Video Game Sales Prediction - Machine Learning Lab

Introduction and Setup

Welcome to this machine learning lab where we'll build a model to predict whether a video game will be a "hit" based on its characteristics and sales data. This notebook will guide you through the entire process, from data loading to model evaluation and optimization.

Learning objectives:

1. Learn to preprocess and explore a real-world dataset
2. Build and evaluate a decision tree classifier
3. Optimize a model through hyperparameter tuning
4. Interpret model results and feature importance

```
#install libraries if necessary

# Import the necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Machine learning libraries
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, RocCurveDisplay

```

```
# Set random seed for reproducibility
np.random.seed(42)
```

```
# Configure visualizations
plt.style.use('seaborn-v0_8-whitegrid')
sns.set_palette("colorblind")
```

```
# Display settings for better output
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 1000)
```

Download the Dataset

```
# You can run this cell to download the dataset directly, or upload it manually!
import requests

url = 'https://www.kaggle.com/datasets/gregorut/videogamesales/download'
response = requests.get(url)

with open('videogamesales.zip', 'wb') as f:
    f.write(response.content)

print("Dataset downloaded successfully.")

```

```
Dataset downloaded successfully.
```

Load the Dataset

```
# Load the dataset
df = pd.read_csv('vgsales.csv')
```

```
# Let's take a look at the first few rows of the dataset
print("First 5 rows of the dataset:")
print(df.head())
```

```
First 5 rows of the dataset:
   Rank                      Name Platform    Year         Genre Publisher  NA_Sales  EU_Sales  JP_Sales  Other_Sales  Global_Sales
0     1                Wii Sports      Wii  2006.0        Sports  Nintendo     41.49     29.02      3.77         8.46         82.74
1     2          Super Mario Bros.      NES  1985.0      Platform  Nintendo     29.08      3.58      6.81         0.77         40.24
2     3             Mario Kart Wii      Wii  2008.0        Racing  Nintendo     15.85     12.88      3.79         3.31         35.82
3     4          Wii Sports Resort      Wii  2009.0        Sports  Nintendo     15.75     11.01      3.28         2.96         33.00
4     5  Pokemon Red/Pokemon Blue       GB  1996.0  Role-Playing  Nintendo     11.27      8.89     10.22         1.00         31.37
```

Dataset Information

```
# Get basic information about the dataset
print("\nDataset basic information:")
print(df.info())

# Get descriptive statistics
print("\nDescriptive statistics:")
print(df.describe())
```

