GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

LECTURE 5: MACHINE LEARNING

I. WHAT IS MACHINE LEARNING?
II. MACHINE LEARNING PROBLEMS
III. CLASSIFICATION PROBLEMS
IV. KNN CLASSIFICATION

I. WHAT IS MACHINE LEARNING?

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from Wikipedia:

“Machine learning, a branch of artificial intelligence, is about the construction and study of systems that can learn from data.”

source: http://en.wikipedia.org/wiki/Machine_learning

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- representation – extracting structure from data

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WHAT IS MACHINE LEARNING?

from Wikipedia:

"Machine learning, a branch of artificial intelligence, is about the construction and study of systems that can learn from data."

"The core of machine learning deals with representation and generalization…"

- representation – extracting structure from data
- generalization – making predictions from data

source: http://en.wikipedia.org/wiki/Machine_learning

II. MACHINE LEARNING PROBLEMS

supervised	
unsupervised	

supervised	*making predictions*
unsupervised	*discovering patterns*

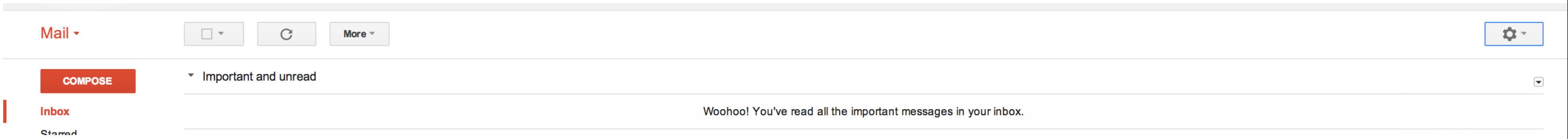
supervised	*labeled examples*
unsupervised	*no labeled examples*

	continuous	*categorical*
	quantitative	*qualitative*

	continuous	categorical
supervised	regression	classification
unsupervised	dimension reduction	clustering

What type of problem is this?

Priority Inbox



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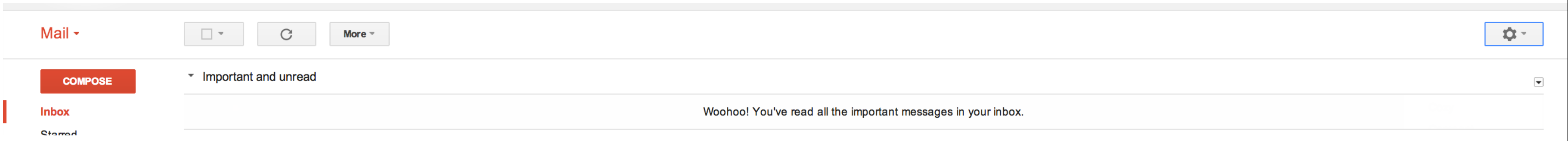
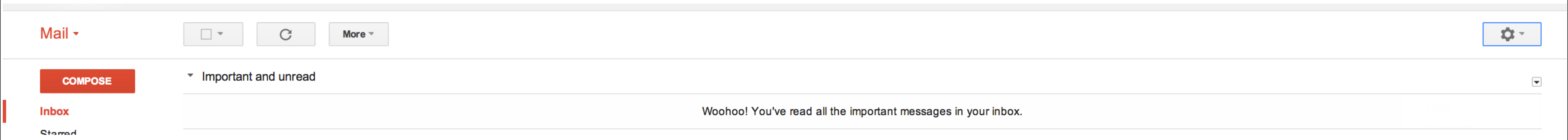


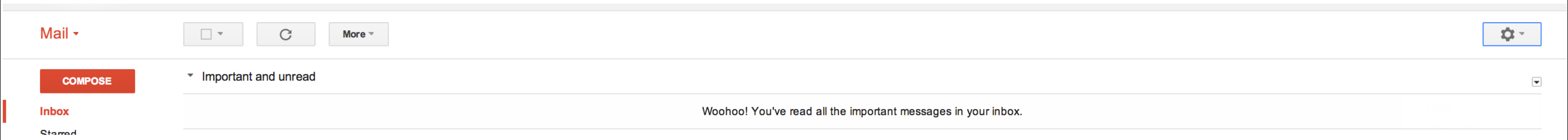
Probably either.

TYPES OF ML SOLUTIONS



Priority Inbox: Supervised Learning

Predict which mails users are most likely to star



Priority Inbox: Unsupervised Learning

Group mails into groups and decide which group represents important mails

What type of problem is this?

Music Recommendation

What type of problem is this?

Music Recommendation

Probably either.

What type of problem is this?

Music Recommendation as Supervised Learning

Predict which songs a user will 'thumbs-up'

What type of problem is this?

Music Recommendation
As Unsupervised Learning

Cluster songs based on attributes
and recommend songs in the same group

QUESTION

HOW DO YOU DETERMINE THE RIGHT APPROACH?

	continuous	categorical
supervised	regression	classification
unsupervised	dimension reduction	clustering

ANSWER

The right approach is determined by the desired solution **and the data available.**

QUESTION

HOW

DO YOU

REPRESENT

YOUR

DATA?

	continuous	*categorical*
	quantitative	*qualitative*

	continuous	categorical
color	RGB-values	{red, blue}
ratings	1 – 10 rating	1-5 star rating

QUESTION

HOW
DO YOU
MEASURE
QUALITY?

supervised	*making predictions*
unsupervised	*extracting structure*

supervised	*test out your predictions*
unsupervised	*...*

QUESTION

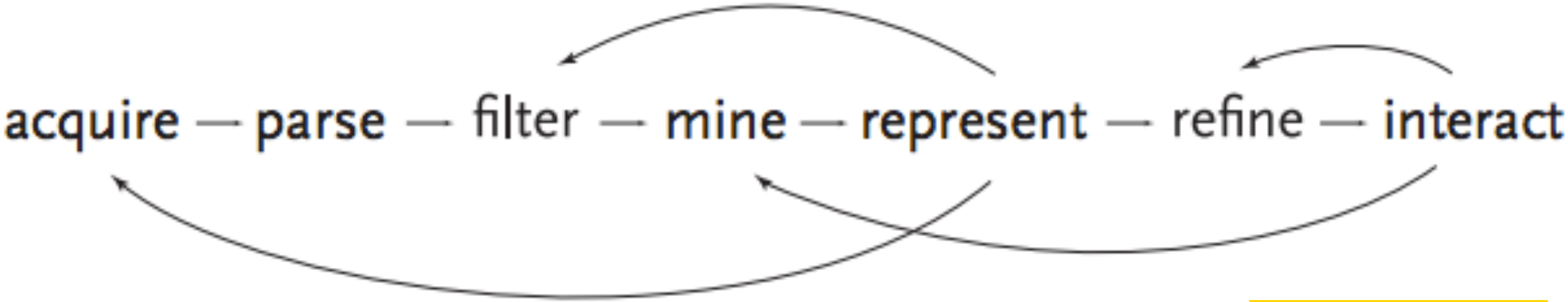
WHAT

DO YOU

DO

WITH YOUR

RESULTS?



ANSWER

Interpret them and react accordingly.

source: http://benfry.com/phd/dissertation-110323c.pdf

III. CLASSIFICATION PROBLEMS

Q: How does a classification problem work?

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A: Data in, predicted labels out.

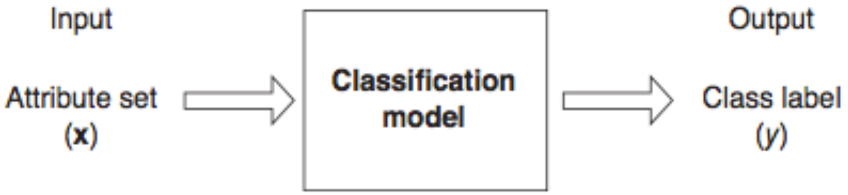

Figure 4.2. Classification as the task of mapping an input attribute set $\mathbf{x}$ into its class label y.

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

	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*
4.6	3.4	1.4	0.3	*I. setosa*
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CLASSIFICATION PROBLEMS

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independent variables

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independent variables

class labels (qualitative)

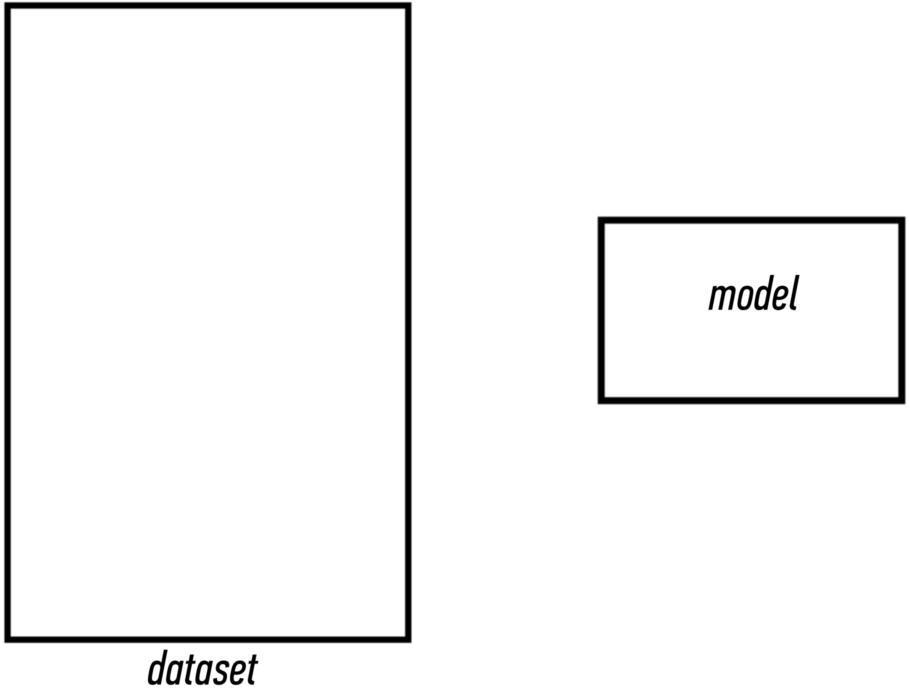
Q: What does "supervised" mean?

Q: What does "supervised" mean?

A: We know the labels.

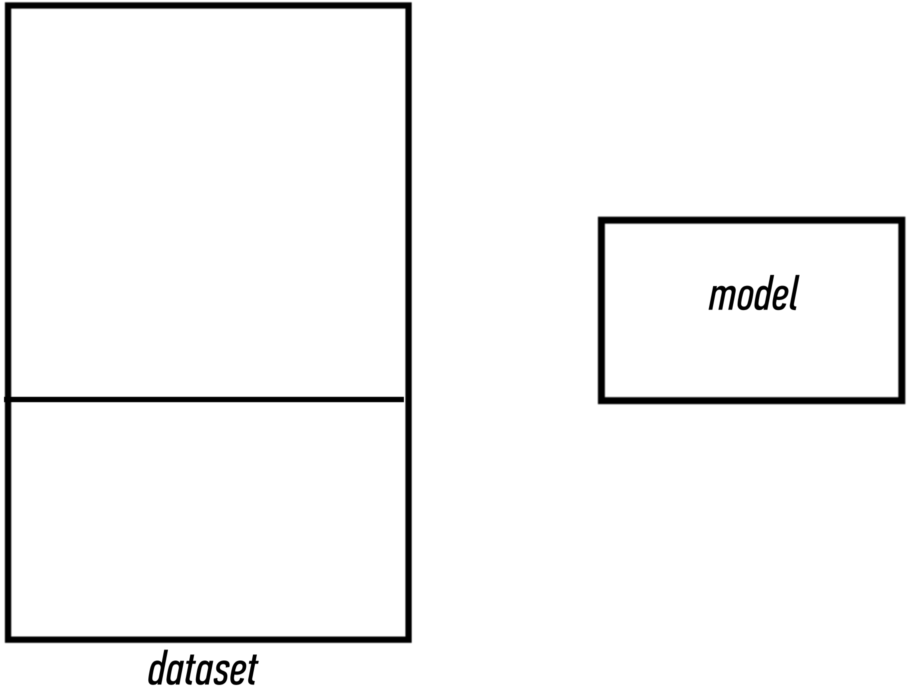
```
Welcome to R! Thu Feb 28 13:07:25 2013
> summary(iris)
  Sepal.Length    Sepal.Width     Petal.Length    Petal.Width   
 Min.   :4.300   Min.   :2.000   Min.   :1.000   Min.   :0.100  
 1st Qu.:5.100   1st Qu.:2.800   1st Qu.:1.600   1st Qu.:0.300  
 Median :5.800   Median :3.000   Median :4.350   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: What steps does a classification problem require?



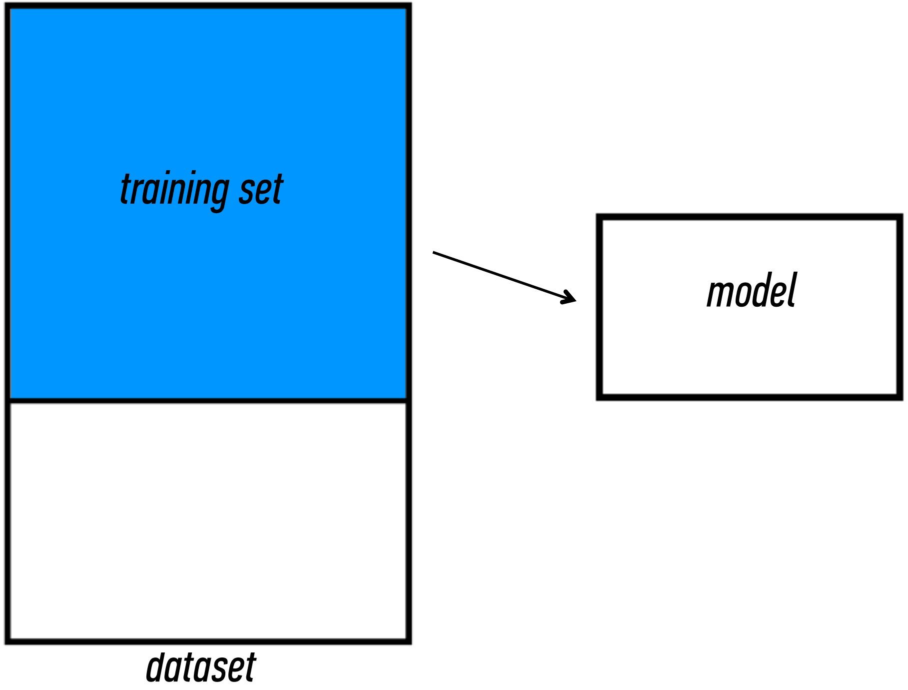
Q: What steps does a classification problem require?

1) *split dataset*



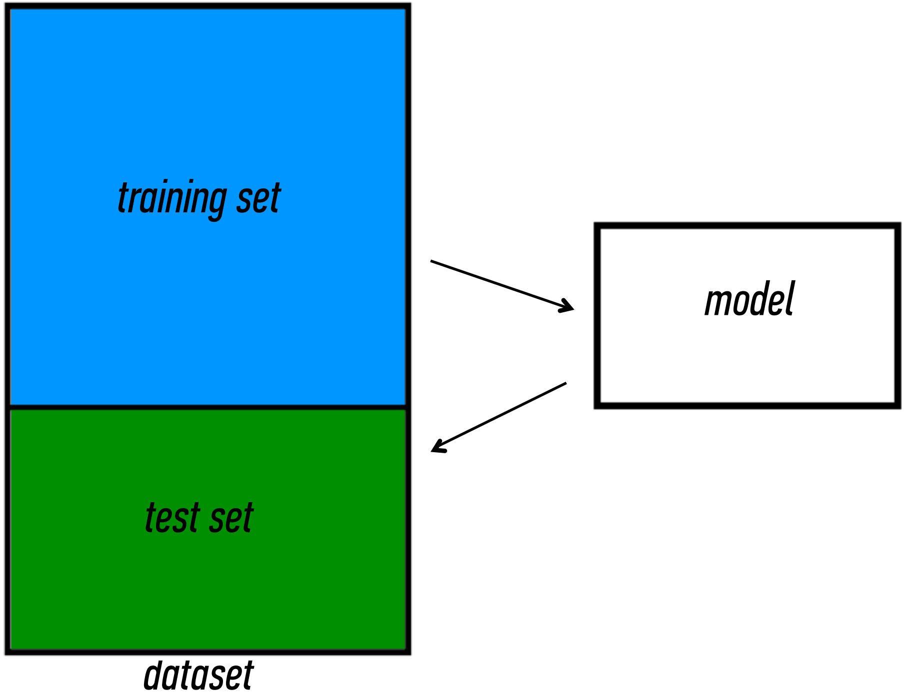
Q: What steps does a classification problem require?

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



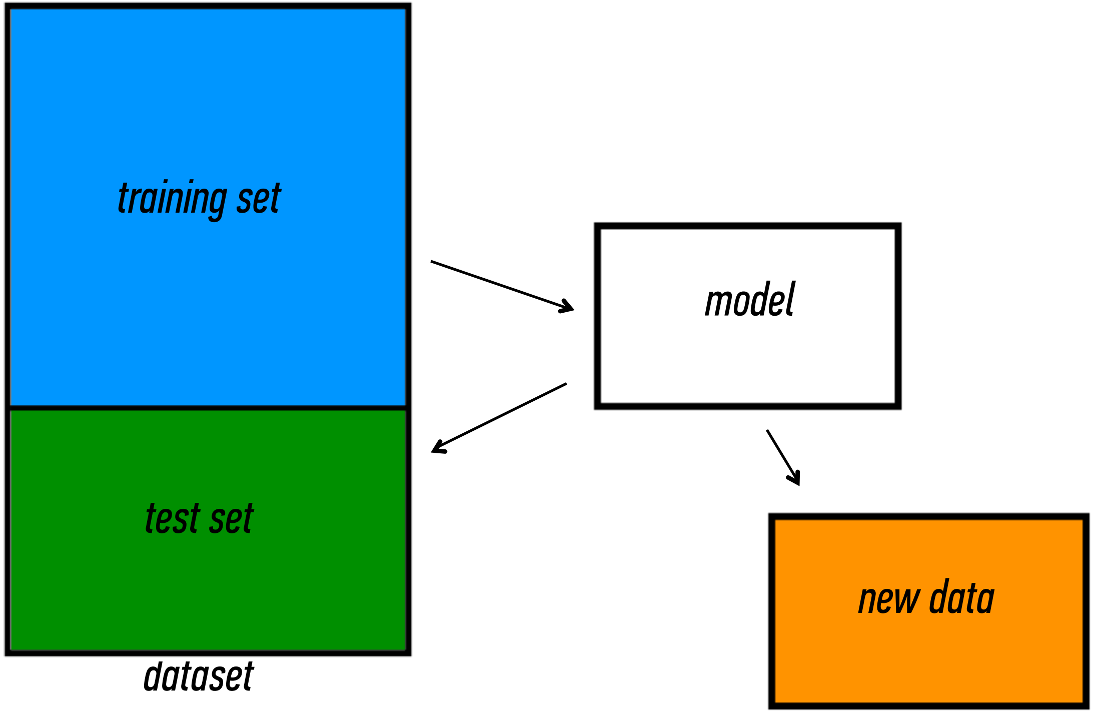
Q: What steps does a classification problem require?

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



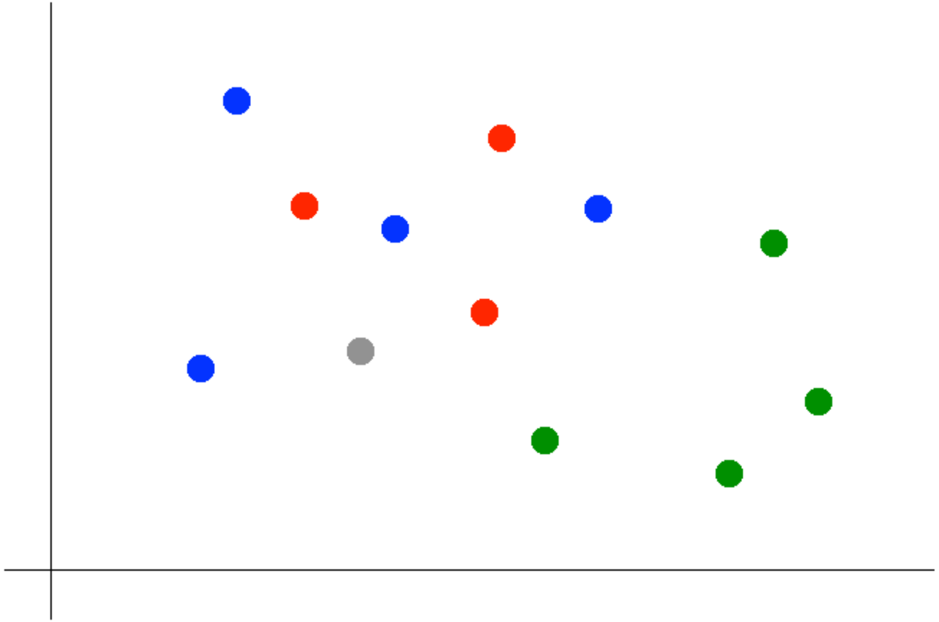
Q: What steps does a classification problem require?

1) split dataset
2) train model
3) test model
4) make predictions



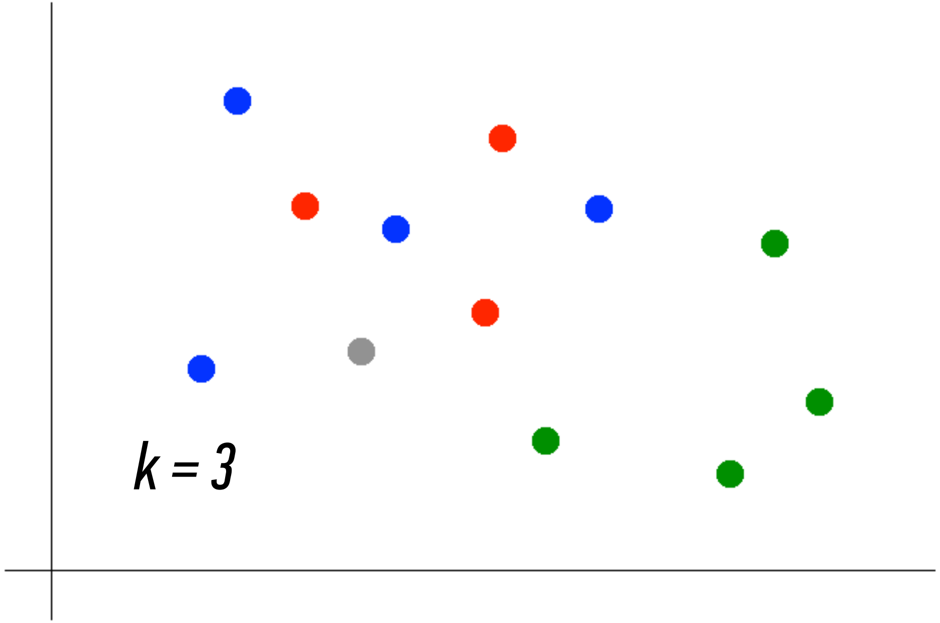
KNN CLASSIFICATION

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



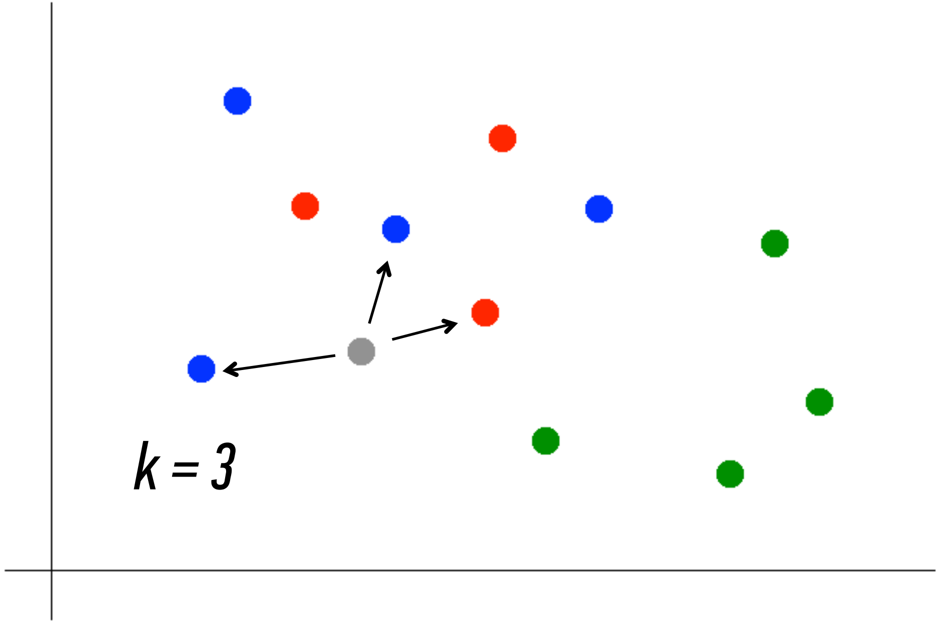
Suppose we want to predict the color of the grey dot.

1) *Pick a value for k.*



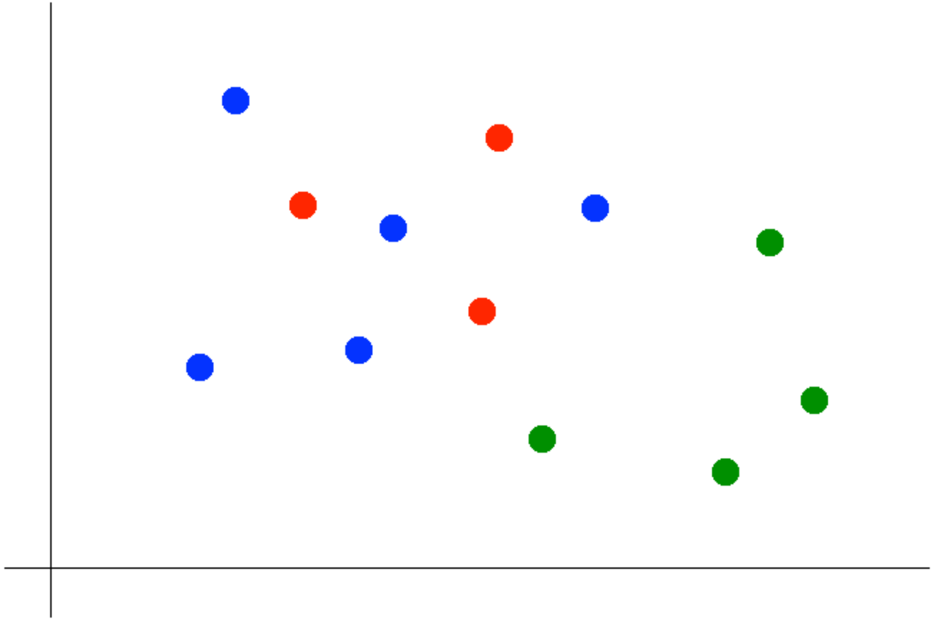
Suppose we want to predict the color of the grey dot.

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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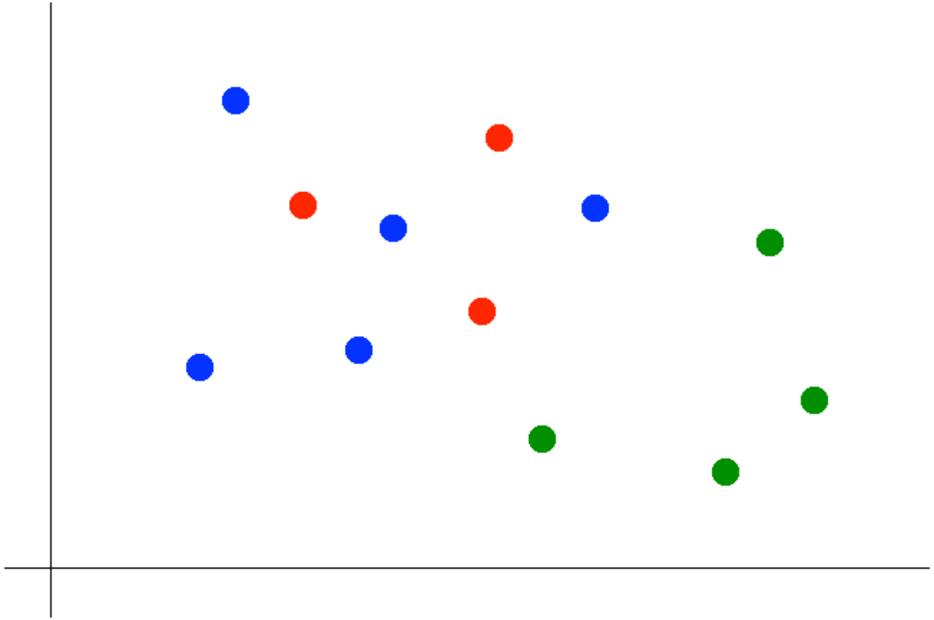
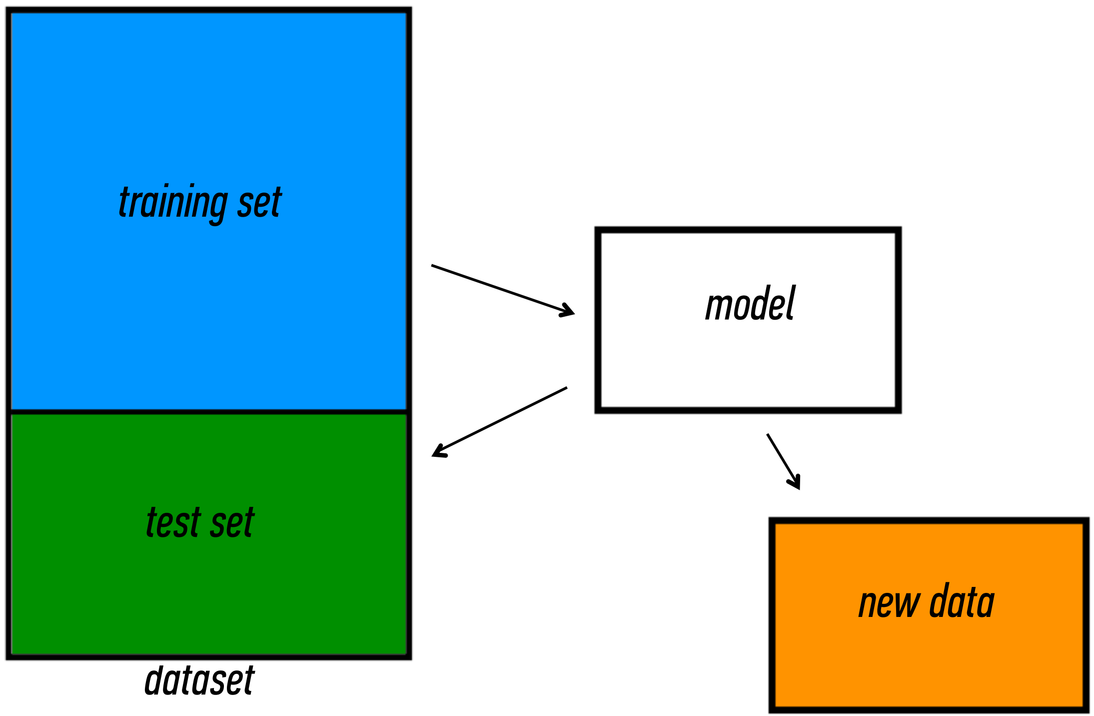


OPTIONAL NOTE

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

BUILDING EFFECTIVE CLASSIFIERS

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



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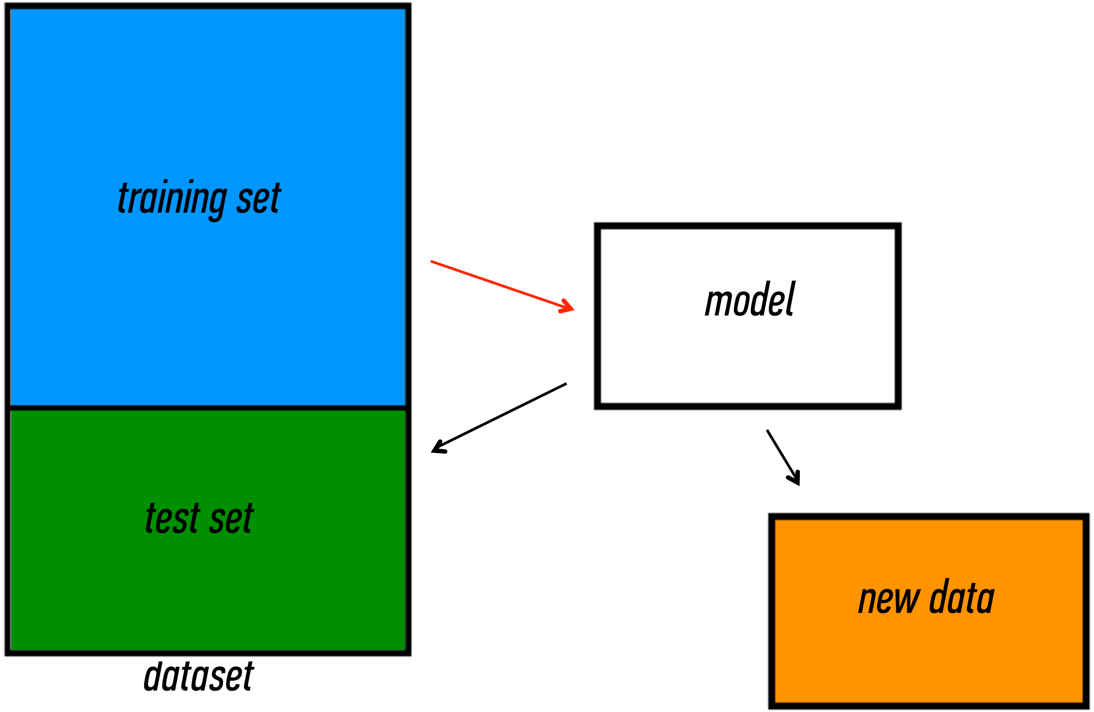
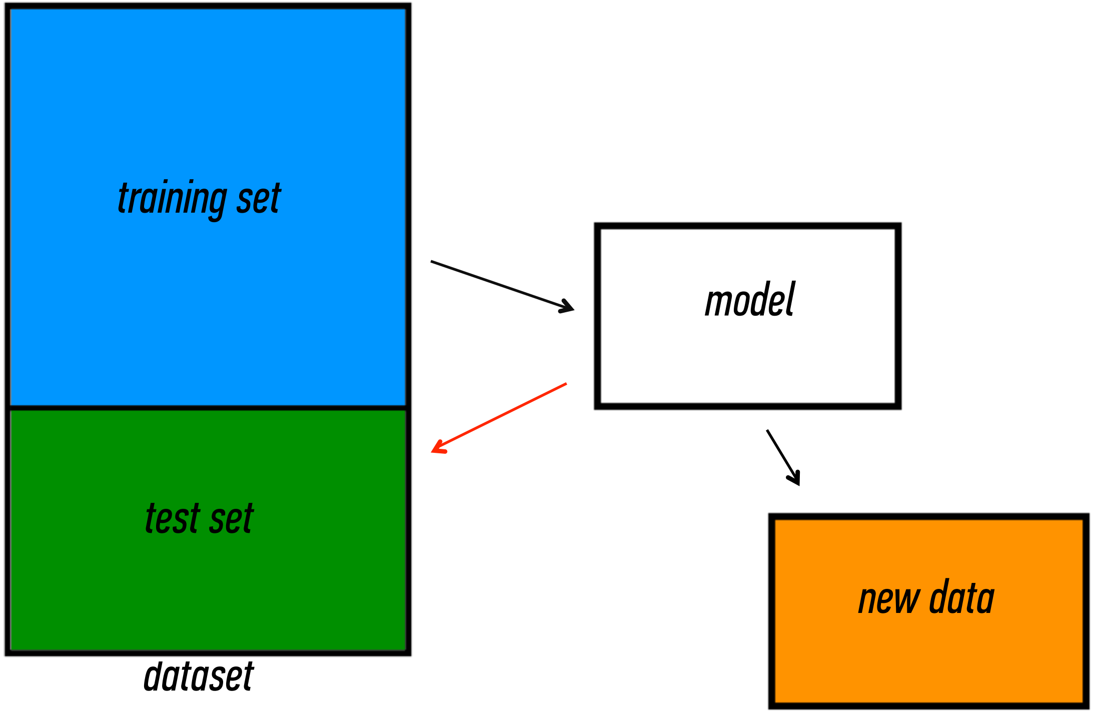


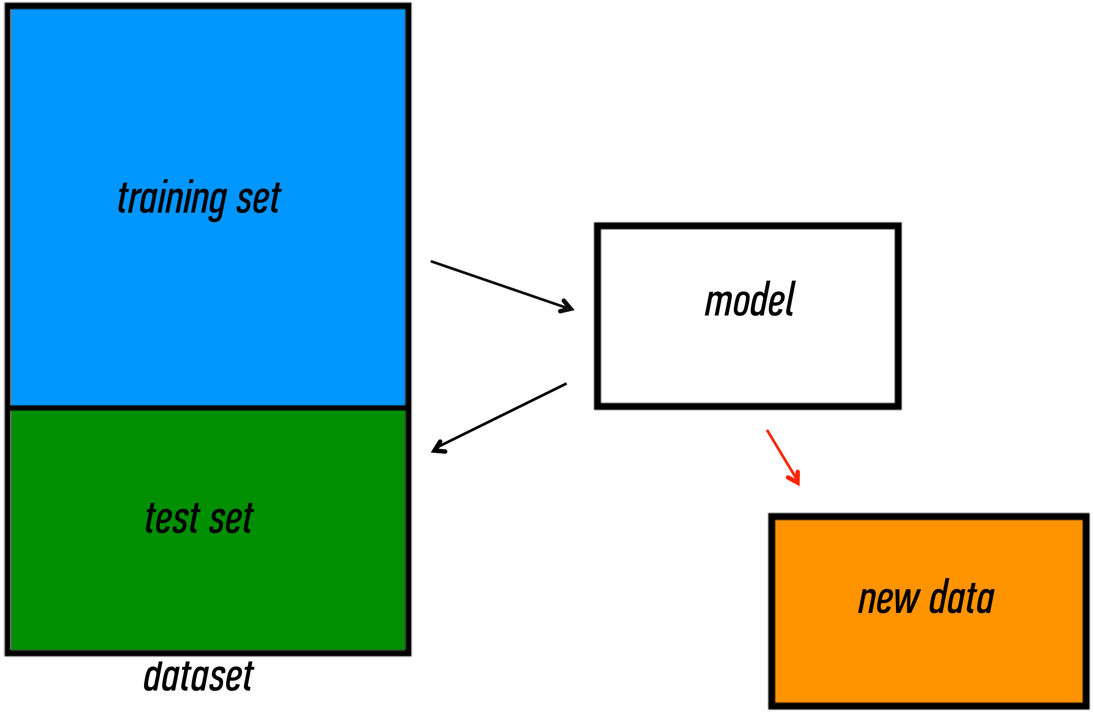
Q: What types of prediction error will we run into?

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



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

1) *training error*
2) *generalization error*
3) *OOS error*



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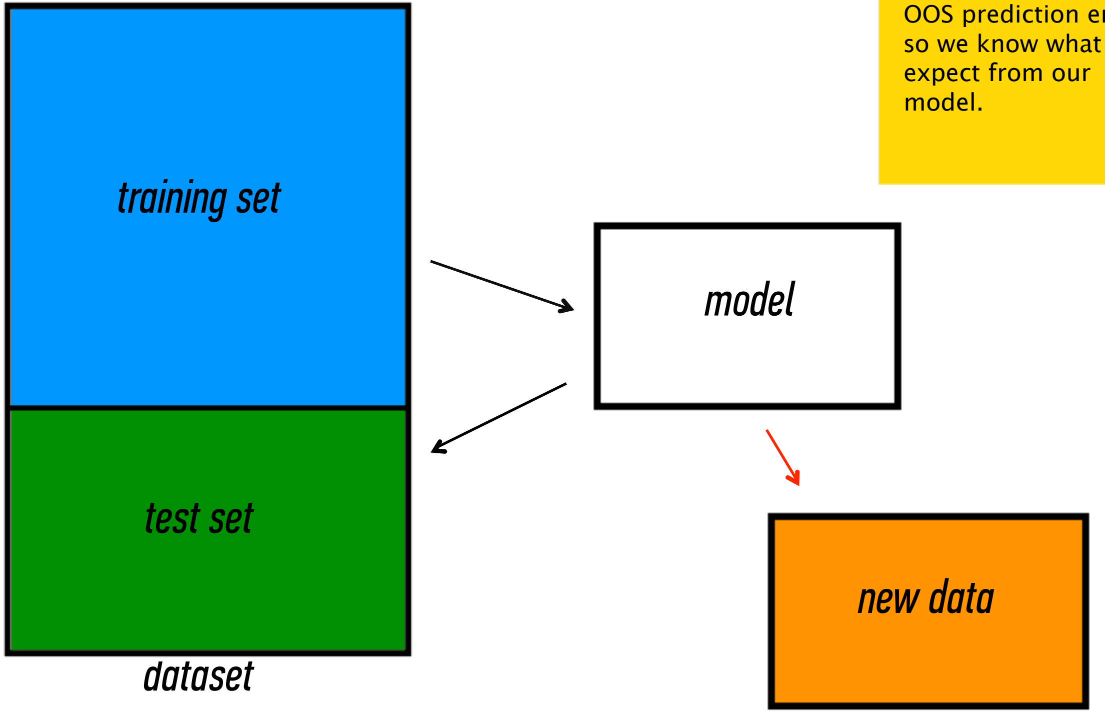

NOTE

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

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Thought experiment:
Suppose instead, we train our model using the entire dataset.

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A: Down to zero!

