OPIM 5604: FINAL PROJECT

GROUP #9

Group Lead : Naveen Abboju

Group member #1: Hany Jagwani

Group member #2: Karol Kuczynski

TITLE: VIDEO GAME SALES

UNIVERSITY OF CONNECTICUT

MSBAPM

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EXECUTIVE SUMMARY:

The video game sales dataset contains sales figures for video games released between 1980 and 2020 for more than 17,000 games from 58 different platforms. It contains information such as the title of the game, the platform the game was released on, the year it was released, the genre the game belongs to, the publisher, the number of players, the sales in different regions, and the total global sales. This dataset is useful to gain valuable insights into the video game industry, such as which genres are the most popular, which platforms are the most successful, and which publishers have the highest sales. Additionally, the dataset can be used to identify trends in the industry, such as the increasing popularity of mobile gaming and the increasing focus on digital sales. This dataset is ideal for those looking to gain a better understanding of the video game industry and its development over time.

It can be used to identify trends in the video game industry, analyze the performance of different platforms, and compare the success of different genres. The dataset is an invaluable resource for those interested in video game history, sales, and analytics.

The video game sales dataset is to provide an analysis of the sales of video games across all platforms worldwide. The dataset includes titles, platforms, year of release, genre, publisher, NA_sales, EU_sales, JP_sales, and Other_sales. This allows for the analysis of the different types of games, the sales of those games across different regions, and the trends in video game sales over time.

Based on our findings, developers should utilize the Decision Tree model derived from our dataset to calculate which type of video game will sell the best in any given area, as well as tell the gamer which game will be worthwhile to pick up and play.

INTRODUCTION:

Video game sales data and market analysis

This dataset offers data on the sales figures and performance of video games. It covers all regions and provides detailed information on the platforms, release dates, genres, publishers, developers, and other relevant data.

This data set is perfect for anyone looking to analyze the video game market and identify trends. It can be used to track the sales of individual games, discover which genres are most popular, and forecast future sales.

Data on video game sales is essential for anyone involved in the video game industry, from developers and publishers to retailers and investors. This dataset provides the most comprehensive and up-to-date data available, making it an invaluable resource for anyone looking to understand the video game market.

It is important to analyze the most successful video games in terms of their genre and region. The success of a video game also depends on the type of platform it is created for. This can help in understanding the target audience of the video game and can be a useful guide for game developers.

From this analysis, we predict the most successful video games which will help us understand the reasons behind the success or failure of video games. The analysis can be used to modify the production of video games by the most lucrative strategy since the development of video games requires a substantial investment.

ABOUT THE DATA SET:

The dataset includes information such as the name of the game, the platform on which it was released, the region in which it was released, the release date, the genre, the publisher, and the number of copies sold. This dataset contains 16,598 items and includes a list of video games that have sold more than 100,000 copies. It was created from data that was scraped from Charts.

Fields included in the dataset:

- Rank - Ranking of overall sales
- Name - The games name
- Platform - Platform of the game's release (i.e. PC, PS4, etc.)
- Year - Year of the game's release
- Genre - Genre of the game
- Publisher - Publisher of the game
- NA_Sales - Sales in North America (in millions)
- EU_Sales - Sales in Europe (in millions)
- JP_Sales - Sales in Japan (in millions)
- Other_Sales - Sales in the rest of the world (in millions)
- Global_Sales - Total worldwide sales.

Predictors of the dataset:

- Overall sales: the total number of units sold
- Average price: the average price of a game
- Platform: the platform the game was released on

- Genre: the genre of the game
- Year: the year the game was released

Reviews

- Overall reviews: the total number of reviews for the game
- Positive reviews: the number of positive reviews for the game
- Negative reviews: the number of negative reviews for the game

Forecasts

- Sales forecast: the projected sales for the game in the future
- Price forecast: the projected price for the game in the future

DATA SOURCE:

There are 16,598 records in the data collection regarding video game sales that were obtained from Kaggle. The variables in this data set are the rank of total sales, name of the game, gaming platforms, year of release, genre, publisher, sales in North America, Europe, Japan, the rest of the globe, and worldwide sales.

SEMMA (SAMPLE, EXPLORE, MODIFY, MODEL, & ASSES):

SAMPLE: This stage involves choosing a portion of the suitable volume dataset from the larger dataset to create the model. To identify variables influencing the process at this early stage, the information will be separated into training, validation, and testing sets. We'll use JMP's Make Validation Column tool to build these samples.

EXPLORE: The analysis of the correlations among the various data elements as well as the identification of missing information is done in this step using both univariate and multivariate techniques. While univariate analysis focuses on each factor separately, multivariate analysis examines the relationships between variables. All these elements could have an impact on the

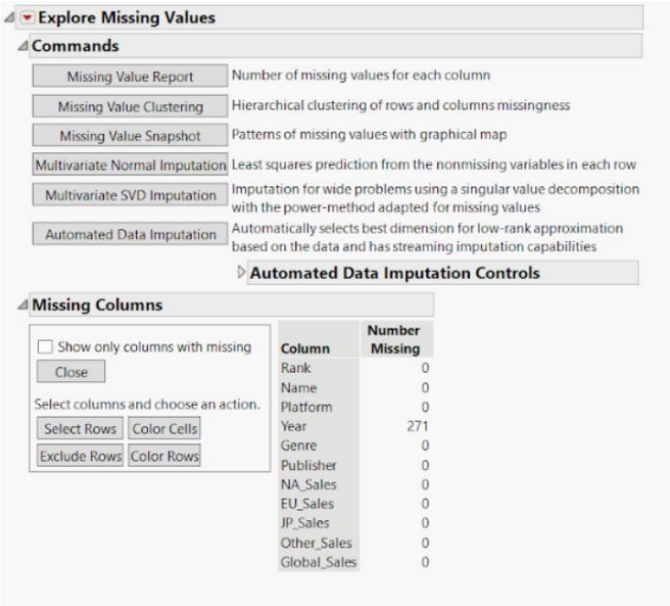
analysis's conclusion, which will rely primarily on data visualization. JMP's distribution, multivariate, and correlation tools will be used for this.

MODIFY: Using application logic, we will extract what we discover through research. Before being passed on to the modeling stage, the data is analyzed, cleaned, improved, and transformed. From this, we derive JMP's formula columns and tools like the missing data pattern, outlier analysis, principal component analysis, recode, binning, transformations, and standardization.

MODEL: The variables are modified, and the data is cleaned. Data mining methods can be applied to develop a predicted model of how the data produces the desired outcome. The JMP modeling tools fit model, partition, bootstrap forest, boosted tree, and model screening will all be used.

ASSES: We assess the effectiveness and dependability of the model. The data can now be used to determine performance efficacy after being tested.

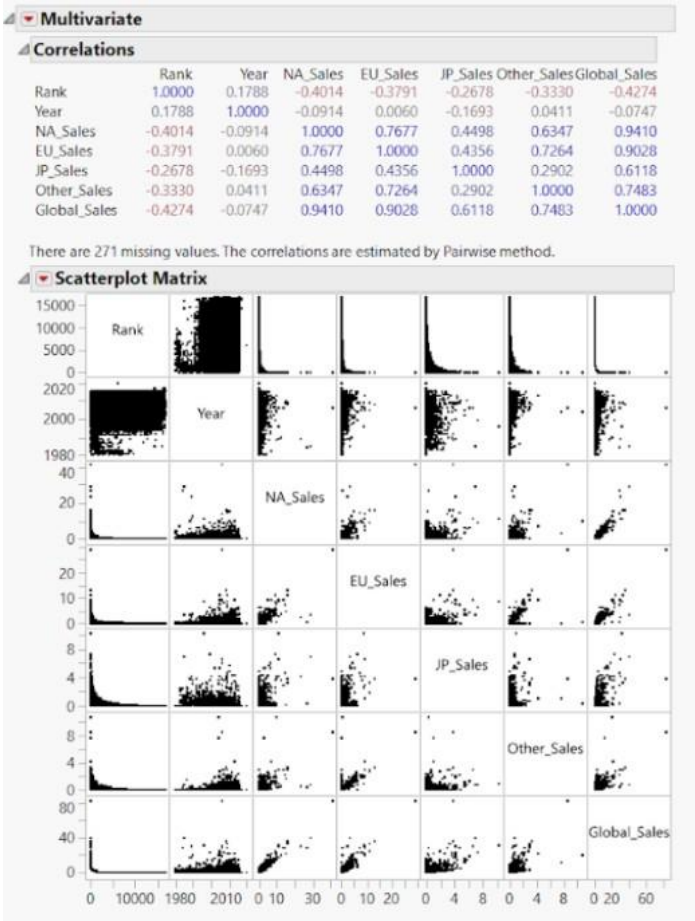
ANALYZING THE MISSING VALUES:



By analyzing the missing values in the dataset, there are 271 missing values present in the year. The number is low compared to the total number of records present in the original dataset. And no missing values are present in the remaining fields of the dataset. So, we can exclude the missing values from the year field.

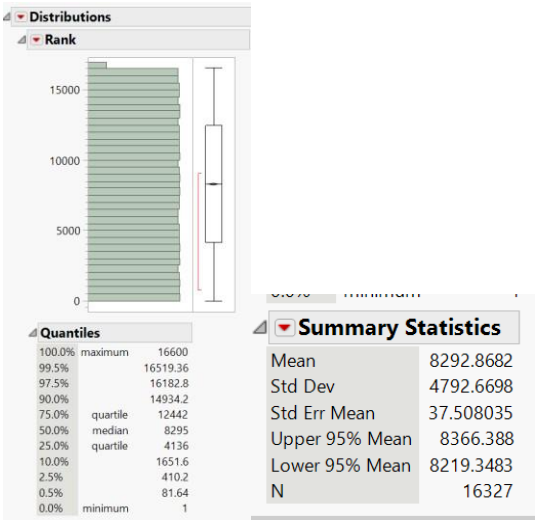
MULTIVARIATE ANALYSIS:

The multivariate analysis is used to find the correlation among the variables. By performing multivariate analysis on the video game sales data set we found that all the variables are strongly correlated to the target variable. Hence, we are not excluding the fields as they are strongly correlated.

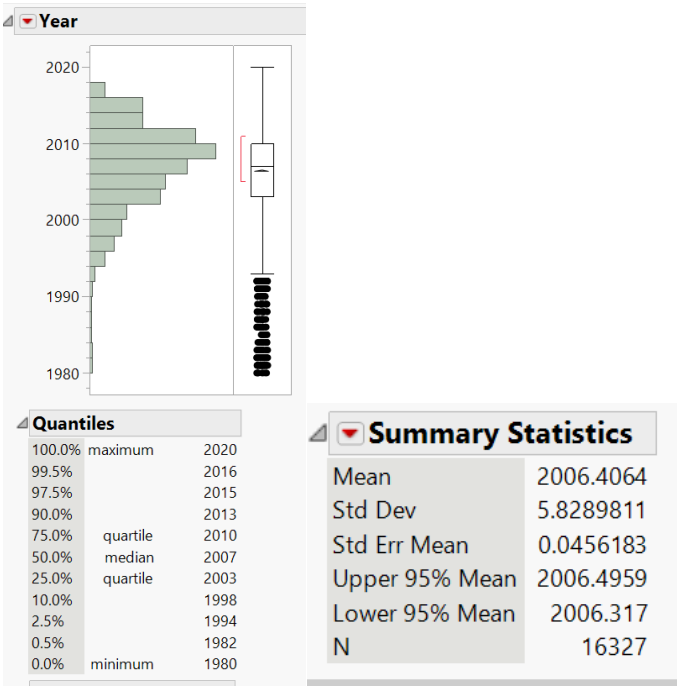


DISTRIBUTION ANALYSIS:

Rank: The distribution analysis for the rank variable depicts that it is uniformly distributed.

