-----------------------------Features with different variance-------------------------------

In [2]:

```
#importing required libraries
import numpy as np
import pandas as pd
from matplotlib import pyplot
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 sklearn.linear_model import SGDClassifier
```

In [3]:

```
data = pd.read_csv('task_b.csv') #Load data into pandas dataframe
print(data)
data=data.iloc[:,1:]
```

```
     index           f1            f2        f3    y
0        0  -195.871045 -14843.084171  5.532140  1.0
1        1 -1217.183964  -4068.124621  4.416082  1.0
2        2     9.138451   4413.412028  0.425317  0.0
3        3   363.824242  15474.760647  1.094119  0.0
4        4  -768.812047  -7963.932192  1.870536  0.0
..     ...          ...           ...       ...  ...
195    195   119.423142  -2985.720392  0.929967  0.0
196    196   -37.805502  13061.298176  5.421253  0.0
197    197   181.626647   3179.754101  3.059868  0.0
198    198   443.199825  -1053.252455  5.467800  0.0
199    199   -51.189253   7442.423346  9.528478  1.0

[200 rows x 5 columns]
```

In [4]:

```
data.head()
```

Out[4]:

	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 [5]:

```
data.corr()['y'] #correlation of features with target variable
```

Out[5]:

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

In [6]:

```
data.std()      #standard deviations of each features
```

Out[6]:

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

In [7]:

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

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

LR without standardization

In [20]:

```
lr=SGDClassifier(loss="log_loss")          #training logistic regression with non standardized data
lr.fit(X,Y)
```

Out[20]:

```
▾        SGDClassifier
SGDClassifier(loss='log_loss')
```

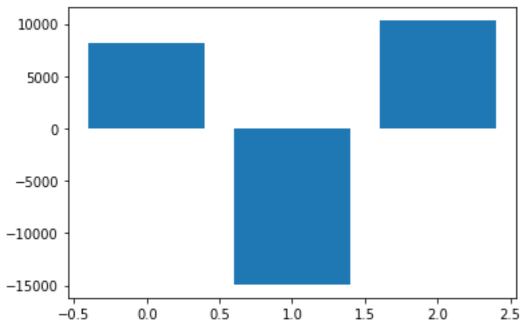
In [21]:

```
importance = lr.coef_[0]            #getting weight vector
```

In [22]:

```
# summarize feature importance       #reference taken from: https://machinelearningmastery.com/calculate-feature-importance-with-python/
for i,v in enumerate(importance):
    print('Feature: %0d, Score(weight): %.5f' % (i,v))
# plot feature importance
pyplot.bar([x for x in range(len(importance))], importance)
pyplot.show()
```

```
Feature: 0, Score(weight): 8209.07514
Feature: 1, Score(weight): -14916.21020
Feature: 2, Score(weight): 10287.78040
```



SVM without standardization

In [29]:

```
svm=SGDClassifier(loss="hinge")              #training SVM with non standardized data
svm.fit(X,Y)
```

Out[29]:

```
▾ SGDClassifier
SGDClassifier()
```

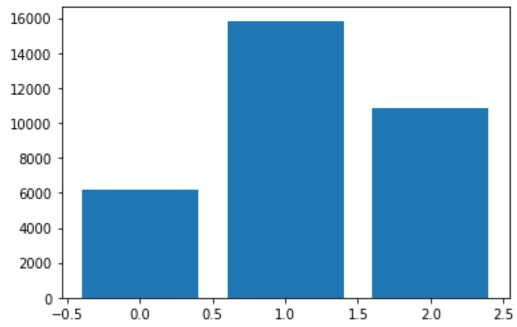
In [30]:

```
importance = svm.coef_[0]                   #getting weight vector
```

