Logistic Regression and Support Vector Machines

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Activity Overview

This activity is designed to consolidate your knowledge about logistic regression and support vector machines (SVMs) from a practical point of view.

In particular, we'll try to diagnostically predict whether a patient has diabetes by using the `Python` libraries `pandas` and `sklearn` . We will begin by reading the dataset [diabetes (https://www.kaggle.com/uciml/pima-indians-diabetes-database)](https://www.kaggle.com/uciml/pima-indians-diabetes-database) from Kaggle.

This activity is designed to help you apply the machine learning algorithms you have learned using the packages in `Python` . `Python` concepts, instructions, and starter code are embedded within this Jupyter Notebook to help guide you as you progress through the activity. Remember to run the code of each code cell prior to submitting the assignment. Upon completing the activity, we encourage you to compare your work against the solution file to perform a self-assessment.

Logistic Regression and Support Vector Machines

Logistic regression is a powerful fundamental machine learning method used for classification, but it built on a regression framework.

Support vector machines (SVMs) are supervised learning models with associated learning algorithms that analyze data for classification and regression analysis.

Importing the Dataset and Exploratory Data Analysis (EDA)

We begin by using the library `pandas` to import the dataset. To do so, we import `pandas` first and read the file using the `.read_csv()` function by passing the name of the dataset we want to read as a string.

In [1]:
```python
import pandas as pd #import the library


df = pd.read_csv("diabetes.csv") #read the dataset
```

Before performing any algorithm on the dataframe, it's always good practice to perform exploratory data analysis.

We begin by visualizing the first ten rows of the dataframe `df` using the function `.head()`. By default, `.head()` displays the first five rows of a dataframe.

Complete the code cell below by passing the desired number of rows to the function `.head()` as an integer.

In [2]:
```
df.head(10)

#df.head( )
```

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctic
0	6	148	72	35	0	33.6	0.62
1	1	85	66	29	0	26.6	0.35
2	8	183	64	0	0	23.3	0.67
3	1	89	66	23	94	28.1	0.16
4	0	137	40	35	168	43.1	2.28
5	5	116	74	0	0	25.6	0.20
6	3	78	50	32	88	31.0	0.24
7	10	115	0	0	0	35.3	0.13
8	2	197	70	45	543	30.5	0.15
9	8	125	96	0	0	0.0	0.23

Next, we retrieve some more information about our dataframe by using the properties `.shape` and `columns` and the function `.describe()`.

Here's a brief description of what each of the above functions do:

- `.shape` : Returns a tuple representing the dimensionality of the dataframe;
- `.columns` : Returns the column labels of the dataframe;
- `describe()` : Returns a statistical summary of the dataframe.

Run the cells below to get information aboout the dataframe.

In [3]:
```
df.shape
```

Out[3]: (768, 9)

In [4]:
```
df.columns
```

Out[4]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', '
Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

In [5]:
```
df.describe()
```

Out[5]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabe
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

Understanding the Problem

Before we start setting up the problem in `Python` using logistic regression and SVMs, it is fundamental to understand which variable we're trying to predict and why the approach we are planning on using may work.

- **Observe the dataframe `df` above. Which variable would you like to predict for this problem?**

YOUR ANSWER HERE: Outcome

Understanding which variable we are trying to predict is important as we need to split our dataframe `df` into `X` and `y` dataframes. The `X` dataframe will contain all the variables in `df` that will be used to make the prediction; `y` will contain the dependent variable, in this case `Outcome` .

Run the code cell below to create our `X` dataframe and to visualize the first five rows using the command `head()` .

In [6]:
```
X = df.iloc[:, :-1] #select all the columns in df except the last one

X.head() #visualize the first 5 rows
```

Out[6]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctic
0	6	148	72	35	0	33.6	0.62
1	1	85	66	29	0	26.6	0.35
2	8	183	64	0	0	23.3	0.67
3	1	89	66	23	94	28.1	0.16
4	0	137	40	35	168	43.1	2.28

Next, we need to separate the `Outcome` from our original dataframe `df`. In the code cell below, fill in the ellipsis with the name of our target variable.

In [7]:
```
y = df["Outcome"] # select only the last column in df
```

In the code cells below, use the function `head()` to visualize the first five rows of `y`.

