Rolando_lab2

December 14, 2022

1 Lab 2 - EDA Visualizations

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[32]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib_venn import venn3
```

Here the clean(er) data from the last lab is loaded:

[2]:
```
df_realEst = pd.read_csv('./clean_sacramento_real_estate.csv')
df_realEst.head()
```

[2]:
```
            street        city    zip state  beds  baths  sq__ft  \
0      3526 HIGH ST  SACRAMENTO  95838    CA     2      1     836
1       51 OMAHA CT  SACRAMENTO  95823    CA     3      1    1167
2    2796 BRANCH ST  SACRAMENTO  95815    CA     2      1     796
3  2805 JANETTE WAY  SACRAMENTO  95815    CA     2      1     852
4   6001 MCMAHON DR  SACRAMENTO  95824    CA     2      1     797

          type                     sale_date  price   latitude   longitude  \
0  Residential  Wed May 21 00:00:00 EDT 2008  59222  38.631913 -121.434879
1  Residential  Wed May 21 00:00:00 EDT 2008  68212  38.478902 -121.431028
2  Residential  Wed May 21 00:00:00 EDT 2008  68880  38.618305 -121.443839
3  Residential  Wed May 21 00:00:00 EDT 2008  69307  38.616835 -121.439146
4  Residential  Wed May 21 00:00:00 EDT 2008  81900  38.519470 -121.435768

   empty_lot street_type
0      False          ST
1      False          CT
2      False          ST
3      False         WAY
4      False          DR
```

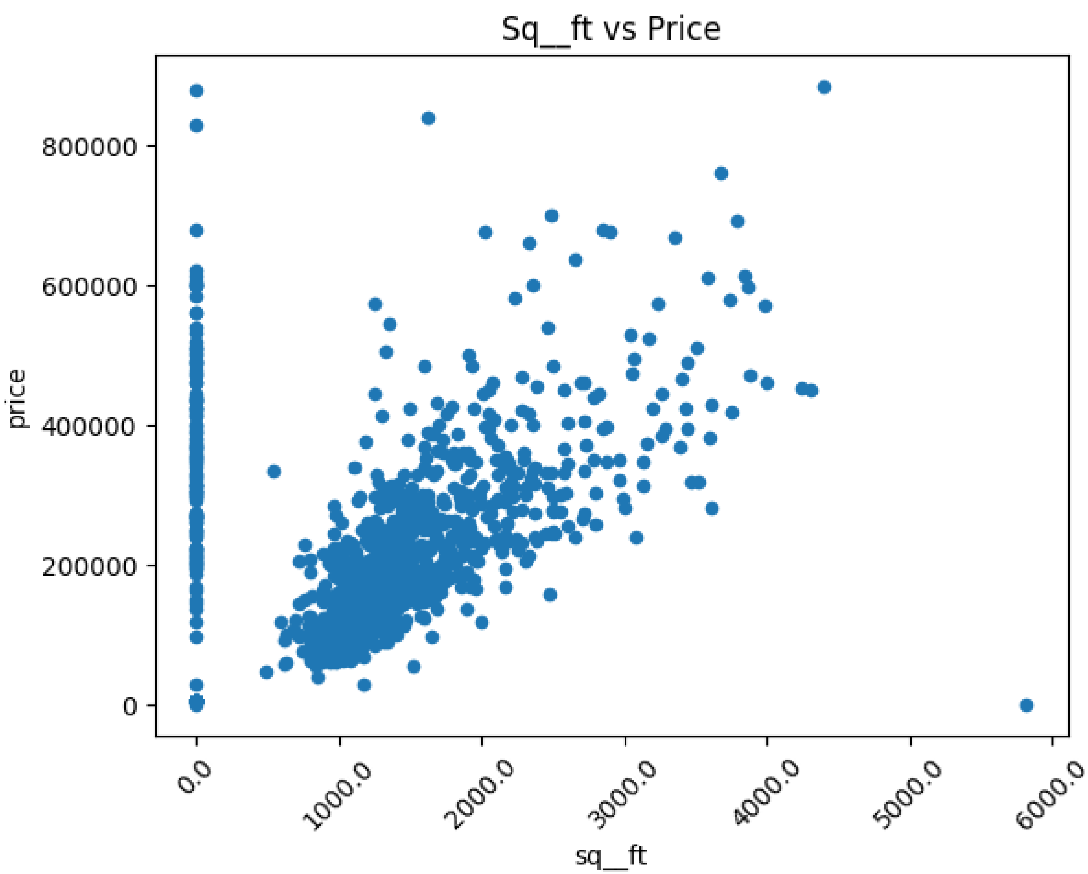
1.1 1: Regression on Price

Here we create scatter plots of the continuous variables against price. Zip code was ommitted, since there isn't much meaning in increasing zip codes or in their average.

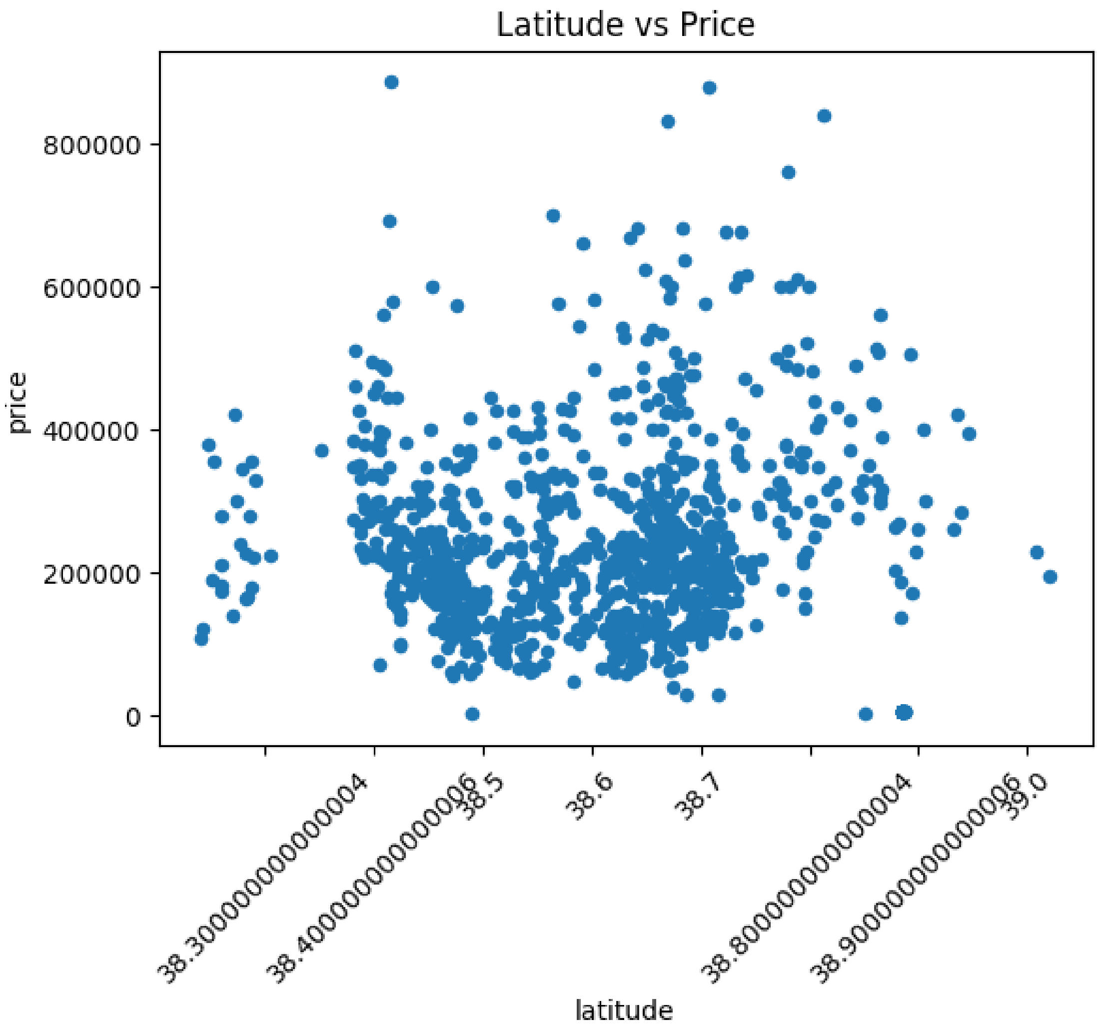
[14]:
```
cont_cols = ['sq__ft', 'latitude', 'longitude']
for col in cont_cols:
    plt.figure(figsize=(12, 8))
    ax = df_realEst.plot.scatter(x=col, y='price')
    ax.set_title(col.capitalize() + ' vs Price')
    ax.set_xticklabels(ax.get_xticks(), rotation = 45)
    plt.show()
```

```
/tmp/ipykernel_6185/1318838926.py:6: UserWarning: FixedFormatter should only be
used together with FixedLocator
  ax.set_xticklabels(ax.get_xticks(), rotation = 45)
```

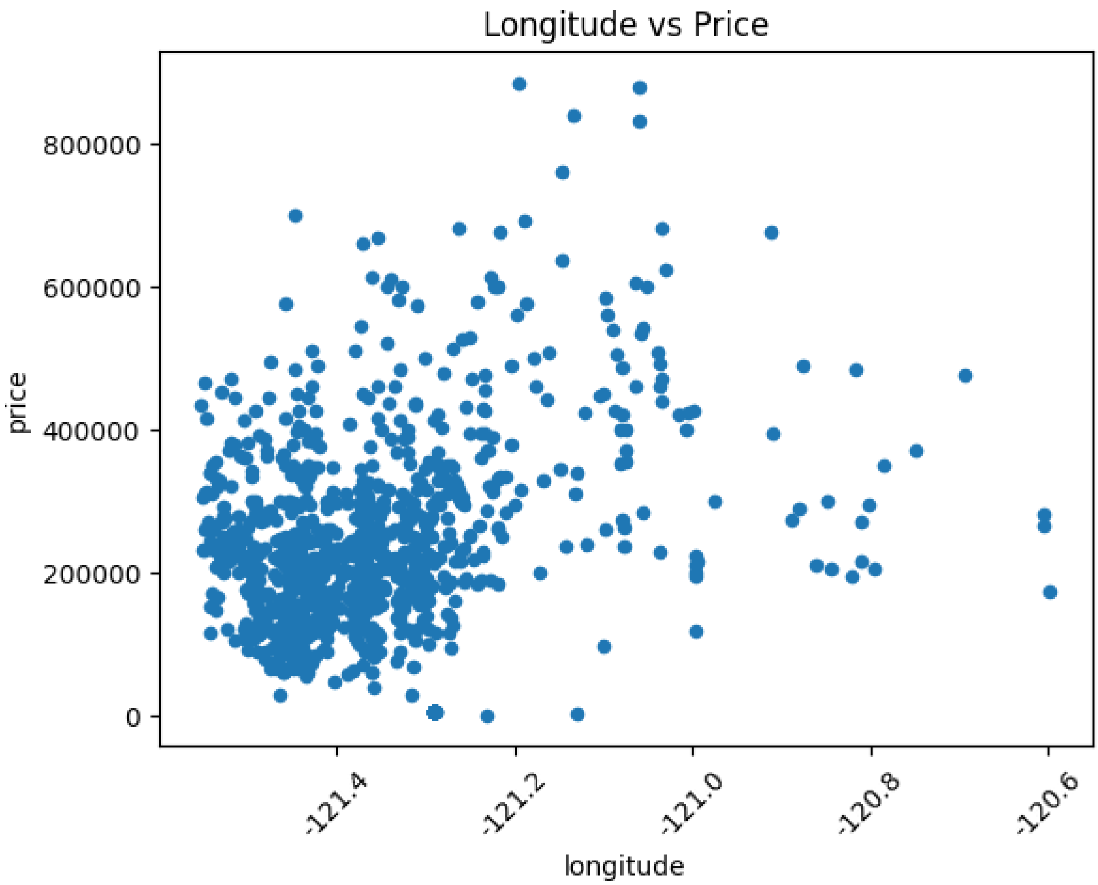
```
<Figure size 1200x800 with 0 Axes>
```




```
<Figure size 1200x800 with 0 Axes>
```




```
<Figure size 1200x800 with 0 Axes>
```



It looks like square footage has the most obvious correlation with price.

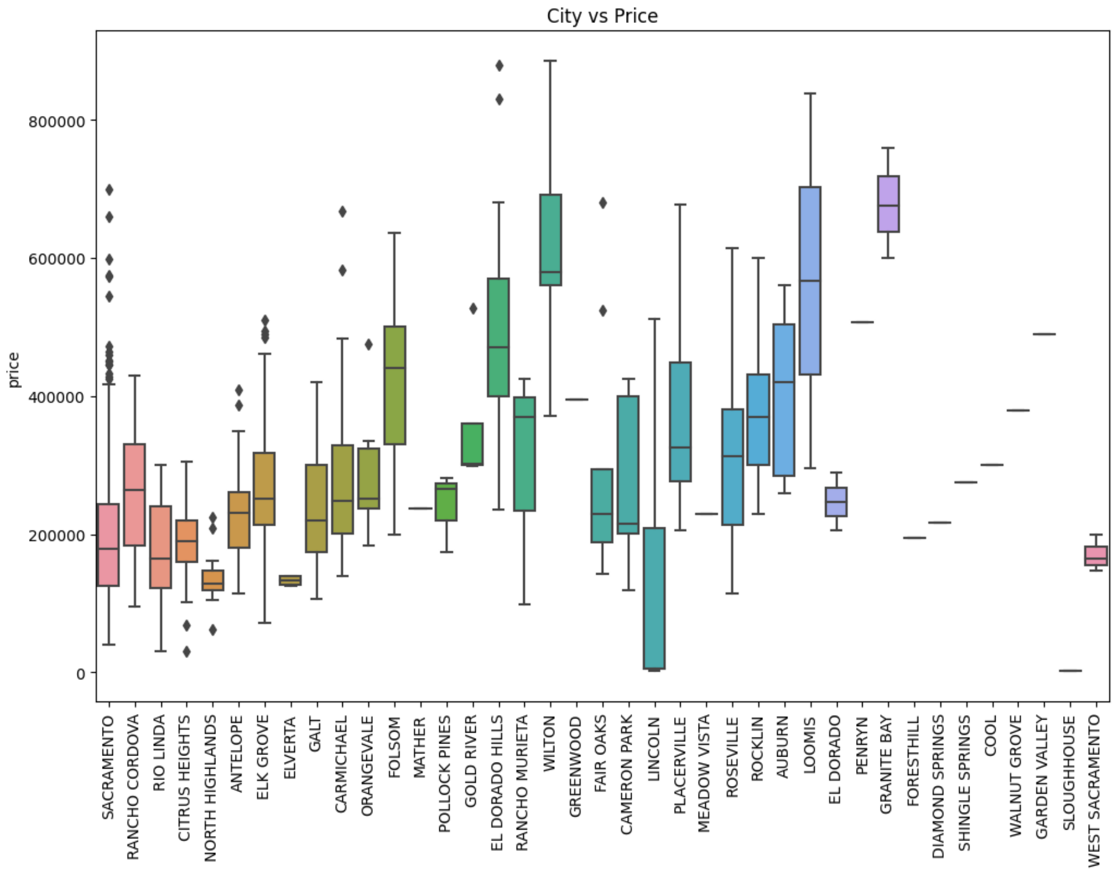
Here's a table describing their ability to predict price:

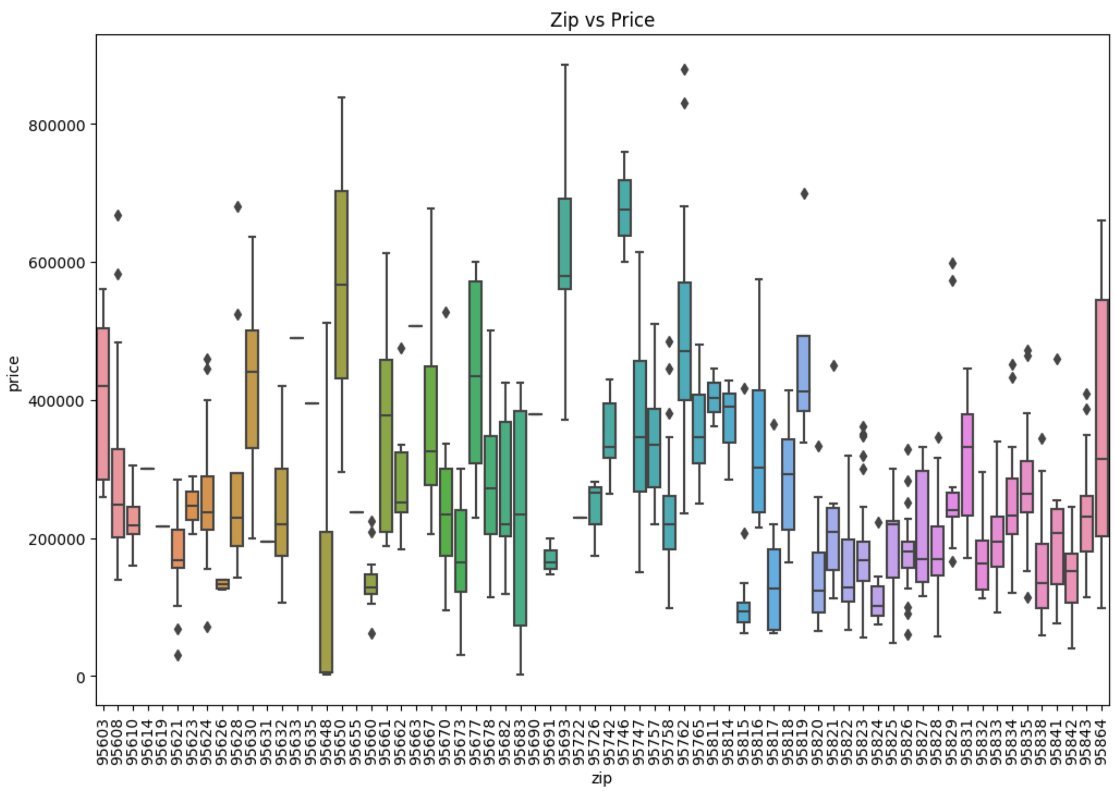
column	predictive?	why?
sq_ft	yes	generally, as the square footage increases, so does the price
latitude	no	while there are some groups, the price doesn't increase or decrease as the latitude increases
longitude	no	same as latitude

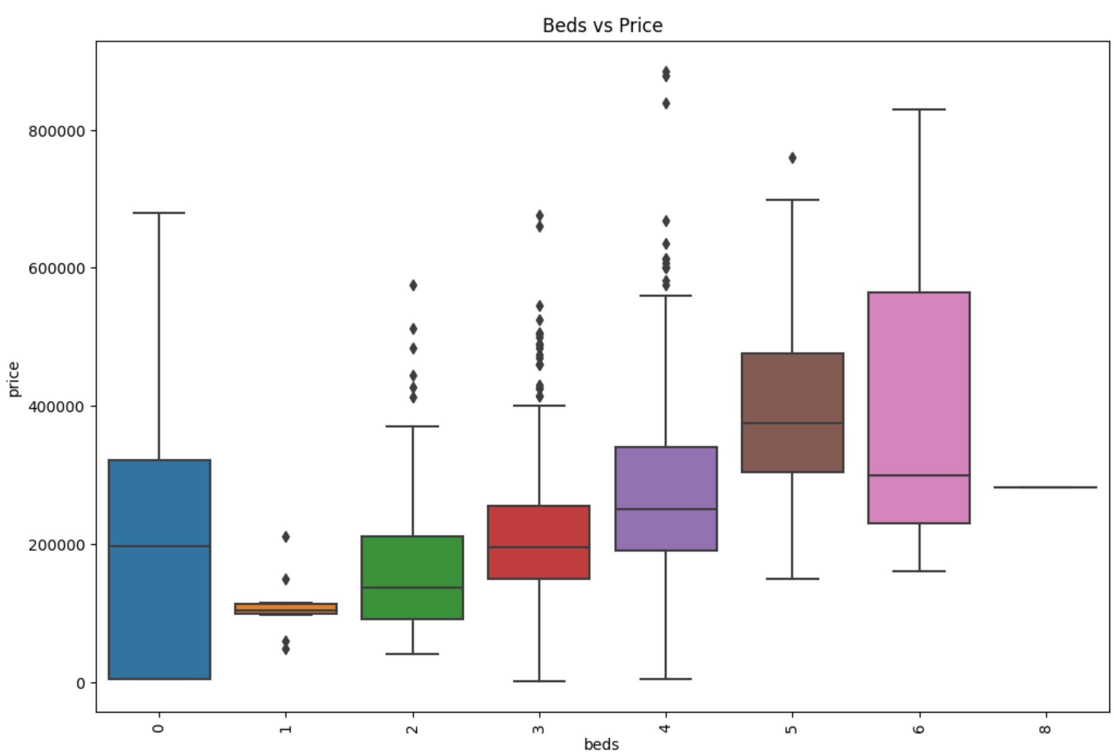
Here are box plots for the categorical variables (including zip codes):

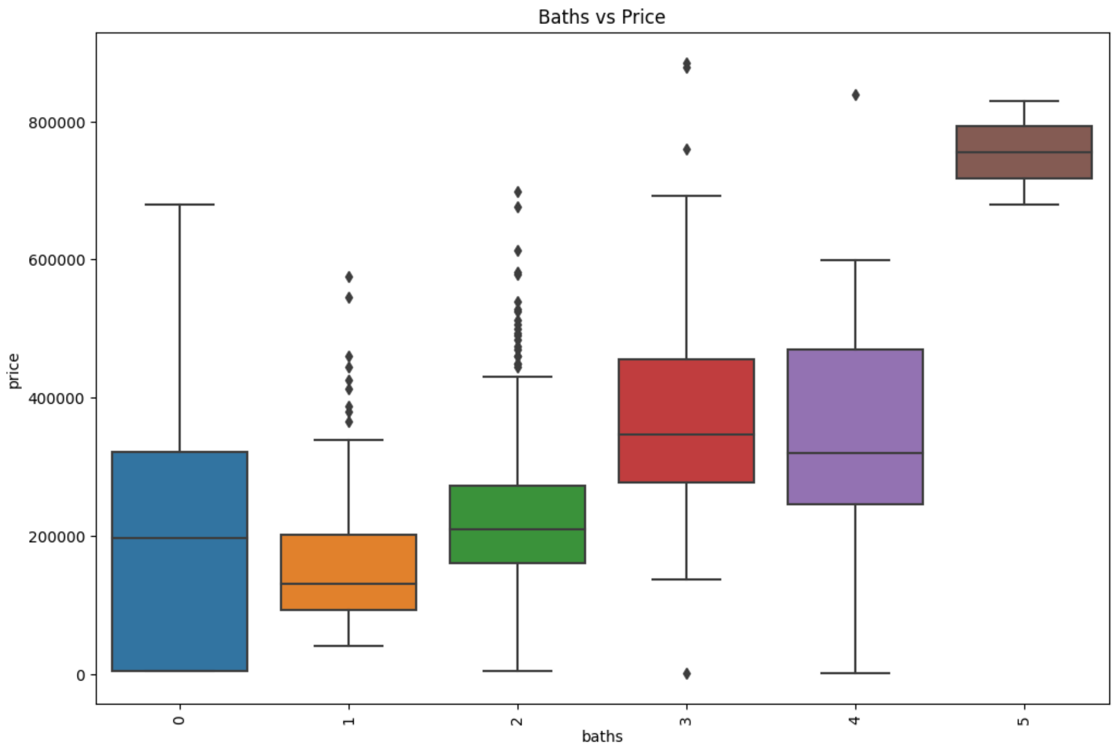
[23]:
```
cat_cols = ['city', 'zip', 'beds', 'baths', 'type', 'sale_date', 'empty_lot',␣
↪'street_type']
for col in cat_cols:
    plt.figure(figsize=(12, 8))
```

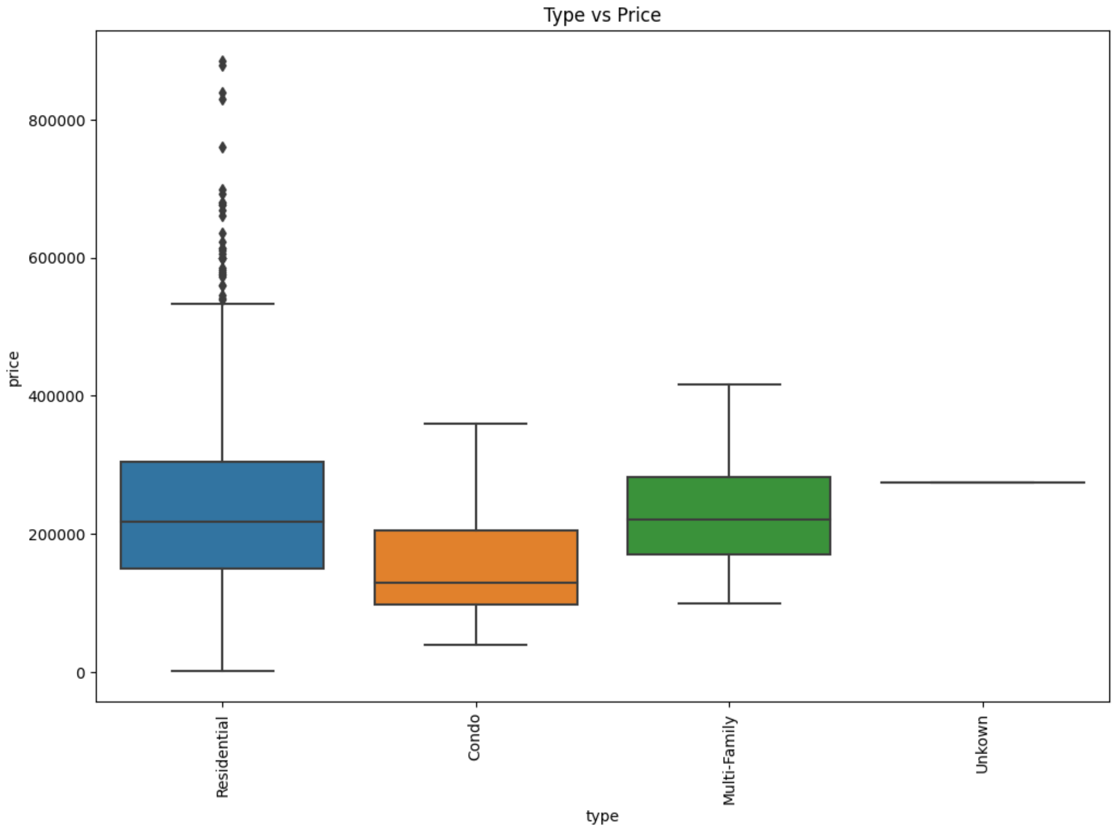
```
ax = sns.boxplot(x=col, y='price', data=df_realEst)
ax.set_title(col.capitalize() + " vs Price")
ax.set_xticklabels(ax.get_xticklabels(), rotation = 90)
plt.show()
```

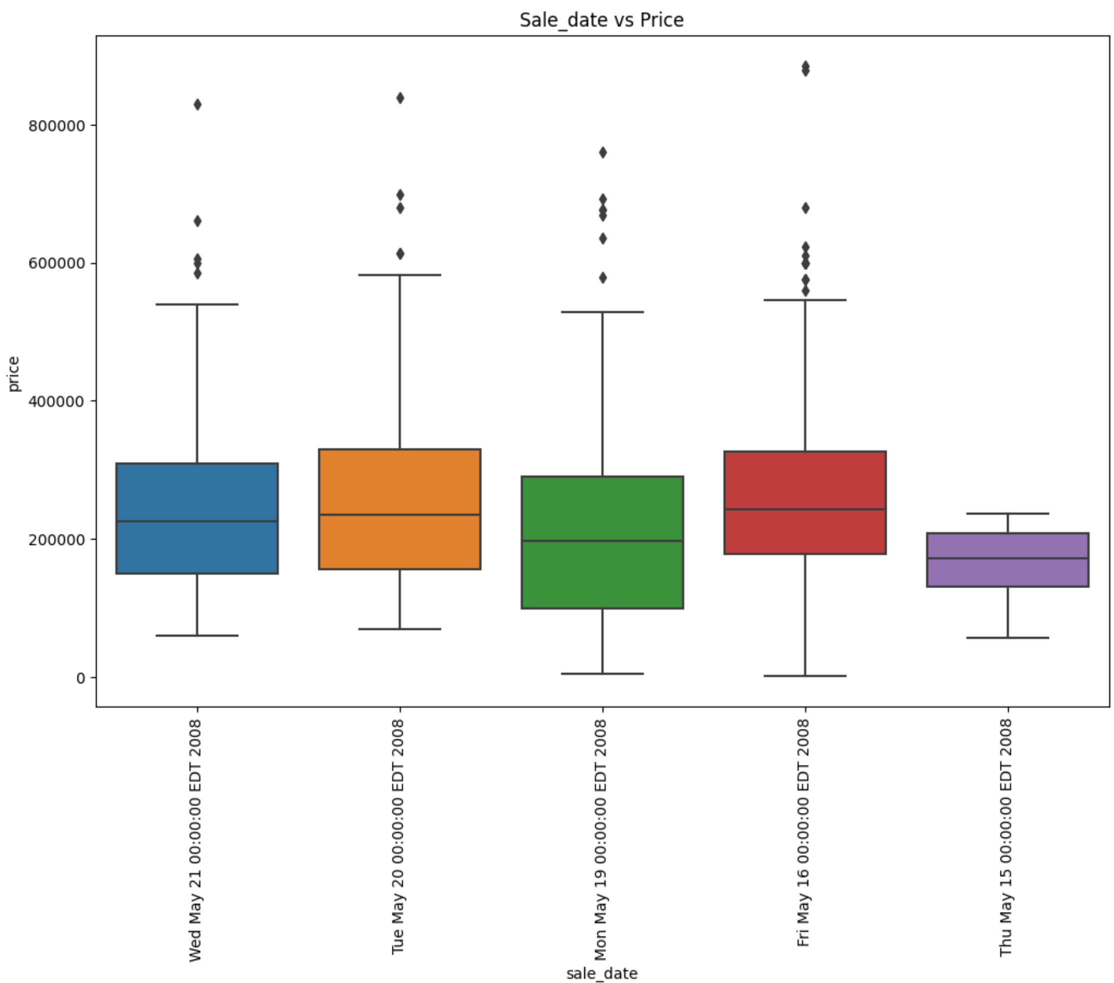


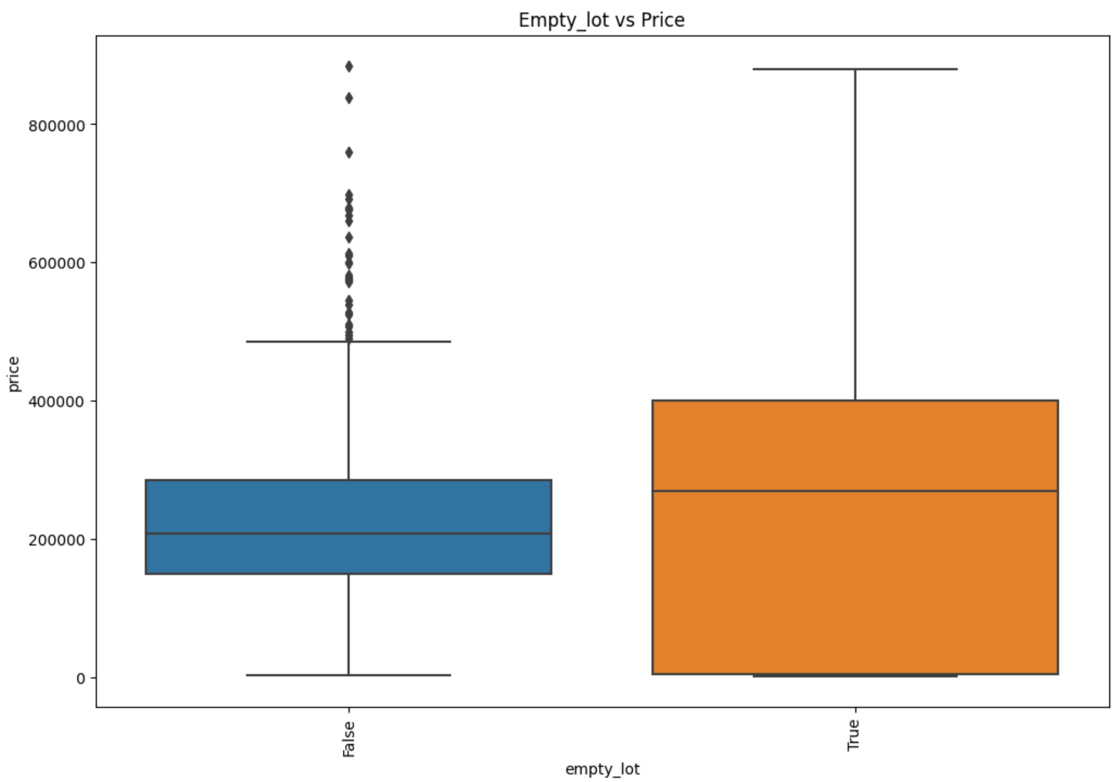

Zip vs Price
price
zip

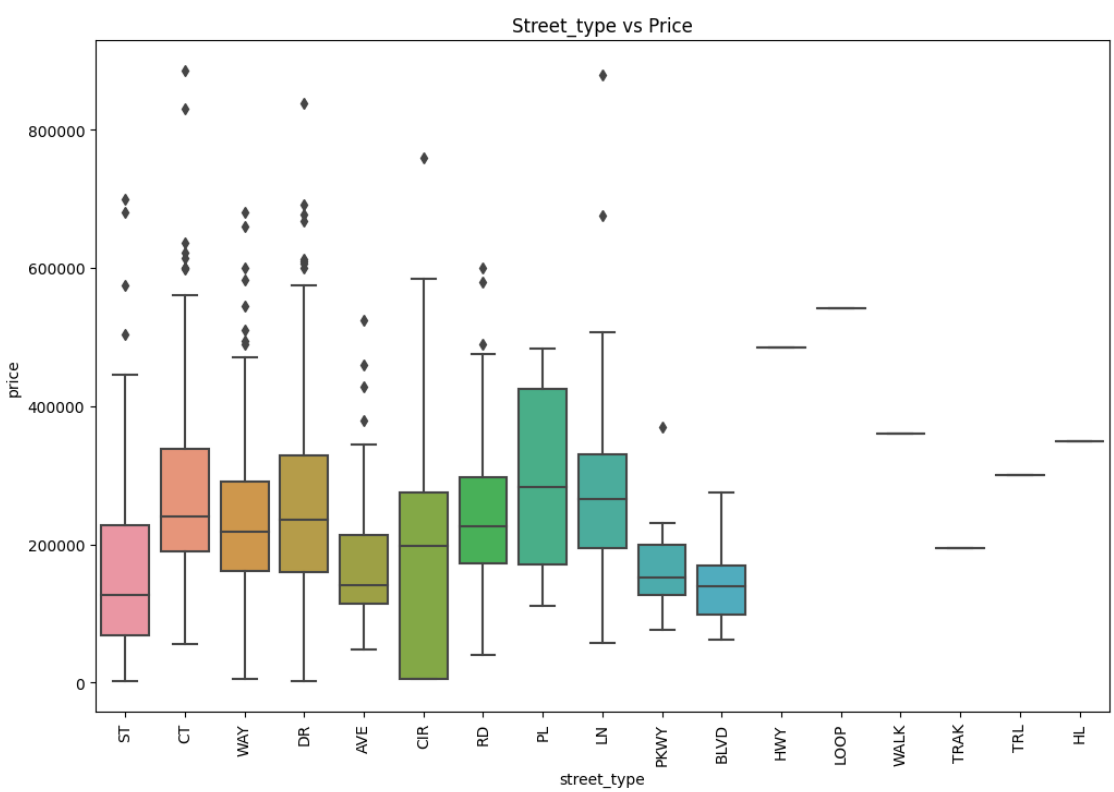

Beds vs Price
price
beds
0
1
2
3
4
5
6
8


Baths vs Price
800000
600000
400000
200000
0
price
0
1
2
3
4
5
baths


Type vs Price
800000
600000
400000
200000
0
price
Residential
Condo
Multi-Family
Unkown
type


Sale_date vs Price
price
800000
600000
400000
200000
0
Wed May 21 00:00:00 EDT 2008
Tue May 20 00:00:00 EDT 2008
Mon May 19 00:00:00 EDT 2008
Fri May 16 00:00:00 EDT 2008
Thu May 15 00:00:00 EDT 2008
sale_date


Empty_lot vs Price
price
800000
600000
400000
200000
0
False
True
empty_lot


Street_type vs Price
price
800000
600000
400000
200000
0
ST
CT
WAY
DR
AVE
CIR
RD
PL
LN
PKWY
BLVD
HWY
LOOP
WALK
TRAK
TRL
HL
street_type

Here's a table describing their ability to predict price:

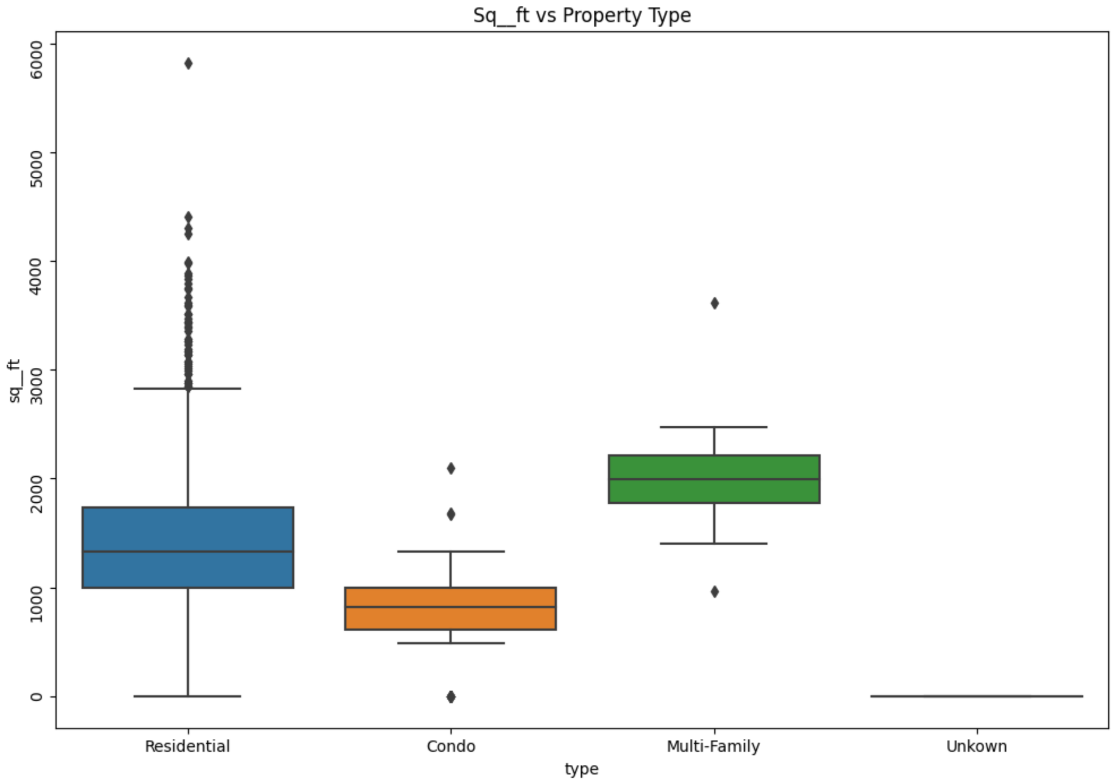
column	predictive?	why?
city	yes	For many cities, they have a very small distribution that doesn't overlap much with other cities, this could be useful.
zip	yes	same as city
bed	yes	This is the most obvious categorical variable with predictive qualities. As long as the number of beds isn't zero or six, it's pretty easy to draw some conclusion about where the price will fall based on the number of bedrooms.
baths	yes	for 1, 2, 3, and 5 baths, there is also very clear separation of the prices between categories.
type	no	a lot of overlap between most categories
sale date	no	a lot of overlap between most categories
empty lot	no	a lot of overlap between most categories
street type	no	a lot of overlap between most categories

1.2 2: Classification on Property Type

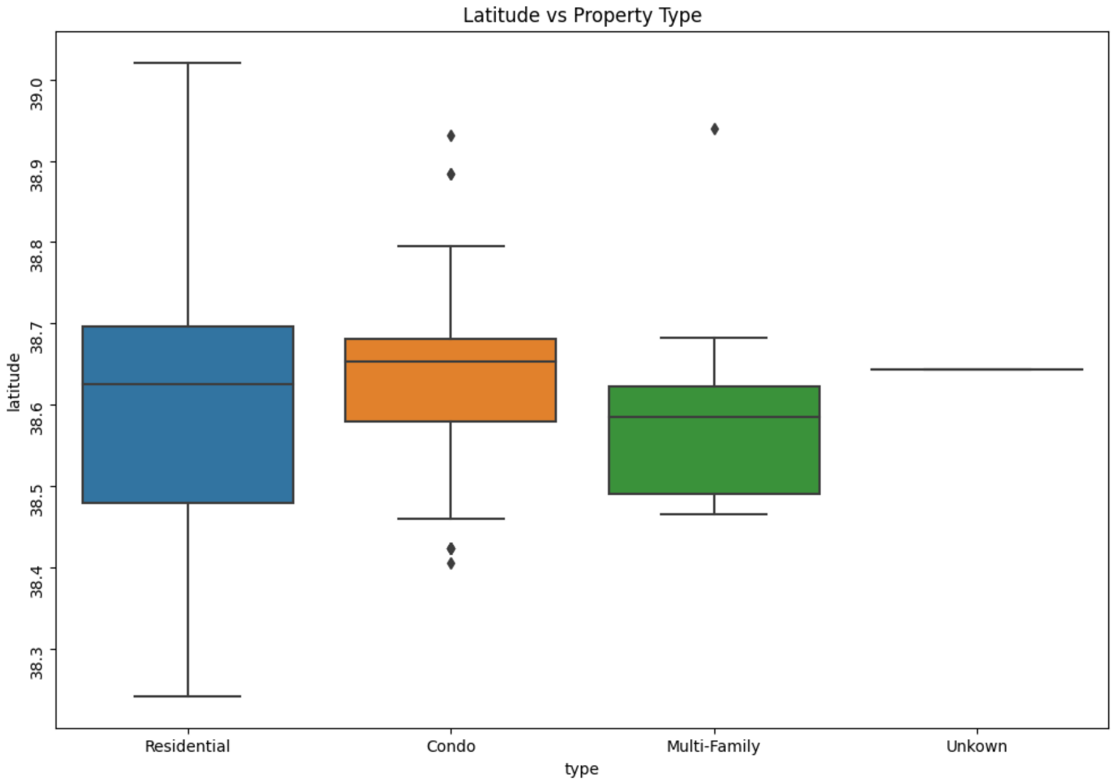
Here are box plots of each regression variable as they compare to the property type:

[26]:
```python
cont_cols = ['sq__ft', 'latitude', 'longitude', 'price']
for col in cont_cols:
    plt.figure(figsize=(12, 8))
    ax = sns.boxplot(y=col, x='type', data=df_realEst)
    ax.set_title(col.capitalize() + " vs Property Type")
    ax.set_yticklabels(ax.get_yticklabels(), rotation = 90)
    plt.show()
```

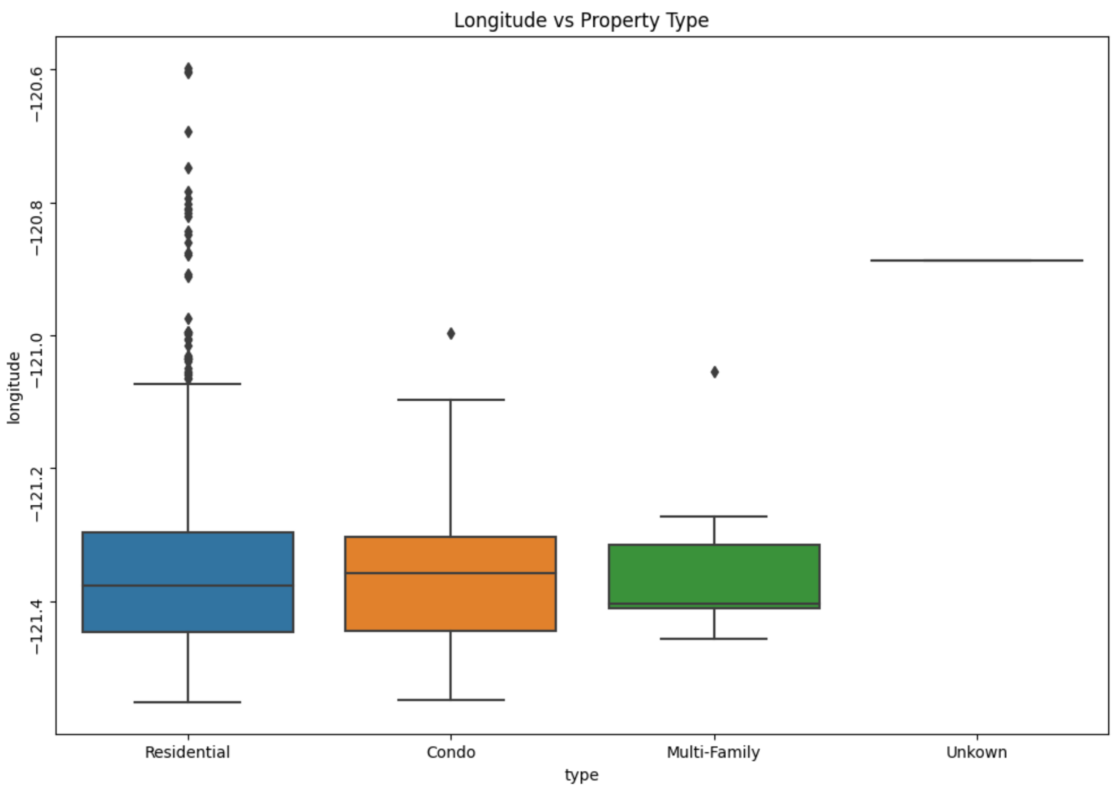
```
/tmp/ipykernel_6185/3145545652.py:6: UserWarning: FixedFormatter should only be
used together with FixedLocator
  ax.set_yticklabels(ax.get_yticklabels(), rotation = 90)
```



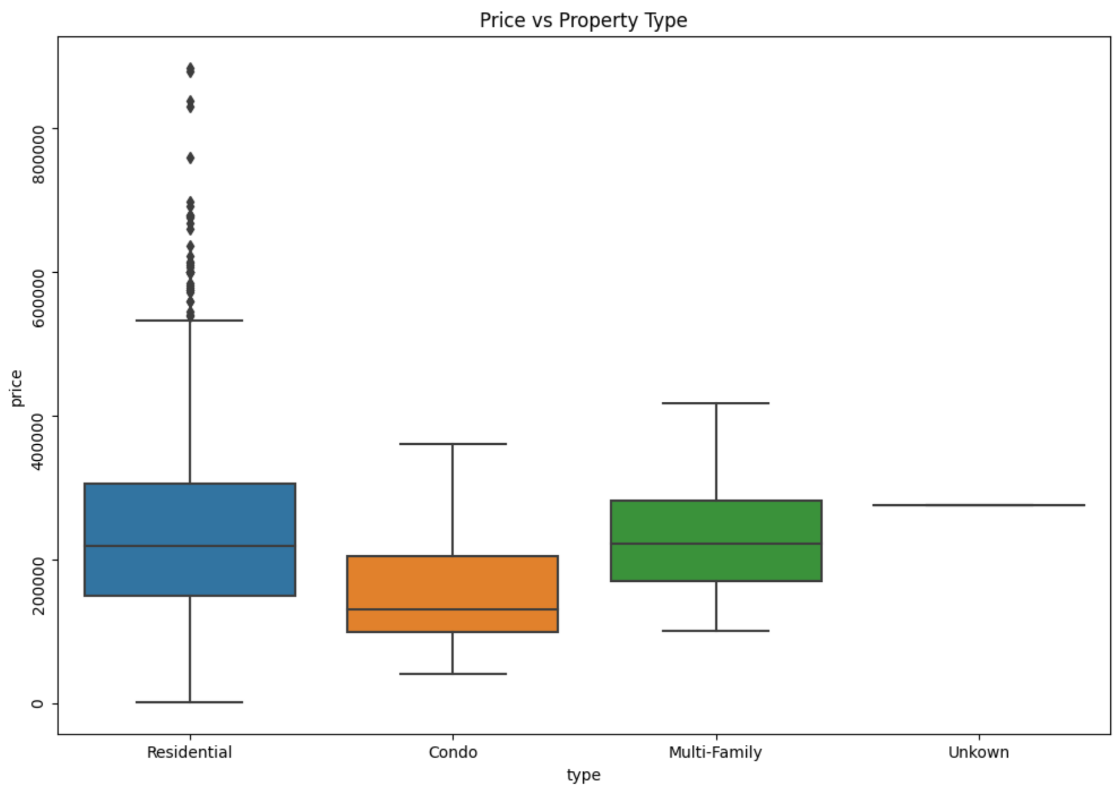

```
/tmp/ipykernel_6185/3145545652.py:6: UserWarning: FixedFormatter should only be
used together with FixedLocator
  ax.set_yticklabels(ax.get_yticklabels(), rotation = 90)
```




```
/tmp/ipykernel_6185/3145545652.py:6: UserWarning: FixedFormatter should only be
used together with FixedLocator
  ax.set_yticklabels(ax.get_yticklabels(), rotation = 90)
```




```
/tmp/ipykernel_6185/3145545652.py:6: UserWarning: FixedFormatter should only be
used together with FixedLocator
  ax.set_yticklabels(ax.get_yticklabels(), rotation = 90)
```



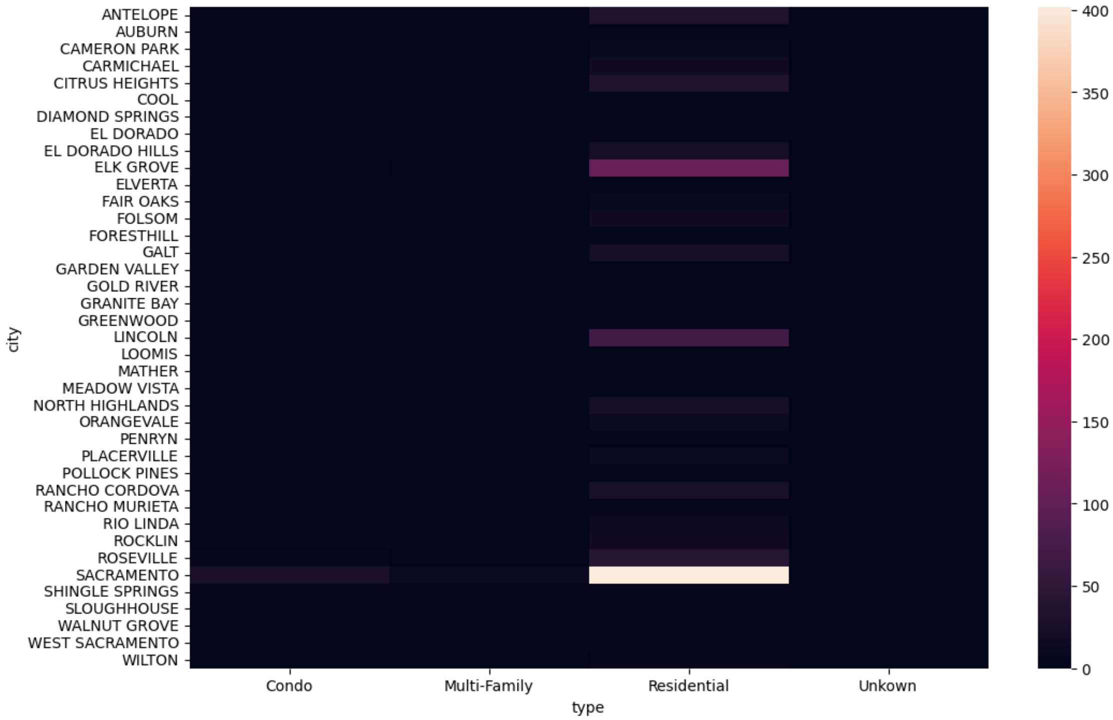
Here's a table describing their ability to predict property type:

column	predictive?	why?
sq_ft	yes	This seems to break up the property types almost perfectly
latitude	no	All of the property types overlap significantly
longitude	no	same as latitude
price	no	same as latitude

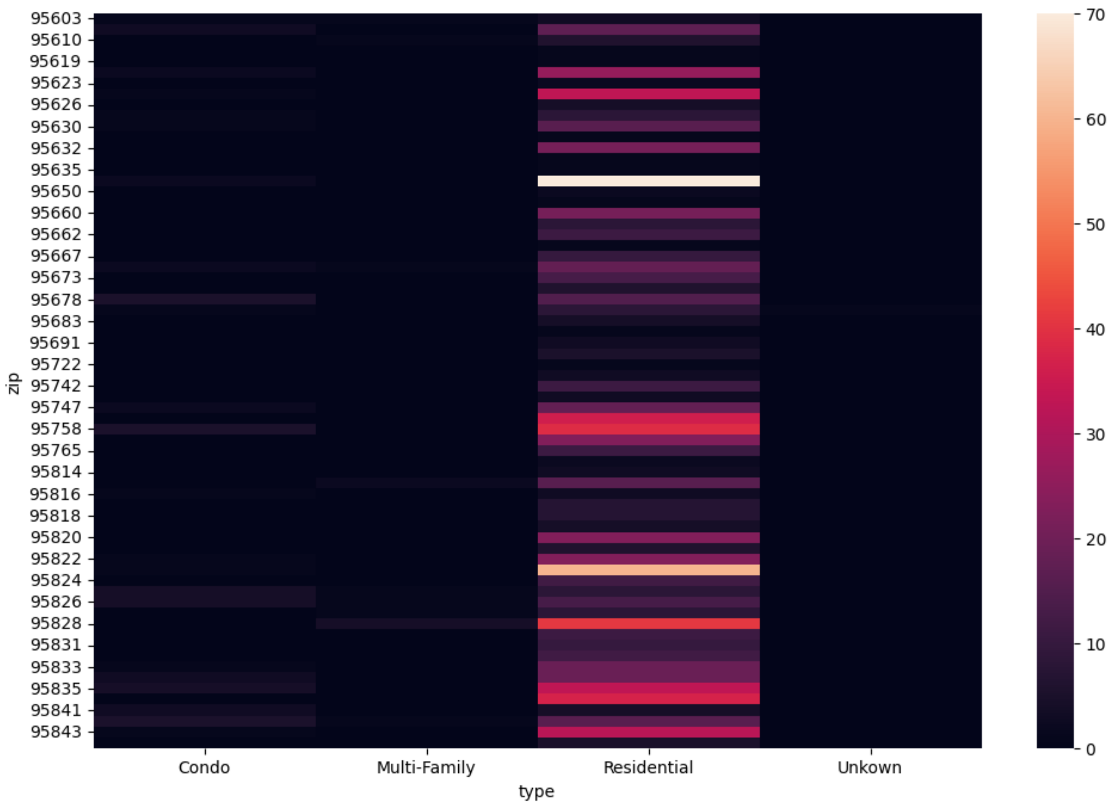
Here is a heat map of each categorical variable as they compare to property type:

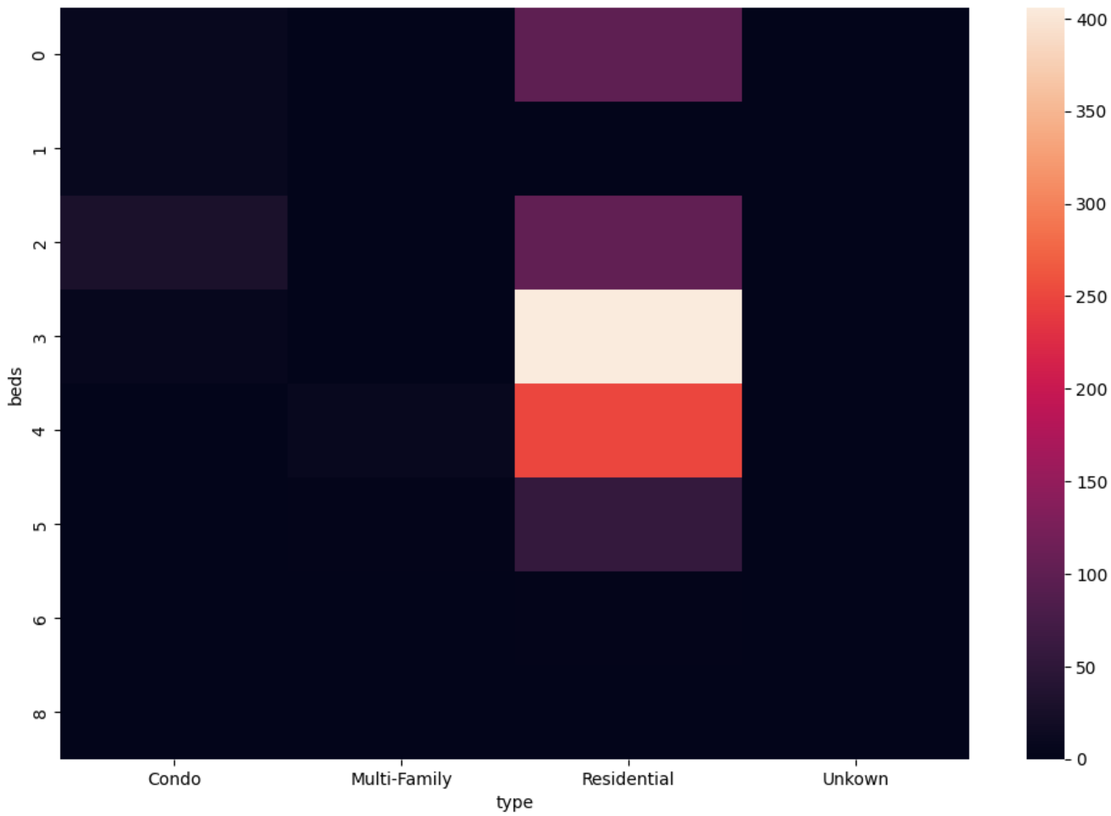
[29]:
```
cat_cols = ['city', 'zip', 'beds', 'baths', 'sale_date', 'empty_lot',␣
↪'street_type']
for col in cat_cols:
    plt.figure(figsize=(12, 8))
    sns.heatmap(df_realEst.value_counts(subset=["type", col]).unstack(level=0).
↪fillna(0))
    ax.set_title(col.capitalize() + " vs Price")
    ax.set_xticklabels(ax.get_xticklabels(), rotation = 90)
```

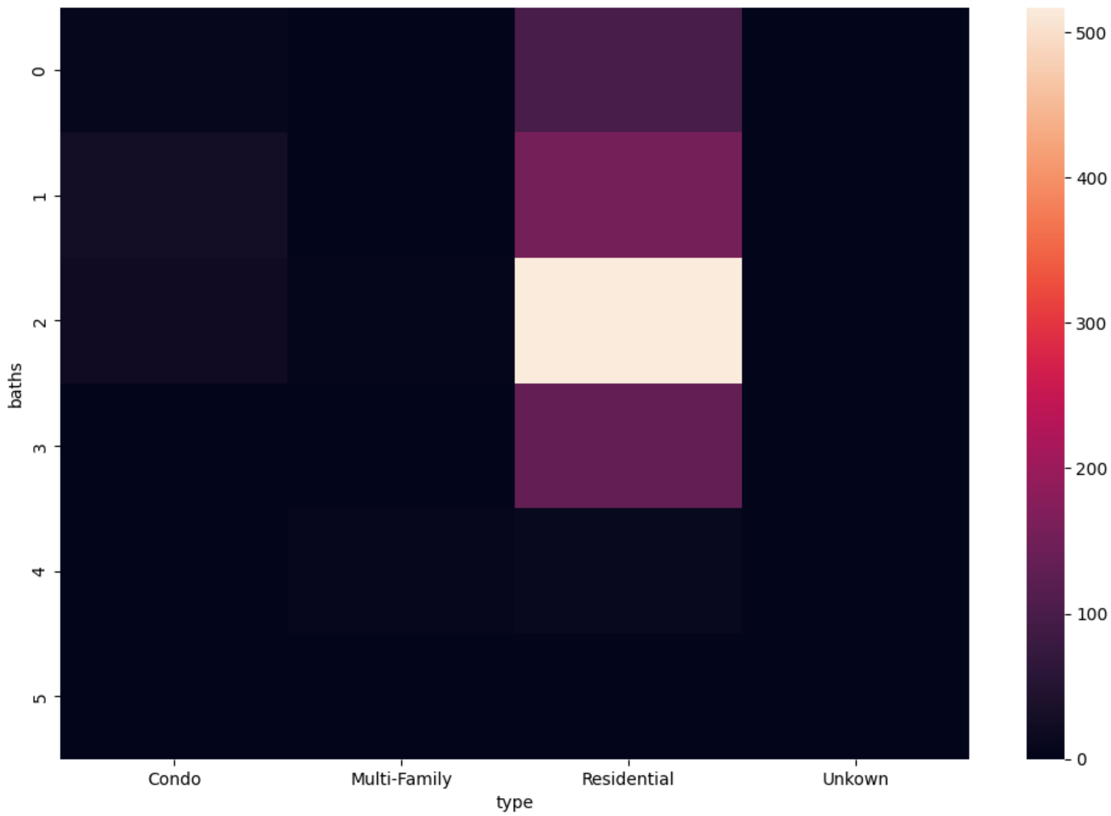
```
plt.show()
```

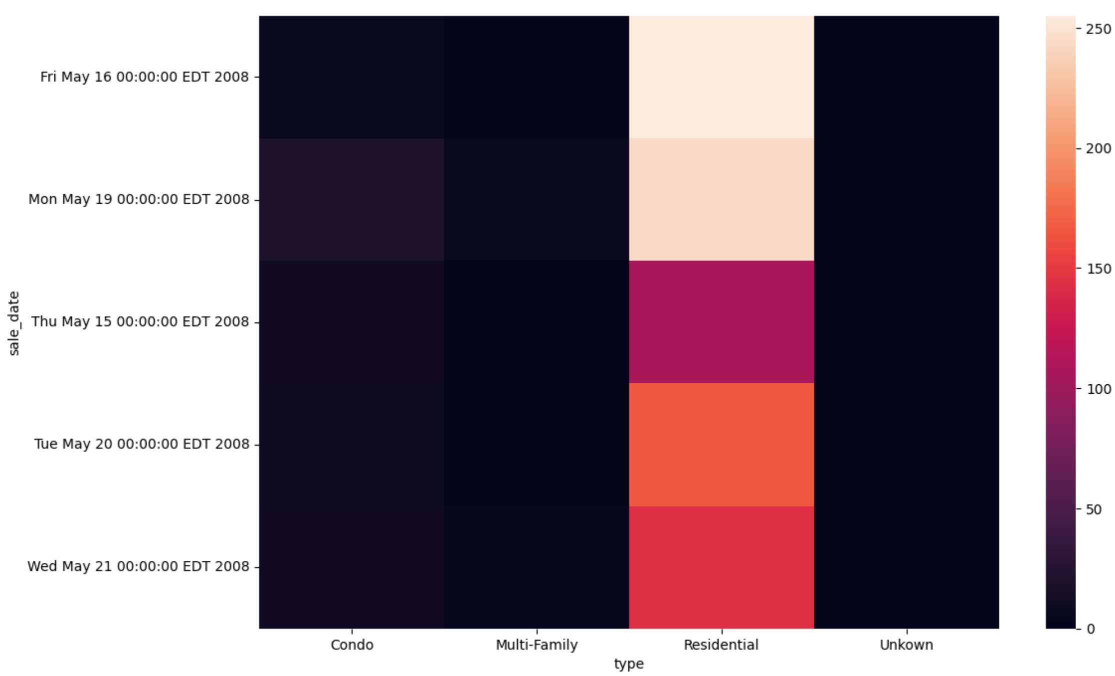


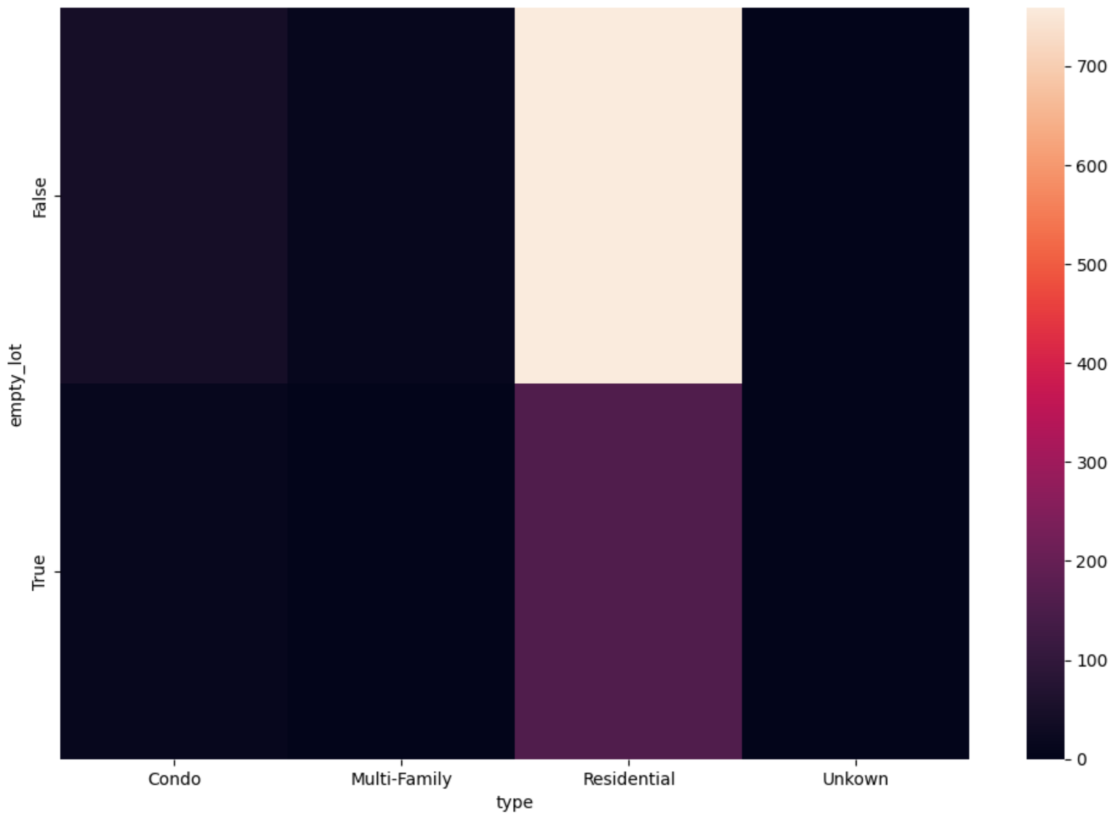
ANTELOPE
AUBURN
CAMERON PARK
CARMICHAEL
CITRUS HEIGHTS
COOL
DIAMOND SPRINGS
EL DORADO
EL DORADO HILLS
ELK GROVE
ELVERTA
FAIR OAKS
FOLSOM
FORESTHILL
GALT
GARDEN VALLEY
GOLD RIVER
GRANITE BAY
GREENWOOD
LINCOLN
LOOMIS
MATHER
MEADOW VISTA
NORTH HIGHLANDS
ORANGEVALE
PENRYN
PLACERVILLE
POLLOCK PINES
RANCHO CORDOVA
RANCHO MURIETA
RIO LINDA
ROCKLIN
ROSEVILLE
SACRAMENTO
SHINGLE SPRINGS
SLOUGHHOUSE
WALNUT GROVE
WEST SACRAMENTO
WILTON
city
Condo
Multi-Family
Residential
Unkown
type
400
350
300
250
200
150
100
50
0


95603
95610
95619
95623
95626
95630
95632
95635
95650
95660
95662
95667
95673
95678
95683
95691
95722
95742
95747
95758
95765
95814
95816
95818
95820
95822
95824
95826
95828
95831
95833
95835
95841
95843
zip
Condo
Multi-Family
Residential
Unkown
type
70
60
50
40
30
20
10
0

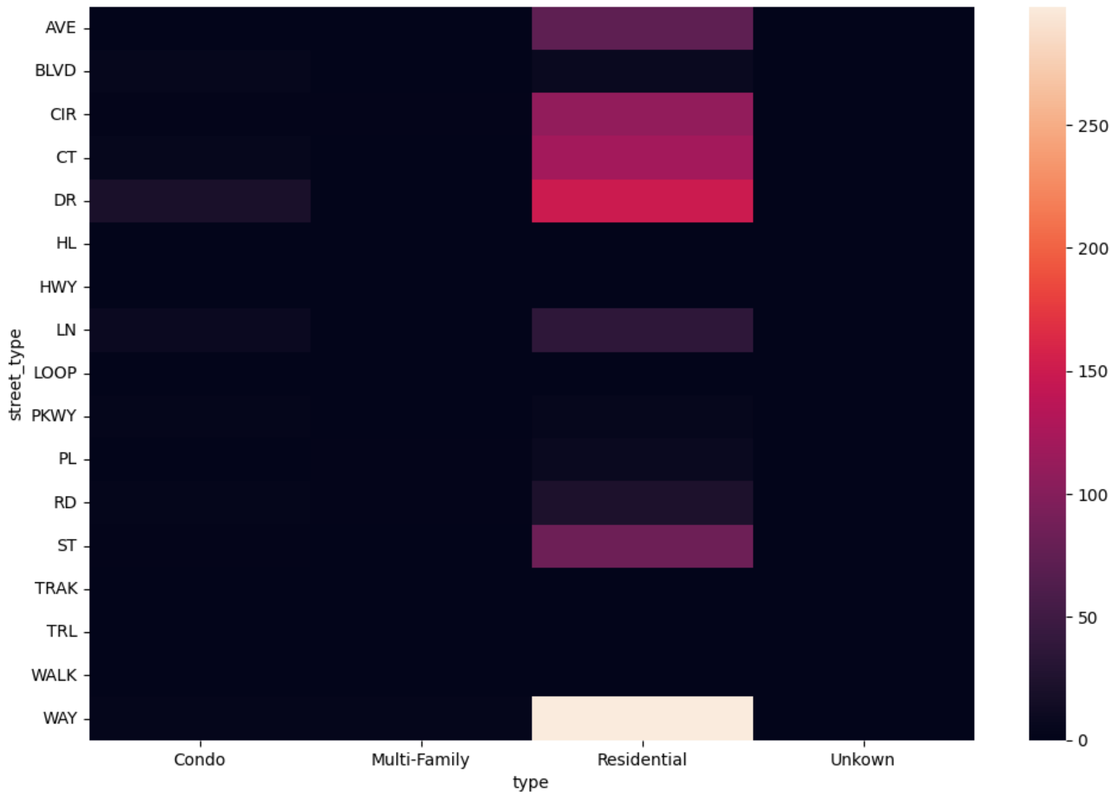

0
1
2
3
4
5
6
8
beds
Condo
Multi-Family
Residential
Unkown
type
400
350
300
250
200
150
100
50
0


0
1
2
3
4
5
baths
Condo
Multi-Family
Residential
Unkown
type
500
400
300
200
100
0


Fri May 16 00:00:00 EDT 2008
Mon May 19 00:00:00 EDT 2008
Thu May 15 00:00:00 EDT 2008
Tue May 20 00:00:00 EDT 2008
Wed May 21 00:00:00 EDT 2008
sale_date
Condo
Multi-Family
Residential
Unkown
type
250
200
150
100
50
0



False
True
empty_lot
Condo
Multi-Family
Residential
Unkown
type
700
600
500
400
300
200
100
0



Here's a table describing their ability to predict property type:

column	predictive?	why?
city	no	obviously sacramento is the most common city, regardless of the type of property
zip	no	same as city
bed	sort of	There are a couple of very clear clategories that light up for residential, where the rest of the categories don't occur very often in the residential category. This could just mean that the number of beds didn't occur very often.
baths	sort of	many of the possible values light up for residential, though there is a clear winner, so it could be used.
sale date	no	all of the categories light up for the residential type
empty lot	no	both categories light up for the residential type

column	predictive?	why?
street type	no	Many of the different categories light up for the residential type

None of the categorical variables would be super useful for determining the type of property. If anything, these graphs just highlight what configurations are most likely to occur in a residential setting, since it's the only type that has any significant occurances in any category. Differentiation between the different property types is a lost cause with these heat maps given the disproportion of the amount of data for residential types vs other types. If anything, one could *possibly* use these categorical variables to determine whether a property is residential or not, nothing more granular.

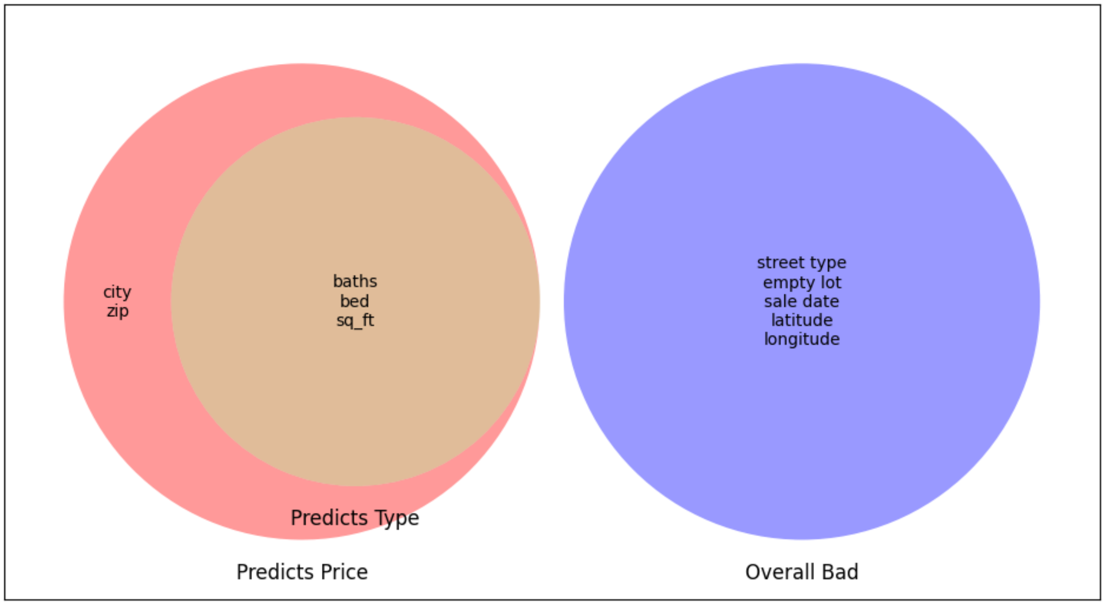
1.3 3: Compare Predictive Variables

> note: I hesitate to label beds or paths as predictive for property type, but they were the most predictive out of all of the categories. Overall, more data is needed for non-residential properties to make clearer distinctions

[35]:
```
fig = plt.figure(figsize=(12, 8))
price = set(['sq_ft', 'city', 'zip', 'bed', 'baths'])
types = set(['sq_ft', 'bed', 'baths'])
neither = set(['latitude', 'longitude', 'sale date', 'empty lot', 'street␣
 ↪type'])

v = venn3([price, types, neither], ('Predicts Price', 'Predicts Type', 'Overall␣
 ↪Bad'))

v.get_label_by_id('100').set_text('\n'.join(map(str,price-types)))
v.get_label_by_id('110').set_text('\n'.join(map(str,price&types)))
v.get_label_by_id('001').set_text('\n'.join(map(str, neither)))
plt.axis('on')
plt.show()
```



The number of beds, number of baths, and square footage are good(ish) predictors for both property type and price.

For good predictors:

column	predictive for	why?
sq_ft	both	This is one of the most basic attributes of a house. If you take two properties of the same type in the same place, the one with more square footage is bigger, and will be the more expensive property unless there are other odd factors at play (murder). It is also a good indicator of property type, as condos are usually smaller than normal residential houses, which are usually smaller than multi-family homes.
beds	both	This is similar to square footage, as it is also a basic, easily quantifyable attribute of a house. I'd say this is slightly less important than square footage, but still very much influences the price and can be representative of property type in a similar way as well.
baths	both	Same as bedrooms
city	price	Neighborhood can drastically affect price. How safe a neighborhood is, what the schools are like, and the sorts of recreational options nearby often correlate to property value.
zip	price	This is a more granular metric for location than city, but the effect is similar.