Hollywood Stars:
Enabling Exploration and Trend Examination within the Oscar Award Dataset

ABSTRACT

This paper follows the creation of a set of interactive visualizations on the movie industry, concerned with providing descriptive data and possible future predictive performance. Methodologies included leveraging the User-Centered Design framework to ideate, create, test, and iterate upon visualizations with user goals in mind. Final visualizations were produced based on several rounds of iteration. The final visualizations allow for exploration of Oscar nominated movies, as well as examining ratings and runtime trends of the Oscar movie dataset. Our visualizations are hosted on the following domain: http://hollywoodstars.me.

Ankur Agrawal
Monica Caraway
Wengqi Li
Matt Yukubousky
HCDE 511, Autumn 2014

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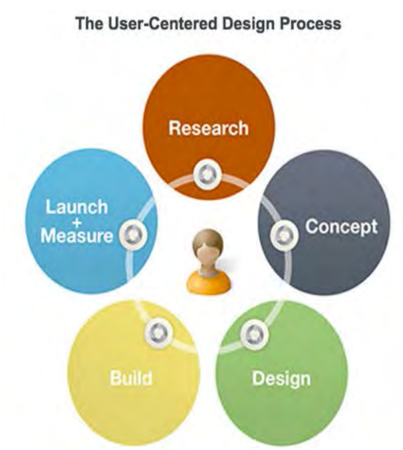
INTRODUCTION

For our group, we decided that it was important that any undertaking for our visualizations meet two key criteria. For one, the subject matter should involve a shared interest for all of the group members. Secondly, the subject matter should be a topic that has a considerable data set behind it. After some discussion, we settled on entertainment topics, and finally movies as a form of entertainment. We were positive that this field would provide us with sufficient data to work with and make claims about, especially in light of movies being an industry which pulled in roughly $36 billion in box office receipts globally in 2013 (MPAA, 2014, p 2). Furthermore, we wanted to ensure that we were analyzing movies that were significant enough to the general populace and to movie watchers. We decided that award winning movies, the Oscars in particular, offered a culturally significant set of movies to examine. The Oscars claimed 43 million viewers domestically in 2014, creating an opportunity for us to produce something of wide appeal (Faughnder, 2014, p 1).

Our initial aim was concerned with providing an in-depth analysis about a large data set of Oscar nominated movies. We also believed that this visualization could serve as a movie picker or recommendation feature. However, further research showed that this had already been attempted, and that making this into a useful visualization during the quarter's timeframe would not be possible if this was the main goal of the project. We then became interested in the possibility of developing a predictive model for Oscar winning films. Knowing that we had data only up to 2006, we believed that it would be possible to use data post 2007 concerning winning movies to validate our predictive approach. Ultimately, developing such a model to test against fell outside of our scope. We decided to focus on visualizing the aspects of what makes a film Oscar-worthy. Our question became, "How can we use our visualizations to highlight the differences between movies that won Oscars and those that didn't? Can we see what is valued as being award-worthy in the movie industry?" Our results were intended to be both exploratory and explanatory.

OUR USER CENTERED DESIGN PROCESS



In approaching this project, we followed a relatively standard user-centered design (UCD) process of iteratively cycling through the phases of Research – Concept – Design – Build – Launch & Test, with a couple key differences. We worked within our constraints, both internal and external, to define a research question that would satisfy each team member, meet class requirements, and that we had reasonable expectations of completing within our given timeframe. Our milestones proposed to accomplish this were sketching ideas, conducting a user research survey, implementing collected data in Tableau, conducting usability tests and guerilla testing, and completing final visualizations.

For the first phase, each team member did some preliminary research into what data was readily available, concurrent with individual brainstorming on project ideas. Following individual research, brainstorming, and ideation, we bounced ideas around as a group until we agreed upon a topic that was interesting to all of us and could potentially yield a successful visualization. Our team set out to create a visualization tool that would provide insights using data on the Academy Awards.

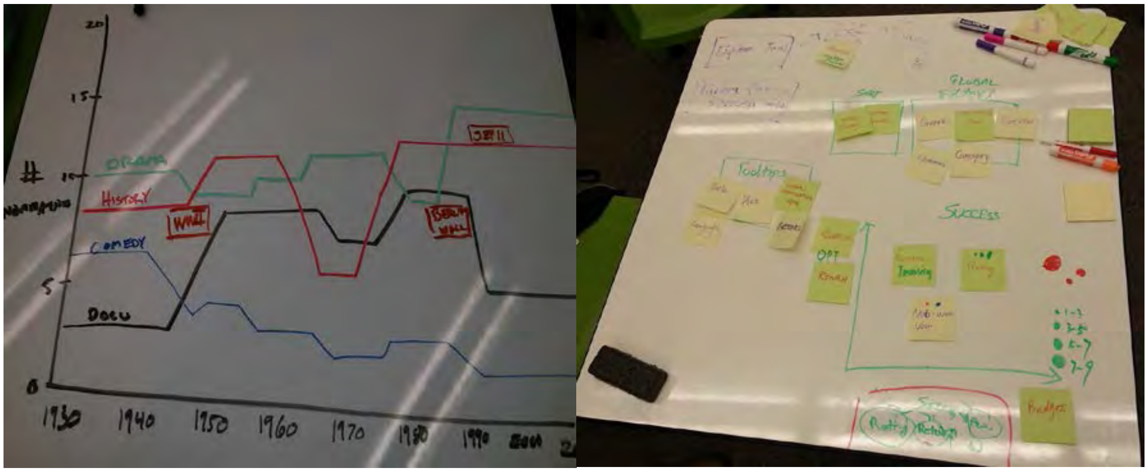


Figure 1: Team sketching of ideas

One key difference to the normal UCD process was that, in addition to meeting project goals, we were also learning the software and skillset to complete the project. None of us had much experience with cleaning data or encoding data in visualizations, and we were all completely new to Tableau as well. So, it was difficult to reasonably estimate what we would be able to accomplish with the tool without first knowing the tool's complete capabilities. During the initial ideation phase, we were also unsure what data sets we would be able to find, and what the quality of those data sets would be. Since we had little experience cleaning data, it was also difficult to estimate how long that part of our project would take.

The initial goals we set out to accomplish changed based on: 1) the availability of datasets that we could use and that had significant overlap with each other to provide insights; and 2) based on our user research which led to revised personas and subsequent changes to our user tasks. We wanted the end product to provide insights that were both practical and interesting to the intended audience. With one iteration, we sought to create a predictive model that would allow users to predict Oscar winners. Following additional user research, we revised that goal to provide broader insights into Oscar winners and trends over time. We conducted heuristic reviews and cognitive walkthroughs, in addition to user testing, and after each round of testing, we iterated on our visualization and followed up with more user testing. Our preliminary user research as well as usability testing is described in detail below.

The second key difference we experienced was that, unlike most UCD projects, paper prototyping had limited use in our situation. Rather, it was helpful to approach "Design" and "Build" as a single concurrent phase, rather than as two separate tasks (i.e., first design, then build). This was the case for a couple reasons. Firstly, jumping straight into using Tableau once we had a reasonable chunk of our data set cleaned helped us to learn the tool by making its features and functionalities more concrete. Secondly, we each had varying knowledge of the Oscars and other movie data, but none of us knew the data well enough to have predictions prior to working with the actual data. In this sense, we were ourselves using Tableau for its "exploratory" aspect and to generate new insights, not just to present facts we already knew. We found that any conjectures we made might not be supported by the data. Initially, we had two sizable datasets available to us: the Academy Awards database on Oscar nominees and winners. Towards the end of the quarter, we also gained access to the Rotten Tomatoes dataset, which contained both critics and audience ratings. Using Tableau as both a tool for simultaneous exploration via prototyping, and then later, as a tool for presentation and exploration for users, was a useful approach since we also procured the Rotten Tomatoes data much later in the process, after we had already designed, built, and tested several of our earlier iterations.

DATA COLLECTION

To get the data related to Oscar movies that we needed, we used the official Academy Award database, as it is the most trusted source for Oscar related data. To collect other details of the movies in that list, we chose to use IMDb and Rotten Tomatoes. Both sources have an extension database and carry high credibility among the audience as information sources.

To start, we downloaded the list of movies from the Academy Award database, and generated an ID number for every movie. This gave us a record for 8832 movies in the dataset. Using an ID for each would help to ease the merging process later on when we had additional data. Afterwards, we started collecting data from IMDb using a free web service API, OMDb. This API allows input for name and year of the movie, and provides additional details about that movie (if any record exists) in JSON format. Once we had the JSON data for all of the movies, we used a text editor (we chose Sublime Text) to reformat it. From here, we used OpenRefine to convert the data into tabular format, which is readable in Excel. This gave us the in-depth movie details data, which was then merged with the Oscar movie dataset using a custom Excel macro coded in Visual Basic. Later, we extracted Rotten Tomatoes' data for their critics' and users' ratings. For this purpose, we used Rotten Tomatoes' web API interface, and wrote a Python script to get the data in JSON format. We then merged it with the Oscar dataset following almost the same process as for the previous data merges.

Due to the inconsistent naming convention of IMDb, we had to manually search for approximately 1200 movies on the IMDb site in order to either correct the name or the movie release year, as many times Oscar nomination year and release year are different. Additionally, we used OpenRefine to correct any typos in the titles. Since many of our dimensions have multiple values, we were not able to use them for anything in Tableau other than as a filter using a calculated field and custom parameters. This created an issue for us in exploring our data. We addressed this by creating a natural join between the list of genre and the movie list, thus allowing us to use the genre field as a dimension that can be used in a graph. This would enable us to provide better data filtration methods for an end user.

Though we eventually created a cohesive data set suitable for our purposes, we did experience some challenges. One of our biggest challenges in making meaning of this data was that the majority of the values were nominal data. This left us with few quantitative values that could be used for analysis. Fortunately, some of the nominal fields we had to work with make meaningful differences with regards to movie audiences, especially genre. One way we considered dealing with this challenge was to take the plot text data and classify each movie into a story type. The plan was to make this a filter in the data, so that users see comparisons between not only a movie's genre, but a movie's mood or plot as well. Ultimately, we discovered this to be a larger undertaking than would be worth undertaking, given the short time frame, and likely much more difficult than we would be prepared for as well. Previous research had been attempted using a machine learning algorithm and custom scripts to classify movies into strict genres using the plot synopsis found in IMDb. Unfortunately, this approach yielded results of only 12% accuracy (Tanenbaum, p6.) A possible reason for this is that most movies can accompany more than one genre type, which is also an issue we discovered within our dataset. For this reason, we decided to abandon this as a possible approach.

Additionally, there were also some technological challenges with our data and approach. For one, many of these APIs put a rate limit on requests, leaving us to make extended sessions of time in which we were pulling data from these sources. Some also required requesting access for use. One in particular, Rotten Tomatoes, provided us with a unique challenge in this department. Access to this API required applying for and confirming email validation in order to make requests. After having applied for this API multiple times, our team was confused on why we were apparently being denied. However, we later discovered that certain email services (in this case, MyUW) did not permit mail from this source, as it was considered malicious or spam. Re-applying with a Gmail address gave us immediate access to this source. It is partly for this reason that we only integrated Rotten Tomatoes data at a later time, leaving us to enable interactions with this data as future work.

INITIAL RESEARCH PHASE

With our initial proposal of developing a movie suggestion model based on awards and rating criteria being deemed not specific enough, we wanted to go deeper. We discussed creating visualizations that could demonstrate the components of a successful movie. This could include specific actors, budget, length, or several other factors. Success, of course, could be defined in many different ways by different people. Since we needed a key metric of definite success, in movie terms, we decided that winning an award represented a concrete example of success. As far as movie awards go, the Oscars (Academy Awards) represent the highest prestige or honor a film can receive from Hollywood.

Survey

Once we knew the scope of our work, we decided to find out more about which topics were of interest to our potential users. Our team conducted a 10 question multiple choice survey and open-ended survey. This survey was distributed via social media, through the FaceBook networks of the team members, as well as the HCDE Peeps FaceBook group, and returned 65 respondents.

We found that movie watching, as expected, is a popular pastime, with the majority of respondents (n=60) reporting that they watched at least one movie a month. Almost half (n=30) reported watching movies once or twice weekly, and six respondents reported watching movies very frequently at three times or more per week. Almost half (n=28) reported that they had previously tried to predict the winner of an Oscar, which supported our plans for developing a predictive model.

Of great interest to us were the results concerning the influence of information source on likelihood of viewing a movie recommended by that source. Participants were asked to rate the likelihood that they would be influenced to see a movie based on the following sources or values, using a five-point Likert scale:

- *Awards lists (Oscars, Golden Globes, etc)*
- *Audience voted ratings (IMDb, Rotten Tomatoes)*
- *Inclusion of a certain actor/actress/director*
- *Genre or story type*
- *Box office sales amounts*

Of these, there were four that were clearly influential in audience's movie watching choices, and one that was not. 38% of respondents indicated that they would be "much more likely" to see a movie based on audience chosen ratings. Additionally, respondents were "somewhat more likely" to "much more likely" to watch a movie from 72% for awards, 75% for audience ratings, 78% for actors/actresses/directors, and 69% for genre or story type. It is clear that these values can play a role in a person's viewing choices. However, it was equally clear that respondents did not care about box office sales amounts. In fact, nearly half (44%) of respondents indicated that this would be a negative factor in their decision, and that it would make them less likely to see a certain film. With this in mind, we decided to ignore any collection of data surrounding movie box office sales. So much for summer blockbusters!

We do recognize a possible limitation for our survey data. First, there always exists the risk with self-reported data that what people say they do may be different from what they actually do. Recalling or estimating movie watching frequency may not reflect actual amounts of movie watching behavior. However, it is clear that this is a popular hobby or pastime for many, regardless of accuracy. Second, the demographics of our respondents skew towards a younger crowd. All but eight respondents indicated that they were within the 18-34 year old age range. This is likely not representative of the full range of movie viewers, and may have some unknown influence on our results.

OUR USERS

Through our user research, we were able to create two personas of potential users of our visualizations. These would help us to focus our tasks to potential goals and use case scenarios.

Primary persona: Movie Newbie Marina

Marina likes watching movies, but she doesn't often watch them in theaters. As an engineering grad student with a full-time job, she simply doesn't have time to waste deliberating over which movies to watch. When she goes to the movies with friends, Marina is happy to let them choose the movie.

When she chooses to watch a movie at home, however, she always turns to Oscar winners to inform her selection. Marina is not interested in watching the Oscar ceremonies, but watching only Oscar-winning movies gives her peace of mind that what she watches will be good. If it's good enough to win an Academy Award, it's probably good enough for her tastes. Marina would love to have a tool that would show her at a glance which kinds of movies were most popular, and when. This would help her narrow even further the choices of which movies to watch.

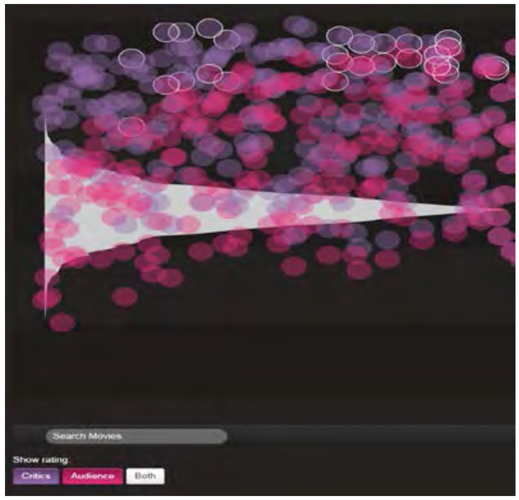
Secondary persona: Cinephile Cecile

Cecile loves all things movie-related. On average, Cecile goes to the theater at least once a week, but she also spends several hours a week watching movies at home. She keeps a long list of movies she wants to see, and her plans for the weekend often revolve around watching movies on their premiere night. Cecile enjoys her active lifestyle, and when she's not working as a PR rep for a hot L.A. advertising agency, she is often found working out at the gym or going out with friends. One of her favorite traditions is hosting an annual Oscar party for her friends to watch the Academy Awards. She even has a small following of fans for her Oscar party posts on Pinterest. Cecile enjoys being in the know about celebrities, movie stats, and trivia, and she would love to be able to see trends and predict winners before they are announced.

RELATED WORK

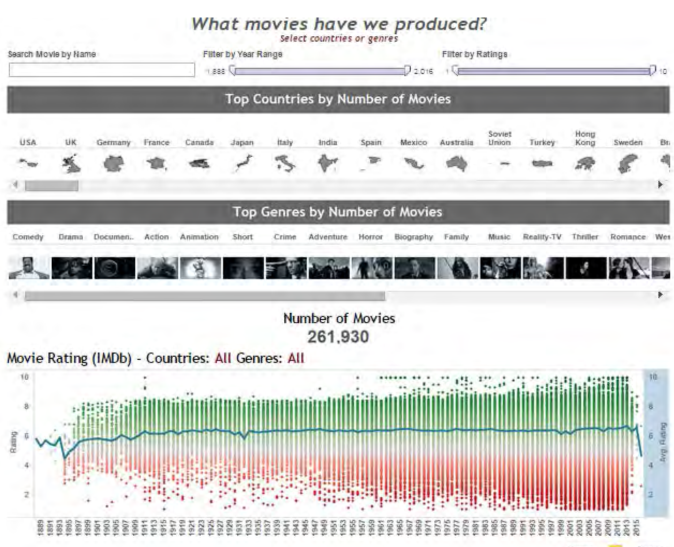
Our team discovered a range of visualizations regarding movies during our research. These range in content from the serious to the absurd, including Oscar predictability, use of time travel in popular movies, six degrees of separation from Kevin Bacon, and attempts at visualizing an entire movie's contents in one image. Given the wide range of focus, there is clearly a market for, and an interest in, movie visualizations. While many remain out of our scope, we will profile some works that are most related to our project vision and work.

1. *Blimp Design - Confluence Movie Searcher*



This interactive visualization includes budget, critic rating, actors, and story lines. These categories allow for filtration. Each category shows these variables in relation to how well a movie scored from both critic and user ratings, with the variation between these being shown by the distance between the two plotted points. The creators attempt to show the continuum for the difference in these values with the white shape that is banded across the visualization. However, this function is not immediately obvious, and leads to confusion upon first view. This visualization excels at plotting a large amount of information in a small space, and supports deep exploration for more than 600 movies, though it is not clear what the criteria for inclusion for these movies were. The small amount of movie titles included is an additional limitation of this visualization.

2. *IMDb Movies Visualized - What Movies Have we Produced?*



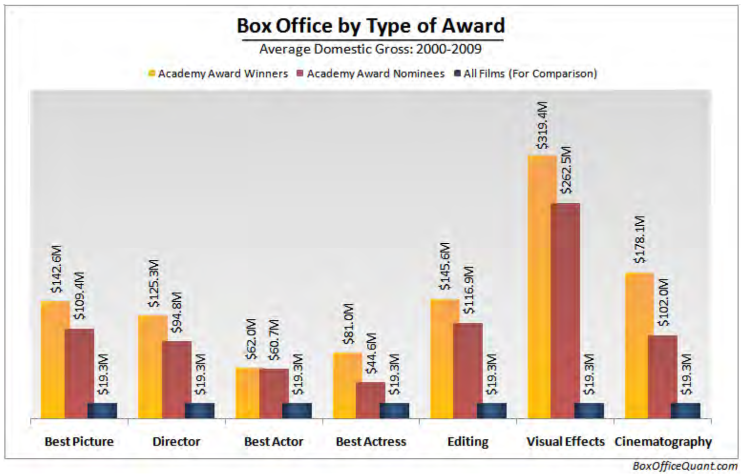
This visualization attempts to take a regional look at movies produced by country. It encompasses a large number of movies, broken down by both country of origin and genre of the movie. It offers a broad look at movies in an overview at the bottom of the visualization, but suffers from latency issues, perhaps due to the size of the data set. This visualization offers both a text search and sliders to filter. Unfortunately, the slider for year range is labeled in a confusing manner, starting at 1,888 and extending to 2,016. This visualization excels in offering images of the geographic location for the country of origin, but also incorrectly makes some assumptions with their image use. The genre filter uses images from popular films in that genre. However, it is not likely that each user will know the genre by the image, as they are not all readily identifiable, nor would it be expected that a group of users would agree on one particular image as being representative of each genre.

3. *Visualization of Characteristics of Individual Movies*

The Cinemetrics project uses movie data to "reveal the characteristics of films and to create a visual 'fingerprint' for them." Their creator, Frederic Brodbeck, created graphic representations of individual movies, incorporating data algorithmically extracted from the movies themselves to capture such aspects as editing structure, color, speech, and motion. The designer intentionally chose to use individual movies themselves as data sources, rather than "meta-data related to film and cinema (budget, box office data, awards won, relationship between characters etc.)," with the goal of capturing an entire movie in a single visual. He states that his intended audiences include those already passionate about movies, but that he also hopes that "an alternative way of looking at movies could provide an interesting new way of choosing movies based on formal criteria." As the creator points out, each movie has a unique "fingerprint" and can be compared side by side for immediate comparison of similarities and differences.

Representing individual movies, the visualizations are essentially static and are notable for their visual expressivity rather than for their immediate usefulness as a tool. We sought to extend this idea by creating a tool that is both visually appealing and a practical way to explore trends and choose movies based on their attributes.

4. The Value of an Oscar



This static visualization concerns box office gross values, and enables comparisons across Academy Award categories. Viewers can evaluate the average domestic gross box office between Oscar nominees, winners, and all films by awards category. This shows us the relative amounts of money made for Oscar nominees, versus the smaller amount made by all films from those years. One possibility for the difference appearing to be so large is the lower total amount of movies in the Oscar category, versus a large set of movies encompassed by the "All movies" category. With such a wide range of movies in theaters, it is likely that many will perform poorly, which will bring down the average for non-nominees. This graph also highlights the influence on box office results of different award types. While this is interesting in that it can show the value of an award category at a glance, it is ultimately not of interest to our users, who indicated that they put little stock on box office amounts.

USABILITY TESTING

Our goal was to test our visualizations early and often. We knew that we would have easy access to our target users, so we set the goal to perform at least one usability testing session per major iteration of our visualization. All participants were to use the "Think Aloud Protocol" in order for us to best understand their thoughts as they navigated our visualizations.

For our initial usability study, we recruited one potential user in the class who watches movies semi regularly. This test was largely exploratory, as we wanted to validate the initial approach of allowing users to navigate the dataset with movies broken down by genre. This test only included one focused task with user P1 to see if they could locate a particular movie within the dataset. At this point, we made the following refinements before taking the visualization to the class audience for feedback:

- Dashboards that were disconnected were merged
- Added context to the focused movie or genre selection to include what was being filtered

- Changed the bar or "pill" style UI elements in the main Gantt chart in order to enable easier selection and clicking

An additional round of testing was conducted after refining our visualizations from the midterm showing. Feedback was positive at this point, and the team felt encouraged by the audience's interests in trend data. Our second round of testing added in four focused tasks in addition to the exploratory method. The tasks were created to follow a user's route through an information seeking process when looking for one point of data in particular within a large dataset. The tasks were as follows:

- *Please locate a movie from the genre of your choosing from a year of your choice*
- *Please find the winner of an Oscar from a category of your choosing from any year you like.*
- *Please locate an individual that has been nominated for ten or more Oscars than the amount that they have won.*
- *Please compare two Oscar categories of your choosing with each other. What trends or other interesting things do you see?*

Based on the test with user P2, we made the following changes and refinements:

- We fixed a bug with the bottom line graph below the top bar chart. This chart gave inconsistent feedback, and clearing the box selections to "none" erased all data. No data was added back once the "all" box was selected once more. We fixed this bug of not re-adding the data, and added a "reset" button to the visualization.
- Year of release data was added to the tooltip to address the issue of P2 being unable to locate the year data for the movie once they had located the film. ("I actually found it by accident….I still have no idea what year it came out).
- Labeling was added to the bottom line graph. As of this iteration, it was not clear what was being filtered into the bottom line graph when data was selected above. P2 was unsure what data was being shown. ("I'm given no information on what I'm looking at.")
- Labeling was added to the blank text entry searches for genre and actor/actress. ("Because these are blank, I didn't notice them.")

GUERILLA TESTING SESSION

Seattle is lucky to be the location of one of the largest specialty movie stores in the United States, Scarecrow Video. By their own count, the store houses over 110,000 individual movie titles. To us, this presented the perfect opportunity to perform some Guerilla testing on movie viewers. While this audience was more likely to be skewed towards cinephiles that represent our secondary persona, we knew their feedback would be equally important. We decided we would aim to test 3-4 users on site, if possible.

Methods

After our previous test and iterations, we focused our script and tasks more closely on what we saw as our primary visualization going forward, with later tasks aimed at testing smaller interactions of a secondary visualization.

This test began with an unguided exploration of the visualization, and then proceeded with five more specific tasks. The participants were asked to complete the following directed tasks:

- Please locate a movie from the genre of your choosing from a year of your choice
- Please find the winner of an Oscar award category of your choosing. This can be from any year you like
- Please locate a movie that stars your favorite actor/actress, or one of your choosing.
- Please compare two Oscar categories of your choosing with each other. What trends or other interesting things do you see?
- Choose a movie by Oscar awards category. Can you see if this movie is above or below the average rating for movies of that year?

After the tasks were concluded, short follow up questions concerning what the participant would like to see or investigate further were to be asked. For their assistance, participants were to receive a $5.00 gift certificate to Scarecrow Video.

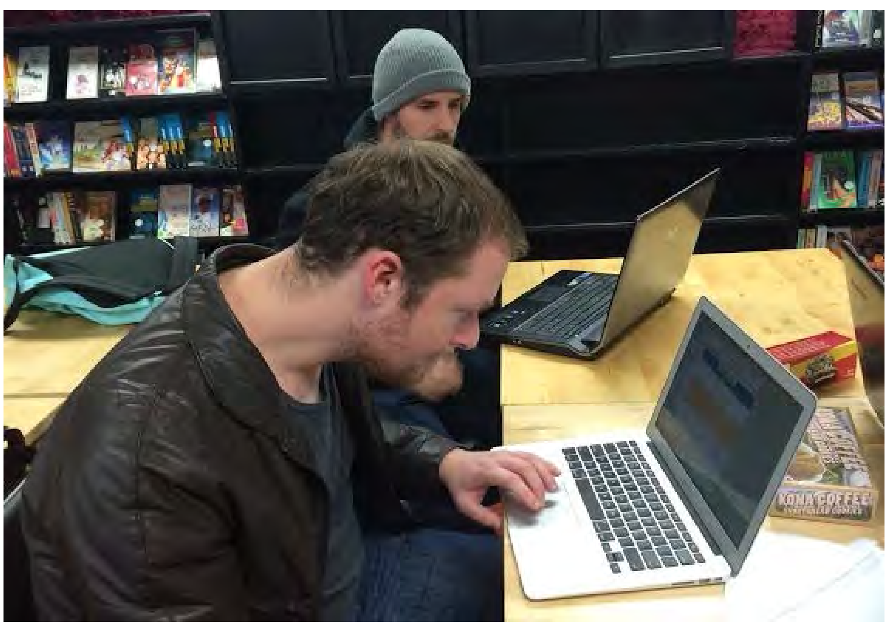


Fig 2: Conducting test sessions on site at Scarecrow Video

Results

Unfortunately, the team fell short of its testing goals during this session, though were still several important takeaways related to both the visualization and the guerilla testing method. One test was successfully completed before needing to end the testing session. The participant (P3) mostly overlooked elements of our UI which were intended to enable easy searching through the results. Our main takeaway from this session was that we needed to make the search field more prominent, and to include movie titles within the search field. Up to this point, the search field only included actors and actresses. Additionally, P3 was able to complete the comparison task easily, and noted that one of their favorite genres (horror) was often overlooked by voters when it came to Oscar movies, as they had very few nominations.

Our group also came away from this session having learned some valuable lessons on guerilla testing in general. To start, it is important to check with the owners or managers of your intended test location before performing your sessions. While the Scarecrow staff eventually agreed to let us test in a corner of their store, they were at first apprehensive of letting us proceed. This likely could have been mitigated by contacting the store in advance to let them know of our intentions. Further, though the location may represent an ideal setting for your intended users, guerilla testing may not always turn out the optimal participants. Without recruiting, there is no knowledge of who the user is before testing with them. The participant in this case was very reserved, and may have been less tech savvy than an average user. Ultimately, testing with a novice user helps to see where the barriers for entry are, but the finer details may be missed as they are not discovered or are overlooked. Though, it cannot be assumed, participants recruited from Scarecrow would likely be more representative of our secondary personas. This is due to the nature of the store, which is aimed at cinephiles and those more knowledgeable about movies.

FURTHER TESTING

Following our semi-successful guerilla testing session at Scarecrow, we conducted an additional round of tests with potential users. These tests were structured in a similar manner to the guerilla sessions. They did not include any compensation in the form of gift certificates, however. Results were then collected, compared, and discussed as a group. The results informed the following changes:

- P4 indicated that they were not sure what the visualization was about. To address this rather obvious oversight on our part, we added a title and larger headings to our visualization.
- P5 indicated that the search field should include an "actress" label in addition to the "actor." This was added as a result.
- We changed labeling of the movie plot points to "Nominated" and "Won Oscar" from "Won" and "Not won." ("I'm not sure what won/not won is. To me, the winner's section should be nominated/didn't win instead of not won." P4).

- We also added the ability to search for movies in addition to actors and actresses. ("Why can't I search for movies directly?" P5).

Our team owes a huge amount of gratitude to each of our testers. Without their participation, we would not have been able to achieve these results. At times, we suffered from having looked over our own work time and time again. Bringing fresh eyes to your creation is an invaluable part of the design process.

ITERATIONS AND DESIGN PROCESS

OSCAR MOVIE EXPLORER

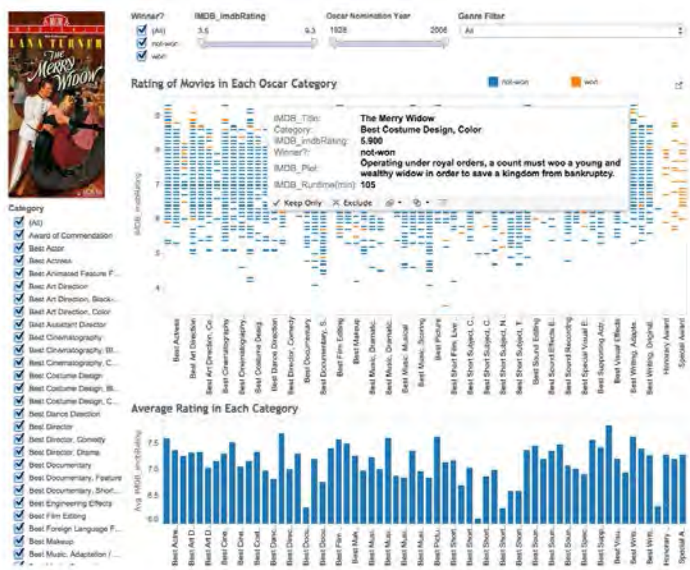


Figure 3: Initial version of the Oscar Movie Explorer

Our main visualization began with the goal in mind of helping our primary persona explore movies within the Oscar data set. To enable this, we kept Schneiderman's Information Seeking Mantra in mind - "Overview first, zoom and filter, then details on demand" (Schneiderman, p 3). Data was encoded in our first Gantt chart according to Mackinlay's rankings of encoding (Mackinlay, p 10). We used position each movie in a category, knowing that this was effective for both quantitative and nominal data. Color was chosen to indicate our nominal data concerning a movie being nominated or awarded an Oscar. Blue and orange were used for contrast, as it is the Tableau standard, and is also a safe choice for color blind viewers. The Information Seeking Mantra was implemented through the following interactions:

Overview:

The first iteration of the Oscar movie explorer provides an overview of all movies contained in the Oscar movie dataset aggregated into one view. The categories of awards and ranges of ratings for the dataset are visible from this view. Our scales were created using Few's notion of optimal quantitative scales, with our ratings beginning just under the lowest value and ending just above the highest in the set (Few, p 93).

Zoom and Filter:

From here, the user has several filters than can be employed to narrow down the data to their interests. We used both checkboxes and drop down lists to filter categorical data including awards category, movie genre, and winning movies versus nominated. Additionally, we used range sliders to filter temporal data and movie ratings. Filters chosen are those which we believe would be of most interest to our users when selecting a movie, according to our research. Additionally, directly manipulating a category on the chart brushes the data and links to the details below.

Details on Demand:

Drilling down, users can see details of the selected movie plot through the tooltip implemented in Tableau. This gives the user more information about their selection in context of the dataset. The information that was initially included was the movie title, the award category it was nominated for, its rating in IMDb, the movie plot summary, movie runtime, and an indication of whether or not it won the award in question. We also allow our users to see the average rating of each category in the bar chart below. Knowing that bar charts are appropriate for nominal comparison and ranking, we chose this to display the average ranking of each category, with the length of the bar encoding the rating (Few, p 90).

Figure 4: Second iteration, main visualization

Our second iteration included many adjustments suggested from our usability tests, as well as other changes we believed could improve it. To start, the plot points in our Gantt chart were changed from pills to circles. Changing shape made it easier for users to select a data point. However, we noticed that there were plots that would not show the tooltip on hover. This is where we began to wrestle with data occlusion. To address this, we jittered the data to make more points viewable within a category (Few, p 120). Additionally, there were categories which were not visible on the X-axis, due to the amount of categories, which would be detrimental to an overview first design. Based on our research of categories of interest to our users, we removed several categories which were not ranked highly (Best Writing - Title Writing, Best Sound Editing, Best Sound Effects Editing, Best Sound Mixing, Gordon E. Sawyer Award, Irving G. Thalberg Memorial Award, Jean Hersholt Humanitarian Award, Special Award, Award of Commendation, and Best Engineering effects). Many of these either had been awarded only a handful of times, or had no movie titles associated with their awards.

Filtering behavior was also changed in this version. Our tests indicated that users wanted to sort by genre first, so this filter was moved to be more prominent on the left side. Additionally, users indicated that they wanted to search by their favorite actors and actresses, something that we did not previously support. With a large dataset, we felt it was appropriate to add a search feature using dynamic queries. Information concerning actor and actress were also added to the details on demand tool tip.

At this time, we decided to include more aggregate information for categories. We knew that we could use a reference line to display deviations, and considered using it to replace the separate bar chart below. We could not use this display in our first iteration, because our chart contained non-continuous data, where using a reference line would be displaying not truthful information between categorical data. As we were now using temporal data for this second chart, we could use a reference line to show deviation from the average rating of a category by year (Few, p 103). In this version, we also discovered a way to use the "fill" option of reference line, so that the colored fill area indicated movies below average ratings in the top chart.

Highlighting and linking behavior was also improved between the two charts. Clicking a circle in the first view added highlighting the same plot below. This enabled users to make comparisons between the current selected movie rating and the average rating.

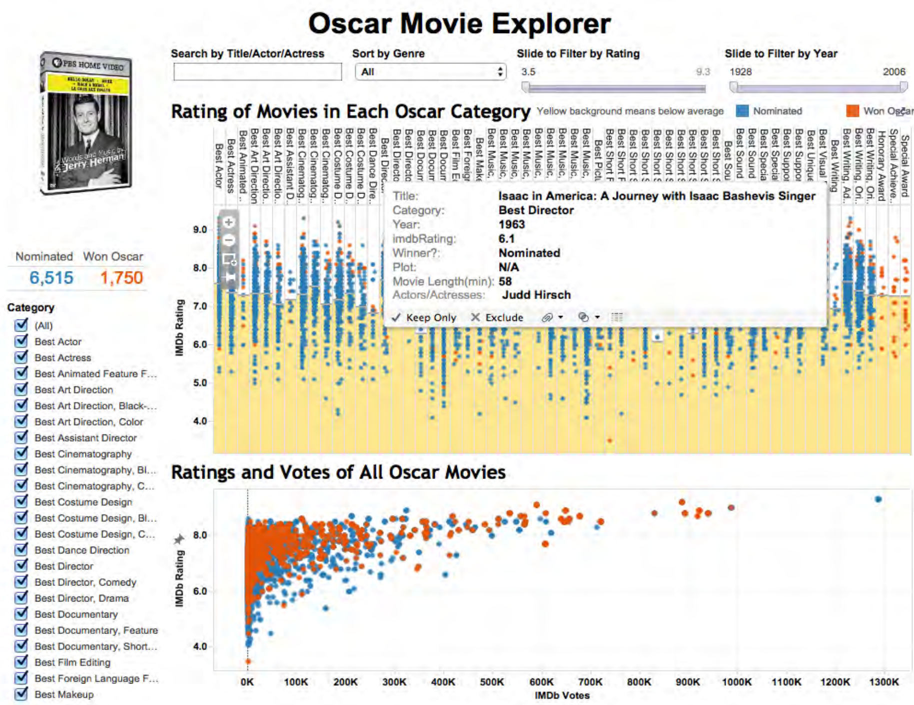


Figure 5: Third iteration, main visualization

After more testing and discussion, we arrived at the third iteration of our visualization. Filtering behaviors were again adjusted and now had improved labeling. This was intended to make our filters more prominent, and included formatting changes to the text. A colored legend filter was added, so that users could click on the number displaying the nominated or Oscar winning movies to allow a quick sort of these two categories. We made sure to map the colors appropriately to the data being displayed, so it would be obvious that clicking the blue numbers would show only nominated movies. This also supported greater detail on demand, as it was now visible how many movies were included in that aggregated filter. Further, when searching for an actor or actress, users could see the number of times that person was nominated versus how many times they won. This addition was made directly by user request.

Our second chart was again re-worked to address feedback. Previously, users indicated that they were confused by the chart, and didn't find it useful. We considered to encode the amount of votes by size in the first chart initially, but realized it would cause too much occlusion. We saw an opportunity to use votes in our second chart to support the first chart, again using brushing and linking between the two.

Further, formatting changes were made to improve the basic layout. Tooltip information was adjusted to be more legible to the user. As the designers, we were familiar with what measures such as imdb_title and imdb_runtime, but realized our users might not be. As a result, we stripped "imdb" from our tooltip values and changed "runtime" to a more familiar "length" in order to accommodate user terminology. One somewhat obvious, in retrospect, oversight was pointed out to us through this round of testing as well - our visualization did not have a title! From here on, our visualization was officially dubbed the "Oscar Movie Explorer."

