

Visual Data Analytics

A Short Tutorial

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Associate Professor & ML Area Leader, College of Computing

Associate Director, MS Analytics

Georgia Tech

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Alternative Title

11 Lessons Learned

from Working with Tech Companies
(Facebook, Google, Intel, eBay, Symantec)

Google “Polo Chau” if interested in my professional life.

Bio CV Students Papers Teaching Funding Press Design



POLO CHAU

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POSITIONS

- May 2014 - Associate Director
[MS in Analytics](#), Georgia Tech
- Aug 2018 - Associate Professor
[School of Computational Science & Engineering](#), Georgia Tech
- Aug 2012 - Aug 2018 Assistant Professor
[School of Computational Science & Engineering](#), Georgia Tech
- Dec 2012 - Dec 2015 Adjunct Assistant Professor

My research group website:



Polo Club
of
DATA SCIENCE

**Scalable. Interactive.
Interpretable.**

Students [\(see all\)](#)

[Haekyu Park](#), CS PhD
[Scott Freitas](#), ML PhD
[Nilaksh Das](#), CSE PhD
[Fred Hohman](#), CSE PhD
[Shang-Tse Chen](#), CS PhD
[Minsuk \(Brian\) Kahng](#), CS PhD
[Siwei \(Bob\) Li](#), CS UG
[Ángel \(Alex\) Cabrera](#), CS UG
[Joon Kim](#), CS UG
[Sudeep Agarwal](#), CS UG
[Kristina Marotta](#), CS OMS
[Matthew Keezer](#), MS CS

Recent Alumni [\(see all\)](#)















Polo Club
— of —
DATA SCIENCE

Scalable. Interactive. Interpretable.

At **Georgia Tech**, we innovate **scalable, interactive, and interpretable** tools that amplify human's ability to understand and interact with billion-scale data and machine learning models. Our current research thrusts: **human-centered AI** (interpretable, fair, safe AI; adversarial ML); **large graph visualization and mining**; **cybersecurity**; and **social good** (health, energy).

At Georgia Tech, I teach **Data** & **Visual Analytics**

Year	Semester	Course Websites		Students
2019	Spring	Campus	Online	1000 
2018	Fall	Campus	Online	677 
2018	Spring	Campus	Online	287 
2017	Fall	Campus		273 
2017	Spring	Campus		214 
2016	Fall	Campus		215 
2016	Spring	Campus		187 
2015	Fall	Campus		146 
2015	Spring	Campus		113 
2014	Fall	Campus		118 
2014	Spring	Campus		95 
2013	Spring	Campus		35 

Lesson 1

You need to learn
many things.

Good news! Many jobs!

Most companies looking for “data scientists”

*The data scientist role is critical for organizations looking to extract insight from information assets for ‘big data’ initiatives and requires a **broad combination** of skills that may be fulfilled better as a team*

- Gartner (<http://www.gartner.com/it-glossary/data-scientist>)

Breadth of knowledge is important.

THE WORLD OF DATA

NUMBER OF EMAILS SENT EVERY SECOND

2.9

MILLION

DATA CONSUMED BY HOUSEHOLDS EACH DAY

375

MEGABYTES

VIDEO UPLOADED TO YOUTUBE EVERY MINUTE

20

HOURS

DATA PER DAY PROCESSED BY GOOGLE

24

PETABYTES

TWEETS PER DAY

50

MILLION

TOTAL MINUTES SPENT ON FACEBOOK EACH MONTH

700

BILLION

DATA SENT AND RECEIVED BY MOBILE INTERNET USERS

1.3

EXABYTES

PRODUCTS ORDERED ON AMAZON PER SECOND

72.9

ITEMS

SOURCES: Cisco; comScore; MapReduce; Radicati Group; Twitter; YouTube

IN THE 21ST CENTURY, we live a large part of our lives online. Almost everything we do is reduced to bits and sent through cables around the world at light speed. But just how much data are we generating? This is a look at just some of the massive amounts of information that human beings create every single day.

What are the “ingredients”?

What are the “ingredients”?

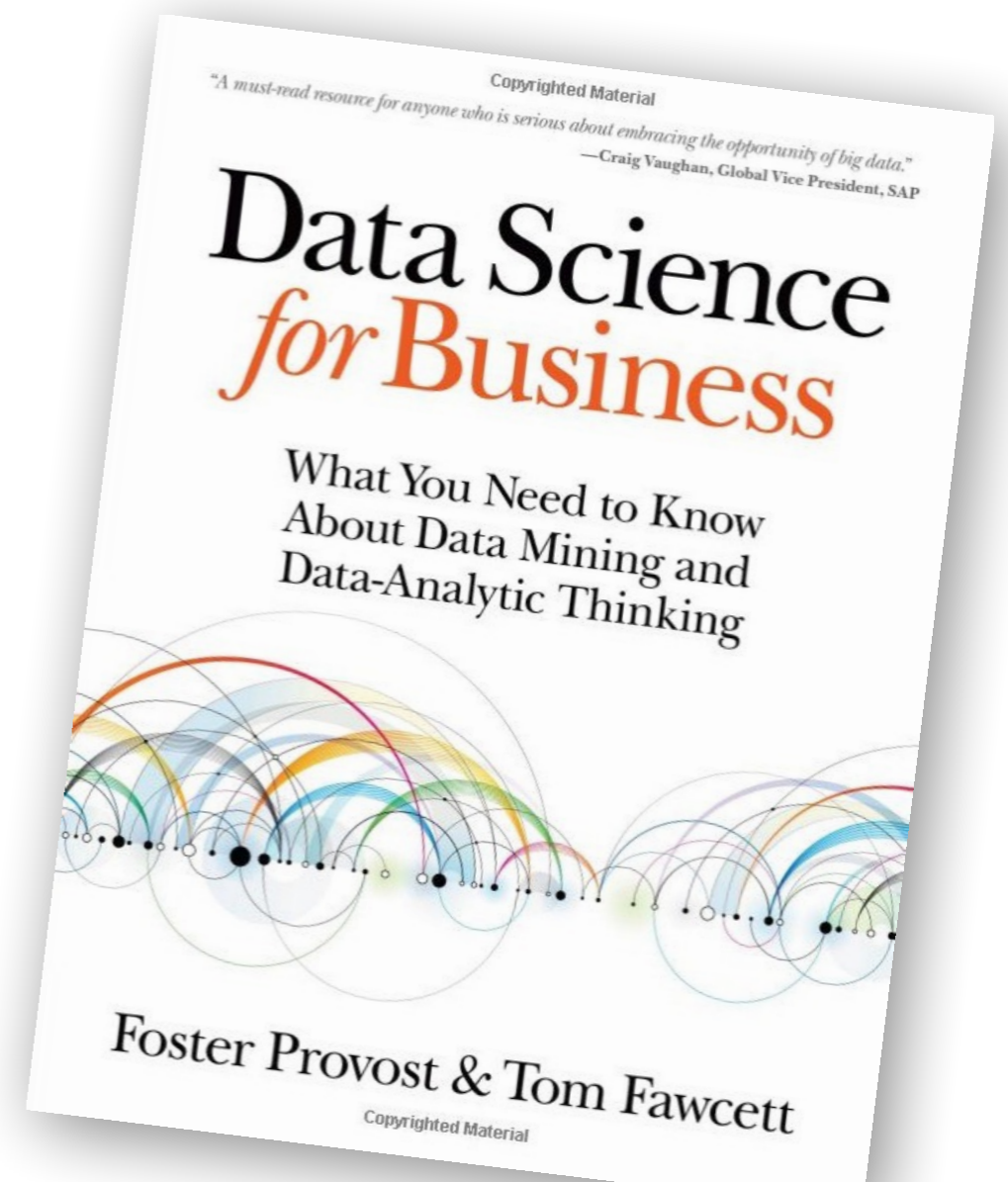
Need to think (a lot) about: storage, complex system design, scalability of algorithms, visualization techniques, interaction techniques, statistical tests, etc.

Lesson 2

Learn **data science concepts** and
key generalizable techniques to
future-proof yourselves.

