In [1]:
```
# Question 1 - Import and Explore Data
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
from sklearn import metrics, linear_model, svm
from sklearn.model_selection import train_test_split

os.chdir('C:\\Users\\micha\\Documents\\DAAN862')

df = pd.read_csv('breastcancer.csv')
display(df)
```

	Age	BMI	Glucose	Insulin	HOMA	Leptin	Adiponectin	Resistin	MCP.1	Cl
0	48	23.500000	70	2.707	0.467409	8.8071	9.702400	7.99585	417.114	
1	83	20.690495	92	3.115	0.706897	8.8438	5.429285	4.06405	468.786	
2	82	23.124670	91	4.498	1.009651	17.9393	22.432040	9.27715	554.697	
3	68	21.367521	77	3.226	0.612725	9.8827	7.169560	12.76600	928.220	
4	86	21.111111	92	3.549	0.805386	6.6994	4.819240	10.57635	773.920	
...	...	...	...	...	...	...	...	...	...	
111	45	26.850000	92	3.330	0.755688	54.6800	12.100000	10.96000	268.230	
112	62	26.840000	100	4.530	1.117400	12.4500	21.420000	7.32000	330.160	
113	65	32.050000	97	5.730	1.370998	61.4800	22.540000	10.33000	314.050	
114	72	25.590000	82	2.820	0.570392	24.9600	33.750000	3.27000	392.460	
115	86	27.180000	138	19.910	6.777364	90.2800	14.110000	4.35000	90.090	

116 rows × 10 columns

In [2]:
```
# Question 1 Cont - Explore data
display(df.describe())
display(df.corr())
```

	Age	BMI	Glucose	Insulin	HOMA	Leptin	Adiponectin
count	116.000000	116.000000	116.000000	116.000000	116.000000	116.000000	116.000000
mean	57.301724	27.582111	97.793103	10.012086	2.694988	26.615080	10.180874
std	16.112766	5.020136	22.525162	10.067768	3.642043	19.183294	6.843341
min	24.000000	18.370000	60.000000	2.432000	0.467409	4.311000	1.656020
25%	45.000000	22.973205	85.750000	4.359250	0.917966	12.313675	5.474283
50%	56.000000	27.662416	92.000000	5.924500	1.380939	20.271000	8.352692
75%	71.000000	31.241442	102.000000	11.189250	2.857787	37.378300	11.815970
max	89.000000	38.578759	201.000000	58.460000	25.050342	90.280000	38.040000

	Age	BMI	Glucose	Insulin	HOMA	Leptin	Adiponectin
Age	1.000000	0.008530	0.230106	0.032495	0.127033	0.102626	-0.219813
BMI	0.008530	1.000000	0.138845	0.145295	0.114480	0.569593	-0.302735
Glucose	0.230106	0.138845	1.000000	0.504653	0.696212	0.305080	-0.122121
Insulin	0.032495	0.145295	0.504653	1.000000	0.932198	0.301462	-0.031296
HOMA	0.127033	0.114480	0.696212	0.932198	1.000000	0.327210	-0.056337
Leptin	0.102626	0.569593	0.305080	0.301462	0.327210	1.000000	-0.095389
Adiponectin	-0.219813	-0.302735	-0.122121	-0.031296	-0.056337	-0.095389	1.000000
Resistin	0.002742	0.195350	0.291327	0.146731	0.231101	0.256234	-0.252363
MCP.1	0.013462	0.224038	0.264879	0.174356	0.259529	0.014009	-0.200694
Classification	-0.043555	-0.132586	0.384315	0.276804	0.284012	-0.001078	-0.019490

In [3]:
```
# Question 2 - Build and Evaluate SVM Models

# Start with splitting data
X = df.iloc[:, 0:9]
y = df.Classification

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
```

In [4]:
```
# Start with Linear SVM
svm_linear = svm.SVC(kernel='linear')
svm_linear.fit(X_train, y_train)
```

Out[4]:
```
▾ SVC
SVC(kernel='linear')
```

In [5]:
```
# Find coefs of SVM
print(svm_linear.coef0)

print(svm_linear.coef_)
```

```
0.0
[[-0.02584147 -0.08217591  0.10106202  0.11505145 -0.22113645 -0.01446274
  -0.02750599  0.0050329   0.0007635 ]]
```

