In [1]:

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

In [2]:

```
df = pd.read_csv("midterm_data_2.csv")
df = df.drop("row", axis = 1)
df.head()
```

Out[2]:

	response	feat.a	feat.b	feat.c	feat.d	feat.e	feat.f	feat.g	feat.h	feat.i
0	1	-0.681427	-5.493698	b	0.0	-0.800615	-4.427602	z	10.254199	-0.828073
1	1	0.309468	-5.559933	d	1.0	-1.155514	-0.799094	x	9.084749	-1.109698
2	1	5.676125	-4.026970	b	1.0	-3.396331	-0.631966	y	8.753848	-3.417417
3	1	1.211525	-4.198263	a	1.0	-1.894569	-16.273262	y	12.191295	-1.904801
4	1	1.387863	-7.824014	c	1.0	4.696980	-22.208877	z	9.626686	4.715903

In [3]:

```
eda = pp.ProfileReport(df)
eda.to_file("midterm2_initial.html")
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]
/home/matthias/anaconda3/lib/python3.8/site-packages/multimethod/__init__.py:315: FutureWarning: I
n a future version, `df.iloc[:, i] = newvals` will attempt to set the values inplace instead of al
ways setting a new array. To retain the old behavior, use either `df[df.columns[i]] = newvals` or,
if columns are non-unique, `df.isetitem(i, newvals)`
  return func(*args, **kwargs)
/home/matthias/anaconda3/lib/python3.8/site-packages/multimethod/__init__.py:315: FutureWarning: T
he default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will def
ault to False. Select only valid columns or specify the value of numeric_only to silence this warn
ing.
  return func(*args, **kwargs)
Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]
Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]
Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

In [4]:

```
df = df.fillna(df.median())
```

```
/tmp/ipykernel_598/3493596106.py:1: FutureWarning: The default value of numeric_only in DataFrame.
median is deprecated. In a future version, it will default to False. In addition, specifying 'nume
ric_only=None' is deprecated. Select only valid columns or specify the value of numeric_only to si
lence this warning.
  df = df.fillna(df.median())
```

In [5]:

```
df = pd.get_dummies(df)
```

In [6]:

```
df["response"] = df["response"].astype("category")
```

In [7]:

```
eda = pp.ProfileReport(df)
eda.to_file("midterm2_processed.html")
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]
/home/matthias/anaconda3/lib/python3.8/site-packages/multimethod/__init__.py:315: FutureWarning: I
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  return func(*args, **kwargs)
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if columns are non-unique, `df.isetitem(i, newvals)`
  return func(*args, **kwargs)
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ways setting a new array. To retain the old behavior, use either `df[df.columns[i]] = newvals` or,
if columns are non-unique, `df.isetitem(i, newvals)`
  return func(*args, **kwargs)
/home/matthias/anaconda3/lib/python3.8/site-packages/multimethod/__init__.py:315: FutureWarning: I
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if columns are non-unique, `df.isetitem(i, newvals)`
  return func(*args, **kwargs)
/home/matthias/anaconda3/lib/python3.8/site-packages/multimethod/__init__.py:315: FutureWarning: I
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  return func(*args, **kwargs)
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ing.
  return func(*args, **kwargs)
Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]
Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]
Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

In [8]:

```
from sklearn.model_selection import train_test_split
```

In [9]:

```
X = df.iloc[:,1:]
y = df.iloc[:,:1]
```

In [10]:

```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.25, random_state=101)
```

In [11]:

```
X_train
```

Out[11]:

	feat.a	feat.b	feat.d	feat.e	feat.f	feat.h	feat.i	feat.c_a	feat.c_b	feat.c_c	feat.
968	0.767383	-5.152486	1.0	4.698983	3.782216	8.833376	4.646257	0	0	1	
205	-0.428741	-2.355008	1.0	0.302588	-8.706767	12.470171	0.243201	0	1	0	
231	0.729041	-1.069498	1.0	1.836253	-5.205855	12.177760	1.863613	0	0	0	
147	3.063750	-2.204384	1.0	-0.393614	-12.184535	10.133663	-0.489800	0	1	0	
531	-0.519001	-3.360978	1.0	-1.025356	-21.881031	7.331405	-1.074075	1	0	0	
...	...	...	...	...	...	...	...	...	...	...	
575	5.110012	-2.770558	1.0	2.938986	-15.433695	10.117951	2.873882	0	1	0	
838	1.168645	-1.901514	0.0	0.203994	-7.300704	8.540716	0.124096	0	1	0	
337	0.397657	-6.165239	1.0	-1.516048	-10.910291	10.687109	-1.510253	0	0	1	
523	0.172164	-4.473905	0.0	2.133786	-13.002548	8.696168	2.103452	0	0	0	
863	-1.598113	-4.302695	0.0	-4.397054	-2.040715	11.784249	-4.426607	0	0	1	

