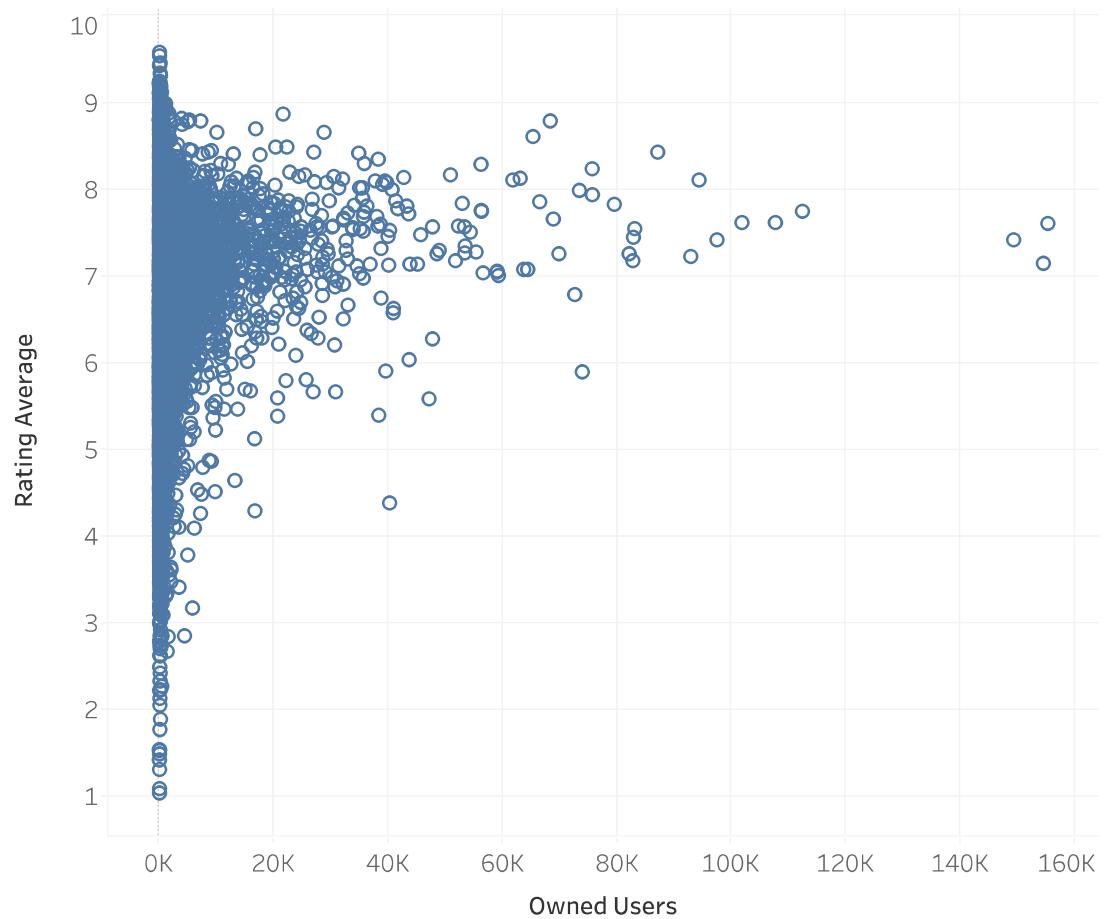
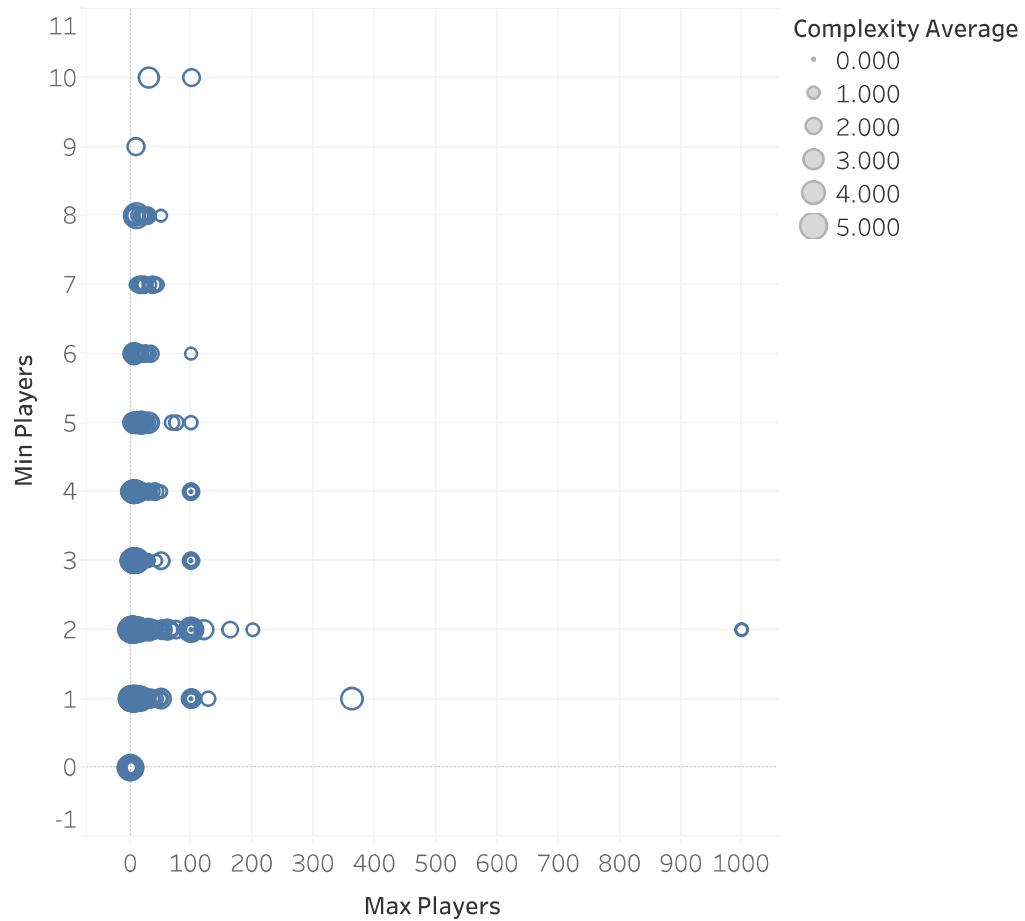


## Owned Users vs Rating Average



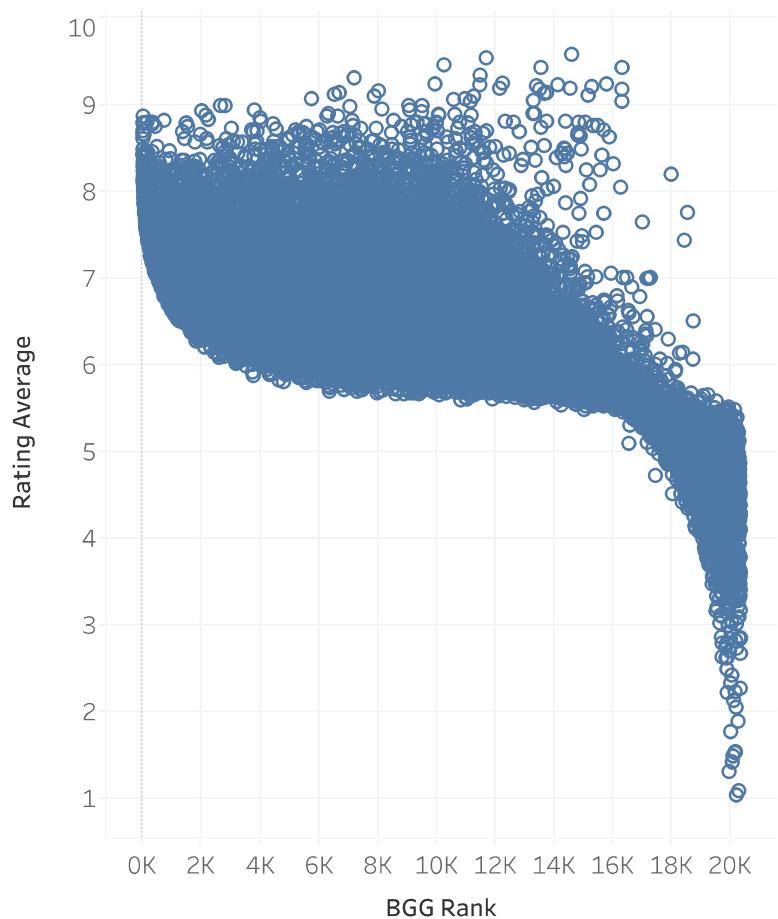
Owned Users vs. Rating Average.

## Min-Max players vs Complexity Avg



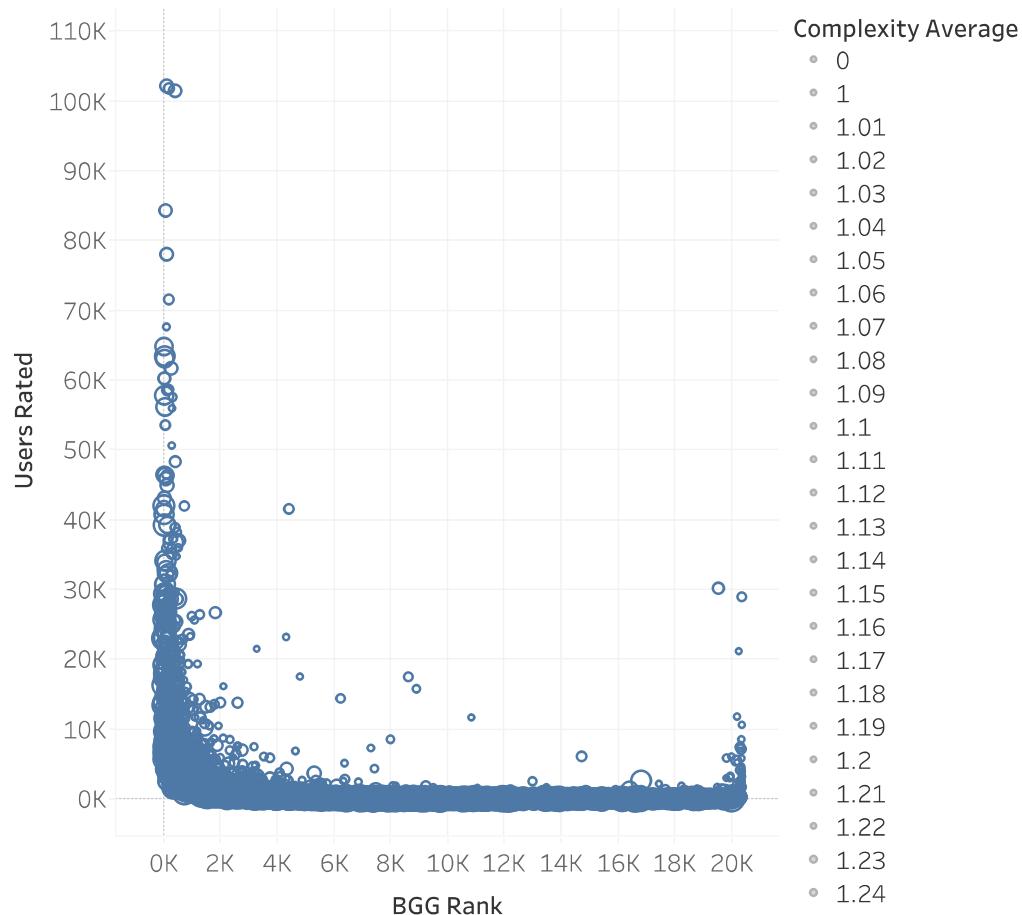
Max Players vs. Min Players. Size shows details about Complexity Average.

## Rank vs Rating Avg



BGG Rank vs. Rating Average. The data is filtered on Domains (group), which keeps 9 of 9 members.

## Rank vs Users Rated

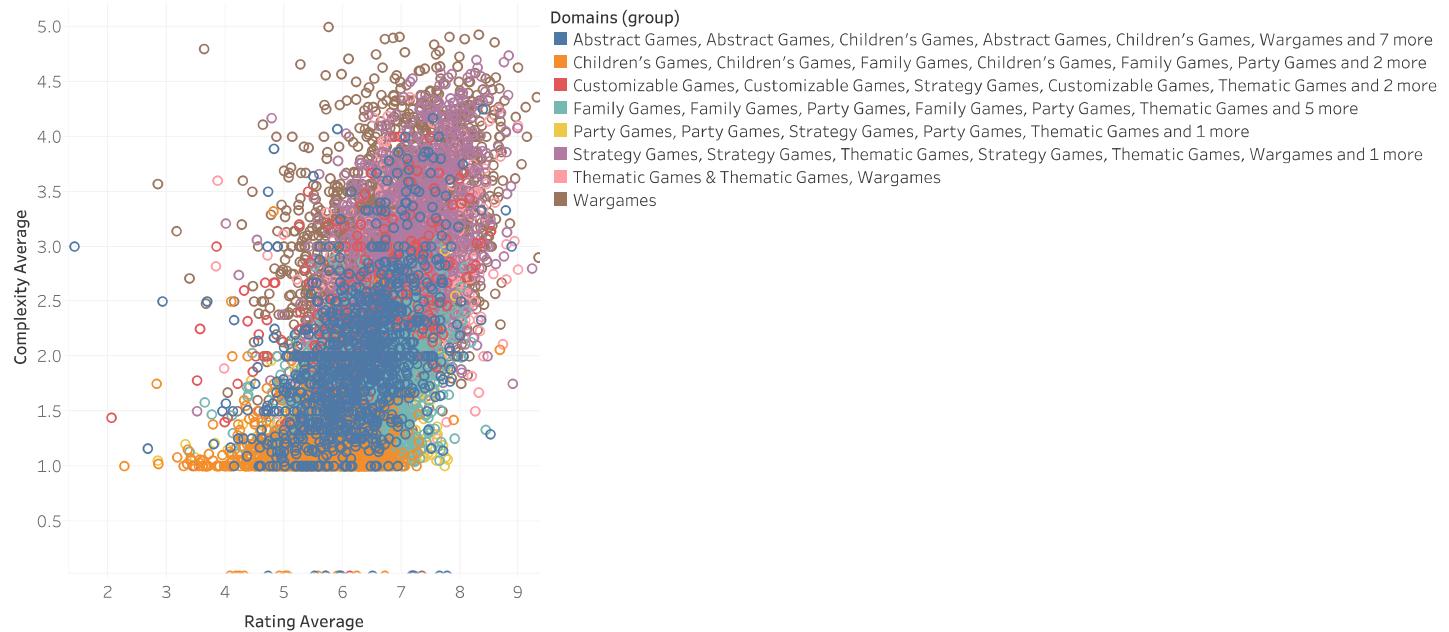


BGG Rank vs. Users Rated. Size shows details about Complexity Average.

### Complexity Average

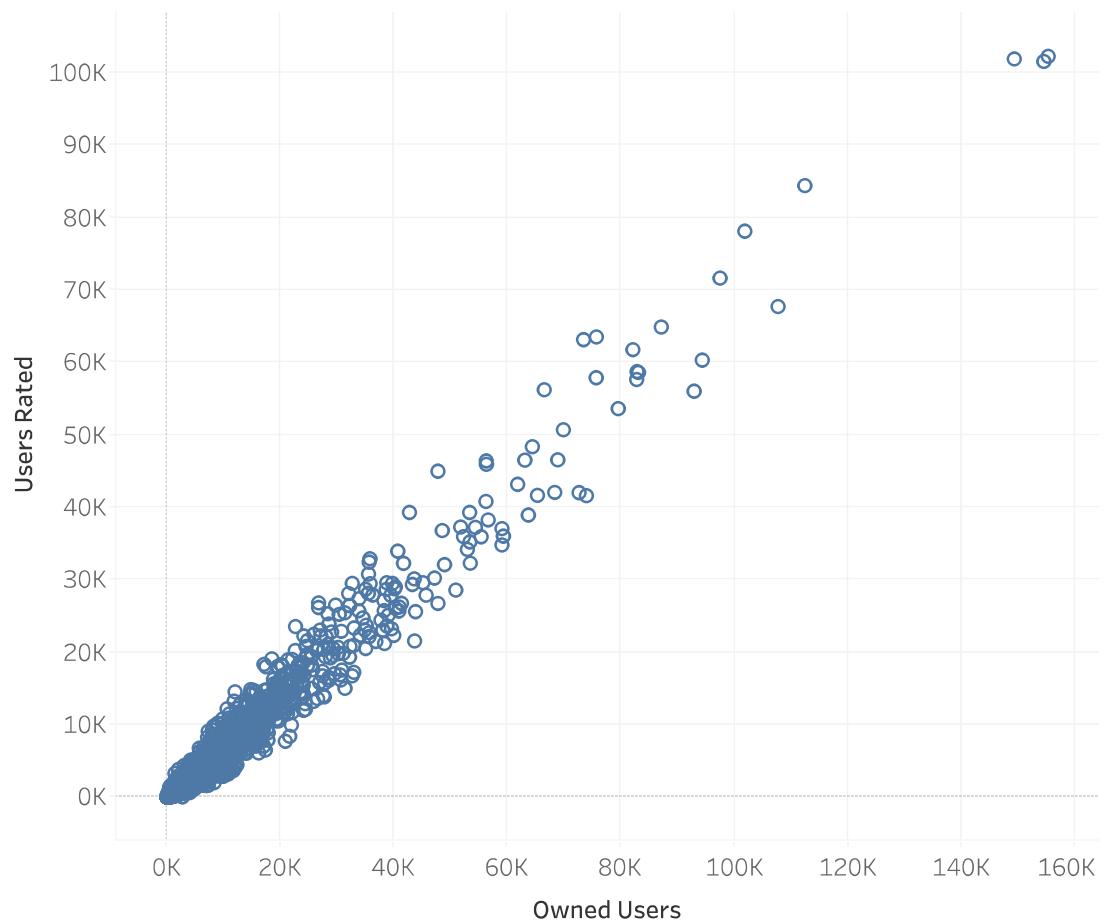
- 0
- 1
- 1.01
- 1.02
- 1.03
- 1.04
- 1.05
- 1.06
- 1.07
- 1.08
- 1.09
- 1.1
- 1.11
- 1.12
- 1.13
- 1.14
- 1.15
- 1.16
- 1.17
- 1.18
- 1.19
- 1.2
- 1.21
- 1.22
- 1.23
- 1.24
- 1.25
- 1.26
- 1.27
- 1.28
- 1.29
- 1.3
- 1.31
- 1.32
- 1.33
- 1.34
- 1.35
- 1.36
- 1.37
- 1.38
- 1.39
- 1.4
- 1.41
- 1.42
- 1.43
- 1.44
- 1.45
- 1.46
- 1.47
- 1.48
- 1.49
- 1.5
- 1.51
- 1.52

## Rating vs Complexity Average vs Domain



Rating Average vs. Complexity Average. Color shows details about Domains (group). The view is filtered on Domains (group), which excludes Null.

## owned users vs users rated

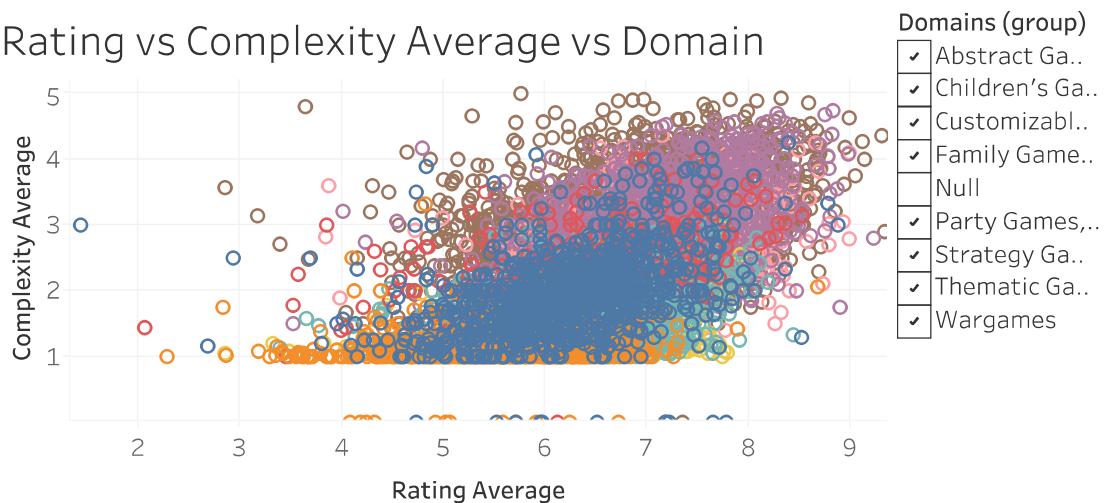


Owned Users vs. Users Rated.

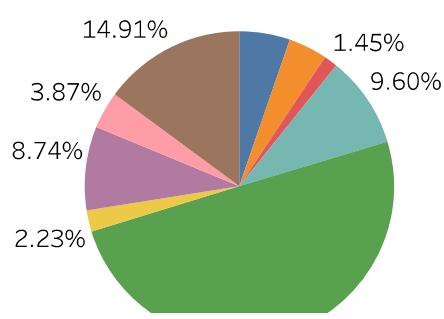
Games  
Rated

## Rating vs Complexity Average vs Domain

20,320



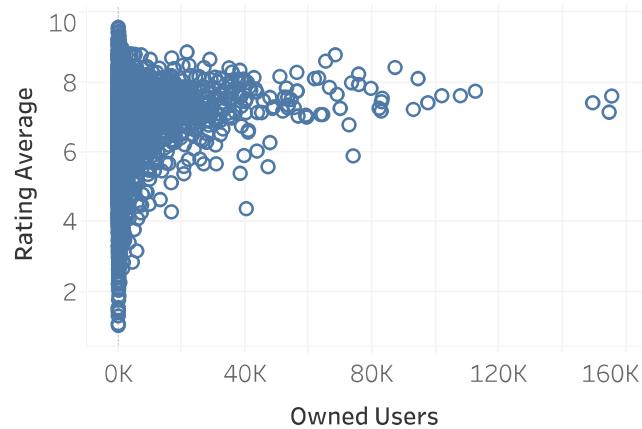
## Grouped Domains



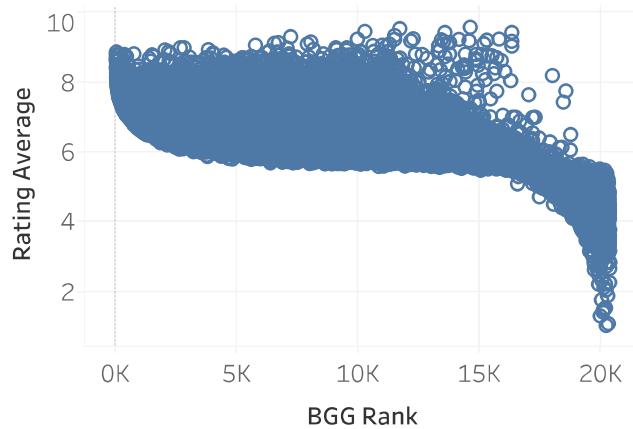
## Grouped Domains



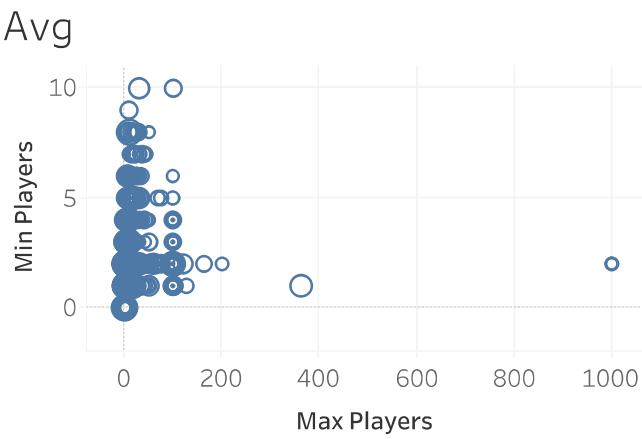
Owned Users vs Rating Average



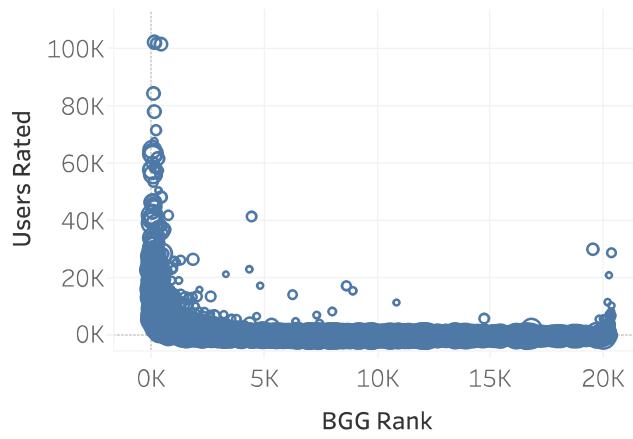
Rank vs Rating Avg



Min-Max players vs Complexity Avg



Rank vs Users Rated



Games

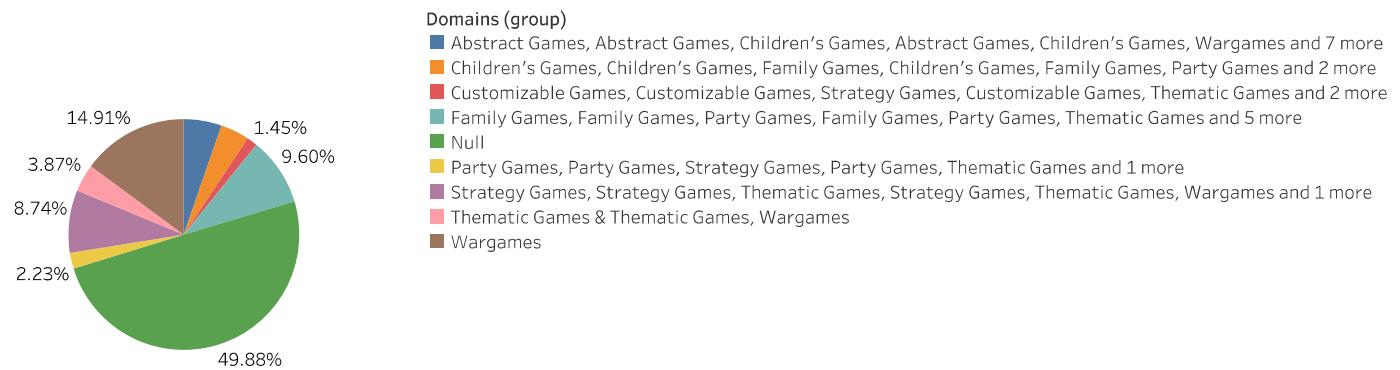
Rated

20,320

Count of

games.

## Grouped Domains



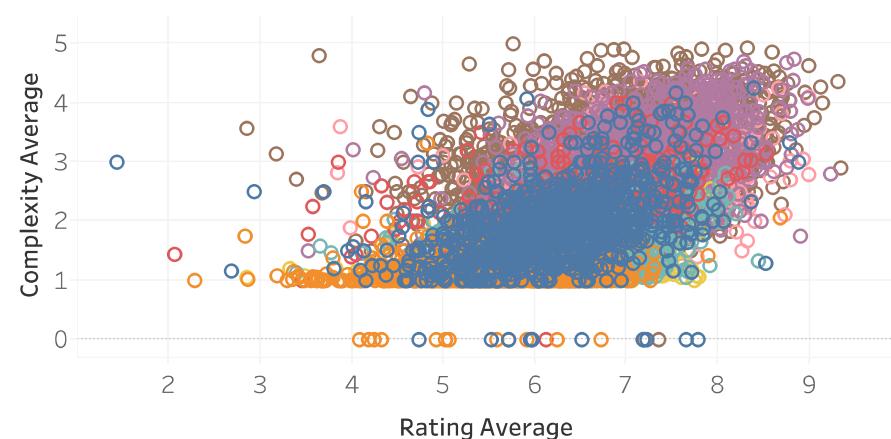
% of Total Count of games. Color shows details about Domains (group). The marks are labeled by % of Total Count of games.

# Board Games

Ranking, complexity av..	Exploration	Binning Domains	Scale and run the model	Domains Confusion Ma..	Ratings Logistic Regr..
-----------------------------	-------------	--------------------	----------------------------	---------------------------	----------------------------

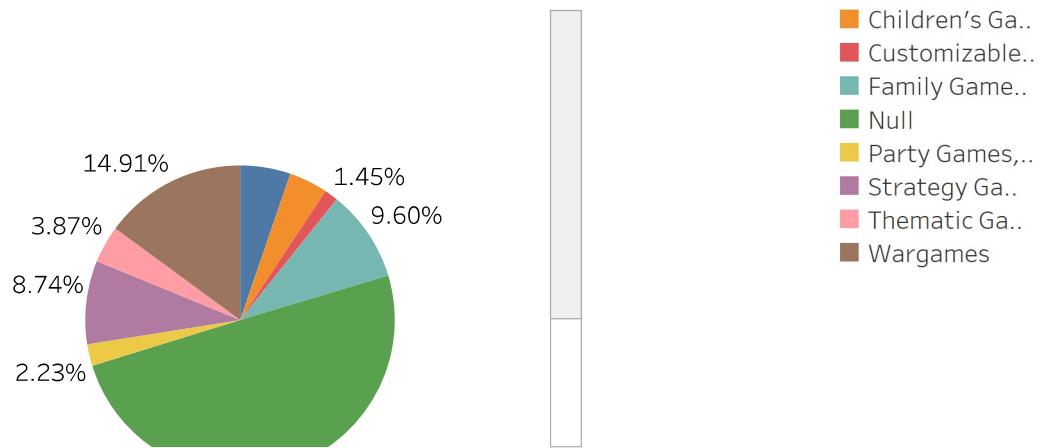
Games Rated  
20,320

Rating vs Complexity Average vs Domain



- Domains (group)
- ✓ Abstract Ga..
  - ✓ Children's Ga..
  - ✓ Customizabl..
  - ✓ Family Game..
  - Null
  - ✓ Party Games..
  - ✓ Strategy Ga..
  - ✓ Thematic Ga..
  - ✓ Wargames

Grouped Domains



# Board Games

Ranking,  
complexity av...

