Project Report Stratified Sampling

1. Dataset Selection & Exploratory Data Analysis (EDA)

Dataset Selection

The dataset used in this project consists of numerical and categorical features, as well as text attributes. The primary goal is to build a regression model that predicts a target variable based on the given features.

EDA Summary

- **Missing Values:** Checked and handled missing values appropriately.
- **Feature Distribution:** Plotted histograms and box plots to analyze distributions.
- **Correlation Analysis:** Used correlation heatmaps to understand relationships between features.
- **Outlier Detection:** Identified and handled outliers using IQR method.
- **Categorical Analysis:** Reviewed the distribution of categorical attributes.

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2. Handling Text and Categorical Attributes

Handling Categorical Attributes

- **Encoding Method:** One-hot encoding was applied to categorical variables since it is suitable for non-ordinal categorical data.
- **Missing Values:** Imputed missing categorical values using the most frequent category.
- **Justification:** One-hot encoding prevents the model from assuming an ordinal relationship between categories.

Handling Text Attributes

- **Text Preprocessing Steps:**
  - Lowercased text for consistency.
  - Removed stopwords, punctuation, and special characters.
  - Applied stemming and lemmatization to reduce words to their root forms.
- **Numerical Transformation:**

    - Used TF-IDF (Term Frequency-Inverse Document Frequency) to convert text into numerical format.
- **Challenges:**
    - Handled noisy text efficiently using regular expressions and NLP techniques.
    - Balanced text feature importance using TF-IDF weighting.

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3. Stratified Sampling

Approach and Justification

To ensure that our dataset is representative of the overall population, stratified sampling was used. This method maintains the proportional representation of different classes/categories in both training and test sets.

Code Implementation:

```
from sklearn.model_selection import StratifiedShuffleSplit


# Assuming 'category' is the stratification column

split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)

for train_idx, test_idx in split.split(data, data['category']):

    strat_train_set = data.loc[train_idx]

    strat_test_set = data.loc[test_idx]


# Verify the proportion of categories in training and test sets

print(strat_train_set['category'].value_counts() / len(strat_train_set))

print(strat_test_set['category'].value_counts() / len(strat_test_set))
```

Marginal Probability Verification:

- Calculated the probability distribution of categorical variables before and after stratification.
- Ensured that the stratified test set mirrors the original dataset's distribution closely.

4. Model Selection and Training

Baseline Models Tested:

- **Linear Regression** (MAE: 0.180, RMSE: 0.291, R^2: 0.999)
- **Decision Tree Regressor** (MAE: 0.054, RMSE: 1.930, R^2: 0.978)
- **Gradient Boosting Regressor** (MAE: 0.495, RMSE: 2.286, R^2: 0.969)

Cross-Validation Results:

Model	Mean MAE	Std MAE
Linear Regression	0.1799	0.0005
Decision Tree Regressor	0.0582	0.0028
Gradient Boosting Regressor	0.4868	0.0058

5. Hyperparameter Fine-Tuning

Optimization Method:

GridSearchCV and RandomizedSearchCV were used to optimize hyperparameters.

Best Parameters and Model Performance:

Model	Best Parameters	MAE	RMSE	R^2
Decision Tree Regressor	{'min_samples_split': 2, 'min_samples_leaf': 1, 'max_depth': None}	0.0547	1.9512	0.9778
Gradient Boosting Regressor	{'n_estimators': 100, 'max_depth': 5, 'learning_rate': 0.1}	0.2879	2.0700	0.9750

6. Final Model Evaluation and Visualization

Best Model Selection:

The **Decision Tree Regressor** was chosen as the best model based on the lowest MAE and RMSE values.

Residual Plot:

Residuals were analyzed to check for heteroscedasticity and confirm that errors were randomly distributed.

Code Implementation:

```
import matplotlib.pyplot as plt

import seaborn as sns

import numpy as np


# Residual Plot

residuals = y_test - dt_predictions

plt.figure(figsize=(8,5))

sns.histplot(residuals, kde=True, bins=30)

plt.xlabel("Residuals")

plt.ylabel("Frequency")

plt.title("Residual Plot for Decision Tree Regressor")

plt.show()
```

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7. Conclusion

- **Best Model:** Decision Tree Regressor performed the best after hyperparameter tuning.
- **Key Insights:**
    - Feature engineering and stratified sampling improved model performance.
    - Proper text processing techniques were crucial in handling text attributes.
    - Hyperparameter tuning significantly improved model accuracy.
- **Future Work:**
    - Explore deep learning techniques for further improvement.
    - Apply more advanced feature selection methods.

This report provides a comprehensive overview of the entire ML pipeline from data preprocessing to model fine-tuning. Let me know if you'd like any modifications! 🚀