Housing Prices Regression – Supervised Learning

The project is a regression machine learning study aimed at predicting house prices using a dataset containing various features of houses. I plan on implementing a random forest regressor along with a gradient boosting model and compare their performance using different evaluation metrics. It is broken off into three main portions/notebooks

1) **Extract, Transform, Load**
2) **Explanatory Data Analysis**
3) **Training a model**

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```
executed in 6.42s, finished 20:23:20 2023-03-02

Load Data

Data collected by Dr. DeCock in the Journal of Statistical Education (2011). Additional information can be found here [https://jse.amstat.org/v19n3/decock.pdf (https://jse.amstat.org/v19n3/decock.pdf)](https://jse.amstat.org/v19n3/decock.pdf)

In [39]:
```python
ames = pd.read_csv(r'..\data\raw\ames.csv', low_memory=False)
```
executed in 43ms, finished 20:26:48 2023-03-02

In [40]:
```python
# Remove the '.' from column names
ames.columns = [x.replace('.', '') for x in ames.columns]
```
executed in 17ms, finished 20:26:49 2023-03-02

A total of 2,930 rows and 82 columns. 20 of which are quantitative values, the rest are categorical or ordinal.

In [62]:
```python
ames.shape
```
executed in 15ms, finished 20:55:12 2023-03-02

Out[62]:
```
(2930, 82)
```

Instead of iterating through all available features we can choose a subset that we think is important based off of our experience with real estate prices. While the subset we choose isn't guaranteed to be the best subset out there it will massively help with the EDA process and the time take to complete the project.

In [63]:
```python
# Select subset of columns to use
categorical = ['MSSubClass', 'MSZoning', 'Street', 'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'Neighborhood',
               'BldgType', 'HouseStyle', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtFinType1',
               'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenAbvGr', 'KitchenQual', 'Functional', 'GarageType',
               'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', 'X3SsnPorch', 'ScreenPorch', 'PoolArea',
               'SaleCondition', 'OverallQual', 'OverallCond']

numerical = ['price', 'LotArea', 'BsmtFinSF1', 'TotalBsmtSF', 'X1stFlrSF', 'X2ndFlrSF', 'LowQualFinSF',
             'area', 'BedroomAbvGr', 'TotRmsAbvGrd', 'Fireplaces', 'GarageCars', 'GarageArea']

to_engineer = ['YearRemodAdd', 'YrSold']
```
executed in 16ms, finished 20:55:14 2023-03-02

In [64]:
```python
columns_to_use = categorical+numerical+to_engineer
```
executed in 13ms, finished 20:55:15 2023-03-02

In [65]:
```python
ames_truncated = ames[columns_to_use].copy()
```
executed in 15ms, finished 20:55:16 2023-03-02

In [66]:
```python
ames_truncated.shape
```
executed in 7ms, finished 20:55:17 2023-03-02

Out[66]:
```
(2930, 49)
```

In [45]:
```python
# Quick glance at the data
with pd.option_context("display.max_columns", None):
    display(ames_truncated[sorted(ames_truncated.columns)].sample(10))
```

executed in 50ms, finished 20:26:50 2023-03-02

	BedroomAbvGr	BldgType	BsmtCond	BsmtFinSF1	BsmtFinType1	BsmtQual	CentralAir	Electrical	EnclosedPorch	ExterCond	ExterQual	Fireplaces	Fou
1531	3	1Fam	TA	0.0	Unf	Gd	Y	SBrkr	112	Fa	TA	1	
2183	2	1Fam	TA	77.0	Rec	TA	Y	SBrkr	35	TA	TA	0	
1283	3	1Fam	TA	96.0	GLQ	TA	N	SBrkr	0	TA	TA	0	
1084	2	1Fam	TA	0.0	Unf	Gd	Y	SBrkr	0	TA	Gd	1	
82	2	1Fam	TA	0.0	Unf	TA	N	FuseA	80	Fa	TA	0	
195	3	1Fam	TA	264.0	LwQ	TA	Y	FuseA	0	Gd	TA	2	
840	3	1Fam	TA	0.0	Unf	Gd	Y	SBrkr	0	TA	TA	0	
1171	2	TwnhsE	TA	1238.0	GLQ	Ex	Y	SBrkr	0	TA	Gd	1	
1481	1	TwnhsE	TA	697.0	GLQ	Gd	Y	SBrkr	0	TA	Gd	1	
2176	5	Duplex	NaN	0.0	NaN	NaN	Y	SBrkr	0	TA	TA	0	

Deal with Missing Values

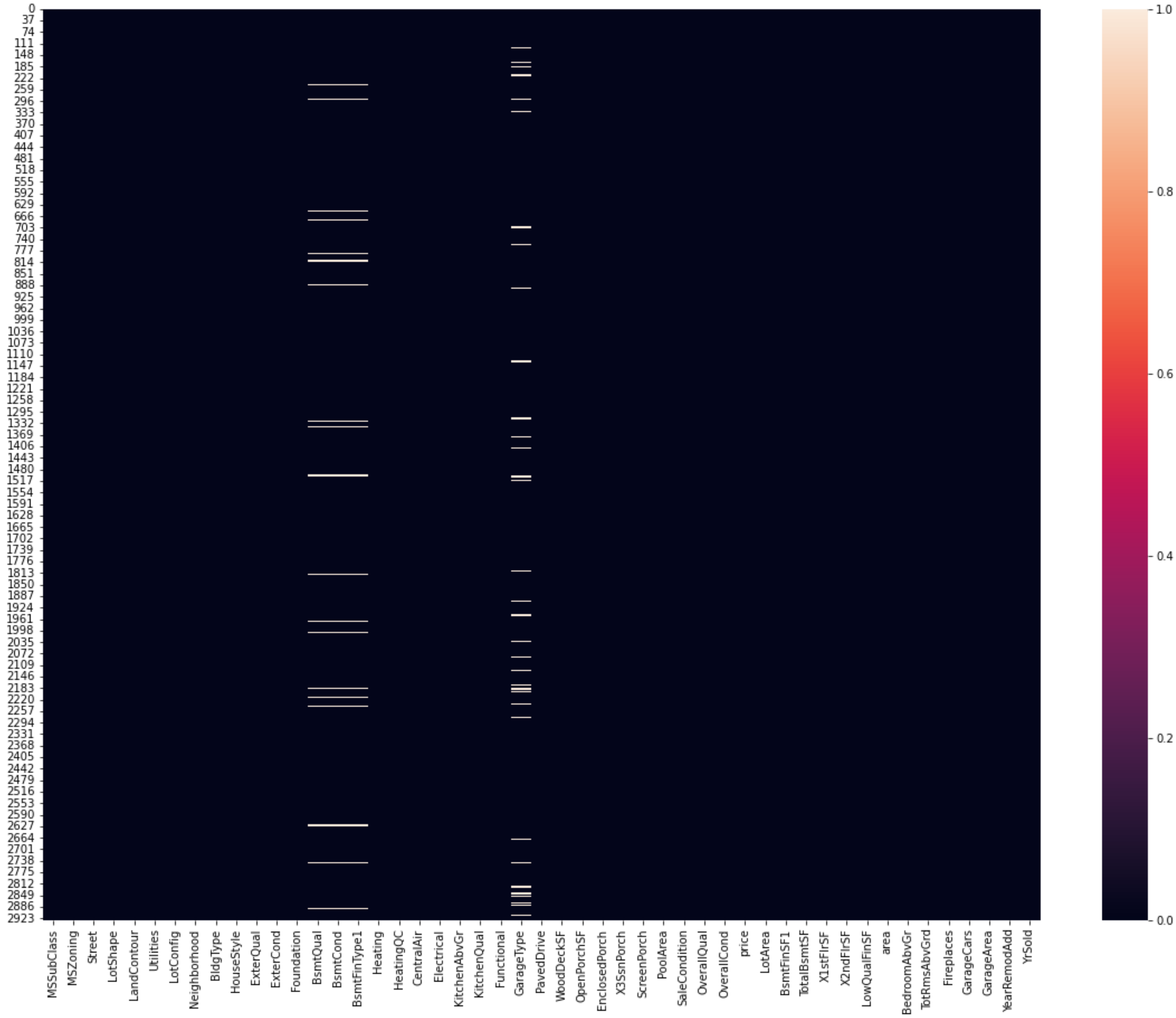
In [46]:
```python
# Look at percentage of missing NA's
ames_truncated.isna().sum().loc[lambda x: x > 0].divide(ames_truncated.shape[0]).sort_values(ascending=False).round(5)*100
```

