Build Regression Model based on data_per_zipcode

As seen during our collinearity analysis it seems that zipcode might affect the property price.

Build Regression Model based on data_per_zipcode to predict property price

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So the question is How does that work ?.

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Prep-work

In [1]:
```
# Import useful librairies and set auto reload
import pandas as pd
import numpy as np
import housing_data as hd
import seaborn as sns
import matplotlib.pyplot as plt
import pickle
from statsmodels.formula.api import ols

%load_ext autoreload
%autoreload 2
```

##EDA dataset per zipcode

In [2]:
```
# Load dataset
data = hd.load_housing_data(with_cat_columns=False)
data.head()
```

Out[2]:

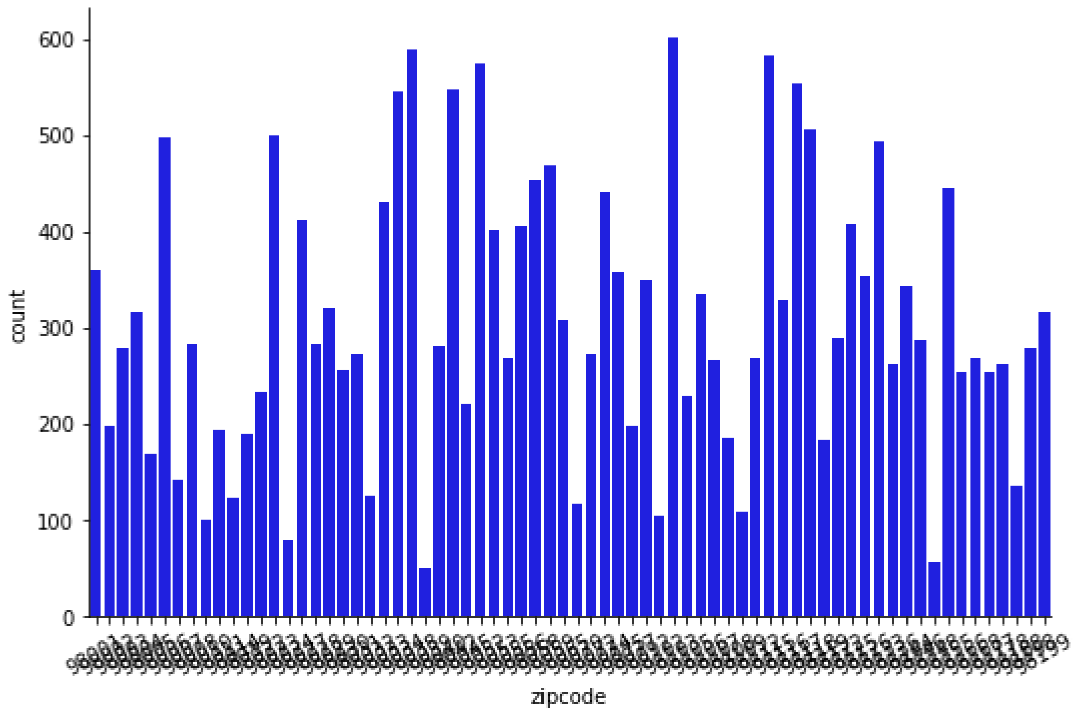
	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	False	0.0
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	False	0.0
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0	False	0.0
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	False	0.0
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	False	0.0

5 rows × 21 columns

In [3]:
```
# Plot property count per zipcode
g = sns.factorplot("zipcode", data=data, aspect=1.5, kind="count", color="b
g.set_xticklabels(rotation=30)
```

```
/Users/flatironstudentaccount/anaconda3/lib/python3.7/site-packages/seabo
rn/categorical.py:3666: UserWarning: The `factorplot` function has been r
enamed to `catplot`. The original name will be removed in a future releas
e. Please update your code. Note that the default `kind` in `factorplot`
(`'point'`) has changed `'strip'` in `catplot`.
  warnings.warn(msg)
```

Out[3]:
```
<seaborn.axisgrid.FacetGrid at 0x1c25e29048>
```



It looks like we got enough data per zipcode.

Display price against sqft_living

In [4]:
```
# Split dataset in two group of zipcode for display purpose.
zipcodes = data['zipcode'].unique()
zipcodes.sort()
zipcodes_median = zipcodes[(len(zipcodes) // 2): (len(zipcodes) // 2) + 1][

data_set1 = data.loc[data['zipcode'] <= zipcodes_median]
data_set2 = data.loc[data['zipcode'] > zipcodes_median]
```

In [5]:
```
# Display price vs sqft_living on the first subset
plt.figure(figsize=(10,10))
g = sns.FacetGrid(data_set2, col="zipcode", col_wrap=3)
g.map(plt.scatter, "sqft_living", "price")
g.set(xlim=(0, 6000), ylim=(0, 3000000))
g.set_xlabels('')
g.set_ylabels('Property price')
```

Out[5]:
```
<seaborn.axisgrid.FacetGrid at 0x1c2863e128>

<Figure size 720x720 with 0 Axes>
```

Conclusion : The plots seem to be linear. Let's validate this hypothesis by building a model on a specific zipcode.

Scale and normalise variables

In [6]:
```
# Scale Variables data
log_sqft_living = np.log(data['sqft_living'])
scaled_sqft_living = (log_sqft_living-min(log_sqft_living))/(max(log_sqft_l

data_fin = pd.DataFrame([])
data_fin['sqft_living'] = scaled_sqft_living

scaled_data = data.drop(['sqft_living'], axis=1)
scaled_data = pd.concat([scaled_data, data_fin], axis=1)
```

Building the model

We are now going to try to run a simple Regression against our dataset

In [9]:
```
# Get sample data from specific zipcode
zipcode = 98072
data_per_zipcode = scaled_data.loc[scaled_data['zipcode'] == zipcode]
```

In [8]:
```
# Build formula
# Notes that we are especting a corrolation between sqft_living and price_s
formula = 'price ~ sqft_living'
```

In [10]:
```
# Run simple prediction
model = ols(formula=formula, data=data_per_zipcode).fit()
model.summary()
```

Out[10]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.584
Model:	OLS	**Adj. R-squared:**	0.582
Method:	Least Squares	**F-statistic:**	380.3
Date:	Wed, 08 May 2019	**Prob (F-statistic):**	1.59e-53
Time:	16:17:35	**Log-Likelihood:**	-3621.7
No. Observations:	273	**AIC:**	7247.
Df Residuals:	271	**BIC:**	7255.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-2.444e+05	4.26e+04	-5.734	0.000	-3.28e+05	-1.6e+05
sqft_living	1.636e+06	8.39e+04	19.501	0.000	1.47e+06	1.8e+06

Omnibus:	77.482	**Durbin-Watson:**	1.839
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	220.083
Skew:	1.262	**Prob(JB):**	1.62e-48
Kurtosis:	6.603	**Cond. No.**	12.4

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Observations : The Adj. R-squared is pretty low and our variables coef p-values are low. This doesn't look good.

Conclusion

We saw that the model built based on zipcode proximity is not really accurate We need to come up with a more precise model.