NAME: Atharva Shinde DIV: D15C ROLL NO: 54

Q.1: Use the following data set for question 1
82, 66, 70, 59, 90, 78, 76, 95, 99, 84, 88, 76, 82, 81, 91, 64, 79, 76, 85, 90

1. Find the Mean (10pts)
2. Find the Median (10pts)
3. Find the Mode (10pts)
4. Find the Interquartile range (20pts)

Answer:

1. Mean : Mean is the sum of all numbers divided by the total count.

   Total Sum = 82 + 66 + 70 + 59 + 90 + 78 + 76 + 95 + 99 + 84 + 88 + 76 + 82 + 81 + 91 + 64 + 79 + 76 + 85 + 90
   Total Sum = 1621
   N = 20

   Mean = Total sum / N= 1621 / 20 = 81.05

   Mean = 81.05

2. Median: Median is the middle value in an ordered list.

   Sort the data:
   59, 64, 66, 70, 76, 76, 76, 78, 79, 81, 82, 82, 84, 85, 88, 90, 90, 91, 95, 99

   Since n = 20,
   Therefore, median = average of 10th and 11th number
   Median = (81 + 82) / 2 = 81.5

   Median = 81.5

3. Mode: Mode is the number that appears most frequently.

   76 appears 3 times that is maximum than other

   Mode = 76

4. Interquartile Range (IQR):

   Step 1: Sort the data:
   59, 64, 66, 70, 76, 76, 76, 78, 79, 81, 82, 82, 84, 85, 88, 90, 90, 91, 95, 99

   Divide it into 2 halves

Step 2: First half (1st to 10th):
59, 64, 66, 70, 76, 76, 76, 78, 79, 81

Median of the first half:

5th and 6th values: 76 and 76
Q1 = (76 + 76)/2 = 76

Step 3: Second half (11th to 20th):
82, 82, 84, 85, 88, 90, 90, 91, 95, 99

Median of the second half:
5th and 6th values: 88 and 90
Q3 = (88 + 90)/2 = 89

Step 4:
IQR = Q3 − Q1 = 89 − 76 = 13

Interquartile Range (IQR) = 13

Q.2

1) Machine Learning for Kids

Target Audience:

- **School students, generally in middle or high school.**
- **Teachers aiming to introduce AI and ML concepts to young learners.**
- **Beginners with no prior experience in coding.**

Usage:

- **Students provide sample inputs like text, images, or numbers with assigned labels (e.g., happy/sad, dog/cat).**
- **The platform uses this data to create a machine learning model.**
- **Once trained, students can test it by giving new inputs and checking predictions.**
- **They can integrate these models into creative projects using Scratch or Python — such as games that react to emotions or image-based quizzes.**

Advantages:

- **Simple and engaging interface using visual blocks (Scratch) and easy navigation.**
- **Makes learning ML fun, interactive, and suitable for young minds.**
- **Web-based — no software installation required.**

- **Encourages creative thinking and problem-solving skills.**

Limitations:

- **Only useful for understanding basic ML concepts — not fit for advanced ML or data science.**
- **Not ideal for large-scale or professional-grade projects.**
- **Needs continuous internet access to function.**

Type of Analytics:

- **Predictive Analytics:**
  The system learns from past labeled data and forecasts the label for new inputs.
  Example: **Input: "I'm feeling great!" → Output: Happy.**
  This kind of future prediction aligns with predictive analytics.

Type of Learning:

- **Supervised Learning:**
  The user provides labeled training examples (e.g., "I love pizza" = Happy), and the model learns based on these inputs.
  It then uses the learned patterns to predict labels for new, unseen data.

