# Playtime Matters: Analyzing Steam Games DSA210 Project Presentation

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# **Project Overview**

• **Objective:** Investigate how game genres, prices, playtime lengths, and popularity are related on Steam.

#### Datasets:

- Steam dataset (Kaggle): Game details (genres, prices, estimated owners).
- HowLongToBeat (HLTB) dataset: Completion times for games.
- Goal: Analyze the influence of playtime on popularity and identify trends in genres and pricing.
- Hypothesis:
  - H0: No significant relationship between playtime and popularity.
  - H1: Longer playtime increases popularity.

## **Data Preparation**

 Merging Datasets: Combined Steam and HLTB datasets using game names, resulting in merged\_data.csv.

#### • Cleaning:

- Removed unnecessary columns (e.g., appid, developer).
- Renamed steamspy\_tags to genres.

#### • Time Formatting:

- Converted Steam playtime (minutes to hours).
- Rounded HLTB time columns for consistency.

## Handling Missing Values:

- Dropped columns with 50% missing data (e.g., main\_story, completionist).
- Removed rows with missing time values (12,089 to 6,271 rows).
- Final Dataset: Saved as clean\_merged\_data.csv with 12 columns (e.g., name, genres, positive\_ratings, average\_completion\_time).



# Hypothesis Testing

- Test: Pearson correlation between average\_completion\_time and positive\_ratings.
- Results:
  - Correlation: 0.165 (weak positive relationship).
  - P-value: 9.86e-40 (0.05, statistically significant).
- **Conclusion:** Rejected H0, accepted H1. Longer playtime slightly increases popularity, but the effect is weak, suggesting other factors may be more influential.

# Visualizations: Playtime and Popularity

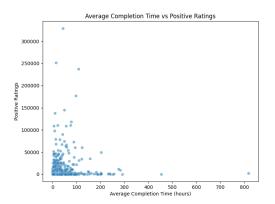


Figure: Scatter Plot: Average Completion Time vs Positive Ratings

- Scatter Plot (Completion Time vs Positive Ratings):
  - Shows a weak positive trend (correlation coefficient: 0.165).
  - Most games cluster below 200 hours with ratings under 50,000.

# Visualizations: Playtime and Popularity

- Scatter Plot (Completion Time vs Positive Ratings) Detailed Analysis:
  - The weak positive trend (correlation coefficient: 0.165) indicates that longer playtime is associated with slightly higher positive ratings, though the relationship is not strong.
  - Most games cluster below 200 hours with ratings under 50,000, suggesting that the majority of Steam games have moderate playtimes and popularity.
  - Outliers with higher ratings (up to 300,000) for longer playtimes (up to 800 hours) may represent content-rich games (e.g., MMORPGs or strategy titles), appealing to niche audiences.
  - The sparse data points beyond 200 hours imply that very long games are rare, and their popularity might depend on factors like genre or community engagement beyond playtime alone.

# Visualizations: Average Completion Time by Genre

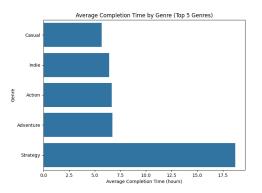


Figure: Bar Chart: Average Completion Time by Genre (Top 5 Genres)

## Bar Chart (Average Completion Time by Genre):

- Strategy: 18.5 hours (longest).
- Casual: 5 hours (shortest).
- Action, Indie, Adventure: 5.5–7 hours.

# Visualizations: Average Completion Time by Genre

- Bar Chart (Average Completion Time by Genre) Detailed Analysis:
  - Strategy games take 18.5 hours on average, reflecting their complex mechanics and deep strategic elements.
  - Casual games, averaging 5 hours, are designed for quick and accessible play sessions.
  - Action, Indie, and Adventure genres (5.5–7 hours) balance challenge and accessibility, appealing to a broader audience.
  - The significant gap between Strategy and Casual highlights how genre design (depth vs simplicity) influences playtime.
  - This suggests players prefer shorter sessions for casual gaming, while strategy titles cater to longer, more engaged play.

# Visualizations: Average Ownership by Genre

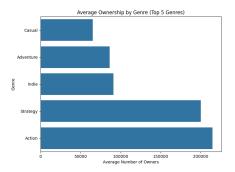


Figure: Bar Chart: Average Ownership by Genre (Top 5 Genres)

- Bar Chart (Average Ownership by Genre):
  - (Approximate Numbers)
  - Action: 200,000 owners (most popular).
  - Casual: 50,000 owners (least popular).
  - Strategy, Indie, Adventure: 175,000, 100,000, 75,000 owners.

## Visualizations: Average Ownership by Genre

#### Bar Chart (Average Ownership by Genre) - Detailed Analysis:

- Action games lead with 200,000 owners, likely due to their fast-paced gameplay and wide appeal.
- Casual games, with only 50,000 owners, target a niche market seeking quick entertainment.
- Strategy, Indie, and Adventure genres (175,000, 100,000, 75,000 owners) show varying market penetration, possibly due to marketing differences.
- Action games' dominance suggests dynamic gameplay drives ownership, while Indie games' lower numbers may reflect limited visibility.
- This distribution underscores the importance of genre-specific marketing to boost ownership numbers.

# Machine Learning: Setup and Decision Tree

## Data Preparation:

- Loaded clean\_merged\_data.csv.
- Converted genres to numerical (one-hot encoding).
- Normalized owners to owners\_numeric.

#### Decision Tree Model:

- Train-test split (80%-20%, random\_state=42).
- Trained a Decision Tree Regressor (max\_depth=10).
- Results:  $R^2 = 0.574$ , RMSE = 15,416.

## Machine Learning: Decision Tree Results

#### **Feature Importance:**

- owners\_numeric: 0.642.
- average\_completion\_time: 0.195.

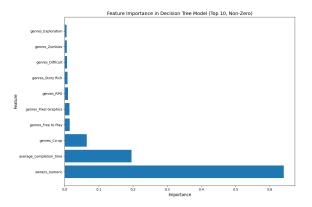
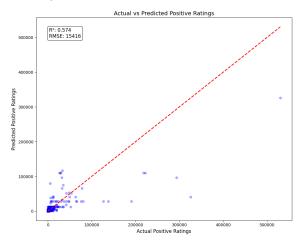


Figure: Feature Importance

## Machine Learning: Decision Tree Results

#### • Actual vs Predicted Plot:

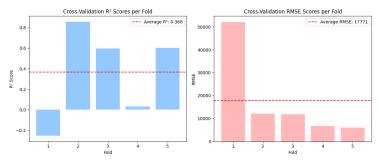
• Good performance for low ratings, struggles with high ratings (>400,000).



## Machine Learning: Decision Tree Results

## Cross-Validation (5-Fold):

- Average R<sup>2</sup>: 0.368, RMSE: 17,770.
- High variability (std dev R<sup>2</sup>: 0.412, RMSE: 17,355).
- Indicates potential overfitting.



## Machine Learning: Random Forest

#### Random Forest Model:

- Same train-test split as Decision Tree.
- Trained a Random Forest Regressor (n\_estimators=100, max\_depth=10).
- Results:  $R^2 = 0.564$ , RMSE = 15,595.

#### • Actual vs Predicted Plot:

Similar to Decision Tree, struggles with high ratings.

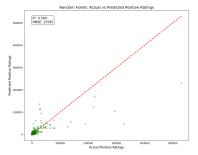


Figure: Random Forest: Actual vs Predicted Positive Ratings



## Machine Learning: Random Forest Cross-Validation

#### Cross-Validation (5-Fold):

- Average R<sup>2</sup>: 0.479, RMSE: 16,119.
- Lower variability (std dev R<sup>2</sup>: 0.132, RMSE: 11,286).
- Better generalization than Decision Tree.

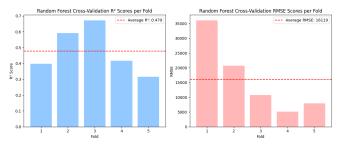


Figure: Random Forest Cross-Validation Scores

## Conclusion

#### Summary:

- Playtime has a weak positive effect on popularity (correlation: 0.165).
- Strategy games have the longest playtime (17.5 hours), Action games the highest ownership (200,000).
- Decision Tree: R<sup>2</sup> = 0.574 (train-test), 0.368 (cross-validation).
- Random Forest: R<sup>2</sup> = 0.564 (train-test), 0.479 (cross-validation).

#### Model Comparison:

- Random Forest outperforms Decision Tree in cross-validation (R<sup>2</sup>: 0.479 vs 0.368, RMSE: 16,119 vs 17,770).
- Random Forest shows better generalization (lower variability).

## • Future Improvements:

- Hyperparameter tuning (e.g., max\_depth, n\_estimators).
- Collecting more data or engineering new features.



## Future Improvements and Limitations

#### Limitations:

- High missing data: Reduced dataset from 12,089 to 6,271 rows after dropping rows/columns with >50% missing values (e.g., main\_story, completionist).
- Imbalanced data: Most games under 200 hours and 50,000 ratings, affecting model performance on outliers.
- Missing external factors: Marketing, updates, and community effects not captured in the dataset.
- Limited data scope: Only Steam and HLTB datasets used, potentially missing broader trends.
- Model performance: High variance in Decision Tree ( $R^2$ : 0.368, std dev: 0.412) indicates overfitting.

## Future Improvements and Limitations

#### • Future Improvements:

- Collect more data: Include broader datasets (e.g., other platforms) and reduce missing values.
- Feature engineering: Add external factors like marketing spend, update frequency, or community metrics.
- Advanced modeling: Explore deep learning or hybrid models for better prediction.
- Address imbalance: Use techniques like SMOTE or weighted loss functions for imbalanced data.

## Thank You and Note

Thank you for reviewing this presentation!

Note: For detailed information, including datasets, code, and additional analysis, please refer to the .md files in my GitHub repository: https://github.com/esraesen/DSA210-Spring2025-Project.