GENERAL ASSEMBLY

DATA SCIENCE

LECTURE 4: K-NEAREST NEIGHBORS CLASSIFICATION

YUCHEN ZHAO / DAT-14

LAST TIME:

I. DATA RETRIEVAL (API, JSON)

II. ETL INTRO (DATABASE)

III. VISUALIZATION (D3.JS)

EXERCISES:

IV. PANDAS

V. MINING TWITTER VIA API

QUESTIONS?

I. CLASSIFICATION PROBLEMS
II. BUILDING EFFECTIVE CLASSIFIERS

EXERCISES:
III. THE KNN CLASSIFICATION MODEL

I. CLASSIFICATION PROBLEMS

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

	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*
5.0	3.6	1.4	0.2	*I. setosa*
5.4	3.9	1.7	0.4	*I. setosa*
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independent variables

class labels (qualitative)

CLASSIFICATION PROBLEMS

Q: What does "supervised" mean?

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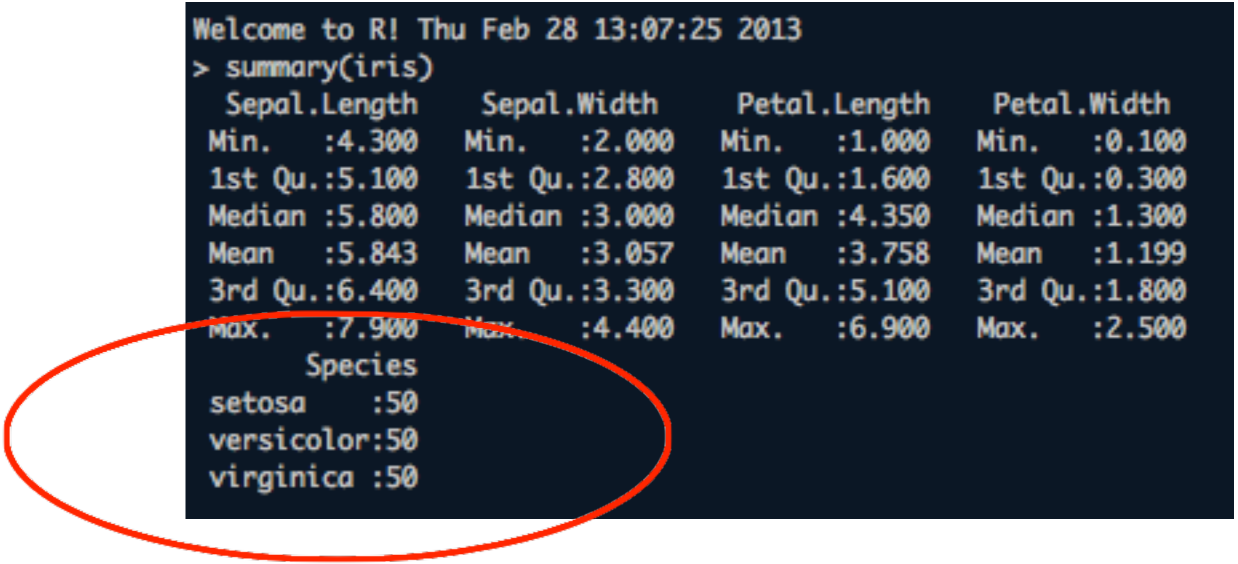
A: We know the labels.



```
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?

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A: Data in, predicted labels out.

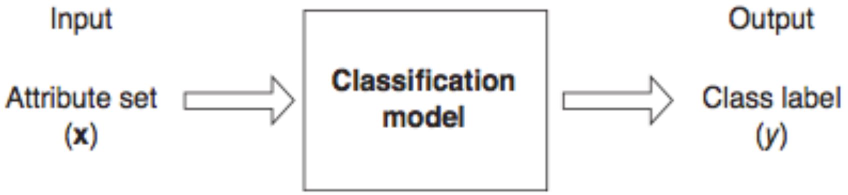
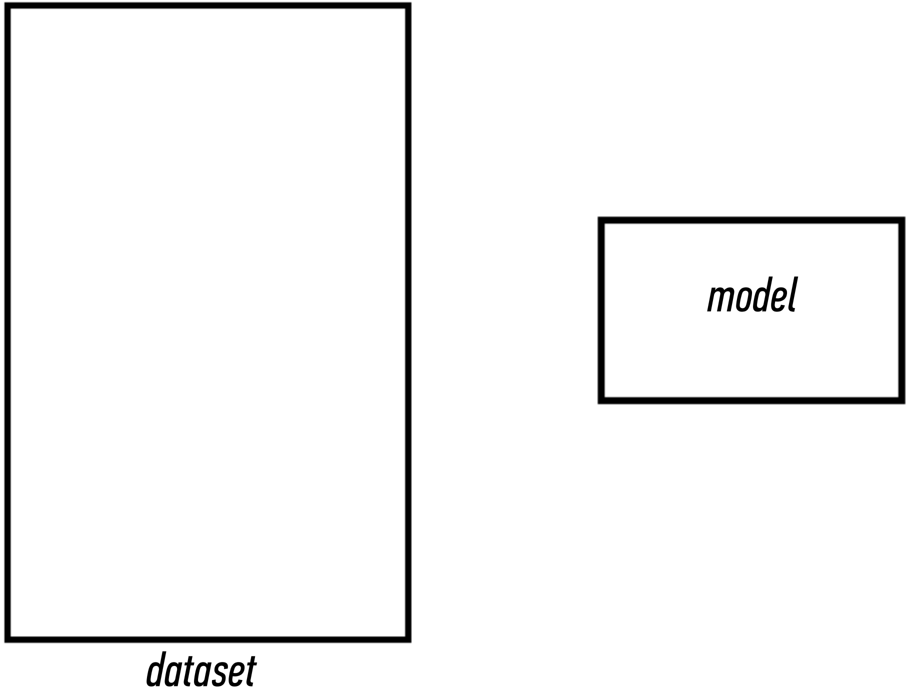


Figure 4.2. Classification as the task of mapping an input attribute set $\mathbf{x}$ into its class label y.

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

Q: What steps does a classification problem require?



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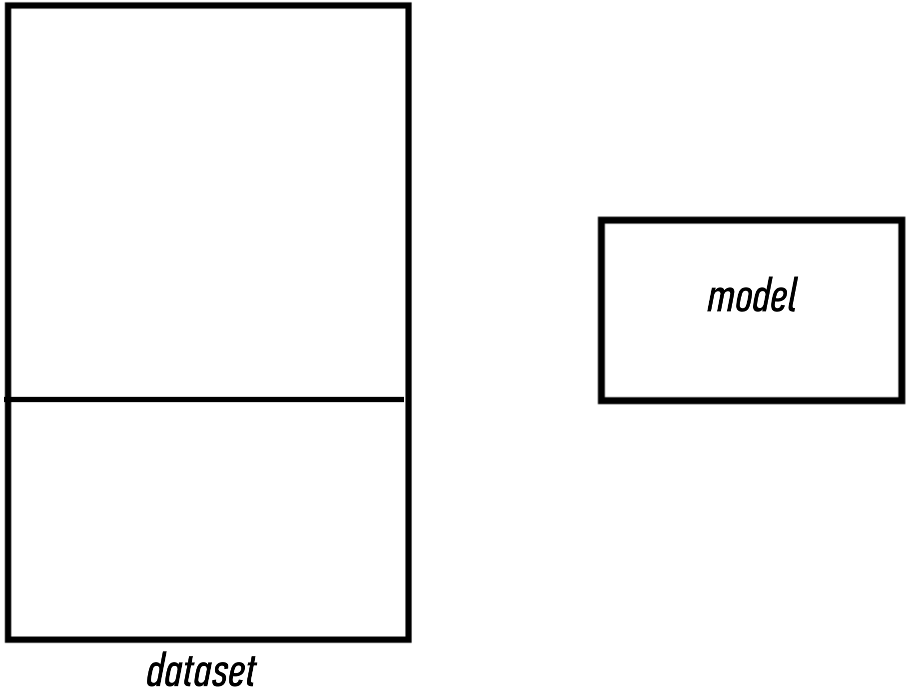
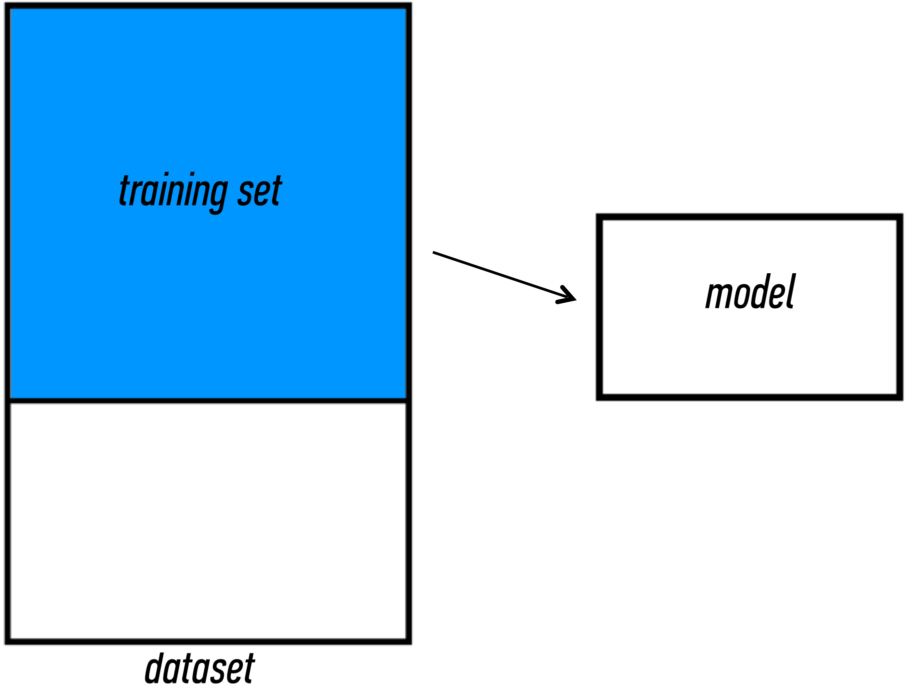


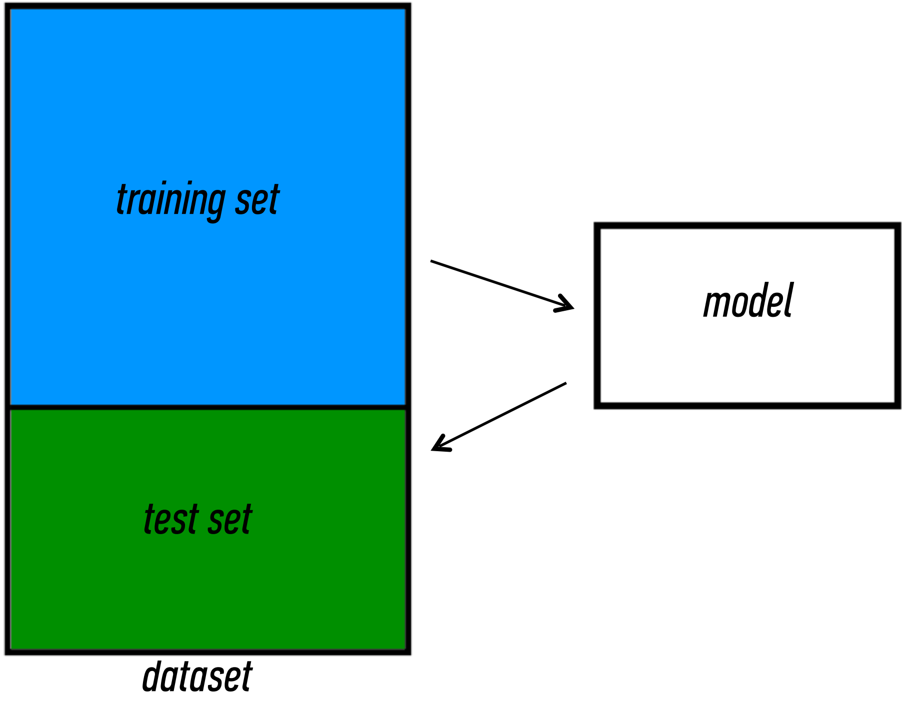
Q: What steps does a classification problem require?

1) split dataset
2) train model



Q: What steps does a classification problem require?

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



Q: What steps does a classification problem require?

1) *split dataset*
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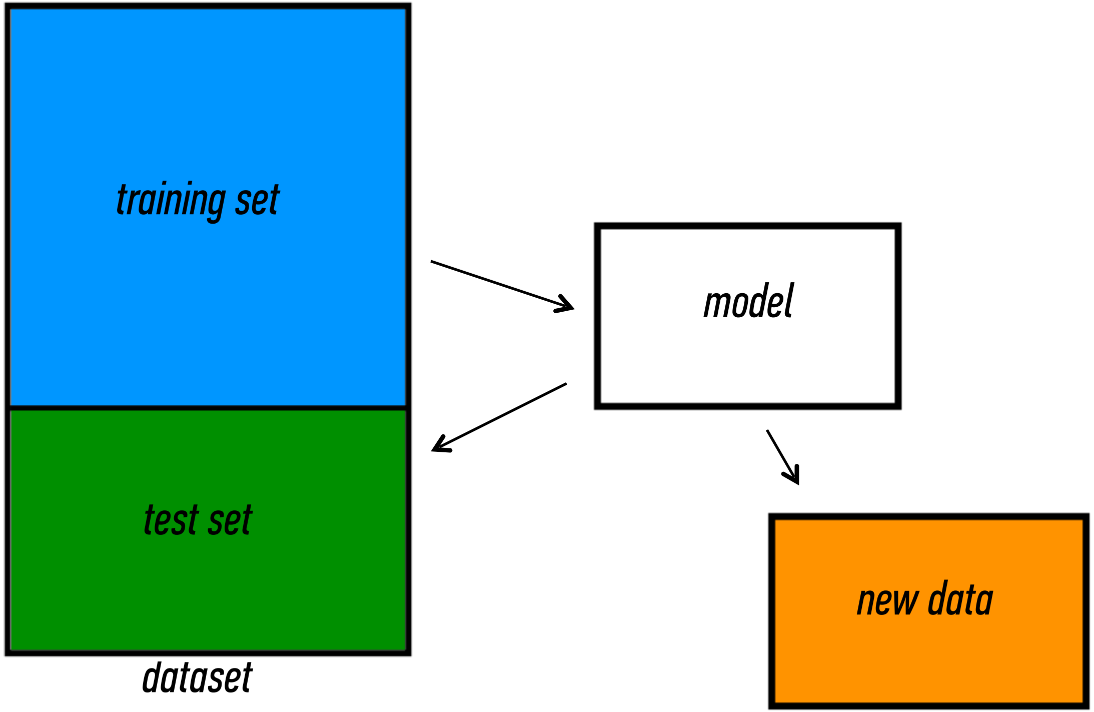
4) *make predictions*



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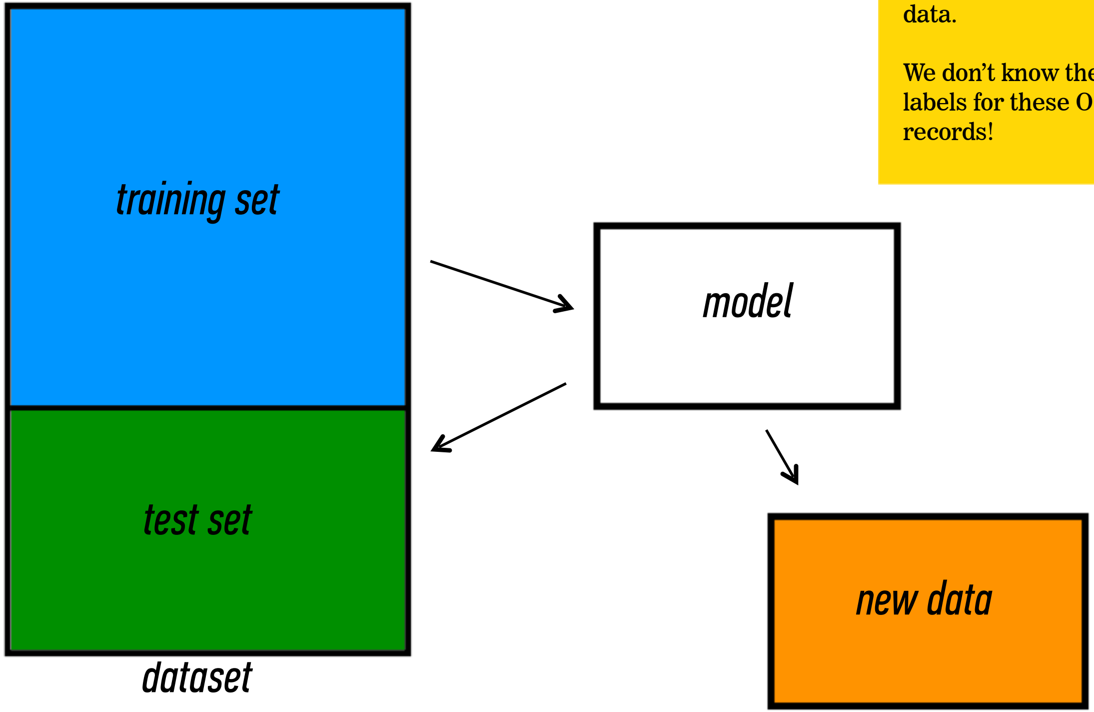
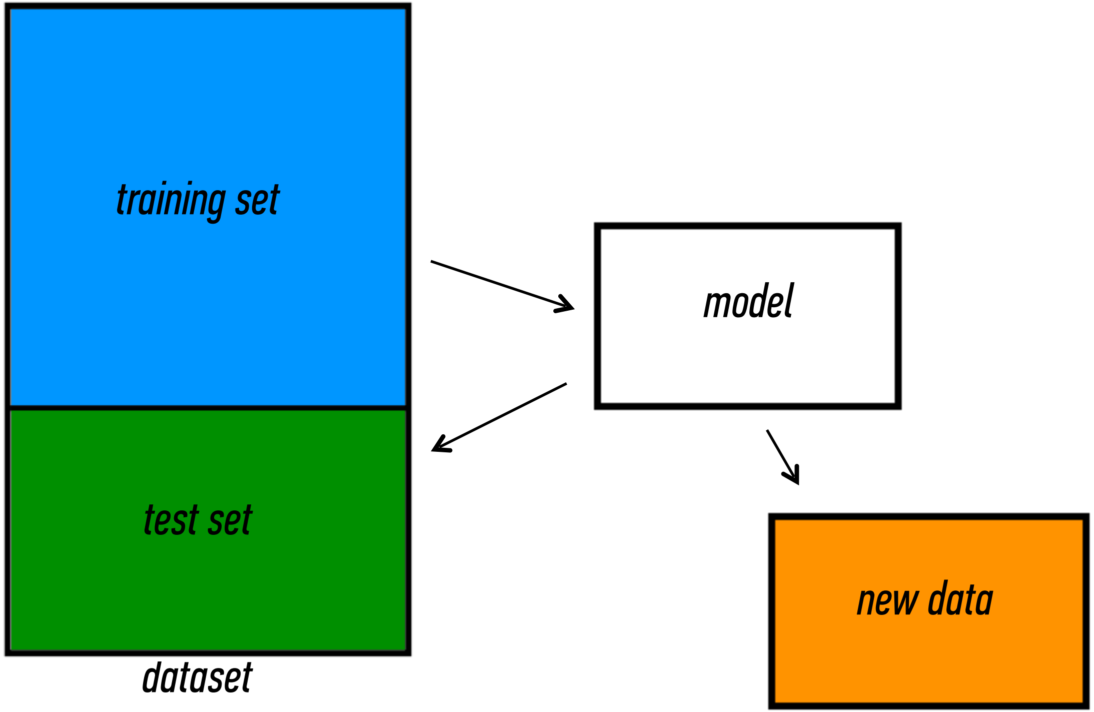


NOTE
This new data is called out of sample data.

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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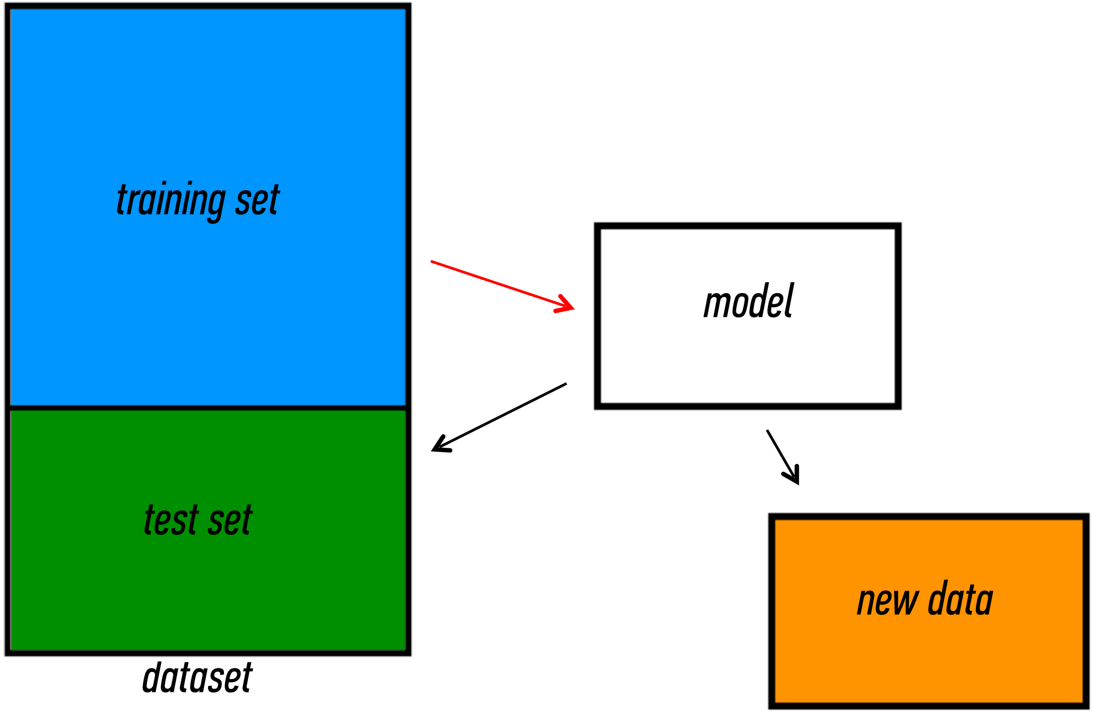
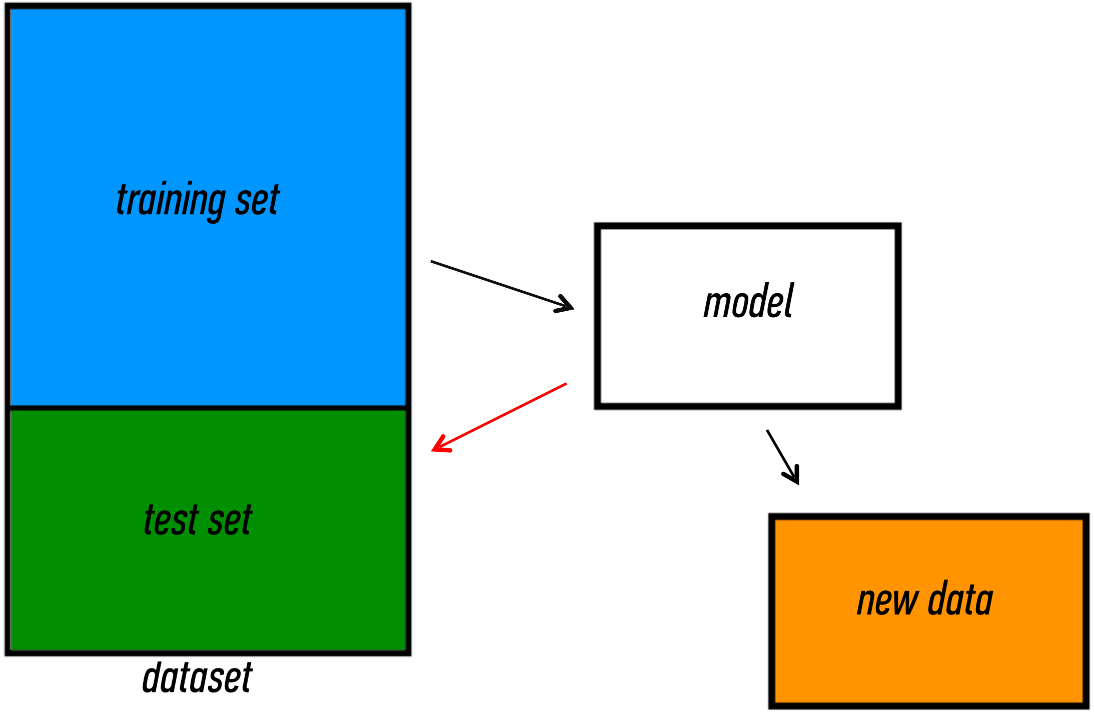


Q: What types of prediction error will we run into?

1) *training error*
2) *generalization error*

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



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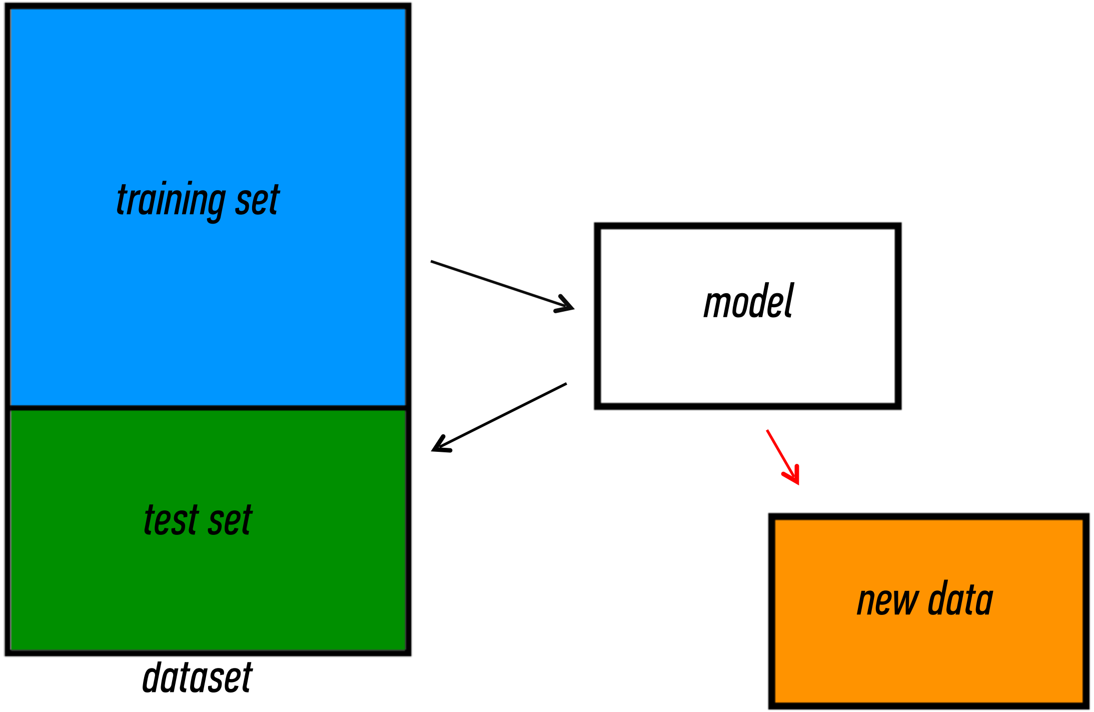
3) OOS error



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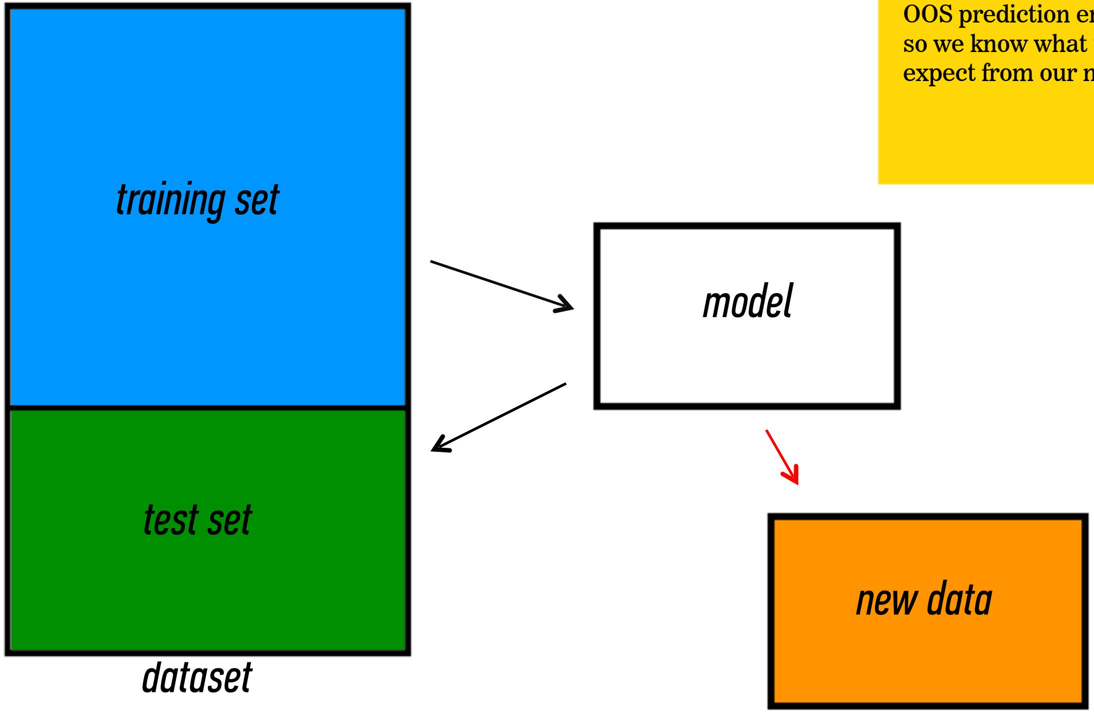

NOTE

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

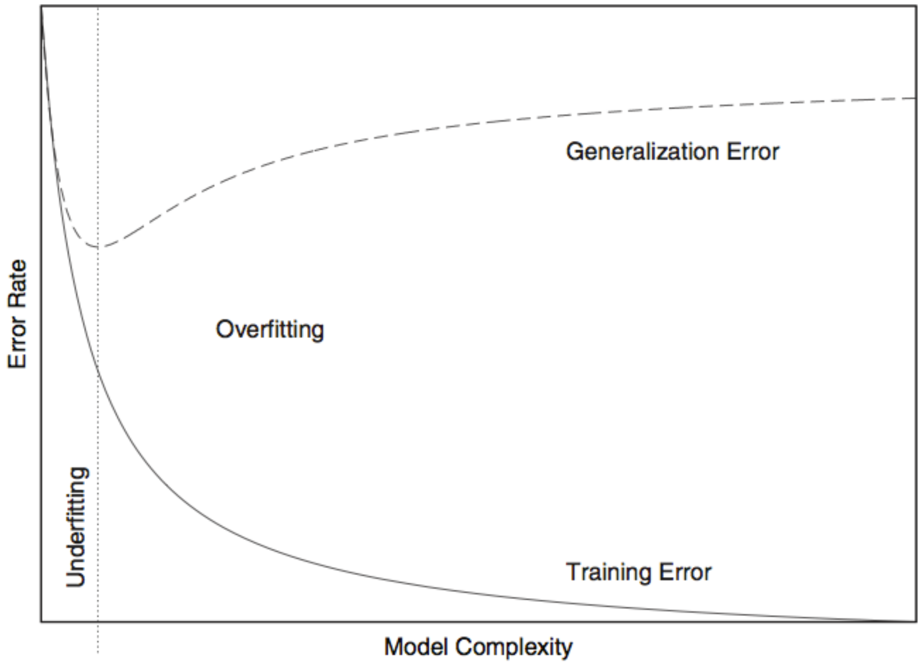
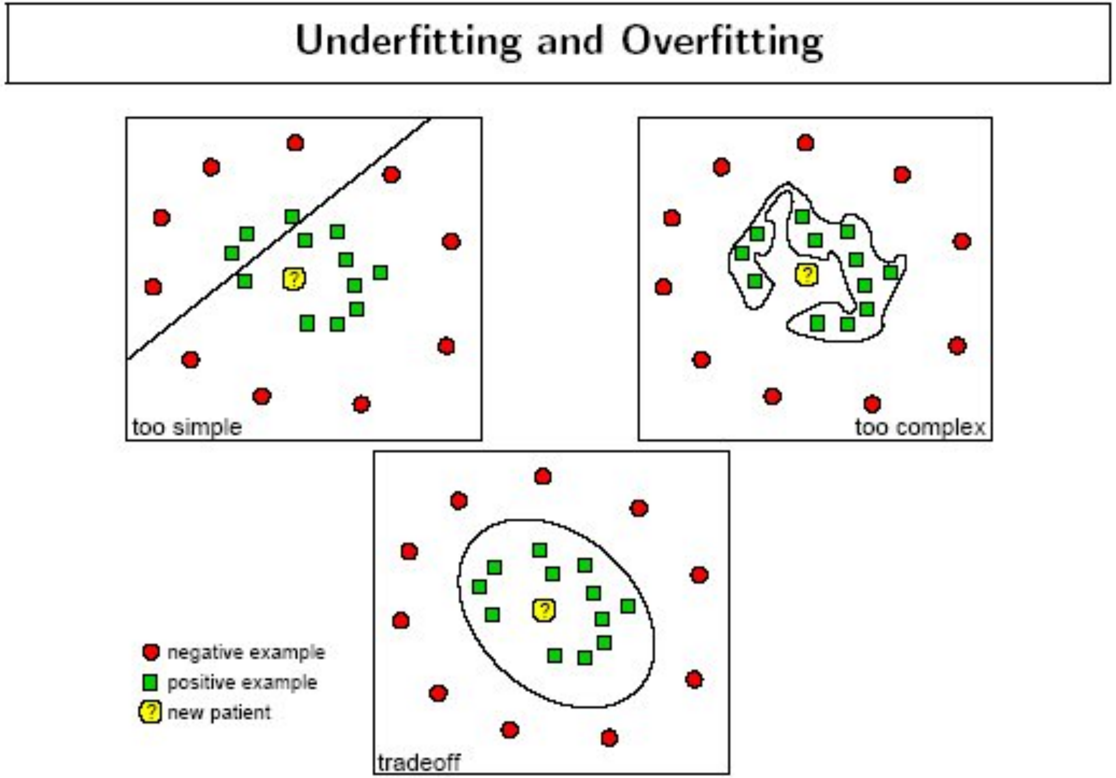


FIGURE 18-1. Overfitting: as a model becomes more complex, it becomes increasingly able to represent the training data. However, such a model is overfitted and will not generalize well to data that was not used during training.

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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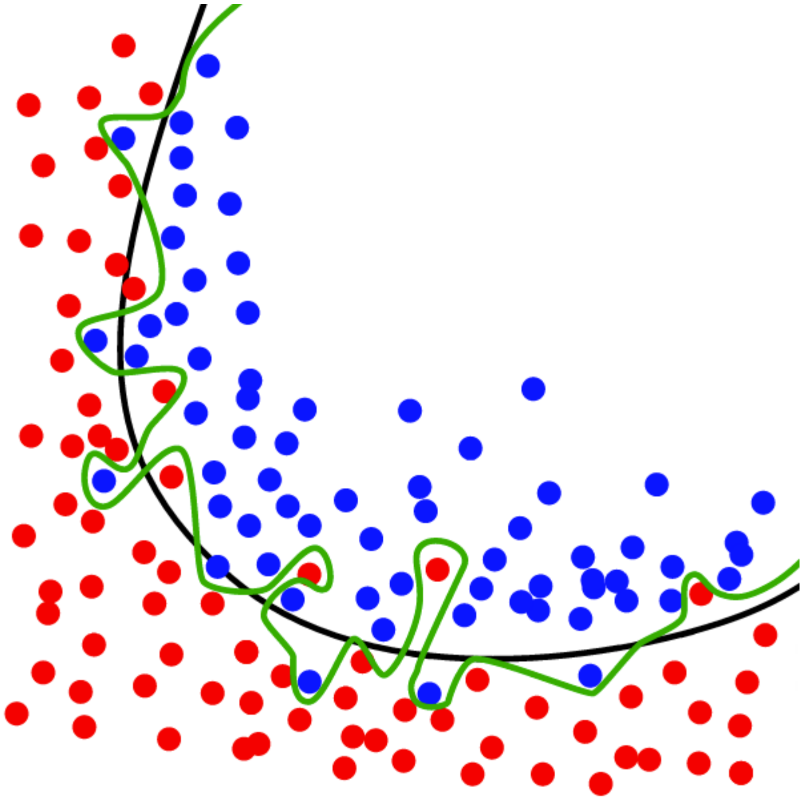

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A: Training error is not a good estimate of OOS accuracy.

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Suppose we had done a different train/test split.

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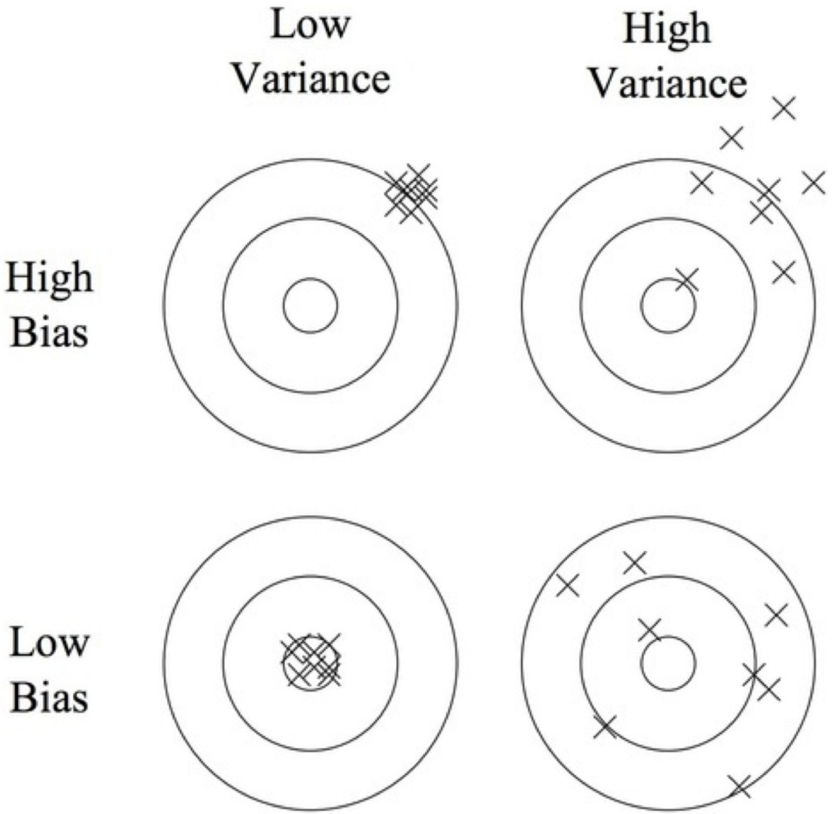
NOTE

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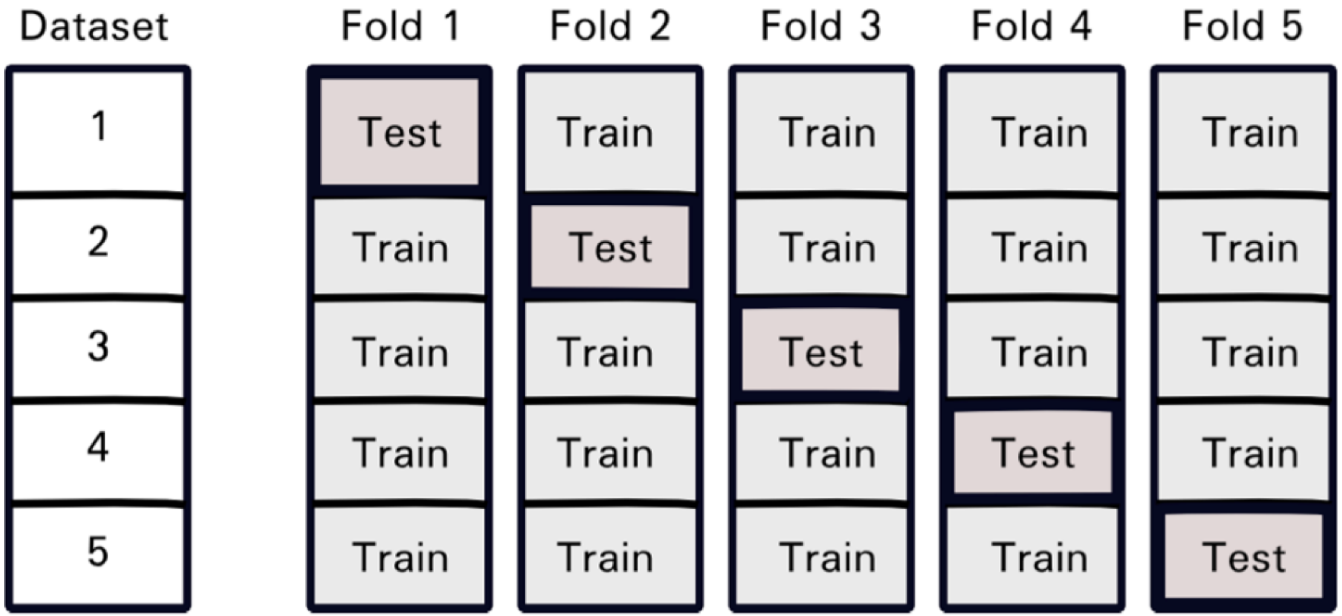
5) *Take the average generalization error as the estimate of OOS accuracy.*

CROSS-VALIDATION: 5-FOLD EXAMPLE



<u>*Accuracy*</u>

k_1 %

k_2 %

k_3 %

k_4 %

k_5 %

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

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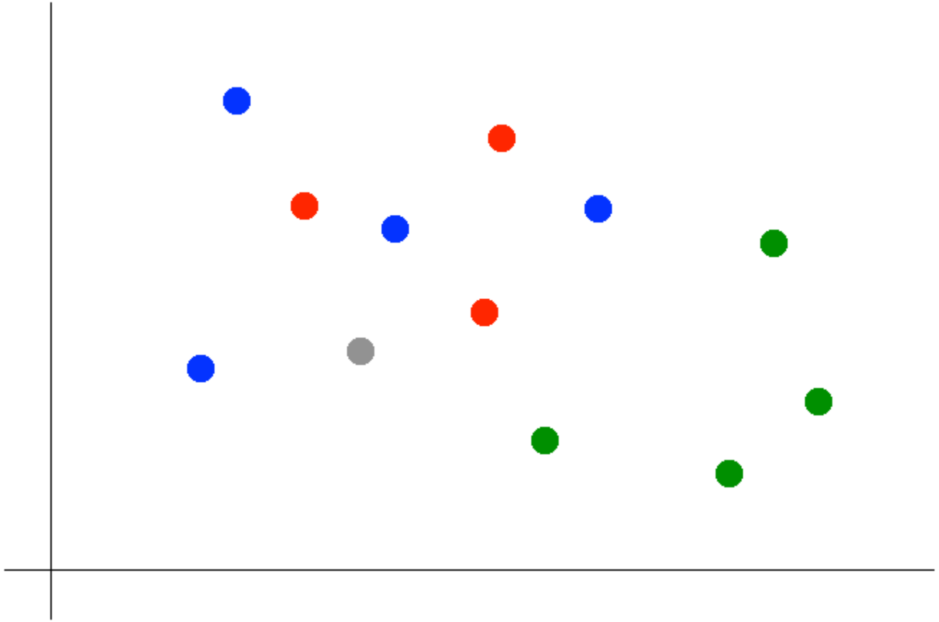
3) *Presents tradeoff between efficiency and computational expense.*
   - *10-fold CV is 10x more expensive than a single train/test split*
4) *Can be used for model selection.*

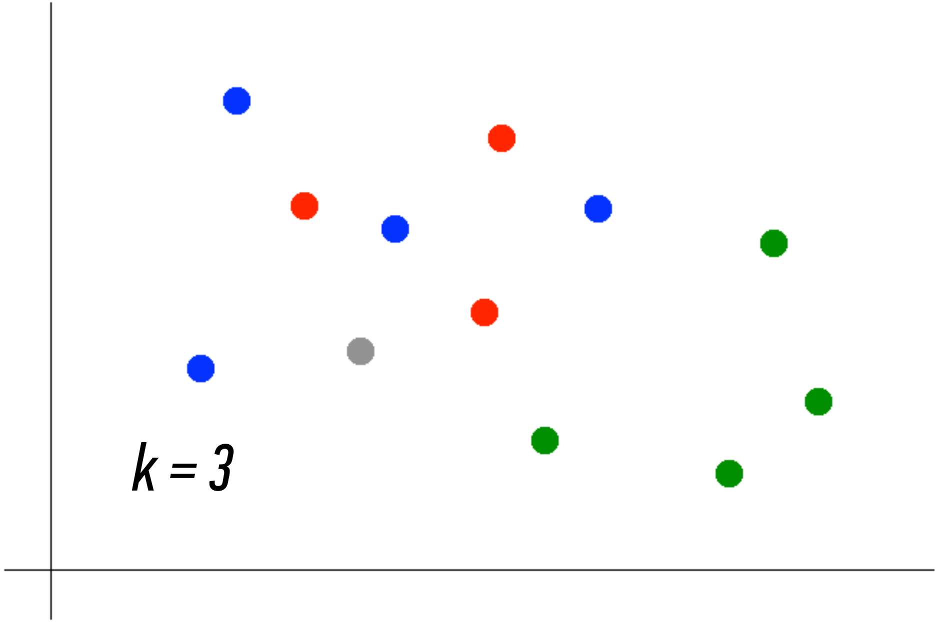
