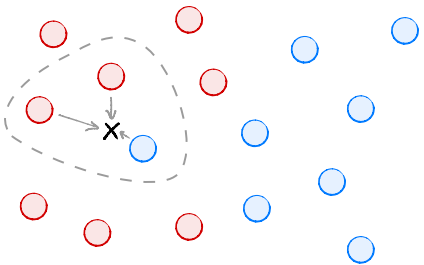


CSE 151A

Intro to Machine Learning

Lecture 02 – Part 01

What is Machine Learning?

Announcements

- First homework will be posted today (April 1).
- Due via Gradescope next Wednesday.
- Covers only today's lecture, basic probability.

What is Machine Learning?

- Computers can do things very quickly.

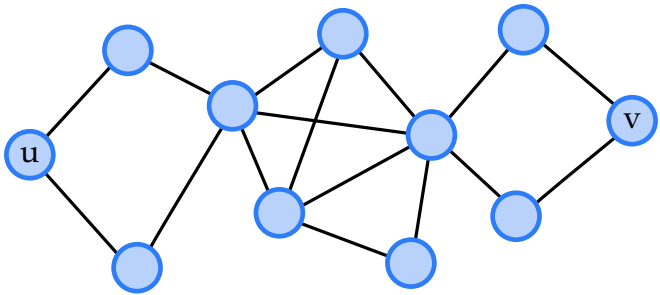
What is Machine Learning?

- Computers can do things very quickly.
- But must be given really specific instructions.

What is Machine Learning?

- Computers can do things very quickly.
- But must be given really specific instructions.
- **Problem**: Not all tasks are easy to dictate.

Example



What is the shortest path between *u* and *v*?

Example

How old is this person?

The Trick: Use Data

age = 28

age = 42

age = 63

age = 24

age = 37

age = 39

age = ?

age = 35

What is Machine Learning?

- Before: Computer is **told** how to do a task.
- Instead: **learn** how to do a task using data.

What is Machine Learning?

- Before: Computer is **told** how to do a task.
- Instead: **learn** how to do a task using data.
- We still have to **tell** the computer how to learn.

A **machine learning algorithm** is a set of precise instructions telling the computer how to learn from data.

A **machine learning algorithm** is a set of precise instructions telling the computer how to learn from data.

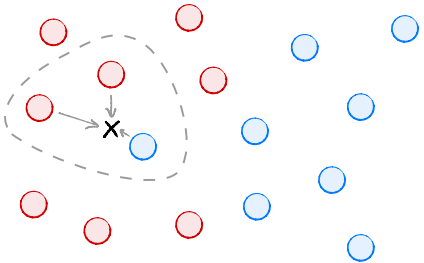
Spoiler: the algorithms are usually pretty simple. It's the **data** that does the real work.

Machine Learning Tasks

- Prediction
- Clustering
- Representation Learning
- Reinforcement Learning
- Anomaly Detection
- ...

Machine Learning Tasks

- **Prediction**
- Clustering
- Representation Learning
- Reinforcement Learning
- Anomaly Detection
- ...



CSE 151A

Intro to Machine Learning

Lecture 02 – Part 02

Prediction

Prediction

How old is this person?

Prediction

- **Given**: a 1024 × 1024 RGB image of a face.
- **Predict**: the age of the person.

Prediction Functions

- **Input Space**, $\mathcal{X}$ = set of all possible 1024 × 1024 images
- **Output Space**, $\mathcal{Y} = \mathbb{R}$
- We want a **prediction function**, $f : \mathcal{X} \to \mathcal{Y}$ which makes **accurate predictions**.

Regression

- **Regression**: when $\mathcal{Y} = \mathbb{R}$
- Example: Predict tomorrow's air quality index.
- Example: Predict someone's life expectancy.

Regression

- **Regression**: when $\mathcal{Y} = \mathbb{R}$
- Example: Predict tomorrow's air quality index.
- Example: Predict someone's life expectancy.
- What are suitable inputs ($\mathcal{X}$) in each case?

Classification

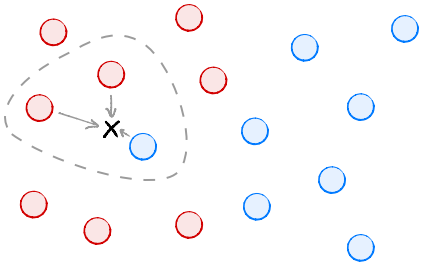
- **Classification**: when $\mathcal{Y}$ is a discrete set.
- **Binary classification**: $|\mathcal{Y}| = 2$
  - Example: Is this picture of a hot dog?
    $\mathcal{Y}$ = {Yes, No}.
- **Multiclass classification**: $|\mathcal{Y}| > 2$
  - Example: What food is in this picture?
    $\mathcal{Y}$ = {hot dog, pizza, sushi, ...}

Probability Estimation

- **Probability Estimation**: when $\mathcal{Y} = [0, 1]$
  - interpret output as a probability
- **Example**: credit card transaction.
- **Given**: details of transaction.
- **Predict**: prob. that the transaction is fraudulent.

Up next...

A simple learning algorithm for prediction.



CSE 151A

Intro to Machine Learning

Lecture 02 – Part 03

Nearest Neighbors

Example: NBA

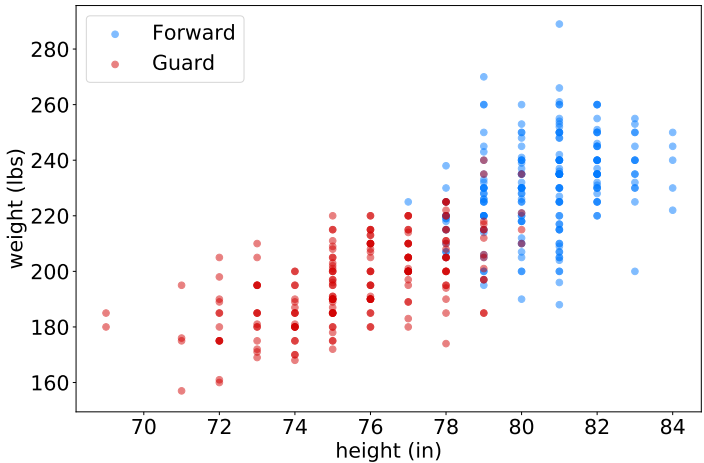
Guards → Forwards → Centers

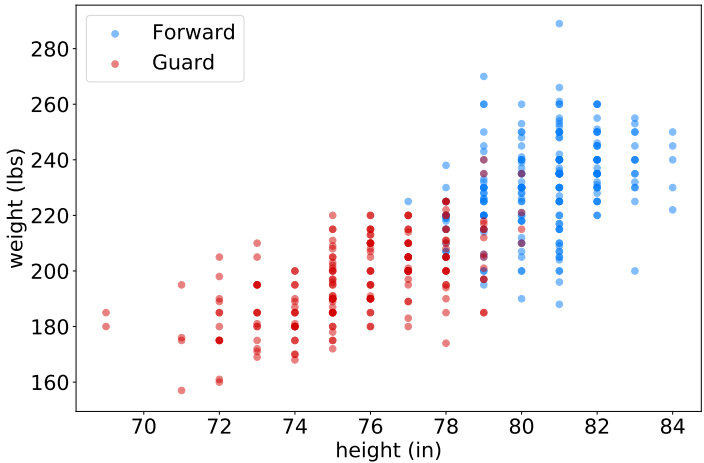
- **Given** a new player's height and weight.
- **Classify** them as a guard, forward, or center.


23
30

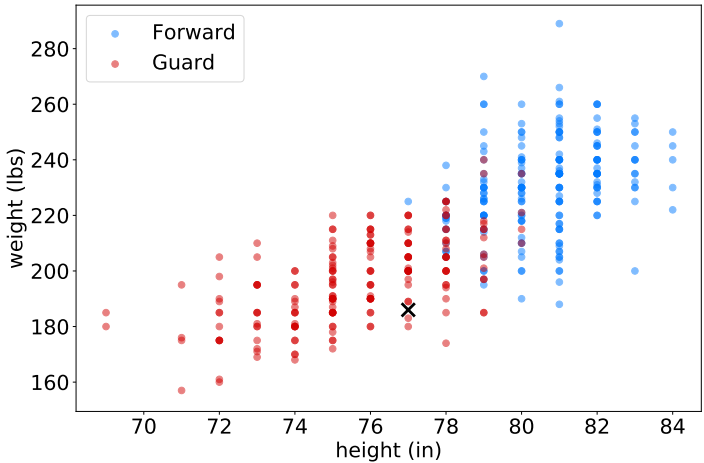
↑
forward

↑
guard

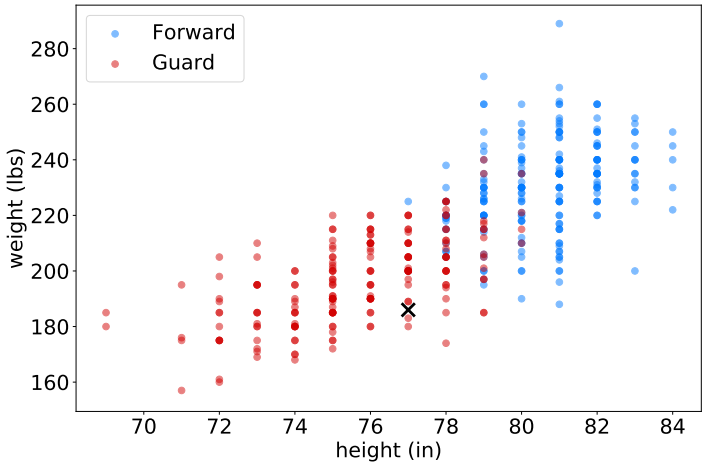

Forward
Guard
weight (lbs)
height (in)
160
180
200
220
240
260
280
70
72
74
76
78
80
82
84



A new player is 77 inches tall and 186 pounds.
What position do they play?

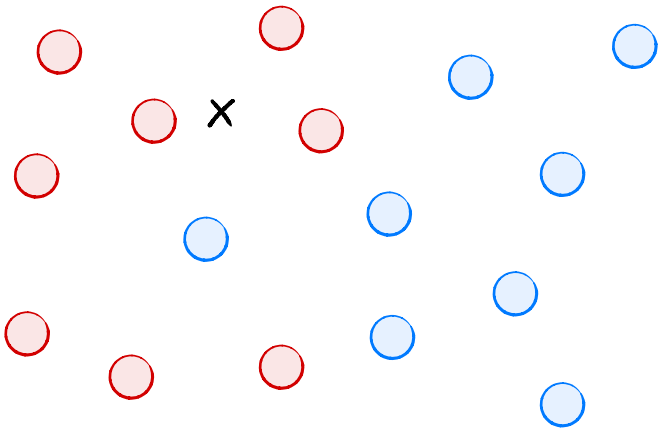


A new player is 75 inches tall and 240 pounds.
What position do they play?

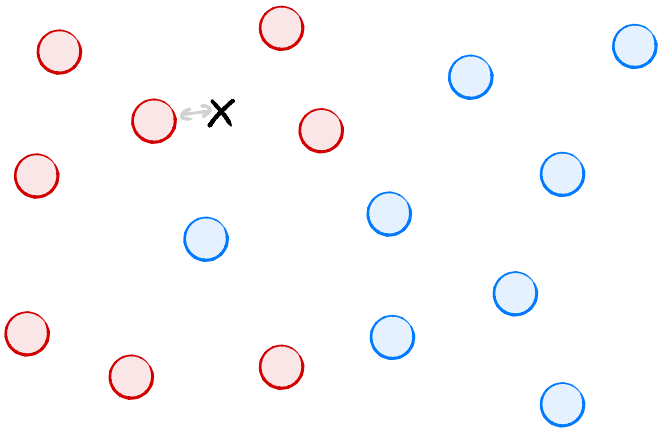


A new player is 75 inches tall and 240 pounds.
What position do they play? **Guard**.

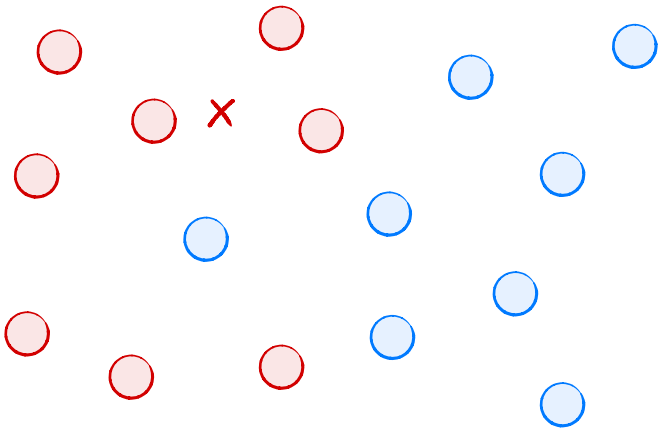
Nearest Neighbor Classification



Nearest Neighbor Classification

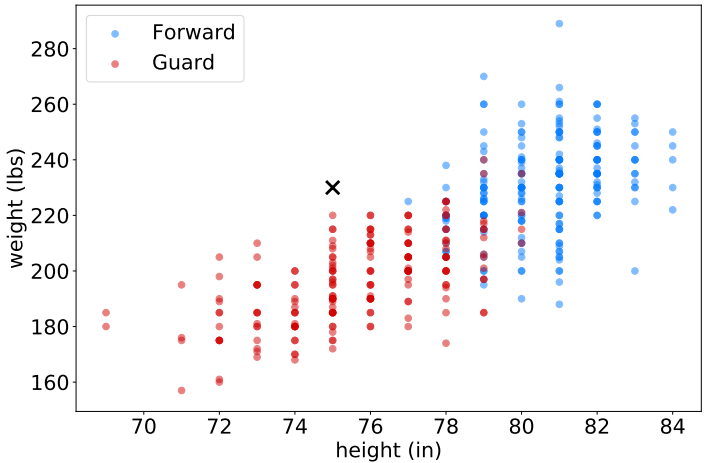


Nearest Neighbor Classification

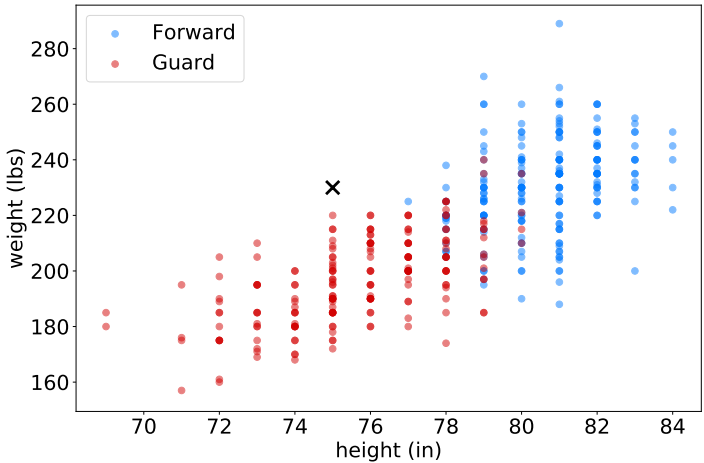


Nearest Neighbor Classification

- **Given**: an input data point.
- **Output**: the class label of the **nearest** point in data set.

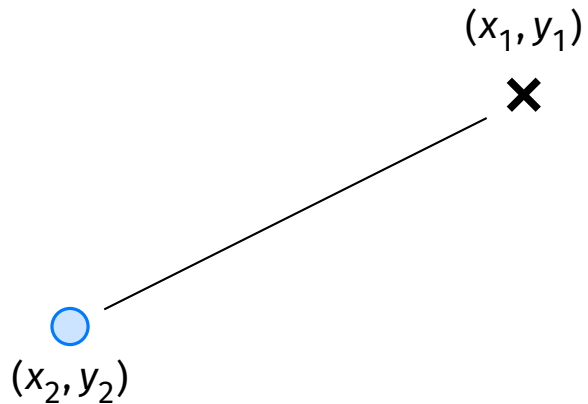


A new player is 75 inches tall and 230 pounds.
What position do they play?

