In [137…

```python
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
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)

from matplotlib import pyplot as plt
```

In [138…

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

In [139…

```python
data.head()
```

Out[139]:

	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

In [140…

```python
# How Features are correlated with output/predicted/target variable
data.corr()['y']
```

Out[140]:

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

In [141…

```python
data.corr()
```

Out[141]:

	f1	f2	f3	y
f1	1.000000	0.065468	0.123589	0.067172
f2	0.065468	1.000000	-0.055561	-0.017944
f3	0.123589	-0.055561	1.000000	0.839060
y	0.067172	-0.017944	0.839060	1.000000

In [142…

```python
data.std()
```

Out[142]:

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

In [143…

```python
X=data[['f1','f2','f3']].values
Y=data['y'].values
print(X.shape)
print(Y.shape)
```

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

What if our features are with different variance

```
* As part of this task you will observe how linear models work in case of data having feautres with different variance
* from the output of the above cells you can observe that var(F2)>>var(F1)>>Var(F3)

> Task1:
    1. Apply Logistic regression(SGDClassifier with logloss) on 'data' and check the feature importance
    2. Apply SVM(SGDClassifier with hinge) on 'data' and check the feature importance

> Task2:
    1. Apply Logistic regression(SGDClassifier with logloss) on 'data' after standardization
       i.e standardization(data, column wise): (column-mean(column))/std(column) and check the feature importance
    2. Apply SVM(SGDClassifier with hinge) on 'data' after standardization
       i.e standardization(data, column wise): (column-mean(column))/std(column) and check the feature importance
```

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

In [144…

```python
# unique class values for targeted|output variable
np.unique(Y)
```

Out[144]:

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

As there are 2 unique values in Y, so coef_ will return (1, d)

In [145…

```python
def get_features(lossType, X, Y):
    '''
        Apply the Classification Training on entire data (ie considering all data as Train Data)
    '''
    n_iter = np.ceil(10**6 / len(Y))
    classifier = SGDClassifier(loss=lossType, max_iter=n_iter)
    classifier.fit(X, Y)
    print('# Loss: {} iterations -> {}'.format(lossType, classifier.n_iter_))
    return classifier.coef_[0]


def plot_features(f):
    tx = np.argsort(f)
    x = [*range(len(f))]
    print('Feature Sorted', tx)
    y = sorted(f)
    print('Weights ', y)
    plt.bar(x, y, width=0.2)
    plt.xticks(x, tx)
    plt.xlabel('Features')
    plt.ylabel('Weights')
    plt.show()
```

Task 1 (No PreProcessing)

In [146…

```python
from sklearn.linear_model import SGDClassifier
```

In [147…

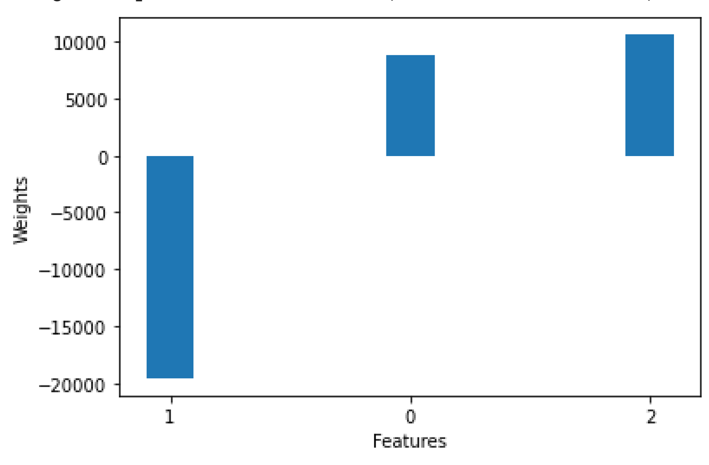
```python
'''
Training donee on Entire Data (as For now purpose is to check the Feature Importance & Variance Relation,
not much considering the Innference for New/Real Data
'''
# Logistic Regression
logreg_w = get_features('log', X, Y)

# SVM (Linear)
svm_w = get_features('hinge', X, Y)

# ref :- https://machinelearningmastery.com/calculate-feature-importance-with-python/
# summarize feature importance
print('\nLogistic Regression --- ')

for i,v in enumerate(logreg_w, start=1):
        print('Feature: %0d, Score: %.5f' % (i,v))

print('\nSVM --- ')
for i,v in enumerate(svm_w, start=1):
        print('Feature: %0d, Score: %.5f' % (i,v))
```

```
# Loss: log iterations -> 41
# Loss: hinge iterations -> 47

Logistic Regression ---
Feature: 1, Score: 8859.92695
Feature: 2, Score: -19555.08501
Feature: 3, Score: 10590.62774

SVM ---
Feature: 1, Score: 3171.42370
Feature: 2, Score: 13486.37360
Feature: 3, Score: 10974.01709
```

In [148…

```python
# plot feature importance (Logistic Regression)
plot_features(logreg_w)
```

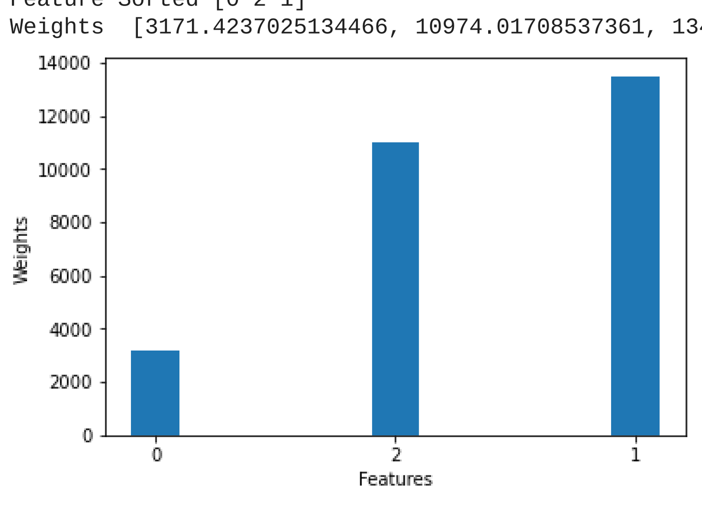
```
Feature Sorted [1 0 2]
Weights  [-19555.08500652657, 8859.926947677297, 10590.627741140375]
```



In [149…

```python
# plot feature importance (SVM)
plot_features(svm_w)
```

```
Feature Sorted [0 2 1]
Weights  [3171.4237025134466, 10974.01708537361, 13486.373597756816]
```



Task 2 (With PreProcessing)

In [150…

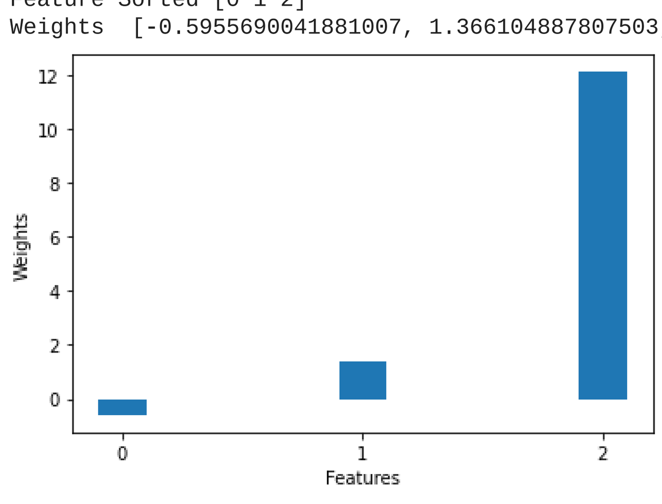
```python
'''
Training done on Entire Data (as For now purpose is to check the Feature Importance & Variance Relation,
not much considering the Innference for New/Real Data
'''
scaler = StandardScaler()
nX = scaler.fit_transform(X)

# Logistic Regression
logreg_w = get_features('log', nX, Y)

# SVM (Linear)
svm_w = get_features('hinge', nX, Y)

# ref :- https://machinelearningmastery.com/calculate-feature-importance-with-python/
# summarize feature importance
print('\nLogistic Regression --- ')

for i,v in enumerate(logreg_w, start=1):
        print('Feature: %0d, Score: %.5f' % (i,v))

print('\nSVM --- ')
for i,v in enumerate(svm_w, start=1):
        print('Feature: %0d, Score: %.5f' % (i,v))
```

```
# Loss: log iterations -> 23
# Loss: hinge iterations -> 22

Logistic Regression ---
Feature: 1, Score: -0.59557
Feature: 2, Score: 1.36610
Feature: 3, Score: 12.09715

SVM ---
Feature: 1, Score: -2.35810
Feature: 2, Score: -1.35696
Feature: 3, Score: 16.38142
```

In [151…

```python
# plot feature importance (Logistic Regression)
plot_features(logreg_w)
```

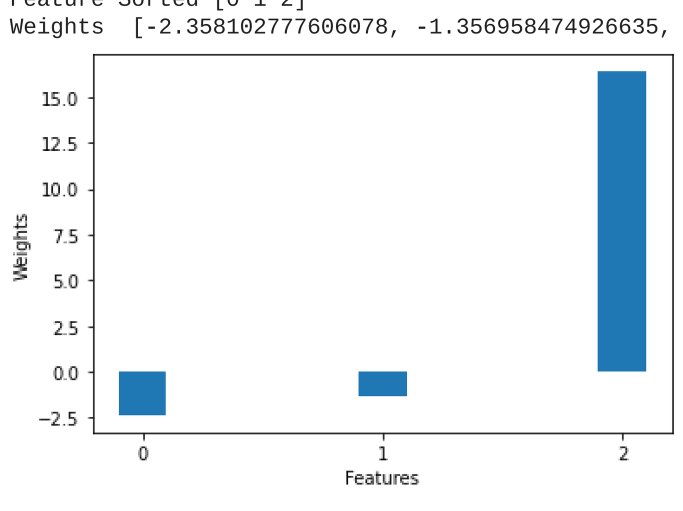
```
Feature Sorted [0 1 2]
Weights  [-0.5955690041881007, 1.366104887807503, 12.097146890456353]
```



In [152…

```python
# plot feature importance (SVM)
plot_features(svm_w)
```

```
Feature Sorted [0 1 2]
Weights  [-2.358102777606078, -1.356958474926635, 16.381424099010967]
```



Observations

- When Features are Pre-Processed (ie Standardised) generally it tooks less iteration to converge for weights
- The weight difference between 2 Models is less in case of Standardised Features compare to Non-PreProcessed Features

In [ ]: