Loading Python modules

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sqlite3 as sqldatabase
from scipy.stats import normaltest
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

Retrieving data

In [2]:
```
dfDonations = pd.read_csv("donations.csv", index_col=0, header=0, thousands=',')
dfDonations.head(5)
```

Out[2]:

	type	amount	payment_type_name	donor_id	donation_date	donation_typ
nationbuilder_id						
1	Donation	$125.00	Credit Card	541	1/8/2020 12:41	Na
10	Donation	$25.00	Credit Card	5509	5/11/2020 22:10	annual_membership_fe
100	Donation	$15.00	Credit Card	6039	6/1/2020 16:53	general_donatio
1000	Donation	$15.00	Credit Card	7233	6/11/2020 17:30	general_donatio
1001	Donation	$100.00	Credit Card	7234	6/11/2020 17:38	general_donatio

In [3]:
```
dfDonations.shape[0]
```

Out[3]:
```
1594
```

In [4]:
```
columns = dfDonations.columns
columns
```

Out[4]:
```
Index(['type', 'amount', 'payment_type_name', 'donor_id', 'donation_date',
       'donation_type', 'recurring_donation_status', 'billing_city',
       'billing_state', 'billing_FSA', 'billing_country',
       'billing_country_code', 'signup_email_opt_in', 'signup_mobile_opt_in',
       'signup_point_person_name_or_email', 'signup_tag_list'],
      dtype='object')
```

Preliminary EDA

In [5]:
```
dfDonations.dtypes
```

Out[5]:
```
type                                  object
```

```
amount                               object
payment_type_name                    object
donor_id                              int64
donation_date                        object
donation_type                        object
recurring_donation_status            object
billing_city                         object
billing_state                        object
billing_FSA                          object
billing_country                      object
billing_country_code                 object
signup_email_opt_in                  object
signup_mobile_opt_in                 object
signup_point_person_name_or_email    object
signup_tag_list                      object
dtype: object
```

In [6]:

```
dfDonations.isnull().sum()
```

Out[6]:

```
type                                   0
amount                                 0
payment_type_name                      0
donor_id                               0
donation_date                          0
donation_type                          1
recurring_donation_status           1181
billing_city                           0
billing_state                         35
billing_FSA                            0
billing_country                        0
billing_country_code                   0
signup_email_opt_in                  568
signup_mobile_opt_in                  11
signup_point_person_name_or_email   1055
signup_tag_list                       19
dtype: int64
```

In [7]:

```
# Turning amounts into numbers.
dfDonations["amount"] = dfDonations["amount"].replace({r'\$':''}, regex = True)
dfDonations["amount"]
```

Out[7]:

```
nationbuilder_id
1       125.00
10       25.00
100      15.00
1000     15.00
1001    100.00
         ...
995      25.00
996      74.15
997     500.00
998      25.00
999      50.00
Name: amount, Length: 1594, dtype: object
```

In [8]:

```
def is_number(x):
    try:
        float(x)
    except ValueError:
        return False
    else:
        return True

dfDonations[ ~dfDonations["amount"].apply(is_number) ]
```

Out[8]:

nationbuilder_id	type	amount	payment_type_name	donor_id	donation_date	donation_type	rec
1002	Donation	1,000.00	Credit Card	7236	6/11/2020 18:54	general_donation	
1057	Donation	2,000.00	Credit Card	7350	6/15/2020 17:32	general_donation	
106	Donation	1,000.00	Credit Card	6046	6/1/2020 17:41	general_donation	
1104	Donation	1,200.00	Credit Card	7533	6/25/2020 21:52	general_donation	
1115	Donation	2,200.00	Credit Card	7558	6/29/2020 15:24	general_donation	
1180	Donation	2,000.00	Credit Card	7666	7/13/2020 16:28	general_donation	
1196	Donation	1,688.46	Credit Card	7714	7/27/2020 13:02	general_donation	
1203	Donation	1,310.00	Credit Card	7727	7/29/2020 14:38	general_donation	
132	Donation	1,500.00	Credit Card	6081	6/1/2020 23:49	general_donation	
1429	Donation	1,000.00	Credit Card	8276	12/24/2020 11:01	general_donation	
1512	Donation	5,000.00	Credit Card	8753	2/19/2021 16:10	general_donation	
1523	Donation	1,000.00	Credit Card	8875	2/28/2021 15:00	general_donation	
169	Donation	3,500.00	Credit Card	6127	6/2/2020 11:22	general_donation	
324	Donation	1,000.00	Credit Card	6319	6/2/2020 16:45	general_donation	
510	Donation	1,000.00	Credit Card	6571	6/3/2020 12:22	general_donation	
684	Donation	1,000.00	Credit Card	6794	6/4/2020 13:00	general_donation	
879	Donation	1,100.00	Credit Card	7049	6/6/2020 19:37	general_donation	
943	Donation	1,000.00	Credit Card	7141	6/8/2020 19:56	general_donation	
979	Donation	1,300.00	Credit Card	7204	6/10/2020 17:26	general_donation	

In [9]:

```
dfDonations["amount"] = dfDonations["amount"].str.replace(',', '').astype(float)
```

In [10]:

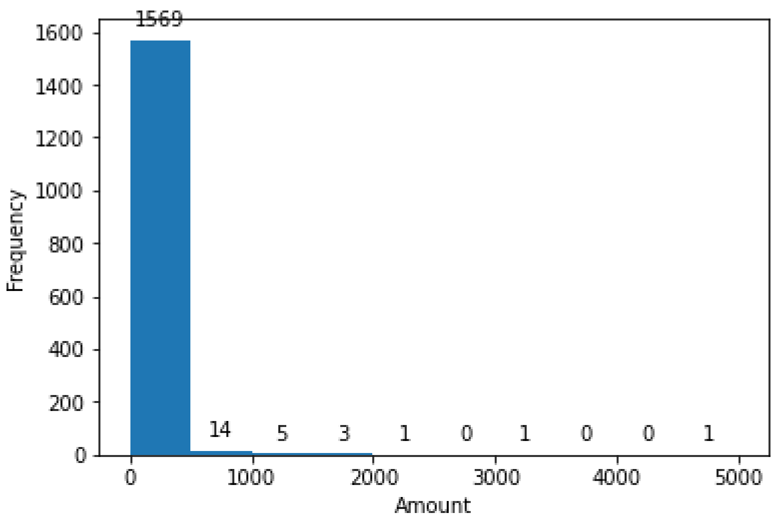
```
dfDonations["amount"].describe()
```

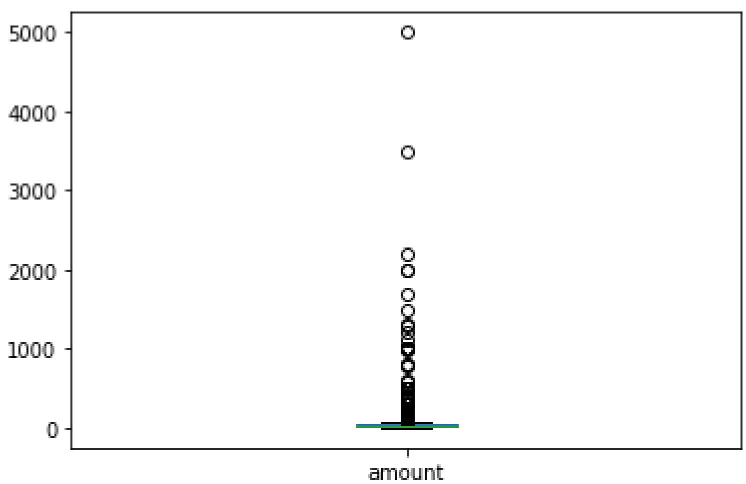
Out[10]:

```
count    1594.000000
mean       69.636468
std       215.649679
min         0.500000
25%        25.000000
```

```
50%         25.000000
75%         50.000000
max       5000.000000
Name: amount, dtype: float64
```

In [11]:
```
# Amount distribution.
Amt = dfDonations["amount"]

def plot_dist(Amt):
  fig, ax = plt.subplots()
  ax.hist(Amt, density=False)

  for rect in ax.patches:
      height = rect.get_height()
      ax.annotate(f'{int(height)}', xy=(rect.get_x()+rect.get_width()/2, height),
                  xytext=(0, 5), textcoords='offset points', ha='center', va='bottom')
  plt.xlabel("Amount")
  plt.ylabel("Frequency")
  plt.show()

  Amt.plot.box()
  plt.show()

plot_dist(Amt)
```





In [12]:
```
normaltest(dfDonations["amount"])
```

```
NormaltestResult(statistic=2913.1881559041867, pvalue=0.0)
```

Out[12]:

In [13]:
```
# We can tell from graphs and stats that the donation amounts are not normal distribute
```

In [14]:
```
# We are creating a dataframe that would contain the smaller values to get a better und
# Beucase the value of donations are not normal distributed, there are no outliers
# However, we will remove the extremely large donation values that are 3 std away from
donation_threshold = dfDonations['amount'].mean() + 3 * dfDonations['amount'].std()
dfDonations[dfDonations['amount'] >= donation_threshold]
```

Out[14]:

	type	amount	payment_type_name	donor_id	donation_date	donation_type	rec
nationbuilder_id							
1002	Donation	1000.00	Credit Card	7236	6/11/2020 18:54	general_donation	
1057	Donation	2000.00	Credit Card	7350	6/15/2020 17:32	general_donation	
106	Donation	1000.00	Credit Card	6046	6/1/2020 17:41	general_donation	
1104	Donation	1200.00	Credit Card	7533	6/25/2020 21:52	general_donation	
1115	Donation	2200.00	Credit Card	7558	6/29/2020 15:24	general_donation	
1180	Donation	2000.00	Credit Card	7666	7/13/2020 16:28	general_donation	
1193	Donation	782.00	Credit Card	7699	7/22/2020 15:12	general_donation	
1196	Donation	1688.46	Credit Card	7714	7/27/2020 13:02	general_donation	
1203	Donation	1310.00	Credit Card	7727	7/29/2020 14:38	general_donation	
1287	Donation	980.00	Credit Card	7881	9/8/2020 16:35	general_donation	
132	Donation	1500.00	Credit Card	6081	6/1/2020 23:49	general_donation	
1333	Donation	800.00	Credit Card	7966	10/6/2020 10:00	general_donation	
1398	Donation	813.50	Credit Card	8150	12/1/2020 21:38	general_donation	
1429	Donation	1000.00	Credit Card	8276	12/24/2020 11:01	general_donation	
1512	Donation	5000.00	Credit Card	8753	2/19/2021 16:10	general_donation	
1523	Donation	1000.00	Credit Card	8875	2/28/2021 15:00	general_donation	
169	Donation	3500.00	Credit Card	6127	6/2/2020 11:22	general_donation	
324	Donation	1000.00	Credit Card	6319	6/2/2020 16:45	general_donation	
510	Donation	1000.00	Credit Card	6571	6/3/2020 12:22	general_donation	

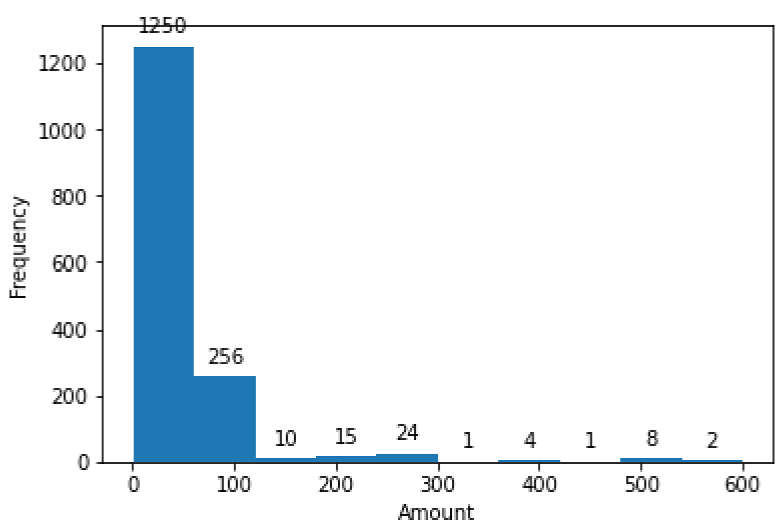
	type	amount	payment_type_name	donor_id	donation_date	donation_type	rec
nationbuilder_id							
684	Donation	1000.00	Credit Card	6794	6/4/2020 13:00	general_donation	
879	Donation	1100.00	Credit Card	7049	6/6/2020 19:37	general_donation	
943	Donation	1000.00	Credit Card	7141	6/8/2020 19:56	general_donation	
979	Donation	1300.00	Credit Card	7204	6/10/2020 17:26	general_donation	

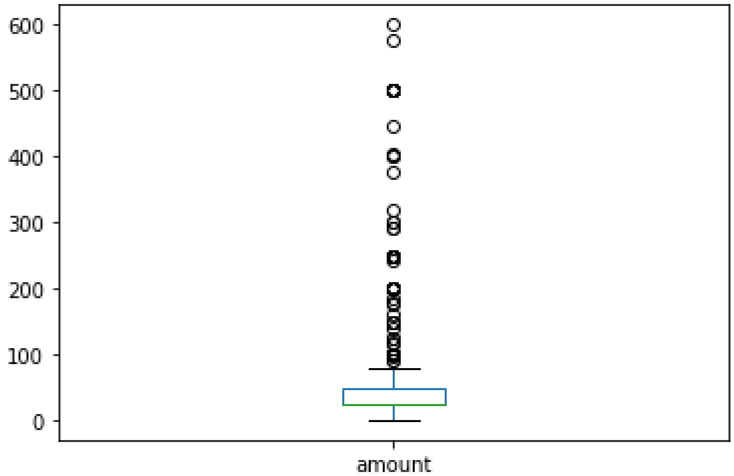
In [15]:
```
donationsNoOutliers = dfDonations[dfDonations['amount'] < donation_threshold]
donationsNoOutliers.head(5)
```

Out[15]:

	type	amount	payment_type_name	donor_id	donation_date	donation_typ
nationbuilder_id						
1	Donation	125.0	Credit Card	541	1/8/2020 12:41	Na
10	Donation	25.0	Credit Card	5509	5/11/2020 22:10	annual_membership_fe
100	Donation	15.0	Credit Card	6039	6/1/2020 16:53	general_donatio
1000	Donation	15.0	Credit Card	7233	6/11/2020 17:30	general_donatio
1001	Donation	100.0	Credit Card	7234	6/11/2020 17:38	general_donatio

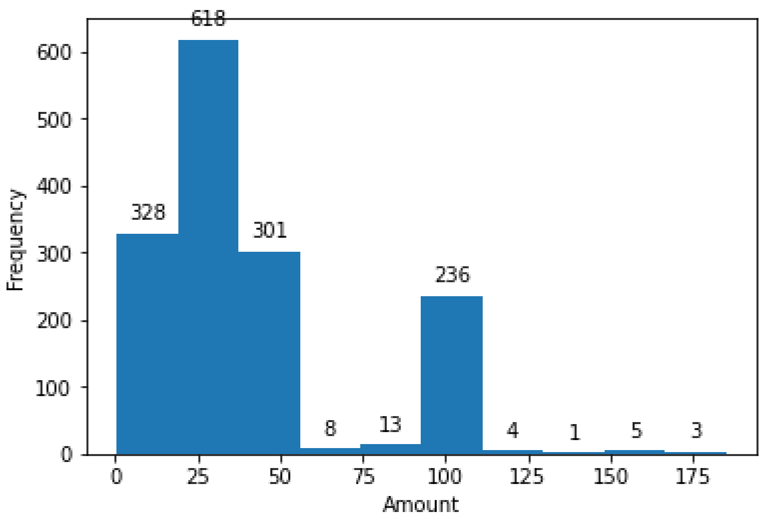
In [16]:
```
# Amount distribution.
Amt = donationsNoOutliers["amount"]

plot_dist(Amt)
```

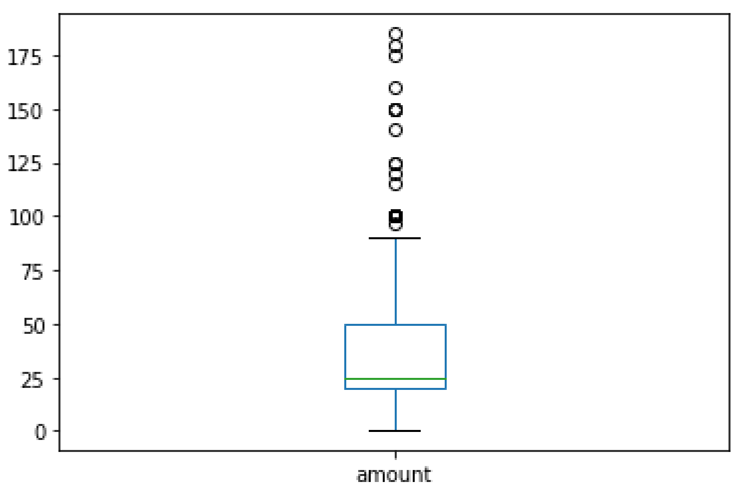




In [17]:
```
# Looking at the distribution after removing the extremely high values, we can see that
# Because of this, we will directly remove any values higher than $200 to take get a be
```

In [18]:
```
twoHundredDonations = dfDonations[dfDonations['amount'] < 200]
Amt = twoHundredDonations["amount"]

plot_dist(Amt)
```





In [19]:
```
Amt.describe()
```

Out[19]:
```
count    1517.000000
mean       39.772142
std        31.678353
min         0.500000
25%        20.200000
50%        25.000000
75%        50.000000
max       185.000000
Name: amount, dtype: float64
```

In [20]:
```
# From the results above, we can see that there seems to be a particular pattern, two v
# The vast amount of donations are less than $50 in value, while there is another influ
# What is interesting is that between these two ranges, from $50-$100, there is very li
# This could be a behavior pattern, where people tend to donate in even amounts, and in
# "Might as well donate $100 if i am going to donate $80, it is a nice even number"
```

In [21]:
```
# With data without outliers, we are able to predict future donation amounts better. Ho
# specific time period, specific region or donors with specific demographics. Hope to g
# to receive large donations.
```

In [22]:
```
# Identifying one-time donor and recurring donors.
DonorId = dfDonations.donor_id.value_counts()
dfRec = dfDonations[dfDonations["recurring_donation_status"].notnull()]
dfRec.head(5)
```

Out[22]:

	type	amount	payment_type_name	donor_id	donation_date	donation_typ
nationbuilder_id						
1006	Donation	25.0	Credit Card	5711	6/12/2020 2:48	annual_membership_fe
1015	Donation	5.0	Credit Card	7252	6/12/2020 14:17	general_donatio
1016	Donation	10.0	Credit Card	7253	6/12/2020 14:30	general_donatio
1031	Donation	10.0	Credit Card	7278	6/13/2020 16:21	general_donatio
1034	Donation	100.0	Credit Card	7282	6/13/2020 17:23	general_donatio

In [23]:
```
dfRec["amount"].describe()
```

Out[23]:
```
count    413.000000
mean      21.590799
std       20.987505
min        3.000000
25%       10.000000
50%       25.000000
75%       25.000000
max      100.000000
Name: amount, dtype: float64
```

In [24]:
```
dfOne = dfDonations[dfDonations["recurring_donation_status"].isnull()]
dfOne.head(5)
```

Out[24]:

	type	amount	payment_type_name	donor_id	donation_date	donation_typ

nationbuilder_id	type	amount	payment_type_name	donor_id	donation_date	donation_typ
nationbuilder_id						
1	Donation	125.0	Credit Card	541	1/8/2020 12:41	Na
10	Donation	25.0	Credit Card	5509	5/11/2020 22:10	annual_membership_fe
100	Donation	15.0	Credit Card	6039	6/1/2020 16:53	general_donatio
1000	Donation	15.0	Credit Card	7233	6/11/2020 17:30	general_donatio
1001	Donation	100.0	Credit Card	7234	6/11/2020 17:38	general_donatio

In [25]:

```
dfOne["amount"].describe()
```

Out[25]:

```
count    1181.000000
mean       86.438213
std       248.066911
min         0.500000
25%        25.000000
50%        50.000000
75%       100.000000
max      5000.000000
Name: amount, dtype: float64
```

Recurring Donors & Non-Recurring Ones

In [26]:

```
print("Number of donations made by recurring donors: ", dfRec.shape[0])
print("Number of donations made by one-time donors: ", dfOne.shape[0])
```

```
Number of donations made by recurring donors:  413
Number of donations made by one-time donors:  1181
```

In [27]:

```
# However, we found out that there are some non-recurring donors who donated more than
DonorId = dfOne.donor_id.value_counts()
dfNonRec = dfOne[dfOne.donor_id.isin(DonorId.index[DonorId.gt(1)])]
dfNotRec = dfNonRec.sort_values(by="donor_id")
dfNotRec
```

Out[27]:

	type	amount	payment_type_name	donor_id	donation_date	donation_type	rec
nationbuilder_id							
119	Donation	50.0	Credit Card	6063	6/1/2020 20:50	general_donation	
1432	Donation	100.0	Credit Card	6063	12/26/2020 14:24	general_donation	
358	Donation	25.0	Credit Card	6273	6/2/2020 17:53	general_donation	
283	Donation	25.0	Credit Card	6273	6/2/2020 14:53	general_donation	
333	Donation	125.0	Credit Card	6328	6/2/2020 16:56	general_donation	

	type	amount	payment_type_name	donor_id	donation_date	donation_type	rec
nationbuilder_id							
...	...	...	...	...	...	...	
1172	Donation	15.0	Credit Card	7657	7/10/2020 21:15	general_donation	
1192	Donation	10.0	Credit Card	7694	7/21/2020 18:12	general_donation	
1191	Donation	10.0	Credit Card	7694	7/21/2020 18:07	general_donation	
1516	Donation	100.0	Credit Card	8829	2/24/2021 18:48	general_donation	
1529	Donation	500.0	Credit Card	8829	3/2/2021 22:12	general_donation	

61 rows × 16 columns

In [28]:
```
dfOneNotNoDup = dfNotRec.drop_duplicates(subset=['donor_id'], keep='first')
print("Total number of non-recurring donors who donated more than once: ", dfOneNotNoDu
```

```
Total number of non-recurring donors who donated more than once:  24
```

In [29]:
```
# Creating a dataset without duplicated donor ids.
dfDonationsNoDup = dfDonations.drop_duplicates(subset=['donor_id'], keep='first')
dfDonationsNoDup.head(5)
```

Out[29]:

	type	amount	payment_type_name	donor_id	donation_date	donation_typ
nationbuilder_id						
1	Donation	125.0	Credit Card	541	1/8/2020 12:41	Na
10	Donation	25.0	Credit Card	5509	5/11/2020 22:10	annual_membership_fe
100	Donation	15.0	Credit Card	6039	6/1/2020 16:53	general_donatio
1000	Donation	15.0	Credit Card	7233	6/11/2020 17:30	general_donatio
1001	Donation	100.0	Credit Card	7234	6/11/2020 17:38	general_donatio

In [30]:
```
dfDonationsNoDup['billing_state'].unique()
```

Out[30]:
```
array(['Ontario', 'Quebec', 'ON', 'BC', 'QC', 'Qc', 'Alberta',
       'Quebec, Canada', 'Quebec ', 'NS', 'Qu', 'Québec', nan,
       'British Columbia', 'British Colombia', 'Bc', 'OR', 'Ontario ',
       'Ab', 'AB', 'YT', 'MB', 'NS ', 'QUEBEC', 'sk', 'NL', 'QC - Quebec',
       'Saskatchewan', 'On', 'FL', 'NB', 'Ab ', 'Nova Scotia ',
       'British Columbia ', 'Newfoundland and Labrador', 'MA', 'qc',
       'CA-Quebec', 'bc', 'Aylmer', 'GA', 'CA', 'WA', 'MN', 'Nova Scotia',
       'Ont', 'New Brunswick', 'Newfoundland', 'Province', 'Québec ',
```

```
'Canada', 'Manitoba', 'V7P2H5', 'NY', 'SK', 'Alberta ',
 'ON - Ontario', 'RI', 'ontario', 'ONTARIO', 'Saskatchewan ',
 'alberta', 'QC ', 'AB - Alberta', 'AB ', 'Western Australia',
 'BC ', 'Vancouver', 'CA|-_-|QC', 'PE', 'CA-AB',
 'BC - British Columbia', 'on', 'quebec', 'B.C.', 'Sk ', 'ONT',
 'KY', 'British columbia', 'Newfoundland &amp; Labrador', 'Sk'],
dtype=object)
```

In [31]:

```
dfRecNoDup = dfDonationsNoDup[dfDonationsNoDup["recurring_donation_status"].notnull()]
dfRecNoDup.head(5)
```

Out[31]:

nationbuilder_id	type	amount	payment_type_name	donor_id	donation_date	donation_typ
1006	Donation	25.0	Credit Card	5711	6/12/2020 2:48	annual_membership_fe
1015	Donation	5.0	Credit Card	7252	6/12/2020 14:17	general_donatio
1016	Donation	10.0	Credit Card	7253	6/12/2020 14:30	general_donatio
1031	Donation	10.0	Credit Card	7278	6/13/2020 16:21	general_donatio
1034	Donation	100.0	Credit Card	7282	6/13/2020 17:23	general_donatio

In [32]:

```
dfOneNoDup = dfDonationsNoDup[dfDonationsNoDup["recurring_donation_status"].isnull()]
dfOneNoDup.head(5)
```

Out[32]:

nationbuilder_id	type	amount	payment_type_name	donor_id	donation_date	donation_typ
1	Donation	125.0	Credit Card	541	1/8/2020 12:41	Na
10	Donation	25.0	Credit Card	5509	5/11/2020 22:10	annual_membership_fe
100	Donation	15.0	Credit Card	6039	6/1/2020 16:53	general_donatio
1000	Donation	15.0	Credit Card	7233	6/11/2020 17:30	general_donatio
1001	Donation	100.0	Credit Card	7234	6/11/2020 17:38	general_donatio

In [33]:

```
print("Total number of donors: ", dfDonationsNoDup.shape[0])
print("Total number of recurring donors: ", dfRecNoDup.shape[0])
print("Total number of one-time donors: ", dfOneNoDup.shape[0])
```

```
Total number of donors:  1180
Total number of recurring donors:  40
Total number of one-time donors:  1140
```

In [34]:
```
GroupId = dfDonations.groupby("donor_id")
DonorId = GroupId.count()
DonorId.sort_values(by="type", ascending=False)
```

Out[34]:

donor_id	type	amount	payment_type_name	donation_date	donation_type	recurring_donation_status
5806	15	15	15	15	15	14
6641	15	15	15	15	15	14
5710	15	15	15	15	15	14
6137	14	14	14	14	14	14
6942	14	14	14	14	14	14
...	...	...	...	...	...	...
6436	1	1	1	1	1	0
6435	1	1	1	1	1	0
6434	1	1	1	1	1	0
6433	1	1	1	1	1	0
9537	1	1	1	1	1	0

1180 rows × 15 columns

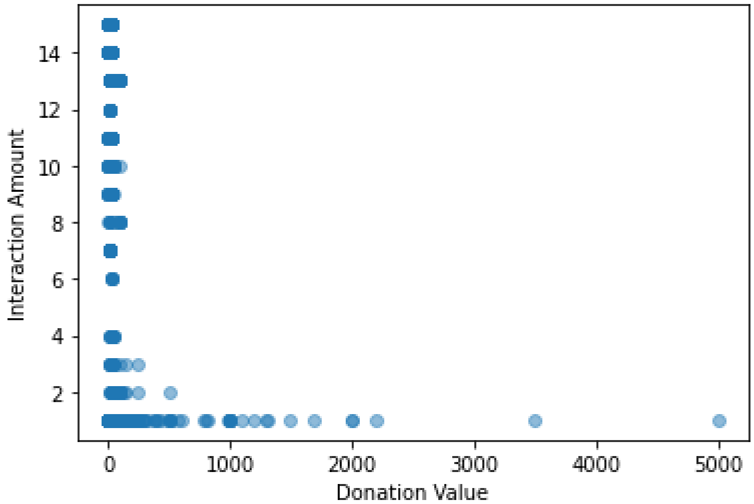
In [35]:
```
dfMerge = pd.merge(dfDonations, DonorId["type"], on='donor_id')
dfMerge.sort_values(by="type_y", ascending=False).head(5)
```

Out[35]:

	type_x	amount	payment_type_name	donor_id	donation_date	donation_type	recurring_donat
430	Donation	25.0	Credit Card	5806	1/2/2021 14:07	general_donation	
95	Donation	25.0	Credit Card	5710	6/14/2020 9:50	general_donation	
105	Donation	25.0	Credit Card	5710	2/14/2021 8:51	general_donation	
104	Donation	25.0	Credit Card	5710	5/14/2020 8:50	general_donation	
103	Donation	25.0	Credit Card	5710	1/14/2021 8:51	general_donation	

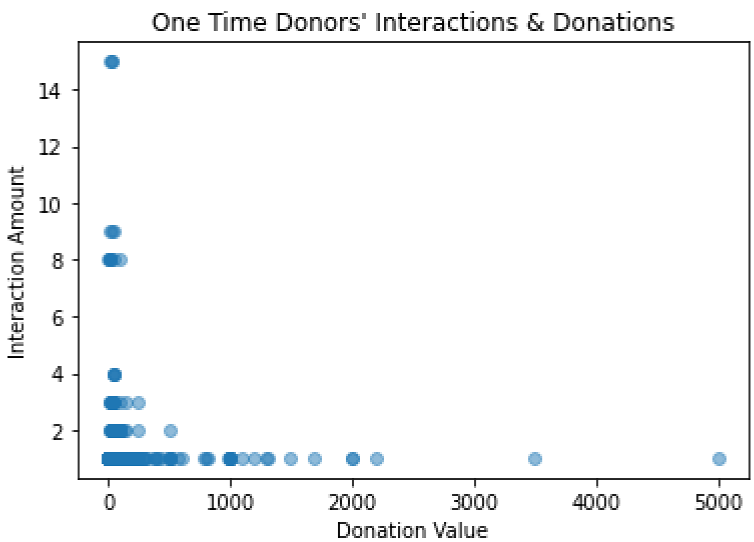
Correlation Interaction & Value

In [36]:
```
plt.scatter(dfMerge["amount"], dfMerge["type_y"], alpha=0.5)
plt.xlabel("Donation Value")
plt.ylabel("Interaction Amount")
plt.show()
```



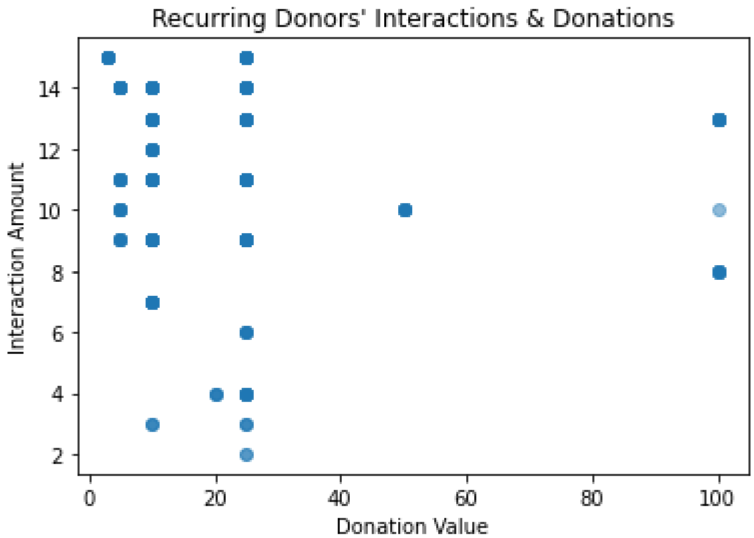
In [37]:

```
dfMergeOne = dfMerge[dfMerge["recurring_donation_status"].isnull()]
plt.scatter(dfMergeOne["amount"], dfMergeOne["type_y"], alpha=0.5)
plt.xlabel("Donation Value")
plt.ylabel("Interaction Amount")
plt.title("One Time Donors' Interactions & Donations")
plt.show()
```



In [38]:

```
dfMergeRec = dfMerge[dfMerge["recurring_donation_status"].notnull()]
plt.scatter(dfMergeRec["amount"], dfMergeRec["type_y"], alpha=0.5)
plt.xlabel("Donation Value")
plt.ylabel("Interaction Amount")
plt.title("Recurring Donors' Interactions & Donations")
plt.show()
```



In [39]:
```
dfMerge[["amount","type_y"]].corr("kendall")
```

Out[39]:

	amount	type_y
amount	1.000000	-0.351083
type_y	-0.351083	1.000000

In [40]:
```
# The graph and stats suggests that higher interaction might not associate with higher
# the higher value donations comes from one-time donors.
```

Donation Demographics

Donation Cities

In [41]:
```
dfDonationsNoDup["billing_city"].unique()
```

Out[41]:
```
array(['Markham', 'St-Hubert', 'Ottawa', 'Orillia', 'Mississauga',
       'Burnaby', 'Montreal', 'Toronto', 'Laval', 'Ddo', 'Westmount',
       'Stratford', 'Edmonton', 'Montreal ', 'Westmount ', 'Hubbards',
       'Vanier', 'Hampstead', 'Calgary', 'Saint-Zotique', 'quebec',
       'Vancouver', 'toronto', 'Caledon', 'Oshawa', 'Brossard',
       'Gatineau', 'Abbotsford', 'Kelowna', 'Victoria', 'St. Catharines',
       'Eugene', 'North York', 'Windsor', 'Sherwood Park', 'Sarnia',
       'Okotoks', 'Whitehorse', 'st-laurent', 'Wainwright', 'Longueuil',
       'Kitchener', 'Oakville', 'Winnipeg', 'Montréal', 'Belleville',
       'Pierrefonds', 'Burnaby ', 'St margarets bay ', 'Waterloo',
       'Coquitlam', 'Carman', 'St-Eustache', 'København K', 'Surrey',
       'West Pennant', 'montreal', 'Orleans', 'Regina', 'North Bay',
       'Brampton', 'Newmarket', 'Cbs', 'Mississauga, ON', 'Keene',
       'Schumacher', 'West Vancouver', 'Kanata', 'Emerald Park', 'Guelph',
       'Port Williams', 'Leduc County', 'Weston', 'Fredericton',
       'Chatham ', 'Richmond Hill', 'Lennoxville', 'vaughan', 'Camrose',
       "St. John's", 'Hawkesburyry', 'New Westminster', 'Sherbrooke',
       'Chilliwack', 'Port Williams ', 'Scarborough', 'Cambridge',
       'Ottawa ', 'Port Coquitlam ', 'Halifax', 'Conception Bay South',
       'Grande Prairie', 'Lanark', 'Boston', 'Trois-Rivières',
       'Hamilton Canada', 'North Vancouver', 'Brantford', 'Saint Laurent',
       'Burlington ', 'Sainte-Thérèse', 'Gloucester', 'Almonte',
       'Grand Falls-Windsor', 'Georgetown', 'Milton', 'Unionville',
       'Cambridge ', 'Kingston ', 'Brampton ', 'Brossard ', 'victoria',
```

```
'Mississauga ', 'Halifax ', 'Nanaimo', 'London', 'Atlanta',
'Kingston', 'Duncan', 'Russell', 'Riverview', 'Scarborough ',
'Courtice', 'Quispamsis', 'Amherstburg ', 'Hamilton', 'Thornhill',
'Ancaster', 'Redwood City', 'Seattle', 'Orangeville ', 'Dunrobin',
'Boisbriand', 'Minneapolis', 'Aurora', 'Hañifax', 'Branchton',
'St Hubert', 'Carp', 'Clarenville', 'Edmonton ', 'Dartmouth ',
'Charters Settlement ', 'St. John’s ', 'Whitby', 'Pickering',
'Toronto ', 'Bowmanville', 'St-Laurent', 'Greely', 'Quebec',
'Moose Jaw ', 'vancouver', 'Chateauguay', 'St. Davids',
'East Gwillimbury ', 'Chatham', 'Thorold', 'Dartmouth',
'Saint-Hubert', 'York', 'Thornbury', 'Burlington', 'Nepean',
'Bedford', 'East York', 'Petawawa', 'Etobicoke',
'North  Vancouver', 'Shelburne', 'Fort Saskatchewan',
'Kapuskasing', 'Kirkland', 'Thunder Bay', 'Oakville ',
'Fort Mcmurray', 'calgary', 'Kitchener ', 'Brooklyn', 'Moose Jaw',
'Sudbury', 'Barrie', 'Paradise', 'Richmond', 'Corunna', 'Beaumont',
'Langley', 'Oro Medonte', 'Beaconsfield', 'Parksville',
'Pointe-Claire', 'Sherwood park ', 'Windsor ', 'Outremont',
'Tofino', 'Cranston', 'King City ', 'ancaster', 'Saskatoon ',
'St. John’s', 'Stony plain', 'Ajax', 'Melville', 'St albert',
'St. Albert', 'Medicine Hat', 'Vernon', 'Guelpg', 'Gananoque',
'Leamington', 'Maple Ridge', 'Longueuil ', 'Fort McMurray',
'Surrey ', 'Severn Bridge', 'Trenton', 'Bonnyville', 'Orangeville',
'St. Catharines ', 'Holland Landing', 'Wasaga Beach', 'Crawley',
'Fort St. John', 'Delta', 'Chilliwack Proper Village West',
'Porcupine Plain', 'Esquimalt ', 'Perth', 'Ottawa-Vanier',
'Pakenham', 'Jacksons Point', 'Vancouver ', 'Corner Brook',
'Margaree', 'Cote-Saint-Luc', 'Truro',
'Scarborough (Malvern / Rouge River)', 'Collingwood ', 'Embrun',
'Niagara Falls', 'Manotick', 'Red Deer', 'Cornwall', 'Lansdowne ',
'Hay Lakes', 'REgina', "Portugal Cove-St. Philip's",
'Garibaldi Highlands', 'Charlottetown', 'Glen Levit', 'King City',
'Fort St John', 'St Albert ', 'Maxwell', 'Prince George',
'Peterborough ', 'Carlsbad Springs', 'Galiano Island', 'Bc',
'Stittsville', 'Verdun', 'Courtenay', 'Kanata ', 'Brandon',
'Kamloops', 'Saint John', 'Lasalle', 'Radville', 'Sorel-Tracy',
'Dundalk', 'Monteeal', 'Candiac', 'Cobourg', 'Mount Brydges',
'South surrey ', 'Grimsby', 'Lac Superieur ', 'outremont',
'Airdrie', 'Cobble Hill', 'Regina ', 'Squamish', 'Calgary ',
'Saskatoon', 'Englehart ', 'Waterdown', 'Labelle', 'Vaughan',
'Côte Saint-Luc', 'Maple', 'North Hatley', 'etobicoke',
'St. Laurent', 'Bowen Island', 'Huntsville', 'Missisauga',
'Cochrane', 'edmonton', 'Leduc', 'Newcastle', 'Rawdon',
'Saint Lambert', 'MeathPark', 'Otonabee', 'Stoney Creek',
'lachine', 'ottawa ', 'Eston ', 'Sainte Anne de Bellevue',
'Guadalajara', 'Severn', 'Onoway', 'Cochrane ', 'Mooretown',
'Port moody', 'Dundas', 'Canmore', 'Jasper', 'Lethbridge ',
'Morgantown', 'Warkworth', 'LaSalle', 'Pitt Meadows', 'Fort Mckay',
'Comox ', 'Pefferlaw', 'Sidney', 'Belleville ', 'Waverley',
'ottawa', 'Stouffville ', 'Uxbridge', 'Listowel', 'Blenheim',
'Sylvan Lake', "St John's", 'West Kelowna', 'Bouctouche', 'Winlaw',
'OTtawa ', 'Richmond ', 'honey harbour', 'Gibsons', 'Corman Park',
'Boisbriand ', 'Munich', 'Vulcan'], dtype=object)
```

In [42]:

```
groupCity = dfDonationsNoDup.groupby("billing_city")
DonorCity = groupCity.count()
DonorCity.sort_values(by="donor_id", ascending=False)
```

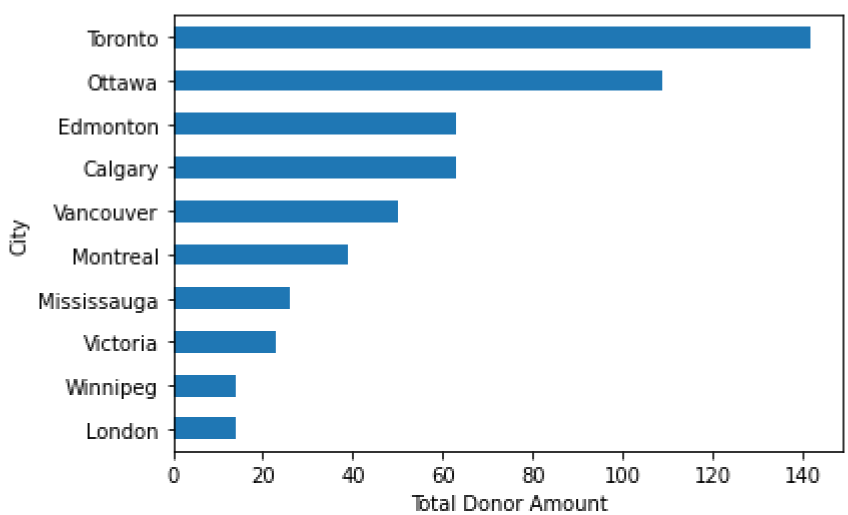
Out[42]:

	type	amount	payment_type_name	donor_id	donation_date	donation_type	recurring_dor
billing_city							
Toronto	142	142	142	142	142	142	

	type	amount	payment_type_name	donor_id	donation_date	donation_type	recurring_dor
billing_city							
Ottawa	109	109		109	109	109	109
Calgary	63	63		63	63	63	63
Edmonton	63	63		63	63	63	63
Vancouver	50	50		50	50	50	50
...	...	...		...	...	...	...
Lansdowne	1	1		1	1	1	1
Lasalle	1	1		1	1	1	1
Leamington	1	1		1	1	1	1
Lennoxville	1	1		1	1	1	1
victoria	1	1		1	1	1	1

347 rows × 15 columns

In [43]:
```
DonorCount = DonorCity["type"].sort_values(ascending=False).head(10)
DonorCount.sort_values(ascending=True).plot.barh()
plt.ylabel("City")
plt.xlabel("Total Donor Amount")
plt.show()
```



In [44]:
```
DonorCount
```

Out[44]:
```
billing_city
Toronto        142
Ottawa         109
Calgary         63
Edmonton        63
Vancouver       50
Montreal        39
Mississauga     26
Victoria        23
London          14
```

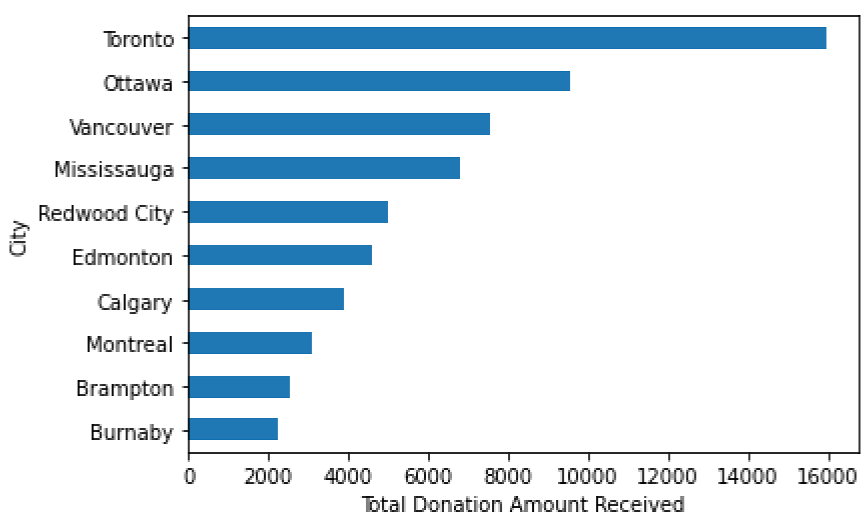
```
Winnipeg        14
Name: type, dtype: int64
```

In [45]:
```
# The top 10 cities ranked according to the total amount of donations received
cityAmountSum = dfDonations[['amount', 'billing_city']].groupby("billing_city").sum()
cityAmountSum.sort_values(by="amount", ascending=False).head(10)
```

Out[45]:

billing_city	amount
Toronto	15957.49
Ottawa	9538.00
Vancouver	7547.00
Mississauga	6807.15
Redwood City	5000.00
Edmonton	4602.40
Calgary	3903.13
Montreal	3072.00
Brampton	2530.00
Burnaby	2230.00

In [46]:
```
CityCount = cityAmountSum.sort_values(by="amount", ascending=False).head(10)
CityCount["amount"].sort_values(ascending=True).plot.barh()
plt.ylabel("City")
plt.xlabel("Total Donation Amount Received")
plt.show()
```



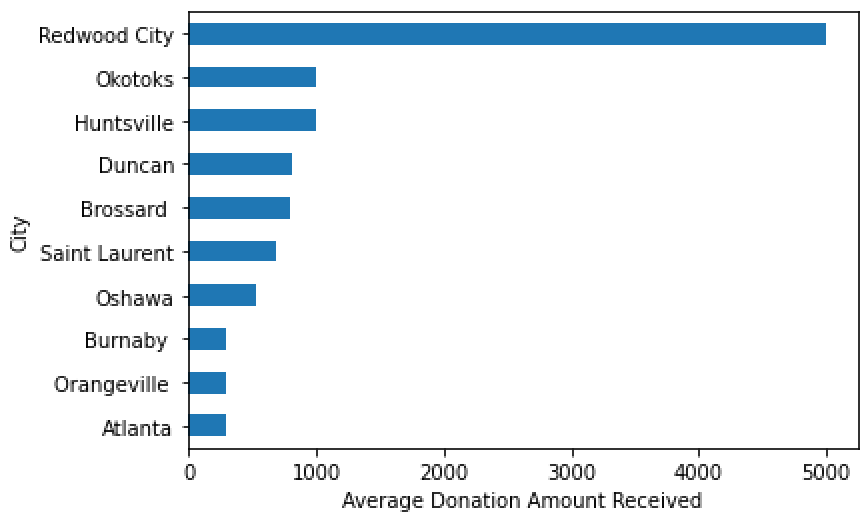
In [47]:
```
# The top 10 cities ranked according to the average amount of donations received
cityAmountAvg = dfDonations[['amount', 'billing_city']].groupby('billing_city').mean()
cityAmountAvg.sort_values(by="amount", ascending=False).head(10)
```

Out[47]:

billing_city	amount

	amount
billing_city	
Redwood City	5000.0
Okotoks	1002.5
Huntsville	1000.0
Duncan	813.5
Brossard	800.0
Saint Laurent	680.0
Oshawa	525.0
Orangeville	300.0
Burnaby	300.0
Atlanta	290.0

In [48]:
```
CityCountAvg = cityAmountAvg.sort_values(by="amount", ascending=False).head(10)
CityCountAvg["amount"].sort_values(ascending=True).plot.barh()
plt.ylabel("City")
plt.xlabel("Average Donation Amount Received")
plt.show()
```



In [49]:
```
# We can see Toronto has the most donation amount in total and average and are a lot la
# in other cities as well.
# The result for the demographics may due to different exposures to FBC, we are not sur
# different regions across canada.
```

Donation Provinces

In [50]:
```
groupState = dfDonationsNoDup.groupby("billing_state")
DonorState = groupState.count()
DonorState.sort_values(by="donor_id", ascending=False)
```

Out[50]:

type	amount	payment_type_name	donor_id	donation_date	donation_type	recurring_doı

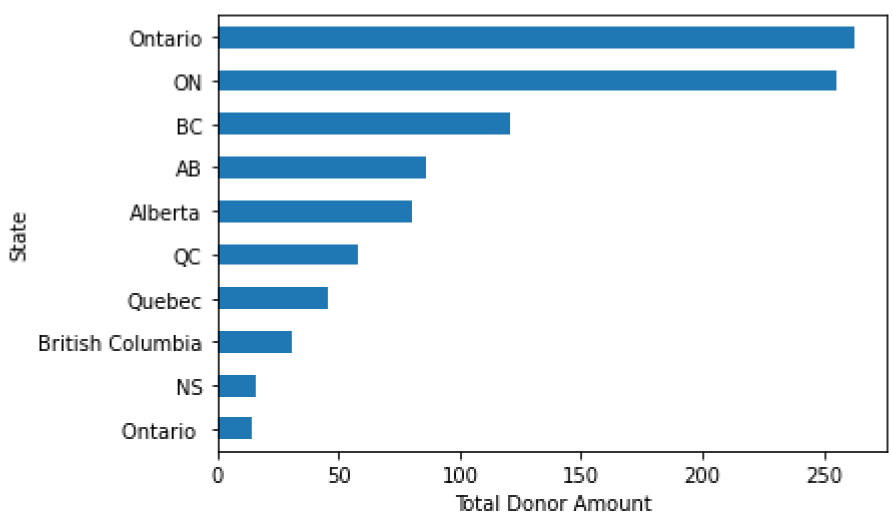
	type	amount	payment_type_name	donor_id	donation_date	donation_type	recurring_dor
billing_state							
Ontario	263	263	263	263	263	262	
ON	255	255	255	255	255	255	
BC	121	121	121	121	121	121	
AB	86	86	86	86	86	86	
Alberta	80	80	80	80	80	80	
...	...	...	...	...	...	...	
OR	1	1	1	1	1	1	
Ont	1	1	1	1	1	1	
Province	1	1	1	1	1	1	
QC	1	1	1	1	1	1	
sk	1	1	1	1	1	1	

80 rows × 15 columns

In [50]:

In [51]:

```
ProvinceCount = DonorState["type"].sort_values(ascending=False).head(10)
ProvinceCount.sort_values(ascending=True).plot.barh()
plt.ylabel("State")
plt.xlabel("Total Donor Amount")
plt.show()
```



In [52]:

```
ProvinceCount
```

Out[52]:

```
billing_state
Ontario            263
ON                 255
BC                 121
```

```
AB                    86
Alberta               80
QC                    58
Quebec                46
British Columbia      31
NS                    16
Ontario               14
Name: type, dtype: int64
```

In [53]:
```
# The top 10 states ranked according to the total amount of donations received
stateAmountSum = dfDonations[['amount', 'billing_state']].groupby("billing_state").sum(
stateAmountSum.sort_values(by="amount", ascending=False).head(10)
```

Out[53]:

billing_state	amount
Ontario	30718.80
ON	21991.34
BC	12446.25
Alberta	6392.23
AB	6058.30
CA	6025.00
Quebec	3968.00
QC	3950.50
British Columbia	2070.00
MB	1507.50

In [54]:
```
# We can see that Toronto has the highest number of donations among the billing cities
# cannot draw this conclusion yet. Because the format of the input data might not be co
# when we dealing with specific questions regarding the billing states.
```

In [55]:
```
groupTag = dfDonationsNoDup.groupby("signup_tag_list")
DonorTag = groupTag.count()
DonorTag.sort_values(by="type", ascending=False)
```