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NOTE

This phenomenon is called overfitting.

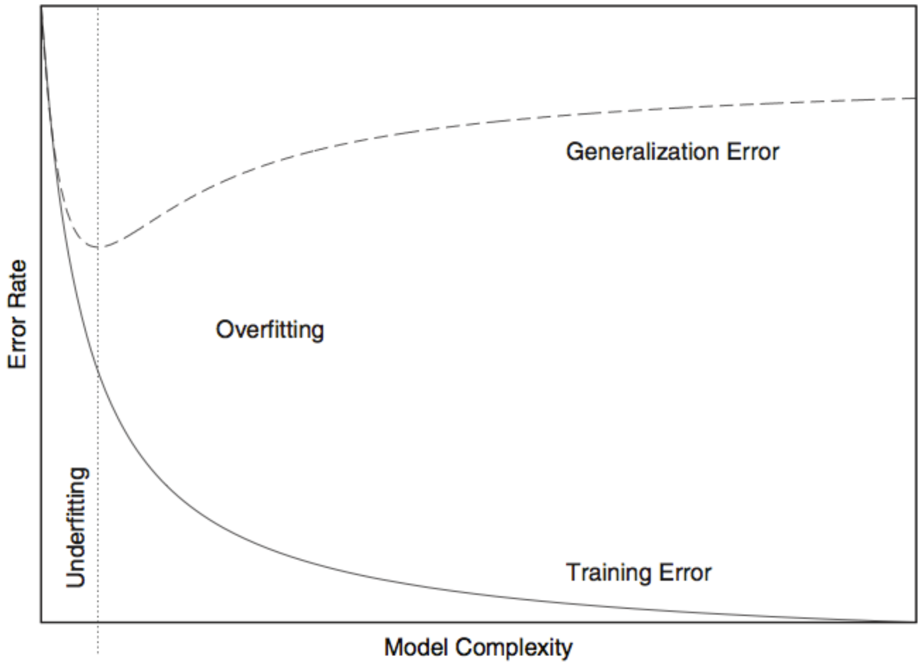
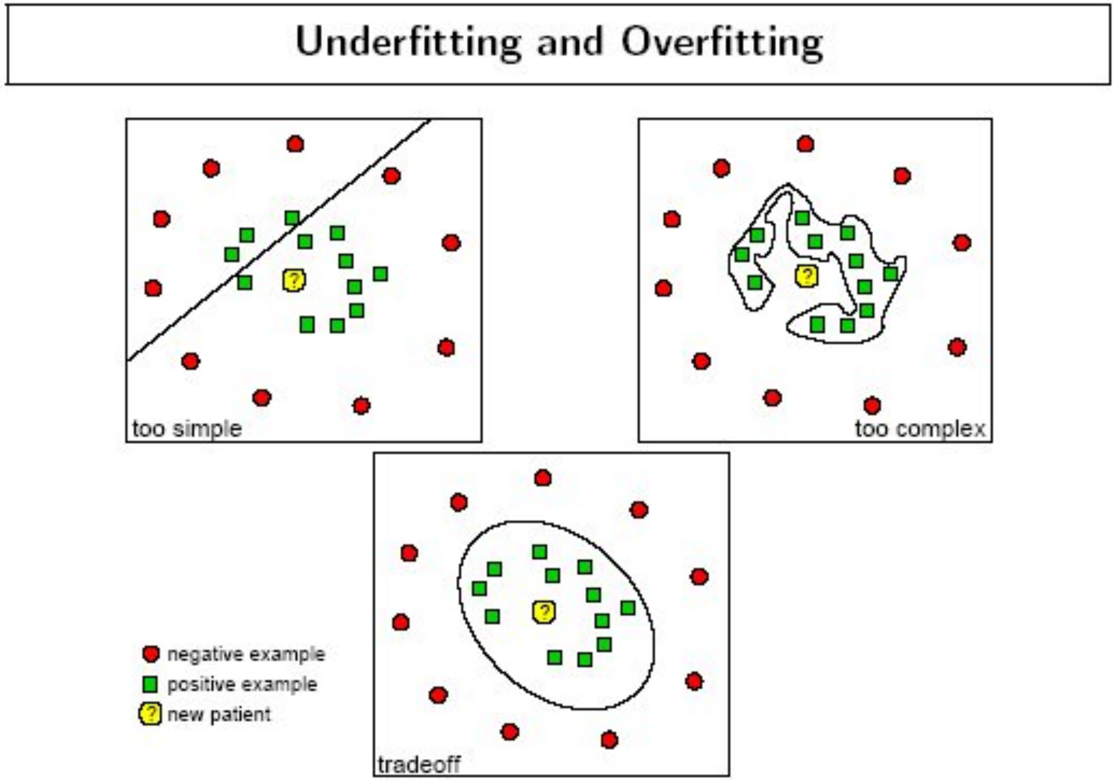


FIGURE 18-1. Overfitting: as a model becomes more complex, it becomes increasingly able to represent the training *data. However, such a model is overfitted and will not generalize well to data that was not used during training.*

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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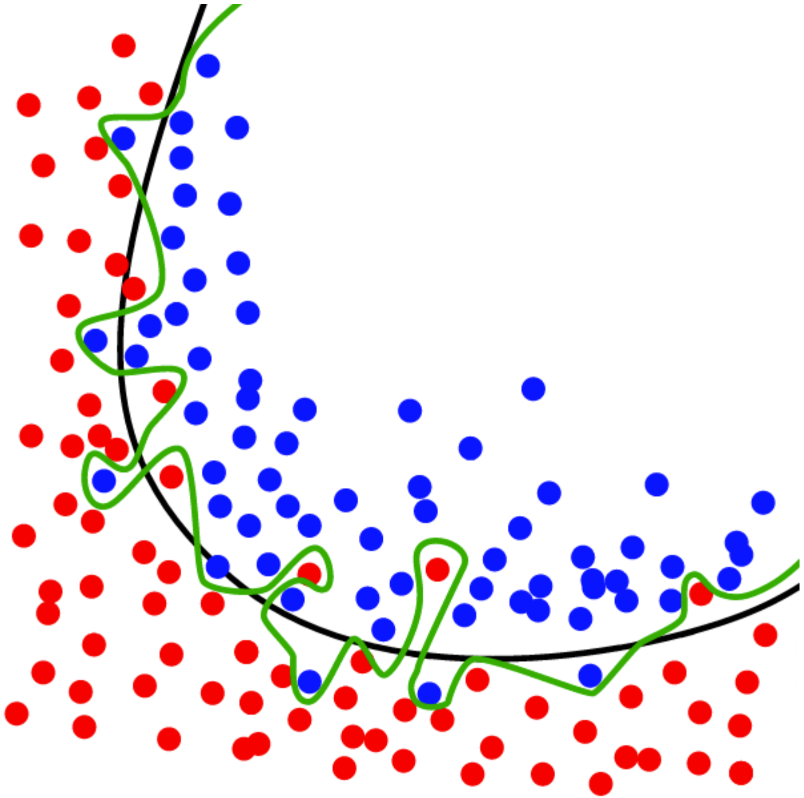

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Q: How low can we push the training error?

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NOTE

This phenomenon is called overfitting.

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

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Q: How well does generalization error predict OOS accuracy?

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Thought experiment:

Suppose we had done a different train/test split.

Q: Would the generalization error remain the same?

A: Of course not!

Suppose we do the train/test split.

Q: How well does generalization error predict OOS accuracy?

Thought experiment:

Suppose we had done a different train/test split.

Q: Would the generalization error remain the same?

A: Of course not!

A: On its own, not very well.

Something is still missing!

Something is still missing!

Q: How can we do better?

Something is still missing!

Q: How can we do better?

Thought experiment:

Different train/test splits will give us different generalization errors.

Something is still missing!

Q: How can we do better?

Thought experiment:

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A: Now you're talking!

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A: Cross-validation.

Steps for n-fold cross-validation:

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Steps for n-fold cross-validation:

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2) *Use partition 1 as test set & union of other partitions as training set.*
3) *Find generalization error.*
4) *Repeat steps 2-3 using a different partition as the test set at each iteration.*
5) *Take the average generalization error as the estimate of OOS accuracy.*

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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.*

DISCUSSION