2) Teachable Machine

Target Audience:

- **Students, hobbyists, or beginners eager to build AI-based projects without code.**
- **Educators and presenters who want to show AI applications interactively.**
- **Creators looking to include ML models in games, apps, or websites easily.**

Usage:

- **Users provide labeled data using images, audio, or poses.**
- **The platform builds a machine learning model from these examples.**
- **It allows real-time testing (e.g., using webcam or microphone) and exporting the model for use in external applications like TensorFlow.js or Unity.**

Advantages:

- **Requires no programming — users can train models with a few clicks.**
- **Visually appealing and interactive — good for demonstrations and beginners.**
- **Models can be used in real-world applications or shared across platforms.**
- **Perfect for rapid experimentation.**

Limitations:

- **Limited customization over the training process — algorithms and settings can't be changed.**
- **May perform poorly with too many categories or complex inputs.**
- **Requires hardware like a webcam and internet for full functionality.**

Type of Analytics:

- **Predictive Analytics:**
  It forecasts user actions or inputs based on the training data.
  Example: **A thumbs-up gesture gets recognized as "Like."**
  This ability to classify new input highlights its predictive nature.

Type of Learning:

- **Supervised Learning:**
  Models are trained using labeled data (e.g., "clap" or "wave" gestures).
  The system learns from these examples and uses that learning to make future predictions.

Q.3 Data Visualization: Read the following two short articles:

- Read the article Kakande, Arthur. February 12. "What's in a chart? A Step-by-Step guide to Identifying Misinformation in Data Visualization." *Medium*
- Read the short web page Foley, Katherine Ellen. June 25, 2020. "How bad Covid-19 data visualizations mislead the public." *Quartz*
- Research a current event which highlights the results of misinformation based on data visualization. Explain how the data visualization method failed in presenting accurate information. Use newspaper articles, magazines, online news websites or any other legitimate and valid source to cite this example. Cite the news source that you found.

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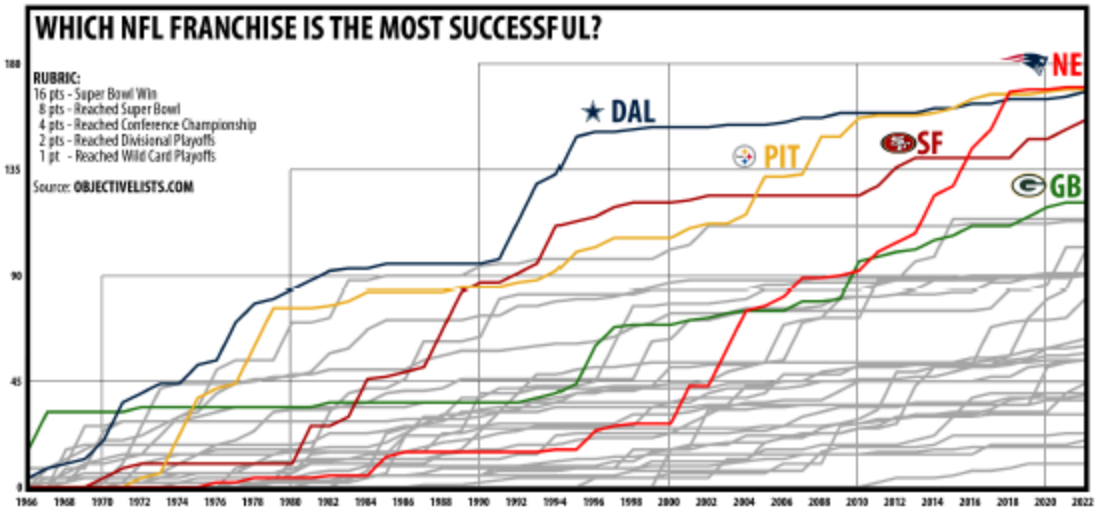

Fig. 8. Contrived metric

Based on the research paper "Misinformative Data Visualizations in the Sports Media Domain" by Drew Scott, I can identify several examples of how data visualizations can mislead readers, specifically in sports media.

One particularly interesting example from the paper is Figure 8, labeled as "Contrived Metric." The author identifies this as a case where a visualization creates a metric without an objective basis, which leads to questionable narratives. This type of misinformation is particularly problematic because it gives the appearance of scientific rigor while actually presenting subjective or arbitrary measurements. The paper categorizes this under "Lie with Statistics" in the Input stage of visualization, and notes that this was one of the most common issues found in their corpus (14 instances).

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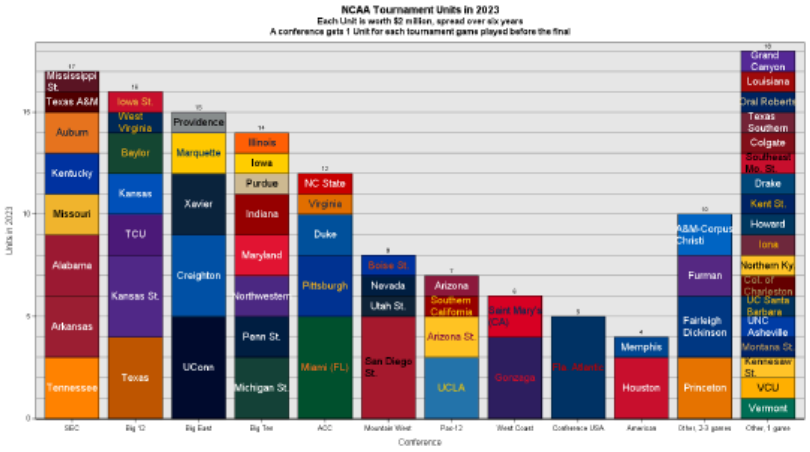

Fig. 3. Stacked bar chart for college basketball conference data

This relates to a current event from March 2023, when ESPN released a "Championship Leverage Index" during the NCAA basketball tournament that purported to show which teams had the most favorable paths to winning. The visualization used a complex formula combining multiple metrics that hadn't been validated, and presented the results as objective analysis. Several sports analysts, including those at The Athletic, criticized the visualization for creating a seemingly scientific metric that actually incorporated significant subjective weighting, leading fans to misunderstand team strengths. The contrived nature of the metric wasn't adequately explained, yet the presentation with precise decimal values and professional graphics gave it an air of authority.

The visualization failed by creating what Scott would categorize as a "Contrived Metric" - a transformation applied to otherwise good data without an apparent or well-explained objective basis. This is particularly misleading because casual viewers typically trust data presented in visual form, especially when it comes from established media outlets. Without proper explanation of methodology or limitations, such visualizations can significantly shape public perception based on questionable analytical foundations.

The paper effectively demonstrates that the sports media domain, despite being considered more "lighthearted" than domains like public health or politics, still exhibits numerous examples of misinformative visualizations that can significantly impact public understanding of the subject matter.

Cite as: Drew Scott. Misinformative Data Visualizations in the Sports Media Domain. *TechRxiv.* April 03, 2024.

DOI: 10.36227/techrxiv.171216651.10279711/v1

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Q. 4 Train Classification Model and visualize the prediction performance of trained model required information

Pima Indians Diabetes Database

Dataset link: https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database

Dataset Description: Pima Indians Diabetes

This dataset contains medical diagnostic information of women of Pima Indian heritage, aged 21 and above. The goal is to predict whether a patient has diabetes based on several health-related measurements.

Feature Descriptions

- **Pregnancies**: Number of times the patient has been pregnant
- **Glucose**: Plasma glucose concentration (mg/dL) after 2 hours in an oral glucose tolerance test
- **BloodPressure**: Diastolic blood pressure (mm Hg)
- **SkinThickness**: Skin fold thickness (mm)
- **Insulin**: 2-Hour serum insulin (mu U/ml)
- **BMI**: Body Mass Index (weight in kg / height in m²)
- **DiabetesPedigreeFunction**: A score showing the likelihood of diabetes based on family history
- **Age**: Age of the patient (in years)
- **Outcome**: Target variable — `0` = No diabetes, `1` = Has diabetes

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Step 1: Data loading

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, ConfusionMatrixDisplay
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from imblearn.over_sampling import SMOTE
import matplotlib.pyplot as plt
import seaborn as sns
```

```
[2] df = pd.read_csv('/content/diabetes.csv')
    df.head()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

Step 2: Data preprocessing:

```
# Features and label
X = df.drop('Outcome', axis=1)
y = df['Outcome']

# Handle missing values in features (replace zeros with NaN where invalid)
cols_with_zero = ['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI']
X[cols_with_zero] = X[cols_with_zero].replace(0, np.nan)

# Fill NaNs with mean values
X = X.fillna(X.mean())

# Feature scaling
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Step 3: Handle Class Imbalance

```
from imblearn.over_sampling import SMOTE

# Apply SMOTE
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X_scaled, y)
```

We used SMOTE (Synthetic Minority Over-sampling Technique) to balance the dataset.
It creates synthetic examples of the minority class by interpolating between existing ones.
This helps prevent the model from being biased toward the majority class during training.

Step 4: Train, Validation and Test Split should be 70/20/10, Train and Test split must be randomly done:

```
# First split (10% test)
X_train_val, X_test, y_train_val, y_test = train_test_split(
    X_resampled, y_resampled, test_size=0.10, random_state=42, stratify=y_resampled)

# Second split (20% of remaining for validation)
X_train, X_val, y_train, y_val = train_test_split(
    X_train_val, y_train_val, test_size=2/9, random_state=42, stratify=y_train_val)

print(f"Train: {X_train.shape}, Validation: {X_val.shape}, Test: {X_test.shape}")
```

```
Train: (700, 8), Validation: (200, 8), Test: (100, 8)
```

Step 5: Train SVM with Hyperparameter Tuning

```
param_grid = {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'rbf'],
    'gamma': ['scale', 'auto']
}

grid = GridSearchCV(SVC(), param_grid, refit=True, cv=5, scoring='accuracy')
grid.fit(X_train, y_train)

print("Best Parameters:", grid.best_params_)
print("Validation Accuracy:", grid.score(X_val, y_val))
```

```
Best Parameters: {'C': 10, 'gamma': 'auto', 'kernel': 'rbf'}
Validation Accuracy: 0.8
```

In this step, we are training an SVM (Support Vector Machine) model to classify the data.
We use GridSearchCV to test different combinations of parameters like C, kernel, and gamma.
It finds the best combination that gives the highest accuracy through cross-validation.
This helps us choose the most effective settings for the SVM model automatically.

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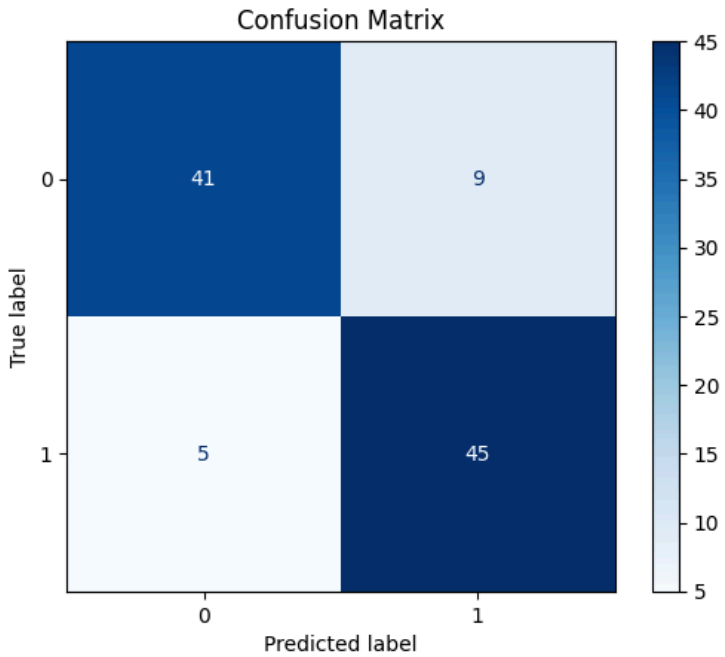
Step 6: Evaluate on Test Data

```
# Best model from GridSearchCV
best_model = grid.best_estimator_
y_pred = best_model.predict(X_test)

# Accuracy
print("Test Accuracy:", accuracy_score(y_test, y_pred))

# Classification report
print("\nClassification Report:\n", classification_report(y_test, y_pred))

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix")
plt.show()
```

```
Test Accuracy: 0.86

Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.82      0.85        50
           1       0.83      0.90      0.87        50

    accuracy                           0.86       100
   macro avg       0.86      0.86      0.86       100
weighted avg       0.86      0.86      0.86       100
```



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Q.5 Train Regression Model and visualize the prediction performance of trained model

Dataset Description:

This dataset is focused on heart disease prediction, where several features (patient demographics, clinical measures, and medical history) are used to predict various health indicators related to the heart. Let's break down the columns:

1. Unnamed: 0:
    - A non-essential index column (likely used for row identification).
2. Age:
    - The age of the patient (numeric).
    - Age plays a significant role in the risk of heart disease.
3. Sex:
    - Gender of the patient (binary: 0 for female, 1 for male).
4. ChestPain:
    - Type of chest pain experienced by the patient (categorical).
    - Values like "typical", "asymptomatic", "nonanginal", and "nontypical" are used to classify the type of chest pain, which can be a symptom of heart disease.
5. RestBP (Resting Blood Pressure):
    - Resting blood pressure (mm Hg).
    - Blood pressure is a key indicator of heart disease risk.
6. Chol (Cholesterol):
    - Serum cholesterol level in mg/dl.
    - High cholesterol is often associated with heart disease.
7. Fbs (Fasting Blood Sugar):
    - Fasting blood sugar (binary: 0 if < 120 mg/dl, 1 if ≥ 120 mg/dl).
    - High fasting blood sugar may indicate a higher risk of heart disease.
8. RestECG (Resting Electrocardiographic Results):
    - Results of the resting electrocardiogram (categorical).
    - Possible values could indicate normal, ST-T wave abnormality, or left ventricular hypertrophy.
9. MaxHR (Maximum Heart Rate):
    - Maximum heart rate achieved during exercise (numeric).
    - A lower maximum heart rate can indicate poor cardiovascular fitness.
10. ExAng (Exercise Induced Angina):
    - Whether or not exercise induced angina (chest pain) occurred (binary: 0 or 1).
    - Induces a measure of the patient's ability to exercise without chest pain.
11. Oldpeak:
    - Depression of the ST segment in the electrocardiogram during exercise (numeric).
    - It's used to evaluate heart ischemia, which indicates potential coronary artery disease.

12. Slope:
    - The slope of the peak exercise ST segment (categorical).
    - This is related to the degree of heart disease, showing if the heart rate response is abnormal during exercise.
13. Ca (Number of Major Vessels Colored by Fluoroscopy):
    - The number of major blood vessels (0 to 3) that have been colored by fluoroscopy during an angiogram (numeric).
    - Used as a measure of coronary artery disease severity.
14. Thal:
    - A blood disorder associated with the heart (categorical).
    - Values like "fixed", "normal", or "reversible" could indicate various stages of the heart disease or the condition of the coronary arteries.
15. AHD (Heart Disease):
    - Whether the patient has heart disease (binary: "Yes" or "No").
    - The target variable for classification, indicating if the patient has a heart condition.

Step 1: Import necessary libraries

```
import pandas as pd
import numpy as np

# Visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns

# For preprocessing and model building (if needed later)
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error

# For linear models (if doing regression on numerical columns like views/downloads/etc.)
from sklearn.linear_model import LinearRegression, Ridge
```

Step 2: Load the dataset

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```
# Step 2: Load the dataset

import pandas as pd

# Load your dataset (update the path if needed)
df = pd.read_csv('/content/Kaggle_Datasets.csv')  # Change filename as per your actual CSV

# Drop index column if present
df.drop(columns=['Unnamed: 0'], errors='ignore', inplace=True)

# Optional: Convert categorical columns to numerical for correlation/EDA
# (Useful columns to encode might be 'medal', 'types_of_files', etc.)
df_encoded = pd.get_dummies(df, drop_first=True)

# Display first few rows
df_encoded.head()
```

Step 3: Define the Linear Regression Model using OOP

```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
import numpy as np

# Step 3: Define the Linear Regression Model using OOP
class LinearModelForTarget:
    def __init__(self, target, top_features):
        self.target = target
        self.features = top_features
        self.model = LinearRegression()

    def train_and_evaluate(self, data):
        x = data[self.features]
        y = data[self.target]

        X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=42)

        self.model.fit(X_train, y_train)
        y_pred = self.model.predict(X_test)

        r2 = r2_score(y_test, y_pred)
        n, p = X_test.shape
        adj_r2 = 1 - (1 - r2) * (n - 1)/(n - p - 1)
        mae = mean_absolute_error(y_test, y_pred)
        rmse = np.sqrt(mean_squared_error(y_test, y_pred))

        print(f"\nMetrics for predicting '{self.target}':")
        print(f"R2 Score: {r2:.4f}")
        print(f"Adjusted R2: {adj_r2:.4f}")
        print(f"MAE: {mae:.4f}")
        print(f"RMSE: {rmse:.4f}")
```

Step 4: Train the model and evaluate the model then plot the predictions:

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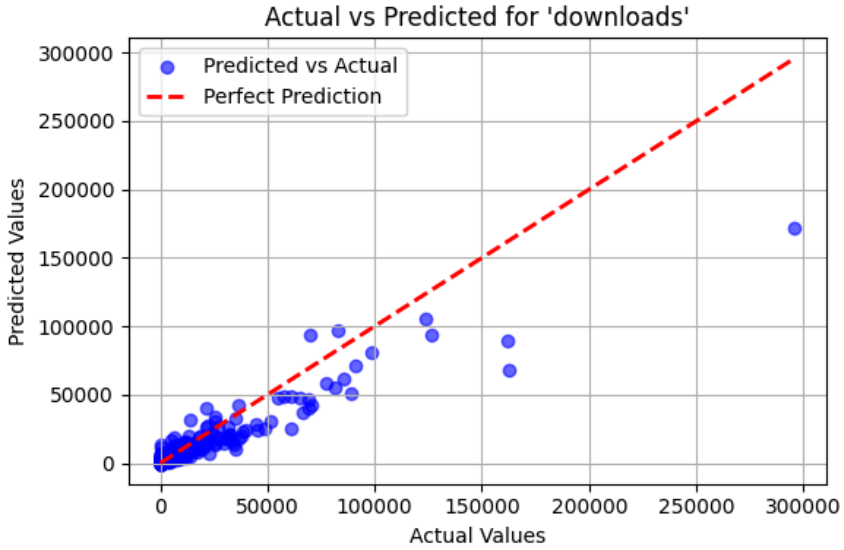
```
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import numpy as np

feature_sets = {
    'downloads': ['views', 'vote_counts', 'usability', 'download_per_view']
}

for target, features in feature_sets.items():
    print(f"\n|| Training model for '{target}' with features: {features}")

    # Handle missing values by dropping rows
    data = df_encoded[features + [target]].dropna()

    # Create and evaluate model
    model = LinearModelForTarget(target, features)
    model.train_and_evaluate(data)

    # Get data for plotting
    X = data[features]
    y = data[target]
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
    y_pred = model.model.predict(X_test)

    # Plot Actual vs Predicted
    plt.figure(figsize=(6, 4))
    plt.scatter(y_test, 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)], 'r--', lw=2, label='Perfect Prediction')
    plt.xlabel("Actual Values")
    plt.ylabel("Predicted Values")
    plt.title(f"Actual vs Predicted for '{target}'")
    plt.legend()
    plt.grid(True)
    plt.tight_layout()
    plt.show()
```

```
|| Training model for 'downloads' with features: ['views', 'vote_counts', 'usability', 'download_per_view']

Metrics for predicting 'downloads':
R2 Score: 0.8286
Adjusted R2: 0.8282
MAE: 1545.2736
RMSE: 5494.1888
```



Q.6 What are the key features of the wine quality data set? Discuss the importance of each feature in predicting the quality of wine? How did you handle missing data in the wine quality data set during the feature engineering process? Discuss the advantages and disadvantages of different imputation techniques.

Dataset: http://kaggle.com/datasets/yasserh/wine-quality-dataset

Key Features of the Wine Quality Dataset

1. Fixed Acidity
   - Represents non-volatile acids like tartaric acid.
   - Importance: Impacts wine's freshness and stability. Too much or too little affects taste.
2. Volatile Acidity
   - Mainly acetic acid (vinegar-like smell).
   - Importance: High levels lead to unpleasant aroma, reducing quality.
3. Citric Acid
   - Found naturally in wine, adds freshness and flavor.
   - Importance: Enhances flavor, contributes to acidity balance.
4. Residual Sugar
   - Sugar left after fermentation.

    - Importance: Affects sweetness; balance is key for quality perception.
5. Chlorides
    - Amount of salt in wine.
    - Importance: High levels negatively affect taste; small amounts may enhance flavor.
6. Free Sulfur Dioxide
    - Prevents microbial growth and oxidation.
    - Importance: Crucial for wine preservation but must be balanced.
7. Total Sulfur Dioxide
    - Includes both free and bound SO_2.
    - Importance: Excess leads to a pungent smell; impacts shelf life and safety.
8. Density
    - Related to sugar and alcohol content.
    - Importance: Indicates fermentation status and body of wine.
9. pH
    - Measures acidity or basicity.
    - Importance: Affects stability, color, and taste.
10. Sulphates
    - Antimicrobial and antioxidant.
    - Importance: Contributes to SO_2 levels; affects preservation and flavor.
11. Alcohol
    - Ethanol content in wine.
    - Importance: Strongly correlated with quality. Higher alcohol often perceived as higher quality.

Handling Missing Data During Feature Engineering

1. Detection:
    - Used df.isnull().sum() in Pandas to check missing values.
2. Imputation Techniques Used:
    - Numerical columns (e.g., alcohol, pH):
        - Used mean or median imputation depending on skewness.
        - For example:
          df['alcohol'].fillna(df['alcohol'].mean(), inplace=True)

1. Mean Imputation

Advantages:

- Simple and fast to implement.
- Maintains dataset size.
  Works well with symmetric, normally distributed data.

Disadvantages:

- Affected by outliers.
- Reduces data variability.
- Can introduce bias in skewed distributions.

2. Median Imputation

Advantages:

- Robust to outliers.
- Better suited for skewed data.
- Preserves central tendency better than mean for non-normal data.

Disadvantages:

- Still doesn't account for correlation between features.
- Less effective for normally distributed data.

3. Mode Imputation (for categorical or discrete data)

Advantages:

- Simple to apply.
- Maintains most frequent category.

Disadvantages:

- Not suitable for continuous data.
- Can cause overrepresentation of the mode.

4. Dropping Missing Rows

Advantages:

- Very simple to apply.
- Avoids introducing potential bias from imputation.

Disadvantages:

- Leads to data loss.
- Not suitable if many rows have missing values.
- May reduce model performance due to smaller training set.