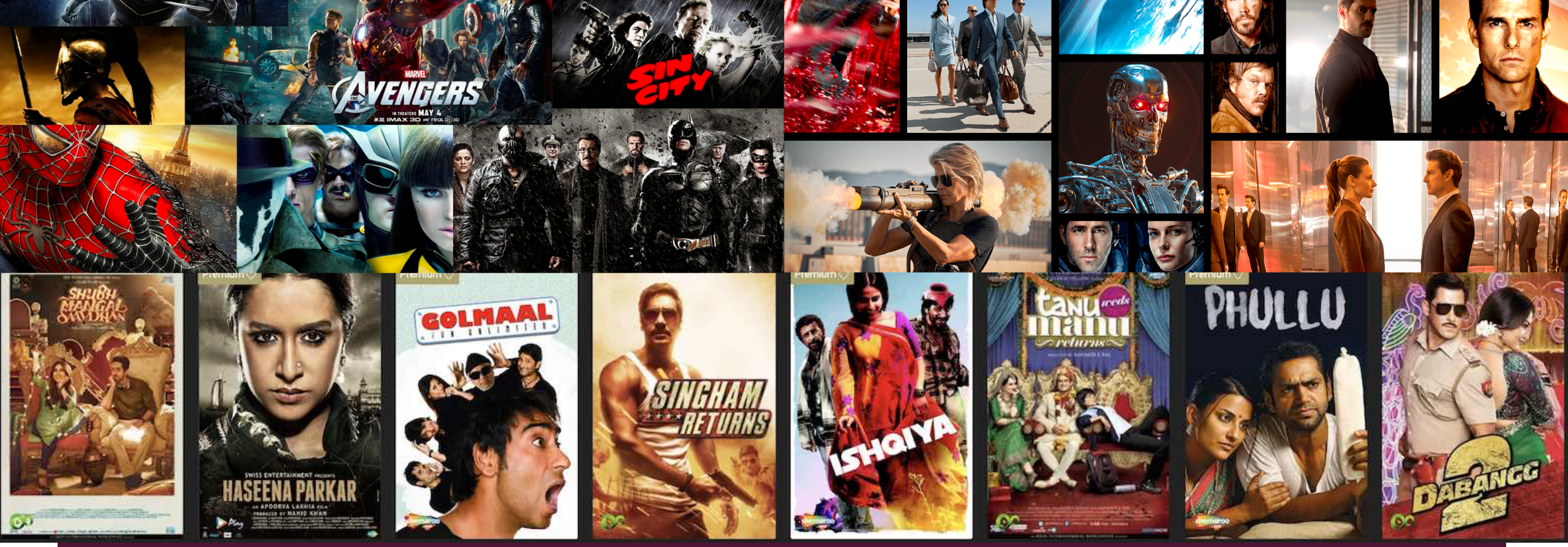


MOVIE RECOMMENDATIONS

SMES

AMRITA DUTTA, METIKA SIKKA, SANCHYA SAHAY, AND MALIN ORTENBLAD

TABLE OF CONTEXT

- Movie Market Overview
- Word Clouds
- Recommendation Algorithms:
  - Shortest Path (by movie title)
  - Cosine similarity (by movie title)
  - TF-IDF (by keywords)
  - Cosine similarity (by keywords and genre)
- Conclusion

People spend on average nearly an hour(51 min to be exact) per day deciding what to watch

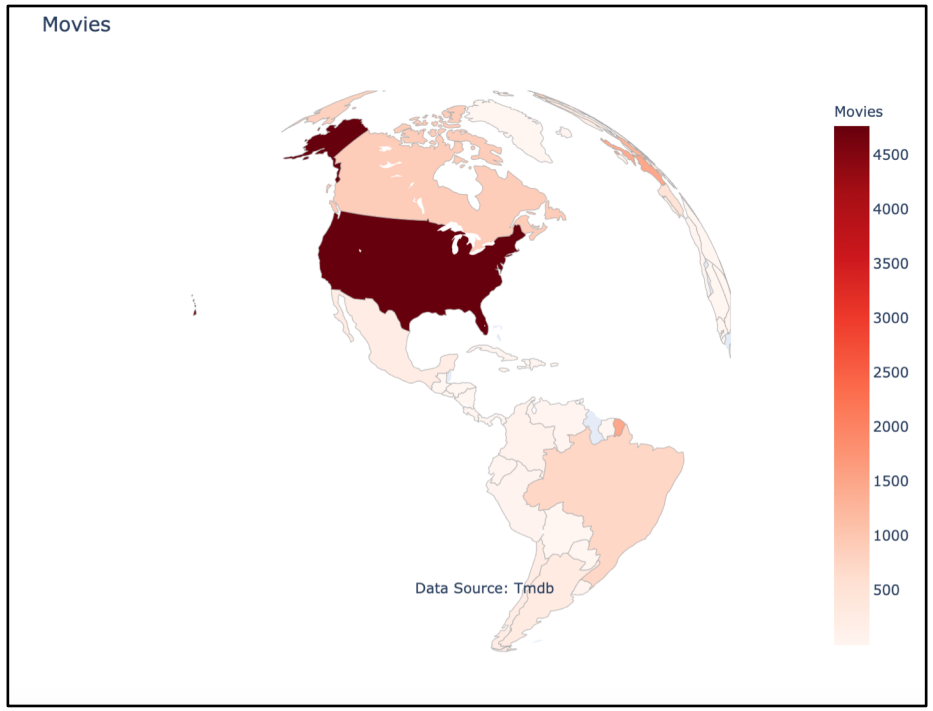
51 min per day, 7 days a week → **357 minutes per week** → **18564 minutes per year** → **309.4 hours per year**

- **Issues:**
  - More movie options than ever before
  - A big time-loss trying to choose between these options
  - Sometimes you have a movie in mind and sometimes you have a "feeling"
- **Solution:**
  - We decided to build models with two functionalities:
    - People searching for recommendations based on a movie title that they had watched and liked
    - People searching for recommendation based on their mood, thoughts and specific keywords
- **The Data:**
  - Used APIs to extract the data from the TMDB
  - All movies released worldwide in the past 2 years (2018 & 2019)

SOURCE: HTTPS://LOVIN.IE/ENTERTAINMENT/TV-MOVIES/HERES-HOW-LONG-WE-SPEND-LOOKING-FOR-TV-SHOWS-A-DAY

About 17,000 new movies are released each year, US is the clear market leader

Movie Releases by Country (Oct 18- Oct 19)



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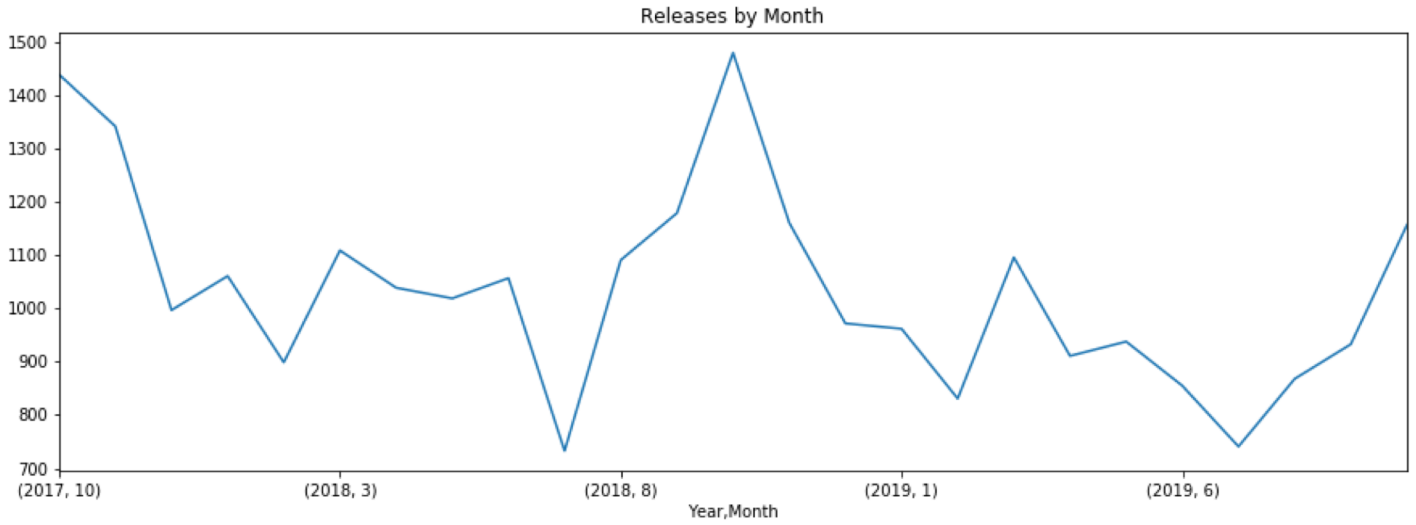

Link: file:///Users/sanchyasahay/Documents/Fall%202019/Data%20Analytics/DA%20projec/Movies%20Reco/Code/temp-plot.html

Word clouds provide a good overview of common words by Genre

Genre: Animation

Genre: Romance

Genre: Crime

Genre: Horror

The first model calculates the shortest path between movies in a network with the edge weight representing two movies' similarity scores

1. Calculate similarity scores between all movies in our data

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Director

$$Director\ Overlap$$

Production Country

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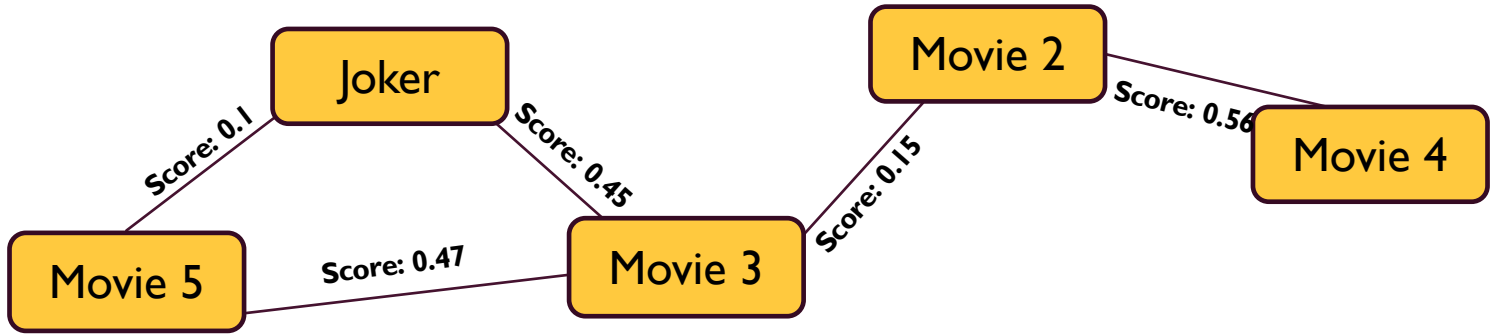

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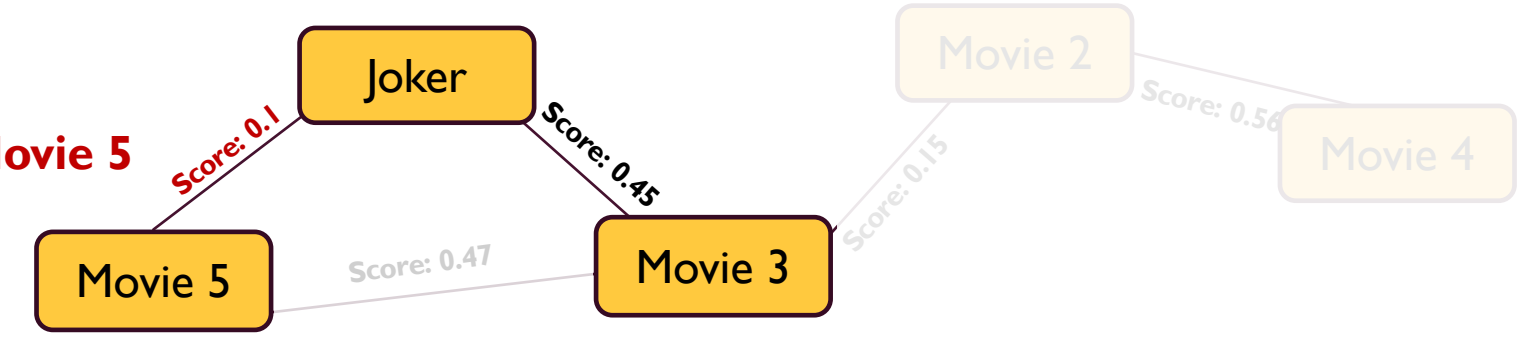
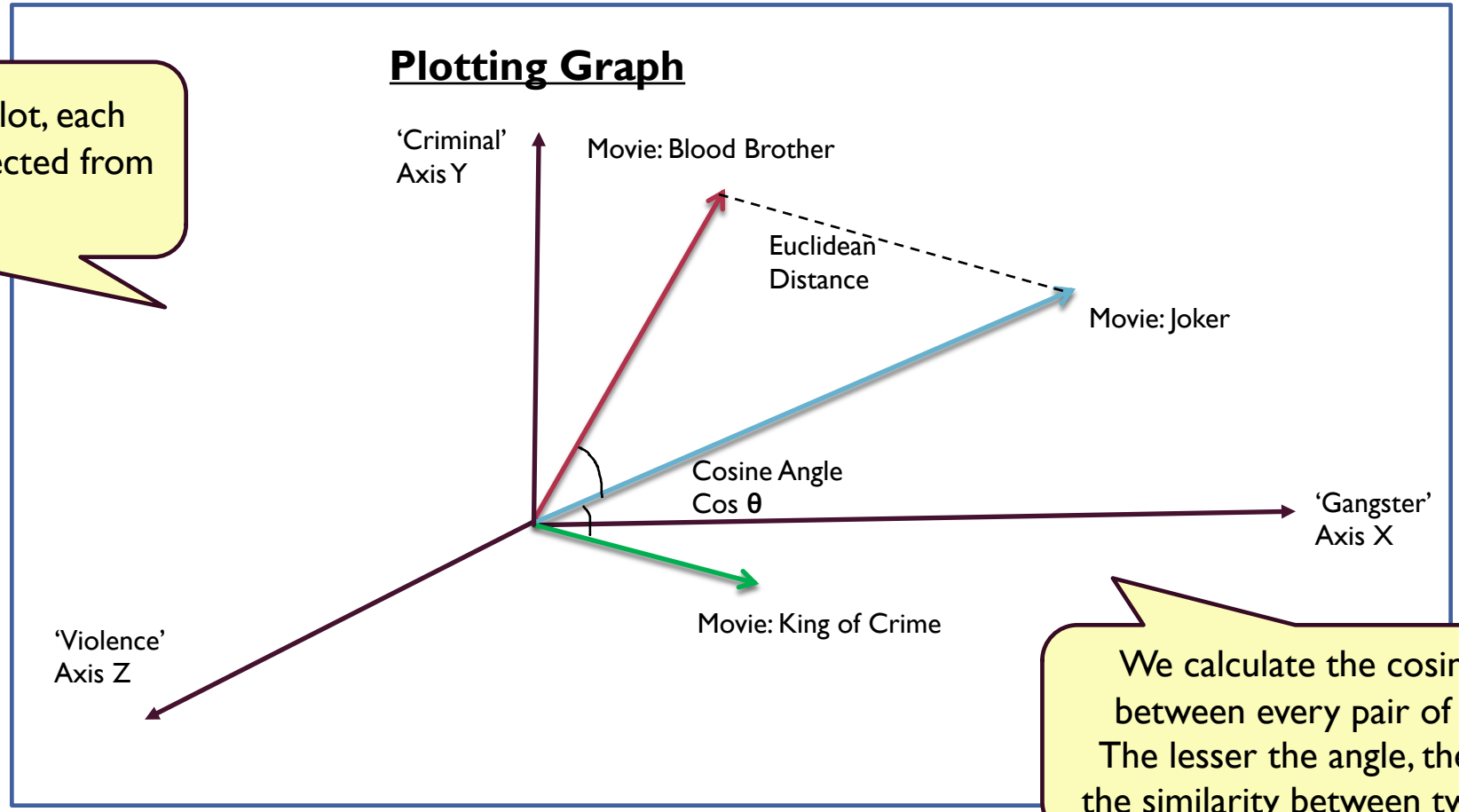
Shortest path: 0.1
Recommended Movie: Movie 5



The second model is based on cosine similarity and matches movies based on genre, director, and movie overview

In the multidimensional plot, each axis represents a word selected from the movie data



We calculate the cosine angle between every pair of movies. The lesser the angle, the greater the similarity between two movies

Source : machineleaningplus.com

The third model, recommends movies based on similarity of plot by taking keywords as input

We tried two model methods:

1. TF-IDF
2. Cosine Similarity

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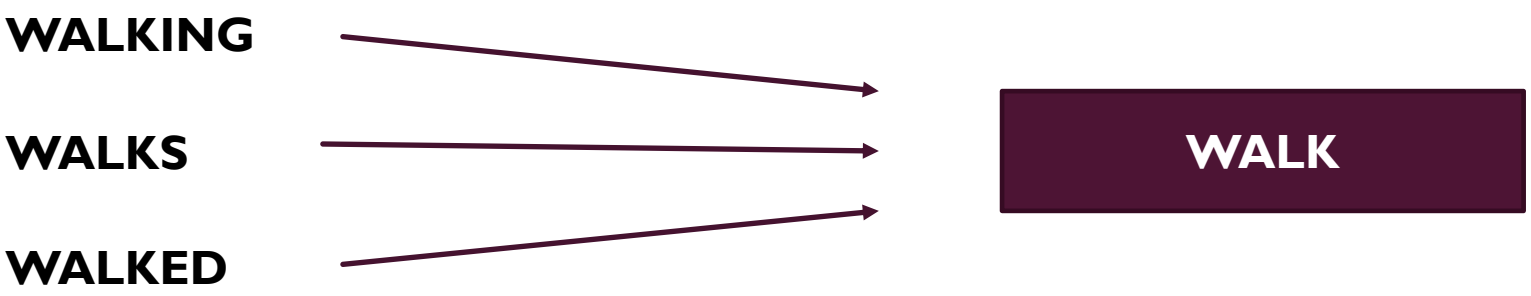
Data preparation: Removing stop words, lemmatizing words (Converting words with 'inflections' to their root verbs)



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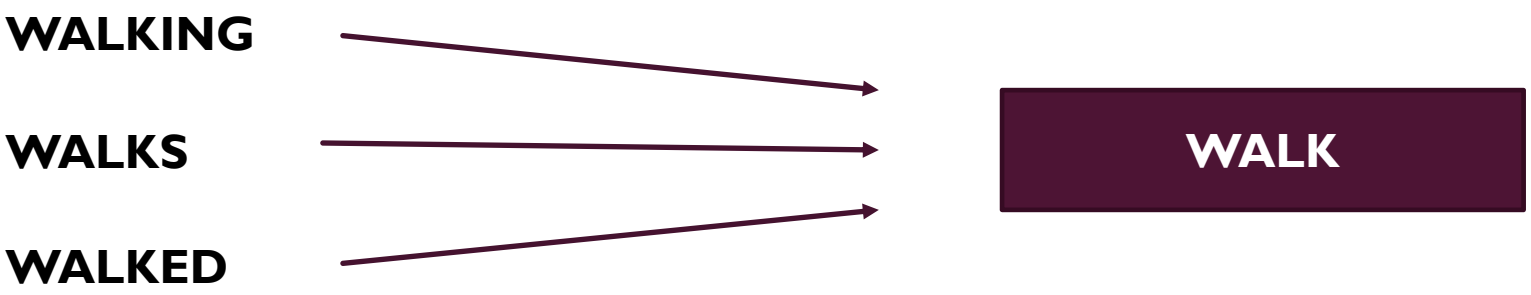

Testing: It's the Holiday Season! We feel like watching Christmas movies…

So we feed the models 'Snow Christmas Holiday' 🎄 👯

Comparing the results…which is better?

TF-IDF

Movies	Score
Santa World	0.505354
Dark Horizon	0.363008
Snow Dinosaur	0.358279
Prince of Peoria A Christmas Moose Miracle	0.307477
A Christmas Movie Christmas	0.305620

Cosine Similarity

Movies	Score
Christmas Made to Order	0.375823
The Christmas Pact	0.370991
A Christmas Movie Christmas	0.368932
Jingle Around the Clock	0.344691
Christmas in Evergreen: Letters to Santa	0.339683

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The recommendations seem good enough but wait…the TF-IDF model recommends 'Dark Horizon' for our search words.

Let's look at it's plot…

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TF-IDF: Gives importance to '**rare**' words

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The recommendations seem good enough but wait…the TF-IDF model recommends 'Dark Horizon' for our search words.

Let's look at it's plot…

"*Between here and there, we do not belong anywhere. The world collapses into* ***snow*** *and flames*"

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Subjectivity and data capture were the main challenges we faced…

Joker Recommendations

Once Upon a Time… in Hol… 7.5 ★

Spider-Man: Far from Home 7.6 ★

It Chapter Two 6.8 ★

We compared our model results to the TMDB website recommendations and picked the models that most aligned with their results and our preferences

Thank You