GENERAL ASSEMBLY

DATA SCIENCE
LECTURE 4: K-NEAREST NEIGHBORS CLASSIFICATION

YUCHEN ZHAO / DAT-14

RECAP

LAST TIME:

I. DATA RETRIEVAL

II. ETL INTRO

III. VISUALIZATION

RECAP

LAST TIME:

I. DATA RETRIEVAL (API, JSON)

II. ETL INTRO (DATABASE, SQL)

III. VISUALIZATION (D3.JS)

EXERCISES:

IV. PANDAS

V. MINING TWITTER VIA API

QUESTIONS?

AGENDA

I. CLASSIFICATION PROBLEMS

II. BUILDING EFFECTIVE CLASSIFIERS

III. KNN CLASSIFICATION

EXERCISES:

IV. EXPLORING & IMPLEMENTING K-NN CLASSIFICATION

I. CLASSIFICATION PROBLEMS

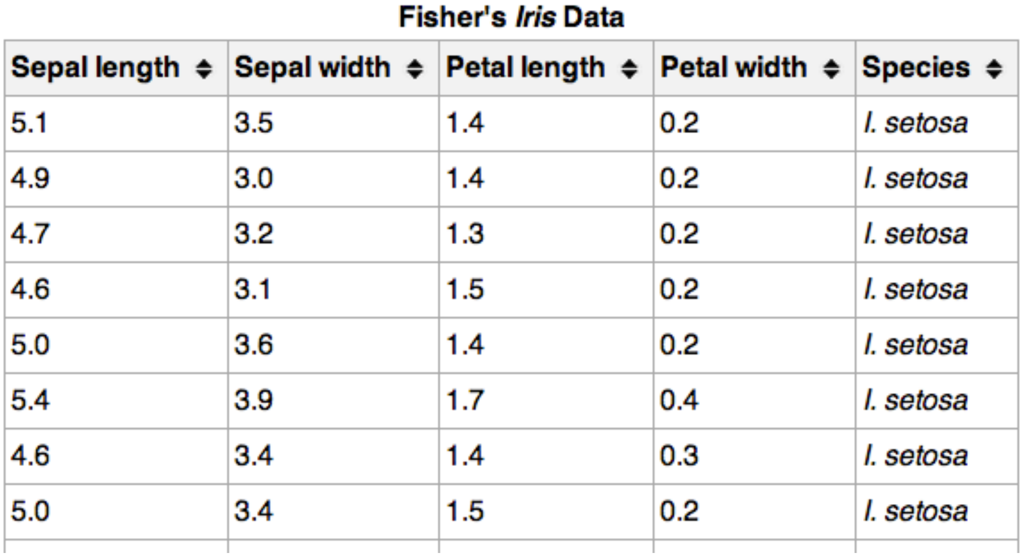
CLASSIFICATION PROBLEMS

	continuous	*categorical*
supervised	???	???
unsupervised	???	???

CLASSIFICATION PROBLEMS

	continuous	categorical
supervised	regression	classification
unsupervised	dimension reduction	clustering

Here's (part of) an example dataset:



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*
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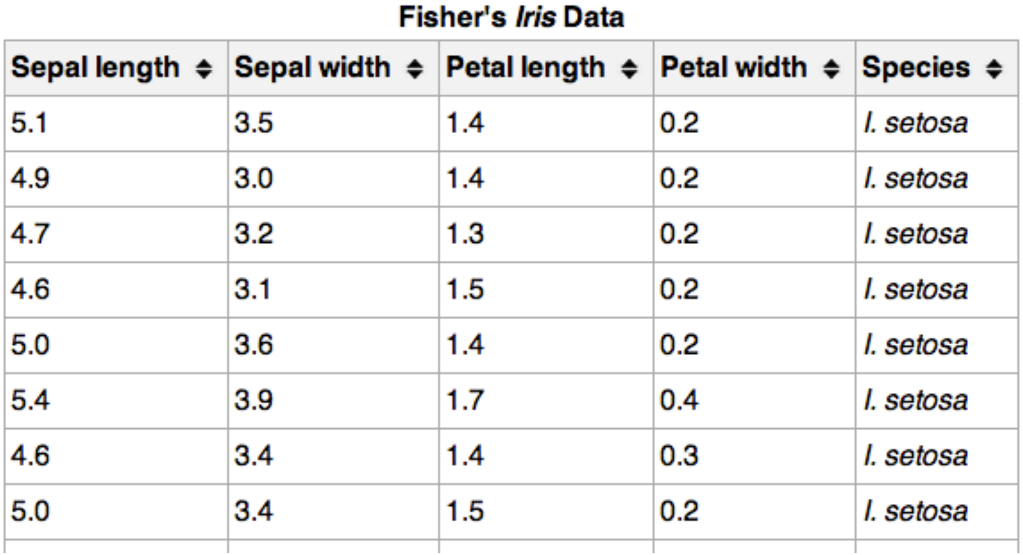
independent variables



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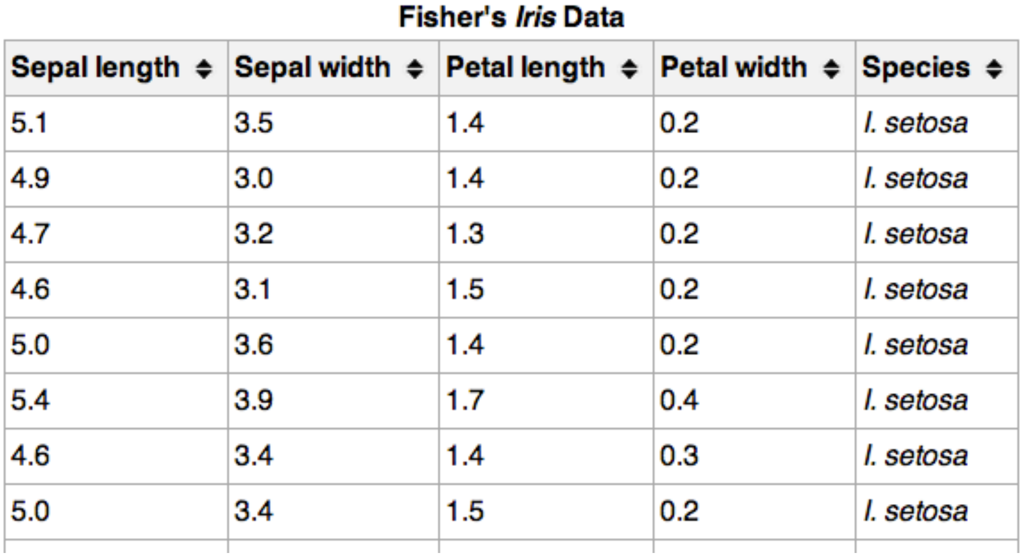

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independent variables

class labels (qualitative)

CLASSIFICATION PROBLEMS

Q: What does “supervised” mean?

