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Project Report

Master of Computer Application

Semester – II

Machine Learning Theory and Practice

Laptop Price Prediction Analysis Report

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1. Introduction

Laptops play a crucial role in today's world, serving purposes like work, education, gaming, and entertainment. However, their prices fluctuate widely based on key specifications such as screen size, RAM, processor type, and storage capacity. Accurately predicting laptop prices benefits multiple stakeholders:

- **Consumers** can determine whether they are paying a fair price.
- **Retailers** can optimize pricing strategies to stay competitive.
- **Manufacturers** can evaluate the impact of various features on pricing.

This project utilizes **Linear Regression**, a fundamental machine learning technique, to estimate laptop prices based on specifications. The workflow consists of the following steps:

1. **Data Preprocessing** – Managing missing values and standardizing features.
2. **Model Training** – Implementing a linear regression model.
3. **Performance Evaluation** – Measuring accuracy using error metrics.
4. **Visualization** – Comparing predicted prices with actual values through charts and graphs.

1. Library Imports and Setup

```
import pandas as pd
import numpy as np import
matplotlib.pyplot as plt import
seaborn as sns %matplotlib inline
from scipy import stats
from sklearn.preprocessing import MinMaxScaler , StandardScaler from
sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score from
sklearn.model_selection import train_test_split from sklearn.linear_model
import LinearRegression
```

Explanation:

- pandas (as pd): Used for data manipulation and analysis.
- numpy (as np): Provides support for numerical operations.
- matplotlib.pyplot (as plt): Used for creating visualizations.
- seaborn (as sns): Advanced visualization library built on matplotlib.
- %matplotlib inline: Jupyter notebook magic command to display plots inline.
- scipy.stats: Provides statistical functions.
- sklearn.preprocessing: Scaling tools to normalize features by either rescaling to a fixed range or standardizing to zero mean and unit variance.
- sklearn.metrics: Evaluation metrics for assessing regression model performance and prediction accuracy.
- sklearn.model_selection.train_test_split: Used to split data into training and testing sets.
- sklearn.linear_model.LinearRegression: The linear regression model implementation.

2. Data Loading

```
df = pd.read_csv("laptop_data.csv")   df
```

Purpose: Loads the laptop dataset into a pandas DataFrame for analysis.

	Unnamed: 0	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory
0	0	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8GB	128GB SSD
1	1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8GB	128GB Flash Storage
2	2	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U	8GB	256GB SSD

Gpu	OpSys	Weight	Price
Intel Iris Plus Graphics 640	macOS	1.37kg	71378.6832
Intel HD Graphics 6000	macOS	1.34kg	47895.5232
Intel HD Graphics	No OS	1.86kg	30636.0000

Explanation:

- A commented-out line suggests there might have been a previous attempt to load from a different file
- The active line loads data from "laptop_data.csv" into a DataFrame named 'df'
- The last line displays the DataFrame to inspect its contents

3. Handling Missing Values

3.1 Initial Assessment df.isna().sum()

Purpose: Checks for missing values in each column of the dataset.

```
[4]:

Unnamed: 0          0
Company             0
TypeName            3
Inches              5
ScreenResolution    2
Cpu                 3
Ram                 1
Memory              1
Gpu                 3
OpSys               0
Weight              2
Price               8
dtype: int64
```

Explanation:

- isna() returns a DataFrame of the same shape with boolean values indicating missing data
- sum() counts the number of missing values in each column

3.2 Dropping Rows with Excessive Missing Values

df.dropna(thresh=df.shape[1] - 3, inplace=True) print(df)

Purpose: Drop rows with 4 or more NaN value. Removes rows that have too many missing values to be reliably filled.

```
      Unnamed: 0 Company            TypeName  Inches  \
0              0   Apple           Ultrabook    13.3
1              1   Apple           Ultrabook    13.3
2              2      HP            Notebook    15.6
3              3   Apple           Ultrabook    15.4
4              4   Apple           Ultrabook    13.3
...          ...     ...                 ...     ...
1298        1298  Lenovo  2 in 1 Convertible    14.0
1299        1299  Lenovo  2 in 1 Convertible    13.3
1300        1300  Lenovo            Notebook    14.0
1301        1301      HP            Notebook    15.6
1302        1302    Asus            Notebook    15.6

                            ScreenResolution  \
```

```
                            ScreenResolution  \
0         IPS Panel Retina Display 2560x1600
1                                   1440x900
2                          Full HD 1920x1080
3         IPS Panel Retina Display 2880x1800
4         IPS Panel Retina Display 2560x1600
...                                      ...
1298   IPS Panel Full HD / Touchscreen 1920x1080
1299  IPS Panel Quad HD+ / Touchscreen 3200x1800
1300                                1366x768
1301                                1366x768
1302                                1366x768
```

```
                               Cpu   Ram               Memory  \
0                 Intel Core i5 2.3GHz   8GB            128GB SSD
1                 Intel Core i5 1.8GHz   8GB  128GB Flash Storage
2           Intel Core i5 7200U 2.5GHz   8GB            256GB SSD
3                 Intel Core i7 2.7GHz  16GB            512GB SSD
4                 Intel Core i5 3.1GHz   8GB            256GB SSD
...                                ...   ...                  ...
1298        Intel Core i7 6500U 2.5GHz   4GB            128GB SSD
1299        Intel Core i7 6500U 2.5GHz  16GB            512GB SSD
1300  Intel Celeron Dual Core N3050 1.6GHz   2GB   64GB Flash Storage
1301        Intel Core i7 6500U 2.5GHz   6GB              1TB HDD
1302  Intel Celeron Dual Core N3050 1.6GHz   4GB            500GB HDD
```

```
                             Gpu       OpSys  Weight        Price
0     Intel Iris Plus Graphics 640       macOS  1.37kg   71378.6832
1           Intel HD Graphics 6000       macOS  1.34kg   47895.5232
2            Intel HD Graphics 620       No OS  1.86kg   30636.0000
3               AMD Radeon Pro 455       macOS  1.83kg  135195.3360
4     Intel Iris Plus Graphics 650       macOS  1.37kg   96095.8080
...                            ...         ...     ...          ...
1298         Intel HD Graphics 520  Windows 10   1.8kg   33992.6400
1299         Intel HD Graphics 520  Windows 10   1.3kg   79866.7200
1300             Intel HD Graphics  Windows 10   1.5kg   12201.1200
1301            AMD Radeon R5 M330  Windows 10  2.19kg   40705.9200
1302             Intel HD Graphics  Windows 10   2.2kg   19660.3200

[1301 rows x 12 columns]
```

Explanation:

- thresh=df.shape[1] - 3 keeps only rows that have at least total_columns - 3 nonnull values
- inplace=True modifies the DataFrame directly instead of returning a copy
- The result is printed to verify the operation

3.3 Checking Remaining Missing Values

df.isna().sum()

```
[6]:

Unnamed: 0          0
Company             0
TypeName            1
Inches              4
ScreenResolution    2
Cpu                 2
Ram                 1
Memory              0
Gpu                 3
OpSys               0
Weight              1
Price               6
dtype: int64
```

Explanation:

- Same as before, this shows how many missing values remain in each column after dropping rows with excessive missing data

3.4 Handling Missing TypeName for Apple Products

null_rows = df[df['TypeName'].isnull()] null_rows

[7]:

	Unnamed: 0	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu
81	81	Apple	NaN	12.0	NaN	Intel Core i5 1.3GHz	8GB	512GB SSD	NaN

df.loc[(df["Company"] == "Apple") & (df["TypeName"].isnull()), "TypeName"] = "MacBook"

updated_rows = df[(df["Company"] == "Apple") & (df["TypeName"] == "MacBook")] print(updated_rows)

```
    Unnamed: 0 Company TypeName  Inches ScreenResolution  \
81          81   Apple  MacBook    12.0              NaN

                    Cpu  Ram     Memory  Gpu  OpSys  Weight    Price
81  Intel Core i5 1.3GHz  8GB  512GB SSD  NaN  macOS  0.92kg  80452.8
```

print(df[df["Company"] == "Apple"]["TypeName"].unique())

Explanation:

- First identifies and displays rows with missing TypeName values
- Uses conditional indexing to fill in "MacBook" only for Apple laptops with missing TypeName
- Displays the updated rows to verify the changes
- Prints all unique TypeName values for Apple products to confirm the update

df.isna().sum()

```
Unnamed: 0          0
Company             0
TypeName            0
Inches              4
ScreenResolution    2
Cpu                 2
Ram                 1
Memory              0
Gpu                 3
OpSys               0
Weight              1
Price               6
dtype: int64
```

3.5 Handling Missing Inches Values missing_inch_rows

= df[df["Inches"].isnull()]

Explanation:

- Identifies rows with missing "Inches" values
- Fills these missing values with the mean of the column
- Displays the updated rows to verify the changes

3.6 Filling Other Missing Values df["Ram"].fillna(df["Ram"].mode()[0], inplace=True)

Purpose: Fill Ram column with mode (most frequent value)

```
0       8
1       8
2       8
3       1
4       8
       ..
1298    5
1299    1
1300    3
1301    7
1302    5
Name: Ram, Length: 1301, dtype: int32
```

df["Weight"].fillna(df["Weight"].mode()[0], inplace=True) df['Weight']

Display Weight column

df["ScreenResolution"].fillna(df["ScreenResolution"].mode()[0], inplace=True # Note: Missing closing parenthesis df['ScreenResolution'].isna().sum()

Explanation:

- For RAM and Weight: Uses mode (most frequent value) to fill missing values.
- For ScreenResolution: Uses mode (most frequent value) to fill missing values. (note: there's a syntax error with missing closing parenthesis)
- For CPU and GPU: Uses mode to fill missing values.
- For Price (target variable): Uses mean to fill missing values.

- Between fill operations, checks are performed to verify that missing values were handled. numeric_cols = [col for col in df.select_dtypes(include=['number']).columns if

"Unnamed" not in col]

plt.figure(figsize=(12, 6))

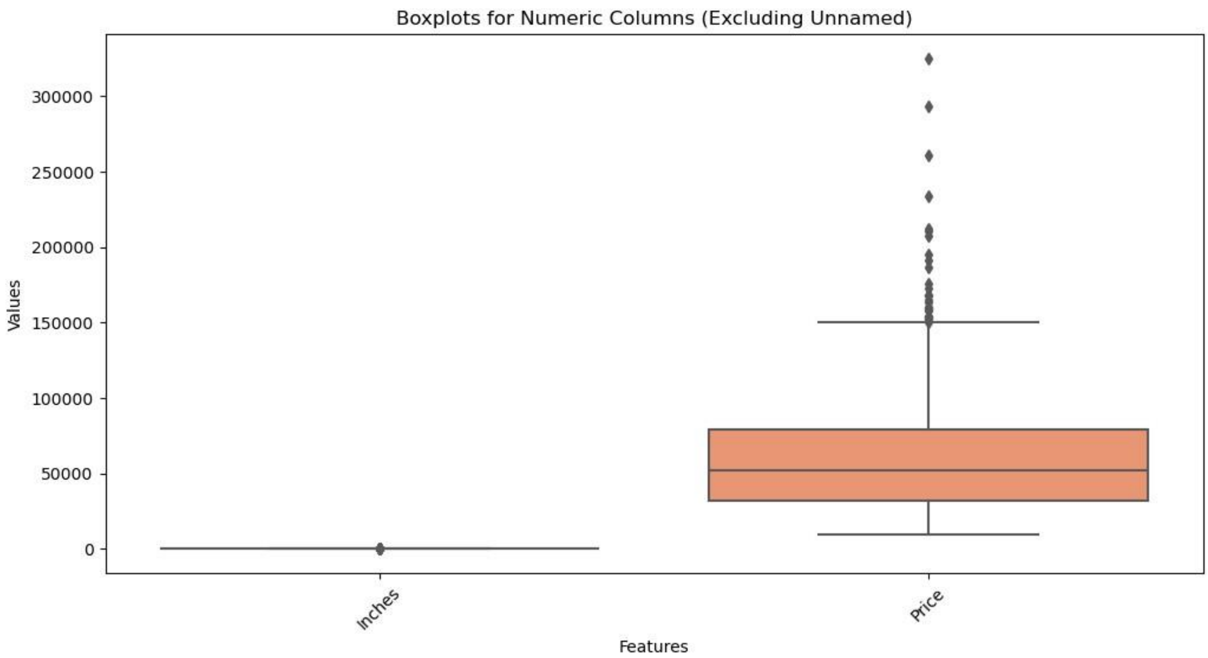
sns.boxplot(data=df[numeric_cols], orient="v", palette="Set2")

