

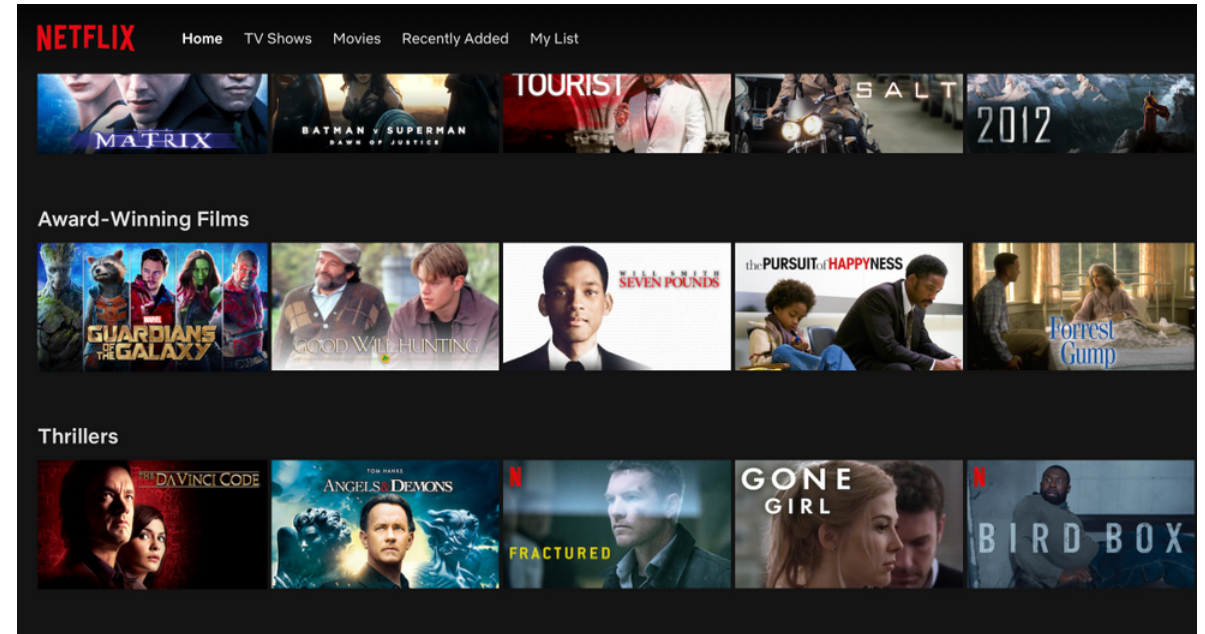
Netflix Recommender System

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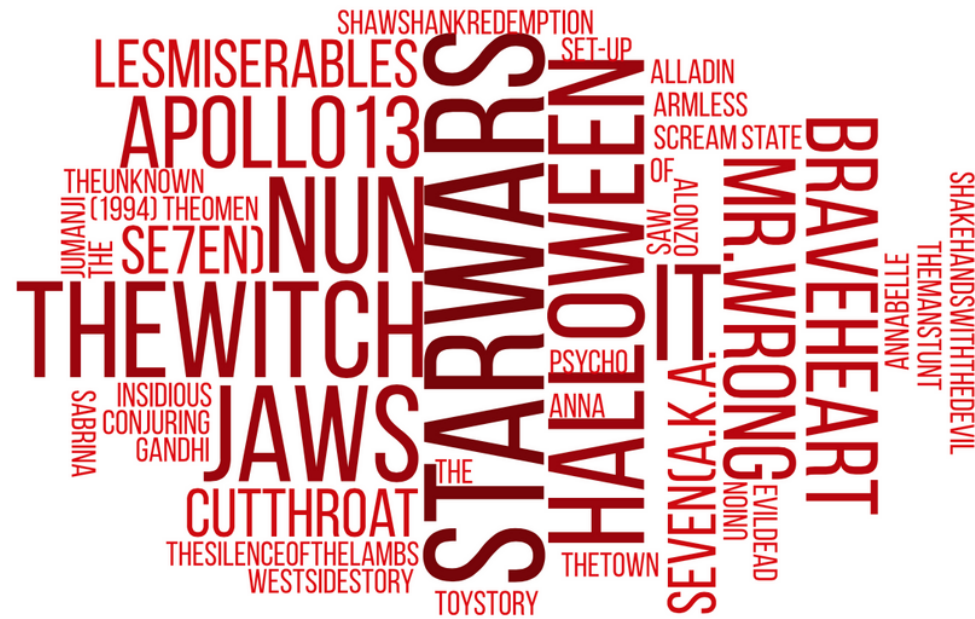
Everything is a recommendation!

Over 80% of what people watch comes from recommendations.

Recommendations are driven by **algorithms** and **machine learning**.



What is a Recommender System?

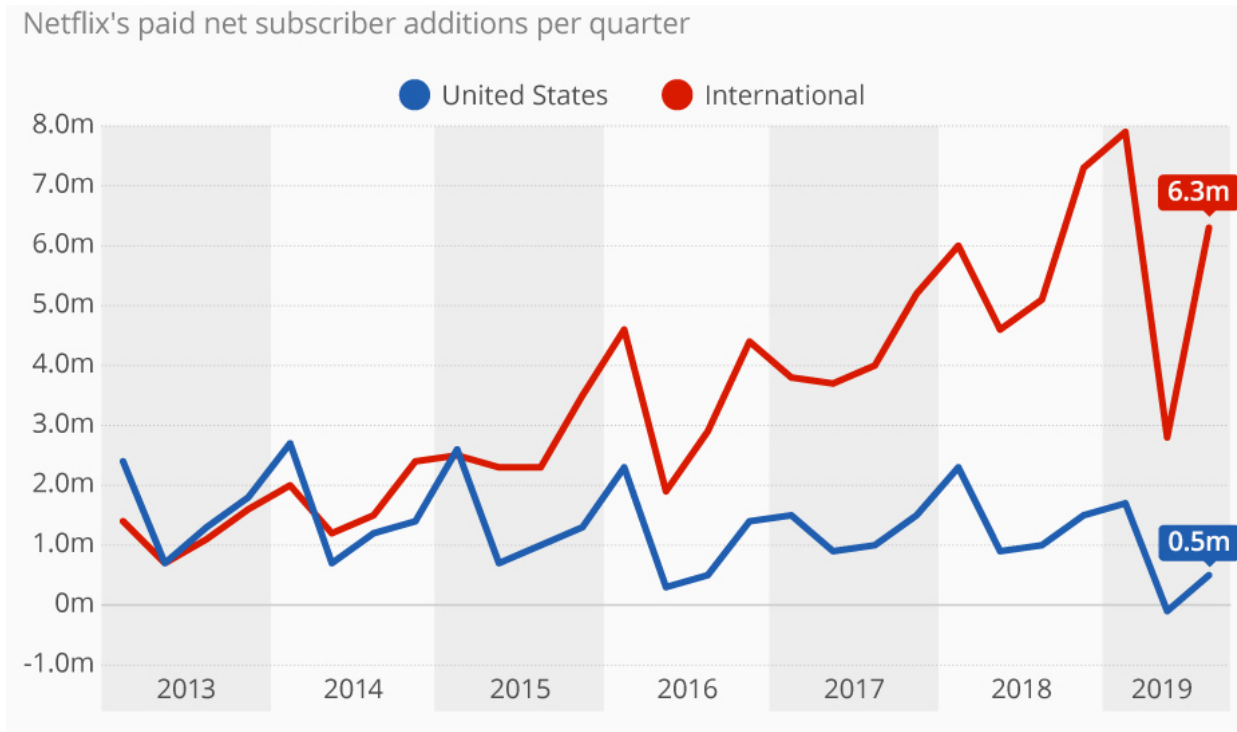


A recommender system (RS) helps users that have no time to evaluate the overwhelming, number of alternatives offered by a web site.

In their simplest form, RS recommend to their users personalized and ranked lists of items

Business Problem

Why are the Subscription rates going down?



- **The content behind in what is currently premiering**

Hulu, or Amazon have quicker rates of premiering the recent content

Content Providers moving to alternative platforms



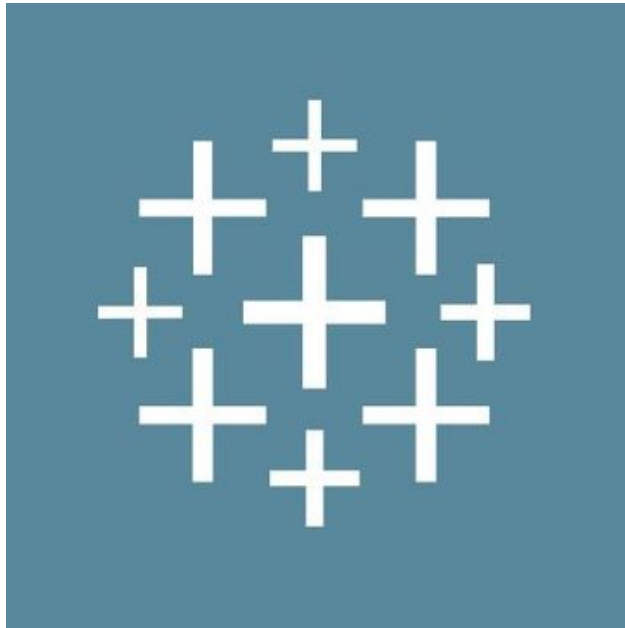
- **More competitors**

recommendation engine needs to be updated to be more personalized

Business Solution

The Prototype

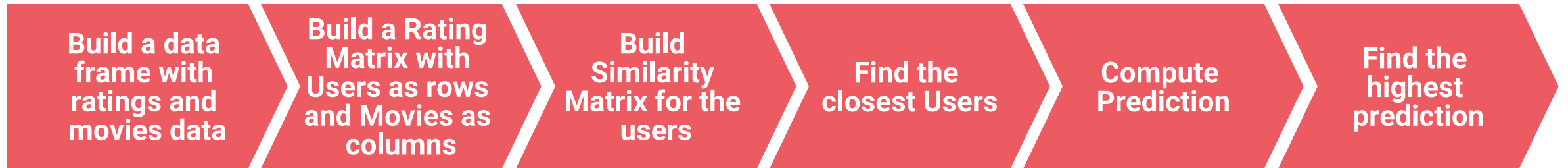
Preparing the data



- **Tableau prep**

To deal with *inconsistent* data and other *data issues*

Building the Algorithm



Build a data frame with ratings and movies data

	movieId	userId	rating	title
1	1	73302	5.0	Toy Story (1995)
2	1	113839	2.0	Toy Story (1995)
3	1	65457	2.0	Toy Story (1995)
4	1	83356	3.5	Toy Story (1995)
5	1	39527	5.0	Toy Story (1995)
6	1	68116	4.5	Toy Story (1995)
7	1	91115	5.0	Toy Story (1995)
8	1	46945	3.5	Toy Story (1995)
9	1	130425	2.5	Toy Story (1995)
10	1	25436	3.0	Toy Story (1995)

- **Create a data frame**

Merge the *ratings* and the *movies* data

Build a rating matrix with users and movies

	'burbs, The (1989)	10,000 BC (2008)	101 Dalmatians (1996)	102 Dalmatians (2000)	12 Angry Men (1957)	13 Tzameti (2005)	17 Again (2009)	2 Days in the Valley (1996)	2 Fast 2 Furious (Fast and the Furious 2, The) (2003)
8405	0.0000000	0.375	0.0	0.0000000	0	0.0	0.25	0.0000000	0.0
34576	0.0000000	0.000	0.0	0.0000000	0	0.0	0.00	0.0000000	0.0
74142	0.0000000	0.000	0.0	0.0000000	0	0.0	0.00	0.0000000	0.0
82418	0.0000000	0.000	0.0	0.0000000	0	0.0	0.00	0.0000000	0.0
83090	0.0000000	0.000	0.0	0.0000000	0	0.0	0.00	0.0000000	0.0
118205	0.3333333	0.000	0.0	0.0000000	0	0.0	0.00	0.0000000	0.0
121535	0.0000000	0.000	0.0	0.3333333	0	0.0	0.00	0.5555556	0.0
125794	0.0000000	0.000	0.5	0.0000000	0	0.5	0.00	0.3333333	0.5
131904	0.0000000	0.000	0.0	0.0000000	1	0.0	0.00	0.0000000	0.0

- **Dataframe -> Matrix**

With *Users* as rows and *Movies* as columns

Build Similarity Matrix for the users

	8405	34576	74142	82418	83090	118205	121535	125794	131904
8405	1.00000000	0.02565105	0.022947181	0.017240876	0.021111051	0.04351798	0.05207691	0.01719920	0.03757748
34576	0.02565105	1.00000000	0.047299854	0.025584419	0.02321188	0.01881706	0.02589055	0.02274442	0.02901758
74142	0.02294718	0.04729985	1.00000000	0.003504749	0.03969629	0.02264896	0.00360150	0.03238302	0.02706820
82418	0.01724088	0.02558442	0.003504749	1.00000000	0.02063901	0.02548678	0.03421702	0.02779233	0.01275883
83090	0.021111051	0.02321188	0.039696294	0.020639007	1.00000000	0.01815405	0.02862490	0.03835906	0.02316084
118205	0.04351798	0.01881706	0.022648956	0.025486775	0.01815405	1.00000000	0.05404819	0.02708391	0.03607282
121535	0.05207691	0.02589055	0.003601500	0.034217017	0.02862490	0.05404819	1.00000000	0.02439537	0.02319427
125794	0.01719920	0.02274442	0.032383022	0.027792332	0.03835906	0.02708391	0.02439537	1.00000000	0.02186883
131904	0.03757748	0.02901758	0.027068201	0.012758828	0.02316084	0.03607282	0.02319427	0.02186883	1.00000000

- User based collaborative method - Cosine similarity

Find the closest Users and build the ratings matrix

	userId		'burbs, The (1989)	102 Dalmatians (2000)	12 Angry Men (1957)	2 Days in the Valley (1996)	2012 (2009)	25th Hour (2002)	28 Days Later (2002)
1	121535								
2	118205								
3	131904								
4	34576								
5	74142								
		34576	NA	NA	NA	NA	NA	NA	0.08977868
		74142	NA	NA	NA	NA	NA	NA	NA
		118205	0.1305539	NA	NA	NA	NA	0.1740719	NA
		121535	NA	0.1041538	NA	0.1562307	0.1562307	NA	NA
		131904	NA	NA	0.1690986	NA	NA	NA	NA

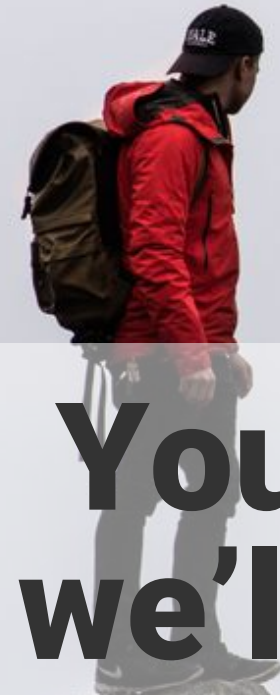
- Ratings matrix of the closest users

Compute the highest prediction

	titles
1	West Side Story (1961)
2	Set-Up, The (1949)
3	Shake Hands with the Devil (1959)
4	Shawshank Redemption, The (1994)
5	State of the Union (1948)
6	Stunt Man, The (1980)
7	Tae Guk Gi: The Brotherhood of War (Taegukgi hwinalrimyeo) (2004)
8	Town, The (2010)
9	Unknown, The (a.k.a. Alonzo the Armless) (1927)
10	Silence of the Lambs, The (1991)

- **Using weighted value**

Similarity values * ratings



**You give us 3 seconds,
we'll give you the world.**

NETFLIX

You give us three seconds...we'll give you the world

Choose a Movie

Toy Story (1995)

Choose a Movie

Toy Story (1995)

Choose a Movie

Toy Story (1995)

Rating 1-5

1.0

Rating 1-5

1.0

Rating 1-5

1.0

Choose a Movie

Toy Story (1995)

Choose a Movie

Toy Story (1995)

Rating 1-5

1.0

Rating 1-5

1.0

Submit My Ratings

Business Gain

Users: Better Personalization

**Becoming a bigger and more powerful platform
could help in winning new movies rights, subscribers**

**Netflix: Increase in loyalty from Users and Content providers,
leading to higher data and revenue generation**

**Content Providers: Better visualization of real size of audience and the
target audience for their content**

The next steps..

**Processing
time**

Improve the *processing time* and include more *ratings*

Analysis Methods

Include *regression, clustering* and other computation methods

Compute RMSEs

Finding the *least* RMSE value methods

Machine learning

Deploy methods like *gradient descent*

NETFLIX

Questions?