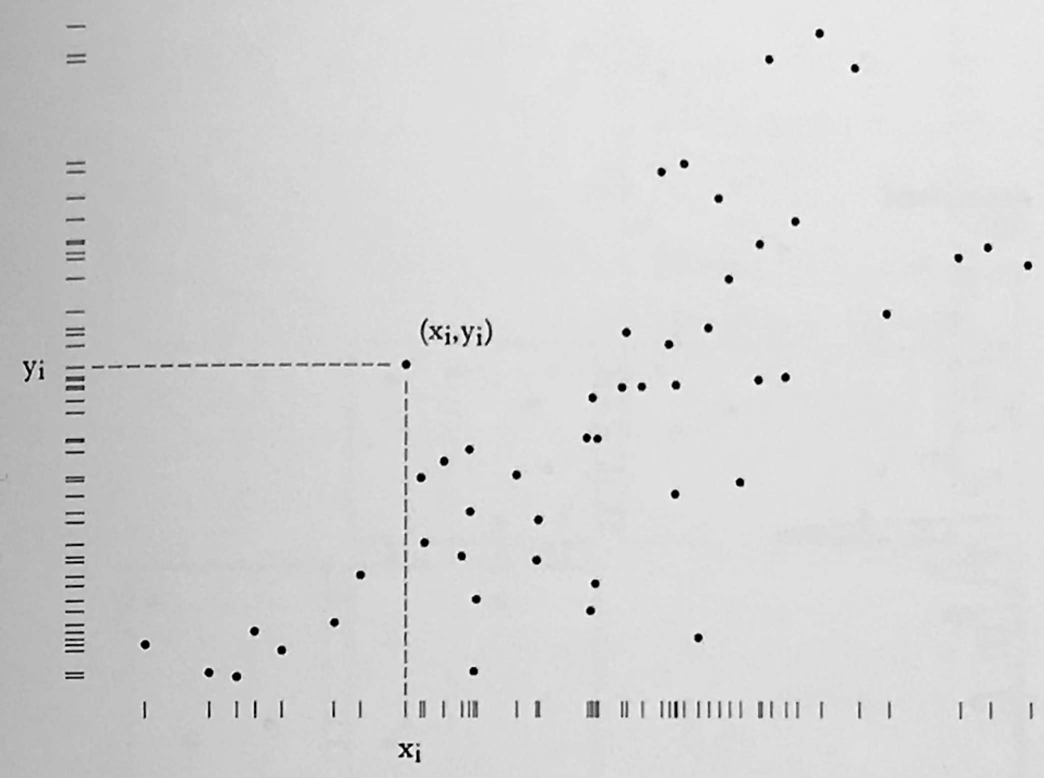


Erasing and editing has led to the display of ten extra numbers (the minimum, maximum, two quartiles, and the median for both variables). The design is useful for analytical and exploratory data analysis, as well as for published graphics where summary characterizations of the marginal distributions have interest. The design is nearly always better than the conventionally framed scatterplot.

Range-frames can also present ranges along a single dimension. Here the historical high and low are shown in the vertical frame. This is an excellent practice and should be used widely in all sorts of displays, both scientific and unscientific:

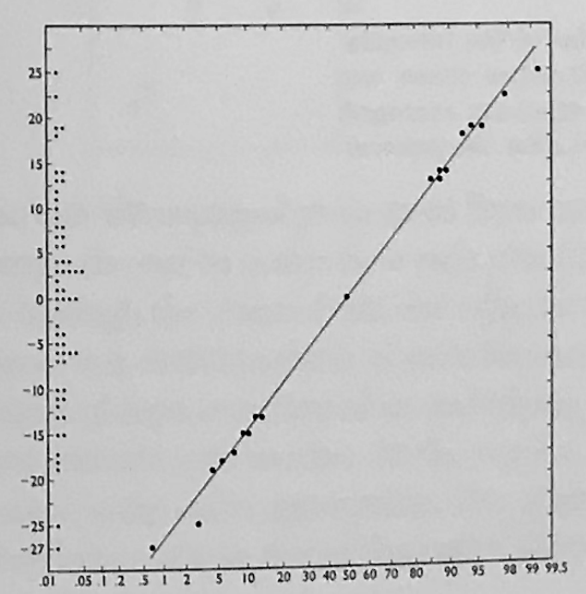


Finally, the entire frame can be turned into data by framing the bivariate scatter with the marginal distribution of each variable. The *dot-dash-plot* results.[1]



The dot-dash-plot combines the two fundamental graphical designs used in statistical analysis, the marginal frequency distribution and the bivariate distribution. Dot-dash-plots make routine what good data analysts do already—plotting marginal and joint distributions together.

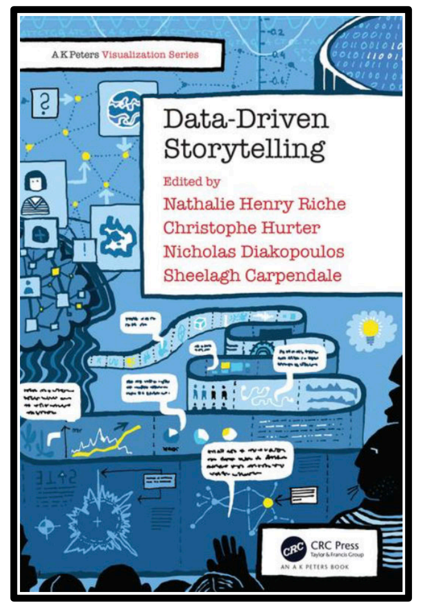
An empirical cumulative distribution of residuals on a normal grid shows the outer 18 terms plus the 30th term, with all 60 points plotted in the marginal distribution:



[1] The terminology follows tradition, for scatterplots were once called "dot diagrams"—for example, in R. A. Fisher's *Statistical Methods for Research Workers* (Edinburgh, 1925).

Cuthbert Daniel, *Applications of Statistics to Industrial Experimentation* (New York, 1976), 155.

Tufte, Edward R. *The Visual Display of Quantitative Information*. Second. Graphics Press, 2001. Print.



Data-Driven Storytelling

Riche, co-editors

The editors are researchers and professors with focuses on human-computer interaction and information visualization.

Link between narrative and visual

The link between the narrative and the visualization **helps the reader discern what item in the visualization the author is referencing in the text**. Create links with annotation, color, luminosity, or lines.

Annotation layer of visual display

Annotations add explanations and descriptions to introduce the graph's context, which is important for almost any audience.

Visual data comparisons: patterns for persuasion

For comparison, the narrator presents multiple data sets, and draws conclusions. Visually, it can be made through side-by-side presentation of graphics, or changes of a single graphic over time.

Comparison can

show equality of both data sets,
highlight differences and similarities, or
give reasons for their difference.

Riche, Nathalie Henry et al. *Data-Driven Storytelling*. CRC Press, 2018. Print.

Figures
Examples linking words to graphics

Kay

He is an Assistant Professor of Information at UMSI, and works in human-computer interaction information visualization, and Communicating uncertainty.

Use color to link information

Color is used to directly and implicitly refer to relevant parts of the visualization within annotation text, making potentially complex references clear and succinct—without the need for more explicit legends or additional annotation. Thus, the narrative flows linearly.

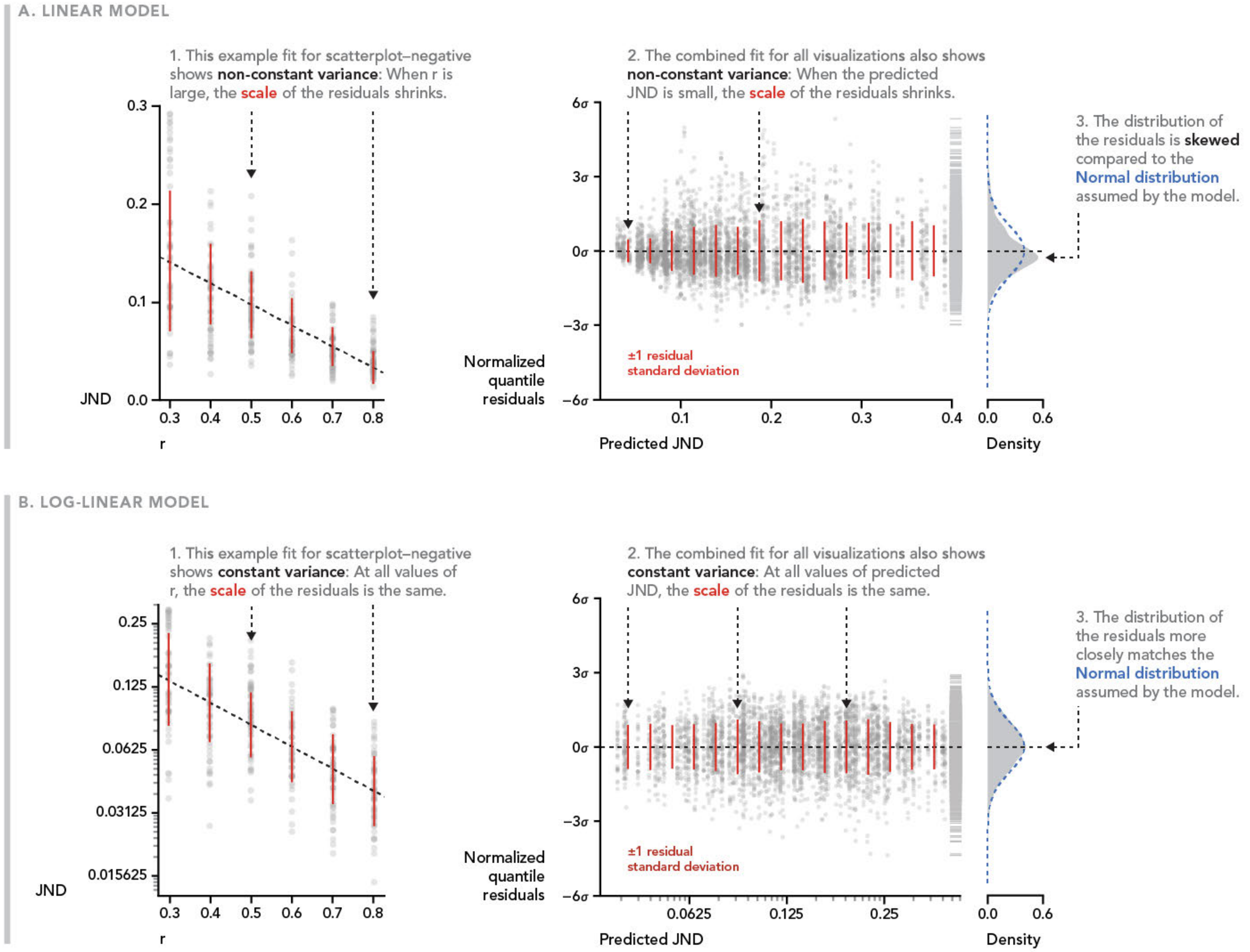


Fig. 3 Comparison of fits of the linear model (Section 3) and the log-linear model (Section 4). Example fits of each model to scatterplot–negative are shown in A.1 and B.1. Plots of normalized residuals for all visualization × direction pairs are shown in A.2 and B.2. Density plots of normalized residuals with comparison to the standard normal distribution are shown in A.3 and B.3.

Kay, Matthew. *Figures*. http://www.mjskay.com/figures.html N.p., 2019. Web. 12 Feb. 2019.

Group work on analytics projects

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 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

Turn in final 250-word memo

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!