750 rows × 14 columns

In [12]:

```
import statsmodels.api as sm
import statsmodels.formula.api as smf

mod = sm.GLM(y_train, sm.add_constant(X_train), family=sm.families.Binomial()).fit()
```

In [13]:

```
mod.summary()
```

Out[13]:

Generalized Linear Model Regression Results

Dep. Variable:	response	**No. Observations:**	750
Model:	GLM	**Df Residuals:**	737
Model Family:	Binomial	**Df Model:**	12
Link Function:	Logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-268.57
Date:	Wed, 23 Nov 2022	**Deviance:**	537.14
Time:	15:35:20	**Pearson chi2:**	9.53e+03
No. Iterations:	6	**Pseudo R-squ. (CS):**	0.4836
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.8430	0.429	4.292	0.000	1.001	2.685
feat.a	0.0050	0.037	0.136	0.892	-0.067	0.077
feat.b	-0.0584	0.074	-0.790	0.430	-0.203	0.087
feat.d	0.6477	0.220	2.941	0.003	0.216	1.079
feat.e	-4.7070	2.958	-1.591	0.112	-10.505	1.091
feat.f	0.3482	0.026	13.562	0.000	0.298	0.398
feat.h	-0.0822	0.055	-1.490	0.136	-0.190	0.026
feat.i	4.7236	2.960	1.596	0.111	-1.078	10.526
feat.c_a	0.6930	0.222	3.115	0.002	0.257	1.129
feat.c_b	0.3469	0.199	1.742	0.081	-0.043	0.737
feat.c_c	0.1691	0.230	0.734	0.463	-0.282	0.621
feat.c_d	0.6340	0.226	2.802	0.005	0.190	1.078
feat.g_x	1.2340	0.224	5.503	0.000	0.794	1.674
feat.g_y	-0.1905	0.196	-0.970	0.332	-0.575	0.194
feat.g_z	0.7995	0.221	3.623	0.000	0.367	1.232

In [14]:

```
import statsmodels.api as sm
import statsmodels.formula.api as smf
X_train_r = X_train.loc[:, ~X_train.columns.isin(['feat.a', 'feat.b', 'feat.e', 'feat.i', 'feat.h']
X_test_r = X_test.loc[:, ~X_test.columns.isin(['feat.a', 'feat.b', 'feat.e', 'feat.i', 'feat.h'])]

reduced_mod = sm.GLM(y_train, sm.add_constant(X_train_r), family=sm.families.Binomial()).fit()
```

In [15]:

```
reduced_mod.summary()
```

Out[15]:

Generalized Linear Model Regression Results

Dep. Variable:	response	**No. Observations:**	750
Model:	GLM	**Df Residuals:**	742
Model Family:	Binomial	**Df Model:**	7
Link Function:	Logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-271.43
Date:	Wed, 23 Nov 2022	**Deviance:**	542.86
Time:	15:35:20	**Pearson chi2:**	1.04e+04
No. Iterations:	6	**Pseudo R-squ. (CS):**	0.4796
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.4368	0.146	9.859	0.000	1.151	1.722
feat.d	0.6650	0.217	3.060	0.002	0.239	1.091
feat.f	0.3431	0.025	13.630	0.000	0.294	0.392
feat.c_a	0.5624	0.195	2.889	0.004	0.181	0.944
feat.c_b	0.2252	0.175	1.290	0.197	-0.117	0.567
feat.c_c	0.0668	0.201	0.333	0.739	-0.327	0.460
feat.c_d	0.5825	0.203	2.875	0.004	0.185	0.980
feat.g_x	1.1232	0.177	6.360	0.000	0.777	1.469
feat.g_y	-0.3334	0.155	-2.148	0.032	-0.638	-0.029
feat.g_z	0.6470	0.162	3.986	0.000	0.329	0.965

In [16]:

```
y1 = mod.predict(sm.add_constant(X_train))
y2 = mod.predict(sm.add_constant(X_test))
y3 = reduced_mod.predict(sm.add_constant(X_train_r))
y4 = reduced_mod.predict(sm.add_constant(X_test_r))
```

In [17]:

```
from sklearn import metrics
```

In [18]:

```
fpr1, tpr1, _ = metrics.roc_curve(y_train,  y1)
fpr2, tpr2, _ = metrics.roc_curve(y_test,  y2)
fpr3, tpr3, _ = metrics.roc_curve(y_train,  y3)
fpr4, tpr4, _ = metrics.roc_curve(y_test,  y4)
auc1 = metrics.auc(fpr1, tpr1)
auc2 = metrics.auc(fpr2, tpr2)
auc3 = metrics.auc(fpr3, tpr3)
auc4 = metrics.auc(fpr4, tpr4)
```

In [19]:

```
from sklearn.metrics import accuracy_score
```

In [20]:

```
a1 = 0
a2 = 0
a3 = 0
a4 = 0
for t in np.linspace(0,1,101):
    y_pred1 = np.where(y1>t, 1, 0)
    if accuracy_score(y_train, y_pred1) > a1:
        a1 = accuracy_score(y_train, y_pred1)
for t in np.linspace(0,1,101):
    y_pred2 = np.where(y2>t, 1, 0)
    if accuracy_score(y_test, y_pred2) > a2:
        a2 = accuracy_score(y_test, y_pred2)
for t in np.linspace(0,1,101):
    y_pred3 = np.where(y3>t, 1, 0)
    if accuracy_score(y_train, y_pred3) > a3:
        a3 = accuracy_score(y_train, y_pred3)
for t in np.linspace(0,1,101):
    y_pred4 = np.where(y4>t, 1, 0)
    if accuracy_score(y_test, y_pred4) > a4:
        a4 = accuracy_score(y_test, y_pred4)
```

In [21]:

