

Lecture 5: K-Nearest Neighbor Fall 2018

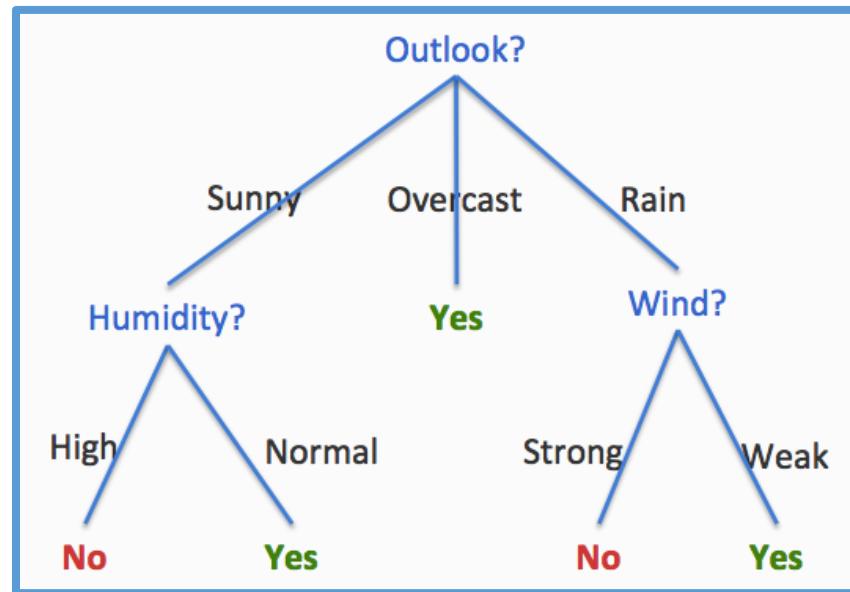
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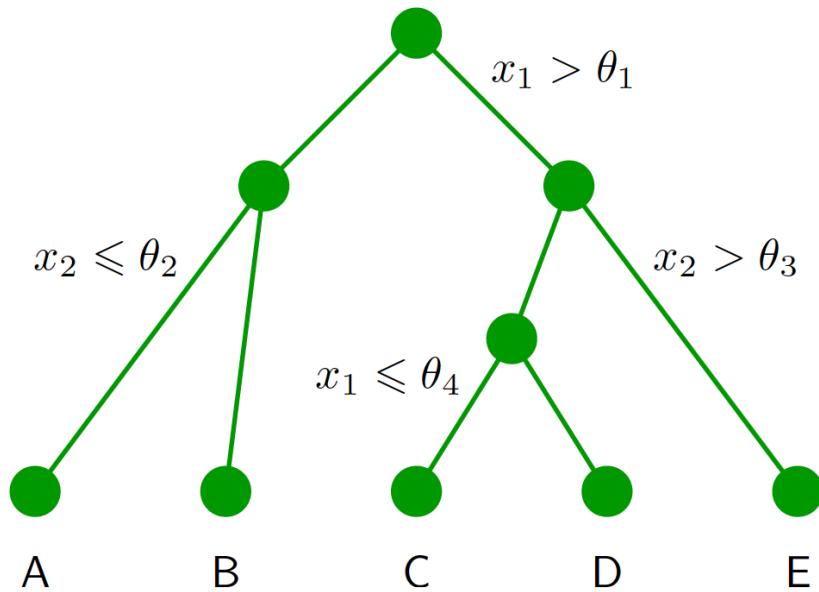
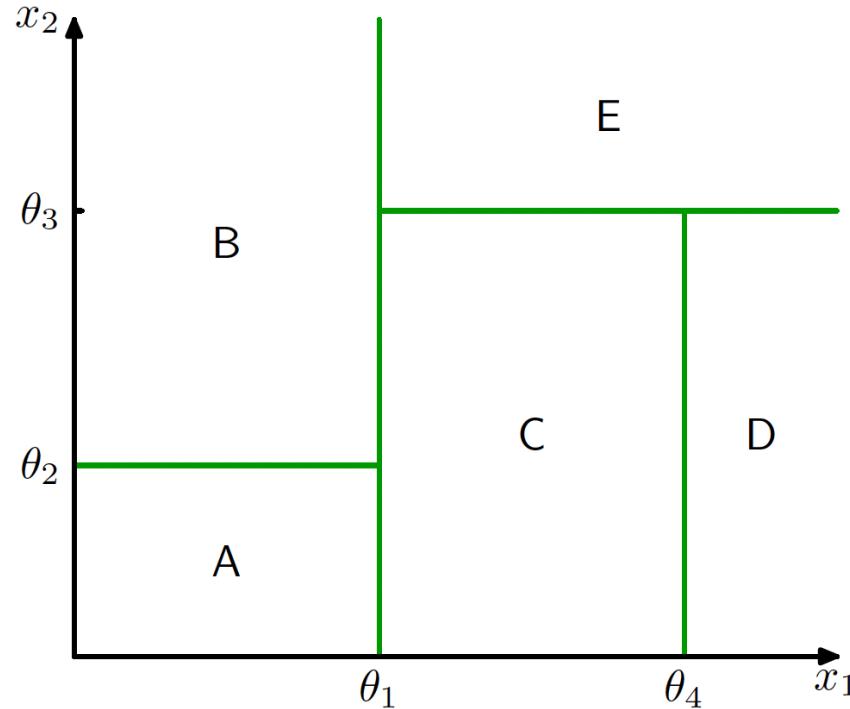
The instructor gratefully acknowledges Dan Roth, Vivek Srikumar, Sriram Sankararaman, Fei Sha, Ameet Talwalkar, Eric Eaton, and Jessica Wu whose slides are heavily used, and the many others who made their course material freely available online.

Recap: Decision tree

- ❖ The attribute for splitting is picked based on the information gain



A tree partitions the feature space



Other ways for splitting the input space?

Motivation: spam mail

hi Spam x

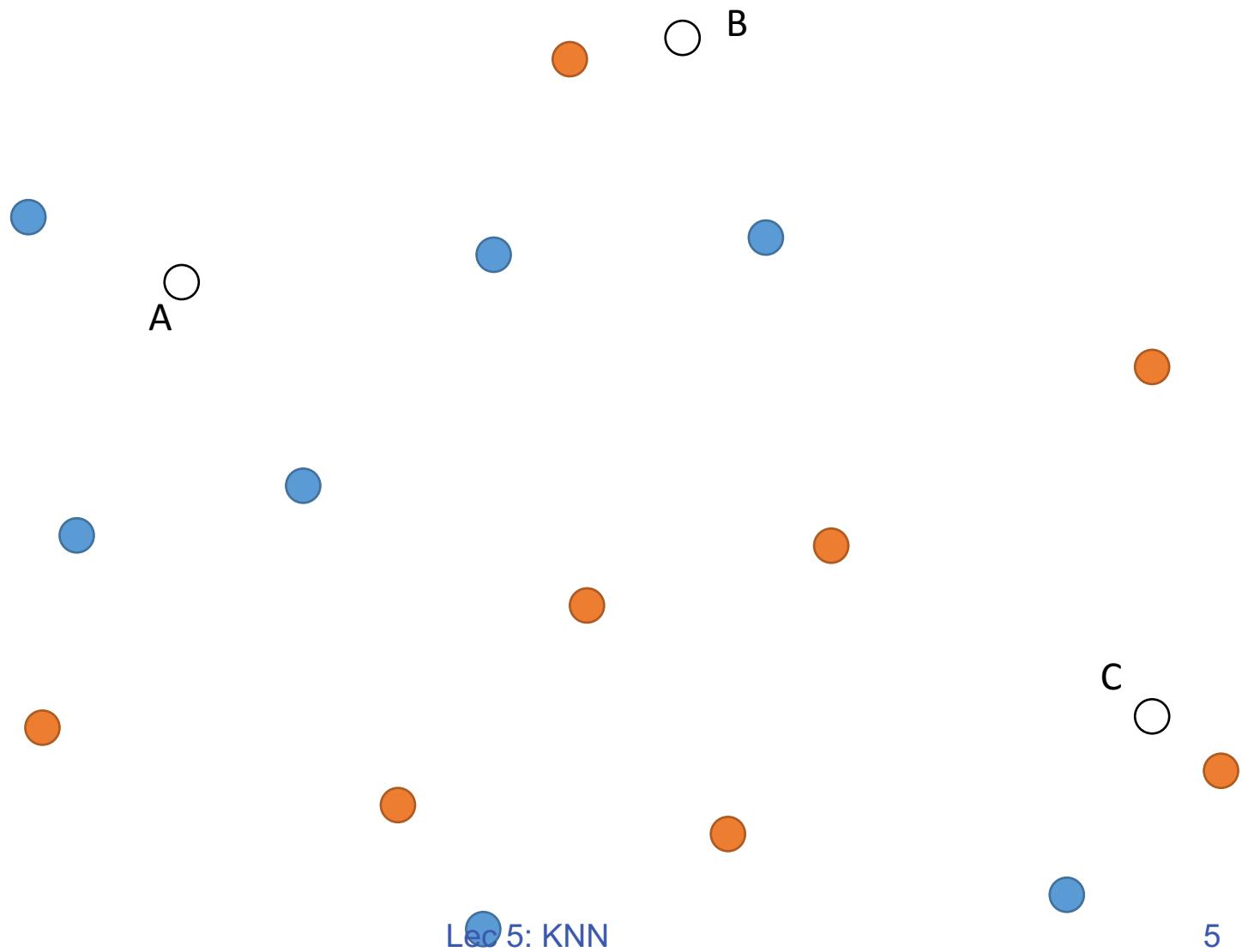
! marina <marina0279@static.vnpt.vn> Jan 16 (7 days ago) ★
to kw ↗

This message has a from address in static.vnpt.vn but has failed static.vnpt.vn's required tests for authentication. [Learn more](#)

You seem like my type and I would like to know you more! Write me if you are interested, here is my email denisavafursula@rambler.ru and, if you want, I will send some of my photos.
Hugs, marina

| | | | | |
|--------------------------|--|----------|---|--------|
| <input type="checkbox"/> | | Victoria | hi - You seem like my type and I would like to know you more! Write me if you are interested, here is my email vanesammrenate@ | Jan 17 |
| <input type="checkbox"/> | | Oksana | hi - You seem like my type and I would like to know you more! Write me if you are interested, here is my email elenarzpilse@rambl | Jan 16 |
| <input type="checkbox"/> | | Oksana | hi - You seem like my type and I would like to know you more! Write me if you are interested, here is my email venhelgarjxq@raml | Jan 16 |
| <input type="checkbox"/> | | Victoria | hi - You seem like my type and I would like to know you more! Write me if you are interested, here is my email elipetrayk@rambler | Jan 16 |
| <input type="checkbox"/> | | Natasha | hi - You seem like my type and I would like to know you more! Write me if you are interested, here is my email lucietmsabine@rar | Jan 16 |
| <input type="checkbox"/> | | Daria | hi - You seem like my type and I would like to know you more! Write me if you are interested, here is my email rokcmingrid@rambl | Jan 16 |
| <input type="checkbox"/> | | Katya | hi - You seem like my type and I would like to know you more! Write me if you are interested, here is my email michaelavat62@rar | Jan 16 |
| <input type="checkbox"/> | | Yulia | hi - You seem like my type and I would like to know you more! Write me if you are interested, here is my email elisa4inge@ramble | Jan 16 |
| <input type="checkbox"/> | | Veronika | hi - You seem like my type and I would like to know you more! Write me if you are interested, here is my email venlsajutta@ramble | Jan 16 |
| <input type="checkbox"/> | | Tanya | hi - You seem like my type and I would like to know you more! Write me if you are interested, here is my email ellairxt6t@rambler.r | Jan 16 |

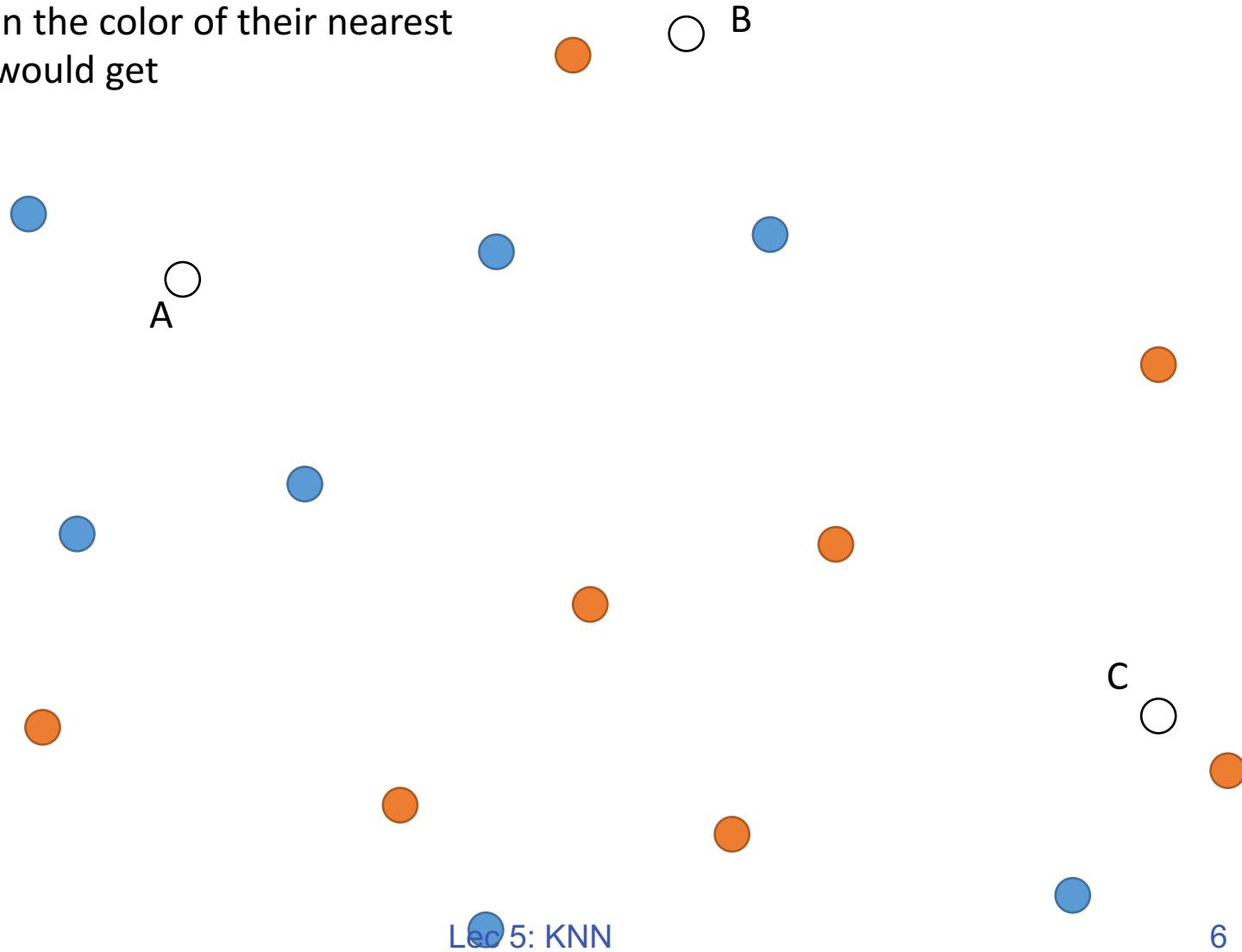
Motivation: How would you color the blank circles?



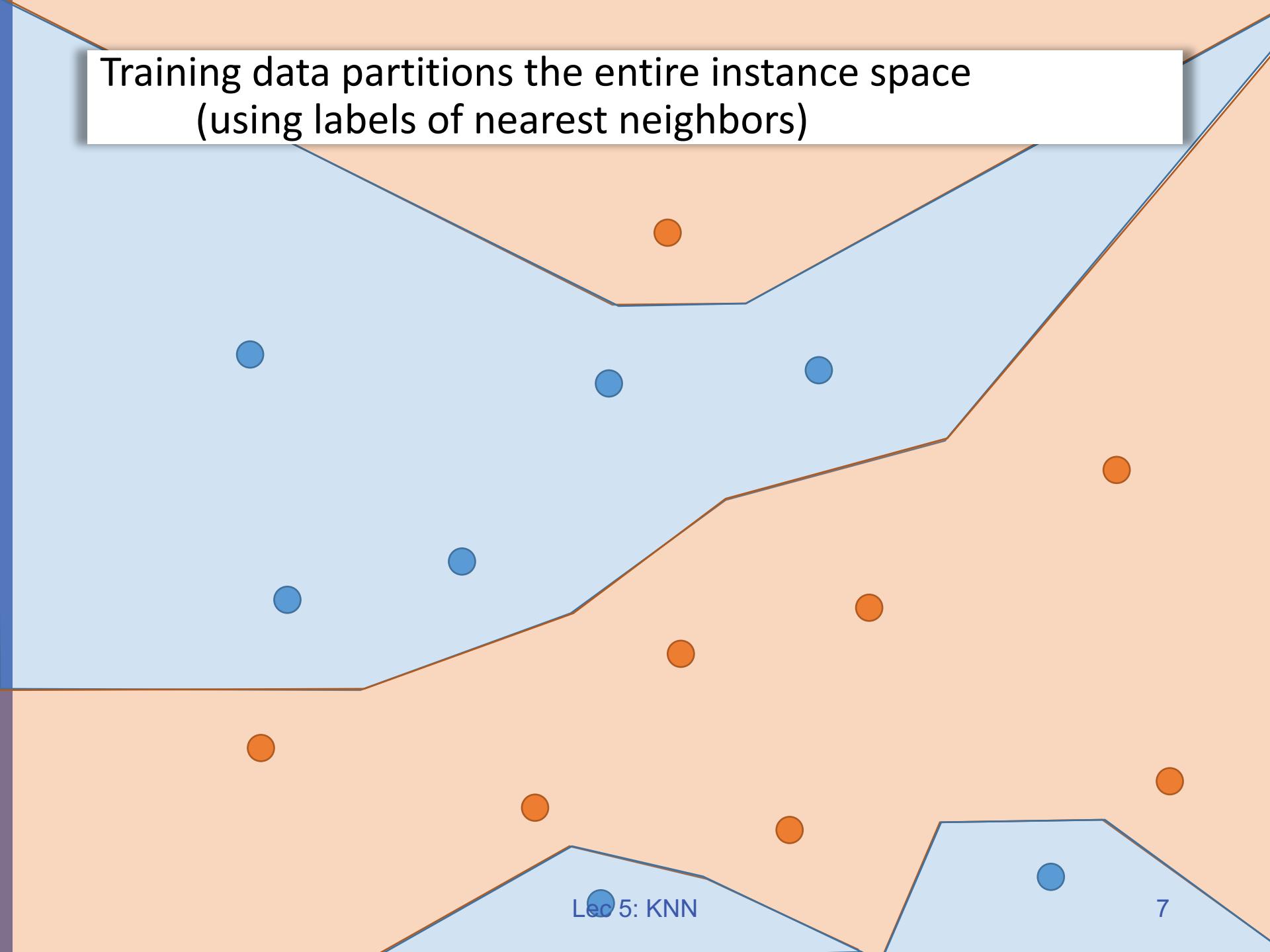
How would you color the blank circles?

If we based it on the color of their nearest neighbors, we would get

- A: Blue
- B: Red
- C: Red



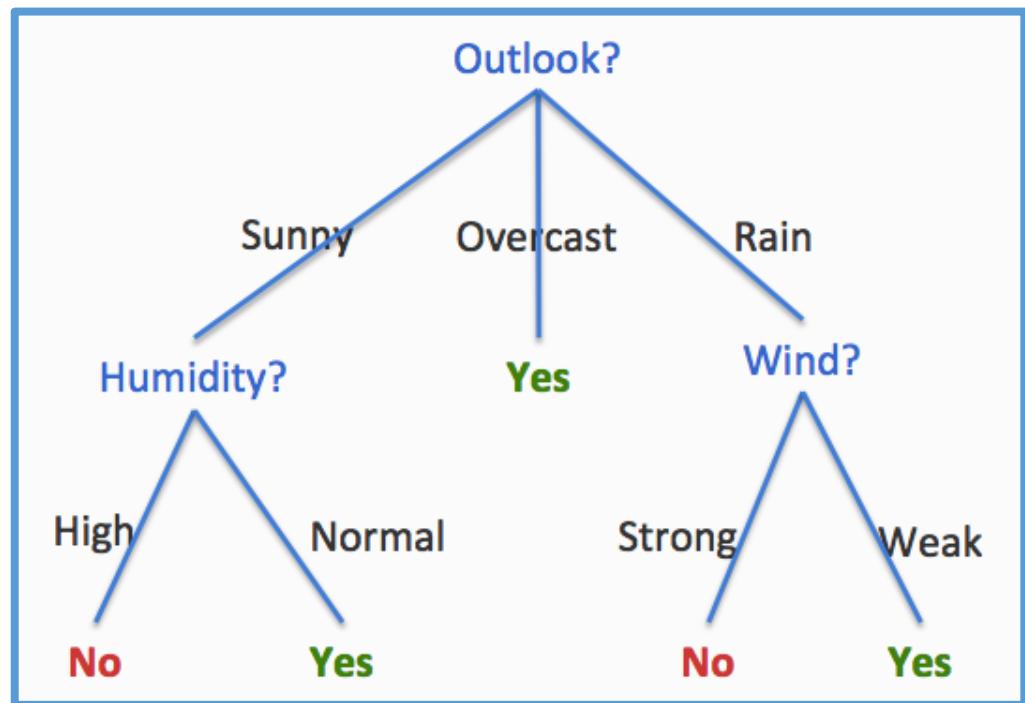
Training data partitions the entire instance space
(using labels of nearest neighbors)

