SCIKIT LEARN

CSE 599 Prototyping Interactive Systems | Lecture 15 | May 21

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DESIGN USE BUILD

MAKEABILITY LAB

PAUL G. ALLEN SCHOOL
OF COMPUTER SCIENCE & ENGINEERING

UNIVERSITY of WASHINGTON

TODAY

LEARNING GOALS

Using **machine learning toolkits** like scikit-learn

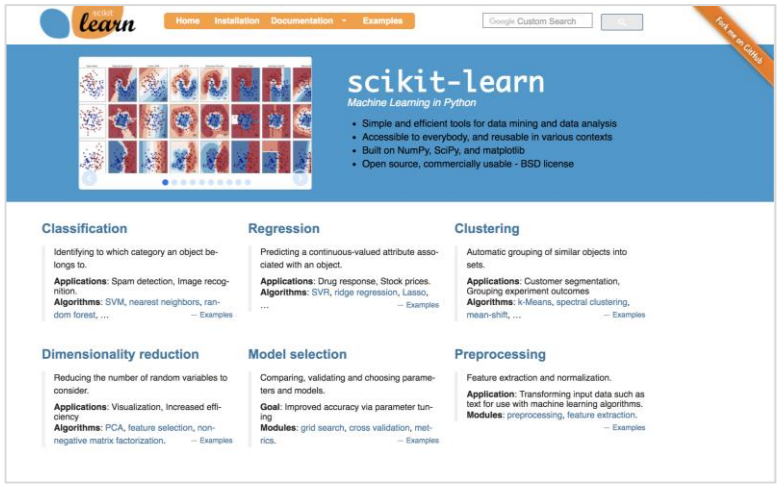
The **scikit-learn** ML framework

How the **K-Nearest Neighbor (kNN)** classification model works

How the **Support Vector Machine (SVM)** classification model works

Briefly: **feature selection**, **feature scaling**, **parameter tuning**

ML TOOLKITS: LANGUAGES AND LIBRARIES

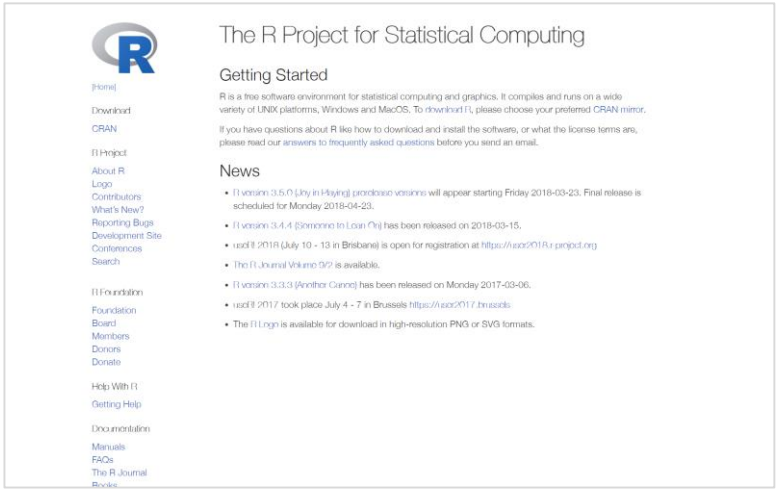


Scikit-Learn

Python-based library for classification, regression, clustering, dimensionality reduction, model selection, preprocessing data, etc.

Weka

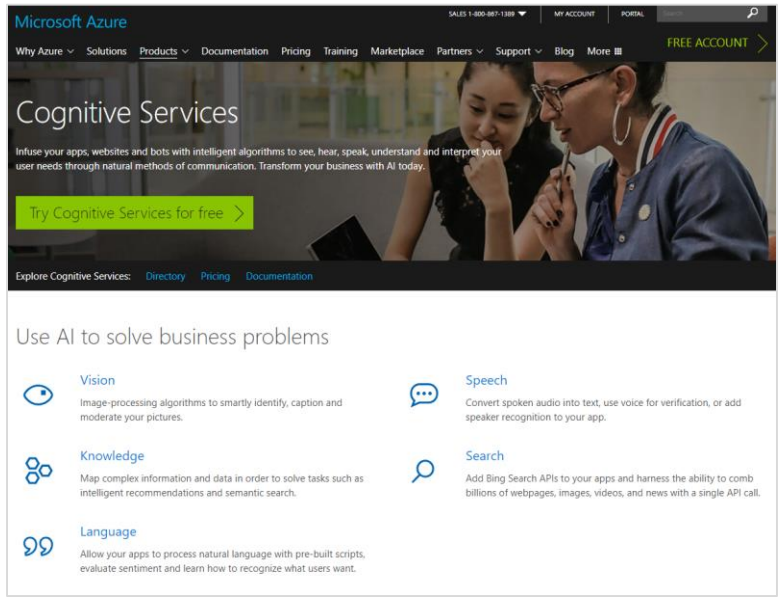
Java-based library for pre-processing, classification, regression, clustering, and visualizing data. Used to be the standard. People now shifting to sci-kit learn, R, and cloud-based APIs.



R

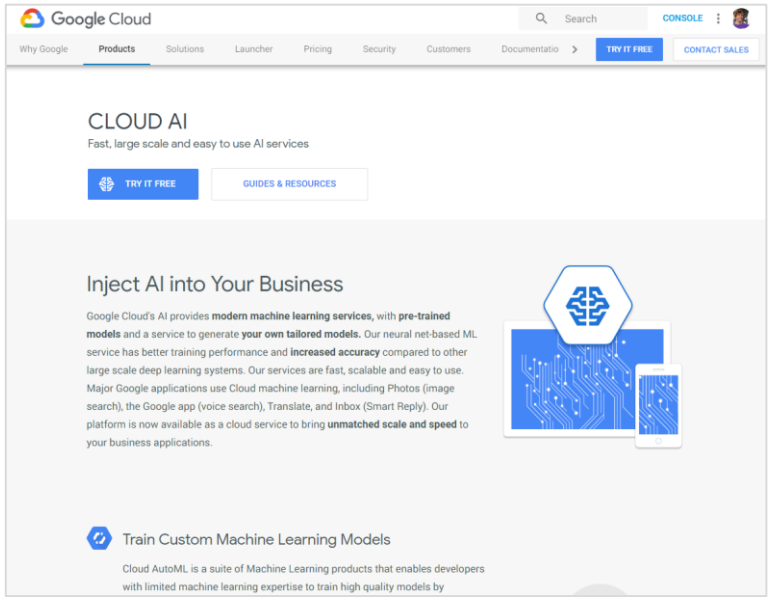
R arose as a statistical computing language but is now widely used in ML and has a number of well-respected ML packages.

ML TOOLKITS: CLOUD APIS



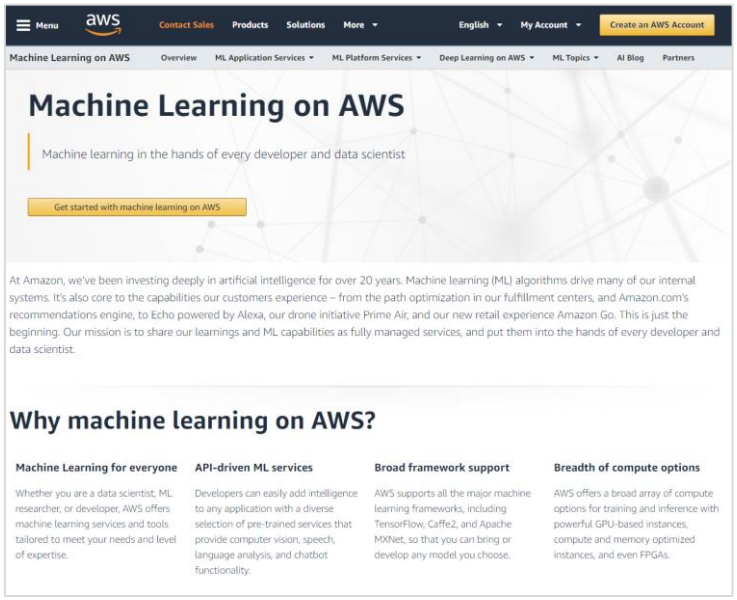
Microsoft Cognitive Services

Cloud API for computer vision, NLP, speech recognition, knowledge representation, chatbots, and search.



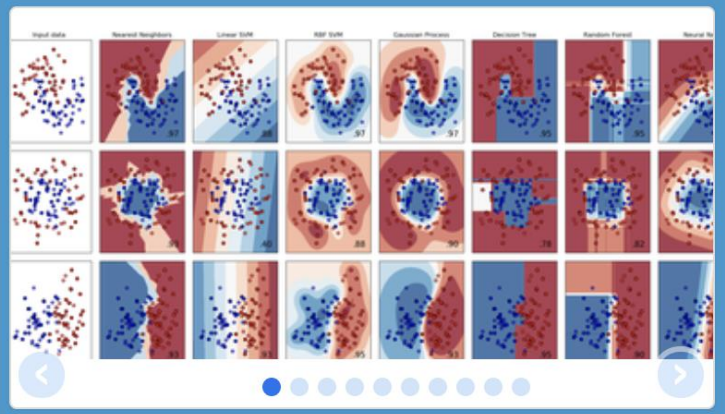
Google Cloud AI

Cloud API for large-scale machine learning, including video and image analysis, speech recognition, speech synthesis, NLP, and language translation



Amazon AWS ML Platform

Cloud API for general ML with image and video analysis, chatbots, and language services such as NLP, translation, transcription, and speech synthesis.



scikit-learn

Machine Learning in Python

- Simple and efficient tools for data mining and data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable - BSD license

Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.
Algorithms: SVM, nearest neighbors, random forest, …

— Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: SVR, ridge regression, Lasso, …

— Examples

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: k-Means, spectral clustering, mean-shift, …

— Examples

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency
Algorithms: PCA, feature selection, non-negative matrix factorization.

— Examples

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning
Modules: grid search, cross validation, metrics.

— Examples

Preprocessing

Feature extraction and normalization.

Application: Transforming input data such as text for use with machine learning algorithms.
Modules: preprocessing, feature extraction.

— Examples

ML TOOLKITS

SCIKIT-LEARN FEATURES INCLUDE

FEATURE EXTRACTION, SELECTION, & REDUCTION

Feature Extraction: helper methods for extracting features from image and text data.

Feature Selection: for identifying meaningful attributes from which to create supervised models.

Dimensionality Reduction: for reducing the number of features (*e.g.,* Principal component analysis)

ML MODELS

Clustering Algorithms: for grouping unlabeled data such as KMeans.

Supervised Models: a vast array of supervised models, including naive bayes, neural networks, SVMs and decision trees.

Ensemble Methods: for combining the predictions of multiple supervised models.

EVALUATION

Cross Validation: for estimating the performance of supervised models on unseen data.

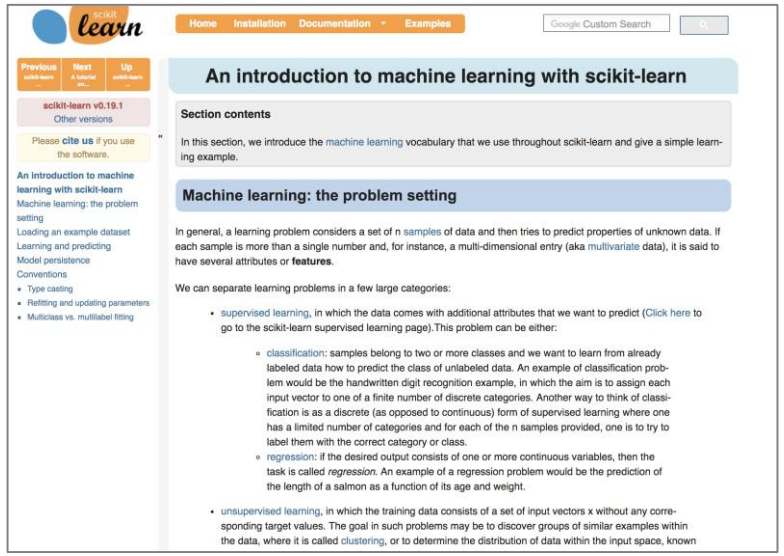
Parameter Tuning: for getting the most out of supervised models.

Datasets: for test datasets and for generating datasets with specific properties for investigating model behavior.

Source: http://scikit-learn.org/; https://machinelearningmastery.com/a-gentle-introduction-to-scikit-learn-a-python-machine-learning-library/

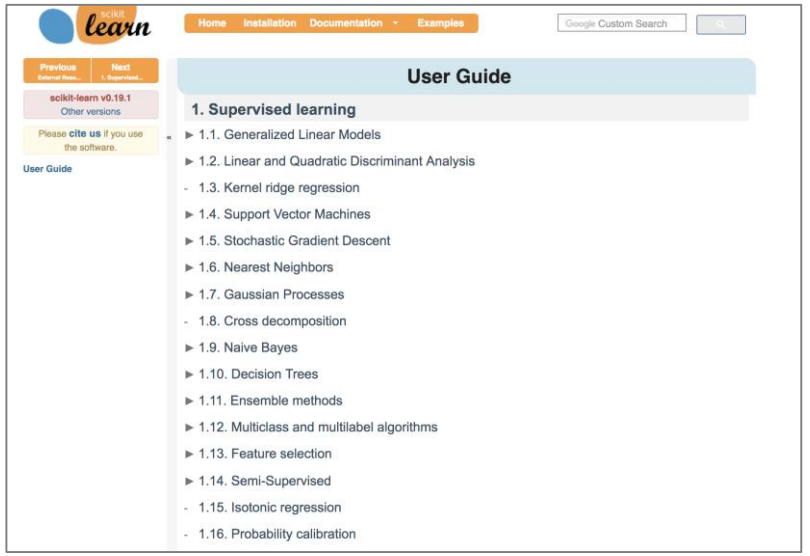
SCIKIT LEARN

GETTING STARTED



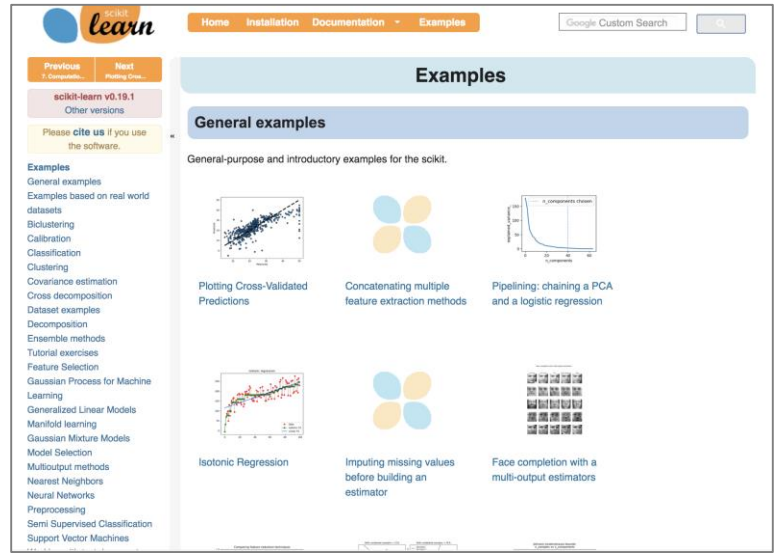
Quick Start Tutorial

Introduces some basic vocabulary and walks through a simple example



User Guide

Goes through each major component of the sci-kit library from supervised and unsupervised models to model selection and evaluation.



Examples

Lots of different examples of using, visualizing, and evaluating models

SCIKIT LEARN CLASSIFICATION FRAMEWORK

```
# Create classifier (often abbreviated clf for classifier)
clf = MyClassifier()

# Train the classifier with the training data and labels
clf.fit(training_data, class_labels)
```

SCIKIT LEARN CLASSIFICATION FRAMEWORK

```
# Create classifier (often abbreviated clf for classifier)
clf = MyClassifier()

# Train the classifier with the training data and labels
clf.fit(training_data, class_labels)
```

Training Data Class Labels

mag_p.max	mag_p_avg_peak	mag_p_std	gesture
198.900715	124.898957	66.913586	Midair Zorro 'Z'
185.104321	111.061818	55.435780	Midair Zorro 'Z'
155.287426	155.287426	50.887685	Midair Zorro 'Z'
147.918587	147.918587	49.347788	Midair Zorro 'Z'
187.198179	120.283442	48.289167	Baseball Throw
243.532742	243.532742	55.737110	Baseball Throw
290.012557	190.527641	66.258158	Baseball Throw
311.963850	180.246706	81.009928	Baseball Throw

SCIKIT LEARN CLASSIFICATION FRAMEWORK

```
# Create classifier (often abbreviated clf for classifier)
clf = MyClassifier()

# Train the classifier with the training data and labels
clf.fit(training_data, class_labels)

# Provide input test features and obtain a prediction
clf_prediction = clf.predict(test_features)
```

Test Data

mag_p.max	mag_p_avg_peak	mag_p_std
150.356560	100.060016	54.067795

SCIKIT LEARN CLASSIFICATION FRAMEWORK

```
# Create classifier (often abbreviated clf for classifier)
clf = MyClassifier()

# Train the classifier with the training data and labels
clf.fit(training_data, class_labels)

# Provide input test features and obtain a prediction
clf_prediction = clf.predict(test_features)

# Print out prediction (prints out predicted class label)
print(clf_prediction[0])
```

>>> “Baseball Throw”

SCIKIT LEARN FRAMEWORK: SINGLE INPUT ROW

```
# Create classifier
clf = MyClassifier()

# Train the classifier with the training data & labels
clf.fit(training_data, class_labels)

# Provide input test features and obtain a prediction
clf_prediction = clf.predict(test_features)

# Print out prediction
print(clf_prediction[0])
```

>>> "Baseball Throw"

Training Data

mag_p.max	mag_p_avg_peak	mag_p_std
198.900715	124.898957	66.913586
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243.532742	243.532742	55.737110
290.012557	190.527641	66.258158
311.963850	180.246706	81.009928

Class Labels

gesture
Midair Zorro 'Z'
Midair Zorro 'Z'
Midair Zorro 'Z'
Midair Zorro 'Z'
Baseball Throw
Baseball Throw
Baseball Throw
Baseball Throw

Test Data

mag_p.max	mag_p_avg_peak	mag_p_std
150.356560	100.060016	54.067795

SCIKIT LEARN FRAMEWORK: MULTIPLE ROWS

```
# Create classifier
clf = MyClassifier()

# Train the classifier with the training data & labels
clf.fit(training_data, class_labels)

# Provide input test features and obtain a prediction
clf_prediction = clf.predict(test_features_array)

# Print out prediction
print(clf_prediction)
```

>>> ["Baseball Throw", "Midair Zorro 'Z'", "Bunny Hops", "Forehand Tennis"]

Test Data

mag_p.max	mag_p_avg_peak	mag_p_std
150.356560	100.060016	54.067795
144.241369	106.726920	49.411597
129.416905	105.980495	49.794466
157.691803	122.343194	56.925764

Training Data

mag_p.max	mag_p_avg_peak	mag_p_std
198.900715	124.898957	66.913586
185.104321	111.061818	55.435780
155.287426	155.287426	50.887685
147.918587	147.918587	49.347788
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243.532742	243.532742	55.737110
290.012557	190.527641	66.258158
311.963850	180.246706	81.009928

Class Labels

gesture
Midair Zorro 'Z'
Midair Zorro 'Z'
Midair Zorro 'Z'
Midair Zorro 'Z'
Baseball Throw
Baseball Throw
Baseball Throw
Baseball Throw

SCIKIT LEARN

SWAPPING OUT MODELS

```
clf = svm.SVC(kernel='linear’)
clf.fit(training_data, class_labels)
svm_prediction = clf.predict(test_features)
```

```
clf = KNeighborsClassifier(n_neighbors=3)
clf.fit(training_data, class_labels)
knn_prediction = clf.predict(test_features)
```

```
clf = DecisionTreeClassifier(random_state=0)
clf.fit(training_data, class_labels)
tree_prediction = clf.predict(test_features)
```

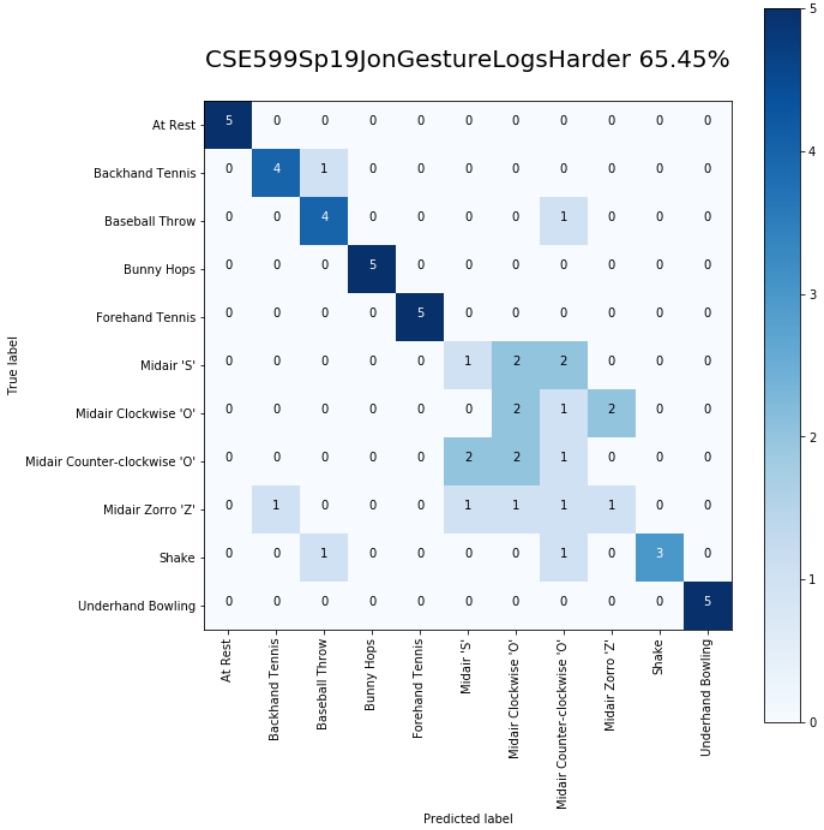
```
clf = MLPClassifier(solver='lbfgs', random_state=0, hidden_layer_sizes=[100])
clf.fit(training_data, class_labels)
tree_prediction = clf.predict(test_features)
```

MODELS

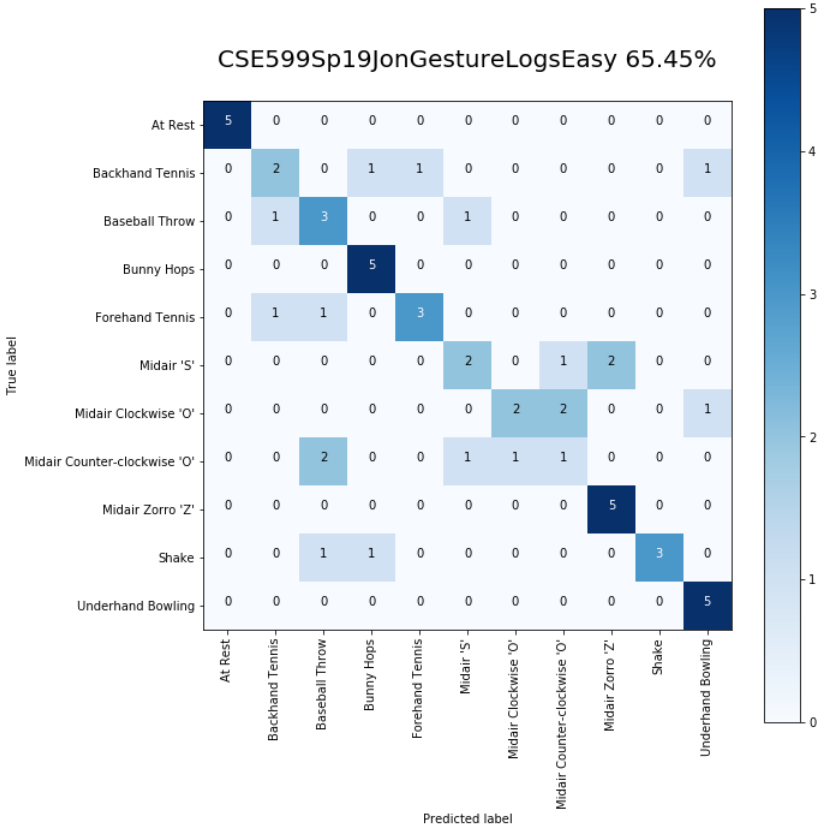
DECISION TREE CLASSIFIER RESULTS

```
clf = DecisionTreeClassifier(random_state=0)
clf.fit(training_data, class_labels)
tree_prediction = clf.predict(test_features)
```

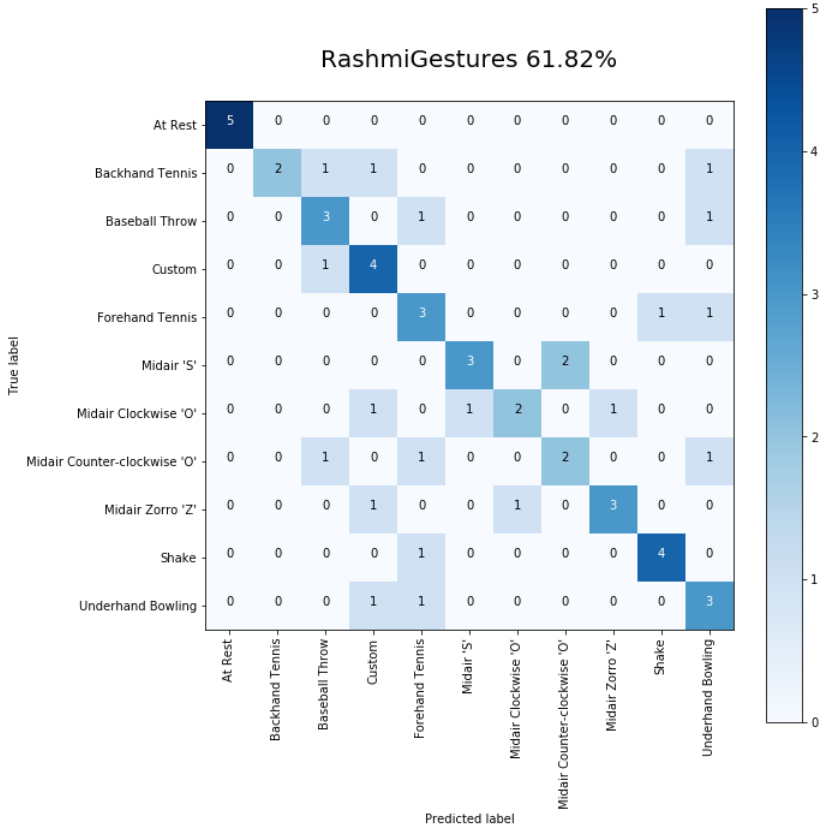
Jon Gestures (Hard): 65.45%



Jon Gestures (Easy): 65.45%



Rashmi: 61.82%

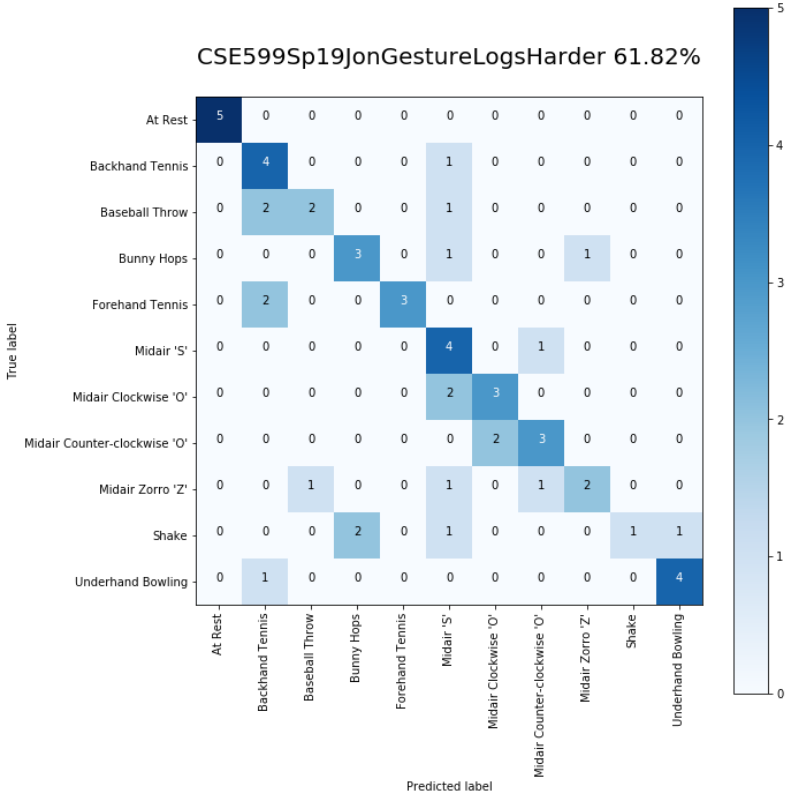


MODELS

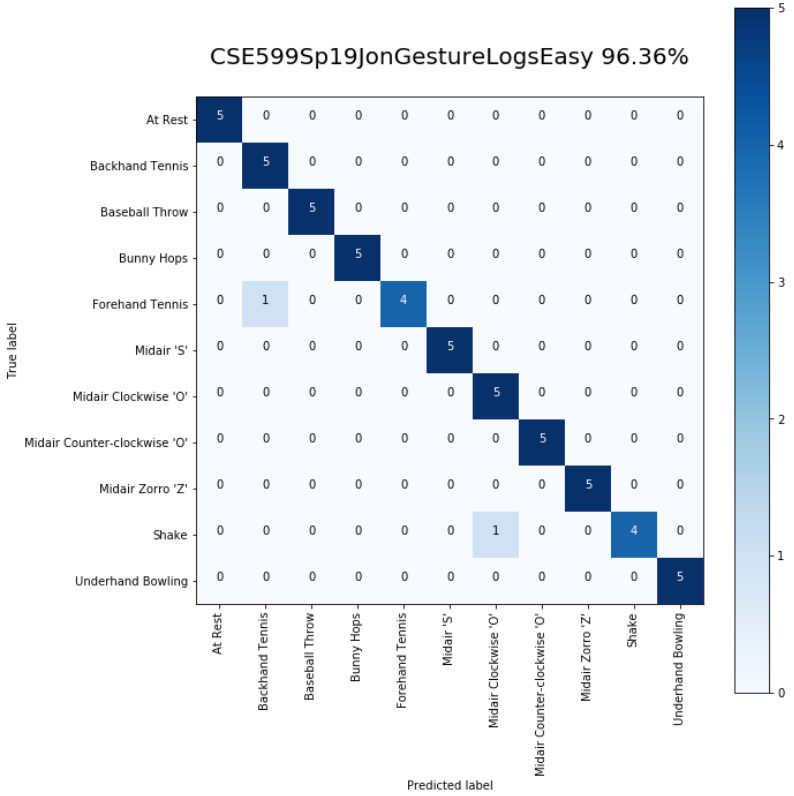
KNN RESULTS

```
clf = KNeighborsClassifier(n_neighbors=3)
clf.fit(training_data, class_labels)
knn_prediction = clf.predict(test_features)
```

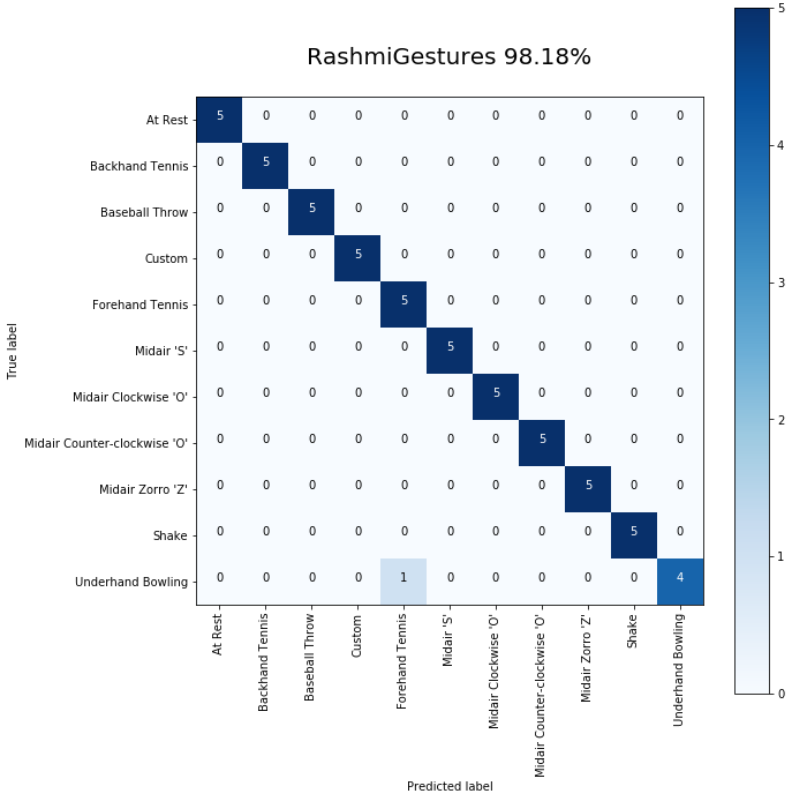
Jon Gestures (Hard): 61.82%



Jon Gestures (Easy): 96.36%



Rashmi: 98.18%

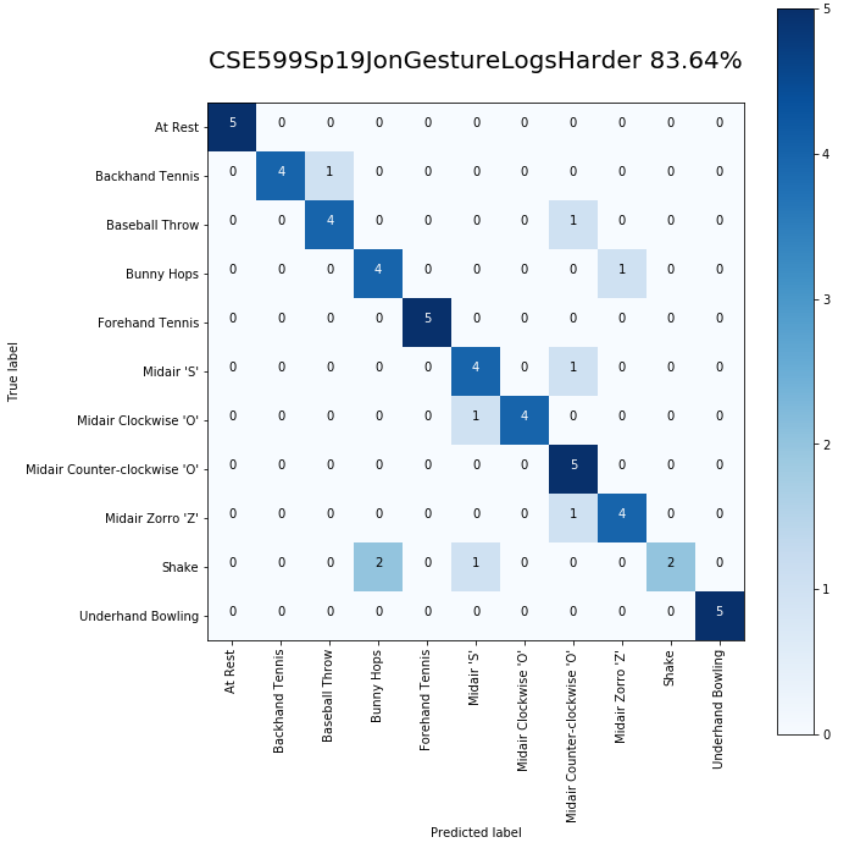


MODELS

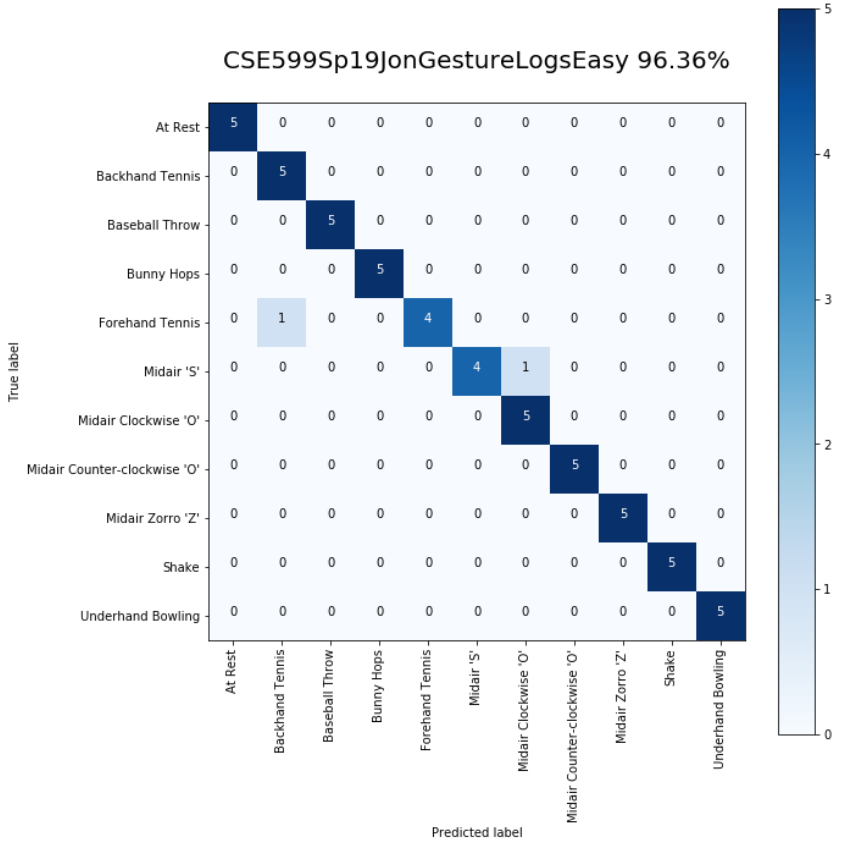
NEURAL NET CLASSIFIER RESULTS

```
clf = MLPClassifier(solver='lbfgs', hidden_layer_sizes=[100])
clf.fit(training_data, class_labels)
tree_prediction = clf.predict(test_features)
```