executed in 35ms, finished 20:26:51 2023-03-02

Out[46]:
```
GarageType      5.358
BsmtQual        2.730
BsmtCond        2.730
BsmtFinType1    2.730
Electrical      0.034
BsmtFinSF1      0.034
TotalBsmtSF     0.034
GarageCars      0.034
GarageArea      0.034
dtype: float64
```

In [67]:
```python
# We can plot a heatmap to see nulls
plt.figure(figsize=(20,15))
sns.heatmap(ames_truncated.isna())
```
executed in 923ms, finished 20:55:54 2023-03-02

Out[67]: <AxesSubplot: >



We need to analyze individual nulls to understand whether we need to impute or remove the observation

In [47]:
```python
ames_truncated['BsmtQual'].value_counts(dropna=False)
```
executed in 16ms, finished 20:26:54 2023-03-02

Out[47]:
```
TA     1283
Gd     1219
Ex      258
Fa       88
NaN      80
Po        2
Name: BsmtQual, dtype: int64
```

In [48]:
```
# Missing basement quality usually means no basement
ames_truncated[ames_truncated['BsmtQual'].isna()][[x for x in ames_truncated.columns if 'Bsmt' in x]]
```
executed in 24ms, finished 20:26:54 2023-03-02

Out[48]:

	BsmtQual	BsmtCond	BsmtFinType1	BsmtFinSF1	TotalBsmtSF
83	NaN	NaN	NaN	0.0	0.0
154	NaN	NaN	NaN	0.0	0.0
206	NaN	NaN	NaN	0.0	0.0
243	NaN	NaN	NaN	0.0	0.0
273	NaN	NaN	NaN	0.0	0.0
...	...	...	...	...	...
2739	NaN	NaN	NaN	0.0	0.0
2744	NaN	NaN	NaN	0.0	0.0
2879	NaN	NaN	NaN	0.0	0.0
2892	NaN	NaN	NaN	0.0	0.0
2903	NaN	NaN	NaN	0.0	0.0

80 rows × 5 columns

In [49]:
```
ames_truncated[ames_truncated['GarageType'].isna()][[x for x in ames_truncated.columns if 'Garage' in x]]
```
executed in 17ms, finished 20:26:55 2023-03-02

Out[49]:

	GarageType	GarageCars	GarageArea
27	NaN	0.0	0.0
119	NaN	0.0	0.0
125	NaN	0.0	0.0
129	NaN	0.0	0.0
130	NaN	0.0	0.0
...	...	...	...
2913	NaN	0.0	0.0
2916	NaN	0.0	0.0
2918	NaN	0.0	0.0
2919	NaN	0.0	0.0
2927	NaN	0.0	0.0

157 rows × 3 columns

In [50]:
```
# Fill with None for missing category values
for column in ['BsmtQual', 'BsmtCond', 'BsmtFinType1', 'GarageType']:
    ames_truncated[column].fillna('None', inplace=True)
```
executed in 21ms, finished 20:26:56 2023-03-02

In [51]:
```
# Fill with zeros for category values
for column in ['TotalBsmtSF', 'BsmtFinSF1', 'GarageCars', 'GarageArea']:
    ames_truncated[column].fillna(0, inplace=True)
```
executed in 12ms, finished 20:26:57 2023-03-02

In [52]:
```
ames_truncated['Electrical'].value_counts(dropna=False)
```
executed in 22ms, finished 20:26:58 2023-03-02

Out[52]:
```
SBrkr    2682
FuseA     188
FuseF      50
FuseP       8
NaN         1
Mix         1
Name: Electrical, dtype: int64
```

In [53]:
```
ames_truncated['Electrical'].fillna(ames_truncated['Electrical'].mode().values[0], inplace=True)
```
executed in 14ms, finished 20:26:59 2023-03-02

In [54]:
```
assert ames_truncated.isna().sum().sum() == 0, 'Some NAs still present in data'
```
executed in 24ms, finished 20:26:59 2023-03-02

Missing values do not indicate an issue with the data, missing value for Pool Quality simply means that there is no pool. If all of these were to be overwritten the feature would not be that useful.

Fix Datatypes

In [55]:
```
# Change categorical columns to categories
ames_truncated[categorical] = ames_truncated[categorical].astype('category')
ames_truncated[numerical] = ames_truncated[numerical].astype('int64')
```
executed in 40ms, finished 20:27:01 2023-03-02

In [56]:
```
# All existing numerical types are already int
all(ames_truncated[numerical].dtypes == 'int64')
```
executed in 8ms, finished 20:27:01 2023-03-02

Out[56]:
```
True
```

In [57]:
```
ames_truncated.to_parquet(r'..\data\processed\training_cleaned.parquet')
```
executed in 36ms, finished 20:27:02 2023-03-02

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```
executed in 1.73s, finished 20:30:00 2023-03-02

In [2]:
```
# Read the clean dataset
prices = pd.read_parquet(r'..\data\processed\training_cleaned.parquet')
```
executed in 187ms, finished 20:30:08 2023-03-02

In [3]:
```
# Look at columns
with pd.option_context("display.max_columns", None):
    display(prices[sorted(prices.columns)].sample(10))
```
executed in 55ms, finished 20:30:13 2023-03-02

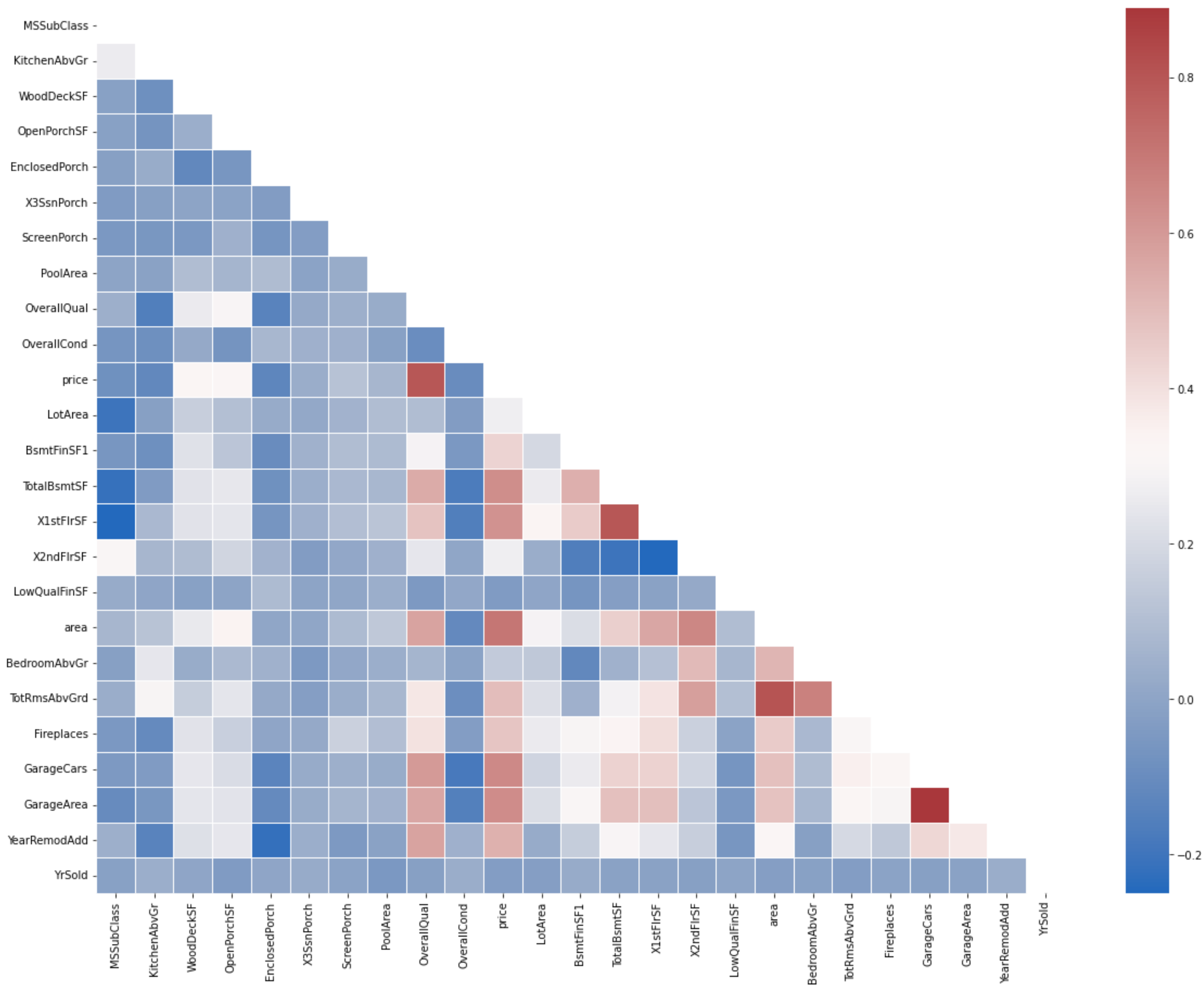
	BedroomAbvGr	BldgType	BsmtCond	BsmtFinSF1	BsmtFinType1	BsmtQual	CentralAir	Electrical	EnclosedPorch	ExterCond	ExterQual	Fireplaces	Fou
557	2	1Fam	TA	864	BLQ	TA	Y	SBrkr	0	TA	TA	0	
2255	2	TwnhsE	TA	949	GLQ	Gd	Y	SBrkr	0	TA	Gd	2	
2813	3	1Fam	TA	0	Unf	Gd	Y	SBrkr	0	TA	TA	0	
2137	3	1Fam	TA	539	ALQ	Gd	Y	SBrkr	0	TA	TA	0	
917	3	1Fam	Fa	0	Unf	TA	Y	SBrkr	0	TA	TA	1	
684	3	1Fam	TA	1148	BLQ	TA	Y	SBrkr	0	TA	TA	0	
1489	3	1Fam	Gd	456	ALQ	Gd	Y	SBrkr	0	TA	TA	0	
2246	2	TwnhsE	TA	1573	GLQ	Gd	Y	SBrkr	0	TA	Gd	1	
2386	4	1Fam	TA	0	Unf	Ex	Y	SBrkr	0	TA	Gd	1	
341	2	1Fam	Fa	564	Rec	Fa	Y	SBrkr	0	TA	TA	0	

Exploratory Data Analysis

In [4]:
```
# Plot correlation
corr = prices.corr()
mask = np.triu(np.ones_like(corr, dtype=bool))

plt.figure(figsize=(20,15))
sns.heatmap(corr,
            cmap="vlag",
            mask=mask,
            linewidths=1)
```

executed in 449ms, finished 20:30:15 2023-03-02

Out[4]: <AxesSubplot: >



We see high correlations for OverallQuality and some other area based features. These are expected as the former is just an aggregate of how good of a condition the house is in. The latter also has a positive correlation because land prices come into account.

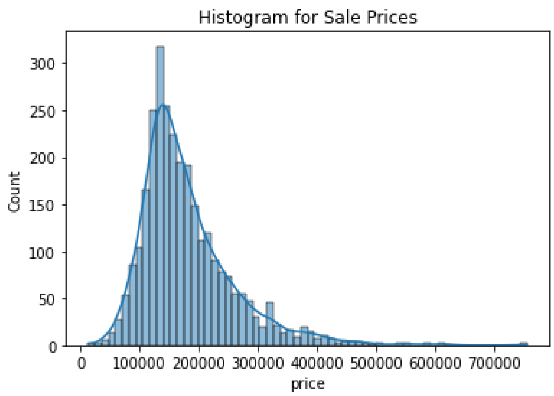
In [15]:
```
ohc_prices = pd.get_dummies(prices.select_dtypes('category'))\
                .merge(prices['price'],
                       left_index=True,
                       right_index=True)\
                .corr()['price']\
                .to_frame()\
                .reset_index()
```

executed in 152ms, finished 20:58:42 2023-03-02

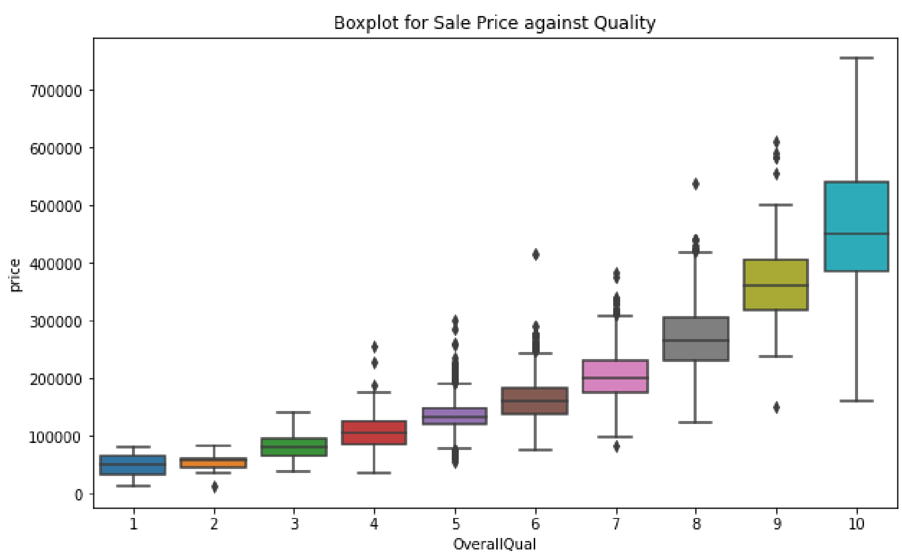
In [17]:
```
plt.figure(figsize=(6, 0.25*len(ohc_prices)))
sns.barplot(ohc_prices.sort_values(by='price'),
            y='index',
            x='price',
            orient='h')
```
executed in 5ms, finished 21:07:20 2023-03-02

In [46]:
```
print(prices['price'].skew())
g = sns.histplot(x=prices['price'],
                kde=True)\
       .set(title='Histogram for Sale Prices')
```
executed in 171ms, finished 23:57:52 2023-03-01

```
1.7435000757376466
```

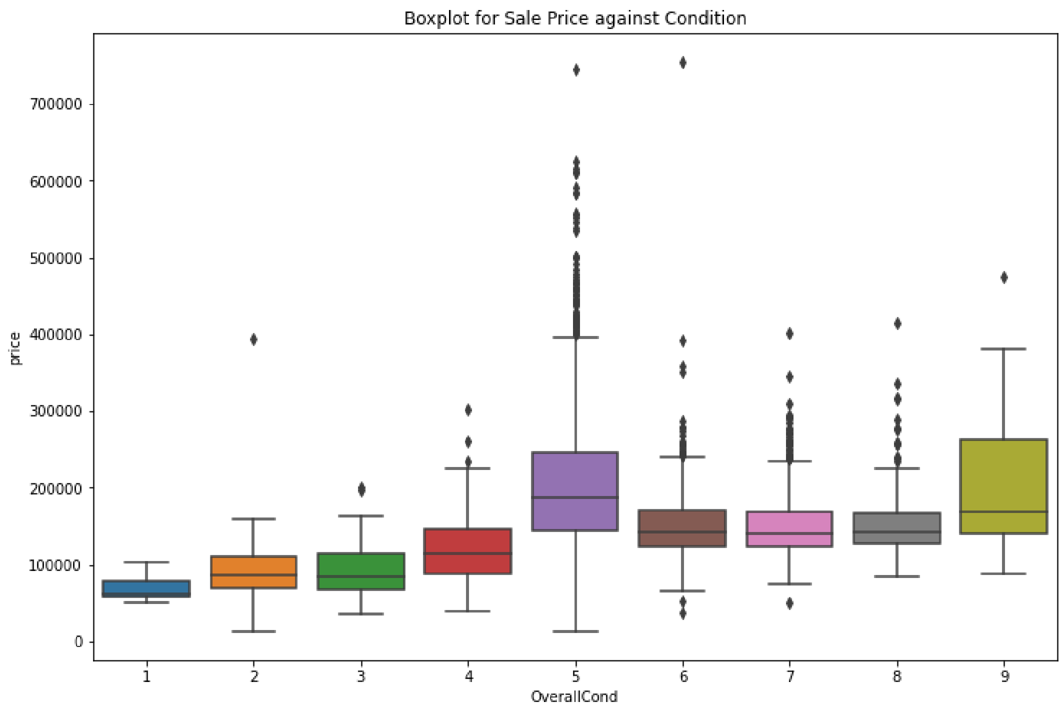


In [11]:
```
plt.figure(figsize=(10,6))
g = sns.boxplot(data=prices,
             y='price',
             x='OverallQual')\
       .set(title='Boxplot for Sale Price against Quality')
```
executed in 236ms, finished 20:33:52 2023-03-02



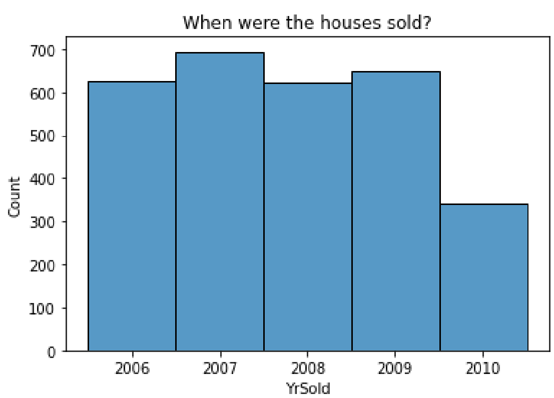
In [49]:
```
plt.figure(figsize=(12,8))
g = sns.boxplot(data=prices,
            y='price',
            x='OverallCond')\
       .set(title='Boxplot for Sale Price against Condition')
```

executed in 176ms, finished 23:57:53 2023-03-01



In [51]:
```
g = sns.histplot(x=prices['YrSold'].astype('category'))\
       .set(title='When were the houses sold?')
```

executed in 119ms, finished 23:57:54 2023-03-01

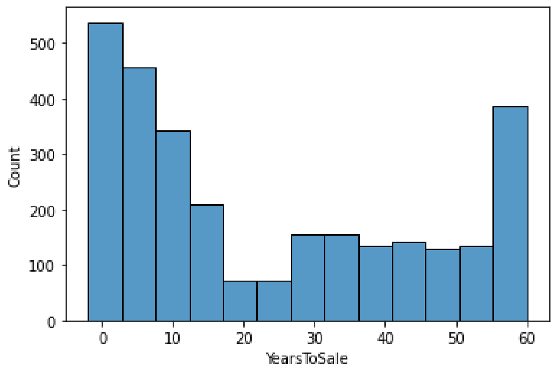


Engineer Additional Columns

In [52]:
```
# Add Years To Sale column
prices['YearsToSale'] = prices['YrSold'] - prices['YearRemodAdd']
prices.drop(columns=['YrSold', 'YearRemodAdd'], inplace=True)
```

executed in 14ms, finished 23:57:56 2023-03-01

In [53]:
```
g = sns.histplot(x=prices['YearsToSale'])
```
executed in 184ms, finished 23:57:56 2023-03-01

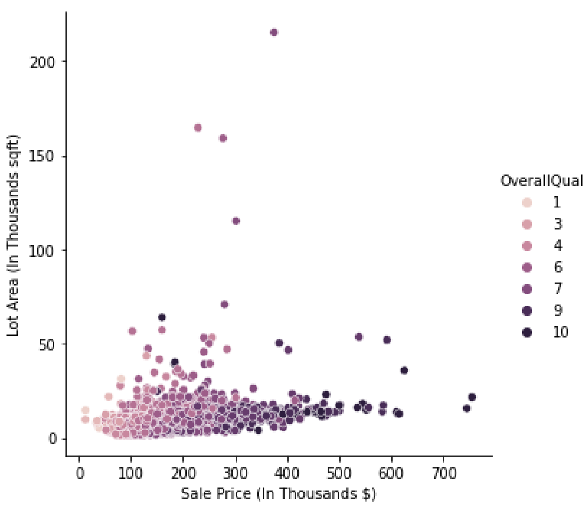


In [54]:
```
prices.select_dtypes(exclude='category').columns
```
executed in 17ms, finished 23:57:57 2023-03-01

Out[54]:
```
Index(['MSSubClass', 'KitchenAbvGr', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', 'X3SsnPorch', 'ScreenPorch', 'PoolArea', 'OverallQual',
       'OverallCond', 'price', 'LotArea', 'BsmtFinSF1', 'TotalBsmtSF',
       'X1stFlrSF', 'X2ndFlrSF', 'LowQualFinSF', 'area', 'BedroomAbvGr',
       'TotRmsAbvGrd', 'Fireplaces', 'GarageCars', 'GarageArea',
       'YearsToSale'],
      dtype='object')
```

In [55]:
```
sns.relplot(data=prices,
           x=prices['price']/1000,
           y=prices['LotArea']/1000,
           hue='OverallQual')

plt.xlabel('Sale Price (In Thousands $)')
plt.ylabel('Lot Area (In Thousands sqft)')
```
executed in 497ms, finished 23:57:58 2023-03-01

Out[55]:
```
Text(30.236805555555563, 0.5, 'Lot Area (In Thousands sqft)')
```



In [35]:
```
prices = prices[prices['LotArea'] < 1e5] # Remove houses more than 1e5 feet in lot area
prices = prices[prices['price'] > 20000] # Remove houses costing less than 20k
```
executed in 14ms, finished 20:33:24 2023-03-01

In [33]:
```
prices.to_parquet(r'..\data\processed\training_cleaned_engineered.parquet')
```
executed in 17ms, finished 12:38:03 2023-02-28

In [26]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
from pprint import pprint

import lightgbm as lgb
import optuna.integration.lightgbm as opt_lgb
import scikitplot as skplt
import joblib

from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.tree import DecisionTreeRegressor, plot_tree
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_percentage_error
from sklearn.inspection import permutation_importance
```

executed in 17ms, finished 20:42:05 2023-03-02

In [3]:
```
%load_ext watermark
%watermark -v -n -m -p numpy,sklearn,lightgbm,pandas,seaborn
```

executed in 44ms, finished 20:37:09 2023-03-02

```
Python implementation: CPython
Python version       : 3.8.8
IPython version      : 7.22.0

numpy   : 1.23.5
sklearn : 1.2.0
lightgbm: 3.3.2
pandas  : 1.4.3
seaborn : 0.12.2

Compiler    : MSC v.1916 64 bit (AMD64)
OS          : Windows
Release     : 10
Machine     : AMD64
Processor   : Intel64 Family 6 Model 140 Stepping 1, GenuineIntel
CPU cores   : 8
Architecture: 64bit
```

In [4]:
```
# Import cleaned dataset
prices = pd.read_parquet(r'..\data\processed\training_cleaned_engineered.parquet')
```

executed in 61ms, finished 20:37:10 2023-03-02

Since we'll only be using decision trees (RF, LightGBM), we can simply use numeric categories as these models do not associate numeric data to be ordinal.

In [5]:
```
## Alternately we can use dummy variables
# prices_ohc = pd.get_dummies(prices.select_dtypes('category'))\
#                  .merge(prices.select_dtypes(exclude='category'),
#                         left_index=True,
#                         right_index=True)

for col in prices.select_dtypes('category').columns:
    prices[col] = prices[col].cat.codes
```

executed in 21ms, finished 20:37:13 2023-03-02

In [6]:
```
X_train, X_test, y_train, y_test = train_test_split(prices.drop('price', axis=1),
                                                    prices['price'],
                                                    test_size= 0.25,
                                                    random_state=42)
```

executed in 27ms, finished 20:37:14 2023-03-02

In [7]:
```
# Collect models and test metrics
all_results = []

def regression_metrics(model,
                       model_name,
                       collect=True):
    """Function to measure and store model metrics for X_test y_test,
        for an updated model the name should have some variation
    """
    model_params = {}
    model_params['model_name'] = model_name
    model_params['model'] = model
    model_params['timestamp'] = str(datetime.datetime.now())
    for dataset_type, scores in zip(['train', 'test'],
                                [(y_train, model.predict(X_train)),
                                 (y_test, model.predict(X_test))]):
        model_params[dataset_type] = {}
        model_params[dataset_type]['R2 Score'] = r2_score(scores[0], scores[1])
        model_params[dataset_type]['RMSE'] = np.sqrt(mean_squared_error(scores[0], scores[1]))
        model_params[dataset_type]['MAPE'] = mean_absolute_percentage_error(scores[0], scores[1])

    pprint(model_params)

    if collect:
        all_results.append(model_params)
```
executed in 27ms, finished 20:37:14 2023-03-02

In [8]:
```
def metrics():
    """Function to create a pretty dataframe out of metrics"""
    # Create a model dataframe
    model_df = pd.DataFrame(all_results)
    model_df.columns = pd.MultiIndex.from_product([['Model'], model_df.columns]) # Add column

    if model_df.empty:
        return 'No Metrics'

    for dataset in ['test', 'train']:
        df = pd.DataFrame(all_results)[dataset].apply(pd.Series)
        df.columns = pd.MultiIndex.from_product([[dataset], df.columns])
        model_df = model_df.merge(df,
                                  left_index=True,
                                  right_index=True)
        #display(model_df)
    cm = sns.light_palette("seagreen",
                           reverse=True,
                           as_cmap=10)
#     model_df.set_index(('Model','model_name'), inplace=True)
#     model_df.index.rename('Model Name', inplace=True)
    return model_df.drop(['train', 'test'], axis=1, level=1).drop_duplicates(subset=[('Model', 'model_name'), ('Model','timestamp
```
executed in 9ms, finished 20:37:15 2023-03-02

Train and Plot a Decision Tree

In [9]:
```
dt_reg = DecisionTreeRegressor()
dt_reg.fit(X_train,
           y_train)
```
executed in 60ms, finished 20:37:17 2023-03-02

Out[9]:
```
DecisionTreeRegressor()
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [10]:
```
# Out of bag score will be used as the minimum for the model
regression_metrics(dt_reg, 'Decision Tree')
```
executed in 19ms, finished 20:37:19 2023-03-02

```
{'model': DecisionTreeRegressor(),
 'model_name': 'Decision Tree',
 'test': {'MAPE': 0.13552425379829233,
          'R2 Score': 0.7128687904188071,
          'RMSE': 41686.855769051625},
 'timestamp': '2023-03-02 20:37:19.565429',
 'train': {'MAPE': 2.617310864038917e-05,
           'R2 Score': 0.9999980087748153,
           'RMSE': 113.33091920928732}}
```

In [12]:
```
# plot_tree(dt_reg, feature_names=['Quality', 'Area'], impurity=False)
```
executed in 8ms, finished 20:37:30 2023-03-02

Random Forest Regression

In [13]:
```
randomf_reg = RandomForestRegressor(random_state=42,
                                      oob_score=True,
                                      n_jobs=-1)
randomf_reg.fit(X_train, y_train)
```
executed in 712ms, finished 20:38:13 2023-03-02

Out[13]:
```
RandomForestRegressor(n_jobs=-1, oob_score=True, random_state=42)
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [14]:
```
# Out of bag score will be used as the minimum for the model
print(randomf_reg.oob_score_, '\n')
regression_metrics(randomf_reg, 'Random Forest Regression')
```
executed in 69ms, finished 20:38:14 2023-03-02

```
0.8863250281647154

{'model': RandomForestRegressor(n_jobs=-1, oob_score=True, random_state=42),
 'model_name': 'Random Forest Regression',
 'test': {'MAPE': 0.08645636457230998,
          'R2 Score': 0.866963462204083,
          'RMSE': 28375.557731905883},
 'timestamp': '2023-03-02 20:38:14.038386',
 'train': {'MAPE': 0.03668910608412481,
           'R2 Score': 0.984526179698846,
           'RMSE': 9990.494787111083}}
```

In [15]:
```
metrics()
```
executed in 113ms, finished 20:38:17 2023-03-02

Out[15]:

			Model	test			train		
	model_name	model	timestamp	R2 Score	RMSE	MAPE	R2 Score	RMSE	MAPE
0	Decision Tree	DecisionTreeRegressor()	2023-03-02 20:37:19.565429	0.712869	41686.855769	0.135524	0.999998	113.330919	0.000026
1	Random Forest Regression	RandomForestRegressor(n_jobs=-1, oob_score=True, random_state=42)	2023-03-02 20:38:14.038386	0.866963	28375.557732	0.086456	0.984526	9990.494787	0.036689

In [53]:
```
# Look at the random forest features to understand what should be tuned
randomf_reg.get_params()
```
executed in 6ms, finished 20:39:10 2023-03-01

Out[53]:
```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'criterion': 'squared_error',
 'max_depth': None,
 'max_features': 1.0,
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 100,
 'n_jobs': -1,
 'oob_score': True,
 'random_state': 42,
 'verbose': 0,
 'warm_start': False}
```

In [17]:
```
param_grid = {
    'max_depth': np.arange(20, 200, 50),
    'max_features': ('sqrt', 'log2'),
    'min_samples_leaf': np.arange(3, 8, 2),
    'min_samples_split': np.arange(5, 15, 4),
    'n_estimators': np.arange(100, 1000, 200)
}

rf_grid = GridSearchCV(estimator = randomf_reg,
                       param_grid = param_grid,
                       scoring = 'neg_root_mean_squared_error',
                       cv = 3,
                       n_jobs = -1)
```
executed in 22ms, finished 20:39:51 2023-03-02

In [18]:
```
rf_grid.fit(X_train, y_train)
```
executed in 1m 3.76s, finished 20:40:59 2023-03-02

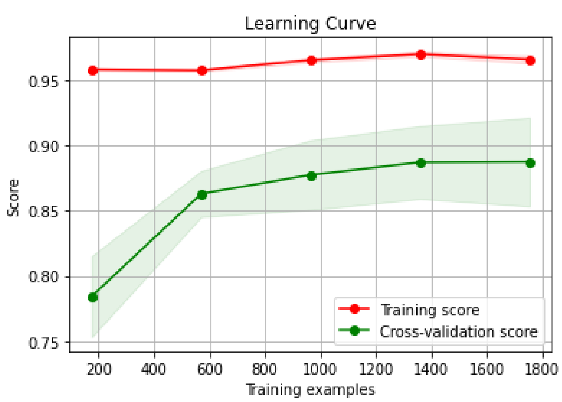
Out[18]:
```
GridSearchCV(cv=3,
             estimator=RandomForestRegressor(n_jobs=-1, oob_score=True,
                                             random_state=42),
             n_jobs=-1,
             param_grid={'max_depth': [70, 100], 'min_samples_leaf': [3, 5],
                         'min_samples_split': [4, 6],
                         'n_estimators': [800, 100]},
             scoring='neg_root_mean_squared_error')
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [20]:
```
rf_grid.best_params_
```
executed in 13ms, finished 00:13:50 2023-03-01

Out[20]:
```
{'max_depth': 70,
 'max_features': 'sqrt',
 'min_samples_leaf': 3,
 'min_samples_split': 5,
 'n_estimators': 900}
```

In [56]:
```
# A plot of the train and test learning curves for a classifier.
skplt.estimators.plot_learning_curve(rf_grid.best_estimator_,
                                     X_train,
                                     y_train,
                                     n_jobs=-1)
```
executed in 4.20s, finished 20:42:34 2023-03-01

Out[56]:
```
<AxesSubplot: title={'center': 'Learning Curve'}, xlabel='Training examples', ylabel='Score'>
```



In [19]:
```
# Out of bag score will be used as the minimum for the model
print(rf_grid.best_estimator_, '\n')
regression_metrics(rf_grid.best_estimator_, 'Random Forest Regression - Grid Search Tuned')
```
executed in 60ms, finished 20:41:11 2023-03-02

```
RandomForestRegressor(max_depth=70, min_samples_leaf=3, min_samples_split=4,
                      n_jobs=-1, oob_score=True, random_state=42)

{'model': RandomForestRegressor(max_depth=70, min_samples_leaf=3, min_samples_split=4,
                      n_jobs=-1, oob_score=True, random_state=42),
 'model_name': 'Random Forest Regression - Grid Search Tuned',
 'test': {'MAPE': 0.08618557292207135,
          'R2 Score': 0.8659191664255618,
          'RMSE': 28486.70971810993},
 'timestamp': '2023-03-02 20:41:11.324318',
 'train': {'MAPE': 0.04994321571754982,
           'R2 Score': 0.9671337282899479,
           'RMSE': 14560.069354076828}}
```

In [20]:
```
metrics()
```
executed in 36ms, finished 20:41:13 2023-03-02

Out[20]:

	Model			test			train		
	model_name	model	timestamp	R2 Score	RMSE	MAPE	R2 Score	RMSE	MAPE
0	Decision Tree	DecisionTreeRegressor()	2023-03-02 20:37:19.565429	0.712869	41686.855769	0.135524	0.999998	113.330919	0.000026
1	Random Forest Regression	RandomForestRegressor(n_jobs=-1, oob_score=True, random_state=42)	2023-03-02 20:38:14.038386	0.866963	28375.557732	0.086456	0.984526	9990.494787	0.036689
2	Random Forest Regression - Grid Search Tuned	RandomForestRegressor(max_depth=70, min_samples_leaf=3, min_samples_split=4, n_jobs=-1, oob_score=True, random_state=42)	2023-03-02 20:41:11.324318	0.865919	28486.709718	0.086186	0.967134	14560.069354	0.049943

In [21]:
```
# Look at the feature importance for the tree model
features_and_scores = []
for name, score in zip(X_train.columns, rf_grid.best_estimator_.feature_importances_):
    features_and_scores.append([name, round(score, 3)])

sorted(features_and_scores, key = lambda x: x[1], reverse=True)[:15]
```
executed in 32ms, finished 20:41:17 2023-03-02

Out[21]:
```
[['OverallQual', 0.633],
 ['area', 0.139],
 ['TotalBsmtSF', 0.041],
 ['X1stFlrSF', 0.031],
 ['X2ndFlrSF', 0.024],
 ['BsmtFinSF1', 0.021],
 ['LotArea', 0.017],
 ['GarageArea', 0.014],
 ['YearsToSale', 0.012],
 ['GarageCars', 0.011],
 ['KitchenQual', 0.005],
 ['WoodDeckSF', 0.005],
 ['MSZoning', 0.004],
 ['Neighborhood', 0.004],
 ['BsmtQual', 0.004]]
```

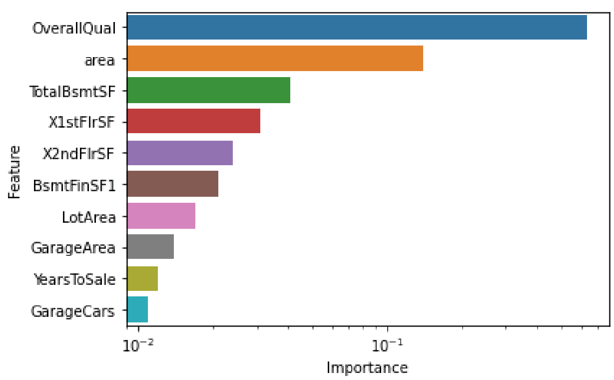
In [22]:
```python
# Tree based estimators will be biased towards continius features
# or higher dimensional features, look at permutation importance
# this is model dependent, based model -> invalid importance
perm_importance = permutation_importance(randomf_reg, X_train, y_train,
                                         n_repeats=30,
                                         random_state=42,
                                         n_jobs=-1)

# Look at the feature importance for the tree model
p_importance = []
for name, score in zip(X_train.columns, perm_importance.importances_mean):
    p_importance.append([name, round(score, 3)])

sorted(p_importance, key = lambda x: x[1], reverse=True)[:15]
```

executed in 13.3s, finished 20:41:32 2023-03-02

Out[22]:
```
[['OverallQual', 0.509],
 ['area', 0.186],
 ['TotalBsmtSF', 0.036],
 ['BsmtFinSF1', 0.025],
 ['X1stFlrSF', 0.023],
 ['YearsToSale', 0.017],
 ['LotArea', 0.016],
 ['X2ndFlrSF', 0.013],
 ['GarageCars', 0.012],
 ['GarageArea', 0.012],
 ['MSZoning', 0.004],
 ['Neighborhood', 0.004],
 ['WoodDeckSF', 0.004],
 ['OpenPorchSF', 0.004],
 ['OverallCond', 0.004]]
```

In [27]:
```python
features_df = pd.DataFrame(features_and_scores, columns=['Feature', 'Importance']).sort_values(by='Importance', ascending=False).
sns.barplot(data=features_df,
            y='Feature',
            x='Importance',
            orient='h')
plt.xscale('log')
```

executed in 403ms, finished 20:42:16 2023-03-02



LightGBM

In [28]:
```python
# Create validation sets
X2_train, X2_validate, y2_train, y2_validate = train_test_split(X_train,
                                                                y_train,
                                                                test_size= 0.25,
                                                                random_state=42)
```

executed in 17ms, finished 20:42:26 2023-03-02

In [29]:
```python
lgb_train = lgb.Dataset(X2_train, y2_train)
validation_set = lgb.Dataset(X2_validate, y2_validate)
```

executed in 10ms, finished 20:42:27 2023-03-02

In [30]:
```python
# Train a vanilla model
params = {
    'boosting_type': 'gbdt',
    'objective': 'regression',
    'metric': 'mse',
}

booster = lgb.train(params,
                    lgb_train)
```
executed in 111ms, finished 20:42:28 2023-03-02

```
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of testing was 0.000658 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 2503
[LightGBM] [Info] Number of data points in the train set: 1644, number of used features: 43
[LightGBM] [Info] Start training from score 180104.953163
```

In [31]:
```python
regression_metrics(booster, 'LightGBM')
metrics()
```
executed in 52ms, finished 20:42:29 2023-03-02

```
{'model': <lightgbm.basic.Booster object at 0x000001B422CCE430>,
 'model_name': 'LightGBM',
 'test': {'MAPE': 0.08254212699344546,
          'R2 Score': 0.875114246779076,
          'RMSE': 27492.573084624106},
 'timestamp': '2023-03-02 20:42:29.779579',
 'train': {'MAPE': 0.05295803543264103,
           'R2 Score': 0.9574743359457822,
           'RMSE': 16562.037933623462}}
```

Out[31]:

			Model	test			train		
	model_name	model	timestamp	R2 Score	RMSE	MAPE	R2 Score	RMSE	MAPE
0	Decision Tree	DecisionTreeRegressor()	2023-03-02 20:37:19.565429	0.712869	41686.855769	0.135524	0.999998	113.330919	0.000026
1	Random Forest Regression	RandomForestRegressor(n_jobs=-1, oob_score=True, random_state=42)	2023-03-02 20:38:14.038386	0.866963	28375.557732	0.086456	0.984526	9990.494787	0.036689
2	Random Forest Regression - Grid Search Tuned	RandomForestRegressor(max_depth=70, min_samples_leaf=3, min_samples_split=4, n_jobs=-1, oob_score=True, random_state=42)	2023-03-02 20:41:11.324318	0.865919	28486.709718	0.086186	0.967134	14560.069354	0.049943
3	LightGBM		2023-03-02 20:42:29.779579	0.875114	27492.573085	0.082542	0.957474	16562.037934	0.052958

In [32]:
```python
lgb_train = lgb.Dataset(X2_train, y2_train)
validation_set = lgb.Dataset(X2_validate, y2_validate)
```
executed in 9ms, finished 20:42:34 2023-03-02

In [33]:
```python
# Integration only tunes the following
# lambda_l1, lambda_l2, num_leaves, feature_fraction, bagging_fraction, bagging_freq and min_child_samples
params = {
    'boosting_type': 'gbdt',
    'objective': 'regression',
    'metric': 'rmse',
    'num_leaves': 31,
    'learning_rate': 0.05,
    'feature_fraction': 0.9,
    'bagging_fraction': 0.8,
    'bagging_freq': 5,
    'verbose': 0,
}

# Using Optuna to tune, create a study to tune for final model
tuned_booster = opt_lgb.train(params,
                             lgb_train,
                             valid_sets=[validation_set],
                             early_stopping_rounds=1000,
                             show_progress_bar = True)
```

executed in 1m 13.9s, finished 20:43:55 2023-03-02

```
[I 2023-03-02 20:42:41,133] A new study created in memory with name: no-name-42226250-2d1a-4060-a48f-03b2c0d5227f
feature_fraction, val_score: inf:   0%|                                                             | 0/7 [00:00<?, ?it/s]C:\Prog
ramData\Anaconda3\lib\site-packages\lightgbm\engine.py:181: UserWarning: 'early_stopping_rounds' argument is deprecated and wi
ll be removed in a future release of LightGBM. Pass 'early_stopping()' callback via 'callbacks' argument instead.
  _log_warning("'early_stopping_rounds' argument is deprecated and will be removed in a future release of LightGBM. "

[LightGBM] [Warning] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000797 seconds.
You can set `force_col_wise=true` to remove the overhead.
[1]     valid_0's rmse: 78699.9
Training until validation scores don't improve for 1000 rounds
[2]     valid_0's rmse: 75647.4
[3]     valid_0's rmse: 72746.9
[4]     valid_0's rmse: 70045.1
[5]     valid_0's rmse: 67531.9
[6]     valid_0's rmse: 65133.2
[7]     valid_0's rmse: 62860.9
[8]     valid_0's rmse: 60784.6
[9]     valid_0's rmse: 58847.5
[10]    valid_0's rmse: 57036.3
[11]    valid_0's rmse: 55231.9
```

In [34]:
```python
print(f'Validation Set Best Score\n: {tuned_booster.best_score} \n')
regression_metrics(tuned_booster, 'LightGBM Optuna Tuned', collect=True)
```

executed in 61ms, finished 20:44:11 2023-03-02

```
Validation Set Best Score
: defaultdict(<class 'collections.OrderedDict'>, {'valid_0': OrderedDict([('rmse', 24771.51147325579)])})

{'model': <lightgbm.basic.Booster object at 0x000001B422D5C070>,
 'model_name': 'LightGBM Optuna Tuned',
 'test': {'MAPE': 0.07597770400002897,
          'R2 Score': 0.8782770612169689,
          'RMSE': 27142.20673013889},
 'timestamp': '2023-03-02 20:44:11.467397',
 'train': {'MAPE': 0.02605187752257108,
           'R2 Score': 0.9759083786209063,
           'RMSE': 12465.831079971773}}
```

