NoteBook3-Modeling

March 24, 2020

[17]:
```
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:100% !important; height:100%}</style>"))
```

```
<IPython.core.display.HTML object>
```

1 Modelling

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn import ensemble
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn import metrics
```

```
C:\Users\sagar\Anaconda3\lib\site-
packages\sklearn\ensemble\weight_boosting.py:29: DeprecationWarning:
numpy.core.umath_tests is an internal NumPy module and should not be imported.
It will be removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
```

[2]:
```
data = pd.read_csv('cleaned_counties.csv').fillna(0)
print(data.shape)
data.head()
```

```
(2457, 19)
```

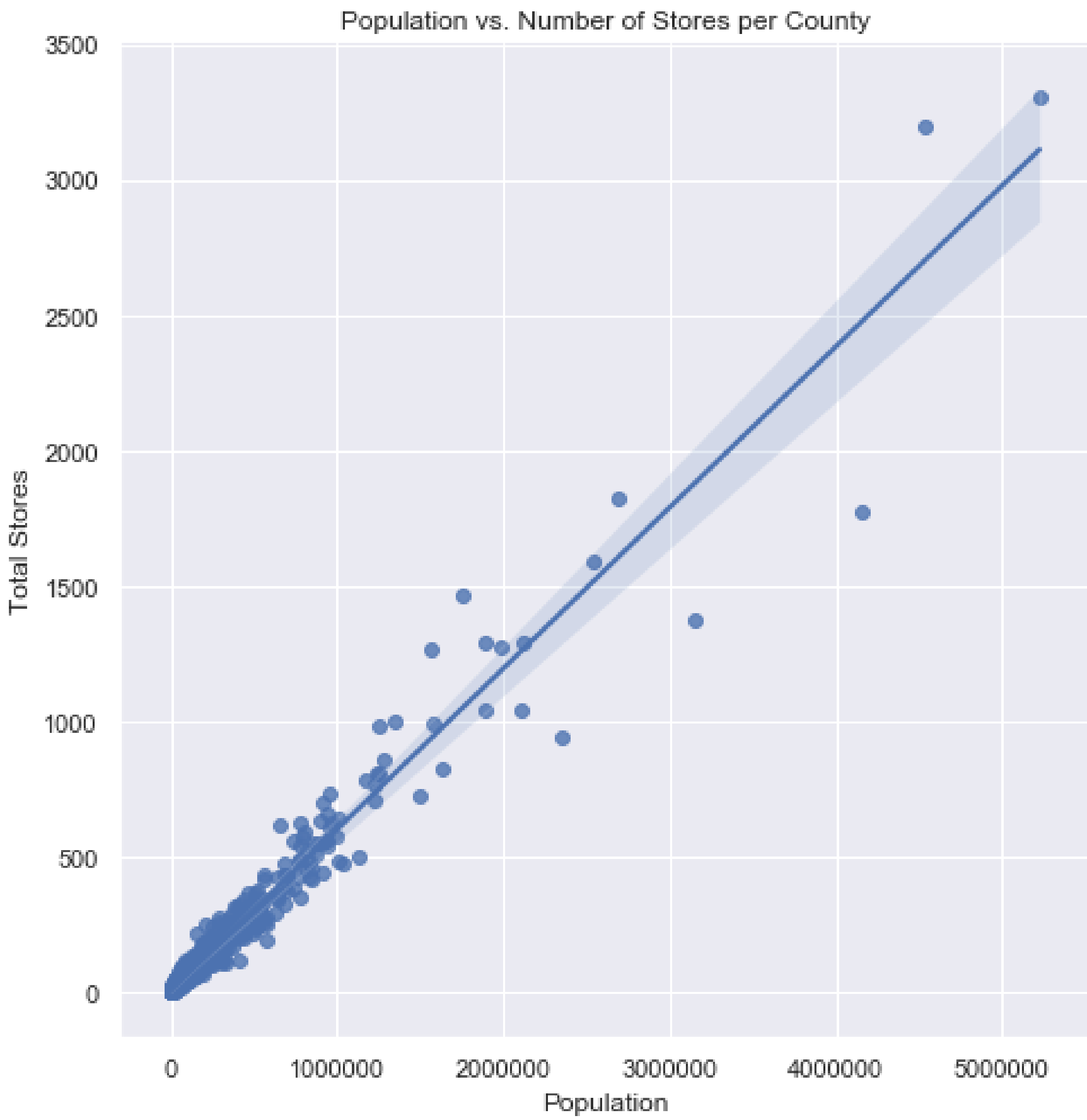
[2]:
```
   FIPS    State   County  Population  Hispanic  White  Black  Native  Asian  \
0  1001  Alabama  Autauga       55035       2.6   75.8   18.5     0.4    1.0
1  1003  Alabama  Baldwin      203690       4.5   83.1    9.5     0.6    0.7
2  1005  Alabama  Barbour       26270       4.6   46.2   46.7     0.2    0.4
3  1007  Alabama     Bibb       22561       2.2   74.5   21.4     0.4    0.1
```

```
4  1009   Alabama    Blount        57676        8.6    87.9     1.5      0.3     0.1

   Pacific    Income   Poverty  Unemployment  Civilian Labor Force  \
0      0.0   51281.0      12.9           7.6                 25602
1      0.0   50254.0      13.4           7.5                 87705
2      0.0   32964.0      26.7          17.6                  8609
3      0.0   38678.0      16.8           8.3                  8572
4      0.0   45813.0      16.7           7.7                 24473

   Grocery Stores  Supercenters  Convenience Stores  Specialty Stores  \
0               4             1                  30                 2
1              29             6                 118                26
2               5             1                  19                 2
3               5             1                  15                 1
4               6             1                  27                 0

   Total Stores
0            37
1           179
2            27
3            22
4            34
```

[3]:
```
data = data.fillna(0)
```

[4]:
```
sns.set()

g = sns.lmplot(x="Population", y="Total Stores", truncate=True, size=7,␣
 ↪data=data)
plt.title("Population vs. Number of Stores per County")
plt.show()
```

```
C:\Users\sagar\Anaconda3\lib\site-packages\seaborn\regression.py:546:
UserWarning: The `size` paramter has been renamed to `height`; please update
your code.
  warnings.warn(msg, UserWarning)
C:\Users\sagar\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713:
FutureWarning: Using a non-tuple sequence for multidimensional indexing is
deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will
be interpreted as an array index, `arr[np.array(seq)]`, which will result either
in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

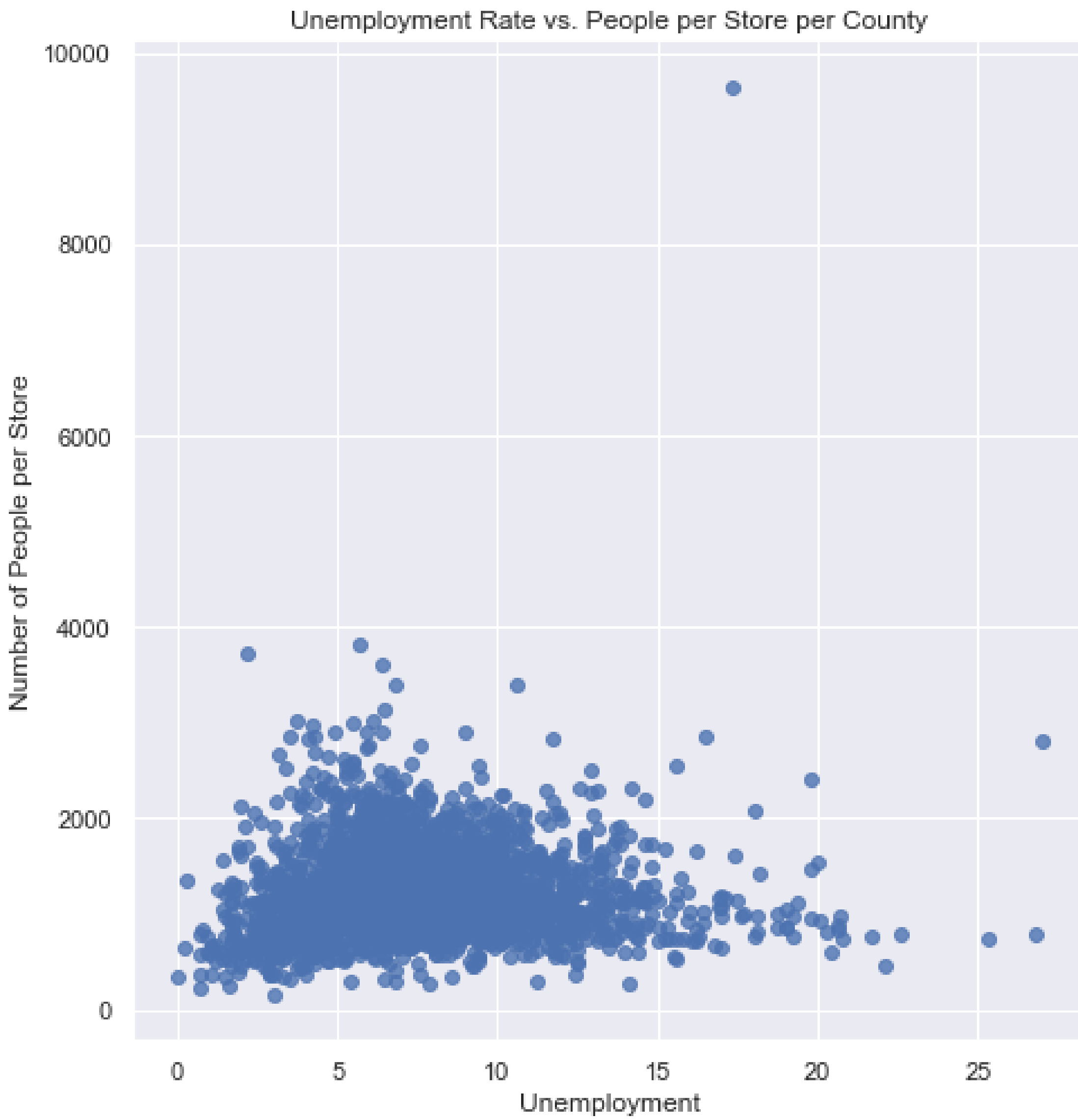


As population increases, so do the total number of stores.

[5]:
```
sns.set()

data['Number of People per Store']= data['Population']/data["Total Stores"]
g = sns.lmplot(x="Poverty", y="Number of People per Store", truncate=True,␣
 ↪size=7, data=data)
plt.title("Poverty Rate vs. People per Store per County")
plt.show()
```

There does not seem to be any connection between the poverty rate and the number of people per store. There is one outlier which might be interesting to investigate.

[6]:
```
sns.set()

g = sns.lmplot(x="Unemployment", y="Number of People per Store", truncate=True,␣
 ↪size=7, data=data)
plt.title("Unemployment Rate vs. People per Store per County")
plt.show()
```



There does not seem to be any connection between the unemployment rate and the number of people per store. There is one outlier which might be interesting to investigate.

[7]:
```
# dataframe of the features
X = data.loc[:, ["Hispanic", "White", "Black", "Native", "Asian", "Pacific",␣
↪"Income", "Poverty", "Unemployment"]]
X["Civilian Labor Force %"] = data['Civilian Labor Force'] / data["Population"]␣
↪* 100
X.head()
```

[7]:
```
   Hispanic  White  Black  Native  Asian  Pacific   Income  Poverty  \
0       2.6   75.8   18.5     0.4    1.0      0.0  51281.0     12.9
1       4.5   83.1    9.5     0.6    0.7      0.0  50254.0     13.4
2       4.6   46.2   46.7     0.2    0.4      0.0  32964.0     26.7
```

```
3        2.2    74.5    21.4     0.4     0.1       0.0  38678.0      16.8
4        8.6    87.9     1.5     0.3     0.1       0.0  45813.0      16.7

   Unemployment  Civilian Labor Force %
0           7.6               46.519488
1           7.5               43.058078
2          17.6               32.771222
3           8.3               37.994770
4           7.7               42.431861
```

[8]:
```
# list of the target, people per store
y = data['Population'] / data['Total Stores']
y = y.replace(float('inf'), value = 0)
y.head()
```

[8]:
```
0    1487.432432
1    1137.932961
2     972.962963
3    1025.500000
4    1696.352941
dtype: float64
```

[ ]:
```

```

[9]:
```
# compute covariance between each feature and people per store
all_ = X.copy(deep=True)
all_['People per Store'] = y
all_.cov().loc[:, ['People per Store']]
```

[9]:
```
                        People per Store
Hispanic                    6.390389e+02
White                      -4.104964e+02
Black                      -5.703030e+02
Native                     -5.006583e+01
Asian                       2.882093e+02
Pacific                     8.830140e+00
Income                      2.081861e+06
Poverty                    -5.272893e+02
Unemployment                3.680510e+01
Civilian Labor Force %     -2.627420e+01
People per Store            2.458045e+05
```

[10]:
```
# divide up data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(1965, 10) (492, 10) (1965,) (492,)
```

[11]:
```
# create multiple regression model
clf = ensemble.GradientBoostingRegressor(learning_rate=.05)
```

```
clf.fit(X_train, y_train)
```

[11]:
```
GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=None,
              learning_rate=0.05, loss='ls', max_depth=3, max_features=None,
              max_leaf_nodes=None, min_impurity_decrease=0.0,
              min_impurity_split=None, min_samples_leaf=1,
              min_samples_split=2, min_weight_fraction_leaf=0.0,
              n_estimators=100, presort='auto', random_state=None,
              subsample=1.0, verbose=0, warm_start=False)
```

[12]:
```
clf.score(X_test, y_test)
```

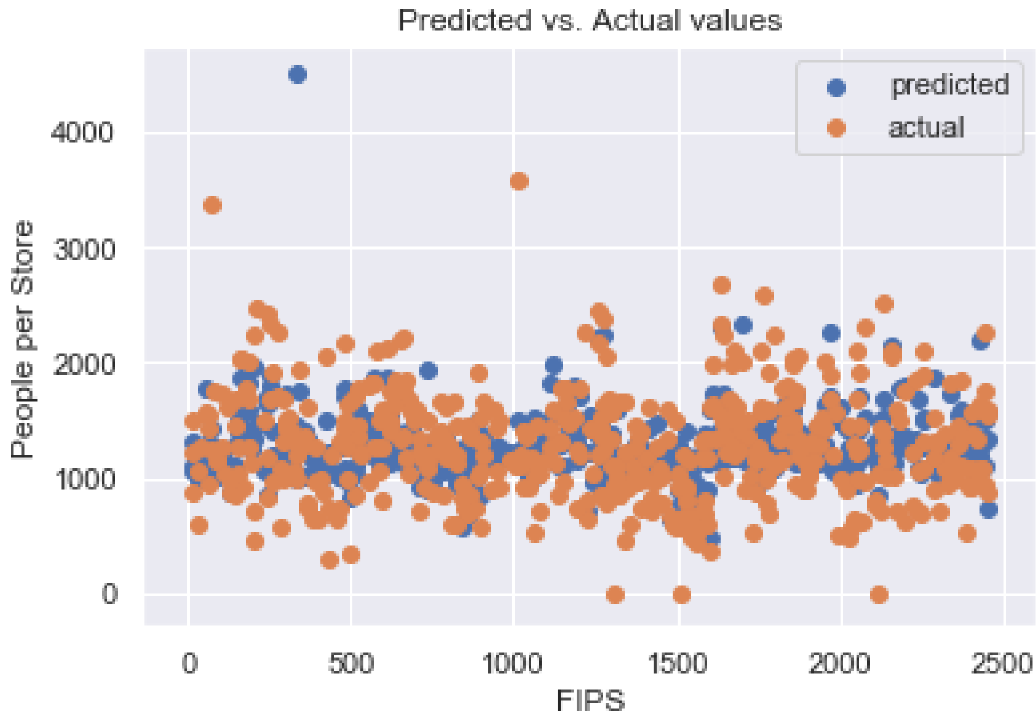
[12]:
```
0.2903684236768489
```

[13]:
```
# cross validation score
scores = cross_val_score(clf, X, y, cv=10)
print('Average Score:', np.mean(scores))
print('SD of Score:', np.std(scores))
```

```
Average Score: 0.25808522741676054
SD of Score: 0.09794461511141186
```

[14]:
```
predictions = clf.predict(X_test)
```

[15]:
```
plt.scatter(X_test.index, predictions, label='predicted')
plt.scatter(X_test.index, y_test, label='actual')
plt.title("Predicted vs. Actual values")
plt.xlabel("FIPS")
plt.ylabel("People per Store")
plt.legend()
plt.show()
```



[16]:
```
results = data.loc[:, ['FIPS', 'State', 'County']]
results['predicted'] = clf.predict(X)
results['actual'] = y
results.head()
```

[16]:

	FIPS	State	County	predicted	actual
0	1001	Alabama	Autauga	1399.739961	1487.432432
1	1003	Alabama	Baldwin	1324.512139	1137.932961
2	1005	Alabama	Barbour	1267.243662	972.962963
3	1007	Alabama	Bibb	1104.593798	1025.500000
4	1009	Alabama	Blount	1334.378477	1696.352941

2 Conclusion

The model has an r^2 (coefficient of determination) value of about 0.25.

This means that about 25% of the variance of the y variable (people per store) can be accounted for by the set of features. Because using data about the demographics of the county, like race and poverty rate, explained so little of the variance of the y variable, it leads me to believe that there is not a strong correlation between the demographics of a county and the occurance of stores.

The unaccounted for variance could be caused by the geographic size of the county or the type of county it is. I used population size to adjust the number of stores for each county.

However, a better metric to use for adjustment could be the geographic size of the county. In addition, if the county is a rural, farming county, there are more likely to be fewer stores because more people would buy their groceries from farmers markets and local stores. Further analysis is needed to determine if these factors could better explain the variance in number of people per store.

[ ]:
```

```

[ ]:
```

```