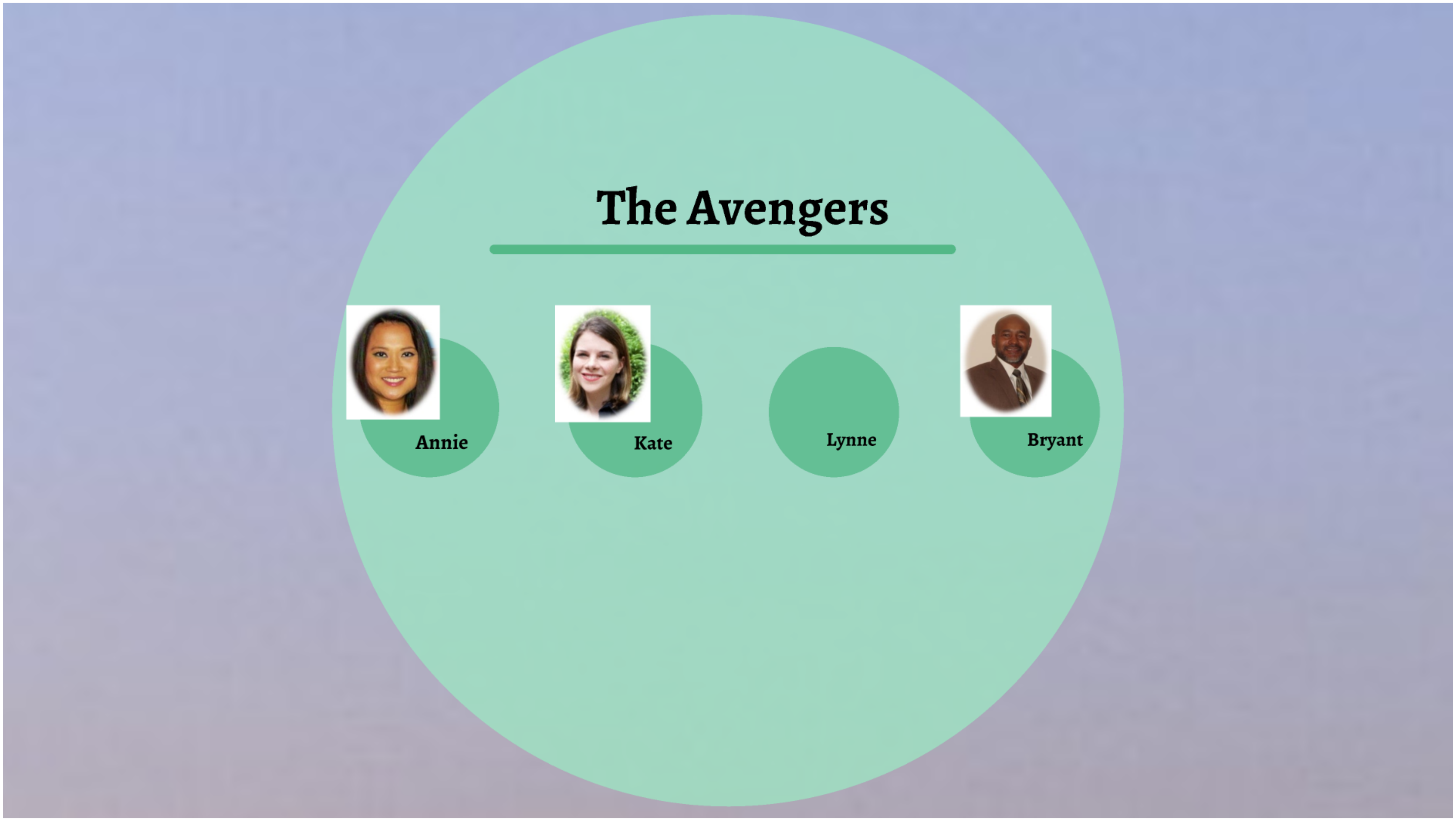

Introduction
Project Goal
Strategy
Analysis
Outputs
Recommendation
Airbnb Avengers
Q&A


The Avengers
Annie
Kate
Lynne
Bryant

Annie Lai

Kate Prevost

Lynne Koppang

Bryant Springer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Goal
Help potential Airbnb Host determine where to establish a new Airbnb in Washington, DC
Question 1
Density?
Question 2
Price?
Question 3
Location?

Question 1

What is the distribution of Airbnb rentals throughout the District's neighborhoods?

Price

What is the average price of an Airbnb in relation to neighborhoods in D.C.?

Location

Which neighborhoods present the best opportunities for success for a new Airbnb host?


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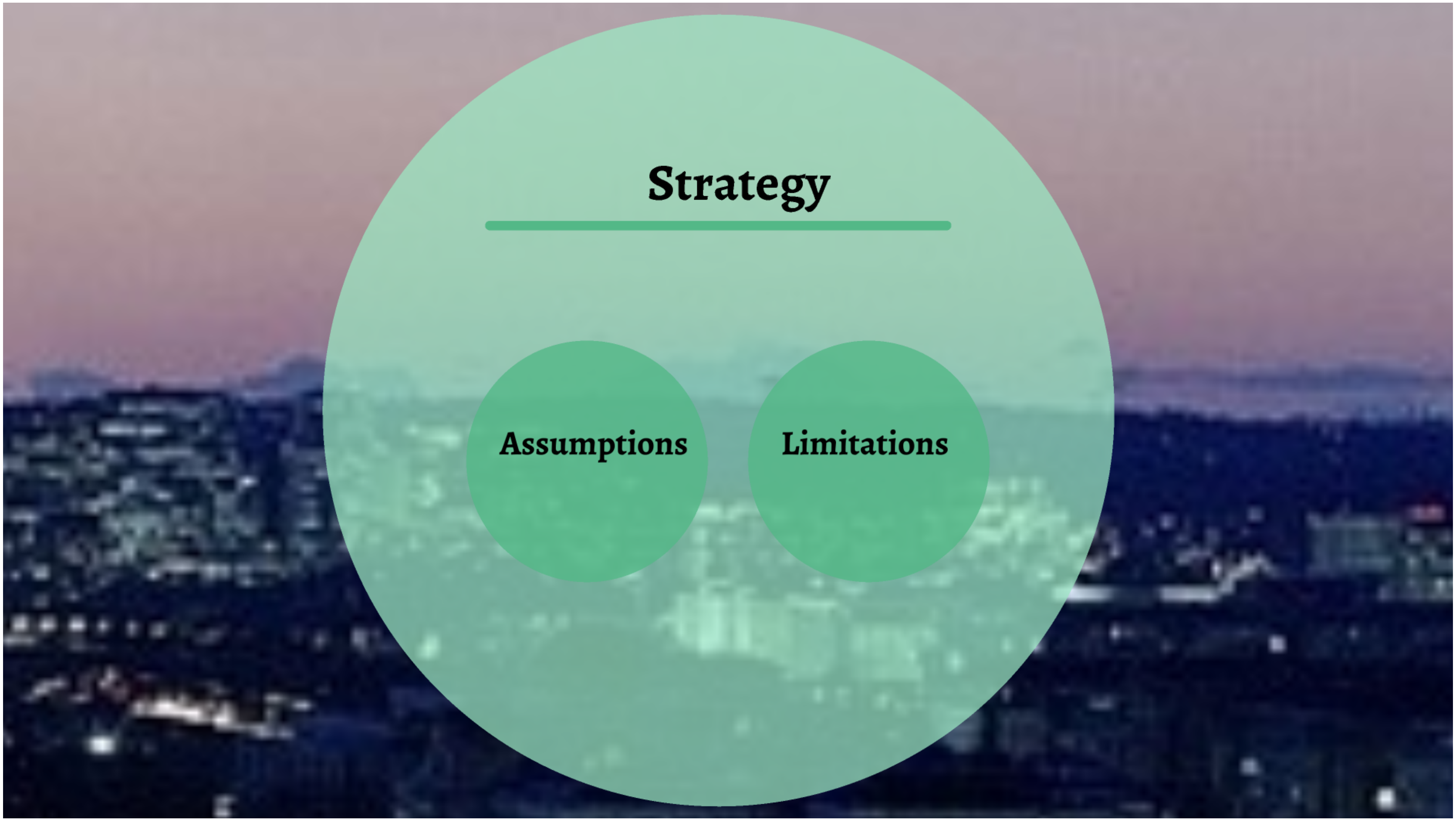
Strategy
Assumptions
Limitations

Limitations

- Future construction data not available
- Expert Knowledge of area used

Assumptions

- Zero days availability = unit not ready
- Entire units only
- Low density with high average price


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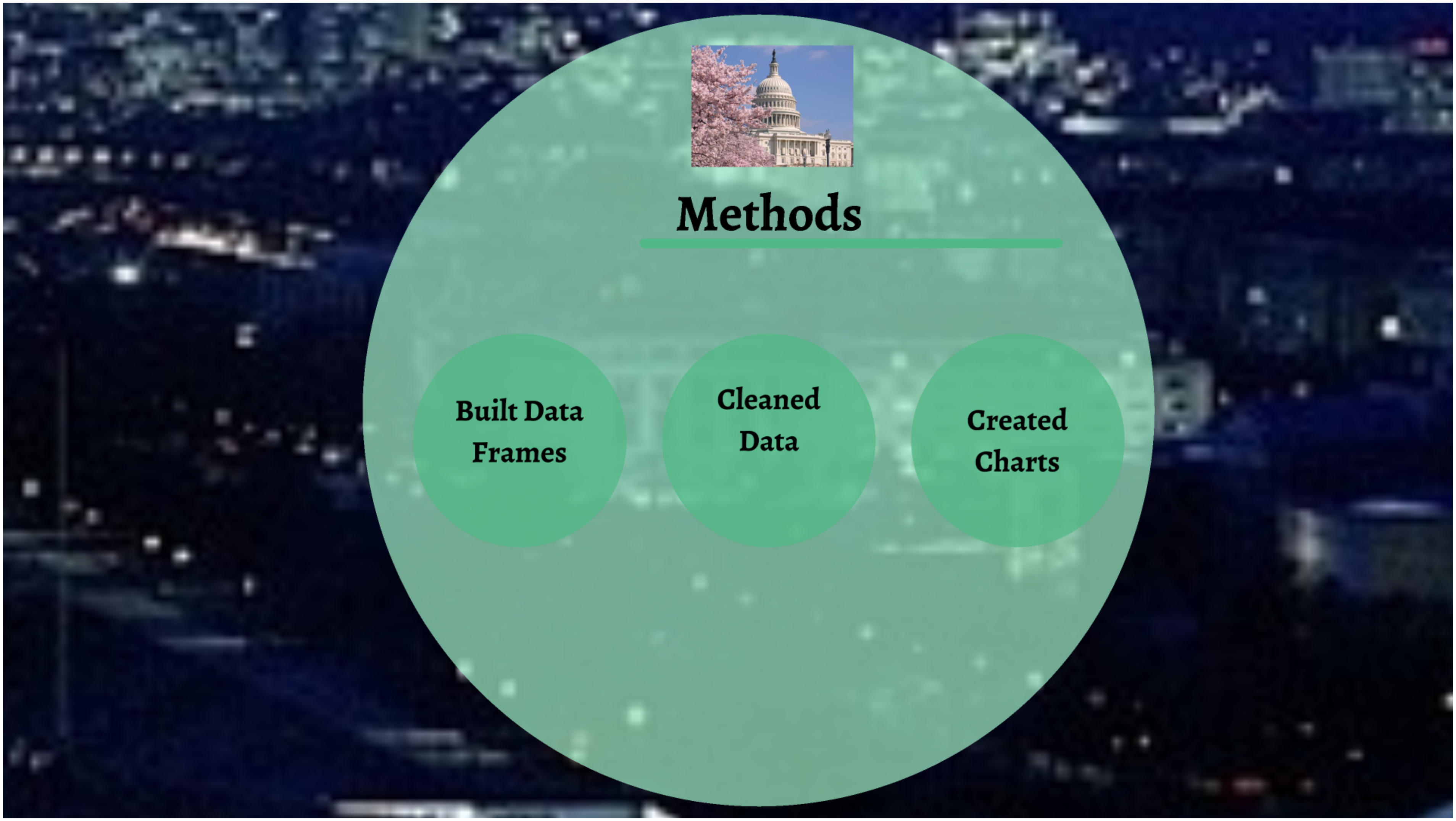
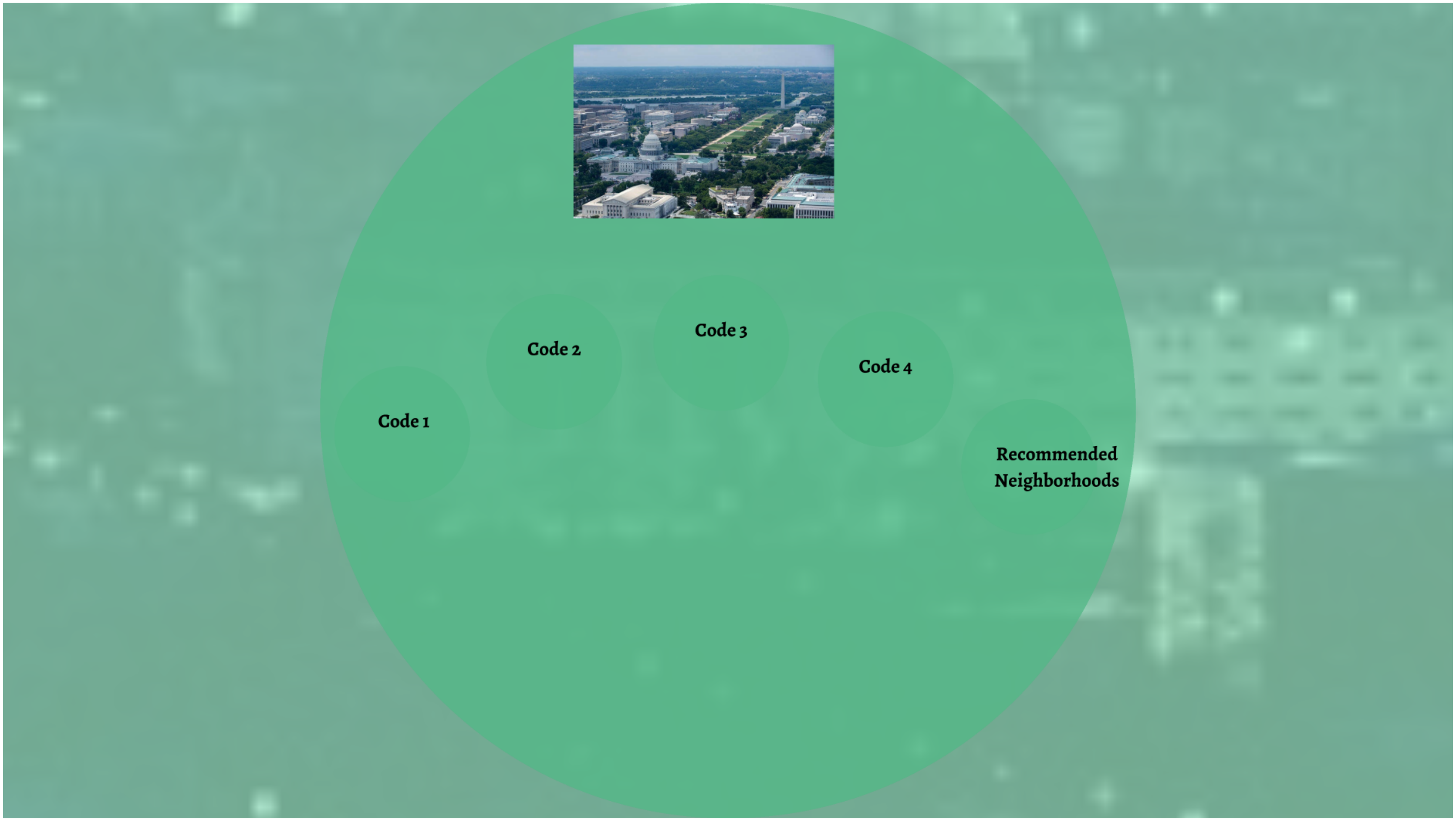

Methods
Built Data Frames
Cleaned Data
Created Charts

- renamed columns
- removed columns
- merged files based on the Listings ID


Code 1
Code 2
Code 3
Code 4
Recommended Neighborhoods

```python
###  filter by room_type='entire house'
nothouse = dlistings_df[dlistings_df["room_type"] != "Entire home/apt" ].index

# Delete these row indexes from dataFrame
dlistings_df.drop(nothouse , inplace=True)

dlistings_df.head()
```

	id	neighbourhood	zipcode	latitude	longitude	property_type	room_type	price	review_scores_rating	reviews_per_month
0	3362	Shaw, Logan Circle	20001	38.910461	-77.019331	Townhouse	Entire home/apt	$433.00	96.0	1.27
4	4002	North Michigan Park, Michigan Park, University...	20017	38.940084	-76.989360	House	Entire home/apt	$120.00	85.0	1.22
6	4283	Kalorama Heights, Adams Morgan, Lanier Heights	20009	38.922032	-77.044474	Apartment	Entire home/apt	$135.00	100.0	0.12
10	5589	Kalorama Heights, Adams Morgan, Lanier Heights	20009	38.919327	-77.041238	Apartment	Entire home/apt	$118.00	90.0	0.7
15	9641	Dupont Circle, Connecticut Avenue/K Street	20005	38.911465	-77.036361	Loft	Entire home/apt	$195.00	95.0	1.23

```python
###  Convert the price column from string to float  ###
#remove the $'s'
dlistings_df['price'] = [x.replace("$", "") for x in dlistings_df["price"]]
#remove the ,'s'
dlistings_df['price'] = [x.replace(",", "") for x in dlistings_df["price"]]
#convert to
dlistings_df['price'] = dlistings_df['price'].astype(float)
dlistings_df.head()
```

	id	neighbourhood	zipcode	latitude	longitude	property_type	room_type	price	review_scores_rating	reviews_per_month
0	3362	Shaw, Logan Circle	20001	38.910461	-77.019331	Townhouse	Entire home/apt	433.0	96.0	1.27

```python
###  merge the 2 dataframes

byhood_df = pd.merge(prcbyhood_dfg, ratebyhood_dfg, on=['neighbourhood'])
del byhood_df["Room_type_y"]
byhood_df.rename(columns={'Room_type_x':'Room_type'}, inplace=True)

#strip the neighborhood names to be just the first neighborhood in the lsit
abbr_name = byhood_df['neighbourhood'].str.split(',').str.get(0)
byhood_df['neighbourhood'] = abbr_name
byhood_df
```

	neighbourhood	Room_type	max rent	min rent	median rent	mean rent	avg rating	avg # reviews / month	# of propertie
0	Brightwood Park	Entire home/apt	2500.0	35.0	100.0	180.629139	95.586873	2.023436	302
1	Brookland	Entire home/apt	1638.0	42.0	91.5	174.714286	95.783784	2.369865	84
2	Capitol Hill	Entire home/apt	5995.0	50.0	150.0	264.990783	96.608939	2.156451	651
3	Capitol View	Entire home/apt	450.0	30.0	99.0	132.052632	94.333333	2.354667	19
4	Cathedral Heights	Entire home/apt	1500.0	50.0	115.0	272.604938	96.176471	1.384630	81
5	Cleveland Park	Entire home/apt	2400.0	40.0	119.5	237.836735	95.486111	1.556622	98

```
#create a table finding the max, min and median price for each neighborhood
prcbyhood_dfg = dlistings_df.groupby(["neighbourhood", "room_type"]).agg({"price":["max","min","median", "mean"]})
#remove the 'price' level
prcbyhood_dfg.columns = prcbyhood_dfg.columns.droplevel()

prcbyhood_dfg.rename(columns={'max':'max rent', 'min':'min rent', 'median':'median rent', 'mean':'mean rent'}, inplace=True)
#reset index to remove mult-index
prcbyhood_dfg = prcbyhood_dfg.rename_axis(['neighbourhood', 'Room_type']).reset_index()

prcbyhood_dfg.head()

avg_density_dfg = dlistings_df.groupby(["neighbourhood", "room_type"]).agg({"price":["max","min","median", "mean"]})
```

```
#create a table finding the max, min and median price for each neighborhood
ratebyhood_dfg = dlistings_df.groupby(["neighbourhood", "room_type"]).agg({"review_scores_rating":"mean", "reviews_per_month":"me
                                                                            "id":"count"})

ratebyhood_dfg.rename(columns={'review_scores_rating':'avg rating', 'reviews_per_month':'avg # reviews / month', 'id':'# of propert
#reset index to remove mult-index
ratebyhood_dfg = ratebyhood_dfg.rename_axis(['neighbourhood', 'Room_type']).reset_index()

ratebyhood_dfg.head()
```

	neighbourhood	Room_type	avg rating	avg # reviews / month	# of properties
0	Brightwood Park, Crestwood, Petworth	Entire home/apt	95.586873	2.023436	302
1	Brookland, Brentwood, Langdon	Entire home/apt	95.783784	2.369865	84
2	Capitol Hill, Lincoln Park	Entire home/apt	96.608939	2.156451	651
3	Capitol View, Marshall Heights, Benning Heights	Entire home/apt	94.333333	2.354667	19
4	Cathedral Heights, McLean Gardens, Glover Park	Entire home/apt	96.176471	1.384630	81

```
###  Create a new df to hold the avg rent and avg density for each neighborhood
###  compared to the DC overall averages

dc_avg_s = prcbyhood_dfg['mean rent'].mean()
mean_hood = byhood_df['mean rent']
prop_density = byhood_df['# of properties']
diff_mean = mean_hood - dc_avg_s
hood = byhood_df['neighbourhood']
dc_density_avg = byhood_df['# of properties'].mean()
diff_density_mean = prop_density - dc_density_avg

compare_avg = pd.DataFrame({
    "neighbourhood":hood,
    "mean by neighbourhood": mean_hood,
    "Distance from DC mean": diff_mean,
    "# of AirBnB rentals": prop_density,
    "distance from DC density": diff_density_mean
})
compare_avg.head()
```

	neighbourhood	mean by neighbourhood	Distance from DC mean	# of AirBnB rentals	distance from DC density
0	Brightwood Park	180.629139	-47.427143	302	138.435897
1	Brookland	174.714286	-53.341997	84	-79.564103
2	Capitol Hill	264.990783	36.934501	651	487.435897
3	Capitol View	132.052632	-96.003651	19	-144.564103
4	Cathedral Heights	272.604938	44.548656	81	-82.564103

```
###  remove any rows with avg rent > dc avg and with property denisty < dc avg  ###
compare_avg2 = compare_avg[compare_avg['mean by neighbourhood'] > dc_avg_s]
compare_avg = compare_avg2[compare_avg['distance from DC density'] < 0]
compare_avg = compare_avg.reset_index()
del compare_avg['index']
compare_avg
```

	neighbourhood	mean by neighbourhood	Distance from DC mean	# of AirBnB rentals	distance from DC density
0	Cathedral Heights	272.604938	44.548656	81	-82.564103
1	Cleveland Park	237.836735	9.780452	98	-65.564103
2	Douglas	251.900000	23.843718	10	-153.564103
3	Hawthorne	417.972222	189.915940	36	-127.564103
4	River Terrace	357.722222	129.665940	18	-145.564103
5	Sheridan	322.909091	94.852809	11	-152.564103
6	Southwest Employment Area	321.390000	93.333718	100	-63.564103
7	Spring Valley	405.261538	177.205256	65	-98.564103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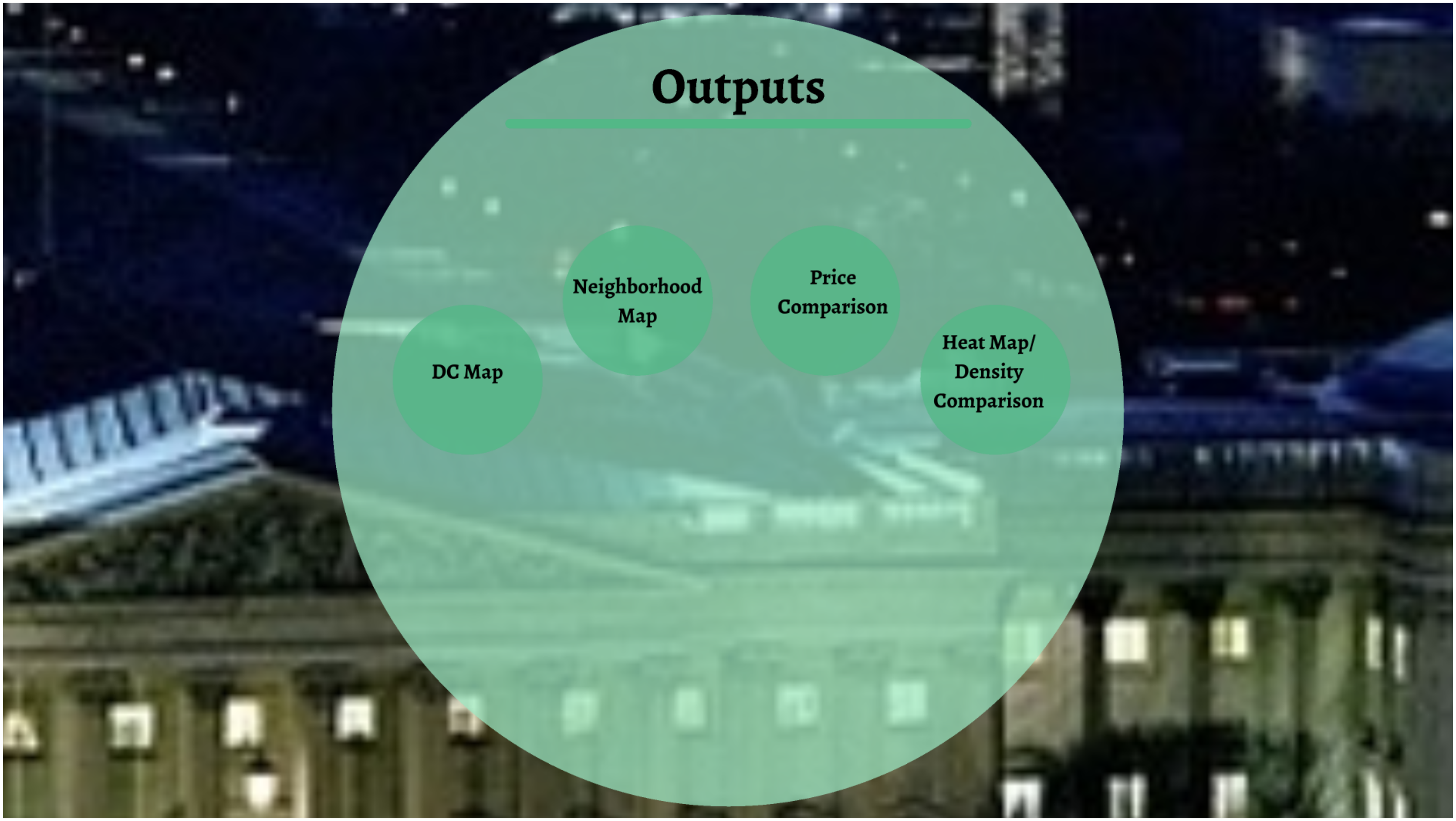
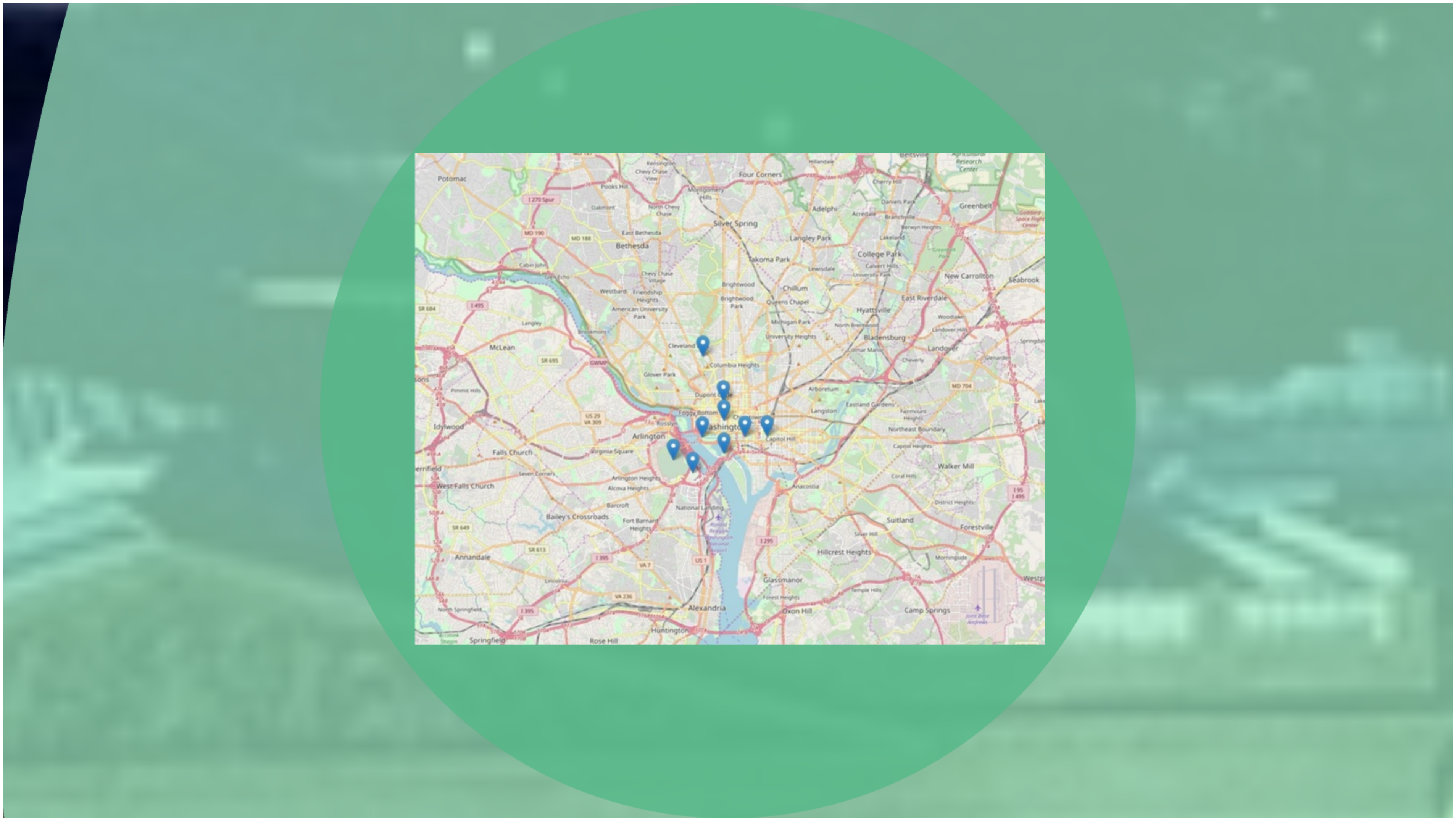
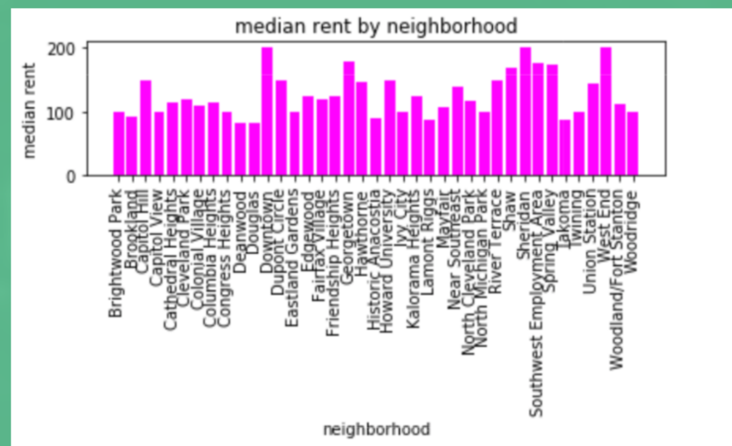

