PDD

Lecture 1: Introduction

Prepared by Jacek Sroka

Organization

- Assessment criteria
  - Labs:
    - Working during labs/homework (20 points in total)
    - Two big programming assignments (2 * 20 points)
    - Very important to obey the deadlines
      penalties apply: -1 point per every started 12h period after the deadline (up to 14 points of penalty)
      more than one week of delay: don't bother
    - Total 60 points from labs and minimum 30 points to pass
  - Exam:
    - Written exam with total of 40 points
    - First term (only for people who pass the labs) and Second term (for everyone, grade only from exam)
    - Easy if you attended classes and participate

- There are lots of possibilities to extend the assignments (e.g., into MSc thesis)
  - We are open to good ideas (please discuss them first with your lab teacher)

    e.g. genome scale bioinformatics
  - Implementing and testing algorithms from papers
  - Working on research papers

Questions?

Materials

- Scientific papers
- Framework presentations on youtube / tutorials
- *Mining of Massive Datasets*
  Anand Rajaraman, Jure Leskovec, Jeffrey D. Ullman
- Some Coursera / edX / Stanford online courses

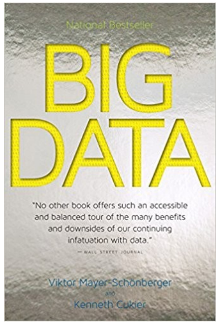
What is Big data and why it is interesting?


BIG
DATA

What is big data?

“Big data is like teenage sex: everybody talks about it, nobody really knows how to do it, everyone thinks everyone else is doing it, so everyone claim they are doing it.”

--Dan Ariely, Duke University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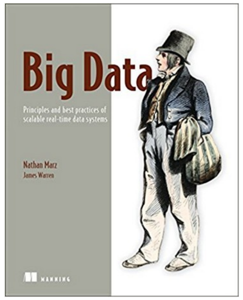
"No other book offers such an accessible and balanced tour of the many benefits and downsides of our continuing infatuation with data."
Viktor Mayer-Schönberger
Kenneth Cukier

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Nathan Marz
James Warren
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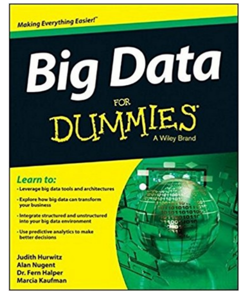
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Big Data
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Learn to:
Judith Hurwitz
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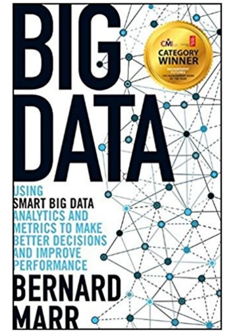
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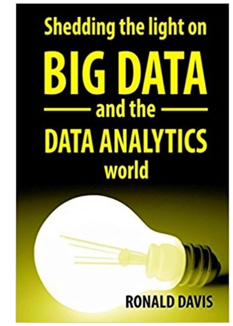
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BIG DATA
and the
DATA ANALYTICS
world
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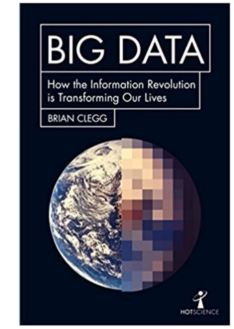
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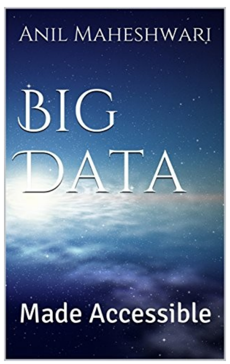
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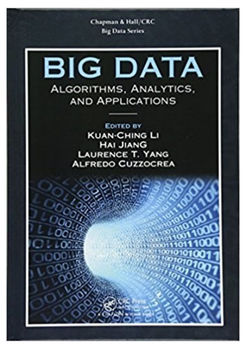
Made Accessible

