Video Game Sales on Steam Prediction Report

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Preprocessing

Preprocessing DLCs and Demos CSVs

```
Demo File Columns: ['appid', 'demo_appid', 'name']
DLC File Columns: ['appid', 'dlc_appid', 'name']
```

1. Dropped the auto incremented column in Demos "Unnamed".
2. Made column names consistent.

```
demo_df.head()
```
✓ 0.0s

	Unnamed: 0	full_game_appid	demo_appid	name
0	0	2214650	2573370	Rolando Deluxe Demo
1	1	1439980	2573460	Outrunner: Neon Nights Demo
2	2	2412240	2572840	Bubble Ghost Remake Demo
3	3	2448830	2572240	Time Handlers Demo
4	4	2379590	2570800	Hope's Final Defense Demo

```
dlc_df.head()
```
✓ 0.0s

	base_appid	dlc_appid	name
0	1786750	2568660	家出王女 - 全年齢版ストーリー&グラフィック追加 DLC
1	1981700	2563730	Jacob's Quest - Voyage
2	2009450	2552980	Invector: Rhythm Galaxy - Latin Power Song Pack
3	1133420	2550750	Hero or Villain: Genesis — Supercharged!
4	2533950	2551000	Hot And Lovely ：Uniform - adult patch

3. Removed duplicated rows.
4. Cleaned the Demos'/DLCs' names by removing leading or trailing whitespace, non-alphanumeric characters, and the words "Demo" or "DLC".
5. Engineered 4 new features for the main games
    1. has_dlc
    2. has_demo
    3. demo_count
    4. dlc_count

Note

We didn't extract features from the Demos'/DLCs' names since we are gamers ourselves, and based on our domain-knowledge in games we strongly believe that the names of the Demos/DLCs of the games don't affect the number of copies sold by any means, on the other hand we extracted multiple features from the main game name.

Merging CSVs and Creating Training, Validation, and Test Sets

Merging CSVs

We merged both the `gamalytic_steam_games` and `info_base_games` CSVs together based on that for a game to be merged, it must exist in both. This resulted in `69426` rows instead of the original `99167` in `info_base_games`. We then merged the 4 features we engineered from `demos` and `dlcs` with the games we had using the game id.

Splitting Data Into Training, Validation, and Test Sets

We performed this step early on so that all the next preprocessing steps can fit only on the training data, and then transform all the training, validation, and test sets to **avoid data leakage**.

After research on the size of our data, we decided to do a 8-1-1 split, which resulted in the below datasets

```
Training set:   (55541, 23)
Validation set: (6942, 23)
Testing set:    (6943, 23)
```

We initially thought we needed a validation set to use to tune the hyperparameters of the models, although later on we used Grid Search to tune the hyperparameters with less/cleaner code and Grid Search automatically creates a validation set inside the training set using cross validation, whcih meant that the validation set we created was not needed, so later on during feature selection and model training we would first combine the validation and testing sets into one bigger testing set, so the actual split ratio we have is **training (8) -> testing (2)**.

Note
In all of the below preprocessing, we fit on the training data, and transform the training, validation, and test sets.

Preprocessing Info Base Games CSV

	appid	name	metacritic	steam_achievements	steam_trading_cards	workshop_support	genres	achievements_total	release_date	supported_platforms
0	2574000	Femboy Burgers	NaN	True	True	True	Casual, Indie	NaN	Oct 9, 2023	['windows', 'mac', 'linux']
1	2574120	PPA Pickleball Tour 2025	NaN	True	True	True	Indie, Simulation, Sports	18	Jul 16, 2024	['windows', 'mac', 'linux']
2	2573200	Squeaky Squad	NaN	True	True	True	Action, Adventure, Indie	27	Mar 29, 2024	['windows', 'mac', 'linux']
3	2573440	Paradox Metal	NaN	True	True	True	Action, Early Access	NaN	Coming soon	['windows', 'mac', 'linux']
4	2569520	Naturpark Lillebælt VR	NaN	True	True	True	Action, Adventure	NaN	Sep 18, 2023	['windows', 'mac', 'linux']

Note

It is standard that we check if a column contains null values, if I didn't mention it, then we checked and found out that it doesn't contain any null values.

Preproccess App ID Column

1. Dropped a corrupted row/sample that contained the column names

	appid	name	metacritic	steam_achievements	steam_trading_cards	workshop_support	genres	achievements_total	supported_platforms
9929	steam_appid	name	metacritic	True	True	True	genres	achievements_total	['windows', 'mac', 'linux']

Preproccess Name Column

1. Removed punctuation.
2. Transformed names to lowercase.
3. Feature Engineered the below features
    1. Name Length
    2. Word count
    3. Ratio of capital letters to total length
    4. Is a sequel (if the game is e.g., part 2 of another game), we did this by using regex to check if the game name contains any english or roman numbers.
    5. Multiple boolean features each indicating if the game contains any of these keywords (vr, remaster, collector, edition, bundle, playtest)

name_len	name_words	name_cap_ratio	is_sequel	name_has_vr	name_has_remaster	name_has_collector	name_has_collection	name_has_edition	name_has_bundle	name_has_playtest
16	2	0.125000	0	0	0	0	0	0	0	0
13	3	0.230769	0	0	0	0	0	0	0	0
23	3	0.260870	0	0	0	0	0	0	0	0
16	4	0.250000	0	1	0	0	0	0	0	0
9	1	0.111111	0	0	0	0	0	0	0	0

4. Standardized the numerical features engineered using `StandardScaler`

5. Converted game names to word embeddings using pre-trained models `SentenceTransformer('all-MiniLM-L6-v2')`

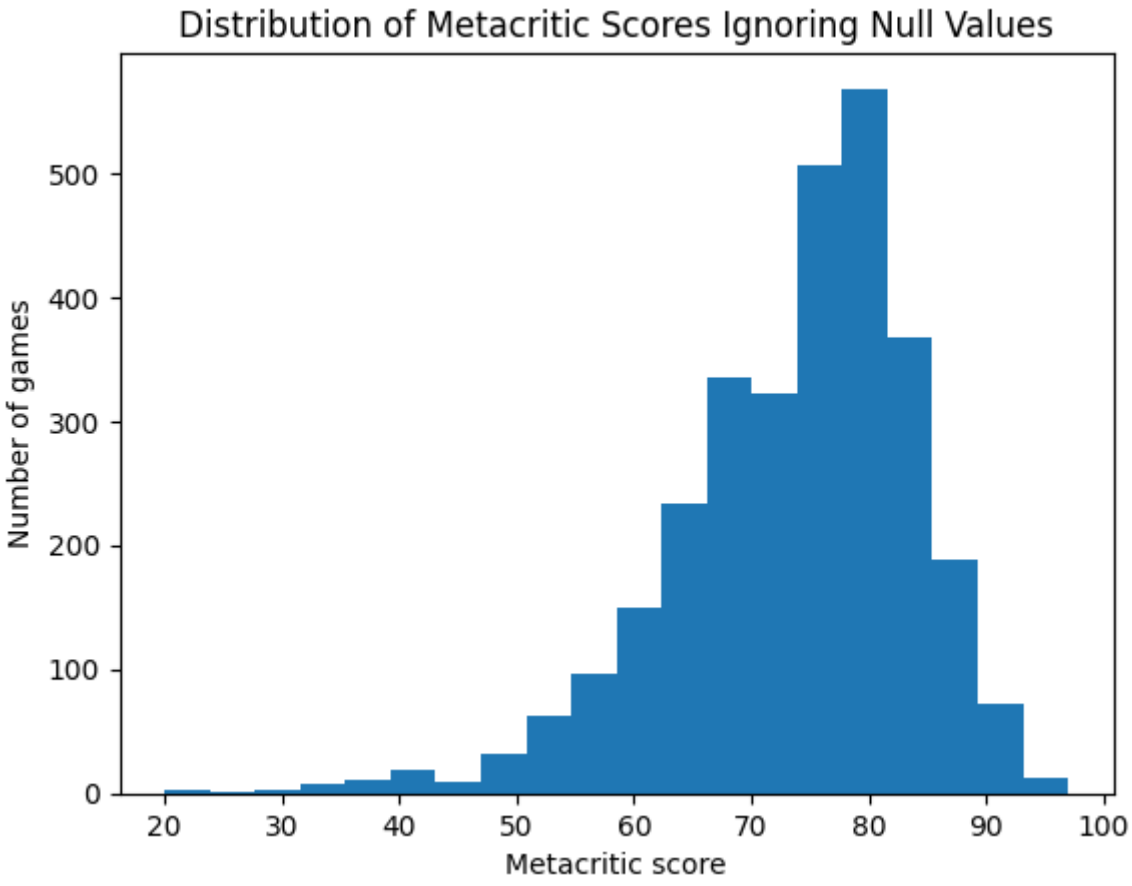
Note

We didn't test the effictivness of word embeddings since they had very high dimensionality (around 380 features), due to the time constraints and the low probability that they will be useful, we deprioritized trying to apply PCA on them and testing them during feature selection.

