Introduction to Scikit-Learn: Machine Learning with Python

Classification

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Supervised Learning

About supervised learning

In **Supervised Learning**, we have a dataset consisting of both features and labels. The task is to construct an estimator which is able to predict the label of an object given the set of features.

Some more complicated examples are:

- given a multicolor image of an object through a telescope, determine whether that object is a star, a quasar, or a galaxy.
- given a photograph of a person, identify the person in the photo.
- given a list of movies a person has watched and their personal rating of the movie, recommend a list of movies they would like (So-called *recommender systems*: a famous example is the [Netflix Prize (http://en.wikipedia.org/wiki/Netflix_prize)](http://en.wikipedia.org/wiki/Netflix_prize)).

Supervised learning is further broken down into two categories

- Classification
- Regression

In classification, the label is discrete, while in regression, the label is continuous

- Classification: Credit card approval/rejection
- Regression: Monthly credit limit

K nearest neighbors

About K nearest neighbors

K nearest neighbors (kNN) is one of the simplest learning strategies: given a new, unknown observation, look up in your reference database which ones have the closest features and assign the predominant class.

In [1]:
```
import pandas as pd
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import Imputer

train_url = "https://storage.googleapis.com/kaggle_datasets/Titanic-Machine-Learni
ng-from-Disaster/train.csv"
train = pd.read_csv(train_url)
X_train = train[["Fare", "Age"]].values
imputer = Imputer(strategy="median")
X_train = imputer.fit_transform(X_train)
y_train = train["Survived"].values
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
```

Out[1]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

In [2]:

```
test_url = "https://storage.googleapis.com/kaggle_datasets/Titanic-Machine-Learnin
g-from-Disaster/test.csv"
test = pd.read_csv(test_url)
```

In [3]:
```
test.head()
```

Out[3]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S

In [4]:

```
# How would our current kNN model predict the first passenger with Age=34.5, and F
are=7.8292?
import numpy as np

X_test = np.array([[34.5, 7.8292]]).reshape(1, 2)
knn.predict(X_test)
```

Out[4]:

```
array([0])
```

We can also do probabilistic predictions:

In [5]:
```
knn.predict_proba(X_test)
```

Out[5]:
```
array([[ 0.6,  0.4]])
```

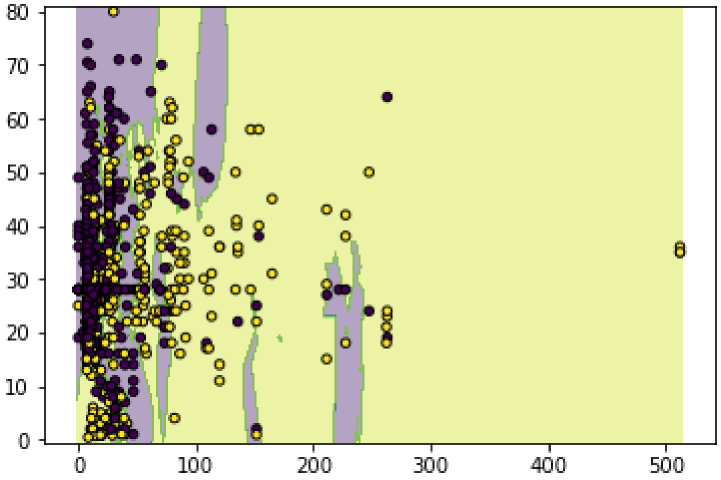
Let's draw the decision boundary for our current kNN model:

In [6]:
```
import matplotlib.pyplot as plt

# Plotting decision regions
x_min, x_max = X_train[:, 0].min() - 1, X_train[:, 0].max() + 1
y_min, y_max = X_train[:, 1].min() - 1, X_train[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                     np.arange(y_min, y_max, 0.1))
Z = knn.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, alpha=0.4)
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, s=20, edgecolor='k')
```

Out[6]:
```
<matplotlib.collections.PathCollection at 0x105ae9748>
```

In [7]:

```
plt.show()
```

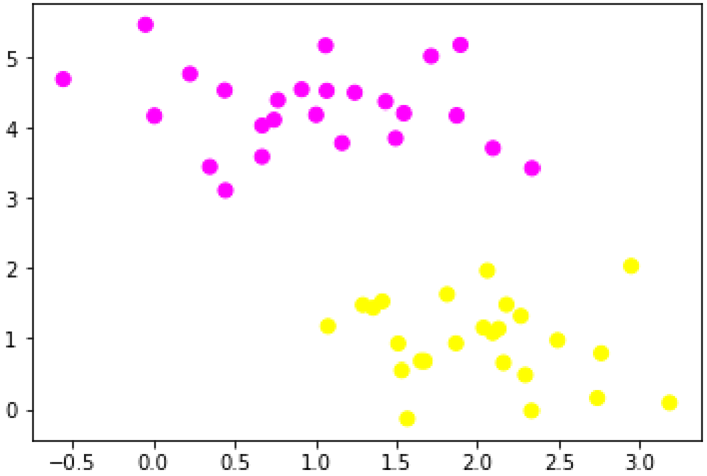


Support Vector Machines

About SVM

Support Vector Machines (SVMs) are a powerful supervised learning algorithm used for **classification**. SVMs are a **discriminative** classifier: that is, they draw a boundary between clusters of data.

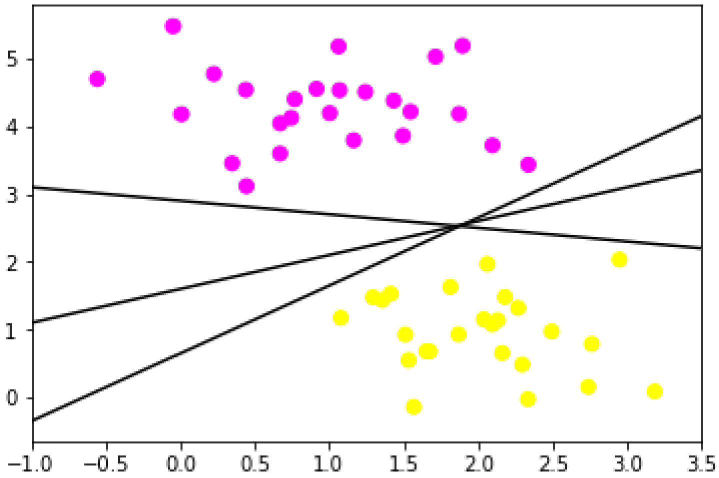
In [9]:
```
plt.show()
```



A discriminative classifier attempts to draw a line between the two sets of data

We could come up with several possibilities which perfectly discriminate between the classes.

In [11]:
```
plt.show()
```

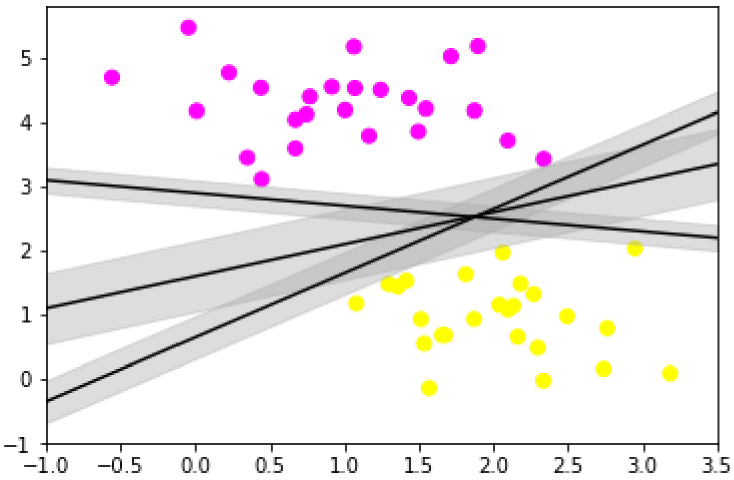


How can we improve on this?

Maximizing the *Margin*

Support vector machines are one way to address this. What support vector machined do is to not only draw a line, but consider a *region* about the line of some given width.

In [13]:
```
plt.show()
```



If we want to maximize this width, the middle fit is clearly the best

Fitting a Support Vector Machine

Now we'll fit a Support Vector Machine Classifier.

In [14]:

```
import pandas as pd
from sklearn.preprocessing import Imputer
from sklearn.svm import SVC  # "Support Vector Classifier"

train_url = "https://storage.googleapis.com/kaggle_datasets/Titanic-Machine-Learni
ng-from-Disaster/train.csv"
train = pd.read_csv(train_url)
X_train = train[["Fare", "Age"]].values
imputer = Imputer(strategy="median")
X_train = imputer.fit_transform(X_train)
y_train = train["Survived"].values
svc = SVC(kernel='linear')
svc.fit(X_train, y_train)
```

Out[14]:

```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='linear',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

Plot SVM decision boundaries

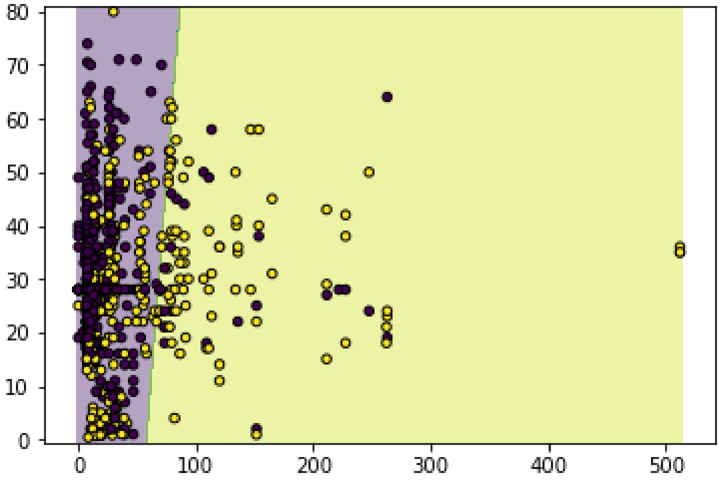
In [15]:

```
import matplotlib.pyplot as plt

# Plotting decision regions
x_min, x_max = X_train[:, 0].min() - 1, X_train[:, 0].max() + 1
y_min, y_max = X_train[:, 1].min() - 1, X_train[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                     np.arange(y_min, y_max, 0.1))
Z = svc.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, alpha=0.4)
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, s=20, edgecolor='k')
```

Out[15]:

```
<matplotlib.collections.PathCollection at 0x1a22acce80>
```

In [16]:
```
plt.show()
```



Kernel Methods

Where SVM gets incredibly exciting is when it is used in conjunction with *kernels*, which is some functional transformation of the input data.

In [17]:

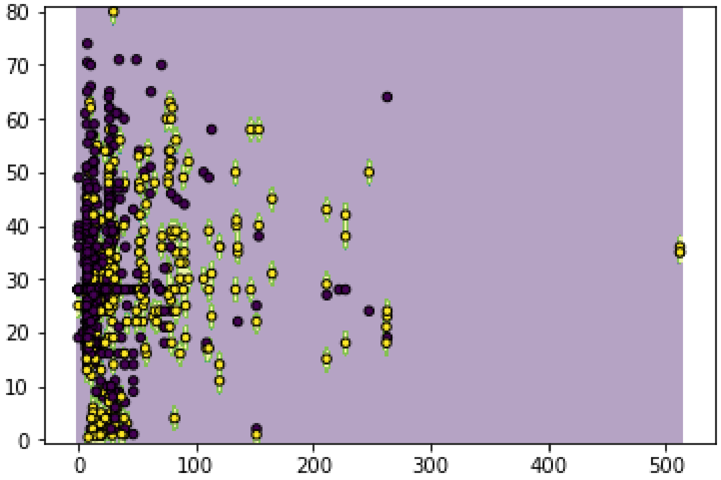
```
svc = SVC(kernel='rbf')
svc.fit(X_train, y_train)

# Plotting decision regions
Z = svc.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, alpha=0.4)
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, s=20, edgecolor='k')
```

Out[17]:

```
<matplotlib.collections.PathCollection at 0x1a22a64470>
```

In [18]:

```
plt.show()
```



Random Forest

About Random Forest

Random forests are an example of an ensemble learner built on decision trees. Decision trees are extremely intuitive ways to classify or label objects: you simply ask a series of questions designed to zero-in on the classification.

Creating a Decision Tree

In [19]:

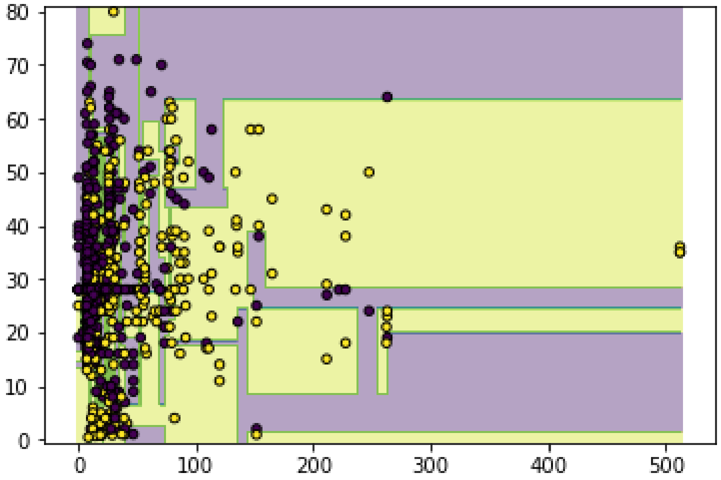
```
from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)

# Plotting decision regions
Z = dt.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, alpha=0.4)
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, s=20, edgecolor='k')
```

Out[19]:

```
<matplotlib.collections.PathCollection at 0x1a2722ff28>
```

In [20]:

```
plt.show()
```



Ensembles of Estimators

An **Ensemble Method** is a meta-estimator which essentially averages the results of many individual estimators. Somewhat surprisingly, the resulting estimates are much more robust and accurate than the individual estimates which make them up!

One of the most common ensemble methods

Random Forest, in which the ensemble is made up of many decision trees.

In [21]:

```
from sklearn.ensemble import RandomForestClassifier

forest = RandomForestClassifier(n_estimators=100)
forest.fit(X_train, y_train)

# Plotting decision regions
Z = forest.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, alpha=0.4)
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, s=20, edgecolor='k')
```

Out[21]:

```
<matplotlib.collections.PathCollection at 0x1a27b0afd0>
```

In [22]:

```
plt.show()
```