

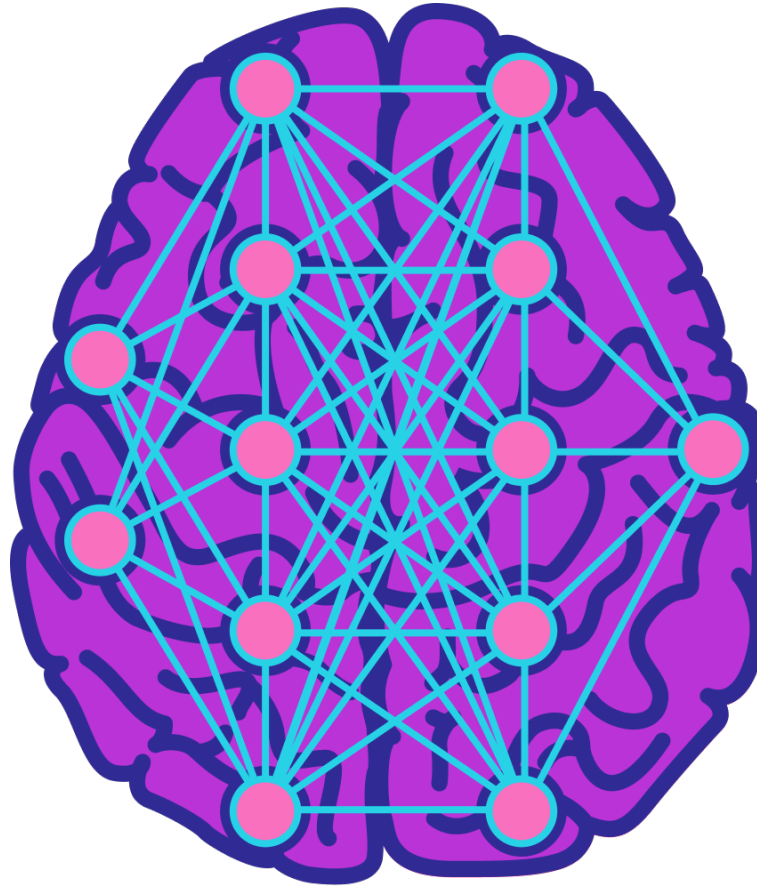
DS 5220

Supervised Machine Learning and Learning Theory

Alina Oprea
Associate Professor, CCIS
Northeastern University

September 4 2019

Welcome to DS 5220!

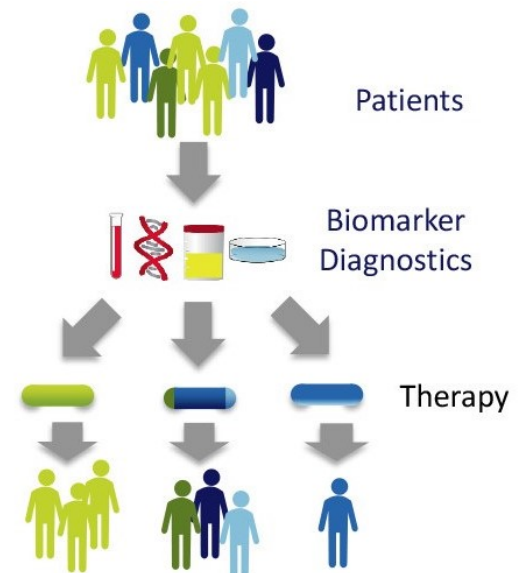
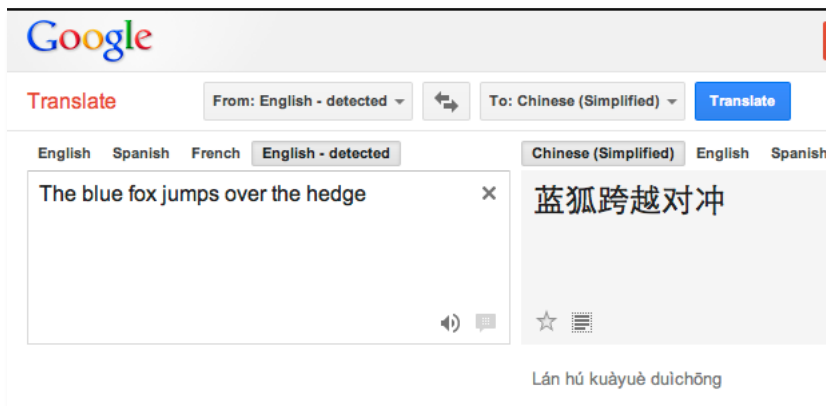
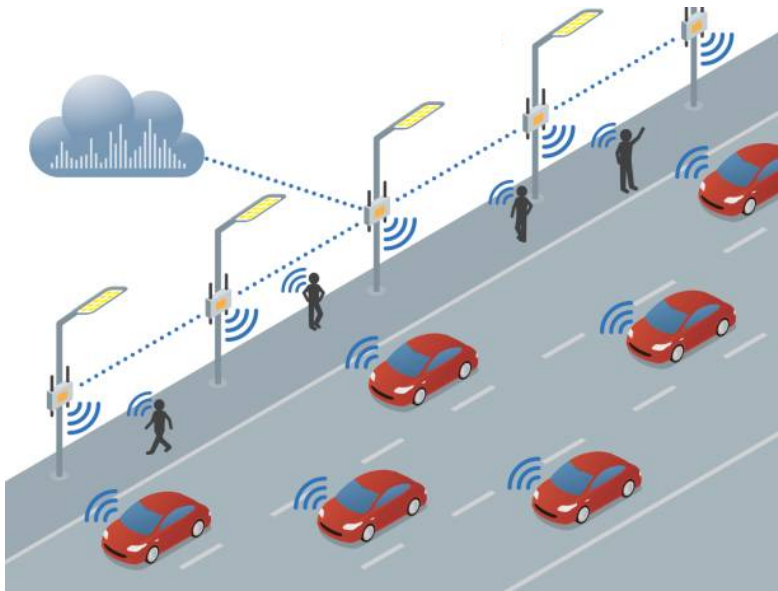


Supervised Machine Learning and
Learning Theory

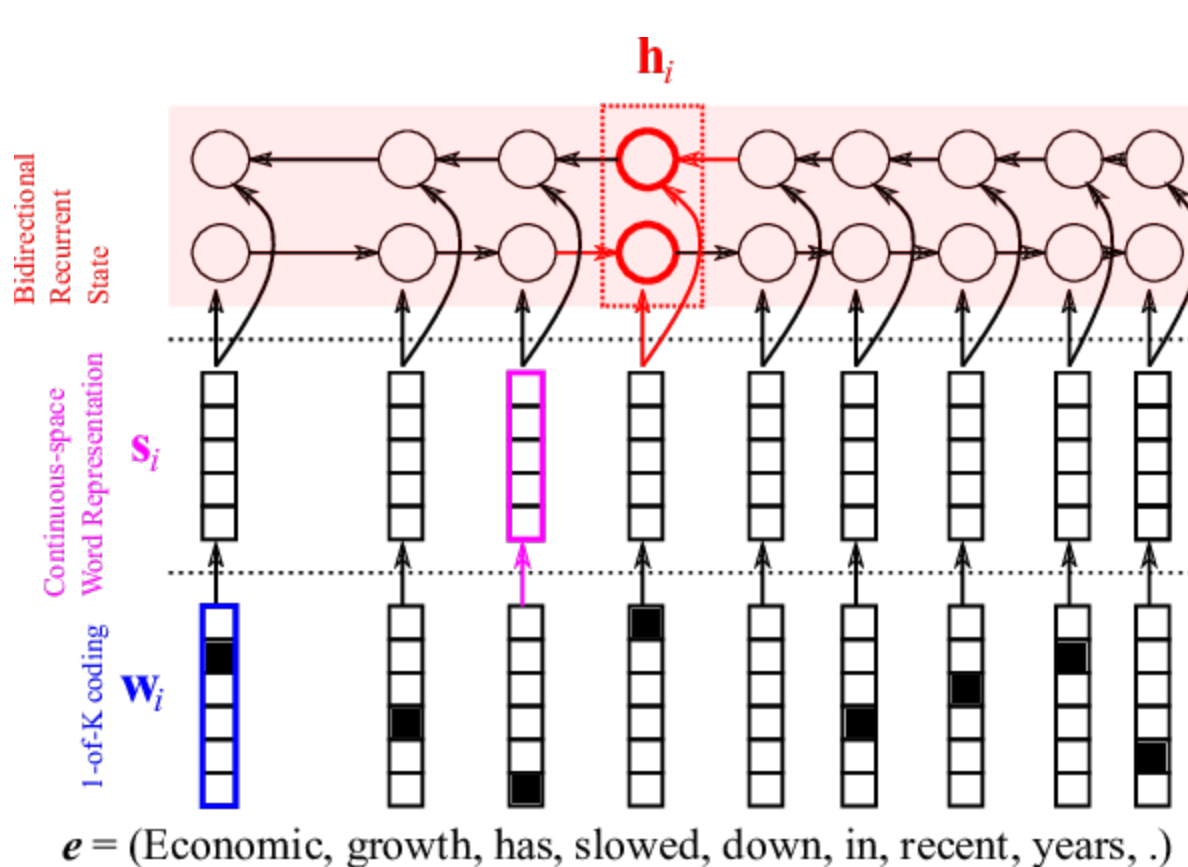
Introduction

- **Ph.D. at CMU**
 - Research in storage security & cryptographic file systems
- **RSA Laboratories**
 - Cloud security, applied cryptography
 - Security analytics (ML in security)
- **NEU CCIS – since Fall 2016**
 - ML for security applications (attack detection, IoT, connected car security)
 - Adversarial ML (study the vulnerabilities of ML in face of attacks and design defenses)

Machine learning is everywhere



Natural Language Processing (NLP)



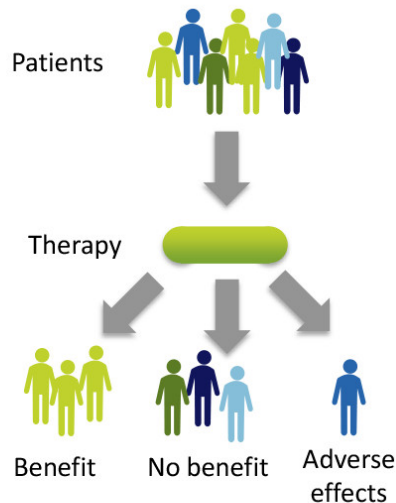
- Understand language semantics
- Real-time translation, speech recognition

