Problem Set 2 Answer

1. "This submission is my work alone and complies with the 30538 integrity policy." Add your initials to indicate your agreement: ***HX***
2. "I have uploaded the names of anyone I worked with on the problem set here" ***HX*** (2 point)
3. Late coins used this pset: ***0*** Late coins left after submission: ***4*** 4. Knit your ps2.qmd to a pdf named ps2.pdf. • The PDF should not be more than 25 pages. Use head() and re-size figures when appropriate.
4. Push ps2.qmd and ps2.pdf to your github repo. It is fine to use Github Desktop. 6. Submit ps2.pdf via Gradescope (8 points)
5. Tag your submission in Gradescope

```python
import pandas as pd
import altair as alt
import os
alt.renderers.enable('png')

# Read in the csv file
# Warning message is suppressed for output clarity.
data = pd.read_csv(
    'problem_sets/ps2/data/parking_tickets_one_percent.csv',
    index_col=[0]
    )
df = pd.DataFrame(data)
```

Data Cleaning continued

Q1

```python
# Define the function to count NAs
def count_na(df):
    labels = []
    na_counts = []
    for label, content in df.items():
        count = content.isna().sum()
        labels.append(label)
        na_counts.append(count)
    result_dict = {'Variable': labels, 'NA Count': na_counts}
    result_df = pd.DataFrame.from_dict(result_dict)
    return result_df


# Conduct a test
df_test = pd.DataFrame({
    'A': [1, 2, None, None],
    'B': [1, 2, 3, 4],
    'C': [1, 'Apple', 3, None]
})
print(df_test, '\n')
print(count_na(df_test), '\n')

print('So the function works.\nApplying to our dataset:', '\n')
print(count_na(df))
```

```
     A  B      C
0  1.0  1      1
1  2.0  2  Apple
2  NaN  3      3
3  NaN  4   None

  Variable  NA Count
0        A         2
1        B         0
2        C         1

So the function works.
Applying to our dataset:

                 Variable  NA Count
0           ticket_number         0
1              issue_date         0
2      violation_location         0
3    license_plate_number         0
4     license_plate_state        97
```

```
5       license_plate_type      2054
6                  zipcode     54115
7           violation_code         0
8    violation_description         0
9                     unit        29
10        unit_description         0
11            vehicle_make         0
12      fine_level1_amount         0
13      fine_level2_amount         0
14      current_amount_due         0
15          total_payments         0
16            ticket_queue         0
17       ticket_queue_date         0
18            notice_level     84068
19     hearing_disposition    259899
20           notice_number         0
21                 officer         0
22                 address         0
```

Q2

The zipcode, notice_level and hearing_disposition are missing much more frequently than others, probably because of the way data was collected. According to the dictionary, zipcode is the ZIP code associated with the vehicle registration. If the registration information is unclear or incomplete, this field might be left empty. notice_level describes the type of notice the city has sent a motorist. If no notice was sent, this field would be blank. Similarly, hearing_disposition represents the outcome of a hearing. If the ticket was not contested, this field would be blank.

In conclusion, these three variables contain more NAs than average because of their data entry styles. These fields are filled only if certain conditions are met, such as ticket got contested. Other variables that capture essential information, such as ticket numbers and issue dates, are routinely collected with each ticket issued. Thus, they are more likely to be NA than others.

Q3

```python
df_Q3 = df[df['violation_description'].str.contains('NO CITY STICKER', na=False)]
print(df_Q3['violation_code'].unique()) # Ordered by first apperance in dataset
```

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

By inspection, we know that 0976170 and 0964125C are extremely rare cases in the dataset. Here we ignore these two values. Old violation code: 0964125; New violation code: 0964125B.

Q4

Accoding to the articles, citations for not having a required vehicle sticker rose from $120 to $200. So we have the cost under old violation code: $120; under new code: $200. In the dataset, we refer to the variable of fine_level1_amount.

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

```
[120]
```

```
# For '0964125B'
print(df[df['violation_code'] == '0964125B']['fine_level1_amount'].unique())
# '0964125C' ignored as instructed.
```

```
[200]
```

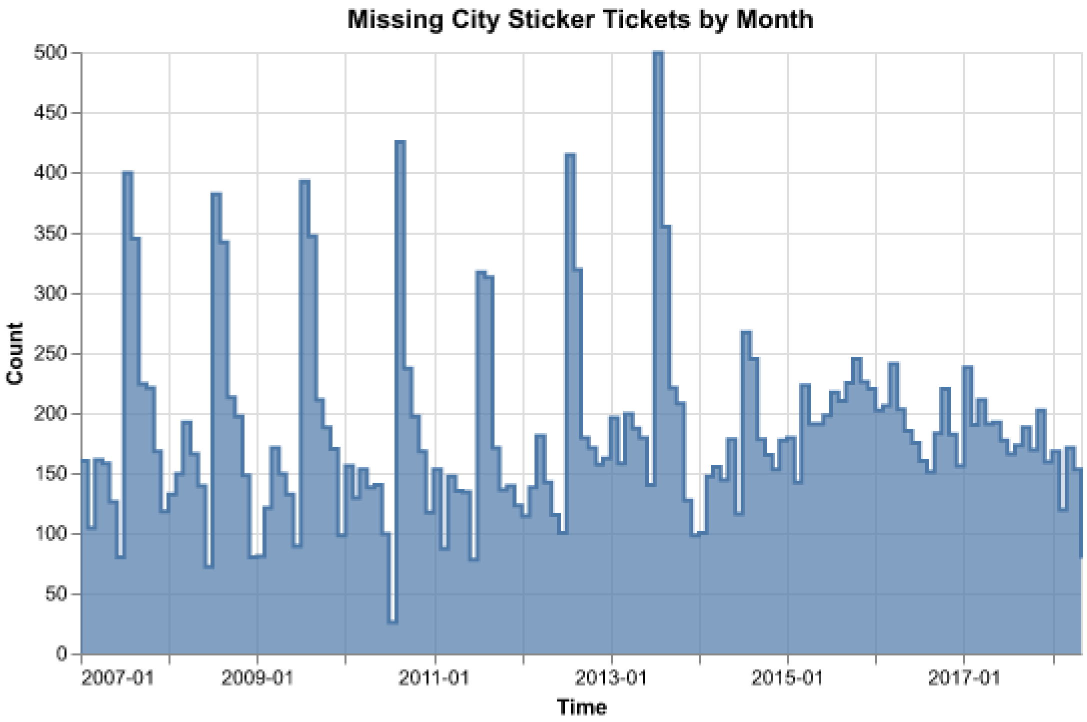
The result above aligns with the article. To be more specific, the cost of an initial offense under 0964125 was $120, and the cost of an initial offense under 0964125B was $200.

Revenue increase from 'missing city sticker' tickets

Q1

```
# Unify the codes with 000
df_unified = df.copy()
df_unified =  df_unified.replace('0964125', '000')
df_unified =  df_unified.replace('0964125B', '000')
df_unified = df_unified[df_unified['violation_code'] == '000']
# Extract year-month and count
df_unified['issue_date'] = pd.to_datetime(
df_unified['issue_date'])
df_unified['issue_y_m'] = df_unified['issue_date'].dt.strftime('%Y-%m')
grouped_date = df_unified.groupby('issue_y_m')
Q1_count = grouped_date.size().reset_index(name='count')
print(Q1_count.head(10))

# Aggregate by year and month
chart_1 = alt.Chart(Q1_count).mark_area(
    interpolate='step-after',
    line=True
).encode(
    alt.X(
        'issue_y_m:T',
        title='Time',
        axis=alt.Axis(format='%Y-%m')
        ),
    alt.Y(
        'count:Q',
        title='Count'
        )
).properties(
    width=500,
    title='Missing City Sticker Tickets by Month'
)

chart_1
```

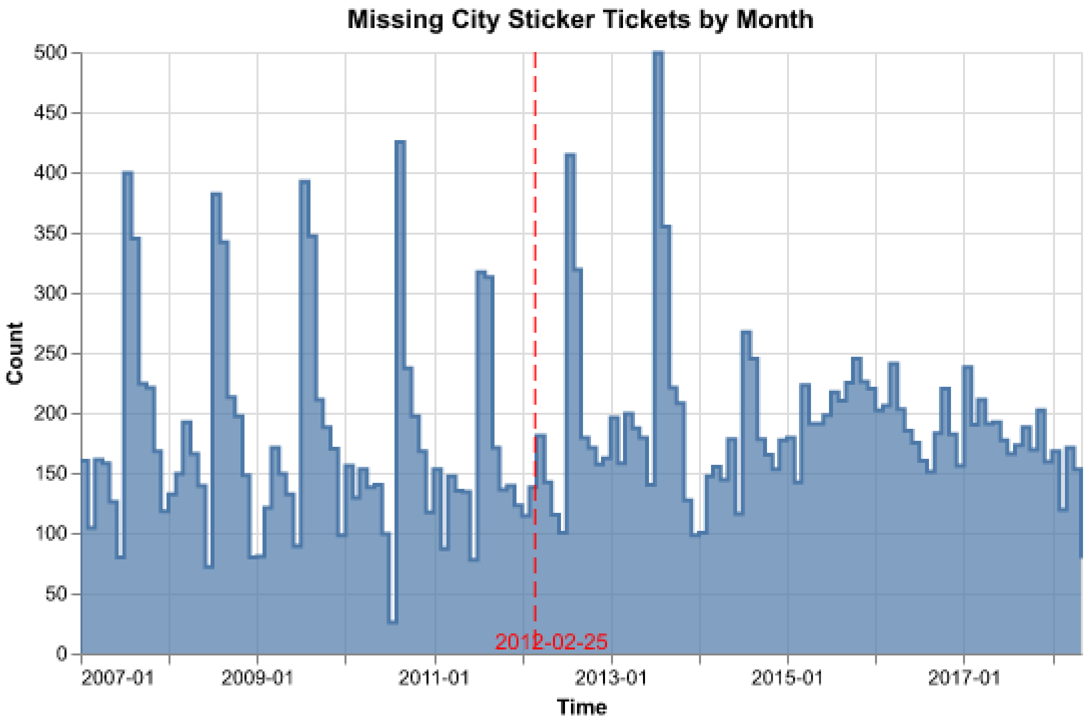
```
  issue_y_m  count
0   2007-01    160
1   2007-02    104
2   2007-03    161
3   2007-04    158
4   2007-05    126
5   2007-06     80
6   2007-07    399
7   2007-08    345
8   2007-09    224
9   2007-10    221
```



Q2

```
# Find the date of cost increase
df_new_code = df_unified[df_unified['fine_level1_amount'] == 200]
print(df_new_code['issue_date'].iloc[0])
print('So we know the date of cost increase was 2012-02-25.')
cost_increase_date = '2012-02-25'

# Add a vertical line at 2012-02-25
rule = alt.Chart(
    pd.DataFrame(
        {
            'cost_increase_date': [cost_increase_date],
            'label': ['Cost Increase']
            }
        )
    ).mark_rule(
    color='red',
    strokeDash=[8, 4]
).encode(
    x='cost_increase_date:T',
    tooltip=['label']
)

# Label for cost increase
text = alt.Chart(
    pd.DataFrame(
        {
            'cost_increase_date': [cost_increase_date],
            'label': ['2012-02-25']
            }
        )
    ).mark_text(
    align='left',
    baseline='bottom',
    dx=-20,
    dy=150,
    color='red'
).encode(
    x='cost_increase_date:T',
    text='label'
)

chart_1 + rule + text
```

```
2012-02-25 02:00:00
So we know the date of cost increase was 2012-02-25.
```



Help page (https://altair-viz.github.io/user_guide/marks/rule.html#)

Q3

```
# Filter out data in 2011
df_2011 = df_unified[df_unified['issue_date'].dt.year == 2011]
tickets_2011 = df_2011.shape[0]
print(f'{tickets_2011} no city sticker tickets were issued in 2011.')
# We assume the same amount later on
revenue_increase = tickets_2011 * (200 - 120) * 100 # Dataset is one percent
print(revenue_increase)
```

```
1933 no city sticker tickets were issued in 2011.
15464000
```

So they should have expected $15464000 of revenue increase, which is approximately 15.5 million US dollars per year.

Q4

```
# Before price increased
df_before_increase = df_unified[df_unified['fine_level1_amount'] == 120]
df_before_paid = df_before_increase[df_before_increase['ticket_queue'] == 'Paid']
paid_rate_before = df_before_paid.shape[0] / df_before_increase.shape[0]
print(f'Before increase, the repayment rate was {paid_rate_before}.')

# Filter out data in 2013
df_2013 = df_unified[df_unified['issue_date'].dt.year == 2013]
df_2013_paid = df_2013[df_2013['ticket_queue'] == 'Paid']
paid_rate_2013 = df_2013_paid.shape[0] / df_2013.shape[0]
print(f'In the calendar year after increase, repayment rate was {paid_rate_2013}.')

print('So we see a drop in repayment rate in tickets after the price was increased.')
print('From around 54% to 41%.')

# Under repayment rate of 41%
# We still assume 1933 tickets per year
revenue_increase_rate = (
    tickets_2011 * paid_rate_2013 * 200 - tickets_2011 * paid_rate_before * 120
    ) * 100
print(revenue_increase_rate)
```

```
Before increase, the repayment rate was 0.5431306934374419.
In the calendar year after increase, repayment rate was 0.40592130892209194.
So we see a drop in repayment rate in tickets after the price was increased.
From around 54% to 41%.
3094458.2379078404
```

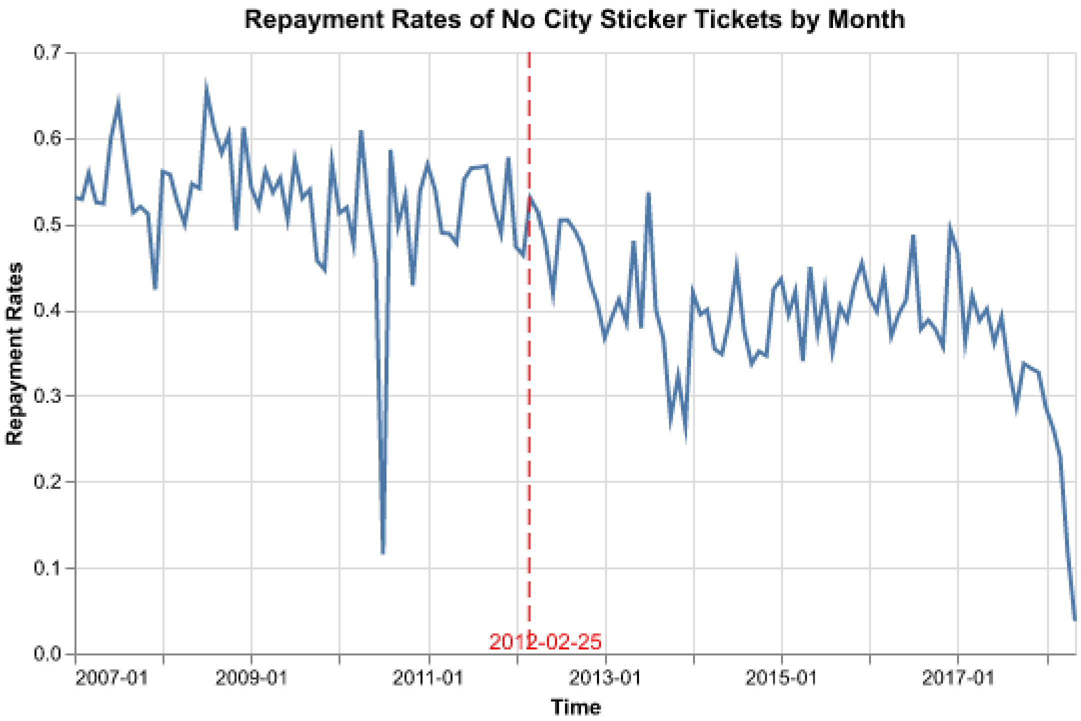
Under the new repayment rates, the change in revenue should have been about approximately 3.1 million US dollars per year.

Q5

```
# Again use the dataframe aggregated by month and year
# We already have total tickets for each month-year in the previous question
# Now we only need to count paid tickets
df_paid = df_unified[df_unified['ticket_queue'] == 'Paid']
group_paid = df_paid.groupby('issue_y_m')
df_paid_count = group_paid.size().reset_index(name='count_paid')
```

```python
# Combine with the count of total tickets
Q5_count = pd.merge(df_paid_count, Q1_count)
# Calculate repayment rates in a new column
Q5_count['repayment_rate'] = Q5_count['count_paid'] / Q5_count['count']
print(Q5_count.head(10)) # Ready for plotting

chart2 = alt.Chart(Q5_count).mark_line().encode(
    alt.X('issue_y_m:T', title='Time', axis=alt.Axis(format='%Y-%m')),
    alt.Y('repayment_rate:Q', title='Repayment Rates')
).properties(
    width=500,
    title='Repayment Rates of No City Sticker Tickets by Month'
)

# The verticle line and annotation have been set in Question 2.
chart2 + rule + text
```

```
  issue_y_m  count_paid  count  repayment_rate
0   2007-01          85    160        0.531250
1   2007-02          55    104        0.528846
2   2007-03          90    161        0.559006
3   2007-04          83    158        0.525316
4   2007-05          66    126        0.523810
5   2007-06          48     80        0.600000
6   2007-07         255    399        0.639098
7   2007-08         198    345        0.573913
8   2007-09         115    224        0.513393
9   2007-10         115    221        0.520362
```



From the plot, we can see a downward trend in repayment rates of no city sticker tickets over time, after the new policy was introduced. The repayment rates kept fluctuating, but after the price went up, repayment rates were in general significantly lower than before. The average level under the new policy was apparently below that under the old code. Moreover, toward the end of our dataset, there was an ongoing sharp decline in repayment rates. The rates dropped to extremely low by 2018.

This indicates the need to balance repayment rates and penalty amounts, in order to boost the government revenue.

Q6

```
# 000 represents no city sticker
df_Q6 = df.copy()
df_Q6 = df_Q6.replace('0964125', '000')
df_Q6 = df_Q6.replace('0964125B', '000')

# Filter out records before 2012
df_Q6['issue_date'] = pd.to_datetime(df_Q6['issue_date'])
df_Q6 = df_Q6[df_Q6['issue_date'].dt.year < 2012]

# Calculate repayment rates
grouped_code = df_Q6.groupby('violation_code')
```

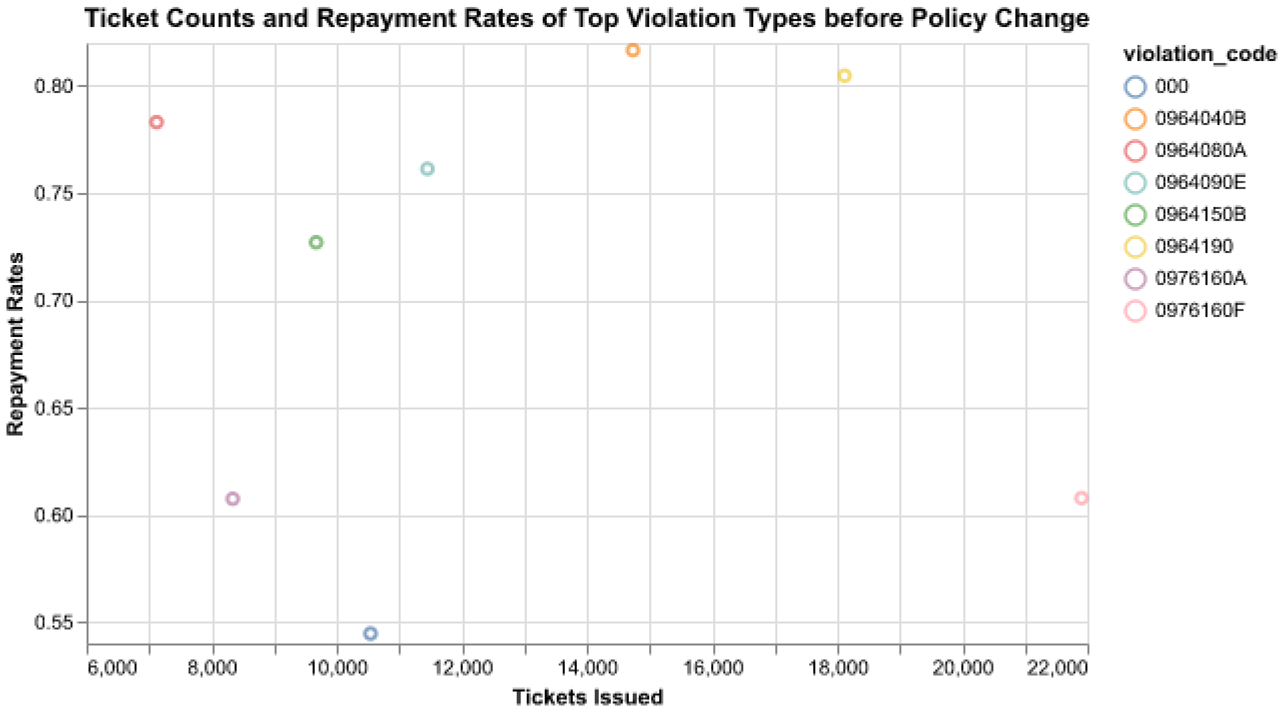
```
df_code_count = grouped_code.size().reset_index(name='total_tickets')
# Those never paid are ignored here, they are missed in filter and merge
# Never paid tickets are of no relevance
df_Q6_paid = df_Q6[df_Q6['ticket_queue'] == 'Paid']
grouped_code_paid = df_Q6_paid.groupby('violation_code')
df_code_count_paid = grouped_code_paid.size().reset_index(name='paid_tickets')

Q6_count = pd.merge(df_code_count, df_code_count_paid)
Q6_count['repayment_rates'] = Q6_count['paid_tickets'] / Q6_count['total_tickets']
# We have both ticket counts and repayment rates

# Explore the dataset: tickets issued
Q6_count = Q6_count.sort_values(by='total_tickets', ascending=False)
print(Q6_count.head(15))
```

```
   violation_code  total_tickets  paid_tickets  repayment_rates
73       0976160F          21906         13316         0.607870
51        0964190          18117         14580         0.804769
10       0964040B          14740         12037         0.816621
20       0964090E          11452          8718         0.761264
0             000          10543          5742         0.544627
43       0964150B           9673          7032         0.726972
69       0976160A           8339          5066         0.607507
18       0964080A           7121          5576         0.783036
52       0964190A           3503          2951         0.842421
19       0964080B           3435          2643         0.769432
41       0964140B           3276          2290         0.699023
23       0964100A           2967          2083         0.702056
46       0964170A           2323          1670         0.718898
40        0964130           1594           817         0.512547
30       0964110A           1409           905         0.642300
```

The suggested three violation types would be 0964190 (‘EXPIRED METER OR OVERSTAY’), 0964040B (‘STREET CLEANING’), and 0964090E (‘RESIDENTIAL PERMIT PARKING’).

This is because we need to consider both total number of tickets and the repayment rates. Both need to be maximized to boost revenue effectively. From the dataframe Q6_count as shown above, we could tell that these three violation codes have relatively higher total_ticket counts and repayment rates.

```
# To boost revenue, the amount of tickets should be large to make a difference.
# By inspection, we set the bar of 5000 total tickets before 2012 here.
Q6_count = Q6_count[Q6_count['total_tickets'] > 5000]

chart_3 = alt.Chart(Q6_count).mark_point().encode(
    alt.X('total_tickets:Q', title='Tickets Issued').scale(zero=False),
    alt.Y('repayment_rates:Q', title='Repayment Rates').scale(zero=False),
    color='violation_code:N').properties(
    width=500,
    title='Ticket Counts and Repayment Rates of Top Violation Types before Policy Change'
)

chart_3
```



The plot supports the argument by providing a contrast among different violation codes. To increase revenue efficiently, we need to identify points that are positioned both high on the y-axis, indicating higher repayment rates, and far to the right on the x-axis, representing a larger number of tickets issued. In this plot, we could find 0964040B, 0964090E and 0964190 might be the three best choices.

Headlines and sub-messages

Q1

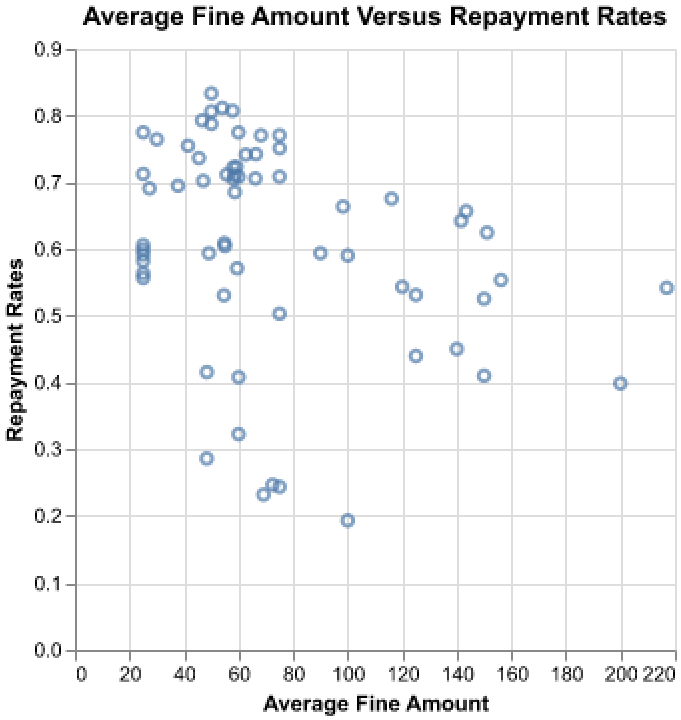
```python
grouped_description = df.groupby('violation_description')

# Description and repayment rate
total_count = grouped_description.size().reset_index(name='total_tickets')

df_paid = df[df['ticket_queue'] == 'Paid'].copy()
grouped_des_paid = df_paid.groupby('violation_description')
paid_count = grouped_des_paid.size().reset_index(name='paid_tickets')

# Those left out in df_paid are violation never paid
all_violations = df['violation_description'].unique()
paid_violations = df_paid['violation_description'].unique()
unpaid_violations = [item for item in all_violations if item not in paid_violations]
# Fill in with 0 paid tickets for these three types
unpaid_dict = {
    'violation_description': unpaid_violations,
    'paid_tickets': [0, 0, 0]
    }
unpaid_df = pd.DataFrame(unpaid_dict)
paid_count = pd.concat([paid_count, unpaid_df], ignore_index=True)

description_payment = pd.merge(
    total_count, paid_count,
    on='violation_description'
    )
description_payment['repayment_rates'] = description_payment['paid_tickets'] / \
                                         description_payment['total_tickets']

# Description and average fine amount
description_price = grouped_description['fine_level1_amount'].mean()
description_price = description_price.reset_index(name='avg_price')

description_summary = pd.merge(description_payment, description_price)

# Sort by frequency and print most common 5
Q_3_1 = description_summary.sort_values('total_tickets', ascending=False)
Q_3_1 = Q_3_1[['violation_description', 'repayment_rates', 'avg_price']]
print(Q_3_1.head(5))
```

```
                         violation_description  repayment_rates  avg_price
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
```

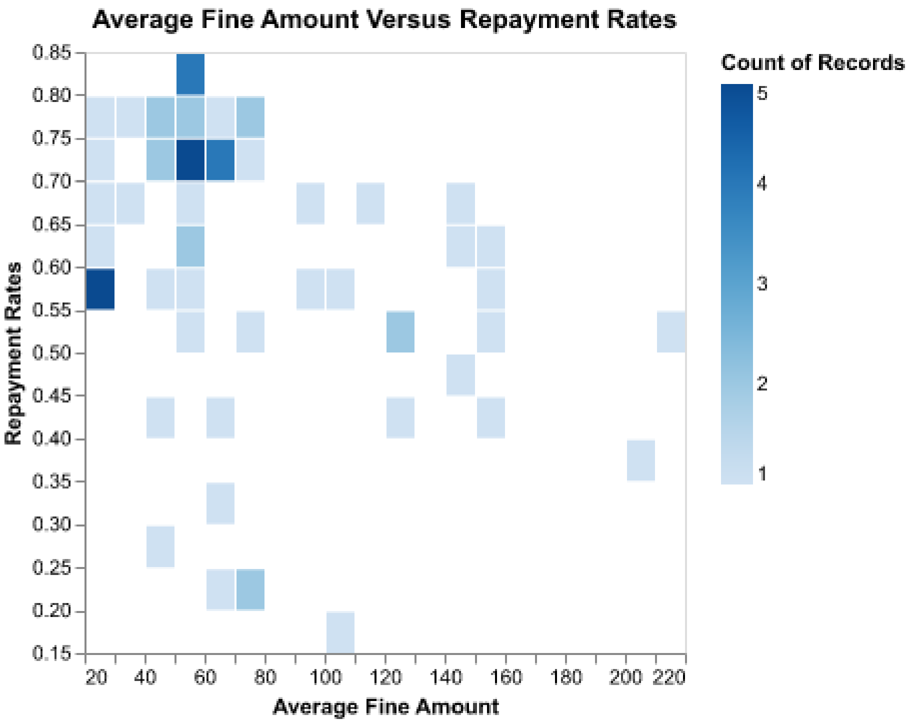
Q2

```
# Filter out types more than 100 times
Q_3_2 = description_summary[description_summary['total_tickets'] > 99]

# Exclude the extreme value with high fine amount
print(Q_3_2.sort_values('avg_price', ascending=False)[0: 5])
print('So we need to exclude NO CITY STICKER VEHICLE OVER 16,000 LBS.')
Q_3_2 = Q_3_2[Q_3_2['violation_description'] != 'NO CITY STICKER VEHICLE OVER 16,000 LBS.']

# Scatter plot
chart_4 = alt.Chart(Q_3_2).mark_point().encode(
    alt.X('avg_price:Q', title='Average Fine Amount'),
    alt.Y('repayment_rates:Q', title='Repayment Rates')
).properties(
    title='Average Fine Amount Versus Repayment Rates'
)

chart_4
```

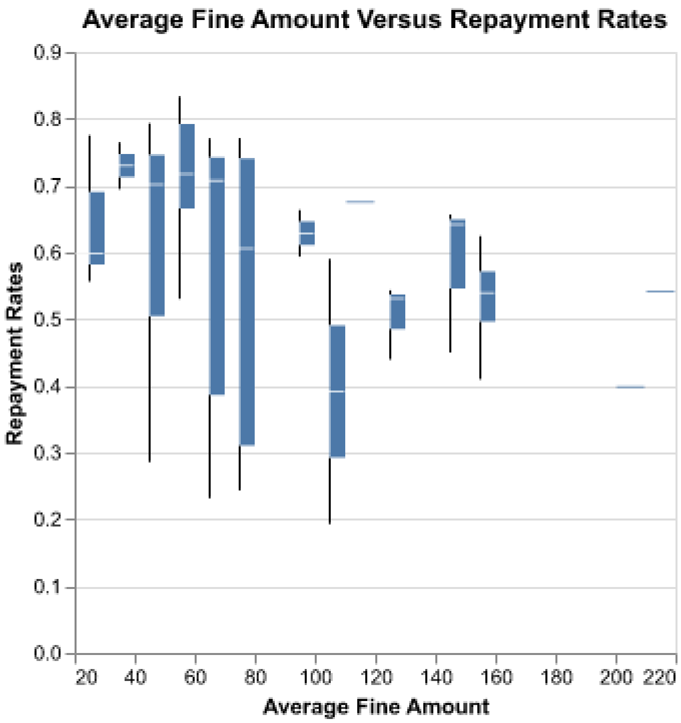
```
                                 violation_description  total_tickets  \
42           NO CITY STICKER VEHICLE OVER 16,000 LBS.            131
15                                 DISABLED PARKING ZONE           2034
43  NO CITY STICKER VEHICLE UNDER/EQUAL TO 16,000 ...          14246
54            OBSTRUCTED OR IMPROPERLY TINTED WINDOWS            271
95              SMOKED/TINTED WINDOWS PARKED/STANDING           1697

    paid_tickets  repayment_rates   avg_price
42            16         0.122137  500.000000
15          1102         0.541790  216.986234
43          5675         0.398357  200.000000
54           150         0.553506  156.180812
95          1060         0.624632  151.090159
So we need to exclude NO CITY STICKER VEHICLE OVER 16,000 LBS.
```



