




# TV Show Platforms and Ratings

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# Background

Our goal is to use R to determine which streaming service has the highest rated shows according to IMDb and Rotten Tomatoes. Our dataset contains information about shows from Netflix, Hulu, Prime Video, and Disney+

Our models focused on analyzing the relationships between the rating of a show and its availability on different streaming service platforms

# Tasks

- Does platform availability have a relationship with the ratings?
- Is there a relationship between IMDb and Rotten Tomatoes scores?
- Is it possible to predict ratings based on platform availability?

# Data Source & Preprocessing

- <https://www.kaggle.com/ruchi798/tv-shows-on-netflix-prime-video-hulu-and-disney>
- Dataset was found on Kaggle
- Preprocessing
  - Removed any rows with empty values
  - Added a column named "Index" that assigns a number to each TV show so it's easily identifiable during analysis

	Index	Title	Year	Age	IMDb	Rotten.Tomatoes	Netflix	Hulu	Prime.Video	Disney.	type
1	0	Breaking Bad	2008	18+	9.5	0.96	1	0	0	0	1
2	1	Stranger Things	2016	16+	8.8	0.93	1	0	0	0	1
3	2	Money Heist	2017	18+	8.4	0.91	1	0	0	0	1
4	3	Sherlock	2010	16+	9.1	0.78	1	0	0	0	1
5	4	Better Call Saul	2015	18+	8.7	0.97	1	0	0	0	1
6	5	The Office	2005	16+	8.9	0.81	1	0	0	0	1

Global Environment									
Data									
movies.df	931 obs. of 8 variables								
testSet	372 obs. of 2 variables								
trainingSet	559 obs. of 2 variables								
Values									
predictions	Factor w/ 2 levels "0","1": 2 2 2 2 ...								
testOutcomes	Factor w/ 2 levels "0","1": 1 1 1 1 ...								
trainingOutc...	Factor w/ 2 levels "0","1": 2 2 2 2 ...								
		Year	Age	IMDb	R_Tomatoes	Netflix	Hulu	Prime.Video	Disney.
		1 2008	18+	9.5	9.6	1	0	0	0
		2 2016	16+	8.8	9.3	1	0	0	0
		3 2017	18+	8.4	9.1	1	0	0	0
		4 2010	16+	9.1	7.8	1	0	0	0
		5 2015	18+	8.7	9.7	1	0	0	0
		6 2005	16+	8.9	8.1	1	0	0	0
		7 2011	18+	8.8	8.3	1	0	0	0
		8 2005	16+	8.4	9.3	1	0	0	0
		9 2013	18+	8.8	9.2	1	0	0	0
		10 2005	7+	9.2	10.0	1	0	0	0
		11 2010	18+	8.2	8.1	1	0	0	0
		12 2017	16+	8.7	9.4	1	0	0	0
		13 2017	18+	8.4	8.1	1	0	0	0