Personalized Medicine



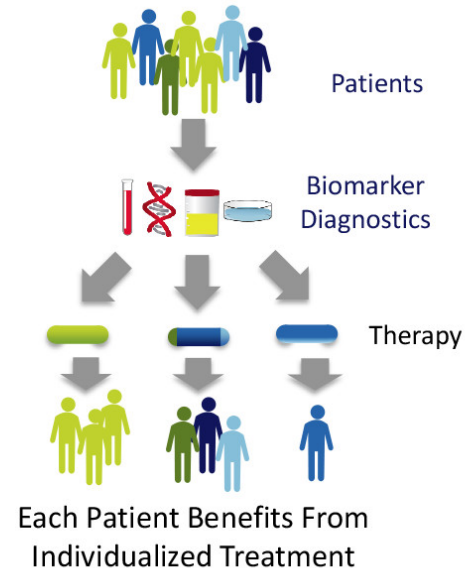
Without Personalized Medicine:

Some Benefit, Some Do Not



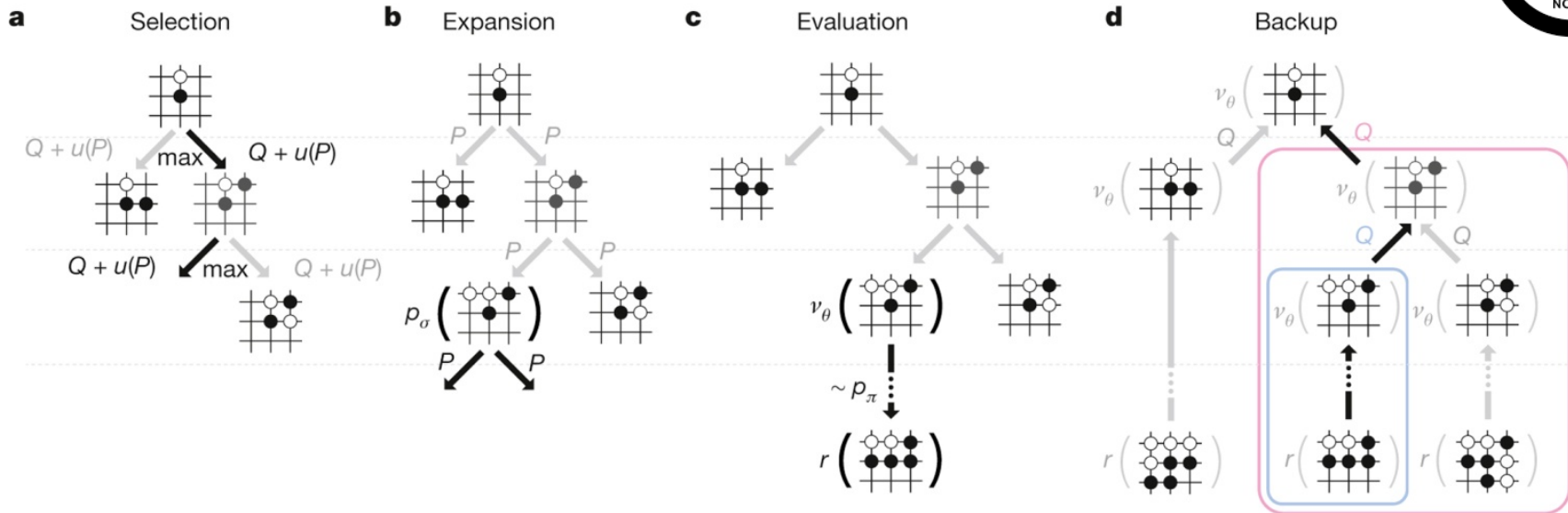
With Personalized Medicine:

Each Patient Receives the Right Medicine For Them



- Treatment adjusted to individual patients
- Predictive models using a variety of features
- Better outcome and reduced cost

Playing games



Reinforcement learning

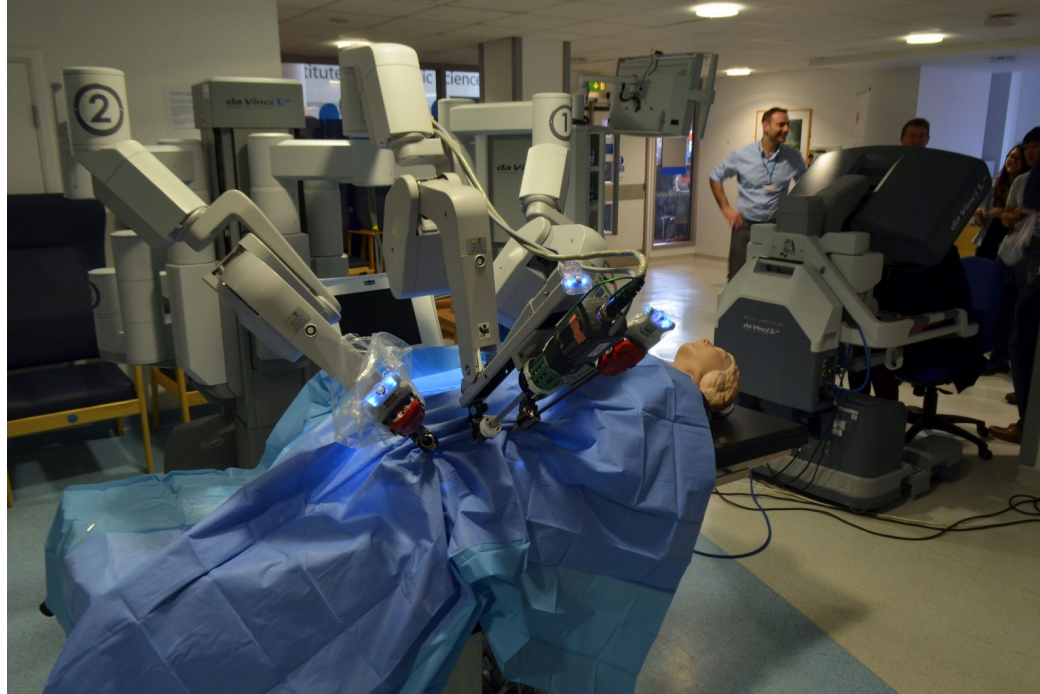
- AlphaGo
- Chess

Fast Forward in the Near Future



AI Transportation in Cities of the Future (10-20 years)

Fast Forward in the Near Future



AI Robots in Medicine of the Future (10-20 years)

Short History

- Legendre and Gauss – linear regression, 1805
 - Astronomy applications
- Bayes and Laplace - Bayes Theorem, 1812
- Markov chains, 1913
- Fisher – linear discriminant analysis, 1936
 - Logistic regression, 1940
- Widrow and Hoff ADELIN neural network, 1959
- Nelder, Wedderburn, generalized linear models, 1970
- “AI winter”, limitations of perceptron, 1970
- Breiman, Friedman, Olshen, Stone, decision trees, 1980
- More work on neural networks, 1980
- Cortes and Vapnik , SVM with kernels, 1990
- IBM Deep Blue beats Kasparov at chess, 1996
- Geoffrey Hinton, Deep learning, back propagation, 2006

DS-5220

- What is *machine learning*?
 - The science of teaching machines how to learn
 - Design predictive algorithms that learn from data
 - Replace humans in critical tasks
 - Subset of Artificial Intelligence (AI)
- **Machine learning** very successful in:
 - Machine translation
 - Precision medicine
 - Recommendation systems
 - Self-driving cars
- Why the hype?
 - **Availability**: data created/reproduced in 2010 reached 1,200 exabytes
 - **Reduced cost of storage**
 - **Computational power** (cloud, multi-core CPUs, GPUs)

DS-5220 Course objectives

- Become familiar with main machine learning tasks
 - Supervised learning vs unsupervised learning
 - Classification vs Regression
- Study most well-known algorithms
 - Regression (linear regression, spline regression)
 - Classification (SVM, decision trees, Naïve Bayes, ensembles, etc.)
 - Deep learning (different neural network architectures)
- Learn the theory and foundation behind ML algorithms and learn to apply them to real datasets
- Learn about security challenges of ML
 - Introduction to adversarial ML

<http://www.ccs.neu.edu/home/alina/classes/Fall2019>

Class Outline

- **Introduction**
 - Probability and linear algebra review
- **Regression - 2 weeks**
 - Linear regression, polynomial, spline regression
- **Classification - 4 weeks**
 - Linear classification (logistic regression, LDA)
 - Non-linear models (decision trees, SVM, Naïve Bayes)
 - Ensembles (random forest, AdaBoost)
 - Model selection, regularization, cross validation
- **Neural networks and deep learning – 2 weeks**
 - Back-propagation, gradient descent
 - NN architectures (feed-forward, convolutional, recurrent)
- **Adversarial ML – 1 lecture**
 - Security of ML at testing and training time

Resources

- Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani. [An Introduction to Statistical Learning with Applications in R](#)
- Trevor Hastie, Rob Tibshirani, and Jerry Friedman, [Elements of Statistical Learning](#), Second Edition, Springer, 2009.
- Christopher Bishop. [Pattern Recognition and Machine Learning](#). Springer, 2006.
- A. Zhang, Z. Lipton, and A. Smola. [Dive into Deep Learning](#)

Policies

- **Instructors**
 - Alina Oprea
 - TAs: Yuxuan (Ewen) Wang; Christopher Gomes
- **Schedule**
 - Mon, Wed 2:50-4:30pm
 - West Village H 108
 - Office hours:
 - Alina: Wed 4:30 – 6:00 pm (ISEC 625)
 - Christopher : Monday 5:00-6:00pm (ISEC 605)
 - Ewen: Thursday 5:00-6:00pm (ISEC 605)
- **Online resources**
 - Slides will be posted after each lecture on public website
 - Piazza for questions and discussion
 - Gradescope for homework and project submission

Policies, cont.

- **Your responsibilities**
 - Please be on time, attend classes, and take notes
 - Participate in interactive discussion in class
 - Submit assignments/ programming projects on time
- **Late days for assignments**
 - 5 total late days, after that loose 20% for every late day
 - Assignments are due at 11:59pm on the specified date
 - No need to email for late days, Gradescope shows submission time

Grading

- **Assignments – 20%**
 - 4-5 assignments and programming exercises based on studied material in class
- **Midterm – 25%**
- **Final exam – 25%**
- **Final project – 25%**
 - Select your own project, public dataset
 - Submit short project proposal and milestone
 - Project pitch and final presentation
 - Project report
- **Class participation – 5%**
 - Participate in class discussion and on Piazza

Assignments

- Programming exercises, and theory questions
 - Prefer Latex/Word/... write up
- Language
 - Use R or Python
 - Jupyter notebooks recommended
- Submission
 - Submit PDF report in Gradescope
 - Includes all the results, as well as link to code and instructions to run it

Final project

- **Goal:** work on a larger data science project
 - Build your portfolio and increase your experience
- **Requirements**
 - Large dataset: at least 10,000 records (public source)
 - Not recommended to collect your own data
 - Pick application of interest, but instructor will also provide potential list of projects
 - Experiment with at least 3 ML models
 - Perform in-depth analysis (which features contribute mostly to prediction, which model performs best)
- **Timeline**
 - Proposal: mid class; milestone 2-3 weeks after (Instructors will provide early feedback)
 - Final presentation (10 mins) and report (5-6 pages)

Academic Integrity

- Homework is done individually!
- Rules
 - Can discuss with colleagues or instructor
 - Can post and answer questions on Piazza
 - Code cannot be shared with colleagues
 - Cannot use code from the Internet
 - Use python or R packages, but not directly code for ML analysis written by someone else
- **NO CHEATING WILL BE TOLERATED!**
- Any cheating will automatically result in grade F and report to the university administration
- <http://www.northeastern.edu/osccr/academic-integrity-policy/>

Outline

- Supervised learning
 - Classification
 - Regression
- Unsupervised learning
 - Clustering
- Bias-Variance Tradeoff
- Occam's Razor

Slides adapted from

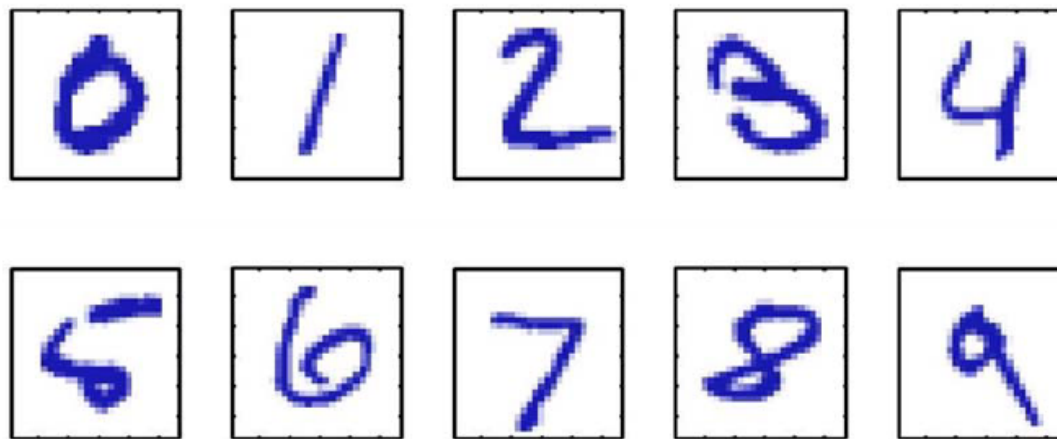
- A. Zisserman, University of Oxford, UK
- S. Ullman, T. Poggio, D. Harari, D. Zysman, D Seibert, MIT
- D. Sontag, MIT
- Figures from “An Introduction to Statistical Learning”, James et al.

Introduction

- What is Machine Learning?
 - Subset of AI
 - Design algorithms that learn from real data and can automate critical tasks
- When can it be applied?
 - It cannot solve any problem!
 - When task can be expressed as learning task
 - When high-quality data is available
 - Labeled data (by human experts) is preferable!
 - When some error is acceptable (can rarely achieve 100% accuracy)
 - Example: recommendation system, advertisement engine

Example 1

Handwritten digit recognition



Images are 28 x 28 pixels

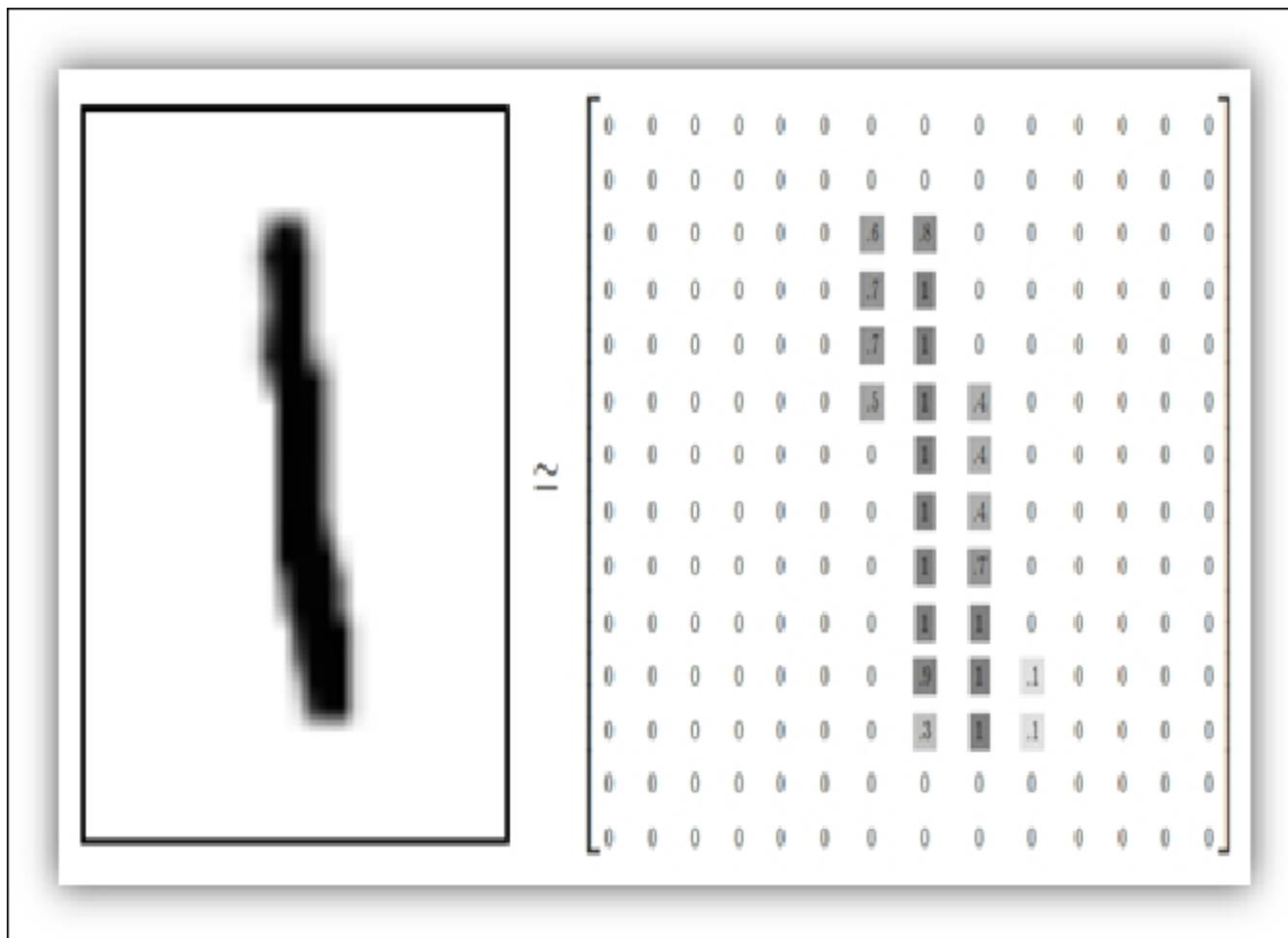
Represent input image as a vector $\mathbf{x} \in \mathbb{R}^{784}$

Learn a classifier $f(\mathbf{x})$ such that,

$$f : \mathbf{x} \rightarrow \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$$

MNIST dataset: Predict the digit
Multi-class classifier

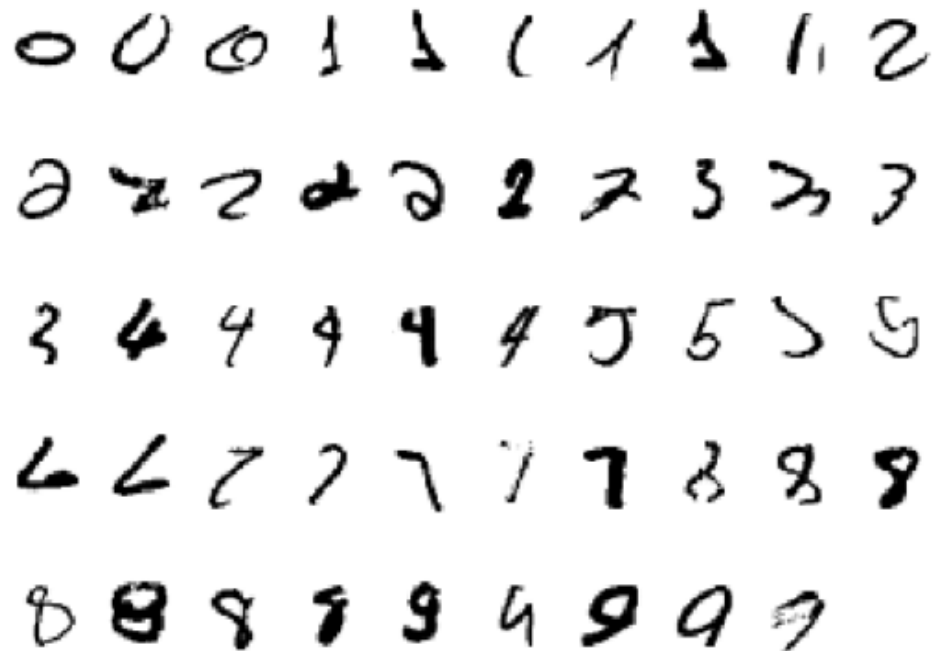
Data Representation



Model the problem

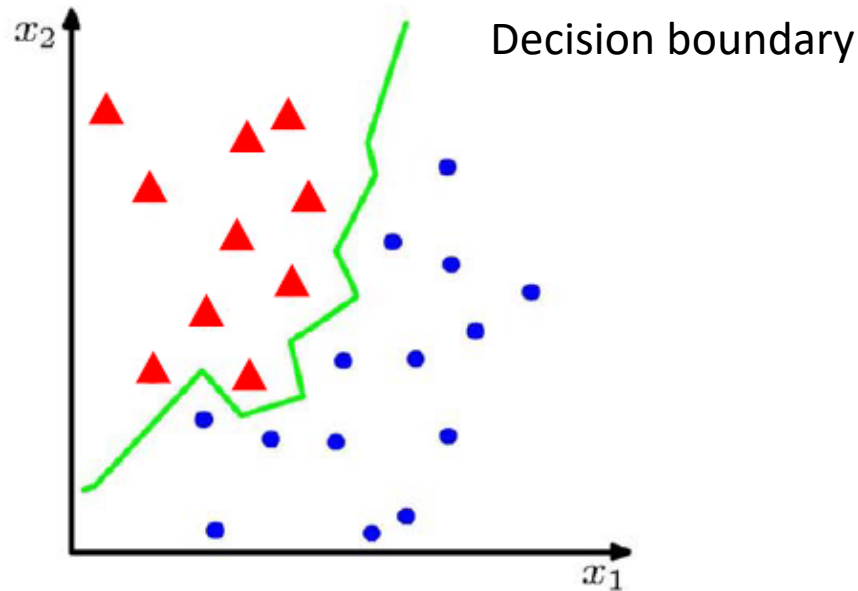
As a supervised classification problem

Start with training data, e.g. 6000 examples of each digit



- Can achieve testing error of 0.4%
- One of first commercial and widely used ML systems (for zip codes & checks)

Classification



- Suppose we are given a training set of N observations

(x_1, \dots, x_N) and (y_1, \dots, y_N) , $x_i \in \mathbb{R}^d$, $y_i \in \{0, 1\}$

- Classification problem is to estimate $f(x)$ from this data such that

$$f(x_i) = y_i$$

Extended to multi-class classification

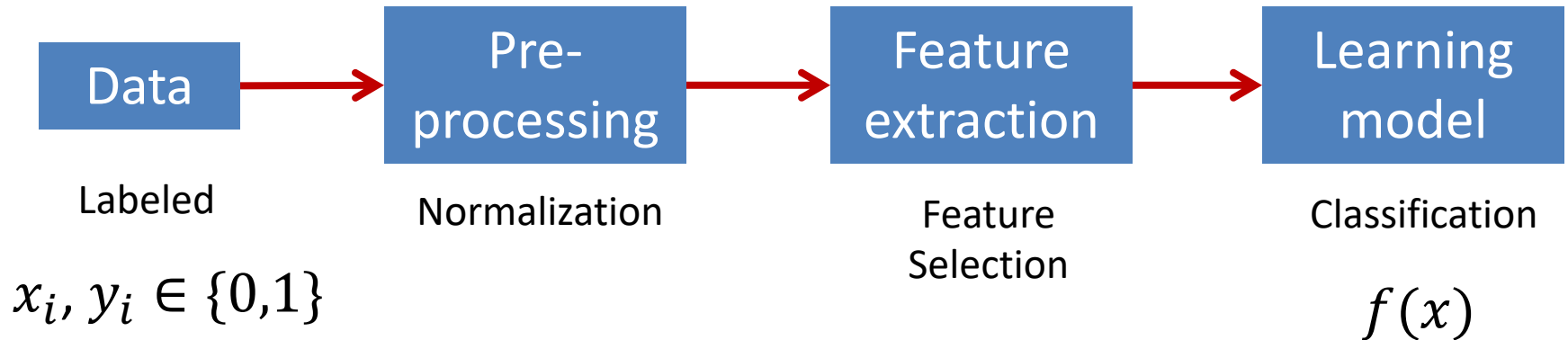
- Handwritten digit recognition: $y_i \in \{0, 1, \dots, 9\}$

Classification

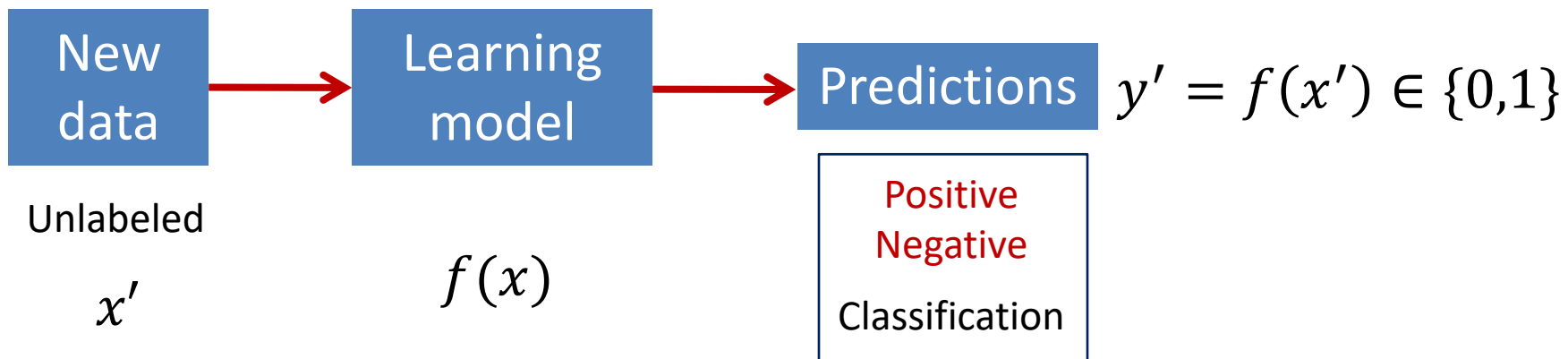
- **Training data**
 - $x_i = [x_{i,1}, \dots, x_{i,d}]$: vector of image pixels (features)
 - Size $d = 28 \times 28 = 784$
 - y_i : image label
- **Models (hypothesis)**
 - Example: Linear model (parametric model)
 - $f(x) = wx + b$
 - Classify 1 if $f(x) > T$; 0 otherwise
- **Classification algorithm**
 - Training: Learn model parameters w, b to minimize error (number of training examples for which model gives wrong label)
 - Output: “optimal” model
- **Testing**
 - Apply learned model to new data and generate prediction $f(x)$

Supervised Learning: Classification

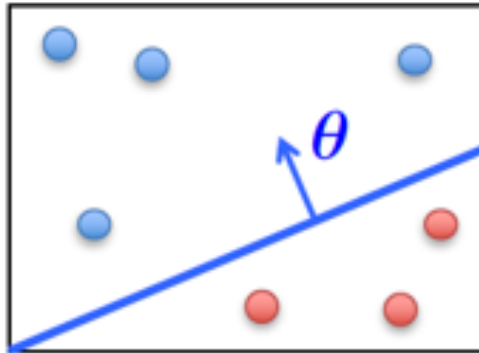
Training



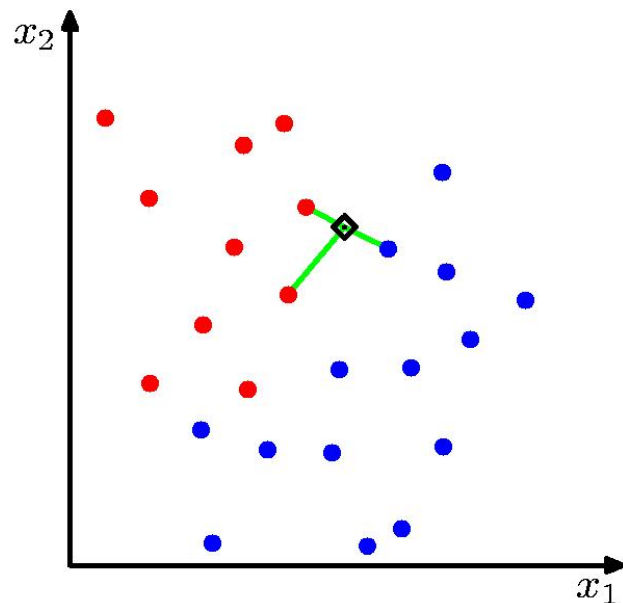
Testing



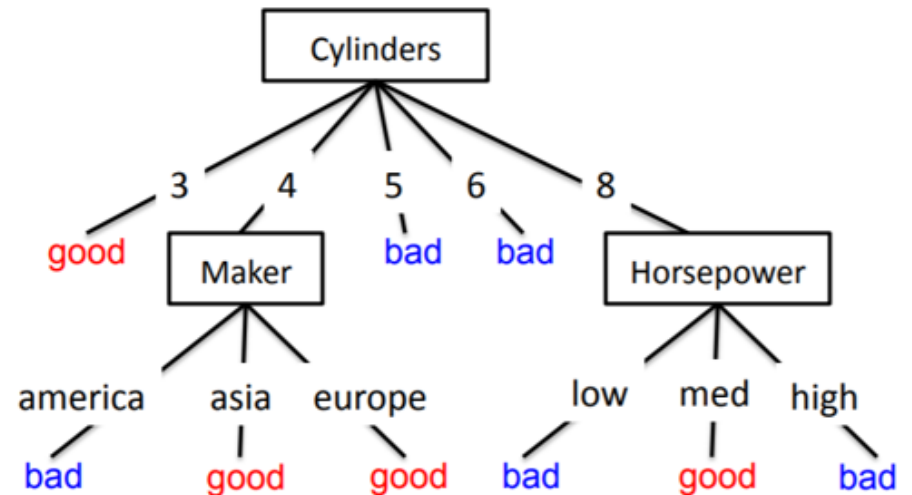
Example Classifiers



Linear classifiers: logistic regression, LDA (parametric)

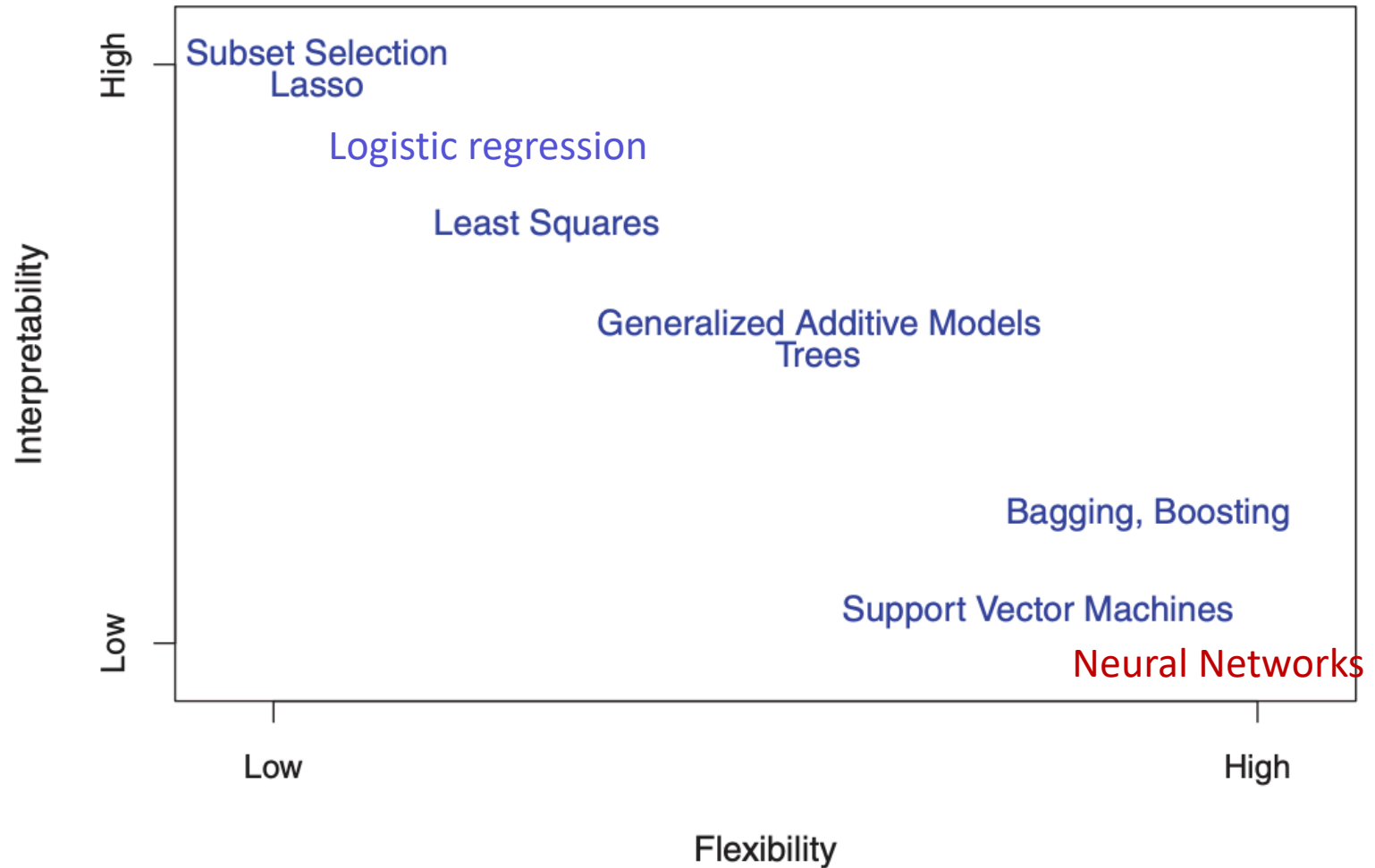


Nearest Neighbors: kNN (non-parametric)

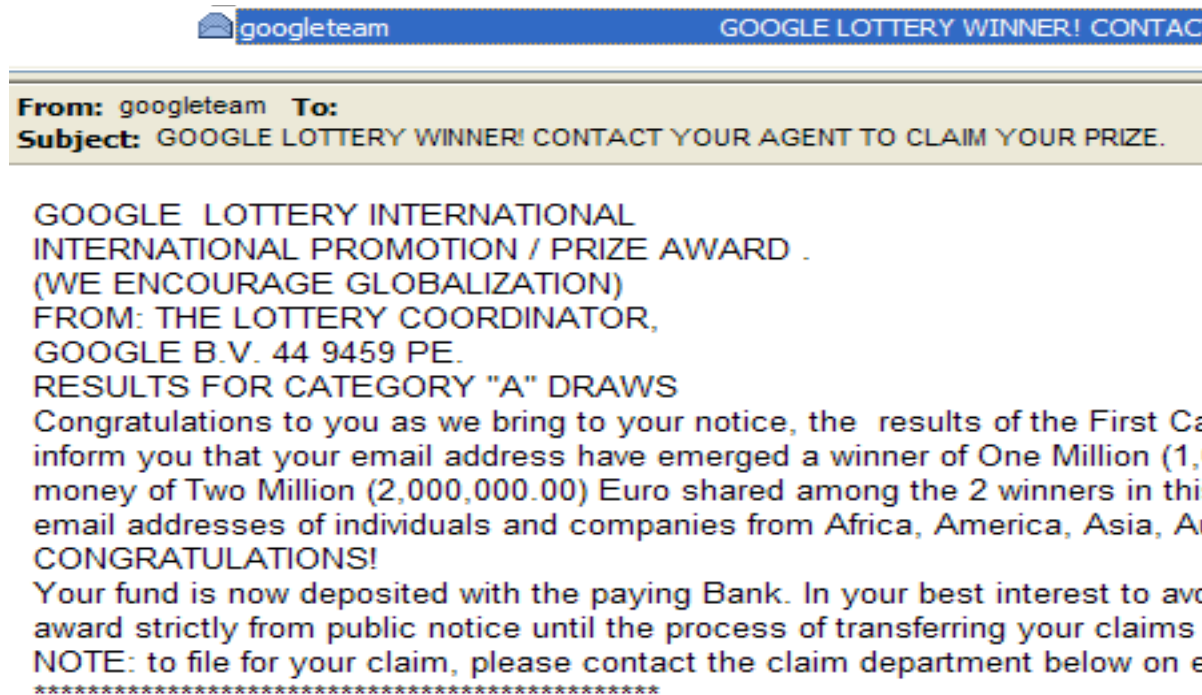


Decision trees
(non-parametric)

Interpretability



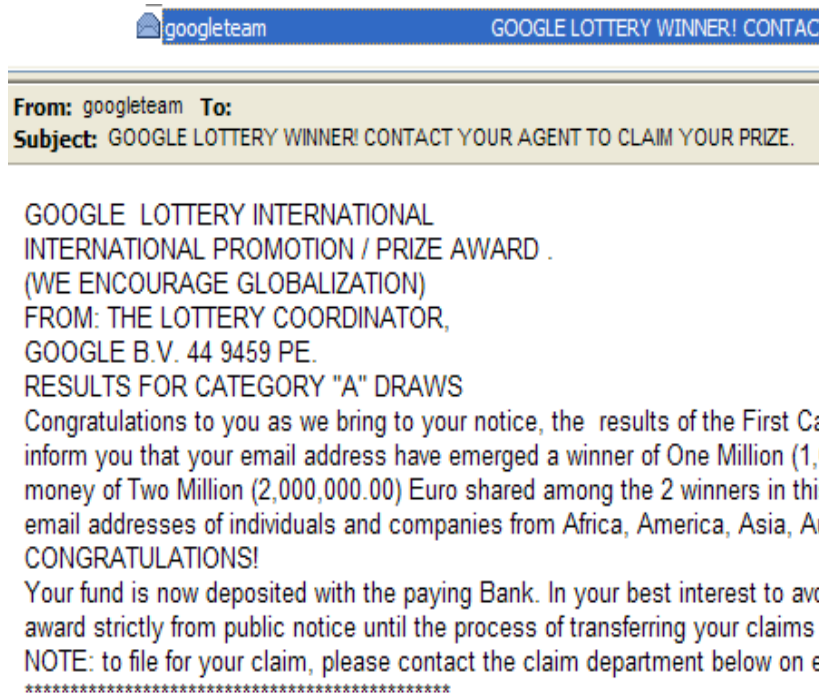
Real-world example: Spam email



SPAM email

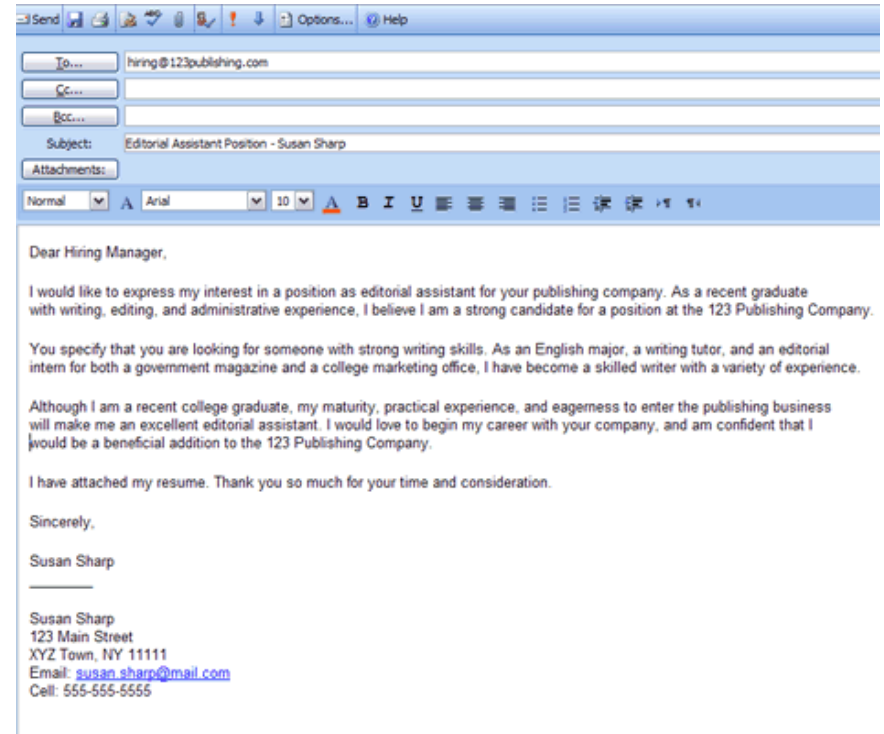
- Unsolicited
- Advertisement
- Sent to a large number of people

