Report

Zillow Home Value Prediction using Machine Learning

Submitted in partial fulfillment of the requirements for the award of degree of Bachelor of Technology

(Computer Science Engineering)

Submitted to

LOVELY PROFESSIONAL UNIVERSITY

JALANDHAR, PUNJAB

SUBMITTED BY

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Student Declaration

To whom so ever it may concern

I, Aswin S Krishna, 12114780, hereby declare that the work done by me on "Zillow Home Value Prediction using Machine Learning" from Feb 2023 to April 2023, is a record of original work for the partial fulfilment of the requirements for the award of the degree, Bachelor of Technology.

Name of the student: Aswin S Krishna

Registration Number: 12114780

Dated: 26TH APRIL 2023

ACKNOWLEDGEMENT

Primarily I would like to thank God for being able to learn a new technology. Then I would like to express my special thanks of gratitude to the teacher and instructor of the course Machine Learning who provided me the golden opportunity to learn a new technology.

I would like to also thank my own college Lovely Professional University for offering such a course which not only improve my programming skill but also taught me other new technology.

Then I would like to thank my parents and friends who have helped me with their valuable suggestions and guidance for choosing this course.

Finally, I would like to thank everyone who have helped me a lot.

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Abstract

This research project is intended to increase the accuracy of Zillow's Zestimate home prices by implementing some algorithms to predict the log errors of Zillow's sold price estimates for the years 2016-2017 in California. Zillow, being the top real estate marketplace, supplies consumers with great data information about the house value through its Zestimate tool that uses millions of statistical and machine learning models to analyze multiple factors for each property. Through the application of linear regression and gradient boosting algorithm, this study evaluates the success of different modeling methods in reducing the error margins of Zillow estimates. The MSE model is utilized for assessing model's performance, and the gradient boosting is identified as the best approach for predicting log errors. This project is in line with Zillow's mission of educating consumers with all the details concerning home values having the end effect of improving the accuracy of estimates. This ultimately leads to better informed decision making in the housing market.

Objective

The main target of this research is using several predictive models to analyze log errors in Zillow's estimates of home sale prices for the years 2016-2017 in California. undefined Assess the performance of different algorithms such as linear regression and gradient boosting in the prediction of log errors related to Zillow's estimates. Identify Zillow's inaccuracy contributors by scrutinizing log error patterns and trends. Support the on-going mission of advancing the accuracy and authenticity of Zillow's Zestimate, thereby providing the public with better and more precise information about home appraisals. Offer views and suggestions on improving real estate valuation methodologies in order to create a better environment for the real estate market to make better and more informed decisions.

Introduction

The real estate market holds a crucial place in the overall personal and family financial outlook as home buying, which is one of the most notable investments in a person's life, is a goal for every individual. Over the past few years, portals like Zillow have upset the status quo of consumer access to information about property value; its Zestimate which uses data and sophisticated techniques to get an estimate of property value are the reasons behind this. As a result, although the methods of evaluating real estate properties have been considerably improved, there is still scoped to increase the precision and stability of these assessments.

This study highlights a need that is caused by log-error in Zillow estimates of home sale prices and attempts to resolve it using predictive modelling techniques. To be precise, the study draws its data from the years 2016-2017, a region popularly known for its dynamic and multi-faceted real estate market, California. The good project is undertaken with a purpose of finding out the patterns and factors that cause inaccuracies in the estimates by comparing Zillow's logs and actual house sale prices.

The objectives of this research are twofold: first, to compare the performance of different algorithms, including linear regression and gradient boosting, of predicting log errors of the estimate and secondly, to help the overall initiative of improvement of the accuracy of the Zestimate by Zillow. Finally, the idea is to have the consumers more accurate and reliable data about home values, that will enable them to make decision based on the actual market situation.

The first section of this research represents the preparation for the next ones. Now the methodology, the results, and the implications of the research will be further discussed. By utilizing more sophisticated modeling and increasing the dataset size, this research aims to supplement the knowledge on real estate

valuation by introducing tools akin to Zestimate, thus improving the transparency of property transactions.

Theoretical background

The theoretical foundation for this project involves various fundamental and important topics like valuation principles of real estate, predictive modeling, and the development of estimation algorithms.

- Zillow's Zestimate: Zillow's Zestimate is a Zestimate tool that can automatically create estimates of property values based on data that is collected from prior sales and geospatial analysis. These models use varied data points as inputs, like property features, location data plus market statistics, to come up with value predictions recommendations for property. At its essence, Zestimate is a management tool offered to consumers for the access to intelligent market information and enablement of informed decision-making.

- Log Error Analysis: Error log analysis compares two values: the first one is a predicted value, potentially from Zillow, and the second one is an observed value which could be, for instance, a sale price and then difference is calculated with [logarithmic] scale. The log error analysis process helps to evaluate the accuracy of predictions and to find out notes in predations. Researchers, by way of log errors analysis, gain clues into the aspects that are responsible for inaccuracies of prediction models and ways to improve the same.

- Predictive Modeling Techniques: Predictive models use sought-after statistical and machine learning algorithms to generate prediction based on data currently available. Linear regression is one of the techniques that can be employed more often as it is used to model the relationship between a dependent variable (this could be, for instance, home sale price) and independent variable(s) (which can be property characteristics). Gradient boosting is an effective ensemble learning

approach that integrates multiple weak learners, for instance, decision trees, to create a model with strong prediction power. The random forests, support vector machines and neural networks are still likely to be used, with the matter of the type of data being the determinant.

- Evaluation Metrics: MSE is a well-known metric that is used to analyze the quality of models that can predict. MSE accounts for the mean squared deviation, with lower MSE connoting and denoting that an MSE model performs better. In addition to RMSE and MAE, as other evaluation metrics can also be used for evaluation of model accuracy.

- Feature Engineering: Trial engineering is a process of selecting, modifying and inventing the features of raw data, which enhances the efficiency of predictive models. For example, given the purpose of the real estate valuation which is to obtain the relevant information from the properties such as the square footage and number of bedrooms and bathrooms and furthermore the specifics like pool or garages. Moreover, using the information on the geographical features, like community demographics, amenities nearby, and quality of school districts helps to achieve the higher accuracy of the model.

- Overfitting and Underfitting: Two kinds of error can arise in the process of machine learning: overfitting and poor generalization. The first time, the predictive model learns to capture noise or random fluctuation within the training data instead of more general phenomenon; as a result, the model performs poorly to unseen data. Overfitting, which stands for a model being too complex to recognize the relevant patterns in the data is on the one hand. However, underfitting which is the symptom of a not complex enough model to discern the valuable patterns in the data is on the other hand. The problem side involves overfitting and underfitting, which determine models' performance concerning new data. For instance, methods like regularization, cross-validation and model selection render it possible to reduce the negative consequences of overfitting.

- Ensemble Learning: Ensemble learning is when individual models are combined to make a more accurate and smaller risk of getting it wrong. There are techniques available like bagging, boosting, and stacking which are able to harness the diversity of individual models to create more correct final aggregated prediction. Gradient boosting, a well-known ensemble method, constructs in a sequential manner a group of weak learners, such that each of them looks at the mistakes performed by the preceding one, resulting in highly accurate predictive model.

- Interpretability and Explainability: Interpretability means the mechanisms through which decisions made by predictive model can be explored and understood by humans, while explainability is the advanced human understand ability of the decisions made. In the case of real estate valuation, the interpretable and explainable models will play the role of authenticity and validation, and they will give the confidence to the stakeholders like home buyers and sellers, as well as real estate officers, that the models used are appropriate. For instance, there are methods including feature importance analysis, partial dependence plots, and model-agnostic techniques which reveal the inner workings or predictive models' explanations.

Through the implementation of such theoretical ideas, this project tries to make the analysis not only correct but also interpretable and accurate. Accordingly, this project accomplishes the purpose of Zillow the Zestimate. The research plan involves feature engineering, model selection, and evaluation to improve the reliability, transparency, and the usability of Zillow's home value estimates. This will help the consumers to be more empowered, using the insights they have, and make the proper decisions relevant in the real estate market.

Methodology

Data Acquisition

In [1]:
```
# Import essential libraries
from imports import *

# Set up display format
pd.options.display.float_format = '{:,.2f}'.format

# Calling the function to make the connection to database, run the query, and store the table in the form of a dataframe
messy_df = acquire.get_zillow_data()

# Check the shape of our messy dataframe
messy_df.shape
```

Out[1]: (52441, 11)

Data Preparation - Data Cleaning

In [2]:
```
# Cleaning the data using function from prepare.py
df = prepare.prep_zillow(messy_df)

# Checking the shape of our cleaned dataframe
df.shape
```

Out[2]: (45324, 23)

Data Preparation - Splitting Data

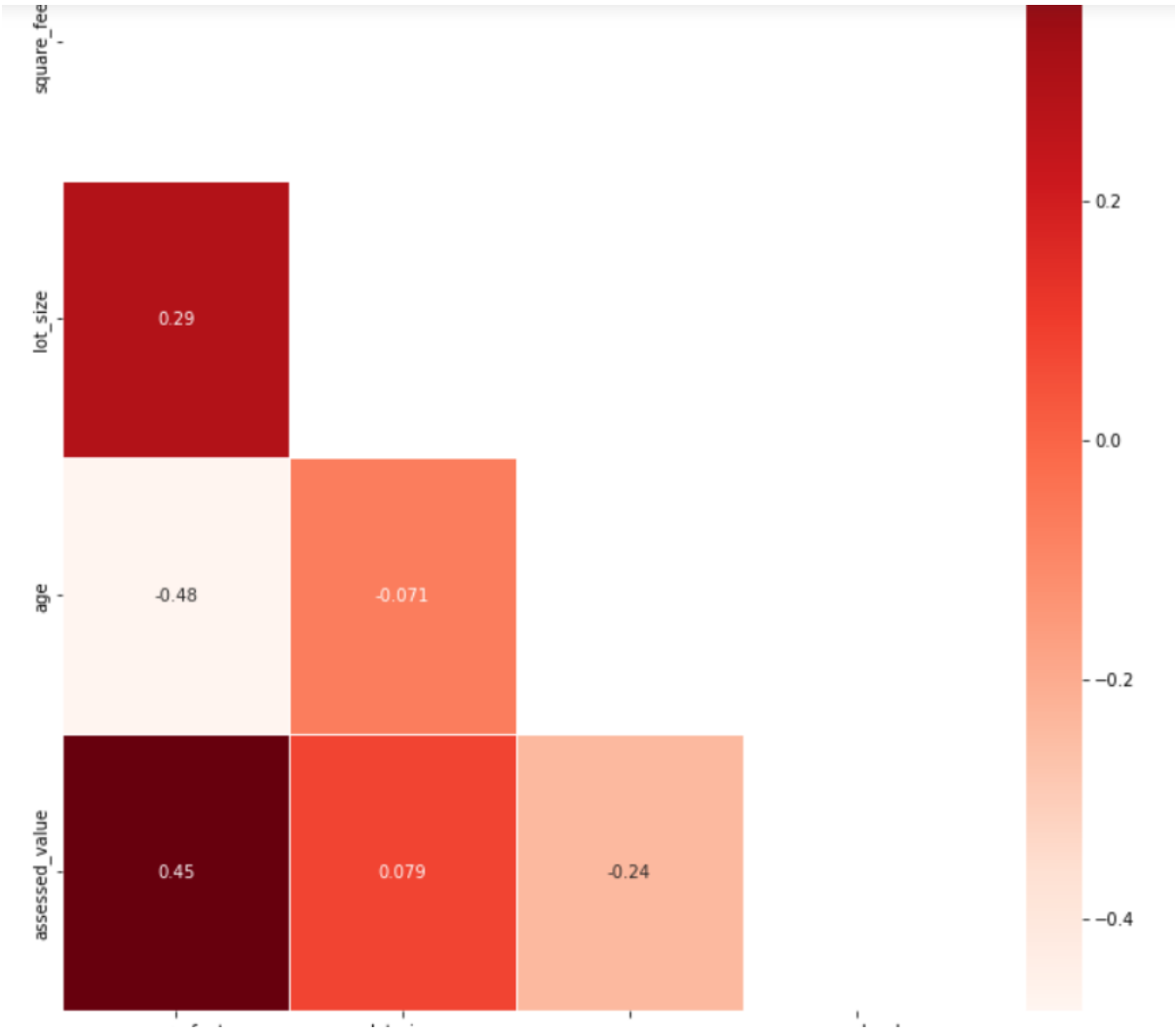
In [3]:
```
# Split the data into train, validate, test using user-defined function from prepare.py
train, validate, test = prepare.split(df)

# Checking the size of each dataset
train.shape, validate.shape, test.shape
```

Out[3]: ((25381, 23), (10878, 23), (9065, 23))

Exploratory Analysis

In [4]:
```
# Input continuous features
continuous_cols = ['square_feet', 'lot_size', 'age', 'assessed_value']

# Calcualte correlation between features
train_corr = train[continuous_cols].corr()

# Visualize correlaiton
plt.figure(figsize = (12,12))
sns.heatmap(train_corr,cmap='Reds', annot=True, linewidth=0.5, mask= np.triu(train_corr))
```

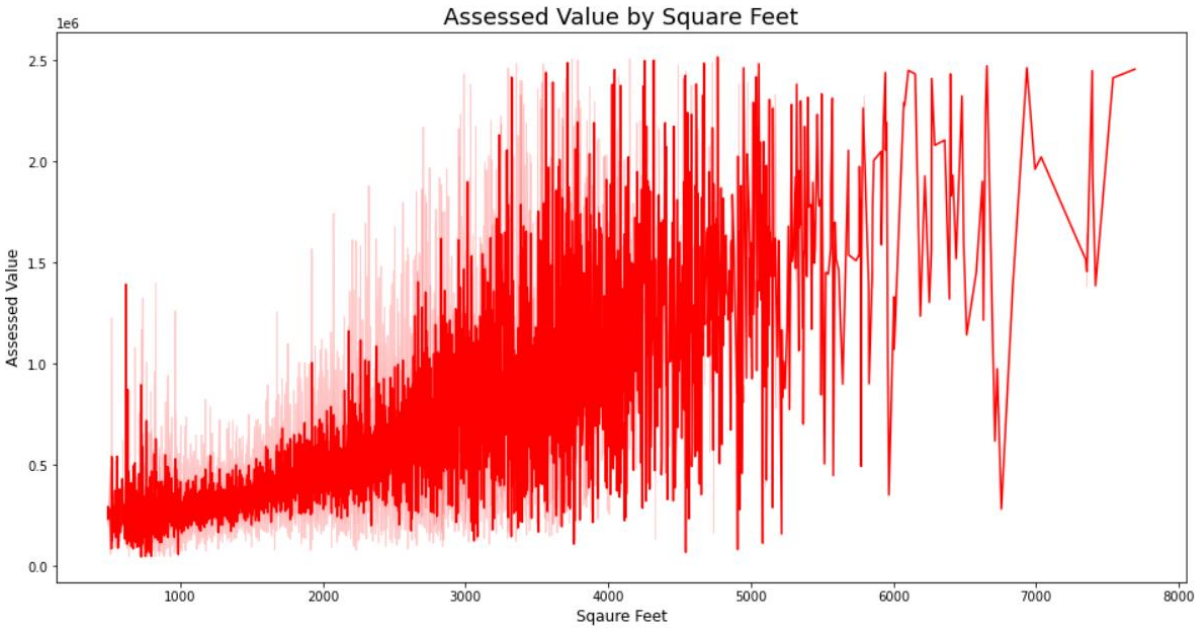
Out[4]: <AxesSubplot:>



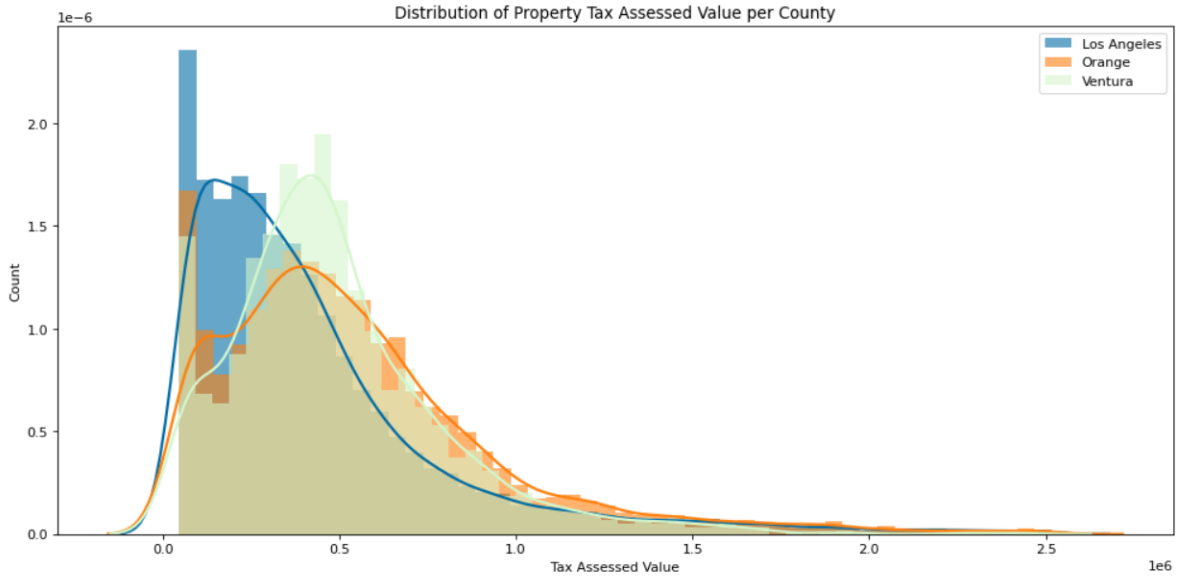
square_feet has strong positive (0.58) correlation with **assessed_value**

In [11]:
```
plt.figure(figsize = (16,8))
sns.lineplot(x = train.square_feet, y = train.assessed_value, color = 'red', data = train)
plt.xlabel('Sqaure Feet', fontsize = 12)
plt.ylabel('Assessed Value', fontsize = 12)
plt.title('Assessed Value by Square Feet', fontsize = 18)
```

Out[11]: Text(0.5, 1.0, 'Assessed Value by Square Feet')



In [14]:
```
# Visualizing distribution of assessed_value per county

losangeles = train[train['county'] == 'Los Angeles'].assessed_value
orange = train[train['county'] == 'Orange'].assessed_value
ventura = train[train['county'] == 'Ventura'].assessed_value

kwargs = dict(hist_kws={'alpha':.6}, kde_kws={'linewidth':2})
plt.figure(figsize=(15,7), dpi= 80)
sns.distplot(losangeles, color="#006ba4", label="Los Angeles", **kwargs)
sns.distplot(orange, color="#ff800e", label="Orange", **kwargs)
sns.distplot(ventura, color="#D4F6CC", label="Ventura", **kwargs)
plt.xlabel('Tax Assessed Value')
plt.ylabel('Count')
plt.title('Distribution of Property Tax Assessed Value per County')
plt.legend();
```



In [8]:
```
# Set alpha
alpha = 0.05

# Comparing mean of 3 independent samples
t, p = stats.f_oneway(losangeles, orange, ventura)
if p < alpha:
    print("We reject H0.")
    print(Fore.BLUE + '\nMean of property tax assessed value of Los Angeles, Orange, and Ventura County are not all equal. ')
else:
    print("We fail to reject H0")
```

```
We reject H0.

Mean of property tax assessed value of Los Angeles, Orange, and Ventura County are not all equal.
```

Bedroom size

In [33]:
```
# Visualizing the 5-number summary of property assessed value of different size of bedrooms

fig = px.box(train, x="bedrooms_size", y="assessed_value", points="all", color = 'bedrooms_size',  color_discrete_sequence=['#fec
fig.update_xaxes(categoryorder = 'category descending')
fig.update_layout(title_text='Property Assessed Value per Bedrooms Size', title_x=0.5)
fig.show()
```

Anova test

In [22]:
```
# Set alpha
alpha = 0.05

# Comparing mean of each sample and draw conclusion
smallbed = train[train['bedrooms_size']=='small'].assessed_value
mediumbed = train[train['bedrooms_size']=='medium'].assessed_value
largebed = train[train['bedrooms_size']=='large'].assessed_value

# Decide and draw conclusion
t, p = stats.f_oneway(smallbed, mediumbed, largebed)
if p < alpha:
    print("We reject H0. ")
    print(Fore.BLUE +"\nMean of property tax assessed value of small, medium, large bedrooms are not all equal. ")
else:
    print("We fail to reject H0")
```

```
We reject H0.
```

Bathroom size

In [23]:
```
# Visualizing the 5-number summary of property assessed value of different size of bathroom
fig = px.box(train, x="bathrooms_size", y="assessed_value", points="all", color = 'bathrooms_size', color_discrete_sequence=['#a
fig.update_xaxes(categoryorder = 'category descending')
fig.update_layout(title_text='Property Assessed Value per Bathrooms Size', title_x=0.5)
fig.show()
```

Anova test

In [24]:
```
# Set alpha
alpha = 0.05

# Comparing mean of independent sample
smallbath = train[train['bathrooms_size']=='small'].assessed_value
mediumbath = train[train['bathrooms_size']=='medium'].assessed_value
largebath = train[train['bathrooms_size']=='large'].assessed_value

# Decide and draw conclusion
t, p = stats.f_oneway(smallbath, mediumbath, largebath)
if p < alpha:
    print("We reject H0.")
    print(Fore.BLUE+ "\nMean of property tax assessed value of small, medium, large bathrooms are not all equal. ")
else:
    print("We fail to reject H0")
```

```
We reject H0.
```

Swimming Pool number

In [19]:
```
# Visualizing the five-number summary of properties with pool and without pool

fig = px.box(train, x="has_pool", y="assessed_value", points="all", color = 'has_pool', color_discrete_sequence=['#ff800e','#006b
fig.show()
```

Independent T test

In [12]:
```
# Set alpha
alpha = 0.05

# Comparing mean of 2 independent samples
t, p = stats.ttest_ind(pool, no_pool, equal_var=False)

# Decide and draw conclusion
if p/2 < alpha:
    print("We reject H0.")
    print(Fore.BLUE+"\nMean of property tax assessed value of property with pool > Mean of property tax assessed value of propert
else:
    print("We fail to reject H0")
```

```
We reject H0.
```

Modelling

Scaling Data

In [4]:
```
# Copy a new dataframe to perform feature engineering
scaled_df = df.copy()

# Initiate MinMaxScaler
scaler = MinMaxScaler()

# Fit numerical features to scaler
scaler.fit(scaled_df[['square_feet', 'lot_size', 'age', 'bedrooms', 'bathrooms']])

# Set the features to transformed value
scaled_df[['square_feet', 'lot_size', 'age', 'bedrooms', 'bathrooms']] = scaler.transform(scaled_df[['square_feet', 'lot_size', '

# Split the scaled data into train, validate, test
s_train, s_validate, s_test = prepare.split(scaled_df)

# Split each dataset into X, y
cols = ['square_feet', 'lot_size', 'has_pool', 'age', 'county_Los Angeles', 'county_Orange', 'bedrooms', 'bathrooms']
X_train = s_train[cols]
y_train = s_train.assessed_value
X_validate = s_validate[cols]
y_validate = s_validate.assessed_value
X_test = s_test[cols]
y_test = s_test.assessed_value
```

Base Line prediction

In [6]:
```
train_predictions = pd.DataFrame({
    'actual': s_train.assessed_value
})
train_predictions['baseline'] = y_train.mean()
rmse = mean_squared_error(train_predictions.actual, train_predictions.baseline, squared = False)
print(Fore.BLUE+ "\nRoot mean of squared error of baseline prediction is: ", "{:10.2f}".format(rmse))
```

```
Root mean of squared error of baseline prediction is:   237872.07
```

Multiple Regression + RFE

In [7]:
```
# Notes: I looped through k and found out the model performs the best when k=7
# Initiate the linear regression model
lm = LinearRegression()

# Transform our X
rfe = RFE(lm, n_features_to_select=7)
rfe.fit(X_train, y_train)

# Use the transformed x in our model
X_train_rfe = rfe.transform(X_train)
X_validate_rfe = rfe.transform(X_validate)
X_test_rfe = rfe.transform(X_test)
lm.fit(X_train_rfe, y_train)

# Make predictions and add that to the train_predictions dataframe
train_predictions['multiple_rfe_k=7'] = lm.predict(X_train_rfe)
```

Polynomial Features

In [8]:
```
# Notes: I looped through k and found out the model performs the best when degree(k)=3
poly = PolynomialFeatures(degree=3, include_bias=False, interaction_only=False)

# Generate polynomial features
poly.fit(X_train)

# Transform X_train
X_train_poly = pd.DataFrame(
    poly.transform(X_train),
    columns=poly.get_feature_names(X_train.columns),
    index=X_train.index,
)

# Use the features
lm = LinearRegression()
lm.fit(X_train_poly, y_train)

# Make predictions and add that to the train_predictions dataframe
train_predictions['polynomial degree 3'] = lm.predict(X_train_poly)
```

Lasso-Lars

In [9]:
```
# create the model object
lars = LassoLars(alpha=1)

# fit the model to our training data
lars.fit(X_train, y_train)

# predict validate
X_train_pred_lars = lars.predict(X_train)

# Add lassolars predictions to our predictions DataFrame
train_predictions['lasso_lars'] = X_train_pred_lars
```

Generalized Linear Model

In [10]:
```
# create the model object
glm = TweedieRegressor(power=1, alpha=0)

# fit the model to our training data
glm.fit(X_train, y_train)

# predict train
X_train_predict_glm = glm.predict(X_train)

# Add lassolars predictions to our predictions DataFrame
train_predictions['glm'] = X_train_predict_glm
```

Train Evaluation

In [11]:
```
# Calculating rmse of each model's performance on train and concluded the top 3 models
def calculate_rmse(y_predicted):
    return mean_squared_error(train_predictions.actual, y_predicted, squared = False)

train_predictions.apply(calculate_rmse).sort_values()
print("TOP 3 MODELS:")
print(Fore.BLUE+"1. Polynomial degree=3 \n2. Lasso-Lars \n3. Multiple Regression + KFE K=7")
```

```
TOP 3 MODELS:
1. Polynomial degree=3
2. Lasso-Lars
3. Multiple Regression + KFE K=7
```

In [12]:
```
# Displaying rmse of each model's performance on train
def calculate_rmse(y_predicted):
    return mean_squared_error(train_predictions.actual, y_predicted, squared = False)

train_predictions.apply(calculate_rmse).sort_values()
```

Out[12]:
```
actual                      0.00
polynomial degree 3   200,429.35
multiple_rfe_k=7      207,896.69
lasso_lars            207,897.50
glm                   208,244.28
baseline              237,872.07
dtype: float64
```

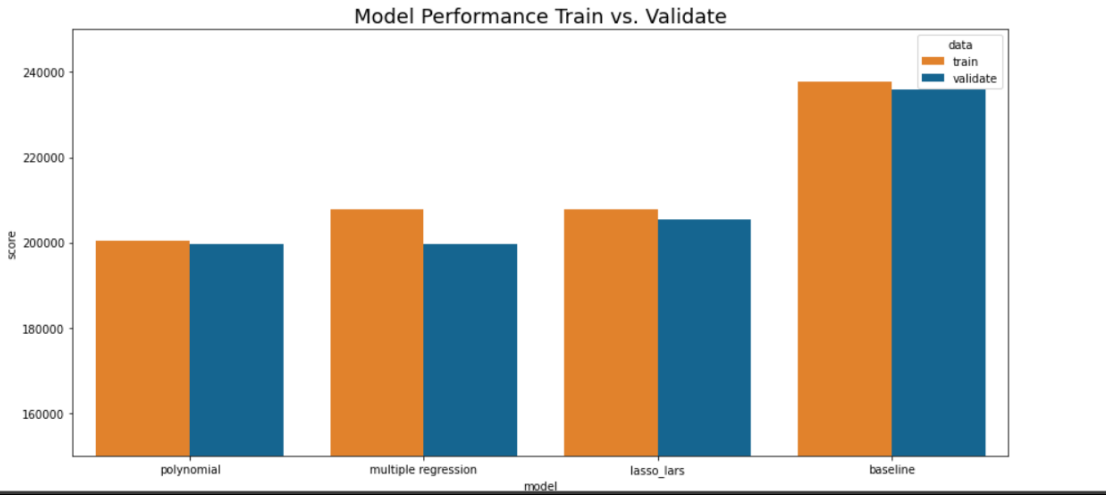
Models validation evaluation

In [13]:
```
# Create validat predictions dataframe for all models performance on validate
validate_predictions = pd.DataFrame({
    'actual': s_validate.assessed_value
})
validate_predictions['baseline'] = y_validate.mean()
# Transform validate dataset with poly features, and put predictions into validate dataframe
X_validate_poly = poly.transform(X_validate)
validate_predictions['Polynomial Degree=3'] = lm.predict(X_validate_poly)

# Using lasso lars to make prediction and put in our validate dataframe
X_validate_pred_lars = lars.predict(X_validate)
validate_predictions['Lasso-Lars'] = X_validate_pred_lars

# Using multiple regression model and put prediction in our validate dataframe
X_validate_rfe = rfe.transform(X_validate)
validate_predictions['Multiple Regression + KFE K=7'] = lm.predict(X_validate_poly)

# Evaluate performace using RMSE
def calculate_rmse(y_predicted):
    return mean_squared_error(validate_predictions.actual, y_predicted, squared = False)

validate_predictions.apply(calculate_rmse).sort_values()
```

Out[13]:
```
actual                          0.00
Polynomial Degree=3           199,529.27
Multiple Regression + KFE K=7 199,529.27
Lasso-Lars                    205,508.69
baseline                      235,949.69
dtype: float64
```

In [71]:
```
# Visualizing model performance
plt.figure(figsize = (15,7))
# Load model performance from csv
model = pd.read_csv('model_performance.csv')
plt.title('Model Performance Train vs. Validate', fontsize = 18)
g = sns.barplot(x='model', y='score', hue='data', data = model, palette = ['#ff800e','#006ba4'])
g.set(ylim=(150000,250000))
```

Out[71]:
```
[(150000.0, 250000.0)]
```

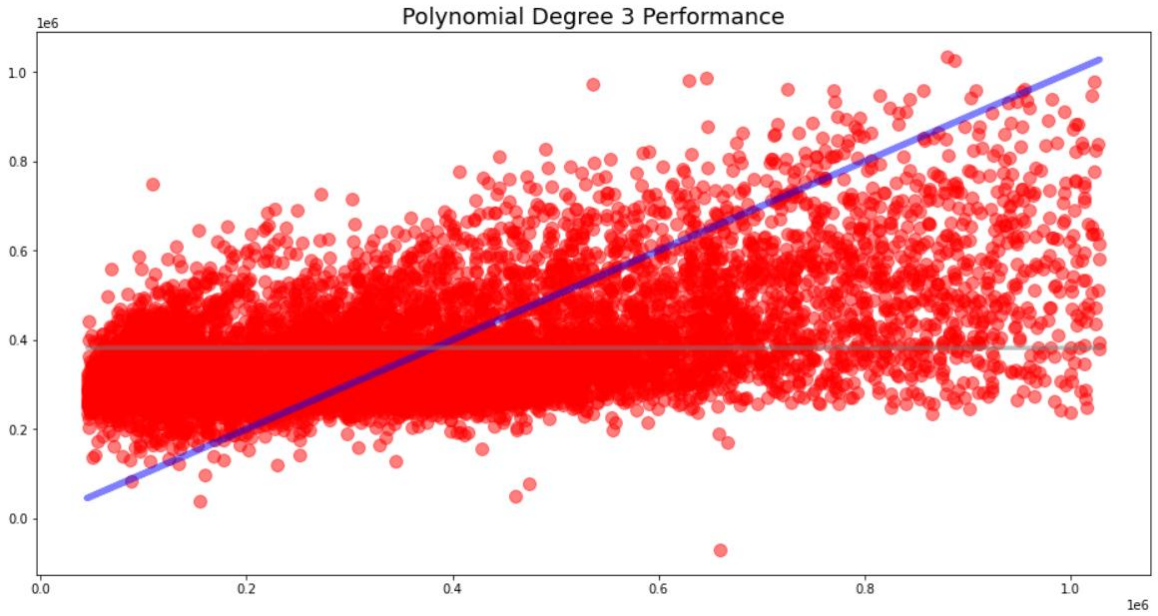


In [45]:
```
# Create test prediction dataframe to fit actual, baseline, model
test_predictions = pd.DataFrame({
    'actual': s_test.assessed_value
})
# Put baseline value into dataframe
test_predictions['baseline'] = y_test.mean()
X_test_poly = poly.transform(X_test)

# Make prediction using polynomial model
test_predictions['Polynomial Degree=3'] = lm.predict(X_test_poly)
rmse = mean_squared_error(test_predictions.actual, test_predictions['Polynomial Degree=3'], squared = False)
print(Fore.BLUE+"Polynomial degree=3 RMSE on test: ", "{:10.2f}".format(rmse), '\nModel performance is 15% better than baseline.'
```

```
Polynomial degree=3 RMSE on test:   202015.80
Model performance is 15% better than baseline.
```

In [42]:
```
# Visualizing how the model will perform against actual assessed value
plt.figure(figsize=(16,8))
# Plotting actual assessed values
plt.plot(y_test,y_test, alpha=0.5, linewidth=5, color='blue')
plt.title('Polynomial Degree 3 Performance', fontsize = 18)
# Plotting baseline predictions
plt.plot(y_test,test_predictions['baseline'], alpha=0.5, linewidth=3,color='grey', label = 'baseline prediction')
# Plotting polynomial model predictions
plt.scatter(test_predictions['actual'],test_predictions['Polynomial Degree=3'], alpha = 0.5, color = 'red', s=100)
```

Out[42]: <matplotlib.collections.PathCollection at 0x7fdba4b2fa30>



Model performance score.

	A	B	C
1	model	data	score
2	polynomial	train	200429
3	polynomial	validate	199529
4	multiple re	train	207896
5	multiple re	validate	199529
6	lasso_lars	train	207897
7	lasso_lars	validate	205508
8	baseline	train	237872
9	baseline	validate	235949

Result

Based on the provided performance metrics

- There is a noticeably strong perfect correlation between the square footage and assessed tax value. This implies that bigger properties which are usually seen as higher value have higher assessment of their property tax.
- The size of bathrooms and bedrooms are considered when assessing the property tax-listing, which hints that properties with more bedrooms and bathrooms may have a higher tax-assessment.
- There is occurrence of mean discrepancy in property tax assessed value individually in the counties. Los Angeles County has the lowest average assessed value, followed by San Diego County that is the second, then Orange County that is the highest. Such details could be useful in distinguishing a regional variation of local tax assessments.
- Typically, properties that have pools tend to produce higher property tax assessed values than those that do not possess pools. This demonstrates the role of those amenities like pools in price determination and property taxes assessment.
- Property age as calculated through the difference between the current year (2017) and the year it was built shows a negative connection with the assessed value of the property tax. This proves that the overall estimate of the value of properties that are older could be less, possibly because of wear and tear or because the maintenance costs are high.
- The poly model features are predicted to be within a range of $\ 202.015.80$ on unaccounted data. This devises a measure of the model's probable accuracy and can be employed to gauge the confidence levels of future observations.

Finally, these findings deliver some useful data on the determinants of property tax assessed valuations and a good platform for developing accurate projections of real estate valuation in similar studies.

Summary

This project was concerned with the subtleties of real estate appraisal which was mainly focused on the causes that motivate or undermine assessed property values. With thorough evaluation of various dimensions, including the size of the living space, number of rooms and baths, presence of additional facilities like pools, as well as the age of the property, the major takeaways were ascertained.

Firstly, a strong positive correlation was established in connection with the square footage and property tax assessed value which stresses a significant aspect of property value, its size. Furthermore, the effect of amenities like swims was highlighted as houses with possible amenities like pools normally attract more and higher assessed values.

Another factor that contributed to this impact was the discovery of significant regional disparities in property tax assessments with Los Angeles County being the lowest average while Orange County had the highest. This shows the essence of taking into account the variations in areas when such instances are being studied.

In addition, the association of higher age of the properties with lower assessed values highlights the impact of age on real estate valuations which is an important area to consider in long-term value appraisals.

As a result, the project propped me up to gain comprehension about the predictive modeling especially with the findings that derivatives features retained an acceptance error range against past data. This forecast is a critical guide to the next model improvements and implementation planning.

Essentially, the paper concludes that property attributes, amenities, regional influences, and assessed values are complex components that interact with each other in real estate valuation to quite a great extent. Via application of this intelligence, principal actors can take their decisions on investments in the real estate, tax planning among others, and thereby upgrade the transparency and effectiveness in the real estate market.

Conclusion

At this point, it is worth mentioning that this project has benefited me by giving me invaluable lessons on the determinants of property tax assessed values in real estate valuation. By examining variables like square footage, amenities, property age, regional differences, we have gotten the knowledge of the deepen wise acuteness of the requiring conditions of property valuations.

Such results affirm the vitality to look away from just physical characteristics of a property when assessing property value besides demographic factors of location and area. Through these findings phenomenon the stakeholders of the real estate sector make use of them by making more righteous decisions in terms of property investments, tax planning and market assessments.

Looking ahead, the predictive modeling model is an auspicious path that produces higher levels of accuracy and dependability in property evaluation. The introduction of more sophisticated modeling techniques and combining this with the astute findings from the analysis enables subsequent research to maintain the level of accuracy and comprehensibility on the model.

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