```
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```

Exploratory Data Analysis: Spending at Trump Properties

```
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```

This is an open source notebook! You can visit the Github repository for more information about this project here. In this notebook, we take a look the dataset on Trump campaign and administration spending compiled by ProPublica.

Ultimately, I want to see if there are any valuable insights we can derive from the material.

Overview

In this notebook, we take a look the dataset on Trump campaign and administration spending compiled by ProPublica.

While there aren't any explicit starting points, we should be able to answer the following questions high-level about the dataset:

1. How many records are there in the dataset?
2. What features are included in the dataset?

Question 1

How many records are there within the dataset?

In [1]:
```python
# Import useful data science packages.
%matplotlib inline
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
```

In [2]:
```python
# Read data into a pandas dataframe.
df = pd.read_csv("../src/data.csv")
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1193 entries, 0 to 1192
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   type               1193 non-null   object
 1   source             1193 non-null   object
 2   date               1193 non-null   object
 3   amount             1193 non-null   float64
 4   purpose_scrubbed   1193 non-null   object
 5   property_scrubbed  1193 non-null   object
 6   purpose            1182 non-null   object
 7   property           1193 non-null   object
 8   city               1160 non-null   object
 9   state              1158 non-null   object
dtypes: float64(1), object(9)
memory usage: 93.3+ KB
```

We've now established that there are `1193` entries in the entire dataset.

Question 2

What features are included in the dataset?

In [3]:
```python
# Identify the list of features.
features = pd.Series(df.columns)
features
```

Out[3]:
```
0                 type
1               source
2                 date
3               amount
4     purpose_scrubbed
5    property_scrubbed
6              purpose
7             property
8                 city
9                state
dtype: object
```

In [4]:
```python
# Count the number of features.
features.count()
```

Out[4]: `10`

We've identified `10` unique features for this dataset.

Now, we can determine details about each unique feature.

In [5]:
```python
# Find unique values for each feature.
unique_features = { col: pd.Series(df[col].sort_values().unique()) for col in features
```

1. type

`type` contains two unique values: `FEC` and `government`.

- `FEC` stands for the Federal Election Commission, representing expenditures by the Trump campaign.
- `government` stands for Federal and state agencies, representing expenditures by the Trump administration.

In [6]:
```python
# List unique values in the 'type' field.
unique_features['type']
```

Out[6]:
```
0           FEC
1    government
dtype: object
```

In [7]:
```python
# Describe the type list.
df['type'].describe()
```

Out[7]:
```
count     1193
unique       2
top        FEC
freq       841
Name: type, dtype: object
```

2. source

`source` contains the organization that made the payment. There are `137` unique `source` entries in the dataset.

In [8]:
```python
# Count the number of unique values.
unique_features['source'].count()
```

Out[8]: `137`

In [9]:
```python
# List a random 5 samples of unique values in the 'source' field.
unique_features['source'].sample(n=5)
```

Out[9]:
```
76       Marino for Congress
66      Kansans for Marshall
67    Kansas Leadership PAC
56         Great America PAC
15       Citizens for Turner
dtype: object
```

In [10]:
```python
# Describe the source
df['source'].describe()
```

Out[10]:
```
count                                   1193
unique                                   137
top       Donald J. Trump for President, Inc.
freq                                     493
Name: source, dtype: object
```

Some important information to keep in mind here:

- The most frequent payer source is Donald J. Trump for President, Inc. with 493 transactions.
- There are `137` unique `source` entries in the dataset.
- A uniform distribution would have meant roughly ~8 transactions per source - we know our data will be skewed.

3. date

`date` contains the transaction date.

In [11]:
```python
# Print last five dates out.
unique_features['date'].tail(5)
```

Out[11]:
```
508    Sep 7, 2017
509    Sep 8, 2016
510    Sep 8, 2017
511    Sep 9, 2016
512      undefined
dtype: object
```

Here, we identify `513` unique date entries, where `undefined` is one of them.

In [12]:
```python
df['date'].describe()
```

Out[12]:
```
count             1193
unique             513
top       Apr 28, 2017
freq                22
Name: date, dtype: object
```

Notice how the `dtype` is `object`. Our `DataFrame` won't sort our dates by their values, instead treating them like plain strings. We should convert this value into the `datetime` format, so that we can make comparisons with the value of a given date, as well as perform numeric calculations based on the `datetime` value.

In [13]:
```python
# Convert column to date time.
df['date'] = pd.to_datetime(df['date'], format='%b %d, %Y', errors='coerce')
df['date']
```

Out[13]:
```
0      2015-04-30
1      2015-05-05
2      2015-06-16
3      2015-06-16
4      2015-06-16
          ...
1188          NaT
1189          NaT
1190          NaT
1191          NaT
1192   2017-01-24
Name: date, Length: 1193, dtype: datetime64[ns]
```

In [14]:
```python
unique_features['date'] = pd.Series(df['date'].sort_values().unique())
unique_features['date']
```

Out[14]:
```
0     2015-04-30
1     2015-05-03
2     2015-05-05
3     2015-06-16
4     2015-06-17
         ...
508   2018-05-01
509   2018-05-02
510   2018-05-03
511   2018-05-08
512          NaT
Length: 513, dtype: datetime64[ns]
```

4. amount

`amount` contains the transaction amount.

In [15]:
```python
# Display info.
pd.set_option('display.float_format', lambda x: '%.2f' % x)
df['amount'].describe()
```

Out[15]:
```
count      1193.00
mean      13483.58
std       70755.00
min      -11541.20
25%         174.04
50%         662.99
75%        2679.33
max     1271944.00
Name: amount, dtype: float64
```

Positive amounts are payments from the `source` payer to the `property` payee. Negative amounts are likely refunds.

Of note, the largest payment was $\$1,271,944.00$ and the smallest was $\$11,541.20$.

5. purpose_scrubbed

The `purpose_scrubbed` is the reason for the transaction. These classification labels were picked by ProPublica to categorize the values in the `purpose` feature.

In [16]:
```python
# List unique `purpose_scrubbed` items.
unique_features['purpose_scrubbed']
```

Out[16]:
```
0      Event
1       Food
2      Legal
3    Lodging
4      Other
5    Payroll
6       Rent
7     Travel
dtype: object
```

There are `8` unique `purpose_scrubbed` entries.

In [17]:
```python
# Describe the feature.
df['purpose_scrubbed'].describe()
```

Out[17]:
```
count        1193
unique          8
top       Lodging
freq          438
Name: purpose_scrubbed, dtype: object
```

`Lodging` is the most frequent `purpose_scrubbed` with `438` transactions associated with the purpose.

6. property_scrubbed

The `property_scrubbed` is the `payee` institution receiving payment.

In [18]:
```python
# List last 5 unique `property_scrubbed` items.
unique_features['property_scrubbed']
```

Out[18]:
```
0                          BLT Prime D.C
1               Benjamin Bar & Lounge D.C
2      Eric Trump Wine Manufacturing, LLC
3                   Mar-a-Lago Club LLC
4                                  Other
5                         Tag Air, Inc.
6                  The Trump Corporation
7                        Trump CPS LLC
8                        Trump Cafe NY
9                       Trump Golf Club
10            Trump Golf Club Bedminster
11          Trump Golf Club Bedminster
12            Trump Golf Club Charlotte
13                  Trump Golf Club D.C
14                 Trump Golf Club D.C.
15             Trump Golf Club Doonberg
16              Trump Golf Club Jupiter
17                 Trump Golf Club L.A.
18                Trump Golf Club Miami
19           Trump Golf Club Palm Beach
20          Trump Golf Club Westchester
21           Trump Golf Resort Scotland
22                       Trump Grill NY
23                   Trump Hotel Chicago
24                       Trump Hotel D.C
25                      Trump Hotel D.C.
26                  Trump Hotel Honolulu
27                 Trump Hotel Las Vegas
28                       Trump Hotel NY
29                    Trump Hotel Panama
30                 Trump Hotel Vancouver
31                        Trump Ice LLC
32                    Trump Payroll Corp
33                      Trump Plaza LLC
34                Trump Restaurants LLC
35                        Trump Soho NY
36           Trump Tower Commercial LLC
37      Trump Virginia Acquisitions, LLC
dtype: object
```

There are `38` unique `property_scrubbed` items. Like `purpose_scrubbed`, these are categorization labels that apply to the values found in the unscrubbed feature - in this case, for `property`.

But look closely at the list - there's a couple hidden duplicates lying about.

In [19]:
```python
# Describe the feature.
df['property_scrubbed'].describe()
```

Out[19]:
```
count                1193
unique                 38
top       Trump Hotel D.C
freq                  197
Name: property_scrubbed, dtype: object
```

`Trump Hotel D.C` is the most common `property_scrubbed` item but it definitely will have some sort of impact on the dataset. Some `property_scrubbed` entries for `D.C.` don't consistently place the second punctuation mark, so duplicates go untreated.

In [20]:
```python
# First, find all rows that match the 'D.C' prompt.
df['property_scrubbed'] = df['property_scrubbed'].replace({
    "Trump Hotel D.C": "Trump Hotel D.C.",
    "Trump Golf Club D.C": "Trump Golf Club D.C.",
    "Benjamin Bar & Lounge D.C": "Benjamin Bar & Lounge D.C.",
    "BLT Prime D.C": "BLT Prime D.C."
})
df['property_scrubbed'].describe()
```

Out[20]:
```
count                 1193
unique                  36
top       Trump Hotel D.C.
freq                   267
Name: property_scrubbed, dtype: object
```

After cleaning the feature, there are `36` unique scrubbed properties and the most frequent property is `Trump Hotel D.C.`.

7. purpose

Various, unscrubbed `purpose` data.

In [21]:
```python
unique_features['purpose']
```

Out[21]:
```
0                                   002 Travel Parking
1      1ST BANKCARD PMT [SB21B.15922]: EVENT EXPENSE:...
2      1ST BANKCARD PMT [SB21B.15922]: FUNDRAISING EX...
3      1ST BANKCARD PMT [SB21B.18545]: EVENT EXPENSE:...
4        1ST BANKCARD PMT [SB21B.19723]: MEETING EXPENSE
                             ...
228                                    meeting expense
229                             political contribution
230                               staff retreat dinner
231                                             travel
232                                                NaN
Length: 233, dtype: object
```

The `purpose` feature would be useful if we were to require a predictive model that determines an output `purpose_scrubbed` classification.

In [22]:
```python
df['purpose'].describe()
```

Out[22]:
```
count              1182
unique              232
top       Hotels-Lodging
freq                201
Name: purpose, dtype: object
```

8. property

Various, unscrubbed `property` data.

In [23]:
```python
unique_features['property']
```

Out[23]:
```
0           BENJAMIN BAR & LOUNGE
1         BENJAMIN BAR AND LOUNGE
2                             BLT
3                       BLT PRIME
4          BLT PRIME BY DAVID BURKE
                 ...
112                    Trump Soho
113                   Trump Tower
114     Trump Tower Hotel New York
115               Trump Turnberry
116                  Wollman Rink
Length: 117, dtype: object
```

In [24]:
```python
df['property'].describe()
```

Out[24]:
```
count                                    1193
unique                                    117
top       Trump International Hotel Las Vegas
freq                                      128
Name: property, dtype: object
```

Interestingly, the unscrubbed field reports the `Trump International Hotel Las Vegas` as the most common `property`, but our `property_scrubbed` suggests that `Trump Hotel D.C.` is the most common.

In [25]:
```python
# Search for all property_scrubbed entries containing D.C. and select their property
dc_properties = pd.Series(df[df['property_scrubbed'].str.contains('Hotel D.C.')]['prop
dc_properties
```

Out[25]:
```
0                         TRUMP OLD POST OFFICE LLC
1                         TRUMP INTERNATIONAL HOTEL
2              TRUMP INTERNATIONAL HOTEL WASHINGTON
3           TRUMP INTERNATIONAL HOTEL WASHINGTON DC
4                              THE TRUMP INTL HOTEL
5                         Trump International Hotel
6              Trump International Hotel Washington
7                                       Trump Hotel
8     TRUMP INTERNATIONAL HOTEL WDC                 ...
9                      Trump International Hotel DC
10                      OPO LOUNGE AT TRUMP HOTEL
11        TRUMP INTERNATIONAL HOTEL WASHINGTON, D.C.
12                           TRUMP OLD POST OFFICE
13                    TRUMP INTERNATIONAL HOTEL WDC
14                                TRUMP INT'L HOTEL
15                                      TRUMP HOTEL
16             TRUMP INTERNATIONAL HOTEL RESTAURANT
17          Trump International Hotel - Washington DC
18                              Trump International
19                         TRUMP INTERNATONAL HOTEL
20          Trump International Hotel Washington D.C.
21         Trump International Hotel Washington, D.C.
dtype: object
```

There are some interesting things at play here. At first glance, someone reading the transaction details might wonder why `TRUMP OLD POST OFFICE` (and similar variations) were classified as `Trump Hotel D.C.`.

The answer isn't immediately clear but a quick search turns up a Wikipedia entry) with this information:

> In 2013, the U.S. General Services Administration (GSA) leased the property for 60 years to a consortium headed by "DJT Holdings LLC", a holding company that Donald Trump owns through a revocable trust. Trump developed the property into a luxury hotel, the Trump International Hotel Washington, D.C., which opened in September 2016.

9. city

The city supposedly refers to the location where the transaction took place.

In [26]:
```python
# Display unique feature values.
unique_features['city']
```

Out[26]:
```
0            561-8322600
1             Bedminister
2              Bedminster
3              Bradenton
4       Briarcliff Manor
5        Charlottesville
6                Chicago
7               Doonberg
8                  Doral
9             Hicksville
10              Honolulu
11               Jupiter
12             Lafayette
13            Las Veagas
14             Las Vegas
15                 Miami
16           Mooresville
17           Moorseville
18              New York
19            Palm Beach
20          Panama City
21         Potomac Falls
22          Rancho Palos
23   Rancho Palos Verdes
24           S61-8322600
25         San Francisco
26              Sterling
27             Turnberry
28             Vancouver
29            Washington
30       West Palm Beach
31                   NaN
dtype: object
```

In [27]:
```python
# Display feature description.
df['city'].describe()
```

Out[27]:
```
count           1160
unique            31
top       Washington
freq             350
Name: city, dtype: object
```

There are some confusing entries and typos in the `city` feature. Here is a list of the issues I could find:

- `561-8322600` isn't a city, but it could be a telephone number. Could we use the zipcode to solve our missing city dilemma?
- `561-8322600` and `S61-8322600` are close enough to be related. Which is the typo?
- `Bedminister` vs. `Bedminster`
- `Las Veagas` vs. `Las Vegas`
- `Moorseville` vs. `Mooresville`
- `NaN` entries could have states or it could refer to a place like `Washington D.C.`.
- Does `Washington` refer to `Washington State` or `Washington D.C.`? Or is it (in the worst case) referring to both?

Let's use the state field in order to check where each of our problem states are from.

In [28]:
```python
# Create lookup table of city, state.
city_state = df[['city', 'state']]

# Service method to facilitate similarity searches easily.
def is_similar(table, feature, term, case=False, na=False):
    return table[feature].str.contains(term, case=case, na=na)
```

In [29]:
```python
# Bedminister vs. Bedminster
city_state[is_similar(city_state, 'city', 'Bedmin')]['city'].unique()
```

Out[29]: `array(['Bedminster', 'Bedminister'], dtype=object)`

In [30]:
```python
# Las Vaegas vs. Las Vegas
city_state[is_similar(city_state, 'city', 'Las Vea?gas')]['city'].unique()
```

Out[30]: `array(['Las Vegas', 'Las Veagas'], dtype=object)`

In [31]:
```python
# Moorseville vs. Mooresville
city_state[is_similar(city_state, 'city', 'Moor.[es]ville')]['city'].unique()
```

Out[31]: `array(['Moorseville', 'Mooresville'], dtype=object)`

In [32]:
```python
# Figure out city 561 belongs to.
city_state[city_state['city'].str.contains('561', case=False, na=False)]
```

Out[32]:

	city	state
930	561-8322600	FL
1072	561-8322600	FL

Let's fix those typos. Our first pass will use the `pd.DataFrame.replace` method, taking in a dictionary with the correct spellings. We'll change the data in the following ways:

- `S61-8322600` and `561-8322600` will become `West Palm Beach`, FL.
- `Bedminister` will become `Bedminster` (as in Bedminster, NJ).
- `Las Veagas` will become `Vegas` (as in Las Vegas, NV).
- `Moorseville` will become `Mooresville` (as in Mooresville, NC).

In [33]:
```python
# Replace typoes.
df['city'] = df['city'].replace({
    "S61-8322600": "West Palm Beach",
    "561-8322600": "West Palm Beach",
    "Bedminister": "Bedminster",
    "Moorseville": "Mooresville"
})

# Update unique feature values
unique_features['city'] = pd.Series(df['city'].unique())
unique_features['city']
```

Out[33]:
```
0                New York
1              Hicksville
2         West Palm Beach
3               Las Vegas
4              Washington
5                   Miami
6                 Chicago
7         Charlottesville
8                 Jupiter
9              Bedminster
10       Briarcliff Manor
11            Mooresville
12          Potomac Falls
13                  Doral
14               Sterling
15             Las Veagas
16              Lafayette
17    Rancho Palos Verdes
18             Palm Beach
19              Bradenton
20               Honolulu
21              Turnberry
22            Panama City
23                    NaN
24              Vancouver
25               Doonberg
26          San Francisco
27           Rancho Palos
dtype: object
```

In [34]:
```python
df['city'].describe()
```

Out[34]:
```
count           1160
unique            27
top       Washington
freq             350
Name: city, dtype: object
```

Now we know there are 27 unique cities.

10. state

In [35]:
```python
unique_features['state']
```

Out[35]:
```
0     British Columbia
1                   CA
2                   DC
3                   FL
4                   HI
5                   IL
6              Ireland
7                   LA
8                   NC
9                   NJ
10                  NV
11                  NY
12              Panama
13            Scotland
14                  VA
15                 NaN
dtype: object
```

In [36]:
```python
df['state'].describe()
```

Out[36]:
```
count     1158
unique      15
top         NY
freq       394
Name: state, dtype: object
```

Charting Data

Are there trends we can visualize?

A good starting point is with a time-series plotting transactions over time.

In [37]:
```python
# Get special table that just lists the date and the amount.
ts_amount = df[['date','amount']]
ts_amount.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1193 entries, 0 to 1192
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   date    1188 non-null   datetime64[ns]
 1   amount  1193 non-null   float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 18.8 KB
```

In [38]:
```python
# Groupby date.
date_idx = ts_amount['date']
date_amount = ts_amount.groupby(date_idx).sum()
date_amount
```

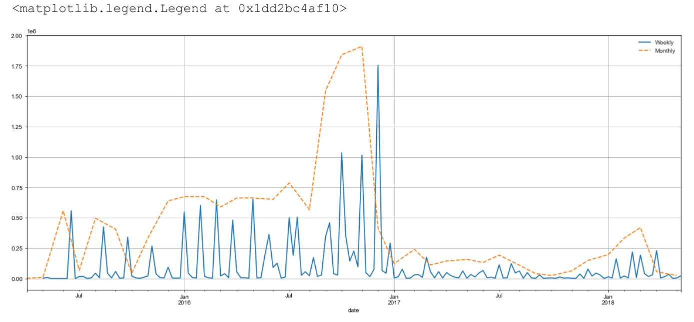
Out[38]:

	amount
date	
2015-04-30	1380.54
2015-05-03	1303.46
2015-05-05	9583.33
2015-06-16	557303.33
2015-06-17	814.24
...	...
2018-04-30	861.77
2018-05-01	1635.10
2018-05-02	247.90
2018-05-03	1737.04
2018-05-08	21835.63

512 rows × 1 columns

In [39]:
```python
# Plot figure/grid.
fig, ax = plt.subplots(figsize=(20,8))
plt.style.use('seaborn')

# date_amount.plot(ax=ax, alpha=0.5, style='-')
date_amount.resample('W').sum().plot(ax=ax, style='-')
date_amount.resample('M').sum().plot(ax=ax, style='--')
ax.legend(['Weekly', 'Monthly'])
```

Out[39]: `<matplotlib.legend.Legend at 0x1dd2bc4af10>`



What about organizing payments by payers?

In [40]:
```python
df[['date', 'purpose_scrubbed', 'amount']]
```

Out[40]:

	date	purpose_scrubbed	amount
0	2015-04-30	Lodging	1380.54
1	2015-05-05	Rent	9583.33
2	2015-06-16	Event	37993.04
3	2015-06-16	Lodging	3240.96
4	2015-06-16	Rent	9583.33
...	...	...	...
1188	NaT	Other	5583.13
1189	NaT	Other	4853.29
1190	NaT	Other	10398.33
1191	NaT	Other	592.13
1192	2017-01-24	Other	103.25

1193 rows × 3 columns

In [41]:
```python
df2 = df.groupby(['date', 'purpose_scrubbed'])
df2.sum()
```

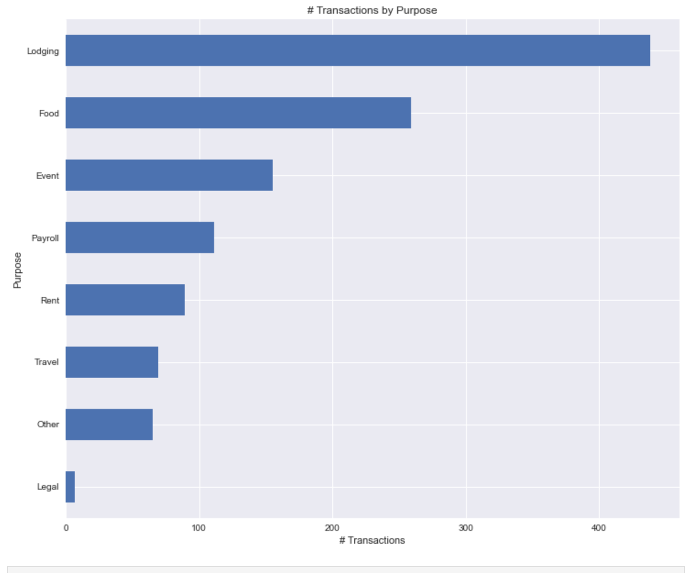
Out[41]:

		amount
date	**purpose_scrubbed**	
2015-04-30	**Lodging**	1380.54
2015-05-03	**Event**	1303.46
2015-05-05	**Rent**	9583.33
2015-06-16	**Event**	37993.04
	Lodging	3240.96
...	**...**	...
2018-04-30	**Lodging**	686.50
2018-05-01	**Food**	1635.10
2018-05-02	**Lodging**	247.90
2018-05-03	**Lodging**	1737.04
2018-05-08	**Event**	21835.63

766 rows × 1 columns

In [42]:
```python
# Prepare data to graph.
df_purpose = df.groupby(['purpose_scrubbed']).count()['amount'].sort_values()

# Plot figure/grid.
fig, ax = plt.subplots(figsize=(12,10))

# Plot the chart.
df_purpose.plot.barh(ax=ax)

# Style the plot.
ax.set_xlabel('# Transactions')
ax.set_ylabel('Purpose')
ax.set_title('# Transactions by Purpose')
ax.grid(True)

# Describe the data.
df_purpose.describe()
```

Out[42]:
```
count      8.00
mean     149.12
std      138.52
min        7.00
25%       68.00
50%      100.00
75%      181.00
max      438.00
Name: amount, dtype: float64
```



In [43]:

```
# Prepare data to graph.
df_purpose = df.groupby(['property_scrubbed']).count()['amount'].sort_values(ascendin

# Plot figure/grid.
fig, ax = plt.subplots(figsize=(10,20))

# Plot the chart.
df_purpose.plot.barh(ax=ax)

# Style the plot.
ax.set_xlabel('# Transactions')
ax.set_ylabel('Property')
ax.set_title('# Transactions by Payee')
ax.grid(True)

# Describe the data.
df_purpose.describe()
```

Out[43]:

```
count     36.00
mean      33.14
std       52.59
min        1.00
25%        6.00
50%       11.50
75%       39.25
max      267.00
Name: amount, dtype: float64
```