

PYTHON WORKSHOP

- Session 1: environment setup, Monday, 8/28 5-6pm, E208
- Session 2: basic Python, Friday 9/1, 5-6:30pm
- (tentative) Session 3: Python ML workflow, Wednesday 9/20, 5:30-6:30pm
- (tentative) Session 4: beyond linear modeling, Monday 9/25, 5-6:30pm



PYTHON IN DATA SCIENCE WORKSHOP

Session 1: Data Science
Environment Setup with
Anaconda

Purpose: This workshop is intended to refresh/update Python skills, which will NOT be covered in class or during office hours.

Who: Students in CS 534, CS 334, CS 325. All 300-500 level students are welcome.



MSC E208



**Monday, August
28th 2023
5:00 - 6:00 PM**

No registration needed!

Bring your laptop!



COURSE OUTLINE

- Algorithms for **supervised learning**: nearest neighbors, decision trees, linear regression, logistic regression, neural networks, naïve bayes, ensembles, boosting, **deep learning**
- Algorithms for **unsupervised learning**: principal component analysis
- **Model assessment and model selection**
- **New learning paradigms and emerging topics**

K-NEAREST NEIGHBORS

CS 334: Machine Learning



BREAKOUT ACTIVITY



NETFLIX PRIZE (2006-2009)

\$1M prize for 10% improvement

NETFLIX DATASET

	Star Wars I:The Phantom Menace	Star Wars IV: A New Hope	Star Wars VII: The Force Awakens	Raiders of the Lost Arc	Casablanca	Singing in the Rain
Sam	3	4	3	4	1	2
Alice	4	5	5	4	2	1
Bob	1	2	3	2	5	3
Matt	2	3	3	1	4	4
Joyce	5	5	5	?	?	2

What are Joyce's missing ratings and why?

NETFLIX DATASET

		Star Wars I:The Phantom Menace	Star Wars IV: A New Hope	Star Wars VII: The Force Awakens	Raiders of the Lost Arc	Casablanca	Singing in the Rain
Most similar	Sam	3	4	3	4	1	2
	Alice	4	5	5	4	2	1
	Bob	1	2	3	2	5	3
	Matt	2	3	3	1	4	4
	Joyce	5	5	5	?	?	2

What are Joyce's missing ratings and why?

EXAMPLE: IMAGE RECOGNITION



Distance Metric $\left| \begin{array}{c} \text{query cat} \\ \text{training cat} \end{array} \right| \rightarrow \mathbb{R}$

Nearest Neighbor (NN) Classifier

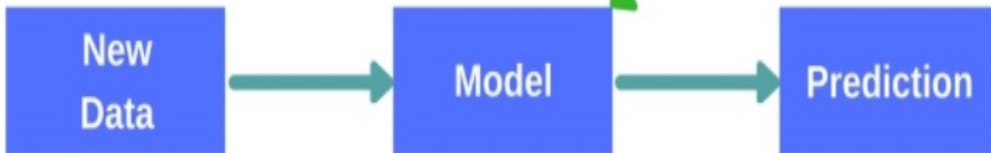
Learning phase



```
def train(images, labels):  
    # Machine learning!  
    return model
```

Memorize all
data and labels

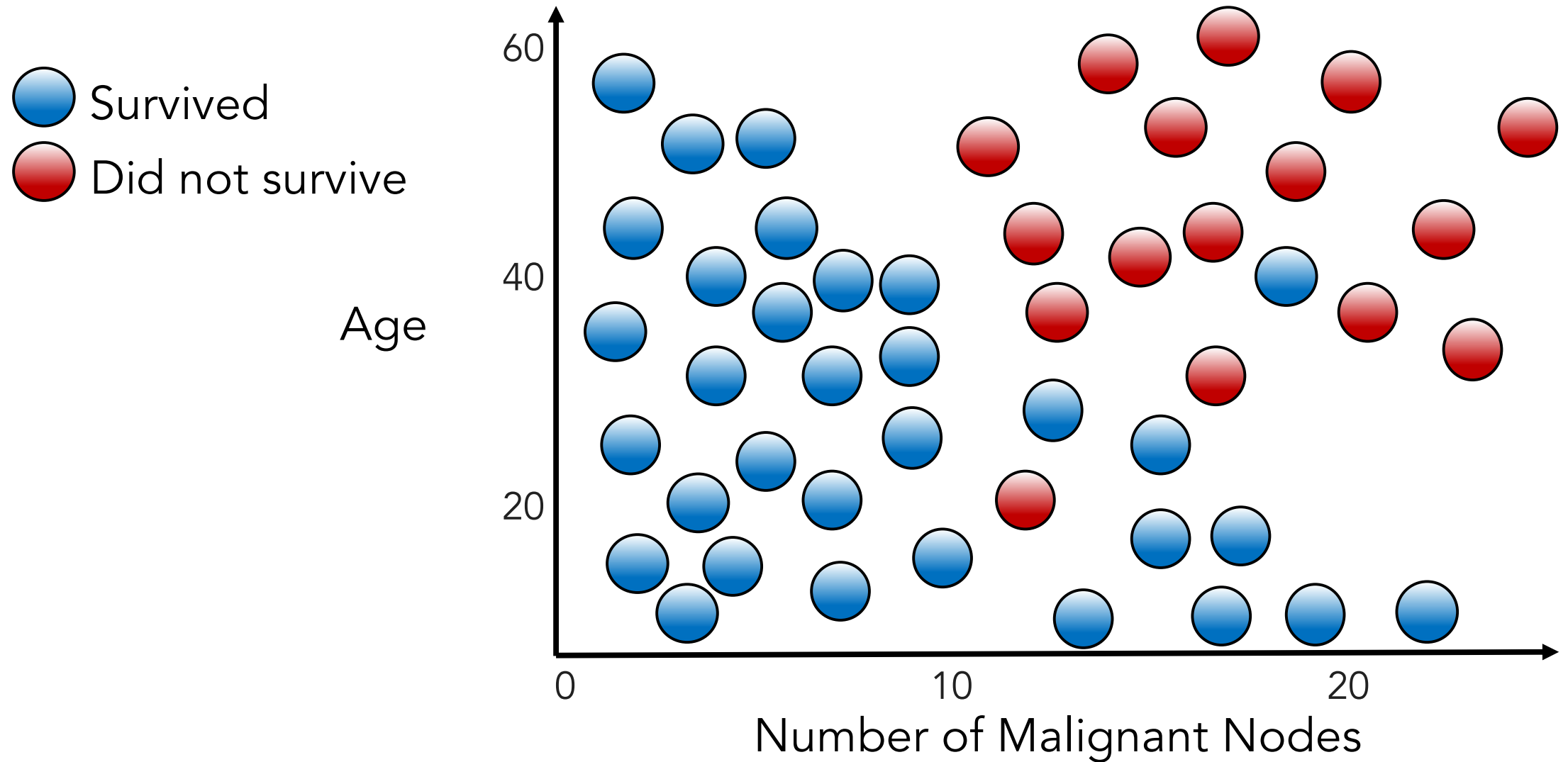
Prediction phase



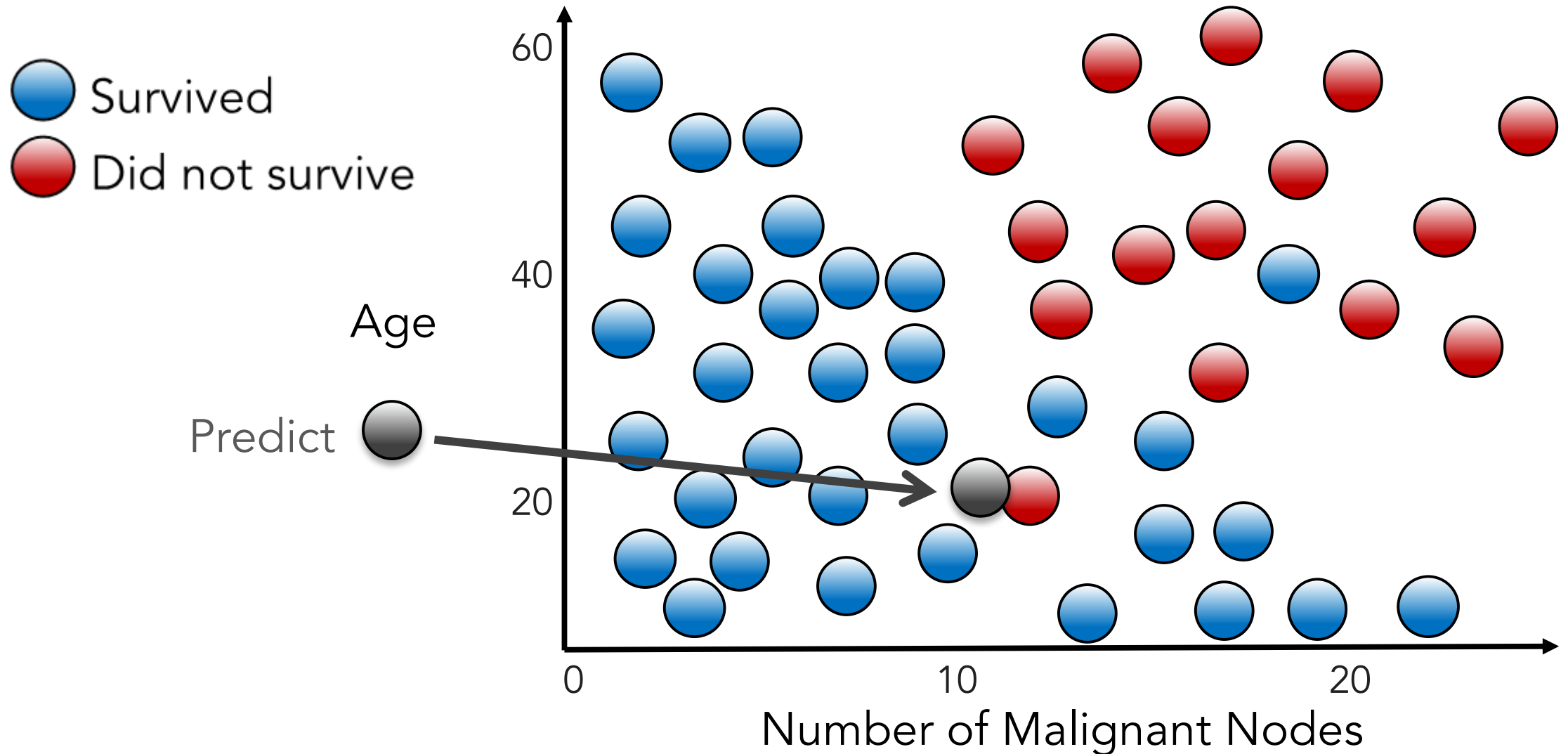
```
def predict(model, test_images):  
    # Use model to predict labels  
    return test_labels
```

