

Libs

```
import arrow
from icecream import ic
from matplotlib import pyplot as plt
import numpy as np
import pandas as pd
from pandas.tseries.holiday import AbstractHolidayCalendar, Holiday,
MO, USFederalHolidayCalendar
from prophet import Prophet
```

```
C:\Users\DV\AppData\Local\Programs\Python\Python310\lib\site-packages\tqdm\auto.py:22: TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See https://ipywidgets.readthedocs.io/en/stable/user\_install.html
    from .autonotebook import tqdm as notebook_tqdm
```

Load Data

```
data = pd.read_csv("data_wf.csv")
data.head()
```

```
      Date  No_of_calls_from_commercial_card
No_of_calls_from_retail_card \
0   1/1/2017                      264.0
403.0
1   1/2/2017                      528.0
792.0
2   1/3/2017                     2505.0
3774.0
3   1/4/2017                     2145.0
3236.0
4   1/5/2017                     2164.0
3265.0
```

```
      No_of_calls_from_student_card
0                      860.0
1                      1681.0
2                      7639.0
3                      6513.0
4                      6604.0
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1765 entries, 0 to 1764
Data columns (total 4 columns):
 #   Column           Non-Null Count  Dtype  
 ---  -- 
 0   Date             1765 non-null   object 
 1   No_of_calls_from_commercial_card  1765 non-null   float64
 2   No_of_calls_from_retail_card     1765 non-null   float64
 3   No_of_calls_from_student_card   1765 non-null   float64
```

```

0   Date                      1673 non-null  object
1   No_of_calls_from_commercial_card  1581 non-null  float64
2   No_of_calls_from_retail_card     1581 non-null  float64
3   No_of_calls_from_student_card   1581 non-null  float64
dtypes: float64(3), object(1)
memory usage: 55.3+ KB

```

EDA

```

# Copy Data
df = data.copy()

df = df.dropna(how='any')

df.rename(columns={"Date":"date",
"No_of_calls_from_commercial_card":"cc",
"No_of_calls_from_retail_card":"rc",
"No_of_calls_from_student_card":"sc"}, inplace=True)

df['date'] = df['date'].apply(lambda row: arrow.get(row,
"M/D/YYYY").format("DD/MM/YYYY"))

df['day'] = df['date'].apply(lambda row: arrow.get(row,
"DD/MM/YYYY").day)
df['month'] = df['date'].apply(lambda row: arrow.get(row,
"DD/MM/YYYY").month)
df['year'] = df['date'].apply(lambda row: arrow.get(row,
"DD/MM/YYYY").year)

df.head()

```

	date	cc	rc	sc	day	month	year
0	01/01/2017	264.0	403.0	860.0	1	1	2017
1	02/01/2017	528.0	792.0	1681.0	2	1	2017
2	03/01/2017	2505.0	3774.0	7639.0	3	1	2017
3	04/01/2017	2145.0	3236.0	6513.0	4	1	2017
4	05/01/2017	2164.0	3265.0	6604.0	5	1	2017

```

# 2017 Dataframe
df_17 = df[df['year'] == 2017]

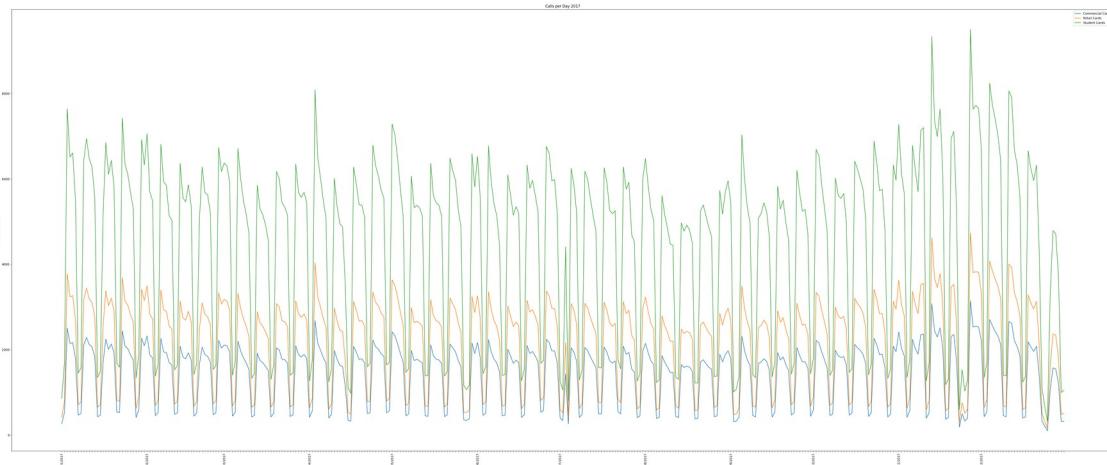
# Plot calls per day for Commercial, Retail, and Student Cards
x = range(len(df_17['date']))
cc_values = df_17.cc
rc_values = df_17.rc
sc_values = df_17.sc
fig = plt.figure()
fig.set_figheight(20)
fig.set_figwidth(50)
ax = fig.add_axes([1,1,1,1])
ax.plot(x, cc_values, label='Commercial Cards')

```

```

ax.plot(x, rc_values, label='Retail Cards')
ax.plot(x, sc_values, label='Student Cards')
ax.set_xticks(x, [ dt if arrow.get(dt, "DD/MM/YYYY").day==1 else ""
for dt in df_17['date'] ], rotation=90)
ax.set_xlabel("Date")
ax.set_ylabel("Number of Calls")
ax.set_title("Calls per Day 2017")
ax.legend()
plt.show()

```



```

# Trend Observed
# cc is lowest for every observation
# rc is middle
# sc is highest
obs = df_17.shape[0]
print(((df_17.cc < df_17.rc) & (df_17.rc < df_17.sc)).sum() == obs)

```

True

```

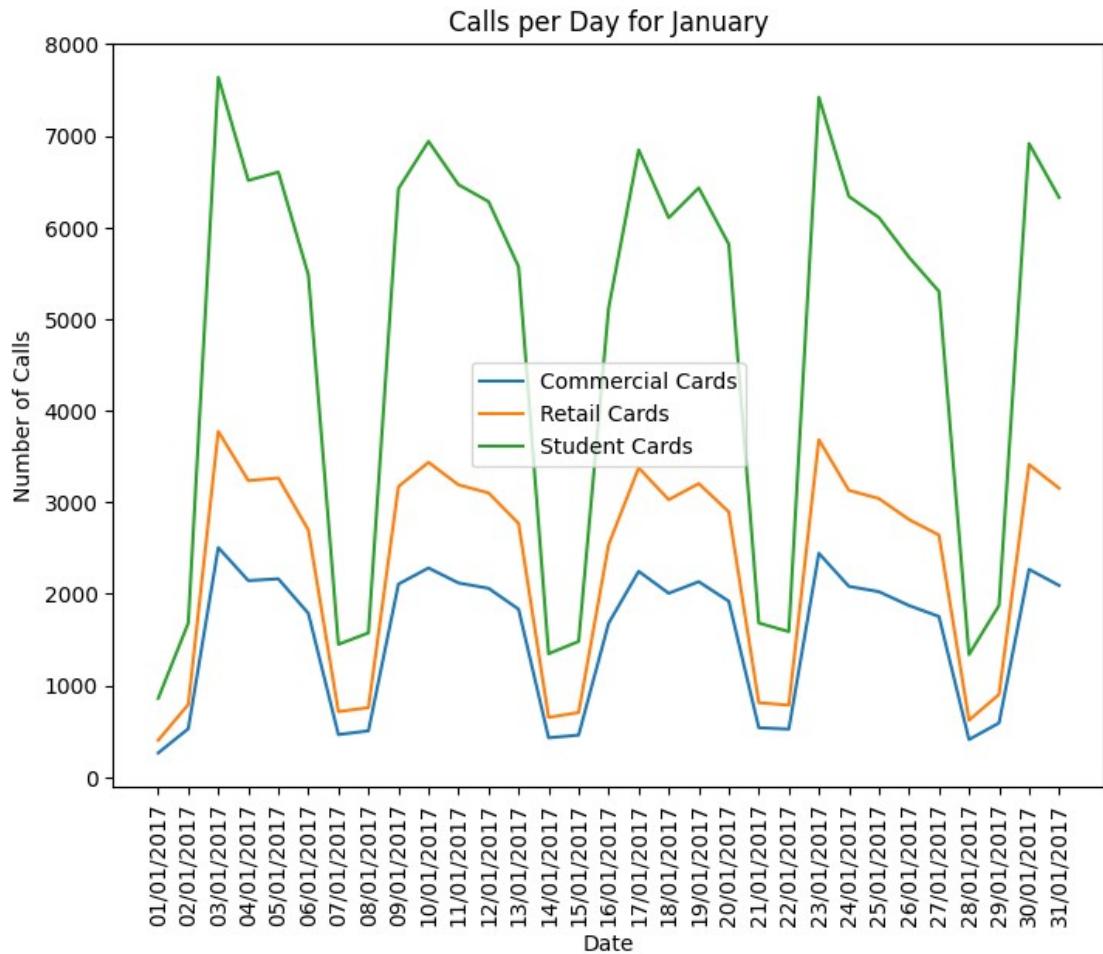
# 2017 data for each month
# Low number of calls on weekends
# Low number of calls on Big Holidays
months = df_17.month.unique()
for m in months:
    x = range((df_17.month == m).sum())
    cc_values = df_17[df_17.month == m].cc
    rc_values = df_17[df_17.month == m].rc
    sc_values = df_17[df_17.month == m].sc
    fig = plt.figure()
    ax = fig.add_axes([1,1,1,1])
    ax.plot(x, cc_values, label='Commercial Cards')
    ax.plot(x, rc_values, label='Retail Cards')
    ax.plot(x, sc_values, label='Student Cards')
    ax.set_xticks(x, df_17[df_17.month == m].date, rotation=90)
    ax.set_xlabel("Date")
    ax.set_ylabel("Number of Calls")

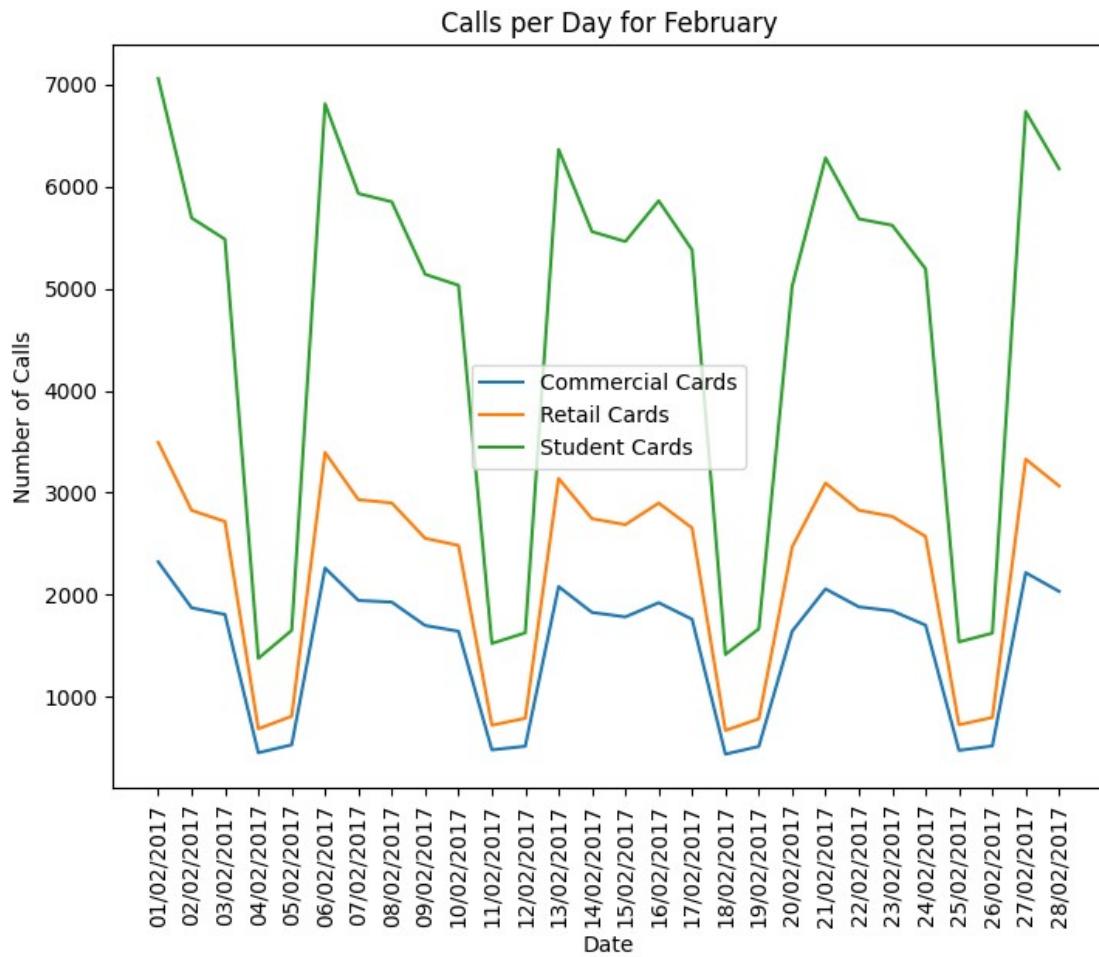
```

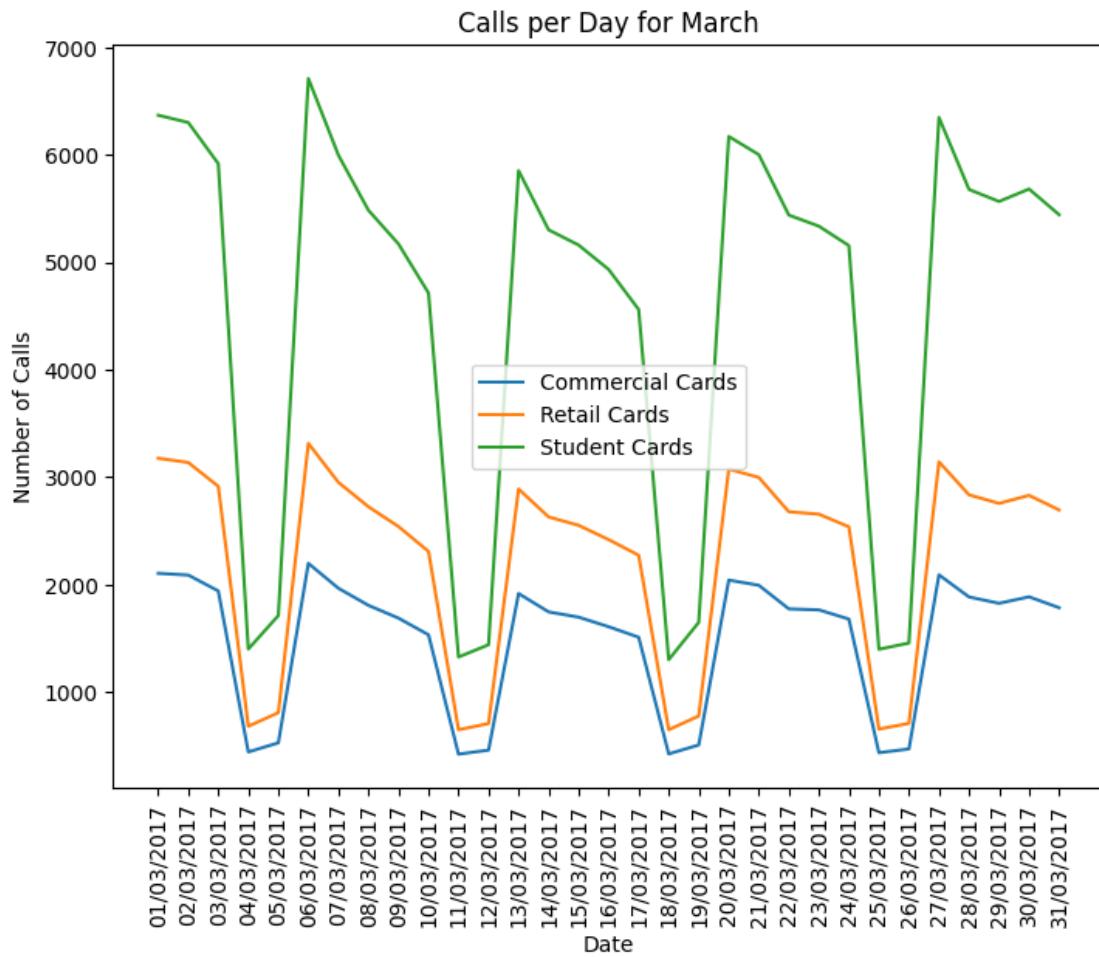
```

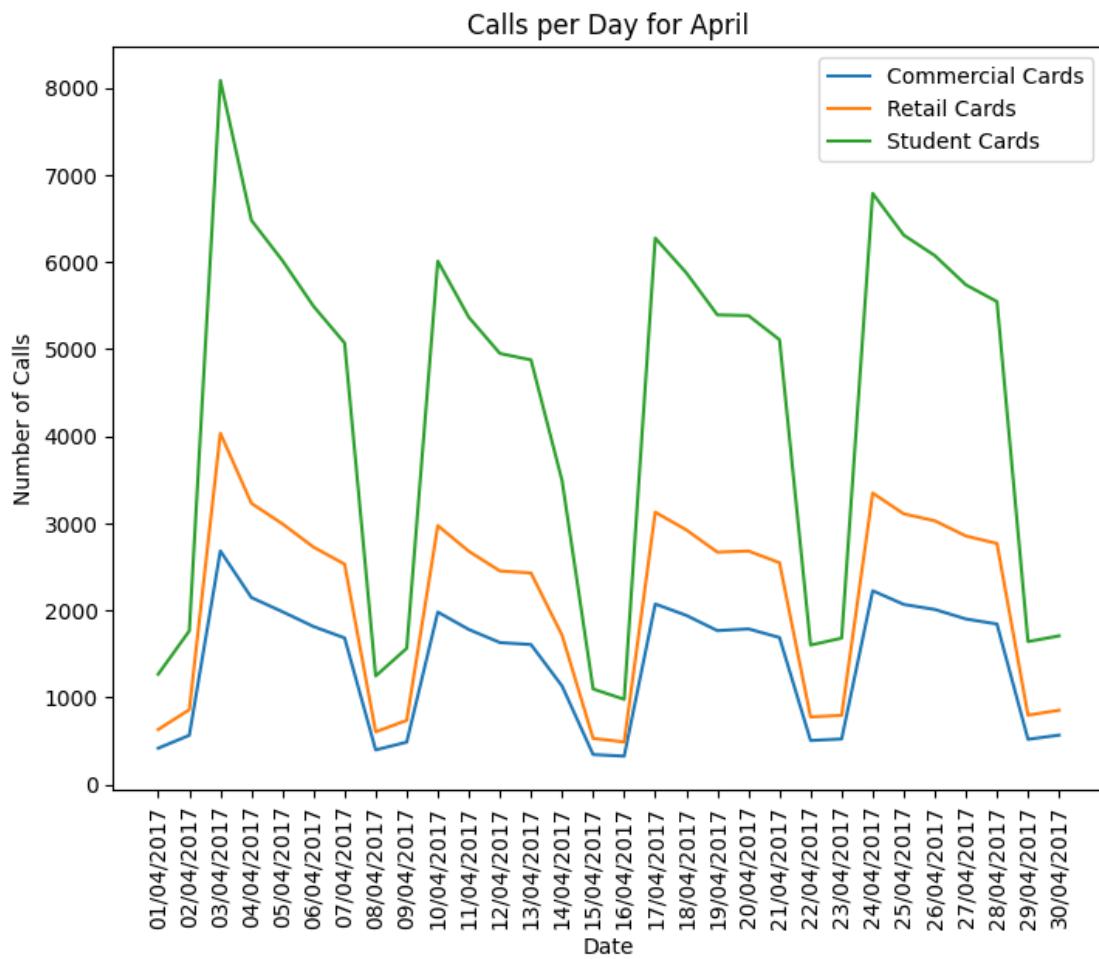
ax.set_title(f"Calls per Day for {arrow.get(str(m),
'M')).format('MMMM')}")
ax.legend()
plt.show()

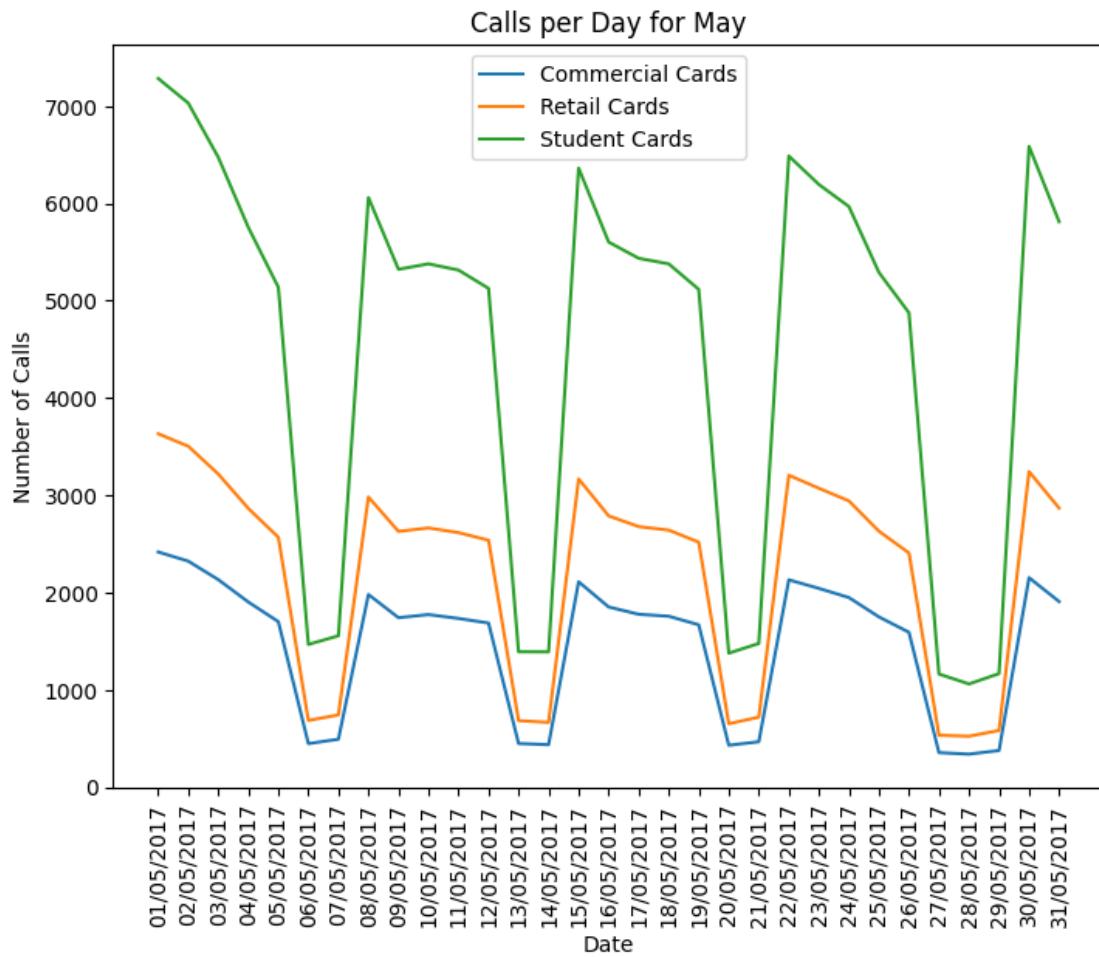
```

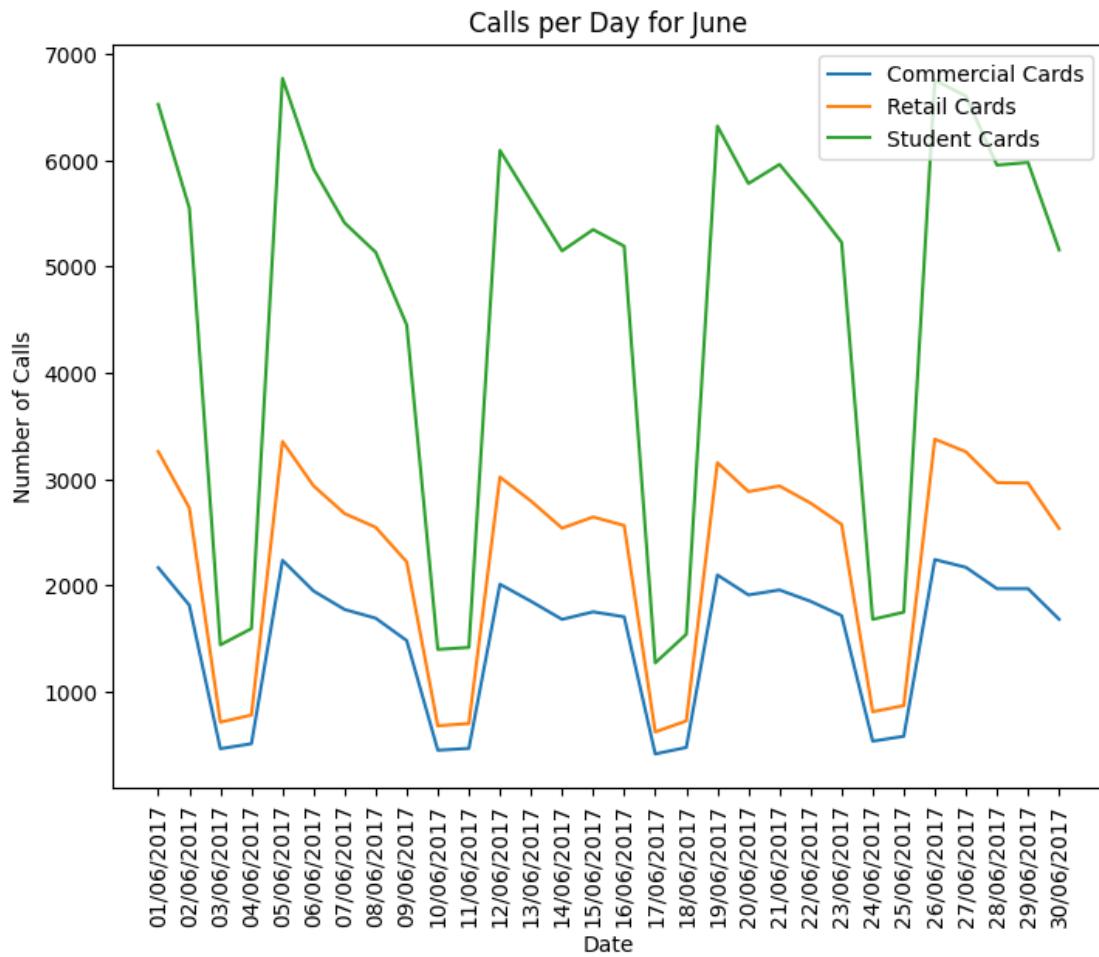




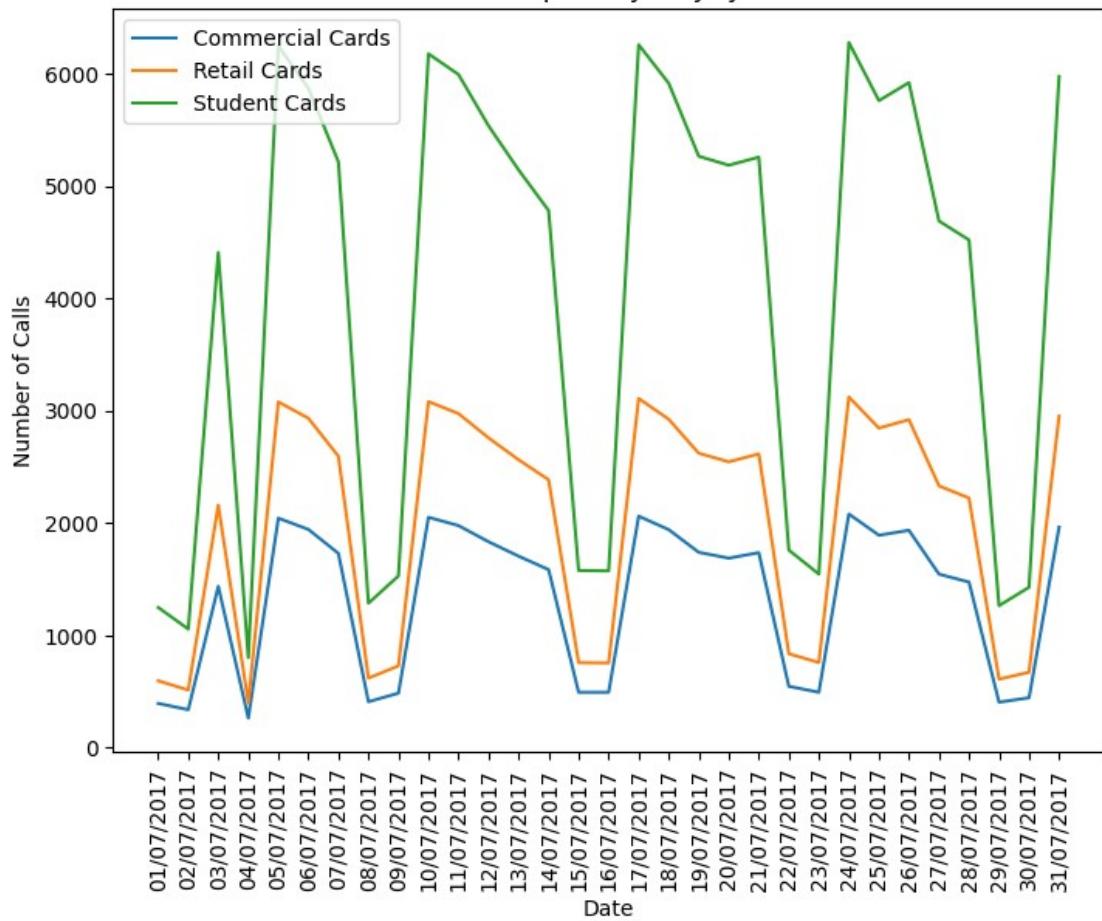




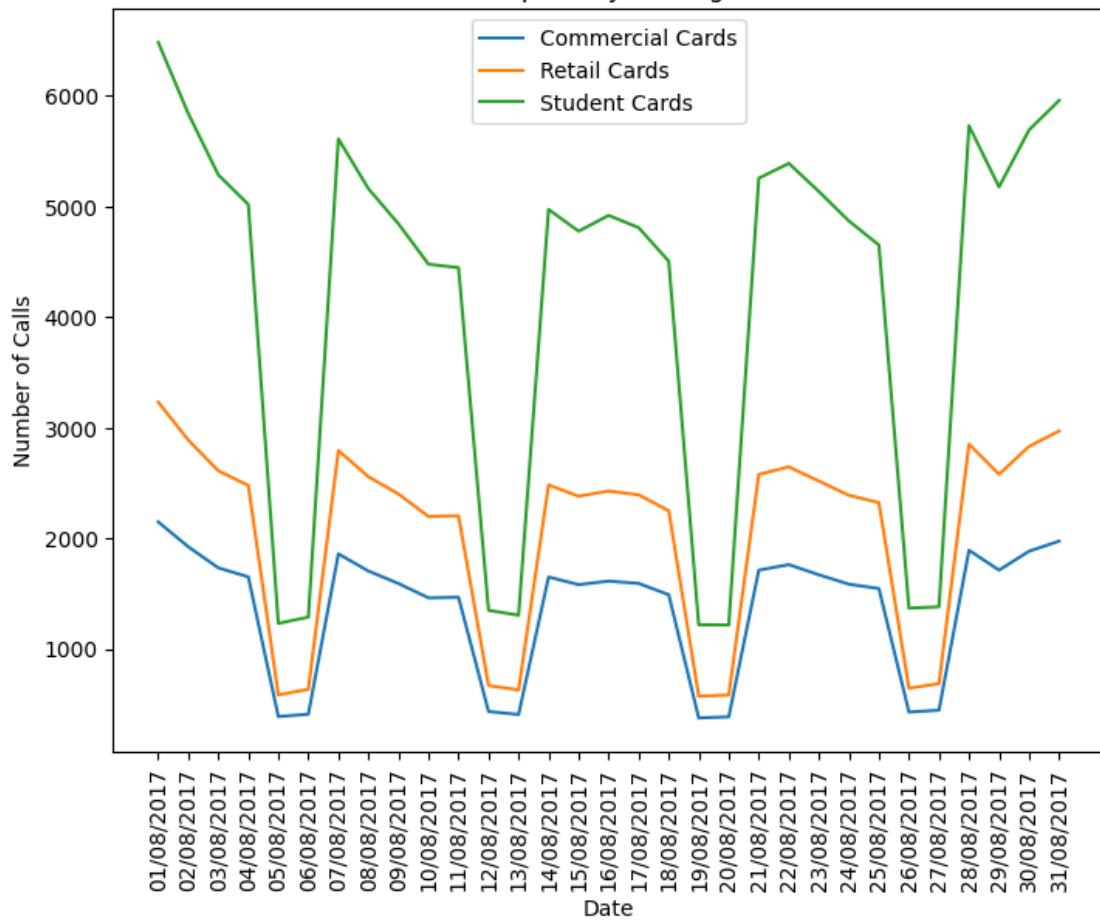




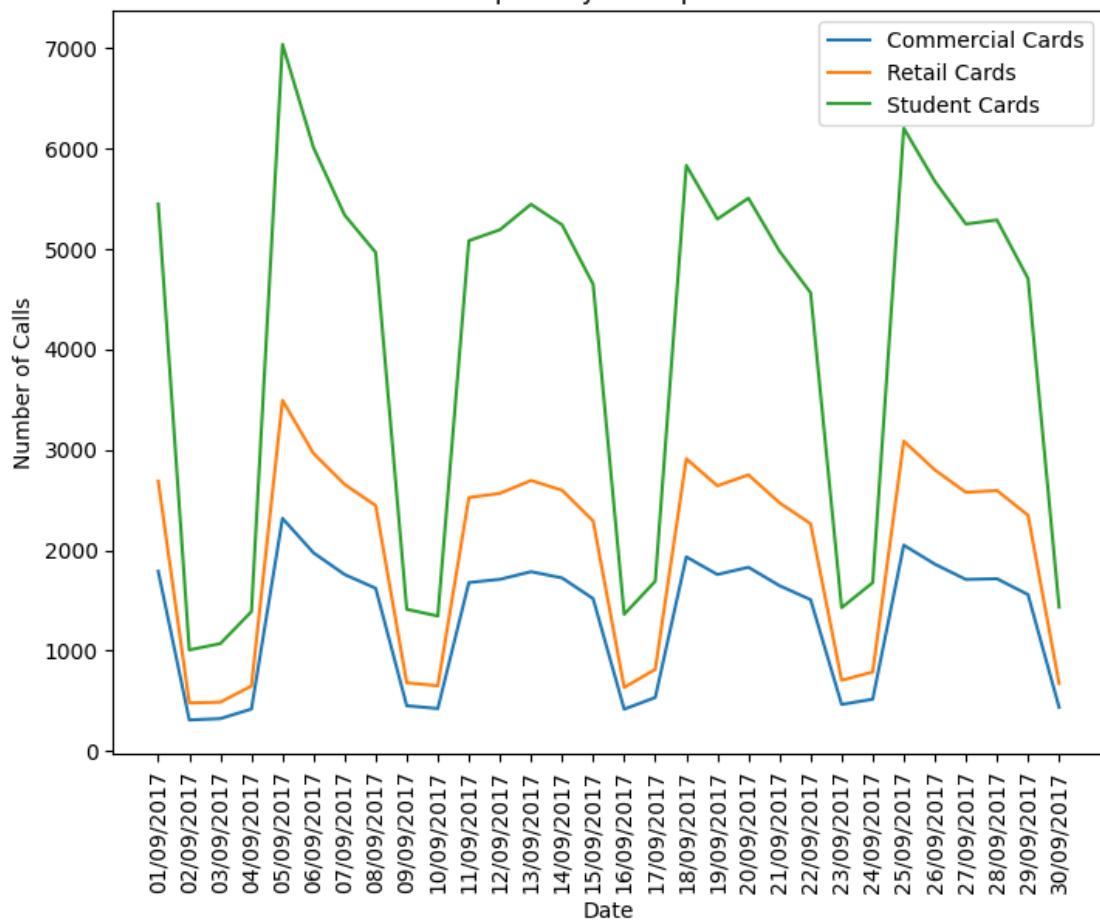
Calls per Day for July



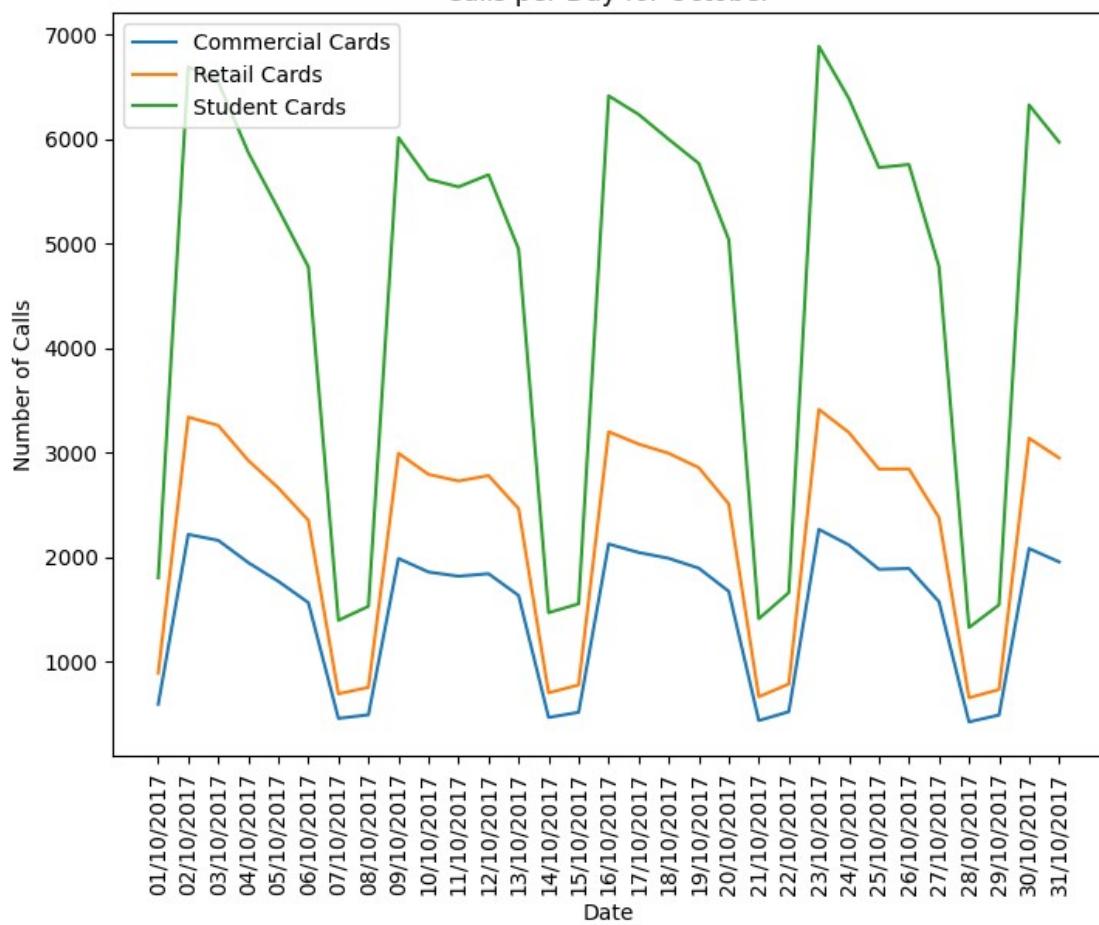
Calls per Day for August



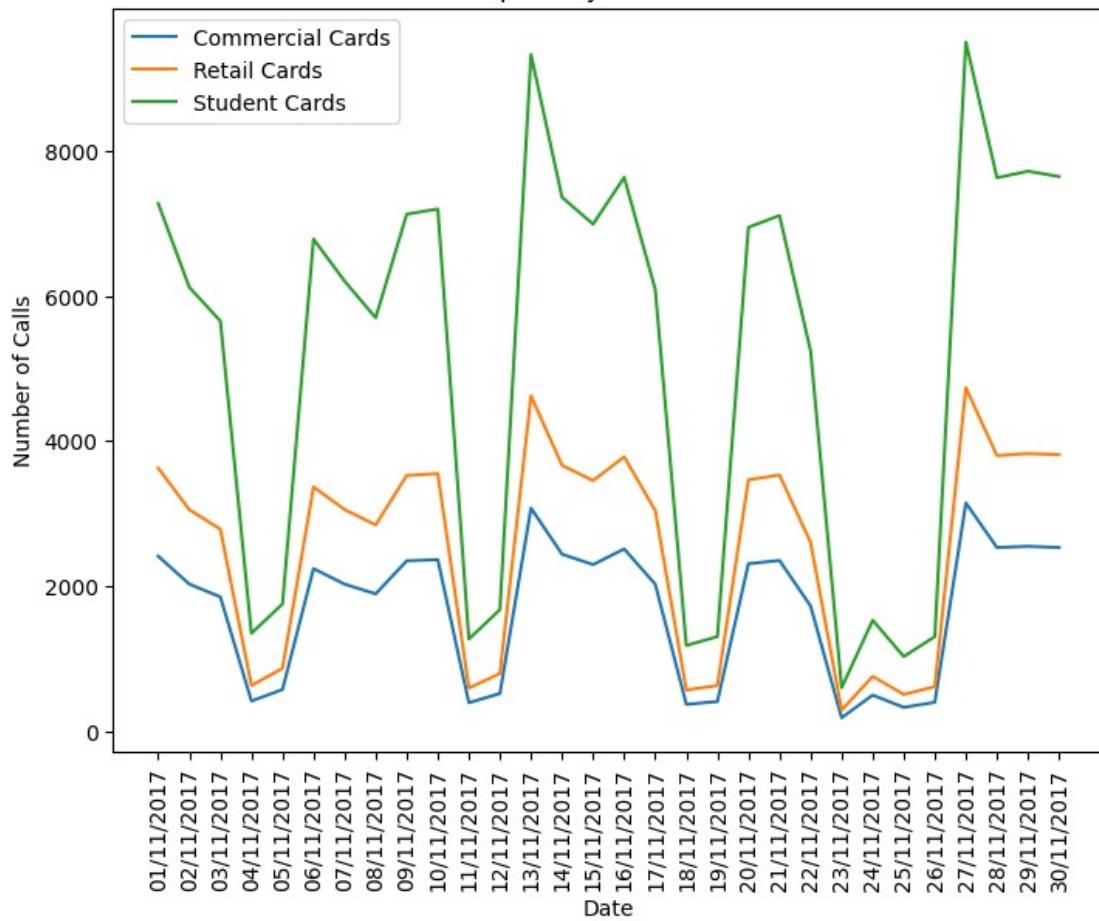
Calls per Day for September

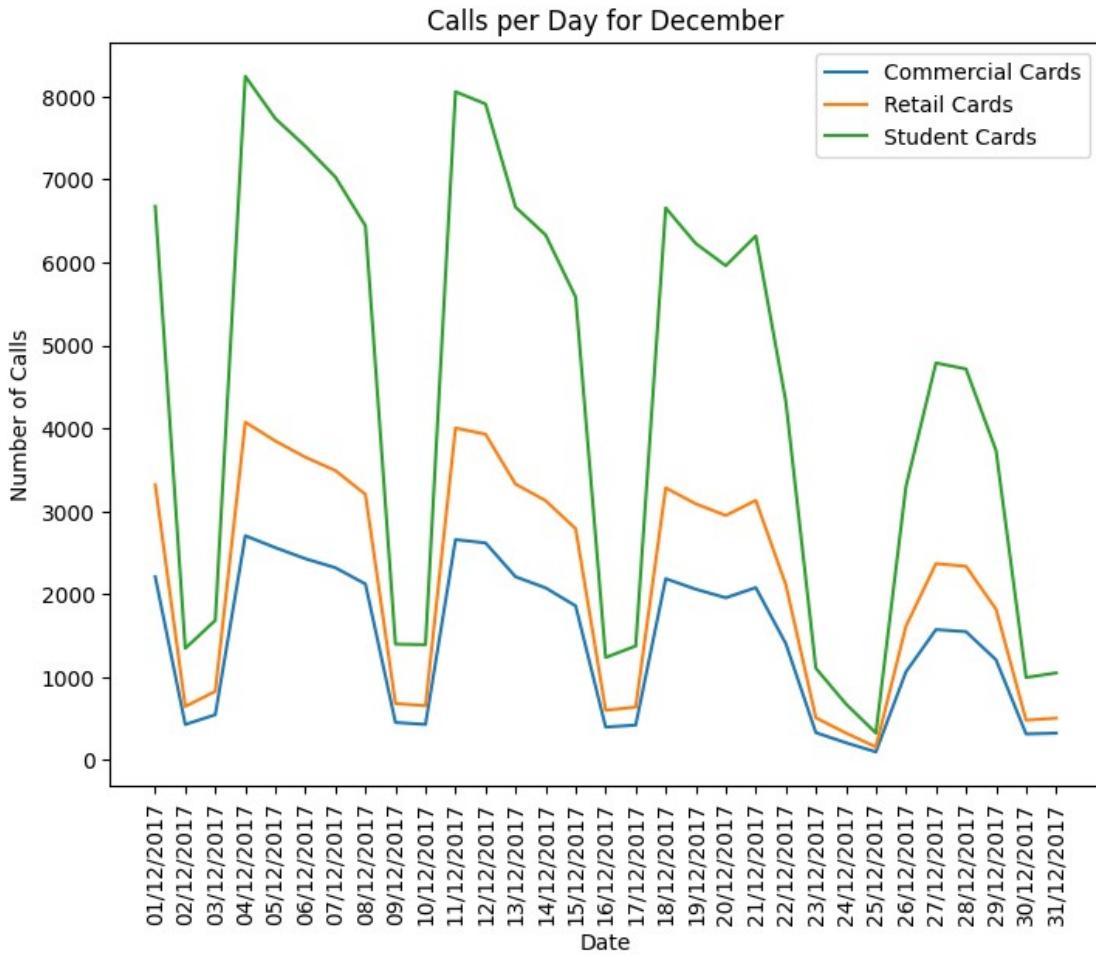


Calls per Day for October



Calls per Day for November





```
# 2018-2021 Dataframe
df_not17 = df[df['year'] != 2017]

df_not17.reset_index(drop=True, inplace=True)

df_not17.head()

      date      cc      rc      sc  day  month  year
0  01/01/2018  200.0  305.0  709.0   1     1  2018
1  02/01/2018 3529.0 7136.0 2343.0   2     1  2018
2  03/01/2018 6862.0 2257.0 3404.0   3     1  2018
3  04/01/2018 2024.0 3036.0 6153.0   4     1  2018
4  05/01/2018 5934.0 1970.0 2961.0   5     1  2018

# Sorting data according to trend -> (cc < rc < sc) for every day observed
df_not17_sorted = pd.DataFrame(columns=['date', 'cc', 'rc', 'sc',
                                         'day', 'month', 'year'])
for index, row in df_not17.iterrows():
    values = sorted([row.cc, row.rc, row.sc])
    row_data = [row.date]
    row_data.extend(values)
```

```

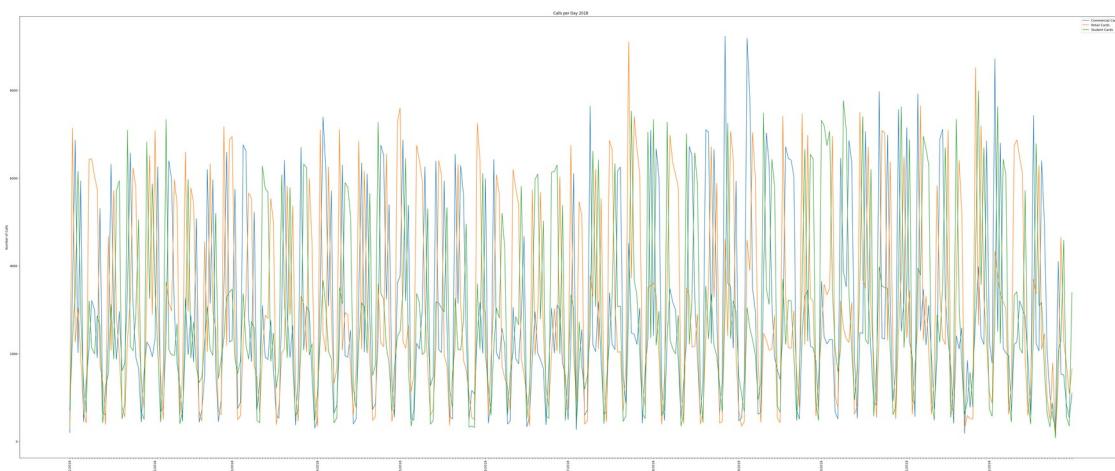
row_data.extend([row.day, row.month, row.year])
df_not17_sorted.loc[index] = row_data

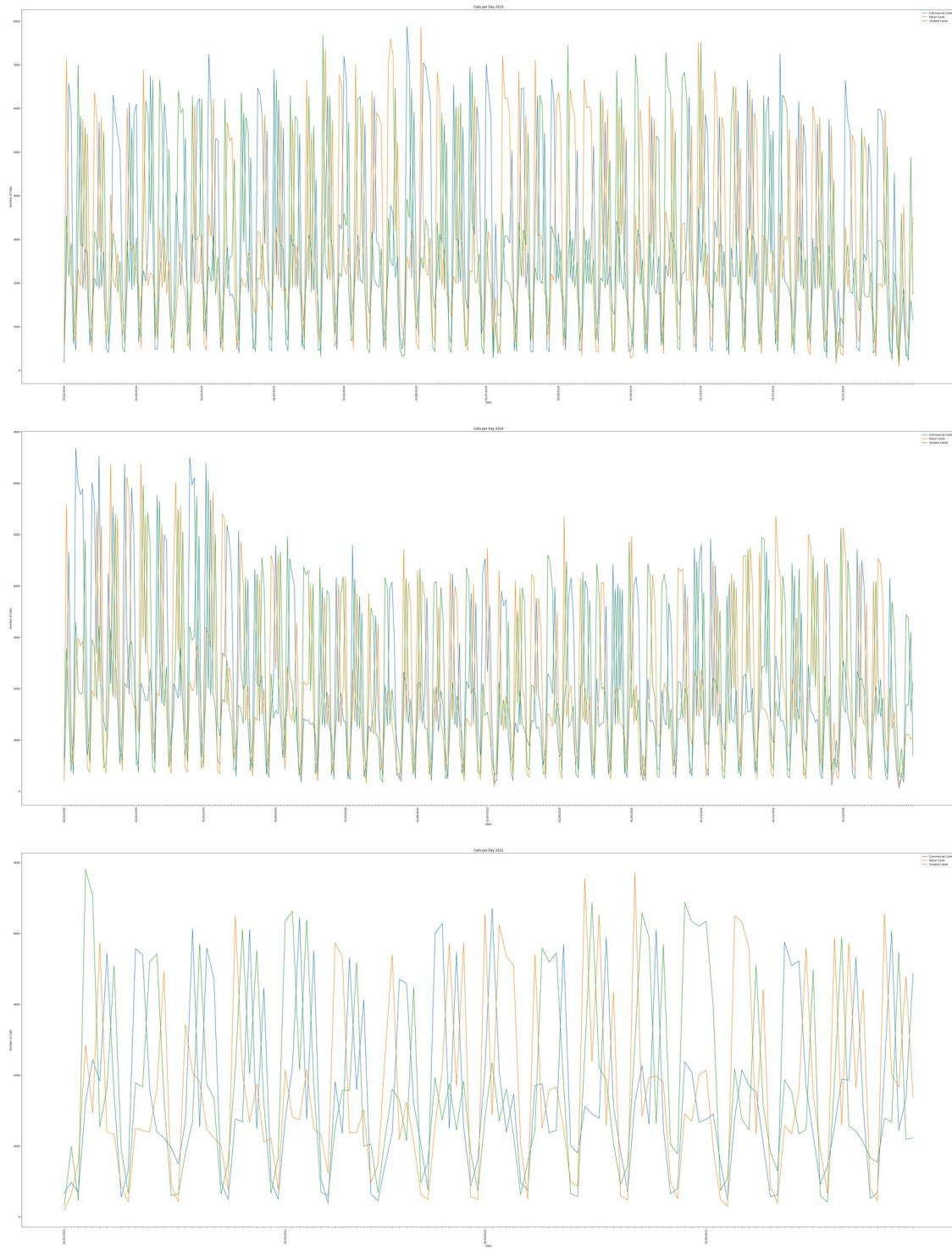
df_not17_sorted.head()

      date      cc      rc      sc  day  month  year
0  01/01/2018  200.0  305.0  709.0   1      1  2018
1  02/01/2018 2343.0 3529.0 7136.0   2      1  2018
2  03/01/2018 2257.0 3404.0 6862.0   3      1  2018
3  04/01/2018 2024.0 3036.0 6153.0   4      1  2018
4  05/01/2018 1970.0 2961.0 5934.0   5      1  2018

# Plot unsorted data
years = df_not17.year.unique()
for y in years:
    x = range((df_not17['year'] == y).sum())
    cc_values = df_not17[df_not17.year == y].cc
    rc_values = df_not17[df_not17.year == y].rc
    sc_values = df_not17[df_not17.year == y].sc
    fig = plt.figure()
    fig.set_figheight(20)
    fig.set_figwidth(50)
    ax = fig.add_axes([1,1,1,1])
    ax.plot(x, cc_values, label='Commercial Cards')
    ax.plot(x, rc_values, label='Retail Cards')
    ax.plot(x, sc_values, label='Student Cards')
    ax.set_xticks(x, [dt if arrow.get(dt, "DD/MM/YYYY").day==1 else
    "" for dt in df_not17[df_not17.year == y]['date']], rotation=90)
    ax.set_xlabel("Date")
    ax.set_ylabel("Number of Calls")
    ax.set_title(f"Calls per Day {y}")
    ax.legend()
    plt.show()

```



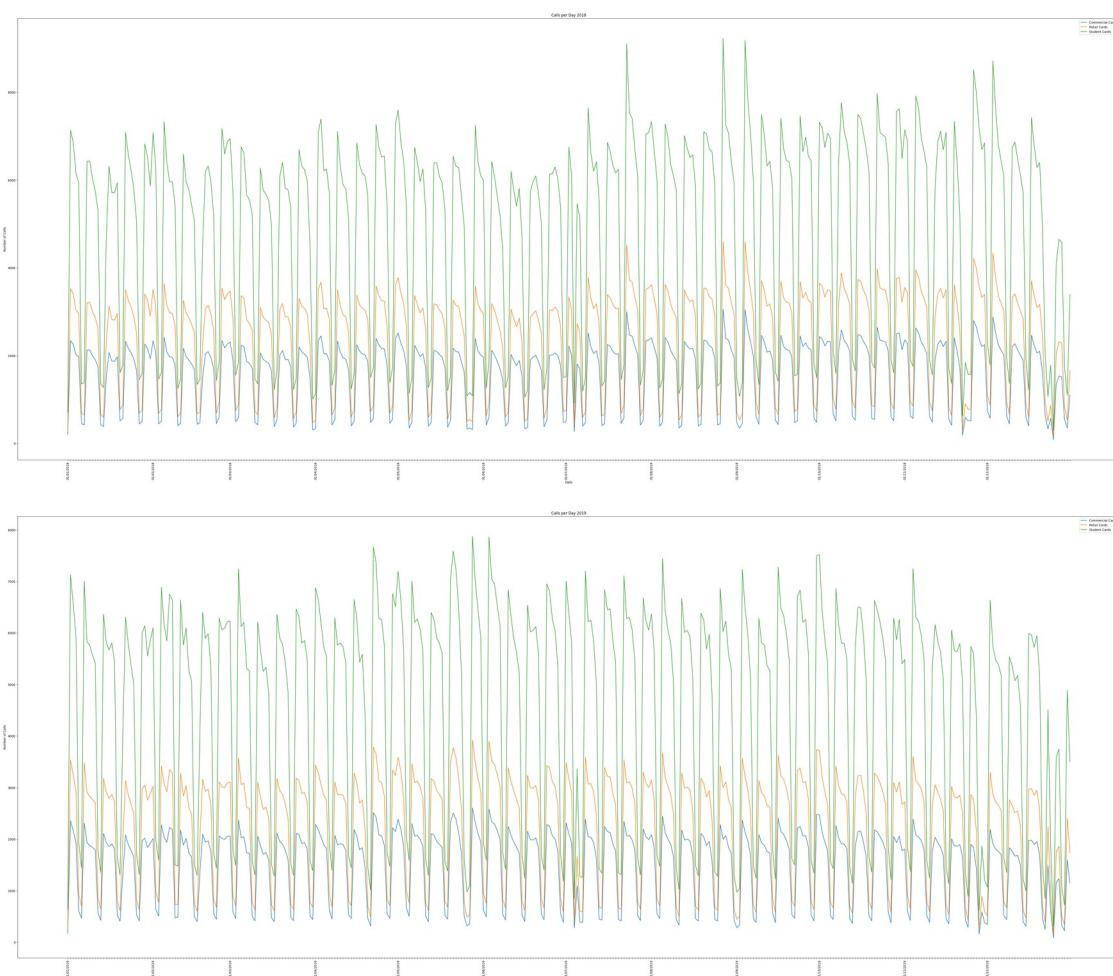


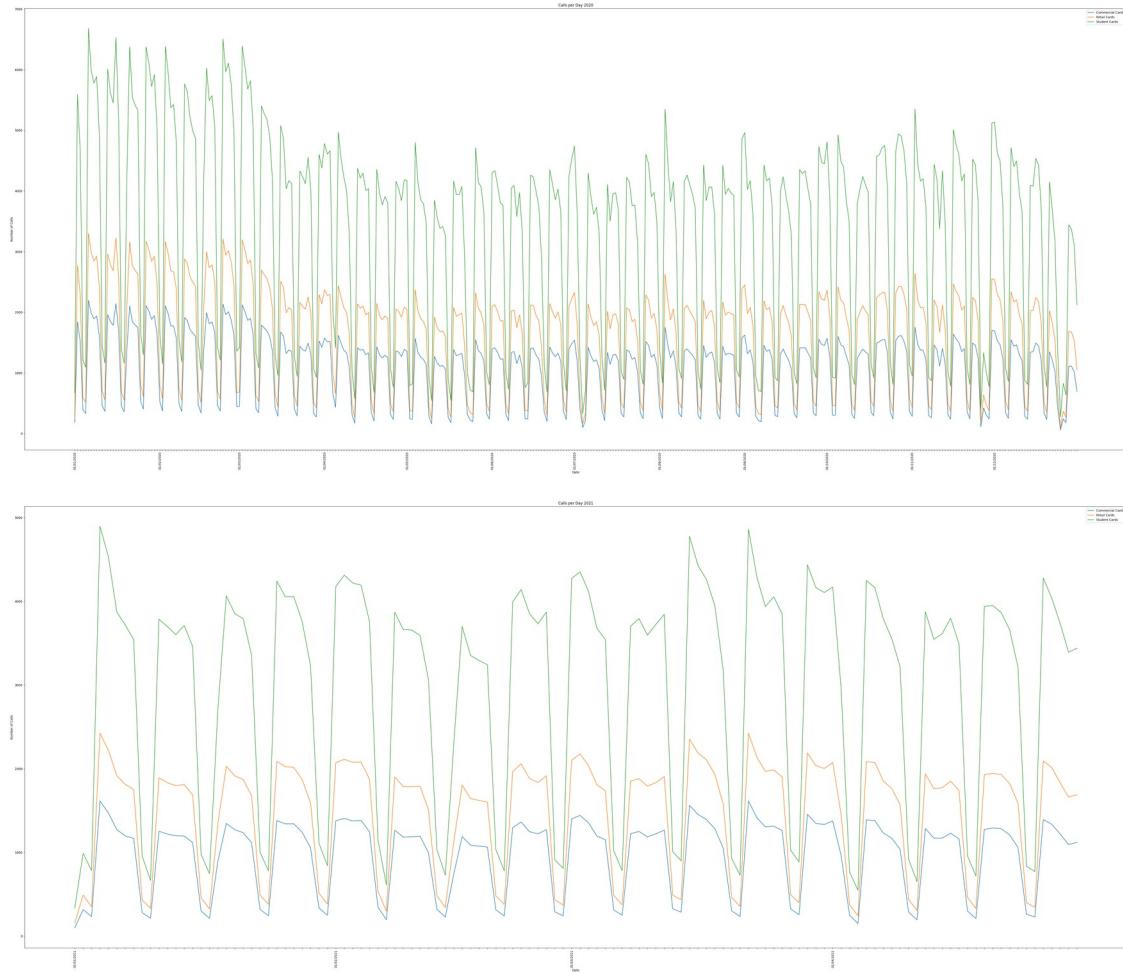
```
# Plot sorted data
years = df_not17_sorted.year.unique()
for y in years:
    x = range((df_not17_sorted['year'] == y).sum())
    cc_values = df_not17_sorted[df_not17_sorted.year == y].cc
    rc_values = df_not17_sorted[df_not17_sorted.year == y].rc
```

```

sc_values = df_not17_sorted[df_not17_sorted.year == y].sc
fig = plt.figure()
fig.set_figheight(20)
fig.set_figwidth(50)
ax = fig.add_axes([1,1,1,1])
ax.plot(x, cc_values, label='Commercial Cards')
ax.plot(x, rc_values, label='Retail Cards')
ax.plot(x, sc_values, label='Student Cards')
ax.set_xticks(x, [ dt if arrow.get(dt, "DD/MM/YYYY").day==1 else
"" for dt in df_not17_sorted[df_not17_sorted.year == y]['date'] ],
rotation=90)
ax.set_xlabel("Date")
ax.set_ylabel("Number of Calls")
ax.set_title(f"Calls per Day {y}")
ax.legend()
plt.show()

```



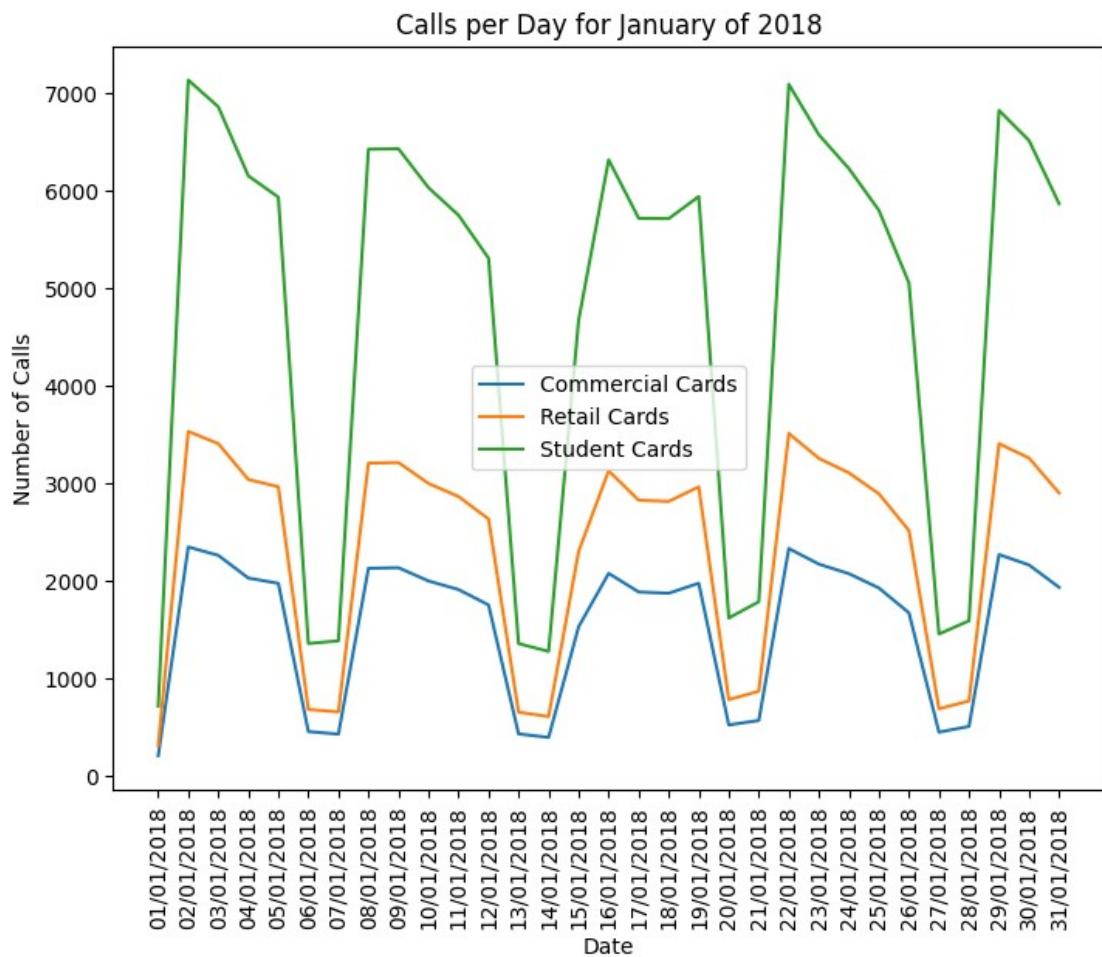


```
# Plot monthly sorted data for every year 2018-2021
years = df_not17_sorted.year.unique()
for y in years:
    df_not17_sorted_yearly = df_not17_sorted[df_not17_sorted.year == y]
    months = df_not17_sorted_yearly.month.unique()
    for m in months:
        x = range((df_not17_sorted_yearly.month == m).sum())
        cc_values =
        df_not17_sorted_yearly[df_not17_sorted_yearly.month == m].cc
        rc_values =
        df_not17_sorted_yearly[df_not17_sorted_yearly.month == m].rc
        sc_values =
        df_not17_sorted_yearly[df_not17_sorted_yearly.month == m].sc
        fig = plt.figure()
        ax = fig.add_axes([1,1,1,1])
        ax.plot(x, cc_values, label='Commercial Cards')
        ax.plot(x, rc_values, label='Retail Cards')
        ax.plot(x, sc_values, label='Student Cards')
        ax.set_xticks(x,
df_not17_sorted_yearly[df_not17_sorted_yearly.month == m].date,
```

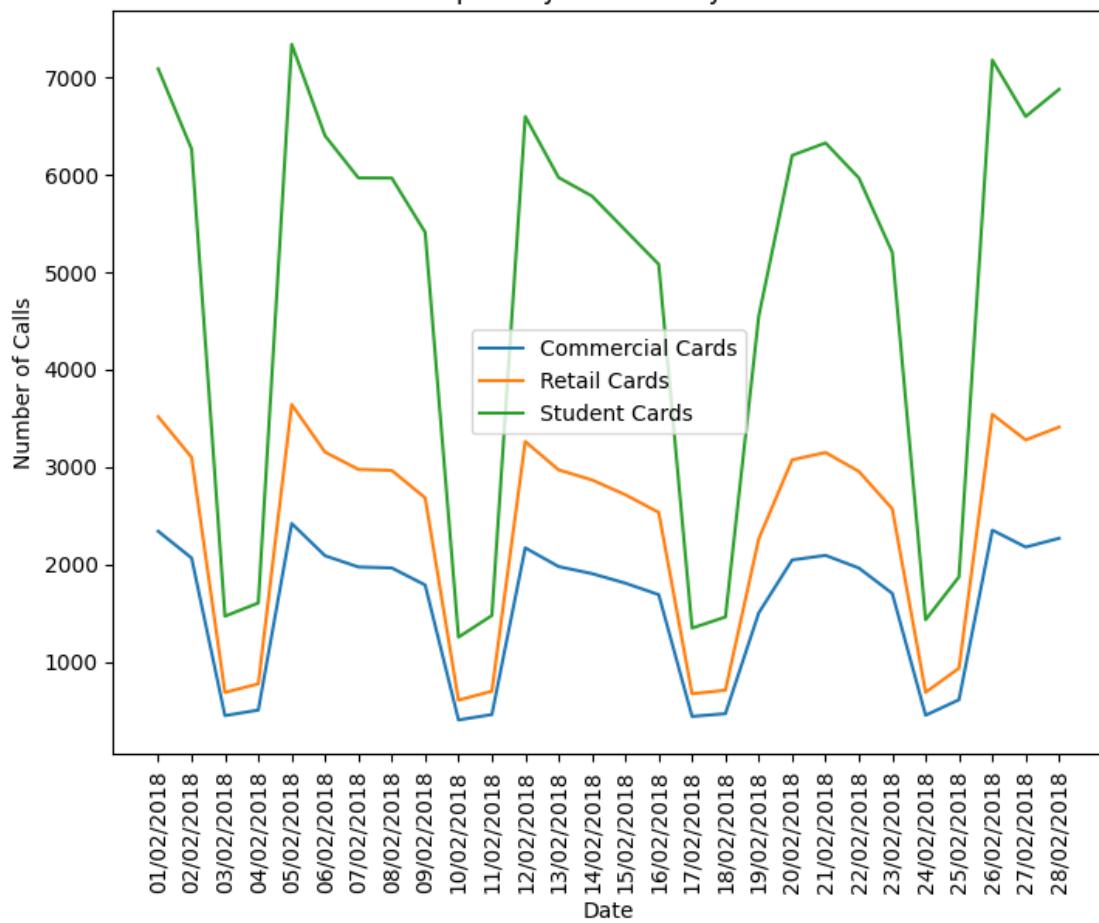
```

rotation=90)
ax.set_xlabel("Date")
ax.set_ylabel("Number of Calls")
ax.set_title(f"Calls per Day for {arrow.get(str(m),
'M').format('MMMM')} of {y}")
ax.legend()
plt.show()

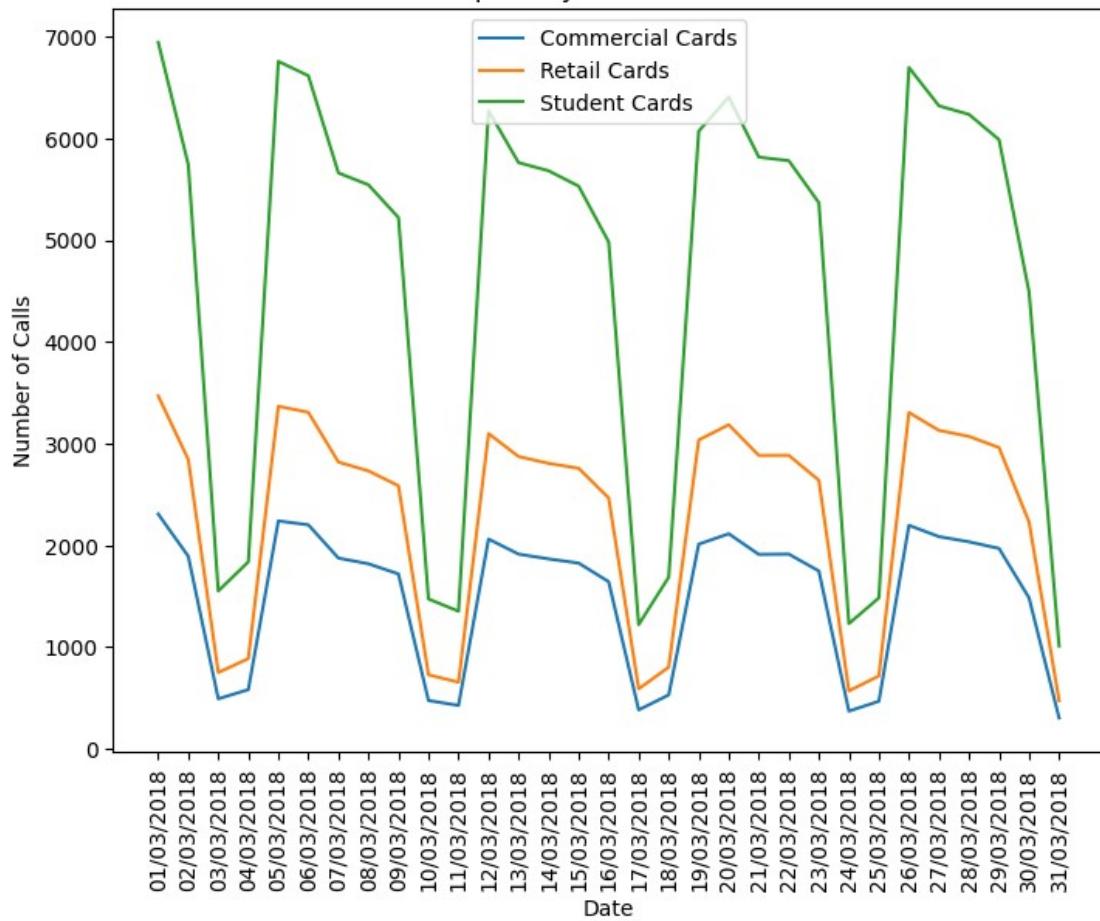
```



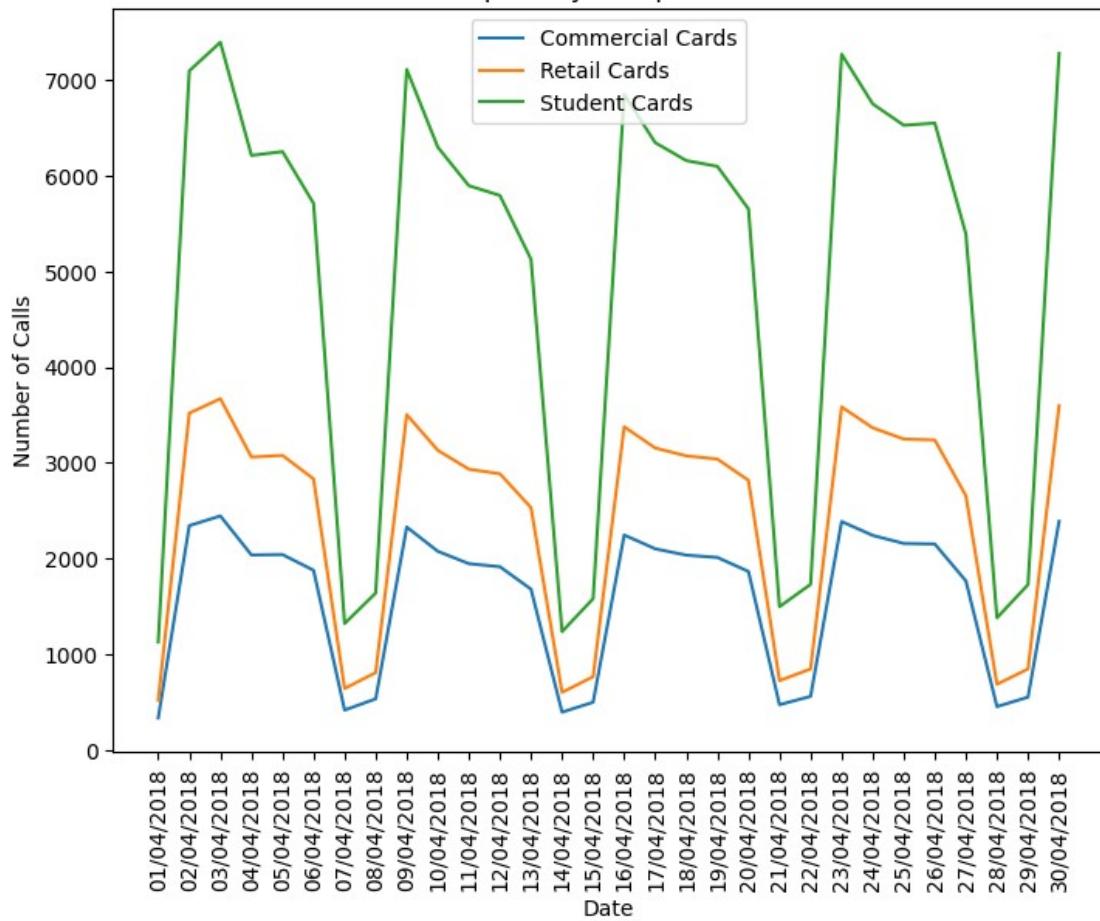
Calls per Day for February of 2018



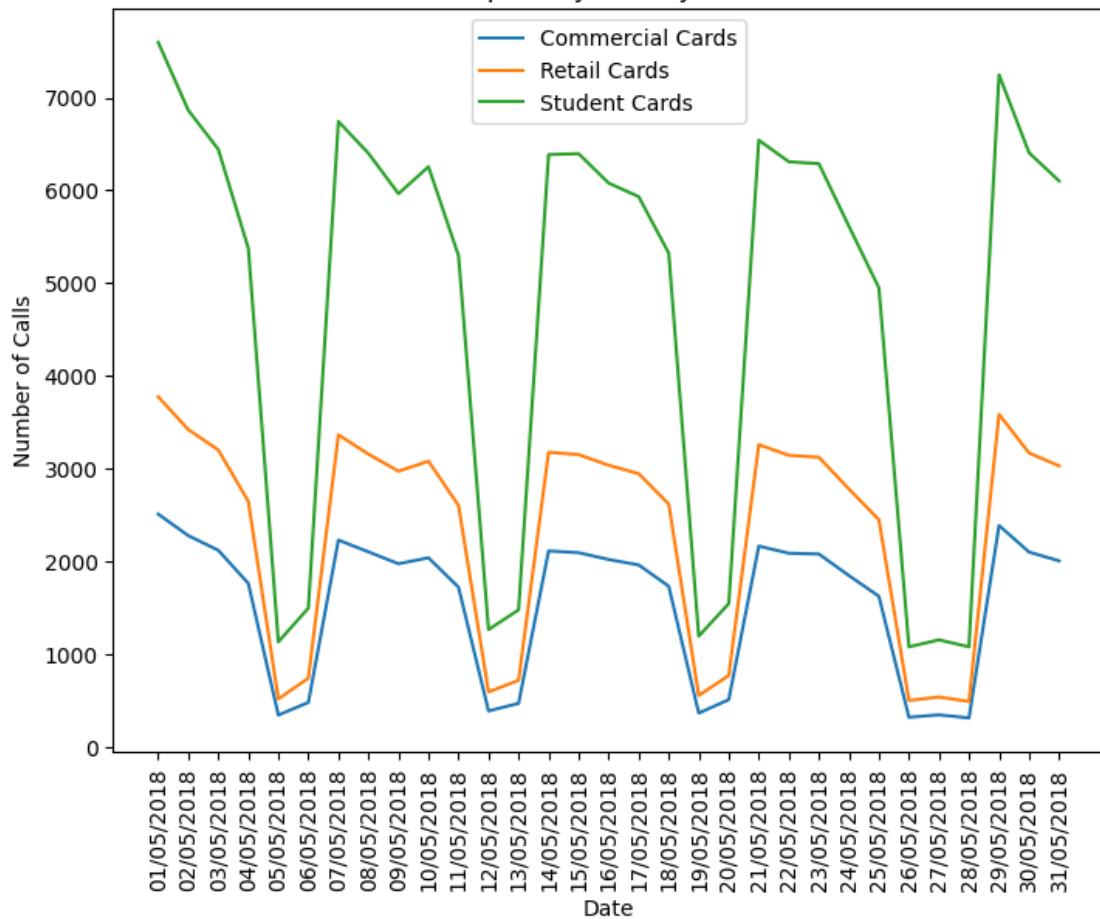
Calls per Day for March of 2018



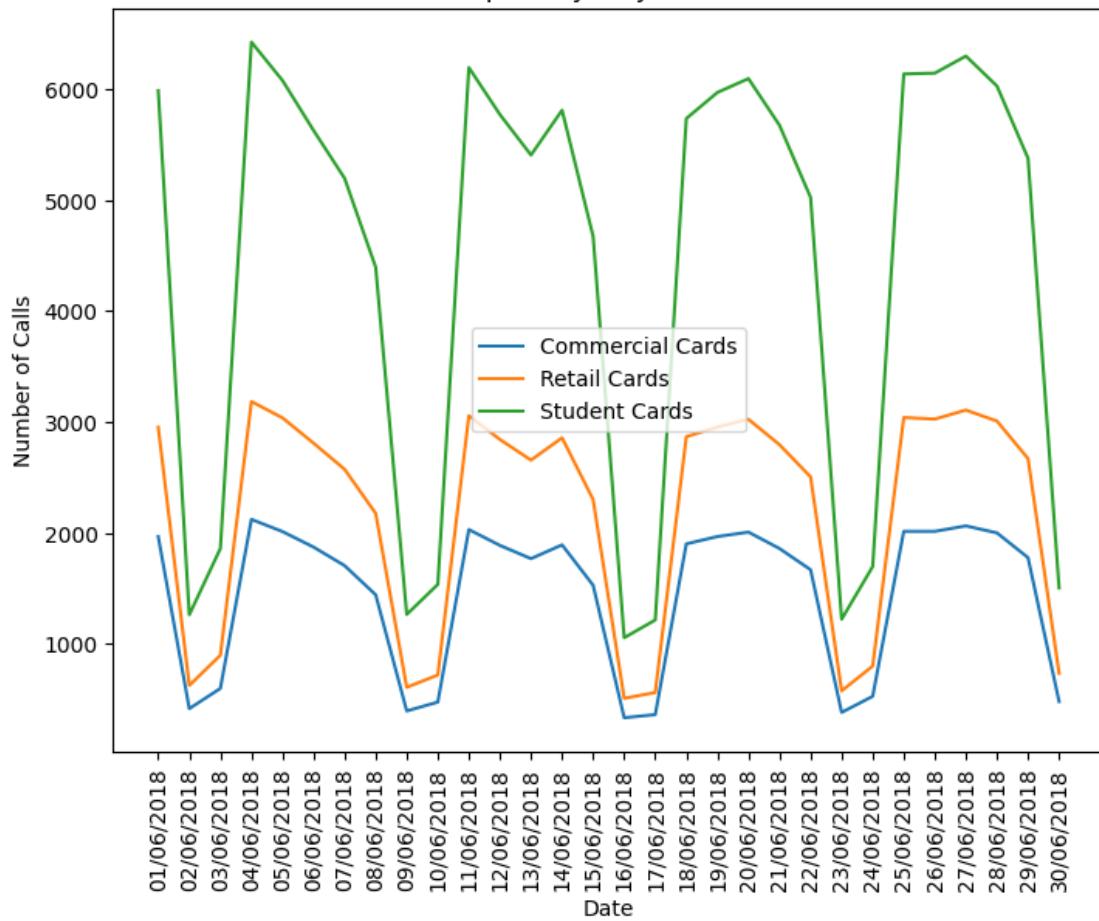
Calls per Day for April of 2018



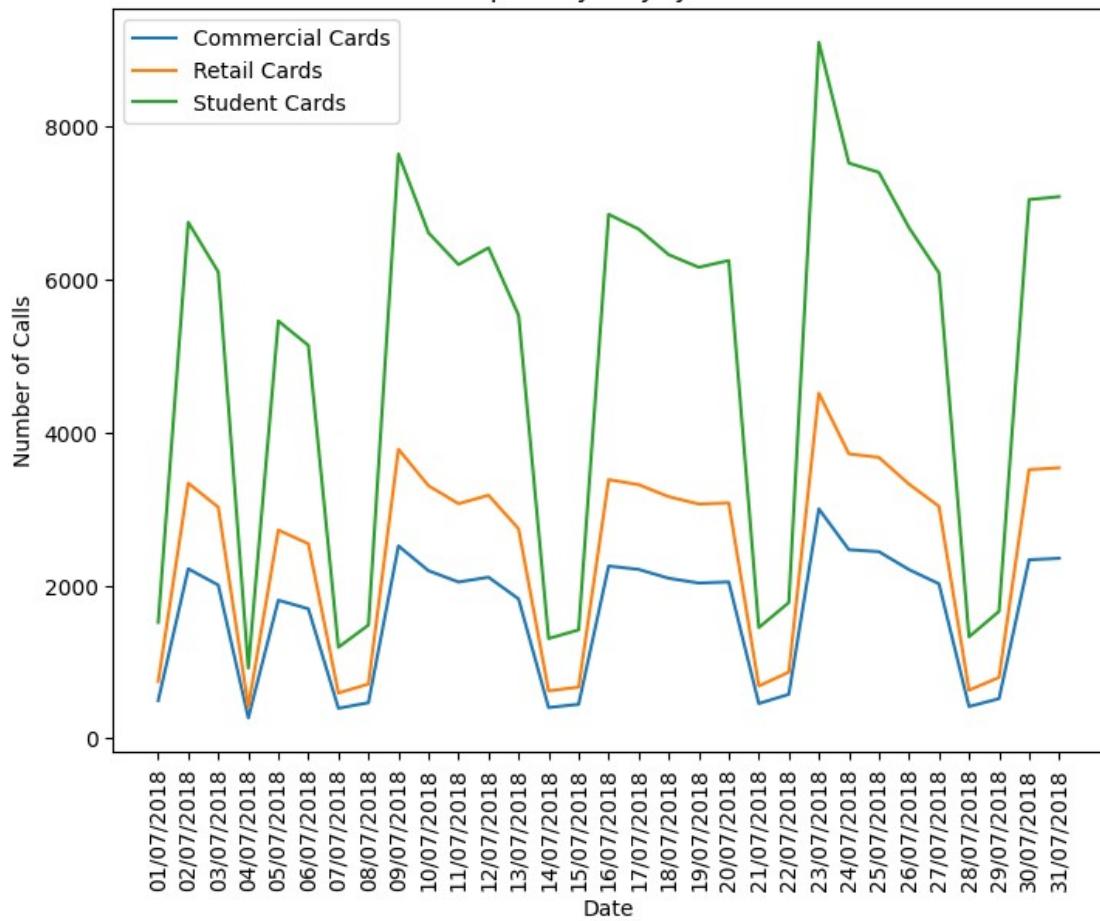
Calls per Day for May of 2018



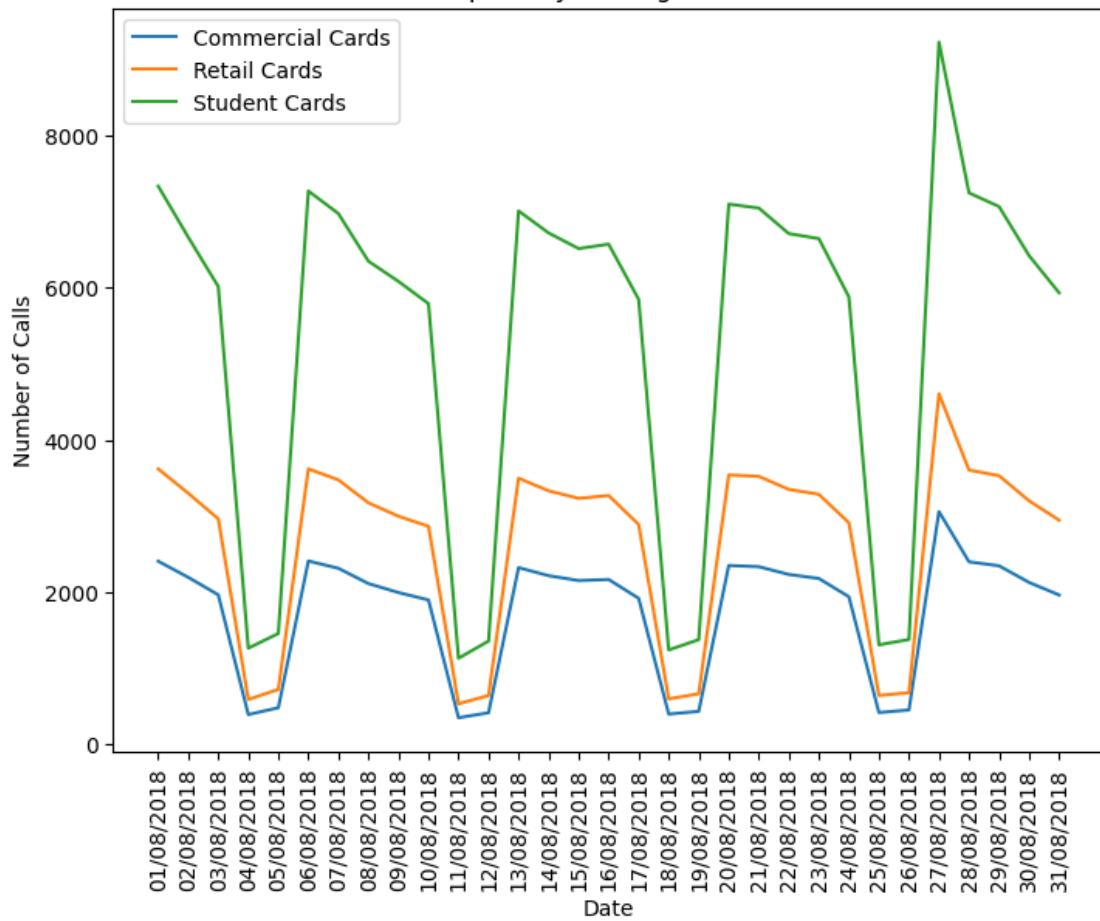
Calls per Day for June of 2018



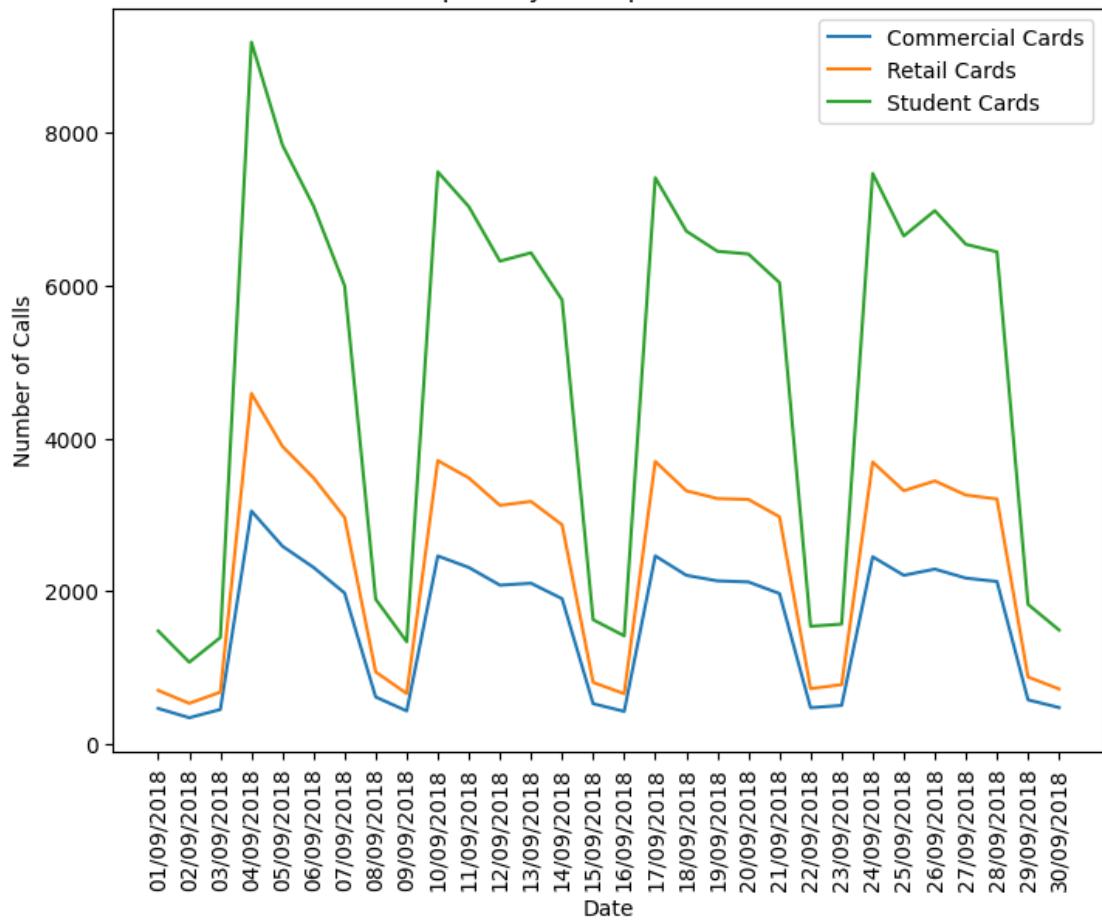
Calls per Day for July of 2018



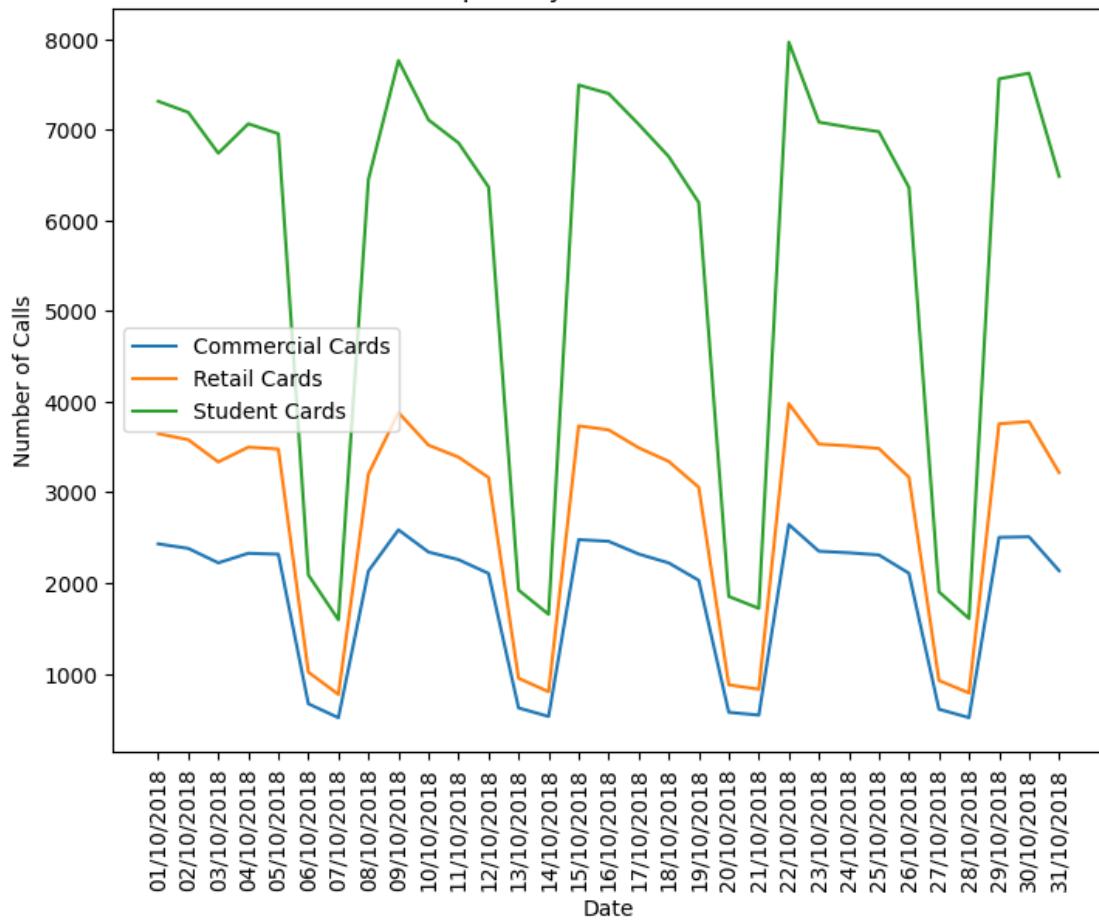
Calls per Day for August of 2018



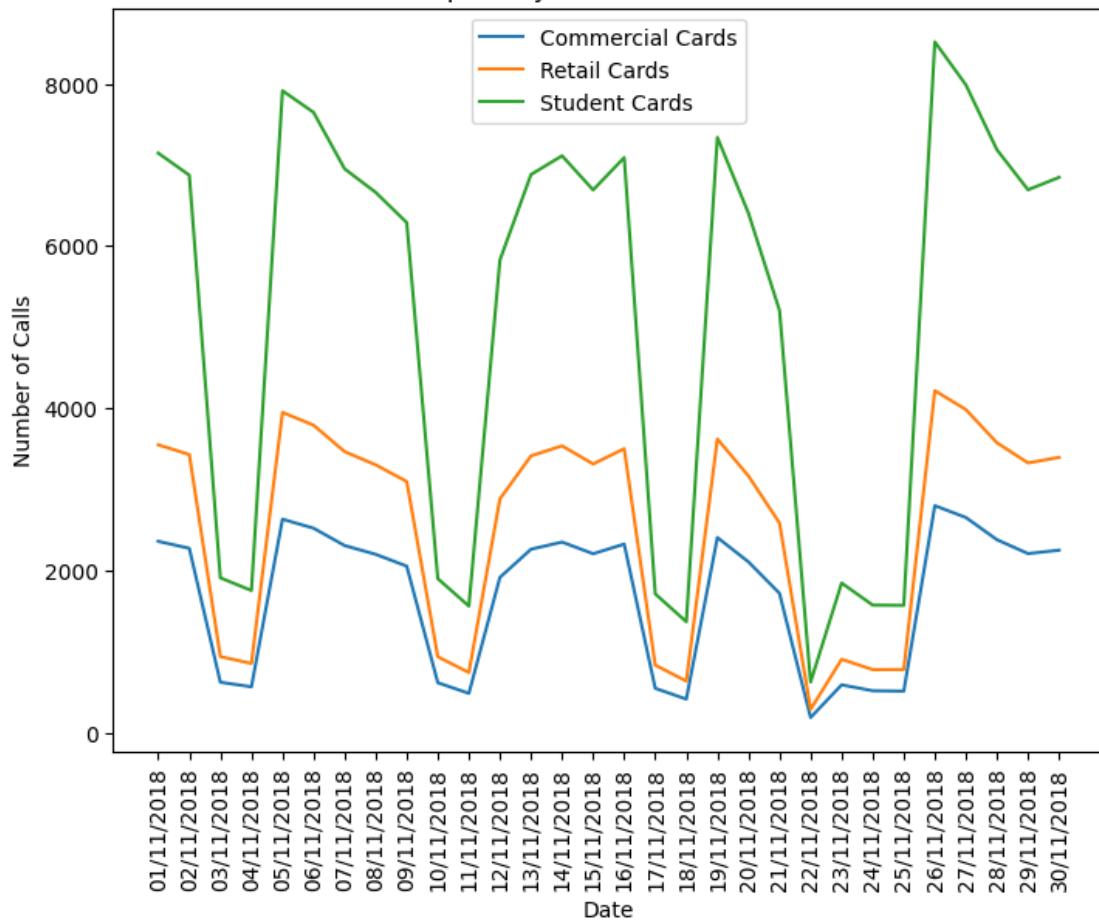
Calls per Day for September of 2018



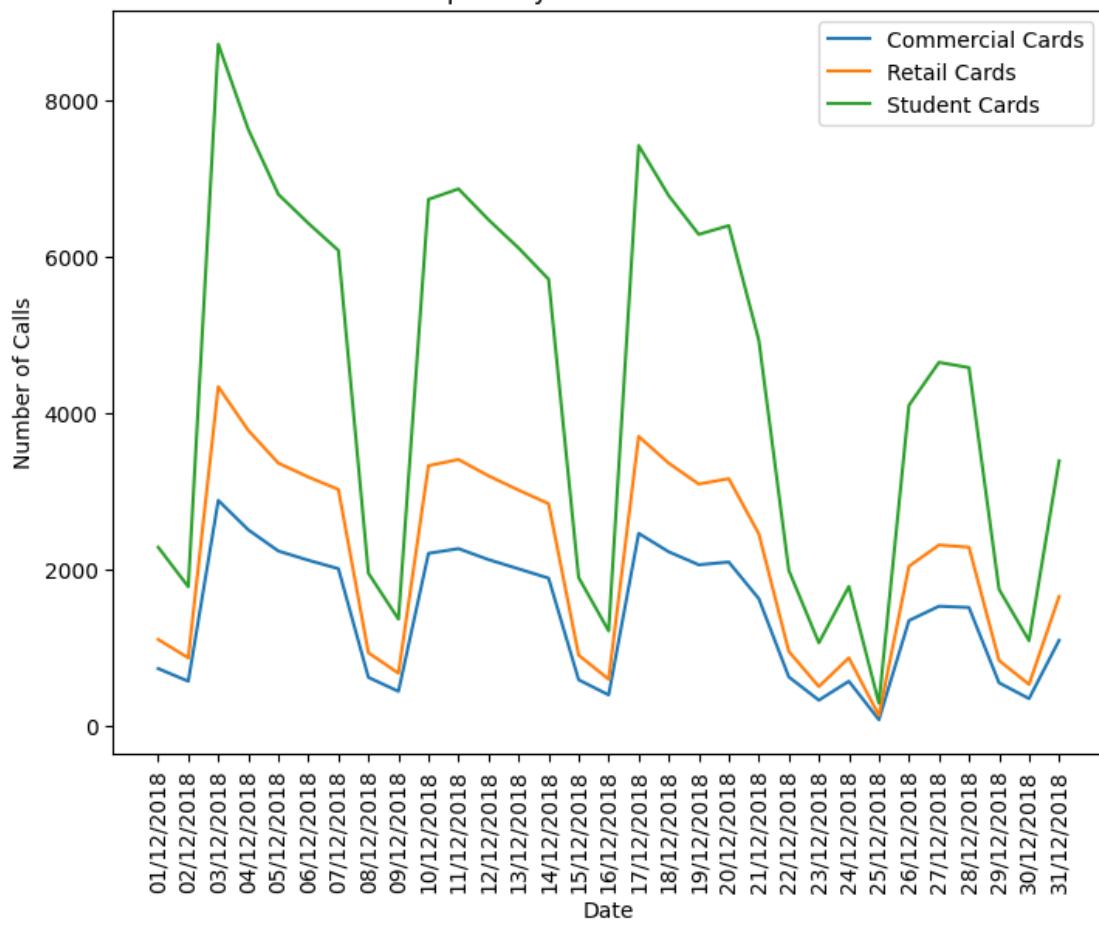
Calls per Day for October of 2018



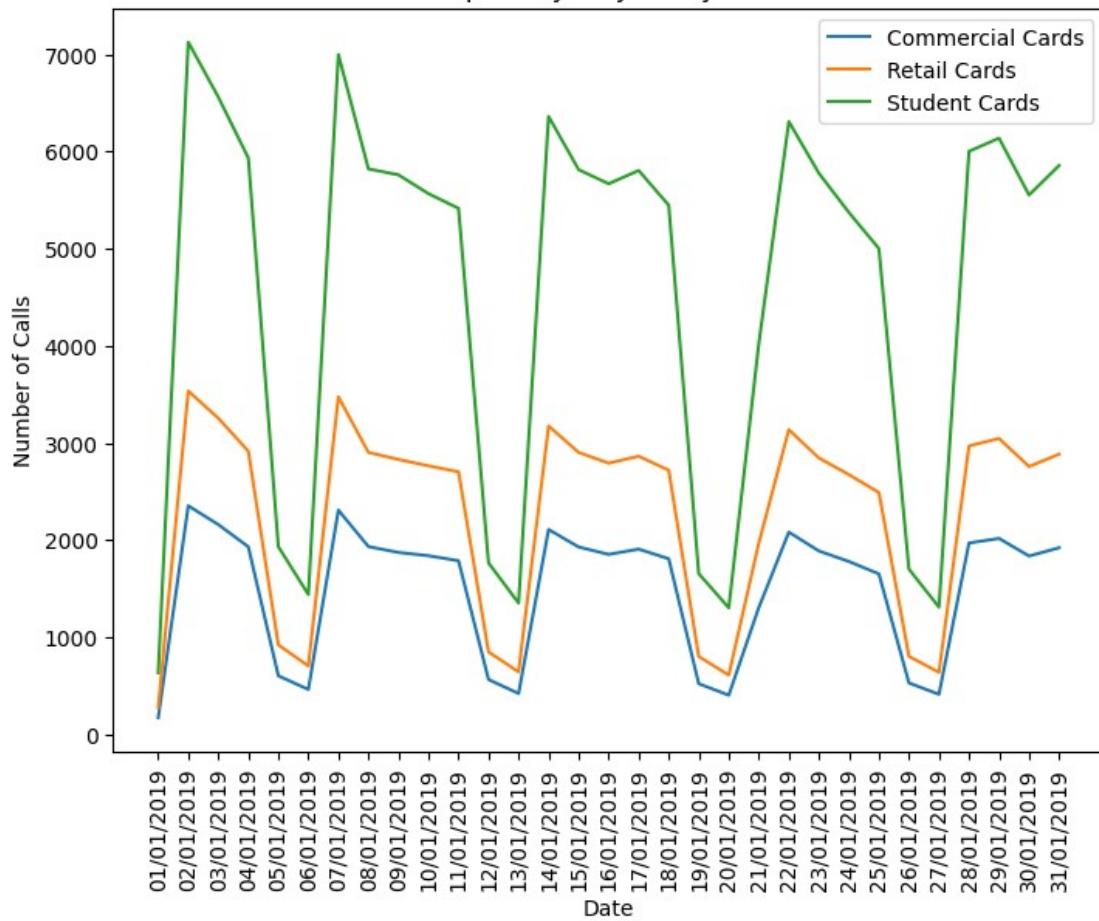
Calls per Day for November of 2018



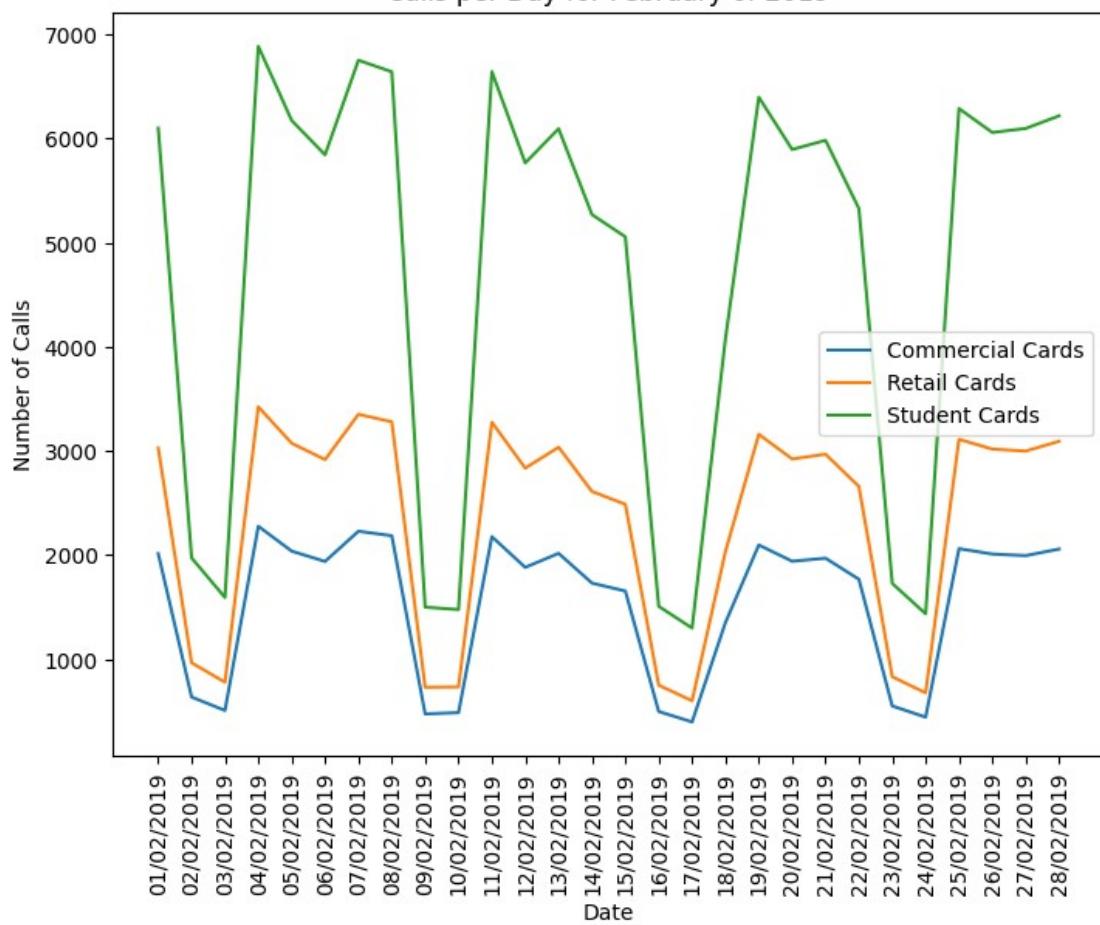
Calls per Day for December of 2018



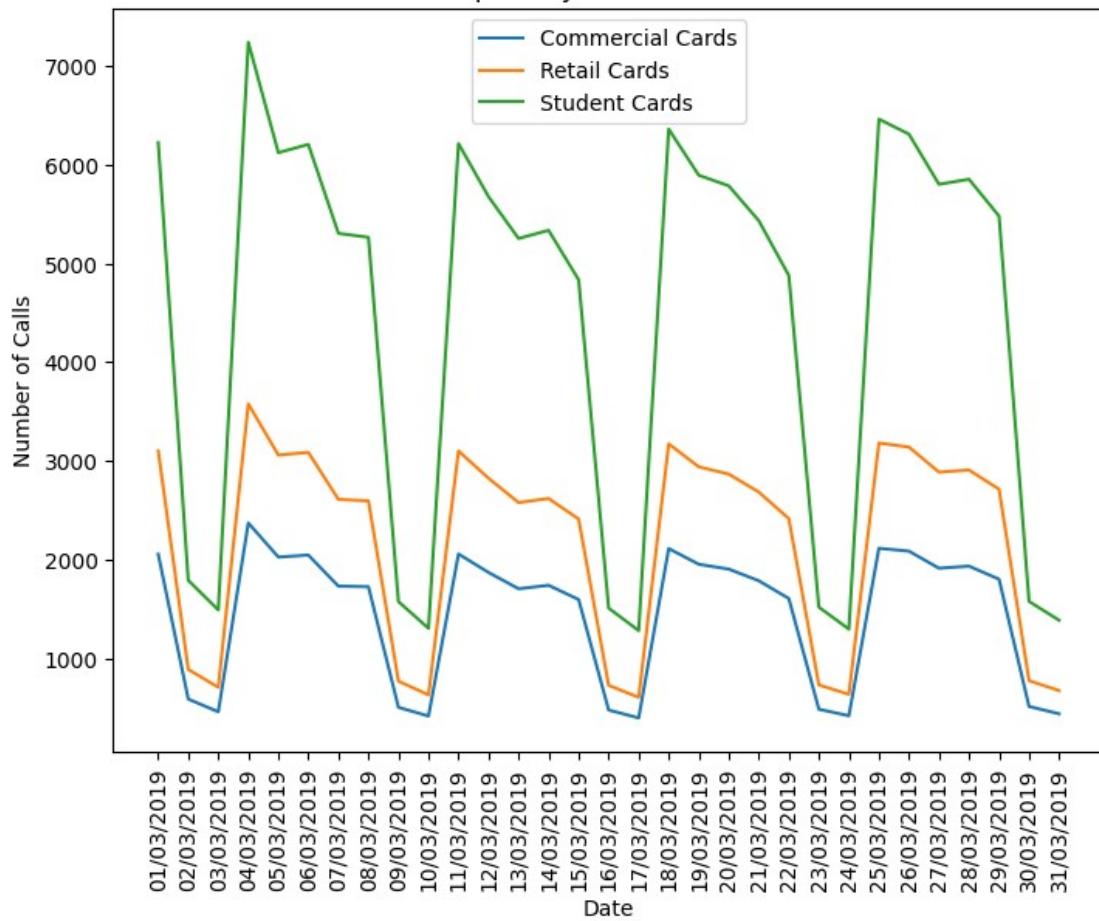
Calls per Day for January of 2019

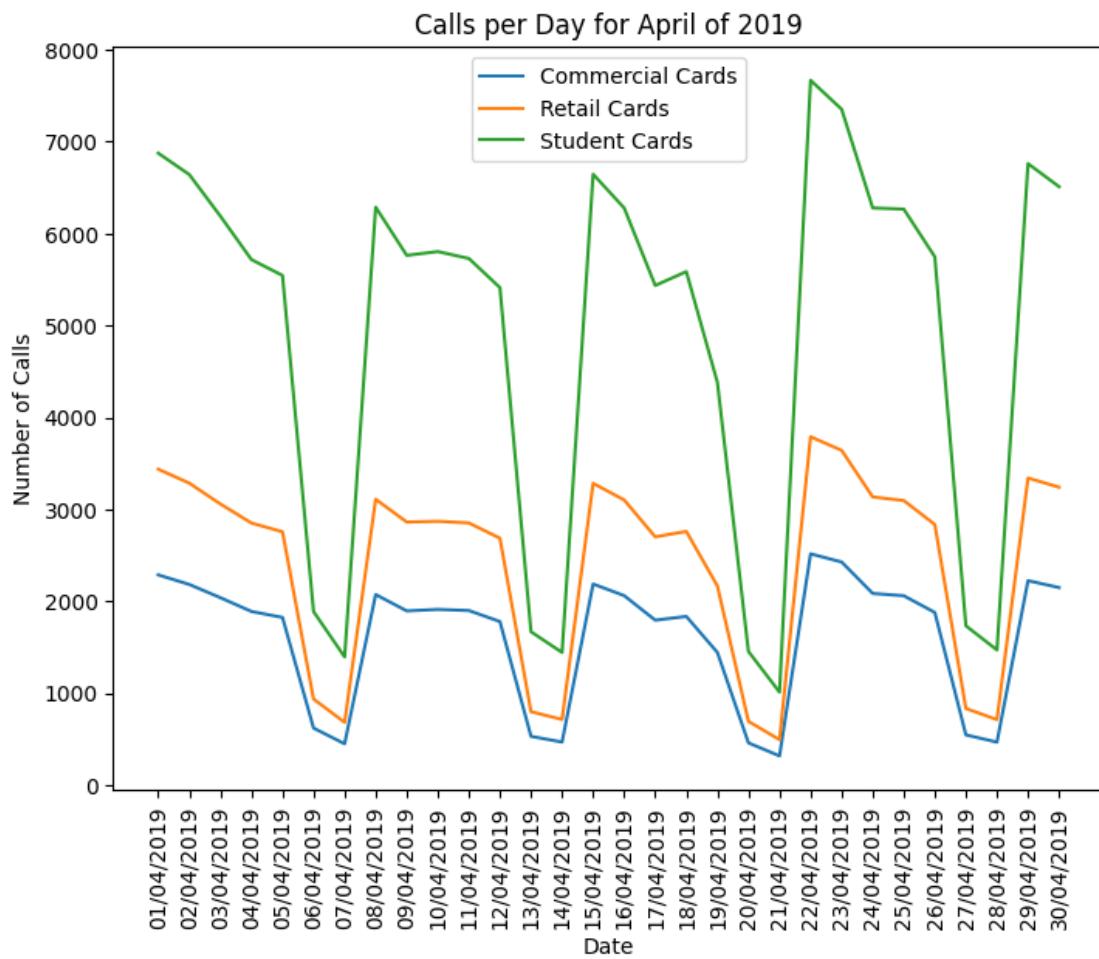


Calls per Day for February of 2019

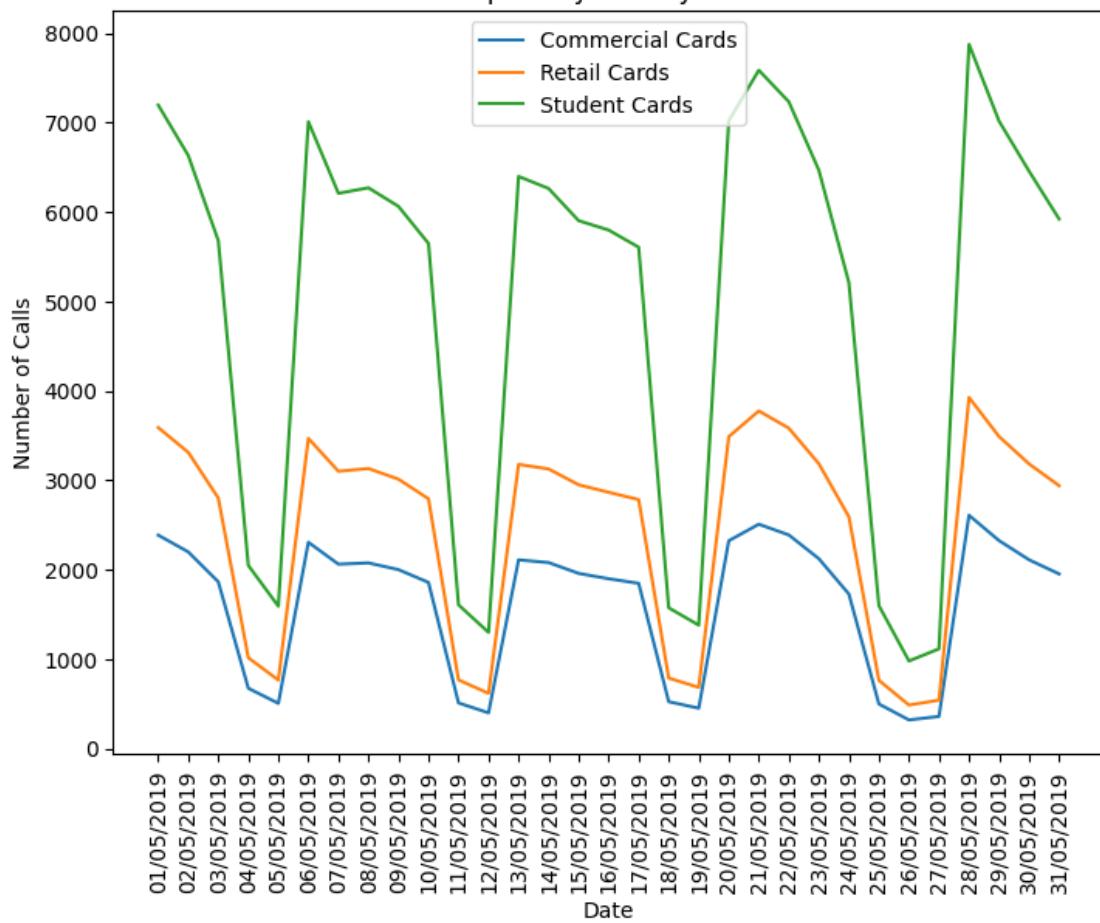


Calls per Day for March of 2019

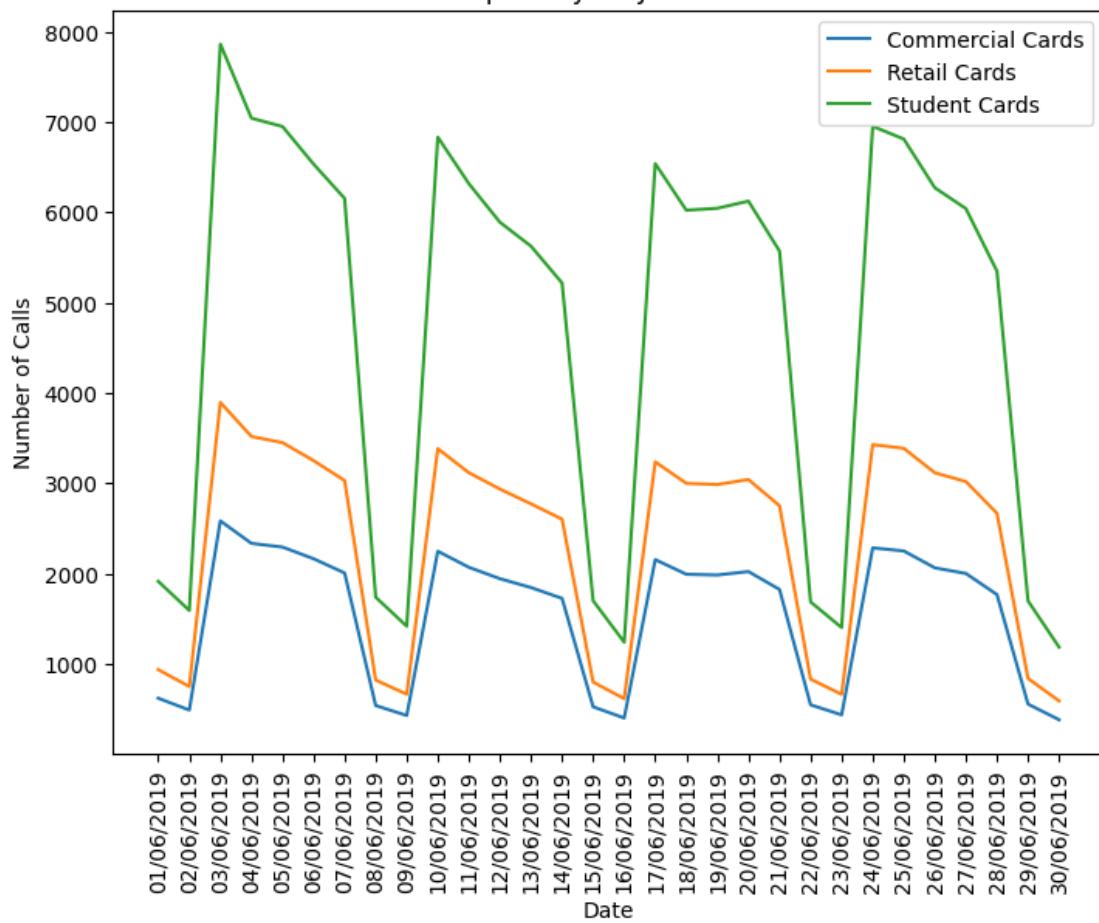




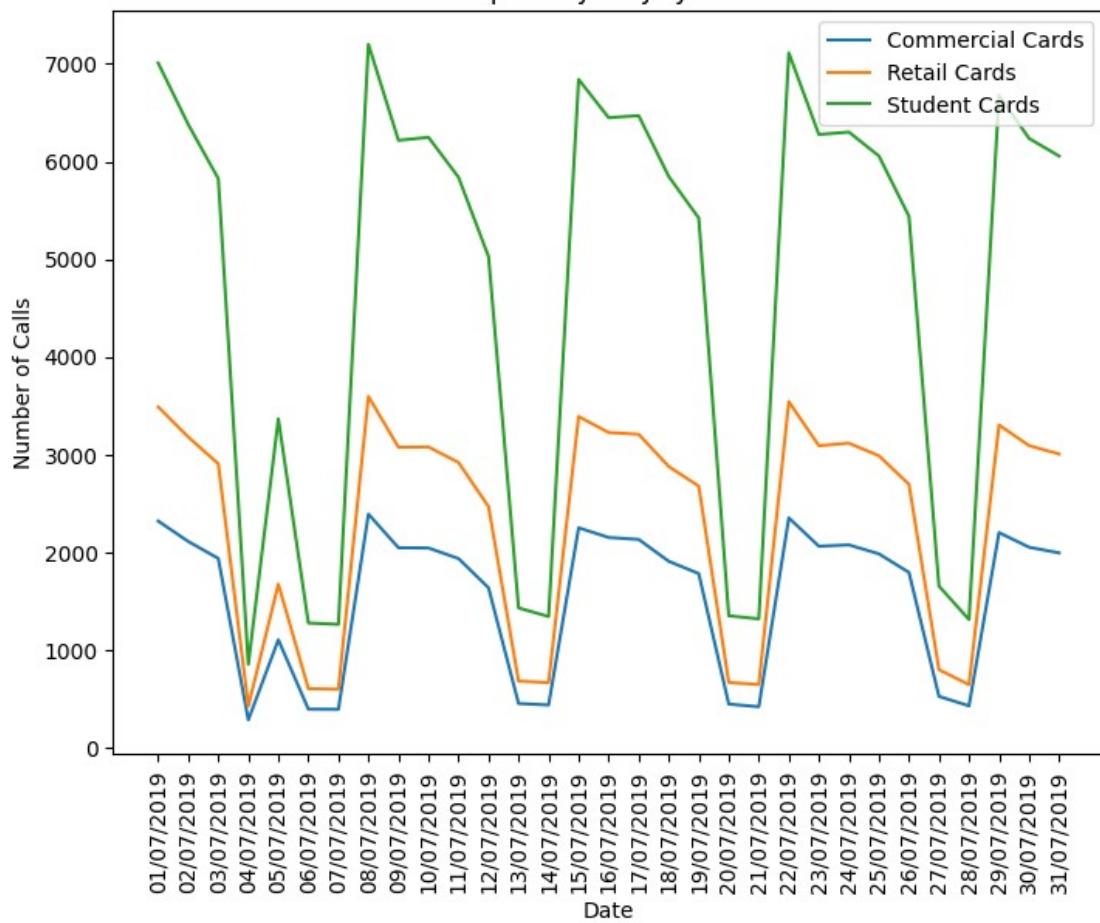
Calls per Day for May of 2019



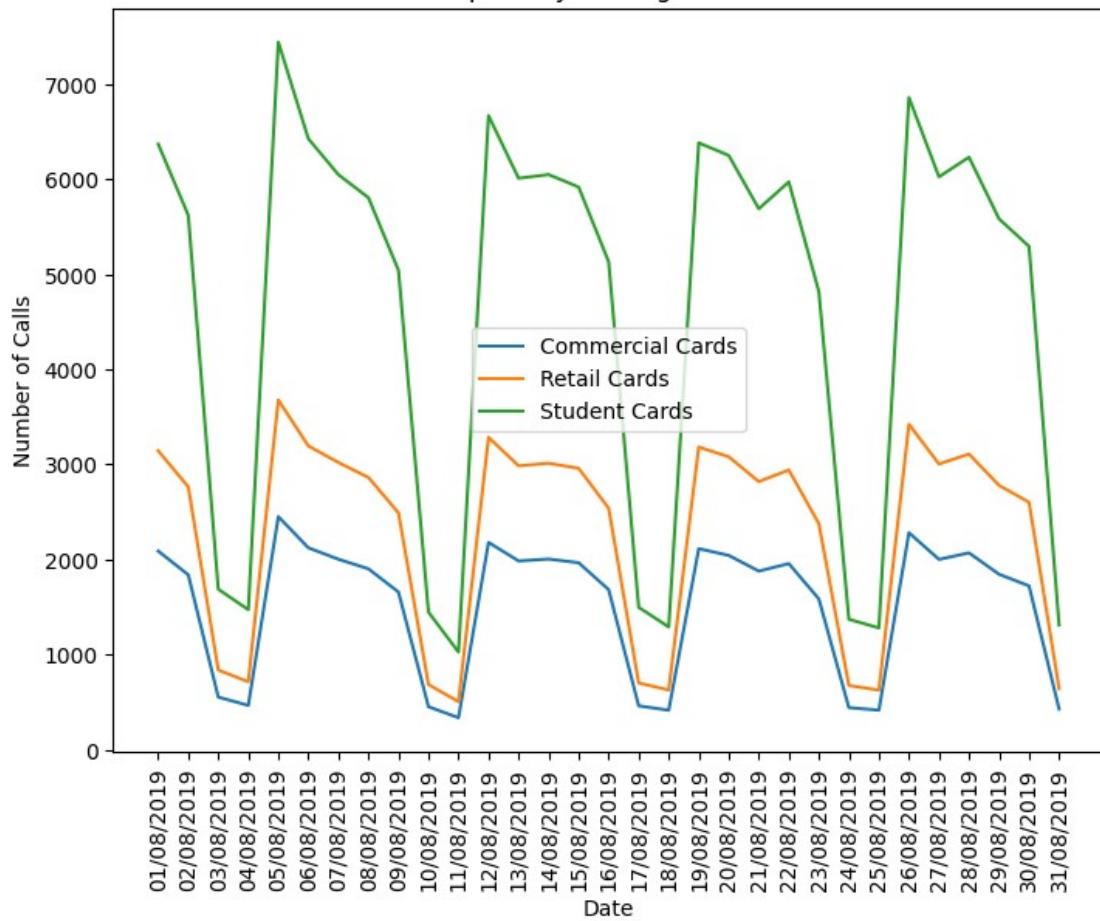
Calls per Day for June of 2019



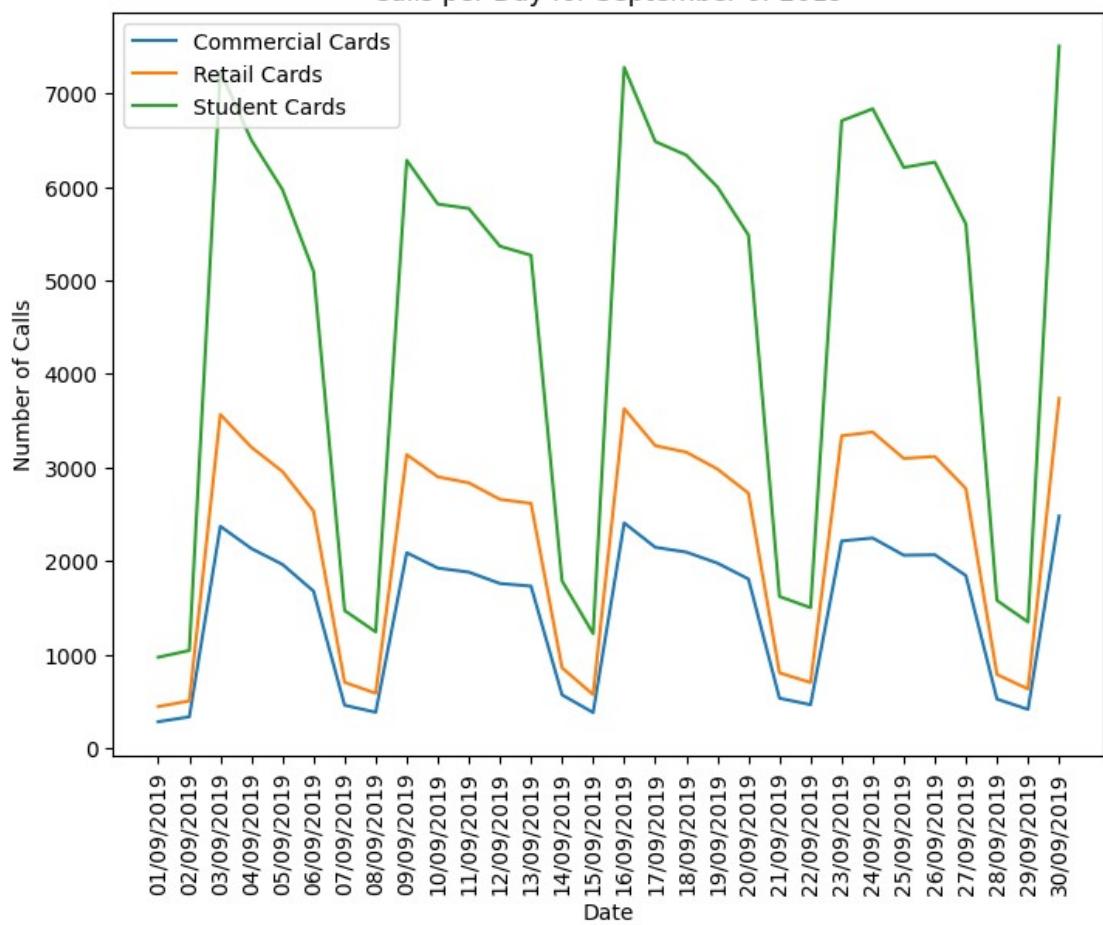
Calls per Day for July of 2019



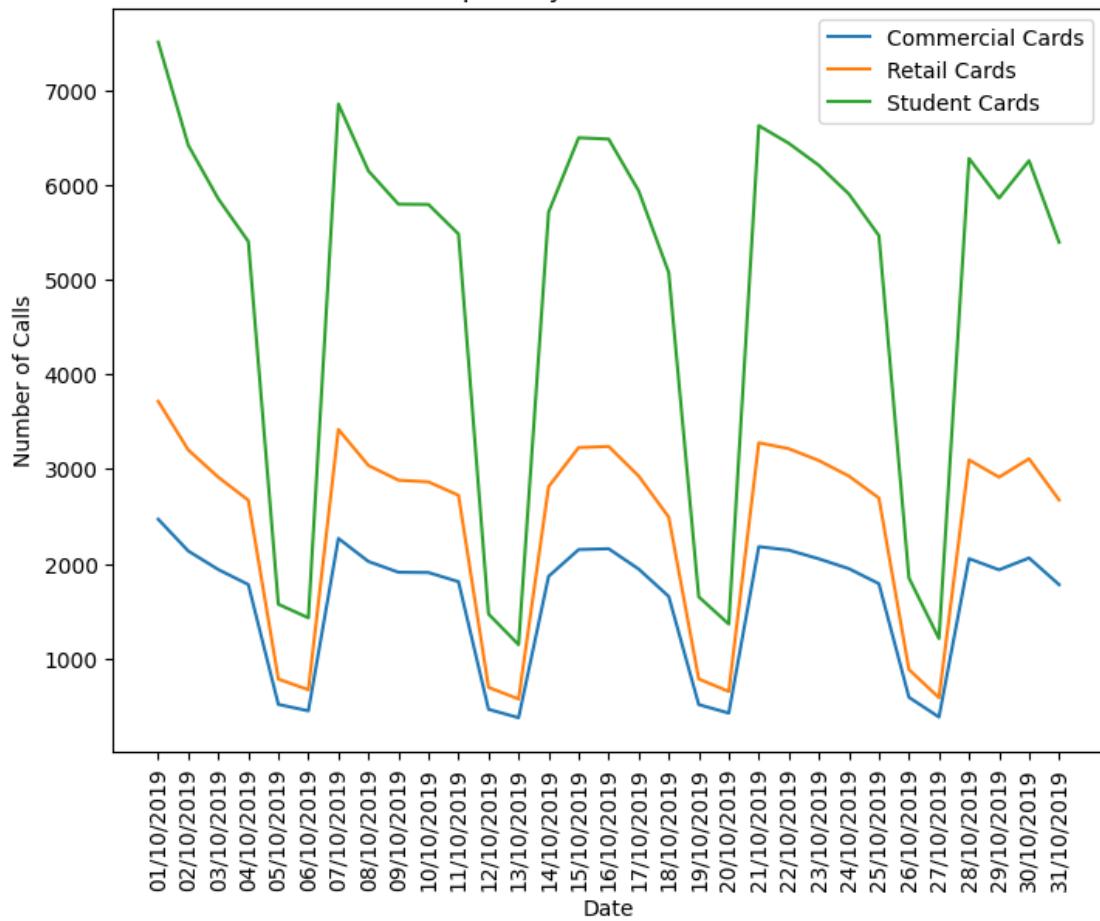
Calls per Day for August of 2019



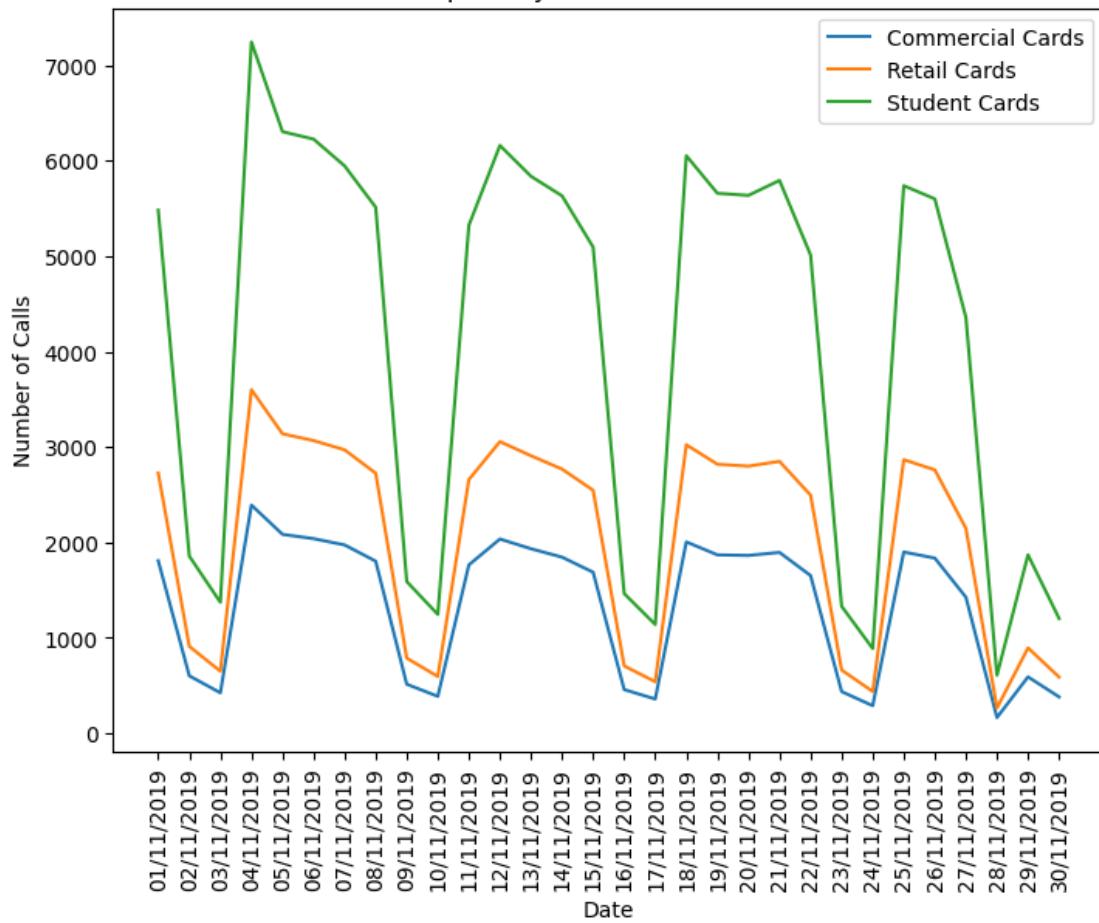
Calls per Day for September of 2019



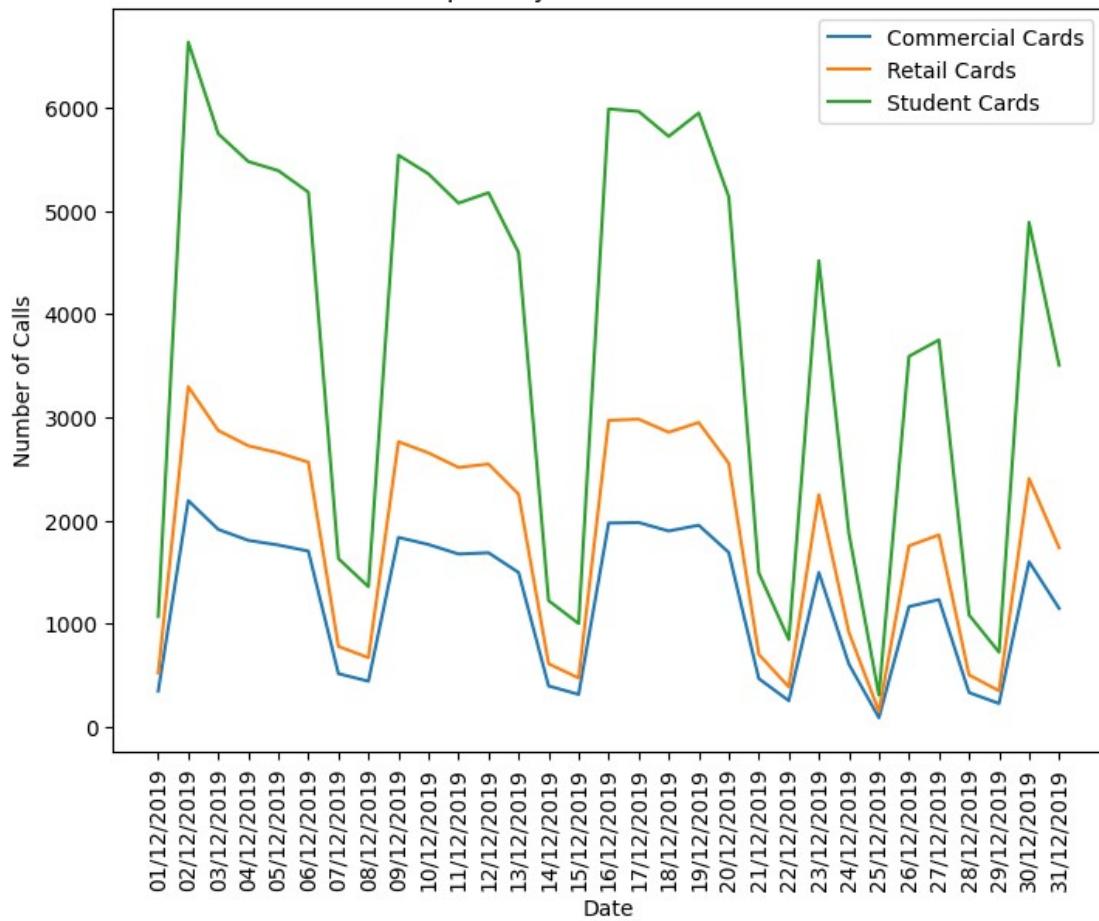
Calls per Day for October of 2019

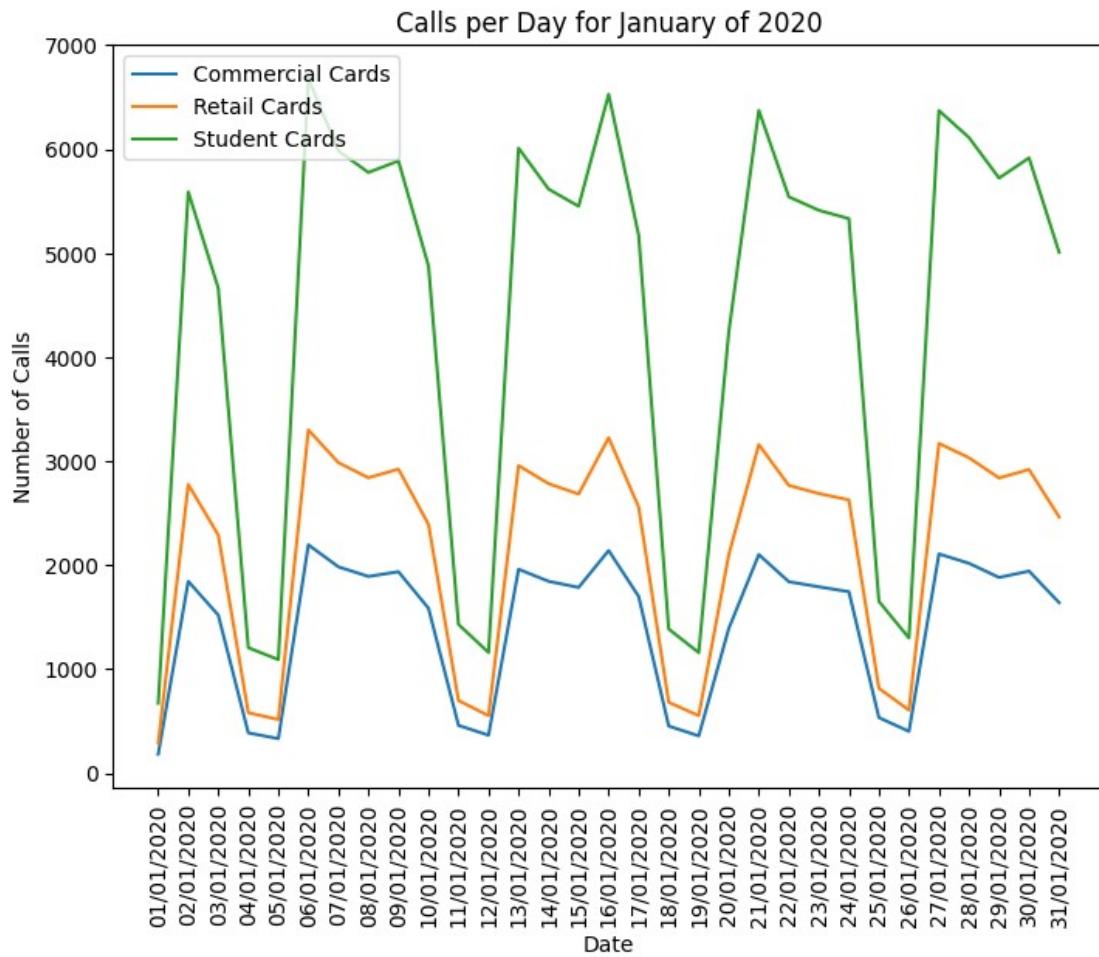


Calls per Day for November of 2019

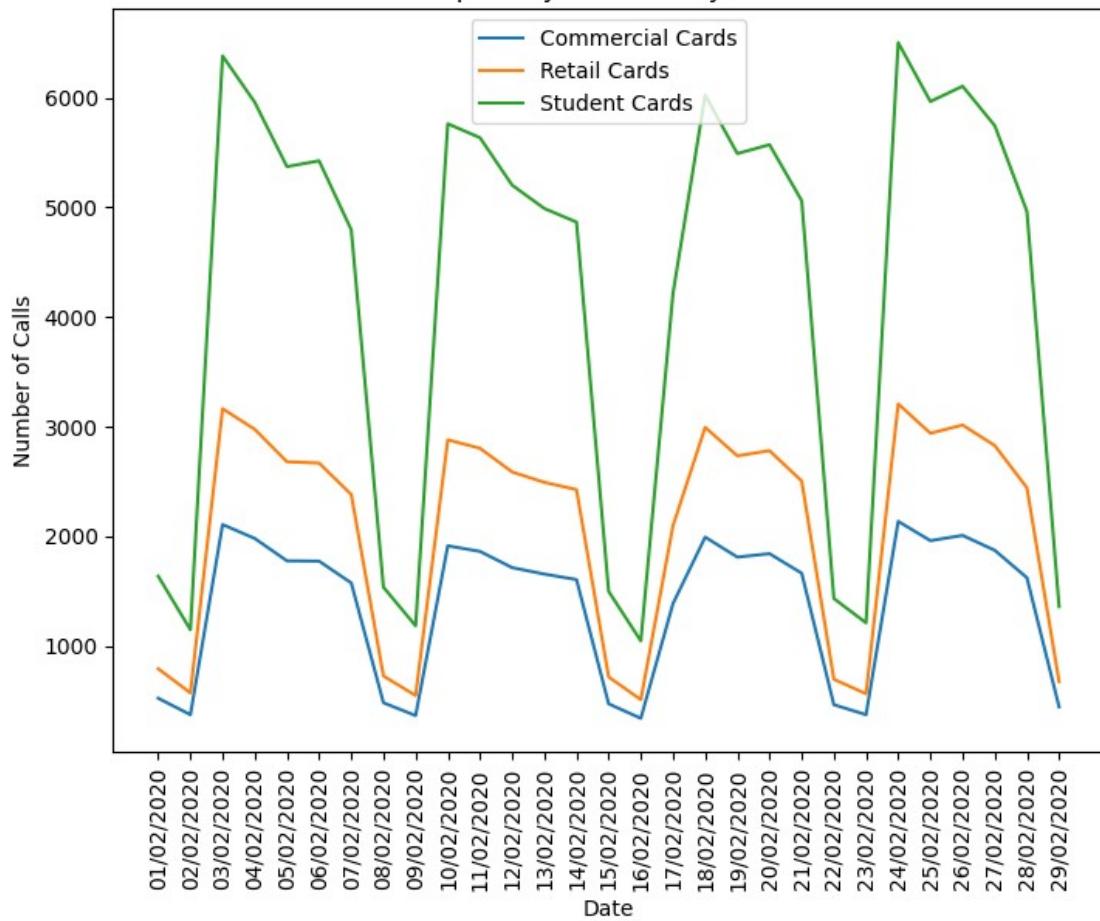


Calls per Day for December of 2019

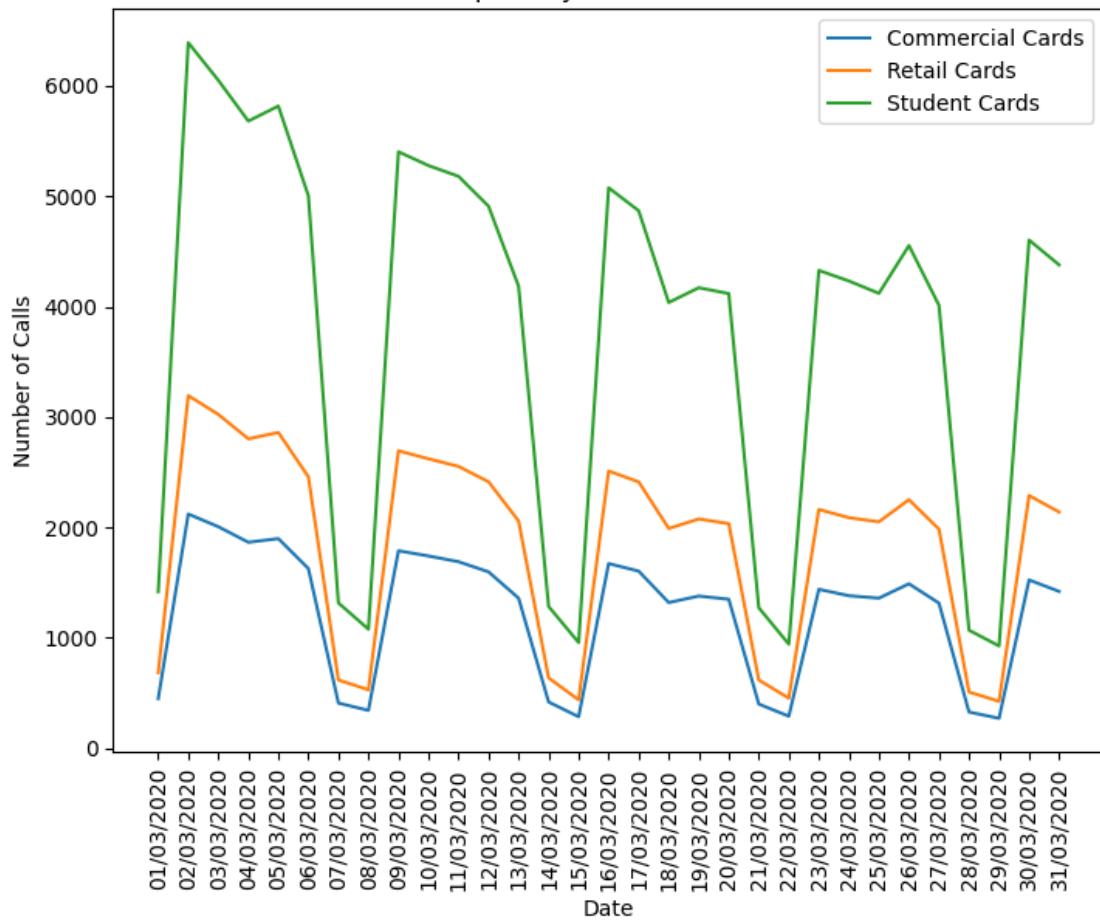




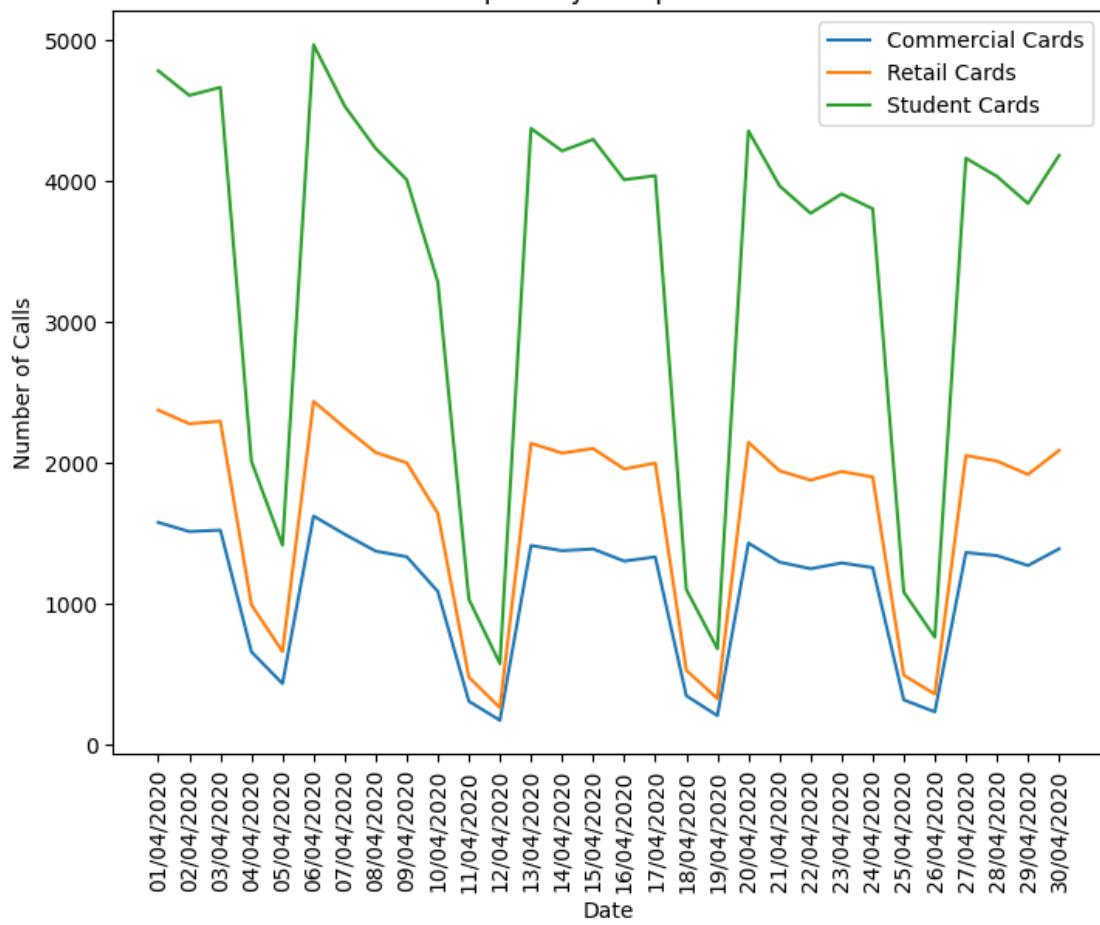
Calls per Day for February of 2020

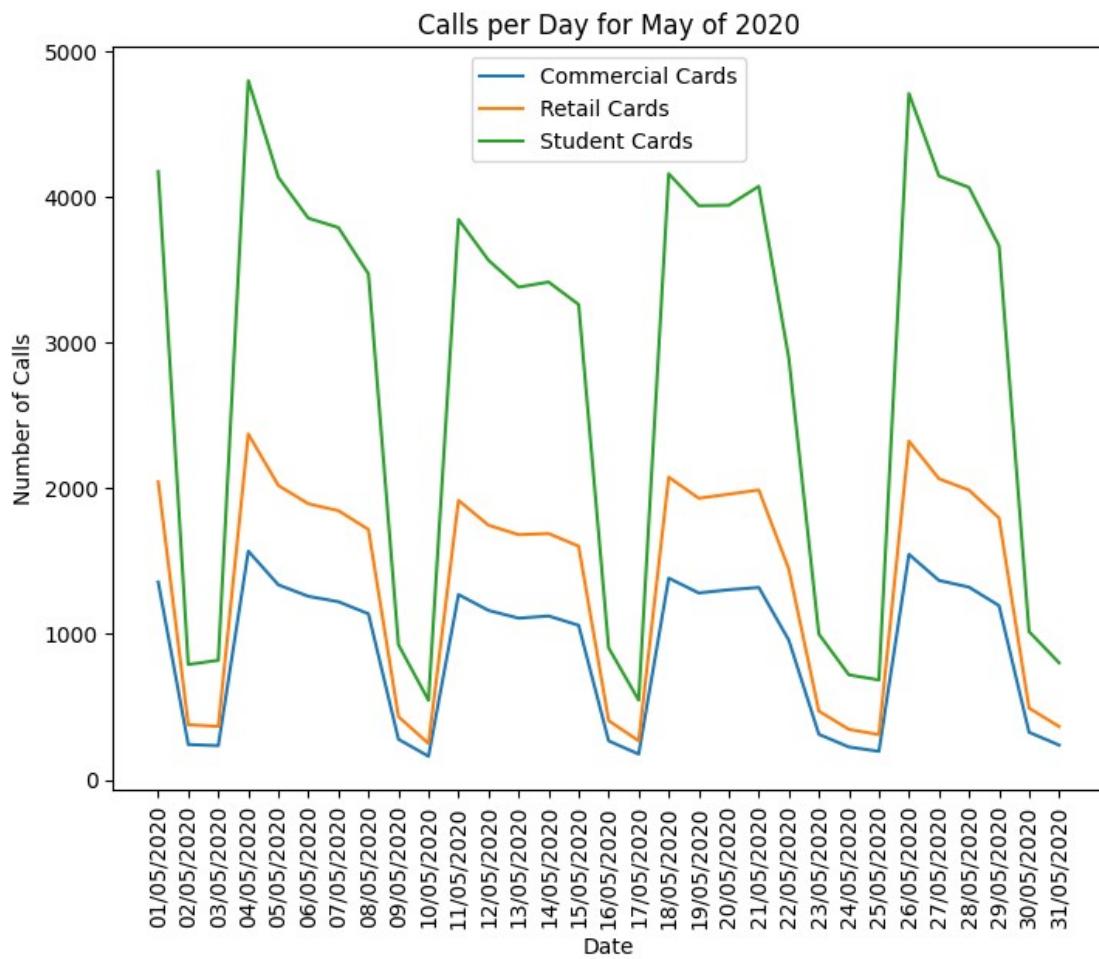


Calls per Day for March of 2020

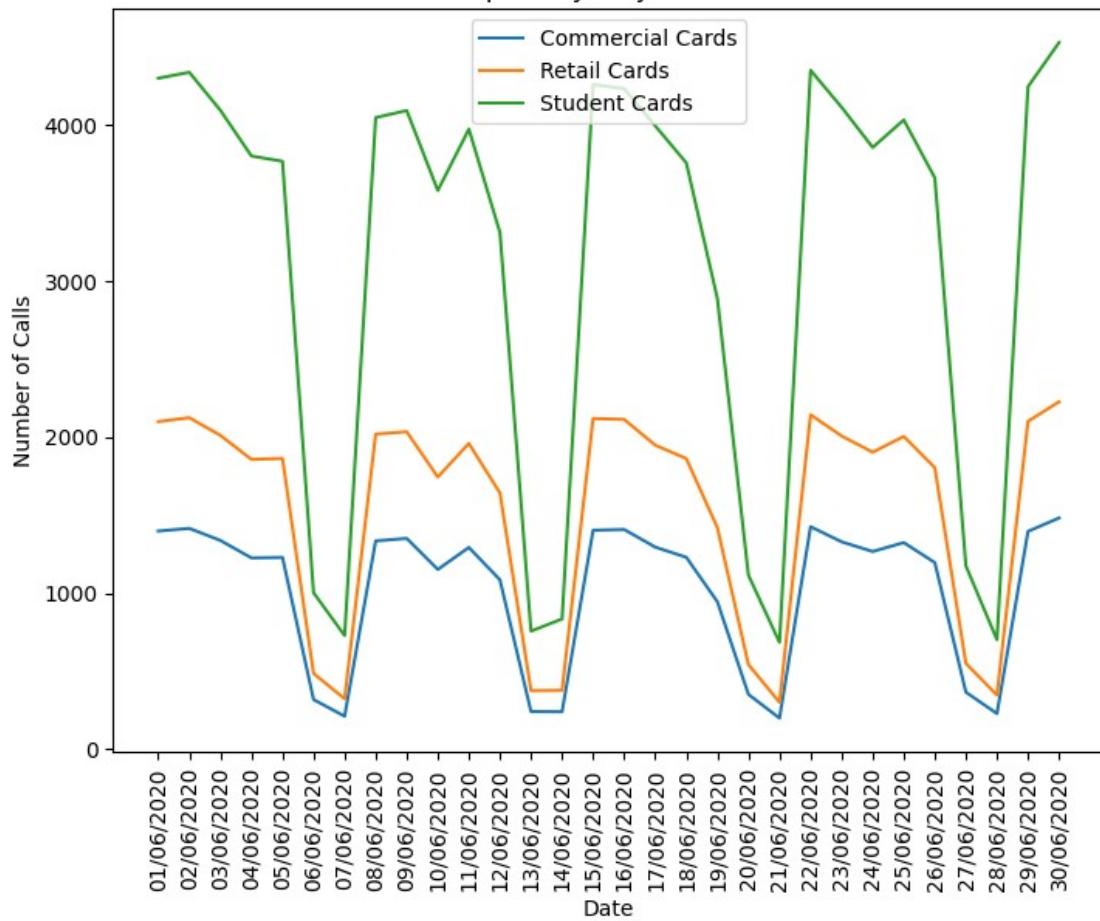


Calls per Day for April of 2020

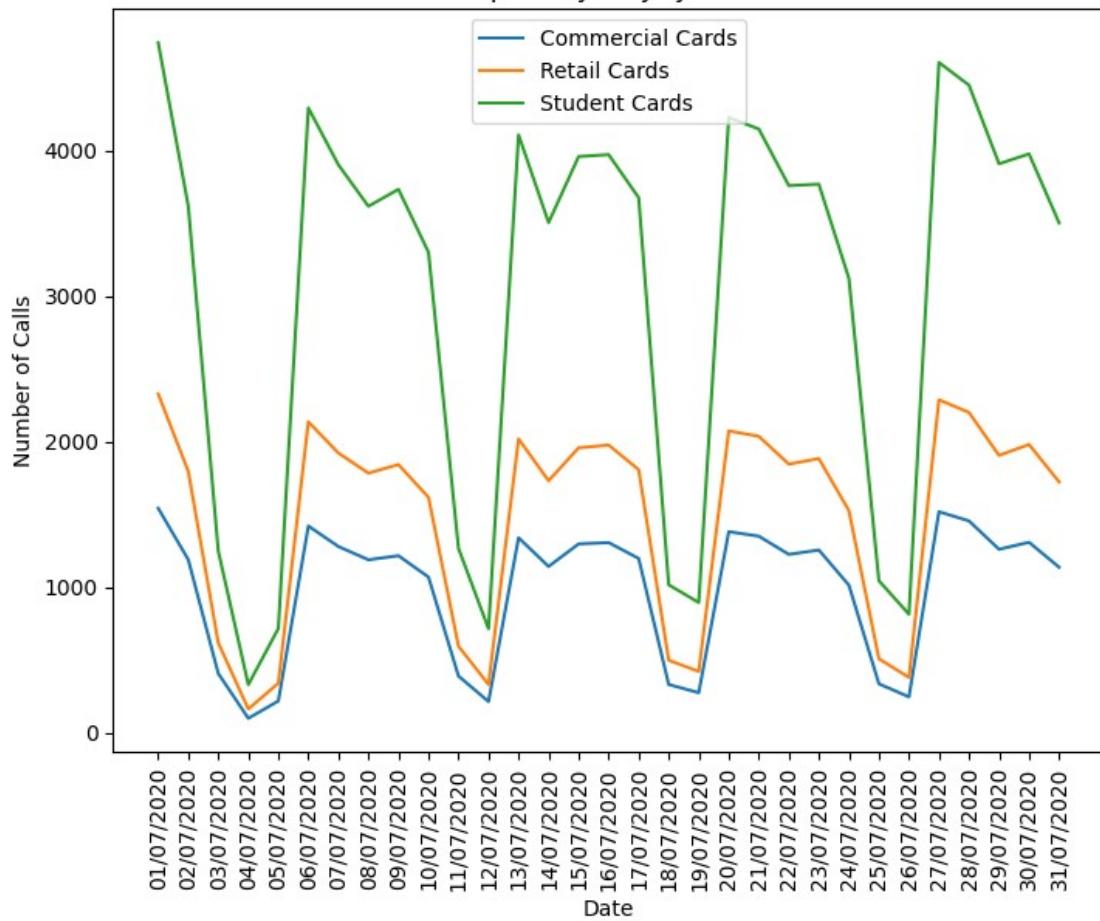




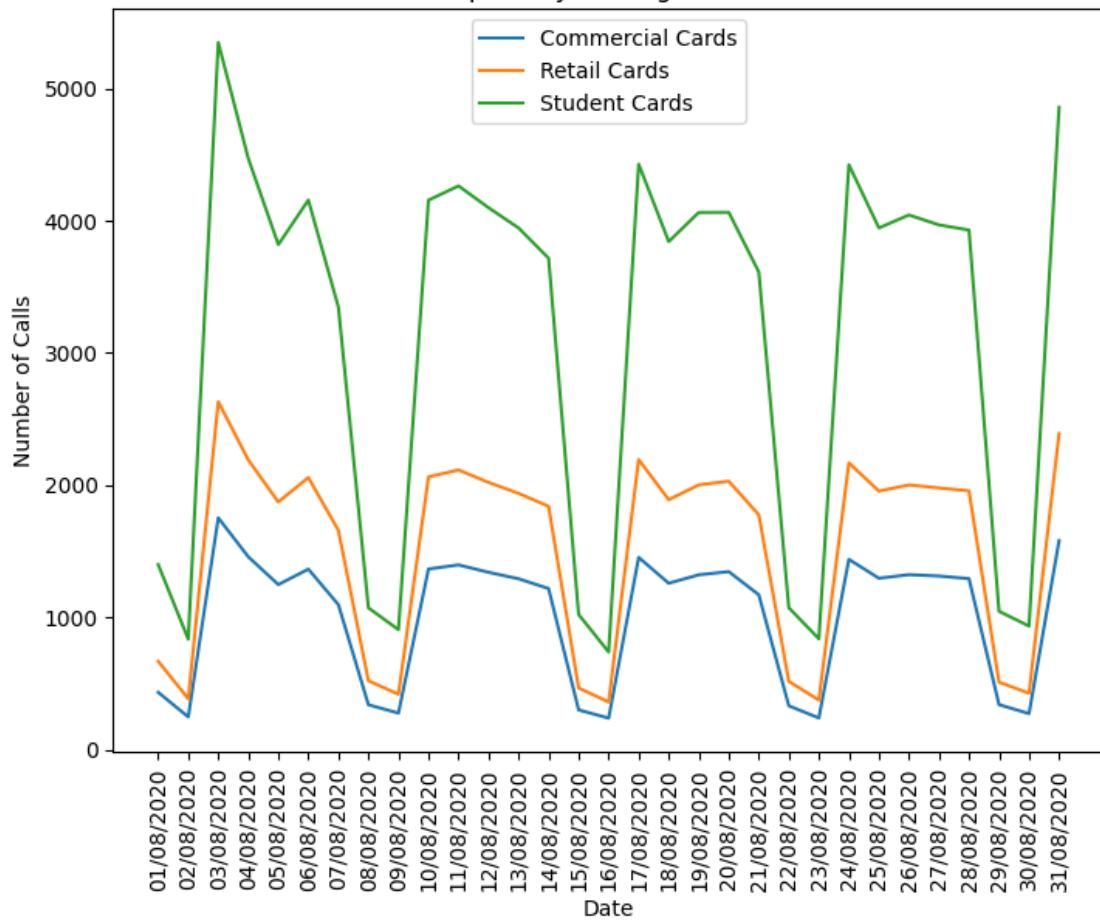
Calls per Day for June of 2020



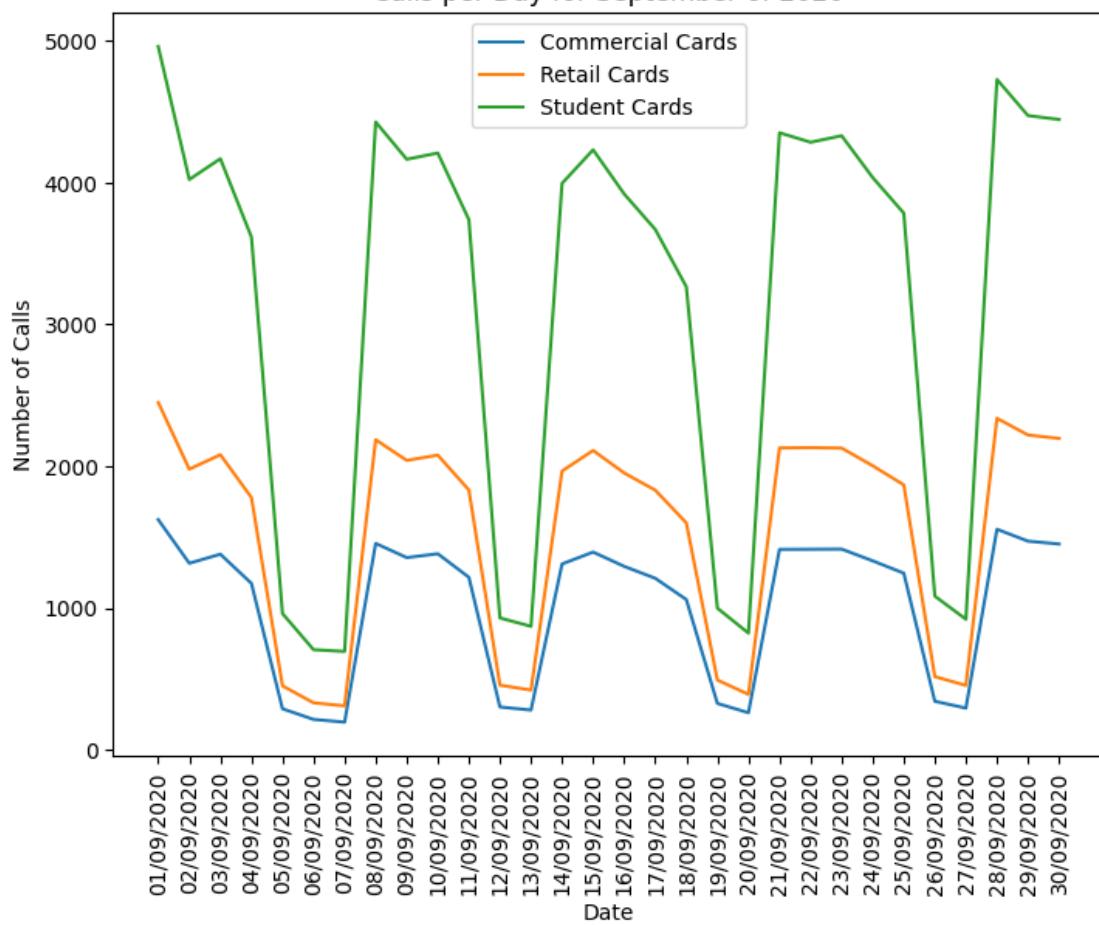
Calls per Day for July of 2020



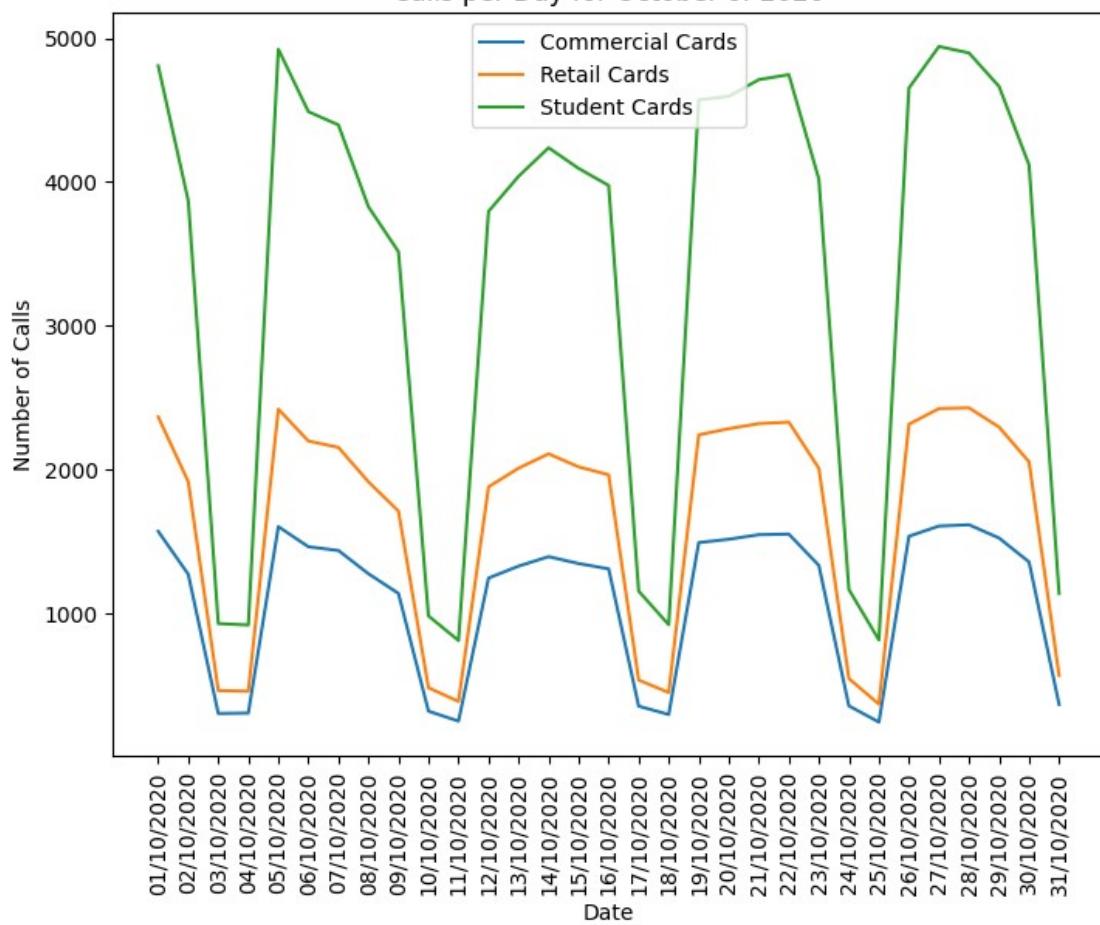
Calls per Day for August of 2020



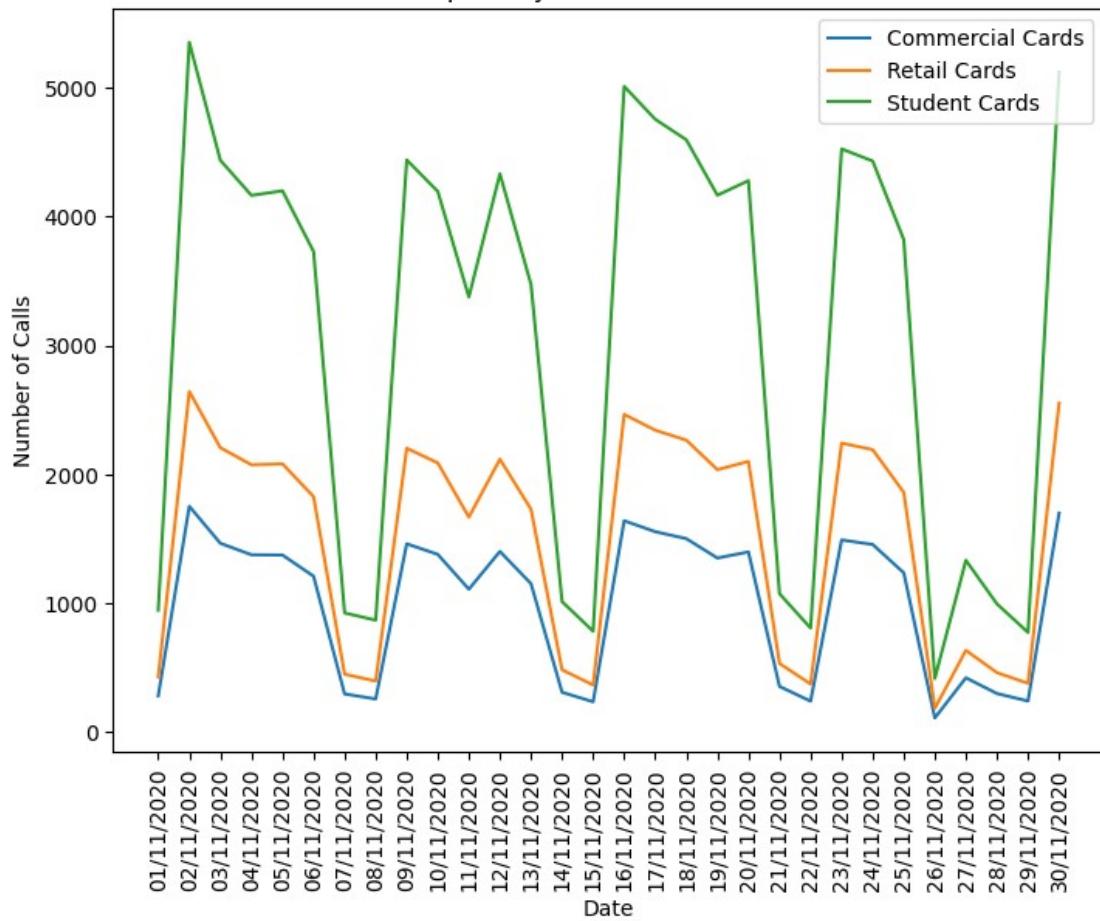
Calls per Day for September of 2020



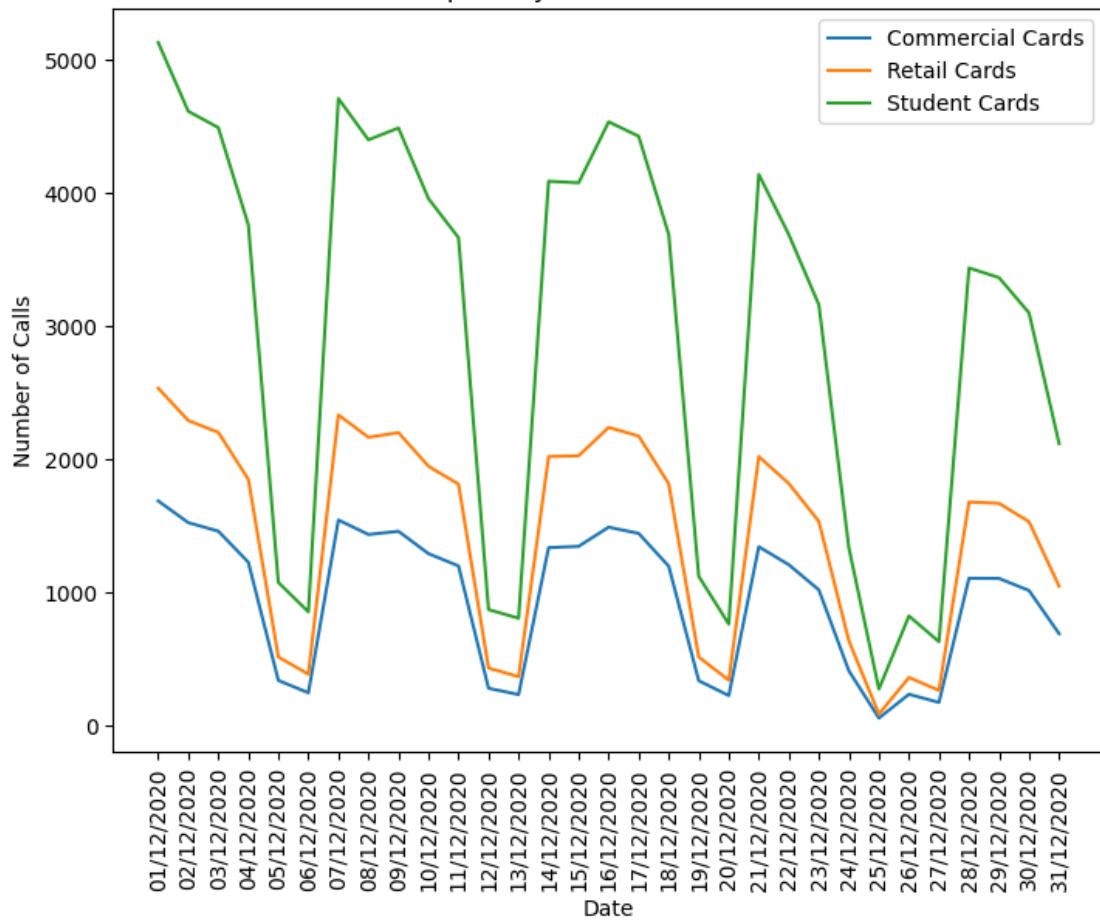
Calls per Day for October of 2020



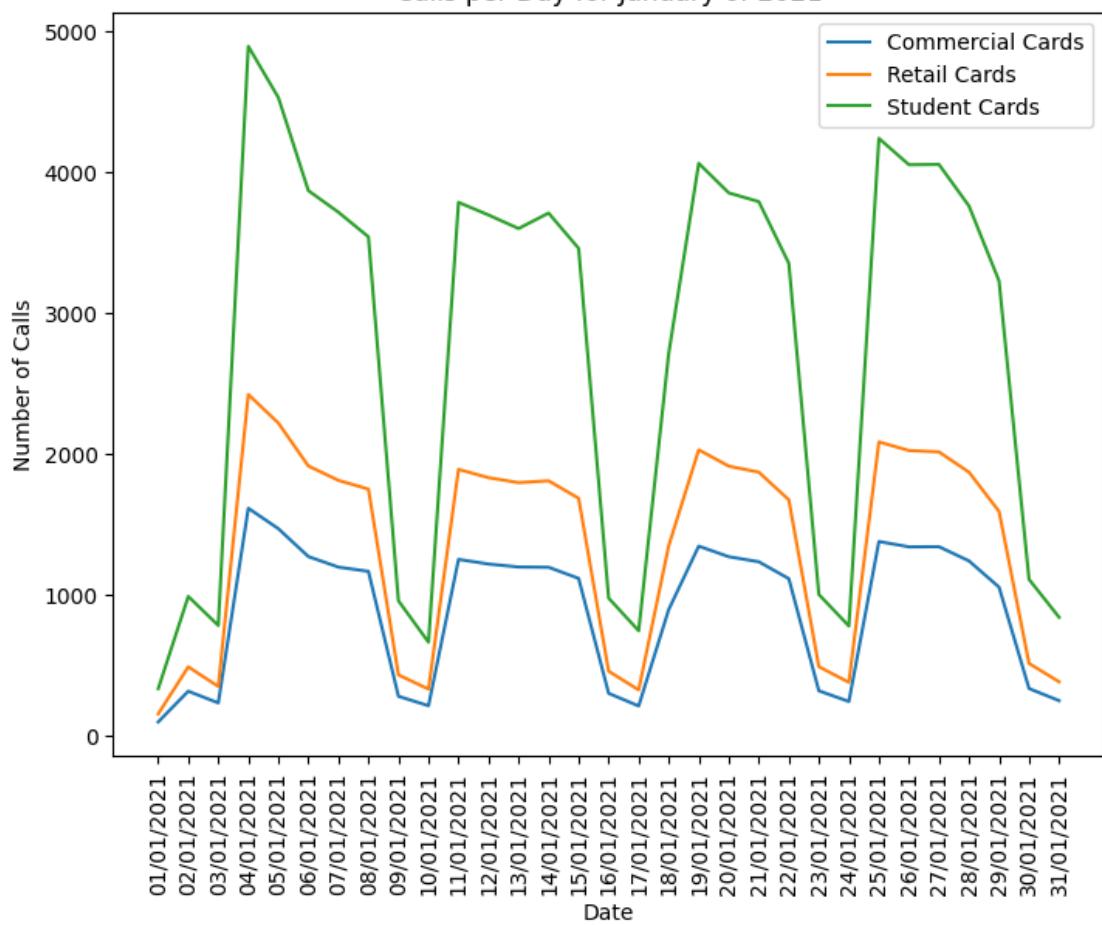
Calls per Day for November of 2020



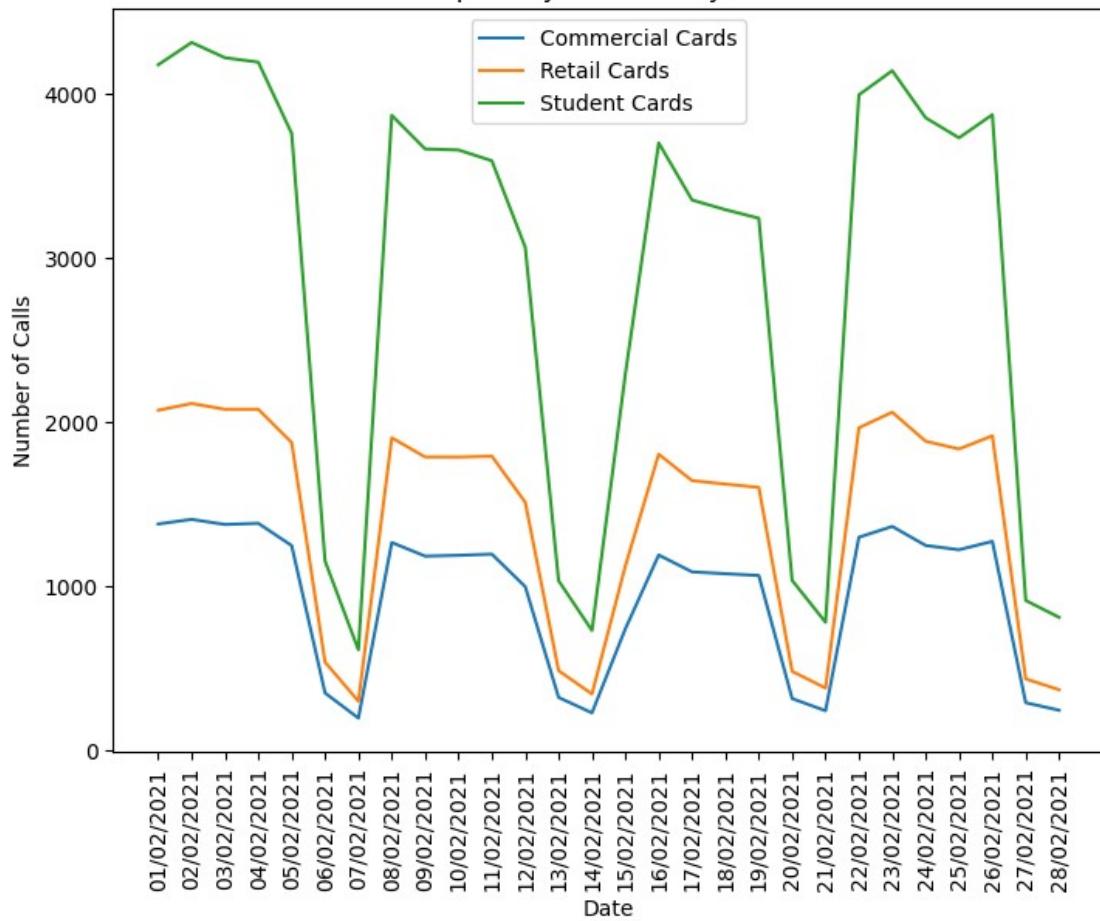
Calls per Day for December of 2020



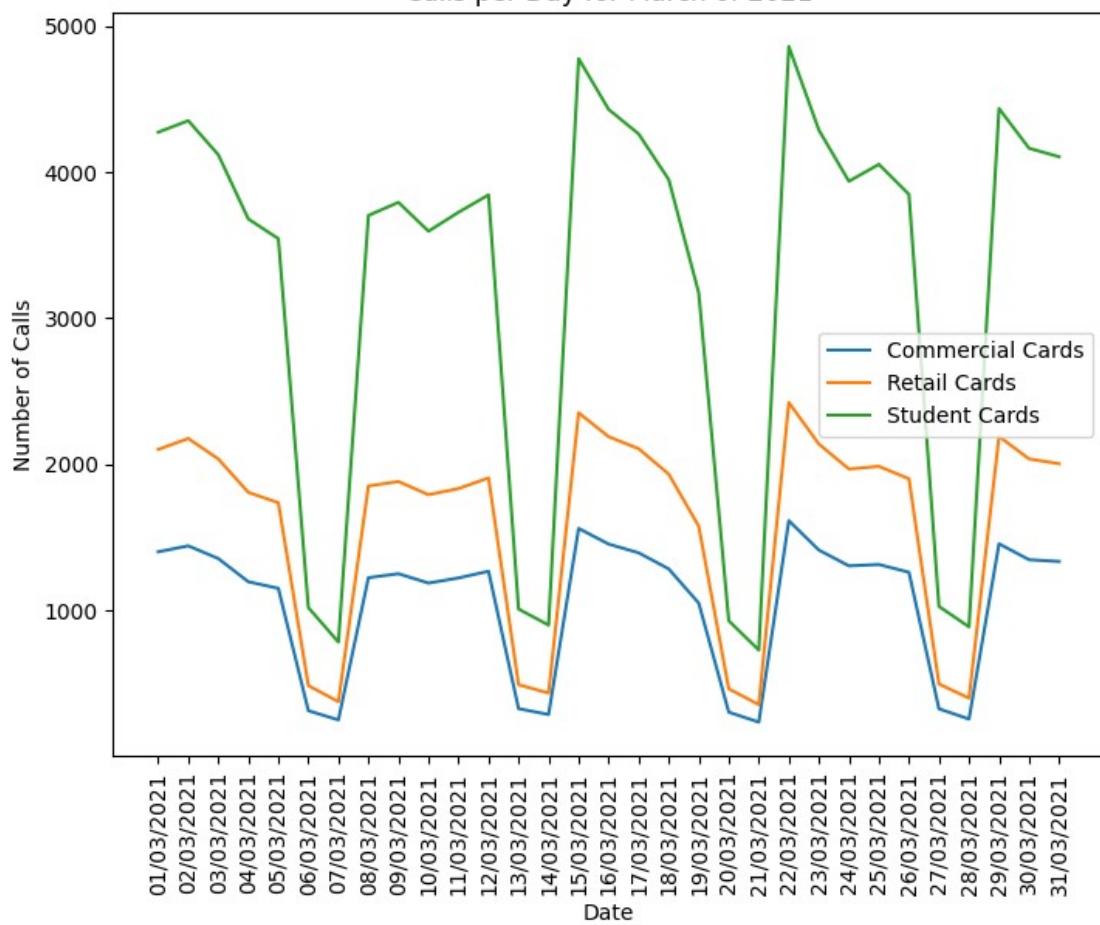
Calls per Day for January of 2021

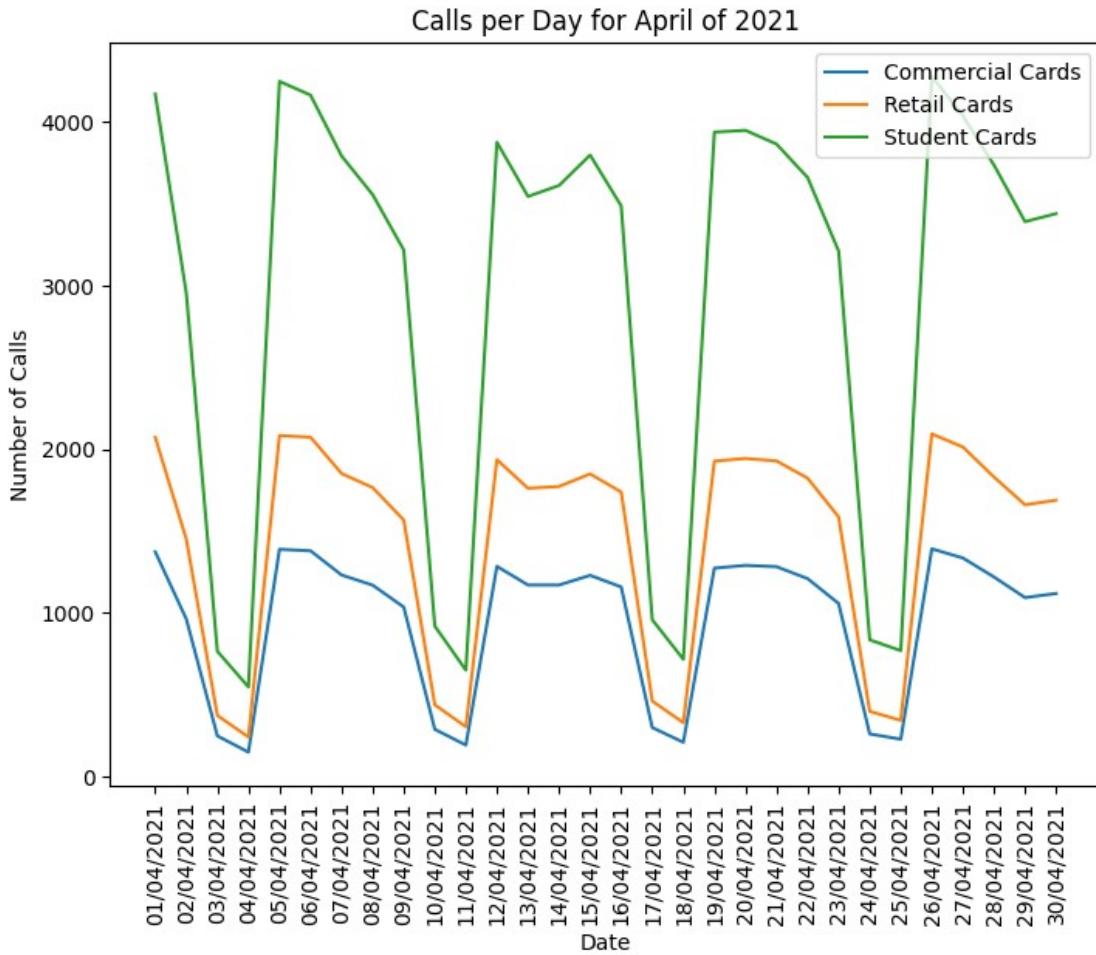


Calls per Day for February of 2021



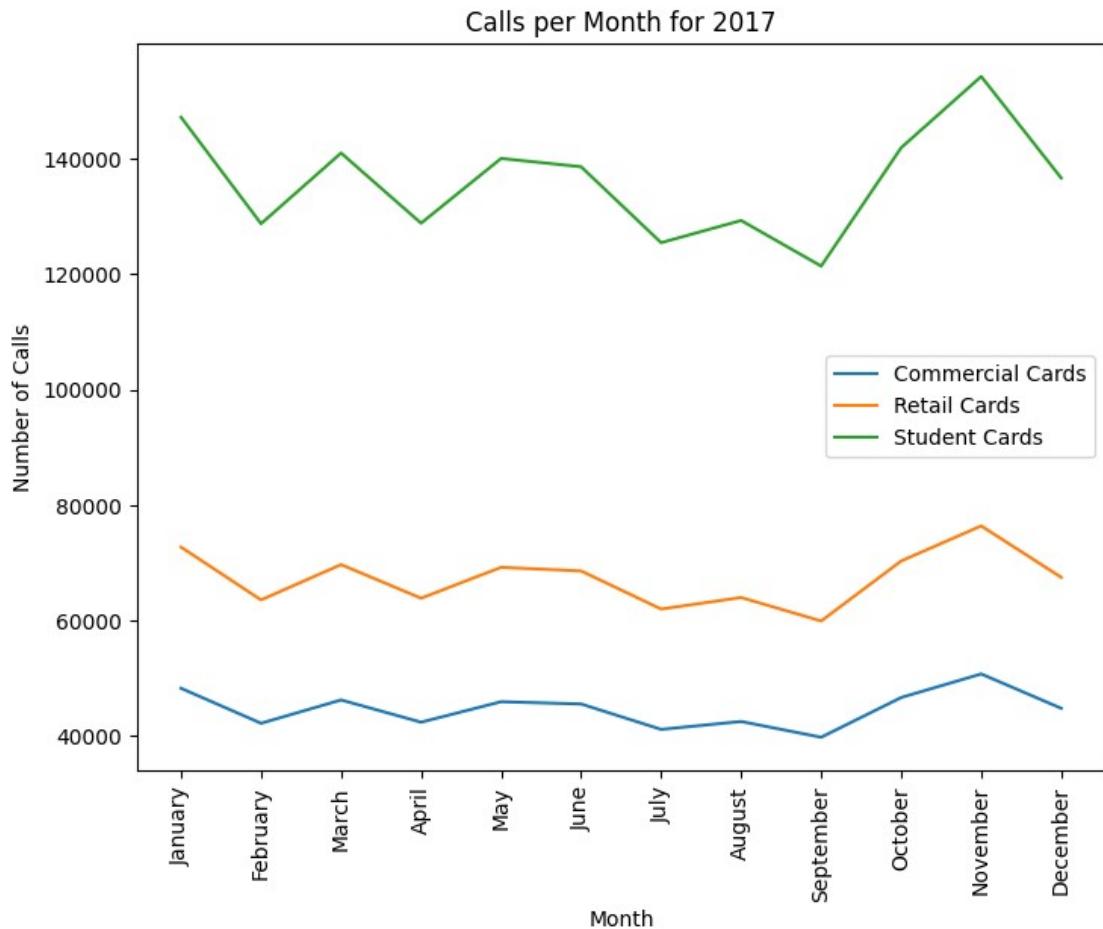
Calls per Day for March of 2021





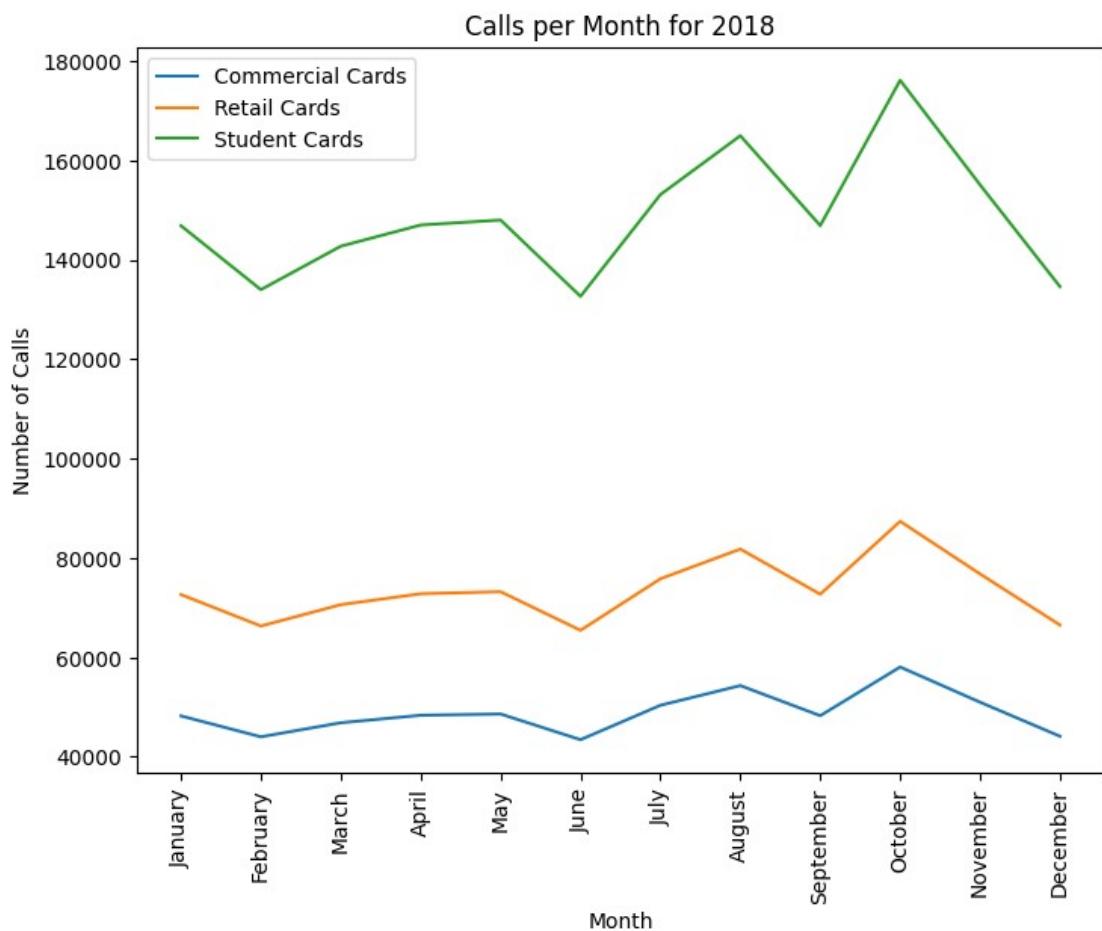
```
# Cumulative Montly Data
df_17_cumm = df_17[['cc', 'rc', 'sc', 'month']].groupby('month').sum()

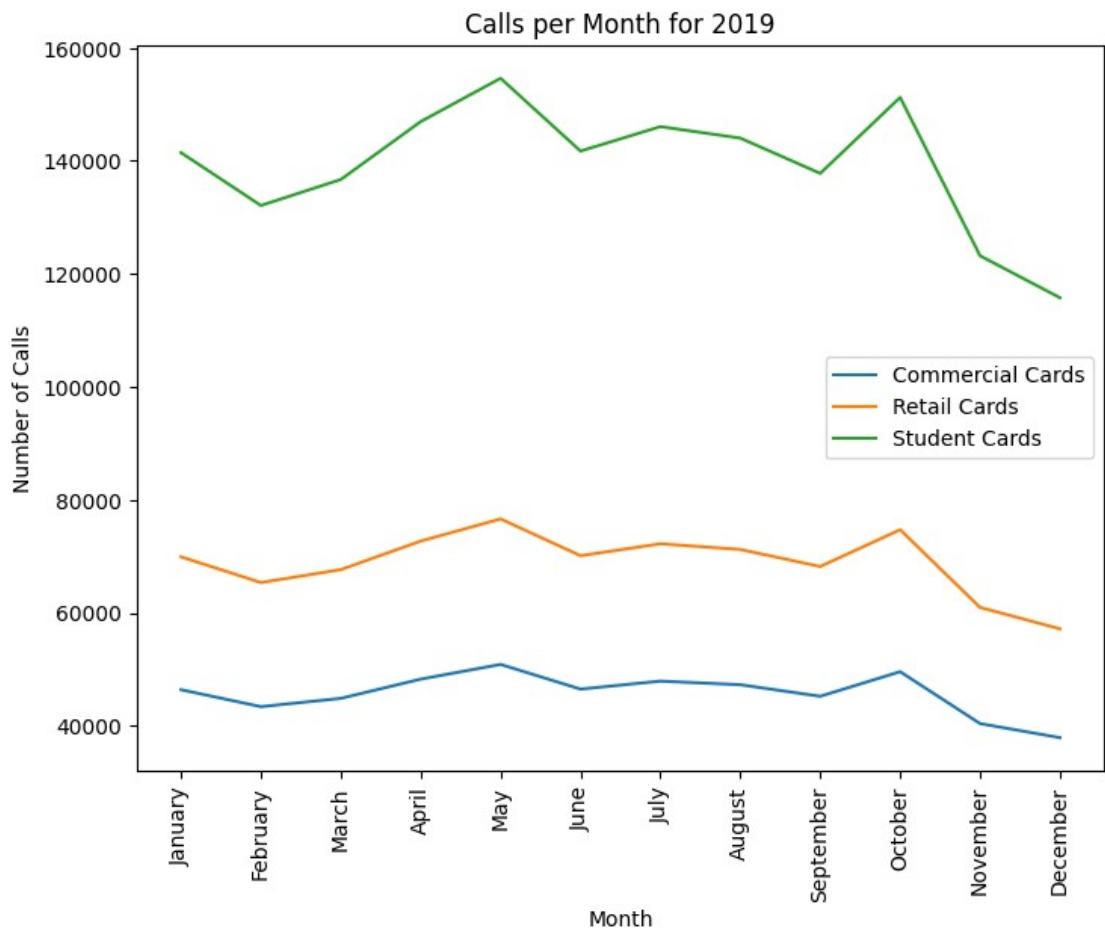
# Plot Cumulative Monthly Data for 2017
x = range(len(df_17_cumm))
cc_values = df_17_cumm.cc
rc_values = df_17_cumm.rc
sc_values = df_17_cumm.sc
fig = plt.figure()
ax = fig.add_axes([1,1,1,1])
ax.plot(x, cc_values, label='Commercial Cards')
ax.plot(x, rc_values, label='Retail Cards')
ax.plot(x, sc_values, label='Student Cards')
ax.set_xticks(x, [arrow.get(str(m), "M").format("MMMM") for m in df_17_cumm.index], rotation=90)
ax.set_xlabel("Month")
ax.set_ylabel("Number of Calls")
ax.set_title(f"Calls per Month for 2017")
ax.legend()
plt.show()
```

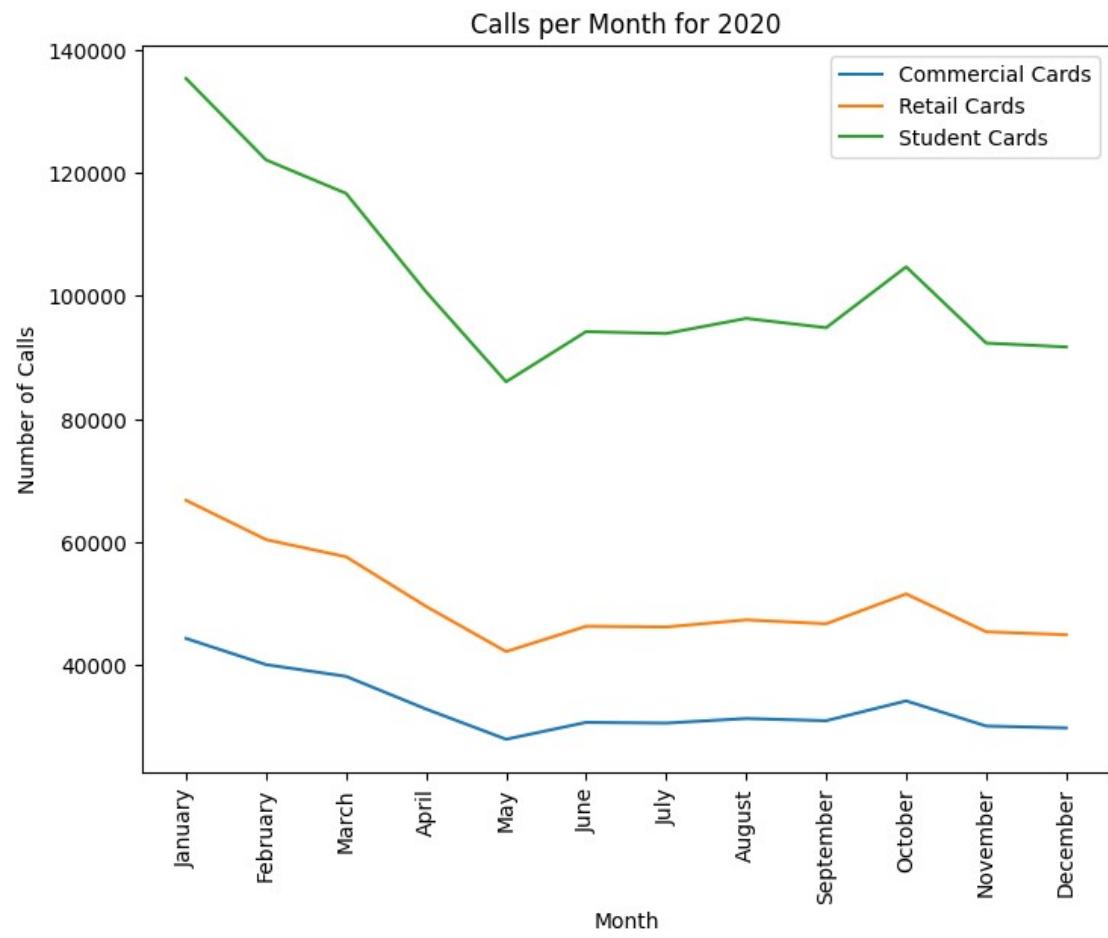


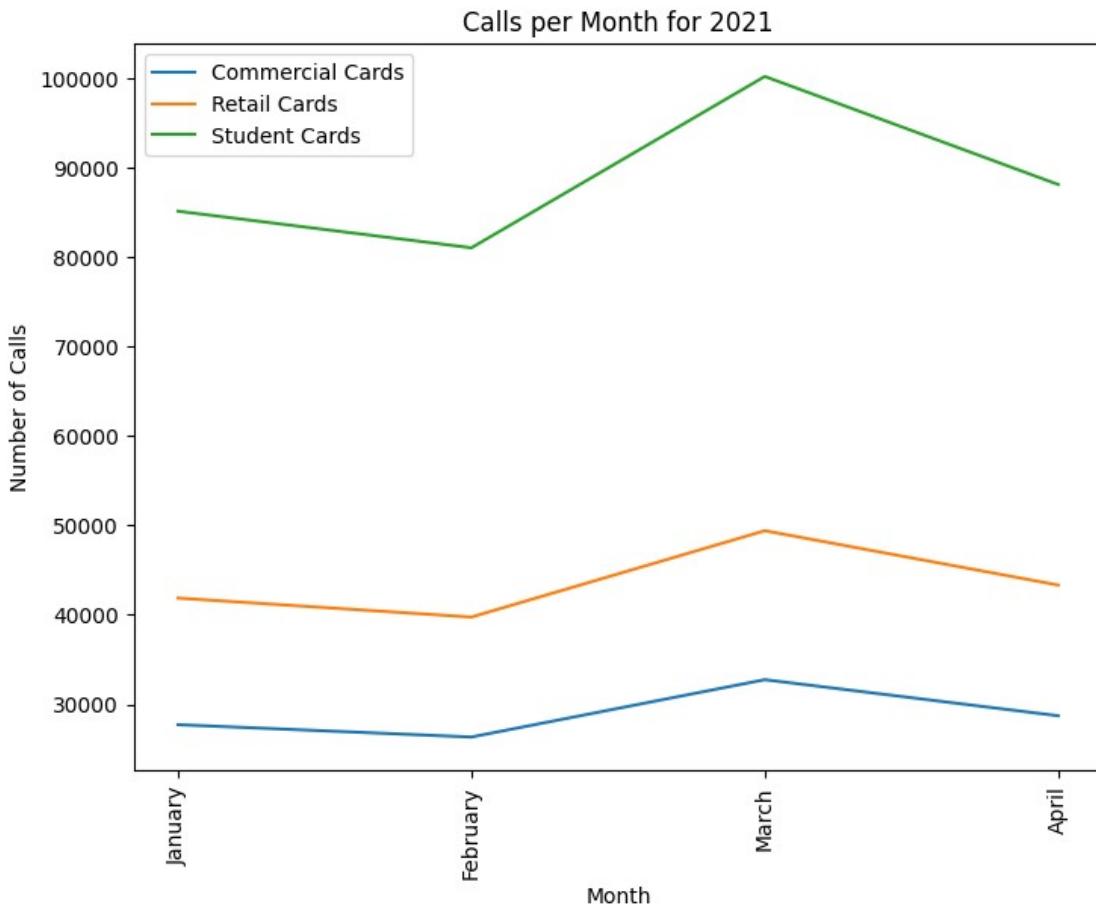
```
# Plot Cumulative Monthly Data for 2018-2021
years = df_not17_sorted.year.unique()
for y in years:
    df_not17_sorted_yearly = df_not17_sorted[df_not17_sorted.year == y]
    df_cumm = df_not17_sorted_yearly[['cc', 'rc', 'sc',
'month']].groupby('month').sum()
    x = range(len(df_cumm))
    cc_values = df_cumm.cc
    rc_values = df_cumm.rc
    sc_values = df_cumm.sc
    fig = plt.figure()
    ax = fig.add_axes([1,1,1,1])
    ax.plot(x, cc_values, label='Commercial Cards')
    ax.plot(x, rc_values, label='Retail Cards')
    ax.plot(x, sc_values, label='Student Cards')
    ax.set_xticks(x, [arrow.get(str(m), "M").format("MMMM") for m in
df_cumm.index], rotation=90)
    ax.set_xlabel("Month")
    ax.set_ylabel("Number of Calls")
    ax.set_title(f"Calls per Month for {y}")
```

```
ax.legend()  
plt.show()
```









```

# Add US Federal Holidays
cal = USFederalHolidayCalendar()
holidays_series = cal.holidays(start='2017-01-01', end='2021-04-30',
return_name=True)
holidays = holidays_series.to_frame("name")
holidays.reset_index(inplace=True)
holidays.rename(columns={"index": "date"}, inplace=True)

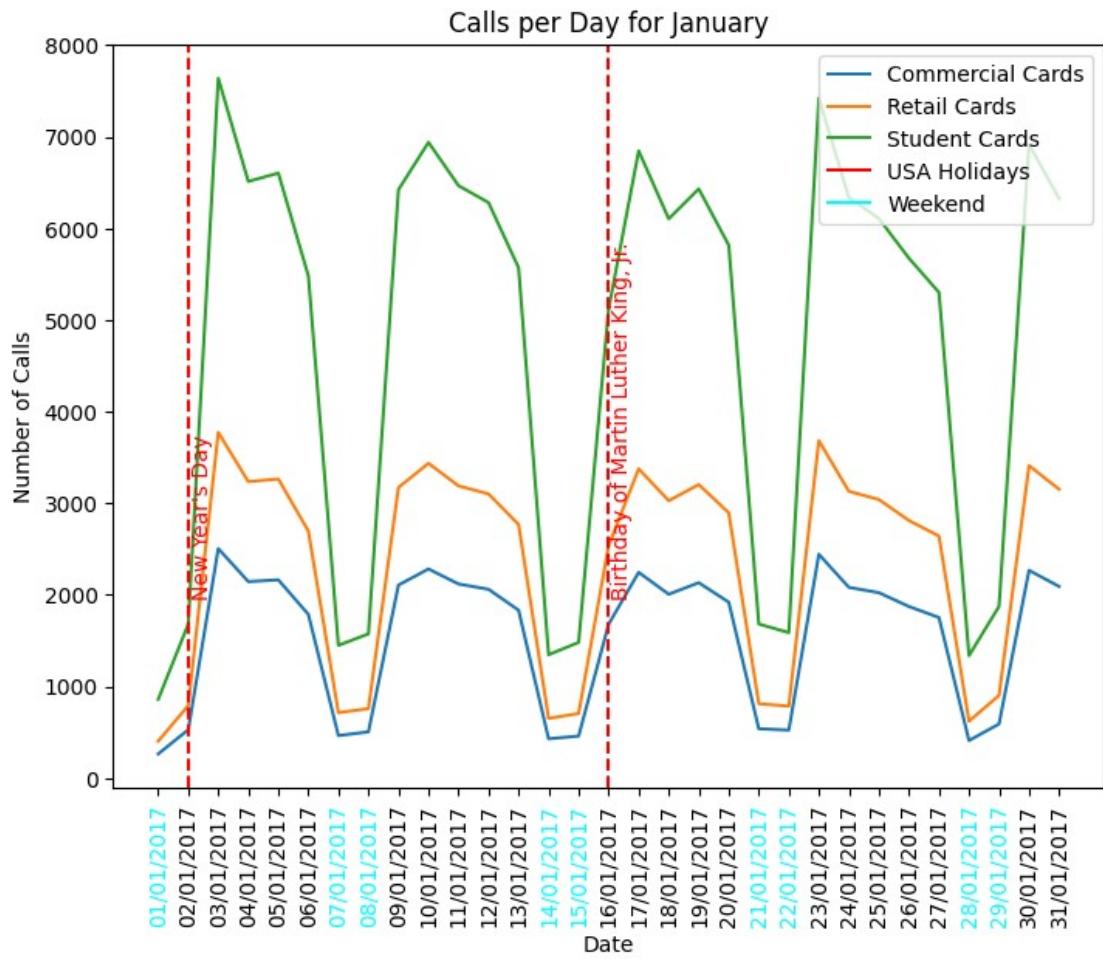
# 2017 data for each month
# Low number of calls on weekends
# Low number of calls on Big Holidays
holidays_2017 = holidays[[True if dt.year == 2017 else False for dt in
holidays.date]]
months = df_17.month.unique()
for m in months:
    x = range((df_17.month == m).sum())
    cc_values = df_17[df_17.month == m].cc
    rc_values = df_17[df_17.month == m].rc
    sc_values = df_17[df_17.month == m].sc
    month_holidays = holidays_2017[[True if dt.month == m else False
for dt in holidays_2017.date]]
    monhol_values = [(dt.date.day-1, dt['name']) for i, dt in
month_holidays.iterrows()]
    for i in range(x):
        cc_values[i] = monhol_values[i][0]
        rc_values[i] = monhol_values[i][1]
        sc_values[i] = monhol_values[i][1]
df_17['cc'] = cc_values
df_17['rc'] = rc_values
df_17['sc'] = sc_values

```

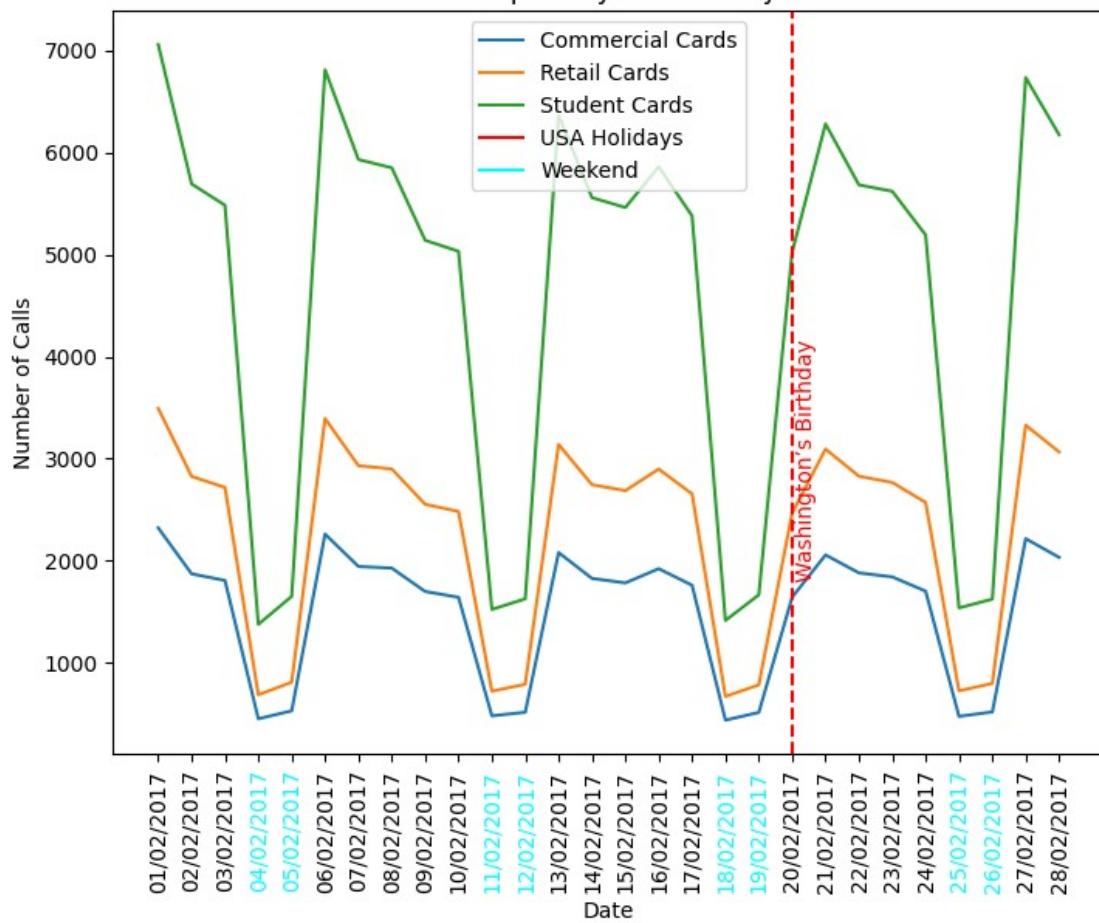
```

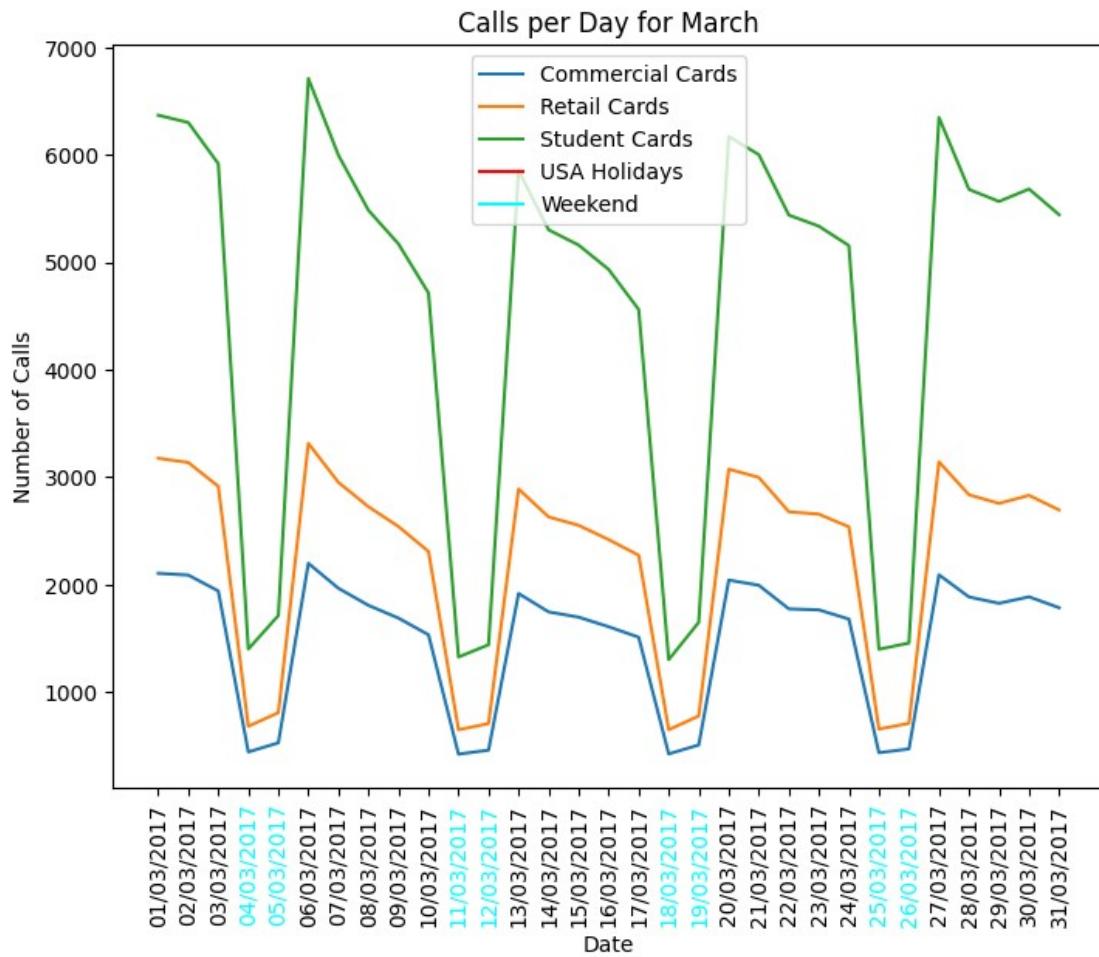
month_holidays.iterrows()):
    fig = plt.figure()
    ax = fig.add_axes([1,1,1,1])
    ax.plot(x, cc_values, label='Commercial Cards')
    ax.plot(x, rc_values, label='Retail Cards')
    ax.plot(x, sc_values, label='Student Cards')
    ax.plot([], [], label='USA Holidays', c='red')
    ax.plot([], [], label='Weekend', c='cyan')
    for mhd, mhn in monhol_values:
        if mhn == 'Thanksgiving Day':
            ax.axvline(mhd+1, c='red', ls='--')
            ax.text(mhd+1.1, ax.get_ylim()[1]//4, "Black Friday",
rotation=90, c='red')
        if mhn == 'Christmas Day':
            ax.axvline(mhd-1, c='red', ls='--')
            ax.text(mhd-0.9, ax.get_ylim()[1]//4, "Christman Eve",
rotation=90, c='red')
            ax.axvline(mhd, c='red', ls='--')
            ax.text(mhd+0.1, ax.get_ylim()[1]//4, mhn, rotation=90,
c='red')
        ax.set_xticks(x, df_17[df_17.month == m].date, rotation=90)
        for i, dt in enumerate(df_17[df_17.month == m].date):
            if arrow.get(dt, "DD/MM/YYYY").format("ddd") in ["Sat",
"Sun"]:
                ax.get_xticklabels()[i].set_color('cyan')
    ax.set_xlabel("Date")
    ax.set_ylabel("Number of Calls")
    ax.set_title(f"Calls per Day for {arrow.get(str(m),
'M').format('MMMM')}"))
    ax.legend()
    plt.show()

```

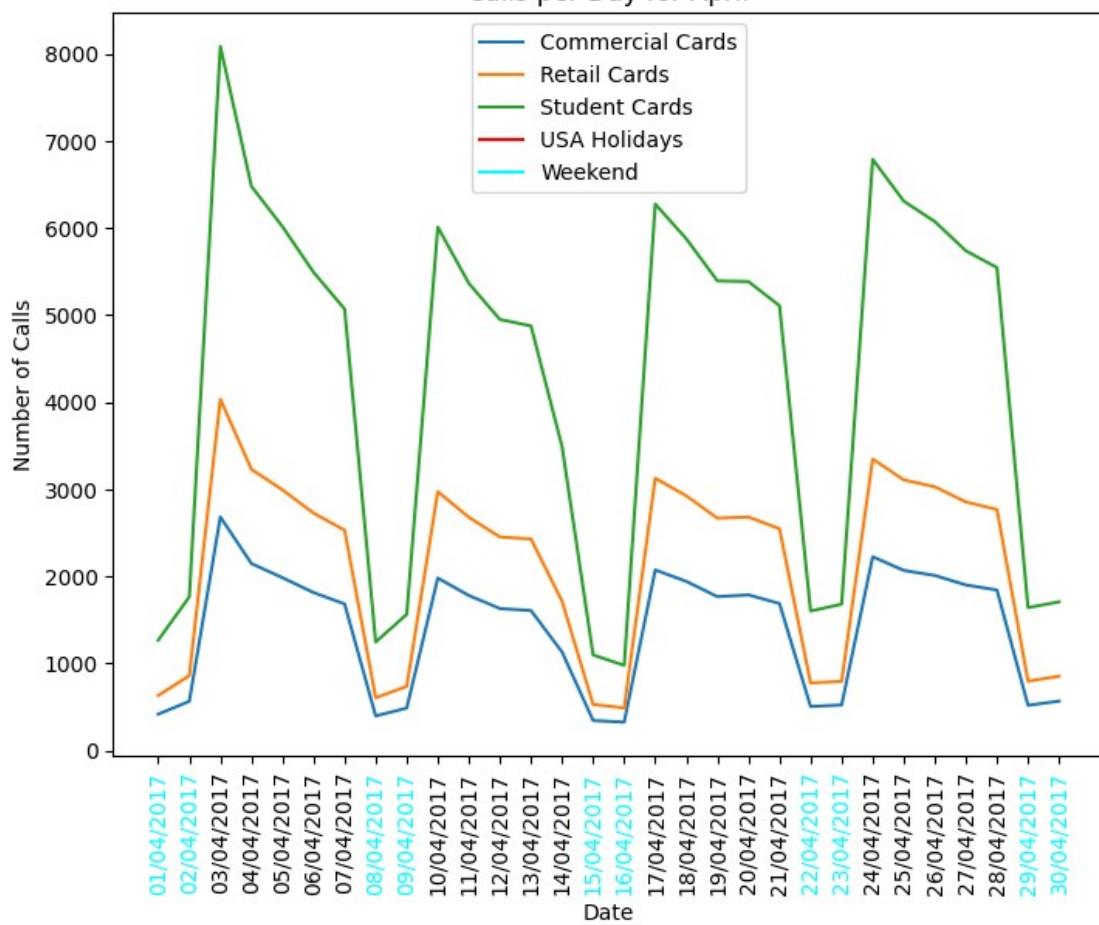


Calls per Day for February

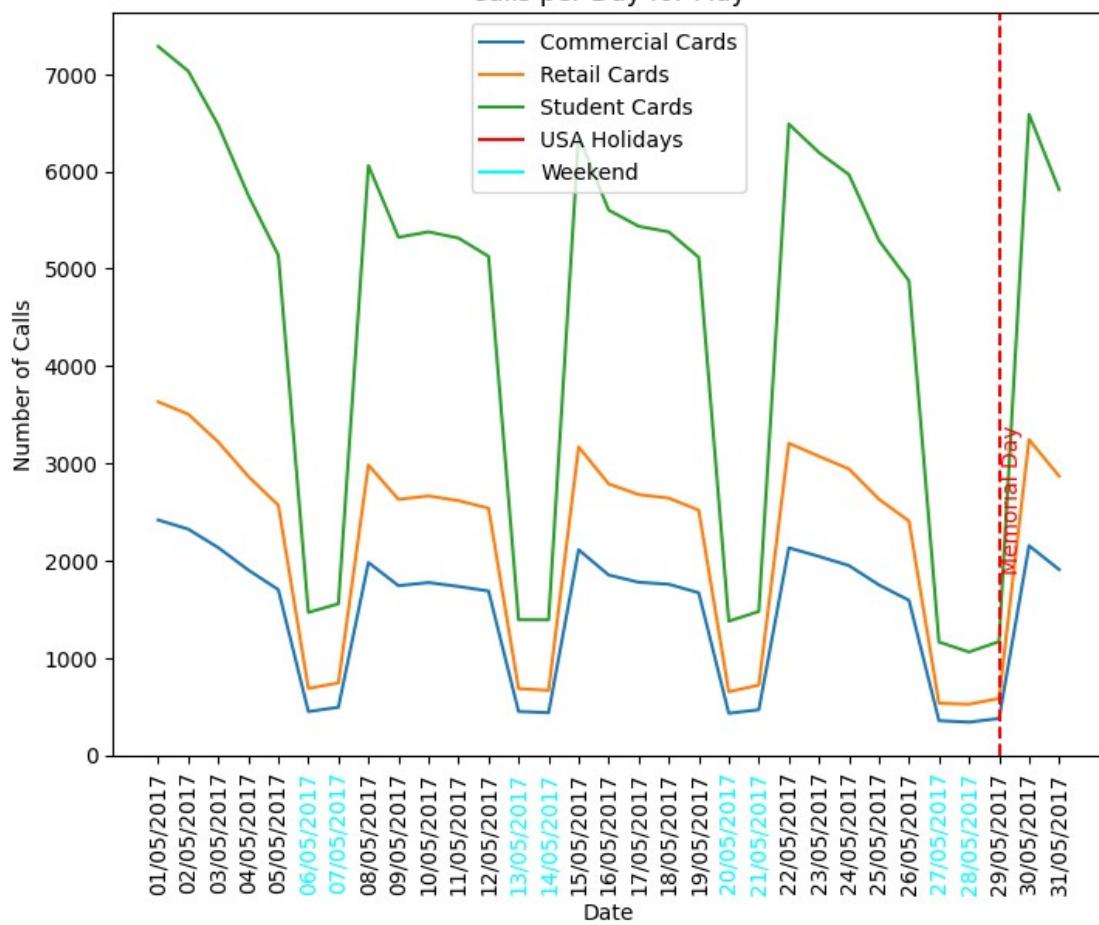


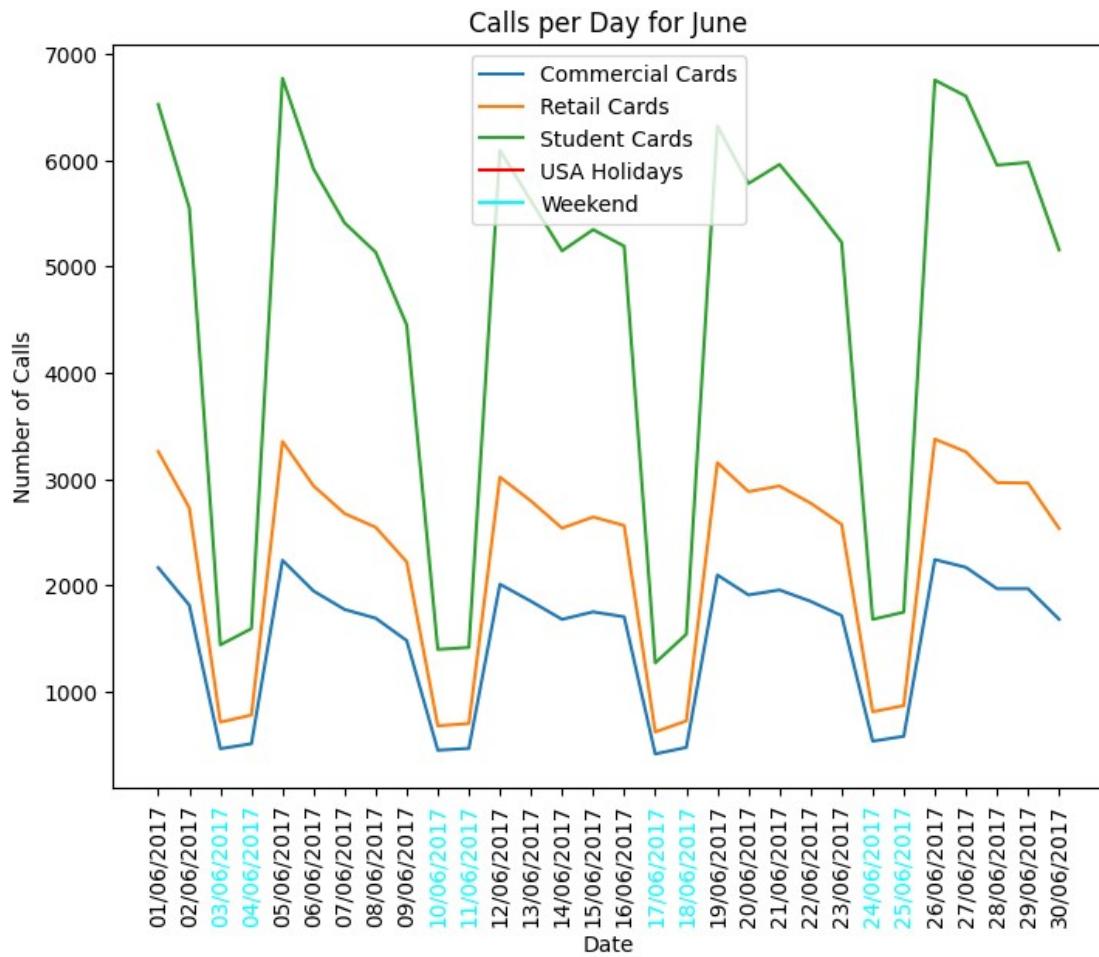


Calls per Day for April

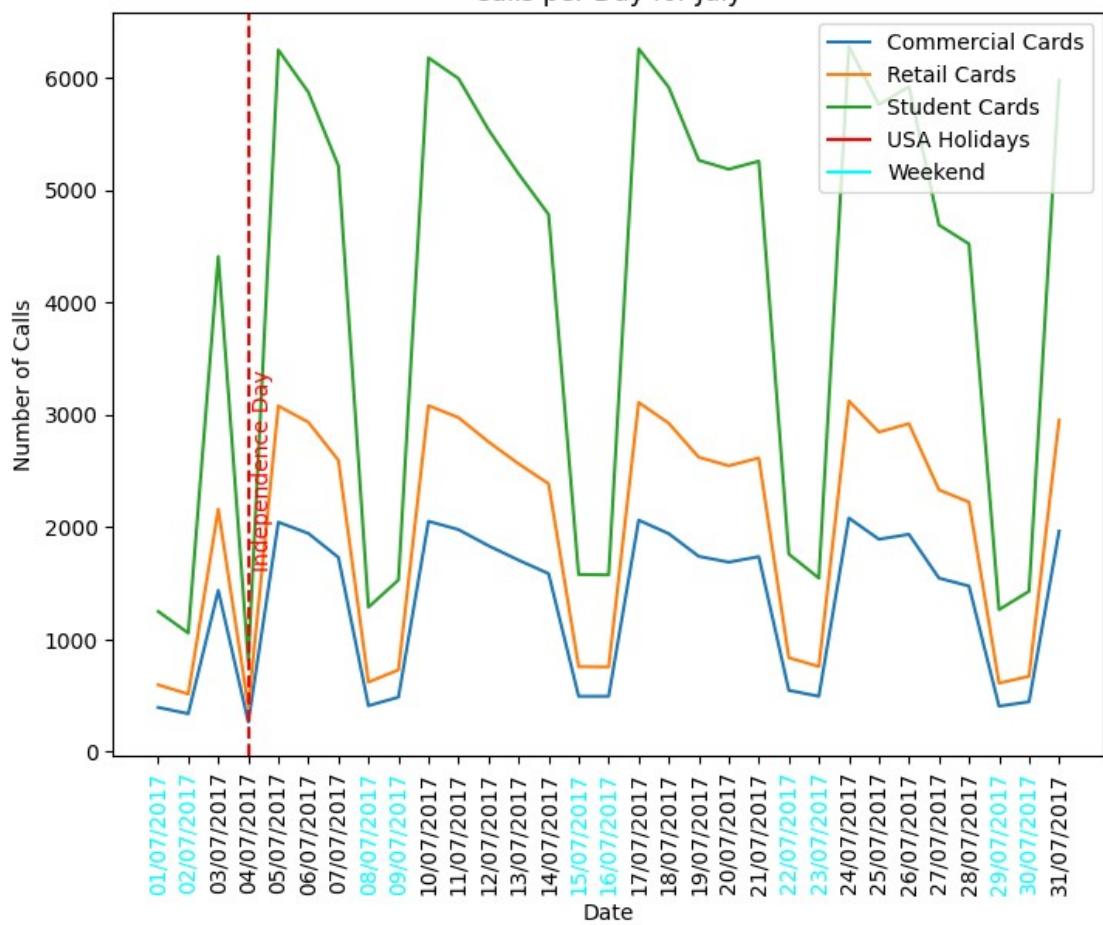


Calls per Day for May

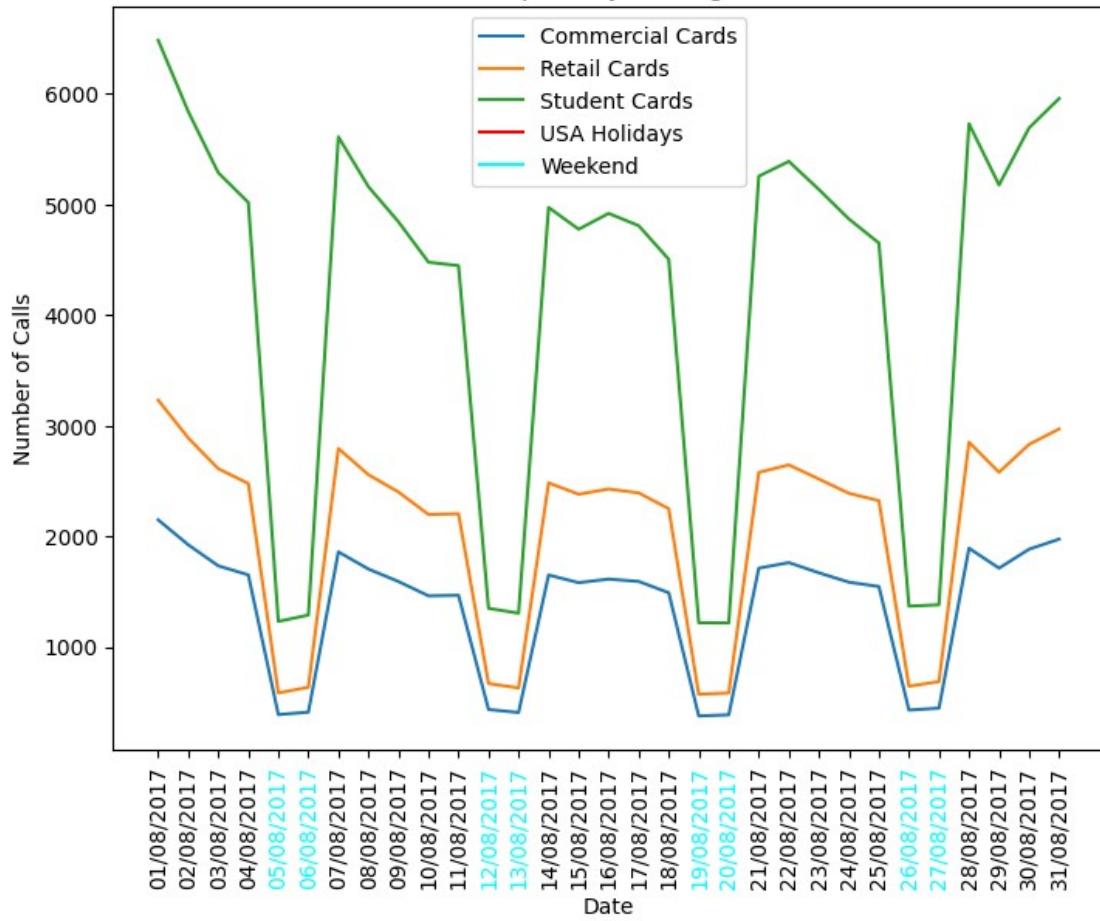




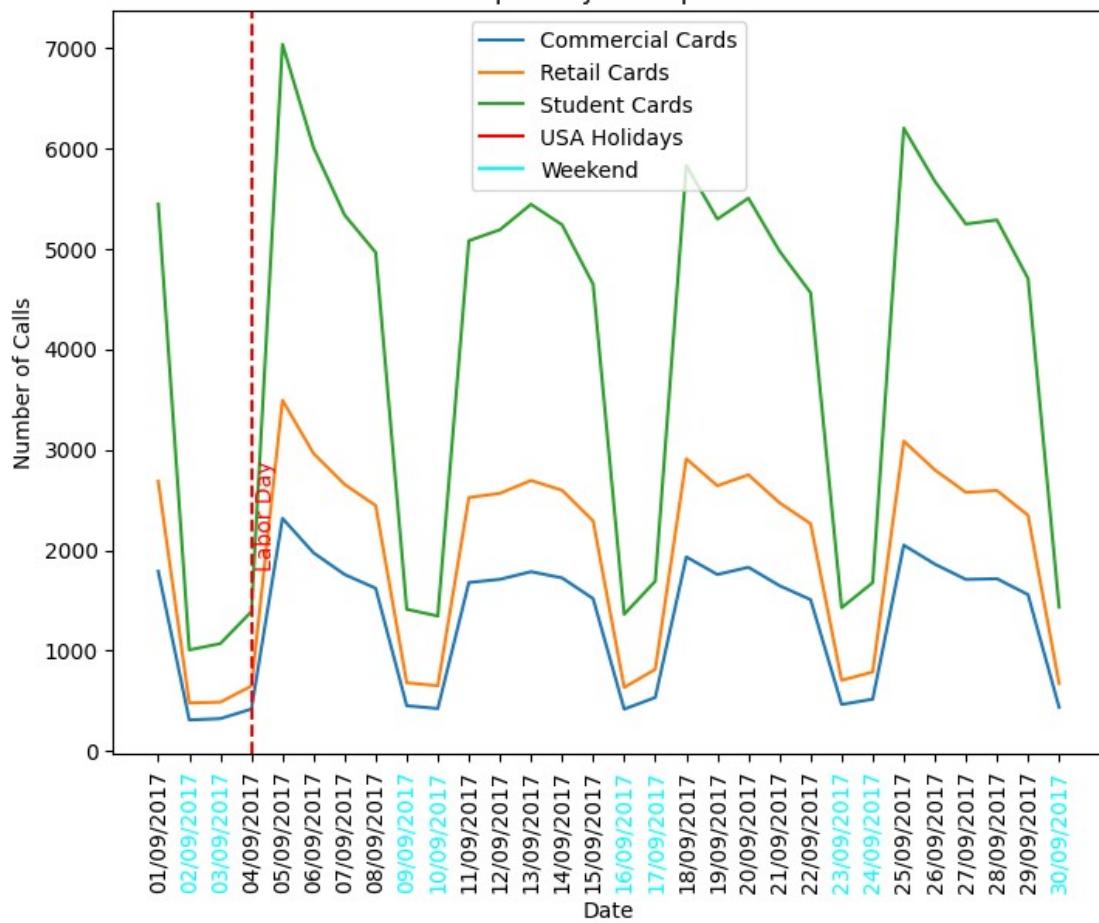
Calls per Day for July



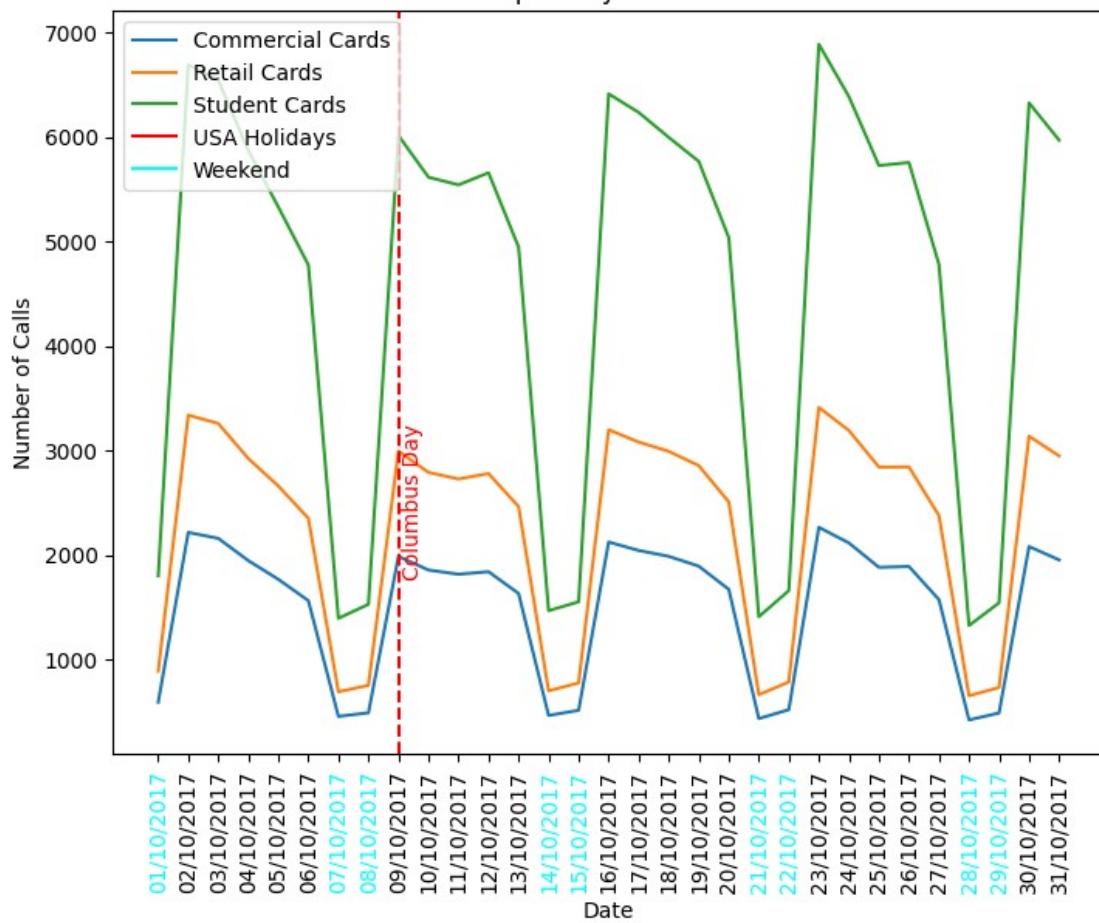
Calls per Day for August



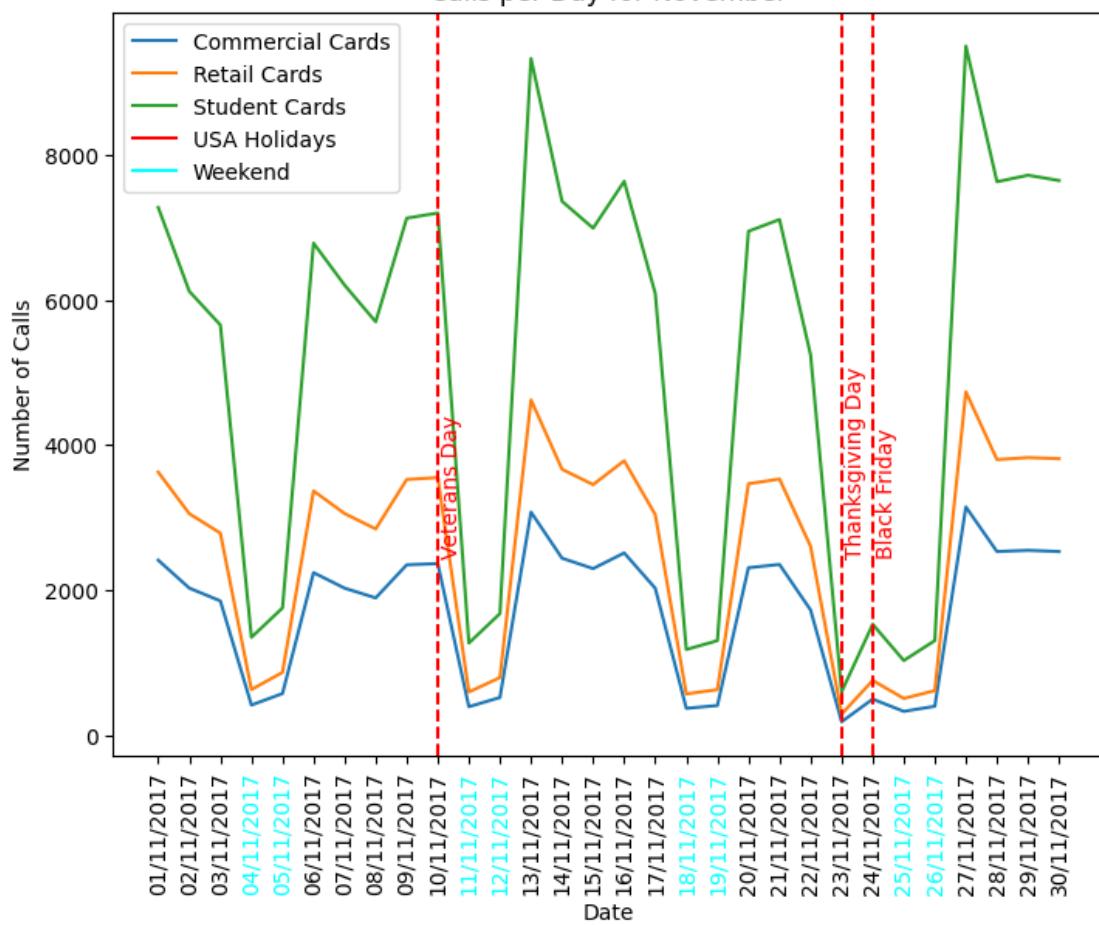
Calls per Day for September

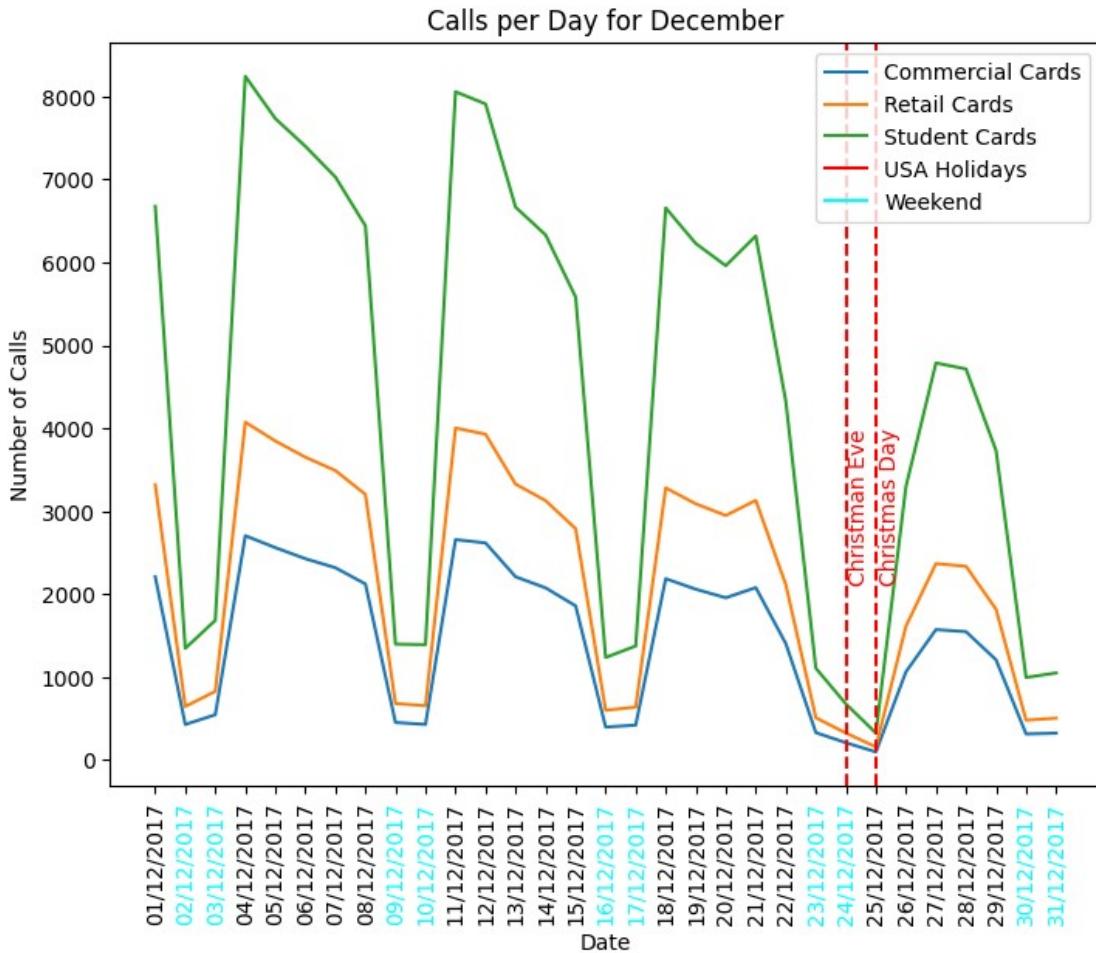


Calls per Day for October



Calls per Day for November





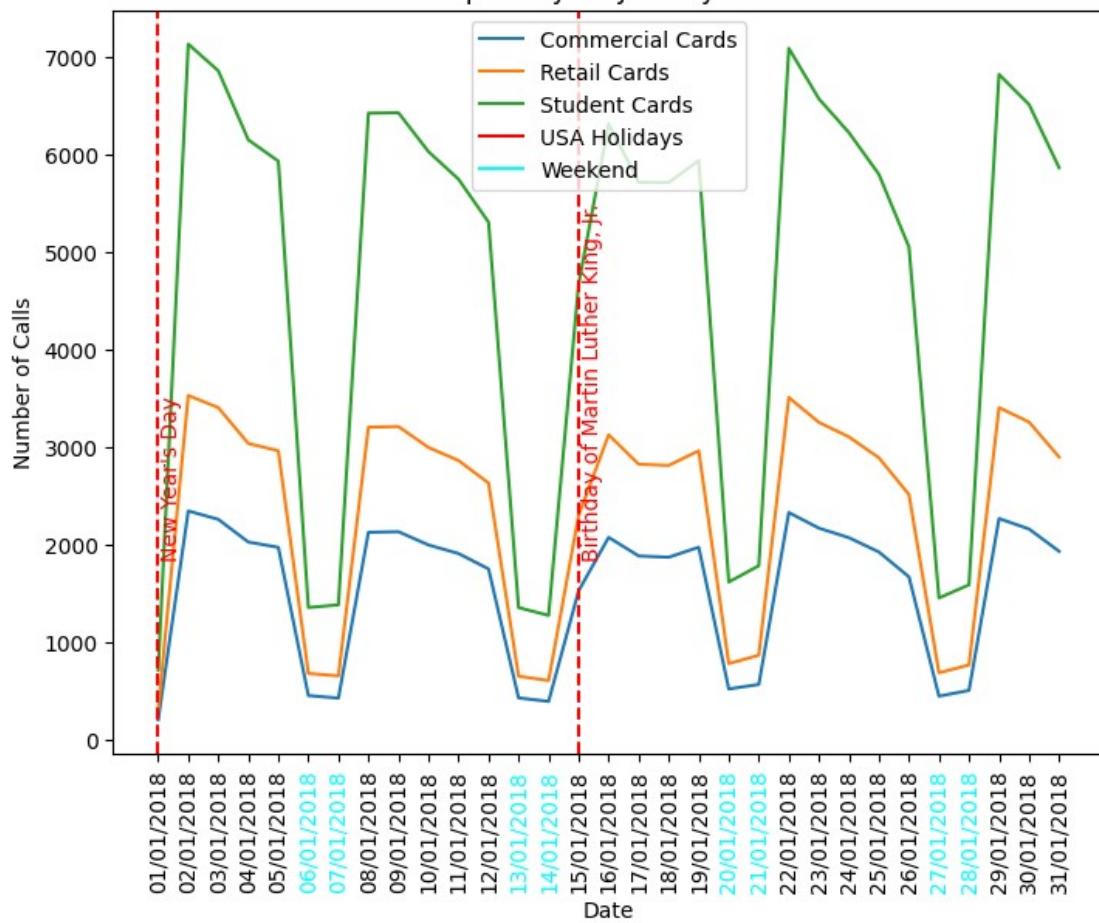
```
# 2018-2021 data for each month
# Low number of calls on weekends
# Low number of calls on Big Holidays
years = df_not17_sorted.year.unique()
for y in years:
    holidays_yearly = holidays[[True if dt.year == y else False for dt
in holidays.date]]
    df_not17_sorted_yearly = df_not17_sorted[df_not17_sorted.year ==
y]
    months = df_not17_sorted_yearly.month.unique()
    for m in months:
        x = range((df_not17_sorted_yearly.month == m).sum())
        cc_values =
df_not17_sorted_yearly[df_not17_sorted_yearly.month == m].cc
        rc_values =
df_not17_sorted_yearly[df_not17_sorted_yearly.month == m].rc
        sc_values =
df_not17_sorted_yearly[df_not17_sorted_yearly.month == m].sc
        month_holidays = holidays_yearly[[True if dt.month == m else
False for dt in holidays_yearly.date]]
        monhol_values = [(dt.date.day-1, dt['name']) for i, dt in
month_holidays]
```

```

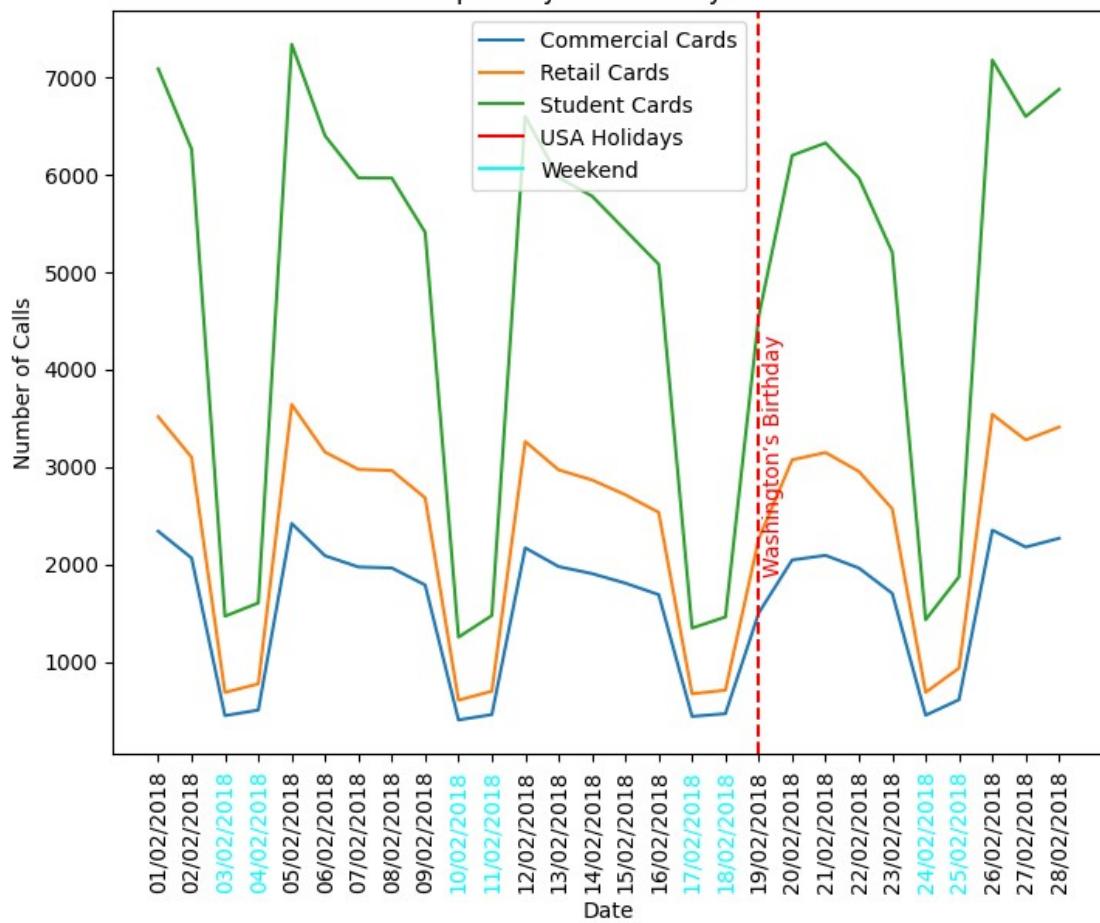
month_holidays.iterrows()):
    fig = plt.figure()
    ax = fig.add_axes([1,1,1,1])
    ax.plot(x, cc_values, label='Commercial Cards')
    ax.plot(x, rc_values, label='Retail Cards')
    ax.plot(x, sc_values, label='Student Cards')
    ax.plot([], [], label='USA Holidays', c='red')
    ax.plot([], [], label='Weekend', c='cyan')
    for mhd, mhn in monhol_values:
        if mhn == 'Thanksgiving Day':
            ax.axvline(mhd+1, c='red', ls='--')
            ax.text(mhd+1.1, ax.get_ylim()[1]//4, "Black Friday",
rotation=90, c='red')
        if mhn == 'Christmas Day':
            ax.axvline(mhd-1, c='red', ls='--')
            ax.text(mhd-0.9, ax.get_ylim()[1]//4, "Christman Eve",
rotation=90, c='red')
            ax.axvline(mhd, c='red', ls='--')
            ax.text(mhd+0.1, ax.get_ylim()[1]//4, mhn, rotation=90,
c='red')
        ax.set_xticks(x,
df_not17_sorted_yearly[df_not17_sorted_yearly.month == m].date,
rotation=90)
        for i, dt in
enumerate(df_not17_sorted_yearly[df_not17_sorted_yearly.month ==
m].date):
            if arrow.get(dt, "DD/MM/YYYY").format("ddd") in ["Sat",
"Sun"]:
                ax.get_xticklabels()[i].set_color('cyan')
        ax.set_xlabel("Date")
        ax.set_ylabel("Number of Calls")
        ax.set_title(f"Calls per Day for {arrow.get(str(m),
'M')).format('MMMM')} of {y}")
        ax.legend()
    plt.show()

```

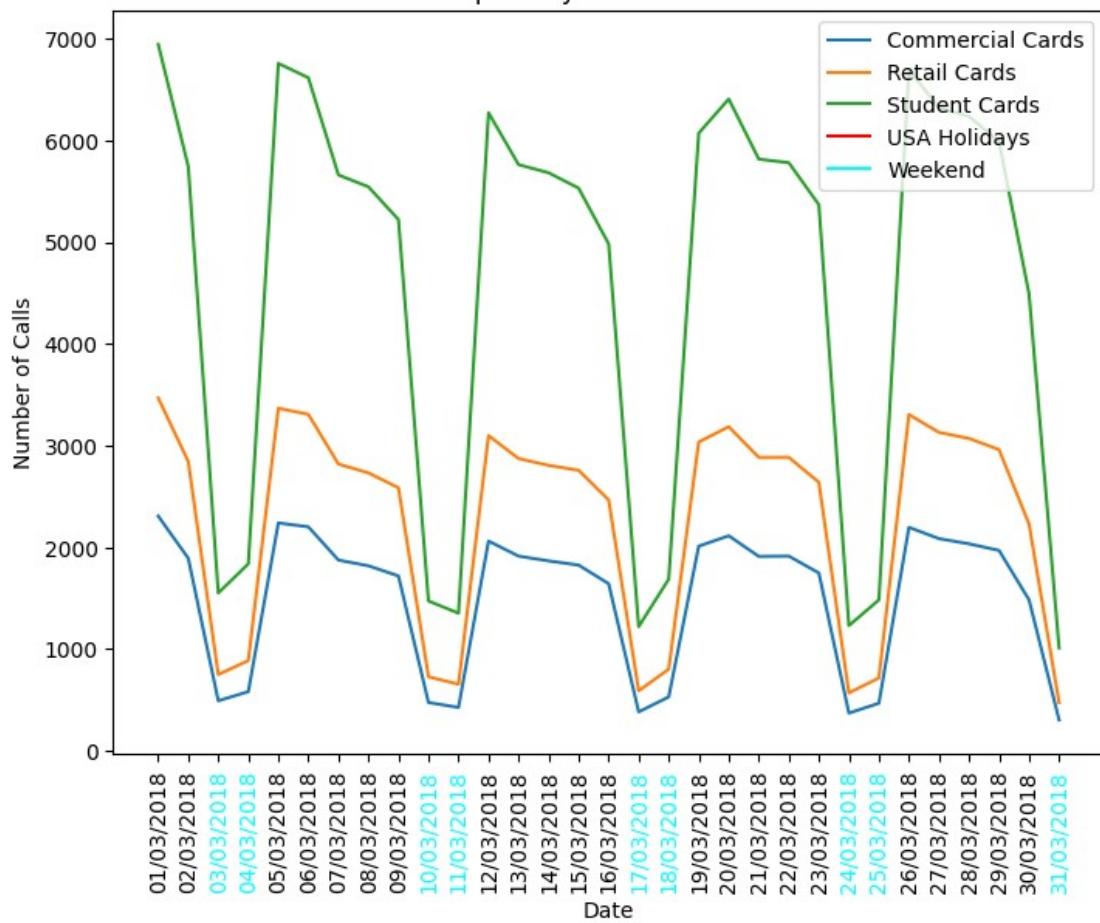
Calls per Day for January of 2018



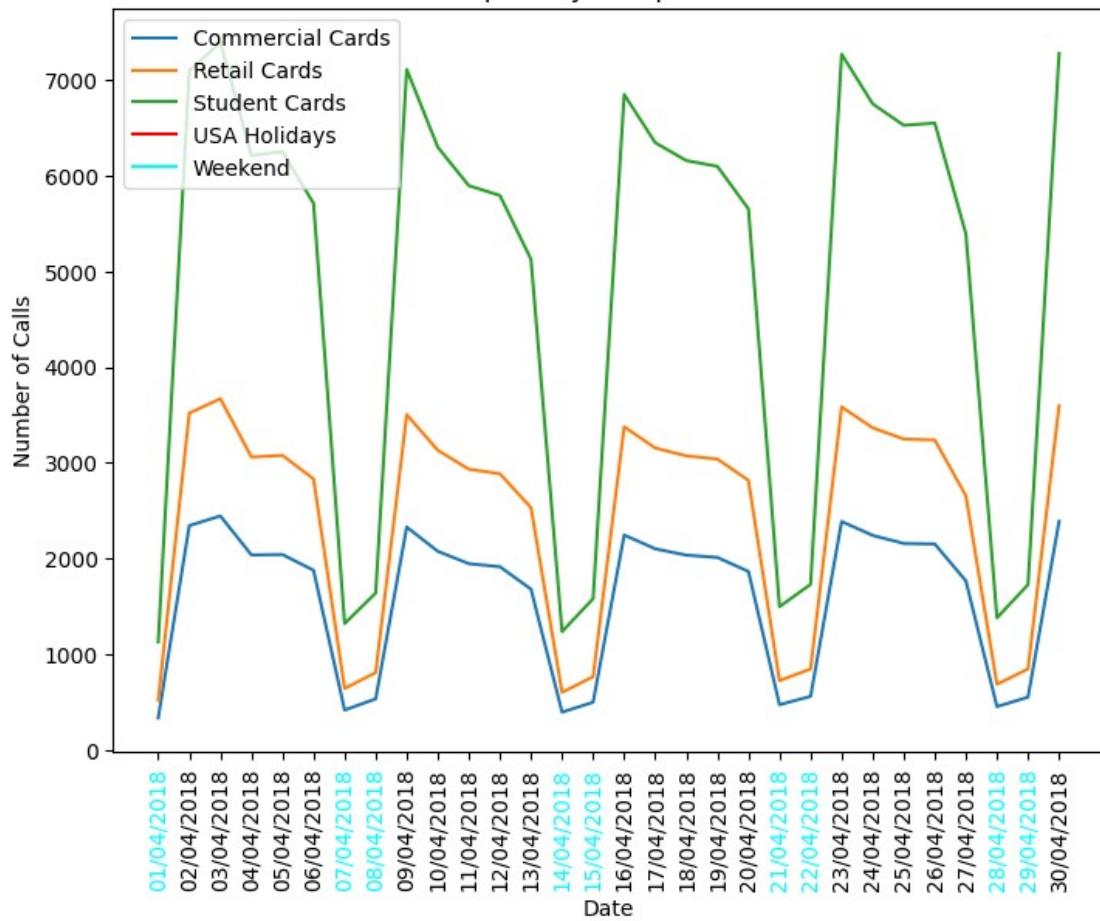
Calls per Day for February of 2018



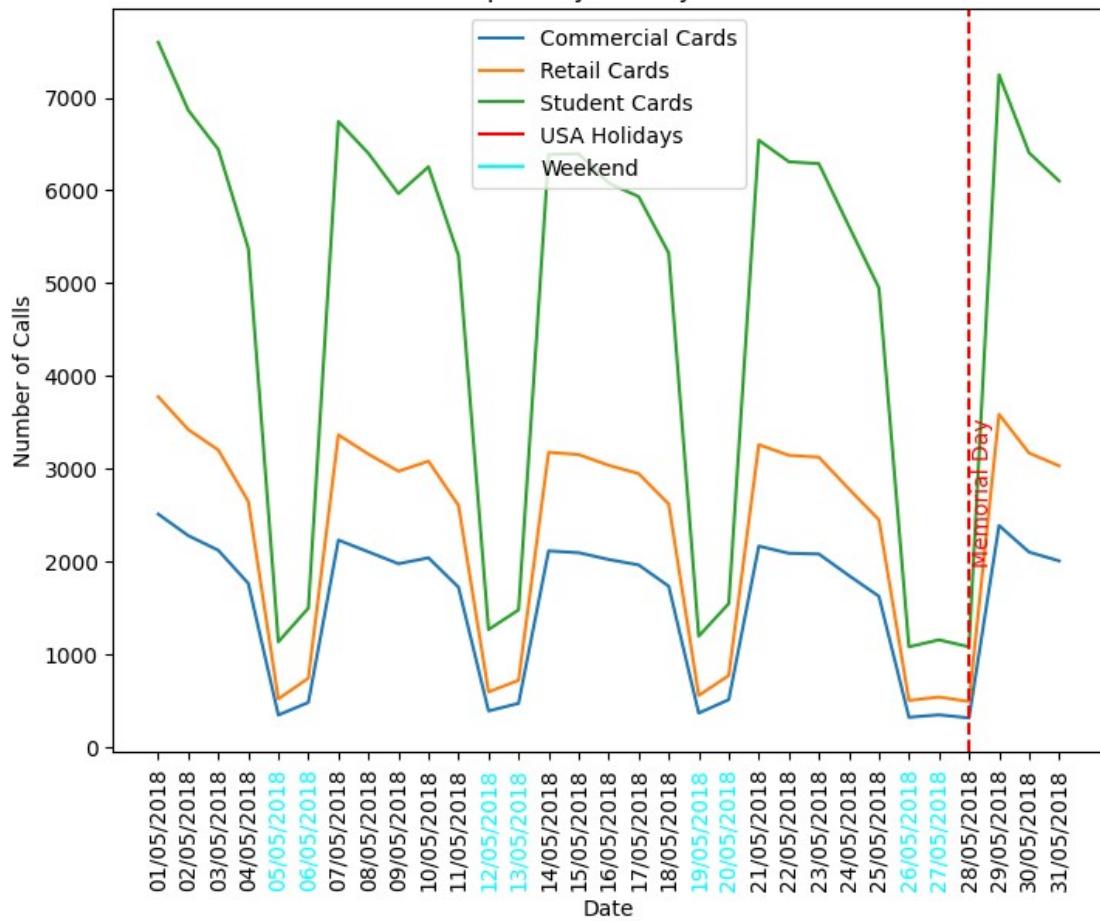
Calls per Day for March of 2018



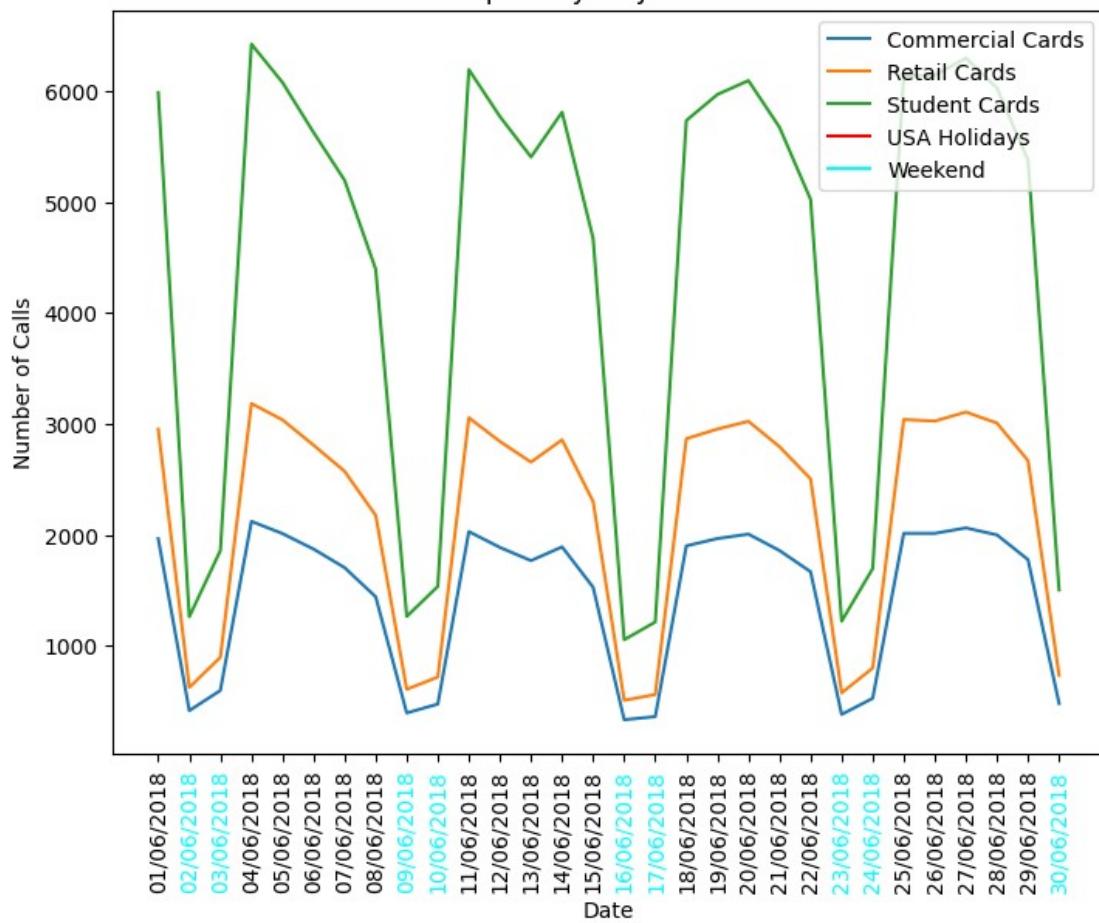
Calls per Day for April of 2018



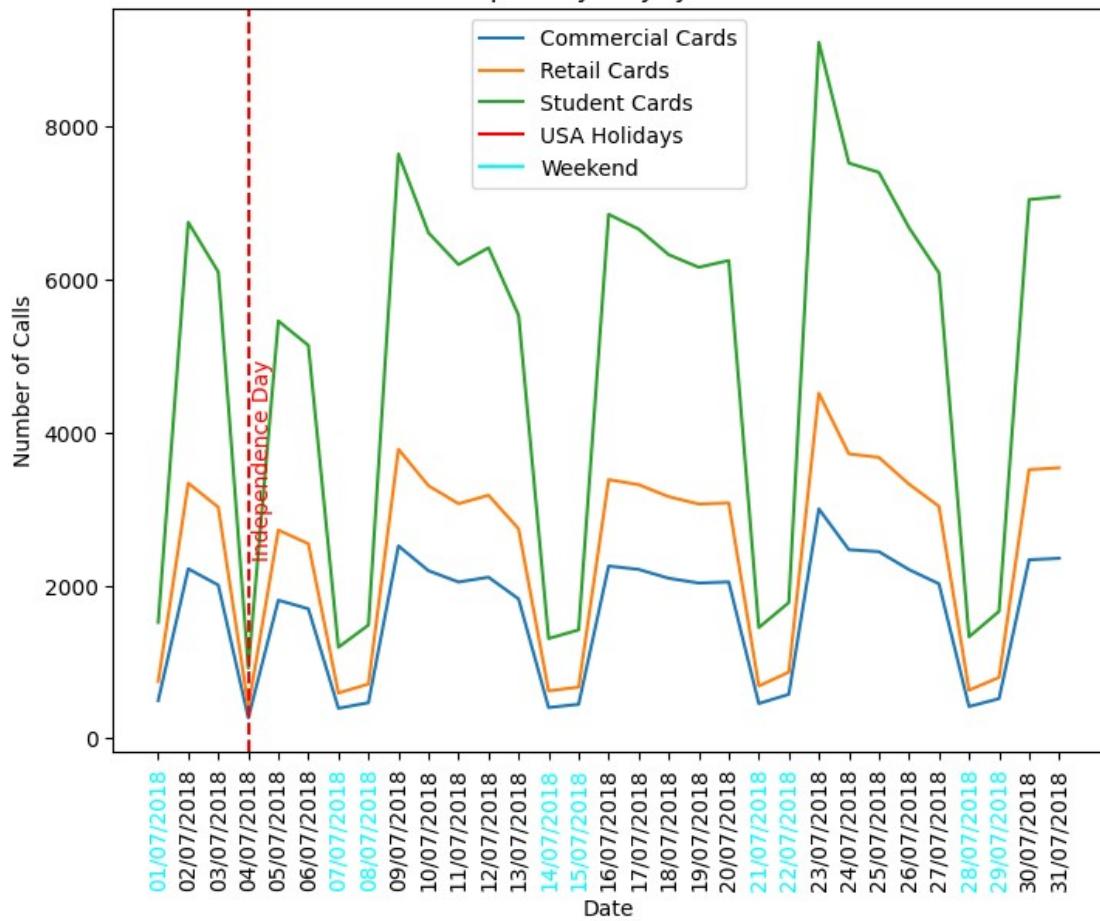
Calls per Day for May of 2018



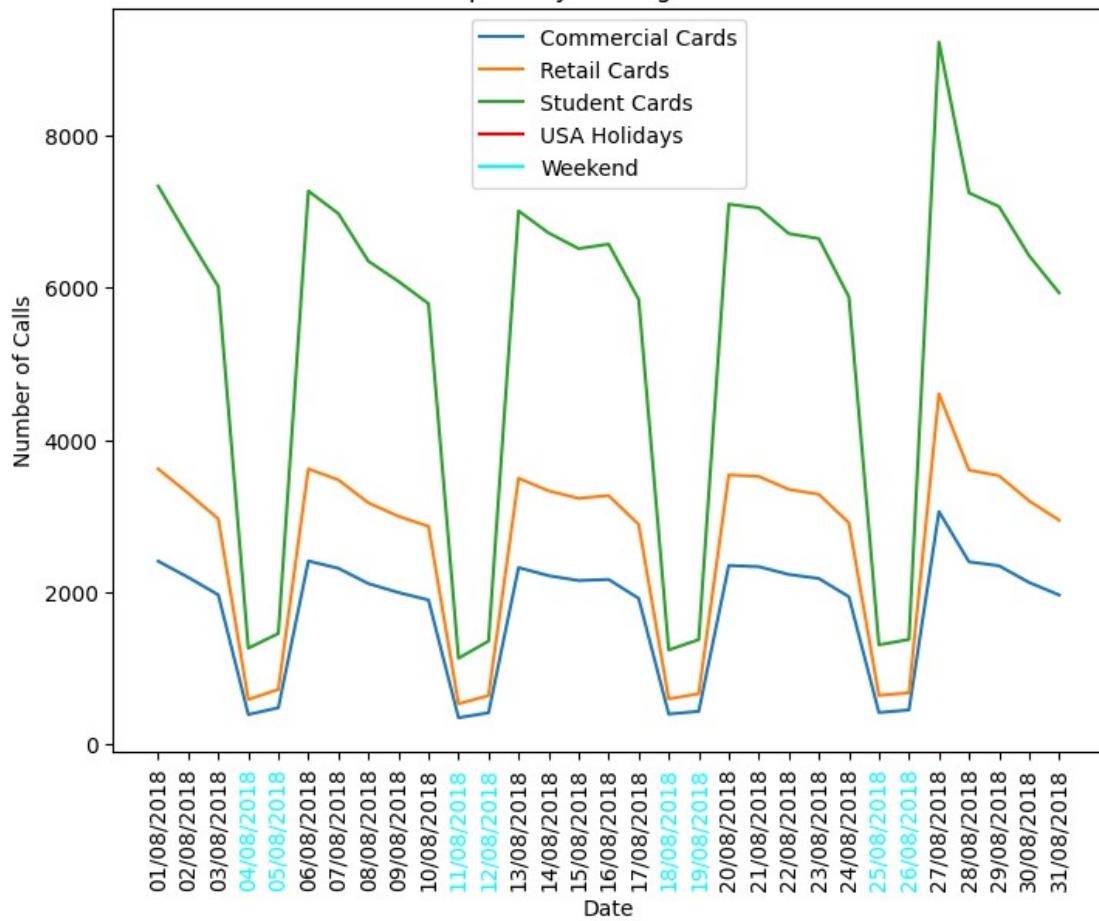
Calls per Day for June of 2018



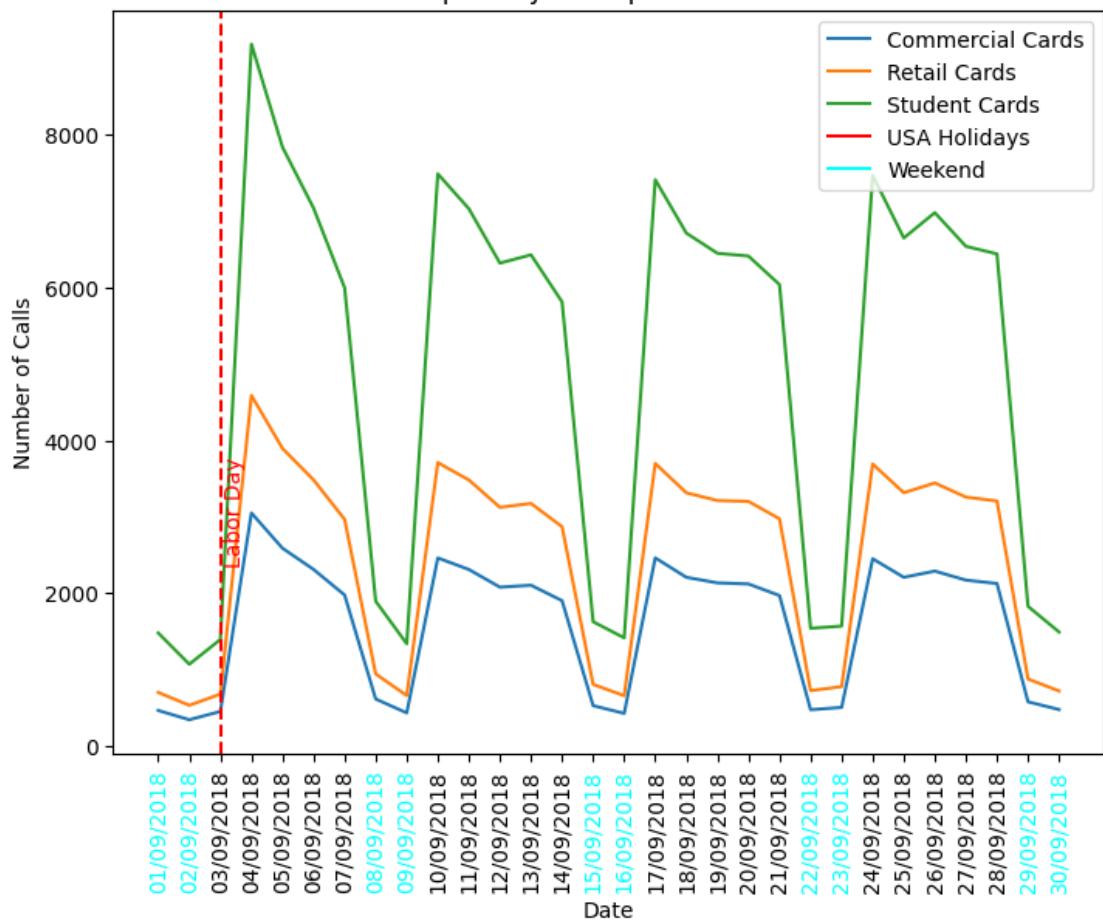
Calls per Day for July of 2018



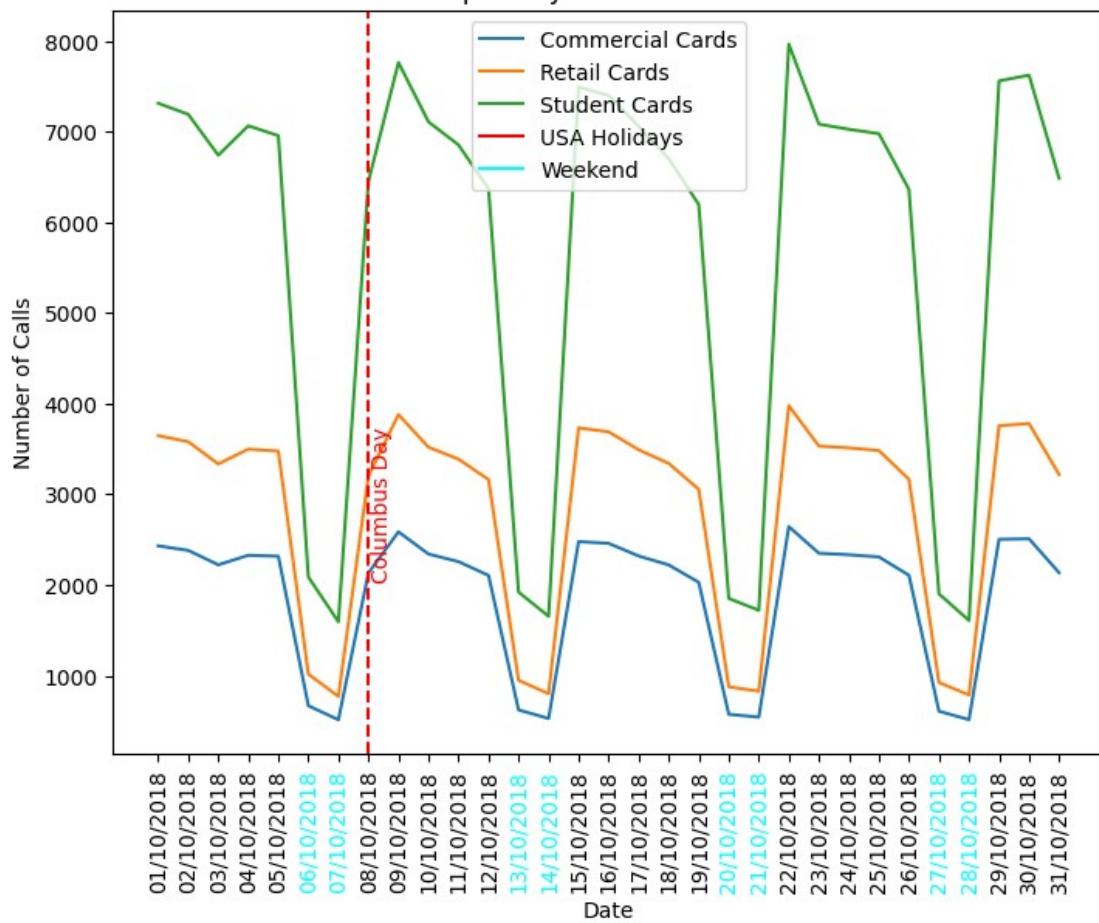
Calls per Day for August of 2018



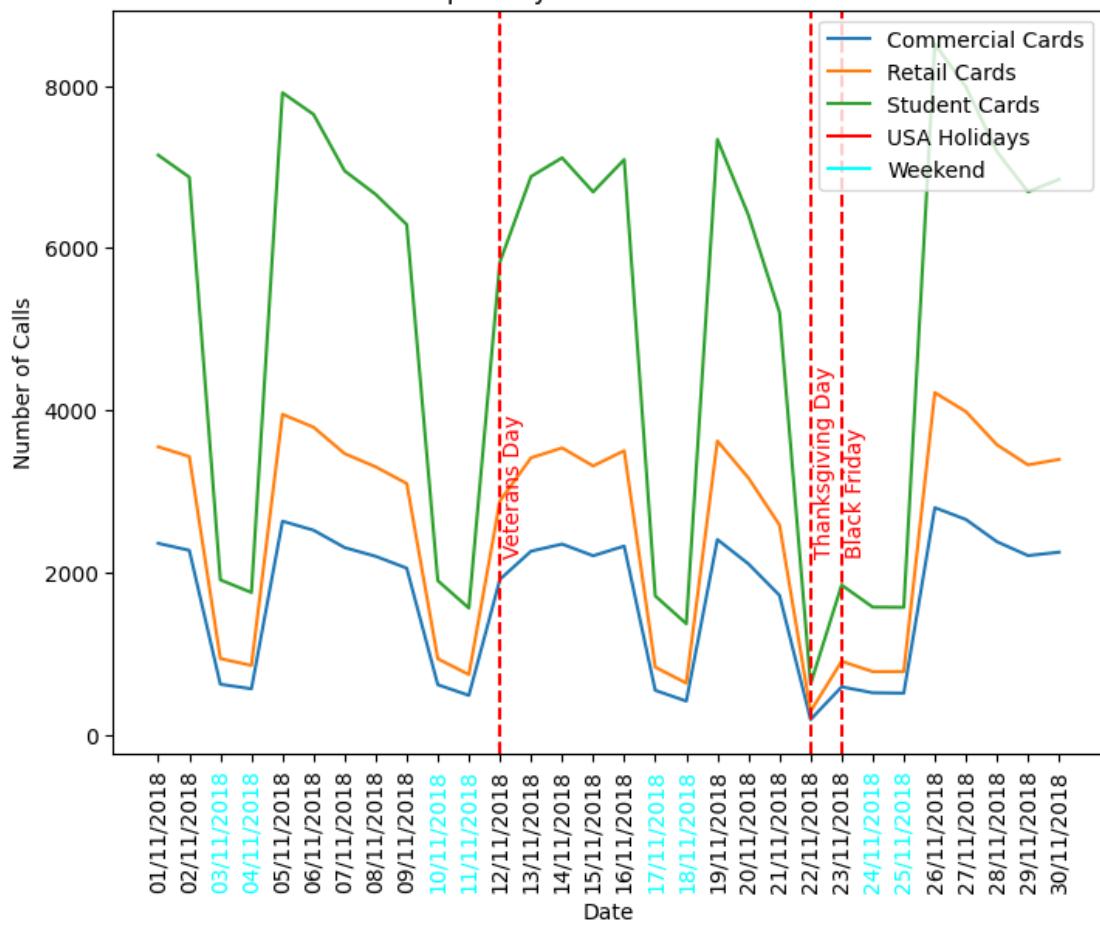
Calls per Day for September of 2018



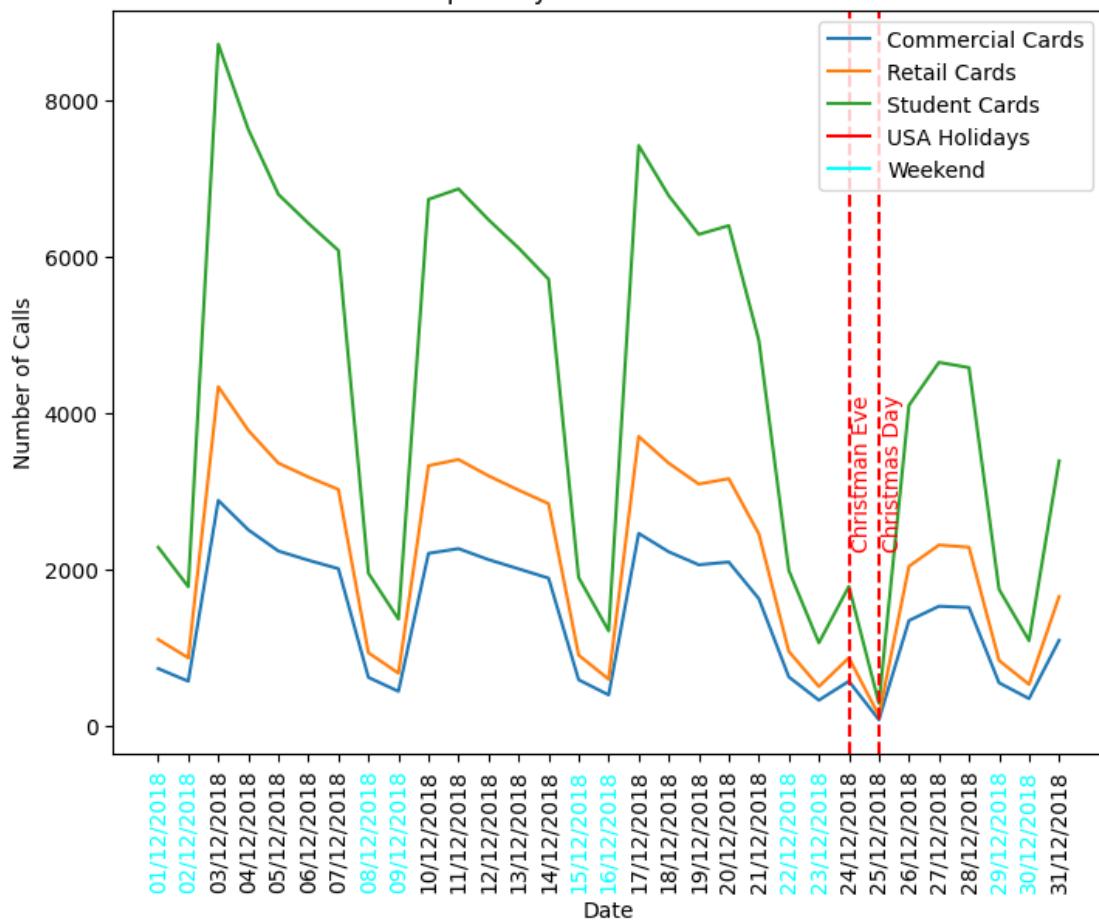
Calls per Day for October of 2018



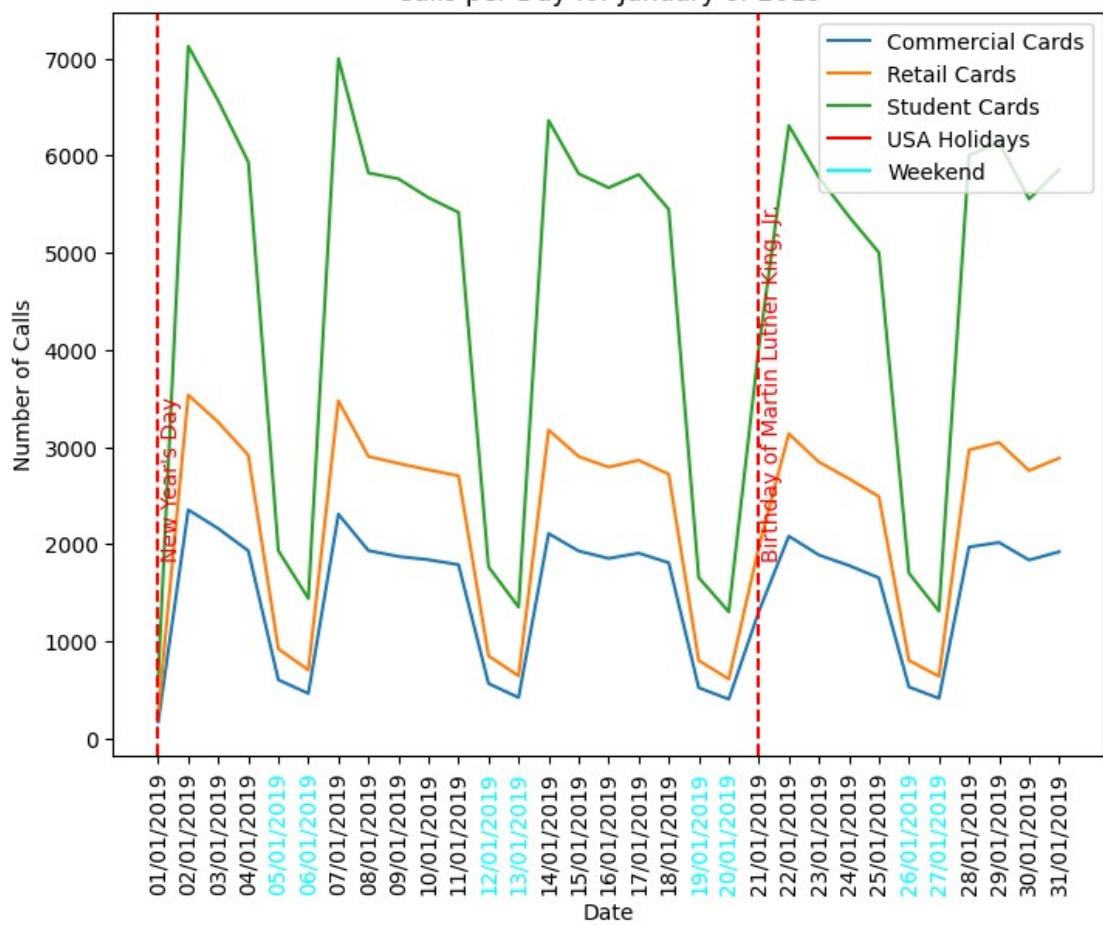
Calls per Day for November of 2018



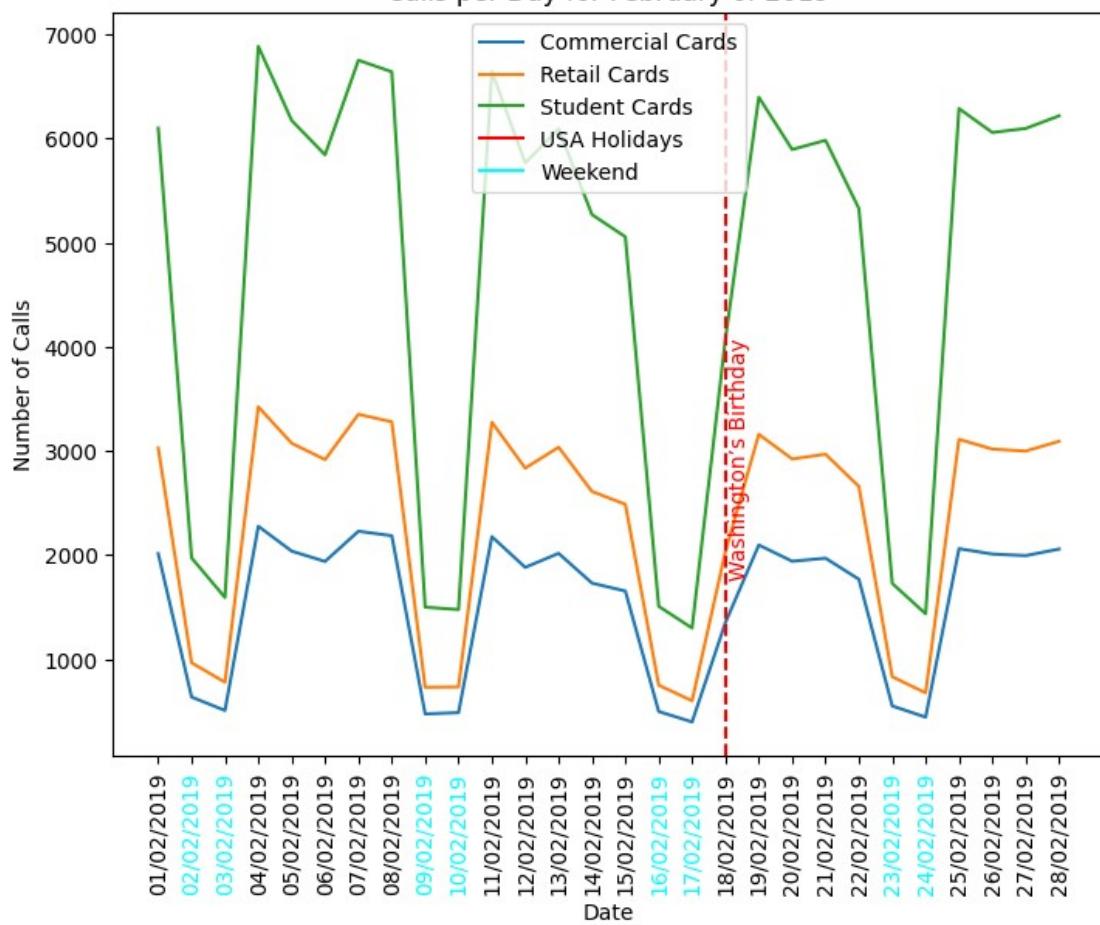
Calls per Day for December of 2018



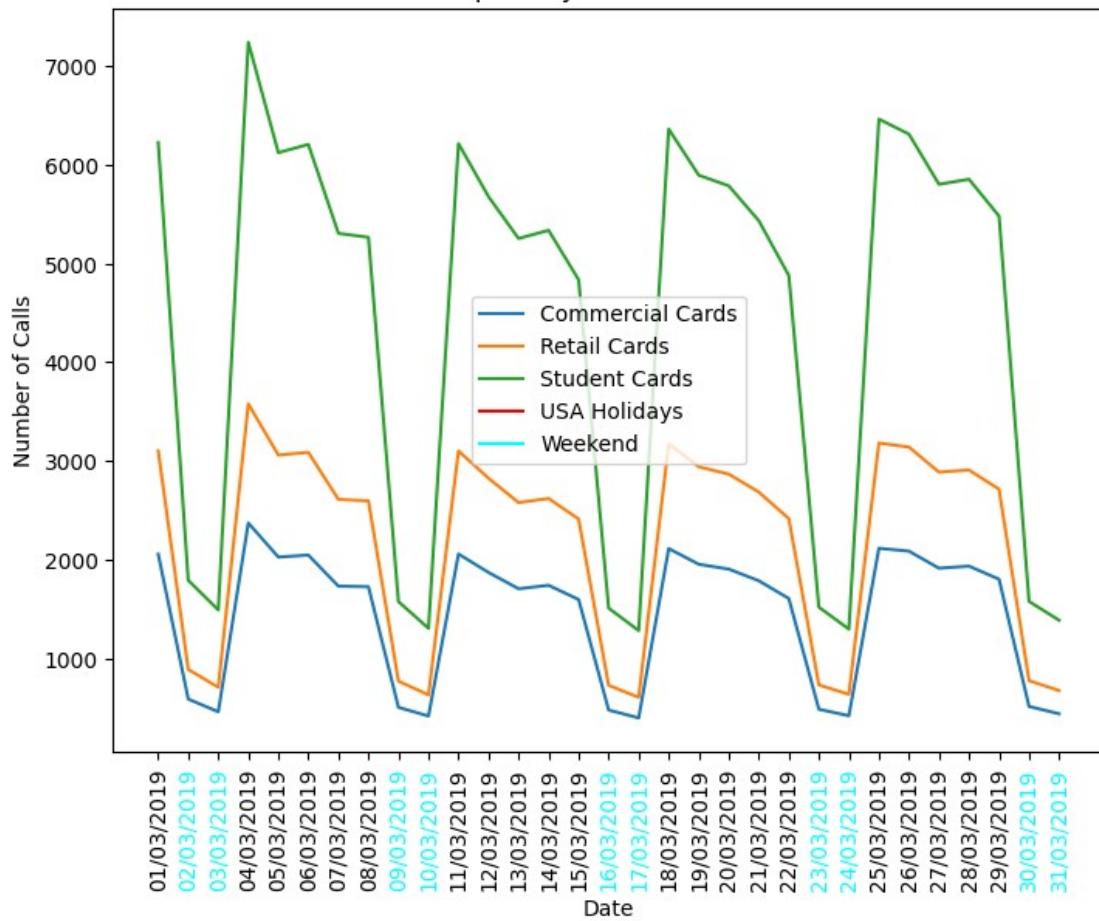
Calls per Day for January of 2019

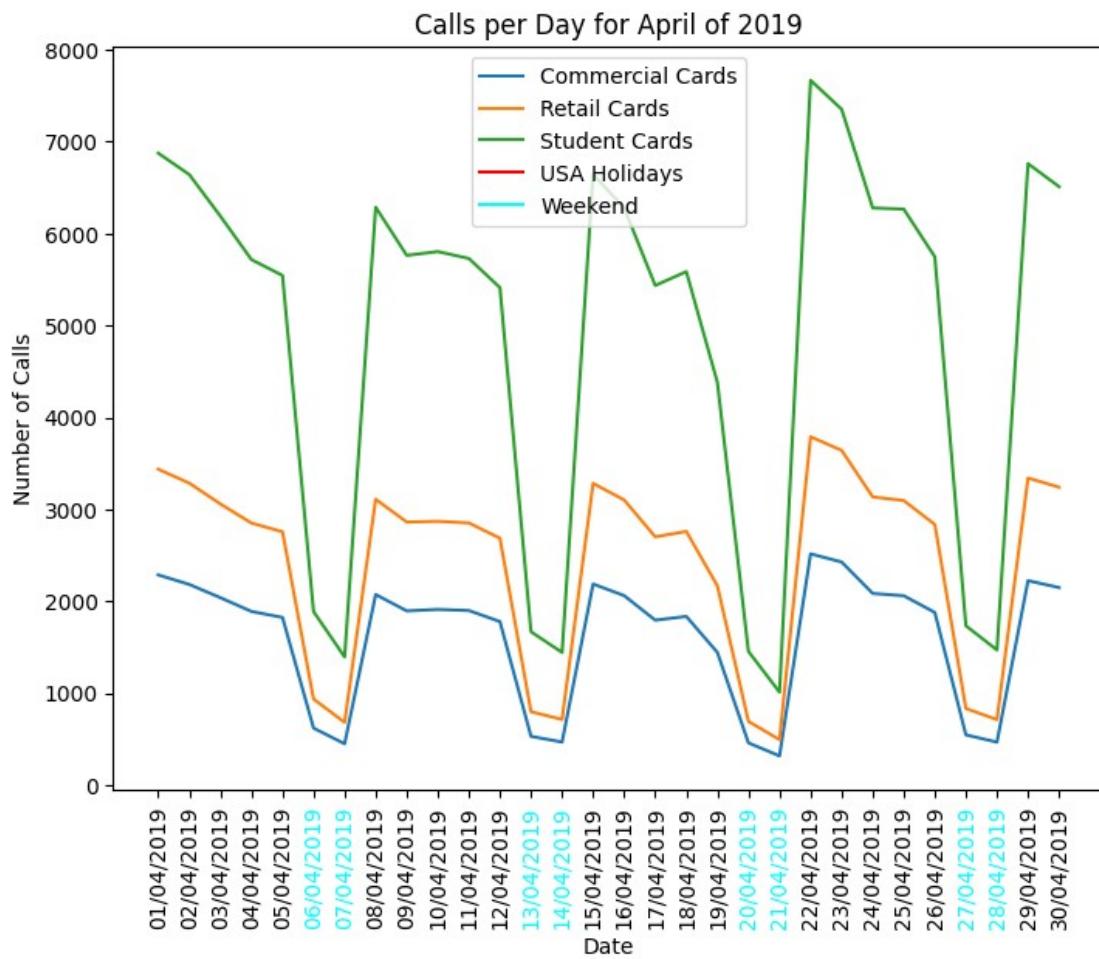


Calls per Day for February of 2019

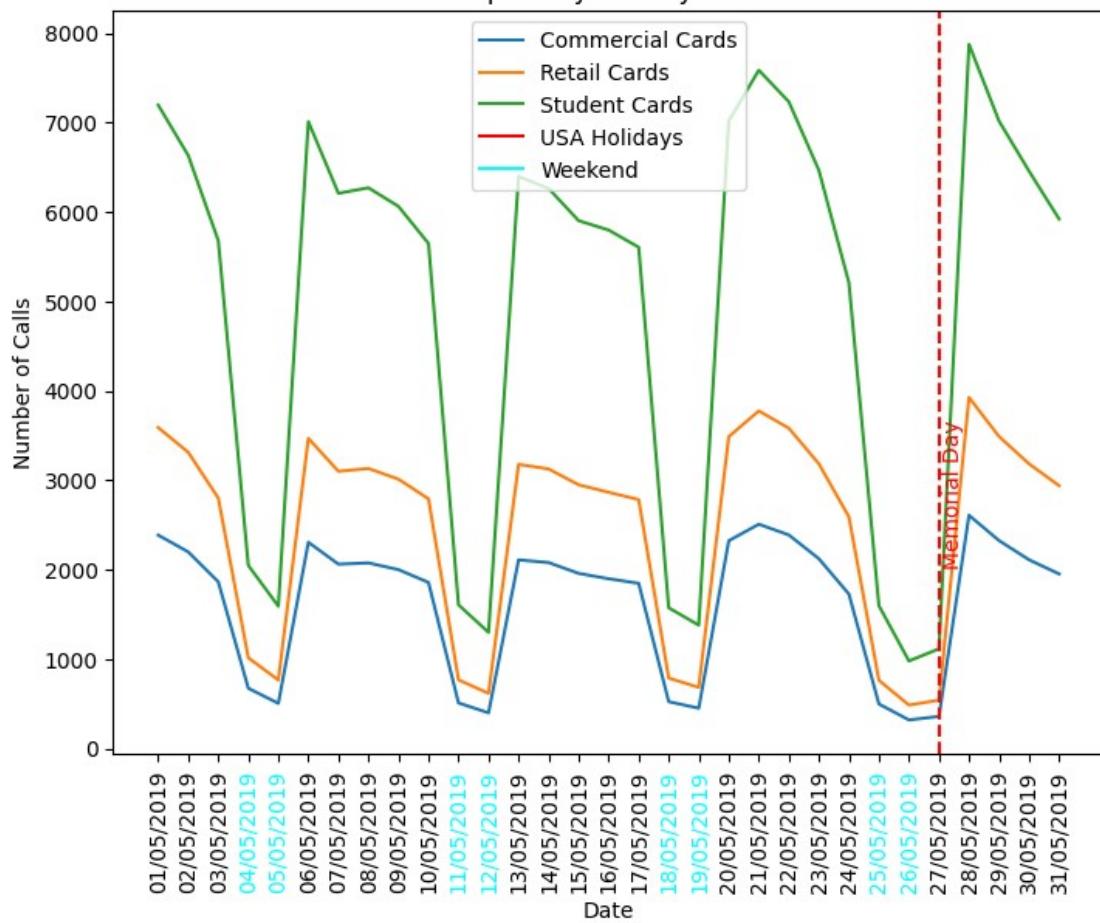


Calls per Day for March of 2019

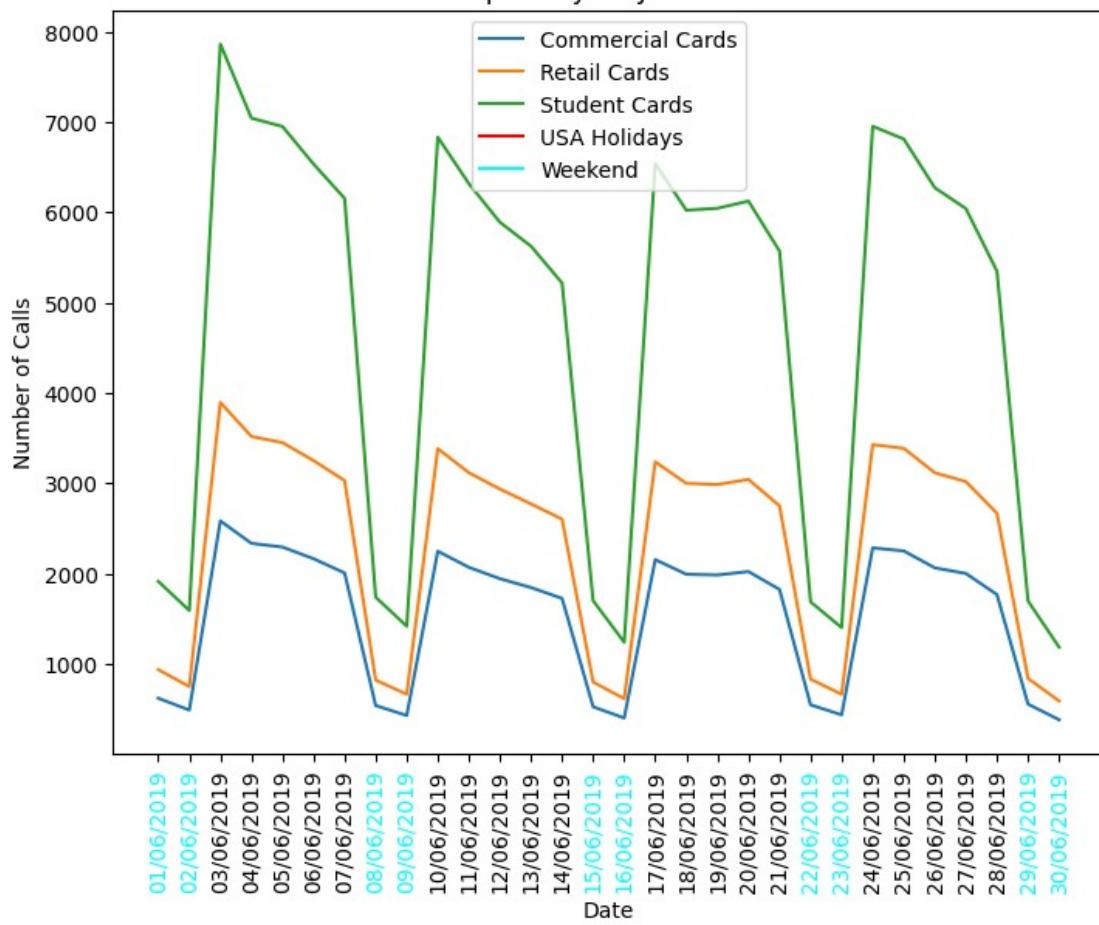




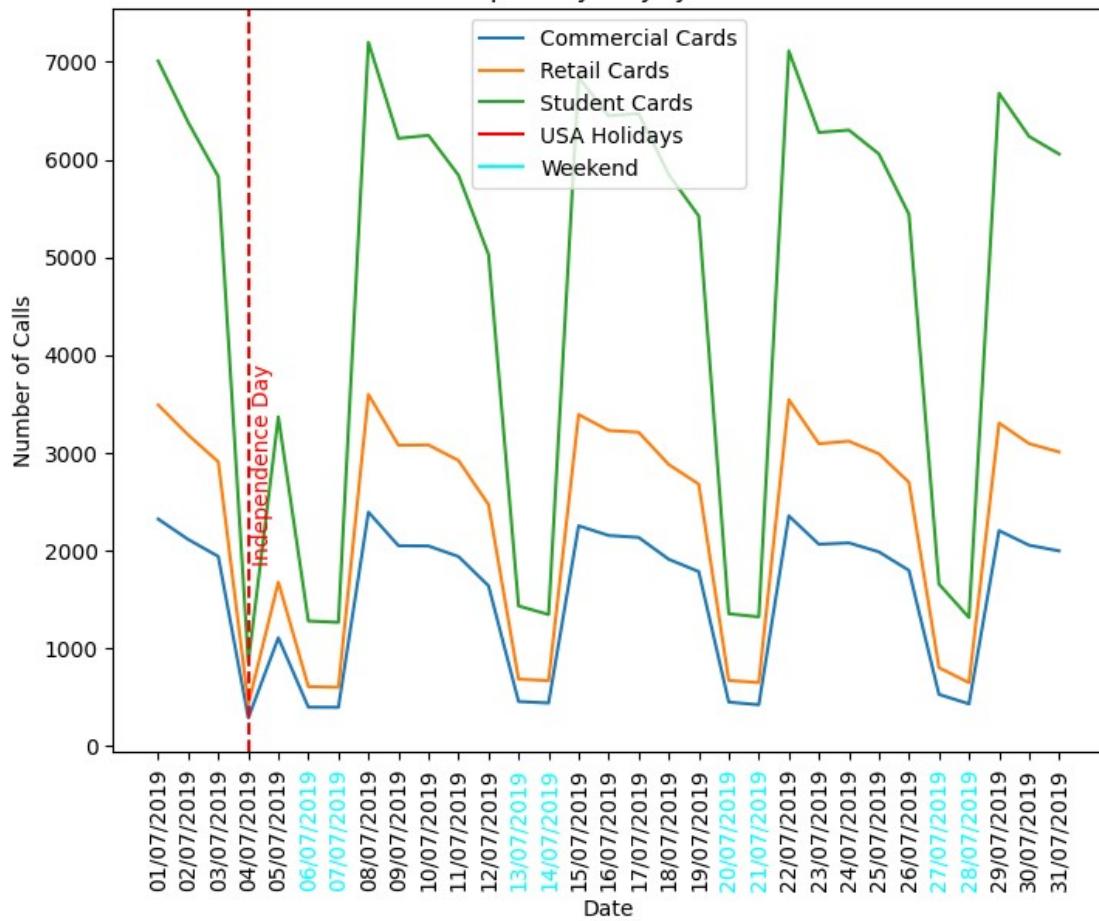
Calls per Day for May of 2019



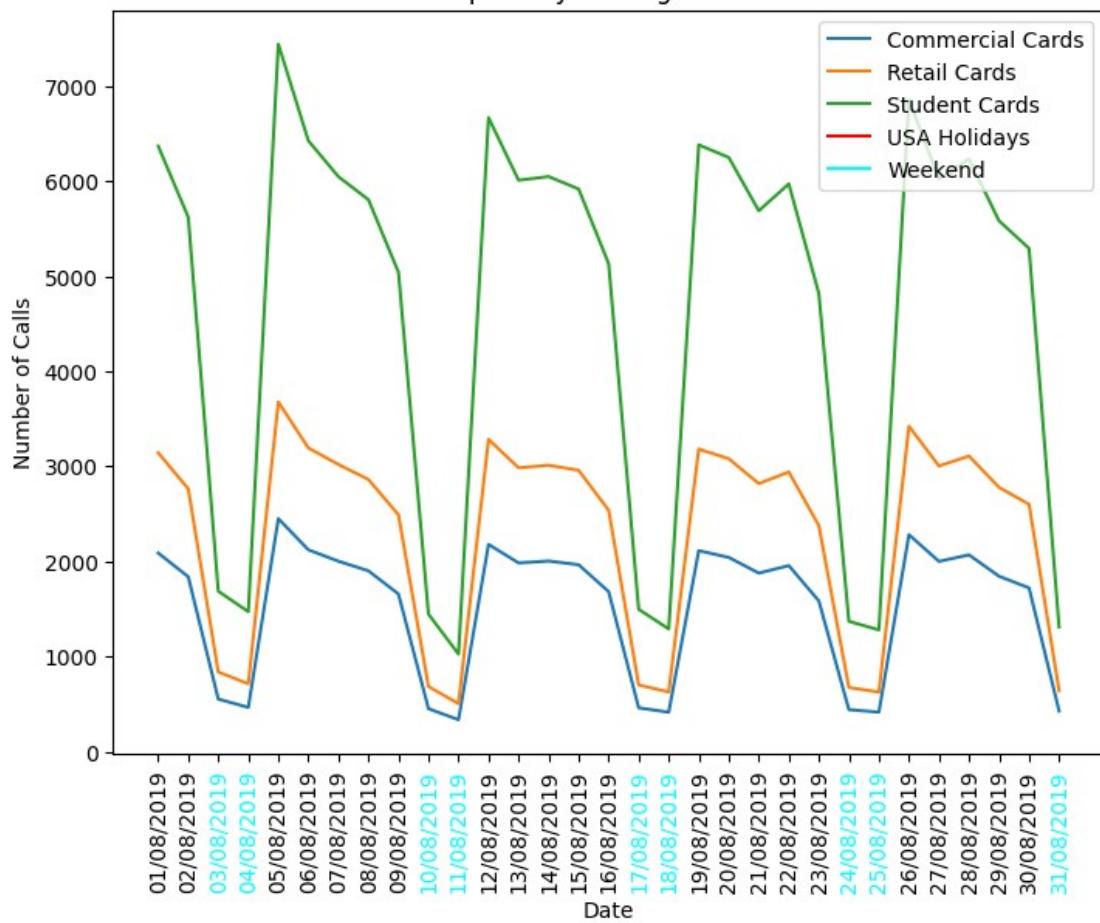
Calls per Day for June of 2019



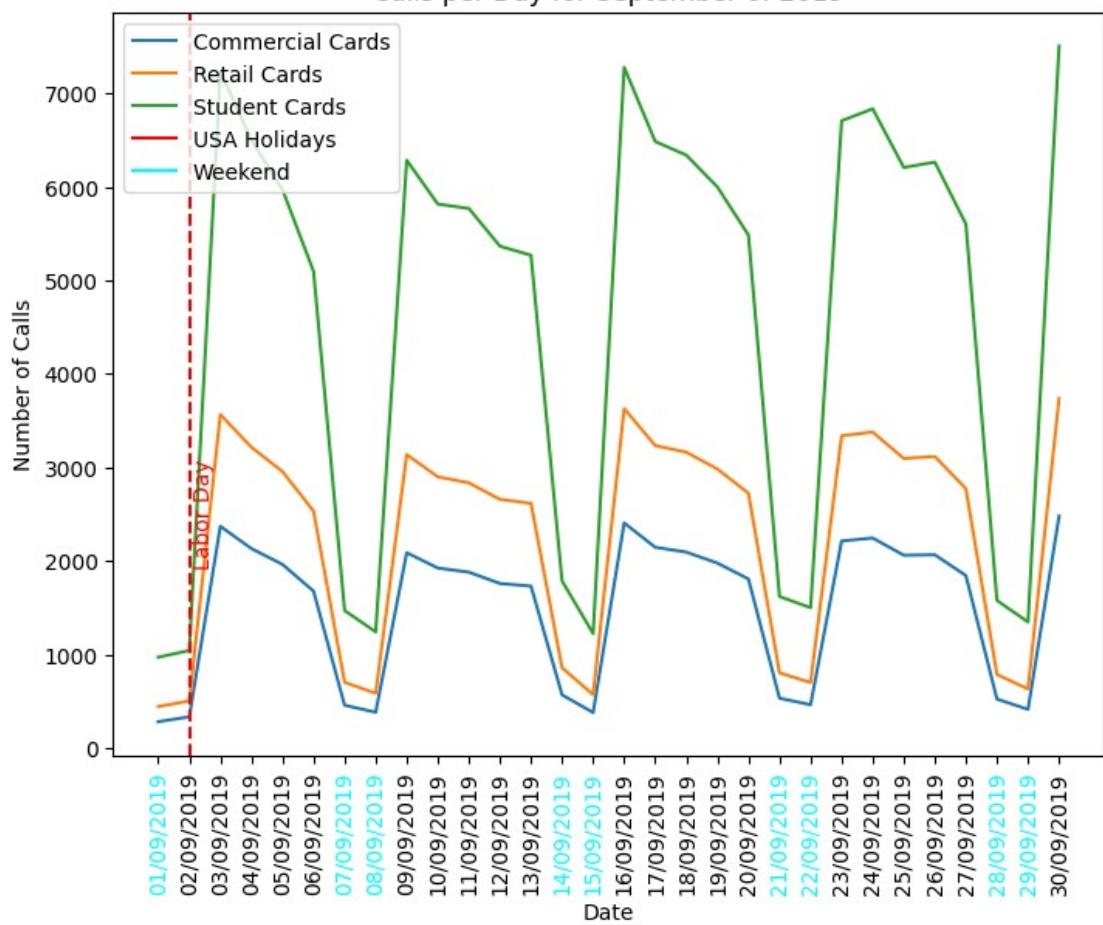
Calls per Day for July of 2019



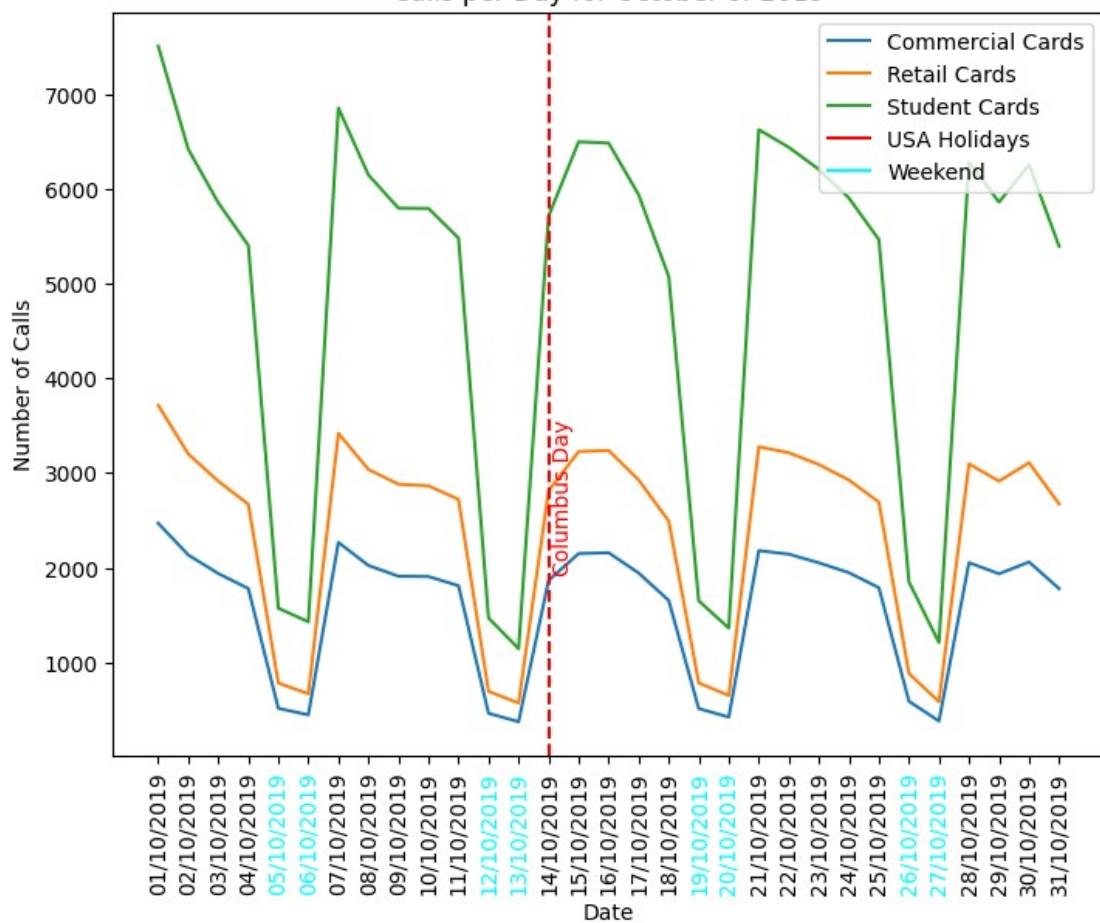
Calls per Day for August of 2019



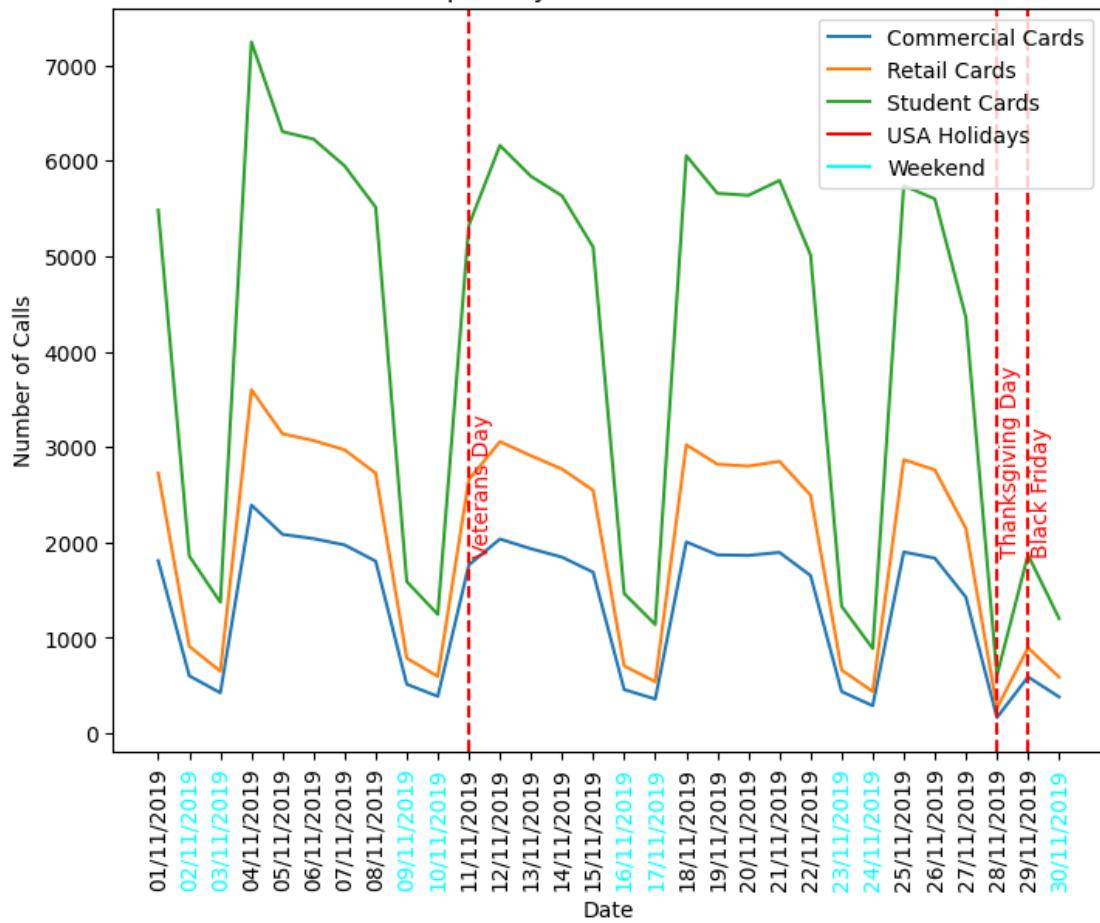
Calls per Day for September of 2019



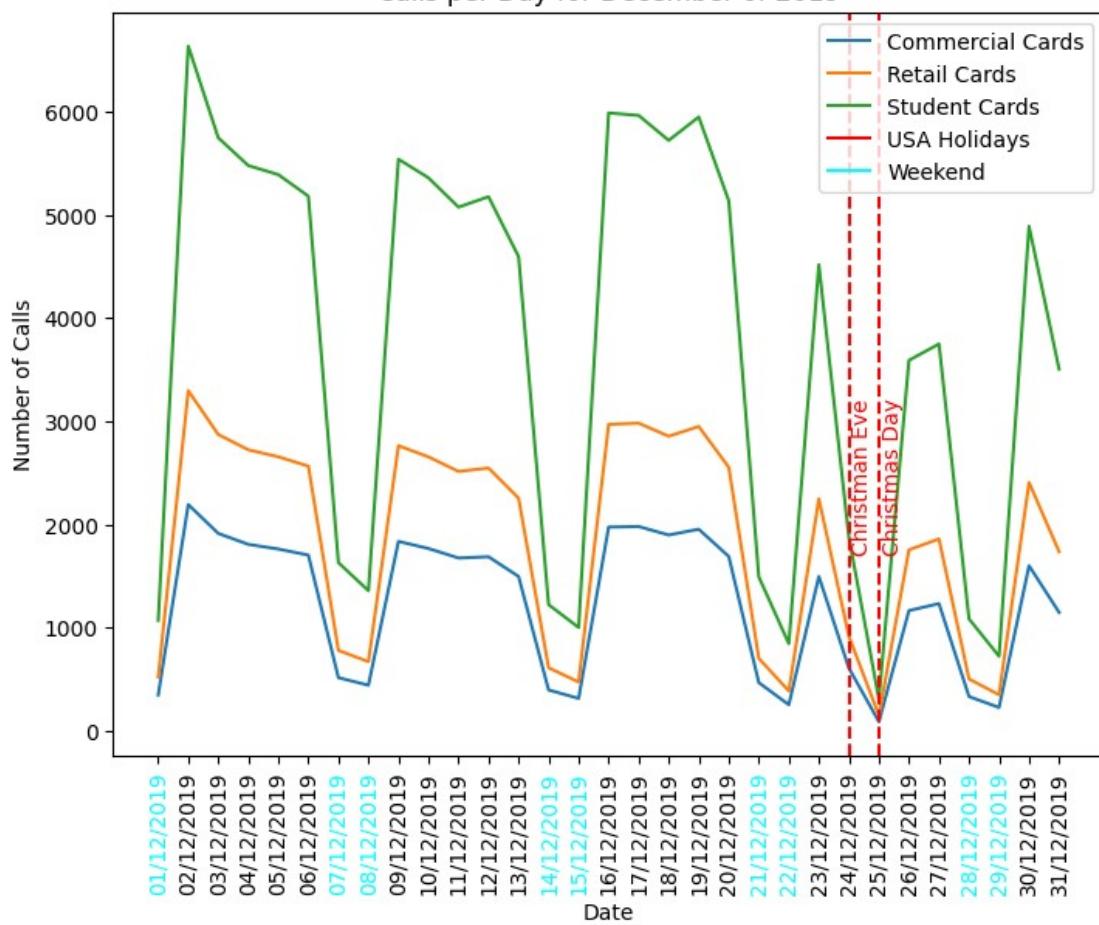
Calls per Day for October of 2019

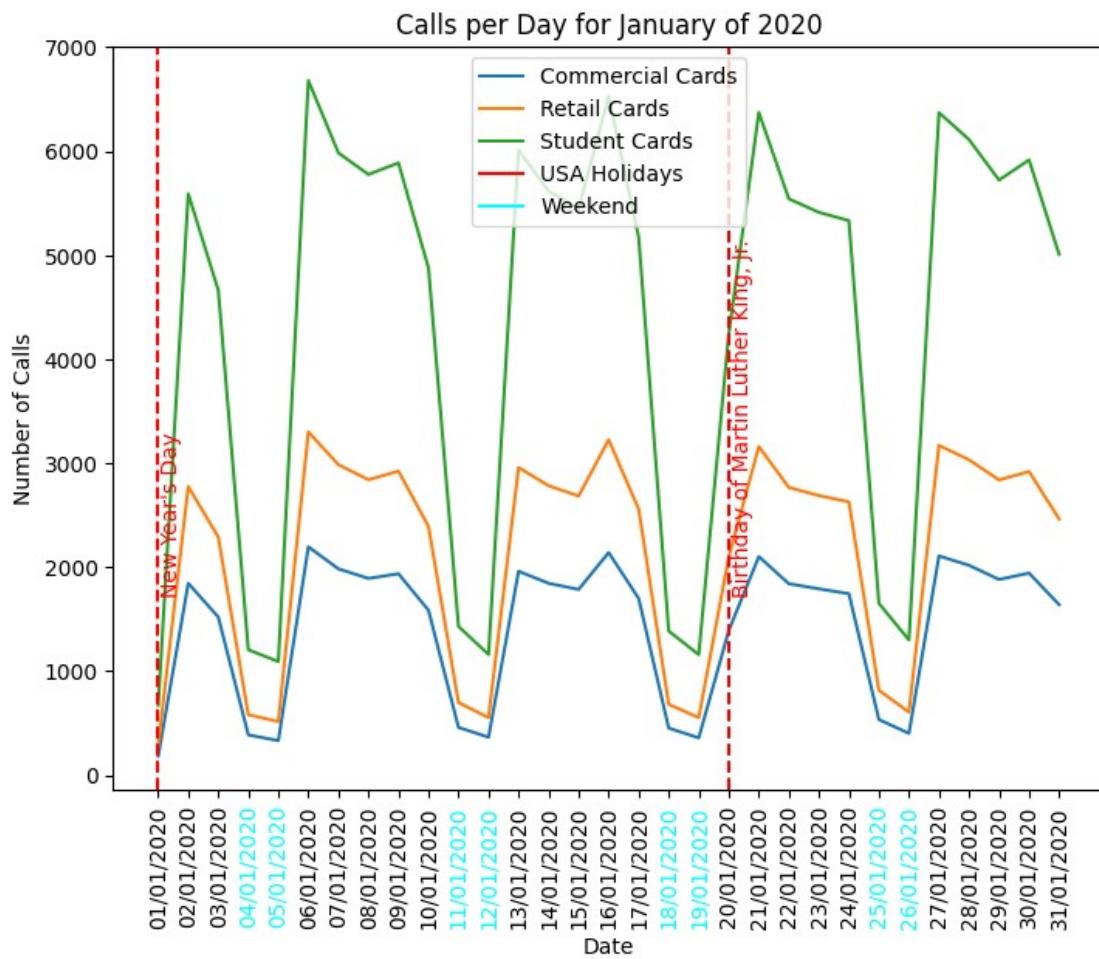


Calls per Day for November of 2019

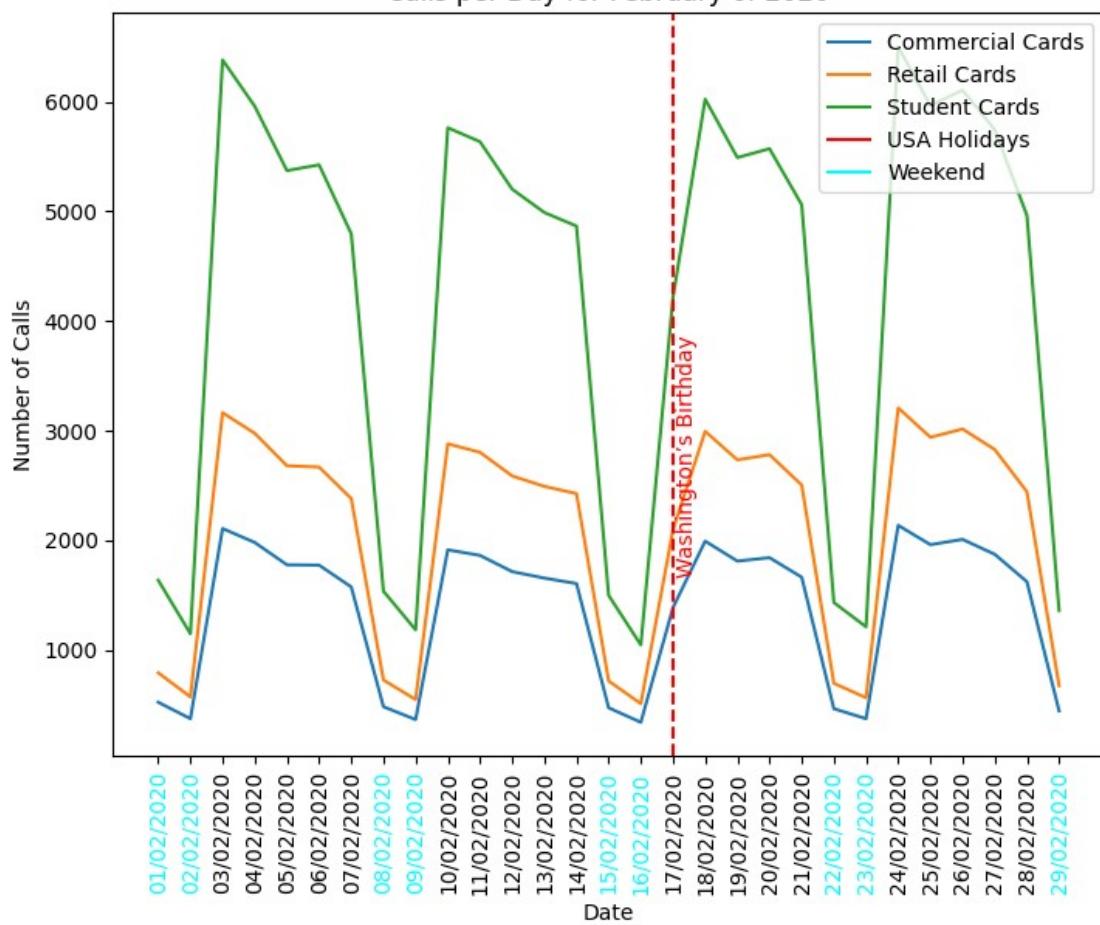


Calls per Day for December of 2019

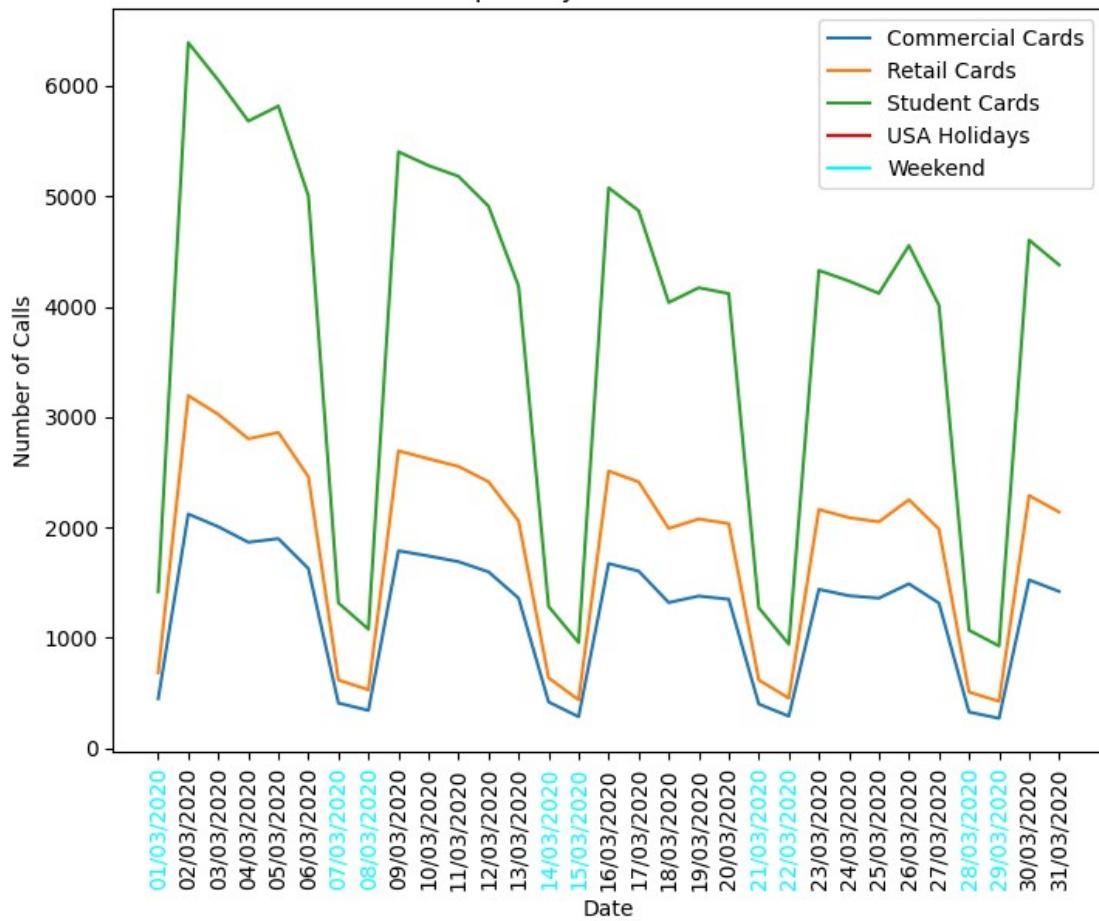




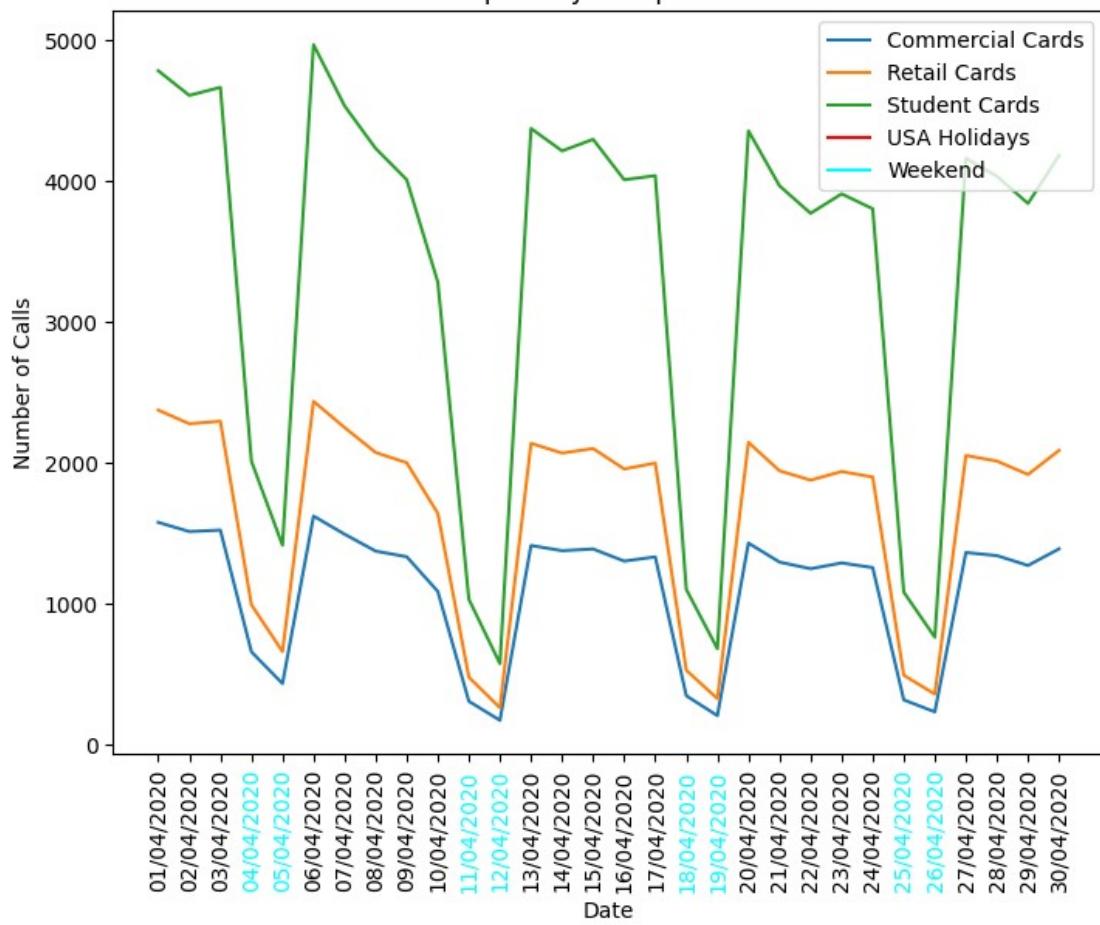
Calls per Day for February of 2020

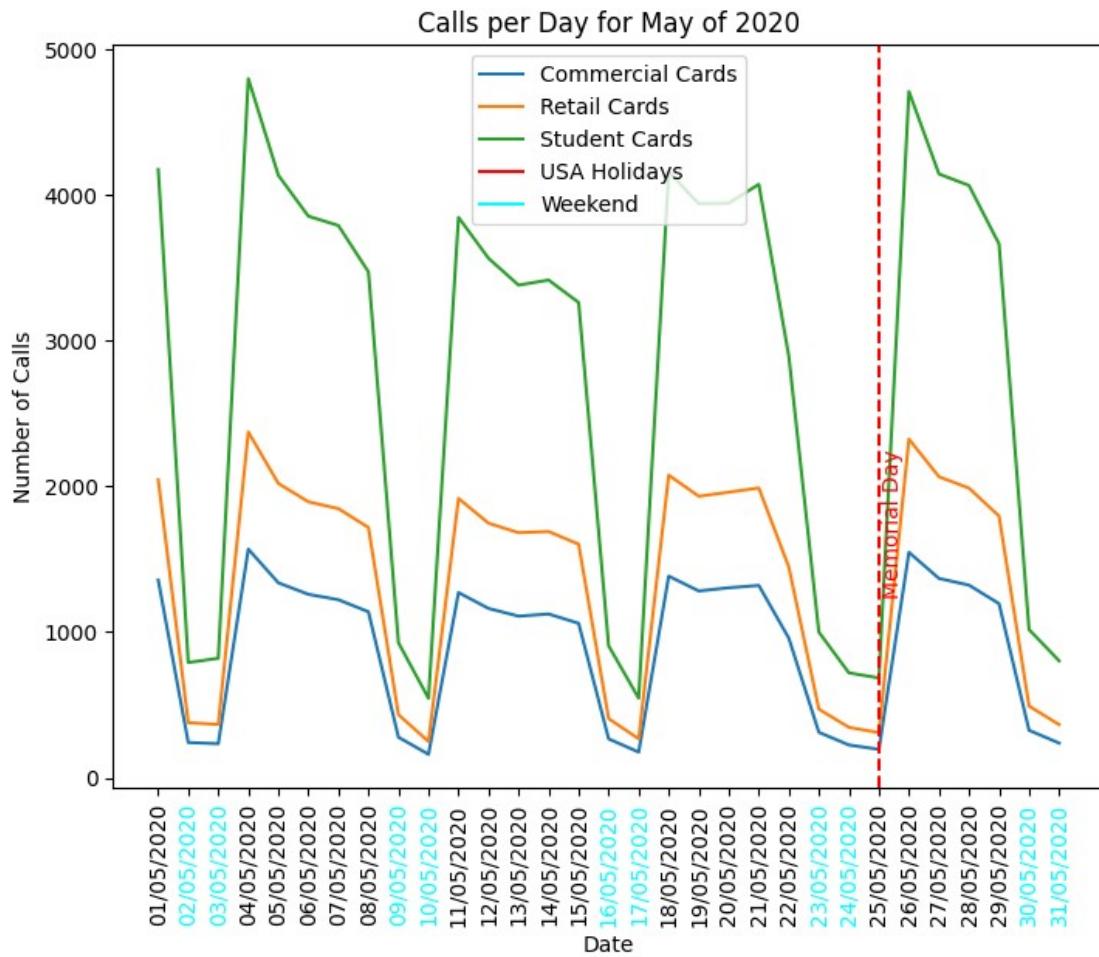


Calls per Day for March of 2020

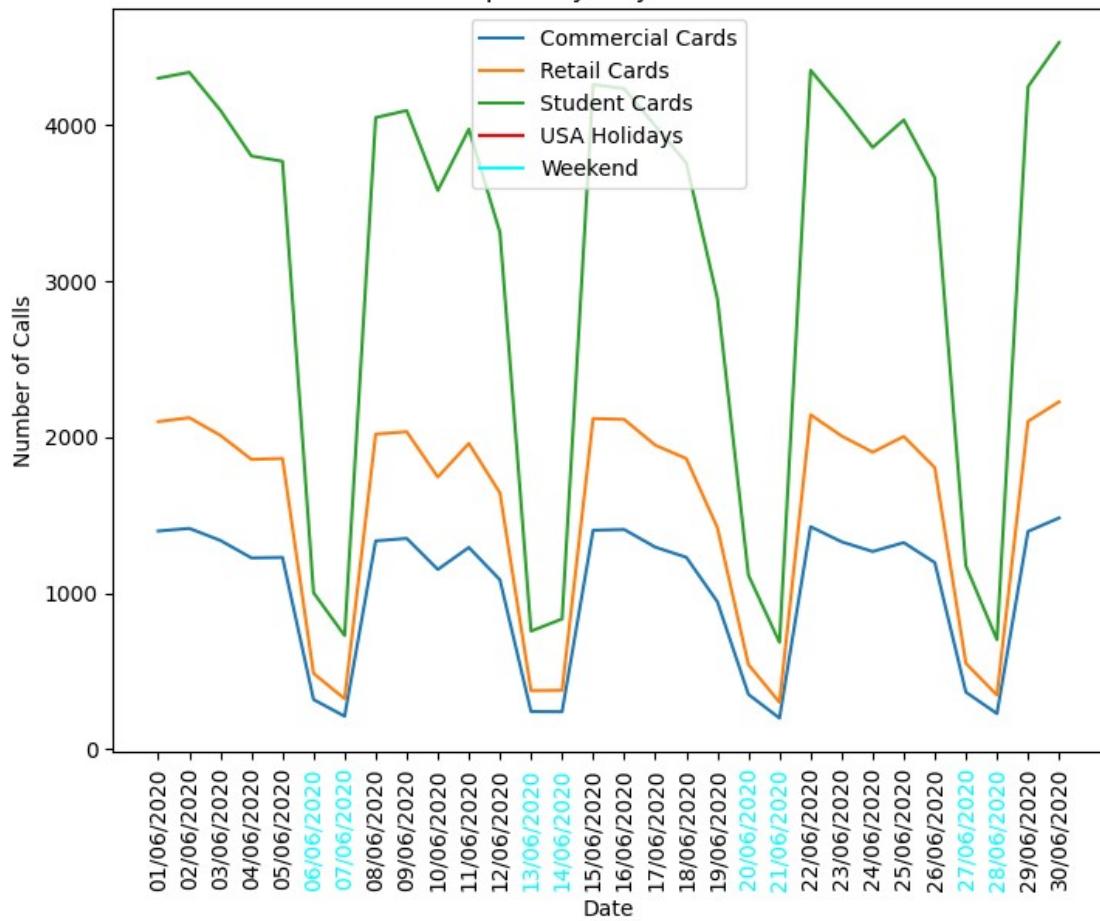


Calls per Day for April of 2020

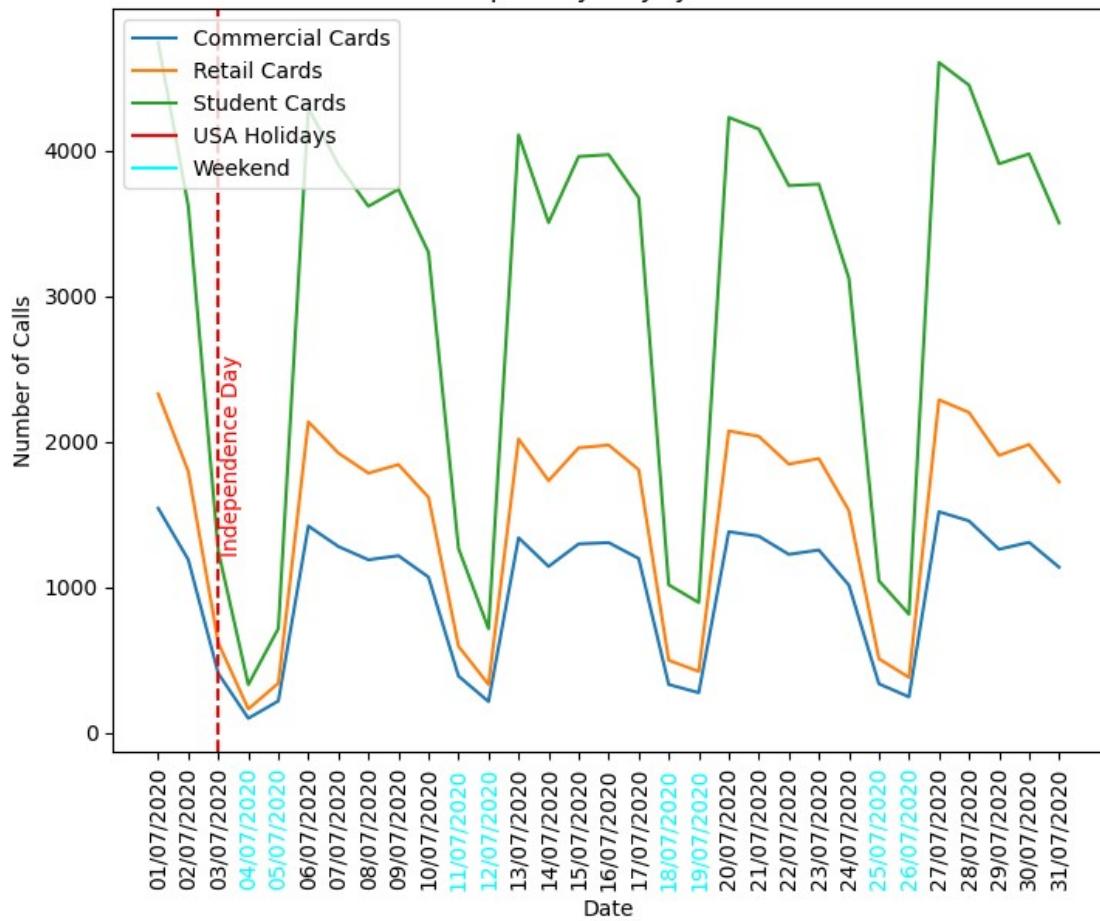




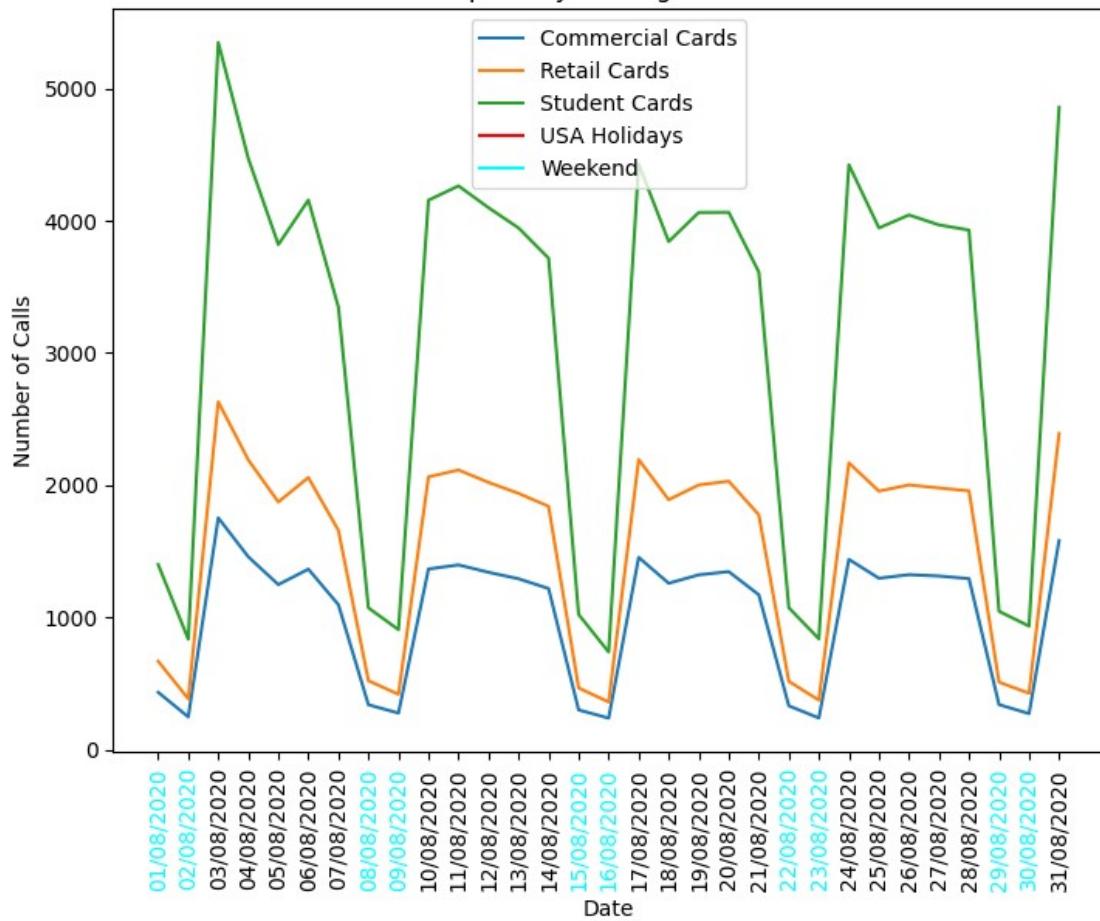
Calls per Day for June of 2020



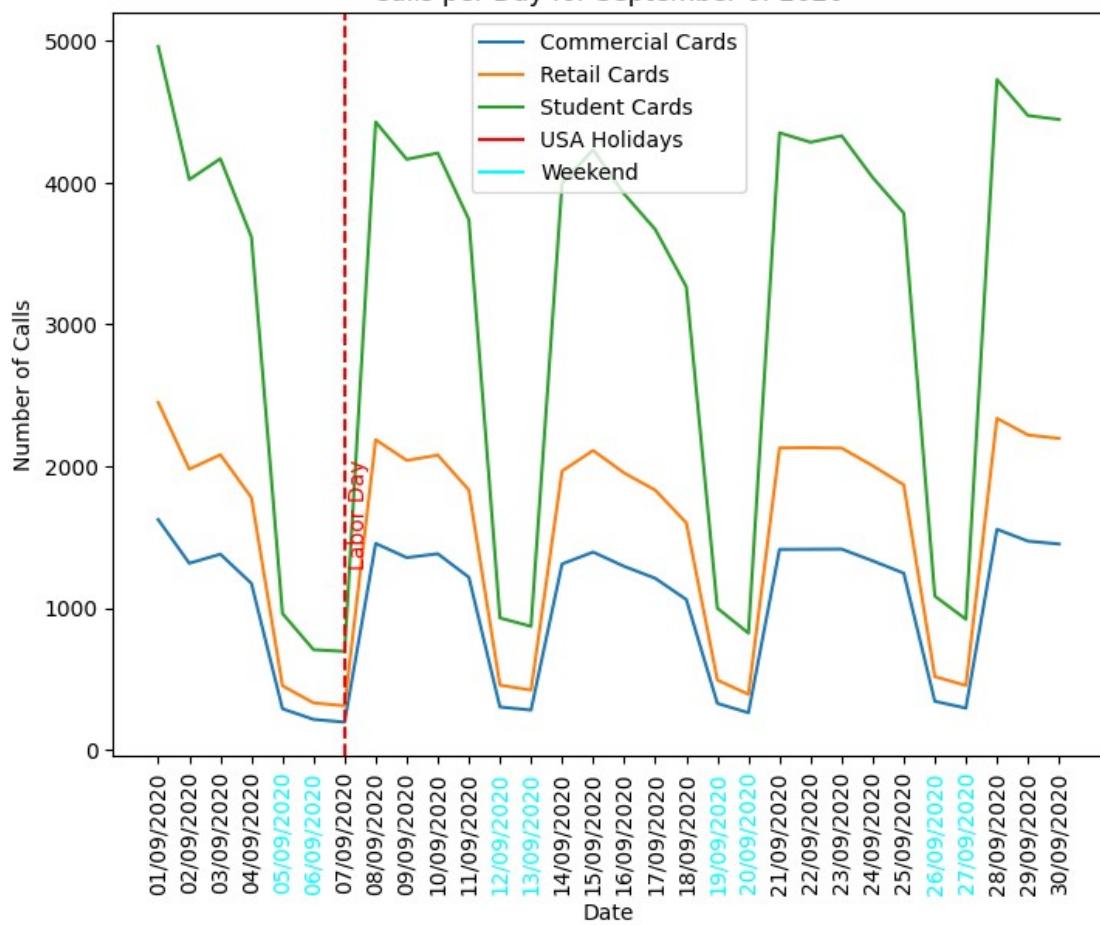
Calls per Day for July of 2020



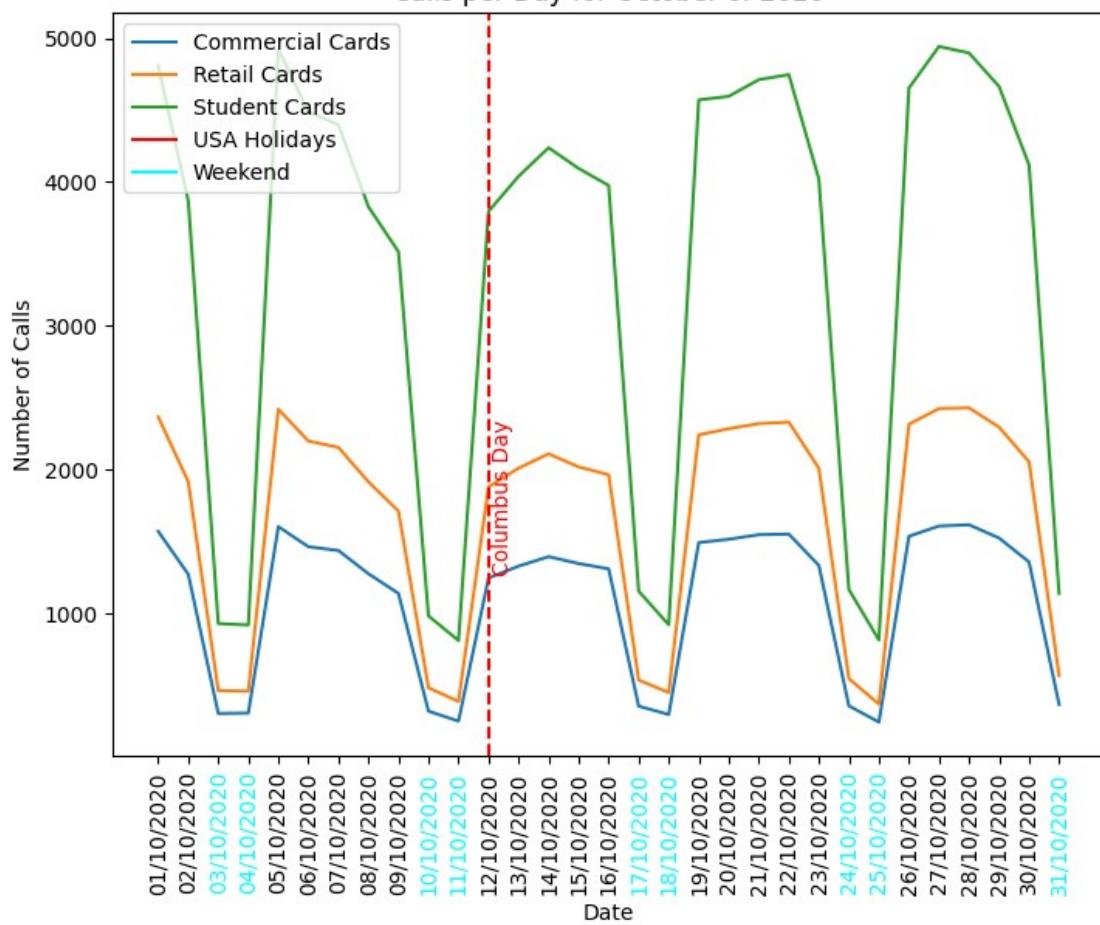
Calls per Day for August of 2020



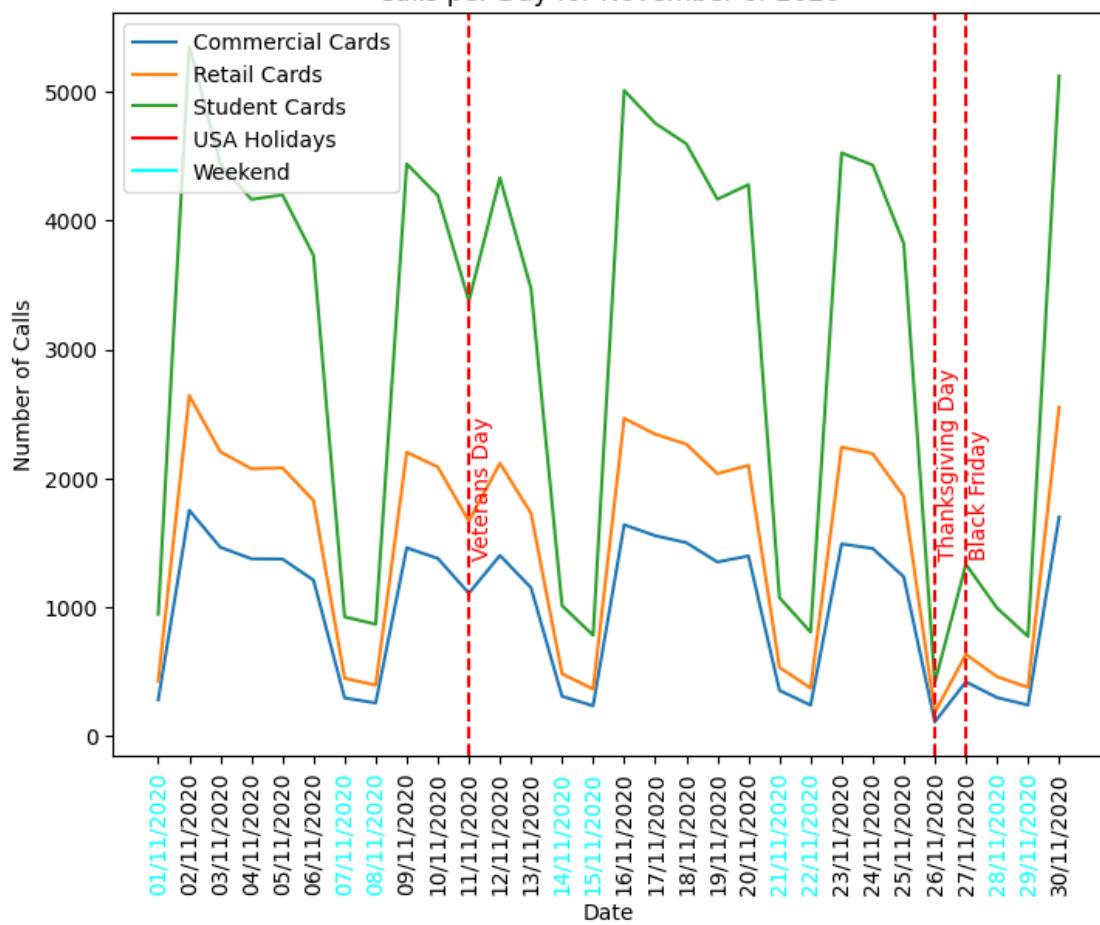
Calls per Day for September of 2020



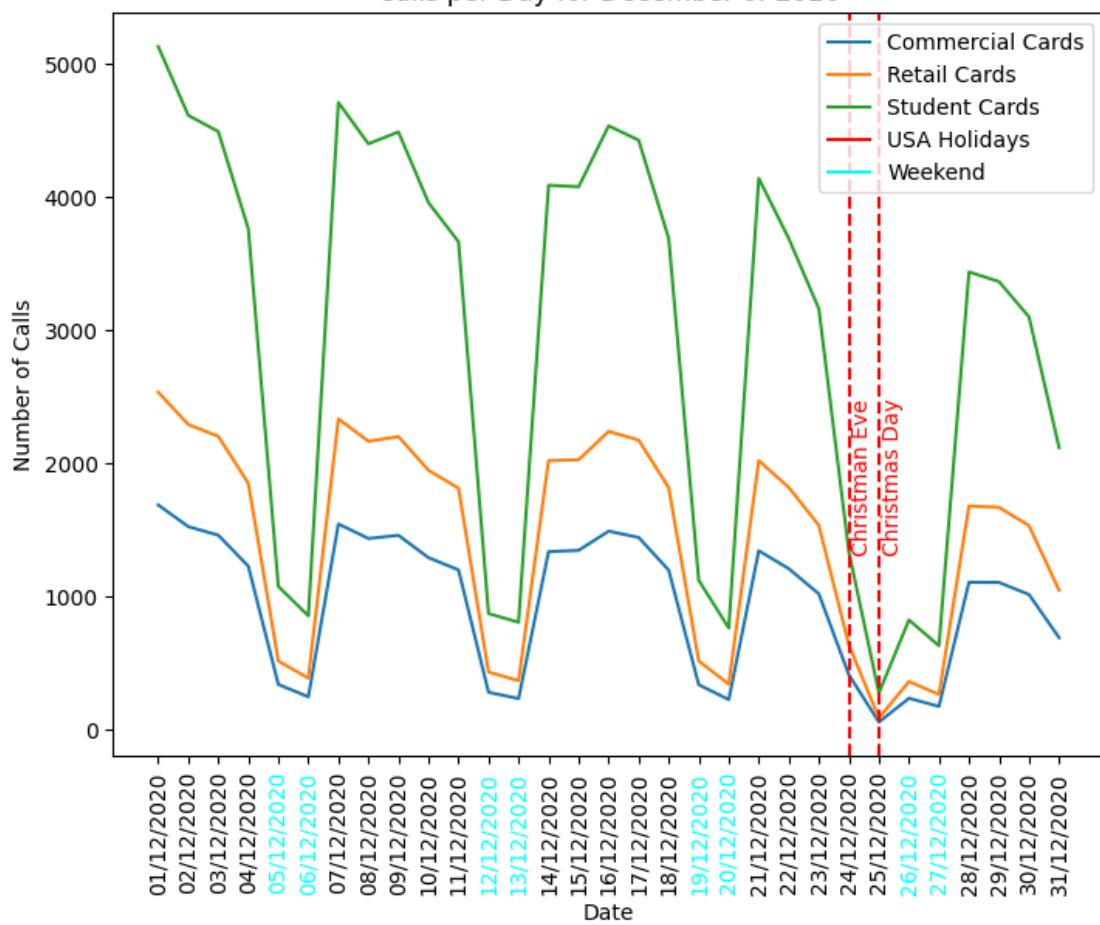
Calls per Day for October of 2020



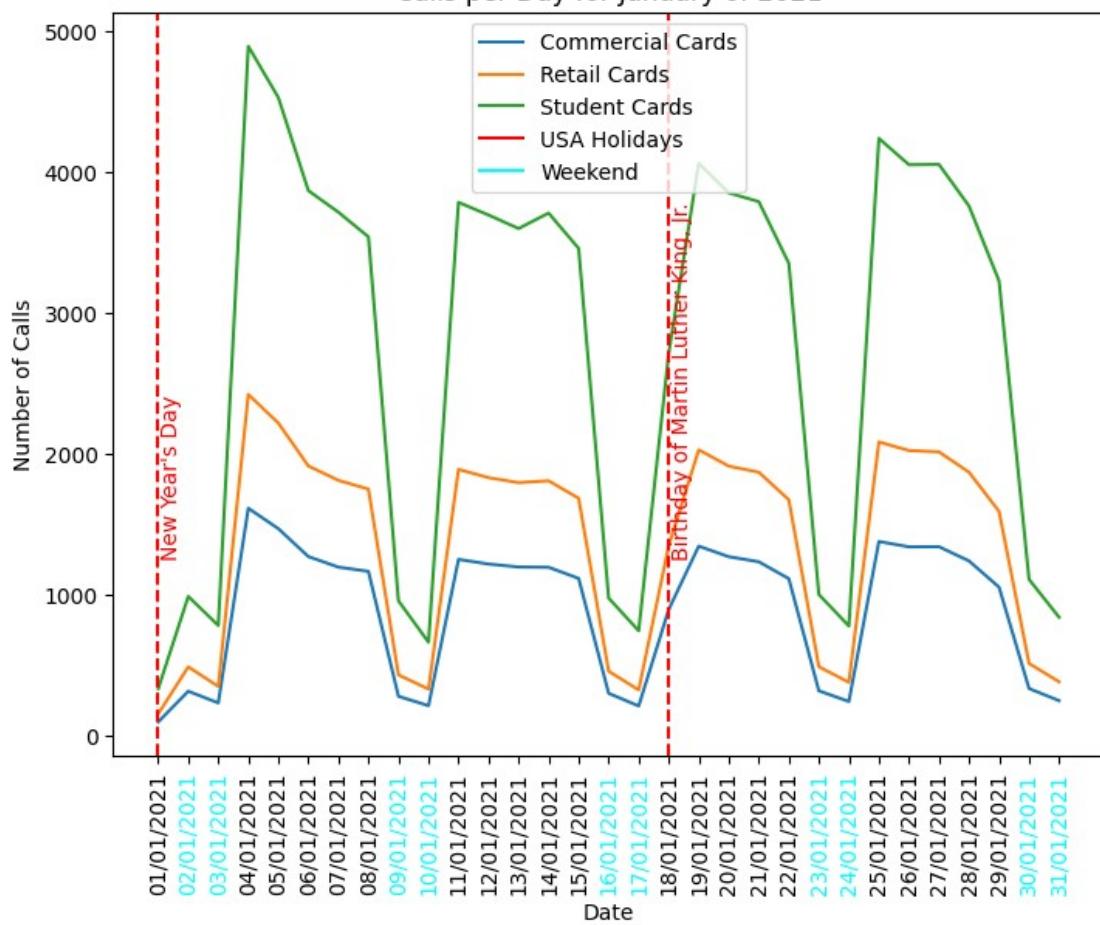
Calls per Day for November of 2020



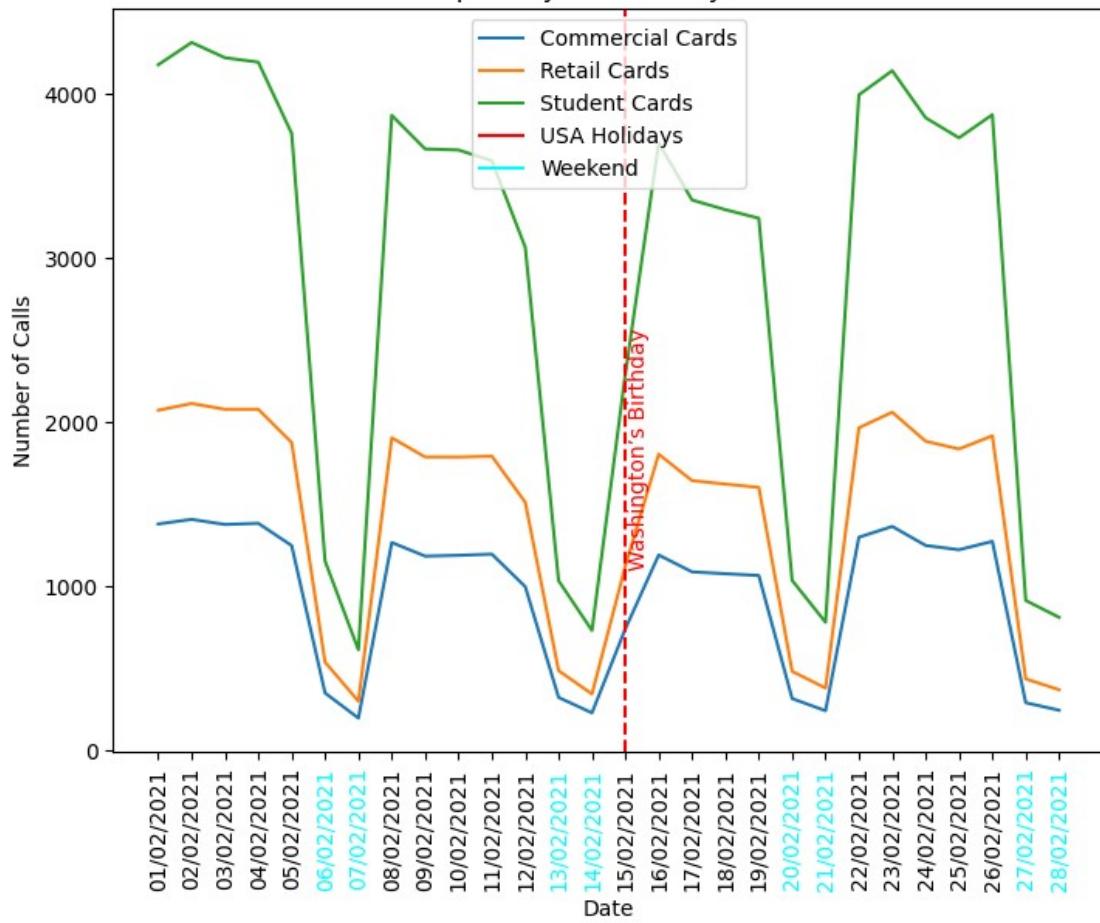
Calls per Day for December of 2020



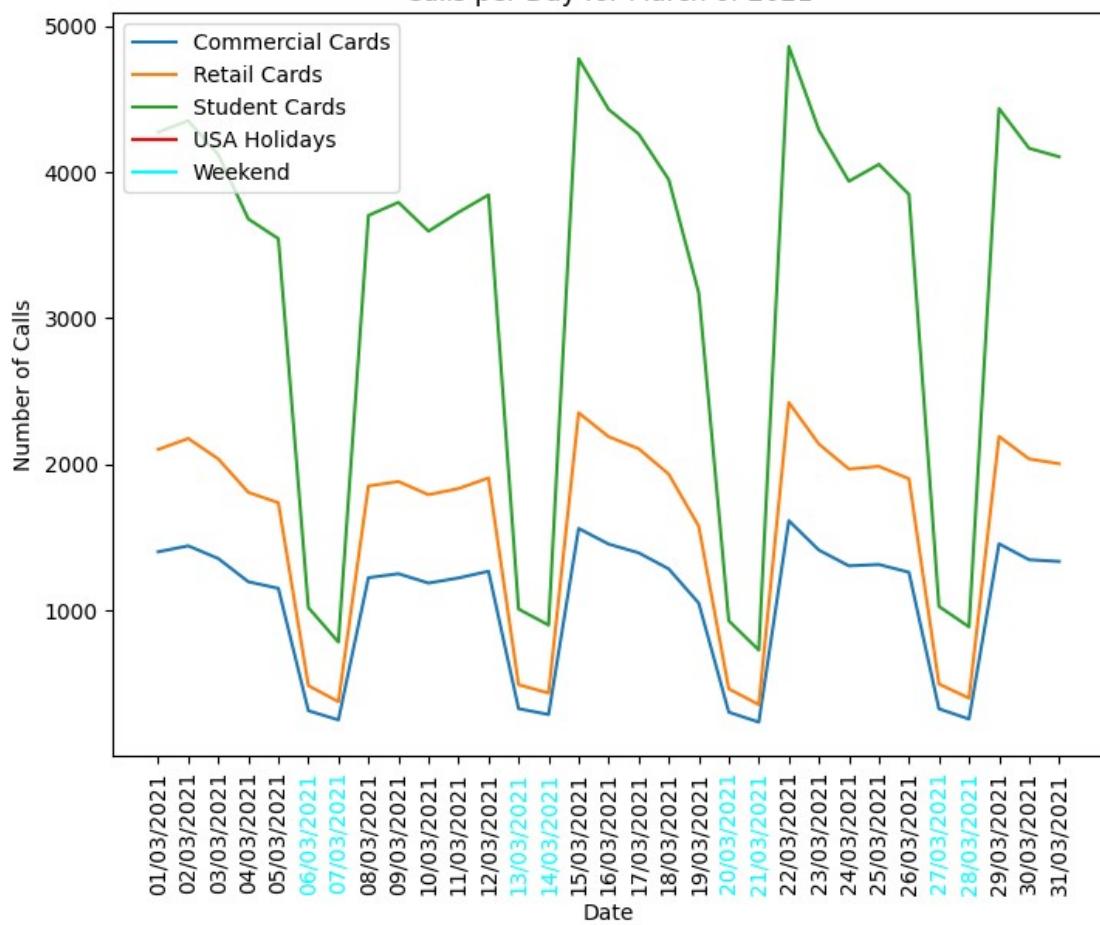
Calls per Day for January of 2021

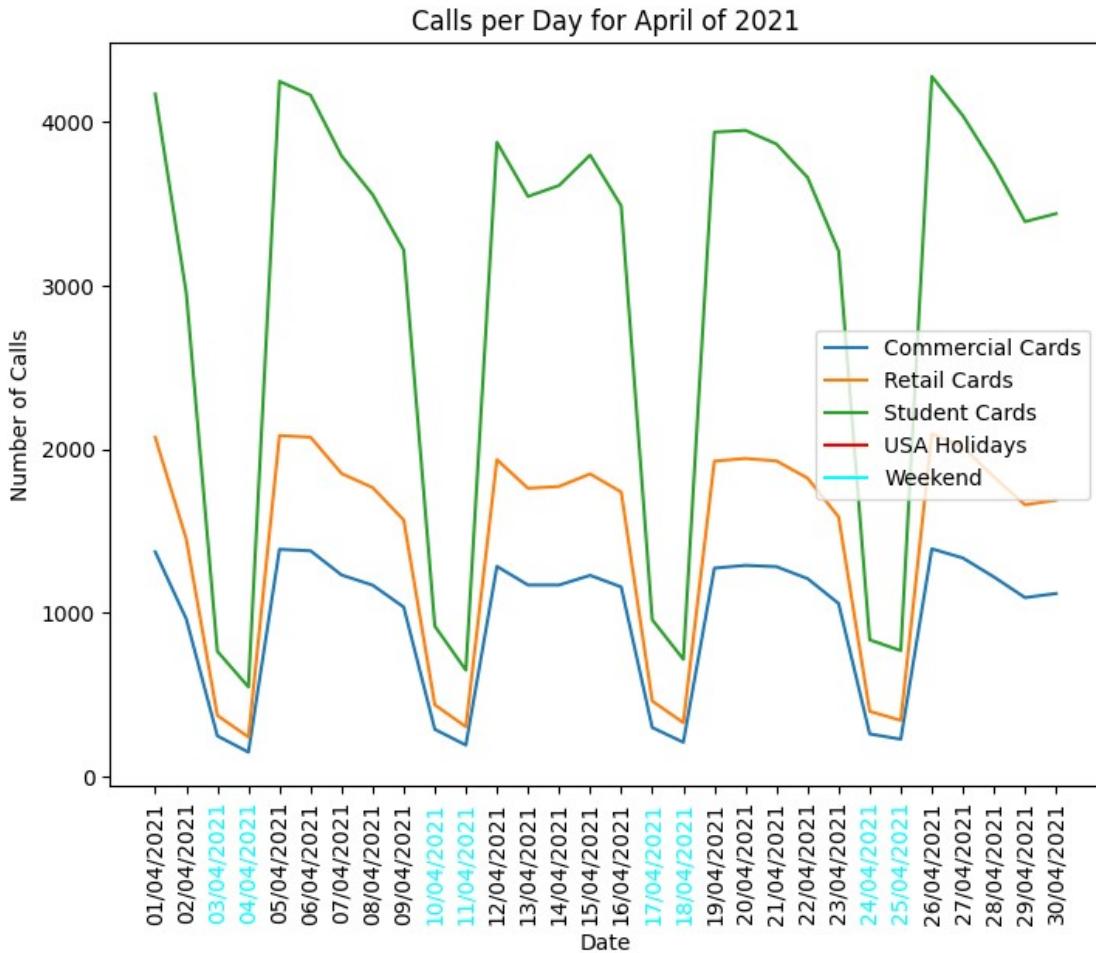


Calls per Day for February of 2021



Calls per Day for March of 2021





```
# Manila Holiday Calendar
class idcalen(AbstractHolidayCalendar):
    rules=[

        Holiday("New Year",month=1,day=1),
        Holiday("Day of Valor",month=4,day=9),
        Holiday("Labor Day",month=5,day=1),
        Holiday("Independence Day",month=6,day=12),
        Holiday("National heroes
day",month=8,day=31,offset=pd.DateOffset(weekday=M0(-1))),
        Holiday("Bonifacio",month=11,day=30),
        Holiday("Christmas",month=12,day=25),
        Holiday("Rizal",month=12,day=30),
        Holiday("Maundy Thursday",month=4,day=13,year=2017),
        Holiday("Maundy Thursday",month=3,day=29,year=2018),
        Holiday("Maundy Thursday",month=4,day=18,year=2019),
        Holiday("Maundy Thursday",month=4,day=9,year=2020),
        Holiday("Maundy Thursday",month=4,day=1,year=2021),
        Holiday("Good Friday",month=4,day=14,year=2017),
        Holiday("Good Friday",month=3,day=30,year=2018),
        Holiday("Good Friday",month=4,day=19,year=2019),
        Holiday("Good Friday",month=4,day=10,year=2020),
```

```

        Holiday("Good Friday",month=4,day=2,year=2021)
    ]

manila_cal=idcalen()
manila_holidays = manila_cal.holidays(start="2017-01-01",end="2021-04-30",return_name=True)
m_holidays = manila_holidays.to_frame("name")
m_holidays.reset_index(inplace=True)
m_holidays.rename(columns={"index":"date"}, inplace=True)

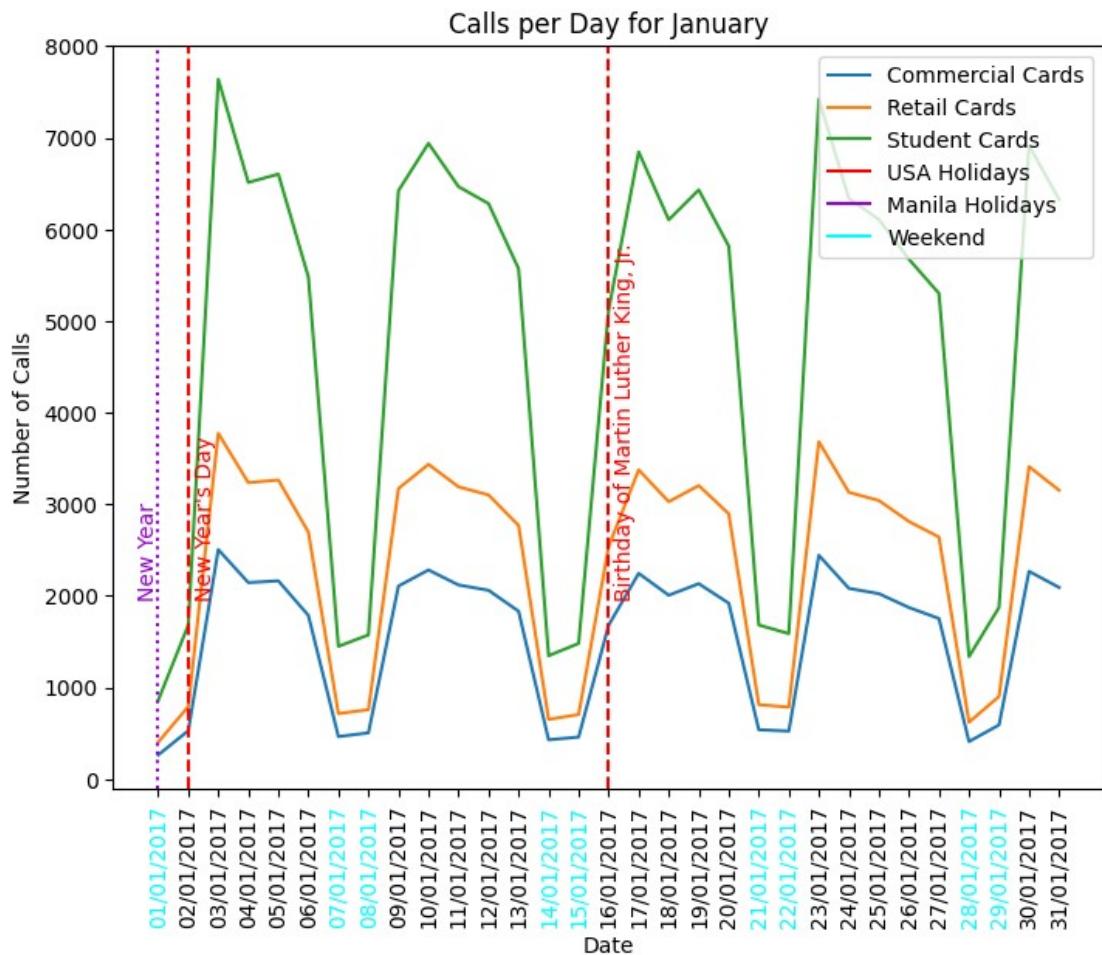
# 2017 data for each month
# Low number of calls on weekends
# Low number of calls on Big Holidays
holidays_2017 = holidays[[True if dt.year == 2017 else False for dt in
holidays.date]]
m_holidays_2017 = m_holidays[[True if dt.year == 2017 else False for
dt in m_holidays.date]]
months = df_17.month.unique()
for m in months:
    x = range((df_17.month == m).sum())
    cc_values = df_17[df_17.month == m].cc
    rc_values = df_17[df_17.month == m].rc
    sc_values = df_17[df_17.month == m].sc
    month_holidays = holidays_2017[[True if dt.month == m else False
for dt in holidays_2017.date]]
    monhol_values = [(dt.date.day-1, dt['name']) for i, dt in
month_holidays.iterrows()]
    m_month_holidays = m_holidays_2017[[True if dt.month == m else
False for dt in m_holidays_2017.date]]
    m_monhol_values = [(dt.date.day-1, dt['name']) for i, dt in
m_month_holidays.iterrows()]
    fig = plt.figure()
    ax = fig.add_axes([1,1,1,1])
    ax.plot(x, cc_values, label='Commercial Cards')
    ax.plot(x, rc_values, label='Retail Cards')
    ax.plot(x, sc_values, label='Student Cards')
    ax.plot([], [], label='USA Holidays', c='red')
    ax.plot([], [], label='Manila Holidays', c='darkviolet')
    ax.plot([], [], label='Weekend', c='cyan')
    for mhd, mhn in monhol_values:
        if mhn == 'Thanksgiving Day':
            ax.axvline(mhd+1, c='red', ls='--')
            ax.text(mhd+1.1, ax.get_ylim()[1]//4, "Black Friday",
rotation=90, c='red')
        if mhn == 'Christmas Day':
            ax.axvline(mhd-1, c='red', ls='--')
            ax.text(mhd-0.9, ax.get_ylim()[1]//4, "Christman Eve",
rotation=90, c='red')
            ax.axvline(mhd, c='red', ls='--')
            ax.text(mhd+0.2, ax.get_ylim()[1]//4, mhn, rotation=90,
c='red')

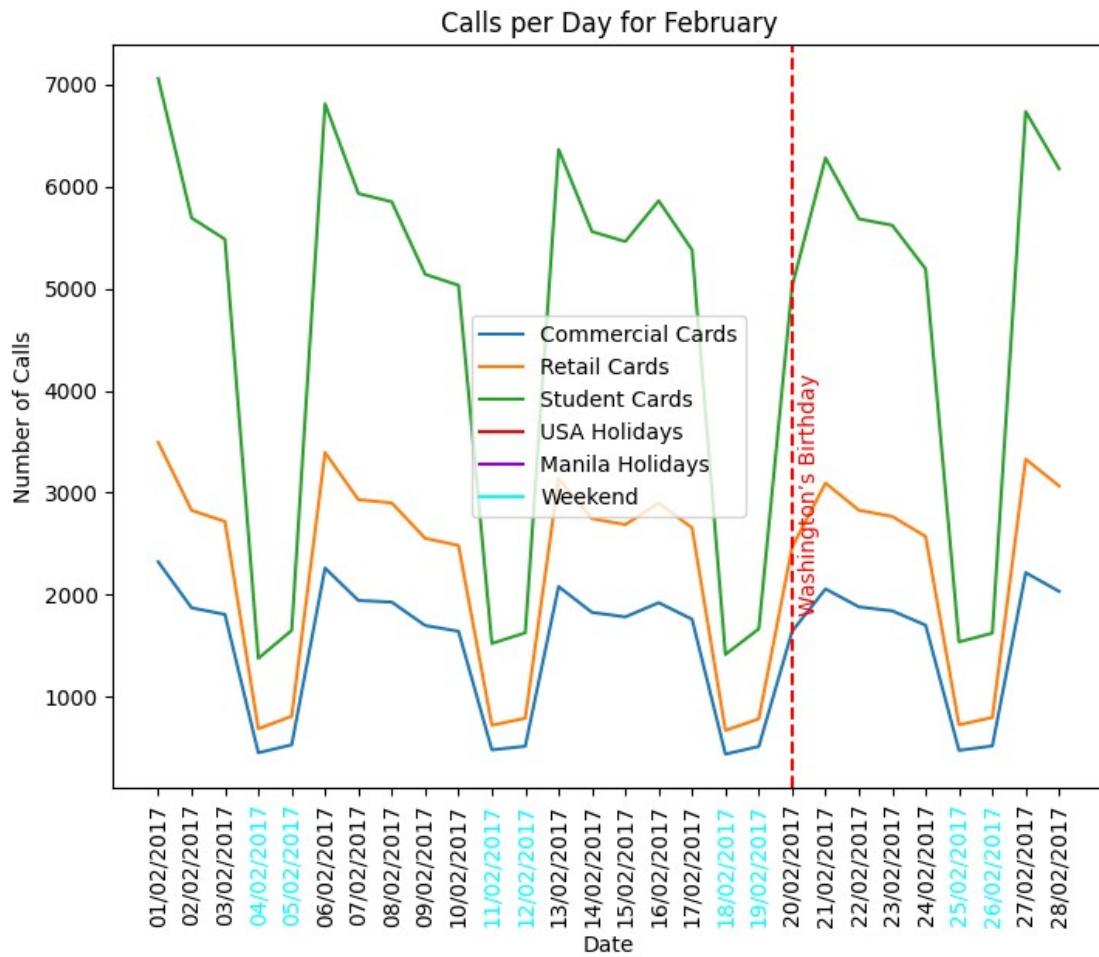
```

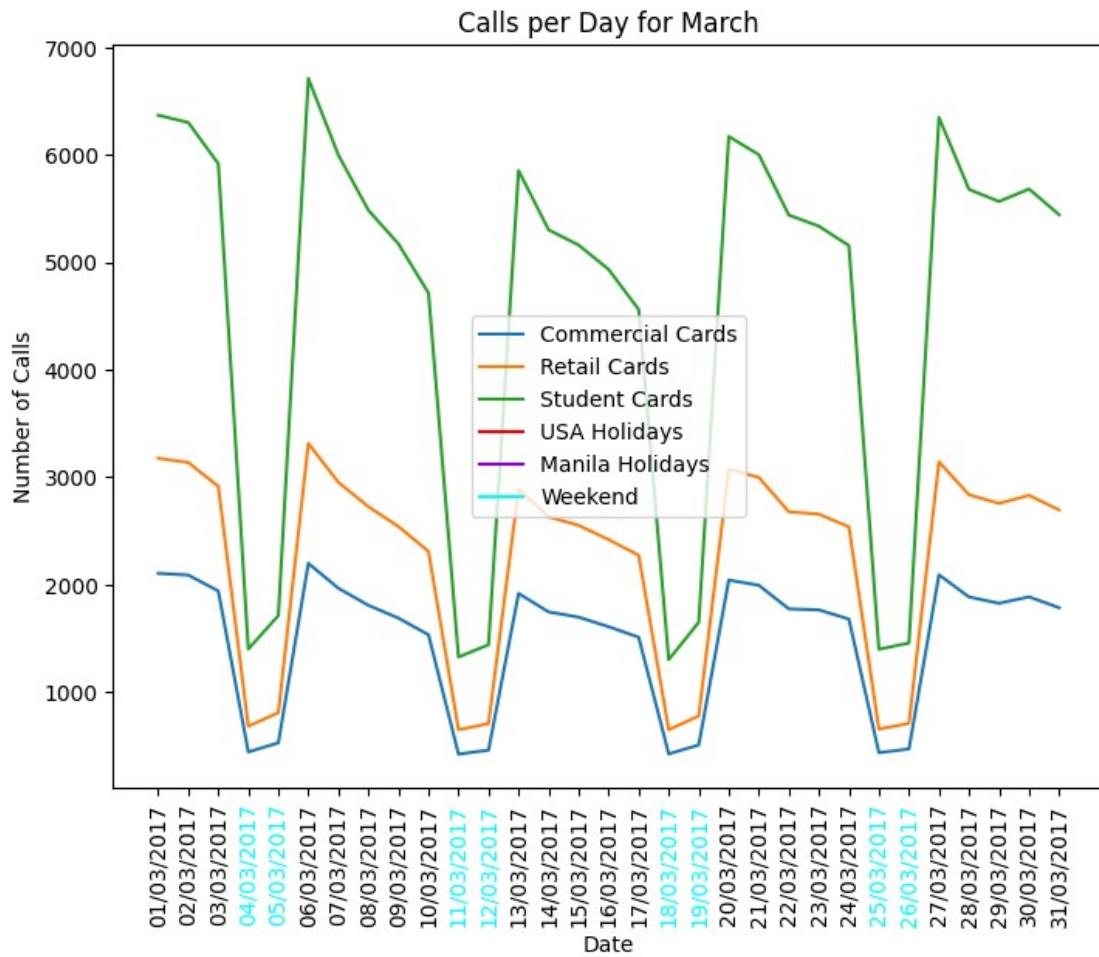
```

for mhd, mhn in m_monhol_values:
    ax.axvline(mhd, c='darkviolet', ls=':')
    ax.text(mhd-0.7, ax.get_ylim()[1]//4, mhn, rotation=90,
c='darkviolet')
    ax.set_xticks(x, df_17[df_17.month == m].date, rotation=90)
    for i, dt in enumerate(df_17[df_17.month == m].date):
        if arrow.get(dt, "DD/MM/YYYY").format("ddd") in ["Sat",
"Sun"]:
            ax.get_xticklabels()[i].set_color('cyan')
ax.set_xlabel("Date")
ax.set_ylabel("Number of Calls")
ax.set_title(f"Calls per Day for {arrow.get(str(m),
'M')).format('MMMM')}"))
ax.legend()
plt.show()

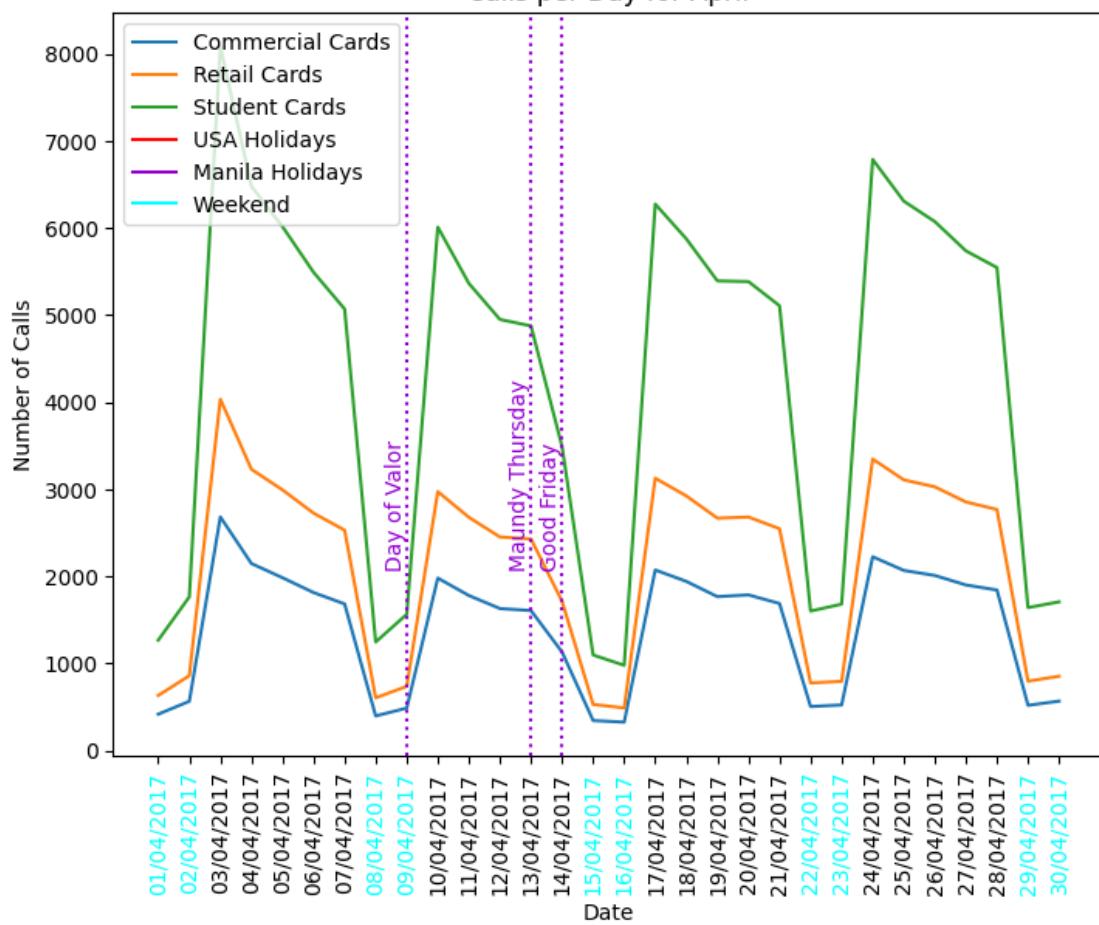
```