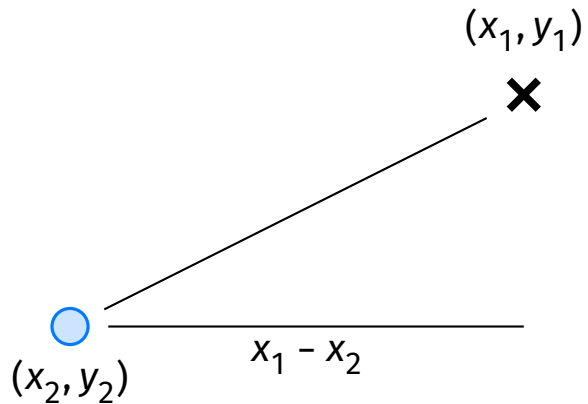


A new player is 75 inches tall and 230 pounds.
What position do they play? **Forward**.

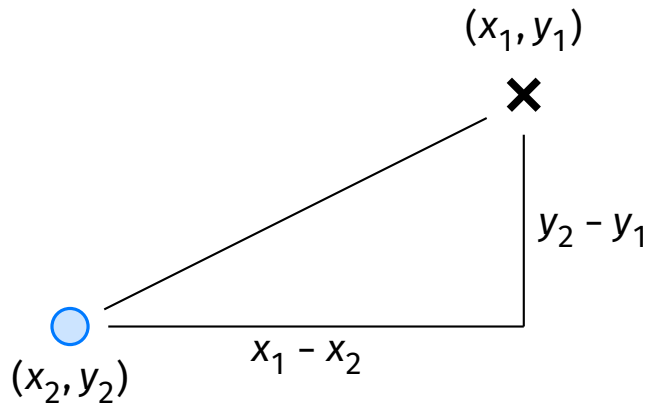
The (Euclidean) Distance



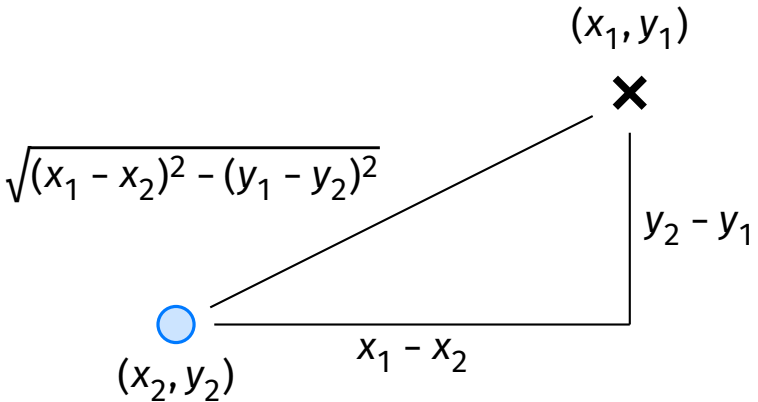
The (Euclidean) Distance

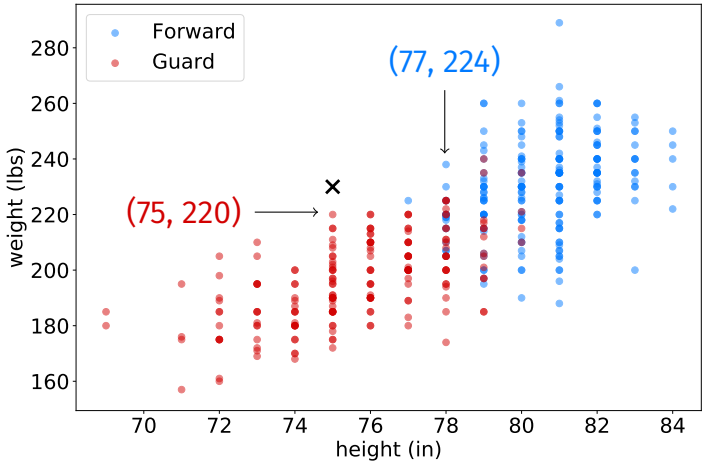


The (Euclidean) Distance

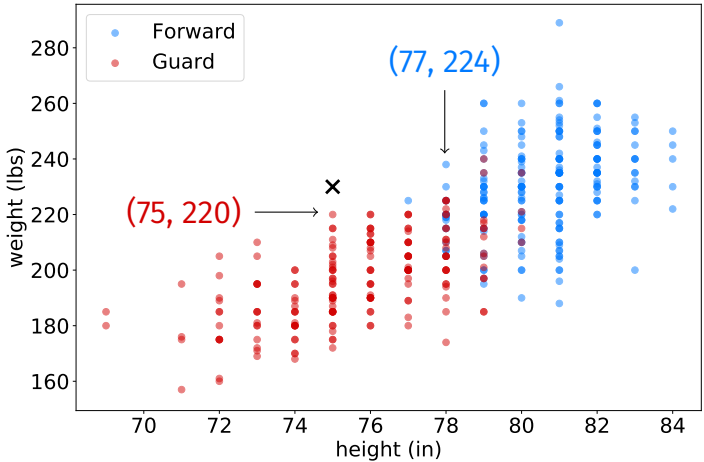


The (Euclidean) Distance





A new player is 75 inches tall and 230 pounds.
What position do they play?



A new player is 75 inches tall and 230 pounds.
What position do they play? **Forward**.

Calculating Distance

- Remember, the input: $(75, 230)$.
- Distance between $(75, 230)$ and $(75, 220)$:

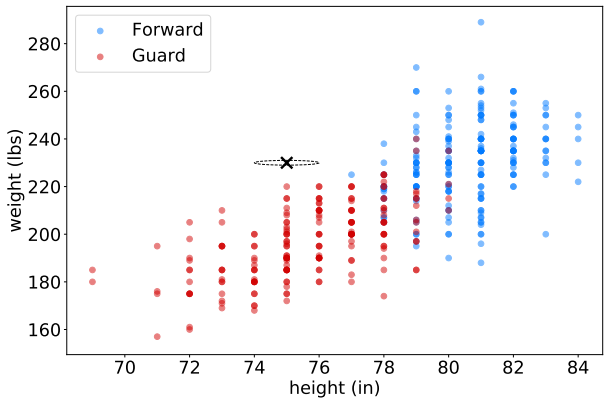
$$\sqrt{(75 - 75)^2 - (230 - 220)^2} = \sqrt{0 - 10^2} = 10$$

- Distance between $(75, 230)$ and $(77, 224)$:

$$\sqrt{(75 - 77)^2 - (230 - 224)^2} = \sqrt{2^2 + 6^2} = \sqrt{40} \approx \mathbf{6.3}$$

Scale Matters!

- Height and weight are on **different** scales.



Scale Matters!

- Height and weight are on **different** scales.
- **Solution**: put them on the same scale.
- **Question:** How might you do this?

Standard Units

- To standardize a height, h:

$$\frac{h - (\text{mean height})}{(\text{STD of heights})}$$

- To standardize a weight, w:

$$\frac{w - (\text{mean weight})}{(\text{STD of weights})}$$

Example

- What is $(75, 230)$ in standard units?
- Standardize the height and weight separately.

Example

- What is 75 inches in standard units?
- Heights: mean = 79.1, STD = 3.45

$$\frac{75 - 79.1}{4.35} \approx -1.18$$

Example

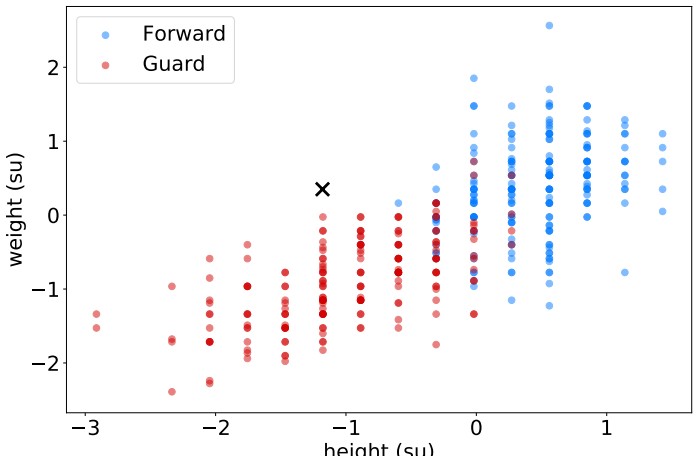
- What is 230 pounds in standard units?
- Weights: mean = 220.7, STD = 26.6

$$\frac{230 - 220.7}{26.6} \approx 0.35$$

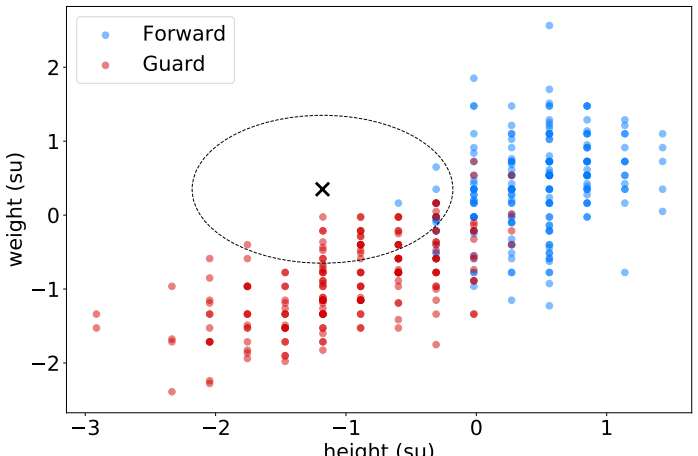
Example

- What is $(75, 230)$ in standard units?
- Answer: $(-1.18, 0.35)$

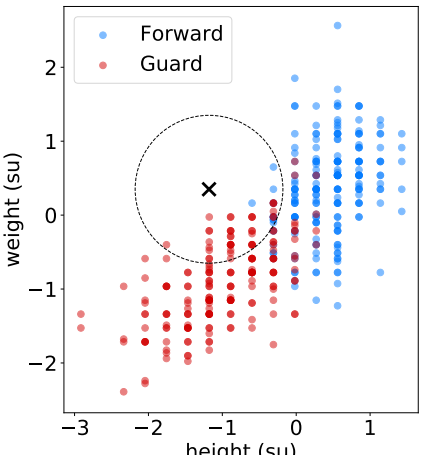
Standard Units



Standard Units



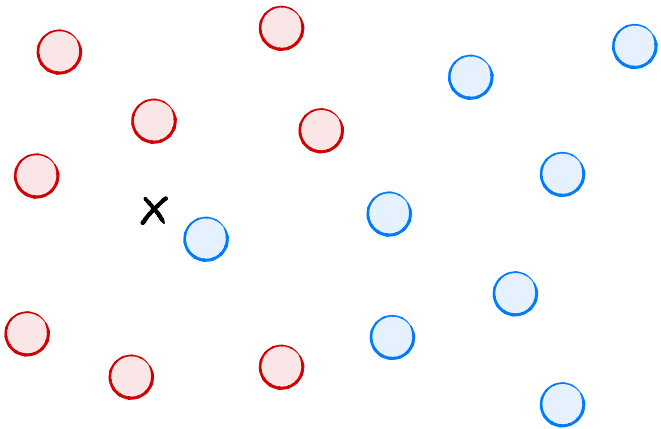
Standard Units



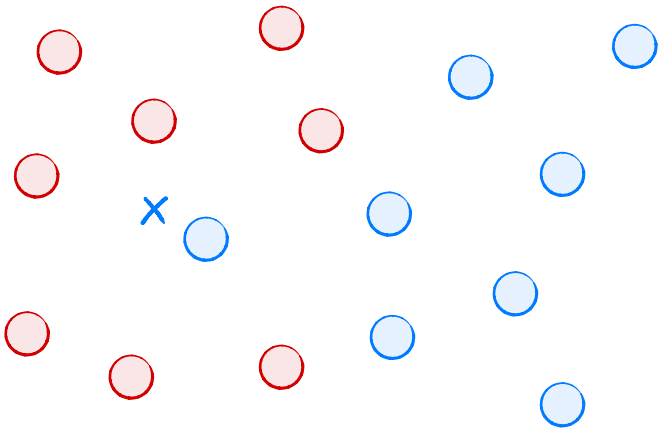
Summary: Nearest Neighbor

- Nearest neighbor is very simple.
- Given a new input, predict the class of closest point in data set.
- Often makes sense to **standardize** data first.
- But nearest neighbor has a problem...

Nearest Neighbor Classification



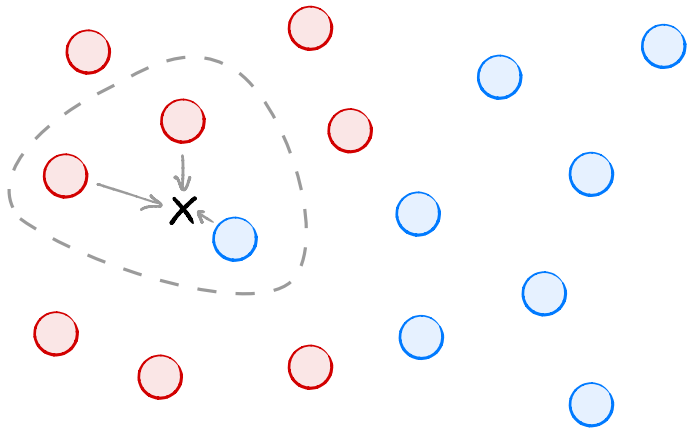
Nearest Neighbor Classification



k-Nearest Neighbors

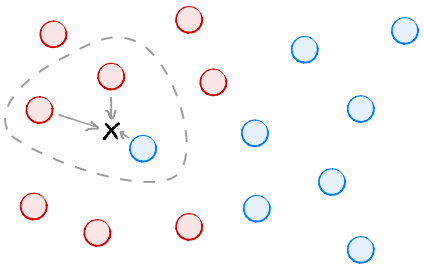
- Nearest neighbor is sensitive.
- Solution: have the nearest few neighbors “vote”.
- **Given**: an input data point, parameter k.
- **Output**: the most common class label of the k nearest points in data set.

Nearest Neighbor Classification



Up next...

- k-NN is a very simple algorithm.
- But often works well in spite of its simplicity...



CSE 151A

Intro to Machine Learning

Lecture 02 – Part 04

Application: Classifying Handwritten Digits

The Problem

- **Given** an image of a handwritten digit.
- **Classify** the image as a one, two, three, etc.

The Machine Learning Approach

- Gather a **training set** of images with **labels**.
- Let the computer **learn** the underlying patterns.
- We'll use a freely available data set, **MNIST**:

MNIST

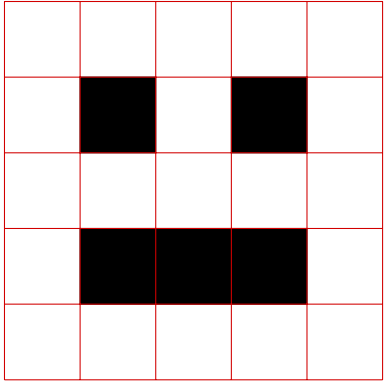
- 60,000 training images and associated labels.
- Each image is 28 × 28 pixels.
- Each pixel is 8 bit grayscale (0 - 255)

kNN on MNIST

- We'll use kNN to do **character recognition**.
  - $\mathcal{X}$ = set of 28 × 28, 8-bit grayscale images
  - $\mathcal{Y} = \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$.

- How do we treat an image as a point in space?

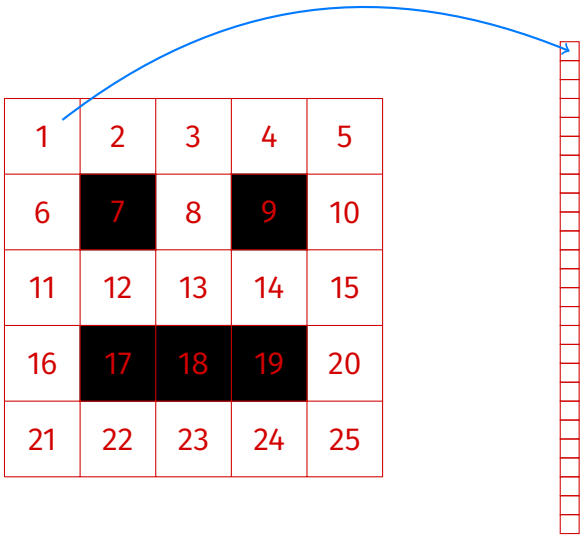
Images as Points in Space



Images as Points in Space

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20
21	22	23	24	25

Images as Points in Space



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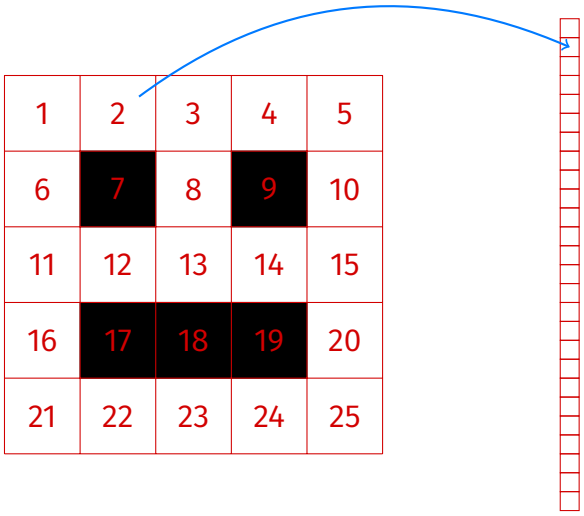

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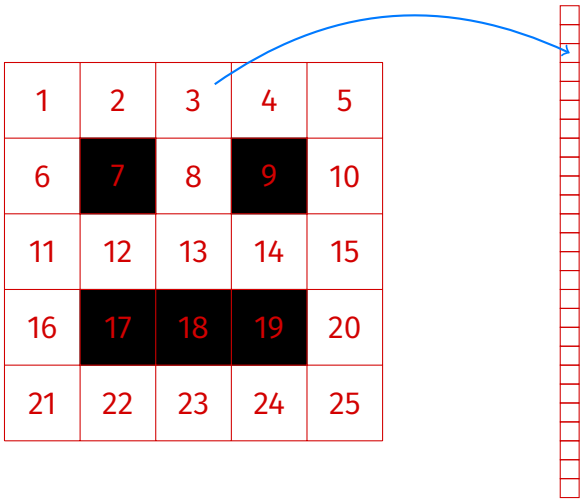

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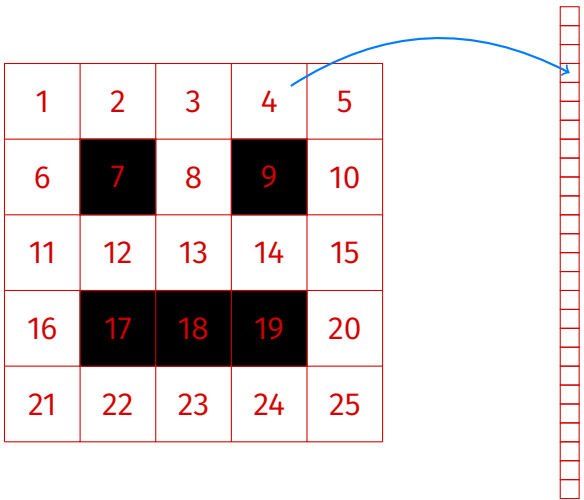

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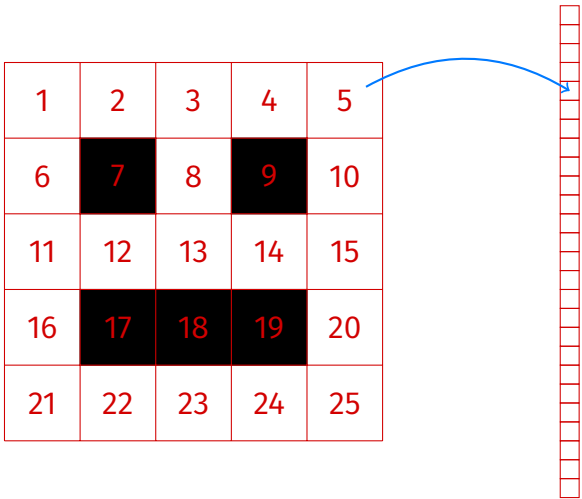

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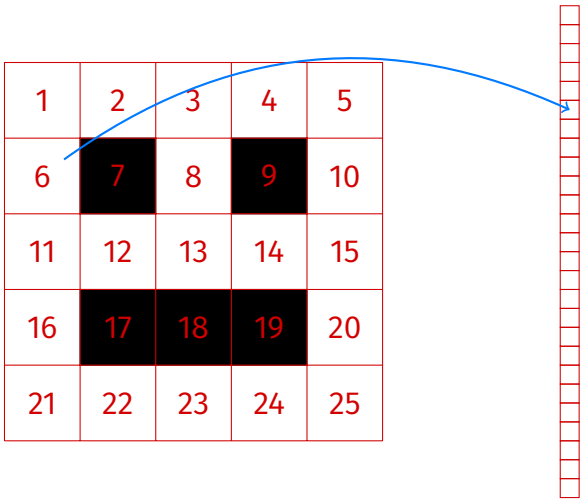
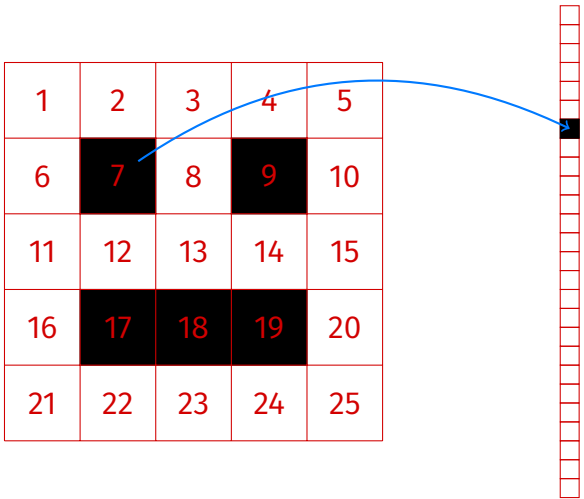
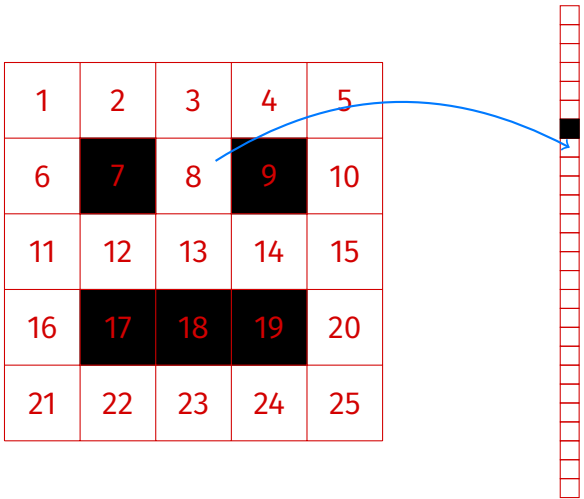


Images as Points in Space



Images as Points in Space



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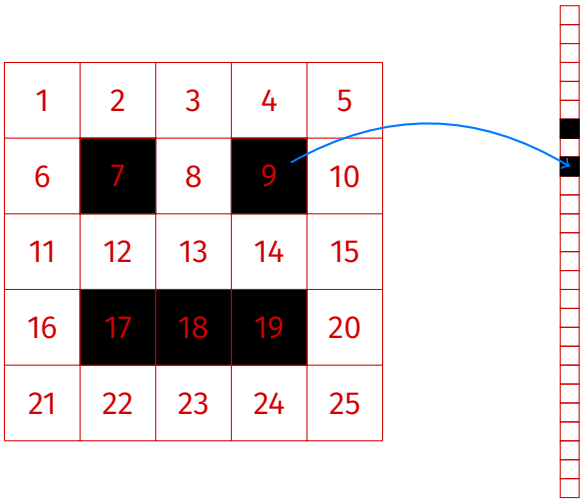

Images as Points in Space

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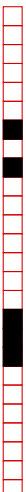
21	22	23	24	25



Euclidean Distance Between Images

- We “unroll” a 28×28 image into a vector in $\mathbb{R}^{784}$.
- Euclidean distance between two images $\vec{p}^{(1)}$, $\vec{p}^{(2)}$ in $\mathbb{R}^{784}$:

$$\|\vec{p}^{(1)} - \vec{p}^{(2)}\| = \sqrt{\left(p_1^{(1)} - p_1^{(2)}\right)^2 + \left(p_2^{(1)} - p_2^{(2)}\right)^2 + \ldots + \left(p_{784}^{(1)} - p_{784}^{(2)}\right)^2}$$

$$= \sqrt{\sum_{i=1}^{784} \left(p_i^{(1)} - p_i^{(2)}\right)^2}$$

How well does it work?

- Does this make accurate predictions?
- Use 1-NN to classify each image in **training set**.
- **Question**: What will be the accuracy?

$$\text{error} = \frac{\#\ \textbf{incorrect}\ \text{predictions}}{60{,}000}$$

How well does it work?

- The error will be 0!
- Accuracy on training set is **misleading**, overly-optimistic.
- MNIST also includes a **test set** of 10,000 images and labels. Let's test on this set.

The Test Error

- Test set contains 1,000 images from each digit.
- Suppose our classifier always guesses 7.
  Question: what will be the test error?

The Test Error

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- Suppose our classifier always guesses 7.
  Question: what will be the test error?
- **Answer**: 90%.

The Test Error

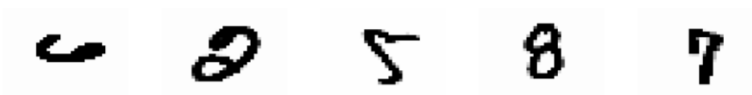
- Test set contains 1,000 images from each digit.
- Suppose our classifier guesses at random.
  Question: what is the expected test error?

The Test Error

- Test set contains 1,000 images from each digit.
- Suppose our classifier guesses at random.
  Question: what is the expected test error?
- **Answer**: 90%.

The Test Error

- The test error of nearest neighbor is only 3.09%.
- Examples of errors:

Input: 

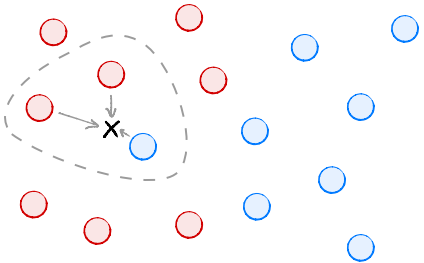
NN: 

Does k-NN do better?

k	1	3	5	7	9	11
Test Error (%):	3.09	2.94	3.13	3.10	3.43	3.34

Up next...

So what's the downside of k-NN?



CSE 151A

Intro to Machine Learning

Lecture 02 – Part 05

Practical Issues

What's right with k-NN?

- k-NN is easy to implement and understand.
- It often works quite well.
- A lot of theory.

What's wrong with k-NN?

- **Memorization**: have to store the whole data set.
- **Slow**: to classify new point, must calculate distance to every data point. Time $\Theta(dn)$.
- **Curse of Dimensionality**: distances are less meaningful in high dimensions.

Practical Improvement #1: Better Data Structures

- Can speed up the NN search by using k-d trees, ball trees, locality sensitive hashing.
- **Problem**: these offer no speed up when d is large.

Practical Improvement #2: Dimensionality Reduction

- Maybe dimensionality can be reduced without losing much info.
  - Example: “background” pixels in MNIST images.
- Use PCA, spectral embeddings, etc.

Practical Improvement #3: Approximate Nearest Neighbor

- We don’t need to find the NNs *exactly*.
- Removes need to search all points.

Next time...

Generative models.