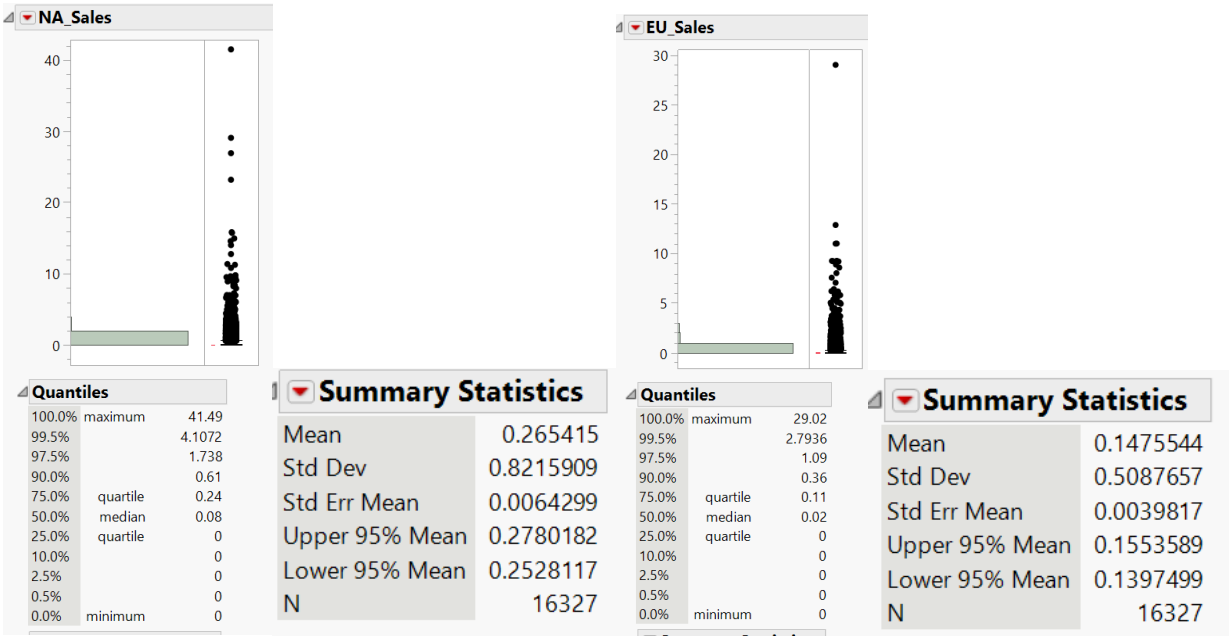


Year: The year variable is normally distributed with few outliers present in the analysis.

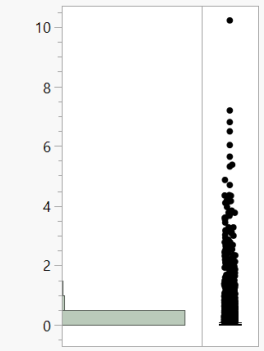


The sales distribution in North America, Europe, Japan, other, and worldwide

is not evenly distributed and it has outliers in the data.



JP_Sales



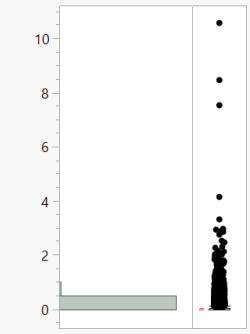
Quantiles

100.0%	maximum	10.22
99.5%		2.02
97.5%		0.66
90.0%		0.18
75.0%	quartile	0.04
50.0%	median	0
25.0%	quartile	0
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	0.0786611
Std Dev	0.311557
Std Err Mean	0.0024383
Upper 95% Mean	0.0834404
Lower 95% Mean	0.0738818
N	16327

Other_Sales



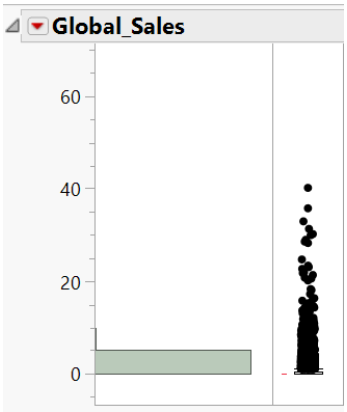
Quantiles

100.0%	maximum	10.57
99.5%		0.99
97.5%		0.33
90.0%		0.11
75.0%	quartile	0.04
50.0%	median	0.01
25.0%	quartile	0
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	0.0483255
Std Dev	0.1898854
Std Err Mean	0.0014861
Upper 95% Mean	0.0512383
Lower 95% Mean	0.0454126
N	16327

Global_Sales



Quantiles

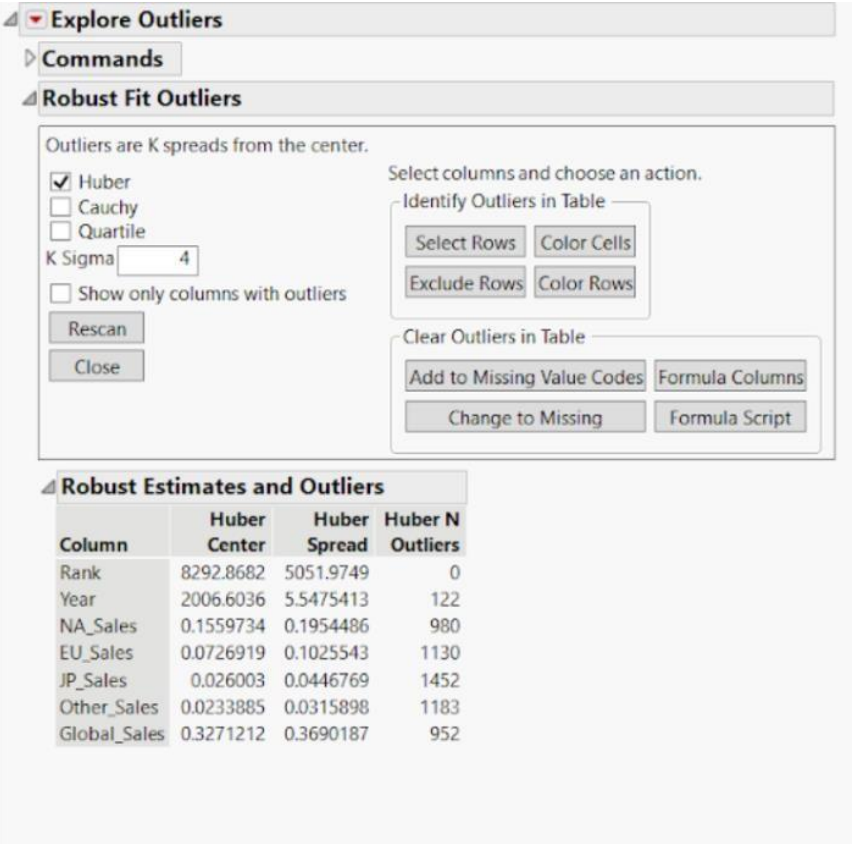
100.0%	maximum	82.74
99.5%		8.3624
97.5%		3.28
90.0%		1.22
75.0%	quartile	0.48
50.0%	median	0.17
25.0%	quartile	0.06
10.0%		0.02
2.5%		0.01
0.5%		0.01
0.0%	minimum	0.01

Summary Statistics

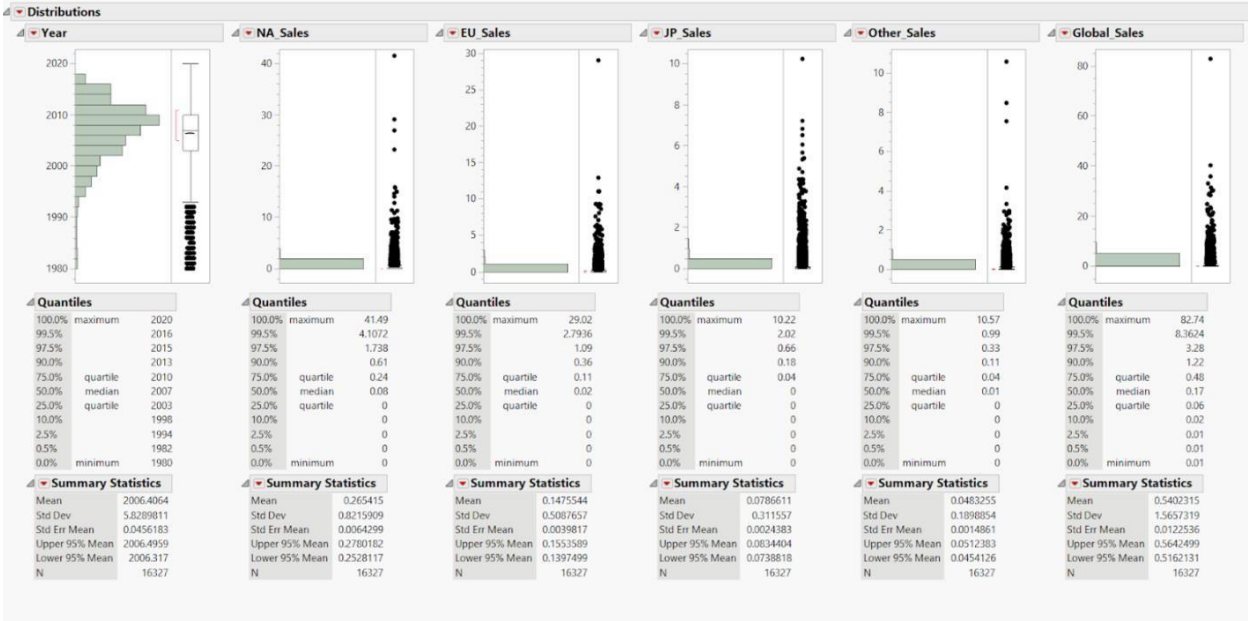
Mean	0.5402315
Std Dev	1.5657319
Std Err Mean	0.0122536
Upper 95% Mean	0.5642499
Lower 95% Mean	0.5162131
N	16327

EXPLORING OUTLIERS IN THE DATASET:

After exploring the outliers in the dataset in each variable of the dataset we found the outliers present in the columns: year, NA_Sales, EU_Sales, JP_Sales, Other_sales, & Global_sales. The below picture shows the number of outliers present in the variables as well as the outliers present outside the whiskers by performing the distribution analysis.

