GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

LECTURE 7: KNN CLASSIFICATION

LAST TIME:

- POLYNOMIAL REGRESSION
- LOGISTIC REGRESSION
- REGULARIZATION

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 Set)

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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class labels (qualitative)

independent variables

Q: What does "supervised" mean?

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A: We know the labels.

```
>>> from sklearn import datasets
>>> iris = datasets.load_iris()
>>> iris.target_names
array(['setosa', 'versicolor', 'virginica'],
      dtype='|S10')
>>> iris.feature_names
['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
>>> iris.data
array([[ 5.1,  3.5,  1.4,  0.2],
       [ 4.9,  3. ,  1.4,  0.2],
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```

Q: How does a classification problem work?

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A: Data in, predicted labels out.

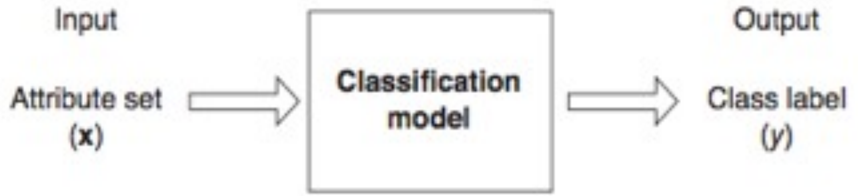
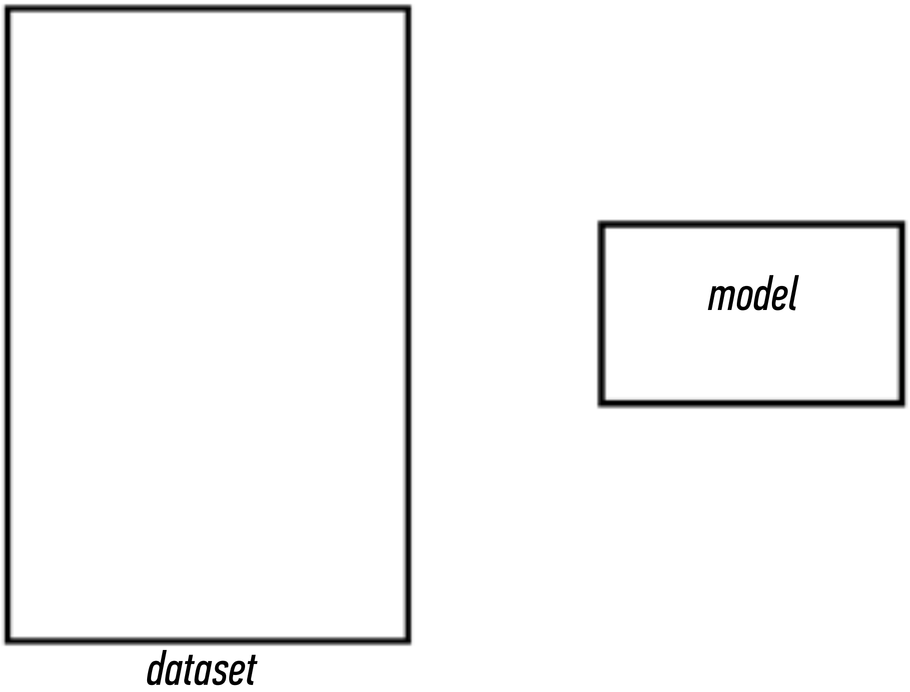


Figure 4.2. Classification as the task of mapping an input attribute set $\mathbf{x}$ into its class label y.

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

CLASSIFICATION PROBLEMS

Q: What steps does a classification problem require?



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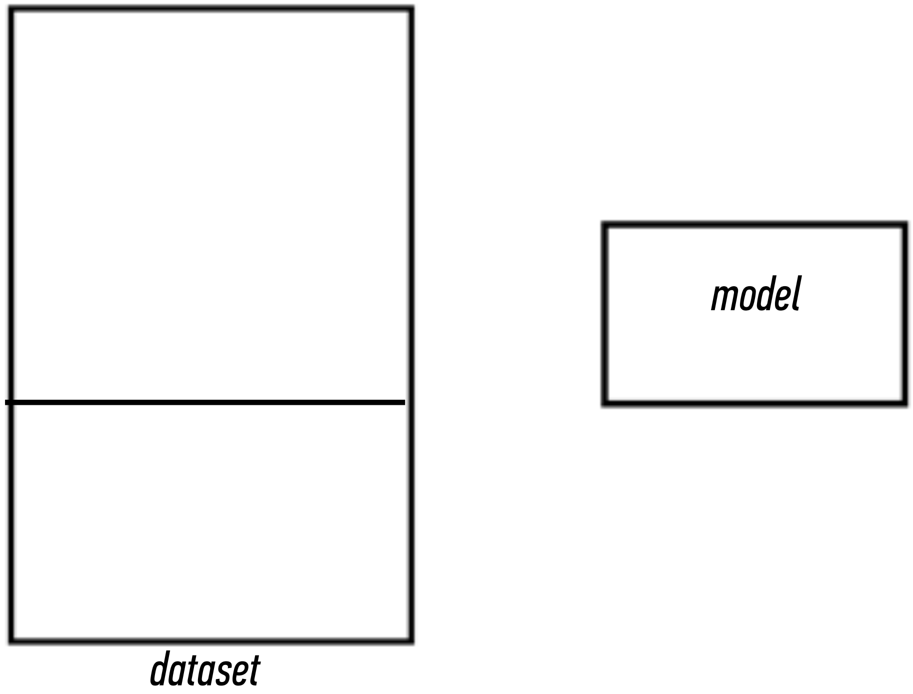
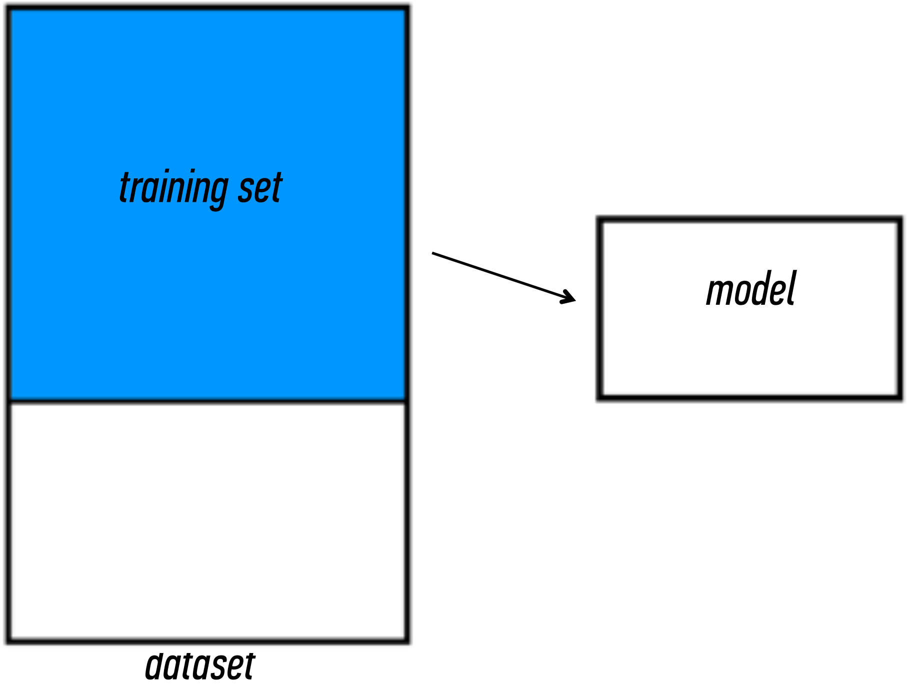


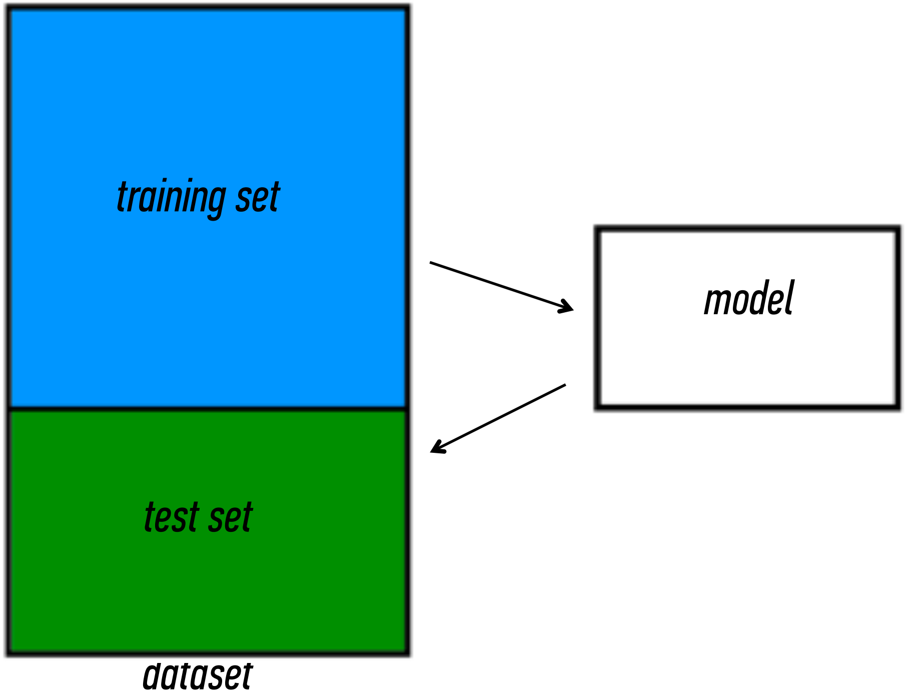
Q: What steps does a classification problem require?

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



Q: What steps does a classification problem require?

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



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1) *split dataset*
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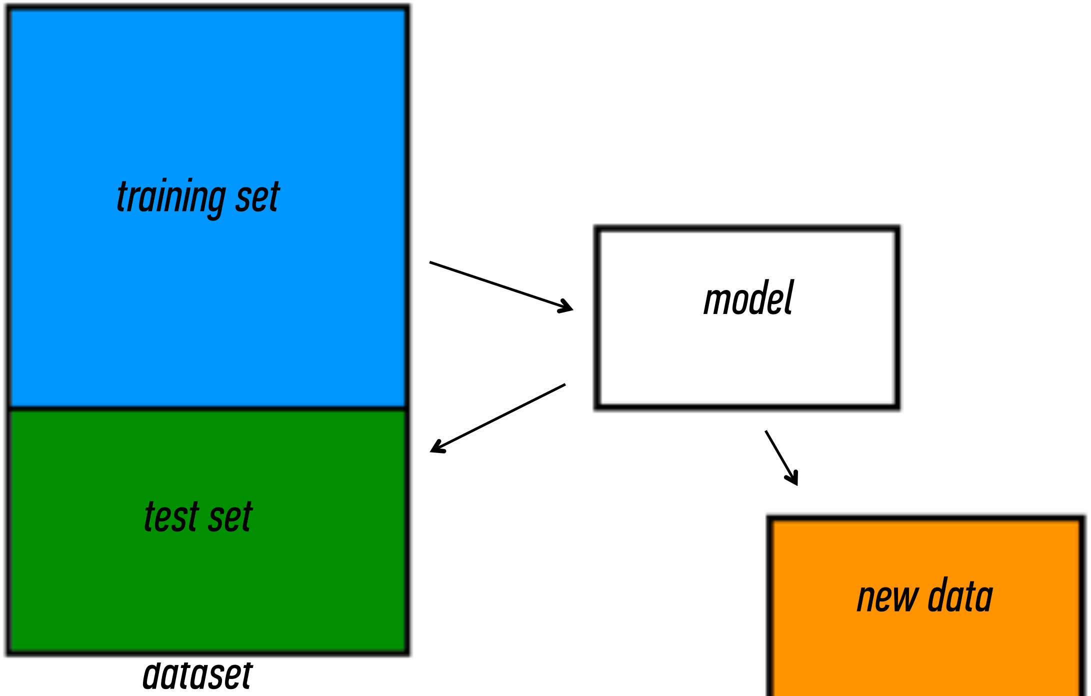

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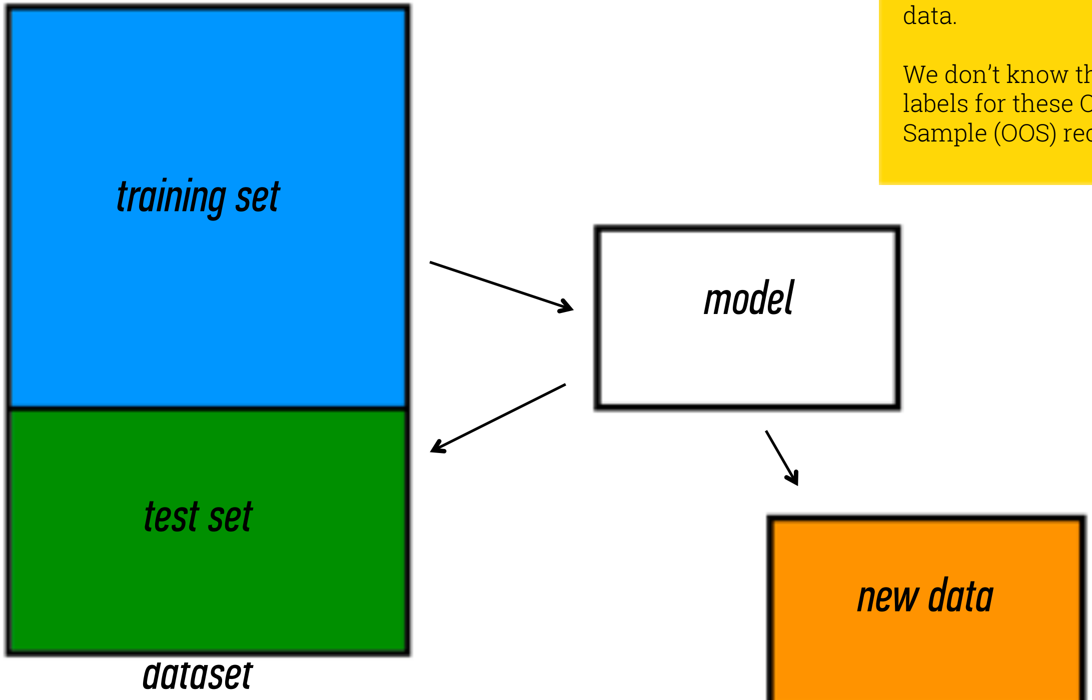


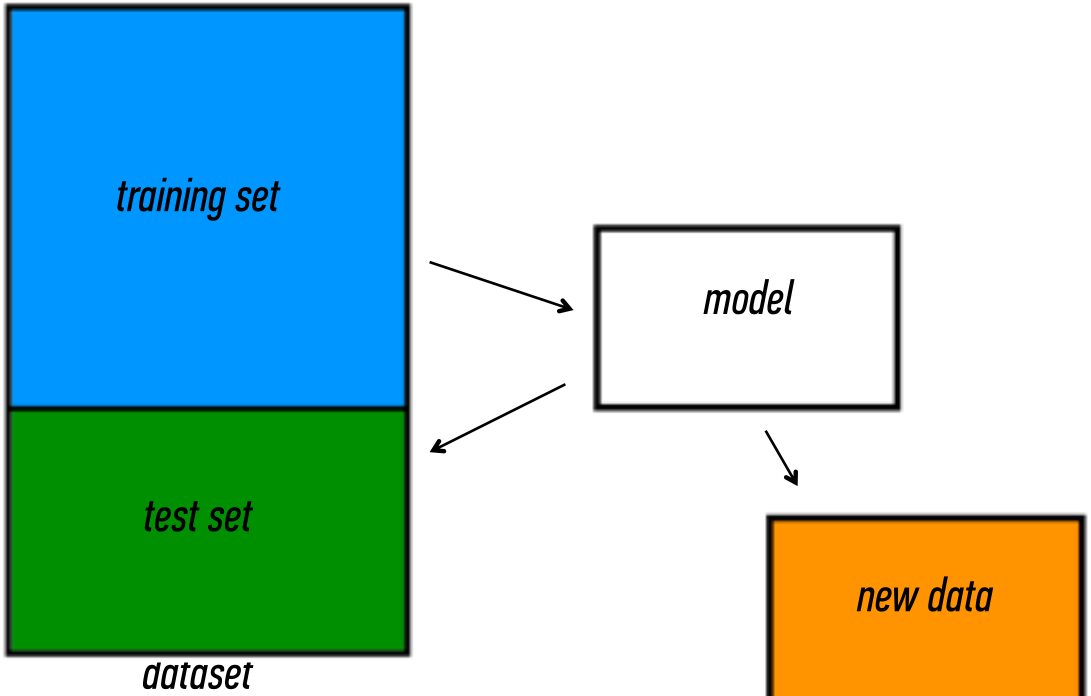
NOTE

This new data is called out of sample data.

We don't know the labels for these Out of Sample (OOS) records!