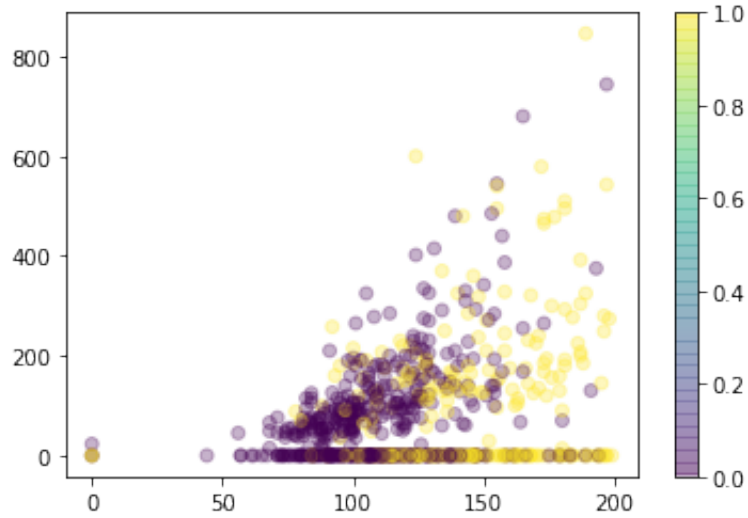
In [8]:
```
y.head()
```

Out[8]:
```
0    1
1    0
2    1
3    0
4    1
Name: Outcome, dtype: int64
```

Single Feature Visualization

One of the more powerful aspects of machine learning, is that predictions can be made based on *many* features. That makes it difficult to fully visualize the model that is built. However, it is still good practice and can be helpful to explore lower dimensional dependencies. Here we plot our output as a function of just two features. You can experiment with changing the horizontal and vertical axes to be other features.

In [9]:
```python
import matplotlib.pyplot as plt
plt.scatter(df["Glucose"],df["Insulin"], c=y, alpha=0.3, cmap='viridis')
plt.colorbar();  # show color scale
```



Splitting the Data Into Training and Testing Set

As we have seen in Video 3 for this week, it is important to split the data into *training* and *testing* sets.

As a reminder, the training set is the portion of the original dataset that we use to train the model. The model sees and learns from this data.

The testing dataset is the sample of data used to provide an unbiased evaluation of a final model fit on the training dataset. It is only used once a model is completely trained.

To split the data into and training a testing datasets we can use the function [`train_test_split` (https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html)](https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html) from `sklearn`. This function splits arrays or matrices into random train and test subsets and returns a list containing train-test split of inputs.

As we observe, in our case, the function `train_test_split` takes four arguments:

- `X` : Input dataframe
- `y` : Outpur dataframe
- `test_size` : Should be between 0.0 and 1.0 and represent the proportion of the dataset to include in the test split
- `random_state` : Controls the shuffling applied to the data before applying the split. Ensures the reproducibility of the results across multiple function calls

In the code cell below, fill in the ellipsis to set the argument `test_size` equal to `0.25` and `random_state` equal to `0`.

In [10]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size= 0
.25, random_state= 0)
```

Setting up the Classifiers

The last step involves initializing the classifiers and running the algorithm.

In the code cell below, we've imported the classifiers [LogisticRegression (https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html)](https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html) and [SVC (https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html?highlight=svc#sklearn.svm.SVC)](https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html?highlight=svc#sklearn.svm.SVC) from `sklearn`.

Run the code cell below.

In [11]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
```

In [12]:
```
names = ["Logistic Regression", "Linear SVM"]

classifiers = [
    LogisticRegression(),
    SVC(kernel="linear")]
```

In the code cell below, we instantiate the `LogisticRegression` classifier and we fit it to our training sets.

Run the code cell below.

In [13]:
```
log_clf = LogisticRegression(max_iter = 150).fit(X_train, y_train)
log_clf.score(X_train, y_train)
```

Out[13]: 0.7604166666666666

In the code cell below, fill in the ellipsis with the name of the classifier we have imported for SVM.

Compute the score by running the code cell below.

In [14]:
```
svm_clf = SVC(random_state=0).fit(X_train, y_train)
svm_clf.score(X_train, y_train)
```

Out[14]: 0.7586805555555556

- **Which model performs better?**

YOUR ANSWER HERE: LR

Testing the Models

Now, it is time to test our model on the testing sets.

In the code cell below, we have used the function `predict()` without the logistic regression classifier `log_clf` to make a prediction on the `y` testing set.

Run the code cell below.

In [15]:
```
y_eval_lr = log_clf.predict(X_test)
```

Next, we want to compute the accuracy for this model.

In [16]:
```
acc = sum(y_eval_lr == y_test) / float(len(y_test))
print("Accuracy: %.2f%%" % (100*acc))
```

```
Accuracy: 80.21%
```

Finally, we are interested in looking at the accuracy of the SVMs model. In the code cell below, compute the prediction on the testing set (y_eval_svm) by following the code above.

In [17]:
```
y_eval_svm = svm_clf.predict(X_test)
```

Run the code cell below to compute the acuracy for this model.

In [18]:
```
acc = sum(y_eval_svm == y_test) / float(len(y_test))
print("Accuracy: %.2f%%" % (100*acc))
```

```
Accuracy: 77.08%
```

- **Which model is more accurate?**

YOUR ANSWER HERE: LR

In [ ]:
```

```