```
In [1]: import numpy as np
         import pandas as pd
         import plotly
         import plotly.figure_factory as ff
         import plotly.graph_objs as go
         from sklearn import linear model
         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)
         data = pd.read_csv('task_b.csv')
In [2]:
         data=data.iloc[:,1:]
         data.head()
In [3]:
                               f2
                                       f3
                                           У
        0 -195.871045 -14843.084171 5.532140 1.0
                       -4068 124621 4 416082 1 0
        1 -1217 183964
        2
              9.138451
                       4413.412028 0.425317 0.0
           363.824242 15474.760647 1.094119 0.0
        4 -768.812047 -7963.932192 1.870536 0.0
In [4]: data.corr()['y']
Out[4]: f1
              0.067172
             -0.017944
        f2
            0.839060
        f3
              1.000000
        Name: y, dtype: float64
In [5]: data.std()
Out[5]: f1
                488.195035
        f2
              10403.417325
        f3
                  2.926662
                  0.501255
        dtype: float64
In [6]: X=data[['f1','f2','f3']].values
         Y=data['y'].values
         print(X.shape)
         print(Y.shape)
         X[0]
        (200, 3)
        (200,)
Out[6]: array([-1.95871045e+02, -1.48430842e+04, 5.53214037e+00])
In [7]: data1 = data.drop('y', axis = 1)
         data1.columns
Out[7]: Index(['f1', 'f2', 'f3'], dtype='object')
```

## 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:

In [24]: imp\_SVM\_std = model\_SVM.coef\_

- 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

Task 1: Fitting the model Before standadization

```
model LR = linear model.SGDClassifier(loss = 'log')
 In [8]:
          model LR.fit(X, Y)
 In [9]:
Out[9]: SGDClassifier(loss='log')
In [10]: imp_LR = model LR.coef
In [12]: print(imp_LR)
         [[5921.87568274 -871.84119588 7885.6477321 ]]
In [13]: model_SVM = linear_model.SGDClassifier()
In [14]: model_SVM.fit(X, Y)
Out[14]: SGDClassifier()
          imp SVM = model SVM.coef
In [15]:
In [16]:
          print(imp_SVM)
         [[ 7105.85630403 -4545.47362328 10301.09462378]]
        Task 2: Fitting the model After Standadization
In [17]: names = ['f1', 'f2', 'f3']
In [18]: for x in names:
           data[x] = (data[x] - np.mean(data[x])) / data[x].std()
In [19]: model_LR = linear_model.SGDClassifier(loss = 'log')
In [20]:
          model_LR.fit(data[names], Y)
Out[20]: SGDClassifier(loss='log')
In [21]:
          imp_LR_std = model_LR.coef_
          print(imp_LR_std)
         [[-3.59743861 4.07524765 19.02553695]]
In [22]: model_SVM = linear_model.SGDClassifier()
In [23]: model_SVM.fit(data[names], Y)
Out[23]: SGDClassifier()
```

print(imp\_SVM\_std)

[[-2.40630821 -0.12672137 16.7315999 ]]

Observation: 1. Applying SGDclassifier for logistic regression and SVM before standadization the feature importance like f3 more important than f1 and f2 f2 is least important f1 is second most important feature 2. Applying SGDclassifier for logistic regression and SVM after standadization the feature importance like values of the coefficients are readable like before f3 more important than f1 and f2 But now f2 become important than f1 f1 is now least important