In [35]:
```python
metrics()
```

executed in 37ms, finished 20:44:11 2023-03-02

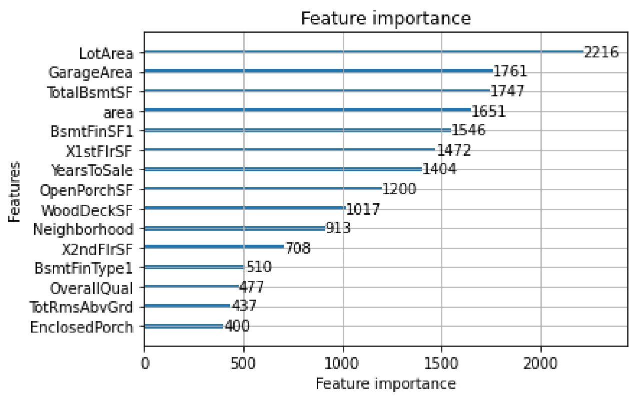
Out[35]:

			Model	test			train		
	model_name	model	timestamp	R2 Score	RMSE	MAPE	R2 Score	RMSE	MAPE
0	Decision Tree	DecisionTreeRegressor()	2023-03-02 20:37:19.565429	0.712869	41686.855769	0.135524	0.999998	113.330919	0.000026
1	Random Forest Regression	RandomForestRegressor(n_jobs=-1, oob_score=True, random_state=42)	2023-03-02 20:38:14.038386	0.866963	28375.557732	0.086456	0.984526	9990.494787	0.036689
2	Random Forest Regression - Grid Search Tuned	RandomForestRegressor(max_depth=70, min_samples_leaf=3, min_samples_split=4, n_jobs=-1, oob_score=True, random_state=42)	2023-03-02 20:41:11.324318	0.865919	28486.709718	0.086186	0.967134	14560.069354	0.049943
3	LightGBM		2023-03-02 20:42:29.779579	0.875114	27492.573085	0.082542	0.957474	16562.037934	0.052958
4	LightGBM Optuna Tuned		2023-03-02 20:44:11.467397	0.878277	27142.206730	0.075978	0.975908	12465.831080	0.026052

In [40]:
```
tuned_booster.params
```
executed in 22ms, finished 20:47:37 2023-03-02

Out[40]:
```
{'boosting_type': 'gbdt',
 'objective': 'regression',
 'metric': 'rmse',
 'num_leaves': 31,
 'learning_rate': 0.05,
 'feature_fraction': 0.44800000000000006,
 'bagging_fraction': 0.9425027593958745,
 'bagging_freq': 6,
 'verbose': 0,
 'feature_pre_filter': False,
 'lambda_l1': 4.645269379905211,
 'lambda_l2': 3.462023380485085e-07,
 'min_child_samples': 5,
 'num_iterations': 1000,
 'early_stopping_round': 1000}
```

In [41]:
```
ax = lgb.plot_importance(tuned_booster, max_num_features=15)
```
executed in 211ms, finished 20:48:08 2023-03-02



In [42]:
```
joblib.dump(tuned_booster, r"models\lightgbm_tuned.pkl")
```
executed in 84ms, finished 20:48:10 2023-03-02

Out[42]:
```
['models\\lightgbm_tuned.pkl']
```

In [43]:
```
metrics().to_excel(f"models\Regression Models {datetime.datetime.today().strftime('%Y-%m-%d_%H-%M')}.xlsx")
```
executed in 112ms, finished 20:48:11 2023-03-02

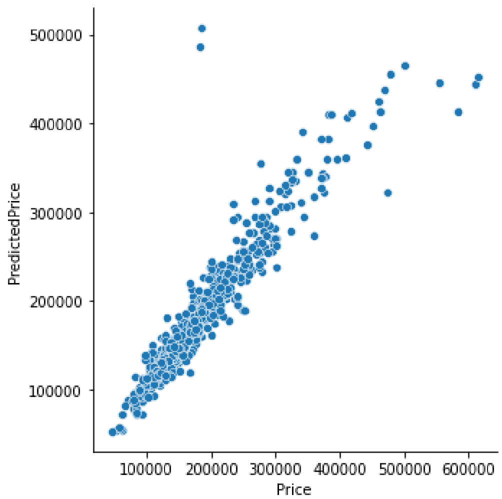
Analyze Predictions

In [44]:
```
# Load trained model
final_model = joblib.load(r"models\lightgbm_tuned.pkl")
```
executed in 39ms, finished 20:48:15 2023-03-02

In [45]:
```
results = X_test.copy()

results['PredictedPrice'] = final_model.predict(X_test)
results['Price'] = y_test
results['PredictionDelta'] = results['Price']-results['PredictedPrice']

# Bin rates to group by
results['StreetRateBins'] = pd.qcut(results['Price'], 10)
```
executed in 68ms, finished 20:48:15 2023-03-02

In [51]:
```
sns.relplot(data=results,
         x='Price',
         y='PredictedPrice')
```
executed in 149ms, finished 20:48:28 2023-03-02

Out[51]:
```
<seaborn.axisgrid.FacetGrid at 0x1b4230c65b0>
```



There are some significant outliers to the predictions themselves as shown above. While the error follows a normal distribution, prices for some houses are predicted to be $300,000 more than what they sold for.

In [52]:
```
def regression_metrics(x):
    """Returns select scores for the predictions vs actual rates"""
    return pd.Series([format(r2_score(x['Price'], x['PredictedPrice']), '.3f'),
                      np.sqrt(mean_squared_error(x['Price'], x['PredictedPrice'])),
                      mean_absolute_percentage_error(x['Price'], x['PredictedPrice'])],
                      index=['R2 Score','RMSE','MAPE'])
```
executed in 12ms, finished 20:48:55 2023-03-02

In [53]:
```
results.groupby(by=['StreetRateBins'])[['Price', 'PredictedPrice']].apply(regression_metrics)
```
executed in 31ms, finished 20:48:59 2023-03-02

Out[53]:

StreetRateBins	R2 Score	RMSE	MAPE
(44999.999, 108000.0]	-0.062	14406.677864	0.118491
(108000.0, 125500.0]	-3.835	10922.273609	0.068707
(125500.0, 138000.0]	-10.414	12391.131545	0.066173
(138000.0, 149000.0]	-7.566	9222.971964	0.049732
(149000.0, 165400.0]	-8.176	12615.343088	0.064377
(165400.0, 180000.0]	-11.837	15148.481355	0.061726
(180000.0, 200500.0]	-84.078	54513.650377	0.105860
(200500.0, 227000.0]	-2.741	14514.839594	0.052992
(227000.0, 276000.0]	-2.971	27752.548319	0.084036
(276000.0, 615000.0]	0.607	50420.295805	0.088051

The model seems to struggle for houses that were sold in the 180-200k range.

In [55]:
```
results.groupby(by=['OverallCond'])[['Price', 'PredictedPrice']].apply(regression_metrics)
```
executed in 34ms, finished 20:49:03 2023-03-02

Out[55]:

OverallCond	R2 Score	RMSE	MAPE
1	0.436	13486.687716	0.131914
2	-1.309	13676.655724	0.183785
3	0.838	18848.741242	0.103906
4	0.805	24108.071627	0.112045
5	0.856	32553.200192	0.075772
6	0.847	16260.255328	0.071542
7	0.891	14529.033869	0.072144
8	0.802	12581.121475	0.059155
9	0.316	24436.745845	0.091490

The model also struggles the most for lower quality houses, and houses with perfect quality scores.