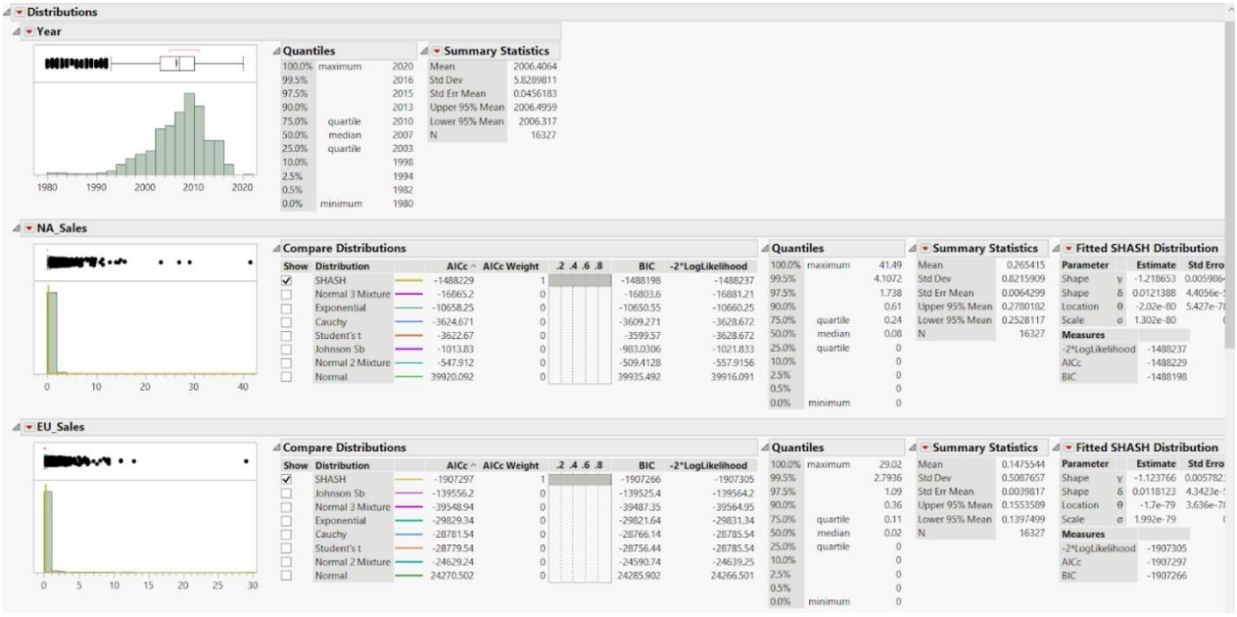


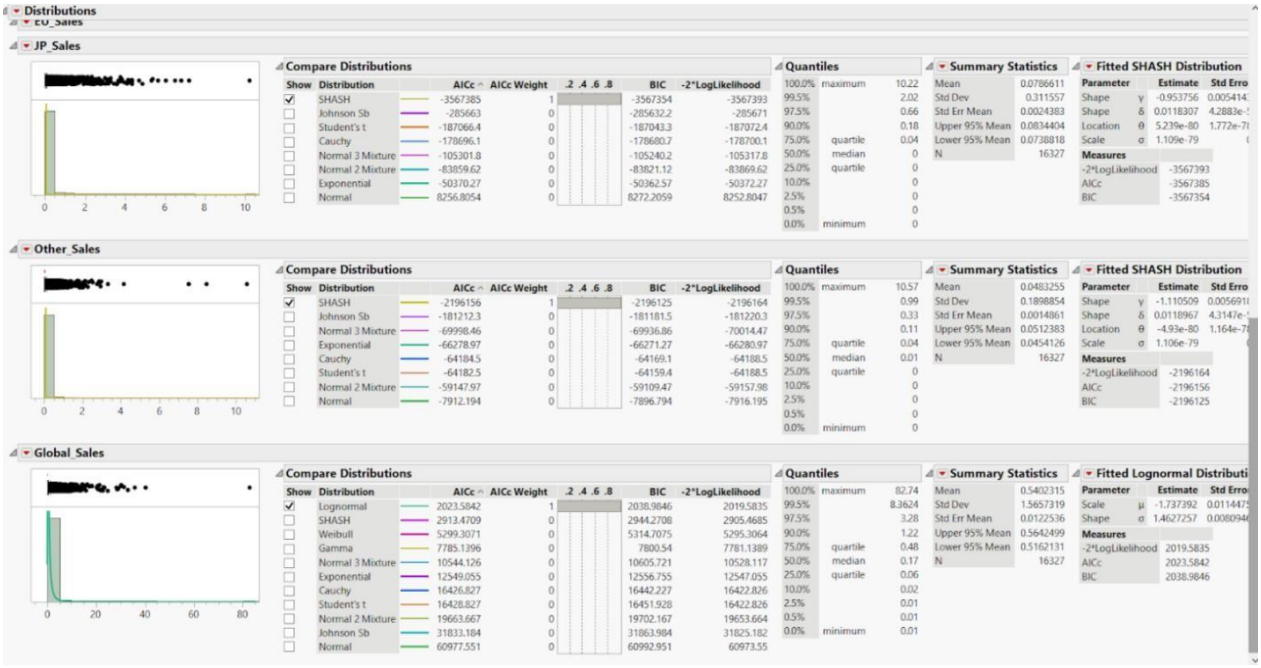
Column	Huber Center	Huber Spread	Huber N Outliers
Rank	8292.8682	5051.9749	0
Year	2006.6036	5.5475413	122
NA_Sales	0.1559734	0.1954486	980
EU_Sales	0.0726919	0.1025543	1130
JP_Sales	0.026003	0.0446769	1452
Other_Sales	0.0233885	0.0315898	1183
Global_Sales	0.3271212	0.3690187	952



TRANSFORMING THE VARIABLES:

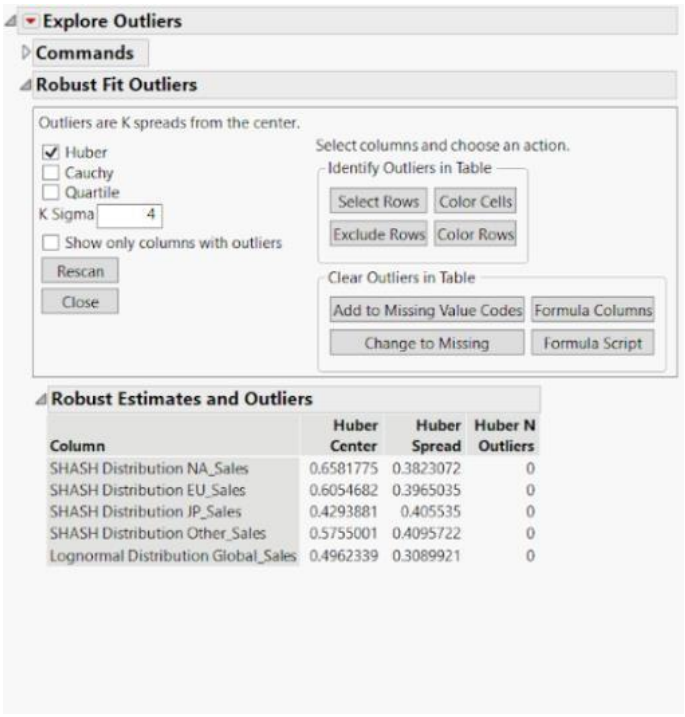
Transforming the variables with their best fit will minimize the outliers present in the variables. So that makes data clean to perform further operations. Here the best fit is SHASH for all variables except for the Global_Sales variable. The Global_Sales variable has lognormal as its best fit.



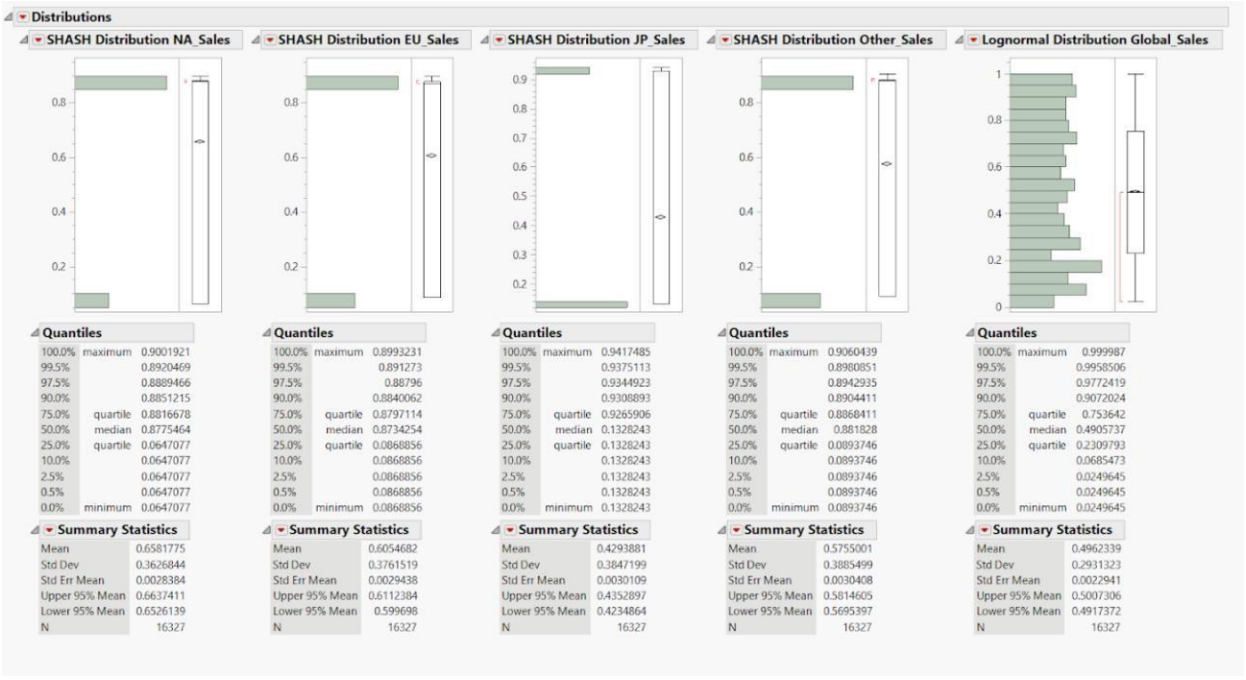


AFTER THE TRANSFORMATION OF VARIABLES:

By performing the outlier analysis on the transformed variables, we found zero outliers in all transformed variables. Hence, we can say that the data is now cleaned and ready to perform further analysis on it. The below pictures show the zero outliers present in each transformed variable and by performing the distribution analysis we can see there are no outliers present outside the whiskers.



