Data Science Test Tutorial for Cryoocyte

March 3, 2019

1 A Tutorial to implement data science model on a high dimensional dataset

Import Python Packages

```
In [458]: # dataframe package
          import numpy as np
          import pandas as pd

          # data preprocessing
          from sklearn.model_selection import train_test_split
          from sklearn.preprocessing import StandardScaler, normalize

          # linear regression
          from sklearn.linear_model import LinearRegression
          # lasso regression
          from sklearn.linear_model import LassoCV
          from sklearn.datasets import make_regression
          from sklearn import linear_model

          # model evalutaion
          from sklearn.metrics import r2_score
          from sklearn.metrics import mean_squared_error
          from math import sqrt

          # plot
          import matplotlib.pyplot as plt
```

1.1 First, we want to read in training dataset and preprocess the dataset

```
In [459]: # Read in all the data.
          # I choose to drop the NA data because they are only a few compared to the whole dat
          # Deleting these NA rows will have negligible effect on the analysis process.

          data = pd.read_csv('cryoocyte_1_regression_train.csv')
          df = data.dropna()
          df_copy=df.copy()
```

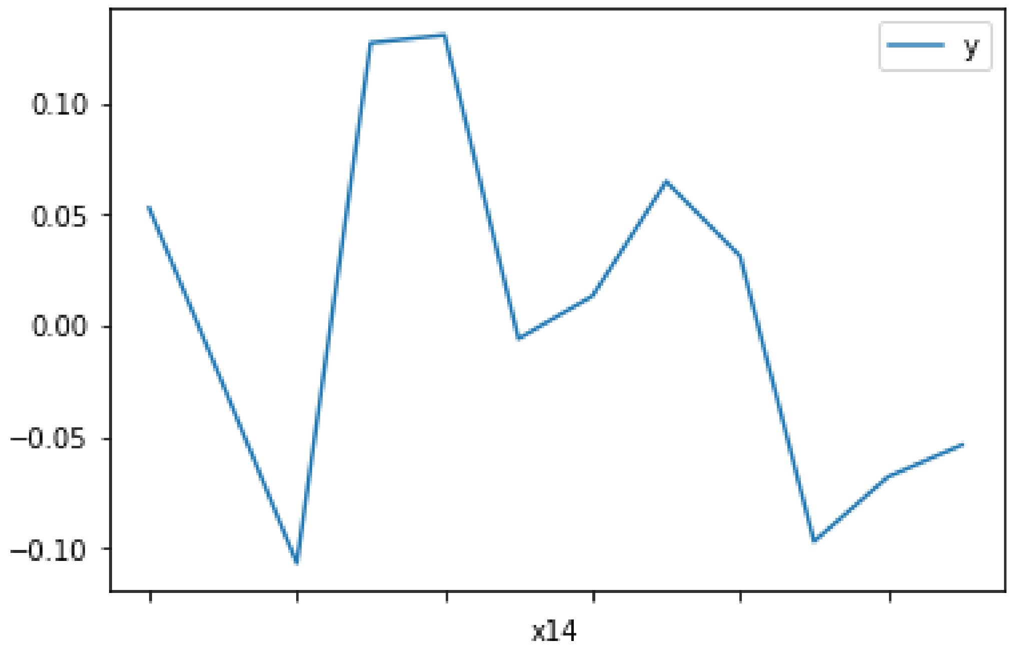
```
In [460]: #filter out the columns which are not float and process each one
          print(df_copy.select_dtypes(include=['object']).head())
```

```
    x14 x48       x52     x83        x84    x97
0   Aug   D   $621.35  Yellow  wednesday  -0.01%
1   Jun   B  $1269.85   Orang    tuesday  -0.01%
2   Jun   B   $972.98   Orang    tuesday  -0.01%
3  July   B  $-153.38   Orang    tuesday    0.0%
4   Jun   B   $-326.5  Yellow  wednesday   0.01%
```

1.1.1 For each of the non-numeric variables, we want to see if they are significant to y by simply plotting the means in each variable. If so, then we keep these variables and transform the data type/format.

```
In [461]: # x14
          df_x14_mean = df_copy[['x14','y']]
          df_x14_mean = df_x14_mean.groupby(['x14']).mean()
          df_x14_mean.plot()
          print (df_x14_mean)
```

```
                y
x14
Apr      0.053122
Aug     -0.026118
Dev     -0.106637
Feb      0.127195
January  0.130706
July    -0.005716
Jun      0.013357
Mar      0.064913
May      0.031390
Nov     -0.096861
Oct     -0.067782
sept.   -0.053503
```



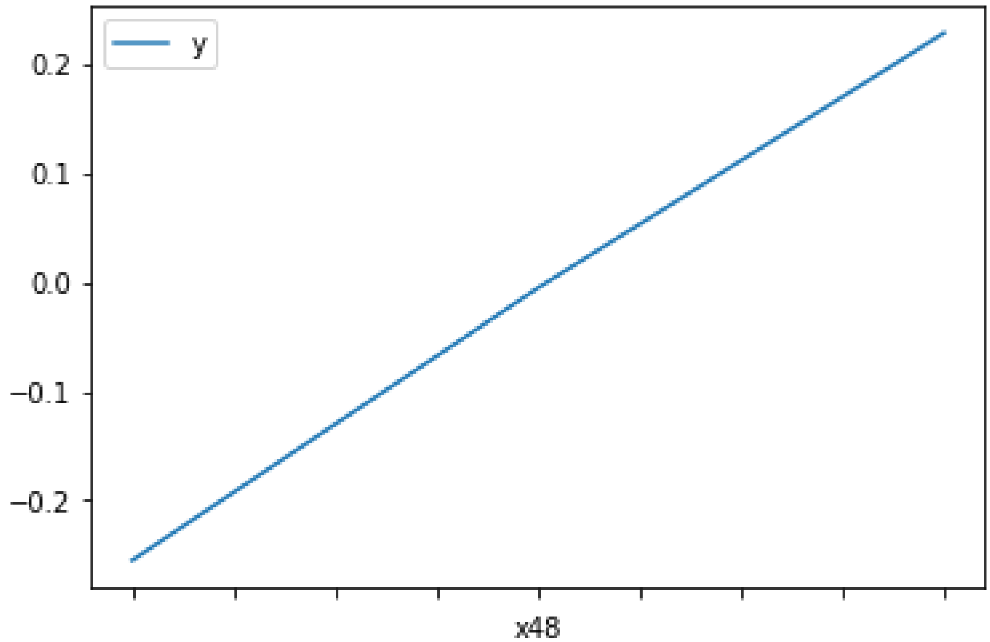
From the plot, we can see that x14 is signicant to y, so we continue to transform the data

```
In [462]: # Assign the numeric value to x14
          d = {'Aug':8, 'Jun':6, 'July':7, 'sept.':9, 'Apr':4 ,'May':5, 'Oct':10 ,'Mar':3 ,'No
          df_copy['x14'] = df_copy['x14'].map(d)
          print(df_copy['x14'].head())
```

```
0    8
1    6
2    6
3    7
4    6
Name: x14, dtype: int64
```

```
In [463]: # Similar to x14, we plot the dataset groupby the mean of y in each category in x48.
          df_x48_mean = df_copy[['x48','y']]
          df_x48_mean = df_x48_mean.groupby(['x48']).mean()
          df_x48_mean.plot()
          print (df_x48_mean)
```

```
            y
x48
A   -0.255165
B   -0.005208
D    0.228908
```




```
In [464]: # x48 is very significant to y. Similar to x14, we assign the numerica value to x48
          dict48 = {'A':1, 'B':2, 'D':3}
          df_copy['x48'] = df_copy['x48'].map(dict48)
          print(df_copy['x48'].head())
```

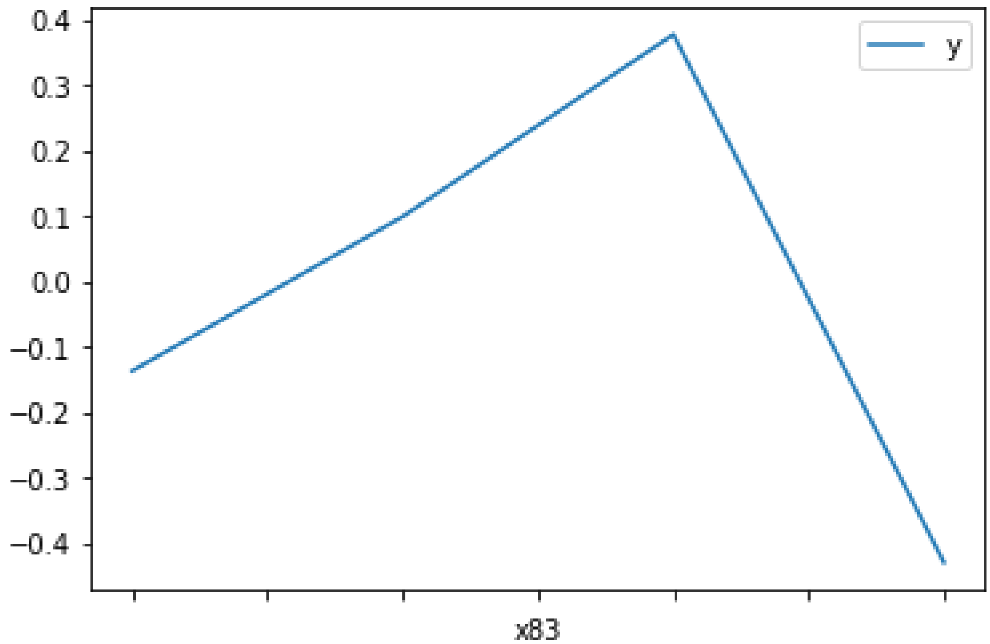
```
0    3
1    2
2    2
3    2
4    2
Name: x48, dtype: int64
```

```
In [465]: # Use string strip to take out the $ sign in x52
          df_copy['x52'] = df_copy['x52'].str.strip('$')
          df_copy['x52'] = pd.to_numeric(df_copy['x52'])
          print(df_copy['x52'].head())
```

```
0     621.35
1    1269.85
2     972.98
3    -153.38
4    -326.50
Name: x52, dtype: float64
```

```
In [466]: # Similar process to x14 and x48
          df_x83_mean = df_copy[['x83','y']]
          df_x83_mean = df_x83_mean.groupby(['x83']).mean()
          df_x83_mean.plot()
          print (df_x83_mean)
```

```
               y
x83
Orang  -0.136016
Yellow  0.099512
blue    0.377305
red    -0.428398
```

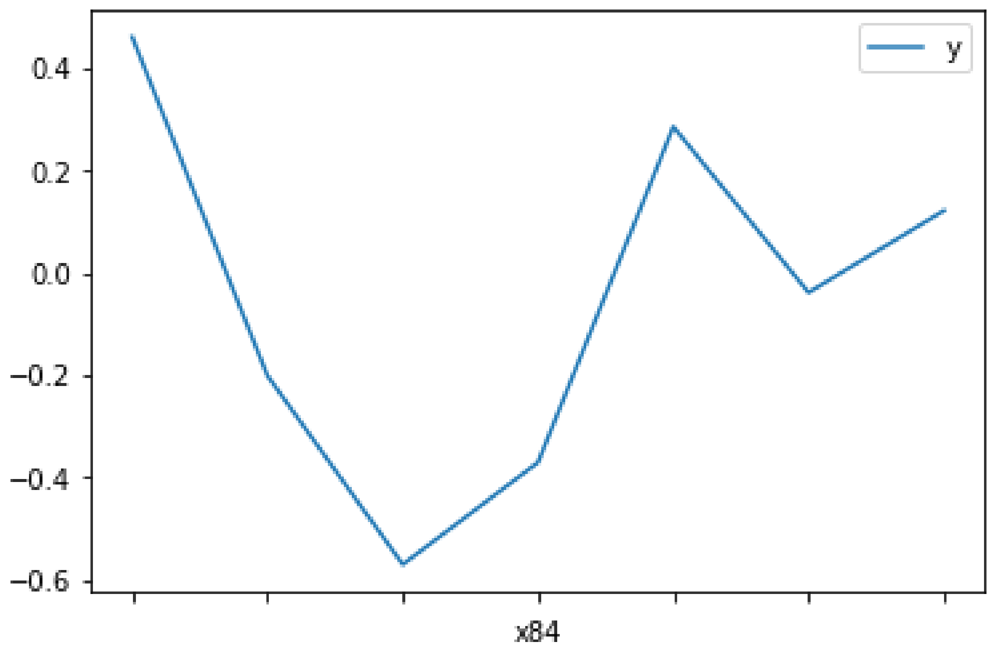



```
In [467]: dict83 = {'Orang':1, 'Yellow':2, 'blue':3,'red':4}
          df_copy['x83'] = df_copy['x83'].map(dict83)
          print(df_copy['x83'].head())
```

```
0    2
1    1
2    1
3    1
4    2
Name: x83, dtype: int64
```

In [468]:
```
# Similar process to x14, x48 and x83
df_x84_mean = df_copy[['x84','y']]
df_x84_mean = df_x84_mean.groupby(['x84']).mean()
df_x84_mean.plot()
print (df_x84_mean)
```

```
                  y
x84
friday     0.462135
monday    -0.200215
sat       -0.569496
sun       -0.370224
thursday   0.286546
tuesday   -0.037676
wednesday  0.122701
```



In [469]:
```
dict84 = {'friday':5, 'monday':1, 'sat':3,'sun':7,'thursday':4, 'tuesday':2, 'wednesd
df_copy['x84'] = df_copy['x84'].map(dict84)
print(df_copy['x84'].head())
```

```
0    3
1    2
2    2
3    2
4    3
```

```
Name: x84, dtype: int64
```

```
In [470]: # Use string strip to take out the % sign in x97

          df_copy['x97'] = df_copy['x97'].str.strip('%')
          df_copy['x97'] = pd.to_numeric(df_copy['x97'])
          df_copy['x97'] = df_copy['x97'].div(100).round(4)
          print(df_copy['x97'].head())
```

```
0   -0.0001
1   -0.0001
2   -0.0001
3    0.0000
4    0.0001
Name: x97, dtype: float64
```

1.2 Second, we want to divide the dataset into Train and Validation set (70%-30%) and rescale the data because of the data scale imbalance.

```
In [471]: # Separate out the x_data and y_data.
          x_data = df_copy.loc[:, df_copy.columns != "y"]
          y_data = df_copy.loc[:, "y"]

In [472]: # The random state to use while splitting the data.
          random_state = 100

In [473]: x_train, x_test, y_train, y_test = train_test_split(x_data,y_data,test_size = 0.3 ,ra

In [474]: # Applying scalar to the x dataset
          scaler_train = StandardScaler().fit(x_train)
          scaler_test = StandardScaler().fit(x_test)
          x_train_s = scaler_train.transform(x_train)
          x_test_s = scaler_test.transform(x_test)
```

1.3 Third, we start to apply models to the preprocessed dataset, both Training and Validation. Then we evaluate which model has a higher accuracy.

1.3.1 Linear Regression Model.

```
In [475]: clflm = LinearRegression()
          clflm.fit(x_train_s,y_train)

          y_pred_lm_train =clflm.predict(x_train_s)
          y_pred_lm_test = clflm.predict(x_test_s)
```

We use r_2 and RMSE to measure the accuracy of the model.
The higher the r2 or the lower RMSE, the better accuracy.

```
In [476]: r2_lm_train= r2_score(y_train, y_pred_lm_train)
          r2_lm_test= r2_score(y_test, y_pred_lm_test)
          print("Linear Reg r2 Train", r2_lm_train)
          print("Linear Reg r2 Test", r2_lm_test)

          mse_lm_train= mean_squared_error(y_train, y_pred_lm_train)
          mse_lm_test = mean_squared_error(y_test, y_pred_lm_test)
          print('Linear Reg RMSE Train', sqrt(mse_lm_train))
          print('Linear Reg RMSE Test', sqrt(mse_lm_test))
```

```
Linear Reg r2 Train 0.9383503727123947
Linear Reg r2 Test 0.9348168892671871
Linear Reg RMSE Train 0.04980092232837731
Linear Reg RMSE Test 0.051469210482093235
```

1.3.2 Lasso Rgression Model

The Lasso is a linear model that estimates sparse coefficients. It is useful in some contexts due to its tendency to prefer solutions with fewer parameter values, effectively reducing the number of variables upon which the given solution is dependent.

Lasso linear model with iterative fitting along a regularization path. The best model is selected by cross-validation. The optimization objective for Lasso is:

(1 / (2 * n_samples)) * ||y - Xw||^2_2 + alpha * ||w||_1

```
In [477]: #lasso regression
          from sklearn.linear_model import LassoCV
          from sklearn.datasets import make_regression
          from sklearn import linear_model
```

```
In [478]: #change tol to 0.01 to make the iter converges in LassoCV
          clf_la = LassoCV(n_alphas = 100,cv=100, random_state=0,normalize=True,tol=0.01)
          clf_la.fit(x_train, y_train)

          y_pred_la_train = clf_la.predict(x_train)
          y_pred_la_test = clf_la.predict(x_test)
```

```
In [479]: r2_la_train= r2_score(y_train, y_pred_la_train)
          r2_la_test= r2_score(y_test, y_pred_la_test)
          print("Lasso Reg r2 Train", r2_la_train)
          print("Lasso Reg r2 Test", r2_la_test)

          mse_la_train= mean_squared_error(y_train, y_pred_la_train)
          mse_la_test = mean_squared_error(y_test, y_pred_la_test)
          print('Lasso Reg RMSE Train', sqrt(mse_la_train))
          print('Lasso Reg RMSE Test', sqrt(mse_la_test))
```

```
Lasso Reg r2 Train 0.9365069284454811
Lasso Reg r2 Test 0.9372997827764117
```

```
Lasso Reg RMSE Train 0.05054001040348781
Lasso Reg RMSE Test 0.050479435294885425
```

1.3.3 Model Comparison

We compare these two model using r2 and rmse in the validation set.
Linear Reg r2 Test: 0.9348168892671871
Lasso Reg r2 Test: 0.9372997827764117
Linear Reg RMSE Test: 0.051469210482093235
Lasso Reg RMSE Test 0.050479435294885425
Both of the regression has high r2 and small RMSE, while Lasso Regression is slightly better then the Linear Regression.

1.4 Predicting Y in the test dataset using Lasso Regression

```
In [480]: # Read in all the data
          data_test = pd.read_csv('cryoocyte_1_regression_test.csv')
          df_copy_test =data_test.copy()
```

Similar to the training data preprocessing:

```
In [481]: dict14 = {'Aug':8, 'Jun':6, 'July':7, 'sept.':9, 'Apr':4 ,'May':5, 'Oct':10 ,'Mar':3
          df_copy_test['x14'] = df_copy_test['x14'].map(dict14)

In [482]: dict48 = {'A':1, 'B':2, 'D':3}
          df_copy_test['x48'] = df_copy_test['x48'].map(dict48)

In [483]: df_copy_test['x52'] = df_copy_test['x52'].str.strip('$')
          df_copy_test['x52'] = pd.to_numeric(df_copy_test['x52'])

In [484]: dict83 = {'Orang':1, 'Yellow':2, 'blue':3,'red':4}
          df_copy_test['x83'] = df_copy_test['x83'].map(dict83)

In [485]: dict84 = {'friday':5, 'monday':1, 'sat':3,'sun':7,'thursday':4, 'tuesday':2, 'wednesd
          df_copy_test['x84'] = df_copy_test['x84'].map(dict84)

In [486]: df_copy_test['x97'] = df_copy_test['x97'].str.strip('%')
          df_copy_test['x97'] = pd.to_numeric(df_copy_test['x97'])
          df_copy_test['x97'] = df_copy_test['x97'].div(100).round(4)
```

1.4.1 Data reprocess and y prediction

In the testing dataset, in order to get all predicted y for the whole test dataset, we can fill in the N/A data with the mean of the column. (small effect on the prediction)

```
In [487]: # new dataset with filled na
          df_update_test = df_copy_test.fillna(df_copy_test.mean())
```

```
In [488]: x_pred = df_update_test.loc[:, df_copy_test.columns != "y"]

          clf_la = LassoCV(n_alphas = 100,cv=100, random_state=0,normalize=True,tol=0.01)
          clf_la.fit(x_train, y_train)

          y_pred = clf_la.predict(x_pred)
```

Write the dataframe with the predicted y to a new csv file

```
In [491]: # create a copy of the original test dataset and append the predicted y to it
          data_new_csv = data_test.copy()
          data_new_csv['y'] = y_pred

          #print the first 5 rows of the new data
          print(data_new_csv.head())

          # write to csv
          data_new_csv.to_csv('test_updated_y.csv')
```

```
         x0        x1        x2        x3        x4        x5        x6  \
0 -0.000960  0.000012 -0.000822  0.000095 -0.000228  0.000386  0.000349
1 -0.000842 -0.000058 -0.000400 -0.000457 -0.000221  0.000046 -0.000093
2 -0.000200 -0.001776  0.000425 -0.000156  0.000885  0.000509 -0.000451
3 -0.000732  0.000539 -0.000806  0.000489 -0.001849  0.000316  0.000564
4  0.000276  0.000122 -0.000073  0.001005 -0.000849 -0.000221 -0.000048

         x7        x8        x9    ...          x91       x92       x93  \
0 -0.000026 -0.000045 -0.000233    ...    -0.000342 -0.000266  0.000702
1  0.000039  0.000220 -0.000225    ...    -0.000132 -0.000120 -0.000369
2 -0.000132 -0.000086 -0.000272    ...    -0.000575 -0.000131  0.000107
3  0.000859  0.000363 -0.001000    ...    -0.000515 -0.000116 -0.000990
4 -0.000667 -0.000191  0.000325    ...    -0.000374  0.000431 -0.000899

        x94       x95       x96     x97       x98       x99         y
0  0.000827 -0.000604 -0.000286  -0.01% -0.000361 -0.000385 -0.074039
1 -0.000053 -0.000078 -0.000284   0.01% -0.000353 -0.000497  0.063769
2  0.000191 -0.000142  0.000027   0.01% -0.000719  0.000246  0.025203
3  0.000799  0.000121 -0.000239  -0.01% -0.000901 -0.000466 -0.048615
4  0.000038 -0.000370  0.000448   0.01% -0.001373  0.000019 -0.183080

[5 rows x 101 columns]
```