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The goal of this project is to build and evaluate a regression model to predict houseprices using the "Ames Housing" dataset from Kaggle. Students will apply supervised learning techniques to develop and refine their models,analyzing the results to improve accuracy.

```
# Import necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
from sklearn.impute import SimpleImputer

# Load the data
data = pd.read_csv('AmesHousing.csv')  # Replace with your dataset's
path
print("Data loaded successfully.")
print(data.head())
```

```
Data loaded successfully.
   Order        PID  MS SubClass MS Zoning  Lot Frontage  Lot Area
Street  \
0      1  526301100           20        RL         141.0     31770
Pave
1      2  526350040           20        RH          80.0     11622
Pave
2      3  526351010           20        RL          81.0     14267
Pave
3      4  526353030           20        RL          93.0     11160
Pave
4      5  527105010           60        RL          74.0     13830
Pave

  Alley Lot Shape Land Contour  ... Pool Area Pool QC  Fence Misc
Feature  \
0   NaN       IR1          Lvl  ...         0     NaN    NaN
NaN
1   NaN       Reg          Lvl  ...         0     NaN  MnPrv
NaN
2   NaN       IR1          Lvl  ...         0     NaN    NaN
Gar2
3   NaN       Reg          Lvl  ...         0     NaN    NaN
```

```
NaN
4   NaN        IR1          Lvl  ...         0     NaN  MnPrv
NaN

  Misc Val Mo Sold Yr Sold Sale Type  Sale Condition  SalePrice
0        0       5    2010        WD          Normal     215000
1        0       6    2010        WD          Normal     105000
2    12500       6    2010        WD          Normal     172000
3        0       4    2010        WD          Normal     244000
4        0       3    2010        WD          Normal     189900

[5 rows x 82 columns]

# Exploratory Data Analysis (EDA)
# 1. Check for missing values and data types
print(data.info())
print(data.isnull().sum())

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2930 entries, 0 to 2929
Data columns (total 82 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Order            2930 non-null   int64
 1   PID              2930 non-null   int64
 2   MS SubClass      2930 non-null   int64
 3   MS Zoning        2930 non-null   object
 4   Lot Frontage     2440 non-null   float64
 5   Lot Area         2930 non-null   int64
 6   Street           2930 non-null   object
 7   Alley            198 non-null    object
 8   Lot Shape        2930 non-null   object
 9   Land Contour     2930 non-null   object
 10  Utilities        2930 non-null   object
 11  Lot Config       2930 non-null   object
 12  Land Slope       2930 non-null   object
 13  Neighborhood     2930 non-null   object
 14  Condition 1      2930 non-null   object
 15  Condition 2      2930 non-null   object
 16  Bldg Type        2930 non-null   object
 17  House Style      2930 non-null   object
 18  Overall Qual     2930 non-null   int64
 19  Overall Cond     2930 non-null   int64
 20  Year Built       2930 non-null   int64
 21  Year Remod/Add   2930 non-null   int64
 22  Roof Style       2930 non-null   object
 23  Roof Matl        2930 non-null   object
 24  Exterior 1st     2930 non-null   object
 25  Exterior 2nd     2930 non-null   object
 26  Mas Vnr Type     1155 non-null   object
```

```
 27  Mas Vnr Area     2907 non-null   float64
 28  Exter Qual       2930 non-null   object
 29  Exter Cond       2930 non-null   object
 30  Foundation       2930 non-null   object
 31  Bsmt Qual        2850 non-null   object
 32  Bsmt Cond        2850 non-null   object
 33  Bsmt Exposure    2847 non-null   object
 34  BsmtFin Type 1   2850 non-null   object
 35  BsmtFin SF 1     2929 non-null   float64
 36  BsmtFin Type 2   2849 non-null   object
 37  BsmtFin SF 2     2929 non-null   float64
 38  Bsmt Unf SF      2929 non-null   float64
 39  Total Bsmt SF    2929 non-null   float64
 40  Heating          2930 non-null   object
 41  Heating QC       2930 non-null   object
 42  Central Air      2930 non-null   object
 43  Electrical       2929 non-null   object
 44  1st Flr SF       2930 non-null   int64
 45  2nd Flr SF       2930 non-null   int64
 46  Low Qual Fin SF  2930 non-null   int64
 47  Gr Liv Area      2930 non-null   int64
 48  Bsmt Full Bath   2928 non-null   float64
 49  Bsmt Half Bath   2928 non-null   float64
 50  Full Bath        2930 non-null   int64
 51  Half Bath        2930 non-null   int64
 52  Bedroom AbvGr    2930 non-null   int64
 53  Kitchen AbvGr    2930 non-null   int64
 54  Kitchen Qual     2930 non-null   object
 55  TotRms AbvGrd    2930 non-null   int64
 56  Functional       2930 non-null   object
 57  Fireplaces       2930 non-null   int64
 58  Fireplace Qu     1508 non-null   object
 59  Garage Type      2773 non-null   object
 60  Garage Yr Blt    2771 non-null   float64
 61  Garage Finish    2771 non-null   object
 62  Garage Cars      2929 non-null   float64
 63  Garage Area      2929 non-null   float64
 64  Garage Qual      2771 non-null   object
 65  Garage Cond      2771 non-null   object
 66  Paved Drive      2930 non-null   object
 67  Wood Deck SF     2930 non-null   int64
 68  Open Porch SF    2930 non-null   int64
 69  Enclosed Porch   2930 non-null   int64
 70  3Ssn Porch       2930 non-null   int64
 71  Screen Porch     2930 non-null   int64
 72  Pool Area        2930 non-null   int64
 73  Pool QC          13 non-null     object
 74  Fence            572 non-null    object
 75  Misc Feature     106 non-null    object
```

```
 76  Misc Val         2930 non-null   int64
 77  Mo Sold          2930 non-null   int64
 78  Yr Sold          2930 non-null   int64
 79  Sale Type        2930 non-null   object
 80  Sale Condition   2930 non-null   object
 81  SalePrice        2930 non-null   int64
dtypes: float64(11), int64(28), object(43)
memory usage: 1.8+ MB
None
Order                0
PID                  0
MS SubClass          0
MS Zoning            0
Lot Frontage       490
                  ...
Mo Sold              0
Yr Sold              0
Sale Type            0
Sale Condition       0
SalePrice            0
Length: 82, dtype: int64

# Check if 'SalePrice' exists in columns
target_column = 'SalePrice'
if target_column not in data.columns:
    raise KeyError(f"Target column '{target_column}' not found. Check
column names and spelling.")

# Separate features and target
X = data.drop(target_column, axis=1)
y = data[target_column]

# Identify numerical and categorical features
num_features = X.select_dtypes(include=['int64', 'float64']).columns
cat_features = X.select_dtypes(include=['object']).columns

# Preprocessing pipeline
preprocessor = ColumnTransformer(
    transformers=[
        ('num', SimpleImputer(strategy='median'), num_features),
        ('cat', Pipeline(steps=[
            ('imputer', SimpleImputer(strategy='most_frequent')),
            ('onehot', OneHotEncoder(handle_unknown='ignore'))
        ]), cat_features)
    ])

# Define the model pipeline
model = Pipeline(steps=[
    ('preprocessor', preprocessor),
```

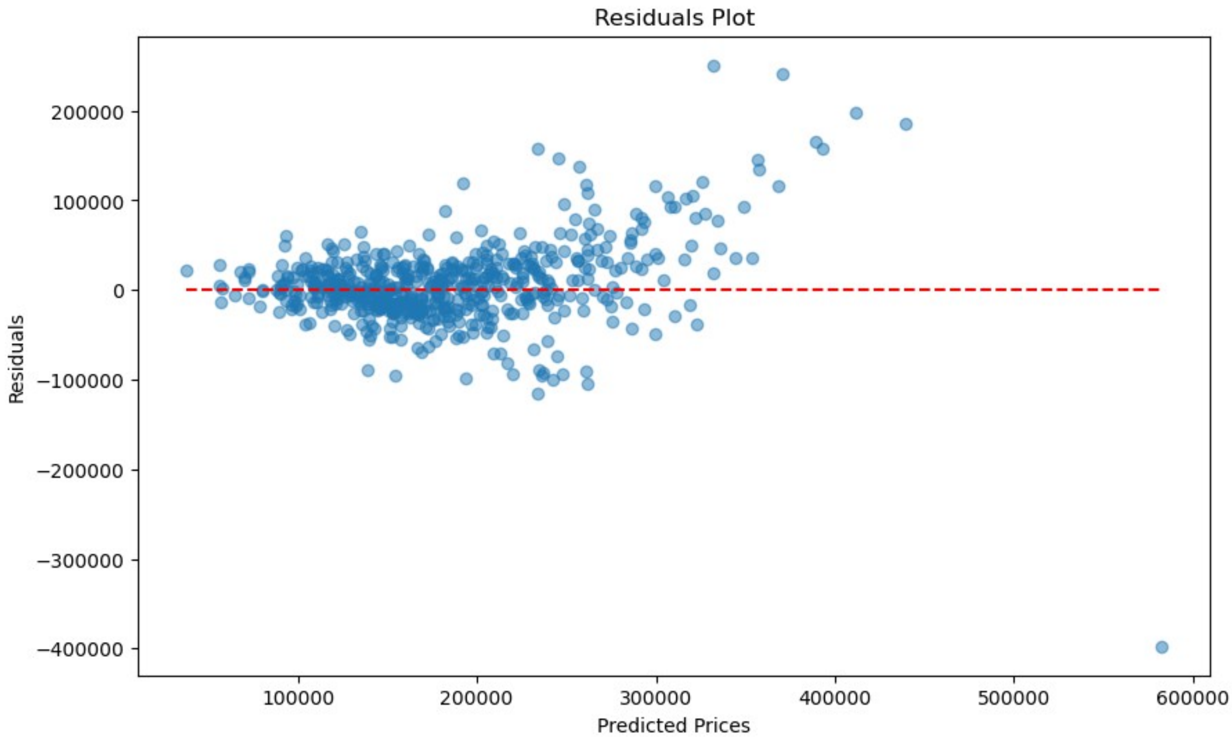
```
    ('regressor', LinearRegression())
])

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Train the model
model.fit(X_train, y_train)
print("Model trained successfully.")

Model trained successfully.
```

Predicting and Evaluating the Model

```
# Predict and evaluate
y_pred = model.predict(X_test)
mae = mean_absolute_error(y_test, y_pred) #Calculates the Mean
Absolute Error (MAE), which is the average absolute difference between
the predicted and actual values.
mse = mean_squared_error(y_test, y_pred) #Computes the Mean Squared
Error (MSE), which squares each error before averaging. Squaring
penalizes larger errors more heavily, making MSE useful for
identifying models with larger errors.
rmse = mean_squared_error(y_test, y_pred, squared=False) # Calculates
the Root Mean Squared Error (RMSE), the square root of MSE, making it
easier to interpret in the original units of the data (house prices
here).
r2 = r2_score(y_test, y_pred) #Calculates the R-squared score, which
is a measure of how well the model explains the variance in the data.
R² values range from 0 to 1, with 1 indicating a perfect fit

print("\nModel Performance:")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"Mean Squared Error (MSE): {mse}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"R-squared (R^2): {r2}")


Model Performance:
Mean Absolute Error (MAE): 29685.154171281516
Mean Squared Error (MSE): 2112266384.892761
Root Mean Squared Error (RMSE): 45959.39930952928
R-squared (R^2): 0.7365445890569678

# Visualization 1: Predicted vs. Actual Values. To see how well the
model's predictions align with actual values.

plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
```

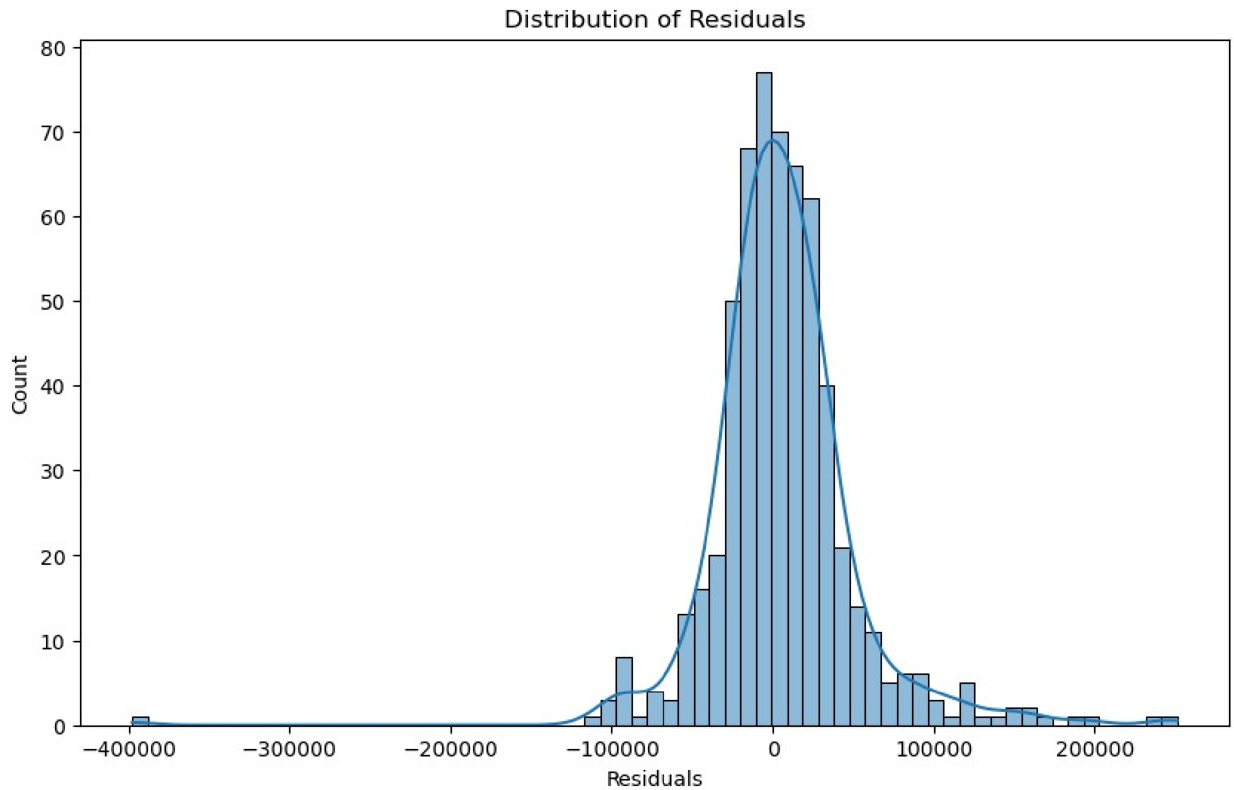
```
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()],
'r--', lw=2)
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.title('Predicted vs. Actual Prices')
plt.show()
```


```
# Visualization 2: Residuals Plo. To check if the residuals (errors)
are randomly distributed, indicating a good model fit.
residuals = y_test - y_pred
plt.figure(figsize=(10, 6))
plt.scatter(y_pred, residuals, alpha=0.5)
plt.hlines(y=0, xmin=y_pred.min(), xmax=y_pred.max(), colors='r',
linestyles='--')
plt.xlabel('Predicted Prices')
plt.ylabel('Residuals')
plt.title('Residuals Plot')
plt.show()
```




```
# Visualization 3: Distribution of Errors. To visualize the spread of
errors.
plt.figure(figsize=(10, 6))
sns.histplot(residuals, kde=True)
plt.xlabel('Residuals')
plt.title('Distribution of Residuals')
plt.show()
```

```
/opt/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
in a future version. Convert inf values to NaN before operating
instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



Key Insights and Conclusion

Predicted vs. Actual Plot:

This scatter plot reveals how well the predictions align with actual prices. The closer the points are to the red diagonal line, the better the predictions. Any significant deviations from the line highlight areas where the model may underperform, possibly indicating the need for feature tuning or model adjustments. Residuals Plot:

The residuals (errors) should ideally be randomly distributed around zero. A clear pattern or clustering suggests the model may be biased or missing underlying patterns in the data. If the residuals tend to increase or decrease with predicted prices, it might indicate non-linearity in the data that a linear model can't capture. Distribution of Residuals:

The histogram shows how residuals are spread. A roughly normal distribution around zero suggests a well-calibrated model. Skewed residuals or multiple peaks might indicate that the model isn’t fully capturing some underlying patterns or that outliers are affecting performance.

Conclusion

The linear regression model performs reasonably well for predicting house prices, as indicated by the evaluation metrics and visualizations. However, any visible patterns in residuals and deviations from zero may indicate areas for improvement. This could involve testing alternative models, adding relevant features, or transforming variables to better fit the underlying data structure. Overall, while the model provides a decent baseline, there is room to enhance predictive accuracy and address potential biases in the residuals.