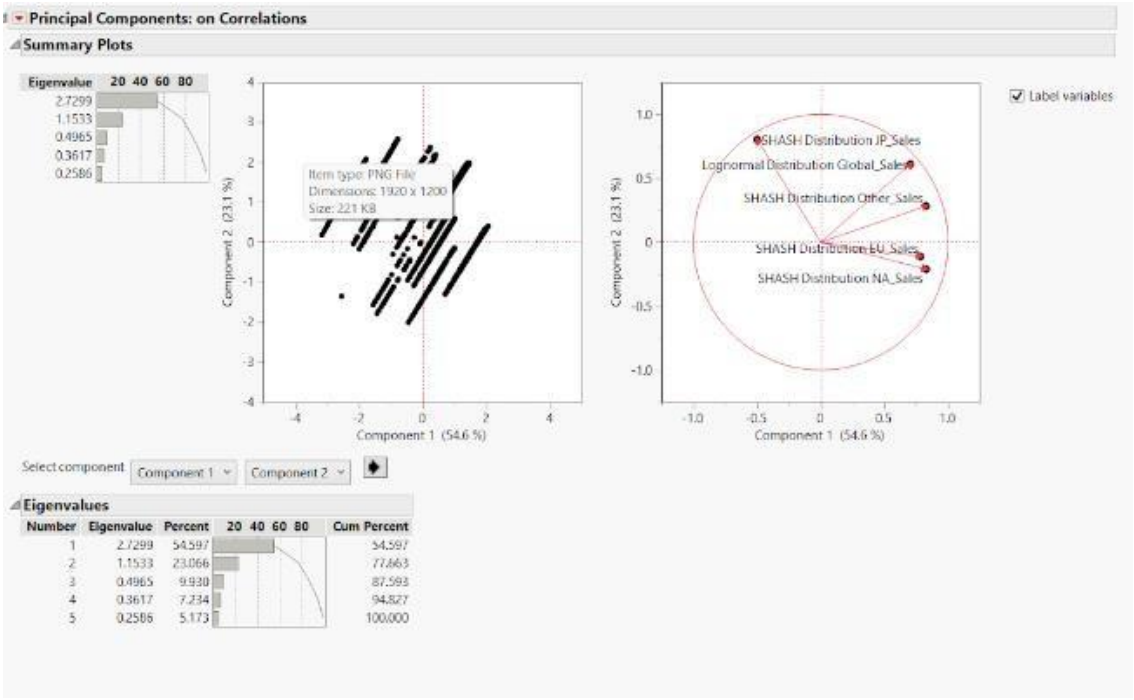
Column	Huber Center	Huber Spread	Huber N Outliers
SHASH Distribution NA_Sales	0.6581775	0.3823072	0
SHASH Distribution EU_Sales	0.6054682	0.3965035	0
SHASH Distribution JP_Sales	0.4293881	0.405535	0
SHASH Distribution Other_Sales	0.5755001	0.4095722	0
Lognormal Distribution Global_Sales	0.4962339	0.3089921	0



Quantiles	SHASH Distribution NA_Sales	SHASH Distribution EU_Sales	SHASH Distribution JP_Sales	SHASH Distribution Other_Sales	Lognormal Distribution Global_Sales
100.0% maximum	0.9001921	0.8993231	0.9417485	0.9060439	0.999987
99.5%	0.8920469	0.891273	0.9375113	0.8980851	0.9958506
97.5%	0.8889466	0.88796	0.9344923	0.8942935	0.9772419
90.0%	0.8851215	0.8840062	0.9308893	0.8904411	0.9072024
75.0% quartile	0.8816678	0.8797114	0.9265906	0.8868411	0.753642
50.0% median	0.8775464	0.8734254	0.1328243	0.881828	0.4905737
25.0% quartile	0.0647077	0.0868856	0.1328243	0.0893746	0.2309793
10.0%	0.0647077	0.0868856	0.1328243	0.0893746	0.0685473
2.5%	0.0647077	0.0868856	0.1328243	0.0893746	0.0249645
0.5%	0.0647077	0.0868856	0.1328243	0.0893746	0.0249645
0.0% minimum	0.0647077	0.0868856	0.1328243	0.0893746	0.0249645

Summary Statistics	SHASH Distribution NA_Sales	SHASH Distribution EU_Sales	SHASH Distribution JP_Sales	SHASH Distribution Other_Sales	Lognormal Distribution Global_Sales
Mean	0.6581775	0.6054682	0.4293881	0.5755001	0.4962339
Std Dev	0.3626844	0.3761519	0.3847199	0.3885499	0.2931323
Std Err Mean	0.0028384	0.0029438	0.0030109	0.0030408	0.0022941
Upper 95% Mean	0.6637411	0.6112384	0.4352897	0.5814605	0.5007306
Lower 95% Mean	0.6526139	0.599698	0.4234864	0.5695397	0.4917372
N	16327	16327	16327	16327	16327

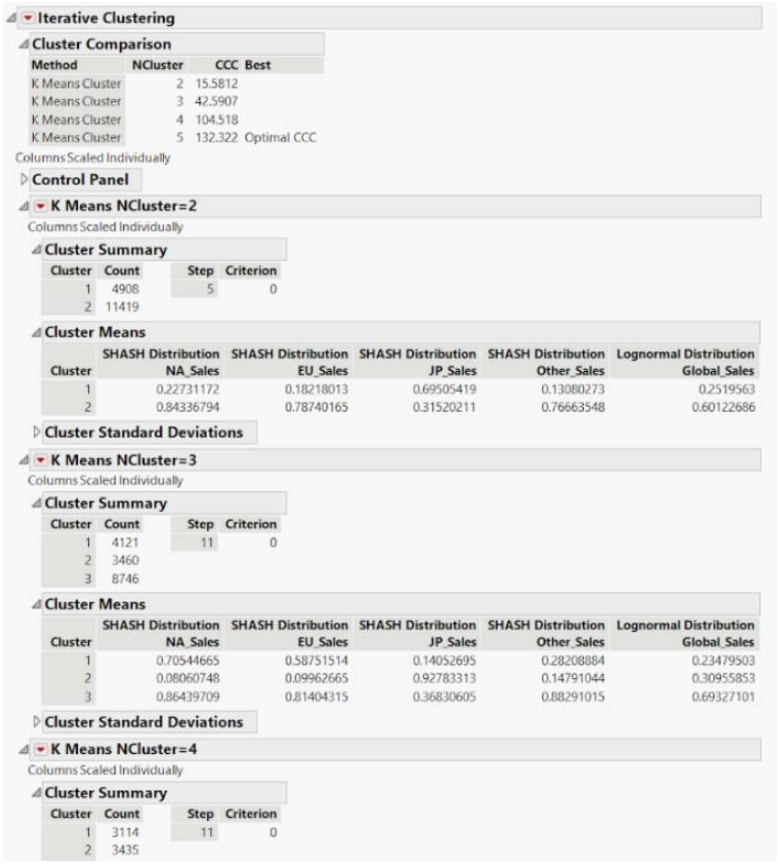
PRINCIPAL COMPONENT ANALYSIS:



The three principal components that should be saved are PC1, PC2, and PC3 as they cover more than 80% of variance. These components explain a large portion of the variance in the dataset, which can provide valuable insights into the underlying factors that influence the data. Additionally, these components can be used to reduce the dimensions of the data and make it more manageable.

CLUSTERING:

Clustering is a technique that is used to know the alike characteristics of the variables present in the dataset. Here we performed K-means on transformed variables. From the analysis, the ideal number of clustering is 5 with an optimal value of 132.32, and the number of clusters is 2473.



Iterative Clustering

Cluster Comparison

Method	NCluster	CCC	Best
K Means Cluster	2	15.5812	
K Means Cluster	3	42.5907	
K Means Cluster	4	104.518	
K Means Cluster	5	132.322	Optimal CCC

Columns Scaled Individually

Control Panel

K Means NCluster=2

Columns Scaled Individually

Cluster Summary

Cluster	Count	Step	Criterion
1	4908	5	0
2	11419		

Cluster Means

Cluster	SHASH Distribution NA_Sales	SHASH Distribution EU_Sales	SHASH Distribution JP_Sales	SHASH Distribution Other_Sales	Lognormal Distribution Global_Sales
1	0.22731172	0.18218013	0.69505419	0.13080273	0.2519563
2	0.84336794	0.78740165	0.31520211	0.76663548	0.60122686

Cluster Standard Deviations

K Means NCluster=3

Columns Scaled Individually

Cluster Summary

Cluster	Count	Step	Criterion
1	4121	11	0
2	3460		
3	8746		

Cluster Means

Cluster	SHASH Distribution NA_Sales	SHASH Distribution EU_Sales	SHASH Distribution JP_Sales	SHASH Distribution Other_Sales	Lognormal Distribution Global_Sales
1	0.70544665	0.58751514	0.14052695	0.28208884	0.23479503
2	0.08060748	0.09962665	0.92783313	0.14791044	0.30955853
3	0.86439709	0.81404315	0.36830605	0.88291015	0.69327101

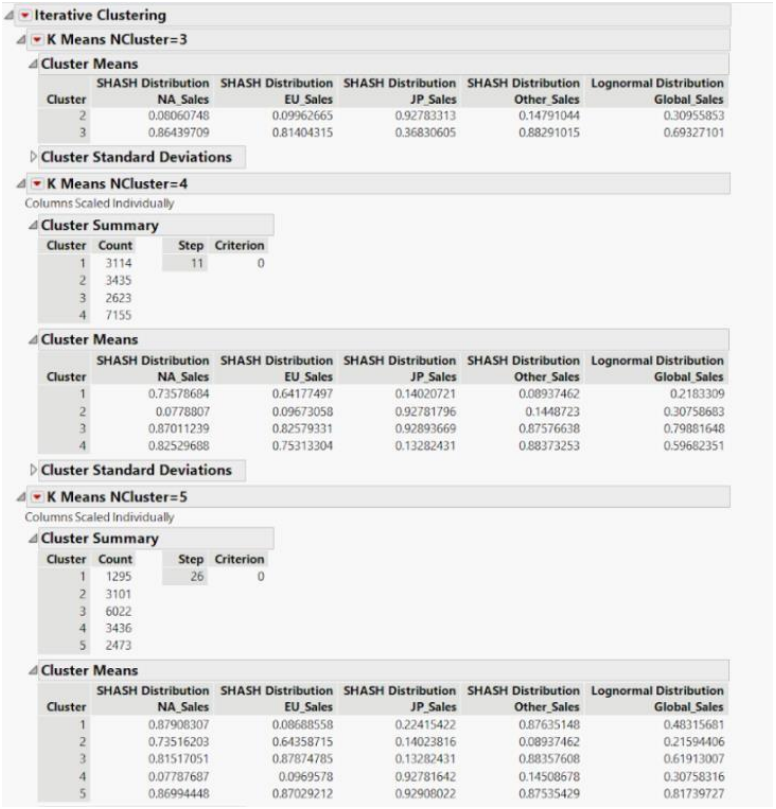
Cluster Standard Deviations

K Means NCluster=4

Columns Scaled Individually

Cluster Summary

Cluster	Count	Step	Criterion
1	3114	11	0
2	3435		



Iterative Clustering

K Means NCluster=3

Cluster Means

Cluster	SHASH Distribution NA_Sales	SHASH Distribution EU_Sales	SHASH Distribution JP_Sales	SHASH Distribution Other_Sales	Lognormal Distribution Global_Sales
2	0.08060748	0.09962665	0.92783313	0.14791044	0.30955853
3	0.86439709	0.81404315	0.36830605	0.88291015	0.69327101

Cluster Standard Deviations

K Means NCluster=4

Columns Scaled Individually

Cluster Summary

Cluster	Count	Step	Criterion
1	3114	11	0
2	3435		
3	2623		
4	7155		

Cluster Means

Cluster	SHASH Distribution NA_Sales	SHASH Distribution EU_Sales	SHASH Distribution JP_Sales	SHASH Distribution Other_Sales	Lognormal Distribution Global_Sales
1	0.73578684	0.64177497	0.14020721	0.08937462	0.2183309
2	0.0778807	0.09673058	0.92781796	0.1448723	0.30758683
3	0.87011239	0.82579331	0.92893669	0.87576638	0.79881648
4	0.82529688	0.75313304	0.13282431	0.88373253	0.59682351

Cluster Standard Deviations

K Means NCluster=5

Columns Scaled Individually

Cluster Summary

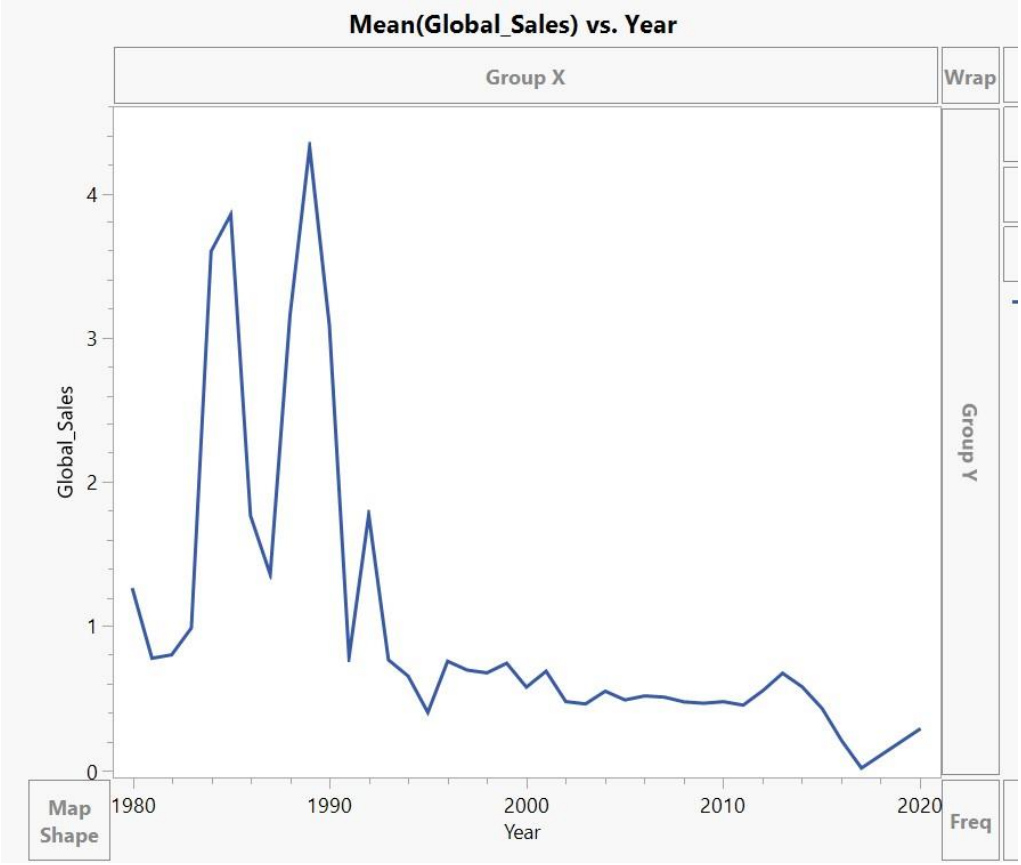
Cluster	Count	Step	Criterion
1	1295	26	0
2	3101		
3	6022		
4	3436		
5	2473		

Cluster Means

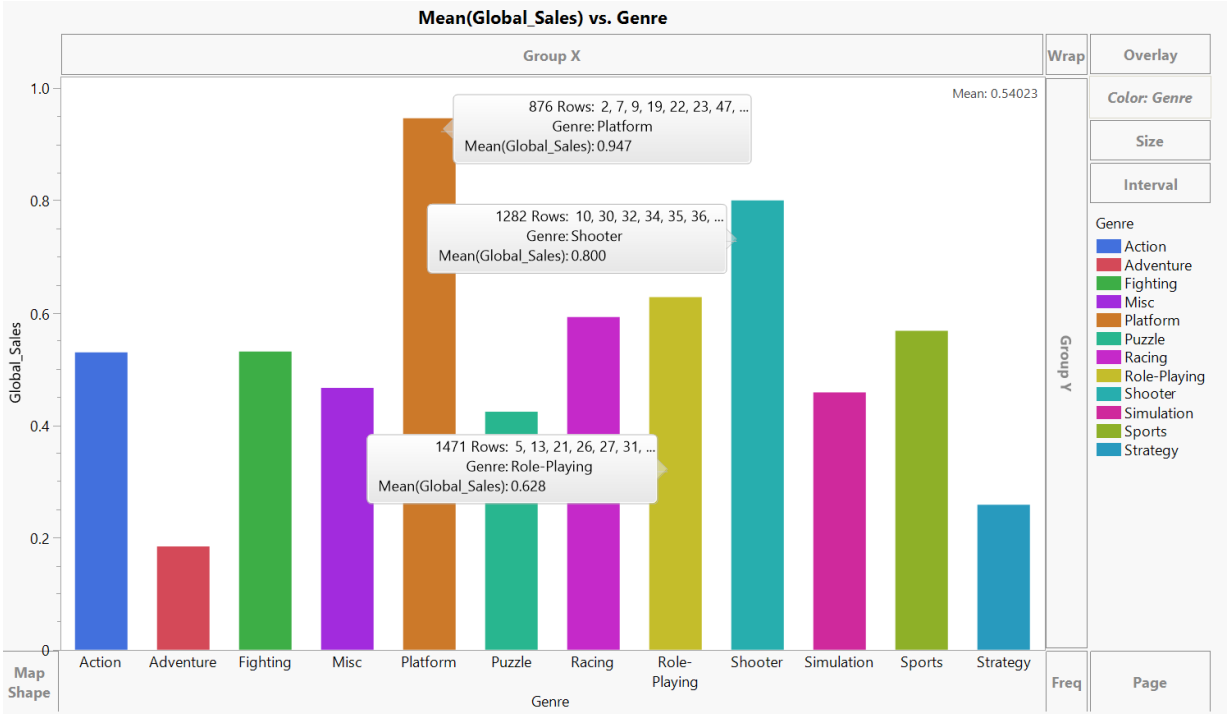
Cluster	SHASH Distribution NA_Sales	SHASH Distribution EU_Sales	SHASH Distribution JP_Sales	SHASH Distribution Other_Sales	Lognormal Distribution Global_Sales
1	0.87908307	0.08688558	0.22415422	0.87635148	0.48315681
2	0.73516203	0.64358715	0.14023816	0.08937462	0.21594406
3	0.81517051	0.87874785	0.13282431	0.88357608	0.61913007
4	0.07787687	0.0969578	0.92781642	0.14508678	0.30758316
5	0.86994448	0.87029212	0.92908022	0.87535429	0.81739727

DATA VISUALIZATION:

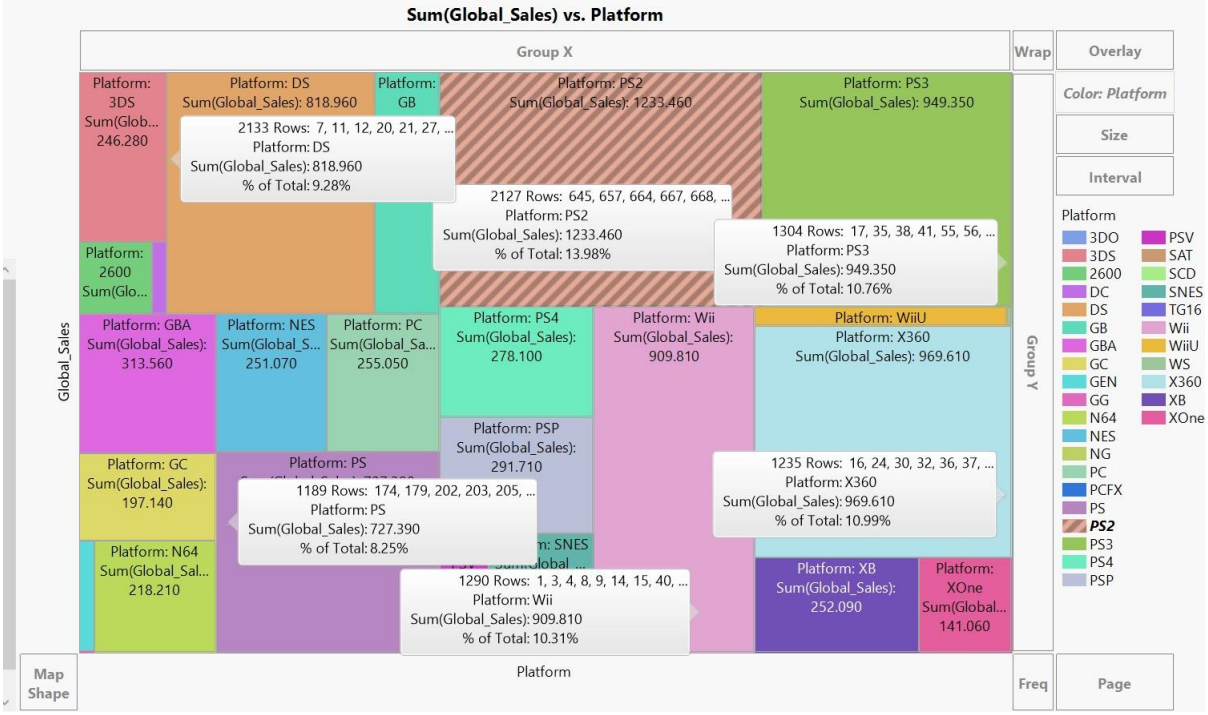
Global_Sales vs. Year: In the early 80s video game sales followed the upward trend and peaked in the mid-80s then declined gradually. And again, in the early start of the 90s, it gradually increased and reached its maximum sales. Then after it has seen some fluctuations as each year passes. From the visualization, we can say that at present video game sales started from their minimum point and it is raising their bar.



