Project 2: AI APPRAISER

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Overview

Our stakeholder is a mortgage lender who would like more accurate appraisals to reduce risk for home loans. We analyzed the King County (CA) House Sales dataset using machine learning to develop a model for predicting the value of a house. The model accurately predicts the value of a house with information available to the bank at time of appraisal, and would be a good tool for making loan decisions. We recommend using this model along with existing appraisers to reduce risk and increase profit margins.

Business Problem

Our stakeholder is a mortgage lender who wants to increase the accuracy of their appraisals in order to reduce the risk of default, especially loans which have the minimum possible down payment (20%) without Private Mortgage Insurance. These loans are worth 80% of the purchase price of the house. If a borrower defaults immediately, our stakeholder wants confidence they'll be able to re-sell the house and cover the entire loan. At the same time, they do not want artificially low appraisals, as those would drive clients to competing lenders. Specifically, we want to maximize the number of appraisals which are between 80% and 105% of the true value of the house in order to minimize risk while remaining attractive to borrowers.

Data Understanding

This project uses the King County House Sales dataset, which can be found in `kc_house_data.csv` in the data folder in this repo. The description of the column names can be found in `column_names.md` in the same folder. As with most real world data sets, the column names are not perfectly described, so you'll have to do some research or use your best judgment if you have questions about what the data means.

- Where did the data come from, and how do they relate to the data analysis questions? The data come from house sales in King County, and they help us relate all of the features we are interested in (sqft, waterfront, renovated or not)
- What do the data represent? Who is in the sample and what variables are included? Only houses that have sold are in the sample, and variables include comparisons to nearby houses (_15 suffixed variables), metrics about the house that was sold and its lot (sqft), whether and when renovations were last done, and the original year it was built.
- What is the target variable? The target variable is the sale price of the house. A secondary target could be views; which could be used as a proxy for time-on-market.
- What are the properties of the variables you intend to use? Almost all of the variables we intend to use are numeric, except one binary variable (waterfront or not). Some of the variables are cyclic in nature (month), which we hope to capture in our feature selection.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pprint
import code.preprocessing as prep
import code.visualization as vis
from sklearn.model_selection import train_test_split
from sklearn import datasets, ensemble, linear_model, neural_network
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.model_selection import GridSearchCV, KFold
from sklearn.feature_selection import RFECV

# NEW
from sklearn.inspection import plot_partial_dependence
from xgboost import XGBRegressor
```

Data Preparation

Clean data:

- Id - remove.
- bedroom - replace outlier data. (33 bedrooms to 3)
- Waterfront - guess for Nan Value.
- Date - seperate year, month and day. Try sin/cos for month to cycle twelve months. remove date.

- sqft_living_dif - sqft_living -sqft_living15.
- sqft_lot_dif - sqft_lot - sqft_lot15.
- year_renovated - fill the Nan with the average of the renovated year, add new column 1 or 0 for renovated.
- sqft_basement - replace '?' to None.
- View -Removed

Since our business problem is making an appraisal, we only used data that would be available during an appraisal. This led us to remove the "views" variable.

Most other changes helped specific models which we did not end up using (changing year_renovated to average, and introducing a new field helped when Scaling Data for input into NN models for example), but did not harm other models so kept the changes so we could evaluate all models on one data set.

For our business problem, explainability of the model was less of a concern than accuracy, so we kept correlated columns like sqft_above and sqft_living.

In [2]:
```
kc_house_data = pd.read_csv('./data/kc_house_data.csv')
copy_data = kc_house_data.copy()
clean_data, target_data = prep.clean_data(copy_data)
```

First Model

After decide use sklean, first thing to try is `LinearRegression()` .

In [3]:
```
RANDOM_SEED = 5
X_train, X_test, y_train, y_test = train_test_split(clean_data, target_da
```

In [4]:
```
prep.model(linear_model.LinearRegression(), X_train, X_test, y_train, y_t
```

Out[4]: 0.7178468857665168

Modeling

Try different model:

- Ridge(random_state = RANDOM_SEED),
- BayesianRidge(),
- LinearRegression(),
- RandomForestRegressor(random_state = RANDOM_SEED),
- GradientBoostingRegressor(random_state = RANDOM_SEED),
- neural_network.MLPRegressor(solver="lbfgs", random_state = RANDOM_SEED)
- XGBRegressor()

Use pipline with PCA, PolynomialFeatures or StandardScaler, use GridSearchCV to found the best hyperparameters:

Questions to consider:

We found explainability was good enough with partial_dependence plots, so we did not restrict our analysis to easily explainable models like linear regression. Explainability was less important because getting the right answer on average is the most important thing for making a profit as a mortgage lender.

Some variables had clear nonlinear effects (yr_built, latitude, longitude), which made it hard to get good performance from a linear model. We tried many different regressors built into scikitlearn with default parameters to decide which models were worth tuning. After we found that GradientBoostingRegressor was best, we decided to install and use xgboost (third party library for boosting decision trees) to see if that improved performance.

We decided xgboost was best, so we used GridSearchCV to find good hyperparameters without overfitting. We had to leave it running overnight several days in a row, but the results got us very

In [5]:
```
xg_model= XGBRegressor(learning_rate=0.008, max_depth=6, gamma=0, n_estim
prep.model(xg_model, X_train, X_test, y_train, y_test)
```

Out[5]: 0.892431332061363

In [6]:
```
for column in X_train.columns:
    plot_partial_dependence(xg_model, clean_data,  [column])
```

```
C:\Users\steve\anaconda3\lib\site-packages\sklearn\inspection\_plot\pa
rtial_dependence.py:863: RuntimeWarning: More than 20 figures have bee
n opened. Figures created through the pyplot interface (`matplotlib.py
plot.figure`) are retained until explicitly closed and may consume too
much memory. (To control this warning, see the rcParam `figure.max_ope
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  _, ax = plt.subplots()
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much memory. (To control this warning, see the rcParam `figure.max_ope
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  _, ax = plt.subplots()
C:\Users\steve\anaconda3\lib\site-packages\sklearn\inspection\_plot\pa
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plot.figure`) are retained until explicitly closed and may consume too
much memory. (To control this warning, see the rcParam `figure.max_ope
n_warning`).
  _, ax = plt.subplots()
```

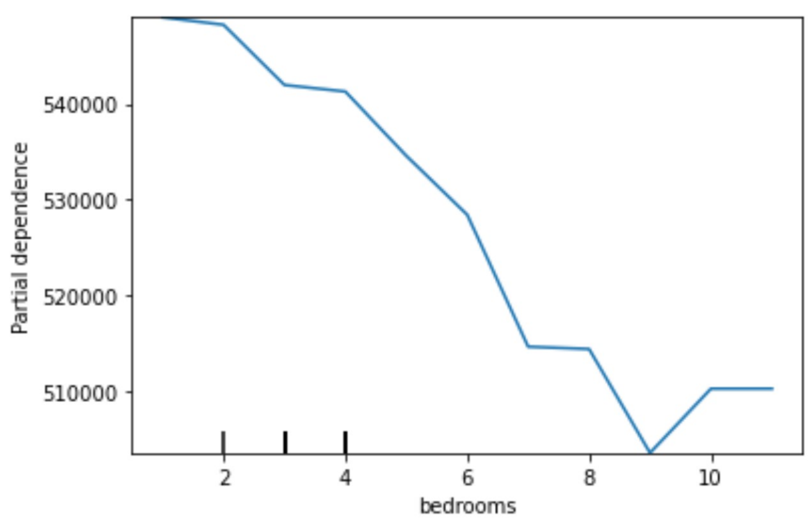

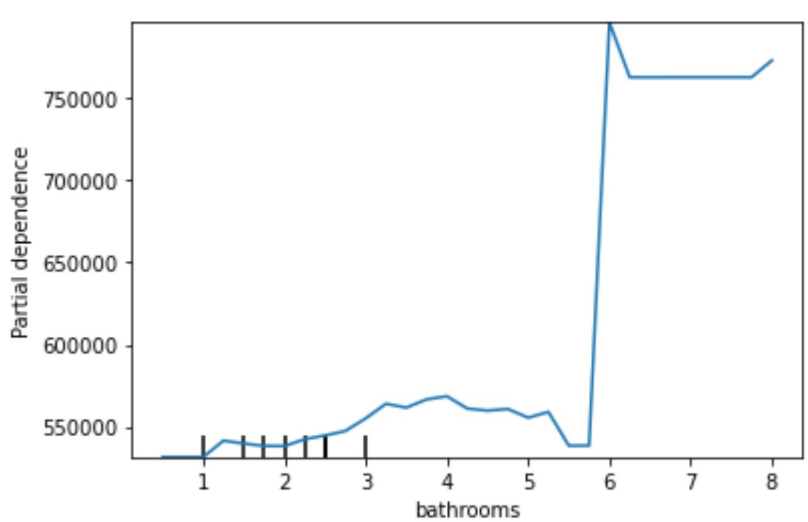

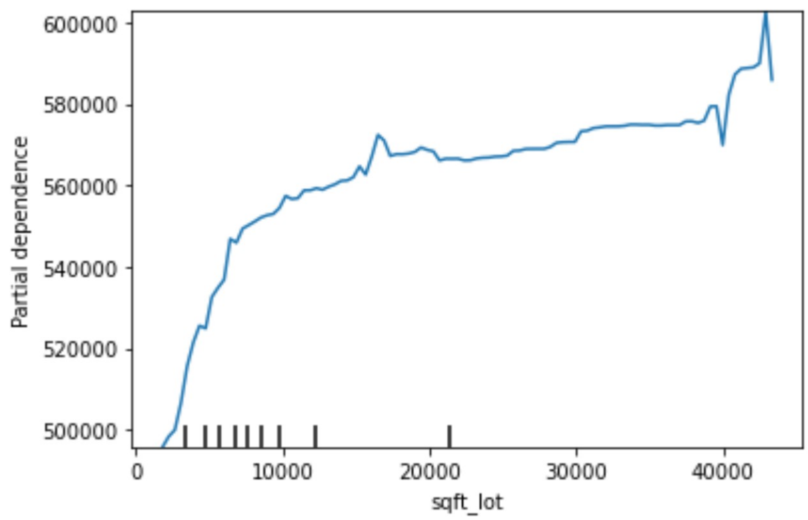
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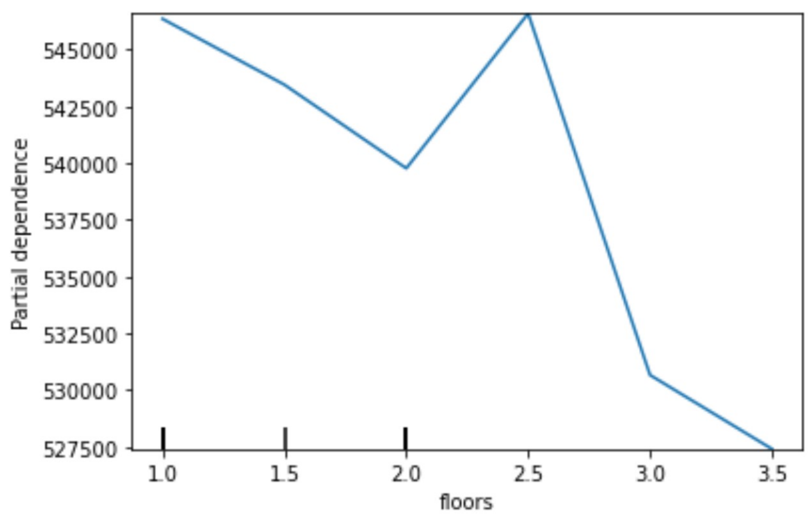
580000
560000
540000
520000
500000
Partial dependence
0
10000
20000
30000
40000
sqft_lot


545000
542500
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527500
Partial dependence
1.0
1.5
2.0
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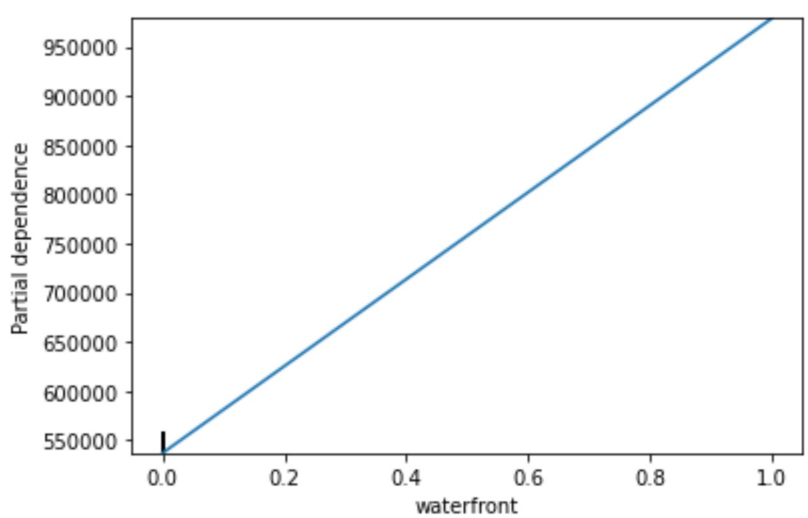
floors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Partial dependence
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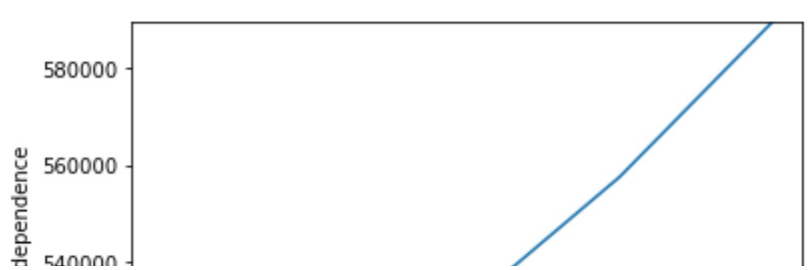
0.8
1.0
waterfront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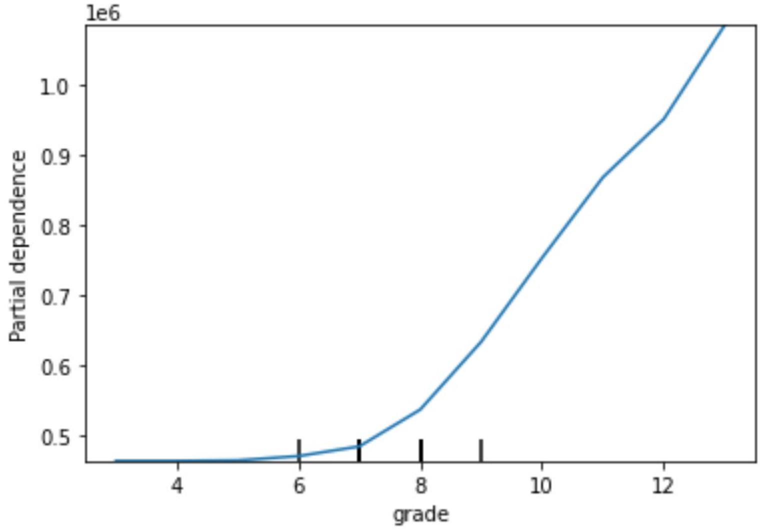
560000


1e6
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0.6
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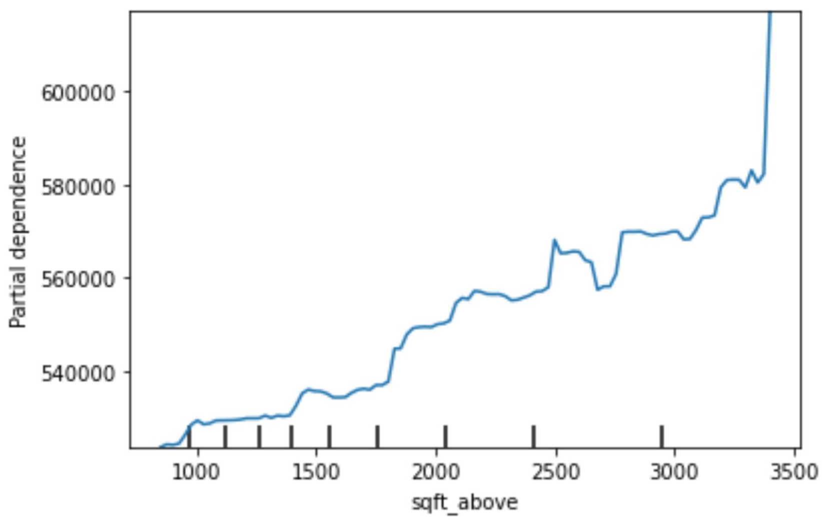
Partial dependence
4
6
8
10
12
grade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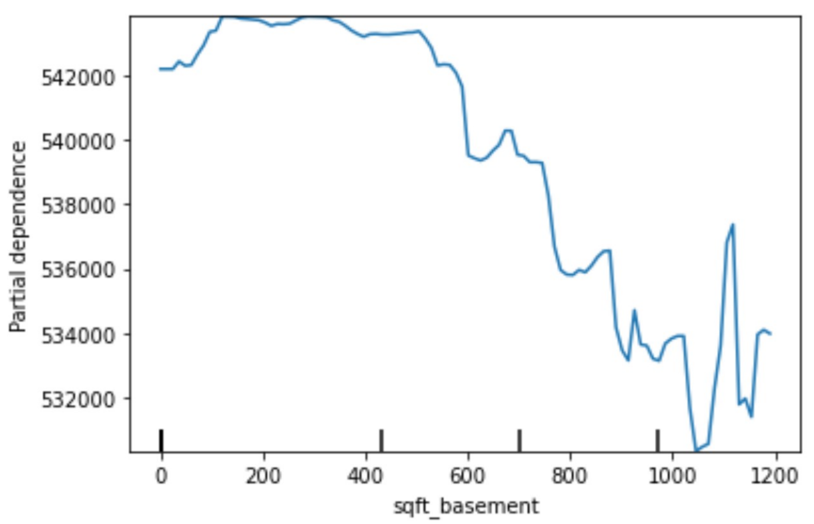
560000
540000
Partial dependence
1000
1500
2000
2500
3000
3500
sqft_above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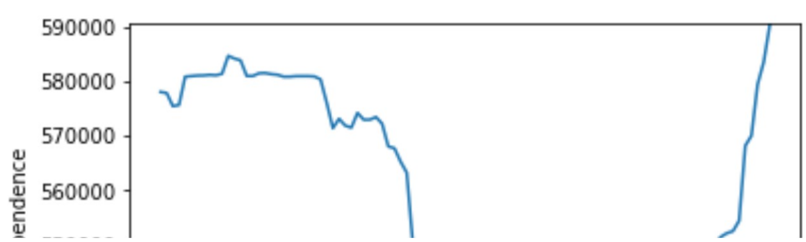
Partial dependence
0
200
400
600
800
1000
1200
sqft_basement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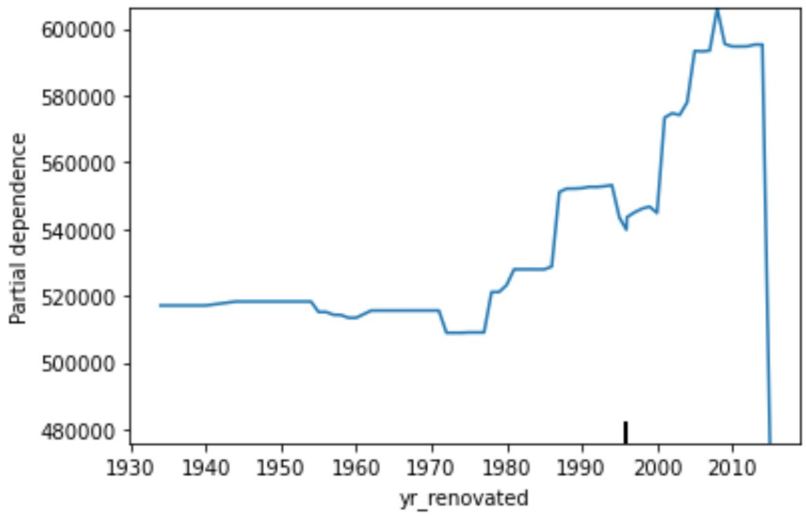
Partial dependence
600000
580000
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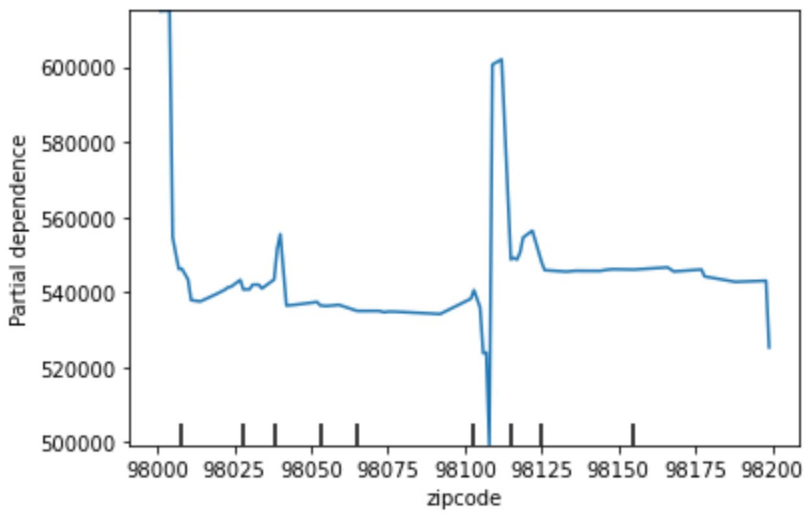
500000
480000
1930
1940
1950
1960
1970
1980
1990
2000
2010
yr_renovated


Partial dependence
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98050
98075
98100
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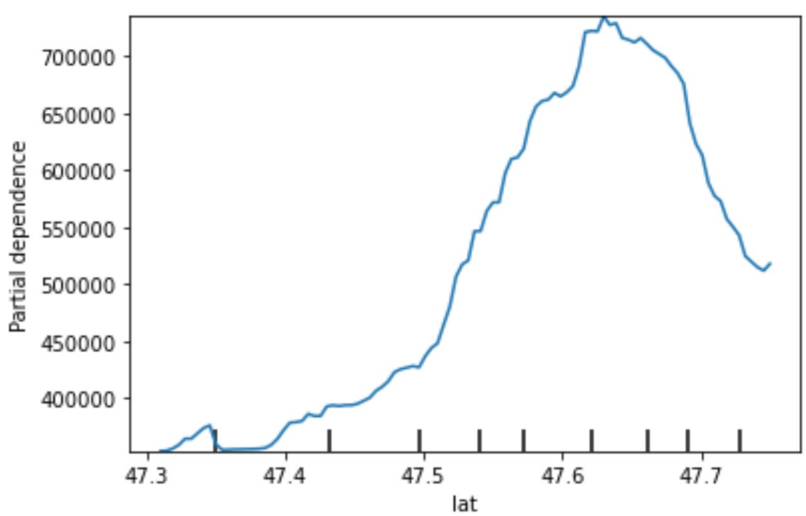
98175
98200
zipcode


Partial dependence
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600000
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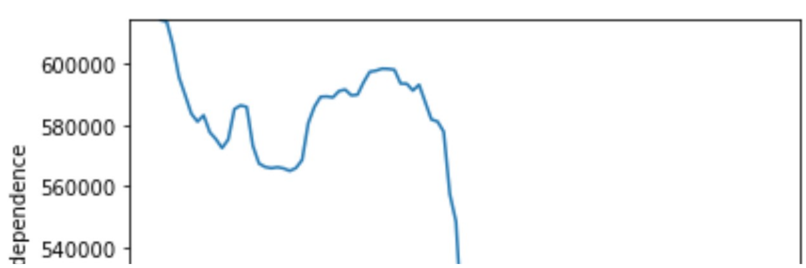
500000
450000
400000
47.3
47.4
47.5
47.6
47.7
lat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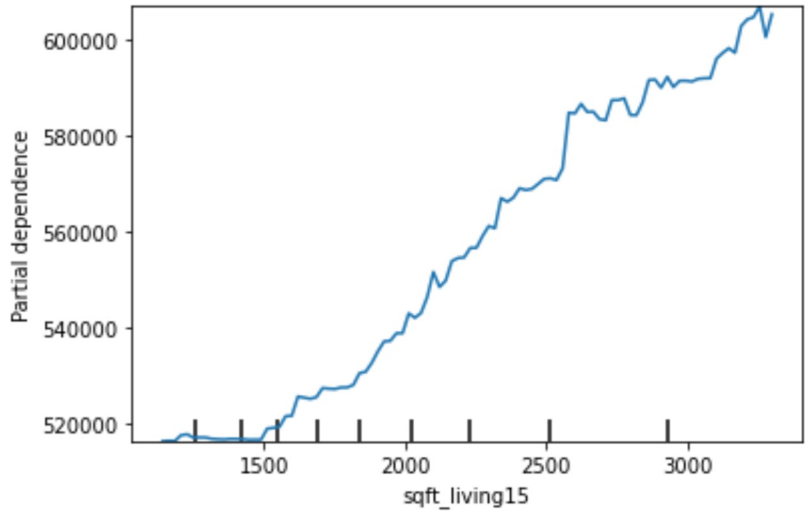
600000
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540000
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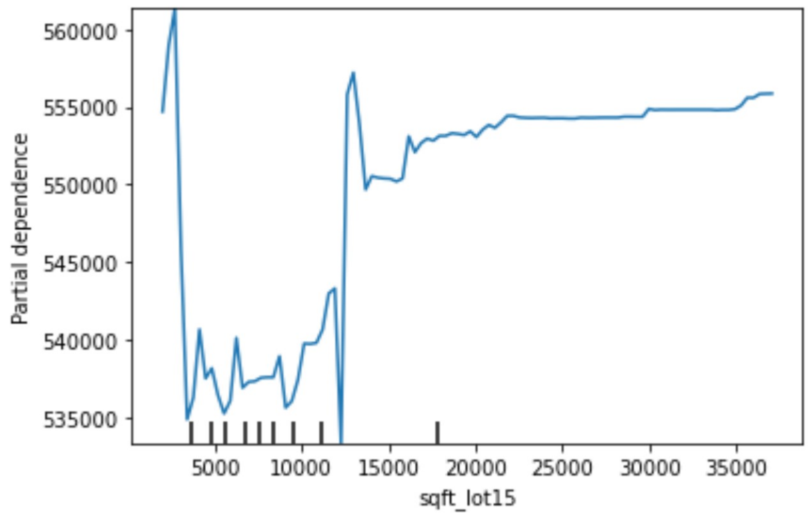
Partial dependence
1500
2000
2500
3000
sqft_living15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Partial dependence
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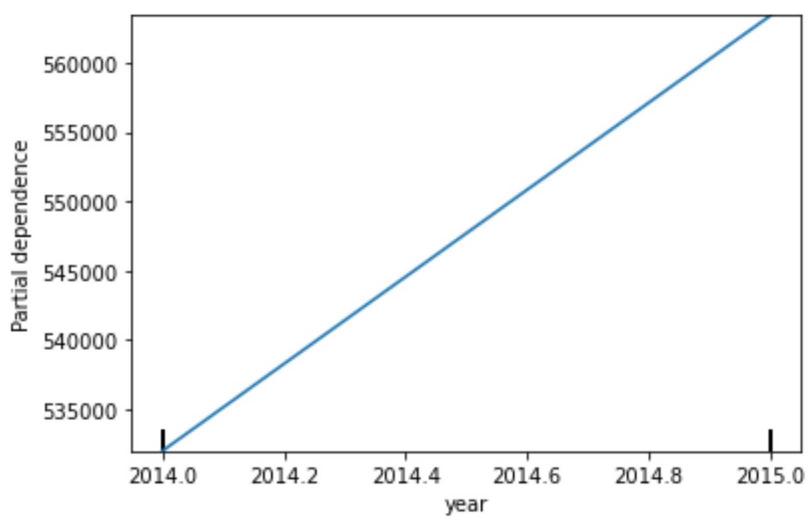
35000
sqft_lot15


560000
555000
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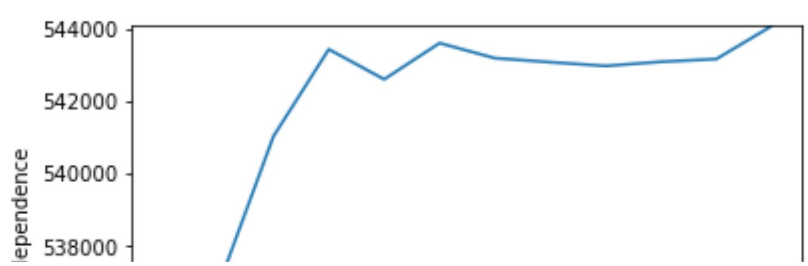
