parth.pandey13103347@gmail.com_10_D

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1 Task-D: Collinear features and their effect on linear models

1.1 Imports

[344]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
from sklearn.datasets import load_iris
from sklearn.linear_model import SGDClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
from beautifultable  import BeautifulTable
```

1.2 Data Prep

[345]:
```
data = pd.read_csv('task_d.csv')
```

[346]:
```
data.head()
```

[346]:

	x	y	z	x*x	2*y	2*z+3*x*x	w	\
0	-0.581066	0.841837	-1.012978	-0.604025	0.841837	-0.665927	-0.536277	
1	-0.894309	-0.207835	-1.012978	-0.883052	-0.207835	-0.917054	-0.522364	
2	-1.207552	0.212034	-1.082312	-1.150918	0.212034	-1.166507	0.205738	
3	-1.364174	0.002099	-0.943643	-1.280666	0.002099	-1.266540	-0.665720	
4	-0.737687	1.051772	-1.012978	-0.744934	1.051772	-0.792746	-0.735054	

	target
0	0
1	0
2	0
3	0
4	0

[347]:
```
x_train = data.drop(['target'], axis=1).values
y_train = data['target'].values
```

1.3 Defining Objective

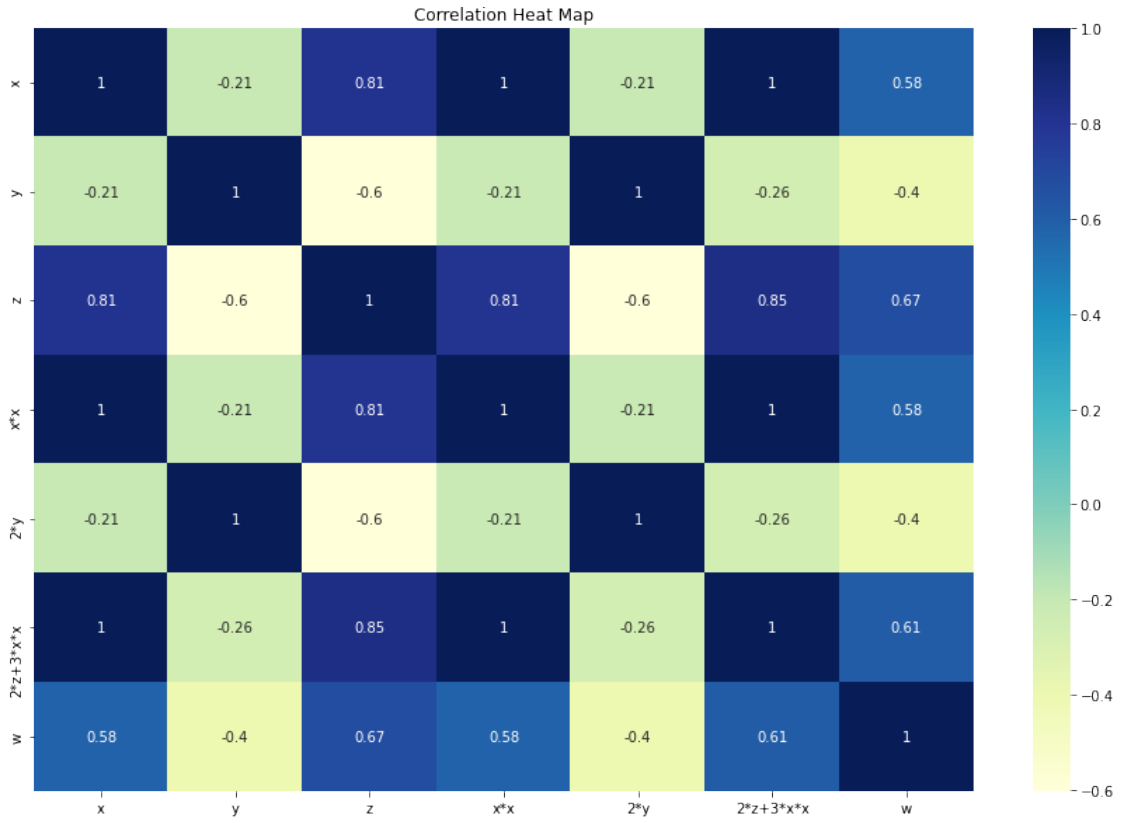
Doing perturbation test to check the presence of collinearity

Task: 1 Logistic Regression

1.3.1 Task 1 : Implementing Logistic Regression

A: Correlation Heat Map

[348]:
```
# Correlation
_, ax = plt.subplots(1,1,figsize=(15,10))
sns.heatmap(np.corrcoef(x_train.T), annot=True, ax=ax, cmap="YlGnBu",␣
 ↪xticklabels=data.columns[:-1].tolist(),
            yticklabels=data.columns[:-1].tolist())
ax.set_title('Correlation Heat Map')
plt.show()
```



B: Logistic Regression With Hyperparamenter Tuning

[349]:
```
clf = SGDClassifier(loss='log', random_state=42)
# chossing value in logspace
parameters = {'alpha':np.logspace(2,5,10,base=2,endpoint=True)}
# Since the task is of classfication and there are only two classes
grid = GridSearchCV(clf, parameters,scoring='accuracy',␣
↪cv=3,return_train_score=True,n_jobs=-1)
grid.fit(x_train,y_train)
# Converting the CV resutls into a dataframe for easy plotting
df = pd.DataFrame(grid.cv_results_)
```

[350]:
```
df.head()
```

[350]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	\
0	0.001623	0.000007	0.000528	0.000003	4	
1	0.001635	0.000006	0.000512	0.000008	5.03968	
2	0.002628	0.001426	0.000616	0.000131	6.3496	
3	0.002645	0.000425	0.000810	0.000006	8	
4	0.002365	0.000203	0.000754	0.000060	10.0794	

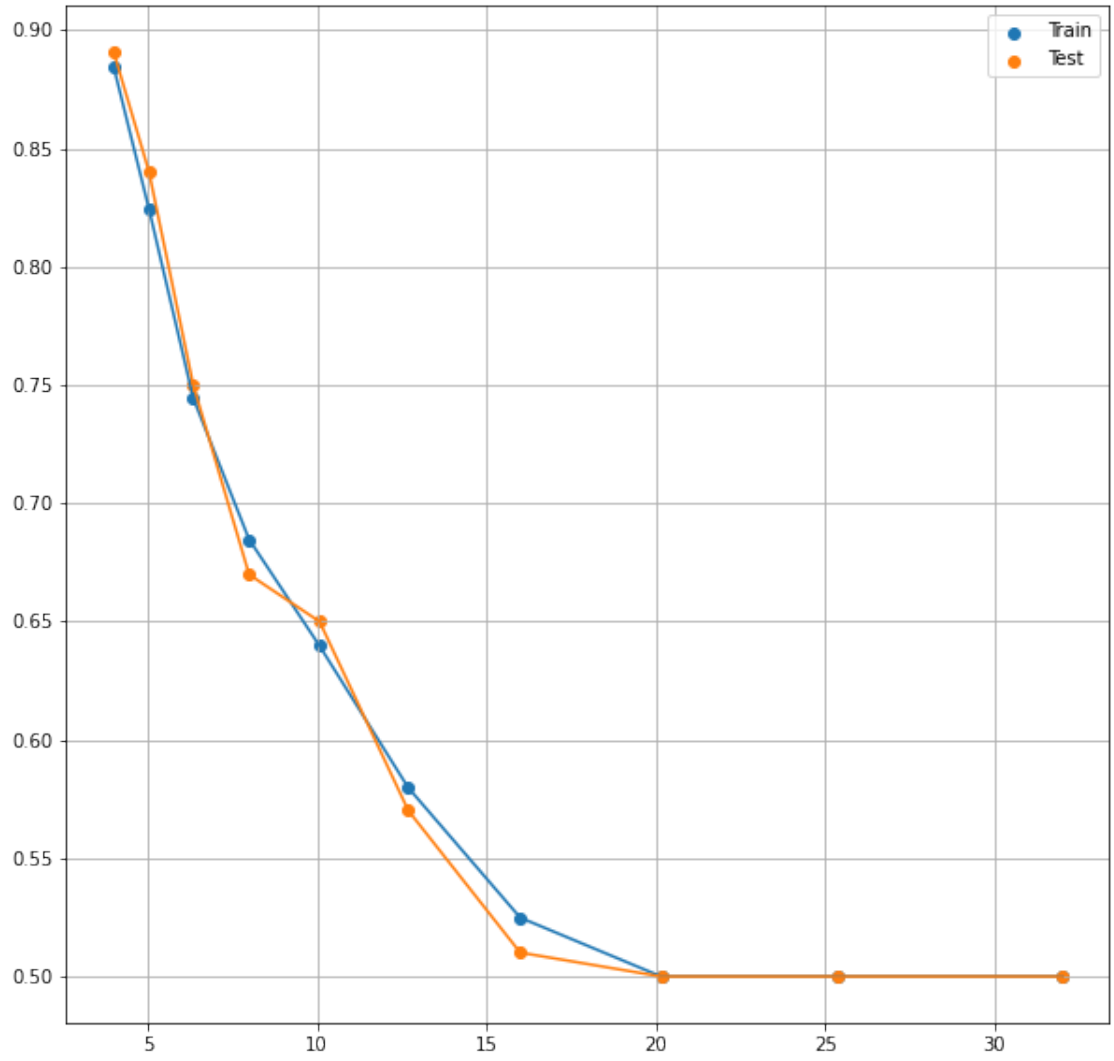
	params	split0_test_score	split1_test_score	\
0	{'alpha': 4.0}	0.794118	1.000000	
1	{'alpha': 5.039684199579493}	0.794118	0.939394	
2	{'alpha': 6.3496042078727974}	0.735294	0.848485	
3	{'alpha': 8.0}	0.676471	0.757576	
4	{'alpha': 10.079368399158984}	0.647059	0.727273	

	split2_test_score	mean_test_score	std_test_score	rank_test_score	\
0	0.878788	0.890969	0.084491	1	
1	0.787879	0.840463	0.070001	2	
2	0.666667	0.750149	0.074966	3	
3	0.575758	0.669935	0.074371	4	
4	0.575758	0.650030	0.061891	5	

	split0_train_score	split1_train_score	split2_train_score	\
0	0.833333	0.880597	0.940299	
1	0.772727	0.850746	0.850746	
2	0.651515	0.761194	0.820896	
3	0.636364	0.686567	0.731343	
4	0.590909	0.641791	0.686567	

	mean_train_score	std_train_score
0	0.884743	0.043767
1	0.824740	0.036779
2	0.744535	0.070145
3	0.684758	0.038796
4	0.639756	0.039079

[351]:
```
_,ax = plt.subplots(1,1,figsize=(10,10))
ax.plot(df['param_alpha'], df['mean_train_score'])
ax.scatter(df['param_alpha'], df['mean_train_score'],label='Train')
ax.plot(df['param_alpha'], df['mean_test_score'])
ax.scatter(df['param_alpha'], df['mean_test_score'], label='Test')
ax.legend()
ax.grid()
```



[352]:
```
best_alpha = df['param_alpha'].iloc[np.argmax(df['mean_test_score'])]
print('Best Alpha {}'.format(best_alpha))
```

