Predicting gentrification in Chicago

Midpoint Report by The Binary Beasts

In this preliminary report, we concentrated on collecting data from the Census Bureau and running a model that could predict gentrification based on basic sociodemographic variables. For the next deriverable, we expect to incorporate more variables related to the actual link between the presence of environmental resources, such as park and garden facilities, natural features, and air pollution, and increased susceptibility to gentrification. As discussed in our literature review, our exact research questions will depend on the specifics of our data, namely if we can locate data corresponding to the construction or enhancement of parks, etc. In that case, we would like to draw out the effect of new environmental access on gentrification, returning to the idea of "green gentrification" discussed earlier. If we can only find static data on parks, we can still look at how their presence impacts the model of gentrification risk by comparing socioeconomic change over time in areas with or without these resources.

Data Collection

For this this midpoint we integrated the following variables as possible features:

- Percentage of the population who is white
- Percentage of the population with high school education
- Employment rate (as percentage)

Note: we also have their respective changes over time

Exploring the dataset

In [ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import requests
import itertools
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import sklearn as sk
from sklearn.linear_model import LogisticRegression, LinearRegression
%matplotlib inline
```

In [ ]:
```
# Import dataset

df = pd.read_csv('data_collection/output_dataset.csv')
df['year'] = pd.to_numeric(df['year'])
df.columns
```

Out[ ]:
```
Index(['zip code tabulation area', 'year', 'med_income', 'med_home_val',
       'med_rent', 'perc_white', 'med_age', 'perc_employed', 'perc_hs_grad',
       'med_income_change', 'med_home_val_change', 'med_rent_change',
       'med_age_change', 'perc_white_change', 'perc_hs_grad_change',
       'perc_employed_change'],
      dtype='object')
```

Outcome variable

Our first step is to create the Y (Outcome) variable, which is based off the Chicago Affordable Requirements Ordinance definition of a Community preservation area: communities that may or may not be high-cost or lowaffordability currently, but which are experiencing or are at high risk of experiencing displacement of existing low-income residents.

Because zip codes aren't an exact match to Chicago neighborhoods which is the unit which the ARO is based off, some zip codes barely overlap with gentrified areas but have to be put down as a gentrified zip code, we tried to use a threshold of around 40% of a zipcode being in a CPA to make the cut.

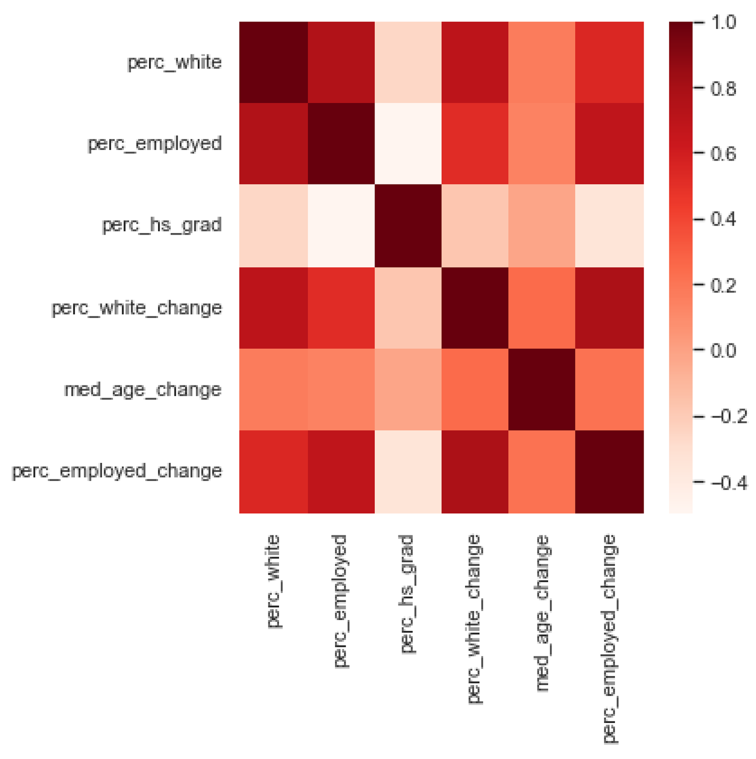
In [ ]:
```
gent_zips = ["60626", "60640", "60625", "60630", "60618", "60641", "60647", "60639", "60651", "60612", "60622", "60624", "60608", "60616", "60637", "60653", "60609", "60641"]
gent_zips_num = [float(x) for x in gent_zips]

df['gentrifying'] = [1 if row[1]['zip code tabulation area'] in gent_zips_num else 0 for row in df.iterrows() ]
features = df[['perc_white', 'perc_employed', 'perc_hs_grad', 'perc_white_change', 'med_age_change', 'perc_employed_change']]
```

Features

In [ ]:
```
features = df[df['year'] > 2012]
features = features[['perc_white', 'perc_employed', 'perc_hs_grad', 'perc_white_change', 'med_age_change', 'perc_employed_change', 'year', 'zip code tabulation area']]
```

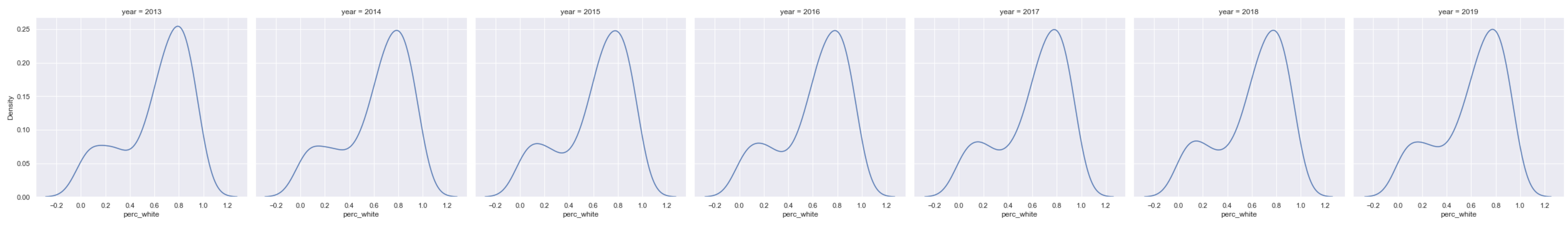
In [ ]:
```
# Correlation matrix
cor_df = features[['perc_white', 'perc_employed', 'perc_hs_grad', 'perc_white_change', 'med_age_change', 'perc_employed_change']]
corr_matrix = cor_df.corr()
plt.figure(figsize=(5, 5))
sns.heatmap(corr_matrix, annot=False, cmap=plt.cm.Reds)
plt.show()
```



In [ ]:
```
# Percentage of the population who is white
print(features.groupby('year').mean()['perc_white'])
sns.set_theme()
sns.displot(data=features, x="perc_white", col="year", kind="kde")
```

```
year
2013    0.615096
2014    0.614727
2015    0.611336
2016    0.609557
2017    0.604979
2018    0.602914
2019    0.600298
Name: perc_white, dtype: float64
```

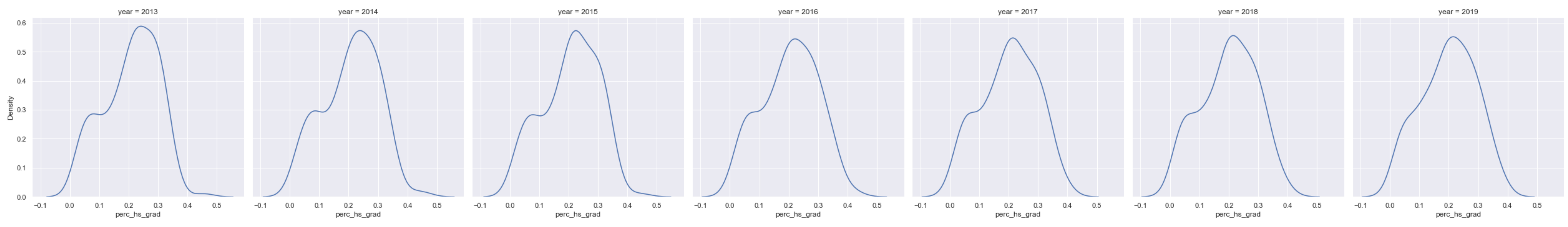
Out[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7fac4561de80>
```



In [ ]:
```
# Percentage of the population with high school education
print(features.groupby('year').mean()['perc_hs_grad'])
sns.set_theme()
sns.displot(data=features, x="perc_hs_grad", col="year", kind="kde")
```

```
year
2013    0.208010
2014    0.207445
2015    0.205875
2016    0.203436
2017    0.201324
2018    0.199518
2019    0.198557
Name: perc_hs_grad, dtype: float64
```

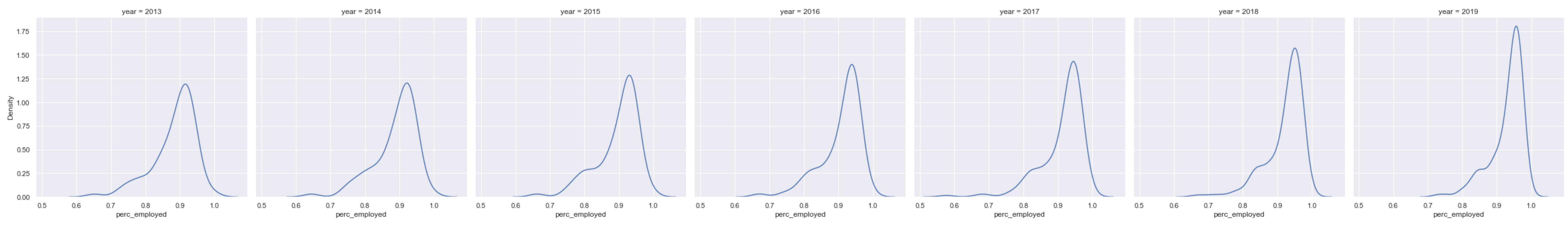
Out[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7fac4a42b640>
```



In [ ]:
```
# Employment rate (as percentage)
print(features.groupby('year').mean()['perc_employed'])
sns.set_theme()
sns.displot(data=features, x="perc_employed", col="year", kind="kde")
```

```
year
2013    0.884283
2014    0.888973
2015    0.897101
2016    0.907620
2017    0.913036
2018    0.921686
2019    0.930044
Name: perc_employed, dtype: float64
```

Out[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7fac4a3ad160>
```



Logistic regression

In [ ]:
```
Model1 = LogisticRegression().fit(features,df['gentrifying'])
params = pd.DataFrame(zip(features.columns, np.transpose(Model1.coef_)), columns=['features', 'coef'])
print(params)

Model2 = LinearRegression().fit(features,df['gentrifying'])
params2 = pd.DataFrame(zip(features.columns, np.transpose(Model2.coef_)), columns=['features', 'coef'])
print(params2)
```

```
               features                    coef
0            perc_white    [-2.2432075899865955]
1         perc_employed  [-0.022317908940155874]
2          perc_hs_grad    [-0.4197746008797609]
3     perc_white_change     [0.5555477516836832]
4        med_age_change     [-2.957216424353154]
5  perc_employed_change    [0.43716899831936645]
               features      coef
0            perc_white -0.265799
1         perc_employed  0.041276
2          perc_hs_grad -0.059697
3     perc_white_change  0.076210
4        med_age_change -0.277456
5  perc_employed_change  0.070197
```