Preproccess Metacritic Column

Around 97% of the games in our data didn't have a metacritic score associated with them and the metacritic score for them is null, this is due to Steam leaving it optional for games' publishers to include a metacritic score on their Steam page.

We plotted the distribution of the Metacritic score



1. Since the Metacritic score is normally distributed, we also applied standardization on it.
2. Imputed the missing values with the mean of the 3% of the data, we didn't want to automatically drop the column since we thought that it might have a value, which later on, it proved it did.
3. We feature engineered a boolean `has_metacritic` feature

metacritic_preprocessed	has_metacritic
0.0	0
0.0	0
0.0	0
0.0	0
0.0	0

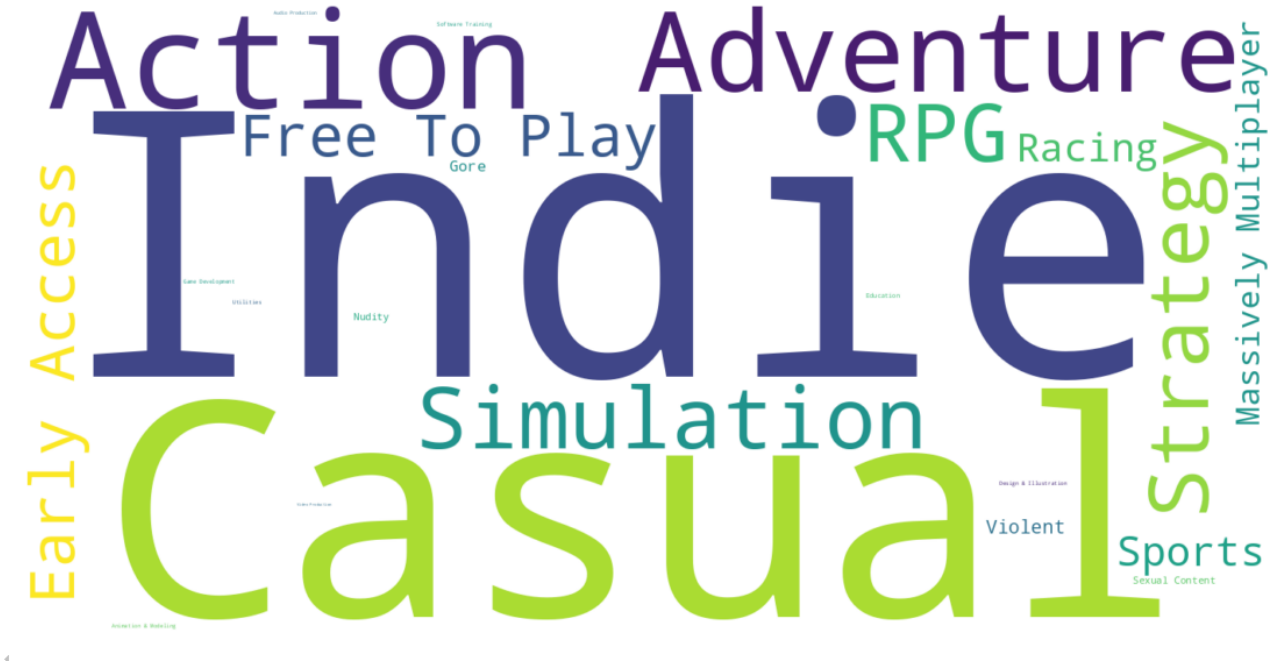
Preproccess Three Boolean Columns

The three boolean columns are `steam_achievements`, `steam_trading_cards`, and `workshop_support`.

We simply converted the boolean values `True`, `False` -> 1, 0.
But `steam_achievements` is a bit tricky since it has a relation with `achievements_total` so we will revist preprocessing it while discussing preprocessing `achievements_total`.

Preprocess Genres Column

1. Analyzed and Visualized the Genres Frequency



2. Replaced genres that are not related to games (which also are the genres that have the lowest frequecy) with an "Other" genre.

```
non_game_genres = [
'Photo Editing', 'Video Production', 'Web Publishing', 'Accounting',
'Audio Production', 'Software Training', 'Design & Illustration',
'Utilities', 'Game Development', 'Education', 'Animation & Modeling'
]
```

3. Multi-Hot Encoded the genres by splitting them into lists and using sklearn's `MultiLabelBinarizer`

genre_Action	genre_Adventure	genre_Casual	genre_Early Access	genre_Free To Play	genre_Gore	genre_Indie	genre_Massively Multiplayer	genre_Nudity	genre_Other	genre_RPG	genre_Racing	genre_Sexual Content	genre_Simulation	genre_Sports	genre_Strategy	genre_Violent
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0

Note

We first tested out multi-hot encoding genres without grouping non-game related genres into an "Other" category and it gave bad results with linear regression, so we applied the non-game related grouping and it improved the results.

Preprocess Achievements Columns

Around 46% of the data in `achievements_total` was missing, and it is important to mention that `achievements_total` is highly related with the boolean feature `steam_achievements`.

1. Made both columns consistent with each other.
    1. if `achievements_total` had a value and `steam_achievements` was False, we converted it into True.
    2. if `steam_achievements` was False, and `achievements_total` was Null, we set `achievements_total` = 0.
2. Tested imputing the null values in `achievements_total` using KNN Imputer but it gave unrealistic results so we didn't use it.
3. Imputed the null values in `achievements_total` with the median of the column.
4. Standardized `achievements_total` using sklearn's `StandardScaler`

Preprocess Release Date Column

This is an interesting column since it contains null values and multiple date formats.

Unified Release Date Formats and Feature Engineering

Release Date Formats

The following release date formats are standardized as described below:

1. **Formats with Day, Month, and Year**
    - Original: `8-Dec-2022`, `8 Dec 2022`, `Dec-8-2022`, `Dec 8, 2022`
    - Standardized: Split into day, month, and year (e.g., `8 Dec 2022`).
2. **Formats with Month and Year Only**
    - Original: `Dec-2022`, `Dec 2022`
    - Standardized: Assign day as `15` (midpoint of the month) for consistency, e.g., `15 Dec 2022`.
3. **Quarterly Formats**
    - Original: `Q1 2023`, `Q2-2024`, etc.
    - Standardized: Assign day as `15` and month as the middle month of the quarter:
        - `Q1`: `15 Feb` (e.g., `15 Feb 2023`)
        - `Q2`: `15 May` (e.g., `15 May 2024`)
        - `Q3`: `15 Aug`
        - `Q4`: `15 Nov`
4. **Formats with Day and Month Only (No Year)**
    - Original: `8-Dec`
    - Standardized: Assign year as `null` (e.g., `8 Dec null`).
5. **Year-Only Formats**
    - Original: `2023`
    - Standardized: Assign day as `1` and month based on release context:
        - Past release: `1 Jan` (e.g., `1 Jan 2023`)
        - Future release: `1 Jun` (e.g., `1 Jun 2023`).
6. **Vague or Placeholder Formats**
    - Original: `Coming soon`, `To be announced`
    - Standardized: Assign as `null` for day, month, and year.

Feature Engineering

The following features are derived from the standardized release dates:

1. **is_upcoming**
    - Type: Boolean
    - Description: Indicates if the release is in the future.
    - Logic: Set to `1` if the year is in the future, or if the date is `Coming soon` or `To be announced`.
2. **is_release_date_known**
    - Type: Boolean
    - Description: Indicates if a specific release date is known.
    - Logic: Set to `1` if the release date is specific (includes day, month, and year, whether past or future). Set to `0` for `Coming soon`, `To be announced`, or dates without a year (e.g., `8-Dec`).
3. **year**
    - Type: Integer
    - Description: The year of the release date, extracted from the standardized format. Set to `null` if not specified.
4. **sin_day**
    - Type: Float
    - Description: Cyclical encoding of the day of the year using sine transformation.
    - Formula: `sin(2 * π * (day_number_in_year / 365))`
    - Purpose: Captures seasonal patterns.
5. **cos_day**
    - Type: Float
    - Description: Cyclical encoding of the day of the year using cosine transformation.
    - Formula: `cos(2 * π * (day_number_in_year / 365))`
    - Purpose: Complements `sin_day` to capture seasonal spikes.

- The `sin_day` and `cos_day` features use cyclical encoding to model periodic patterns, such as seasonal release spikes, by representing the day of the year as a point on a unit circle.
- The day number in the year is calculated based on the standardized date (e.g., `15 Dec 2022` is approximately the 349th day of the year).
- For dates with `null` values (e.g., `Coming soon` or no year), `sin_day` and `cos_day` are not computed and may be set to `null` or a default value depending on the implementation.

Preprocess Supported Platforms Column

Multi-Hot Encoded the supported platforms by converting them into python lists and using sklearn's `MultiLabelBinarizer`.

platform_linux	platform_mac	platform_windows
0	0	1
0	0	1
0	0	1
0	0	1
1	1	1

Preprocessing Gamalytic Steam Games CSV

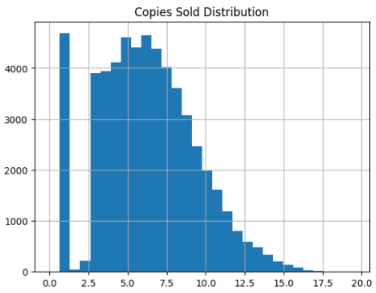
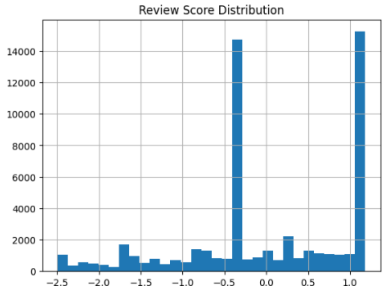
	appid	price	copiesSold	publisherClass	reviewScore	aiContent
0	730	0.0	302158048	AAA	87	NaN
1	570	0.0	212896574	AAA	82	NaN
2	578080	0.0	161971233	AAA	59	NaN
3	440	0.0	99060457	AAA	90	NaN
4	1172470	0.0	67554185	AAA	67	NaN

Preprocess Price, Copies Sold, and Review Score Columns

1. Checked duplicates, missing values, and negative values.
2. Analyzed Skewness

```
Price skewness: 35.86
CopiesSold skewness: 98.31
reviewScore skewness: -1.28
```

3. Applied Log Transformation for the skewed data (Price, Copies Sold) using `np.log1p`
4. Handled Outliers in Review Score using Interquartile range (IQR).
5. Standardized Price and Review Score, didn't standardize Copies Sold since it's the target variable and this won't help models, we tested standardizing it but it didn't have any effect so we removed it.
6. Analyzed the data's distribution

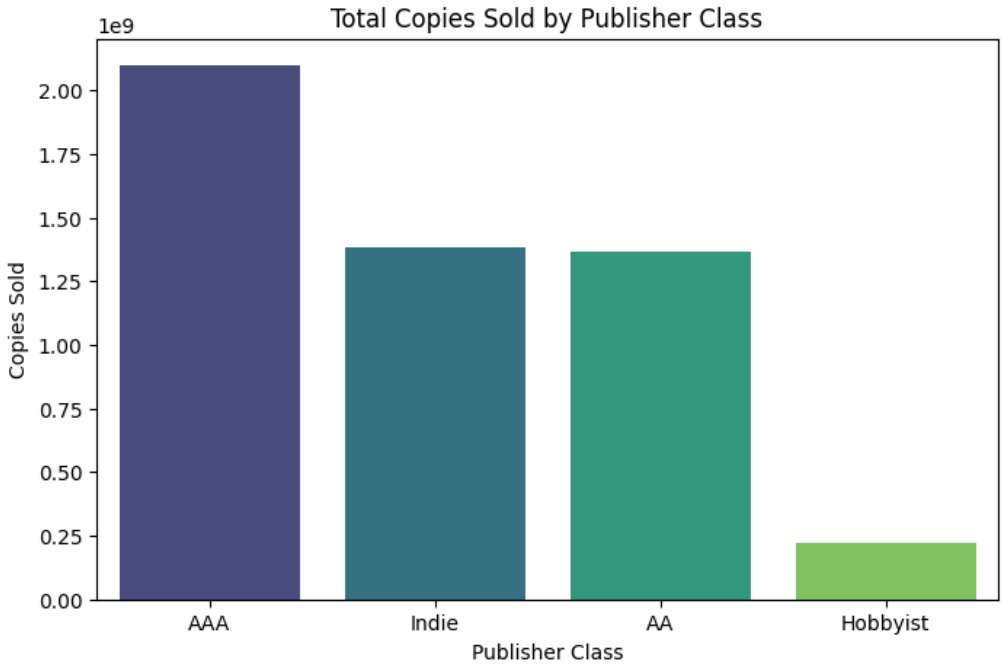
1	2	3
		

Preprocess Publisher Class and AI Content

1. Analyzed Publisher Class Data

Frequency Of Class	Copies Sold Per Class

publisherClass
Hobbyist 31643
Indie 21502
AA 1748
AAA 648



This strongly indicates that AA and AAA publishers sell a lot more copies that Indie and Hobbyists.

2. Based on the above frequency of the classes and since AA and AAA publishers are closely related, we decided to merge AA and AAA publishers into an "Others" publishers category.

publisherClass
Hobbyist 31643
Indie 21502
Other 2396

3. Used Dummy Encoding (A smarter way of doing one-hot encoding that makes us need `n - 1` columns, where `n` is the original number of categories to encode) to encode the publisher classes using sklearn's `OneHotEncoder`

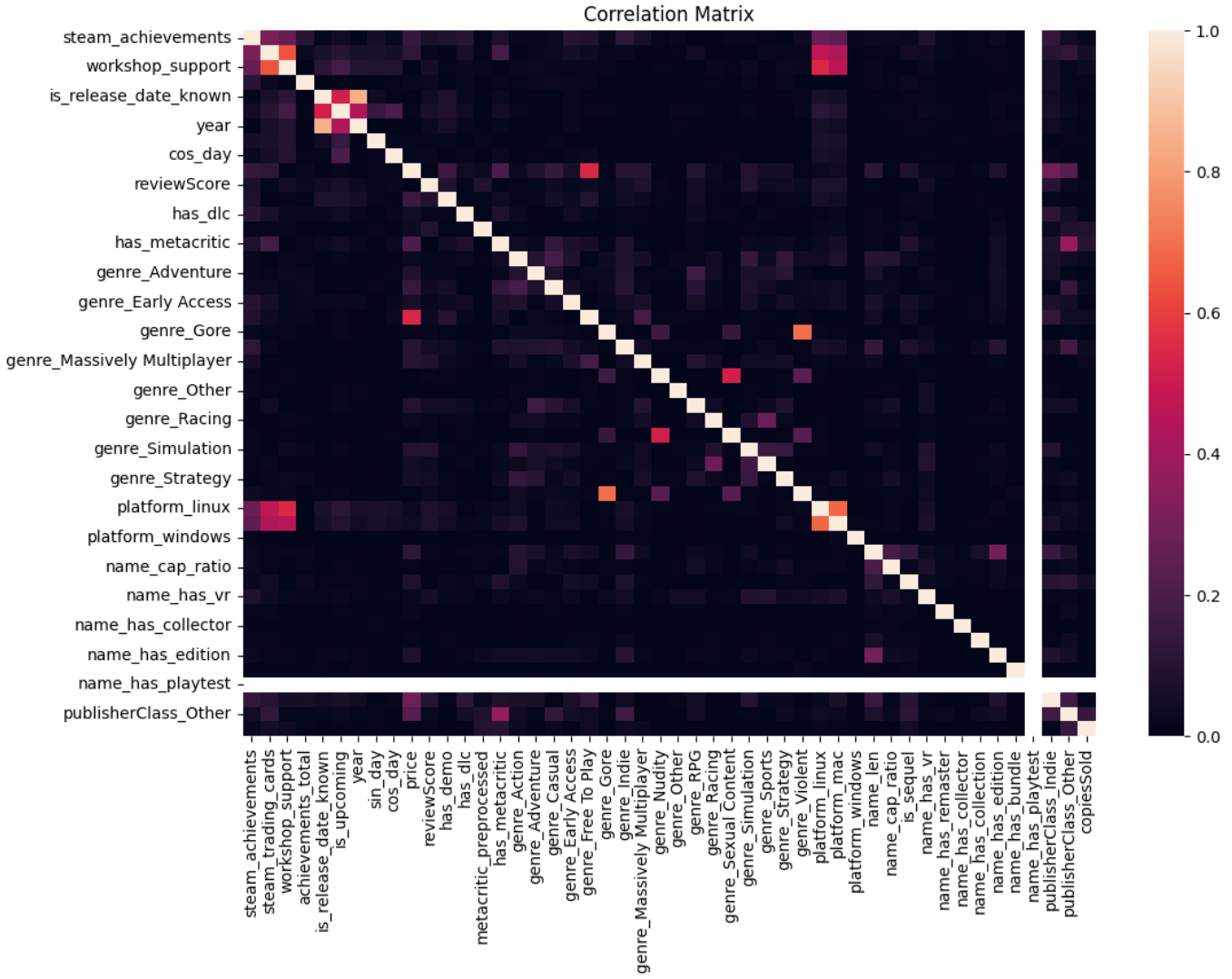
publisherClass_Indie	publisherClass_Other
0.0	0.0
1.0	0.0

4. Dropped AI Content column since it contained 100% NULL values.

Feature Selection

Regression

Correlation Matrix

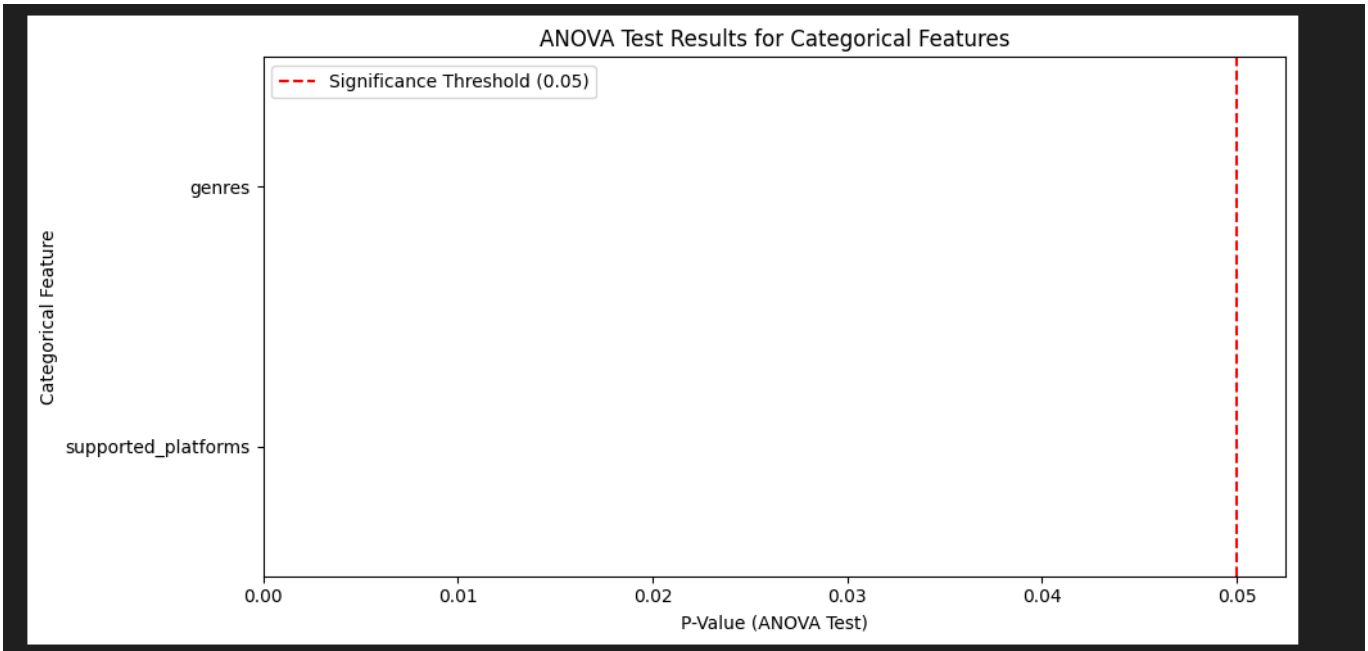



```
Dropped 3 highly correlated features: ['demo_count', 'dlc_count',
'name_words']
Pairs of features (dropped, highly correlated with dropped):
[('demo_count', 'has_demo'), ('dlc_count', 'has_dlc'), ('name_words',
'name_len')]
```

Top 10 Features Correlation To Target

	feature	correlation
0	publisherClass_Indie	0.420848
1	publisherClass_Other	0.356039
2	has_metacritic	0.345728
3	genre_Free To Play	0.206717
4	steam_trading_cards	0.178930
5	steam_achievements	0.174274
6	has_dlc	0.169345
7	genre_Casual	0.132183
8	is_sequel	0.098338
9	is_upcoming	0.092252

ANOVA



	Feature	P-Value
0	genres	0.000000e+00
1	supported_platforms	6.974636e-125

Both categorical features have ANOVA values that indicate their correlation with the target variable.

Recursive Feature Elimination (RFE)

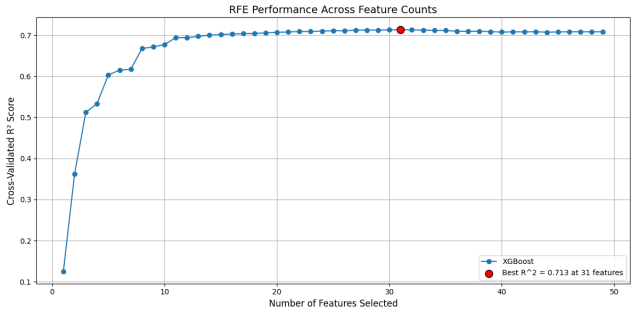
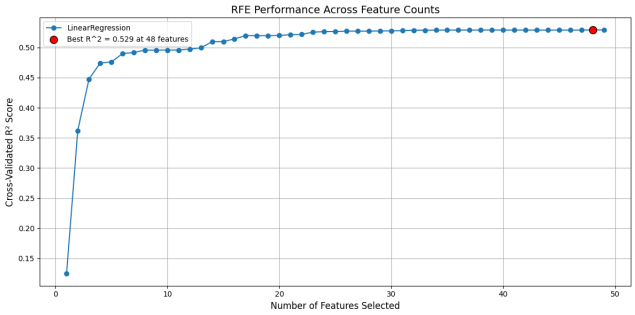
RFE is a wrapper method that needs as input the number of features to select, at first, we manually implemented RFECV ourselves so we can see how R2 score changes with the number of features.

Note

At first we didn't know that we should invert the log transformation applied on the target variable before evaluating error metrics. After research we are not sure if for R2 the correct way is to invert the log transformation.

RFE Performance With Linear Regression & XGBoost With Different # Of Features

For now, these are our best results before inverting the log transformation

1	2
	

XGBoost Features Selected

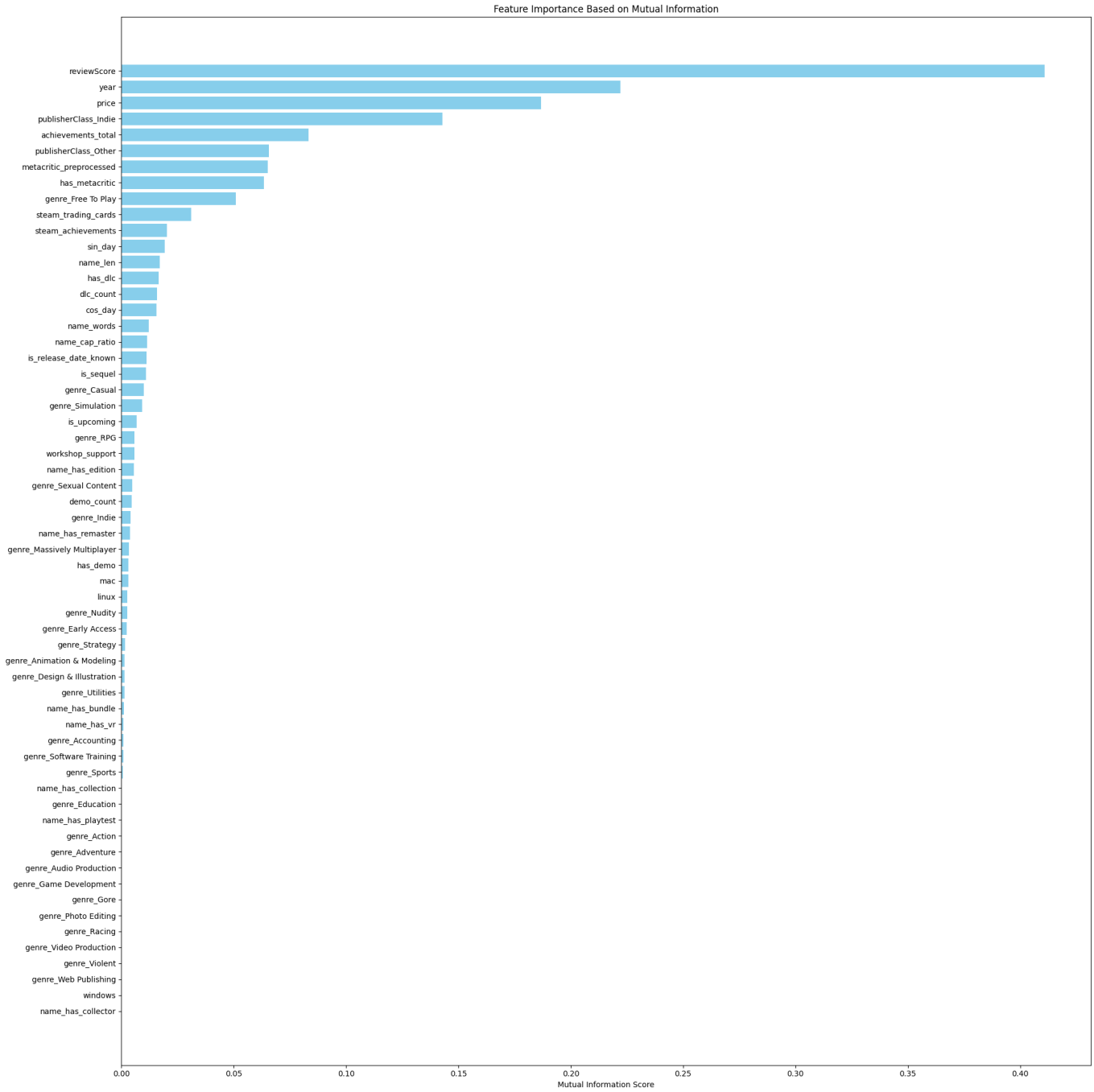
```
→ Number of Features: 31
R² Score: 0.7130
Selected Features (31): ['steam_achievements', 'steam_trading_cards',
'workshop_support', 'achievements_total', 'is_release_date_known', 'year',
'has_metacritic', 'genre_Action', 'genre_Adventure', 'genre_Casual',
'genre_Early Access', 'genre_Free To Play', 'genre_Indie', 'genre_Massively
Multiplayer', 'genre_Nudity', 'genre_RPG', 'genre_Racing',
'genre_Simulation', 'genre_Sports', 'genre_Strategy', 'linux', 'mac',
'is_sequel', 'name_has_vr', 'name_has_edition', 'price', 'reviewScore',
'publisherClass_Indie', 'publisherClass_Other', 'has_demo', 'has_dlc']
```

Linear Regression Features Selected

```
→ Number of Features: 48
R² Score: 0.5290
Selected Features (48): ['steam_achievements', 'steam_trading_cards',
'workshop_support', 'achievements_total', 'is_release_date_known',
'is_upcoming', 'year', 'sin_day', 'cos_day', 'has_metacritic',
'genre_Action', 'genre_Adventure', 'genre_Casual', 'genre_Early Access',
'genre_Free To Play', 'genre_Gore', 'genre_Indie', 'genre_Massively
Multiplayer', 'genre_Nudity', 'genre_Other', 'genre_RPG', 'genre_Racing',
'genre_Sexual Content', 'genre_Simulation', 'genre_Sports',
'genre_Strategy', 'genre_Violent', 'linux', 'mac', 'windows', 'name_len',
'name_words', 'name_cap_ratio', 'is_sequel', 'name_has_vr',
'name_has_remaster', 'name_has_collector', 'name_has_collection',
'name_has_edition', 'name_has_bundle', 'price', 'reviewScore',
'publisherClass_Indie', 'publisherClass_Other', 'has_demo', 'demo_count',
'has_dlc', 'dlc_count']
```

Later on, for cleaner code, we removed our implementation of RFECV and directly used sklearn's RFECV.

Mutual Information



Classification

We used RFE for feature selection in classification.

Hyper Parameter Tuning, Training, and Testing

Regression

Results Using RFECV and GridSearch After Inverting The Log Transformation On Target Variable

In the RFE code, we defined 2 models (Linear Regression and XGBoost), we used `RFECV` to feature select, `GridSearchCV` to cleanly hyperparameter tune, we trained on the training set and then used the generated model to predict on the testing set, later on we tried inverting the log transformation on the target variable and then calculating the error metrics.

Important Note
Our training using RFE did not yield good R2 results after removing log transformation on the target variable, so **our final regression models** were obtained with the training code that **uses mutual information feature selection**.

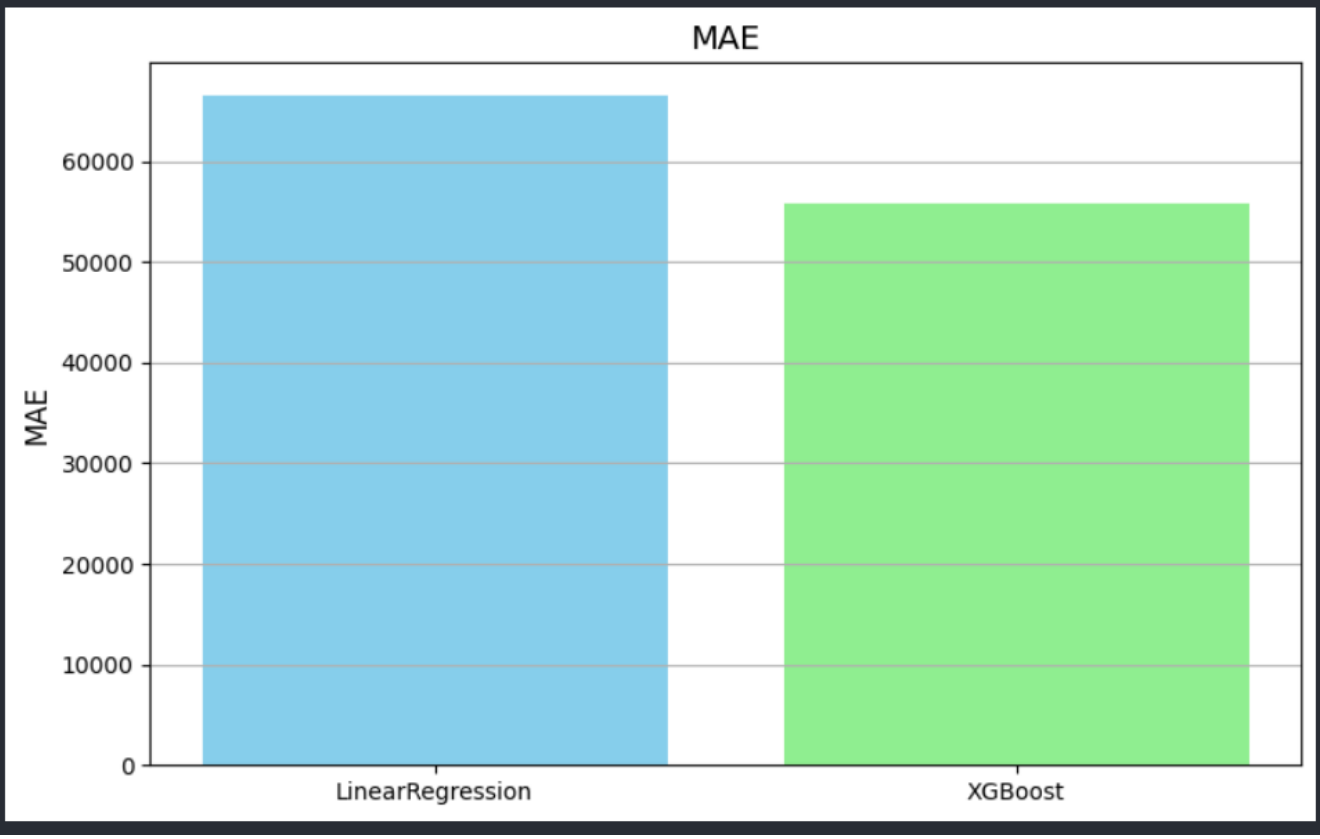
```
Running RFECV for LinearRegression...
Selected 50 features for LinearRegression.
Selected features: ['steam_achievements', 'steam_trading_cards',
'workshop_support', 'achievements_total', 'is_release_date_known',
'is_upcoming', 'year', 'sin_day', 'cos_day', 'price', 'reviewScore',
'has_demo', 'has_dlc', 'has_metacritic', 'genre_Action', 'genre_Adventure',
'genre_Casual', 'genre_Early Access', 'genre_Free To Play', 'genre_Gore',
'genre_Indie', 'genre_Massively Multiplayer', 'genre_Nudity',
'genre_Other', 'genre_RPG', 'genre_Racing', 'genre_Sexual Content',
'genre_Simulation', 'genre_Sports', 'genre_Strategy', 'genre_Violent',
'platform_linux', 'name_has_collection', 'name_has_edition',
'name_has_bundle', 'name_has_playtest', 'publisherClass_Indie',
'publisherClass_Other']

Running GridSearchCV for LinearRegression...
Best parameters for LinearRegression: {'fit_intercept': True, 'positive':
False}

Running RFECV for XGBoost...
Selected 30 features for XGBoost.
Selected features: ['steam_achievements', 'steam_trading_cards',
'workshop_support', 'achievements_total', 'is_release_date_known', 'year',
'price', 'reviewScore', 'has_demo', 'has_dlc', 'metacritic_preprocessed',
'has_metacritic', 'genre_Action', 'genre_Adventure', 'genre_Casual',
'genre_Early Access', 'genre_Free To Play', 'genre_Indie', 'genre_Massively
Multiplayer', 'genre_Nudity', 'genre_RPG', 'genre_Simulation',
'genre_Sports', 'genre_Strategy', 'platform_linux', 'platform_mac',
'is_sequel', 'name_has_edition', 'publisherClass_Indie',
'publisherClass_Other']

Running GridSearchCV for XGBoost...
Best parameters for XGBoost: {'learning_rate': 0.1, 'max_depth': 6,
'n_estimators': 200}
```

[66442.2099, 55800.1438]

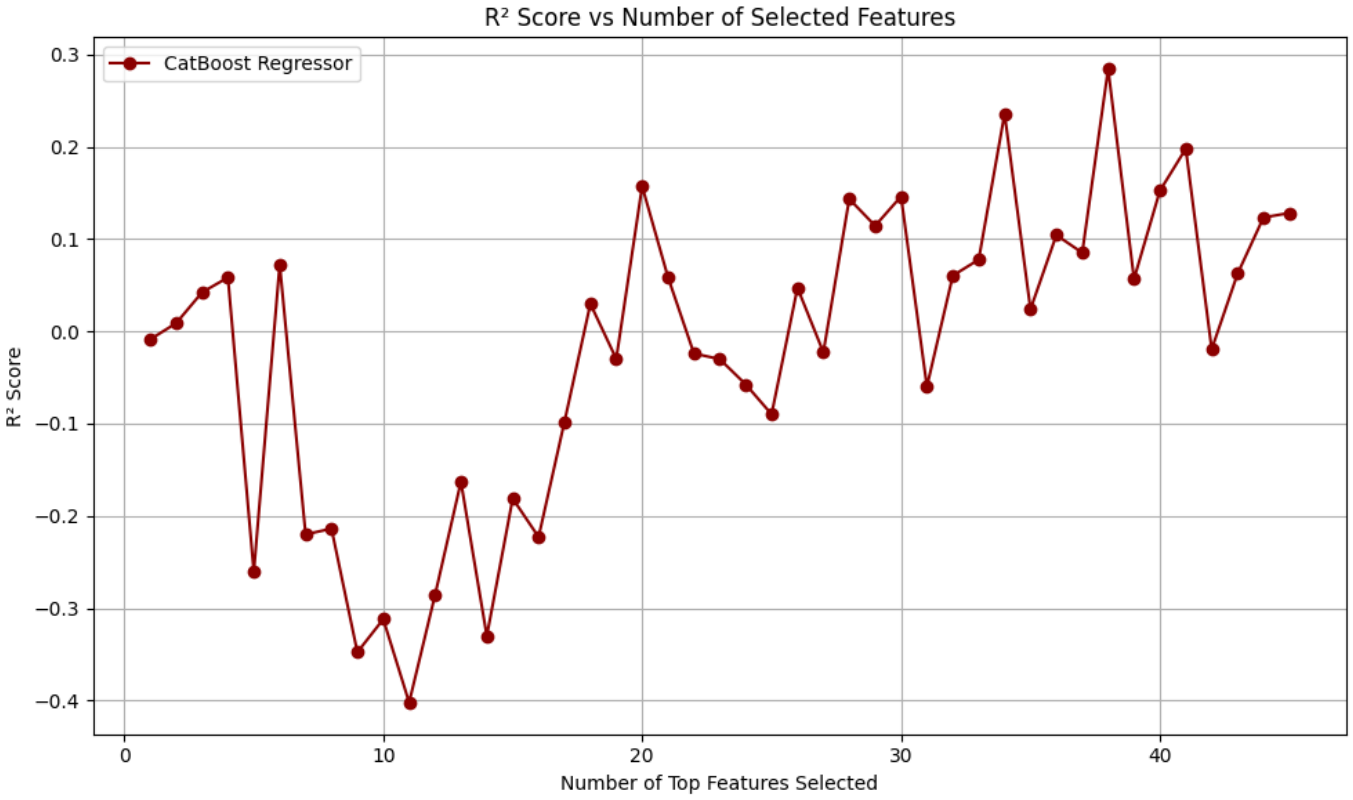


Results Using Mutual Information Feature Selection With Applying Quantile Transformer On The Target Variable And Inverting The Transformation After Making Predictions

Important Note

These are our best regression results. We tried multiple Gradient Bosting Algorithms, Decision Trees, and Linear Regression, but I only included a couple of figures here.

CatBoost




```
Max R² = 0.2842 at 38 features
MIN MSE = 312678264912.1818 at 38 features
MIN MAE = 53109.8411 at 38 features
```

XGBoost

```
Max R² = 0.2467 at 24 features
MIN MSE = 329091993209.9749 at 24 features
MIN MAE = 55327.5016 at 24 features
```

Linear Regression

```
Max R² = 0.2537 at 11 features
MIN MSE = 326023882144.2681 at 11 features
```

Classification

We label encoded the target variable, used RFE to feature select, and created code that can hyperparameter tune multiple hyperparameters for each model.

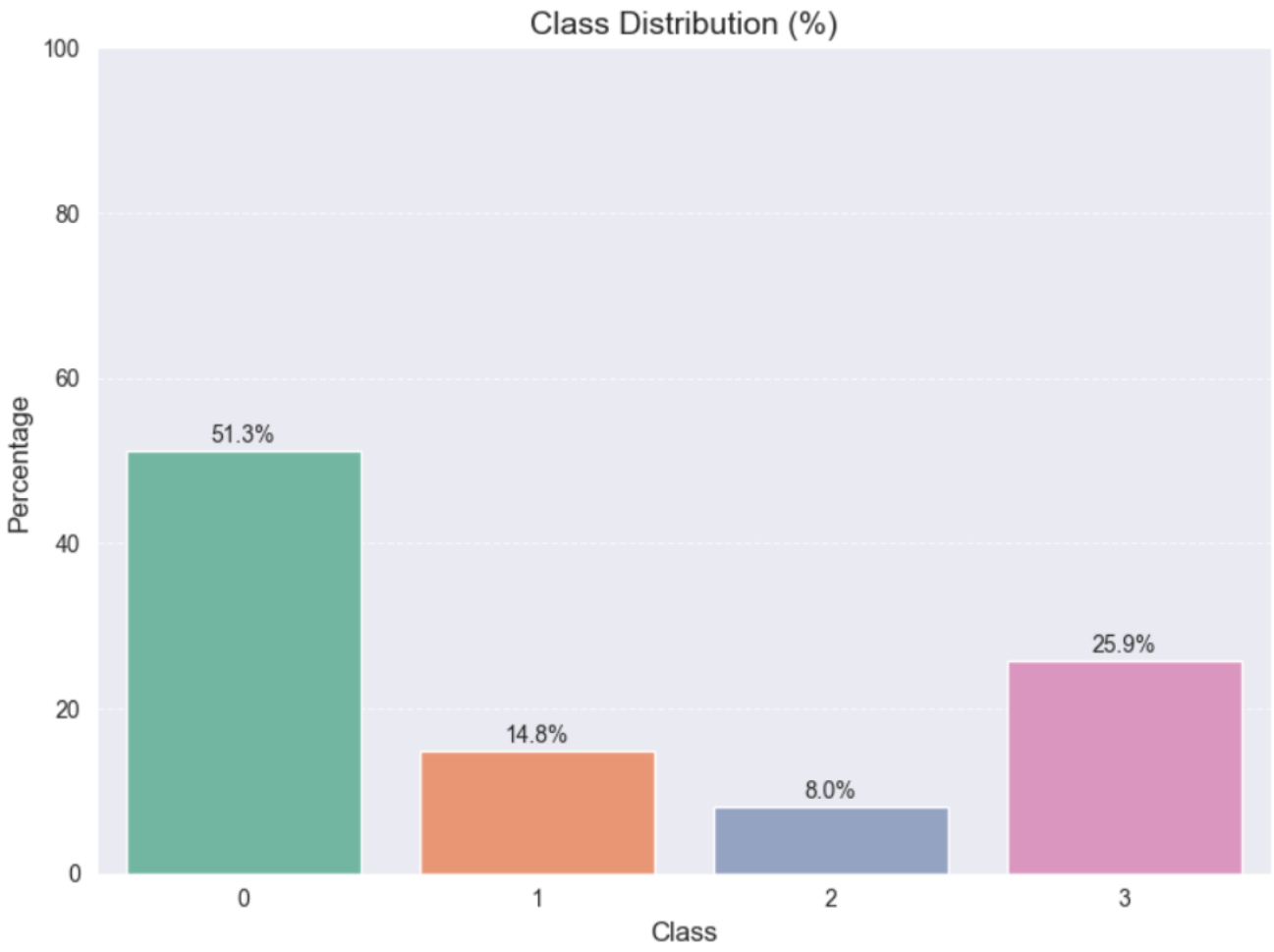
Data Visualization

The dataset demonstrates a notable class imbalance. To mitigate this issue, we employed specific strategies in our modeling process.

We incorporated class weight adjustments into our models to account for the imbalance. Specifically, we used the `class_weight='balanced'` parameter in the following algorithms:

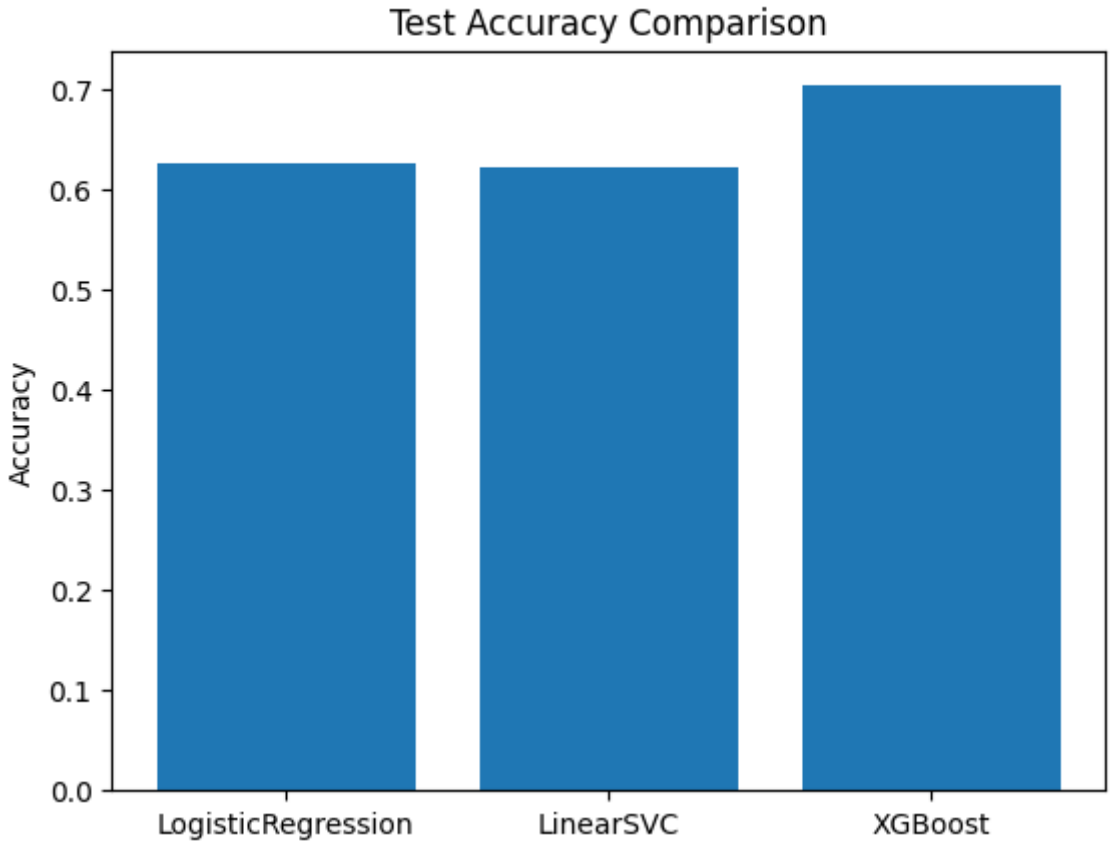
- **Logistic Regression**
- **LinearSVC**

This parameter automatically adjusts the weights assigned to each class in inverse proportion to their respective frequencies in the training data. This helps the models treat all classes more fairly.

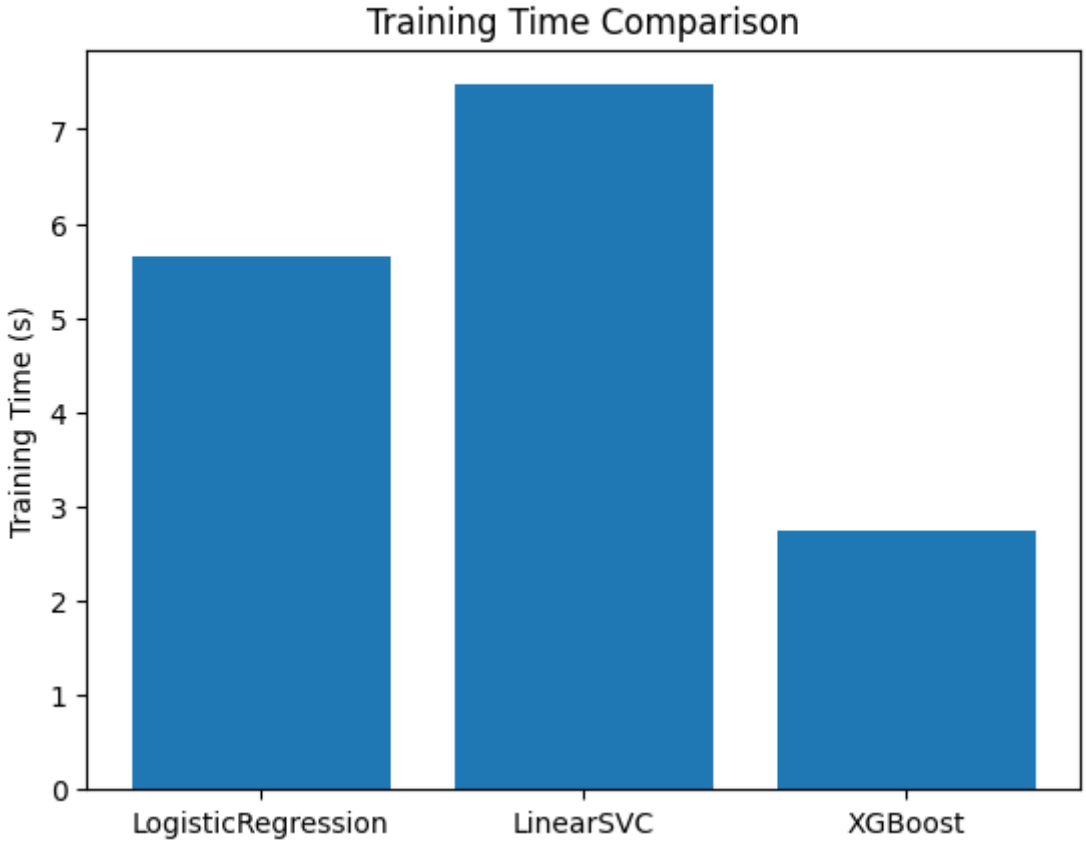


Classification Summaries

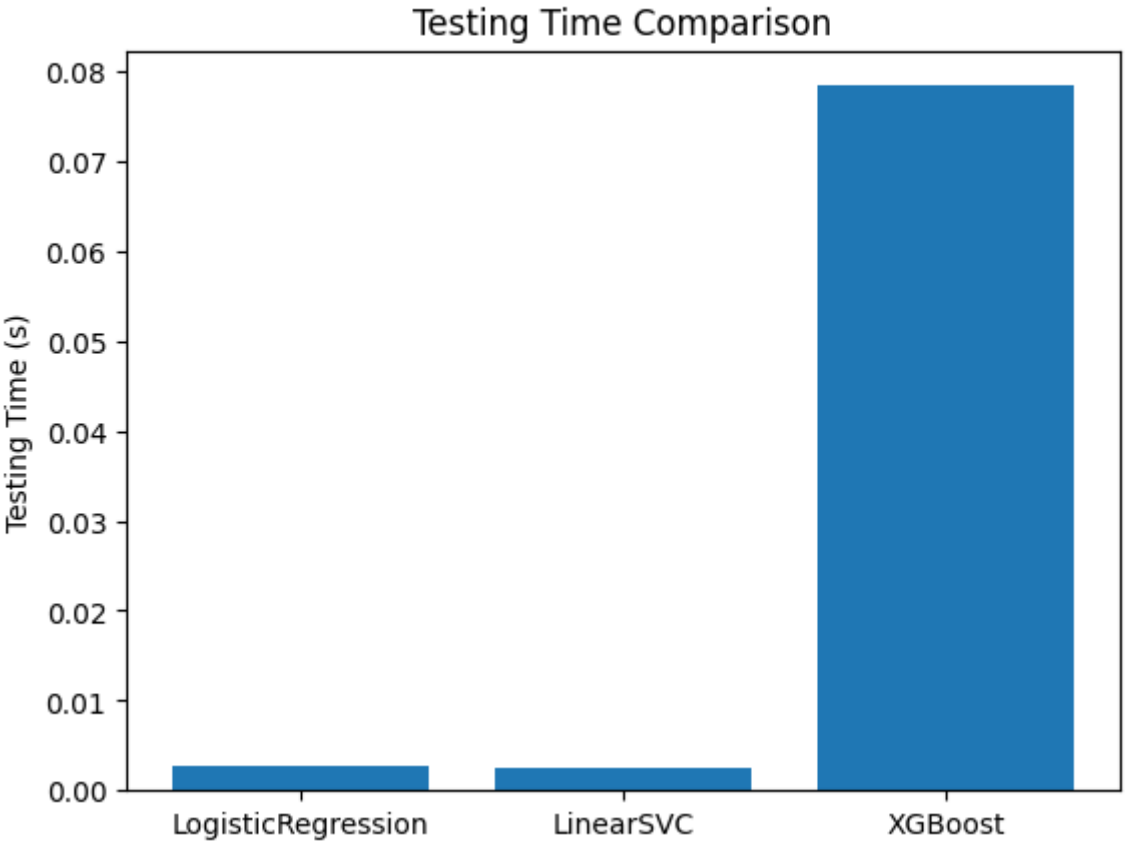
```
['LogisticRegression', 'LinearSVC', 'XGBoost']
[0.627, 0.623, 0.704]
```



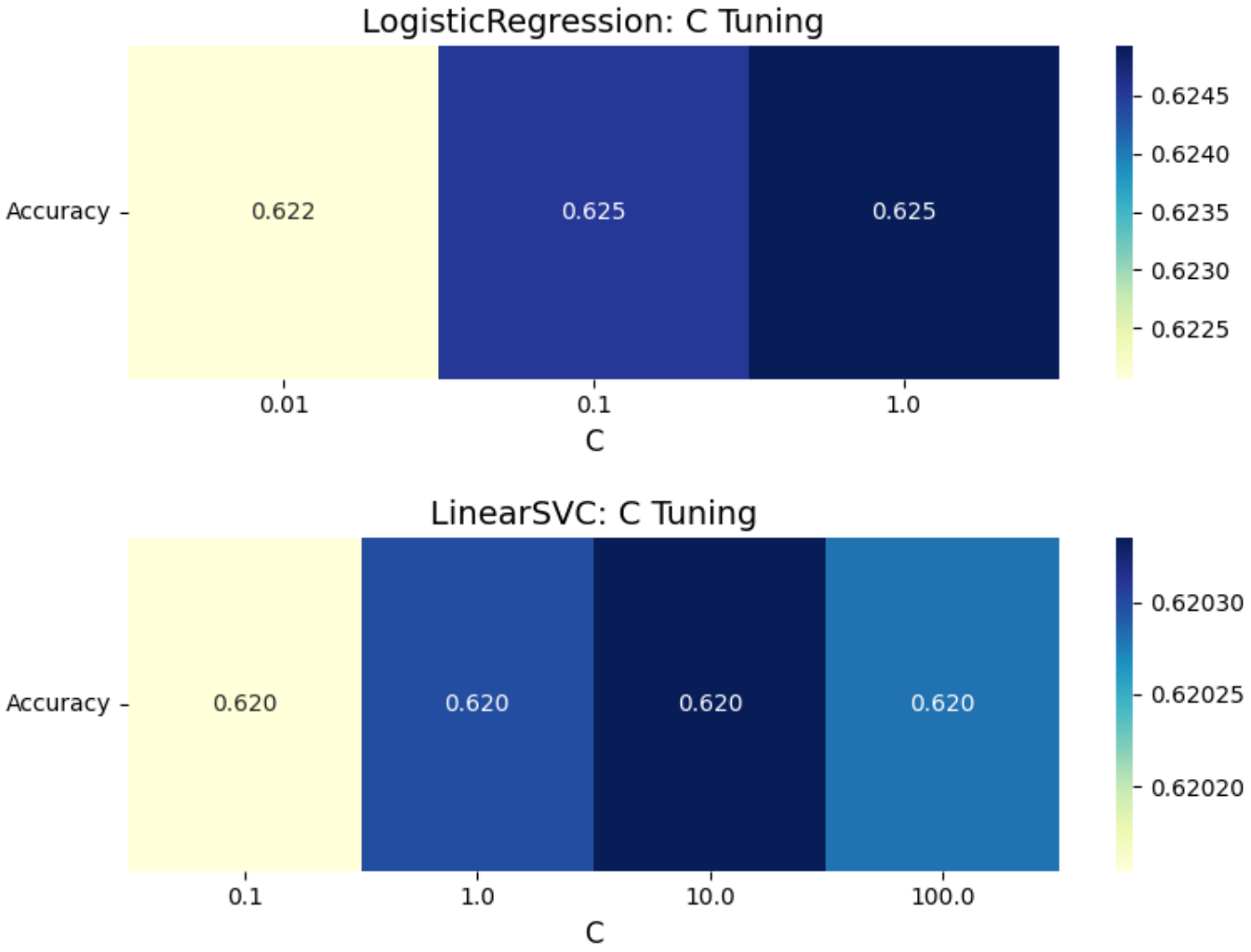
```
['LogisticRegression', 'LinearSVC', 'XGBoost']
[5.648, 7.47, 2.736]
```

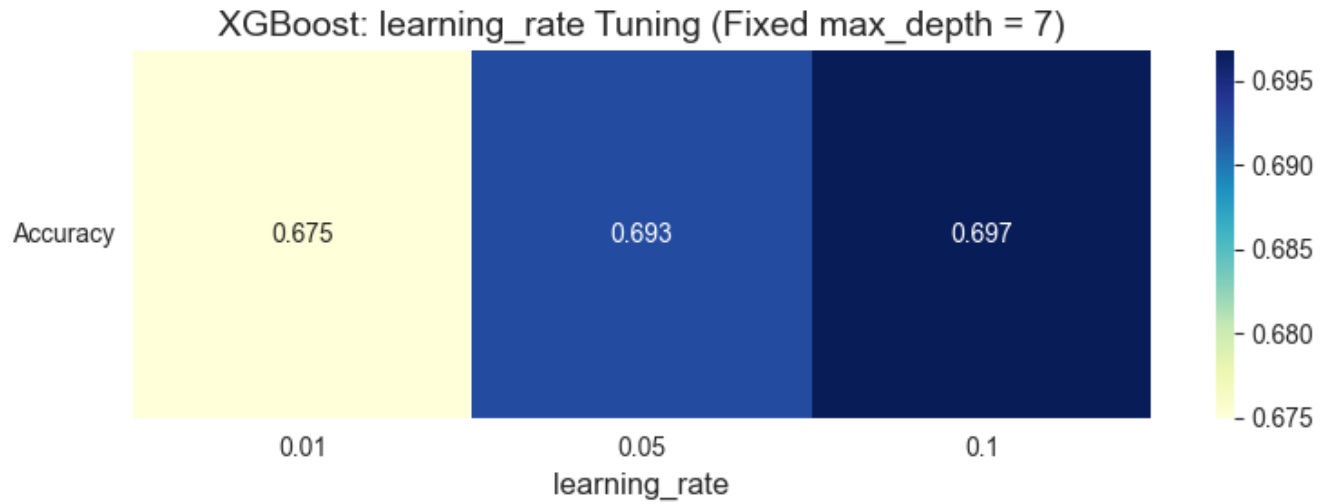


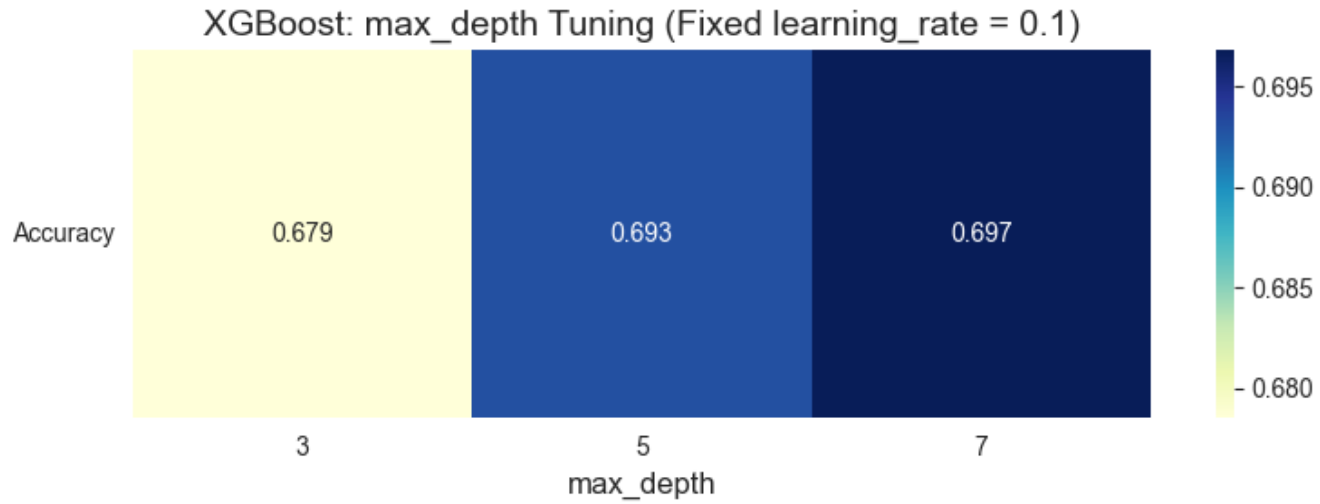

```
['LogisticRegression', 'LinearSVC', 'XGBoost']
[0.003, 0.003, 0.078]
```



Hyperparameter Tuning







Conclusions

Regression

The real conclusion is the amount of learning me and my team obtained throughout this milestone.

In regards to the surprises

1. How much the game publisher affects the copies sold.
2. How tree-based models perform a lot better than linear models on this problem.
3. The release date was very effective in the performance, which is very surprising.
4. `has_metacritic` was also unexpectedly beneficial

There is a lot more, but this is a sample of the surprises.

Classification

Our model likely performs better at classification than regression. Compared to other university teams, we achieved higher classification accuracy, even though some teams had better regression results than us. Initially, I expected our classification accuracy to be lower, but the results surprisingly proved the opposite.