**Content-Based Analysis: Netflix Thumbnails**

**Can a recommendation system replicate similar results to an existing public product?**

Using a ready-made dataset from Kaggle (Soeiro, 2022) I will analyse the recommendations in such a way that I can compare the results visually to a user on Netflix. The most up to date version of Netflix has improved to widespread individualization of the streaming service enabling users to have seamless recommendations before their eyes. Artificial intelligence integration on the application, 20 years after its initial launch, provides its customers with supposedly ‘the greatest possible service and experience’ (Simplilearn, 2023).

AI, data science and machine learning are now running the operations for Netflix. The key offering being tailored movie recommendations. Netflix individually customises the data it obtains for each user. One account may have ownership in multiple locations - such as a family account - meaning that each user will be shown different recommendations on each equivalent profile within that account. The implemented AI is responsible for this functioning. Therefore, logging more screen-time hours will increase the improvement of the algorithm.

Users want to be offered recommendations with minimal effort, so the system needs to understand what you like and dislike and other options that may appeal to you. So, what does Netflix take into account when you’re watching content from the application? Your interactions: viewing history, your ratings; similar users; content-based data: titles, genres, categories, actors, release date, etc (Netflix, 2023).

Besides this, the application takes in profile information such as the time of day you watch; the devices you are watching Netflix on and how long you watch for. Supposedly, the algorithm *does not* take demographic information in account. I was also interested to find that the presentation of the homepage is definitively stylised in accordance with recommendations, so much so that the Netflix algorithm will rank each title within a row, then rank the row themselves. The best possible ordering is arranged just for you.

Can a simple recommendation system replicate the results of the Netflix algorithm? I have taken a dataset, as referenced above, and I will compare this alongside a new user profile within my family account. Whether this takes into consideration the other profiles, that is one layer deep in which I am not sure.

A screenshot of a computer

Description automatically generated

I welcome Peter, the innocent profile with no screen time as of time of writing. This will be my test user for analysis. I selected the language to be in ‘English’ and for Netflix to automatically assume 3 movies Peter liked for its initial recommendations.

Using a content-based recommender system: K-NN approach, inclusive of the Netflix dataset that I have obtained, I will take recommendations of randomised content (a selection of both movies and shows, however I will refer to them all as ‘movies’ for ease) and analyse this in further detail. In essence, the recommender system does not know any details demographically about me *and* Netflix does not know anything about me and my interests as a new user.

For seeking identical titles to what the K-NN recommender system produces, I will set the system up to produce 15 recommendations and compare this to the titles recommended on the search page for that given film in the browser on my laptop. (More than 15 I would suggest reduces the essence of ‘minimal’ effort to have content recommended to you). See Appendix 1.

For there to be so few matches in the testing of this, I was surprised with the results. I would have expected to see more correlation between a content-based recommender system and the Netflix algorithm. We often say in society that we are ‘quite predictable’. Though, my initial thoughts prior to trialling this was that we would have several matches on each piece of content. I would now argue that the content mass on Netflix is so wide and varied that it is highly unlikely to receive any matches in this way and the lack of prior knowledge by each system means that the content recommended is often very similar to the one option you provide.

Having said this, I found through my trialling that Netflix would recommend the same piece of content throughout my searches. If I expand, I will see a singular movie recommended time and time again despite the search I was trailing. For example, having searched for ‘Knight Rider’ as I also would for ‘Thomas & Friends’; an American crime thriller against a children’s animated television series; I would see some thumbnails that were the same recommended throughout my searches, like an assumed anomaly. Or for example so other unlikely recommendations such as seeing ‘F9: The Fast Saga’ as a recommendation against ‘Thomas and Friends’; a children's animation. Or again, I saw ‘She’s the Man’ be recommended for ‘Super Monsters’.