Exploration

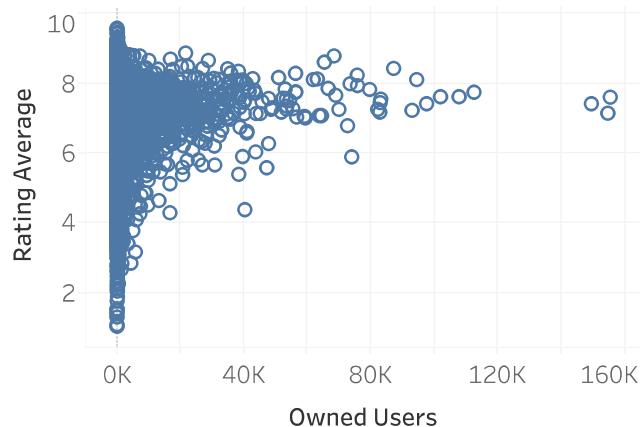
Binning  
Domains

Scale and run  
the model

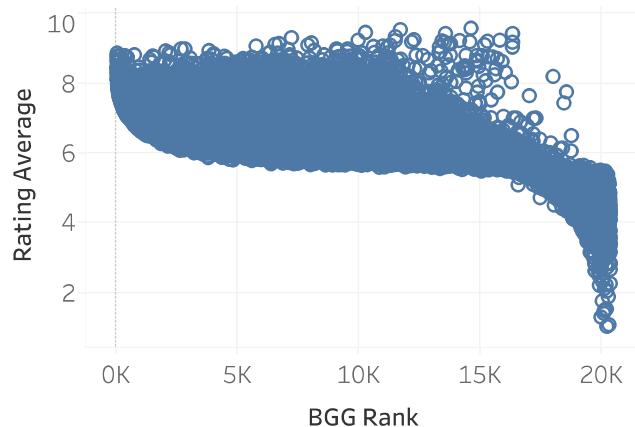
Domains  
Confusion Ma...

Ratings  
Logistic Regr...

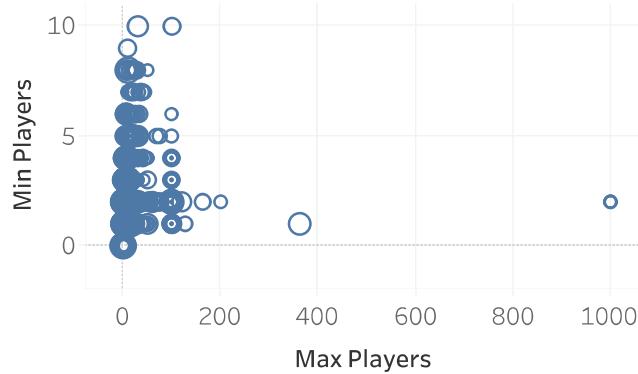
Owned Users vs Rating Average



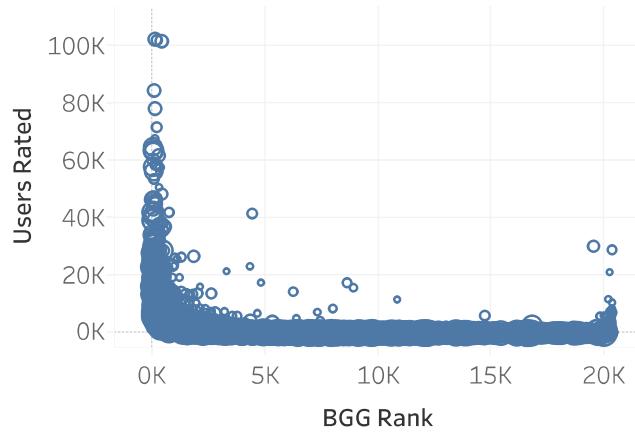
Rank vs Rating Avg



Min-Max players vs Complexity  
Avg



Rank vs Users Rated



# Board Games

Ranking, complexity av..	Exploration	Binning Domains	Scale and run the model	Domains Confusion Ma..	Ratings Logistic Regr..
-----------------------------	-------------	--------------------	----------------------------	---------------------------	----------------------------

```
1 # Replace smaller domains with "Other"
2 replace_domains = list(domain_counts[domain_counts<400].index)
3
4 for domain in replace_domains:
5     games_df.Domains = games_df.Domains.replace(domain,"Other")
6
7 games_df.Domains.value_counts()
```

```
Wargames          3029
Other             1727
Strategy Games   1455
Family Games     1340
Abstract Games   869
Children's Games  708
Thematic Games   647
Party Games       409
Name: Domains, dtype: int64
```

```
1 # Drop ID and Name
2 games_df = games_df.drop(["ID","Name","index","Year Published"], axis =1)
3 games_df.head()
```

	Min Players	Max Players	Play Time	Min Age	Users Rated	Rating Average	BGG Rank	Complexity Average	Owned Users	Domains
0	1	4	120	14	42055	8.79	1	3.86	68323	3
1	2	4	60	13	41643	8.61	2	2.84	65294	3
2	2	4	120	14	19217	8.66	3	3.91	28785	5
3	1	5	120	12	64864	8.43	4	3.24	87099	5
4	3	6	480	14	13468	8.70	5	4.22	16831	3

# Board Games

Ranking,  
complexity av..

Exploration

Binning  
Domains

Scale and run  
the model

Domains  
Confusion Ma..

Ratings  
Logistic Regr..

```
1 # Scale the data
2 scaler=StandardScaler()
3 # Fit the scaler with the training data
4 X_scaler=scaler.fit(X_train)
5
6 # Scale the data
7 X_train_scaled = X_scaler.transform(X_train)
8 X_test_scaled = X_scaler.transform(X_test)
```

```
1 # Instantiate Logistic Regression model
2 classifier=LogisticRegression(solver='lbfgs',max_iter=500,random_state=1)
```

```
1 # Train the model
2 classifier.fit(X_train_scaled, y_train)
```

```
LogisticRegression(max_iter=500, random_state=1)
```

```
1 # Test the model
2 y_pred=classifier.predict(X_test_scaled)
```

```
1 # Check the accuracy score
2 from sklearn.metrics import accuracy_score
3 print(accuracy_score(y_test,y_pred))
```

```
0.5616653574234093
```

# Board Games

Ranking, complexity av..	Exploration	Binning Domains	Scale and run the model	Domains Confusion Ma..	Ratings Logistic Regr..
-----------------------------	-------------	--------------------	----------------------------	---------------------------	----------------------------

	Predicted Abstract Games	Children's Games	Family Games	Other	Party Games	Strategy Games	Thematic Games	Wargames
Actual Abstract Games	66	30	25	44	1	10	0	46
Children's Games	7	134	26	1	3	0	0	4
Family Games	5	23	166	83	13	9	4	11
Other	28	20	89	117	11	93	12	79
Party Games	0	3	24	4	50	0	1	2
Strategy Games	2	0	3	65	0	220	9	70
Thematic Games	5	1	21	50	1	56	15	31
Wargames	27	5	5	19	1	32	2	662

# Board Games

Ranking, complexity av..	Exploration	Binning Domains	Scale and run the model	Domains Confusion Ma..	Ratings Logistic Regr..
-----------------------------	-------------	--------------------	----------------------------	---------------------------	----------------------------

```
# Bin Rating Average above and below average "Rating Average" of 6.40
# 0 is below average, 1 is above average
bins = [0, 6.4, 10]
labels = ["0", "1"]
games_domainsplit_df["rating_bins"] = pd.cut(games_domainsplit_df["rating_average"], bins, labels=labels)
games_domainsplit_df
```

Unnamed: 0	year_published	min_players	max_players	play_time	min_age	users_rated	rating_average	bgg_rank	complexity_average	owned_users	children_games
0	0	2017	1	4	120	14	42.055	8.79	1	3.86	68.323
1	1	2015	2	4	60	13	41.643	8.61	2	2.84	65.294
2	2	2018	2	4	120	14	19.217	8.66	3	3.91	28.785
3	3	2016	1	5	120	12	64.864	8.43	4	3.24	87.099
4	4	2017	3	6	480	14	13.468	8.70	5	4.22	16.831

```
# Label variables
y= games_binned_df["rating_bins"]
X= games_binned_df.drop(columns="rating_bins")
```

```
# get accuracy score
from sklearn.metrics import accuracy_score
print(accuracy_score(y_test, y_pred))
```

0.7836614173228347

```
# Split
X_train, X_test, y_train, y_test = train_test_split(X,
y, random_state=1, stratify=y)
```

```
from sklearn.metrics import confusion_matrix, classification_report
matrix = confusion_matrix(y_test, y_pred)
print(matrix)
```

[[1934 547]  
[ 552 2047]]

```
# Model
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(solver='lbfgs',
max_iter=200,
random_state=1)
```

```
report = classification_report(y_test, y_pred)
print(report)
```

	precision	recall	f1-score	support
0	0.78	0.78	0.78	2481
1	0.79	0.79	0.79	2599
accuracy			0.78	5080
macro avg	0.78	0.78	0.78	5080
weighted avg	0.78	0.78	0.78	5080

```
# Train
classifier.fit(X_train, y_train)
```

```

1 # Replace smaller domains with "Other"
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Strategy Games	1455
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Party Games	409

Name: Domains, dtype: int64

```

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```
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```

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1	1	2015	2	4	60	13	41.643	8.61	2	2.84	65.294	0
2	2	2018	2	4	120	14	19.217	8.66	3	3.91	28.785	0
3	3	2016	1	5	120	12	64.864	8.43	4	3.24	87.099	0
4	4	2017	3	6	480	14	13.468	8.70	5	4.22	16.831	0

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matrix = confusion_matrix(y_test, y_pred)
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```

[[1934 547]  
[ 552 2047]]

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print(report)
```

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accuracy			0.78	5080
macro avg	0.78	0.78	0.78	5080
weighted avg	0.78	0.78	0.78	5080