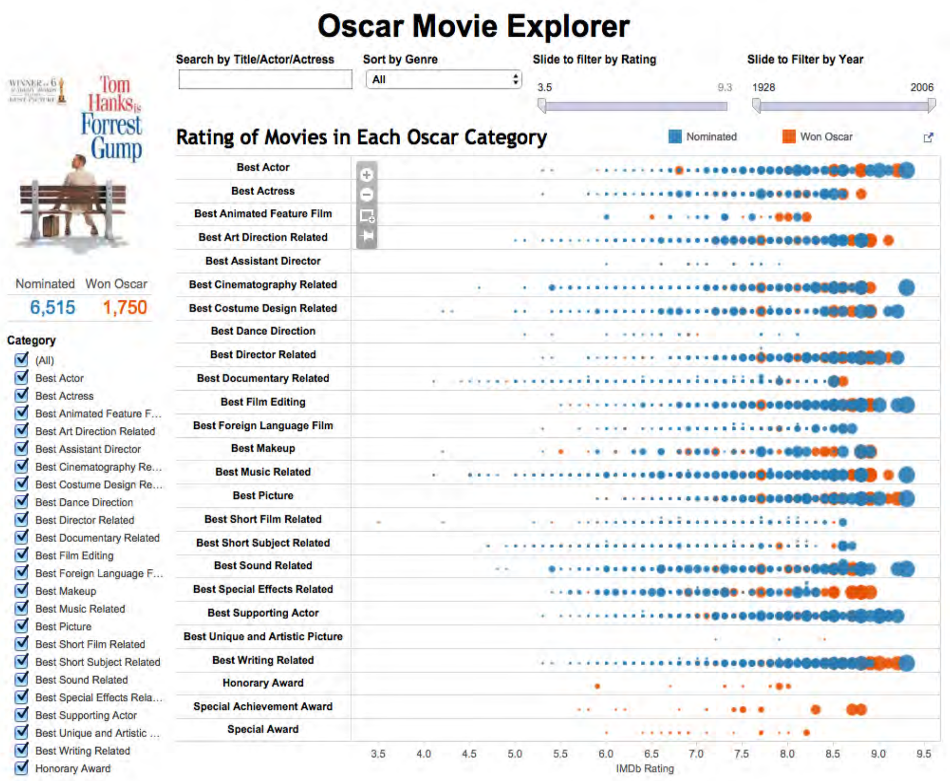


Figure 6: Fourth iteration, main visualization

With this next version, we made more drastic visual changes. Seeing that the X-axis was not legible enough, we decided to reverse the X and Y axis measures to make the visualization more clear. Further clutter was reduced by grouping similar categories. For example, "Best Director", "Best Director, Comedy" and "Best Director, Drama" were merged into a "Best Director Related" category. We now had all categories visible under our filter without necessitating a scroll bar, enabling a more effective overview for users. Now that there was less ink on the chart, we were able to utilize a measure we had previously hoped to include. IMDb vote numbers were now added by being encoded in the size of our shapes. Additional ink was removed by taking away the area shaded to indicate below and above average movies. This would help us create a better visual hierarchy that was leading the user to the most important information contained in the visualization rather than an item that might be of secondary or tertiary interest.

TREND VISUALIZATIONS (Genre and runtime)

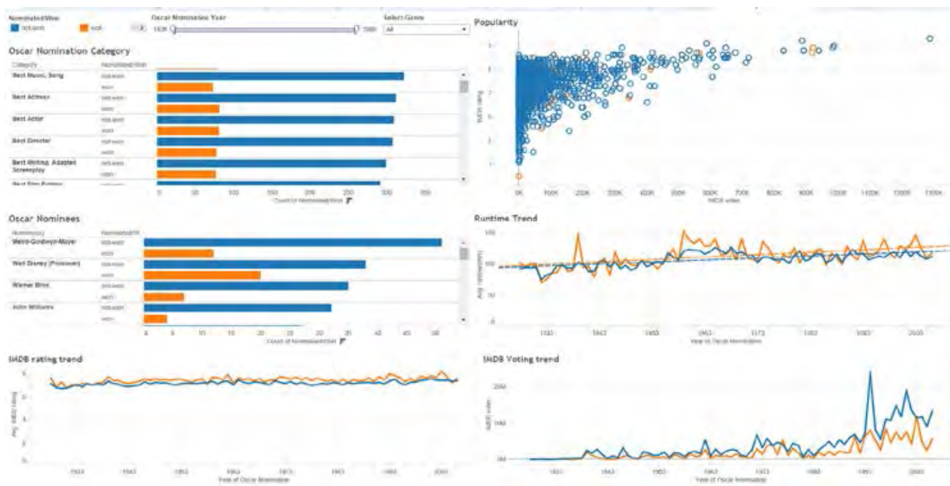


Figure 7: Initial version, genre/runtime

This visualization was created for our secondary persona, Cinephile Cecile, who is interested in movie trends. It has 6 different yet connected visualizations. The top-left chart shows the number of nominations in each of the Oscar categories. We used a bar chart for this because we had a nominal dimension on one axis and quantitative data on the other. In our second, top-right chart, we have a scatter plot showing the number of IMDb votes and IMDb rating. This chart helps us to understand the performance of a movie in terms of its rating, and establishes the credibility of the rating by the number of votes. A scatter plot was chosen to show this data as both of the dimensions were quantitative and can be shown most accurately by using position. Further, the chart on the middle-left shows the number of nominations per nominees, with the right-middle chart showing the trend in runtime over time. Line charts are best at showing trends over a time series, so we also leveraged this to show trends in rating and voting on IMDb.

At this point we didn't have a solution for the one-to-many problem within our genre data. We were only using the genre dimension as a filter using Tableau's calculated field and parameters. Filtering was also implemented for year data. Having both of these gave users flexibility of filtering based on their interest. Sorting was implemented on the bar chart by ordering based on the number of nominations.

Additionally, selecting the Oscar category from the first graph highlighted the points related to that category in the scatter plot and filtered the trend charts for the related data.

Figure 8: Second iteration, genre/runtime

Our second version removed a number of charts. We followed Few's suggestion not to show too much information at once. To keep the chart clutter minimal, we restructured our dashboard to only show information about nomination in each Genre and Runtime trend. Since we removed category bar chart and hence the filter associated with it, we added a multi-select category filter on the left hand side. As with the previous version, we used two colors to show Oscar winning and nominated movie data. In the line chart, we used color to indicate different genres. However, due to the number of different genres, we realized we were running into a perceptual issue with the hues not varying significantly enough to separate (Few, p 48), which we would address in later versions.

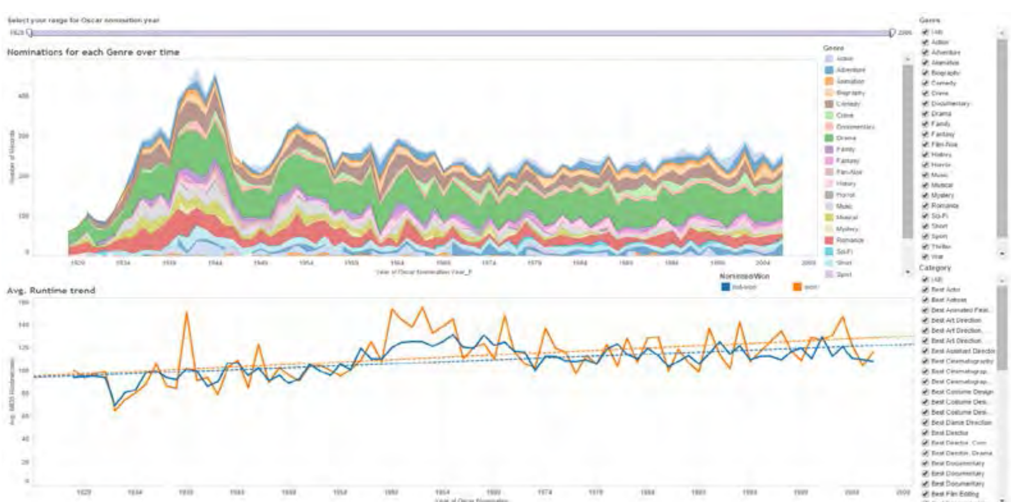


Figure 9: Third iteration, genre/runtime

Version 3 saw us reducing the amount of ink even further. We switched to an area chart to show the number of nominations in each genre over time. The benefit of using an area plot over bar chart was being able to show how the number of nomination varied over time. This was not possible to show using a bar chart without animation, which was not possible given our tool choice. The area plot was linked with the runtime trend line below it, enabling selection of any genre in the area plot to filter the chart below. Further, our trend line chart changed to show aggregated data instead of showing separate lines for each genre. This was done to reduce cognitive effort on the user's side. Additionally, a linear dotted trend line was added to show the general trend in movie length over time.

Filtering behaviors remained mostly unchanged. However, we moved the category filter from the left hand side to the right to provide more horizontal space for the charts. Also, we figured that having filters may be detrimental to users, who would need to move from one side to the other to change filters. Using Fitt's Law, we decided that these similar behaviors should be grouped together, reducing the amount of space a user would need to travel (Berkun, p 1).

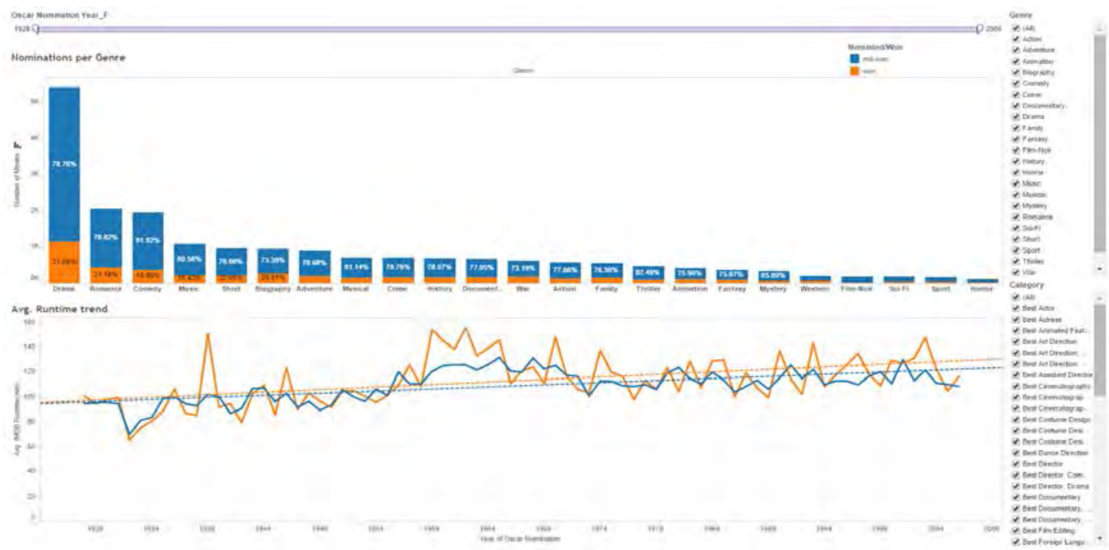


Figure 10: Fourth iteration, genre/runtime

With this iteration, we realized that genre was too difficult to compare using an area plot. We returned to the bar chart for number of nominations in each genre and used aggregate runtime trend line chart with it. This chart allows users to view nominations in genres and runtime trend in a neat way with minimum clutter not having them to apply a lot of cognitive effort. All filters and other interactions were unchanged in this iteration.

TREND VISUALIZATIONS (Genre and rating)

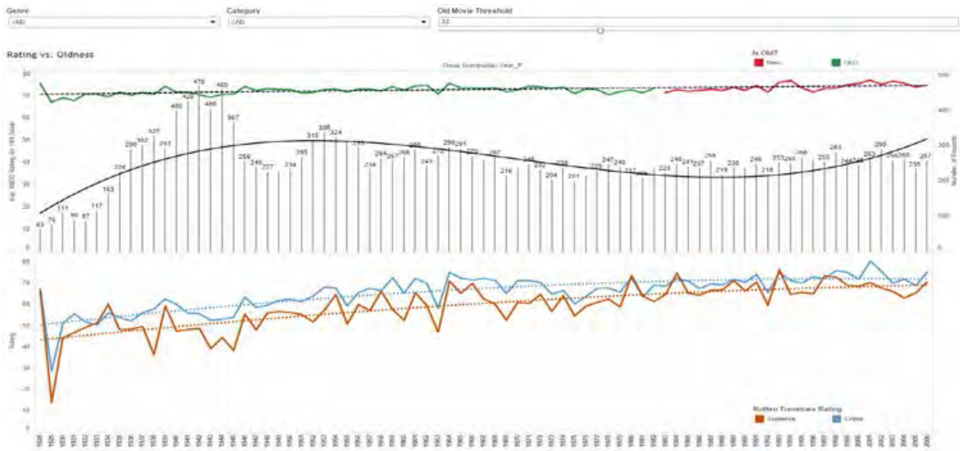


Figure 11: Initial version, genre/rating

The purpose of this visualization was to show trends over time for ratings. First, only IMDb ratings were used, though we would later include audience and critics ratings from Rotten Tomatoes. We used bar charts along with line chart to show the number of nominations over time using a dual axis, with the left for IMDb rating and the right for nomination count. An additional parameter is employed for users to define an "old movies" threshold, which is based on the line charts that are split into two parts with different colors. The idea behind this was to allow users to compare the difference in rating of older and newer movies. The thickness of the bars in the bar chart was reduced to avoid this component becoming visually dominant. The same filtering techniques as were used on our previous runtime trend visualization were added, with the exception of nomination year. These were made global such that filters applied on any of the two visualizations will be applied to the other charts automatically.

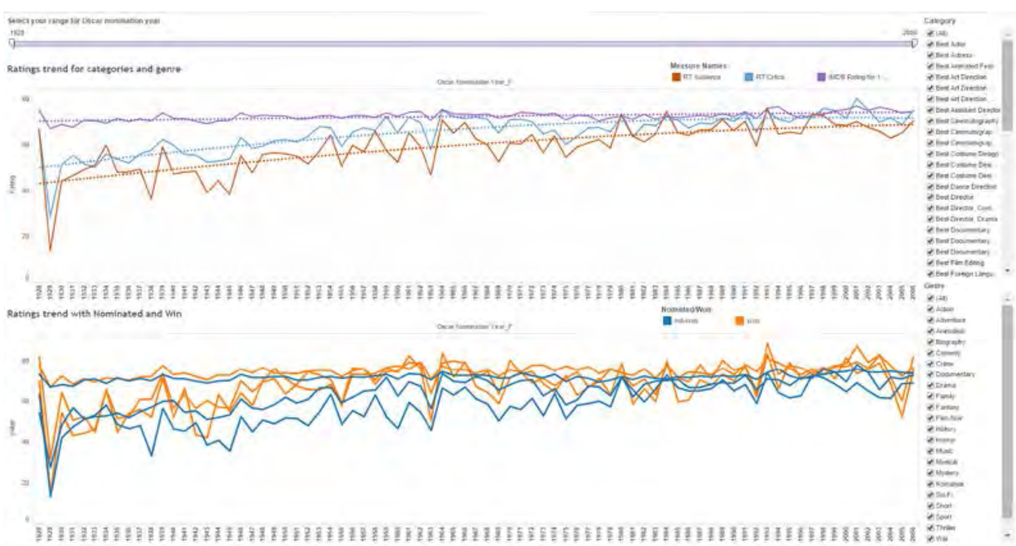


Figure 12: Second iteration, genre/rating

Continuing on, we removed the "old movies" rating comparison feature, and instead included a comparison of the three ratings in one chart. We used a line chart to compare trends in three different ratings each with a different color. Following the concept of including multiple concurrent views, we added a line chart for winning movies and nominated movies for each of the ratings. An additional filter was added for Oscar nomination year to allow users to select the year range they would like to see. The category and genre filters were changed from multi-select dropdown to multi-select list view and grouped in order to accommodate ease of access. To encourage selection and brushing, we added an action on the dashboard to allow user to select the rating trend line for each of the three ratings types. This would highlight the trends line for the same rating in the lower chart.

FINAL VISUALIZATIONS AND EVALUATION

Figure 13: Final version of the Oscar Movie Explorer

Our final visualizations are hosted on the following domain: http://hollywoodstars.me.

Overall, we attempted to follow Mackinlay's design criteria for both expressiveness and effectiveness. We aimed to encode the most salient information in the most effective ways for our users. We also tried to achieve graphical excellence by revealing data at several levels of detail, by allowing users to navigate from the overview, to details of the movie, and on to genre and category trends in our related visualizations.

There were several issues with our prior versions that we decided to address with the final versions of our visualizations. Perhaps the largest of these issues was the problem of occlusion. We learned that it is very difficult to avoid occlusion when creating visualization that includes thousands of data points in a single view. Some small fixes that we implemented helped us to create more room on our scales to address this issue. We started by removing the word "best" from the beginning of our category filters, as it was redundant. Additionally, certain awards categories were removed that were found to not be of interest to our users (Honorary award, Special award, and Special Achievement award). Additionally, we wanted to create a more obvious visual hierarchy to draw viewer's eyes to the data points which would be the most relevant to their searches. We considered using movie posters as icons to represent the movies that were highest in each rated category. With the exploratory goal in mind, we decided that was not the optimal approach. However, we knew we could use contrast to highlight and differentiate, which aided us in pursuing a color theme change (Stone, pp 5). Keeping this in mind along with our user's suggestion of making the visualization more visually appealing, we decided to change from a white background with blue and orange data plots to a black background with red and gold data points. This also meant removing the shaded area that we had previously used to show the average rating for a category, as it was too visually dominant while calling viewer's eyes to a less important piece of encoded data. This not only assisted us in creating a visually appealing scene, but also matched the color theme of the Oscars itself, which helped in creating a strong identity for our visualization that mapped to its purpose.

Following the idea that we wanted to enable comparisons of movies between each other, and not categories, we moved away from a Gantt chart to a scatterplot. This allowed us to move away from displaying nominal data on one axis to quantitative on both. We realized that we were losing a strength by using position for another quantitative value in favor of using it for nominal, and opted to make this change in order to better encode to the data type (Mackinlay, p 10). Removing these categories as an axis also encourages users to make use of the filters and search options. This also provides more information at a glance through the overview.

After adjusting our encoding on the axes, we also realized that we were not utilizing other elements for multi-variate analysis properly. Now that we had quantitative values on both axes, we were able to incorporate area into our encodings. Previously, we were not able to leverage it effectively, due to issues of occlusion, as well as its limitations with regards to encoding nominal data (Mackinlay, p 10). This allowed us to create buckets for votes using size and distribution of the amount of votes in each bucket. More comparisons were enabled for viewers now that each nominated and award winning movie choice had four different sized circles in the Oscar Explorer.

One feature we decided not to include in our visualization was animation. This was deemed not necessary for our purposes. For one, we knew that we had a large dataset being presented in a small space, and were therefore wary of further overwhelming our users. Previous research indicates that analysis errors are more likely to occur when animation is used with a large dataset (Robertson et al, p 8). Second, we were primarily using our visualization for exploration and not presentation. Showing trends in this sense would not map to user's goals of wanting to explore the Oscar dataset. Finally, Tableau presents a limitation to animation in general, as animated tasks in this visualization software can be both slow and cumbersome to implement.

Our group does recognize some limitations with our final visualizations. While we did take steps to address the issue of occlusion, our solutions may not be optimal. Additionally, due to the many to one relationships of our data points, with each movie possibly recognized for several awards, our visualization does still include overlap in data points. Ideally, these would be separated, or would include details on the tooltip to indicate which categories were included for each movie.

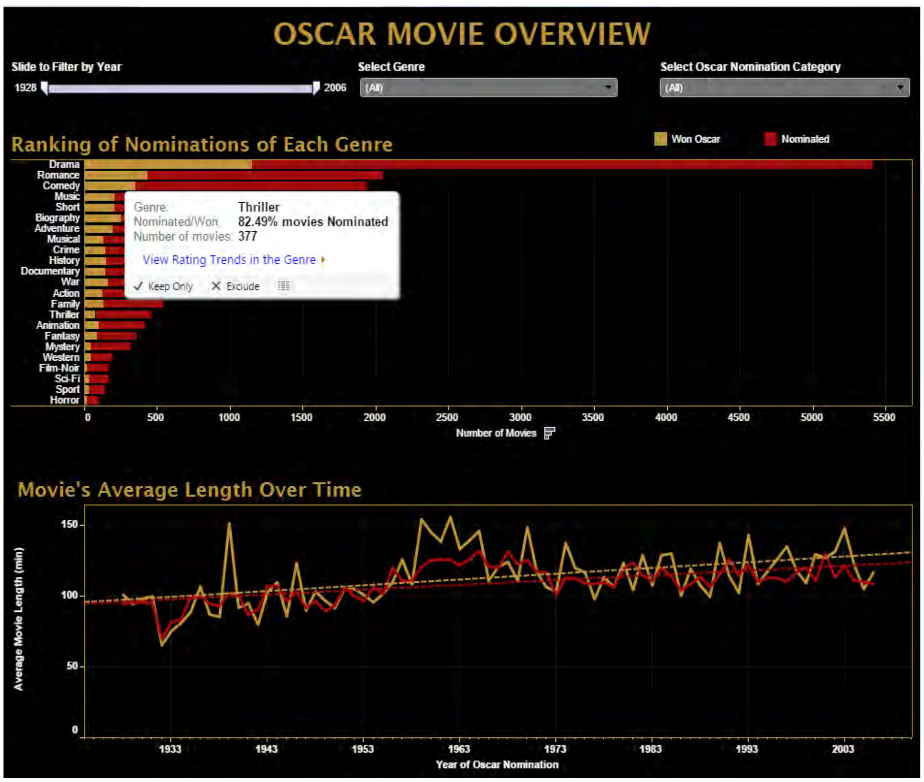


Figure 14: Final version, genre/runtime

We also made several changes to the final versions of our trend charts for ratings and runtime. In order to incorporate the Oscar color scheme and give the data more context, we matched the colors from the Oscar Movie Explorer for our secondary visualizations as well. The bar chart's genre category was shifted to the vertical axis to make the nominals more legible. This had the additional positive outcome of creating more space for bar length, which would make it easier for viewers to make quick comparisons. Filtering was changed from a multi-select list to multi-select dropdown and moved to the top alongside the slider. This also allowed for more space for the charts. Selecting any genre from the bar chart brushed the runtime trend line chart to show the trend for that genre. It also highlighted the bar that was selected.

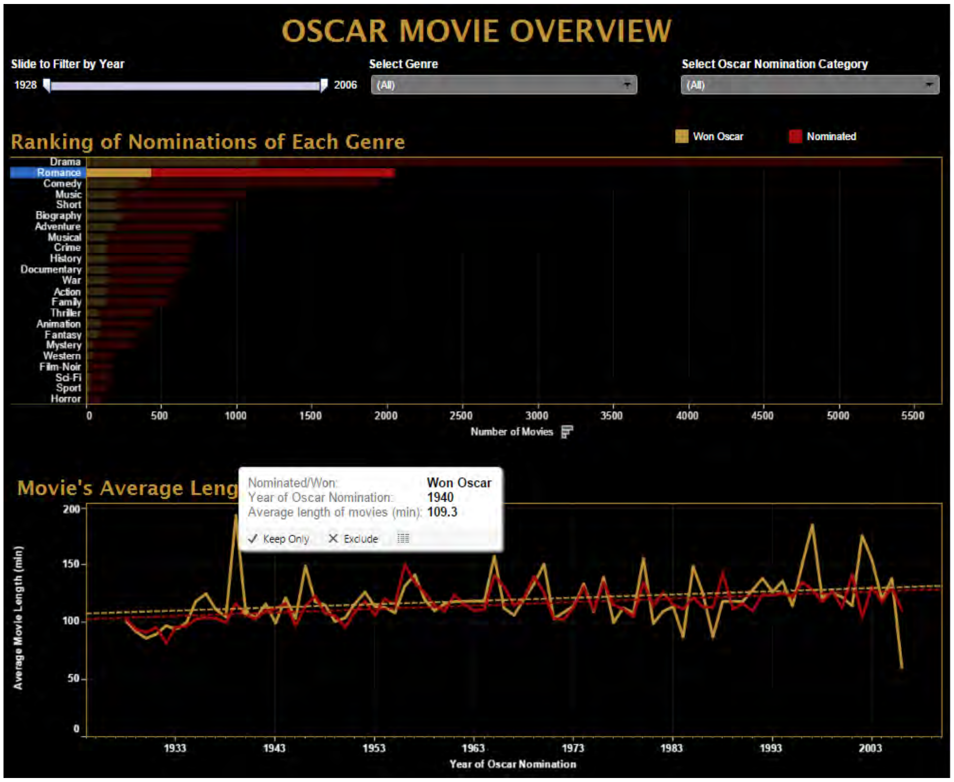


Figure 15: Highlighting and linking in genre/runtime trends

In order to provide detail on demand as suggested by Shneiderman, we added tooltips to both charts. These presented additional information including genre, percentage of movies nominated or won in that genre, and total number of movies nominated in that genre. A link was added to navigate to the rating trend visualization on our third tab with that genre's filter applied by default. As for the line chart, the tooltip gives details about the trend line selected. This shows the aggregate for the winners and nominated movies, as well as average runtime for that year.

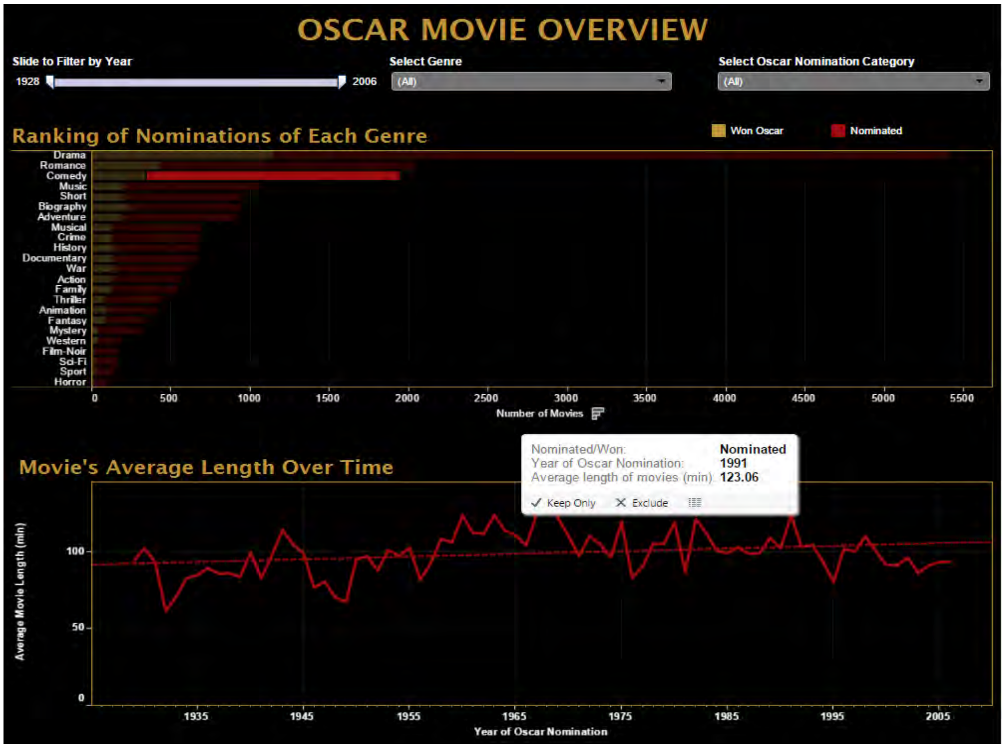


Figure 16: Details on demand with brushing and linking

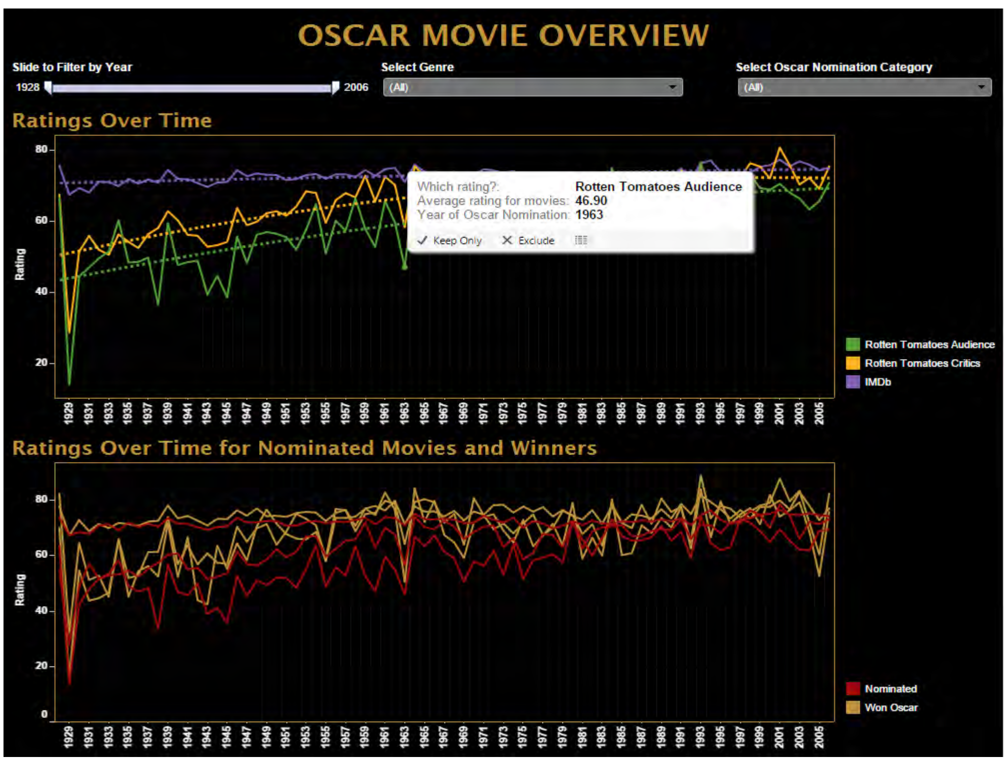
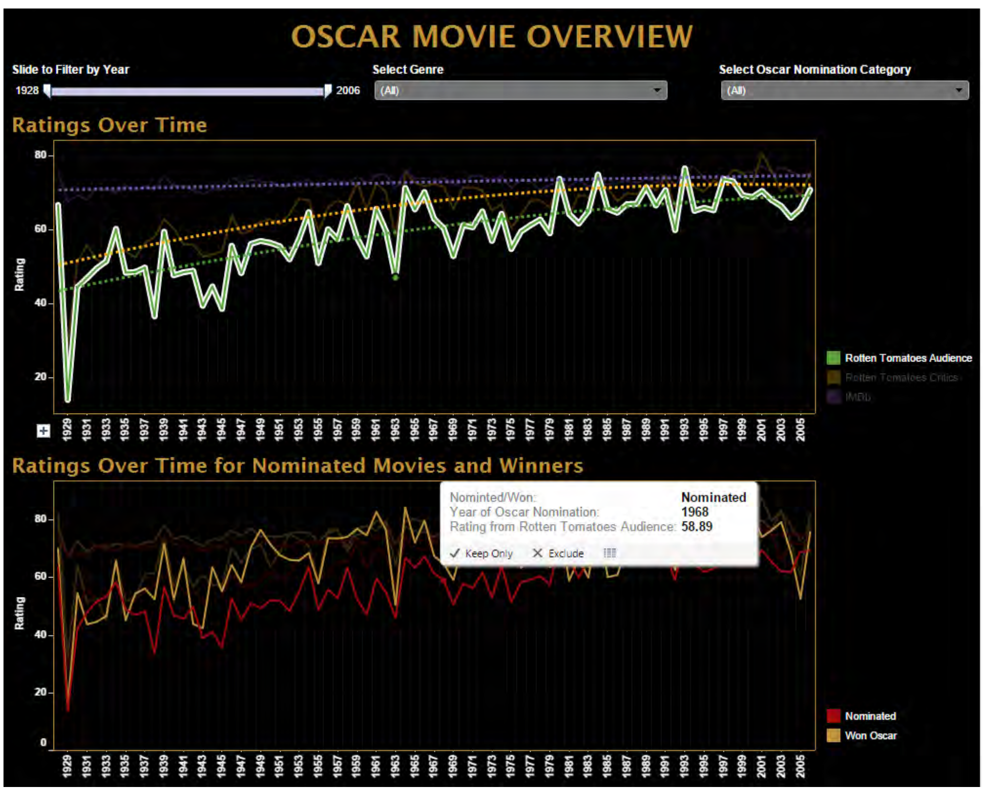