The reliability between both the K-NN recommender system and visually looking at the thumbnails on Netflix I feel varies significantly enough to say that not all of the recommendations given by Netflix in the searches are relevant to the content you provide to it. The K-NN means system very effectively, one hundred percent of the time, will recommend movies based on the exact genre or genres given to the system that is the same as the content you put into it. That is the way it is programmed directly and will not vary. However, the downside to this is that you will not receive variation in the results. Something which is hard to program unless you are running a collaborative filtering algorithm - which Netflix has built in within the number of factors it adheres to (Invisibly, 2021).

The thumbnails which appeared from these searches do feel like attempts to replicate purely the genre much like the K-NN means method, however they do not feel like popular choices as such and lack the variation I would usually see Netflix offering. I feel as though what the search results gave was content which was aiming to be as identical as the search as possible either by the nature of the content or by name. For a piece of content to be ‘related’ to another means that it will either belong to the same group or type. So likely what we will see is as said identical content type or sequels. This may not necessarily take into consideration other similar users as the algorithm hasn’t learnt enough about Peter.

While Netflix is under the impression of Peter, an unknown user, Netflix clearly does struggle to provide variation and very rarely provides results that differ. The anomaly-like pieces of content that do get provided in this way often seem like absurd results. This may be due to Netflix trying to learn Peter’s interests from previous searches having had no content be viewed. The K-NN means recommendation system admittedly does well if you want exact content replicas that provide the same characteristics to your input content. The K-NN model does provide content which I could argue is not necessarily the most popular choice however, this seems like the best approach it must recommend different and varied content. Often the recommendations will be of the same genre and be labelled with other genres on top of that, so you will never see content of a contradictory nature to the input.

While there are some results which have 1 or 2 matches (confirming that the model is correctly providing genre-related content), the K-NN model is great for initial recommendations and proves to recommend items which Netflix doesn’t. However, if you as a user want to have variation and different genres to watch, Netflix’s algorithm shows signs of this learning process very early on which is incomparable to the K-NN means model. The K-NN means will not differ beyond this to learn a more holistic approach to you as a user.

In addition to this, I similarly trialled the cosine similarity approach against Netflix. See appendix 2. The results were almost identical in nature to the K-NN means. The cosine similarity model also at best produces 2 matches for recommendations for one title. However, the recommendations were not identical or too like the K-NN means. The results here were much like the Netflix model in which there is often a result which feels like an absurd recommendation, yet the content may have the same labels associated with it.

**Bibliography**

1. Invisibly (2021) *Behind The Scenes of The Netflix Recommendation Algorithm.*  Available at: https://www.invisibly.com/learn-blog/netflix-recommendation-algorithm/#:~:text=The%20system%20filters%20over%203%2C000,on%20an%20individual%20user%27s%20preferences (Accessed: 6 June 2023).
2. Netflix (2023) *How Netflix’s Recommendations System Works.* Available at: https://help.netflix.com/en/node/100639 (Accessed 5 June 2023).
3. Simplilearn (2023) *Netflix Recommendations: How Netflix Uses AI, Data Science, And ML.* Available at: https://www.simplilearn.com/how-netflix-uses-ai-data-science-and-ml-article#:~:text=How%20does%20the%20Netflix%20algorithm,that%20the%20member%20has%20consumed (Accessed: 5 June 2023).
4. Soeiro, V. (2022) ‘Netflix TV Shows and Movies’. Available at: https://www.kaggle.com/datasets/victorsoeiro/netflix-tv-shows-and-movies (Accessed: 5 June 2023).

**Appendices**

**Appendix 1: K-NN Mean Results** (8 movies/shows selected at random).

*\*Recommended movie match*

*\*\* Recommended movie match, sequel title.*

See results overleaf.

*Selected Movie:  Thomas & Friends*

Recommended Movies:

Ever After High | Genres: 'action','animation','comedy','drama','family','fantasy','music','romance' | Rating: 7.7

Dokidoki! PreCure | Genres: 'action','animation','comedy','drama','family','fantasy' | Rating: 6.2

Maya and the Three | Genres: 'action','animation','comedy','drama','family','fantasy' | Rating: 8.1

\*\*Thomas & Friends: All Engines Go! | Genres: 'animation','comedy','drama','family','fantasy','music' | Rating: 2.0

Yu-Gi-Oh! | Genres: 'action','animation','comedy','drama','family','fantasy','scifi' | Rating: 7.3

My Little Pony: Friendship Is Magic | Genres: 'animation','comedy','drama','family','fantasy','music','scifi' | Rating: 7.6

The Legend of Korra | Genres: 'action','animation','comedy','drama','family','fantasy','scifi' | Rating: 8.4

\*Talking Tom and Friends | Genres: 'action','animation','comedy','drama','european','family','fantasy' | Rating: 6.1

Pac-Man and the Ghostly Adventures | Genres: 'action','animation','comedy','drama','family','fantasy','scifi' | Rating: 4.6

Trollhunters: Tales of Arcadia | Genres: 'action','animation','comedy','drama','family','fantasy','scifi' | Rating: 8.4

Voltron: Legendary Defender | Genres: 'action','animation','comedy','drama','family','fantasy','scifi' | Rating: 8.1

Dragons: Race to the Edge | Genres: 'action','animation','comedy','drama','family','fantasy','scifi' | Rating: 8.2

Rise of the Teenage Mutant Ninja Turtles | Genres: 'action','animation','comedy','drama','family','fantasy','scifi' | Rating: 4.9

She-Ra and the Princesses of Power | Genres: 'action','animation','comedy','drama','family','fantasy','scifi' | Rating: 7.8

Little Witch Academia | Genres: 'action','animation','comedy','drama','family','fantasy','scifi' | Rating: 7.9

Thomas & Friends = 1 MatcA screenshot of a computer

Description automatically generatedhes

*Selected Movie:  Knight Rider*

Recommended Movies:

Arrow | Genres: 'action','crime','drama','scifi','thriller' | Rating: 7.5

Gotham | Genres: 'action','crime','drama','scifi','thriller' | Rating: 7.8

Vanished 46 | Genres: 'action','crime','drama','scifi','thriller' | Rating: 8.2

Wu Assassins | Genres: 'action','crime','drama','fantasy','scifi' | Rating: 6.4

In from the Cold | Genres: 'action','crime','drama','scifi','thriller' | Rating: 6.2

The One | Genres: 'action','crime','drama','scifi','thriller' | Rating: 6.6

Stargate SG-1 | Genres: 'action','drama','scifi' | Rating: 8.4

The 100 | Genres: 'action','drama','scifi' | Rating: 7.6

DC's Legends of Tomorrow | Genres: 'action','drama','scifi' | Rating: 6.8

Supergirl | Genres: 'action','drama','scifi' | Rating: 6.2

Wanted | Genres: 'action','crime','drama' | Rating: 7.6

The Paper | Genres: 'action','crime','drama' | Rating: 7.4

Mind Game | Genres: 'action','crime','drama' | Rating: 7.5

Black Lightning | Genres: 'action','drama','scifi' | Rating: 6.1

Ad Vitam | Genres: 'crime','drama','scifi' | Rating: 6.4

Knight Rider = No Matches

A screenshot of a computer

Description automatically generated

*Selected Movie:  We Are: The Brooklyn Saints*

Recommended Movies:

Last Chance U | Genres: 'documentation','sport' | Rating: 8.4

Sunderland 'Til I Die | Genres: 'documentation','sport' | Rating: 8.1

Becoming Champions | Genres: 'documentation','sport' | Rating: 6.7

Formula 1: Drive to Survive | Genres: 'documentation','sport' | Rating: 8.6

The Least Expected Day: Inside the Movistar Team 2019 | Genres: 'documentation','sport' | Rating: 7.4

The Playbook | Genres: 'documentation','sport' | Rating: 7.4

Basketball or Nothing | Genres: 'documentation','sport' | Rating: 7.4

Home Game | Genres: 'documentation','sport' | Rating: 7.0

Cricket Fever: Mumbai Indians | Genres: 'documentation','sport' | Rating: 7.2

Last Chance U: Basketball | Genres: 'documentation','sport' | Rating: 8.3

Neymar: The Perfect Chaos | Genres: 'documentation','sport' | Rating: 6.6

Naomi Osaka | Genres: 'documentation','sport' | Rating: 6.2

Race: Bubba Wallace | Genres: 'documentation','sport' | Rating: 5.9

The Last Dance | Genres: 'documentation','history','sport' | Rating: 9.1

The Family | Genres: 'documentation','reality','sport' | Rating: 6.4

We Are: The Brooklyn Saints = No Matches

A screenshot of a computer

Description automatically generated

*Selected Movie:  Seinfeld*

Recommended Movies:

\*\*Monty Python's Fliegender Zirkus | Genres: 'comedy' | Rating: 8.1

High Risk | Genres: 'comedy' | Rating: 3.8

The Parkers | Genres: 'comedy' | Rating: 6.8

H | Genres: 'comedy' | Rating: 7.4

Community | Genres: 'comedy' | Rating: 8.5

\*Arrested Development | Genres: 'comedy' | Rating: 8.7

Half & Half | Genres: 'comedy' | Rating: 7.0

One on One | Genres: 'comedy' | Rating: 7.0

Nuevo Rico Nuevo Pobre | Genres: 'comedy' | Rating: 7.1

Meet the Adebanjos | Genres: 'comedy' | Rating: 7.6

Zach Stone Is Gonna Be Famous | Genres: 'comedy' | Rating: 8.3

Schitt's Creek | Genres: 'comedy' | Rating: 8.5

Crazy Ex-Girlfriend | Genres: 'comedy' | Rating: 7.8

Kim's Convenience | Genres: 'comedy' | Rating: 8.2

Wet Hot American Summer: First Day of Camp | Genres: 'comedy' | Rating: 7.3

Seinfeld = 2 Matches

A screenshot of a computer

Description automatically generated

*Selected Movie:  Sweet Tooth*

Recommended Movies:

The Protector | Genres: 'action','drama','fantasy','scifi' | Rating: 6.5

Warrior Nun | Genres: 'action','drama','fantasy','scifi' | Rating: 6.8

Cursed | Genres: 'action','drama','fantasy','scifi' | Rating: 5.8

Shadow and Bone | Genres: 'action','drama','fantasy','scifi' | Rating: 7.6

Fate: The Winx Saga | Genres: 'action','drama','fantasy','scifi' | Rating: 6.8

Tribes of Europa | Genres: 'action','drama','fantasy','scifi' | Rating: 6.7

Merlin | Genres: 'action','drama','european','fantasy','scifi' | Rating: 7.9

Van Helsing | Genres: 'action','drama','fantasy','horror','scifi' | Rating: 6.2

Fate/Apocrypha | Genres: 'action','animation','drama','fantasy','scifi' | Rating: 6.6

\*The Umbrella Academy | Genres: 'action','comedy','drama','fantasy','scifi' | Rating: 8.0

The Witcher | Genres: 'action','drama','fantasy','horror','scifi' | Rating: 8.2

Alice in Borderland | Genres: 'action','drama','fantasy','scifi','thriller' | Rating: 7.6

Ragnarok | Genres: 'action','drama','fantasy','scifi','thriller' | Rating: 7.5

Wu Assassins | Genres: 'action','crime','drama','fantasy','scifi' | Rating: 6.4

Ultraman | Genres: 'action','animation','drama','fantasy','scifi' | Rating: 6.8

Sweet Tooth = 1 Match

**A screenshot of a computer

Description automatically generated**

*Selected Movie:  After Life*

Recommended Movies:

Gilmore Girls | Genres: 'comedy','drama' | Rating: 8.2

Girlfriends | Genres: 'comedy','drama' | Rating: 7.2

Midnight Diner | Genres: 'comedy','drama' | Rating: 8.6

El Escamoso | Genres: 'comedy','drama' | Rating: 7.5

\*Shameless | Genres: 'comedy','drama' | Rating: 8.6

EastSiders | Genres: 'comedy','drama' | Rating: 6.8

Jane the Virgin | Genres: 'comedy','drama' | Rating: 7.8

Incomplete Life | Genres: 'comedy','drama' | Rating: 8.5

Two Fathers | Genres: 'comedy','drama' | Rating: 8.0

Grace and Frankie | Genres: 'comedy','drama' | Rating: 8.2

Unbreakable Kimmy Schmidt | Genres: 'comedy','drama' | Rating: 7.6

Master of None | Genres: 'comedy','drama' | Rating: 8.3

Easy | Genres: 'comedy','drama' | Rating: 6.9

Gilmore Girls: A Year in the Life | Genres: 'comedy','drama' | Rating: 7.6

Lady Dynamite | Genres: 'comedy','drama' | Rating: 7.3

After Life = 1 Match

**A screenshot of a computer

Description automatically generated**

*Selected Movie:  Super Monsters*

Recommended Movies:

\*Hotel Transylvania: The Series | Genres: 'animation','comedy','family','fantasy','horror' | Rating: 5.3

Tayo the Little Bus | Genres: 'animation','comedy','family' | Rating: 5.3

Dreamworks Happy Holidays from Madagascar | Genres: 'animation','comedy','family' | Rating: 6.5

Comedians in Cars Getting Coffee | Genres: 'animation','comedy','family' | Rating: 8.0

Barbie: Life in the Dreamhouse | Genres: 'animation','comedy','family' | Rating: 7.4

Ask the Storybots | Genres: 'animation','comedy','family' | Rating: 8.4

Simon | Genres: 'animation','comedy','family' | Rating: 7.0

Cocomelon | Genres: 'animation','comedy','family' | Rating: 4.7

Barbie: Dreamhouse Adventures | Genres: 'animation','comedy','family' | Rating: 6.7

Rainbow High | Genres: 'animation','comedy','family' | Rating: 5.8

\*\*Shaun the Sheep: Adventures from Mossy Bottom | Genres: 'animation','comedy','family' | Rating: 8.1

Alien TV | Genres: 'animation','comedy','family' | Rating: 6.1

Pinky Malinky | Genres: 'animation','comedy','family' | Rating: 5.5

Rhyme Time Town | Genres: 'animation','comedy','family' | Rating: 7.6

Go! Go! Cory Carson | Genres: 'animation','comedy','family' | Rating: 7.9

Super Monsters = 2 Matches

**A screenshot of a computer

Description automatically generated**

*Selected Movie:  Intimacy*

Recommended Movies:

Breaking Bad | Genres: 'crime','drama','thriller' | Rating: 9.5

The Blacklist | Genres: 'crime','drama','thriller' | Rating: 8.0

How to Get Away with Murder | Genres: 'crime','drama','thriller' | Rating: 8.1

Wentworth | Genres: 'crime','drama','thriller' | Rating: 8.6

Narcos | Genres: 'crime','drama','thriller' | Rating: 8.8

Quantico | Genres: 'crime','drama','thriller' | Rating: 6.6

The Method | Genres: 'crime','drama','thriller' | Rating: 7.4

Close Your Eyes Before It's Dark | Genres: 'crime','drama','thriller' | Rating: 7.0

The Sinner | Genres: 'crime','drama','thriller' | Rating: 7.9

Ozark | Genres: 'crime','drama','thriller' | Rating: 8.5

Mindhunter | Genres: 'crime','drama','thriller' | Rating: 8.6

Manhunt | Genres: 'crime','drama','thriller' | Rating: 8.1

Elite | Genres: 'crime','drama','thriller' | Rating: 7.4

Deadwind | Genres: 'crime','drama','thriller' | Rating: 7.2

Collateral | Genres: 'crime','drama','thriller' | Rating: 6.7

Intimacy = No Matches

**A screenshot of a computer

Description automatically generated**

**Appendix 2: Cosine Similarity Results**

*Selected Movie: Thomas & Friends*

2513                    The Who Was? Show

2248                          Llama Llama

421                          Horrid Henry

\*\*5298    Thomas & Friends: All Engines Go!

\*308                             Octonauts

120                            Goosebumps

4104                  Go! Go! Cory Carson

2147      Final Fantasy XIV: Dad of Light

1310        David Brent: Life on the Road

4578                                 Gone

*Thomas & Friends  = 2 matches*

*Selected Movie: Knight Rider*

164                                     Knight Rider 2000

699                                              The Rite

2748    Michael Bolton's Big, Sexy Valentine's Day Spe...

638                                      Brother's Shadow

1140                                             The Take

5051                                 DOTA: Dragon's Blood

3871                            Michael McIntyre: Showman

3959                          The Knight Before Christmas

4704                              How to Change Your Mind

1533                                     The Blind Christ

*Knight Rider = No matches*

*Selected Movie: We Are: The Brooklyn Saints*

1554                Coach Snoop

325             We Are Marshall

734                  Undefeated

1806            Black Lightning

2949               Project Papa

5035          Jump Like a Witch

3906                 Mismatched

1543          You Are My Sunday

1964    VeggieTales in the City

4287            Mi amigo Alexis

*We Are: The Brooklyn Saints = No matches*

*Selected Movie: Seinfeld*

3899                   Pete Davidson: Alive from New York

2433                                            Relatable

3534                             Michelle Wolf: Joke Show

1821                            James Acaster: Repertoire

1309                                                Barry

4824                                              Passing

4605                    David Batra: Elephant in The Room

\*\*597          Jeff Dunham's Very Special Christmas Special

1873    Jim & Andy: The Great Beyond - Featuring a Ver...

5182                      Saturday Morning All Star Hits!

*Seinfeld = 1 Match*

*Selected Movie: Sweet Tooth*

3214           Kipo and the Age of Wonderbeasts

4916                                   Tomorrow

2567                            Half Girlfriend

3602                                   Vampires

405                                 Half & Half

1307                                   Dinotrux

4890    Chickenhare and the Hamster of Darkness

36                                   GoodFellas

5214                                   Sharkdog

4842                                 Black Crab

*Sweet Tooth = No Matches*

*Selected Movie: After Life*

2046                               The Good Cop

5734                Tony Parker: The Final Shot

2264                                   Burn Out

2306                      The Little Vampire 3D

4371                            Blood Will Tell

1110                     The Royal Bengal Tiger

2232                          Happy Anniversary

1477           Tony Robbins: I Am Not Your Guru

3745    LEGO Marvel Avengers: Climate Conundrum

3556                  Fast & Furious Spy Racers

*After Life = No Matches*

*Selected Movie: Super Monsters*

4911                            Fate: The Winx Saga

2156                                 Fun Mom Dinner

739     Maria Bamford: The Special Special Special!

3915                                   Glitch Techs

1537                                       Kazoops!

4000                                    Monster Run

\*2066                                Chip and Potato

54                                     Endless Love

3412                              See You Yesterday

3323                               We Can Be Heroes

*Super Monsters = 1 Match*

*Selected Movie: Intimacy*

2649                        Unbridled

3329                       High Score

2264                         Burn Out

4044        Room 2806: The Accusation

4717             Anatomy of a Scandal

5324                  The Five Juanas

4542    David A. Arnold Fat Ballerina

5398                      Tattoo Redo

414                       Cairo 6,7,8

3006                Puriyaatha Puthir

*Intimacy = No Matches*