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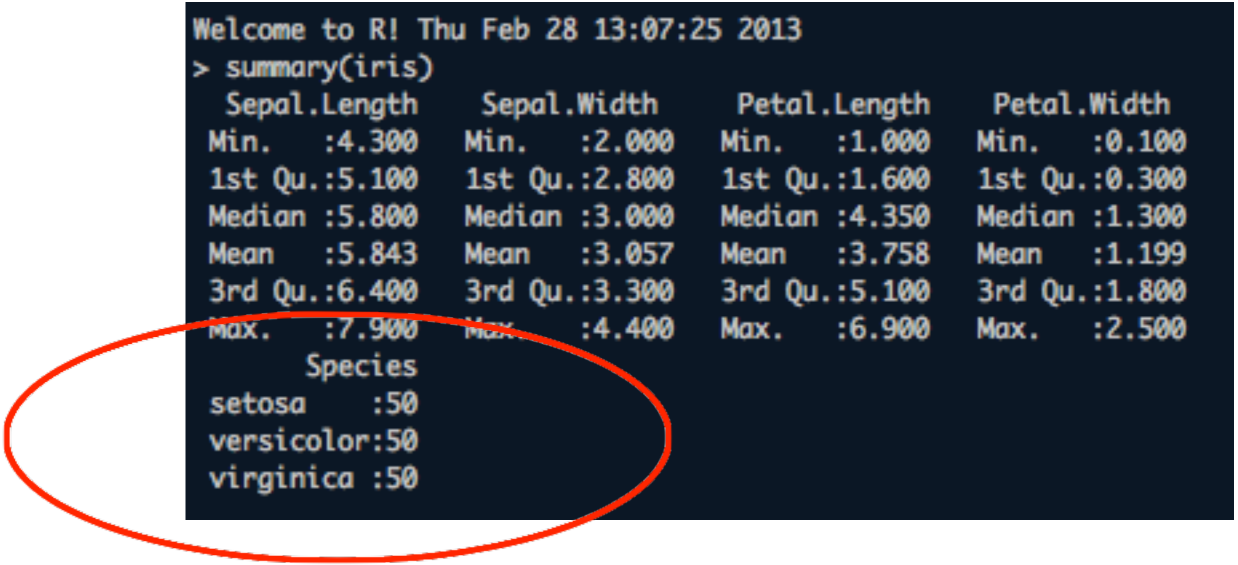
A: We know the labels.



```
Welcome to R! Thu Feb 28 13:07:25 2013
> summary(iris)
  Sepal.Length    Sepal.Width     Petal.Length    Petal.Width   
 Min.   :4.300   Min.   :2.000   Min.   :1.000   Min.   :0.100  
 1st Qu.:5.100   1st Qu.:2.800   1st Qu.:1.600   1st Qu.:0.300  
 Median :5.800   Median :3.000   Median :4.350   Median :1.300  
 Mean   :5.843   Mean   :3.057   Mean   :3.758   Mean   :1.199  
 3rd Qu.:6.400   3rd Qu.:3.300   3rd Qu.:5.100   3rd Qu.:1.800  
 Max.   :7.900   Max.   :4.400   Max.   :6.900   Max.   :2.500  
       Species  
 setosa    :50  
 versicolor:50  
 virginica :50  
```

Q: How does a classification problem work?

CLASSIFICATION PROBLEMS

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A: Data in, predicted labels out.

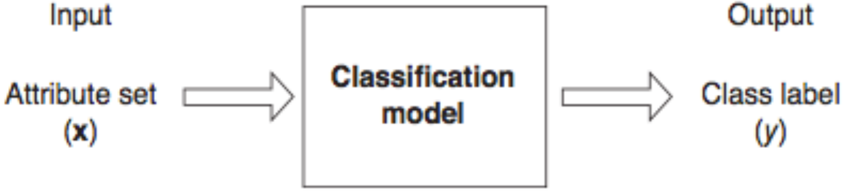
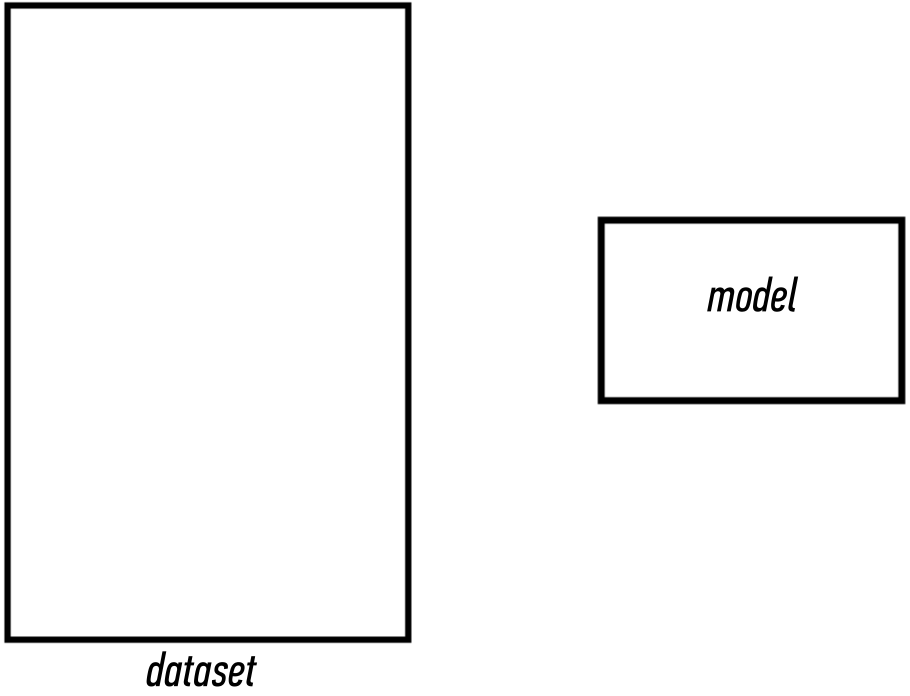


Figure 4.2. Classification as the task of mapping an input attribute set $\mathbf{x}$ into its class label y.

source: http://www-users.cs.umn.edu/~kumar/dmbook/ch4.pdf

CLASSIFICATION PROBLEMS

Q: What steps does a classification problem require?



dataset

model

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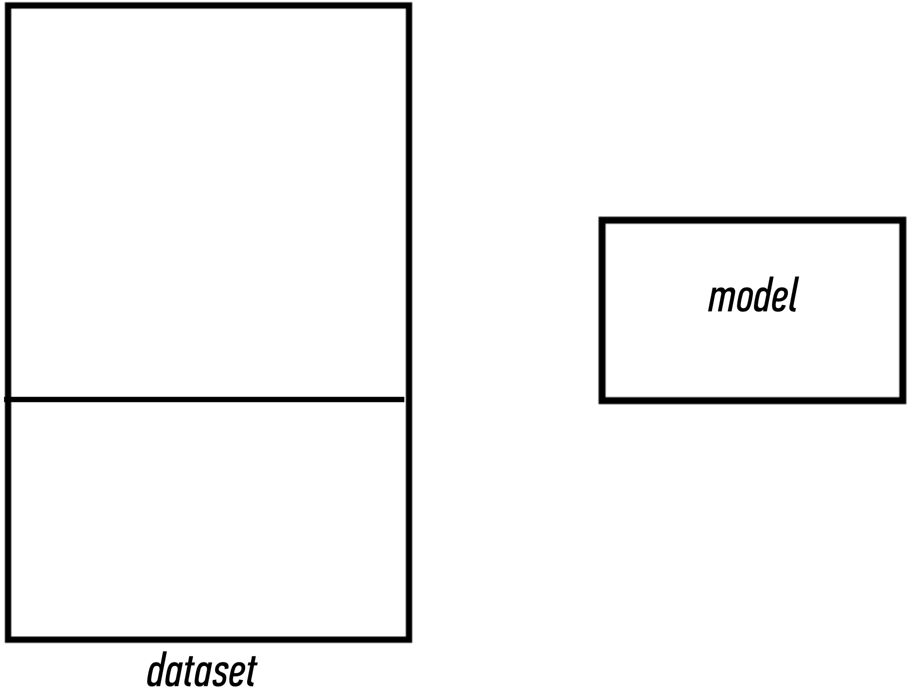

