

Step 1: Business and Data Understanding

1. What decisions needs to be made?

Ans: Perform an analysis to recommend the city for Pawdacity's newest store, based on predicted yearly sales.
But this project is just to get the data ready before the prediction.

... ..: Awesome!

2. What data is needed to inform those decisions?

Ans: The manager gives 4 csv files with the following info:

- 1. monthly sales for all Pawdacity stores in 2010
- 2. NAICS(North American Industry Classification System) data of competitors
- 3. partially parsed data for population
- 4. demographic data in wyoming

... ..: Awesome!

Step 2: Building the Training Set

| Column | Sum | Mean | median |
|--------------------------|-----------|---------|---------|
| Census Population | 213,862 | 19,442 | 12,359 |
| Total Pawdacity Sales | 3,773,304 | 290,254 | 273,024 |
| Households with Under 18 | 34,064 | 3096.73 | 2646.0 |
| Land Area | 33,071 | 3006.49 | 2748.85 |
| Population Density | 63 | 5.71 | 2.78 |
| Total Families | 62,653 | 5695.71 | 5556.49 |

... ..: Awesome : All averages are correct!

The calucation details are as follows

```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
% matplotlib inline
store = pd.read_csv("p2-2010-pawdacity-monthly-sales.csv")
nakes = pd.read_csv("p2-wy-453910-naics-data.csv")
popul = pd.read_csv("p2-partially-parsed-wy-web-scrape.csv")
demog = pd.read_csv("p2-wy-demographic-data.csv")
```

calculate total Pawdacity sales and collect city names

```
In [2]: print(store.iloc[:,5:].sum(axis=1).sum()) # 3773304
print(store.iloc[:,5:].sum(axis=1).median()) # 290254
```

3773304
273024.0

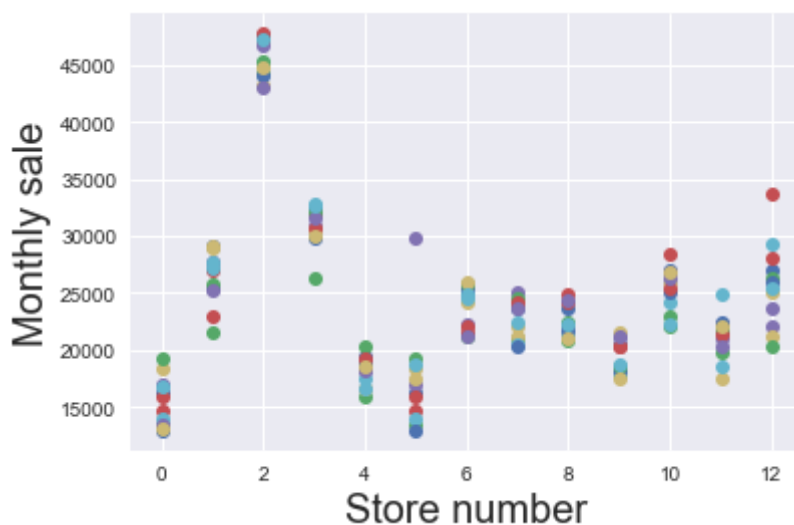
```
In [3]: store.head()
```

```
Out[3]:
```

| | NAME | ADDRESS | CITY | STATE | ZIP | January | February | March | April | May |
|---|-----------|---------------------------------------|----------|-------|-------|---------|----------|-------|-------|-------|
| 0 | Pawdacity | 509 Fort St # A | Buffalo | WY | 82834 | 16200 | 13392 | 14688 | 17064 | 18300 |
| 1 | Pawdacity | 601 SE Wyoming Blvd Unit 252 | Casper | WY | 82609 | 29160 | 21600 | 27000 | 27648 | 29100 |
| 2 | Pawdacity | 1400 Dell Range Blvd | Cheyenne | WY | 82009 | 47520 | 44280 | 47088 | 46656 | 43200 |
| 3 | Pawdacity | 3769 E Lincolnway | Cheyenne | WY | 82001 | 32400 | 26352 | 31968 | 30888 | 30400 |
| 4 | Pawdacity | 2625 Big Horn Ave | Cody | WY | 82414 | 19440 | 15984 | 19008 | 18144 | 16600 |

```
In [4]: plt.plot(store[store.columns[5:]], 'o')
plt.xlabel("Store number", fontsize=20)
plt.ylabel("Monthly sale", fontsize=20)
```

```
Out[4]: <matplotlib.text.Text at 0x10e5a4f28>
```



```
In [5]: store.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13 entries, 0 to 12
Data columns (total 17 columns):
NAME          13 non-null object
ADDRESS       13 non-null object
CITY           13 non-null object
STATE         13 non-null object
ZIP           13 non-null int64
January       13 non-null int64
February      13 non-null int64
March         13 non-null int64
April         13 non-null int64
May           13 non-null int64
June          13 non-null int64
July          13 non-null int64
August        13 non-null int64
September     13 non-null int64
October       13 non-null int64
November      13 non-null int64
December      13 non-null int64
dtypes: int64(13), object(4)
memory usage: 1.8+ KB
```

```
In [6]: store["CITY"].value_counts()
```

```
Out[6]: Gillette          2
Cheyenne          2
Evanston          1
Casper            1
Douglas           1
Powell            1
Rock Springs      1
Sheridan          1
Riverton          1
Cody              1
Buffalo           1
Name: CITY, dtype: int64
```

```
In [7]: cities = store["CITY"].unique() # numpy array of shape 11
```

