05_visualization

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1 Visualizing Data

1.1 Introduction to Python

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2 Contents:

1. Setup
2. `matplotlib`
3. `seaborn`
4. `plotly`

2.1 Data

The specific file names are: - bike_thefts_joined.csv - neighbourhoods.csv

2.2 Supporting packages and data

Let's import `numpy` and `pandas` and load up some data to work with.

[1]:
```
import numpy as np
import pandas as pd
pd.set_option("display.max_columns", None)
```

[2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[3]:
```
# load data
thefts_joined = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/data/
 ↪bike_thefts_joined.csv',
                            dtype={'n_id': str})
neighbourhoods = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/data/
 ↪neighbourhoods.csv',
```

```
                            dtype={'n_id': str})

# fix dates
thefts_joined['occurrence_date'] = pd.
 ↪to_datetime(thefts_joined['occurrence_date'])
thefts_joined['report_date'] = pd.to_datetime(thefts_joined['report_date'])
```

[4]:
```
thefts_joined.head()
```

[4]:

	_id	objectid	event_unique_id	primary_offence	occurrence_date	occurrence_year	occurrence_month	occurrence_dayofweek	occurrence_dayofmonth	occurrence_dayofyear	occurrence_hour	report_date	report_year	report_month	report_dayofweek	report_dayofmonth	report_dayofyear	report_hour	division	city	hood_id	neighbourhoodname	location_type
0	1	17744	GO-20179016397	THEFT UNDER	2017-10-03	2017	October	Tuesday	3	276	14	2017-10-03	2017	October	Tuesday	3	276	18	D22	Toronto	15	Kingsway South (15)	Streets, Roads, Highways (Bicycle Path, Privat…
1	2	17759	GO-20172033056	THEFT UNDER - BICYCLE	2017-11-08	2017	November	Wednesday	8	312	3	2017-11-08	2017	November	Wednesday	8	312	22	D22	Toronto	15	Kingsway South (15)	Single Home, House (Attach Garage, Cottage, Mo…
2	3	17906	GO-20189030822	THEFT UNDER - BICYCLE	2018-09-14	2018	September	Friday	14	257	9	2018-09-17	2018	September	Monday	17	260	16	D22	Toronto	15		
3	4	17962	GO-2015804467	THEFT UNDER	2015-05-07	2015	May	Thursday	7	127	18	2015-05-14	2015	May	Thursday	14	134	14	D22	Toronto	15		
4	5	17963	GO-20159002781	THEFT UNDER	2015-05-16	2015	May	Saturday	16	136	12	2015-05-16	2015	May	Saturday	16	136	15	D22	Toronto	15		

```
2  Kingsway South (15)                                  Ttc Subway Station
3  Kingsway South (15)                                  Ttc Subway Station
4  Kingsway South (15)                                  Ttc Subway Station

  premises_type     bike_make  bike_model bike_type  bike_speed bike_colour  \
0       Outside            GI    ESCAPE 2        OT           7         BLK
1         House  UNKNOWN MAKE         NaN        TO           1         BLK
2       Transit            OT  CROSSTRAIL        MT          24         BLK
3       Transit            GT         NaN        TO          10      BLKDGR
4       Transit            GI         NaN        MT           6         RED

   bike_cost     status  objectid2  \
0      700.0     STOLEN          1
1     1100.0  RECOVERED          2
2      904.0     STOLEN          3
3      400.0     STOLEN          4
4      600.0     STOLEN          5

                                             geometry   neighbourhood n_id  \
0  {'type': 'Point', 'coordinates': (-79.50655965…  Kingsway South   15
1  {'type': 'Point', 'coordinates': (-79.50484874…  Kingsway South   15
2  {'type': 'Point', 'coordinates': (-79.51170915…  Kingsway South   15
3  {'type': 'Point', 'coordinates': (-79.51170915…  Kingsway South   15
4  {'type': 'Point', 'coordinates': (-79.51132657…  Kingsway South   15

      designation  pop_2016  pop_2011  pop_change  private_dwellings  \
0  No Designation    9271.0    9170.0       0.011             3710.0
1  No Designation    9271.0    9170.0       0.011             3710.0
2  No Designation    9271.0    9170.0       0.011             3710.0
3  No Designation    9271.0    9170.0       0.011             3710.0
4  No Designation    9271.0    9170.0       0.011             3710.0

   occupied_dwllings  pop_dens  area  total_commuters   drive  car_passenger  \
0             3584.0    3593.0  2.58           3735.0  2210.0          120.0
1             3584.0    3593.0  2.58           3735.0  2210.0          120.0
2             3584.0    3593.0  2.58           3735.0  2210.0          120.0
3             3584.0    3593.0  2.58           3735.0  2210.0          120.0
4             3584.0    3593.0  2.58           3735.0  2210.0          120.0

   transit   walk  bike  other  pct_bike
0   1185.0  115.0  30.0   50.0  0.008032
1   1185.0  115.0  30.0   50.0  0.008032
2   1185.0  115.0  30.0   50.0  0.008032
3   1185.0  115.0  30.0   50.0  0.008032
4   1185.0  115.0  30.0   50.0  0.008032
```

[5]:
```
# exclude the City of Toronto
neighbourhoods = neighbourhoods.loc[neighbourhoods['neighbourhood'] != 'City of␣
↪Toronto']
neighbourhoods.head()
```

[5]:

	neighbourhood	n_id	designation	pop_2016	pop_2011	\
0	Agincourt North	129	No Designation	29113	30279	
1	Agincourt South-Malvern West	128	No Designation	23757	21988	
2	Alderwood	20	No Designation	12054	11904	
3	Annex	95	No Designation	30526	29177	
4	Banbury-Don Mills	42	No Designation	27695	26918	

	pop_change	private_dwellings	occupied_dwllings	pop_dens	area	\
0	-0.039	9371	9120	3929	7.41	
1	0.080	8535	8136	3034	7.83	
2	0.013	4732	4616	2435	4.95	
3	0.046	18109	15934	10863	2.81	
4	0.029	12473	12124	2775	9.98	

	total_commuters	drive	car_passenger	transit	walk	bike	other	pct_bike
0	11820	7155	930	3350	265	70	45	0.005922
1	10160	6135	665	2985	280	35	65	0.003445
2	6045	4090	355	1285	195	65	65	0.010753
3	14910	3290	290	6200	3200	1675	225	0.112341
4	11395	7150	500	2945	615	65	140	0.005704

[6]:
```
# add new columns showing % of commuters for each mode
def calc_pct(mode):
    return round(mode/neighbourhoods['total_commuters'], 3)

# new column names
pct_cols = ['pct_drive', 'pct_cp', 'pct_transit', 'pct_walk']
neighbourhoods[pct_cols] = neighbourhoods.loc[:, 'drive':'walk'].apply(calc_pct)
#.apply() applies a function along an axis of the DataFrame
```

```
<ipython-input-6-06e20841055d>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  neighbourhoods[pct_cols] = neighbourhoods.loc[:,
'drive':'walk'].apply(calc_pct)
<ipython-input-6-06e20841055d>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  neighbourhoods[pct_cols] = neighbourhoods.loc[:,
'drive':'walk'].apply(calc_pct)
<ipython-input-6-06e20841055d>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  neighbourhoods[pct_cols] = neighbourhoods.loc[:,
'drive':'walk'].apply(calc_pct)
<ipython-input-6-06e20841055d>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  neighbourhoods[pct_cols] = neighbourhoods.loc[:,
'drive':'walk'].apply(calc_pct)
```

3 Overview

3.1 Data visualization in Python

So far, we have gotten data, wrangled it, and scratched the surface of exploratory analyses. As part of that exploration, we created charts with `pandas`. However, there are dedicated visualization libraries let us customize our charts further.

4 `matplotlib`

4.1 `matplotlib`

`matplotlib` is *the* foundational data visualization library in Python. `pandas`'s visualization functions are, at their core, `matplotlib` functions. Other popular libraries like `seaborn` similarly build on `matplotlib`.

For historical reasons, when we import `matplotlib`, we really import `matplotlib.pyplot`. The conventional alias is `plt`.

[7]:
```
# jupyter-specific "magic" command to render plots in-line
%matplotlib inline

import matplotlib.pyplot as plt
```

4.2 Anatomy of a plot

`matplotlib` visuals consist of one or more Axes in a Figure. An *Axes*, confusingly, is what we would consider a graph, while the *Figure* is a container for those graphs. An Axes has an x-*Axis*

and a y-*Axis*.

More details can be found at: https://matplotlib.org/stable/tutorials/introductory/quick_start.html

4.3 Plotting with `matplotlib`

`matplotlib` provides two ways to create visualizations: * by having **`pyplot`** automatically create and manage Figures and Axes, keeping track of which Figure and Axes we are currently working on * by taking an **object-oriented approach**, where we explicitly create Figures and Axes and modify them

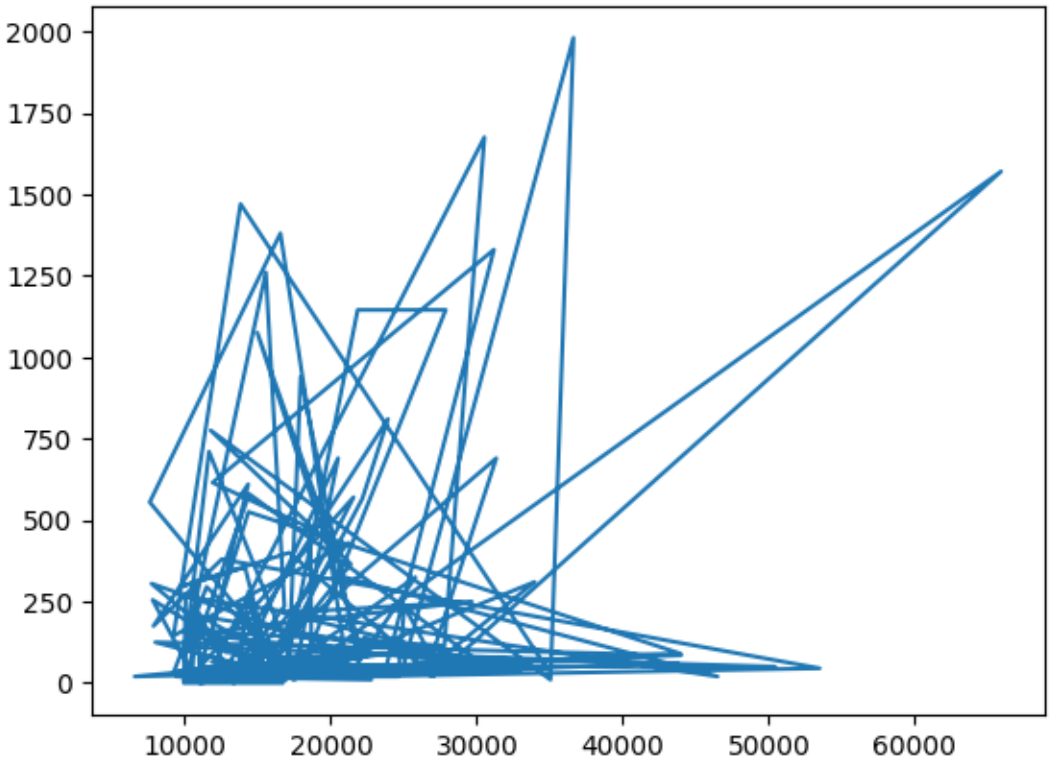
The object-oriented approach is recommended, but the `pyplot` approach is convenient for quick plots.

4.4 `pyplot`-style plotting

`pyplot`-style plotting is convenient for quick, exploratory plots, where we don't plan on doing a lot of customization. When we plotted data in `pandas`, `pandas` took this approach. Let's plot the neighbourhood data with the `pyplot` approach. `plot()` produces a line plot by default.

[8]:
```
plt.plot(neighbourhoods['pop_2016'],
         neighbourhoods['bike'])
```

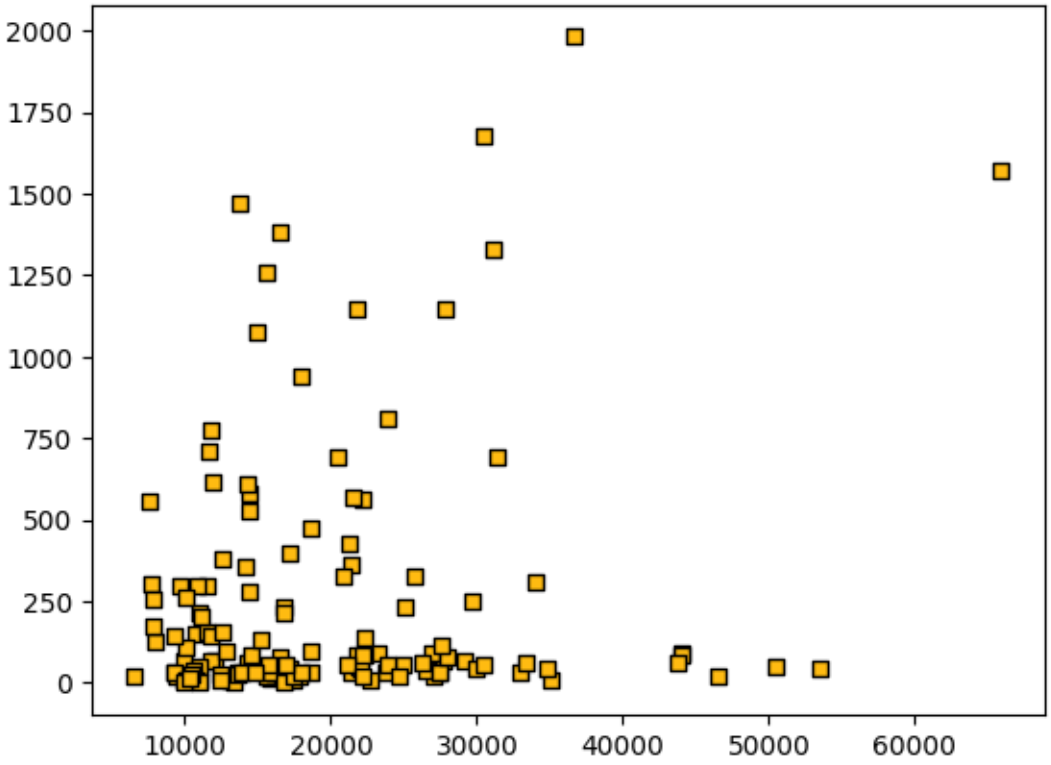
[8]:
```
[<matplotlib.lines.Line2D at 0x7c4f7d0ff220>]
```



Let's make it a scatterplot instead with the `scatter()` function. We can use keyword arguments like `facecolor` and `edgecolor` to change the styling. `matplotlib` lets us specify colour with RGB(A) tuples, hexadecimal strings, single-character shortcodes, and even xkcd colours.

[9]:
```
plt.scatter(neighbourhoods['pop_2016'],
            neighbourhoods['bike'],
            marker='s',  # square marker
            facecolor='#fb1',
            edgecolor='k') # black
```

[9]:
```
<matplotlib.collections.PathCollection at 0x7c4f7cfee680>
```

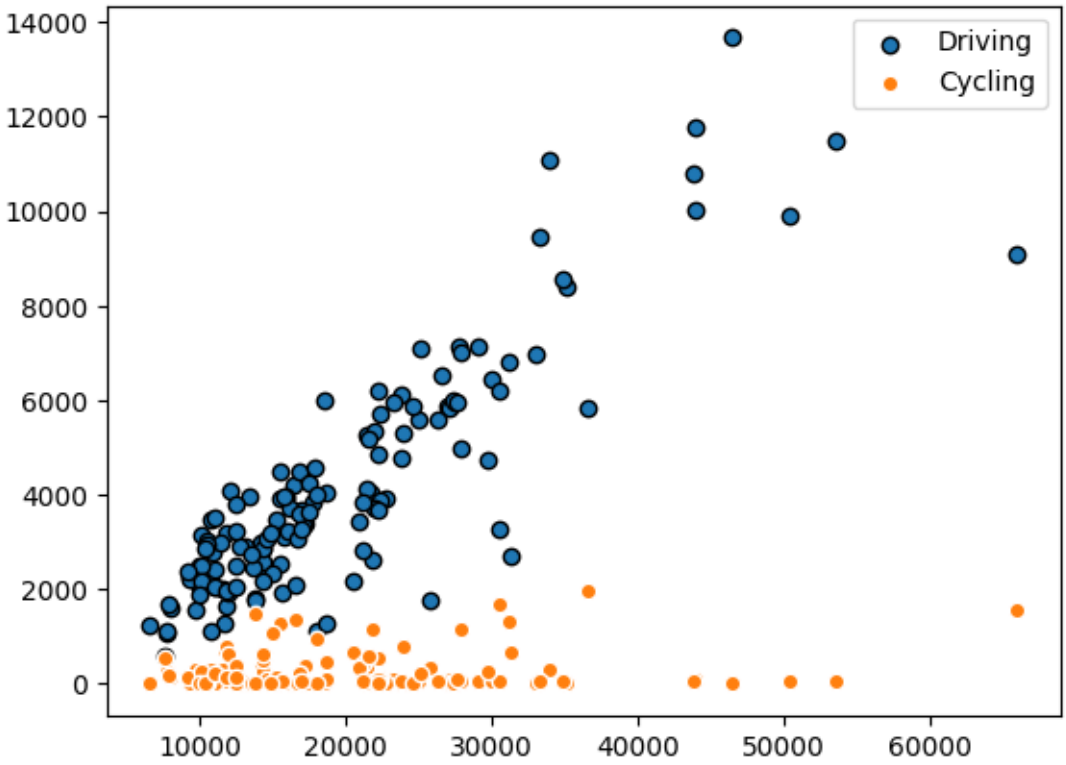


Using the `pyplot` approach, the outputs of successive function calls in the same cell context are layered on. Let's layer driving and biking commuter counts and add a legend.

[10]:
```
plt.scatter(neighbourhoods['pop_2016'],
            neighbourhoods['drive'],
            edgecolor='k',
            label='Driving')
plt.scatter(neighbourhoods['pop_2016'],
            neighbourhoods['bike'],
            edgecolor='w',
            label='Cycling')
```

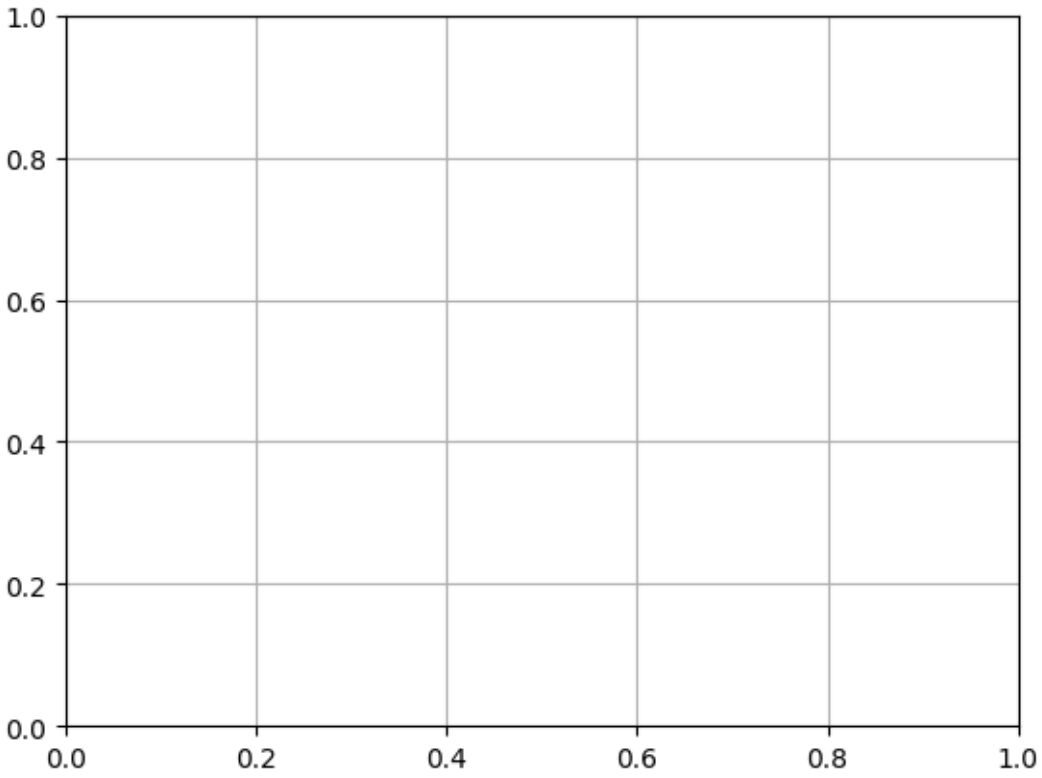
```
plt.legend()
```

[10]: `<matplotlib.legend.Legend at 0x7c4f7c692410>`



Calls in a different cell are treated as a new Axes.

[11]:
```
plt.grid()
```



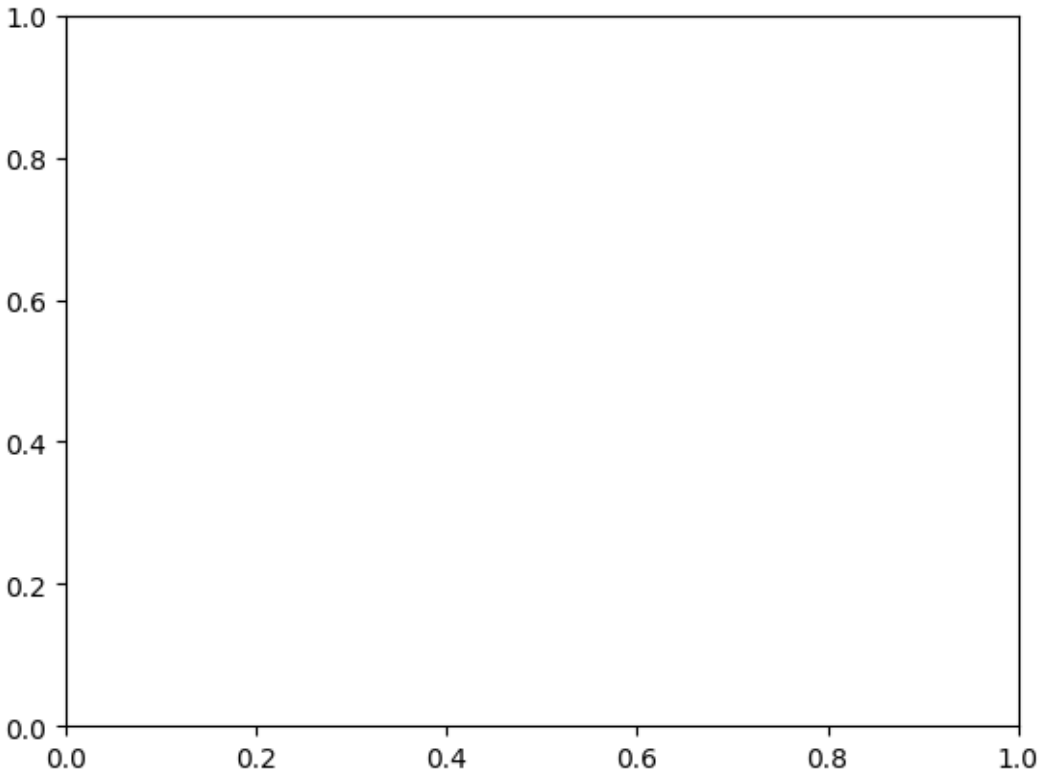
4.5 Object-oriented approach to plotting

The object-oriented approach is the preferred method of plotting with `matplotlib`. In this approach, we use the `subplots()` function to create plot objects, then call methods to modify them.

By default, `subplots()` returns one Figure and one Axes. We can use Python's unpacking syntax to assign the Figure and Axes to their own variables in one line.

[12]:
```
fig, ax = plt.subplots()
print(f'{type(fig)}, {type(ax)}')
```

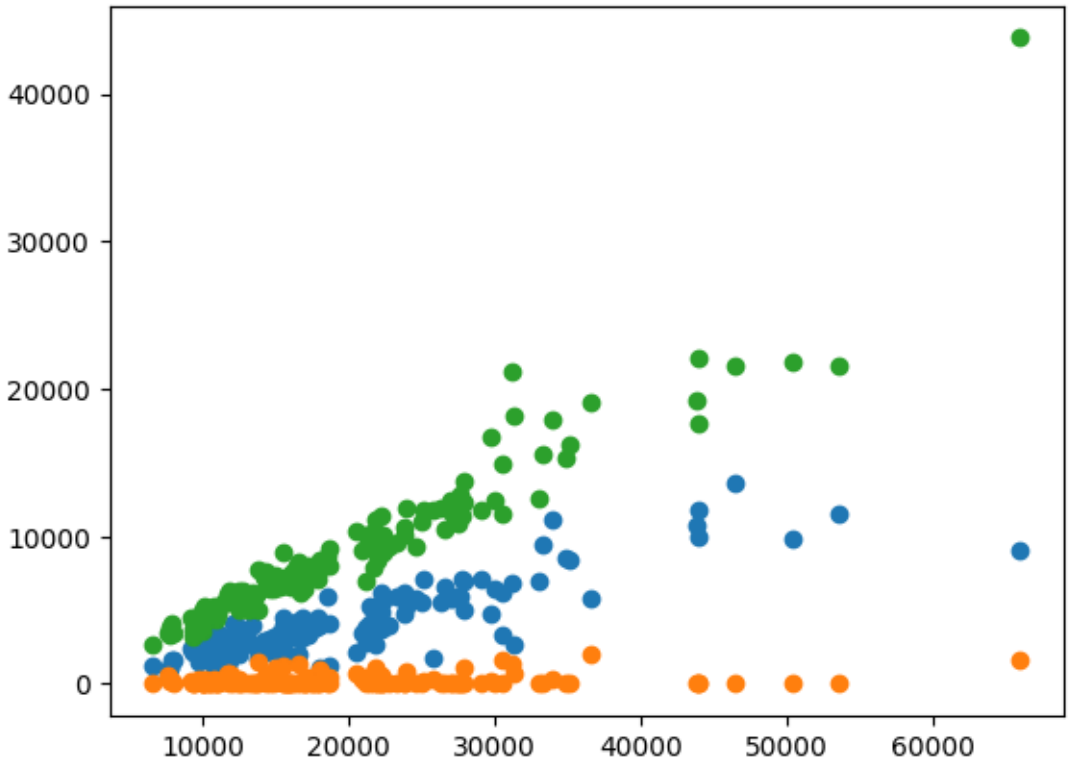
```
<class 'matplotlib.figure.Figure'>, <class 'matplotlib.axes._axes.Axes'>
```



The Axes is empty. Let's plot data on it with the Axes `scatter()` method. This method updates `ax` with a scatterplot. To make it easier to refer to each scatterplot later, we assign the outputs to their own variables, `drivers` and `cyclists`.

[13]:
```
drivers = ax.scatter(neighbourhoods['pop_2016'],
           neighbourhoods['drive'])
cyclists = ax.scatter(neighbourhoods['pop_2016'],
           neighbourhoods['bike'])
total = ax.scatter(neighbourhoods['pop_2016'],
                   neighbourhoods['total_commuters'])
fig
```

[13]:

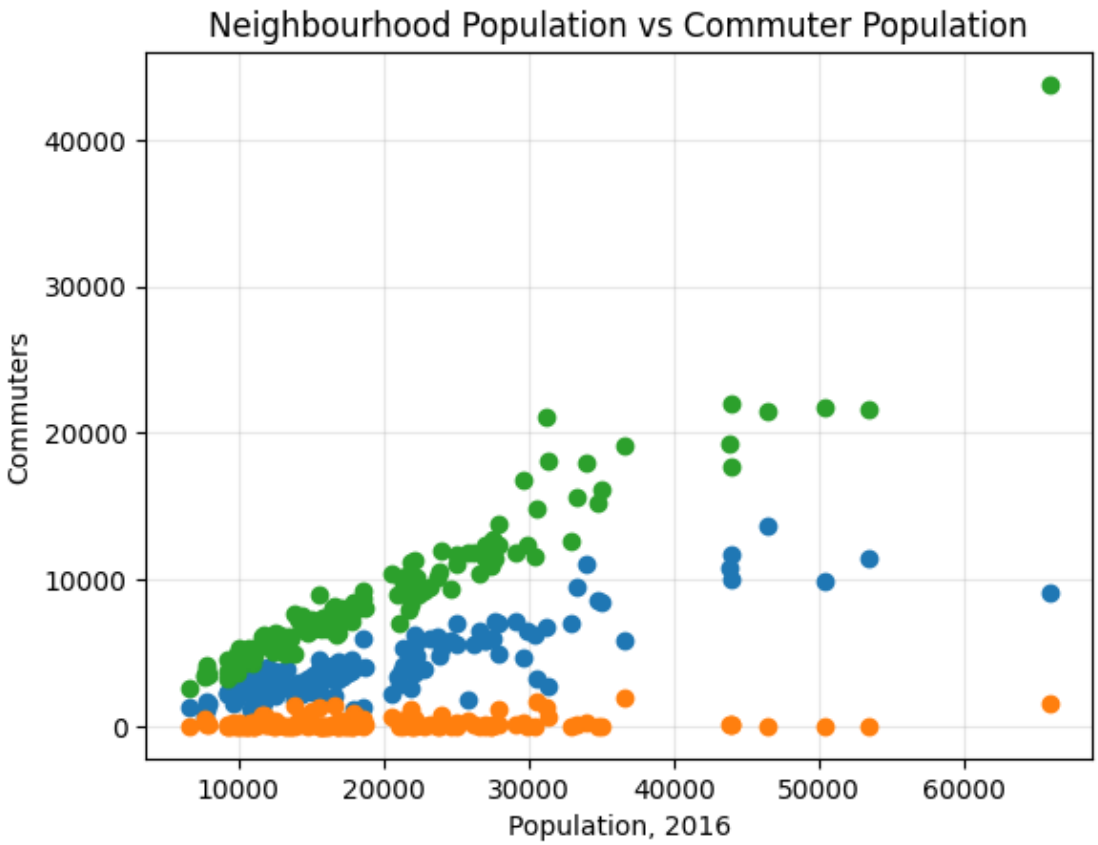


4.6 Adding labels, a title, and grid

This graph doesn't give much context. To add a title, we can use the Axes `set_title()` method, which takes the title as a string, plus optional arguments like `fontsize`. Similarly, we can set x and y labels with the `set_xlabel()` and `set_ylabel()` methods. Finally, let's add a grid with the Axes `grid()` method, and use the `alpha` parameter to make it translucent. We'll also use the `set_axisbelow()` method to make sure markers draw over the grid.

[14]:
```
ax.set_title('Neighbourhood Population vs Commuter Population')
ax.set_xlabel('Population, 2016')
ax.set_ylabel('Commuters')
ax.set_axisbelow(True)
ax.grid(alpha=0.3)
fig
```

[14]:

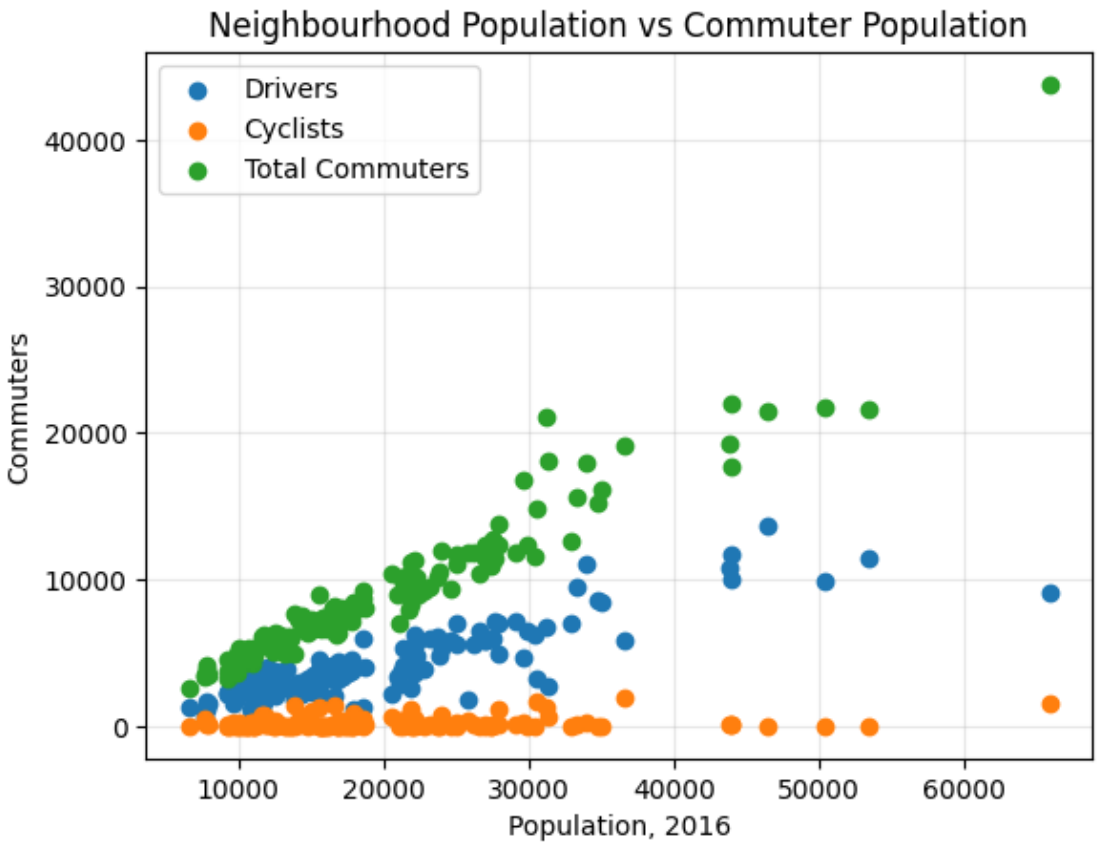


4.7 Adding a legend

This graph could use a legend. To add one, we call the Axes `legend()` method. If we passed a `label` argument in the `scatter()` calls, `legend()` would use those labels. However, because we did not, we pass a list of the geometries to use in the legend, plus a list of labels to show.

[15]:
```
ax.legend([drivers, cyclists, total],
          ['Drivers', 'Cyclists', 'Total Commuters'])
fig
```

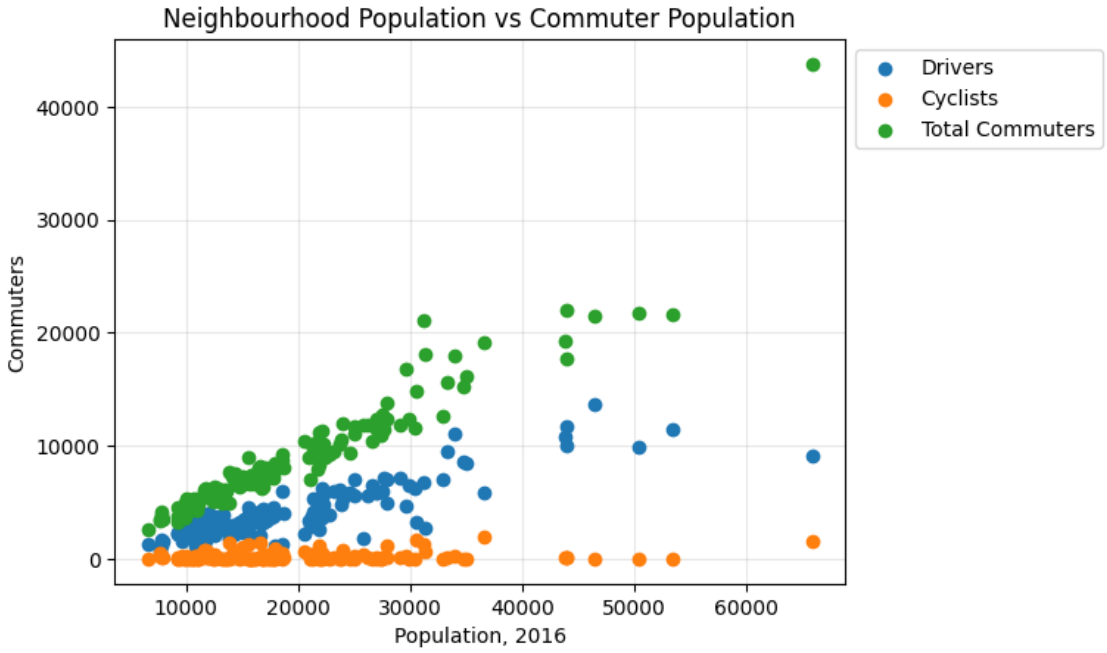
[15]:



To place the legend outside the Axes, we can pass a tuple with the `bbox_to_anchor` argument. The legend's `loc` corner will be placed at the coordinates in the `bbox_to_anchor` tuple.

[16]:
```
ax.legend([drivers, cyclists, total],
          ['Drivers', 'Cyclists', 'Total Commuters'],
          bbox_to_anchor=(1, 1),
          loc='upper left')
fig
```

[16]:



4.8 Modifying axis ticks

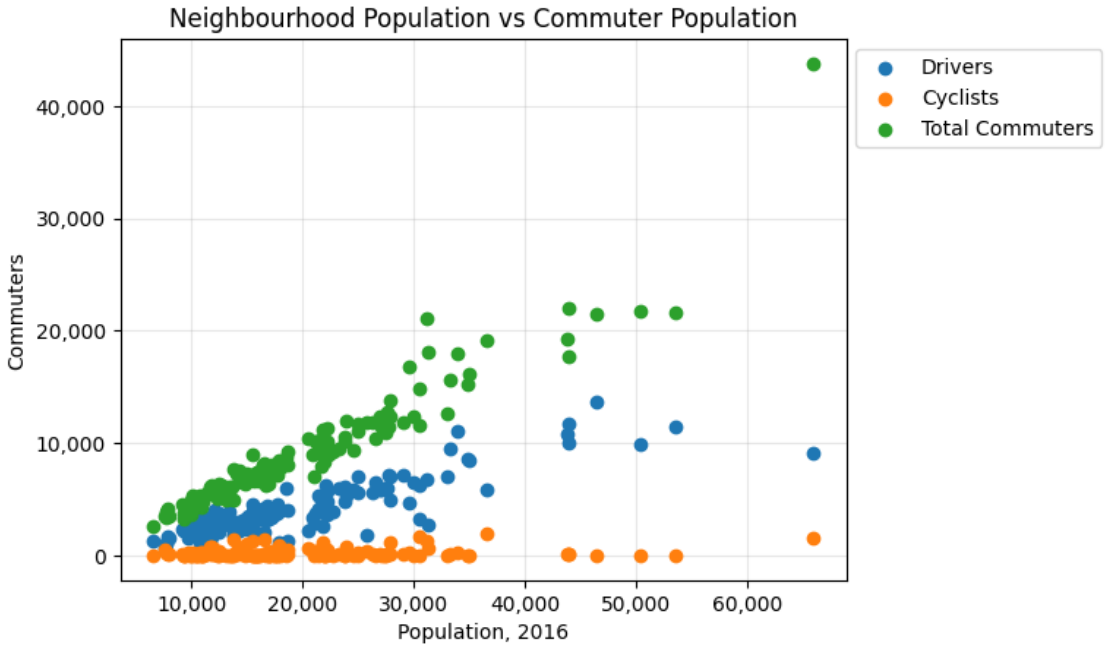
We can change how the x-axis and y-axis are formatted by accessing an Axes `xaxis` and `yaxis` attributes and calling methods like `set_ticks()` or `set_major_formatter()`.

Some configurations of Python and `matplotlib` allow us to pass a format string by itself to `set_major_formatter()`. Older versions require that we import `matplotlib`'s `ticker` submodule and create a `StrMethodFormatter` with the format string we want to use.

[17]:
```
import matplotlib.ticker as tick
```

[18]:
```
# label with a thousands place comma and zero decimal places
ax.xaxis.set_major_formatter(tick.StrMethodFormatter('{x:,.0f}'))
ax.yaxis.set_major_formatter(tick.StrMethodFormatter('{x:,.0f}'))
# %:, use comma as thousand separator
# .0f zero decimal places
fig
```

[18]:



We can also change axis limits.

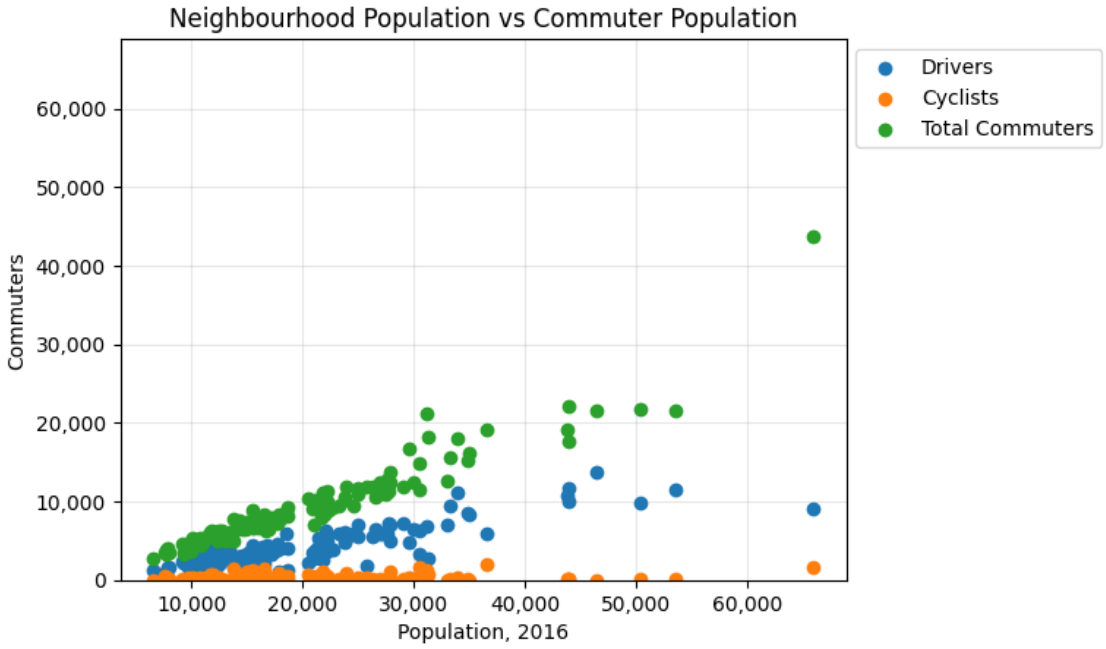
[19]:
```
#ax.xaxis.set_ticks(np.arange(0, max(neighbourhoods['pop_2016']+10), 10000))
```

[20]:
```
ax.axis()
```

[20]:
```
(3610.2, 68879.8, -2189.25, 45974.25)
```

[21]:
```
ax.set(ylim=(0, ax.axis()[1])) # make the y-axis match the x-axis
fig
```

[21]:



4.9 Changing styles

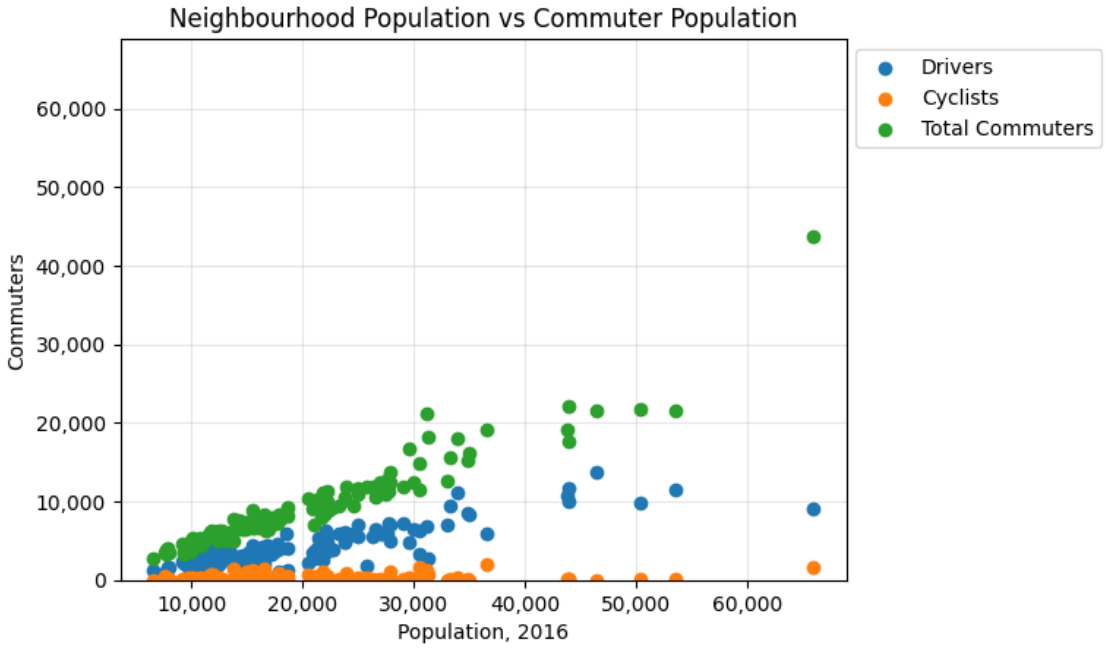
`matplotlib` comes with a bunch of predefined styles. We can view the available ones with `plt.style.available`. Passing one of the options to `style.use()` makes it the aesthetic style for all new plots. **Already created Figures and Axes are not affected.**

[22]:
```
plt.style.available[5:10]  # print a subset
```

[22]:
```
['classic', 'dark_background', 'fast', 'fivethirtyeight', 'ggplot']
```

[23]:
```
# set style for new plots
plt.style.use('fivethirtyeight')

# notice that the style of fig did not change
fig
```

[23]:



4.10 Other plot types

Of course, `matplotlib` offers more than just line plots and scatterplots. Among the many kinds of plots we can make are bar plots, histograms, and boxplots. To create each the object-oriented way, we call the appropriate Axes method, like `Axes.boxplot()` or `Axes.barh()`, for a horizontal bar plot.

[24]:
```
# review the neighbourhoods data
neighbourhoods.head()
```

[24]:

	neighbourhood	n_id	designation	pop_2016	pop_2011	pop_change	private_dwellings	occupied_dwllings	pop_dens	area	total_commuters	drive	car_passenger	transit	walk	bike	other
0	Agincourt North	129	No Designation	29113	30279	-0.039	9371	9120	3929	7.41	11820	7155	930	3350	265	70	45
1	Agincourt South-Malvern West	128	No Designation	23757	21988	0.080	8535	8136	3034	7.83							
2	Alderwood	20	No Designation	12054	11904	0.013	4732	4616	2435	4.95							
3	Annex	95	No Designation	30526	29177	0.046	18109	15934	10863	2.81							
4	Banbury-Don Mills	42	No Designation	27695	26918	0.029	12473	12124	2775	9.98							

```
1            10160   6135            665     2985   280    35     65
2             6045   4090            355     1285   195    65     65
3            14910   3290            290     6200  3200  1675    225
4            11395   7150            500     2945   615    65    140

   pct_bike  pct_drive  pct_cp  pct_transit  pct_walk
0  0.005922      0.605   0.079        0.283     0.022
1  0.003445      0.604   0.065        0.294     0.028
2  0.010753      0.677   0.059        0.213     0.032
3  0.112341      0.221   0.019        0.416     0.215
4  0.005704      0.627   0.044        0.258     0.054
```

[25]:
```
# get just the 10 biggest neighbourhoods to plot
top10_pop = neighbourhoods.sort_values('pop_2016', ascending=False).head(10)
top10_pop
```

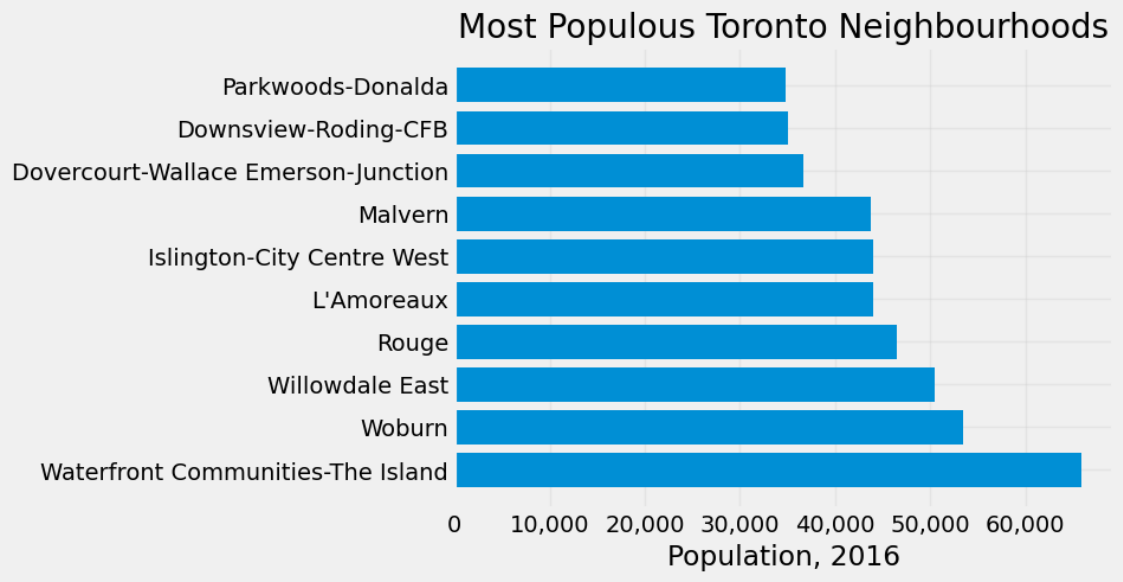
[25]:
```
                          neighbourhood n_id             designation  \
123    Waterfront Communities-The Island   77          No Designation
133                              Woburn  137                     NIA
130                      Willowdale East   51          No Designation
106                                Rouge  131          No Designation
66                           L'Amoreaux  117  Emerging Neighbourhood
59            Islington-City Centre West   14          No Designation
74                               Malvern  132  Emerging Neighbourhood
33   Dovercourt-Wallace Emerson-Junction   93          No Designation
34                  Downsview-Roding-CFB   26                     NIA
96                     Parkwoods-Donalda   45          No Designation

     pop_2016  pop_2011  pop_change  private_dwellings  occupied_dwllings  \
123     65913     43361       0.520              47209              40756
133     53485     53350       0.003              19098              18436
130     50434     45041       0.120              23901              22304
106     46496     45912       0.013              13730              13389
66      43993     44919      -0.021              15486              15037
59      43965     38084       0.154              19911              19328
74      43794     45086      -0.029              13936              13426
33      36625     34631       0.058              16248              15320
34      35052     34659       0.011              14244              13121
96      34805     34617       0.005              13921              13315

     pop_dens   area  total_commuters  drive  car_passenger  transit   walk  \
123      8943   7.37            43785   9100            760    10915  20855
133      4345  12.31            21595  11505           1405     7635    780
130     10087   5.00            21785   9890            695     9390   1550
106      1260  36.89            21500  13665           1510     5935    220
66       6144   7.16            17715  10005           1220     5895    370
59       2712  16.21            22055  11775            975     8205    795
```

74	4948	8.85	19225	10785	1400	6425	425
33	9819	3.73	19090	5825	820	8950	1215
34	2337	15.00	16165	8405	1060	6085	460
96	4691	7.42	15270	8580	820	5275	420

	bike	other	pct_bike	pct_drive	pct_cp	pct_transit	pct_walk
123	1570	610	0.035857	0.208	0.017	0.249	0.476
133	45	210	0.002084	0.533	0.065	0.354	0.036
130	50	215	0.002295	0.454	0.032	0.431	0.071
106	20	160	0.000930	0.636	0.070	0.276	0.010
66	85	120	0.004798	0.565	0.069	0.333	0.021
59	90	195	0.004081	0.534	0.044	0.372	0.036
74	60	115	0.003121	0.561	0.073	0.334	0.022
33	1980	310	0.103719	0.305	0.043	0.469	0.064
34	10	145	0.000619	0.520	0.066	0.376	0.028
96	45	115	0.002947	0.562	0.054	0.345	0.028

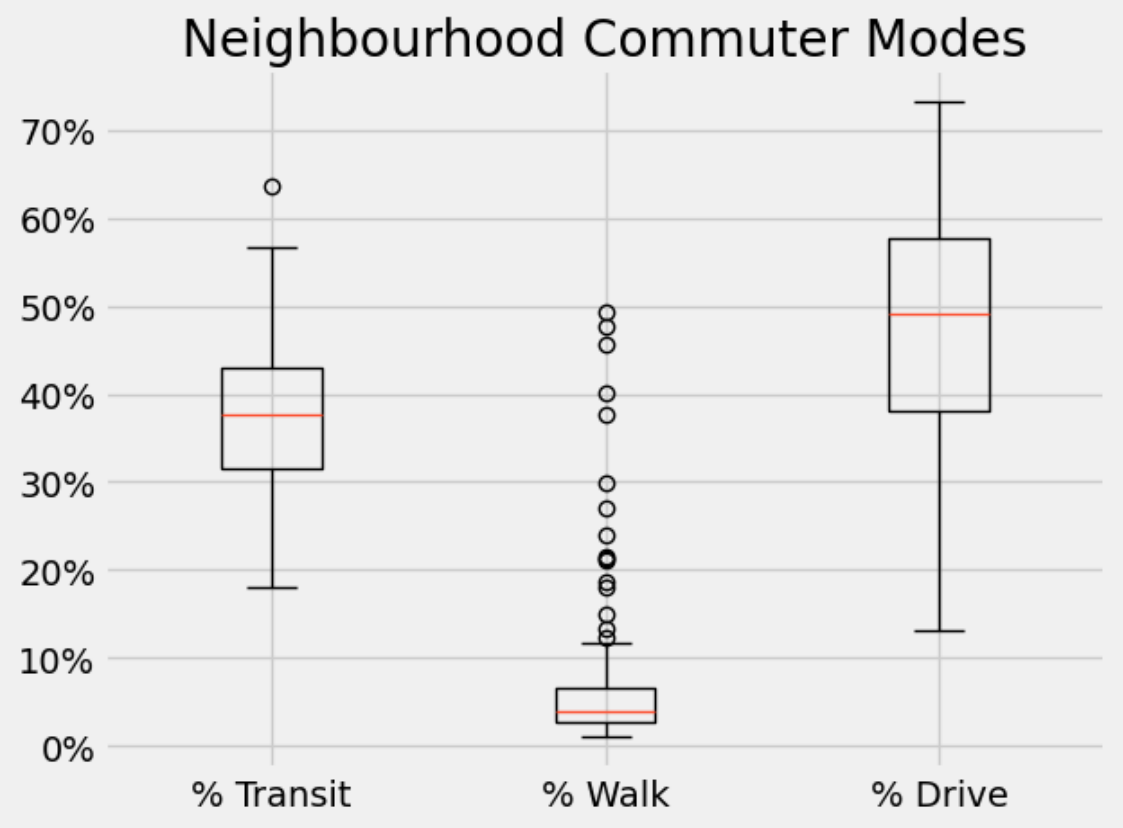
[26]:
```
bar_fig, bar_ax = plt.subplots()
bar_ax.barh(top10_pop['neighbourhood'], top10_pop['pop_2016'])
bar_ax.xaxis.set_major_formatter(tick.StrMethodFormatter('{x:,.0f}'))
bar_ax.set_axisbelow(True)
bar_ax.grid(alpha=0.3)
bar_ax.set_title('Most Populous Toronto Neighbourhoods')
bar_ax.set_xlabel('Population, 2016')
```

[26]:
```
Text(0.5, 0, 'Population, 2016')
```



[27]:
```
# create a box plot
box_fig, box_ax = plt.subplots()
box_ax.boxplot([neighbourhoods['pct_transit'],
                neighbourhoods['pct_walk'],
                neighbourhoods['pct_drive']],
               # add labels so we know which box is which var
               labels=['% Transit', '% Walk', '% Drive'])
box_ax.yaxis.set_major_formatter(tick.StrMethodFormatter('{x:.0%}'))
# percentage format
box_ax.set_title('Neighbourhood Commuter Modes')
```

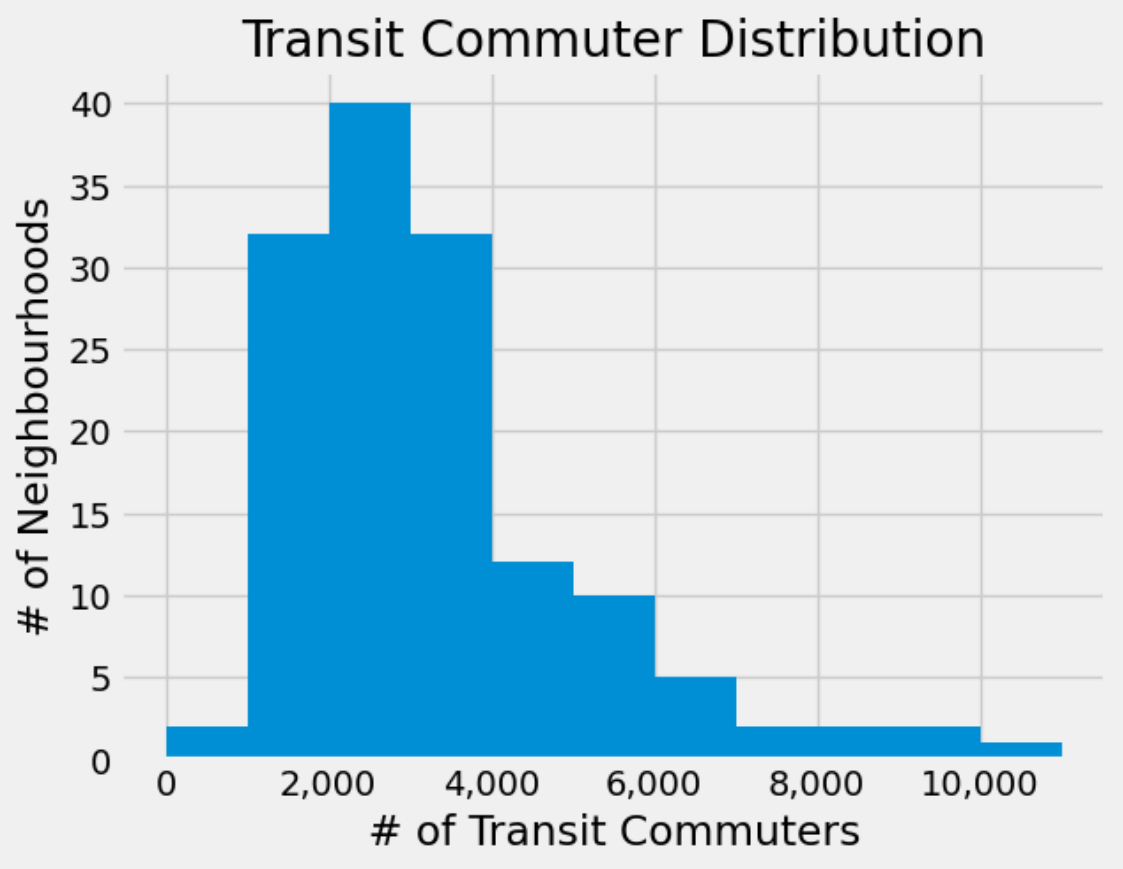
[27]:
```
Text(0.5, 1.0, 'Neighbourhood Commuter Modes')
```



[28]:
```
# create a histogram
hist_fig, hist_ax = plt.subplots()
hist_ax.hist(neighbourhoods['transit'],
             # count the neighbourhoods with 0-1000 transit commuters,
             # 1001-2000 transit commuters, etc
             bins=range(0, 12000, 1000))
hist_ax.xaxis.set_major_formatter(tick.StrMethodFormatter('{x:,.0f}'))
hist_ax.set_title('Transit Commuter Distribution')
```

```
hist_ax.set_xlabel('# of Transit Commuters')
hist_ax.set_ylabel('# of Neighbourhoods')
```

[28]: `Text(0, 0.5, '# of Neighbourhoods')`



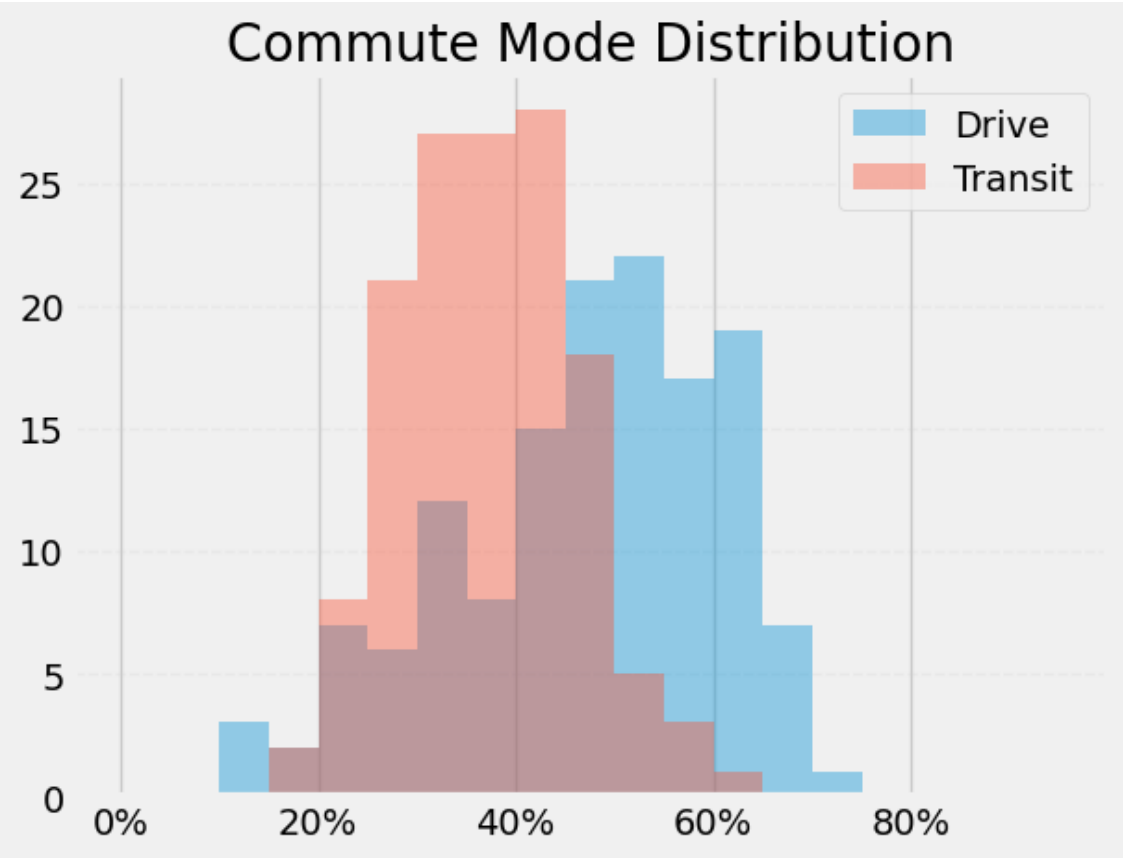
4.11 Layering plots

We've seen that a single Axes can have more than one set of data points plotted on it with our multi-modal scatterplot. We can similarly layer on other graphics, using the `alpha` argument to set transparency.

[29]:
```
layer_fig, layer_ax = plt.subplots()

settings = {'alpha': 0.4, 'bins': np.arange(0, 1, .05)}

layer_ax.hist(neighbourhoods['pct_drive'], label='Drive', **settings)
layer_ax.hist(neighbourhoods['pct_transit'], label='Transit', **settings)
layer_ax.xaxis.set_major_formatter(tick.StrMethodFormatter('{x:.0%}'))
layer_ax.set_axisbelow(True)
layer_ax.grid(alpha=0.2, linestyle='--', axis='y')
```

```
layer_ax.set_title('Commute Mode Distribution')
layer_ax.legend()
layer_ax
```

[29]: `<Axes: title={'center': 'Commute Mode Distribution'}>`



4.12 More complex plots

Let's try plotting the number of reported bike thefts each year by whether the bike was recovered or not. We'll need to wrangle the theft data a bit to get counts by year and status. Then, we'll use the data to make a `stackplot()`. Finally, we'll style it.

[30]:
```
# review the available columns
thefts_joined.columns
```

[30]:
```
Index(['_id', 'objectid', 'event_unique_id', 'primary_offence',
       'occurrence_date', 'occurrence_year', 'occurrence_month',
       'occurrence_dayofweek', 'occurrence_dayofmonth', 'occurrence_dayofyear',
       'occurrence_hour', 'report_date', 'report_year', 'report_month',
       'report_dayofweek', 'report_dayofmonth', 'report_dayofyear',
```

```
       'report_hour', 'division', 'city', 'hood_id', 'neighbourhoodname',
       'location_type', 'premises_type', 'bike_make', 'bike_model',
       'bike_type', 'bike_speed', 'bike_colour', 'bike_cost', 'status',
       'objectid2', 'geometry', 'neighbourhood', 'n_id', 'designation',
       'pop_2016', 'pop_2011', 'pop_change', 'private_dwellings',
       'occupied_dwllings', 'pop_dens', 'area', 'total_commuters', 'drive',
       'car_passenger', 'transit', 'walk', 'bike', 'other', 'pct_bike'],
      dtype='object')
```

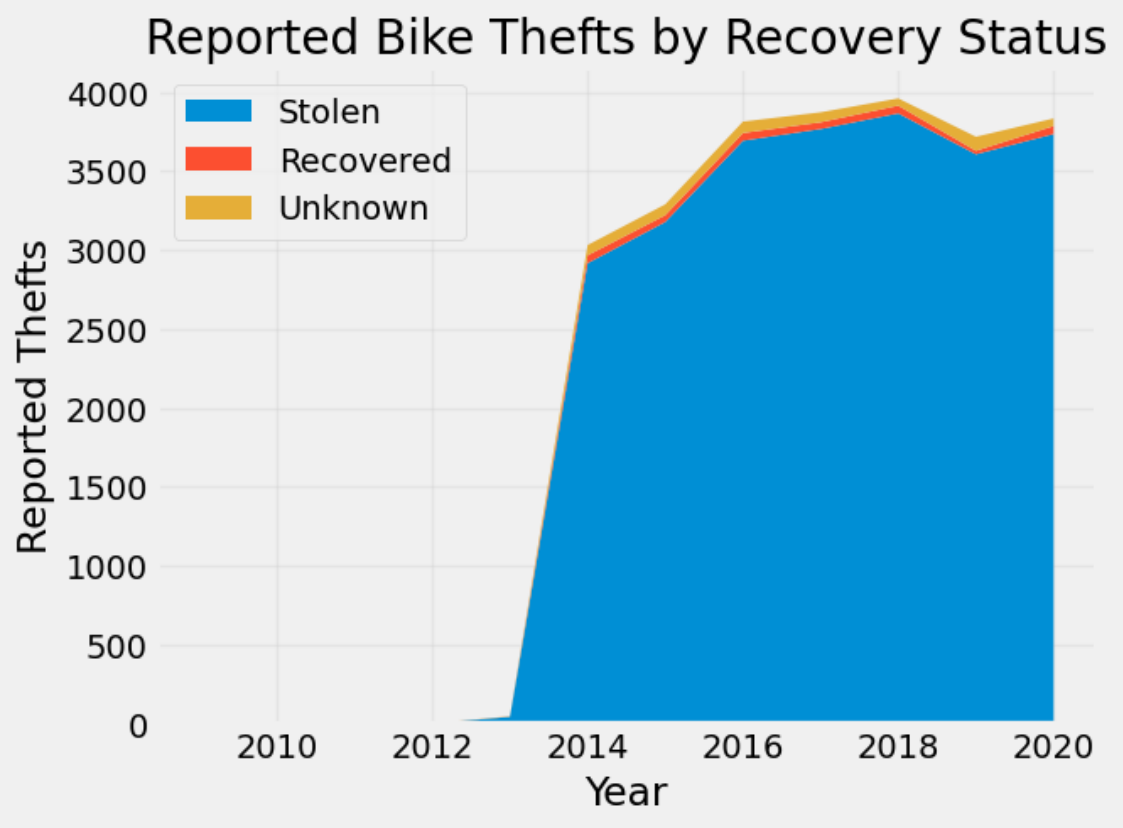
[31]:
```
thefts_grouped = (thefts_joined
                  .groupby(['occurrence_year', 'status'])
                  .agg(thefts=('_id', 'count'))
                  .reset_index()  # make occurrence year a regular col
                  .pivot(index='occurrence_year', columns='status',␣
 ↪values='thefts')
                  .reset_index()  # ...and again
                  .fillna(0))
thefts_grouped
```

[31]:

status	occurrence_year	RECOVERED	STOLEN	UNKNOWN
0	2009	0.0	1.0	0.0
1	2010	0.0	2.0	0.0
2	2011	0.0	3.0	0.0
3	2012	0.0	2.0	0.0
4	2013	1.0	43.0	2.0
5	2014	50.0	2916.0	65.0
6	2015	43.0	3177.0	69.0
7	2016	49.0	3692.0	72.0
8	2017	43.0	3766.0	63.0
9	2018	49.0	3865.0	46.0
10	2019	22.0	3606.0	89.0
11	2020	51.0	3734.0	48.0

[32]:
```
stfig, stax = plt.subplots()

stax.stackplot(thefts_grouped['occurrence_year'], thefts_grouped['STOLEN'],
        thefts_grouped['RECOVERED'], thefts_grouped['UNKNOWN'],
       labels=['Stolen', 'Recovered', 'Unknown'])
stax.set_axisbelow(True)
stax.grid(alpha=0.3)
stax.legend(loc='upper left')
stax.set_title('Reported Bike Thefts by Recovery Status')
stax.set_ylabel('Reported Thefts')
stax.set_xlabel('Year')
```

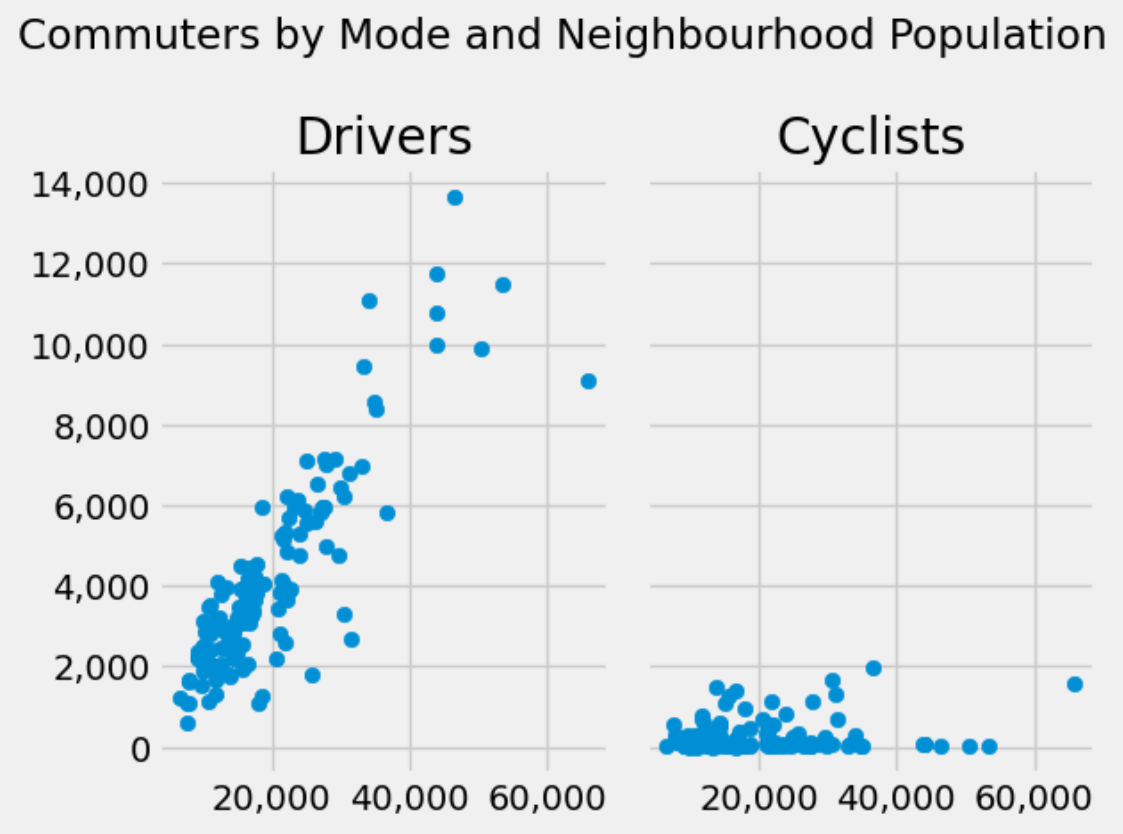
[32]:
```
Text(0.5, 0, 'Year')
```



4.13 Subplots

We can create multiple Axes in one Figure by passing `nrows` and `ncols` arguments to `subplots()`. The number of Axes we get equals `nrows` * `ncols`. Multiple Axes are returned as a `numpy` array.

[33]:
```
modefig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, sharey=True)
ax1.scatter(neighbourhoods['pop_2016'],
            neighbourhoods['drive'])
ax2.scatter(neighbourhoods['pop_2016'],
            neighbourhoods['bike'])
ax1.set_title('Drivers')
ax2.set_title('Cyclists')
ax1.yaxis.set_major_formatter(tick.StrMethodFormatter('{x:,.0f}'))
ax1.xaxis.set_major_formatter(tick.StrMethodFormatter('{x:,.0f}'))
ax2.xaxis.set_major_formatter(tick.StrMethodFormatter('{x:,.0f}'))
modefig.suptitle('Commuters by Mode and Neighbourhood Population')
modefig.tight_layout()
```

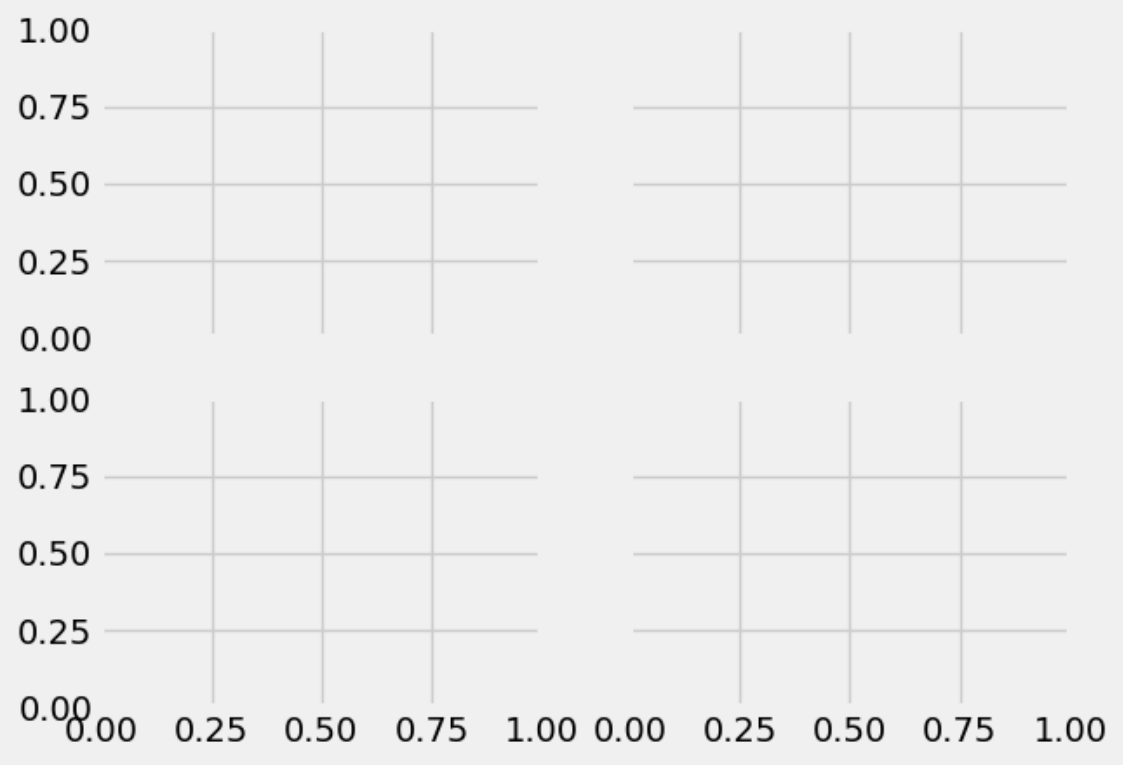


4.13.1 Unpacking subplots

As the number of subplots grows, it gets cumbersome to unpack them in the assignment statement. We can temporarily assign all of them to a single variable.

[34]:
```
# make a 2x2 grid of subplots
modefig2, mode_ax = plt.subplots(nrows=2, ncols=2, sharey=True, sharex=True)
mode_ax
```

[34]:
```
array([[<Axes: >, <Axes: >],
       [<Axes: >, <Axes: >]], dtype=object)
```



The Axes are arranged in a 2x2 array. It would be more straightforward to refer to them if we had a 1x4 array instead.

[35]:
```
# accessing items in a 2x2 array can be annoying
mode_ax
```

[35]:
```
array([[<Axes: >, <Axes: >],
       [<Axes: >, <Axes: >]], dtype=object)
```

[36]:
```
# example: getting the bottom left Axes
mode_ax[1, 0]
```

[36]:
```
<Axes: >
```

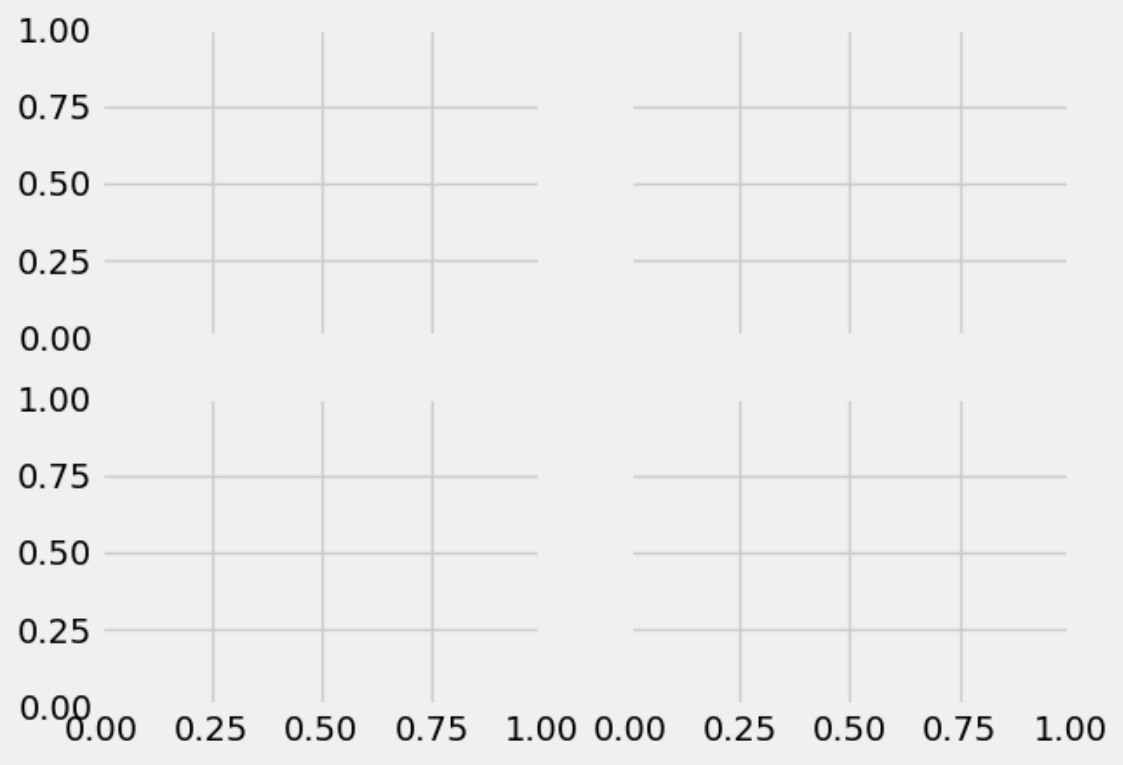
We can take advantage of `numpy` arrays' `flatten()` method. Recall that `flatten()` returns a new array with all the elements arranged in a single row. We can then unpack the elements of that row and assign them to individual variables.

[37]:
```
# recall what flatten() does
mode_ax.flatten()
```

[37]:
```
array([<Axes: >, <Axes: >, <Axes: >, <Axes: >], dtype=object)
```

[38]:
```
a1, a2, a3, a4 = mode_ax.flatten()
modefig2  # we haven't changed the Figure
```

[38]:



4.13.2 Plotting with helper functions

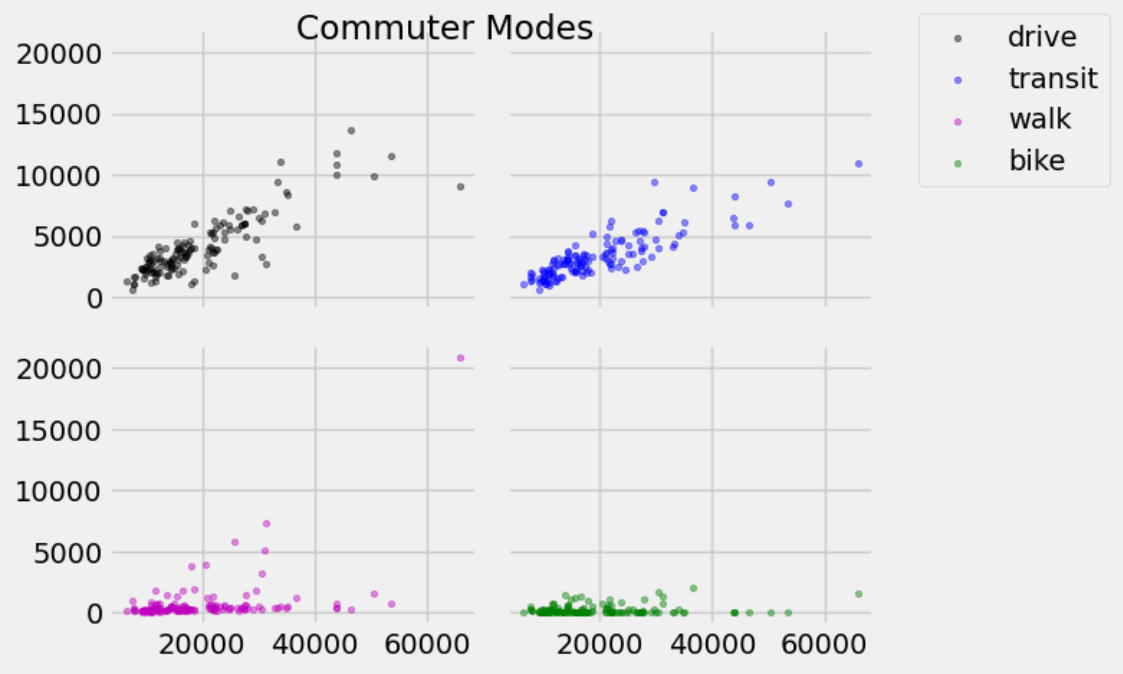
Plotting commute mode against total population four times will be tedious. To reuse code, we can write a helper function that takes an Axes, the mode we're plotting, and a dictionary of style parameters and updates the Axes. `**param_dict` unpacks the dictionary of parameters and arguments passed to `plot_modes()` and passes them on to `scatter()`.

[39]:
```
def plot_modes(ax, mode, param_dict):
    '''
    Helper function to plot neighbourhood pop
    against commuting mode.
    '''
    defaults = {'alpha': 0.45, 's': 10} #'s' --> style
    defaults.update(param_dict)
    out = ax.scatter(neighbourhoods['pop_2016'],
                     neighbourhoods[mode],
                     **defaults)
    return out
```

Then, we can call `plot_modes` to plot each of the subplots.

[40]:
```
# add data to each axes
plot_modes(a1, 'drive', {'label': 'drive', 'facecolor': 'k'})
plot_modes(a2, 'transit', {'label': 'transit', 'facecolor': 'b'})
plot_modes(a3, 'walk', {'label': 'walk', 'facecolor': 'm'})
plot_modes(a4, 'bike', {'label': 'bike', 'facecolor': 'g'})
modefig2.legend(bbox_to_anchor=(1, 1), loc='upper left')
modefig2.tight_layout()
modefig2.suptitle('Commuter Modes')
modefig2
```

[40]:



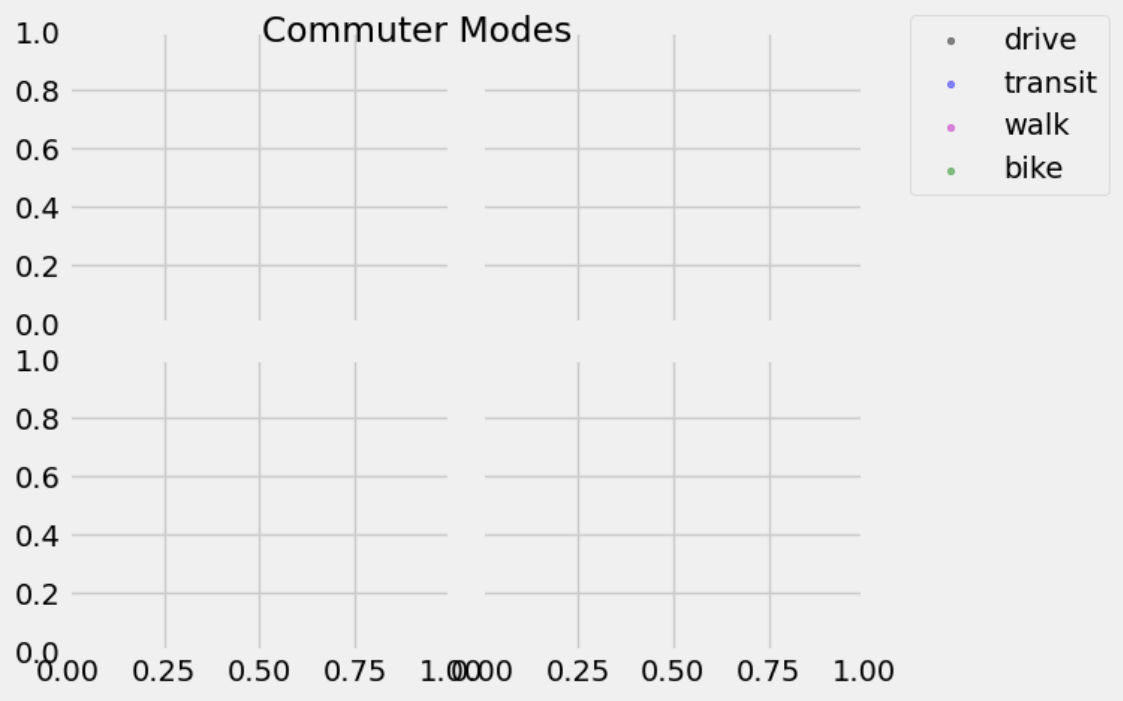
4.13.3 Clearing plots

Successive method calls on an Axes object layer on graphics. To clear everything from an Axes, we can use its `clear()` method. To clear every subplot in a Figure, we can loop through the flattened array of Axes and `clear()` each Axes in turn.

[41]:
```
for axes in mode_ax.flatten():
    axes.clear()
```

[42]:
```
modefig2
```

[42]:



[43]:
```
# let's reset our style before moving on
plt.style.use('default')
```

5 seaborn

5.1 Easier plotting with seaborn

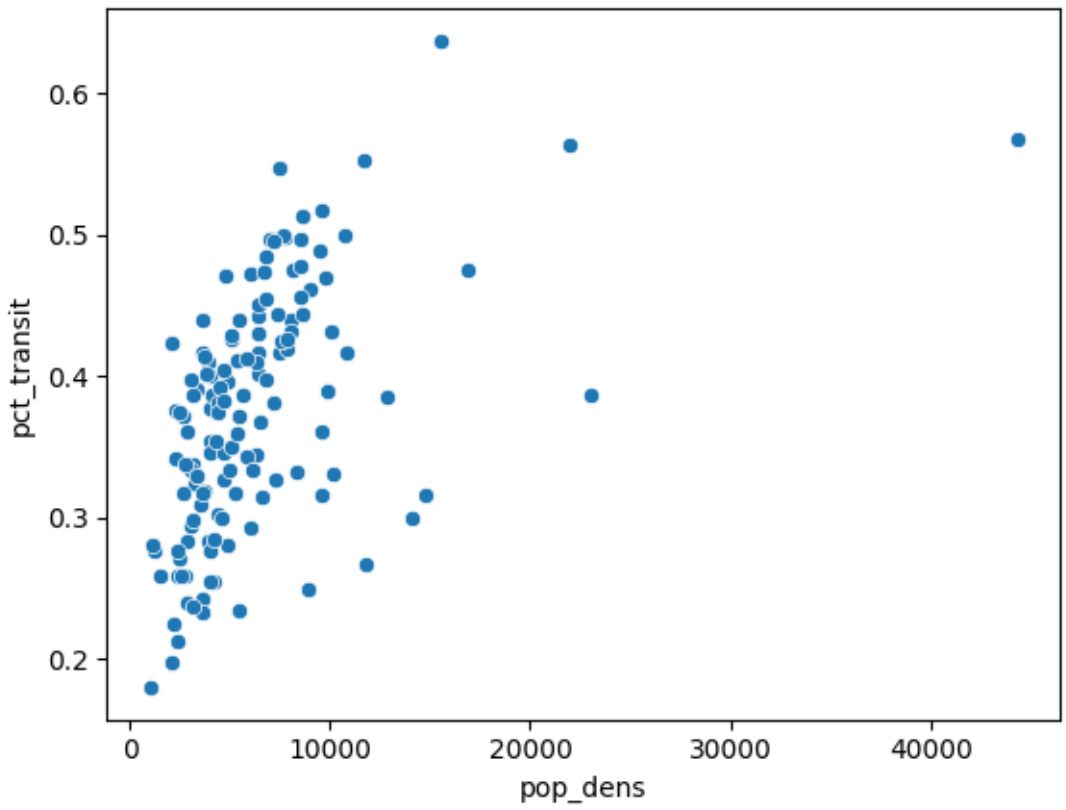
`seaborn` builds upon and complements `matplotlib`, producing nicer-looking Axes with less code, and giving us a few more convenient plot types. `seaborn` is typically given the alias `sns`, after a pop culture reference.

[44]:
```
import seaborn as sns
```

With `seaborn`, we have two ways of structuring arguments to plotting functions: * specifying the `x` and `y` axis columns * specifying the `data` we are visualizing, then the `x` and `y` axis columns

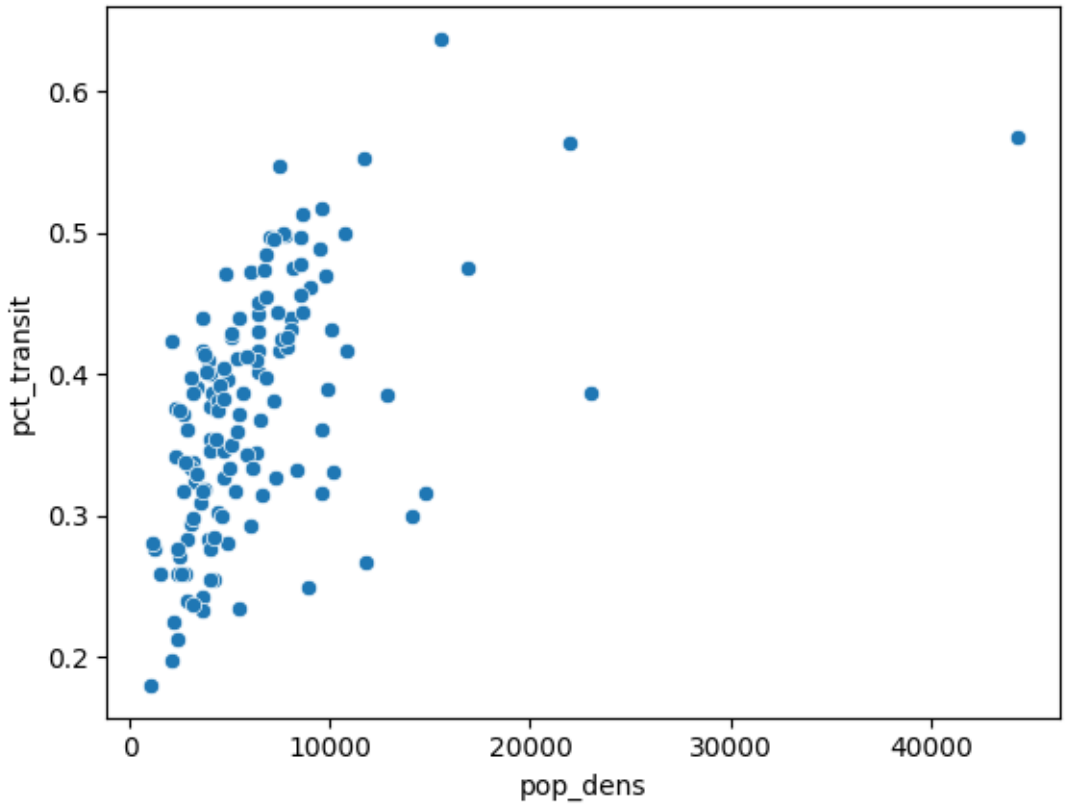
[45]:
```
# use x and y axis columns
sns.scatterplot(x=neighbourhoods['pop_dens'],
                y=neighbourhoods['pct_transit'])
```

[45]:
```
<Axes: xlabel='pop_dens', ylabel='pct_transit'>
```



[46]:
```
# use the dataframe and column names
sns.scatterplot(data=neighbourhoods,
                x='pop_dens',
                y='pct_transit')
```

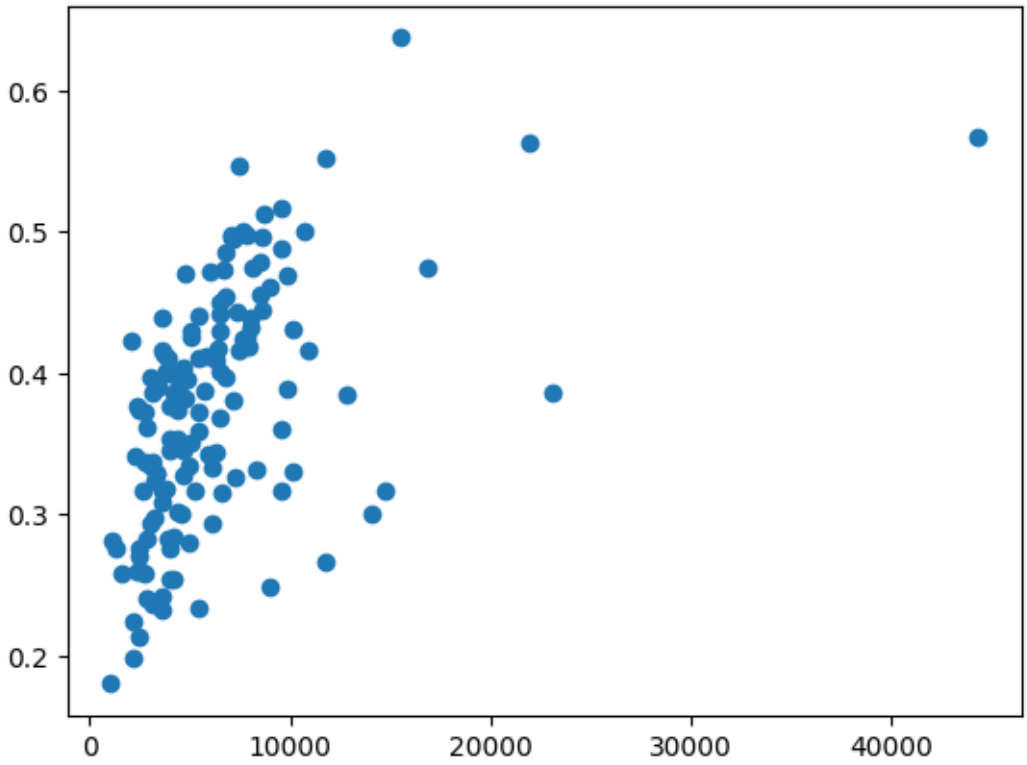
[46]: <Axes: xlabel='pop_dens', ylabel='pct_transit'>



For comparison, we can create the same plot using `matplotlib`'s `pyplot` approach.

[47]:
```
plt.scatter(neighbourhoods['pop_dens'],
            neighbourhoods['pct_transit'])
```

[47]:
```
<matplotlib.collections.PathCollection at 0x7c4f6d16ae30>
```



5.2 `seaborn` and object-oriented `matplotlib`

We can use `seaborn` as a complement to `matplotlib`'s object-oriented approach. `seaborn` functions that work in individual plots have an optional keyword argument that lets us pass in an existing Axes to update. As a bonus, they return the Axes we're working with, making it easy to chain methods together.

Let's revisit our 10 biggest Toronto neighbourhoods chart.

This was the code to create that plot. We'll recreate it with `seaborn`.

```
bar_fig, bar_ax = plt.subplots()
bar_ax.barh(top10_pop['neighbourhood'], top10_pop['pop_2016'])
bar_ax.xaxis.set_major_formatter('{x:,.0f}')
bar_ax.set_axisbelow(True)
bar_ax.grid(alpha=0.3)
bar_ax.set_title('Most Populous Toronto Neighbourhoods')
bar_ax.set_xlabel('Population, 2016')
```

[48]:
```
top10_pop = neighbourhoods.sort_values('pop_2016', ascending=False).head(10)
top10_pop
```

[48]:

	neighbourhood	n_id	designation	\
123	Waterfront Communities-The Island	77	No Designation	
133	Woburn	137	NIA	
130	Willowdale East	51	No Designation	
106	Rouge	131	No Designation	
66	L'Amoreaux	117	Emerging Neighbourhood	
59	Islington-City Centre West	14	No Designation	
74	Malvern	132	Emerging Neighbourhood	
33	Dovercourt-Wallace Emerson-Junction	93	No Designation	
34	Downsview-Roding-CFB	26	NIA	
96	Parkwoods-Donalda	45	No Designation	

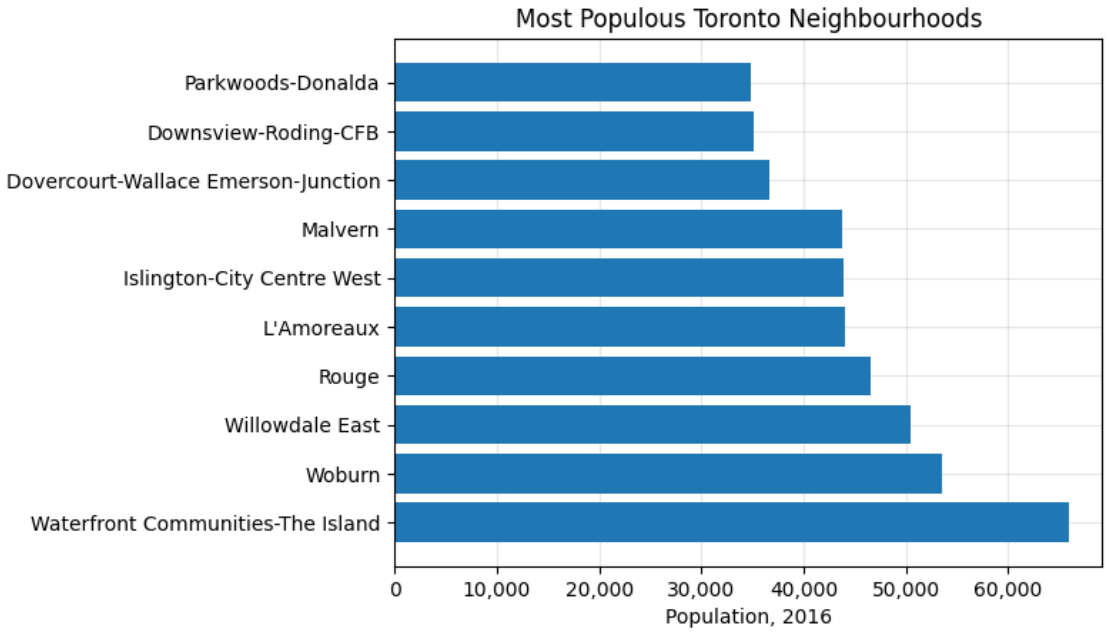
	pop_2016	pop_2011	pop_change	private_dwellings	occupied_dwllings	\
123	65913	43361	0.520	47209	40756	
133	53485	53350	0.003	19098	18436	
130	50434	45041	0.120	23901	22304	
106	46496	45912	0.013	13730	13389	
66	43993	44919	-0.021	15486	15037	
59	43965	38084	0.154	19911	19328	
74	43794	45086	-0.029	13936	13426	
33	36625	34631	0.058	16248	15320	
34	35052	34659	0.011	14244	13121	
96	34805	34617	0.005	13921	13315	

	pop_dens	area	total_commuters	drive	car_passenger	transit	walk	\
123	8943	7.37	43785	9100	760	10915	20855	
133	4345	12.31	21595	11505	1405	7635	780	
130	10087	5.00	21785	9890	695	9390	1550	
106	1260	36.89	21500	13665	1510	5935	220	
66	6144	7.16	17715	10005	1220	5895	370	
59	2712	16.21	22055	11775	975	8205	795	
74	4948	8.85	19225	10785	1400	6425	425	
33	9819	3.73	19090	5825	820	8950	1215	
34	2337	15.00	16165	8405	1060	6085	460	
96	4691	7.42	15270	8580	820	5275	420	

	bike	other	pct_bike	pct_drive	pct_cp	pct_transit	pct_walk
123	1570	610	0.035857	0.208	0.017	0.249	0.476
133	45	210	0.002084	0.533	0.065	0.354	0.036
130	50	215	0.002295	0.454	0.032	0.431	0.071
106	20	160	0.000930	0.636	0.070	0.276	0.010
66	85	120	0.004798	0.565	0.069	0.333	0.021
59	90	195	0.004081	0.534	0.044	0.372	0.036
74	60	115	0.003121	0.561	0.073	0.334	0.022
33	1980	310	0.103719	0.305	0.043	0.469	0.064
34	10	145	0.000619	0.520	0.066	0.376	0.028
96	45	115	0.002947	0.562	0.054	0.345	0.028

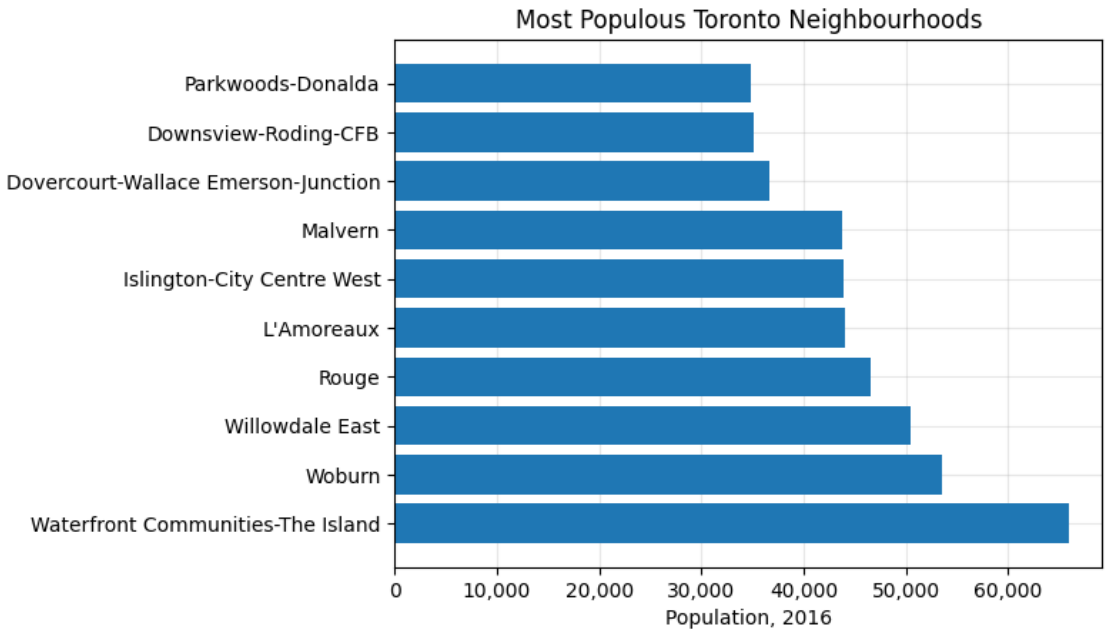
[49]:
```
bar_fig, bar_ax = plt.subplots()
bar_ax.barh(top10_pop['neighbourhood'], top10_pop['pop_2016'])
bar_ax.xaxis.set_major_formatter(tick.StrMethodFormatter('{x:,.0f}'))
bar_ax.set_axisbelow(True)
bar_ax.grid(alpha=0.3)
bar_ax.set_title('Most Populous Toronto Neighbourhoods')
bar_ax.set_xlabel('Population, 2016')
```

[49]:
```
Text(0.5, 0, 'Population, 2016')
```



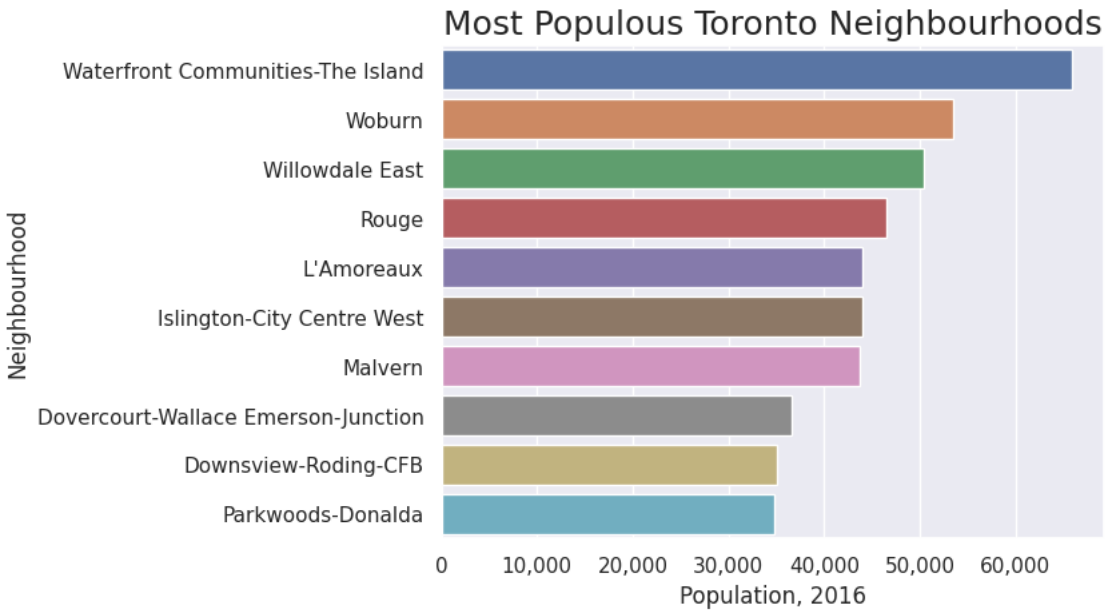
[50]:
```
bar_fig
```

[50]:



And with `seaborn`:

[51]:
```
sns.set_theme()  # use seaborn's default style settings going forward

sns_fig, sns_ax = plt.subplots()  # create a Figure and Axes
(sns.barplot(data=top10_pop,  # set datasource
             x='pop_2016',  # for a horizontal bar graph
             y='neighbourhood',
             ax=sns_ax)  # plot on an existing Axes
 .set(xlabel='Population, 2016',
      ylabel='Neighbourhood'))

# .set() returns text, so we can't chain .set_title()
sns_ax.set_title('Most Populous Toronto Neighbourhoods',
                 fontdict={'fontsize': 18})
sns_ax.xaxis.set_major_formatter(tick.StrMethodFormatter('{x:,.0f}'))
```



5.3 Facets

With `matplotlib`, we created individual subplots and updated them with a helper function to visualize data for different categories. With `seaborn`, we can create a `FacetGrid` and then use its `map()` method to visualize data by category. `map()` takes the name of the plotting function to use, then the needed arguments, such as the columns to use for the x-axis and y-axis.

[52]:
```
# reshape neighbourhood data to support faceting
neighbourhoods_reshaped = (neighbourhoods[['neighbourhood',
                                           'pct_transit',
                                           'pct_drive',
                                           'pct_walk',
                                           'pct_bike']]
                           .melt(id_vars='neighbourhood'))
neighbourhoods_reshaped.head()
```

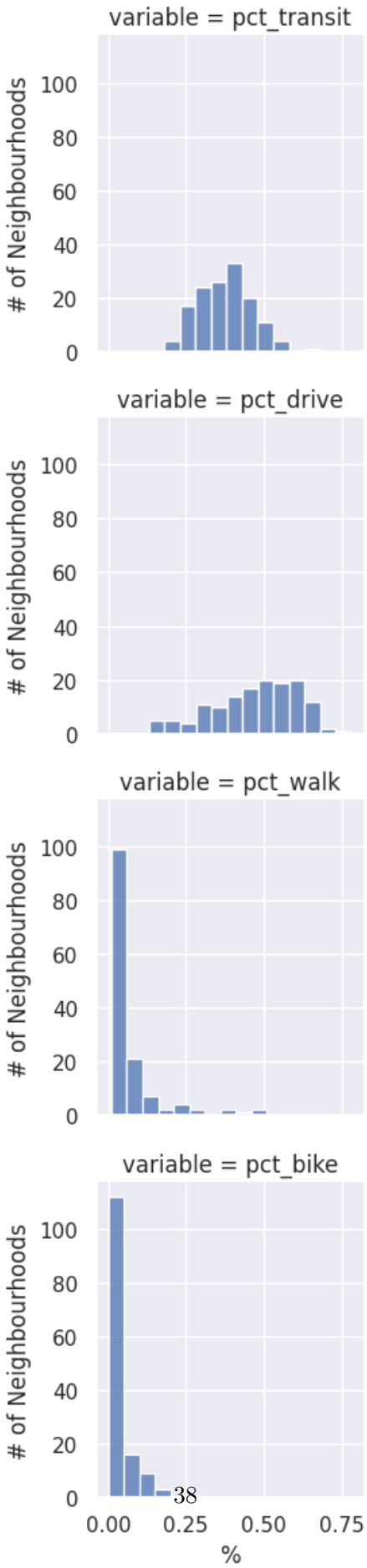
[52]:

	neighbourhood	variable	value
0	Agincourt North	pct_transit	0.283
1	Agincourt South-Malvern West	pct_transit	0.294
2	Alderwood	pct_transit	0.213
3	Annex	pct_transit	0.416
4	Banbury-Don Mills	pct_transit	0.258

[53]:
```
# specify the data to use and the column to facet by
# we'll give each variable its own row
facets = sns.FacetGrid(data=neighbourhoods_reshaped,
                       row='variable')
```

```
# create a histogram for each mode
facets.map(sns.histplot, 'value', binwidth=0.05)
facets.set_axis_labels('%', '# of Neighbourhoods')
```

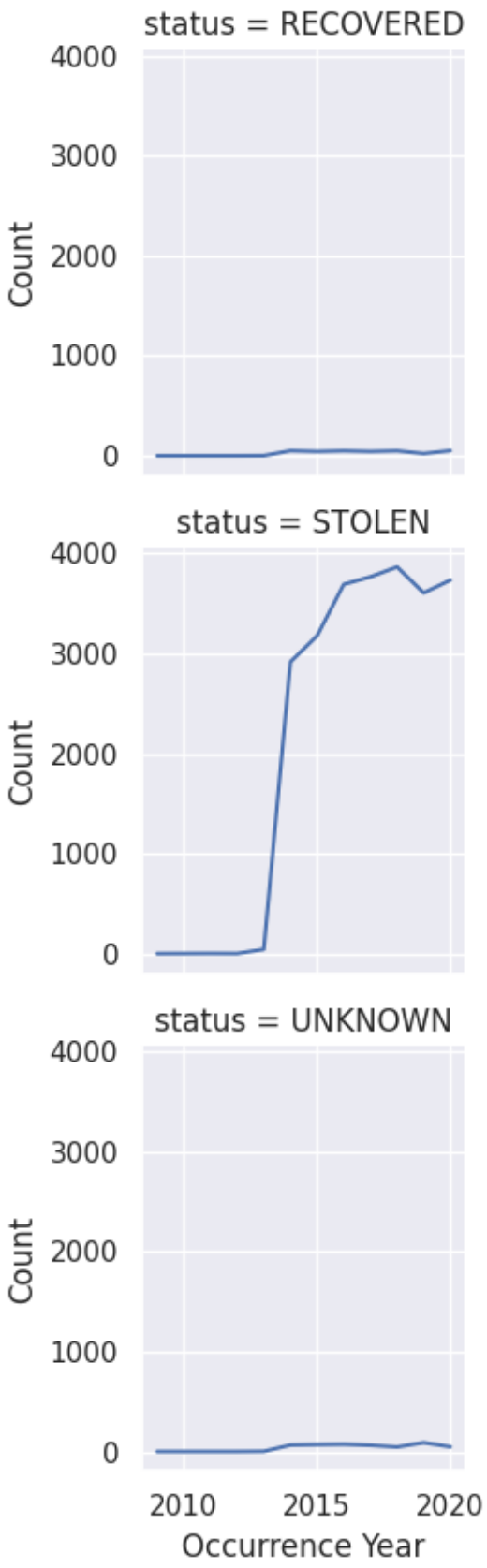
[53]: <seaborn.axisgrid.FacetGrid at 0x7c4f6d245240>


variable = pct_transit
variable = pct_drive
variable = pct_walk
variable = pct_bike
# of Neighbourhoods
0
20
40
60
80
100
0.00
0.25
0.50
0.75
%

For another example, we can plot reported bike thefts by year, faceted by status.

[54]:
```
# reshape the theft counts to support faceting
theft_counts_long = thefts_grouped.melt(id_vars='occurrence_year',
                                        value_name='Count')

# specify the data to use and the column to facet by
# we'll give each status its own row
facets = sns.FacetGrid(data=theft_counts_long, row='status')

# for each status, create a lineplot of counts by year
facets.map(sns.lineplot, 'occurrence_year', 'Count')
facets.set_axis_labels('Occurrence Year')
```

[54]:
```
<seaborn.axisgrid.FacetGrid at 0x7c4f6ce768f0>
```


status = RECOVERED
status = STOLEN
status = UNKNOWN
Count
4000
3000
2000
1000
0
2010
2015
2020
Occurrence Year

5.3.1 Visualization for EDA

`seaborn`'s pair plots are particularly useful for exploratory analyses. `pairplot()` takes a DataFrame or series of columns and creates a Figure containing grid of scatterplots, allowing us to visually look for relationships between variables.

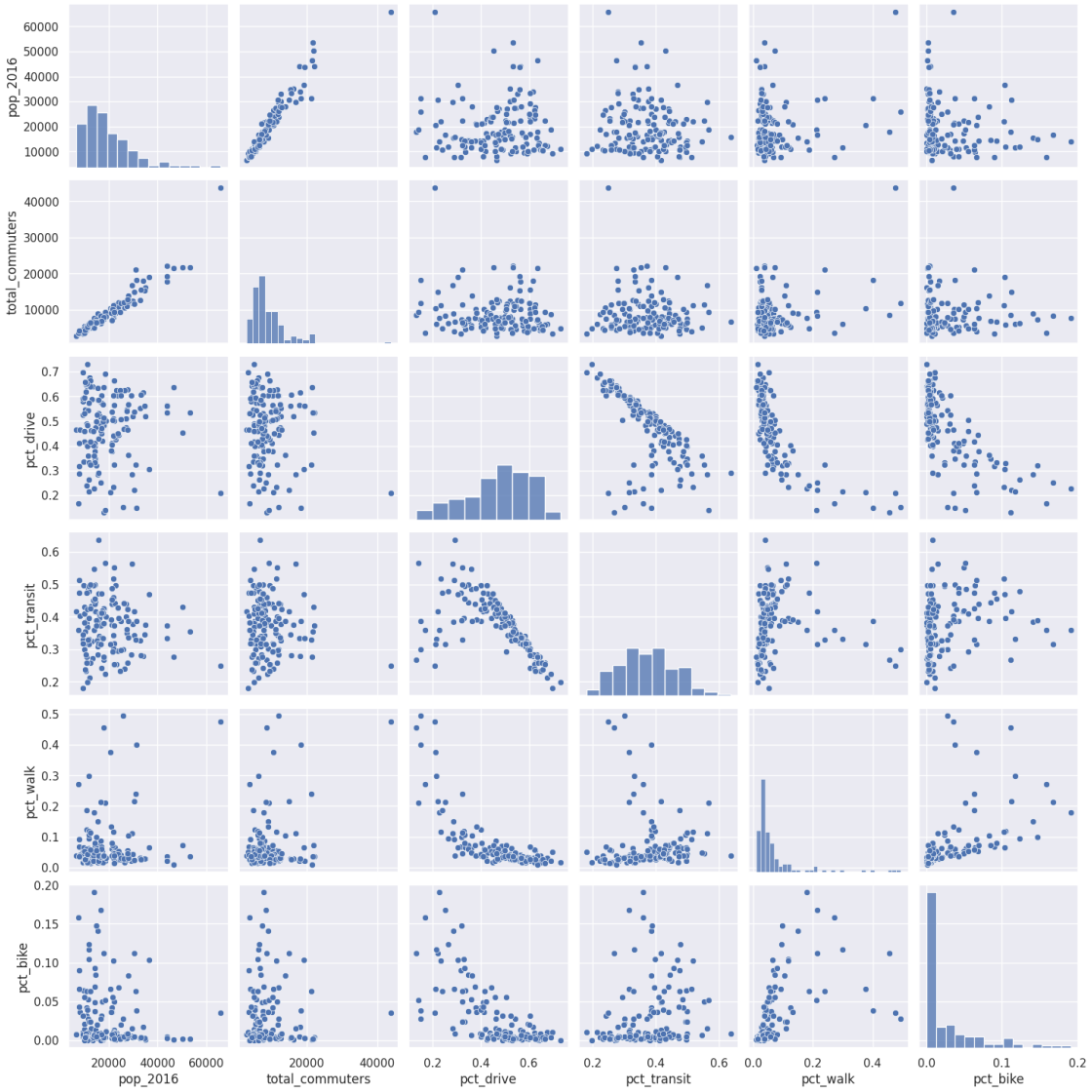
[55]:
```
# review the columns available
neighbourhoods.columns
```

[55]:
```
Index(['neighbourhood', 'n_id', 'designation', 'pop_2016', 'pop_2011',
       'pop_change', 'private_dwellings', 'occupied_dwllings', 'pop_dens',
       'area', 'total_commuters', 'drive', 'car_passenger', 'transit', 'walk',
       'bike', 'other', 'pct_bike', 'pct_drive', 'pct_cp', 'pct_transit',
       'pct_walk'],
      dtype='object')
```

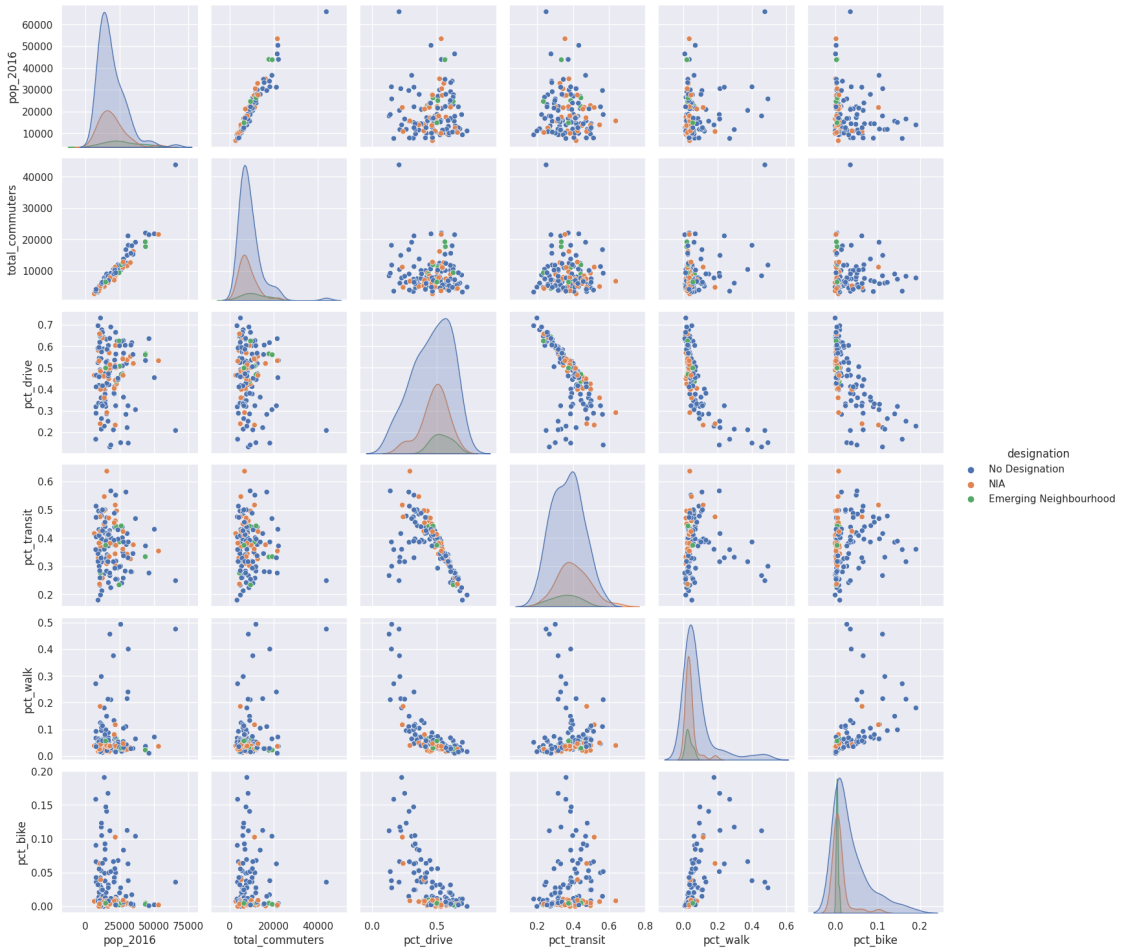
[56]:
```
# review just the numeric columns
neighbourhoods.select_dtypes('number').columns
```

[56]:
```
Index(['pop_2016', 'pop_2011', 'pop_change', 'private_dwellings',
       'occupied_dwllings', 'pop_dens', 'area', 'total_commuters', 'drive',
       'car_passenger', 'transit', 'walk', 'bike', 'other', 'pct_bike',
       'pct_drive', 'pct_cp', 'pct_transit', 'pct_walk'],
      dtype='object')
```

[57]:
```
# select some columns to use in the pair plot
cols = ['pop_2016', 'total_commuters', 'pct_drive', 'pct_transit', 'pct_walk',␣
 ↪'pct_bike']
simple_pairs = sns.pairplot(neighbourhoods[cols])
```



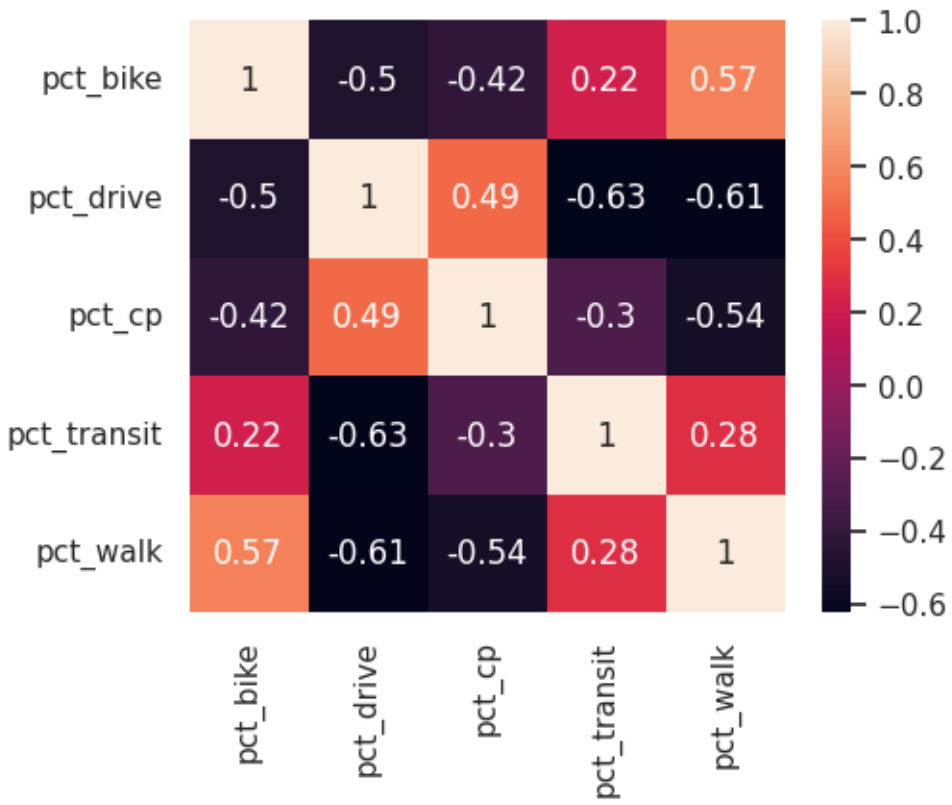
[58]:
```
# if we include non-numeric variables, they won't be plotted, but we can use␣
 ↪them for hue
cols = ['pop_2016', 'designation', 'total_commuters', 'pct_drive',␣
 ↪'pct_transit', 'pct_walk', 'pct_bike']
pairwise_fig = sns.pairplot(neighbourhoods[cols], hue='designation')
```



We can combine `seaborn`'s `heatmap()` function with the `pandas` Dataframe `corr()` method to explore correlations in our data.

[59]:
```
# calculate correlations with pandas
correlations = neighbourhoods.loc[:, 'pct_bike':].corr('kendall')

# create a figure and axes
corr_fig, corr_ax = plt.subplots()
corr_fig.set_size_inches(5, 4)
sns.heatmap(correlations, ax=corr_ax, annot=True)
```

[59]: <Axes: >



5.4 Saving Plots

To save a plot, use the Figure `savefig()` method, which supports exporting figure in common formats like PNG, PDF, and SVG. Setting `bbox_inches='tight'` will make `matplotlib` try to figure out the dimensions of the plot and crop the image appropriately. Note that `seaborn` does not have a plot saving function of its own.

[60]:
```
pairwise_fig.savefig('pairs.svg', bbox_inches='tight')
corr_fig.savefig('correlations.png', bbox_inches='tight')
```

link text# `plotly`

5.5 Interactive visualizations with `plotly`

`plotly` gives us a way to create interactive graphics within Python, building on the plotly.js library rather than `matplotlib`. Plotly Express provides an entry point to making data visualizations with the package. Let's re-create the drivers vs cyclists scatterplot to start.

[61]:
```
import plotly.express as px
```

[62]:
```
plotly_fig = px.scatter(neighbourhoods,
                        x='drive',
```

```
                        y='bike',
                        title='Commute Modes')
plotly_fig.show()  # ensure plot renders nicely in notebook mode
```

[63]:
```
# add hover data
plotly_fig = px.scatter(neighbourhoods,
                        x='drive',
                        y='bike',
                        hover_name='neighbourhood',  # show neighbourhood on␣
 ↪hover
                        labels={'bike': 'Bike', 'drive':'Drive'},
                        title='Commute Modes')
plotly_fig.show()  # ensure plot renders nicely in notebook mode
```

[64]:
```
print(top10_pop.columns)

hist_fig = px.bar(top10_pop,
                  x=['pct_drive', 'pct_cp', 'pct_transit', 'pct_walk',␣
 ↪'pct_bike'],
                  y='neighbourhood',
                  hover_name='neighbourhood',
                  hover_data=['drive', 'car_passenger', 'transit', 'walk',␣
 ↪'bike'],
                  labels={'variable': 'Mode',
                          'value': '%'}
                 )
hist_fig.show()
```

```
Index(['neighbourhood', 'n_id', 'designation', 'pop_2016', 'pop_2011',
       'pop_change', 'private_dwellings', 'occupied_dwllings', 'pop_dens',
       'area', 'total_commuters', 'drive', 'car_passenger', 'transit', 'walk',
       'bike', 'other', 'pct_bike', 'pct_drive', 'pct_cp', 'pct_transit',
       'pct_walk'],
      dtype='object')
```

5.5.1 Re-create the population bar chart

[65]:
```
# view available themes
import plotly.io as pio
pio.templates
```

[65]:
```
Templates configuration
-----------------------
    Default template: 'plotly'
    Available templates:
        ['ggplot2', 'seaborn', 'simple_white', 'plotly',
         'plotly_white', 'plotly_dark', 'presentation', 'xgridoff',
```

```
          'ygridoff', 'gridon', 'none']
```

[66]:
```
bar_fig = px.bar(top10_pop,
                 x='pop_2016',
                 y='neighbourhood',
                 text='pop_2016',
                 labels={'pop_2016': 'Population, 2016',
                         'neighbourhood': 'Neighbourhood'},
                 hover_data={'neighbourhood': False,
                             'pop_2016':False,
                             'pop_change': ':.2p'},  # add pop change,␣
 ↪formatted as %
                 title='Top Toronto Neighbourhoods by Population',
                 template='seaborn'
                )
bar_fig.show()
```

5.6 Futher customizing plotly graphs

For added control over visualizations, we can import plotly's graph_objects submodule.

[67]:
```
import plotly.graph_objects as go
```

[68]:
```
transit_hist = go.Histogram(x=neighbourhoods['pct_transit'], name='Transit')
drive_hist = go.Histogram(x=neighbourhoods['pct_drive'], name='Drive')

data = [drive_hist, transit_hist]

layout = go.Layout(template='seaborn',
                   title='Commute Mode Distribution',
                   xaxis={'title': 'Mode %'},
                   yaxis={'title': 'Neighbourhoods'}
                   )

fig = go.Figure(data=data, layout=layout)
fig.update_layout(hovermode='x')
fig.show()
```

5.7 Saving plotly visualizations

We can save visualizatons created in plotly to image or PDF with the write_image() Figure method. Note that write_image() needs the kaleido package to work.

[ ]:
```
!pip install -U kaleido
```

```
Collecting kaleido
  Downloading kaleido-0.2.1-py2.py3-none-manylinux1_x86_64.whl (79.9 MB)
                             79.9/79.9 MB
```

```
8.9 MB/s eta 0:00:00
```

```
[ ]: import kaleido
```

```
[ ]: fig.write_image('fig.pdf', format='pdf')
```

6 References

- Matplotlib development team. *Basic usage*. https://matplotlib.org/stable/tutorials/introductory/usage.htm
- Matplotlib development team. *The lifecycle of a plot*. https://matplotlib.org/stable/tutorials/introductory/lifecycle.html#sphx-glr-tutorials-introductory-lifecycle-py
- Matplotlib development team. *API reference*. https://matplotlib.org/stable/api/index.html
- Plotly. *Getting started*. https://plotly.com/python/getting-started/
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- Waskom, M. *An introduction to seaborn*. https://seaborn.pydata.org/introduction.html
- Waskom, M. *API reference*. https://seaborn.pydata.org/api.html