How to Build a Real Estate Price Prediction Model?

BEGINNER DATA VISUALIZATION DEEP LEARNING PYTHON REGRESSION

Introduction

As a data scientist, you have the power to revolutionize the real estate industry by developing models that can accurately predict house prices. This blog post will teach you how to build a real estate price prediction model from start to finish. Get ready to learn about data collection and analysis, model selection, and evaluation. With this guide, you'll have the skills to make informed decisions and guide your clients toward the best investment opportunities. Let's get started!

Learning Objectives:
In this article, we will:
1. Understand building a price prediction model.
2. understand the process of building the model, such as data analysis, selection, prediction, interpretation, etc.
3. Learn how to make an informed decision with a given dataset.
This article was published as a part of the Data Science Blogathon.

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Understanding the Data and Problem Statement

The data we will be using is the Ames Housing Dataset, which is a dataset that contains 79 explanatory variables describing (almost) every aspect of residential homes in Ames, Iowa. The dataset is available on

Kaggle, and you can download it here. The dataset contains 1460 rows and 81 columns; the target variable is the SalePrice column. The dataset is split into two parts: train.csv and test.csv. The train.csv file contains the target variable, and the test.csv file does not. The test.csv file tests the model's performance on unseen data.

Problem Statement

The problem statement is to predict the sale price of a house, given the features of the house. The features are the columns in the dataset, and the target variable is the SalePrice column. The problem is a regression problem, as the target variable is continuous.

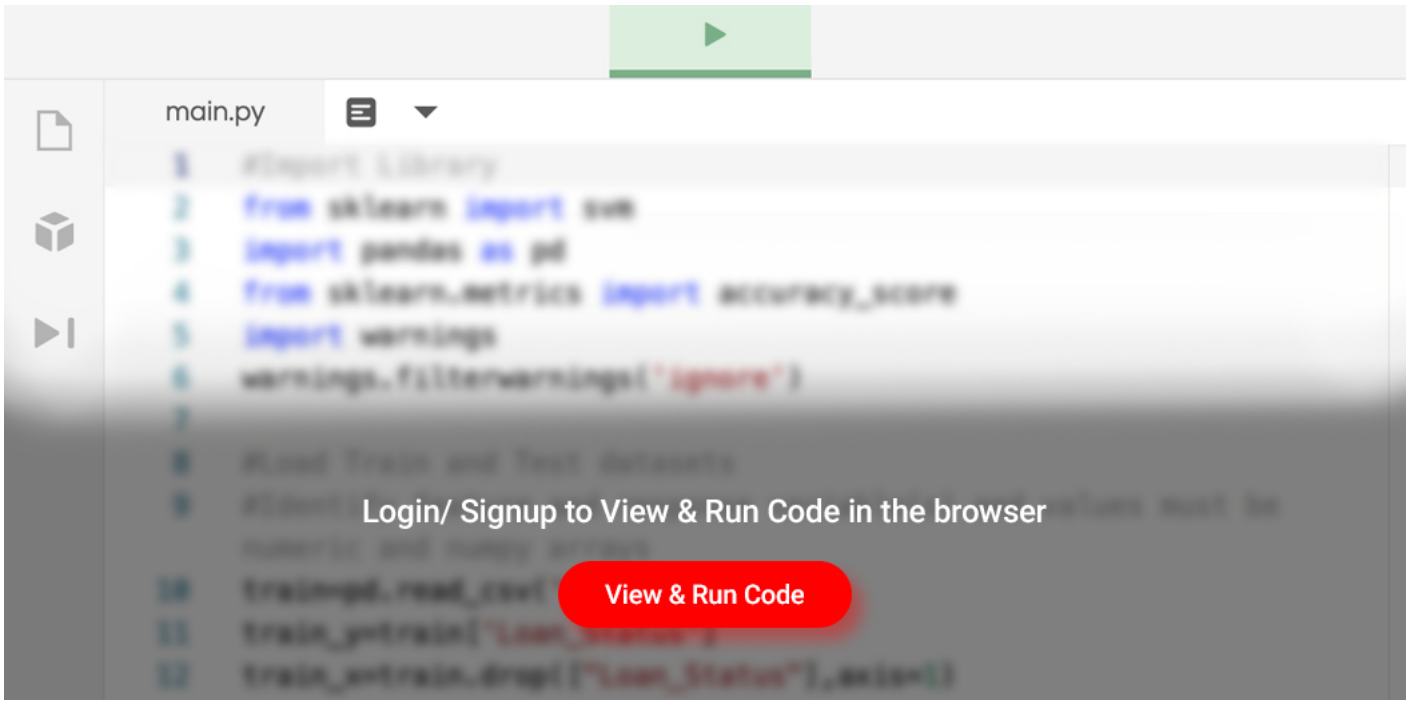
Data Description

The data description is available on Kaggle, and you can find it here. The data description contains a detailed description of each column in the dataset. The data description is very useful, as it provides a detailed description of each column in the dataset. It also provides information about the missing values in the dataset.

Data Analysis of the Price Prediction Model

This section will find missing values and outliers and the relationship between the target variable and the features.

Python Code:



Missing Values

```
# Making a list of columns with missing values missing_values = [col for col in data.columns if data[col].isnull().any()]
```

# Printing the number of missing values and percentage of missing values in each column
for col in missing_values:
print(col, round(data[col].isnull().mean(), 3), ‘ % missing values’)

```
LotFrontage 0.177  % missing values
Alley 0.938  % missing values
MasVnrType 0.005  % missing values
MasVnrArea 0.005  % missing values
BsmtQual 0.025  % missing values
BsmtCond 0.025  % missing values
BsmtExposure 0.026  % missing values
BsmtFinType1 0.025  % missing values
BsmtFinType2 0.026  % missing values
Electrical 0.001  % missing values
FireplaceQu 0.473  % missing values
GarageType 0.055  % missing values
GarageYrBlt 0.055  % missing values
GarageFinish 0.055  % missing values
GarageQual 0.055  % missing values
GarageCond 0.055  % missing values
PoolQC 0.995  % missing values
Fence 0.808  % missing values
MiscFeature 0.963  % missing values
```

Output

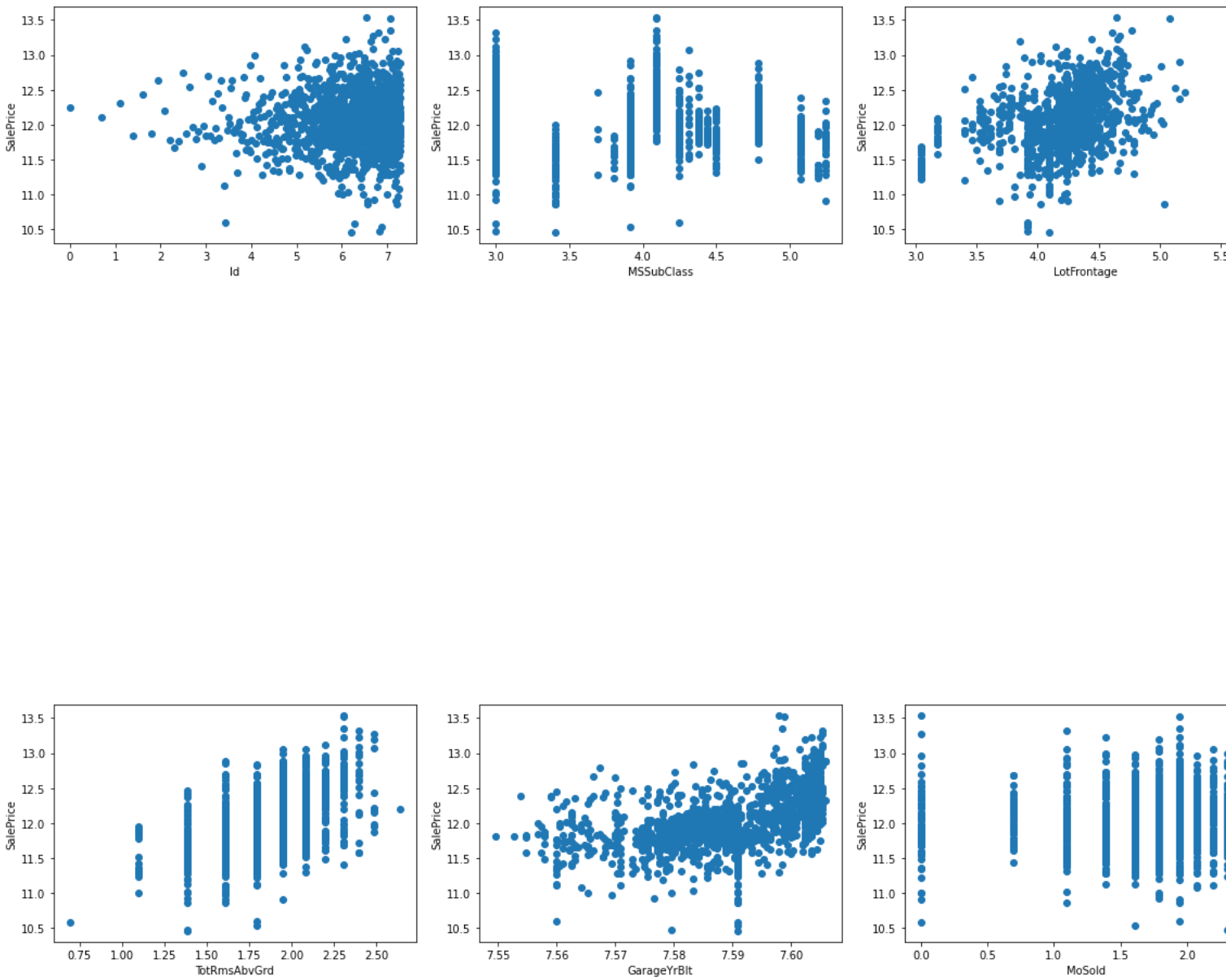
Handling the Missing Values

```
# Dropping the columns with more than 15% missing values data.drop(['Alley', 'FireplaceQu', 'PoolQC', 'Fence', 'MiscFeature'], axis=1, inplace=True)
```

```
# Filling the missing values in the remaining columns with the most frequent value new_missing_values = [col for col in data.columns if data[col].isnull().any()] for col in new_missing_values: if data[col].dtype == 'O': data[col].fillna(data[col].mode()[0], inplace=True) else: data[col].fillna(data[col].median(), inplace=True)
```

Outliers

```
continuous_features = [col for col in data.columns if data[col].dtype != 'O'] for col in continuous_features: data_copy = data.copy() if 0 in data_copy[col].unique(): pass else: data_copy[col] = np.log(data_copy[col]) data_copy['SalePrice'] = np.log(data_copy['SalePrice']) plt.scatter(data_copy[col], data_copy['SalePrice']) plt.xlabel(col) plt.ylabel('SalePrice')
```



Output

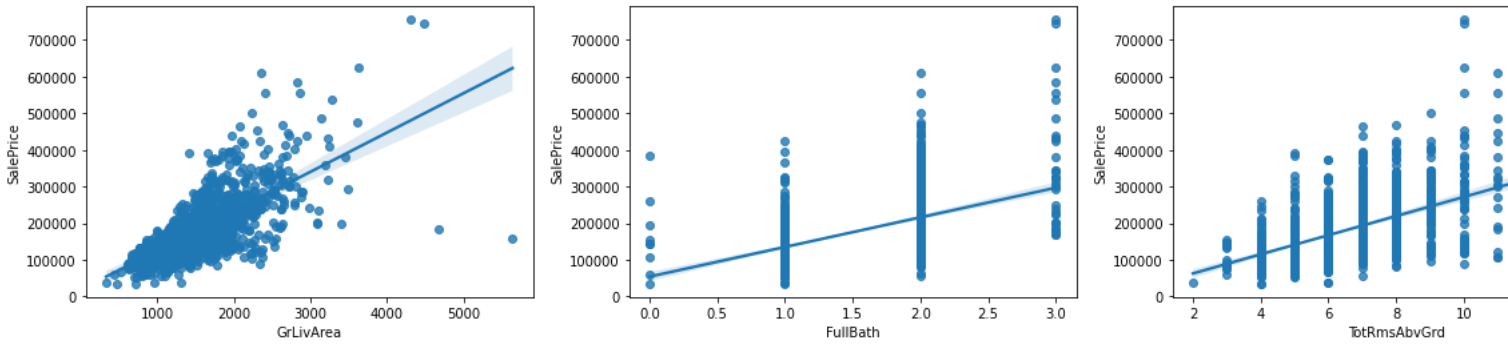
Exploratory Data Analysis

```
plt.figure(figsize=(10, 15)) # Plotting the heatmap with respect to the correlation of the features with the target variable 'SalePrice' sns.heatmap(data.corr()[['SalePrice']].sort_values(by='SalePrice', ascending=False), annot=True, cmap='viridis')
```

Output

We can see that ‘OverallQual,’ ‘GrLivArea,’ and ‘TotalBsmtSF’ strongly correlate with ‘SalePrice.’ Check the below scatter plots.

```
# Regression plot between the target variable and the most correlated variables who have a correlation greater than 0.5 for col in data.corr()[data.corr()['SalePrice'] > 0.5].index: if col == 'SalePrice': pass else: sns.regplot(x=data[col], y=data['SalePrice']) plt.show()
```



Output

All the features have a positive correlation with the target variable.

Model Development

Now that we have cleaned and visualized the data. The next step is to build a model to predict the sale price of a house. Several different prediction models can be used, including multiple linear regression, KNN regressor, etc. We will use a series of models and pipelines to find the best model by evaluating the model's accuracy, precision, and recall. I will also use cross-validation to ensure that the model is generalizing well.

```
# Encoding the categorical variables to the numeric datatype from sklearn.preprocessing import LabelEncoder for col in data.columns: if data[col].dtype == 'O': label_encoder = LabelEncoder() data[col] = label_encoder.fit_transform(data[col])
```

```
# Let's use Ridge Regression to build the model from sklearn.linear_model import Ridge from sklearn.model_selection import cross_val_score from sklearn.metrics import mean_squared_error
```

```
# create X and y variables from Features and target variable X = data[['OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea', 'TotalBsmtSF', '1stFlrSF', 'FullBath', 'TotRmsAbvGrd', 'YearBuilt', 'YearRemodAdd']] y = data['SalePrice']
```

```
# Function to perform ridge regression def ridge_regression(alpha, data): ridge = Ridge(alpha=alpha) ridge.fit(X, y) scores = cross_val_score(ridge, X, y, scoring='neg_mean_squared_error', cv=5) rmse = np.sqrt(-scores) return rmse
```

```
# Finding the best value of hyper-parameter of Ridge - alpha alpha = [0.001, 0.01, 0.1, 1, 10, 100, 1000] for i in alpha: print('Alpha: ', i) print('Mean RMSE: ', ridge_regression(i, data).mean()) print('Standard Deviation: ', ridge_regression(i, data).std()) print()
```

Output

For alpha = 100, the RMSE is the lowest, and the model performs the best. The RMSE is 38464. The model is performing the best with alpha = 100.

```
# I will be using the ridge regression model with alpha = 100 ridge = Ridge(alpha=100) ridge.fit(X, y)


# Loading the test data test_data = pd.read_csv('test.csv')


# Doing all the changes that were done in the training data test_data.drop(['Alley', 'FireplaceQu', 'PoolQC', 'Fence', 'MiscFeature'], axis=1, inplace=True) new_missing_values = [col for col in test_data.columns if test_data[col].isnull().any()] for col in new_missing_values: if test_data[col].dtype == 'O': test_data[col].fillna(test_data[col].mode()[0], inplace=True) else: test_data[col].fillna(test_data[col].median(), inplace=True)


# Encoding the categorical variables of test data for col in test_data.columns: if test_data[col].dtype == 'O': label_encoder = LabelEncoder() test_data[col] = label_encoder.fit_transform(test_data[col])


# Selecting Features X_test = test_data[['OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea', 'TotalBsmtSF', '1stFlrSF', 'FullBath', 'TotRmsAbvGrd', 'YearBuilt', 'YearRemodAdd']] # Predicting the target variable y_pred = ridge.predict(X_test)


# Saving the predictions in a csv file output = pd.DataFrame({'Id': test_data.Id, 'SalePrice': y_pred}) output.to_csv('my_submission.csv', index=False)
```

Conclusion

In this article, we have chosen the Ames housing dataset as the price prediction model, understand the problem statement, and perform Exploratory Data Analysis. We have also performed missing value imputation and encoding of categorical variables on the train and test data sets. Then we applied Ridge regression with different alpha values and found the best value of alpha to minimize the RMSE.

Key Takeaways:

- Three features, 'OverallQual,' 'GrLivArea,' and 'TotalBsmtSF,' were found to have strong positive correlations with the target variable 'SalePrice.'
- The model performed best with alpha = 100, resulting in amses of 38464.
- The analysis showed the importance of considering multiple features in real estate price prediction models.
- Regularization techniques like Ridge regression can reduce the model's complexity and prevent overfitting.
- The results of this project highlight the potential for using data science in real estate to make more informed decisions and improve predictions.

Article Url - https://www.analyticsvidhya.com/blog/2023/02/how-to-build-a-real-estate-price-prediction-model/

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