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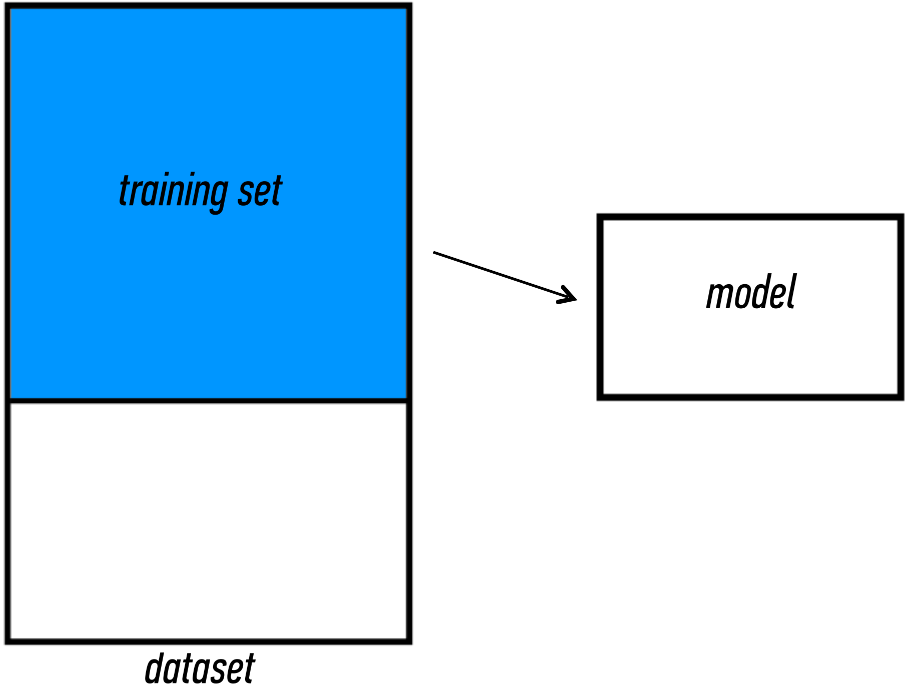
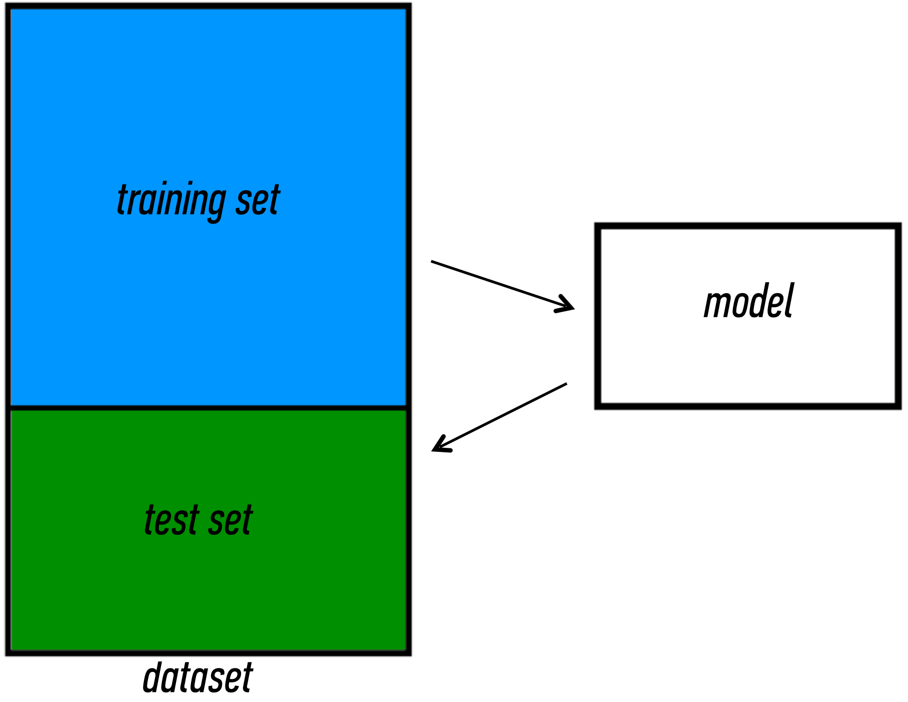
2) train model



Q: What steps does a classification problem require?

1) *split dataset*
2) *train model*
3) *test model*



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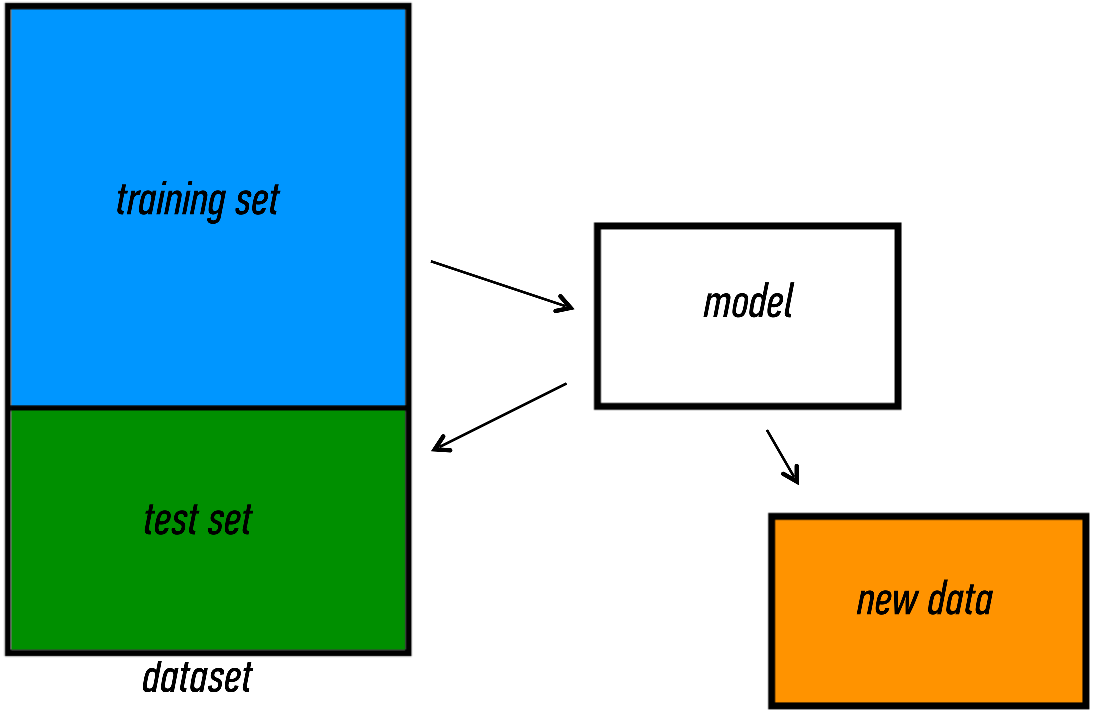

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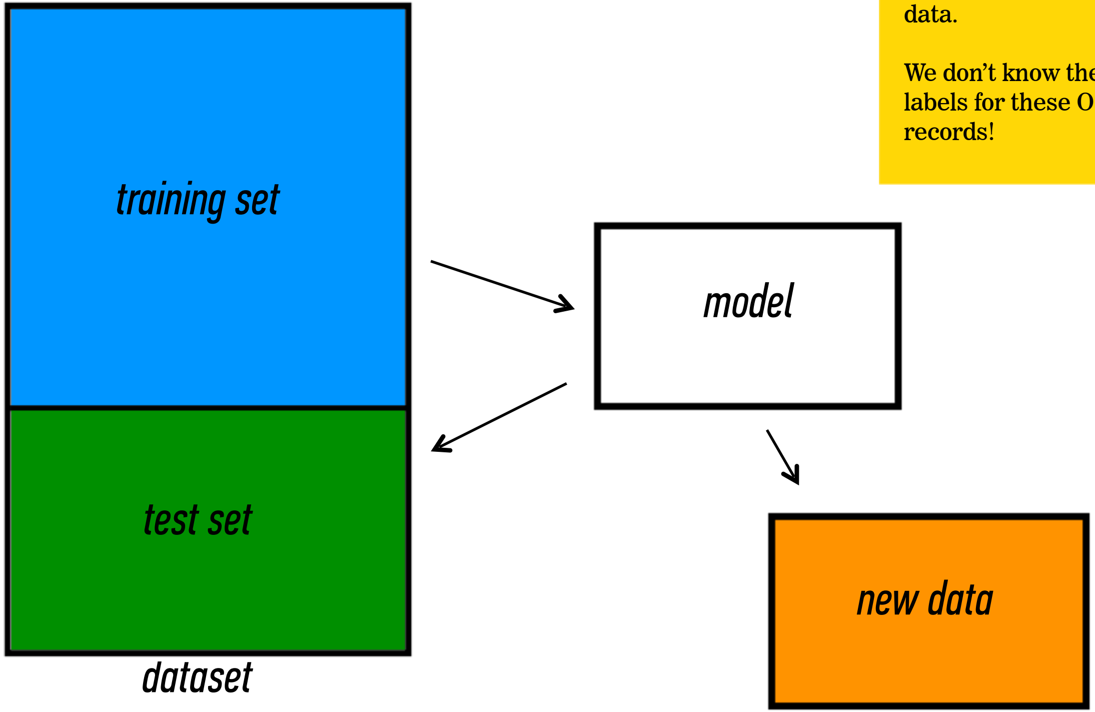
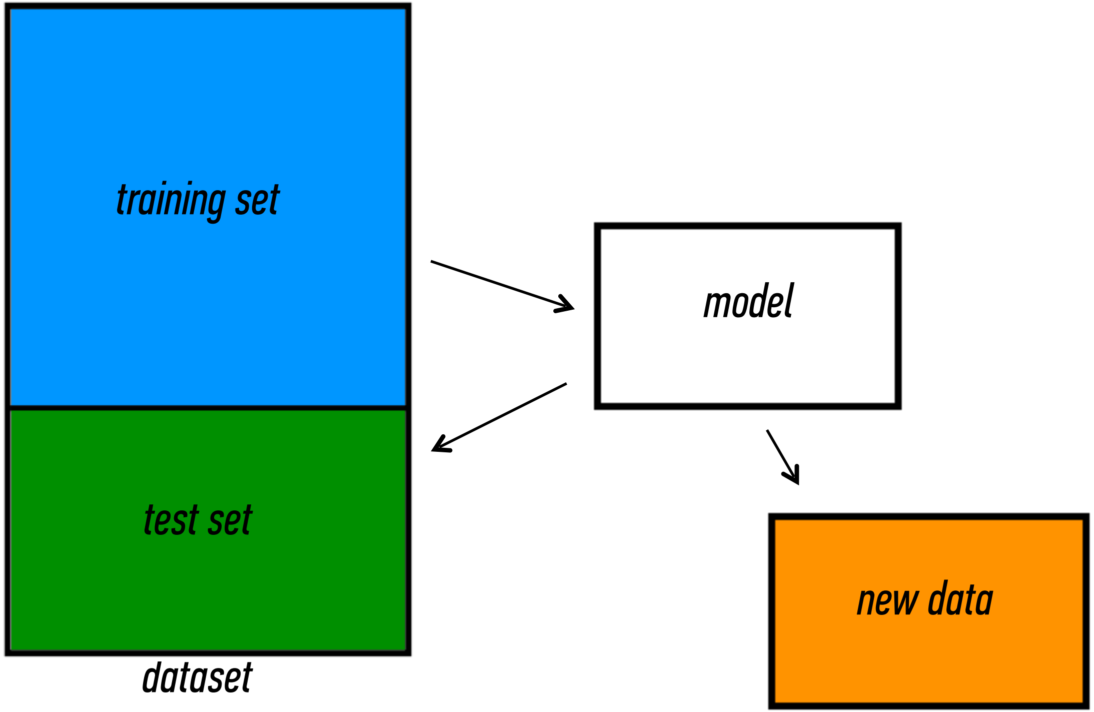


NOTE
This new data is called out of sample data.

We don't know the labels for these OOS records!

II. BUILDING EFFECTIVE CLASSIFIERS

Q: What types of prediction error will we run into?



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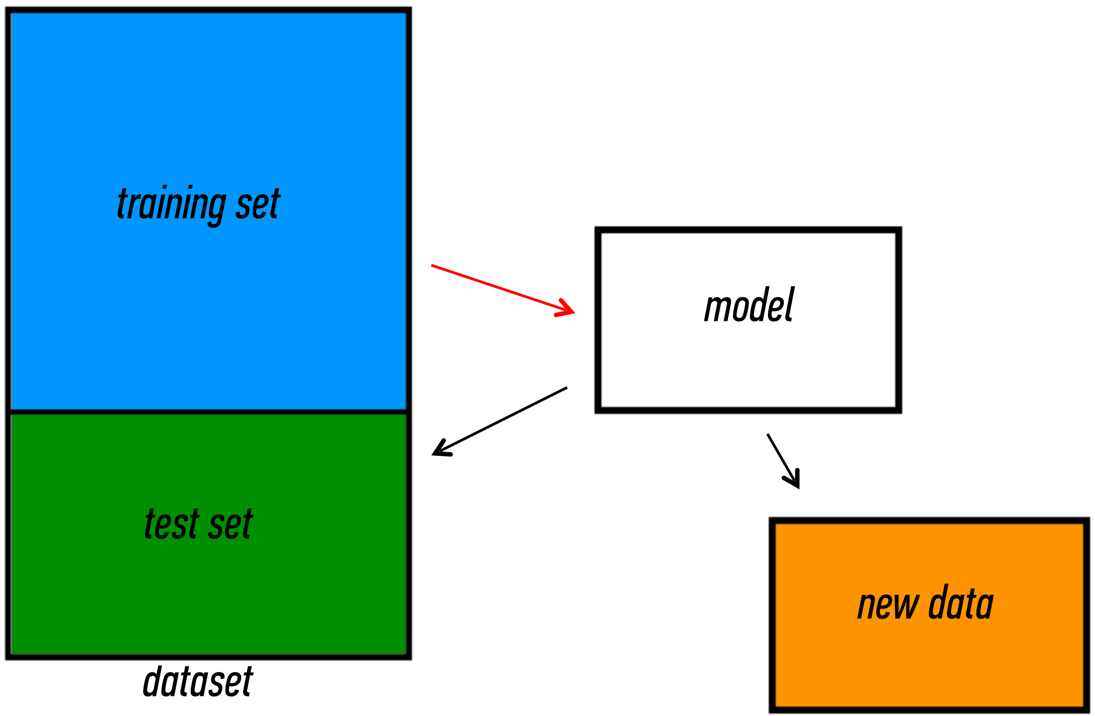
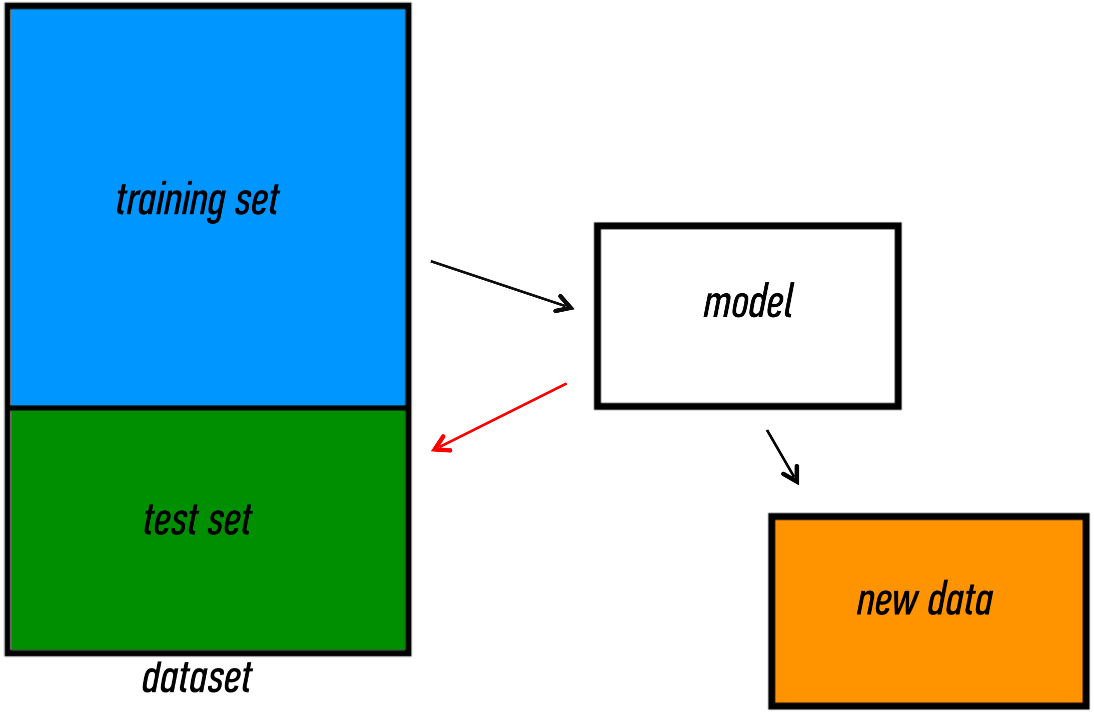


Q: What types of prediction error will we run into?

