Predicting Bechdel Test Results through Statistical Modeling

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Abstract

The Bechdel Test is a simple measurement designed to analyze the representation of women in film. To pass, a movie must have two female characters who have a conversation that is not about a man. The present research aims to use genre, release year, movie budget, user ratings, and critics rating scores to predict the probability a movie will pass the test. Logistic regression analysis reveals more recent movies are predicted to have a higher probability of passing the test. For most years, genres such as Romance and Comedy are predicted to have a higher probability of passing, while genres such as Action, Sport, War, and Western are predicted to have a lower probability of passing the test. Although the Bechdel Test has its flaws, the test is a useful metric to bring attention to the roles women hold in film.

Introduction

If you think of your all-time favorite movie, try to think about how many of the main characters were women. In 2023, 35% of speaking roles in movies belonged to women, and only 28% of the top grossing films contained female protagonists (Lauzen, 2024). Just one decade before, in 2013, women occupied 30% of all speaking roles and just 15% of protagonists were women (Lauzen, 2014). This is a small change for a span of 10 years, showcasing the under-representation of women in film, and the slow steps towards progress the film industry seems to be taking. As we examine the portrayal of women's roles in film, it is useful to explore various criteria used to measure their representation. One notable measure is the Bechdel Test, unintentionally introduced by American cartoonist Alison Bechdel in 1986, and the primary measure of women in film that is the focus of the present analysis.

The Bechdel Test originated from a comic strip titled "The Rule", a part of her comic *Dykes To Watch Out For*. The comic depicts two women discussing certain criteria necessary for them to watch a movie. The criteria for a movie included: two named women, who talked to each other, and held a conversation with each other that was not about a man. In the early 2000s, the test quickly gained popularity online and has since been used as a common tool for analyzing the role of women in film.

The test has only three basic requirements, meaning that a film can pass with just one line. Because of the simplicity of this tool, many have come forward with fair criticisms of the test. For example, the test does not take into account demographic factors, such as age, the voices of women of color, or those who do not speak English as their first language (O'Meara, 2016). Other flaws of the test include the oversight of conversations that are not directly about a man, but may be indirectly about them, where the conclusion of the test are unclear.

Regardless of its flaws, the Bechdel Test is a straightforward and easy tool that allows people to quickly make base assumptions about the presence of women in film. For this reason, this analysis will be examining the characteristics of thousands of movies in an attempt to use logistic regression analysis to model the likelihood of passing the Bechdel Test.

Read the comic here.

Data

The data used for the present analysis comes from a combination of multiple online sources. A data set containing 10,183 movie titles was available through IMDb Non-Commercial Datasets. Release dates for these movies range from 1874 to 2023. Variables included in this data set can be seen in the preview of the data below.

IMDb Non-Commercial Data set:

tconst	originalTitle	startYear	runtimeMinutes	genres
tt27502426	Les filles d'Olfa	2023	107	Documentary
tt15398776	Oppenheimer	2023	180	Biography,Drama,History
tt15326988	Ghosted	2023	116	Action,Adventure,Comedy
tt8400584	The Perfect Find	2023	99	Comedy,Drama,Romance
tt14230388	Asteroid City	2023	105	Comedy,Drama,Romance
tt18257464	Polite Society	2023	104	Action,Comedy

The code manual for the data from IMDb:

- **tconst**: alphanumeric unique identifier of the title
- **originalTitle**: title of the movie
- **startYear**: release year of the movie
- **runtimeMinutes**: runtime in minutes
- **genres**: up to three genres associated with the title

Other data that was used in this analysis comes from the Bechdel Test Movie List, where users can submit movies with their Bechdel test rating through their online platform. The data set pulled from this website contains 10,251 movies with release dates ranging from 1874 to 2024. For the rating variable, a movie is given a rating from one to three, directly corresponding with the number of requirements of the Bechdel test that it passes. A preview of this data can be shown below.

id	title	imdbid	year	rating
11166	Hunger Games: The Ballad of Songbirds & Snakes, The	10545296	2023	3
11169	Marvels, The	10676048	2023	3
11171	Royal Hotel, The	18363072	2023	3
11172	Nowhere	15789472	2023	3
11173	Leo	15654328	2023	3
11230	Book of Clarence , The	22866358	2023	1

The code manual for the Bechdel Test Movie List data:

- **id**: ID number
- **title**: title of the movie
- **imdbid**: IMDb number ID
- **year**: release year

- **rating**: Bechdel Test rating (0-3)

The data from IMDb Non-Commercial Datasets was joined with the data set pulled from the Bechdel test movie list to be used in the final model concerning genres.

The final data set that was used in this analysis comes from the TidyTuesday social data project through GitHub. This data set contains 1,794 movies released from 1970 up to 2013.

year	imdb	title	test	clean_test	binary	budget
2013	tt0770828	Man of Steel	ok-disagree	ok	PASS	2.25e+08
2013	tt1821549	Nebraska	ok-disagree	ok	PASS	1.20e+07
2013	tt1670345	Now You See Me	notalk-disagree	notalk	FAIL	7.50e+07

domgross	intgross	code	budget_2013	domgross_2013	intgross_2013
291045518	687999518	2013PASS	2.25e+08	291045518	687999518
17482517	17482517	2013PASS	1.20e+07	17482517	17482517
117723989	351723989	2013FAIL	7.50e+07	117723989	351723989

period_code	decade_code	imdb_id	response	rated	language	runtime
1	1	0770828	TRUE	PG-13	English	143 min
1	1	1821549	TRUE	R	English, Spanish	115 min
1	1	1670345	TRUE	PG-13	English	115 min

plot
A young itinerant worker is forced to confront his secret extrastellar origin when Earth is invaded by members of his own race.
An aging, booze-addled father makes the trip from Montana to Nebraska with his estranged son in order to claim a million-dollar Mega Sweepstakes Marketing prize.
An FBI agent and an Interpol detective track a team of illusionists who pull off bank heists during their performances and reward their audiences with the money.

writer
David S. Goyer (screenplay), David S. Goyer (story), Christopher Nolan (story), Jerry Siegel (Superman created by), Joe Shuster (Superman created by)
Bob Nelson

writer
Ed Solomon (screenplay), Boaz Yakin (screenplay), Edward Ricourt (screenplay), Boaz Yakin (story), Edward Ricourt (story)

country	metascore	imdb_rating	director	released	imdb_votes
USA, Canada, UK	55	7.4	Zack Snyder	14 Jun 2013	359556
USA	86	7.9	Alexander Payne	24 Jan 2014	33503
France, USA	50	7.3	Louis Leterrier	31 May 2013	280199

actors	genre	awards
Henry Cavill, Amy Adams, Michael Shannon, Diane Lane	Action, Adventure, Fantasy	4 wins & 16 nominations.
Bruce Dern, Will Forte, June Squibb, Bob Odenkirk	Adventure, Drama	Nominated for 6 Oscars. Another 26 wins & 61 nominations.
Jesse Eisenberg, Mark Ruffalo, Woody Harrelson, Isla Fisher	Crime, Mystery, Thriller	1 win & 3 nominations.

The code manual for the TidyTuesday data:

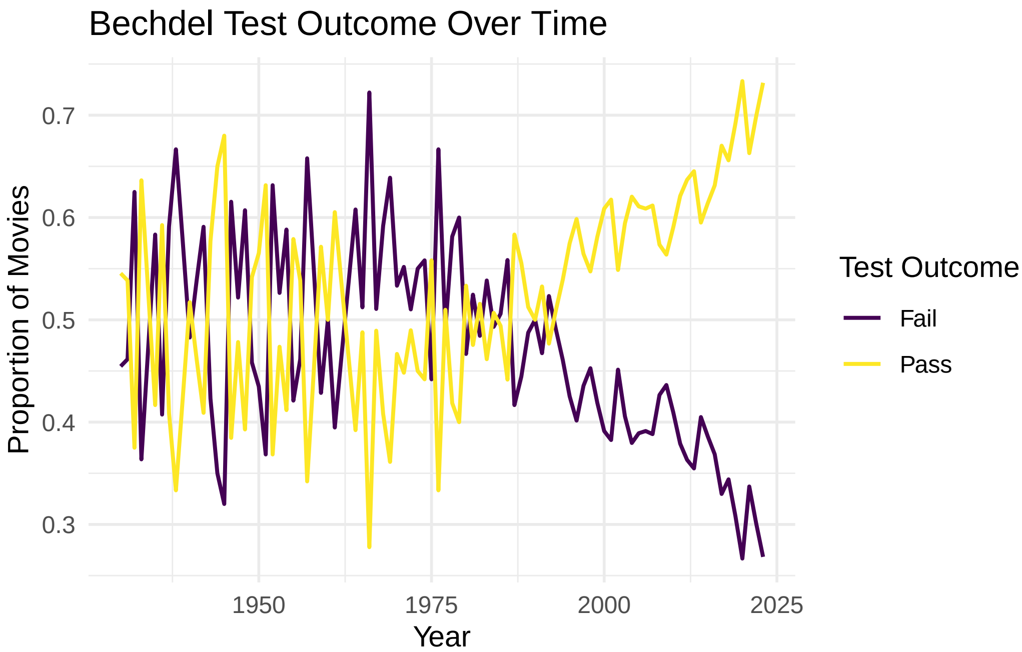
- **year**: release year
- **imdb**: IMDb id
- **title**: title of movie
- **test**: Bechdel Test outcome
- **clean_test**: Bechdel Test outcome (cleaned)
- **binary**: binary Pass or Fail of the Bechdel Test
- **budget**: budget as of release year
- **domgross**: domestic gross in release year
- **intgross**: international gross in release year
- **code**: code for movie ###

- **budget_2013**: budget normalized to 2013
- **domgross_2013**: domestic gross normalized to 2013
- **intgross_2013**: international gross normalized to 2013
- **period_code**: period code ###
- **decade_code**: decade code
- **imdb_id**: IMDb ID ###
- **plot**: plot summary of the movie
- **rated**: content rating of movie
- **response**: ??? ###
- **language**: language of movie
- **country**: country movie is produced in
- **writer**: writer of the film
- **metascore**: Metascore (critic) rating (0-100)
- **imdb_rating**: IMDb (user) rating (0-10)
- **director**: Director(s) of movie
- **released**: released date
- **actors**: main actors in movie
- **genre**: genre
- **awards**: awards won
- **runtime**: runtime in minutes
- **type**: type of film ###
- **imdb_votes**: number of IMDb votes

Exploratory Overview

Looking into the IMDb movie data set, the overall percentage of movies that pass the Bechdel Test is 57.0%, with the remaining 43.0% failing the test. The plot below demonstrates the proportion of movies each year that pass and fail the test each year, starting in 1930 up to 2023. The movies released in the years before 1930 have been excluded from this plot because of the amount of variation coming from a small number of movies each year, with an average of around 4 movies per year.

```r
basics_movies |>
  mutate(binary = if_else(rating == 3, "Pass", "Fail")) |>
  select(year, binary) |>
  group_by(year, binary) |>
  summarise(n = n()) |>
  filter(year >= 1930) |>
  pivot_wider(names_from = binary, values_from = n) |>
  mutate(Pass = if_else(is.na(Pass), 0, Pass),
         Fail = if_else(is.na(Fail), 0, Fail)) |>
  mutate(total_movies = sum(Pass, Fail)) |>
  mutate(Fail = Fail / total_movies,
         Pass = Pass / total_movies) |>
  pivot_longer(c(Fail, Pass), names_to = "binary", values_to = "prop") |>
  ggplot(aes(x = year, y = prop)) +
  geom_line(aes(color = binary), linewidth = 0.7) +
  scale_color_viridis_d(name = "Test Outcome") +
  labs(x = "Year",
       y = "Proportion of Movies",
       title = "Bechdel Test Outcome Over Time") +
  theme_minimal()
```



As seen in this plot, the proportion of movies passing and failing the test has much variation from the 1930s up until the early 90s. After the early 90s, however, the difference between the proportion of those that pass and fail each year becomes much more prominent. The proportion of movies that are passing the Bechdel Test are increasing each year.

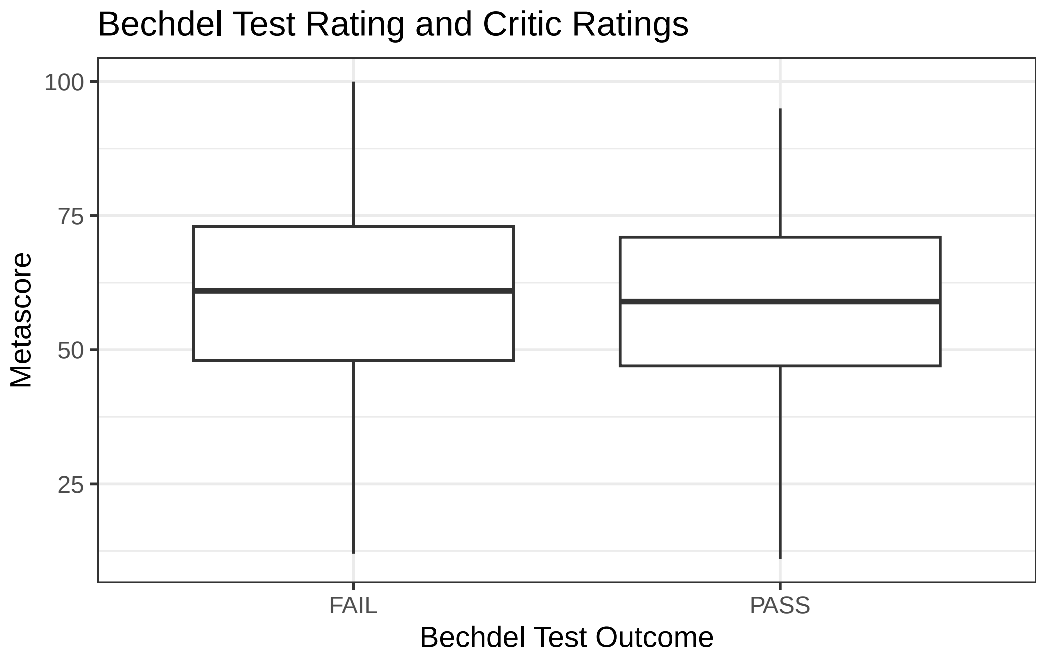
```
# movies appear multiple times for multiple listed genres
movies_model <- basics_movies |> separate_rows(genres, sep = ",")
movies_model <- movies_model |> mutate(binary = if_else(rating == 3, "1", "0")) |>
  mutate(binary = as.numeric(binary)) |>
  filter(!genres %in% c("News", "Adult", "Talk-Show", "\\N")) |>
  relocate(binary)
```

[enter some visual about genres here?]

Exploring the TidyTuesday data set allows us to examine other characteristics of movies, such as movie budget and different types of ratings. The plot below shpws the difference in critic ratings, or Metascore, between movies that pass and fail the Bechdel Test.

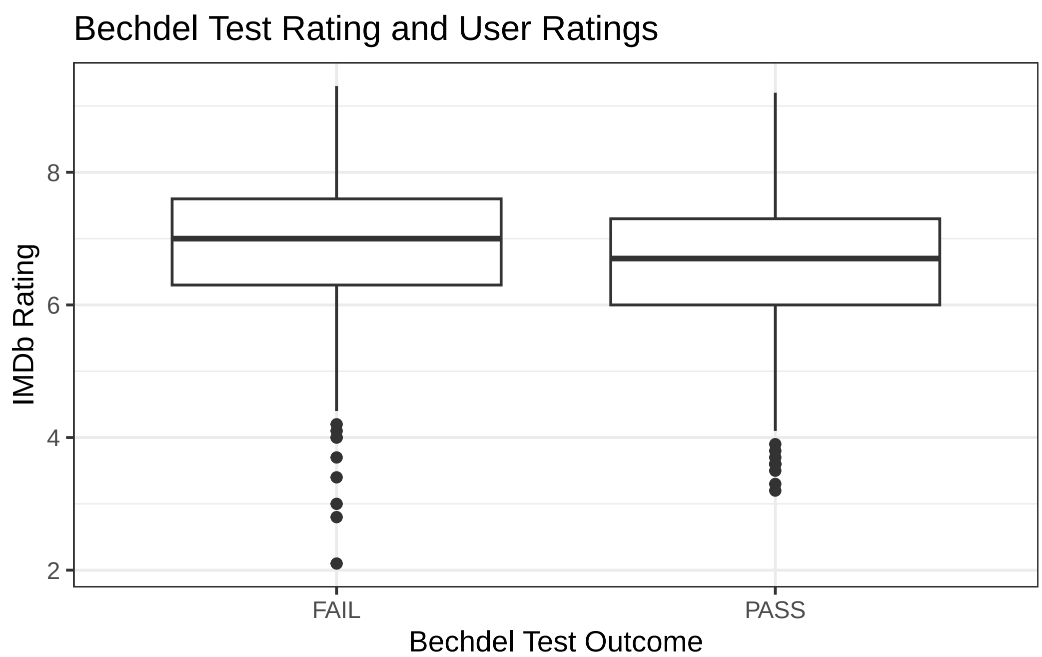
```
movies |>
  ggplot(aes(x = binary, y = metascore)) +
  geom_boxplot() +
  theme_bw() +
  labs(x = "Bechdel Test Outcome",
```

```
        y = "Metascore",
        title = "Bechdel Test Rating and Critic Ratings")
```