# IMDb vs Rotten Tomatoes

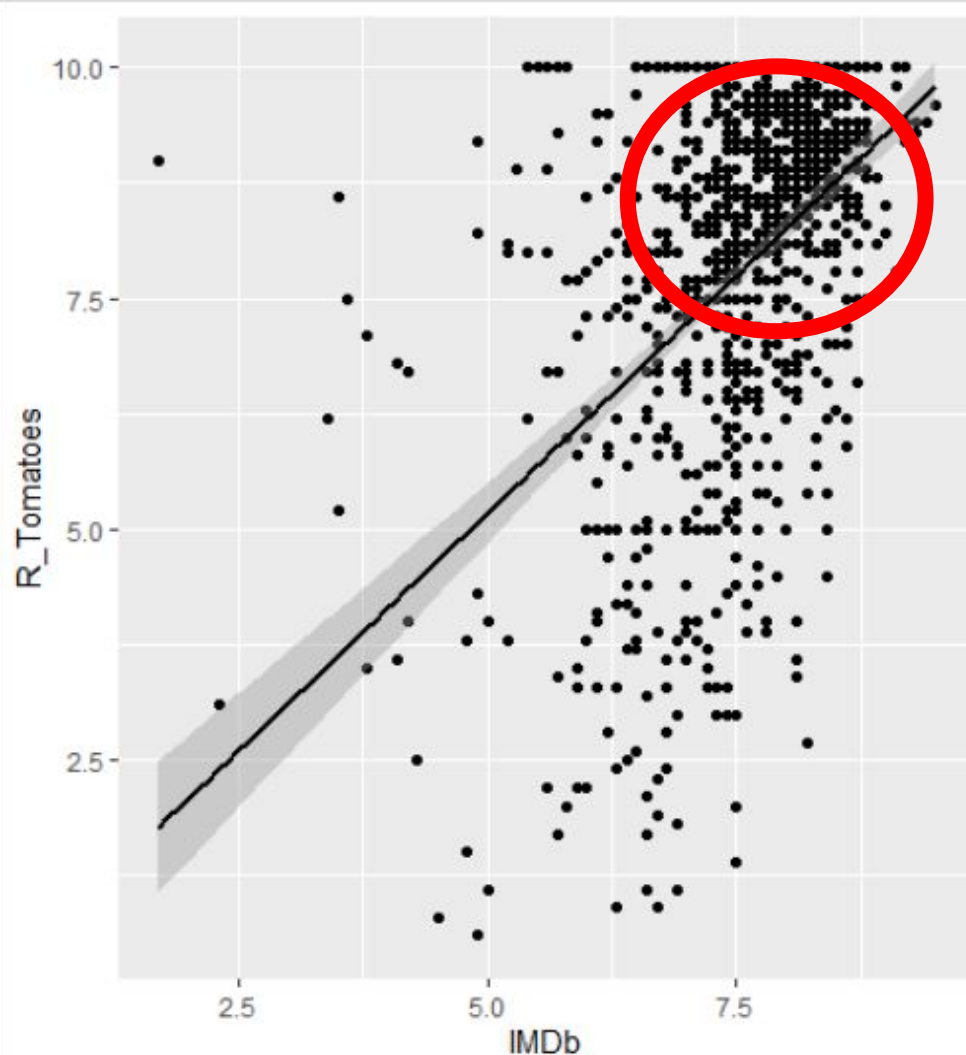
Correlation of numerical data:  
A check to see if IMDb and Rotten Tomatoes gives similar ratings

```
ggplot(data = movies.df, mapping = aes(x = IMDb, y = R_Tomatoes)) + geom_point()  
+ geom_smooth(method = "lm", color = "black", show.legend = FALSE)
```

Notable outliers  
Strong relationship of two rating systems

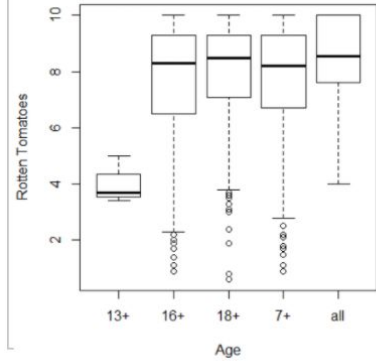
```
# no applicable method  
> table(movies.df$Age)
```

13+	16+	18+	7+	all
3	359	376	177	16

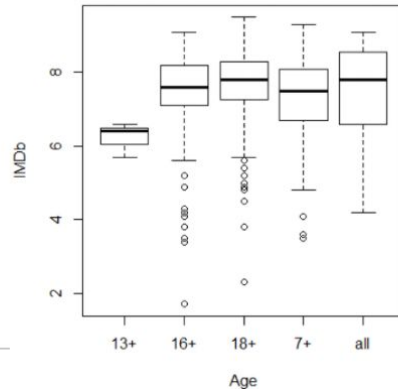


# Age and Ratings

The distribution of AGE and Rotten Tomatoes

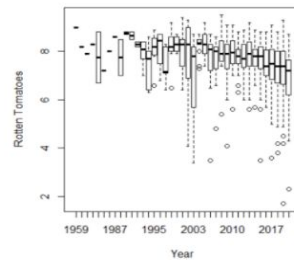


The distribution of AGE and IMDb

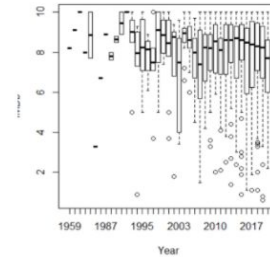


# Year and Ratings

The distribution of Year and Rotten Tomatoes



The distribution of Year and IMDb



# KNN Predictive Model

- Used R to create a KNN model that predicts platform availability using the two rating systems and its relationship with platform access.

Randomized data

Split Training and Testing Data by 60/40

Based on rows 3:4 (R\_Tomatoes/IMDb)

Set k to 30 due to the approximate sq rt of n (count = 931)

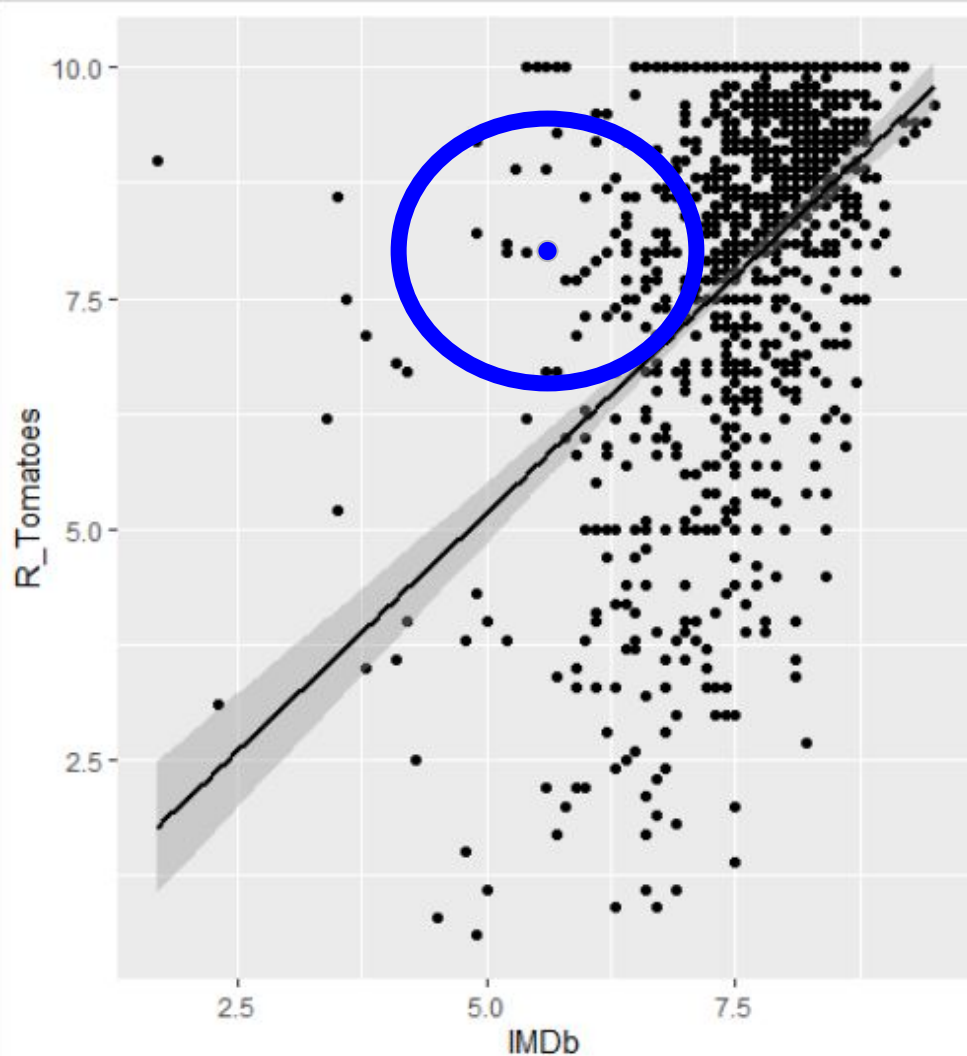
```
set.seed(1234)
rows <- sample(nrow(movies.df))
movies.df <- movies.df[rows,]
trainingSet <- movies.df[1:559, 3:4]
testSet <- movies.df[560:931, 3:4]

trainingOutcomes <- movies.df[1:559, 8] |
trainingOutcomes <- trainingOutcomes$Disney.

testOutcomes <- movies.df[560:931, 8]
testOutcomes <- testOutcomes$Disney.

library(class)
predictions <- knn(train = trainingSet, cl = trainingOutcomes, k = 30 ,test = testSet)
table(testOutcomes, predictions)
```

# Basic KNN Overview





```
           predictions
testOutcomes  0    1
0    153    47
1    130    42
```

1.  
195 shows predicted correctly  
**52.4% accuracy model (Netflix)**  
 $42/(42+130) = 24.4\%$  Actual positive - Recall

```
           predictions
testOutcomes  0    1
0    206    16
1    143     7
```