1) training error
2) generalization error

NOTE
measures how well a learning machine generalizes to unseen(test) data



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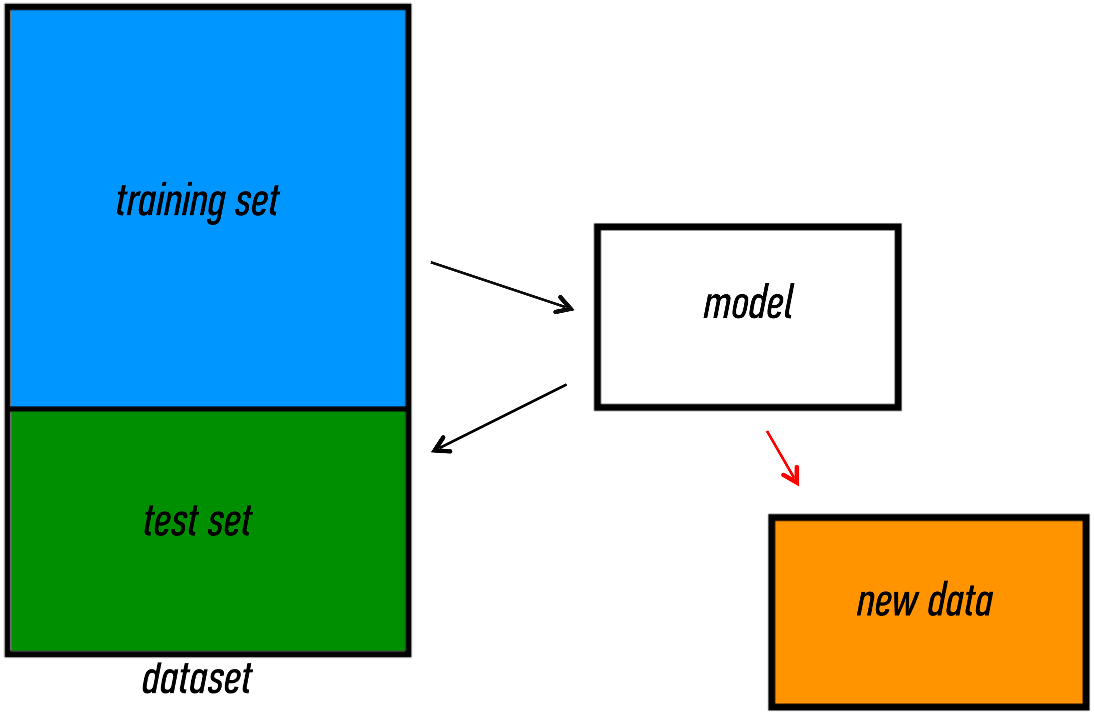

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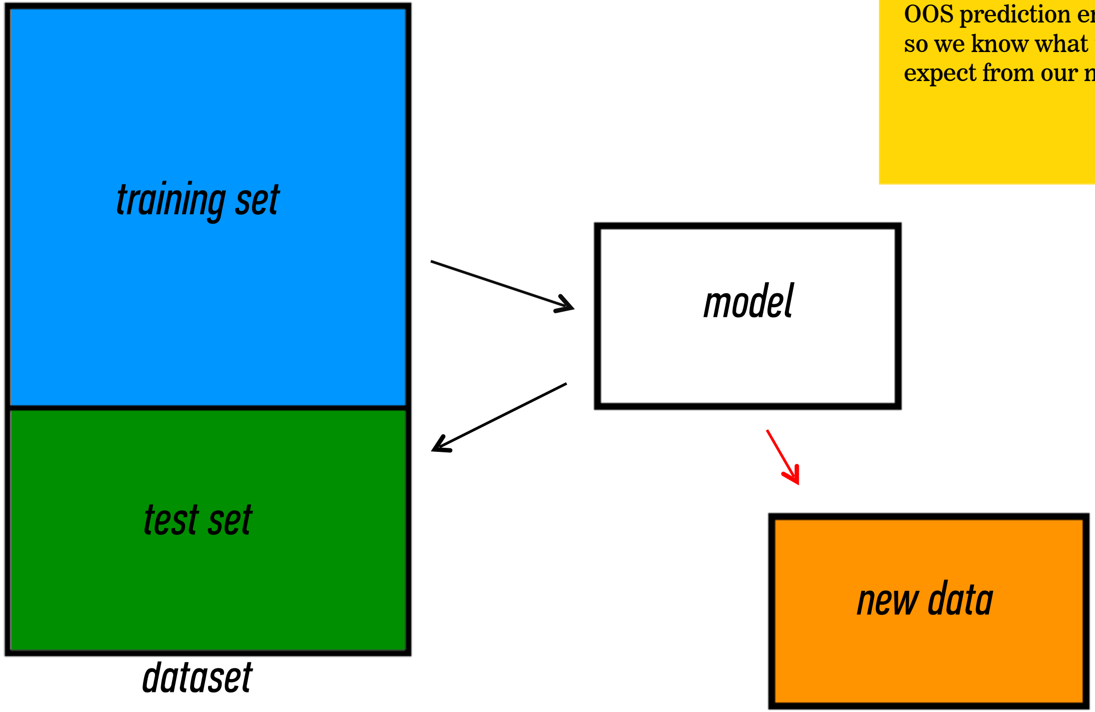

NOTE

We want to estimate OOS prediction error so we know what to expect from our model.

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This phenomenon is called overfitting.

OVERFITTING

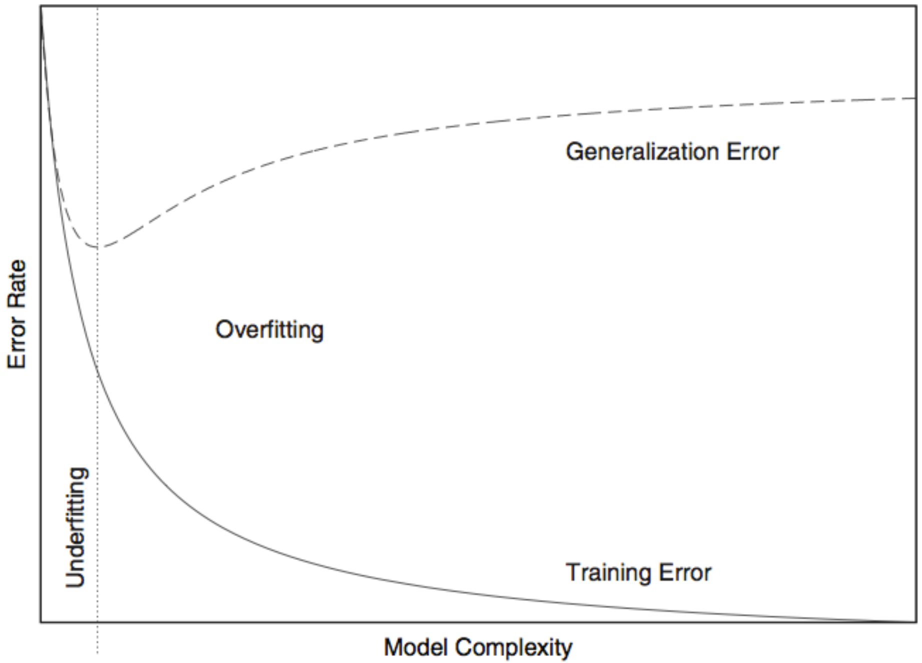
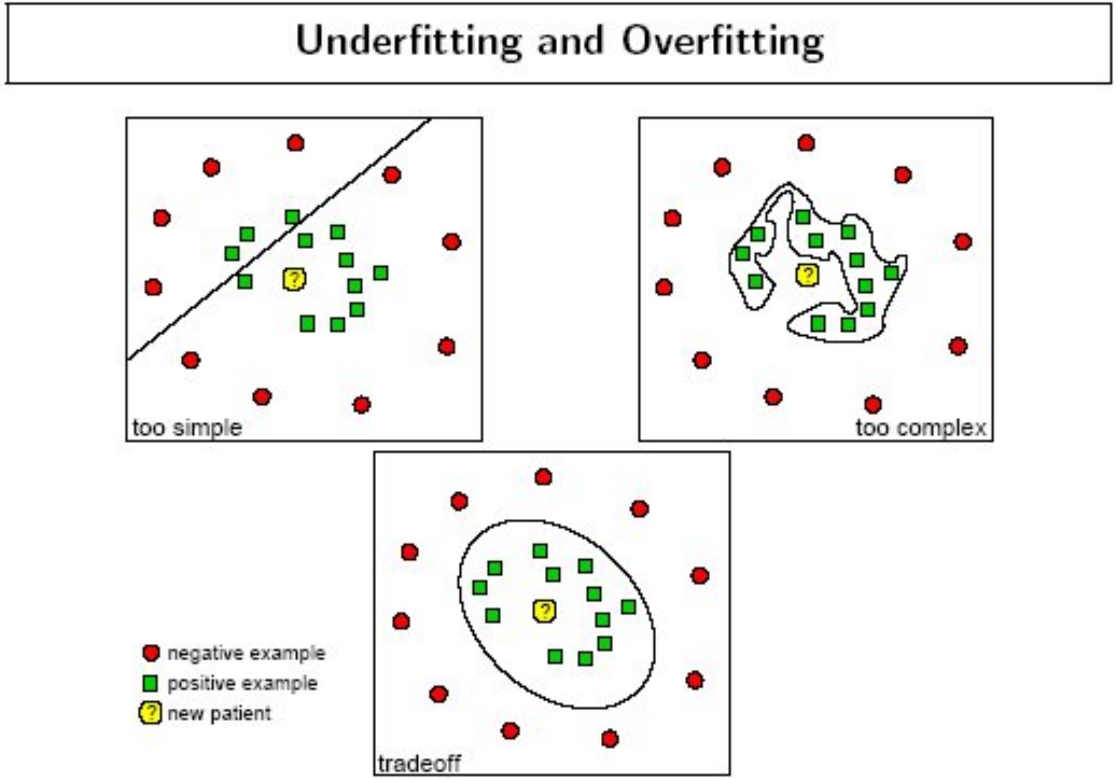


