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1 Assignment 10 B

1.1 Imports

[117]:
```
import numpy as np
import pandas as pd
import plotly
import plotly.figure_factory as ff
import plotly.graph_objs as go
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
init_notebook_mode(connected=True)

import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

1.2 Data Prep

[43]:
```
data = pd.read_csv('task_b.csv')
data=data.iloc[:,1:]
```

[44]:
```
data.head()
```

[44]:

	f1	f2	f3	y
0	-195.871045	-14843.084171	5.532140	1.0
1	-1217.183964	-4068.124621	4.416082	1.0
2	9.138451	4413.412028	0.425317	0.0
3	363.824242	15474.760647	1.094119	0.0
4	-768.812047	-7963.932192	1.870536	0.0

[45]:
```
data.corr()['y']
```

[45]:
```
f1    0.067172
f2   -0.017944
f3    0.839060
y     1.000000
Name: y, dtype: float64
```

[93]:
```
print(data.std())
variation_value = data.std().tolist()[:-1]
```

```
f1      488.195035
f2    10403.417325
f3        2.926662
y         0.501255
dtype: float64
```

[94]:
```
variation_value
```

[94]:
```
[488.19503543233304, 10403.417325366105, 2.9266616724509307]
```

[47]:
```
x_train=data[['f1','f2','f3']].values
y_train=data['y'].values
print(x_train.shape)
print(y_train.shape)
```

```
(200, 3)
(200,)
```

[48]:
```
np.unique(y_train)
```

[48]:
```
array([0., 1.])
```

1.3 Objective: What if our features are with different variance

Make sure you write the observations for each task, why a particular feautre got more importance than others

[49]:
```
hyperparam_list = [0.001, 1, 100]
```

1.3.1 Task1

Apply Logistic Regression

[50]:
```
## Logistic Regression

non_standrd_results = []
for ind, param in enumerate(hyperparam_list):
    print('Hyperparameter = {}'.format(param))
    clf = SGDClassifier(loss='log',alpha=param, random_state=42)
    clf.fit(x_train, y_train)
```

```
    print(clf.coef_[0])
    non_standrd_results.append(np.abs(clf.coef_[0]))
```

```
Hyperparameter = 0.001
[  928.42803044 -1122.76033708  1166.37055976]
Hyperparameter = 1
[ 0.82107703 -1.0493408   1.18822044]
Hyperparameter = 100
[ 0.00984986 -0.01074521  0.0118282 ]
```

Apply Linear SVM

[51]:
```
# SVM
non_standrd_results_svm = []
for param in [0.001, 1, 100]:
    print('Hyperparameter = {}'.format(param))
    clf = SGDClassifier(loss='hinge',alpha=param, random_state=42)
    clf.fit(x_train, y_train)
    print(clf.coef_[0])
    non_standrd_results_svm.append(np.abs(clf.coef_[0]))
```

```
Hyperparameter = 0.001
[ 1149.60853255 -1064.77386911  1163.90648999]
Hyperparameter = 1
[ 1.18137149 -1.0941929   1.19606449]
Hyperparameter = 100
[0.01114799 0.00725793 0.01230957]
```

1.3.2 Task2

Apply Logistic Regression On Standardized Data

[52]:
```
# Standardizing the data
std = StandardScaler()
x_train = std.fit_transform(x_train)
```

[53]:
```
## Logistict Regression
results = []
for param in [0.001, 1, 100]:
    clf = SGDClassifier(loss='log',alpha=param, random_state=42)
    clf.fit(x_train, y_train)
    print(clf.coef_[0])
    results.append(np.abs(clf.coef_[0]))
```

```
[-0.25528984  0.17163414  5.45803937]
[ 0.01875157 -0.00353376  0.33664917]
[ 3.34037859e-04 -8.87677440e-05  4.18828215e-03]
```

Apply Linear SVM on Standardized Data

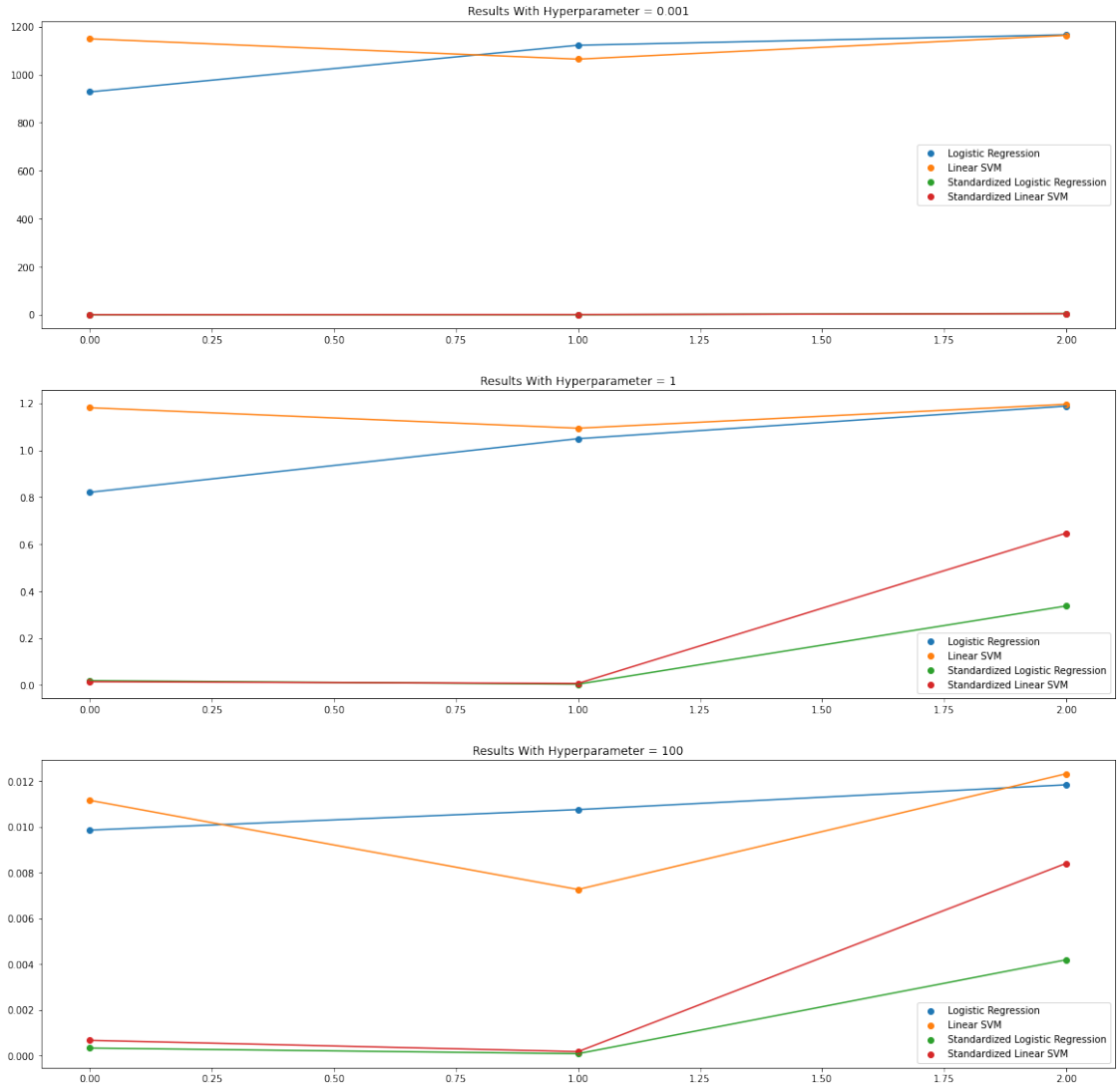
[54]:
```
# SVM
results_svm = []
for param in [0.001, 1, 100]:
    clf = SGDClassifier(loss='hinge',alpha=param, random_state=42)
    clf.fit(x_train, y_train)
    print(clf.coef_[0])
    results_svm.append(np.abs(clf.coef_[0]))
```

```
[-0.29382397 -0.79663131  4.41150327]
[ 0.01415135 -0.00678538  0.64702268]
[ 0.00067226 -0.00017958  0.00839737]
```

[69]:
```
_, ax = plt.subplots(3,1, figsize=(20,20))

for i in range(3):
    ax[i].scatter(y=non_standrd_results[i], x= range(0,3), label='Logistic␣
 ↪Regression')
    ax[i].scatter(y=non_standrd_results_svm[i], x=range(0,3), label='Linear␣
 ↪SVM')
    ax[i].scatter(y=results[i], x=range(0,3), label='Standardized Logistic␣
 ↪Regression')
    ax[i].scatter(y=results_svm[i], x=range(0,3),label='Standardized Linear␣
 ↪SVM')

    ax[i].plot(non_standrd_results[i])
    ax[i].plot(non_standrd_results_svm[i])
    ax[i].plot(results[i])
    ax[i].plot(results_svm[i])
    ax[i].set_title('Results With Hyperparameter = {}'.
 ↪format(hyperparam_list[i]))
    ax[i].legend()
```



Observations:

- Due standarization the absolute values of the weight vector is way lower than the non standardized datapoints

[112]:
```
_, ax = plt.subplots(3,3, figsize=(20,20))

for i in range(3):
    for j in range(3):
        ax[i][j].set_title('Results With Hyperparameter = {} and feature = {}\n␣
 ↪Standard Deviation = {}'.format(hyperparam_list[i], j+1, variation_value[j]))

        ax[i][j].bar(x=1, height=non_standrd_results[i][j], label='LR')
```

```
      ax[i][j].text(0.80, non_standrd_results[i][j] + 0.005 *␣
↪non_standrd_results[i][j] , str(round(non_standrd_results[i][j],4)),␣
↪color='black', fontweight='bold')
      ax[i][j].bar(x=2, height=non_standrd_results_svm[i][j], label='Lr. SVM')
      ax[i][j].text(1.80, non_standrd_results_svm[i][j] + 0.005 *␣
↪non_standrd_results_svm[i][j] , str(round(non_standrd_results_svm[i][j],4)),␣
↪color='black', fontweight='bold')
      ax[i][j].bar(x=3, height=results[i][j], label='Std LR')
      ax[i][j].text(2.80, results[i][j] + 0.005 * results[i][j] ,␣
↪str(round(results[i][j],4)), color='black', fontweight='bold')
      ax[i][j].bar(x=4, height=results_svm[i][j], label='Std Lr. SVM')
      ax[i][j].text(3.80, results_svm[i][j] + 0.005 * results_svm[i][j] ,␣
↪str(round(results_svm[i][j],4)), color='black', fontweight='bold')
      ax[i][j].legend()
      plt.tight_layout()
```

Observation:

- Features Having Least standard deviation have the highest absolute value of the weight vector and vice versa.Which means that the feature which has lesser standard deviation has more importance to the model.

Question:

- Reffered to a question on cross validated website https://stats.stackexchange.com/questions/202221/for-linear-classifiers-do-larger-coefficients-imply-more-important-features it has some contradicting answers can you guys clarify

[130]:
```
sns.pairplot(data,hue='y')
```

[130]:
```
<seaborn.axisgrid.PairGrid at 0x7fece9df3a10>
```