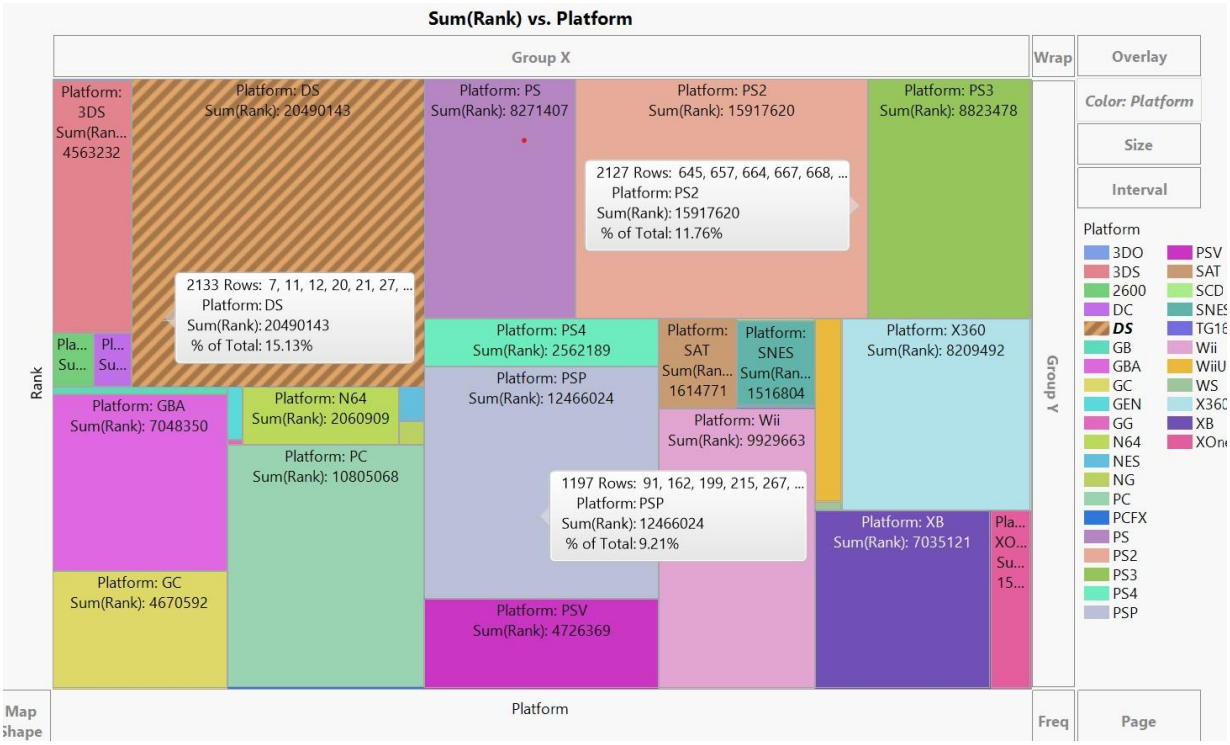
Global_Sales vs. Genre: The Visualization below depicts that the Platform genre has the highest sale which is followed by Shooter & Role-playing genres respectively.



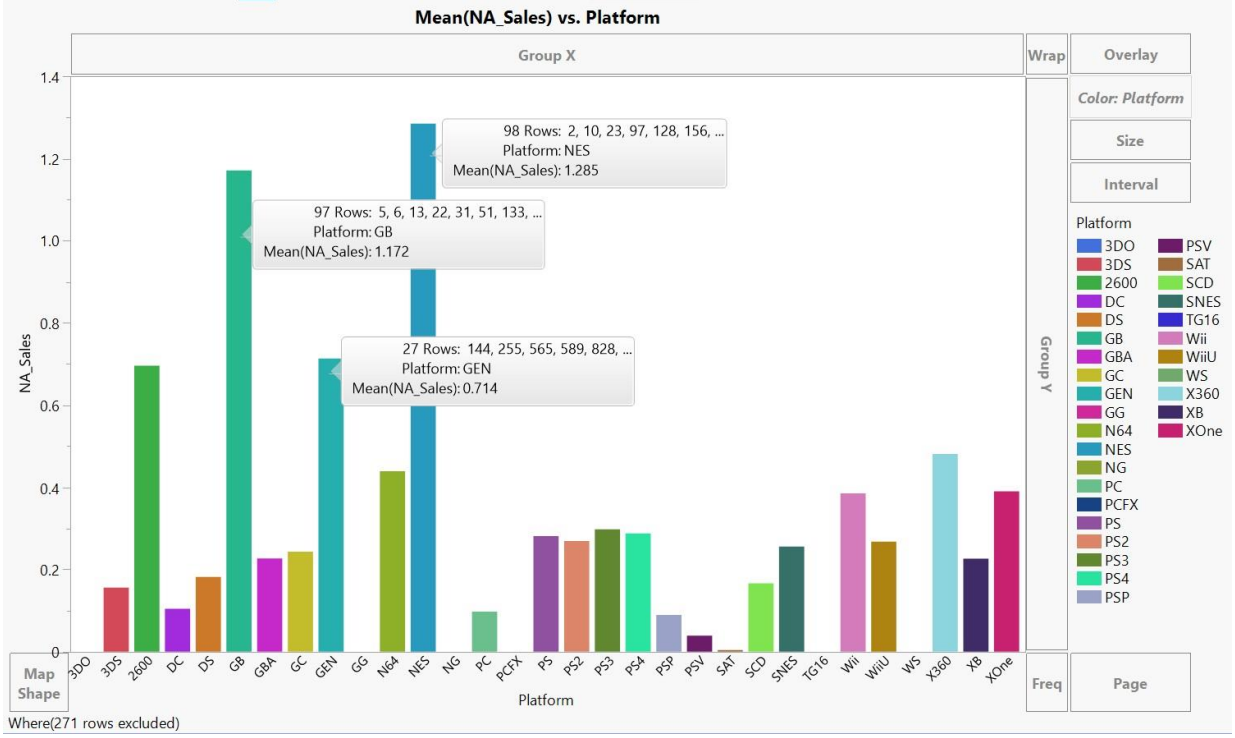
Global_Sales vs. Platform (gaming console): The picture below shows that Sony PS2 has the highest sales. And in the second position is Microsoft X360. And then it is followed by PS3 in third and Wii in the fourth position.



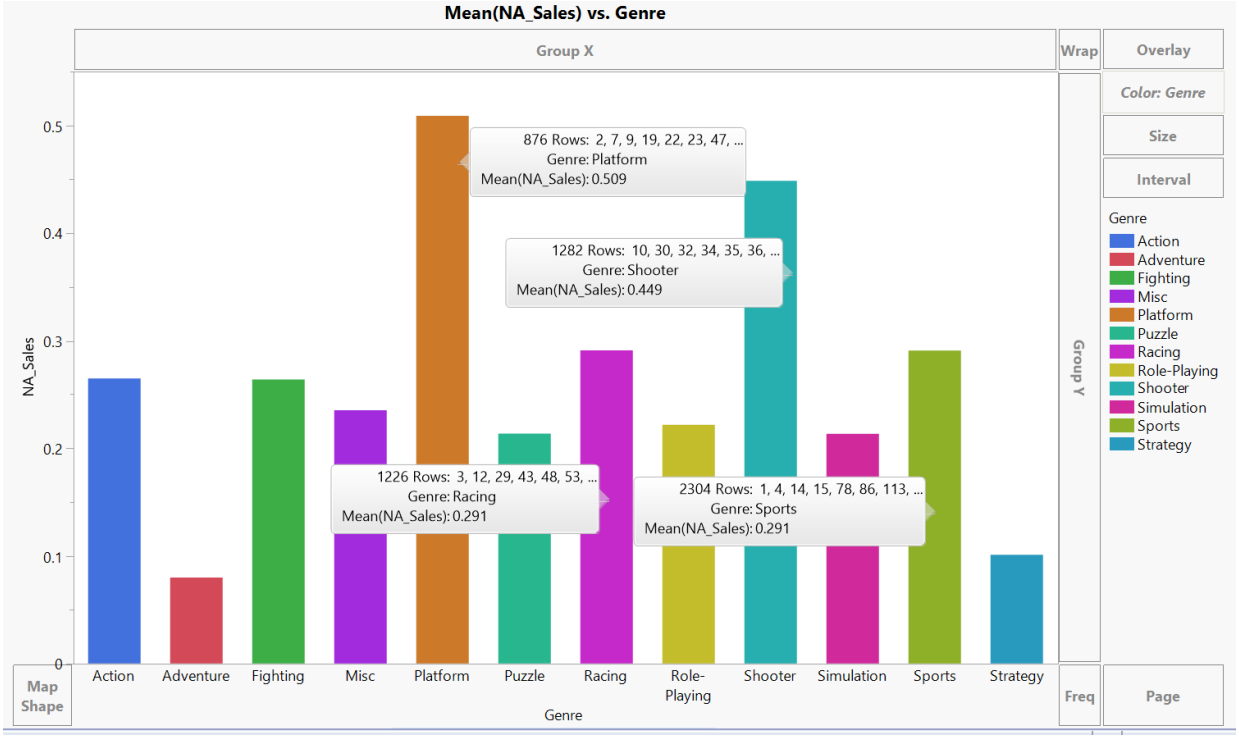
Rank vs. Platform: As per rankings the platform DS secured the highest rank and then PS2 & PSP are in the second and third position respectively.



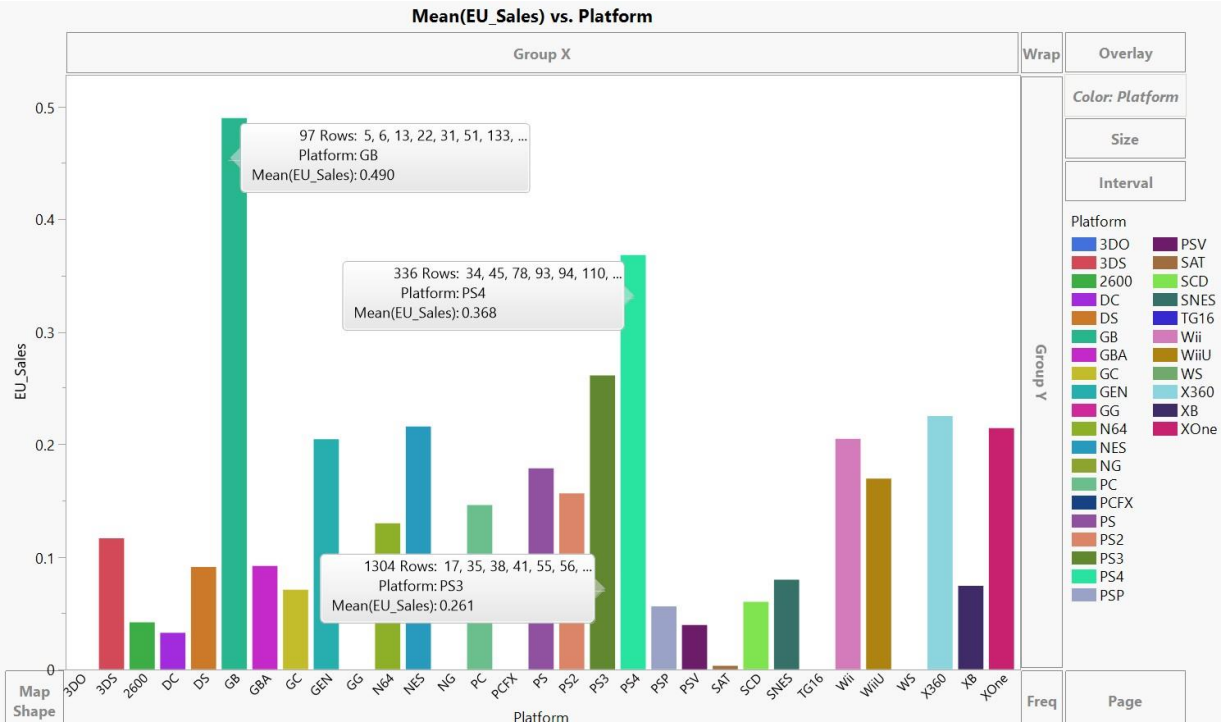
NA_Sales vs. Platform: The bar plots below indicate which gaming platform has the highest sales in North America. As per the plot, the NES platform has the highest sales. GB gaming platform is in the second position which is then followed by the GEN platform.



