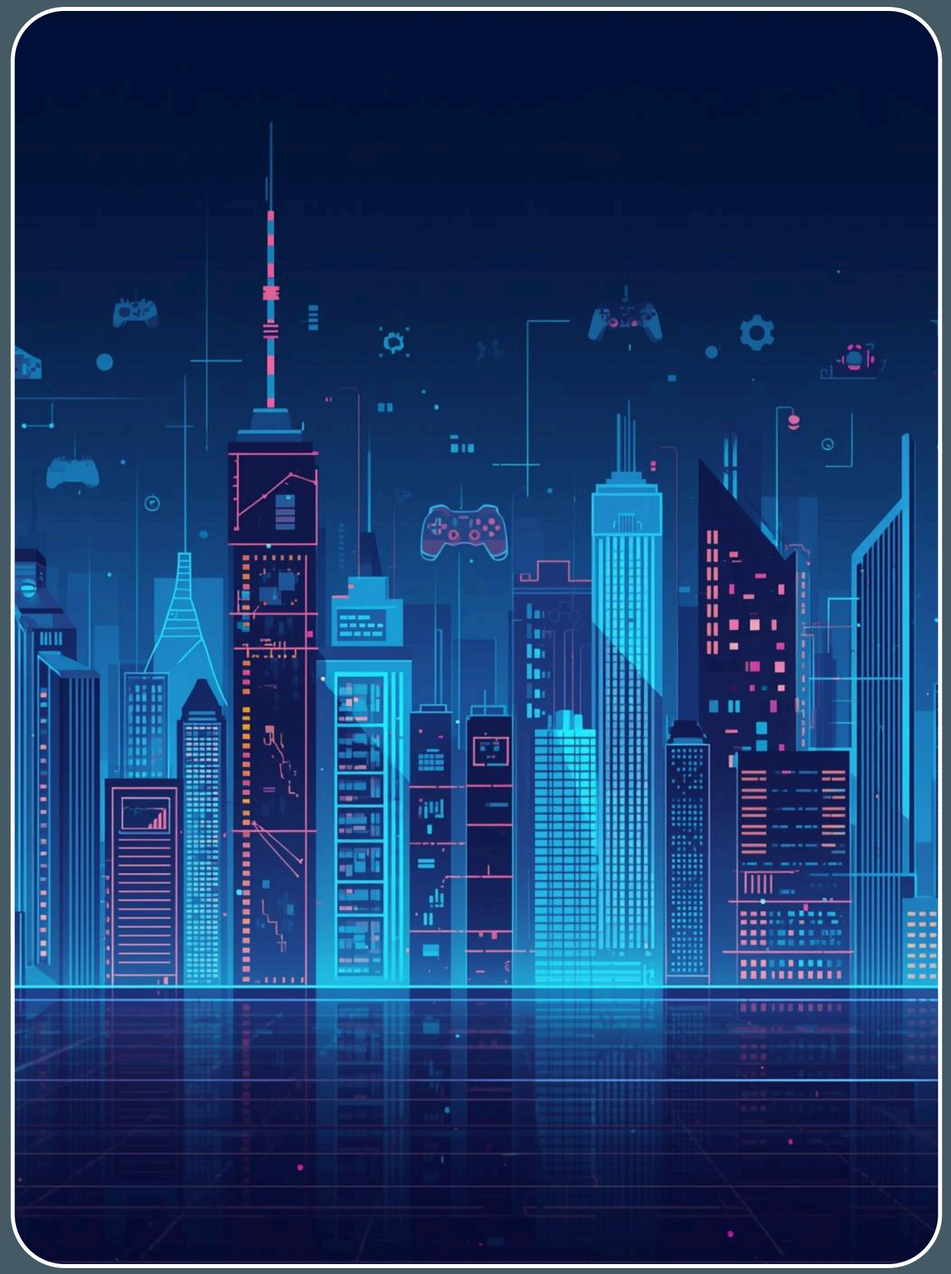


Video Game Analytics & Prediction

Insights From Steam, RAWG, and VGSales (2000-2020)

Sinan Disi | DSCI510 Final Project

Introduction:

Goal: Analyze two decades of video game data (2000–2020) to identify the features that influence positive player feedback and apply a Ridge regression model to quantify their impact

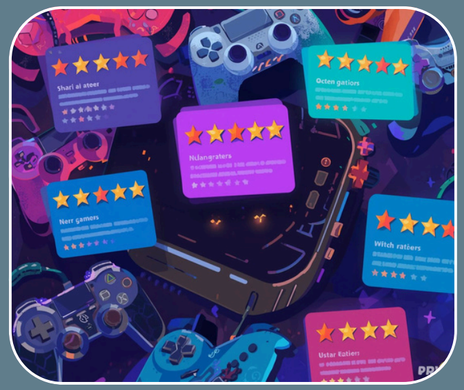
Objective #1: Investigate ratings by platforms and genre

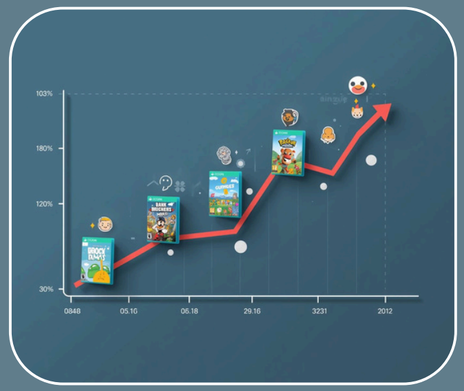
Objective #2: Examine whether game price or feedback volume effect positivity

Objective #3: Identify years with high positivity (rating)

Objective #4: Link feedback patterns to global sales

Objective #5: Build a Ridge regularized linear regression model to predict positive ratings





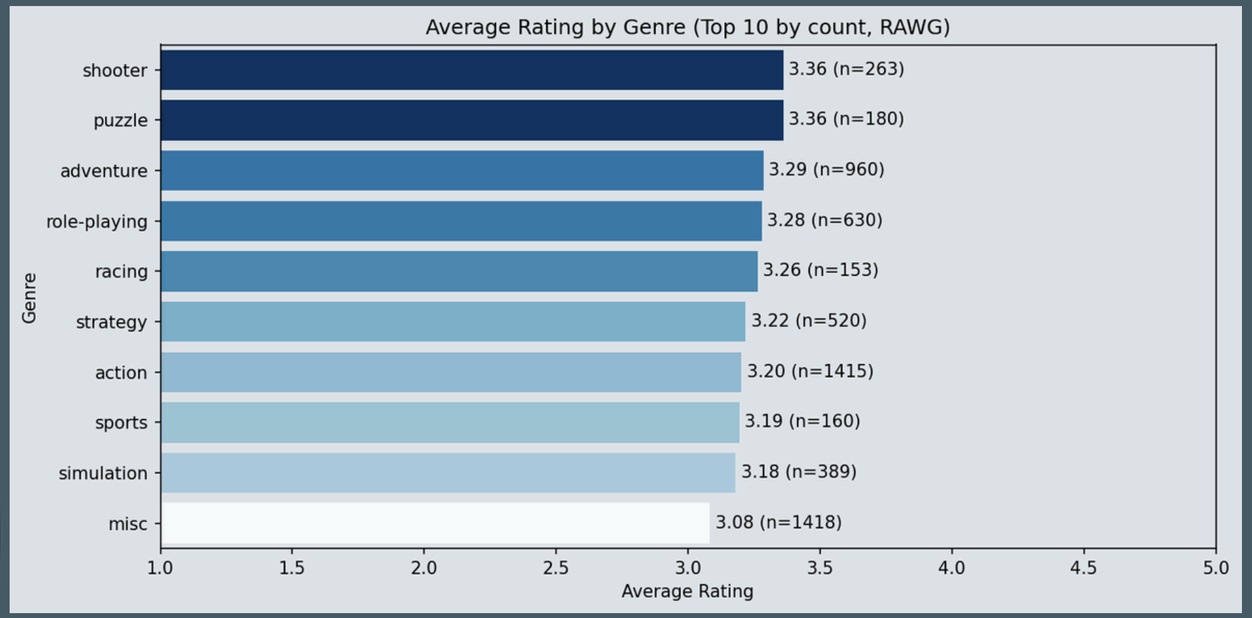
Data Sources

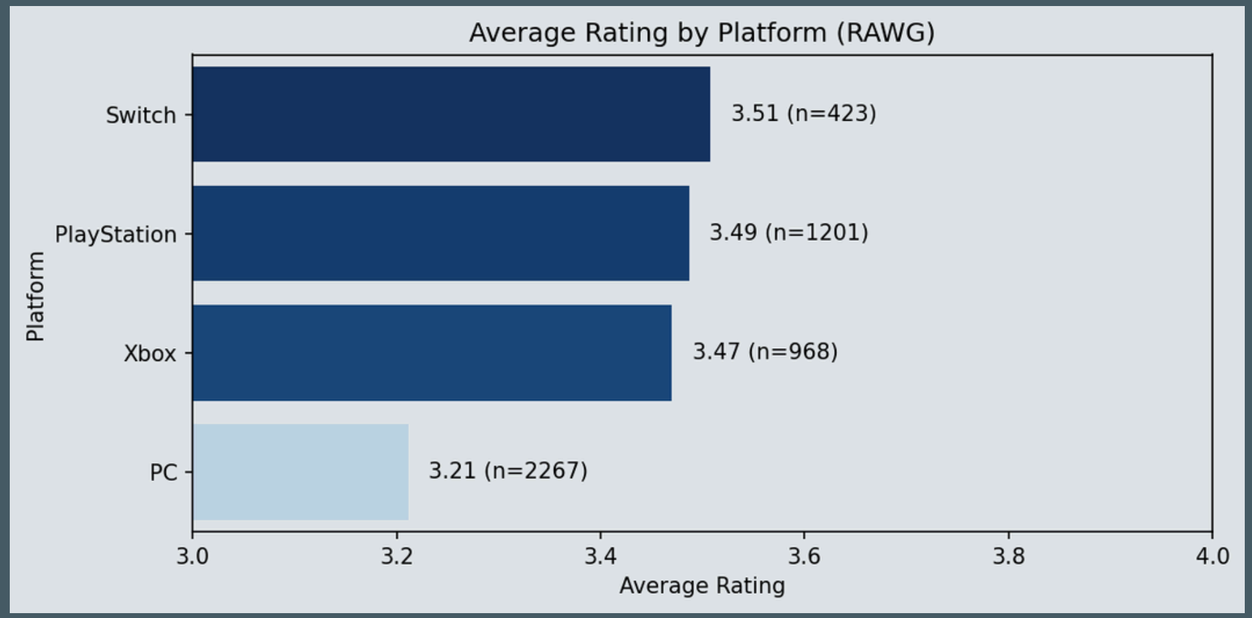
#	Name / Short Description	List of fields	Type	Format	Raw Data Size
1	**Steam Games Dataset (Kaggle)**	name, release_date, price, positive_ratings, negative_ratings, genres, median_play_time, owners	API Call	CSV	27,075
2	**RAWG Video Games Database**	name, released date, rating, genres, platforms	API Call	JSON --> CSV	10,000
3	**Video Game Sales Dataset (Kaggle)**	Global_Sales, Genre, Name, Platform, Year_of_Release, Platform	API Call	CSV	16,587

Approach: Collected data via APIs into CSV files, then cleaned and filtered all datasets (2000–2020) by removing non-gaming titles and entries with missing key fields. Consolidated and standardized platforms and genres, and performed binning and bucketing to analyze game feedback volume and price.

Objective #1

How Platform and Genre Influence Game Rating



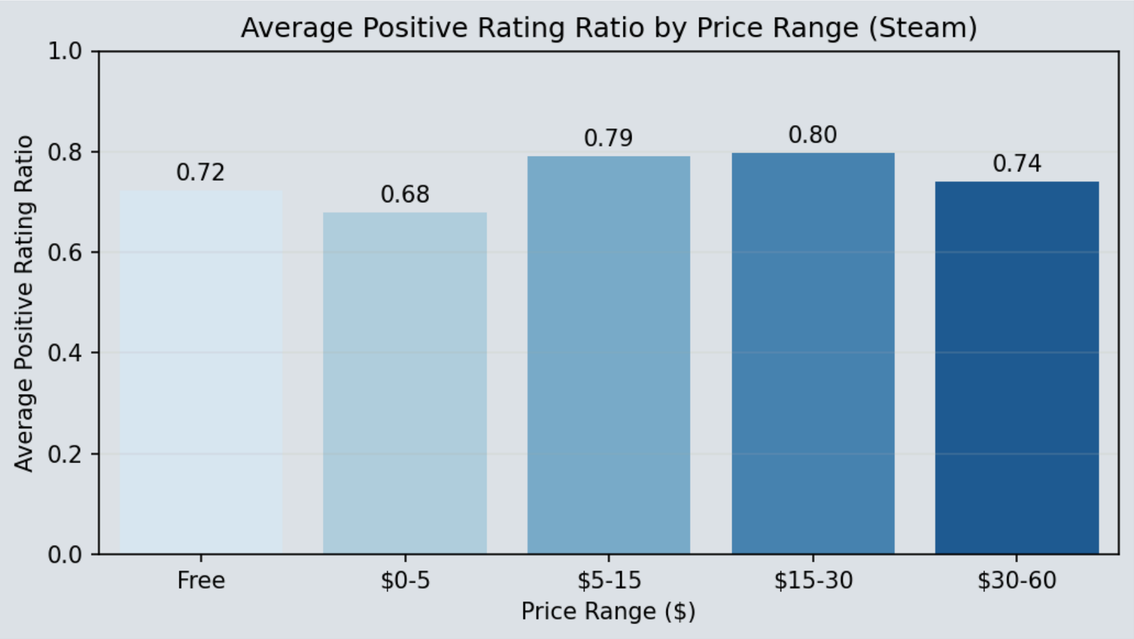


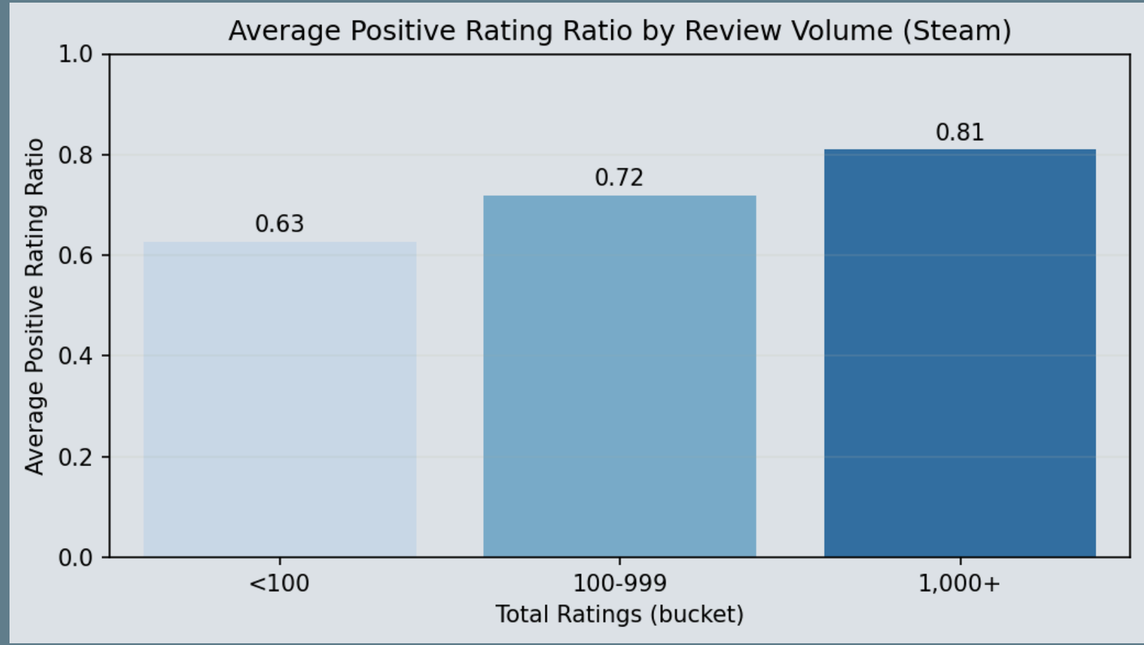
- Shooter & Puzzle genres rate the highest.
- Simulation and Misc have the lowest genre ratings.

- PC has the lowest platform ratings.
- Switch, PlayStation, and Xbox have similar ratings

Objective #2

How Rating Volume and Price Affect Feedback Positivity





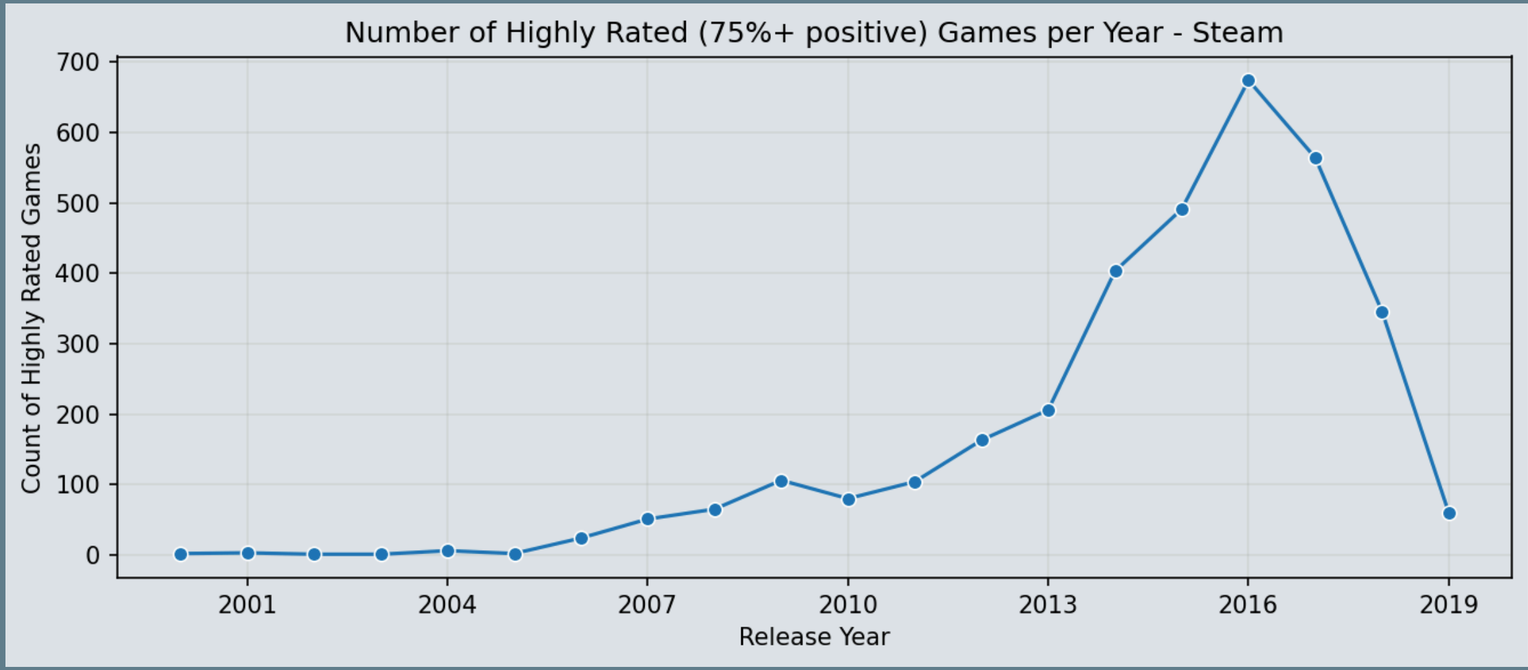
- Free games are not rated the highest
- Mid-priced games ($5–30) have the best positivity
- Very cheap games ($0–5) have the lowest positivity

- Note: Correlation between price and average positive rating ratio: 0.189 (n=6,073)

- Games with more reviews tend to have higher positivity
- Titles with 1,000+ reviews show the strongest positive feedback

Objective #3

How Release Timing Influences Positive Ratings

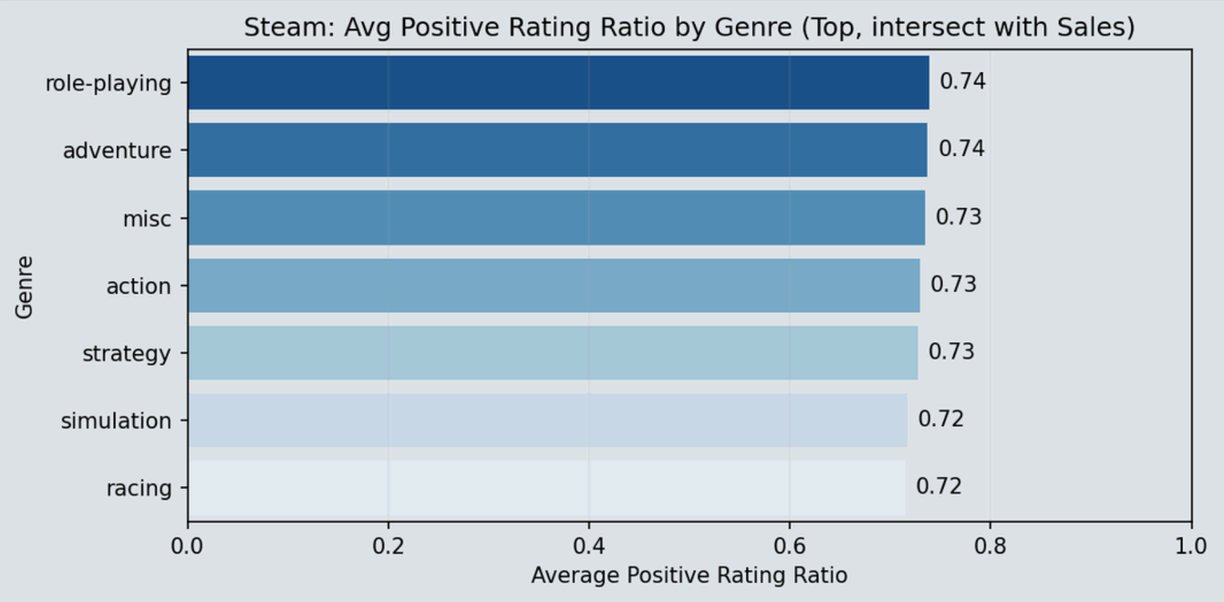


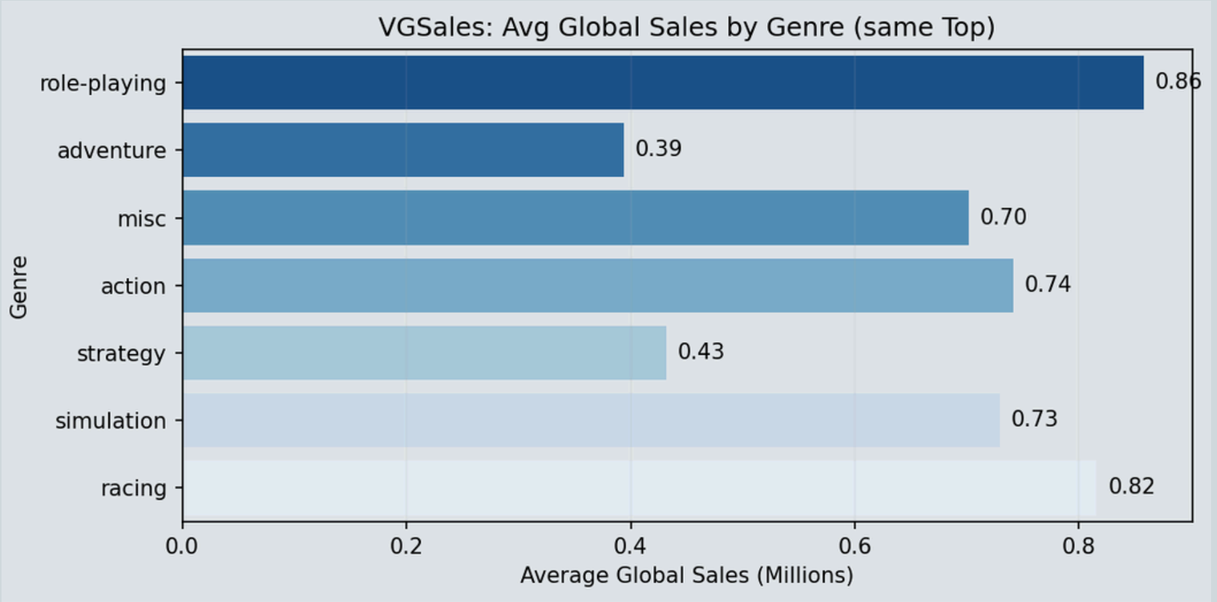
- Only games with 75%+ positive ratings
- The volume of highly rated games stays low between 2000-2007
- It rises gradually between 2008-2012
- The peak is in 2016

Note: Steam's massive expansion between 2012-2016 aligns with the volume of highly rated games. The decline after 2016 may indicate a market plateau.

Objective #4

How Global Sales Relate to Positive Ratings



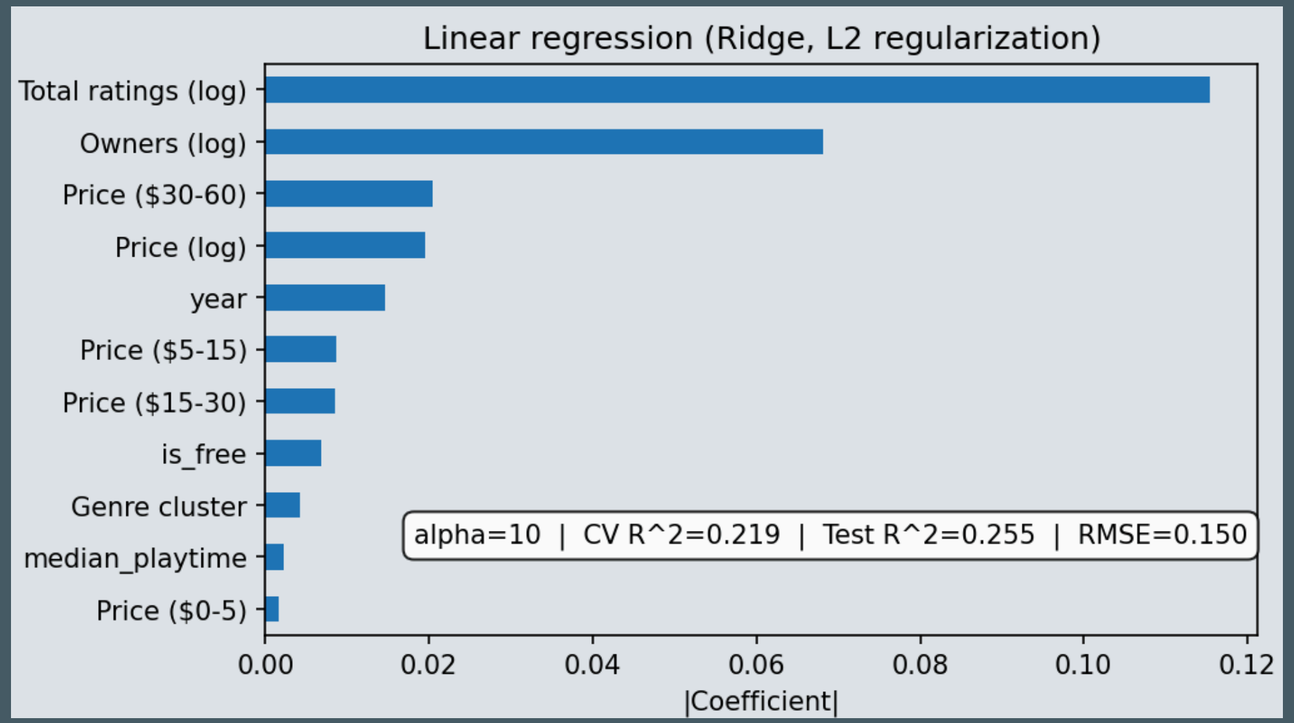


- Genres with similar positive rating ratios (≈0.72–0.74) show very different global sales outcomes
- RPG titles achieve high average global sales, while Adventure titles remain much lower despite similar ratings
- Overall relationship is weak and slightly negative (corr ≈ –0.32)
- Conclusion: High player ratings do not necessarily translate into higher global sales

Objective #5

Ridge regularized linear regression model

- Model tuning: A Ridge penalty of α = 10 was selected via 5-fold cross-validation, achieving a balanced level of L2 regularization that keeps coefficients in check and limits overfitting
- Cross-validation fit: CV R^2 ≈ 0.22 indicates the model explains about 22% of the variance in positive feedback % on unseen folds, indicating a genuine yet modest signal
- Test performance: Test R^2 ≈ 0.26 is close to the CV value, suggesting stable and limited overfitting to the training data
- Error scale: RMSE ≈ 0.15 on a target in [0, 1] implies that the model is usually off by about 0.15, which adds some noise
- Total ratings and owners are the most influential features; playtime or genre had minimal influence



- Note #1: Ridge handles connected features and keeps the model stable.
- Note #2: L2 keeps all inputs, just softens their influence.
- Note #3: Standardization puts features on the same scale for evaluation.

Challenges

- Cleaning and filtering large datasets
- Managing missing or low-quality Steam data (many games with 0 playtime or no feedback)
- Modeling a noisy target variable (positive rating ratio)
- Applying log scaling and building game-price bins and feedback-volume buckets to stabilize skewness
- Handling inconsistent genre labels: standardized genres (canonical labels → 12 unified labels → consolidated to 5 clusters for the prediction model).
  Note: Steam and VGSales only had 8 overlapping genres, so cross-dataset analysis was limited to that

Thank You!