# 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.

Problem Statements to Tackle:

- Housing Prices, how to go about predicting it?
- What features most influence the price of a house?
- How well does a regression model predicting prices for a house perform?

It is broken off into three main portions/notebooks

1) **Extract, Transform, Load**

2) **Explanatory Data Analysis**

3) **Training a model**

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

## 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

In [39]:
```
ames = pd.read_csv(r'..\data\raw\ames.csv', low_memory=False)
```

In [40]:
```
# Remove the '.' from column names
ames.columns = [x.replace('.', '') for x in ames.columns]
```

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

In [62]:
```
ames.shape
```

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]:
```
# Select subset of columns to use
categorical = ['MSSubClass', 'MSZoning', 'Street', 'LotShape', 'LandContour', 'Utilit
               'BldgType', 'HouseStyle', 'ExterQual', 'ExterCond', 'Foundation', 'Bsm
               'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenAbvGr', 'K
               'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', 'X3SsnPorc
               'SaleCondition', 'OverallQual', 'OverallCond']

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

to_engineer = ['YearRemodAdd', 'YrSold']
```

In [64]:
```
columns_to_use = categorical+numerical+to_engineer
```

In [65]:
```
ames_truncated = ames[columns_to_use].copy()
```

In [66]:
```
ames_truncated.shape
```

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

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

| | BedroomAbvGr | BldgType | BsmtCond | BsmtFinSF1 | BsmtFinType1 | BsmtQual | CentralAir | Electrical | Encl |
|---|---|---|---|---|---|---|---|---|---|
| **1531** | 3 | 1Fam | TA | 0.0 | Unf | Gd | Y | SBrkr | |
| **2183** | 2 | 1Fam | TA | 77.0 | Rec | TA | Y | SBrkr | |
| **1283** | 3 | 1Fam | TA | 96.0 | GLQ | TA | N | SBrkr | |
| **1084** | 2 | 1Fam | TA | 0.0 | Unf | Gd | Y | SBrkr | |
| **82** | 2 | 1Fam | TA | 0.0 | Unf | TA | N | FuseA | |
| **195** | 3 | 1Fam | TA | 264.0 | LwQ | TA | Y | FuseA | |
| **840** | 3 | 1Fam | TA | 0.0 | Unf | Gd | Y | SBrkr | |
| **1171** | 2 | TwnhsE | TA | 1238.0 | GLQ | Ex | Y | SBrkr | |
| **1481** | 1 | TwnhsE | TA | 697.0 | GLQ | Gd | Y | SBrkr | |
| **2176** | 5 | Duplex | NaN | 0.0 | NaN | NaN | Y | SBrkr | |