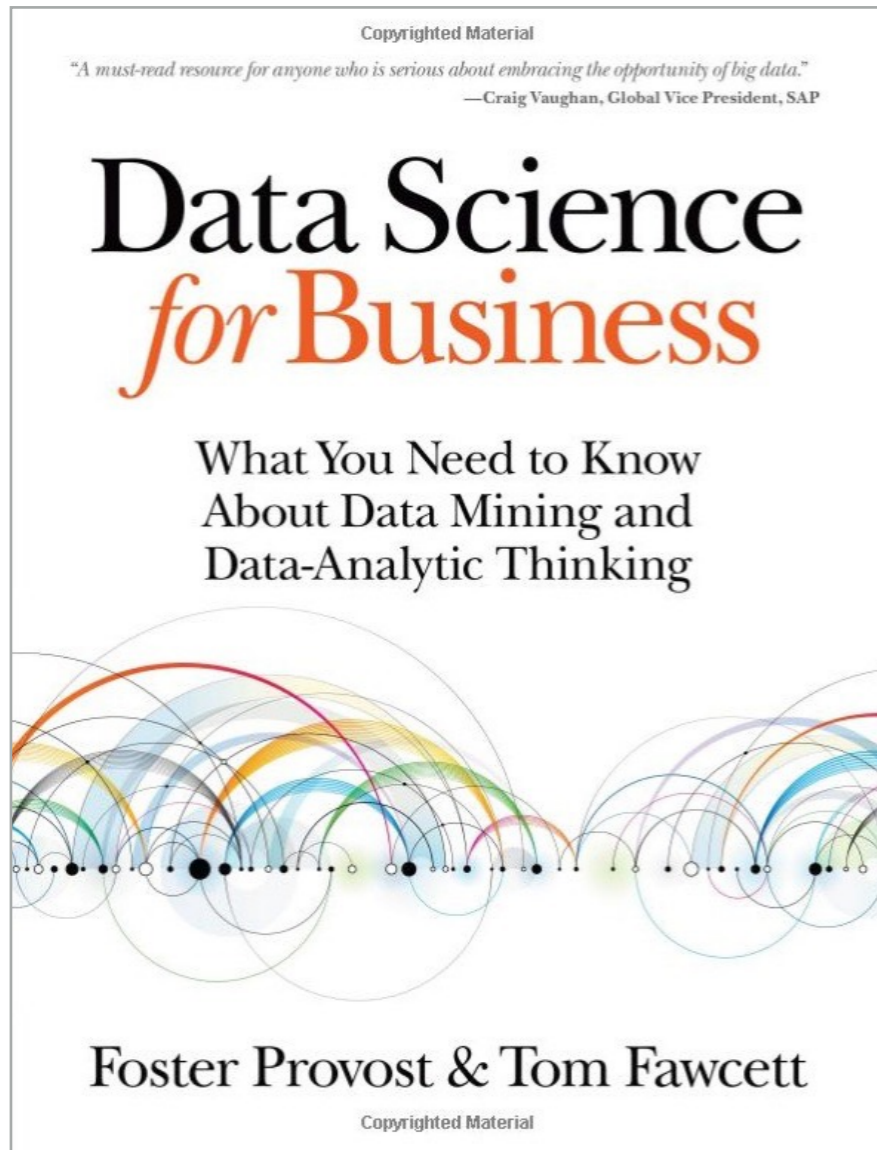
And here's a good book.

A critical skill in data science is the ability to decompose a data-analytics problem into pieces such that each piece matches a known task for which tools are available. Recognizing familiar problems and their solutions avoids wasting time and resources reinventing the wheel. It also allows people to focus attention on more interesting parts of the process that require human involvement—parts that have not been automated, so human creativity and intelligence must come in-to play.



<http://www.amazon.com/Data-Science-Business-data-analytic-thinking/dp/1449361323>

Great news! Few principles!!



1. **Classification**
2. **Regression**
3. **Similarity Matching**
4. **Clustering**
5. **Co-occurrence grouping**
(aka frequent items mining, association rule discovery, market-basket analysis)
6. **Profiling**
(related to pattern mining, anomaly detection)
7. **Link prediction / recommendation**
8. **Data reduction**
(aka dimensionality reduction)
9. **Causal modeling**

Data are dirty.

Always have been.

And always will be.

You will likely spend majority of your time cleaning data. And that's important work!

Otherwise, **garbage in, garbage out.**

A large pile of garbage, including plastic bags, tires, and other debris, with a blue tractor in the background and many birds flying overhead. The scene is set outdoors under a clear blue sky.

Data Cleaning

Why data can be dirty?

How dirty is real data?



Examples

- Jan 19, 2016
- January 19, 16
- 1/19/16
- 2006-01-19
- 19/1/16

How dirty is real data?

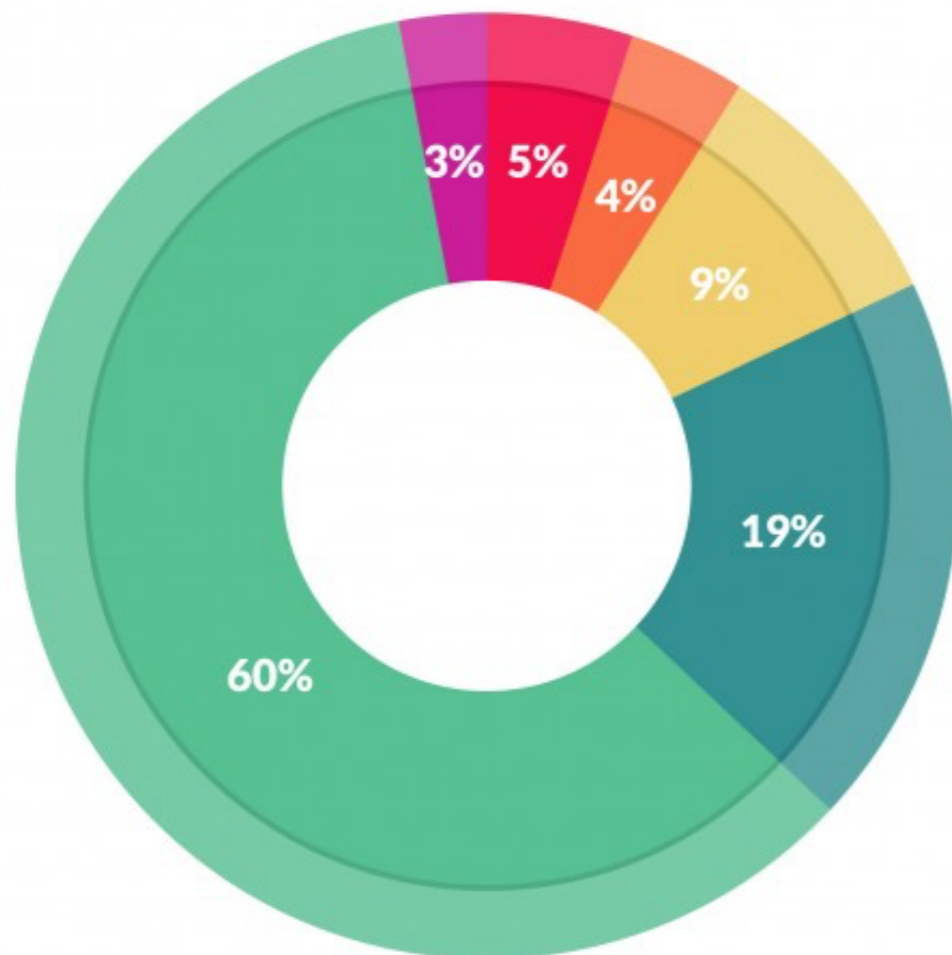
Examples

- duplicates
- empty rows
- abbreviations (different kinds)
- difference in scales / inconsistency in description/ sometimes include units
- typos
- missing values
- trailing spaces
- incomplete cells
- synonyms of the same thing
- skewed distribution (outliers)
- bad formatting / not in relational format (in a format not expected)

“80%” Time Spent on Data Preparation

Cleaning Big Data: Most Time-Consuming, Least Enjoyable Data Science Task, Survey Says [Forbes]

<http://www.forbes.com/sites/gilpress/2016/03/23/data-preparation-most-time-consuming-least-enjoyable-data-science-task-survey-says/#73bf5b137f75>



What data scientists spend the most time doing

- Building training sets: 3%
- Cleaning and organizing data: 60%
- Collecting data sets; 19%
- Mining data for patterns: 9%
- Refining algorithms: 4%
- Other: 5%

We are all Data Janitor!



The Silver Lining

“Painful process of cleaning, parsing, and proofing one’s data”

— one of the three sexy skills of data geeks (the other two: statistics, visualization)

<http://medriscoll.com/post/4740157098/the-three-sexy-skills-of-data-geeks>



@BigDataBorat tweeted

**“Data Science is 99% preparation,
1% misinterpretation.”**

Refine

OPEN

*A free, open source, powerful tool
for working with messy data*

Home

Download

Documentation

Community

Post archive

[A Governance Model for OpenRefine](#)

[Using OpenRefine: a manual](#)

Welcome!

OpenRefine (formerly Google Refine) is a powerful tool for working with messy data: cleaning it; transforming it from one format into another; extending it with web services; and linking it to databases like [Freebase](#).

Please note that since October 2nd, 2012, Google is not actively supporting this project, which has now been rebranded to OpenRefine. Project development, documentation and promotion is now fully supported by volunteers. Find out more about the [history of OpenRefine](#) and how you can [help the community](#).

Using OpenRefine - The Book



Using OpenRefine, by Ruben Verborgh and Max De Wilde, offers a great introduction to OpenRefine. Organized by recipes with hands on examples, the book covers the following topics:

1. Import data in various formats
2. Explore datasets in a matter of seconds

Python is a king.

Some say **R** is.

In practice, you may want to use the ones that have the widest community support.

Python

One of “**big-3**” programming languages at tech firms like Google.

- **Java** and **C++** are the other two.

Easy to write, read, run, and debug

- General programming language, tons of libraries
- Works well with others (a great “glue” language)

You've got to know **SQL** and **algorithms** (and Big-O)

(Even though job descriptions may not mention them.)

Why?

- (1) Many datasets stored in databases.
- (2) You need to know if an algorithm can **scale** to large amount of data

Visualization is **NOT** only about
“making things look pretty”

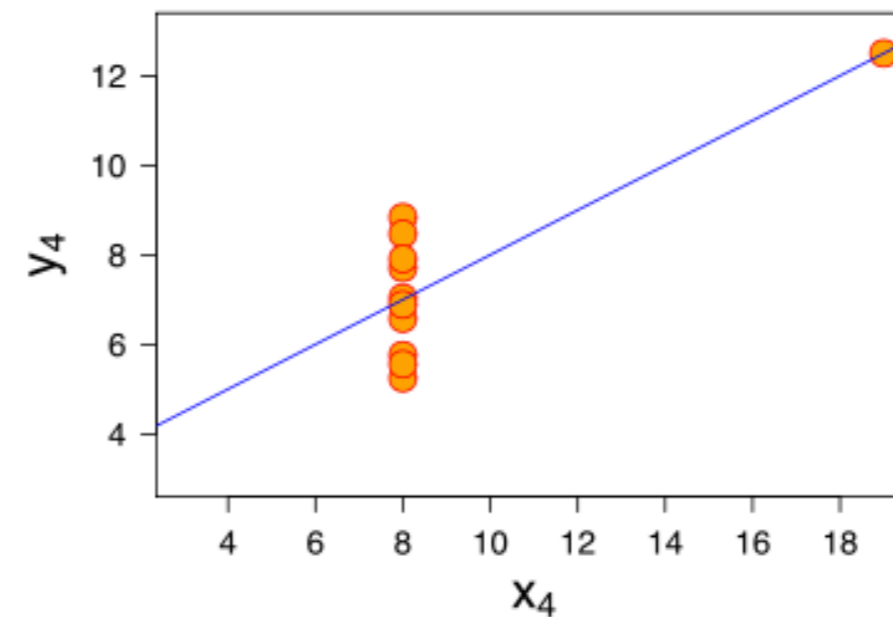
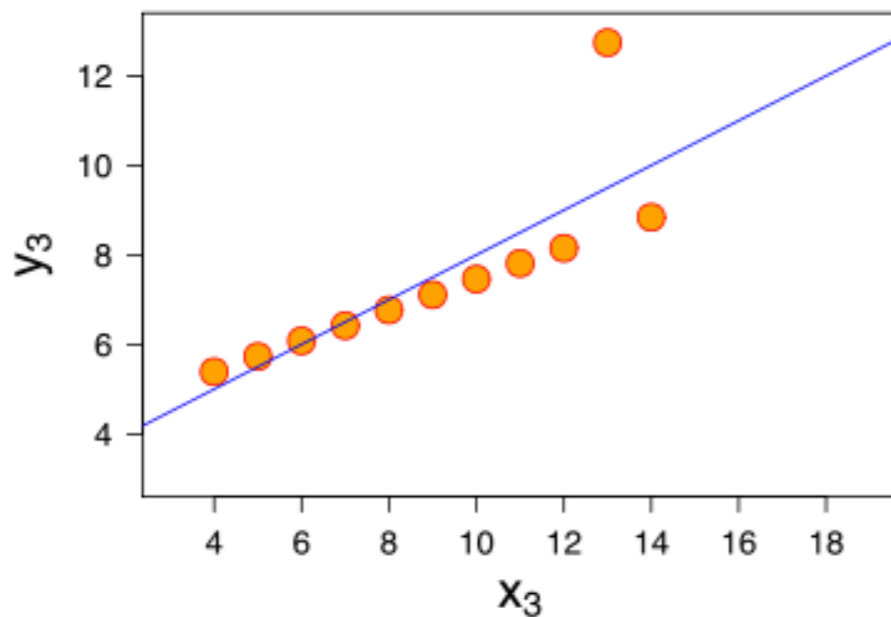
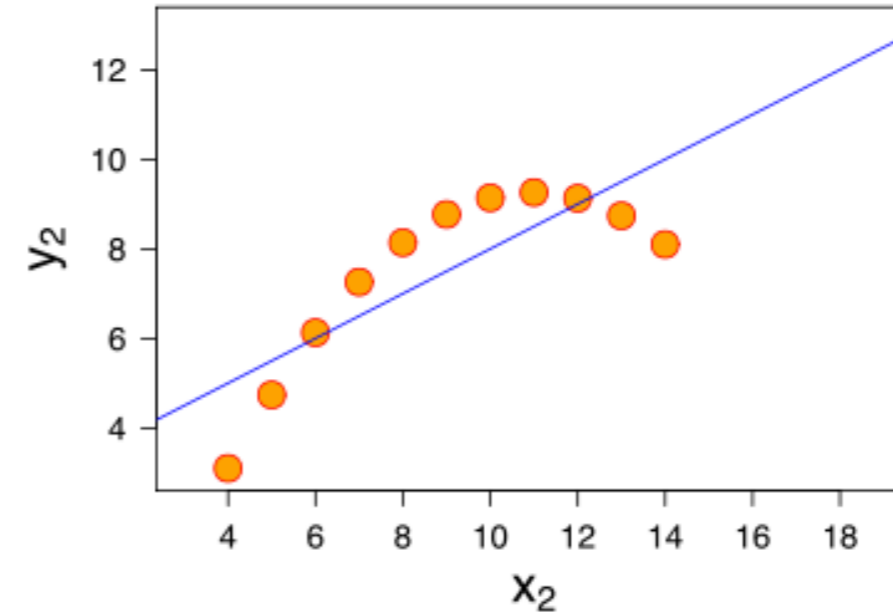
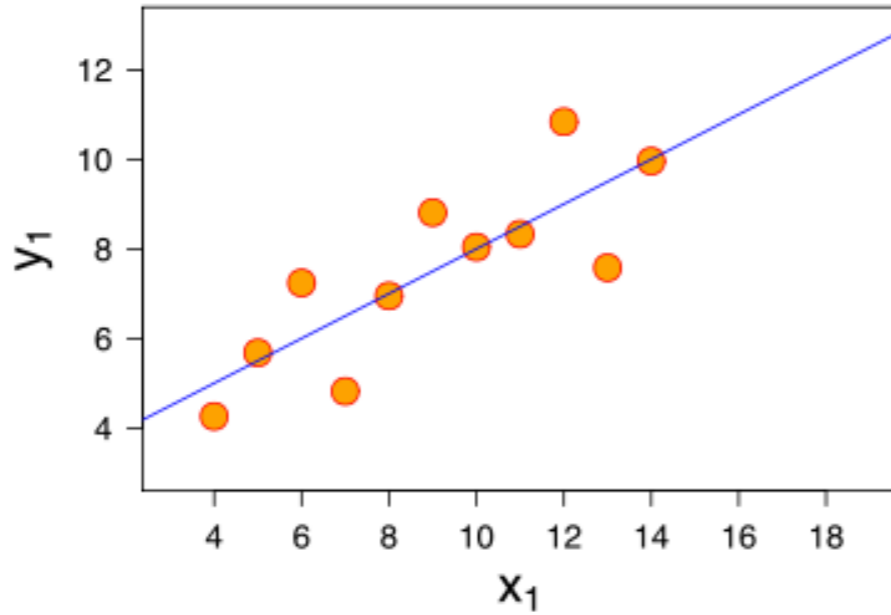
(Aesthetics is important too)

Key is to design **effective** visualization to:

- (1) **communicate** and
- (2) help people **gain insights**

Why **visualize** data? Why not automate?

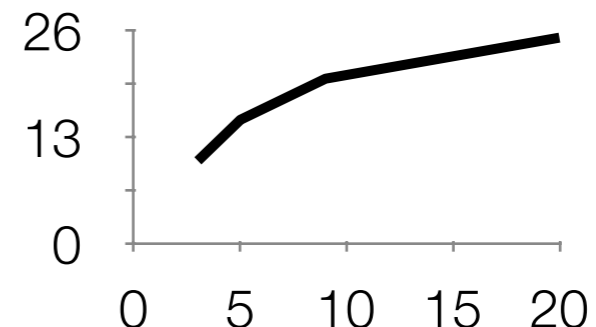
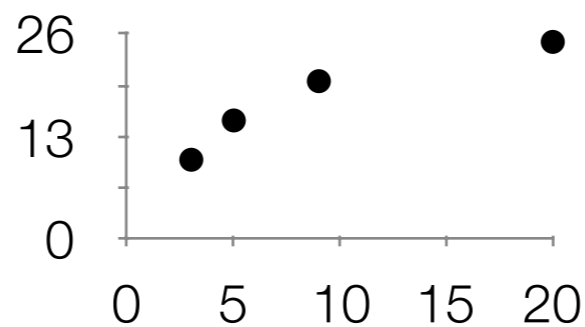
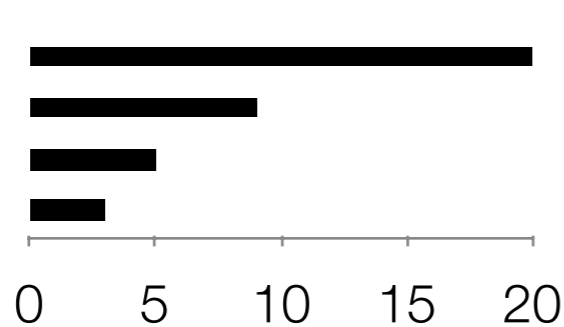
Anscombe's Quartet



Designing **effective** visualization is **not hard if you learn the principles.**

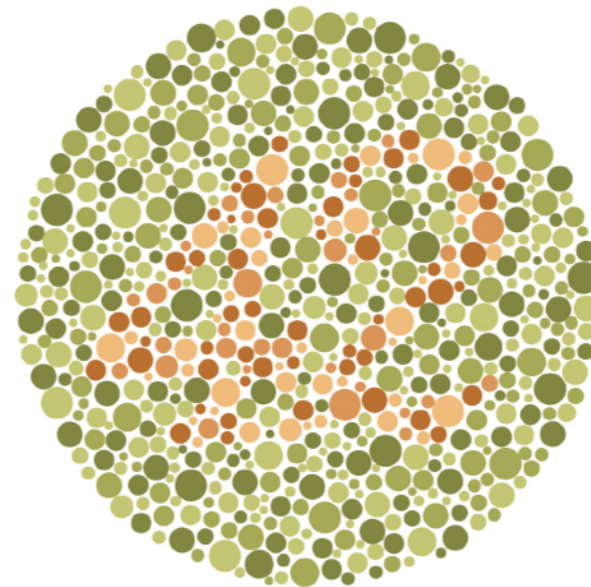
Easy, because...

Simple charts (bar charts, line charts, scatterplots) are incredibly effective; handles most practical needs!



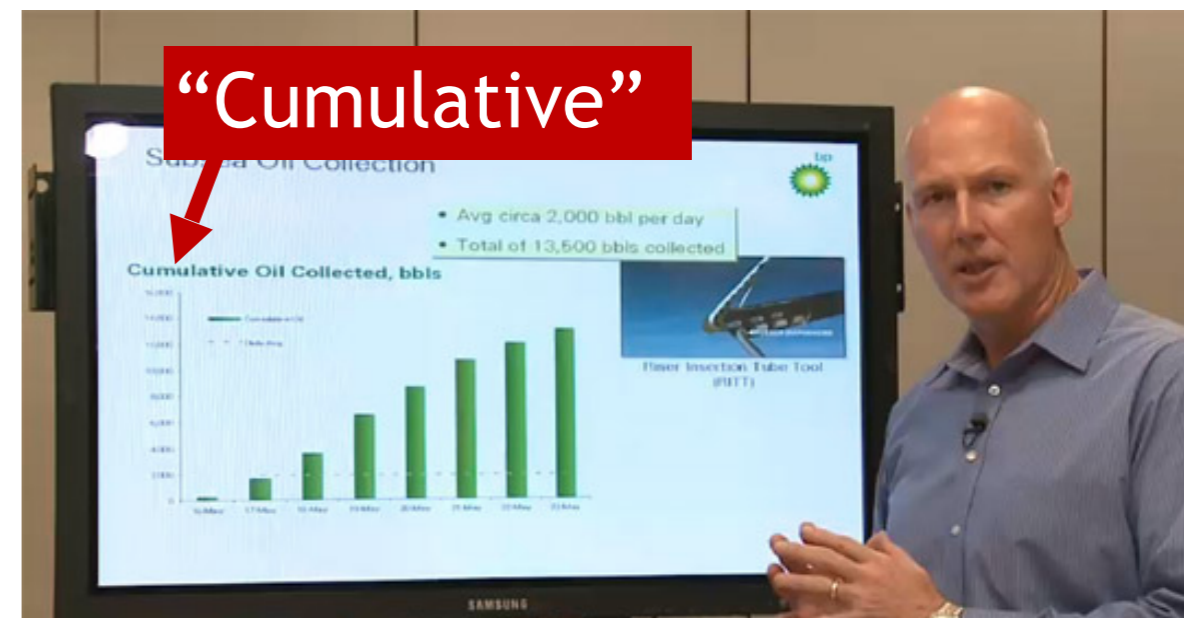
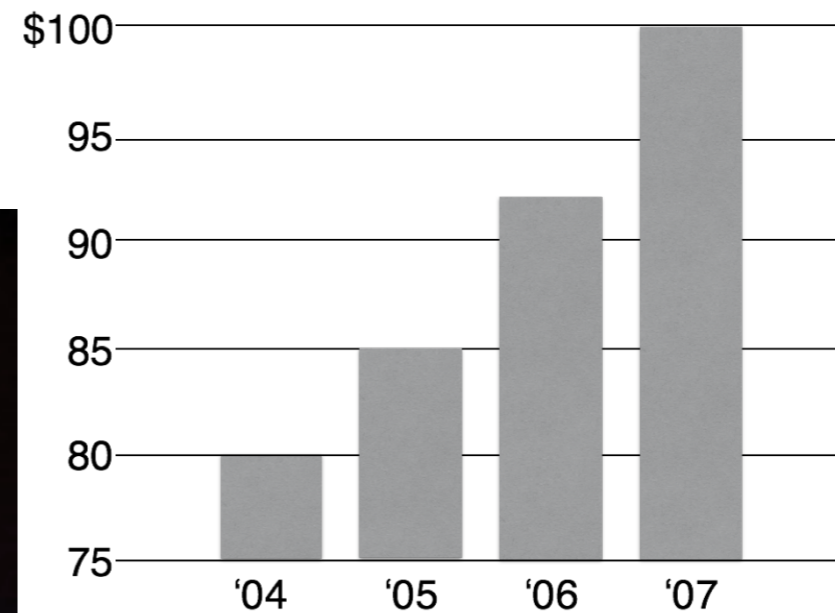
Designing **effective** visualization is **not hard if you learn the principles.**

Colors (even grayscale) must be used carefully

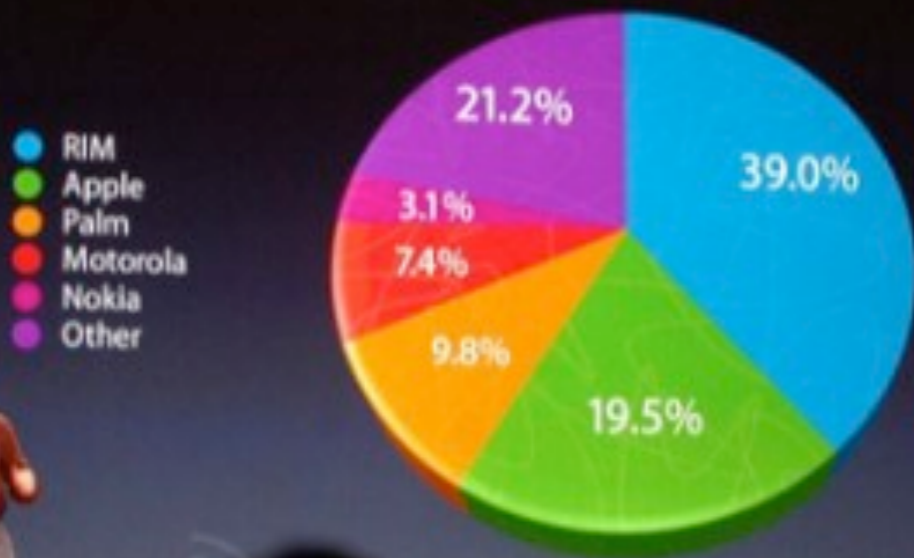


Designing **effective** visualization is **not hard if you learn the principles.**

Charts can mislead (sometimes intentionally)



U.S. SmartPhone Marketshare



Lesson 7

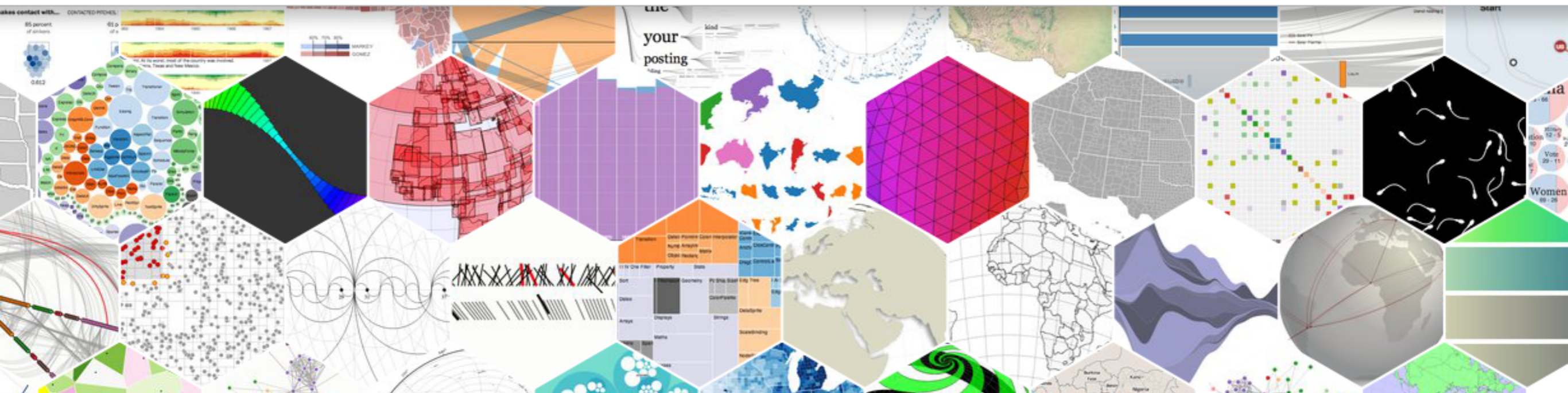
Learn **D3** and visualization basics

Seeing is believing.
A huge competitive edge.

[Overview](#) [Examples](#) [Documentation](#) [Source](#)

 Data-Driven Documents

Fork me on GitHub



Lesson 8

Scalable interactive visualization

easier to deploy than ever before.

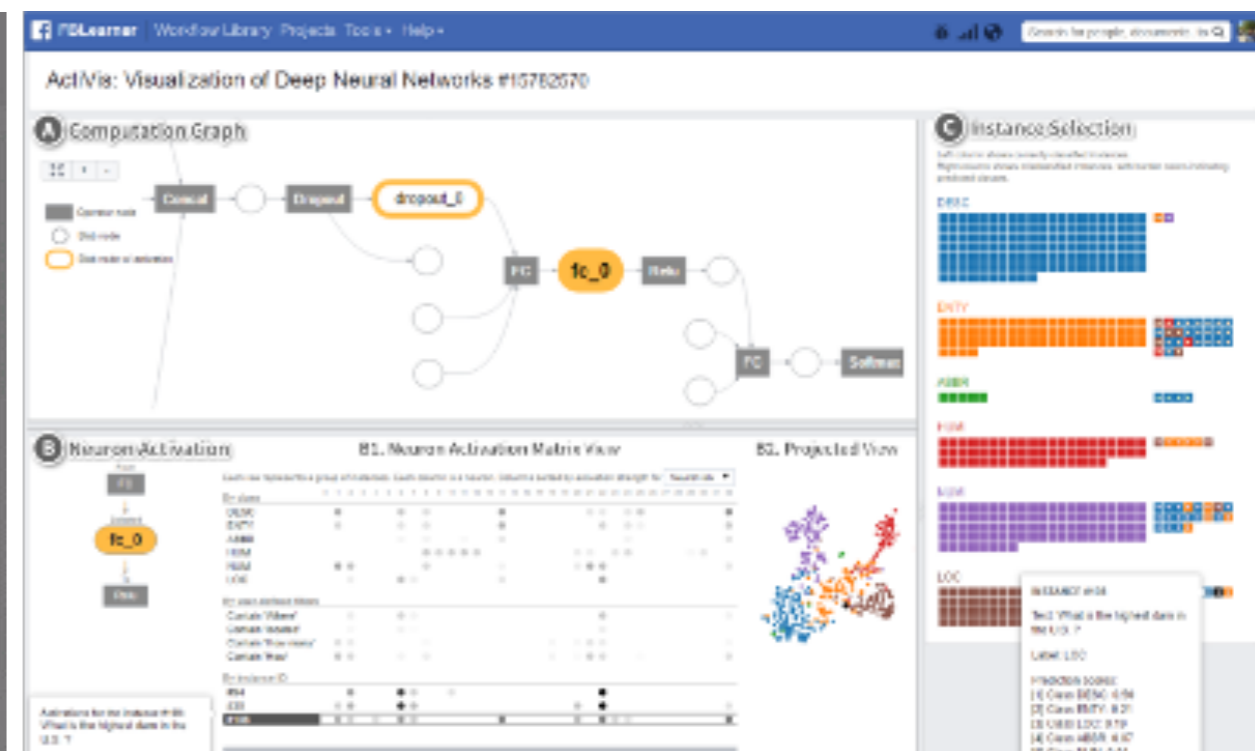
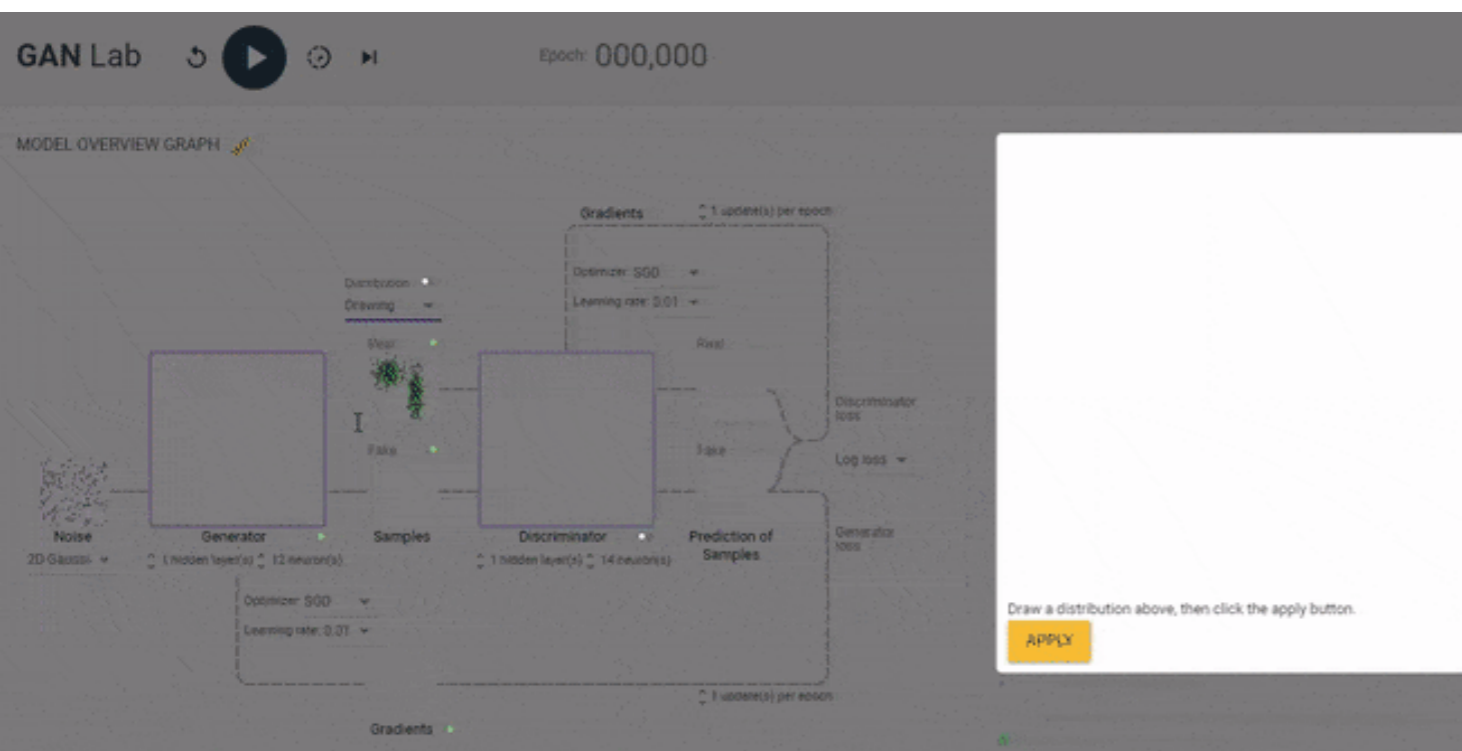
Many tools (internal + external) now run in browser.

GAN Lab (with Google)

Play with **Generated Adversarial Networks (GAN)** in browser

ActiVis (with Facebook)

Visual Exploration of Deep Neural Network Models



Lesson 8

Scalable interactive visualization

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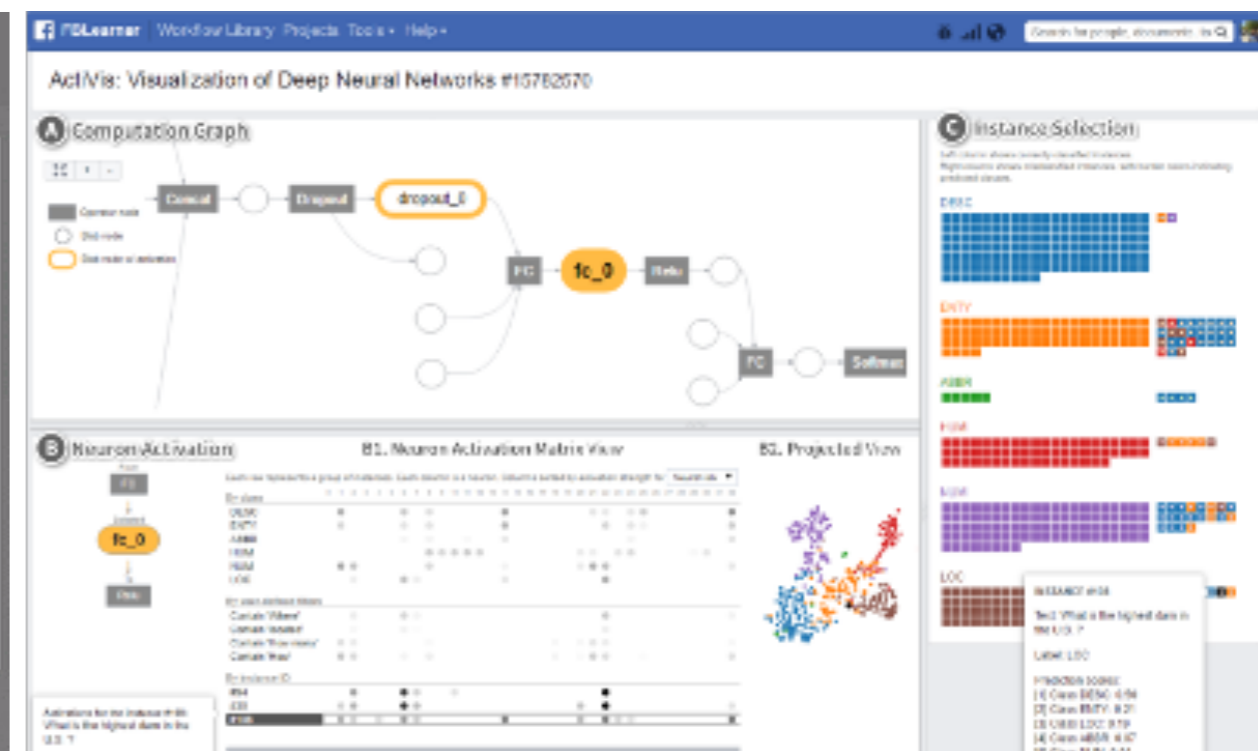
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Companies expect
you-all to know the “basic”

big data technologies

(e.g., Hadoop, Spark)

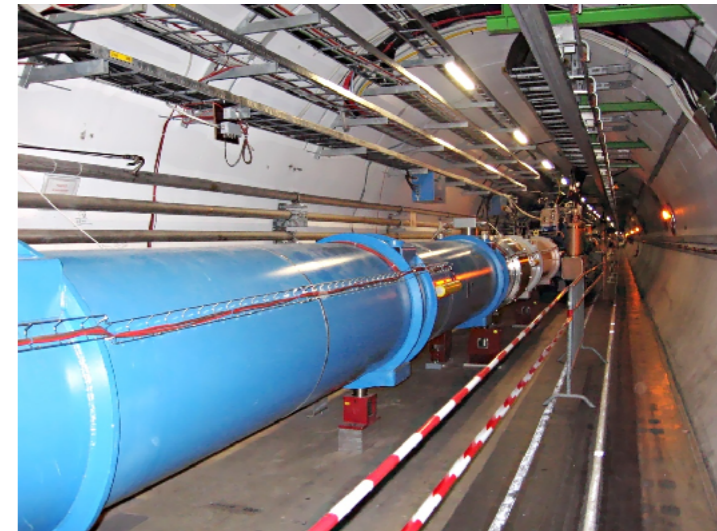
“Big Data” is Common...

Google processed **24 PB / day**
(2009)

Facebook's add **0.5 PB / day** to its
data warehouses

CERN generated **200 PB** of data
from “Higgs boson” experiments

Avatar's 3D effects took **1 PB** to store



http://www.theregister.co.uk/2012/11/09/facebook_open_sources_corona/

<http://thenextweb.com/2010/01/01/avatar-takes-1-petabyte-storage-space-equivalent-32-year-long-mp3/>

<http://dl.acm.org/citation.cfm?doid=1327452.1327492>



Open-source software for reliable, scalable, distributed computing

Written in Java

Scale to **thousands of machines**

- **Linear** scalability (with good algorithm design): if you have 2 machines, your job runs twice as fast

Uses **simple** programming model (MapReduce)

Fault tolerant (HDFS)

- Can recover from machine/disk failure (no need to restart computation)

Why learn Hadoop?

Fortune 500 companies use it

Many research groups/projects use it

Strong community support, and favored/backed by major companies, e.g., IBM, Google, Yahoo, eBay, Microsoft, etc.

It's free, open-source

Low cost to set up (works on commodity machines)

Will be an “essential skill”, like SQL

<http://strataconf.com/strata2012/public/schedule/detail/22497>

Why learn Spark?

Spark project started in 2009 at UC Berkeley AMP lab,
open sourced 2010



Became **Apache Top-Level Project** in Feb 2014

Shark/Spark SQL started summer 2011

Built by 250+ developers and people from 50 companies

Scale to **1000+ nodes** in production

In use at Berkeley, Princeton, Klout, Foursquare, Conviva,
Quantifind, Yahoo! Research, ...

Why a New Programming Model?

MapReduce greatly simplified big data analysis

But as soon as it got popular, users wanted more:

- » More **complex**, multi-stage applications (e.g. iterative **graph algorithms** and **machine learning**)
- » More **interactive** ad-hoc queries

Why a New Programming Model?

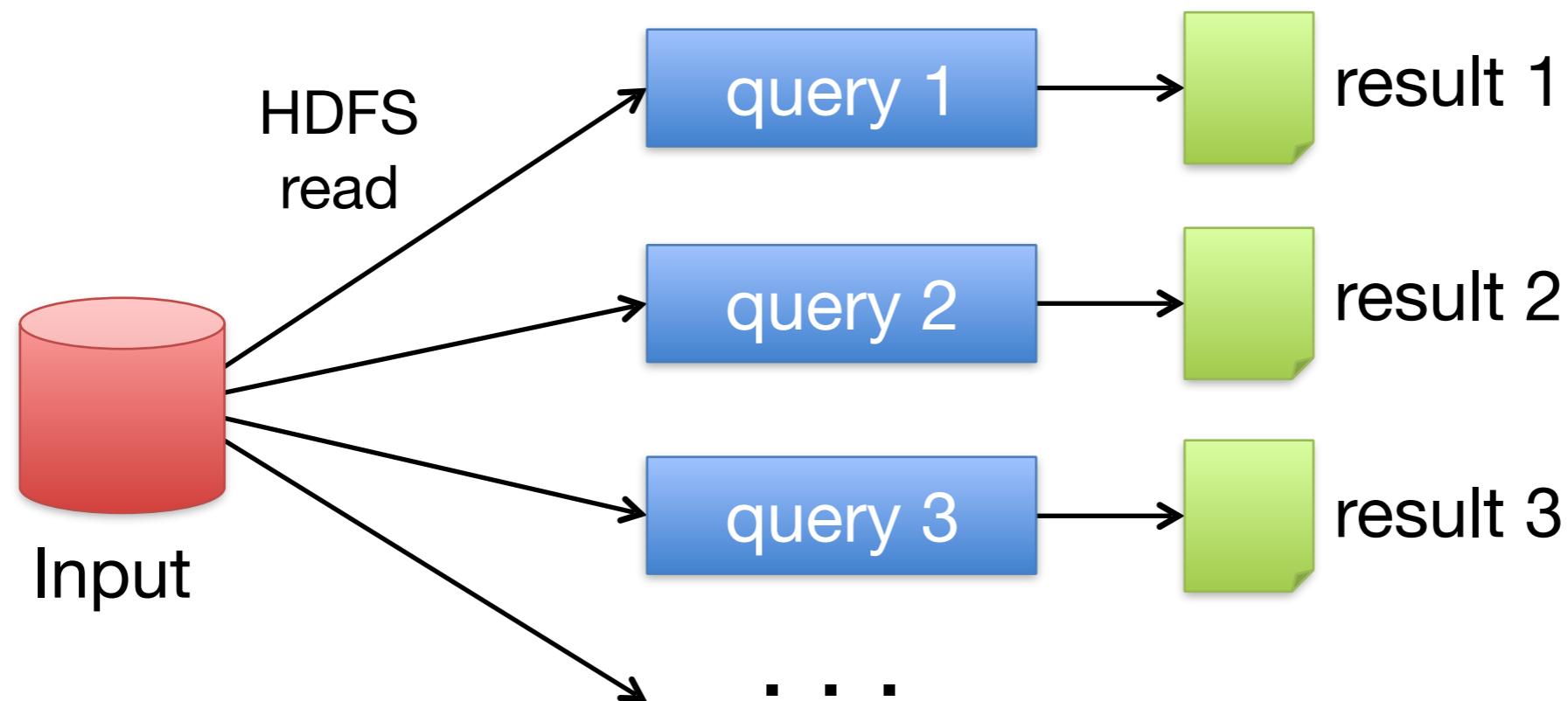
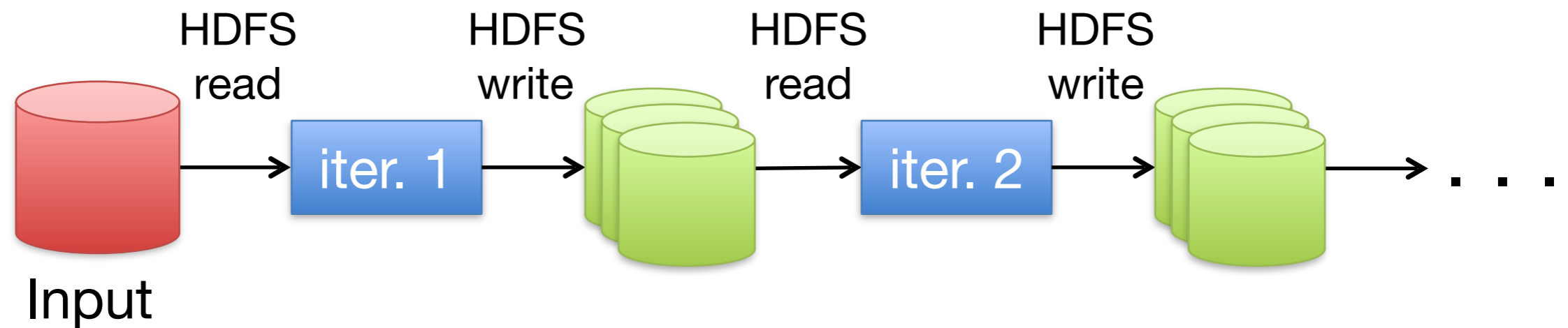
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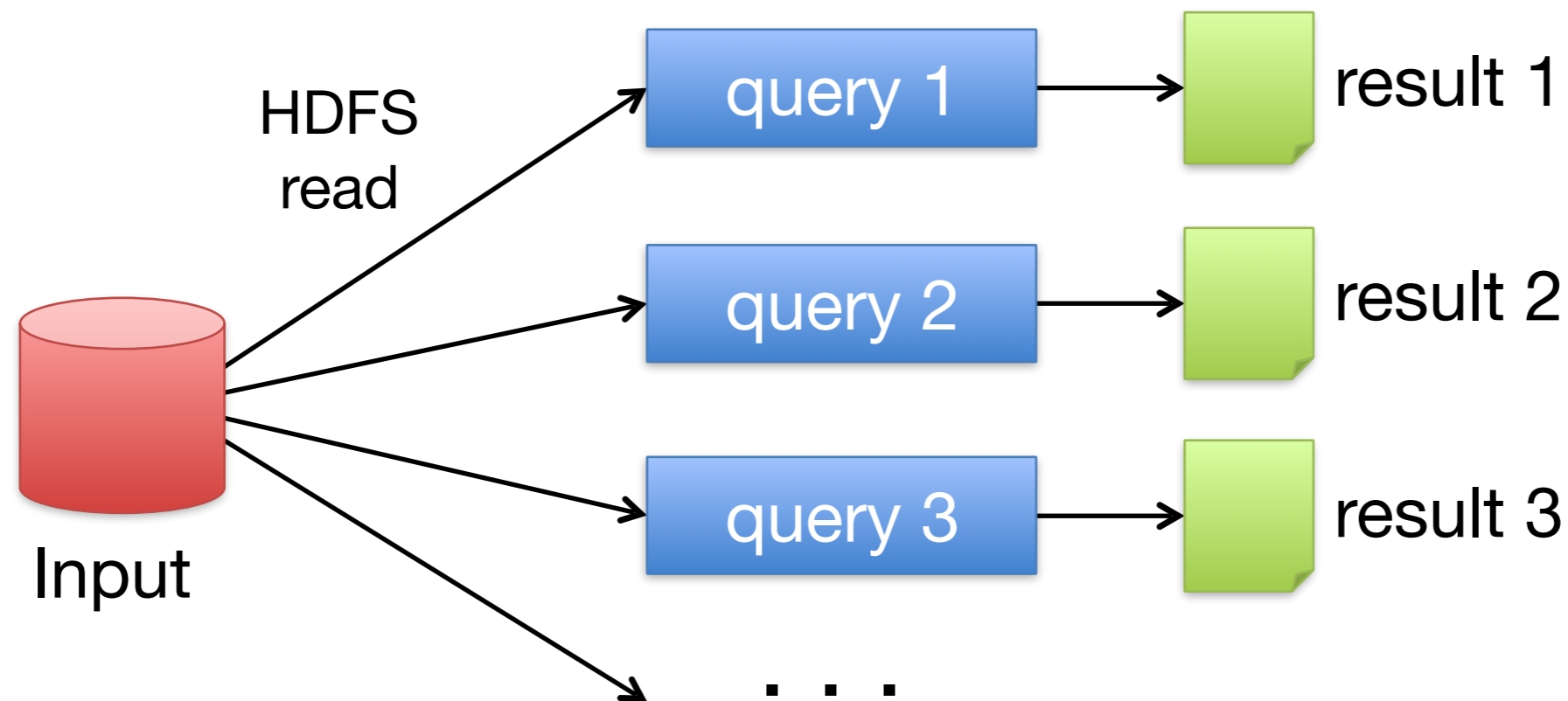
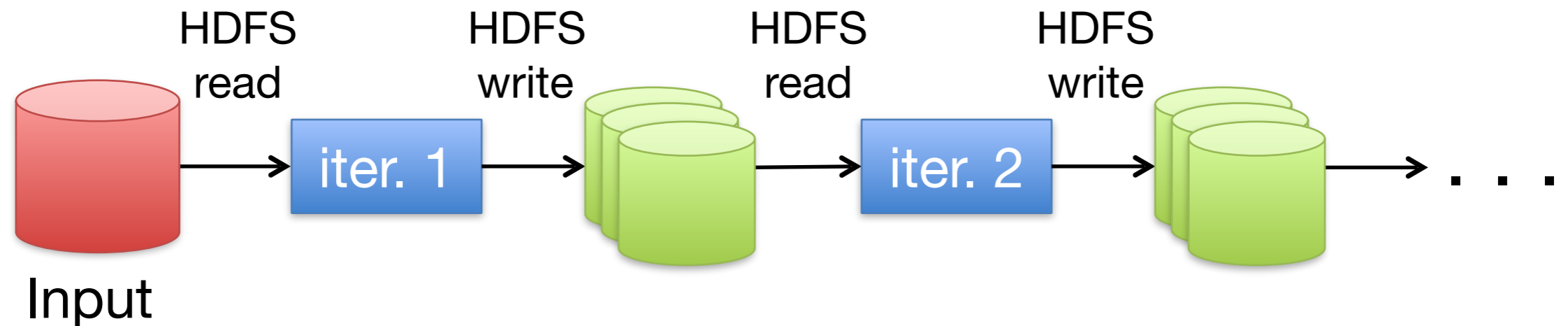
- » More **complex**, multi-stage applications (e.g. iterative **graph algorithms** and **machine learning**)
- » More **interactive** ad-hoc queries

Require faster **data sharing** across parallel jobs

Data Sharing in MapReduce

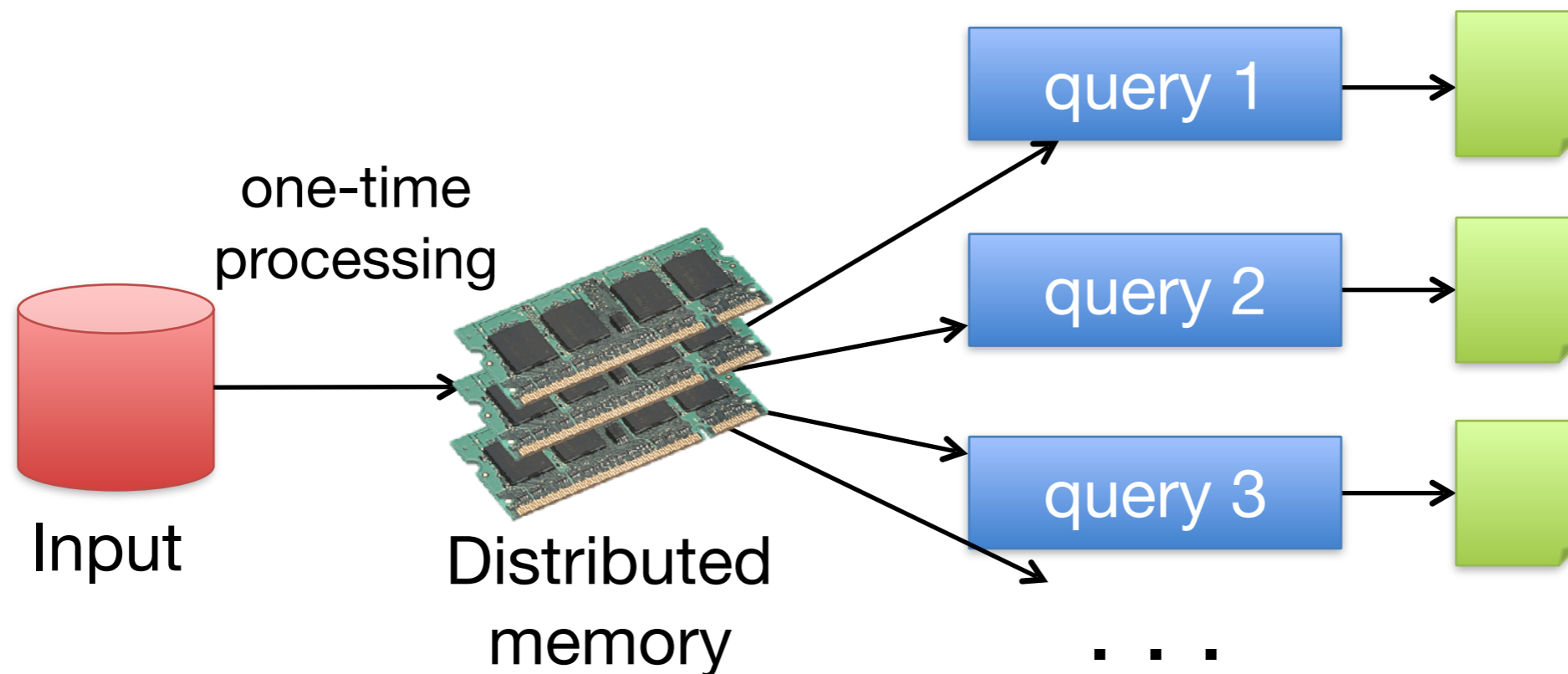
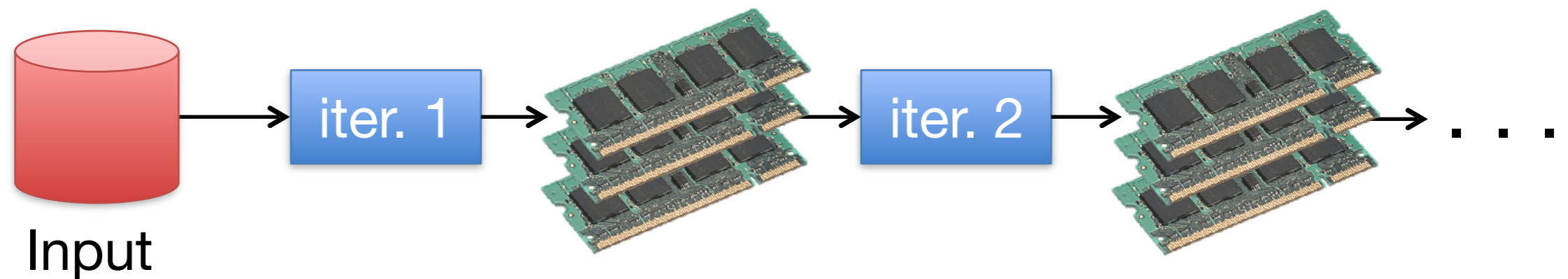


Data Sharing in MapReduce

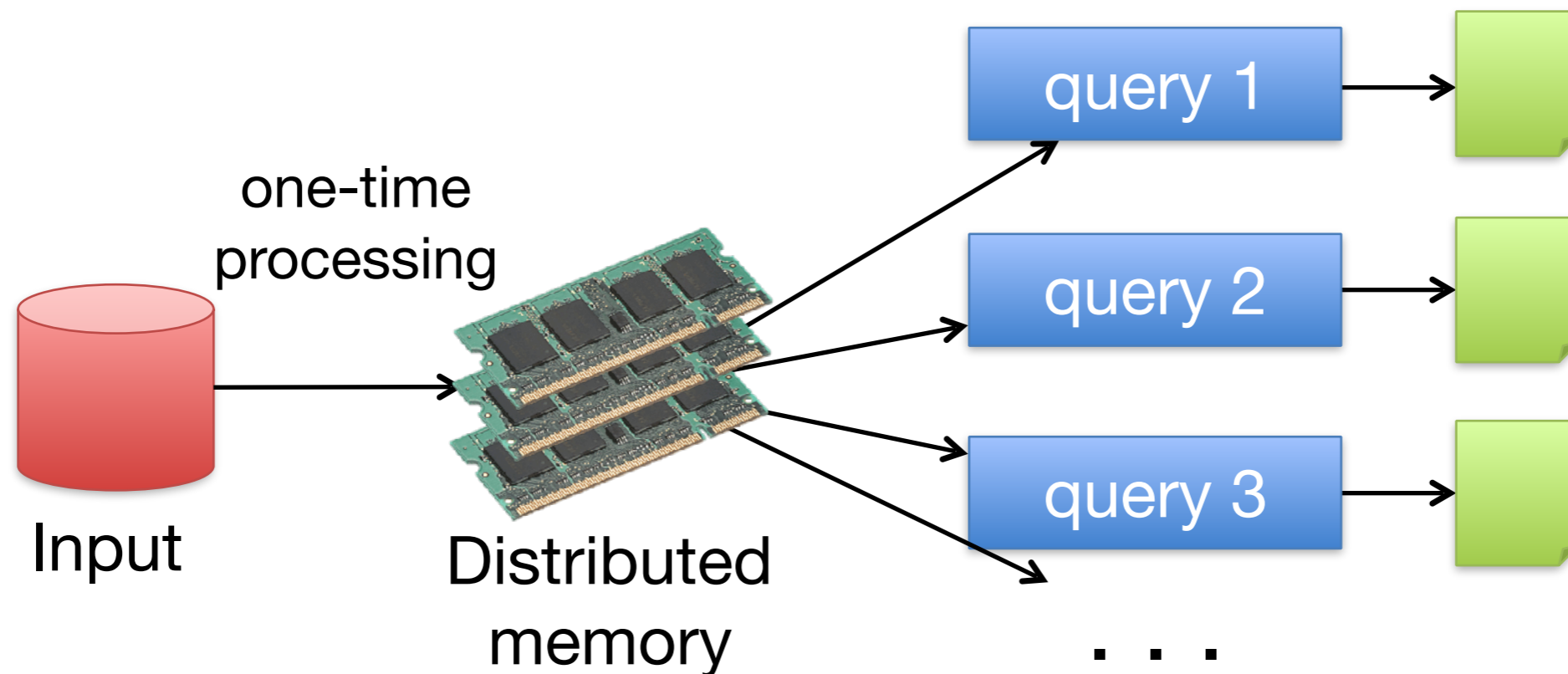
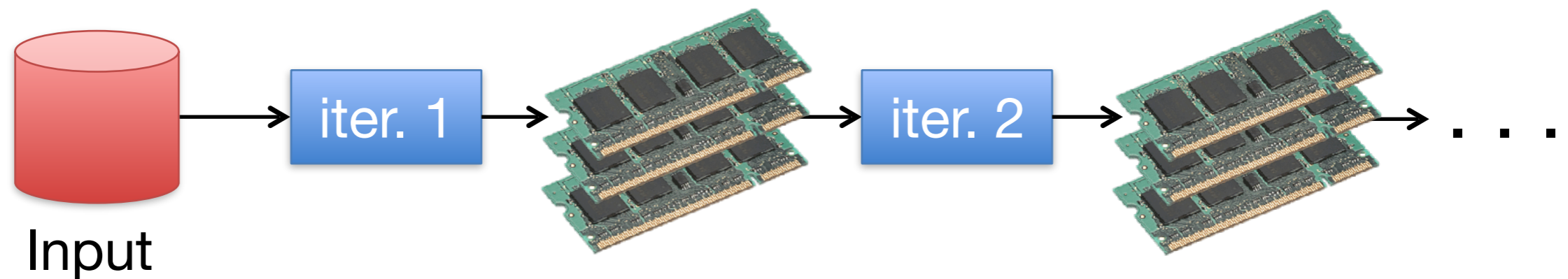


Slow due to replication, serialization, and disk IO

Data Sharing in Spark



Data Sharing in Spark



10-100x faster than network and disk

Is MapReduce dead? No!

Google Dumps MapReduce in Favor of New Hyper-Scale Analytics System

<http://www.datacenterknowledge.com/archives/2014/06/25/google-dumps-mapreduce-favor-new-hyper-scale-analytics-system/>

http://www.reddit.com/r/compsci/comments/296aqr/on_the_death_of_mapreduce_at_google/



COMPSCI

comments

related

other discussions (3)

↑ On the Death of Map-Reduce at Google. (the-paper-trail.org)

87 submitted 3 months ago by qkdhfjdjdhd

↓ 20 comments share

all 20 comments

sorted by: **best** ▼

↑ [-] **tazzy531** 47 points 3 months ago

↓ As an employee, I was surprised by this headline, considering I just ran some mapreduces this past week.

After digging further, this headline and article is rather inaccurate.

Cloud DataFlow is the external name for what is internally called Flume.

Flume is a layer that runs on top of MapReduce that abstracts away the complexity into something that is much easier



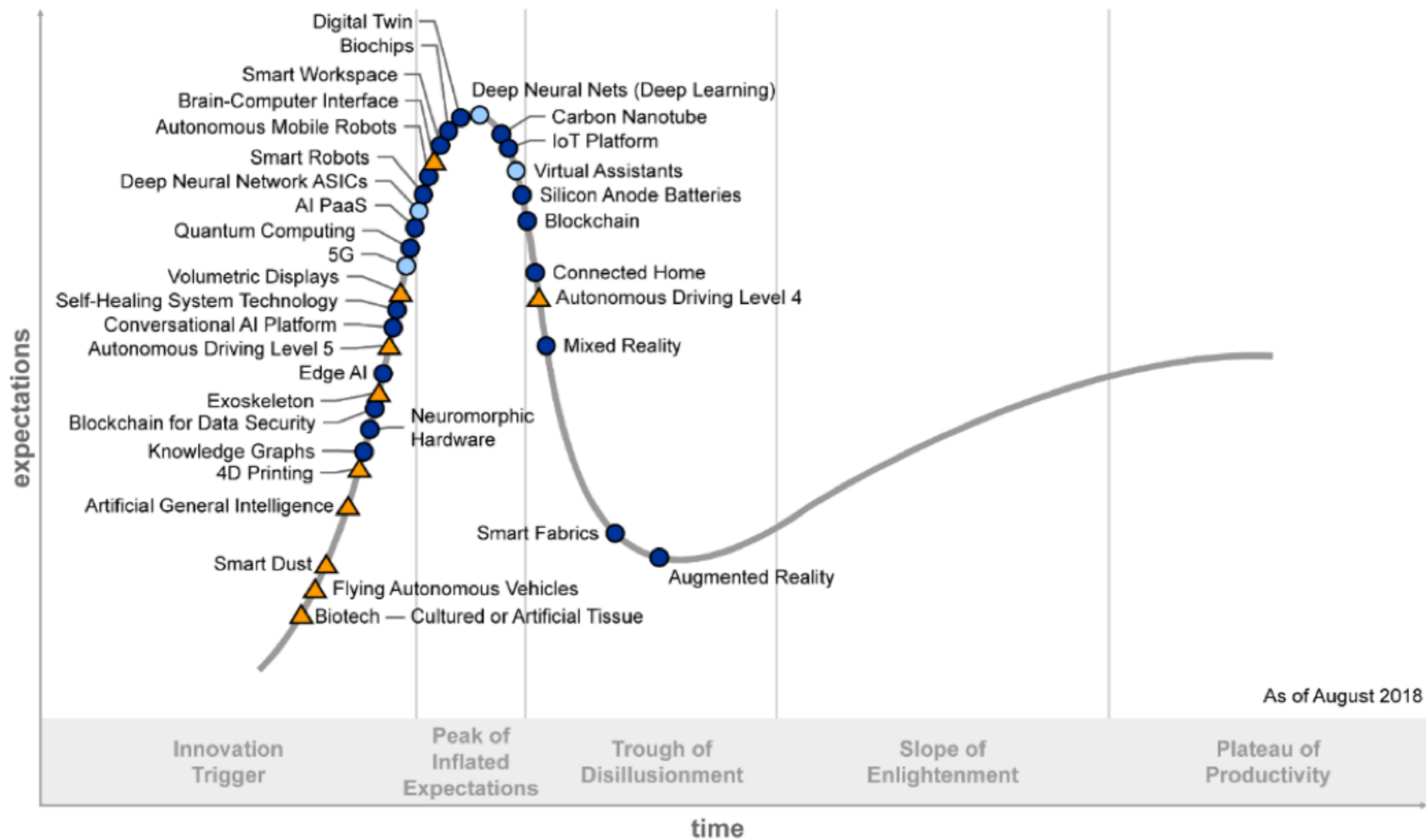
**Industry moves fast.
So should you.**

Be **cautiously optimistic**.
And be very careful of **hype**.

There were 2 AI winters.

https://en.wikipedia.org/wiki/History_of_artificial_intelligence

Gartner **Hype Cycle** for Emerging Technologies *Debatable!*



Plateau will be reached:

- less than 2 years
- 2 to 5 years
- 5 to 10 years
- ▲ more than 10 years
- ⊗ obsolete before plateau

Your **soft skills** can be more important than your **hard skills**.

If people don't understand your approach, they won't appreciate it.

Visual Data Analytics

A Short Tutorial

Duen Horng (Polo) Chau

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Associate Director, MS Analytics

Georgia Tech

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