Out[55]:

signup_tag_list	type	amount	payment_type_name	donor_id	donation_date	dona
donor	1001	1001		1001	1001	1001
donor,General Member,Ontario,Recruit Survey Apr 2020 Completed	13	13		13	13	13
Alberta,donor,General Member,Recruit Survey Apr 2020 Completed,Youth Council Prospects	11	11		11	11	11
Alberta,donor,General Member,Recruit Survey Apr 2020 Completed	10	10		10	10	10

signup_tag_list	type	amount	payment_type_name	donor_id	donation_date	dona
donor,General Member,Ontario,Recruit Survey Apr 2020 Completed,Youth Council Prospects	7	7		7	7	7
...	...	...		...	...	...
Elder Prospects,General Member,Recruit Survey Apr 2020 Completed,Saskatchewan,Volunteer	1	1		1	1	1
EN,FR,General Member,Membership fee,newsletter,Ontario,Paid Member	1	1		1	1	1
Covid Call RSVPs March 2020,defundpolicesurvey,donor,Elder Prospects,General Member,newsletter,Ontario,Paid Member,Recruit Survey Apr 2020 Completed,Sign-Up	1	1		1	1	1
British Columbia; BC Hub 001,donor	1	1		1	1	1
donor,newsletter,Ontario,Recruit Survey Apr 2020 Completed	1	1		1	1	1

104 rows × 15 columns

In [56]:
```
# We can look into the donor tags later when studying donor profiles.
```

Donor Opt-in Status

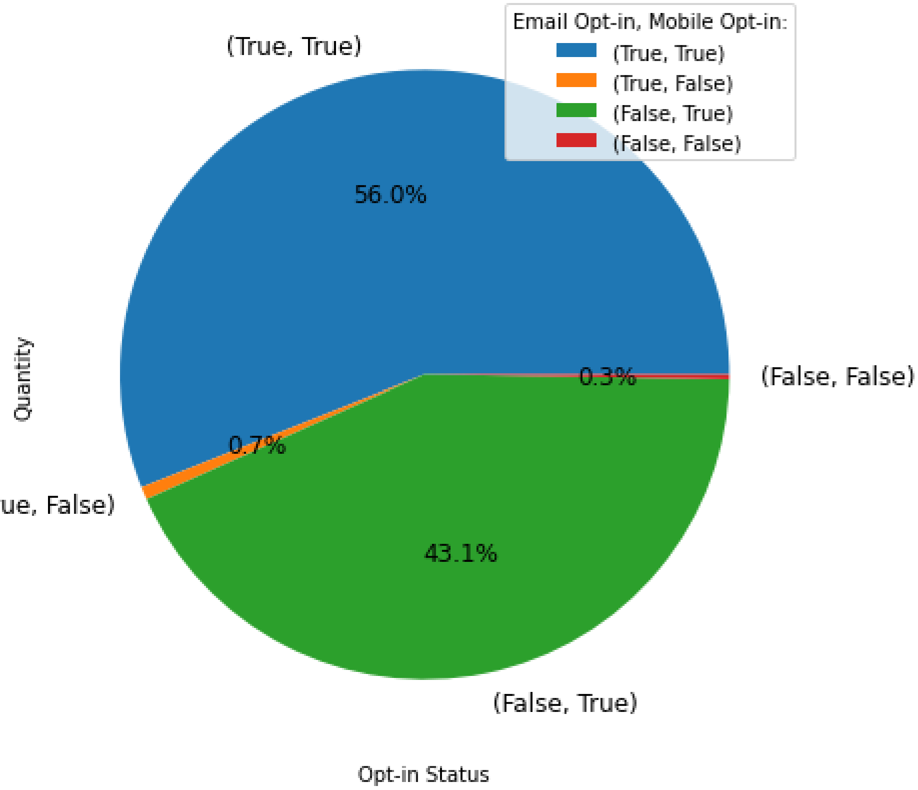
In [57]:
```
# Donor opted-in status.
dfDonationsNoDupFill = dfDonationsNoDup.fillna({"recurring_donation_status":'One-Time',
groupOpt = dfDonationsNoDupFill.groupby(["signup_email_opt_in","signup_mobile_opt_in"])
groupOpt.count()
```

Out[57]:

signup_email_opt_in	signup_mobile_opt_in	type	amount	payment_type_name	donor_id	donation_date
True	**True**	661	661		661	661
	False	8	8		8	8
False	**True**	508	508		508	508
	False	3	3		3	3

In [58]:
```
groupOpt.count()['type'].plot.pie(autopct="%.1f%%", figsize=(10,7), fontsize=12)
plt.xlabel("Opt-in Status")
plt.ylabel("Quantity")
```

```
plt.legend(title = "Email Opt-in, Mobile Opt-in:")
plt.show()
```



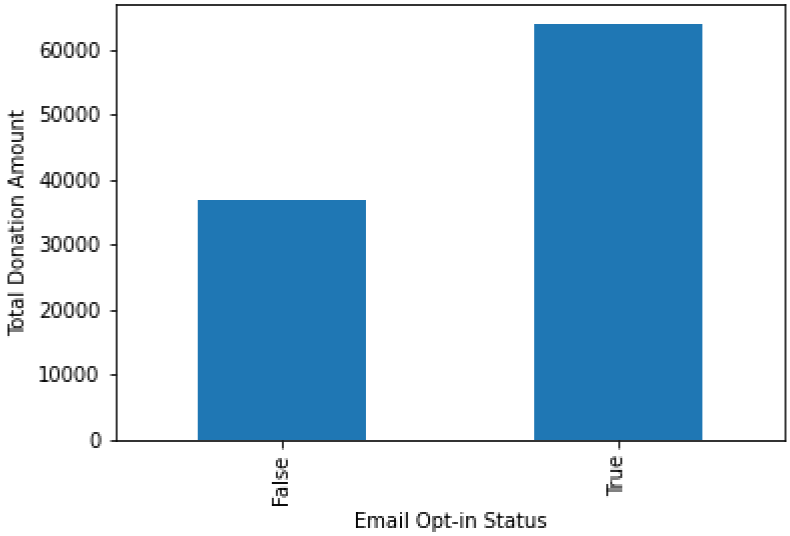
In [59]:
```
# Most of the donors have signed up for mobile opt in, does mobile opt in a better way
# the donation amount? We can look into this later.
```

In [60]:
```
EmailSum = dfDonationsNoDupFill[["signup_email_opt_in", "amount"]].groupby(["signup_ema
EmailSum
```

Out[60]:

	amount
signup_email_opt_in	
True	63744.66
False	36791.77

In [61]:
```
EmailSum["amount"].sort_values(ascending=True).plot.bar()
plt.ylabel("Total Donation Amount")
plt.xlabel("Email Opt-in Status")
plt.show()
```

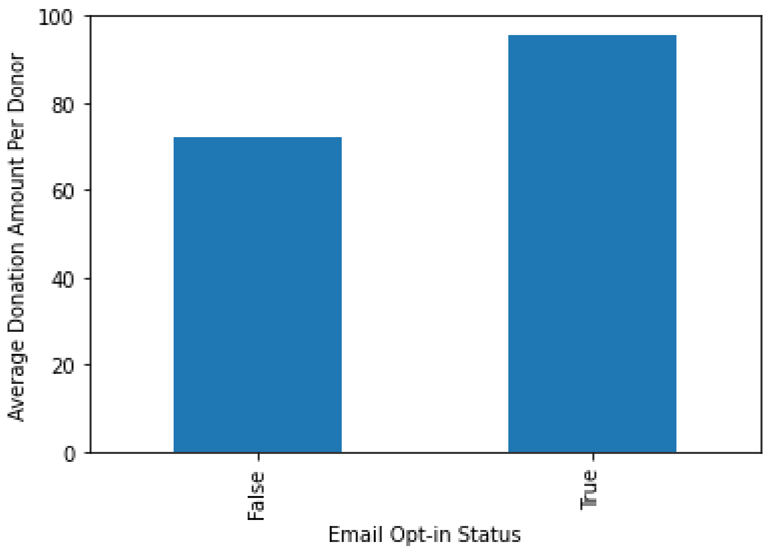


In [62]:
```
EmailAvg = dfDonationsNoDupFill[["signup_email_opt_in", "amount"]].groupby(["signup_ema
EmailAvg
```

Out[62]:

signup_email_opt_in	amount
True	95.283498
False	71.999550

In [63]:
```
EmailAvg["amount"].sort_values(ascending=True).plot.bar()
plt.ylabel("Average Donation Amount Per Donor")
plt.xlabel("Email Opt-in Status")
plt.show()
```



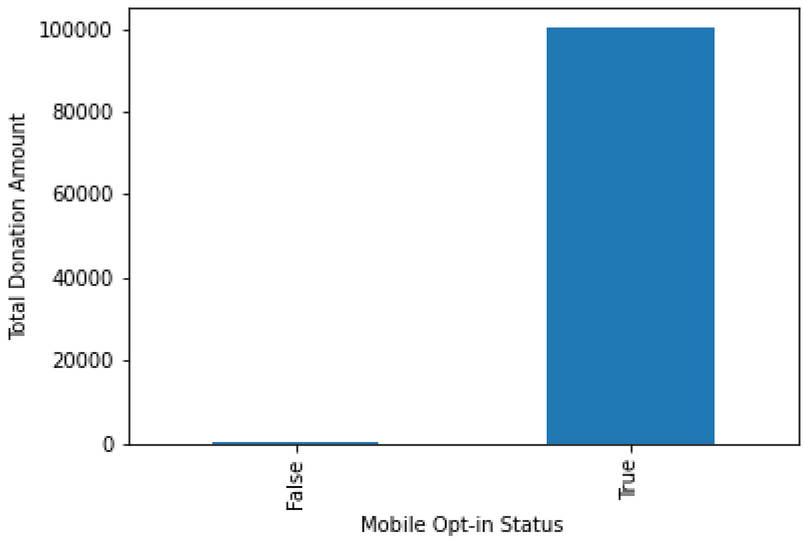
In [64]:
```
MobileSum = dfDonationsNoDupFill[["signup_mobile_opt_in", "amount"]].groupby(["signup_m
MobileSum
```

Out[64]:

signup_mobile_opt_in	amount

signup_mobile_opt_in	amount
True	100061.43
False	475.00

In [65]:
```
MobileSum["amount"].sort_values(ascending=True).plot.bar()
plt.ylabel("Total Donation Amount")
plt.xlabel("Mobile Opt-in Status")
plt.show()
```

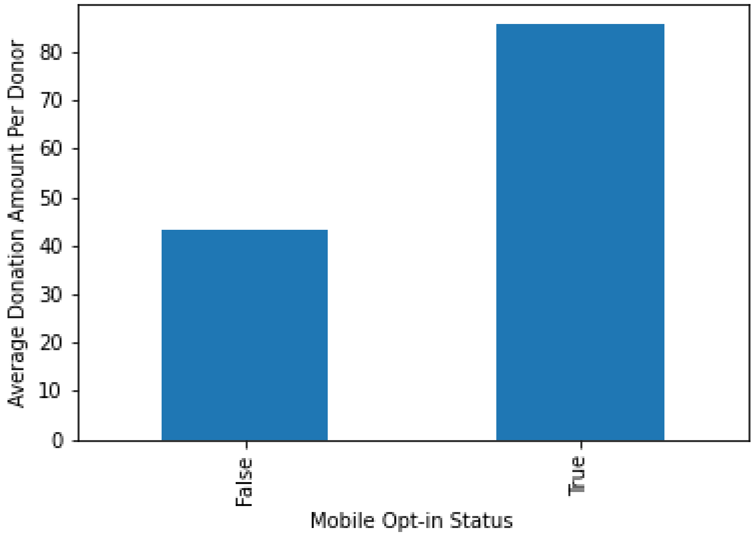


In [66]:
```
MobileAvg = dfDonationsNoDupFill[["signup_mobile_opt_in", "amount"]].groupby(["signup_m
MobileAvg
```

Out[66]:

signup_mobile_opt_in	amount
True	85.595749
False	43.181818

In [67]:
```
MobileAvg["amount"].sort_values(ascending=True).plot.bar()
plt.ylabel("Average Donation Amount Per Donor")
plt.xlabel("Mobile Opt-in Status")
plt.show()
```



Cross-Table

In [68]:
```
dfCrossTable = dfDonationsNoDupFill[["signup_email_opt_in", "signup_mobile_opt_in"]]
dfCrossTable.describe()
```

Out[68]:

	signup_email_opt_in	signup_mobile_opt_in
count	1180	1180
unique	2	2
top	True	True
freq	669	1169

In [69]:
```
a = dfCrossTable["signup_email_opt_in"] == True
b = dfCrossTable["signup_mobile_opt_in"] == True
dfDonorFreq = pd.crosstab(a,b)
dfDonorFreq
```

Out[69]:

signup_mobile_opt_in	False	True
signup_email_opt_in		
False	3	508
True	8	661

In [70]:
```
# Almost every donor chose to have mobile-opt-in.
# Out of a total 1180 unique donors, 1169 donors choose to have mobile opt-in
# Only 11 donors do not have mobile-opt-in

# Meanwhile, email-opt-in is a much more mixed among the donations
# 511 donors do not have email-opt-in
# 669 donors have email-opt-in

# 661 donors have both
# 508 only mobile
# 8 only email
# 3 neither
```

Opt-In Status and Donation Frequency

In [71]:
```
dfDonations.columns
```

Out[71]:
```
Index(['type', 'amount', 'payment_type_name', 'donor_id', 'donation_date',
       'donation_type', 'recurring_donation_status', 'billing_city',
       'billing_state', 'billing_FSA', 'billing_country',
       'billing_country_code', 'signup_email_opt_in', 'signup_mobile_opt_in',
       'signup_point_person_name_or_email', 'signup_tag_list'],
      dtype='object')
```

In [72]:
```
dfDonationFrequency = dfDonations[["signup_mobile_opt_in", "signup_email_opt_in"]]
dfDonationFrequency = dfDonationFrequency.fillna({"signup_email_opt_in":'False', "signu
dfDonationFrequency.describe()
```

Out[72]:

	signup_mobile_opt_in	signup_email_opt_in
count	1594	1594
unique	2	2
top	True	True
freq	1583	1026

In [73]:
```
x = dfDonationFrequency["signup_email_opt_in"] == True
y = dfDonationFrequency["signup_mobile_opt_in"] == True
dfDonationFreq = pd.crosstab(x,y)
dfDonationFreq
```

Out[73]:

signup_mobile_opt_in	False	True
signup_email_opt_in		
False	3	565
True	8	1018

In [74]:
```
# Ratio of amount of donations to the amount of donors for each opt-in status
dfDonationFreq/dfDonorFreq
```

Out[74]:

signup_mobile_opt_in	False	True
signup_email_opt_in		
False	1.0	1.112205
True	1.0	1.540091

Opt-In Findings

In [75]:
```
# From the opt-in status analysis, we have come to a couple conclusions
# First, we discovered that the total donation amount for both email-opt-in and
# mobile-opt-in are higher when the donors have opted in.
# For donors with email-opt-in, the total donation amounted to $63,744.66
# without email-opt-in, the total donation amounted to $36,791.77
# The average donation amount with email-opt-in is $95.28
# The average without email-opt-in is $71.99
```

```
# For donors with mobile-opt-in, the total donation amounted to $100,061.43
# without mobile-opt-in, the total donation amounted to $475
# The average donation amount with mobile-opt-in is $85.60
# The average without mobile-opt-in is $43.18

# From looking at the raw donation amounts and averages, we can see that
# donors who have opted for mobile-opt-in on average donate more, and
# have a higher donation total

# In cell 73, we can see the ratio of the number of donations to the number of donors
# categorized by the opt-in status they choose to have.
# For donors who have both email and mobile opt-in, the ratio of donations to donors is
# For donors who have only mobile but not email, the ratio is 1.11
# All other categories have a 1-to-1 donation to donor ratio.
# This shows that donors who are subscribed to both email and mobile
# donate more frequently on average

# From a managerial perspective, the FBC can make use of this knowledge to plan how the
# wish to promote the organisation with respect to the notification opt-in status.
# While both opt-in options seem to increase the donation amounts, on average and in wh
# mobile-opt-in seems to have a better effect among donors.
# There could be many reasons why FBC's clientele are more responsive with mobile.
# This should be one of the main goals, taking a look into the donor profiles with
# the objective of not donation amounts, but specifically mobile usage.
# Having this question answered, FBC could continue and improve the ways they
# communicate through mobile. As well as discovering ways to increase mobile
# opt-in statuses.
```

Donation Timing

In [76]:

```
# Donation in different months.
dfDonations['donation_month_year'] = pd.to_datetime(dfDonations['donation_date']).dt.to
dfDonations.head(5)
```

Out[76]:

	type	amount	payment_type_name	donor_id	donation_date	donation_typ
nationbuilder_id						
1	Donation	125.0	Credit Card	541	1/8/2020 12:41	Na
10	Donation	25.0	Credit Card	5509	5/11/2020 22:10	annual_membership_fe
100	Donation	15.0	Credit Card	6039	6/1/2020 16:53	general_donatio
1000	Donation	15.0	Credit Card	7233	6/11/2020 17:30	general_donatio
1001	Donation	100.0	Credit Card	7234	6/11/2020 17:38	general_donatio

In [77]:

```
groupDate = dfDonations.groupby("donation_month_year")
DonationDate = groupDate.count()
DonationDate.sort_values(by="donor_id", ascending=False)
```