Classifying spam email



Content-related features

- Use of certain words
- Word frequencies
- Language
- Sentence



Structural features

- Sender IP address
- IP blacklist
- DNS information
- Email server
- URL links (non-matching)

SPAM

[illegible]

- SPAM
- REGULAR

Testing

- Content
- Structural

Numerical

- Logistic regression
- Decision tree
- SVM

New email

Model

SPAM

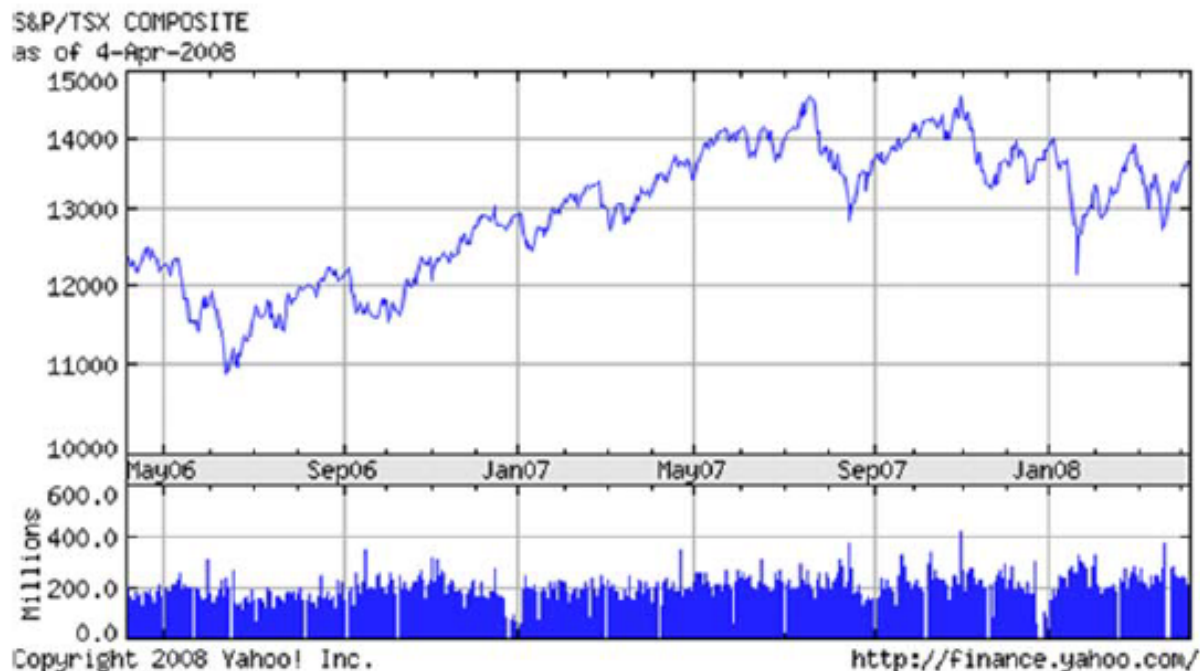
Filter

REGULAR

Allow

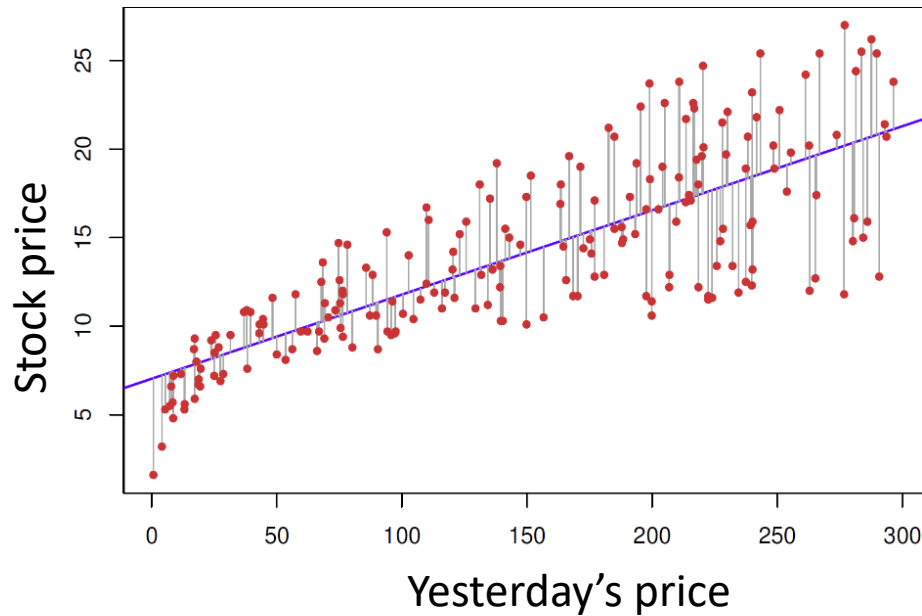
Example 2

Stock market prediction



- Task is to predict stock price at future date
- This is a regression task, as the output is continuous

Regression



Linear regression
1 dimension

- Suppose we are given a training set of N observations

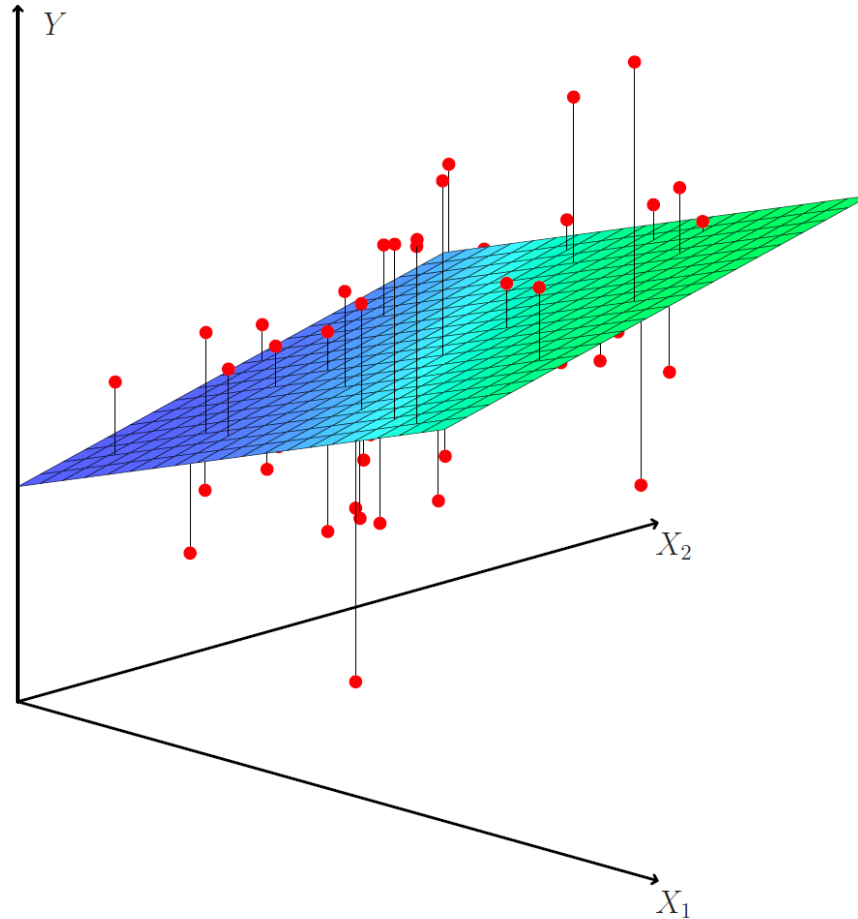
(x_1, \dots, x_N) and (y_1, \dots, y_N)

- Regression problem is to estimate $y(x)$ from this data

$x_i = (x_{i1}, \dots, x_{id})$ - d predictors (features)

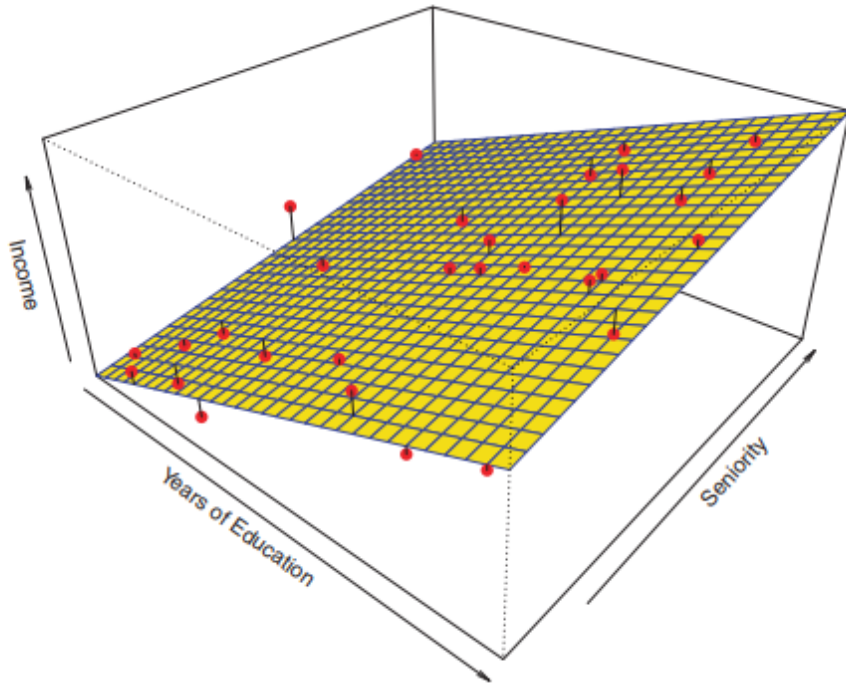
y_i - response variable, numerical

Multi-dimensional linear regression

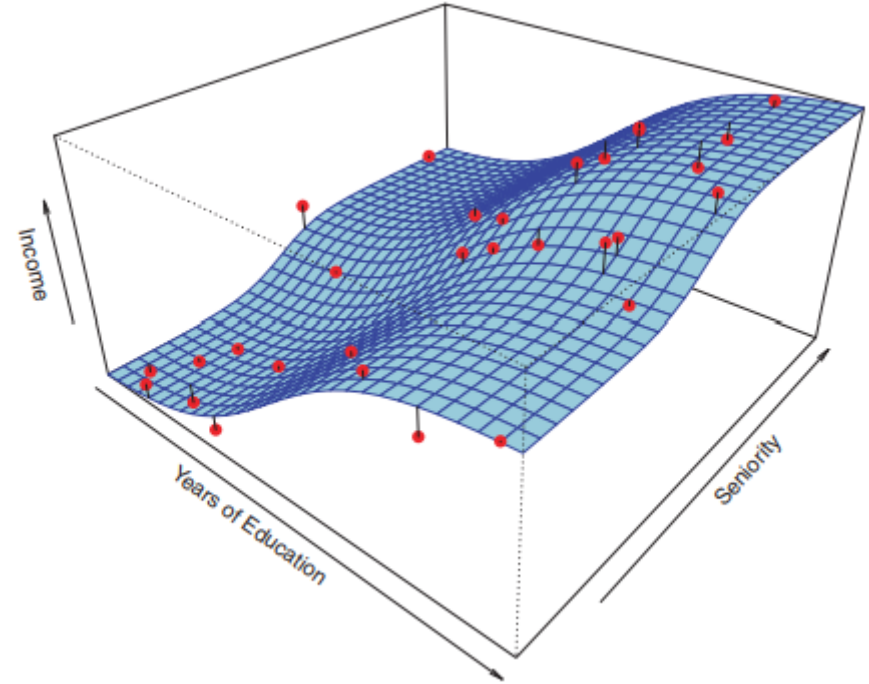


Minimize sum of square error
(error/loss function)

