

Regression Model

Load Data

```
In [1]: %autosave 20

#basic library
import pandas as pd
import numpy as np
import collections
from collections import defaultdict

#model training
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# visulization
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('seaborn')

# Data statistics
from scipy import stats

# print all the outputs in a cell
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

Autosaving every 20 seconds

```
In [2]: df = pd.read_excel('databaseForFunction.xlsx', index_col=0)
```

```
In [3]: df.head()
```

```
Out[3]:
```

	State	County	Year	Month	PDensity	Population	SNAP_Applications	numberOfWorkers
0	California	Alameda	2019	1	1898.5	1559308	5515	44
1	California	Alameda	2019	2	1898.5	1559308	4478	39
2	California	Alameda	2019	3	1898.5	1559308	5041	19
3	California	Alameda	2019	4	1898.5	1559308	5253	80
4	California	Alameda	2019	5	1898.5	1559308	8074	50

Add one more feature - dummy value for state

```
In [4]: # split CA and texas using dummy

# create dummy variables
dummies = pd.get_dummies(df['State'], prefix='State')

# concatenate the dummy variables with the original dataframe
df = pd.concat([df, dummies], axis=1)
```

```
In [5]: # drop State_Texas since using dummy

df = df.drop(columns='State_Texas')
```

Update DatabaseForFunction, May 8, 2023

1. Delete column 'snap_per_capita'
2. Delete column 'last_google_snap' and 'google_snap' because of overlap meaning with google word 'supplemental nutrition assistance program'
3. Add seasonal dummy variable
 - Summer: whether last month is 6/7/8
 - holiday: whether last month is 11/12

In [12]: `df.head()`

Out[12]:

	State	County	Year	Month	PDensity	Population	SNAP_Applications	numberOfWorker:
0	California	Alameda	2019	1	1898.5	1559308	5515	44
1	California	Alameda	2019	2	1898.5	1559308	4478	39
2	California	Alameda	2019	3	1898.5	1559308	5041	19
3	California	Alameda	2019	4	1898.5	1559308	5253	80
4	California	Alameda	2019	5	1898.5	1559308	8074	50

```
In [8]: # 3. Add seasonal dummy variables

# 3.1 add 'summer' -> whether last month is 6/7/8
# 3.2 add 'holiday' -> whether last month is 11/12
summer_month = [6, 7, 8]
holiday_month = [11, 12]

df['summer'] = 0
df['holiday'] = 0

for i in range(len(df)):
    if df.iloc[i,16].month in summer_month:
        df.iloc[i, -2] = 1

    if df.iloc[i,16].month in holiday_month:
        df.iloc[i, -1] = 1
```

```
In [11]: # 1. Delete column 'snap_per_capita'
# 2. Delete columns related with google research work snap application

df = df.drop(columns=['google_snap', 'last_google_snap'])
```

updated database May 8, 2023

```
In [13]: df.to_excel('databaseForFunction_May8.xlsx')
```

Choose columns to train

- use last month date to predict this month's snap applications

```
In [14]: col_keepinmodel = list(df.columns)
```

```
In [15]: coltomove = ['State', 'County', 'Year', 'Month', 'date_time', 'last_date_time',
                    'numberOfWorkers', 'numberOfDisaster', 'google_calfresh', \
                    'google_food_bank', 'google_food_pantry', 'google_food_stamps',
                    'google_supplemental']

for c in coltomove:
    col_keepinmodel.remove(c)

col_keepinmodel
```

```
Out[15]: ['PDensity',
          'Population',
          'SNAP_Applications',
          'last_snap',
          'last_worker',
          'last_disaster',
          'last_google_calfresh',
          'last_google_food_bank',
          'last_google_food_pantry',
          'last_google_food_stamps',
          'last_google_supplemental',
          'State_California',
          'summer',
          'holiday']
```

```
In [16]: df = df[col_keepinmodel]
```

```
In [17]: df.head()
```

```
Out[17]:
```

	PDensity	Population	SNAP_Applications	last_snap	last_worker	last_disaster	last_google_c
0	1898.5	1559308	5515	0	0	0	
1	1898.5	1559308	4478	5515	45	0	
2	1898.5	1559308	5041	4478	397	0	
3	1898.5	1559308	5253	5041	191	0	
4	1898.5	1559308	8074	5253	808	0	

Build the Model

1. check the correlation

```
In [18]: df.corr()[ 'SNAP_Applications' ]
```

```
Out[18]: PDensity          0.631942
Population          0.933607
SNAP_Applications    1.000000
last_snap           0.947601
last_worker          0.392523
last_disaster        0.036997
last_google_calfresh 0.192687
last_google_food_bank 0.004543
last_google_food_pantry 0.011594
last_google_food_stamps 0.045971
last_google_supplemental 0.043198
State_California     0.217959
summer               0.004451
holiday              -0.006436
Name: SNAP_Applications, dtype: float64
```

```
In [19]: X = df.drop(columns=[ 'SNAP_Applications' ])
y = df.SNAP_Applications
```

2. Result of the linear regression model

```
In [20]: import statsmodels.api as sm
import pandas as pd

# Add constant term to X
X = sm.add_constant(X)

# Fit linear regression model
model = sm.OLS(y, X).fit()

# Print summary of regression results
print(model.summary())
```

OLS Regression Results

```

=====
=====
Dep. Variable:          SNAP_Applications    R-squared:
0.925
Model:                  OLS                Adj. R-squared:
0.925
Method:                 Least Squares       F-statistic:
1.040e+04
Date:                   Mon, 08 May 2023    Prob (F-statistic):
0.00
Time:                   17:24:40            Log-Likelihood:
-94156.
No. Observations:      10908              AIC:
1.883e+05
Df Residuals:          10894              BIC:
1.884e+05
Df Model:              13
Covariance Type:       nonrobust
=====
=====

```

		coef	std err	t	P> t

[0.025	0.975]				

const		231.0256	53.814	4.293	0.000
125.540	336.511				
PDensity		-0.1757	0.039	-4.507	0.000
-0.252	-0.099				
Population		0.0027	5e-05	54.998	0.000
0.003	0.003				
last_snap		0.5937	0.007	82.494	0.000
0.580	0.608				
last_worker		-0.1092	0.014	-7.749	0.000
-0.137	-0.082				
last_disaster		316.9914	30.853	10.274	0.000
256.513	377.470				
last_google_calfresh		-2.9388	1.920	-1.531	0.126
-6.702	0.824				
last_google_food_bank		5.2657	1.654	3.184	0.001
2.024	8.507				
last_google_food_pantry		-4.4055	1.090	-4.042	0.000
-6.542	-2.269				
last_google_food_stamps		7.6416	4.091	1.868	0.062
-0.378	15.661				
last_google_supplemental		-12.9203	4.276	-3.022	0.003
-21.302	-4.539				
State_California		-190.9197	99.244	-1.924	0.054
-385.457	3.617				
summer		51.8136	32.650	1.587	0.113
-12.186	115.813				
holiday		73.0949	40.481	1.806	0.071
-6.255	152.445				
=====					
=====					
Omnibus:		23129.931		Durbin-Watson:	
1.757					

Prob(Omnibus):	0.000	Jarque-Bera (JB):	2576
55248.865			
Skew:	18.079	Prob(JB):	
0.00			
Kurtosis:	755.058	Cond. No.	
6.12e+06			
=====			
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Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 6.12e+06. This might indicate that there are strong multicollinearity or other numerical problems.

For question SVD did not converge

<https://blog.csdn.net/lijieling123/article/details/112910530>

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