AFFORDABLE HOUSING DEVELOPMENT

Group 4
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Executive Summary

Affordable housing developments aid cities in promoting diversity and inclusion, improving quality of life, enriching neighborhoods, and growing the local economy. In this study, we investigate whether the locations of affordable housing developments provide positive features for its population, relating to accessibility to public transportation, amenities, active commercial scene, walkability, and general neighborhood activity.

Through our investigations, we discovered stark discrepancies between neighborhoods with a multitude of affordable housing developments and those without. Generally, areas with scarce access to transit and worse socio-economic performance contain most affordable housing developments.

Project Objective

This project seeks to develop an end-to-end data pipeline for affordable housing data to:

- Examine data between the location, price, and size of affordable housing developments and standard-of-life features available for tenants.
- Foster a better understanding of:
  - Factors that affect location, prices, amenities, and quality of affordable housing developments.
  - The distribution of socio-economic indicators, economic activity, access to transit and parks, in each neighborhood.
- Potentially identify correlations that may confirm or deny the team’s initial hypotheses related to affordable housing.

Business Use Cases

Understanding affordable housing development's characteristics' relationship to socio-economic features could be used to develop more conscious policies and drive significant investments that provide inhabitants of affordable housing a better quality of life (i.e. development of additional public transportation in isolated neighborhoods, investment in local businesses, etc.)

Data

Data sources included:

- City of Chicago: Affordable Housing Development Dataset, Business Licenses Dataset, Park Dataset, Abandoned Property Datasets
- Zillow and Cook County Records API
- Neighborhood Shapefiles and Boundary files for GIS-type applications including generation of Table Keys (Neighborhoods), Public Transit and City Park GIS data points.
- Web-Scraping Walk-Scores of Chicago neighborhoods

Data Profile:

- 428 data points, 75 columns, 85.5K rows

Tools

Ingestion and Cleanup

Storage

Delivery and Insights

- Data was scraped via Python (Walk-Scores), downloaded from online sources (City of Chicago for Housing Developments, Commerce, Park) and gathered using APIs (Google Geocoding, Zillow, Cook County).
- Pandas was used for data cleanup.
- R was used to build an additional Geocoding API (Google's) to obtain coordinates from address.
- Our data database was built using MySQL. DDL and DML tables were created for each table.
- Tableau was used to generate tables and charts to draw insights from our data.

Data Cleanup

Out-of-scope Geographically

A	B	C	D	E	F	G	H	I	J
ID	LICENSI	ACCOU	SITE NU	LEGAL I	DOING	ADDRE!	CITY	STATE	ZIP COD
1888878-2	2570948	21545	1	PSF MECH	PSF MECH	11621 E	SEATTLE	WA	98168
1888878-2	2705036	21545	1	PSF MECH	PSF MECH	11621 E	SEATTLE	WA	98168

Overwrote Assessed Value with Sale Value (where available)

```python
df.loc[df['most_recent_sale_price'] == ('nan' or 'NaN')] = 0
df.most_recent_sale_price

#printing header names not values
def f(row):
    if 'most_recent_sale_price' != ('nan' or 'NaN'):
        'most_recent_sale_price'
    else:
        ('pri_est_land'+'pri_est_bldg')

df['price'] = df.apply(f,axis=1)

df.price
df['pri_est'] = (df.pri_est_land + df.pri_est_bldg)
df.pri_est
del df['pri_est_land']
del df['pri_est_bldg']
```

GIS Conversions

```python
from geopy.geocoders import Nominatim
locator = Nominatim(user_agent="myGeocoder")
ln = locator.geocode("455 Cityfront Plaza Dr, Chicago, IL 60611")
print(ln.latitude, ln.longitude)
```

```
41.8903132 -87.62168978061763
```

```python
In [10]: from shapely.geometry import Point
         def ca_assign4(pt):
             for i, v in enumerate(CA_boundaries):
                 if pt[0]>v[2]:
                     continue
                 if v[1]>pt[1]:
                     continue
                 if pt[1]>v[3]:
                     continue
                 if v[0]>pt[0]:
                     continue
                 elif CA_shapes[i].contains(Point(pt[0], pt[1])):
                     return i
                     break
```

```python
In [11]: from shapely.geometry import Point
         import pickle
         CA_names = pickle.load(open("C:/Users/Martin/Desktop/CA_names.pkl", "rb"))
         CA_boundaries = pickle.load(open("C:/Users/Martin/Desktop/CA_boundaries.pkl", "rb"))
         CA_shapes = pickle.load(open("C:/Users/Martin/Desktop/CA_shapes.pkl", "rb"))
         nbc_tow = (ln.longitude, ln.latitude)
         CA_names[ca_assign4(nbc_tow)]

Out[11]: 'NEAR NORTH SIDE'
```

Source on Save   Run   Source

```r
getwd()

# Geocoding a csv column of "addresses" in R

#load ggmap
library(ggmap)

# Select the file from the file chooser
fileToLoad <- file.choose(new = TRUE)

# Read in the csv data and store it in a variable
origAddress <- read.csv(fileToLoad, stringsAsFactors = FALSE)

# Initialize the data frame
geocoded <- data.frame(stringsAsFactors = FALSE)

# Loop through the addresses to get the latitude and longitude of each address and add it to the
# origAddress data frame in new columns lat and lon
for(i in 1:nrow(origAddress))
{
  # Print("Working...")
  result <- geocode(origAddress$addresses[i], output = "latlona", source = register_google(key = "AIzaSyDe9YqYsf7_OpqUD21
  origAddress$lon[i] <- as.numeric(result[1])
  origAddress$lat[i] <- as.numeric(result[2])
  origAddress$geoAddress[i] <- as.character(result[3])
}
# Write a CSV file containing origAddress to the working directory
write.csv(origAddress, "geocoded.csv", row.names=FALSE)
```

