Diabetes and Machine Learning via Python

The economic burden of diabetes is astronomical. Diabetes cost the United States over 176 billion dollars in 2012. In 2017, costs exceeded 327 billion (including 237 billion for direct medical costs and an additional 90 billion for reduced productivity).

Given this, I was interested in exploring some different machine learning models on a diabetes dataset that I've also posted as well (diab.csv).

Sources: https://care.diabetesjournals.org/content/early/2018/03/20/dci18-0007 (https://care.diabetesjournals.org/content/early/2018/03/20/dci18-0007)
https://care.diabetesjournals.org/content/41/5/929 (https://care.diabetesjournals.org/content/41/5/929)

To run these models, please make sure to install matplotlib, pandas, and numpy. I also recommend using the interface "anaconda" after installing python.

Links are below for more information.

Helpful link for writing code via python using jupyter notebook:
https://jupyter.readthedocs.io/en/latest/install.html (https://jupyter.readthedocs.io/en/latest/install.html)

Installing python/ anaconda on windows: https://problemsolvingwithpython.com/01-Orientation/01.03-Installing-Anaconda-on-Windows/ (https://problemsolvingwithpython.com/01-Orientation/01.03-Installing-Anaconda-on-Windows/)

I recommend googling how to install "pandas" into anaconda and doing the same for "matplotlib" and "numpy"

So much of running a good model is trouble shooting and making sure all libraries (for example, pandas is a library) is installed before / during running the model.

I'm more than happy to provide more details upon request.

In [1]:

```
import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd
import numpy as np
import seaborn as sns
```

In [2]:

```
diab = pd.read_csv('diab.csv')
print(diab.columns)
diab.head()
```

```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insuli
n',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

Out[2]:

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

In [3]:

```
print("diabetes data dimension: {}". format(diab.shape))
```

```
diabetes data dimension: (768, 9)
```

In [4]:

```
diab.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

In [5]:

```
print(diab.groupby('Outcome').size())
```

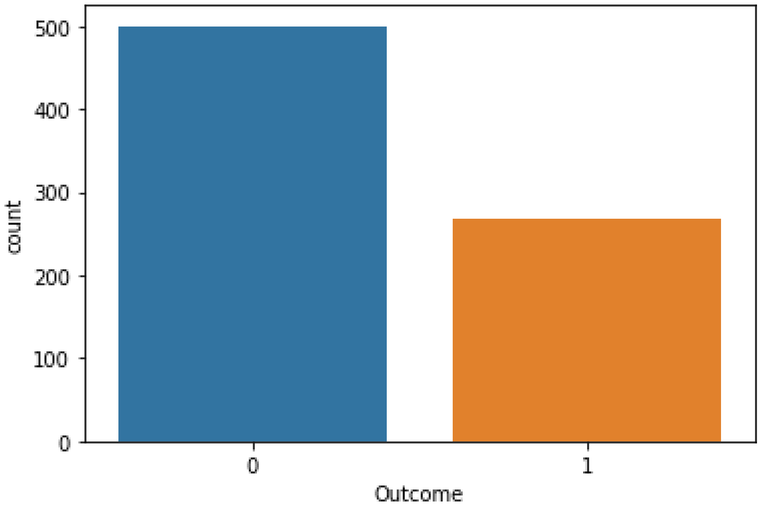
```
Outcome
0    500
1    268
dtype: int64
```

In [6]:

```
sns.countplot(diab['Outcome'],label="Count")
```

Out[6]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x19929f57fc8>
```



In [7]:

```
diab.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

Main takeaway: This model shows a ~72% test accuracy.

K-NEAREST NEIGHBORS

Most think of this as one of the simplest models to use for predictive analytics.

In this simplicity, there are some decided advantages.

Mainly: No assumptions required No training step required Can be used for both regression and classification Simple and intuitive

Methodology: k-Nearest Neighbors works by literally finding its "nearest neighbors" ... it's a simple algorithm that finds the closest data points in the training datatset. In finding it's nearest neighbor it can make a prediction about a future data point.

