**HIGH EMPHASIS ON DATA THAT WE HAVE!**

* AIM TO USE ONLY DATA THAT WE HAVE

**Big Screen Vs. Small Screen:**

**Premise:** With the rise of streaming services (e.g. Netflix, Tiktok, etc.), more people are getting their video entertainment on the small screen.

Also, the first x weeks audience (proxy: movie rater) and the post-first-x-weeks audience (proxy: movie rater) may have different characteristics (e.g. really big fan of movie vs trend follower). Rating behaviors may differ across time, and these differences may differ across genres.

* Separate by genre or other factors (e.g. winning an Oscar)

1. Rating differences between people who watch in the cinema vs. after the small screen?
2. Are less people watching movies during the big screen now versus 10 years ago?
3. How long should a movie be in theaters for?

**Genre/Type Contagion Effect**

**Premise:** Every genre has top-grossing and low-grossing movies. However, some genres may exhibit “contagion effect”, in which the average audience of one movie of a certain genre is more likely to watch another movie in that same genre, as compared to another genre. For example, an average Marvel film rater might be more likely to rate another Marvel film, compared to a horror film rater rating more than 1 horror film.

**Data Analysis:**

* Visualize graph networks for specific genres to evaluate contagion effect
* Visualize graph networks for multiple genres to discover cross-genre contagion effect, discover unintuitive links between tags and genres through clustering machine learning algorithms

**Implications:**

* Discovering the most binge-able genres or categories; might be useful for streaming services seeking to break into the market (network effect).
* Uncovering potential biases in certain genres/types e.g. Marvel reviewers may have a higher opinion of Marvel in general that inflate their rating for say an average-doing Marvel film.

**Research Question 2: Finding Factors that Influence Recommender Systems**