30538 Problem Set 2: Parking Tickets

AUTHOR
Emma Brady

PUBLISHED
October 19, 2024

1. "This submission is my work alone and complies with the 30538 integrity policy." Add your initials to indicate your agreement: EB
2. "I have uploaded the names of anyone I worked with on the problem set **here**" EB (1 point)
3. Late coins used this pset: 1 Late coins left after submission: 2
4. Knit your `ps2.qmd` to make `ps2.pdf`.
    - The PDF should not be more than 25 pages. Use `head()` and re-size figures when appropriate.
5. Push `ps2.qmd` and `ps2.pdf` to your github repo. It is fine to use Github Desktop.
6. Submit `ps2.pdf` via Gradescope (4 points)
7. Tag your submission in Gradescope

```
import pandas as pd
import altair as alt
import numpy as np
alt.renderers.enable("png")
import time

import warnings
warnings.filterwarnings('ignore')
```

Data cleaning continued (15 points)

1. Read csv file

```
df = pd.read_csv('data/parking_tickets_one_percent.csv')
```

```
#Function that creates a new dataframe with variables and NA Count
def na_function(df):
    """create a data frame with variables and NA count"""
    count_na = pd.DataFrame({
        'Variable': df.columns,
        'NA': df.isna().sum()
    })
    return count_na
```

```
#Testing out the function
##Creating test dataframe
test_df = pd.DataFrame({
    'test1': [None, 1, 1, 1, 1],
    'test2': [2, None, 2, None, 2],
    'test3': [3, 3, None, None, None],
    'test4': [4, 4, 4, 4, 4]
```

```
})

##testing the function on the test dataframe

testing_na = na_function(test_df)
print(testing_na)
```

```
      Variable  NA
test1    test1   1
test2    test2   2
test3    test3   3
test4    test4   0
```

```
#Using the function on the parking tickets data frame
parking_tickets_na = na_function(df)
print(parking_tickets_na)
```

```
                                  Variable      NA
Unnamed: 0                     Unnamed: 0       0
ticket_number                ticket_number       0
issue_date                     issue_date       0
violation_location        violation_location       0
license_plate_number    license_plate_number       0
license_plate_state      license_plate_state      97
license_plate_type        license_plate_type    2054
zipcode                             zipcode   54115
violation_code               violation_code       0
violation_description  violation_description       0
unit                                   unit      29
unit_description            unit_description       0
vehicle_make                 vehicle_make       0
fine_level1_amount        fine_level1_amount       0
fine_level2_amount        fine_level2_amount       0
current_amount_due        current_amount_due       0
total_payments               total_payments       0
ticket_queue                 ticket_queue       0
ticket_queue_date          ticket_queue_date       0
notice_level                 notice_level   84068
hearing_disposition      hearing_disposition  259899
notice_number                notice_number       0
officer                           officer       0
address                           address       0
```

Referred to the following webpages: https://saturncloud.io/blog/how-to-count-nan-values-in-a-pandas-dataframe-column/ https://www.geeksforgeeks.org/different-ways-to-create-pandas-dataframe/ https://stackoverflow.com/questions/45579525/returning-a-dataframe-in-python-function

2. notice_level, hearing_disposition, and zipcode are missing more often than others.

Notice level is missing often because if the field is blank no notice was sent. All the NAs indicate that no notice was sent.

While hearing disposition is not defined in the data dictionary, it may refer to whether there was a hearing disposition for the ticket, and the NAs may indicate that there wasn't.

Zipcode refers to the ZIPcode associated with the vehicle registration, and if the ticket is associated to a lack of vehicle registration than there will be an NA there.

3.

```
##Create a function that gives the corresponding value in the 'violation_code' column
##for any value in the 'violation_description' that contains the words "city sticker"
def city_sticker_function(df):
    sticker_violation = df[df['violation_description'].str.contains('NO CITY STICKER')]
    return sticker_violation['violation_code']

city_sticker_violation_codes = city_sticker_function(df).unique()
print(city_sticker_violation_codes)
```

```
['0964125' '0976170' '0964125B' '0964125C']
```

```
##check that each code pulled is for no city sticker
print(df['violation_description'].loc[df['violation_code'] == '0964125'].unique())
print(df['violation_description'].loc[df['violation_code'] == '0976170'].unique())
print(df['violation_description'].loc[df['violation_code'] == '0964125B'].unique())
print(df['violation_description'].loc[df['violation_code'] == '0964125C'].unique())
```

```
['NO CITY STICKER OR IMPROPER DISPLAY']
['NO CITY STICKER OR IMPROPER DISPLAY']
['NO CITY STICKER VEHICLE UNDER/EQUAL TO 16,000 LBS.']
['NO CITY STICKER VEHICLE OVER 16,000 LBS.']
```

The original violation code was 0964125 and the new violation code is 0976170. Violation codes also included 0964125B for no city sticker on vehicles under/equal to 16,000 lbs and 0964125C for no city sticker on vehicles over 16,000 lbs.

4.

```
print(df['fine_level1_amount'].loc[df['violation_code'] == '0964125'].unique())
```

```
[120]
```

The cost of an initial offense for violation code 0964125 is $120

```
print(df['fine_level1_amount'].loc[df['violation_code'] == '0976170'].unique())
```

```
[120]
```

The cost of an initial offense for violation code 0976170 is $120

```
print(df['fine_level1_amount'].loc[df['violation_code'] == '0964125B'].unique())
```

```
[200]
```

The cost of an initial offense for violation code 0964125B is $200.