III. KNN CLASSIFICATION

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



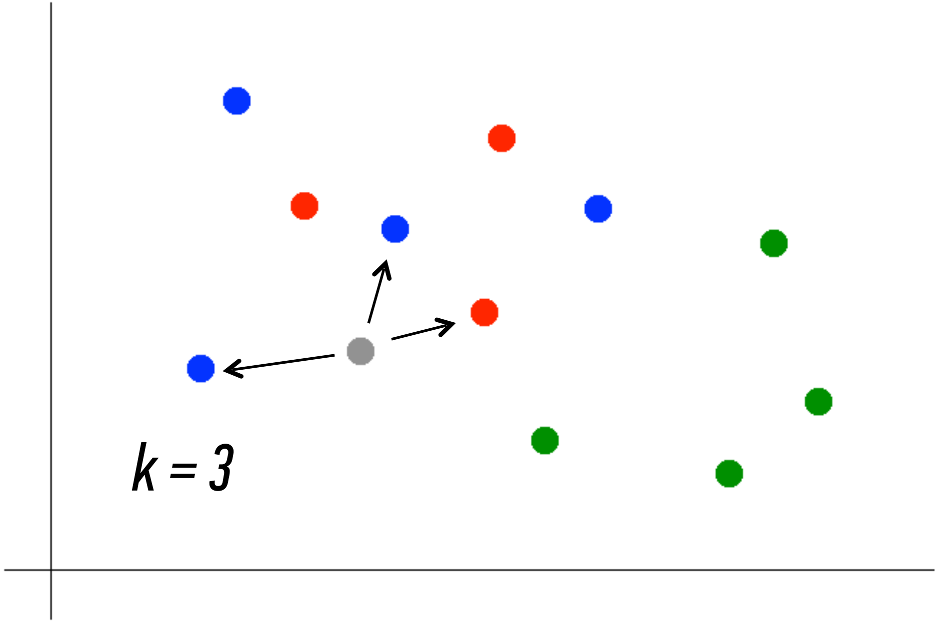
Suppose we want to predict the color of the grey dot.

1) *Pick a value for k.*



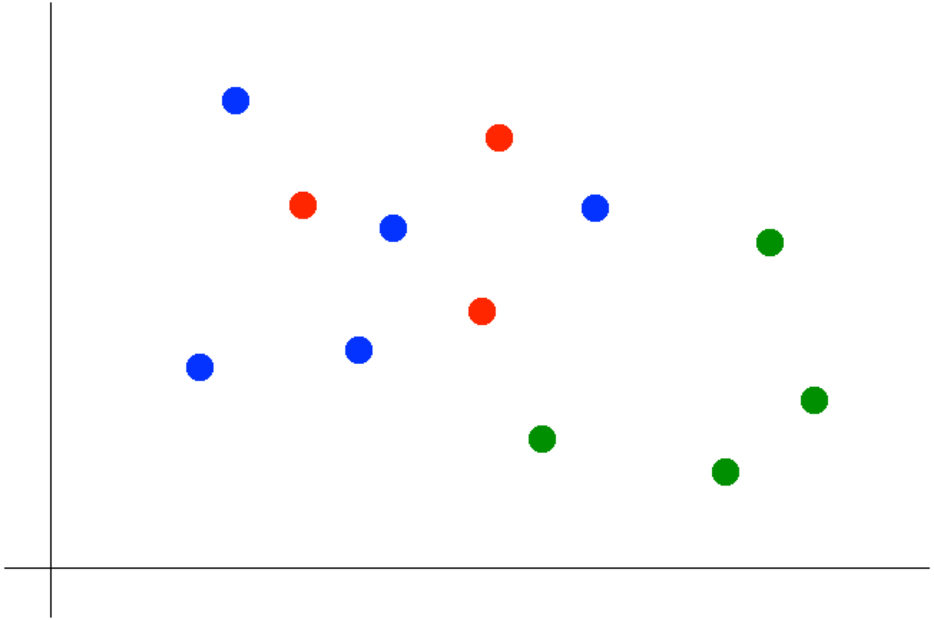
Suppose we want to predict the color of the grey dot.

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.*
2) *Find colors of k nearest neighbors.*
3) *Assign the most common color to the grey dot.*



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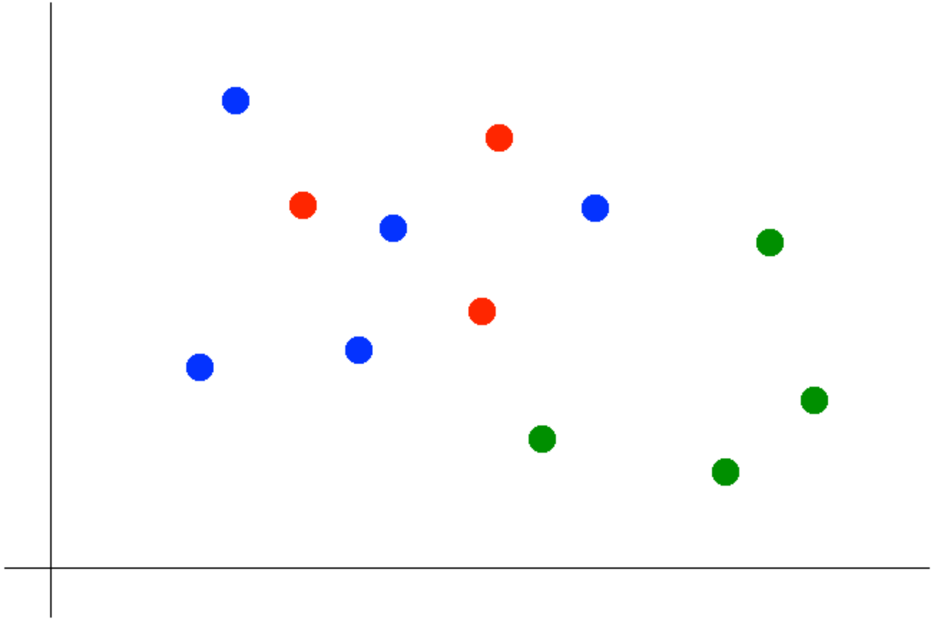
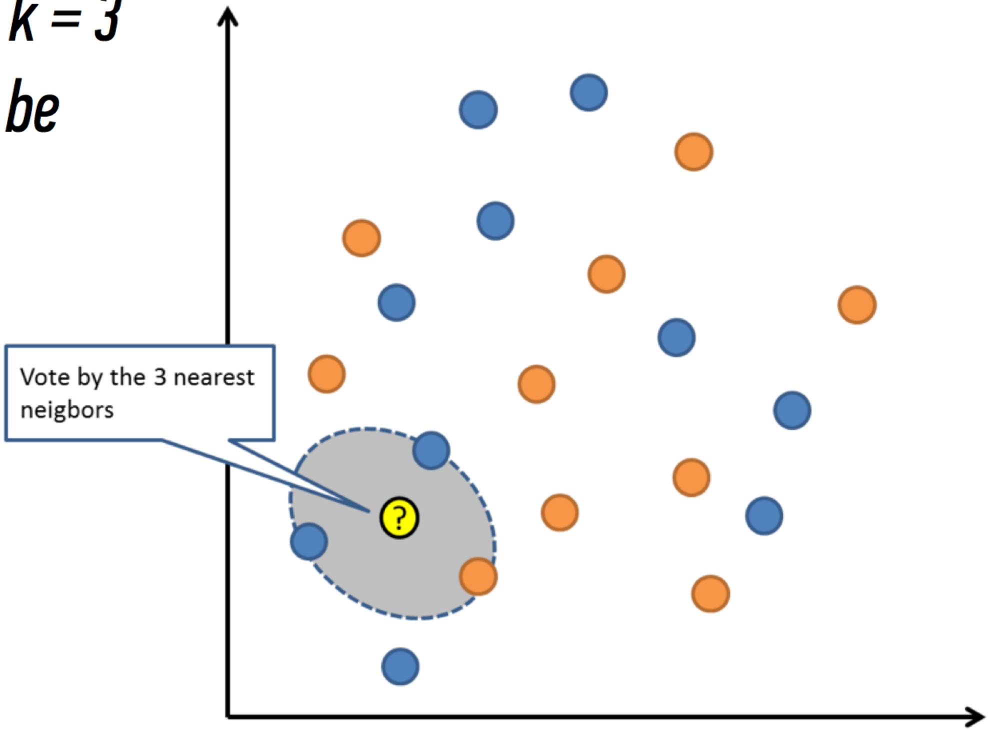


OPTIONAL NOTE

Our definition of "nearest" implicitly uses the Euclidean distance function.

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



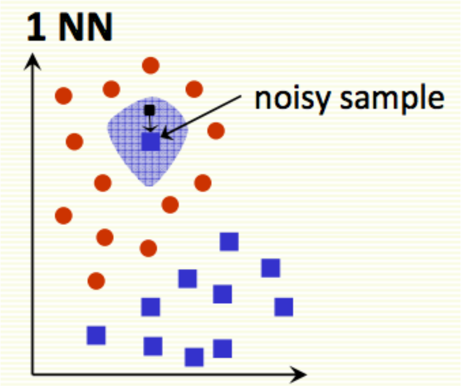
In theory, if infinite number of samples available, the larger is k, the better is classification

The caveat is that all k neighbors have to be close

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

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

Advantages

- *Can be applied to the data from any distribution*
- *Very simple and intuitive*
- *Good classification if the number of samples is large enough*

Disadvantages

- *Choosing k may be tricky*
- *Test stage is computationally expensive (no training stage)*
- *Need large number of samples for accuracy*

LAB