Analytics & Machine Learning in Data Systems

Course Textbook Chapters 25 Newer Material:

Data Lake: https://en.wikipedia.org/wiki/Data_lake

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Transaction Processing vs Analytics

Online Transaction Processing (OLTP)

- ➤ Many small queries:
 - Freq. use of indexes
 - Many writes
 - Concurrency and Logging
- ➤ Managing the "Now"
 - Source of truth
- Fairly simple queries with few predicates and relations

Online Analytics Processing (OLAP) & Data Mining/ML

- ➤ Exploratory Full Table Queries
 - e.g., Agg. Sales Per Market
 - Infrequent (but bulk) writes
 - Limited transaction processing
- Recording the history
 - What was our inventory at the end of last two quarters
- Complex queries with many predicates and many relations

Analytics & ML queries:

- What was our total sales by market last quarter?
 - Summarization
- ➤ What is our predicted sales for next quarter?
 - Forecasting
- ➤ Which users will likely leave our service?
 - Churn prediction
- ➤ If a user buys X what else are they likely to buy?
 - Collaborative filtering & Recommender Systems





Inventory

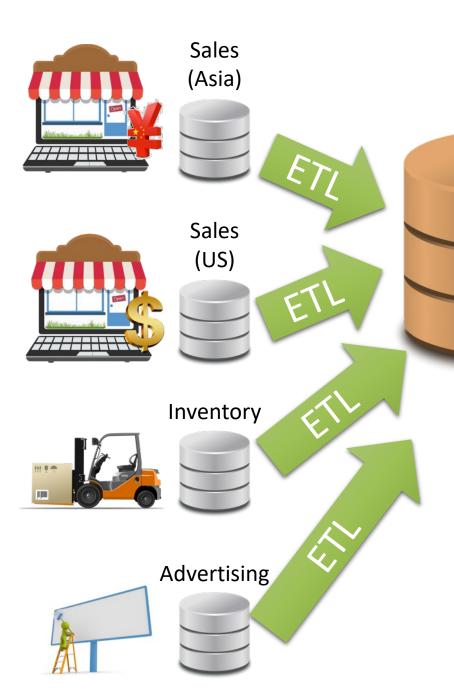




Data Everywhere

- ➤ Stored Across Multiple
 Operational OLTP Systems
 - Different formats (e.g., currency)
 - Different schemas (acquisitions ...)
 - Mission critical
 - Serving live sales traffic
 - Managing inventory
 - ... Be careful!
- ➤ Often limited historical data

We would like a consolidated, cleaned, historical snapshot of the data.



Data Warehouse

Collects and organizes historical data from multiple sources

Data is *periodically* **ETL**ed into the data warehouse:

- **Extracted** from remote sources
- Transformed to standard schemas
- Loaded into the (typically) relational system

Extracting Data from Sources

- ➤ Need to collect data from multiples sources
 - Various RDBMS vendors
 - Structured files JSON, XML

- ➤ Often done using SQL interfaces
- ➤ Validate extracted data
 - Flag corrupted records ...

Transforming "Cleaning" Data

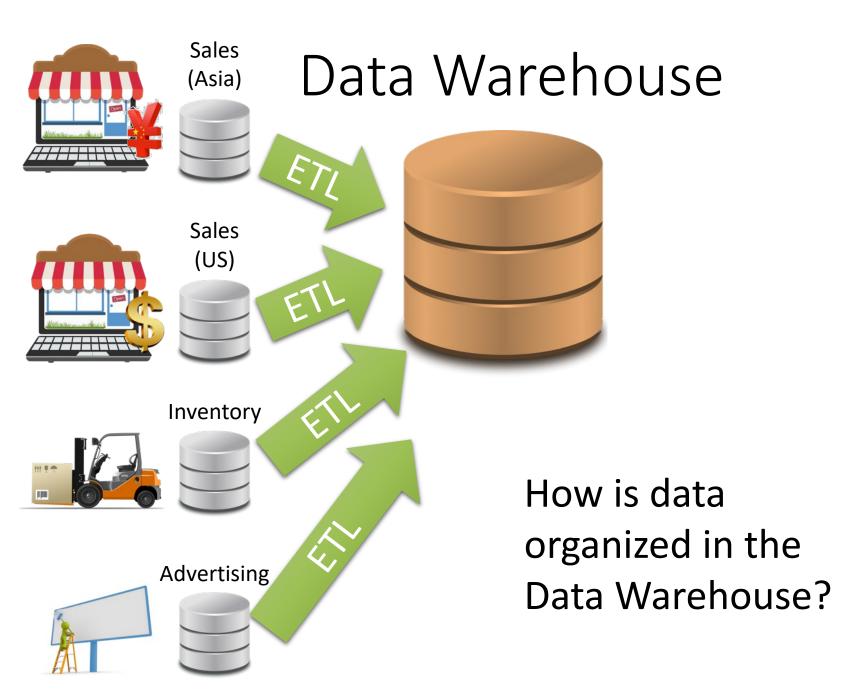
>Additional data validation and filtering