II. BUILDING EFFECTIVE CLASSIFIERS

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



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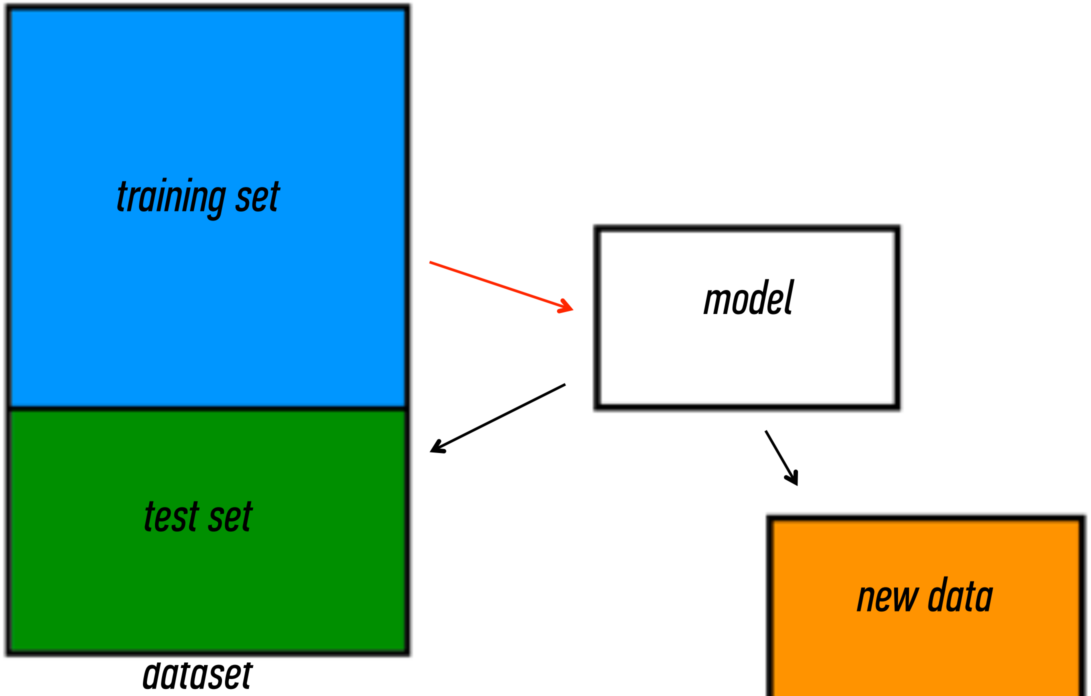

Q: What types of prediction error will we run into?

1) *training error*
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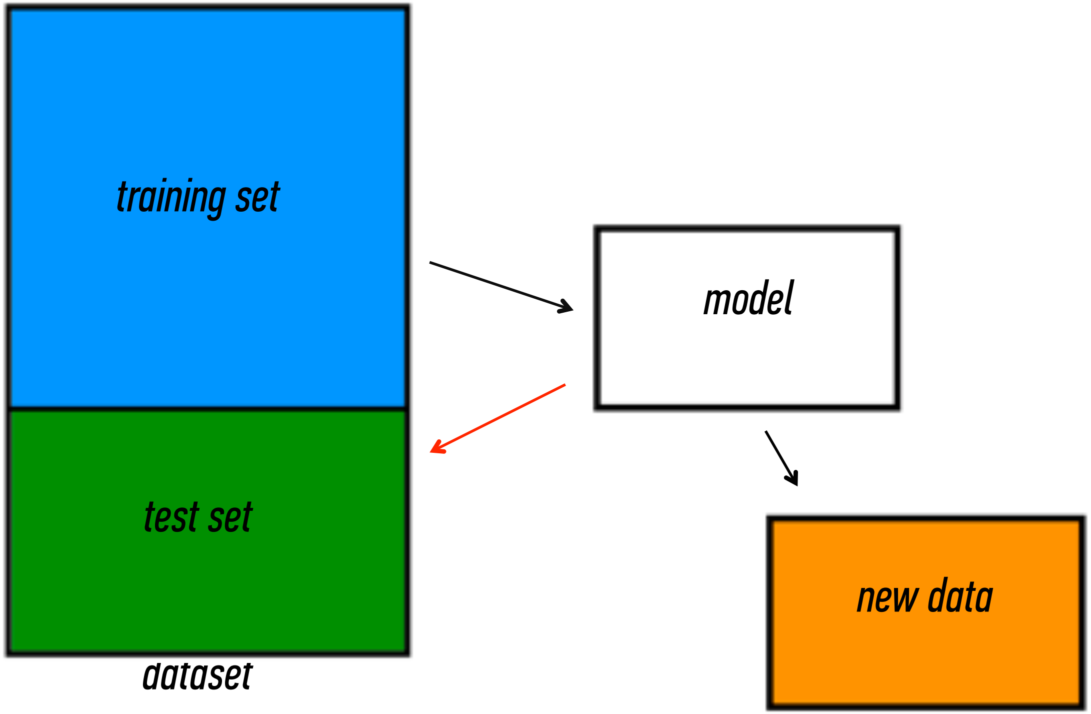

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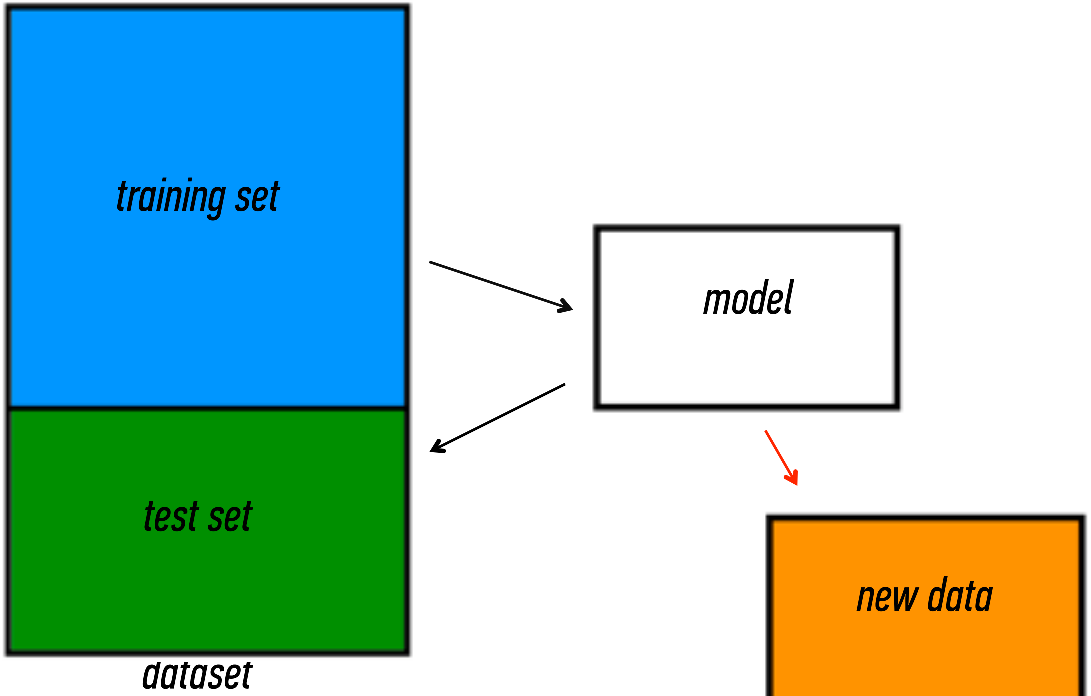

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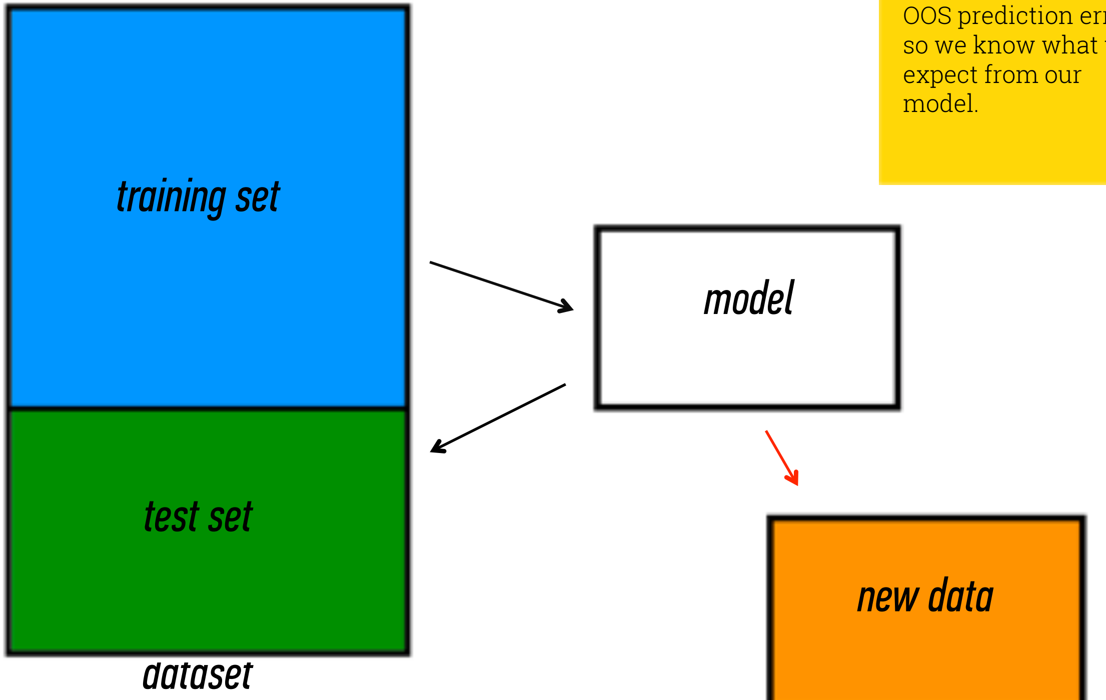

NOTE

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

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TRAINING ERROR

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NOTE

This phenomenon is called overfitting.

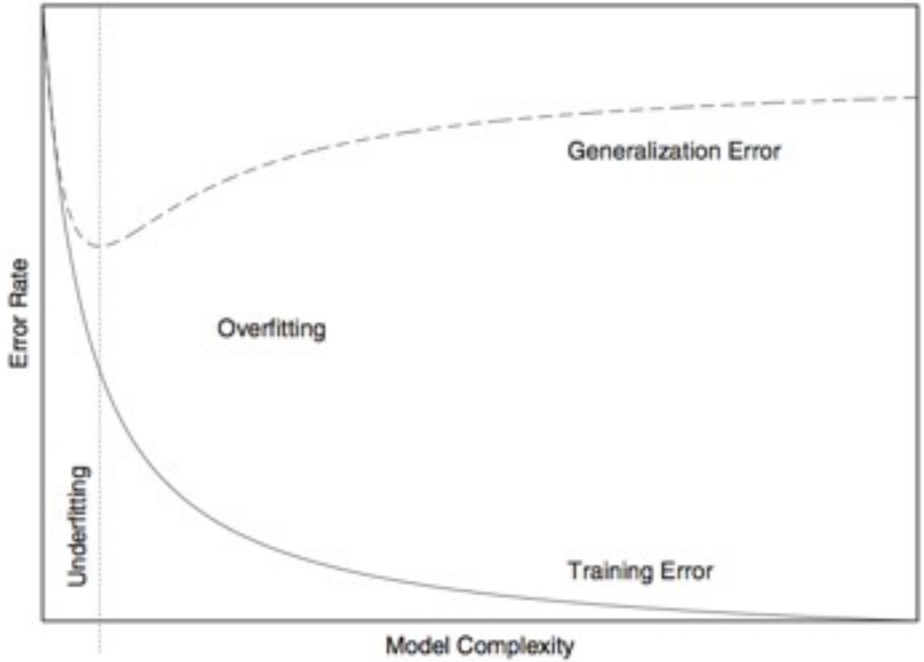
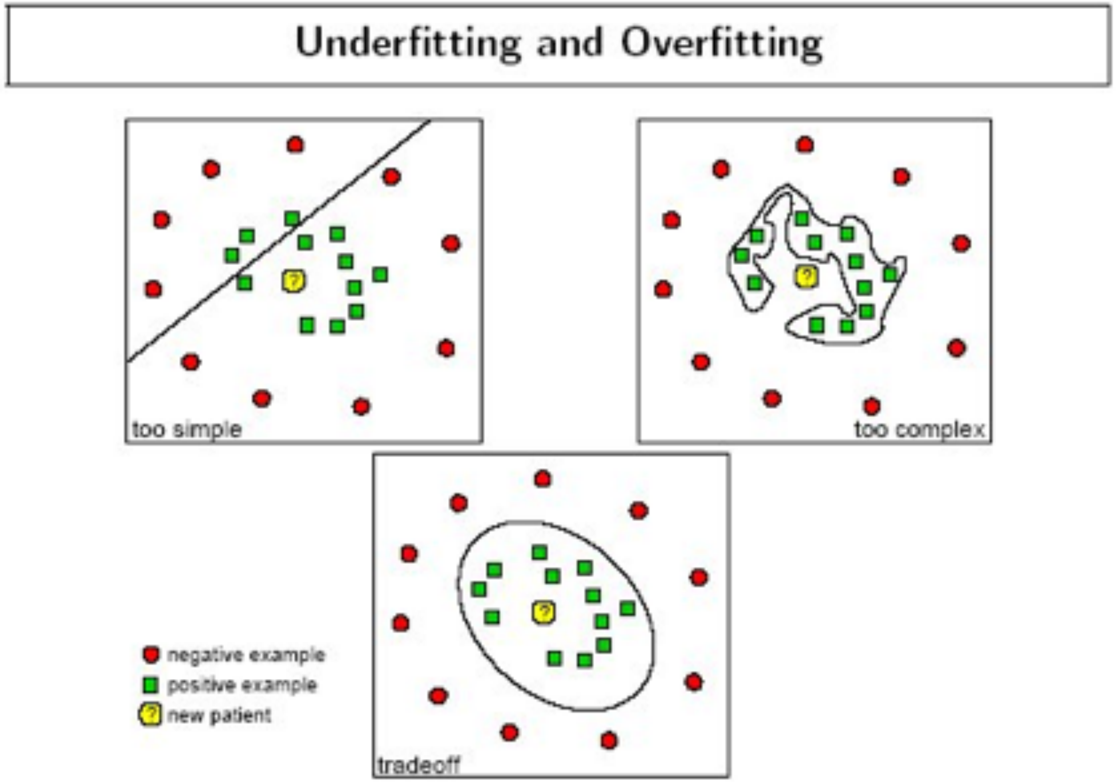


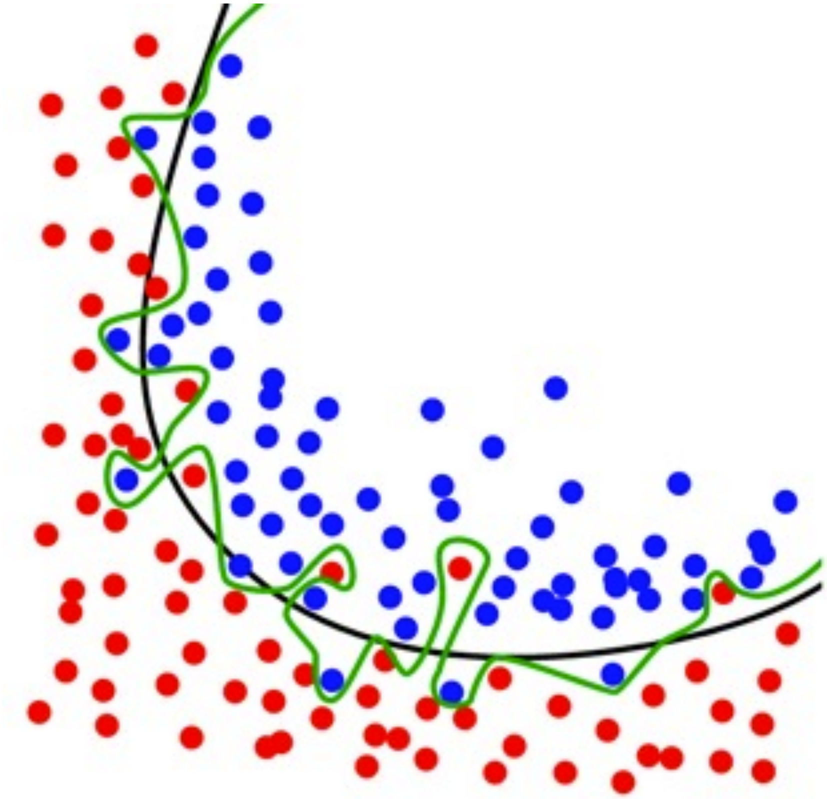
FIGURE 18-1. Overfitting: as a model becomes more complex, it becomes increasingly able to represent the training data. However, such a model is overfitted and will not generalize well to data that was not used during training.

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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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.

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A: Cross-validation.

