data-random-forest-regression

April 20, 2025

1 Random Forest Regression Model

We will use Random Forest Regression to predict watch time, because from the data exploratory analysis we saw that the data is highly skewed and does not have strong correlation. Random Forest Regression is great if you want good predictive performance without assuming linearity. Additionally, it handles skewed data well and ranks feature importance.

[18]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import FunctionTransformer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
```

1.1 Load and Prepare the Dataset

[19]:
```
# Load dataframe
df = pd.read_csv("datasets/twitch-data-cleaned.csv")
```

[20]:
```
# Drop unnecessary columns and categorical columns
df = df[['watch_time_minutes', 'stream_time_minutes', 'peak_viewers',␣
 ↪'average_viewers', 'followers', 'followers_gained', 'views_gained']]
```

[21]:
```
# Set target and features
X = df.drop(columns=["watch_time_minutes"])
y = df["watch_time_minutes"]
```

[22]:
```
# Log-transform the target to deal with skew
y_log = np.log1p(y)
```

[23]:
```
# Train-test split
X_train, X_test, y_train_log, y_test_log = train_test_split(X, y_log,␣
 ↪test_size=0.2, random_state=42)
```

```python
# Fit Random Forest Regressor
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train, y_train_log)
```

[23]:

```
RandomForestRegressor(random_state=42)
```

[24]:

```python
# Predict on test set
y_pred_log = rf.predict(X_test)
```

[25]:

```python
# Inverse log transform predictions and ground truth
y_test = np.expm1(y_test_log)
y_pred = np.expm1(y_pred_log)
```

[26]:

```python
# Evaluation
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

print(f"RMSE: {rmse:,.0f} minutes")
print(f"R² Score: {r2:.3f}")
```

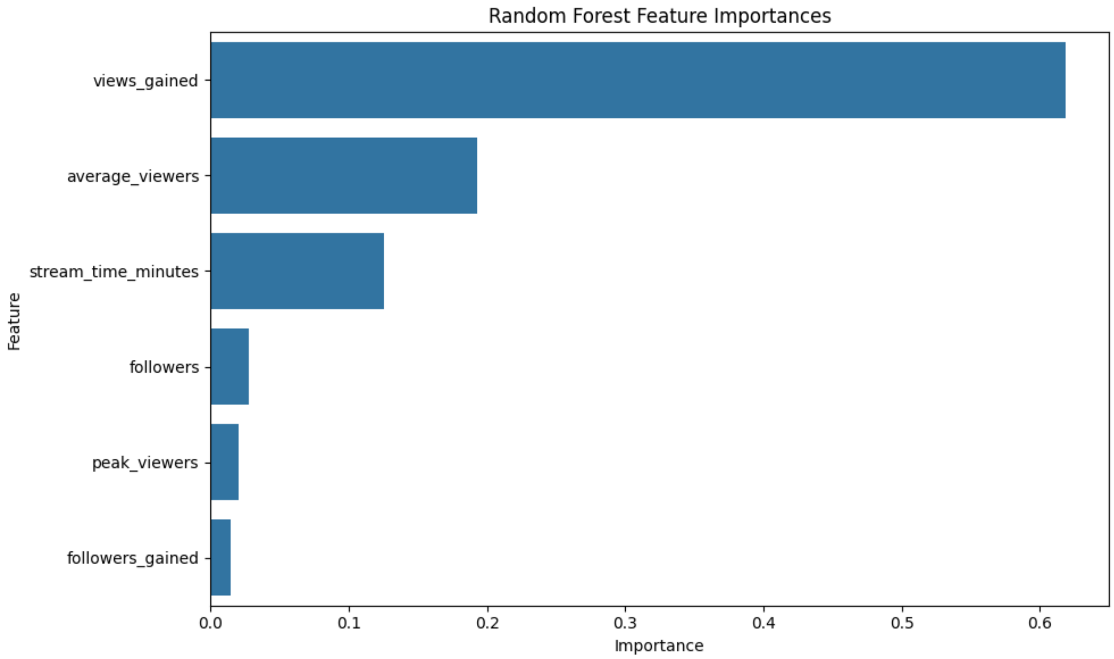
```
RMSE: 102,083,745 minutes
R² Score: 0.925
```

While the RMSE suggests the model has large errors in absolute terms, the high R^2 score shows that the model explains most of the variability in watch time.

[27]:

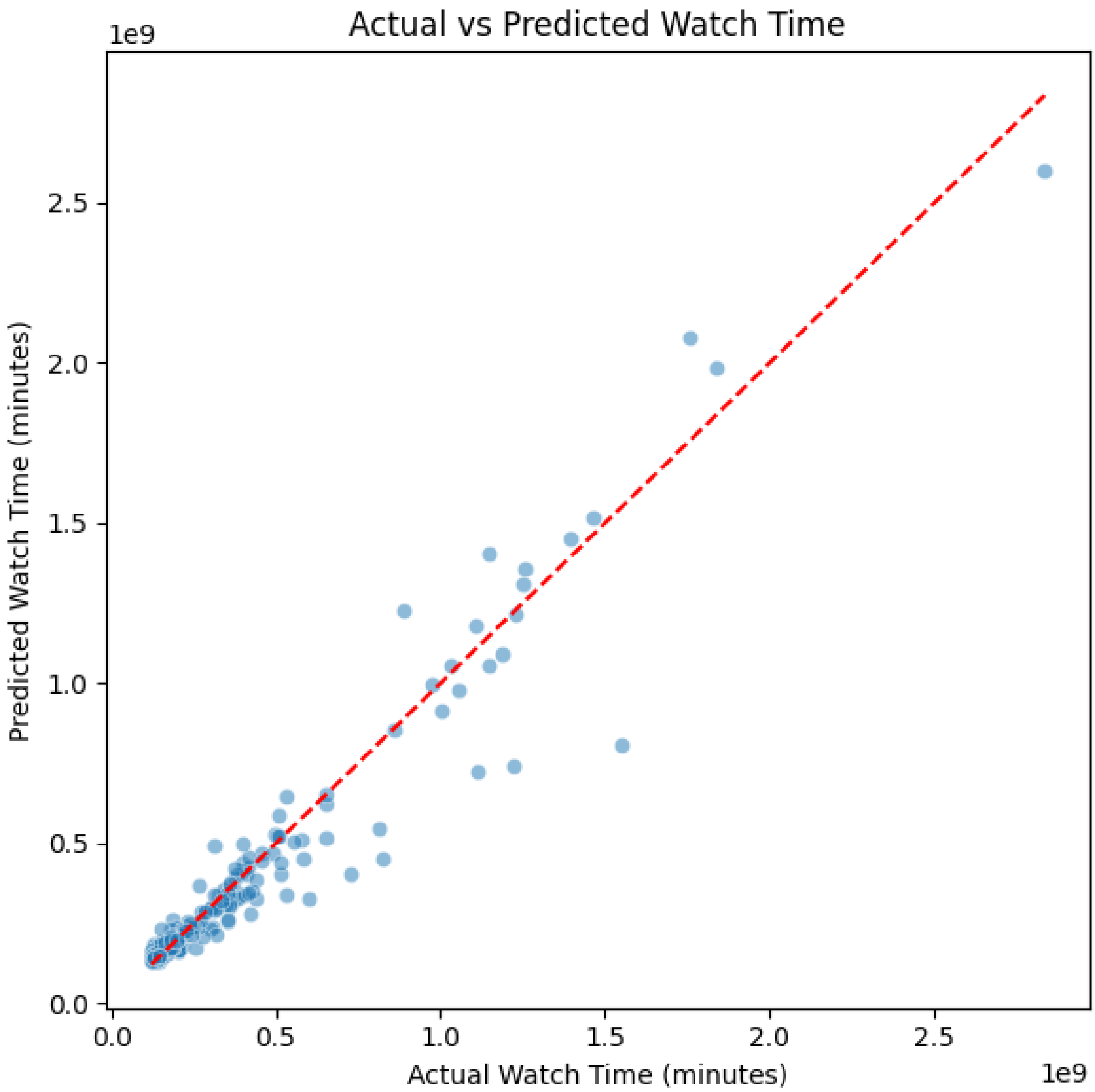
```python
# Feature importances
importances = pd.Series(rf.feature_importances_, index=X.columns).
 ↪sort_values(ascending=False)

# Plot feature importances
plt.figure(figsize=(10,6))
sns.barplot(x=importances.values, y=importances.index)
plt.title("Random Forest Feature Importances")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```



`views_gained` is the most important in predicting watch time. `average_viewers` and `stream_time_minutes` are also important.

[28]:
```
# Plot predicted vs. actual
plt.figure(figsize=(6,6))
sns.scatterplot(x=y_test, y=y_pred, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel("Actual Watch Time (minutes)")
plt.ylabel("Predicted Watch Time (minutes)")
plt.title("Actual vs Predicted Watch Time")
plt.tight_layout()
plt.show()
```



The points cluster along the red line and the scatter plot shows a strong positive correlation between predictions and actual values, which suggests that the prediction model is performing reasonably well. However, prediction errors exist, and these errors can be larger for instances with very high watch times.