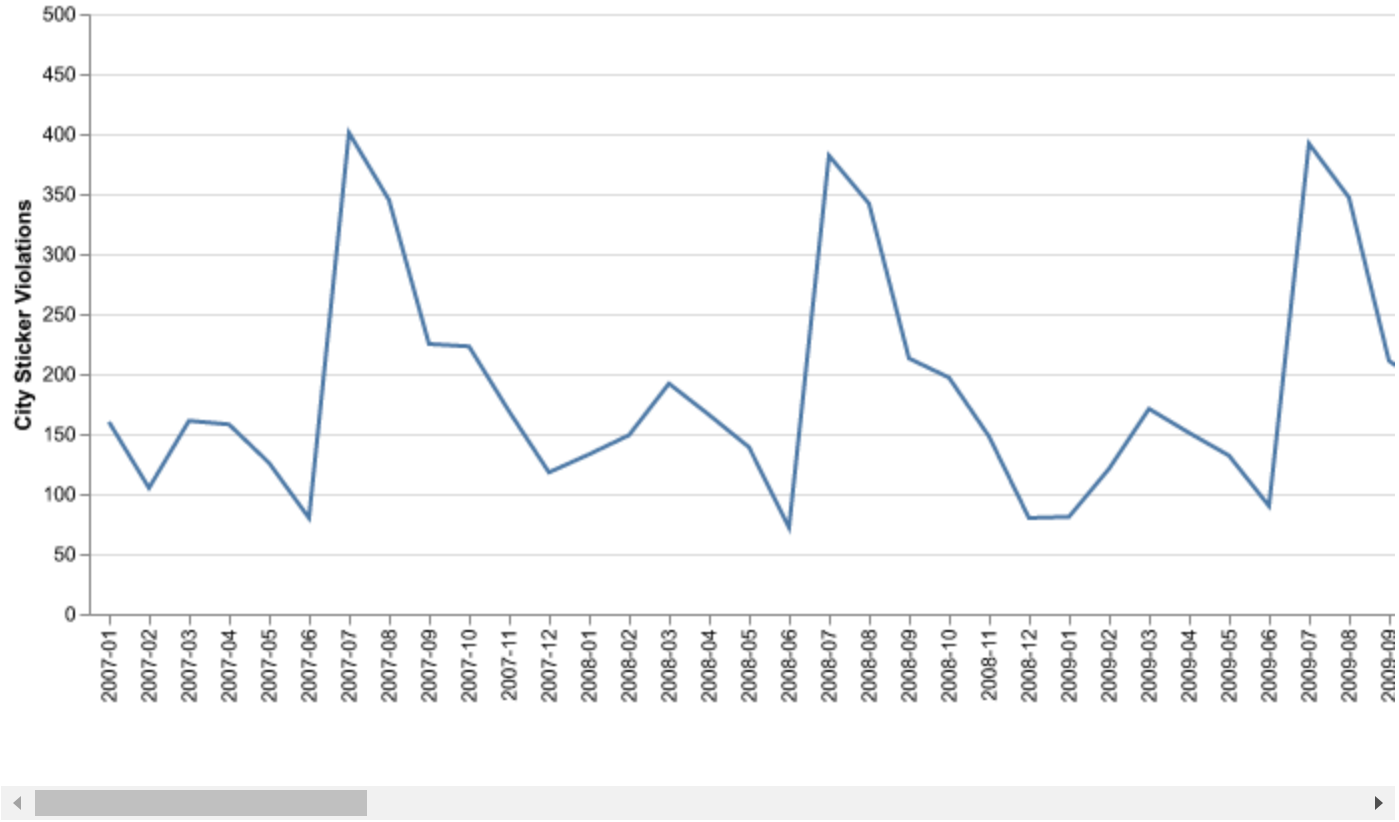
Revenue increase from “missing city sticker” tickets (20 Points)

1.

```
#Create a new value for violation codes which combines the two city sticker violation codes.
df['violation_code'] = df['violation_code'].replace(
    ['0964125', '0976170', '0964125B'], '1111111')
```

```
##Collapse the data to capture the number of missing city sticker tickets by month.
df['issue_date'] = pd.to_datetime(df['issue_date'])
filtered_df = df[df['violation_code'] == '1111111']

filtered_df['month'] = filtered_df['issue_date'].dt.to_period('M')
stickers_by_month = filtered_df.groupby('month')['violation_code'].count().reset_index()
stickers_by_month['month'] = stickers_by_month['month'].astype(str)
```

```
##Use Altair to plot the number of tickets over time
sticker_violations_by_month_chart = alt.Chart(stickers_by_month).mark_line().encode(
    alt.X('month:O', title='Issue Month'),
    alt.Y('violation_code:Q', title='City Sticker Violations')
)
sticker_violations_by_month_chart
```



Referred to the following page: https://www.statology.org/pandas-group-by-month/

2.
3.

```
violations_2011 = df[(df['violation_code'] == '1111111') & (df['issue_date'].dt.year == 2011)]
violations_2011.shape[0]
```

```
1935
```

In this 1% sample of the data, there were 1935 sticker violation tickets in 2011, implying that there were roughly 193,500 total sticker violations. With an $80 increase in the ticket charge, the city would raise revenue by $15,480,000.

4.

```
#calculate total number of no city sticker violations in 2011
violations_2011 = df[(df['violation_code'] == '1111111') & (df['issue_date'].dt.year == 2011)]
violations_2011.shape[0]
```

```
1935
```

```
#calculate paid number of no city sticker violations in 2011
violations_2011_unpaid = df[
```

```
    (df['violation_code'] == '1111111') & (df['issue_date'].dt.year == 2011) & (df['ticket_queue'
violations_2011_unpaid.shape[0]
```

```
1044
```

There were 1935 no sticker violation tickets issued in this sample set in 2011 and 1044 were paid, so there waas a repayment rate of 54%.

```
#calculate total number of no city sticker violations in 2012
violations_2012 = df[(df['violation_code'] == '1111111') & (df['issue_date'].dt.year == 2012)]
violations_2012.shape[0]
```

```
2192
```

```
#calculate paid number of no city sticker violations in 2012
violations_2012_unpaid = df[
    (df['violation_code'] == '1111111') & (df['issue_date'].dt.year == 2012) & (df['ticket_queue'
violations_2012_unpaid.shape[0]
```

```
1057
```

There were 2192 no sticker violation tickets issued in this sample set in 2012 and 1057 were paid, so there was a repayment rate decreased to 48%.

If the number of tickets issues was unchanged after the price increase and we only calculated changes based on the new and old repayment rates, the revenue in 2011 would be: 193,500 x 120 = 23,220,000 23,220,00 x 54% repayment rate = $12,538,800

And assuming the same number of tickets are issued in 2012, with the only changes being the price increasing and the repayment rate decreasing, the revenue in 2012 would be: 193,500 x 200 = 38,700,000 38,700,000 x 48% repayment rate = $18,576,000

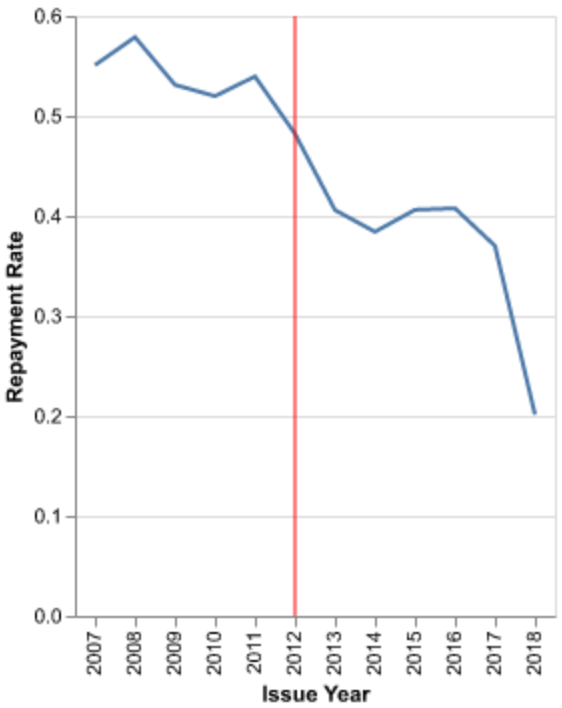
The increase in revenue from 2011 to 2012 with raising the ticket cost to $200 and the repayment rate decreasing 4 percentage point would only be $6,037,200.

5.

```
##Create a new column to find rate of paid ticket
filtered_df['paid'] = filtered_df['ticket_queue'].apply(lambda x: 1 if x == 'Paid' else 0)

##group by year
yearly_df = filtered_df.groupby(filtered_df['issue_date'].dt.year).agg(
    repayment_rate=('paid', 'mean')).reset_index()
print(yearly_df)
```

	issue_date	repayment_rate
0	2007	0.550859
1	2008	0.578852
2	2009	0.531134
3	2010	0.519879
4	2011	0.539535
5	2012	0.482208
6	2013	0.405921
7	2014	0.384198
8	2015	0.406161
9	2016	0.407686
10	2017	0.370124
11	2018	0.201449

```
lines = alt.Chart(yearly_df).mark_line().encode(
    alt.X('issue_date:N', title='Issue Year'),
    alt.Y('repayment_rate:Q', title='Repayment Rate')
)

rules = alt.Chart(pd.DataFrame({
    'Date': [2012]})
).mark_rule(color='red').encode(
    alt.X('Date:O')
)

(lines + rules)
```



While the repayment rate was already on downward trajectory, with the introduction of the new policy in 2012 the repayment rate continued to delcine from approximately 52% in 2011 all the way down to approximately 20% in 2018.

6.

```
##create a new column to calculate repayment rate
df['paid'] = df['ticket_queue'].apply(lambda x: 1 if x == 'Paid' else 0)
```

```
##subset data to just pre-policy implemenation yeat
df_before_2012 = df[df['issue_date'].dt.year < 2012]
```

```
##find the violation codes that are issued most often
df_before_2012['violation_code'].value_counts().head(10)
```

```
violation_code
0976160F    21906
0964190     18117
0964040B    14740
0964090E    11452
1111111     10558
0964150B     9673
0976160A     8339
0964080A     7121
0964190A     3503
0964080B     3435
Name: count, dtype: int64
```

```
##calculating repayment rate for violation code 0976160F
rate_1_test = df_before_2012[df_before_2012['violation_code'] == '0976160F']
print(rate_1_test['paid'].mean())
```

```
0.6078699899570894
```

```
##calculating total number of paid tickets for violation code 0976160F
rate_1_test['paid'].sum()
```

```
np.int64(13316)
```

Number of tickets given for violation code 0976160F: 21906

Repayment rate for violation code 0976160F: 61%

Number of tickets paid: 13316

```
rate_2_test = df_before_2012[df_before_2012['violation_code'] == '0964190']
print(rate_2_test['paid'].mean())
```

```
0.8047690014903129
```

```
rate_2_test['paid'].sum()
```

```
np.int64(14580)
```

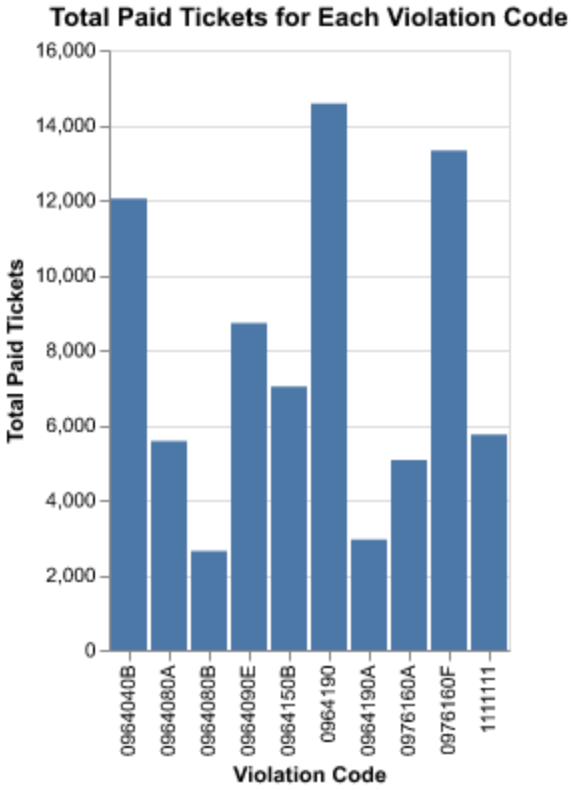
Number of tickets given for violation code 0964190: 18117

Repayment rate for violation code 0976160F: 80%

Number of tickets paid: 14580

```
##filter the df to only contain the top 10 most frequently given tickets
top_10_tickets = [
    '0976160F', '0964190', '0964040B', '0964090E', '1111111', '0964150B', '0976160A', '0964080A',

most_frequent_tickets_df = df_before_2012[
    df_before_2012['violation_code'].isin(top_10_tickets)]

##group by 'violation_code' and sum the 'paid' column to get the total count of paid tickets
grouped_by_code_df = most_frequent_tickets_df.groupby(
    'violation_code', as_index=False)['paid'].sum()
```

```
##Create the bar chart in Altair
q_2_6_chart = alt.Chart(grouped_by_code_df).mark_bar().encode(
    x=alt.X('violation_code:N', title='Violation Code'),
    y=alt.Y('paid:Q', title='Total Paid Tickets'),
    tooltip=['violation_code', 'paid']
).properties(
    title="Total Paid Tickets for Each Violation Code"
)
q_2_6_chart
```



Based on the number of paid tickets by violation types before 2012, if the city raised the price for each ticket by the same amount (say by $80 as it was raised for the no city sticker violation) and wanted to raise the highest number of revenue, by looking at this chart we can see that they should increase the price of violation codes 0964190, 0976160F, and 0964040B.

Headlines and sub-messages (20 points)

1.

```
##create new dataframe grouped by violation description and aggregated by other factors
q_3_1_df = df.groupby('violation_description').agg(
    paid_tickets=('paid', 'mean'),
    avg_level1_fine=('fine_level1_amount', 'mean'),
    ticket_count=('ticket_number', 'count')
).reset_index()

##sort dataframe by ticket count
q_3_1_df = q_3_1_df.sort_values(by=['ticket_count'], ascending=False)
```

```
print(q_3_1_df.head(5))
```

```
                      violation_description  paid_tickets  avg_level1_fine  \
23   EXPIRED PLATES OR TEMPORARY REGISTRATION      0.604361        54.968869
101                          STREET CLEANING      0.811612        54.004249
90                RESIDENTIAL PERMIT PARKING      0.742262        66.338302
19   EXP. METER NON-CENTRAL BUSINESS DISTRICT      0.792913        46.598058
```

```
81        PARKING/STANDING PROHIBITED ANYTIME      0.705817        66.142864
```

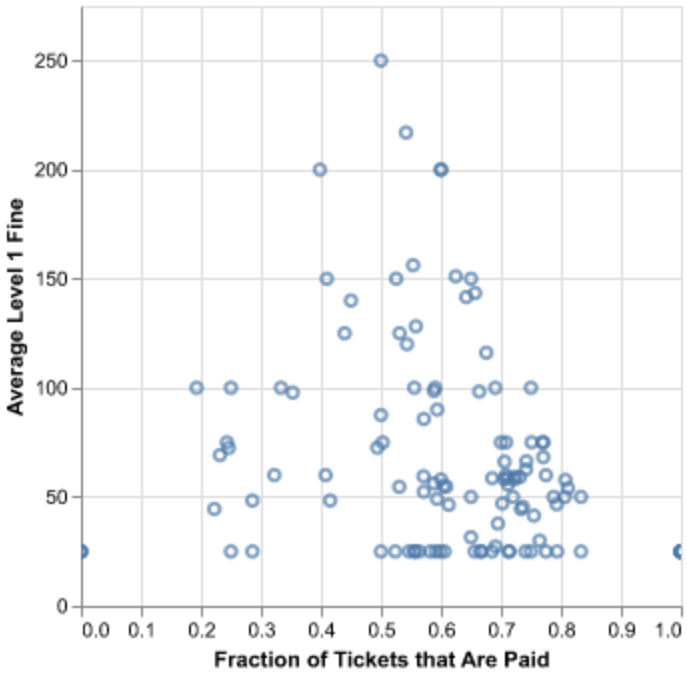
```
     ticket_count
23          44811
101         28712
90          23683
19          20600
81          19753
```

Referred to the following pages:
https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.aggregate.html
https://www.geeksforgeeks.org/how-to-sort-pandas-dataframe/

2.

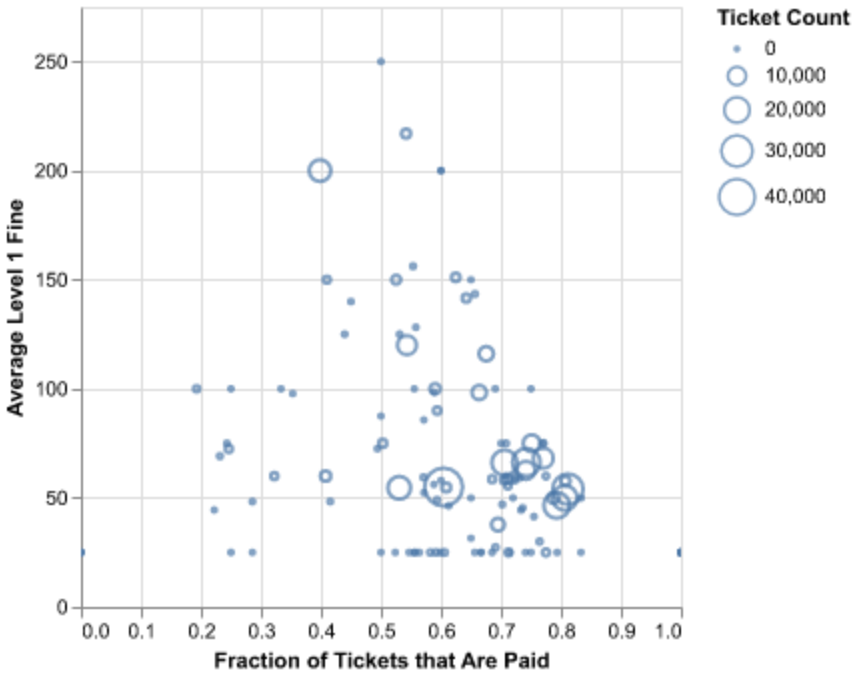
```
#filter the dataframe to only contain violations that appear at least 100 times
at_least_100_df = q_3_1_df[q_3_1_df['ticket_count'] >= 100]
```

```
##make a scatterplot in Altair
chart_1 = alt.Chart(q_3_1_df).mark_point(clip=True).encode(
    alt.X('paid_tickets', title='Fraction of Tickets that Are Paid'),
    alt.Y('avg_level1_fine', title='Average Level 1 Fine').scale(domain=(0, 275))
)

chart_1
```



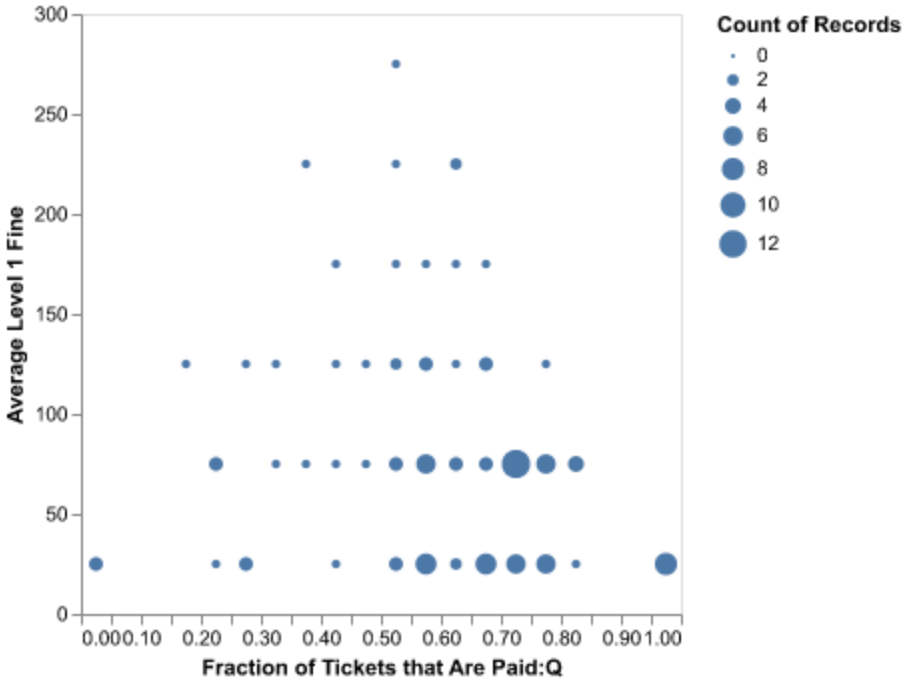
The main message one would take away from this plot is that there looks to be a normal distrubtion around the fraction of tickets that are paid in relation to the fine amount. There is slightly more crowding of the data between tickets are are paid 50-70% of the time and have a fine level of $25-$75.

```
chart_2 = alt.Chart(q_3_1_df).mark_point(clip=True).encode(
    alt.X('paid_tickets', title='Fraction of Tickets that Are Paid'),
    alt.Y('avg_level1_fine', title='Average Level 1 Fine').scale(domain=(0, 275)),
    alt.Size('ticket_count:Q', title='Ticket Count')
)

chart_2
```



In addition to what we gathered from the last chart, in this chart we can also see that there is the highest count of tickets given out that are approximately $50-$60 and they are paid back around 50%-80% of the time.

```
chart_3 = alt.Chart(q_3_1_df).mark_circle(clip=True).encode(
    alt.X('paid_tickets:Q', bin=alt.BinParams(maxbins=20),
    title='Fraction of Tickets that Are Paid:Q'),
    alt.Y('avg_level1_fine', bin=alt.BinParams(maxbins=20),
    title='Average Level 1 Fine').scale(domain=(0, 300)),
    alt.Size('count()')
)

chart_3
```



This chart simplifies the other charts and brings the eye to notice that tickets are most often paid back when they are $25-$75. It deemphasizes the fines that are $175 or more, as it appears in this chart that they are rarely given out.

Referred to the following: https://altair-viz.github.io/user_guide/customization.html

3. I am going to bring the City Clerk the third chart because it simplifies the data the most and brings your attention to the fact that tickets are most often paid when they are $25-$75.

Understanding the structure of the data and summarizing it (Lecture 5, 20 Points)

1.

```
q_4_df = df.groupby('violation_description').agg(
    avg_level1_fine=('fine_level1_amount', 'mean'),
    avg_level2_fine=('fine_level2_amount', 'mean'),
    ticket_count=('ticket_number', 'count')
).reset_index()

##create a new column that shows if fines double in price if unpaid
q_4_df['does_it_double'] = q_4_df['avg_level2_fine'] / q_4_df['avg_level1_fine']
```

```
##find the rows where the violaiton code does not double
print(q_4_df[(q_4_df['does_it_double'] < 2) & (q_4_df['ticket_count'] > 100)])
```

```
                    violation_description  avg_level1_fine  \
5       BLOCK ACCESS/ALLEY/DRIVEWAY/FIRELANE       141.592780
```

```
15                     DISABLED PARKING ZONE       216.986234
42  NO CITY STICKER VEHICLE OVER 16,000 LBS.       500.000000
54   OBSTRUCTED OR IMPROPERLY TINTED WINDOWS       156.180812
62                       PARK OR BLOCK ALLEY       150.000000
79                 PARK/STAND ON BICYCLE PATH       143.432203
95     SMOKED/TINTED WINDOWS PARKED/STANDING       151.090159

    avg_level2_fine  ticket_count  does_it_double
5         266.751108          1579        1.883932
15        358.308751          2034        1.651297
42        955.343511           131        1.910687
54        225.645756           271        1.444773
62        259.926829          2050        1.732846
79        278.601695           236        1.942393
95        209.516794          1697        1.386700
```

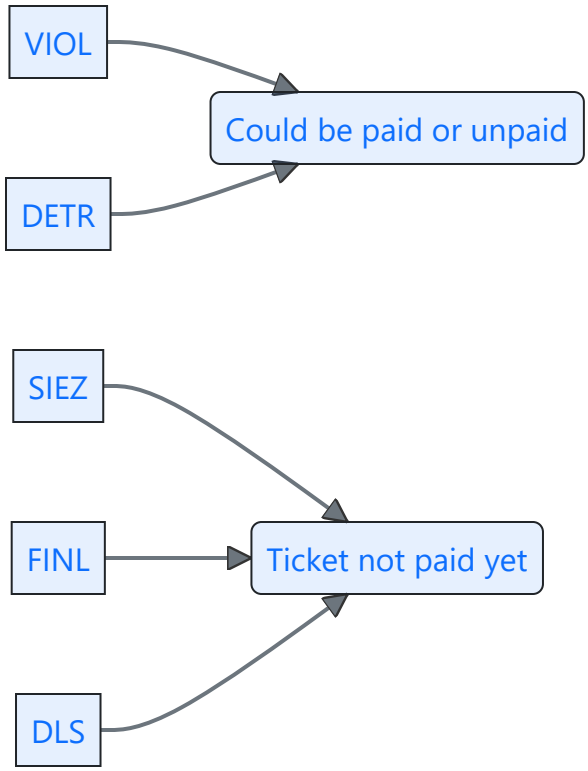
The following violations have at least 100 citations and do not double. Each increases by the following:

Violation	Increase Amount
Block access/alley/driveway/firelane	1.88
Disabled parking zone	1.65
No city sticker vehicle over 16,000 lbs.	1.91
Obstructed or improperly tinted windows	1.44
Park or block alley	1.73
Park/stand on bicycle path	1.94
Smoked/tinted windows parked/standing	1.39

2.

Notice Level

```
flowchart LR
A[VIOL] --> B(Could be paid or unpaid)
C[DETR] --> B
D[SIEZ] --> E(Ticket not paid yet)
F[FINL] --> E
G[DLS] --> E
```



VIOL: Notice of violation is sent

SIEZ: The vehicle is now on the city's boot list

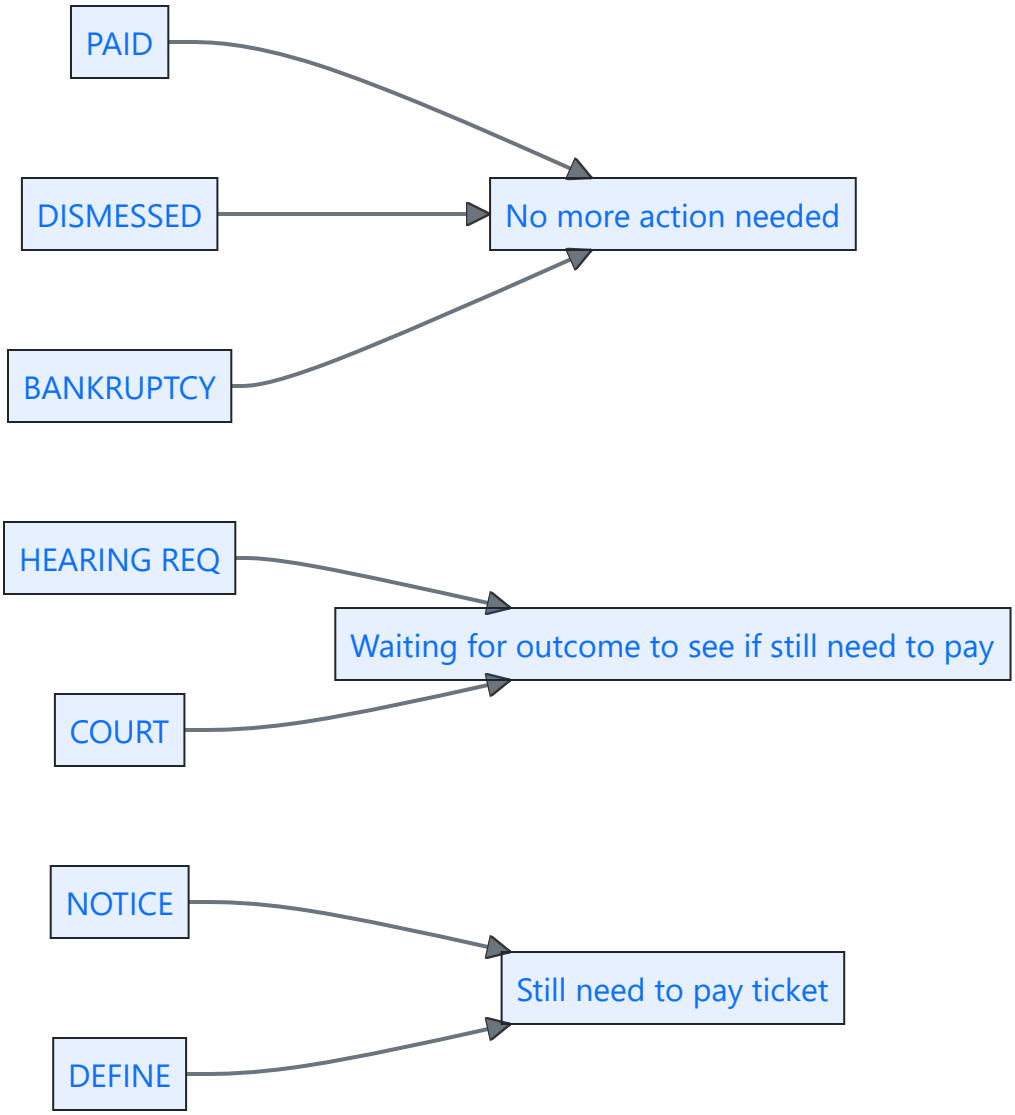
DETR: hearing officer found vehicle owner liable for the citation

FINL: unpaid ticket was sent to collections

DLS: city intends to seek a license suspension

Ticket Queue

```
flowchart LR
A[PAID] --> B[No more action needed]
C[DISMESSED] --> B
D[BANKRUPTCY] --> B
E[HEARING REQ] --> F[Waiting for outcome to see if still need to pay]
G[COURT] --> F
H[NOTICE] --> I[Still need to pay ticket]
J[DEFINE] --> I
```



PAID: The ticket was paid

DISMISSED: The ticket was dismissed

HEARING REQ: The ticket was contested and awaiting a hearing at the time the data was pulled

NOTICE: The ticket was not yet paid and the city sent a notice to the address on file for that vehicle

COURT: The ticket is involved in some sort of court case, not including bankruptcy

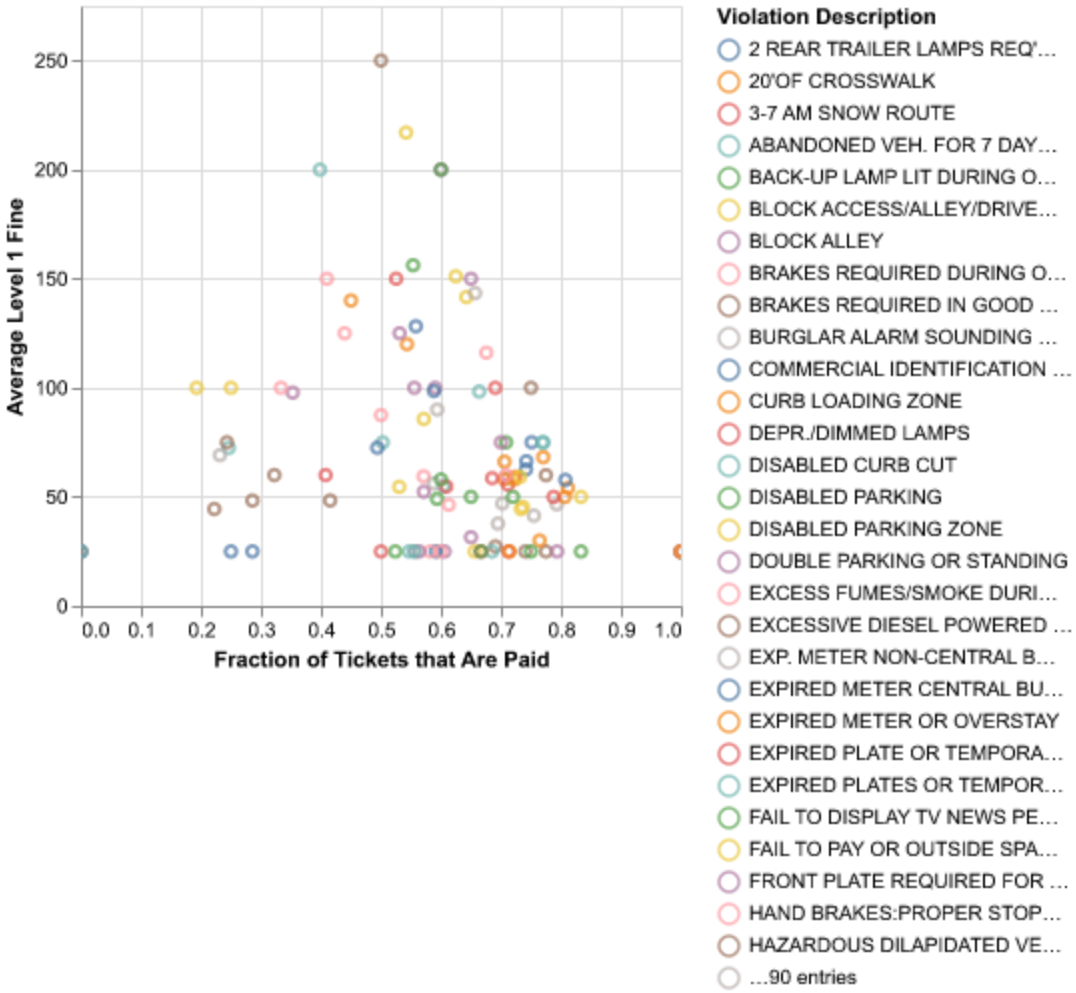
BANKRUPTCY: The ticket was unpaid and included as a debt in a consumer bankruptcy case

DEFINE: The city cannot identify the vehicle owner and collect on a debt

3.

```
##original chart with messy legend
Final_chart = alt.Chart(q_3_1_df).mark_point(clip=True).encode(
    alt.X('paid_tickets', title='Fraction of Tickets that Are Paid'),
    alt.Y('avg_level1_fine', title='Average Level 1 Fine').scale(domain=(0, 275)),
    alt.Color('violation_description:N', title='Violation Description')
```

```
)

Final_chart
```



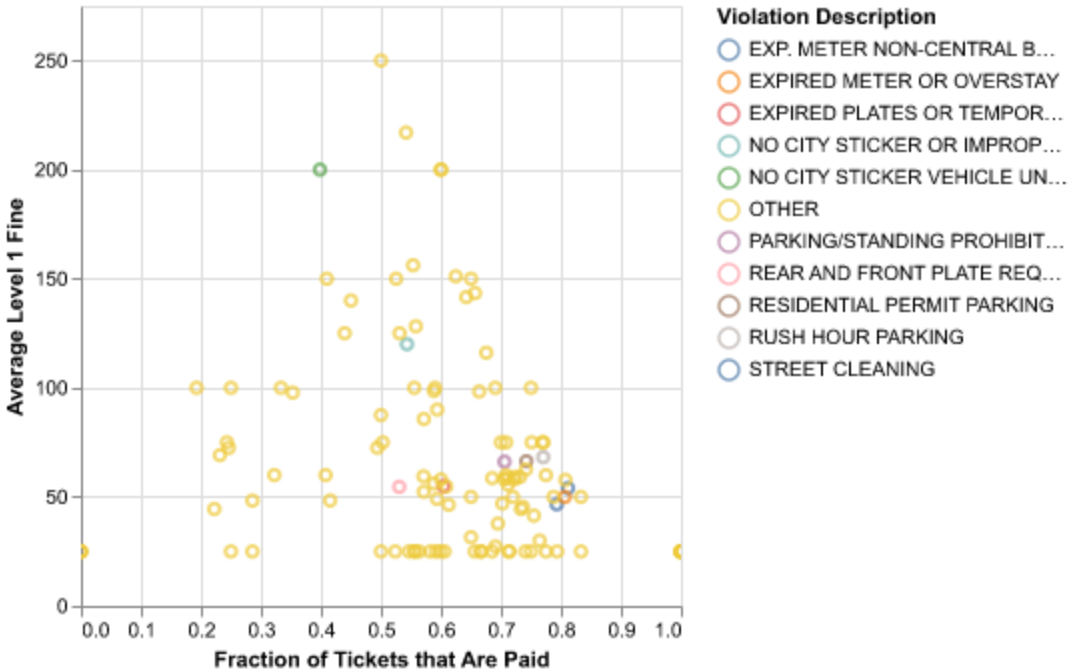

```
##find the 'ticket_count' cutoff for the 10 most common
print(q_3_1_df.sort_values(by=['ticket_count'], ascending=False).head(11))

##dfine the function to categorize based on ticket_count
def categorize_violation(row):
    if row['ticket_count'] > 10000:
        return row['violation_description']
    else:
        return 'OTHER'

##apply the function to create the '10_most_common' column
q_3_1_df['10_most_common'] = q_3_1_df.apply(categorize_violation, axis=1)
```

```
                              violation_description  paid_tickets  \
23            EXPIRED PLATES OR TEMPORARY REGISTRATION      0.604361
101                                 STREET CLEANING      0.811612
90                        RESIDENTIAL PERMIT PARKING      0.742262
19            EXP. METER NON-CENTRAL BUSINESS DISTRICT      0.792913
```

81	PARKING/STANDING PROHIBITED ANYTIME	0.705817
21	EXPIRED METER OR OVERSTAY	0.806355
85	REAR AND FRONT PLATE REQUIRED	0.530482
43	NO CITY STICKER VEHICLE UNDER/EQUAL TO 16,000 ...	0.398357
91	RUSH HOUR PARKING	0.770414
41	NO CITY STICKER OR IMPROPER DISPLAY	0.543303
20	EXPIRED METER CENTRAL BUSINESS DISTRICT	0.741680

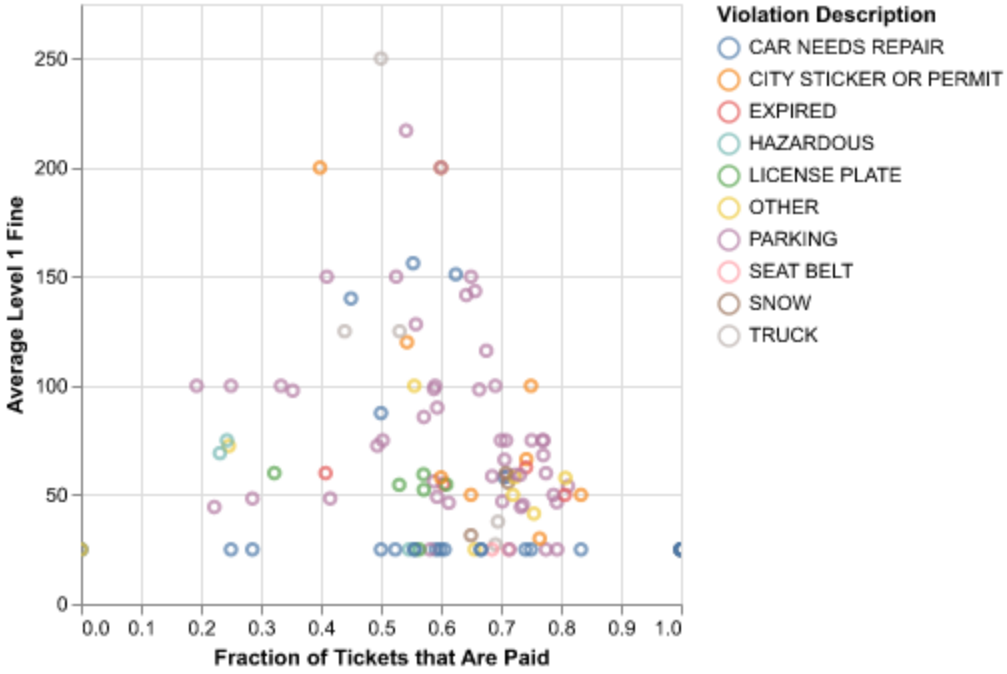
	avg_level1_fine	ticket_count
23	54.968869	44811
101	54.004249	28712
90	66.338302	23683
19	46.598058	20600
81	66.142864	19753
21	50.000000	18756
85	54.610525	15829
43	200.000000	14246
91	68.209779	11965
41	120.000000	10773
20	62.608361	9736

```
##second chart with ten most commonly used violation descriptions
Final_chart_part_2 = alt.Chart(q_3_1_df).mark_point(clip=True).encode(
    alt.X('paid_tickets', title='Fraction of Tickets that Are Paid'),
    alt.Y('avg_level1_fine', title='Average Level 1 Fine').scale(domain=(0, 275)),
    alt.Color('10_most_common:N', title='Violation Description')
)

Final_chart_part_2
```



```
#organize into categories
def categorize_violation_description(row):
    description = row['violation_description']

    if 'EXPIRED' in description:
        return 'EXPIRED'
    elif 'PLATE' in description:
        return 'LICENSE PLATE'
    elif 'SNOW' in description:
        return 'SNOW'
    elif 'SAFETY BELT' in description:
        return 'SEAT BELT'
    elif any(keyword in description for keyword in ['CITY STICKER', 'PERMIT', 'PLACARD', 'IDENTIF
        return 'CITY STICKER OR PERMIT'
    elif any(keyword in description for keyword in ['TRUCK', 'DIESEL']):
        return 'TRUCK'
    elif any(keyword in description for keyword in ['HAZARDOUS', 'UNSAFE']):
        return 'HAZARDOUS'
    elif any(keyword in description for keyword in ['LAMP', 'REFLECTORS', 'LAMPS', 'LIGHTS', 'WIN
        return 'CAR NEEDS REPAIR'
    elif any(keyword in description for keyword in ['PARK', 'OBSTRUCT', 'PARKING', 'ENTRANCE', 'B
        return 'PARKING'
    else:
        return 'OTHER'
# Apply the function to create the 'categories' column
q_3_1_df['categories'] = q_3_1_df.apply(categorize_violation_description, axis=1)
```

```
##second chart with ten most commonly used violation descriptions
Final_chart_really = alt.Chart(q_3_1_df).mark_point(clip=True).encode(
    alt.X('paid_tickets', title='Fraction of Tickets that Are Paid'),
    alt.Y('avg_level1_fine', title='Average Level 1 Fine').scale(domain=(0, 275)),
    alt.Color('categories:N', title='Violation Description')
)

Final_chart_really
```



Extra Credit (max 5 points)

1.
2.