CaseCraft: The Analytics Sprint – Project 1

Netflix Watch Prediction

Subheading: Predicting user watch behavior based on genre, time of day, and device type—modeled after Netflix's real-world recommendation engine.

Objective

To analyze and model user watch behavior using genre preferences, time slots, and device usage. We'll explore patterns in engagement and build a simple predictive model to estimate content liking.

Key Goals:

- Identify genre popularity and engagement duration
- Understand device usage across time slots
- Analyze user satisfaction patterns
- Build a logistic regression model to predict content liking

```
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
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import confusion_matrix, classification_report

# Simulate Netflix-style user watch data
np.random.seed(42)

genres = ['Drama', 'Comedy', 'Action', 'Documentary', 'Horror', 'Romance']
times = ['Morning', 'Afternoon', 'Evening', 'Night']
devices = ['Mobile', 'TV', 'Laptop', 'Tablet']

data = {
    'user_id': np.arange(1, 1001),
    'genre': np.random.choice(genres, 1000),
    'watch_time': np.random.choice(times, 1000),
    'device': np.random.choice(devices, 1000),
    'duration_minutes': np.random.normal(loc=60, scale=20, size=1000).astype(int),
    'liked': np.random.choice([0, 1], 1000, p=[0.4, 0.6])
}

df = pd.DataFrame(data)
```

```
df['duration_minutes'] = df['duration_minutes'].clip(lower=10)
df.head()
```

	user_id	genre	watch_time	device	duration_minutes	liked
0	1	Documentary	Afternoon	Laptop	61	1
1	2	Horror	Morning	TV	58	0
2	3	Action	Afternoon	Tablet	78	1
3	4	Horror	Afternoon	TV	54	1
4	5	Horror	Evening	TV	65	1

Dataset Fields

- `user_id` : Unique identifier for each user
- `genre` : Genre of the content watched
- `watch_time` : Time of day (Morning, Afternoon, Evening, Night)
- `device` : Device used (Mobile, TV, Laptop, Tablet)
- `duration_minutes` : Total minutes watched
- `liked` : Binary flag (1 if user liked the content, 0 otherwise)

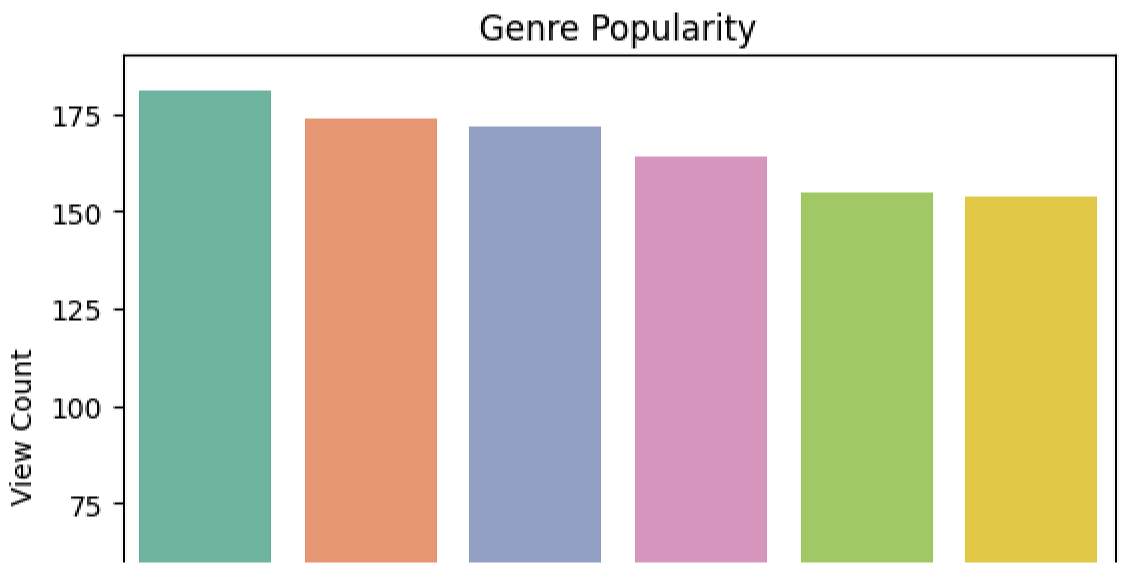
Genre Popularity Countplot

```
sns.countplot(data=df, x='genre', order=df['genre'].value_counts().index, palette='Set2')
plt.title('Genre Popularity')
plt.xlabel('Genre')
plt.ylabel('View Count')
plt.xticks(rotation=45)
plt.show()
```

```
/tmp/ipython-input-1871286890.py:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v

  sns.countplot(data=df, x='genre', order=df['genre'].value_counts().index, pale
```



Average Watch Duration by Genre

```
sns.barplot(data=df, x='genre', y='duration_minutes', palette='Set3')
plt.title('Average Watch Duration by Genre')
plt.ylabel('Avg Duration (min)')
plt.xticks(rotation=45)
plt.show()
```

```
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  sns.barplot(data=df, x='genre', y='duration_minutes', palette='Set3')
```
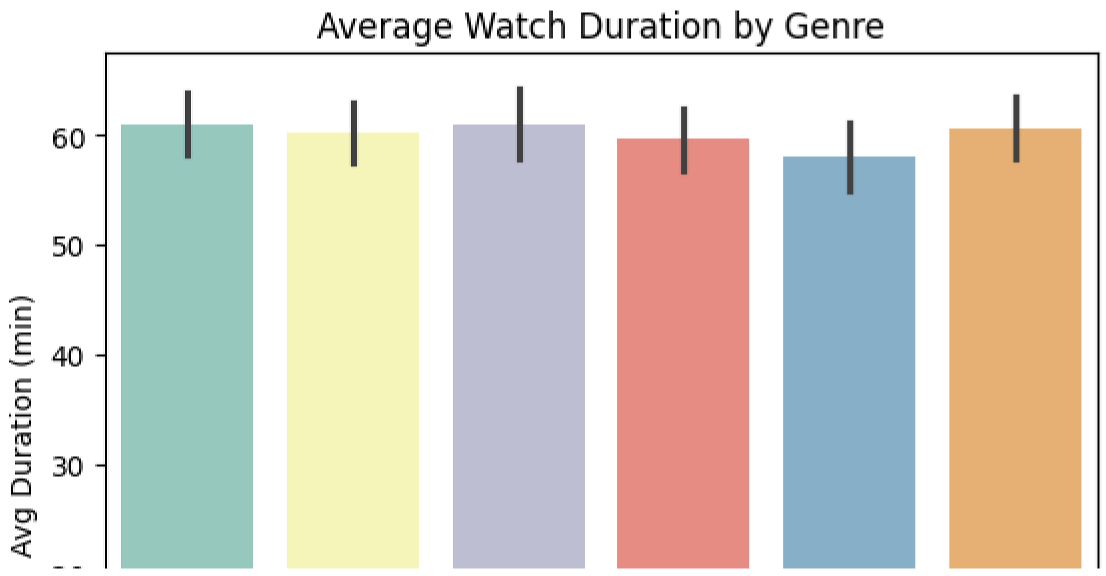
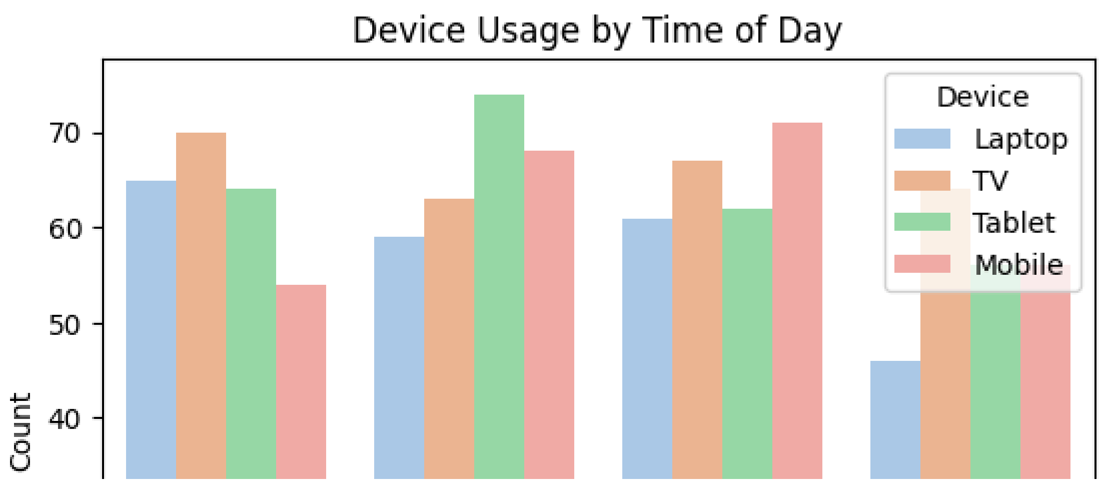