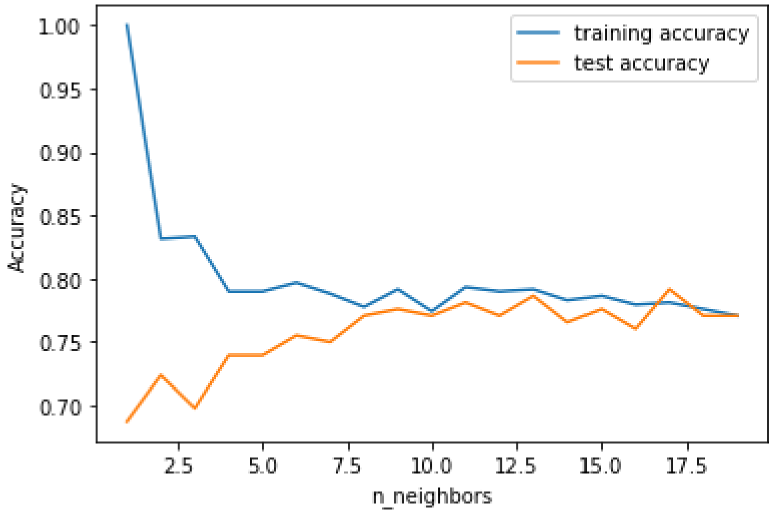
Although this is the simplest model, it takes a bit of time for it to become intuitive and that is okay.

In [8]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(diab.loc[:, diab.columns != 'Outcom
e'], diab['Outcome'], stratify=diab['Outcome'], random_state=66)
```

In [9]:

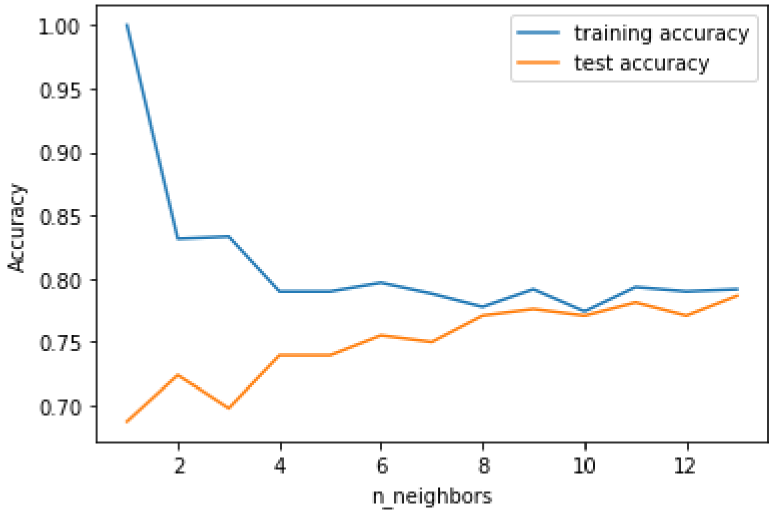
```
from sklearn.neighbors import KNeighborsClassifier

training_accuracy = []
test_accuracy = []
# I start by setting my range... in this case I will try setting the range n_neighbors
 from 1 to 19
# You can always go back and adjust your range
neighbors_settings = range(1, 20)

for n_neighbors in neighbors_settings:
    # first - we will build the model
    knn = KNeighborsClassifier(n_neighbors=n_neighbors)
    knn.fit(X_train, y_train)
    # secondly - we will record training set accuracy
    training_accuracy.append(knn.score(X_train, y_train))
    # finally - we will record test set accuracy
    test_accuracy.append(knn.score(X_test, y_test))

plt.plot(neighbors_settings, training_accuracy, label="training accuracy")
plt.plot(neighbors_settings, test_accuracy, label="test accuracy")
plt.ylabel("Accuracy")
plt.xlabel("n_neighbors")
plt.legend()
plt.savefig('knn_compare_model')
```



Based on the above graph we see the nearest neighbor point looks to be somewhere in between 7.5 and 10. To see this graph in more detail, I am going to adjust our training range so that I can find the value between 7.5 and 10 that is most appropriate for our nearest neighbor analysis.

In [10]:

```
from sklearn.neighbors import KNeighborsClassifier

training_accuracy = []
test_accuracy = []
# I start by setting my range... in this case I will try setting the range n_neighbors
 from 2 to 15
# You can always go back and adjust your range
neighbors_settings = range(1, 14)

for n_neighbors in neighbors_settings:
    # first - we will build the model
    knn = KNeighborsClassifier(n_neighbors=n_neighbors)
    knn.fit(X_train, y_train)
    # secondly - we will record training set accuracy
    training_accuracy.append(knn.score(X_train, y_train))
    # finally - we will record test set accuracy
    test_accuracy.append(knn.score(X_test, y_test))

plt.plot(neighbors_settings, training_accuracy, label="training accuracy")
plt.plot(neighbors_settings, test_accuracy, label="test accuracy")
plt.ylabel("Accuracy")
plt.xlabel("n_neighbors")
plt.legend()
plt.savefig('knn_compare_model')
```



Based on the above, the best points to use would be somewhere around 9.

In [11]:

```
knn = KNeighborsClassifier(n_neighbors=9)
knn.fit(X_train, y_train)

print('Accuracy of K-NN classifier on training set: {:.2f}'.format(knn.score(X_train, y
_train)))
print('Accuracy of K-NN classifier on test set: {:.2f}'.format(knn.score(X_test, y_test
)))
```

```
Accuracy of K-NN classifier on training set: 0.79
Accuracy of K-NN classifier on test set: 0.78
```

LOGISTIC REGREESION

Logistic regression, a classification algorithm, is one of the most common models to use.

Some of its advantages include:

Go to method for binary outcomes. A great example is looking at people with diabetes and those without.

So basically any "yes or no" answer for whether or not someone has a disease... testing logistic regression models can be useful and probably a good place to start.

In [12]:

```
from sklearn import preprocessing
import numpy as np
from sklearn.linear_model import LogisticRegression

logreg = LogisticRegression().fit(X_train, y_train)
print("Training set accuracy: {:.3f}".format(logreg.score(X_train, y_train)))
print("Test set accuracy: {:.3f}".format(logreg.score(X_test, y_test)))
```

```
Training set accuracy: 0.786
Test set accuracy: 0.771

C:\Users\Tiffany Taylor\newfolder\lib\site-packages\sklearn\linear_model\_
logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-reg
ression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

In [13]:

```
logreg001 = LogisticRegression(C=0.01).fit(X_train, y_train)
print("Training set accuracy: {:.3f}".format(logreg001.score(X_train, y_train)))
print("Test set accuracy: {:.3f}".format(logreg001.score(X_test, y_test)))
```

```
Training set accuracy: 0.762
Test set accuracy: 0.760

C:\Users\Tiffany Taylor\newfolder\lib\site-packages\sklearn\linear_model\_
logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-reg
ression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

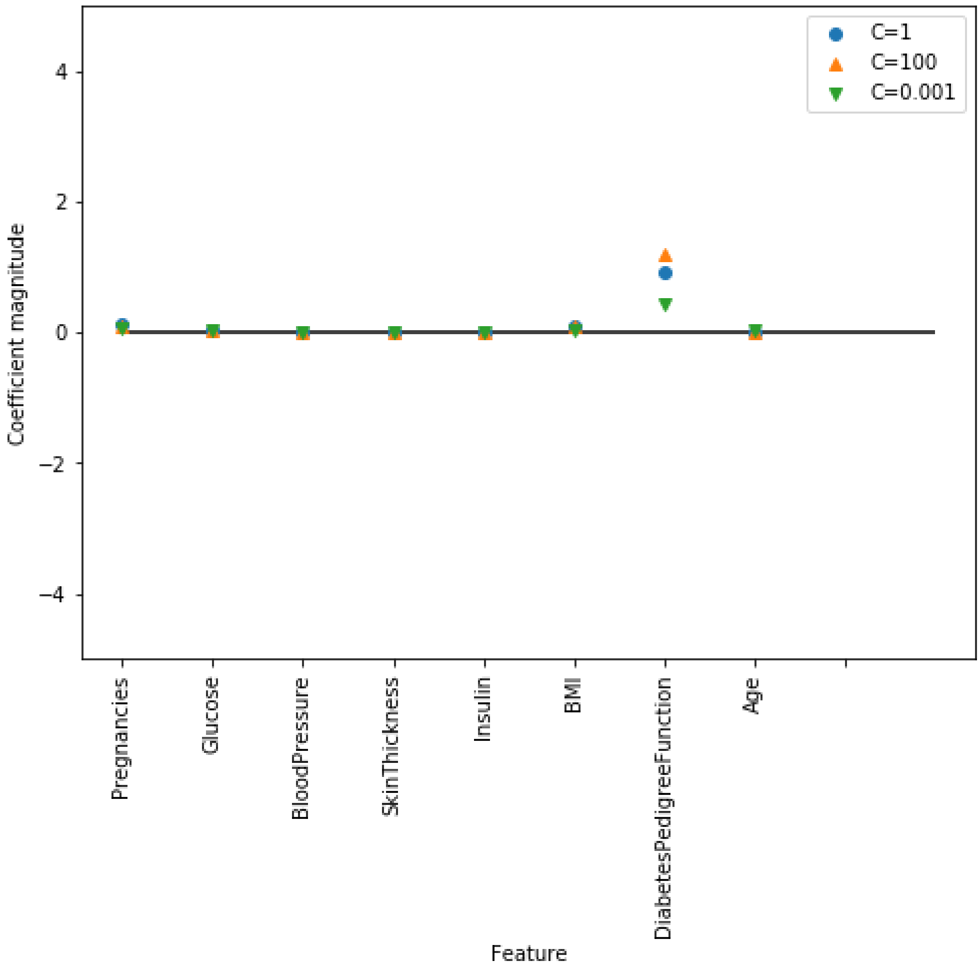
In [14]:

```
logreg100 = LogisticRegression(C=100).fit(X_train, y_train)
print("Training set accuracy: {:.3f}".format(logreg100.score(X_train, y_train)))
print("Test set accuracy: {:.3f}".format(logreg100.score(X_test, y_test)))
```

```
Training set accuracy: 0.783
Test set accuracy: 0.781

C:\Users\Tiffany Taylor\newfolder\lib\site-packages\sklearn\linear_model\_
logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-reg
ression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

In [15]:

```
diab_features = [x for i,x in enumerate(diab.columns) if i!=8]

plt.figure(figsize=(8,6))
plt.plot(logreg.coef_.T, 'o', label="C=1")
plt.plot(logreg100.coef_.T, '^', label="C=100")
plt.plot(logreg001.coef_.T, 'v', label="C=0.001")
plt.xticks(range(diab.shape[1]), diab_features, rotation=90)
plt.hlines(0, 0, diab.shape[1])
plt.ylim(-5, 5)
plt.xlabel("Feature")
plt.ylabel("Coefficient magnitude")
plt.legend()
plt.savefig('log_coef')
```



DECISION TREE

In [16]:

```
from sklearn.tree import DecisionTreeClassifier

tree = DecisionTreeClassifier(random_state=0)
tree.fit(X_train, y_train)
print("Accuracy on training set: {:.4f}".format(tree.score(X_train, y_train)))
print("Accuracy on test set: {:.4f}".format(tree.score(X_test, y_test)))
```

```
Accuracy on training set: 1.0000
Accuracy on test set: 0.7135
```

In [17]:

```
tree = DecisionTreeClassifier(max_depth=3, random_state=0)
tree.fit(X_train, y_train)

print("Accuracy on training set: {:.4f}".format(tree.score(X_train, y_train)))
print("Accuracy on test set: {:.4f}".format(tree.score(X_test, y_test)))
```

```
Accuracy on training set: 0.7726
Accuracy on test set: 0.7396
```

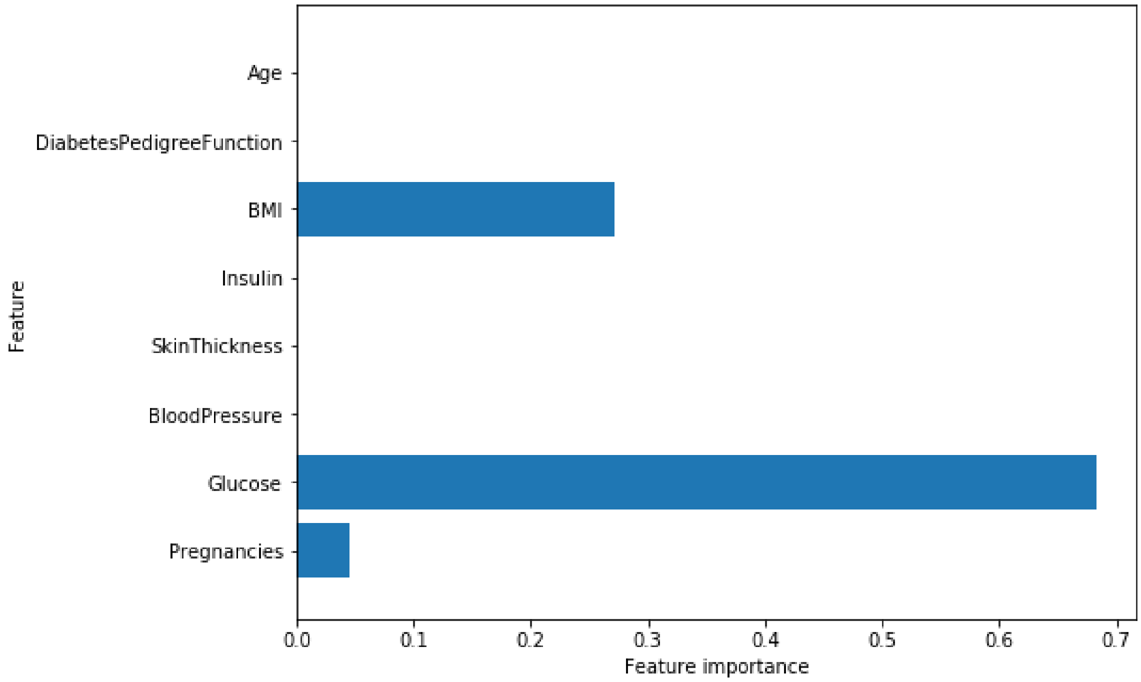
In [18]:

```
print("Feature importances:\n{}".format(tree.feature_importances_))
```

```
Feature importances:
[0.04554275 0.6830362  0.         0.         0.         0.27142106
 0.         0.        ]
```

In [19]:

```
def plot_feature_importances_diab(model):
    plt.figure(figsize=(8,6))
    n_features = 8
    plt.barh(range(n_features), model.feature_importances_, align='center')
    plt.yticks(np.arange(n_features), diab_features)
    plt.xlabel("Feature importance")
    plt.ylabel("Feature")
    plt.ylim(-1, n_features)

plot_feature_importances_diab(tree)
plt.savefig('feature_importance')
```



SVM: SUPPORT VECTOR MACHINES

I am going to start off this analysis with SVM.

One of SVM's noted advantages is that it works well when there is a clear separtion of classes. It's also a great starting place when working with unfamiliar data sets, especially semi structured data and unstructured data such as text, images, decision trees etc.,

In [20]:

```
from sklearn.svm import SVC

svc = SVC()
svc.fit(X_train, y_train)

print("Accuracy on training set: {:.2f}".format(svc.score(X_train, y_train)))
print("Accuracy on test set: {:.2f}".format(svc.score(X_test, y_test)))
```

```
Accuracy on training set: 0.77
Accuracy on test set: 0.76
```

In [21]:

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.fit_transform(X_test)

svc = SVC()
svc.fit(X_train_scaled, y_train)

print("Accuracy on training set: {:.2f}".format(svc.score(X_train_scaled, y_train)))
print("Accuracy on test set: {:.2f}".format(svc.score(X_test_scaled, y_test)))
```

```
Accuracy on training set: 0.79
Accuracy on test set: 0.80
```

In [22]:

```
svc = SVC(C=1000)
svc.fit(X_train_scaled, y_train)

print("Accuracy on training set: {:.3f}".format(
    svc.score(X_train_scaled, y_train)))
print("Accuracy on test set: {:.3f}".format(svc.score(X_test_scaled, y_test)))
```

```
Accuracy on training set: 0.944
Accuracy on test set: 0.724
```

In [ ]:

```

```