In [31]:

```
# summarize feature importance
for i,v in enumerate(importance):
    print('Feature: %0d, Score(weight): %.5f' % (i,v))
# plot feature importance
pyplot.bar([x for x in range(len(importance))], importance)
pyplot.show()
```

```
Feature: 0, Score(weight): 6192.68951
Feature: 1, Score(weight): 15840.99046
Feature: 2, Score(weight): 10835.00169
```



- feature 2 which had highest variance got the highest feature importance score

LR with standardization

In [33]:

```
# define standard scaler
scaler = StandardScaler()
# standardising data
scaled = scaler.fit_transform(X)
#print(scaled)
```

In [34]:

```
df1 = pd.DataFrame(scaled, columns = ['f1','f2','f3'])
```

In [36]:

```
df1.std()
```

Out[36]:

```
f1    1.002509
f2    1.002509
f3    1.002509
dtype: float64
```

In [37]:

```
df2 = pd.DataFrame(Y, columns=["y"])
df=pd.concat([df1, df2], axis=1)
```

In [38]:

```
df.corr()['y']           #variance of the data is changed but the correlation remains same
```

Out[38]:

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

In [39]:

```
lr=SGDClassifier(loss="log_loss")            #training logistic regression with standardized data
lr.fit(scaled,Y)
```

Out[39]:

```
▾       SGDClassifier
SGDClassifier(loss='log_loss')
```

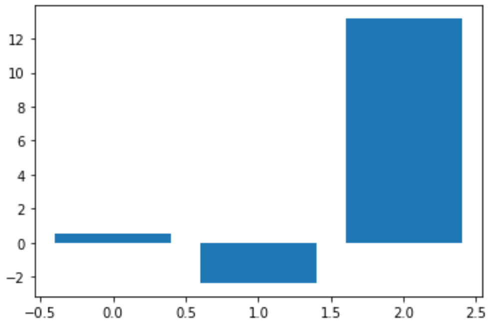
In [40]:

```
importance = lr.coef_[0]          #getting weight vector
```

In [41]:

```
# summarize feature importance
for i,v in enumerate(importance):
    print('Feature: %0d, Score: %.5f' % (i,v))
# plot feature importance
pyplot.bar([x for x in range(len(importance))], importance)
pyplot.show()
```

```
Feature: 0, Score: 0.53957
Feature: 1, Score: -2.35989
Feature: 2, Score: 13.16421
```



SVM with standardization

In [42]:

```
svm=SGDClassifier(loss="hinge")#training SVM with  standardized data
svm.fit(scaled,Y)
```

Out[42]:

```
▾ SGDClassifier
SGDClassifier()
```

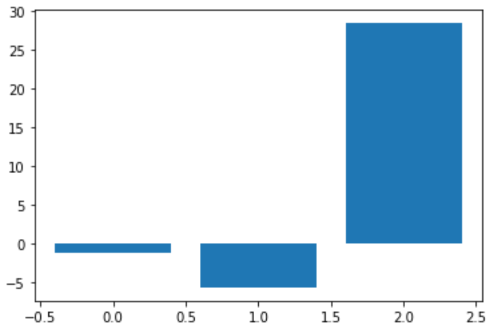
In [43]:

```
importance = svm.coef_[0]        #getting weight vector
```

In [44]:

```
# summarize feature importance
for i,v in enumerate(importance):
    print('Feature: %0d, Score: %.5f' % (i,v))
# plot feature importance
pyplot.bar([x for x in range(len(importance))], importance)
pyplot.show()
```

```
Feature: 0, Score: -1.19281
Feature: 1, Score: -5.71115
Feature: 2, Score: 28.46407
```



Observation

- Before standardisation we can see that the feature 2 which had a **least correlation(=-0.017944)** with prediction has got **highest importance score(weight)**.
- But once the data is **column standardised**, feature which had the **highest correlation** (feature 3) got the **highest importance score(weight)**

- so standardisation of numerical value is very important to avoid the scenario where high variance feature tend to influence models performance irrespective of whether they are highly correlated or not.