```
Best Alpha 4.0
```

[353]:
```
best_model = SGDClassifier(loss='log',alpha=best_alpha, random_state=42)
model_weights = []
best_model.fit(x_train,y_train)
print(best_model.coef_[0])
y_pred = best_model.predict(x_train)
model_weights.append(best_model.coef_[0])
```

```
[ 0.0701358  -0.07022977  0.09765571  0.06907139 -0.07022977  0.07395507
  0.0619306 ]
```

[354]:
```
accuracy_list = []
accuracy = accuracy_score(y_train,y_pred )
accuracy_list.append(accuracy)
```

C: Logistic Regression And Hyperparameter Tuning on Noisy Data

[355]:
```
x_train = x_train + 5 * 10**-2
```

[356]:
```
clf = SGDClassifier(loss='log', random_state=42)
# Since the task is of classfication and there are only two classes
grid = GridSearchCV(clf, parameters,scoring='accuracy',␣
↪cv=3,return_train_score=True,n_jobs=-1)
grid.fit(x_train,y_train)
# Converting the CV resutls into a dataframe for easy plotting
df = pd.DataFrame(grid.cv_results_)
```

[357]:
```
df.head()
```

[357]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	\
0	0.001037	0.000232	0.000368	0.000060	4	
1	0.001159	0.000317	0.000355	0.000079	5.03968	
2	0.001337	0.000405	0.000441	0.000052	6.3496	
3	0.001451	0.000334	0.000470	0.000114	8	
4	0.001035	0.000129	0.000389	0.000069	10.0794	

	params	split0_test_score	split1_test_score	\
0	{'alpha': 4.0}	0.794118	1.000000	
1	{'alpha': 5.039684199579493}	0.794118	0.969697	
2	{'alpha': 6.3496042078727974}	0.764706	0.848485	
3	{'alpha': 8.0}	0.676471	0.757576	
4	{'alpha': 10.079368399158984}	0.647059	0.727273	

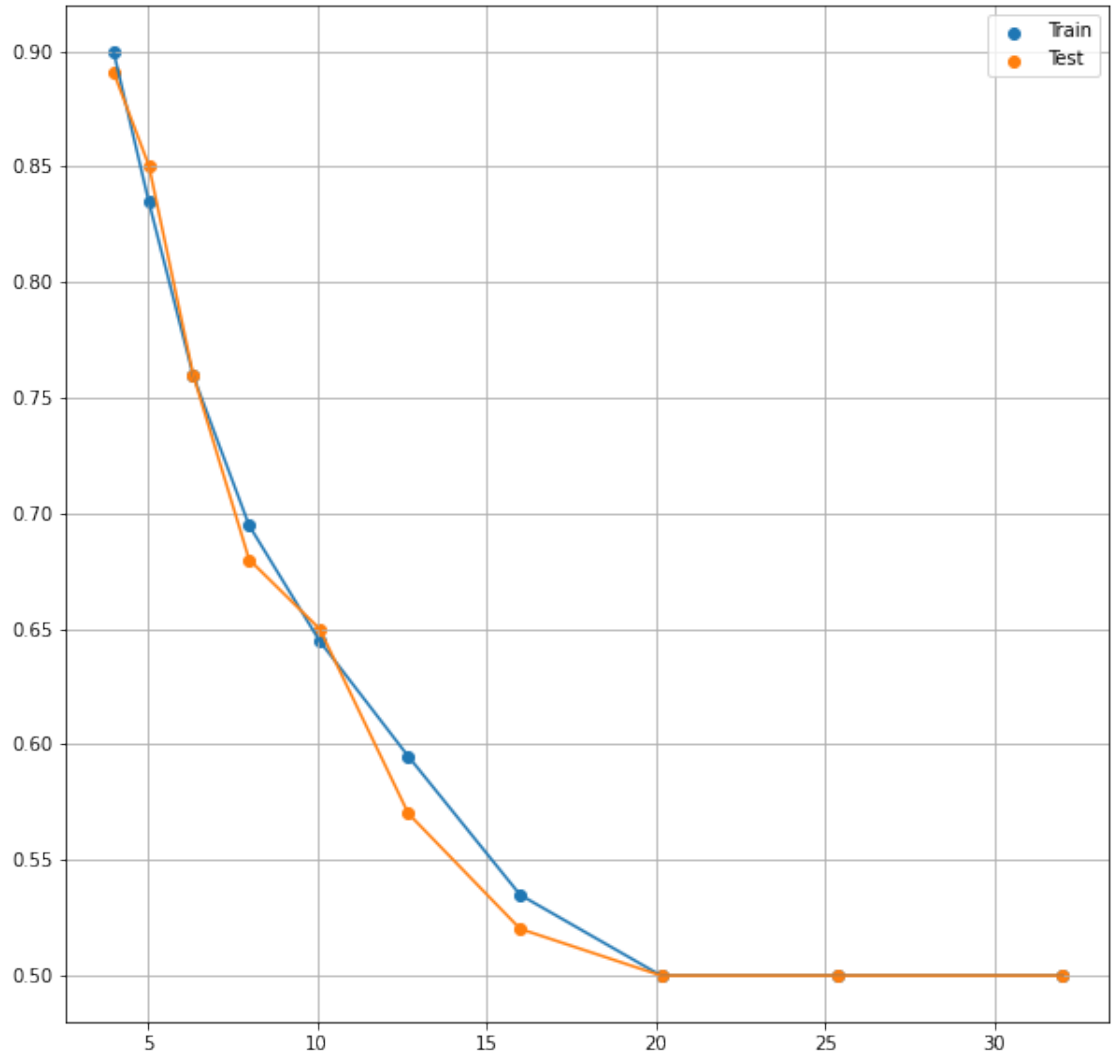
	split2_test_score	mean_test_score	std_test_score	rank_test_score	\
0	0.878788	0.890969	0.084491	1	
1	0.787879	0.850564	0.084278	2	
2	0.666667	0.759952	0.074303	3	
3	0.606061	0.680036	0.061907	4	

```
4           0.575758         0.650030        0.061891                5

   split0_train_score  split1_train_score  split2_train_score  \
0            0.863636            0.895522            0.940299
1            0.787879            0.865672            0.850746
2            0.681818            0.776119            0.820896
3            0.651515            0.701493            0.731343
4            0.606061            0.641791            0.686567

   mean_train_score  std_train_score
0          0.899819         0.031444
1          0.834766         0.033709
2          0.759611         0.057966
3          0.694784         0.032933
4          0.644806         0.032936
```

[358]:
```
_,ax = plt.subplots(1,1,figsize=(10,10))
ax.plot(df['param_alpha'], df['mean_train_score'])
ax.scatter(df['param_alpha'], df['mean_train_score'],label='Train')
ax.plot(df['param_alpha'], df['mean_test_score'])
ax.scatter(df['param_alpha'], df['mean_test_score'], label='Test')
ax.legend()
ax.grid()
```



[359]:
```
best_alpha = df['param_alpha'].iloc[np.
 ↪argmax(df[df['mean_test_score']<1]['mean_test_score'])]
print('Best Alpha {}'.format(best_alpha))
```

```
Best Alpha 4.0
```

[360]:
```
best_model = SGDClassifier(loss='log',alpha=best_alpha, random_state=42)
best_model.fit(x_train,y_train)
print(best_model.coef_[0])
y_pred = best_model.predict(x_train)
model_weights.append(best_model.coef_[0])
```

```
[ 0.06930855 -0.07125635  0.09677754  0.06824302 -0.07125635  0.07312498
  0.06103127]
```

[361]:
```
accuracy = accuracy_score(y_train, y_pred)
accuracy_list.append(accuracy)
```

1.3.2 Task 2 : Implementing Linear SVM

Do write the observations based on the results you get from the deviations of weights in both Logistic Regression and linear SVM

B: Linear SVM With Hyperparameter Tuning

[362]:
```
x_train = data.drop(['target'], axis=1).values
y_train = data['target'].values
```

[363]:
```
clf = SGDClassifier(loss='hinge', random_state=42)
# chossing value in logspace
parameters = {'alpha':np.logspace(2,5,10,base=2,endpoint=True)}
# Since the task is of classfication and there are only two classes
grid = GridSearchCV(clf, parameters,scoring='accuracy',␣
↪cv=7,return_train_score=True,n_jobs=-1)
grid.fit(x_train,y_train)
# Converting the CV resutls into a dataframe for easy plotting
df = pd.DataFrame(grid.cv_results_)
```

[364]:
```
df.head()
```

[364]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	\
0	0.001307	0.000399	0.000419	0.000088	4	
1	0.001313	0.000312	0.000414	0.000104	5.03968	
2	0.001439	0.000262	0.000481	0.000043	6.3496	
3	0.001251	0.000388	0.000378	0.000096	8	
4	0.001293	0.000330	0.000407	0.000093	10.0794	

	params	split0_test_score	split1_test_score	\
0	{'alpha': 4.0}	1.000000	1.000000	
1	{'alpha': 5.039684199579493}	1.000000	1.000000	
2	{'alpha': 6.3496042078727974}	0.933333	0.933333	
3	{'alpha': 8.0}	0.466667	0.666667	
4	{'alpha': 10.079368399158984}	0.466667	0.533333	

	split2_test_score	split3_test_score	…	rank_test_score	\
0	1.000000	1.000000	…	1	
1	1.000000	1.000000	…	2	
2	1.000000	1.000000	…	3	
3	0.785714	1.000000	…	4	
4	0.642857	0.928571	…	5	

	split0_train_score	split1_train_score	split2_train_score	\
0	0.988235	0.988235	0.965116	

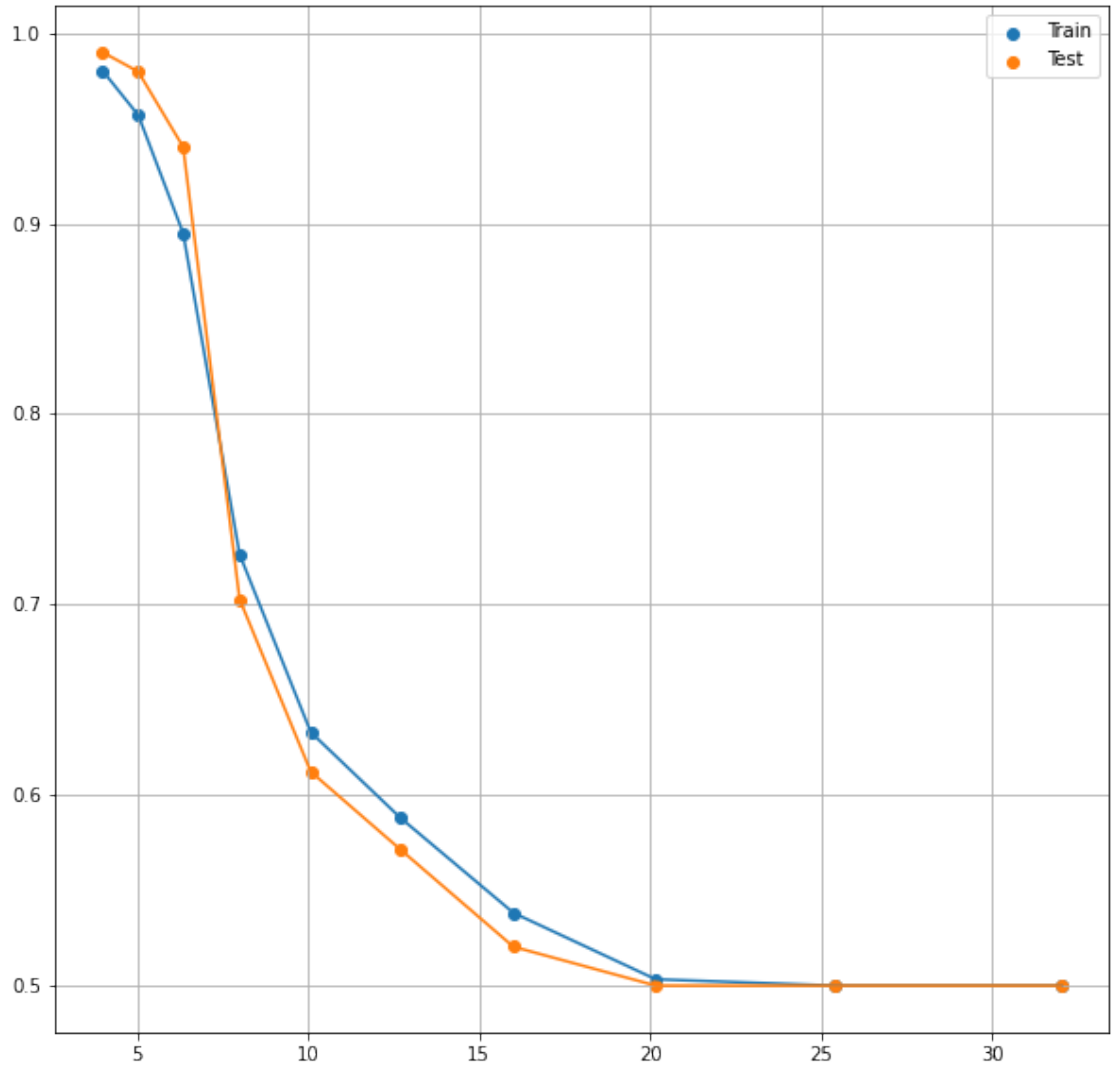
```
1            0.976471            0.988235            0.941860
2            0.835294            0.882353            0.895349
3            0.635294            0.588235            0.767442
4            0.529412            0.517647            0.686047