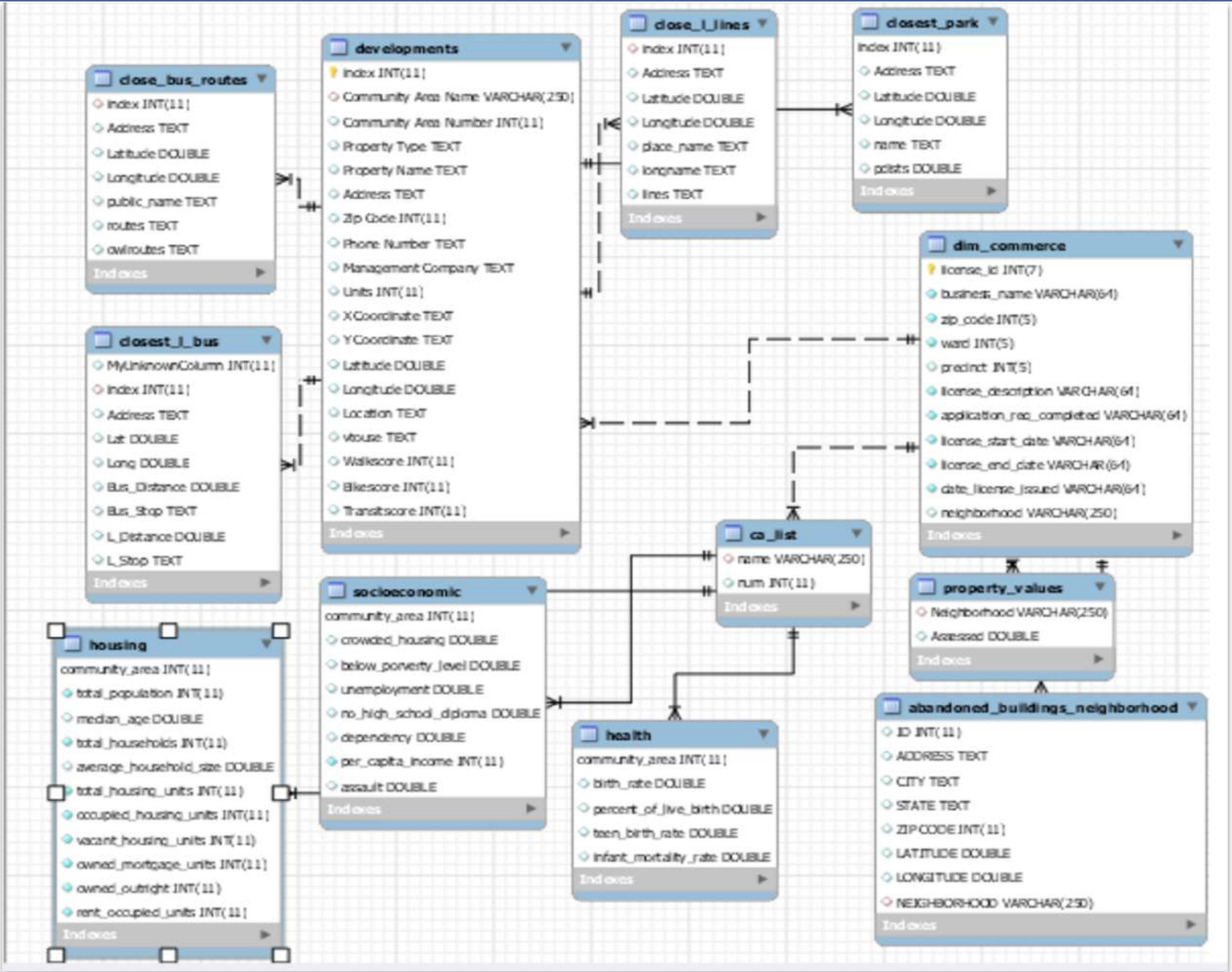
Design Considerations I: Data

- ETL Scripts written in Python and R
- Keys were generated for tables (neighborhood from latitude and longitude, or from address):
  - Chicago neighborhood shapefiles
  - Geocodes via GeoPy and Google's Geocoding API via GCP to obtain Latitude and Longitude from address
  - Web-scraping Walk-Scores to calculate "walkability" of area

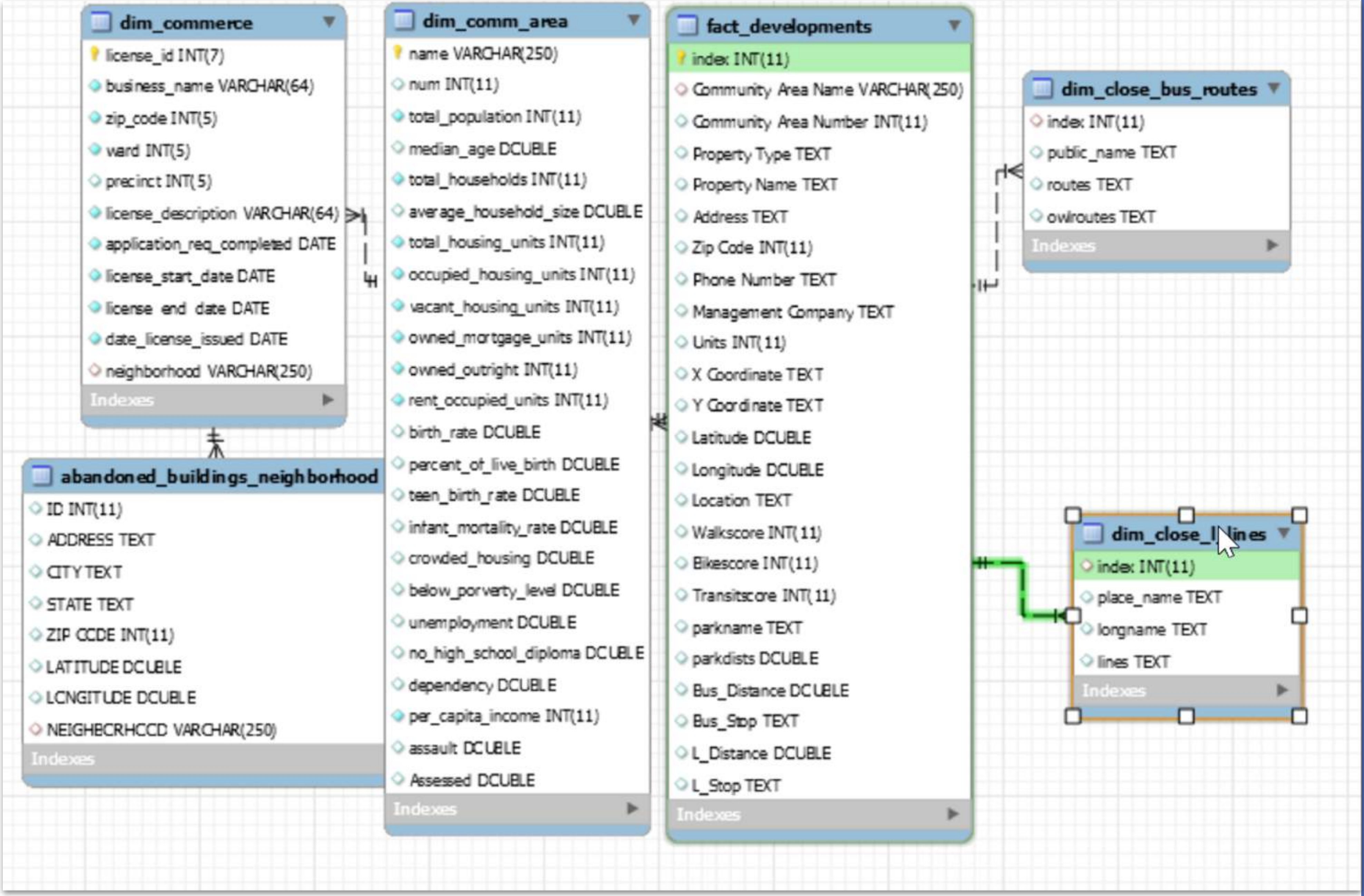
Design Considerations II: Implementation

- Number of tables and joins are not extensive, so this pipeline can be implemented locally given enough disk space
- Due to the archival nature of our data, our application can be used as an OLAP system.
- Snowflake data model
- One to many relationship between individual address and neighborhood requires definition of granularity at neighborhood level

EER Diagram


close_bus_routes
index INT(11)
Address TEXT
Latitude DOUBLE
Longitude DOUBLE
public_name TEXT
routes TEXT
owlroutes TEXT
developments
index INT(11)
Community Area Name VARCHAR(250)
Community Area Number INT(11)
Property Type TEXT
Property Name TEXT
Address TEXT
Zip Code INT(11)
Phone Number TEXT
Management Company TEXT
Units INT(11)
X Coordinate TEXT
Y Coordinate TEXT
Latitude DOUBLE
Longitude DOUBLE
Location TEXT
Vhouse TEXT
Walkscore INT(11)
Bikescore INT(11)
Transitscore INT(11)
close_l_lines
index INT(11)
Address TEXT
Latitude DOUBLE
Longitude DOUBLE
place_name TEXT
longname TEXT
lines TEXT
closest_park
index INT(11)
Address TEXT
Latitude DOUBLE
Longitude DOUBLE
name TEXT
points DOUBLE
closest_l_bus
MyUnknownColumn INT(11)
index INT(11)
Address TEXT
Lat DOUBLE
Long DOUBLE
Bus_Distance DOUBLE
Bus_Stop TEXT
L_Distance DOUBLE
L_Stop TEXT
dim_commerce
license_id INT(7)
business_name VARCHAR(64)
zip_code INT(5)
ward INT(5)
precinct INT(5)
license_description VARCHAR(64)
application_req_completed VARCHAR(64)
license_start_date VARCHAR(64)
license_end_date VARCHAR(64)
date_license_issued VARCHAR(64)
neighborhood VARCHAR(250)
ca_list
name VARCHAR(250)
num INT(11)
property_values
Neighborhood VARCHAR(250)
Assessed DOUBLE
socioeconomic
community_area INT(11)
crowded_housing DOUBLE
below_poverty_level DOUBLE
unemployment DOUBLE
no_high_school_diploma DOUBLE
dependency DOUBLE
per_capita_income INT(11)
assault DOUBLE
housing
community_area INT(11)
total_population INT(11)
median_age DOUBLE
total_households INT(11)
average_household_size DOUBLE
total_housing_units INT(11)
occupied_housing_units INT(11)
vacant_housing_units INT(11)
owned_mortgage_units INT(11)
owned_outright INT(11)
rent_occupied_units INT(11)
health
community_area INT(11)
birth_rate DOUBLE
percent_of_live_birth DOUBLE
teen_birth_rate DOUBLE
infant_mortality_rate DOUBLE
abandoned_buildings_neighborhood
ID INT(11)
ADDRESS TEXT
CITY TEXT
STATE TEXT
ZIP CODE INT(11)
LATITUDE DOUBLE
LONGITUDE DOUBLE
NEIGHBORHOOD VARCHAR(250)
Indexes

Dimensional Model



Preliminary Expectations

Greater number of affordable housing developments

- In less affluent areas
- Near abandoned buildings
- In highly-commercialized areas

