

Lab Sessions Day

3

Exercise

1

Linear regression

#Make two vector X and y

```
X=np.array([1,2,4,3,5])
y=np.array([1,3,3,2,5])
```

#With simple linear regression we want to model our data as follows:

$y = B_0 + B_1 * x$

#We can start off by estimating the value for B1 as: # $B_1 = \frac{\sum((X_i - \text{mean}(X)) * (y_i - \text{mean}(y)))}{\sum((X_i - \text{mean}(X))^2)}$

```
X_mean=X-X.mean() print(X_mean)
sqr_X_mean=X_mean*X_mean y_mean=y-y.mean()
print(y_mean) Sqr_X_mean_y_mean=X_mean*y_mean
print(Sqr_X_mean_y_mean)
Sum_Sqr_X_mean_y_mean=Sqr_X_mean_y_mean.sum()
print(Sum_Sqr_X_mean_y_mean)
```

```
B1=
Sum_Sqr_X_mean_y_mean/sqr_X_mean.sum()
print(B1)
```

#We can calculate B0 using B1 and some statistics from our dataset, as follows:

$B_0 = \text{mean}(y) - B_1 * \text{mean}(X)$

```
B0 = y.mean()-(B1*X.mean())
print(B0)
```

#Making Predictions (y_{hat} is a predicted

```
y) y_hat=B0+B1*X
```

```
y_hat=B0+B1*  
X  
print(X,y,y_hat)
```

```
#Evaluation RMSE = sqrt( sum(  
(y_hat_i - yi)^2 )/n )
```

```
n=np.size(X) error=y_hat - y  
print(error) error_sqr=error*error  
print(error) RMSE = np.sqrt(  
error_sqr.sum()/n) print(RMSE)
```

Exercise 2

Logistic regression

```
from sklearn.linear_model import  
LogisticRegression from sklearn.datasets import  
load_breast_cancer from sklearn.model_selection  
import train_test_split
```

```
cancer=load_breast_cancer()  
X_train,X_test,y_train,y_test=train_test_split(cancer.data,cancer.target,stratify=cancer.target,ra  
ndom_state=42)
```

```
#####default C=1#####  
lgr=LogisticRegression().fit(X_train,y_train) print("training  
set score: %f" % lgr.score(X_train, y_train)) print("\n"test  
set score: %f" % lgr.score(X_test, y_test))
```

```
#####increase C to 100#####  
lgr100=LogisticRegression(C=100).fit(X_train,y_train) print("\n"training  
set score of lgr100: %f" % lgr100.score(X_train, y_train)) print("\n"test set  
score of lgr100: %f" % lgr100.score(X_test, y_test))
```

```

Change C value and compare the performance metric #####decrease
C to 0.01##### lgr001=LogisticRegression(C=0.01).fit(X_train,y_train)
print('\n""training set score of lgr001: %f" % lgr001.score(X_train, y_train))
print('\n""test set score of lgr001: %f" % lgr001.score(X_test, y_test))

```

```

import matplotlib.pyplot as plt
plt.plot(lgr.coef_.T,'o',label='C=1')
plt.plot(lgr100.coef_.T,'+',label='C=100')
plt.plot(lgr001.coef_.T,'-',label='C=0.01')
plt.xticks(range(cancer.data.shape[1]),cancer.feature_names,rotation=90)
plt.ylim(-5,5) plt.legend() plt.show()

```

####If we desire a more interpretable model, using L1 regularization might help
 ####As LogisticRegression applies an L2 regularization by default, the result
 ####looks similar to Ridge in Figure ridge_coefficients. Stronger regularization
 ####pushes coefficients more and more towards zero, though coefficients never
 ####become exactly zero.

```

import numpy as np
import math
n=np.arange(-2,3)
print(n)
r=pow(float(10),n)
print(r) for C in r:
  lr_l1=LogisticRegression(C=C,penalty="l1").fit(X_train,y_train) print("\n""Training Accuracy of
  L1 LogRess with C=%f:%f"%(C,lr_l1.score(X_train,y_train))) print("\n""Test Accuracy of L1
  LogRegss with C=%f: %f"%(C,lr_l1.score(X_test,y_test)))
  plt.plot(lr_l1.coef_.T,'o',label="C=%f"%C)
  plt.xticks(range(cancer.data.shape[1]),cancer.feature_names,rotation=90) plt.ylim(-5,5)
  plt.legend(loc='best') plt.show()

```