Outputs
Neighborhood Map
Price Comparison
DC Map
Heat Map/ Density Comparison


Potomac
Four Corners
Silver Spring
Bethesda
Takoma Park
Langley Park
College Park
Greenbelt
New Carrollton
Hyattsville
Bladensburg
Landover
McLean
Arlington
Falls Church
West Falls Church
Annandale
Bailey's Crossroads
Walker Mill
Suitland
Forestville
Hillcrest Heights
Alexandria
Oxon Hill
Camp Springs
Springfield
Rose Hill
Huntington
Glassmanor


Silver Spring
Adelphi
Bethesda
College Park
College Park Airport
Chillum
East Riverdale
Landover
MD 704
Washington
Bailey's Crossroads
Ronald Reagan Washington National Airport
Suitland
Glassmanor
I-395
Alexandria
Oxon Hill
Camp Springs
Huntington
Rose Hill


median rent by neighborhood
median rent
200
100
0
Brightwood Park
Brookland
Capitol Hill
Capitol View
Cathedral Heights
Cleveland Park
Colonial Village
Columbia Heights
Congress Heights
Deanwood
Douglas
Downtown
Dupont Circle
Eastland Gardens
Edgewood
Fairfax Village
Friendship Heights
Georgetown
Hawthorne
Historic Anacostia
Howard University
Ivy City
Kalorama Heights
Lamont Riggs
Mayfair
Near Southeast
North Cleveland Park
North Michigan Park
River Terrace
Shaw
Sheridan
Southwest Employment Area
Spring Valley
Takoma
Twining
Union Station
West End
Woodland/Fort Stanton
Woodridge
neighborhood


Silver Spring
Adelphi
Bethesda
College Park
College Park Airport
East Riverdale
Landover
MD 704
Walker M
Bailey's Crossroads
Suitland
Ronald Reagan Washington National Airport
I-395
Alexandria
Oxon Hill
Camp Springs
Huntington
Church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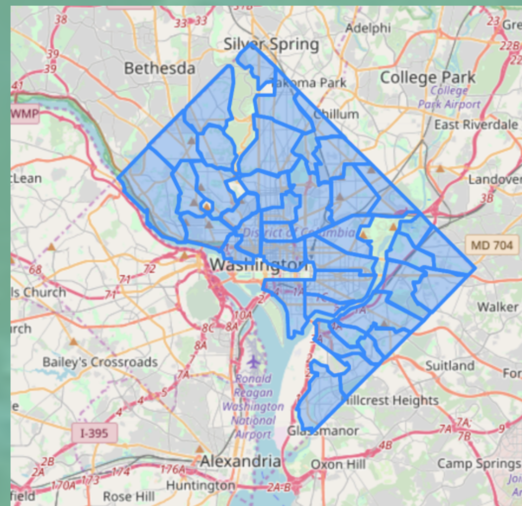
Best area for new investment



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