MATH 154 - Final Project Writeup

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Introduction / Motivation (include a visualization maybe)

The Academy Awards, colloquially known as the Oscars, are an iconic American cultural institution approaching its century-long anniversary. As a defining force in Hollywood, the arts, and the global audience it captivates, the Oscars have evolved into the foremost arbiter in determining which films are immortalized in history. Over time, the ceremony has come to shape not only the landscape of cinema but also public perception of artistic achievement.

Since its inception, the Oscars have been accompanied by the phenomenon of 'Oscar Bait' — the idea that certain movies are intentionally created to appeal to the Academy's tastes in order to secure an Oscar. Factors such as a late release date, typically around the time of the Oscar submission deadline, being a drama, historical piece, or biopic, and featuring a star-studded cast and director are common traits in many Oscar-winning films ("Hooked on Oscar Bait – Is There a Hack to Winning an Oscar?" 2021; Franklin 2019).

The Deer Hunter (1978) is cited as the first example of explicit Oscar Bait. Rather than first appealing to the masses to gain revenue, their strategy was to win an Oscar to catapult the movie to broad audiences and generate hype. The filmakers made deliberate choices in mind: mainly only showing the movie to those within the Academy and other high profile individuals for the minimum requirement of two weeks, having a famed ensemble and director, and a

thematic focus on war, their efforts paid off, winning Best Picture for that year. Overall, it went on to gross $48.9 million overall. (Hofler 2010)

Considering the Oscars has become the primary authority of American film taste, it is important to critically consider the media which we consume, and the people behind the Academy who decide what becomes gilded for the rest of time. As we explore what makes an Oscar Award winner versus a nominee, we question the authenticity of such wins, especially when there is a prominent trend of who wins an Oscar award, and the recorded phenomena of directors gaming the system to increase their odds to win one. In this chicken-and-egg situation of which came first, it is important to question if the winners may not purely be based on the film's artistic quality, but its features which cater to the Academy.

Motivated by the idea of Oscar Bait, our project aims to explore the factors that contribute to a film winning an Oscar. By using variables such as revenue, budget, and genres, we first seek to identify patterns that reveal the Academy's preferences. Although the concept of the Oscars is inherently qualitative to judge an art form, we question if the revealed qualitative trends are significant enough to determine a clear distinction between Oscar winners versus nominees. Ultimately, we question if the Academy's preferences to follow measurable trends are distinct enough to predict the outcomes of the 2025 ceremony.

Data

We began by using this dataset of Oscar nominees and winners from 1927-2024. This dataset had info on each film, its release year, the category it was nominated for, and whether or not it won.

```
library(tidyverse)
oscar_nominees <- read.csv("the_oscar_award.csv")
```

(Wickham et al. 2019)

For each film in this dataset, we used the TMDB API to info on its budget, popularity, revenue, runtime, release date, vote average, vote count, genres, production countries, and spoken languages. (Team 2023)

To set up authorization with the TMDB API, make an account and set the API key as an environment variable by creating a `.Renviron` file and listing the API key as below (**in the `.Renviron` file):

```
TMDB_API_KEY=YOURAPIKEY # No spaces or quotation marks!
```

Note that the `.Renviron` file should be at the same level of the `.Rproj` of the project in order for this to work.

Now, run `readRenviron(".Renviron")` in the console.

```
library(httr)
library(jsonlite)
library(dplyr)

url <- "https://api.themoviedb.org/3/authentication"

personal_authorization <- paste0('Bearer ', Sys.getenv("TMDB_API_KEY"))

response <- VERB("GET", url, add_headers('Authorization' =  personal_authorization),
                 content_type("application/octet-stream"), accept("application/json"))
```

(Wickham 2022; Ooms 2014; Wickham et al. 2023)

In order to get the movie data, we first had to make an API call to search for the movie in the TMDB database and get its TMDB id. We search using the film name and year from the Oscar nominees dataset, then take the result with the highest popularity. We assume here movies that get nominated are much more popular than non-nominated movies.

The following function does exactly as described above, make an API call to retrieve an identified movie and then returns the movie with the highest popularity.

```
# function to search for a movie by title and year
search_movie <- function(auth, movie_title, year) {
  url <- "https://api.themoviedb.org/3/search/movie"

  # parameters for the query
  queryString <- list(
    query = movie_title,
    year = as.character(year)
  )

  response <- VERB("GET", url, query = queryString,
                   add_headers('Authorization' = auth),
                   content_type("application/octet-stream"),
                   accept("application/json"))

  # check for response status
  if (http_error(response)) {
    stop("Failed to retrieve movie data. HTTP Status: ", status_code(response))
  }
```

```
  # parse json
  response_content <- content(response, "text")
  json_data <- fromJSON(response_content)

  # return the top movie hit
  if (length(json_data$results) > 0) {
    return(
      as.data.frame(json_data$results |>
        arrange(desc(popularity)) |> # choose based on popularity
        head(1)
    ))
  } else { # modify to search +/- 1
    return(NULL) # No results found
  }
}
```

We now try this on an example movie, Parasite, to exhibit the information that is returned:

```
# Example: Search for Parasite
parasite <- search_movie(personal_authorization, "Parasite", 2020)
print(parasite)
```

```
  adult                    backdrop_path  genre_ids     id original_language
1 FALSE /hiKmpZMGZsrkA3cdce8a7Dpos1j.jpg 35, 53, 18 496243                ko
  original_title
1

1 All unemployed, Ki-taek's family takes peculiar interest in the wealthy and glamorous Parks
  popularity                      poster_path release_date    title video
1     99.231 /7IiTTgloJzvGI1TAYymCfbfl3vT.jpg   2019-05-30 Parasite FALSE
  vote_average vote_count
1        8.505      18352
```

We then applied this function to all observations in the Oscar nominations dataset to get our initial dataframe.

Now that we have the all of the movies' TMDB id, we can make another API call to get more details about the movie including its spoken language, budget, revenue, etc. The following function uses a given movie's TMDB id to retrieve more detailed information on each movie.

```r
search_movie_extra <- function(auth, movie_id, fields) {
  parse_field <- function(json_data, field) {
    return(ifelse(!is.null(json_data[[field]]), json_data[[field]], NA))
  }

  url <- paste0("https://api.themoviedb.org/3/movie/", movie_id)

  # Make the GET request with the Authorization header and JSON accept header
  response <- GET(url,
                  add_headers('Authorization' = auth),
                  content_type("application/octet-stream"),
                  accept("application/json"))

  # Check for response status
  if (http_error(response)) {
    stop("Failed to retrieve movie data. HTTP Status: ", status_code(response))
  }

  # Parse the JSON response
  response_content <- content(response, "text")
  json_data <- fromJSON(response_content)

  result <- data.frame(matrix(ncol = length(fields), nrow = 1))
  colnames(result) <- fields

  # Safely extract all the available fields
  if (length(json_data) > 0) {
    for (field in fields) {
      result[[field]] = parse_field(json_data, field)
    }

    return(result)
  } else {
    return(data.frame())
  }
}
```

More specifically, we wanted to retrieve the following columns/data to utilize later.

```r
# Define fields to search for
input_fields <- c("adult", "backdrop_path", "belongs_to_collection", "budget",
                  "genres", "homepage", "id", "imdb_id", "original_language",
```

```
                    "original_title", "overview", "popularity", "poster_path",
                    "production_companies", "production_countries", "release_date",
                    "revenue", "runtime", "spoken_languages", "status", "tagline",
                    "title", "video", "vote_average", "vote_count")
```

Hence, we have all of the qualities of the function necessary to retrieve this data! For example we can run this function to get extra details on Fightclub:

```
# Example: Get details for Fightclub
fightclub <- search_movie_extra(personal_authorization, 550, input_fields)
print(fightclub)
```

```
  adult                     backdrop_path belongs_to_collection   budget genres
1 FALSE /hZkgoQYus5vegHoetLkCJzb17zJ.jpg                    NA 63000000     18
                                    homepage  id   imdb_id original_language
1 http://www.foxmovies.com/movies/fight-club 550 tt0137523                en
  original_title
1     Fight Club

1 A ticking-time-bomb insomniac and a slippery soap salesman channel primal male aggression
  popularity                      poster_path      production_companies
1     88.976 /pB8BM7pdSp6B6Ih7QZ4DrQ3PmJK.jpg 711, 508, 4700, 25, 20555
  production_countries release_date   revenue runtime spoken_languages   status
1               DE, US   1999-10-15 100853753     139          English Released
                  tagline      title video vote_average vote_count
1 Mischief. Mayhem. Soap. Fight Club FALSE        8.437      29486
```

Now that we understand it works, we can run this function for every unique movie that appeared in our initial dataset

So now that we have all of the details needed to analyze the Oscar and movie data, it is a good time to talk about our actual data. As mentioned before, at this point in the process, we have two datasets: one providing detailed information on and characteristics about movies and one providing insights on how movies performed at the Oscars. So, when we join these two datasets (in the Data Wrangling section below), our data will only consist of movies that *have been nominated* for an Oscar. That is to say, that any insights we retrieve from the following data analysis may only be applied to the population of Oscar nominees.

Data Wrangling

Now, we have all of the data necessary for us to pursue our project goal. That said, the data doesn't exactly come in a simple form for us to easily use in data visualization and in building a model. So, we have to transform it a bit.

First, we want to combine our datasets into one, easily manageable dataframe. So, we join by the film name and since we found some slight discrepencies in the year of release of some films, we accounted for a buffer of 1 in year. Joining this data creates a data frame where each row represents a movie nominated for a specific category of a given year. So, there are repeats of movies since many movies are nominated for several different categories. Note that in the following code we also created a new column called `won_at_least_one` which helps us to track whether a movie won an oscar, even if it wasn't necessarily in the category that the observation belongs to.

```
all_data <- left_join(oscar_nominees, movie_data, by = c("film" = "title")) |>
  filter(abs(year_film - release_year) <= 1) |>
  group_by(film, year_film) |>
  mutate(won_at_least_one = ifelse(sum(winner == "True") >= 1, TRUE, FALSE)) |>
  ungroup()
```

Our next hurdle was the fact that many columns in the dataset (including `genre_ids`, `production_countries`, and `spoken_languages`) were columns of lists. For example, in order to get the genre of a given observation, you could not just call `obs$genre_ids` because that could return to you a list of genre_ids associated with that given observation. Additionally (specifically for the genre variable), the vector initially came encoded as an integer vector (where the integers mapped to a specific genre). So, in order to handle this, we created a function to widen the dataset by genre, where a new binary column was made for each possible genre indicating whether or not the movie classified as that genre.

The following, `wider_by_genre` does exactly as explained and mutates the column names to be decoded into their string representations.

```
# function for unnesting genre list columns
wider_by_genre <- function(df) {
  # make sure all values are vectors
  df$genre_ids <- map(df$genre_ids, ~ if (is.list(.)) unlist(.) else .)

  # now, change all the number values to be genres(char)
  new_df <- df |>
    unnest(genre_ids) |>
    distinct() |>
    mutate(genre_ids = genres_dict[as.character(genre_ids)]) |>
```

```
    filter(!is.na(genre_ids)) |>
    mutate(valid_id = 1) |> # create binary value for the pivot_wider to use
    pivot_wider(names_from = genre_ids, values_from = valid_id,
                values_fill = 0) # use names_prefix if want "genre_"

  return(new_df)
}
```

The `production_countries` and `spoken_languages` columns had a similar format of list, but we did not need to decode its value names. The following function `flatten_lists` does exactly as described, widening the data so we did not have to worry about handling lists any longer. Additionally included in the following code is the idea of `top_vector`. The motivation for and explanation of this will be described in the Random Forest section.

```
# more generic flattening of lists
flatten_lists <- function(df, feature, top_vector, prefix) {
  # make sure all values in the specified column are vectors
  df[[feature]] <- map(df[[feature]], ~ if (is.list(.)) unlist(.) else .)
  df$feature[is.null(df$feature)] <- NA

  # now, change all the number values
  new_df <- df |>
    unnest({{feature}}) |>  # unnest the specified column
    mutate(valid_value = 1, # create binary value for pivot_wider
           temp_feature = case_when(
             .data[[feature]] %in% top_vector ~ as.character(.data[[feature]]),
             TRUE ~ "Other")) |>
    select(-{{feature}}, -feature) |>
    distinct() |>
    pivot_wider(names_from = temp_feature, values_from = valid_value,
                names_prefix = prefix, values_fill = 0)

  return(new_df)
}
```

Visualizations

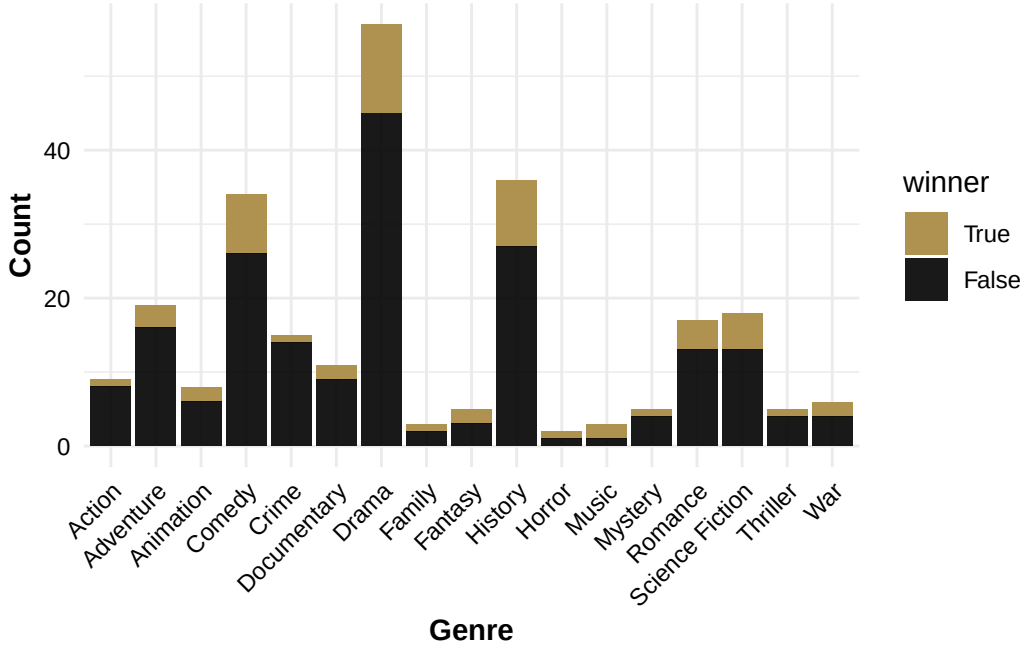
Now that we have wrangled the data to be in a form that we can easily work with. We look to do some data analyzation. Motivated by this idea of oscar baiting, we initially wanted to look at the characteristics that were specifically listed as elements of oscar baiting. (Franklin

2019) More specifically, the traits that we had data on included Genre, Budget, and Release Date.

Since the first notion of "oscar baiting" was in 1978 ("The Deer Hunter"), we decided to use data from the last 50 years of the Oscars to analyze the trends of a possible oscar baiting phenomena. Note, once again, all of the analysis done below is based on *Oscar nominated* films and so conclusions or observations may *not* be generalized to the entire population of films.

(Wickham 2016)

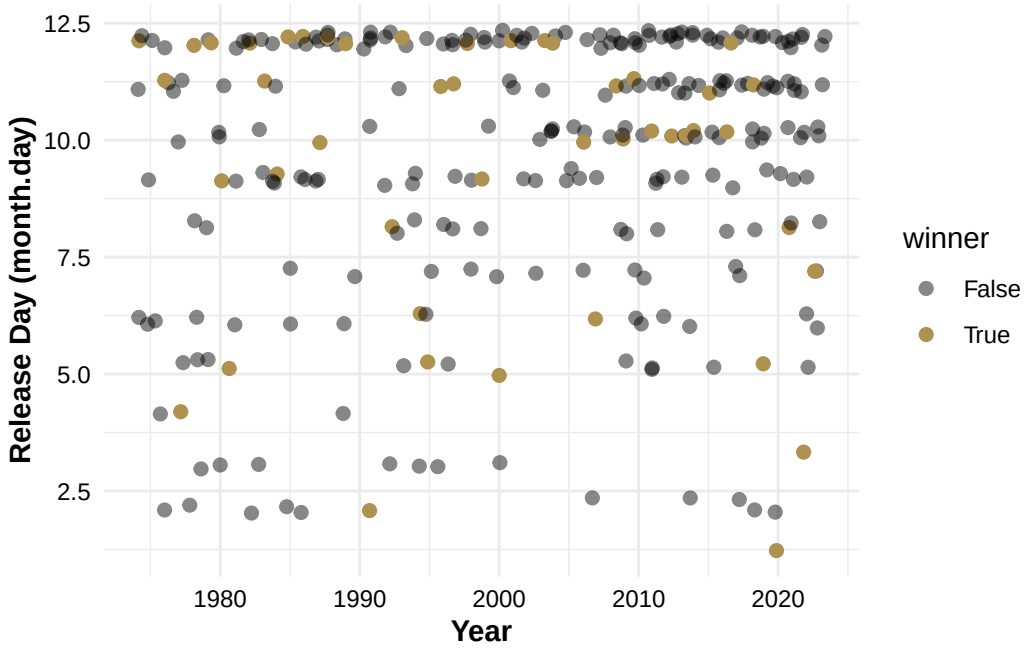
Specifically, we firstlooked at the year 2024 and the movies that were nominated for the 2024 Oscars (ie. they were 2023 films). It is notable how dominant the Drama category is among all of these movies, both in overall nominations and in winners. Additionally, following behind are historical films. Note that these results are consistent with a category of oscar baiting being a dramatic, historical period piece.



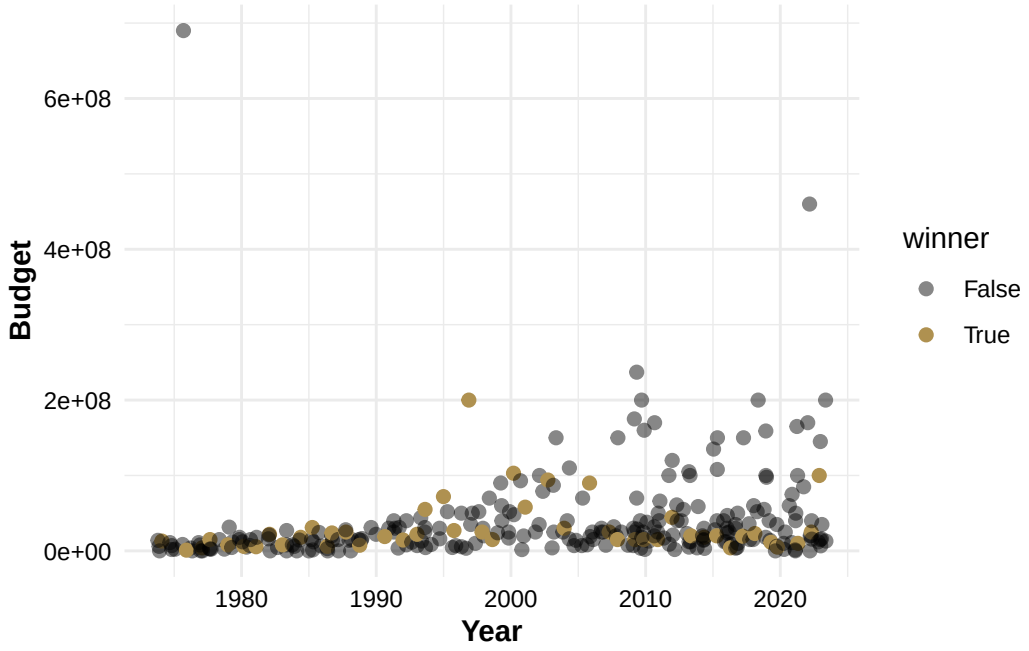
Now that we can acknowledge there is definitely some type of commonality between oscar nominees/winners, we can also look at these variables/traits over time to see how these trends have progressed throughout the years of the Oscars. So as to not make the graph too convoluted, we filtered the following graphs to only consist of nominees/winners of the "Best Picture" category over the last 50 years.

The following graph exhibits nominations over the years in terms of release day. As we can tell, while in 1975 release day of films were generally very scattered, as years passed, films

nominated for "Best Picture" definitely showed a tendency of being released later in the year, around the time of the cutoff of movies for Oscar nominations.



Similarly, the following plot shows nominations over the years in terms of budget. Note that the budget data is not normalized. Though this trend is not as significantly obvious as the previous two, we still continue to see a trend of nominated films having a higher and higher budget (meaning higher production) for a movie.



**It is important to note that these visualizations are not entirely accurate as they may have some corrupted values due to IMDB being a user informed site. For example, there is a movie called "Taxi Driver" that is listed as having a budget of about 600 million dollars (observation seen in the top left corner of the graph above) whereas its real budget is somewhere closer to about 2 million dollars.

From all of these visualizations, we were able to understand and convince ourselves that oscar baiting is a very real phenomena. That is, many Oscar nominated (and awarded) films have oddly similar traits in regards to their genre, budget, and release day of the year.

Random Forest

As we saw in the above visualizations, there are definitely trends in what kind of movies get nominated for Oscars. The next question we wanted to answer was whether we could train a random forest model to be able to predict which of those nominees actually wins the Oscar.

To use our data, we first had to do some preprocessing. Much of this preprocessing was done prior (details in the data wrangling section) but more specifically, making this data more feedable to a random forest was essential. In order to do this, we decided to add the `top_vector` variable in our `flatten_lists` function. The purpose of this variable was to help make a column for only the top 5 or 6 features of `spoken_languages` and `production countries`. That is, we created a new binary column for only the top 6 (most-occuring) production companies and the top 5 (most-occurring) spoken languages and for all movies

that did not have a highly occuring production country or spoken language, we classified their country and language as "other".

The motivation behind this was to simplify the dataset that we hoped to feed our random forest model enough so that it would not be thrown off by any outliers.

The following vectors contain the countries and languages that we found to be most-occurring.

```
top_countries <- c("US", "GB", "FR",  "DE", "IT", "CA")
top_languages <- c("English", "French", "German", "Spanish", "Italian")
```

Now, we apply all of this data preprocessing to render a dataframe that the random forest will easily be able to understand and work with.

```
# preprocess data for nominees since 1975
rf_data <- all_data |>
  # first make df wider (flatten all data)
  mutate(genre_ids = genres) |>
  select(-genres) |>
  wider_by_genre() |>
  flatten_lists("production_countries", top_countries, "country_") |>
  flatten_lists("spoken_languages", top_languages, "lang_") |>
  select(-belongs_to_collection, -production_companies) |>
  filter(year_ceremony >= 1975) # filter for last 50 years
```

In addition to flattening the lists, we made sure to get rid of any and all information that we did not want to use as predictors. For instance, any identifiers and repetitive data is what we got rid of.

```
rf_data <- rf_data |>
  mutate(won_at_least_one = as.factor(won_at_least_one))

rf_data <- rf_data |>
  ungroup() |>
  distinct(film, .keep_all = TRUE) |>
  select(-year_film, -year_ceremony, -ceremony, -category, -name, -film, -winner,
         -adult, -backdrop_path, -homepage, -id, -imdb_id, -original_title,
         -overview, -poster_path, -release_date, -status, -tagline, -video,
         -original_language)
```

Now that our data has been preprocessed, we are ready to train a model. Keep in mind that our model will be predicting the variable `won_at_least_one`. Again, since we adjusted the

dataset earlier to account for any model that won at least one Oscar award, the model will be predicting whether or not it will win *any* award. We also perform cross-validation on the `mtry`, `trees`, and `min_n` parameters.

```
library(tidymodels)

# Partition data into train / test sets
set.seed(47)
movie_split <- initial_split(rf_data)
movie_train <- training(movie_split)
movie_test <- testing(movie_split)

# Recipe
recipe <-
  recipe(won_at_least_one ~ . ,
         data = movie_train)

# Model
movie_rf <- rand_forest(mtry = tune(),
                        trees = tune(),
                        min_n = tune()) |>
  set_engine("ranger", importance = "permutation") |>
  set_mode("classification")

# Workflow
movie_rf_wflow <- workflow() |>
  add_model(movie_rf) |>
  add_recipe(recipe)

# CV
movie_folds <- vfold_cv(movie_train, v = 4)

# Tuning parameters
movie_grid <- grid_regular(mtry(range = c(1,40)),
                           trees(range = c(10,500)),
                           min_n(range = c(1,20)),
                           levels = 5)

# Tune (CV)
movie_rf_tune <-
  movie_rf_wflow |>
  tune_grid(resamples = movie_folds,
            grid = movie_grid)
```

```
select_best(movie_rf_tune, metric = "accuracy")
```

```
# A tibble: 1 x 4
   mtry trees min_n .config
  <int> <int> <int> <chr>
1    10   132    15 Preprocessor1_Model082
```

(Kuhn and Wickham 2020; Wright and Ziegler 2017)

After performing CV, we can select the best model and finalize it.

```
movie_rf_best <- finalize_model(
  movie_rf,
  select_best(movie_rf_tune, metric = "accuracy"))

movie_rf_final <-
  workflow() |>
  add_model(movie_rf_best) |>
  add_recipe(recipe) |>
  fit(data = movie_train)

movie_rf_final
```

```
== Workflow [trained] ==========================================================
Preprocessor: Recipe
Model: rand_forest()

-- Preprocessor ----------------------------------------------------------------
0 Recipe Steps

-- Model -----------------------------------------------------------------------
Ranger result

Call:
 ranger::ranger(x = maybe_data_frame(x), y = y, mtry = min_cols(~10L,      x), num.trees = ~1

Type:                             Probability estimation
Number of trees:                  132
Sample size:                      1455
Number of independent variables:  40
Mtry:                             10
```

```
Target node size:                 15
Variable importance mode:         permutation
Splitrule:                        gini
OOB prediction error (Brier s.):  0.1748917
```

Now that we have finalized our model, we can predict on our test data to see how well our model does on unseen data.

```
# Test on testing data
preds <- movie_rf_final |>
  predict(new_data = movie_test) |>
  cbind(movie_test)

preds |>
  metrics(truth = won_at_least_one, estimate = .pred_class) |>
  filter(.metric == "accuracy")
```

```
# A tibble: 1 x 3
  .metric  .estimator .estimate
  <chr>    <chr>          <dbl>
1 accuracy binary         0.716
```

```
conf_matrix <- conf_mat(preds, truth = won_at_least_one, estimate = .pred_class)
conf_matrix
```

```
          Truth
Prediction FALSE TRUE
     FALSE   306  117
     TRUE     21   42
```

We observe that our model has a 72% accuracy rate on our test data. From our confusion matrix, we see that the true positive rate is 74% and the true negative rate is 94%. Note that there are much fewer movies that win Oscars than are nominated, so as seen in the confusion matrix, there are much more "False" observations in our data than "True" observations, causing the skew towards "False".

Additionally, we note that our model is limited by the fact that it was trained on data/observations of which were *all nominated* for an Oscar. That is to say that our model is quite uninformed on all of the qualities of movies that are not nominated, and hence cannot distinguish exactly what makes a winner a *true* winner. Further, in our Shiny app, when you "predict" if a movie is going to win an Oscar, it is likely going to be False a significant more amount since it is likely being fed movies that have not yet been recognized as an Oscar nominee. (Chang et al. 2024)

Ethical Considerations

Though we are very proud of the model and analytics we created, that doesn't come without other considerations. In fact, the biggest implication of our model may be the very thing that we are critiquing. That is, creating a model that may predict an Oscar winner and hence that identifies probable qualities of an Oscar nominee/winner, may simply produce more film makers to latch on to the "Oscar bait" phenomena that has become so popular. Identifying the problem as we have done in this project could lead to more and more talk and consideration of the various qualities that produces an Oscar winning film; thus leading to a continuously more formulaic method of winning an Oscar. All in all, marking creativity in a quantitative manner, may in fact inhibit the quality of the media we consume.

Conclusion

In terms of learning technical skills, we learned how to work with live data from an API and using it to call functions with queries from another data set. We also learned how to create a fully publishable shiny app which works dynamically with data and an API. We strengthened our other skills such as doing extensive preprocessing, exploratory data analysis, training a model, and understanding the data pipeline overall.

Since our model has a 72% accuracy for test data, although the Oscars judges films, an inherently subjective process, this sugggests that there are distinctive quantitative trends that can be modeled to determine an Oscar winner. It is also important to note our limitations, such as the available variables and creating a general model to win any Oscar, versus a specific category.

In the future, we plan to normalize the revenue variable to account for inflation and create category-specific models in order to increase accuracy. Finding more data sets which can provide more variables, such as a way to quantify the success and fame of cast members and the director could also help create more complex models. Additionally, finding data on non-nominated films may help further inform our question and model into a more generalizable result.

In conclusion, it is important to stay diligent in the way we consume and appraise media, and to understand the many factors which shape cultural arbiters like the Oscars. While the ceremony awards and celebrates the artistry of film, the Oscars also exist at the intersection of art, business, and culture, which continuously affect each other. Although the Oscars are primarily an American-focused film awards ceremony, it is still a global force of influence, especially as it has expanded to include recognize international films. Thus, their opinions impact audiences worldwide. While we enjoy the 2025 ceremony and the many more after, we can also interrogate the weight of the Academy's opinion on films. Although the artistic qualities of a film will continue to be immeasurable, our findings highlight distinct trends in quantifiable variables that challenge the role and implications of such an institution.

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