FIGURE 18-1. Overfitting: as a model becomes more complex, it becomes increasingly able to represent the training data. However, such a model is overfitted and will not generalize well to data that was not used during training.

source: Data Analysis with Open Source Tools, by Philipp K. Janert. O'Reilly Media, 2011.

OVERFITTING - EXAMPLE



source: http://www.dtreg.com

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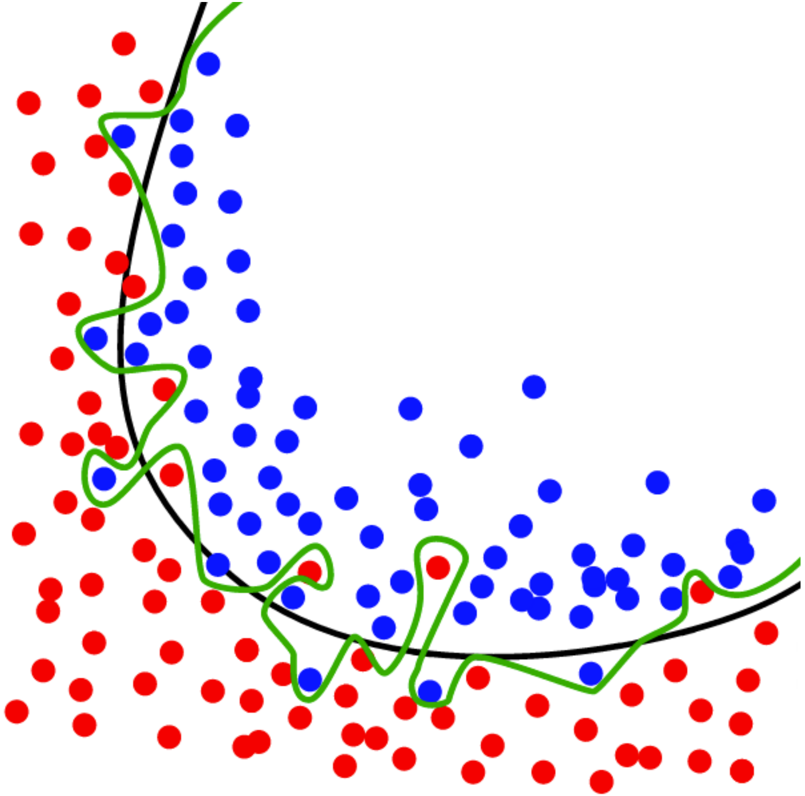

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This phenomenon is called overfitting.

A: Training error is not a good estimate of OOS accuracy.

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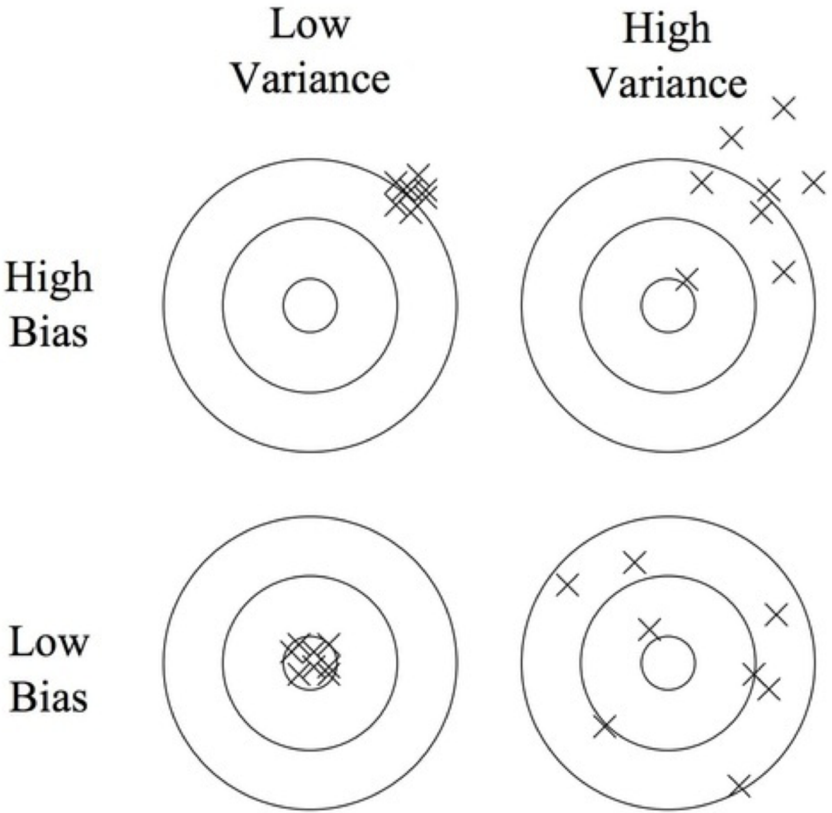
NOTE

The generalization error gives a high-variance estimate of OOS accuracy.

BIAS-VARIANCE



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A: Cross-validation.

CROSS-VALIDATION

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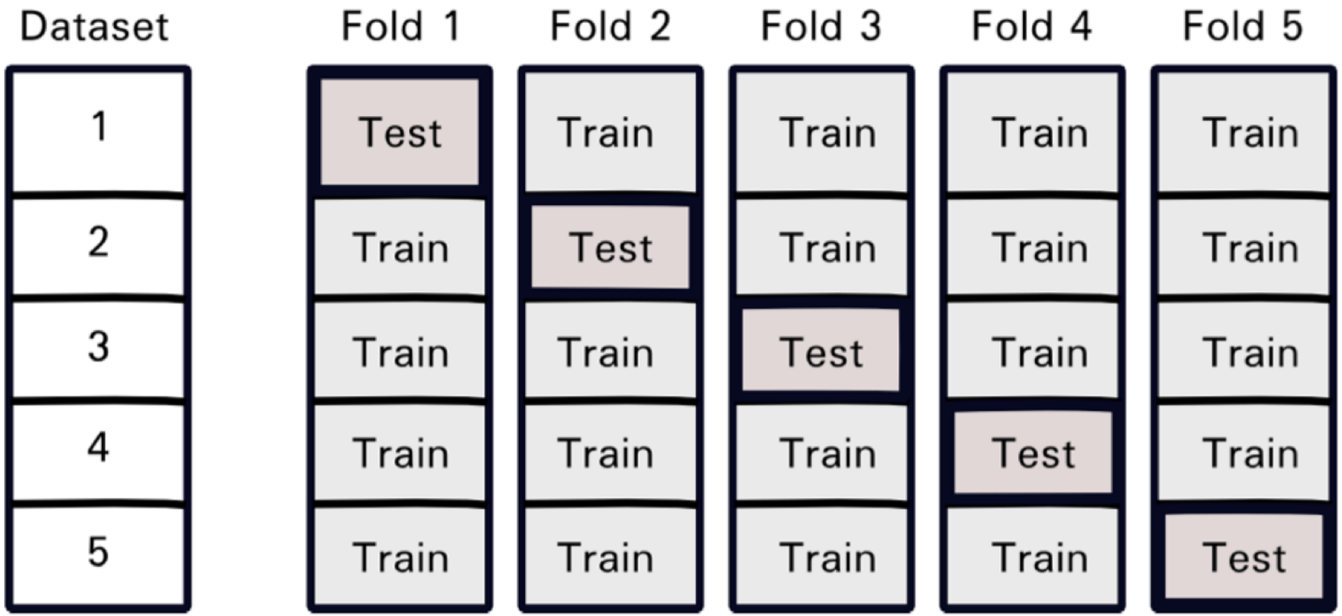
5) *Take the average generalization error as the estimate of OOS accuracy.*

CROSS-VALIDATION: 5-FOLD EXAMPLE



Dataset	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Accuracy
1	Test	Train	Train	Train	Train	k_1 %
2	Train	Test	Train	Train	Train	k_2 %
3	Train	Train	Test	Train	Train	k_3 %
4	Train	Train	Train	Test	Train	k_4 %
5	Train	Train	Train	Train	Test	k_5 %

overall accuracy: $(k_1 + k_2 + k_3 + k_4 + k_5) / 5$

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    - *10-fold CV is 10x more expensive than a single train/test split*

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- *Each record in our dataset is used for both training and testing.*

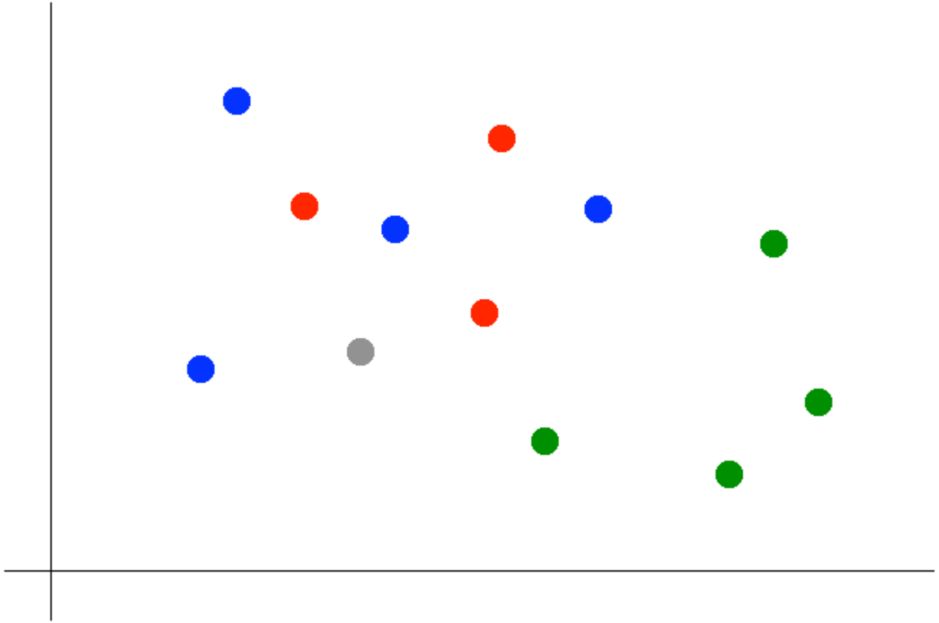
3) Presents tradeoff between efficiency and computational expense.

- *10-fold CV is 10x more expensive than a single train/test split*

4) Can be used for model selection.

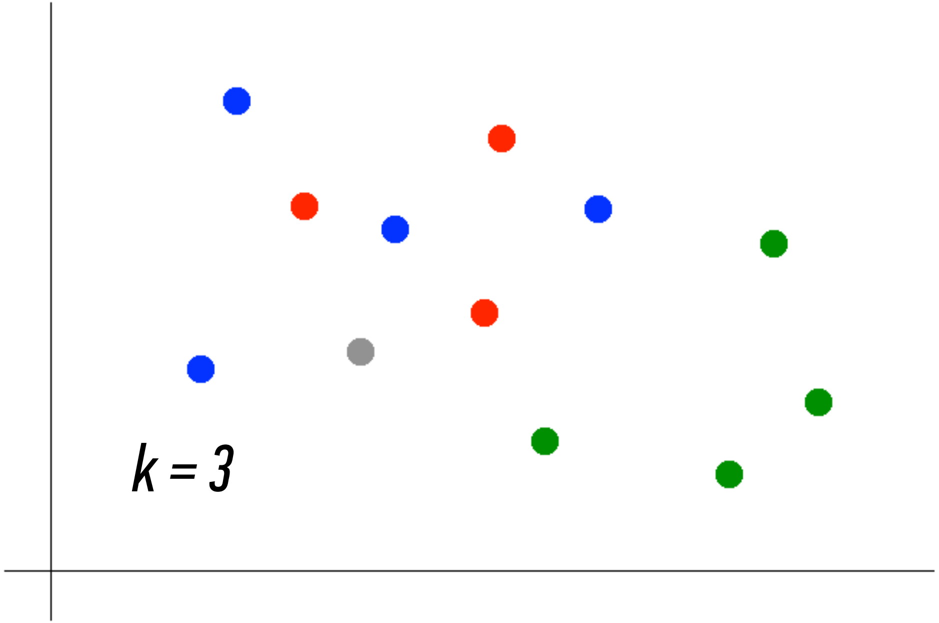
III. KNN CLASSIFICATION

Suppose we want to predict the color of the grey dot.



Suppose we want to predict the color of the grey dot.

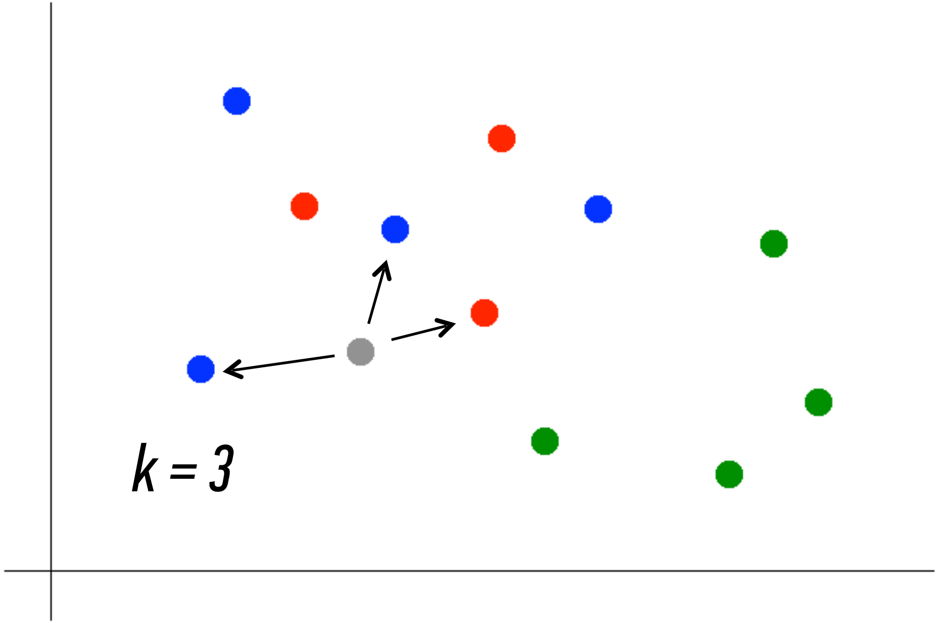
1) Pick a value for k.



k = 3

Suppose we want to predict the color of the grey dot.