545000
540000
535000
Partial dependence
2014.0
2014.2
2014.4
2014.6
2014.8
2015.0
year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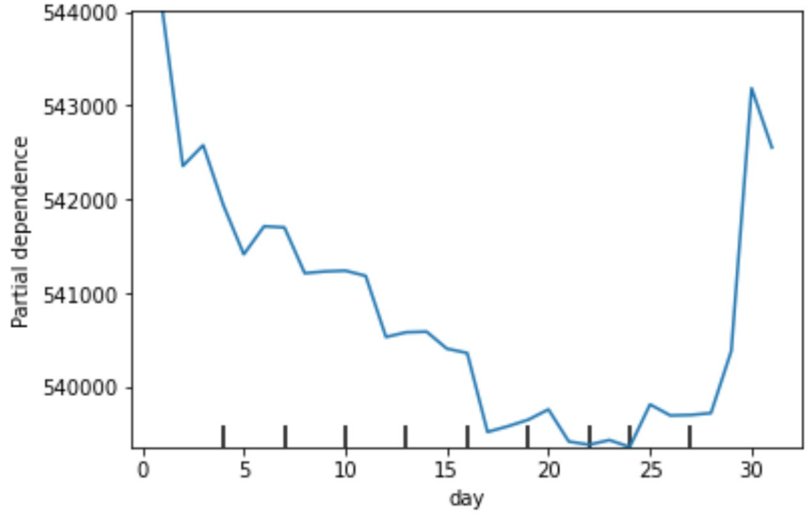
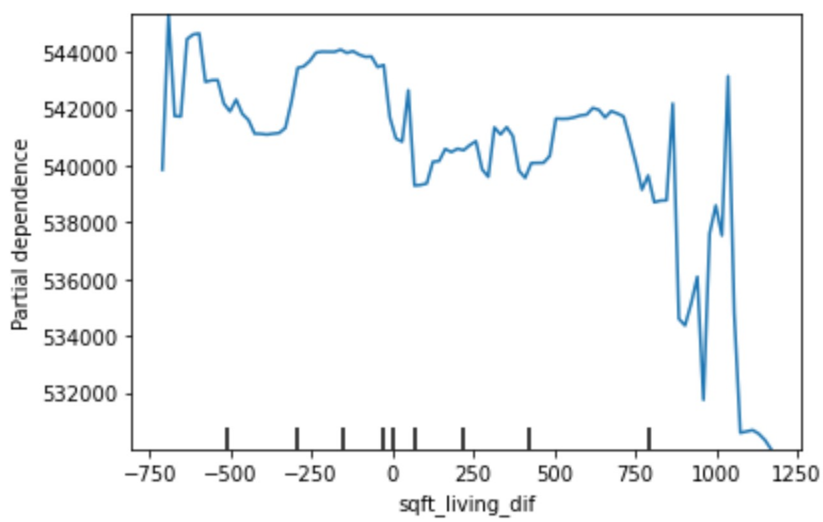
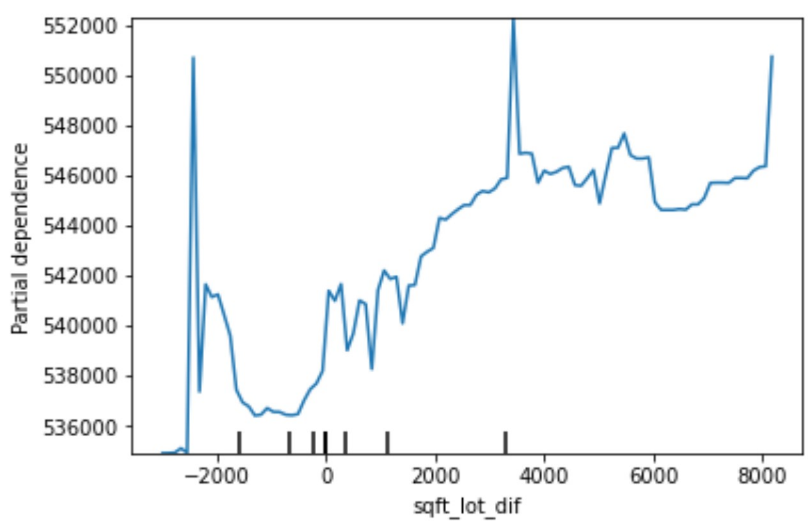
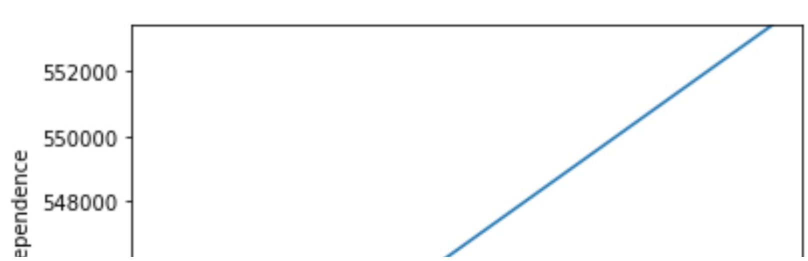

Partial dependence
day

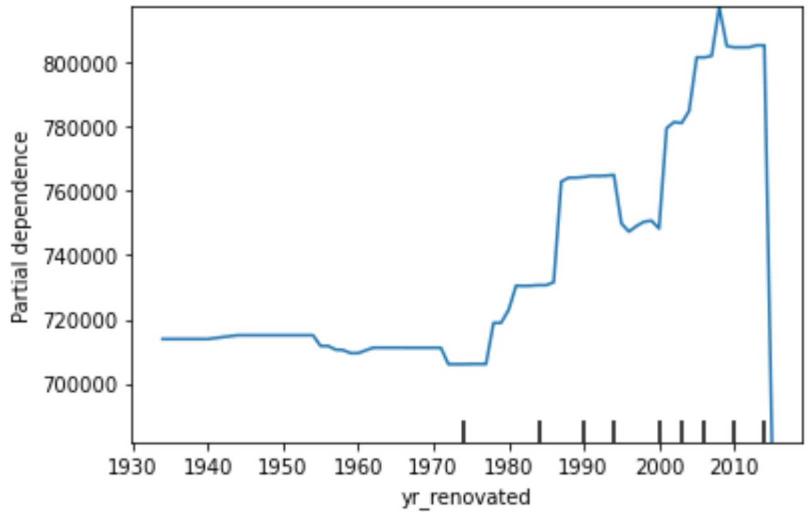

Partial dependence
sqft_living_dif


Partial dependence
sqft_lot_dif



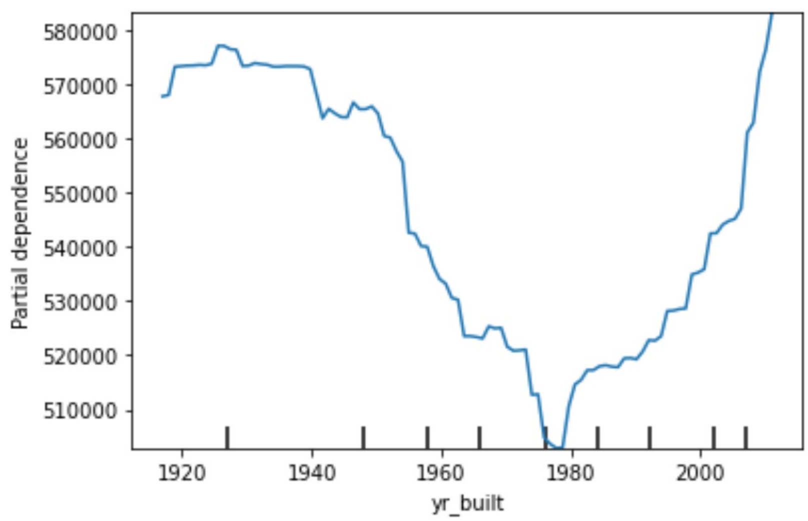
In [7]:
```
plot_partial_dependence(xg_model, clean_data[clean_data["renovated"]==1],
```

Out[7]:
```
<sklearn.inspection._plot.partial_dependence.PartialDependenceDisplay
at 0x1c8043e40a0>
```



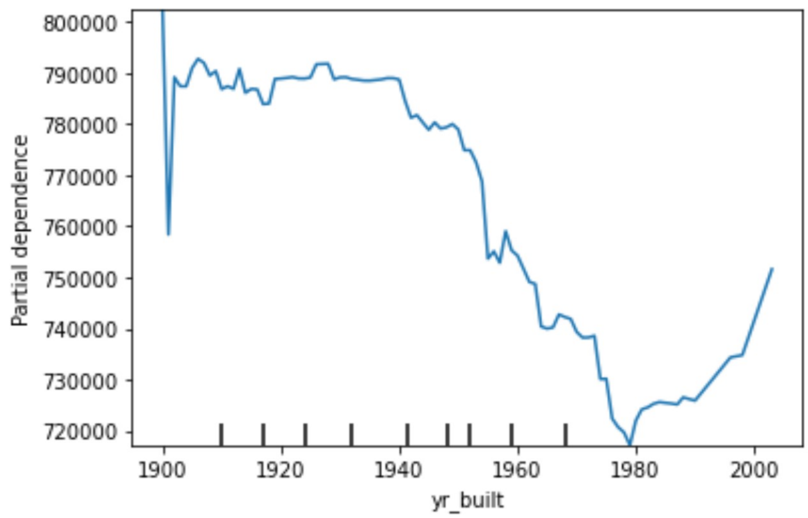
In [8]:
```
plot_partial_dependence(xg_model, clean_data[clean_data["renovated"]==0],
```

Out[8]:
```
<sklearn.inspection._plot.partial_dependence.PartialDependenceDisplay
at 0x1c804d60c70>
```



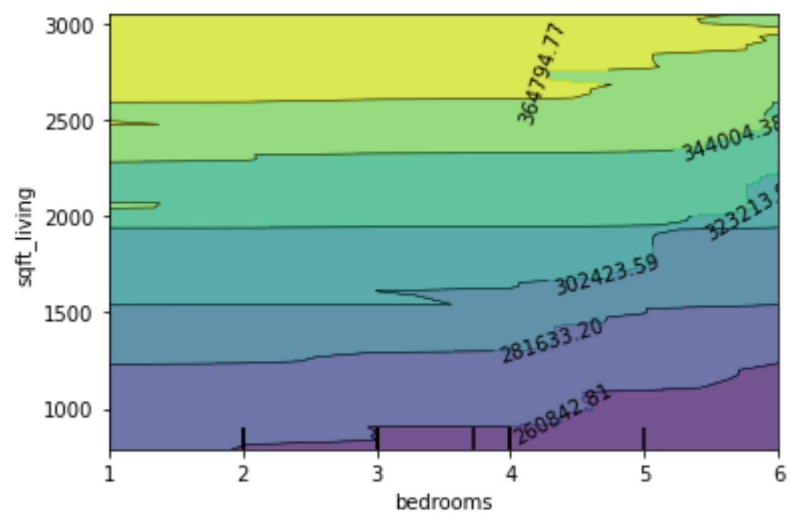
In [9]:
```
plot_partial_dependence(xg_model, clean_data[clean_data["renovated"]==1],
```

Out[9]:
```
<sklearn.inspection._plot.partial_dependence.PartialDependenceDisplay
at 0x1c8655a0fa0>
```



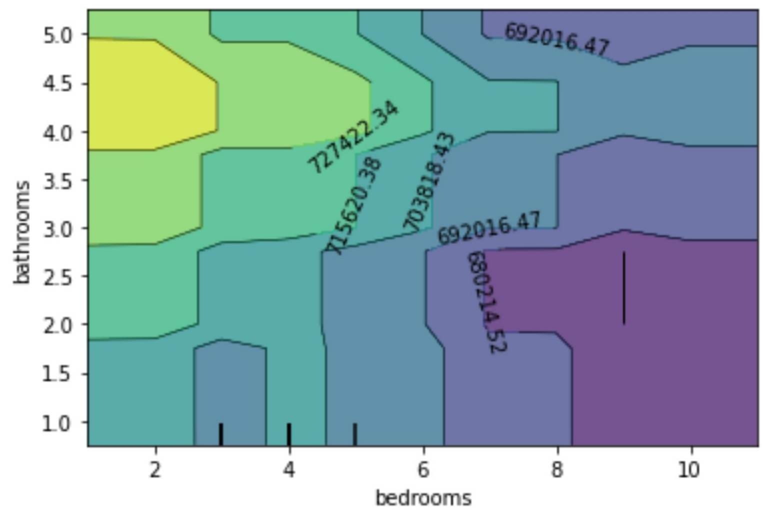
In [10]:
```
plot_partial_dependence(xg_model, clean_data[clean_data['zipcode'] == 981
```

Out[10]:
```
<sklearn.inspection._plot.partial_dependence.PartialDependenceDisplay
at 0x1c8043b7a90>
```



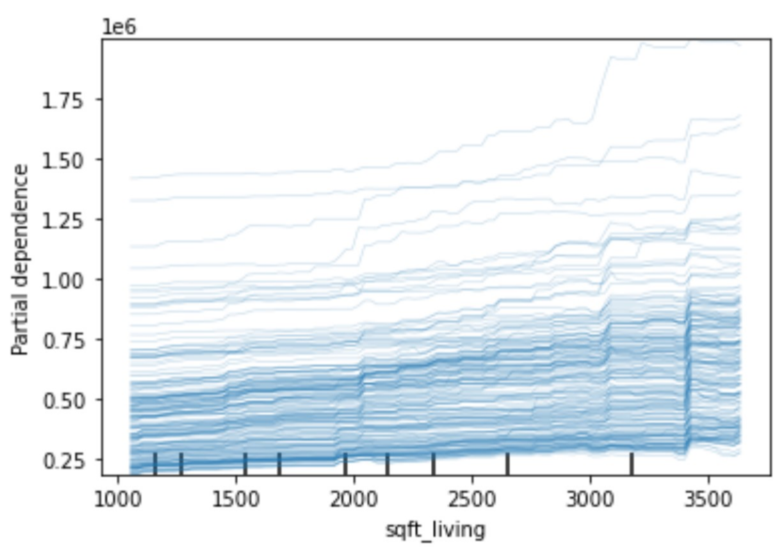
In [11]:
```
plot_partial_dependence(xg_model,
                        clean_data[(clean_data['sqft_living'] < 3500)
                                   & (clean_data['sqft_living'] > 2500)],
                        [('bedrooms', 'bathrooms')])
```

Out[11]:
```
<sklearn.inspection._plot.partial_dependence.PartialDependenceDisplay
at 0x1c804f0f5b0>
```



In [12]:
```
plot_partial_dependence(xg_model, clean_data[:200], ['sqft_living'], kind
```

Out[12]:
```
<sklearn.inspection._plot.partial_dependence.PartialDependenceDisplay
at 0x1c804e2ee50>
```



Evaluation

In [13]:
```
waterfront = (clean_data["waterfront"] == 1)
not_waterfront = (clean_data["waterfront"] == 0)
pred_data = xg_model.predict(clean_data)
```

In [23]:
```
high_appraisals = pred_data * .8> target_data
good_appraisals = (pred_data * .8 <= target_data) & (pred_data * 1.05 >=
low_appraisals = pred_data *1.05 < target_data
```

```
# Houses where 80% of appraised value exceeded sale price
# Risk of losing money if borrowers default on these loans
print("80% of Appraisal > Sale Price (High Appraisal): ",len(clean_data[h

# Houses where 100% of appraised value fell short of sale price
# Difficult to find borrowers for these loans
print("Sale Price between 80% and 105% of appraisal (Good Appraisal): ",

# Borrowers will walk away
print("105% of appraisal < Sale Price (Low Appraisal): ", len(clean_data[
```

```
80% of Appraisal > Sale Price (High Appraisal):  1128
Sale Price between 80% and 105% of appraisal (Good Appraisal):  14427
105% of appraisal < Sale Price (Low Appraisal):  6042
```

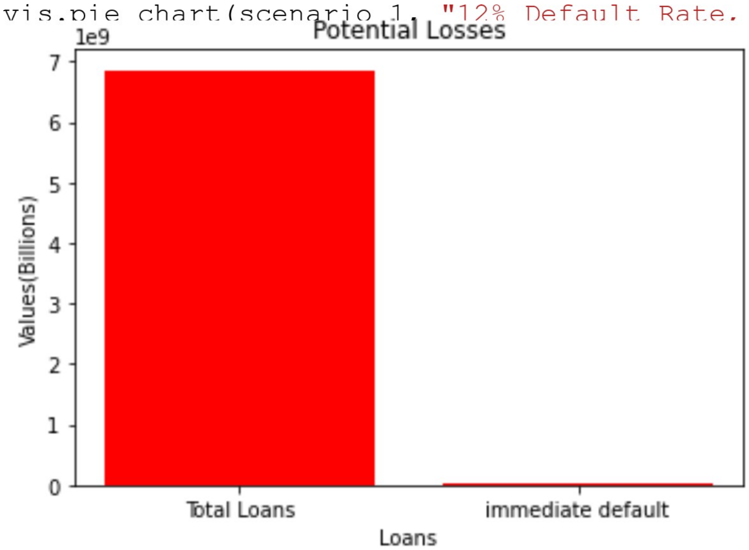
In [24]:
```
total_low_loans = sum(pred_data[low_appraisals]*.8)
total_good_loans = sum(pred_data[good_appraisals]*.8)
total_high_loans = sum(pred_data[high_appraisals]*.8)
# Do not include low, we assume low appraisals scared off borrowers
total_loans = total_high_loans +  total_good_loans

print("Total missed loans (Low Appraisals): ", total_low_loans)
print("Total loans (Good Appraisals): ", total_good_loans)
print("Total loans (High Appraisals): ", total_high_loans)
print("Total loans (total): ", total_loans)
print()

print("Average missed loan (Low Appraisals): ", total_low_loans/ len(pred_
print("Average loan (Good Appraisals): ", total_good_loans/ len(pred_data
print("Average loan (High Appraisals): ", total_high_loans/ len(pred_data
print()