2.  
213 shows predicted correctly  
**57.2% accuracy model (HULU)**  
 $7/(7+143) = 4.66\%$  Actual positive - Recall

```
           predictions
testOutcomes  0    1
0    295     0
1     77     0
```

3.  
295 shows predicted correctly  
**79.3% accuracy model (Amazon Prime.Video)**  
 $0/(0+77) = 0\%$  Actual positive - Recall

```
           predictions
testOutcomes  0    1
0    365     0
1     7      0
```

4.  
365 shows predicted correctly  
**98% accuracy model (Disney +)**  
 $0/(0+7) = 0\%$  Actual positive - Recall

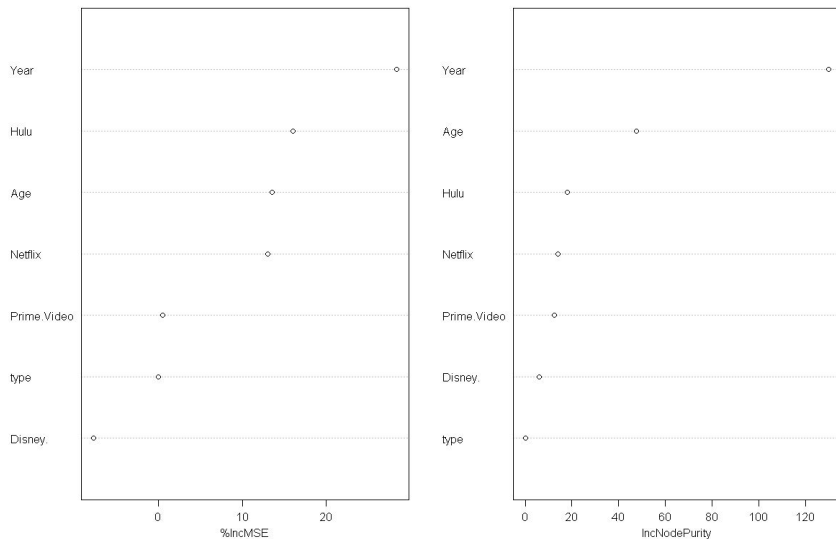
# Random Forest Predictive Model

- Used R to create a random forest model (a collection of decision trees) to predict both IMDb and Rotten Tomatoes scores using Age, Year, and platform availability.
- Randomly selected rows into testing and training set with a 40/60 split
- Code(RandomForest Library):
  - Models:
    - `lmdb.forest <- randomForest(IMDb~., data=train[,-4], mtry = 4, importance =T, na.action=na.omit )`
    - `Rotten.forest <- randomForest(Rotten.Tomatoes~., data=train[,-3], mtry = 4, importance =T, na.action=na.omit )`
  - 4 variables randomly sampled as candidates at each split
  - importance of predictors to be assessed
  - 500 trees created(default)

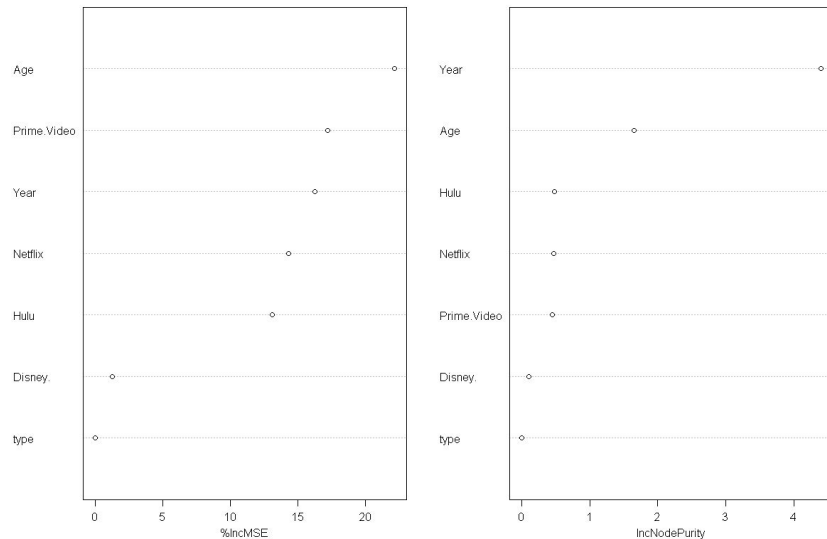
# The Model

- %INCMSE = percent increase in mean squared error from variable being permuted
- IncNodePurity = finds the average split which has a high inter node 'variance' and a small intra node 'variance'

Random Foresting Imdb



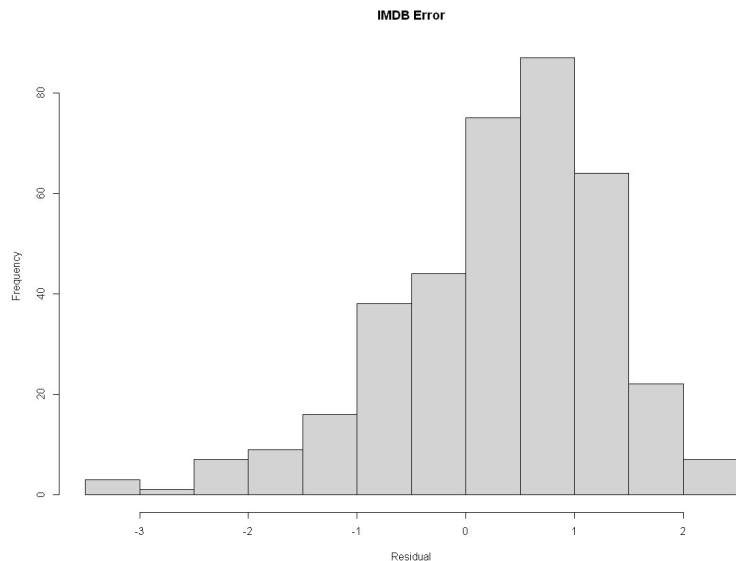
Random Foresting Rotten Tomatoes



# Results and Accuracy

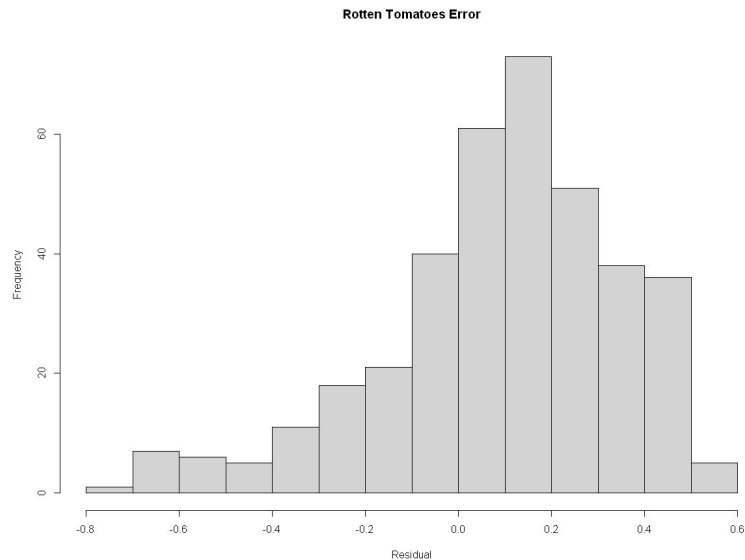
- RMSE

- IMDb = 1.036 stars
- Rotten Tomatoes = 27.18%



- Average Residual

- IMDb = .30112 stars
- Rotten Tomatoes = 9.385%



# Conclusion

- There is a positive correlation between both scores, which was expected
- We weren't able to accurately predict the scores using the random forest model
  - Using RMSE: 1 star is a big difference in ratings, rotten tomatoes is worse as 27% is too big ignore
  - We cannot say at this time that there is a relationship between availability and rating
- From using KNN predictive models, we are able to see prediction accuracy for the 4 platforms, however a closer look at our data shows that high prediction does not necessarily measure accuracy.
  - Most shows are not on Disney+, but the model predicted the highest accuracy based on prevalence of non-present shows in a database.
  - Some streaming platforms have significantly more shows than others
  - Recall is consistently low between evaluations/predictions
  - This most likely occurred because of a small dataset and not much range of usable variables

# Summary | Discussion | Questions?

1. Important to understand how the data was processed
  - Finding correlation between two variables shapes the data
  - Using factor data to identify variables by category (general clustering)
2. Not all predictive models are accurate
  - Low accuracy rate, not enough data, low correlation etc.
  - Other metrics can be more telling of a model than accuracy (recall)
3. Couldn't effectively predict with either of our models - meaning that the variables we selected are not significant in prediction of platform availability
4. Real world this makes sense - many values in our dataset are locked due to exclusivity and not necessarily the ratings of the show itself