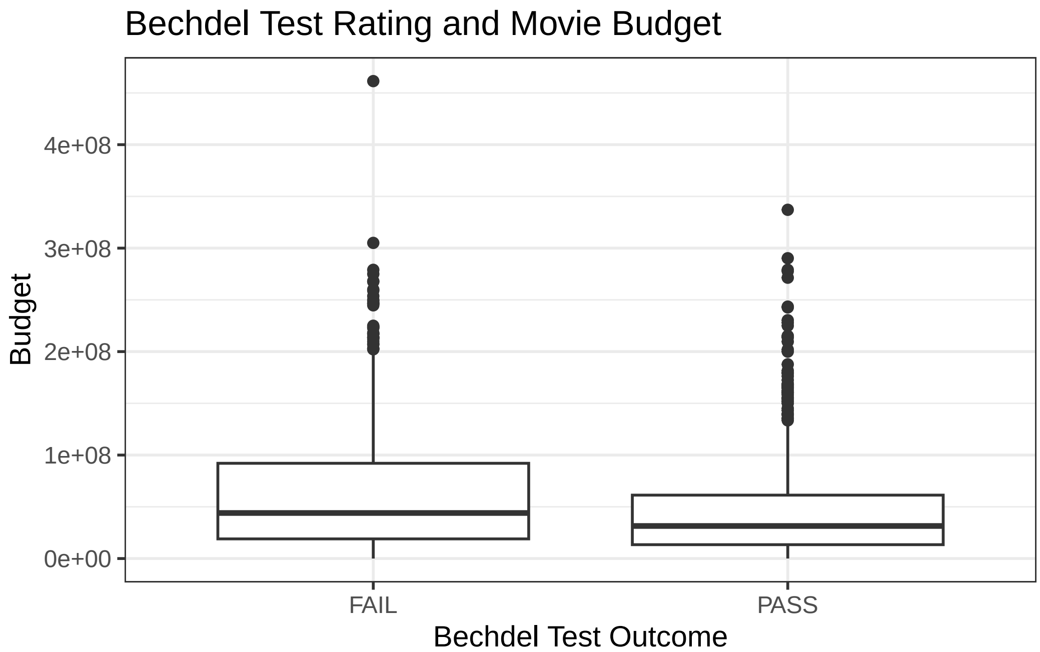
The plot above suggests a slight increase in average Metascore ratings for the movies that do not pass the Bechdel Test, but the difference appears to be too small to be notable. Demonstrated in the following plot, movies that do not pass the Bechdel Test also appear to have higher average user ratings than movies that pass.

```
movies |>
  ggplot(aes(x = binary, y = imdb_rating)) +
  geom_boxplot() +
  theme_bw() +
  labs(x = "Bechdel Test Outcome",
       y = "IMDb Rating",
       title = "Bechdel Test Rating and User Ratings")
```



In terms of movie budget, it appears that movies that fail tend to show larger movie bugdets than movies that pass the test, as shown in the following plot.

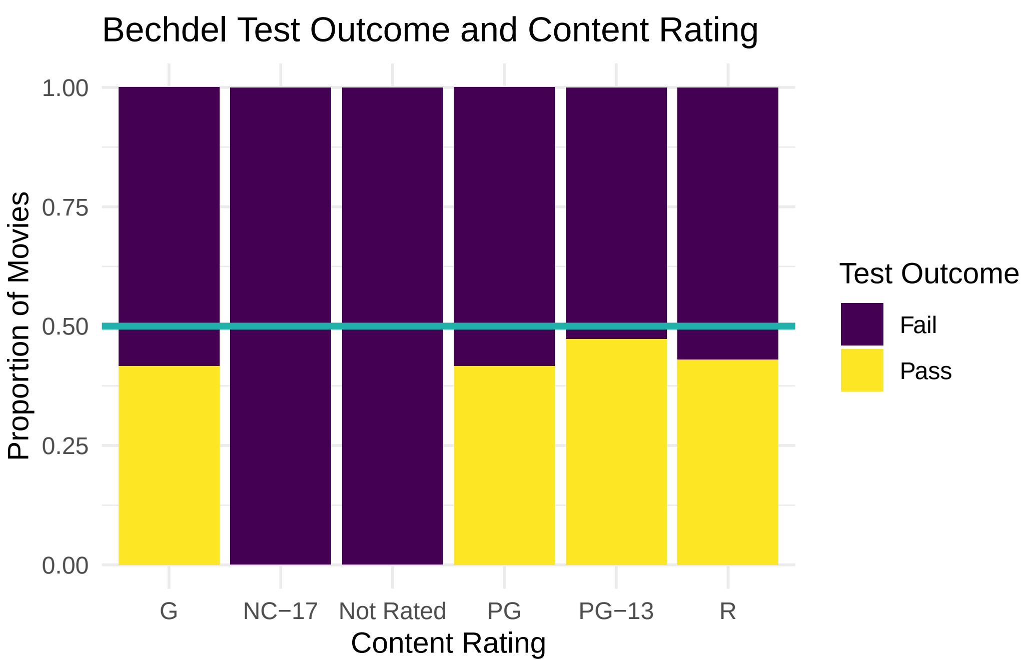
```
movies |>
  ggplot(aes(x = binary, y = budget_2013)) +
  geom_boxplot() +
  theme_bw() +
  labs(x = "Bechdel Test Outcome",
       y = "Budget",
       title = "Bechdel Test Rating and Movie Budget")
```



Another interesting variable in this data set is content rating. The content rating is designed to classify movies based on the audiences they are suitable for, based on factors like profanity, violence, sexual content, substance use, and any other topics that are not recommend for children to watch. The plot below contains five different content ratings with the proportion of movies that pass and fail the Bechdel Test in those categories.

```
movies |>
  select(rated, binary) |>
  group_by(rated, binary) |>
  summarise(n = n()) |>
  filter(n > 4) |>
  pivot_wider(names_from = binary, values_from = n) |>
  mutate(Pass = if_else(is.na(PASS), 0, PASS),
         Fail = if_else(is.na(FAIL), 0, FAIL)) |>
  mutate(total_movies = sum(Pass, Fail)) |>
  mutate(Fail = Fail / total_movies,
         Pass = Pass / total_movies) |>
  pivot_longer(c(Fail, Pass), names_to = "binary", values_to = "prop") |>
  filter(rated != "N/A") |>
  ggplot(aes(x = rated, y = prop)) +
  geom_col(aes(fill = binary), position = "stack") +
  geom_hline(yintercept = 0.5, linewidth = 1.2, color = "lightseagreen") +
  theme_minimal() +
```

```
labs(x = "Content Rating",
     y = "Proportion of Movies",
     title = "Bechdel Test Outcome and Content Rating") +
scale_fill_viridis_d(name = "Test Outcome")
```



The blue line represents the point of indifference, where the proportion of movies that pass is equal to 50%. The proportion of movies that pass the test does not reach half for any of the content rating categories, revealing that the majority of movies in each of these categories do not seem to pass.

Modeling

Genre Analysis

The goal of this analysis is to determine which genres have a higher likelihood of passing the Bechdel Test, and how that trend varies over time. To do this, a logistic regression model was created to model this probability, using all genres provided by the data and their interactions with release year. The full model with all coefficients is shown below. This model was created using the data from the IMDb database and the Bechdel Test Movie List.

$$\text{logit}(\pi) = \beta_0 + \beta_1 \cdot \text{Year} + \beta_2 \cdot \text{Animation} + \beta_3 \cdot \text{Action} + \beta_4 \cdot \text{Adult}$$

$$
\begin{gathered}
+\beta_5 \cdot \text{Adventure} + \beta_6 \cdot \text{Biography} + \beta_7 \cdot \text{Comedy} + \beta_8 \cdot \text{Crime} + \ \beta_9 \cdot \text{Documentary} \\
+\beta_{10} \cdot \text{Drama} + \beta_{11} \cdot \text{Family} + \beta_{12} \cdot \text{Fantasy} + \ \beta_{13} \cdot \text{History} + \beta_{14} \cdot \text{Horror} \\
+\beta_{15} \cdot \text{Music} + \beta_{16} \cdot \text{Musical} + \ \beta_{17} \cdot \text{Mystery} + \beta_{18} \cdot \text{Romance} + \beta_{19} \cdot \text{Short} \\
+\beta_{20} \cdot \text{Sport} + \ \beta_{21} \cdot \text{Thriller} + \beta_{22} \cdot \text{War} + \beta_{23} \cdot \text{Western} \\
+ \ \beta_{24} \cdot \text{Year:Animation} + \beta_{25} \cdot \text{Year:Action} + \beta_{26} \cdot \text{Year:Adult} + \ \beta_{27} \cdot \text{Year:Adventure} \\
+\beta_{28} \cdot \text{Year:Biography} + \beta_{29} \cdot \text{Year:Comedy} + \ \beta_{30} \cdot \text{Year:Crime} + \beta_{31} \cdot \text{Year:Documentary} \\
+\beta_{32} \cdot \text{Year:Drama} + \ \beta_{33} \cdot \text{Year:Family} + \beta_{34} \cdot \text{Year:Fantasy} + \beta_{35} \cdot \text{Year:History} \\
+ \ \beta_{36} \cdot \text{Year:Horror} + \beta_{37} \cdot \text{Year:Music} + \beta_{38} \cdot \text{Year:Musical} + \ \beta_{39} \cdot \text{Year:Mystery} \\
+\beta_{40} \cdot \text{Year:Romance} + \beta_{41} \cdot \text{Year:Short} + \ \beta_{42} \cdot \text{Year:Sport} + \beta_{43} \cdot \text{Year:Thriller} \\
+\beta_{44} \cdot \text{Year:War} + \beta_{45} \cdot \text{Year:Western}
\end{gathered}
$$

Within this model, π represents the probability of passing the test and *logit* represents the log odds of passing the test. Each genre in the present model is an indicator variable, with values 1 and 0 representing if the movie is that genre or not, respectively. For example, if a movie is an action film, the Action term in the model would be the value 1. If a different movie is entered in the model and not considered an action film, then the Action term would be 0. Interaction terms representing the changes in probability over time are included in the model for every genre as well. Each β value with its statistical significance is shown in the table below.

```r
## basics_movies with indicator variable for each genre
movies_indi <- read_csv(here::here("data/movies_indicator.csv"))

new_grid <- read_csv(here::here("data/movies_grid1.csv"))
library(modelr)
library(broom)

genre_model <- glm(factor(binary) ~ year + Animation + Action + Adult +
                     Adventure + Biography + Comedy + Crime +
                     Documentary + Drama + Family + Fantasy +
                     History + Horror + Music + Musical +
                     Mystery + Romance + Short + Sport +
                     Thriller + War + Western + year:Animation +
                     year:Action + year:Adult + year:Adventure +
                     year:Biography + year:Comedy + year:Crime +
                     year:Documentary + year:Drama + year:Family +
                     year:Fantasy + year:History + year:Horror +
                     year:Music + year:Musical + year:Mystery +
```

```
                 year:Romance + year:Short + year:Sport +
                 year:Thriller + year:War + year:Western,
               family = "binomial", data = movies_indi)
```

Table 10: Logistic Model Coefficients

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-37.56	6.867	-5.471	4.483e-08
year	0.01908	0.00344	5.546	2.916e-08
Animation	-24.18	11	-2.198	0.02798
Action	-15.97	7.381	-2.164	0.03046
Adult	31.48	18752	0.001679	0.9987
Adventure	-22.12	6.641	-3.331	0.0008664
Biography	5.874	9.814	0.5985	0.5495
Comedy	7.334	4.872	1.505	0.1322
Crime	13.73	5.736	2.393	0.0167
Documentary	-6.955	19.51	-0.3564	0.7215
Drama	10.29	5.026	2.048	0.04059
Family	1.427	8.118	0.1758	0.8604
Fantasy	-2.324	7.531	-0.3086	0.7576
History	2.483	10.03	0.2475	0.8046
Horror	-4.725	6.937	-0.6811	0.4958
Music	2.424	12.14	0.1997	0.8417
Musical	4.9	10.15	0.4829	0.6292
Mystery	8.571	7.066	1.213	0.2251
Romance	5.439	4.928	1.104	0.2697
Short	-26.7	13.9	-1.921	0.05469
Sport	-15.28	21.04	-0.7263	0.4676
Thriller	10.38	6.921	1.5	0.1336
War	26.5	10.91	2.429	0.01514
Western	21.96	18.45	1.19	0.2339
year:Animation	0.01204	0.00549	2.192	0.02835
year:Action	0.007626	0.003685	2.069	0.03853
year:Adult	-0.009716	9.432	-0.00103	0.9992
year:Adventure	0.01093	0.003322	3.291	0.0009967
year:Biography	-0.003053	0.0049	-0.6229	0.5333
year:Comedy	-0.003677	0.002439	-1.508	0.1316
year:Crime	-0.007114	0.002871	-2.478	0.01321
year:Documentary	0.003333	0.00974	0.3422	0.7322
year:Drama	-0.005127	0.002516	-2.037	0.0416
year:Family	-0.0005071	0.004068	-0.1247	0.9008

	Estimate	Std. Error	z value	Pr(>|z|)
year:Fantasy	0.001091	0.003769	0.2896	0.7721
year:History	-0.001418	0.005022	-0.2823	0.7777
year:Horror	0.002513	0.003472	0.7238	0.4692
year:Music	-0.001224	0.006075	-0.2015	0.8403
year:Musical	-0.002443	0.005126	-0.4766	0.6336
year:Mystery	-0.00426	0.003536	-1.205	0.2283
year:Romance	-0.002575	0.002473	-1.041	0.2977
year:Short	0.0127	0.006953	1.827	0.06775
year:Sport	0.007197	0.01051	0.6847	0.4935
year:Thriller	-0.005301	0.003461	-1.532	0.1256
year:War	-0.01378	0.005508	-2.502	0.01237
year:Western	-0.01187	0.009348	-1.27	0.2041

Adventure -22.12 6.641 -3.331 0.0008664

```r
exp(-22.12)  ## adventure
```

```
[1] 2.474036e-10
```

```r
exp(0.01093) ## interaction between year and adventure
```

```
[1] 1.01099
```

To understand the relationship between specific genres and predictability of the Bechdel Test,

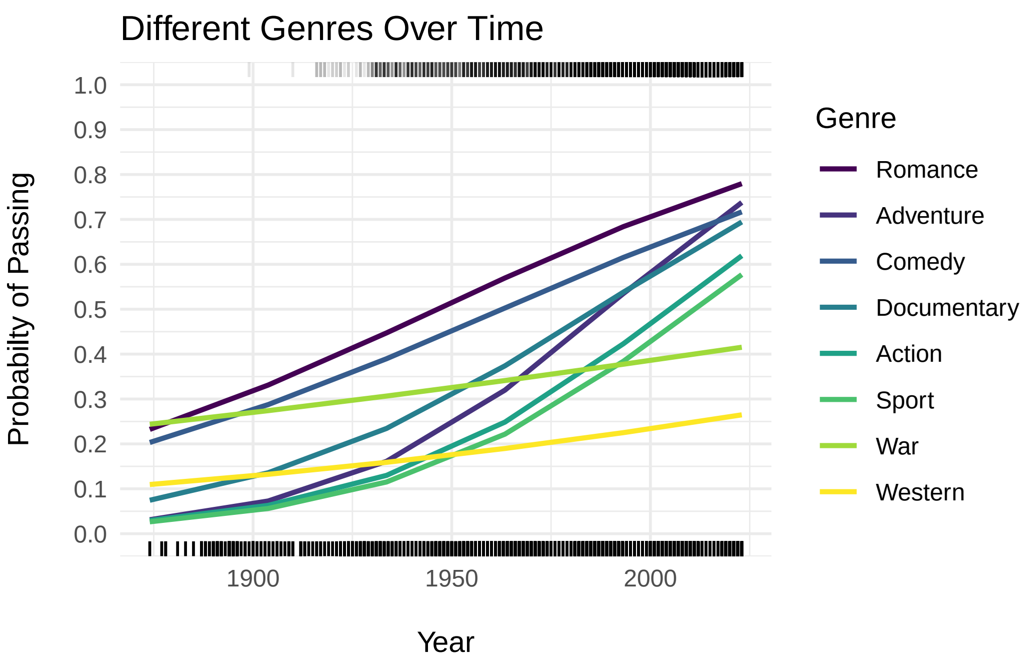
However, as revealed by the interaction between the Adventure genre and release year, the opposite effect is observed.

```r
aug_mod3 <- augment(genre_model, newdata = new_grid, se_fit = TRUE)

aug_mod3 <- aug_mod3 |> mutate(.pi = exp(.fitted) / (1 + exp(.fitted)))

list3 <- aug_mod3 |> pivot_longer(cols = c(Animation, Action, Adult,
                                          Adventure, Biography, Comedy,
                                          Crime, Documentary, Drama,
                                          Family, Fantasy, History,
                                          Horror, Music, Musical, Mystery,
                                          Romance, Short,
```

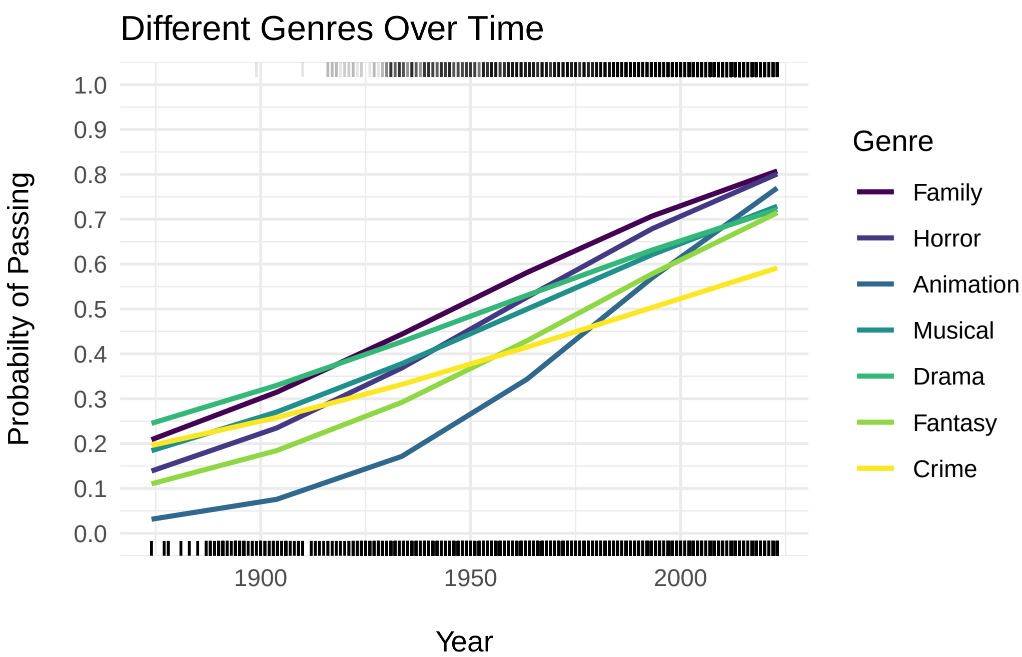
```
                                            Sport, Thriller,
                                            War, Western), names_to = "genre",
                                   values_to = "values")

movies_pass <- movies_indi |> filter(binary == 1)
movies_fail <- movies_indi |> filter(binary == 0)
```

The following plots

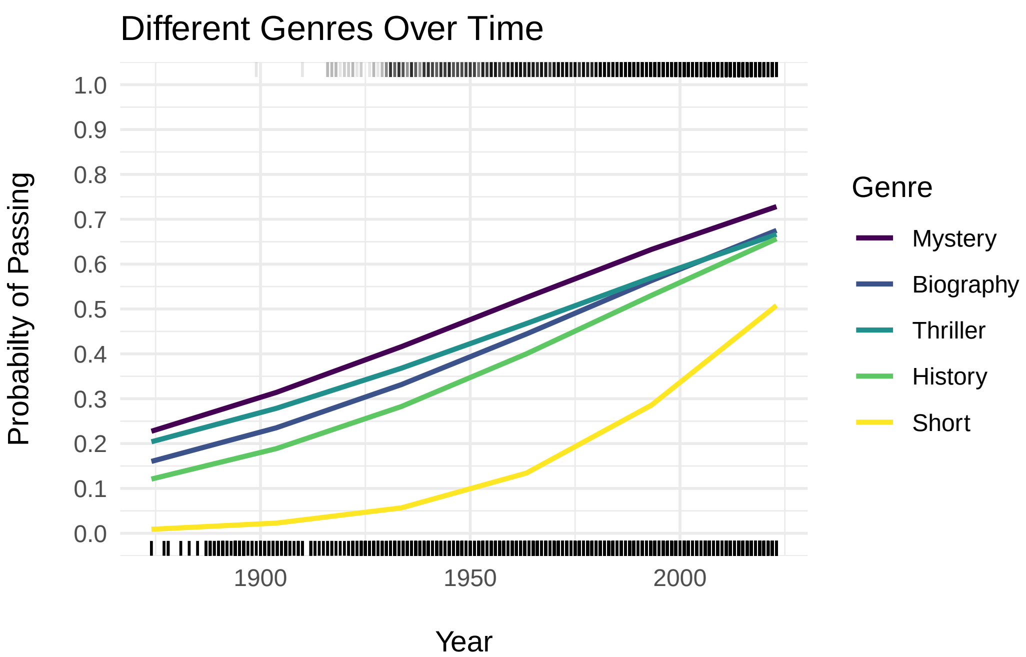
```
list3 |> filter(values == 1, genre %in%
                  c("Sport", "Comedy", "Romance", "Adventure",
                    "Action", "Documentary", "War", "Western")) |>
  mutate(genre = fct_reorder2(genre, .x = year, .y = .pi)) |>
  ggplot(aes(x = year, y = .pi)) +
  geom_line(aes(color = genre), linewidth = 0.9) +
  geom_rug(data = movies_pass,
           aes(x = year,
               y = as.numeric(binary)),
           sides = "t", alpha = 0.1) +
  geom_rug(data = movies_fail,
           aes(x = year,
               y = as.numeric(binary)),
           sides = "b") +
  scale_y_continuous(breaks = seq(0, 1, by = 0.1),
                     limits = c(0, 1)) +
  theme_minimal() +
  labs(x = "\nYear",
       y = "Probabilty of Passing\n",
       color = "Genre",
       title = "Different Genres Over Time") +
  scale_color_viridis_d()
```




```
list3 |> filter(values == 1, genre %in%
                  c("Horror", "Family", "Fantasy", "Drama",
                    "Animation", "Crime", "Sci-Fi", "Musical")) |>
  mutate(genre = fct_reorder2(genre, .x = year, .y = .pi)) |>
  ggplot(aes(x = year, y = .pi)) +
  geom_line(aes(color = genre), linewidth = 0.9) +
  geom_rug(data = movies_pass,
           aes(x = year,
               y = as.numeric(binary)),
           sides = "t", alpha = 0.1) +
  geom_rug(data = movies_fail,
           aes(x = year,
               y = as.numeric(binary)),
           sides = "b") +
  scale_y_continuous(breaks = seq(0, 1, by = 0.1),
                     limits = c(0, 1)) +
  theme_minimal() +
  labs(x = "\nYear",
       y = "Probabilty of Passing\n",
       color = "Genre",
       title = "Different Genres Over Time") +
  scale_color_viridis_d()
```




```
list3 |> filter(values == 1, genre %in%
                  c("Thriller", "Biography", "Mystery", "History",
                    "Short", "Talk-Show", "News", "Film-Noir")) |>
  mutate(genre = fct_reorder2(genre, .x = year, .y = .pi)) |>
  ggplot(aes(x = year, y = .pi)) +
  geom_line(aes(color = genre), linewidth = 0.9) +
  geom_rug(data = movies_pass,
           aes(x = year,
               y = as.numeric(binary)),
           sides = "t", alpha = 0.1) +
  geom_rug(data = movies_fail,
           aes(x = year,
               y = as.numeric(binary)),
           sides = "b") +
  scale_y_continuous(breaks = seq(0, 1, by = 0.1),
                     limits = c(0, 1)) +
  theme_minimal() +
  labs(x = "\nYear",
       y = "Probabilty of Passing\n",
       color = "Genre",
       title = "Different Genres Over Time") +
  scale_color_viridis_d()
```



Rating Analysis

Since the TidyTuesday data contained a variety of movie characteristics that is not provided by IMDb or the Bechdel Test Movie List, a logistic regression model was constructed to investigate the effects of movie budget, year, IMDb rating, and Metascore rating on a movie's likelihood of passing the Bechdel Test. The full model with all coefficients is shown below. The cost of the budget has been normalized to 2013, as this is where the data set ends.

$$logit(\pi) = \beta_0 + \beta_1 \cdot \text{Budget} + \beta_2 \cdot \text{Year} + \beta_3 \cdot \text{IMDb Rating} + \ \beta_4 \cdot \text{Metascore}$$

Similar to the model created in the previous section, π represents the probability of passing the Bechdel Test and $logit$ represents the log odds of passing the test. The β values of this model with the statistical significance for each is shown in the table below.

```
movies <- movies %>% mutate(binary_0 = ifelse(binary == "PASS", 1, 0))

mod_year <- glm(binary_0 ~  budget_2013 +
                  year +
                  imdb_rating +
                  metascore,
                data = movies, family = "binomial")
```

Table 11: Logistic Model Coefficients

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-26.36	15.38	-1.714	0.08654
budget_2013	-6.397e-09	1.078e-09	-5.935	2.939e-09
year	0.01461	0.007634	1.914	0.05566
imdb_rating	-0.5625	0.08984	-6.261	3.821e-10
metascore	0.01745	0.004819	3.622	0.0002928

Interpreting the coefficient values produced by the logistic regression can be helpful in understanding their relationship with Bechdel Test outcome. For example, the value of the coefficient for budget is -4.773e-09, indicating a negative relationship between budget and passing the Bechdel Test. In other words, movies with higher budgets tend to be less likely to pass the Bechdel Test. A seen by the very small p-value, this relationship reveals to be significant.

Among the other predictors, IMDb rating and Metascore also demonstrate significant relationships when predicting Bechdel Test outcome. The model output reveals that when the IMDb rating of a movie increases by 1 point, the log odds of a movie passing the test decreases by 0.571. This signifies that movies that pass the Bechdel Test tend to have lower ratings on IMDb, confirming what was observed in the exploratory analysis. In contrast, the relationship between critic rating and Bechdel Test outcome appears to show the opposite effect. As the Metascore rating for a movie increases by 1 point, the log odds of a movie passing the test increases by 0.021, meaning that movies that pass the Bechdel Test are predicted to have higher critic ratings.

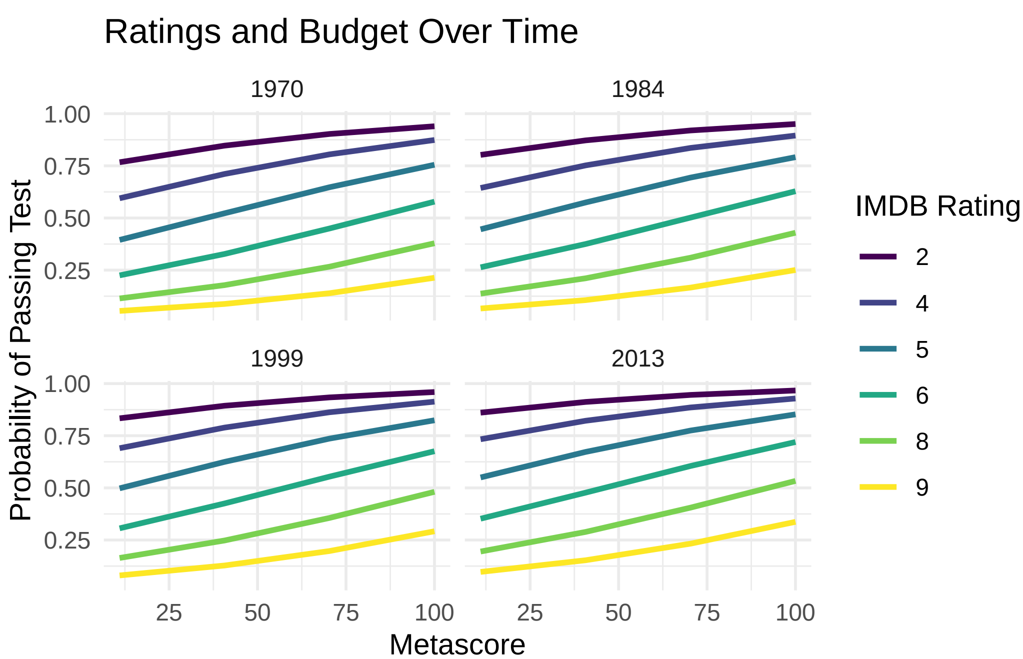
The last predictor in this model is year, predicting that as the release year increases by 1, the log odds of passing the test increase by 0.0161. This demonstrates that newer movies are more likely to pass the test than older movies. This relationship is only approaching significance, but it was determined that year plays a crucial role when it comes the role women play in film, so it was kept in the model.

The following plot visualizes this model using year, Metascore, and IMDb ratings to predict the probability that a movie will pass the Bechdel Test.

```r
grid <- movies |>
  data_grid(
    year = seq_range(year, n = 4),
    binary_0 = c(0, 1),
    imdb_rating = seq_range(imdb_rating, n = 6),
    budget_2013 = median(movies$budget_2013, na.rm = T),
    metascore = seq_range(metascore, n = 4)
    )
```

```r
aug_year <- augment(mod_year, newdata = grid, se_fit = TRUE)
aug_year <- aug_year |> mutate(.pi = exp(.fitted) / (1 + exp(.fitted))) |>
  mutate(year = round(year, 0))
```

```r
ggplot(data = aug_year, aes(x = metascore, y = .pi)) +
  geom_line(aes(color = as.factor(round(imdb_rating))), linewidth = 1) +
  facet_wrap(~ year) +
  labs(y = "Probability of Passing Test",
       x = "Metascore",
       title = "Ratings and Budget Over Time") +
  scale_color_viridis_d(name = "IMDB Rating") +
  theme_minimal()
```



From this plot we can observe how movies rated lower on IMDb tend to have a higher predicted probability of passing the test. This is shown through the different colored trend lines representing IMDb ratings, as lower lines representing lower ratings appear towards higher probabilities. Furthermore, the upward direction of the lines in the plot visualize how movies with higher critic ratings have a higher predicted probability of passing the Bechdel Test. Lastly, the plot is split into four different graphs to represent the change in probability over time. The difference appears to be small, but predicted probability increases when moving from past to present years.

Conclusion

Overall, this analysis was designed to investigate the Bechdel Test, a test created to assess the roles of women in film.

Limitations

Future Work

References

1. Bechdel, A. (1986). Dykes to watch out for. *Firebrand Books.*
2. Lauzen, M. (2024). It's a Man's (Celluloid) World: Portrayals of female characters in the top grossing U.S. Films of 2023. *Center for the Study of Women in Television & Film.* https://womenintvfilm.sdsu.edu/its-a-mans-celluloid-world-portrayals-of-female-characters-in-the-top-grossing-u-s-films-of-2023/
3. Lauzen, M. (2014). It's a Man's (Celluloid) World: On-Screen Representations of Female Characters in the Top 100 Films of 2013. *Center for the Study of Women in Television & Film.* https://womenintvfilm.sdsu.edu/files/2013_It's_a_Man's_World_Report.pdf