Figure 17: Final version, genre/rating

Following the suggestion of using subtle grids, we aimed to reduce chart junk by making gridlines lighter. Recognizing that our data presented may be complex at times, we decided that a lighter grid would provide less distraction for our viewers (Stone and Bartram, p 2). Additionally, we made the decision to bucket years on the time series to show every three years, rather than every year from 1929 to 2006. The color of the rating lines were adjusted to make them more differentiable from the colors given to "winning" and "nominated". For consistency's sake, we used the same color for winning movies and nominated throughout our visualization.

Some formatting issues were addressed in this version as well. Labels were changed to make the filters and charts more readable and understandable. Additionally, the legends were adjusted to be more prominent. This also involved changing the category and genre filters from multi-select list to multi-select dropdown. This time, though, they were made a little wider for easy access, as per Fitts's law. Following the same principle we moved them from the right to the top, which arranged all of the filters side by side.

Finally, we added a select feature where a user can select a rating trend line from the top chart, which highlights the corresponding trend lines for the same rating in the bottom line chart.



DISCUSSION

Once we had completed our visualizations, we were able to revisit our goals from the initial proposal. Primarily, we wanted to allow for easy exploration of Oscar nominated movies, and to allow for comparison of trends between movie genres. With our primary visualization, we accomplished these goals. Users are able to search for any movie within the set, as well as by actor, actress, and director names that were involved with the movies. They can then get more detail on demand for the title, including the rating from IMDB, the runtime length of the movie.

Additionally, we proposed the following tasks for users to be able to accomplish. Reflecting on these now, we can see whether or not we were able to support these, or whether they fit into the scope of our final visualization.

- Investigating the commonalities or differences between movies which win awards, and those that do not.

We consider this task to be supported. Users can evaluate movies side by side, and see at a glance if a movie had won an Oscar or not. This includes being able to see how each movie performed versus an average rating.

- Finding trends in the movie industry over time. For example, how have budgets and runtime changed?

We consider this task to be supported. Our second visualization shows genre data over a time series. Currently, this visualization supports showing runtime (movie length) trends over time. We will aim to include audience ratings and other variables over a time value as well.

- Enabling comparison of award winning movies versus ratings of viewers via critic scores.

We consider this task to be semi-supported at this time. Audience ratings via Rotten Tomatoes were incorporated at a later time in the development process. This interaction is not yet fully refined, but this data has been included versus critic ratings from IMDB. There are additional ratings we could include, such as MetaCritic, which would make this comparison more robust.

- Comparison of trends to historical events. What changes in culture or world events might have contributed?

This task is not supported. The purpose of our main visualization is exploratory, with our second being more explanatory towards trend data. This portion of our visualization is not in the polished state it would need to be in able to see any such correlations. Additionally, we wanted to be careful in making any assumptions about seeming correlations being causal. This is certainly one area of further interest for our project. However, we would need much more clear results and obvious changes in time data to express this. Our team would wager there are likely correlations for, as the old saying goes, art imitates life.

- Users evaluate whether or not they might be interested in watching a movie based on the predictability of Oscar winning. Allows user to consider whether watching the movie would be worth their time.

We consider this task to be semi supported, because the evaluation is subjective. Users should be able to evaluate some areas of interest for them within the movie industry by using our visualizations. Whether or not they choose to watch the movie, or consider it worth their time, is immeasurable without it being linked to a movie viewing service and rating of some sort.

FINDINGS

Through our visualizations concerning trends within the movie industry, we located several findings that we found to be compelling.

One of the more compelling findings showed that the selections of the Academy are generally validated by viewers. While a few of our survey respondent's reported that they believed awards were generally won based on connections and were viewed as a popularity contest," it appears that this may not be the case. Oscar winning movies are more highly rated by audiences as well, showing agreement between those who chose the awards and regular viewers. However, there is the possibility that the higher ratings may be a result of hype generated from winning an award. Does just hearing about the movie in a positive sense make it more interesting in some way? The hype aspect is not one that our visualization can prove or disprove.

Additionally, we saw several other points of interest that were made visible through investigations of this data. These were:

- Movies categorized in the drama genre are nominated and win at a higher rate than any other genre by a large margin
- Runtime of Oscar nominated movies are increasing over time for all genres
- Runtime for movies that have won the Oscar are increasing at a higher rate than the movies that have been nominated but have not won
- The average rating of the Oscar nominated movies is increasing over time. Rotten Tomatoes rating is increasing more rapidly over time, and is converging in agreement with IMDb in the

more recent years.

- Users from IMDb rate films higher on average than users on Rotten Tomatoes. Rotten Tomatoes users also rate films lower than the critics. These two services likely have a different user base with differing values in movie choices. Rotten Tomatoes users appear to be more critical.

As for the tools that were utilized, ultimately, Tableau proved to be effective for creating our visualizations. Tableau excels at enabling the exploratory process for a visualization, which was the goal for our primary visualization. There were some discussions early in our process concerning switching to D3. However, there were some limitations associated with this tool which made it appropriate for us to stick with Tableau. For one, D3 has a large learning curve, and our group contained only one member that was strongly versed in coding. This would have made it difficult for us to progress in a collaborative fashion. Additionally, as data exploration is a dynamic process, it would have been very difficult for us to predict what we could find along the way. Since we weren't seeking to explain with our primary visualization, it would have been more difficult to ideate.

Despite Tableau's strengths in data exploration, the software does come with its own set of limitations. For one, it lacks the customizability that a tool such as D3 could afford. This was noticeable in certain areas such as the tooltip pop up. We were not able to use images in the tooltip, which would have afforded us more detail on demand as well as available space on our visualization. Though Tableau support using custom symbols for data points, the process of implementing this is cumbersome. We were not able to link the set of IMDb movie posters to a hosted site, meaning we would have had to store the images locally. This would have been difficult to support with a set including over 8,000 data points, and thus nearly that many custom symbols. Additionally, using colors and saturation simultaneously is not possible within Tableau, leaving us to utilize area and color alone for our main visualization.

Further difficulties were presented by having one-to-many relationships with our plots. Tableau creates of each "one" for every "many," so one plot may represent several different points in a data set if there were category or genre overlap. Creating multiple inner joins with our data was not feasible, as this would have increased the size of our dataset to potentially millions of points.

While Tableau served us in creating a functionally exploratory tool, a future version would be well served being remade in a tool such as D3. With this, we could also support animations for our visualizations of trends in our second and third tabs, which would aid in telling a story or explaining.

FUTURE WORK

Reflecting back on what our stated goals were, as well as what we learned along the way, we do see some opportunities for future work and improvement.

Though we drifted from a planned predictive model, we believe that there is still exploration to be done in this space. During our research, we did not discover any visualized predictive models for this. According to our user research, our potential users were not that interested in this as a feature, which is one reason we decided against this pursuit during our project timeframe. Of interest to us is whether commonalities between award winning movies can be visualized. Namely, can a selection of certain criteria with relation to an award winning movie highlight other movies which are similar, or elements which may make a later movie more likely to win an award in that category?

Additionally, we realize that our scope of movie data is limited at this time. However, the Oscars were broad enough to encompass many well known and recognized movies. Additionally, this set put us around 8,800 entries, which was a suitable number for the scope of this project. However, in order to make this more comprehensive, we would aim to include a wider range of movies for exploration. Though this would not likely assist in creating the predictive model aspect of our visualization, there are other features we could leverage this for, apart from creating broader interest to a wider range of users. We generated the idea of visualizing a certain actor, actress, or director's career path as chosen by the user. This could potentially show how this person's focus has changed over the course of their career. Did they tend to be in more highly rated movies as they went along? Did their main genre or movie type change? This would create a more visually informative filmography. Such a feature would benefit from having a larger set of movies included, as a career timeline would be otherwise incomplete, since it is only a small number of movies which are nominated for awards.

From our research, we noticed that audience and critic scores were highly influential in a user's choice of whether or not to watch a movie. Currently, IMDb scores are implemented. We would like to include a wider range of audience and critic rated scores, as these are important to the user when judging a film. Though we initially had some difficulty collecting data from Rotten Tomatoes, we are currently working on implementing this score. This score is generally held in high regard by viewers.

Further, we would aim to conduct additional tests as well as perform detailed interviews with potential users. Though we performed usability evaluations with every iteration of our visualizations, we were not able to user test the final product. Additional tests could aid in evaluating the effectiveness of our results and direct possible future work as a whole. One potential interview candidate that would be of interest to us would be employees of Scarecrow. Currently, Scarecrow has two kiosks in the store which assist visitors in locating products. However, the system is antiquated and does nothing in the way of guiding visitors in making choices from a store that has a potentially overwhelming amount of selections. Our visualization could potentially replace or augment this system, allowing visitors to make more informed choices about their viewing.

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