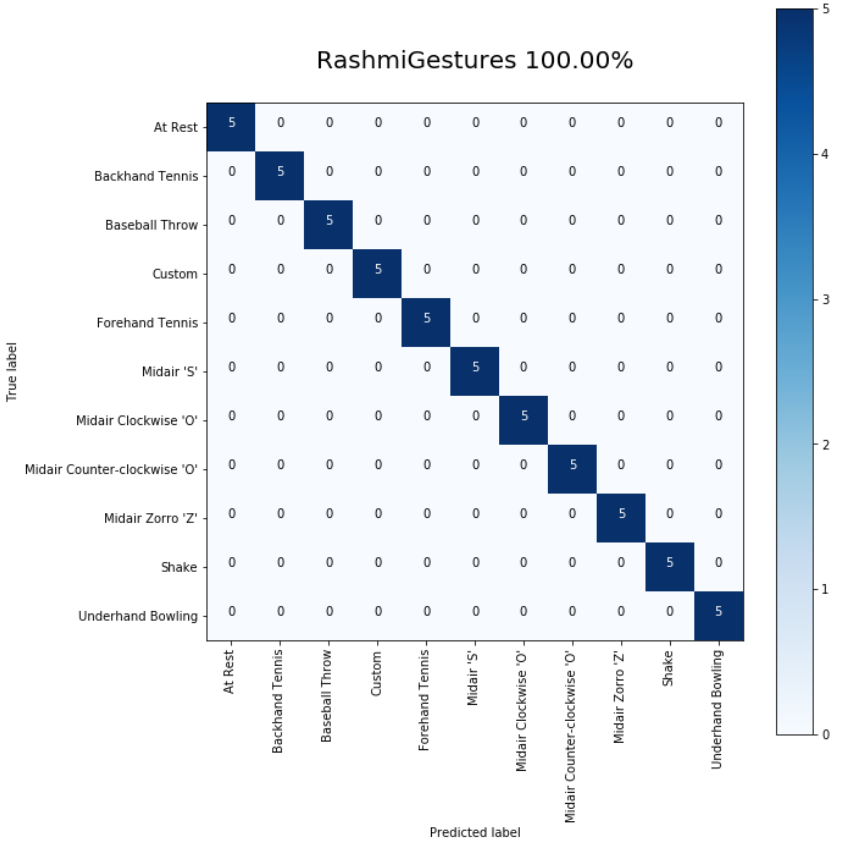
Jon Gestures (Hard): 83.64%



Jon Gestures (Easy): 96.36%



Rashmi: 100%

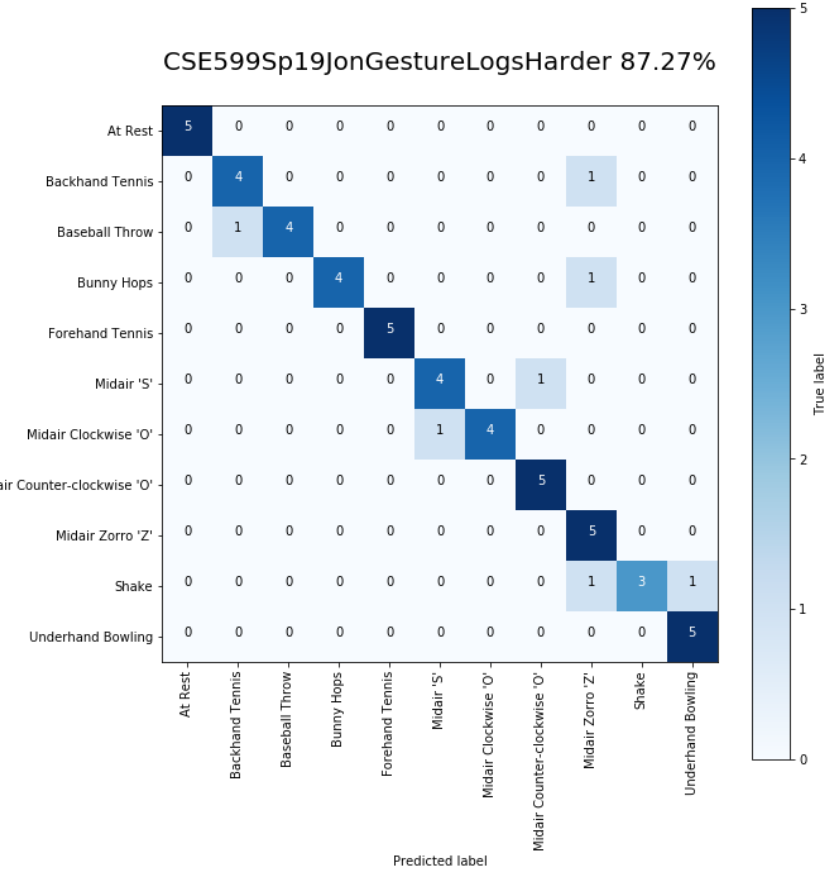


MODELS

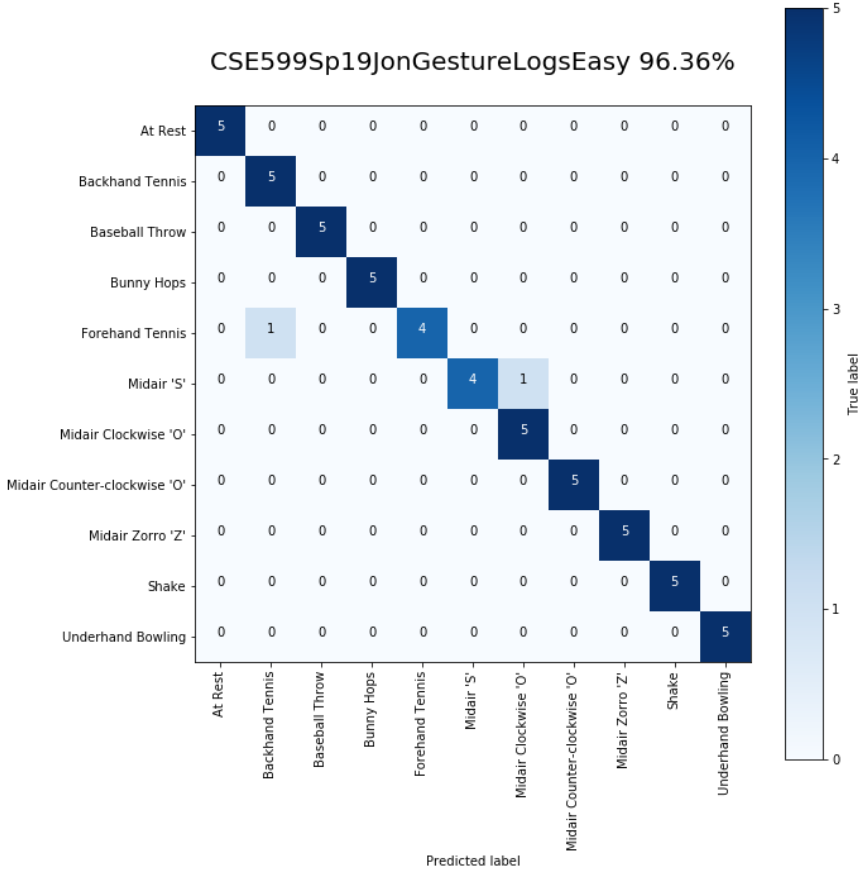
SVM RESULTS

```
clf = svm.SVC(kernel='linear')
clf.fit(training_data, class_labels)
svm_prediction = clf.predict(test_features)
```

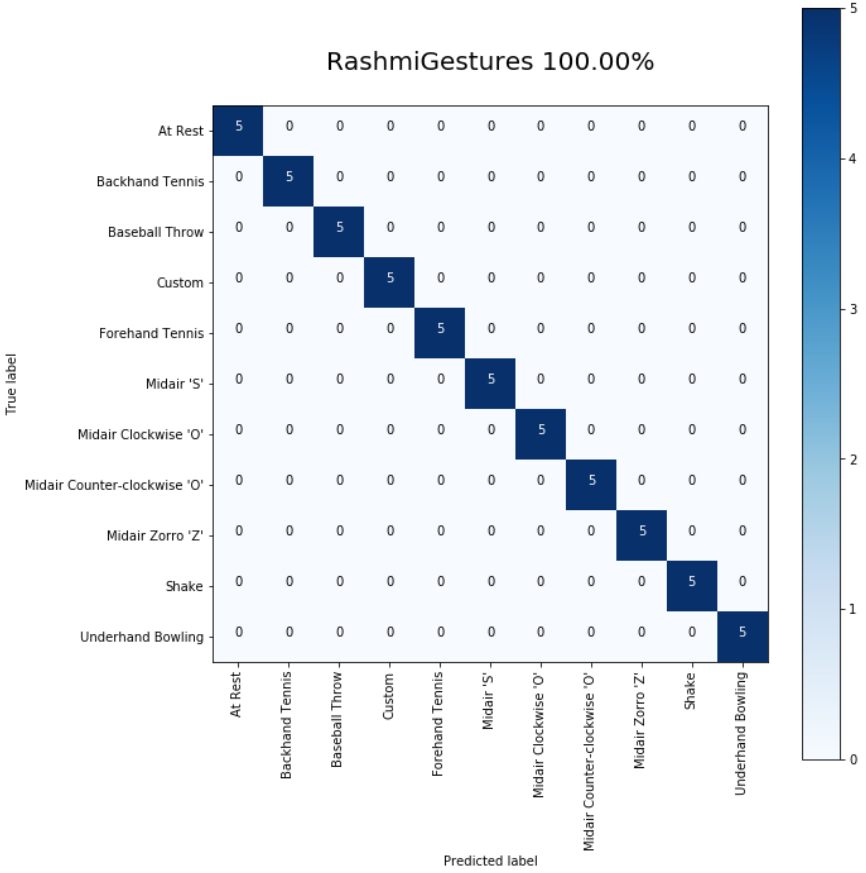
Jon Gestures (Hard): 87.27%



Jon Gestures (Easy): 96.36%



Rashmi: 100%



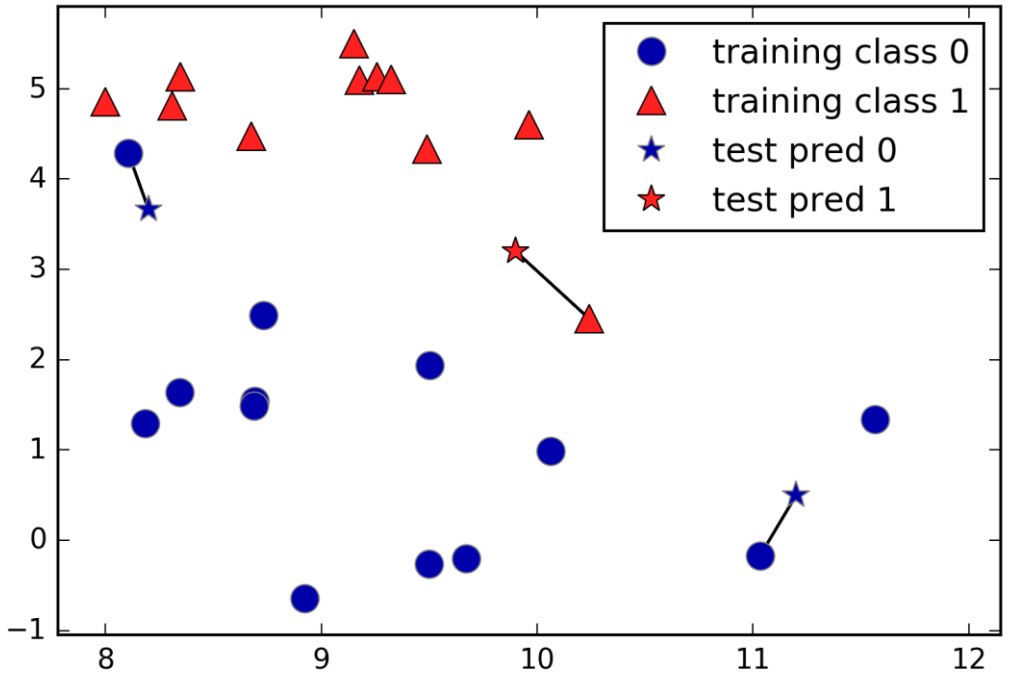
K-NEAREST NEIGHBORS (KNN)

Arguably the simplest ML algorithm

Model consists of only "storing" the training set

To make a prediction for a new data point, the algorithm finds the closest data points in the training dataset—its "nearest neighbors."

Simplest kNN Model Where k=1



When k=1, the prediction is always the closest training point

Source: Chapter 2, Guido and Müller, *Introduction to Machine Learning with Python*, Oct 2016

K-NEAREST NEIGHBORS

KNN WHERE K=1

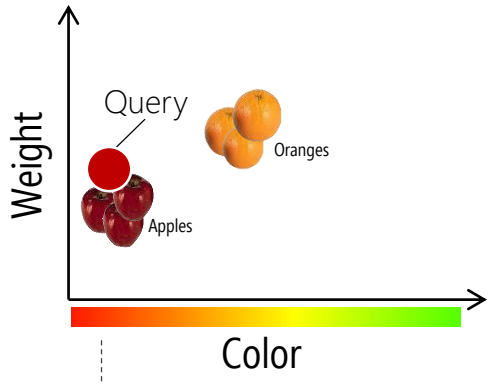
Input Features

Class Label
(aka Ground Truth Label)

Color	Weight	Label
Red	200g	Apple
Orange	300g	Orange
Red	150g	Apple
...		

Training Data

ML Model



kNN

Color	Weight	Label
Red	170g	Unknown

Query Input

K-NEAREST NEIGHBORS

KNN WHERE K=1

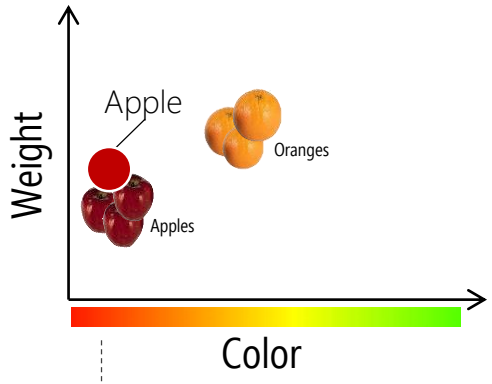
Input Features

Class Label
(aka Ground Truth Label)

Color	Weight	Label
Red	200g	Apple
Orange	300g	Orange
Red	150g	Apple
...		

Training Data

ML Model



kNN

Color	Weight	Label
Red	170g	Unknown

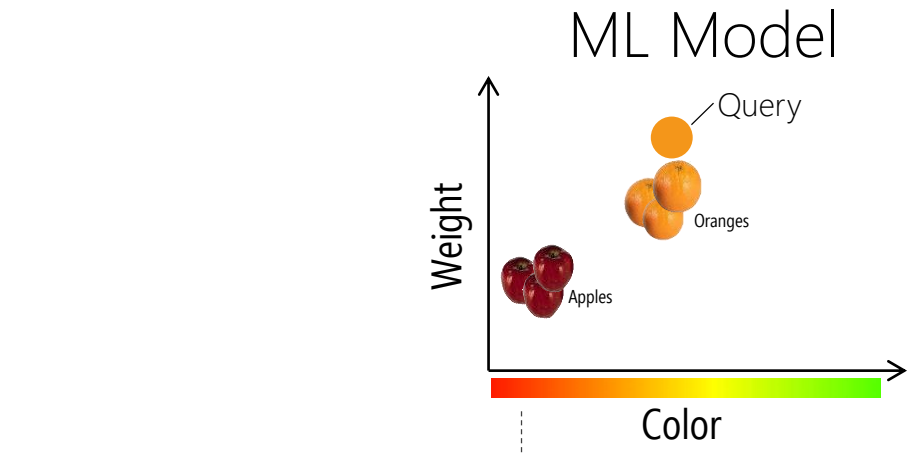
Query Input

Color	Weight	Label
Red	170g	Apple

Prediction

K-NEAREST NEIGHBORS

KNN WHERE K=1

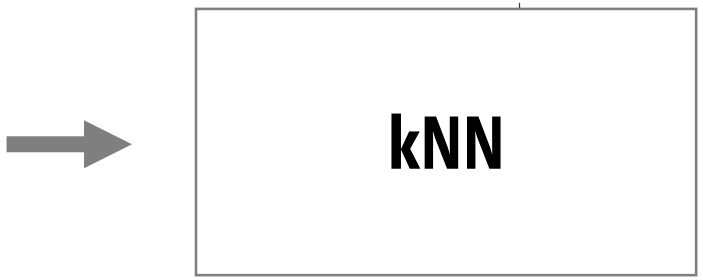


Input Features

Class Label
(aka Ground Truth Label)

Color	Weight	Label
Red	200g	Apple
Orange	300g	Orange
Red	150g	Apple
...		

Training Data

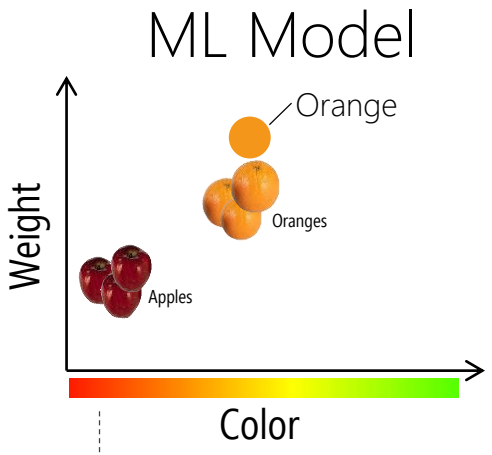


Color	Weight	Label
Orange	350g	Unknown

Query Input

K-NEAREST NEIGHBORS

KNN WHERE K=1



Input Features

Class Label
(aka Ground Truth Label)

Color	Weight	Label
Red	200g	Apple
Orange	300g	Orange
Red	150g	Apple
...		

Training Data

kNN

Color	Weight	Label
Orange	350g	Orange

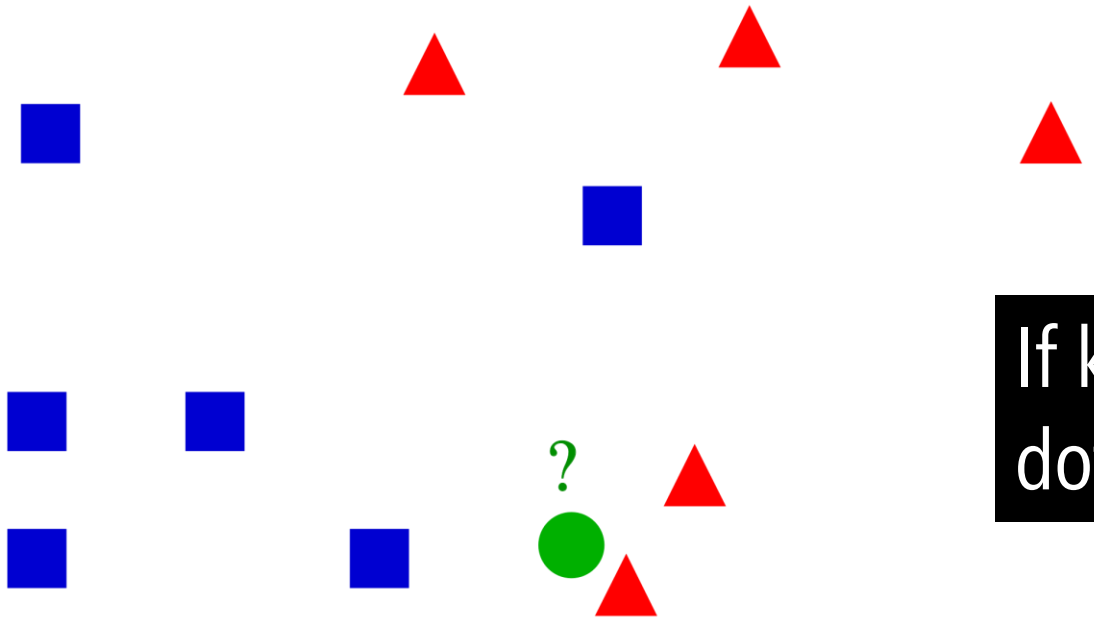
Prediction

Color	Weight	Label
Orange	350g	Unknown

Query Input

K-NEAREST NEIGHBORS

EXAMPLE KNN CLASSIFICATION

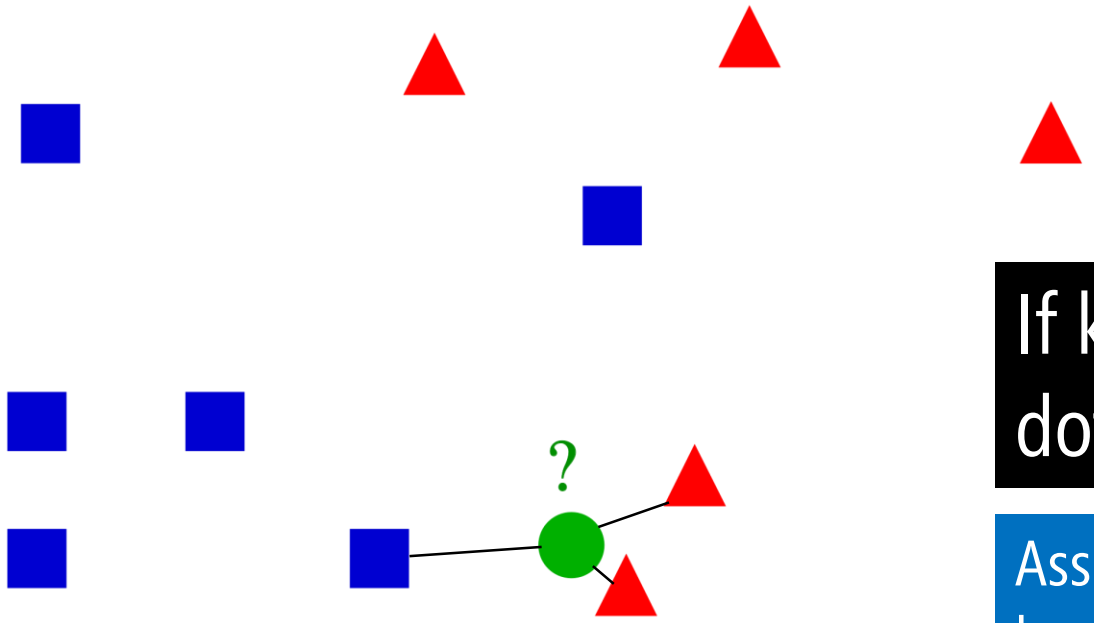


If k=3, what is the green dot classified as?

Modified from: https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm

K-NEAREST NEIGHBORS

EXAMPLE KNN CLASSIFICATION



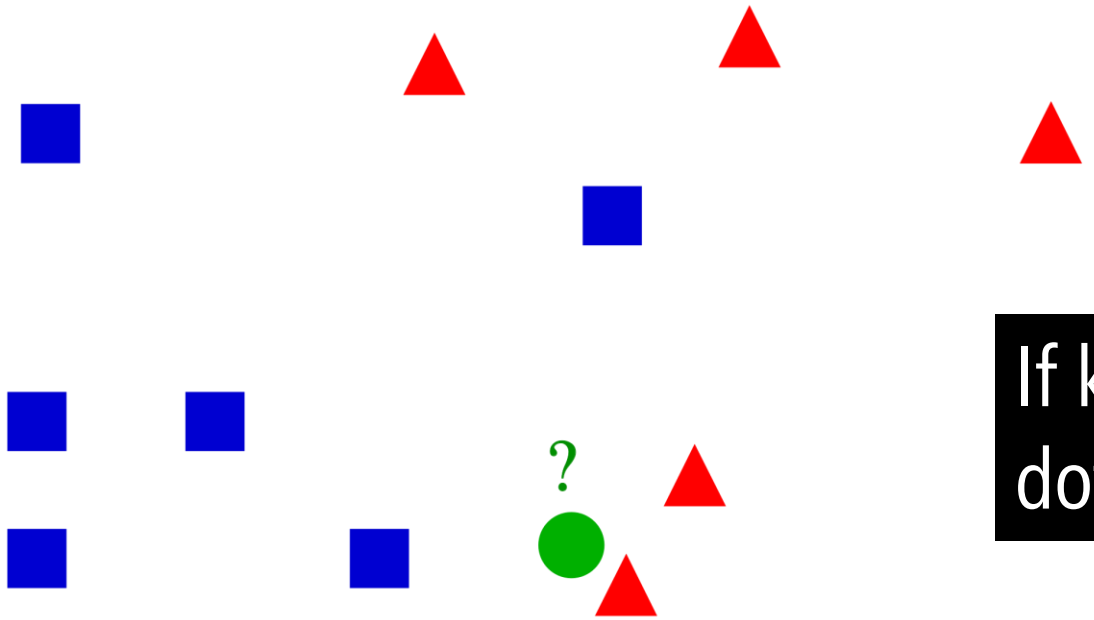
If k=3, what is the green dot classified as?

Assigned to the “triangle” class because of the k=3 closest neighbors, 2 are triangles and one is a square.

Modified from: https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm

K-NEAREST NEIGHBORS

EXAMPLE KNN CLASSIFICATION

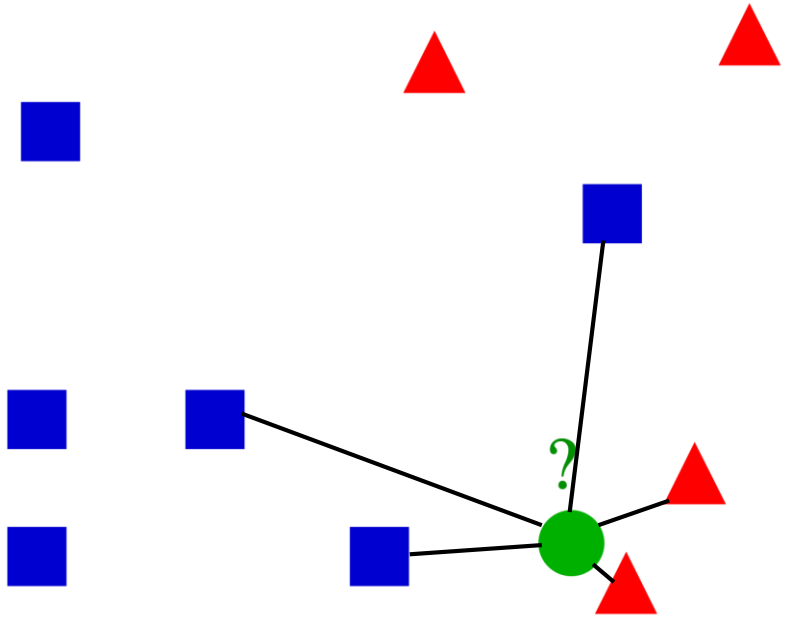


If k=5, what is the green dot classified as?

Modified from: https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm

K-NEAREST NEIGHBORS

EXAMPLE KNN CLASSIFICATION

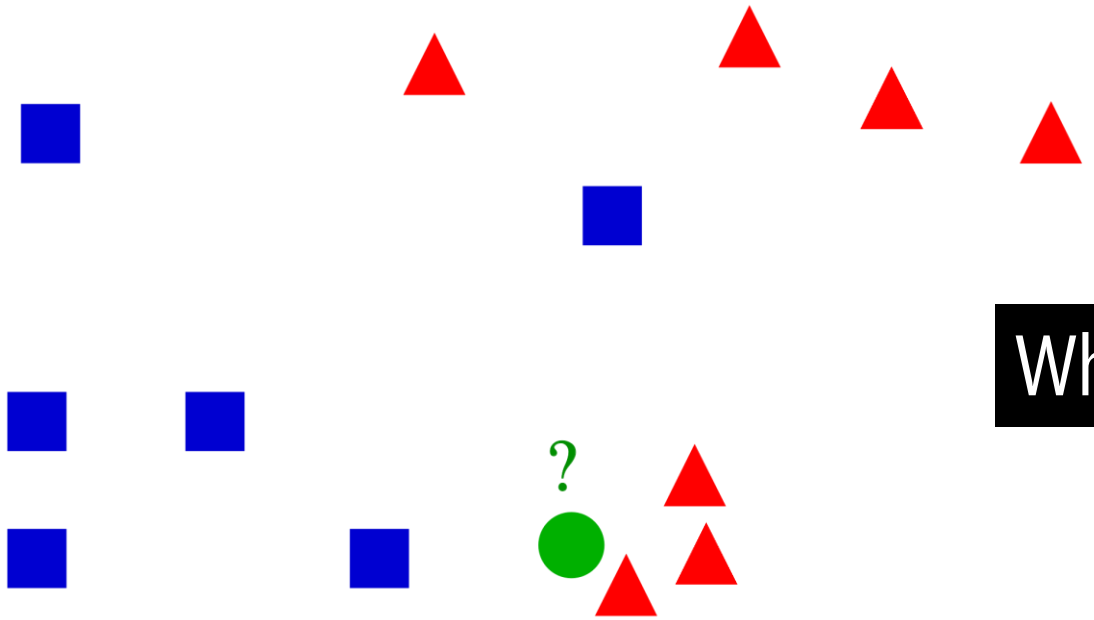


If k=5, what is the green dot classified as?

Assigned to the "square" class because of the k=5 closest neighbors, 3 are squares and two are triangles.

Modified from: https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm

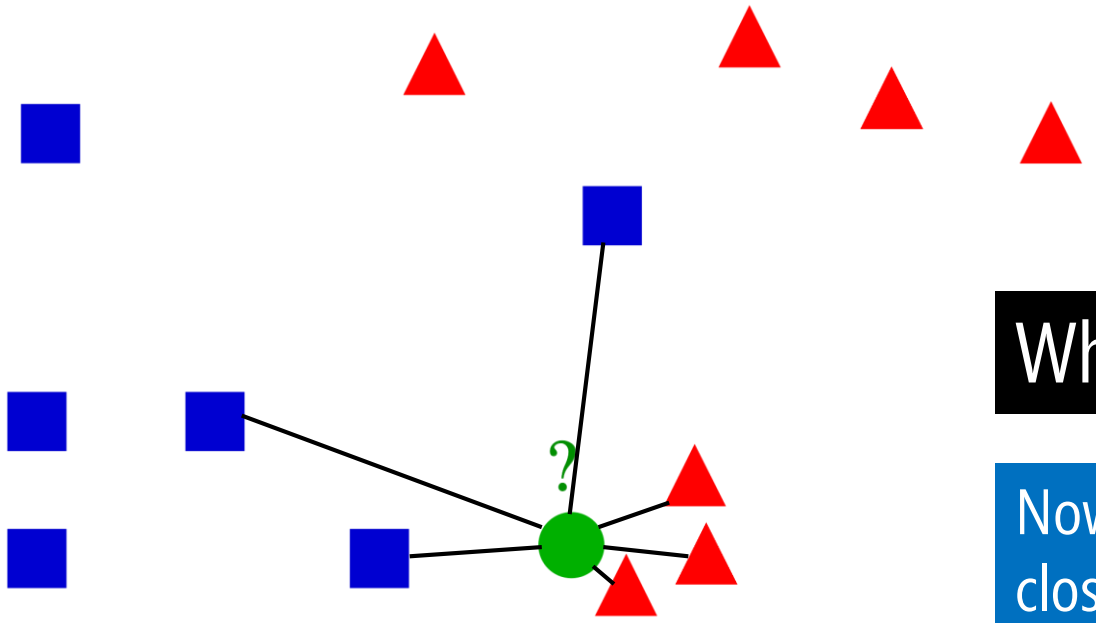
EXAMPLE KNN CLASSIFICATION



What happens if k=6?

Modified from: https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm

EXAMPLE KNN CLASSIFICATION

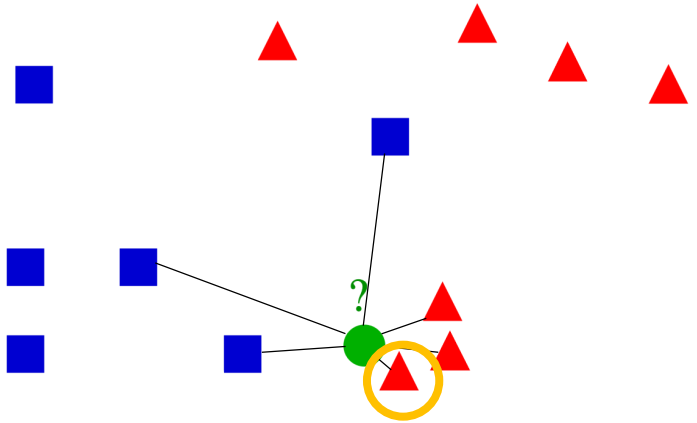


What happens if k=6?

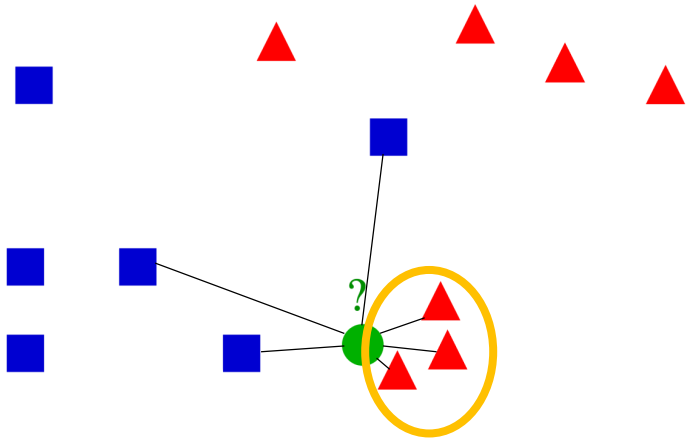
Now we have a tie, the six closest neighbors are three blue squares & three blue triangles.

Modified from: https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm

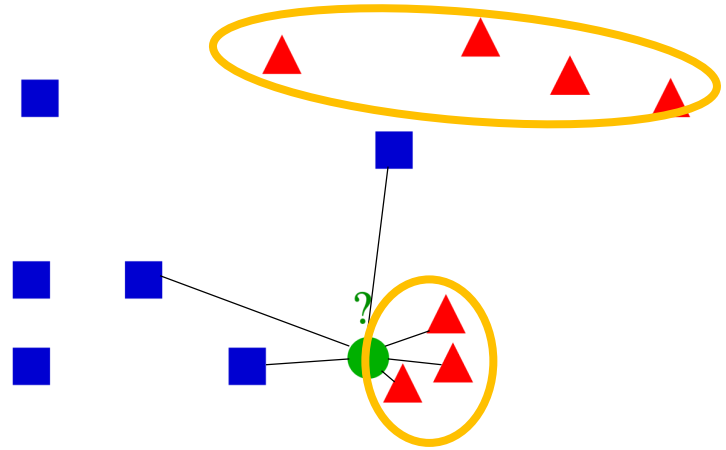
HOW DOES KNN BREAK TIES?



Pick the closest class (*i.e.,* degrade to a k=1)



Pick the class with average lowest distance within the k-neighbor cluster



Pick the class based on some weighting (*e.g.,* class that is observed most in dataset)

Modified from: https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm

K-NEAREST NEIGHBORS

STRENGTHS AND WEAKNESSES

Strengths

Model is easy to understand

Often gives reasonable performance for low-dimensionality datasets

Good baseline model to try

Weaknesses

Data needs to be preprocessed (scaled)

Model building is fast, but prediction can be slow for large datasets

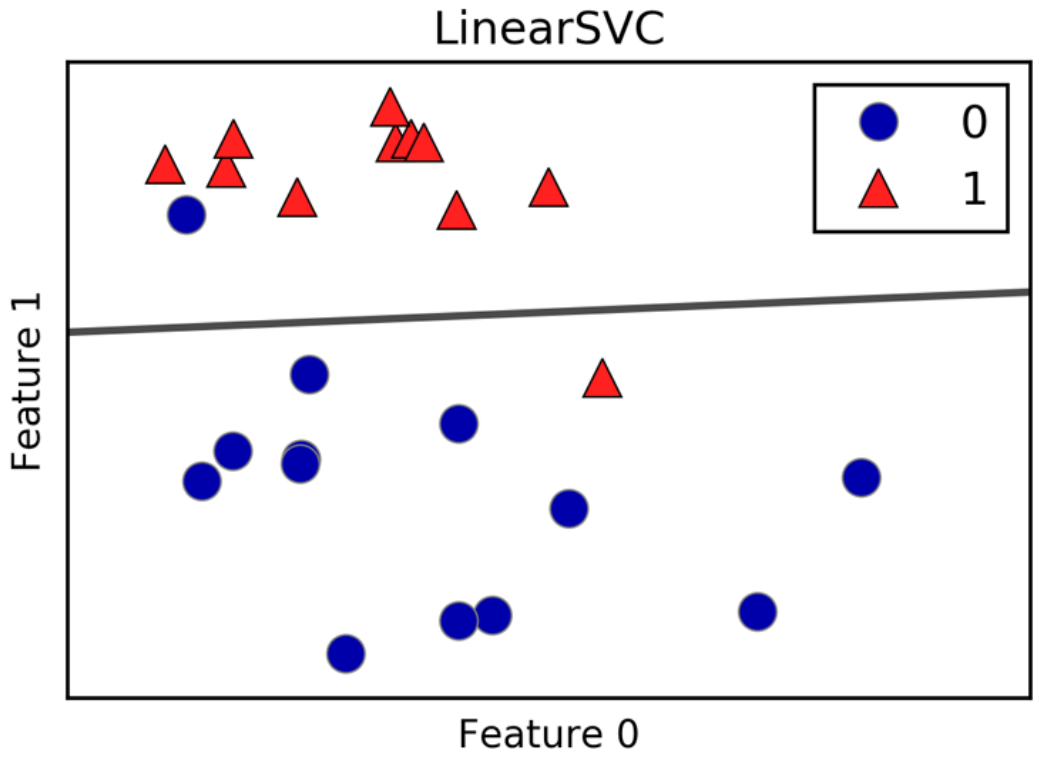
Does not perform well for sparse datasets

Source: Chapter 2, Guido and Müller, *Introduction to Machine Learning with Python*, Oct 2016

SUPPORT VECTOR MACHINES

SVMs are a type of linear classifier that separates two classes using a line (in 2D) or a hyperplane (in higher dimensions)

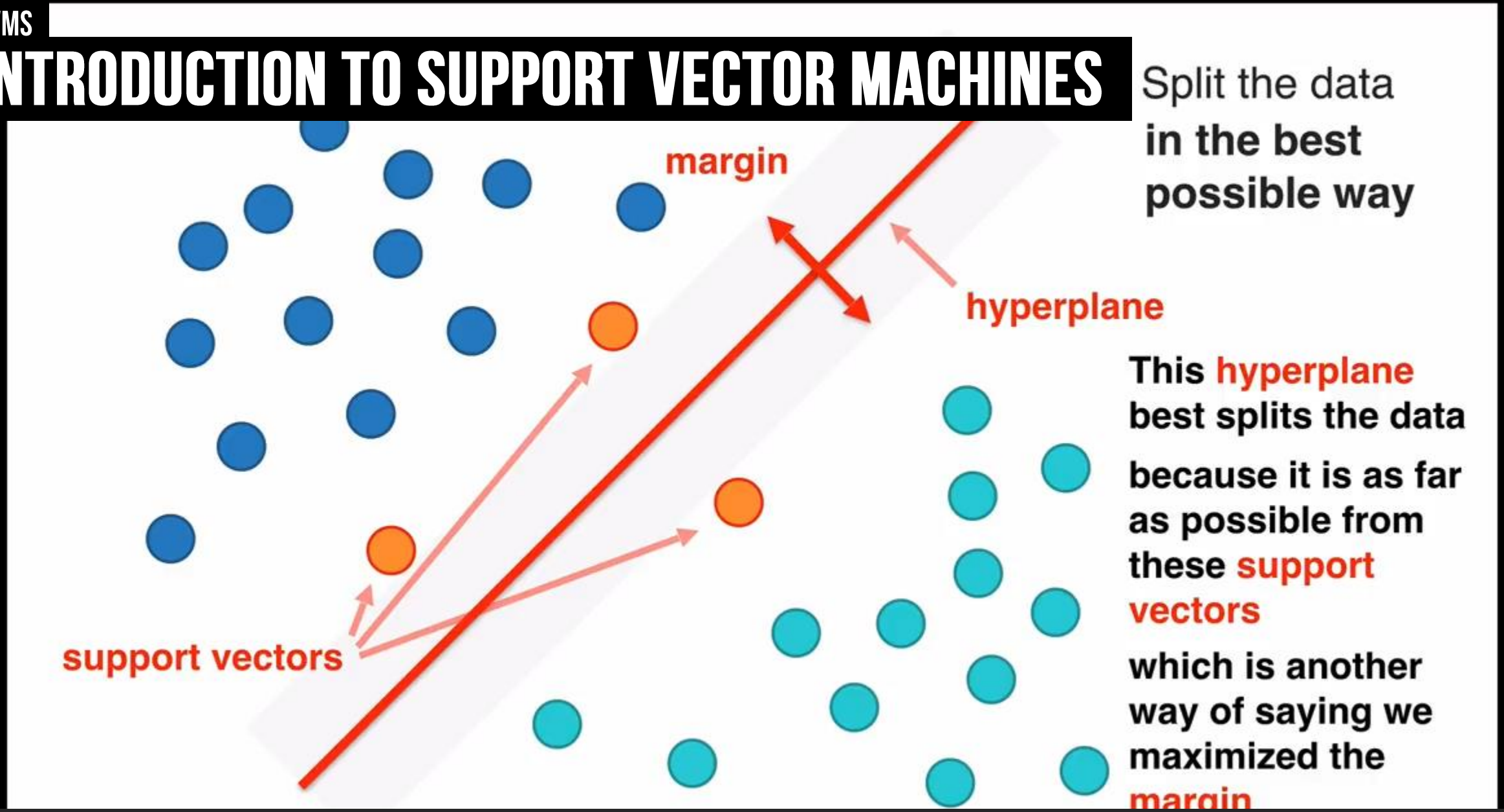
This is called a decision boundary



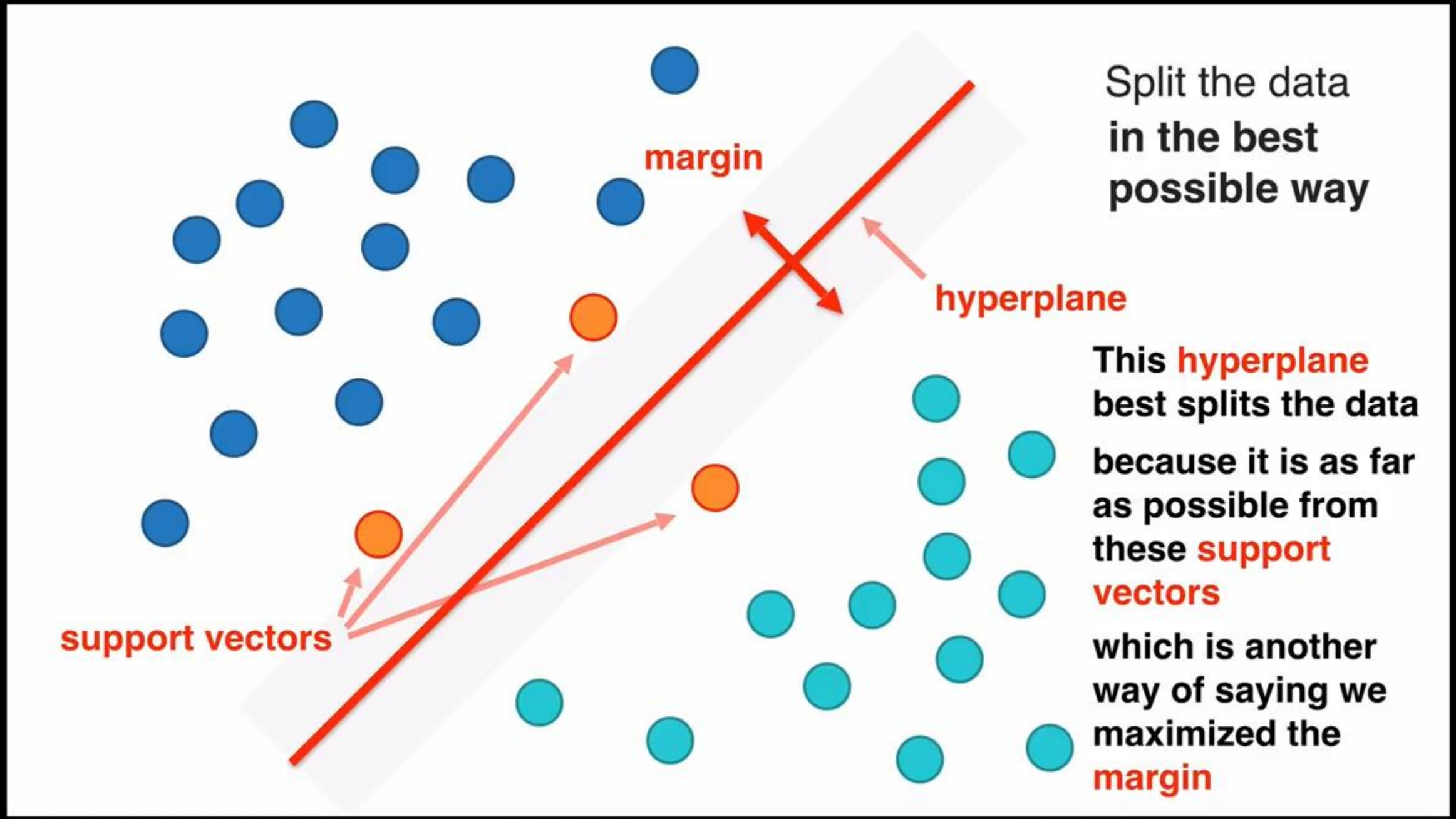
Source: Chapter 2, Guido and Müller, *Introduction to Machine Learning with Python*, Oct 2016

SVMS

INTRODUCTION TO SUPPORT VECTOR MACHINES



Source: Alice Zhao, Support Vector Machines: A Visual Explanation with Sample Python Code, https://youtu.be/N1vOgolbjSc



Split the data **in the best possible way**

This **hyperplane** best splits the data

because it is as far as possible from these **support vectors**

which is another way of saying we maximized the **margin**

SVM EXAMPLE

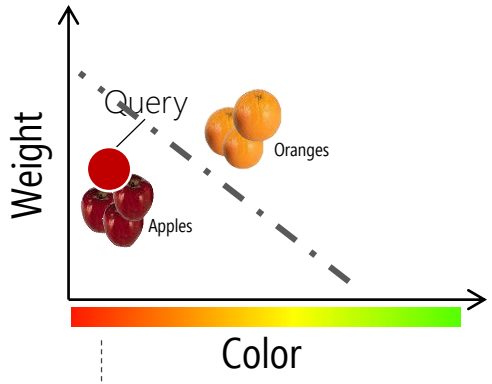
Input Features

Class Label
(aka Ground Truth Label)

Color	Weight	Label
Red	200g	Apple
Orange	300g	Orange
Red	150g	Apple
...		

Training Data

ML Model



SVM

Color	Weight	Label
Red	170g	Unknown

Query Input

K-NEAREST NEIGHBORS

SVM EXAMPLE

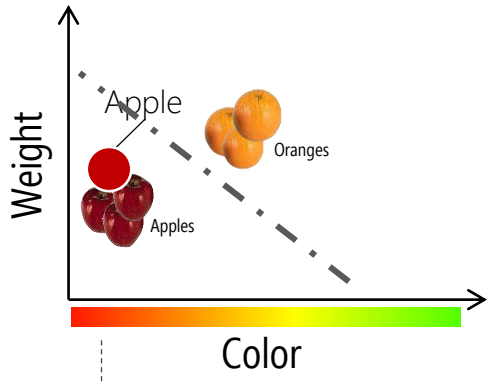
Input Features

Class Label
(aka Ground Truth Label)

Color	Weight	Label
Red	200g	Apple
Orange	300g	Orange
Red	150g	Apple
...		

Training Data

ML Model



SVM

Color	Weight	Label
Red	170g	Unknown

Query Input

Color	Weight	Label
Red	170g	Apple

Prediction

K-NEAREST NEIGHBORS

SVM EXAMPLE

Input Features

Class Label
(aka Ground Truth Label)

Color	Weight	Label
Red	200g	Apple
Orange	300g	Orange
Red	150g	Apple
...		

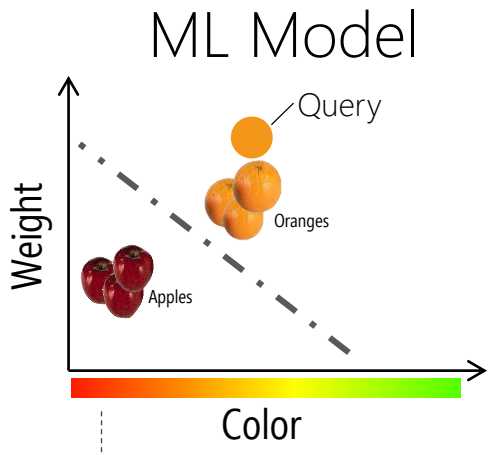
Training Data

SVM

Color	Weight	Label
Orange	350g	Unknown

Query Input

ML Model



K-NEAREST NEIGHBORS

SVM EXAMPLE

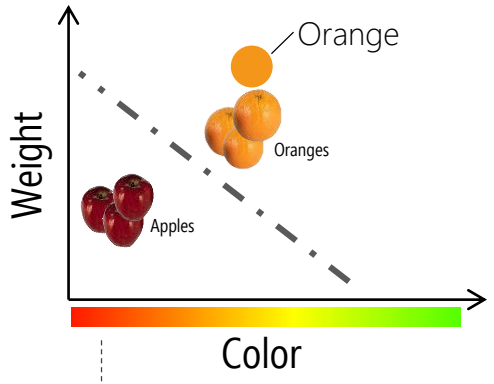
Input Features

Class Label
(aka Ground Truth Label)

Color	Weight	Label
Red	200g	Apple
Orange	300g	Orange
Red	150g	Apple
...		

Training Data

ML Model



SVM

Color	Weight	Label
Orange	350g	Unknown

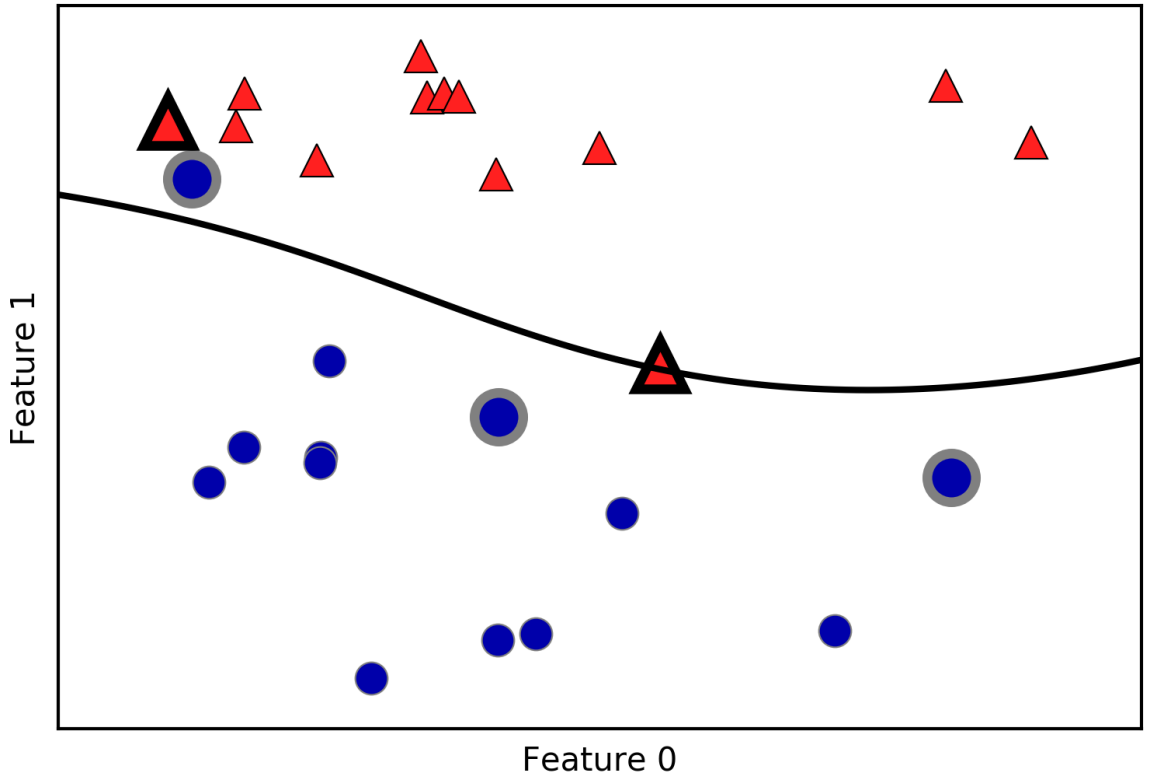
Query Input

Color	Weight	Label
Orange	350g	Orange

Prediction

SVM

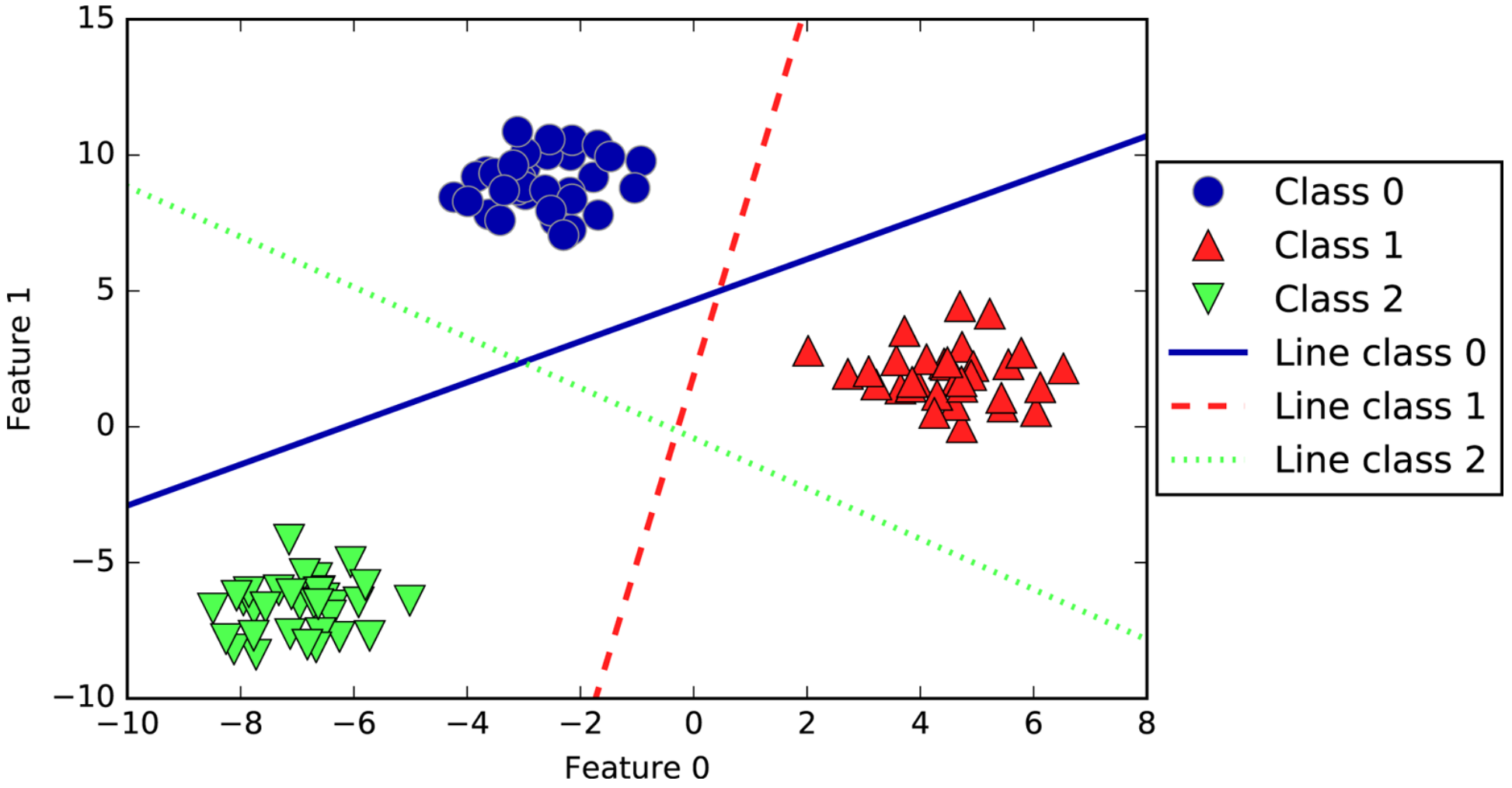
NON-LINEAR KERNEL



Decision boundary and support vectors found by an SVM with RBF kernel

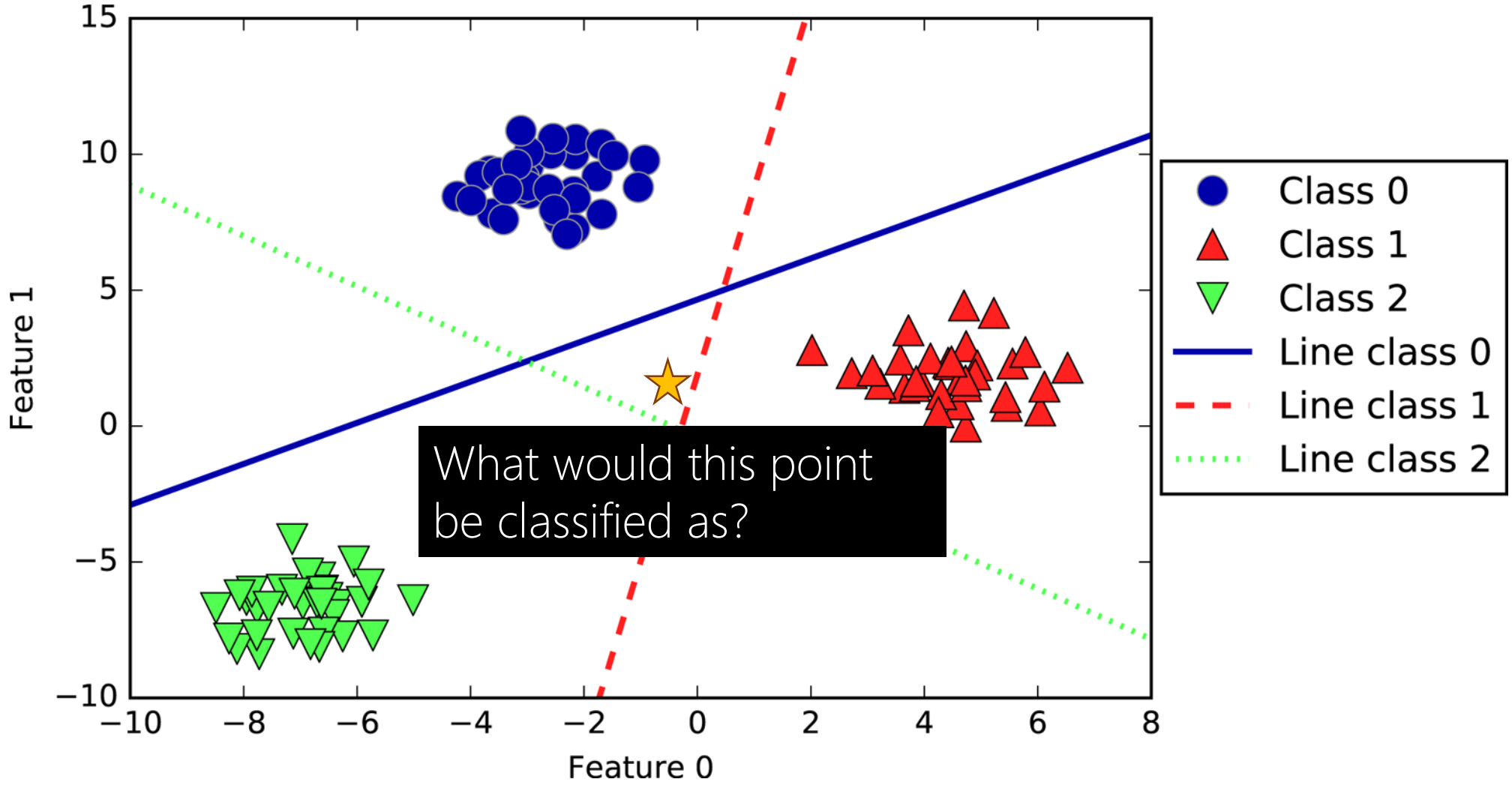
Source: Chapter 2, Guido and Müller, *Introduction to Machine Learning with Python*, Oct 2016

MULTICLASS: ONE VS. REST APPROACH



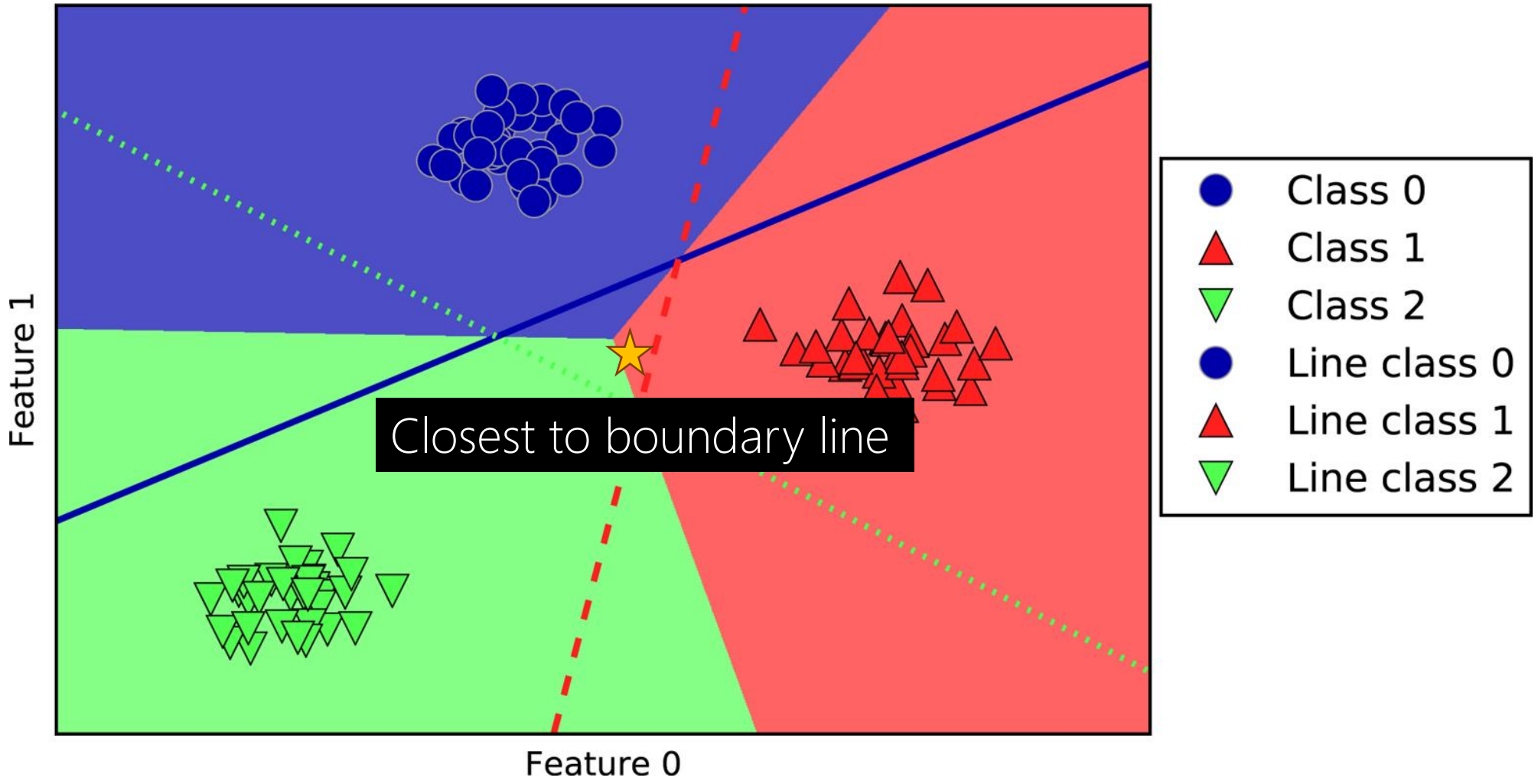
Source: Chapter 2, Guido and Müller, *Introduction to Machine Learning with Python*, Oct 2016

MULTICLASS: ONE VS. REST APPROACH



Source: Chapter 2, Guido and Müller, *Introduction to Machine Learning with Python*, Oct 2016

MULTICLASS: ONE VS. REST APPROACH



Source: Chapter 2, Guido and Müller, *Introduction to Machine Learning with Python*, Oct 2016

SVMS

STRENGTHS AND WEAKNESSES

Strengths

Powerful models that perform well on a variety of datasets

Allow for complex decision boundaries, even if the data has only a few features

Works well for both low- and high-dimensional data (*i.e.*, few and many features)

Weaknesses

Require careful preprocessing of data and tuning of parameters (*e.g.*, gamma and C)

Hard to inspect and interpret the model and why a particular prediction was made

Source: Chapter 2, Guido and Müller, *Introduction to Machine Learning with Python*, Oct 2016

ITERATING ON OUR MODEL

Feature selection

Feature processing

Parameter tuning

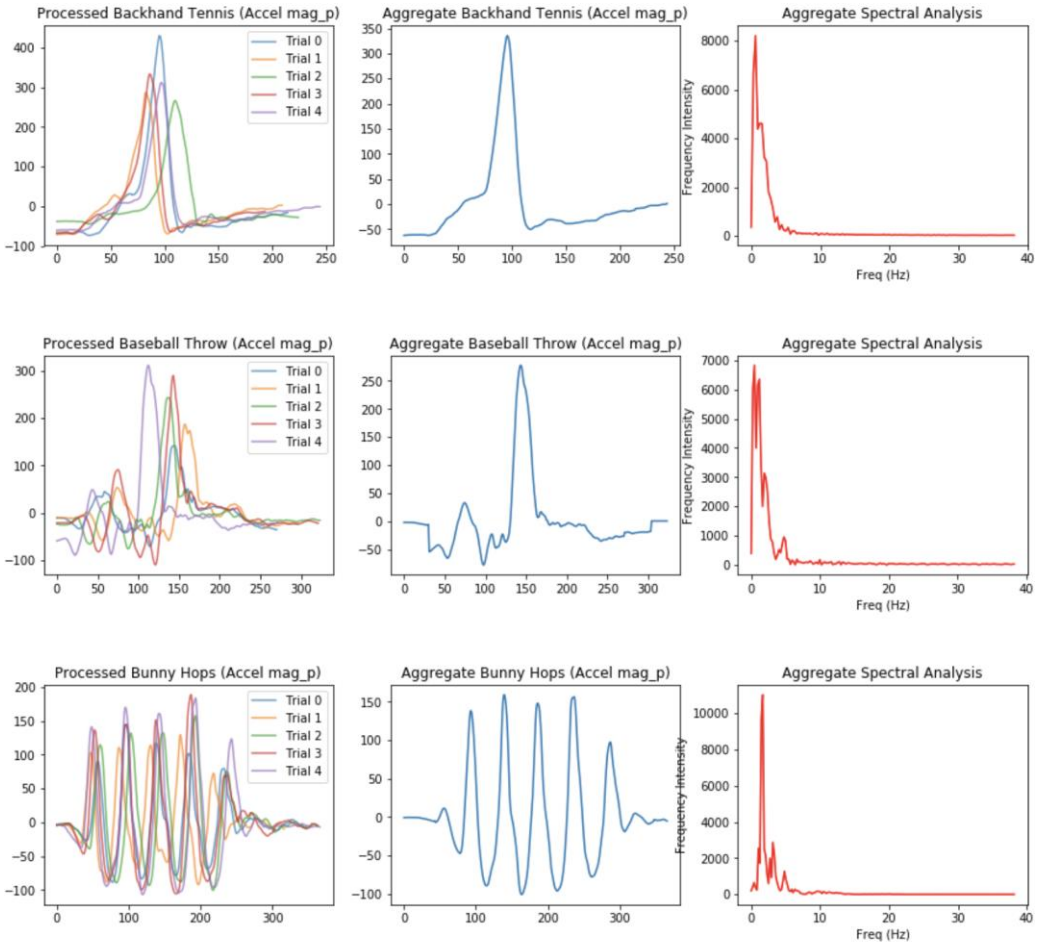
Coming up with features is difficult, time-consuming, requires expert knowledge. "Applied machine learning" is basically feature engineering.

Andrew Ng

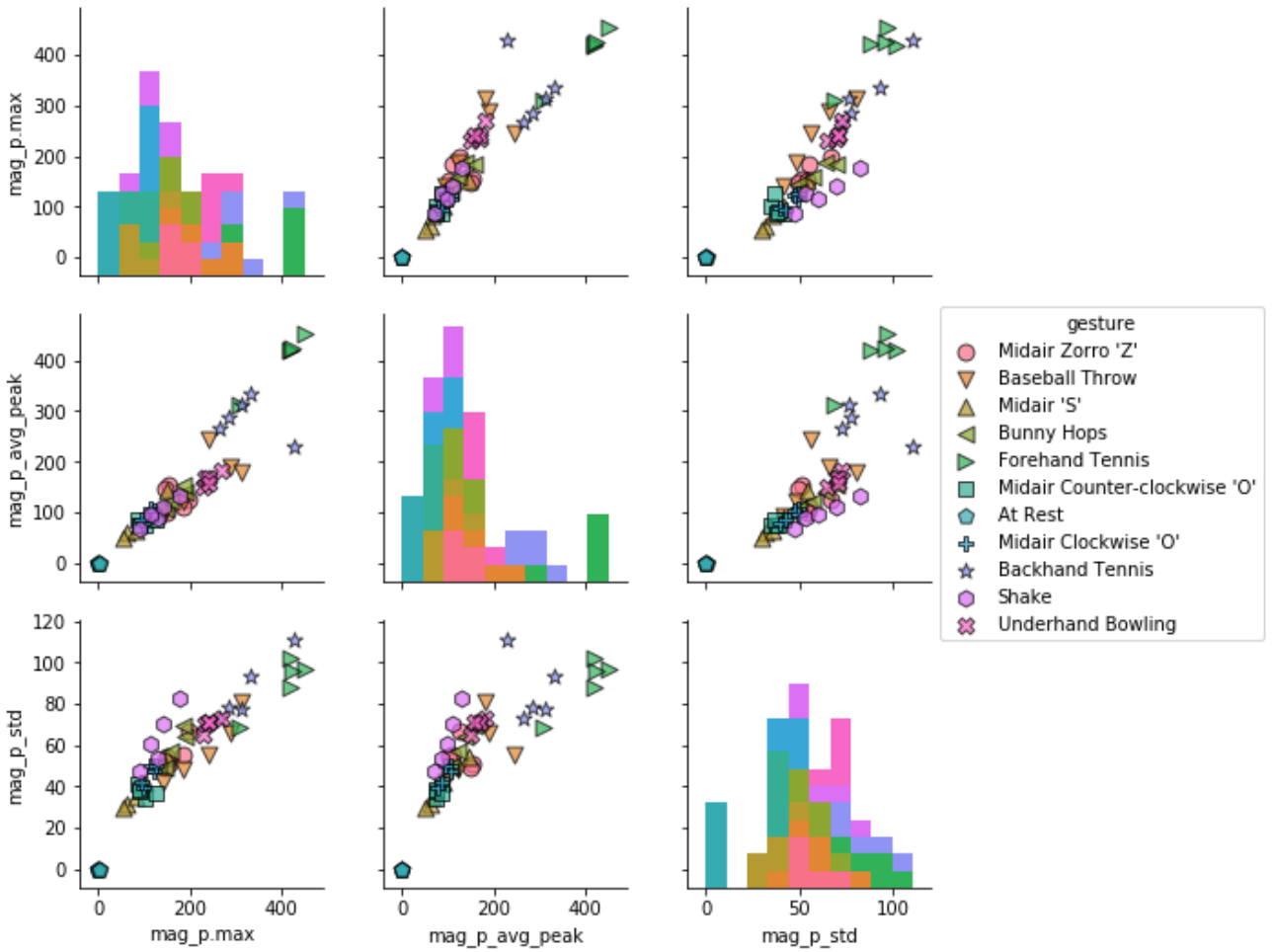
FEATURE SELECTION

SIGNAL EXPLORATIONS

Time-series Explorations



Feature Explorations



HOW DO WE SELECT FEATURES?

Based on **domain expertise** (*e.g.*, a medical doctor helping select features for automatic melanoma recognition in images)

Based on **intuitions, experimentations,** and **plotting the data**

Feature selection algorithms!

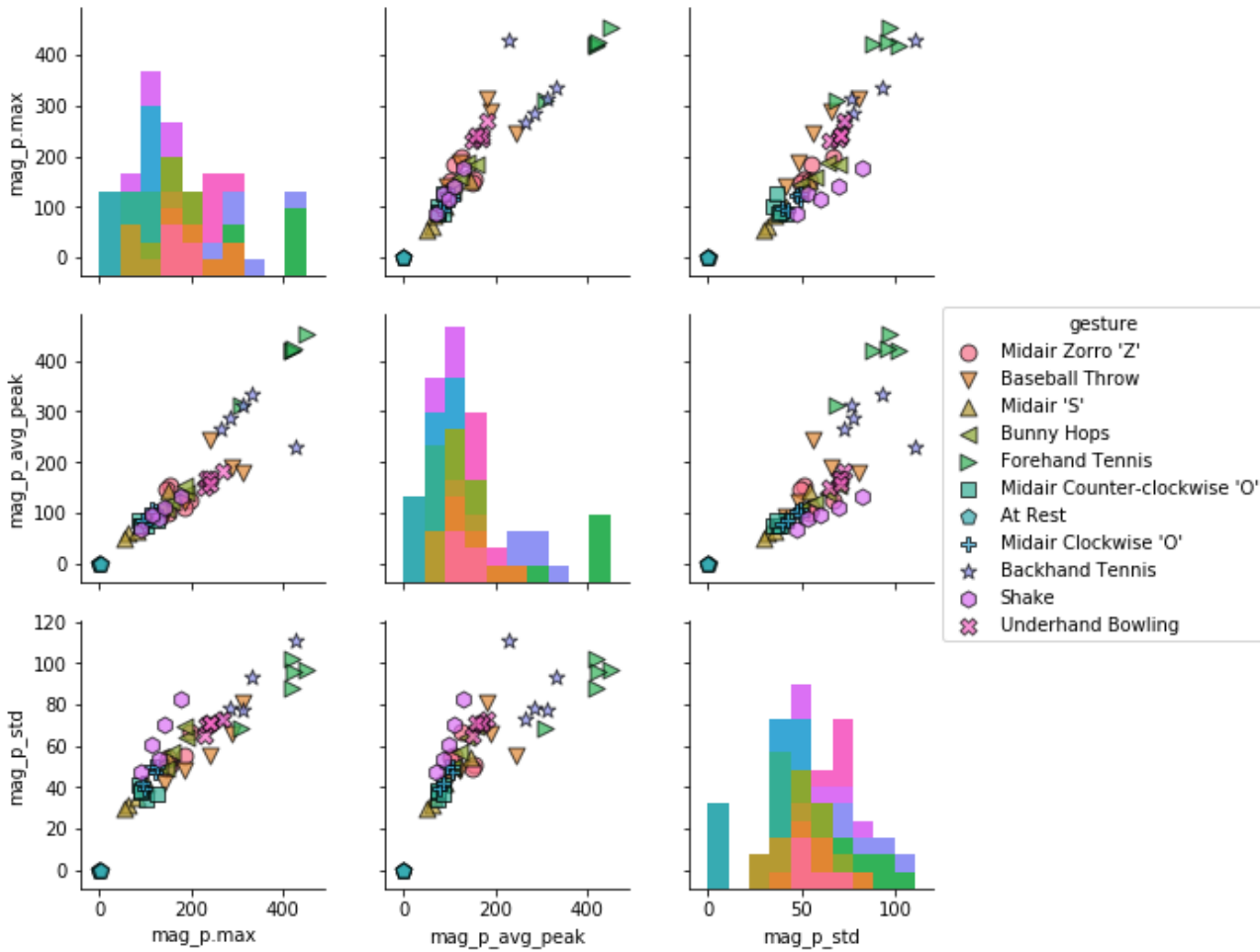
FEATURE SELECTION

PAIR PLOTS

Pair plots formalize some of our 2D explorations of features from last time

The diagonal is filled with histograms of each features (or density plots)

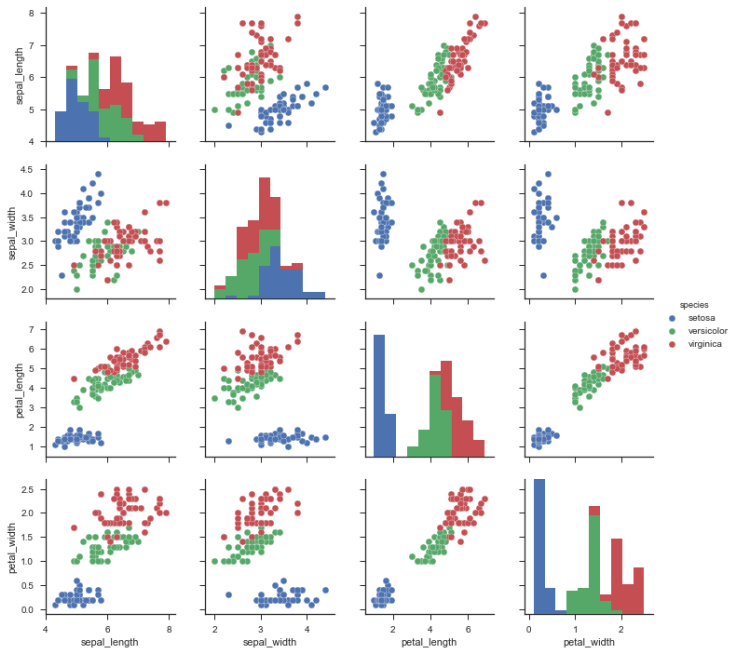
Other cells are 2D combinations



FEATURE SELECTION

PAIR PLOTS: PLAYING WITH ML NOTEBOOK

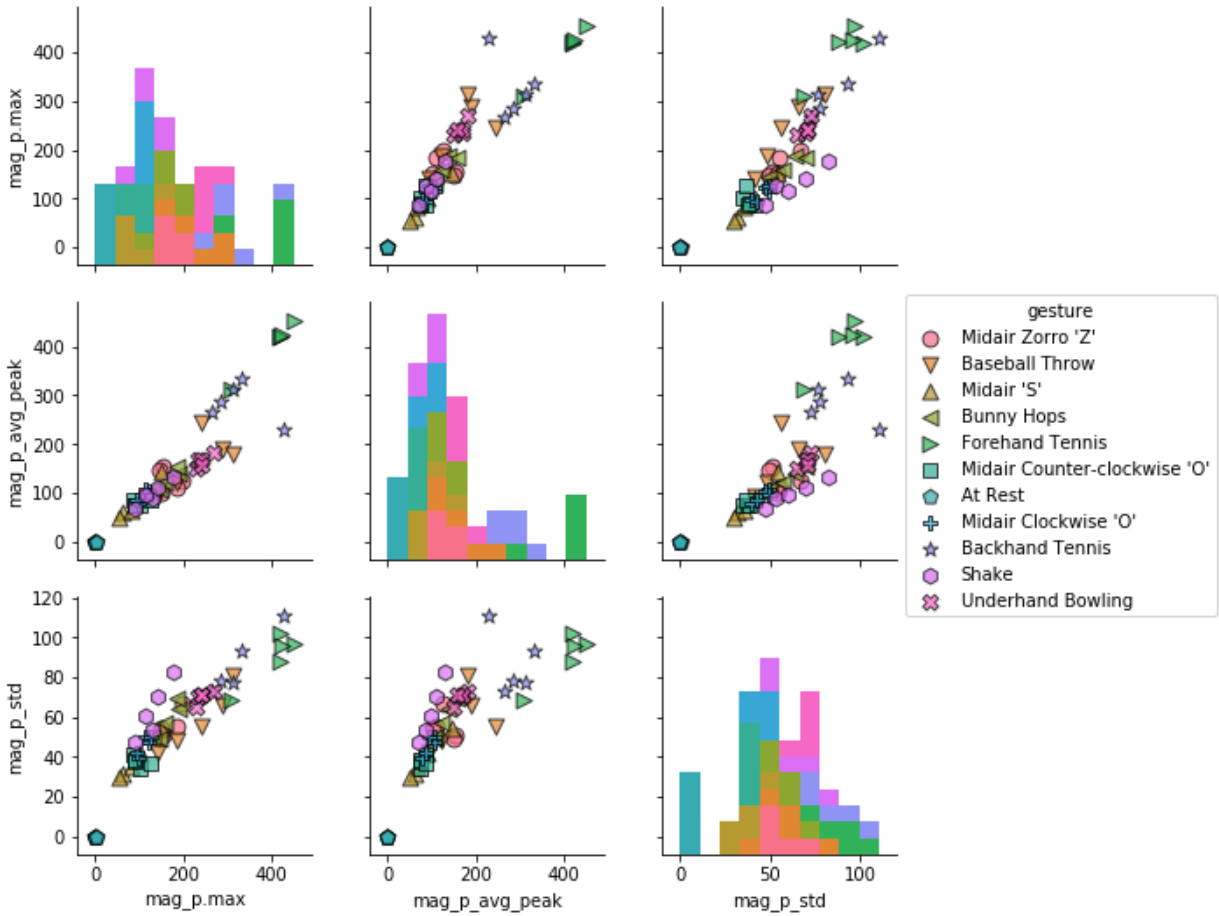
```
# Draw scatterplots for joint relationships and histograms for univariate distributions
# See: https://seaborn.pydata.org/generated/seaborn.pairplot.html
import seaborn as sns
sns.set(style="ticks", color_codes=True)
iris = sns.load_dataset("iris")
g = sns.pairplot(iris)

# Show different levels of a categorical variable by the color of plot elements:
g = sns.pairplot(iris, hue="species")
```



FEATURE SELECTION

PAIR PLOTS: PLAYING WITH ML NOTEBOOK

```
import pandas as pd
import seaborn as sns

features = dict()
for gesture_name, gesture_trials in selected_gesture_set.map_gestures_to_trials.items():
    for trial in gesture_trials:
        if 'mag_p.max' not in features:
            features['mag_p.max'] = list()
        features['mag_p.max'].append(trial.accel.mag_p.max())

        if 'mag_p_std' not in features:
            features['mag_p_std'] = list()
        features['mag_p_std'].append(np.std(trial.accel.mag_p))

        # peak count
        min_distance_between_peaks = 77 / 3.0 # 77 is the sampling frequency
        peak_indices, peak_properties = sp.signal.find_peaks(trial.accel.mag_p, height=30, distance=min_distance_between_peaks)

        # average of peak values
        if 'mag_p_avg_peak' not in features:
            features['mag_p_avg_peak'] = list()

        mag_p_avg_peak_cnt = 0
        if len(peak_indices) > 0:
            mag_p_avg_peak_cnt = np.average(trial.accel.mag_p[peak_indices])

        features['mag_p_avg_peak'].append(mag_p_avg_peak_cnt)

        if 'gesture' not in features:
            features['gesture'] = list()

        features['gesture'].append(gesture_name)


df = pd.DataFrame(data=features)

markers = ['o','v','^','<','>','s','p','P','*','h','X','D','d','|','_',0,1,2,3,4,5,6,7,8,9,10,'1','2','3','4',',']
markers = markers[:len(selected_gesture_set.map_gestures_to_trials)]

g = sns.pairplot(df, hue="gesture",
                 plot_kws = {'alpha': 0.7, 's': 80, 'edgecolor': 'k'}, markers = markers)
```



FEATURE SELECTION ALGORITHMS

Given a giant list of input features, a feature selection algorithm can be seen as a search technique for finding the best combination of feature subsets

Brute force: test each possible subset of features finding the one that minimizes the error rate. This is computationally intractable.

Scikit learn and other toolkits have support for this.
https://scikit-learn.org/stable/modules/feature_selection.html

Source: https://en.wikipedia.org/wiki/Feature_selection

1.13. Feature selection

The classes in the `sklearn.feature_selection` module can be used for feature selection/dimensionality reduction on sample sets, either to improve estimators' accuracy scores or to boost their performance on very high-dimensional datasets.

1.13.1. Removing features with low variance

`VarianceThreshold` is a simple baseline approach to feature selection. It removes all features whose variance doesn't meet some threshold. By default, it removes all zero-variance features, i.e. features that have the same value in all samples.

As an example, suppose that we have a dataset with boolean features, and we want to remove all features that are either one or zero (on or off) in more than 80% of the samples. Boolean features are Bernoulli random variables, and the variance of such variables is given by

$$\mathrm{Var}[X] = p(1-p)$$

so we can select using the threshold `.8 * (1 - .8)`:

```
>>> from sklearn.feature_selection import VarianceThreshold
>>> X = [[0, 0, 1], [0, 1, 0], [1, 0, 0], [0, 1, 1], [0, 1, 0], [0, 1, 1]]
>>> sel = VarianceThreshold(threshold=(.8 * (1 - .8)))
>>> sel.fit_transform(X)
array([[0, 1],
       [1, 0],
       [0, 0],
       [1, 1],
       [1, 0],
       [1, 1]])
```

As expected, `VarianceThreshold` has removed the first column, which has a probability $p = 5/6 > .8$ of containing a zero.

1.13.2. Univariate feature selection

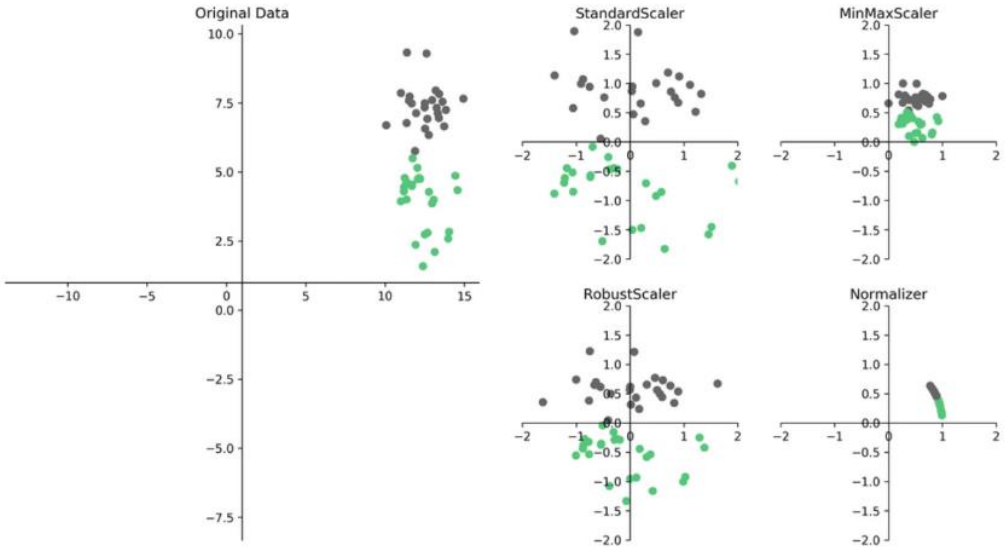
Univariate feature selection works by selecting the best features based on univariate statistical tests. It can be seen as a preprocessing step to an estimator. Scikit-learn exposes feature selection routines as objects that implement the `transform` method:

- `SelectKBest` removes all but the k highest scoring features
- `SelectPercentile` removes all but a user-specified highest scoring percentage of features
- using common univariate statistical tests for each feature: false positive rate `SelectFpr`, false discovery rate `SelectFdr`, or family wise error `SelectFwe`.

FEATURE PROCESSING

Need to ensure that the feature vectors are scaled appropriately.

For example, if you have a two-dimensional input vector [x,y] and the x values are orders of magnitude larger than the y-values, the y-values are inconsequential



FEATURE PROCESSING

SCALING DATA IN SCIKIT LEARN

Unscaled

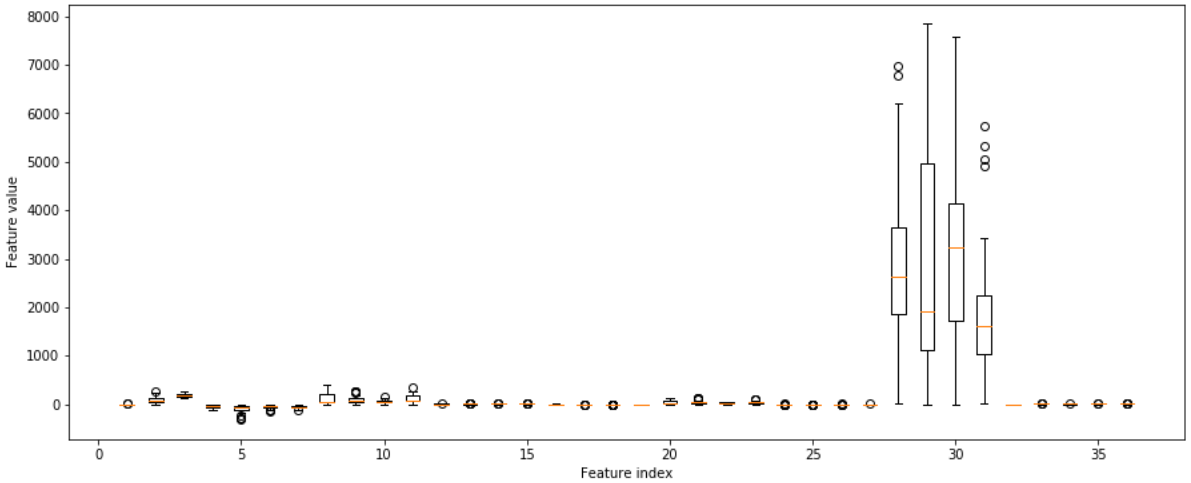
```
trainingData = np.array(trainingData)
clf = svm.SVC(kernel='linear') # kernel='rbf'
clf.fit(trainingData, classLabels)

# make predictions for this test set
for testGestureName, testTrial in testFold.items():
    features = extract_features_example(testTrial)

    svmPrediction = clf.predict([features])
    y_true.append(testGestureName)
    y_pred.append(svmPrediction)

    if testGestureName == svmPrediction[0]:
        mapGestureToCorrectMatches[testGestureName] += 1
```

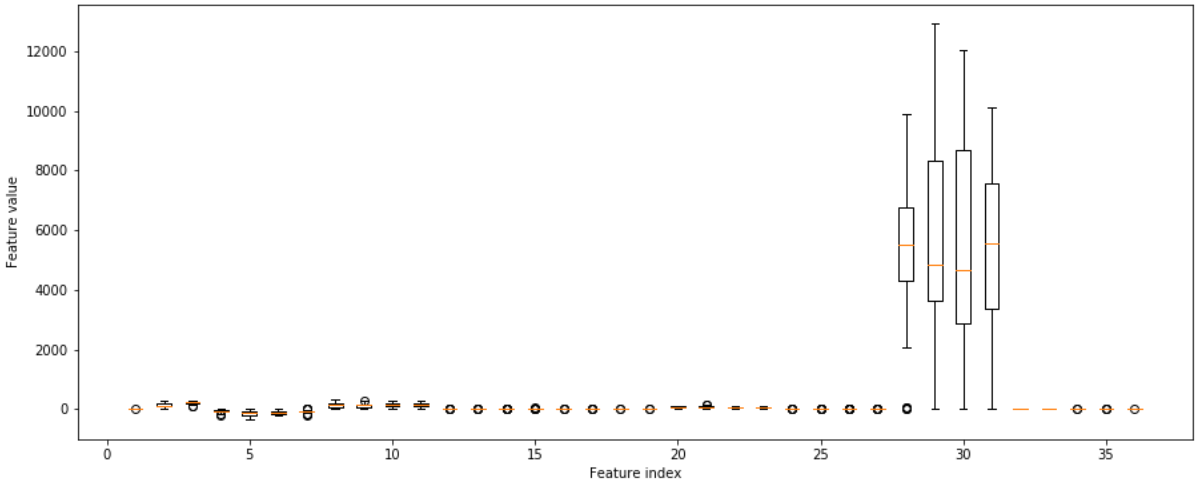
Scaled

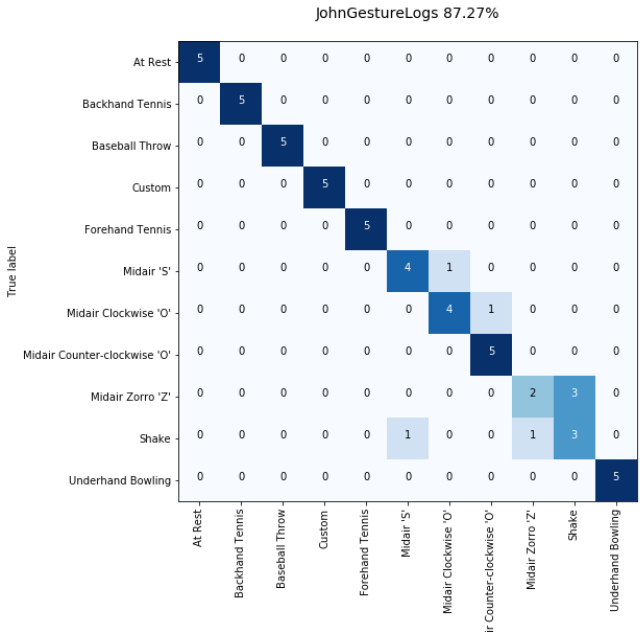
```
trainingData = np.array(trainingData)
scaler = StandardScaler()
scaler.fit(trainingData)
training_data_scaled = scaler.transform(trainingData)

clf = svm.SVC(kernel='linear') # kernel='rbf'
clf.fit(training_data_scaled, classLabels)

# make predictions for this test set
for testGestureName, testTrial in testFold.items():
    features = np.array(extract_features(testTrial))
    features_scaled = scaler.transform([features])
    svmPrediction = clf.predict(features_scaled)
    y_true.append(testGestureName)
    y_pred.append(svmPrediction)

    if testGestureName == svmPrediction[0]:
        mapGestureToCorrectMatches[testGestureName] += 1
```

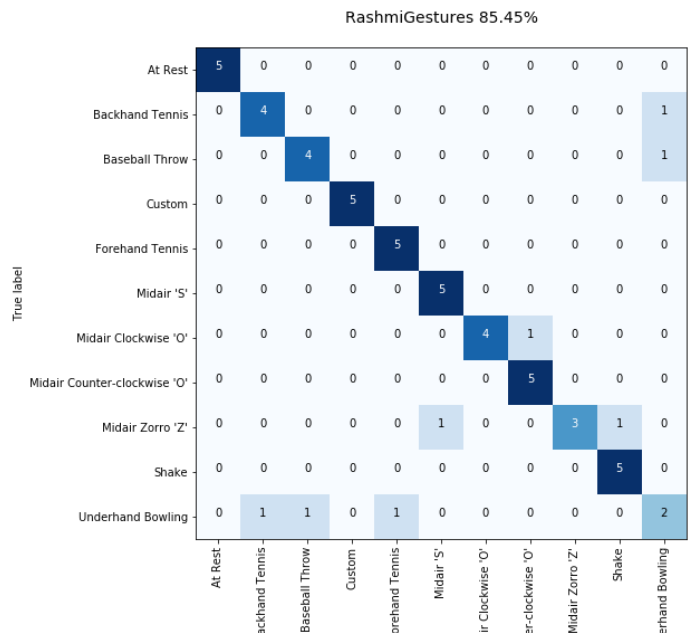
FEATURE SCALING

UNSCALED SVM CLASSIFICATION RESULTS



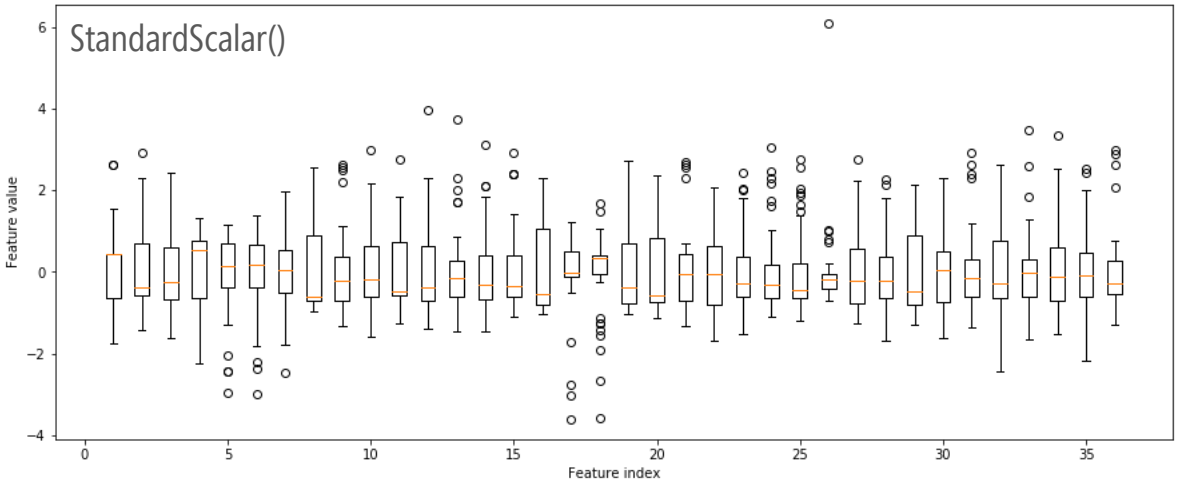


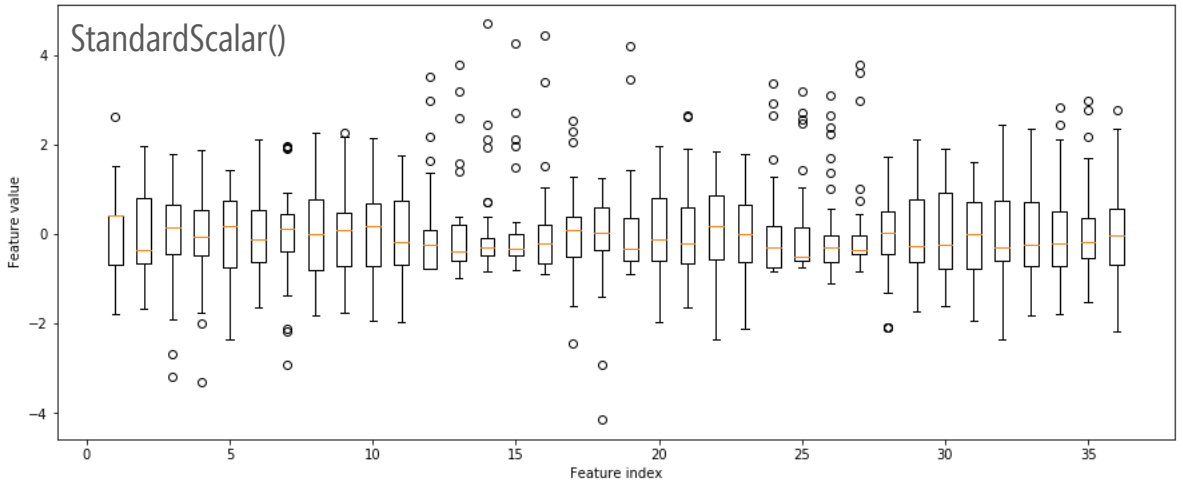


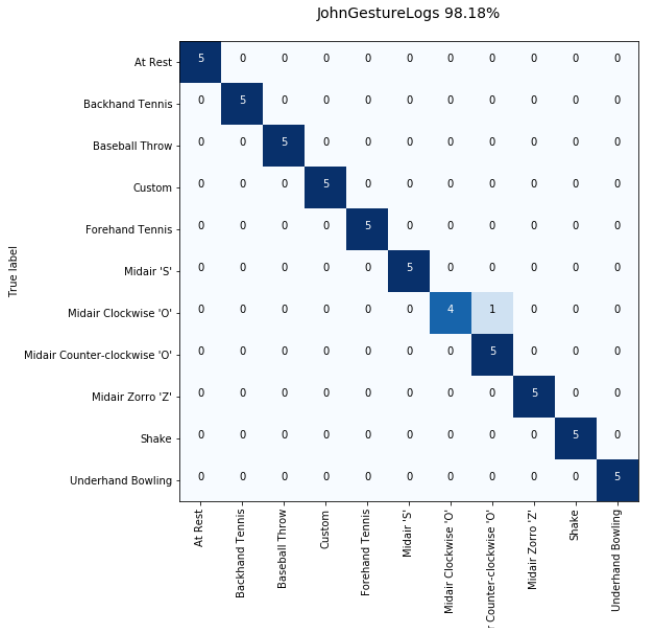


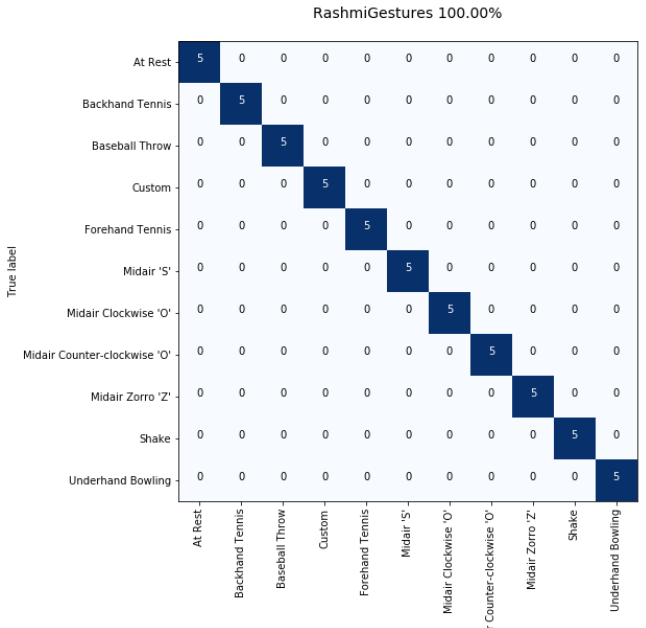
FEATURE SCALING

SCALED SVM CLASSIFICATION RESULTS



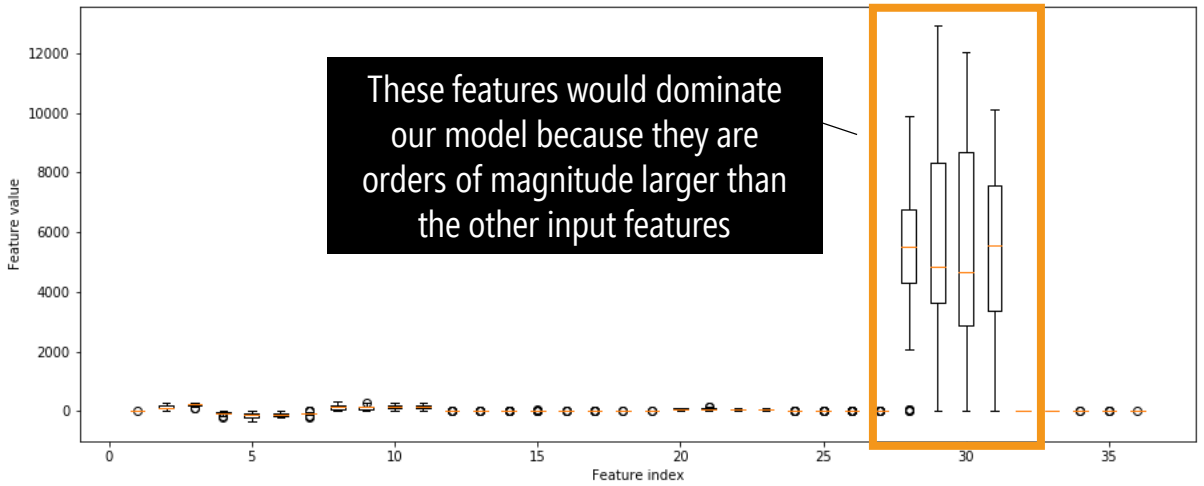




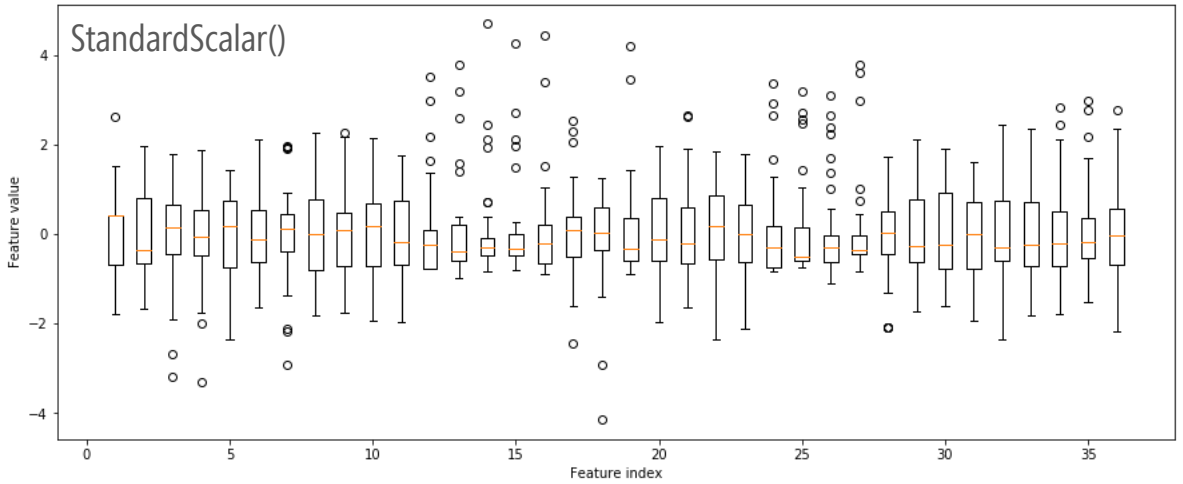


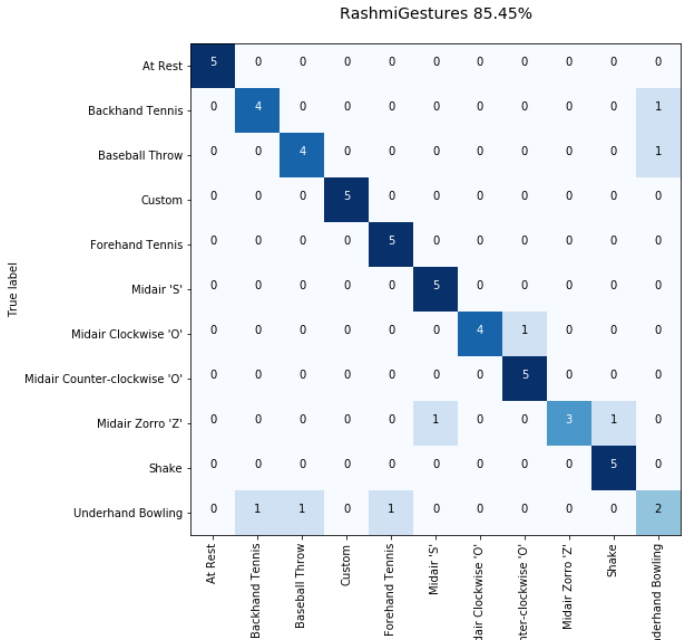
FEATURE SCALING

COMPARING UNSCALED VS. SCALED

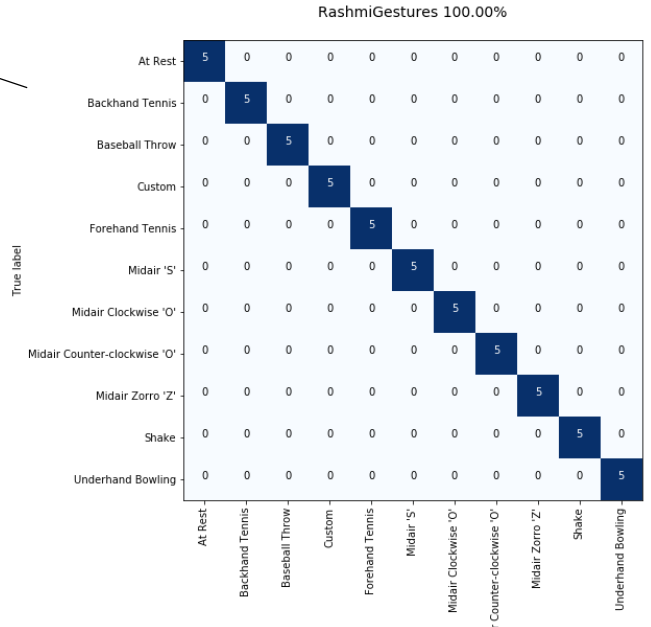


These features would dominate our model because they are orders of magnitude larger than the other input features



