Logistic Model

May 16, 2018

First, we want to fit the data with a logistic model.

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib
        import matplotlib.pyplot as plt
```

```
In [3]: names = ['age','workclass','fnlwgt','education','education-num','marital-status' ,  'oc
        'capital-gain','capital-loss','hours-per-week','native-country','income']
        df = pd.read_csv('adult_data.txt',header=None,delim_whitespace=True,names=names,na_valu
        df_test = pd.read_csv('adult_test.txt',header=None,delim_whitespace=True,names=names,na
        df.dropna()
        df_test.dropna()
        df.head(6)
        df_test.head(6)
```

```
Out[3]:    age  workclass  fnlwgt     education  education-num      marital-status  \
        0   25    Private  226802          11th              7       Never-married
        1   38    Private   89814       HS-grad              9  Married-civ-spouse
        2   28  Local-gov  336951    Assoc-acdm             12  Married-civ-spouse
        3   44    Private  160323  Some-college             10  Married-civ-spouse
        4   18        NaN  103497  Some-college             10       Never-married
        5   34    Private  198693          10th              6       Never-married

                  occupation   relationship   race     sex  capital-gain  \
        0  Machine-op-inspct      Own-child  Black    Male             0
        1    Farming-fishing        Husband  White    Male             0
        2    Protective-serv        Husband  White    Male             0
        3  Machine-op-inspct        Husband  Black    Male          7688
        4                NaN      Own-child  White  Female             0
        5      Other-service  Not-in-family  White    Male             0

           capital-loss  hours-per-week native-country  income
        0             0              40  United-States  <=50K.
        1             0              50  United-States  <=50K.
        2             0              40  United-States   >50K.
        3             0              40  United-States   >50K.
```

```
4            0            30  United-States  <=50K.
5            0            30  United-States  <=50K.
```

```
In [4]: print(df.dtypes)
```

```
age                 int64
workclass          object
fnlwgt              int64
education          object
education-num       int64
marital-status     object
occupation         object
relationship       object
race               object
sex                object
capital-gain        int64
capital-loss        int64
hours-per-week      int64
native-country     object
income             object
dtype: object
```

Some of the features are categorical, so we need to encode them with either one-hot coding or linear encoder.

```
In [5]: # One-hot coding
        from sklearn.preprocessing import LabelEncoder
        ohc_category = ['workclass', 'education', 'marital-status', 'occupation', 'relationshi
                         ,'native-country']
        le_category=['sex','income']

        df_ohc_train = pd.get_dummies(df,columns=ohc_category)
        df_ohc_test = pd.get_dummies(df_test,columns=ohc_category)
```

```
In [6]: # linear encoder
        df_le_train = df_ohc_train.copy()
        df_le_test = df_ohc_test.copy()
        for item in le_category:
            df_le_train[item] = LabelEncoder().fit_transform(df_le_train[item])  #bug
            df_le_test[item] = LabelEncoder().fit_transform(df_le_test[item])
```

```
In [7]: # get training data and labels
        X_train_df = df_le_train.drop(['income'],axis=1)
        X_train = np.array(X_train_df)
        y_train = np.array(df_le_train['income'])

        # get test data and labels
        X_test = np.array(df_le_test.drop(['income'],axis=1))
        y_test = np.array(df_le_test['income'])
```

```
In [8]: print(X_train_df.dtypes)
        X_train_df.head(6)
```

```
age                                          int64
fnlwgt                                       int64
education-num                                int64
sex                                          int64
capital-gain                                 int64
capital-loss                                 int64
hours-per-week                               int64
workclass_Federal-gov                        uint8
workclass_Local-gov                          uint8
workclass_Never-worked                       uint8
workclass_Private                            uint8
workclass_Self-emp-inc                       uint8
workclass_Self-emp-not-inc                   uint8
workclass_State-gov                          uint8
workclass_Without-pay                        uint8
education_10th                               uint8
education_11th                               uint8
education_12th                               uint8
education_1st-4th                            uint8
education_5th-6th                            uint8
education_7th-8th                            uint8
education_9th                                uint8
education_Assoc-acdm                         uint8
education_Assoc-voc                          uint8
education_Bachelors                          uint8
education_Doctorate                          uint8
education_HS-grad                            uint8
education_Masters                            uint8
education_Preschool                          uint8
education_Prof-school                        uint8
                                             ...
native-country_Germany                       uint8
native-country_Greece                        uint8
native-country_Guatemala                     uint8
native-country_Haiti                         uint8
native-country_Honduras                      uint8
native-country_Hong                          uint8
native-country_Hungary                       uint8
native-country_India                         uint8
native-country_Iran                          uint8
native-country_Ireland                       uint8
native-country_Italy                         uint8
native-country_Jamaica                       uint8
native-country_Japan                         uint8
native-country_Laos                          uint8
```

```
native-country_Mexico                          uint8
native-country_Nicaragua                       uint8
native-country_Outlying-US(Guam-USVI-etc)      uint8
native-country_Peru                            uint8
native-country_Philippines                     uint8
native-country_Poland                          uint8
native-country_Portugal                        uint8
native-country_Puerto-Rico                     uint8
native-country_Scotland                        uint8
native-country_South                           uint8
native-country_Taiwan                          uint8
native-country_Thailand                        uint8
native-country_Trinadad&Tobago                 uint8
native-country_United-States                   uint8
native-country_Vietnam                         uint8
native-country_Yugoslavia                      uint8
Length: 103, dtype: object
```

Out[8]:

```
   age  fnlwgt  education-num  sex  capital-gain  capital-loss  \
0   39   77516             13    1          2174             0
1   50   83311             13    1             0             0
2   38  215646              9    1             0             0
3   53  234721              7    1             0             0
4   28  338409             13    0             0             0
5   37  284582             14    0             0             0

   hours-per-week  workclass_Federal-gov  workclass_Local-gov  \
0              40                      0                    0
1              13                      0                    0
2              40                      0                    0
3              40                      0                    0
4              40                      0                    0
5              40                      0                    0

   workclass_Never-worked            ...             native-country_Portugal  \
0                       0            ...                                   0
1                       0            ...                                   0
2                       0            ...                                   0
3                       0            ...                                   0
4                       0            ...                                   0
5                       0            ...                                   0

   native-country_Puerto-Rico  native-country_Scotland  native-country_South  \
0                           0                        0                     0
1                           0                        0                     0
2                           0                        0                     0
3                           0                        0                     0
```

```
4                            0                         0                      0
5                            0                         0                      0

   native-country_Taiwan  native-country_Thailand  \
0                      0                        0
1                      0                        0
2                      0                        0
3                      0                        0
4                      0                        0
5                      0                        0

   native-country_Trinadad&Tobago  native-country_United-States  \
0                               0                             1
1                               0                             1
2                               0                             1
3                               0                             1
4                               0                             0
5                               0                             1

   native-country_Vietnam  native-country_Yugoslavia
0                       0                          0
1                       0                          0
2                       0                          0
3                       0                          0
4                       0                          0
5                       0                          0

[6 rows x 103 columns]
```

We will train the model with all data in the trainin set and test the model with the test data.

```
In [9]: nsamples_tr = X_train.shape[0]
        nsamples_ts = X_test.shape[0]
        nfeatures = X_train.shape[1]

        print('Number of samples for training = %d' % nsamples_tr)
        print('Number of samples for test = %d' % nsamples_ts)
        print('Number of features = %d' % nfeatures)
```

```
Number of samples for training = 32560
Number of samples for test = 16281
Number of features = 103
```

```
In [14]: # data normalization
         Xtr_mean = np.mean(X_train,axis=0)
         Xtr_std = np.std(X_train,axis=0)
         Xtr_s = (X_train-Xtr_mean)/Xtr_std[None,:]
         Xts_s = (X_test-Xtr_mean[None,:])/Xtr_std[None,:]
```

We also want to select a best order for this logistic model. So we decide to transform the numerous features to higher orders and compare accuracy. We didn't transform those OHC features since they are binary.

```
In [13]: # num_category stores features that are continuous
         num_category = ['age','fnlwgt','education-num','capital-gain','capital-loss','hours-pe

         # get columns index of num_category
         ind_num = np.zeros((1,6))
         for ind,item in enumerate(num_category):
             ind_num[0,ind] = int(X_train_df.columns.get_loc(item))

         print(ind_num)
```

```
[[0. 1. 2. 4. 5. 6.]]
```

```
In [15]: # extract columns
         Xtr_num = np.zeros((nsamples_tr,6))
         Xts_num = np.zeros((nsamples_ts,6))

         for i,ind in enumerate(ind_num[0]):
             ind = int(ind)
             Xtr_num[:,i] = Xtr_s[:,ind]
             Xts_num[:, i] = Xts_s[:, ind]
```

Regarding order of transformed features, we will use order 2 to 10. For each of the new training set, a higher order will be included. For example, the original data set only includes the features in num_category of 1st order. The data set with 2nd order includes the features in num_category of both 1st and 2nd order. The data set with 3rd order includes the features of 1st, 2nd and 3rd order. The highest order will have features of 1st to 10th order.

This processing step is done to both training data and test data. Transformed features are stored in add_Xtr and add_Xts.

```
In [16]: # transform features with continuous values
         # to different orders
         add_Xtr = np.zeros((nsamples_tr,54))
         add_Xts = np.zeros((nsamples_ts,54))
         order_v = [2,3,4,5,6,7,8,9,10]
         for i,order in enumerate(order_v):
             Xtri = Xtr_num**i
             add_Xtr[:,(i*6):(i*6+6)] = Xtri

             Xtsi = Xts_num ** i
             add_Xts[:, (i * 6):(i * 6 + 6)] = Xtsi
```

```
In [17]: # create model
         from sklearn import linear_model
         acc = np.zeros((10,2))
```

```
logreg = linear_model.LogisticRegression(C=1e5)
logreg.fit(Xtr_s,y_train)

yhat_tr = logreg.predict(Xtr_s)
acc_tr = np.mean(yhat_tr == y_train)
print("Accuracy of the classfier on training data = %f" % acc_tr)

yhat_ts = logreg.predict(Xts_s)
acc_ts = np.mean(yhat_ts == y_test)
print("Accuracy of the classfier on test data = %f" % acc_ts)

acc[0,:]=[acc_tr,acc_ts]
```

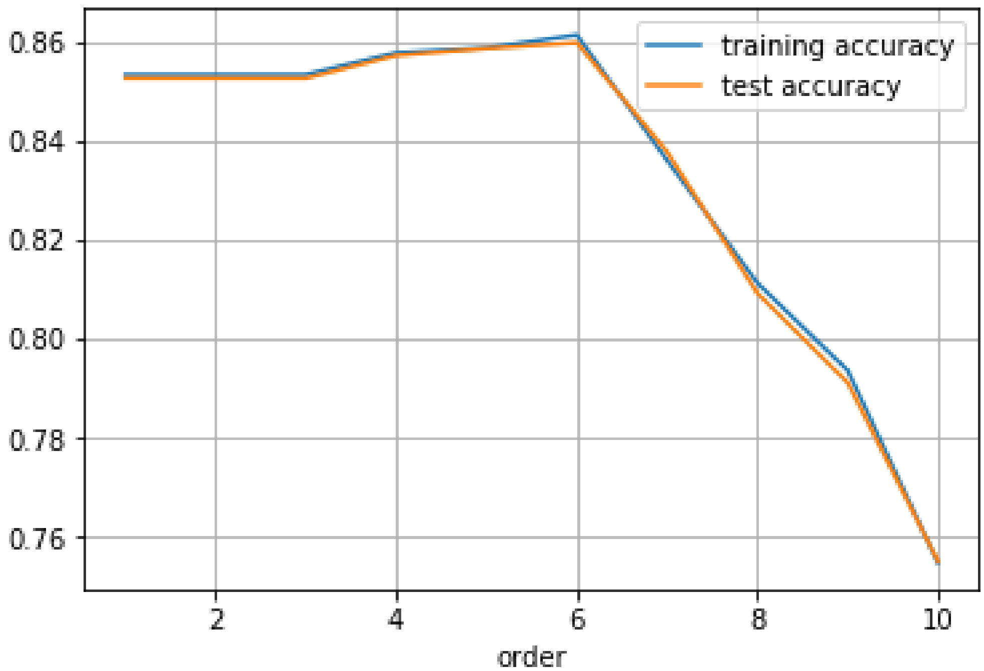
```
Accuracy of the classfier on training data = 0.853317
Accuracy of the classfier on test data = 0.852589
```

This is the accuracy for the original data. Then we train our model with higher order of numerous features in num_category and test its accuracy.

```
In [18]: # add transformed features of different order to training data
         for ind,order in enumerate(order_v):
             addXtr = add_Xtr[:,:(ind*6+6)]
             addXts = add_Xts[:, :(ind * 6 + 6)]
             Xtr_i = np.hstack((Xtr_s,addXtr))
             Xts_i = np.hstack((Xts_s, addXts))
             logregi = linear_model.LogisticRegression(C=1e5)
             logregi.fit(Xtr_i, y_train)

             yhati_tr = logregi.predict(Xtr_i)
             acci_tr = np.mean(yhati_tr == y_train)
             acc[ind+1,0] = acci_tr

             yhati_ts = logregi.predict(Xts_i)
             acci_ts = np.mean(yhati_ts == y_test)
             acc[ind + 1, 1] = acci_ts
```

Then we plot accuracy vs. order of numerous features to see the performance of model using different order of features.

```
In [19]: # plot accuracy vs order
         x_v = [1,2,3,4,5,6,7,8,9,10]
         plt.plot(x_v,acc[:,0])
         plt.plot(x_v,acc[:,1])
         plt.xlabel('order')
         plt.legend(['training accuracy','test accuracy'])
         plt.grid()
         plt.show()

         print(acc)
```




```
[[0.85331695 0.85258891]
 [0.85331695 0.85258891]
 [0.85331695 0.85258891]
 [0.85767813 0.85713408]
 [0.85866093 0.85854677]
 [0.8612715  0.85971378]
 [0.8360258  0.83772496]
 [0.81130221 0.80922548]
 [0.79364251 0.79116762]
 [0.75485258 0.75511332]]
```

As we can see, the highest accuracy is achieved at order of 6 and decreases as the order increases. There is probably overfitting when order is too high.