# Houses where 80% of appraised value exceeded sale price
# Risk of losing money if borrowers default on these loans
immediate_default_losses = pred_data[high_appraisals]*.8 - target_data[hi
print("Total losses from High Appraisals (immediate default): ", sum(imme
print("Losses from High Appraisals (immediate default) as % of total loan
print("Average loss from High Appraisals (immediate default): ", sum(imme
print()
```

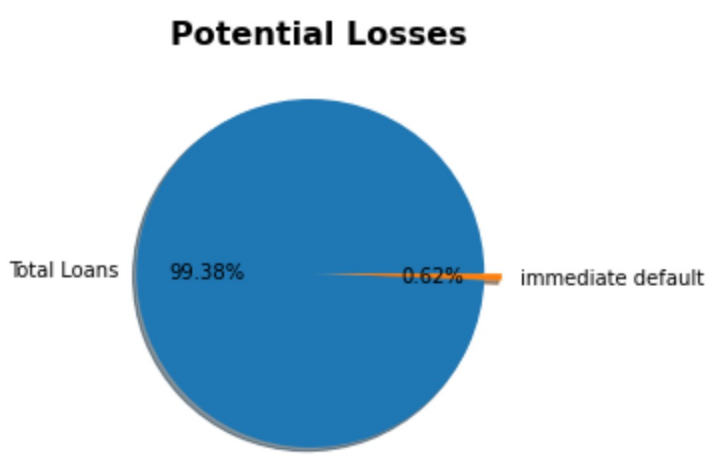
```
Total missed loans (Low Appraisals):  2484016628.9492188
Total loans (Good Appraisals):  6456764666.5078125
Total loans (High Appraisals):  400871010.2578125
Total loans (total):  6857635676.765625

Average missed loan (Low Appraisals):  411124.89721105905
Average loan (Good Appraisals):  447547.28401662246
Average loan (High Appraisals):  355382.10129238694

Total losses from High Appraisals (immediate default):  42868671.25781
25
Losses from High Appraisals (immediate default) as % of total loans :
0.6251231952005845
Average loss from High Appraisals (immediate default):  38004.14118600
399
```

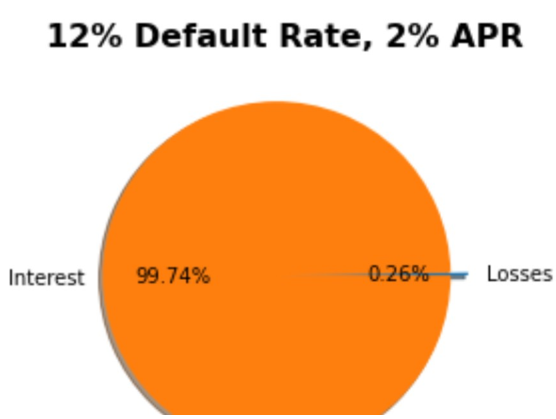
In [25]:
```
loan_values = {'Missed Loans': total_low_loans,
               'Good Loans': total_good_loans,
               'Risky Loans': total_high_loans}
number_appraisal = {'Low Appraisal': len(clean_data[low_appraisals]),
                    'Good Appraisal': len(clean_data[good_appraisals]),
                    'High Appraisal': len(clean_data[high_appraisals])
                   }
risk_loans = {'Total Loans': int(total_loans),
              'immediate default': int(sum(immediate_default_losses))}
```

In [32]:
```
vis.bar_chart(risk_loans, "Loans", "Values(Billions)", "Potential Losses"
```

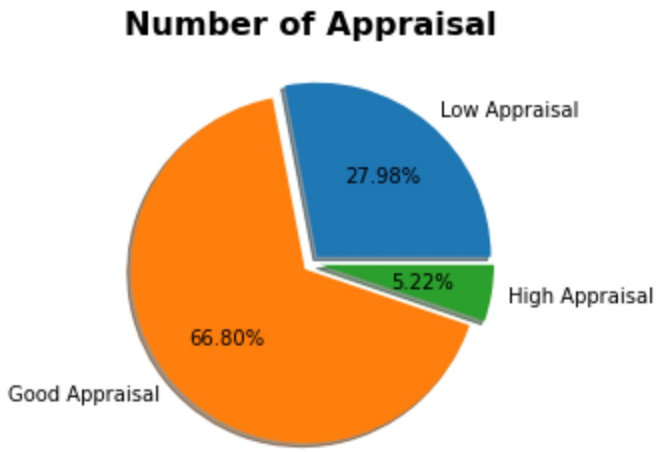
```
# Assume default rate of 50%, all defaults occur immediately.
scenario_1_default_rate  = .12
scenario_1_losses = immediate_default_losses * scenario_1_default_rate
# Assume 1% interest rate.
# A 30 year fixed rate mortgage with a 2% APR would result in about 33% i
scenario_1_interest = (total_loans * (1-scenario_1_default_rate)) * .33

scenario_1 = {
    "Losses": sum(scenario_1_losses),
    "Interest": scenario_1_interest,
}
vis.pie_chart(risk_loans, "Potential Losses")
vis.pie_chart(scenario_1, "12% Default Rate, 2% APR")
```

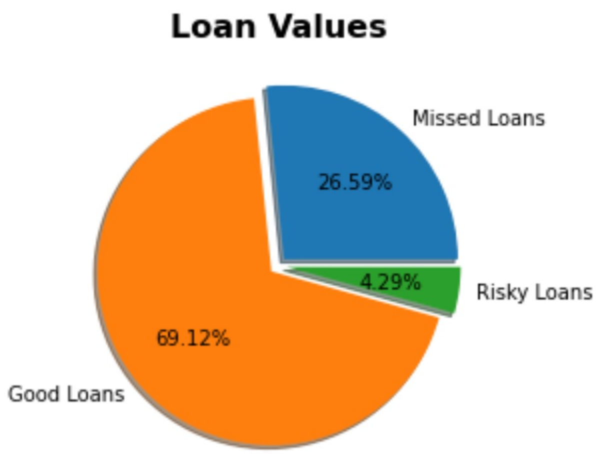






In [27]:
```
vis.pie_chart(number_appraisal, "Number of Appraisal")
vis.pie_chart(loan_values, "Loan Values")
```





In [28]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error
mean_squared_error = mean_squared_error(target_data, pred_data, squared=F
mean_absolute_error = mean_absolute_error(target_data, pred_data)
```

In [29]:
```
mean_house_price = target_data.mean()
```

In [30]:
```
mean_price_error = {"mean_house_price": mean_house_price,
                    "mean_absolute_error": mean_absolute_error}
mean_price_error
```

Out[30]:
```
{'mean_house_price': 540296.5735055795,
 'mean_absolute_error': 44852.386111207576}
```

In [31]:
```
vis.bar_chart(mean_price_error, "", "Values", "Mean Price Error")
```

Conclusions

The model is very good at predicting house prices in 2014-2015. Training on data outside this period will be necessary to help it understand larger trends in housing prices. Using this model to appraise houses nearly guarantees interest made from loans will cover money lost to bad appraisals + default, even under very adverse assumptions (12% foreclosure rate, 2% APR). We assumed the market remained stable during foreclosures; we did not analyze the case where a market crash depresses housing values simultaneously with default. That could increase losses significantly in a worst case scenario This model could definitely generate a profit, but client should work with us to determine expected ROI using more realistic assumptions of default rate and APR to evaluate whether this model is more profitable than their existing process.