Predict the label
of the most similar
training image

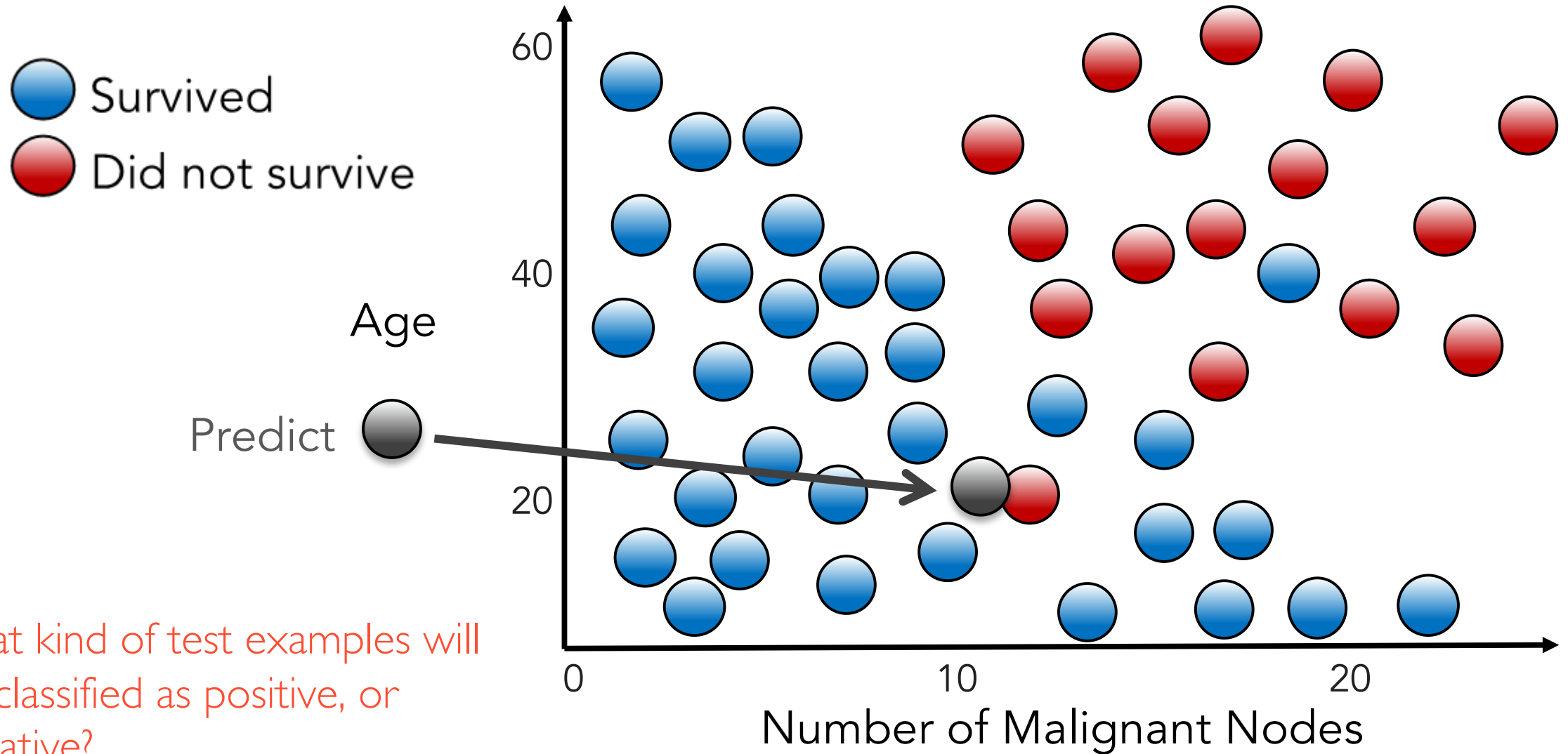
EXAMPLE: CANCER SURVIVAL



EXAMPLE: CANCER SURVIVAL



EXAMPLE: CANCER SURVIVAL

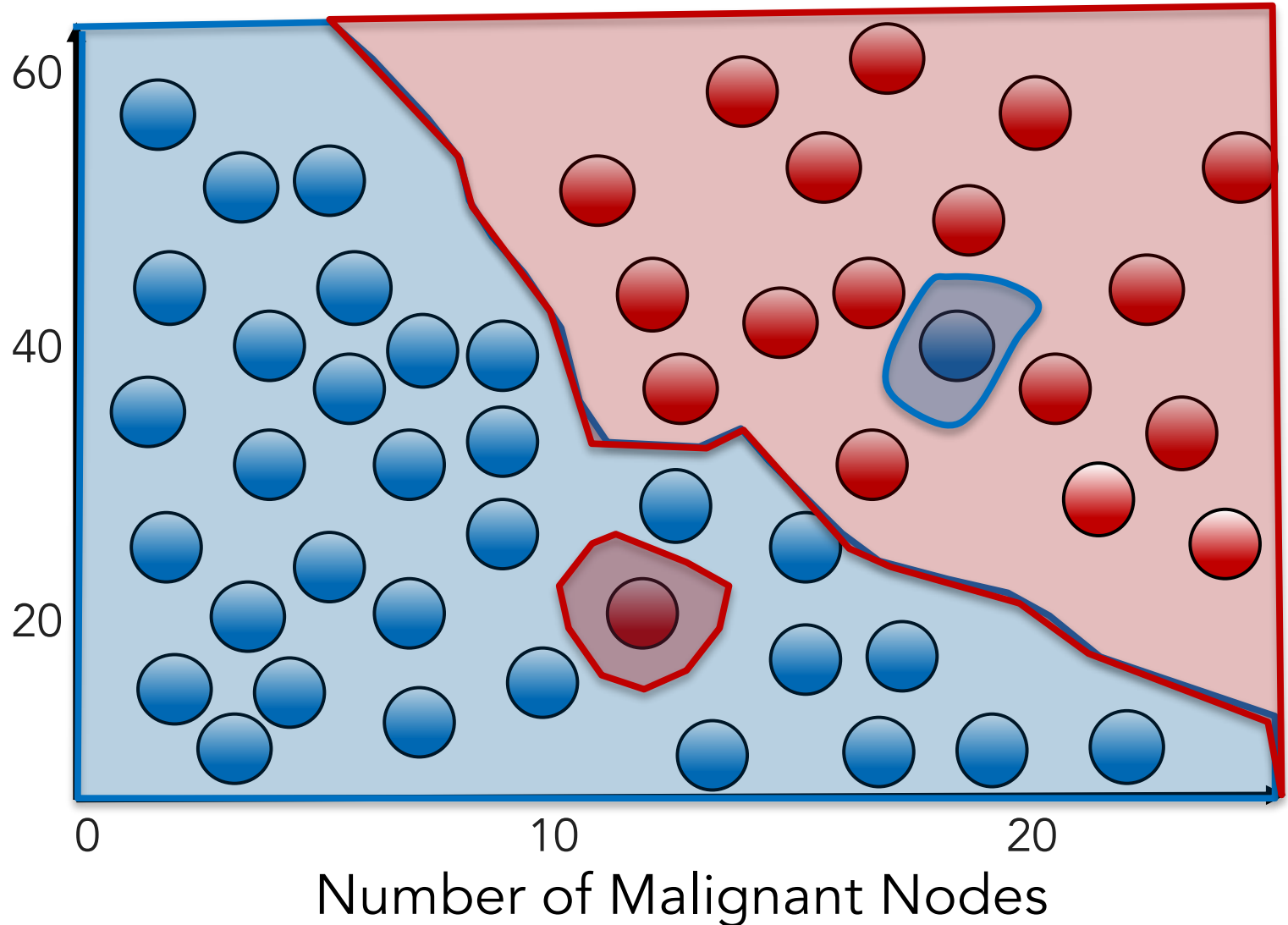


what kind of test examples will be classified as positive, or negative?

NN DECISION BOUNDARIES

- Survived
- Did not survive

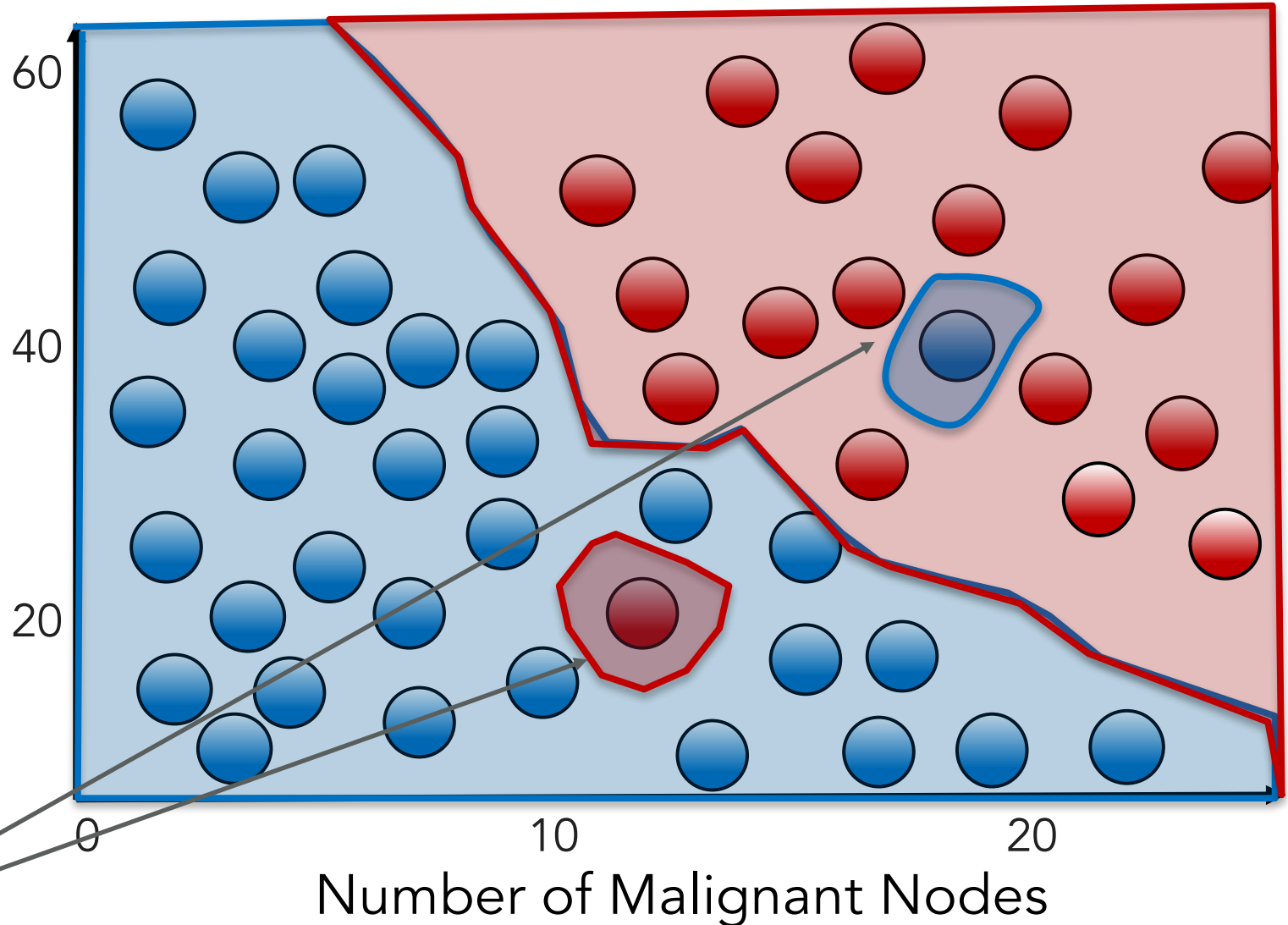
A decision boundary is a line separating the positive regions from the negative regions



NN DECISION BOUNDARIES

- Survived
- Did not survive

Age

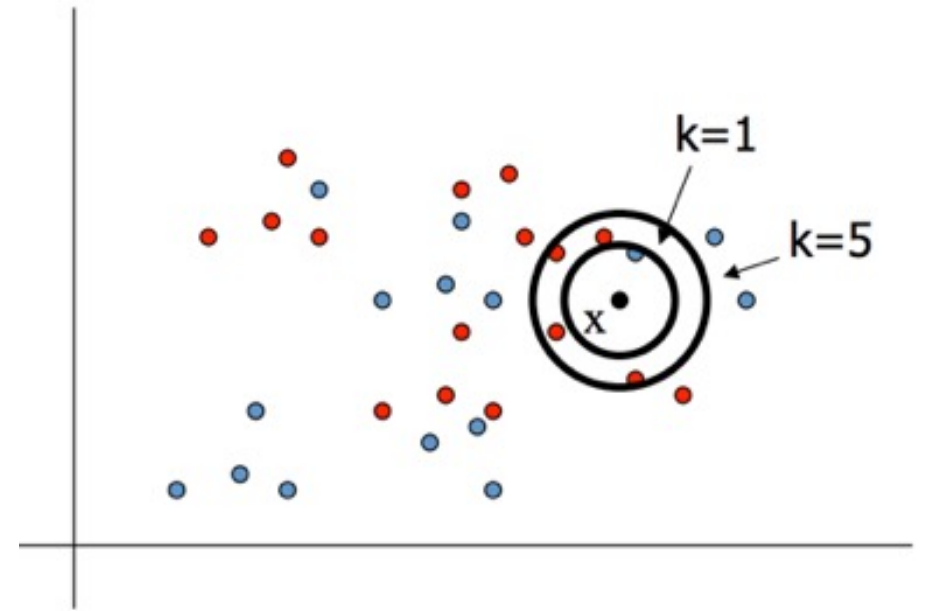


A decision boundary is a line separating the positive regions from the negative regions

Should these two small regions exist? How to avoid it

K-NEAREST NEIGHBOR (K-NN) CLASSIFIER

- Examine the k -“closest” training data points to new point x
- Assign the object the most frequently occurring class (majority vote) or the average value (regression)
- Can have weighted majority or weighted average



<http://cs.nyu.edu/~dsontag/courses/ml13/slides/lecture11.pdf>

K-Nearest Neighbor (kNN) Classifier

- Training:
memorize/store the entire training set including features and labels
- Prediction:
find the **k**-“closest” training data point to the test point
return the **majority class**

```
def train(images, labels):  
    # Machine learning!  
    return model
```



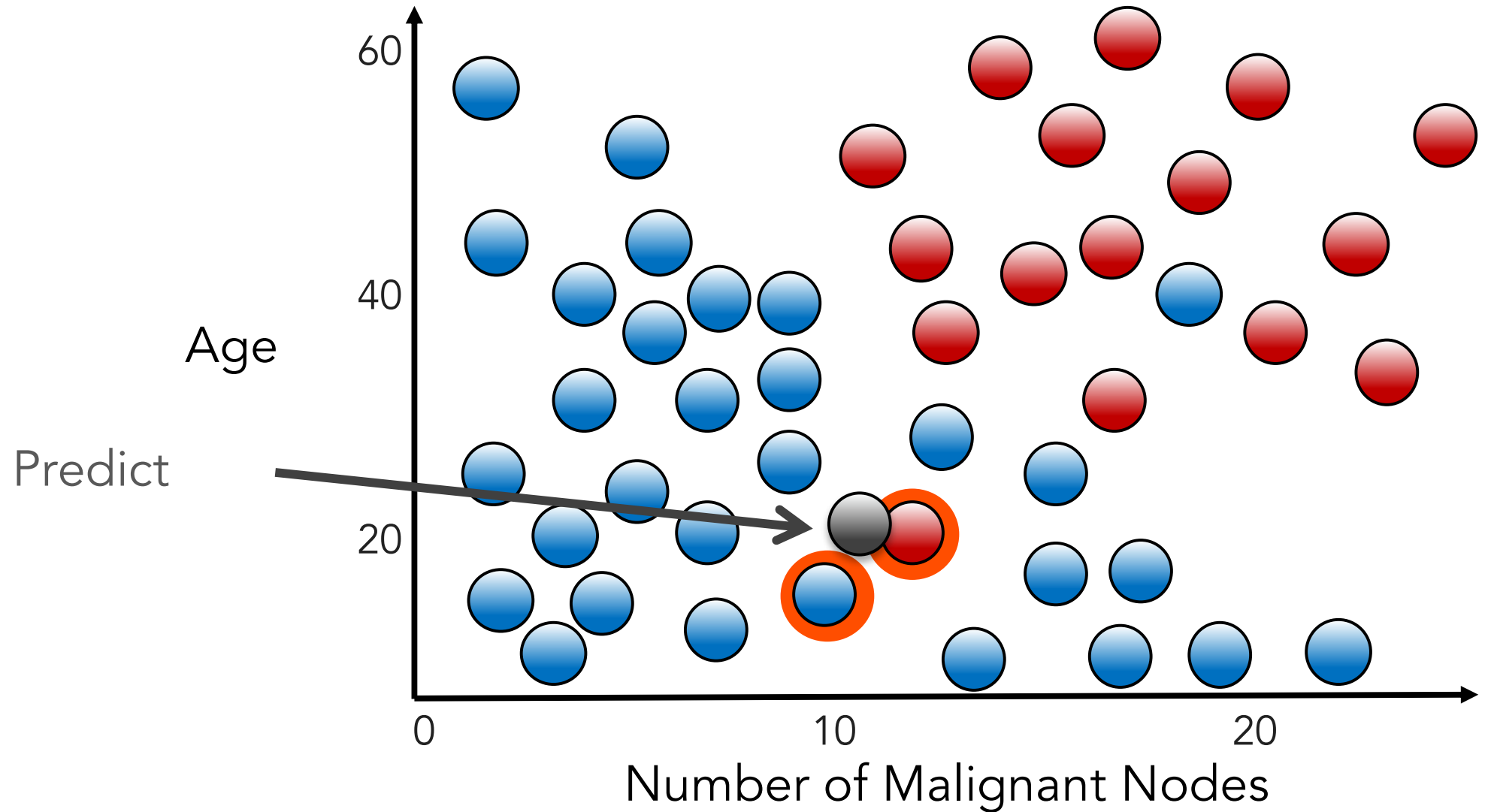
Memorize all
data and labels

```
def predict(model, test_images):  
    # Use model to predict labels  
    return test_labels
```

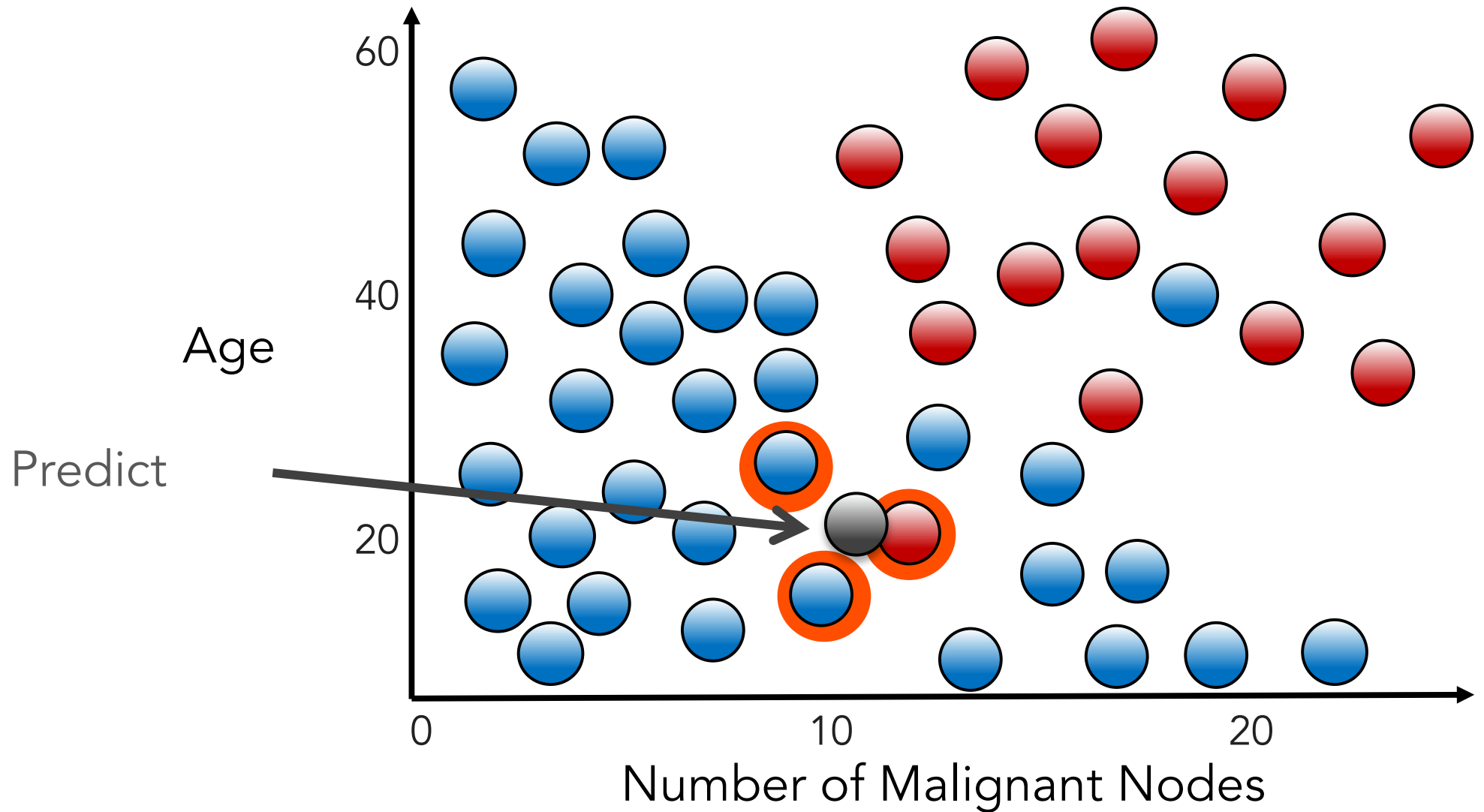


Predict the label
of the most similar
training image

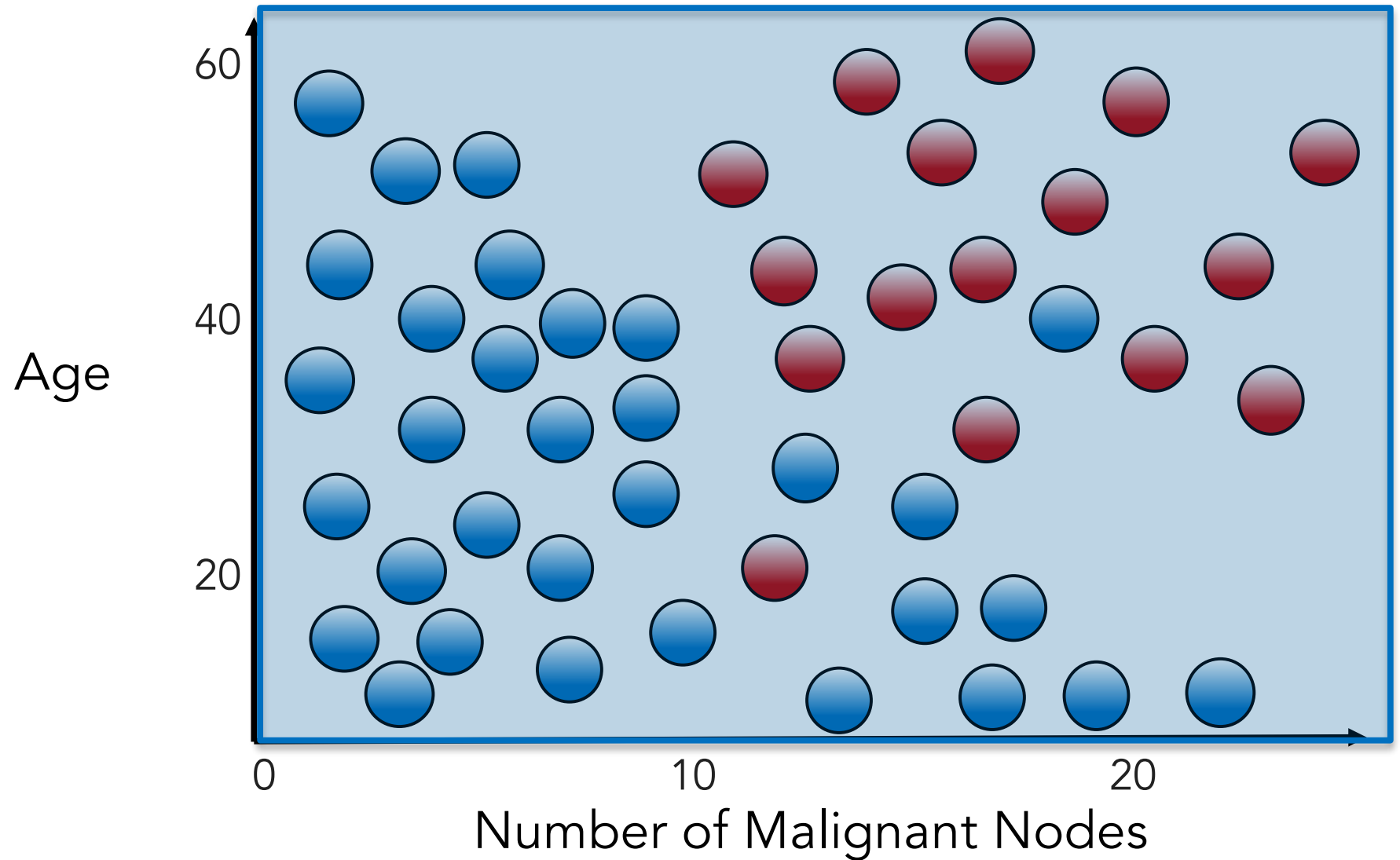
EXAMPLE: $K=2$



EXAMPLE: $K=3$

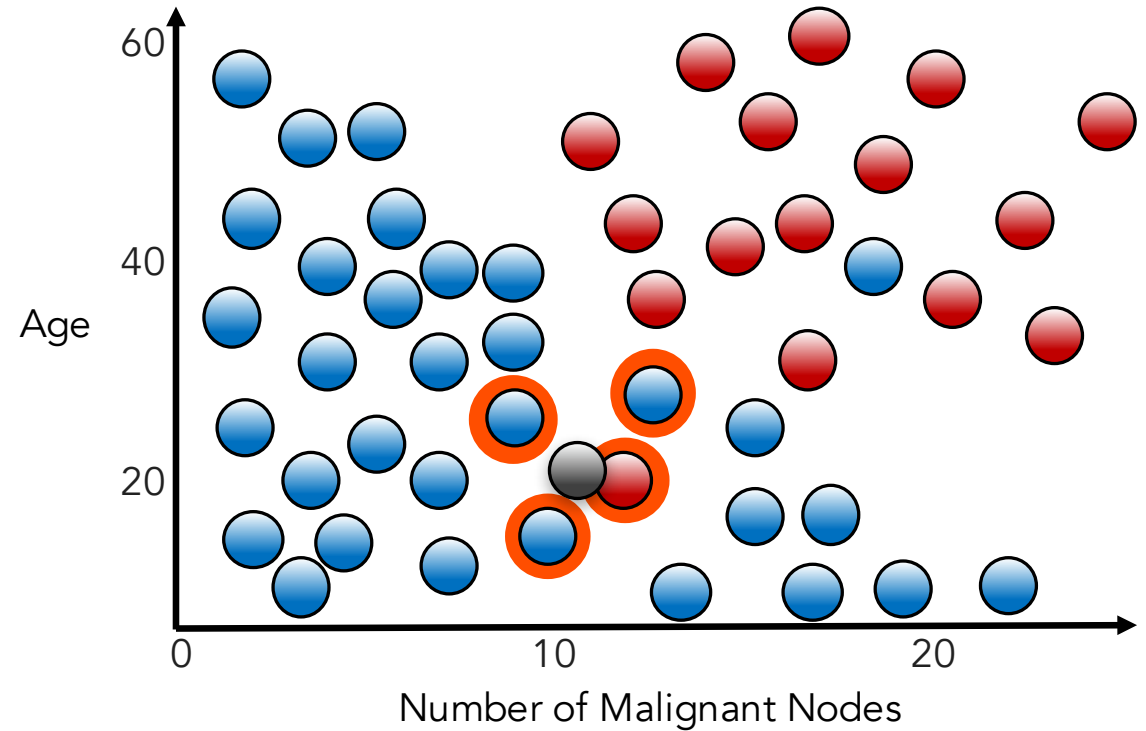


EXAMPLE: $K=N$



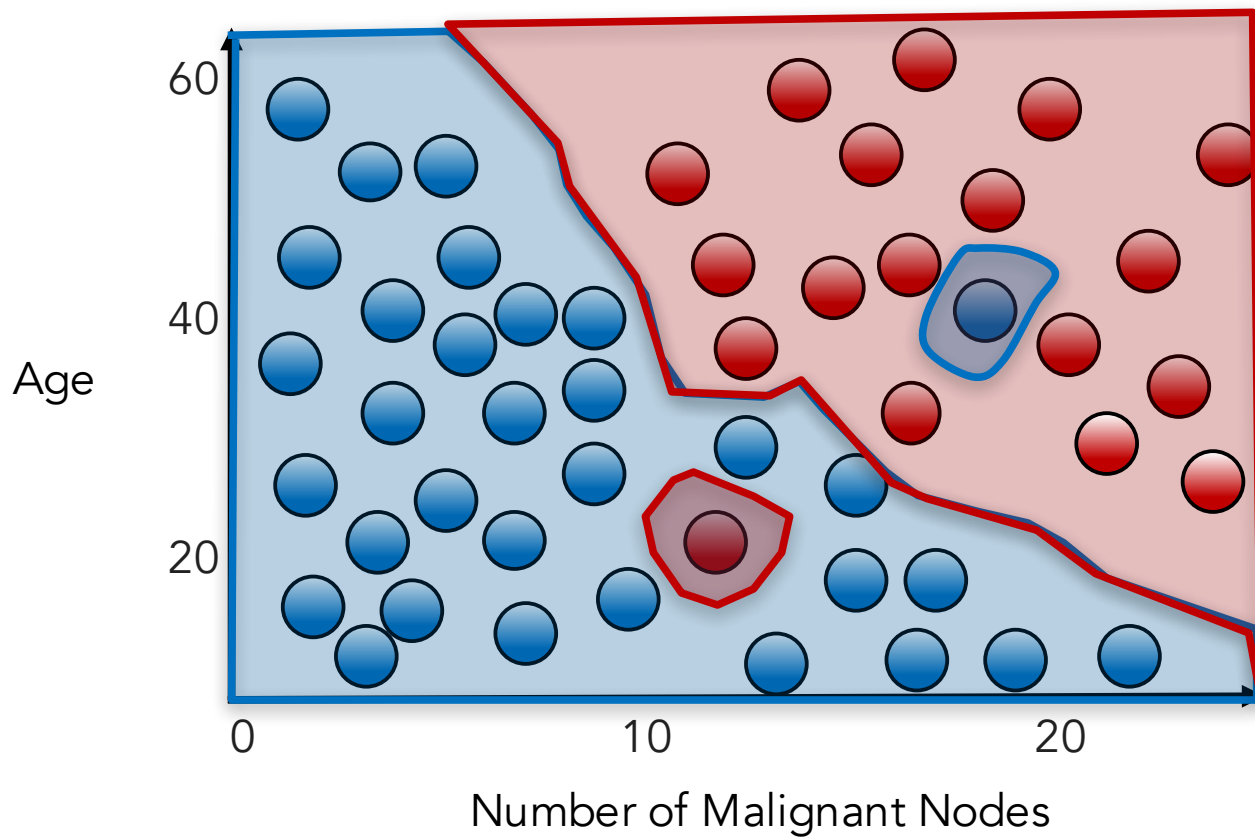
K-NN: PRACTICAL CHALLENGES

- How to pick k ?
- What is the right measure of closeness/distance?

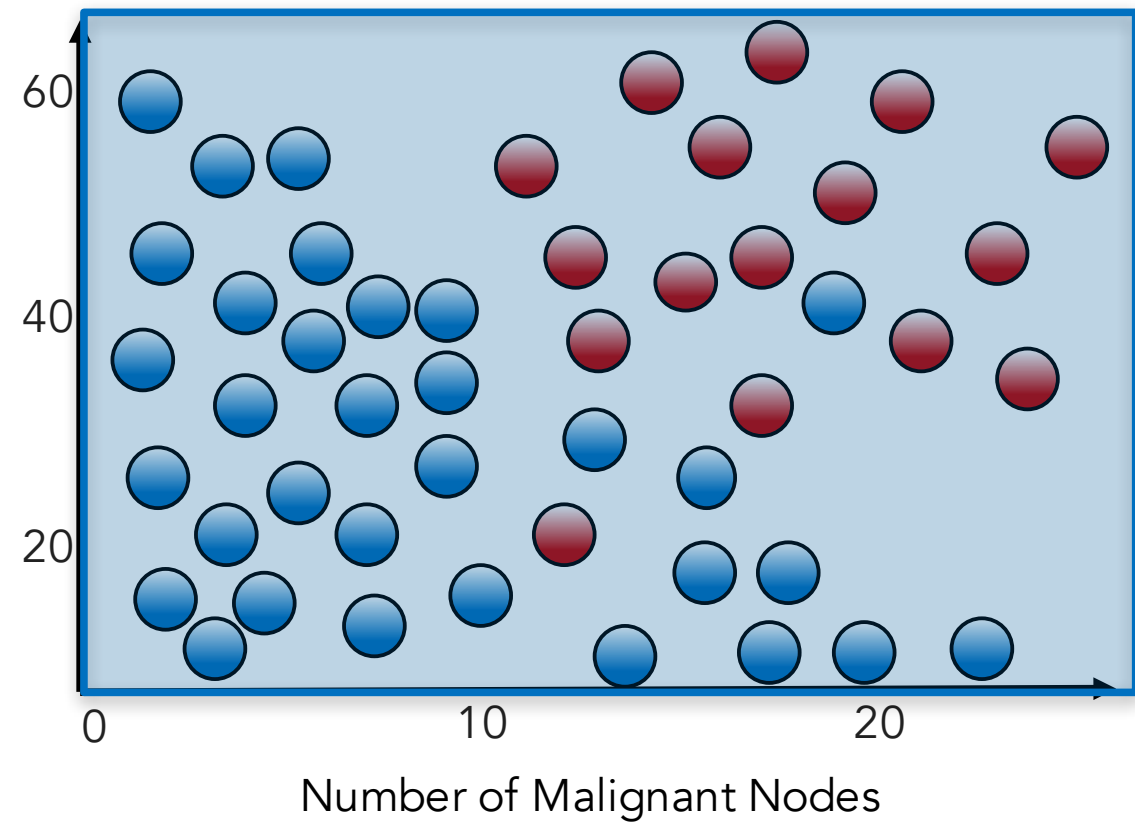


VALUE OF K

$K = 1$

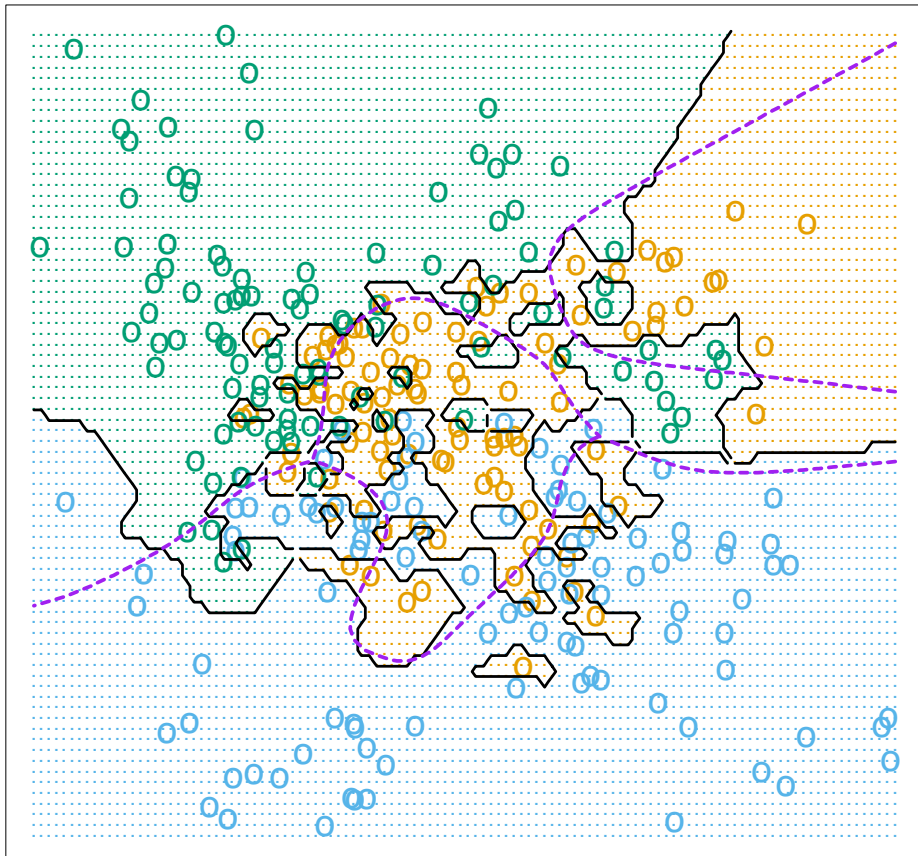


$K = \text{All}$

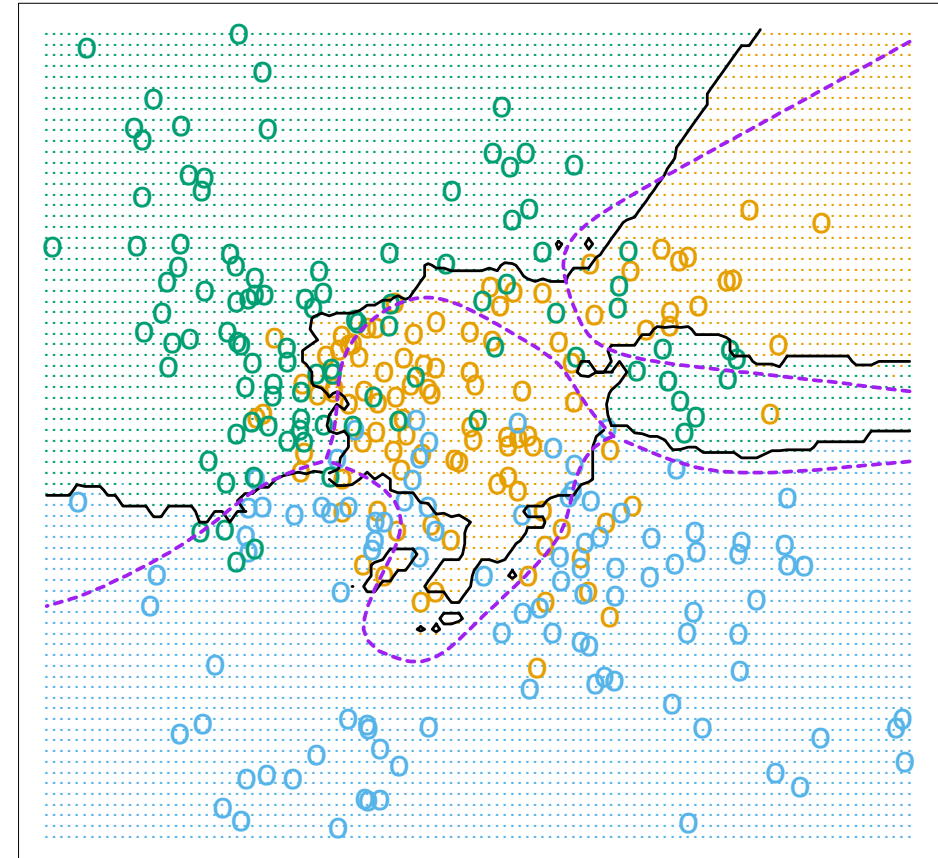


K-NN: SMOOTHING

1-Nearest Neighbor



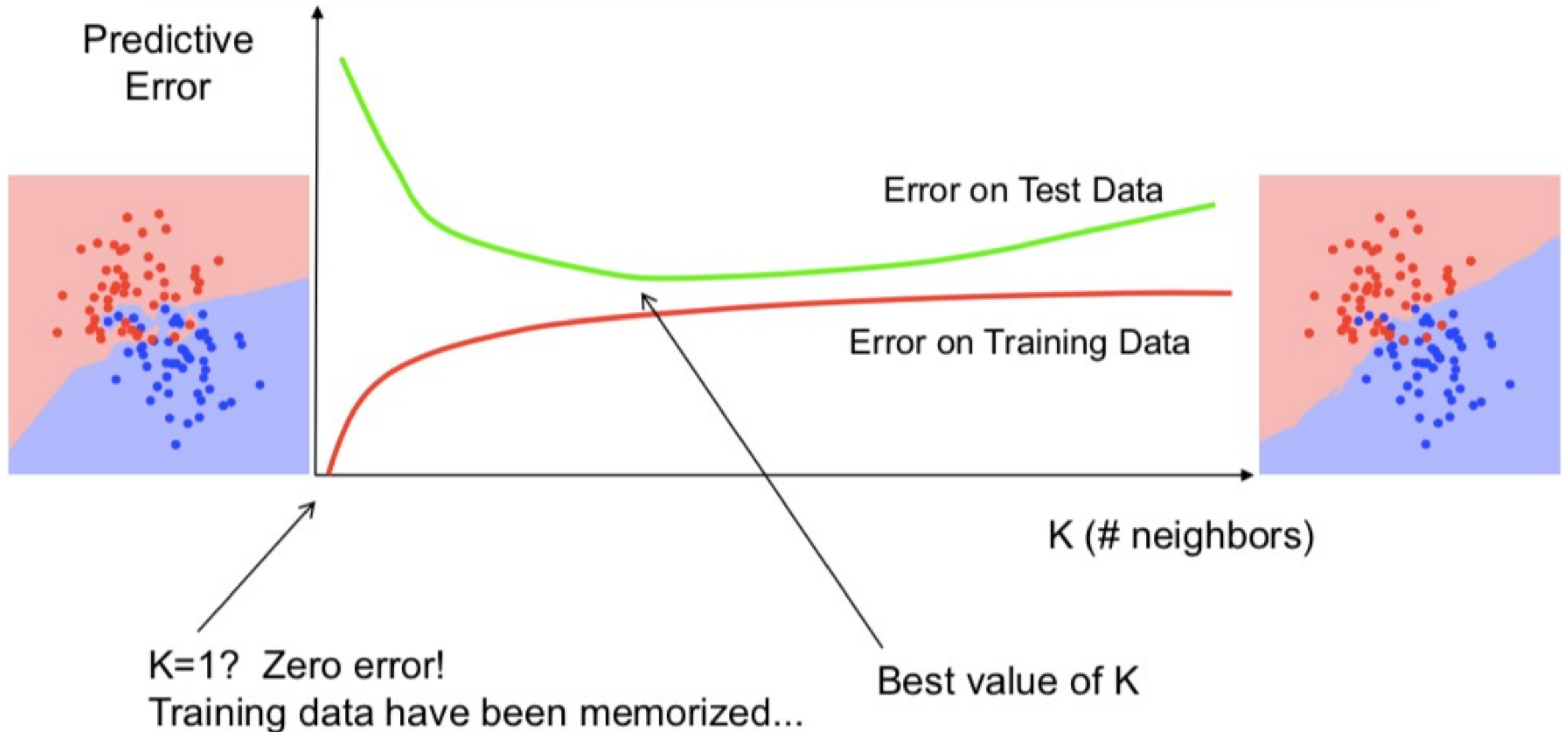
15-Nearest Neighbors



What is the training error when $k=1$?

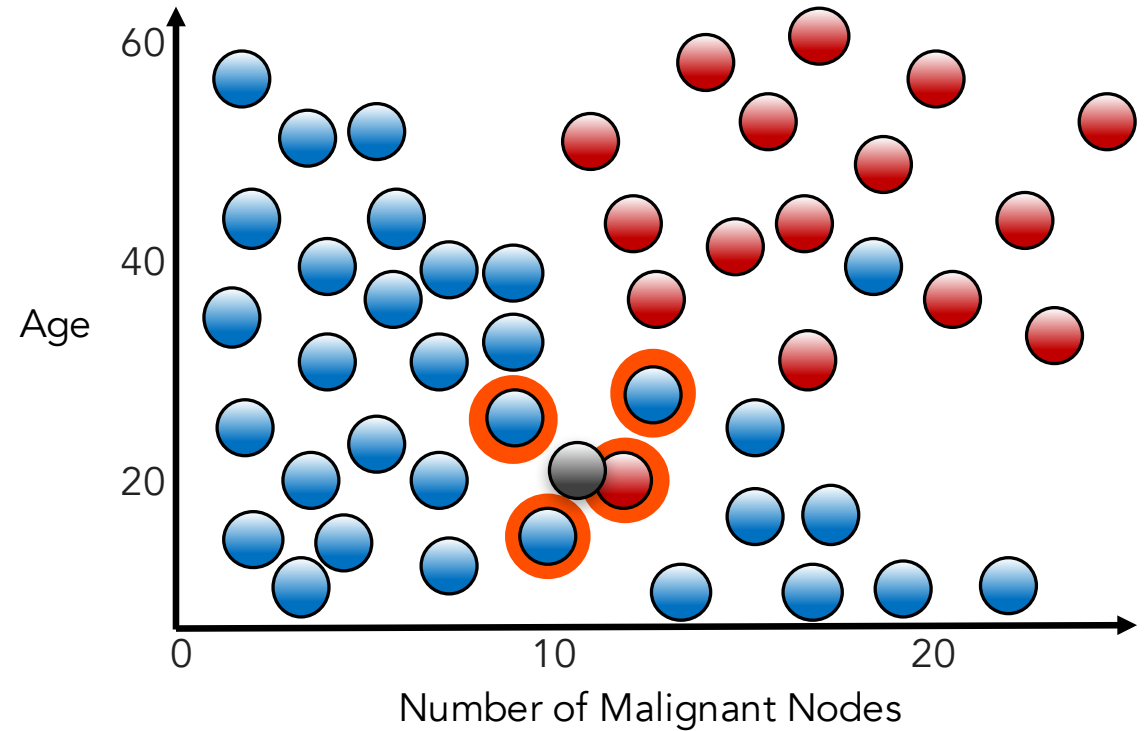
Error rates and K

(More on model selection later)



K-NN: PRACTICAL CHALLENGES

- How to pick k ?
- What is the right measure of closeness/distance?



REVIEW: SUPERVISED LEARNING

- Learning a mapping from input to output, given a labeled set of input-output pairs, i.e. training dataset

D

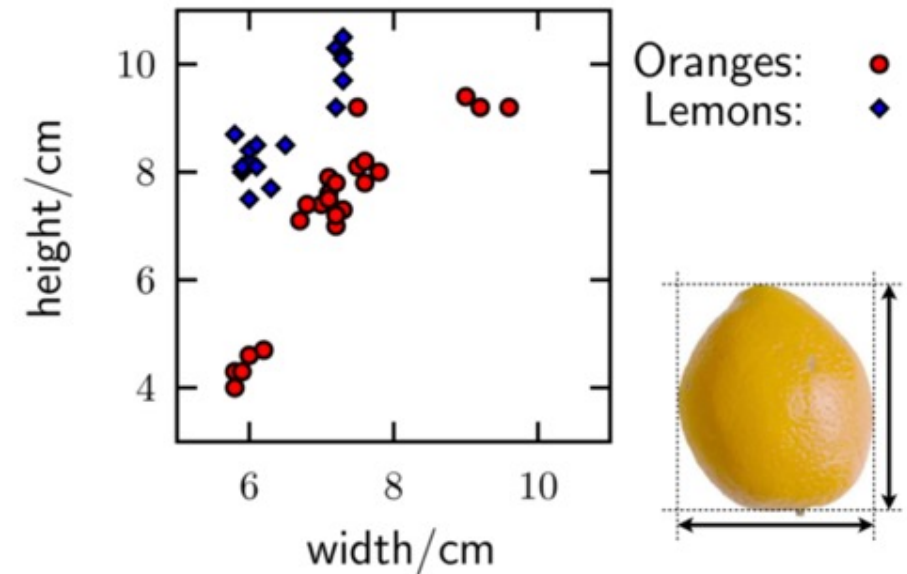
$$\{(\mathbf{x}_i, y_i)\}, i = 1, \dots, N$$

- Each input instance represents an object/sample as a d-dimensional vector of features
- Classification**: output is categorical (e.g. orange, lemon)

$$y_i \in \{1, \dots, C\}$$

- Binary vs. multiclass classification

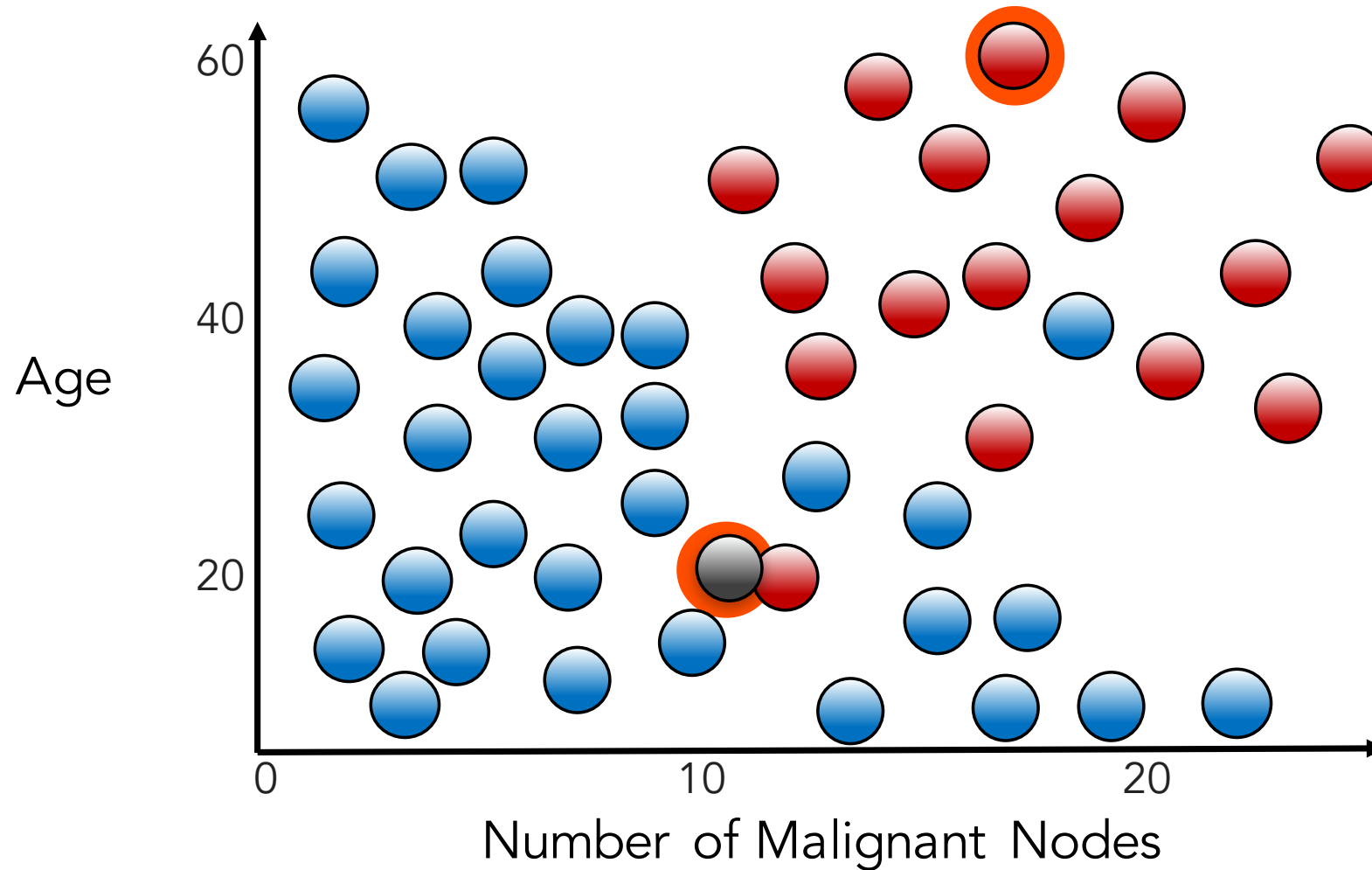
- Regression**: output is real-valued



<http://homepages.inf.ed.ac.uk/imurray2/>

MEASUREMENT OF DISTANCE

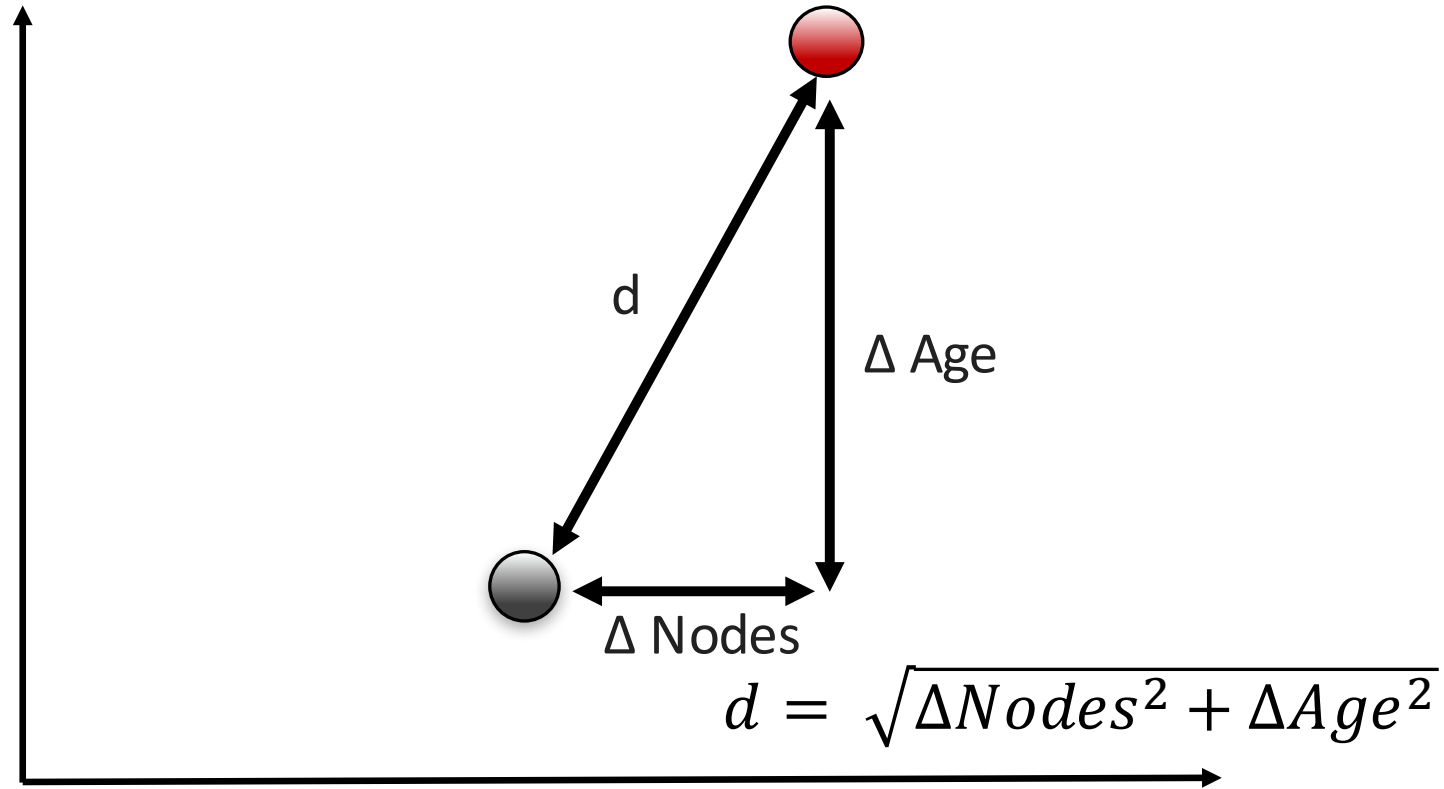
What is the distance of these two points?



EUCLIDEAN DISTANCE



Age



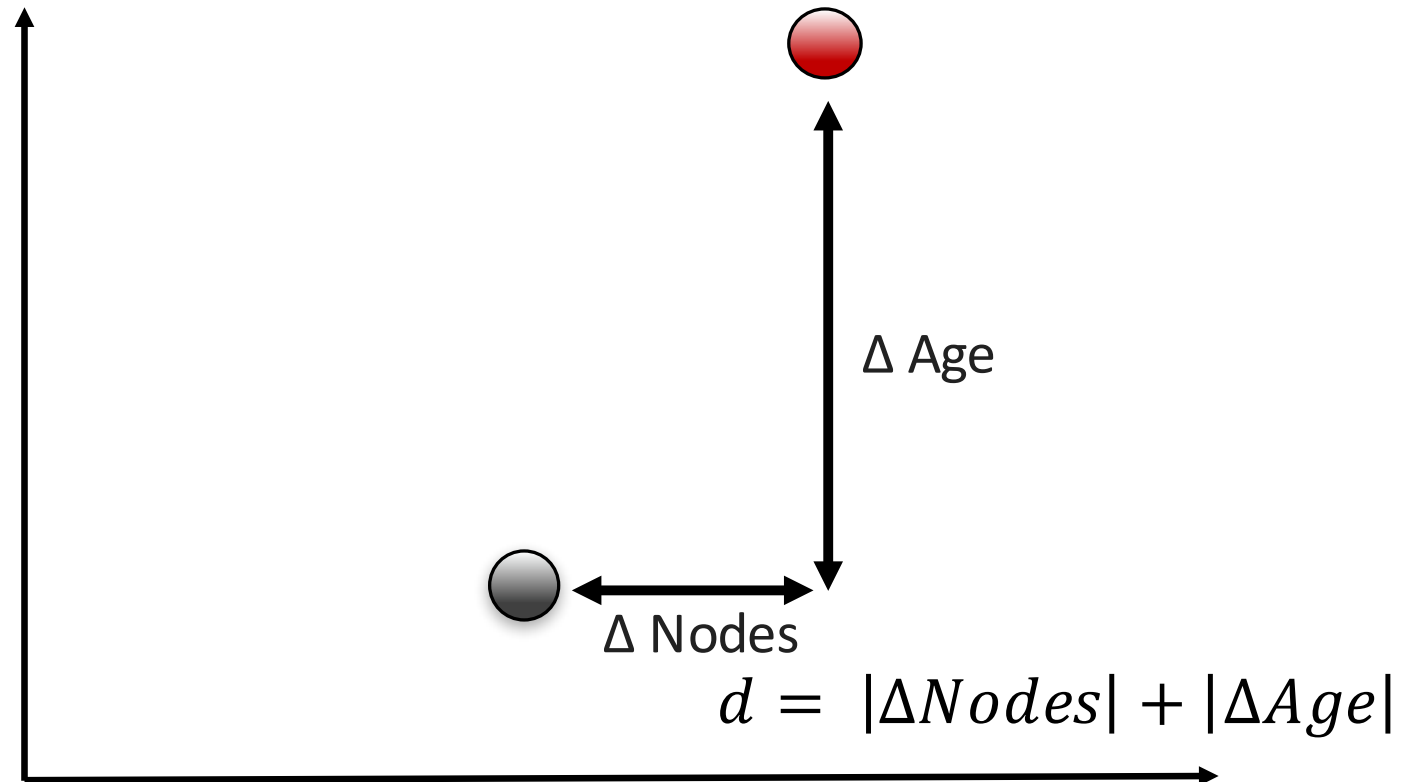
Number of Malignant Nodes

Also known as **crow distance** (green)
or L2 norm of the difference vector

MANHATTAN DISTANCE



Age



Also known as **taxicab distance** (purple)
or L1 norm of the difference vector

Number of Malignant Nodes

COMMON DISTANCE METRICS

Euclidean	$D(\mathbf{x}, \mathbf{z}) = \sqrt{\sum_{i=1}^d (x_i - z_i)^2}$
Manhattan	$D(\mathbf{x}, \mathbf{z}) = \sum_{i=1}^d x_i - z_i $
Minkowski	$D(\mathbf{x}, \mathbf{z}) = \left(\sum_{i=1}^d x_i - z_i ^p \right)^{\frac{1}{p}}$

NORMS

$$\ell_p = \left(\sum_{i=1}^N |x_i|^p \right)^{1/p}, \text{ for } p \geq 1$$

For $p = 1$, we get $\ell_1 = |x_1| + |x_2| + \dots + |x_n|$

For $p = 2$, $\ell_2 = \sqrt{x_1^2 + x_2^2 + \dots + x_n^2}$

For $p = 3$, $\ell_3 = \sqrt[3]{|x_1|^3 + |x_2|^3 + \dots + |x_n|^3}$

For $p \rightarrow \infty$, $\ell_\infty = \max_i (|x_1|, |x_2|, \dots, |x_n|)$

OTHER DISTANCE METRICS

- Categorical/Integer-valued space

- Hamming distance:
$$D(\mathbf{x}, \mathbf{y}) = \frac{N_{\text{different}}(\mathbf{x}, \mathbf{y})}{N_{\text{total}}}$$

- Canberra:
$$D(\mathbf{x}, \mathbf{y}) = \sum \frac{|x_i - y_i|}{|x_i| + |y_i|}$$

- Boolean-valued space

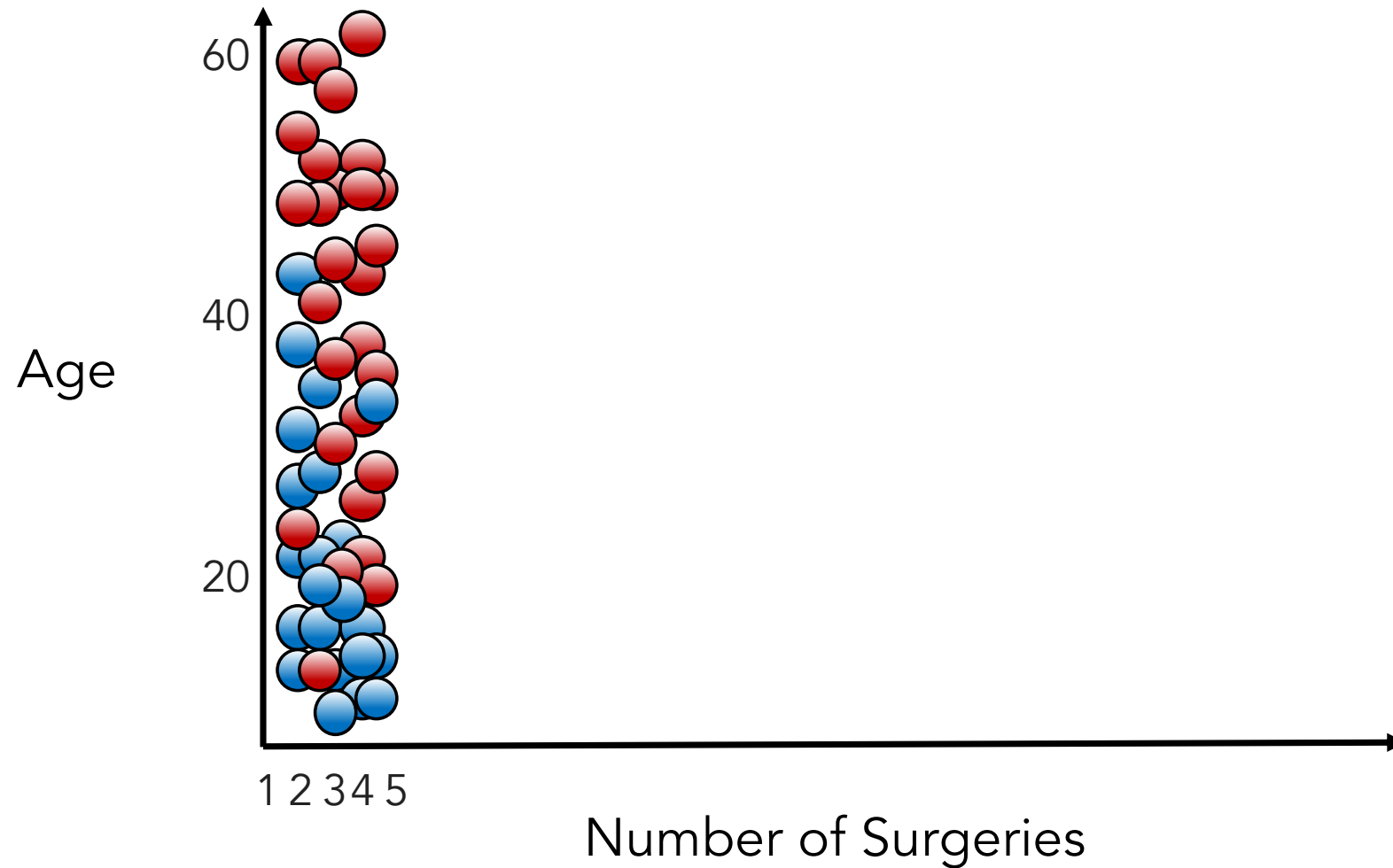
- Jaccard:
$$D(\mathbf{x}, \mathbf{y}) = \frac{|\mathbf{x} \cap \mathbf{y}|}{|\mathbf{x} \cup \mathbf{y}|}$$

OTHER DISTANCE METRICS

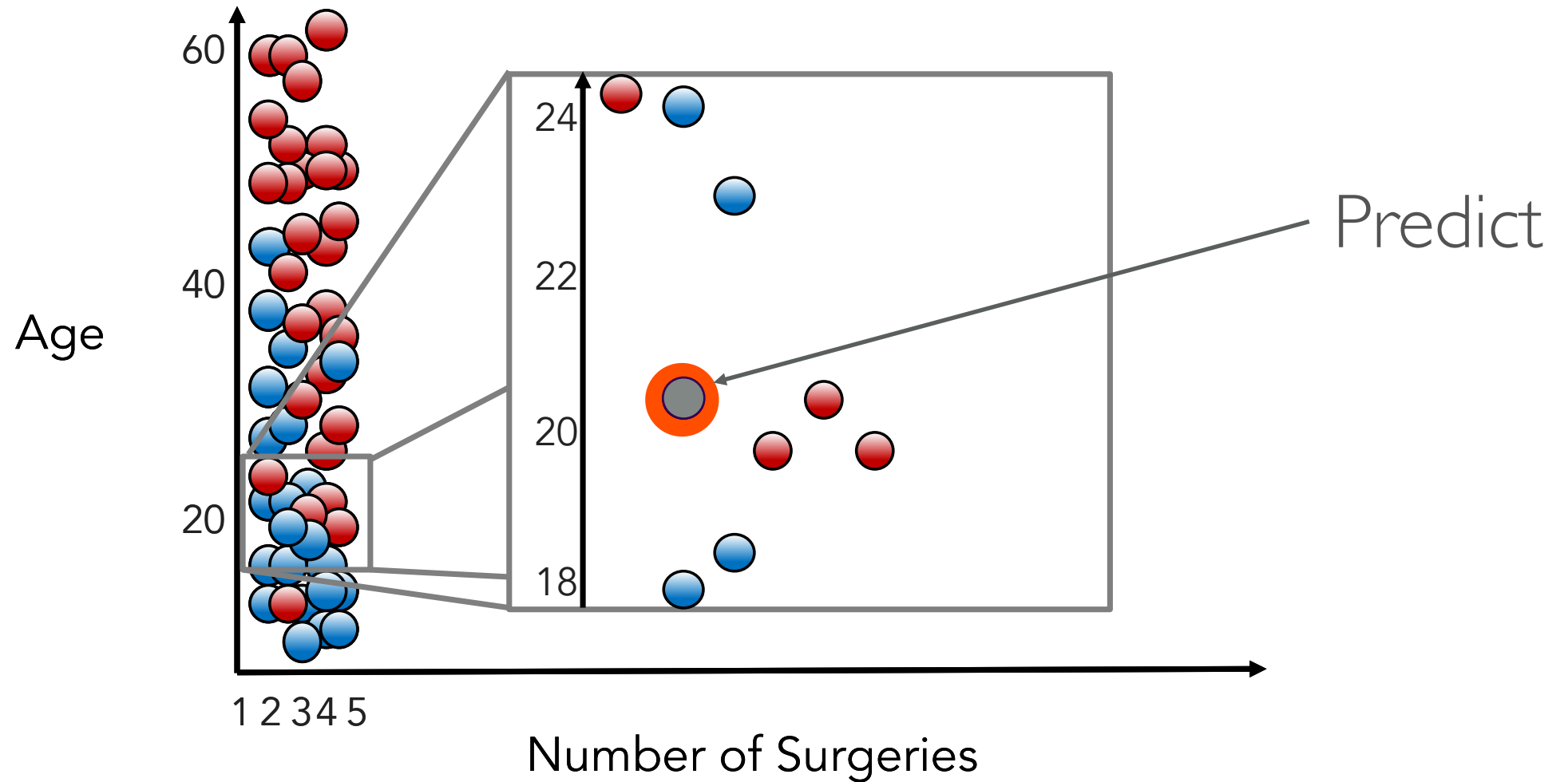
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Joyce	5	5	5	?	?	2

What's the hamming distance of the two records
(considering column 1, 2, 3, 6)?