Fewer number of affordable housing developments

- Near public transit
- Near parks

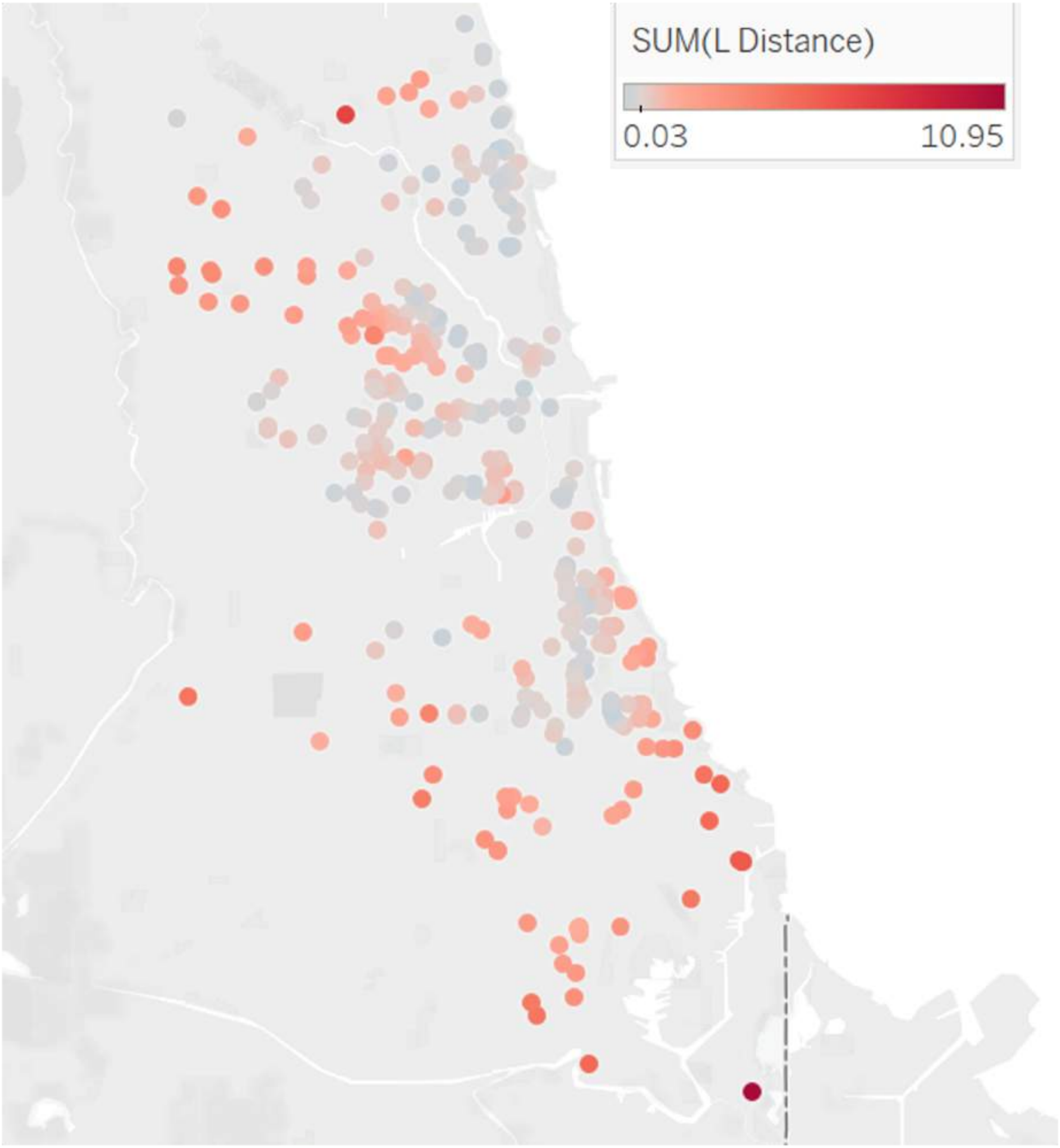
Actual Results

Greater number of affordable housing developments

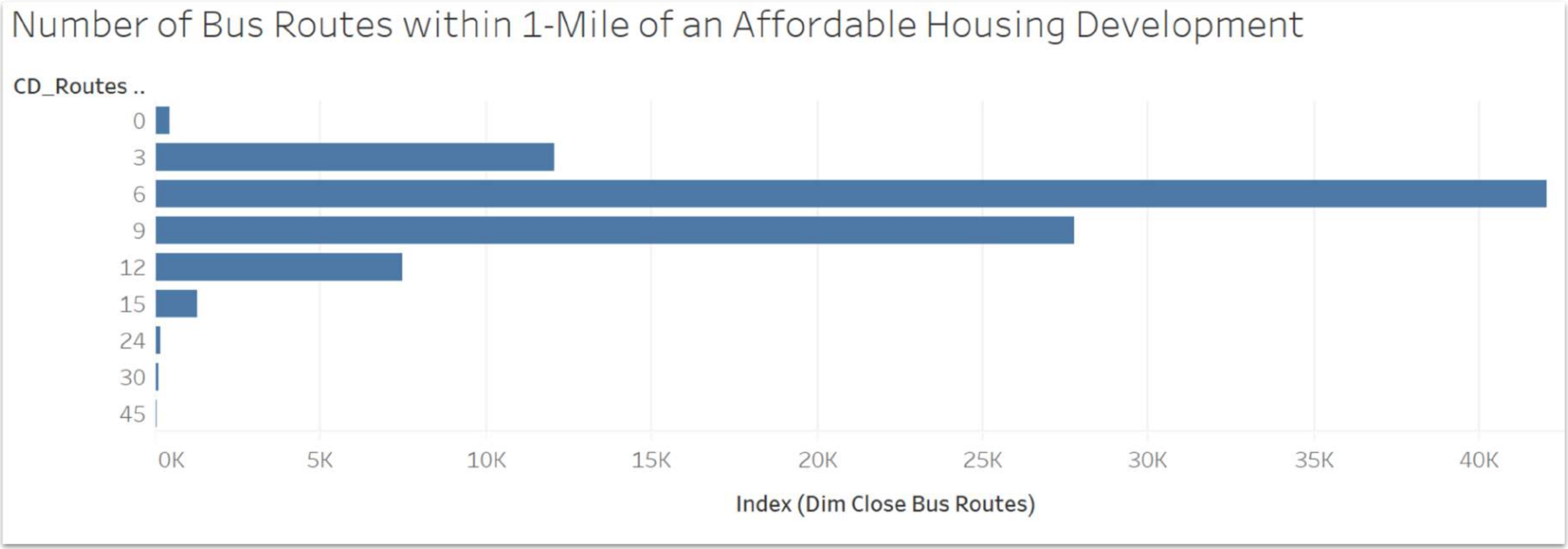
- In less affluent areas ✓
- Near abandoned buildings ~