   split3_train_score  split4_train_score  split5_train_score  \
0            1.000000            0.965116            0.976744
1            0.941860            0.953488            0.941860
2            0.906977            0.918605            0.906977
3            0.720930            0.790698            0.779070
4            0.627907            0.697674            0.674419

   split6_train_score  mean_train_score  std_train_score
0            0.976744          0.980027         0.011952
1            0.953488          0.956752         0.017182
2            0.918605          0.894880         0.027061
3            0.802326          0.726285         0.077254
4            0.697674          0.632969         0.072661

[5 rows x 25 columns]
```

[365]:
```
_,ax = plt.subplots(1,1,figsize=(10,10))
ax.plot(df['param_alpha'], df['mean_train_score'])
ax.scatter(df['param_alpha'], df['mean_train_score'],label='Train')
ax.plot(df['param_alpha'], df['mean_test_score'])
ax.scatter(df['param_alpha'], df['mean_test_score'], label='Test')
ax.legend()
ax.grid()
```



[366]:
```
best_alpha = df['param_alpha'].iloc[np.argmax(df['mean_test_score'])]
print('Best Alpha {}'.format(best_alpha))
```

```
Best Alpha 4.0
```

[367]:
```
best_model = SGDClassifier(loss='hinge',alpha=best_alpha, random_state=42)
best_model.fit(x_train,y_train)
print(best_model.coef_[0])
y_pred = best_model.predict(x_train)
model_weights.append(best_model.coef_[0])
```

```
[ 0.11199595 -0.14155372  0.18549634  0.10759647 -0.14155372  0.1192332
  0.1097006 ]
```

[368]:
```
acccuracy = accuracy_score(y_train,y_pred )
accuracy_list.append(accuracy)
```

C: Linear Regression With Hyperparameter Tuning On Noisy Data

[369]:
```
x_train = x_train + 5 * 10**-2
```

[370]:
```
clf = SGDClassifier(loss='hinge', random_state=42)
# Since the task is of classfication and there are only two classes
grid = GridSearchCV(clf, parameters,scoring='accuracy',␣
 ↪cv=3,return_train_score=True,n_jobs=-1)
grid.fit(x_train,y_train)
# Converting the CV resutls into a dataframe for easy plotting
df = pd.DataFrame(grid.cv_results_)
```

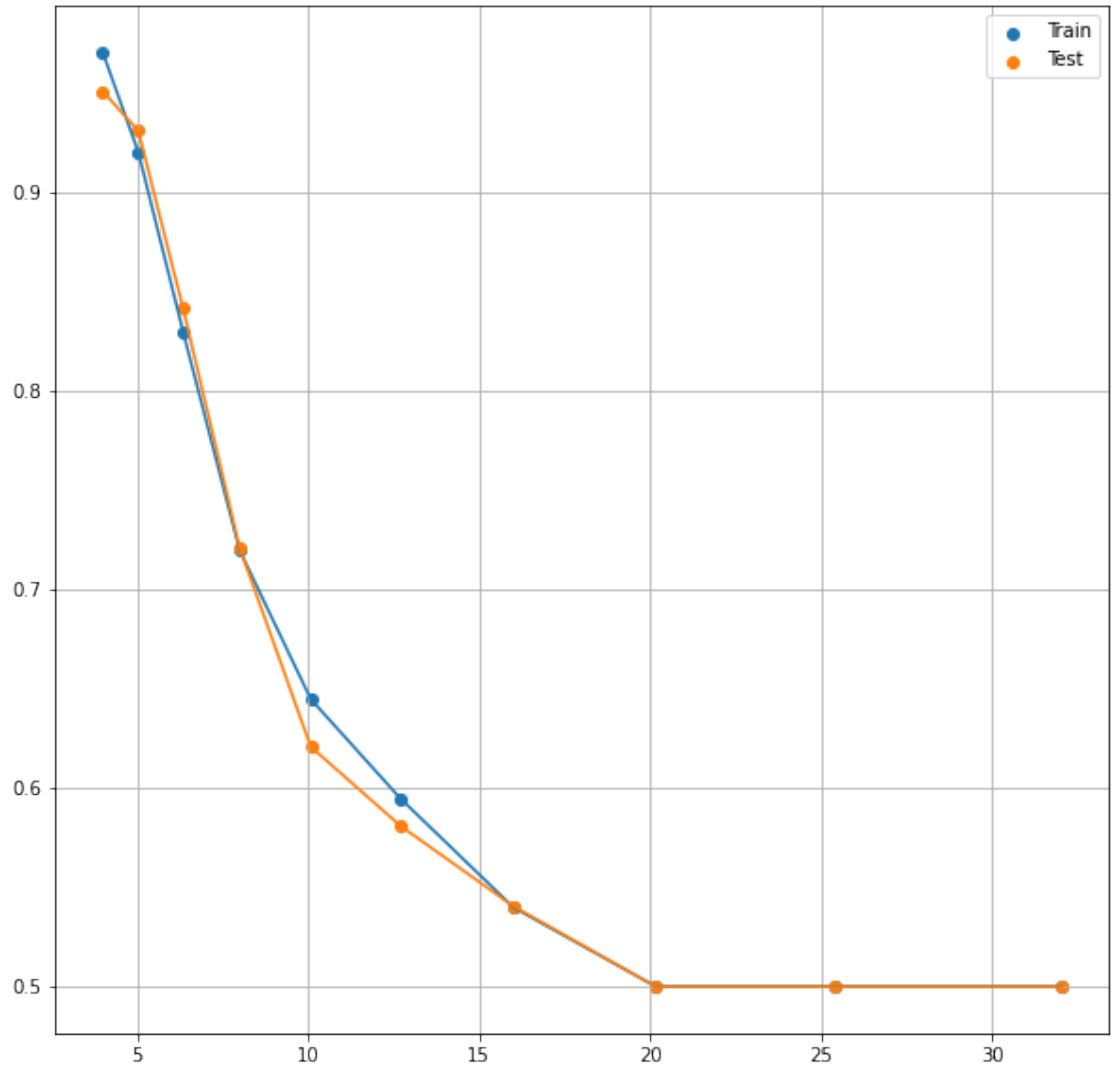
[371]:
```
df.head()
```

[371]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	params	split0_test_score	split1_test_score	split2_test_score	mean_test_score	std_test_score	rank_test_score	split0_train_score	split1_train_score	split2_train_score	mean_train_score	std_train_score
0	0.001291	0.000307	0.000391	0.000068	4	{'alpha': 4.0}	0.911765	1.000000	0.939394	0.950386	0.036851	1	0.969697	0.970149	0.970149	0.969998	0.000213
1	0.002150	0.000464	0.000684	0.000048	5.03968	{'alpha': 5.039684199579493}	0.882353	1.000000	0.909091	0.930481	0.050355	2	0.878788	0.925373	0.955224		
2	0.002176	0.000128	0.000664	0.000090	6.3496	{'alpha': 6.3496042078727974}	0.735294	0.969697	0.818182	0.841058	0.097052	3	0.696970	0.880597	0.910448		
3	0.001869	0.000196	0.000683	0.000157	8	{'alpha': 8.0}	0.647059	0.848485	0.666667	0.720737	0.090686	4	0.621212	0.716418	0.820896		
4	0.001962	0.000423	0.000616	0.000127	10.0794	{'alpha': 10.079368399158984}	0.558824	0.727273	0.575758	0.620618	0.075733	5	0.560606	0.656716	0.716418		

```
1          0.919795          0.031453
2          0.829338          0.094389
3          0.719509          0.081550
4          0.644580          0.064186
```

[372]:
```
_,ax = plt.subplots(1,1,figsize=(10,10))
ax.plot(df['param_alpha'], df['mean_train_score'])
ax.scatter(df['param_alpha'], df['mean_train_score'],label='Train')
ax.plot(df['param_alpha'], df['mean_test_score'])
ax.scatter(df['param_alpha'], df['mean_test_score'], label='Test')
ax.legend()
ax.grid()
```



[373]:
```
best_alpha = df['param_alpha'].iloc[np.argmax(df['mean_test_score'])]
print('Best Alpha {}'.format(best_alpha))
```

```
Best Alpha 4.0
```

[374]:
```
best_model = SGDClassifier(loss='hinge',alpha=best_alpha, random_state=42)
best_model.fit(x_train,y_train)
print(best_model.coef_[0])
y_pred = best_model.predict(x_train)
model_weights.append(best_model.coef_[0])
```

```
[ 0.10972406 -0.14385874  0.18320427  0.10532797 -0.14385874  0.11696468
  0.10734983]
```

[375]:
```
accuracy = accuracy_score(y_train,y_pred )
accuracy_list.append(accuracy)
```

1.4 Observations

[376]:
```
table = BeautifulTable()
table.column_headers =['Model Type', 'Accuracy']
table.append_row(['Logistic Classification + Original Data', accuracy_list[0]])
table.append_row(['Logistic Classification + Modified Data', accuracy_list[1]])
table.append_row(['Linear SVM Classification + Original Data',␣
↪accuracy_list[2]])
table.append_row(['Linear Classification + Modified Data', accuracy_list[3]])
print('Model Accuracy')
print(table)
```

```
Model Accuracy
+-----------------------------------------+----------+
|                Model Type               | Accuracy |
+-----------------------------------------+----------+
|  Logistic Classification + Original Data |   0.89   |
+-----------------------------------------+----------+
|  Logistic Classification + Modified Data |   0.88   |
+-----------------------------------------+----------+
| Linear SVM Classification + Original Data |   0.88   |
+-----------------------------------------+----------+
|   Linear Classification + Modified Data  |   0.99   |
+-----------------------------------------+----------+
```

[377]:
```
table = BeautifulTable()
table.column_headers =['Model Type', 'Delta Accuracy']
table.append_row(['Logistic Regression ', np.absolute(accuracy_list[0] -␣
↪accuracy_list[1])])
```

```
table.append_row(['Linear SVM Model + Modified Data', np.
 ↪absolute(accuracy_list[2] - accuracy_list[3])])
print('Model Accuracy Difference')
print(table)
```

```
Model Accuracy Difference
+-----------------------------------+-----------------+
|            Model Type             | Delta Accuracy |
+-----------------------------------+-----------------+
|       Logistic Regression         |      0.01       |
+-----------------------------------+-----------------+
| Linear SVM Model + Modified Data |      0.11       |
+-----------------------------------+-----------------+
```

[378]:
```
table = BeautifulTable()
lr =  np.round(np.absolute(model_weights[0] - model_weights[1]),4)
svm =  np.round(np.absolute(model_weights[2] - model_weights[3]),4)
col = ['Model Type']
col.extend(data.columns[:-1].tolist())
table.column_headers = col
table.append_row(['Logistic Regression ',lr[0], lr[1], lr[2], lr[3], lr[4],␣
 ↪lr[5], lr[6]])
table.append_row(['Linear SVM Model ', svm[0], svm[1], svm[2], svm[3], svm[4],␣
 ↪svm[5], svm[6]])
print('Model Weigths Difference')
print(table)
```

```
Model Weigths Difference
+--------------------+-------+-------+-------+-------+-------+---------+-------+
|     Model Type     |   x   |   y   |   z   |  x*x  |  2*y  | 2*z+3*x |   w   |
|                    |       |       |       |       |       |   *x    |       |
+--------------------+-------+-------+-------+-------+-------+---------+-------+
| Logistic Regressio | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |  0.001  | 0.001 |
|         n          |       |       |       |       |       |         |       |
+--------------------+-------+-------+-------+-------+-------+---------+-------+
| Linear SVM Model   | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |  0.002  | 0.002 |
+--------------------+-------+-------+-------+-------+-------+---------+-------+
```

[379]:
```
ele_dict = {}

ind = 0
for ele,val in zip(lr,data.columns[:-1].tolist()):
    ele_dict[val] = (ele/model_weights[0][ind]) * 100

lr_dict = {k:v for k,v in sorted(ele_dict.items() , key=lambda x: x[1])}

ele_dict = {}
```

```
ind = 0
for ele,val in zip(svm,data.columns[:-1].tolist()):
    ele_dict[val] = (ele/model_weights[2][ind]) * 100

svm_dict = {k:v for k,v in sorted(ele_dict.items() , key=lambda x: x[1])}

table = BeautifulTable()
print('\nTop 4 changes in weights in Logistic Regression Model')
table.column_headers = ['Feature', 'Absoulte Percent Change in Value']
for key in list(lr_dict.keys())[:4]:
    table.append_row([key, lr_dict[key]])
print(table)

table = BeautifulTable()
table.column_headers = ['Feature', 'Absoulte Percent Change in Value']
print('\nTop 4 changes in weights in Linear SVM Model')
for key in list(svm_dict.keys())[:4]:
    table.append_row([key, svm_dict[key]])

print(table)
```

```
Top 4 changes in weights in Logistic Regression Model
+-----------+-----------------------------------+
|  Feature  | Absoulte Percent Change in Value |
+-----------+-----------------------------------+
|     x     |              1.141                |
+-----------+-----------------------------------+
|    x*x    |              1.141                |
+-----------+-----------------------------------+
| 2*z+3*x*x |              1.141                |
+-----------+-----------------------------------+
|     z     |              1.283                |
+-----------+-----------------------------------+

Top 4 changes in weights in Linear SVM Model
+---------+-----------------------------------+
| Feature | Absoulte Percent Change in Value |
+---------+-----------------------------------+
|    x    |              2.054                |
+---------+-----------------------------------+
|    y    |              2.054                |
+---------+-----------------------------------+
|    z    |              2.054                |
+---------+-----------------------------------+
|   x*x   |              2.054                |
```

+---------+----------------------------------+