- ➤ Schema manipulation
 - Extract key fields
 - Encoding text
 - Verifying and enforcing constraints

➤ Data normalization (time zones, currency)

Loading Data

- ➤ Data is bulk loaded into large relations
 - Fact tables ... (more on this later)
- **≻**Update:
 - Indexes
 - Metadata tables: Data about the data
 - When and how was it collected
 - Meaning of fields
 - Updating materialized views ...
- ➤ Occasionally move older data to archival storage
 - Data aging



Example Sales Data:

pname	category	price	qty	date	day	city	state	country
Corn	Food	25	25	3/30/16	Wed.	Omaha	NE	USA
Corn	Food	25	8	3/31/16	Thu.	Omaha	NE	USA
Corn	Food	25	15	4/1/16	Fri.	Omaha	NE	USA
Galaxy 1	Phones	18	30	1/30/16	Wed.	Omaha	NE	USA
Galaxy 1	Phones	18	20	3/31/16	Thu.	Omaha	NE	USA
Galaxy 1	Phones	18	50	4/1/16	Fri.	Omaha	NE	USA
Galaxy 1	Phones	18	8	1/30/16	Wed.	Omaha	NE	USA
Peanuts	Food	2	45	3/31/16	Thu.	Seoul		Korea
Galaxy 1	Phones	18	100	4/1/16	Fri.	Seoul /		Korea

- **▶ Big** table: many *columns* and *rows*
 - Substantial redundancy -> expensive to store and access
- ➤ Could we organize the data a little better?

Multidimensional Data Model

Sales Fact Table

pid	timeid	locid	sales
11	1	1	25
11	2	1	8
11	3	1	15
12	1	1	30
12	2	1	20
12	3	1	50
12	1	1	8
13	2	1	10
13	3	1	10
11	1	2	35
11	2	2	22
11	3	2	10
12	1	2	26

Locations

locid	city	state	country
1	Omaha	Nebraska	USA
2	Seoul		Korea
5	Richmond	Virginia	USA

Dimension Tables

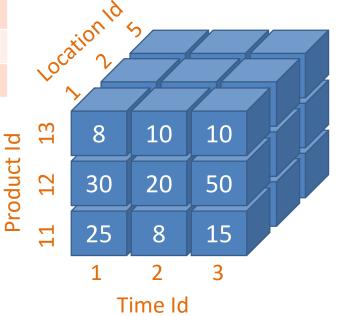
Products

pid	pname	category	price
11	Corn	Food	25
12	Galaxy 1	Phones	18
13	Peanuts	Food	2

Multidimensional "Cube" of data

Time

timeid	Date	Day
1	3/30/16	Wed.
2	3/31/16	Thu.
3	4/1/16	Fri.



Multidimensional Data Model

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pid	timeid	locid	sales
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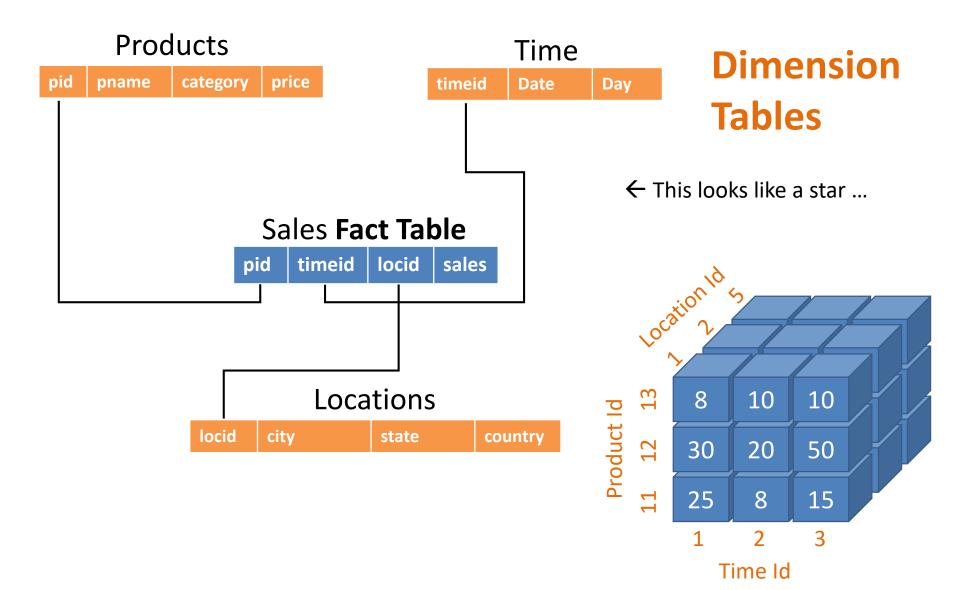
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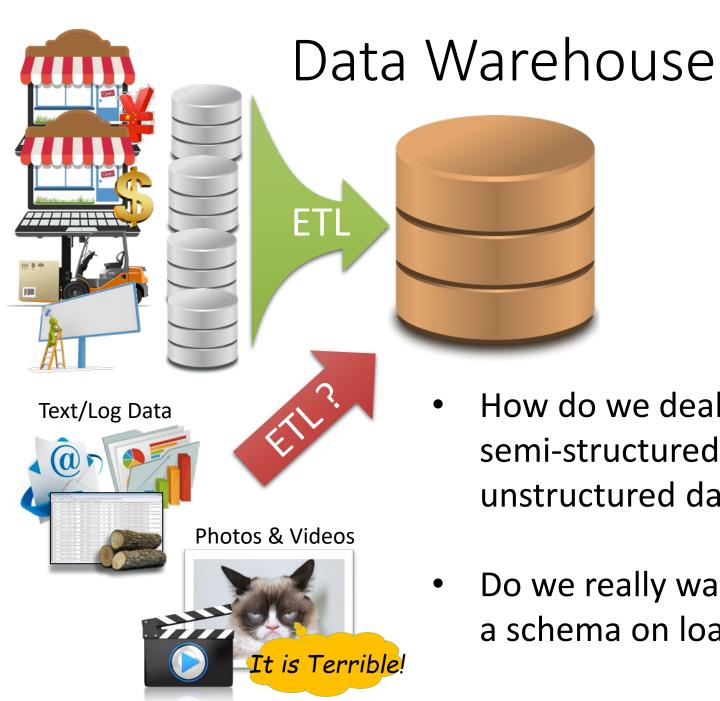
timeid	Date	Day
1	3/30/16	Wed.
2	3/31/16	Thu.
3	4/1/16	Fri.

Time

- Sales Fact Table
 - Contains only foreign keys → Efficient
- Easy to manage **Dimensions**
 - Galaxy1 → Phablet: no need to update **Fact Table**
- **→** Normalization
 - Minimizing redundancy
 - More on this later ...

Multidimensional Data: Star Schema





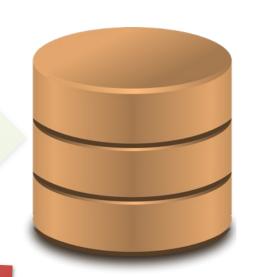
How do we deal with semi-structured and unstructured data?

Do we really want to force a schema on load?

Data Warehouse

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

Depends on use ...





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

Depends on use ... Can be difficult ... Requires thought ...