- In highly-commercialized ~ areas

Fewer number of affordable housing developments

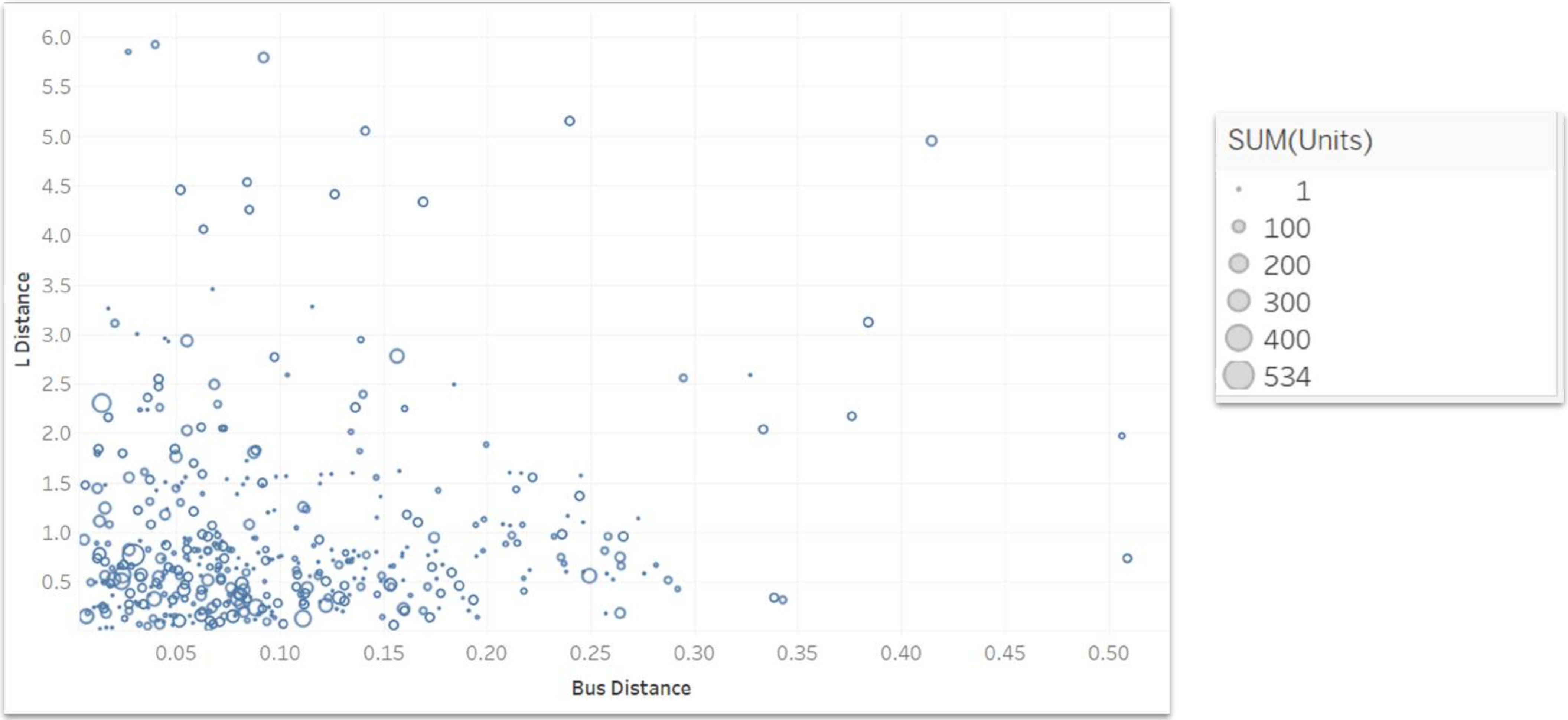
- Near public transit ~
- Near parks X



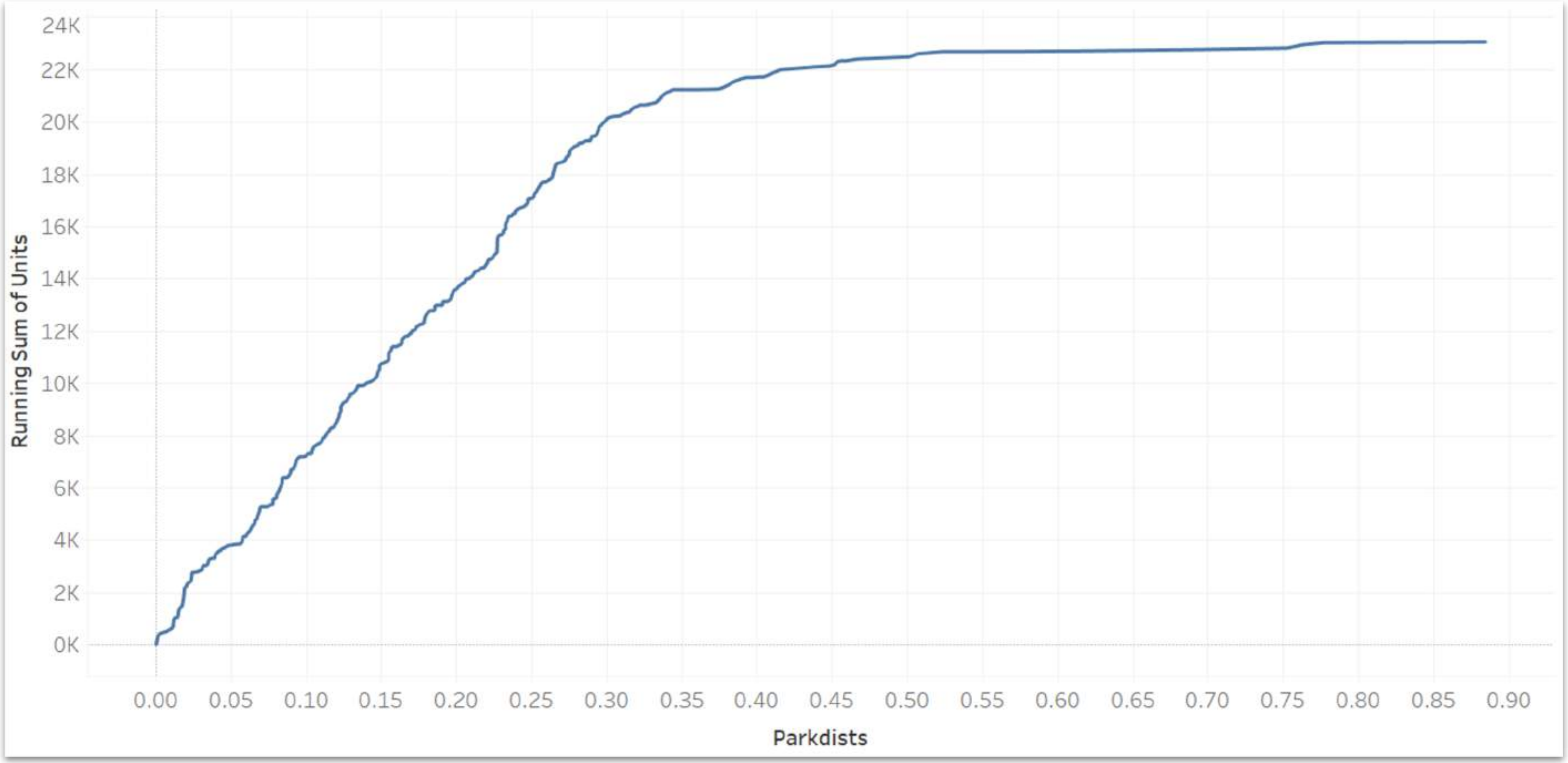
Distance from Housing Developments to One Instance of Public Transportation


Number of Bus Routes within 1-Mile of an Affordable Housing Development
CD_Routes ..
0
3
6
9
12
15
24
30
45
0K
5K
10K
15K
20K
25K
30K
35K
40K
Index (Dim Close Bus Routes)

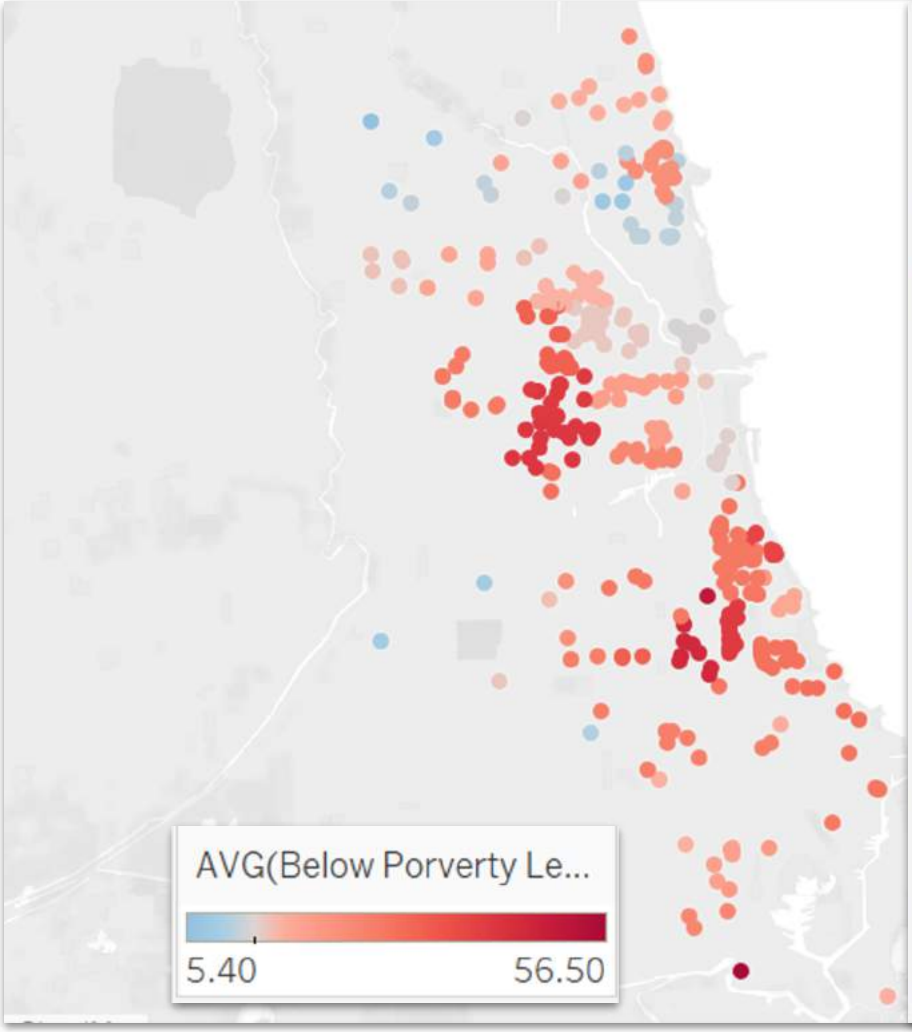
Number of Units by Bus and L Distance

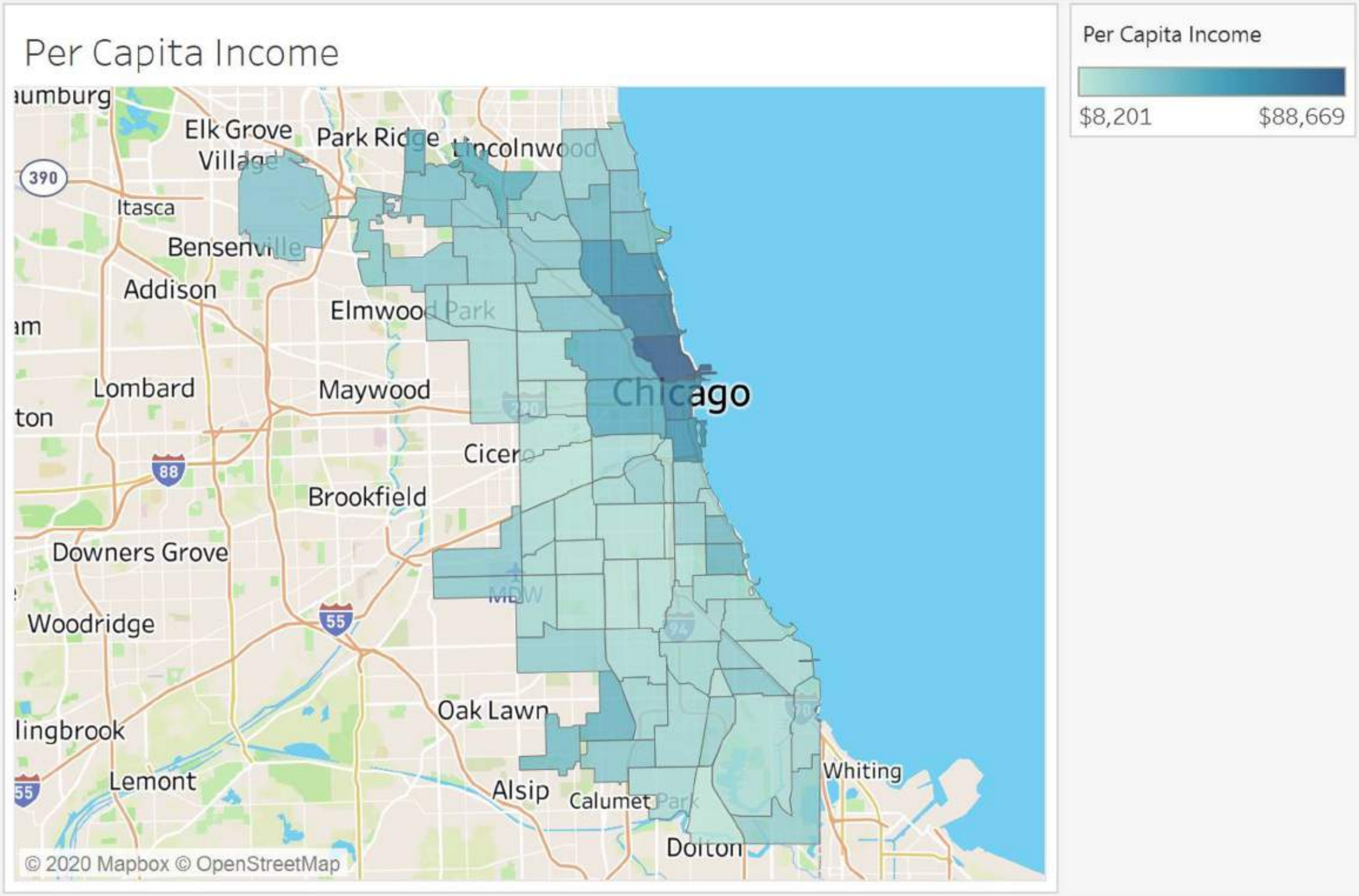


Most units did have access to nearby parks

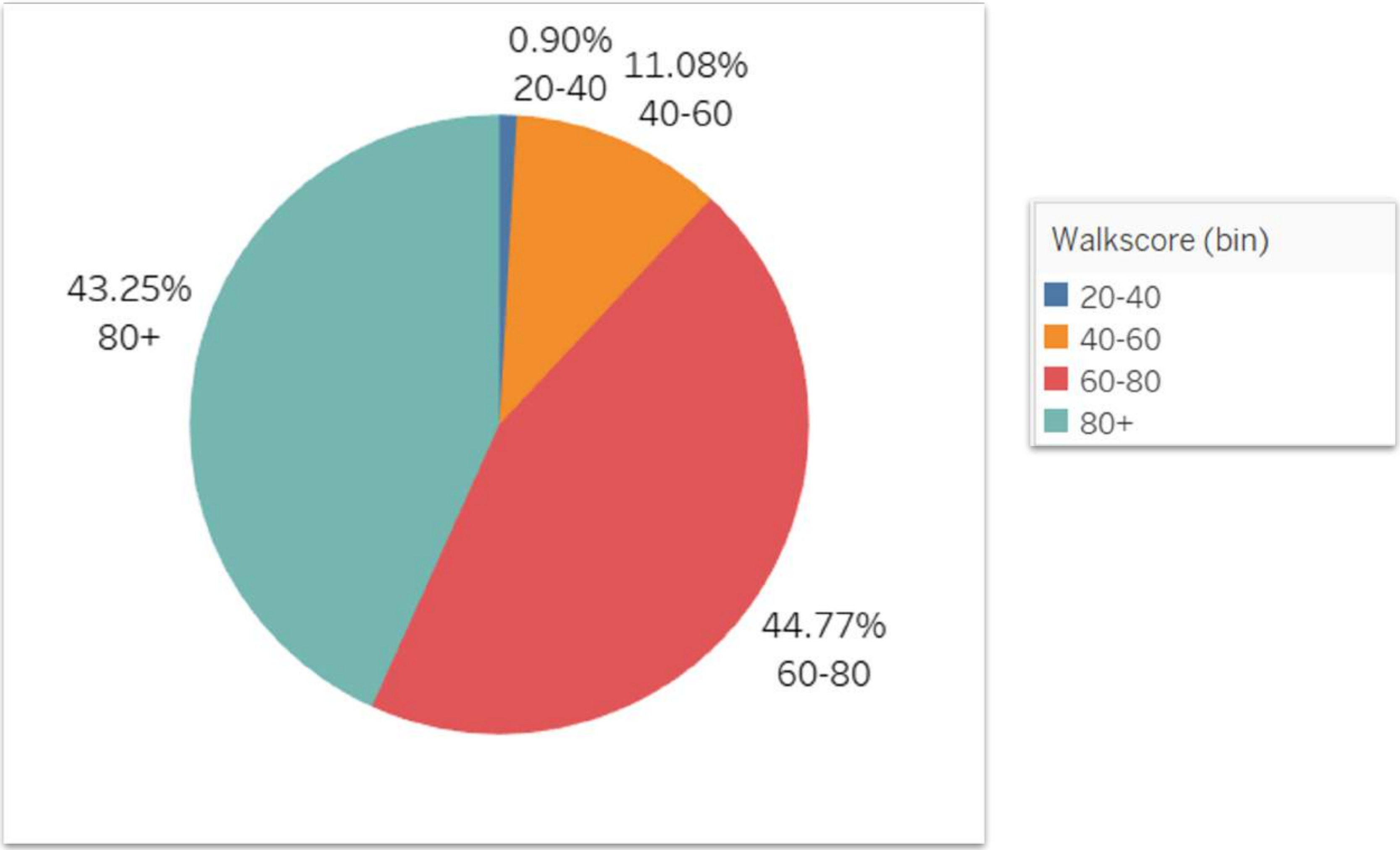


Affordable Housing Developments and Percentage of Neighborhood Below Poverty Line (Centered at 13%)

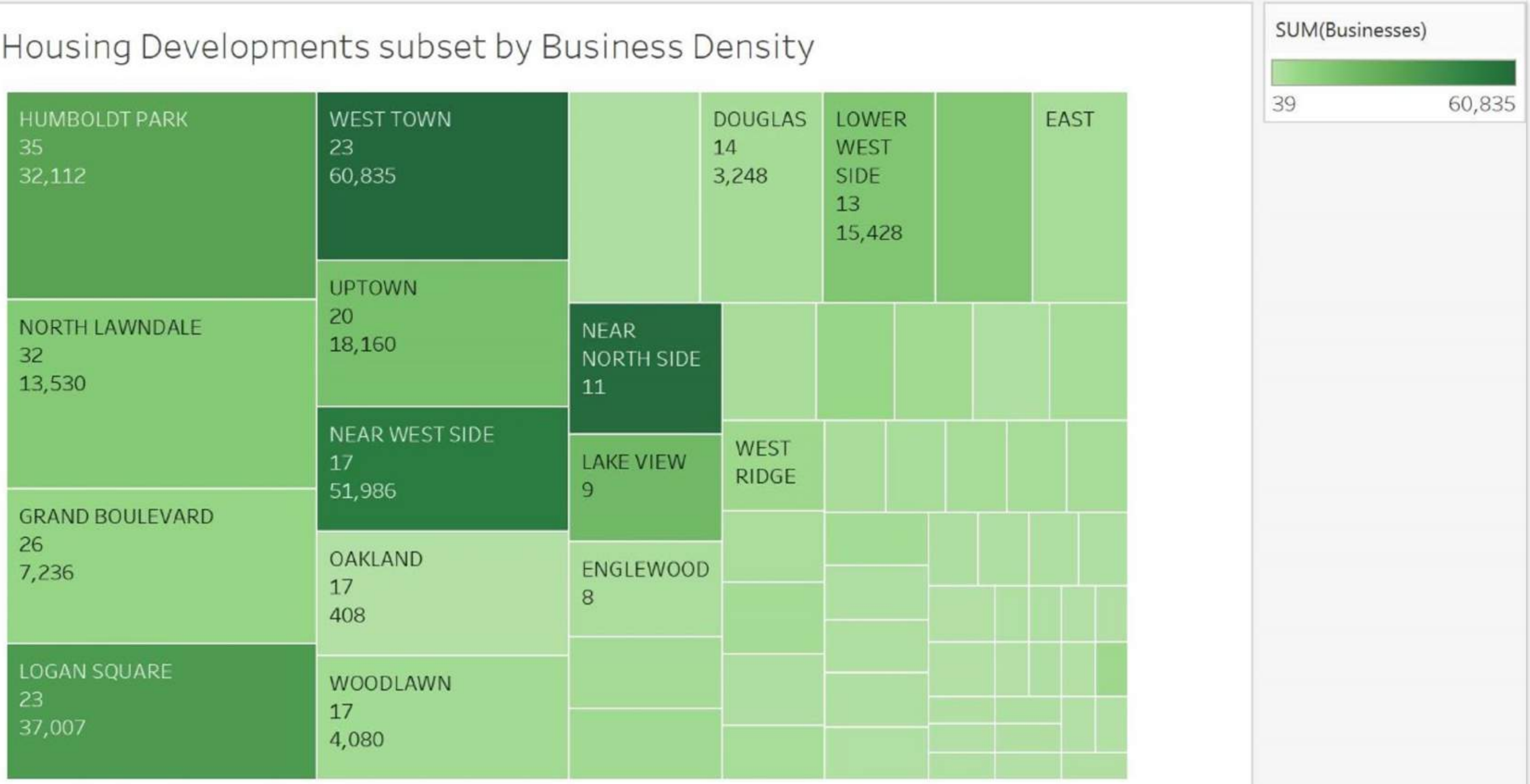




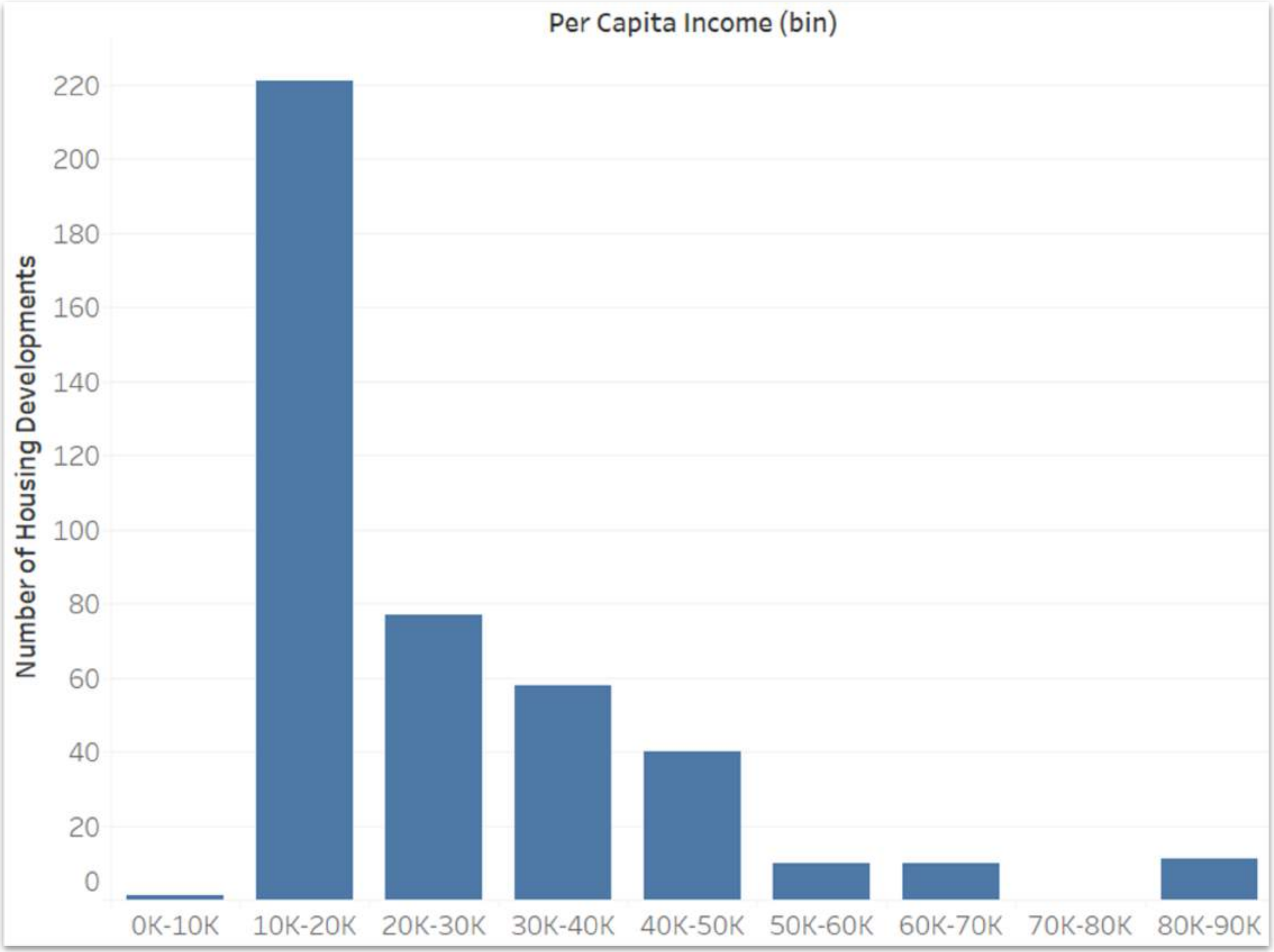
Walkscore (Binned by # of Units)



Housing Developments subset by Business Density

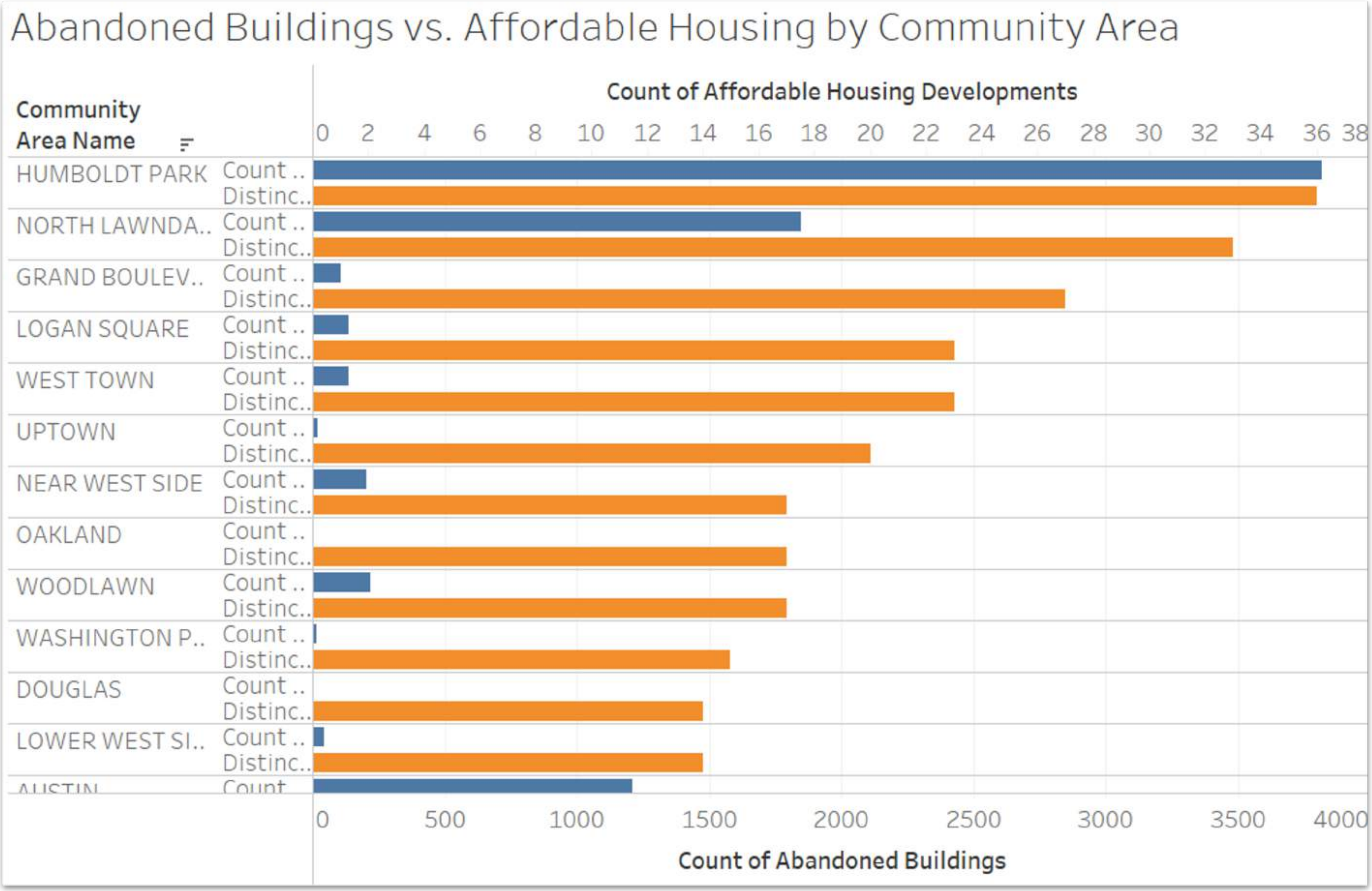


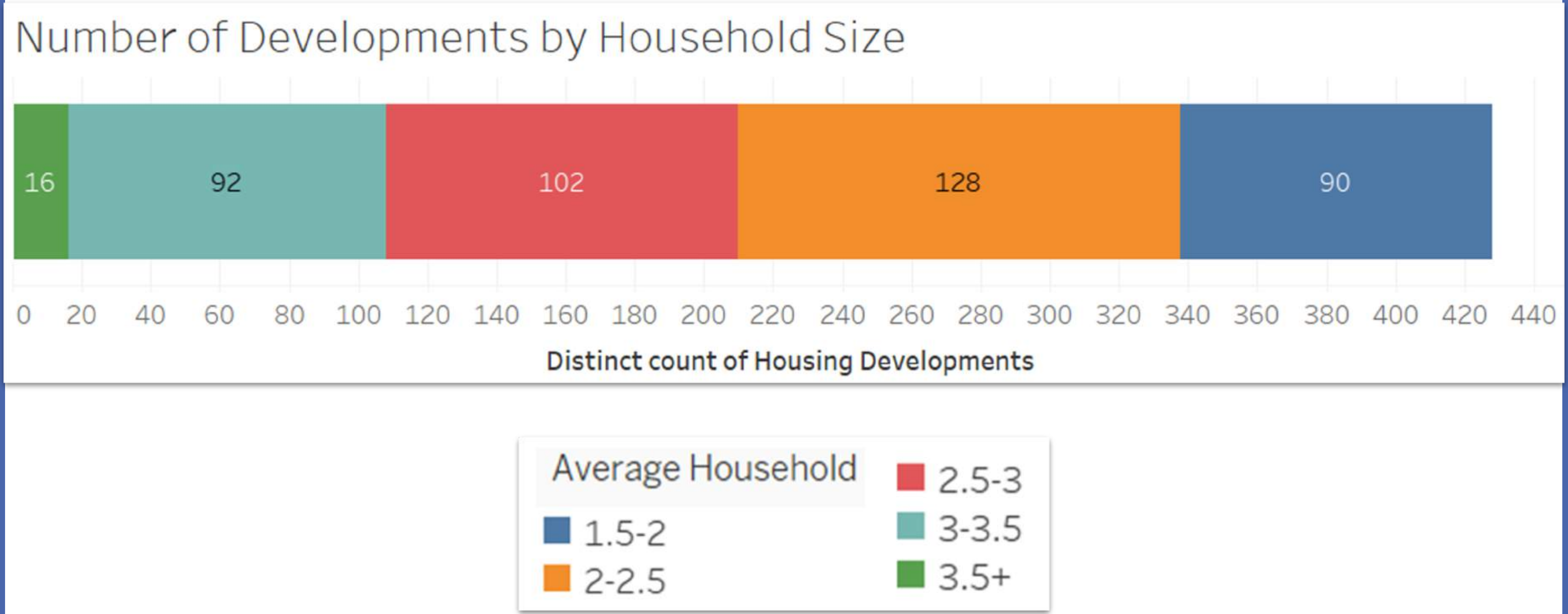
Developments by Per Capita Income



Count of Affordable Housing Developments

Count of Abandoned Buildings





Number of Developments by Household Size
16
92
102
128
90
0
20
40
60
80
100
120
140
160
180
200
220
240
260
280
300
320
340
360
380
400
420
440
Distinct count of Housing Developments
Average Household
1.5-2
2-2.5
2.5-3
3-3.5
3.5+

Conclusion

Through the course of the project, we discovered strong correlations between the count of affordable housing developments per neighborhood and:

- Socioeconomic status of neighborhood, which could perhaps be explained by higher land costs for more affluent neighborhoods
- Transit scores of neighborhood for L trains, which could perhaps further isolate neighborhoods with lower household income per capita.

Additionally, weaker correlations were identified between the count of affordable housing developments per neighborhood and:

- Business density of each neighborhood
- Count of abandoned buildings of each neighborhood

It is difficult to draw conclusions from these weaker correlations.

Areas of Improvement for Project

- With enough computing resources and time, further granularity could be utilized to map by-block impacts, driven by the by address level development, assessment, and transportation data, rather than by the neighborhood or area level. This could yield further insight and inform policy by visualizing ripple effects related to affordable housing developments and the blocks in which they are built.
- Obtaining data from the 2020 U.S. Census and re-evaluate our findings
- Study additional datasets (type of housing, family size, health background, etc.)

References

- City of Chicago Data Portal: https://data.cityofchicago.org/
- Institute for Housing Studies at DePaul University: https://www.housingstudies.org/
- Google Maps Platform: https://developers.google.com/maps/documentation
- Python for Data Analysis: Data Wrangling with Pandas, NumPy, and IPython 1st Edition by Wes McKinney


ANY QUESTIONS?