1) *Pick a value for k.*
2) *Find colors of k nearest neighbors.*



Suppose we want to predict the color of the grey dot.

1) *Pick a value for k.*
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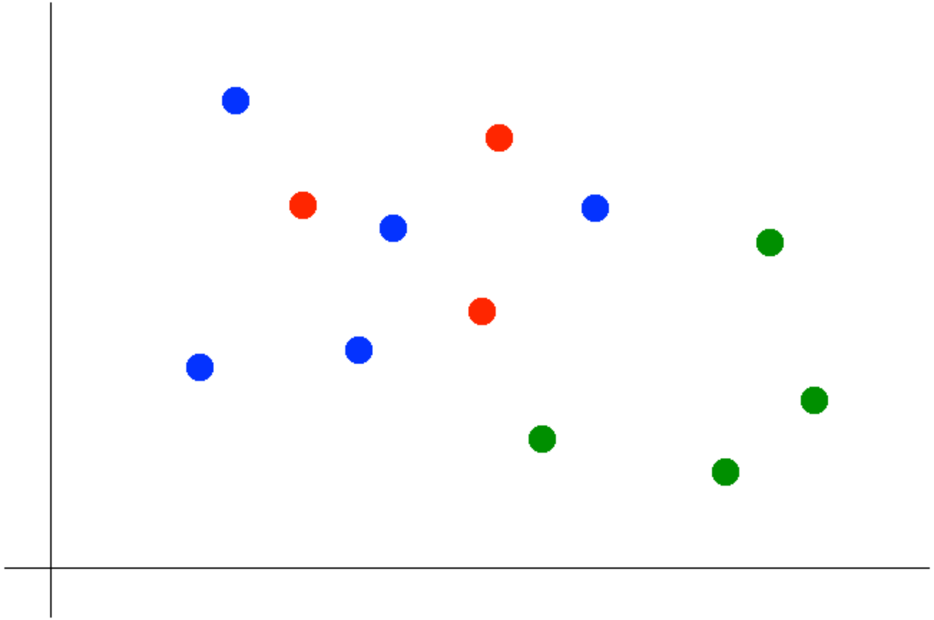
3) *Assign the most common color to the grey dot.*



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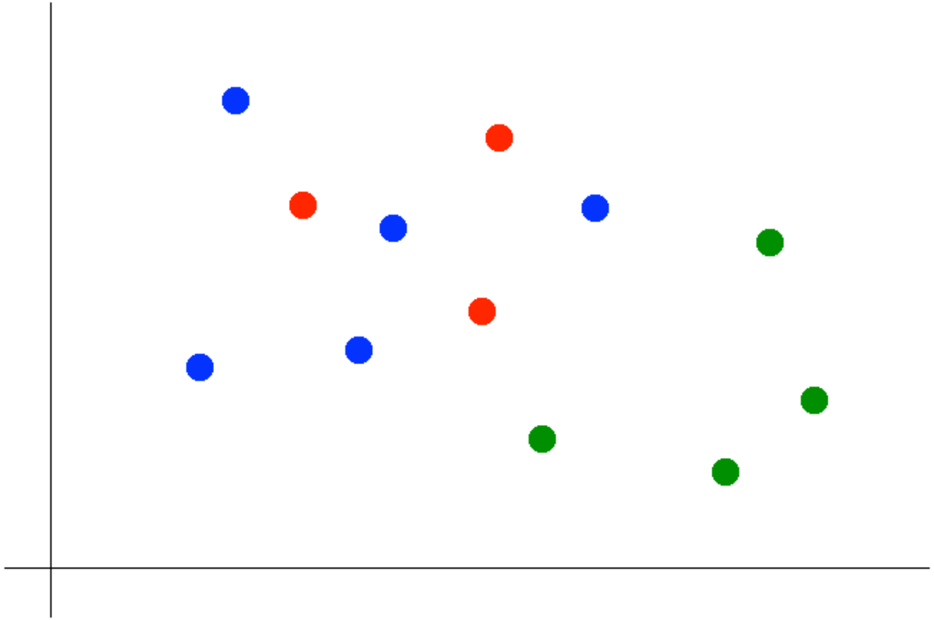
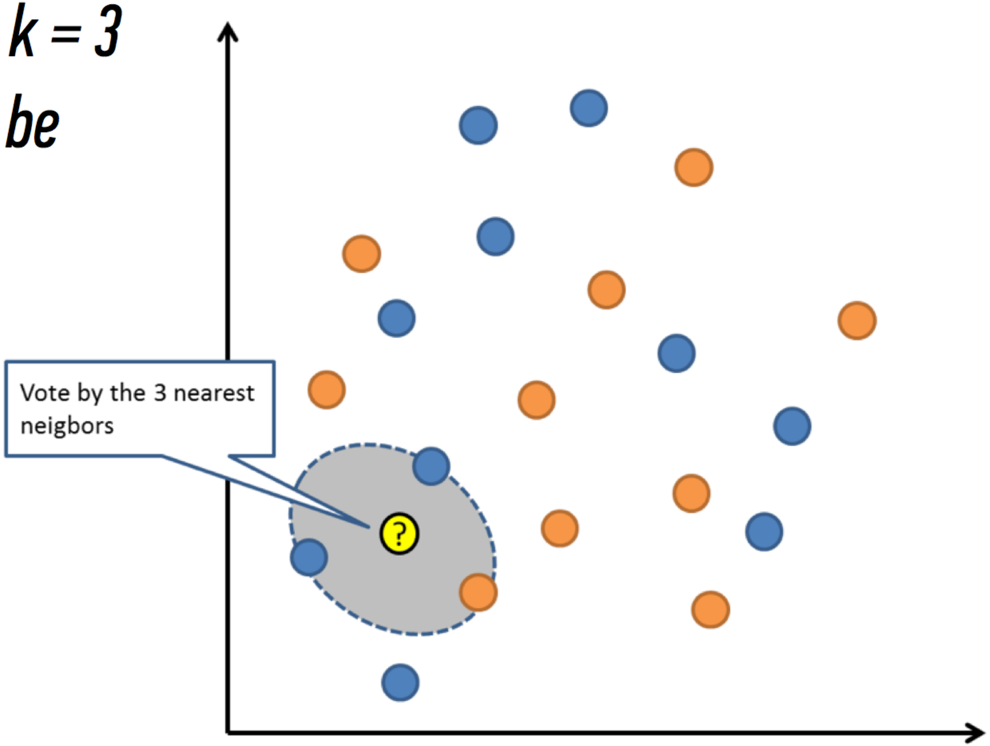


OPTIONAL NOTE

Our definition of “nearest” implicitly uses the Euclidean distance function.

K NEAREST NEIGHBORS CLASSIFICATION

Another example with k = 3
Will our new example be blue or orange?



Vote by the 3 nearest neigbors

KNN CLASSIFICATION – HOW TO CHOOSE K?

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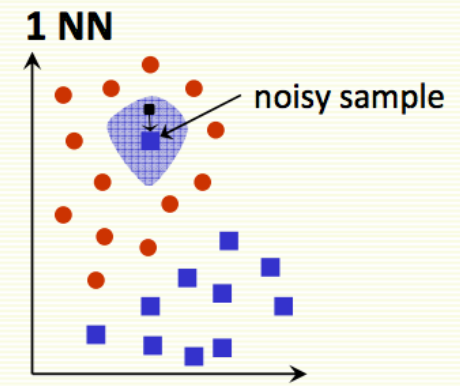
The caveat is that all k neighbors have to be close

- *Possible when infinite # samples available*
- *Impossible in practice since # samples is finite*

KNN CLASSIFICATION - HOW TO CHOOSE K?

Rule of thumb is k < sqrt(n), n is number of examples

- *interesting theoretical properties*
- *In practice, k = 1 is often used for efficiency, but can be sensitive to "noise"*



http://www.csd.uwo.ca/courses/CS9840a/Lecture2_knn.pdf

KNN CLASSIFICATION - HOW TO CHOOSE K?

larger k may improve performance, but too large k destroys locality, i.e. end up looking at samples that are not neighbors

cross-validation may be used to choose k

KNN CLASSIFICATION SUMMARY

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K-NN: WHAT ARE THE PROS AND CONS?

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LAB