In [6]:
```
# Get accuracy of Linear SVM
svm_linear_pred = svm_linear.predict(X_test)

metrics.accuracy_score(y_test, svm_linear_pred)
```

Out[6]: 0.7714285714285715

In [7]:
```
# Build rbf SVM
svm_rbf = svm.SVC(kernel='rbf', gamma=0.1)

svm_rbf.fit(X_train, y_train)
```

Out[7]:

▾ SVC

SVC(gamma=0.1)

In [8]:
```
# Evaluate
svm_rbf_pred = svm_rbf.predict(X_test)

metrics.accuracy_score(y_test, svm_rbf_pred)
```

Out[8]: 0.5142857142857142

In [9]:
```
# Build Poly SVM
svm_poly = svm.SVC(kernel='poly', degree=3)

svm_poly.fit(X_train, y_train)
```

Out[9]:

▾ SVC

SVC(kernel='poly')

In [10]:
```
# Evaluate
svm_poly_pred = svm_poly.predict(X_test)

metrics.accuracy_score(y_test, svm_poly_pred)

# We can see that betwen the three SVMs used, Linear provided the best accuracy
```

Out[10]: 0.5142857142857142

In [11]:
```
# Question 3 - Find the best n-estimator of RBF Model
from sklearn.ensemble import RandomForestClassifier

#Start by building and evaluting RBF with n=100
RF = RandomForestClassifier(n_estimators=100, random_state=42)

RF.fit(X_train, y_train)
```

Out[11]:
```
▾ RandomForestClassifier

RandomForestClassifier(random_state=42)
```

In [12]:
```
# Evaluate
RF_pred = RF.predict(X_test)

metrics.accuracy_score(y_test, RF_pred)
```

Out[12]: 0.7142857142857143

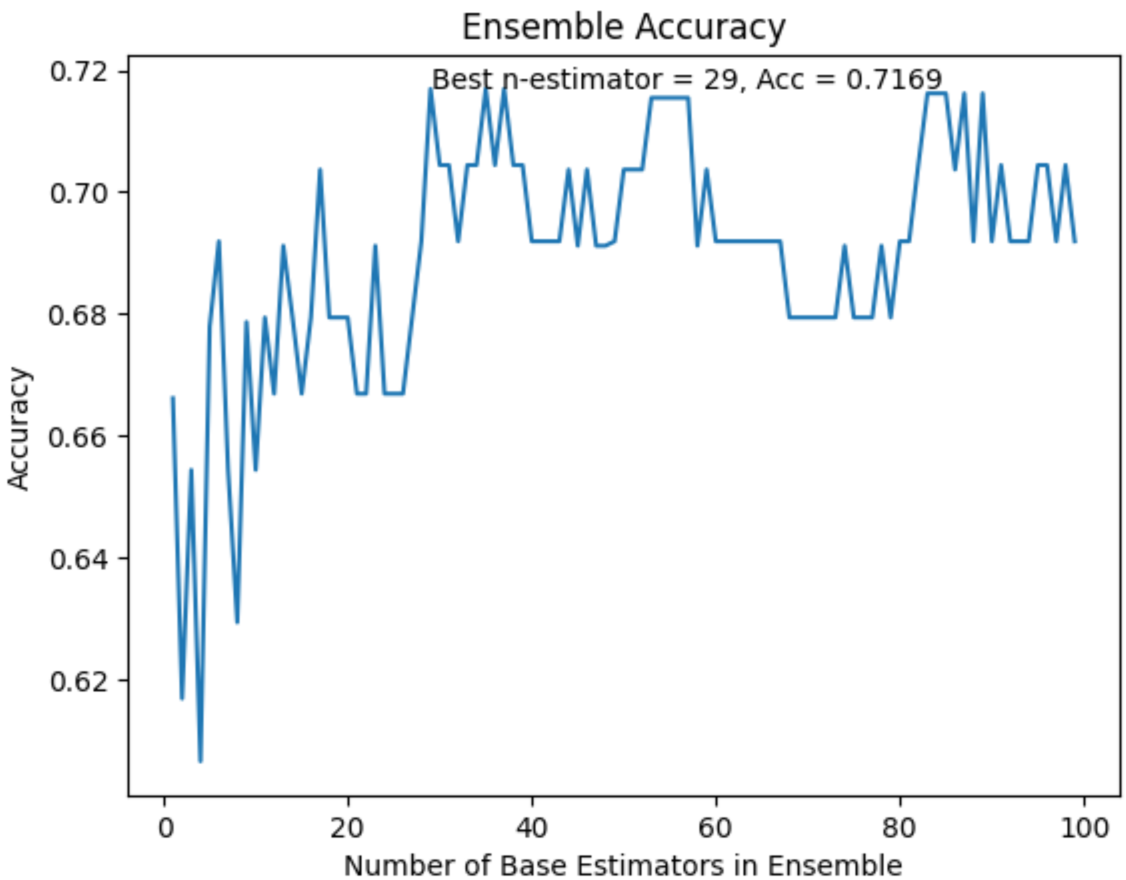
In [13]:
```
# Test to see which values have the most importance to model
pd.DataFrame({'feature':df.columns[0:9],
              'importance':RF.feature_importances_})
```

Out[13]:

	feature	importance
0	Age	0.167139
1	BMI	0.070999
2	Glucose	0.265373
3	Insulin	0.067388
4	HOMA	0.111275
5	Leptin	0.089793
6	Adiponectin	0.069396
7	Resistin	0.079909
8	MCP.1	0.078728

In [49]:
```
# One way of determing the best number of n-estimator is to
# loop through each value and analyze the performance
from sklearn.model_selection import cross_val_score

n_estimator = range(1, 100)

accuracy = []

for i in n_estimator:
    RF = RandomForestClassifier(n_estimators=i, random_state=10)
    scores = cross_val_score(RF, X_train, y_train)
    accuracy.append(scores.mean())
```

In [34]:
```
# We can plot each accuracy in relation to its n-value
plt.figure()
plt.plot(n_estimator, accuracy)
plt.title('Ensemble Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Number of Base Estimators in Ensemble')

ymax = max(accuracy)
xpos = accuracy.index(ymax)
xmax = n_estimator[xpos]
text = 'Best n-estimator = {:.0f}, Acc = {:.4f}'.format(xmax, ymax)
plt.annotate(text, xy=(xmax, ymax))

plt.show()

# As shown, n-estimators of 29 (along with a few other values) can
# give us the best accuracy
```



In [30]:
```
# Alternatively, we can implement GridSearchCV
from sklearn.model_selection import GridSearchCV

n_estimator_params = {'n_estimators':range(1, 100)}

RF_opt = GridSearchCV(RF, n_estimator_params)
```

In [31]:
```
RF_opt.fit(X_train, y_train)
```

Out[31]:
```
▸ GridSearchCV
▸ estimator: RandomForestClassifier
  ▸ RandomForestClassifier
```

In [32]:
```
# Get the best value from optimized model
RF_opt.best_params_

# It matches what we saw in our previous method
```

Out[32]:
```
{'n_estimators': 29}
```

In [36]:
```
# Re-evaluate the accuracy with the optimal param again.
RF_opt_pred = RF_opt.predict(X_test)

metrics.accuracy_score(y_test, RF_opt_pred)

# We went from an accuracy of 0.714 to 0.771 with optimized model
```

Out[36]: 0.7714285714285715

In [55]:
```
# Question 4 - Find the best n-estimator for Adaboost

# We can implement the same methods used in Question 3, this time we
# can start with GridSearchCV
from sklearn.ensemble import AdaBoostClassifier

# Some slight expiermentation was done with learning_rate here, too low of
# a value was initially given where all accuracies were the same independent
# of n_estimators
Ada = AdaBoostClassifier(n_estimators=50, learning_rate=0.5, random_state=42)

Ada_opt = GridSearchCV(Ada, n_estimator_params)
Ada_opt.fit(X_train, y_train)
```

Out[55]:

▸ **GridSearchCV**

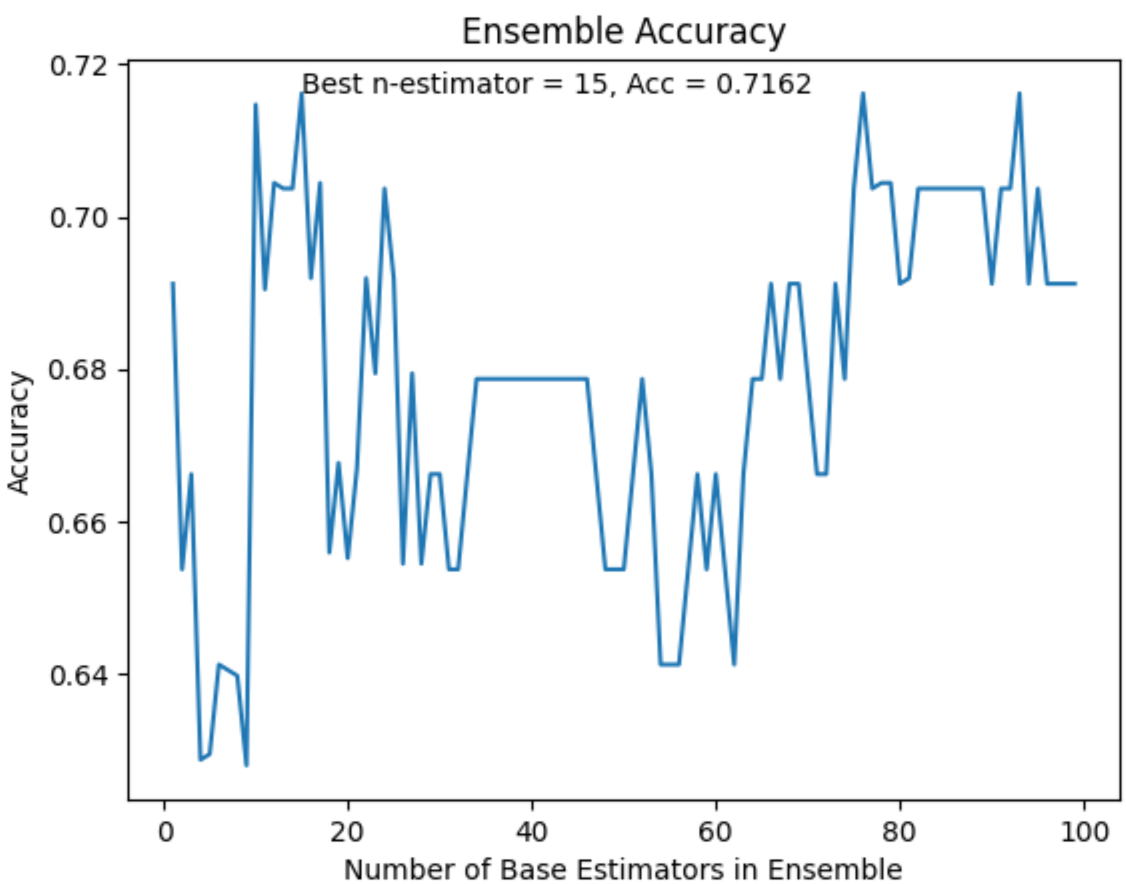
▸ **estimator: AdaBoostClassifier**

▸ AdaBoostClassifier

In [56]:
```
# Call the best param found
Ada_opt.best_params_

# 15 for n is noted as the best values
```

Out[56]: {'n_estimators': 15}

In [54]:
```
# We can verify the above results by using the same plot methodology as
# shown in Question 3

accuracy = []

for i in n_estimator:
    Ada_plot = AdaBoostClassifier(n_estimators=i, learning_rate=0.5, random_state=4
    scores = cross_val_score(Ada_plot, X_train, y_train)
    accuracy.append(scores.mean())

plt.figure()
plt.plot(n_estimator, accuracy)
plt.title('Ensemble Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Number of Base Estimators in Ensemble')

ymax = max(accuracy)
xpos = accuracy.index(ymax)
xmax = n_estimator[xpos]
text = 'Best n-estimator = {:.0f}, Acc = {:.4f}'.format(xmax, ymax)
plt.annotate(text, xy=(xmax, ymax))

plt.show()
```



In [ ]: