An In-Depth Guide to How Recommender Systems Work

builtin.com/data-science/recommender-systems

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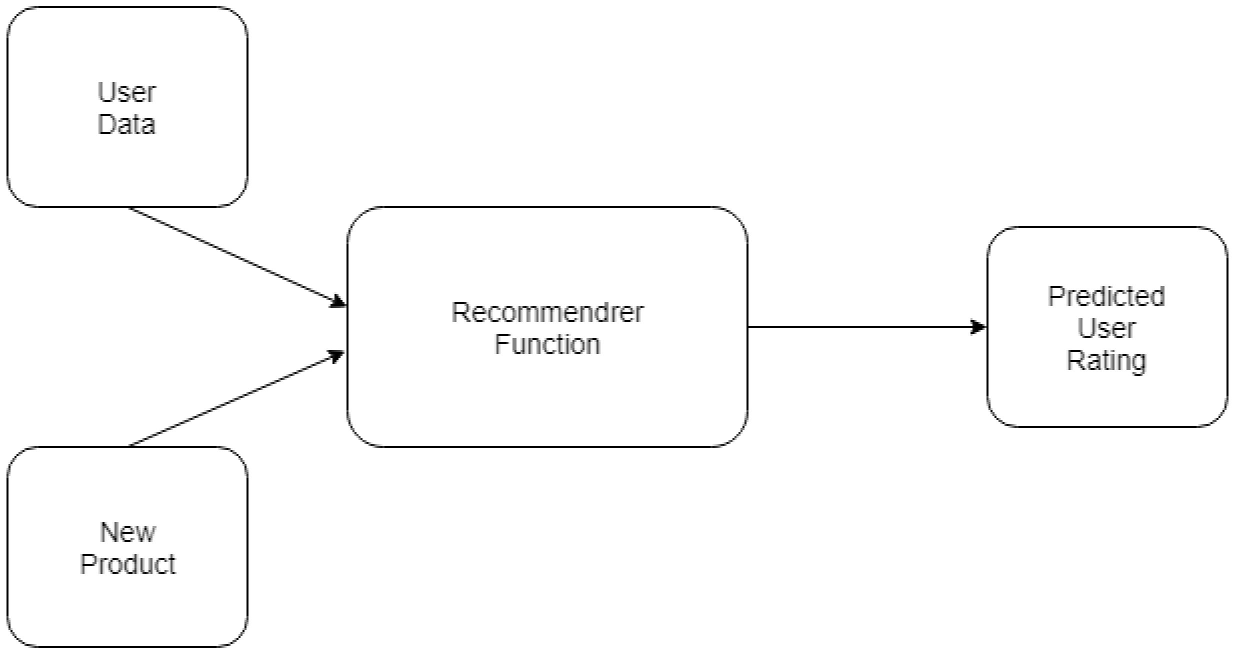
Recommender systems are machine learning systems that help users discover new product and services. Every time you shop online, a recommendation system is guiding you towards the most likely product you might purchase.

Recommender systems are an essential feature in our digital world, as users are often overwhelmed by choice and need help finding what they're looking for. This leads to happier customers and, of course, more sales. Recommender systems are like salesmen who know, based on your history and preferences, what you like.

What Are Recommender Systems?

Recommender systems are so commonplace now that many of us use them without even knowing it. Because we can't possibly look through all the products or content on a website, a recommendation system plays an important role in helping us have a better user experience, while also exposing us to more inventory we might not discover otherwise.

Some examples of recommender systems in action include product recommendations on Amazon, Netflix suggestions for movies and TV shows in your feed, recommended videos on YouTube, music on Spotify, the Facebook newsfeed and Google Ads.



Recommender Function

An important component of any of these systems is the recommender function, which takes information about the user and predicts the rating that user might assign to a product, for example. Predicting user ratings, even before the user has actually provided one, makes recommender systems a powerful tool.

How Do Recommender Systems Work?

Understanding Relationships

Relationships provide recommender systems with tremendous insight, as well as an understanding of customers. There are three main types that occur:

User-Product Relationship

The user-product relationship occurs when some users have an affinity or preference towards specific products that they need. For example, a cricket player might have a preference for cricket-related items, thus the e-commerce website will build a user-product relation of player->cricket.

Product-Product Relationship

Product-product relationships occur when items are similar in nature, either by appearance or description. Some examples include books or music of the same genre, dishes from the same cuisine, or news articles from a particular event.

User-User Relationship

User-user relationships occur when some customers have similar taste with respect to a particular product or service. Examples include mutual friends, similar backgrounds, similar age, etc.

Data & REcommender Systems

In addition to relationships, recommender systems utilize the following kinds of data:

User Behavior Data

Users behavior data is useful information about the engagement of the user on the product. It can be collected from ratings, clicks and purchase history.

User Demographic Data

User demographic information is related to the user’s personal information such as age, education, income and location.

Product Attribute Data

Product attribute data is information related to the product itself such as genre in case of books, cast in case of movies, cuisine in case of food.

How do we provide data for Recommender SystemS?

Data can be provided in a variety of ways. There are two particularly important methods, explicit and implicit rating.

Explicit Ratings

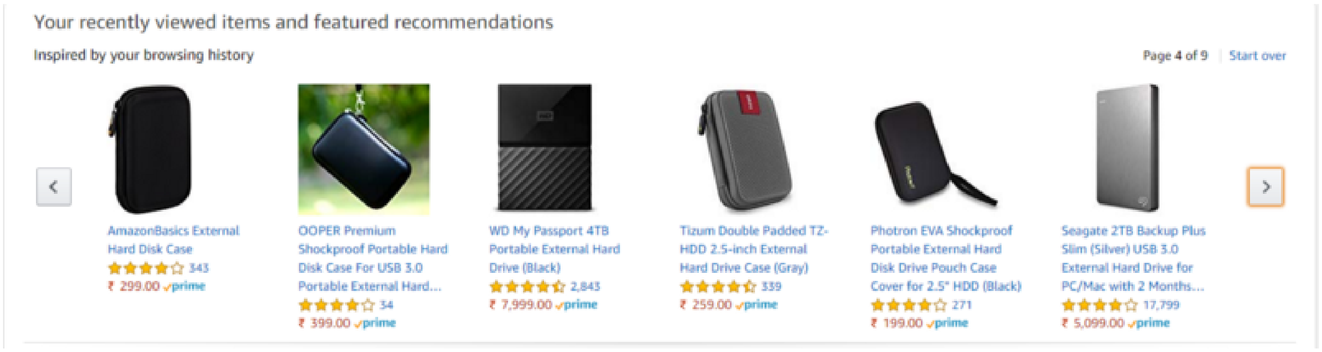
Explicit ratings are provided by the user. They infer the user’s preference. Examples include star ratings, reviews, feedback, likes and following. Since users don't always rate products, explicit ratings can be hard to get.

Implicit Ratings

Implicit ratings are provided when users interact with the item. They infer a user’s behavior and are easy to get as users are subconsciously clicking. Examples include clicks, views and purchases. (Note: Views and purchases can be a better entity to recommend as users will have spent time and money on what is most crucial for them.)

Product Similarity (Item-Item Filtering)

Product similarity is the most useful system for suggesting products based on how much the user would like the product. If the user is browsing or searching for a particular product, they can be shown similar products. Users often expect to find products they want quickly and move on if they have a hard time finding the relevant product. When the user clicks on one product we can show another similar product, or if the user buys the product we can email the user advertisements or coupons based on a similar product. Product similarity is particularly useful when we don't know much about the user yet, but we do know what products they're viewing.


Your recently viewed items and featured recommendations
Inspired by your browsing history
Page 4 of 9
Start over
AmazonBasics External Hard Disk Case 343 ₹ 299.00 prime
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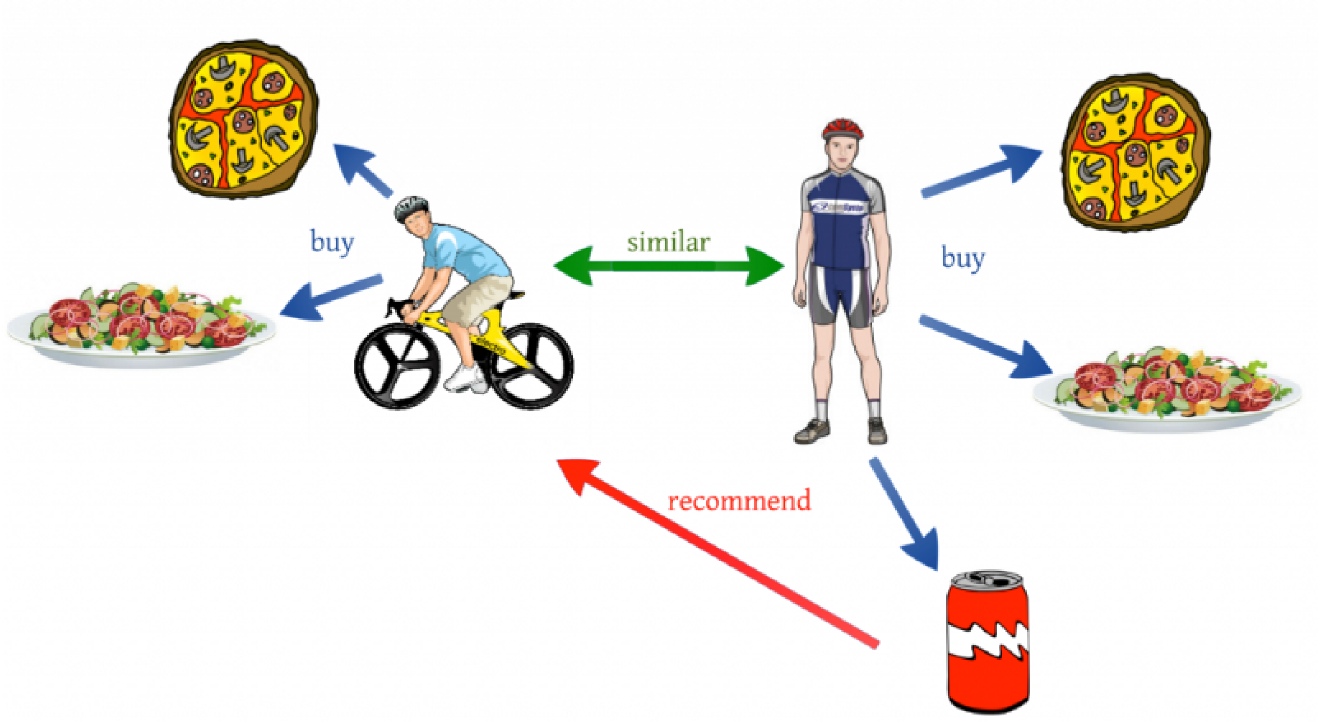
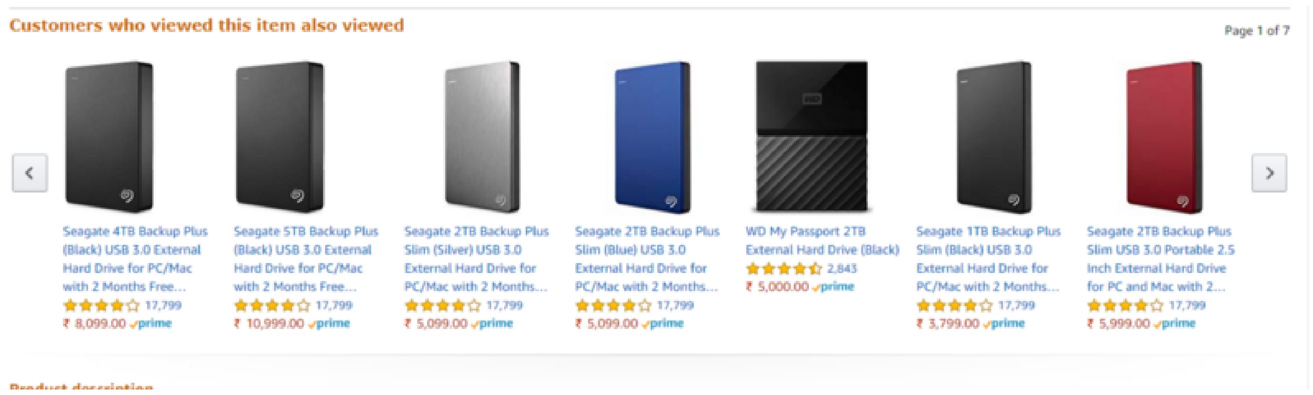
Amazon suggesting similar products.

User Similarity (User-User Filtering)

User similarity is for checking the difference between the similarity of two users. If two users have similar preferences for a product we can assume they have similar interests. It's like a friend recommending a product.



User Similarity


Customers who viewed this item also viewed

Page 1 of 7

Seagate 4TB Backup Plus (Black) USB 3.0 External Hard Drive for PC/Mac with 2 Months Free...
★★★★☆ 17,799
₹ 8,099.00 ✓prime

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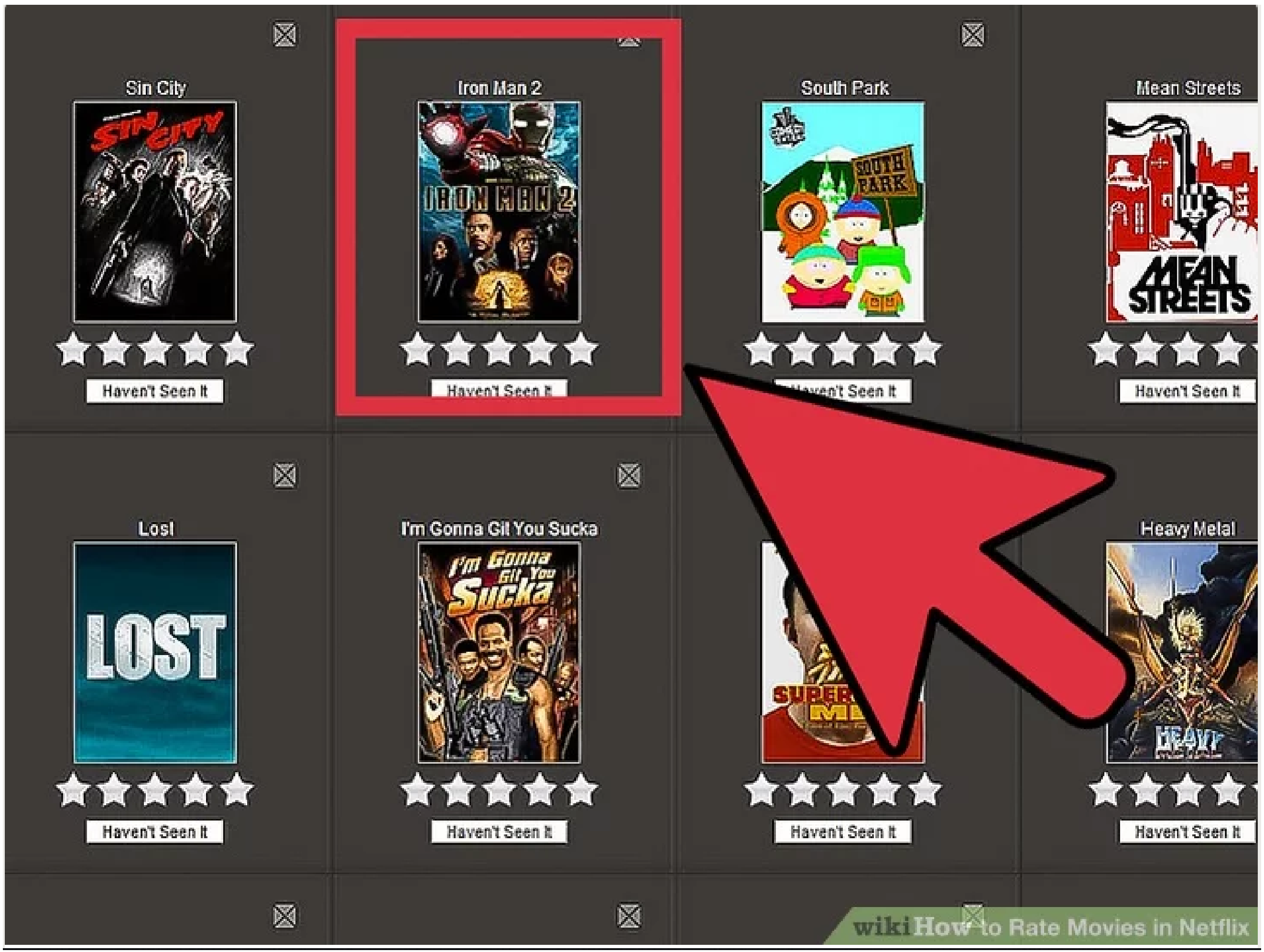
★★★★☆ 17,799
₹ 5,999.00 ✓prime

Amazon Customer Similarity

One shortcoming of user similarity, however, is that it requires all the user data to suggest products. It's called a **cold start problem** because beginning the recommendation process requires previous data from users. A newly launched e-commerce website, for example, suffers from the cold start problem because it doesn't have a large number of users.

Product similarity doesn't have this problem because it just requires product information and the user's preference. Netflix, for example, avoids this issue by asking users their likes when starting a new subscription.



Netflix It

Similarity Measures

Similarity is measured using the distance metric. Nearest points are the most similar and farthest points are the least relevant. The similarity is subjective and is highly dependent on the domain and application. For example, two movies are similar because of genre or length or cast. Care should be taken when calculating distance across dimensions/features that are unrelated. The relative values of each element must be normalized, or one feature could end up dominating the distance calculation.

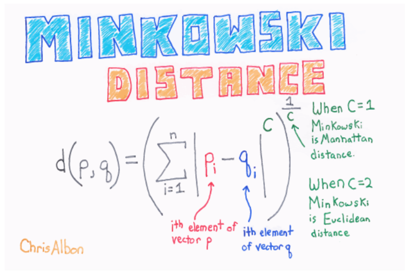
Minkowski Distance: When the dimension of a data point is numeric, the general form is called the **Minkowski distance.**

It is a generic distance metric where Manhattan(r=1) or Euclidean(r=2) distance measures are generalizations of it.

Manhattan Distance: The distance between two points measured along axes at right angles.

$$d(x,y) = (\sum_{i}^{n}(|x_i - y_i|)^q)^{\frac{1}{q}}$$

Minkowski Distance


MINKOWSKI DISTANCE
$d(p,q)=\left(\sum_{i=1}^{n}|p_i-q_i|^C\right)^{\frac{1}{C}}$
When C=1 Minkowski is Manhattan distance.
When C=2 Minkowski is Euclidean distance
ith element of vector p
ith element of vector q
ChrisAlbon

Minkowski Distance

$$d(x,y) = \sum_{i}^{n}|x_i - y_i|$$

Manhattan Distance

MANHATTAN DISTANCE
$\sum_{i=1}^{n}|p_i-q_i|$
Element of a vector
Element of a vector
Imagine you are in Manhattan and can only travel North, South, East, and West.
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L1 NORM
(Manhattan Norm)
Also Called "Taxicab Norm"
$\|x\|_1=\sum_{i=1}^{n}|x_i|$
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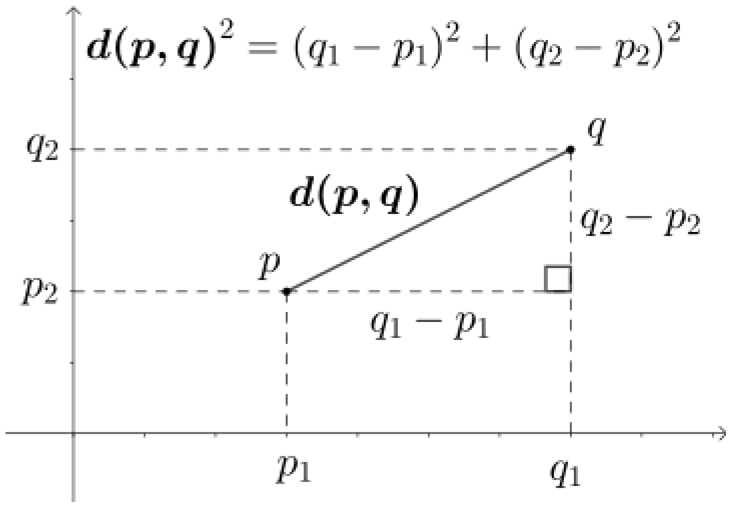
Manhattan Distance

It is also called rectilinear distance, L1-distance/L1-norm, Minkowski's L1- distance, city block distance and taxi cab distance.

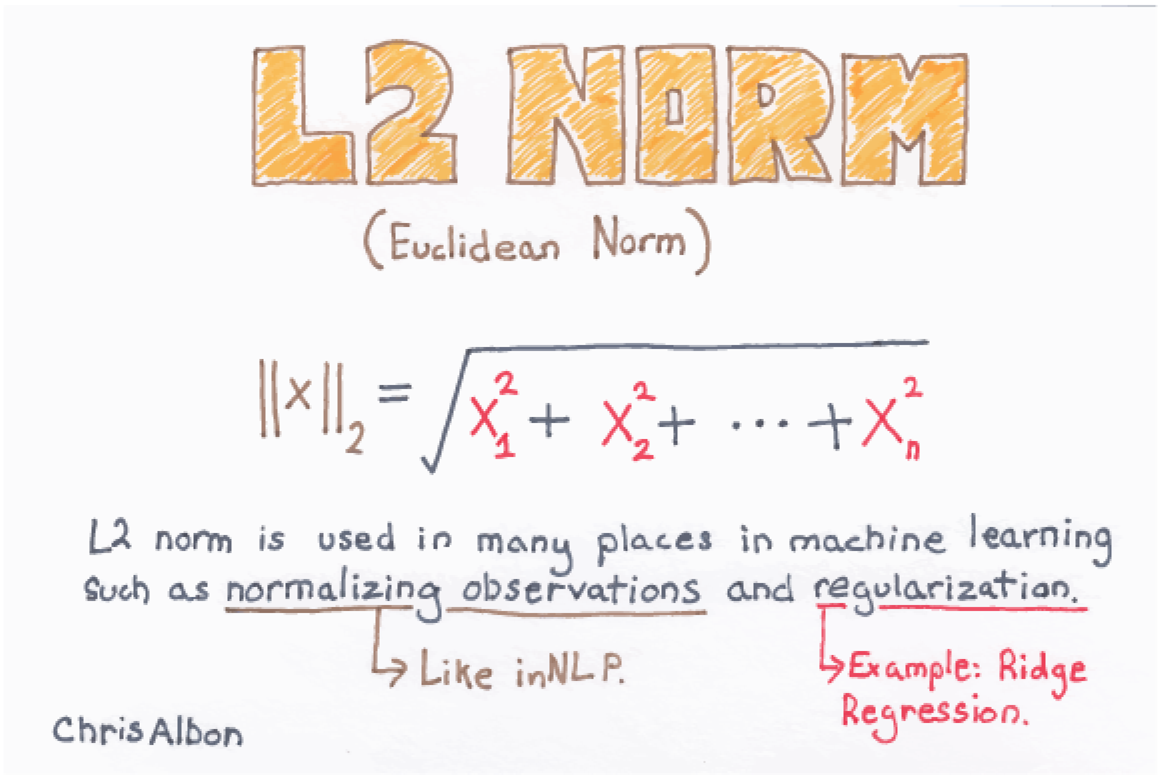
Euclidean Distance: The square root of the sum of squares of the difference between the coordinates and is given by Pythagorean theorem.



Euclidean Distance (General)

$$d(x,y) = \sqrt{\sum_{i}^{n}(x_i - y_i)^2}$$

Euclidean Distance



L2 NORM

(Euclidean Norm)

$$\|x\|_2 = \sqrt{x_1^2 + x_2^2 + \cdots + x_n^2}$$

L2 norm is used in many places in machine learning such as normalizing observations and regularization.

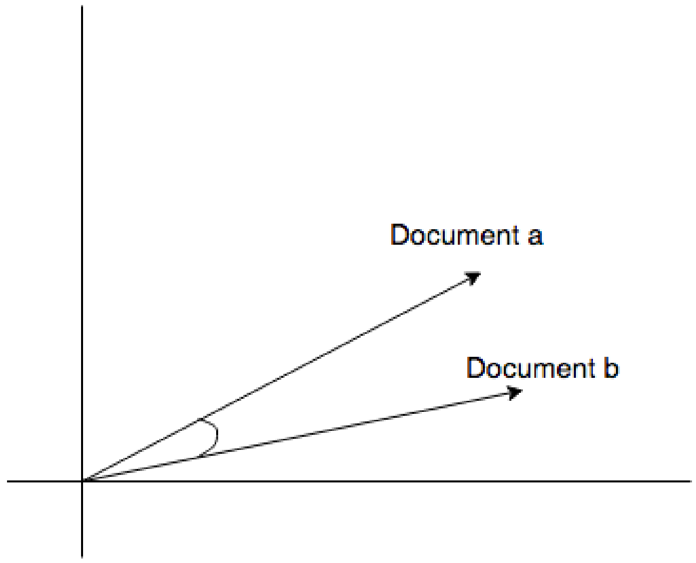
↳ Like in NLP.

↳ Example: Ridge Regression.

Chris Albon

It is also called as L2 norm or ruler distance. In general, default distance is considered Euclidean distance.

Cosine Similarity: Measures the cosine of the angle between two vectors. It is a judgment of orientation rather than magnitude between two vectors with respect to the origin. The cosine of 0 degrees is 1 which means the data points are similar and cosine of 90 degrees is 0 which means data points are dissimilar.



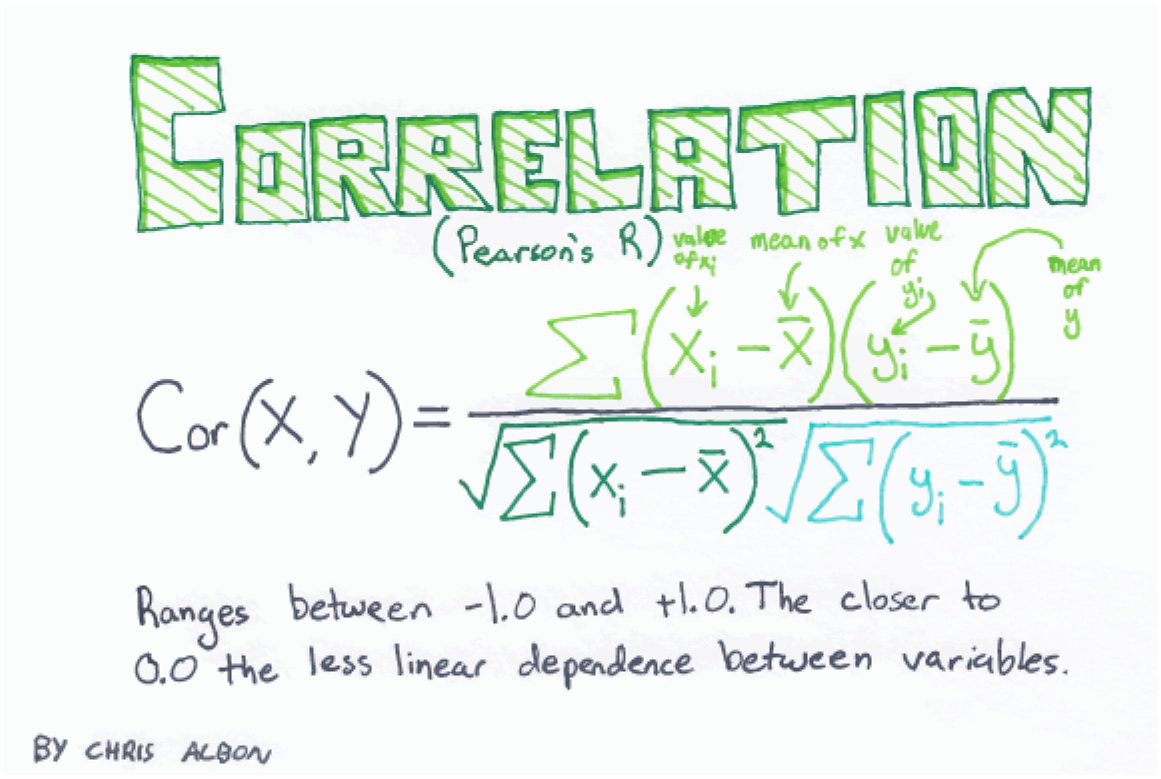
$$sim(a,b) = cos\theta = \frac{\vec{a}.\vec{b}}{\| \vec{a} \| \| \vec{b} \|}$$

Cosine similarity is subjective to the domain and application and is not an actual distance metric. For example data points [1,2] and [100,200], are shown as similar with cosine similarity, whereas the Euclidean distance measure shows them as being far away from each other (i.e., they are dissimilar).

Pearson Coefficient: It is a measure of correlation between two random variables and ranges between [-1, 1].

$$r = \frac{\sum (x-\bar{x})(y-\bar{y})}{\sqrt{\sum (x-\bar{x})^2 \sum (y-\bar{y})^2}}$$

Pearson Correlation Coefficient


CORRELATION
(Pearson's R)
value of x_i
mean of x
value of y_i
mean of y
$Cor(X,Y) = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2} \sqrt{\sum (y_i - \bar{y})^2}}$
Ranges between -1.0 and +1.0. The closer to 0.0 the less linear dependence between variables.
BY CHRIS ALBON

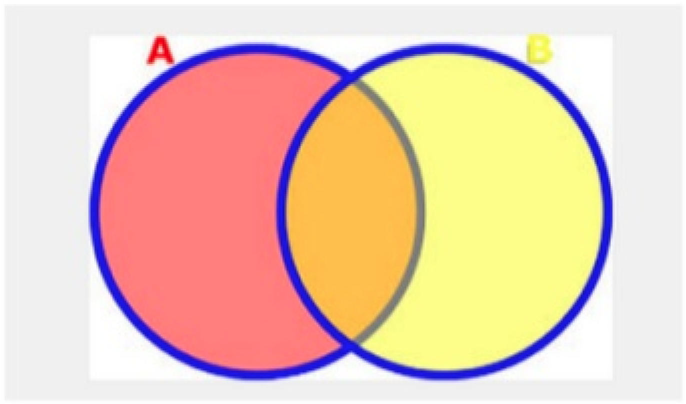
Pearson Correlation Coefficient

If the value is 1, it is a positive correlation, and if -1 then there is a negative correlation among variables.

> *Correlation does not imply causation*

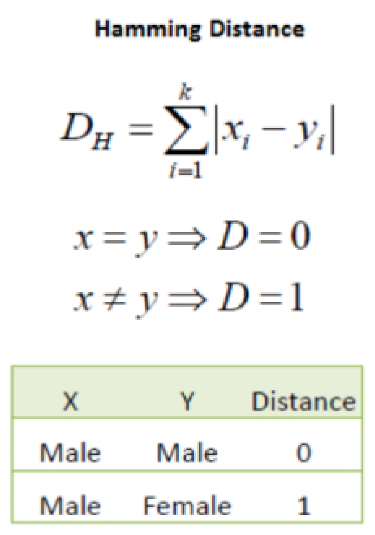
Jaccard Similarity: In the other similarity metrics, we discussed some ways to find the similarity between objects, where the objects are points or vectors. We use Jaccard similarity to find similarities between finite sets. It is defined as the cardinality of the intersection of sets divided by the cardinality of the union of the sample sets.

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}.$$



Jaccard Similarity

Hamming Distance: All the similarities we discussed were distance measures for continuous variables. In the case of categorical variables, Hamming distance must be used.



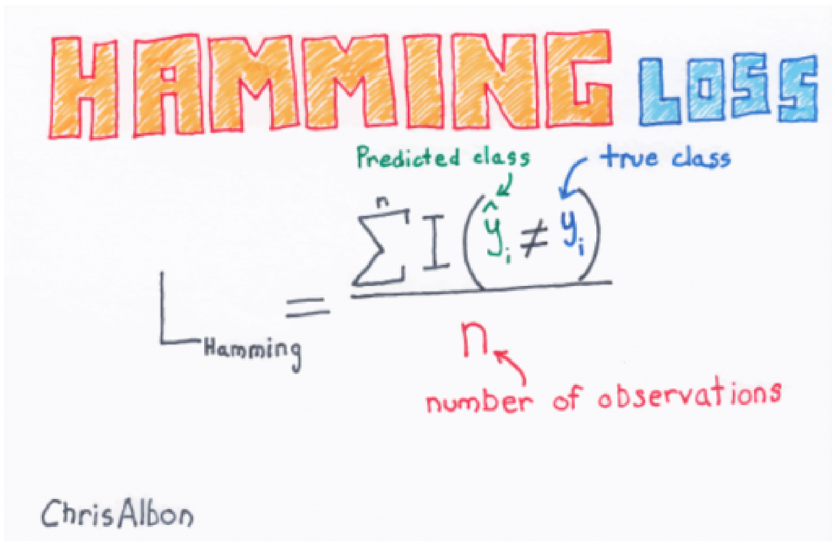
Hamming Distance

$$D_H = \sum_{i=1}^{k} |x_i - y_i|$$

$$x = y \Rightarrow D = 0$$

$$x \neq y \Rightarrow D = 1$$

X	Y	Distance
Male	Male	0
Male	Female	1



Hamming Distance

If the value (x) and the value (y) are the same, the distance D will be equal to 0, otherwise D=1. If we have data that is binary (i.e., classification), one would go for Hamming distance. The lower value means high similarity and higher value means less similarity between variables. For example, the Hamming distance between 1101111 and 1001001 is 3, while the Hamming distance between 'batman' and 'antman' is 2

Approaches to Content-Based Recommender Systems

Content-based recommendation systems uses their knowledge about each product to recommend new ones. Recommendations are based on attributes of the item. Content-based recommender systems work well when descriptive data on the content is provided beforehand. "Similarity" is measured against product attributes.

Suppose I watch a movie in a particular genre, then I will be recommended movies within that specific genre. The movie's attributes, like title, year of release, director and cast, are also helpful in identifying similar movie content.

Approach 1: Using Rated Content to Recommend

In this approach contents of the product are already rated and based on the user's preference, then a rating is predicted for a similar product. We'll use movie recommendations as an example.

User Ratings

User\Movies	Interstellar	Inception	The Shining	Alien
Clark	5 stars			
Bruce			5 stars	
Tony				
Steve		2 stars		1 star

In the example above, Clark and Bruce have given five-star ratings to the movies "Interstellar" and "The Shining," clearly indicating a preference for these films. For Tony, who has rated nothing, and Steve who has provided only low ratings, it's more difficult to discern their preferences.

Movie Attributes

Movie\Attributes	Science	Adventure	Horror	Mystery
Interstellar	5	4	1	2
Inception	5	3	1	2
The Shining	1	2	5	4
Alien	2	3	5	3

In the table above, note that "Interstellar" and "Inception" received 5s in the science category, whereas "The Shining" and "Alien" get the highest marks under the horror genre.

Predicted User Rating

User\Movies	Interstellar	Inception	The Shining	Alien
Clark	5 stars	5 stars		
Bruce			5 stars	5 stars
Tony				
Steve		2 stars		1 star

"Inception" is suggested for Clark because he liked "Interstellar" and the movies share similar attributes. "Alien" is suggested to Bruce because he liked "The Shining," which is in the horror genre.

Advantages: Works even when a product has no user reviews.

Disadvantages: Requires descriptive data of all content to recommend, which is time consuming. It's also difficult to implement on large product databases as user's have different opinions about each item.

Approach 2: Recommendation through Description of the Content

This approach uses the description of the item to make recommendations. The description goes deeper into the product details, like title, summary, tag lines, genre, etc., and it provides much more information about the item. The format of these details are in text format(string) and it's important to convert this into numbers to easily calculate for similarity.

Term Frequency-Inverse Document Frequency (TF-IDF)

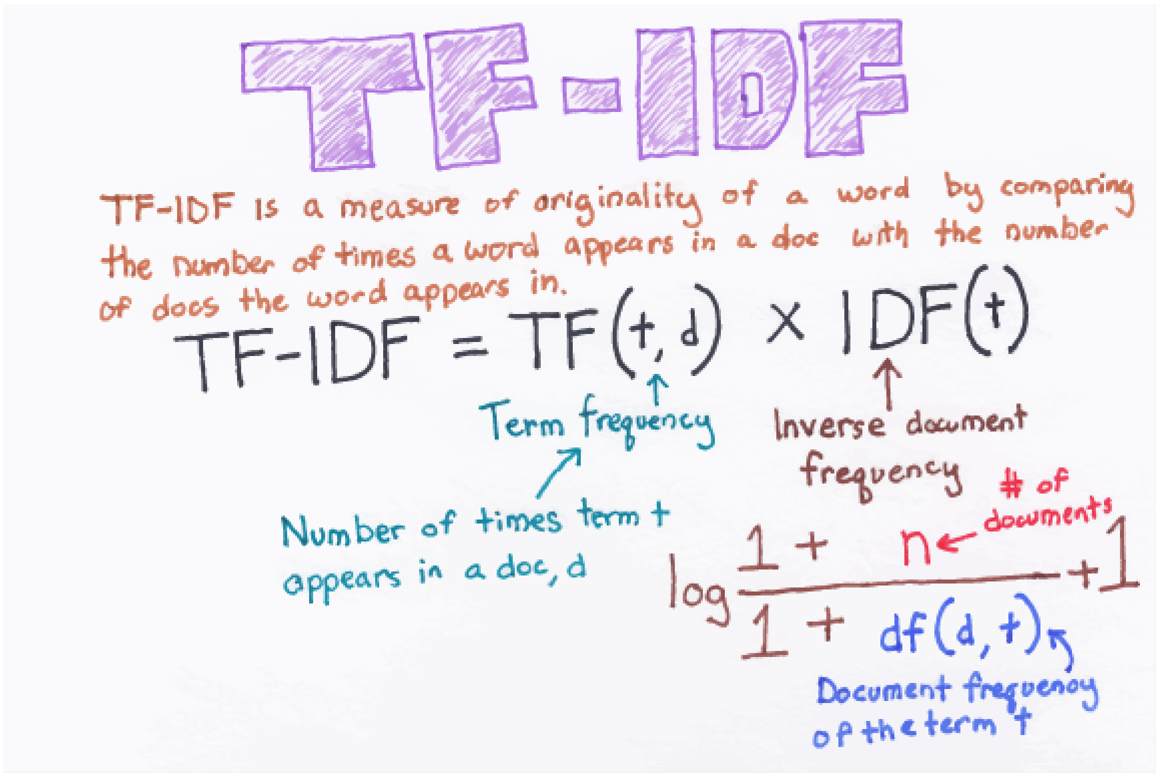
TF-IDF is used in information retrieval for feature extraction purposes and it is a sub-area of natural language processing (NLP).

Term Frequency: Frequency of the word in the current document to the total number of words in the document. It signifies the occurrence of the word in a document and gives higher weight when the frequency is more, so it is divided by document length to normalize.

$$\mathrm{Tf}(t) = \frac{\text{Frequency occurence of term t in document}}{\text{Total number of terms in document}}$$

Inverse Document Frequency: Total number of documents to the frequency occurrence of documents containing the word. It signifies the rarity of the word — the less the word occurs in the document, the IDF increases. It helps in giving a higher score to rare terms in the documents.

$$\text{Idf}(t) = log_{10}\left(\frac{\text{Total Number of documents}}{\text{Number of documents containing term t}}\right)$$


TF-IDF
TF-IDF is a measure of originality of a word by comparing the number of times a word appears in a doc with the number of docs the word appears in.
TF-IDF = TF(t, d) × IDF(t)
Term frequency
Number of times term t appears in a doc, d
Inverse document frequency
# of documents
log (1 + n) / (1 + df(d, t)) + 1
Document frequency of the term t

TF-IDF

In the end, TF-IDF is a measure used to evaluate how important a word is to a document in a document corpus. The importance of the word increases proportionally to the number of times a word appears in the document but is offset by the frequency of the word in the corpus.

Example for TF-IDF

Consider a document containing 100 words wherein the word "odyssey" appears three times. The term frequency for odyssey is then (3 / 100) = 0.03. Now, assume we have 10 lakh documents and the word "odyssey" appears in 1,000 of these. The inverse document frequency is calculated as log(10,00,000 / 1,000) = 3. Thus, the TF-IDF weight for Odyssey is 0.03 * 3= 0.09.

Collaborative Filtering Recommender

Collaborative filtering recommender makes suggestions based on how users rated in the past and not based on the product themselves. It only knows how other customers rated the product. “Similarity” is measured against the similarity of users.

Josie
Josie bought a toaster and a mixer
Suzie
Suize bought a cheese grader
Steve
Steve bought a toaster
What else might Steve buy?

Collaborative Filtering Recommender

Going back to our movie example earlier, we can illustrate this technique.

User Rating

User\Movies	Interstellar	Inception	The Shining	Alien
Clark	5 stars	2 stars	1 star	
Bruce	1 star	5 stars		1 star
Tony	5 star	3 stars	1 star	5 stars
Steve	1 star	5 stars	5 stars	1 star

As we can see from above Clark and Tony have similar tastes as they rated movies similarly.

Predicted User Rating

User\Movies	Interstellar	Inception	The Shining	Alien
Clark	5 stars	2 stars	1 star	5 stars
Bruce	1 star	5 stars	5 stars	1 star
Tony	5 stars	3 stars	1 star	5 stars
Steve	1 star	5 stars	5 stars	1 star

Clark is recommended "Alien" from Tony because of their similarity in rating. Bruce was suggested "The Shining" because Steve rated it highly.

Advantages:

No requirement for product descriptions.