## Data Cleaning - Deal with Missing Values

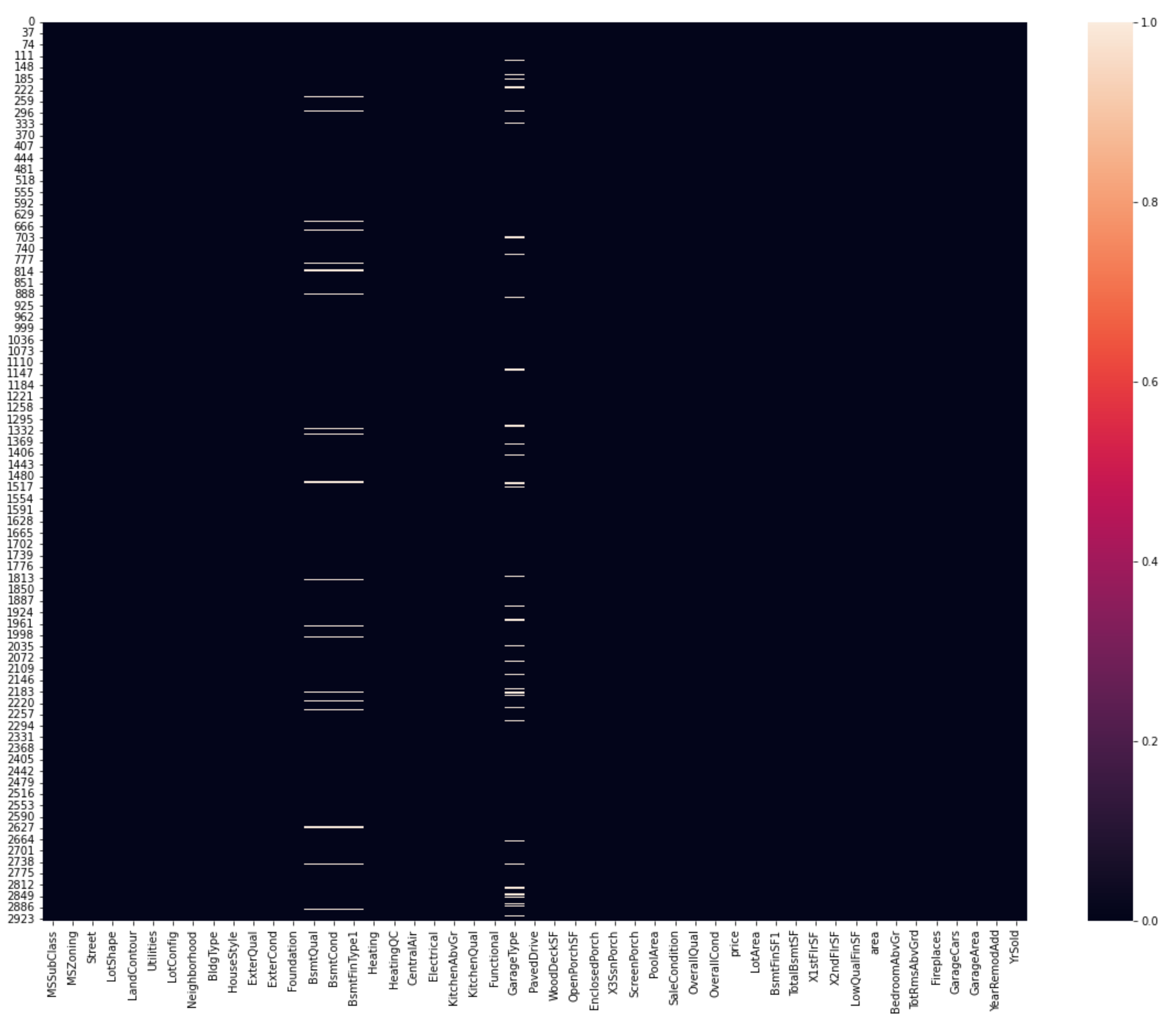
I analyzed individual nulls to understand whether they needed to be impute or removed. Most of them could be imputed from the mode of the feature, or categorized as a valid omission. Existing documentation of the dataset helped with deciding the proper categories.

In [46]:
```
# Look at percentage of missing NA's
ames_truncated.isna().sum().loc[lambda x: x > 0].divide(ames_truncated.shape[0]).sort_
```

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]:
```
# We can plot a heatmap to see nulls
plt.figure(figsize=(20,15))
sns.heatmap(ames_truncated.isna())
```

Out[67]:
```
<AxesSubplot: >
```



In [47]:
```
ames_truncated['BsmtQual'].value_counts(dropna=False)
```

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 :
```

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
```

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)
```

In [51]:
```
# Fill with zeros for category values
for column in ['TotalBsmtSF', 'BsmtFinSF1', 'GarageCars', 'GarageArea']:
    ames_truncated[column].fillna(0, inplace=True)
```

In [52]:
```
ames_truncated['Electrical'].value_counts(dropna=False)
```

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], inp
```

In [54]:
```
assert ames_truncated.isna().sum().sum() == 0, 'Some NAs still present in data'
```

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')
```

In [56]:
```
# All existing numerical types are already int
all(ames_truncated[numerical].dtypes == 'int64')
```

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

In [57]:
```
ames_truncated.to_parquet(r'..\data\processed\training_cleaned.parquet')
```

# Exploratory Data Analysis (EDA)

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
# Read the clean dataset
prices = pd.read_parquet(r'..\data\processed\training_cleaned.parquet')
```

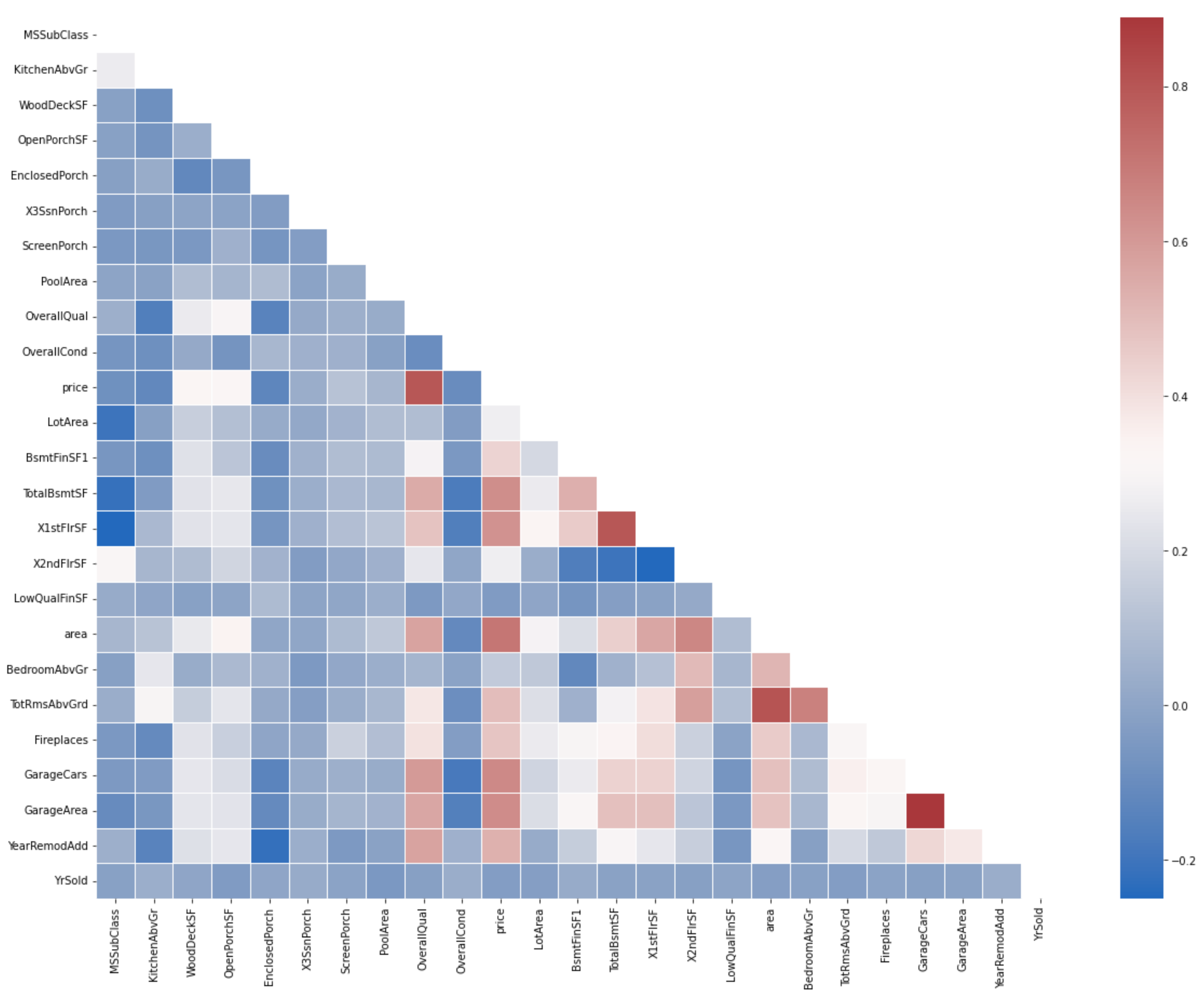
In [3]:
```
# Look at columns
with pd.option_context("display.max_columns", None):
    display(prices[sorted(prices.columns)].sample(10))
```

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

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)
```

Out[4]: <AxesSubplot: >



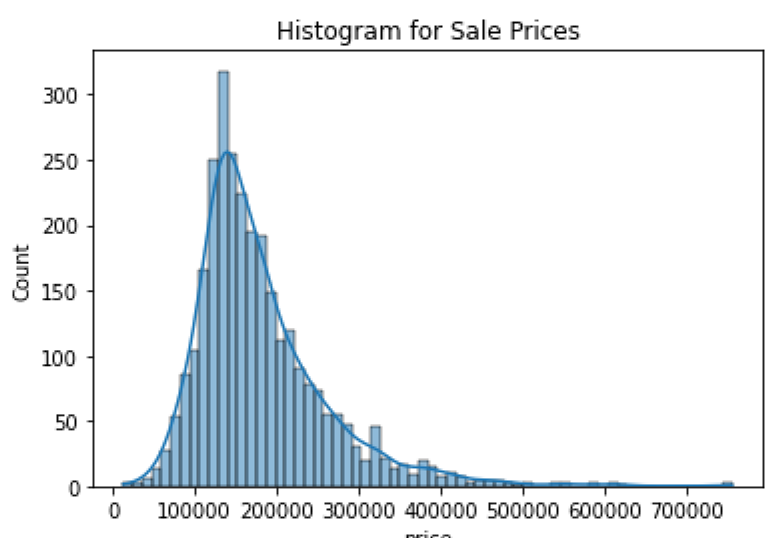

We see high correlations for OverallQuality and some other area based features. These are expected as the former is just an aggregate of how good of a condition the house is in. The latter also has a positive correlation because land prices come into account.

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()
```

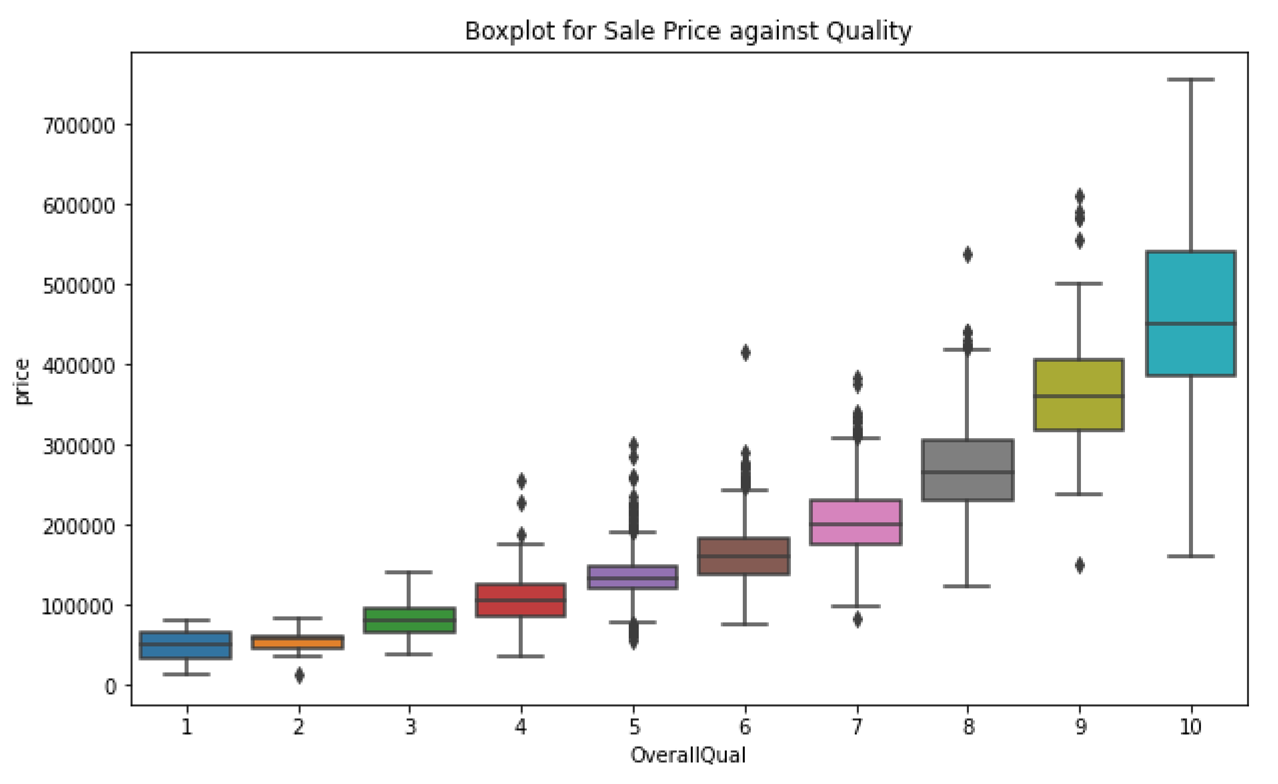
In [17]:
```
plt.figure(figsize=(6, 0.25*len(ohc_prices)))
sns.barplot(ohc_prices.sort_values(by='price'),
            y='index',
            x='price',
            orient='h')
```

In [46]:
```
print(prices['price'].skew())
g = sns.histplot(x=prices['price'],
                 kde=True)\
       .set(title='Histogram for Sale Prices')
```

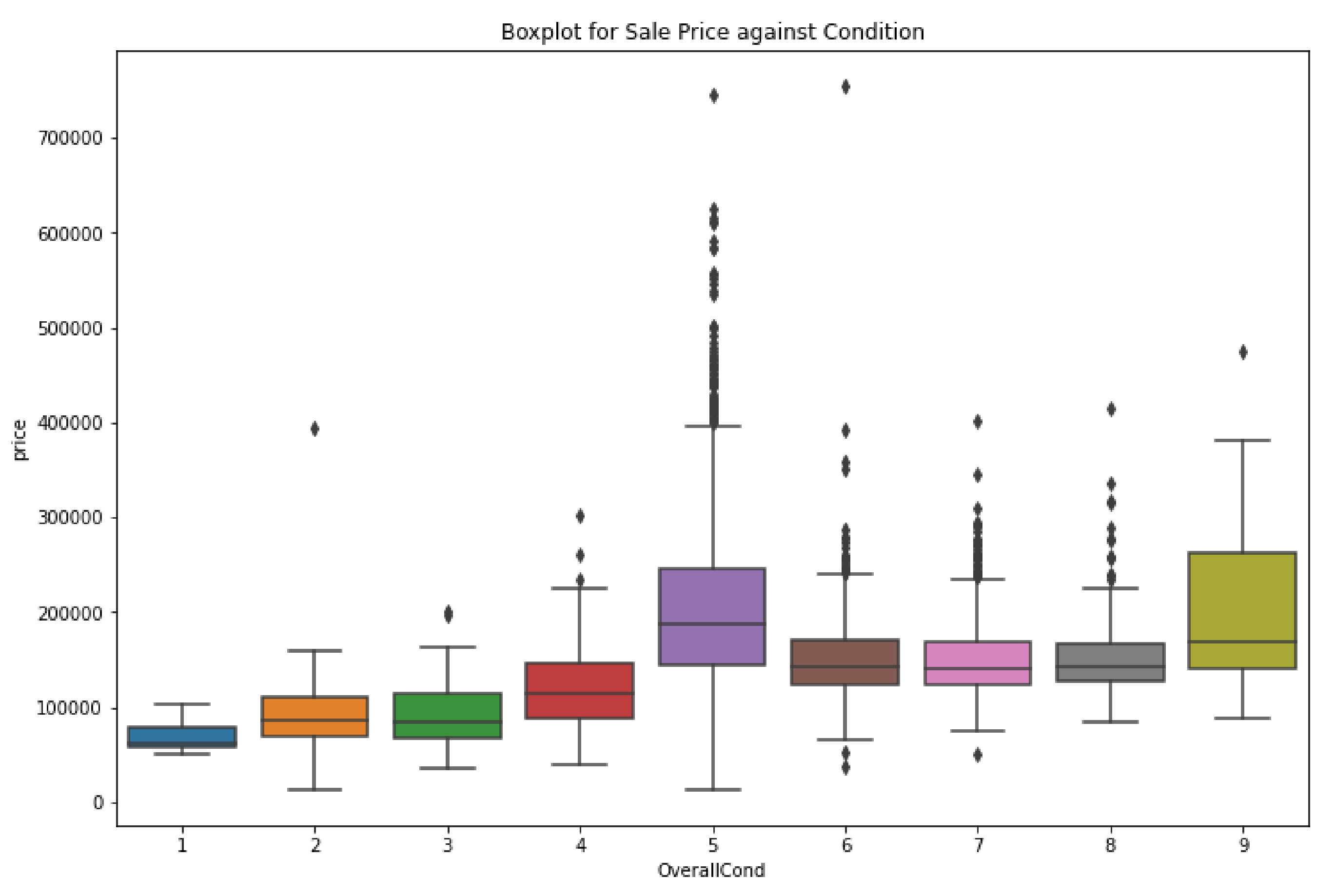
1.7435000757376466



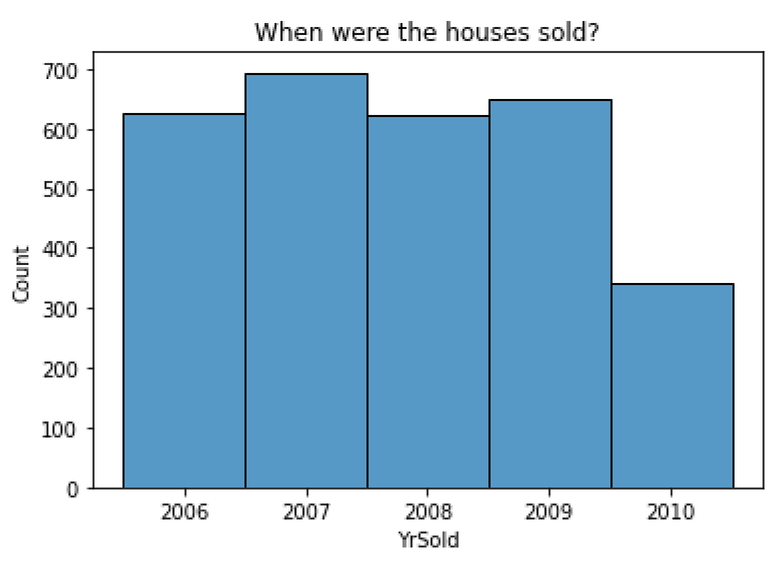

In [11]:
```
plt.figure(figsize=(10,6))
g = sns.boxplot(data=prices,
            y='price',
            x='OverallQual')\
       .set(title='Boxplot for Sale Price against Quality')
```




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



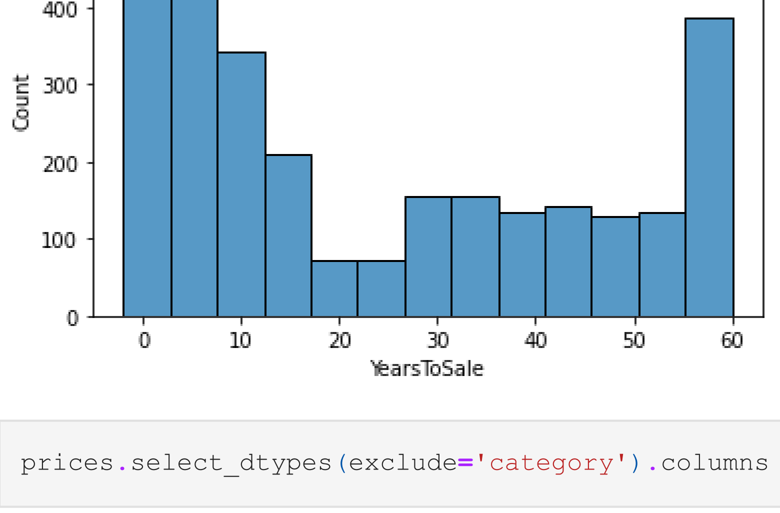

In [51]:
```
g = sns.histplot(x=prices['YrSold'].astype('category'))\
       .set(title='When were the houses sold?')
```




## Engineer Additional Columns

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

In [53]:
```
g = sns.histplot(x=prices['YearsToSale'])
```



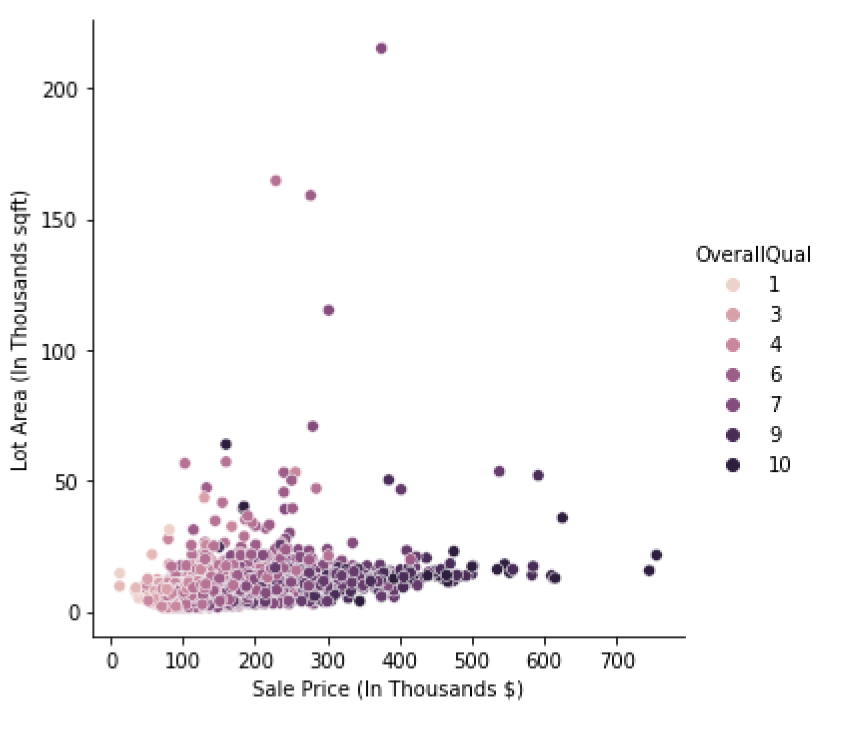

In [54]:
```
prices.select_dtypes(exclude='category').columns
```

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)')
```

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 are
prices = prices[prices['price'] > 20000] # Remove houses costing less than 20k
```

In [33]:
```
prices.to_parquet(r'..\data\processed\training_cleaned_engineered.parquet')
```

# Model

In [1]:
```python
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_er
from sklearn.inspection import permutation_importance
```

```
C:\ProgramData\Anaconda3\lib\site-packages\dask\dataframe\utils.py:369: FutureWarning:
pandas.Int64Index is deprecated and will be removed from pandas in a future version. U
se pandas.Index with the appropriate dtype instead.
  _numeric_index_types = (pd.Int64Index, pd.Float64Index, pd.UInt64Index)
C:\ProgramData\Anaconda3\lib\site-packages\dask\dataframe\utils.py:369: FutureWarning:
pandas.Float64Index is deprecated and will be removed from pandas in a future version.
Use pandas.Index with the appropriate dtype instead.
  _numeric_index_types = (pd.Int64Index, pd.Float64Index, pd.UInt64Index)
C:\ProgramData\Anaconda3\lib\site-packages\dask\dataframe\utils.py:369: FutureWarning:
pandas.UInt64Index is deprecated and will be removed from pandas in a future version.
Use pandas.Index with the appropriate dtype instead.
  _numeric_index_types = (pd.Int64Index, pd.Float64Index, pd.UInt64Index)
```

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

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

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. We also do not need to check of collinearity given the model choice.

In [5]:
```python
## 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
```

In [6]:
```python
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)
```

In [7]:
```python
# 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], sco
        model_params[dataset_type]['MAPE'] = mean_absolute_percentage_error(scores[0],

    pprint(model_params)

    if collect:
        all_results.append(model_params)
```

In [8]:
```python
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]) # Ad

    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=[
```

## Train and Plot a Decision Tree

In [9]:
```python
dt_reg = DecisionTreeRegressor()
dt_reg.fit(X_train,
           y_train)
```

Out[9]:
```
▾ DecisionTreeRegressor
DecisionTreeRegressor()
```

In [10]:
```python
# Out of bag score will be used as the minimum for the model
regression_metrics(dt_reg, 'Decision Tree')
```

```
{'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]:
```python
# plot_tree(dt_reg, feature_names=['Quality', 'Area'], impurity=False)
```

## Random Forest Regression

In [13]:
```python
randomf_reg = RandomForestRegressor(random_state=42,
                                    oob_score=True,
                                    n_jobs=-1)
randomf_reg.fit(X_train, y_train)
```

Out[13]:
```
▾ RandomForestRegressor
RandomForestRegressor(n_jobs=-1, oob_score=True, random_state=42)
```

In [14]:
```python
# 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')
```

```
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]:
```python
metrics()
```

Out[15]:

| | Model | | | test | | | |
|---|---|---|---|---|---|---|---|
| | model_name | model | timestamp | R2 Score | RMSE | MAPE | R2 Score |
| 0 | Decision Tree | DecisionTreeRegressor() | 2023-03-02 20:37:19.565429 | 0.712869 | 41686.855769 | 0.135524 | 0.999998 |
| 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 |

In [53]:
```python
# Look at the random forest features to understand what should be tuned
randomf_reg.get_params()
```

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]:
```python
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)
```

In [18]:
```python
rf_grid.fit(X_train, y_train)
```

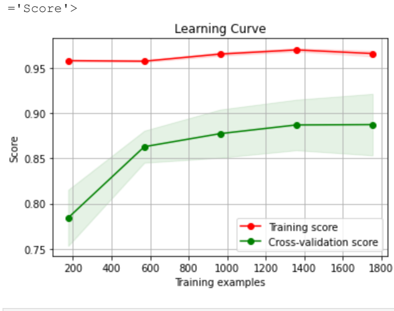
Out[18]:
```
▸ GridSearchCV
▸ estimator: RandomForestRegressor
  ▸ RandomForestRegressor
```

In [20]:
```python
rf_grid.best_params_
```

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

In [56]:
```python
# 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)
```

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




In [19]:
```python
# 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 Tu
```

```
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]:
```python
metrics()
```

Out[20]:

| | Model | | | test | | | |
|---|---|---|---|---|---|---|---|
| | model_name | model | timestamp | R2 Score | RMSE | MAPE | R Sco |
| 0 | Decision Tree | DecisionTreeRegressor() | 2023-03-02 20:37:19.565429 | 0.712869 | 41686.855769 | 0.135524 | 0.99999 |
| 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 | 0.98452 |
| 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 | 0.96713 |

In [21]:
```python
# 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]
```

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]]
```

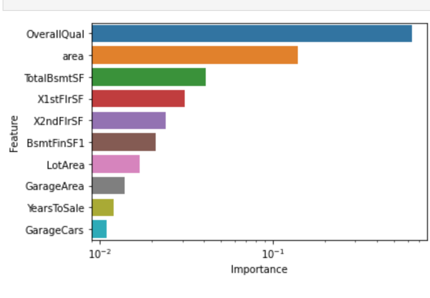
In [22]:
```python
# Tree based estimators will be biased towards continius features
# or higher dimensional features, look at permutation importance
# this is model dependent, based model -> invalid importance
perm_importance = permutation_importance(randomf_reg, X_train, y_train,
                 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

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']).so
sns.barplot(data=features_df,
            y='Feature',
            x='Importance',
            orient='h')
plt.xscale('log')
```




## 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)
```

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

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

booster = lgb.train(params,
                    lgb_train)
```

```
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of testing w
as 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 feature
s: 43
[LightGBM] [Info] Start training from score 180104.953163
```

In [31]:
```python
regression_metrics(booster, 'LightGBM')
metrics()
```

```
{'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 | | | |
|---|---|---|---|---|---|---|---|
| | model_name | model | timestamp | R2 Score | RMSE | MAPE | R Sco |
| 0 | Decision Tree | DecisionTreeRegressor() | 2023-03-02 20:37:19.565429 | 0.712869 | 41686.855769 | 0.135524 | 0.99999 |
| 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 | 0.98452 |
| 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 | 0.96713 |
| 3 | LightGBM | | 2023-03-02 20:42:29.779579 | 0.875114 | 27492.573085 | 0.082542 | 0.95747 |

In [32]:
```python
lgb_train = lgb.Dataset(X2_train, y2_train)
validation_set = lgb.Dataset(X2_validate, y2_validate)
```

In [56]:
```python
# Integration only tunes the following
# lambda_l1, lambda_l2, num_leaves, feature_fraction, bagging_fraction, bagging_freq
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)
```

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

```
Validation Set Best Score
: defaultdict(<class 'collections.OrderedDict'>, {'valid_0': OrderedDict([('rmse', 247
71.51147325579)])})

{'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()
```

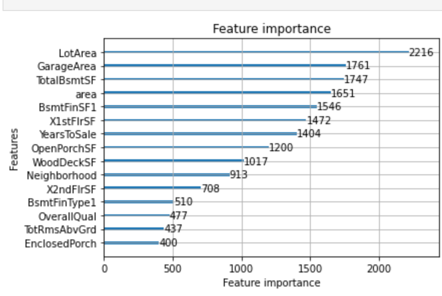
Out[35]:

| | Model | | | test | | | |
|---|---|---|---|---|---|---|---|
| | model_name | model | timestamp | R2 Score | RMSE | MAPE | R Sco |
| 0 | Decision Tree | DecisionTreeRegressor() | 2023-03-02 20:37:19.565429 | 0.712869 | 41686.855769 | 0.135524 | 0.99999 |
| 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 | 0.98452 |
| 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 | 0.96713 |
| 3 | LightGBM | | 2023-03-02 20:42:29.779579 | 0.875114 | 27492.573085 | 0.082542 | 0.95747 |
| 4 | LightGBM Optuna Tuned | | 2023-03-02 20:44:11.467397 | 0.878277 | 27142.206730 | 0.075978 | 0.97590 |

In [40]:
```python
tuned_booster.params
```

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]:
```python
ax = lgb.plot_importance(tuned_booster, max_num_features=15)
```




In [42]:
```python
joblib.dump(tuned_booster, r"models\lightgbm_tuned.pkl")
```

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

In [43]:
```python
metrics().to_excel(f"models\Regression Models {datetime.datetime.today().strftime('%Y-
```

## Analyze Predictions

In [44]:
```python
# Load trained model
final_model = joblib.load(r"models\lightgbm_tuned.pkl")
```

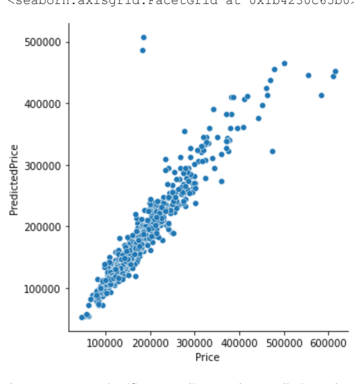
In [45]:
```python
results = X_test.copy()

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)
```

In [51]:
```python
sns.relplot(data=results,
         x='Price',
         y='PredictedPrice')
```

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]:
```python
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'])
```

In [53]:
```python
results.groupby(by=['StreetRateBins'])[['Price', 'PredictedPrice']].apply(regression_r
```

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]:
```python
results.groupby(by=['OverallCond'])[['Price', 'PredictedPrice']].apply(regression_metr
```

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. Overall the predictions are still around 25,000 RMSE (without removing the test outliers) and have a R-squared of 0.89 which is a good fit.