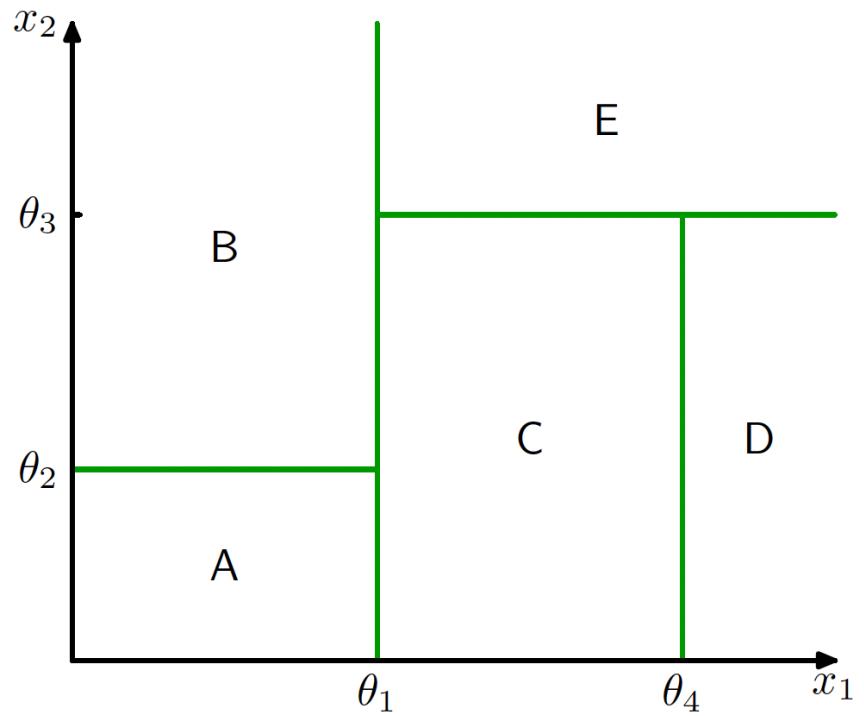
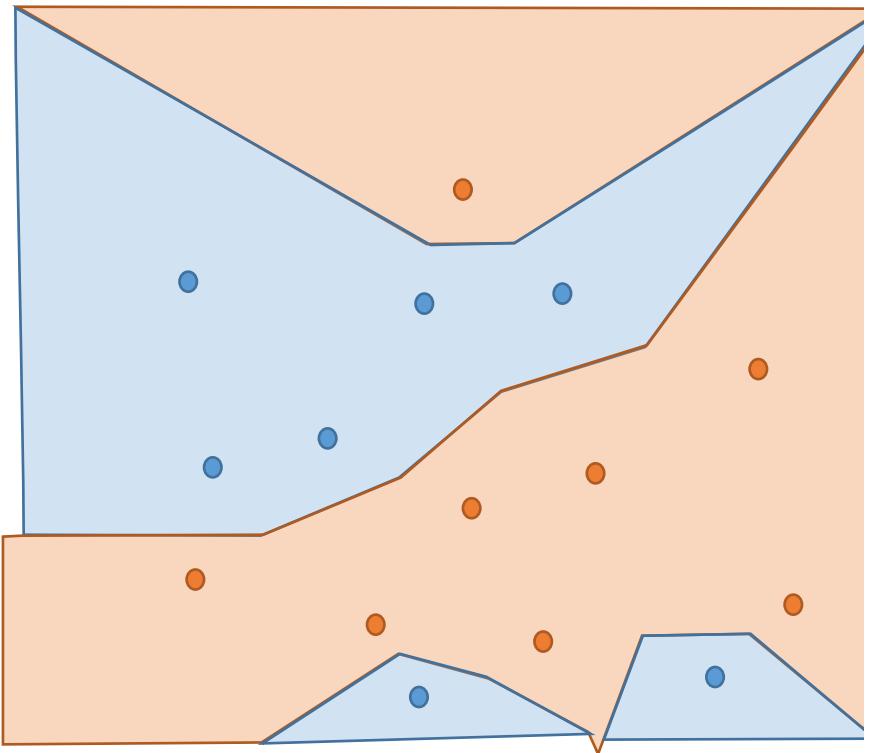


Recap: Decision tree

- ❖ Learning by divided the input space

| | O | T | H | W | Play? |
|----|---|---|---|---|-------|
| 1 | S | H | H | W | - |
| 2 | S | H | H | S | - |
| 3 | O | H | H | W | + |
| 4 | R | M | H | W | + |
| 5 | R | C | N | W | + |
| 6 | R | C | N | S | - |
| 7 | O | C | N | S | + |
| 8 | S | M | H | W | - |
| 9 | S | C | N | W | + |
| 10 | R | M | N | W | + |
| 11 | S | M | N | S | + |
| 12 | O | M | H | S | + |
| 13 | O | H | N | W | + |
| 14 | R | M | H | S | - |





Questions:
How the boundaries are different in KNN and decision tree?

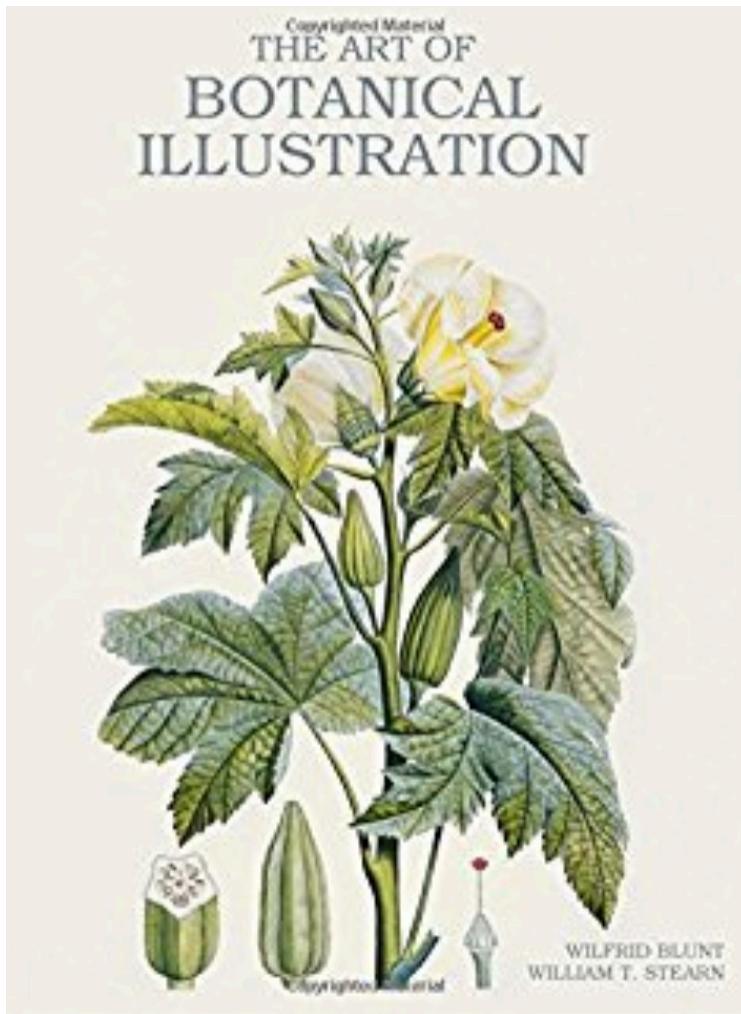
Motivation: Learning from memorization

Recognizing flowers

- ❖ What is this flower called?



Look up at botanical illustration books



Motivation: Learning from memorization

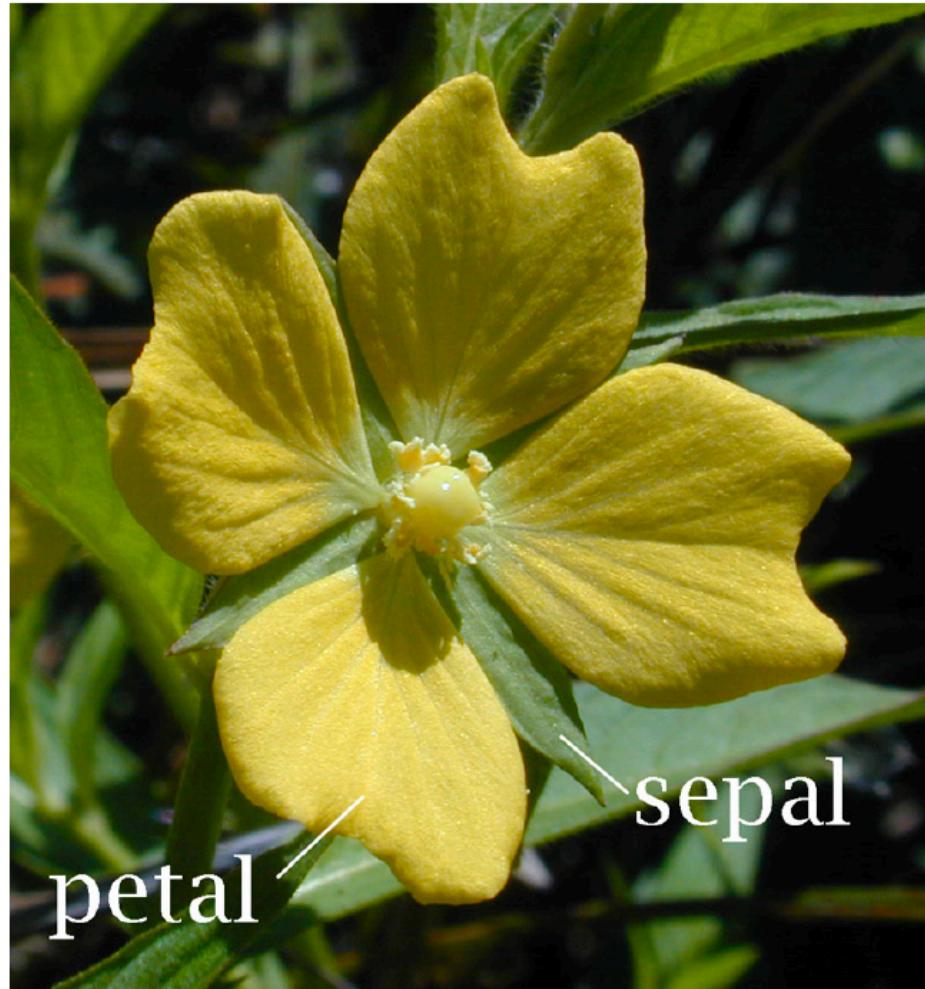
Recognizing flowers

Types of Iris: setosa, versicolor, and virginica



Measuring the properties of the flowers

- ❖ Features: the widths and lengths of sepal and petal



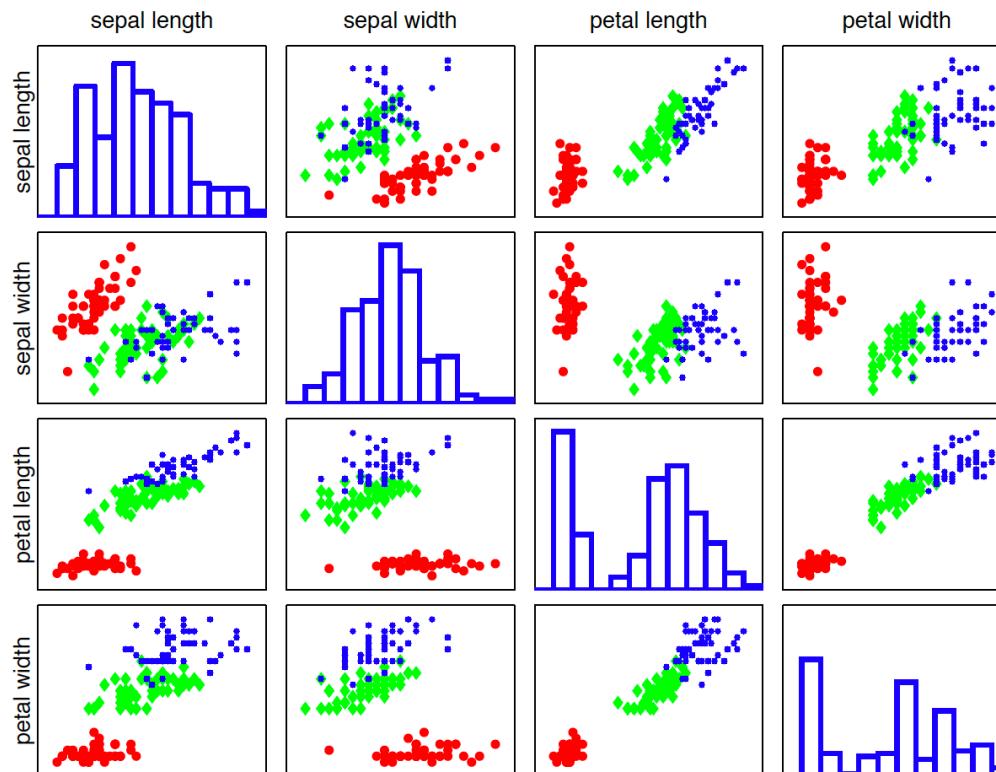
Snapshot of Iris data

- ❖ Existing Iris data
- ❖ 4 features
- ❖ 3 classes

| Fisher's Iris Data | | | | |
|--------------------|-------------|--------------|-------------|-----------|
| Sepal length | Sepal width | Petal length | Petal width | Species |
| 5.1 | 3.5 | 1.4 | 0.2 | I. setosa |
| 4.9 | 3.0 | 1.4 | 0.2 | I. setosa |
| 4.7 | 3.2 | 1.3 | 0.2 | I. setosa |
| 4.6 | 3.1 | 1.5 | 0.2 | I. setosa |
| 5.0 | 3.6 | 1.4 | 0.2 | I. setosa |
| 5.4 | 3.9 | 1.7 | 0.4 | I. setosa |
| 4.6 | 3.4 | 1.4 | 0.3 | I. setosa |
| 5.0 | 3.4 | 1.5 | 0.2 | I. setosa |
| 4.4 | 2.9 | 1.4 | 0.2 | I. setosa |
| 4.9 | 3.1 | 1.5 | 0.1 | I. setosa |

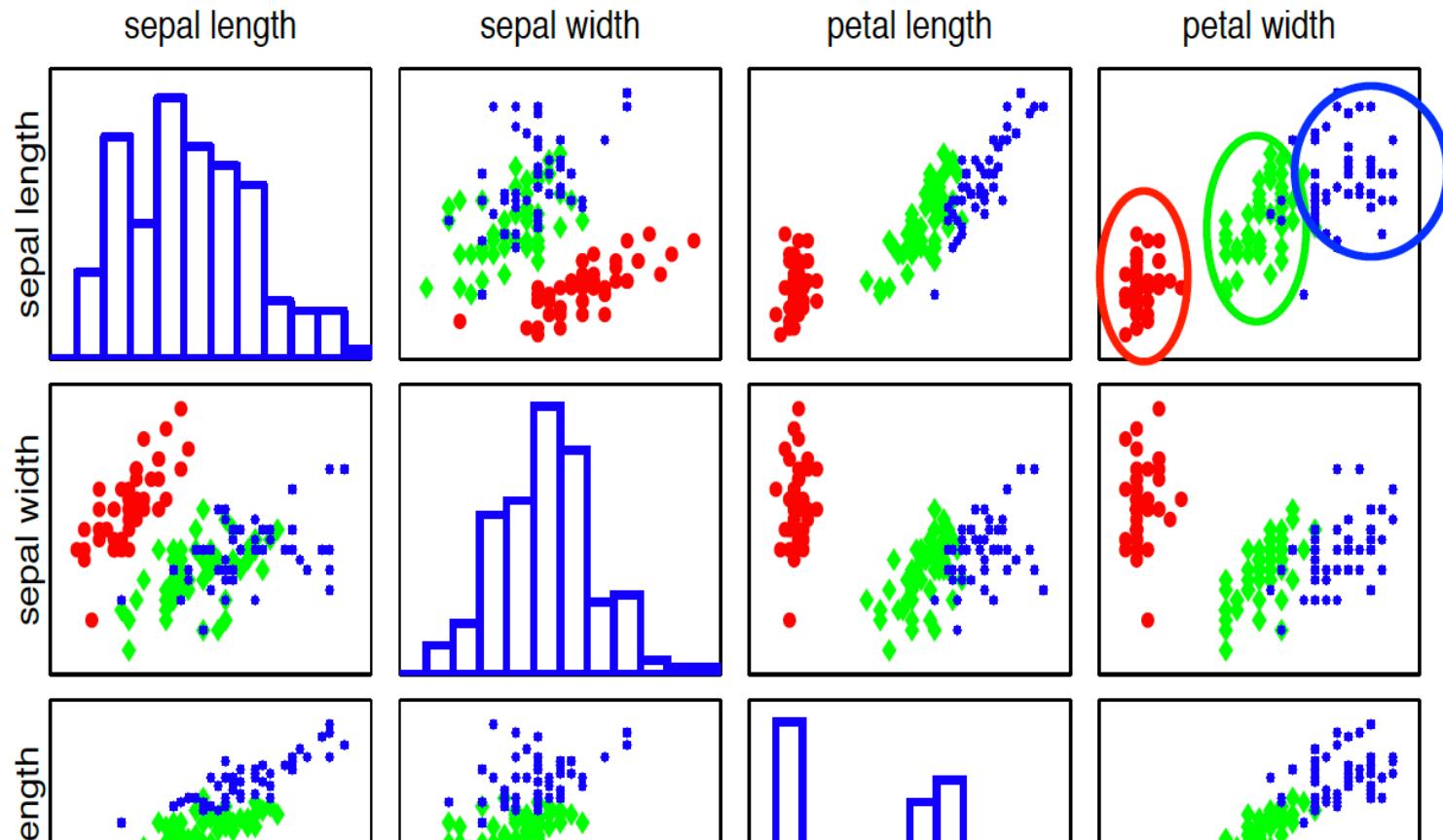
Pairwise scatter plots of 131 flower specimens

Each colored point is an instance (flower specimen): **setosa**, **versicolor**, **virginica**



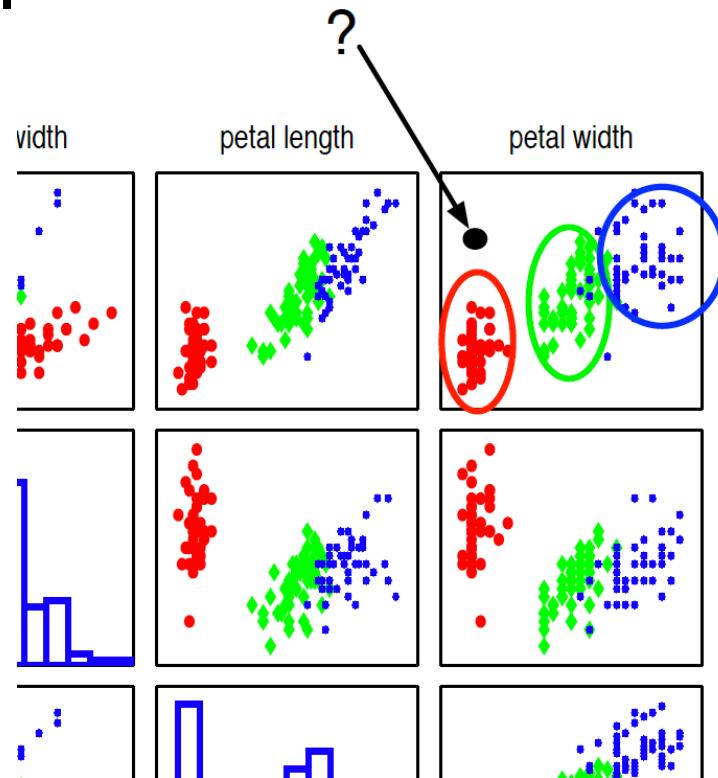
Different types seem well-clustered and separable