Disadvantages:

- Can’t recommend item if no user reviews exist (suffers from the cold start problem).
- Difficult to recommend new users and is inclined to favor popular products with lots of reviews.
- Suffers from a sparsity problem as user will review only selected items.
- Faces the "gray sheep problem" (i.e., useful predictions cannot be made due to sparsity).
- Difficult to recommend new releases since they have less reviews.

Singular Value Decomposition (SVD)

Most collaborative recommender systems perform poorly when dimensions in data increases (i.e., they suffer from the curse of dimensionality). It is a good idea to reduce the number of features while retaining the maximum amount of information. Reducing the features is called dimensionality reduction. Often while reducing we can get a useful part of the data, that is hidden correlation (latent factors) and remove redundant parts. There are many dimensionality reduction algorithms such as principal component analysis (PCA) and linear discriminant analysis (LDA), but SVD is used mostly in the case of recommender systems. SVD uses matrix factorization to decompose matrix.

$$A = U\Sigma V^T$$

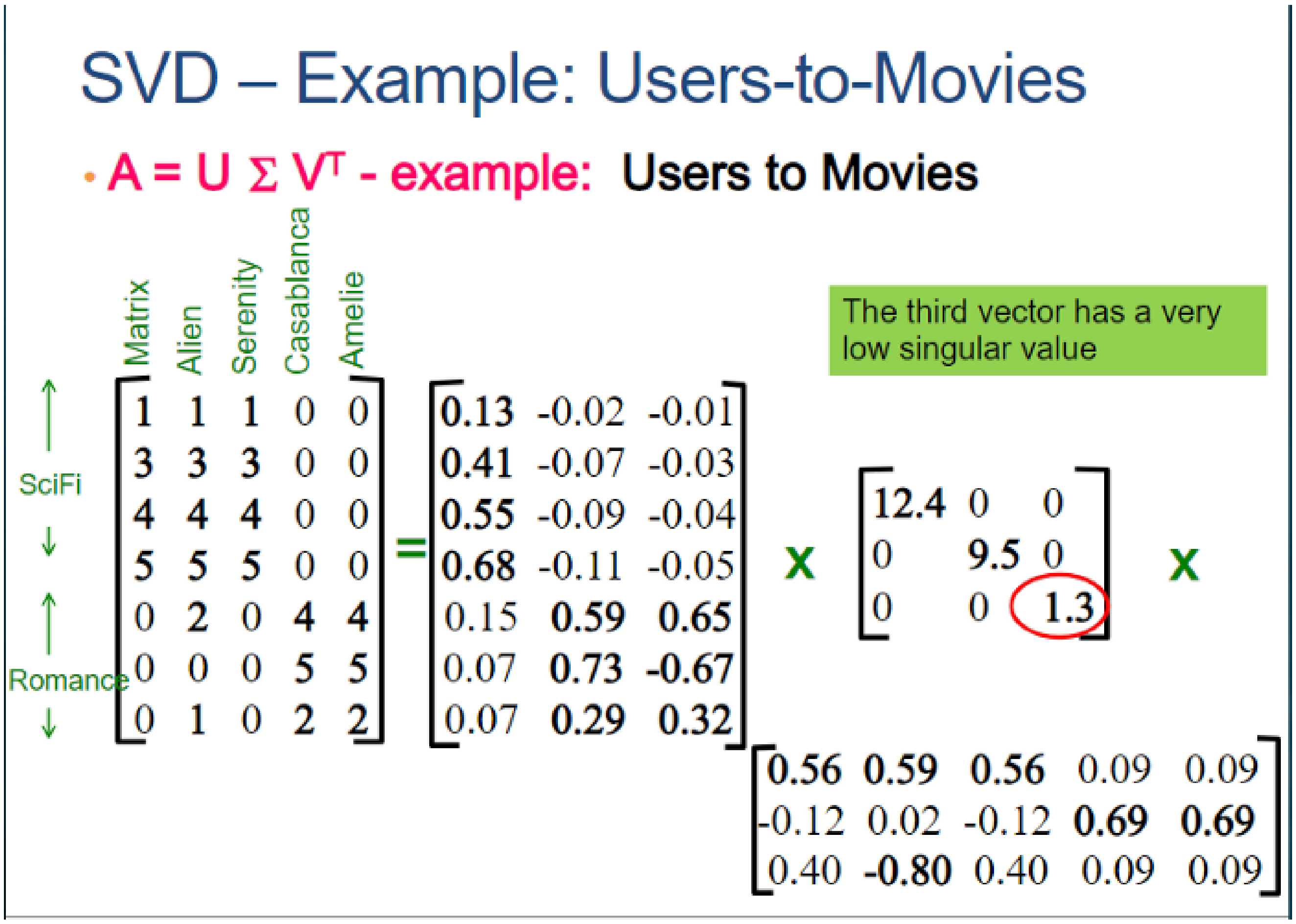
In the case above, A matrix(m*n) can be decomposed into U(m*m) orthogonal matrix, Σ(m*n) non-negative diagonal matrix, and V (n*n) orthogonal matrix

Uis also referred to as the left singular vectors, Σ as singular values, and V as right singular vectors

$$U^T U = V^T V = I$$

Orthogonal Matrix

Let’s take the example of movies rated by users in matrix A:



SVD – Example: Users-to-Movies

- A = U Σ V^T - example: **Users to Movies**

The third vector has a very low singular value

$$\begin{array}{c|ccccc} & \text{Matrix} & \text{Alien} & \text{Serenity} & \text{Casablanca} & \text{Amelie} \\ \hline \uparrow & 1 & 1 & 1 & 0 & 0 \\ \text{SciFi} & 3 & 3 & 3 & 0 & 0 \\ & 4 & 4 & 4 & 0 & 0 \\ \downarrow & 5 & 5 & 5 & 0 & 0 \\ \uparrow & 0 & 2 & 0 & 4 & 4 \\ \text{Romance} & 0 & 0 & 0 & 5 & 5 \\ \downarrow & 0 & 1 & 0 & 2 & 2 \end{array} = \begin{bmatrix} \mathbf{0.13} & -0.02 & -0.01 \\ \mathbf{0.41} & -0.07 & -0.03 \\ \mathbf{0.55} & -0.09 & -0.04 \\ \mathbf{0.68} & -0.11 & -0.05 \\ 0.15 & \mathbf{0.59} & \mathbf{0.65} \\ 0.07 & \mathbf{0.73} & \mathbf{-0.67} \\ 0.07 & \mathbf{0.29} & \mathbf{0.32} \end{bmatrix} \times \begin{bmatrix} 12.4 & 0 & 0 \\ 0 & 9.5 & 0 \\ 0 & 0 & 1.3 \end{bmatrix} \times \begin{bmatrix} \mathbf{0.56} & \mathbf{0.59} & \mathbf{0.56} & 0.09 & 0.09 \\ -0.12 & 0.02 & -0.12 & \mathbf{0.69} & \mathbf{0.69} \\ 0.40 & \mathbf{-0.80} & 0.40 & 0.09 & 0.09 \end{bmatrix}$$

For U it shows user’s similarity to movie genre, so the first column of U represents weights that would match each user’s preference to the science fiction category. We can see that the fourth user rates the sci-fi category highly. While the second column of U represents weights that match each user’s preference to the romance category. We can see that the sixth user rates the romance category highly. For the third column, we need to look at the Σ value given.

For Σ, the first diagonal entry represents the weight (strength) of the sci-fi category (12.4) and the second diagonal entry represents the weight (strength) of the romance category (9.5). And as for the third diagonal entry, it is considered noise because the value is lower compared to other diagonal entries.

For V, the columns show the similarity of movies to a category. So, we can see from the first column of V that the first movie belongs to the sci-fi (0.56) category. Similarly, since the third row is discarded as noise the second movie also belongs to the sci-fi category.

After eliminating the third column from U, third row and third column from Σ, and third row, we get the below matrices.

$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 3 & 3 & 3 & 0 & 0 \\ 4 & 4 & 4 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 2 & 0 & 4 & 4 \\ 0 & 0 & 0 & 5 & 5 \\ 0 & 1 & 0 & 2 & 2 \end{bmatrix} \approx \begin{bmatrix} 0.13 & -0.02 \\ 0.41 & -0.07 \\ 0.55 & -0.09 \\ 0.68 & -0.11 \\ 0.15 & 0.59 \\ 0.07 & 0.73 \\ 0.07 & 0.29 \end{bmatrix} \times \begin{bmatrix} 12.4 & 0 \\ 0 & 9.5 \end{bmatrix} \times \begin{bmatrix} 0.56 & 0.59 & 0.56 & 0.09 & 0.09 \\ -0.12 & 0.02 & -0.12 & 0.69 & 0.69 \end{bmatrix}$$

We have reduced the initial UΣV dimension, so to check if we've lost any information we need to multiply all three matrices.

$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 3 & 3 & 3 & 0 & 0 \\ 4 & 4 & 4 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 2 & 0 & 4 & 4 \\ 0 & 0 & 0 & 5 & 5 \\ 0 & 1 & 0 & 2 & 2 \end{bmatrix} \approx \begin{bmatrix} 0.92 & 0.95 & 0.92 & 0.01 & 0.01 \\ 2.91 & 3.01 & 2.91 & -0.01 & -0.01 \\ 3.90 & 4.04 & 3.90 & 0.01 & 0.01 \\ 4.82 & 5.00 & 4.82 & 0.03 & 0.03 \\ 0.70 & 0.53 & 0.70 & 4.11 & 4.11 \\ -0.69 & 1.34 & -0.69 & 4.78 & 4.78 \\ 0.32 & 0.23 & 0.32 & 2.01 & 2.01 \end{bmatrix}$$

After multiplying we see there is very little loss of information as the elements of a matrix are very similar. It is similarly used for predicting missing values among ratings and suggesting high ratings to the user.

So this is how we decompose a matrix without losing much of the important data and It helps to analyze and acquire important information concerning the matrix data.

References: Data Mining Lecture 7: Dimensionality Reduction PCA—SVD

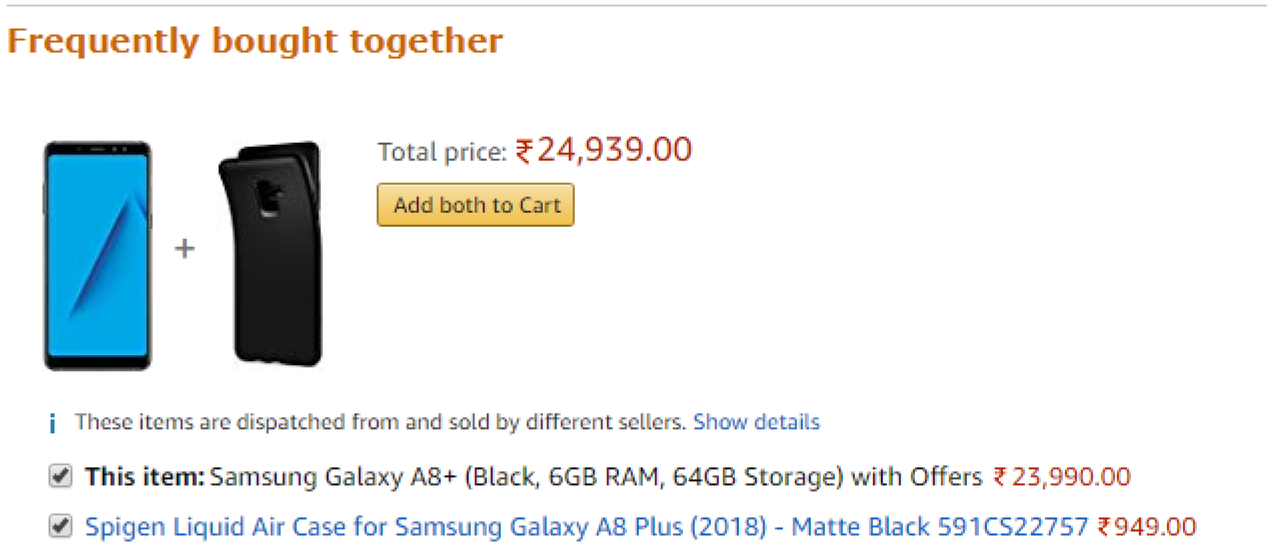
Hybrid Recommender

Hybrid recommender is a recommender that leverages both content and collaborative data for suggestions. In a system, first the content recommender takes place as no user data is present, then after using the system the user preferences with similar users are established.

For example, Netflix deploys hybrid recommender on a large scale. When a new user subscribes to their service they are required to rate content already seen or rate particular genres. Once the user begins using the service, collaborative filtering is used and similar content is suggested to the customer.

Association Rules Learning

Association rules learning is used for recommending complementary products. It helps in associating one product with another product and tries to answer which products are associated with one another. It is mostly used in e-commerce as user's tend to buy a product paired with the main product.


Frequently bought together

Total price: ₹24,939.00

Add both to Cart

These items are dispatched from and sold by different sellers. Show details

☑ **This item:** Samsung Galaxy A8+ (Black, 6GB RAM, 64GB Storage) with Offers ₹23,990.00

☑ Spigen Liquid Air Case for Samsung Galaxy A8 Plus (2018) - Matte Black 591CS22757 ₹949.00

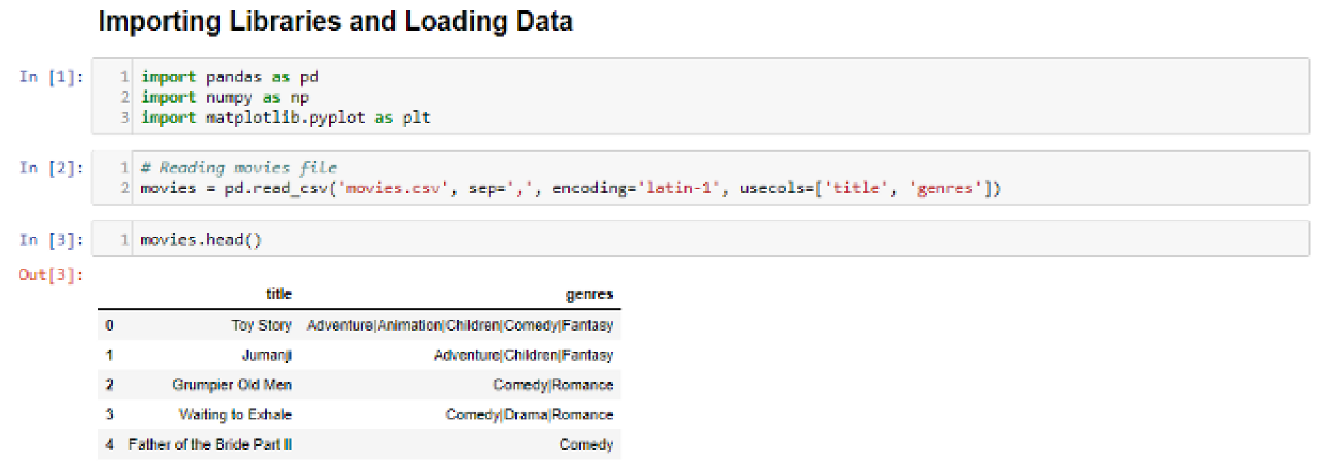
Amazon's Associative Recommendation

For example, cases are complementary to smartphones so it is recommended to the user.

Code:

Content filtering:

Basic Content-Based Filtering Implementation



Importing Libraries and Loading Data

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

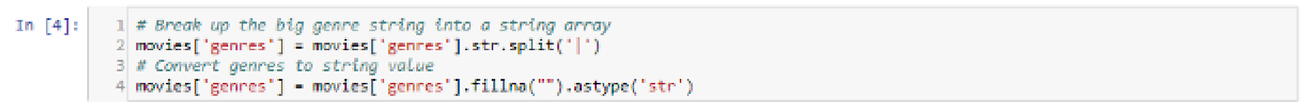
In [2]:
```python
# Reading movies file
movies = pd.read_csv('movies.csv', sep=',', encoding='latin-1', usecols=['title', 'genres'])
```

In [3]:
```python
movies.head()
```

Out[3]:

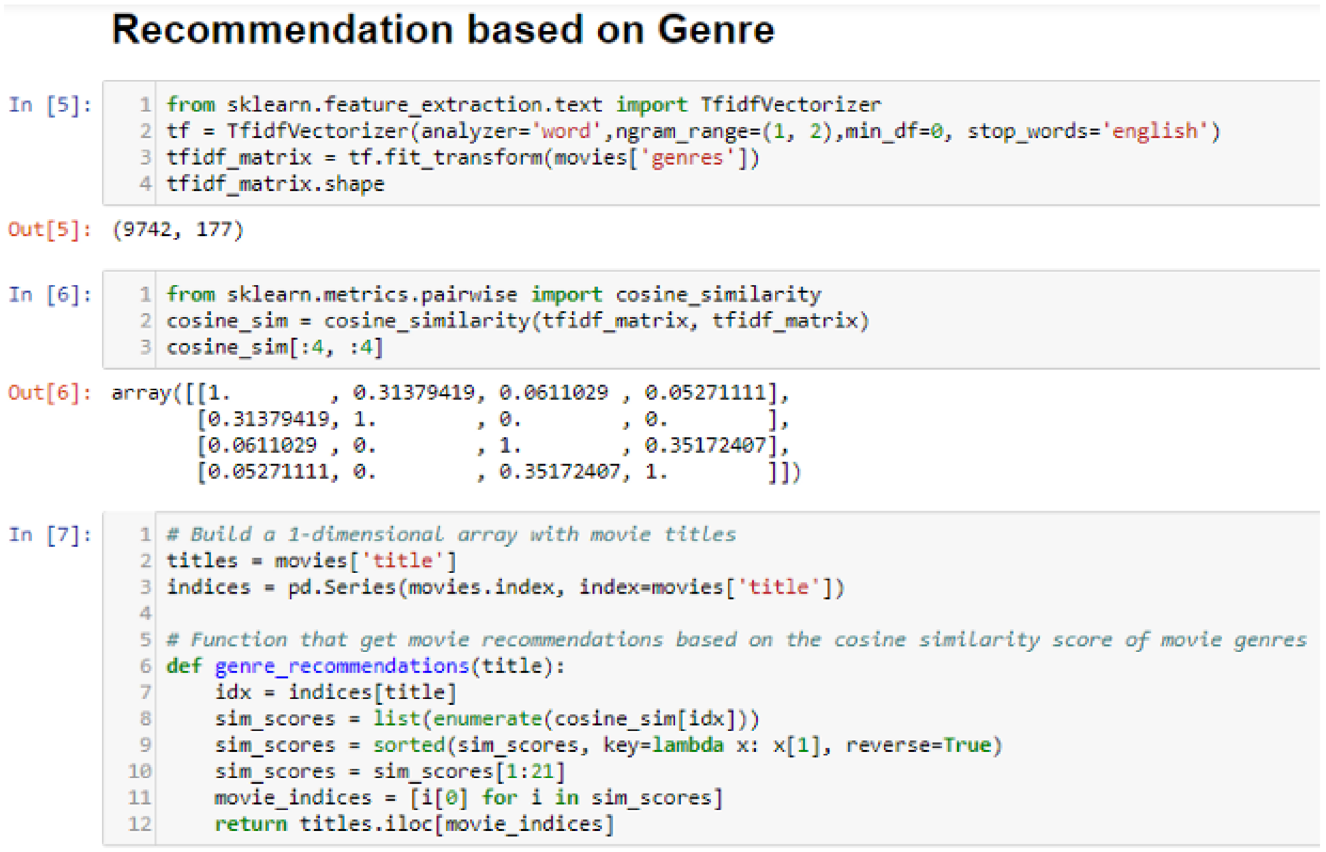
	title	genres
0	Toy Story	Adventure|Animation|Children|Comedy|Fantasy
1	Jumanji	Adventure|Children|Fantasy
2	Grumpier Old Men	Comedy|Romance
3	Waiting to Exhale	Comedy|Drama|Romance
4	Father of the Bride Part II	Comedy

Importing the MovieLens dataset and using only title and genres column



In [4]:
```python
# Break up the big genre string into a string array
movies['genres'] = movies['genres'].str.split('|')
# Convert genres to string value
movies['genres'] = movies['genres'].fillna("").astype('str')
```

Splitting the different genres and converting the values as string type.



Recommendation based on Genre

In [5]:
```python
from sklearn.feature_extraction.text import TfidfVectorizer
tf = TfidfVectorizer(analyzer='word',ngram_range=(1, 2),min_df=0, stop_words='english')
tfidf_matrix = tf.fit_transform(movies['genres'])
tfidf_matrix.shape
```

Out[5]:
```
(9742, 177)
```

In [6]:
```python
from sklearn.metrics.pairwise import cosine_similarity
cosine_sim = cosine_similarity(tfidf_matrix, tfidf_matrix)
cosine_sim[:4, :4]
```

Out[6]:
```
array([[1.        , 0.31379419, 0.0611029 , 0.05271111],
       [0.31379419, 1.        , 0.        , 0.        ],
       [0.0611029 , 0.        , 1.        , 0.35172407],
       [0.05271111, 0.        , 0.35172407, 1.        ]])
```

In [7]:
```python
# Build a 1-dimensional array with movie titles
titles = movies['title']
indices = pd.Series(movies.index, index=movies['title'])

# Function that get movie recommendations based on the cosine similarity score of movie genres
def genre_recommendations(title):
    idx = indices[title]
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:21]
    movie_indices = [i[0] for i in sim_scores]
    return titles.iloc[movie_indices]
```

Using TfidfVectorizer to convert genres in 2-gram words excluding stopwords, cosine similarity is taken between matrix which is transformed. Generating recommendations based on similar genres and having high cosine similarity.

```
In [8]:  genre_recommendations('Dark Knight ').head(20)

Out[8]:  8387                                Need for Speed
         8149        Grandmaster, The (Yi dai zong shi)
         123                                   Apollo 13
         8026                                 Life of Pi
         8396                                       Noah
         38                              Dead Presidents
         341                                 Bad Company
         347                Faster Pussycat! Kill! Kill!
         430                           Menace II Society
         568                              Substitute, The
         665                             Nothing to Lose
         1645                          Untouchables, The
         1696                              Monument Ave.
         2563                                 Death Wish
         2574                           Band of the Hand
         3037                                 Foxy Brown
         3124     Harley Davidson and the Marlboro Man
         3167                                   Scarface
         3217                                  Swordfish
         3301                              Above the Law
         Name: title, dtype: object
```

Based on the genre of "The Dark Knight" (i.e., action, crime, drama, IMAX), closely similar genres are recommended.

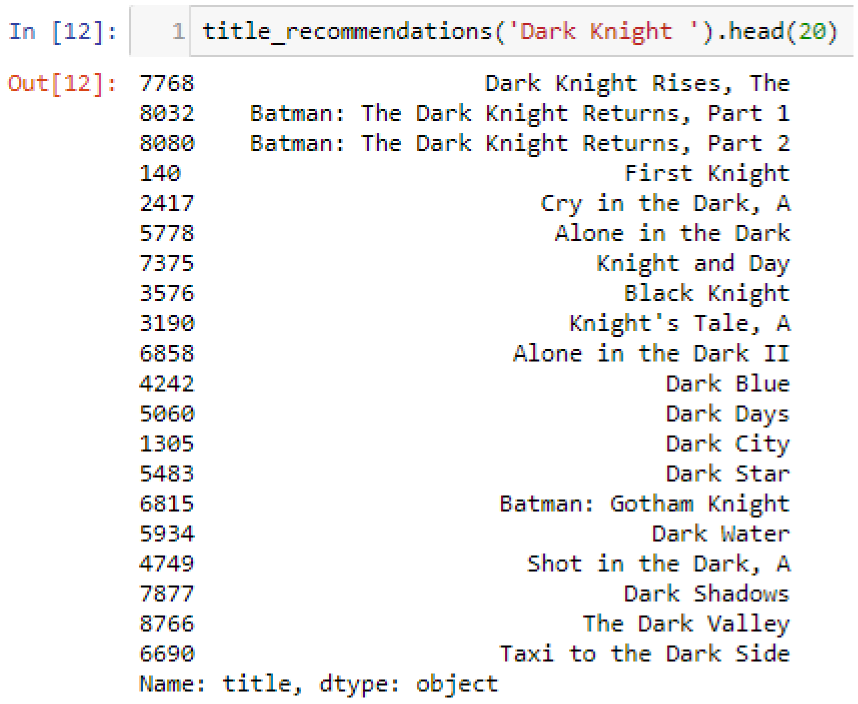
Recommendation based on Title

```
In [9]:  from sklearn.feature_extraction.text import TfidfVectorizer
         tf = TfidfVectorizer(analyzer='word',ngram_range=(1, 2),min_df=0, stop_words='english')
         tfidf_matrix = tf.fit_transform(movies['title'])
         tfidf_matrix.shape

Out[9]:  (9742, 20558)
```

```
In [10]:  from sklearn.metrics.pairwise import cosine_similarity
          cosine_sim = cosine_similarity(tfidf_matrix, tfidf_matrix)
          cosine_sim[:4, :4]

Out[10]:  array([[1., 0., 0., 0.],
                 [0., 1., 0., 0.],
                 [0., 0., 1., 0.],
                 [0., 0., 0., 1.]])
```

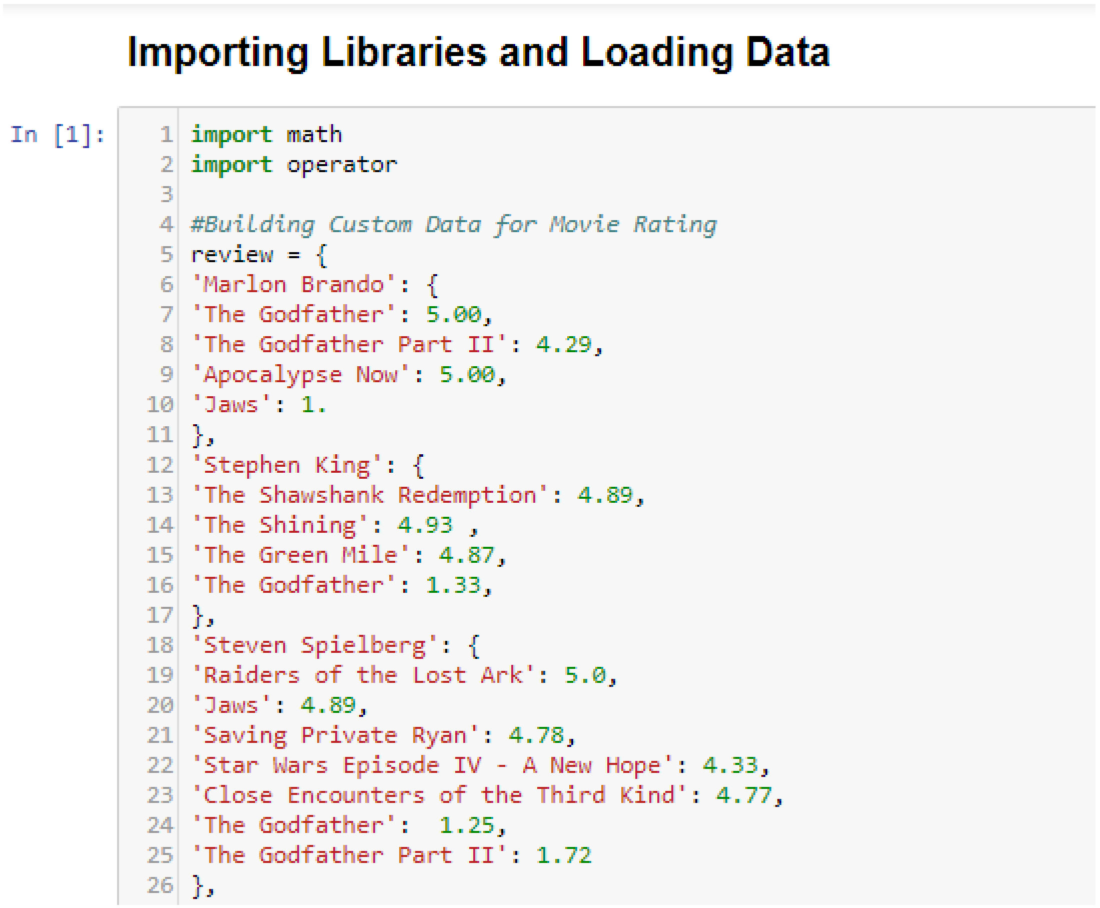
```
In [11]:  # Build a 1-dimensional array with movie titles
          titles = movies['title']
          indices = pd.Series(movies.index, index=movies['title'])

          # Function that get movie recommendations based on the cosine similarity score of movie genres
          def title_recommendations(title):
              idx = indices[title]
              sim_scores = list(enumerate(cosine_sim[idx]))
              sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
              sim_scores = sim_scores[1:21]
              movie_indices = [i[0] for i in sim_scores]
              return titles.iloc[movie_indices]
```

Using TfidfVectorizer to convert titles in 2-gram words excluding stopwords, cosine similarity is taken between matrix which is transformed. Generating recommendations based on similar genres and having high cosine similarity.


```
In [12]: title_recommendations('Dark Knight ').head(20)

Out[12]: 7768                      Dark Knight Rises, The
         8032    Batman: The Dark Knight Returns, Part 1
         8080    Batman: The Dark Knight Returns, Part 2
         140                                First Knight
         2417                           Cry in the Dark, A
         5778                            Alone in the Dark
         7375                              Knight and Day
         3576                                Black Knight
         3190                             Knight's Tale, A
         6858                         Alone in the Dark II
         4242                                   Dark Blue
         5060                                   Dark Days
         1305                                   Dark City
         5483                                   Dark Star
         6815                      Batman: Gotham Knight
         5934                                  Dark Water
         4749                           Shot in the Dark, A
         7877                                Dark Shadows
         8766                             The Dark Valley
         6690                        Taxi to the Dark Side
         Name: title, dtype: object
```

Collaborative Filtering:

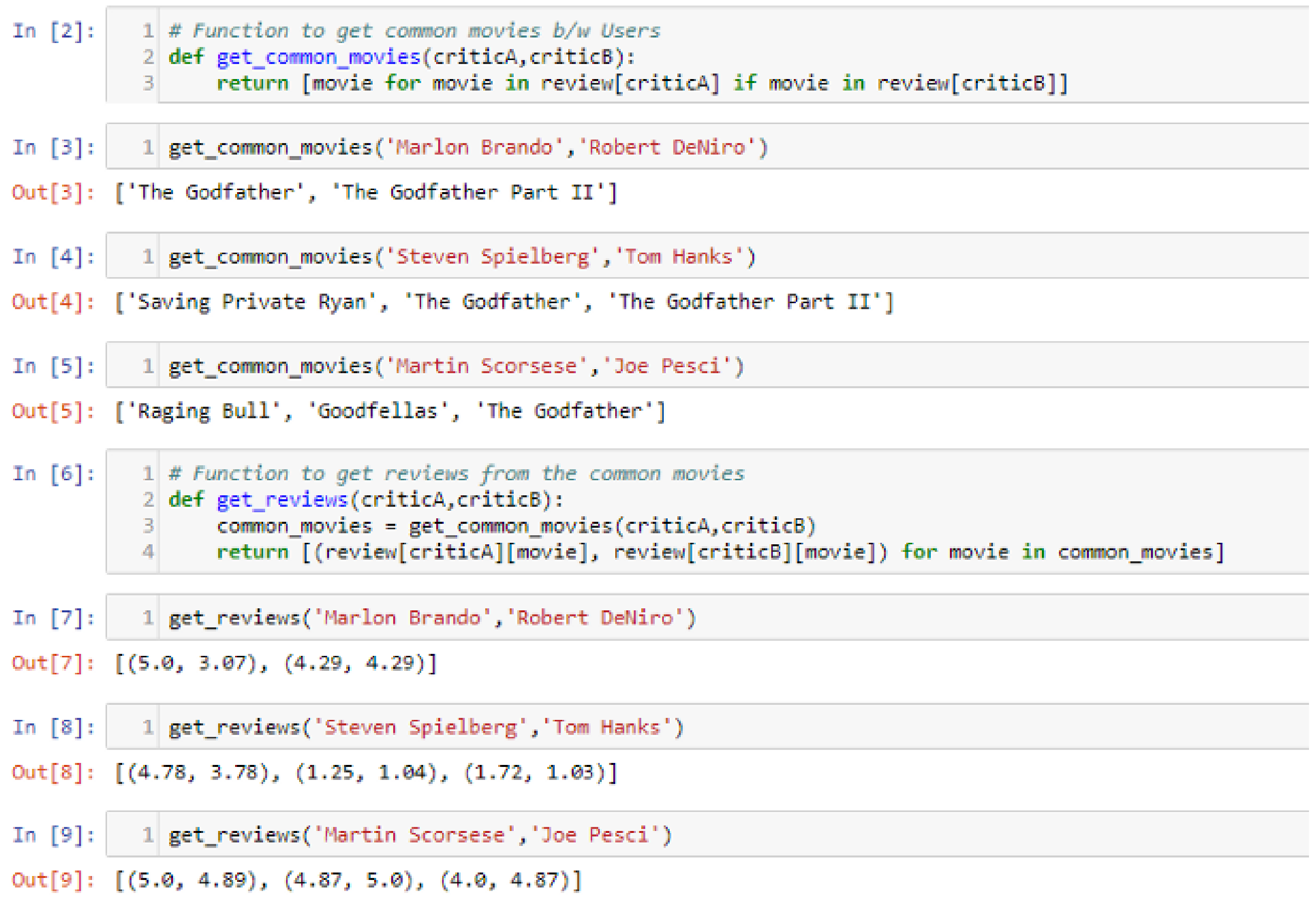
Basic Collaborative Filtering Implementation



Importing Libraries and Loading Data

```
In [1]:
import math
import operator

#Building Custom Data for Movie Rating
review = {
'Marlon Brando': {
'The Godfather': 5.00,
'The Godfather Part II': 4.29,
'Apocalypse Now': 5.00,
'Jaws': 1.
},
'Stephen King': {
'The Shawshank Redemption': 4.89,
'The Shining': 4.93 ,
'The Green Mile': 4.87,
'The Godfather': 1.33,
},
'Steven Spielberg': {
'Raiders of the Lost Ark': 5.0,
'Jaws': 4.89,
'Saving Private Ryan': 4.78,
'Star Wars Episode IV - A New Hope': 4.33,
'Close Encounters of the Third Kind': 4.77,
'The Godfather':  1.25,
'The Godfather Part II': 1.72
},
```

Importing dictionaries with values for user rating on movies.

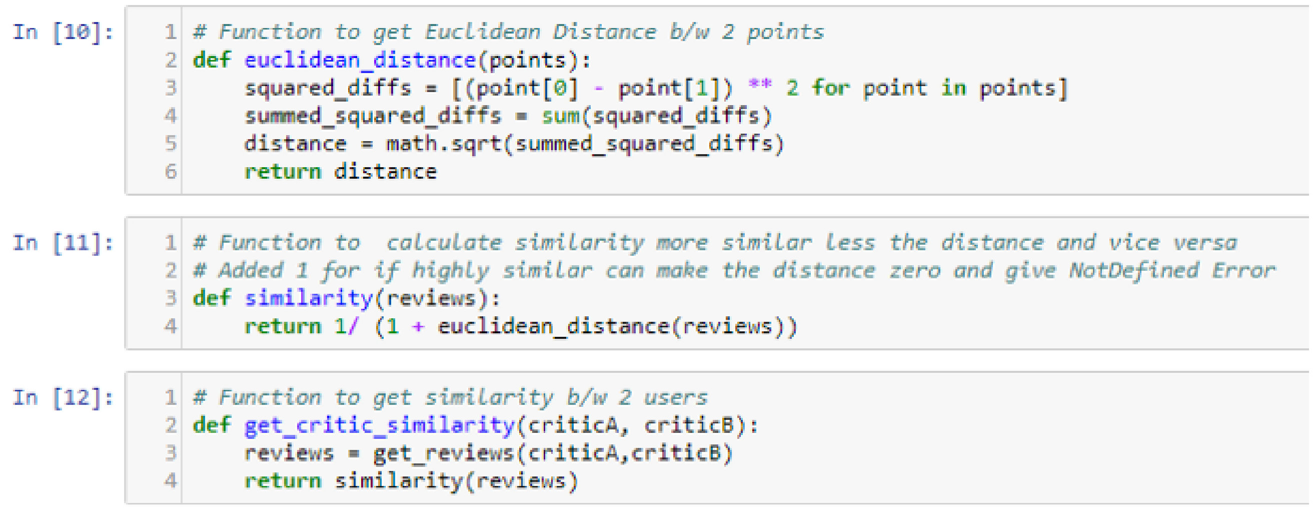


```
In [2]:  # Function to get common movies b/w Users
         def get_common_movies(criticA,criticB):
             return [movie for movie in review[criticA] if movie in review[criticB]]

In [3]:  get_common_movies('Marlon Brando','Robert DeNiro')

Out[3]: ['The Godfather', 'The Godfather Part II']

In [4]:  get_common_movies('Steven Spielberg','Tom Hanks')

Out[4]: ['Saving Private Ryan', 'The Godfather', 'The Godfather Part II']

In [5]:  get_common_movies('Martin Scorsese','Joe Pesci')

Out[5]: ['Raging Bull', 'Goodfellas', 'The Godfather']

In [6]:  # Function to get reviews from the common movies
         def get_reviews(criticA,criticB):
             common_movies = get_common_movies(criticA,criticB)
             return [(review[criticA][movie], review[criticB][movie]) for movie in common_movies]

In [7]:  get_reviews('Marlon Brando','Robert DeNiro')

Out[7]: [(5.0, 3.07), (4.29, 4.29)]

In [8]:  get_reviews('Steven Spielberg','Tom Hanks')

Out[8]: [(4.78, 3.78), (1.25, 1.04), (1.72, 1.03)]

In [9]:  get_reviews('Martin Scorsese','Joe Pesci')

Out[9]: [(5.0, 4.89), (4.87, 5.0), (4.0, 4.87)]
```

Common movies are found in the reviews of each user and based on common movies the reviews are found on each movie.

Euclidean Distance Formula for Calculating similarity

$$d(x,y) = \sqrt{(x1 - y1)^2 + (x2 - y1)^2 + (xn - yn)^2}$$

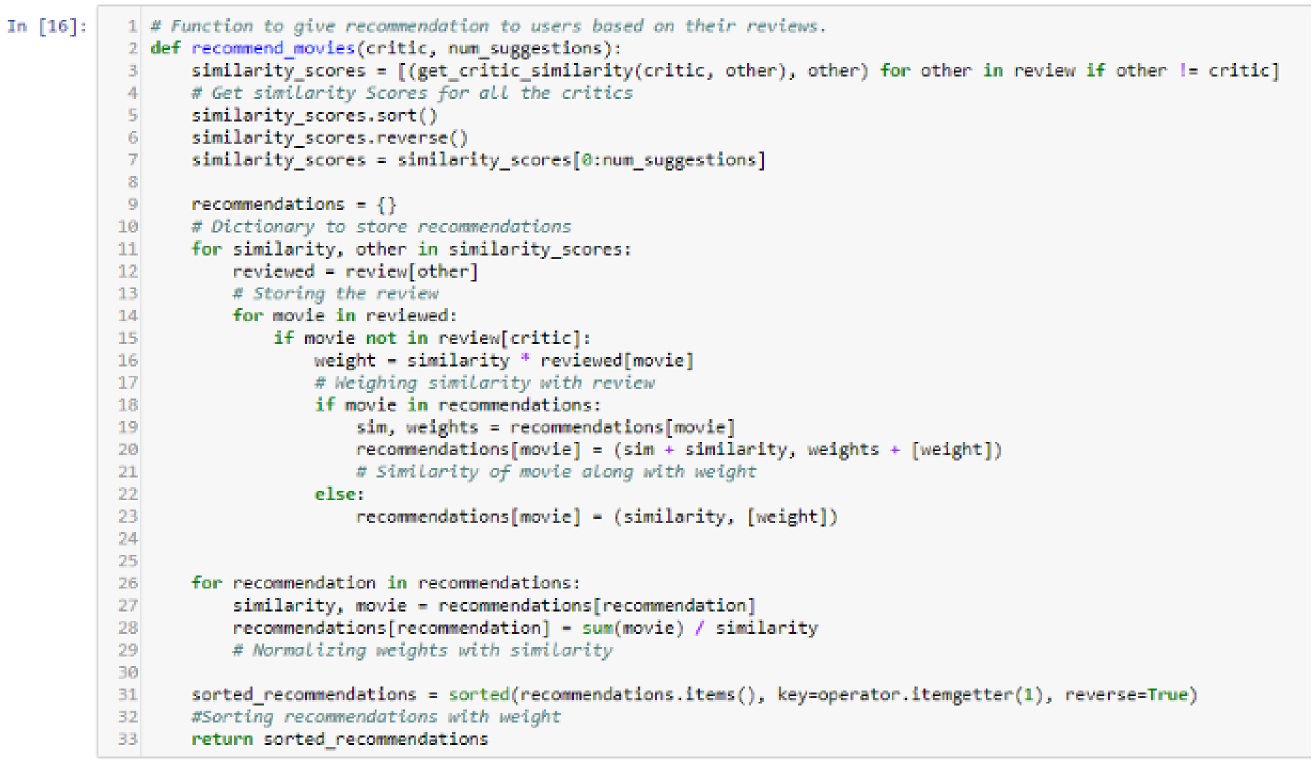


```
In [10]:  # Function to get Euclidean Distance b/w 2 points
          def euclidean_distance(points):
              squared_diffs = [(point[0] - point[1]) ** 2 for point in points]
              summed_squared_diffs = sum(squared_diffs)
              distance = math.sqrt(summed_squared_diffs)
              return distance

In [11]:  # Function to  calculate similarity more similar less the distance and vice versa
          # Added 1 for if highly similar can make the distance zero and give NotDefined Error
          def similarity(reviews):
              return 1/ (1 + euclidean_distance(reviews))

In [12]:  # Function to get similarity b/w 2 users
          def get_critic_similarity(criticA, criticB):
              reviews = get_reviews(criticA,criticB)
              return similarity(reviews)
```

Euclidean distance is calculated between the common movies between users. The similarity is indirectly proportional to distance. As the distance increases, similarity decreases and vice vera. Critic similarity is used to the fine similarity of users.

```
In [13]:  get_critic_similarity('Marlon Brando','Robert DeNiro')
Out[13]:  0.341296928327645

In [14]:  get_critic_similarity('Steven Spielberg','Tom Hanks')
Out[14]:  0.4478352722730117

In [15]:  get_critic_similarity('Martin Scorsese','Joe Pesci')
Out[15]:  0.5300793497254199
```

From above, we can see Martin Scorsese and Joe Pesci are very similar to each other as they have rated common movies very closely.



```
In [16]:
# Function to give recommendation to users based on their reviews.
def recommend_movies(critic, num_suggestions):
    similarity_scores = [(get_critic_similarity(critic, other), other) for other in review if other != critic]
    # Get similarity Scores for all the critics
    similarity_scores.sort()
    similarity_scores.reverse()
    similarity_scores = similarity_scores[0:num_suggestions]

    recommendations = {}
    # Dictionary to store recommendations
    for similarity, other in similarity_scores:
        reviewed = review[other]
        # Storing the review
        for movie in reviewed:
            if movie not in review[critic]:
                weight = similarity * reviewed[movie]
                # Weighing similarity with review
                if movie in recommendations:
                    sim, weights = recommendations[movie]
                    recommendations[movie] = (sim + similarity, weights + [weight])
                    # Similarity of movie along with weight
                else:
                    recommendations[movie] = (similarity, [weight])


    for recommendation in recommendations:
        similarity, movie = recommendations[recommendation]
        recommendations[recommendation] = sum(movie) / similarity
        # Normalizing weights with similarity

    sorted_recommendations = sorted(recommendations.items(), key=operator.itemgetter(1), reverse=True)
    #Sorting recommendations with weight
    return sorted_recommendations
```

At first, all similarity scores are found out w.r.t to critics. Recommendation dictionary is given movie similarity and weight w.r.t each movie. The overall weight is normalized to make suggestions. Then recommended movies are sorted by weight.

```
In [17]: recommend_movies('Marlon Brando',4)

Out[17]: [('Goodfellas', 5.000000000000001),
          ('Raiders of the Lost Ark', 5.0),
          ('Raging Bull', 4.89),
          ('Star Wars Episode IV - A New Hope', 3.8157055214723923),
          ('One Flew Over The Cuckoos Nest', 2.02)]

In [18]: recommend_movies('Robert DeNiro',4)

Out[18]: [('Raiders of the Lost Ark', 5.0),
          ('Star Wars Episode IV - A New Hope', 4.92),
          ('Close Encounters of the Third Kind', 1.2744773851327365)]
```

We can see from above Marlon Brando has rated "Godfather" high, "Goodfellas" is also rated highly where "Godfather" is rated highly, thus "Goodfellas" is recommended to Marlon Brando.

This is a very easy implementation of collaborative filtering, just the crux the similarity between users is implemented. Whereas industry uses matrix factorization, autoencoders and deep learning.

Find the above code in this Github Repo.

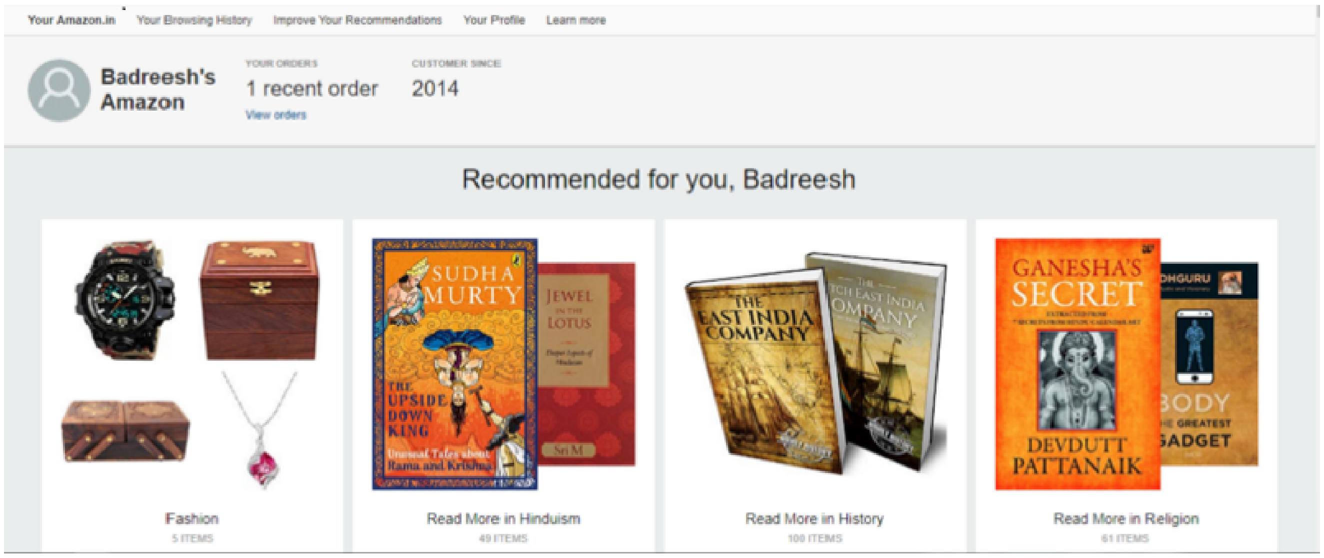
References: Flashcards of Chris Albon from: https://machinelearningflashcards.com/

Six Examples of Recommender Systems

Recommender systems work behind the scenes on many of the world's most popular websites. E-commerce websites, for example, often use recommender systems to increase user engagement and drive purchases, but suggestions are highly dependent on the quality and quantity of data which freemium (free service to use/the user is the product) companies already have.

1. Amazon

When we buy something or browse anything on Amazon, we see recommended products based on our taste or search results on the page.

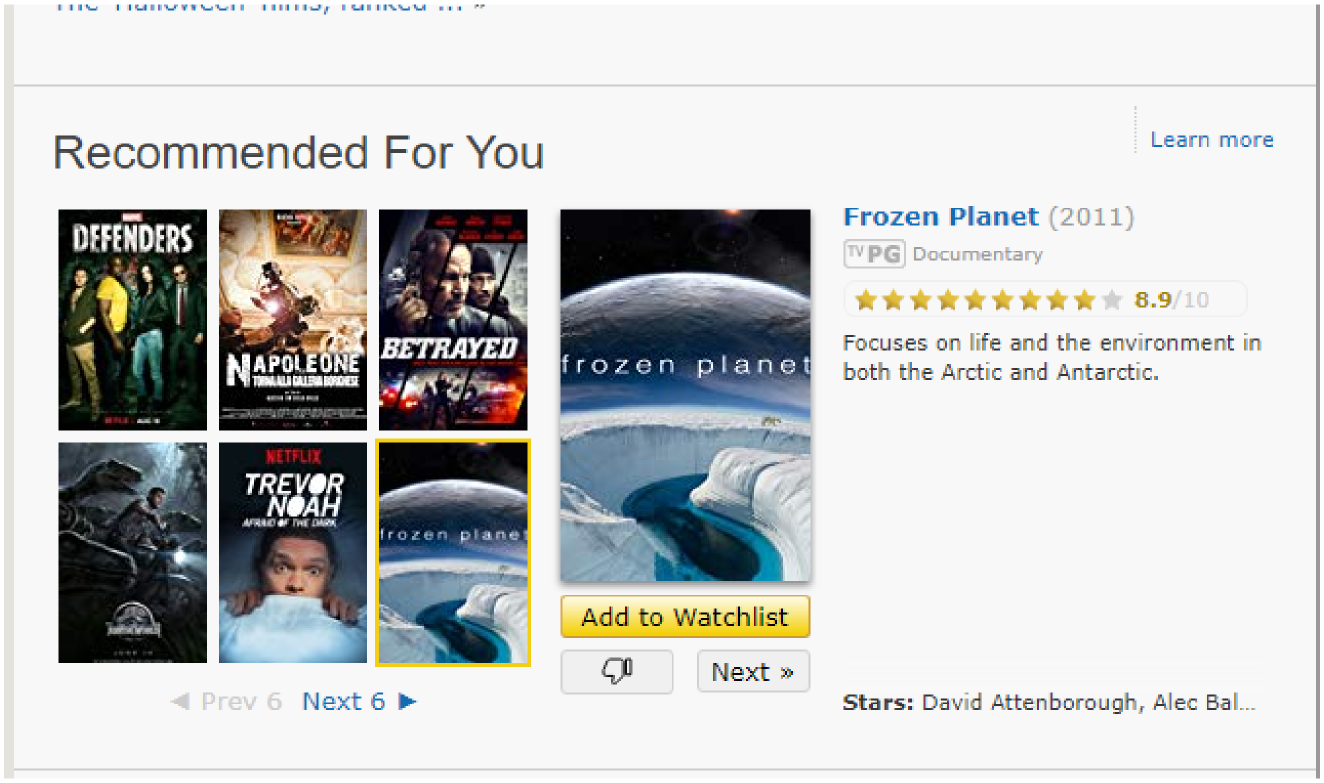


Amazon Recommends

As we can see above, I may have searched for products related to Sudha Murthy, but Amazon clusters it into segments based on other previous search results. A recommender system often biases the user's opinion.

2. IMDb

When we rate a TV show or movie on IMDb it recommends other shows or movies based on important details like cast, genre, sub-genre, plot and summary.

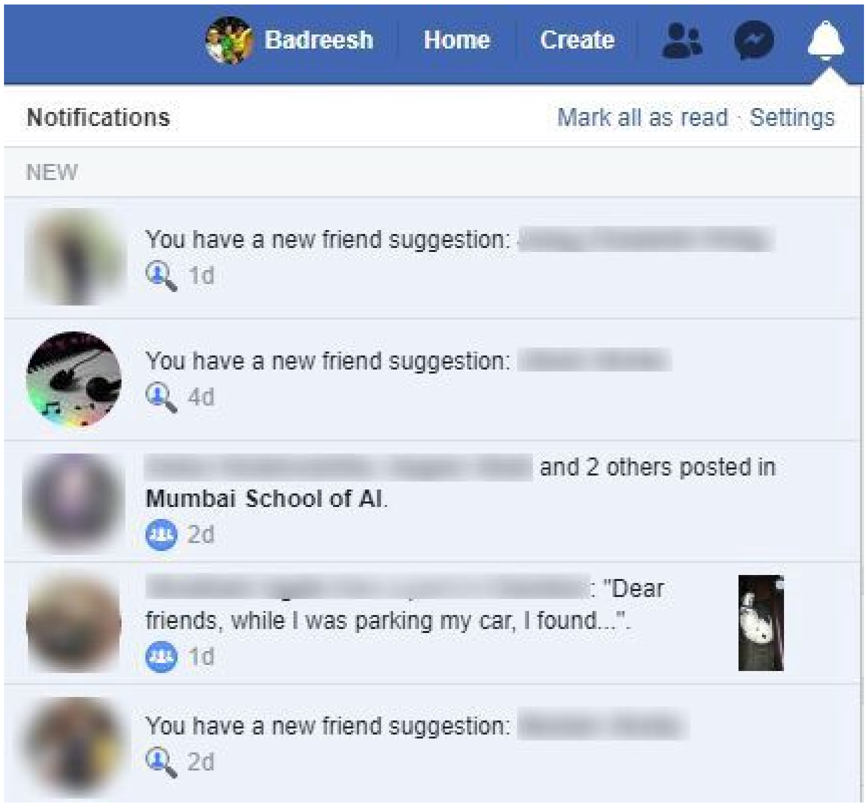


IMDb Recommend's

As we can see above, I was recommended to rate *Frozen Planet* because I've watched David Attenborough's wildlife documentary series. In this case, IMDb suggested this to me based on the cast of the series.

3. Facebook & Instagram

Facebook and Instagram use recommender systems on a wider scale for suggesting friends and stories in the newsfeed.



You have a new friend suggestion:
1d

You have a new friend suggestion:
4d

and 2 others posted in **Mumbai School of AI**.
2d

: "Dear friends, while I was parking my car, I found...".
1d

You have a new friend suggestion:
2d

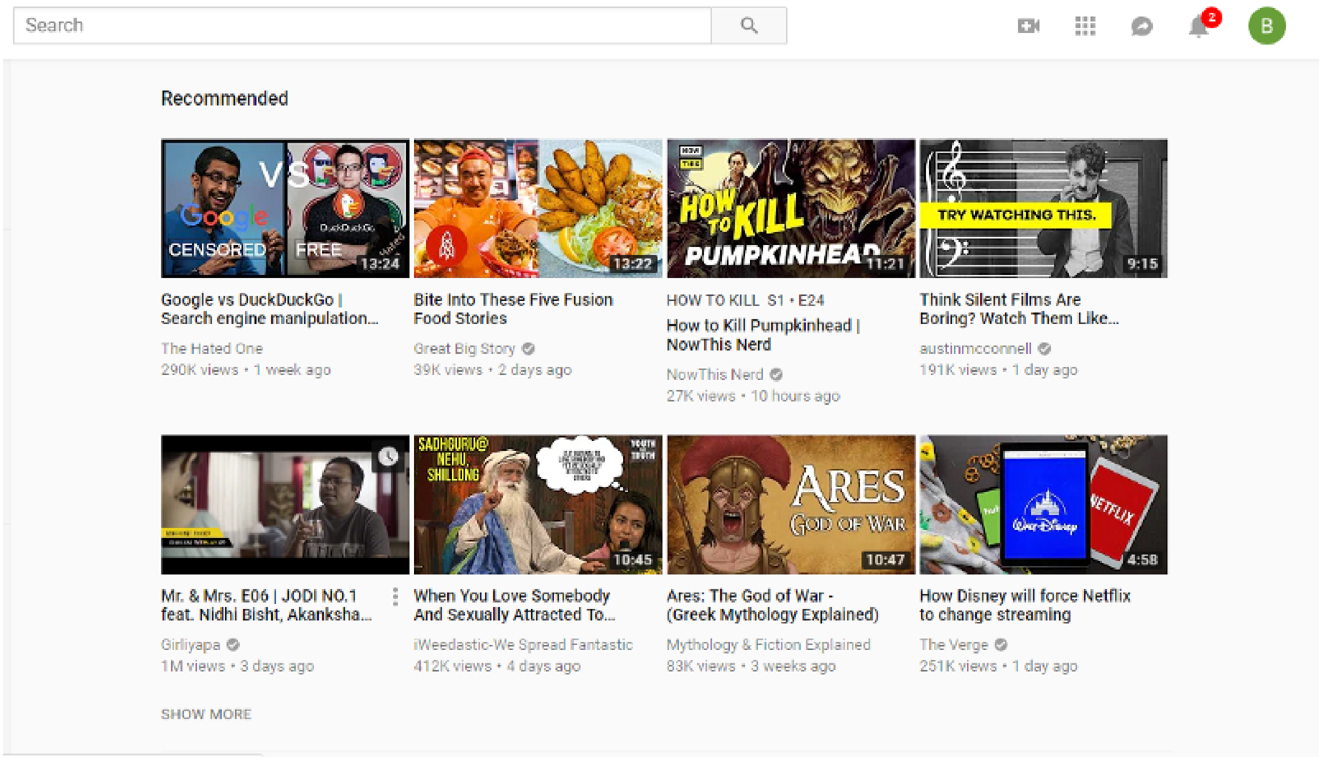
Facebook Recommend's

Often in the newsfeed section, the user is bombarded with articles similar to one another based on the likes and pages they follow. Some argue it creates an unconscious bias among the user, which may be bad or useful depending on how the user interprets something when they have only one side of the argument.

PS: I seldom use Facebook.

4. Youtube

YouTube recommends videos based on previous viewing or clicks.



Google vs DuckDuckGo | Search engine manipulation...
The Hated One
290K views • 1 week ago

Bite Into These Five Fusion Food Stories
Great Big Story
39K views • 2 days ago

HOW TO KILL S1 • E24
How to Kill Pumpkinhead | NowThis Nerd
NowThis Nerd
27K views • 10 hours ago

Think Silent Films Are Boring? Watch Them Like...
austinmcconnell
191K views • 1 day ago

Mr. & Mrs. E06 | JODI NO.1 feat. Nidhi Bisht, Akanksha...
Girliyapa
1M views • 3 days ago

When You Love Somebody And Sexually Attracted To...
iWeedastic-We Spread Fantastic
412K views • 4 days ago

Ares: The God of War - (Greek Mythology Explained)
Mythology & Fiction Explained
83K views • 3 weeks ago

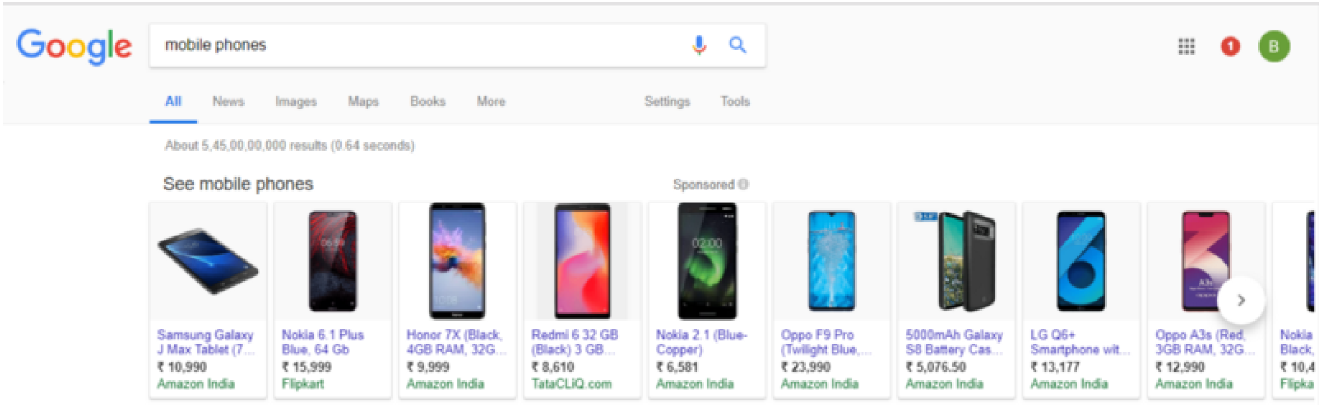
How Disney will force Netflix to change streaming
The Verge
251K views • 1 day ago

Google’s Recommend’s

As we can above, the first video is about Google. While I've seen the video, YouTube recommends it to me to watch again. Basically, YouTube knows my likes and dislikes or bias (inclination).

5. Google

Whenever we are logged in and search for anything on Google, it's registered in our history and recommends products based on previous searches. Not surprisingly, more than 90% of the company's revenue is generated through advertising. Relevant searches also take into account the location of the user.



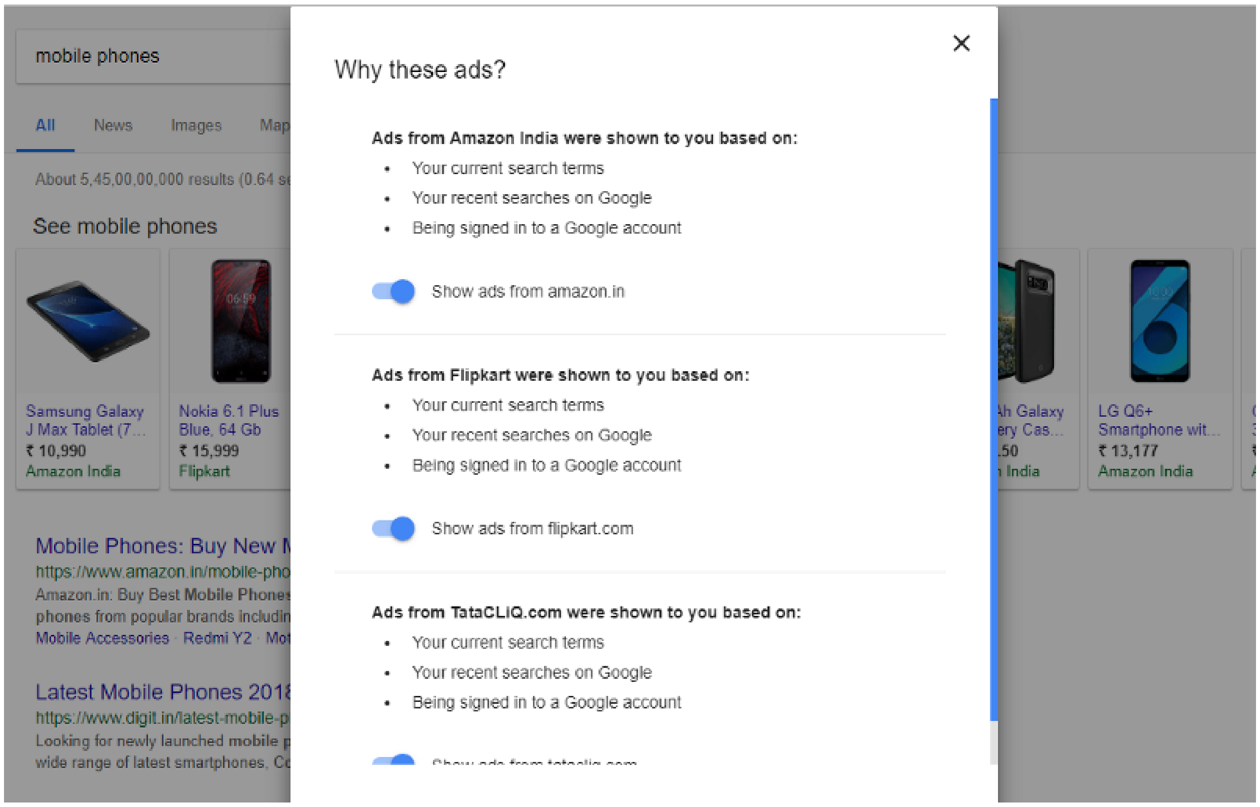
About 5,45,00,00,000 results (0.64 seconds)

See mobile phones

Samsung Galaxy J Max Tablet (7... ₹ 10,990 Amazon India
Nokia 6.1 Plus Blue, 64 Gb ₹ 15,999 Flipkart
Honor 7X (Black, 4GB RAM, 32G... ₹ 9,999 Amazon India
Redmi 6 32 GB (Black) 3 GB... ₹ 8,610 TataCLiQ.com
Nokia 2.1 (Blue-Copper) ₹ 6,581 Amazon India
Oppo F9 Pro (Twilight Blue,... ₹ 23,990 Amazon India
5000mAh Galaxy S8 Battery Cas... ₹ 5,076.50 Amazon India
LG Q6+ Smartphone wit... ₹ 13,177 Amazon India
Oppo A3s (Red, 3GB RAM, 32G... ₹ 12,990 Amazon India
Nokia Black, ₹ 10,4 Flipka

Google Recommend’s

When clicking on the sponsored button, Google shows us why these ads are targeted.



Why these ads?

Ads from Amazon India were shown to you based on:

- Your current search terms
- Your recent searches on Google
- Being signed in to a Google account

Show ads from amazon.in

Ads from Flipkart were shown to you based on:

- Your current search terms
- Your recent searches on Google
- Being signed in to a Google account

Show ads from flipkart.com

Ads from TataCLiQ.com were shown to you based on:

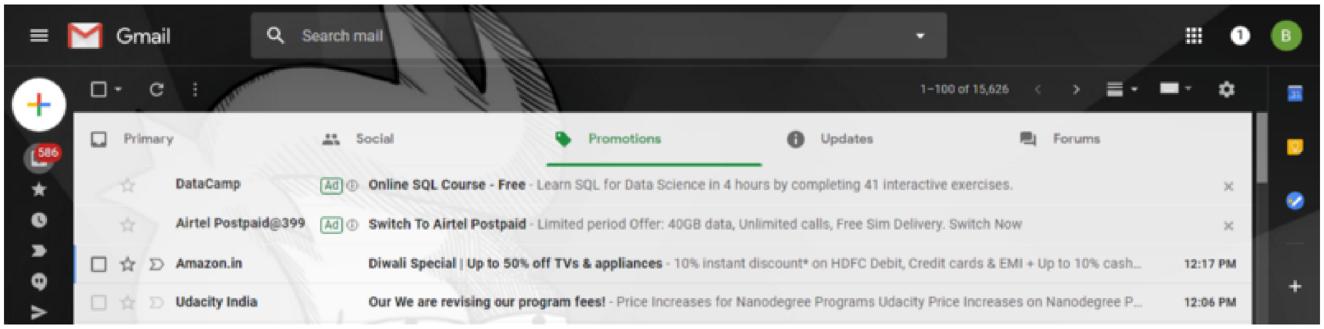
- Your current search terms
- Your recent searches on Google
- Being signed in to a Google account

Google Ads

From the above we can see we were targeted with these ads based on recent search results.

PS: I use ublock origin but for this article, I unblocked Google to track my activities.

6. Another Google Subsidiary- Gmail



DataCamp	Ad	**Online SQL Course - Free** - Learn SQL for Data Science in 4 hours by completing 41 interactive exercises.	
Airtel Postpaid@399	Ad	**Switch To Airtel Postpaid** - Limited period Offer: 40GB data, Unlimited calls, Free Sim Delivery. Switch Now	
Amazon.in		**Diwali Special | Up to 50% off TVs & appliances** - 10% instant discount* on HDFC Debit, Credit cards & EMI + Up to 10% cash...	12:17 PM
Udacity India		**Our We are revising our program fees!** - Price Increases for Nanodegree Programs Udacity Price Increases on Nanodegree P...	12:06 PM

Gmail's Sponsored Ad

Gmail recommends advertisements based on my inbox and the newsletters I've signed up for and the tags they may have generated.

Other examples of recommender systems at work include movies on Netflix, songs on Spotify and profiles on Tinder.

Privacy Vs Personalized Curation

In George Orwell's classic novel *1984,* "Big Brother" is a government that scrutinizes each and every move of its citizenry. In today's world, tech companies like Google and Facebook more accurately fill that role. Each company has immense troves of data about millions of user's and they harvest it for ad targeting and building things like recommender systems.

Most large tech companies offer their services for free, so you are the product. For example, Facebook is releasing ads on Whatsapp. So, Facebook knows your likes, preferences, bookmarks, followers on Instagram, etc. — and they culminate all of that data and target you on Whatsapp.

In the end, less is more, and if consumers feel like a company knows too much about them, they probably do.

Personalized content or services can be an addiction or menace depending on your point of view. It can help us find things we like, but it can also create an unconscious bias among users. Personalization helps us have a better customer user experience, but it's a tradeoff and we need to find a sweet spot between privacy and personalization .

I'll end with a couple of important quotes:

> “Data is the new oil. It’s valuable, but if unrefined it cannot really be used. It has to be changed into gas, plastic, chemicals, etc to create a valuable entity that drives profitable activity; so must data be broken down, analyzed for it to have value.” — Clive Humby, UK mathematician and architect of Tesco’s Clubcard, 2006

> *“The difference between oil and data is that the product of oil does not generate more oil (unfortunately), whereas the product of data (self-driving cars, drones, wearables, etc) will generate more data (where do you normally drive, how fast/well you drive, who is with you, etc).” — Piero Scaruffi, cognitive scientist and author of “History of Silicon Valley”, 2016*