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

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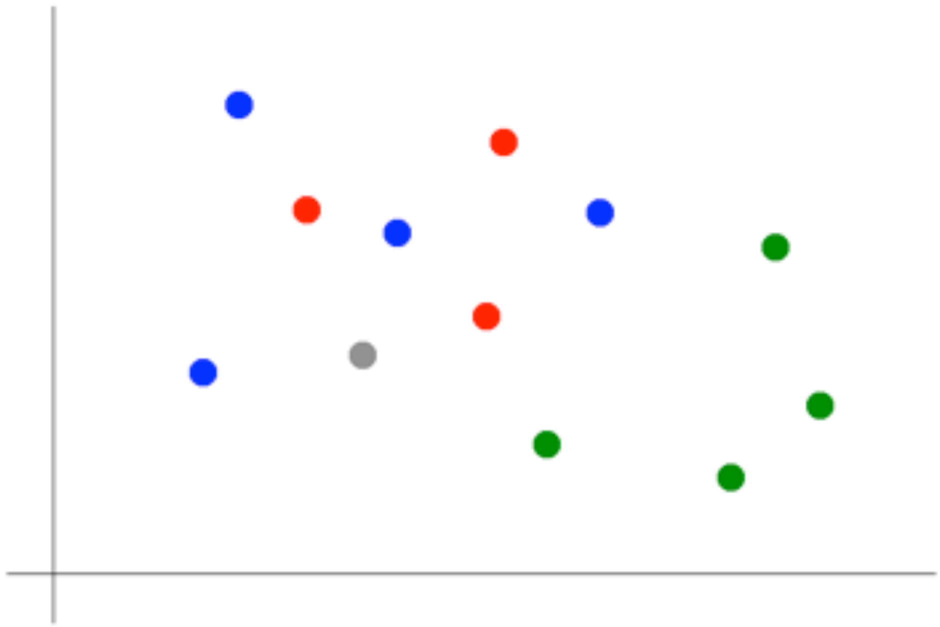
3) *Presents tradeoff between efficiency and computational expense.*
   - *10-fold CV is 10x more expensive than a single train/test split*
4) *Can be used for model selection.*

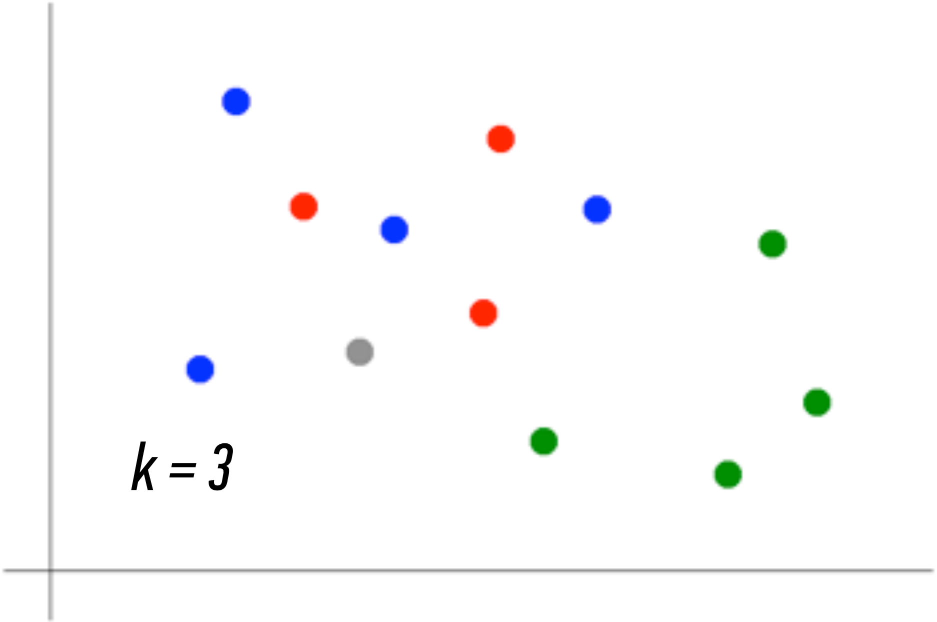
III. KNN CLASSIFICATION

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



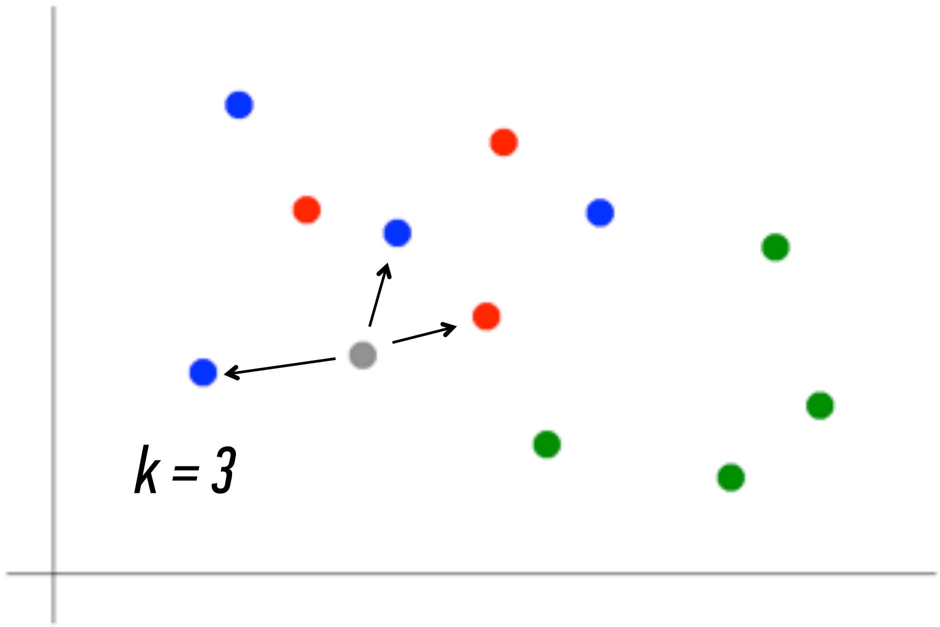
Suppose we want to predict the color of the grey dot.

1) *Pick a value for k.*



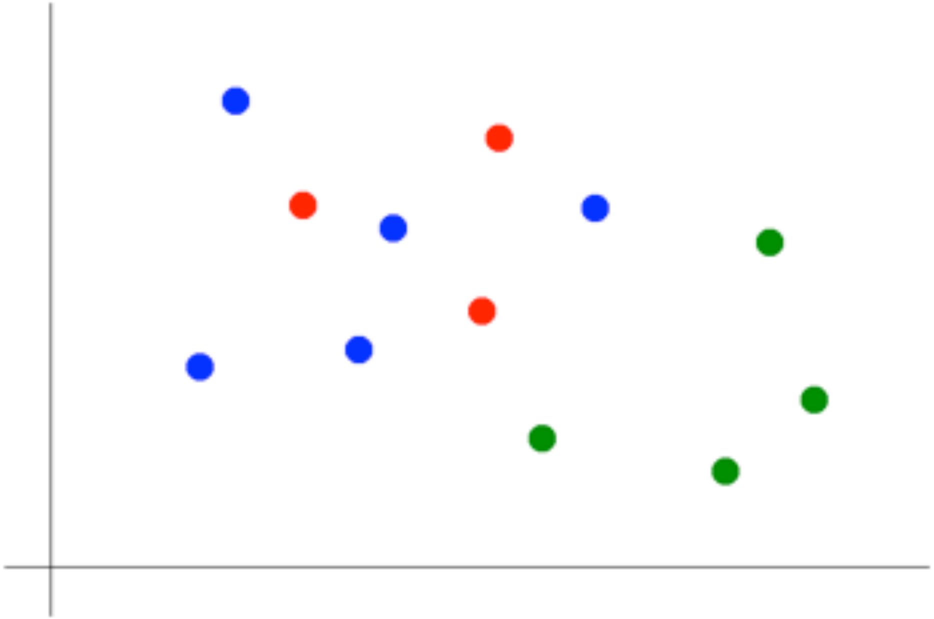
Suppose we want to predict the color of the grey dot.

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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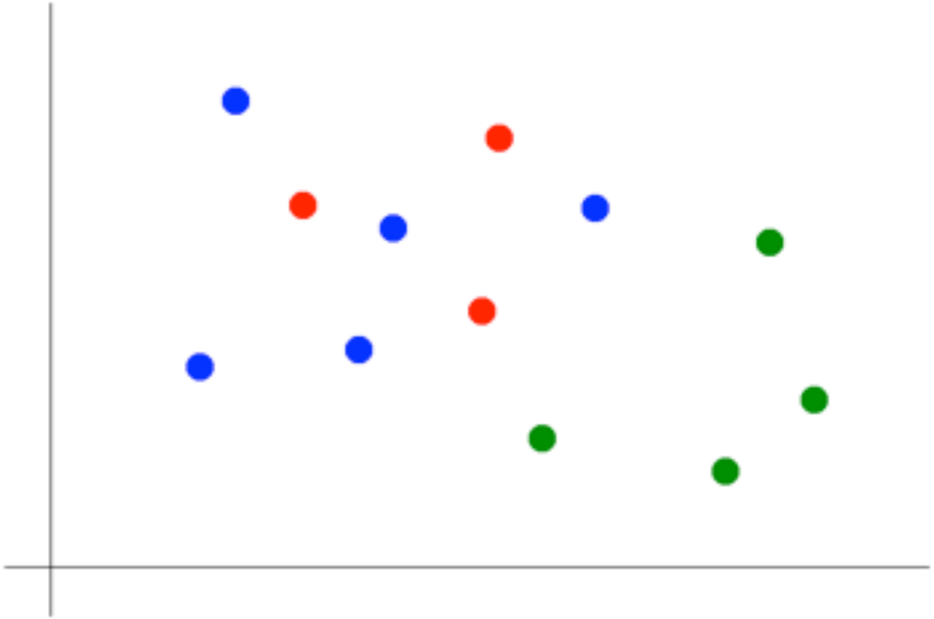

OPTIONAL NOTE

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

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$$d(p, q) = \sqrt{}(p_n - q_n)^2$$

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That is, for each feature of data, we'd measure the distance between two observations.

Consider the iris data set's four features,

Sepal length/width and petal length/width:

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$$d(p, q) = \sqrt{}(p_{s.length} - q_{s.length})^2 + (p_{s.width} - q_{s.width})^2 + (p_{p.length} - q_{p.length})^2 + (p_{p.width} - q_{p.width})^2$$

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$d(p, q) = \sqrt{}((5.1 - 4.9)^{2} + (3.5 - 3.0)^{2} + (1.4 - 1.4)^{2} + (.2 - .2)^{2})$

$d(p, q) = \sqrt{}(.04 + .25 + 0 + 0) = .53$

There are various ways to measure distance between points , so if distance measurement is interesting to you, learn more about ***taxicab geometry*** *(the* ***L1 norm*** *from regressions last week!) and the* ***Minkowski distance****.*

*There are various ways to measure distance between points , so if distance measurement is interesting to you, learn more about **taxicab geometry** (the **L1 norm** from regressions last week!) and the **Minkowski distance**.*

*For a completely different metric, also learn about how computer scientists use the **Levenshtein distance**!*

LAB: KNN CLASSIFICATION

DISCUSSION:

1. WHAT ARE SOME POTENTIAL SETBACKS OR PITFALLS TO THE KNN ALGORITHM?

2. WHAT ARE SOME POTENTIAL IMPLEMENTATION CHANGES TO THE ALGORITHM THAT COULD BE MADE TO GET AROUND THESE PITFALLS?

NEXT CLASS: PROBABILITY AND NAIVE BAYES CLASSIFICATION