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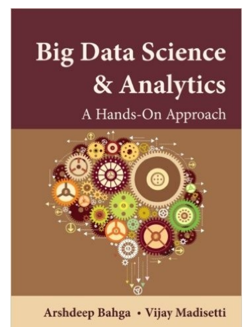
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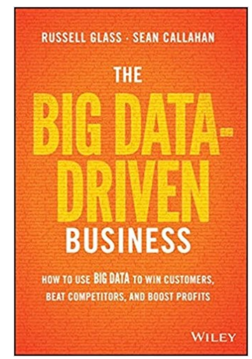
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THE
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HOW TO USE BIG DATA TO WIN CUSTOMERS, BEAT COMPETITORS, AND BOOST PROFITS
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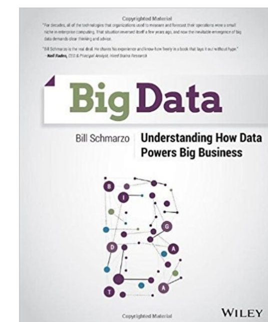
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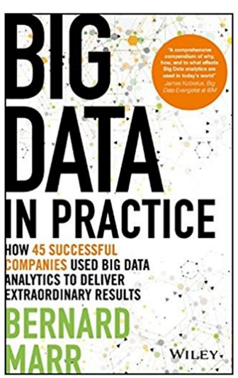
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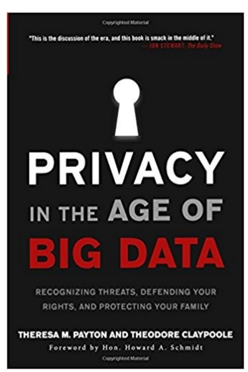
"This is the discussion of the era, and this book is smack in the middle of it."
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IN THE AGE OF
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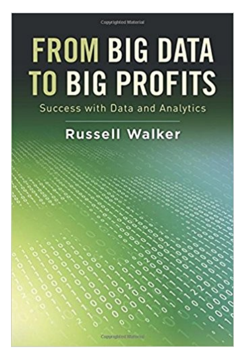
RECOGNIZING THREATS, DEFENDING YOUR RIGHTS, AND PROTECTING YOUR FAMILY
THERESA M. PAYTON AND THEODORE CLAYPOOLE
Foreword by Hon. Howard A. Schmidt

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Success with Data and Analytics
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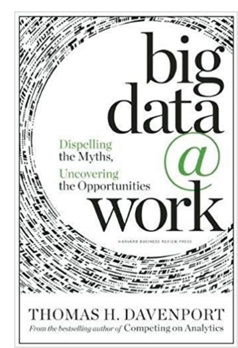
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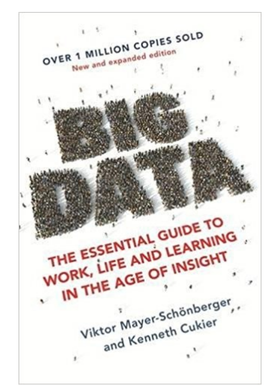
Uncovering the Opportunities
THOMAS H. DAVENPORT
From the bestselling author of Competing on Analytics

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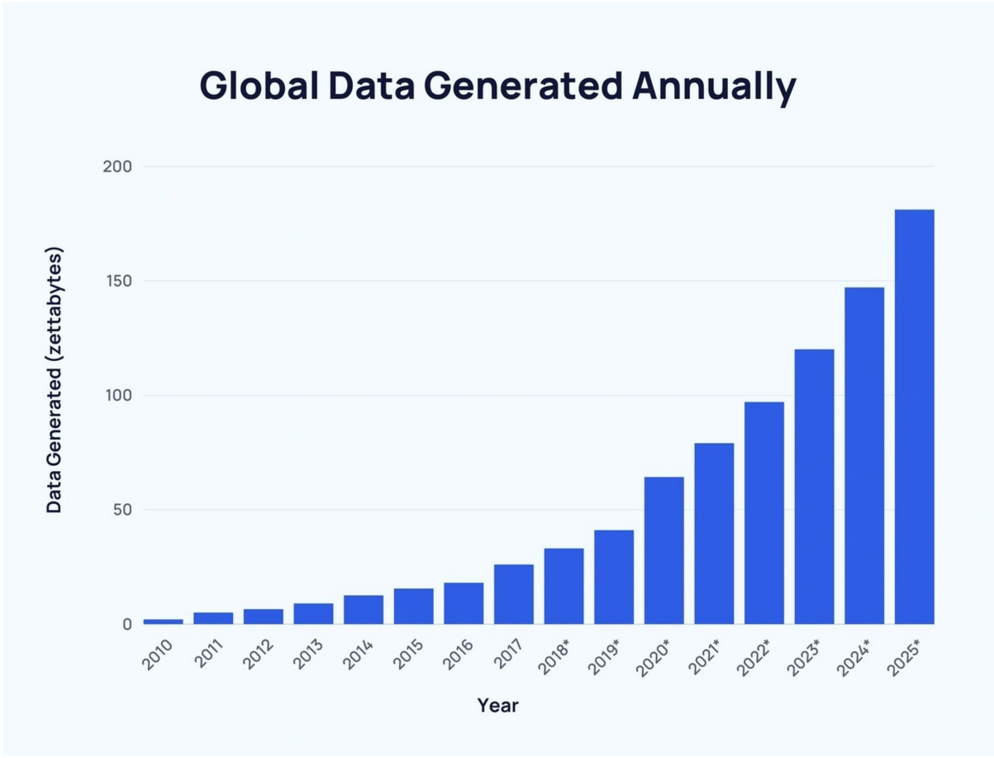
BIG DATA
THE ESSENTIAL GUIDE TO WORK, LIFE AND LEARNING IN THE AGE OF INSIGHT
Viktor Mayer-Schönberger
and Kenneth Cukier

Wikipedia: *„Big data is an all-encompassing term for any collection of data sets so large or complex that it becomes difficult to process them using* ***traditional*** *data processing applications."*

- *Started with Internet companies Google/Facebook/Twitter/Amazon*
  (Statistics from 2012 from Wikibon Blog)
  - *In 2008, Google was processing 20,000 terabytes of data (20 petabytes) a day*
  - *Facebook stores, accesses, and analyzes 30+ Petabytes of user generated data*
  - *100 terabytes of data uploaded daily to Facebook*
  - *According to Twitter's own research in early 2012, it sees roughly 175 million tweets every day, and has more than 465 million accounts*

- *Big data was embraced by „brick and mortar"*
  - *banks, telecoms, insurance companies, ...*



Competitive advantage for brick and mortar business: Frequent itemset problem

transaction ID	items
1	{A,C,D}
2	{B,C,E}
3	{A,B,C,E}
4	{B,E}
5	{A,B,C,E}

- Analyze transaction log from store
- Goal: see what customers buy in the same transaction to organize store layout and plan promotions
  - Place snacks next to beer?
  - Offer antivirus software with new computer sales?

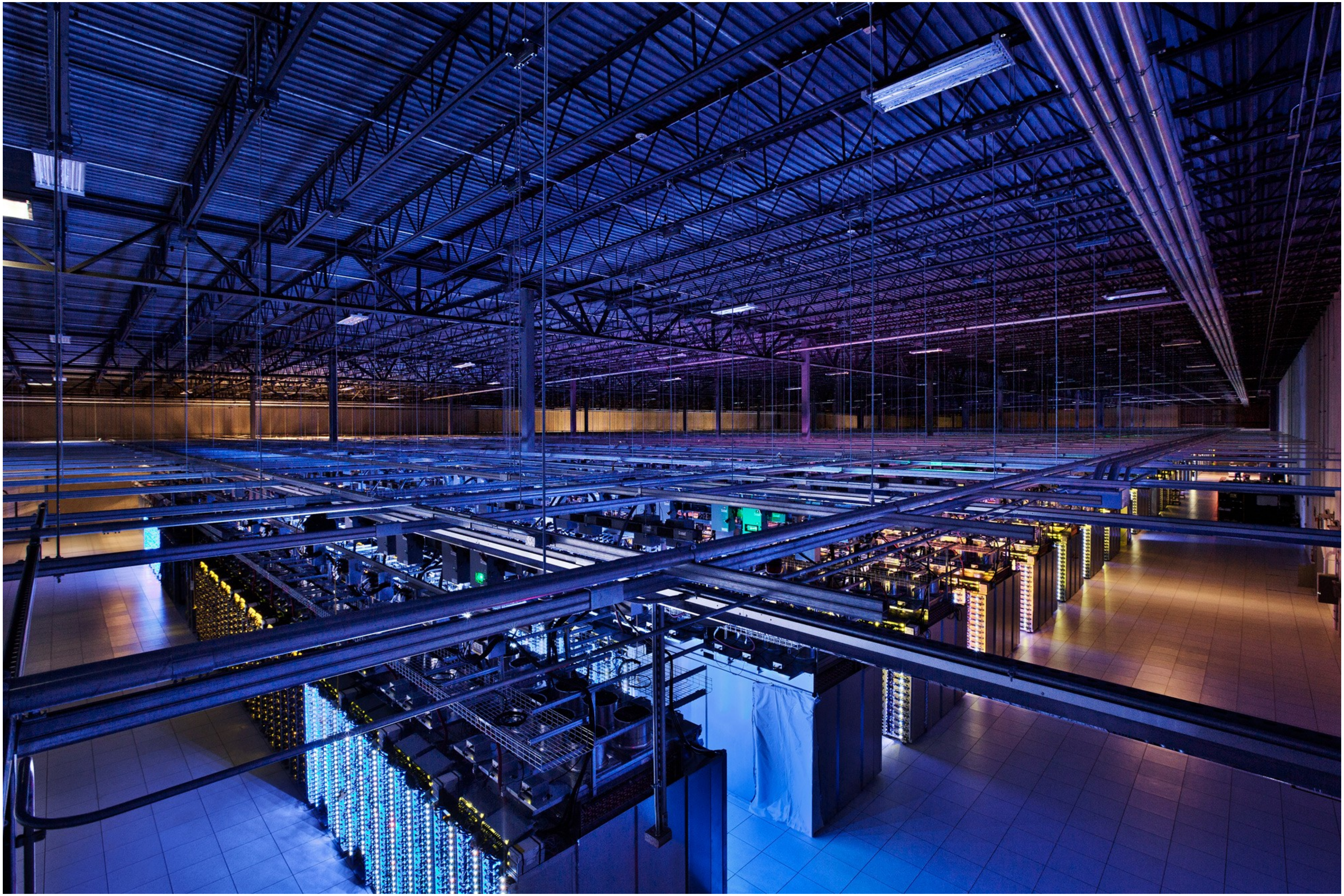
- Support: how frequently the itemset appears in the dataset support({B,E})=4/5

- Association rule learning: [‘milk]^[‘bread’]=>[‘butter’]
- Computer => antivirus_software [support=2%, confidence=60%]
  - usefulness and certainty of discovered rules
  - 2% of all the transactions under analysis show that computer and antivirus software are purchased together: Support(A -> B) = Support_count(A ∪ B)
  - 60% of the customers who purchased a computer also bought the software: Confidence(A->B) = Support(A ∪ B)/Support(A)

Competitive advantage?

What to consider
when processing Big data?

Cluster computing



Picture by: Google Inc.

Cluster computing

- Much less problems (experts do many things for us at scale and automatize)
  - Don’t need to rent server rooms, pay for electricity, hire administrators
  - No network problems (also no „Layer 0” problem – see OSI model for Layers 1-7)
  - DDoS protection and monitoring (distributed denial of service protection)
  - Updating drivers, dealing with machine failures
    (e.g. HDD breaks once in every 4 years, btw. its is more reliable when it is hot)
  - Note that other people may share the same computers!
- Examples
  - Miss Poland beauty pageant
  - Pokemon GO
  - CERN
  - Elections?
  - PRISM@NSA
- Processing data on clusters requires new frameworks
  - Take parallelism into account while designing algorithms (functional based API)
  - No need to rediscover the wheel (similar to DBMS, similar problems in many Google projects)
  - Be ready for failures (many computers, long lasting computation)
  - Deal with skew

Cluster computing

- New technologies
  - Better storage
  - Very strong computers (thousands of cores, terabytes of RAM)
- Software as a service (SaaS)
  - Even less problems, but also less control and higher price

Data science

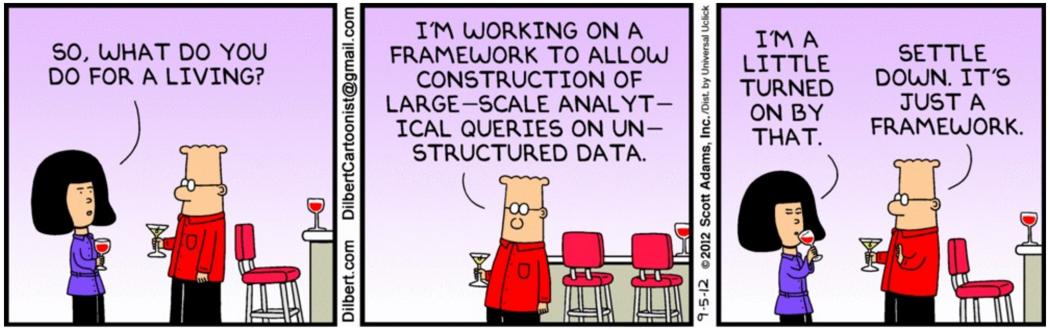
- Data science – make decisions based on how we observed the world to work
- Sometimes better to use many simple models than one sophisticated (Watson on Jeopardy; ensemble methods use multiple learning algorithms to obtain better predictive performance than could be obtained from any of the constituent learning algorithms alone)
- Often we aggregate/summarize data (pagerank, clusterization – centroids i clusteroids) to more useful representation or we find important information (frequent itemsets)
- It will get worse
  - Rate of data production is growing faster than the processing speed
  - With time there will be less and less problems for which we can use reasonable algorithms due to the growing size of input data (polynomial or even linearithmic)
  - Often result guaranteed to be good approximation is good enough
  - Different hardware is good for different problems
    - Single supercomputer with specialized memory and network
    - Cluster of commodity computers
    - Single computer with lots (TB) of RAM
      - Memory needs to be initialized
    - Graphics cards

Don’t make false conclusions

- Consider if the results makes sense and why
  - “data mining” = is the discovery of “models” for data
    where model relates to statistics, machine learning, algorithms, data bases
  - Pejorative at start (conclusion not supported by the data)
  - Bonferroni rule
    - Terrorists in hotels
      W. Bush administration's Total Information Awareness data-collection and data mining plan of 2002
    - Torture the data, and it will confess to anything
      -Ronald Coase, economist, Nobel Prize Laureate
    - The Bible Code
  - The results need interpretation (beer and diapers vs diapers and beer)
  - Correlation does not imply causation (Facebook i Princeton)
  - Watch for Weapons of Math Destruction
    - Teachers vs football
    - Hard to appeal black boxes
    - Use feedback loops
- Check for input data bias
  - Learn from ML projects mistakes
  - Failing to account for cultural bias can have consequences

General plan of the lecture

General plan of the lecture



- Technologies:
  - Spark, MLlib, Parquet
  - Stream processing (Kafka, Apache Beam)
  - ...
- Nice algorithmic ideas and how to apply them:
  - Locality Sensitive Hashing
  - Multiway joins, Minimal MapReduce algorithms
  - Distributing ML algorithms
  - ...
- What matters when distributing:
  - computation vs communication cost
  - skew
- How to pick the right tool to solve a problem
- How to avoid typical mistakes

Evolution of: Technologies, Frameworks, Tools, ...

Big data framework history

(good systems need companies that support them)

- Hadoop, Avro
  - MapReduce
  - HDFS
  - YARN from 2.0
- Spark, Parquet
  - Spark Core, SQL and Streaming
  - GraphX, GraphFrames
  - MLlib
  - AMPLab, UC Berkley, Databricks
- Google Inc.
  - Apache Beam
  - BigQuery
- Snowflake
  - Snowflake
- Nvidia
  - DASK, RAPIDS

Before Big data

- Data warehouses: storing and querying historical business data
  - 1970’s: Relational databases (w/SQL)
  - 1980’s: (more data requires multiple computers) Parallel database systems based on “shared-nothing” architectures (Gamma, GRACE, Teradata)
    - “The term shared nothing architecture was coined by Michael Stonebraker (1986) to describe a multiprocessor database management system in which neither memory nor disk storage is shared among the processors.”
    - “Each node is independent and self-sufficient, and there is no single point of contention across the system”
    - Hash partitioning
  - 2000’s: Netezza, Aster Data, DATAllegro, Greenplum, Vertica, ParAccel,...
    - 100M $ to 1B acquisitions
- On-line transaction processing (OLTP)
  - Order entry, retail sales, and financial transaction systems, …
  - Produces data for data warehouses
  - Shared-nothing also useful for scaling OLTP (1980’s: Tandem’s NonStop SQL)

Parallel database software stack

- Compiler takes query and produces query plan
- Datflow layer executes query plan
- Executed on storage managers on individual machines

- Upper layers orchestrate execution of lower layers

- Often built on top of some open source DBMS with added orchestration software: with node being instances of indexed DBMS and some

- **This stack is closed and expensive!**
- **Access data with SQL only!**

Big data in systems world

- Late 1990 – indexing and querying exploding content of the Web
  - DB technology was used but abandoned
  - Google, Yahoo! *et al* needed something else and built something
- Google
  - Google File System (GFS)
    - Files stored on 1000's of machines
    - Replication for fault-tolerance and availability
  - MapReduce (MR) programming model
    - Think about the data: user provides two simple functions (process one element + group)
    - "Parallel programming for dummies" - partitioning, message passing, fault tolerance
- Yahoo!, Facebook, and other cloned good ideas from Google's "Big Data" infrastructure
  - GFS -> Hadoop Distributed File System (HDFS)
  - MapReduce -> Hadoop MapReduce
  - Used for Web indexing, click stream analysis, log analysis, information extraction, some machine learning

MapReduce@Google

- Typical motivation: the best tools are created to avoid mundane tasks!
- Sanjay Ghemawat, Howard Gobioff, Shun-Tak Leung: **The Google file system.** SOSP 2003: 29-43
  - scalable distributed file system for large distributed data-intensive applications
  - provides fault tolerance
  - tuned to inexpensive commodity hardware
  - delivers high aggregate performance to a large number of clients
- Jeffrey Dean and Sanjay Ghemawat. 2004. **MapReduce: simplified data processing on large clusters.** In Proceedings of the 6th conference on Symposium on Opearting Systems Design & Implementation - Volume 6 (OSDI'04), Vol. 6. USENIX Association, Berkeley, CA, USA, 10-10.
  - partitioning the input data
  - scheduling the program's execution across a set of machines
  - handling machine failures, and
  - managing the required inter-machine communication

  - Simple programming model: need to provide two functions **map** i **reduce** (think about a hammer, do not try to use it for every problem)

Tailor solution to your needs

- How to choose between: snowflake, spark, dask, open source, ...
- Pipeline vs ad hoc
  - Expressive/high level/well know API (SQL, pandas, scikit-learn, etc.) vs human optimization?
  - Hashing/Indexes?
- Computer vs cluster vs cloud vs hpc vs gpu
  - Choose best hardware and framework for your needs or framework for your hardware
- Do we need huge storage (for input, intermediate data, output)
  - store data well (binary vs textual, columnar formats, push down filters)
- Do we need to take failures into account (computation, storage)
- Do we need to scale up/down (on demand)
- Good docs/tutorials and responsive community (problems start with large deployments)
- Paid support
- Integration with other tools
- Distributing is not always good
  - Try single node first (local memory, no network, no framework overhead, no accidental complexity)
  - for some problems it is not easy/possible to design algorithms that scale well
  - for other it may work worse if you do not understand what is going on well (e.g. graph algorithms, wrong configuration of memory, checkpointing, etc.)

MapReduce

MapReduce

- Problems
  - Distributed programming is difficult (it's nice to have a simple model)
  - Network transfer is the main limiting factor (for 1Gbps transfer of 10TB takes 1 day)
  - Long running computations need to be resistant to single node failures
  - Need algorithms with low complexity and small data exchanged
- MapReduce
  - Simple programming model, well tested framework
    - Lots of nice algorithmic ideas available
    - Easy to use as intermediate layer for other high level languages like SQL
    - High **accidental complexity**, but lots of projects that help with that like Crunch, Cascading or Oozie
  - Data replication (based on HDFS)
    - chunk servers are compute servers
    - When possible schedule processing to a node with the data
  - Very pessimistic approach to failures
    - Big overhead for iterative algorithms (data mining, graph processing)
- We won't program in MapReduce but we will use it as introduction to Massively Parallel Computation (MPC) model
  - Goal for the first lab solve simple problems in MapReduce and implement in Spark (which has better API but don't use it yet)

Hello World

- Goal: count number of occurrences of a given word in a large text file
  - Web sever log analysis – finding popular URLs
  - Finding stop words in a given language
- What we need to take into account
  - File is too large to fit in memory
  - Pairs `<word,count>` do not fit in memory

Hello World

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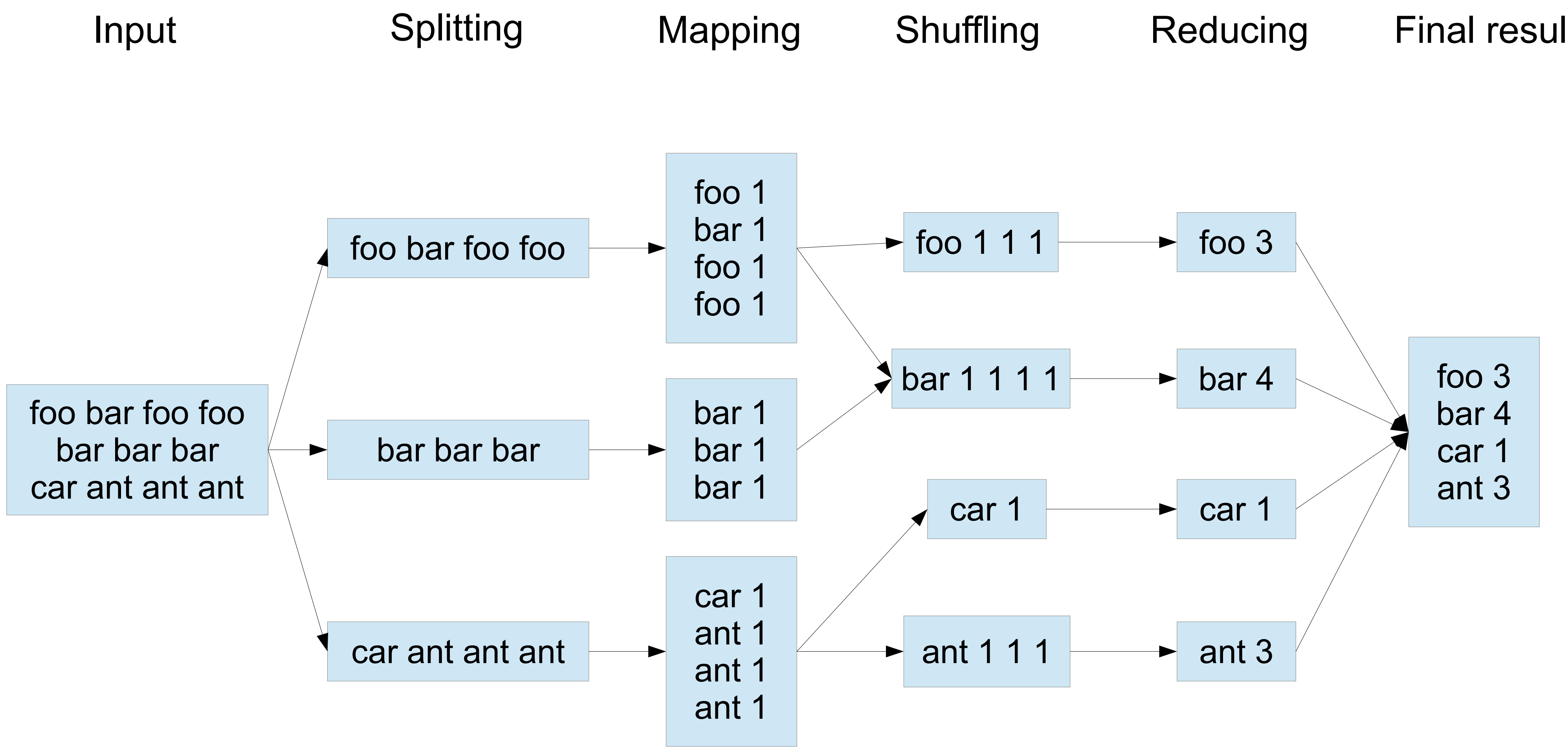
- What we need to take into account
  - File is too large to fit in memory
  - Pairs `<word,count>` do not fit in memory
- Ideas for a solution
  - Use HashTable
    - Easy to distribute (process independently, then integrate results)
  - Start with some grouping or sorting, e.g., with some file system tool, then process smaller files
    - Also easy to distribute

MapReduce

- Map
  - Scan input record by record, do some preprocessing
  - Choose group for the record (based on some key) write in local file
  - Easy to distribute
- Shuffle/Sort
  - Shuffle local files so that records with the same key end up at the same node
- Reduce
  - Assuming that groups can be processed on nodes, i.e., are not materialized in memory or are small enough

- Lots of reasonable ways to choose a key for grouping (depends on the use case)
  - Whole word
  - First letter
  - 0 or 1 for the first or second part of alphabet
  - The goal is to balance the groups as much as possible

MapReduce example



MapReduce c.d.

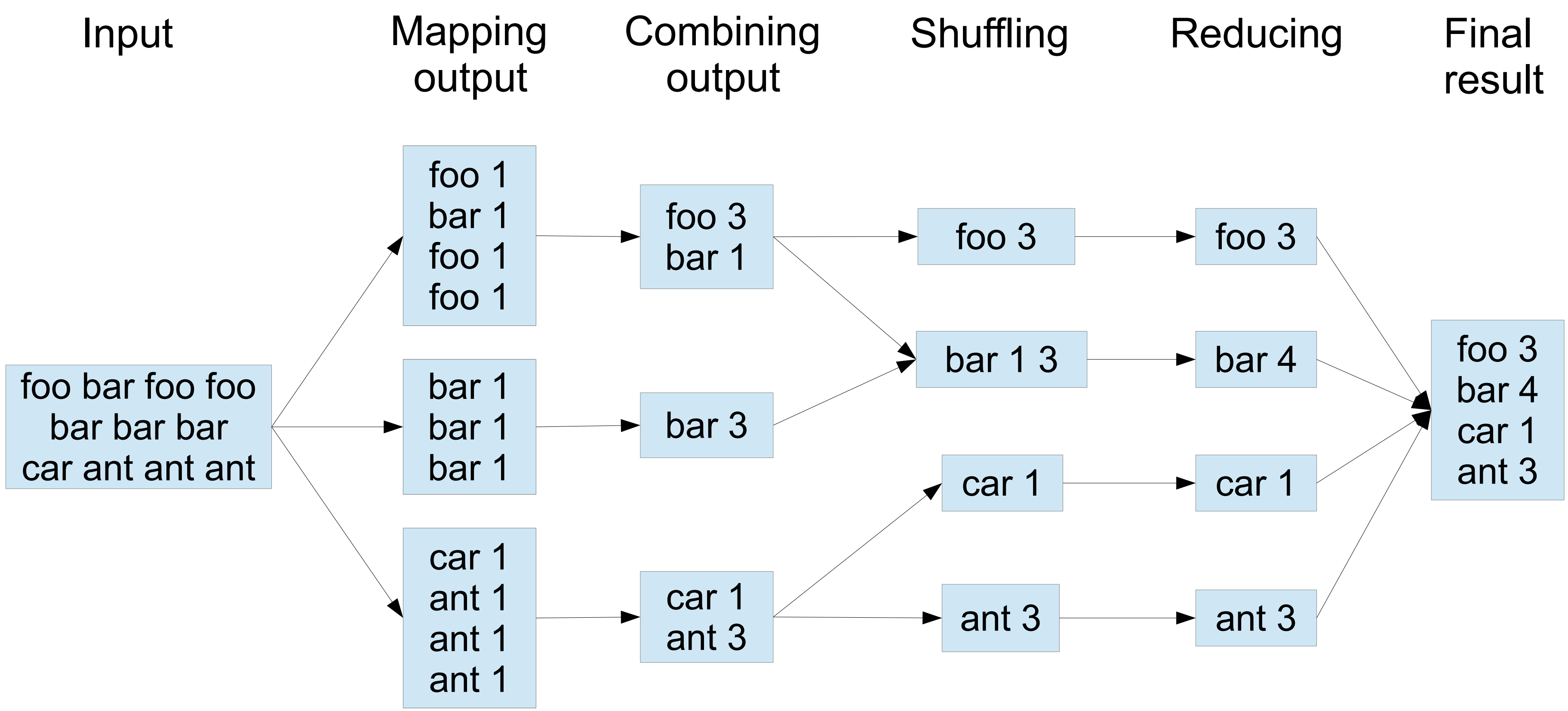
- Input: collection of key/value pairs
- Map(k,v) → <k',v'>*
  - Execute once for each input pair
  - Results in an arbitrary number of intermediate key/value pairs
- Reduce(k', (v1', v2', …)) → <k'',v''>*
  - Execute once for each k'
  - Has access to all values for that key
- Example:
  - Read input in parts, e.g., line by line
  - map: for each line generate pairs <word, 1>
  - reduce: return length of the values list
  - map and reduce are executed on multiple nodes
- Disc access is sequential not random (VERY important for HDDs, but for SDDs too)

Terminology

- Map-Reduce job =
  - Map function (inputs -> key-value pairs)
  - +
  - Reduce function (key and list of values -> outputs)
- Map and Reduce Tasks/Processes apply Map or Reduce function to (typically) many of their inputs.
  - Unit of parallelism
- **Mapper** = application of the Map function to a single input
- **Reducer** = application of the Reduce function to a single key-(list of values) pair

Combiners

- Usually we can pre-aggregate Map task ouputs with reduce function



- Works only for commutative (a + b = b + a) and associative (a + (b + c) = (a + b) + c) functions
  - e.g. for sum we can, but not for avg (1+2+3)/3 != ((1+2)/2 + 3/1)/2
  - often this can be fixes – for avg by emitting (sum, count) and using different Comb. and Red.
  - But not always – median