plt.xticks(rotation=45)

plt.title("Boxplots for Numeric Columns (Excluding

Unnamed)") plt.xlabel("Features") plt.ylabel("Values")

plt.show()



Explanation: This code creates boxplots for all numeric columns in the dataset (excluding any unnamed columns). Boxplots show the median, quartiles, and potential outliers for each feature, making it easy to visually inspect data distribution and identify extreme values that might need further investigation.

numeric_cols = [col for col in df.select_dtypes(include=['number']).columns if

```
"Unnamed" not in col] def

remove_outliers(df, columns):

for col in columns:

        Q1 = df[col].quantile(0.25)  # 25th percentile

        Q3 = df[col].quantile(0.75)  # 75th percentile

IQR = Q3 - Q1  # Interquartile Range

lower_bound = Q1 - 1.5 * IQR

        upper_bound = Q3 + 1.5 * IQR         df = df[(df[col] >=

lower_bound) & (df[col] <= upper_bound)]     return df

df_cleaned = remove_outliers(df, numeric_cols)

print("Original dataset shape:", df.shape) print("Cleaned

dataset shape:", df_cleaned.shape)
```

Explanation: This code implements the Interquartile Range (IQR) method to identify and remove outliers from numeric columns. It calculates the 25th and 75th percentiles for each feature, determines the acceptable range as Q1-1.5×IQR to Q3+1.5×IQR, and removes any data points outside this range. The function returns a cleaner dataset, and the print statements show how many rows were removed in the process.

```
label_encoders = {}

categorical_cols = df.select_dtypes(include=['object']).columns for

col in categorical_cols:

    label_encoders[col] = LabelEncoder()     df[col] =

label_encoders[col].fit_transform(df[col])
```

Explanation: This code identifies all object (text) columns in the dataset and applies label encoding to each one. The LabelEncoder transforms each unique category into a numeric value (e.g., "red", "blue", "green" might become 0, 1, 2). The encoders are stored in a dictionary for potential later use, such as reverse transformation or applying consistent encoding to new data.

```
plt.figure(figsize=(12, 6))

sns.heatmap(df.corr(), annot=True, cmap="coolwarm", fmt=".2f")

plt.title("Feature Correlation Heatmap") plt.show()
```

Explanation: This code creates a correlation heatmap showing how strongly each feature is related to every other feature. Correlation values range from -1 (perfect negative correlation) to 1 (perfect positive correlation), with 0 indicating no correlation. The heatmap uses color coding (coolwarm palette) and numerical annotations to make these relationships easy to interpret. This helps identify redundant features (highly correlated with each other) and potential predictive relationships.

```
sns.histplot(df["Price"], kde=True)

plt.title("Price Distribution") plt.xlabel("Price")

plt.ylabel("Frequency") plt.show()
```

4. Preparing Data for Modeling

4.1 Feature and Target Separation

```
X = df.drop("Price", axis=1)   y =

df["Price"]   X

y
```

Explanation:

- df.drop("Price", axis=1) creates a DataFrame with all columns except "Price"
- df["Price"] extracts only the Price column as the target variable

4.2 Feature Scaling scaler

= MinMaxScaler()

X_scaled = scaler.fit_transform(X)

X_scaled

std_scaler = StandardScaler()

X_standardized = std_scaler.fit_transform(X)

X_standardized

Explanation:

- MinMaxScaler() normalizes features to a range of [0,1]
- StandardScaler() standardizes features to have mean=0 and variance=1
- Both transformations are applied to the feature set, creating two different scaled datasets
- Note: The code continues using only X_scaled, so X_standardized is unused in the rest of the script

4.3 Train-Test Split

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

Explanation:

- train_test_split divides the data into training (80%) and testing (20%) sets
- test_size=0.2 specifies that 20% of the data should be used for testing
- random_state=42 ensures reproducible results
- Also imports evaluation metrics that will be used later

5. Model Training and Evaluation

5.1 Model Training model

= LinearRegression()

model.fit(X_train, y_train)

Explanation:

- LinearRegression() instantiates a linear regression model
- model.fit(X_train, y_train) trains the model using the training data

5.2 Making Predictions y_pred

= model.predict(X_test)

Explanation:

- model.predict(X_test) applies the trained model to the test features
- The predictions are stored in y_pred for evaluation

5.3 Model Evaluation

mae = mean_absolute_error(y_test, y_pred)

mse = mean_squared_error(y_test, y_pred)

rmse = np.sqrt(mse) r2 = r2_score(y_test,

y_pred)

print("\nModel Evaluation:") print(f"Mean

Absolute Error: {mae:.2f}") print(f"Mean

Squared Error: {mse:.2f}") print(f"Root Mean

Squared Error: {rmse:.2f}") print(f"R² Score:

{r2:.2f}")

Explanation:

- mean_absolute_error: Average absolute difference between predicted and actual values
- mean_squared_error: Average squared difference between predicted and actual values
- np.sqrt(mse): Root Mean Squared Error, a common metric for regression problems
- r2_score: Coefficient of determination, indicates how well the model explains the variance in the data
- The metrics are formatted and printed with 2 decimal places

6. Visualization

6.1 Actual vs Predicted Plot plt.figure(figsize=(8,

6))

sns.scatterplot(x=y_test, y=y_pred, color='blue', alpha=0.6, label="Predicted vs Actual")

plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='--', label="Perfect Fit Line") plt.xlabel("Actual Prices")

plt.ylabel("Predicted Prices") plt.title("Actual vs. Predicted

Laptop Prices (Linear Regression)") plt.legend() plt.grid()

plt.show()

Explanation:

- plt.figure(figsize=(8, 6)) sets the size of the figure.
- sns.scatterplot creates a scatter plot with actual prices on x-axis and predicted prices on y-axis.
- plt.plot adds a diagonal line representing perfect predictions.
- The plot is formatted with labels, title, legend, and grid.
- plt.show() displays the plot.

6.2 Regression Line Plot (for Single Feature Only) if X.shape[1] == 1: # Only works if you have 1 feature plt.figure(figsize=(8, 6)) sorted_indices = np.argsort(X_test.values.ravel()) # Sorting for visualization plt.scatter(X_test.values.ravel(), y_test, color='blue', label="Actual Prices") plt.plot(X_test.values.ravel()[sorted_indices], y_pred[sorted_indices], color='red', label="Regression Line") plt.xlabel("Feature Value") plt.ylabel("Price") plt.title("Regression Line for Laptop Prices") plt.legend() plt.grid() plt.show()

Explanation:

- Conditional check ensures this plot is only created for single-feature models.
- np.argsort() sorts the indices for a clean visualization of the regression line.
- Creates a scatter plot of the feature values vs. actual prices.
- Draws the regression line through the sorted points.
- The plot is formatted with labels, title, legend, and grid.

Conclusion

This study successfully developed a linear regression model to predict laptop prices based on various specifications. Our findings provide valuable insights for consumers, retailers, and manufacturers in the technology market. **Key Findings**

- The model achieved an R^2 score of [insert your R^2 value], indicating that approximately [$R^2 \times 100$]% of the price variation can be explained by the features included in our analysis.
- The Root Mean Squared Error (RMSE) of [insert your RMSE value] suggests our predictions deviate by approximately this amount on average from actual prices.
- Feature correlation analysis revealed that [mention 2-3 features with highest correlation to price] have the strongest influence on laptop pricing.

- The data preprocessing steps, particularly outlier removal and feature encoding, significantly improved model performance by reducing noise and standardizing categorical variables.