# ABB - Session 2

## Software 2.0, Data Engineering, & Machine Learning

**Shaw Talebi**

# Today's Session

1. **Housekeeping**
    1.1. Homework 1
    1.2. Software 1.0
2. **Software 2.0**
    2.1. Machine Learning
    2.2. Data Engineering
3. **Example Code**
    3.1. ETL of Survey Data
    3.2. Training an ML Model

# Live Events - Next week!


# Homework 1

## Shoutouts 🎉

**AC Milan Reminder**
Saijai Osika

**Mindbody Scraper**
Rod Morrison

**Automated Emailer**
Christopher Briggs

**Textbook Chapter Splitter**
Bryce

**Ebay iPhone Scraper**
Rakesh Bidhar

**Stock Price Alert System**
Sangeeta Bahri

**Product Data ETL**
Andy Yeo

**Real Estate Image Finder**
Adam Rosenkoetter

**Automated Birthday Emailer**
Mathew Olajide

**Automated Email Reminders**
Divya Mani

# Software 1.0

Rules are explicitly programmed into computer

**You can do a lot with Software 1.0**

**But writing robust logic is hard…**

**… if possible.**

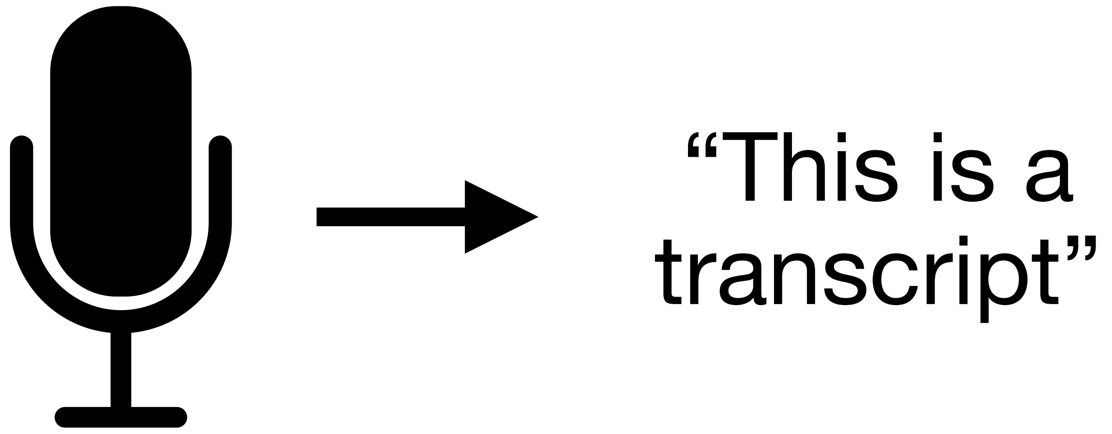
# Software 1.0

Rules are explicitly programmed into computer

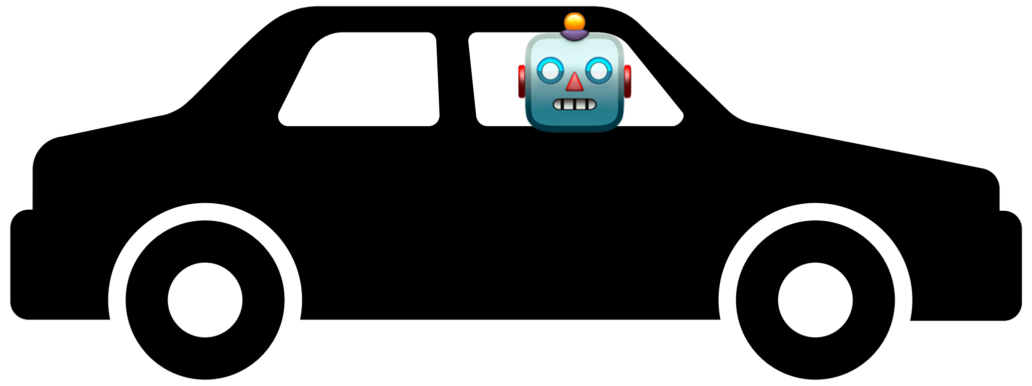
**But writing robust logic is hard…**

**… if possible.**

What happened?




Speech to text

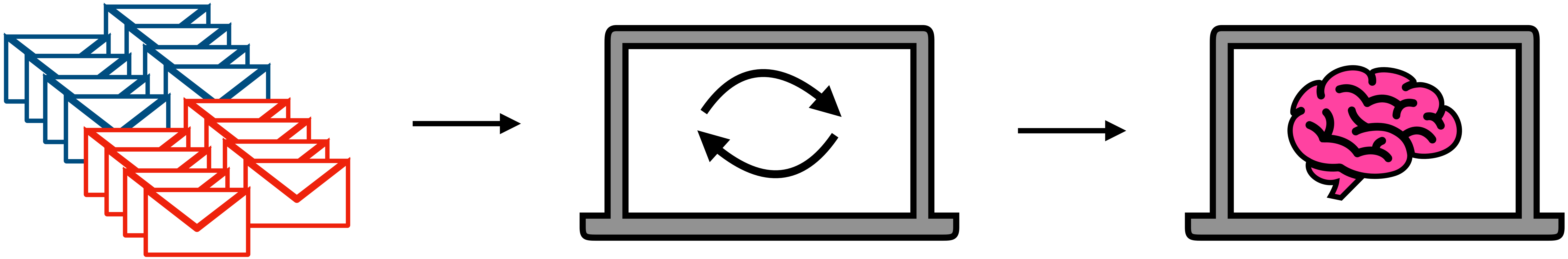


Self-driving

# Software 2.0

# Software 2.0

Programming computers by example (i.e. with data)



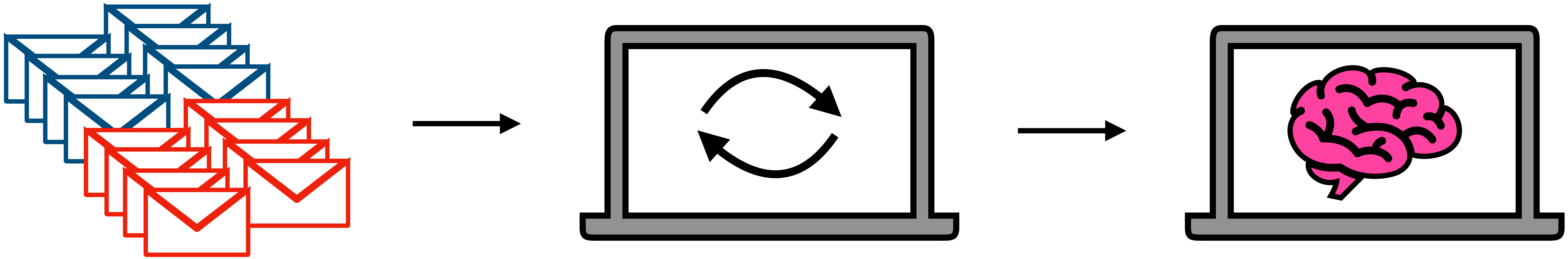
Gather spam/not spam examples

Pass to ML algorithm

ML Model

# Machine Learning

Programming computers by example (i.e. with data)



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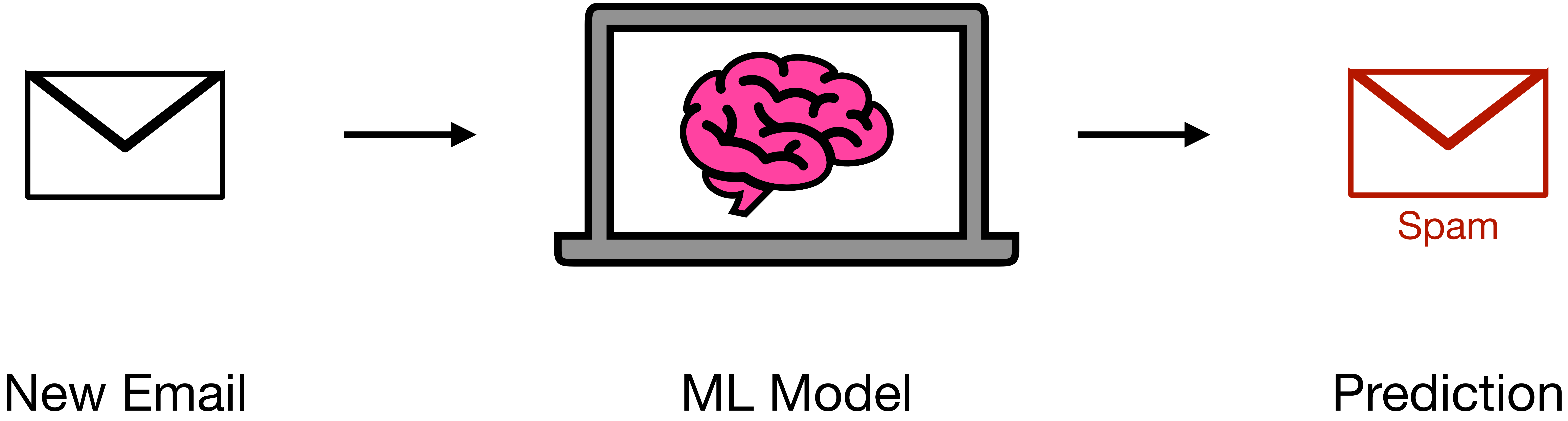
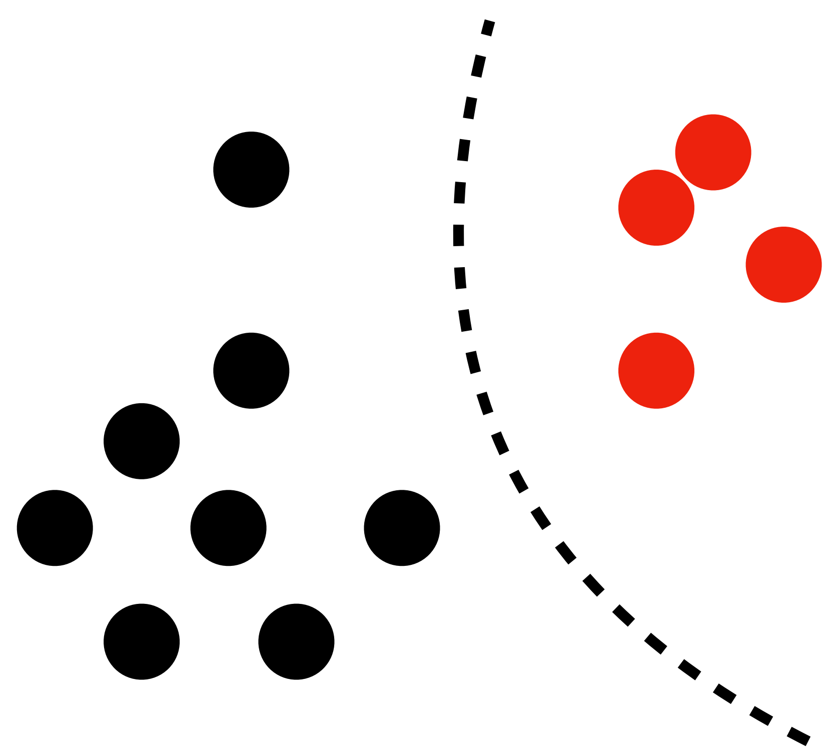
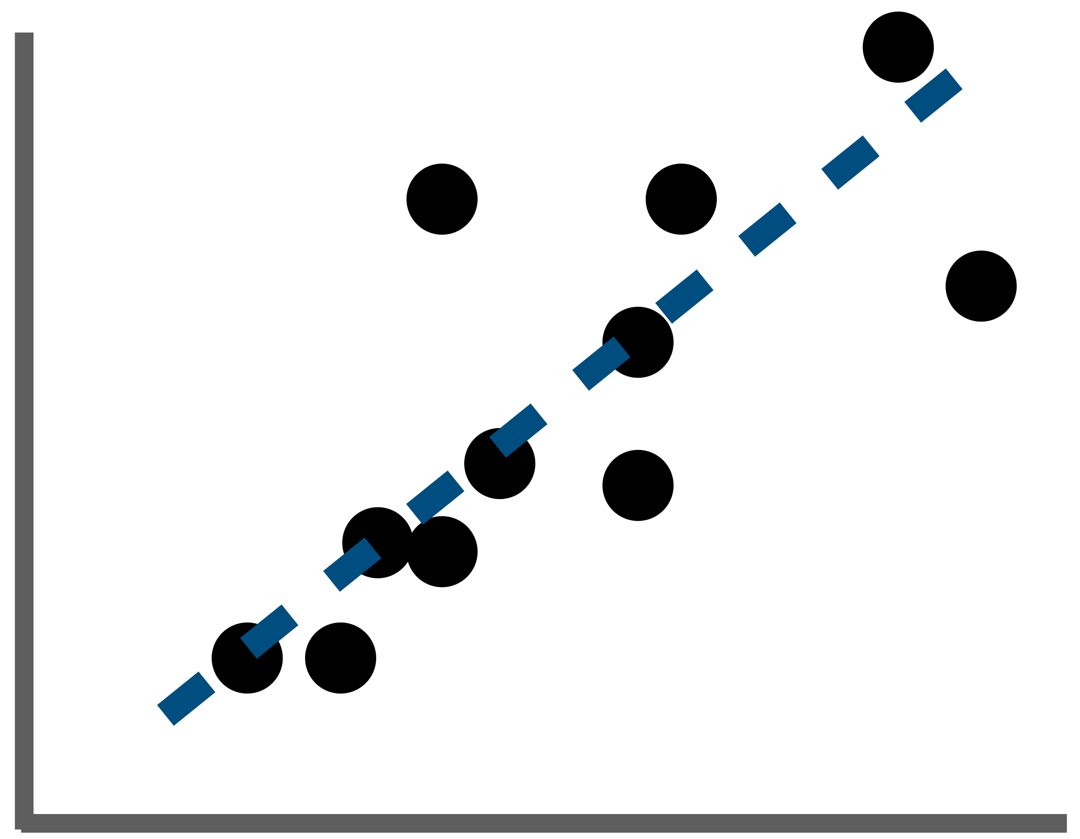


# 3 Flavors of ML

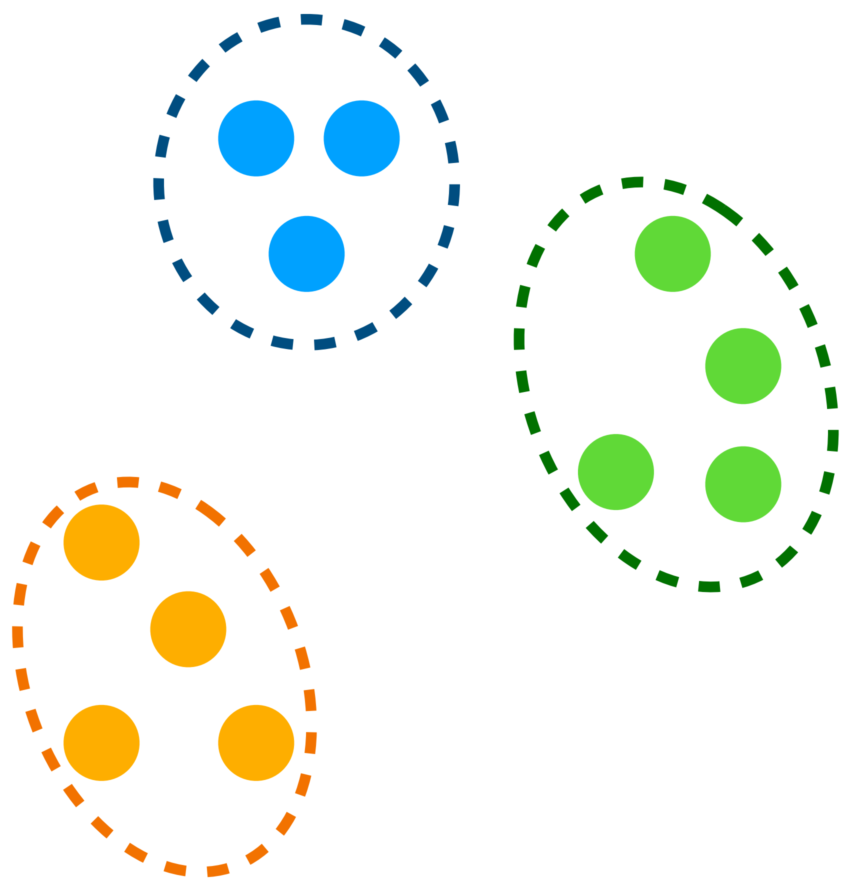
1) Classification



2) Regression

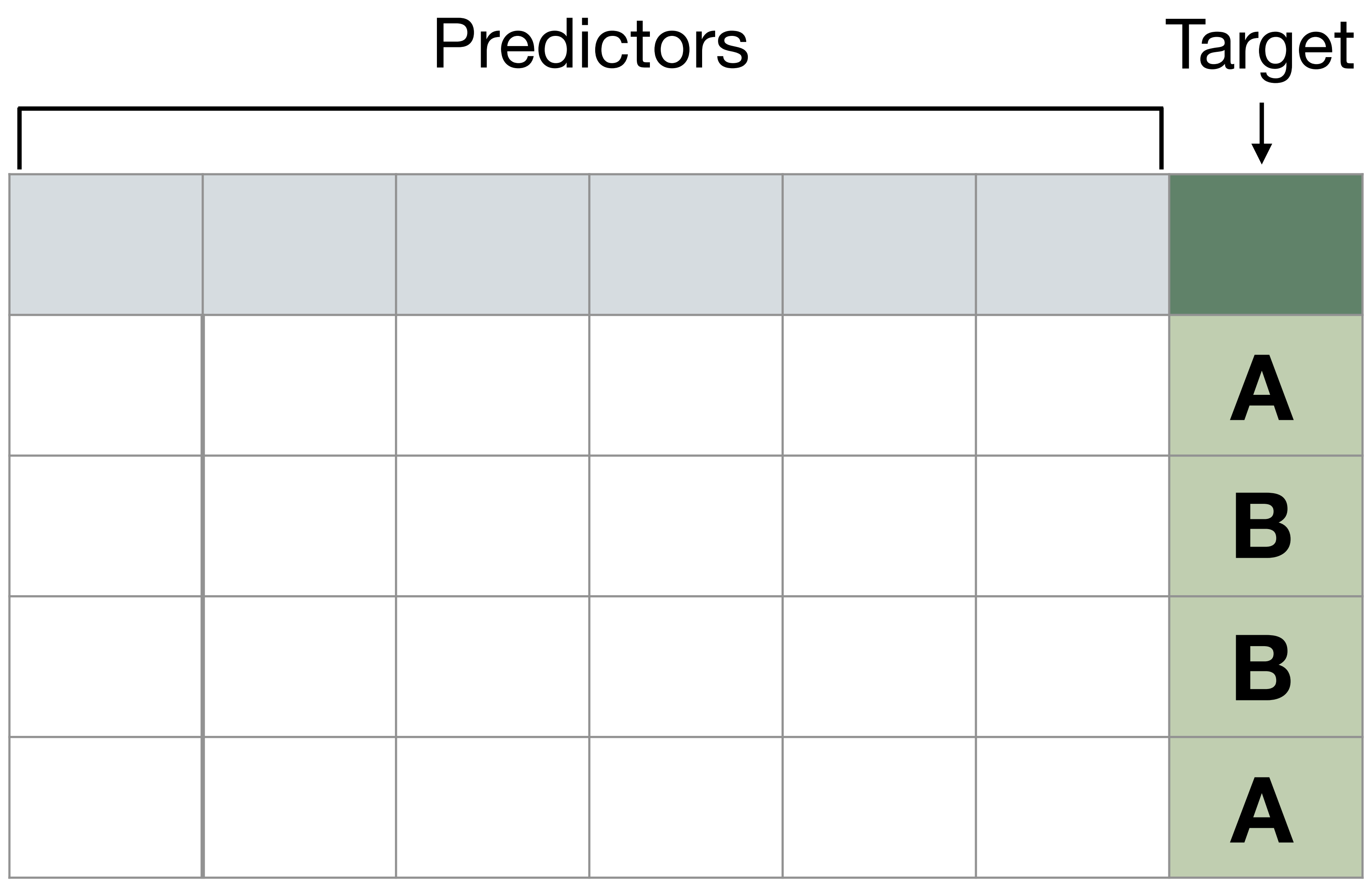


3) Clustering

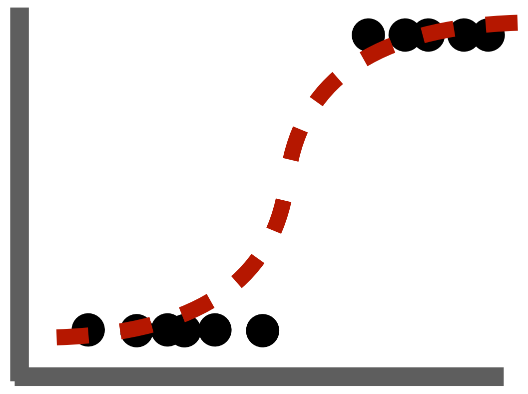


# Flavor 1: Classification

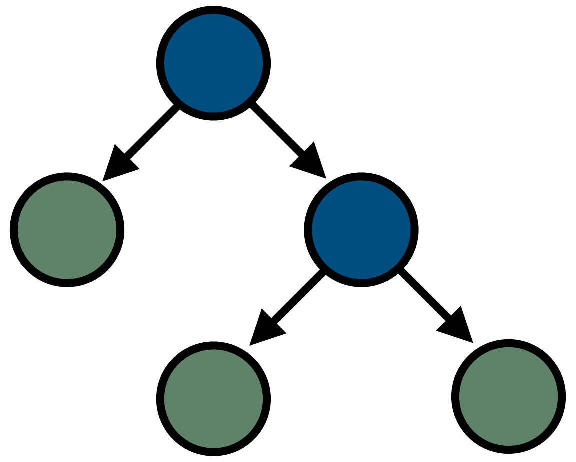
## Labeling data with known categories



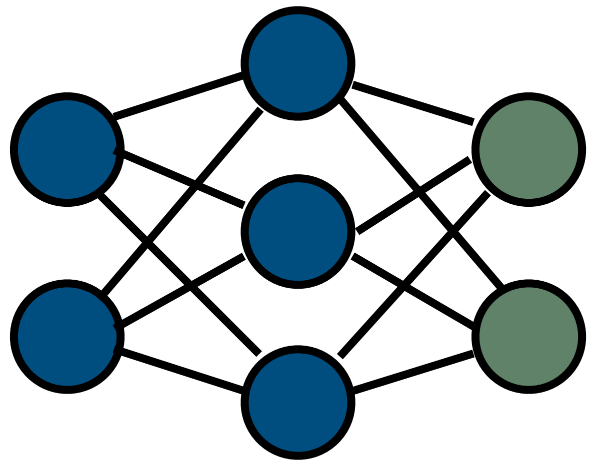

**Training Data**



Logistic Regression



Decision Tree Classifier

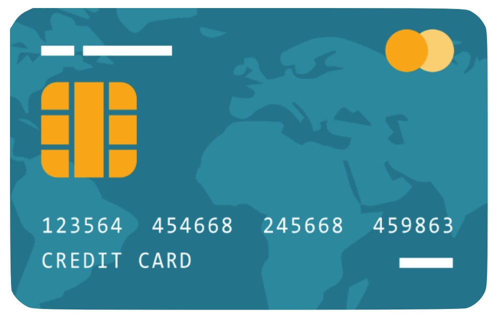


Neural Network

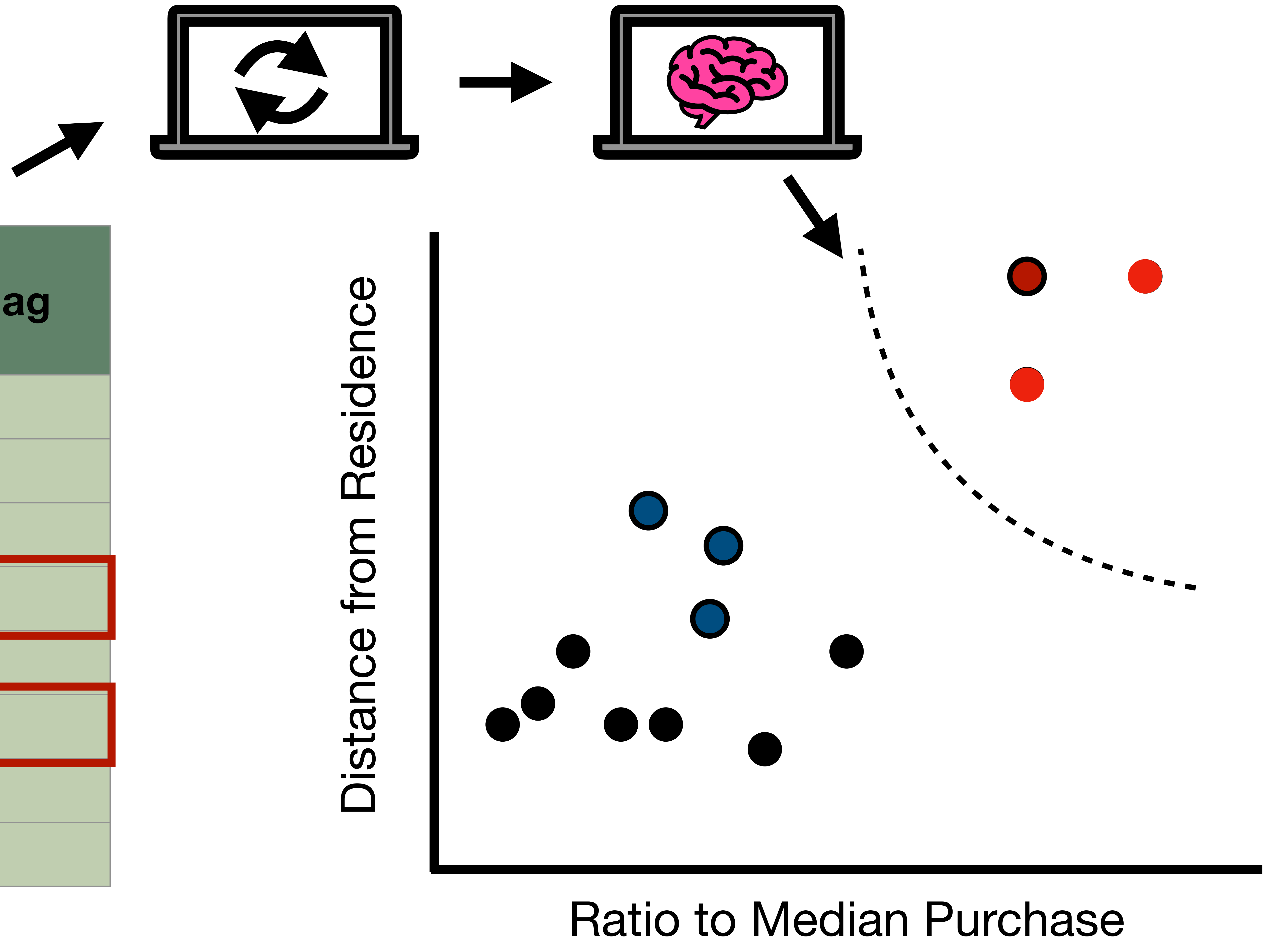
**Techniques**

# Flavor 1: Classification

## Example: Fraud Detection




| Ratio to Median Purchase | Distance from Residence | Fraud Flag |
|---|---|---|
| 1.5 | 10 | 0 |
| 0.8 | 5 | 0 |
| 1.0 | 2 | 0 |
| 2.2 | 55 | 1 |
| 1.3 | 1 | 0 |
| 1.9 | 42 | 1 |
| 0.75 | 3 | 0 |
| 1.1 | 2 | 0 |

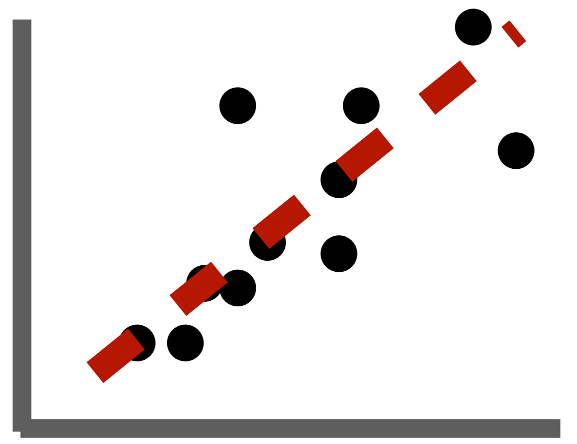


# Flavor 2: Regression

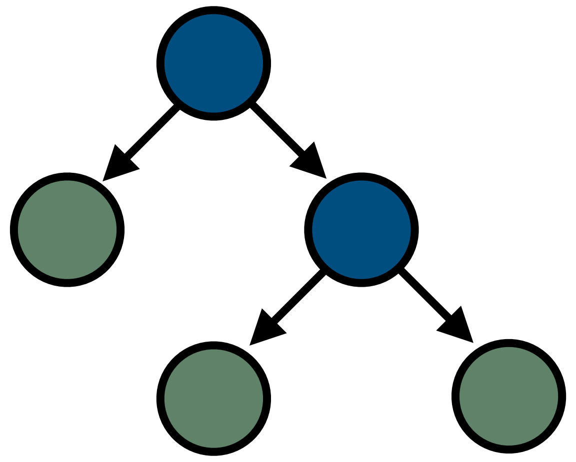
## Predicting a continuous value

| Predictors | | | | | | Target |
|---|---|---|---|---|---|---|
| | | | | | | |
| | | | | | | **0.1** |
| | | | | | | **-0.2** |
| | | | | | | **0.5** |
| | | | | | | **0.3** |

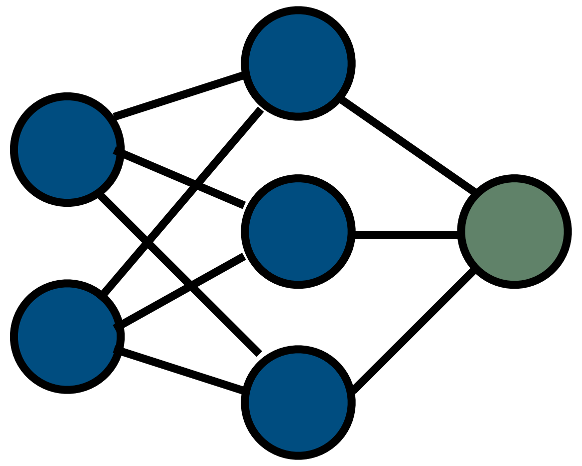
**Training Data**



Linear Regression



Decision Tree Regressor

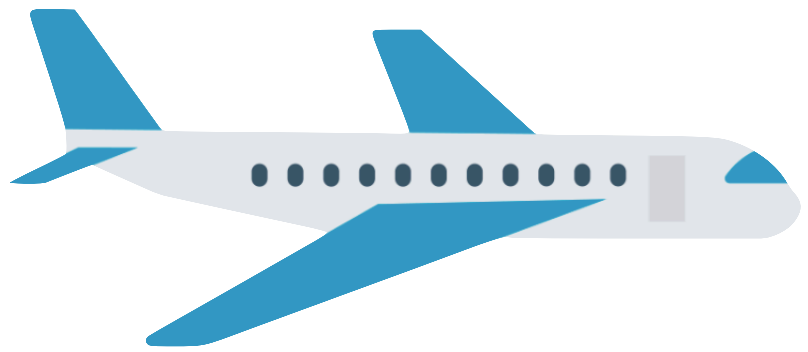


Neural Network

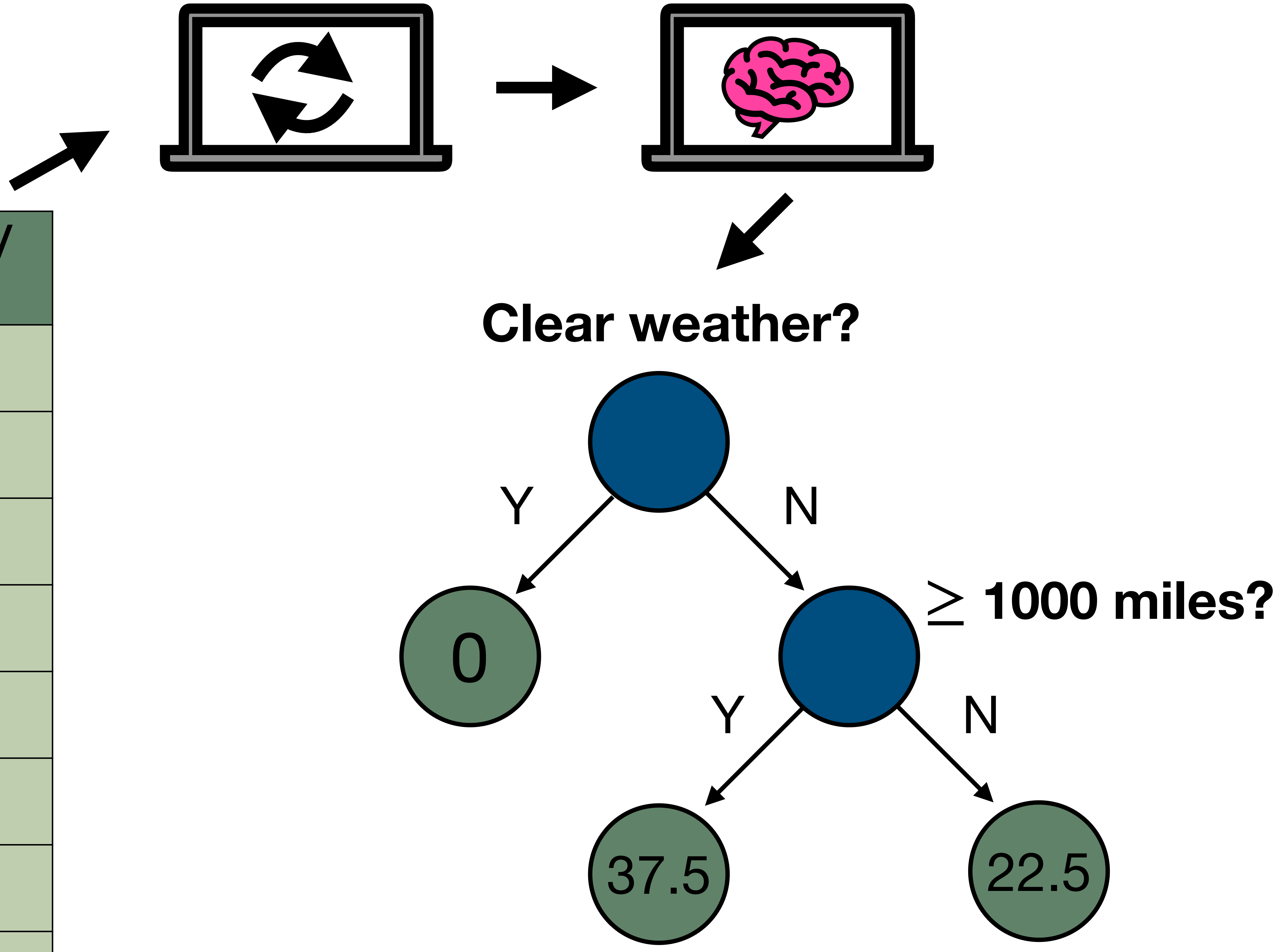
**Techniques**

# Flavor 2: Regression

## Example: Estimating Arrival Times

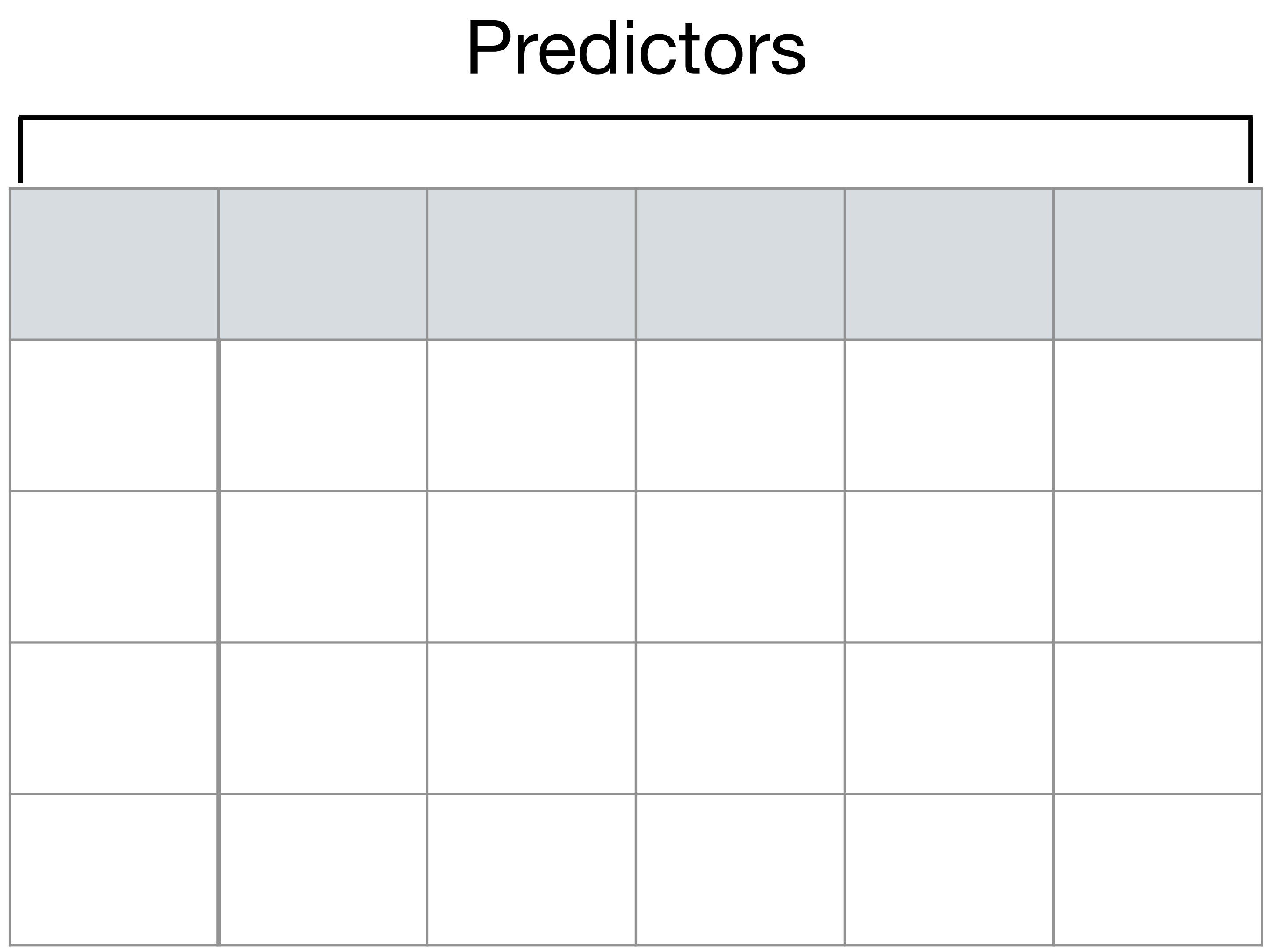


| Distance (miles) | Weather Conditions | Minutes Delayed/ Early |
|---|---|---|
| 500 | Clear | 5 |
| 750 | Rain | 20 |
| 600 | Clear | -5 |
| 800 | Fog | 25 |
| 400 | Clear | 5 |
| 1200 | Snow | 30 |
| 950 | Clear | -10 |
| 1100 | Thunderstorms | 45 |



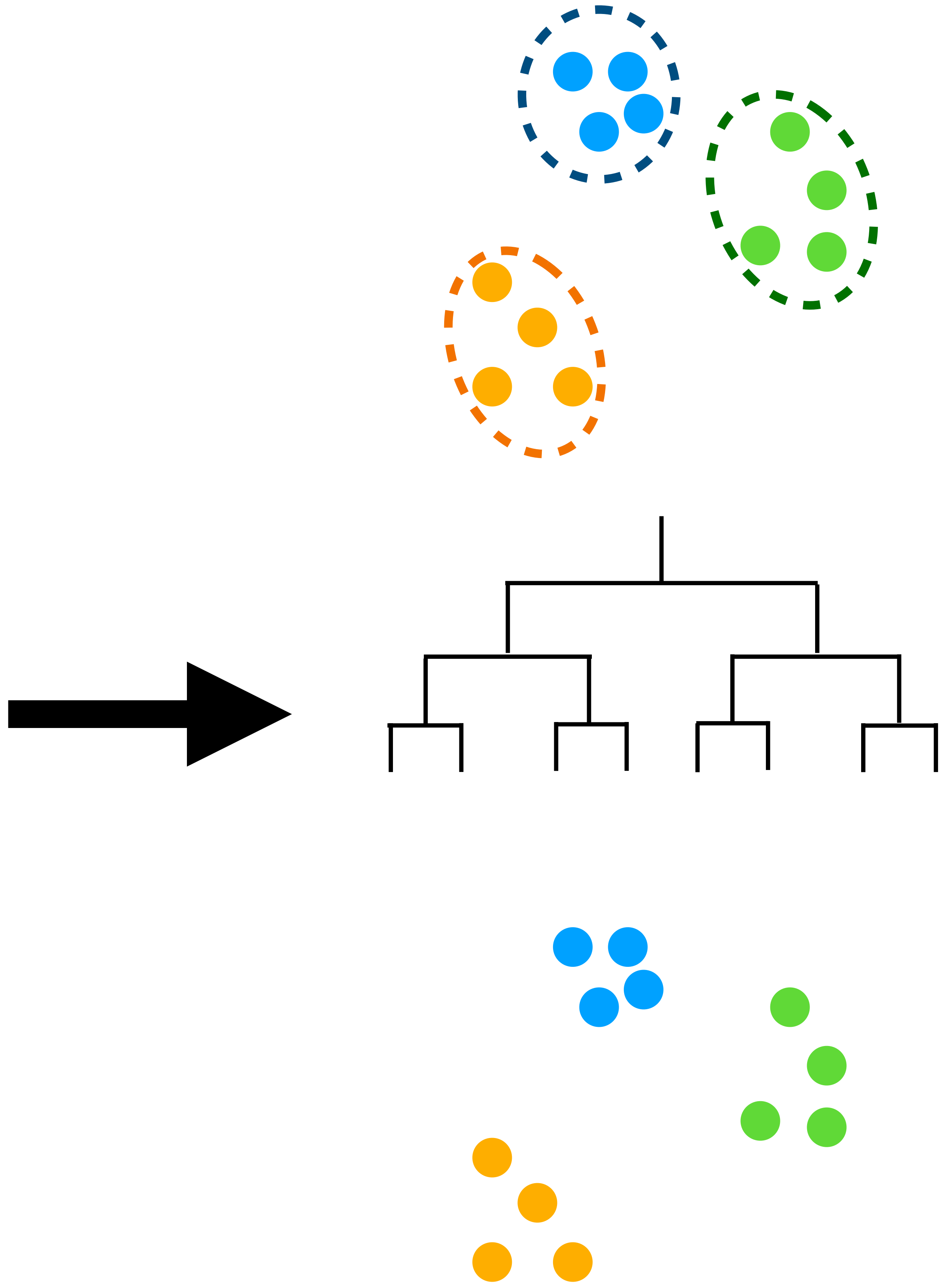
# Flavor 3: Clustering

## Grouping data based on similarity




**No target needed!**

**Training Data**



Gaussian Mixture Model

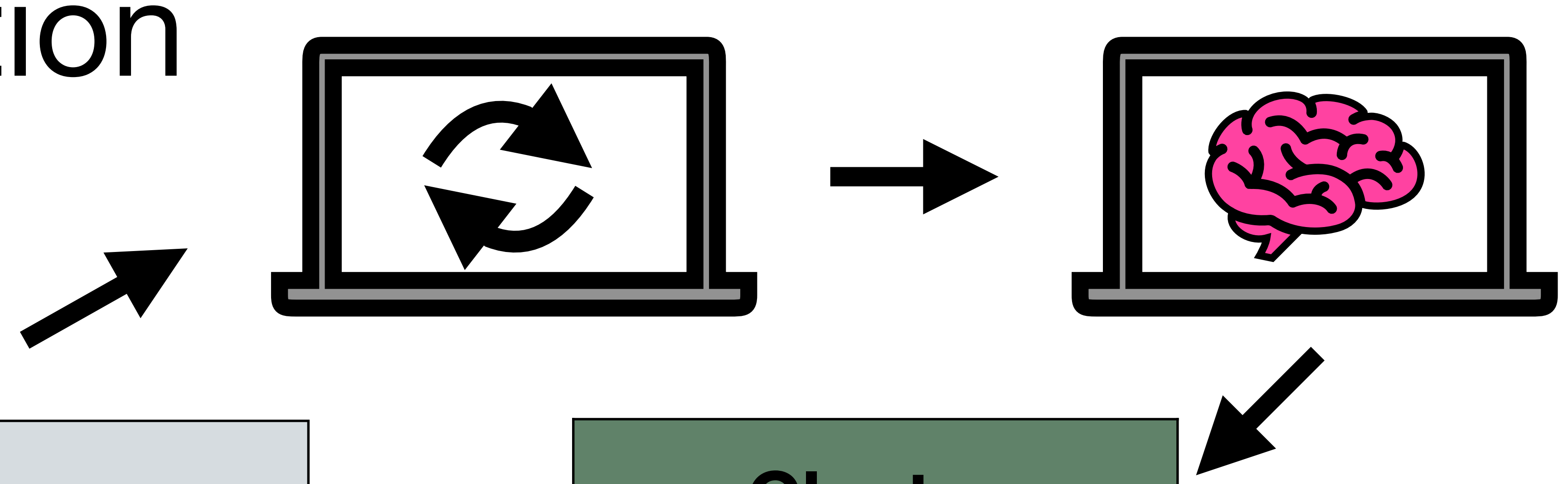
Hierarchical Clustering

K-Means

**Techniques**

# Flavor 3: Clustering

## Example: Customer Segmentation



| Age | Sex | Country |
|---|---|---|
| 25 | Male | USA |
| 30 | Female | Canada |
| 22 | Female | UK |
| 28 | Male | Australia |
| 35 | Female | Germany |
| 40 | Male | France |
| 27 | Female | USA |
| 33 | Male | Canada |
| 29 | Female | UK |
| 31 | Male | Australia |

| Cluster |
|---|
| 2 |
| 1 |
| 2 |
| 1 |
| 3 |
| 3 |
| 2 |
| 1 |
| 1 |
| 1 |

1 = Middle-aged, non-European/US

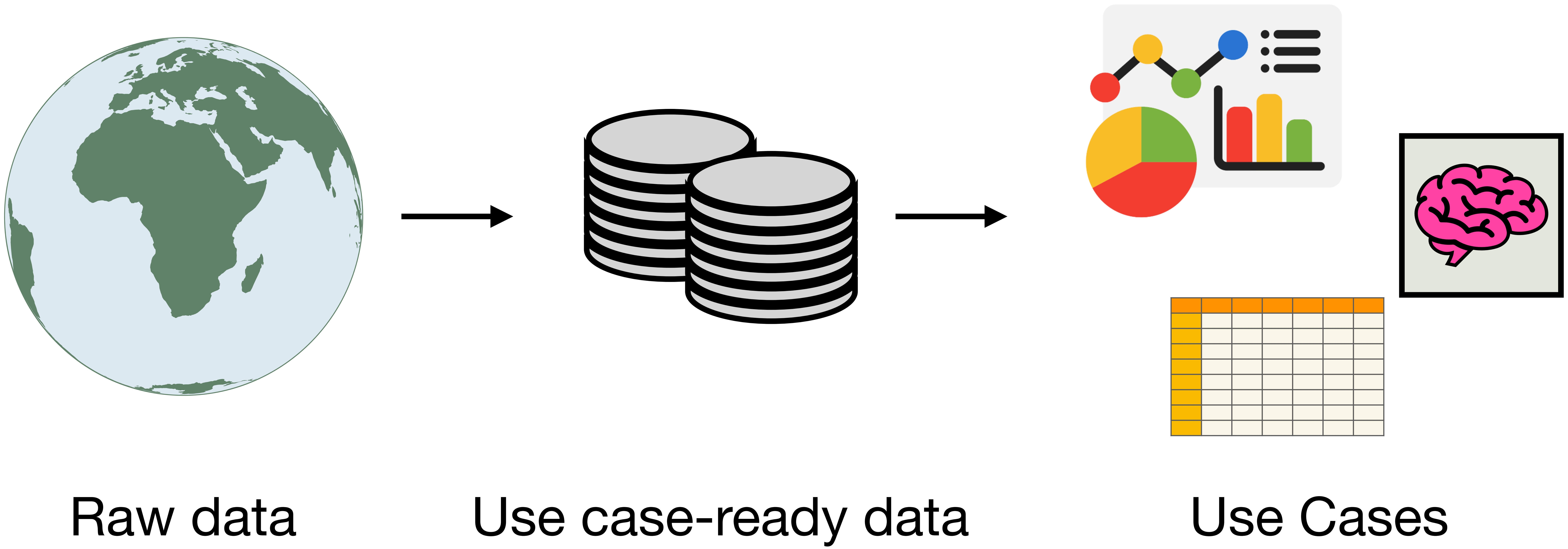
2 = Young, US/UK

3 = Middle-aged, European

# Data Engineering

# Data Engineering

Making data available for analytics and ML applications

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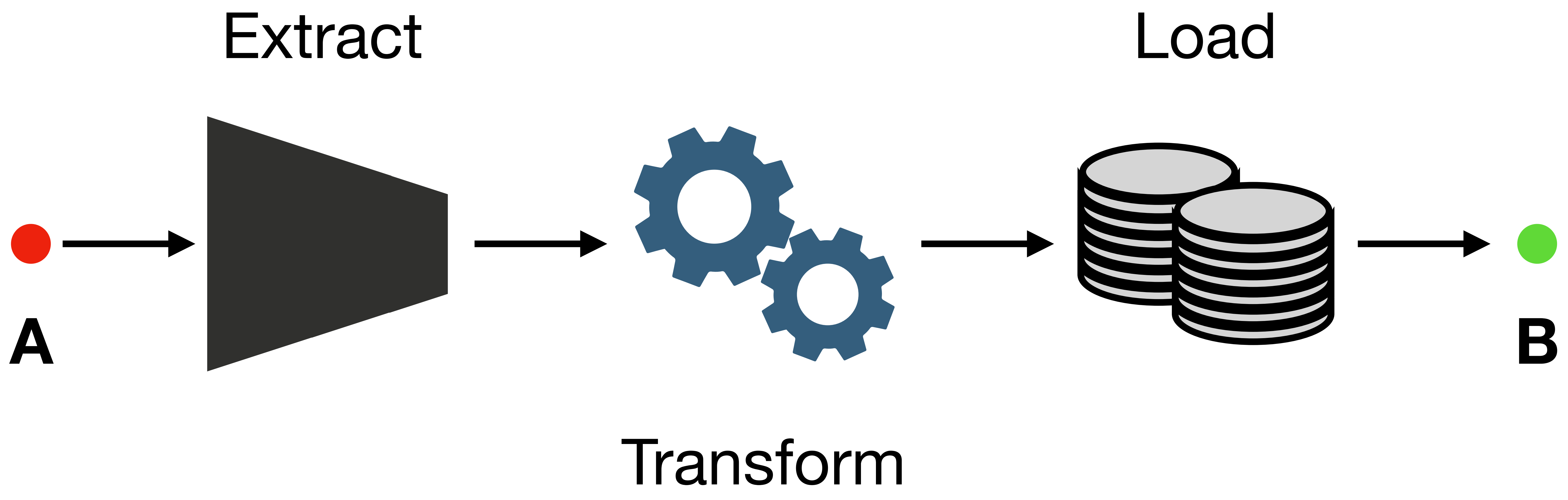
# Data Pipeline

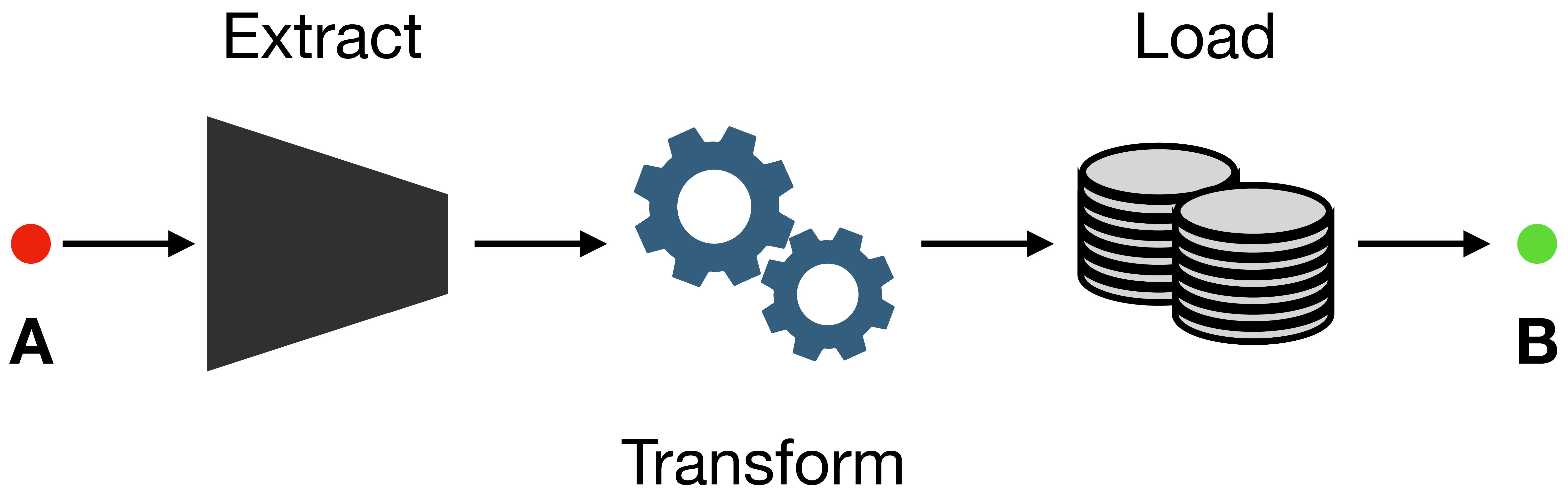
## Getting data from point A to point B




Parsing sales data and
storing in structured format

# Data Pipeline

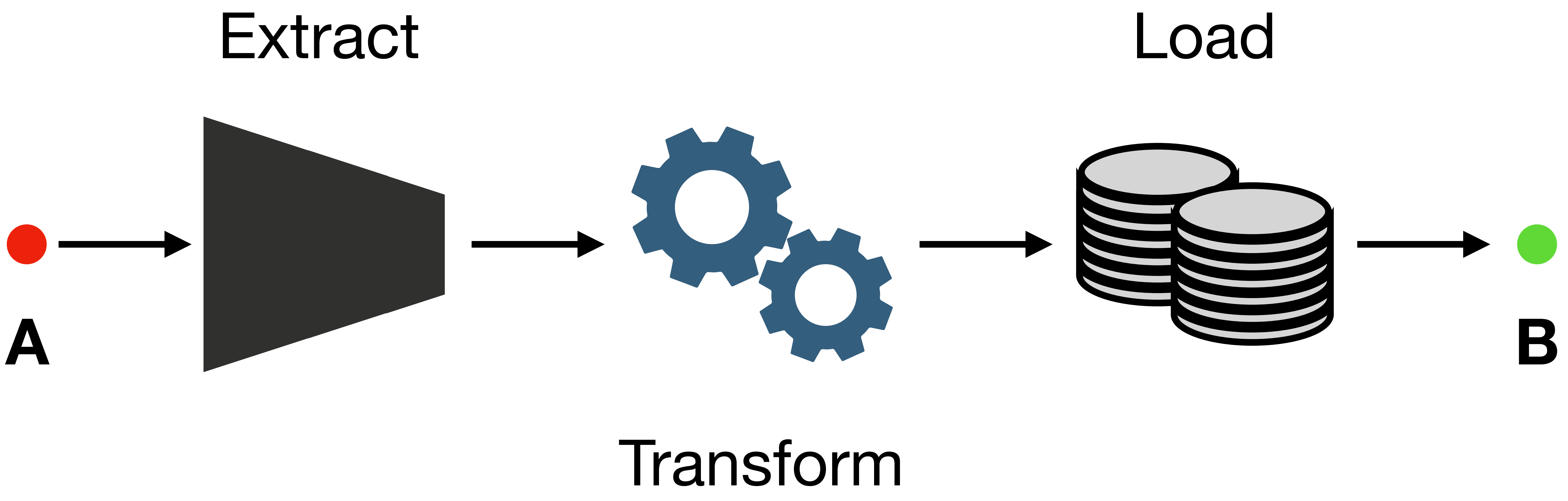
## Getting data from point A to point B




Parsing sales emails and
labelling with status

# Data Pipeline

Getting data from point A to point B




Grabbing transcriptions and
storing them in vector database

# E: Extract

Acquiring data from its source

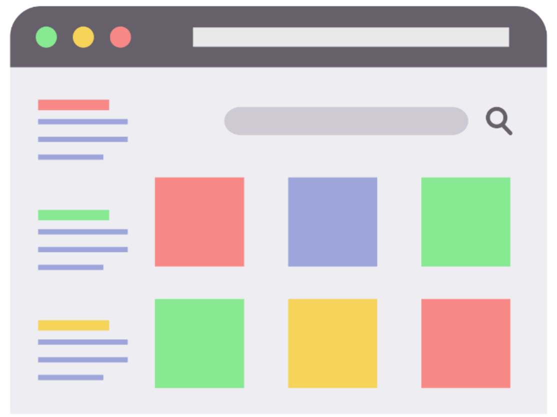
## APIs

→ **Lead Data**

→ **Sales Data**

→ **Social Data**

## Custom Extracts



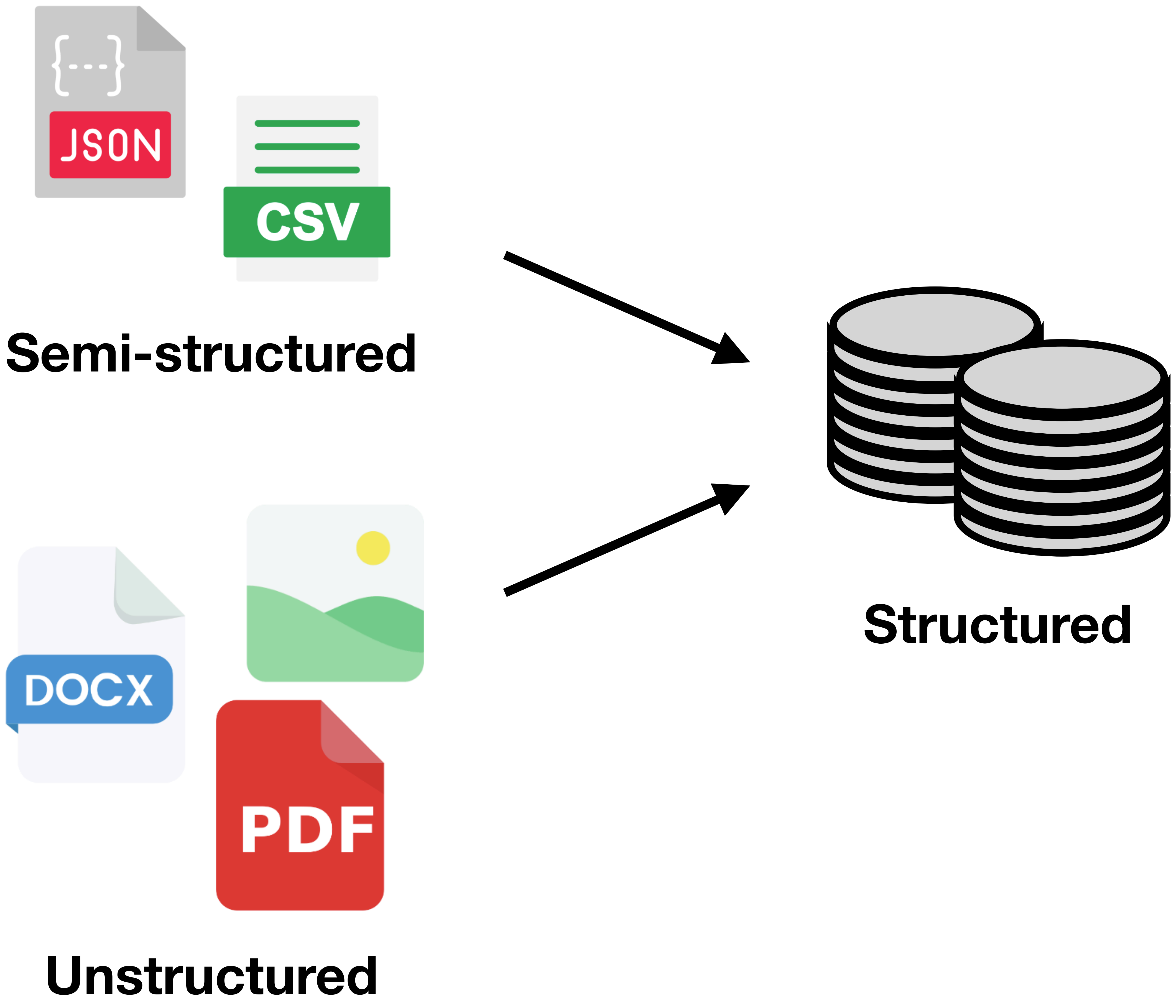
**Scraping Public Webpages**

**Docs from File System**

**Sensor Data**

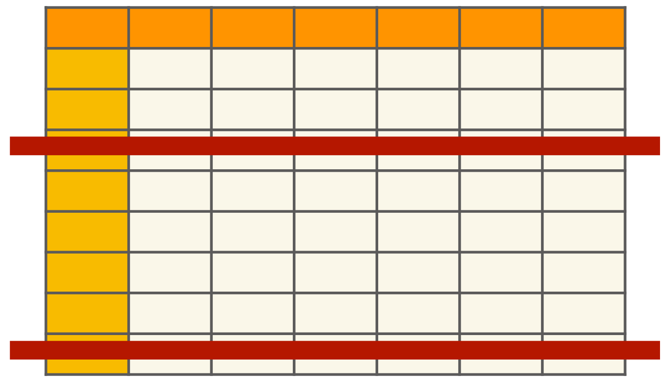
# T: Transform

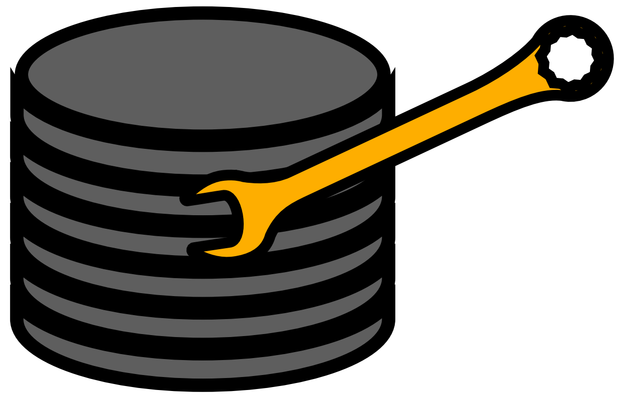
## Translating data into a useful form




### Common Tasks

- Managing data types and ranges
- Deduplication
- Imputing missing values
- Handling special characters and values
- Feature engineering





# L: Load

## Making data available for ML training or inference

**Project Directory**
MB-scale, 1 use
(unstructured + structured data)

**Simple Storage**
GB-scale, few uses
(unstructured data)

**Database**
GB-scale, many uses
(structured data)

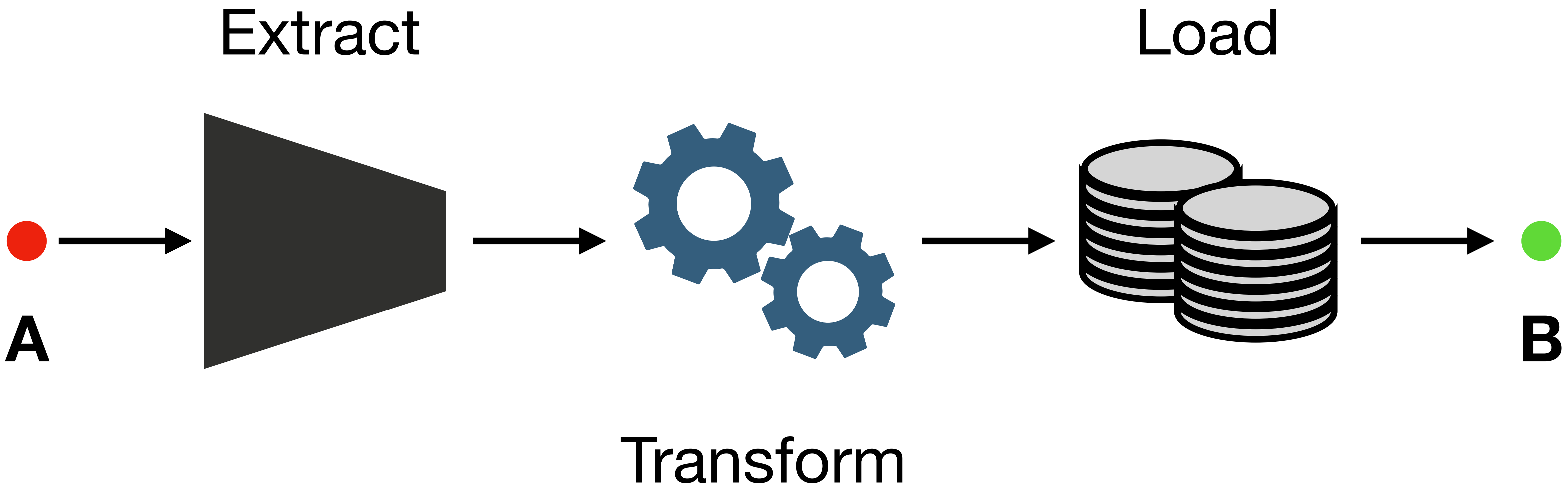
**Data Warehouse**
TB-scale, many uses
(structured data)

**Data Lake**
PB-scale, endless uses
(unstructured + structured data)

# Examples

# Example 1

## ETL of AI Job Data (Overview)




www.themuse.com

Feature engineering and
data labelling

# Example 1

## ETL of AI Job Data (Flowchart)

### Extract

Extract job urls

Extract job details

### Transform

Drop duplicate JDs

Feature engineering: counting key skills for DS and MLE roles

Add target label

### Load

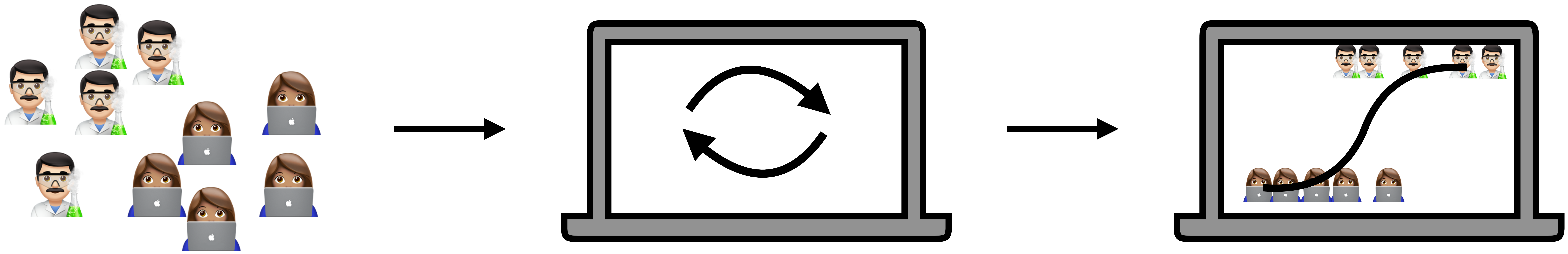
Save to file

# Example 1

## ETL of AI Job Data (Example)

# Example 2

## Training AI Job Classifier (Overview)



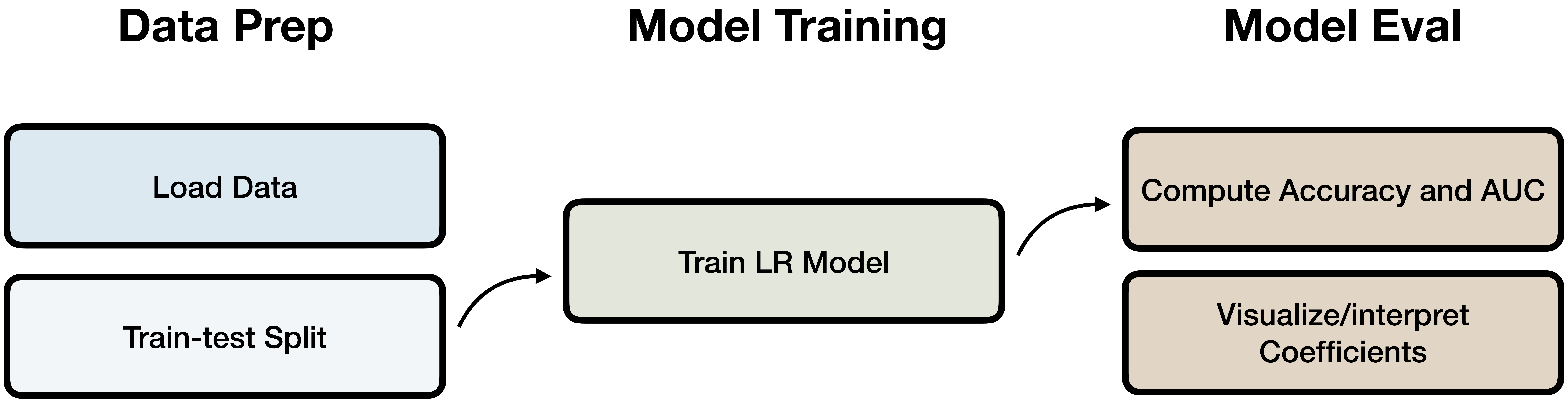
Dataset of DS and MLE job descriptions

Logistic Regression Trainer

Logistic Regression Model

# Example 2

## Training AI Job Classifier (Flowchart)



# Example 2

## Training AI Job Classifier (Example)

# Homework 2

## Project 💻

Build a Simple ETL Pipeline

**Bonus**: train a ML model with it!

## Pre-work ✍️

Session 3: Introduction to LLMs

Session 3: Prompt Engineering

Session 3: OpenAI API

# Live Events - Next week!

## Build End-to-End LLM Solutions

TDE Podcast & Live Q&A

**Paul Iusztin**
Founder @ Decoding ML

**Maxime Labonne**
Head of Post-training @ Liquid AI

**Thurs, Jan 23rd 2025**
**1:00PM CST**

Hosted live from:
**YouTube**

Scan to Register

TDE

## Building RAG Apps for Production

TDE Podcast & Live Q&A

A conversation with
**Jason Liu**
ML Consultant @ 567 Labs

Hosted live from:
**YouTube**

**Sat, Jan 25th 2025**
**11:30AM CST**

Scan to Register

TDE

# References


[1] Machine learning: the power and promise of computers that learn by example

[2] sklearn Classifier Comparison

[3] An Introduction to Decision Trees | Gini Impurity & Python Code

[4] sklearn Supervised Learning

[5] sklearn Unsupervised Learning

[6] How Data Engineering Works

[7] How to Build Data Pipelines for ML Projects (w/ Python Code)