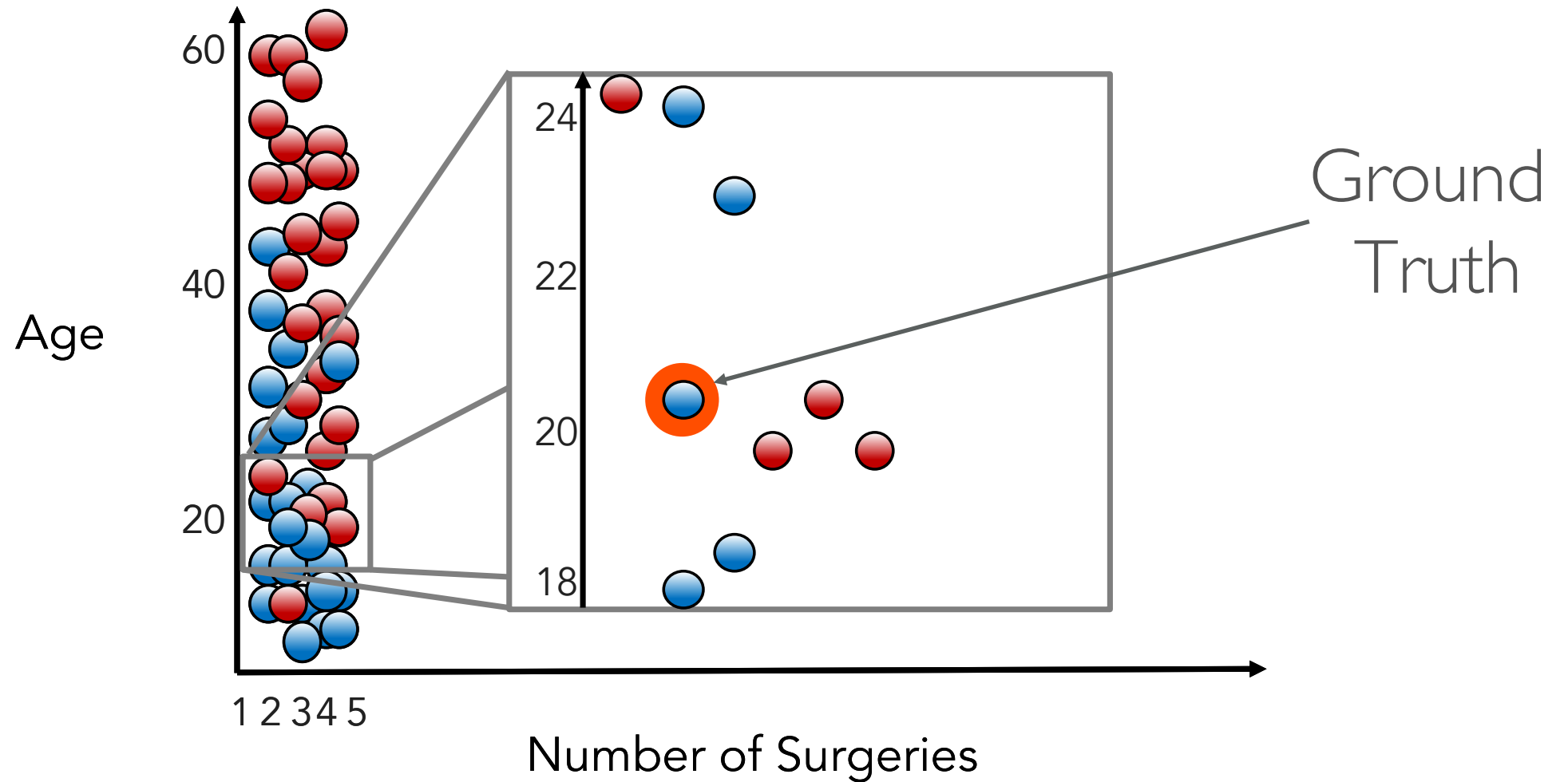
DOES SCALE MATTER?



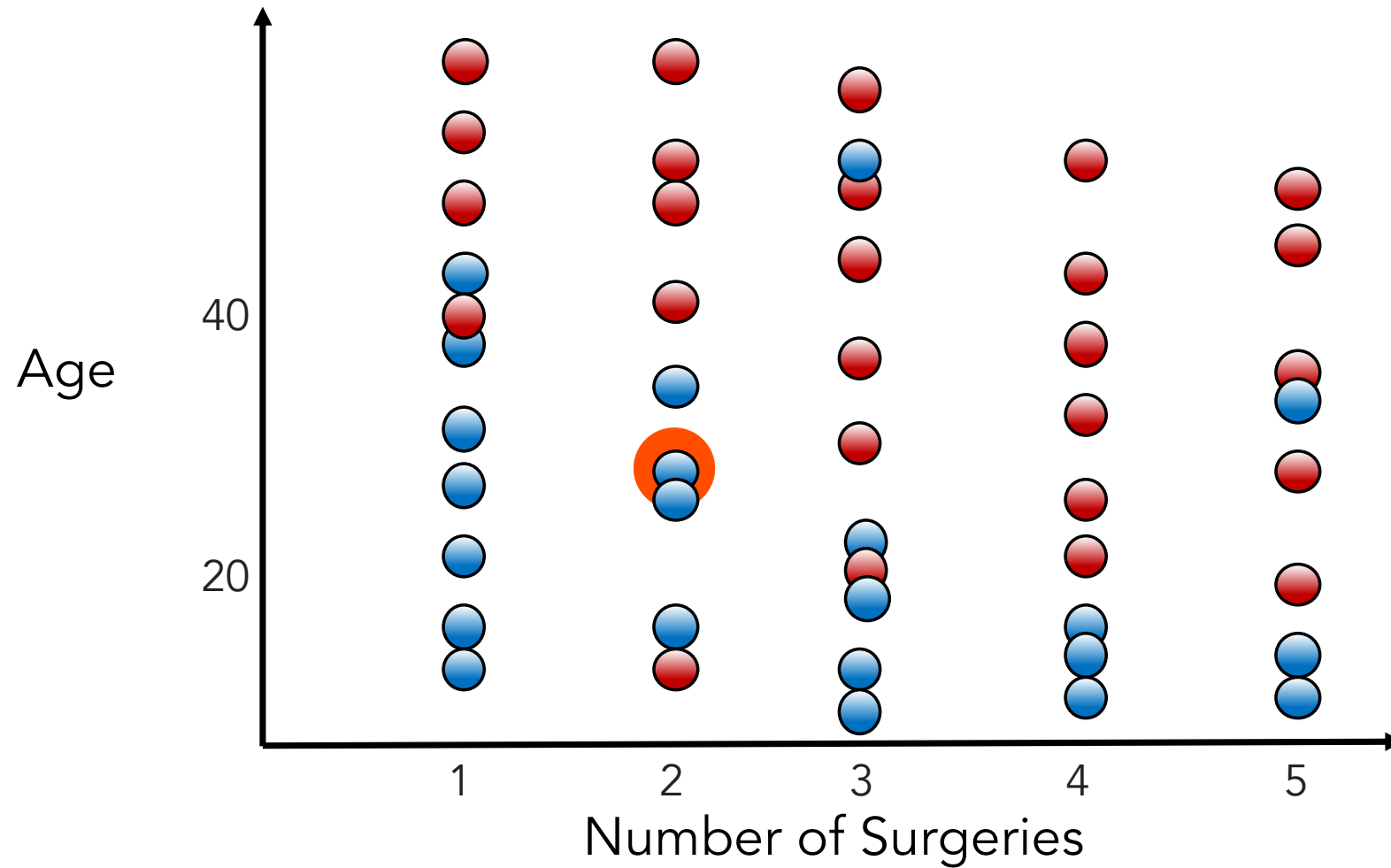
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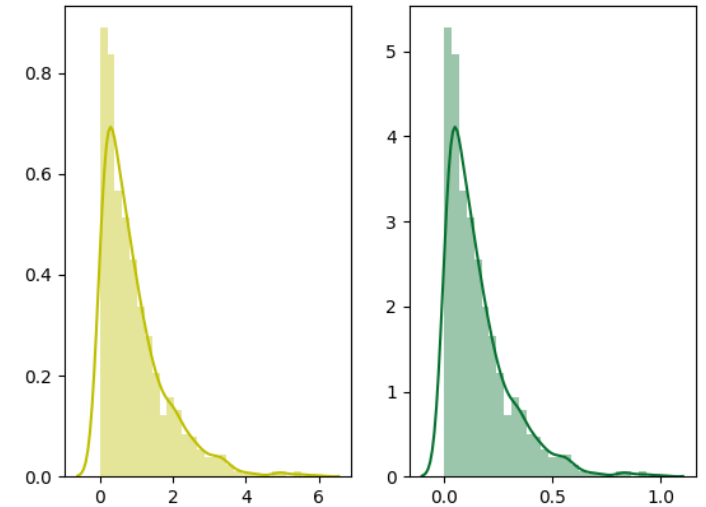
DOES SCALE MATTER?



FEATURE SCALING

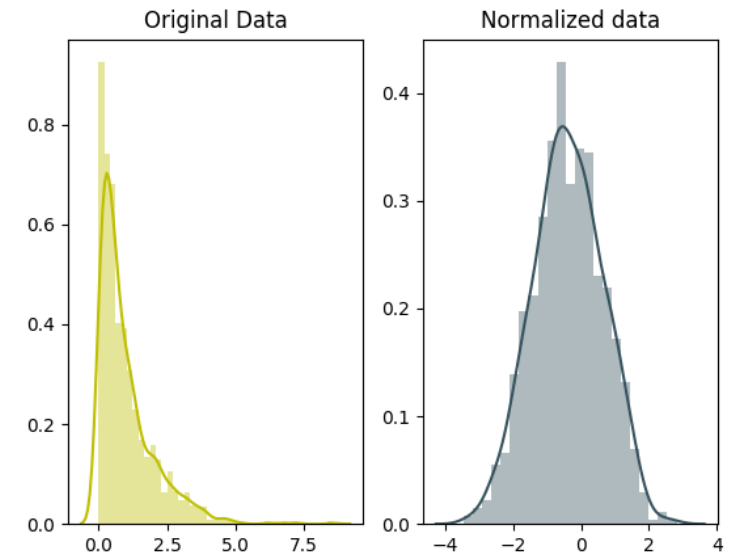
- **Min-max normalization:** Scale data to fixed range $[0, 1]$ or $[a,b]$

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad x' = a + \frac{(x - \min(x))(b - a)}{\max(x) - \min(x)}$$



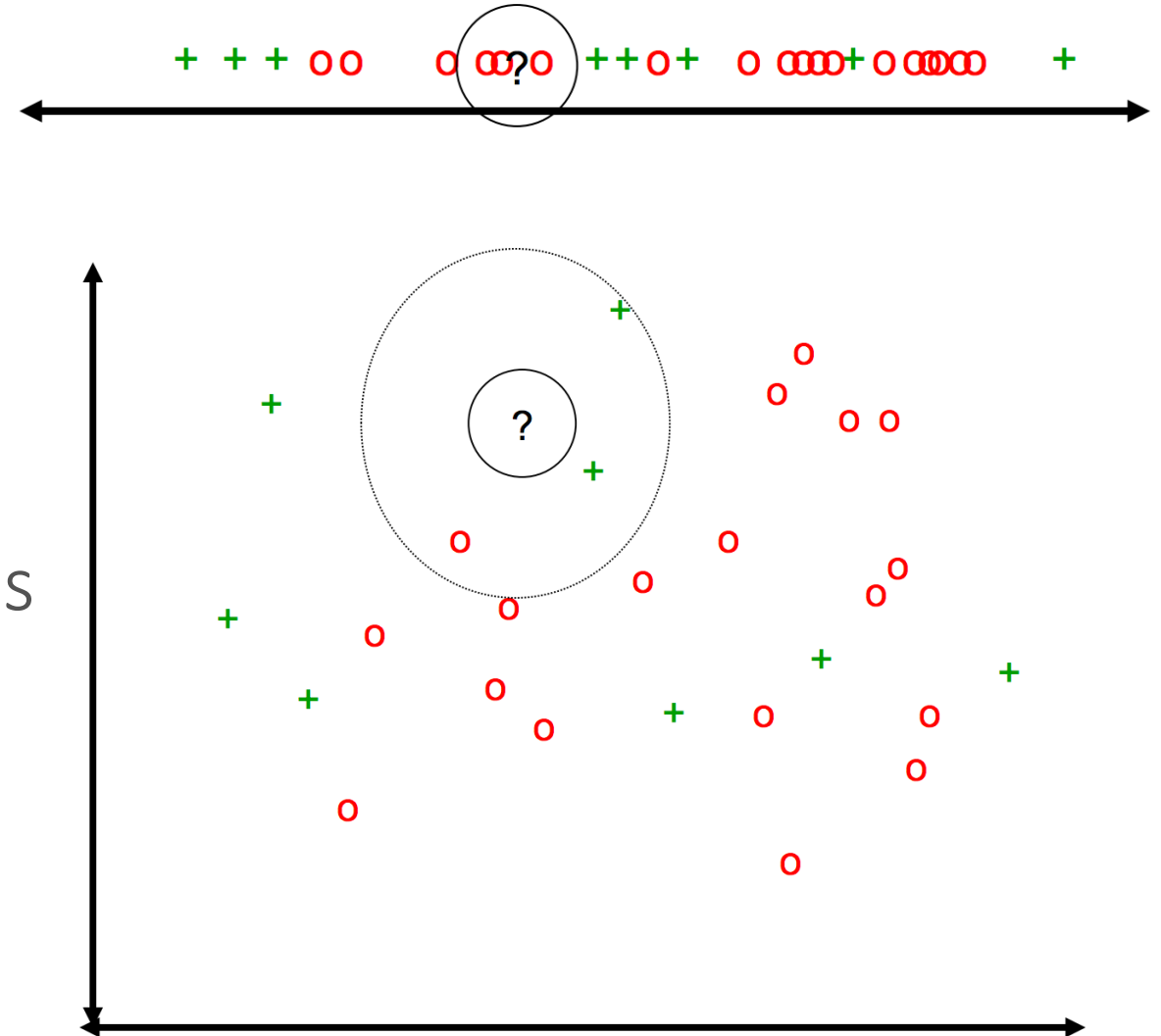
- **Standardization (Z-score normalization):** Center data to zero mean and scale by unit variance

$$x' = \frac{x - \bar{x}}{\sigma}$$



K-NN: IRRELEVANT FEATURES

- Irrelevant / noisy features may hurt performance since it adds random perturbations to the distance measure
- Example: 1-D data, what happens if we add noisy attribute?



K-NN: CHARACTERISTICS

- Instance-based (lazy) learning (as vs. model-based eager learning)
- Non-parametric (as vs. parametric)
- Easy to understand and implement
- Can model complex decision boundaries quite well (depending on k)
- Memory intensive (needs to store all the data) – can use clustering
- Can be fooled by irrelevant features

ONLINE DEMO

<http://vision.stanford.edu/teaching/cs231n-demos/knn/>



NETFLIX PRIZE (2006-2009)

\$1M prize for 10% improvement

Collaborative Filtering

- Estimate rating by user x for item I
- Collaborative filtering
 - User-based: find **similar users** to user x
- Select k -nearest neighbors, compute the rating

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Joyce	5	5	5	?	?	2

Collaborative Filtering

- Estimate rating by user x for item i
- Collaborative filtering
 - User-based: find **similar users** to user x
 - Item-based: find **similar items** rated by user x
- Select k -nearest neighbors, compute the rating

$$r_{xi} = \frac{\sum_{j \in N(i;x)} s_{ij} \cdot r_{xj}}{\sum_{j \in N(i;x)} s_{ij}}$$

s_{ij} ... similarity of items i and j

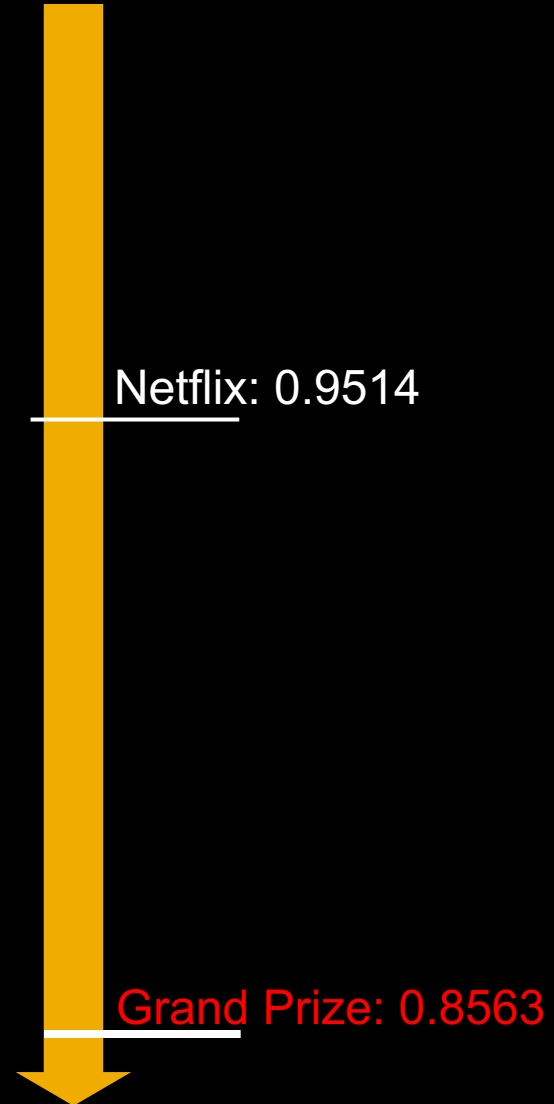
r_{xj} ... rating of user x on item j

$N(i;x)$... items similar to i rated by x

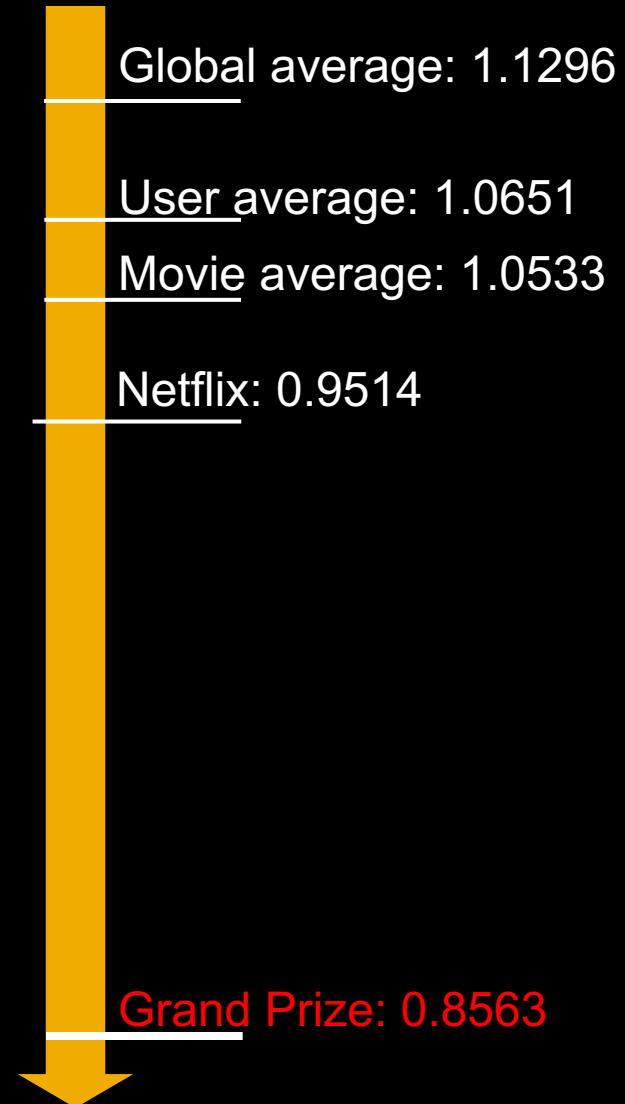
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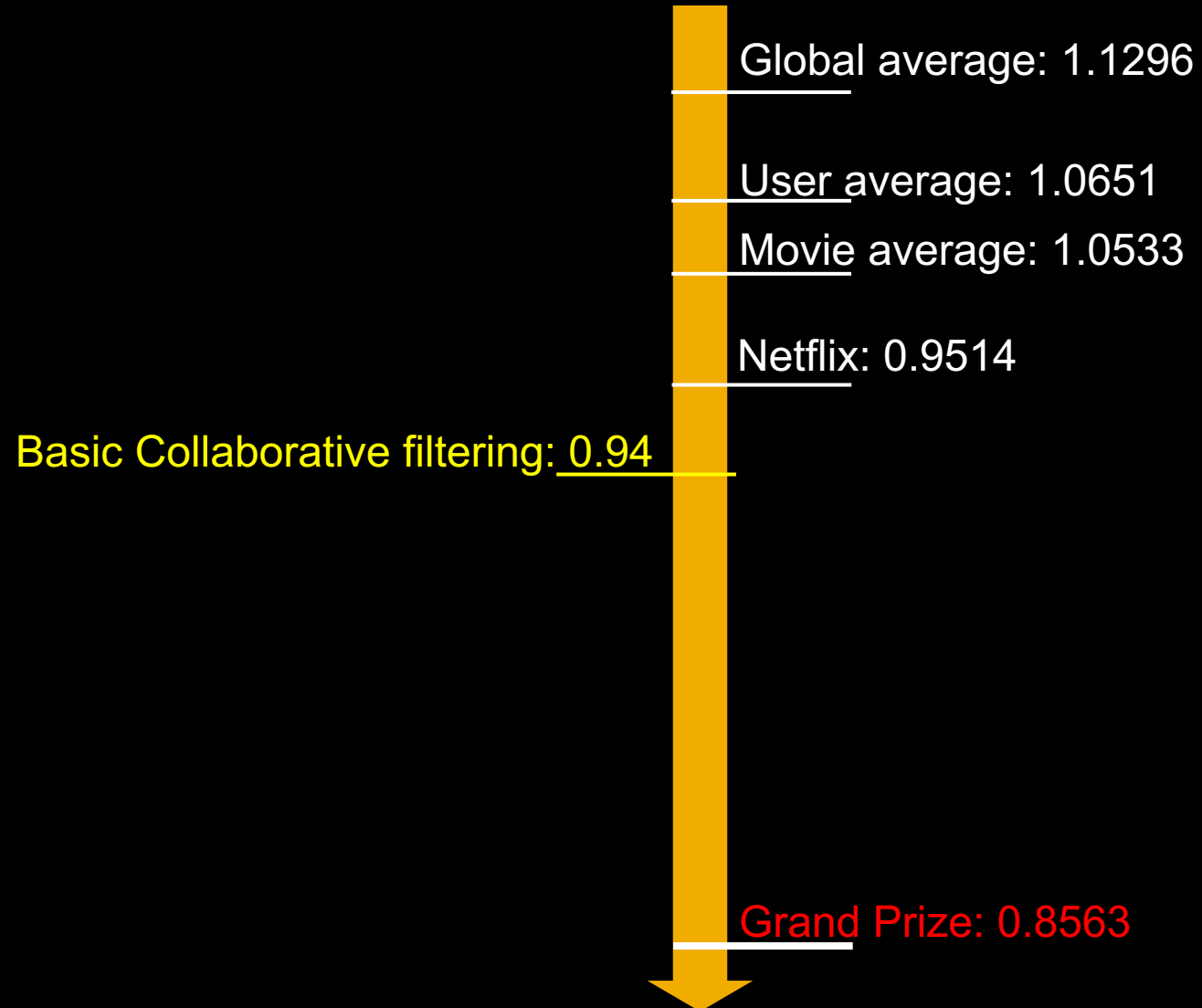
Netflix Prize



Netflix Prize



Netflix Prize



HOMEWORK #1 ANNOUNCEMENT

- Out 8/28, Due 9/12 @ 11:59 PM ET on Gradescope
- 4 questions
 - Q1-Q2: Get familiar with Python
 - Numerical programming (Numpy)
 - Dataset loading and visualization (Pandas and other libraries)
 - Q3-Q4: kNN
 - Implement kNN (use Numpy)
 - Evaluate kNN (use sklearn)

