CMPT 354: Database System I

Lecture 12. Where to go from here

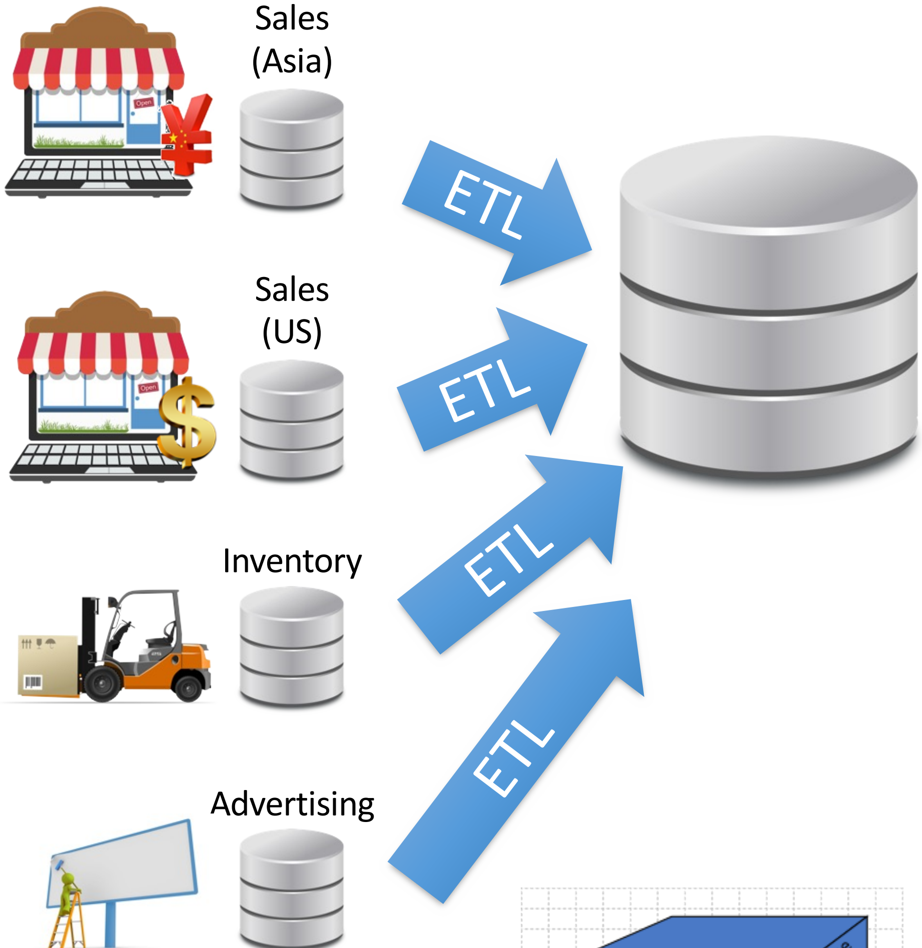
Where are we now

- **How to query a database**
  - SQL (Lec 3-4)
- **How to design a database**
  - ER Model (Lec 8)
  - Design Theory (Lec 9)
  - Relational Model (Lec 2)
- **How to develop a database application**
  - Database Application (Lec 10)
  - Transactions (Lec 12)
- **How to process a SQL query**
  - Relational Algebra (Lec 5)
  - Query Processing (Lec 6)
  - Query Optimization (Lec 12)

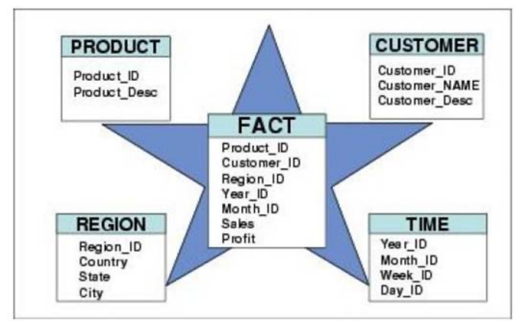
Where to go from here

- Data Warehouse
- Parallel Databases
- Big Data Processing
- Cloud Databases
- Data Science

Data Warehouse

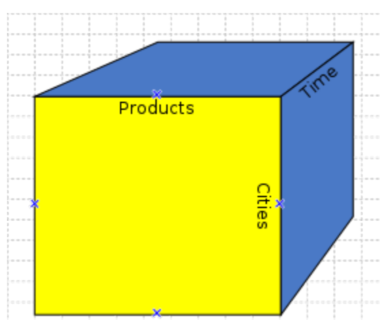


Collects and organizes historical data from multiple sources

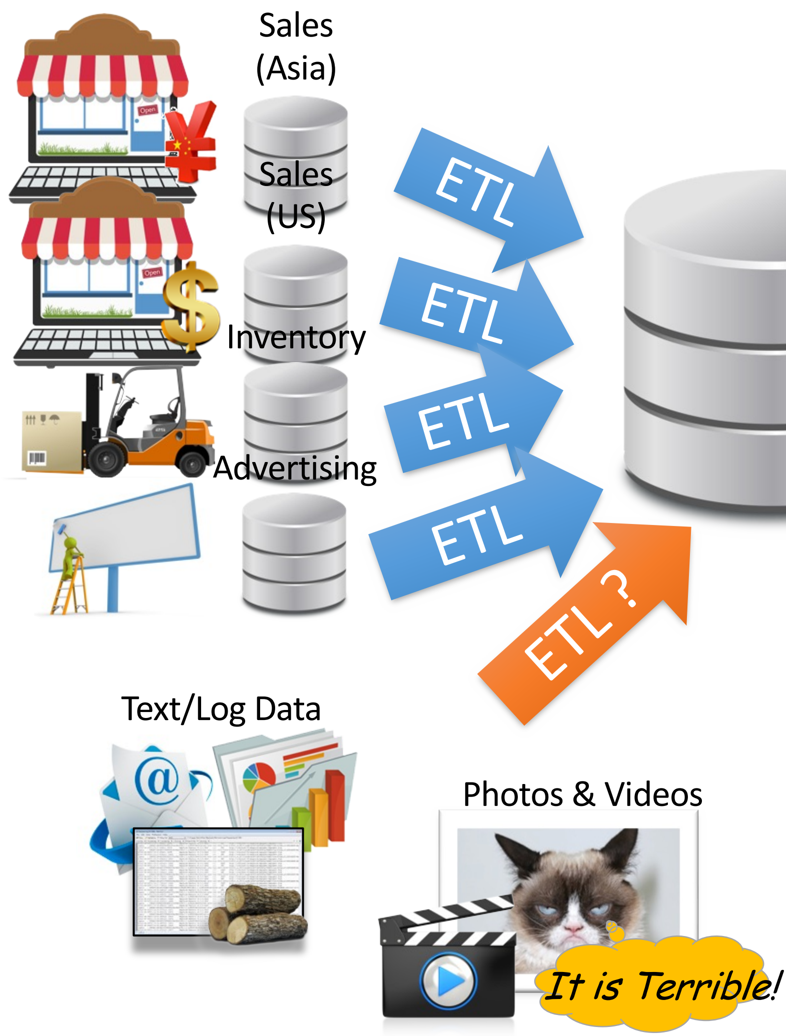


<u>So far …</u>

- Star Schemas
- Data cubes



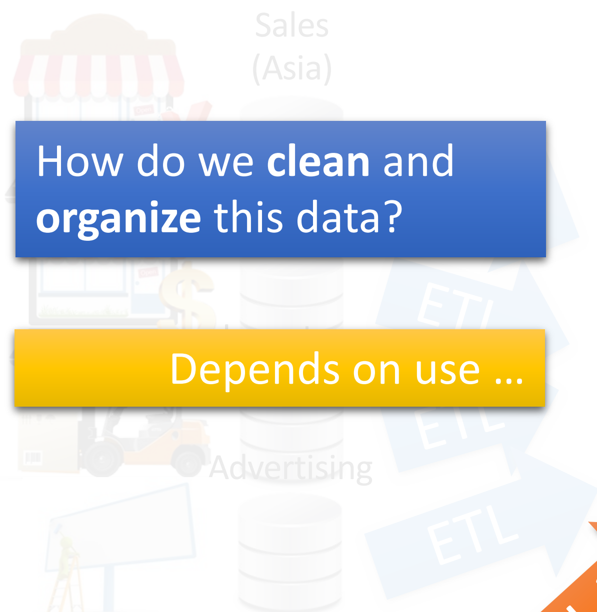
Data Warehouse



Collects and organizes historical data from multiple sources

- How do we deal with semi-structured and unstructured data?
- Do we really want to force a schema on load?

Data Warehouse



How do we **clean** and **organize** this data?

Depends on use …

Collects and organizes historical data from multiple sources

How do we **load** and **process** this data in a relational system?

Depends on use …
Can be difficult …
Requires thought …

Text/Log Data

Photos & Videos

Data Lake *

Store a copy of all the data

- in one place
- in its original "natural" form

Enable data consumers to choose how to transform and use data.

- *Schema on Read*

Enabled by new Tools:
Map-Reduce & Distributed Filesystems

What could go wrong?

*Still being defined…[Buzzword Disclaimer]

The Dark Side of Data Lakes

- Cultural shift: *Curate* → *Save Everything!*
  - Noise begins to dominate signal
- Limited data governance and planning

  Example:
  hdfs://important/joseph_big_file3.csv_with_json
  - **What** does it contain?
  - **When** and **who** created it?
- No cleaning and verification → lots of dirty data
- New tools are more complex and old tools no longer work

Enter the data engineer

A Brighter Future for Data Lakes

Enter the data engineer

- Data engineers bring new skills
  - Distributed data processing and cleaning
  - DevOps and MLOps
- Technologies are improving
  - SQL over large files
  - Self describing file formats & catalog managers
- Organizations are evolving
  - Tracking data usage and file permissions
  - New job title: data engineers

Where to go from here

- Data Warehouse
- **Parallel Databases**
- Big Data Processing
- Cloud Databases
- Data Science

Why compute in parallel?

- Multi-cores:
  - Most processors have multiple cores
  - This trend will likely increase in the future

- Big data: too large to fit in main memory
  - Distributed query processing on 100x-1000x servers
  - Widely available now using cloud services

Parallel DBMSs

- How to evaluate a parallel DBMS?
- How to architect a parallel DBMS?
- How to partition data in a parallel DBMS?

Parallel DBMSs

- **How to evaluate a parallel DBMS?**
- How to architect a parallel DBMS?
- How to partition data in a parallel DBMS?

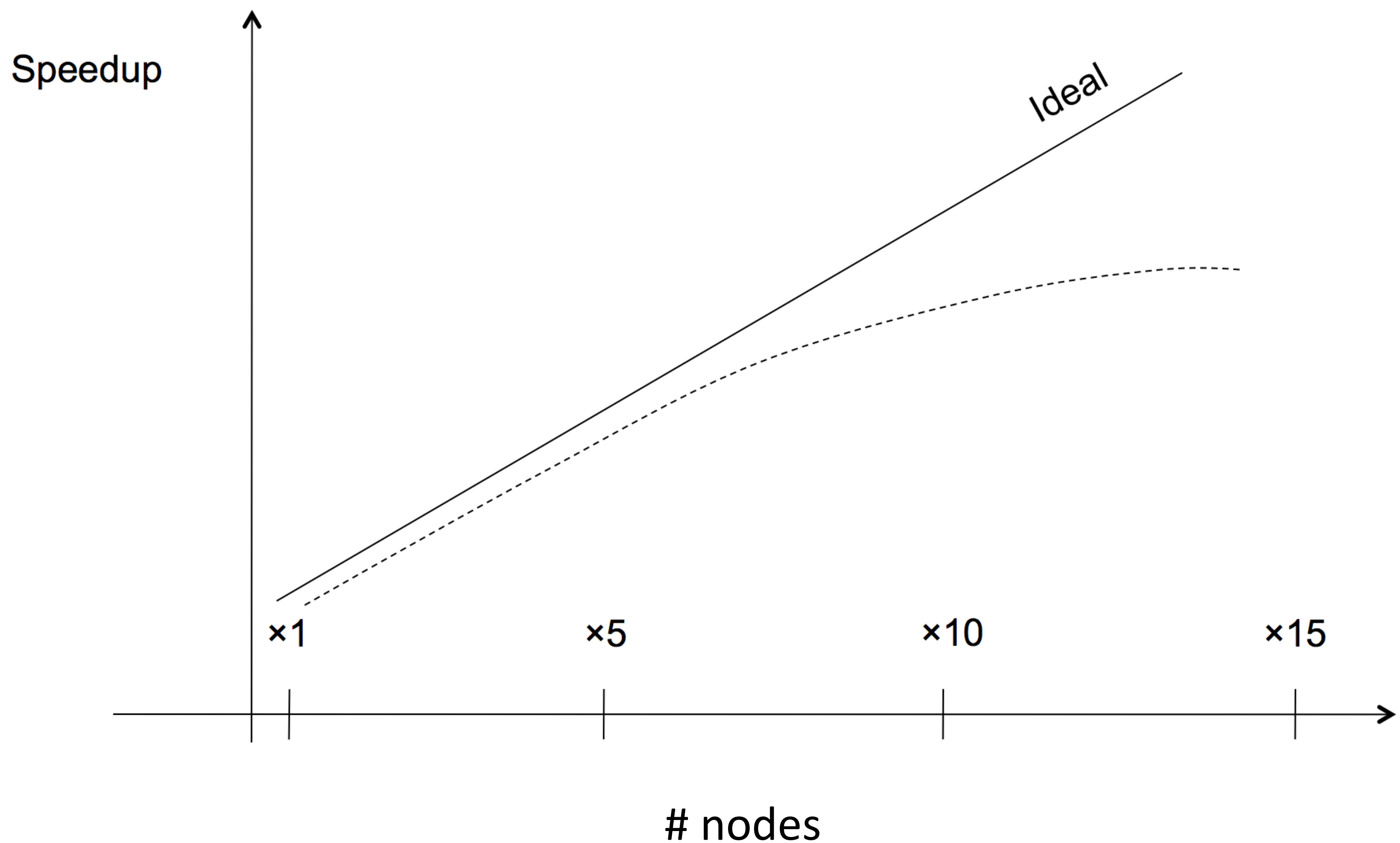
Performance Metrics for Parallel DBMSs

- Nodes = processors, compute

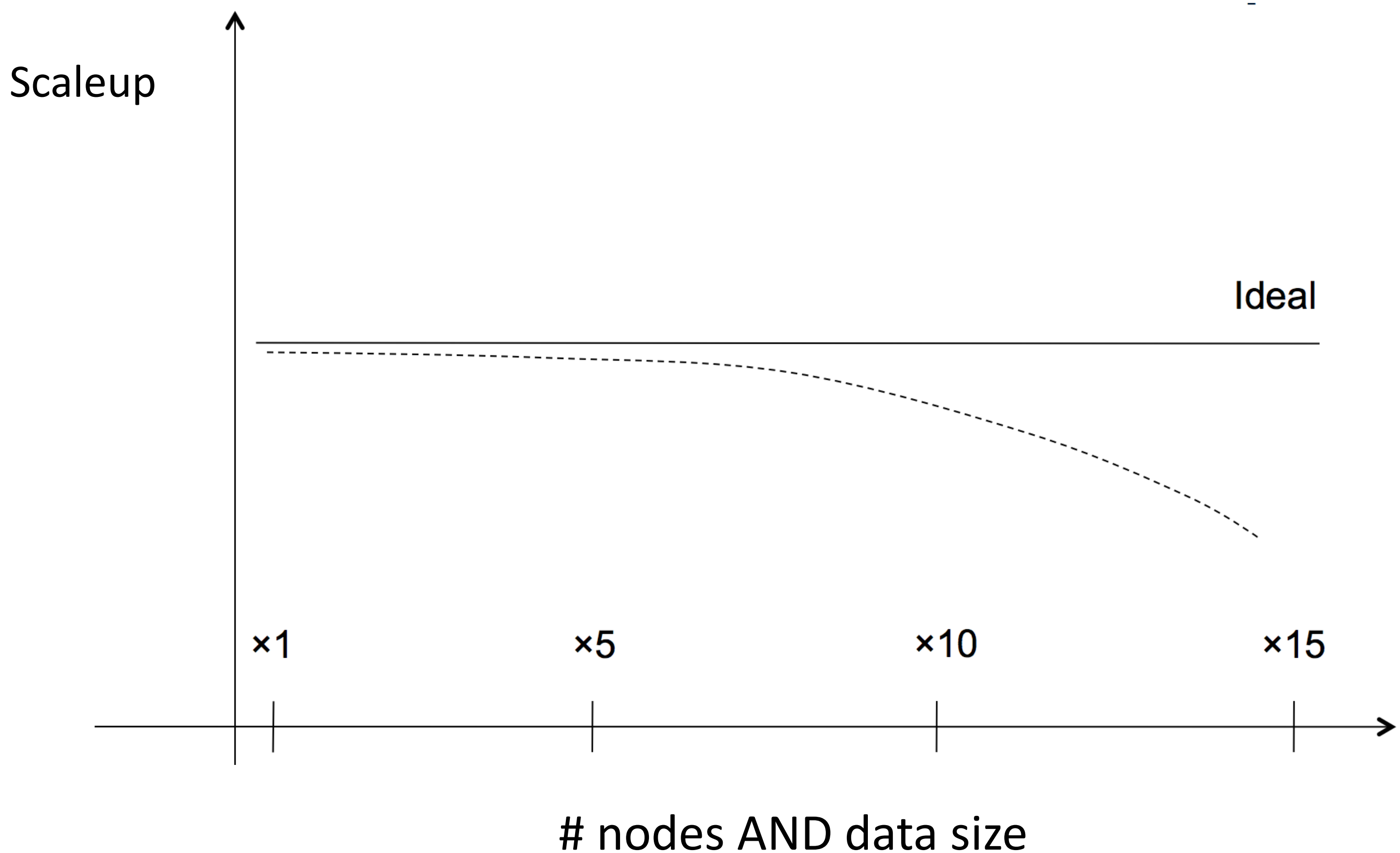
- **Speedup**
  - More nodes, same data → Higher speed

- **Scaleup**
  - More nodes, more data → same speed

Linear v.s. Non-linear Speedup



Linear v.s. Non-linear Scaleup



Parallel DBMSs

- **How to evaluate a parallel DBMS?**
- **How to architect a parallel DBMS?**
- How to partition data in a parallel DBMS?

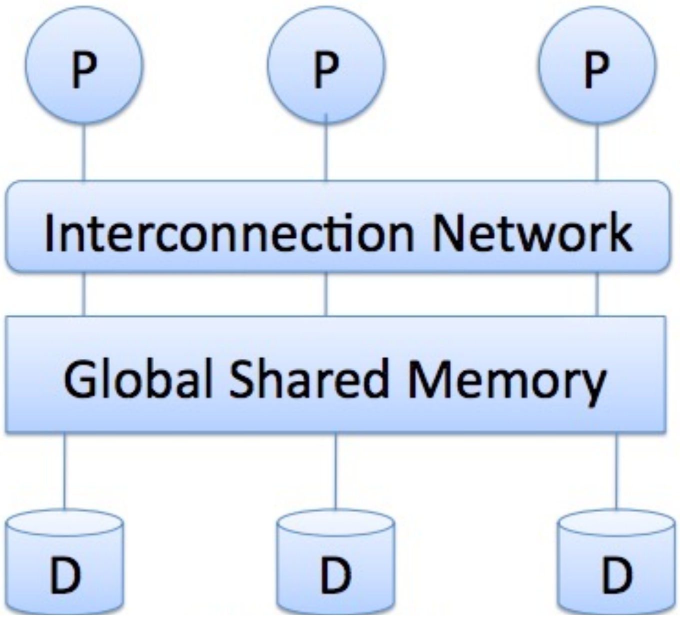
Three Architectures

- **Shared Memory**

- **Shared Nothing**

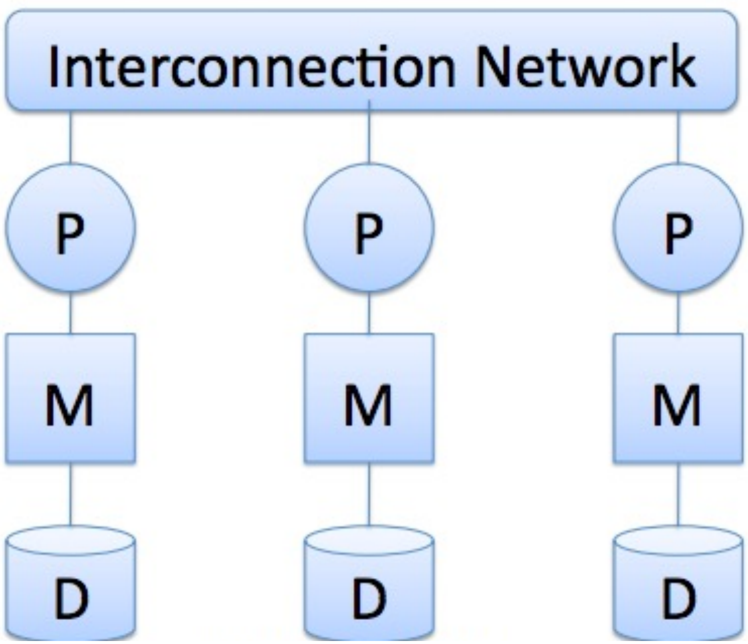
- **Shared Disk**

Shared Memory



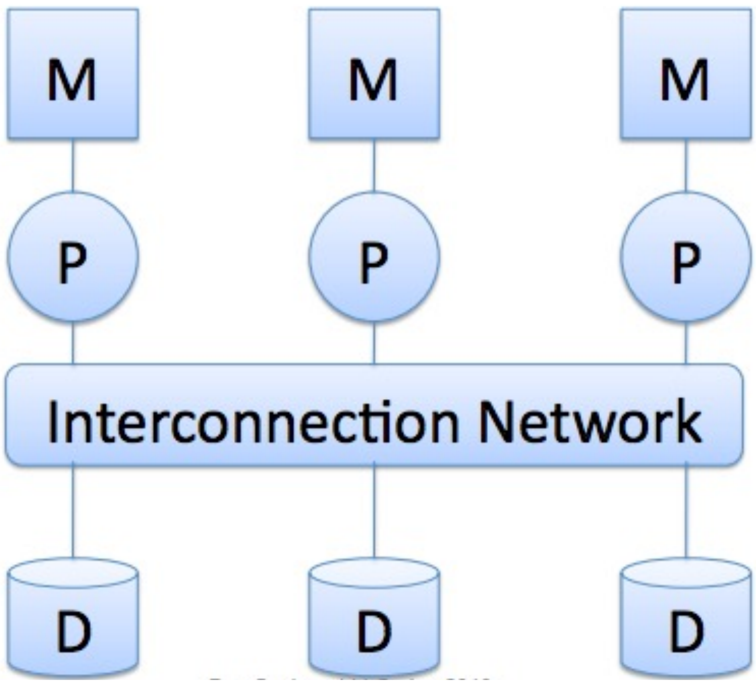
GPU

Shared Nothing



Parallel DBMSs, MapReduce, Spark

Shared Disk



Azure Synapse Analytics

Three Architectures

- **Shared Memory**
- **Shared Nothing**

Computation vs. Communication Trade-offs

- **Shared Disk**

Economic Consideration

Parallel DBMSs

- How to evaluate a parallel DBMS?
- How to architect a parallel DBMS?
- **How to partition data in a parallel DBMS?**

