STEAM COPIES SOLD PREDICTION (CS)

Team:23

Name	University ID
عبدالرحمن تامر محمد عبدالفتاح نجم	2022170230
محمد طارق	2022170617
حسام عبدالرحمن محمد عبدالتواب	2022170557
مصطفى محمد مصطفى ابراهيم الشرقاوي	2022170426
هادي أحمد عثمان عطية الكفراوي	2022170480
يوسف احمد محمد على	2022170506

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Introduction to Our Approach

In our approach, we avoided fetching data from external APIs. Instead, we focused on applying statistical techniques to extract meaningful insights from the dataset itself. By using random sampling, we aimed to design our analysis based on real-world data behavior rather than relying on external sources. We used this approach to simulate real-world AI modeling scenarios, where access to the Steam API is not always available.

Data Preprocessing Techniques

2.1 Cleaning and correcting data type

We began by exploring the dataset. During this process, we found that the `appId` field was stored as a string. Additionally, we noticed a duplicate row containing column headers, which we promptly removed.

Next, we ensured that all columns were correctly formatted according to their expected data types:

- **`info_base_steam_games` table:**
  - Converted the `release_date` column to **Date** format.
  - Any date written in terms of a **quarter** or **month** was reformatted properly. For quarterly entries, we selected the **middle month** of the quarter and used the **first day** of that month as the release date.
  - We also found games with release dates listed as **"Coming Soon"** or **"To Be Announced"**, even though they had reported copies sold. After manually checking these entries on Steam, we confirmed that most had already been released—many in **March 2025**. Therefore, we standardized these entries by setting their release date to **March 1, 2025**.
  - Converted the `appid` column to **Integer**.
- **`gamalytic_steam_games` table:**
  - Converted the `steamId` column to **Integer**.
- **`dlcs` table:**
  - Converted the `base_appid` column to **Integer**.
- **`demos` table:**
  - Converted the `full_game_appid` column to **Integer**.

2.2 Merging

After cleaning and formatting the data, we proceeded with merging the tables. Before merging, we ensured that the ID fields in all relevant tables were correctly formatted to avoid unnecessary complications or misinterpretation of statistics.

Our merging strategy was as follows:

- We first performed an **inner join** between the `info_base_steam_games` table and the `gamalytic_steam_games` table.
    - This was done because:
        - `gamalytic_steam_games` contains our **target variable (Y)**.
        - `info_base_steam_games` includes our **main features**.
    - An inner join ensures we only keep the records that exist in both tables, which are essential for building our model.
- Next, we performed **left joins** with the `dlcs` and `demos` tables.
    - The reason for using a **left join** is that **not all games have DLCs or demos**, and we didn't want to lose those games from the dataset.
    - Instead, we added two new features:
        - `has_dlc`
        - `has_demo`
    - These features were initially set to `null` for games that don't have corresponding DLC or demo entries. Later, during the feature engineering phase, we converted these nulls into meaningful binary indicators (e.g., 0 = no DLC, 1 = has DLC).

We decided to retrieve additional game information for entries that exist in the **`gamalytic_steam_games`** table but are missing in the **`info_base_steam_games`** table. To accomplish this, we used the **Steam API** to fetch the missing data. As a result, we successfully retrieved and added approximately **26,000** new rows of game information.

2.3 Handling Missing Values

Below is a summary of the missing (null) values in our dataset:

Column	Number of Nulls
metacritic	92,501
genres	132
achievements_total	43,998
release_date	3
dlc_appid	91,365
dlc_game_name	91,365
demo_appid	87,031
demo_game_name	87,032

For the **DLC and demo columns**, we created two new boolean columns (FE) :

- has_dlc: 1 if dlc_appid is not null, otherwise 0
- has_demo: 1 if demo_appid is not null, otherwise 0
  After creating these features, we dropped the original dlc_appid, dlc_game_name, demo_appid, and demo_game_name columns.

- The **ai_content** column was entirely null, so we dropped it from the dataset.
- For the **metacritic** column:
  - Initially, we attempted to fill null values with -1, but this negatively impacted the model's accuracy.
  - We then tried filling with 0, which yielded better results.
  - (*Note: Filling with the mean was considered, but not used.*)
- In the **achievements_total** column, we discovered that a null value actually indicated that the game had no achievements. Therefore, we filled all nulls with 0.
- For the **release_date** column, only three values were missing. We manually retrieved and filled them using online sources.
- In the **genres** column:
  - We grouped the data by publisher_class, identified the **mode genre** within each group, and used any mode greater than 40% to fill in the missing genres , if not found we use the top two modes to fill .

2.4 Dealing With Inconsistencies

During data exploration, we identified several inconsistencies within the dataset that required attention:

- **Steam Achievements:**
  - We noticed inconsistencies between the `steam_achievements` flag and the `achievements_total` column.
    - Some games had `steam_achievements = false` but still had a non-zero total count.
    - Others had `steam_achievements = true` but a null value for the total.
  - To resolve this, we decided **not to rely on the `steam_achievements` flag**.
  - Instead, we recreated it , based on actual values found through the Steam API and verified that these were more reliable.
- **Workshop Support & Steam Trading Cards:**
  - While validating the truthfulness of the dataset, we discovered that **some games had incorrect values** for the `workshop_support` and `steam_trading_cards` fields.
  - Upon further investigation, we noticed a **pattern among games that had sold fewer than 20,000 copies**:
    - Many of these games were incorrectly marked as having `workshop_support = true` and `steam_trading_cards = true`.
  - We manually checked over 200 such games on Steam and found that in the majority of cases, both values should actually be `false`.

2.5 Dealing with duplicates

We identified several duplicate entries based on the `steamId`, where values for `workshop_support` and `steam_trading_cards` differed. To resolve this, we manually verified the data on Steam and found that most entries with both values set to `true` were incorrect. These incorrect entries were subsequently removed.

After this cleanup, only two duplicate entries remained. We manually inspected them and removed the inaccurate ones.

It is worth noting that while there are duplicate values in the **game names**, this is expected behavior on Steam, as multiple games can share the same name but have different `steamId`

2.6 Dealing With Outliers

We applied the **Interquartile Range (IQR)** technique to identify outliers in the dataset. The following number of outliers were detected in each feature:

- **price**: 4,796 outliers
- **copiesSold**: 15,861 outliers
- **reviewScore**: 7,379 outliers
- **metacritic**: 3,798 outliers
- **achievements_total**: 5,686 outliers

We tried to handle outliers, but when we removed them, the model's accuracy decreased. Therefore, we conclude that removing outliers is not always beneficial; it might actually be better to keep them when working with real-world data.

Exploratory Data Analysis (EDA)

3.1 Feature Correlations

We used two techniques to measure correlation: Pearson correlation and ANOVA

- **Pearson correlation** was used to measure the linear relationship between continuous numerical features and the target variable.
- **ANOVA** was applied to assess the relationship between categorical features and the target variable

Pearson correlation

Feature	Pearson Correlation
price	0.0227
reviewScore	0.0218
metacritic	0.1163
steam_achievements	0.0253
steam_trading_cards	0.0725
workshop_support	0.0841
achievements_total	0.0145
months_passed	0.0581
days_passed	0.0581
years_passed	0.0584
month	0.0072
day	0.0002
year	-0.0584

ANOVA

Feature	F-Score	P-Value
has_metacritic	18.4638	0.0000000000
encoded_publisherClass	4.9073	0.0000000000
is_free	3.4651	0.0000000000
has_dlc	2.9135	0.0000000000
mac	1.3337	0.0000000000
linux	1.2169	0.0000000000
encoded_genres	1.1093	0.0000000000
encoded_supported_platforms	1.1045	0.0000000000
encoded_sorted_genres	1.0850	0.0000000000
has_demo	1.0056	0.3041007760
windows	0.1859	1.0000000000

3.2 Data Distribution

Regression Techniques Used

We used liner regression and polynomial regression with ridge (L2) and lasso (L1) we use catboost , design tree , Random forest and ElasticNet

Model	Train MSE	Train R^2	Log Test MSE	Log Test R^2	Exp Test MSE	Exp Test R^2	Bias Correction
Linear Regression (Base)	4.26	0.55	4.20	0.56	473,026,948,983.47	0.54	0.92
Ridge Regression (Base)	4.26	0.55	4.20	0.56	472,546,816,461.72	0.54	0.92
CatBoost Regression (Base)	2.25	0.76	2.43	0.75	381,463,203,332.73	0.63	0.87
Lasso Regression (Base)	6.61	0.31	6.59	0.31	964,749,466,654.87	0.06	0.87
ElasticNet Regression (Base)	6.13	0.36	6.09	0.36	938,458,506,398.44	0.08	0.85
DecisionTree Regression (Base)	1.96	0.79	3.07	0.68	860,418,624,980.43	0.16	0.94
RandomForest Regression (Base)	0.54	0.94	2.91	0.69	827,786,070,470.21	0.19	1.00
Linear Regression (Poly)	3.96	0.59	3.90	0.59	15,933,781,302,660.40	-14.54	0.84
Ridge Regression (Poly)	3.96	0.59	3.90	0.59	15,519,413,475,094.73	-14.14	0.84
CatBoost Regression (Poly)	2.21	0.77	2.45	0.74	428,730,120,481.39	0.58	0.86
Lasso Regression (Poly)	4.64	0.51	4.58	0.52	533,861,877,724.61	0.48	0.90
ElasticNet Regression (Poly)	4.54	0.53	4.48	0.53	393,773,762,674.66	0.62	0.91

Model	Performance	Explanation
CatBoost	Very High	Handles categorical features well, prevents overfitting, and is highly optimized for gradient boosting.
RandomForest	Very High	Uses ensemble of decision trees, reduces variance and overfitting, good for complex data patterns.
XGBRegressor	High	Efficient and powerful boosting algorithm, performs well with structured data, slightly sensitive to tuning.
DecisionTree	High	Simple and interpretable, but can overfit without pruning or ensemble techniques.
LinearRegression	Moderate	Assumes linear relationships, may underfit complex data.
Ridge	Moderate	Adds L2 regularization, helps with multicollinearity, but still assumes linearity.
Lasso	Low	L1 regularization can zero out features, not ideal for complex data.
ElasticNet	Low	Combines L1 & L2, but may not add much value if data isn't sparse or highly correlated.

Feature Selection

Feature Name	Justification
`price_log`	Log-transformed game price provides better distribution and captures economic signals influencing purchases.
`reviewScore_log`	Represents player satisfaction and engagement; log transformation reduces skew.
`metacritic_log`	External critic ratings impact user perception and trust in a game.
`premium_score_review_interaction`	Captures interaction between game pricing and user reviews, reflecting perceived value.
`encoded_publisherClass`	Publisher reputation and scale often correlate with game visibility and quality.
`encoded_sorted_genres`	Genre preferences are strong indicators of user interest and game type.
`metacritic_review_interaction`	Combines user and critic feedback for a holistic quality metric.
`year`	Encodes temporal trends and market evolution, affecting game popularity.
`steam_trading_cards`	May influence purchase for collectors or reward-seeking players.
`workshop_support`	Community modding support can increase user retention and value.

Feature Name	Justification
achievements_total_log	Indicates game complexity and engagement level.
has_dlc	Presence of downloadable content can affect user interest and game longevity.
has_demo	Affects user trust and willingness to try a game.
is_free	Price category directly affects accessibility and user base size.
encoded_supported_platforms	Platform availability broadens market reach and accessibility.
encoded_sorted_genres	Genre preferences are strong indicators of user interest and game type.
metacritic_review_interaction	Combines user and critic feedback for a holistic quality metric.

Discarding

Features Discarded via Pearson Correlation (Weak Linear Relationship)

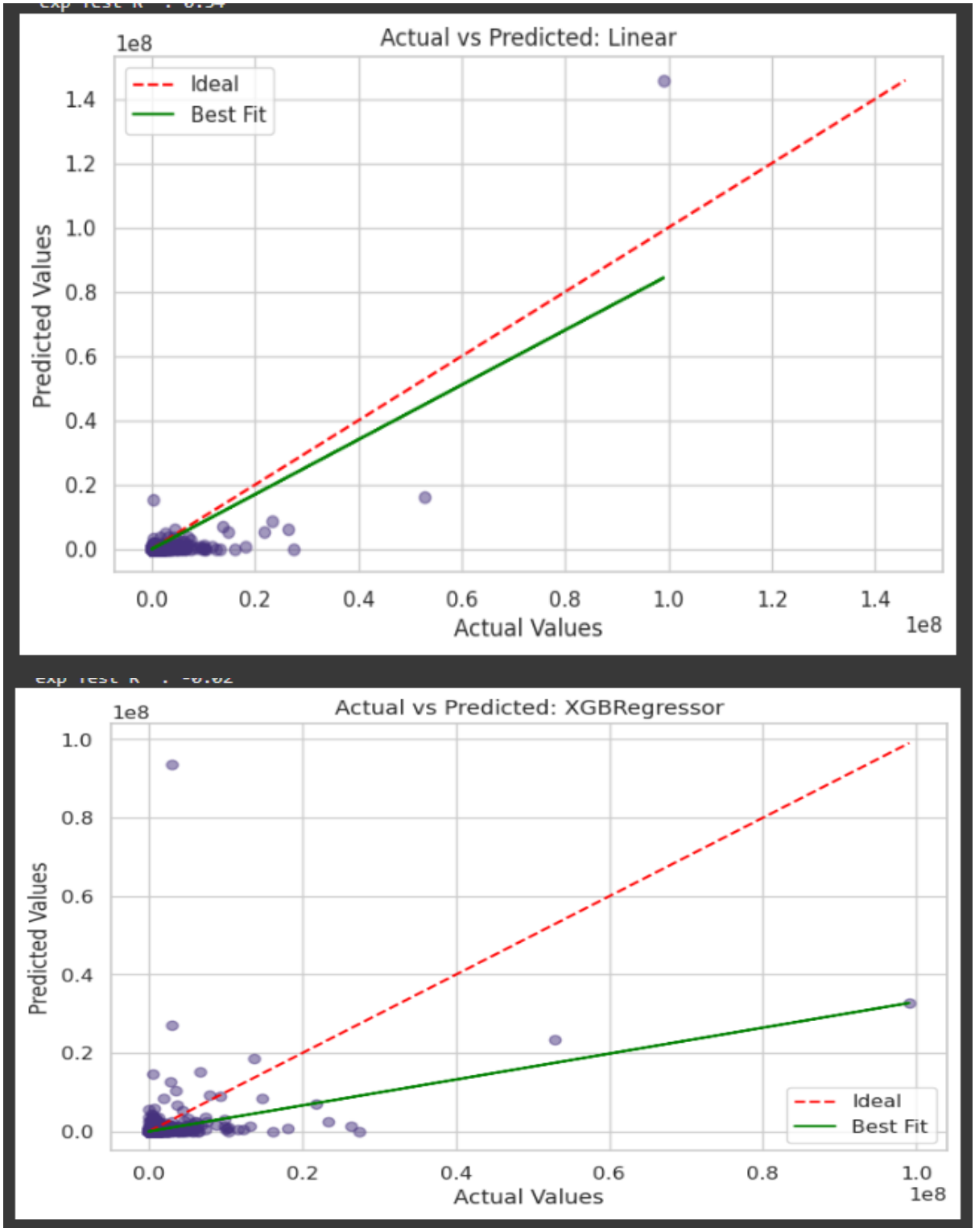
|Pearson correlation| < 0.1 and ANOVA we chose the best from them and make meaning

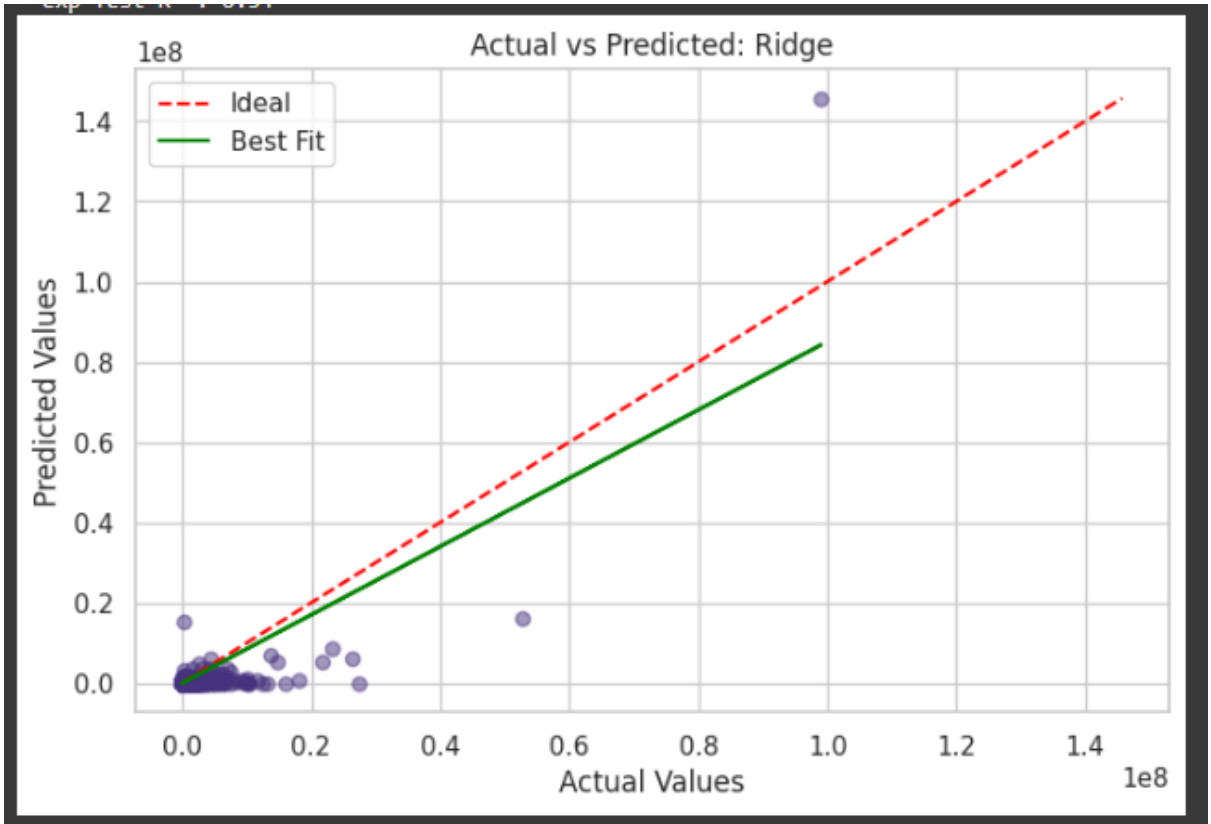
price_log, reviewScore_log, metacritic_log, steam_trading_cards, encoded_sorted_genres, encoded_publisherClass, premium_score_review_interaction, workshop_support, achievements_total_log, has_dlc, has_demo, is_free, encoded_supported_platforms, year, metacritic_review_interaction

Dataset Splitting

We split the data into 80% for training and 20% for testing.

Visualization of Regression Results




Actual vs Predicted: Ridge
1e8
Ideal
Best Fit
Predicted Values
Actual Values
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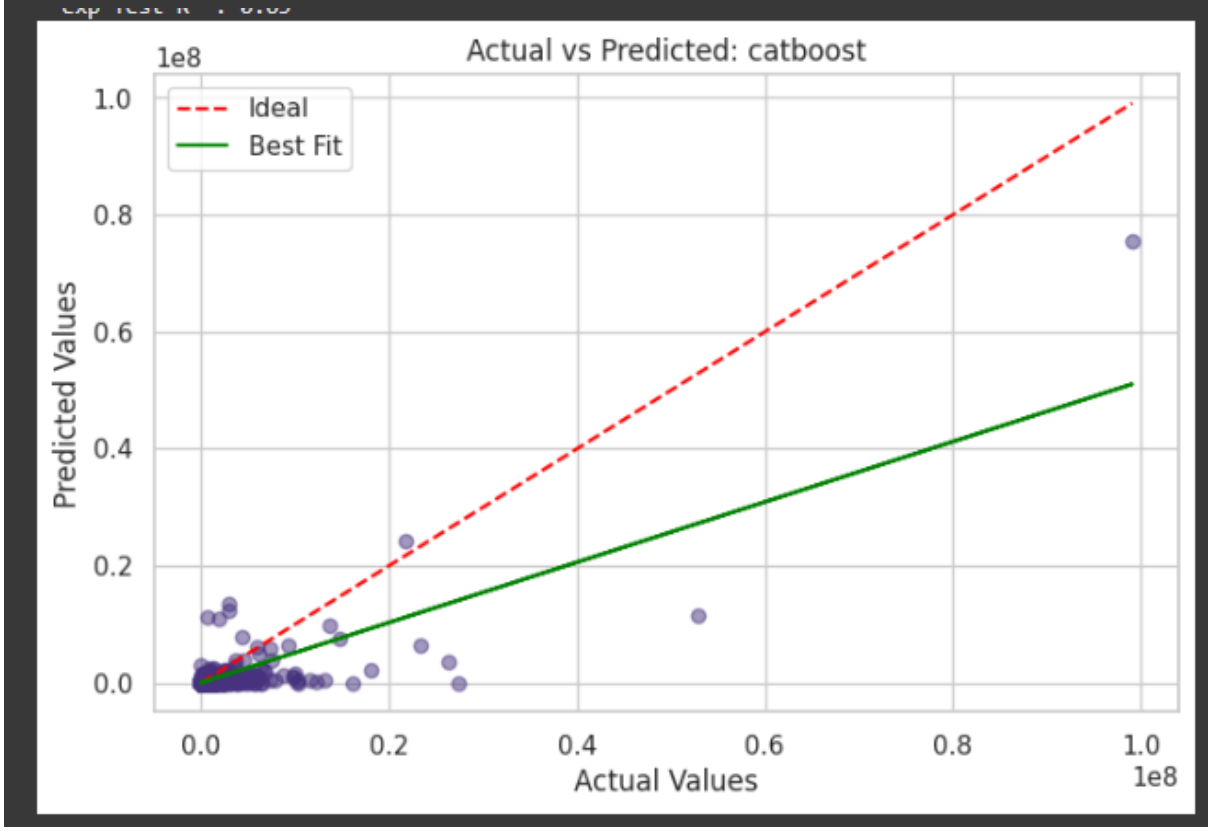
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4


Actual vs Predicted: catboost
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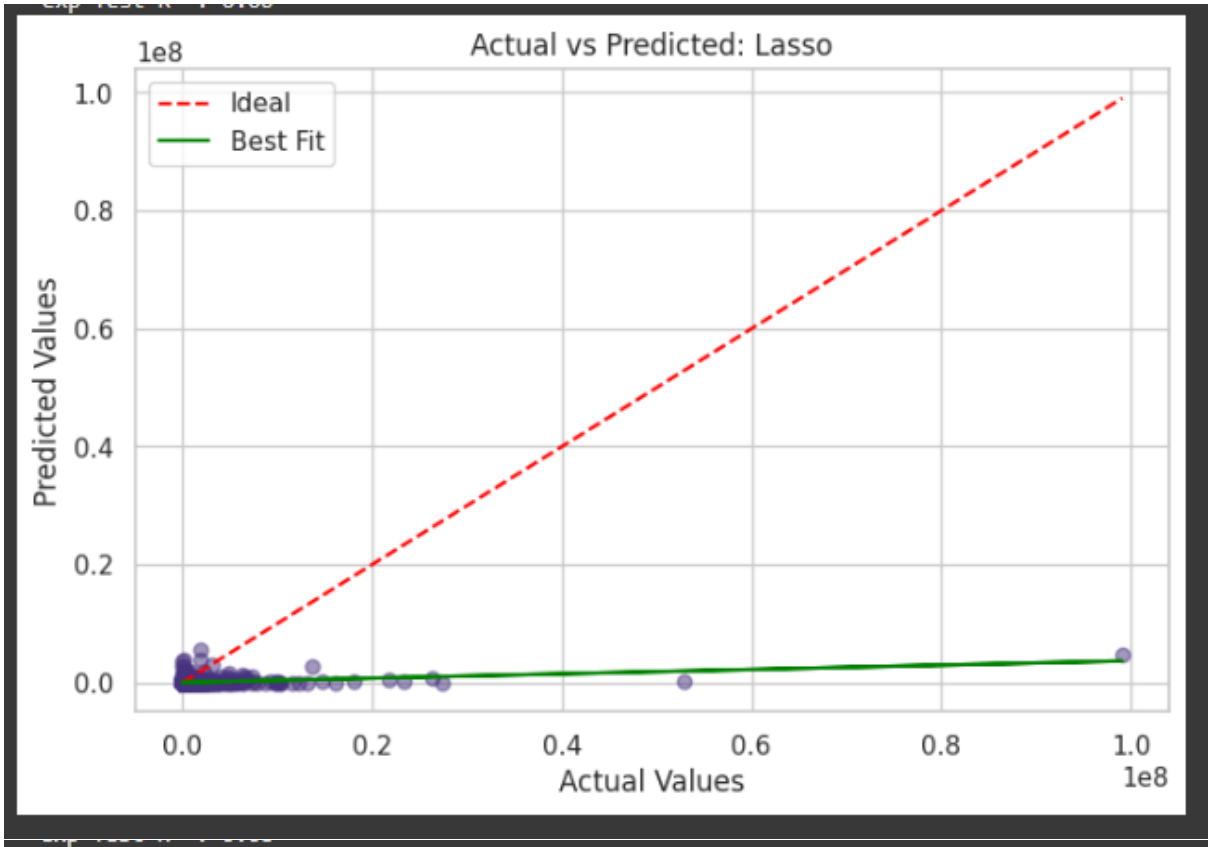
Ideal
Best Fit
Predicted Values
Actual Values
1e8
0.0
0.2
0.4
0.6
0.8
1.0


Actual vs Predicted: Lasso
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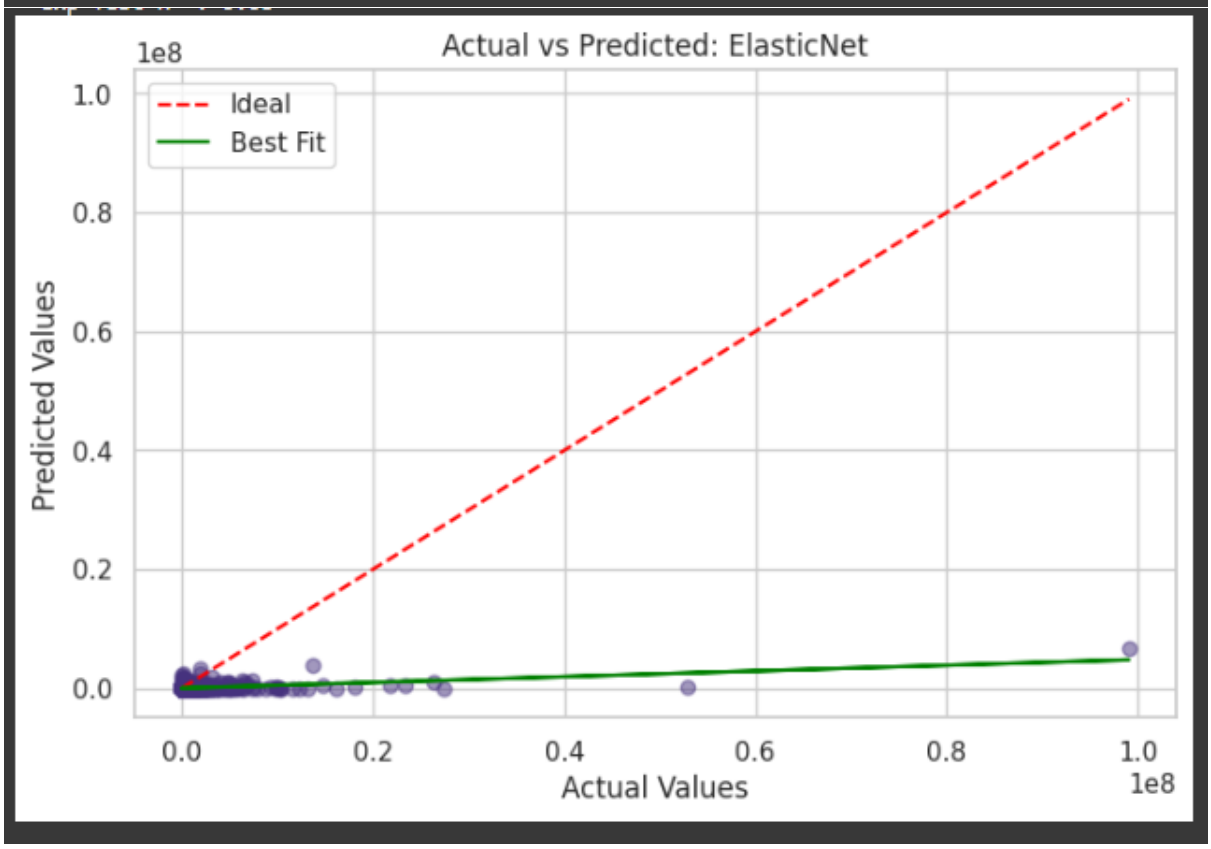
Ideal
Best Fit
Predicted Values
Actual Values
1e8
0.0
0.2
0.4
0.6
0.8
1.0


Actual vs Predicted: ElasticNet
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Ideal
Best Fit
Predicted Values
Actual Values
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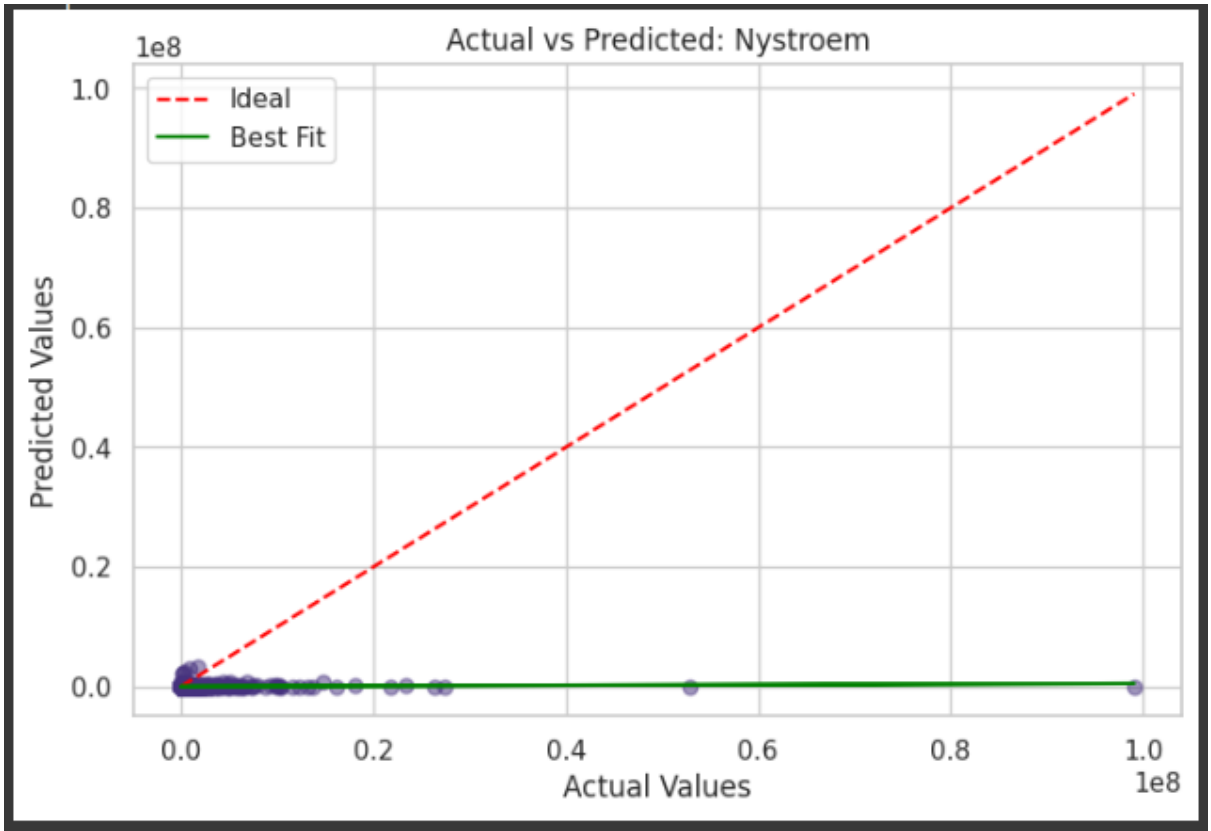
0.0
0.2
0.4
0.6
0.8
1.0


Actual vs Predicted: Nystroem
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Best Fit
Predicted Values
Actual Values
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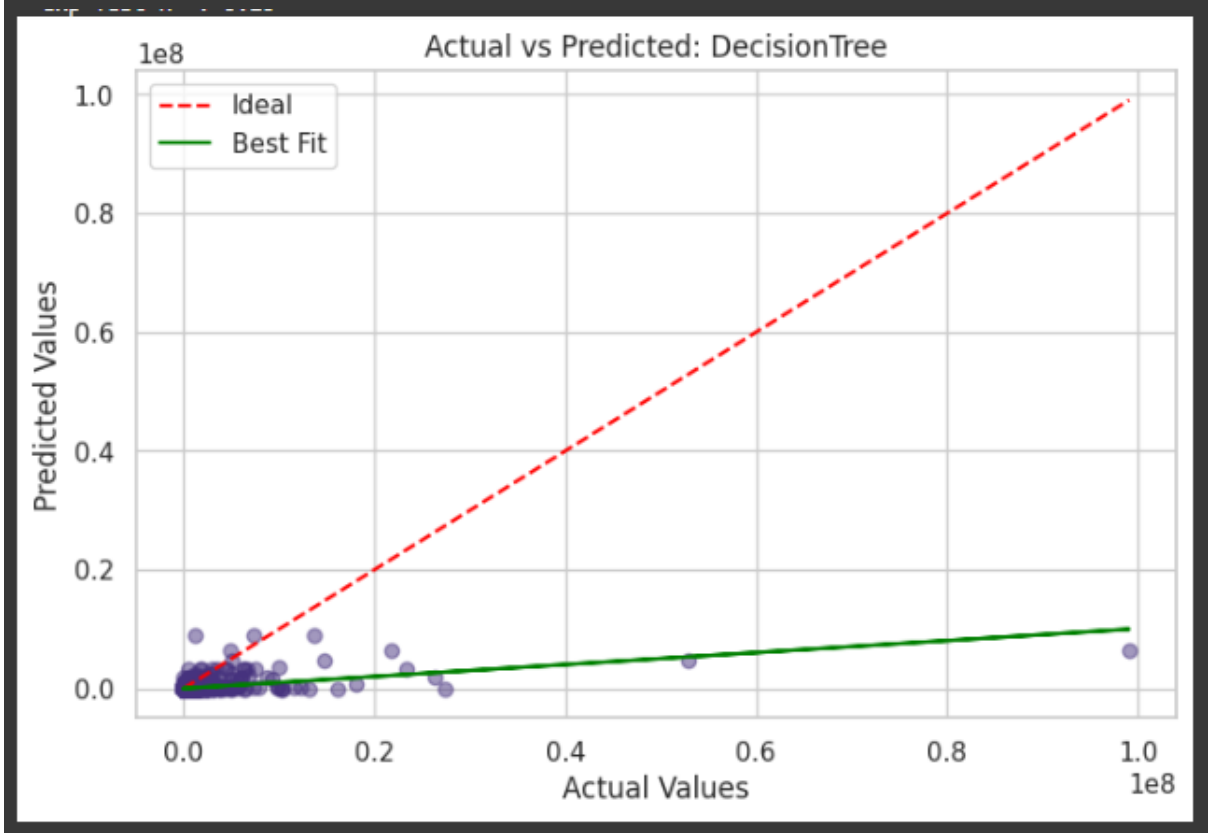
0.0
0.2
0.4
0.6
0.8
1.0


Actual vs Predicted: DecisionTree
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Best Fit
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Actual Values
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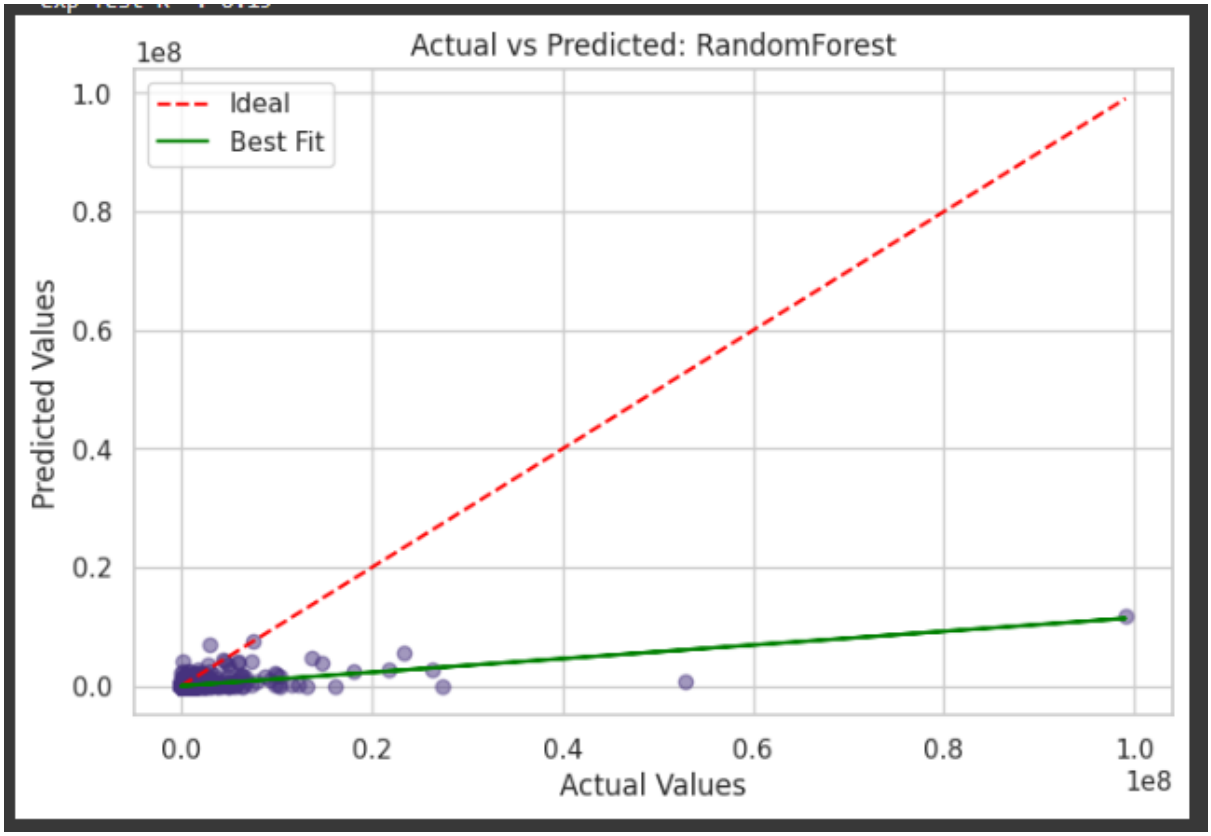
0.2
0.4
0.6
0.8
1.0



Performance Optimization Techniques

Feature Engineering

As part of our data preprocessing and enhancement process, we performed several feature engineering steps to improve model performance:

1. Boolean Feature Creation

We created several binary (Boolean) features based on categorical information, such as:

- `is_free`: Indicates whether the game is free.
- `has_dlc`: Indicates the presence of downloadable content.
- `has_demo`: Indicates whether a demo version is available.
- `has_metacritic`: Indicates the availability of a Metacritic score.

In addition, the `supported_platforms` feature was expanded into separate Boolean columns for each platform:

- `windows`
- `mac`
- `linux`

2. Date-Based Feature Extraction

From the release date, we extracted multiple temporal features to provide more meaningful insights into how time affects game popularity and sales:

- `days_passed`
- `months_passed`
- `years_passed`

3. Derived Features

We engineered a new feature called `premium_score`, which combines indicators of premium game content:

$$\text{premium\_score} = \text{steam\_trading\_cards} + \text{workshop\_support} + \text{has\_dlc} + \text{has\_metacritic}$$

Feature Transformation

We applied logarithmic or normalization transformations to reduce skewness in the following numerical features:

- `metacritic`
- `price`
- `reviewScore`
- `achievements_total`

Label Encoding for Categorical Features

To prepare categorical data for machine learning models, we applied label encoding to the following features:

- `supported_platforms`
- `publisherClass`
- `genres`
- `sorted_genres`
- `copiesSold_class`

6. Feature Scaling we (cancelled it) effect data by revers

Initially, we applied feature scaling to the `X_train` dataset to standardize numerical features with the goal of improving model convergence and overall performance. This is particularly important for models sensitive to feature magnitude, especially when dealing with features that are not normally distributed.

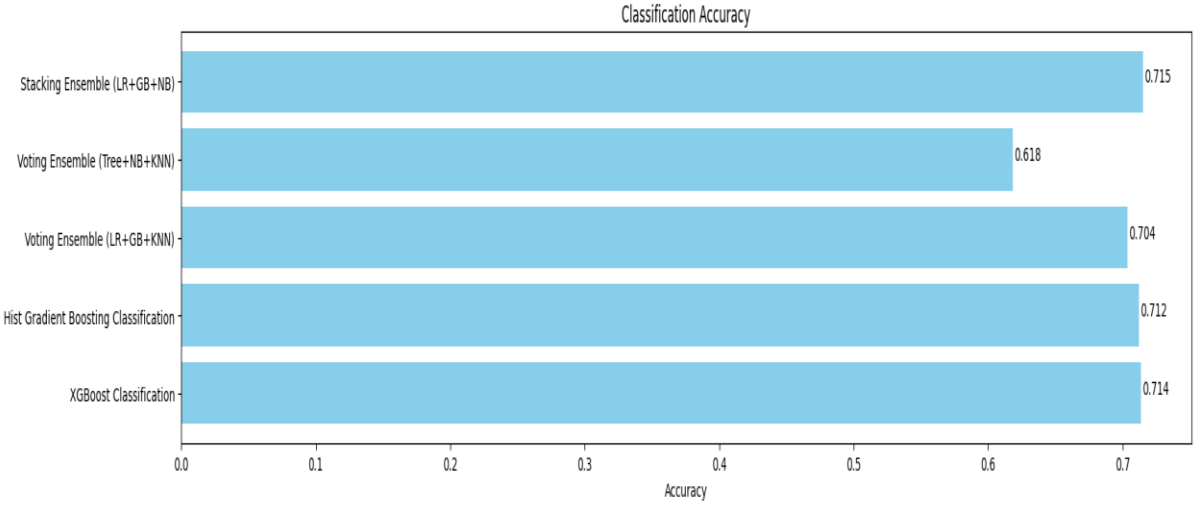
However, after evaluation, we found that scaling negatively impacted model performance, likely due to the disruption of the original data distribution or relationships between features. As a result, we decided to **cancel the scaling step** in order to preserve the natural characteristics of the data, which led to more reliable and accurate model outcomes.

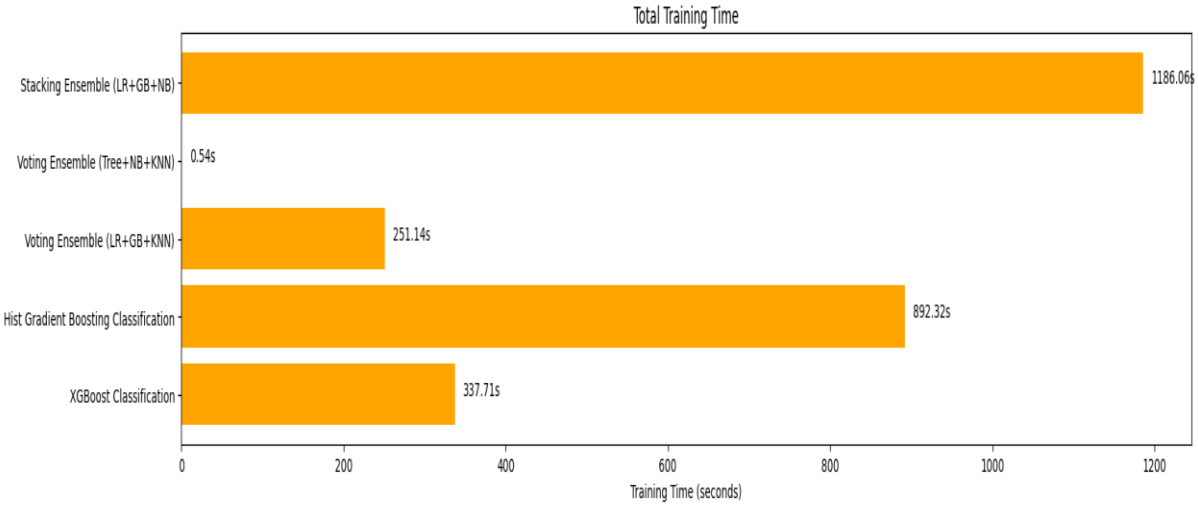
Conclusion and Intuition Reflection

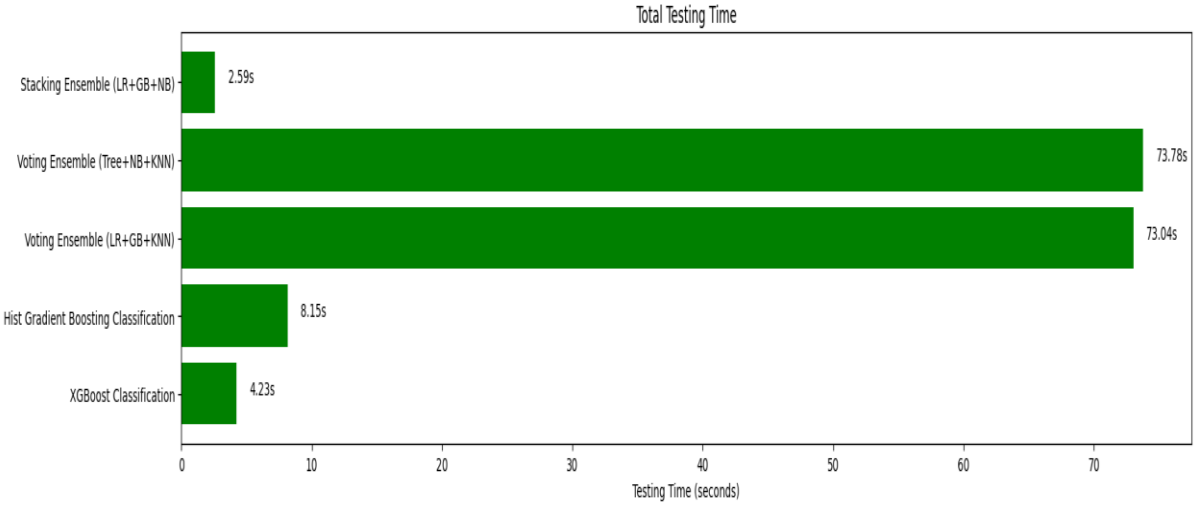
In the preprocessing stage, we observed that while real-world data often contains outliers, handling or removing them did not always lead to improved model performance. In several cases, model accuracy decreased, suggesting that some outliers may carry meaningful patterns, and their removal might distort the true distribution of the data. Similarly, applying feature scaling techniques such as normalization or standardization did not consistently enhance results. Although scaling is essential for certain algorithms ,in our context, it may have disrupted the natural relationships between features and target variables, adversely impacting predictions. From the modeling perspective, introducing polynomial features to capture non-linear patterns occasionally led to underfitting, particularly when the underlying relationship was inherently linear. This underscores that increasing model complexity does not always yield better outcomes and can sometimes obscure valuable patterns. Conversely, simple linear regression frequently delivered the best performance, reinforcing the idea that when the relationship between input and output variables is approximately linear, simpler models are not only more effective but also easier to interpret and more robust.

MS 2

Classification Accuracy, Training Time, and Test Time (Bar Graphs)







Feature Selection

In this classification phase, our feature selection approach differed from the earlier regression phase to better suit the nature of classification tasks. We evaluated potential features including *price*, *reviewScore*, *steam_achievements*, *achievements_total*, *month*, *day*, *year*, *steam_trading_cards*, *workshop_support*, *months_passed*, *days_passed*, and *years_passed*.

To identify the most relevant features, we applied statistical methods such as the *ANOVA* and the *Chi-square* test. These methods helped us assess the strength of association between each feature and the target class.

Then we get this features :

price_log, reviewScore_log, metacritic_log, steam_trading_cards, encoded_sorted_genres, encoded_publisherClass, premium_score_review_interaction, workshop_support, achievements_total_log, has_dlc, has_demo, is_free, encoded_supported_platforms, year, metacritic_review_interaction

Impact of Hyperparameter Tuning (GridSearch)

The model takes too long to train without significant improvement

XGBoost Classifier

Hyperparameters Tuned:

- **`n_estimators`**: [50, 100, 500]
  Number of boosting rounds. More estimators can improve performance but increase training time.
- **`max_features`**: ['log2']
  Determines the number of features to consider when looking for the best split. Using `'log2'` helps reduce overfitting.
- **`learning_rate`**: [0.01, 0.05, 0.1]
  Controls the contribution of each tree. Lower values improve generalization but require more trees.

Histogram-Based Gradient Boosting Classifier

Hyperparameters Tuned:

- **`max_iter`**: [50, 100, 500]
  Equivalent to the number of boosting iterations or trees.
- **`min_samples_leaf`**: [2, 5, 10]
  Minimum number of samples required to be at a leaf node. Helps prevent overfitting by avoiding overly specific splits.
- **`learning_rate`**: [0.01, 0.05, 0.1]
  Shrinks the contribution of each tree. A lower rate typically requires more iterations but generalizes better.

Phase Conclusion and Insights

Hyperparameter tuning had minimal impact, and the stacking ensemble emerged as our best model—its accuracy was only about 0.001 higher than the XGboast . Overall, our classification models outperformed the regression approach. Despite extensive grid searches, hyperparameter adjustments did not yield the expected gains. We also tried to address class imbalance by applying class weights, but this had negligible effect on positive-class performance. Finally, although we experimented repeatedly with an SVM (trying different kernels and regularization values), its training time proved prohibitively long, ruling it out for our use case.