GRT INSTITUTE OF ENGINEERING AND TECHNOLOGY, TIRUTTANI - 631209

Approved by AICTE, New Delhi Affiliated to Anna University chennai

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

PROJECT TITLE

House price prediction using machine learning

COLLEGE CODE:1103

Phase - 3

MOULISHWAR. S

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Reg no. : 110320104030

rishumouli201@gmail.com

3.1DATASET AND ITS DETAIL EXPLANATION AND IMPLEMENTATION OF HOUSE PRICE PREDICTION USING MACHINE LEARNING

FINDING THE DATASET ON KAGGLE:

Visit Kaggle's website (https://www.kaggle.com) and create an account if you don't already have one.

Use the search bar to look for datasets related to "USA Housing" or "House Price Prediction" or any specific keywords related to your project.

DATASET DETAILS:

Once you find the dataset, click on it to access its details.

The dataset page on Kaggle typically includes information on its contents, such as the number of rows, columns, and a description of each column.

DOWNLOADING THE DATASET:

You can download the dataset from Kaggle in various formats, such as CSV. Make sure to read any licensing or usage restrictions associated with the dataset.

EXPLORATORY DATA ANALYSIS (EDA):

After downloading the dataset, load it into your preferred data analysis tool, such as Python with libraries like Pandas and Matplotlib/Seaborn.

Perform EDA to get a better understanding of the data. This might involve data cleaning, handling missing values, and visualizing the data to uncover patterns and insights.

FEATURE SELECTION AND ENGINEERING:

Select relevant features that are likely to impact house prices.

Create new features if needed based on domain knowledge.

MODEL SELECTION:

Choose a machine learning model for your prediction. Linear Regression is a common choice for house price prediction, but you can also explore more complex models like Random Forest, XGBoost, or Neural Networks.

DATA SPLITTING:

Split your dataset into a training set and a testing set. The typical split is around 70-80% for training and 20-30% for testing.

MODEL TRAINING:

Train your chosen model on the training data.

MODEL EVALUATION:

Evaluate the model's performance on the testing data. Common evaluation metrics include Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

HYPERPARAMETER TUNING:

Fine-tune your model by adjusting hyperparameters to optimize its performance.

Deployment:

Once you're satisfied with your model's performance, you can deploy it for practical use.

Regular Maintenance:

Keep the model updated as new data becomes available and retrain it periodically to maintain accuracy.

Documentation:

Properly document your project, including the dataset, preprocessing steps, model details, and results.

Remember that the success of your house price prediction model heavily depends on data quality, feature engineering, and model selection. Additionally, you might want to explore techniques like cross-validation, feature scaling, and regularization to improve your model's performance. Kaggle and other online resources often provide example notebooks and kernels to guide you through similar projects, which can be very helpful.

3.2BEGIN BUILDING THE PROJECT BY LOAD THE DATASET

Assuming you've downloaded the dataset as a CSV file, here's how you can load it into a Pandas DataFrame:

```
import pandas as pd


# Replace 'your_dataset.csv' with the actual file path of your downloaded dataset.

file_path = 'your_dataset.csv'


# Load the dataset into a Pandas DataFrame

data = pd.read_csv(file_path)


# Display the first few rows of the dataset to get an overview

print(data.head())
```

Make sure you replace 'your_dataset.csv' with the actual path to the dataset file on your system. After running this code, the data variable will contain your dataset, and you can start exploring and working with it for your house price prediction project.

You can now proceed with exploratory data analysis, data preprocessing, and building your machine learning model based on the loaded dataset. If you encounter any specific issues or have more questions regarding your project, feel free to ask for further guidance.

3.3PREPROCESSING A DATASET:

HANDLING MISSING VALUES:

Check for missing values in the dataset using data.isnull().sum().

Decide how to handle missing values. You can either remove rows with missing values, fill them with the mean/median, or use more advanced techniques.

```
# Check for missing values
print(data.isnull().sum())

# Handle missing values, for example, by filling with the mean
data['column_name'].fillna(data['column_name'].mean(), inplace=True)
```

ENCODING CATEGORICAL VARIABLES:

If your dataset contains categorical variables, you'll need to encode them into numerical values. You can use one-hot encoding or label encoding, depending on the nature of the data.

```
# Example of one-hot encoding
data = pd.get_dummies(data, columns=['categorical_column'])
```

FEATURE SCALING:

It's often necessary to scale or normalize the features to ensure that they have a similar scale. This helps certain machine learning algorithms perform better.

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
data['numerical_column'] = scaler.fit_transform(data[['numerical_column']])
```

FEATURE SELECTION:

Decide which features are relevant to your prediction task. You can use techniques like feature importance or correlation analysis to select the most important features.

TRAIN-TEST SPLIT:

Split your dataset into training and testing sets. This helps you evaluate the performance of your machine learning model.

```
from sklearn.model_selection import train_test_split


X = data.drop('target_column', axis=1)
y = data['target_column']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
```

ADDITIONAL PREPROCESSING STEPS:

Depending on your specific dataset, you may need to perform other preprocessing steps, such as handling outliers, transforming features, or engineering new features.

DOCUMENTATION:

Make sure to document all the preprocessing steps you've taken so that it's clear how the data has been prepared for your machine learning model.

Remember that preprocessing steps can vary based on your specific dataset and the machine learning algorithms you plan to use. It's important to adapt your preprocessing to the unique characteristics of your dataset and the requirements of your project.

3.3 PERFORMING DIFFERENT ANALYSIS NEEDED

DESCRIPTIVE STATISTICS:

Compute basic statistics to understand the central tendencies and distribution of numerical features (mean, median, standard deviation, etc.). Use the describe() function in Pandas to generate summary statistics.

```
print(data.describe())
```

CORRELATION ANALYSIS:

Calculate the correlation between numerical features to identify relationships between variables. You can use a correlation matrix and visualize it using a heatmap.

```
correlation_matrix = data.corr()
# Visualize the correlation matrix
import seaborn as sns
import matplotlib.pyplot as plt
sns.heatmap(correlation_matrix, annot=True)
plt.show()
```

DATA VISUALIZATION:

Create various plots and graphs to visualize the data. This can include histograms, scatter plots, box plots, and more to identify patterns and outliers.

```
import matplotlib.pyplot as plt
data['numerical_column'].hist()
plt.title('Histogram of Numerical Column')
plt.xlabel('Value')

plt.ylabel('Frequency')

plt.show()
```

GEOSPATIAL ANALYSIS:

If your dataset includes location data (e.g., latitude and longitude), you can create geospatial visualizations to understand the geographical distribution of housing data.

TIME SERIES ANALYSIS:

If your dataset includes a time component (e.g., housing prices over time), you can perform time series analysis to identify trends and seasonality.

HYPOTHESIS TESTING:

Conduct statistical tests to test hypotheses or relationships in the data. For example, you can perform t-tests to compare the means of different groups.

DIMENSIONALITY REDUCTION:

Use techniques like Principal Component Analysis (PCA) or t-Distributed Stochastic Neighbor Embedding (t-SNE) to reduce the dimensionality of your data for visualization or feature selection.

FEATURE IMPORTANCE ANALYSIS:

If you plan to build a predictive model, you can analyze feature importance to understand which features have the most impact on the target variable.

CLUSTERING ANALYSIS:

Apply clustering algorithms (e.g., K-Means) to identify natural groupings in the data.

REGRESSION ANALYSIS:

Perform regression analysis to understand the relationships between independent variables and the target variable (house prices in this case).

CLASSIFICATION ANALYSIS:

If you have categorical target variables (e.g., property types), conduct classification analysis to predict those categories.

ANOMALY DETECTION:

Identify and investigate outliers or anomalies in the data that may affect the quality of your model.

TEXT ANALYSIS (IF APPLICABLE):

If your dataset contains text data (e.g., property descriptions), you can perform text analysis to extract insights.

MACHINE LEARNING MODELS:

Train and evaluate machine learning models to predict house prices. This can include linear regression, decision trees, random forests, or more advanced models like XGBoost and neural networks.

MODEL EVALUATION:

Assess the performance of your predictive models using appropriate evaluation metrics (e.g., Mean Absolute Error, Root Mean Squared Error).

Each of these analyses serves a different purpose, and your choice will depend on your project objectives. Analyzing and understanding your data is a crucial step in preparing for feature engineering and model development.