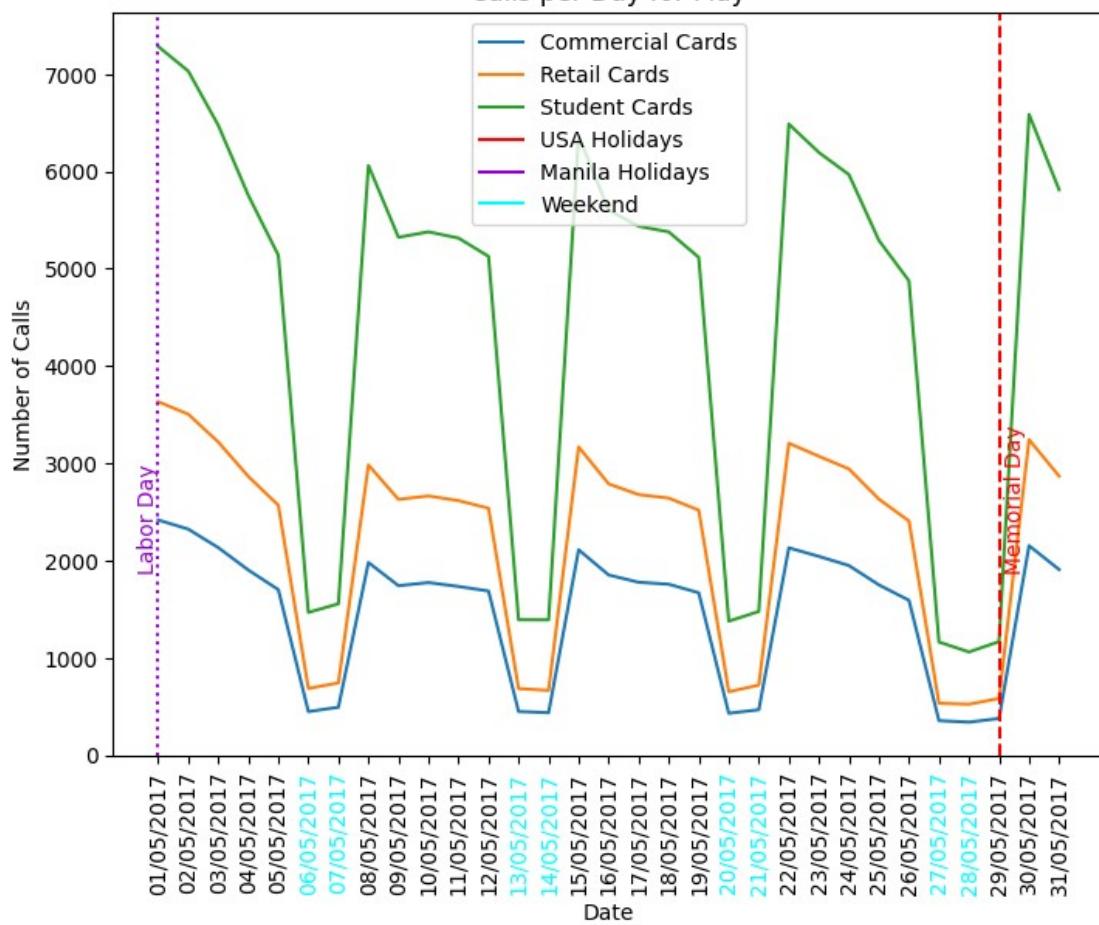


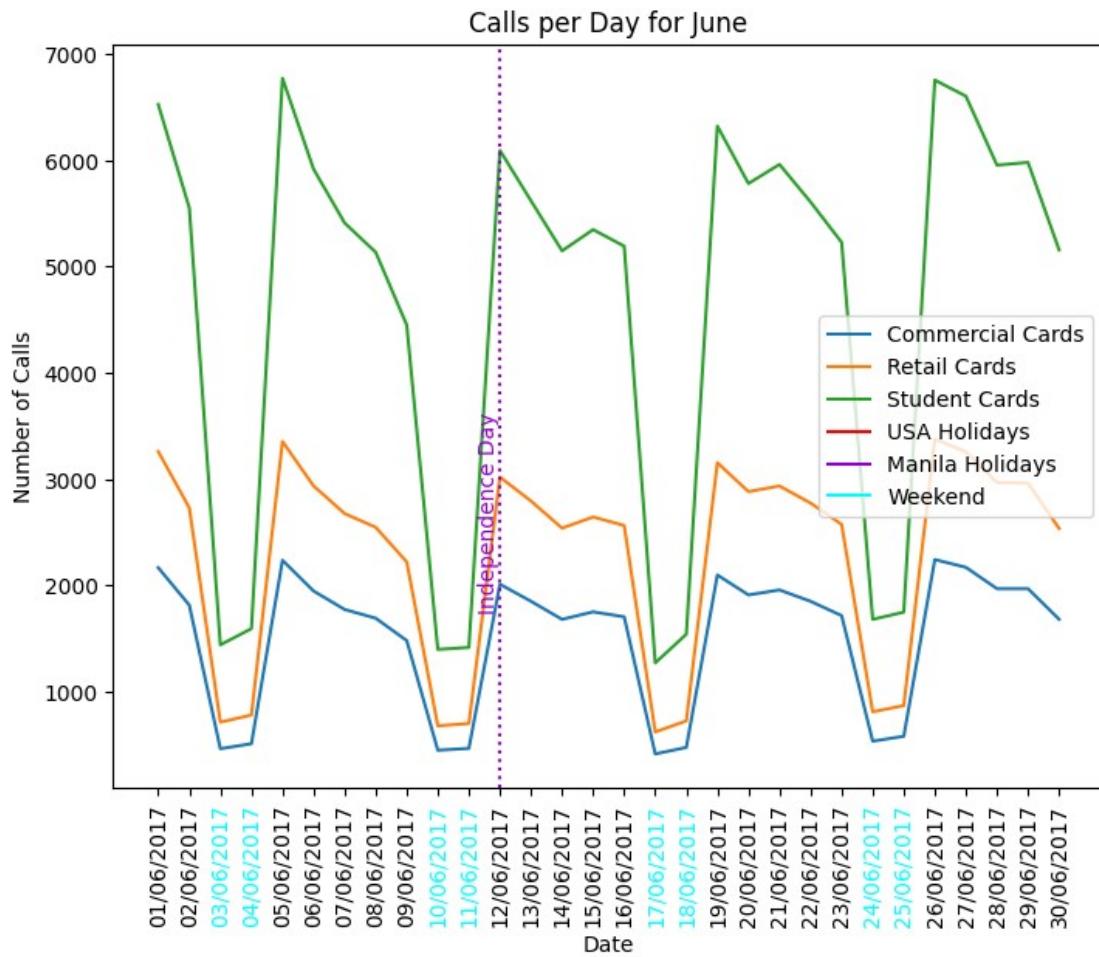


Calls per Day for April

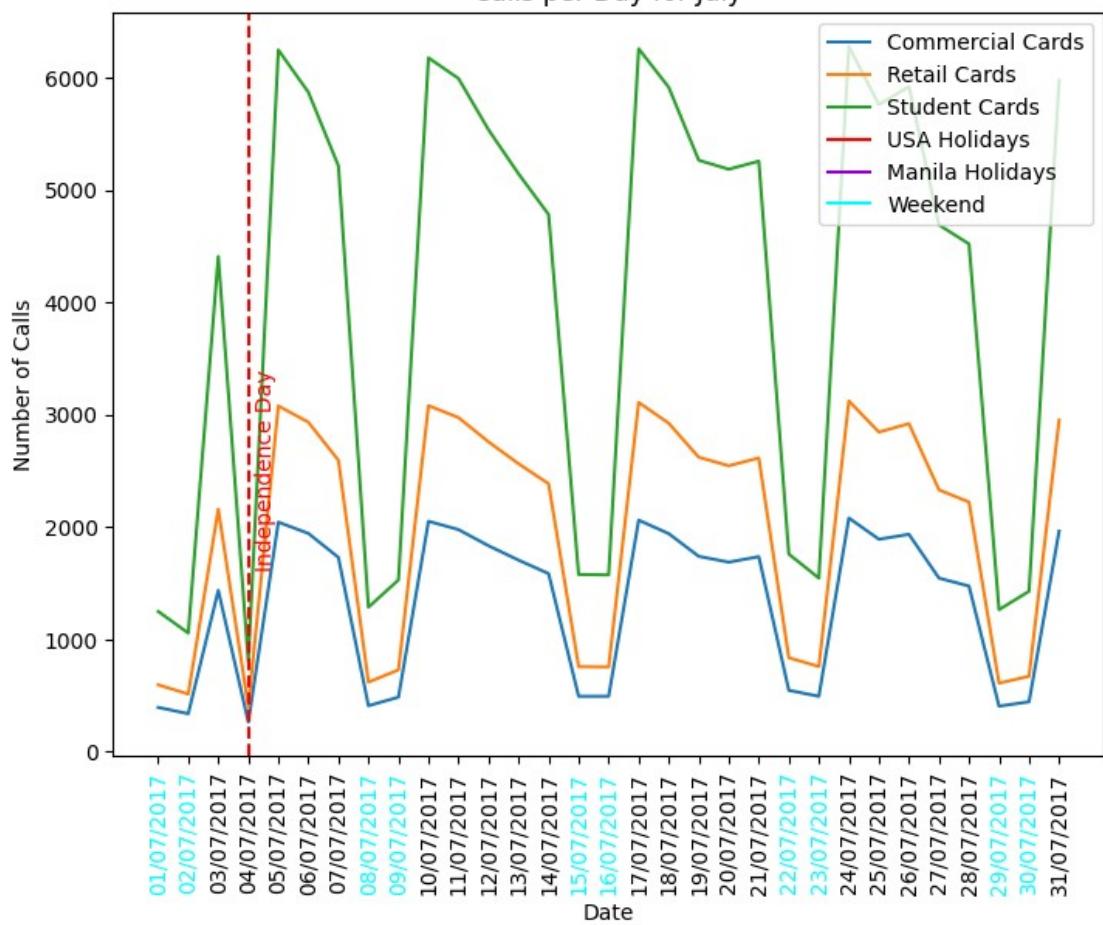


Calls per Day for May

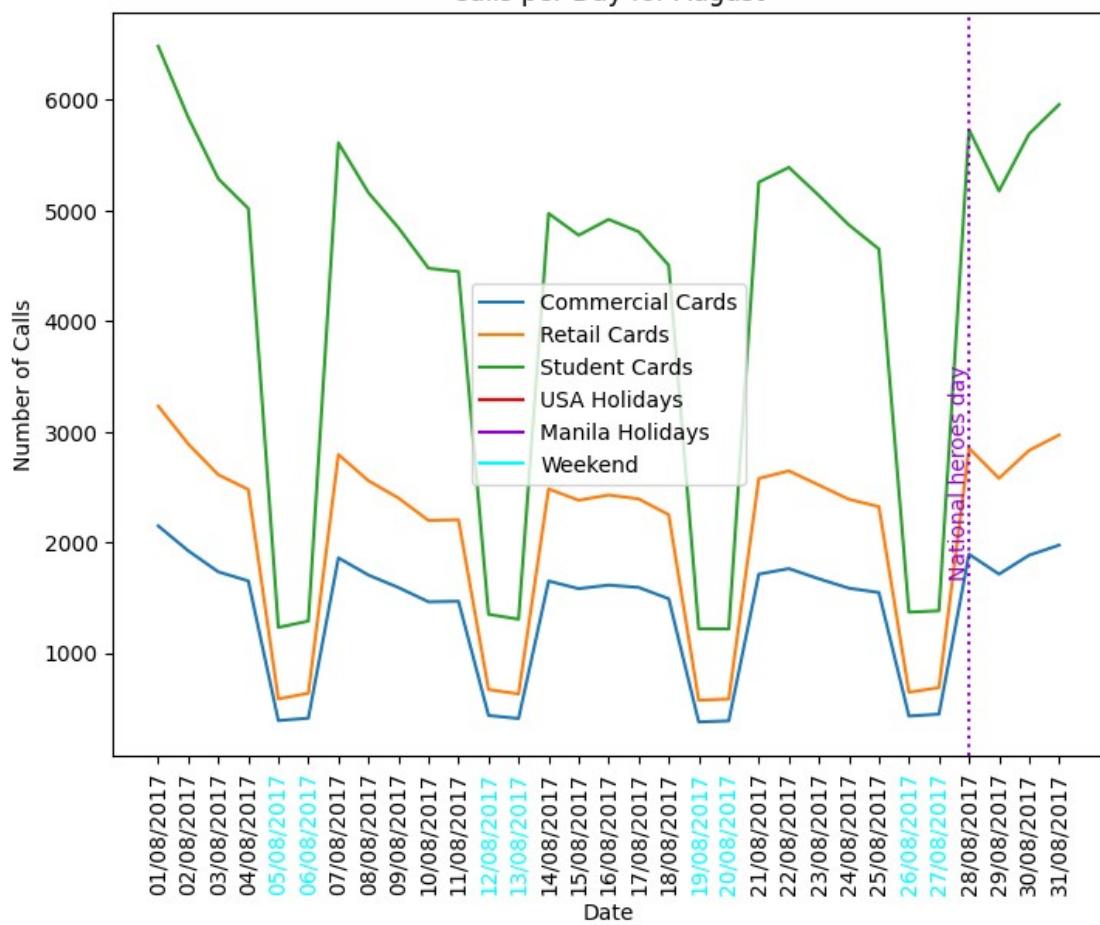




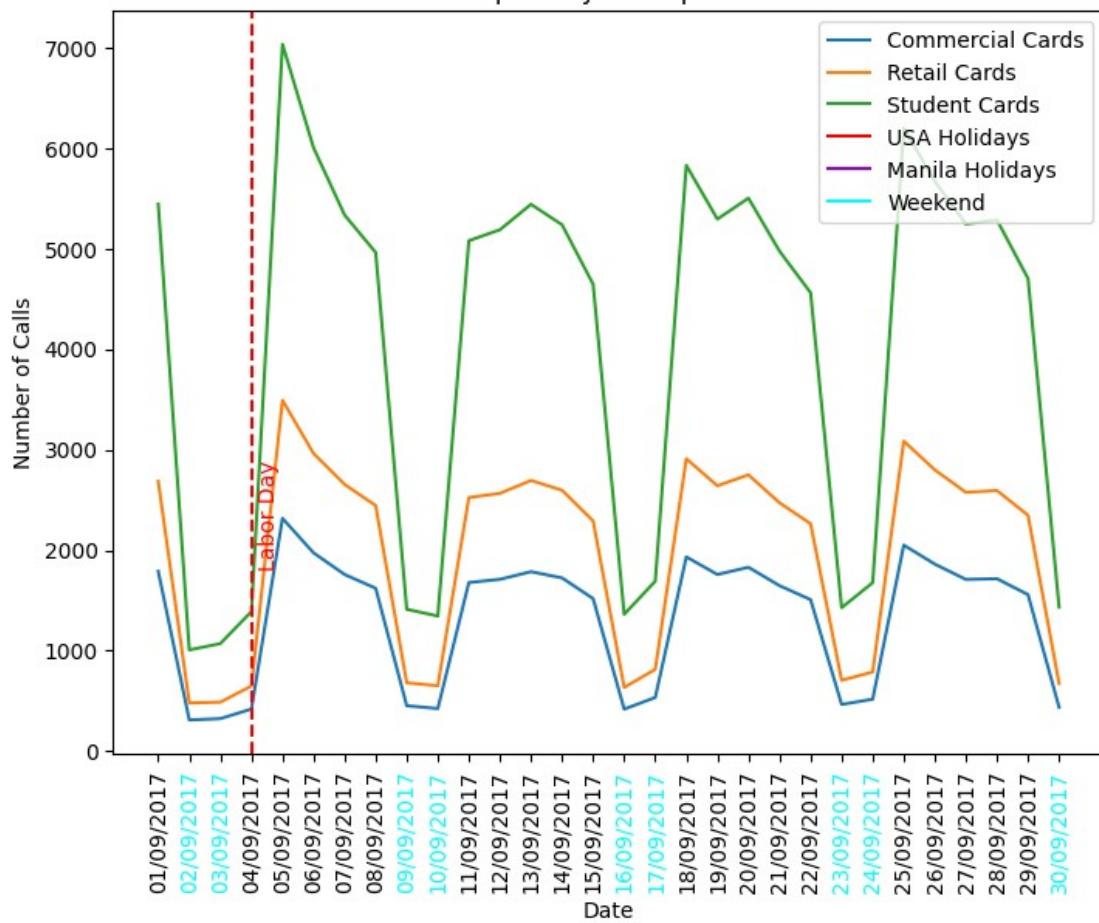
Calls per Day for July



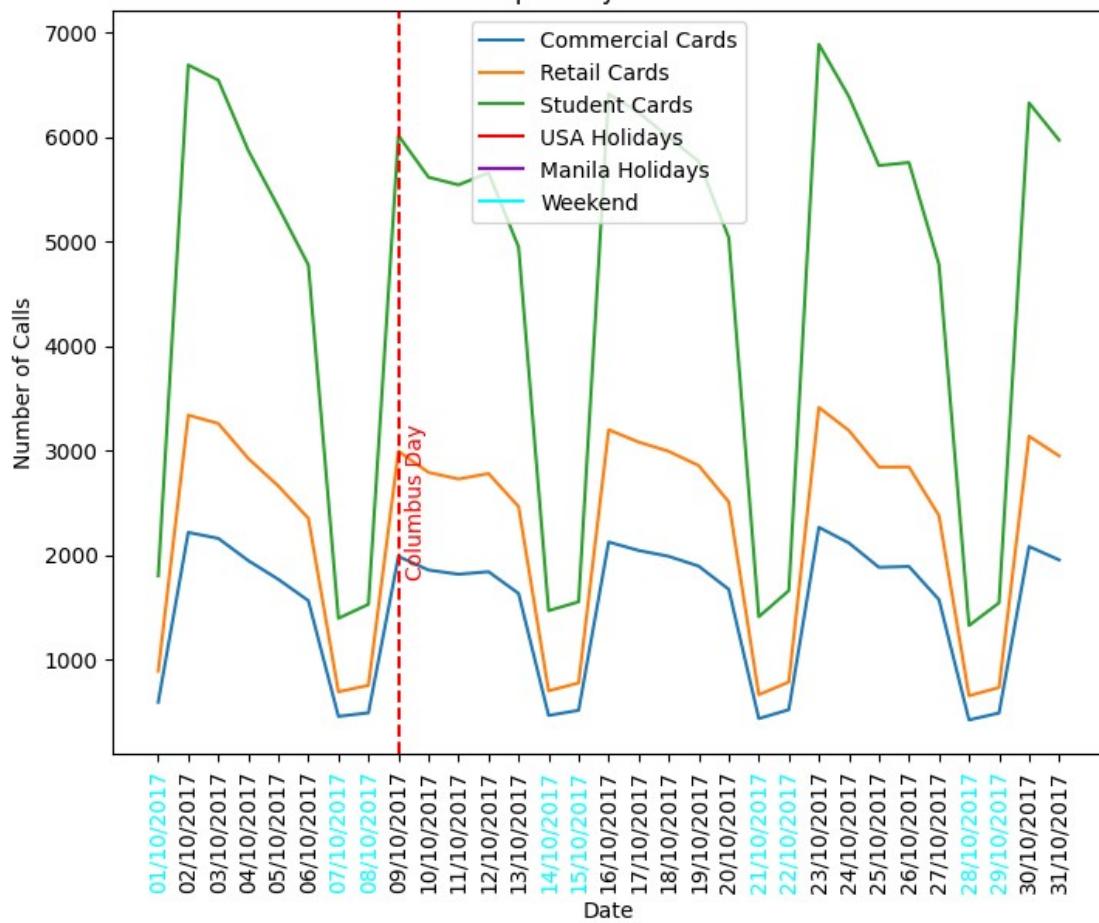
Calls per Day for August



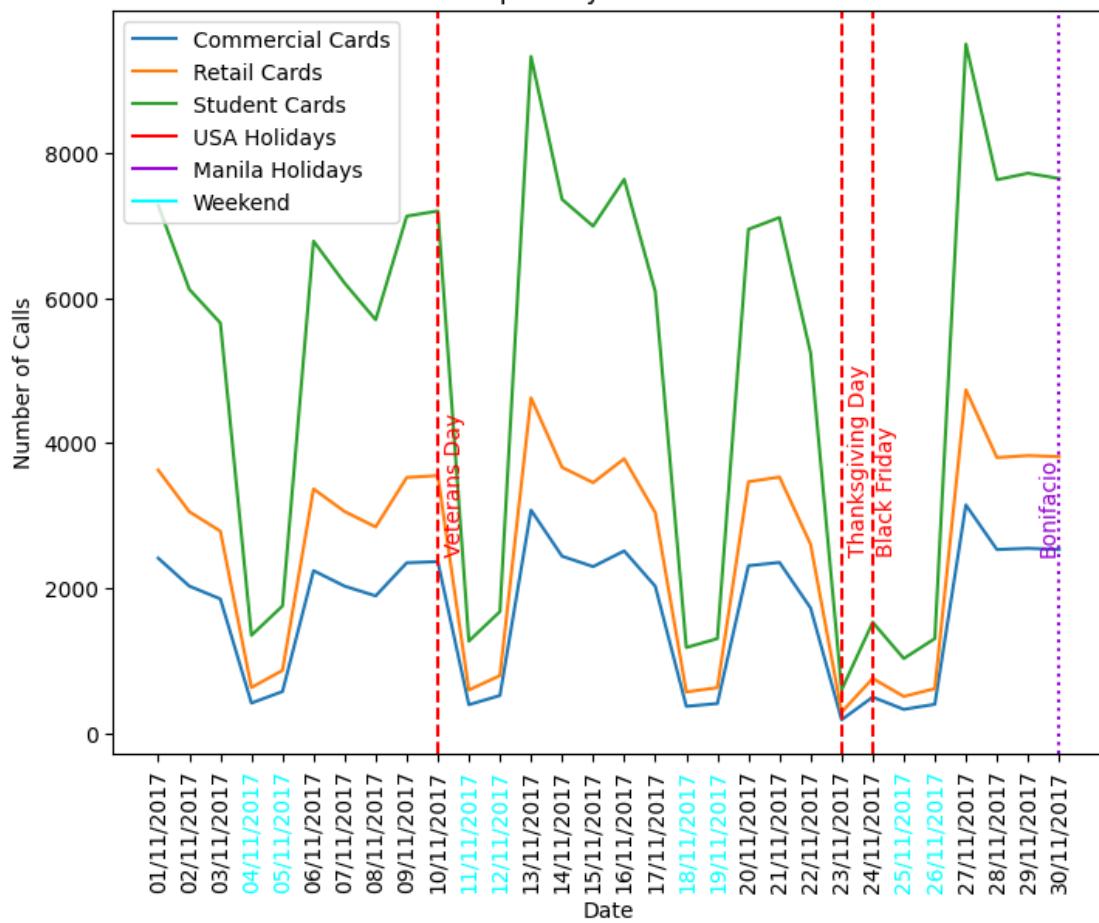
Calls per Day for September

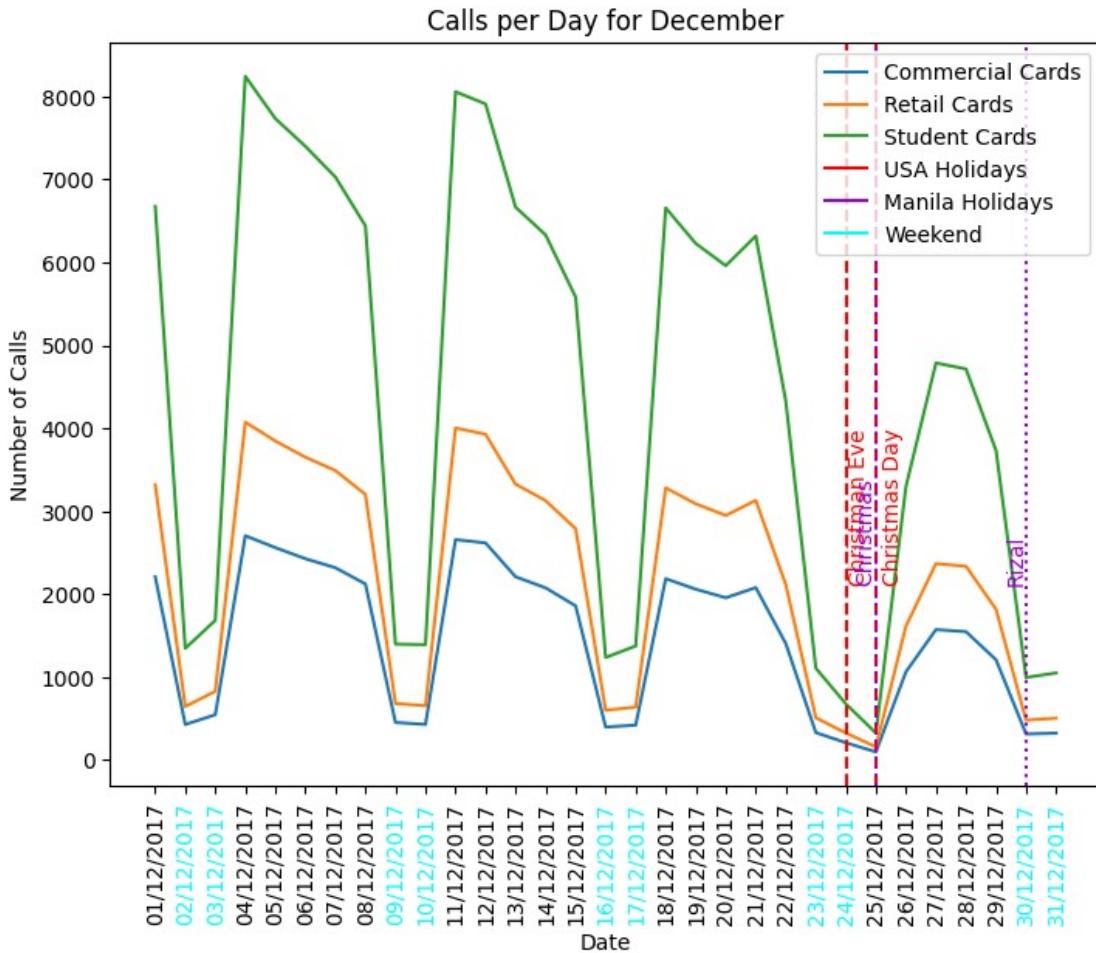


Calls per Day for October



Calls per Day for November





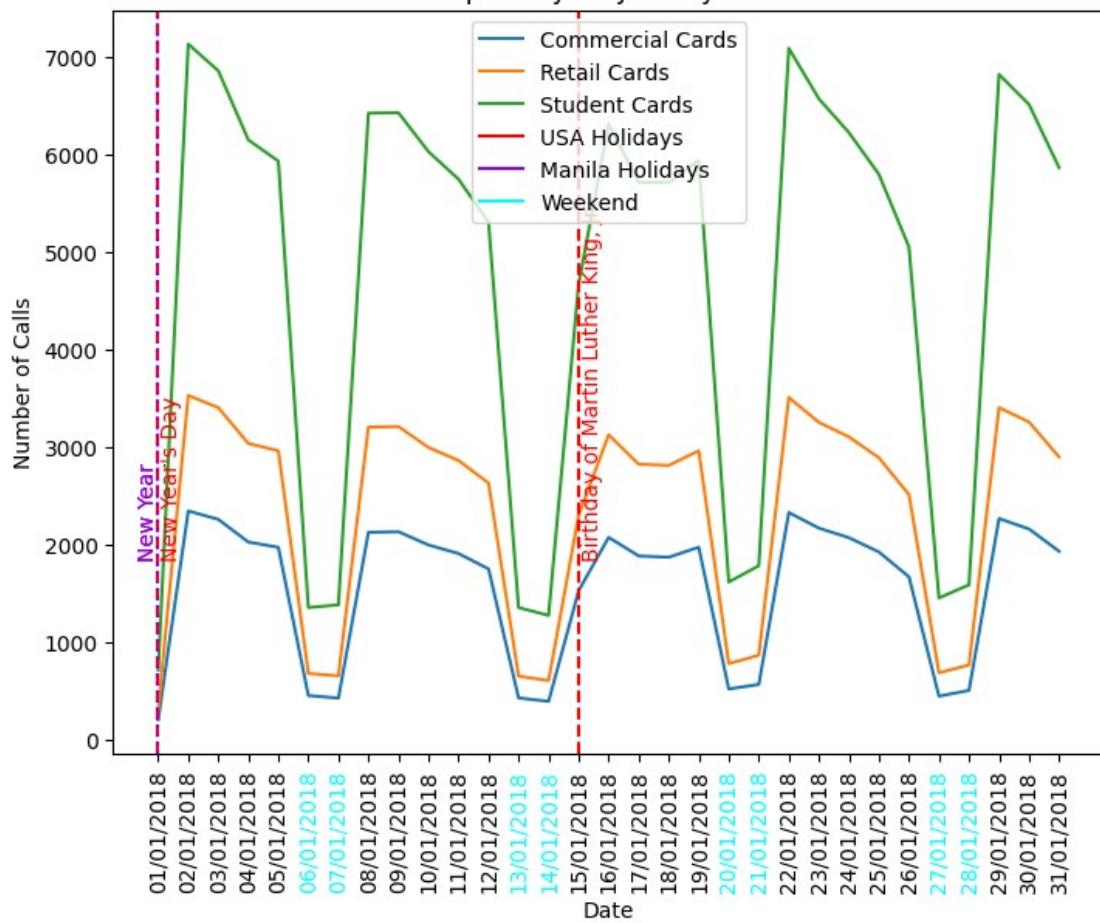
```
# 2018-2021 data for each month
# Low number of calls on weekends
# Low number of calls on Big Holidays
years = df_not17_sorted.year.unique()
for y in years:
    holidays_yearly = holidays[[True if dt.year == y else False for dt
in holidays.date]]
    m_holidays_yearly = m_holidays[[True if dt.year == y else False
for dt in m_holidays.date]]
    df_not17_sorted_yearly = df_not17_sorted[df_not17_sorted.year ==
y]
    months = df_not17_sorted_yearly.month.unique()
    for m in months:
        x = range((df_not17_sorted_yearly.month == m).sum())
        cc_values =
df_not17_sorted_yearly[df_not17_sorted_yearly.month == m].cc
        rc_values =
df_not17_sorted_yearly[df_not17_sorted_yearly.month == m].rc
        sc_values =
df_not17_sorted_yearly[df_not17_sorted_yearly.month == m].sc
        month_holidays = holidays_yearly[[True if dt.month == m else
False
for dt in holidays.date]]
```

```

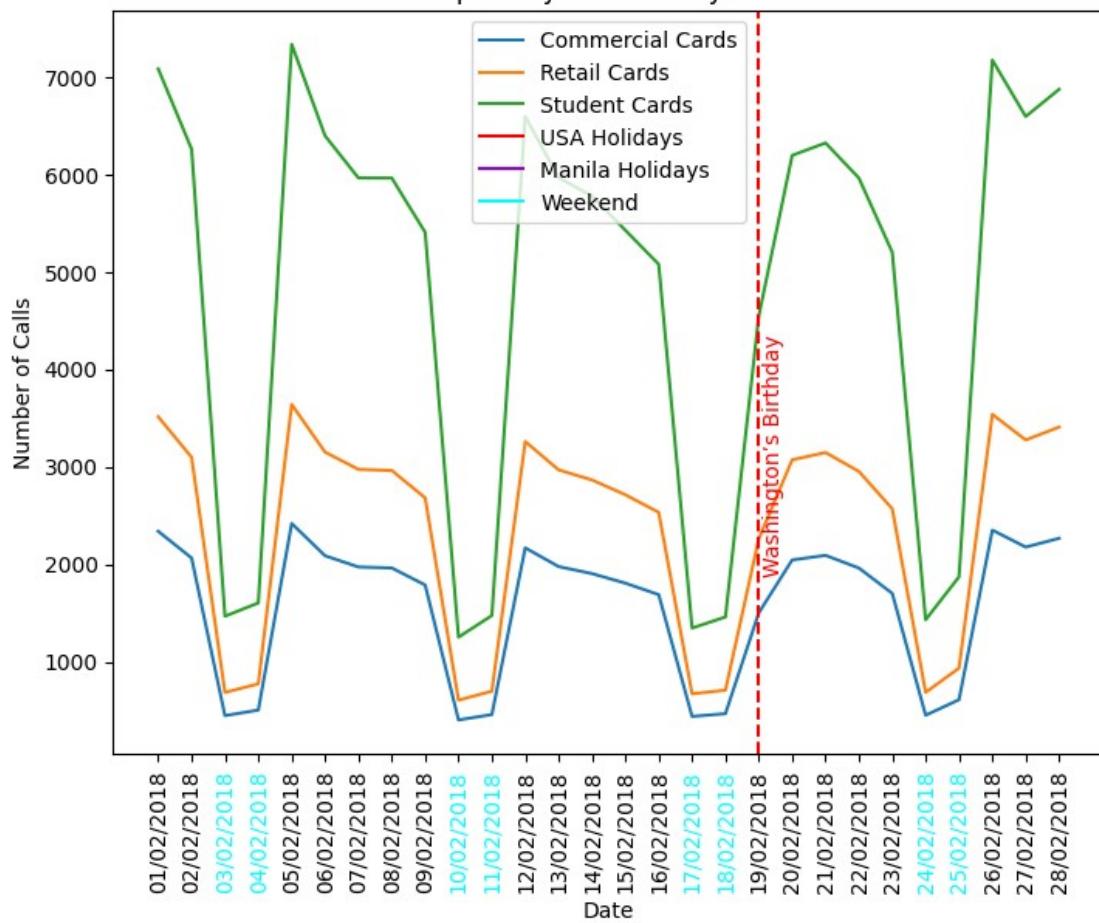
False for dt in holidays_yearly.date]]
    monhol_values = [(dt.date.day-1, dt['name']) for i, dt in
month_holidays.iterrows()]
    m_month_holidays = m_holidays_yearly[[True if dt.month == m
else False for dt in m_holidays_yearly.date]]
    m_monhol_values = [(dt.date.day-1, dt['name']) for i, dt in
m_month_holidays.iterrows()]
    fig = plt.figure()
    ax = fig.add_axes([1,1,1,1])
    ax.plot(x, cc_values, label='Commercial Cards')
    ax.plot(x, rc_values, label='Retail Cards')
    ax.plot(x, sc_values, label='Student Cards')
    ax.plot([], [], label='USA Holidays', c='red')
    ax.plot([], [], label='Manila Holidays', c='darkviolet')
    ax.plot([], [], label='Weekend', c='cyan')
    for mhd, mhn in monhol_values:
        if mhn == 'Thanksgiving Day':
            ax.axvline(mhd+1, c='red', ls='--')
            ax.text(mhd+1.1, ax.get_ylim()[1]//4, "Black Friday",
rotation=90, c='red')
        if mhn == 'Christmas Day':
            ax.axvline(mhd-1, c='red', ls='--')
            ax.text(mhd-0.9, ax.get_ylim()[1]//4, "Christman Eve",
rotation=90, c='red')
            ax.axvline(mhd, c='red', ls='--')
            ax.text(mhd+0.1, ax.get_ylim()[1]//4, mhn, rotation=90,
c='red')
        for mhd, mhn in m_monhol_values:
            ax.axvline(mhd, c='darkviolet', ls=':')
            ax.text(mhd-0.7, ax.get_ylim()[1]//4, mhn,
rotation=90, c='darkviolet')
    ax.set_xticks(x,
df_not17_sorted_yearly[df_not17_sorted_yearly.month == m].date,
rotation=90)
    for i, dt in
enumerate(df_not17_sorted_yearly[df_not17_sorted_yearly.month ==
m].date):
        if arrow.get(dt, "DD/MM/YYYY").format("ddd") in ["Sat",
"Sun"]:
            ax.get_xticklabels()[i].set_color('cyan')
    ax.set_xlabel("Date")
    ax.set_ylabel("Number of Calls")
    ax.set_title(f"Calls per Day for {arrow.get(str(m),
'M')).format('MMMM')} of {y}")
    ax.legend()
    plt.show()

```

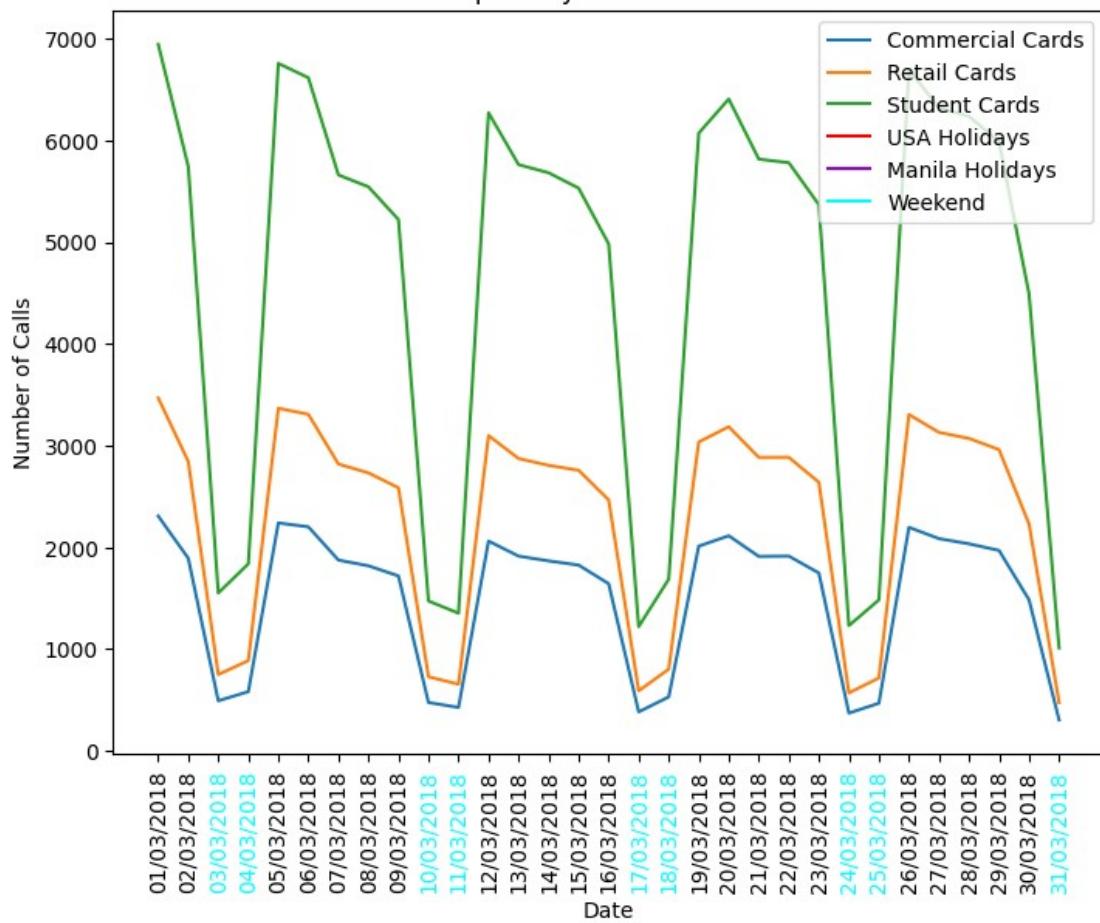
Calls per Day for January of 2018



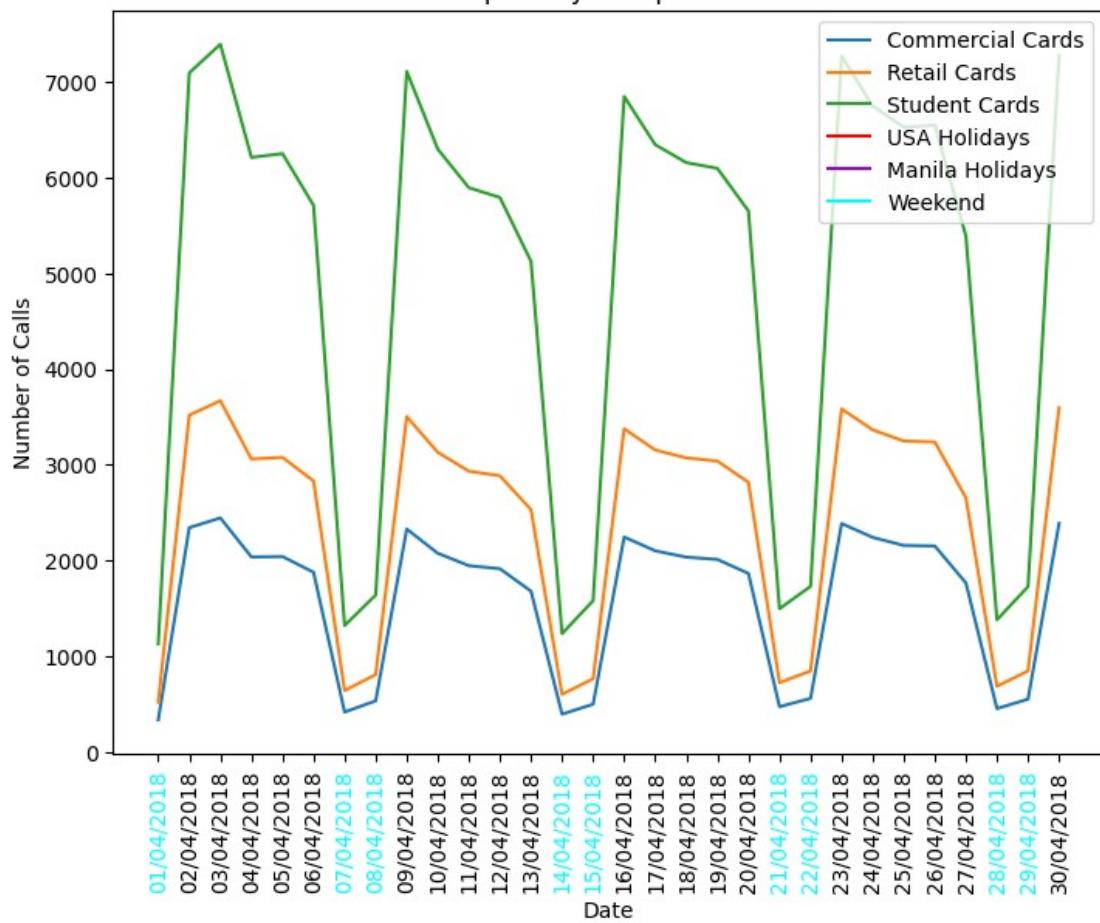
Calls per Day for February of 2018



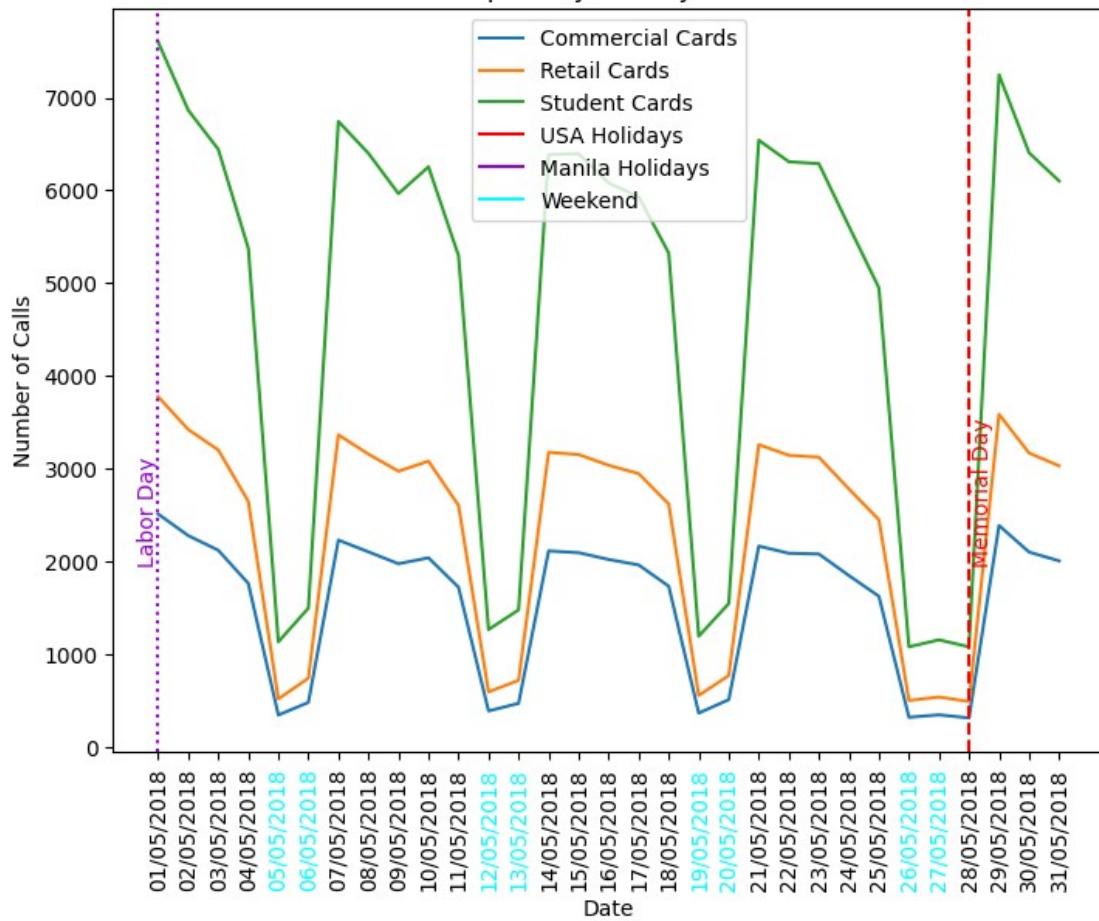
Calls per Day for March of 2018



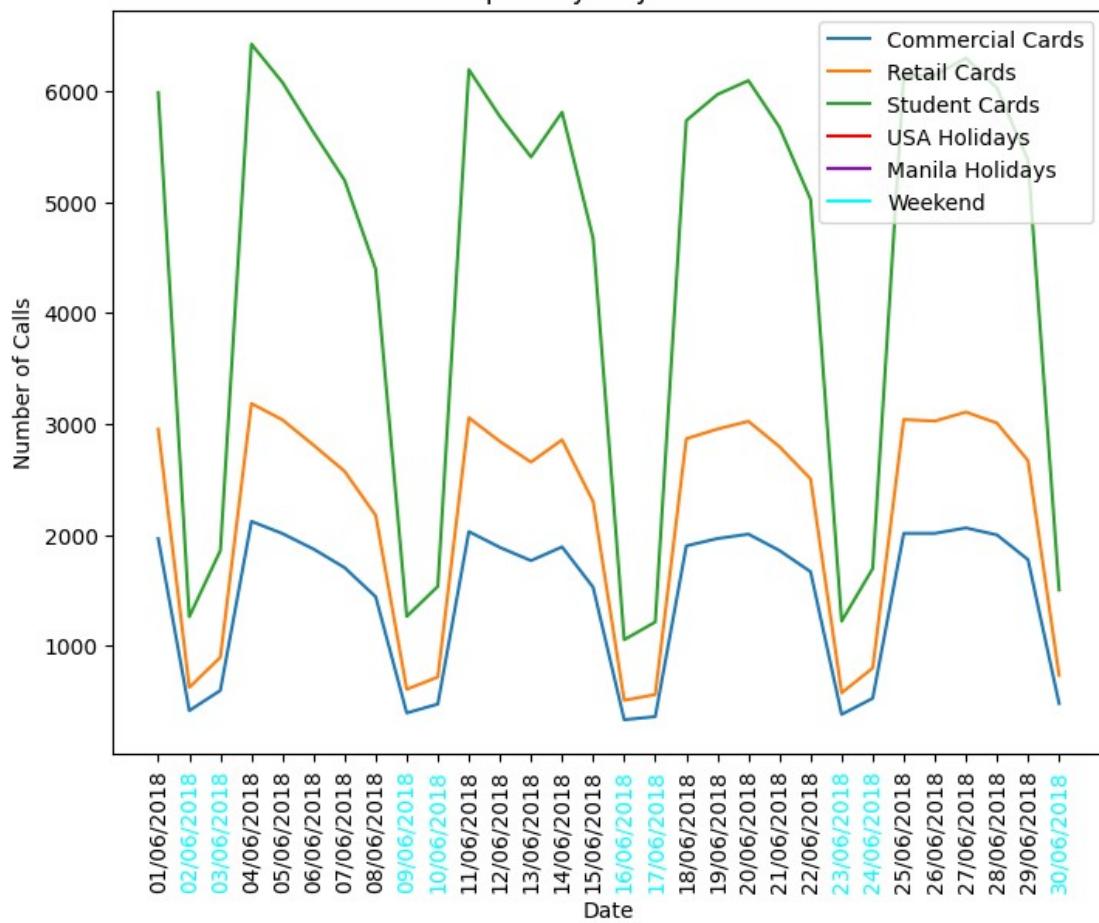
Calls per Day for April of 2018



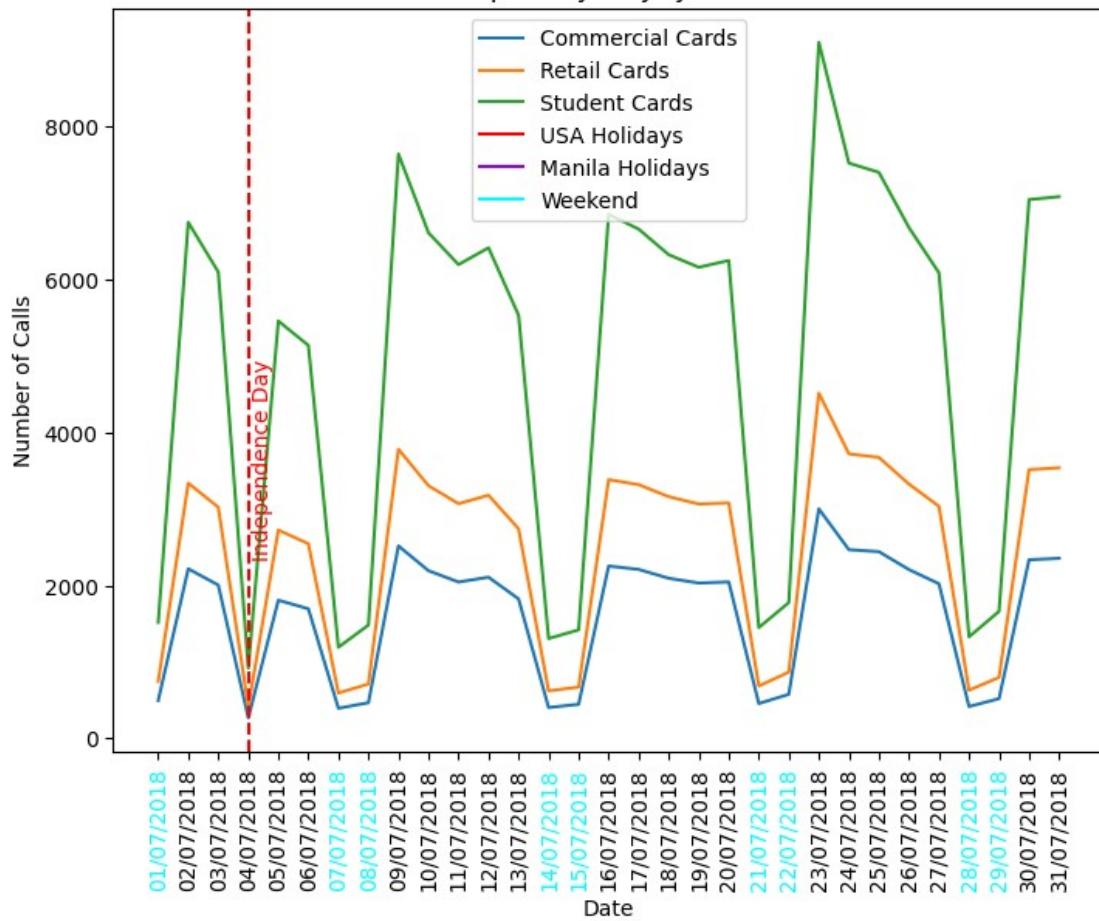
Calls per Day for May of 2018



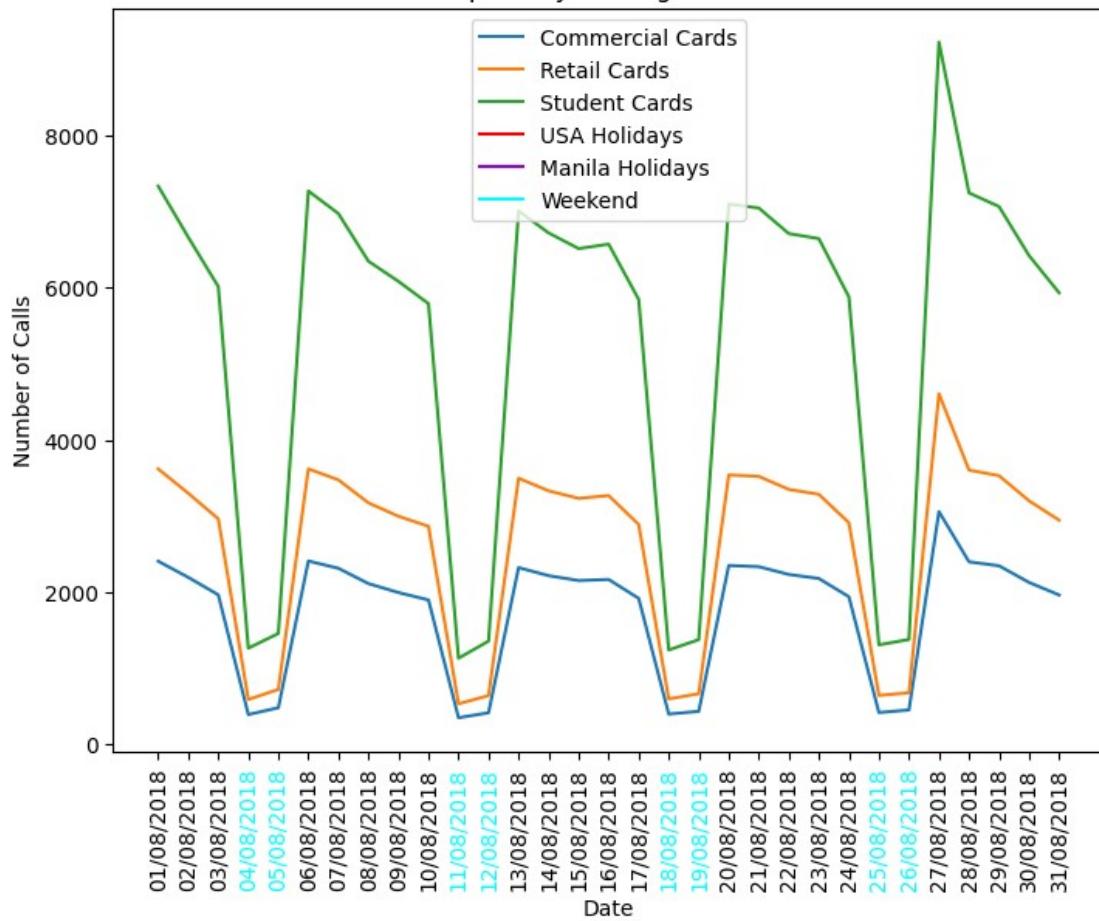
Calls per Day for June of 2018



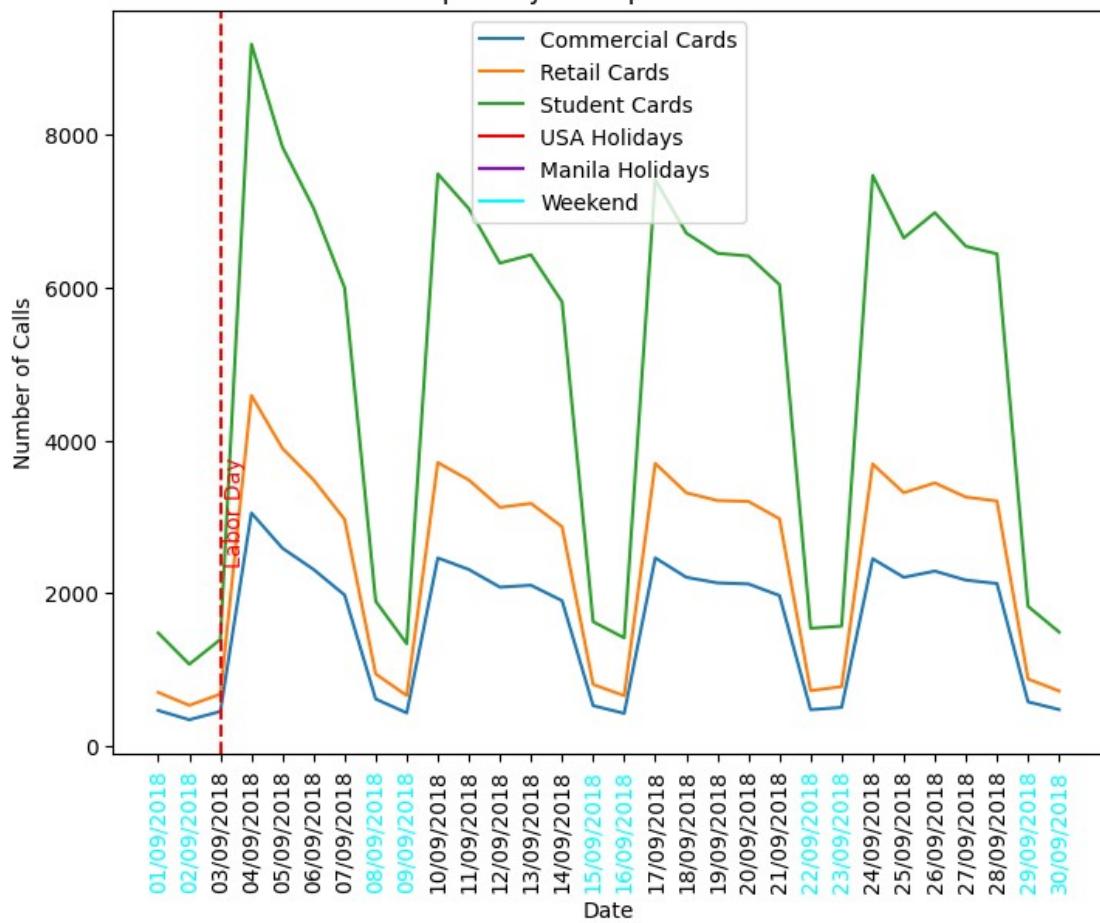
Calls per Day for July of 2018



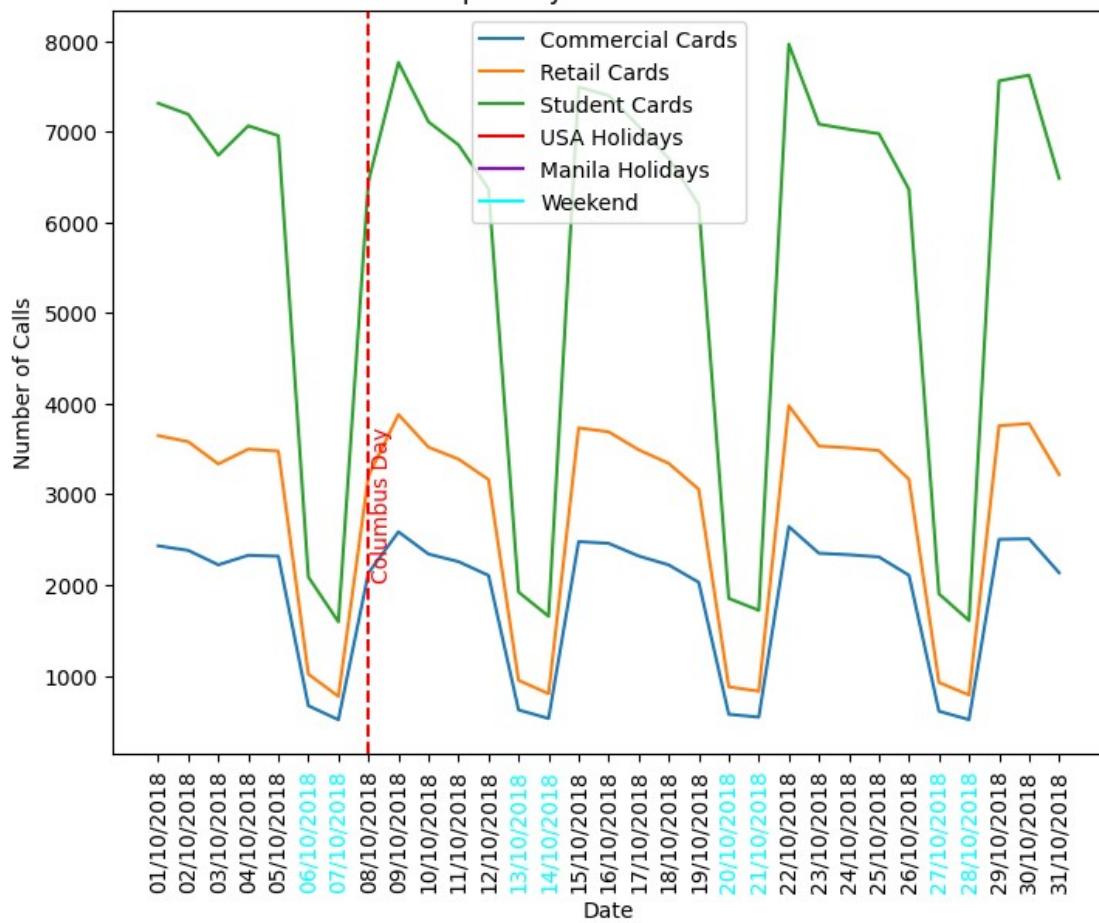
Calls per Day for August of 2018



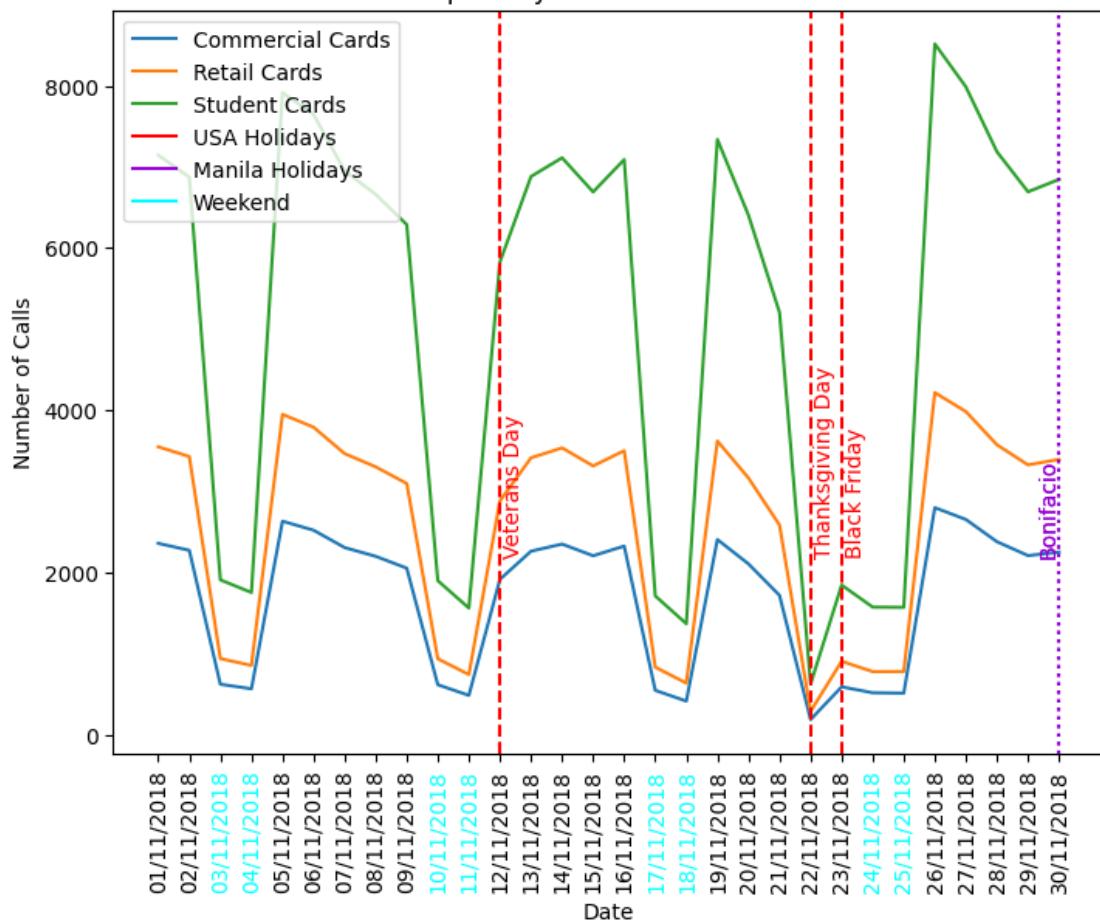
Calls per Day for September of 2018



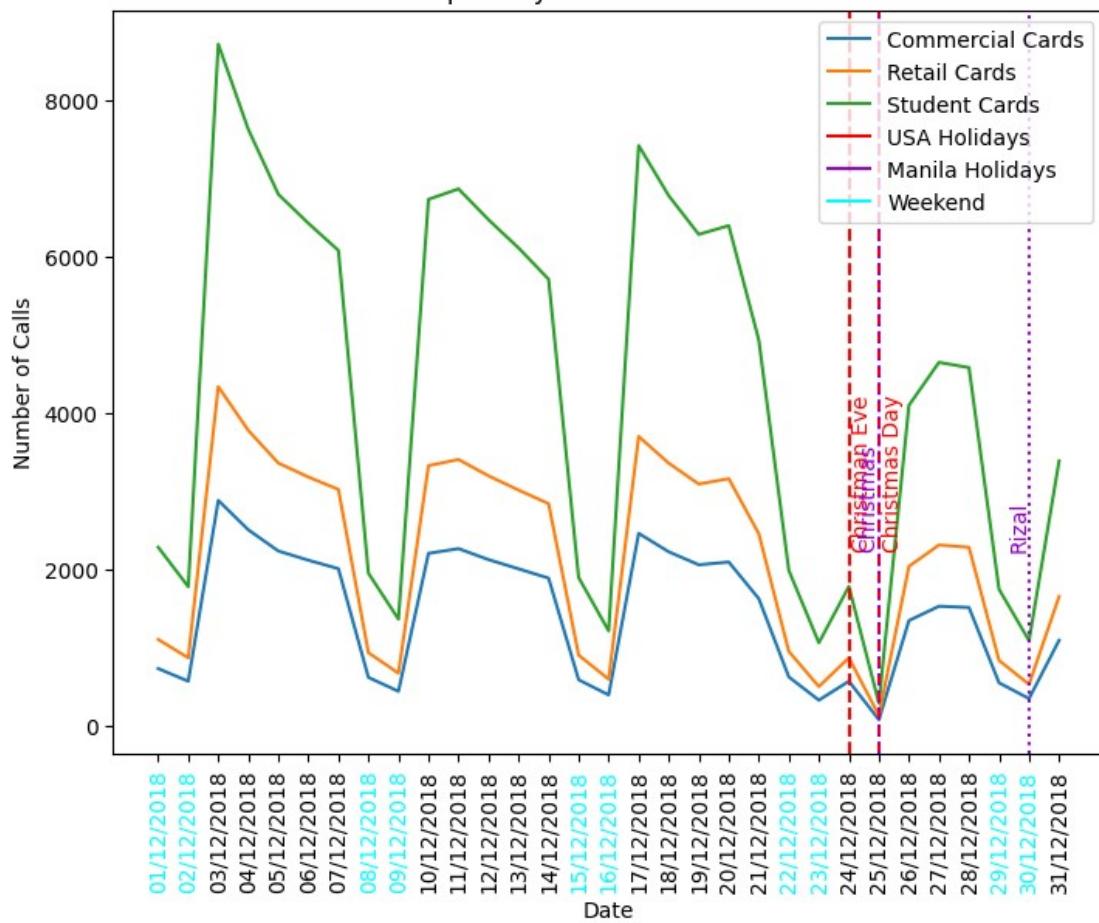
Calls per Day for October of 2018



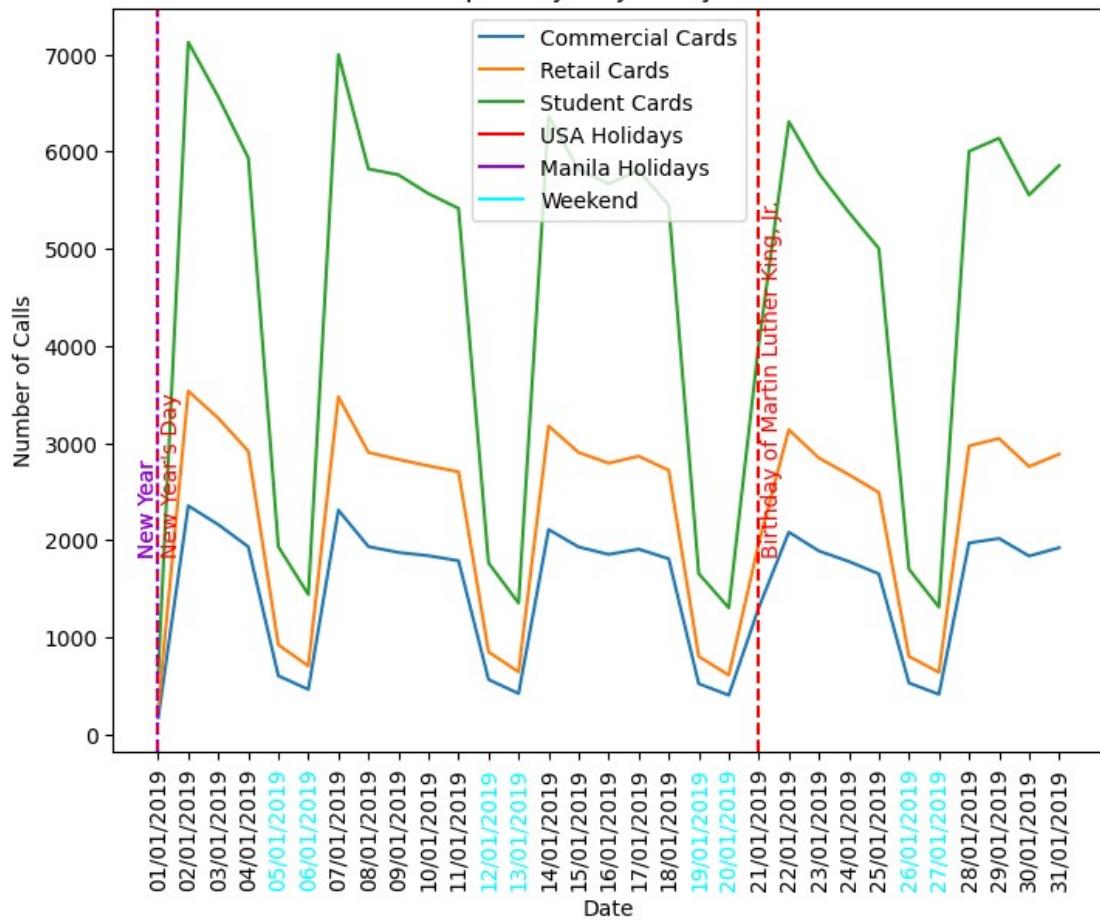
Calls per Day for November of 2018



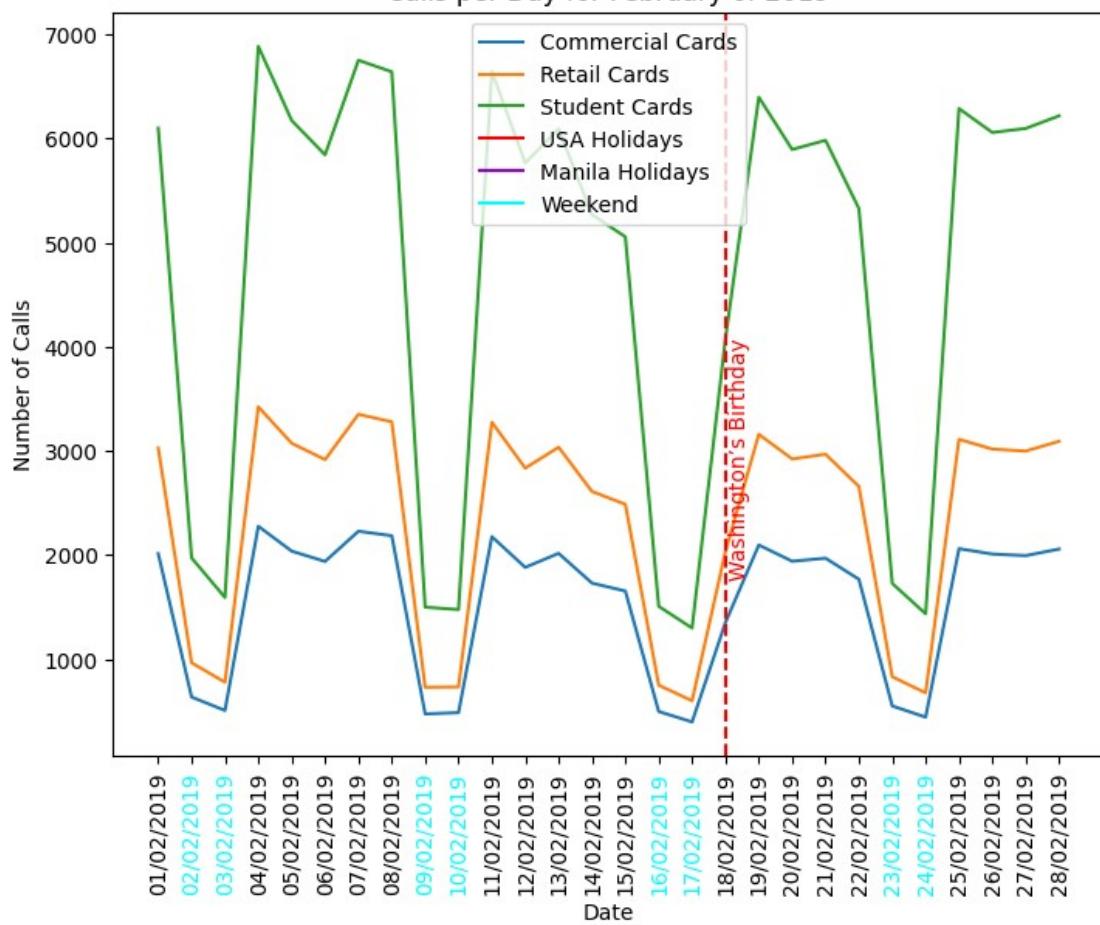
Calls per Day for December of 2018



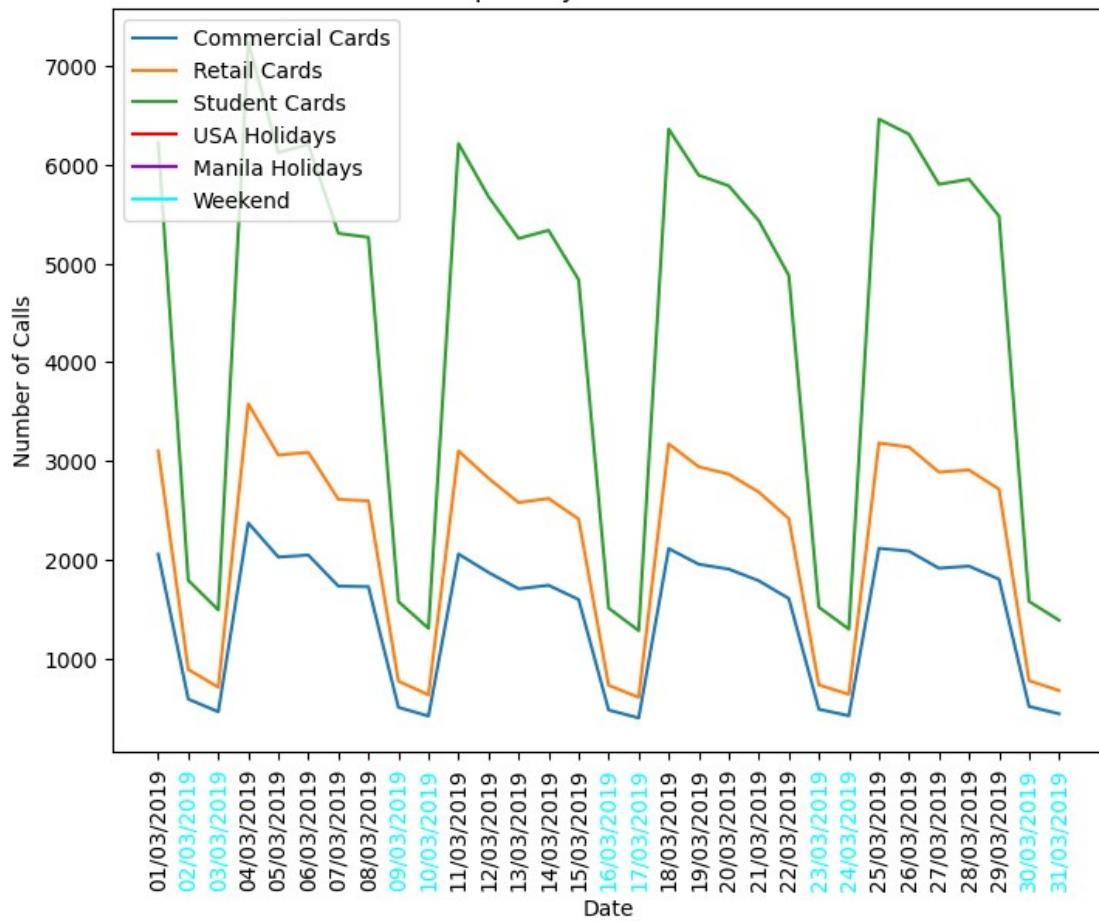
Calls per Day for January of 2019

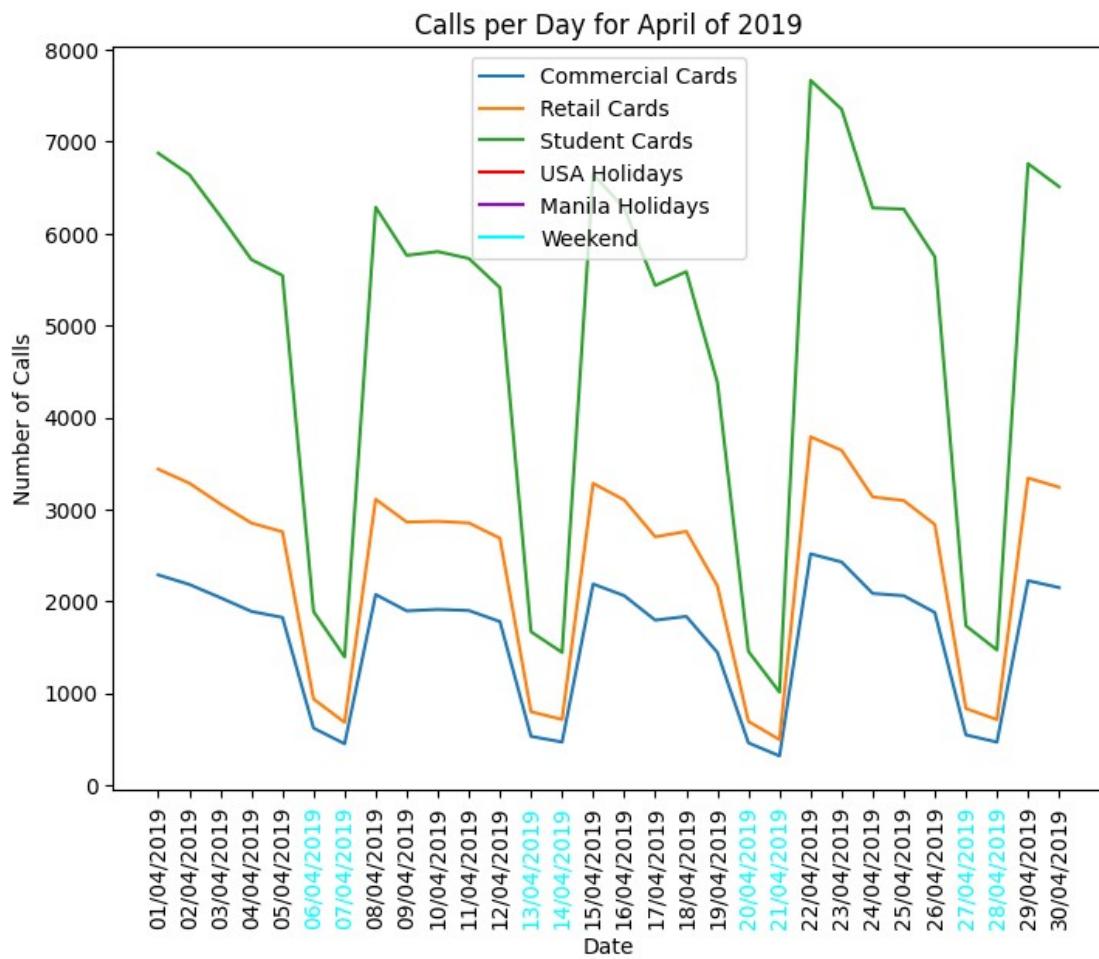


Calls per Day for February of 2019

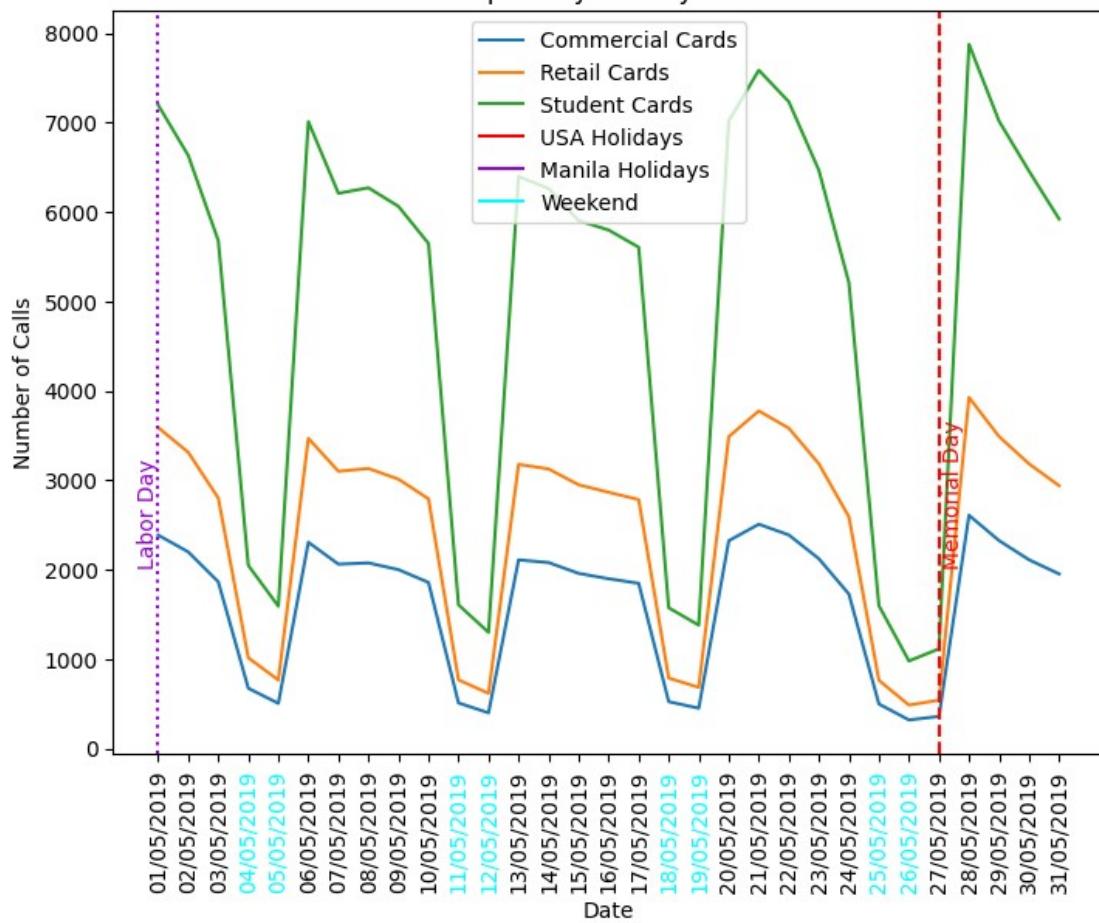


Calls per Day for March of 2019

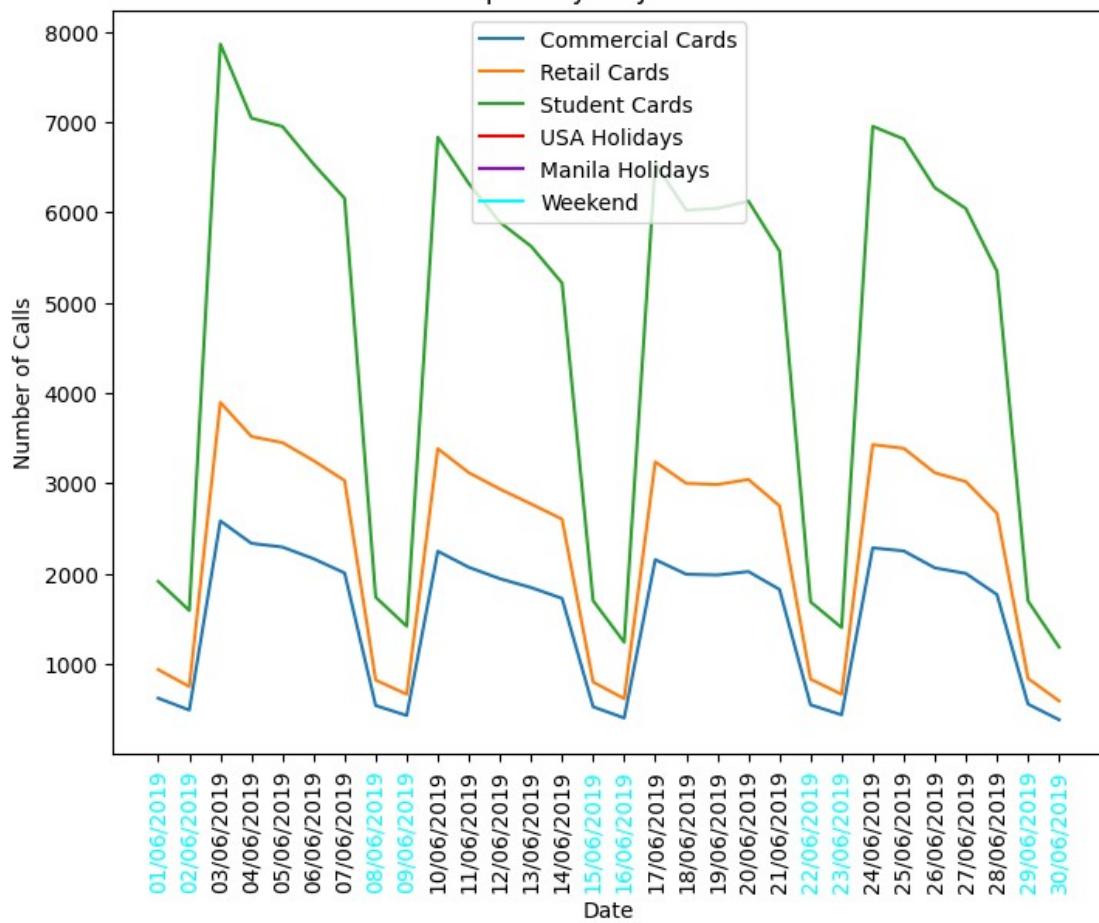




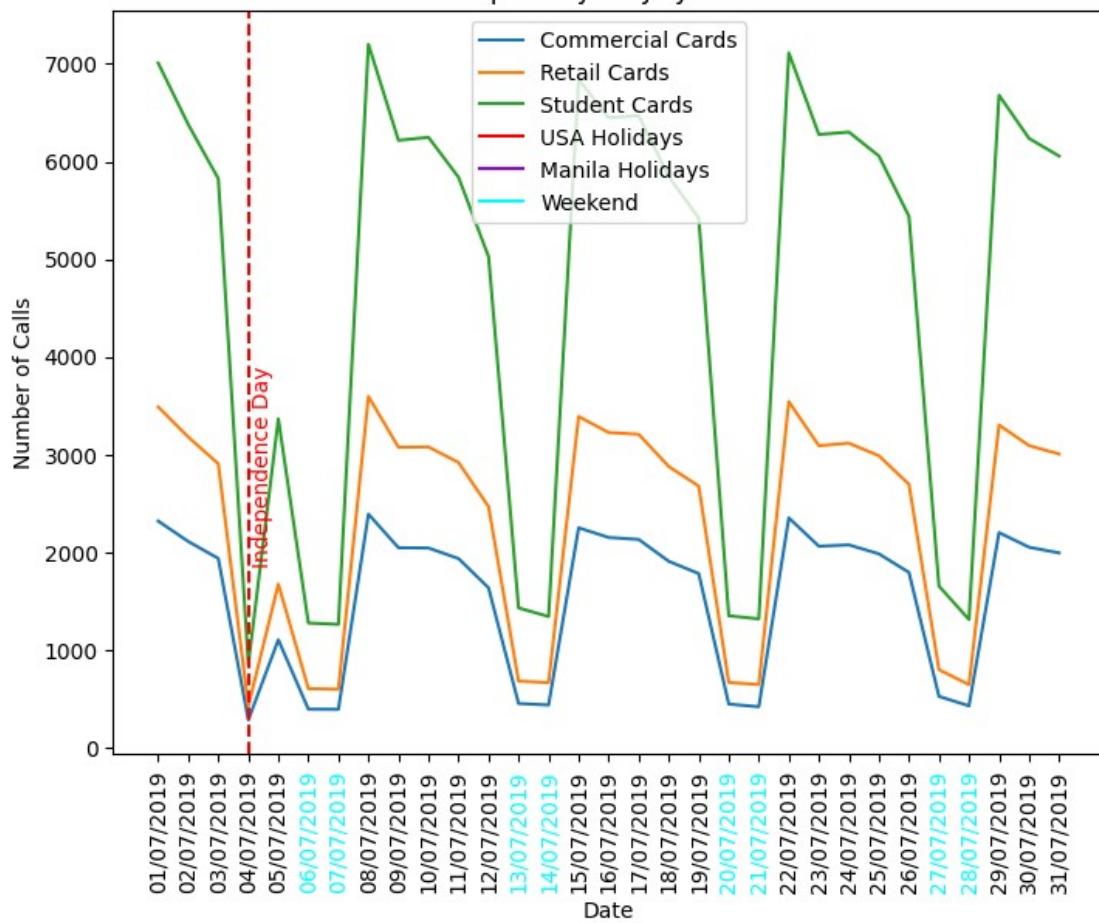
Calls per Day for May of 2019



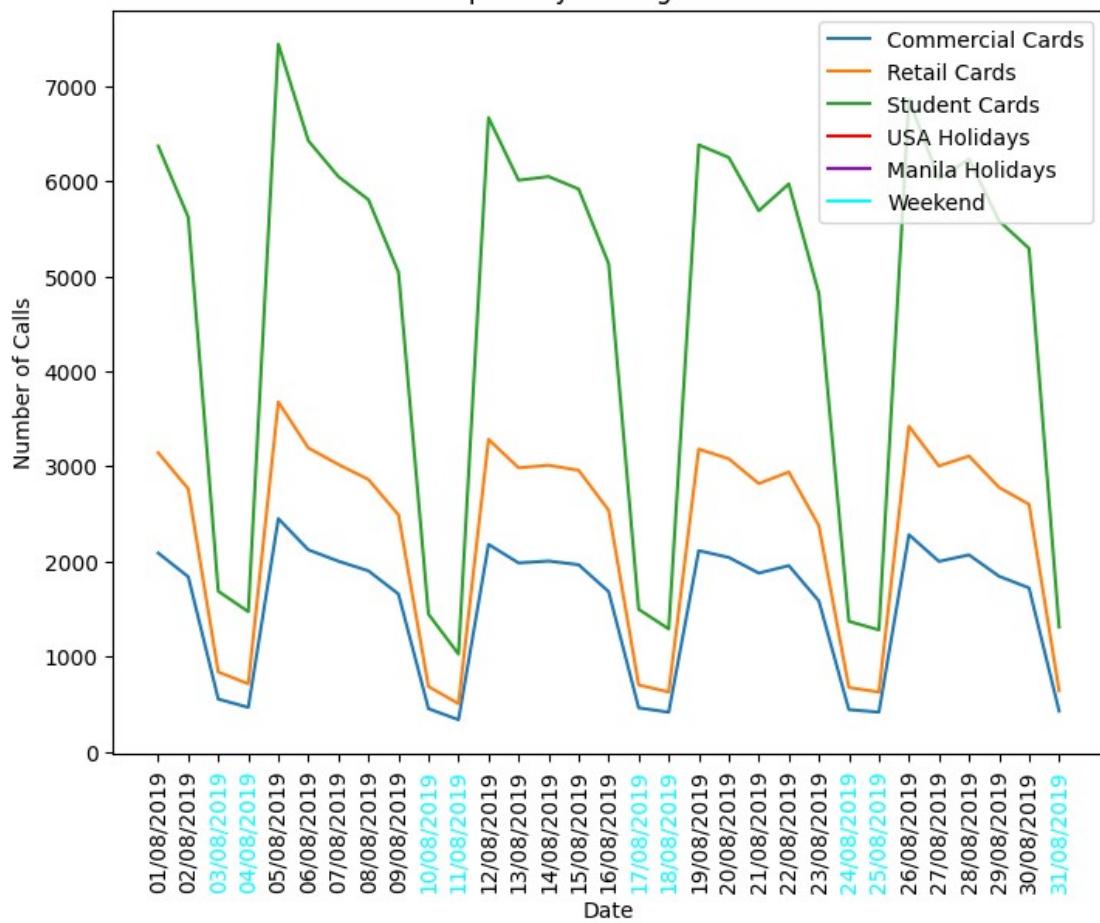
Calls per Day for June of 2019



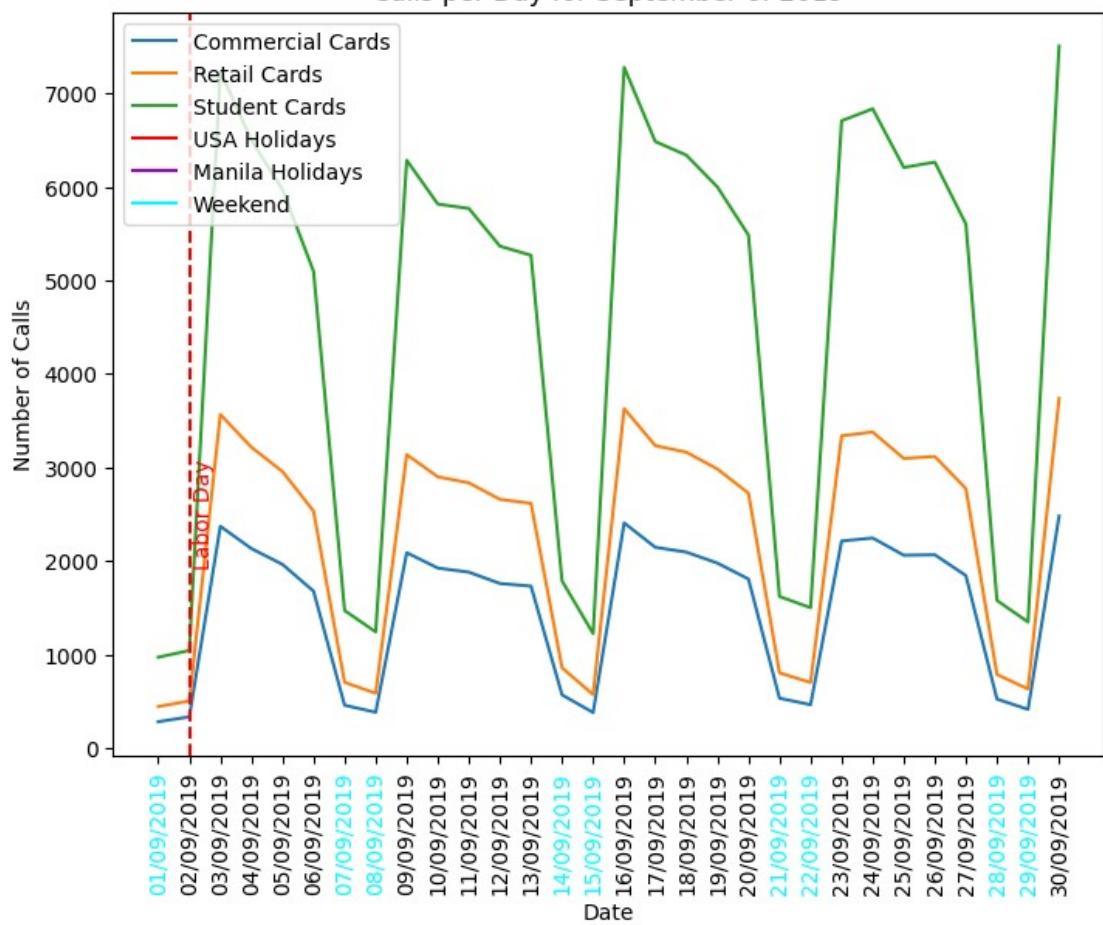
Calls per Day for July of 2019



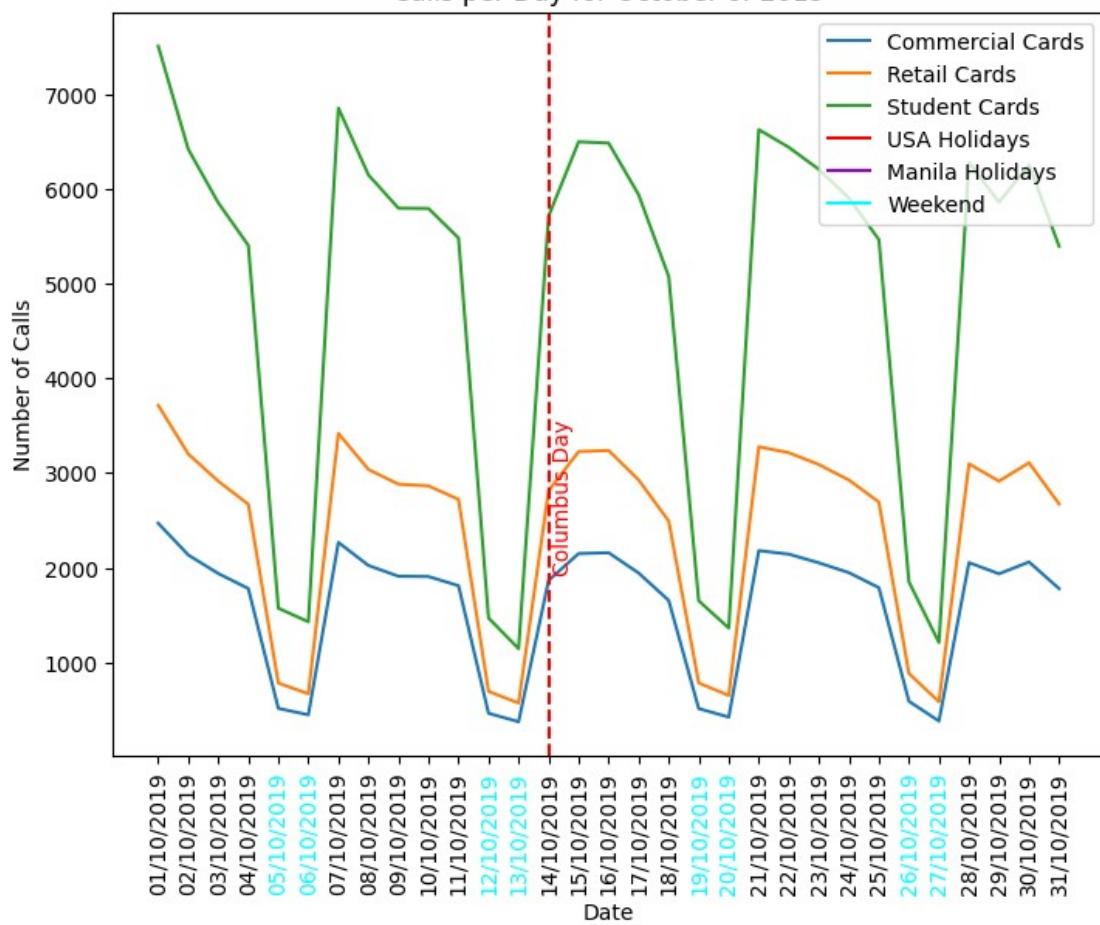
Calls per Day for August of 2019



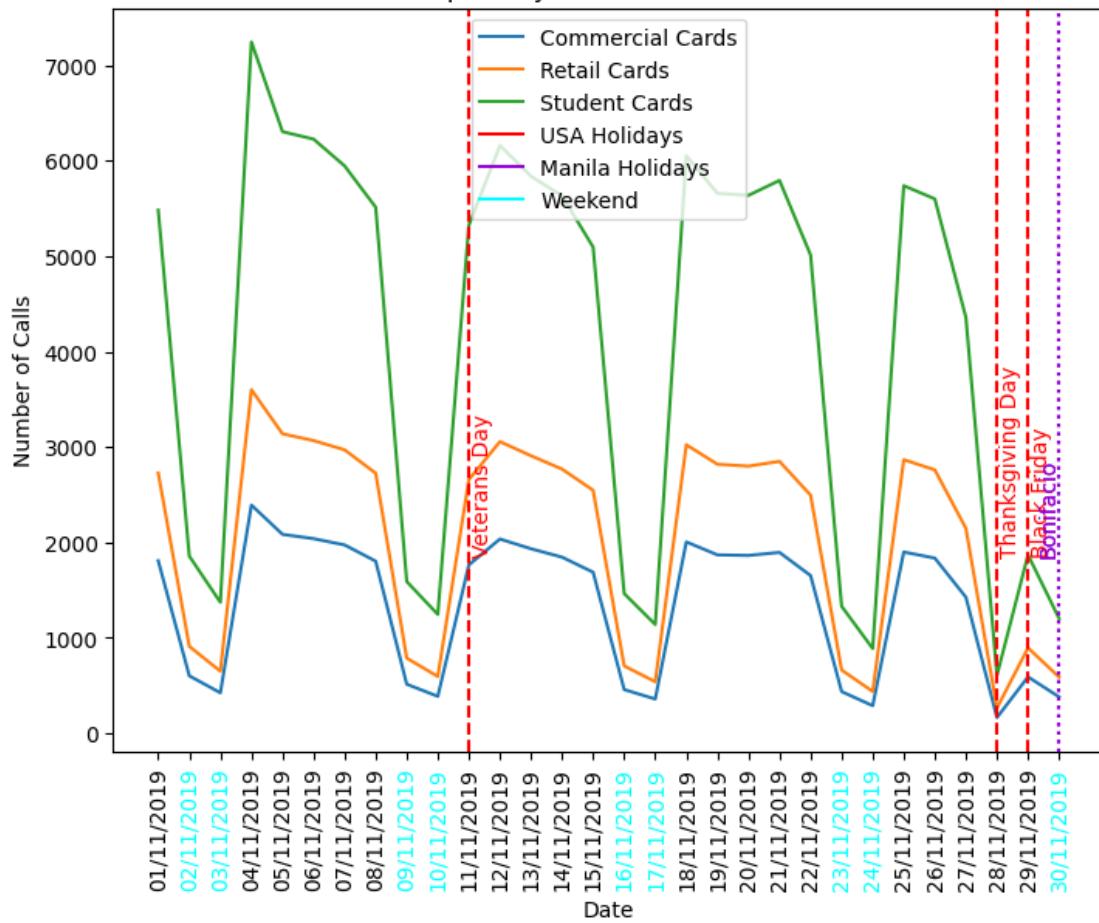
Calls per Day for September of 2019



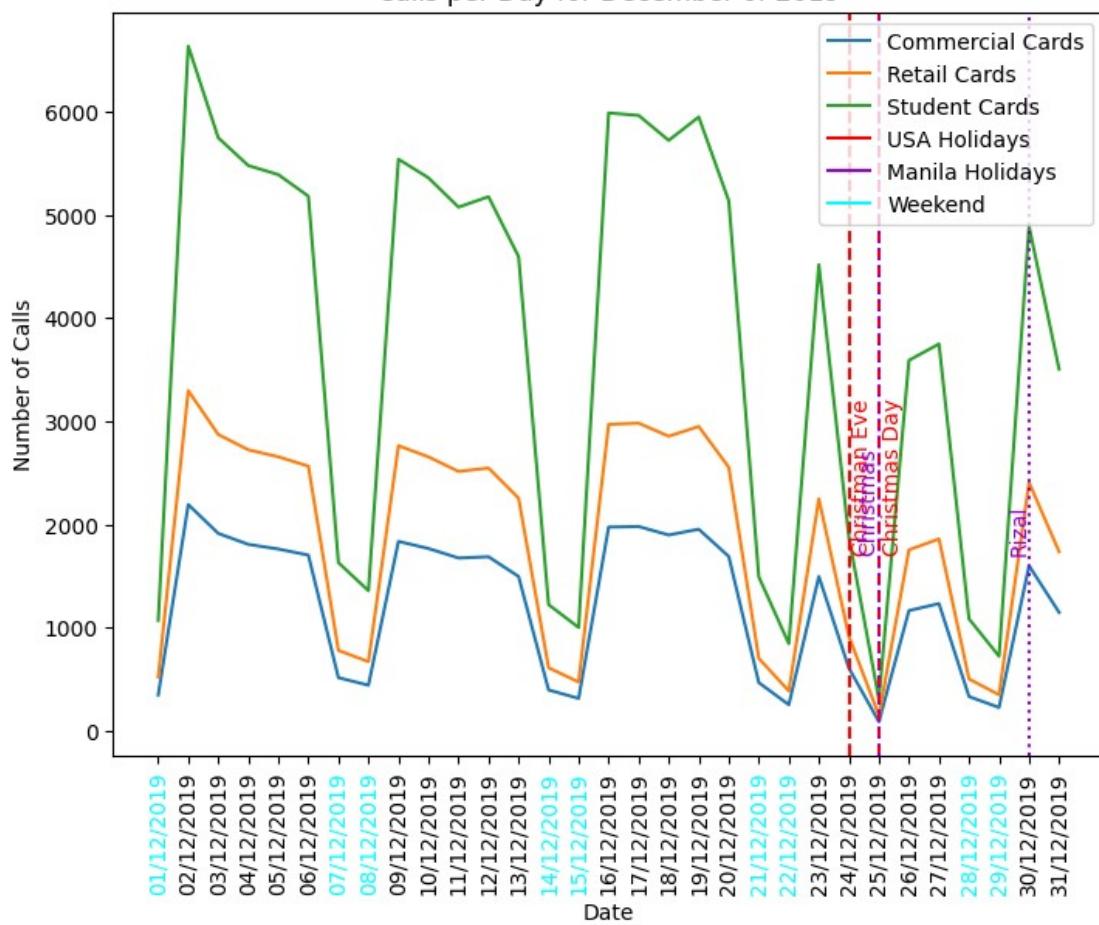
Calls per Day for October of 2019

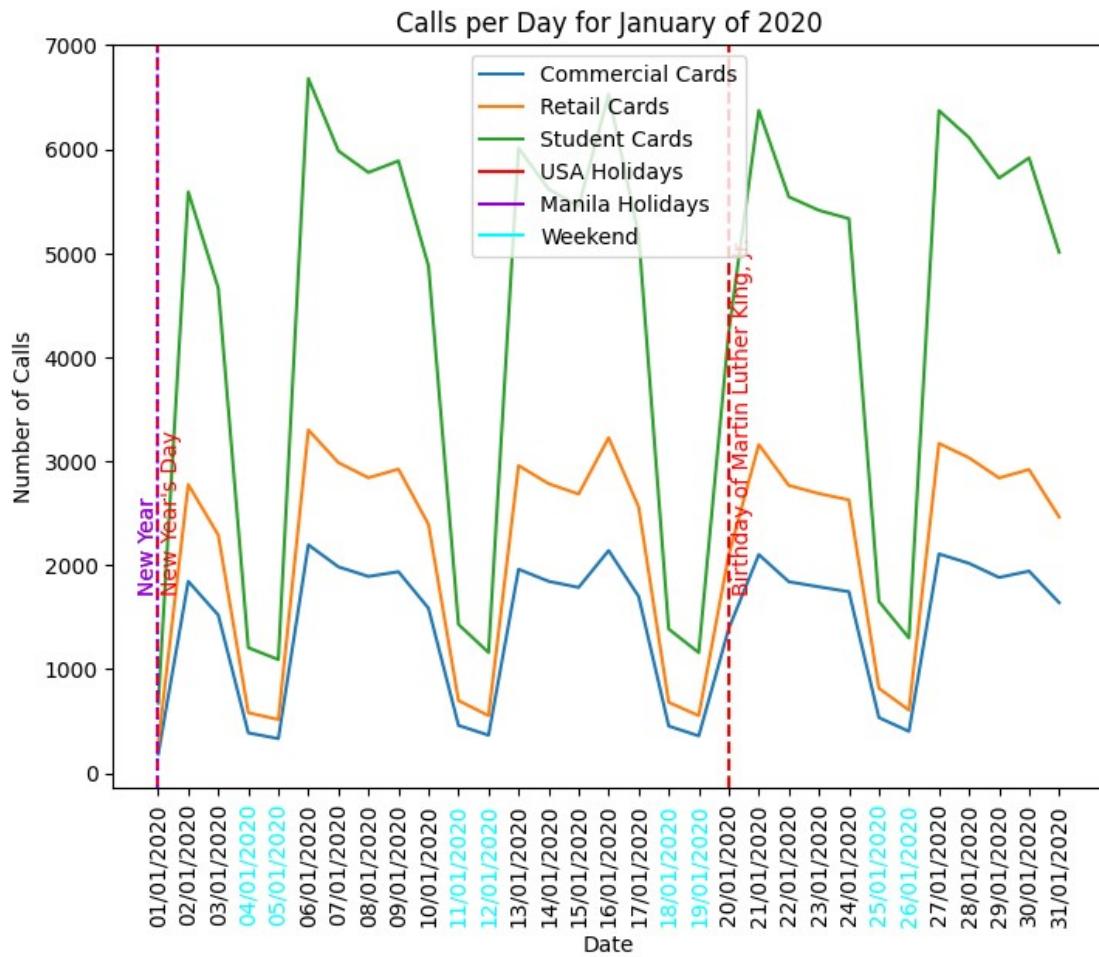


Calls per Day for November of 2019

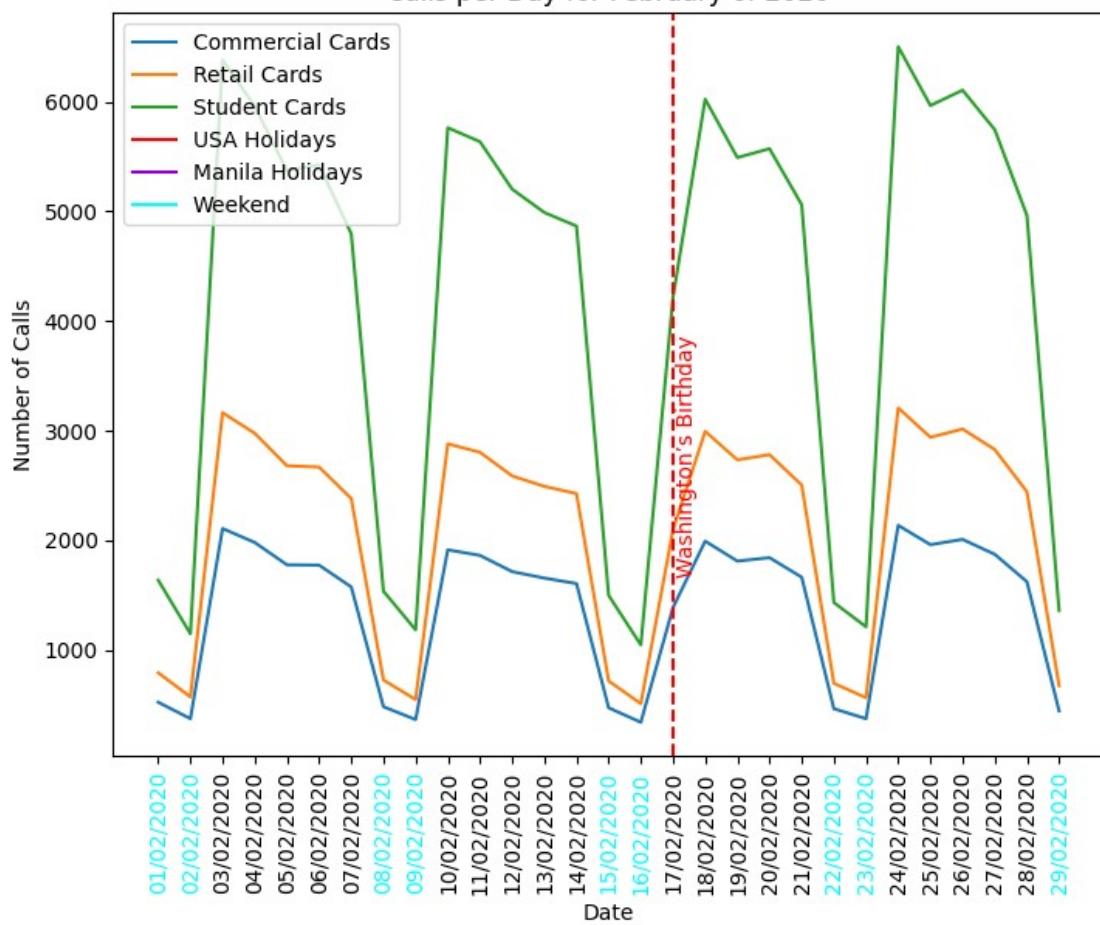


Calls per Day for December of 2019

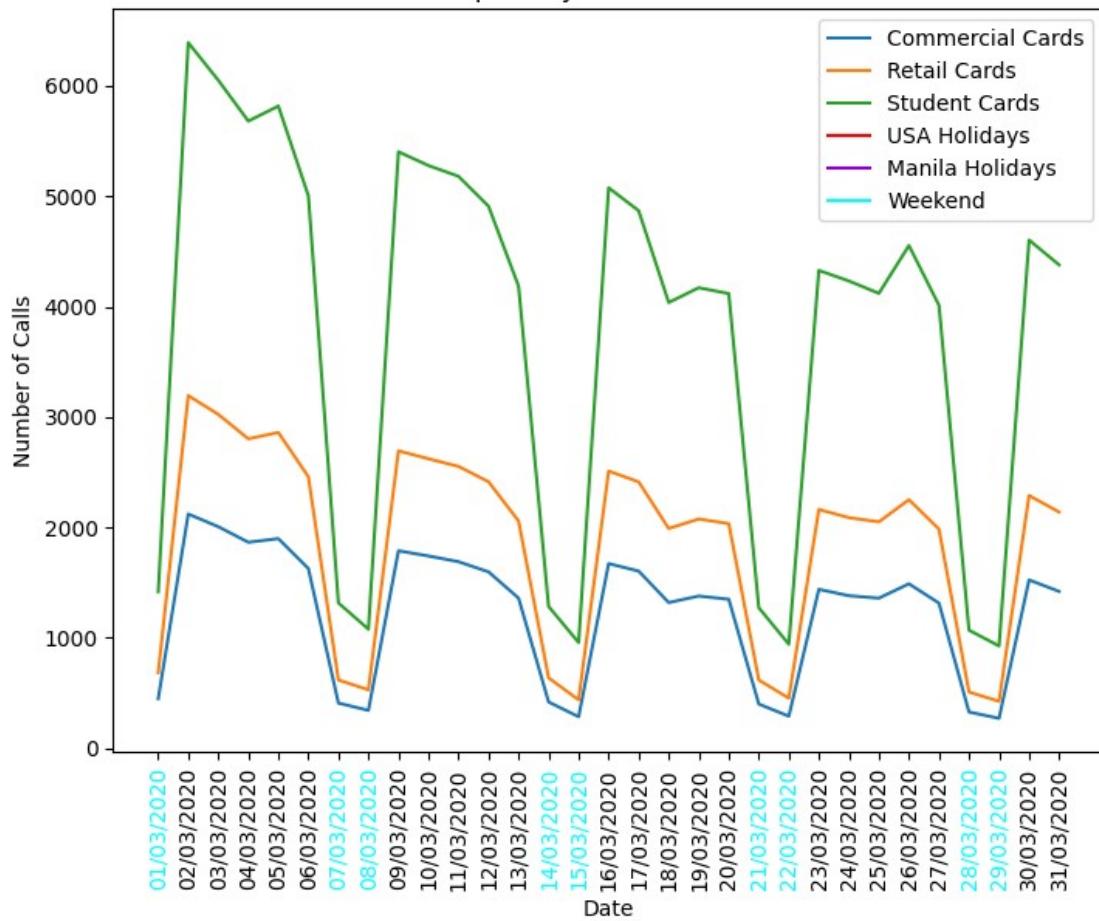




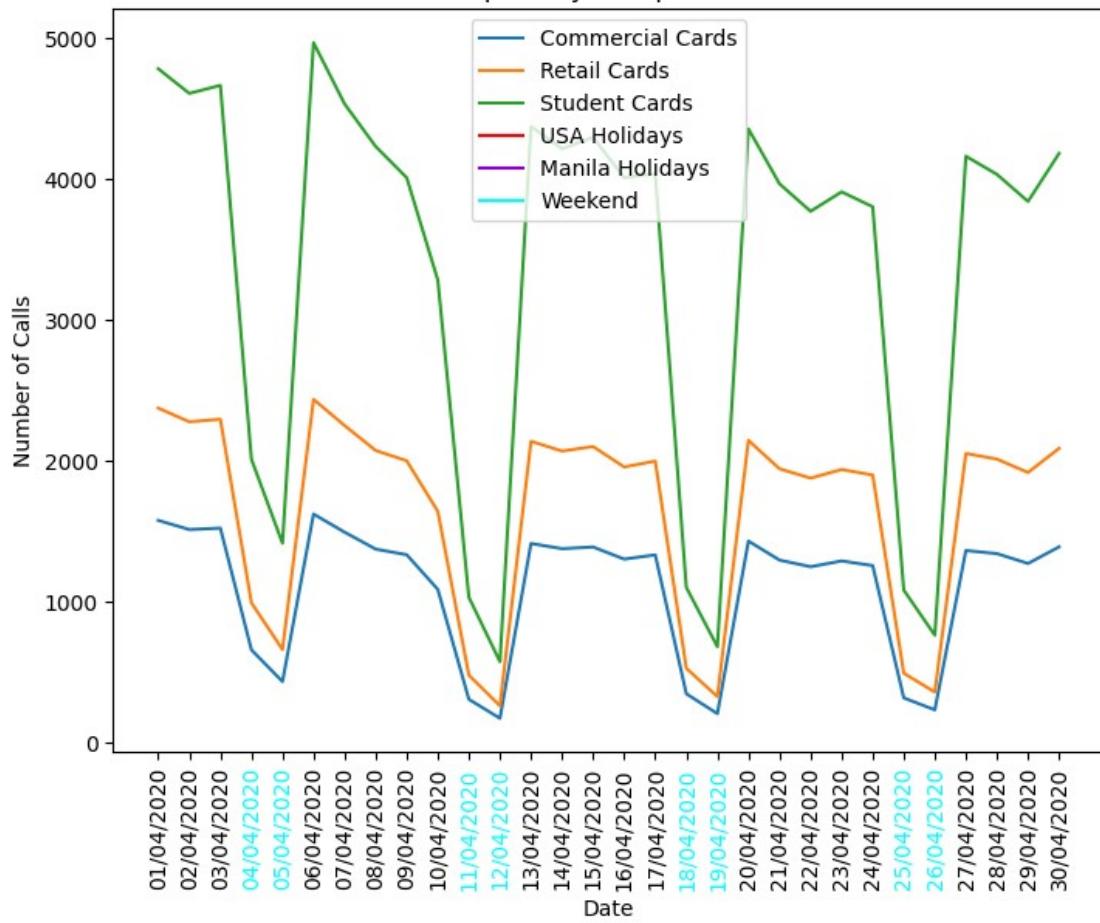
Calls per Day for February of 2020



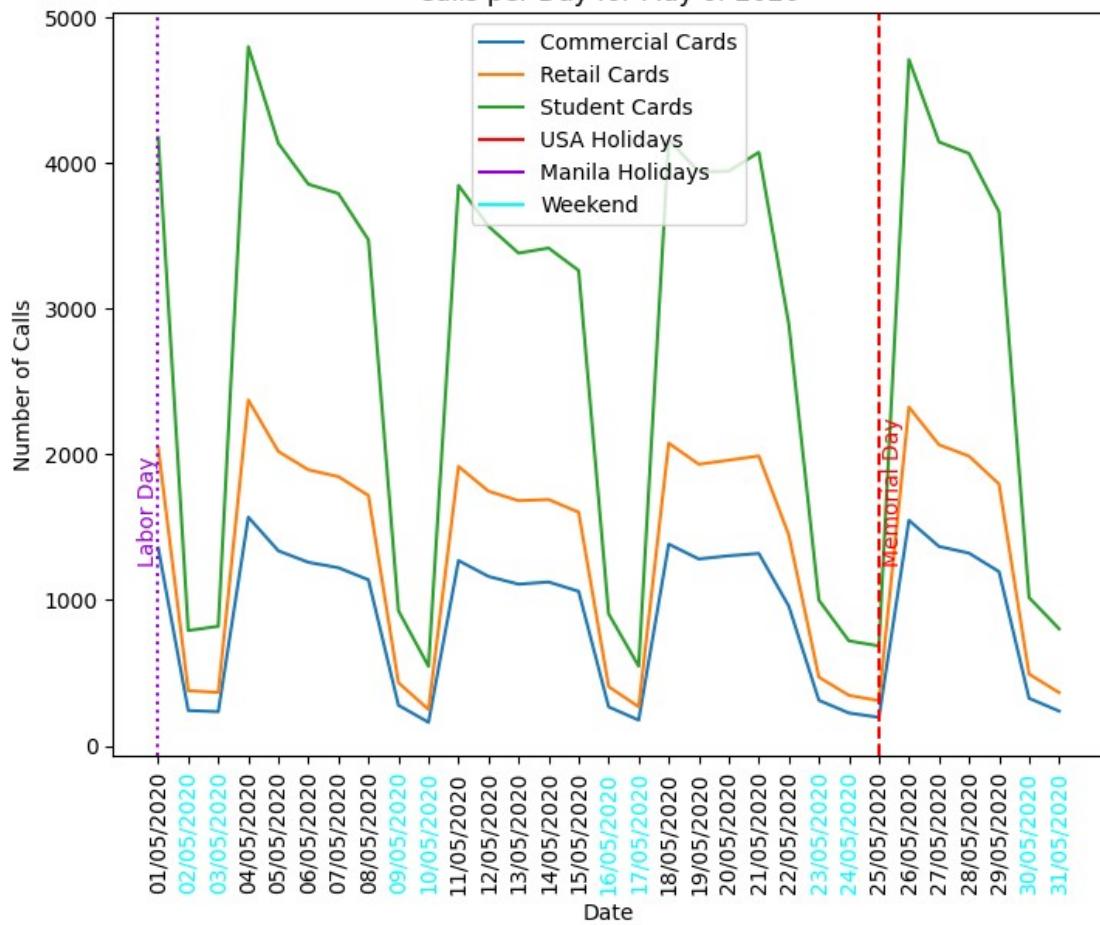
Calls per Day for March of 2020



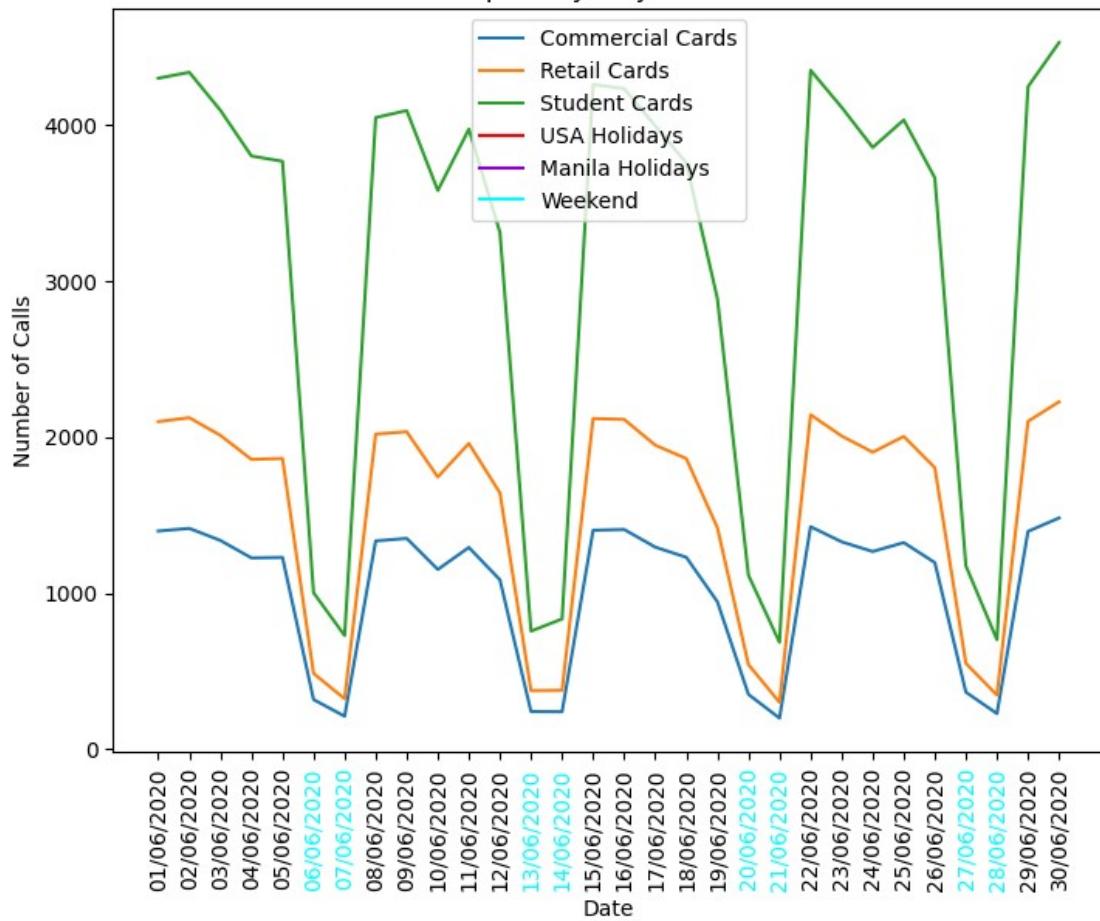
Calls per Day for April of 2020



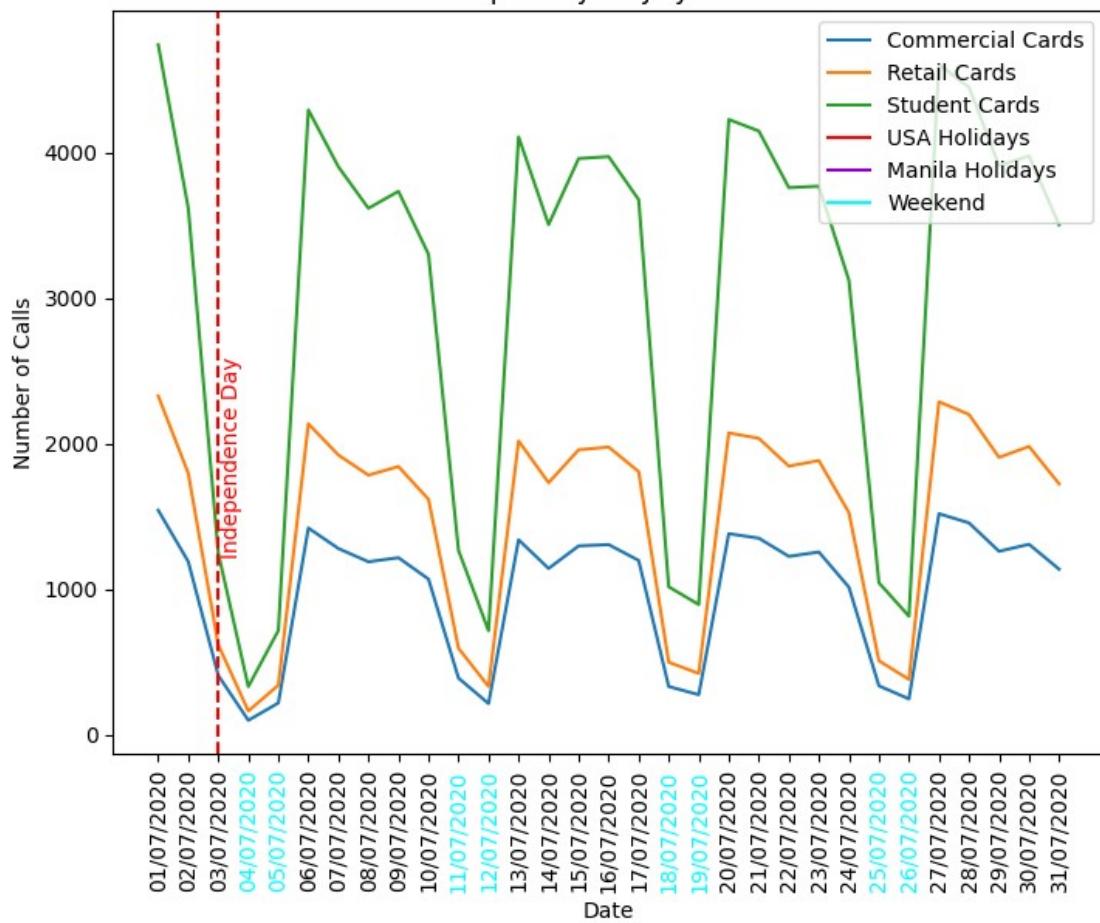
Calls per Day for May of 2020



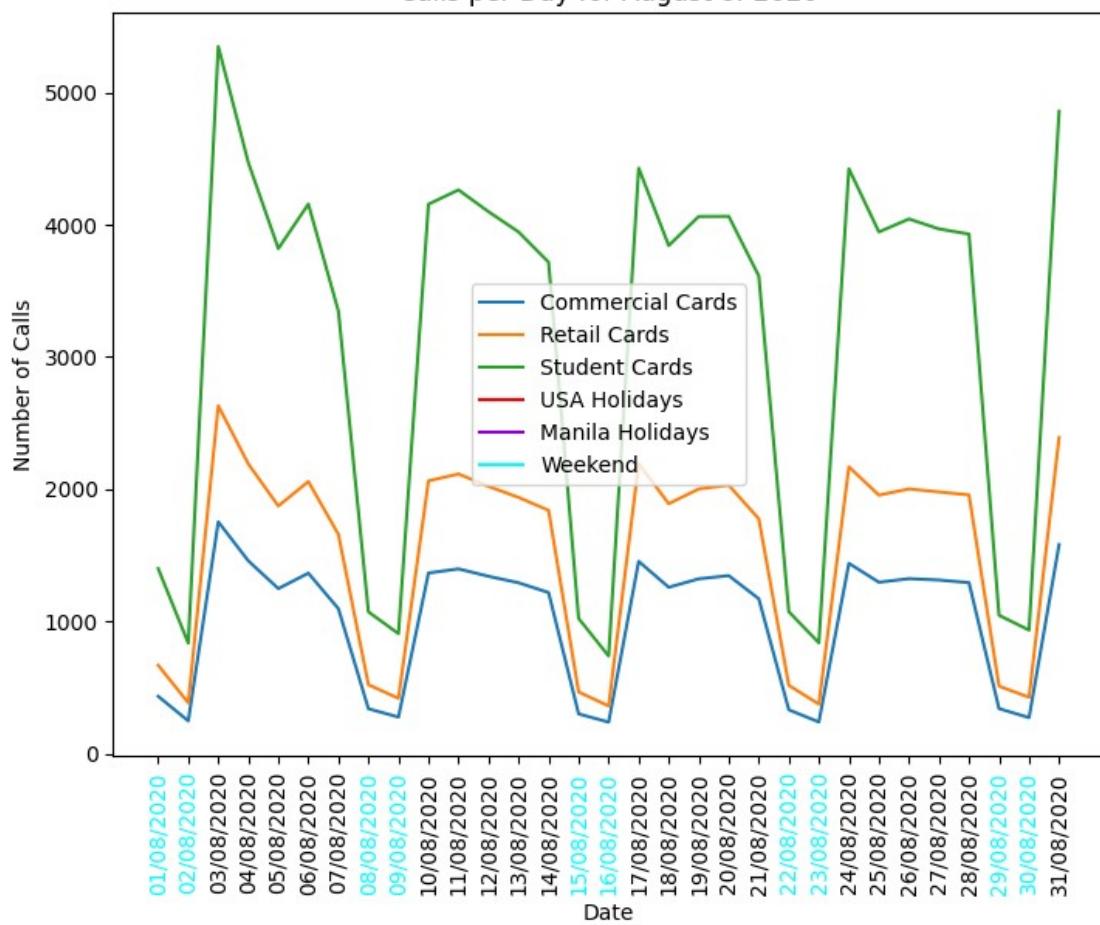
Calls per Day for June of 2020



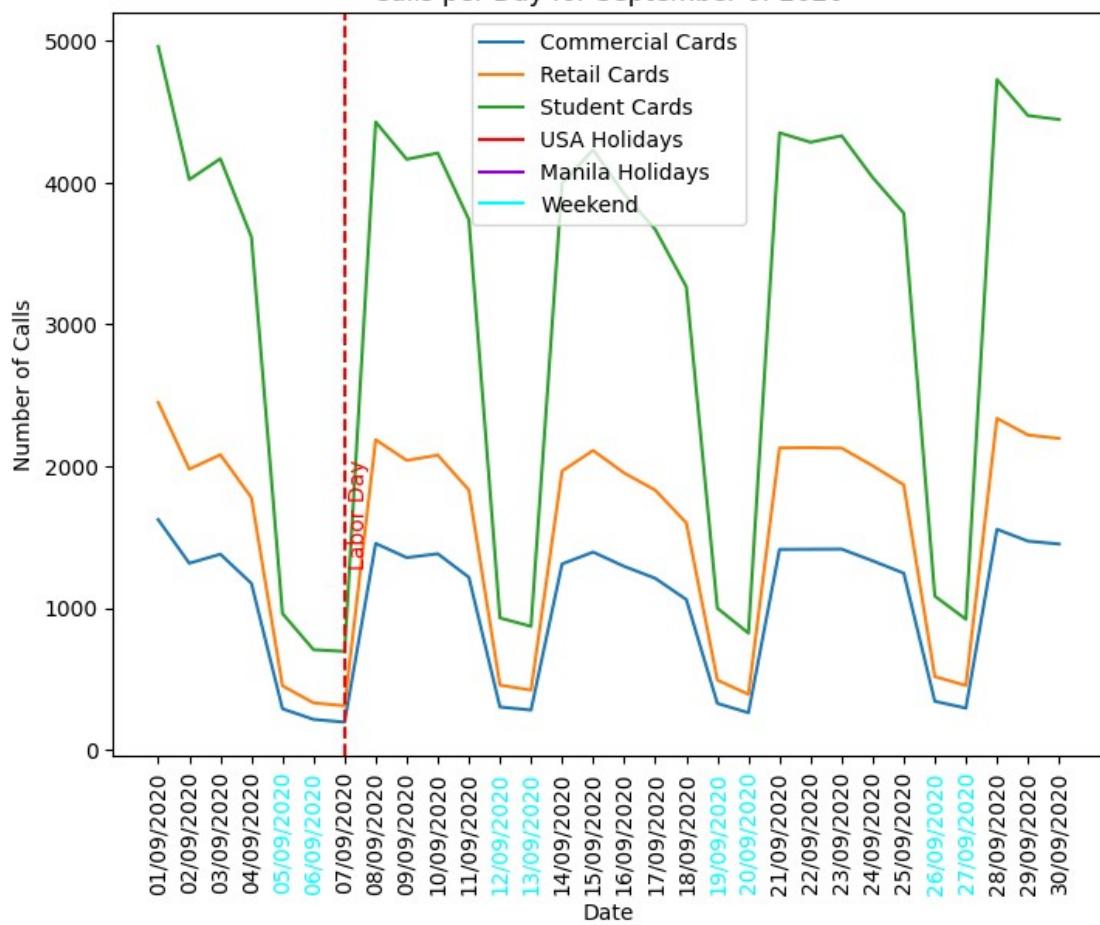
Calls per Day for July of 2020



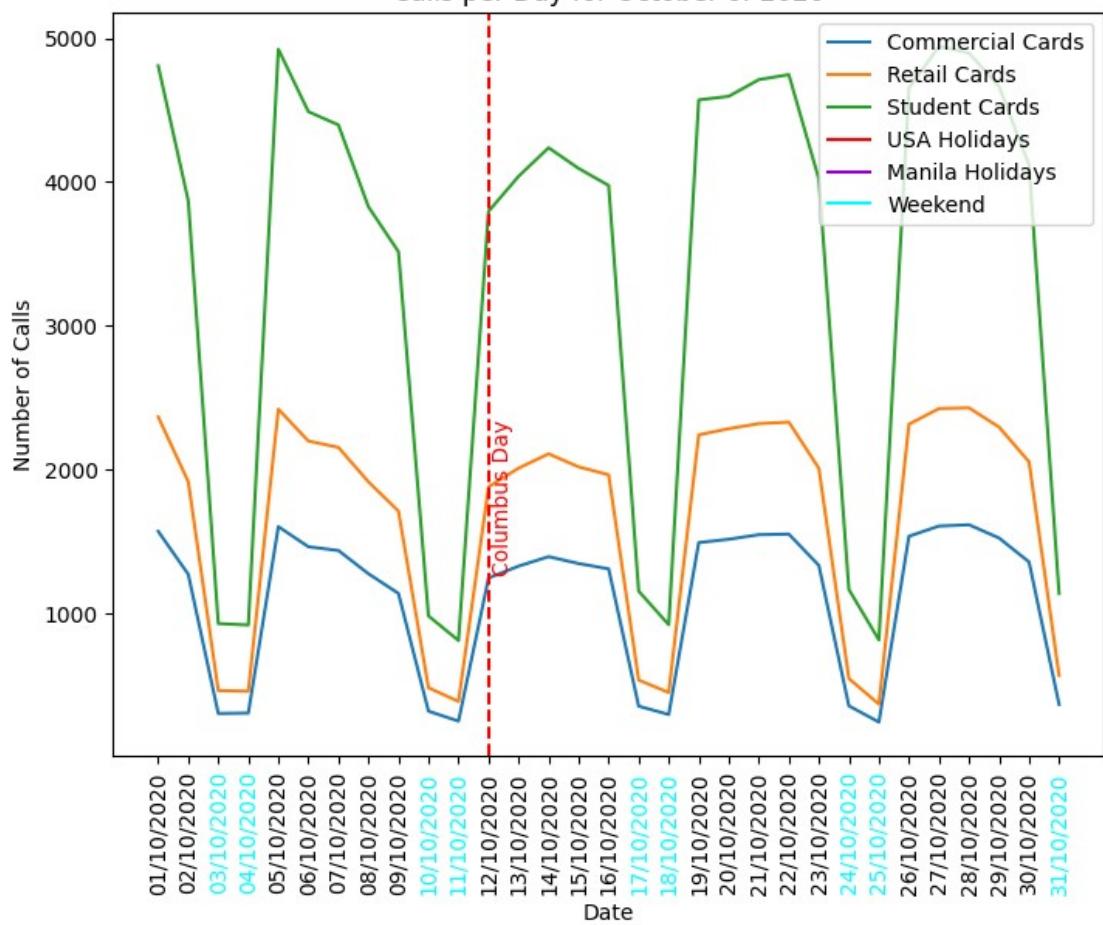
Calls per Day for August of 2020



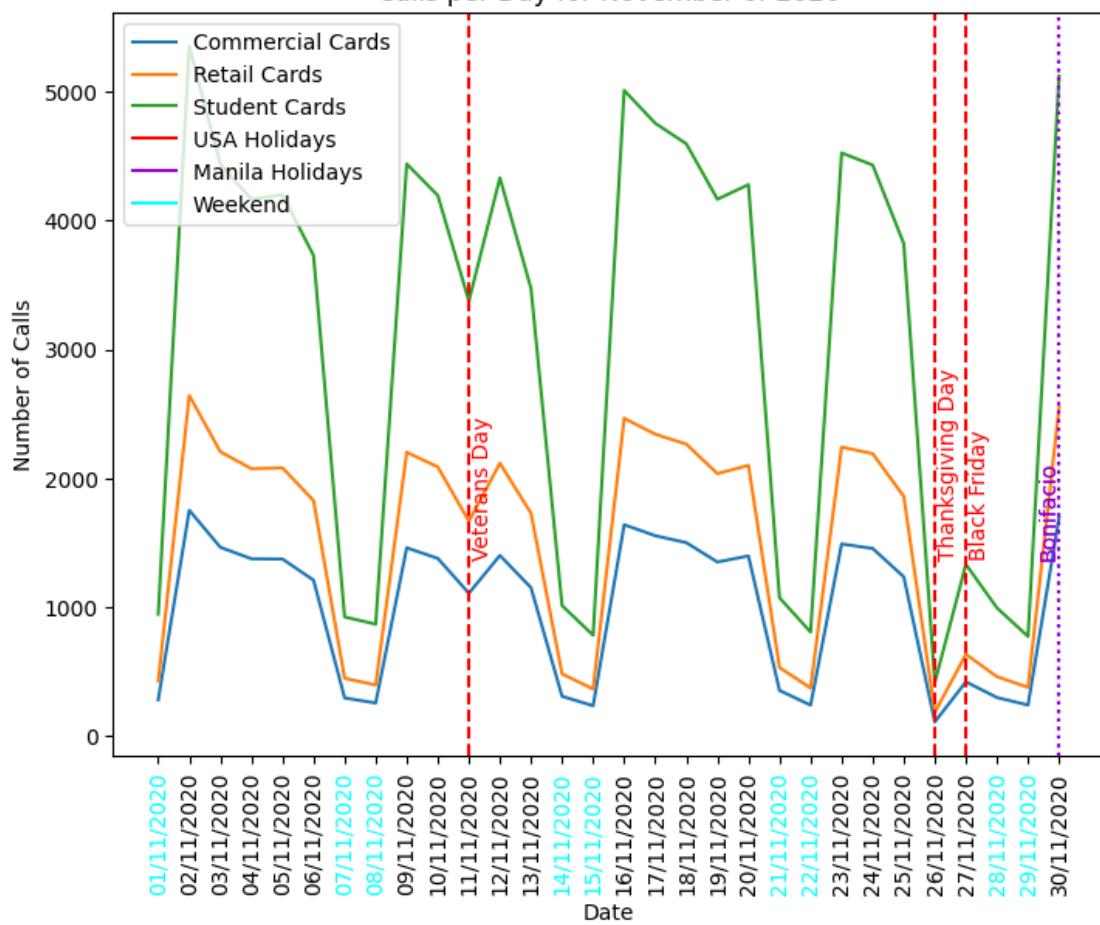
Calls per Day for September of 2020

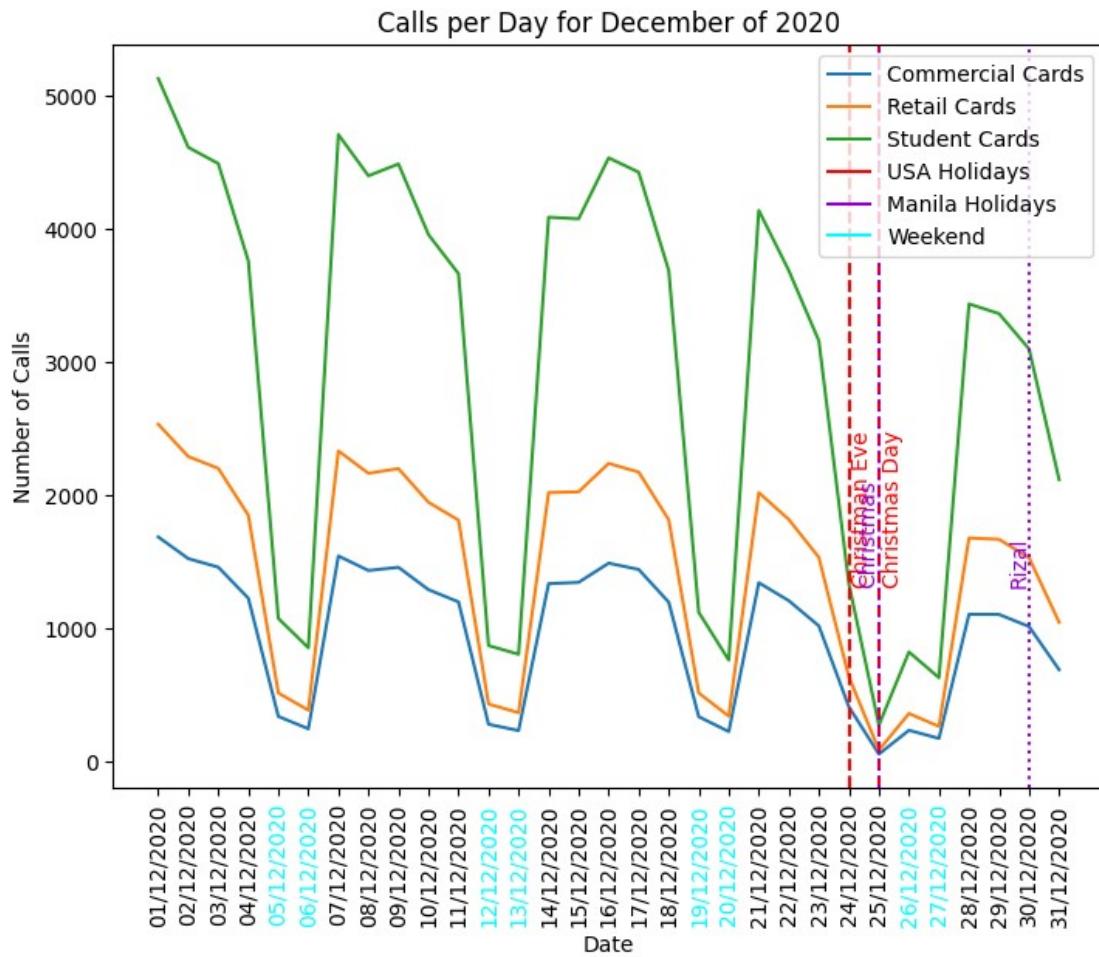


Calls per Day for October of 2020

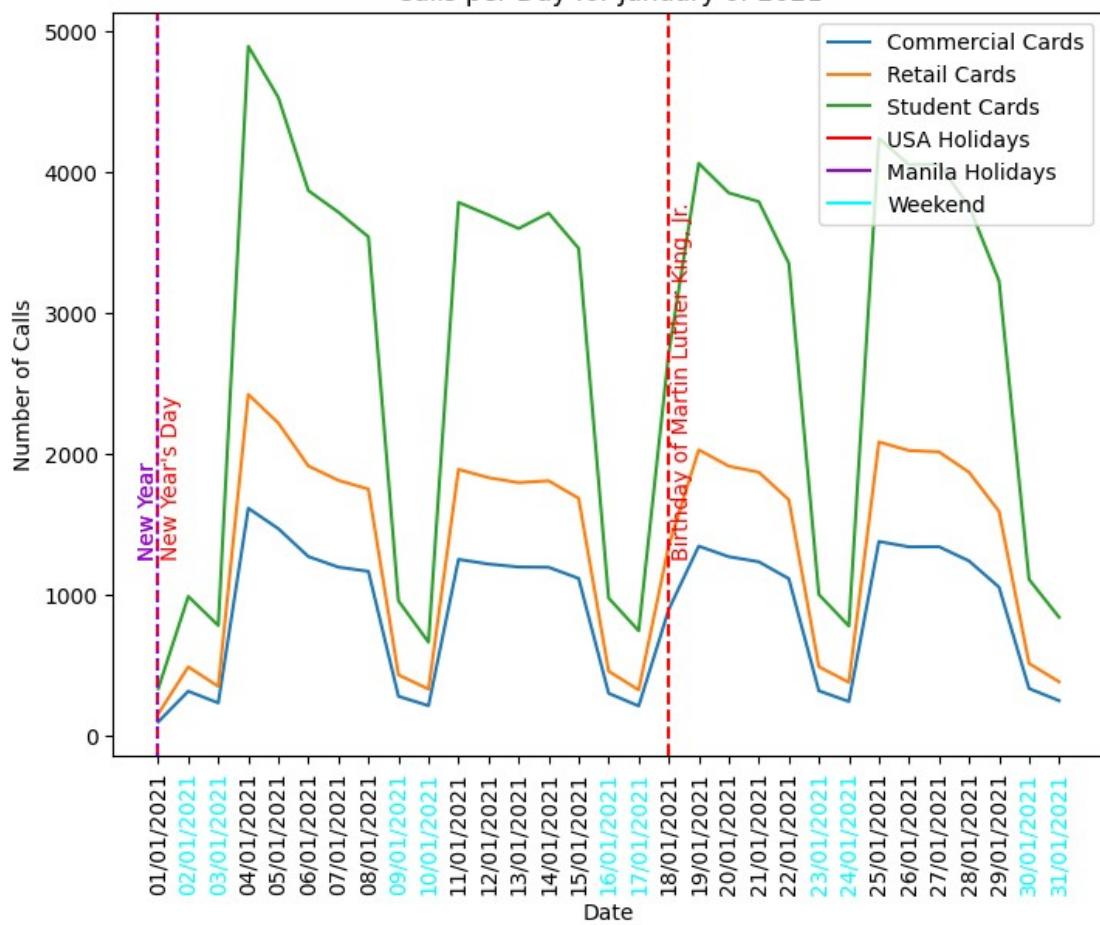


Calls per Day for November of 2020

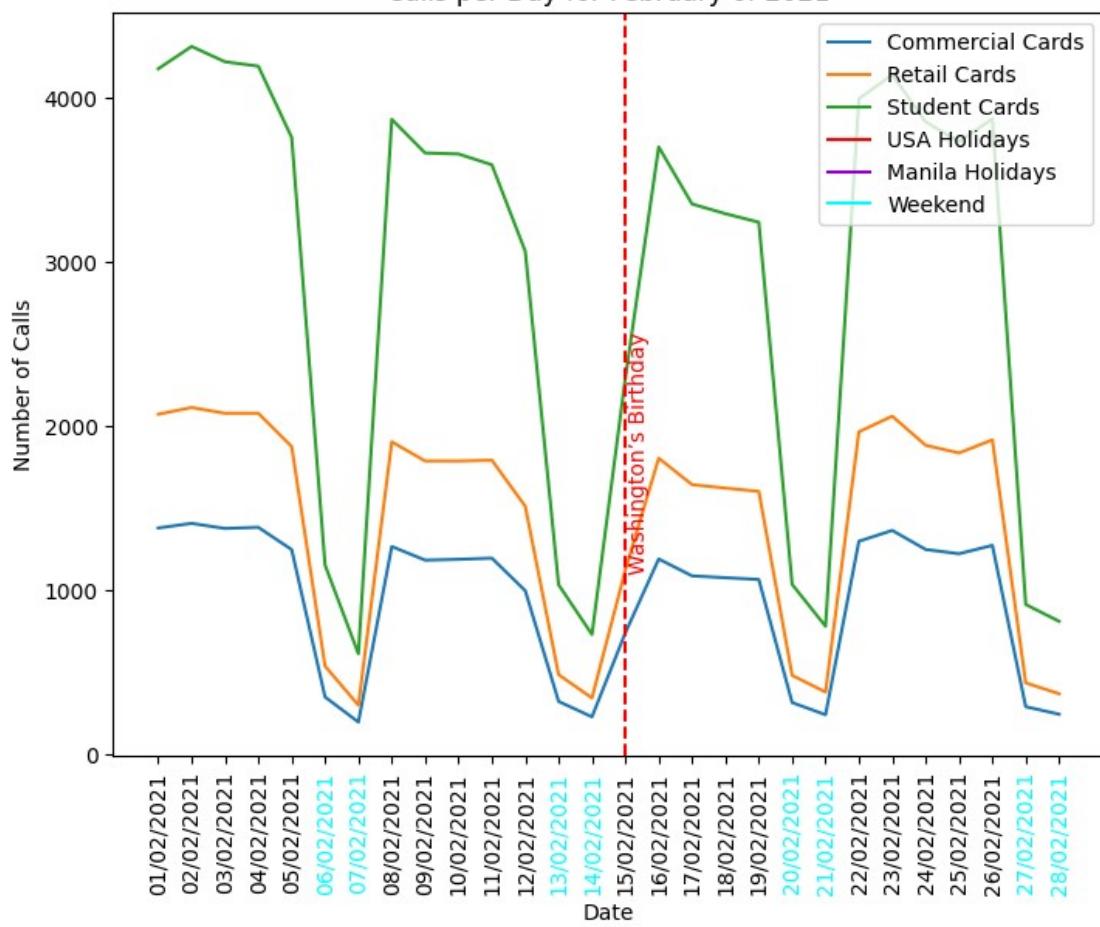




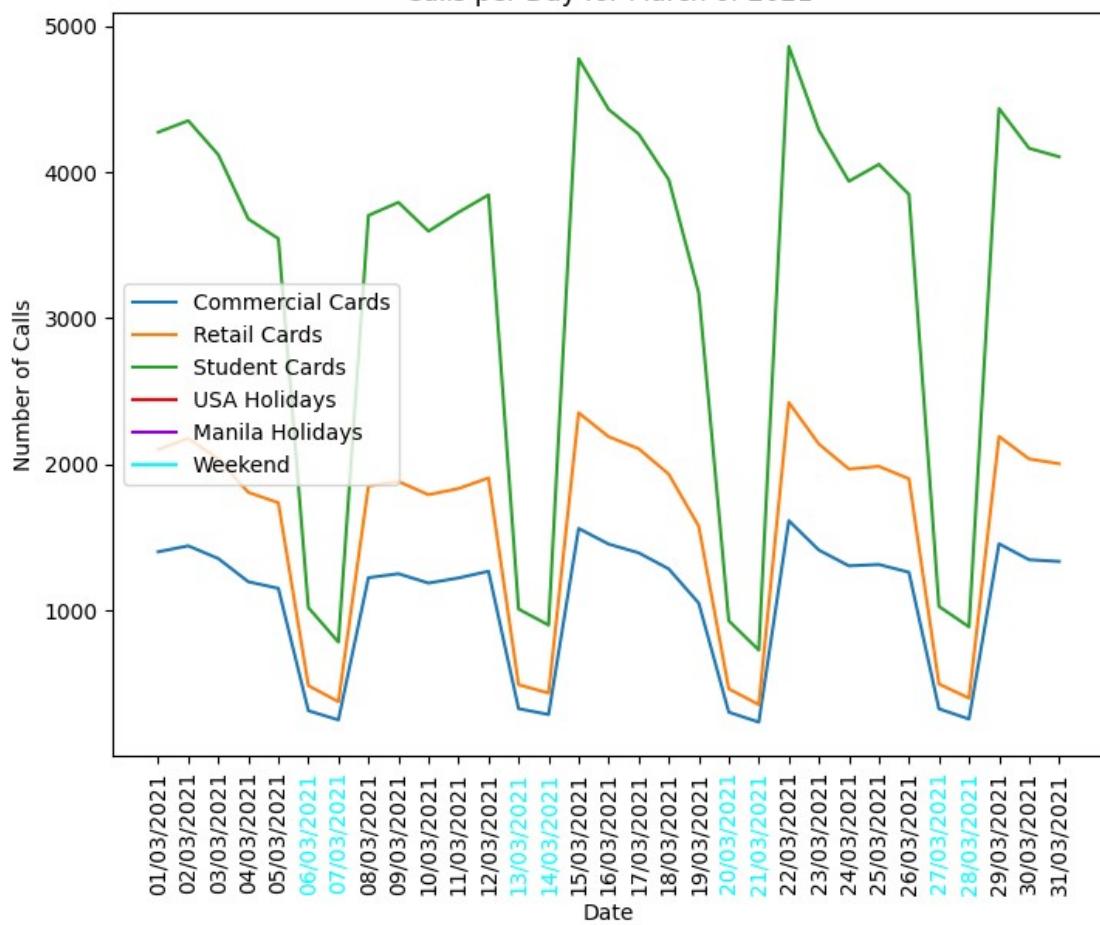
Calls per Day for January of 2021

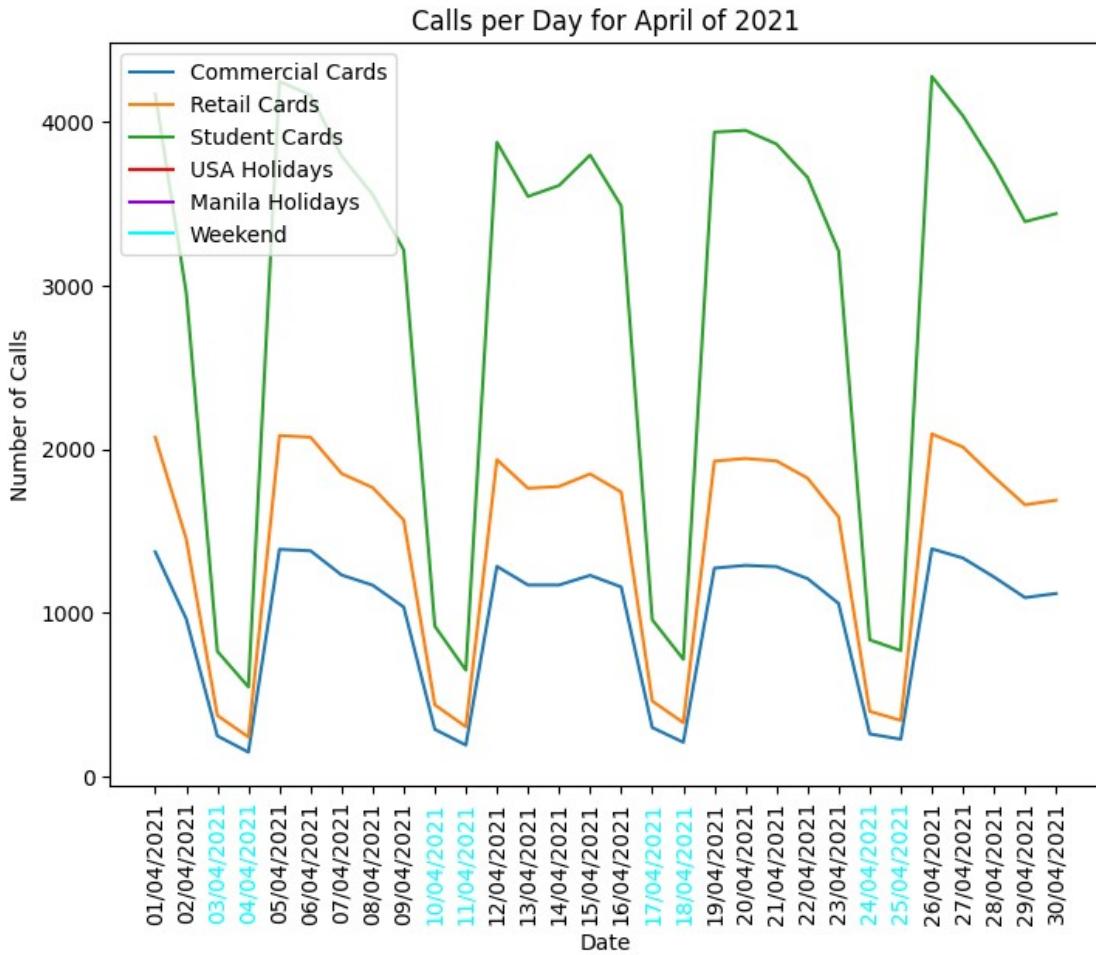


Calls per Day for February of 2021



Calls per Day for March of 2021





Prediction

```

dates17 = df_17.date.values
dates_not17 = df_not17_sorted.date.values
all_dates = list(dates17)
all_dates.extend(list(dates_not17))
# print(all_dates)
all_dates = pd.to_datetime(all_dates, format="%d/%m/%Y")
# print(all_dates)

cc17 = df_17.cc.values
cc_not17 = df_not17_sorted.cc.values
all_cc = list(cc17)
all_cc.extend(cc_not17)
# print(all_cc)

lstm_data = pd.DataFrame({
    "ds": all_dates,
    "y": all_cc
})
lstm_data

```

```

          ds      y
0    2017-01-01  264.0
1    2017-01-02  528.0
2    2017-01-03 2505.0
3    2017-01-04 2145.0
4    2017-01-05 2164.0
...
1576 2021-04-26 1392.0
1577 2021-04-27 1336.0
1578 2021-04-28 1220.0
1579 2021-04-29 1094.0
1580 2021-04-30 1119.0

[1581 rows x 2 columns]

import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Flatten

# preparing independent and dependent features
def prepare_data(timeseries_data, n_features):
    X, y = [], []
    for i in range(len(timeseries_data)):
        # find the end of this pattern
        end_ix = i + n_features
        # check if we are beyond the sequence
        if end_ix > len(timeseries_data)-1:
            break
        # gather input and output parts of the pattern
        seq_x, seq_y = timeseries_data[i:end_ix],
        timeseries_data[end_ix]
        X.append(seq_x)
        y.append(seq_y)
    return np.array(X), np.array(y)

# define input sequence
timeseries_data = all_cc
# choose a number of time steps
n_steps = 7
# split into samples
X, y = prepare_data(timeseries_data, n_steps)

# reshape from [samples, timesteps] into [samples, timesteps,
features]
n_features = 1
X = X.reshape((X.shape[0], X.shape[1], n_features))

# define model
model = Sequential()

```

```
model.add(LSTM(50, activation='relu', return_sequences=True,
input_shape=(n_steps, n_features)))
model.add(LSTM(50, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
# fit model
model.fit(X, y, epochs=500, verbose=1)

Epoch 1/500
50/50 [=====] - 2s 3ms/step - loss:
1113896.0000
Epoch 2/500
50/50 [=====] - 0s 3ms/step - loss:
195022.7969
Epoch 3/500
50/50 [=====] - 0s 3ms/step - loss:
136563.2969
Epoch 4/500
50/50 [=====] - 0s 3ms/step - loss:
118197.0859
Epoch 5/500
50/50 [=====] - 0s 3ms/step - loss:
104599.4922
Epoch 6/500
50/50 [=====] - 0s 3ms/step - loss:
177772.3594
Epoch 7/500
50/50 [=====] - 0s 3ms/step - loss:
181992.1094
Epoch 8/500
50/50 [=====] - 0s 3ms/step - loss:
208646.7500
Epoch 9/500
50/50 [=====] - 0s 3ms/step - loss:
236557.4375
Epoch 10/500
50/50 [=====] - 0s 3ms/step - loss:
154889.8125
Epoch 11/500
50/50 [=====] - 0s 3ms/step - loss:
138113.7344
Epoch 12/500
50/50 [=====] - 0s 3ms/step - loss:
139994.6562
Epoch 13/500
50/50 [=====] - 0s 3ms/step - loss:
136935.1719
Epoch 14/500
50/50 [=====] - 0s 3ms/step - loss:
126615.7266
```

Epoch 15/500
50/50 [=====] - 0s 3ms/step - loss:
109311.1328
Epoch 16/500
50/50 [=====] - 0s 3ms/step - loss:
101247.6250
Epoch 17/500
50/50 [=====] - 0s 3ms/step - loss:
98932.4297
Epoch 18/500
50/50 [=====] - 0s 3ms/step - loss:
97167.6328
Epoch 19/500
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103274.7656
Epoch 20/500
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98956.2266
Epoch 21/500
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103466.6719
Epoch 22/500
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100932.4766
Epoch 23/500
50/50 [=====] - 0s 3ms/step - loss:
94971.2734
Epoch 24/500
50/50 [=====] - 0s 3ms/step - loss:
98537.5312
Epoch 25/500
50/50 [=====] - 0s 3ms/step - loss:
93551.8359
Epoch 26/500
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99746.5781
Epoch 27/500
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108707.4375
Epoch 28/500
50/50 [=====] - 0s 3ms/step - loss:
95745.2422
Epoch 29/500
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93859.4141
Epoch 30/500
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87338.0625
Epoch 31/500
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89907.8359
Epoch 32/500
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93018.9141
Epoch 33/500
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85993.1016
Epoch 34/500
50/50 [=====] - 0s 3ms/step - loss:
90065.1719
Epoch 35/500
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88101.5469
Epoch 36/500
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89085.3906
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88349.7344
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84216.1094
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90629.8359
Epoch 40/500
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93599.0156
Epoch 41/500
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88702.8984
Epoch 42/500
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93061.6406
Epoch 43/500
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83411.6172
Epoch 44/500
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83725.5156
Epoch 45/500
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87212.5781
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92420.4531
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92949.0859
Epoch 48/500

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90891.3203
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92886.4453
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96329.6172
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88877.4922
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89462.2188
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91325.3125
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91177.2031
Epoch 55/500
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87200.4062
Epoch 56/500
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91140.1250
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87608.9531
Epoch 58/500
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88015.9297
Epoch 59/500
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106718.4688
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89783.9062
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115887.0625
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123937.5234
Epoch 63/500
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122897.4141
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137507.4688

Epoch 65/500
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173537.3281
Epoch 66/500
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133203.3281
Epoch 67/500
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114230.3906
Epoch 68/500
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108054.7266
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101692.2109
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100125.5312
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91233.2266
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89865.5312
Epoch 77/500
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97578.3047
Epoch 78/500
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99155.8516
Epoch 79/500
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Epoch 80/500
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92436.1953
Epoch 81/500
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91920.1797
Epoch 82/500
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90216.8672
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80526.2500
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151400.3594
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89749.1094
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81234.4688
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78591.2578
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75836.2266
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74756.7812
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77278.5078
Epoch 131/500

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73977.4297
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75407.0938
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77371.6562
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75932.5703
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81042.1016
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73258.6641
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72889.4453
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72747.9453
Epoch 140/500
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72602.0859
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71413.0156
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68528.8438
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71513.5938
Epoch 144/500
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76260.9219
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68628.2266
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70423.9453

Epoch 148/500
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69218.4375
Epoch 149/500
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69192.3125
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69013.6953
Epoch 151/500
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70837.2031
Epoch 152/500
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73026.7969
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67946.5078
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65295.7109
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66146.4766
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67786.1719
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66701.1016
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64647.1562
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70723.2969
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64331.9648
Epoch 163/500
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65686.6016
Epoch 164/500
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62415.6797
Epoch 165/500
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62610.6367
Epoch 166/500
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66478.7969
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66925.0078
Epoch 168/500
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62333.9062
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64400.8320
Epoch 170/500
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82322.4688
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79206.2500
Epoch 172/500
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75738.1250
Epoch 174/500
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71826.9141
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67113.5938
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67577.8203
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64545.7344
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75179.8203
Epoch 181/500

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70668.6875
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75449.6641
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73071.2188
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63543.9531
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62241.3320
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60393.1992
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60029.3047
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64028.3945
Epoch 198/500
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90664.1797
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87862.4375
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68848.2812
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Epoch 203/500
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57038.6055
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60827.0195
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58143.3945
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57932.0391
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60313.8594
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60519.8672
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61503.9883
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63713.7422
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63664.7891
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56087.8672
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90245.6484
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64300.2344
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62191.5430
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64488.8047

Epoch 231/500
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61112.6953
Epoch 232/500
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62740.2539
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58733.2109
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57544.7266
Epoch 235/500
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55057.9570
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55955.5156
Epoch 240/500
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55525.7070
Epoch 241/500
50/50 [=====] - 0s 3ms/step - loss:
56831.7500
Epoch 242/500
50/50 [=====] - 0s 3ms/step - loss:
59257.9219
Epoch 243/500
50/50 [=====] - 0s 3ms/step - loss:
54419.0859
Epoch 244/500
50/50 [=====] - 0s 3ms/step - loss:
64931.8008
Epoch 245/500
50/50 [=====] - 0s 3ms/step - loss:
59571.7852
Epoch 246/500
50/50 [=====] - 0s 3ms/step - loss:
59937.0977
Epoch 247/500
50/50 [=====] - 0s 3ms/step - loss:

58396.6094
Epoch 248/500
50/50 [=====] - 0s 3ms/step - loss:
57908.4727
Epoch 249/500
50/50 [=====] - 0s 3ms/step - loss:
55285.7070
Epoch 250/500
50/50 [=====] - 0s 3ms/step - loss:
55906.8320
Epoch 251/500
50/50 [=====] - 0s 3ms/step - loss:
52458.9492
Epoch 252/500
50/50 [=====] - 0s 3ms/step - loss:
51149.0977
Epoch 253/500
50/50 [=====] - 0s 3ms/step - loss:
50869.2266
Epoch 254/500
50/50 [=====] - 0s 3ms/step - loss:
54454.4297
Epoch 255/500
50/50 [=====] - 0s 3ms/step - loss:
52510.8711
Epoch 256/500
50/50 [=====] - 0s 3ms/step - loss:
52144.7148
Epoch 257/500
50/50 [=====] - 0s 3ms/step - loss:
51565.8594
Epoch 258/500
50/50 [=====] - 0s 3ms/step - loss:
50779.6484
Epoch 259/500
50/50 [=====] - 0s 3ms/step - loss:
52701.2188
Epoch 260/500
50/50 [=====] - 0s 3ms/step - loss:
50140.8281
Epoch 261/500
50/50 [=====] - 0s 3ms/step - loss:
51309.5039
Epoch 262/500
50/50 [=====] - 0s 3ms/step - loss:
58178.9688
Epoch 263/500
50/50 [=====] - 0s 3ms/step - loss:
51746.7539
Epoch 264/500

50/50 [=====] - 0s 3ms/step - loss:
50348.4844
Epoch 265/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 266/500
50/50 [=====] - 0s 3ms/step - loss:
49224.8789
Epoch 267/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 268/500
50/50 [=====] - 0s 3ms/step - loss:
52665.3477
Epoch 269/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 270/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 271/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 272/500
50/50 [=====] - 0s 3ms/step - loss:
51334.8125
Epoch 273/500
50/50 [=====] - 0s 3ms/step - loss:
54320.9219
Epoch 274/500
50/50 [=====] - 0s 3ms/step - loss:
47620.9219
Epoch 275/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 276/500
50/50 [=====] - 0s 3ms/step - loss:
54241.2852
Epoch 277/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 278/500
50/50 [=====] - 0s 3ms/step - loss:
50121.9961
Epoch 279/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 280/500
50/50 [=====] - 0s 3ms/step - loss:
52615.2422

Epoch 281/500
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Epoch 282/500
50/50 [=====] - 0s 3ms/step - loss:
51299.1406
Epoch 283/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 284/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 285/500
50/50 [=====] - 0s 3ms/step - loss:
53424.3516
Epoch 286/500
50/50 [=====] - 0s 3ms/step - loss:
52594.0469
Epoch 287/500

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Epoch 288/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 289/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 290/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 291/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 292/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 293/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 294/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 295/500
50/50 [=====] - 0s 3ms/step - loss:
52035.3594
Epoch 296/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 297/500

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Epoch 298/500
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Epoch 299/500
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Epoch 300/500
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Epoch 301/500
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Epoch 302/500
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Epoch 303/500
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Epoch 305/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 306/500
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Epoch 307/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 308/500
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48635.7422
Epoch 309/500
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Epoch 310/500
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48348.0547
Epoch 311/500
50/50 [=====] - 0s 3ms/step - loss:
48923.4727
Epoch 312/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 313/500
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Epoch 314/500
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Epoch 315/500
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Epoch 317/500
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Epoch 318/500
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Epoch 319/500
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Epoch 320/500
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Epoch 321/500
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Epoch 322/500
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Epoch 323/500
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Epoch 324/500
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Epoch 325/500
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Epoch 326/500
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Epoch 327/500
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Epoch 328/500
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Epoch 329/500
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Epoch 330/500
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55466.8750
Epoch 331/500
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Epoch 332/500
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Epoch 333/500
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Epoch 334/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 335/500
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Epoch 336/500
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Epoch 337/500
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Epoch 338/500
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Epoch 340/500
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Epoch 341/500
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Epoch 342/500
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Epoch 343/500
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Epoch 344/500
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Epoch 345/500
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Epoch 346/500
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Epoch 347/500

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Epoch 349/500
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Epoch 353/500
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Epoch 354/500
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Epoch 355/500
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Epoch 357/500
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Epoch 358/500
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Epoch 359/500
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Epoch 360/500
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Epoch 361/500
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Epoch 362/500
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Epoch 363/500
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Epoch 364/500
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Epoch 365/500
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Epoch 366/500
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Epoch 367/500
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Epoch 368/500
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Epoch 369/500
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Epoch 370/500
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Epoch 371/500
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Epoch 373/500
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Epoch 374/500
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Epoch 375/500
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Epoch 376/500
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Epoch 377/500
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Epoch 378/500
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Epoch 379/500
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Epoch 380/500
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Epoch 381/500
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Epoch 382/500

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Epoch 385/500
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Epoch 386/500
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Epoch 387/500
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Epoch 388/500
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Epoch 389/500
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Epoch 391/500
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Epoch 392/500
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Epoch 393/500
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Epoch 394/500
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Epoch 399/500
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Epoch 408/500
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Epoch 409/500
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Epoch 410/500
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Epoch 411/500
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Epoch 413/500
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Epoch 414/500
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Epoch 419/500
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Epoch 420/500
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Epoch 421/500
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Epoch 429/500
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Epoch 430/500

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Epoch 437/500
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Epoch 442/500
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Epoch 443/500
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Epoch 444/500
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Epoch 445/500
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Epoch 446/500
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Epoch 447/500
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Epoch 467/500
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Epoch 469/500
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Epoch 470/500
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Epoch 472/500
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Epoch 473/500
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Epoch 474/500
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Epoch 475/500
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Epoch 476/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 477/500

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Epoch 478/500
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Epoch 479/500
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Epoch 480/500
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Epoch 481/500
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Epoch 483/500
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Epoch 484/500
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Epoch 486/500
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Epoch 488/500
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Epoch 490/500
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Epoch 491/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 492/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 493/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 494/500
50/50 [=====] - 0s 3ms/step - loss:
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Epoch 495/500
50/50 [=====] - 0s 3ms/step - loss:
45578.9766
Epoch 496/500
50/50 [=====] - 0s 3ms/step - loss:

```

45210.8398
Epoch 497/500
50/50 [=====] - 0s 3ms/step - loss:
44550.3906
Epoch 498/500
50/50 [=====] - 0s 3ms/step - loss:
48720.3867
Epoch 499/500
50/50 [=====] - 0s 3ms/step - loss:
46457.8906
Epoch 500/500
50/50 [=====] - 0s 3ms/step - loss:
46670.2891

<keras.callbacks.History at 0x2582469bee0>

from numpy import array
# demonstrate prediction for next 10 days
x_input = array(all_cc[-7:])
temp_input=list(x_input)
lst_output=[]
i=0
while(i<7):

    if(len(temp_input)>7):
        x_input=array(temp_input[1:])
    #    print("{} day input {}".format(i,x_input))
        #print(x_input)
        x_input = x_input.reshape((1, n_steps, n_features))
        #print(x_input)
        yhat = model.predict(x_input, verbose=0)
    #    print("{} day output {}".format(i,yhat))
        temp_input.append(yhat[0][0])
        temp_input=temp_input[1:]
        #print(temp_input)
        lst_output.append(yhat[0][0])
        i=i+1
    else:
        x_input = x_input.reshape((1, n_steps, n_features))
        yhat = model.predict(x_input, verbose=0)
    #    print(yhat[0])
        temp_input.append(yhat[0][0])
        lst_output.append(yhat[0][0])
        i=i+1

print(lst_output)
[377.71722, 255.75018, 1335.5135, 1292.8608, 1224.441, 1194.5858,
1094.1954]

```

```

pred_data = lstm_data.loc[ [(dt.month==4) & (dt.year==2021) for dt in
lstm_data.ds] ]
pred_data.reset_index(drop=True, inplace=True)
pred_data

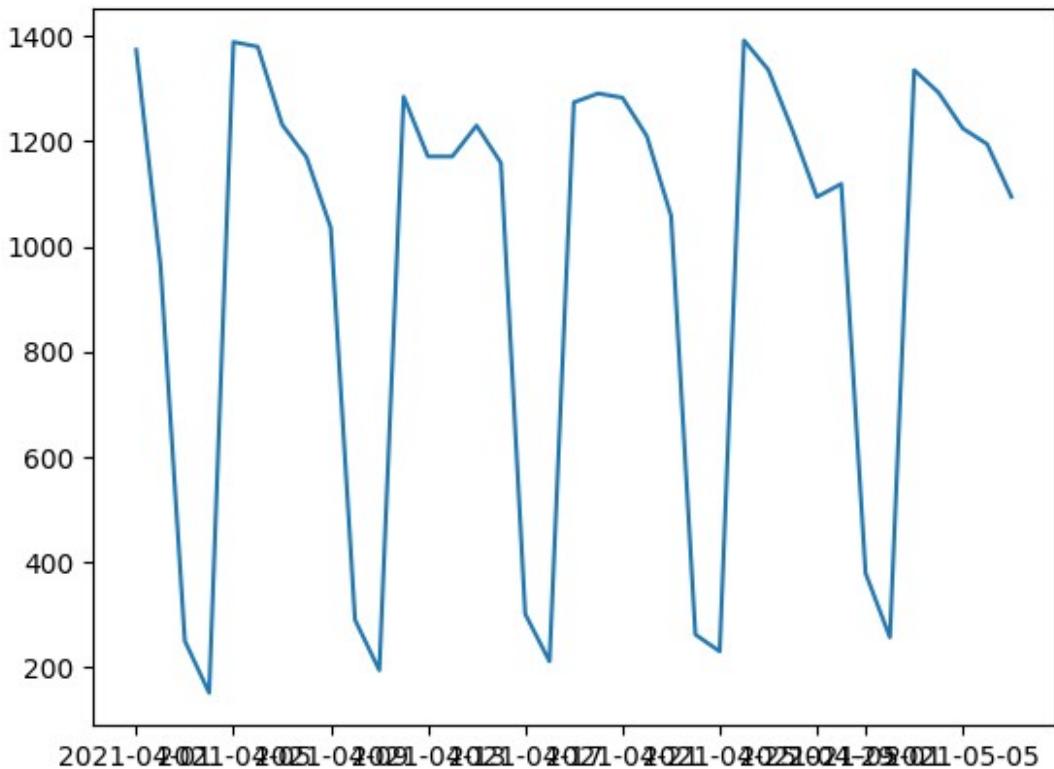
      ds      y
0 2021-04-01  1374.0
1 2021-04-02   963.0
2 2021-04-03   249.0
3 2021-04-04   150.0
4 2021-04-05  1389.0
5 2021-04-06  1380.0
6 2021-04-07  1232.0
7 2021-04-08  1170.0
8 2021-04-09  1036.0
9 2021-04-10   289.0
10 2021-04-11   193.0
11 2021-04-12  1285.0
12 2021-04-13  1171.0
13 2021-04-14  1171.0
14 2021-04-15  1230.0
15 2021-04-16  1159.0
16 2021-04-17   300.0
17 2021-04-18   210.0
18 2021-04-19  1274.0
19 2021-04-20  1291.0
20 2021-04-21  1283.0
21 2021-04-22  1210.0
22 2021-04-23  1058.0
23 2021-04-24   261.0
24 2021-04-25   229.0
25 2021-04-26  1392.0
26 2021-04-27  1336.0
27 2021-04-28  1220.0
28 2021-04-29  1094.0
29 2021-04-30  1119.0

tmp = pd.concat((pred_data, pd.DataFrame({
    "ds": pd.date_range(start='5/1/2021', periods=7).strftime('%Y-%m-%d'),
    "y": lst_output
})))
# pd.DataFrame({
#     "ds": pd.date_range(start='5/1/2021', periods=10).strftime('%Y-%m-%d'),
#     "y": lst_output
# })

plt.plot(tmp.ds, tmp.y)

[<matplotlib.lines.Line2D at 0x258243408b0>]

```



```
tmp[-7:]
```

	ds	y
0	2021-05-01	377.717224
1	2021-05-02	255.750183
2	2021-05-03	1335.513550
3	2021-05-04	1292.860840
4	2021-05-05	1224.441040
5	2021-05-06	1194.585815
6	2021-05-07	1094.195435

```
pd.DataFrame({
    "Date": pd.date_range(start='5/1/2021',
    periods=7).strftime('%m/%d/%Y'),
    "No_calls_Offered_predicted": tmp[-7:].y.to_list()
}).to_csv("week_prediction.csv", index=False)
```

```
df_17_cumm = df_17[['cc', 'rc', 'sc',
'month']].groupby('month').sum()
```

```

years = df_not17_sorted.year.unique()
for y in years:
    df_not17_sorted_yearly = df_not17_sorted[df_not17_sorted.year == y]
    df_cumm = df_not17_sorted_yearly[['cc', 'rc', 'sc', 'month']].groupby('month').sum()
#    print(df_cumm)
    df_17_cumm = pd.concat((df_17_cumm, df_cumm))

df_17_cumm

```

	cc	rc	sc
month			
1	48239.0	72702.0	147207.0
2	42176.0	63558.0	128753.0
3	46218.0	69673.0	140998.0
4	42362.0	63850.0	128841.0
5	45914.0	69202.0	140060.0
6	45519.0	68574.0	138623.0
7	41117.0	61970.0	125464.0
8	42484.0	63969.0	129310.0
9	39754.0	59901.0	121404.0
10	46640.0	70304.0	141922.0
11	50725.0	76379.0	154269.0
12	44771.0	67468.0	136665.0
1	48219.0	72631.0	146842.0
2	44012.0	66305.0	133977.0
3	46840.0	70598.0	142715.0
4	48348.0	72800.0	146984.0
5	48600.0	73208.0	147975.0
6	43434.0	65439.0	132629.0
7	50356.0	75806.0	153101.0
8	54320.0	81786.0	164943.0
9	48260.0	72703.0	146870.0
10	58059.0	87372.0	176099.0
11	50977.0	76781.0	155070.0
12	44124.0	66501.0	134578.0
1	46429.0	69940.0	141465.0
2	43424.0	65387.0	132108.0
3	44893.0	67669.0	136703.0
4	48295.0	72723.0	146956.0
5	50901.0	76649.0	154618.0
6	46533.0	70136.0	141740.0
7	47944.0	72248.0	146063.0
8	47310.0	71243.0	144031.0
9	45262.0	68223.0	137787.0
10	49613.0	74738.0	151231.0
11	40431.0	60984.0	123209.0
12	37935.0	57195.0	115784.0
1	44327.0	66784.0	135340.0
2	40076.0	60391.0	122104.0

```

3      38164.0   57598.0   116659.0
4      32852.0   49543.0   100659.0
5      27944.0   42197.0   86044.0
6      30685.0   46308.0   94196.0
7      30571.0   46190.0   93885.0
8      31314.0   47345.0   96343.0
9      30954.0   46713.0   94828.0
10     34179.0   51560.0   104724.0
11     30091.0   45409.0   92336.0
12     29783.0   44933.0   91702.0
1      27722.0   41872.0   85114.0
2      26341.0   39751.0   81023.0
3      32751.0   49402.0   100177.0
4      28718.0   43325.0   88096.0

```

```

lstm_data = pd.DataFrame({
    "ds": df_17_cumm.index,
    "y": df_17_cumm.cc
})
lstm_data

```

	ds	y
month		
1	1	48239.0
2	2	42176.0
3	3	46218.0
4	4	42362.0
5	5	45914.0
6	6	45519.0
7	7	41117.0
8	8	42484.0
9	9	39754.0
10	10	46640.0
11	11	50725.0
12	12	44771.0
1	1	48219.0
2	2	44012.0
3	3	46840.0
4	4	48348.0
5	5	48600.0
6	6	43434.0
7	7	50356.0
8	8	54320.0
9	9	48260.0
10	10	58059.0
11	11	50977.0
12	12	44124.0
1	1	46429.0
2	2	43424.0
3	3	44893.0
4	4	48295.0

```

5      5  50901.0
6      6  46533.0
7      7  47944.0
8      8  47310.0
9      9  45262.0
10     10 49613.0
11     11 40431.0
12     12 37935.0
1      1  44327.0
2      2  40076.0
3      3  38164.0
4      4  32852.0
5      5  27944.0
6      6  30685.0
7      7  30571.0
8      8  31314.0
9      9  30954.0
10     10 34179.0
11     11 30091.0
12     12 29783.0
1      1  27722.0
2      2  26341.0
3      3  32751.0
4      4  28718.0

# define input sequence
timeseries_data = df_17_cumm.cc.to_list()
# choose a number of time steps
n_steps = 12
# split into samples
X, y = prepare_data(timeseries_data, n_steps)

# reshape from [samples, timesteps] into [samples, timesteps,
features]
n_features = 1
X = X.reshape((X.shape[0], X.shape[1], n_features))

# define model
model = Sequential()
model.add(LSTM(50, activation='relu', return_sequences=True,
input_shape=(n_steps, n_features)))
model.add(LSTM(50, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
# fit model
model.fit(X, y, epochs=500, verbose=1)

Epoch 1/500
2/2 [=====] - 2s 6ms/step - loss:
1711399168.0000
Epoch 2/500

```

2/2 [=====] - 0s 5ms/step - loss:
1733785216.0000
Epoch 3/500
2/2 [=====] - 0s 5ms/step - loss:
1751710976.0000
Epoch 4/500
2/2 [=====] - 0s 4ms/step - loss:
1630898816.0000
Epoch 5/500
2/2 [=====] - 0s 7ms/step - loss:
1698453888.0000
Epoch 6/500
2/2 [=====] - 0s 7ms/step - loss:
1739772544.0000
Epoch 7/500
2/2 [=====] - 0s 5ms/step - loss:
1713522688.0000
Epoch 8/500
2/2 [=====] - 0s 5ms/step - loss:
1706387840.0000
Epoch 9/500
2/2 [=====] - 0s 7ms/step - loss:
1659777280.0000
Epoch 10/500
2/2 [=====] - 0s 7ms/step - loss:
1615126144.0000
Epoch 11/500
2/2 [=====] - 0s 5ms/step - loss:
1606615296.0000
Epoch 12/500
2/2 [=====] - 0s 5ms/step - loss:
1520372096.0000
Epoch 13/500
2/2 [=====] - 0s 6ms/step - loss:
1704055936.0000
Epoch 14/500
2/2 [=====] - 0s 6ms/step - loss:
1781650432.0000
Epoch 15/500
2/2 [=====] - 0s 5ms/step - loss:
1763167488.0000
Epoch 16/500
2/2 [=====] - 0s 5ms/step - loss:
1737465600.0000
Epoch 17/500
2/2 [=====] - 0s 6ms/step - loss:
1679264512.0000
Epoch 18/500
2/2 [=====] - 0s 6ms/step - loss:
1657613824.0000

Epoch 19/500
2/2 [=====] - 0s 5ms/step - loss:
1617176576.0000
Epoch 20/500
2/2 [=====] - 0s 5ms/step - loss:
1601027328.0000
Epoch 21/500
2/2 [=====] - 0s 7ms/step - loss:
1512570496.0000
Epoch 22/500
2/2 [=====] - 0s 5ms/step - loss:
1418384384.0000
Epoch 23/500
2/2 [=====] - 0s 4ms/step - loss:
1544785408.0000
Epoch 24/500
2/2 [=====] - 0s 6ms/step - loss:
1467401216.0000
Epoch 25/500
2/2 [=====] - 0s 7ms/step - loss:
1103120896.0000
Epoch 26/500
2/2 [=====] - 0s 6ms/step - loss:
604009920.0000
Epoch 27/500
2/2 [=====] - 0s 4ms/step - loss:
460667648.0000
Epoch 28/500
2/2 [=====] - 0s 6ms/step - loss:
346994080.0000
Epoch 29/500
2/2 [=====] - 0s 6ms/step - loss:
235416880.0000
Epoch 30/500
2/2 [=====] - 0s 5ms/step - loss:
134898272.0000
Epoch 31/500
2/2 [=====] - 0s 6ms/step - loss:
111967768.0000
Epoch 32/500
2/2 [=====] - 0s 7ms/step - loss:
94308400.0000
Epoch 33/500
2/2 [=====] - 0s 6ms/step - loss:
87055600.0000
Epoch 34/500
2/2 [=====] - 0s 5ms/step - loss:
92430704.0000
Epoch 35/500
2/2 [=====] - 0s 5ms/step - loss:

82411504.0000
Epoch 36/500
2/2 [=====] - 0s 6ms/step - loss:
63449652.0000
Epoch 37/500
2/2 [=====] - 0s 4ms/step - loss:
57254472.0000
Epoch 38/500
2/2 [=====] - 0s 5ms/step - loss:
74420992.0000
Epoch 39/500
2/2 [=====] - 0s 5ms/step - loss:
60901864.0000
Epoch 40/500
2/2 [=====] - 0s 5ms/step - loss:
58956576.0000
Epoch 41/500
2/2 [=====] - 0s 4ms/step - loss:
54460512.0000
Epoch 42/500
2/2 [=====] - 0s 6ms/step - loss:
54095500.0000
Epoch 43/500
2/2 [=====] - 0s 4ms/step - loss:
56365024.0000
Epoch 44/500
2/2 [=====] - 0s 4ms/step - loss:
54878604.0000
Epoch 45/500
2/2 [=====] - 0s 6ms/step - loss:
56152536.0000
Epoch 46/500
2/2 [=====] - 0s 6ms/step - loss:
47412568.0000
Epoch 47/500
2/2 [=====] - 0s 5ms/step - loss:
39923320.0000
Epoch 48/500
2/2 [=====] - 0s 5ms/step - loss:
43489632.0000
Epoch 49/500
2/2 [=====] - 0s 6ms/step - loss:
56389784.0000
Epoch 50/500
2/2 [=====] - 0s 5ms/step - loss:
69883688.0000
Epoch 51/500
2/2 [=====] - 0s 6ms/step - loss:
91846192.0000
Epoch 52/500

2/2 [=====] - 0s 6ms/step - loss:
81893464.0000
Epoch 53/500
2/2 [=====] - 0s 7ms/step - loss:
79905248.0000
Epoch 54/500
2/2 [=====] - 0s 7ms/step - loss:
58530240.0000
Epoch 55/500
2/2 [=====] - 0s 5ms/step - loss:
55558136.0000
Epoch 56/500
2/2 [=====] - 0s 5ms/step - loss:
76524952.0000
Epoch 57/500
2/2 [=====] - 0s 6ms/step - loss:
73806288.0000
Epoch 58/500
2/2 [=====] - 0s 7ms/step - loss:
83651216.0000
Epoch 59/500
2/2 [=====] - 0s 6ms/step - loss:
57914784.0000
Epoch 60/500
2/2 [=====] - 0s 5ms/step - loss:
52215360.0000
Epoch 61/500
2/2 [=====] - 0s 6ms/step - loss:
54818964.0000
Epoch 62/500
2/2 [=====] - 0s 6ms/step - loss:
56918296.0000
Epoch 63/500
2/2 [=====] - 0s 5ms/step - loss:
61419040.0000
Epoch 64/500
2/2 [=====] - 0s 5ms/step - loss:
62542900.0000
Epoch 65/500
2/2 [=====] - 0s 8ms/step - loss:
55681876.0000
Epoch 66/500
2/2 [=====] - 0s 8ms/step - loss:
51960264.0000
Epoch 67/500
2/2 [=====] - 0s 5ms/step - loss:
49496776.0000
Epoch 68/500
2/2 [=====] - 0s 5ms/step - loss:
46800624.0000

Epoch 69/500
2/2 [=====] - 0s 5ms/step - loss:
45799792.0000
Epoch 70/500
2/2 [=====] - 0s 7ms/step - loss:
51362756.0000
Epoch 71/500
2/2 [=====] - 0s 8ms/step - loss:
43207412.0000
Epoch 72/500
2/2 [=====] - 0s 6ms/step - loss:
49633752.0000
Epoch 73/500
2/2 [=====] - 0s 5ms/step - loss:
41920480.0000
Epoch 74/500
2/2 [=====] - 0s 6ms/step - loss:
45115092.0000
Epoch 75/500
2/2 [=====] - 0s 7ms/step - loss:
50119104.0000
Epoch 76/500
2/2 [=====] - 0s 7ms/step - loss:
61677120.0000
Epoch 77/500
2/2 [=====] - 0s 5ms/step - loss:
56030632.0000
Epoch 78/500
2/2 [=====] - 0s 5ms/step - loss:
62001920.0000
Epoch 79/500
2/2 [=====] - 0s 7ms/step - loss:
70496744.0000
Epoch 80/500
2/2 [=====] - 0s 7ms/step - loss:
74757336.0000
Epoch 81/500
2/2 [=====] - 0s 5ms/step - loss:
76514920.0000
Epoch 82/500
2/2 [=====] - 0s 4ms/step - loss:
76084720.0000
Epoch 83/500
2/2 [=====] - 0s 7ms/step - loss:
75197648.0000
Epoch 84/500
2/2 [=====] - 0s 7ms/step - loss:
72916624.0000
Epoch 85/500
2/2 [=====] - 0s 6ms/step - loss:

69426920.0000
Epoch 86/500
2/2 [=====] - 0s 4ms/step - loss:
67598296.0000
Epoch 87/500
2/2 [=====] - 0s 6ms/step - loss:
61422632.0000
Epoch 88/500
2/2 [=====] - 0s 6ms/step - loss:
60241160.0000
Epoch 89/500
2/2 [=====] - 0s 4ms/step - loss:
69370600.0000
Epoch 90/500
2/2 [=====] - 0s 6ms/step - loss:
61073208.0000
Epoch 91/500
2/2 [=====] - 0s 8ms/step - loss:
59684076.0000
Epoch 92/500
2/2 [=====] - 0s 6ms/step - loss:
62912160.0000
Epoch 93/500
2/2 [=====] - 0s 5ms/step - loss:
59243712.0000
Epoch 94/500
2/2 [=====] - 0s 5ms/step - loss:
56298424.0000
Epoch 95/500

2/2 [=====] - 0s 6ms/step - loss:
54145240.0000
Epoch 96/500
2/2 [=====] - 0s 5ms/step - loss:
54033600.0000
Epoch 97/500
2/2 [=====] - 0s 5ms/step - loss:
51446060.0000
Epoch 98/500
2/2 [=====] - 0s 6ms/step - loss:
50044096.0000
Epoch 99/500
2/2 [=====] - 0s 7ms/step - loss:
50847176.0000
Epoch 100/500
2/2 [=====] - 0s 7ms/step - loss:
50968440.0000
Epoch 101/500
2/2 [=====] - 0s 6ms/step - loss:
50552676.0000

Epoch 102/500
2/2 [=====] - 0s 5ms/step - loss:
78714296.0000
Epoch 103/500
2/2 [=====] - 0s 6ms/step - loss:
63657504.0000
Epoch 104/500
2/2 [=====] - 0s 7ms/step - loss:
40070064.0000
Epoch 105/500
2/2 [=====] - 0s 5ms/step - loss:
36426584.0000
Epoch 106/500
2/2 [=====] - 0s 5ms/step - loss:
48976960.0000
Epoch 107/500
2/2 [=====] - 0s 6ms/step - loss:
55400244.0000
Epoch 108/500
2/2 [=====] - 0s 6ms/step - loss:
48157144.0000
Epoch 109/500
2/2 [=====] - 0s 7ms/step - loss:
40440816.0000
Epoch 110/500
2/2 [=====] - 0s 5ms/step - loss:
38757808.0000
Epoch 111/500
2/2 [=====] - 0s 5ms/step - loss:
40548392.0000
Epoch 112/500
2/2 [=====] - 0s 6ms/step - loss:
48155304.0000
Epoch 113/500
2/2 [=====] - 0s 7ms/step - loss:
44133484.0000
Epoch 114/500
2/2 [=====] - 0s 6ms/step - loss:
40120608.0000
Epoch 115/500
2/2 [=====] - 0s 4ms/step - loss:
37735528.0000
Epoch 116/500
2/2 [=====] - 0s 5ms/step - loss:
42221300.0000
Epoch 117/500
2/2 [=====] - 0s 8ms/step - loss:
41872404.0000
Epoch 118/500
2/2 [=====] - 0s 8ms/step - loss:

44152104.0000
Epoch 119/500
2/2 [=====] - 0s 4ms/step - loss:
39156808.0000
Epoch 120/500
2/2 [=====] - 0s 5ms/step - loss:
36378856.0000
Epoch 121/500
2/2 [=====] - 0s 6ms/step - loss:
37823748.0000
Epoch 122/500
2/2 [=====] - 0s 7ms/step - loss:
39561888.0000
Epoch 123/500
2/2 [=====] - 0s 5ms/step - loss:
39030428.0000
Epoch 124/500
2/2 [=====] - 0s 5ms/step - loss:
37321928.0000
Epoch 125/500
2/2 [=====] - 0s 8ms/step - loss:
35164764.0000
Epoch 126/500
2/2 [=====] - 0s 4ms/step - loss:
33436100.0000
Epoch 127/500
2/2 [=====] - 0s 5ms/step - loss:
51067796.0000
Epoch 128/500
2/2 [=====] - 0s 6ms/step - loss:
47314024.0000
Epoch 129/500
2/2 [=====] - 0s 6ms/step - loss:
42698568.0000
Epoch 130/500
2/2 [=====] - 0s 5ms/step - loss:
41492024.0000
Epoch 131/500
2/2 [=====] - 0s 5ms/step - loss:
42718416.0000
Epoch 132/500
2/2 [=====] - 0s 6ms/step - loss:
43472960.0000
Epoch 133/500
2/2 [=====] - 0s 6ms/step - loss:
41246580.0000
Epoch 134/500
2/2 [=====] - 0s 5ms/step - loss:
38423392.0000
Epoch 135/500

2/2 [=====] - 0s 5ms/step - loss:
38397572.0000
Epoch 136/500
2/2 [=====] - 0s 8ms/step - loss:
39158552.0000
Epoch 137/500
2/2 [=====] - 0s 6ms/step - loss:
38885776.0000
Epoch 138/500
2/2 [=====] - 0s 4ms/step - loss:
39120952.0000
Epoch 139/500
2/2 [=====] - 0s 4ms/step - loss:
39555184.0000
Epoch 140/500
2/2 [=====] - 0s 6ms/step - loss:
40323252.0000
Epoch 141/500
2/2 [=====] - 0s 5ms/step - loss:
41742008.0000
Epoch 142/500
2/2 [=====] - 0s 4ms/step - loss:
41583352.0000
Epoch 143/500
2/2 [=====] - 0s 7ms/step - loss:
41058572.0000
Epoch 144/500
2/2 [=====] - 0s 11ms/step - loss:
41319784.0000
Epoch 145/500
2/2 [=====] - 0s 8ms/step - loss:
42103720.0000
Epoch 146/500
2/2 [=====] - 0s 6ms/step - loss:
42681228.0000
Epoch 147/500
2/2 [=====] - 0s 5ms/step - loss:
42296468.0000
Epoch 148/500
2/2 [=====] - 0s 5ms/step - loss:
40730324.0000
Epoch 149/500
2/2 [=====] - 0s 5ms/step - loss:
40051128.0000
Epoch 150/500
2/2 [=====] - 0s 8ms/step - loss:
41520812.0000
Epoch 151/500
2/2 [=====] - 0s 9ms/step - loss:
41103924.0000

Epoch 152/500
2/2 [=====] - 0s 7ms/step - loss:
41183288.0000
Epoch 153/500
2/2 [=====] - 0s 4ms/step - loss:
40552532.0000
Epoch 154/500
2/2 [=====] - 0s 5ms/step - loss:
40456504.0000
Epoch 155/500
2/2 [=====] - 0s 7ms/step - loss:
40312152.0000
Epoch 156/500
2/2 [=====] - 0s 6ms/step - loss:
40281208.0000
Epoch 157/500
2/2 [=====] - 0s 6ms/step - loss:
40483384.0000
Epoch 158/500
2/2 [=====] - 0s 6ms/step - loss:
41052700.0000
Epoch 159/500
2/2 [=====] - 0s 6ms/step - loss:
41789792.0000
Epoch 160/500
2/2 [=====] - 0s 7ms/step - loss:
41606492.0000
Epoch 161/500
2/2 [=====] - 0s 5ms/step - loss:
41051336.0000
Epoch 162/500
2/2 [=====] - 0s 5ms/step - loss:
39782336.0000
Epoch 163/500
2/2 [=====] - 0s 5ms/step - loss:
39334124.0000
Epoch 164/500
2/2 [=====] - 0s 7ms/step - loss:
39628792.0000
Epoch 165/500
2/2 [=====] - 0s 5ms/step - loss:
41638472.0000
Epoch 166/500
2/2 [=====] - 0s 5ms/step - loss:
44383812.0000
Epoch 167/500
2/2 [=====] - 0s 5ms/step - loss:
43886920.0000
Epoch 168/500
2/2 [=====] - 0s 7ms/step - loss:

42095888.0000
Epoch 169/500
2/2 [=====] - 0s 8ms/step - loss:
40140568.0000
Epoch 170/500
2/2 [=====] - 0s 5ms/step - loss:
39329644.0000
Epoch 171/500
2/2 [=====] - 0s 5ms/step - loss:
39331596.0000
Epoch 172/500
2/2 [=====] - 0s 6ms/step - loss:
42119624.0000
Epoch 173/500
2/2 [=====] - 0s 8ms/step - loss:
41411356.0000
Epoch 174/500
2/2 [=====] - 0s 5ms/step - loss:
41826136.0000
Epoch 175/500
2/2 [=====] - 0s 5ms/step - loss:
42900264.0000
Epoch 176/500
2/2 [=====] - 0s 6ms/step - loss:
41696300.0000
Epoch 177/500
2/2 [=====] - 0s 7ms/step - loss:
42061800.0000
Epoch 178/500
2/2 [=====] - 0s 5ms/step - loss:
42698436.0000
Epoch 179/500
2/2 [=====] - 0s 5ms/step - loss:
43486732.0000
Epoch 180/500
2/2 [=====] - 0s 7ms/step - loss:
42652072.0000
Epoch 181/500
2/2 [=====] - 0s 7ms/step - loss:
41528012.0000
Epoch 182/500
2/2 [=====] - 0s 4ms/step - loss:
40757656.0000
Epoch 183/500
2/2 [=====] - 0s 4ms/step - loss:
38814268.0000
Epoch 184/500
2/2 [=====] - 0s 6ms/step - loss:
39063060.0000
Epoch 185/500

2/2 [=====] - 0s 7ms/step - loss:
37334248.0000
Epoch 186/500
2/2 [=====] - 0s 5ms/step - loss:
37797332.0000
Epoch 187/500
2/2 [=====] - 0s 5ms/step - loss:
38377868.0000
Epoch 188/500
2/2 [=====] - 0s 5ms/step - loss:
44277464.0000
Epoch 189/500

2/2 [=====] - 0s 7ms/step - loss:
47277444.0000
Epoch 190/500
2/2 [=====] - 0s 5ms/step - loss:
37843008.0000
Epoch 191/500
2/2 [=====] - 0s 5ms/step - loss:
39021112.0000
Epoch 192/500
2/2 [=====] - 0s 7ms/step - loss:
37581944.0000
Epoch 193/500
2/2 [=====] - 0s 6ms/step - loss:
32806118.0000
Epoch 194/500
2/2 [=====] - 0s 5ms/step - loss:
33484246.0000
Epoch 195/500
2/2 [=====] - 0s 6ms/step - loss:
25744468.0000
Epoch 196/500
2/2 [=====] - 0s 6ms/step - loss:
25867676.0000
Epoch 197/500
2/2 [=====] - 0s 7ms/step - loss:
29323244.0000
Epoch 198/500
2/2 [=====] - 0s 5ms/step - loss:
31888918.0000
Epoch 199/500
2/2 [=====] - 0s 6ms/step - loss:
29079402.0000
Epoch 200/500
2/2 [=====] - 0s 7ms/step - loss:
30805908.0000
Epoch 201/500
2/2 [=====] - 0s 8ms/step - loss:

30575156.0000
Epoch 202/500
2/2 [=====] - 0s 4ms/step - loss:
28914628.0000
Epoch 203/500
2/2 [=====] - 0s 5ms/step - loss:
32545498.0000
Epoch 204/500
2/2 [=====] - 0s 7ms/step - loss:
30923508.0000
Epoch 205/500
2/2 [=====] - 0s 5ms/step - loss:
26985158.0000
Epoch 206/500
2/2 [=====] - 0s 5ms/step - loss:
23873220.0000
Epoch 207/500
2/2 [=====] - 0s 6ms/step - loss:
27718566.0000
Epoch 208/500
2/2 [=====] - 0s 8ms/step - loss:
33284288.0000
Epoch 209/500
2/2 [=====] - 0s 4ms/step - loss:
43905468.0000
Epoch 210/500
2/2 [=====] - 0s 5ms/step - loss:
63465976.0000
Epoch 211/500
2/2 [=====] - 0s 6ms/step - loss:
58564756.0000
Epoch 212/500
2/2 [=====] - 0s 6ms/step - loss:
50805508.0000
Epoch 213/500
2/2 [=====] - 0s 4ms/step - loss:
50725192.0000
Epoch 214/500
2/2 [=====] - 0s 5ms/step - loss:
52229032.0000
Epoch 215/500
2/2 [=====] - 0s 6ms/step - loss:
51406448.0000
Epoch 216/500
2/2 [=====] - 0s 6ms/step - loss:
48509144.0000
Epoch 217/500
2/2 [=====] - 0s 5ms/step - loss:
45750176.0000
Epoch 218/500

2/2 [=====] - 0s 5ms/step - loss:
45089388.0000
Epoch 219/500
2/2 [=====] - 0s 7ms/step - loss:
44796596.0000
Epoch 220/500
2/2 [=====] - 0s 5ms/step - loss:
44385324.0000
Epoch 221/500
2/2 [=====] - 0s 5ms/step - loss:
44359800.0000
Epoch 222/500
2/2 [=====] - 0s 7ms/step - loss:
43717080.0000
Epoch 223/500
2/2 [=====] - 0s 6ms/step - loss:
42732328.0000
Epoch 224/500
2/2 [=====] - 0s 4ms/step - loss:
42152988.0000
Epoch 225/500
2/2 [=====] - 0s 5ms/step - loss:
42412196.0000
Epoch 226/500
2/2 [=====] - 0s 8ms/step - loss:
42223984.0000
Epoch 227/500
2/2 [=====] - 0s 5ms/step - loss:
41690036.0000
Epoch 228/500
2/2 [=====] - 0s 4ms/step - loss:
40761432.0000
Epoch 229/500
2/2 [=====] - 0s 6ms/step - loss:
41484828.0000
Epoch 230/500
2/2 [=====] - 0s 7ms/step - loss:
40635112.0000
Epoch 231/500
2/2 [=====] - 0s 6ms/step - loss:
39738120.0000
Epoch 232/500
2/2 [=====] - 0s 5ms/step - loss:
39518936.0000
Epoch 233/500
2/2 [=====] - 0s 6ms/step - loss:
38828168.0000
Epoch 234/500
2/2 [=====] - 0s 6ms/step - loss:
38546152.0000

Epoch 235/500
2/2 [=====] - 0s 5ms/step - loss:
39586444.0000
Epoch 236/500
2/2 [=====] - 0s 5ms/step - loss:
39196684.0000
Epoch 237/500
2/2 [=====] - 0s 6ms/step - loss:
38308708.0000
Epoch 238/500
2/2 [=====] - 0s 5ms/step - loss:
37609196.0000
Epoch 239/500
2/2 [=====] - 0s 4ms/step - loss:
33248548.0000
Epoch 240/500
2/2 [=====] - 0s 5ms/step - loss:
34794904.0000
Epoch 241/500
2/2 [=====] - 0s 7ms/step - loss:
35752288.0000
Epoch 242/500
2/2 [=====] - 0s 8ms/step - loss:
34675672.0000
Epoch 243/500
2/2 [=====] - 0s 6ms/step - loss:
35056484.0000
Epoch 244/500
2/2 [=====] - 0s 4ms/step - loss:
40715776.0000
Epoch 245/500
2/2 [=====] - 0s 5ms/step - loss:
39282368.0000
Epoch 246/500
2/2 [=====] - 0s 6ms/step - loss:
38469796.0000
Epoch 247/500
2/2 [=====] - 0s 4ms/step - loss:
37788712.0000
Epoch 248/500
2/2 [=====] - 0s 5ms/step - loss:
38992840.0000
Epoch 249/500
2/2 [=====] - 0s 6ms/step - loss:
39411352.0000
Epoch 250/500
2/2 [=====] - 0s 5ms/step - loss:
38807980.0000
Epoch 251/500
2/2 [=====] - 0s 5ms/step - loss:

36847020.0000
Epoch 252/500
2/2 [=====] - 0s 6ms/step - loss:
32613772.0000
Epoch 253/500
2/2 [=====] - 0s 7ms/step - loss:
36287592.0000
Epoch 254/500
2/2 [=====] - 0s 6ms/step - loss:
39579216.0000
Epoch 255/500
2/2 [=====] - 0s 6ms/step - loss:
38800408.0000
Epoch 256/500
2/2 [=====] - 0s 5ms/step - loss:
36279764.0000
Epoch 257/500
2/2 [=====] - 0s 6ms/step - loss:
34981996.0000
Epoch 258/500
2/2 [=====] - 0s 5ms/step - loss:
37854596.0000
Epoch 259/500
2/2 [=====] - 0s 5ms/step - loss:
36531892.0000
Epoch 260/500
2/2 [=====] - 0s 7ms/step - loss:
35524776.0000
Epoch 261/500
2/2 [=====] - 0s 4ms/step - loss:
47908064.0000
Epoch 262/500
2/2 [=====] - 0s 4ms/step - loss:
47786296.0000
Epoch 263/500
2/2 [=====] - 0s 6ms/step - loss:
41735168.0000
Epoch 264/500
2/2 [=====] - 0s 6ms/step - loss:
36719208.0000
Epoch 265/500
2/2 [=====] - 0s 4ms/step - loss:
36421432.0000
Epoch 266/500
2/2 [=====] - 0s 6ms/step - loss:
43573288.0000
Epoch 267/500
2/2 [=====] - 0s 7ms/step - loss:
43408748.0000
Epoch 268/500

2/2 [=====] - 0s 4ms/step - loss:
39619108.0000
Epoch 269/500
2/2 [=====] - 0s 5ms/step - loss:
36456864.0000
Epoch 270/500
2/2 [=====] - 0s 6ms/step - loss:
36166304.0000
Epoch 271/500
2/2 [=====] - 0s 5ms/step - loss:
38173172.0000
Epoch 272/500
2/2 [=====] - 0s 5ms/step - loss:
39252940.0000
Epoch 273/500
2/2 [=====] - 0s 6ms/step - loss:
38315416.0000
Epoch 274/500
2/2 [=====] - 0s 6ms/step - loss:
35328932.0000
Epoch 275/500
2/2 [=====] - 0s 5ms/step - loss:
31722310.0000
Epoch 276/500
2/2 [=====] - 0s 5ms/step - loss:
34322236.0000
Epoch 277/500
2/2 [=====] - 0s 6ms/step - loss:
34624992.0000
Epoch 278/500
2/2 [=====] - 0s 6ms/step - loss:
33693368.0000
Epoch 279/500
2/2 [=====] - 0s 5ms/step - loss:
33820904.0000
Epoch 280/500
2/2 [=====] - 0s 6ms/step - loss:
35001416.0000
Epoch 281/500
2/2 [=====] - 0s 6ms/step - loss:
35316112.0000
Epoch 282/500
2/2 [=====] - 0s 7ms/step - loss:
34716564.0000
Epoch 283/500

2/2 [=====] - 0s 6ms/step - loss:
35015628.0000
Epoch 284/500
2/2 [=====] - 0s 5ms/step - loss:

34945284.0000
Epoch 285/500
2/2 [=====] - 0s 5ms/step - loss:
35351360.0000
Epoch 286/500
2/2 [=====] - 0s 7ms/step - loss:
35358164.0000
Epoch 287/500
2/2 [=====] - 0s 4ms/step - loss:
34867624.0000
Epoch 288/500
2/2 [=====] - 0s 5ms/step - loss:
35386568.0000
Epoch 289/500
2/2 [=====] - 0s 5ms/step - loss:
35709736.0000
Epoch 290/500
2/2 [=====] - 0s 6ms/step - loss:
35737032.0000
Epoch 291/500
2/2 [=====] - 0s 5ms/step - loss:
34921608.0000
Epoch 292/500
2/2 [=====] - 0s 5ms/step - loss:
34773888.0000
Epoch 293/500
2/2 [=====] - 0s 6ms/step - loss:
34656984.0000
Epoch 294/500
2/2 [=====] - 0s 5ms/step - loss:
34686784.0000
Epoch 295/500
2/2 [=====] - 0s 5ms/step - loss:
34630200.0000
Epoch 296/500
2/2 [=====] - 0s 6ms/step - loss:
34480056.0000
Epoch 297/500
2/2 [=====] - 0s 6ms/step - loss:
33346624.0000
Epoch 298/500
2/2 [=====] - 0s 5ms/step - loss:
32072364.0000
Epoch 299/500
2/2 [=====] - 0s 6ms/step - loss:
31894678.0000
Epoch 300/500
2/2 [=====] - 0s 7ms/step - loss:
31577328.0000
Epoch 301/500

2/2 [=====] - 0s 5ms/step - loss:
31168980.0000
Epoch 302/500
2/2 [=====] - 0s 5ms/step - loss:
30728166.0000
Epoch 303/500
2/2 [=====] - 0s 6ms/step - loss:
30631636.0000
Epoch 304/500
2/2 [=====] - 0s 6ms/step - loss:
30352700.0000
Epoch 305/500
2/2 [=====] - 0s 4ms/step - loss:
30034540.0000
Epoch 306/500
2/2 [=====] - 0s 6ms/step - loss:
29938964.0000
Epoch 307/500
2/2 [=====] - 0s 7ms/step - loss:
29438804.0000
Epoch 308/500
2/2 [=====] - 0s 5ms/step - loss:
29415708.0000
Epoch 309/500
2/2 [=====] - 0s 5ms/step - loss:
33756536.0000
Epoch 310/500
2/2 [=====] - 0s 7ms/step - loss:
36319608.0000
Epoch 311/500
2/2 [=====] - 0s 6ms/step - loss:
33271236.0000
Epoch 312/500
2/2 [=====] - 0s 5ms/step - loss:
33893776.0000
Epoch 313/500
2/2 [=====] - 0s 5ms/step - loss:
36994152.0000
Epoch 314/500
2/2 [=====] - 0s 7ms/step - loss:
34698112.0000
Epoch 315/500
2/2 [=====] - 0s 6ms/step - loss:
33618560.0000
Epoch 316/500
2/2 [=====] - 0s 4ms/step - loss:
37460628.0000
Epoch 317/500
2/2 [=====] - 0s 6ms/step - loss:
37590376.0000

Epoch 318/500
2/2 [=====] - 0s 8ms/step - loss:
33295092.0000
Epoch 319/500
2/2 [=====] - 0s 5ms/step - loss:
35530120.0000
Epoch 320/500
2/2 [=====] - 0s 4ms/step - loss:
40037208.0000
Epoch 321/500
2/2 [=====] - 0s 6ms/step - loss:
36252268.0000
Epoch 322/500
2/2 [=====] - 0s 6ms/step - loss:
33096682.0000
Epoch 323/500
2/2 [=====] - 0s 5ms/step - loss:
36918120.0000
Epoch 324/500
2/2 [=====] - 0s 6ms/step - loss:
38491736.0000
Epoch 325/500
2/2 [=====] - 0s 7ms/step - loss:
35588952.0000
Epoch 326/500
2/2 [=====] - 0s 6ms/step - loss:
33044908.0000
Epoch 327/500
2/2 [=====] - 0s 4ms/step - loss:
33682272.0000
Epoch 328/500
2/2 [=====] - 0s 8ms/step - loss:
35258792.0000
Epoch 329/500
2/2 [=====] - 0s 8ms/step - loss:
34670316.0000
Epoch 330/500
2/2 [=====] - 0s 11ms/step - loss:
33996364.0000
Epoch 331/500
2/2 [=====] - 0s 5ms/step - loss:
34415208.0000
Epoch 332/500
2/2 [=====] - 0s 6ms/step - loss:
35738408.0000
Epoch 333/500
2/2 [=====] - 0s 5ms/step - loss:
35802936.0000
Epoch 334/500
2/2 [=====] - 0s 6ms/step - loss:

33922420.0000
Epoch 335/500
2/2 [=====] - 0s 6ms/step - loss:
35723416.0000
Epoch 336/500
2/2 [=====] - 0s 6ms/step - loss:
39632472.0000
Epoch 337/500
2/2 [=====] - 0s 4ms/step - loss:
37549204.0000
Epoch 338/500
2/2 [=====] - 0s 6ms/step - loss:
35039732.0000
Epoch 339/500
2/2 [=====] - 0s 6ms/step - loss:
37728652.0000
Epoch 340/500
2/2 [=====] - 0s 5ms/step - loss:
37448836.0000
Epoch 341/500
2/2 [=====] - 0s 5ms/step - loss:
34644040.0000
Epoch 342/500
2/2 [=====] - 0s 6ms/step - loss:
35116396.0000
Epoch 343/500
2/2 [=====] - 0s 7ms/step - loss:
36219336.0000
Epoch 344/500
2/2 [=====] - 0s 5ms/step - loss:
35008916.0000
Epoch 345/500
2/2 [=====] - 0s 5ms/step - loss:
35273236.0000
Epoch 346/500
2/2 [=====] - 0s 7ms/step - loss:
35186176.0000
Epoch 347/500
2/2 [=====] - 0s 6ms/step - loss:
35351420.0000
Epoch 348/500
2/2 [=====] - 0s 5ms/step - loss:
34759268.0000
Epoch 349/500
2/2 [=====] - 0s 5ms/step - loss:
33922320.0000
Epoch 350/500
2/2 [=====] - 0s 7ms/step - loss:
34643688.0000
Epoch 351/500

2/2 [=====] - 0s 5ms/step - loss:
34838316.0000
Epoch 352/500
2/2 [=====] - 0s 5ms/step - loss:
34552964.0000
Epoch 353/500
2/2 [=====] - 0s 5ms/step - loss:
34216508.0000
Epoch 354/500
2/2 [=====] - 0s 7ms/step - loss:
33957492.0000
Epoch 355/500
2/2 [=====] - 0s 5ms/step - loss:
34081784.0000
Epoch 356/500
2/2 [=====] - 0s 5ms/step - loss:
35424480.0000
Epoch 357/500
2/2 [=====] - 0s 6ms/step - loss:
34434724.0000
Epoch 358/500
2/2 [=====] - 0s 5ms/step - loss:
33619964.0000
Epoch 359/500
2/2 [=====] - 0s 5ms/step - loss:
34657588.0000
Epoch 360/500
2/2 [=====] - 0s 6ms/step - loss:
34854776.0000
Epoch 361/500
2/2 [=====] - 0s 5ms/step - loss:
33998384.0000
Epoch 362/500
2/2 [=====] - 0s 5ms/step - loss:
33779240.0000
Epoch 363/500
2/2 [=====] - 0s 5ms/step - loss:
33638216.0000
Epoch 364/500
2/2 [=====] - 0s 6ms/step - loss:
33244042.0000
Epoch 365/500
2/2 [=====] - 0s 5ms/step - loss:
33705976.0000
Epoch 366/500
2/2 [=====] - 0s 5ms/step - loss:
34945220.0000
Epoch 367/500
2/2 [=====] - 0s 7ms/step - loss:
34899612.0000

Epoch 368/500
2/2 [=====] - 0s 5ms/step - loss:
33125888.0000
Epoch 369/500
2/2 [=====] - 0s 4ms/step - loss:
33906136.0000
Epoch 370/500
2/2 [=====] - 0s 5ms/step - loss:
35609048.0000
Epoch 371/500
2/2 [=====] - 0s 6ms/step - loss:
35310904.0000
Epoch 372/500
2/2 [=====] - 0s 4ms/step - loss:
33260394.0000
Epoch 373/500
2/2 [=====] - 0s 5ms/step - loss:
33013850.0000
Epoch 374/500
2/2 [=====] - 0s 6ms/step - loss:
34247356.0000
Epoch 375/500
2/2 [=====] - 0s 5ms/step - loss:
35622184.0000
Epoch 376/500
2/2 [=====] - 0s 4ms/step - loss:
35845588.0000
Epoch 377/500

2/2 [=====] - 0s 7ms/step - loss:
34633456.0000
Epoch 378/500
2/2 [=====] - 0s 5ms/step - loss:
33954496.0000
Epoch 379/500
2/2 [=====] - 0s 4ms/step - loss:
33368314.0000
Epoch 380/500
2/2 [=====] - 0s 5ms/step - loss:
32876852.0000
Epoch 381/500
2/2 [=====] - 0s 6ms/step - loss:
33042524.0000
Epoch 382/500
2/2 [=====] - 0s 5ms/step - loss:
33512244.0000
Epoch 383/500
2/2 [=====] - 0s 5ms/step - loss:
33662200.0000
Epoch 384/500

2/2 [=====] - 0s 6ms/step - loss:
33235028.0000
Epoch 385/500
2/2 [=====] - 0s 7ms/step - loss:
32688592.0000
Epoch 386/500
2/2 [=====] - 0s 6ms/step - loss:
32430564.0000
Epoch 387/500
2/2 [=====] - 0s 5ms/step - loss:
32645952.0000
Epoch 388/500
2/2 [=====] - 0s 6ms/step - loss:
32828756.0000
Epoch 389/500
2/2 [=====] - 0s 6ms/step - loss:
32106662.0000
Epoch 390/500
2/2 [=====] - 0s 4ms/step - loss:
32938630.0000
Epoch 391/500
2/2 [=====] - 0s 6ms/step - loss:
34103348.0000
Epoch 392/500
2/2 [=====] - 0s 6ms/step - loss:
33429920.0000
Epoch 393/500
2/2 [=====] - 0s 5ms/step - loss:
32369866.0000
Epoch 394/500
2/2 [=====] - 0s 5ms/step - loss:
32768036.0000
Epoch 395/500
2/2 [=====] - 0s 6ms/step - loss:
34188352.0000
Epoch 396/500
2/2 [=====] - 0s 6ms/step - loss:
34007336.0000
Epoch 397/500
2/2 [=====] - 0s 5ms/step - loss:
32489274.0000
Epoch 398/500
2/2 [=====] - 0s 5ms/step - loss:
31976950.0000
Epoch 399/500
2/2 [=====] - 0s 7ms/step - loss:
32147322.0000
Epoch 400/500
2/2 [=====] - 0s 6ms/step - loss:
32784864.0000

Epoch 401/500
2/2 [=====] - 0s 4ms/step - loss:
33687088.0000
Epoch 402/500
2/2 [=====] - 0s 5ms/step - loss:
32382150.0000
Epoch 403/500
2/2 [=====] - 0s 7ms/step - loss:
31433814.0000
Epoch 404/500
2/2 [=====] - 0s 6ms/step - loss:
33485900.0000
Epoch 405/500
2/2 [=====] - 0s 4ms/step - loss:
35821644.0000
Epoch 406/500
2/2 [=====] - 0s 6ms/step - loss:
34163996.0000
Epoch 407/500
2/2 [=====] - 0s 6ms/step - loss:
31284668.0000
Epoch 408/500
2/2 [=====] - 0s 5ms/step - loss:
32632806.0000
Epoch 409/500
2/2 [=====] - 0s 5ms/step - loss:
34099576.0000
Epoch 410/500
2/2 [=====] - 0s 7ms/step - loss:
33205926.0000
Epoch 411/500
2/2 [=====] - 0s 6ms/step - loss:
31572598.0000
Epoch 412/500
2/2 [=====] - 0s 5ms/step - loss:
32014698.0000
Epoch 413/500
2/2 [=====] - 0s 6ms/step - loss:
32504908.0000
Epoch 414/500
2/2 [=====] - 0s 6ms/step - loss:
31944874.0000
Epoch 415/500
2/2 [=====] - 0s 5ms/step - loss:
31275782.0000
Epoch 416/500
2/2 [=====] - 0s 5ms/step - loss:
31789376.0000
Epoch 417/500
2/2 [=====] - 0s 7ms/step - loss:

30602096.0000
Epoch 418/500
2/2 [=====] - 0s 6ms/step - loss:
31713184.0000
Epoch 419/500
2/2 [=====] - 0s 5ms/step - loss:
33671176.0000
Epoch 420/500
2/2 [=====] - 0s 6ms/step - loss:
33107706.0000
Epoch 421/500
2/2 [=====] - 0s 7ms/step - loss:
30819158.0000
Epoch 422/500
2/2 [=====] - 0s 5ms/step - loss:
30586570.0000
Epoch 423/500
2/2 [=====] - 0s 5ms/step - loss:
31124588.0000
Epoch 424/500
2/2 [=====] - 0s 7ms/step - loss:
30147844.0000
Epoch 425/500
2/2 [=====] - 0s 6ms/step - loss:
29889732.0000
Epoch 426/500
2/2 [=====] - 0s 4ms/step - loss:
33571480.0000
Epoch 427/500
2/2 [=====] - 0s 6ms/step - loss:
31444516.0000
Epoch 428/500
2/2 [=====] - 0s 7ms/step - loss:
30517988.0000
Epoch 429/500
2/2 [=====] - 0s 4ms/step - loss:
31859562.0000
Epoch 430/500
2/2 [=====] - 0s 5ms/step - loss:
31690224.0000
Epoch 431/500
2/2 [=====] - 0s 6ms/step - loss:
29665148.0000
Epoch 432/500
2/2 [=====] - 0s 4ms/step - loss:
29658934.0000
Epoch 433/500
2/2 [=====] - 0s 5ms/step - loss:
29779802.0000
Epoch 434/500

2/2 [=====] - 0s 6ms/step - loss:
29754314.0000
Epoch 435/500
2/2 [=====] - 0s 5ms/step - loss:
29417856.0000
Epoch 436/500
2/2 [=====] - 0s 5ms/step - loss:
30437236.0000
Epoch 437/500
2/2 [=====] - 0s 5ms/step - loss:
30358490.0000
Epoch 438/500
2/2 [=====] - 0s 5ms/step - loss:
28558300.0000
Epoch 439/500
2/2 [=====] - 0s 5ms/step - loss:
29245530.0000
Epoch 440/500
2/2 [=====] - 0s 6ms/step - loss:
32563412.0000
Epoch 441/500
2/2 [=====] - 0s 6ms/step - loss:
31312500.0000
Epoch 442/500
2/2 [=====] - 0s 5ms/step - loss:
28937140.0000
Epoch 443/500
2/2 [=====] - 0s 5ms/step - loss:
31789708.0000
Epoch 444/500
2/2 [=====] - 0s 6ms/step - loss:
36402456.0000
Epoch 445/500
2/2 [=====] - 0s 5ms/step - loss:
34410264.0000
Epoch 446/500
2/2 [=====] - 0s 5ms/step - loss:
30506074.0000
Epoch 447/500
2/2 [=====] - 0s 6ms/step - loss:
31399542.0000
Epoch 448/500
2/2 [=====] - 0s 6ms/step - loss:
31905754.0000
Epoch 449/500
2/2 [=====] - 0s 5ms/step - loss:
29168694.0000
Epoch 450/500
2/2 [=====] - 0s 5ms/step - loss:
30844000.0000

Epoch 451/500
2/2 [=====] - 0s 6ms/step - loss:
31375584.0000
Epoch 452/500
2/2 [=====] - 0s 6ms/step - loss:
28869648.0000
Epoch 453/500
2/2 [=====] - 0s 5ms/step - loss:
30524044.0000
Epoch 454/500
2/2 [=====] - 0s 6ms/step - loss:
34618040.0000
Epoch 455/500
2/2 [=====] - 0s 6ms/step - loss:
30537766.0000
Epoch 456/500
2/2 [=====] - 0s 5ms/step - loss:
29051866.0000
Epoch 457/500
2/2 [=====] - 0s 5ms/step - loss:
35420616.0000
Epoch 458/500
2/2 [=====] - 0s 6ms/step - loss:
32971770.0000
Epoch 459/500
2/2 [=====] - 0s 4ms/step - loss:
29686164.0000
Epoch 460/500
2/2 [=====] - 0s 5ms/step - loss:
33155540.0000
Epoch 461/500
2/2 [=====] - 0s 6ms/step - loss:
32299552.0000
Epoch 462/500
2/2 [=====] - 0s 6ms/step - loss:
28525300.0000
Epoch 463/500
2/2 [=====] - 0s 4ms/step - loss:
30860880.0000
Epoch 464/500
2/2 [=====] - 0s 5ms/step - loss:
34971032.0000
Epoch 465/500
2/2 [=====] - 0s 7ms/step - loss:
32650388.0000
Epoch 466/500
2/2 [=====] - 0s 6ms/step - loss:
28639108.0000
Epoch 467/500
2/2 [=====] - 0s 5ms/step - loss:

30142778.0000
Epoch 468/500
2/2 [=====] - 0s 6ms/step - loss:
31048938.0000
Epoch 469/500
2/2 [=====] - 0s 5ms/step - loss:
29681068.0000
Epoch 470/500
2/2 [=====] - 0s 5ms/step - loss:
29602522.0000
Epoch 471/500

2/2 [=====] - 0s 5ms/step - loss:
28986698.0000
Epoch 472/500
2/2 [=====] - 0s 6ms/step - loss:
28658938.0000
Epoch 473/500
2/2 [=====] - 0s 6ms/step - loss:
28758948.0000
Epoch 474/500
2/2 [=====] - 0s 4ms/step - loss:
29706368.0000
Epoch 475/500
2/2 [=====] - 0s 6ms/step - loss:
29657092.0000
Epoch 476/500
2/2 [=====] - 0s 5ms/step - loss:
28371226.0000
Epoch 477/500
2/2 [=====] - 0s 5ms/step - loss:
29128202.0000
Epoch 478/500
2/2 [=====] - 0s 4ms/step - loss:
29468544.0000
Epoch 479/500
2/2 [=====] - 0s 7ms/step - loss:
28635014.0000
Epoch 480/500
2/2 [=====] - 0s 5ms/step - loss:
28024636.0000
Epoch 481/500
2/2 [=====] - 0s 5ms/step - loss:
28779030.0000
Epoch 482/500
2/2 [=====] - 0s 6ms/step - loss:
29289590.0000
Epoch 483/500
2/2 [=====] - 0s 6ms/step - loss:
28785818.0000

Epoch 484/500
2/2 [=====] - 0s 5ms/step - loss:
27991142.0000
Epoch 485/500
2/2 [=====] - 0s 6ms/step - loss:
28030228.0000
Epoch 486/500
2/2 [=====] - 0s 7ms/step - loss:
28550298.0000
Epoch 487/500
2/2 [=====] - 0s 10ms/step - loss:
28880048.0000
Epoch 488/500
2/2 [=====] - 0s 7ms/step - loss:
29258196.0000
Epoch 489/500
2/2 [=====] - 0s 6ms/step - loss:
29202604.0000
Epoch 490/500
2/2 [=====] - 0s 6ms/step - loss:
28328118.0000
Epoch 491/500
2/2 [=====] - 0s 5ms/step - loss:
28343084.0000
Epoch 492/500
2/2 [=====] - 0s 6ms/step - loss:
27389914.0000
Epoch 493/500
2/2 [=====] - 0s 8ms/step - loss:
27545386.0000
Epoch 494/500
2/2 [=====] - 0s 7ms/step - loss:
28085494.0000
Epoch 495/500
2/2 [=====] - 0s 5ms/step - loss:
28438276.0000
Epoch 496/500
2/2 [=====] - 0s 6ms/step - loss:
27719268.0000
Epoch 497/500
2/2 [=====] - 0s 7ms/step - loss:
27452474.0000
Epoch 498/500
2/2 [=====] - 0s 5ms/step - loss:
27281204.0000
Epoch 499/500
2/2 [=====] - 0s 5ms/step - loss:
27280700.0000
Epoch 500/500

```

2/2 [=====] - 0s 6ms/step - loss:
26842260.0000

<keras.callbacks.History at 0x25830b31c60>

from numpy import array
# demonstrate prediction for next 10 days
x_input = array(df_17_cumm.cc.to_list()[-12:])
temp_input=list(x_input)
lst_output=[]
i=0
while(i<3):

    if(len(temp_input)>12):
        x_input=array(temp_input[1:])
        # print("{} day input {}".format(i,x_input))
        #print(x_input)
        x_input = x_input.reshape((1, n_steps, n_features))
        #print(x_input)
        yhat = model.predict(x_input, verbose=0)
        # print("{} day output {}".format(i,yhat))
        temp_input.append(yhat[0][0])
        temp_input=temp_input[1:]
        #print(temp_input)
        lst_output.append(yhat[0][0])
        i=i+1
    else:
        x_input = x_input.reshape((1, n_steps, n_features))
        yhat = model.predict(x_input, verbose=0)
        # print(yhat[0])
        temp_input.append(yhat[0][0])
        lst_output.append(yhat[0][0])
        i=i+1

print(lst_output)

[27170.455, 27841.54, 27784.979]

pred_data = lstm_data[-16:]
pred_data.reset_index(drop=True, inplace=True)
pred_data

      ds      y
0      1  44327.0
1      2  40076.0
2      3  38164.0
3      4  32852.0
4      5  27944.0
5      6  30685.0
6      7  30571.0

```

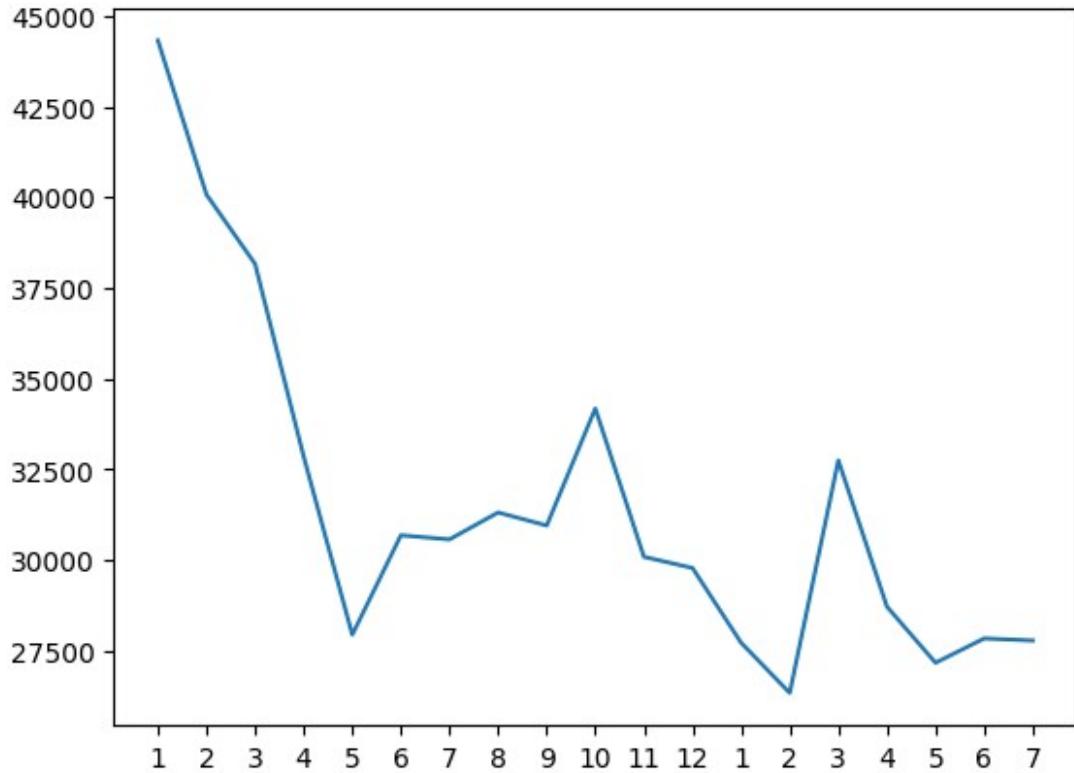
```
7     8  31314.0
8     9  30954.0
9    10  34179.0
10   11  30091.0
11   12  29783.0
12    1  27722.0
13    2  26341.0
14    3  32751.0
15    4  28718.0

tmp = pd.concat((pred_data, pd.DataFrame({
    "ds": [5, 6, 7],
    "y": lst_output
})))

tmp.reset_index(drop=True, inplace=True)

ax = plt.axes()
plt.plot(tmp.index, tmp.y)
ax.set_xticks(tmp.index, tmp.ds)

[<matplotlib.axis.XTick at 0x257eb7a9210>,
 <matplotlib.axis.XTick at 0x257eb7a9e40>,
 <matplotlib.axis.XTick at 0x257eb681060>,
 <matplotlib.axis.XTick at 0x258308dfd90>,
 <matplotlib.axis.XTick at 0x25834173f70>,
 <matplotlib.axis.XTick at 0x258341a0790>,
 <matplotlib.axis.XTick at 0x258341733d0>,
 <matplotlib.axis.XTick at 0x258341a0ee0>,
 <matplotlib.axis.XTick at 0x258341a16c0>,
 <matplotlib.axis.XTick at 0x258341a1ea0>,
 <matplotlib.axis.XTick at 0x258341a2680>,
 <matplotlib.axis.XTick at 0x25834172fe0>,
 <matplotlib.axis.XTick at 0x258341a1360>,
 <matplotlib.axis.XTick at 0x258341a30a0>,
 <matplotlib.axis.XTick at 0x258341a3880>,
 <matplotlib.axis.XTick at 0x258341a3160>,
 <matplotlib.axis.XTick at 0x258341c0880>,
 <matplotlib.axis.XTick at 0x258341a0cd0>,
 <matplotlib.axis.XTick at 0x258341c0a30>]
```



```
tmp[-3:]
```

```
ds      y
16    5  27170.455078
17    6  27841.539062
18    7  27784.978516
```

```
pd.DataFrame({
    "Month": ["01/05/2021", "01/06/2021", "01/07/2021"],
    "No_calls_Offered_predicted": tmp[-3:].y.to_list()
}).to_csv("month_pred.csv", index=False)
```

```
lstm_data
```

```
ds      y
month
1       1  48239.0
```

2	2	42176.0
3	3	46218.0
4	4	42362.0
5	5	45914.0
6	6	45519.0
7	7	41117.0
8	8	42484.0
9	9	39754.0
10	10	46640.0
11	11	50725.0
12	12	44771.0
1	1	48219.0
2	2	44012.0
3	3	46840.0
4	4	48348.0
5	5	48600.0
6	6	43434.0
7	7	50356.0
8	8	54320.0
9	9	48260.0
10	10	58059.0
11	11	50977.0
12	12	44124.0
1	1	46429.0
2	2	43424.0
3	3	44893.0
4	4	48295.0
5	5	50901.0
6	6	46533.0
7	7	47944.0
8	8	47310.0
9	9	45262.0
10	10	49613.0
11	11	40431.0
12	12	37935.0
1	1	44327.0
2	2	40076.0
3	3	38164.0
4	4	32852.0
5	5	27944.0
6	6	30685.0
7	7	30571.0
8	8	31314.0
9	9	30954.0
10	10	34179.0
11	11	30091.0
12	12	29783.0
1	1	27722.0
2	2	26341.0

3 32751.0
4 28718.0

```

from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler(feature_range=(0,1))
all_data = lstm_data.values
all_data.shape
(1581, 2)
train_data = all_data[0:1000,:]
test_data = all_data[1000:1000+400,:]
val_data = all_data[1000+400:,:]

lstm_data.index = lstm_data.ds
lstm_data.drop('ds', axis = 1, inplace = True)

scaled_data = scaler.fit_transform(lstm_data)

x_train_data,y_train_data=[],[]

for i in range(30,len(train_data)):
    x_train_data.append(scaled_data[i-30:i,0])
    y_train_data.append(scaled_data[i,0])

x_train_data,y_train_data=np.array(x_train_data),np.array(y_train_data)
x_train_data=np.reshape(x_train_data,
(x_train_data.shape[0],x_train_data.shape[1],1))

from keras.models import Sequential
from sklearn.pipeline import Pipeline
from keras.layers import LSTM, Dropout, Dense

lstm_model=Sequential()
lstm_model.add(LSTM(units=50,return_sequences=True,input_shape=(x_train_data.shape[1],1)))
lstm_model.add(LSTM(units=50))
lstm_model.add(Dense(1))

inputs_data=lstm_data[len(lstm_data)-len(val_data)-
400:1000+400].values
inputs_data=inputs_data.reshape(-1,1)
inputs_data=scaler.transform(inputs_data)

lstm_model.compile(loss='mean_squared_error',optimizer='adam')
lstm_model.fit(x_train_data,y_train_data,epochs=1,batch_size=1,verbose=1)

```

```
C:\Users\DV\AppData\Local\Programs\Python\Python310\lib\site-packages\
sklearn\base.py:450: UserWarning: X does not have valid feature names,
but MinMaxScaler was fitted with feature names
    warnings.warn(
970/970 [=====] - 8s 6ms/step - loss: 0.0538
<keras.callbacks.History at 0x2579b389960>
X_test=[]
for i in range(30,inputs_data.shape[0]):
    X_test.append(inputs_data[i-30:i,0])
X_test=np.array(X_test)

X_test=np.reshape(X_test,(X_test.shape[0],X_test.shape[1],1))
predicted_closing_price=lstm_model.predict(X_test)
predicted_closing_price=scaler.inverse_transform(predicted_closing_price)

12/12 [=====] - 0s 3ms/step
trd = lstm_data[0:1000]
tsd = lstm_data[1000+30:1000+400]

tsd['Pred'] = predicted_closing_price

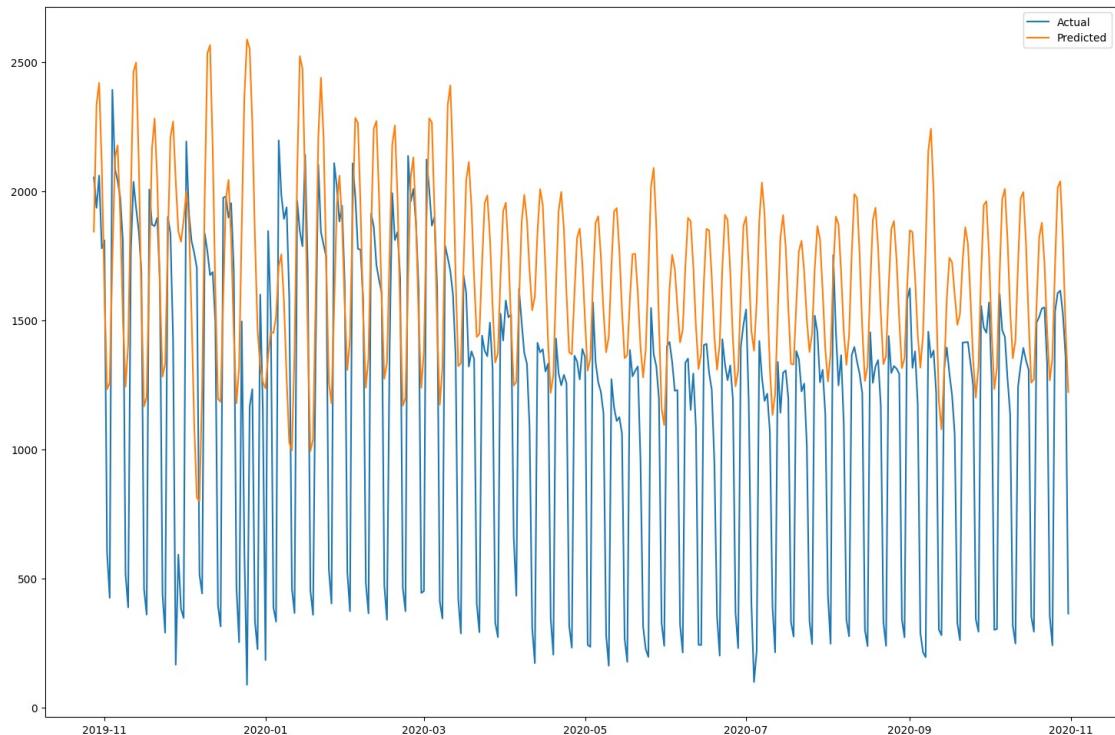
C:\Users\DV\AppData\Local\Temp\ipykernel_19112\3216645329.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy
    tsd['Pred'] = predicted_closing_price

tsd
      y          Pred
ds
2019-10-28  2053.0  1842.804199
2019-10-29  1935.0  2334.072021
2019-10-30  2060.0  2418.739746
2019-10-31  1778.0  2099.878418
2019-11-01  1809.0  1616.503540
...
2020-10-27  1605.0  2013.805908
2020-10-28  1614.0  2037.563477
2020-10-29  1522.0  1800.224731
2020-10-30  1355.0  1464.315430
2020-10-31   363.0  1221.064819
```

```
[370 rows x 2 columns]
```

```
fig, ax = plt.subplots(figsize=(18,12))
plt.plot(tsd.y, label='Actual')
plt.plot(tsd["Pred"], label='Predicted')
plt.legend()
plt.show()
```



```
predicted_closing_price.shape
```

```
(370, 1)
```

```
lstm_data[len(lstm_data)-len(val_data)-30:1000+400].values
```

```
array([[1269.],
       [ 300.],
       [ 303.],
       [1601.],
       [1461.],
       [1435.],
       [1273.],
       [1136.],
       [ 316.],
       [ 247.],
       [1243.],
       [1326.],
       [1392.],
       [1344.],
       [1307.],
       [ 351.],
       [ 293.],
       [1490.],
       [1513.],
       [1545.],
       [1549.],
       [1331.],
       [ 353.],
       [ 240.],
       [1534.],
       [1605.],
       [1614.],
       [1522.],
       [1355.],
       [ 363.]])
```

tsd

ds	y
2019-10-28	2053.0
2019-10-29	1935.0
2019-10-30	2060.0
2019-10-31	1778.0
2019-11-01	1809.0
...	...
2020-10-27	1605.0
2020-10-28	1614.0
2020-10-29	1522.0
2020-10-30	1355.0
2020-10-31	363.0

[370 rows x 1 columns]

predicted_closing_price

```
array([[1842.8042],  
       [2334.072 ],  
       [2418.7397],  
       [2099.8784],  
       [1616.5035],  
       [1232.0956],  
       [1257.5872],  
       [1728.2781],  
       [2129.961 ],  
       [2176.6262],  
       [1903.156 ],  
       [1509.7295],  
       [1241.9193],  
       [1404.8439],  
       [1979.5037],  
       [2462.3196],  
       [2497.6514],  
       [2118.308 ],  
       [1579.0979],  
       [1166.1064],  
       [1201.8636],  
       [1698.9268],  
       [2163.4016],  
       [2280.781 ],  
       [2044.0519],  
       [1625.6841],  
       [1281.4686],  
       [1330.3325],  
       [1794.6653],  
       [2206.1448],  
       [2269.3901],  
       [2040.8314],  
       [1843.9038],  
       [1803.429 ],  
       [1885.5533],  
       [1998.3645],  
       [1878.9131],  
       [1517.6407],  
       [1097.49  ],  
       [ 812.5472],  
       [ 798.4467],  
       [1231.3523],  
       [1988.3202],  
       [2534.499 ],  
       [2565.591 ],  
       [2168.307 ],  
       [1618.0852],  
       [1194.744 ],  
       [1183.6005],  
       [1588.7065],
```

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[2551.1477],
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[1461.6445],
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[1449.8452],
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[1754.6198],
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[1025.7407],
[995.7112],
[1380.5089],
[2066.6484],
[2522.1672],
[2475.3115],
[2035.5383],
[1442.2687],
[992.7454],
[1036.9396],
[1589.3208],
[2207.8],
[2439.056],
[2205.0757],
[1717.8741],
[1257.3066],
[1177.6782],
[1552.9911],
[1945.2794],
[2059.3516],
[1882.3632],
[1556.7161],
[1306.5004],
[1427.3046],
[1914.4003],
[2283.3386],

[2263.852],
[1936.4447],
[1516.9524],
[1237.7552],
[1355.4745],
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[1221.0648]], dtype=float32)  
  
lstm_data[1000+400: ].shape  
(181, 1)  
  
(0.)
```

```
US_holidays_series = cal.holidays(start='2017-01-01', end='2021-07-31', return_name=True)
US_holidays = US_holidays_series.to_frame("name")
US_holidays.reset_index(inplace=True)
US_holidays.rename(columns={"index": "date"}, inplace=True)

prophet_holiday_df = pd.DataFrame(columns=["holiday", "ds",
"lower_window", "upper_window"])
all_US_holidays = US_holidays.name.unique()
for h in all_US_holidays:
    print(h)
```

```

if h == "Thanksgiving Day":
    df_hday = pd.DataFrame({
        'holiday': h,
        'ds': pd.to_datetime(US_holidays[US_holidays.name ==
h].date),
        'lower_window': 0,
        'upper_window': 1
    })
elif h == "Christmas Day":
    df_hday = pd.DataFrame({
        'holiday': h,
        'ds': pd.to_datetime(US_holidays[US_holidays.name ==
h].date),
        'lower_window': -1,
        'upper_window': 0
    })
else:
    df_hday = pd.DataFrame({
        'holiday': h,
        'ds': pd.to_datetime(US_holidays[US_holidays.name ==
h].date),
        'lower_window': 0,
        'upper_window': 0
    })
df_hday.reset_index(drop=True, inplace=True)
prophet_holiday_df = pd.concat((prophet_holiday_df, df_hday))

```

New Year's Day
 Birthday of Martin Luther King, Jr.
 Washington's Birthday
 Memorial Day
 Independence Day
 Labor Day
 Columbus Day
 Veterans Day
 Thanksgiving Day
 Christmas Day
 Juneteenth National Independence Day

prophet_holiday_df

	holiday	ds	lower_window
upper_window			
0	New Year's Day	2017-01-02	0
0	New Year's Day	2018-01-01	0
1	New Year's Day	2019-01-01	0
2	New Year's Day	2020-01-01	0
3	New Year's Day		0
0			

4	New Year's Day	2021-01-01	0
0	Birthday of Martin Luther King, Jr.	2017-01-16	0
0	Birthday of Martin Luther King, Jr.	2018-01-15	0
1	Birthday of Martin Luther King, Jr.	2019-01-21	0
0	Birthday of Martin Luther King, Jr.	2020-01-20	0
0	Birthday of Martin Luther King, Jr.	2021-01-18	0
0	Washington's Birthday	2017-02-20	0
0	Washington's Birthday	2018-02-19	0
1	Washington's Birthday	2019-02-18	0
0	Washington's Birthday	2020-02-17	0
0	Washington's Birthday	2021-02-15	0
0	Memorial Day	2017-05-29	0
0	Memorial Day	2018-05-28	0
1	Memorial Day	2019-05-27	0
0	Memorial Day	2020-05-25	0
0	Memorial Day	2021-05-31	0
0	Independence Day	2017-07-04	0
0	Independence Day	2018-07-04	0
1	Independence Day	2019-07-04	0
0	Independence Day	2020-07-03	0
2	Independence Day	2021-07-05	0
0	Labor Day	2017-09-04	0
0	Labor Day	2018-09-03	0
1	Labor Day	2019-09-02	0
0	Labor Day	2020-09-07	0
2			
3			
0			

```
0 Columbus Day 2017-10-09 0
0
1 Columbus Day 2018-10-08 0
0
2 Columbus Day 2019-10-14 0
0
3 Columbus Day 2020-10-12 0
0
0 Veterans Day 2017-11-10 0
0
1 Veterans Day 2018-11-12 0
0
2 Veterans Day 2019-11-11 0
0
3 Veterans Day 2020-11-11 0
0
0 Thanksgiving Day 2017-11-23 0
1
1 Thanksgiving Day 2018-11-22 0
1
2 Thanksgiving Day 2019-11-28 0
1
3 Thanksgiving Day 2020-11-26 0
1
0 Christmas Day 2017-12-25 -1
0
1 Christmas Day 2018-12-25 -1
0
2 Christmas Day 2019-12-25 -1
0
3 Christmas Day 2020-12-25 -1
0
0 Juneteenth National Independence Day 2021-06-18 0
0

all_Manila_holidays = manila_cal.holidays(start="2017-01-01",end="2021-07-31",return_name=True)
all_m_holidays = all_Manila_holidays.to_frame("name")
all_m_holidays.reset_index(inplace=True)
all_m_holidays.rename(columns={"index":"date"}, inplace=True)

all_Man_holidays = all_m_holidays.name.unique()
for h in all_Man_holidays:
    print(h)
    df_hday = pd.DataFrame({
        'holiday': 'Manila ' + str(h),
        'ds': pd.to_datetime(holidays[h].date),
        'lower_window': 0,
        'upper_window': 0
    })
```

```

df_hday.reset_index(drop=True, inplace=True)
prophet_holiday_df = pd.concat((prophet_holiday_df, df_hday))

New Year
Day of Valor
Maundy Thursday
Good Friday
Labor Day
Independence Day
National heroes day
Bonifacio
Christmas
Rizal

```

prophet_holiday_df

upper_window	holiday	ds	lower_window
0	New Year's Day	2017-01-02	0
0	New Year's Day	2018-01-01	0
1	New Year's Day	2019-01-01	0
0	New Year's Day	2020-01-01	0
3	New Year's Day	2021-01-01	0
0	Birthday of Martin Luther King, Jr.	2017-01-16	0
0	Birthday of Martin Luther King, Jr.	2018-01-15	0
1	Birthday of Martin Luther King, Jr.	2019-01-21	0
0	Birthday of Martin Luther King, Jr.	2020-01-20	0
3	Birthday of Martin Luther King, Jr.	2021-01-18	0
0	Washington's Birthday	2017-02-20	0
0	Washington's Birthday	2018-02-19	0
1	Washington's Birthday	2019-02-18	0
0	Washington's Birthday	2020-02-17	0
3	Washington's Birthday	2021-02-15	0
0	Memorial Day	2017-05-29	0
0	Memorial Day	2018-05-28	0
1			

0		
2	Memorial Day 2019-05-27	0
0		
3	Memorial Day 2020-05-25	0
0		
4	Memorial Day 2021-05-31	0
0		
0	Independence Day 2017-07-04	0
0		
1	Independence Day 2018-07-04	0
0		
2	Independence Day 2019-07-04	0
0		
3	Independence Day 2020-07-03	0
0		
4	Independence Day 2021-07-05	0
0		
0	Labor Day 2017-09-04	0
0		
1	Labor Day 2018-09-03	0
0		
2	Labor Day 2019-09-02	0
0		
3	Labor Day 2020-09-07	0
0		
0	Columbus Day 2017-10-09	0
0		
1	Columbus Day 2018-10-08	0
0		
2	Columbus Day 2019-10-14	0
0		
3	Columbus Day 2020-10-12	0
0		
0	Veterans Day 2017-11-10	0
0		
1	Veterans Day 2018-11-12	0
0		
2	Veterans Day 2019-11-11	0
0		
3	Veterans Day 2020-11-11	0
0		
0	Thanksgiving Day 2017-11-23	0
1		
1	Thanksgiving Day 2018-11-22	0
1		
2	Thanksgiving Day 2019-11-28	0
1		
3	Thanksgiving Day 2020-11-26	0
1		
0	Christmas Day 2017-12-25	-1

```

0
1           Christmas Day 2018-12-25      -1
0
2           Christmas Day 2019-12-25      -1
0
3           Christmas Day 2020-12-25      -1
0
0 Juneteenth National Independence Day 2021-06-18      0
0
0           Manila Labor Day 2017-09-04      0
0
1           Manila Labor Day 2018-09-03      0
0
2           Manila Labor Day 2019-09-02      0
0
3           Manila Labor Day 2020-09-07      0
0
0           Manila Independence Day 2017-07-04      0
0
1           Manila Independence Day 2018-07-04      0
0
2           Manila Independence Day 2019-07-04      0
0
3           Manila Independence Day 2020-07-03      0
0

dates17 = df_17.date.values
dates_not17 = df_not17_sorted.date.values
all_dates = list(dates17)
all_dates.extend(list(dates_not17))
# print(all_dates)
all_dates = pd.to_datetime(all_dates, format="%d/%m/%Y")
# print(all_dates)

cc17 = df_17.cc.values
cc_not17 = df_not17_sorted.cc.values
all_cc = list(cc17)
all_cc.extend(cc_not17)
# print(all_cc)

fbp_data = pd.DataFrame({
    "ds": all_dates,
    "y": all_cc
})
fbp_data

          ds      y
0  2017-01-01  264.0
1  2017-01-02  528.0
2  2017-01-03 2505.0
3  2017-01-04 2145.0

```

```

4    2017-01-05  2164.0
...
1576 2021-04-26  1392.0
1577 2021-04-27  1336.0
1578 2021-04-28  1220.0
1579 2021-04-29  1094.0
1580 2021-04-30  1119.0

[1581 rows x 2 columns]

fbp_model = Prophet(holidays=prophet_holiday_df)
fbp_model_fit = fbp_model.fit(fbp_data)

03:00:39 - cmdstanpy - INFO - Chain [1] start processing
03:00:39 - cmdstanpy - INFO - Chain [1] done processing

future = fbp_model_fit.make_future_dataframe(periods=92)
forecast = fbp_model_fit.predict(future)

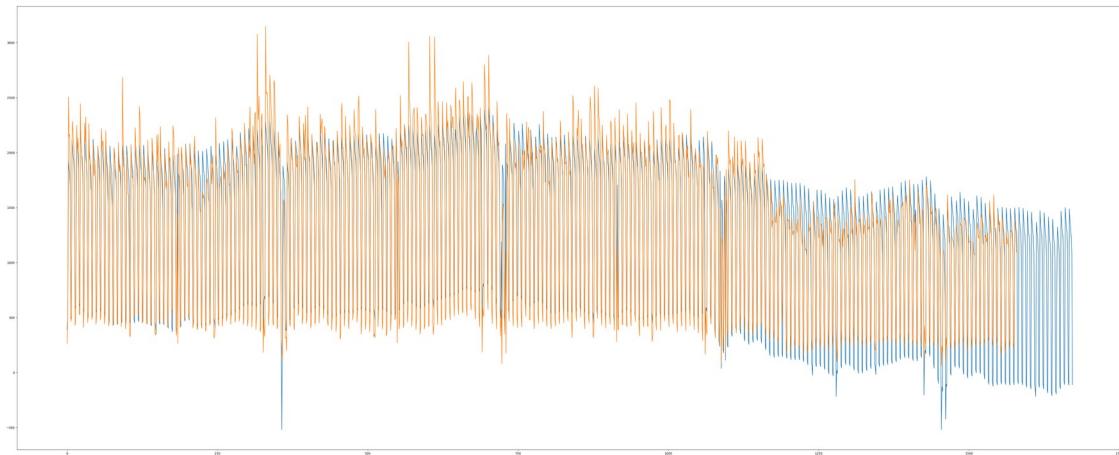
forecast[['ds', 'yhat']]

      ds        yhat
0  2017-01-01  390.268378
1  2017-01-02  510.781987
2  2017-01-03  1919.418719
3  2017-01-04  1844.600461
4  2017-01-05  1818.181766
...
1668 2021-07-27  1382.759824
1669 2021-07-28  1289.212060
1670 2021-07-29  1242.581627
1671 2021-07-30  1081.108678
1672 2021-07-31  -111.662933

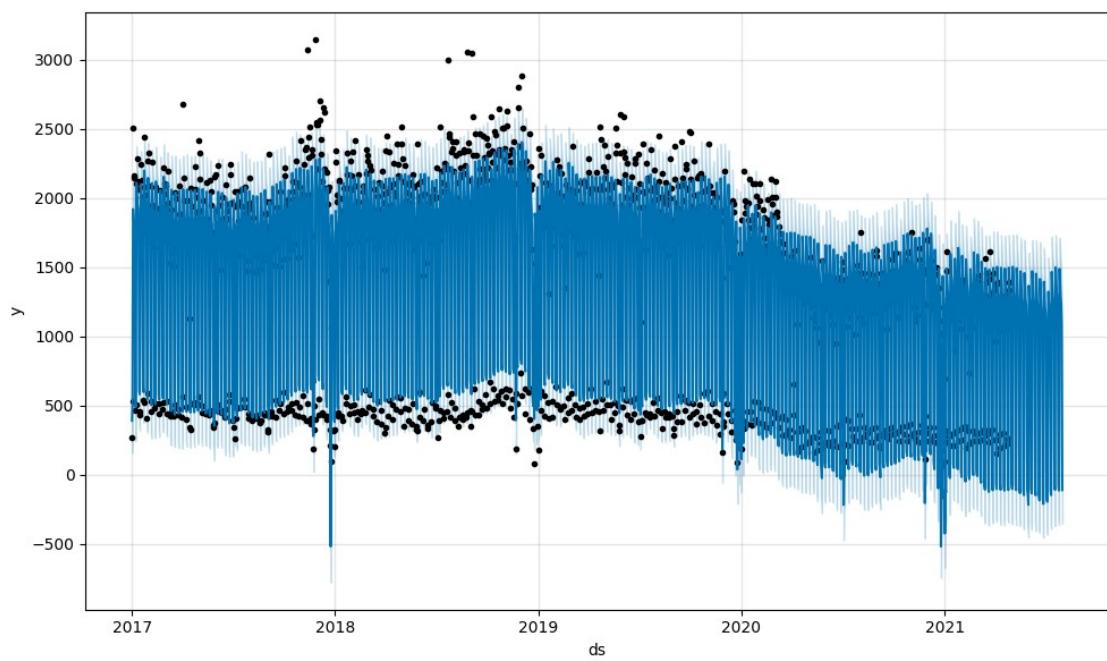
[1673 rows x 2 columns]

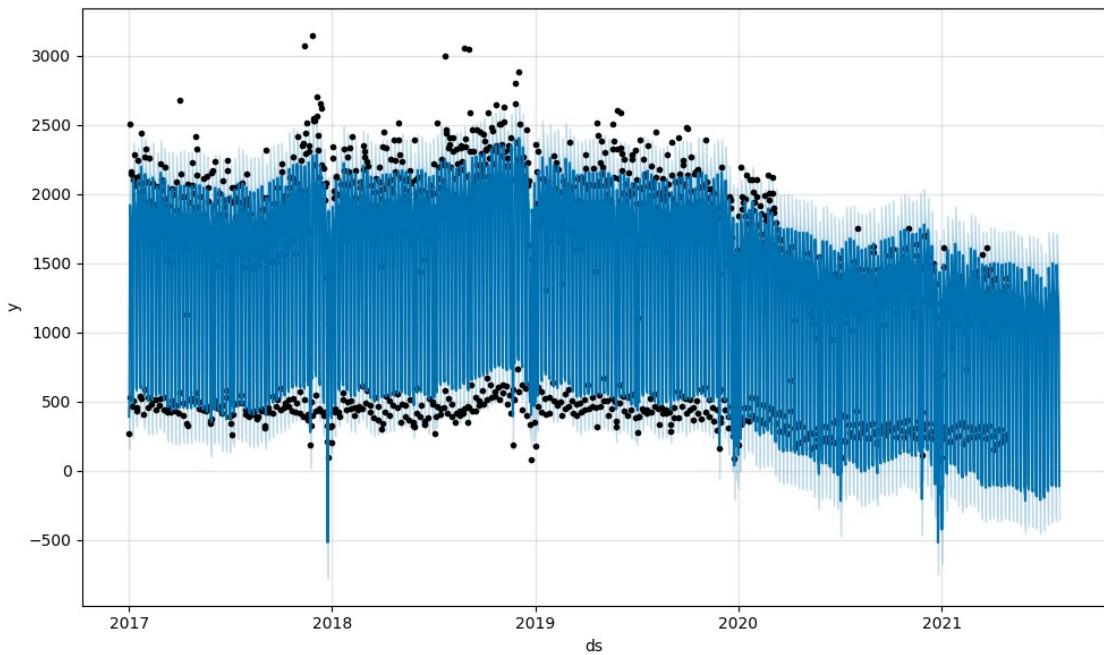
fig = plt.figure()
fig.set_figheight(20)
fig.set_figwidth(50)
ax = fig.add_axes([1,1,1,1])
x = range(len(forecast))
x_org = range(len(fbp_data))
y_fbp = list(forecast.yhat.values)
y_org = all_cc
ax.plot(x, y_fbp)
ax.plot(x_org, all_cc)
plt.show()

```



```
fbp_model_fit.plot(forecast)
```





```
# [ arrow.get(dt, "DD/MM/YYYY").day for dt in df_17['date'] ]
```

```
# df['Date'] = df['Date'].apply(lambda row: arrow.get(str(row),  
"M/D/YYYY").format("DD/MM/YYYY"))
```

```

# df.info()

# df['Year'] = df['Date'].apply(lambda row: arrow.get(row,
"DD/MM/YYYY").year)

# df_17 = df[df['Year'] == 2017]

# df_17

# df_17.rename(columns = {"Date":"date",
"No_of_calls_from_commercial_card":"cc",
"No_of_calls_from_retail_card":"rc",
"No_of_calls_from_student_card":"sc", "Year":"year"}, inplace=True)

# df_17

# plt.figure(figsize=(20, 20))
# plt.plot(df_17['date'], df_17['cc'], c='red', label='cc')
# plt.plot(df_17['date'], df_17['rc'], c='blue', label='rc')
# plt.plot(df_17['date'], df_17['sc'], c='green', label='sc')
# plt.legend()
# plt.show()

# df_17[['cc', 'rc', 'sc']]

# # (df_17.cc < df_17.rc).sum()
# ic(df_17.cc / df_17.rc, df_17.rc / df_17.sc, df_17.cc / df_17.rc ==
df_17.rc / df_17.sc)

# df_not17 = df[df['Year'] != 2017]

# df_not17

# df_not17.rename(columns = {"Date":"date",
"No_of_calls_from_commercial_card":"cc",
"No_of_calls_from_retail_card":"rc",
"No_of_calls_from_student_card":"sc", "Year":"year"}, inplace=True)

# df_not17

# plt.figure(figsize=(20, 20))
# plt.plot(df_not17['date'], df_not17['cc'], c='red', label='cc')
# plt.plot(df_not17['date'], df_not17['rc'], c='blue', label='rc')
# plt.plot(df_not17['date'], df_not17['sc'], c='green', label='sc')
# plt.legend()
# plt.show()

# df_18 = df[df['Year'] == 2018]
# df_18.rename(columns = {"Date":"date",

```

```

"No_of_calls_from_commercial_card":"cc",
"No_of_calls_from_retail_card":"rc",
"No_of_calls_from_student_card":"sc", "Year":"year"}, inplace=True)
# plt.figure(figsize=(20, 20))
# plt.plot(df_18['date'], df_18['cc'], c='red', label='cc')
# plt.plot(df_18['date'], df_18['rc'], c='blue', label='rc')
# plt.plot(df_18['date'], df_18['sc'], c='green', label='sc')
# plt.legend()
# plt.show()

# df_18

# df_not17

# df_not17.reset_index(inplace=True)

# df_not17.drop("index", axis=1, inplace=True)

# df_not17

# df_17.to_csv("df_17.csv")

# df_not17_sorted = pd.DataFrame(columns=['date', 'cc', 'rc', 'sc'])

# for index, row in df_not17.iterrows():
#     values = sorted([row.cc, row.rc, row.sc])
#     row_data = [row.date]
#     row_data.extend(values)
#     # print(row_data)
#     df_not17_sorted.loc[index] = row_data

# df_not17_sorted

# plt.figure(figsize=(30, 30))
# plt.plot(df_not17_sorted['date'], df_not17_sorted['cc'], c='red',
# label='cc')
# plt.plot(df_not17_sorted['date'], df_not17_sorted['rc'], c='blue',
# label='rc')
# plt.plot(df_not17_sorted['date'], df_not17_sorted['sc'], c='green',
# label='sc')
# plt.legend()
# plt.show()

# ic(df_17.cc / df_17.rc, df_17.rc / df_17.sc, df_17.cc / df_17.rc ==
# df_17.rc / df_17.sc)
# ic(df_not17_sorted.cc / df_not17_sorted.rc, df_not17_sorted.rc /
# df_not17_sorted.sc, df_not17_sorted.cc / df_not17_sorted.rc ==
# df_not17_sorted.rc / df_not17_sorted.sc)

```

```
# from math import round

# round(df_17.cc / df_17.rc, 2) == round(df_not17_sorted.cc[:365] /
df_not17_sorted.rc[:365], 2)

# for a, b in zip(df_17.cc / df_17.rc, df_not17_sorted.cc[:365] /
df_not17_sorted.rc[:365]):
#     print('%.1f'%a == '%.1f'%b)

# df_not17_sorted.to_csv("df_not17_sorted.csv")
```