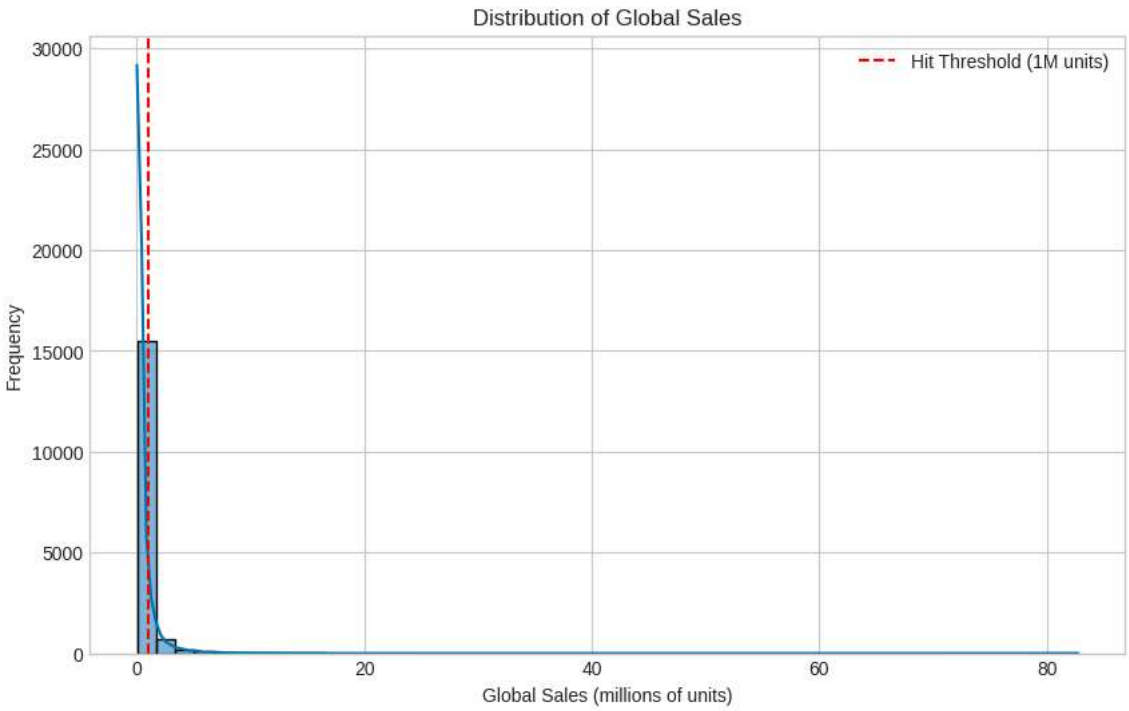
```
Dataset basic information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16598 entries, 0 to 16597
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Rank          16598 non-null  int64
 1   Name          16598 non-null  object
 2   Platform      16598 non-null  object
 3   Year          16327 non-null  float64
 4   Genre         16598 non-null  object
 5   Publisher     16540 non-null  object
 6   NA_Sales      16598 non-null  float64
 7   EU_Sales      16598 non-null  float64
 8   JP_Sales      16598 non-null  float64
 9   Other_Sales   16598 non-null  float64
 10  Global_Sales  16598 non-null  float64
dtypes: float64(6), int64(1), object(4)
memory usage: 1.4+ MB
None

Descriptive statistics:
               Rank          Year      NA_Sales      EU_Sales      JP_Sales   Other_Sales  Global_Sales
count  16598.000000  16327.000000  16598.000000  16598.000000  16598.000000  16598.000000  16598.000000
mean    8300.605254   2006.406443      0.264667      0.146652      0.077782      0.048063      0.537441
std     4791.853933      5.828981      0.816683      0.505351      0.309291      0.188588      1.555028
min        1.000000   1980.000000      0.000000      0.000000      0.000000      0.000000      0.010000
25%     4151.250000   2003.000000      0.000000      0.000000      0.000000      0.000000      0.060000
50%     8300.500000   2007.000000      0.080000      0.020000      0.000000      0.010000      0.170000
75%    12449.750000   2010.000000      0.240000      0.110000      0.040000      0.040000      0.470000
max    16600.000000   2020.000000     41.490000     29.020000     10.220000     10.570000     82.740000
```

```
# Cell 5:Check for missing values
print("\nMissing values per column:")
print(df.isnull().sum())
```

```
Missing values per column:
Rank              0
Name              0
Platform          0
Year            271
Genre             0
Publisher        58
NA_Sales          0
EU_Sales          0
JP_Sales          0
Other_Sales       0
Global_Sales      0
dtype: int64
```

```
# Cell 6: Data Visualization - Global Sales Distribution
# ======================================================
# Visualize the distribution of global sales
```

```
# Visualize the distribution of global sales
plt.figure(figsize=(10, 6))
sns.histplot(df['Global_Sales'], bins=50, kde=True)
plt.title('Distribution of Global Sales')
plt.xlabel('Global Sales (millions of units)')
plt.ylabel('Frequency')
plt.axvline(x=1, color='red', linestyle='--', label='Hit Threshold (1M units)')
plt.legend()
plt.show()
```



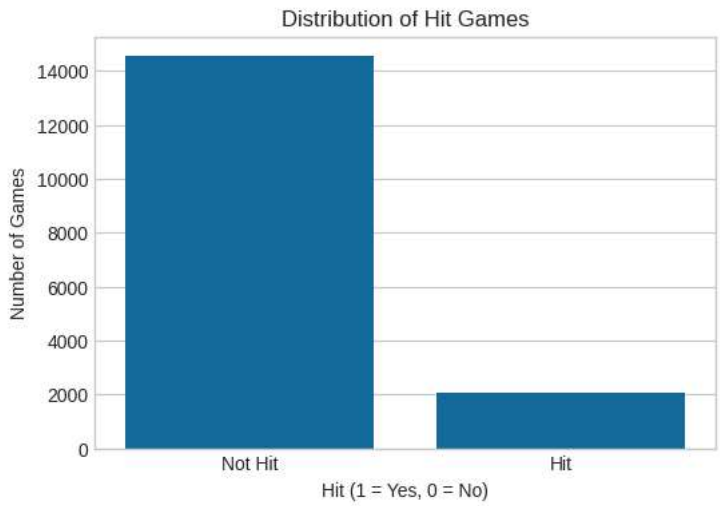

```
# Cell 7: Create Target Variable
# ============================
# TASK: Create a binary target variable for "hit" games
# A game is considered a hit if it sold more than 1 million units (Global_Sales > 1)
# YOUR CODE HERE

df['Hit'] = (df['Global_Sales'] > 1).astype(int)

df[['Name', 'Global_Sales', 'Hit']].head()

```

	Name	Global_Sales	Hit
0	Wii Sports	82.74	1
1	Super Mario Bros.	40.24	1
2	Mario Kart Wii	35.82	1
3	Wii Sports Resort	33.00	1
4	Pokemon Red/Pokemon Blue	31.37	1

```
# Cell 8: Analyze Target Distribution
# ================================
# Let's see the proportion of hits in our dataset
# YOUR CODE HERE

hit_counts = df['Hit'].value_counts()
hit_proportion = df['Hit'].value_counts(normalize=True)

print("Hit Counts:\n", hit_counts)
print("\nHit Proportion:\n", hit_proportion)

plt.figure(figsize=(6, 4))
sns.barplot(x=hit_counts.index, y=hit_counts.values)
plt.title('Distribution of Hit Games')
```

```
plt.xlabel('Hit (1 = Yes, 0 = No)')
plt.ylabel('Number of Games')
plt.xticks([0, 1], ['Not Hit', 'Hit'])
plt.show()
```

```
Hit Counts:
 Hit
0    14544
1     2054
Name: count, dtype: int64

Hit Proportion:
 Hit
0    0.87625
1    0.12375
Name: proportion, dtype: float64
```




```
# Cell 9: Drop Non-Informative Columns
# ==================================
# TASK: Drop non-informative columns
# Think about which columns won't help with prediction
# YOUR CODE HERE

# Drop columns that won’t help with prediction
df.drop(columns=['Rank', 'Name'], inplace=True)

# Preview updated dataframe
df.head()
```

	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales	Hit
0	Wii	2006.0	Sports	Nintendo	41.49	29.02	3.77	8.46	82.74	1
1	NES	1985.0	Platform	Nintendo	29.08	3.58	6.81	0.77	40.24	1
2	Wii	2008.0	Racing	Nintendo	15.85	12.88	3.79	3.31	35.82	1
3	Wii	2009.0	Sports	Nintendo	15.75	11.01	3.28	2.96	33.00	1
4	GB	1996.0	Role-Playing	Nintendo	11.27	8.89	10.22	1.00	31.37	1

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
# Cell 10: Missing Value Analysis
# ============================
# Examine the 'Year' column which might have missing values

# Check for missing values in the 'Year' column
missing_year_count = df['Year'].isnull().sum()
missing_year_percentage = (missing_year_count / len(df)) * 100

print(f"Missing 'Year' values: {missing_year_count}")
print(f"Percentage missing: {missing_year_percentage:.2f}%")
```

```
Missing 'Year' values: 271
Percentage missing: 1.63%
```

```python
# Cell 11: Handle Missing Values
# ============================
# TASK: Handle missing values
# Option 1: Drop rows with missing values
# YOUR CODE HERE

# Option 2: Fill missing values with median or mean
# YOUR CODE HERE
# df_clean['Year'] = df_clean['Year'].fillna(df_clean['Year'].median())

# Option 1: Drop rows with missing values
# df_drop = df.dropna(subset=['Year'])

# Option 2: Fill missing values with the median year
df_fill = df.copy()
df_fill['Year'] = df_fill['Year'].fillna(df_fill['Year'].median())

df_clean = df_fill

df_clean[['Year']].isnull().sum()

```

	0
Year	0

dtype: int64

```python
# Cell 12: Categorical Variable Analysis
# ==================================
# Let's identify categorical columns
categorical_columns = df_clean.select_dtypes(include=['object']).columns.tolist()
print("\nCategorical columns:", categorical_columns)
```

```
Categorical columns: ['Platform', 'Genre', 'Publisher']
```

```python
# Cell 13: Encode Categorical Variables
# ==================================
# TASK: Encode categorical variables using LabelEncoder
# Label Encoder transforms categorical variables into numerical ones
# YOUR CODE HERE

from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

for col in ['Platform', 'Genre', 'Publisher']:
    df_clean[col] = le.fit_transform(df_clean[col].astype(str))  # Convert to string in case of NaNs

df_clean[['Platform', 'Genre', 'Publisher']].head()

```

	Platform	Genre	Publisher
0	26	10	359
1	11	4	359
2	26	6	359
3	26	10	359
4	5	7	359

```python
# Cell 14: Feature Engineering (Optional)
# ====================================
# BONUS TASK: Feature Engineering
# Creating new features might improve model performance
# Example: Total regional sales besides global
```

```
# YOUR CODE HERE

df_clean['Total_Regional_Sales'] = df_clean['NA_Sales'] + df_clean['EU_Sales'] + df_clean['JP_Sales'] + df_clean['Other_Sales']

df_clean[['Total_Regional_Sales', 'Global_Sales']].head()

```

	Total_Regional_Sales	Global_Sales
0	82.74	82.74
1	40.24	40.24
2	35.83	35.82
3	33.00	33.00
4	31.38	31.37

```
# Cell 15: Explore Processed Dataset
# ================================
# Let's look at the processed dataset
# YOUR CODE HERE


print("Shape of dataset:", df_clean.shape)
print("\nData types:\n", df_clean.dtypes)
print("\nFirst 5 rows:\n", df_clean.head())
print("\nSummary statistics:\n", df_clean.describe())

```

```
Shape of dataset: (16598, 11)

Data types:
 Platform                  int64
Year                    float64
Genre                     int64
Publisher                 int64
NA_Sales                float64
EU_Sales                float64
JP_Sales                float64
Other_Sales             float64
Global_Sales            float64
Hit                       int64
Total_Regional_Sales    float64
dtype: object

First 5 rows:
    Platform    Year  Genre  Publisher  NA_Sales  EU_Sales  JP_Sales  Other_Sales  Global_Sales  Hit  Total_Regional_Sales
0        26  2006.0     10        359     41.49     29.02      3.77         8.46         82.74    1                 82.74
1        11  1985.0      4        359     29.08      3.58      6.81         0.77         40.24    1                 40.24
2        26  2008.0      6        359     15.85     12.88      3.79         3.31         35.82    1                 35.83
3        26  2009.0     10        359     15.75     11.01      3.28         2.96         33.00    1                 33.00
4         5  1996.0      7        359     11.27      8.89     10.22         1.00         31.37    1                 31.38

Summary statistics:
            Platform          Year         Genre     Publisher      NA_Sales      EU_Sales      JP_Sales   Other_Sales  Global_Sales
count  16598.000000  16598.000000  16598.000000  16598.000000  16598.000000  16598.000000  16598.000000  16598.000000  16598.000000  165
mean      15.797988   2006.416134      4.928124    294.599169      0.264667      0.146652      0.077782      0.048063      0.537441
std        8.392298      5.781686      3.762015    178.082372      0.816683      0.505351      0.309291      0.188588      1.555028
min        0.000000   1980.000000      0.000000      0.000000      0.000000      0.000000      0.000000      0.000000      0.010000
25%        7.000000   2003.000000      1.000000    137.000000      0.000000      0.000000      0.000000      0.000000      0.060000
50%       16.000000   2007.000000      5.000000    323.000000      0.080000      0.020000      0.000000      0.010000      0.170000
75%       21.000000   2010.000000      8.000000    461.000000      0.240000      0.110000      0.040000      0.040000      0.470000
max       30.000000   2020.000000     11.000000    578.000000     41.490000     29.020000     10.220000     10.570000     82.740000
```

```
# Cell 16: Split Features and Target
# ================================
# TASK: Split the data into features (X) and target (y)
# YOUR CODE HERE

X = df_clean.drop(columns=['Hit'])  # Features
y = df_clean['Hit']                 # Target

```

```
# Cell 17: Train-Test Split
# =======================
# TASK: Split the data into training and testing sets (80/20 split)
```

```python

# X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Print the shapes to confirm the split

from sklearn.model_selection import train_test_split

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

print("Training features shape:", X_train.shape)
print("Testing features shape:", X_test.shape)
print("Training target shape:", y_train.shape)
print("Testing target shape:", y_test.shape)

```

```
Training features shape: (13278, 10)
Testing features shape: (3320, 10)
Training target shape: (13278,)
Testing target shape: (3320,)
```

```python
# Cell 18: Train Initial Model
# ==========================
# TASK: Train a Decision Tree classifier with default parameters
# YOUR CODE HERE

from sklearn.tree import DecisionTreeClassifier

clf = DecisionTreeClassifier(random_state=42)
clf.fit(X_train, y_train)

```

```
DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

```python
# Cell 19: Make Predictions
# =======================
# TASK: Make predictions on the test set
# YOUR CODE HERE
                            # Probability of being a hit

y_pred = clf.predict(X_test)

y_proba = clf.predict_proba(X_test)[:, 1]  # Extract probability for class 1 (hit)
```

```python
# Cell 20: Calculate Evaluation Metrics
# ==================================
# TASK: Calculate evaluation metrics
# YOUR CODE HERE


from sklearn.metrics import accuracy_score, precision_score, recall_score,
f1_score, roc_auc_score

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, zero_division=0)
recall = recall_score(y_test, y_pred, zero_division=0)
f1 = f1_score(y_test, y_pred, zero_division=0)
roc_auc = roc_auc_score(y_test, y_proba)

print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1 Score: {f1:.4f}")
print(f"ROC AUC Score: {roc_auc:.4f}")

```

```
Accuracy: 1.0000
Precision: 1.0000
Recall: 1.0000
F1 Score: 1.0000
ROC AUC Score: 1.0000
```

```python
# Cell 21: Confusion Matrix Visualization
```

```
# ===================================
# TASK: Visualize the confusion matrix
# YOUR CODE HERE

from sklearn.metrics import ConfusionMatrixDisplay

ConfusionMatrixDisplay.from_estimator(clf, X_test, y_test, display_labels=['Not Hit', 'Hit'], cmap='Blues')
plt.title('Confusion Matrix')
plt.show()

```