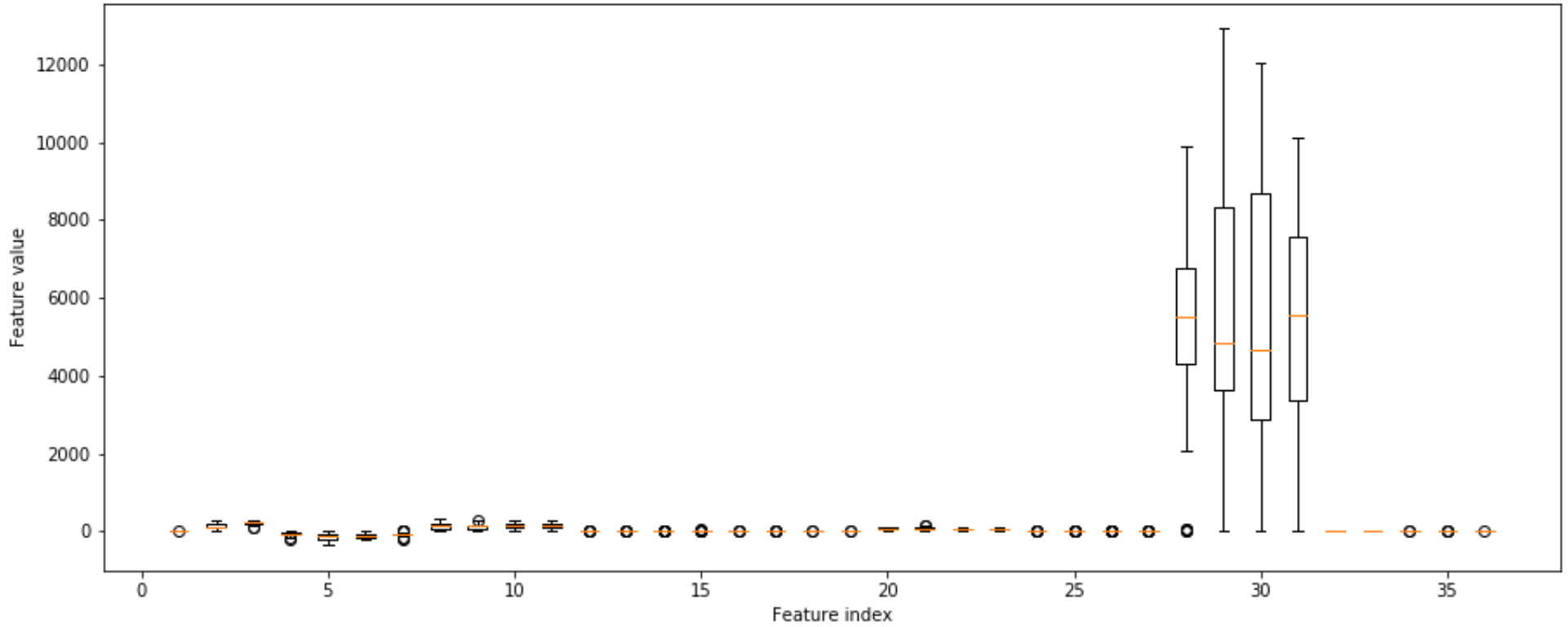


Scaling our features with StandardScalar() leads to a dramatic improvement in accuracy.



AS AN ASIDE: GRAPHING FEATURE BOX PLOTS

```
plt.figure(figsize=(15,6))
plt.boxplot(training_data, manage_xticks=False)
plt.xlabel("Feature index")
plt.ylabel("Feature value")
```



PARAMETER TUNING

Most ML algorithms have parameters to set

When you train a model, you must provide values for those parameters and the efficacy of the model depends on those parameters

The optimal set of parameters is known as *model selection*

Scikit learn and other frameworks also support this…

Source: https://docs.microsoft.com/en-us/azure/machine-learning/studio/algorithm-parameters-optimize

3.2. Tuning the hyper-parameters of an estimator

Hyper-parameters are parameters that are not directly learnt within estimators. In scikit-learn they are passed as arguments to the constructor of the estimator classes. Typical examples include `C`, `kernel` and `gamma` for Support Vector Classifier, `alpha` for Lasso, etc.

It is possible and recommended to search the hyper-parameter space for the best cross validation score.

Any parameter provided when constructing an estimator may be optimized in this manner. Specifically, to find the names and current values for all parameters for a given estimator, use:

```
estimator.get_params()
```

A search consists of:

- an estimator (regressor or classifier such as `sklearn.svm.SVC()`);
- a parameter space;
- a method for searching or sampling candidates;
- a cross-validation scheme; and
- a score function.

Some models allow for specialized, efficient parameter search strategies, outlined below. Two generic approaches to sampling search candidates are provided in scikit-learn: for given values, `GridSearchCV` exhaustively considers all parameter combinations, while `RandomizedSearchCV` can sample a given number of candidates from a parameter space with a specified distribution. After describing these tools we detail best practice applicable to both approaches.

Note that it is common that a small subset of those parameters can have a large impact on the predictive or computation performance of the model while others can be left to their default values. It is recommended to read the docstring of the estimator class to get a finer understanding of their expected behavior, possibly by reading the enclosed reference to the literature.

3.2.1. Exhaustive Grid Search

The grid search provided by `GridSearchCV` exhaustively generates candidates from a grid of parameter values specified with the `param_grid` parameter. For instance, the following `param_grid`:

```
param_grid = [
  {'C': [1, 10, 100, 1000], 'kernel': ['linear']},
  {'C': [1, 10, 100, 1000], 'gamma': [0.001, 0.0001], 'kernel': ['rbf']},
 ]
```

specifies that two grids should be explored: one with a linear kernel and C values in [1, 10, 100, 1000], and the second one with an RBF kernel, and the cross-product of C values ranging in [1, 10, 100, 1000] and gamma values in [0.001, 0.0001].

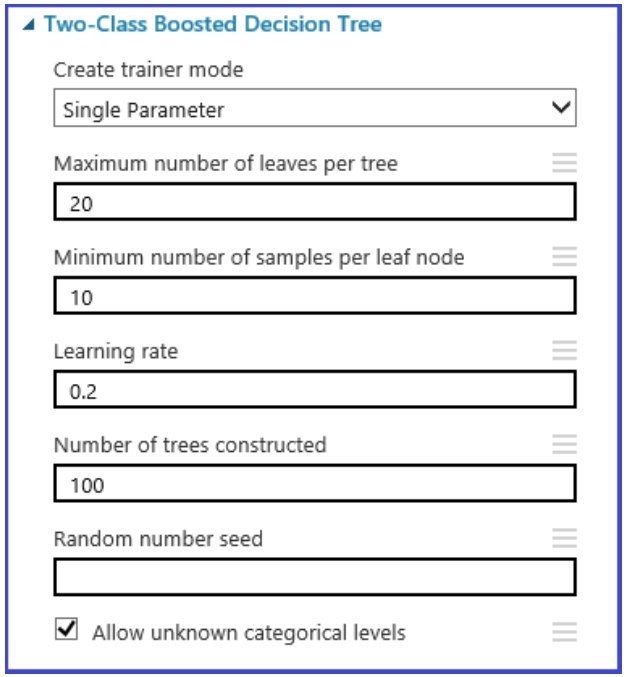
PARAMETER TUNING PROCESS

1. Define the parameter space. For a given ML model, decide what range of parameter values you want to consider.
2. Define the evaluation method (*e.g.*, cross-validation)
3. Define your key metrics (*e.g.*, accuracy, precision, recall, root-mean squared error)
4. Train and evaluate. For each unique combination of the parameter values, cross-validation performed and your key metrics produced.
5. Compare output and choose the best-performing parameters for your model.

Based on: https://docs.microsoft.com/en-us/azure/machine-learning/studio/algorithm-parameters-optimize

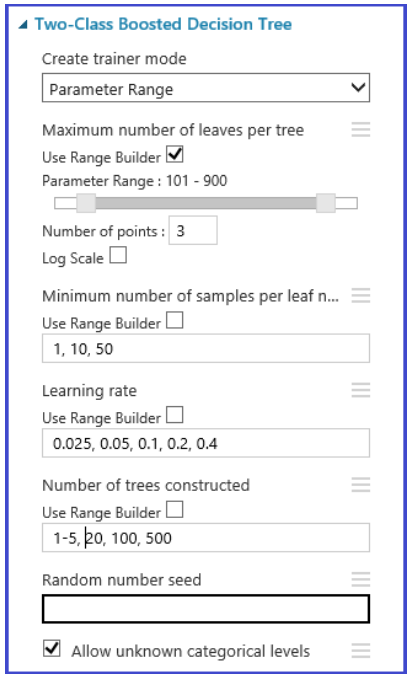
PARAMETER TUNING: DECISION TREE EXAMPLE ON AZURE

Most ML toolkits offer parameter tuning functionality. This example is from Microsoft Azure's ML toolkit.



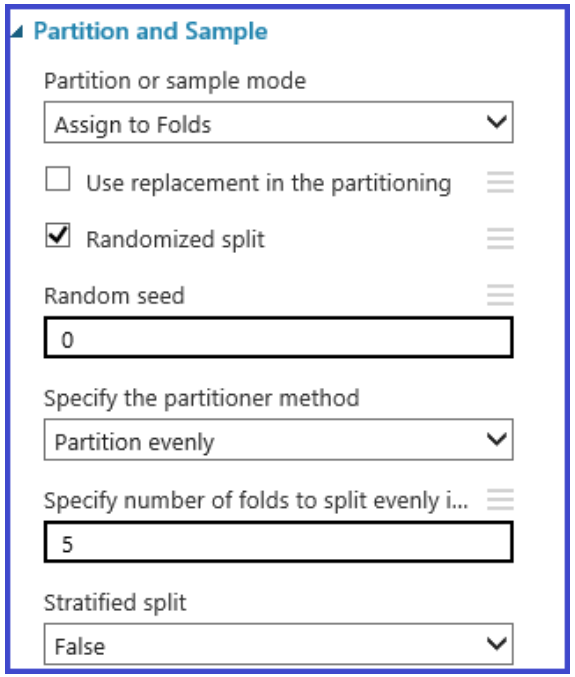
1. Choose and Setup Model

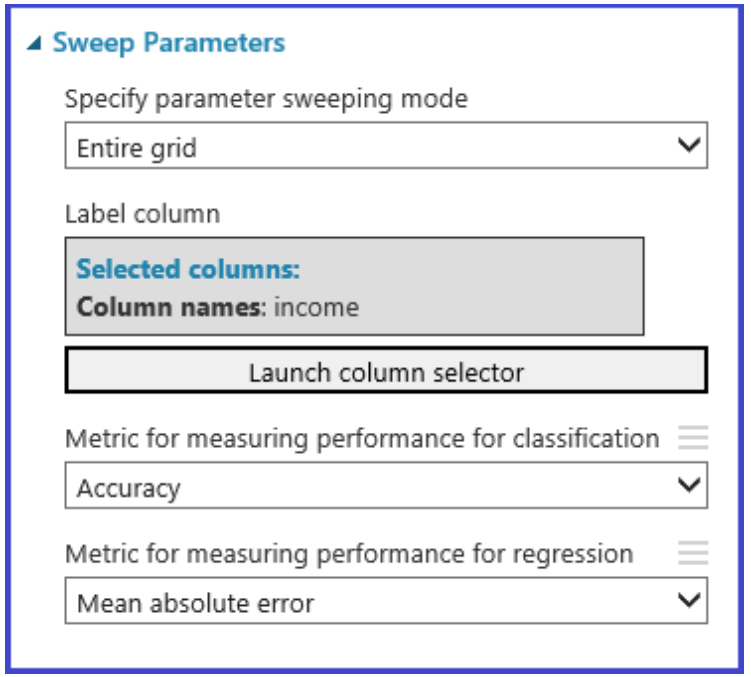
Select an ML model to tune



2. Parameter Ranges

Decide what range of values to input and compare





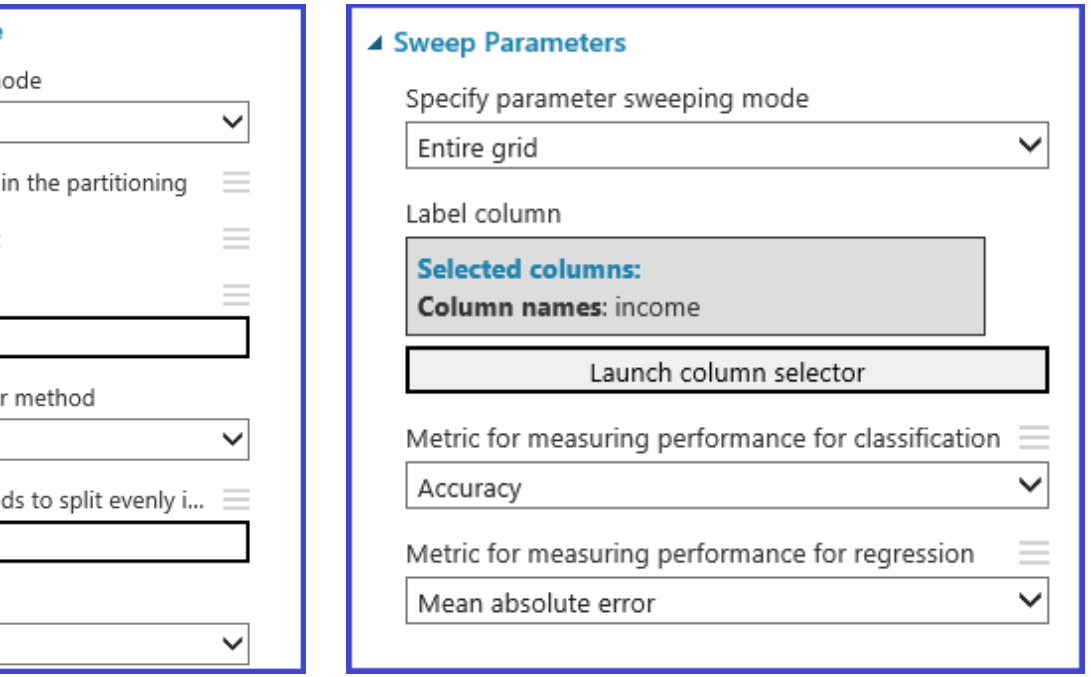
3. Setup Evaluation

Decide how many folds in cross-validation and key error metrics.

Based on: https://docs.microsoft.com/en-us/azure/machine-learning/studio/algorithm-parameters-optimize

PARAMETER TUNING: DECISION TREE EXAMPLE ON AZURE

Most ML toolkits offer parameter tuning functionality. This example is from Microsoft Azure's ML toolkit.



ation

y folds in cross-validation and key error metrics.

rows 180 columns 11

Number of leaves	Minimum leaf instances	Learning rate	Number of trees	Accuracy	Precision	Recall	F-Score	AUC	Average Log Loss	Training Log Loss
8	10	0.1	500	0.866128	0.75785	0.652595	0.701295	0.922837	0.290561	47.363286
8	1	0.05	500	0.866097	0.762796	0.644306	0.698562	0.922672	0.289389	47.575474
8	1	0.2	100	0.865944	0.763813	0.641755	0.697484	0.921469	0.291591	47.176649
32	1	0.05	100	0.865913	0.759367	0.648769	0.699725	0.921503	0.29273	46.970281
8	10	0.2	100	0.865882	0.763821	0.641372	0.697262	0.922052	0.290024	47.46048
32	1	0.025	500	0.865668	0.749604	0.663946	0.70418	0.923187	0.292484	47.014813
8	10	0.05	500	0.865514	0.761322	0.643158	0.697269	0.922803	0.288929	47.658898
32	1	0.1	100	0.865453	0.751234	0.659737	0.702519	0.922703	0.292779	46.961499
8	1	0.025	500	0.865391	0.764778	0.636909	0.695011	0.921386	0.29142	47.207519
8	50	0.05	500	0.865115	0.760932	0.641372	0.696055	0.92261	0.288991	47.647701
32	10	0.025	500	0.865115	0.748308	0.662798	0.702962	0.923435	0.29145	47.202173
8	50	0.025	500	0.865084	0.764336	0.635761	0.694145	0.921226	0.291554	47.183315
32	10	0.05	100	0.865084	0.756395	0.648642	0.698387	0.92155	0.29239	47.031913
8	10	0.025	500	0.864992	0.764066	0.635633	0.693957	0.921674	0.290844	47.312033
32	10	0.2	20	0.864961	0.757939	0.645326	0.697114	0.920488	0.294732	46.607674
8	1	0.1	500	0.864808	0.752756	0.653105	0.699399	0.922545	0.291764	47.145278
32	10	0.1	100	0.864777	0.748626	0.66012	0.701593	0.92295	0.291274	47.234005
8	1	0.1	100	0.864715	0.763255	0.635251	0.693395	0.920514	0.293092	46.904731
8	10	0.1	100	0.864715	0.763416	0.634996	0.693309	0.920639	0.292815	46.954929
8	10	0.4	100	0.864623	0.754863	0.648387	0.697585	0.921302	0.292915	46.936722
32	1	0.2	20	0.864439	0.757089	0.64354	0.695712	0.920124	0.295428	46.481506

4. Train, Evaluate, and compare

You can see the parameters in left-hand columns and the output produced.

Based on: https://docs.microsoft.com/en-us/azure/machine-learning/studio/algorithm-parameters-optimize

SCIKIT LEARN

ACTIVITY: TRY DIFFERENT MODELS, INPUT FEATURES, AND SCALINGS

```
clf = svm.SVC(kernel='linear’)
clf.fit(training_data, class_labels)
svm_prediction = clf.predict(test_features)
```

```
clf = KNeighborsClassifier(n_neighbors=3)
clf.fit(training_data, class_labels)
knn_prediction = clf.predict(test_features)
```

```
clf = DecisionTreeClassifier(random_state=0)
clf.fit(training_data, class_labels)
tree_prediction = clf.predict(test_features)
```

```
clf = MLPClassifier(solver='lbfgs', random_state=0, hidden_layer_sizes=[100])
clf.fit(training_data, class_labels)
tree_prediction = clf.predict(test_features)
```

SCIKIT LEARN

CSE 599 Prototyping Interactive Systems | Lecture 15 | May 21

Jon Froehlich • Jasper O'Leary (TA)

DESIGN USE BUILD

MAKEABILITY LAB

PAUL G. ALLEN SCHOOL
OF COMPUTER SCIENCE & ENGINEERING

UNIVERSITY of WASHINGTON