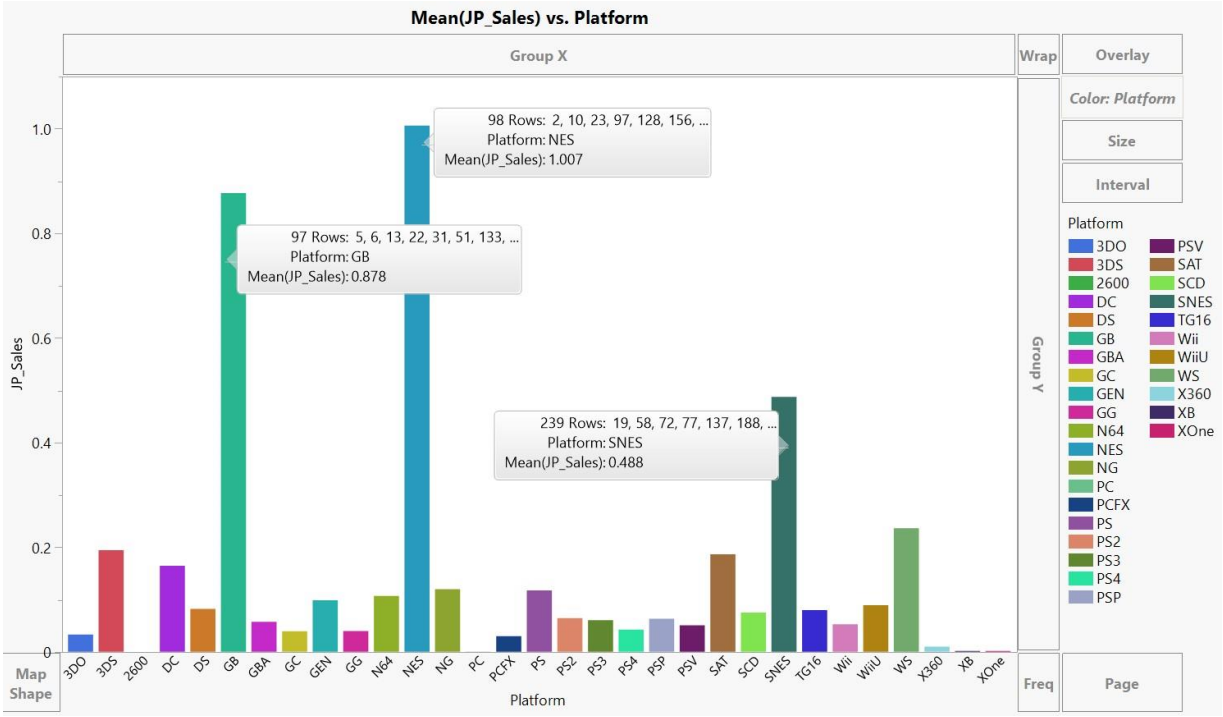
NA_Sales vs Genre: The below box plots show the highest-selling gaming genre in North America. The platform genre (2D games) has the highest sales in North America. And shooter gaming genre is in the second position. Racing and Sports game genres share the third spot.



EU_Sales vs Platform: The bar plot below indicates which gaming platform has the highest sales in Europe. As per the plot, the GB platform has the highest sales. The PS4 gaming platform is in the second position which is then followed by the PS3 platform.



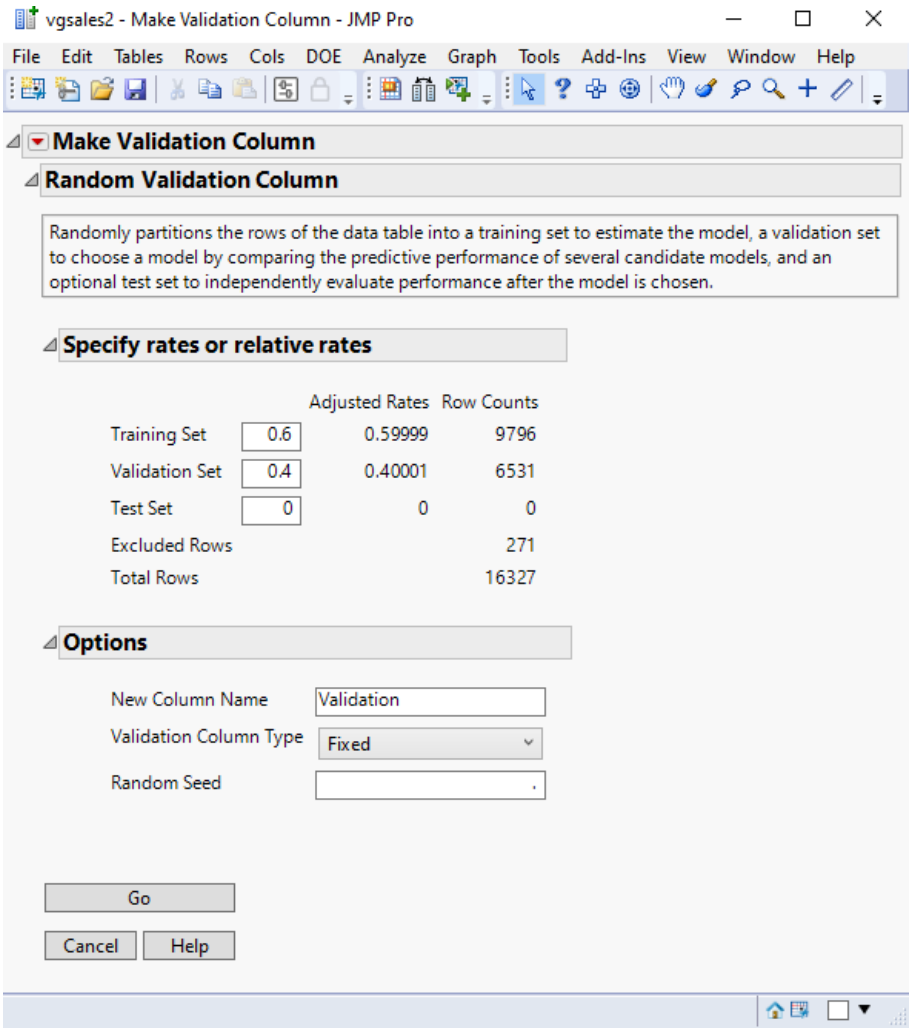
JP_Sales vs Platform: The bar plots below indicate which gaming platform has the highest sales in Japan. As per the plot, the NES platform has the highest sales. GB gaming platform is in the second position which is then followed by the SNES platform.



MAKING VALIDATION COLUMN:

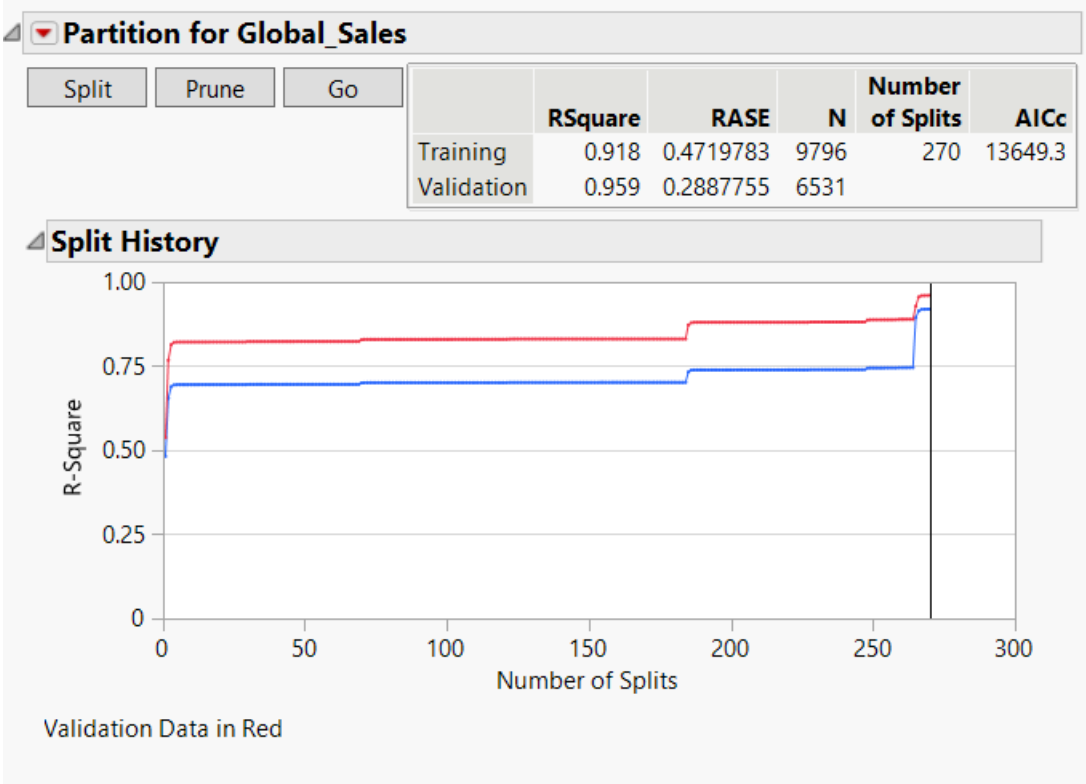
We are considering the 60/40 split between the Training & Validation set to build the models.

This makes a validation column in the dataset of training with 60% and validation with 40%.



MODELING

REGRESSION TREE:



BOOTSTRAP FOREST:

Bootstrap Forest for Global_Sales

Specifications

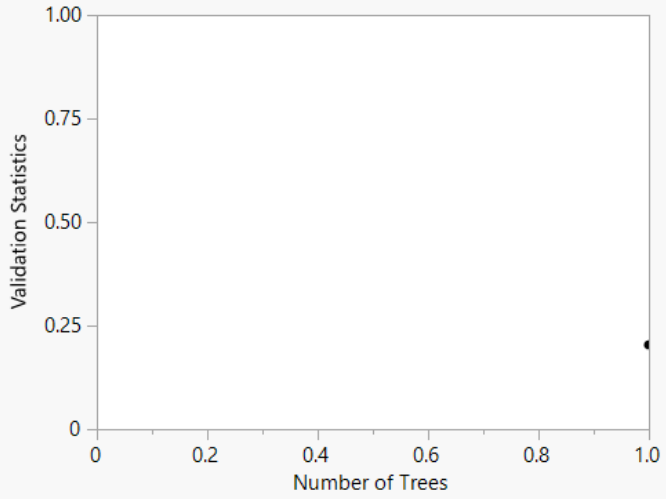
Target	Global_Sales	Training Rows:	9796
Validation Column:	Validation	Validation Rows:	6531
		Test Rows:	0
Number of Trees in the Forest:	1	Number of Terms:	10
Number of Terms Sampled per Split:	8	Bootstrap Samples:	9796
		Minimum Splits per Tree:	10
		Minimum Size Split:	16

Overall Statistics

Individual Trees	RASE
In Bag	0.284167
Out of Bag	1.799766

	RSquare	RASE	N
Training	0.536	1.1248022	9796
Validation	0.202	1.2759041	6531

Cumulative Validation



Cumulative Details

Per-Tree Summaries

Tree	Splits	Rank	OOB Loss	OOB Loss/N	RSquare	IB SSE	IB SSE/N	OOB N	OOB SSE	OOB SSE/N
1	443	1	8963.6313	2.5024096	0.9448	791.03819	0.0807511	3582	11602.665	3.2391582

BOOSTED TREE:

Boosted Tree for Global_Sales

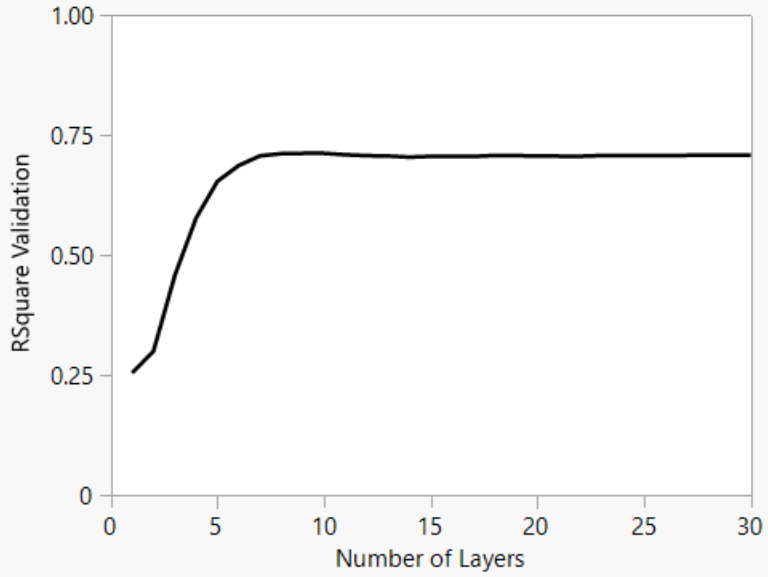
Specifications

Target	Global_Sales	Number of training rows:	9796
Validation Column:	Validation	Number of validation rows:	6531
Number of Layers:	30		
Splits per Tree:	17		
Learning Rate:	0.149		

Overall Statistics

	RSquare	RASE	N
Training	0.972	0.2743491	9796
Validation	0.708	0.7713382	6531

Cumulative Validation



Cumulative Details

NTree	Validation RSquare
1	0.254856
2	0.299761
3	0.457136
4	0.577412
5	0.653882
6	0.686808
7	0.706974
8	0.711476
9	0.712179
10	0.71222
11	0.709321
12	0.707417

MODEL SCREENING:

By making the validation column, we proceed to compare the five different sets of models. Among the five, by comparing them we will find the best model which will provide enough information to build a successful model. The five models we are selecting for our dataset are Decision Tree, Bootstrap Forest, Boosted Tree, Neural networks, and Logistic regression.

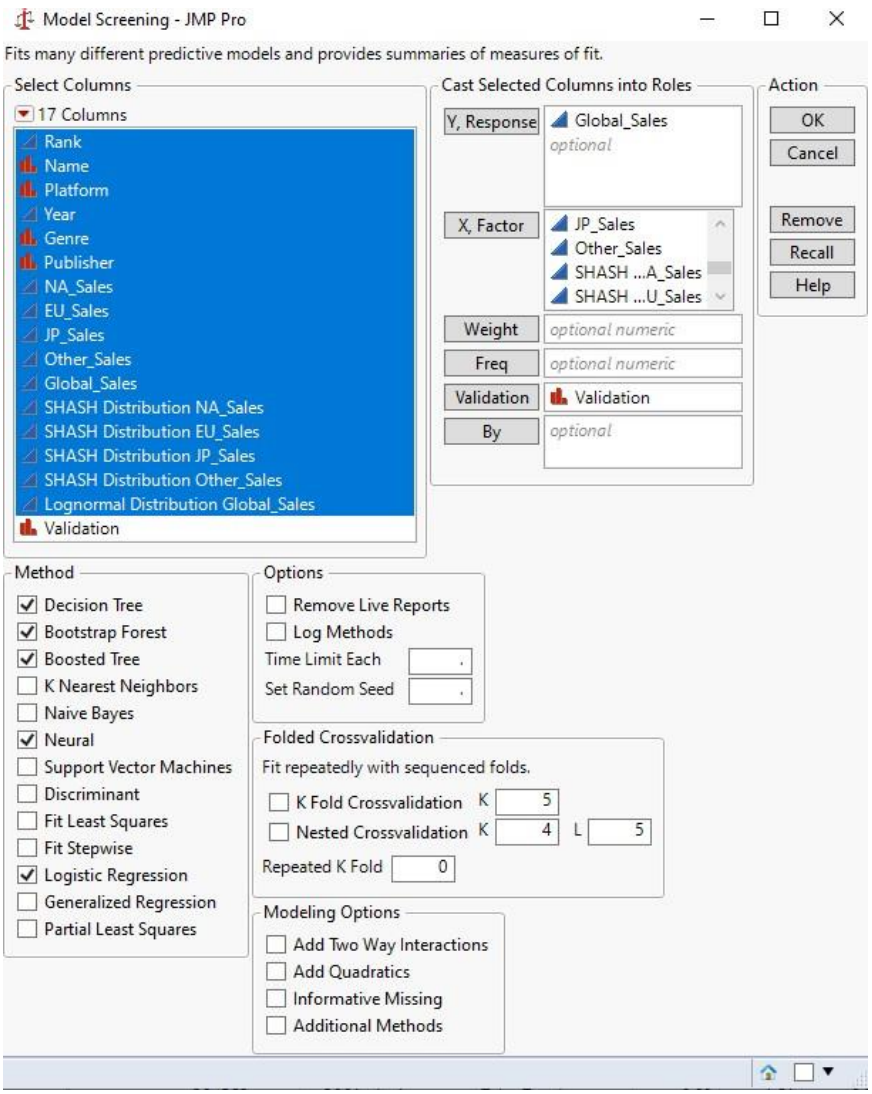
For the Decision Tree, JMP will create a model by partitioning the data into different subsets based on the values of the predictor variables. It will then use a cost function or error rate to evaluate the different splits and determine the best split point. The model will then be pruned to reduce the complexity of the tree and improve its accuracy.

For Bootstrap Forest, JMP will create a forest of decision trees, each one based on a different sample of the data. It will then use an optimization algorithm to find the best combination of trees that minimizes the prediction error.

For Boosted Tree, JMP will build a sequence of models where each model is based on the previous model's predictions. It will then combine the predictions from all the models and use an optimization algorithm to find the best combination of predictors that minimizes the prediction error.

For Neural networks, JMP will create a model based on a set of neurons connected in a network. It will use an optimization algorithm to find the best combination of weights and biases that minimizes the prediction error.

Finally, for Logistic Regression, JMP will create a model based on a set of predictor variables and their associated coefficients. It will use an optimization algorithm


Model Screening - JMP Pro
Fits many different predictive models and provides summaries of measures of fit.
Select Columns
17 Columns
Rank
Name
Platform
Year
Genre
Publisher
NA_Sales
EU_Sales
JP_Sales
Other_Sales
Global_Sales
SHASH Distribution NA_Sales
SHASH Distribution EU_Sales
SHASH Distribution JP_Sales
SHASH Distribution Other_Sales
Lognormal Distribution Global_Sales
Validation
Cast Selected Columns into Roles
Y, Response
Global_Sales
optional
X, Factor
JP_Sales
Other_Sales
SHASH ...A_Sales
SHASH ...U_Sales
Weight
optional numeric
Freq
optional numeric
Validation
Validation
By
optional
Action
OK
Cancel
Remove
Recall
Help
Method
Decision Tree
Bootstrap Forest
Boosted Tree
K Nearest Neighbors
Naive Bayes
Neural
Support Vector Machines
Discriminant
Fit Least Squares
Fit Stepwise
Logistic Regression
Generalized Regression
Partial Least Squares
Options
Remove Live Reports
Log Methods
Time Limit Each
Set Random Seed
Folded Crossvalidation
Fit repeatedly with sequenced folds.
K Fold Crossvalidation K 5
Nested Crossvalidation K 4 L 5
Repeated K Fold 0
Modeling Options
Add Two Way Interactions
Add Quadratics
Informative Missing
Additional Methods

Model Screening for Global_Sales

Table: vgsales2 **Response:** Global_Sales **Validation:** Validation

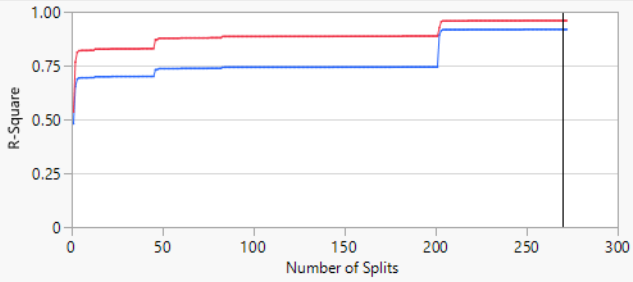
Details

Partition for Global_Sales

Split | Prune | Go

	RSquare	RASE	N	Number of Splits	AICc
Training	0.918	0.4719783	9796	270	136493
Validation	0.959	0.2887755	6531		

Split History



Validation Data in Red

Bootstrap Forest for Global_Sales

Specifications

Target	Global_Sales	Training Rows:	9796
Validation Column:	Validation	Validation Rows:	6531
		Test Rows:	0
Number of Trees in the Forest:	100	Number of Terms:	10
Number of Terms Sampled per Split:	8	Bootstrap Samples:	9796
		Minimum Splits per Tree:	10
		Minimum Size Split:	16

Overall Statistics

Individual Trees	RASE
In Bag	0.285752
Out of Bag	1.019028

	RSquare	RASE	N
Training	0.830	0.6804836	9796
Validation	0.936	0.3618879	6531

Cumulative Validation

Per-Tree Summaries

Boosted Tree for Global_Sales

Specifications

Target	Global_Sales	Number of training rows:	9796
Validation Column:	Validation	Number of validation rows:	6531
Number of Layers:	30		
Splits per Tree:	17		
Learning Rate:	0.149		

Overall Statistics

	RSquare	RASE	N
Training	0.972	0.2743491	9796
Validation	0.708	0.7713382	6531

Cumulative Validation

Neural

Validation Column: Validation

Model Launch

Model NTanH(3)NBoost(15)

Training

Global_Sales

Measures	Value
RSquare	0.2407013
RASE	1.4384424
Mean Abs Dev	0.3569416
-LogLikelihood	17461.364
SSE	20269.065
Sum Freq	9796

Validation

Global_Sales

Measures	Value
RSquare	0.2920439
RASE	1.2020137
Mean Abs Dev	0.4035111
-LogLikelihood	10468.78
SSE	9436.2308
Sum Freq	6531

As we can see, the Decision Tree model is the most accurate when predicting the success of a video game. The model can take in many data points, as well as a variety of different data types, to accurately predict the success of a video game. This model can be used by game developers to make better decisions when developing a game, as well as by gamers to make better decisions when deciding which game to purchase.

Training

Method	N	RSquare	RASE
Boosted Tree	9796	0.9724	0.2743
Decision Tree	9796	0.9183	0.4720
Bootstrap Forest	9796	0.8301	0.6805
Neural Boosted	9796	0.2407	1.4384

Select Dominant Run Selected Save Script Selected

Validation

Method	N	RSquare	RASE
Decision Tree	6531	0.9591	0.2888
Bootstrap Forest	6531	0.9358	0.3619
Boosted Tree	6531	0.7085	0.7713
Neural Boosted	6531	0.2920	1.2020

CONCLUSION:

Overall, the Decision Tree model was the best predictor of game success, with a correlation of 0.9591 and a RASE of 0.2888. This indicates that the model was able to accurately predict the success of games with a high degree of accuracy.