

Big Data Analytics: What is Big Data?



H. Andrew Schwartz

CSE545

Spring 2022

Big Data, what is it?

Big Data, what is it?



traditional
computer science

data that will not fit
in main memory.

Big Data, what is it?



traditional
computer science

data that will not fit
in main memory.

For example...

busy web server access logs

graph of the entire Web

all of Wikipedia

daily satellite imagery over a year

Big Data, what is it?



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computer science

data that will not fit
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data with a *large*
number of observations
and/or features.



statistics

Big Data, what is it?



Tall data:

edge list of a large graph

rgb values per pixel location in large images

data with a *large* number of observations and/or features.



statistics

Wide data: mobile app usage statistics of 100 people



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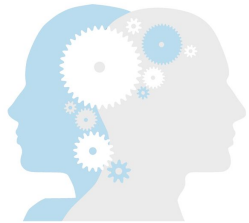
data that will not fit
in main memory.

data with a *large*
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and/or features.



statistics

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



other fields

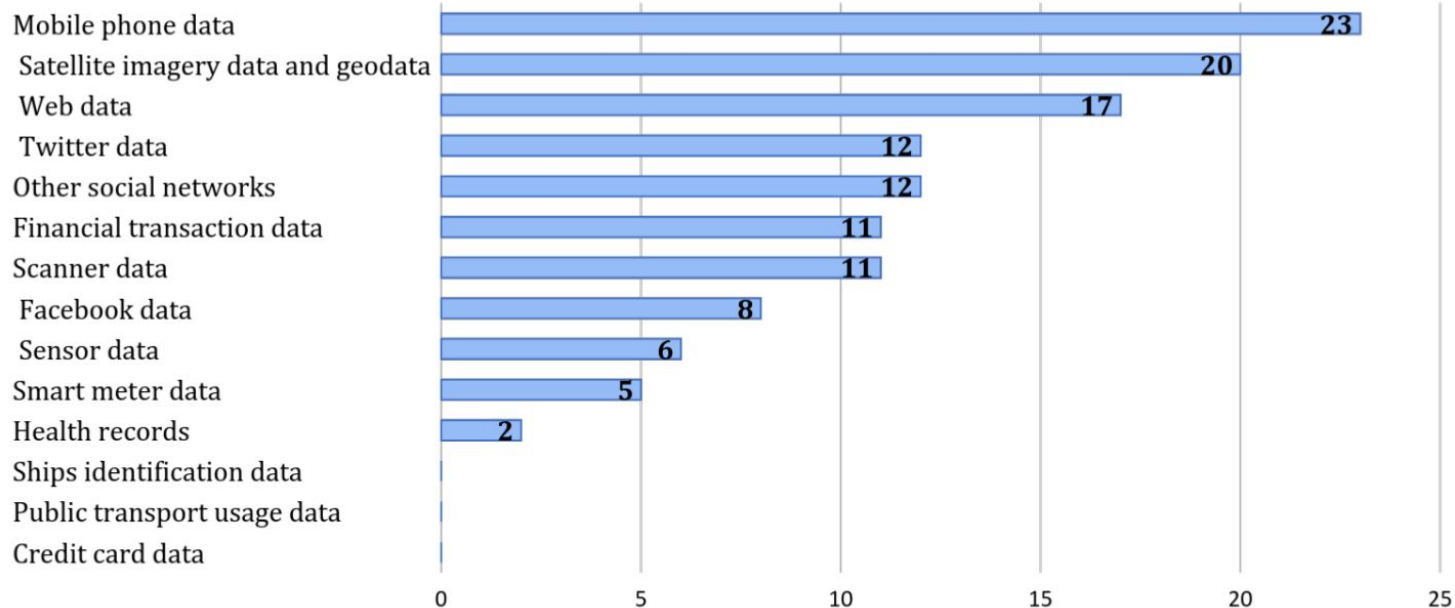


Big Data, what is it? *Government View*



1. Survey of SDG-related Big Data projects

Type of data source(s)

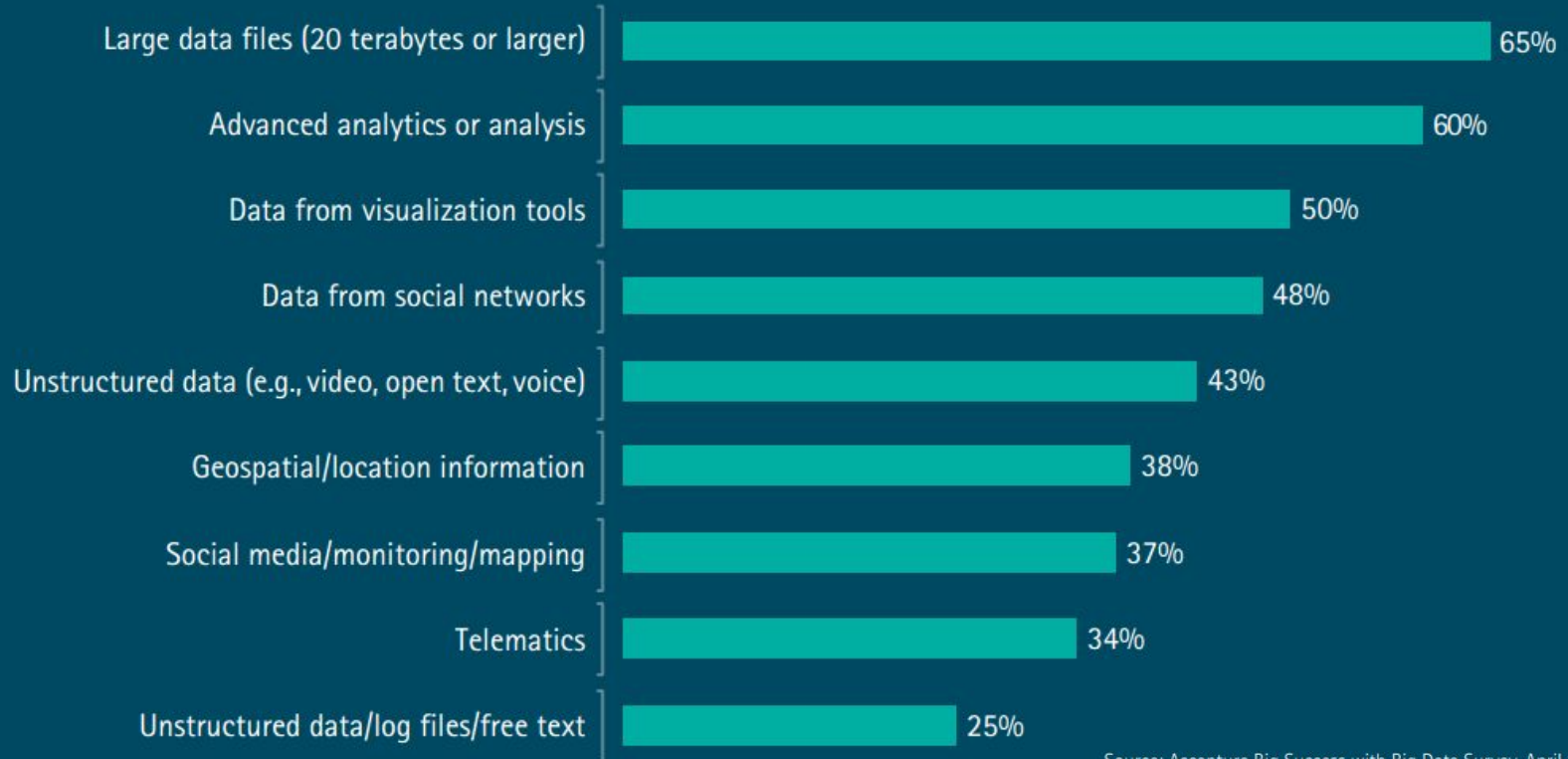


- Mobile (23), Satellite imagery (20) and social media (12+12+8) are the most prominent sources

Big Data, what is it? *Industry View*

Figure 2: Sources of big data

Which of the following do you consider part of big data (regardless of whether your company uses each)?

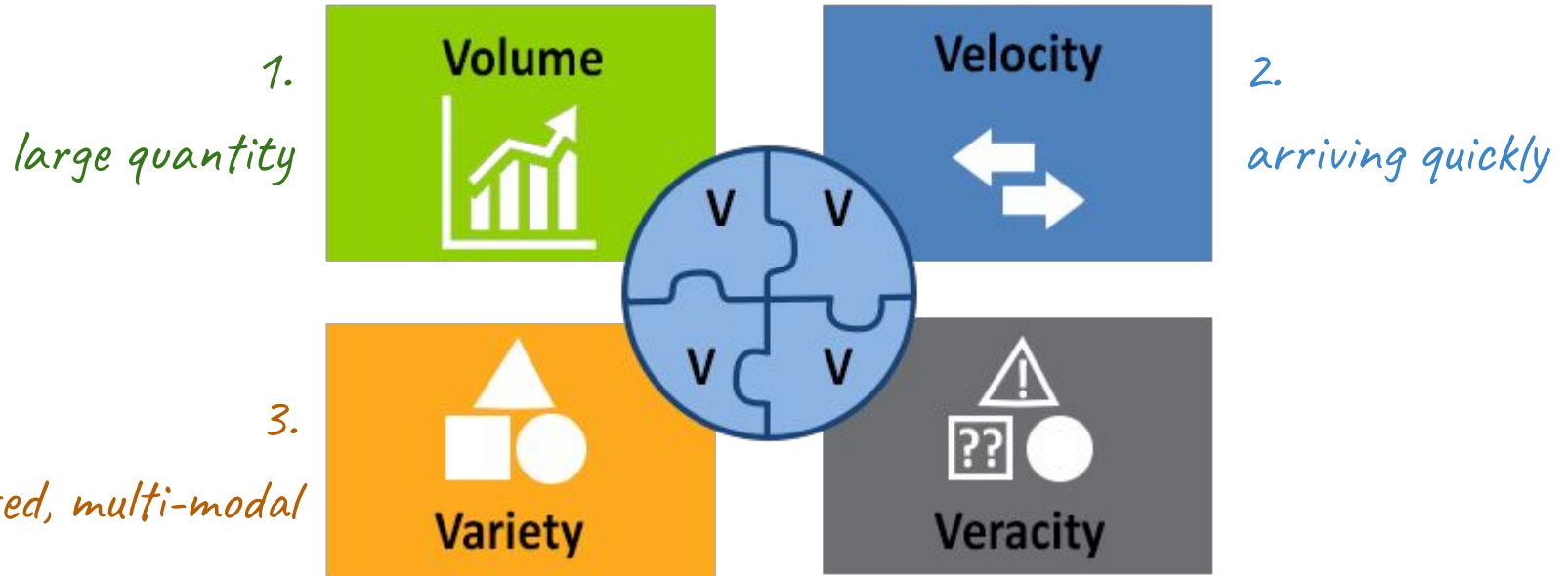


Source: Accenture Big Success with Big Data Survey, April 2014

Big Data, what is it?

Analyses which can handle the 3 Vs and do it with quality (veracity):

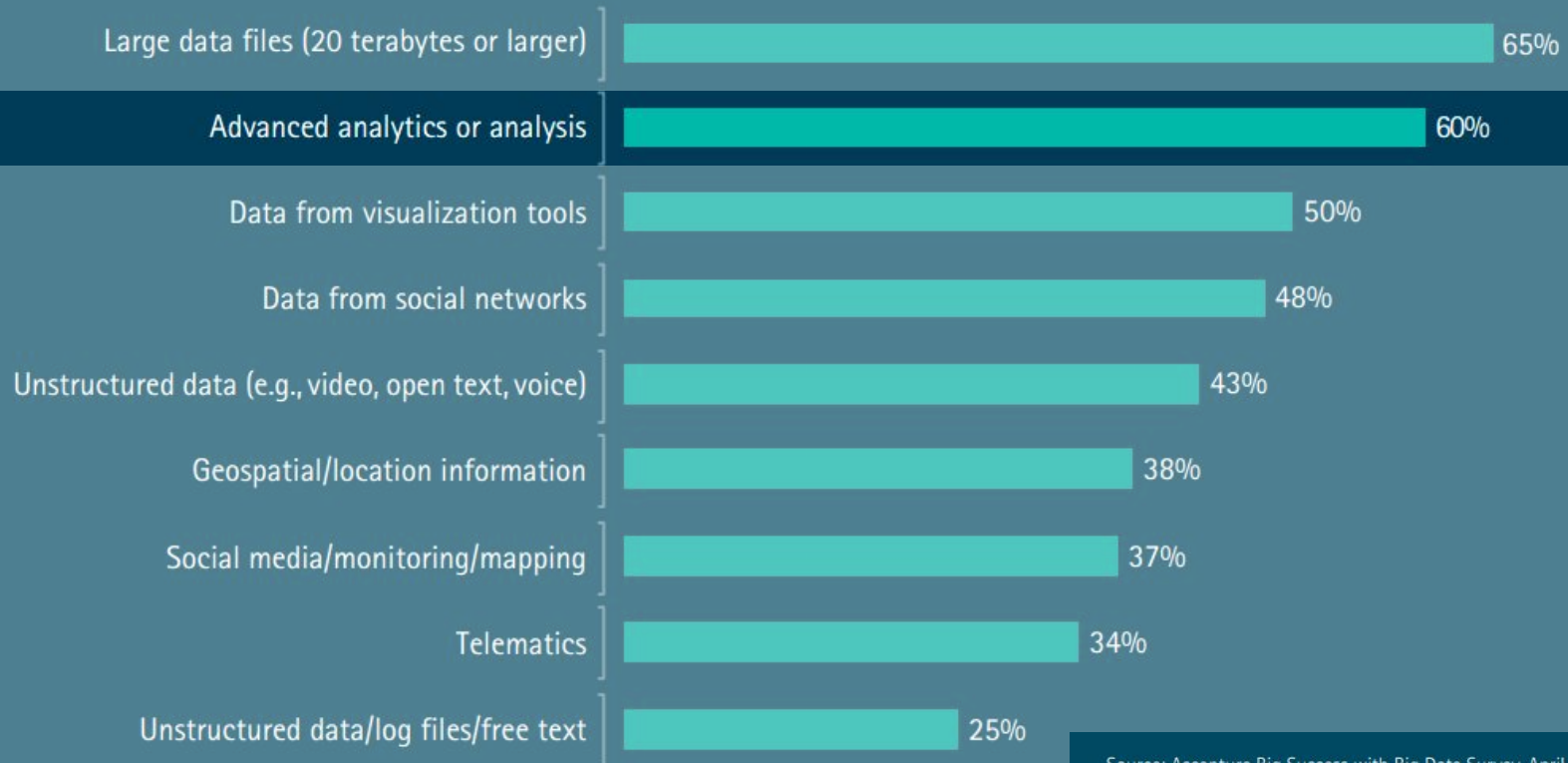
(Laney, 2001: META Group)



Big Data, what is it? *Industry View*

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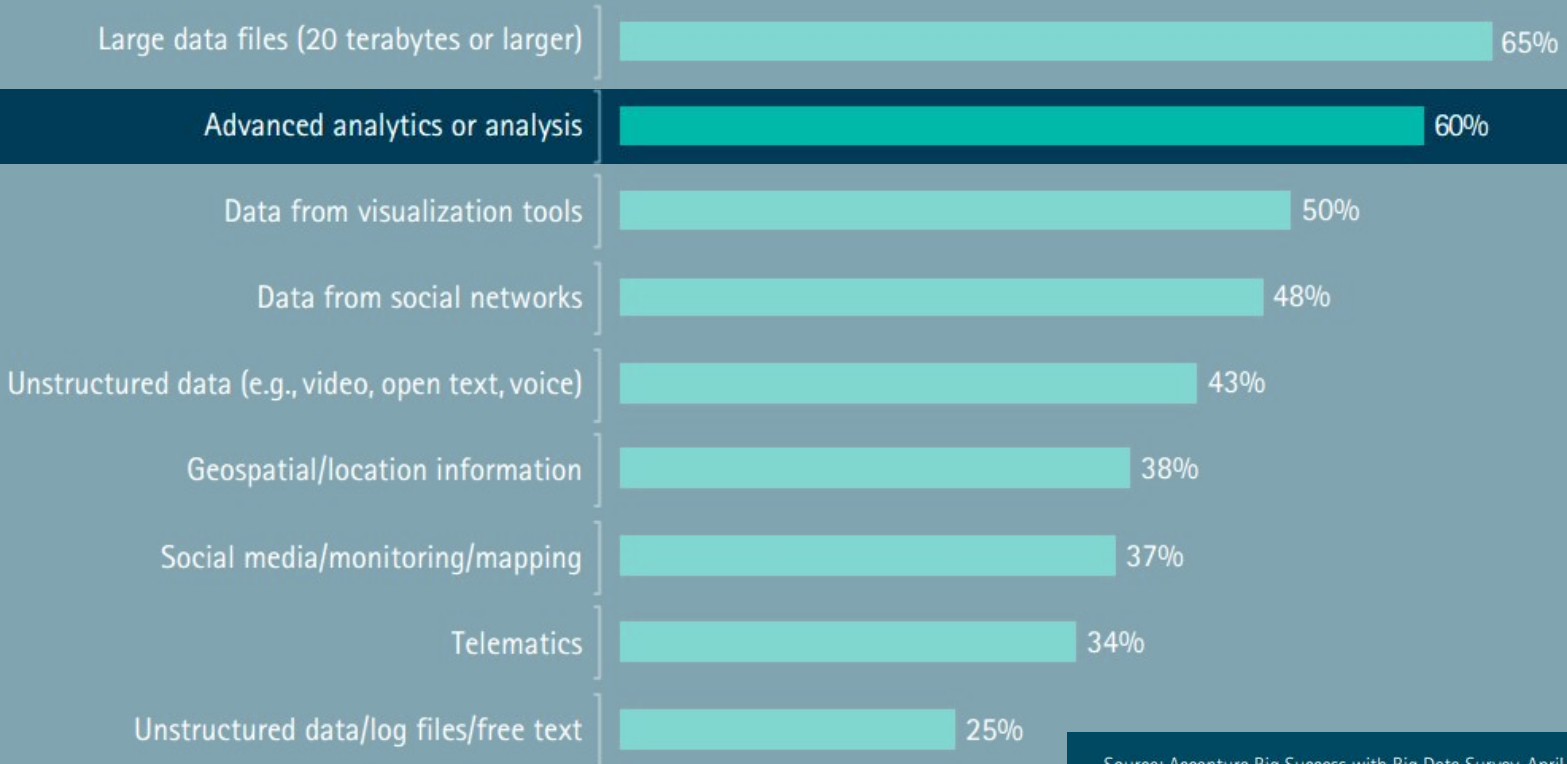


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Big Data, a type of analytics

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Big Data, a type of analytics

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Big Data, a type of analytics



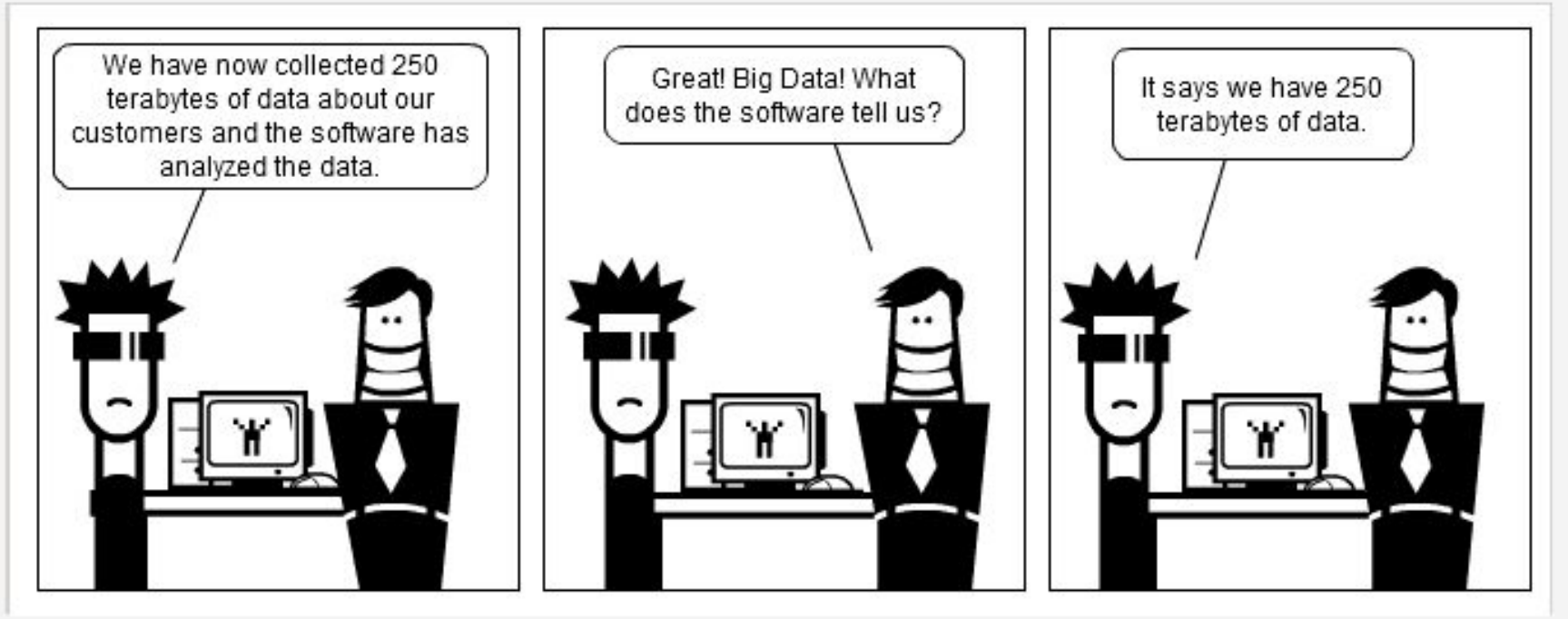
Big Data, a type of analytics



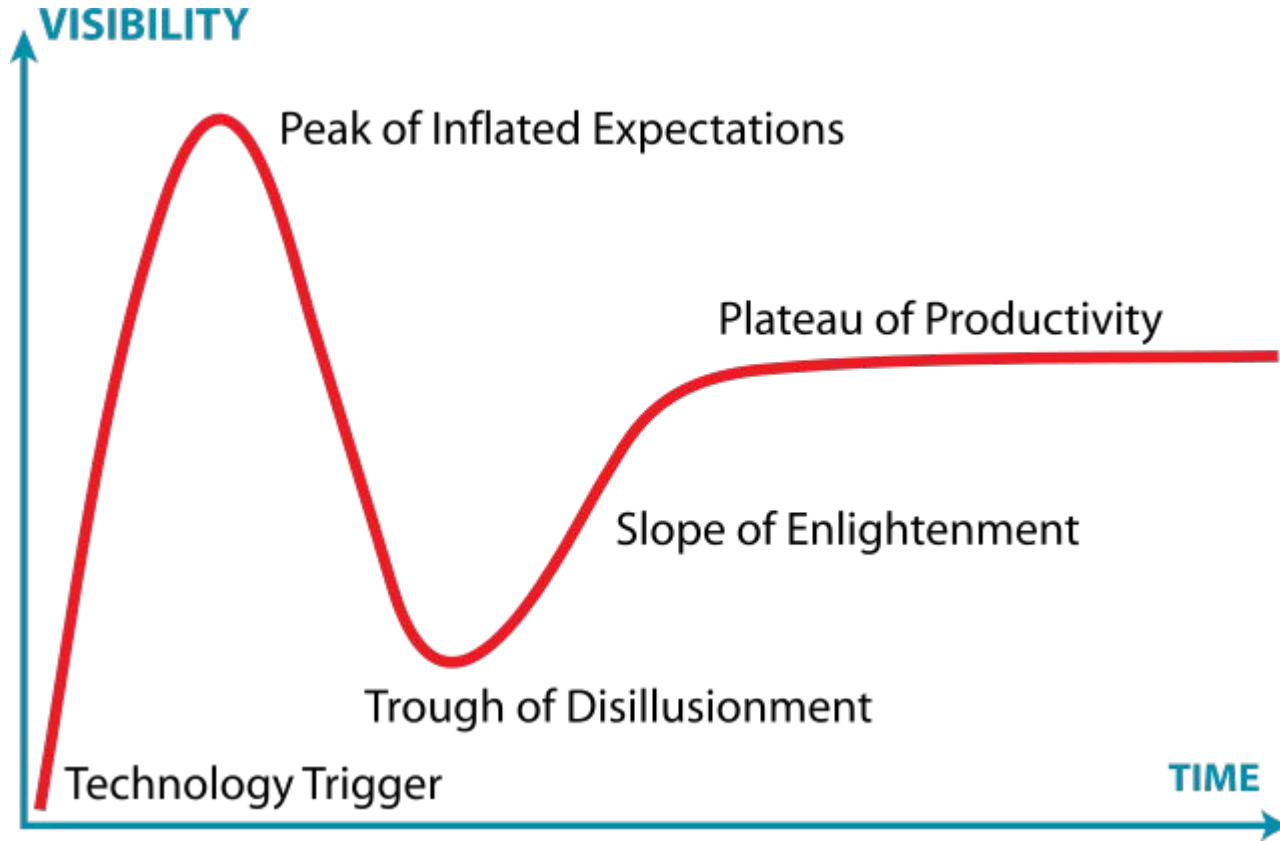
Big Data, a type of analytics

The Big Data Challenge

View more social media cartoons at
www.socmedsean.com



Big Data, a buzz word?



(Gartner Hype Cycle)

Big Data, a buzz word?



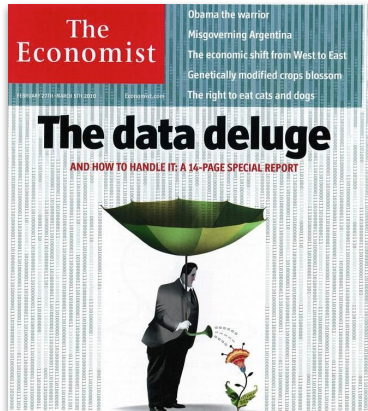
2008



2011



2012



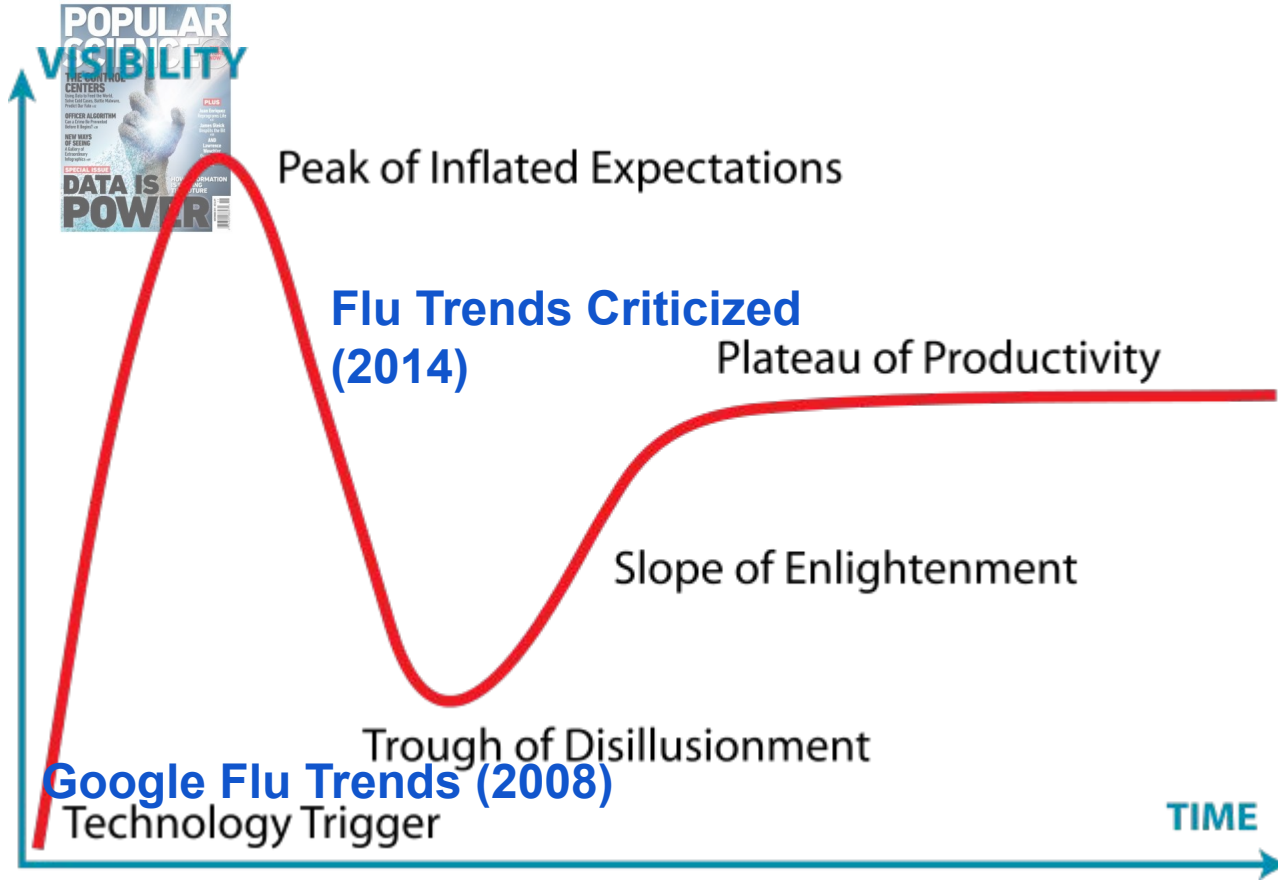
2010

2011



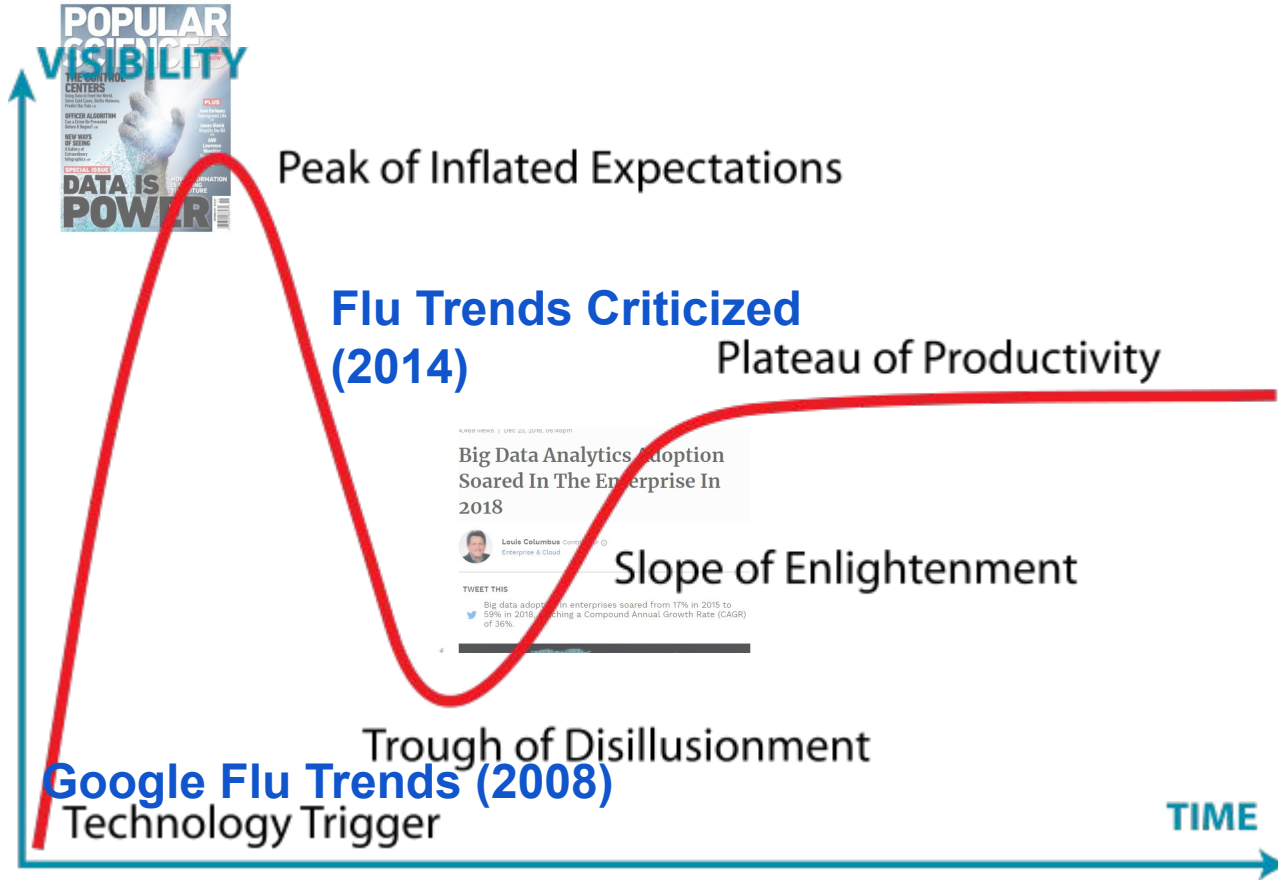
2018

Big Data, a buzz word?



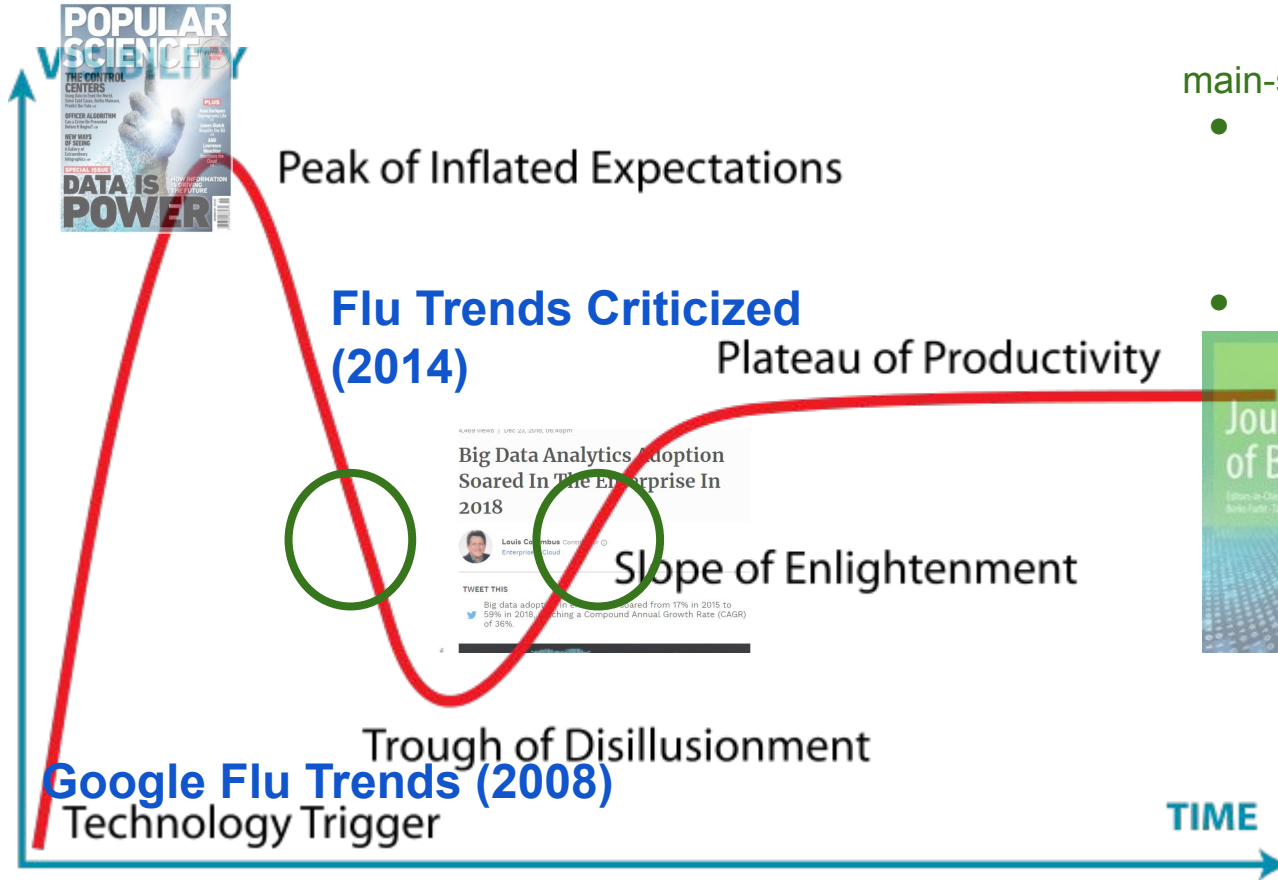
(Gartner Hype Cycle)

Big Data, a buzz word?



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Big Data, a buzz word?



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 established.

(Gartner Hype Cycle)

Big Data, a buzz word?



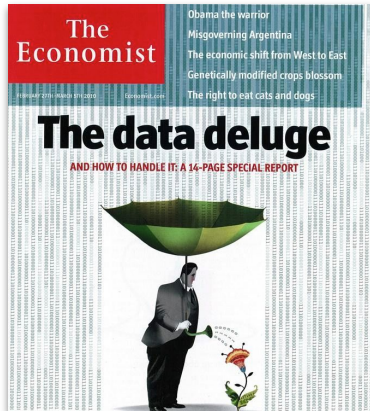
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2022



2018

Big Data, a buzz word?

Google Scholar

Top publications

Categories > Engineering & Computer Science > Data Mining & Analysis ▾

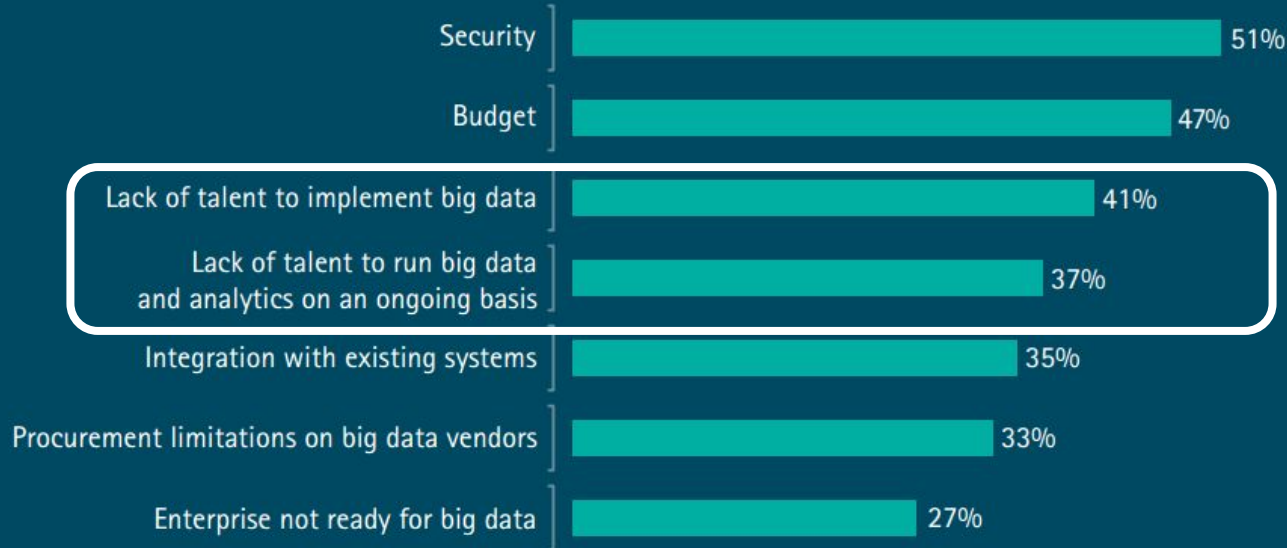
	Publication	h5-index	h5-me
1.	ACM SIGKDD International Conference on Knowledge Discovery & Data Mining	104	183
2.	IEEE Transactions on Knowledge and Data Engineering	87	132
3.	International Conference on Artificial Intelligence and Statistics	68	101
4.	ACM International Conference on Web Search and Data Mining	61	120
5.	IEEE International Conference on Data Mining	54	90
6.	ACM Conference on Recommender Systems	50	84
7.	Knowledge and Information Systems	46	64
8.	IEEE International Conference on Big Data	45	66
9.	Journal of Big Data	42	74
10.	ACM Transactions on Intelligent Systems and Technology (TIST)	40	62
11.	Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery	38	77
12.	Data Mining and Knowledge Discovery	38	68

Big Data, in demand?

Big Data, in demand?

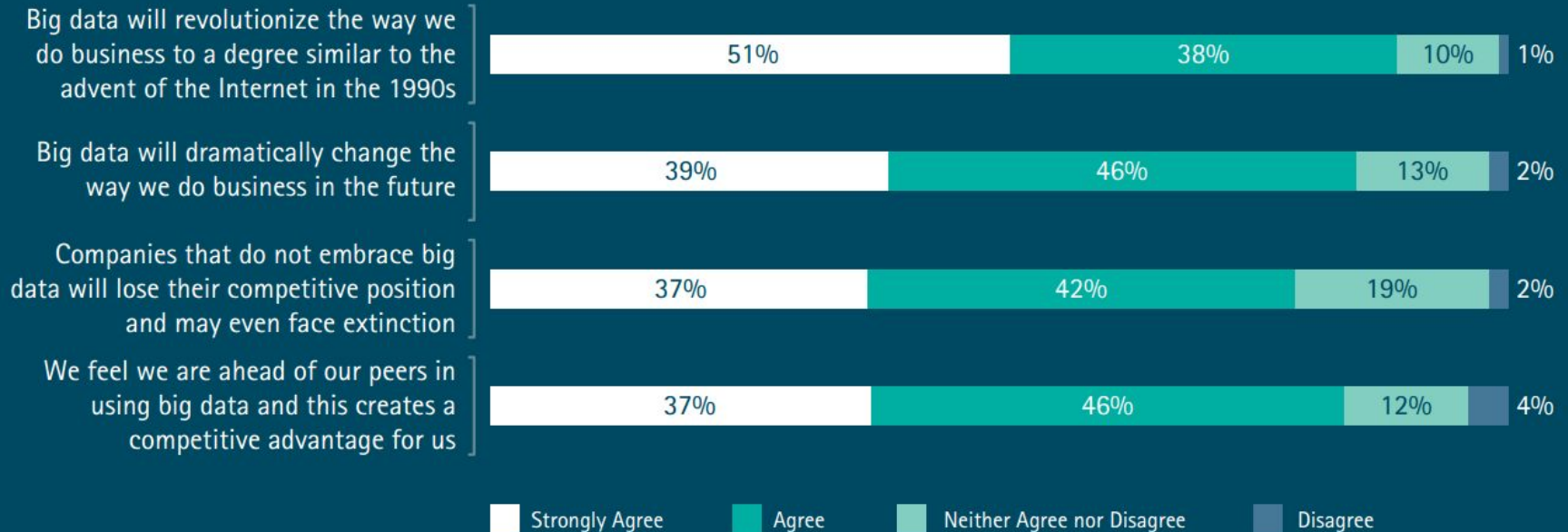
Figure 3: Main challenges with big data projects

What are the main challenges to implementing big data in your company?



Big Data, in demand?

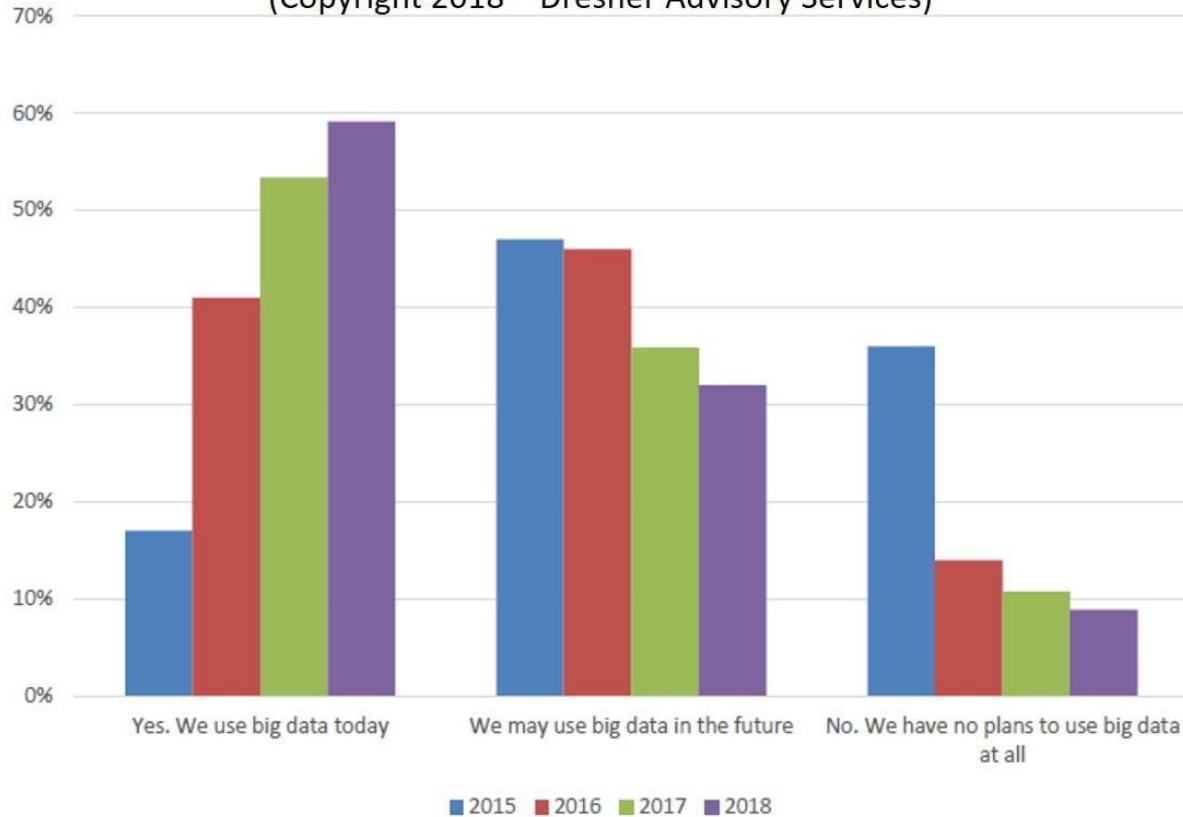
Figure 6: Big data's competitive significance



Source: Accenture Big Success with Big Data Survey, April 2014

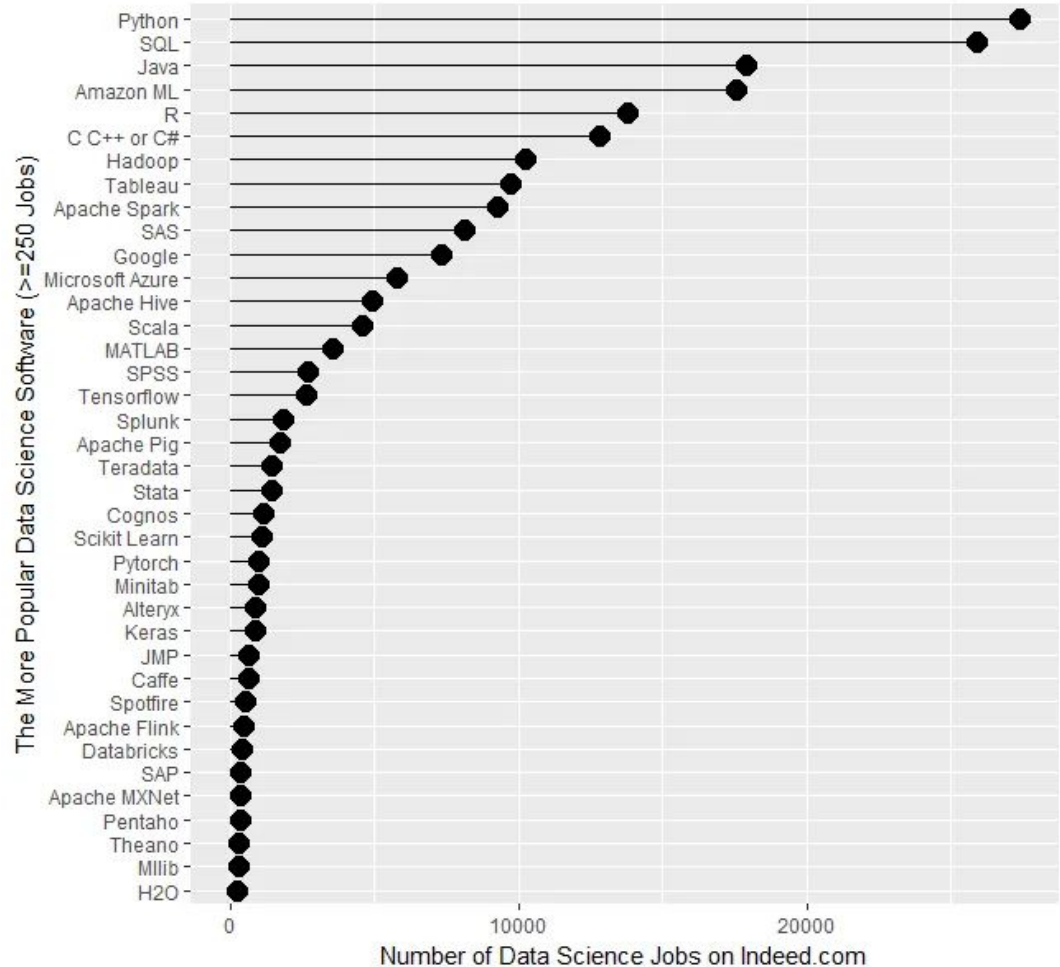
Big Data, in demand?

Adoption of Big Data 2015-2018
(Copyright 2018 – Dresner Advisory Services)

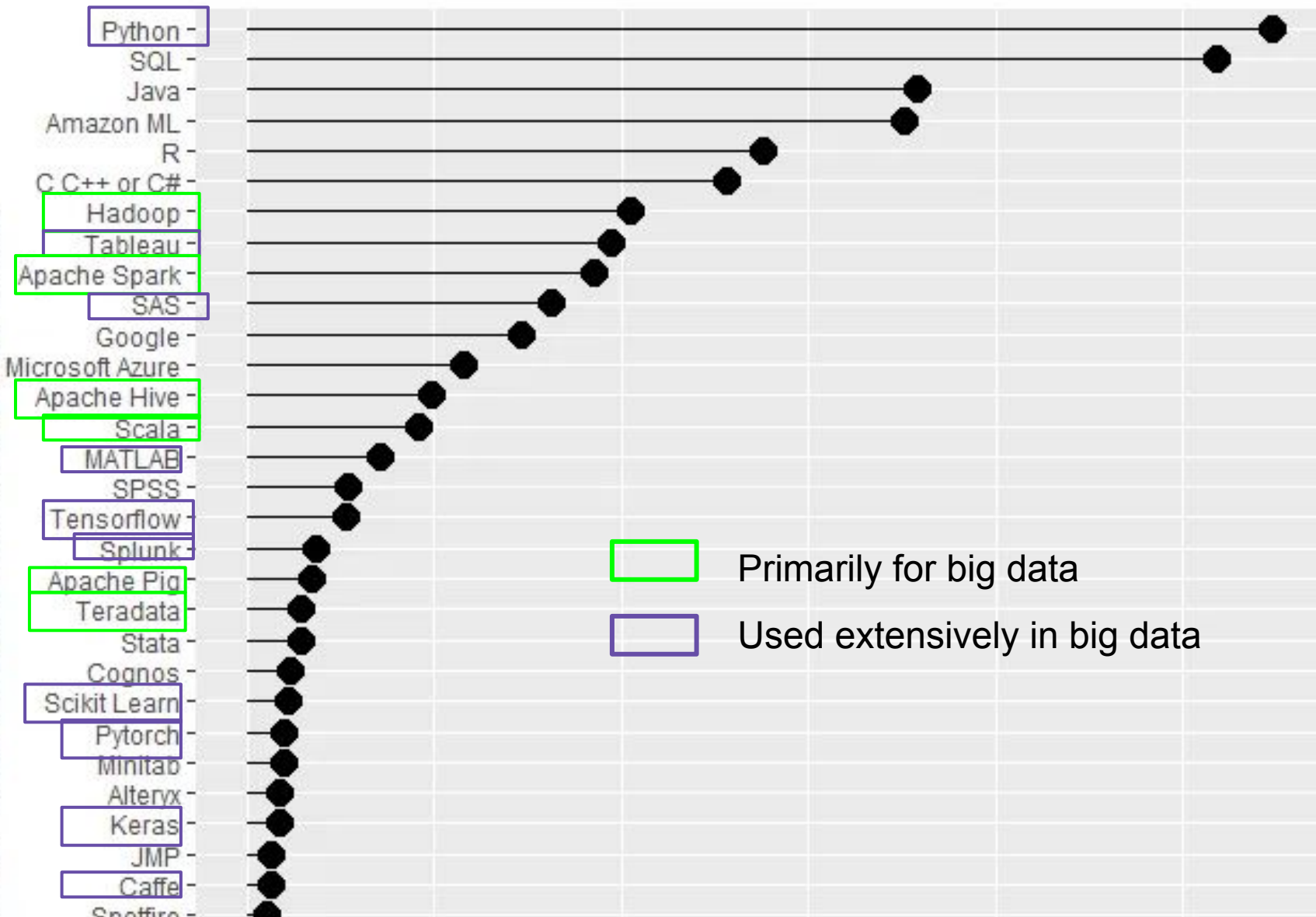


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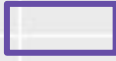
By the requirements
in job ads.
(Muenchen,2019)



More Popular Data Science Software (>=250 Jobs)



Primarily for big data



Used extensively in big data

Big Data, What is it?

Top big data trends in 2021



Edge computing

Explosive growth in data generated from cloud systems, sensors, smart devices and video streaming is driving adoption of edge computing. Data processing is done on the periphery of the network as close to the originating source as possible.



Cloud and hybrid cloud computing

Cloud computing enables organizations to process nearly limitless amounts of data. Hybrid cloud approaches are being developed to enable companies in regulated industries to take advantage of cloud's economic and technical advantages.



Data lakes

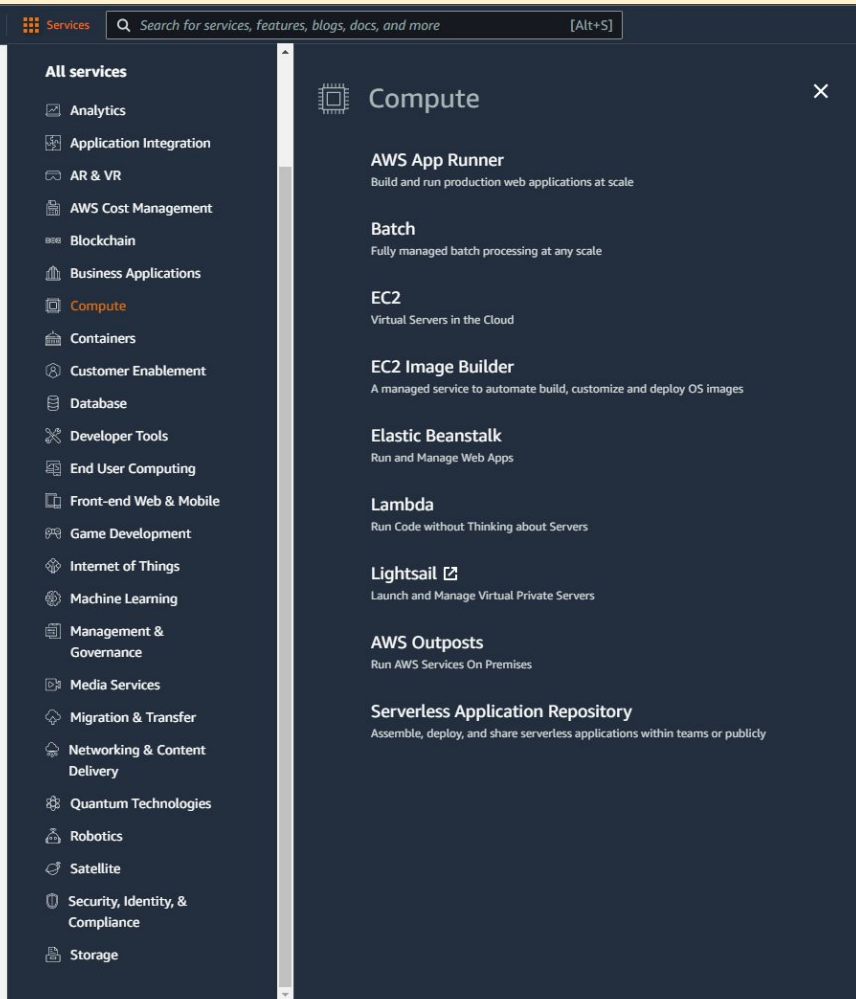
These large repositories store structured and unstructured data in its native format. Data scientists often extract just what's needed for a project, eliminating costly ETL processes required of centralized data warehouses.



Machine learning and AI technologies

Machine learning and other AI technologies are revolutionizing big data analytics. AI's ability to ingest and analyze massive amounts of structured and unstructured data is being used by companies to optimize and improve business operations.

Big Data, What is it?



The image shows a screenshot of the AWS Services console. The left sidebar lists various service categories, with 'Compute' highlighted. The main content area displays a list of services under the 'Compute' category, including AWS App Runner, Batch, EC2, EC2 Image Builder, Elastic Beanstalk, Lambda, Lightsail, AWS Outposts, and Serverless Application Repository.

All services

- Analytics
- Application Integration
- AR & VR
- AWS Cost Management
- Blockchain
- Business Applications
- Compute
- Containers
- Customer Enablement
- Database
- Developer Tools
- End User Computing
- Front-end Web & Mobile
- Game Development
- Internet of Things
- Machine Learning
- Management & Governance
- Media Services
- Migration & Transfer
- Networking & Content Delivery
- Quantum Technologies
- Robotics
- Satellite
- Security, Identity, & Compliance
- Storage

Compute

- AWS App Runner**
Build and run production web applications at scale
- Batch**
Fully managed batch processing at any scale
- EC2**
Virtual Servers in the Cloud
- EC2 Image Builder**
A managed service to automate build, customize and deploy OS images
- Elastic Beanstalk**
Run and Manage Web Apps
- Lambda**
Run Code without Thinking about Servers
- Lightsail** [↗](#)
Launch and Manage Virtual Private Servers
- AWS Outposts**
Run AWS Services On Premises
- Serverless Application Repository**
Assemble, deploy, and share serverless applications within teams or publicly

Libraries, tools and architectures for working with large datasets quickly.

Big Data, What is it?

Short Answer:

Big Data \approx Data Mining \approx Predictive Analytics \approx Data Science

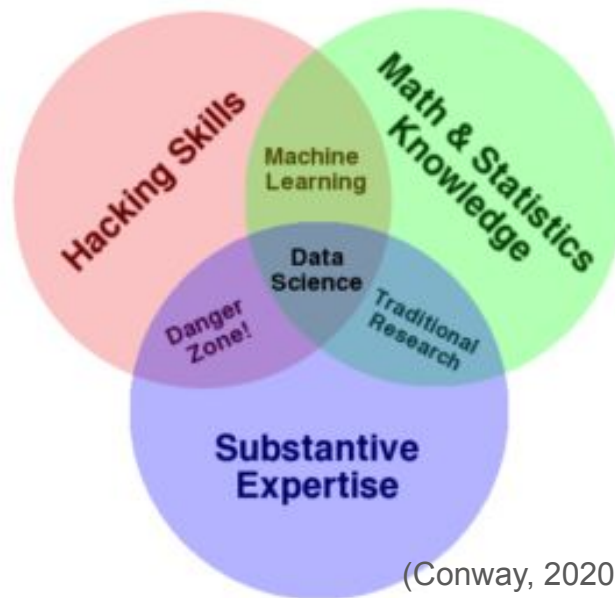
(Leskovec et al., 2017)

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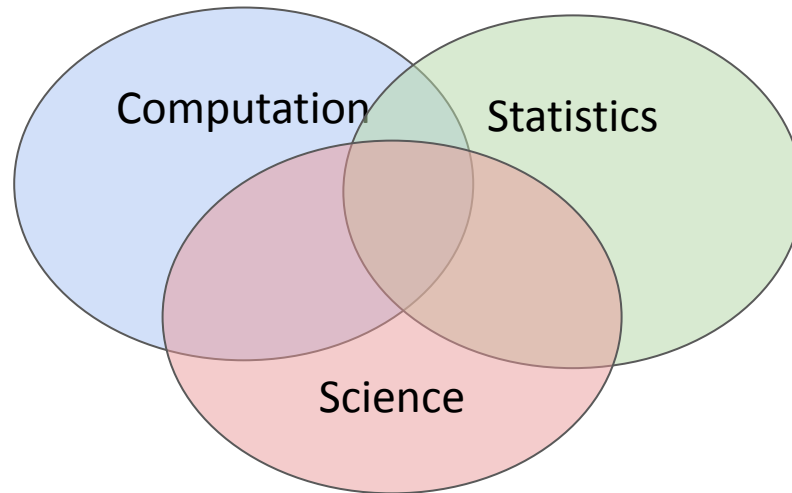
(Conway, 2020)

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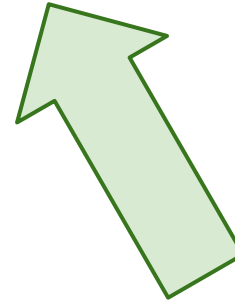
CSE545 focuses on:

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

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

Big Data, What is it?

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.

Big Data, What is it?

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 527:
Computer Vision

CSE 538:
Natural Language Processing

CSE 549:
Computational Biology
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Big Data Analytics, The Class

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Key Distinction:

??

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Applications of Data Science

CSE 527:
Computer Vision

CSE 538:
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CSE 549:
Computational Biology
...

Key Distinction:

Focus on scalability and algorithms/analyses not possible without large data.

Big Data Analytics, The Class

Goal: Generalizations
A model or summarization of the data.

Data/Workflow Frameworks

Analyses and Algorithms

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Hadoop File System Spark
Streaming
MapReduce Tensorflow

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Data/Workflow Frameworks

Analyses and Algorithms

Hadoop File System Spark
Streaming
MapReduce Tensorflow

Similarity Search
Hypothesis Testing
Graph Analysis
Recommendation Systems
Deep Learning

Big Data Analytics, The Class

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



Big Data Analytics, The Class

How to succeed:

1. Do the weekly readings see [syllabus](#)
2. Take notes associated with the lectures. If needed:
 - a. consult lecture recordings in Blackboard.
 - b. watch recordings from MMDS website
3. Practice exercises in the back of each reading.
4. Attend class and actively participate.
5. Begin assignments early and seek help if trouble (e.g. office hours).



Preliminaries

Ideas and methods that will repeatedly appear:

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

Normalization

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

Prototypical example: TF.IDF

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Prototypical example: **TF.IDF** of word i in document j :

Term Frequency:

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

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

Inverse Document Frequency:

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

where docs is the number of documents containing word i .

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Normalization

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

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

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

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)

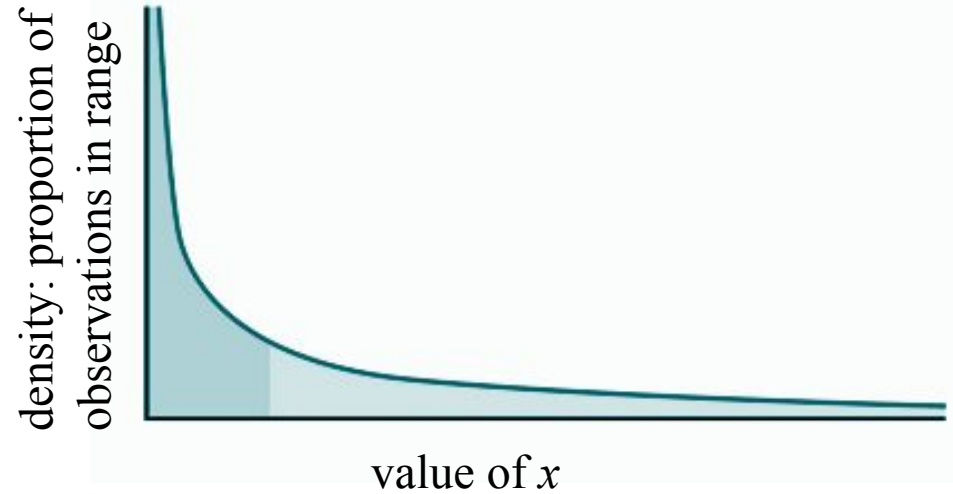
Power Law

$$\log y = b + a \log x$$

raising to the natural log:

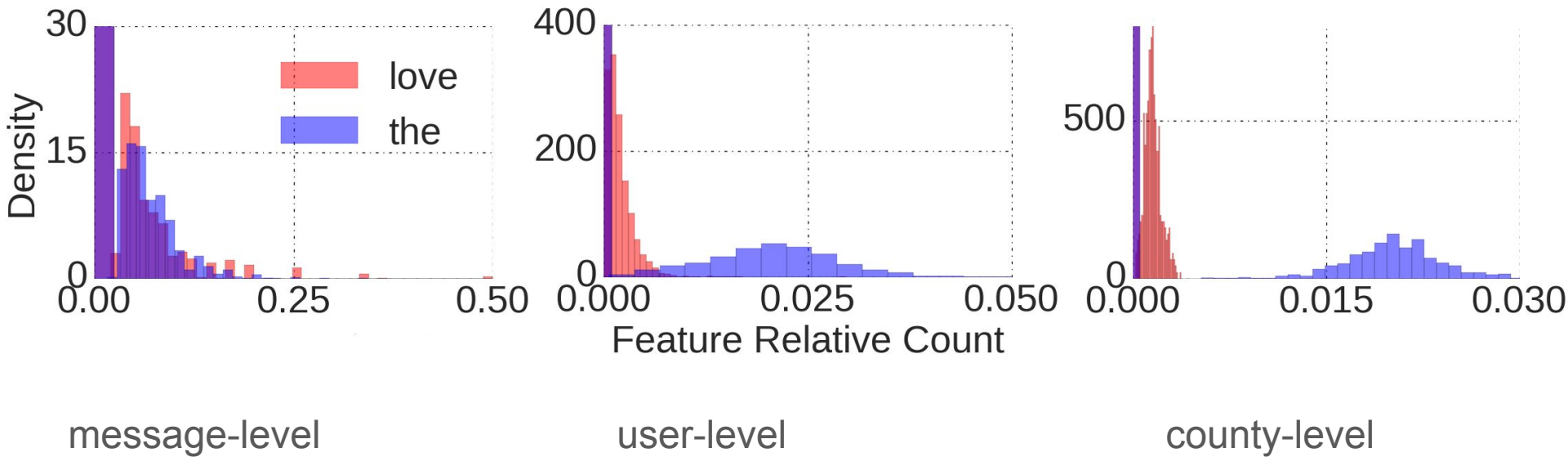
$$y = e^b e^{a \log x} = e^b x^a = cx^a$$

where c is just a constant



Characterizes “the Matthew Effect” -- the rich get richer

Power Law



Almodaresi, F., Ungar, L., Kulkarni, V., Zakeri, M., Giorgi, S., & Schwartz, H. A. (2017). On the Distribution of Lexical Features at Multiple Levels of Analysis. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics* (pp. 79-84).

Hash Functions and Indexes

Review:

h: hash-key -> bucket-number

Objective: uniformly distribute hash-keys across buckets.

Example: storing word counts.

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$$h(\text{word}) = \left(\sum_{\text{char} \in \text{word}} \text{ascii}(\text{char}) \right) \% \# \text{buckets}$$

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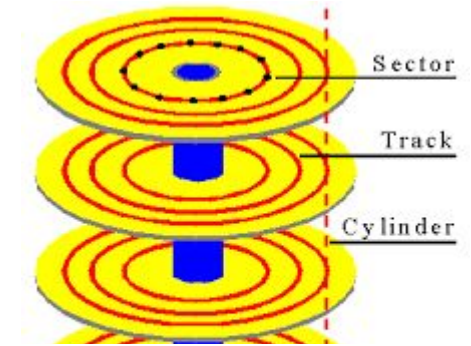
Database Indexes: Retrieve all records with a given *value*. (also review if unfamiliar / forgot)

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.

IO Bounded

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

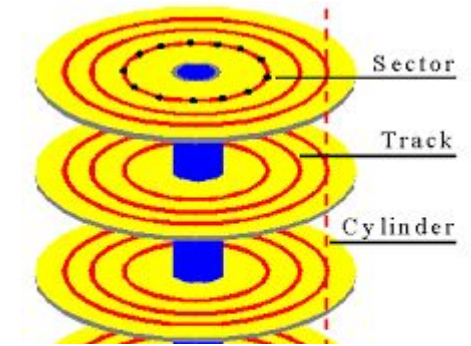
Reading many contiguously stored words is faster per word, but fast modern disks still only reach 150MB/s for sequential reads.



IO 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).

Unstructured Data Continuum

Structured

Unstructured



- Unstructured \approx 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

Unstructured Data Continuum

Structured

Unstructured



mysql table

email header

satellite imagery

images

vectors matrices

facebook likes

text (email body)

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Bonferroni's Principle

Goal: Generalizations

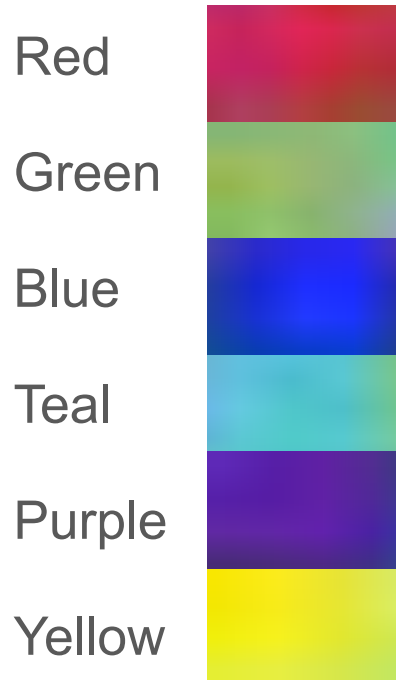
A model or summarization of the data.

Generalize: Find patterns that didn't just happen by chance.

Bonferroni's Principle; Task Example

snazzyphones.com wants to know which case to eliminate.

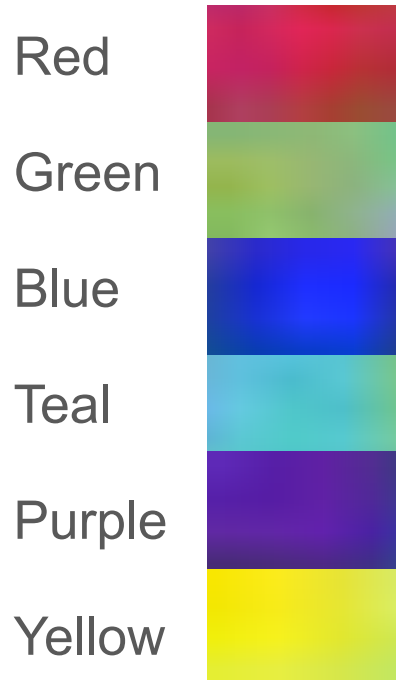
6 total cases:



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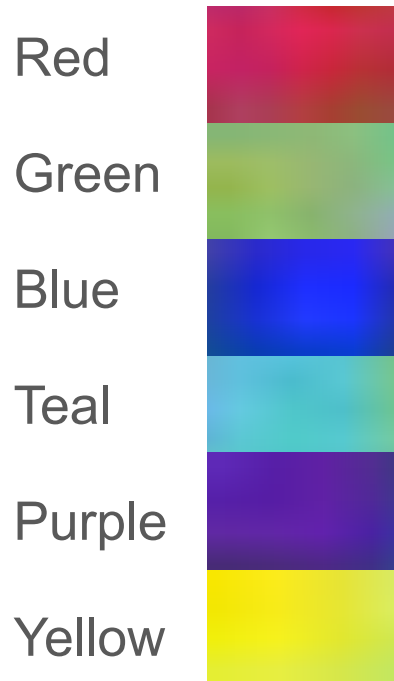


Is a color not selling?

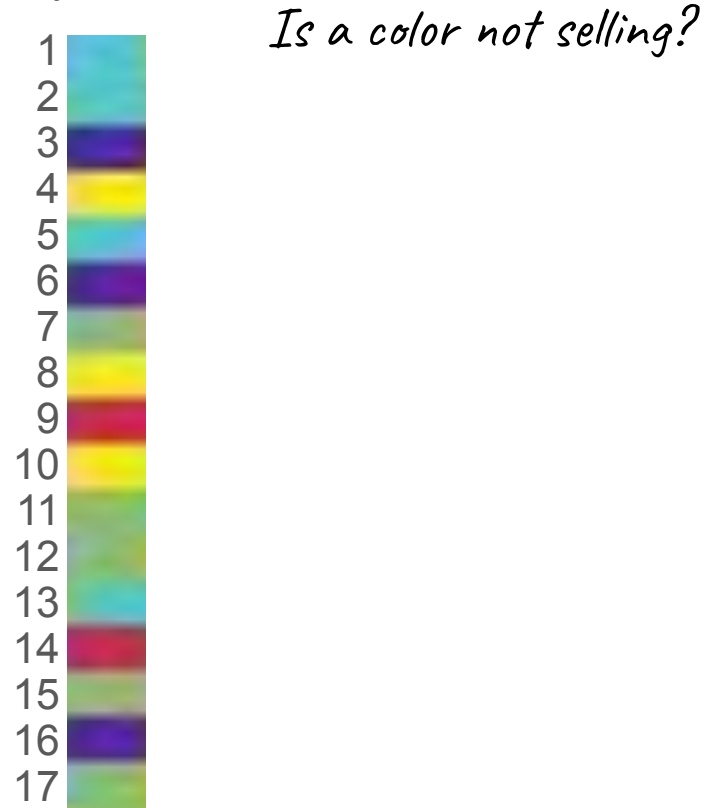
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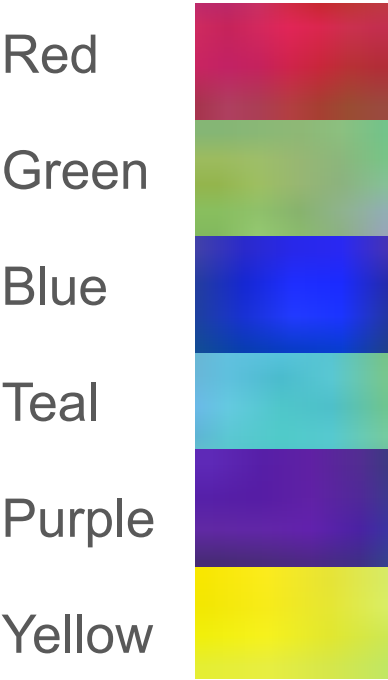
first day, 17 sales:



Bonferroni's Principle; Task Example

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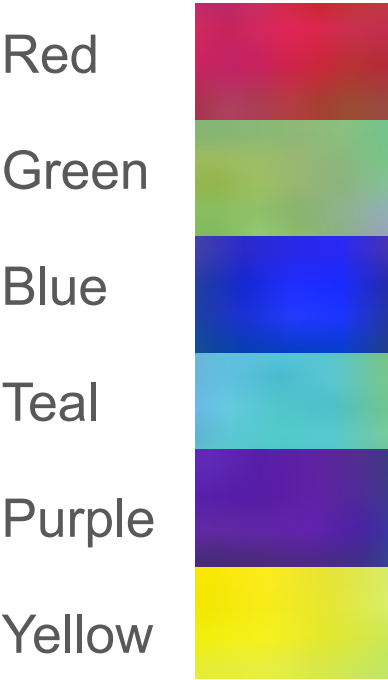
Is a color not selling?

How to define "not selling" so as not to make a mistake?

Bonferroni's Principle; Task Example

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6 total cases:



first day, 17 sales:



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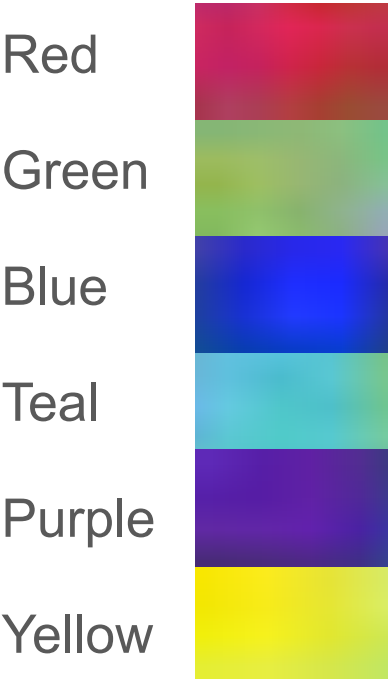
How to define "not selling" so as not to make a mistake?

*Counterfactual argument:
Let's assume the color is as likely to sell as any other. Then what is the probability we observe this many sales?*

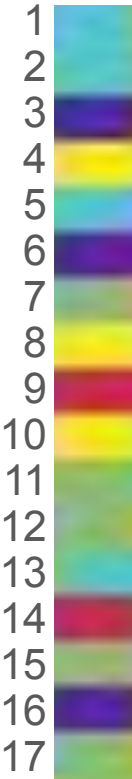
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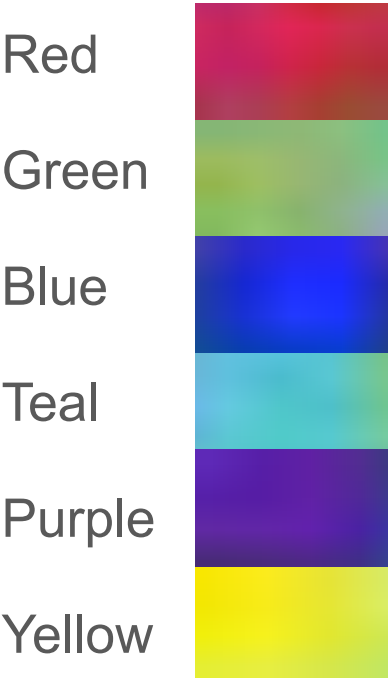
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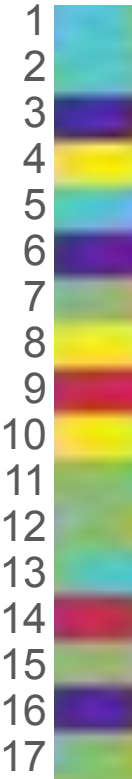
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first day, 17 sales:



Is a color not selling?

Let's assume the color is as likely to sell as any other. Then what is the probability we observe this many sales?

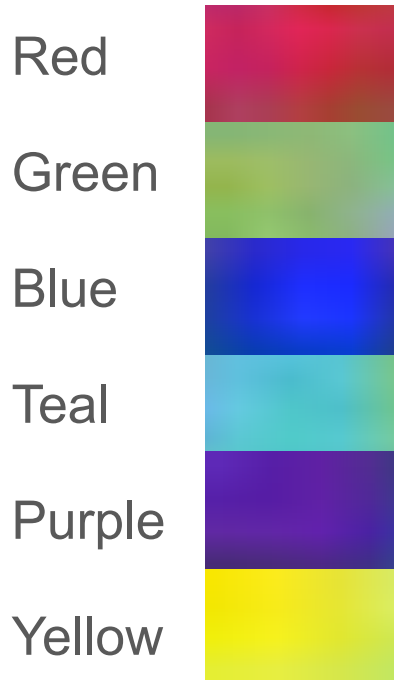
(blue == 0) =

??

Bonferroni's Principle; Task Example

snazzyphones.com wants to know which case to eliminate.

6 total cases:



first day, 17 sales:



Is a color not selling?

Let's assume the color is as likely to sell as any other. Then what is the probability we observe this many sales?