Income Prediction



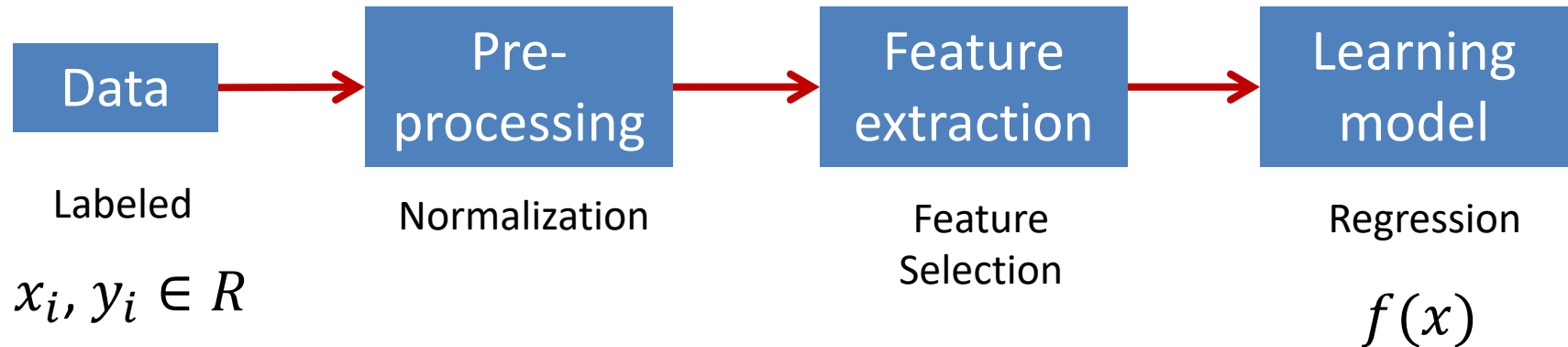
Linear Regression



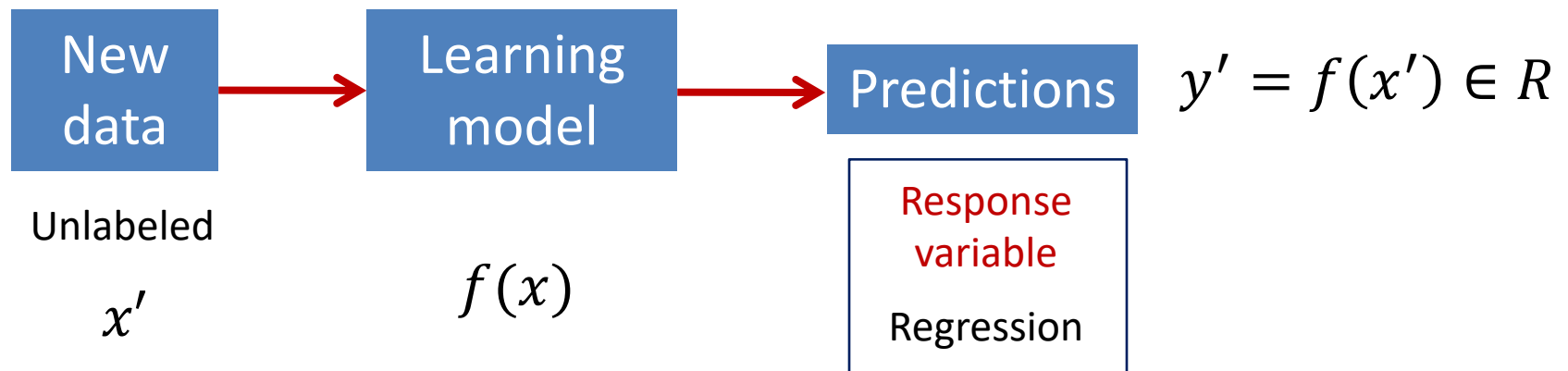
Non-Linear Regression
Polynomial/Spline Regression

Supervised Learning: Regression

Training

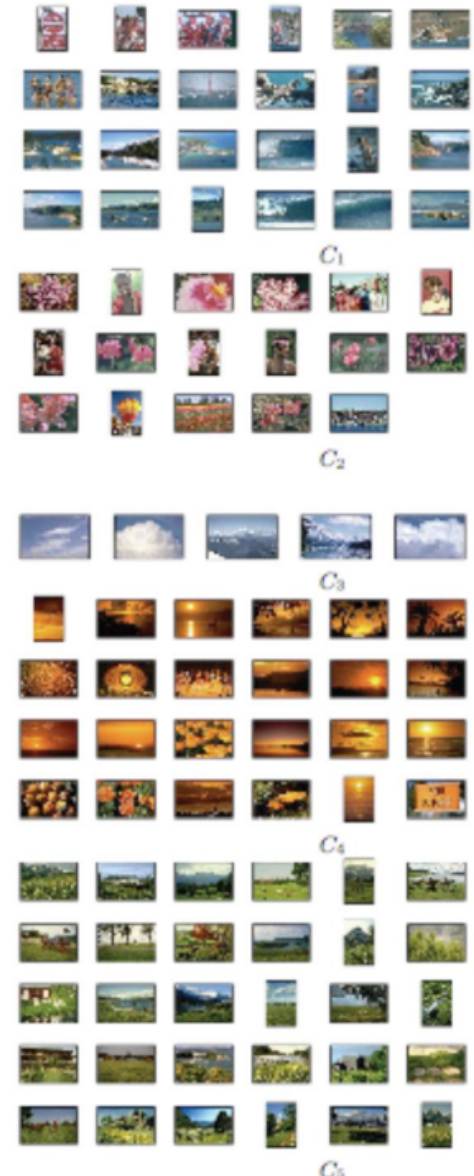
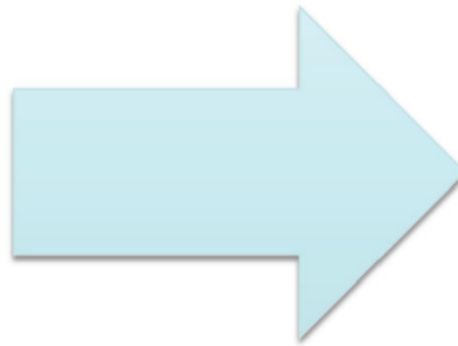
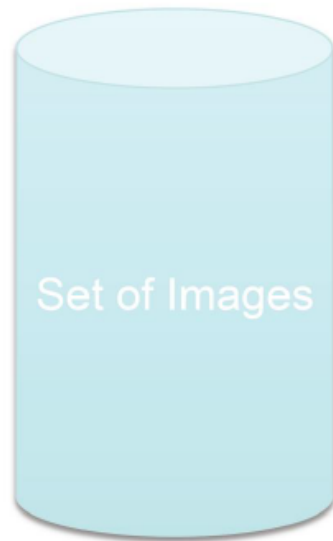


Testing



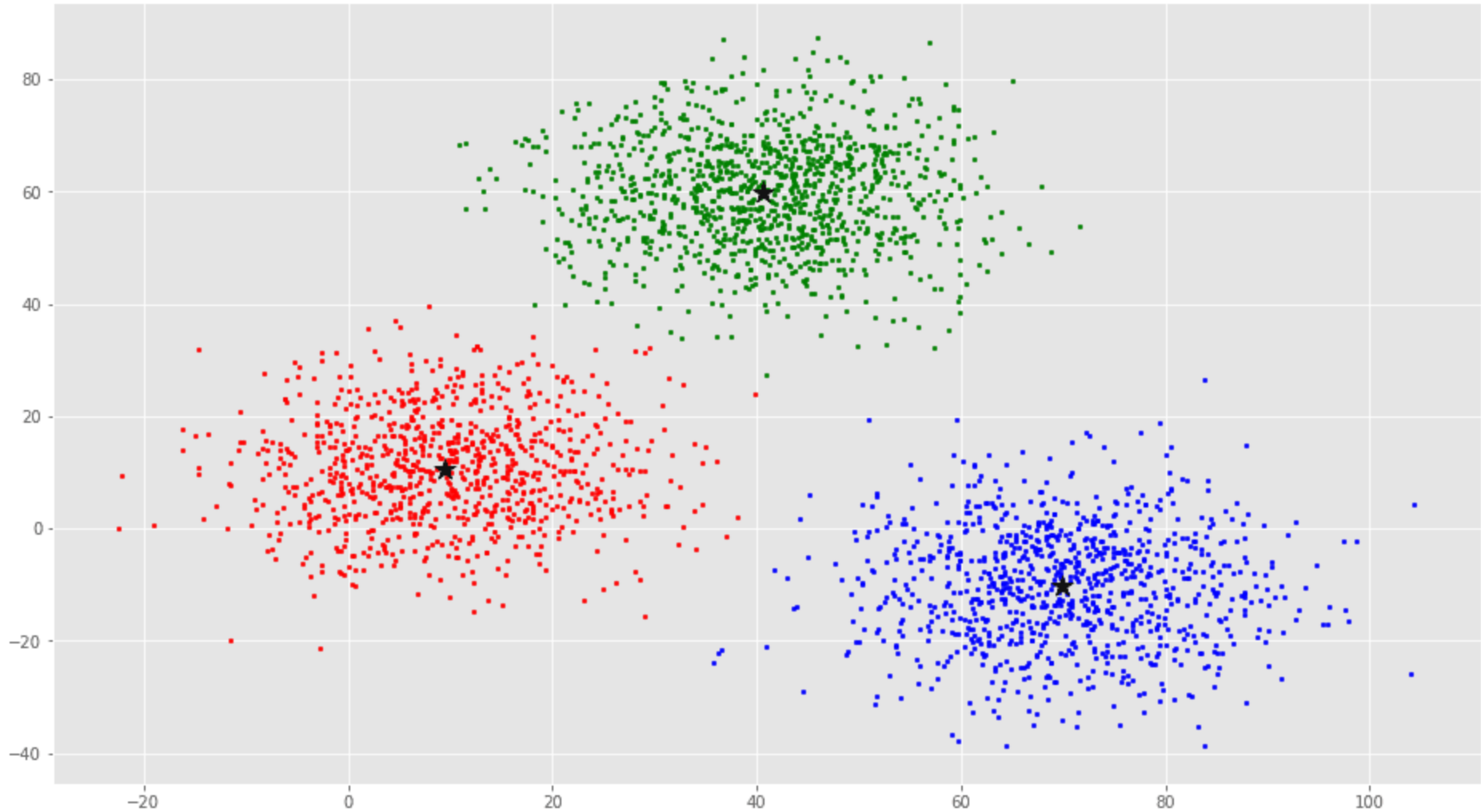
Example 3: image search

Clustering images



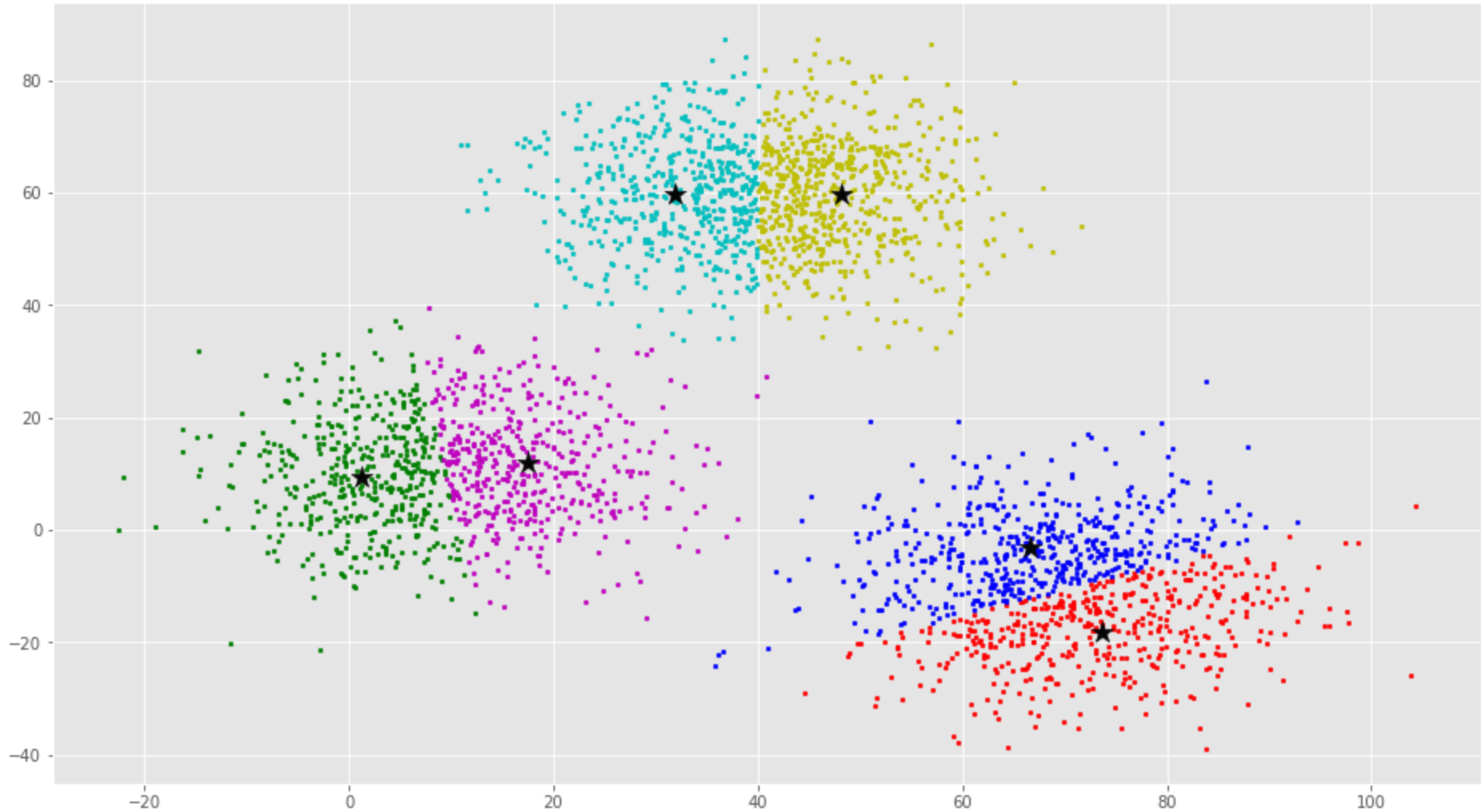
Find similar images to a target one

K-Means Clustering



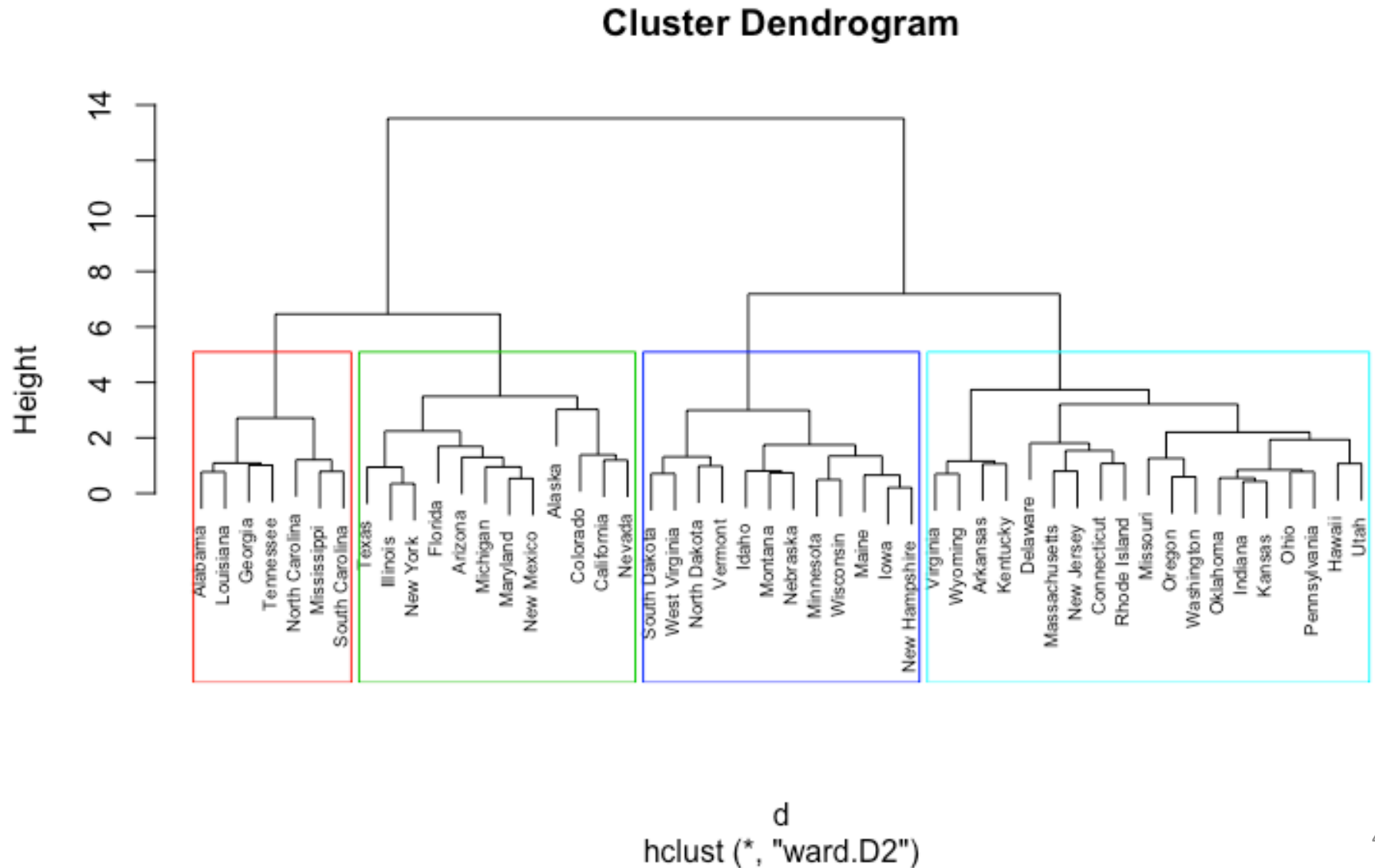
$K=3$

K-means Clustering



$K=6$

Hierarchical Clustering



Unsupervised Learning

- **Clustering**
 - Group similar data points into clusters
 - Example: k-means, hierarchical clustering
- **Dimensionality reduction**
 - Project the data to lower dimensional space
 - Example: PCA (Principal Component Analysis)
- **Feature learning**
 - Find feature representations
 - Example: Autoencoders

Supervised Learning Tasks

- Classification
 - Learn to predict class (discrete)
 - Minimize error $1/N \sum_{i=1}^N [y^{(i)} \neq f(x^{(i)})]$
- Regression
 - Learn to predict response variable (numerical)
 - Minimize MSE (Mean Square Error between prediction and actual values)
- Both classification and regression
 - Training and testing phase
 - “Optimal” model is learned in training and applied in testing