## Predicting the Popularity Index of the restaurants using Yelp Dataset

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## Approach

- Our Objective: Predicting the popularity index of the restaurants in the yelp dataset.
- Focus "Open" restaurants
- Fit a linear regression model on the dataset.
- Split the dataset to have 50 50 training and testing data.
- Built the model using training set and tested it on the test set.

#### Obtain data

- Yelp dataset obtained online from the yelp challenge website.
- The business subset of the entire dataset was considered.
- Considered around 6600+ instances of data.
- More than 100 attributes.
- Data Cleaning:
  - ► Missing values were logically dealt by replacing with 0
  - ▶ Attributes with less than 50% blank values were selected.

#### Libraries

- Standard:
  - ▶ Imported libraries such as pandas, numpy, matplotlib
  - ► Imported linear regression from sklearn.linear\_model
- Custom: Self Library
  - mylibrary.py

#### **Iteration**

- For Loops:
  - Used for iterating the process of joining data from two CSV files
  - Used for filtering open restaurants out of the dataset.
  - Used for generating the column stats iteratively.
  - ▶ Used for checking the attributes if they have atleast 50% populated values

#### File I/O

- Input files:
  - ► The dataset from yelp.
  - ► The final dataset file to fit the model
- Read file:
  - Reading two csv files before combining them
  - ▶ Reading the popularity index restaurants file.
- Output files:
  - ▶ A combined CSV file from the huge dataset.
  - CSV file that contains open restaurants.
  - CSV file that has column stats.
  - CSV file that has the final selected attributes.

#### **Data Structure**

- Have used the following Data Structure:
  - List
  - Dictionary
  - Arrays
  - Data frames
  - Series
  - Stacks

### Object orientation

- Created Class with methods:
  - Giving distribution/histogram of a particular column
  - Giving the mean of a particular column
  - ▶ Giving the Variance of a particular column
  - Giving the frequency of a particular column
  - Giving the maximum & minimum value in the column
  - ► Getting to a particular column
- Creating Objects from the class
- ▶ Inheritance- Inherited one class from the other

#### Flow of code

Import Libraries

Join fa con





Filter the open restaurants



Creating
Regressor
variable for the
popularity index

Apply the linear regression model on the test set



Converting to numeric attribute

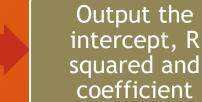


Selecting over 50% populated attributes



Creating column stats

Divide into training and test sets





Apply Ridge regression on the test set



Output the intercept, R squared and coefficient

#### **Importing Libraries**

Joined two files to Form a combined file

```
####This is a Data Science Project
##### We are working on the Yelp Dataset

### importing third party libraries

import pandas
import numpy
import numpy
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
import matplotlib as plt
import matplotlib.pyplot as plt
```

```
colNames = ['business id',
'full address',
'hours/Friday/close',
'hours/Friday/open',
'hours/Tuesday/close',
'hours/Tuesday/open',
 'hours/Thursday/close',
'hours/Thursday/open',
'hours/Wednesday/close',
'hours/Wednesday/open',
'hours/Monday/close',
'hours/Monday/open',
'open',
 'categories/0',
 'categories/1',
'city',
'review count',
 'name',
'longitude',
'state',
 'stars',
 'latitude',
'attributes/Take-out',
'attributes/Drive-Thru',
'attributes/Good For/dessert',
'attributes/Good For/latenight',
'attributes/Good For/lunch',
 'attributes/Good For/dinner',
 'attributes/Good For/brunch',
'attributes/Good For/breakfast',
'attributes/Caters',
 'attributes/Noise Level',
'attributes/Takes Reservations',
```

Combining two csv files into one

Output the file

```
for i in range(13,14):
    fileName = 'CSV '+str(i)+'.csv'
    csvNew = pandas.read_csv(fileName)
    m = len(csvNew)
    df1 = pandas.DataFrame(csvNew, index = range(n,n+m))
    frames = [df,df1]
    df = pandas.concat(frames)
```

df.to\_csv("CombinedCSV.csv")

## Criteria: Select only restaurants which are open

Checked for the word "Restaurants" In the first seven categories.

(We had to do this as if the "Restaurants"
Word appeared in one of the first seven categories, the business is treated as A restaurant.)

These list of open restaurants are written into a CSV file

```
count = 0
for i in range(n):
    if (file['open'][i] == True):
        if(file['categories/0'][i] == 'Restaurants'):
            df.loc[count] = file.loc[i]
            count += 1
        elif(file['categories/1'][i] == 'Restaurants'):
            df.loc[count] = file.loc[i]
            count += 1
        elif(file['categories/2'][i] == 'Restaurants'):
            df.loc[count] = file.loc[i]
            count += 1
        elif(file['categories/3'][i] == 'Restaurants'):
            df.loc[count] = file.loc[i]
        elif(file['categories/4'][i] == 'Restaurants'):
            df.loc[count] = file.loc[i]
            count += 1
        elif(file['categories/5'][i] == 'Restaurants'):
            df.loc[count] = file.loc[i]
            count += 1
        elif(file['categories/6'][i] == 'Restaurants'):
            df.loc[count] = file.loc[i]
            count += 1
        elif(file['categories/7'][i] == 'Restaurants'):
            df.loc[count] = file.loc[i]
            count += 1
        elif(file['categories/8'][i] == 'Restaurants'):
            df.loc[count] = file.loc[i]
            count += 1
        elif(file['categories/9'][i] == 'Restaurants'):
            df.loc[count] = file.loc[i]
            count += 1
df.to csv("OpenRestaurants.csv")
```

Normalized and created three new Attributes - newStars, newCount and popularity Index

Calculated the popularity index
Using the attributes

Wrote the file with popularity index to a CSV file

```
=======Create regressor variable========
file=pandas.read csv("OpenRestaurants.csv")
maxCount = max(file['review count'])
minCount = min(file['review count'])
diffCount = maxCount - minCount
newCount = (file['review count'] - minCount)/diffCount
maxStars = max(file['stars'])
minStars = min(file['stars'])
diffStars = maxStars - minStars
newStars = (file['stars'] - minStars)/diffStars
popularityIndex = newCount * newStars
file['newCount'] = newCount
file['newStars'] = newStars
file['popularityIndex'] = popularityIndex
file.to csv("PopularityIndexRestaurants.csv")
```

Calculated the number of missing, False, true or populated values in the columns

Wrote it to a CSV file

```
#======Creating Column Stats========
file = pandas.read csv("PopularityIndexRestaurants.csv")
file = file.drop(file.columns[[0,1,2]], axis = 1)
colNames = list(file.columns.values)
total = len(file)
cols = len(file.columns)
colStats = pandas.DataFrame(columns = ['ColName','Missing','False','True','Populated','Total'])
for i in range(cols):
    blanks = file[colNames[i]].isnull().sum()
    populated = file[colNames[i]].count()
    temp = list(file[colNames[i]])
    trues = temp.count(True)
    falses = temp.count(False)
    total = blanks + populated
    PercentPopulated=(populated/total) *100
    myData = [{'ColName':colNames[i],'Missing':blanks,'False':falses,'True':trues
               , 'Populated':populated, 'Total':total, 'PercentPopulated':PercentPopulated}]
    colStats = colStats.append(myData,ignore index = True)
colStats.to csv("ColumnStats.csv")
```

Selected only attributes which had atleast half of the values which are populated (populated = not missing)

Wrote it to the final CSV, called the "SelectAtrributesFile". This is our final CSV with all data filtered and cleaned

```
for i in range(cols):
    if (colStats['PercentPopulated'][i] > 50):
        selectedCols = selectedCols.append(colStats.loc[i,:])

selCols = list(selectedCols['ColName'])

selAttributesFile = file[selCols]

selAttributesFile.to_csv('SelectAttributesFile.csv')
```

Importing libraries: numpy, pandas, Scikit Learn And matplotlib

Converting the dataframe type to numeric

Dropped columns which had negligible variance

Separating the Regressor variable from the dataset

```
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
import matplotlib as plt

raw_data=pd.read_csv('SelectAttributesFile.csv')

raw_data.apply(lambda x:pd.to_numeric(x,errors='coerce'))

data=pd.DataFrame(raw_data)

data.drop(data.columns[[0,2,12,24,31,35,36,37,38,39,40,41,58,59,62,63]], inplace=True,axis=1)

feature_cols = list(data.columns[0:50])

target_col = data.columns[-1]
y_all=data[target_col]
X_all = data[feature_cols]
```

Defining function to generate dummy variables for categorical variables

Output and join the result to columns in the dataframe

```
def preprocess_features(X):
    outX = pd.DataFrame(index=X.index)  # output dataframe, initially empty

# Check each column
for col, col_data in X.iteritems():
    # If data type is non-numeric, try to replace all yes/no values with 1/0
    if col_data.dtype == object:
        col_data = col_data.replace([True, False], [1, 0])
    # Note: This should change the data type for yes/no columns to int

# If still non-numeric, convert to one or more dummy variables
    if col_data.dtype == object:
        col_data = pd.get_dummies(col_data, prefix=col)  # e.g. 'school' => 'school_GP', 'sc
    outX = outX.join(col_data)  # collect column(s) in output dataframe

return outX
```

# Making an object from the class in the main program and using the methods

# Making self library "mylibrary.py" having a class named-billu with the mentioned methods

```
class billu():
   def init (self, column):
        self.column=column
   def getColumn(self):
        print (self.column)
   def descriptive stats(self):
        return (self.column.describe())
   def variance (self):
        return (self.column.std())
   def min value(self):
        return(self.column.min())
   def max value(self):
        return(self.column.max())
   def frequency(self):
        return (self.column.count())
   def distribution(self):
        plt.hist(self.column)
        plt.xlabel('Frequency', fontsize=18)
        return (plt.show())
```

## "Pop\_index\_av" from the class "billu"

```
class yelp(billu):
    def __init__(self,column):
        billu.__init__(self,column)

def col_average(self):
    return(self.column.mean())

def del_item(self):
    stack=list(self.column)
    removed=stack.pop()
    print(removed)
```

## Building a Linear Regression Model

Fitting the model on every even sample and testing on every odd sample.

Print out the R Squared value, intercept and the coeff. for the linear regression model

Building & Applying the ridge regression Model to the test set

Print out the R squared, intercept, and the coefficients

```
X_all = preprocess_features(X_all)
y all.fillna(0)
X all=X all.fillna(0)
model=LinearRegression()
model.fit(X all, y all)
print(model.intercept )
print(model.coef .shape)
print (model.coef )
model.fit(X_all[::2],y_all[::2])
print("R2 score: %s" % model.score(X_all[1::2],y all[1::2]))
from sklearn.linear model import Ridge
model2=Ridge(alpha=0.1)
model2.fit(X all,y all)
print(model2.intercept )
print (model2.coef .shape)
print (model2.coef )
model2.fit(X all[::2],y all[::2])
print("R2 score: %s" % model2.score(X_all[1::2],y_all[1::2]))
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Applying the ridge regression Model to the test set

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model.fit(X all[::2],y all[::2])
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model2.fit(X all,y all)
print(model2.intercept )
print (model2.coef .shape)
print(model2.coef)
model2.fit(X all[::2],y all[::2])
print("R2 score: %s" % model2.score(X all[1::2],y all[1::2]))
```

## Output

- There is high multicollinearity among the regressor variables.
- Adding L2 penalty in the Multiple Regression Model constraints variance of beta coefficients & improves R square value considerably.