*Still being defined... [Buzzword Disclaimer]

Text/Log Data



It is Terrible!

Big Idea:

Maintain a copy of all the data in one place and free* data consumers to choose how to transform and use it.

Origin of the Data Lake

>Attributed to James Dixon, CTO of Pentaho, 2010

"If you think of a **datamart** as a store of bottled water – **cleansed** and **packaged** and **structured** for **easy consumption** – the **data lake** is a **large body of water** in a more **natural state**.

The contents of the data lake **stream in** from a source to fill the lake, and various users of the lake can come to examine, dive in, or **take samples**."

Data Lake

- >Store unstructured data in raw form
 - Schema-on-Read: determine the best organization when data is used
 - Contrast: Data Warehouses are Schema-on-Load (ET<u>L</u>)
 - Plan ahead (Fact tables and Dimensions)
- ➤Often much larger than data warehouses
- ➤ Technologies
 - Storage: Large distributed file systems (e.g., HDFS)
 - Semi-structured formats (JSON, Parquet)
 - Computation: Map-Reduce
 - Recent trend to add SQL (or SQL like) functionality
- ➤ More Agile (?):
 - Don't worry about schema & verification when loading
 - Disaggregated compute and storage → BYOF
 - bring your own compute frameworks ...
- ➤ What could go wrong?



Data Lake -> Data Swamp



- ➤ Cultural shift: Curate → Save Everything!
 - Signal to Noise ratio drops ...
- ➤ Limited data governance → more agile →
 - What does it contain? What are all the "fields"
 - When and how and from where was it created

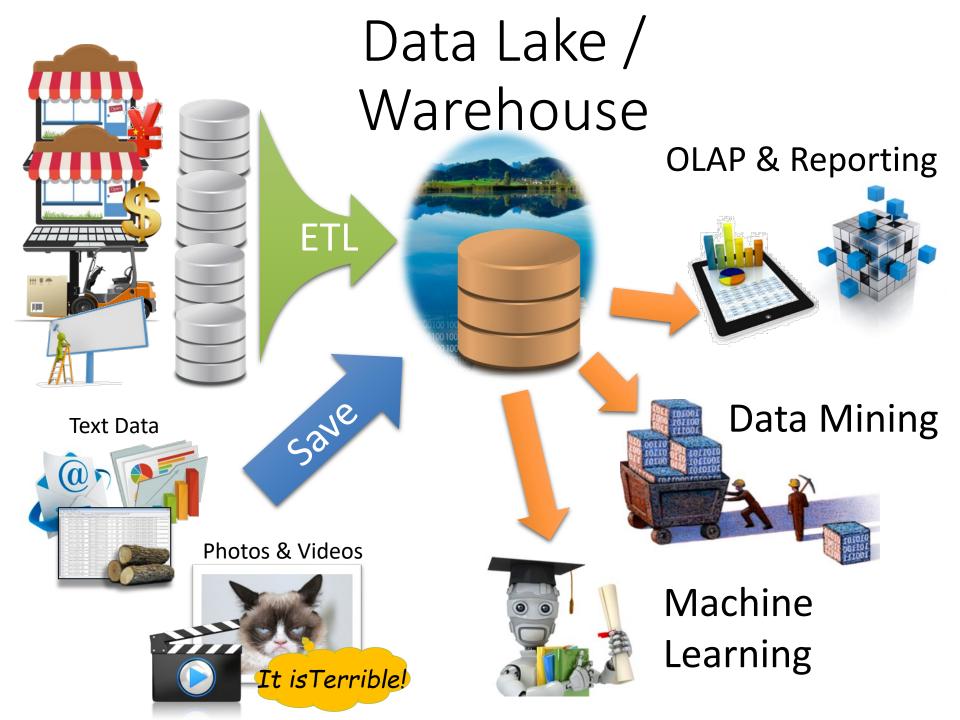
➤ Without cleaning and verification we begin to collect a rich history of **dirty data**

➤ Limited compatible with traditional tools

Data Lakes *Appear* to be Maturing

- ➤ Relational data-models + SQL:
 - **Hive:** SQL on top of Hadoop Map-Reduce
 - SparkSQL: SQL on top of Spark
- ➤ Tools are Improving:
 - Better data cleaning
 - Catalog Managers
 - Improved semi-structured "raw" data formats
- ➤ Improved data governance
 - Organization are recognizing the issues



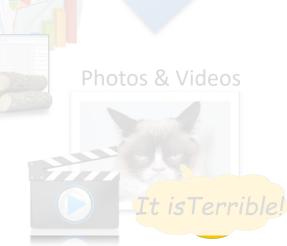
















Machine Learning

Online Analytics Processing (OLAP)

Users interact with multidimensional data:

➤ Constructing ad-hoc and often complex SQL queries

- ➤ Using graphical tools that to construct queries
- ➤ Sharing views that summarize data across important dimensions

Cross Tabulation (Pivot Tables)

Item	Color	Quantity				Item	
Desk	Blue	2			Desk	Sofa	Sum
Desk	Red	3		Blue	2	4	6
Sofa	Blue	4	Color	Red	3	5	8
Sofa	Red	5	0	Sum	5	9	14

- > Aggregate data across pairs of dimensions
 - **Pivot Tables:** *graphical interface* to select dimensions and aggregation function (e.g., SUM, MAX, MEAN)
 - GROUP BY queries
- > Related to contingency tables and marginalization in stats.
- ➤ What about many dimensions?

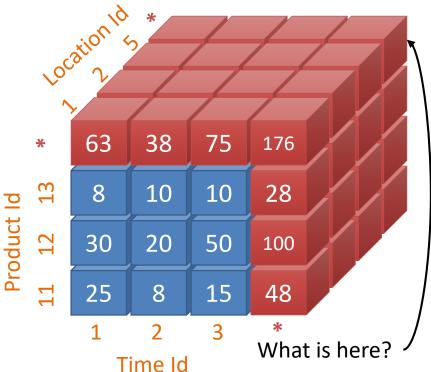
Cube Operator

➤ Generalizes crosstabulation to higher dimensions.

➤In SQL:

SELECT Item, Color, **SUM**(Quantity) **AS** QtySum **FROM** Furniture **GROUP BY** <u>CUBE</u> (Item, Color);

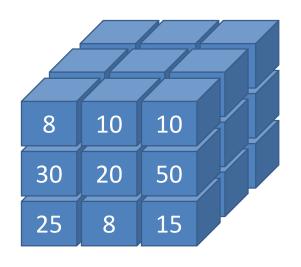
Item	Color	Quantity
Desk	Blue	2
Desk	Red	3
Sofa	Blue	4
Sofa	Red	5

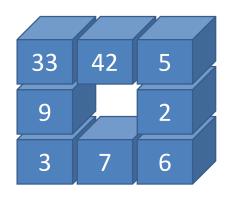


Item	Color	QtySum
Desk	Blue	2
Desk	Red	3
Desk	*	5
Sofa	Blue	4
Sofa	Red	5
Sofa	*	9
*	*	14
*	Blue	6
*	Red	8

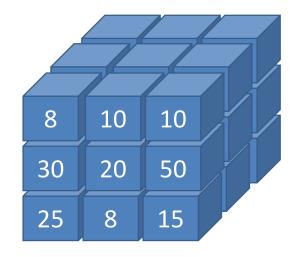
OLAP Queries

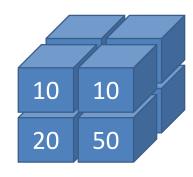
>Slicing: selecting a value for a dimension





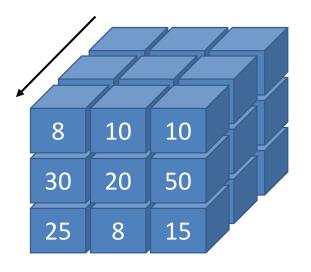
> Dicing: selecting a range of values in multiple dimension