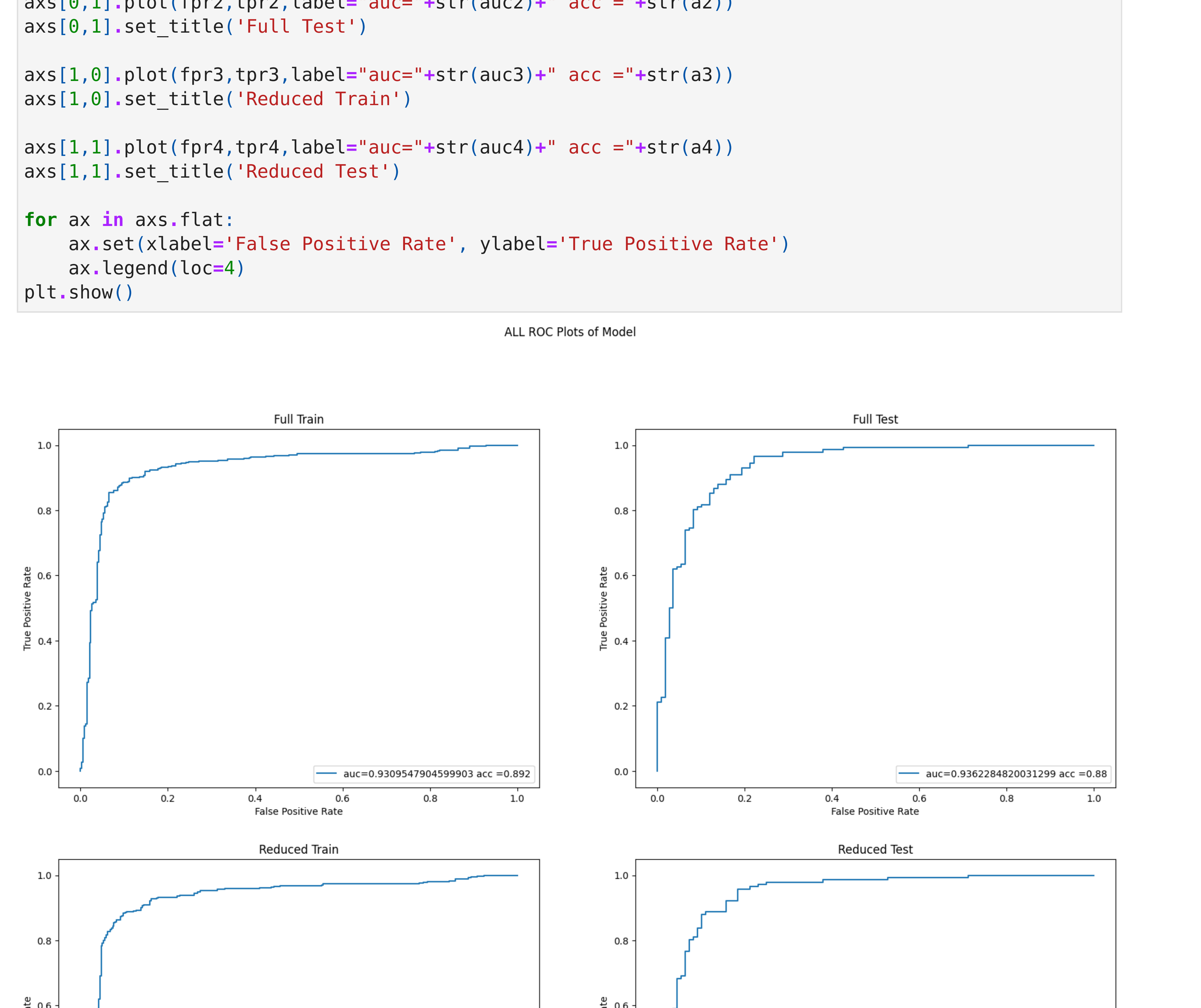
```
fig, axs = plt.subplots(2, 2, figsize=(20, 15))
fig.suptitle('ALL ROC Plots of Model')
axs[0,0].plot(fpr1,tpr1,label="auc="+str(auc1)+" acc ="+str(a1))
axs[0,0].set_title('Full Train')

axs[0,1].plot(fpr2,tpr2,label="auc="+str(auc2)+" acc ="+str(a2))
axs[0,1].set_title('Full Test')

axs[1,0].plot(fpr3,tpr3,label="auc="+str(auc3)+" acc ="+str(a3))
axs[1,0].set_title('Reduced Train')

axs[1,1].plot(fpr4,tpr4,label="auc="+str(auc4)+" acc ="+str(a4))
axs[1,1].set_title('Reduced Test')

for ax in axs.flat:
    ax.set(xlabel='False Positive Rate', ylabel='True Positive Rate')
    ax.legend(loc=4)
plt.show()
```



While there isnt much overfitting, the full model has less gain on the validation set. This means the Reduced model, while scoring similar to the full model in its metrics is preferable to use as the gain is higher (TPR increases faster earlier).

In [22]:

```
y_pred_50 = np.where(y4>0.5, 1, 0)
fpr50, tpr50, _ = metrics.roc_curve(y_test,  y_pred_50)
1 - tpr50[1]
```

Out[22]: 0.04225352112676062

In [23]:

```
accuracy_score(y_test, y_pred_50)
```

Out[23]: 0.892

In [24]:

```
y_pred_65 = np.where(y4>0.65, 1, 0)
fpr65, tpr65, _ = metrics.roc_curve(y_test,  y_pred_65)
1 - tpr65[1]
```

Out[24]: 0.176056338028169

In [25]:

```
accuracy_score(y_test, y_pred_65)
```

Out[25]: 0.86

In [26]:

```
X_test_r_0 = sm.add_constant(X_test_r).copy()
X_test_r_1 = sm.add_constant(X_test_r).copy()
X_test_r_0["feat.d"] = 0
X_test_r_1["feat.d"] = 1
```

In [27]:

```
y_0s = reduced_mod.predict(sm.add_constant(X_test_r_0))
y_1s = reduced_mod.predict(sm.add_constant(X_test_r_1))
```

In [28]:

```
y4.mean()
```

Out[28]: 0.5886888502097679

In [29]:

```
y_0s.mean()
```

Out[29]: 0.5449016036600584

In [30]:

```
y_1s.mean()
```

Out[30]: 0.6294084933258648

In [31]:

```
(y_1s.mean() - y_0s.mean())*100
```

Out[31]: 8.450688966580644

Feat.d = 1 leads to a 8.45% increase in Probability of the response variable being 1 compared to feat.d being set to zero.