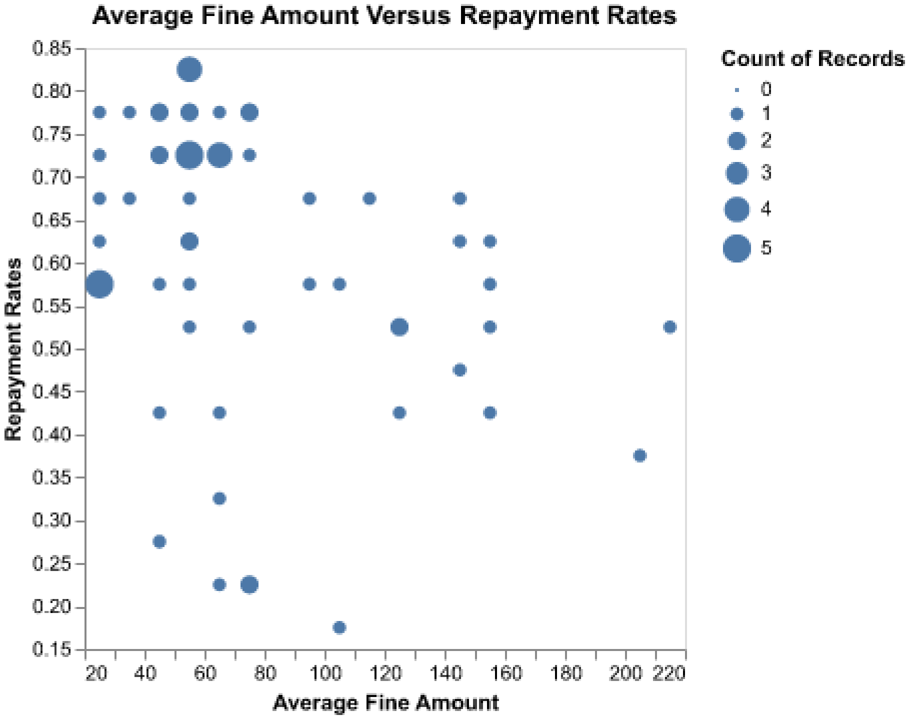
```
chart_5 = alt.Chart(Q_3_2).mark_bar().encode(
    alt.X(
        'avg_price:Q',
        title='Average Fine Amount',
        bin=alt.BinParams(maxbins=20)
        ),
    alt.Y(
        'repayment_rates:Q',
        title='Repayment Rates',
        bin=alt.BinParams(maxbins=20)
        ),
    alt.Color('count()')
).properties(
    title='Average Fine Amount Versus Repayment Rates'
)

chart_5
```



```
chart_6 = alt.Chart(Q_3_2).mark_boxplot().encode(
    alt.X(
        'avg_price:Q',
        title='Average Fine Amount',
        bin=alt.BinParams(maxbins=20)
        ),
    alt.Y(
        'repayment_rates:Q',
        title='Repayment Rates'
        )
).properties(
    title='Average Fine Amount Versus Repayment Rates'
)

chart_6
```



```
alt.Chart(Q_3_2).mark_circle().encode(
    alt.X('avg_price:Q', title='Average Fine Amount', bin=alt.BinParams(maxbins=20)),alt.Y('
    alt.Size('count()')
).properties(
    title='Average Fine Amount Versus Repayment Rates'
)
```


Average Fine Amount Versus Repayment Rates
Repayment Rates
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
20
40
60
80
100
120
140
160
180
200
220
Average Fine Amount
Count of Records
0
1
2
3
4
5