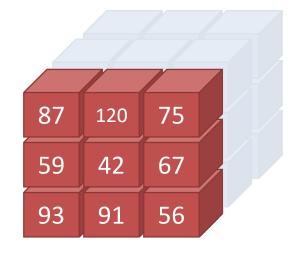




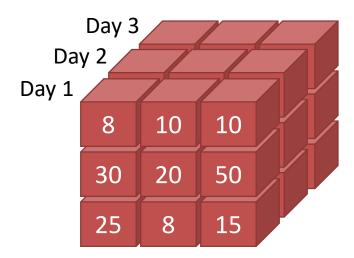
OLAP Queries

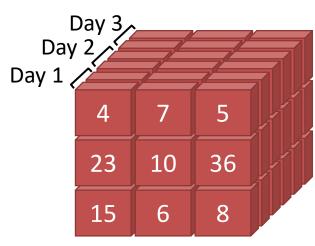
➤ Rollup: Aggregating along a dimension





➤ Drill-Down: de-aggregating along a dimension





Reporting and Business Intelligence (BI)

- ➤ Use high-level tools to interact with their data:
 - Automatically generate SQL queries
 - Queries can get big!
- **≻**Common!



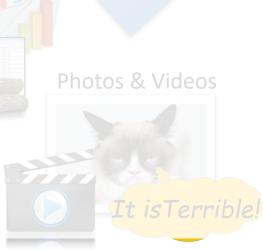
Data Lake / Warehouse



OLAP Analysis & Reporting





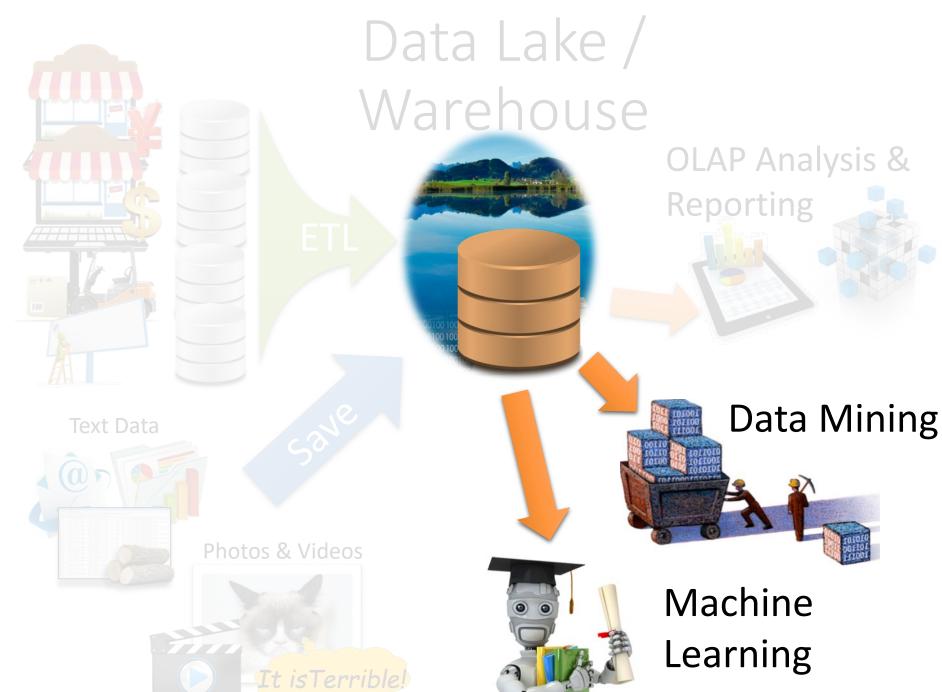








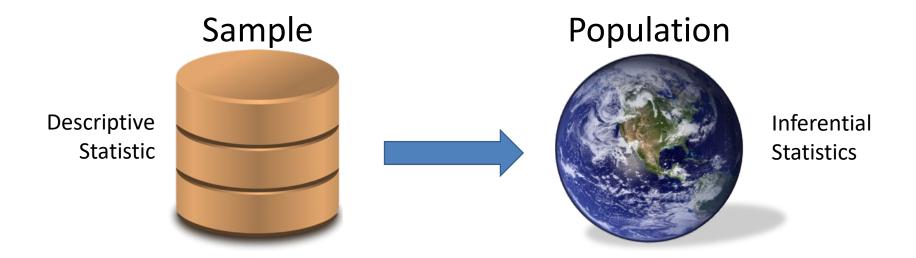
Machine Learning



Knowledge Discovery in Databases (KDD)

- Process of extracting knowledge from a data
 - What does this mean?

Descriptive vs. Inferential Statistics



- > Descriptive Statistics: describe the sample data
 - Example: Average sales last quarter
 - Can be measured directly from the database
- ➤ Inferential Statistics: estimate the population
 - Example: Expected sales next quarter
 - May be **estimated** using descriptive statistics

The Basic KDD Process

- ➤ Data Selection: What data do I need for a given task?
 - If data was already collected, how was the data collected?
- **▶ Data Cleaning:** Preparing the data for a given task
 - Typically most challenging (time consuming) part.
 - Why might ETL not be enough?
- **▶ Data Mining & ML:** Running algorithms to infer patterns
 - The fun part! Many tools, many options, complex tradeoffs.
- **Evaluation:** Verifying that patterns are significant
 - Algorithms will typically find patterns especially when none exist.









Machine Learning

What is Machine Learning?

Study of algorithms that:

- ➤ That improve their **performance**
 - Ability to understand what you are saying
- >at some task
 - Voice recognition
- >through experience
 - Transcribed speech data

-- Prof. Tom Mitchell*, CMU*

"Machine Learning is the **second best** solution to any problem. The **first best** is of course to **solve the problem** directly."

-- Prof. Yaser S. Abu-Mostafa, *Caltech*

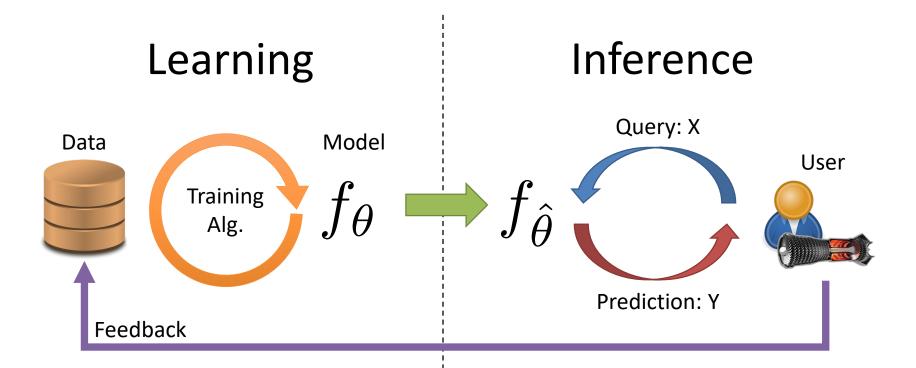
How would you write a program to recognize human speech?

You use ML every day!

What machine learning do you use every day?

- ➤ Spam detection
- ➤ Voice recognition
- ➤ Face tagging on Facebook
- ➤ Ad Targeting
- Credit card fraud detection
- ➤Others? ...

Machine Learning Lifecycle



- Typically a time consuming iterative batch process
 - Feature engineering
 - Validation

- Focus is on making fast robust predictions
 - Monitoring and tracking feedback
 - Materialization + fast model inference

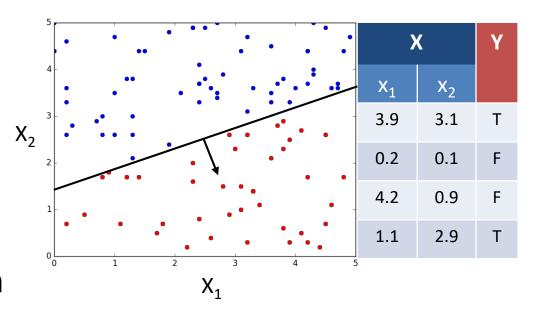
Learning: Fitting the Model

>Training Data

• X: Features

• Y: Label/Obs.

Learn a function that **generalizes** the relationship between X and Y

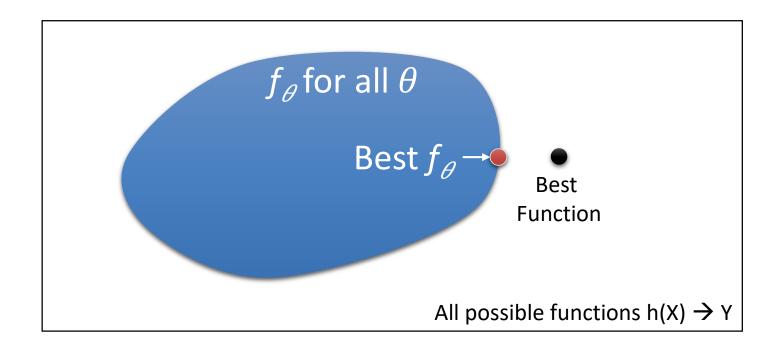


Function class /
$$f_{\theta}(X) \longrightarrow Y \leftarrow \text{Labels / Observations}$$
 Model Parameters

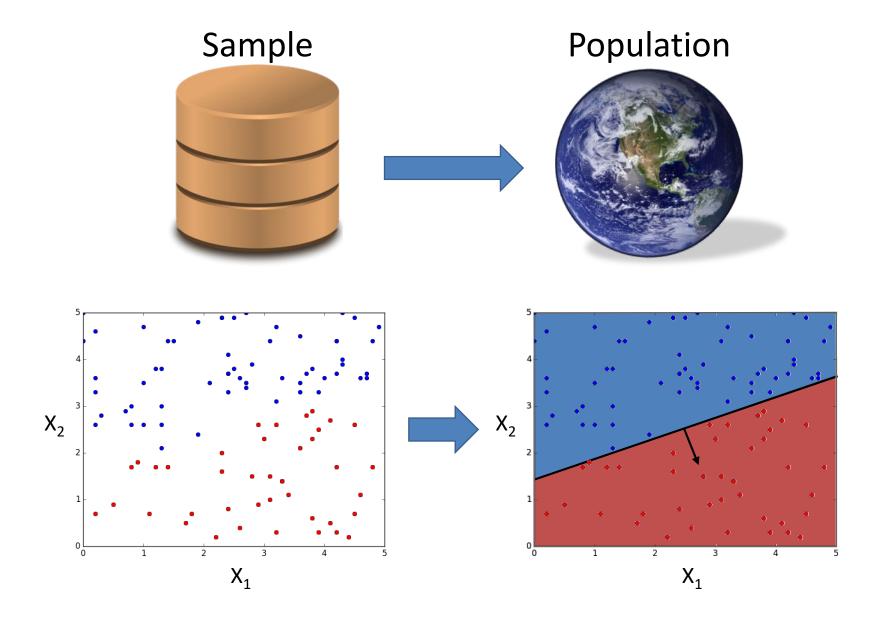
Finding the Best Parameters

$$f_{\theta}(X) \to Y$$

- ➤ Define some **objective** (e.g., prediction error)
- \triangleright Search for best θ with respect to the objective



Generalization ...



Inference: Rendering Predictions

Evaluating the model on input queries:

$$f_{\hat{\theta}}(X) \to Y$$

- ➤Online vs Offline:
 - Pre-computed **offline**: movie rankings
 - Computed online with each query: speech recognition
- ➤ May want to track confidence in prediction
- ➤ May require additional pre and post-processing
 - Feature lookup, content ranking, etc...

Feedback: Incorporating New Data

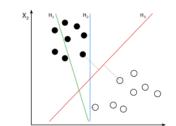
- ➤ After rendering a prediction we may get feedback on the results of the prediction:
 - Explicit: the correct value was "cat"
 - Implicit: the predicted animal was incorrect
 - Can be **noisy** ...
- ➤ Watch out for sample bias:
 - Model affects the data is uses for training in the future
 - Example: only play top40 songs ...



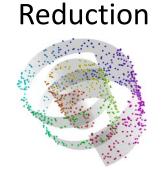
Supervised Learning Reinforcement & Bandit Learning

Unsupervised Learning

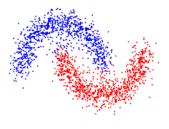
Regression



Classification



Dimensionality



Clustering