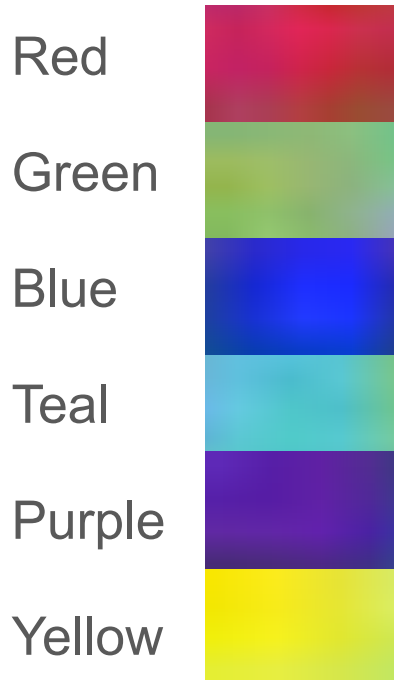
$$(1/6)^{17} =$$

$$(1/6)^{17} = 4.5 \% \text{ chance}$$

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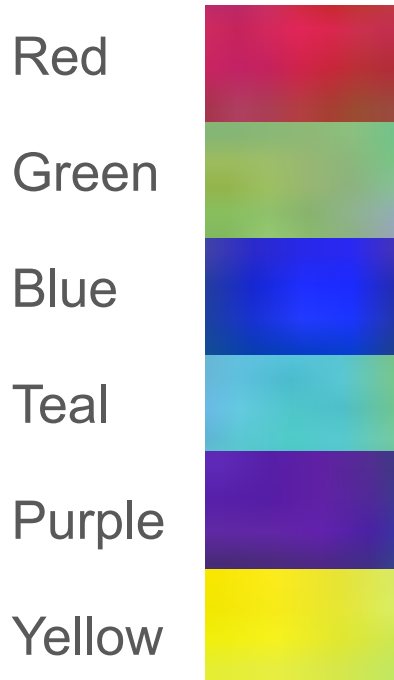
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Let's assume the color is as likely to sell as any other. Then what is the probability we observe this many sales?

$$P(\text{blue} = 0) =$$

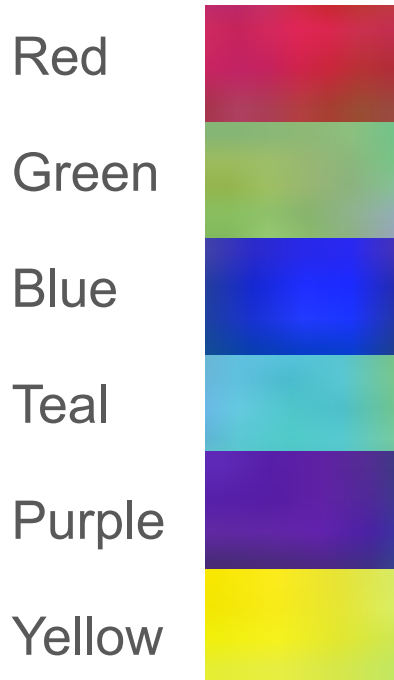
$$\left(\frac{5}{6}\right)^{17} \neq 4.5\% \text{ chance}$$

$$P(\text{!} = 0) = ??$$

Bonferroni's Principle; Task Example

snazzyphones.com wants to know which case to eliminate.

6 total cases:



first day, 17 sales:



Is a color not selling?

Let's assume the color is as likely to sell as any other. Then what is the probability we observe this many sales?

$$P(\text{blue} = 0) =$$

$$\left(\frac{5}{6}\right)^{17} \neq 4.5\% \text{ chance}$$

$$P(\text{any} = 0) = 27.0\% \text{ chance}$$

any single color doesn't appear

Bonferroni's Principle; Task Example

snazzyphones.com wants to know which case to eliminate.

6 total cases:

first day, 17 sales:

Is a color not selling?

27% is roughly a 1 in 4 chance!

In other words, just due to chance, we would expect 1 out of every 4 times that there are 17 sales that at least one color does not appear at all.

Would you trust eliminating a color is a good data-informed decision to make with these odds?
< 5% or 1 in 20 odds is typical standard for science.

*the color is as likely to
ther. Then what is the
we observe this many*

*~~$p(1^1 = 0) =$~~
 $7 \times 4.5\% \text{ chance}$*

$p(1^1 = 0) = 27.0\% \text{ chance}$

any single color doesn't appear

Yellow



15
16
17



Bonferroni's Principle; Task Example

snazzyphones.com wants to know which case to eliminate.

6 total cases:

first day, 17 sales:

Is a color not selling?

27% is roughly a 1 in 4 chance!

In other words, just due to chance, we would expect 1 out of every 4 times that there are 17 sales that at least one color does not appear at all.

Would you trust eliminating a color is a good data-informed decision to make with these odds?
< 5% or 1 in 20 odds is typical standard for science.

Once we look at the data and see a particular pattern, it's easy to think in terms of chance for that specific pattern and forget one started with a broader question.

Yellow



$p(1^1 = 0) = 27.0\% \text{ chance}$

any single color doesn't appear

Bonferroni's Principle; Task Example

snazzyphones.com wants to know which case to eliminate.

6 total cases:

first day, 17 sales:

Is a color not selling?

27% is roughly a 1 in 4 chance.
In other words, just out of every 4 times, at least one color does not sell.

Would you trust eliminating a case based on a data-informed decision with less than a 5% or 1 in 20 odds?

This is often mentioned as one of the main reasons for a so-called "replication crisis" in many sciences: In some fields, it has been suggested that over 50% of findings fail to replicate.

(https://en.wikipedia.org/wiki/Replication_crisis#Tackling_publication_bias_with_pre-registration_of_studies)

the
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Once we look at the data and see a particular pattern, it's easy to think in terms of chance for that specific pattern and forget one started with a broader question.

X

Yellow



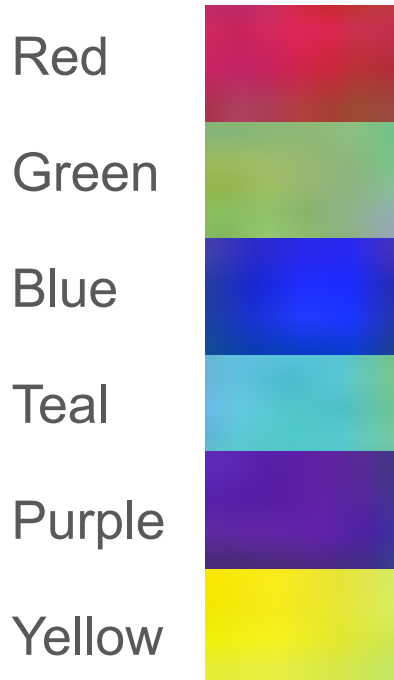
$$p(1^7 = 0) = 27.0\% \text{ chance}$$

any single color doesn't appear

Bonferroni's Principle; Task Example

snazzyphones.com wants to know which case to eliminate.

6 total cases:



first day, 17 sales:



Is a color not selling?

Let's assume the color is as likely to sell as any other. Then what is the probability we observe this many sales?

$$P(\text{blue} = 0) =$$

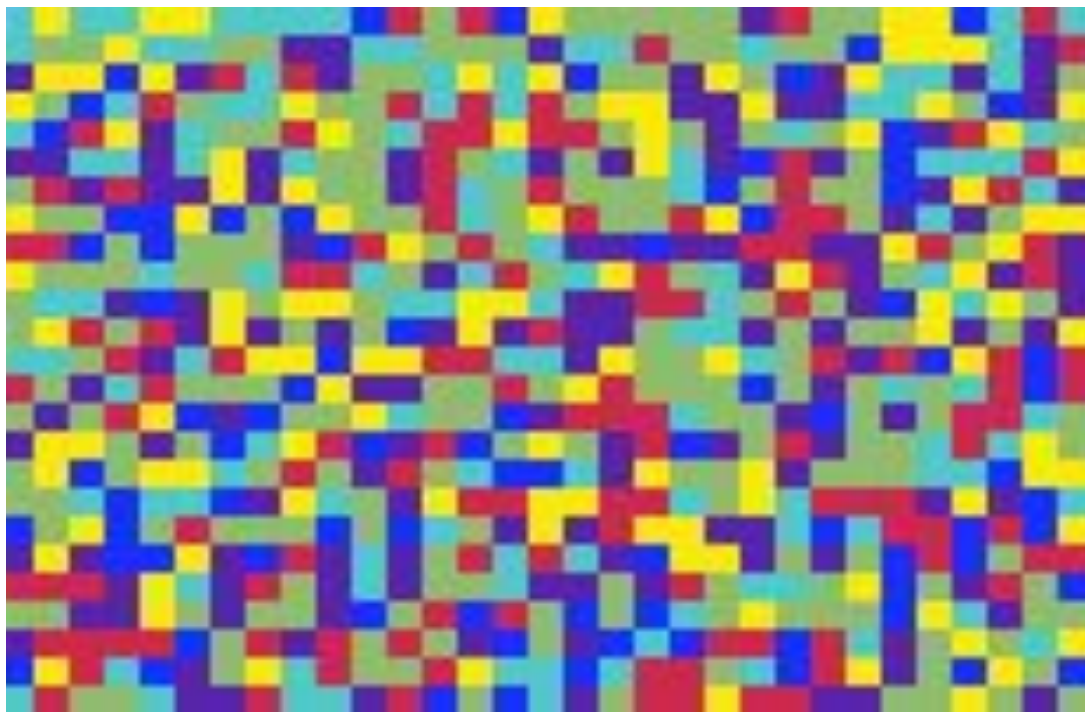
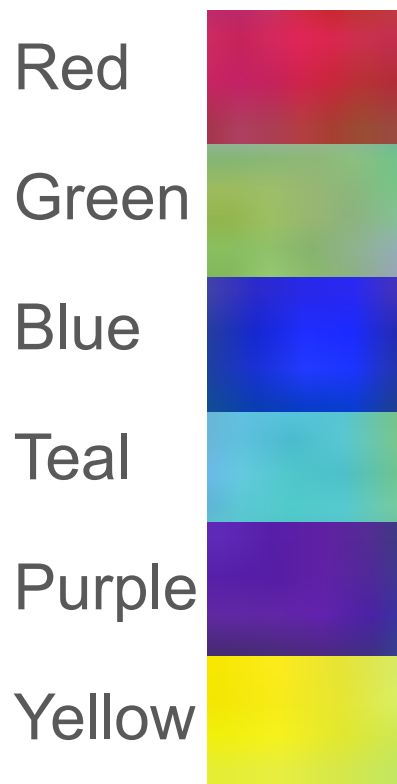
$$\left(\frac{5}{6}\right)^{17} \neq 4.5\% \text{ chance}$$

$$P(\text{any color} = 0) = 27.0\% \text{ chance}$$

any single color doesn't appear

Statistical Limits

Bonferroni's Principle



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 one finds something just by chance (i.e. finding something that does **not** generalize).

“Data mining” is a bad word in some communities!

Bonferroni's Principle

Note: *Bonferroni's principle* is simply an abstract idea inspired by a precisely defined method of hypothesis testing called “Bonferroni correction”.

We will go over this correction method later. The *principle* is the more important idea to understand as a big data practitioner.

In brief, one can only look for so many patterns (i.e. features) in the data before one finds something just by chance (i.e. finding something that does **not** generalize).

“Data mining” is a bad word in some communities!

Bonferroni's Principle

The Many Faces of the Bonferroni Principle

Domain	Concept	Mitigation Techniques
Machine Learning	<i>Overfitting</i>	<i>Regularization; Out-of-Sample Testing (Cross-Validation)</i>
Scientific Process	<i>P-Hacking</i>	<i>Multi-test Correction</i>
Cognitive Bias	<i>Confirmation Bias</i>	Awareness* Turn to Science and Empirical Evidence.
Layman Terms	Falsely believing: "It's not just a coincidence"	Rationality*: Turn to Science / Empirical Evidence.

Preliminaries

Ideas and methods that will repeatedly appear:

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