- ❖ By even just two features



Labeling an unknown flower

- ❖ Closer to the red cluster
=> label



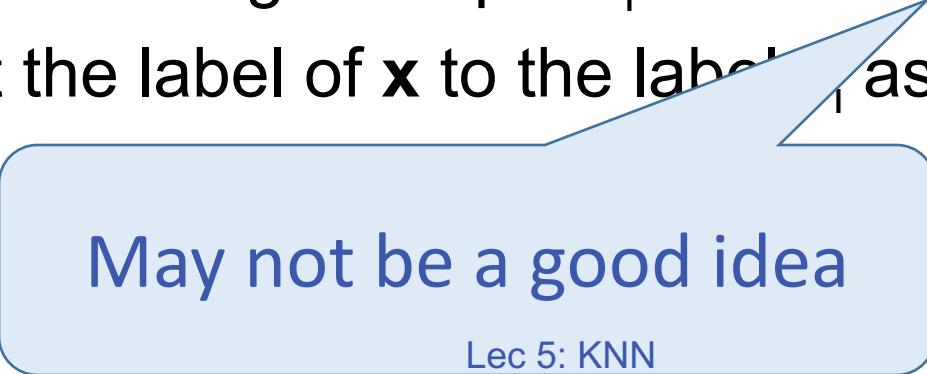
Each colored point is an instance (flower specimen): **setosa**, **versicolor**, **virginica**

What you will learn in this lecture

- ❖ What is the k-NN algorithm
- ❖ How to define distance between two points in the vector space
- ❖ Recap: parameter tuning
- ❖ Advantage/disadvantage of KNN
- ❖ Decision boundary of KNN
- ❖ The curse of the dimensionality
- ❖ Why/when KNN may fail

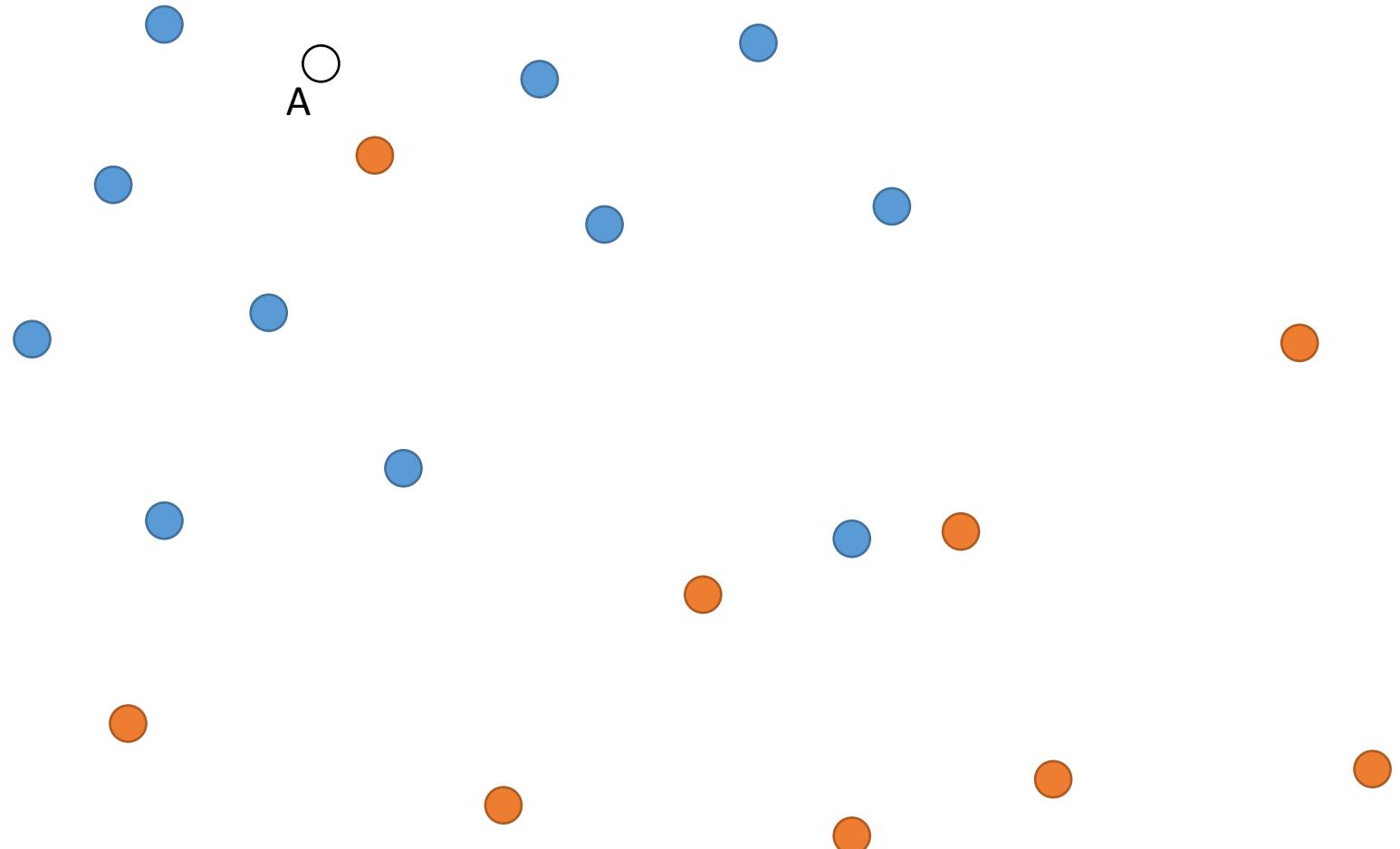
Nearest Neighbors: The basic version

- ❖ Training examples are vectors \mathbf{x}_i associated with a label y_i
 - ❖ E.g. \mathbf{x}_i = a feature vector for an email, y_i = SPAM
- ❖ Learning: Just store all the training examples
- ❖ Prediction: for a new example \mathbf{x}
 - ❖ Find the training example \mathbf{x}_i that is *closest* to \mathbf{x}
 - ❖ Predict the label of \mathbf{x} to the label y_i associated with \mathbf{x}_i



May not be a good idea

Counterexample: How would you color the blank circles?



K-Nearest Neighbors

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 - ❖ Find the k *closest* training examples to \mathbf{x}
 - ❖ Construct the label of \mathbf{x} using these k points.

Issues in designing KNN algorithm (Modeling)

- ❖ Training examples are vectors \mathbf{x}_i associated with a label y_i
 - ❖ E.g. \mathbf{x}_i = a feature vector for an email, y_i = SPAM
- ❖ Learning: Just store all the training examples
 - How to choose k ?
 - How to define distance?
- ❖ Prediction for a new example \mathbf{x}
 - ❖ Find the k closest training examples to \mathbf{x}
 - ❖ Construct the label of \mathbf{x} using these k points.

How to aggregate the information and
make the prediction?

Issues in designing KNN algorithm (computation/algorithim)

- ❖ Training examples are vectors \mathbf{x}_i associated with a label y_i
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 - How to store data?
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How to find the closest points?

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 - ❖ Construct the

How to find the closest points?

This is an important research topic, but I will not cover it in this class.
Reference: e.g. K-d tree (https://en.wikipedia.org/wiki/K-d_tree)
Lec 5: KNN

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How to aggregate the information and
make the prediction?

K-Nearest Neighbors

- ❖ Prediction for a new example \mathbf{x}
 - ❖ Find the k *closest* training examples to \mathbf{x}
 - ❖ Construct the label of \mathbf{x} using these k points.
 - ❖ For classification: Every neighbor votes on the label.
Predict the most frequent label among the neighbors.
 - ❖ For regression:
Predict the mean value



Q: other alternatives?

Issues in designing KNN algorithm (Modeling)

- ❖ Training examples are vectors \mathbf{x}_i associated with a label y_i
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How to define distance?

Distance between instances

- ❖ In general, a good place to inject knowledge about the domain
- ❖ Behavior of this approach can depend on this
- ❖ How do we measure distances between instances?

Distance between instances

Numeric features, represented as n dimensional vectors

Distance between instances

Numeric features, represented as n dimensional vectors

- ❖ Euclidean distance

$$\|\mathbf{x}_1 - \mathbf{x}_2\|_2 = \sqrt{\sum_{i=1}^n (\mathbf{x}_{1,i} - \mathbf{x}_{2,i})^2}$$

Distance between instances

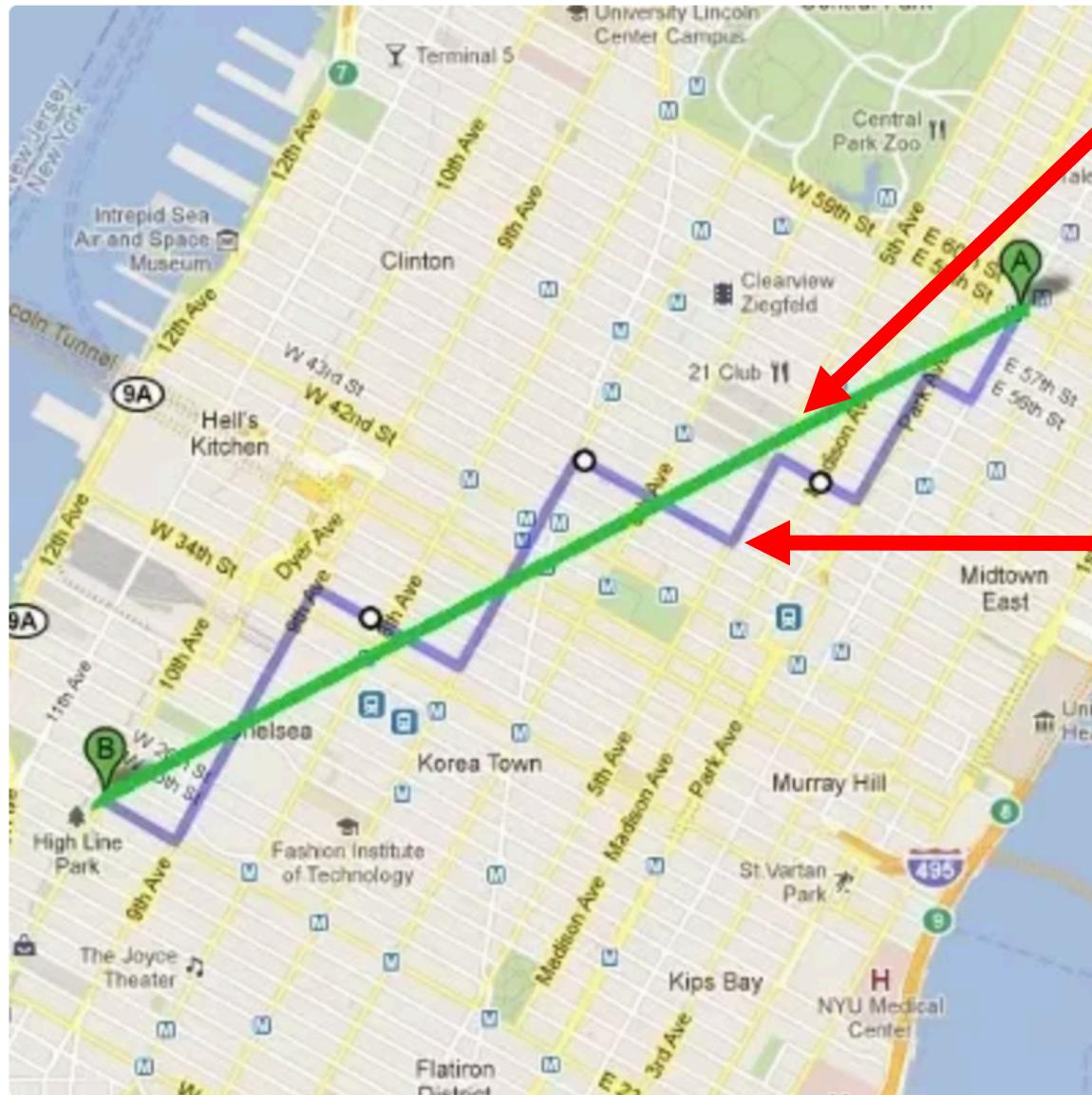
Numeric features, represented as n dimensional vectors