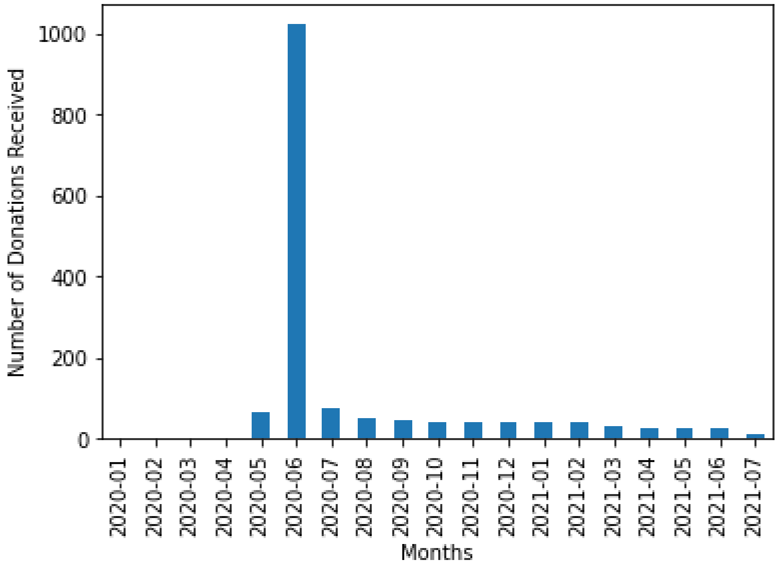
Out[77]:

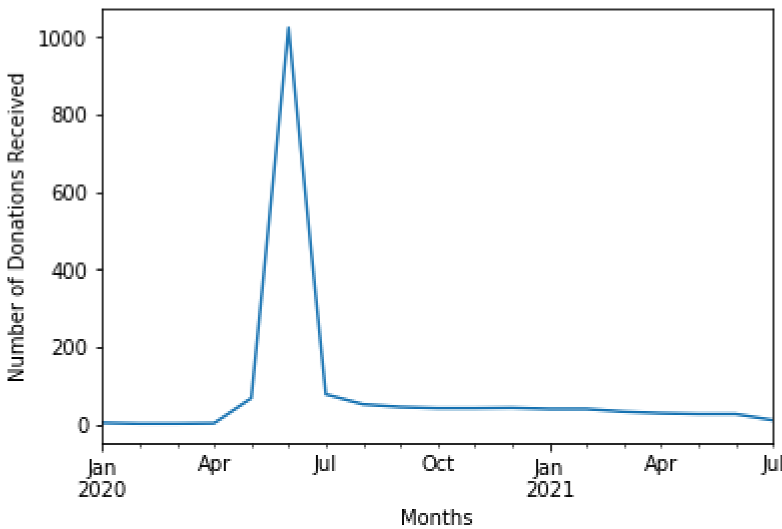
type	amount	payment_type_name	donor_id	donation_date	donation_type	recu

donation_month_year	type	amount	payment_type_name	donor_id	donation_date	donation_type	recu
donation_month_year							
2020-06	1024	1024	1024	1024	1024	1024	
2020-07	77	77	77	77	77	77	
2020-05	67	67	67	67	67	67	
2020-08	51	51	51	51	51	51	
2020-09	44	44	44	44	44	44	
2020-12	42	42	42	42	42	42	
2020-10	41	41	41	41	41	41	
2020-11	41	41	41	41	41	41	
2021-01	39	39	39	39	39	39	
2021-02	39	39	39	39	39	39	
2021-03	32	32	32	32	32	32	
2021-04	28	28	28	28	28	28	
2021-06	26	26	26	26	26	26	
2021-05	26	26	26	26	26	26	
2021-07	10	10	10	10	10	10	
2020-01	3	3	3	3	3	2	
2020-04	2	2	2	2	2	2	
2020-02	1	1	1	1	1	1	
2020-03	1	1	1	1	1	1	

In [78]:

```
DonationDate["type"].plot.bar()
plt.xlabel("Months")
plt.ylabel("Number of Donations Received")
plt.show()

DonationDate["type"].plot.line()
plt.xlabel("Months")
plt.ylabel("Number of Donations Received")
plt.show()
```





In [79]:
```
groupDate["amount"].describe()
```

Out[79]:

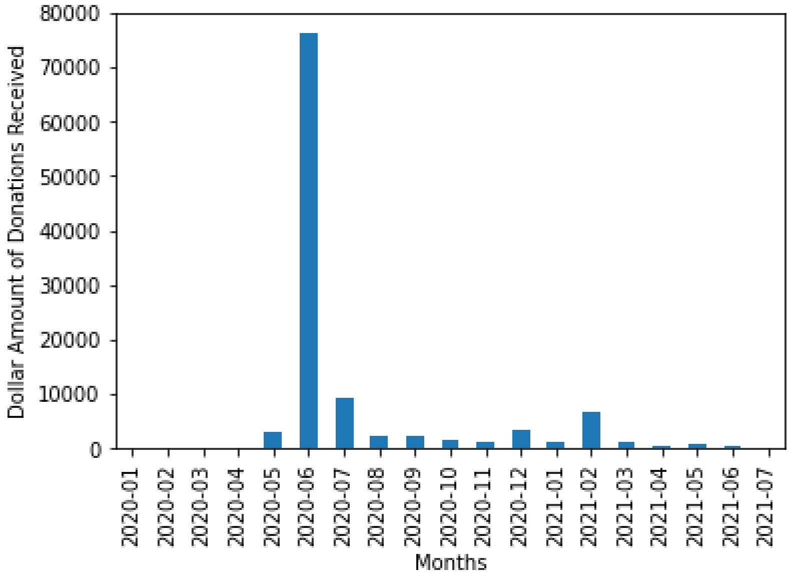
donation_month_year	count	mean	std	min	25%	50%	75%	max
2020-01	3.0	66.666667	52.041650	25.0	37.5	50.00	87.50	125.0
2020-02	1.0	25.000000	NaN	25.0	25.0	25.00	25.00	25.0
2020-03	1.0	25.000000	NaN	25.0	25.0	25.00	25.00	25.0
2020-04	2.0	25.000000	0.000000	25.0	25.0	25.00	25.00	25.0
2020-05	67.0	46.507463	38.344283	5.0	25.0	25.00	50.00	250.0
2020-06	1024.0	74.444365	186.813261	0.5	25.0	40.00	75.35	3500.0
2020-07	77.0	119.263766	333.906767	3.0	15.0	25.00	50.00	2000.0
2020-08	51.0	43.670392	71.284340	3.0	10.0	25.00	27.50	400.0
2020-09	44.0	54.159091	147.742539	3.0	10.0	25.00	25.00	980.0
2020-10	41.0	41.170732	123.241410	3.0	10.0	25.00	25.00	800.0

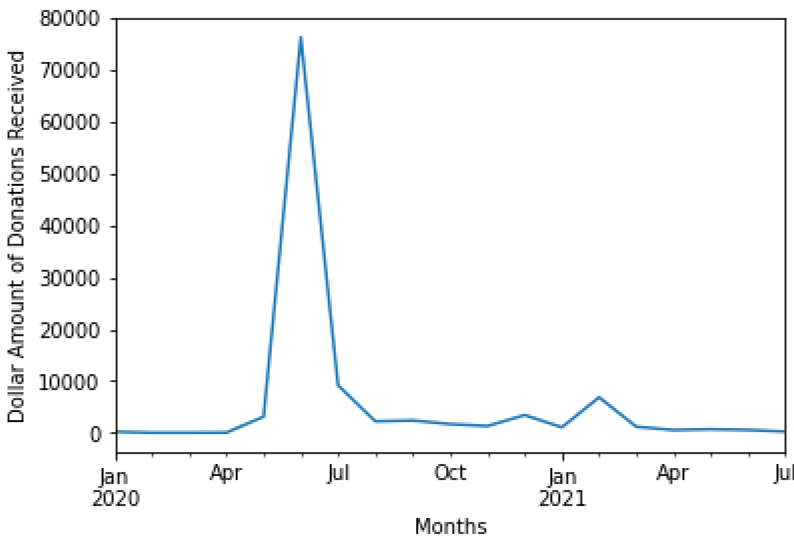
	count	mean	std	min	25%	50%	75%	max
donation_month_year								
2020-11	41.0	32.073171	48.968556	3.0	10.0	25.00	25.00	290.0
2020-12	42.0	81.654762	198.839023	3.0	10.0	25.00	50.00	1000.0
2021-01	39.0	27.512821	27.571793	3.0	10.0	25.00	25.00	100.0
2021-02	39.0	175.769231	808.395339	2.0	10.0	25.00	25.00	5000.0
2021-03	32.0	36.812500	86.689821	3.0	10.0	25.00	25.00	500.0
2021-04	28.0	19.375000	17.928162	3.0	10.0	19.75	25.00	100.0
2021-05	26.0	26.269231	30.930319	3.0	10.0	22.50	25.00	120.0
2021-06	26.0	21.461538	19.192146	3.0	10.0	25.00	25.00	100.0
2021-07	10.0	23.800000	28.224497	3.0	10.0	17.50	25.00	100.0

In [80]:
```
MonthlyAmt = groupDate["amount"].sum()
MonthlyAmt
```

Out[80]:
```
donation_month_year
2020-01      200.00
2020-02       25.00
2020-03       25.00
2020-04       50.00
2020-05     3116.00
2020-06    76231.03
2020-07     9183.31
2020-08     2227.19
2020-09     2383.00
2020-10     1688.00
2020-11     1315.00
2020-12     3429.50
2021-01     1073.00
2021-02     6855.00
2021-03     1178.00
2021-04      542.50
2021-05      683.00
2021-06      558.00
2021-07      238.00
Freq: M, Name: amount, dtype: float64
```

In [81]:
```
MonthlyAmt.plot.bar()
plt.xlabel("Months")
plt.ylabel("Dollar Amount of Donations Received")
plt.show()

MonthlyAmt.plot.line()
plt.xlabel("Months")
plt.ylabel("Dollar Amount of Donations Received")
plt.show()
```





In [82]:
```
# What we can spot is in July 2020, the number of donations we received are significant
# significantly higher as well. We need to investigate how the occurance of certain soc
# more one-time donors through these events and to convert those one-time donors into r
# has received similar numbers of donations but the dollar amount received in those mon
```

Correlations

In [83]:
```
# Are there any sign up factors that can predict a high donation amount?
# From the data, a donor's donation type, recurring status, and opt-in status are recor
# This section will investigate the relationship between these factors and the value of
# We will look to assign a coefficient value for the factors, and look to create a elem
```

In [84]:
```
dfFactors = dfDonations[['amount', 'donation_type', 'recurring_donation_status', 'signu
dfFactors
```

Out[84]:

	amount	donation_type	recurring_donation_status	signup_email_opt_in	signup_
nationbuilder_id					
1	125.00	NaN	NaN	True	
10	25.00	annual_membership_fee	NaN	True	

nationbuilder_id	amount	donation_type	recurring_donation_status	signup_email_opt_in	signup_
100	15.00	general_donation	NaN	NaN	
1000	15.00	general_donation	NaN	NaN	
1001	100.00	general_donation	NaN	True	
...	...	...	...	...	
995	25.00	annual_membership_fee	NaN	True	
996	74.15	general_donation	NaN	NaN	
997	500.00	general_donation	NaN	True	
998	25.00	general_donation	NaN	NaN	
999	50.00	general_donation	NaN	True	

1594 rows × 5 columns

In [85]:
```
# We notice that all donation categorised as “annual_membership_fee" are $25
# The annual membership fees for everyone is $25, with the exception of one person
# The membership fees are likely set in stone and not subject to change from the factor
# Thus we can remove these entries from the dataframe to increase accuracy of our model

dfFactors[(dfFactors["donation_type"] == "annual_membership_fee")]
```

Out[85]:

nationbuilder_id	amount	donation_type	recurring_donation_status	signup_email_opt_in	signup_
10	25.0	annual_membership_fee	NaN	True	
1006	25.0	annual_membership_fee	canceled	True	
1062	25.0	annual_membership_fee	NaN	True	
1081	25.0	annual_membership_fee	NaN	True	
1082	25.0	annual_membership_fee	NaN	True	
11	25.0	annual_membership_fee	NaN	True	
1174	25.0	annual_membership_fee	canceled	True	
12	25.0	annual_membership_fee	NaN	True	
1244	25.0	annual_membership_fee	canceled	True	
13	25.0	annual_membership_fee	canceled	True	
1309	25.0	annual_membership_fee	NaN	True	
1353	25.0	annual_membership_fee	NaN	True	
1372	25.0	annual_membership_fee	NaN	True	
1392	25.0	annual_membership_fee	NaN	True	
14	50.0	annual_membership_fee	NaN	True	

	amount	donation_type	recurring_donation_status	signup_email_opt_in	signup_
nationbuilder_id					
1422	50.0	annual_membership_fee	NaN	True	
1473	25.0	annual_membership_fee	NaN	True	
1475	25.0	annual_membership_fee	NaN	True	
1485	25.0	annual_membership_fee	NaN	True	
1577	25.0	annual_membership_fee	NaN	True	
16	25.0	annual_membership_fee	NaN	True	
1633	25.0	annual_membership_fee	NaN	True	
17	25.0	annual_membership_fee	NaN	True	
819	25.0	annual_membership_fee	NaN	True	
870	25.0	annual_membership_fee	NaN	True	
932	100.0	annual_membership_fee	NaN	NaN	
995	25.0	annual_membership_fee	NaN	True	

In [86]:
```
dfFactors = dfFactors[(dfFactors["donation_type"] != "annual_membership_fee")]
dfFactors["donation_type"].unique()
```

Out[86]:
```
array([nan, 'general_donation'], dtype=object)
```

In [87]:
```
dfFactors[(dfFactors["donation_type"].isna())]
```

Out[87]:

	amount	donation_type	recurring_donation_status	signup_email_opt_in	signup_mobile_
nationbuilder_id					
1	125.0	NaN	NaN	True	

In [88]:
```
# There is one entry where the donation type is no categorized as either annual members
# nor general donation
# We will be removing this from the analysis and only look at general donation
# for both simplicity and as to not skew the analysis

dfFactors[(dfFactors["donation_type"].isna())]
dfFactors = dfFactors[(dfFactors["donation_type"] == "general_donation")]
dfFactors.describe()
```

Out[88]:

	amount
count	1566.000000
mean	70.290888
std	217.492057
min	0.500000

	amount
25%	25.000000
50%	25.000000
75%	50.000000
max	5000.000000

In [89]:

```
dfFactors[(dfFactors["recurring_donation_status"].isna())]
```

Out[89]:

	amount	donation_type	recurring_donation_status	signup_email_opt_in	signup_mobil
nationbuilder_id					
100	15.00	general_donation	NaN	NaN	
1000	15.00	general_donation	NaN	NaN	
1001	100.00	general_donation	NaN	True	
1002	1000.00	general_donation	NaN	NaN	
1003	25.00	general_donation	NaN	True	
...	...	...	...	...	
994	100.00	general_donation	NaN	True	
996	74.15	general_donation	NaN	NaN	
997	500.00	general_donation	NaN	True	
998	25.00	general_donation	NaN	NaN	
999	50.00	general_donation	NaN	True	

1157 rows × 5 columns

In [90]:

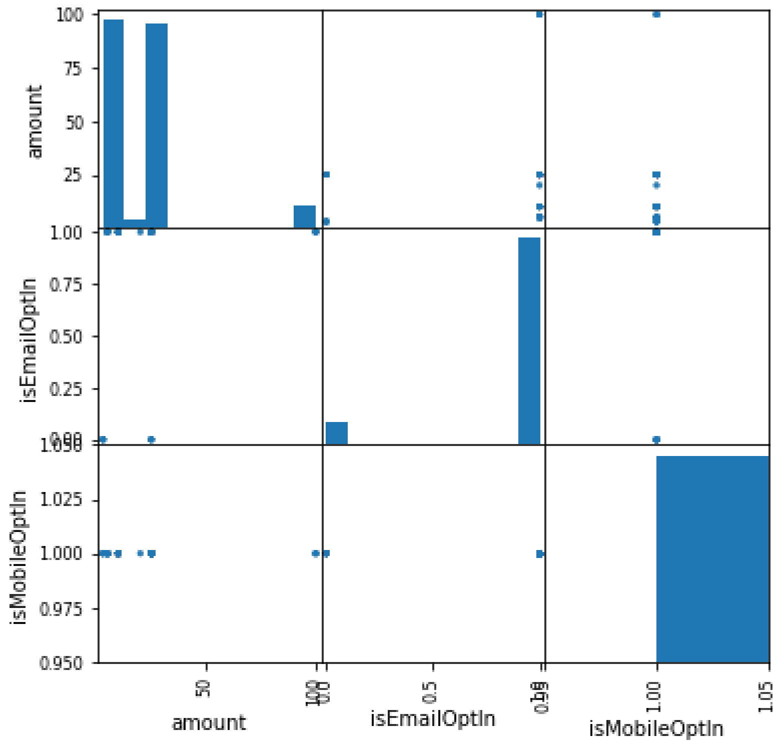
```
# dfFactors isolates the donation amount and the factors that we are taking a look at.
# Below, we have converted the factors, that contain a variety of values into a binary
# For factors that are "true" and "false", such as "signup_email_opt_in", we can easily
# For factors with more than one unique value, such as recurring donation status and do
# specifically look at the status of one unique value in the column.

# All columns have been checked and corrected for the proper unqiue values
dfFactors.loc[:, 'isEmailOptIn'] = np.where(dfFactors['signup_email_opt_in'] == True, 1
dfFactors.loc[:, 'isMobileOptIn'] = np.where(dfFactors['signup_mobile_opt_in'] == True,
```

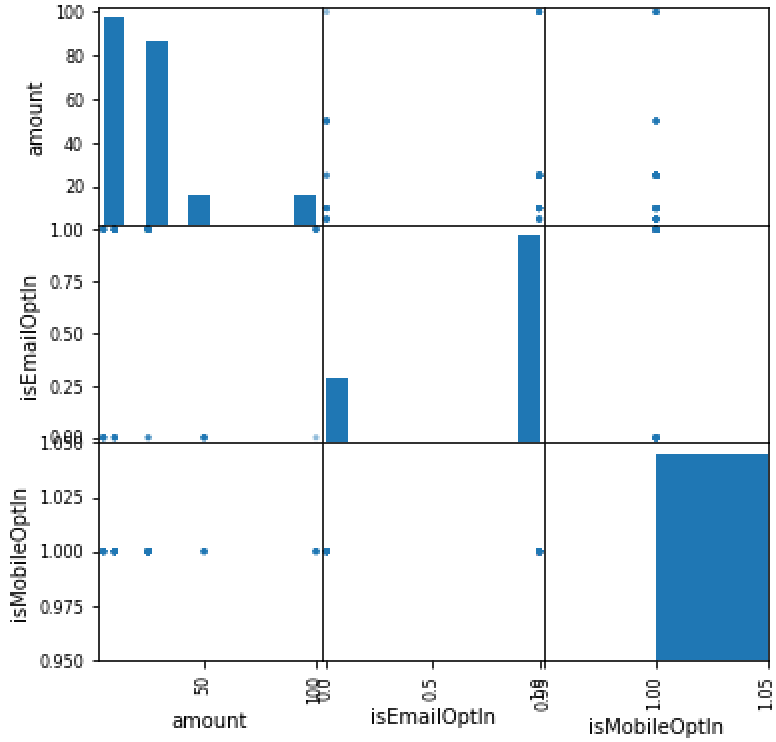
In [91]:

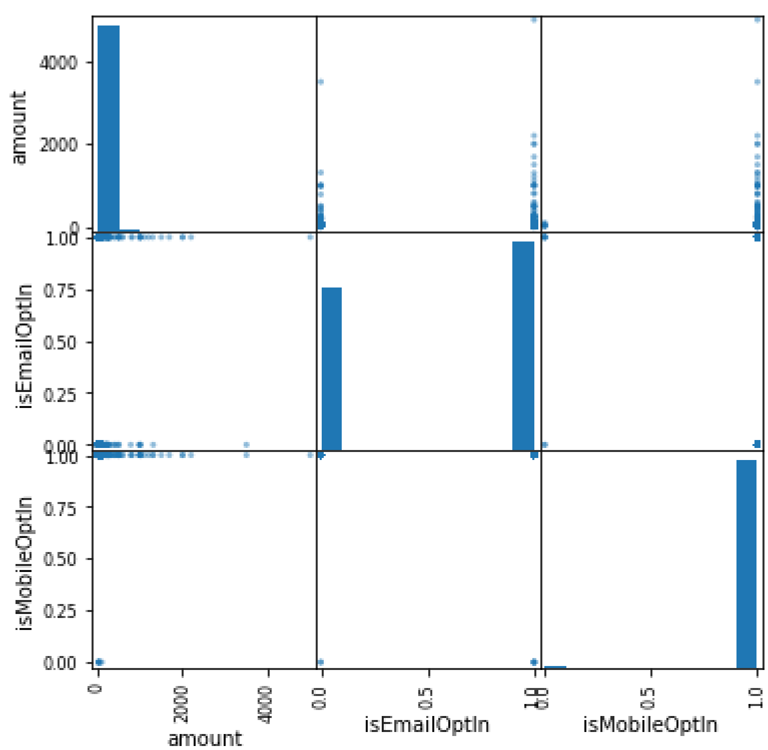
```
# Seperating the donation into three categories between
# recurring donor status
# canceled but previously recurring donors
# donors who are not and never were recurring

# This will allow us to better understand which factors are important
# between donors who have recurring status or not
dfFactorsRec = dfFactors[["amount", "isEmailOptIn", "isMobileOptIn"]][(dfFactors["recur
dfFactorsCan = dfFactors[["amount", "isEmailOptIn", "isMobileOptIn"]][(dfFactors["recur
dfFactorsNonRec = dfFactors[["amount", "isEmailOptIn", "isMobileOptIn"]][(dfFactors["re
```

In [92]:
```
pd.plotting.scatter_matrix(dfFactorsRec, figsize=(6,6))
pd.plotting.scatter_matrix(dfFactorsCan, figsize=(6,6))
pd.plotting.scatter_matrix(dfFactorsNonRec, figsize=(6,6))
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/pandas/plotting/_matplotlib/misc.py:80: UserWarni
ng: Attempting to set identical left == right == 1.0 results in singular transformation
s; automatically expanding.
  ax.set_xlim(boundaries_list[j])
/usr/local/lib/python3.7/dist-packages/pandas/plotting/_matplotlib/misc.py:81: UserWarni
ng: Attempting to set identical bottom == top == 1.0 results in singular transformation
s; automatically expanding.
  ax.set_ylim(boundaries_list[i])
/usr/local/lib/python3.7/dist-packages/pandas/plotting/_matplotlib/misc.py:71: UserWarni
ng: Attempting to set identical left == right == 1.0 results in singular transformation
s; automatically expanding.
  ax.set_xlim(boundaries_list[i])
```







In [93]:
```
dfCorrelationRec = dfFactorsRec.corr('kendall')
dfCorrelationRec
```

Out[93]:

	amount	isEmailOptIn	isMobileOptIn
amount	1.000000	0.158706	NaN
isEmailOptIn	0.158706	1.000000	NaN
isMobileOptIn	NaN	NaN	1.0

In [94]:
```
dfCorrelationCan = dfFactorsCan.corr('kendall')
dfCorrelationCan
```

Out[94]:

	amount	isEmailOptIn	isMobileOptIn
amount	1.000000	0.081931	NaN
isEmailOptIn	0.081931	1.000000	NaN
isMobileOptIn	NaN	NaN	1.0

In [95]:
```
dfCorrelationNonRec = dfFactorsNonRec.corr('kendall')
dfCorrelationNonRec
```

Out[95]:

	amount	isEmailOptIn	isMobileOptIn
amount	1.000000	0.054689	0.008752
isEmailOptIn	0.054689	1.000000	-0.024108
isMobileOptIn	0.008752	-0.024108	1.000000

In [96]:
```
# From the correlation tables, we see that mobile-opt-in is not a factor
# for consideration when talking about recurring or canceled donors
# There is however a positive correlation between donors who have email-opt-in and the

# For non-recurring donors, it is shown that the is a small but positive correlation be
# as well as email-opt-in and donation amount.
# Surprsingly, there is a small negative correlation among non-recurring donors between
# This means that there is a trend among the non-recurring population of having either
```

Recurring Donation Linear Regression

In [97]:
```
# Variables involved for prediction
dfX = dfFactorsRec[['isEmailOptIn', 'isMobileOptIn']]

# Variable to predict
dfY = dfFactorsRec['amount']

# Break the data
X_train, X_test, Y_train, Y_test = train_test_split(dfX, dfY, test_size=0.4, random_sta

# Create linear regression object
linearRegression = LinearRegression()

# Fit data
linearRegression.fit(X_train, Y_train)
```

Out[97]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [98]:
```
# Print the intercepts
linearRegression.intercept_
```

Out[98]:
```
11.799999999999997
```

In [99]:
```
# Coefficients
linearRegression.coef_
```

Out[99]:
```
array([9.01168831, 0.        ])
```

In [100…
```
# Table with coefficients
pd.DataFrame(linearRegression.coef_, dfX.columns, ['Regression Coeffs'])
```

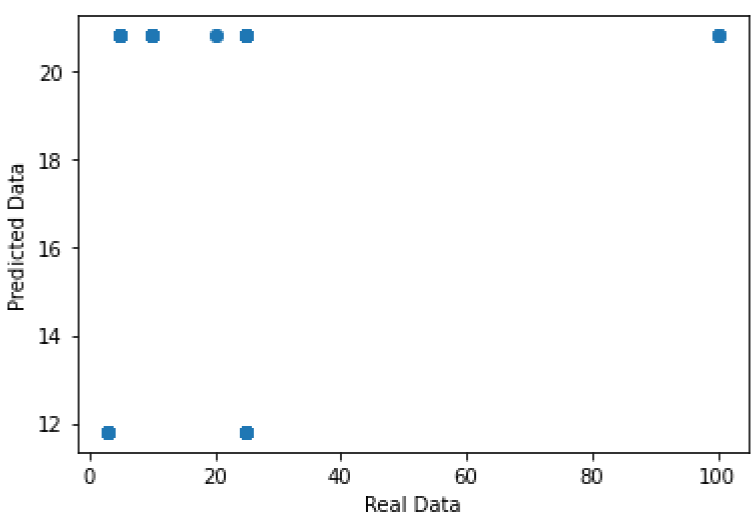
Out[100…

	Regression Coeffs
isEmailOptIn	9.011688
isMobileOptIn	0.000000

In [101…
```
# Prediction table
Y_predicted = linearRegression.predict(X_test)
Y_predicted
```

Out[101…
```
array([20.81168831, 20.81168831, 20.81168831, 20.81168831, 20.81168831,
       20.81168831, 20.81168831, 20.81168831, 20.81168831, 20.81168831,
       20.81168831, 20.81168831, 11.8       , 11.8       , 20.81168831,
       20.81168831, 11.8       , 20.81168831, 20.81168831, 20.81168831,
       11.8       , 20.81168831, 11.8       , 20.81168831, 20.81168831,
       20.81168831, 20.81168831, 20.81168831, 20.81168831, 20.81168831,
       11.8       , 20.81168831, 20.81168831, 11.8       , 20.81168831,
       20.81168831, 20.81168831, 20.81168831, 20.81168831, 20.81168831,
       20.81168831, 20.81168831, 20.81168831, 11.8       , 11.8       ,
       20.81168831, 20.81168831, 20.81168831, 20.81168831, 20.81168831,
       11.8       , 20.81168831, 20.81168831, 20.81168831, 11.8       ,
       20.81168831, 20.81168831, 20.81168831, 20.81168831, 20.81168831,
       20.81168831, 20.81168831, 20.81168831, 20.81168831, 20.81168831,
       20.81168831, 20.81168831, 20.81168831, 20.81168831, 20.81168831,
       20.81168831, 20.81168831, 20.81168831, 20.81168831, 20.81168831,
       20.81168831, 20.81168831, 20.81168831, 20.81168831, 20.81168831,
       20.81168831, 20.81168831, 20.81168831, 20.81168831, 20.81168831,
       20.81168831, 20.81168831, 20.81168831, 11.8       , 20.81168831,
       20.81168831, 20.81168831, 20.81168831, 20.81168831, 11.8       ,
       20.81168831, 20.81168831, 20.81168831, 11.8       , 20.81168831,
       20.81168831, 20.81168831, 11.8       , 20.81168831, 20.81168831,
       11.8       , 11.8       , 20.81168831, 20.81168831, 20.81168831])
```

In [102…
```
# Scatter plot for predicted and real values
plt.scatter(Y_test, Y_predicted)
plt.xlabel('Real Data')
plt.ylabel('Predicted Data')

plt.show()
```



In [103…
```
# Due to the fact that mobile-opt in has no correlation with the donation amount, the m
# essentaully is a binary predictor with whether or not the donor has email opt-in
# It attributes a coefficient of 9.01 with email-opt-in
# Meaning any donation amount that has an email-opt-in is 9.01 times higher than withou
```

In [104…
```
# Accuracy
linearRegression.score(X_test, Y_test)
```

Out[104…
```
0.011978370810257877
```

Canceled Donors Linear Regression

In [105…
```
# Variables involved for prediction
dfX = dfFactorsCan[['isEmailOptIn', 'isMobileOptIn']]

# Variable to predict
dfY = dfFactorsCan['amount']

# Break the data
X_train, X_test, Y_train, Y_test = train_test_split(dfX, dfY, test_size=0.4, random_sta

# Create linear regression object
linearRegression = LinearRegression()

# Fit data
linearRegression.fit(X_train, Y_train)
```

Out[105…
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [106…
```
# Print the intercepts
linearRegression.intercept_
```

Out[106…
```
22.272727272727273
```

In [107…
```
# Coefficients
linearRegression.coef_
```

Out[107…
```
array([4.59167951, 0.        ])
```

In [108…
```
# Table with coefficients
pd.DataFrame(linearRegression.coef_, dfX.columns, ['Regression Coeffs'])
```

Out[108…

	Regression Coeffs
isEmailOptIn	4.59168
isMobileOptIn	0.00000

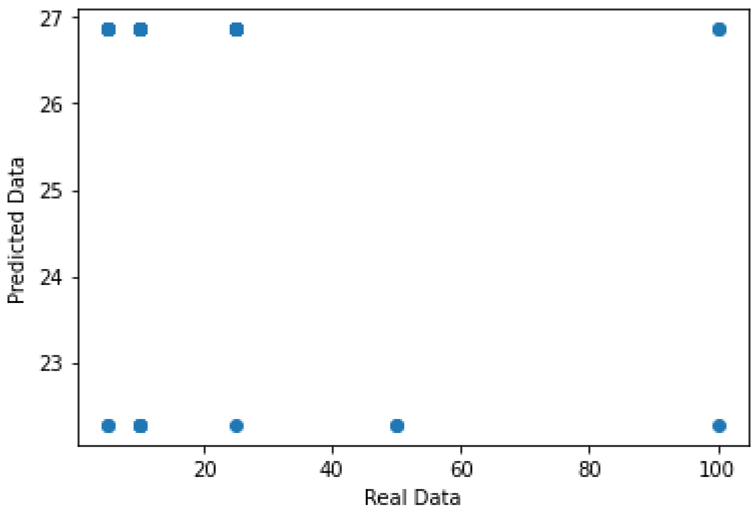
In [109…
```
# Prediction table
Y_predicted = linearRegression.predict(X_test)
Y_predicted
```

Out[109…
```
array([26.86440678, 22.27272727, 26.86440678, 26.86440678, 26.86440678,
       26.86440678, 26.86440678, 26.86440678, 26.86440678, 26.86440678,
       22.27272727, 26.86440678, 26.86440678, 22.27272727, 26.86440678,
       26.86440678, 26.86440678, 26.86440678, 22.27272727, 26.86440678,
```

```
26.86440678, 26.86440678, 26.86440678, 26.86440678, 22.27272727,
22.27272727, 26.86440678, 26.86440678, 26.86440678, 26.86440678,
26.86440678, 22.27272727, 26.86440678, 26.86440678, 26.86440678,
22.27272727, 26.86440678, 22.27272727, 26.86440678, 26.86440678,
26.86440678, 26.86440678, 26.86440678, 26.86440678, 26.86440678,
26.86440678, 26.86440678, 26.86440678, 26.86440678, 22.27272727,
26.86440678, 26.86440678, 26.86440678, 26.86440678])
```

In [110…

```
# Scatter plot for predicted and real values
plt.scatter(Y_test, Y_predicted)
plt.xlabel('Real Data')
plt.ylabel('Predicted Data')

plt.show()
```



In [111…

```
# Similar to the recurring donations model,
# Due to the fact that mobile-opt in has no correlation with the donation amount, the m
# essentailly is a binary predictor with whether or not the donor has email opt-in
# It attributes a coefficient of 9.01 with email-opt-in
# Meaning any donation amount that has an email-opt-in is 9.01 times higher than withou
```

In [112…

```
# Accuracy
linearRegression.score(X_test, Y_test)
```

Out[112…

```
-0.0706808425080161
```

Non_Recurring Donors Linear Regression

In [113…

```
# Variables involved for prediction
dfX = dfFactorsNonRec[['isEmailOptIn', 'isMobileOptIn']]

# Variable to predict
dfY = dfFactorsNonRec['amount']

# Break the data
X_train, X_test, Y_train, Y_test = train_test_split(dfX, dfY, test_size=0.4, random_sta

# Create linear regression object
linearRegression = LinearRegression()

# Fit data
linearRegression.fit(X_train, Y_train)
```

Out[113…
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [114…
```
# Print the intercepts
linearRegression.intercept_
```

Out[114…
```
4.576837192060083
```

In [115…
```
# Coefficients
linearRegression.coef_
```

Out[115…
```
array([32.92316281, 79.14854497])
```

In [116…
```
# Table with coefficients
pd.DataFrame(linearRegression.coef_, dfX.columns, ['Regression Coeffs'])
```

Out[116…

	Regression Coeffs
isEmailOptIn	32.923163
isMobileOptIn	79.148545

In [117…
```
# Prediction table
Y_predicted = linearRegression.predict(X_test)
Y_predicted
```

Out[117…
```
array([116.64854497, 116.64854497,  83.72538217,  83.72538217,
       116.64854497, 116.64854497, 116.64854497,  83.72538217,
       116.64854497, 116.64854497,  83.72538217, 116.64854497,
       116.64854497,  83.72538217,  83.72538217, 116.64854497,
        83.72538217,  83.72538217, 116.64854497, 116.64854497,
       116.64854497, 116.64854497,  83.72538217,  83.72538217,
       116.64854497,  83.72538217,  83.72538217, 116.64854497,
       116.64854497,  83.72538217, 116.64854497,  83.72538217,
        37.5       ,  83.72538217,  83.72538217, 116.64854497,
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       116.64854497, 116.64854497, 116.64854497,  83.72538217,
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       116.64854497,  83.72538217, 116.64854497, 116.64854497,
        83.72538217,  83.72538217, 116.64854497, 116.64854497,
        83.72538217,  83.72538217, 116.64854497, 116.64854497,
        83.72538217,  83.72538217,  83.72538217,  83.72538217,
       116.64854497, 116.64854497, 116.64854497])
```
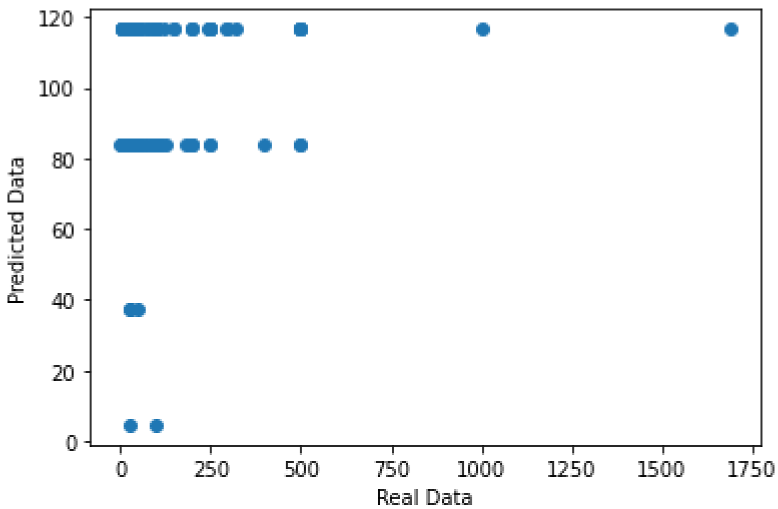

In [118…

```
# Scatter plot for predicted and real values
plt.scatter(Y_test, Y_predicted)
plt.xlabel('Real Data')
plt.ylabel('Predicted Data')

plt.show()
```



In [119…

```
# The linear model with the non-recurring donations has a correlation with both email a
# The results predicted is visualized above.
# The coefficients associated with this model has email-opt-in at 32.93
# and mobile-opt-in at 79.15
```

In [120…

```
# Accuracy
linearRegression.score(X_test, Y_test)
```

Out[120…

```
-0.09215286394706945
```

Linear Regression Conclusions

In [121…

```
# The efficacy of a linear model is rather low is this senario
# There are limited factors that could be quantifiable, and even the quantifiable
# factors end up being discrete.
# In two of the models, one of the factors did not have a correlation at all with
# target factor, thus simplifying the linear model into a single factor model
# The accuracy for each model is rather low.

# The predictions, while within the range of the actual donation values, are rather
```

```
# simplistic in variaety. We can see the same numbers being predicted over and over
# Although, the model does a good job of showing one trend. That is, non-recurring
# donations are generally higher value than recurring donations, or donors who have can
# their recurring status.

# One pattern emerged among the correlations
# For non-recurring donors, there is a small tendency to choose either email-opt-in
# or mobile-opt-in, not both. Perhaps management could make use of this fact to
# further promote their relationship among non-recurring donors.
# By lowering or increasing the frequency of news, notifications, and updates
# while limiting the method of communication to whichever source the donors prefer.

# From a managerial standpoint, the use of a linear model is not feasible.
# There is little need to predict the donation amounts, when elementary analysis
# can already show the trends among donations.
# More complex models such as clustering or trees could draw more relationships
# between factors such as donation time.
# These will be explored further down the analysis.
```

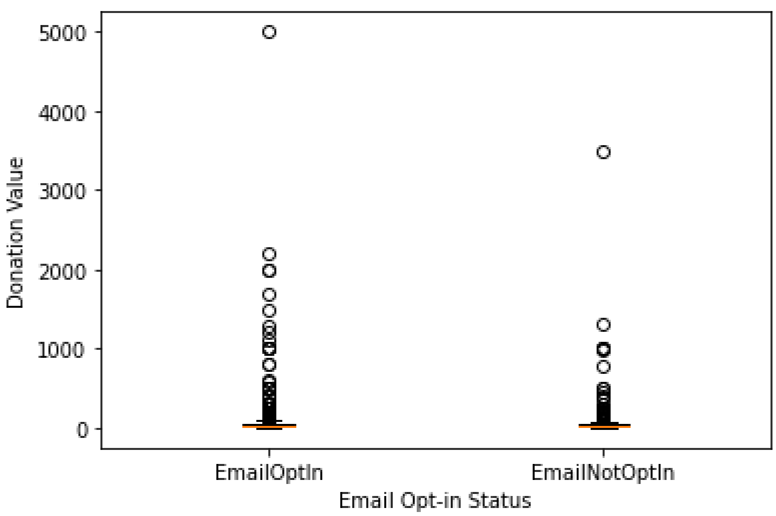
Correlation Opt-in & Value

Email

In [122…

```
dfEmailOptIn = dfFactors[ (dfFactors["isEmailOptIn"] == 1) ]
dfEmailNotOptIn = dfFactors[ (dfFactors["isEmailOptIn"] == 0) ]
data = [dfEmailOptIn["amount"], dfEmailNotOptIn["amount"]]
plt.boxplot(data, labels=["EmailOptIn", "EmailNotOptIn"])
plt.xlabel("Email Opt-in Status")
plt.ylabel("Donation Value")
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/numpy/core/_asarray.py:83: VisibleDeprecationWarn
ing: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists
-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to
do this, you must specify 'dtype=object' when creating the ndarray
  return array(a, dtype, copy=False, order=order)
```



In [123…

```
dfEmailOptIn.describe()
```

Out[123…

	amount	isEmailOptIn	isMobileOptIn

	amount	isEmailOptIn	isMobileOptIn
count	999.000000	999.0	999.000000
mean	72.136897	1.0	0.994995
std	234.168726	0.0	0.070604
min	0.500000	1.0	0.000000
25%	20.000000	1.0	1.000000
50%	25.000000	1.0	1.000000
75%	50.000000	1.0	1.000000
max	5000.000000	1.0	1.000000

In [124…

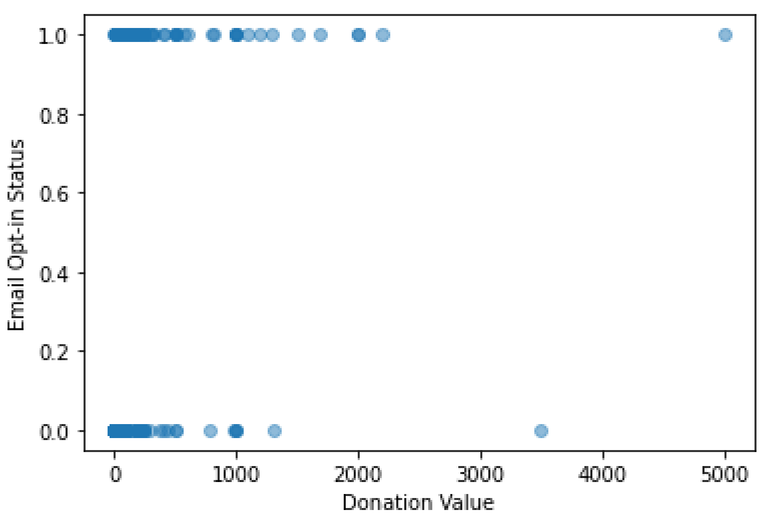
```
dfEmailNotOptIn.describe()
```

Out[124…

	amount	isEmailOptIn	isMobileOptIn
count	567.000000	567.0	567.000000
mean	67.038395	0.0	0.996473
std	184.630993	0.0	0.059339
min	0.500000	0.0	0.000000
25%	25.000000	0.0	1.000000
50%	25.000000	0.0	1.000000
75%	50.000000	0.0	1.000000
max	3500.000000	0.0	1.000000

In [125…

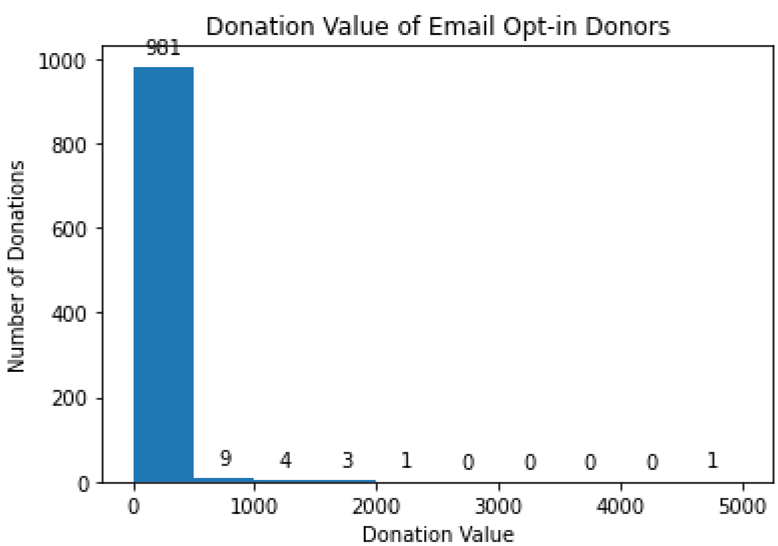
```
plt.scatter(dfFactors["amount"], dfFactors["isEmailOptIn"], alpha=0.5)
plt.xlabel("Donation Value")
plt.ylabel("Email Opt-in Status")
plt.show()
```

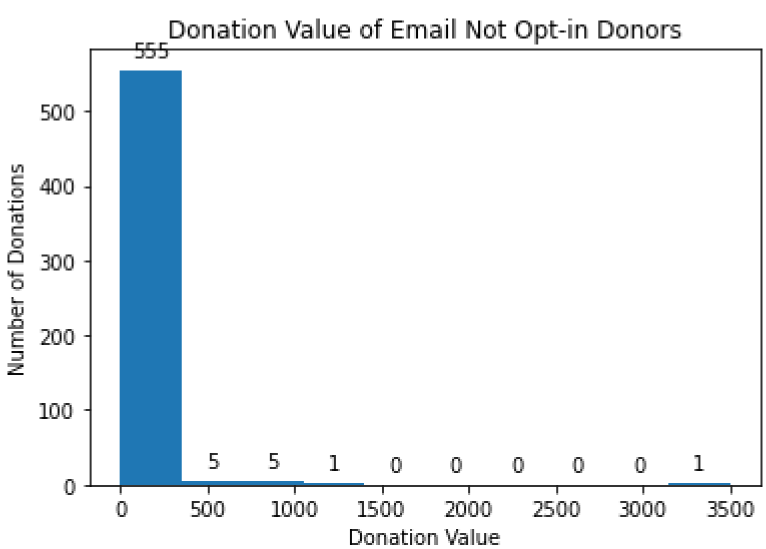


In [126…

```
fig, ax = plt.subplots()
```

```
ax.hist(dfEmailOptIn["amount"], density=False)

for rect in ax.patches:
    height = rect.get_height()
    ax.annotate(f'{int(height)}', xy=(rect.get_x()+rect.get_width()/2, height),
                xytext=(0, 5), textcoords='offset points', ha='center', va='bottom')
plt.xlabel("Donation Value")
plt.ylabel("Number of Donations")
plt.title("Donation Value of Email Opt-in Donors")
plt.show()


fig, ax = plt.subplots()
ax.hist(dfEmailNotOptIn["amount"], density=False)

for rect in ax.patches:
    height = rect.get_height()
    ax.annotate(f'{int(height)}', xy=(rect.get_x()+rect.get_width()/2, height),
                xytext=(0, 5), textcoords='offset points', ha='center', va='bottom')
plt.xlabel("Donation Value")
plt.ylabel("Number of Donations")
plt.title("Donation Value of Email Not Opt-in Donors")
plt.show()
```



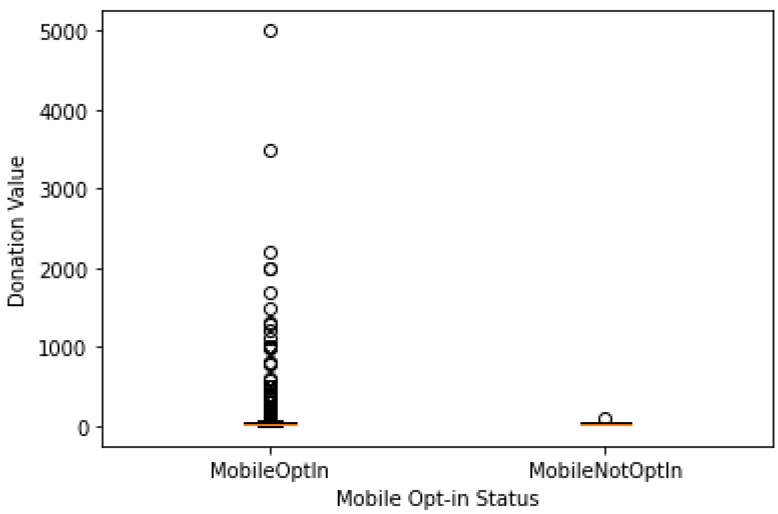


Mobile

In [127…

```
dfMobileOptIn = dfFactors[ (dfFactors["isMobileOptIn"] == 1) ]
dfMobileNotOptIn = dfFactors[ (dfFactors["isMobileOptIn"] == 0) ]
data = [dfMobileOptIn["amount"], dfMobileNotOptIn["amount"]]
plt.boxplot(data, labels=["MobileOptIn", "MobileNotOptIn"])
plt.xlabel("Mobile Opt-in Status")
plt.ylabel("Donation Value")
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/numpy/core/_asarray.py:83: VisibleDeprecationWarn
ing: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists
-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to
do this, you must specify 'dtype=object' when creating the ndarray
  return array(a, dtype, copy=False, order=order)
```



In [128…

```
dfMobileOptIn.describe()
```

Out[128…

	amount	isEmailOptIn	isMobileOptIn
count	1559.000000	1559.000000	1559.0
mean	70.414067	0.637588	1.0
std	217.965472	0.480851	0.0
min	0.500000	0.000000	1.0
25%	25.000000	0.000000	1.0
50%	25.000000	1.000000	1.0
75%	50.000000	1.000000	1.0
max	5000.000000	1.000000	1.0

In [128…

In [129…

```
dfMobileNotOptIn.describe()
```

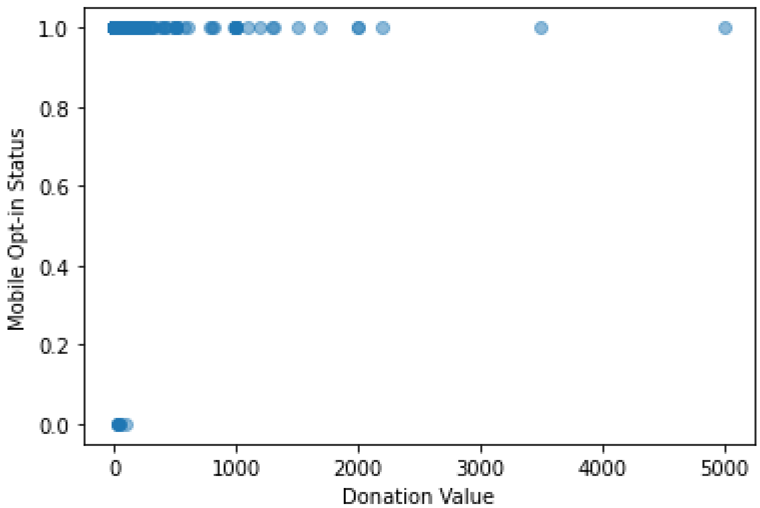
Out[129…

	amount	isEmailOptIn	isMobileOptIn
count	7.000000	7.000000	7.0

	amount	isEmailOptIn	isMobileOptIn
mean	42.857143	0.714286	0.0
std	27.817432	0.487950	0.0
min	25.000000	0.000000	0.0
25%	25.000000	0.500000	0.0
50%	25.000000	1.000000	0.0
75%	50.000000	1.000000	0.0
max	100.000000	1.000000	0.0

In [130…

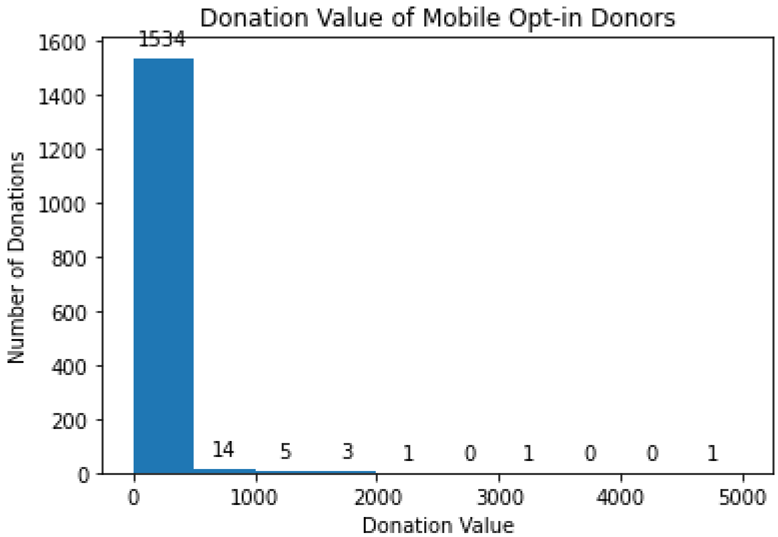
```
plt.scatter(dfFactors["amount"], dfFactors["isMobileOptIn"], alpha=0.5)
plt.xlabel("Donation Value")
plt.ylabel("Mobile Opt-in Status")
plt.show()
```

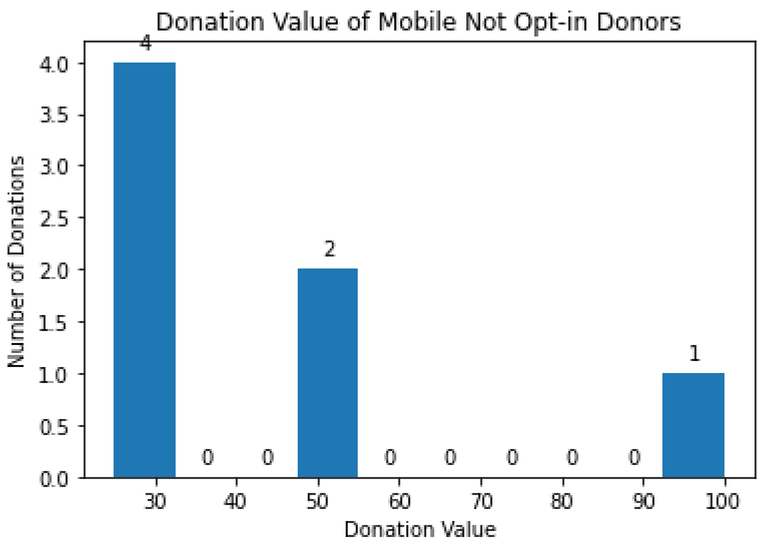


In [131…

```
fig, ax = plt.subplots()
ax.hist(dfMobileOptIn["amount"], density=False)

for rect in ax.patches:
    height = rect.get_height()
    ax.annotate(f'{int(height)}', xy=(rect.get_x()+rect.get_width()/2, height),
                xytext=(0, 5), textcoords='offset points', ha='center', va='bottom')
plt.xlabel("Donation Value")
plt.ylabel("Number of Donations")
plt.title("Donation Value of Mobile Opt-in Donors")
plt.show()


fig, ax = plt.subplots()
ax.hist(dfMobileNotOptIn["amount"], density=False)

for rect in ax.patches:
    height = rect.get_height()
    ax.annotate(f'{int(height)}', xy=(rect.get_x()+rect.get_width()/2, height),
                xytext=(0, 5), textcoords='offset points', ha='center', va='bottom')
plt.xlabel("Donation Value")
plt.ylabel("Number of Donations")
```

```
plt.title("Donation Value of Mobile Not Opt-in Donors")
plt.show()
```





Donation Tenure

In [132…

```
dfDonationType = dfDonations["donation_type"]
dfDonationType.head(5)
```

Out[132…

```
nationbuilder_id
1                      NaN
10      annual_membership_fee
100          general_donation
1000         general_donation
1001         general_donation
Name: donation_type, dtype: object
```

In [132…

```
```

In [133…

```
dfAnnualDonation = dfDonations[ dfDonations["donation_type"] == 'annual_membership_fee'
dfAnnualDonation.head(5)
```

Out[133…

	type	amount	payment_type_name	donor_id	donation_date	donation_typ

nationbuilder_id	type	amount	payment_type_name	donor_id	donation_date	donation_typ
nationbuilder_id						
10	Donation	25.0	Credit Card	5509	5/11/2020 22:10	annual_membership_fe
1006	Donation	25.0	Credit Card	5711	6/12/2020 2:48	annual_membership_fe
1062	Donation	25.0	Credit Card	7368	6/16/2020 0:46	annual_membership_fe
1081	Donation	25.0	Credit Card	7147	6/20/2020 0:12	annual_membership_fe
1082	Donation	25.0	Credit Card	7446	6/20/2020 16:56	annual_membership_fe

In [134…

```
dfAnnualDonation = dfAnnualDonation.groupby('donor_id')
dfAnnualDonation.head(5)
```

Out[134…

	type	amount	payment_type_name	donor_id	donation_date	donation_typ
nationbuilder_id						
10	Donation	25.0	Credit Card	5509	5/11/2020 22:10	annual_membership_fe
1006	Donation	25.0	Credit Card	5711	6/12/2020 2:48	annual_membership_fe
1062	Donation	25.0	Credit Card	7368	6/16/2020 0:46	annual_membership_fe
1081	Donation	25.0	Credit Card	7147	6/20/2020 0:12	annual_membership_fe
1082	Donation	25.0	Credit Card	7446	6/20/2020 16:56	annual_membership_fe
11	Donation	25.0	Credit Card	5383	5/11/2020 23:17	annual_membership_fe
1174	Donation	25.0	Credit Card	5711	7/12/2020 2:48	annual_membership_fe
12	Donation	25.0	Credit Card	5710	5/12/2020 1:14	annual_membership_fe
1244	Donation	25.0	Credit Card	5711	8/12/2020 2:48	annual_membership_fe
13	Donation	25.0	Credit Card	5711	5/12/2020 1:48	annual_membership_fe
1309	Donation	25.0	Credit Card	4353	9/29/2020 13:22	annual_membership_fe
1353	Donation	25.0	Credit Card	8031	10/29/2020 22:46	annual_membership_fe
1372	Donation	25.0	Credit Card	8040	11/4/2020 10:17	annual_membership_fe
1392	Donation	25.0	Credit Card	8133	11/27/2020 0:08	annual_membership_fe

	type	amount	payment_type_name	donor_id	donation_date	donation_typ
nationbuilder_id						
14	Donation	50.0	Credit Card	3518	5/12/2020 1:49	annual_membership_fe
1422	Donation	50.0	Credit Card	8209	12/11/2020 9:56	annual_membership_fe
1473	Donation	25.0	Credit Card	8376	1/15/2021 7:24	annual_membership_fe
1475	Donation	25.0	Credit Card	7823	1/17/2021 17:31	annual_membership_fe
1485	Donation	25.0	Credit Card	8554	2/1/2021 1:20	annual_membership_fe
1577	Donation	25.0	Credit Card	9091	4/4/2021 3:55	annual_membership_fe
16	Donation	25.0	Credit Card	4482	5/14/2020 10:46	annual_membership_fe
1633	Donation	25.0	Credit Card	9319	6/1/2021 21:51	annual_membership_fe
17	Donation	25.0	Credit Card	5720	5/15/2020 17:19	annual_membership_fe
819	Donation	25.0	Credit Card	5964	6/5/2020 18:55	annual_membership_fe
870	Donation	25.0	Credit Card	7037	6/6/2020 16:09	annual_membership_fe
932	Donation	100.0	Credit Card	7124	6/8/2020 14:05	annual_membership_fe
995	Donation	25.0	Credit Card	7227	6/11/2020 14:36	annual_membership_fe

Clustering

In [135…

```
mapping = {'donation_type': {'general_donation':0, 'annual_membership_fee':1}, 'billing
dfIndexed = dfDonations[['amount', 'donation_type', 'billing_city', 'billing_FSA', 'don

cities = sorted(list(set(dfIndexed['billing_city'].values)))
for i, city in enumerate(cities):
  mapping['billing_city'][city] = i

fsas = dfIndexed['billing_FSA'].values
for fsa in fsas:
  num1 = ord(fsa[0])
  num2 = ord(fsa[1])
  num3 = ord(fsa[2])
  mapping['billing_FSA'][fsa] = num1 + num2 + num3

dfIndexed['donation_date'] = pd.to_datetime(dfDonations['donation_date']).astype(int)/
```

```
dfIndexed = dfIndexed.replace(mapping)
dfIndexed = dfIndexed.dropna()

scaler = StandardScaler()
scaler.fit(dfIndexed)
dfIndexed.head()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:15: 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
  from ipykernel import kernelapp as app
```

Out[135…

	amount	donation_type	billing_city	billing_FSA	donation_date
nationbuilder_id					
10	25.0	1.0	275	210	1.589235e+09
100	15.0	0.0	207	195	1.591030e+09
1000	15.0	0.0	202	213	1.591897e+09
1001	100.0	0.0	171	200	1.591897e+09
1002	1000.0	0.0	33	225	1.591902e+09

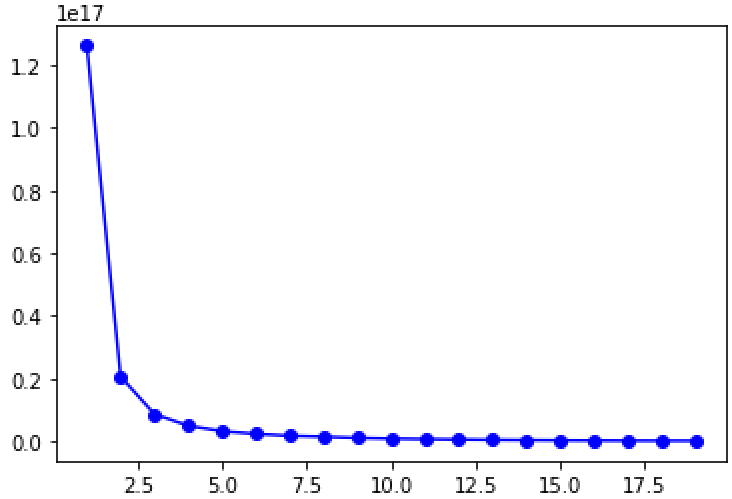
Amount vs Donation Date

In [136…

```
ks = []
distances = []
dfCurr = dfIndexed[['amount', 'donation_date']]
for k in range(1, 20):
  m = KMeans(n_clusters=k, random_state=1).fit(dfCurr)
  distances.append(m.inertia_)
  ks.append(k)

plt.plot(ks, distances, '-bo')
```

Out[136…

```
[<matplotlib.lines.Line2D at 0x7fc7a111c2d0>]
```

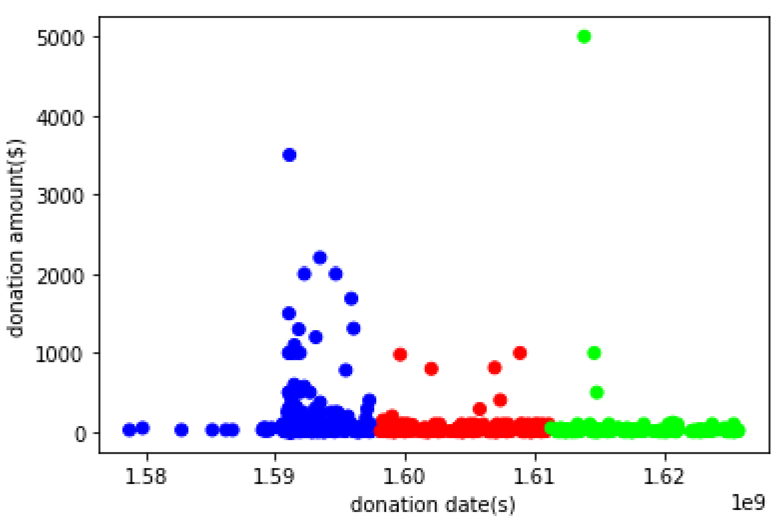


In [137…

```
best_m = KMeans(n_clusters=3, random_state=1).fit(dfCurr)
dfCurr.loc[:, 'cluster'] = best_m.labels_
plt.scatter(dfCurr['donation_date'], dfCurr['amount'], c=dfCurr['cluster'], cmap='brg')
plt.xlabel('donation date(s)')
plt.ylabel('donation amount($)')
```

```
/usr/local/lib/python3.7/dist-packages/pandas/core/indexing.py:1596: SettingWithCopyWarn
ing:
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
  self.obj[key] = _infer_fill_value(value)
/usr/local/lib/python3.7/dist-packages/pandas/core/indexing.py:1781: SettingWithCopyWarn
ing:
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
  self.obj[item_labels[indexer[info_axis]]] = value
```

Out[137… Text(0, 0.5, 'donation amount($)')



In [138…

```
dfCurr.groupby('cluster').mean()
```

Out[138…

	amount	donation_date
cluster		
0	74.544918	1.591688e+09
1	48.120853	1.604399e+09
2	60.860119	1.617833e+09

In [139…

```
dfCurr.groupby('cluster').std()
```

Out[139…

	amount	donation_date
cluster		
0	192.102238	1.462965e+06
1	126.904073	3.869536e+06
2	393.004312	4.218394e+06

In [140…

```
dfCurr.groupby('cluster').max()
```

Out[140…

	amount	donation_date
cluster		
0	3500.0	1.597959e+09
1	1000.0	1.611019e+09
2	5000.0	1.625614e+09

In [141…

```
dfCurr.groupby('cluster').min()
```

Out[141…

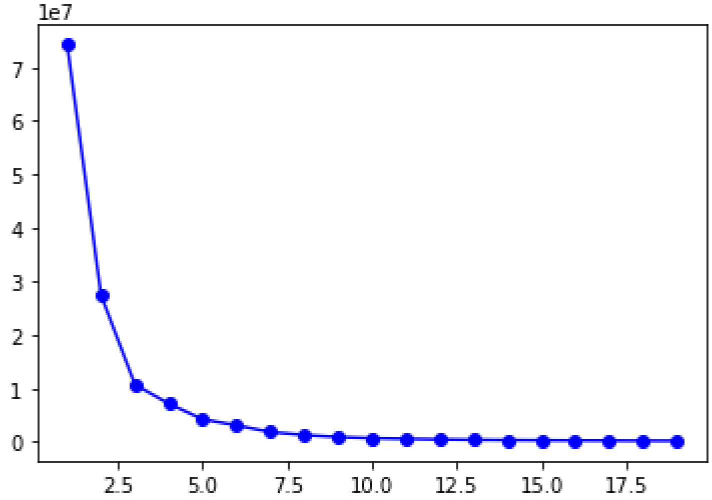
	amount	donation_date
cluster		
0	0.5	1.578775e+09
1	3.0	1.598100e+09
2	2.0	1.611216e+09

Amount vs Billing FSA

In [142…

```
ks = []
distances = []
dfCurr = dfIndexed[['amount', 'billing_FSA']]
for k in range(1, 20):
  m = KMeans(n_clusters=k, random_state=1).fit(dfCurr)
  distances.append(m.inertia_)
  ks.append(k)

plt.plot(ks, distances, '-bo')
```

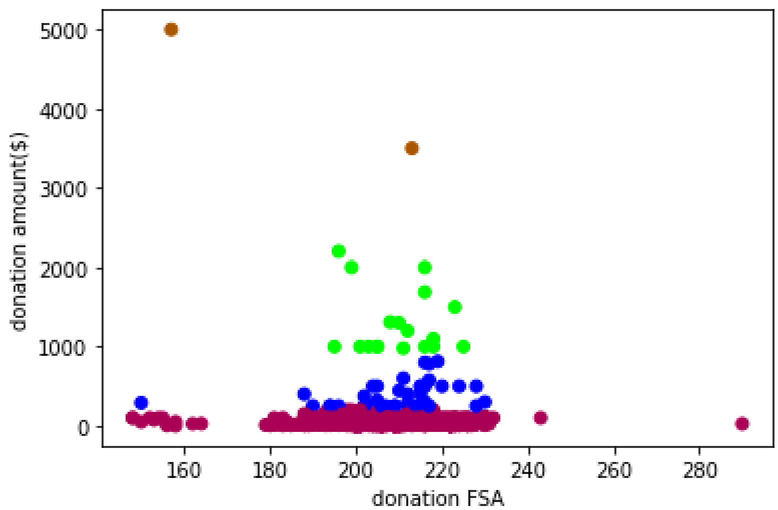
Out[142… [<matplotlib.lines.Line2D at 0x7fc7a24c6c50>]



In [143…
```
best_m = KMeans(n_clusters=4, random_state=1).fit(dfCurr)
dfCurr.loc[:, 'cluster'] = best_m.labels_
plt.scatter(dfCurr['billing_FSA'], dfCurr['amount'], c=dfCurr['cluster'], cmap='brg')
plt.xlabel('donation FSA')
plt.ylabel('donation amount($)')
```

```
/usr/local/lib/python3.7/dist-packages/pandas/core/indexing.py:1596: SettingWithCopyWarn
ing:
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
  self.obj[key] = _infer_fill_value(value)
/usr/local/lib/python3.7/dist-packages/pandas/core/indexing.py:1743: SettingWithCopyWarn
ing:
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
  isetter(ilocs[0], value)
```

Out[143… Text(0, 0.5, 'donation amount($)')



In [144…
```
dfCurr.groupby('cluster').mean()
```

Out[144...

	amount	billing_FSA
cluster		
0	374.133256	208.651163
1	41.182575	206.635948
2	4250.000000	185.000000
3	1293.247778	209.833333

In [145...

```
dfCurr.groupby('cluster').std()
```

Out[145...

	amount	billing_FSA
cluster		
0	162.165014	13.246534
1	34.975909	12.036739
2	1060.660172	39.597980
3	409.632583	8.945916

In [146...

```
dfCurr.groupby('cluster').max()
```

Out[146...

	amount	billing_FSA
cluster		
0	813.5	230
1	200.0	290
2	5000.0	213
3	2200.0	225

In [147...

```
dfCurr.groupby('cluster').min()
```

Out[147...

	amount	billing_FSA
cluster		
0	242.14	150
1	0.50	148
2	3500.00	157
3	980.00	195