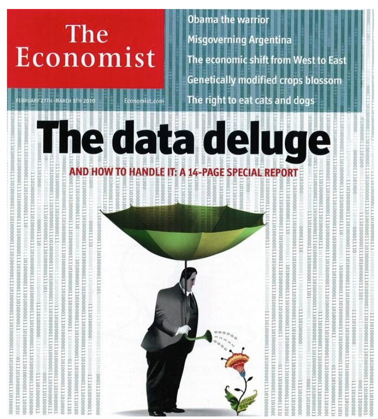
Big Data Analytics: What is Big Data?

H. Andrew Schwartz
Stony Brook University
CSE545, Fall 2017

What's the BIG deal?!

2008



2010

2011

2011

2012

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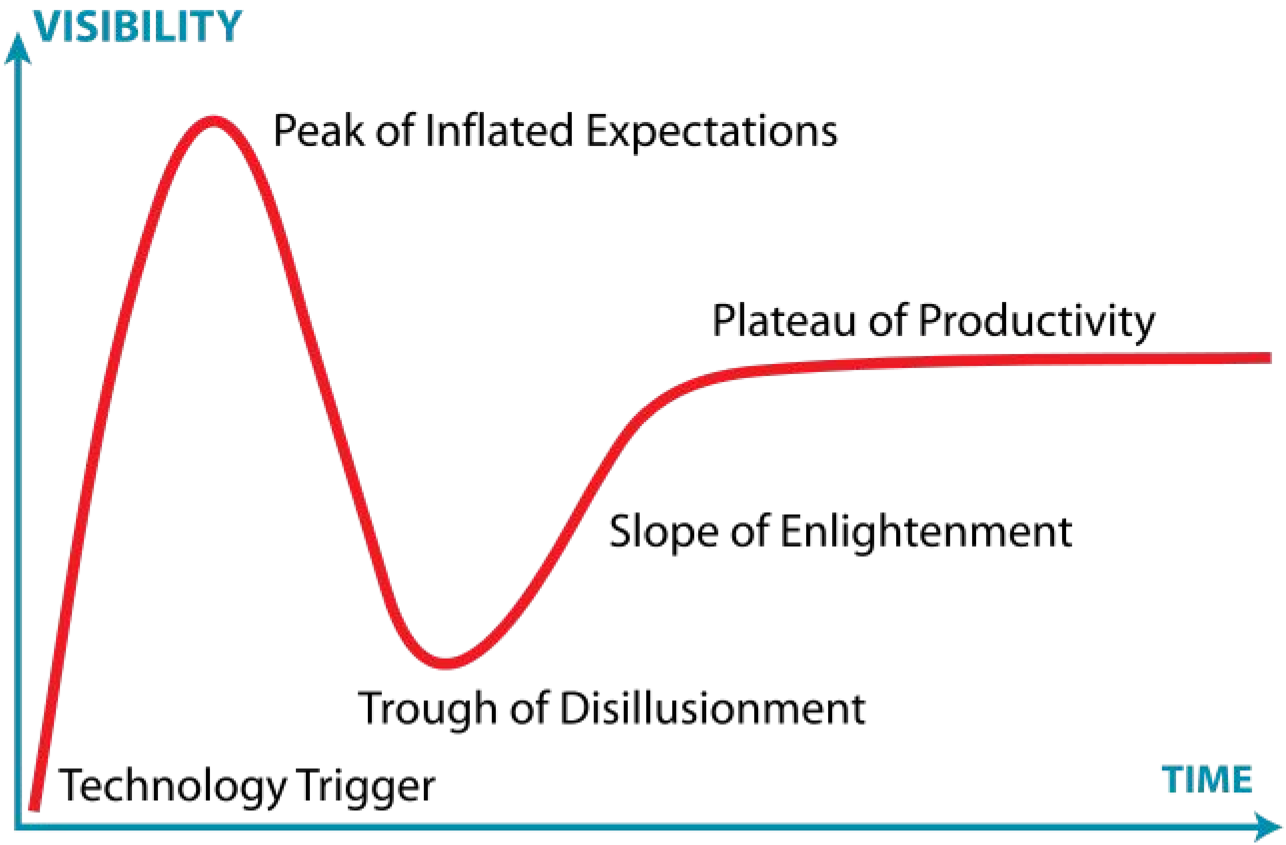

(Gartner Hype Cycle)

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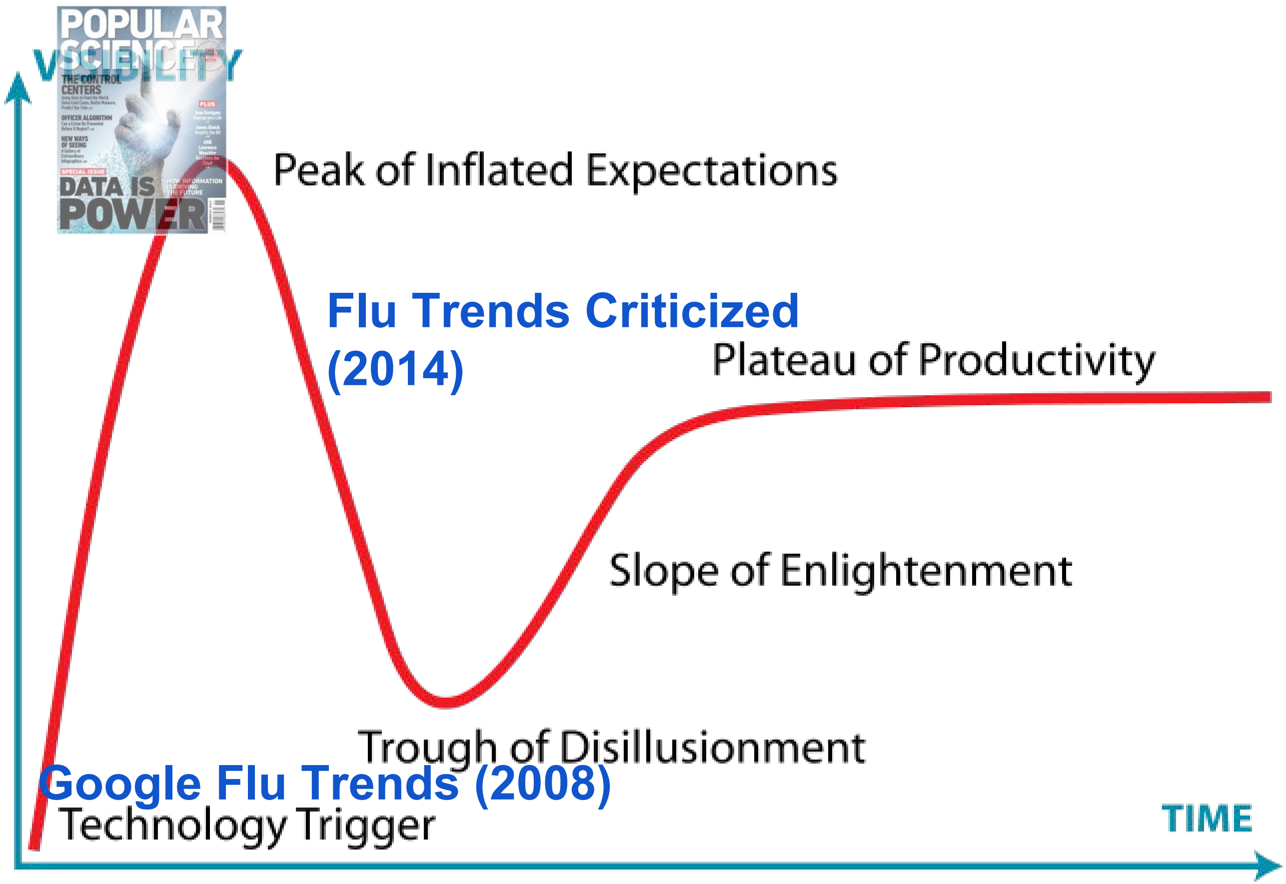

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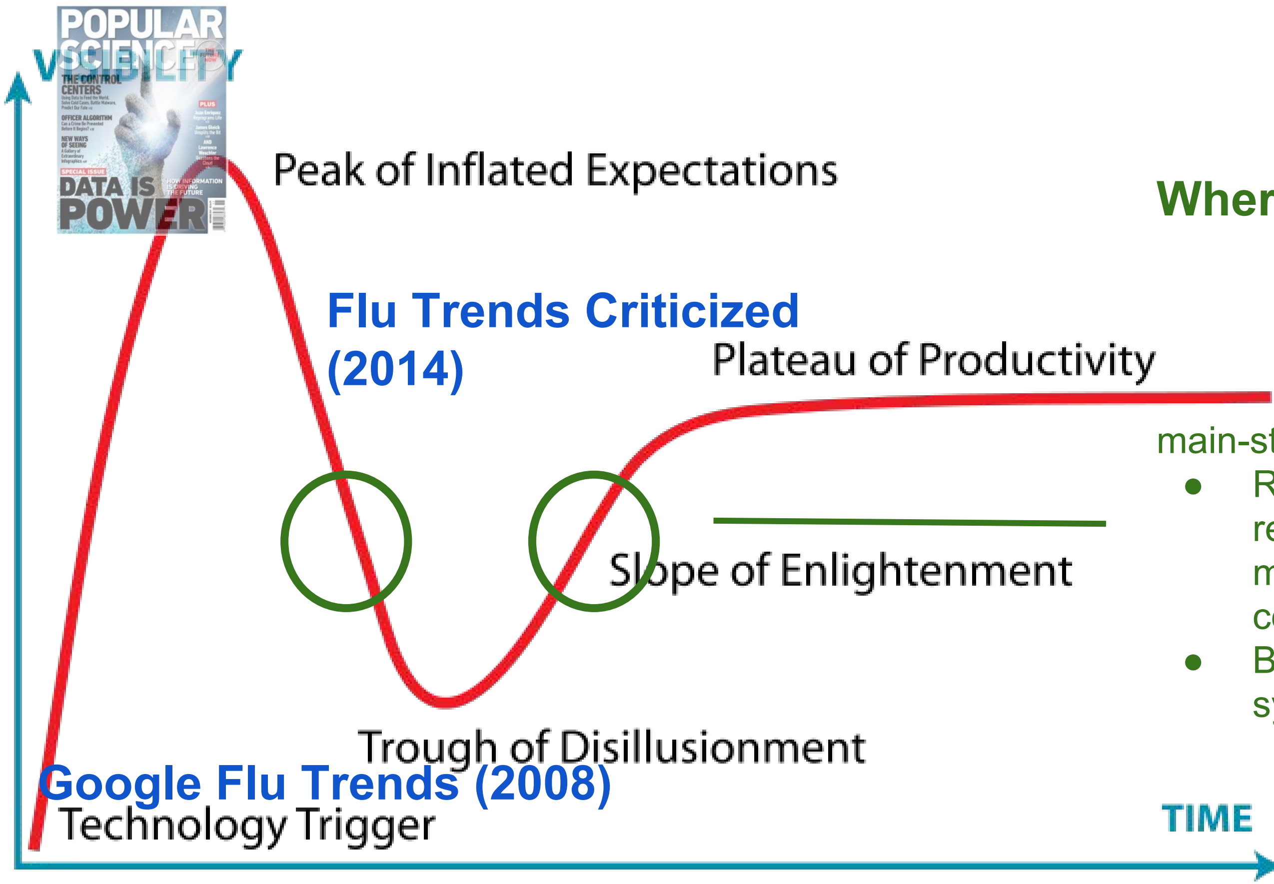

Where are we today?

main-stream study being established

- Realization of what subfields are really doing "big data" (i.e. data mining, ML, Statistics, computational social sciences).
- Best practices being synthesized.

(Gartner Hype Cycle)

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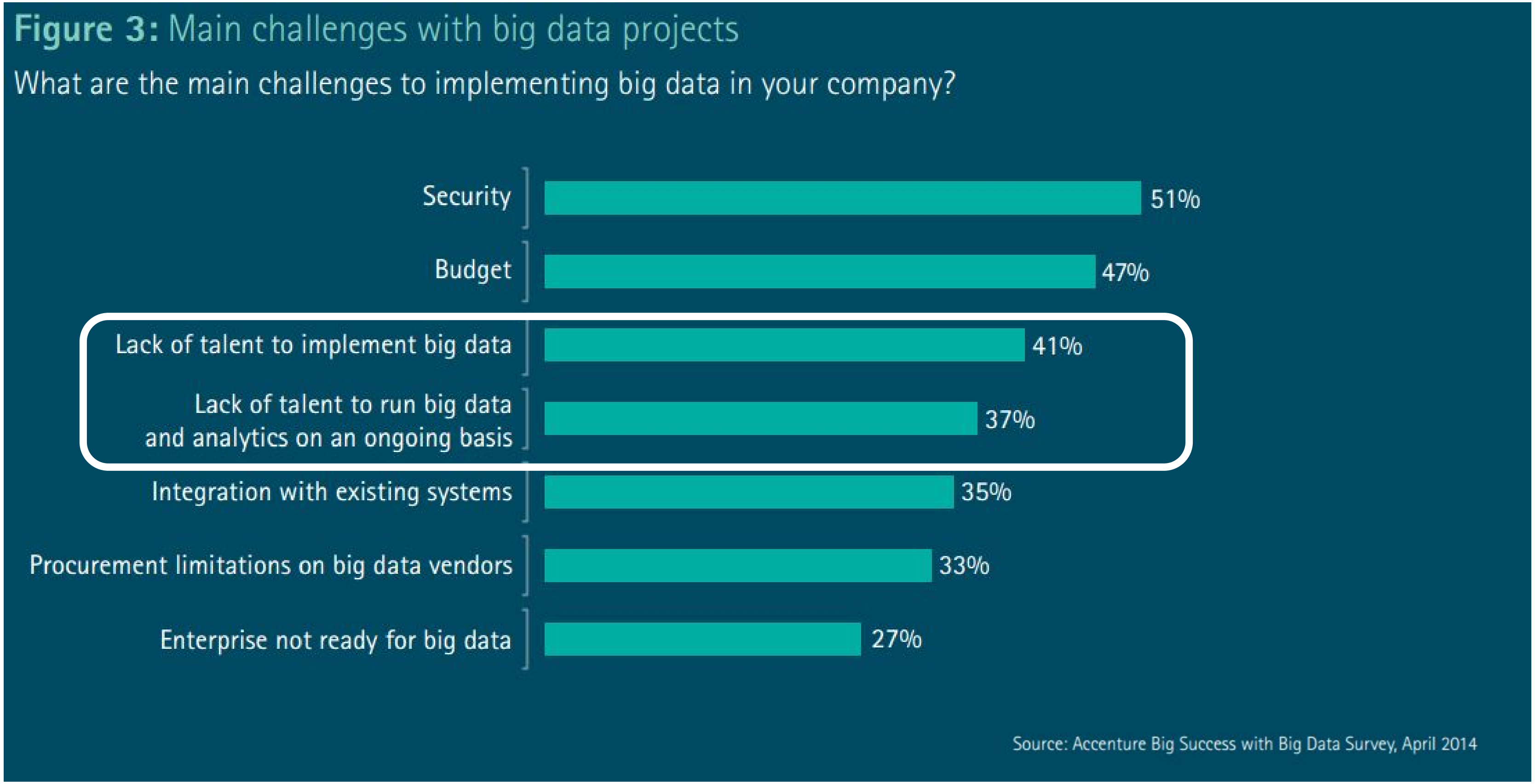

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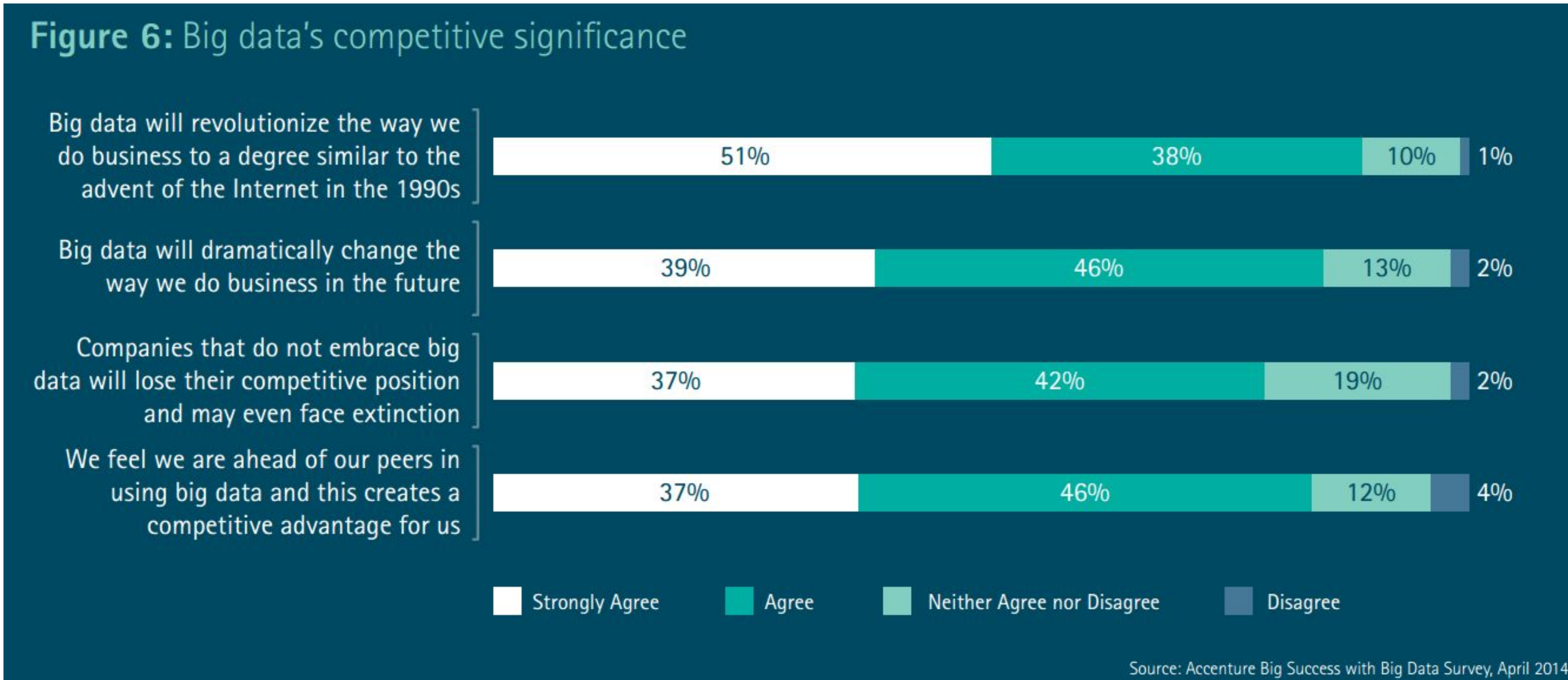

What is Big Data?

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traditional
computer science

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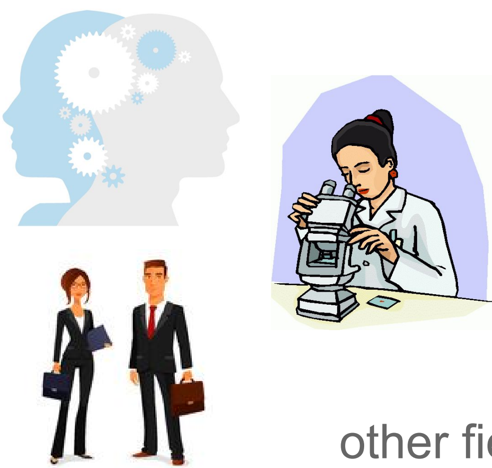
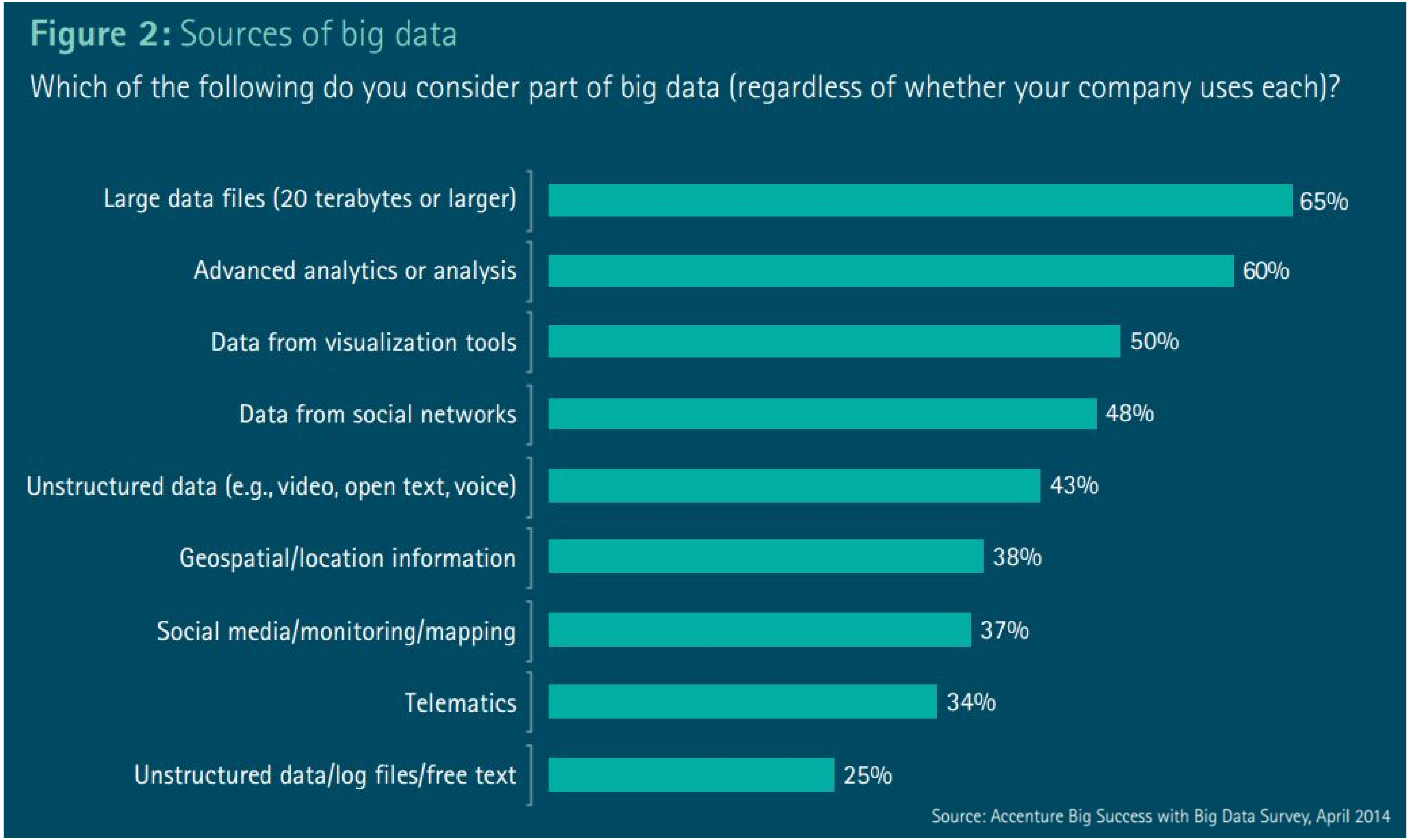


other fields

non-traditional sample size
(i.e. > 100 subjects); can't
analyze in stats tools (Excel).

What is Big Data? Industry view:



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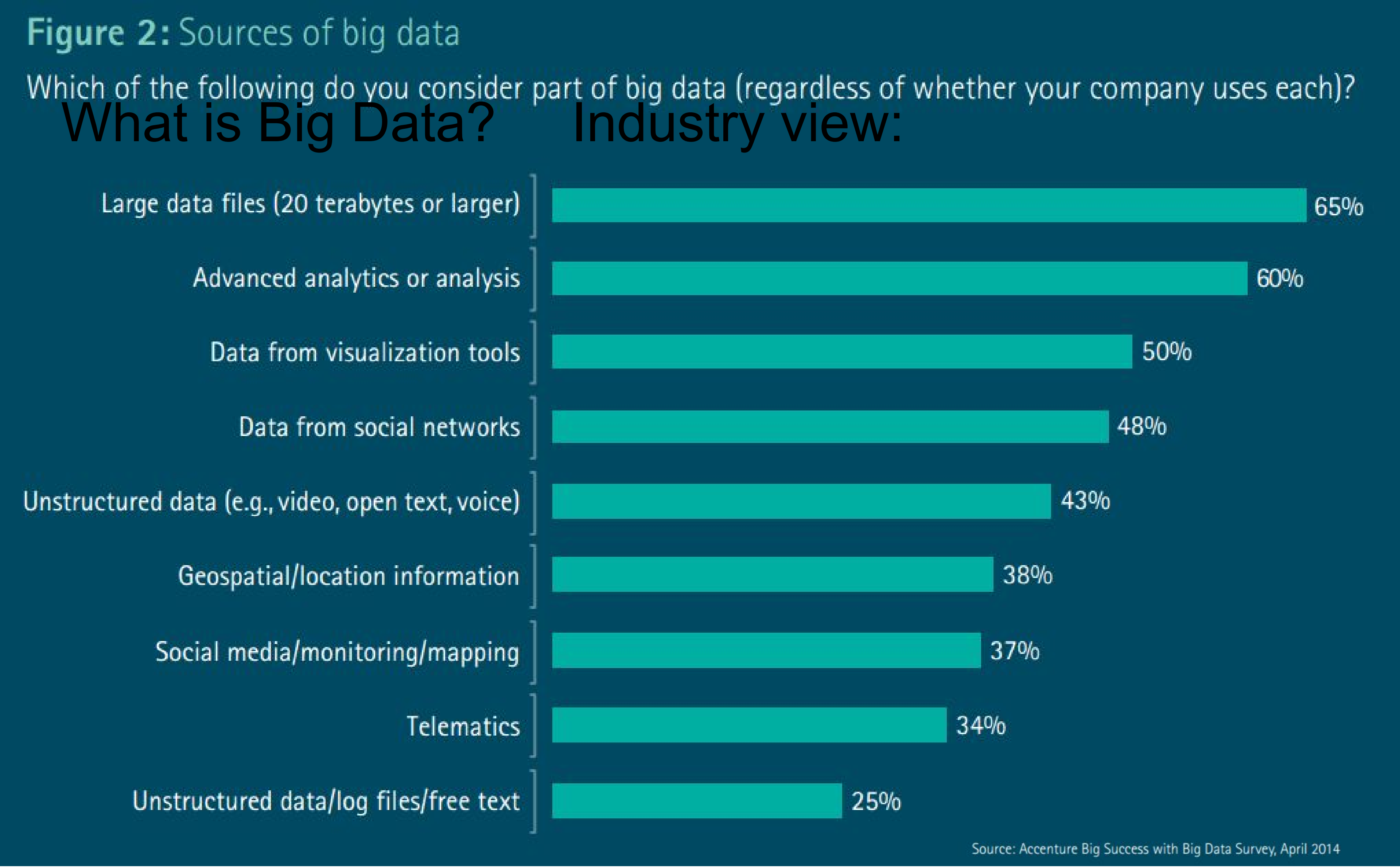


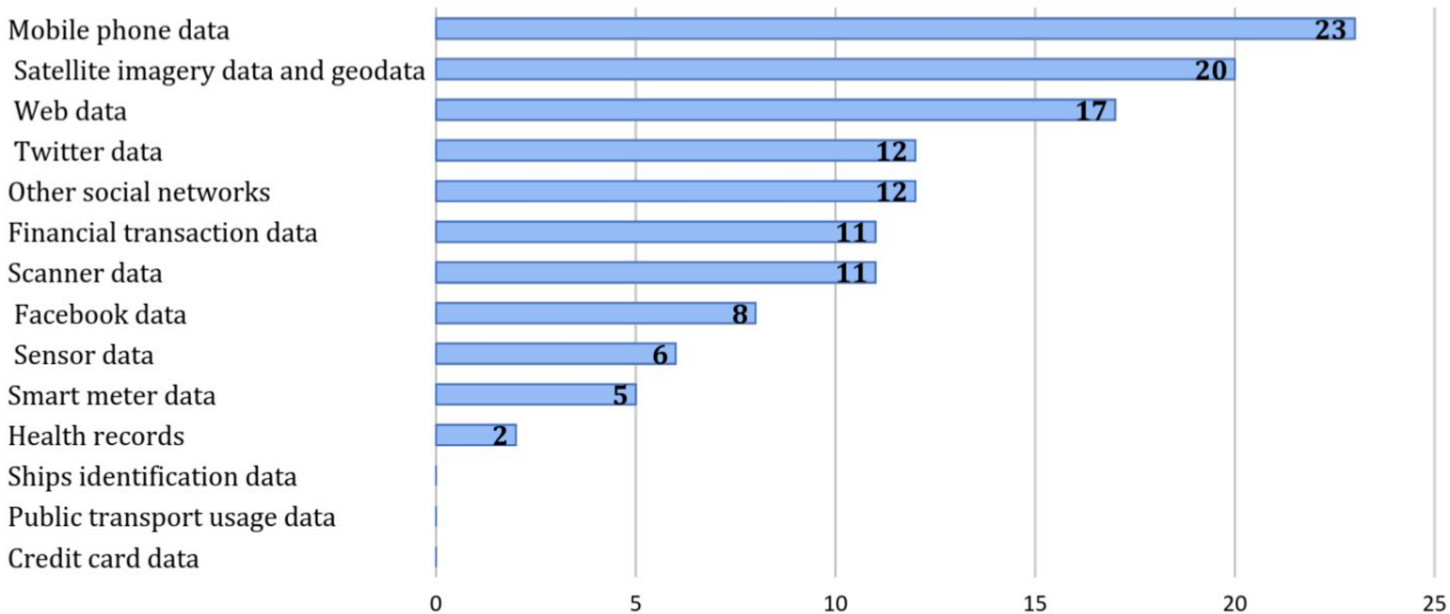
What is Big Data? Government view:

THE WORLD BANK
IBRD • IDA | WORLD BANK GROUP

BigData
UN Global Working Group

1. Survey of SDG-related Big Data projects

Type of data source(s)



- Mobile (23), Satellite imagery (20) and social media (12+12+8) are the most prominent sources

What is Big Data?

Short Answer:

Big Data ≈ Data Mining ≈ Predictive Analytics ≈ Data Science (Leskovec et al., 2014)

This Class:

How to analyze data that is mostly too large for main memory.

Analyses only possible with a *large* number of observations or features.

What is Big Data?

Goal: Generalizations
A *model* or *summarization* of the data.

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E.g.

- Google's PageRank: *summarizes* web pages by a single number.
- Twitter financial market predictions: *Models* the stock market according to shifts in sentiment in Twitter.
- Distinguish tissue type in medical images: *Summarizes* millions of pixels into clusters.
- Mental Health diagnosis in social media: *Models* presence of diagnosis as a distribution (a summary) of linguistic patterns.
- Frequent co-occurring purchases: *Summarize* billions of purchases as items that frequently are bought together.

What is Big Data?

Goal: Generalizations
A *model* or *summarization* of the data.

1. Descriptive analytics
   Describe (generalizes) the data itself

2. Predictive analytics
   Create something *generalizeable* to new data

Big Data Analytics -- The Class

Core Data Science Courses

CSE 519: Data Science Fundamentals

CSE 544: Prob/Stat for Data Scientists

CSE 545: Big Data Analytics

CSE 512: Machine Learning

CSE 537: Artificial Intelligence

CSE 548: Analysis of Algorithms

CSE 564: Visualization

Applications of Data Science

CSE 507:
Computational Linguistics

CSE 527:
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Key Distinction:
Focus on scalability and algorithms / analyses not possible without large data.

Big Data Analytics -- The Class

We will learn:

- to analyze different types of data:
  - high dimensional
  - graphs
  - infinite/never-ending
  - labeled
- to use different models of computation:
  - MapReduce
  - streams and online algorithms
  - single machine in-memory
  - *Spark*

Big Data Analytics -- The Class

We will learn:

- to solve real-world problems
  - Recommendation systems
  - Market-basket analysis
  - Spam and duplicate document detection
  - *Geo-coding data*
- uses of various "tools":
  - linear algebra
  - optimization
  - dynamic programming
  - hashing
  - *functional programming*
  - *tensorflow*

Big Data Analytics -- The Class

http://www3.cs.stonybrook.edu/~has/CSE545/

Preliminaries

Ideas and methods that will repeatedly appear:

- Bonferroni's Principle
- Normalization (TF.IDF)
- Hash functions
- IO Bounded (Secondary Storage)
- Power Laws
- Unstructured Data

Statistical Limits

Bonferroni's Principle

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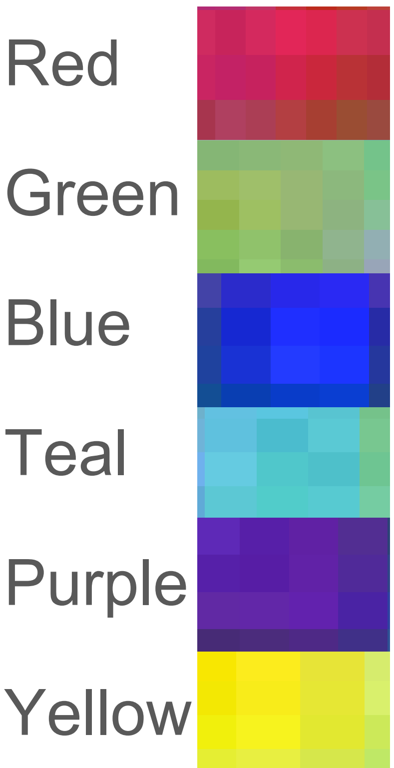
Which iphone case will be least popular?

Bonferroni's Principle



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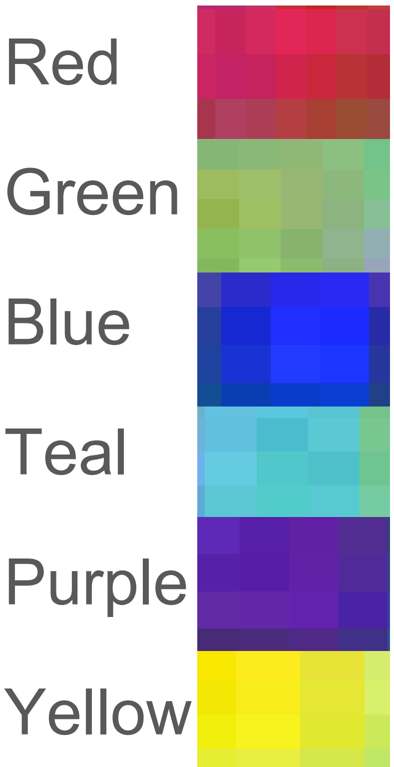

Which iphone case will be least popular?

First 10 sales come in:

Can you make any conclusions?

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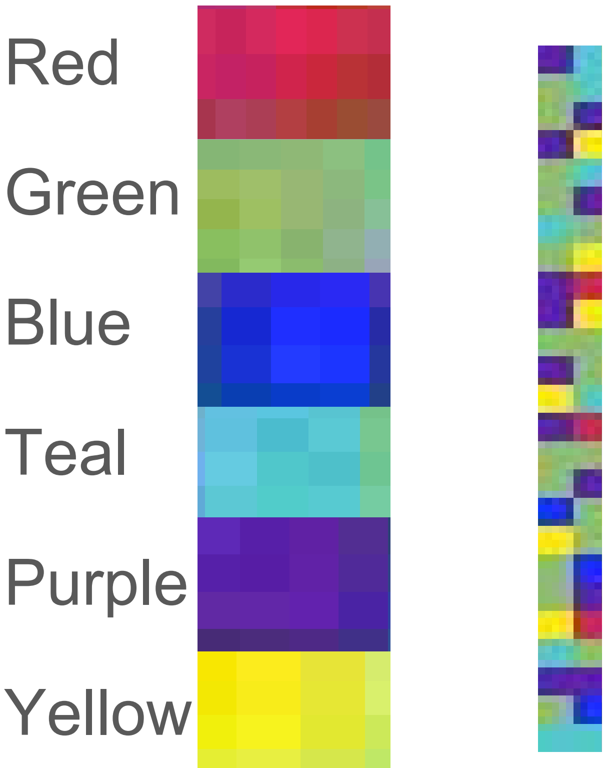
Bonferroni's Principle



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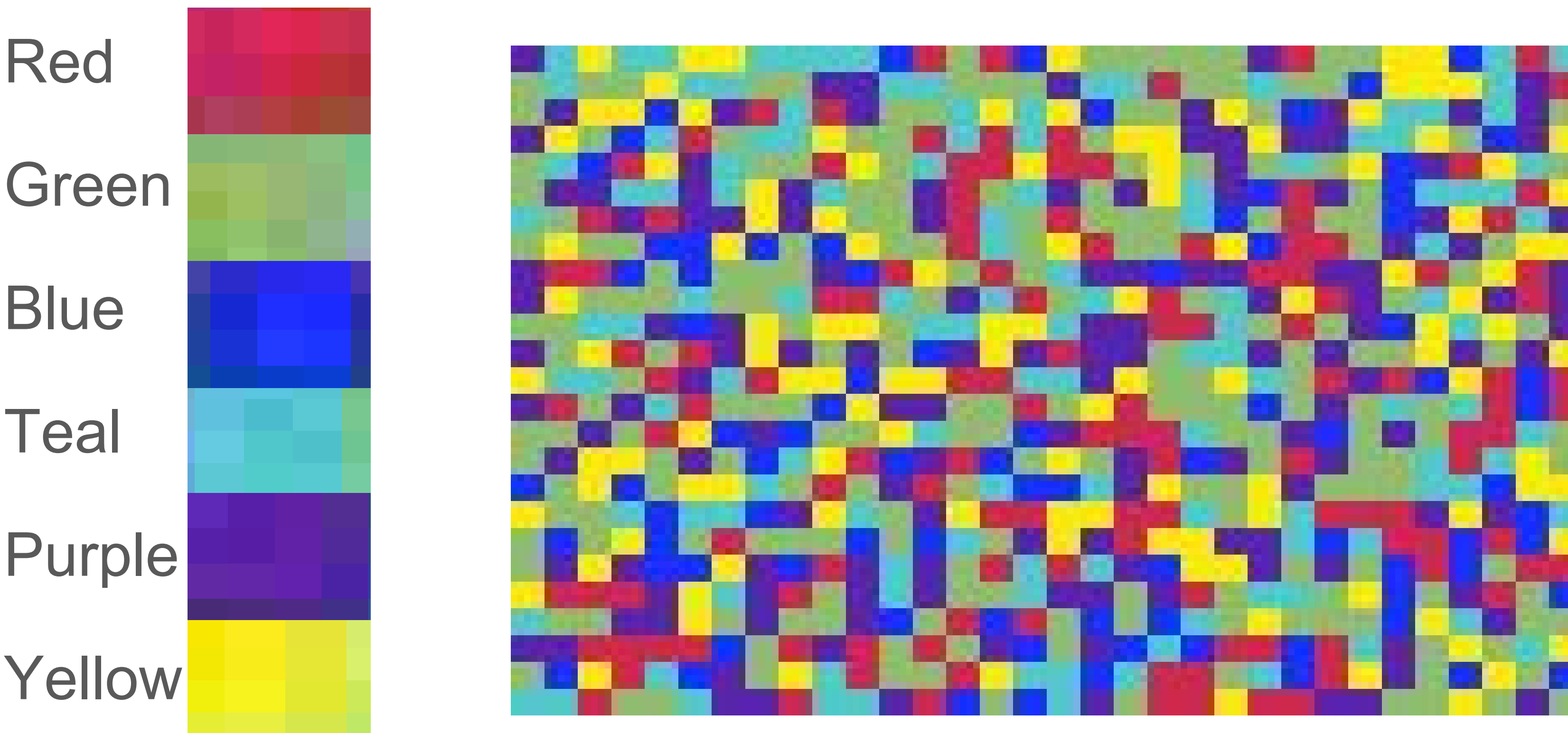

Statistical Limits

Bonferroni's Principle

Roughly, calculating the probability of any of n *findings* being true requires n times the probability as testing for 1 finding.

https://xkcd.com/882/

In brief, one can only look for so many patterns (i.e. features) in the data before you find something just by chance.

“Data mining” was originally a bad word!

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Count data often need *normalizing* -- putting the numbers on the same “scale”.

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Term Frequency:

$$tf_{ij} = \frac{count_{ij}}{\max_k count_{kj}}$$

$$tf.idf_{ij} = tf_{ij} \times idf_i$$

Inverse Document Frequency:

$$idf_i = log_2(\frac{docs_*}{docs_i}) \propto \frac{1}{\frac{docs_i}{docs_*}}$$

where docs is the number of documents containing word *i*.

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Normalizing

Standardize: puts different sets of data (typically vectors or random variables) on the same scale with the came center.

- Subtract the mean (i.e. “mean center”)
- Divide by standard deviation

$$z_i = \frac{x_i - \bar{x}}{s_x}$$

…

Hash Functions and Indexes

Review:

h: *hash-key -> bucket-number*

Objective: send the same number of expected hash-keys to each bucket

Example: storing word counts.

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Data structures utilizing hash-tables (i.e. O(1) lookup; dictionaries, sets in python) are a friend of big data algorithms! Review further if needed.

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Database Indexes: Retrieve all records with a given *value.* (also review if unfamiliar / forgot)

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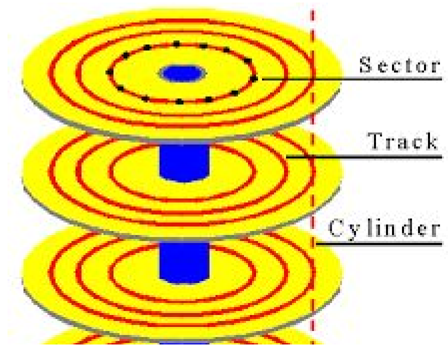
IO Bounded

Reading a word from disk versus main memory: 10^5 slower!

Reading many contiguously stored words is faster per word, but fast modern disks still only reach 150MB/s for sequential reads.



IO Bound: biggest performance bottleneck is reading / writing to disk.

(starts around 100 GBs; ~10 minutes just to read).

Power Law

Characterized many frequency patterns when ordered from most to least:

County Populations [r-bloggers.com]

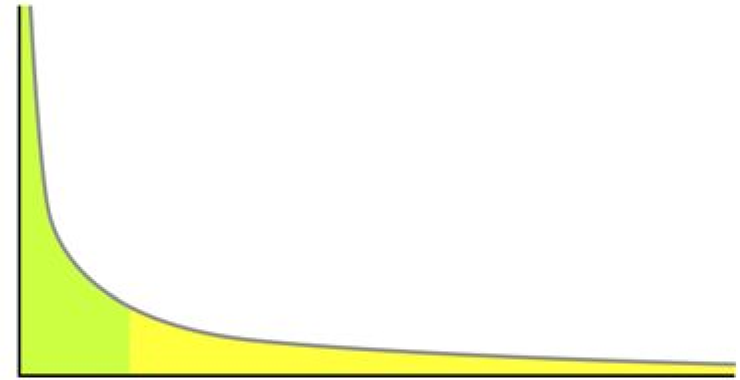
links into webpages [Broader et al., 2000]

Sales of products [see book]

Frequency of words [Wikipedia, “Zipf’s Law”]

(“popularity” based statistics, especially without limits)

Power Law



Power Law: $$\log y = b + a \log x$$

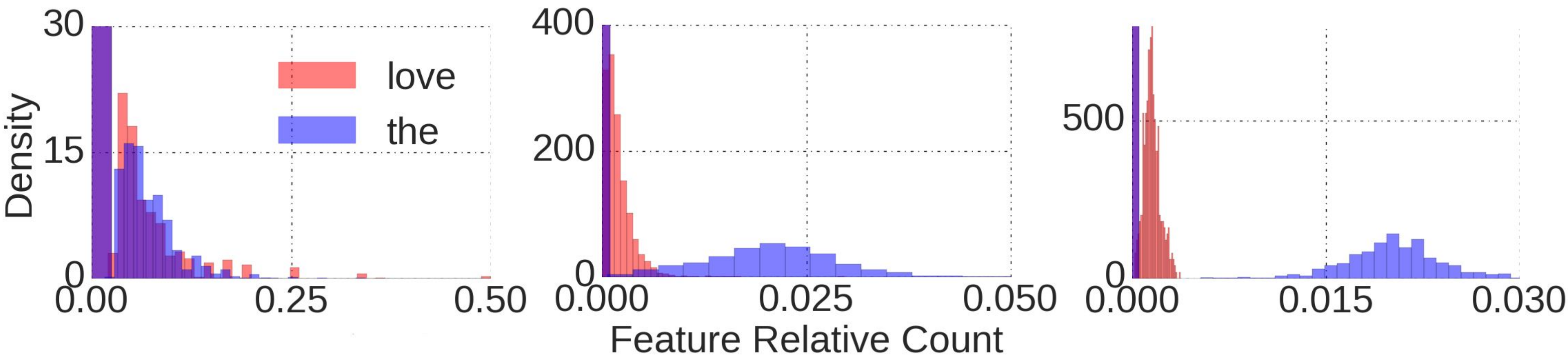
raising to the natural log:

$$y = e^b e^{a \log x} = e^b x^a = cx^a$$

where c is just a constant

Characterizes "the Matthew Effect" -- the rich get richer

Power Law



message-level

user-level

county-level

Data

- Unstructured ≈ requires processing to get what is of interest
- Feature extraction used to turn unstructured into structured
- Near infinite amounts of potential features in unstructured data

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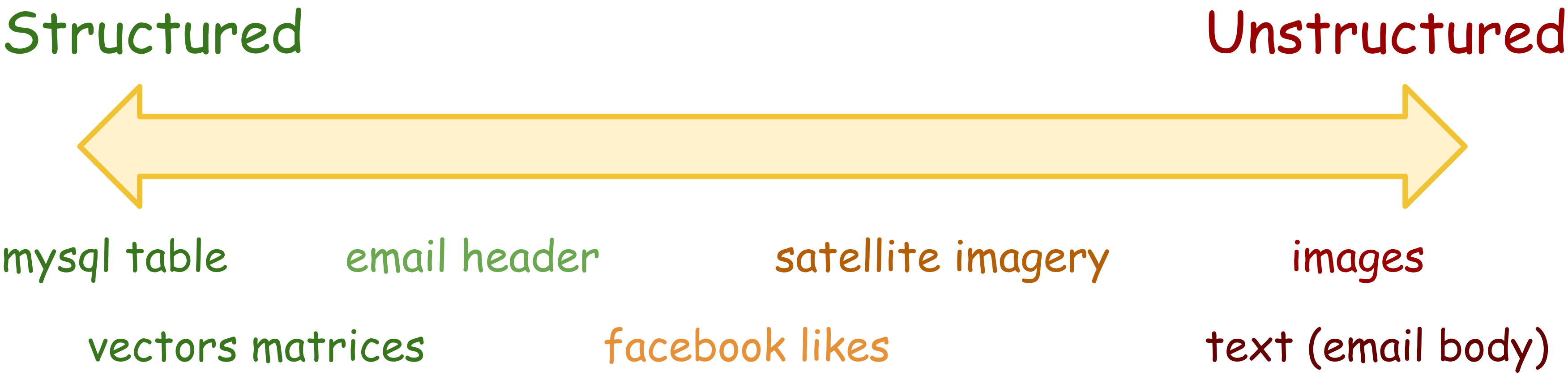

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