Horizontal Data Partitioning

- **Round Robin**
  - ☺ Load Balancing
  - ☹ Bad Query Performance

- **Range Partitioning**
  - ☺ Good for range/point queries
  - ☹ Data Skew (i.e., Bad Load balancing)

- **Hash Partitioning**
  - ☺ Load Balancing, Good for point queries
  - ☹ Hard to answer range queries

Where to go from here

- Data Warehouse
- Parallel Databases
- **Big Data Processing**
- Cloud Databases
- Data Science

3 Vs of Big Data

- Volume: data size
- Velocity: rate of data coming in
- Variety: data sources, formats, workloads

Big Data Systems

Shared Nothing Architecture

How was Spark created?

UC Berkeley's Research Centers

Years	Title	Profs: Director, Co-PIs	Students
1977–1981	X-Tree: Tree Multiprocessor	Despain, Patterson, Sequin	12
1980–1984	RISC: Reduced Instructions	Patterson, Ousterhout, Sequin	17
1983–1986	SOAR: Smalltalk On A RISC	Patterson, Ousterhout	22
1985–1989	SPUR: Symbolic Processing Using RISCs	Patterson, Fateman, Hilfinger, Hodges, Katz, Ousterhout	21
1988–1992	RAID: Redundant Array of Inexpensive Disks	Katz, Ousterhout, Patterson, Stonebraker	16
1993–1998	NOW: Network of Workstations	Culler, Anderson, Brewer, Patterson	25
1997–2002	IRAM: Intelligent RAM	Patterson, Kubiatowicz, Wawrzynek, Yelick	12
2001–2005	ROC: Recovery Oriented Computing Systems	Patterson, Fox	11
2005–2011	RAD Lab: Reliable Adaptive Distributed Computing Lab	Patterson, Fox, Jordan, Joseph, Katz, Shenker, Stoica	30
2007–2013	Par Lab: Parallel Computing Lab	Patterson, Asanovic, Demmel, Fox, Keutzer, Kubiatowicz, Sen, Yelick	40
2011–2017	AMP Lab: Algorithms, Machines, and People	Franklin, Jordan, Joseph, Katz, Patterson, Recht, Shenker, Stoica	40
2013–2018	ASPIRE Lab	Asanovic, Alon, Bachrach, Demmel, Fox, Keutzer, Nikolic, Patterson, Sen, Wawrzynek	40

Requirements

- A common vision
- About 5 years
- At least three faculty
- A dozen students

AMPLab's Vision

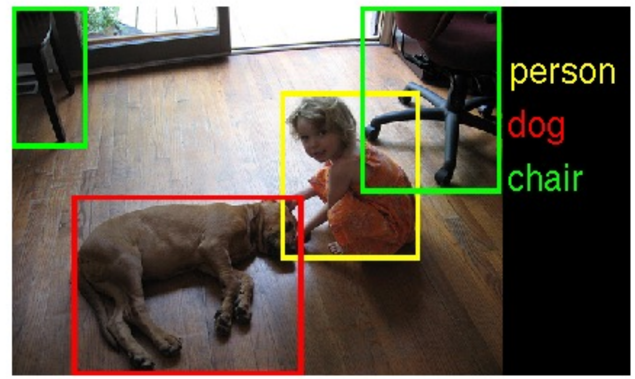
Make sense of BIG DATA by tightly integrating algorithms, machines, and people

+

+

Example: Extract Value From Image Data

What are in the image?



How to solve the problem?

Deep Learning (Algorithms)
GPU Cluster (Machines)
ImageNet (People)

Spark's Initial Idea

Matei Zaharia

- Algorithms + Machines
  - Run ML Algorithms on Hadoop
- Why is it slow?
  1. The algorithms are iterative (i.e., multiple scans of data)
  2. MapReduce writes/reads data to/from **disk** at each iteration
- Solution
  - Keep data in **memory**

How About Fault Tolerance?

Resilient Distributed Datasets (RDD)

Main Idea: Logging the transformations (used to build an RDD) rather than the RDD itself

Zaharia et al. Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing. NSDI 2012: 15-28

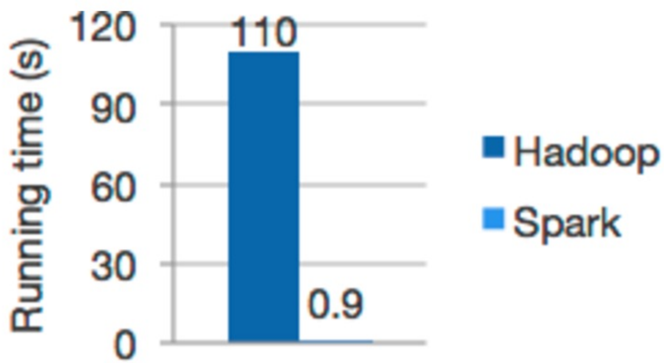
Why Spark?

Fast ✓

Easy to Use ✓

What Makes Spark *Fast*?

- In-memory Computation



Logistic regression in Hadoop and Spark

What you save?

- Serialization/Deserialization
- Compression/Decompression
- I/O cost

“CPU (and not I/O) is often the bottleneck”

Ousterhout et al. Making Sense of Performance in Data Analytics Frameworks. NSDI 2015: 293-307

Hardware Trends

	2010	2016	
Storage	50+MB/s (HDD)	500+MB/s (SSD)	10X
Network	1Gbps	10Gbps	10X
CPU	~3GHz	~3GHz	🙁

What Makes Spark *Fast*?

Project Tungsten: Bringing Apache Spark Closer to Bare Metal

by Reynold Xin and Josh Rosen
Posted in **ENGINEERING BLOG** | April 28, 2015

1. Memory Management and Binary Processing
2. Cache-aware computation
3. Code generation

Why Spark?

Fast

Easy to Use

What Makes Spark *Easy-to-Use*?

- Over 80 High-level Operators

WordCount (Mapreduce)

```java
import java.io.IOException;
import java.util.StringTokenizer;

import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.conf.Configured;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.LongWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.mapreduce.lib.input.TextInputFormat;
import org.apache.hadoop.mapreduce.lib.output.TextOutputFormat;
import org.apache.hadoop.util.Tool;
import org.apache.hadoop.util.ToolRunner;

public class WordCount extends Configured implements Tool {

    public static class TokenizerMapper
    extends Mapper<LongWritable, Text, Text, IntWritable>{

        private final static IntWritable one = new IntWritable(1);
        private Text word = new Text();

        @Override
        public void map(LongWritable key, Text value, Context context
                ) throws IOException, InterruptedException {
            StringTokenizer itr = new StringTokenizer(value.toString());
            while (itr.hasMoreTokens()) {
                word.set(itr.nextToken());
                context.write(word, one);
            }
        }
    }
```

```java
public static class IntSumReducer
extends Reducer<Text, IntWritable, Text, IntWritable> {
    private IntWritable result = new IntWritable();

    @Override
    public void reduce(Text key, Iterable<IntWritable> values,
            Context context
            ) throws IOException, InterruptedException {
        int sum = 0;
        for (IntWritable val : values) {
            sum += val.get();
        }
        result.set(sum);
        context.write(key, result);
    }
}

public static void main(String[] args) throws Exception {
    int res = ToolRunner.run(new Configuration(), new WordCount(), args);
    System.exit(res);
}

@Override
public int run(String[] args) throws Exception {
    Configuration conf = this.getConf();
    Job job = Job.getInstance(conf, "word count");
    job.setJarByClass(WordCount.class);

    job.setInputFormatClass(TextInputFormat.class);

    job.setMapperClass(TokenizerMapper.class);
    job.setCombinerClass(IntSumReducer.class);
    job.setReducerClass(IntSumReducer.class);

    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
    job.setOutputFormatClass(TextOutputFormat.class);
    TextInputFormat.addInputPath(job, new Path(args[0]));
    TextOutputFormat.setOutputPath(job, new Path(args[1]));

    return job.waitForCompletion(true) ? 0 : 1;
}
}
```

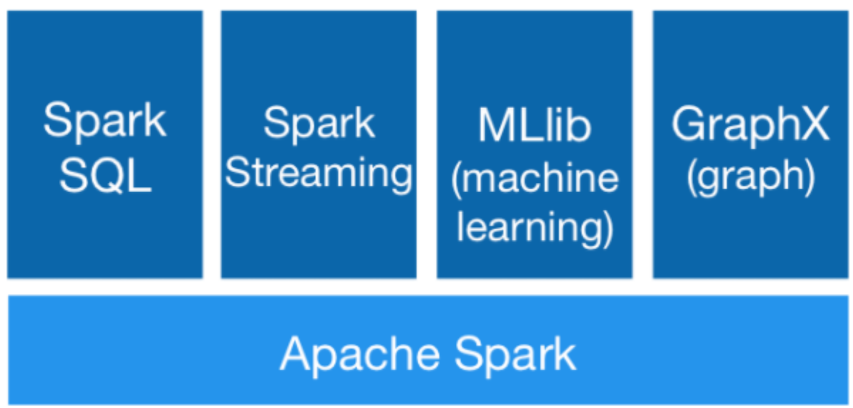
WordCount (Spark)

```python
text_file = spark.textFile("hdfs://...")

text_file.flatMap(lambda line: line.split())
    .map(lambda word: (word, 1))
    .reduceByKey(lambda a, b: a+b)
```

What Makes Spark *Easy-to-Use*?

- **Unified Engine**



Easy to manage, learn, and combine functionality

Analogy

Specialized Devices

Unified Device

What Makes Spark *Easy-to-Use*?

- **Integrate Broadly**

Languages: Scala, python, R, Java

The Big Data world is diversified

Apache Spark

Data Sources: cassandra, MySQL, elastic, Apache HBase, Hive, S3, PostgreSQL, JSON

Environments: AWS, docker, Google Cloud Platform, openstack cloud software, MESOS, hadoop YARN, Azure

Where to go from here

- Data Warehouse
- Parallel Databases
- Big Data Processing
- **Cloud Databases**
- Data Science

Amazon

- **From Wikipedia 2006**

Article Talk Head

Amazon.com

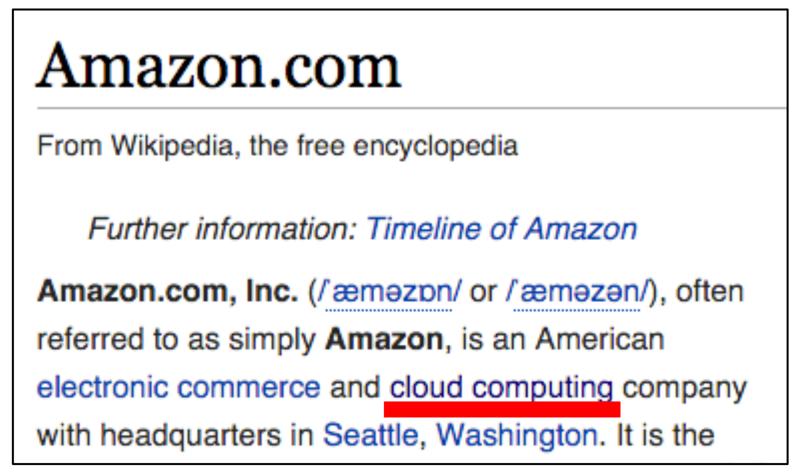
From Wikipedia, the free encyclopedia

This is an **old revision** of this page
05:10, 20 March 2006 (→Customer
permanent link to this revision, wh
revision.

(diff) ← Previous revision | Latest revisi

Amazon.com
(NASDAQ: AMZN) is an American electronic commerce company based in Seattle, Washington. It was one of the

From Wikipedia 2016



Amazon.com

From Wikipedia, the free encyclopedia

Further information: Timeline of Amazon

Amazon.com, Inc. (/ˈæməzɒn/ or /ˈæməzən/), often referred to as simply **Amazon**, is an American electronic commerce and cloud computing company with headquarters in Seattle, Washington. It is the

What is Cloud Computing?

- The buzz word before "Big Data"
  - Larry Ellison's response in 2009 (https://youtu.be/UOEFXaWHppE?t=7s)
  - Berkeley RADLab's paper in 2009 (https://youtu.be/IJCxqoh5ep4)
- A technical point of view
  - Internet-based computing (i.e., computers attached to network)
- A business-model point of view
  - Pay-as-you-go (i.e., rental)

Three Types of Cloud Computing

CourSys	Application + Cloud = **SaaS** (Software as a service)
Database	Platform + Cloud = **PaaS** (Platform as a service)
Servers	Infrastructure + Cloud = **IaaS** (Infrastructure as a service)

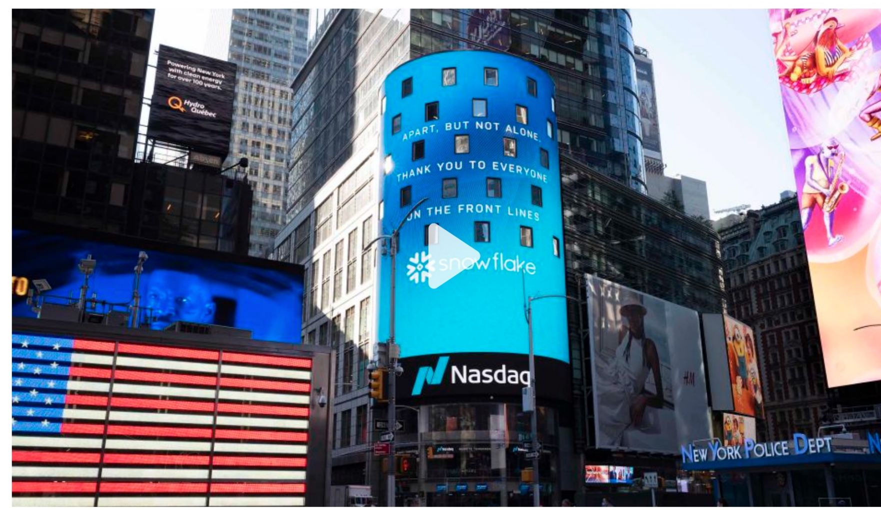
Cloud Databases

- **Amazon**
  - Aurora
  - Redshift

- **Microsoft**
  - Azure SQL Databases
  - Azure Synapse Analytics
- **Google**
  - Spanner
  - BigQuery

Snowflake shares more than double. It's the biggest software IPO ever

By Paul R. La Monica, CNN Business
Updated 3:37 AM EDT, Thu September 17, 2020



Where to go from here

- Data Warehouse
- Parallel Databases
- Big Data Processing
- Cloud Databases
- **Data Science**

Computer Science vs. Data Science

What	When	Who	Goal
Computer Science	1950-	Software Engineer	Write software to make computers work

Plan → Design → Develop → Test → Deploy → Maintain

What	When	Who	Goal
Data Science	2010-	Data Scientist	Extract insights from data to answer questions

Collect → Clean → Integrate → Analyze → Visualize → Communicate

Machine Learning (ML)

- People are not only interested in **understanding the past** but also in **predicting the future**

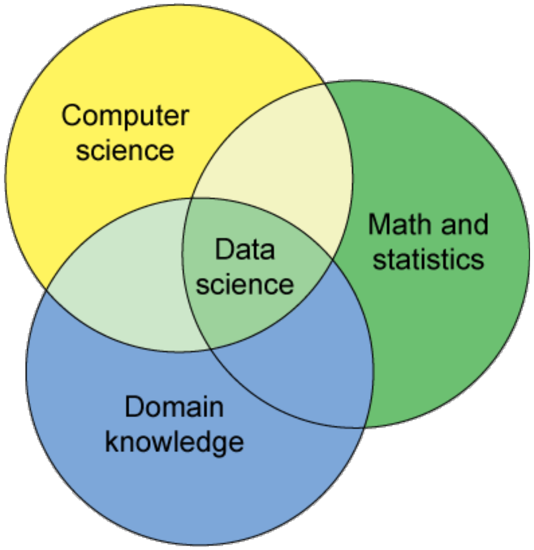
Imagine your boss asks you the following questions

Understanding the past (SQL Analytics)	Predicating the future (Machine Learning)
How many Apple Watches did we sell this year?	How many Apple Watches will we sell next year?
Which movies did “Bob” watch before?	Which movies will “Bob” like to watch in the future?
…	…

New Skillset

What skills are needed to answer these questions?

- Programming Skills
- Machine Learning/Statistics
- Domain Knowledge



Drew Conway's Venn Diagram of Data Science

Data Preparation (The Last Decade)

2013

Big Data Borat
@BigDataBorat

In Data Science, 80% of time spent prepare data, 20% of time spent complain about need for prepare data.

6:47 PM · Feb 26, 2013 · Twitter Web Client

543 Retweets **25** Quote Tweets **397** Likes

2014

The New York Times

For Big-Data Scientists, 'Janitor Work' Is Key Hurdle to Insights

Yet far too much handcrafted work — what data scientists call "data wrangling," "data munging" and "data janitor work" — is still required. Data scientists, according to interviews and expert estimates, spend from 50 percent to 80 percent of their time mired in this more mundane labor of collecting and preparing unruly digital data, before it can be explored for useful nuggets.

Data Preparation Is Still the Bottleneck!!!

2020

ANACONDA

The State of Data Science 2020

Moving from hype toward maturity

We were disappointed, if not surprised, to see that data wrangling still takes the lion's share of time in a typical data professional's day. Our respondents reported that almost half of their time is spent on the combined tasks of data loading and cleansing. Data

2021

"If 80 percent of our work is data preparation, then ensuring data quality is the important work of a machine learning team."

Andrew Ng

Three Questions

1. What makes data preparation hard?
2. Why has this problem not been solved?
3. How to solve it in the next decade?

Three Questions

1. What makes data preparation hard?
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What Makes Data Preparation Hard?

Collection

Cleaning

Integration

Analysis

How much time is spent on preparation?

1. **Too many tasks** (e.g., standardize date, dedup address, etc)
2. Humans have **different levels of expertise** (in data science and programming)
3. **Domain specific** (finance, social science, healthcare, economics, etc.)

Three Questions

1. What makes data preparation hard?
2. Why has this problem not been solved?
    - Academia
    - Industry
3. How to solve it in the next decade?

Three Questions

1. What makes data preparation hard?
2. Why has this problem not been solved?
   - **Academia**
   - Industry
3. How to solve it in the next decade?

Decades of Research

23 years ago

[BOOK] **Data preparation** for data mining
D Pyle - 1999 - books.google.com
Data Preparation for Data Mining addresses an issue unfortunately ignored by most authorities on data mining: **data preparation**. Thanks largely to its perceived difficulty, **data preparation** has traditionally taken a backseat to the more alluring question of how best to …
Cited by 2274 Related articles All 5 versions

22 years ago

[PDF] **Data cleaning**: Problems and current approaches
E Rahm, HH Do - IEEE Data Eng. Bull., 2000 - cs.brown.edu
We classify data quality problems that are addressed by **data cleaning** and provide an overview of the main solution approaches. **Data cleaning** is especially required when integrating heterogeneous data sources and should be addressed together with schema …
Cited by 2402 Related articles All 24 versions

20 years ago

Data integration: A theoretical perspective
M Lenzerini - Proceedings of the twenty-first ACM SIGMOD-SIGACT …, 2002 - dl.acm.org
Data integration is the problem of combining data residing at different sources, and providing the user with a unified view of these data. The problem of designing **data integration** systems is important in current real world applications, and is characterized by
Cited by 3528 Related articles All 25 versions

Why Has Not Been Solved By Academia?

RESEARCH-ARTICLE

The Seattle Report on Database Research

Authors: Daniel Abadi, Anastasia Ailamaki, David Andersen, Peter Bailis, Magdalena Balazinska, Philip Bernstein, Peter Boncz, Surajit Chaudhuri, Alvin Cheung, AnHai Doan, Luna Dong, Michael J. Franklin, Juliana Freire, Alon Halevy, Joseph M. Hellerstein, Stratos Idreos, Donald Kossmann, Tim Kraska, Sailesh Krishnamurthy, Volker Markl, Sergey Melnik, Tova Milo, C. Mohan, Thomas Neumann, Beng Chin Ooi, Fatma Ozcan, Jignesh Patel, Andrew Pavlo, Raluca Popa, Raghu Ramakrishnan, Christopher Ré, Michael Stonebraker, Dan Suciu (Less)
Authors Info & Claims

ACM SIGMOD Record, Volume 48, Issue 4 • December 2019 • pp 44–53 • https://doi.org/10.1145/3385658.3385668

Published: 25 February 2020

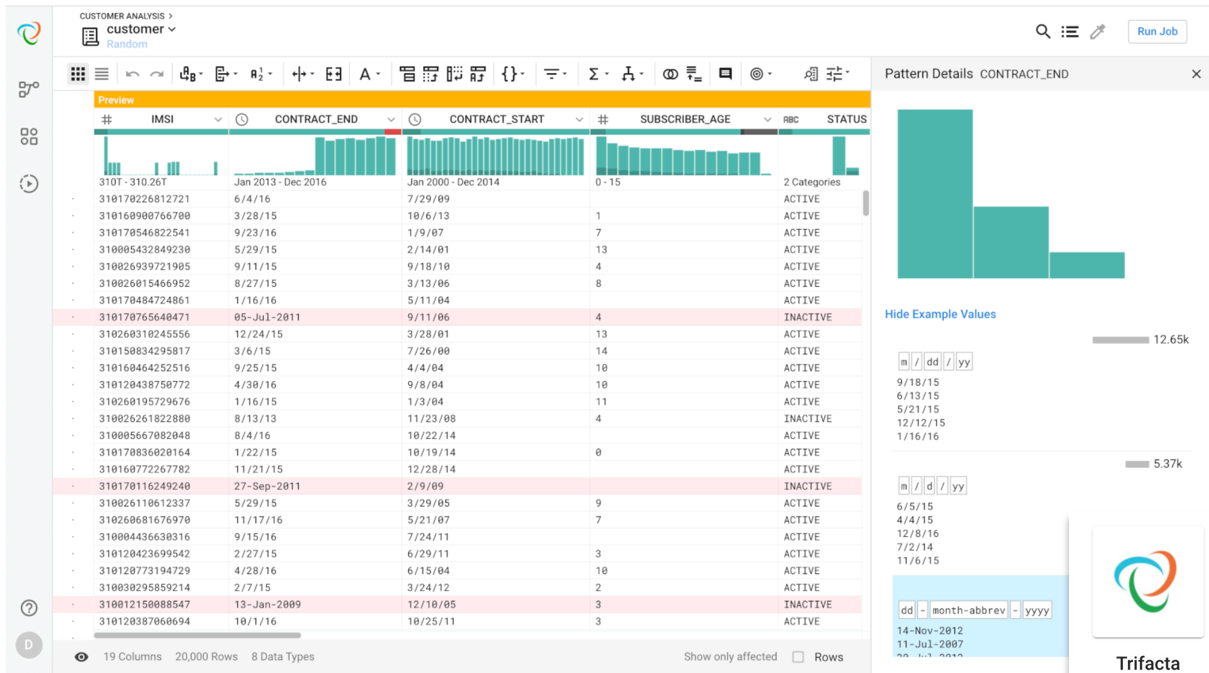
Data integration and wrangling: Data scientists repeatedly say that data integration and data wrangling is 80-90% of their challenge. These are problems the database community has worked on for decades. Thus, it can bring a solid understanding of the core challenges and known solutions. In the past, we have focused much of our efforts on solving "point problems", e.g., algorithms for specific challenges such as entity resolution. Instead, we need

Three Questions

1. What makes data preparation hard?
2. Why has this problem not been solved?
   - Academia
   - **Industry**
3. How to solve it in the next decade?

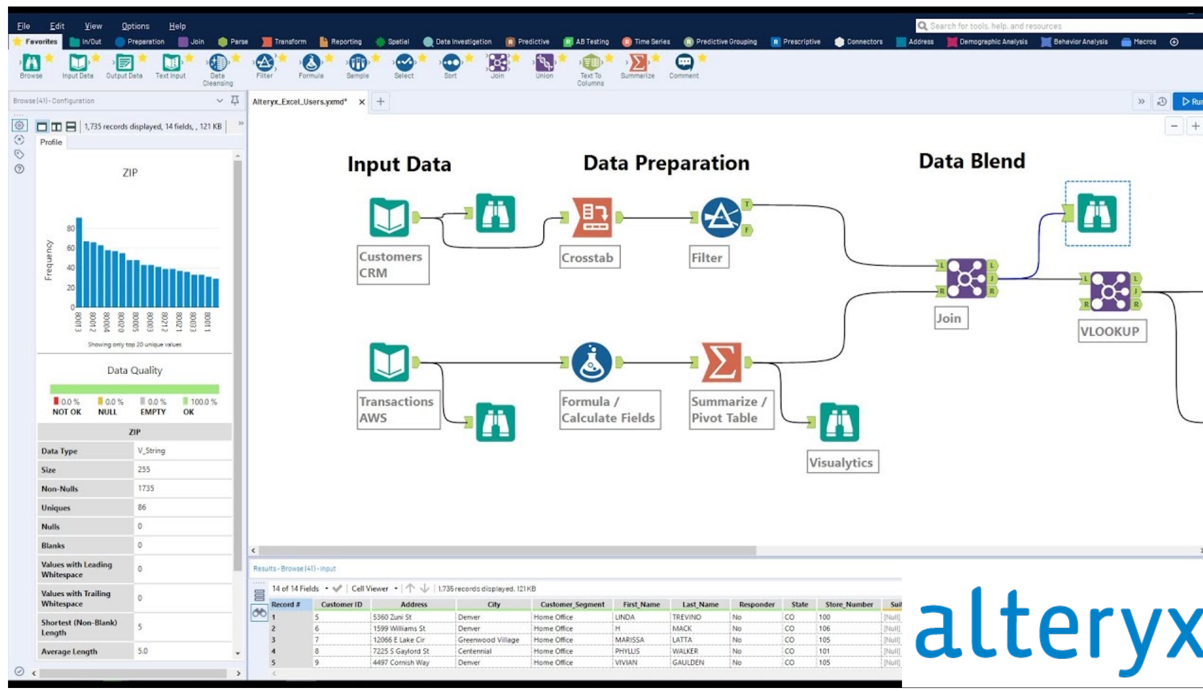
Three Directions

- Spreadsheet GUI
- Workflow GUI
- Notebook GUI



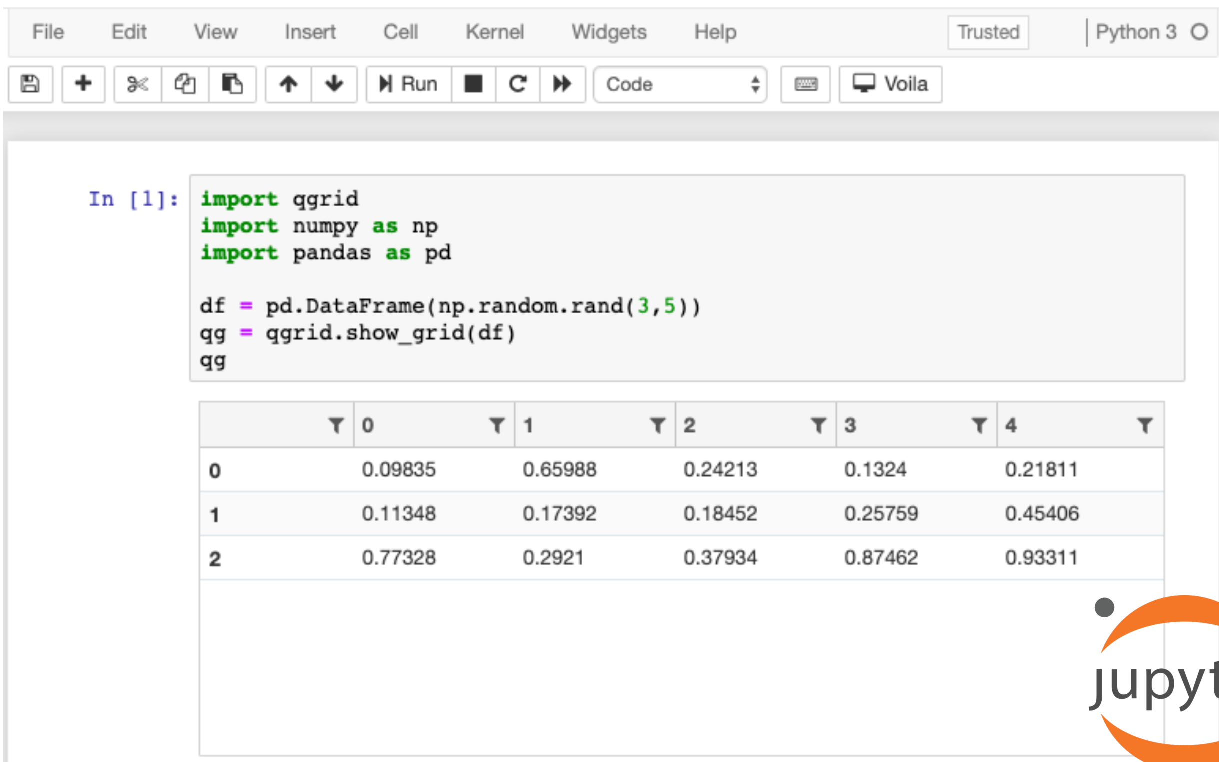
Three Directions

- Spreadsheet GUI
- **Workflow GUI**
- Notebook GUI



Three Directions

- Spreadsheet GUI
- Workflow GUI
- **Notebook GUI**



jupyter

Why Has Not Been Solved By Industry?

Spreadsheet/Workflow GUIs (for non-programmers)	Notebook GUI (for data scientists)
ALTAIR, TRIFACTA, alteryx, OpenRefine, Paxata, tableau, talend, Open for Innovation KNIME, Qlik, rapidminer	???

Three Questions

1. What makes data preparation hard?
2. Why has this problem not been solved?
   - Academia
   - Industry
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Vision

Machine Learning Made Easy

scikit learn

Initial release: 2007; 14 years ago

Big Data Made Easy

APACHE Spark™

Initial release: 2011; 10 years ago

Deep Learning Made Easy

PyTorch

Initial release: 2016; 5 years ago

Data Preparation Made Easy

The next decade

dataprep BigGorilla

SortingHat Data Civilizer …

dataprep

https://dataprep.ai

1000+ Stars

300K+ Downloads

30+ Contributors

DataPrep.Connector
Available to use

DataPrep.EDA
Available to use

DataPrep.Clean
Available to use

DataPrep.Feature
Planning

DataPrep.Integrate
Planning

... and more

DataPrep.EDA

Task-Centric Exploratory Data Analysis

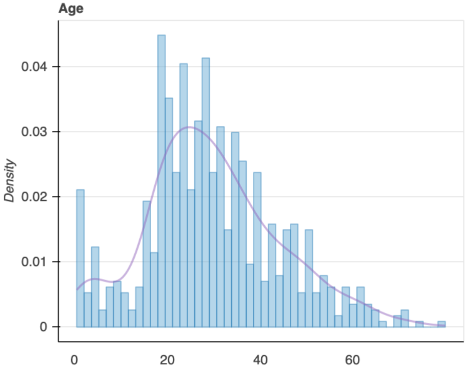
* Co-First Authors
DataPrep.EDA: Task-Centric Exploratory Data Analysis for Statistical Modeling in Python. SIGMOD 2021

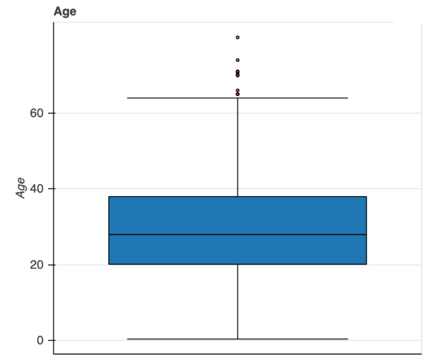
Exploratory Data Analysis (EDA)

Understand and validate data
via data visualization, data summarization, etc.

Understand and validate "Age" column

Minimum	0.42
5-th Percentile	4
Q1	20.125
Median	28
Q3	38
95-th Percentile	56
Maximum	80
Range	79.58
IQR	17.875





Solution 1: Plotting-Centric EDA

☹ Hard to Use

- Beginner: Need to know how to write plotting code
- Expert: Need to write lengthy and repetitive code

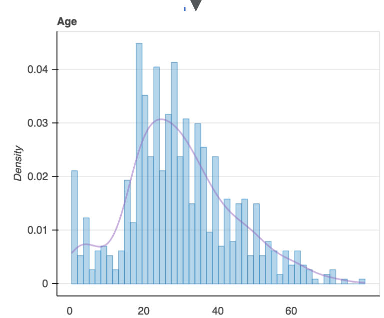
Understand and Validate "Age" column

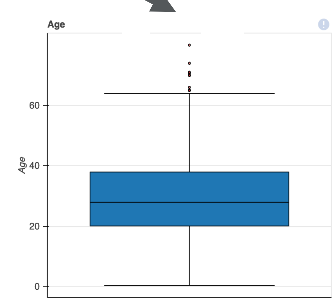
Write Code

Write Code

Write Code

Minimum	0.42
5-th Percentile	4
Q1	20.125
Median	28
Q3	38
95-th Percentile	56
Maximum	80
Range	79.58
IQR	17.875

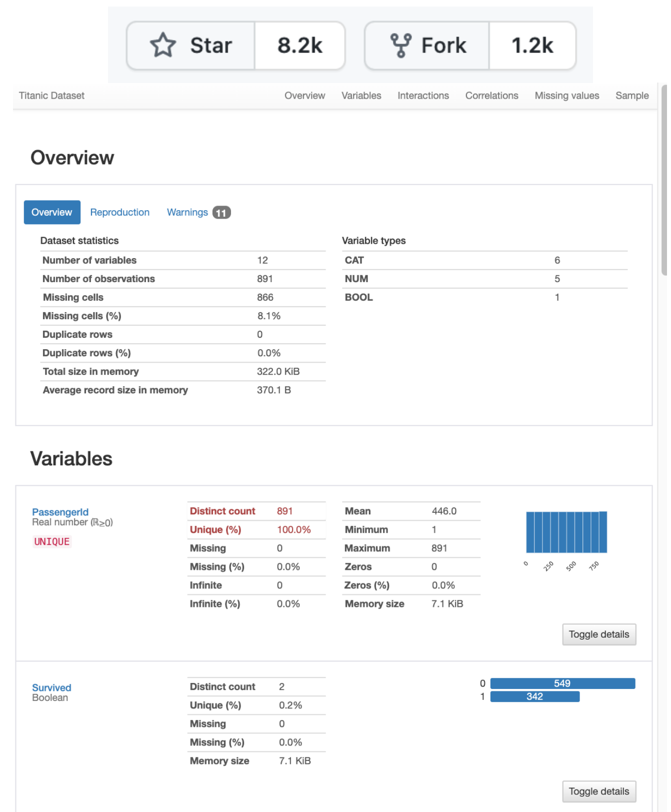




Solution 2: Profiling-Centric EDA

- ☹ Slow
- ☹ Hard to Customize

```
profile = ProfileReport(df, title="Pandas Profiling Report")
```



Our Solution: Task-Centric EDA

Key Idea: Task-Centric API Design

1. Declarative
2. Support both coarse-grained and fine-grained EDA tasks
3. Easy to customize

Example

- plot(df): "I want to see an overview of the dataset"
- plot_missing(df): "I want to understand the missing values of the dataset"
- plot(df, x): "I want to understand the column x"
- plot(df, x, y): "I want to understand the relationship between x and y"
- plot(df, x, config = {hist.bins: 10}): "Set the number of bins of histograms to 10"

Why Task-Centric EDA?

EDA Solutions	Easy to Use	Interactive Speed	Easy to Customize
1. Plotting-Centric	☹	☺	☺
2. Profiling-Centric	☺	☹	☹
3. Task-Centric	☺	☺	☺

User Feedback

Posted by u/jnwang 7 days ago

1.7k

Understand your data with a few lines of code in seconds using DataPrep.eda

apivan191 3 points · 5 months ago

This will save me so much time even just exploring my data, not to mention coding all of it up. You've done good in the world

7 Cool Python Packages Kagglers Are Using Without Telling You

Let me reveal the secrets...

Bex T. Aug 6 · 8 min read

- **DataPrep** — the most comprehensive auto EDA [GitHub, Documentation]

Best Way to do EDA (AutoEDA)

13

Posted in General 14 days ago

I recently got to know about Pandas Profiling which can generate EDA report in a few seconds. But now, I found a better option called **DataPrep** , it is faster than Pandas Profiling and also customizable.👍

Demo Time

https://www.youtube.com/watch?v=nSkQy3ew3EI

Summary

- Data Warehouse
- Parallel Databases
- Big Data Processing
- Cloud Databases
- Data Science

Acknowledge

- Some lecture slides were copied from or inspired by the following course materials
  - "W4111: Introduction to databases" by Eugene Wu at Columbia University
  - "CSE344: Introduction to Data Management" by Dan Suciu at University of Washington
  - "CMPT354: Database System I" by John Edgar at Simon Fraser University
  - "CS186: Introduction to Database Systems" by Joe Hellerstein at UC Berkeley
  - "CS145: Introduction to Databases" by Peter Bailis at Stanford
  - "CS 348: Introduction to Database Management" by Grant Weddell at University of Waterloo
  - UC Berkeley DS100 Fall 2017