- ❖ Euclidean distance

$$\|\mathbf{x}_1 - \mathbf{x}_2\|_2 = \sqrt{\sum_{i=1}^n (\mathbf{x}_{1,i} - \mathbf{x}_{2,i})^2}$$

- ❖ Manhattan distance

$$\|\mathbf{x}_1 - \mathbf{x}_2\|_1 = \sum_{i=1}^n |\mathbf{x}_{1,i} - \mathbf{x}_{2,i}|$$



Euclidean distance

Manhattan distance

Distance between instances

Numeric features, represented as n dimensional vectors

- ❖ Euclidean distance

$$\|\mathbf{x}_1 - \mathbf{x}_2\|_2 = \sqrt{\sum_{i=1}^n (\mathbf{x}_{1,i} - \mathbf{x}_{2,i})^2}$$

- ❖ Manhattan distance

$$\|\mathbf{x}_1 - \mathbf{x}_2\|_1 = \sum_{i=1}^n |\mathbf{x}_{1,i} - \mathbf{x}_{2,i}|$$

- ❖ L_p -norm

- ❖ Euclidean = L_2

- ❖ Manhattan = L_1

$$\|\mathbf{x}_1 - \mathbf{x}_2\|_p = \left(\sum_{i=1}^n |\mathbf{x}_{1,i} - \mathbf{x}_{2,i}|^p \right)^{\frac{1}{p}}$$

$P > 0$

Distance between instances

What about symbolic/categorical features?

Distance between instances

Symbolic/categorical features

Most common distance is the *Hamming distance*

- ❖ Number of bits that are different
- ❖ Or: Number of features that have a different value
- ❖ Example:

\mathbf{X}_1 : {Shape=Triangle, Color=Red, Location=Left, Orientation=Up}

\mathbf{X}_2 : {Shape=Triangle, Color=Blue, Location=Left, Orientation=Down}

Hamming distance = 2

Issues in designing KNN algorithm (Modeling)

- ❖ Training examples are vectors \mathbf{x}_i associated with a label y_i
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- ❖ Learning: Just store all the training examples
 - How to choose k and the distance measure?
- ❖ Prediction for a new example \mathbf{x}
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Hyper-parameters in KNN

- ❖ Parameters:
 - ❖ Choosing K (# nearest neighbors)
 - ❖ Distance measurement (e.g., p in the L_p -norm)
$$\|\mathbf{x}_1 - \mathbf{x}_2\|_p = \left(\sum_{i=1}^n |\mathbf{x}_{1,i} - \mathbf{x}_{2,i}|^p \right)^{\frac{1}{p}}$$
- ❖ Those are not specified by the algorithm itself
 - ❖ Require empirical studies
 - ❖ The best parameter set is task/dataset-specific.

Recap: Turning parameters by using a validation set

Training data (set)

- N samples/instances: $\mathcal{D}^{\text{TRAIN}} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_N, y_N)\}$
- They are used for learning $h(\cdot)$

Test (evaluation) data

- M samples/instances: $\mathcal{D}^{\text{TEST}} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_M, y_M)\}$
- They are used for assessing how well $h(\cdot)$ will do in predicting an unseen $\mathbf{x} \notin \mathcal{D}^{\text{TRAIN}}$

Development (or validation) data

- L samples/instances: $\mathcal{D}^{\text{DEV}} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_L, y_L)\}$
- They are used to optimize hyperparameter(s).

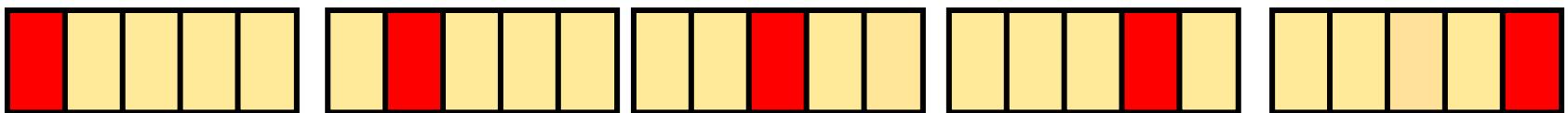
Training data, validation and test data should *not* overlap!

Recap: Recipe of train/dev/test

- ❖ For each possible value of the hyper-parameter (e.g., $K = 1, 2, 3, \dots, 10$)
 - ❖ Train a model using D^{TRAIN}
 - ❖ Evaluate the performance on D^{DEV}
- ❖ Choose the model parameter with the best performance on D^{DEV}
- ❖ (optional) Re-train the model on $D^{TRAIN} \cup D^{DEV}$ with the best parameter set
- ❖ Evaluate the model on D^{TEST}

N-fold cross validation

- ❖ Split data into N equal-sized parts



- ❖ Train and test N different classifiers
- ❖ Report average accuracy and standard deviation of the accuracy
- ❖ If $N == \text{datasize}$, we called it leave-one-out cross validation

Finding parameters based on cross validation

- ❖ Given D^{TRAIN} and D^{TEST} , for each possible value of the hyper-parameter (e.g., $K = 1, 2, 3, \dots, 10$)
 - ❖ Conduct cross validation on D^{TRAIN} with parameter K
- ❖ Choose the model parameter with the best cross validation performance
- ❖ Re-train the model on D^{TRAIN} with the best parameter set
- ❖ Evaluate the model on D^{TEST}

Put together (K=1, distance= Euclidean)

- ❖ Training: Store the entire training set.
- ❖ Test:

$$\boldsymbol{x}(1) = \boldsymbol{x}_{\text{nn}(\boldsymbol{x})}$$

where $\text{nn}(\boldsymbol{x}) \in [N] = \{1, 2, \dots, N\}$, i.e., the index to one of the training instances

$$\text{nn}(\boldsymbol{x}) = \arg \min_{n \in [N]} \|\boldsymbol{x} - \boldsymbol{x}_n\|_2^2 = \arg \min_{n \in [N]} \sum_{d=1}^D (x_d - x_{nd})^2$$

$$y = h(\boldsymbol{x}) = y_{\text{nn}(\boldsymbol{x})}$$

Other tricks

- ❖ In practice, use an odd K. Why?
 - ❖ To break ties
- ❖ Neighbors' labels could be weighted by their distance
 - ❖ Related to Kernel method
- ❖ Feature normalization could be important. Why?
 - ❖ Different features could have different scales (weight, height, etc); but the distance weights them equally
 - ❖ Often, good idea to center the features to make them zero mean and unit standard deviation.

Example: Feature normalization

- ❖ Classify Iris with two features

Training data

| ID (n) | petal width (x_1) | sepal length (x_2) | category (y) |
|--------|-----------------------|------------------------|------------------|
| 1 | 0.2 | 5.1 | setosa |
| 2 | 1.4 | 7.0 | versicolor |
| 3 | 2.5 | 6.7 | virginica |

- ❖ Flower with unknown category

petal width = 1.8 and sepal width = 6.4

Calculating distance = $\sqrt{(x_1 - x_{n1})^2 + (x_2 - x_{n2})^2}$



| ID | distance |
|----|----------|
| 1 | 1.75 |
| 2 | 0.72 |
| 3 | 0.76 |

Example: Feature normalization

- ❖ Change units of x_2 from cm to mm

Training data

| ID (n) | petal width (x_1) | sepal length (x_2) | category (y) |
|--------|-----------------------|------------------------|------------------|
| 1 | 0.2 | 51 | setosa |
| 2 | 1.4 | 70 | versicolor |
| 3 | 2.5 | 67 | virginica |

- ❖ Flower with unknown category

petal width = 1.8 and sepal width = 64

Calculating distance = $\sqrt{(x_1 - x_{n1})^2 + (x_2 - x_{n2})^2}$



| ID | distance |
|----|----------|
| 1 | 13 |
| 2 | 6 |
| 3 | 3 |

Preprocess data

- ❖ Normalize data to have zero mean and unit standard deviation in each dimension

$$\bar{x}_d = \frac{1}{N} \sum_n x_{nd}, \quad s_d^2 = \frac{1}{N-1} \sum_n (x_{nd} - \bar{x}_d)^2$$

- ❖ Scale the feature accordingly

$$x_{nd} \leftarrow \frac{x_{nd} - \bar{x}_d}{s_d}$$

Where are we?

- ❖ What is the k-NN algorithm
- ❖ How to define distance between two points in the vector space
- ❖ Recap: parameter tuning
- ❖ Decision boundary of KNN
- ❖ Advantage/disadvantage of KNN
- ❖ The curse of the dimensionality
- ❖ Why/when KNN may fail

The decision boundary for KNN

Is the K nearest neighbors algorithm explicitly building a function?

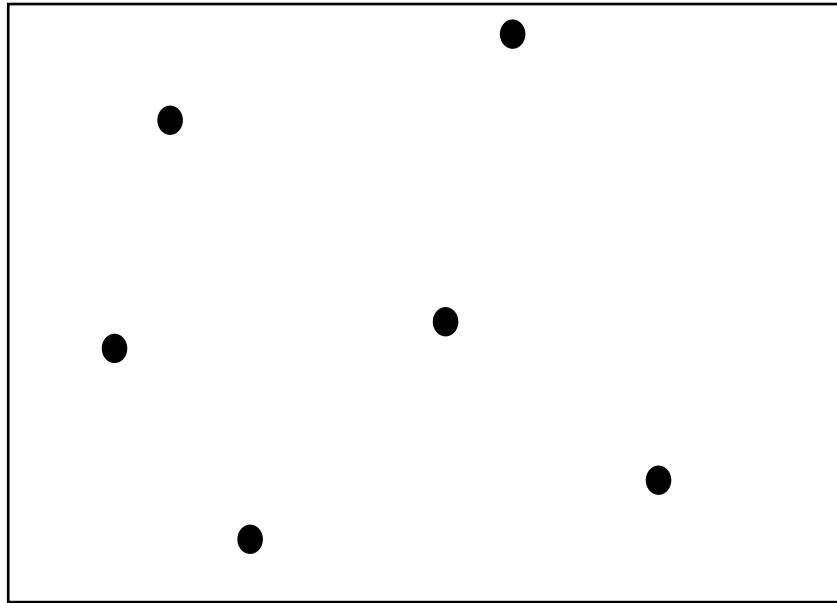
The decision boundary for KNN

Is the K nearest neighbors algorithm explicitly building a function?

- ❖ **No**, it never forms an explicit hypothesis

But we can still ask: Given a training set what is the implicit function that is being computed

The Voronoi Diagram

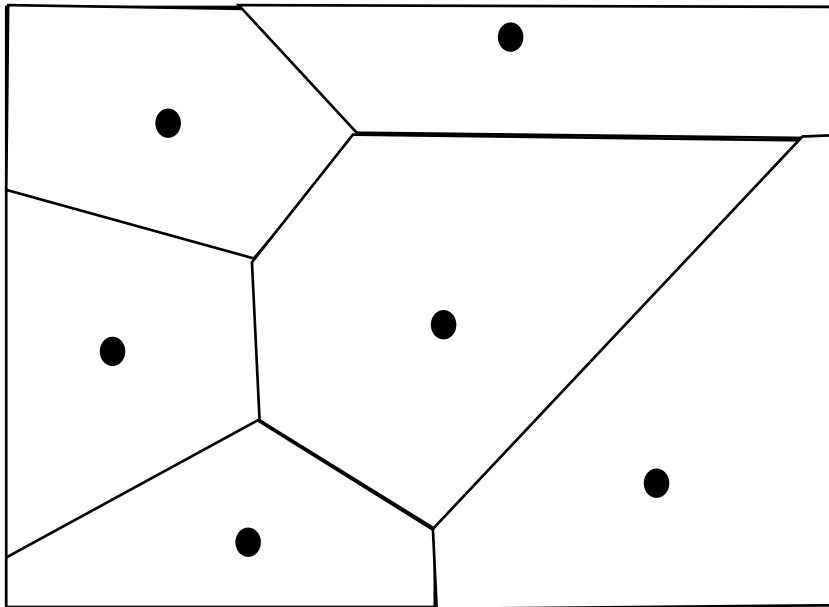


For any point x in a training set S ,
the **Voronoi Cell** of x is a polytope consisting of all points closer to
 x than any other points in S

The **Voronoi diagram** is the union of all Voronoi cells

- Covers the entire space

The Voronoi Diagram (w/ Euclidean distance)

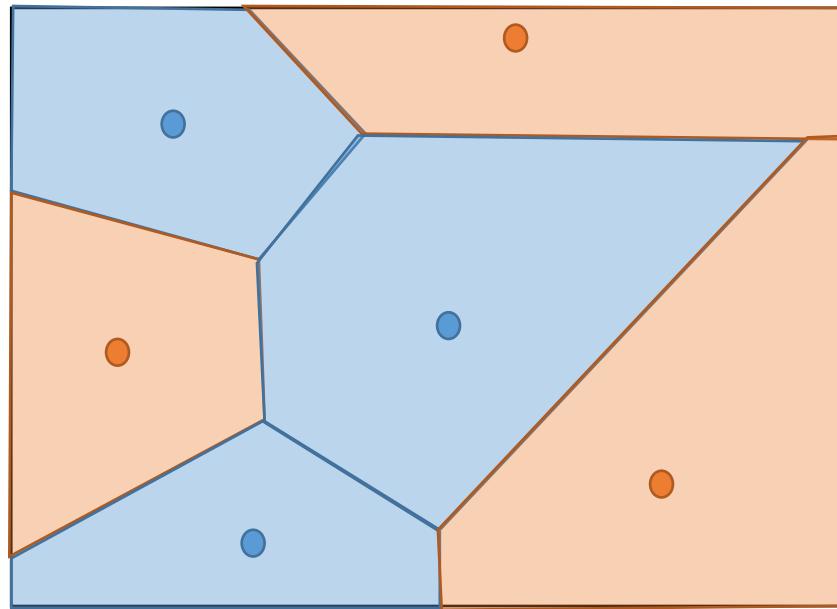


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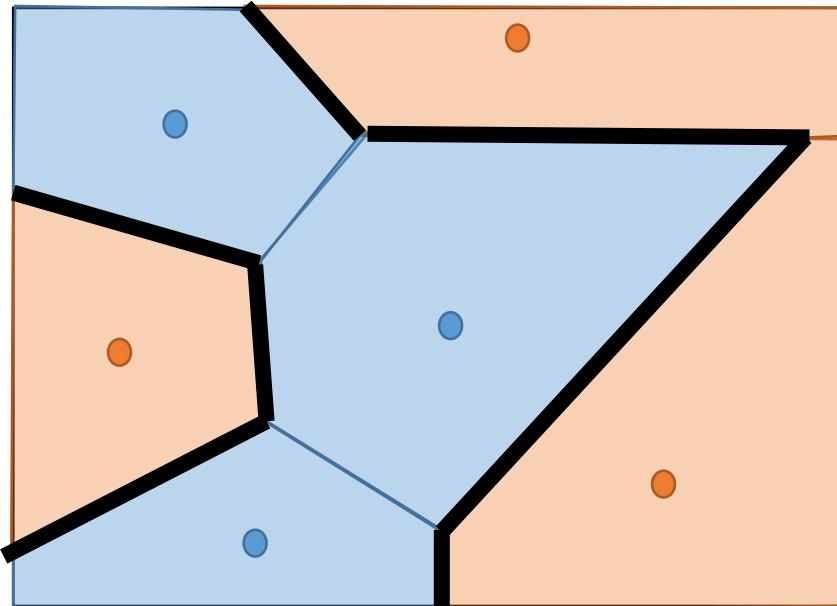
- Covers the entire space

Voronoi diagrams of training examples



Voronoi diagrams colored with the output label
Picture uses Euclidean distance with 1-nearest neighbor.

Decision boundary of 1-NN



What about K-nearest neighbors?

Also partitions the space, but much more complex
decision boundary

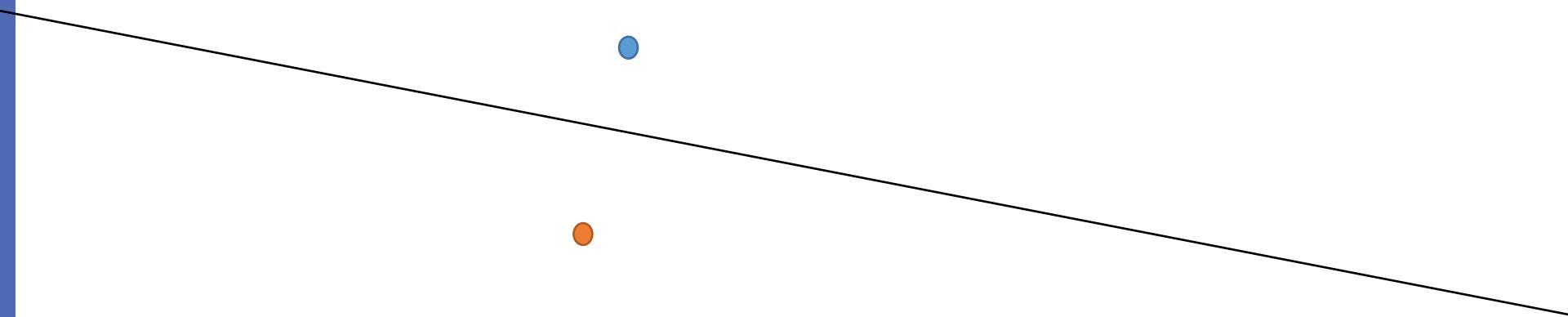
Exercise

If you have only two training points, what will the decision boundary for 1-nearest neighbor be?



Exercise

If you have only two training points, what will the decision boundary for 1-nearest neighbor be?



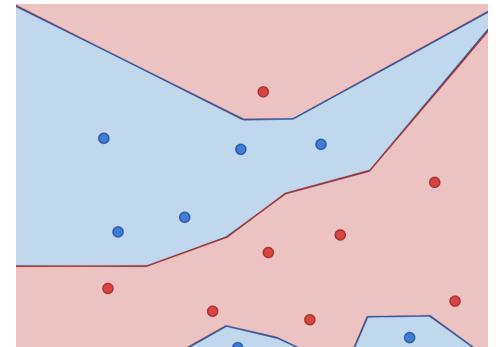
- ❖ A line bisecting the two points

Instance based learning

- ❖ A class of learning methods
 - ❖ Learning: Storing examples with labels
 - ❖ Prediction: When presented a new example, classify the labels using *similar* stored examples
- ❖ K-nearest neighbors algorithm is an example of this class of methods
- ❖ Most of the computation is performed only at prediction time
 - ❖ Open book v.s. closed book exams

Advantages

- ❖ Training is *very fast*
 - ❖ Just adding labeled instances to a list
 - ❖ More complex indexing methods can be used, which slow down learning slightly to make prediction faster
- ❖ Can learn very **complex functions**
- ❖ We always have the training data
 - ❖ For other learning algorithms, after training, we don't store the data anymore. What if we want to do something with it later...



Disadvantages

- ❖ Needs a lot of storage
- ❖ Prediction can be slow!
 - ❖ Naïvely: $O(dN)$ for N training examples in d dimensions
 - ❖ More data will make it slower
- ❖ Nearest neighbors are fooled by irrelevant attributes
 - ❖ Important and subtle
- ❖ Curse of dimensionality
 - ❖ Things can go wrong in the high-dimensional spaces
 - ❖ What might be intuitive for 2 or 3 dimensions do not always apply to high dimensional spaces

Of course, irrelevant attributes will hurt

Suppose we have 1000 dimensional feature vectors

- ❖ But only 10 features are relevant
- ❖ Distances will be dominated by the large number of irrelevant features

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Suppose we have 1000 dimensional feature vectors

- ❖ But only 10 features are relevant
- ❖ Distances will be dominated by the large number of irrelevant features

But even with only relevant attributes, high dimensional spaces behave in odd ways



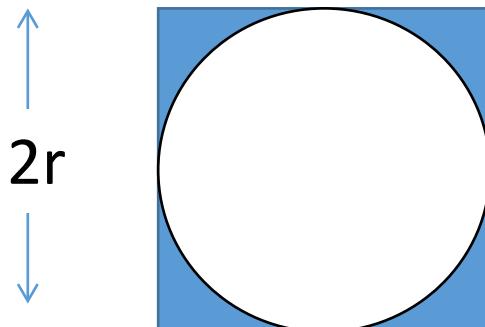
CURSE OF

MISERABILITY

The Curse of Dimensionality

Example 1: What fraction of the points in a cube lie outside the sphere inscribed in it?

In two dimensions

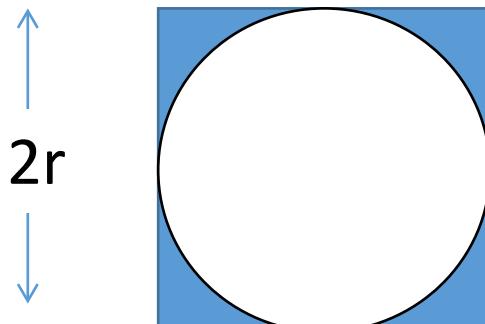


What fraction of the square (i.e the cube) is outside the inscribed circle (i.e the sphere) in two dimensions?

The Curse of Dimensionality

Example 1: What fraction of the points in a cube lie outside the sphere inscribed in it?

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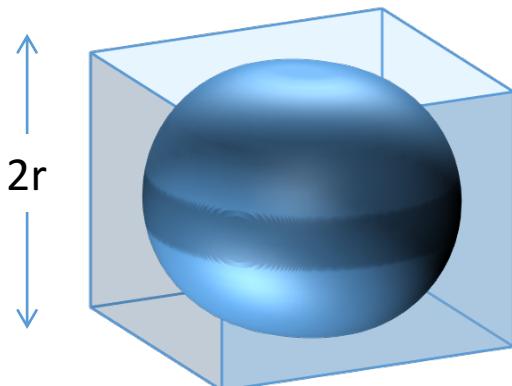
What fraction of the square (i.e the cube) is outside the inscribed circle (i.e the sphere) in two dimensions?

$$1 - \frac{\pi r^2}{4r^2} = 1 - \frac{\pi}{4}$$

The Curse of Dimensionality

Example 1: What fraction of the points in a cube lie outside the sphere inscribed in it?

In three dimensions



What fraction of the square (i.e the cube) is outside the inscribed circle (i.e the sphere) in two dimensions?

$$1 - \frac{\frac{4}{3}\pi r^3}{8r^3} = 1 - \frac{\pi}{6}$$

General form:

https://en.wikipedia.org/wiki/Volume_of_an_N-ball

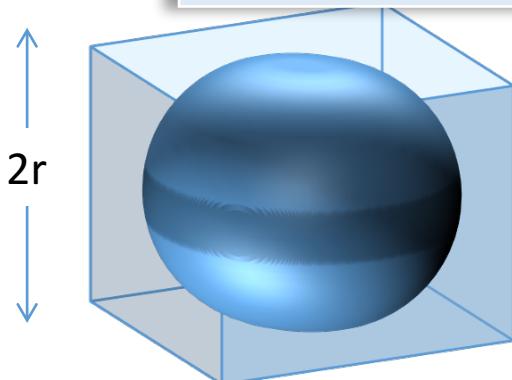
The Curse of Dimensionality

Example 1: What fraction of the points in a cube lie outside the sphere inscribed in it?

In three

As the dimensionality increases,
this fraction approaches 1!!

are

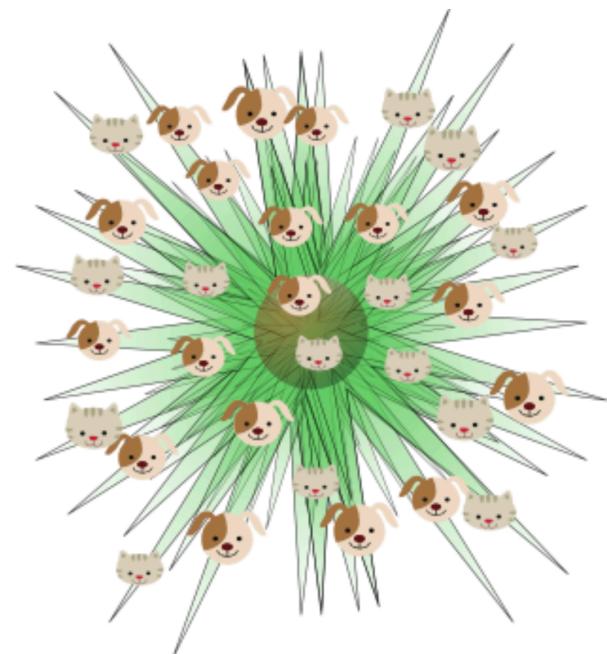
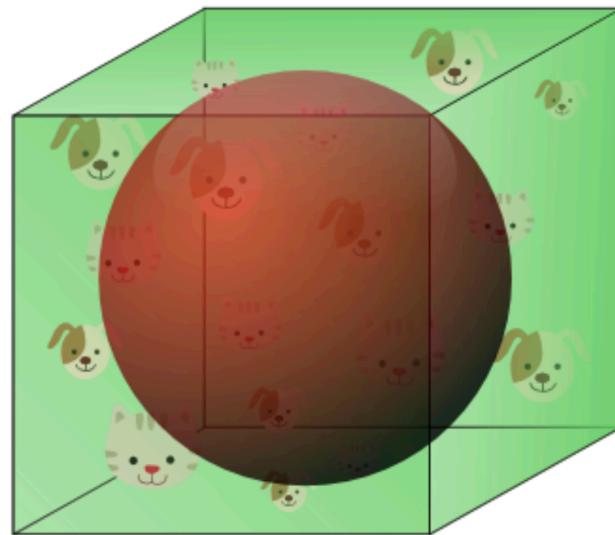
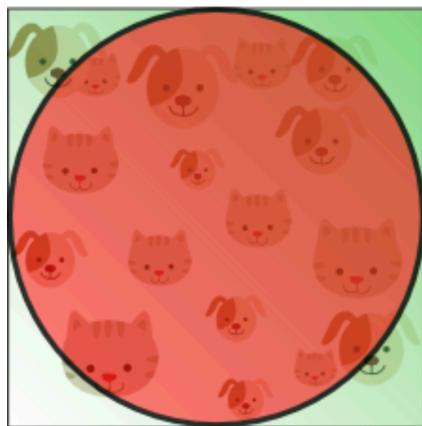


(i.e the cube) is outside the
inscribed circle (i.e the sphere)
in two dimensions?

$$1 - \frac{\frac{4}{3}\pi r^3}{8r^3} = 1 - \frac{\pi}{6}$$

Indication

- ❖ In high dimensions, most of the volume of the cube is far away from the center!

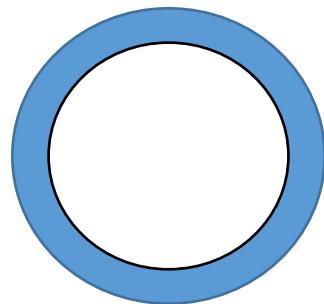


[http://www.woforo.com/blogs/HosseinAbedi/
curse-of-dimensionality](http://www.woforo.com/blogs/HosseinAbedi/curse-of-dimensionality)

The Curse of Dimensionality

Example 2: What fraction of the volume of a unit sphere lies between radius $1 - \epsilon$ and radius 1?

In two dimensions



What fraction of the area of the circle is in the blue region?

$$\frac{\pi \cdot 1^2 - \pi(1 - \epsilon)^2}{\pi \cdot 1^2} = 1 - (1 - \epsilon)^2$$

The Curse of Dimensionality

Example 2: What fraction of the volume of a unit sphere lies between radius $1 - \epsilon$ and radius 1?

In two dimensions $\frac{\pi \cdot 1^2 - \pi(1 - \epsilon)^2}{\pi \cdot 1^2} = 1 - (1 - \epsilon)^2$

In d dimensions $1 - (1 - \epsilon)^d$

When d is large this fraction goes to 1!

In high dimensions, most of the volume of the sphere is far away from the center!

The Curse of Dimensionality

- ❖ Most of the points in high dimensional spaces are far away from the origin!
- ❖ In 2 or 3 dimensions, most points are near the center
 - ❖ Need more data to “fill up the space”
- ❖ Bad news for k-NN in high dimensional spaces
 - ❖ Even if most/all features are relevant, in high dimensional spaces, most points are equally far from each other!
 - ❖ “Neighborhood” becomes very large

Dealing with the curse of dimensionality

- ❖ Most “*real-world*” data is not uniformly distributed in the high dimensional space
 - ❖ Different ways of capturing the *underlying dimensionality* of the space -- dimensionality reduction
- ❖ Feature selection, an art
 - ❖ Select features, (e.g., by information gain)
 - ❖ Try out different feature sets of different sizes and pick a good set based on a validation set
- ❖ Prior knowledge or preferences about the hypotheses can also help

What you will learn in this lecture

- ❖ What is the k-NN algorithm
- ❖ How to define distance between two points in the vector space
- ❖ Recap: parameter tuning
- ❖ Advantage/disadvantage of KNN
- ❖ Decision boundary of KNN
- ❖ The curse of the dimensionality
- ❖ Why/when KNN may fail

Exercises

1. What will happen when you choose K to the number of training examples?
2. Suppose you want to build a nearest neighbors classifier to predict whether a beverage is a coffee or a tea using two features: the volume of the liquid (in milliliters) and the caffeine content (in grams). You collect the following data:

| Volume (ml) | Caffeine (g) | Label |
|-------------|--------------|--------|
| 238 | 0.026 | Tea |
| 100 | 0.011 | Tea |
| 120 | 0.040 | Coffee |
| 237 | 0.095 | Coffee |

What is the label for a test point with
Volume = 120, Caffeine = 0.013?

Why might this be incorrect?

How would you fix the problem?

Exercises

1. What will happen when you choose K to the number of training examples?

The label will always be the most common label in the training data

2. Suppose you want to build a nearest neighbors classifier to predict whether a beverage is a coffee or a tea using two features: the volume of the liquid (in milliliters) and the caffeine content (in grams). You collect the following data:

| Volume (ml) | Caffeine (g) | Label |
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| 238 | 0.026 | Tea |
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| 120 | 0.040 | Coffee |
| 237 | 0.095 | Coffee |

What is the label for a test point with Volume = 120, Caffeine = 0.013?

Coffee

Why might this be incorrect?

Because Volume will dominate the distance

How would you fix the problem?

Rescale the features. Maybe to zero mean, unit variance