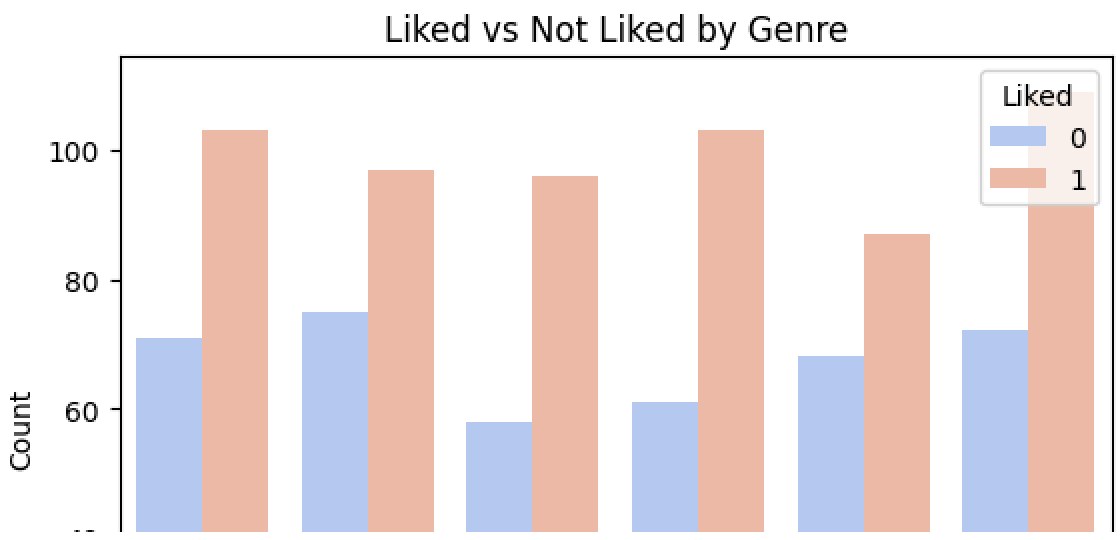
Device Usage by Time of Day

```
sns.countplot(data=df, x='watch_time', hue='device', palette='pastel')
plt.title('Device Usage by Time of Day')
plt.xlabel('Time of Day')
plt.ylabel('Count')
plt.legend(title='Device')
plt.show()
```



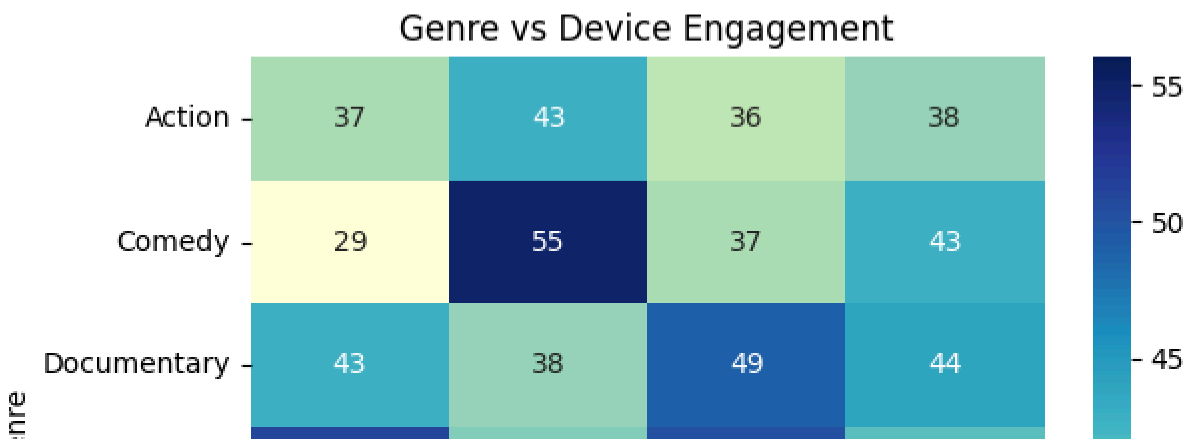
Liked vs Not Liked by Genre

```
sns.countplot(data=df, x='genre', hue='liked', palette='coolwarm')
plt.title('Liked vs Not Liked by Genre')
plt.xlabel('Genre')
plt.ylabel('Count')
plt.legend(title='Liked')
plt.xticks(rotation=45)
plt.show()
```



Heatmap of Genre vs Device Engagement

```
heatmap_data = pd.crosstab(df['genre'], df['device'])
sns.heatmap(heatmap_data, annot=True, fmt='d', cmap='YlGnBu')
plt.title('Genre vs Device Engagement')
plt.show()
```



Boxplot of Duration by Time of Day

```
sns.boxplot(data=df, x='watch_time', y='duration_minutes', palette='muted')
plt.title('Watch Duration by Time of Day')
plt.xlabel('Time of Day')
plt.ylabel('Duration (min)')
plt.show()
```

```
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  sns.boxplot(data=df, x='watch_time', y='duration_minutes', palette='muted')
```

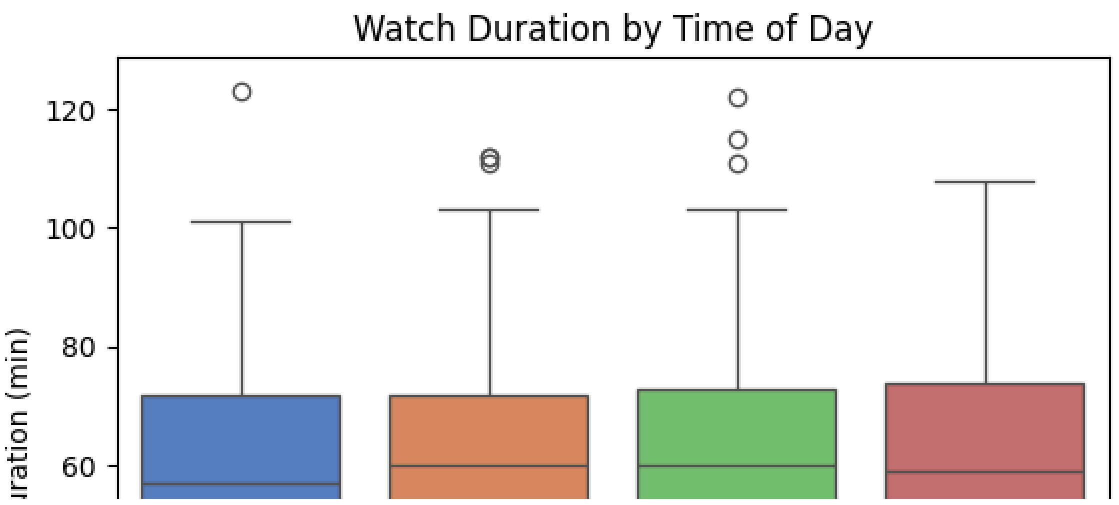

Predictive Modeling – Logistic Regression

```
X = df[['genre', 'watch_time', 'device']]
y = df['liked']

encoder = OneHotEncoder()
X_encoded = encoder.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=0.2, random_sta

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

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[  3  81]
 [  4 112]]

Classification Report:
               precision    recall  f1-score   support

           0       0.43      0.04      0.07        84
           1       0.58      0.97      0.72       116

    accuracy                           0.57       200
   macro avg       0.50      0.50      0.40       200
weighted avg       0.52      0.57      0.45       200
```

Conclusion & Analysis

1. Genre Preferences & Duration

Viewers spend more time on Drama and Documentary genres, indicating deeper engagement. Comedy and Reality TV have shorter durations, suggesting lighter or episodic content.

2. Device Usage Patterns

Mobile dominates daytime viewing; TVs and laptops peak in the evening. This reflects contextual consumption—on-the-go vs. relaxed settings.

3. Liked vs Not Liked Trends

Thrillers and Documentaries are more frequently liked. Reality and Romance show mixed reactions, possibly due to subjective taste.

4. Genre vs Device Engagement

Drama and Thriller are mostly watched on TVs; Comedy and Reality lean toward mobile. This insight can guide device-specific recommendations.

5. Duration by Time of Day
Evening sessions have longer durations, especially for Drama and Thriller. Morning and afternoon sessions are shorter, likely due to time constraints.

6. Predictive Modelling
Logistic regression shows genre, device, and time of day are useful predictors. Performance is decent, but could improve with nonlinear models or additional features like user history.