calculate census population

```
In [8]: popul.dropna(axis=0, how='any', thresh=None, subset=None, inplace=True)
```

```
In [9]: popul['Pawdacity'] = False
```

In [10]: `popul.tail()`

Out[10]:

| | City County | 2014 Estimate | 2010 Census | 2000 Census | Pawdacity |
|----|----------------------|----------------|----------------|----------------|-----------|
| 94 | Wamsutter Sweetwater | <td>503</td> | <td>451</td> | <td>261</td> | False |
| 95 | Wheatland ? Platte | <td>3,659</td> | <td>3,627</td> | <td>3,548</td> | False |
| 96 | Worland ? Washakie | <td>5,366</td> | <td>5,487</td> | <td>5,250</td> | False |
| 97 | Wright Campbell | <td>1,847</td> | <td>1,807</td> | <td>1,347</td> | False |
| 98 | Yoder Goshen | <td>161</td> | <td>151</td> | <td>169</td> | False |

```
In [11]: import re
s="|".join(cities)
s="^("+s+")"
pool = re.compile(s)

from bs4 import BeautifulSoup
def parsenum(text):
    if str(text).isnumeric():
        return text
    soup = BeautifulSoup(text, 'html.parser')
    num = ""
    for digit in soup.find("td").text:
        if digit.isnumeric():
            num += digit
        if digit == "[":
            break
    if num.isnumeric():
        return int(num)
    else:
        return 0
cnt = 0
for i in range(popul.shape[0]):
    row = popul.iloc[i,:]
    popul.set_value(i, "2014 Estimate", parsenum(row["2014 Estimate"]))
    popul.set_value(i, "2010 Census", parsenum(row["2010 Census"]))
    popul.set_value(i, "2000 Census", parsenum(row["2000 Census"]))
    if pool.search(row["City|County"]):
        popul.set_value(i, "Pawdacity", True) # set value to True when fo
und
        cnt +=1
print("found {} cities with Pawdacity".format(cnt))

found 11 cities with Pawdacity
```

In [12]: `popul.iloc[:,1:-1]=popul.iloc[:,1:-1].astype(int)`

```
In [13]: popul[popul["Pawdacity"] == True]
```

Out[13]:

| | City County | 2014 Estimate | 2010 Census | 2000 Census | Pawdacity |
|----|-------------------------|---------------|-------------|-------------|-----------|
| 9 | Buffalo ? Johnson | 4615 | 4585 | 3900 | True |
| 13 | Casper ? Natrona | 40086 | 35316 | 32644 | True |
| 14 | Cheyenne ?? Laramie | 62845 | 59466 | 53011 | True |
| 17 | Cody ? Park | 9740 | 9520 | 8835 | True |
| 24 | Douglas ? Converse | 6423 | 6120 | 5288 | True |
| 29 | Evanston ? Uinta | 12190 | 12359 | 11507 | True |
| 33 | Gillette ? Campbell | 31971 | 29087 | 19646 | True |
| 73 | Powell Park | 6407 | 6314 | 5373 | True |
| 77 | Riverton Fremont | 10953 | 10615 | 9310 | True |
| 79 | Rock Springs Sweetwater | 24045 | 23036 | 18708 | True |
| 82 | Sheridan ? Sheridan | 17916 | 17444 | 15804 | True |

```
In [14]: popul.groupby("Pawdacity").median()
```

Out[14]:

| | 2014 Estimate | 2010 Census | 2000 Census |
|-----------|---------------|-------------|-------------|
| Pawdacity | | | |
| False | 529.5 | 526.5 | 446.0 |
| True | 12190.0 | 12359.0 | 11507.0 |

calcuale demographic info

```
In [15]: demog['Pawdacity'] = False
for i in range(demog.shape[0]):
    if pool.search(demog.iloc[i,:]["City"]):
        demog.set_value(i, "Pawdacity", True)
```

```
In [16]: demog.groupby("Pawdacity").median()
```

Out[16]:

| | Land Area | Households with Under 18 | Population Density | Total Families |
|-----------|-------------|--------------------------|--------------------|----------------|
| Pawdacity | | | | |
| False | 218.720727 | 124.5 | 0.285 | 274.735 |
| True | 2748.852900 | 2646.0 | 2.780 | 5556.490 |

In [17]: demog[demog['Pawdacity']]

Out[17]:

| | City | County | Land Area | Households with Under 18 | Population Density | Total Families | Pawdacity |
|----|--------------|------------|-------------|--------------------------|--------------------|----------------|-----------|
| 10 | Gillette | Campbell | 2748.852900 | 4052 | 5.80 | 7189.43 | True |
| 22 | Douglas | Converse | 1829.465100 | 832 | 1.46 | 1744.08 | True |
| 34 | Riverton | Fremont | 4796.859815 | 2680 | 2.34 | 5556.49 | True |
| 44 | Buffalo | Johnson | 3115.507500 | 746 | 1.55 | 1819.50 | True |
| 48 | Cheyenne | Laramie | 1500.178400 | 7158 | 20.34 | 14612.64 | True |
| 60 | Casper | Natrona | 3894.309100 | 7788 | 11.16 | 8756.32 | True |
| 68 | Cody | Park | 2998.956960 | 1403 | 1.82 | 3515.62 | True |
| 71 | Powell | Park | 2673.574550 | 1251 | 1.62 | 3134.18 | True |
| 80 | Sheridan | Sheridan | 1893.977048 | 2646 | 8.98 | 6039.71 | True |
| 87 | Rock Springs | Sweetwater | 6620.201916 | 4022 | 2.78 | 7572.18 | True |
| 92 | Evanston | Uinta | 999.497100 | 1486 | 4.95 | 2712.64 | True |

Step 3: Dealing with Outliers

Are there any cities that are outliers in the training set? Which outlier have you chosen to remove or impute?

Ans: As shown in the following table and boxplot, the top outlier is the City "Cheyenne", whose **"Total Families"** eight time of the average. The next outlier will be "Casper".

2nd reviewer: We should find one outlier for multiple variables (Cheyenne), and two other outliers which will be flagged for less variables. One of these outliers will be a typo, and the other is really an outlier.

My response:

I will insist my answer. I guess the reviewer will want "Rock Spring" as a outlier because its "Land Area" is the largest. But it really depends what are the predictor variables. I think "Total Families" and "Households with Under 18" weights much more than land.

In additon, I don't find any typo in my mining data from "p2-partially-parsed-wy-web-scrape.csv"

... ..: Required : We do not insist on any one particular answer. There can be 2 or 3 possible outliers in this answer. We just want you to identify atleast 2 potential outliers correctly and then discuss and justify your choice of the outlier city in the report. Post that, you also need to justify the best course of action (imputation/removal) for your choice of outlier city. We accept all the possible outlier choices, provided your reasons are sound. We expect that outliers are calculated by analyzing the Interquartile Range of the data set and calculating the Upper and Lower Fences of the distribution in the training dataset. (As per the lessons in the course). And based on these calculations, we are informing you, that **Casper is not an outlier city in any of the fields of your dataset.**

... ..: Suggestion: To help you with the outlier calculations - Go to 'Creating an Analytical Dataset' section in the course and then go to the Data Issues section, and then go to "what is an outlier" video. Going through the next five video's you arrive at "Identifying Outliers" video. There are formulae mentioned below that video to help you calculate outliers. Apply these formulae to the data in each of the columns of the table you built as per step 2 above. Through this

```
In [18]: selector = (demog["Land Area"]> 5000) | (demog["Population Density"]> 10) |\n          (demog["Total Families"] > 10000)\ndemog[selector]
```

Out[18]:

| | City | County | Land Area | Households with Under 18 | Population Density | Total Families | Pawdacity |
|----|--------------|------------|-------------|--------------------------|--------------------|----------------|-----------|
| 18 | Rawlins | Carbon | 5322.661628 | 1307 | 1.32 | 2722.43 | False |
| 48 | Cheyenne | Laramie | 1500.178400 | 7158 | 20.34 | 14612.64 | True |
| 60 | Casper | Natrona | 3894.309100 | 7788 | 11.16 | 8756.32 | True |
| 87 | Rock Springs | Sweetwater | 6620.201916 | 4022 | 2.78 | 7572.18 | True |

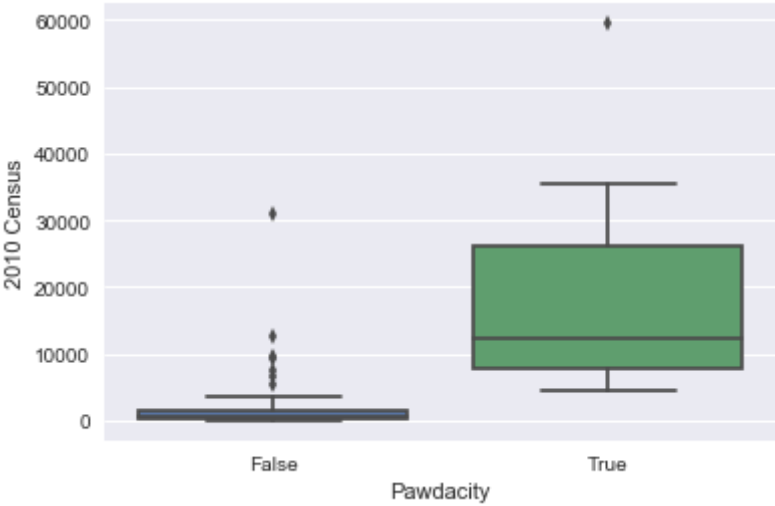
```
In [19]: popul[popul["2010 Census"]>30000]
```

Out[19]:

| | City County | 2014 Estimate | 2010 Census | 2000 Census | Pawdacity |
|----|---------------------|---------------|-------------|-------------|-----------|
| 13 | Casper ? Natrona | 40086 | 35316 | 32644 | True |
| 14 | Cheyenne ?? Laramie | 62845 | 59466 | 53011 | True |
| 52 | Laramie ? Albany | 32081 | 30816 | 27204 | False |

```
In [20]: sns.boxplot(y="2010 Census", x = "Pawdacity",data = popul)
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x10e6d7320>



process ,you will determine the outlier positions of the cities with respect to each of the columns of the data-set you built.You can then go ahead and choose an outlier and take a call to impute or remove the outlier as per the requirement of the project and justify the same in your answer.

... ..: Suggestion : "Largest" Land area should not be the criteria of identifying Rock Springs as an outlier. You should check if its **above the Upper Fence.**

```

In [21]: plt.figure(figsize=(20,10))

plt.subplot(221)
sns.boxplot(x="Pawdacity", y = "Households with Under 18",data = demog)

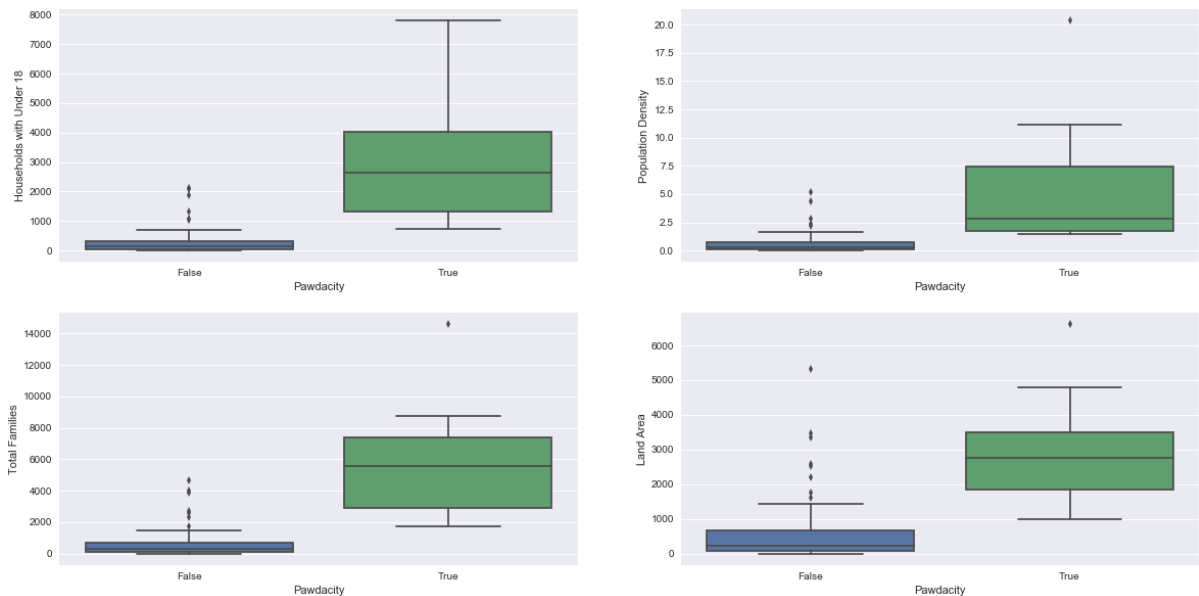
plt.subplot(222)
sns.boxplot(x="Pawdacity", y = "Population Density",data = demog)

plt.subplot(223)
sns.boxplot(x="Pawdacity", y = "Total Families",data = demog)

plt.subplot(224)
sns.boxplot(x="Pawdacity", y = "Land Area",data = demog)

plt.show()

```



Next up

I expect there is a follow-up project to do the actual prediction. But it seems to be removed or somewhere else. So my steps for such prediction is:

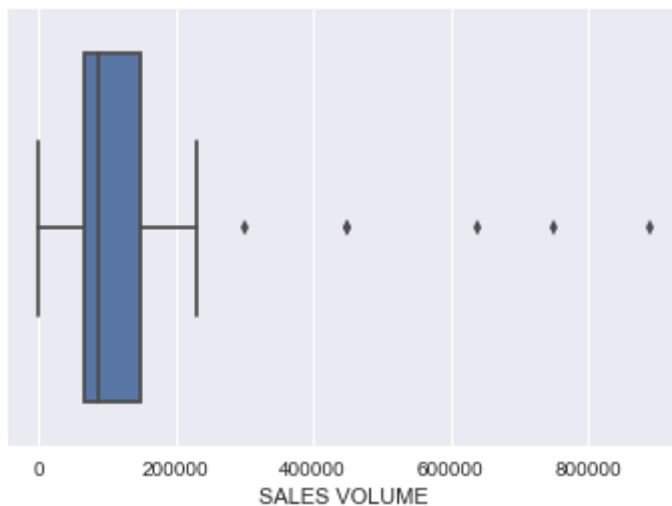
1. With the demographic statistics, figure out which city is above the average but without a Pawdacity store
2. Dig into NAICS to see whether competitors are already in the market of target cities.
3. Use existing data to predict the sales in the target cities, figure out which one will have the best sales.


```
In [22]: nakes["SALES VOLUME"].describe()
```

```
Out[22]: count      32.000000  
mean    173630.875000  
std     222548.908781  
min       0.000000  
25%     65500.000000  
50%     86000.000000  
75%    147743.250000  
max     890000.000000  
Name: SALES VOLUME, dtype: float64
```

```
In [23]: sns.boxplot(nakes["SALES VOLUME"])
```

```
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x10e87b9e8>
```



In [24]: `nakes[nakes["SALES VOLUME"]>2e5]`

Out[24]:

| | BUSINESS NAME | PHYSICAL CITY NAME | SALES VOLUME | CASS_LastLine |
|----|----------------------------|--------------------|--------------|-----------------------------|
| 0 | Mile High Mobile Pet LLC | Cheyenne | 300000 | Cheyenne, WY 82007-3528 |
| 1 | Pets City Inc | Cheyenne | 640000 | Cheyenne, WY 82009-4851 |
| 7 | Don Bruner Sales LLC | Torrington | 750000 | Torrington, WY 82240-3516 |
| 19 | L and C Pets and Gifts LLC | Evansville | 210000 | Evansville, WY 82636 |
| 20 | All Gods Creatures | Gillette | 450000 | Gillette, WY 82716-2919 |
| 21 | Camelot Pet Castle | Gillette | 230000 | Gillette, WY 82716-1704 |
| 23 | Pet Food Outlet | Gillette | 450000 | Gillette, WY 82718-6330 |
| 26 | Zoobecks Inc | Rock Springs | 890000 | Rock Springs, WY 82901-5105 |

In []: