

Recommender Systems

By: Sarah Nooravi

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I WANT TO WATCH A MOVIE



CAN'T THINK OF ANYTHING TO
WATCH

Made on Imgur

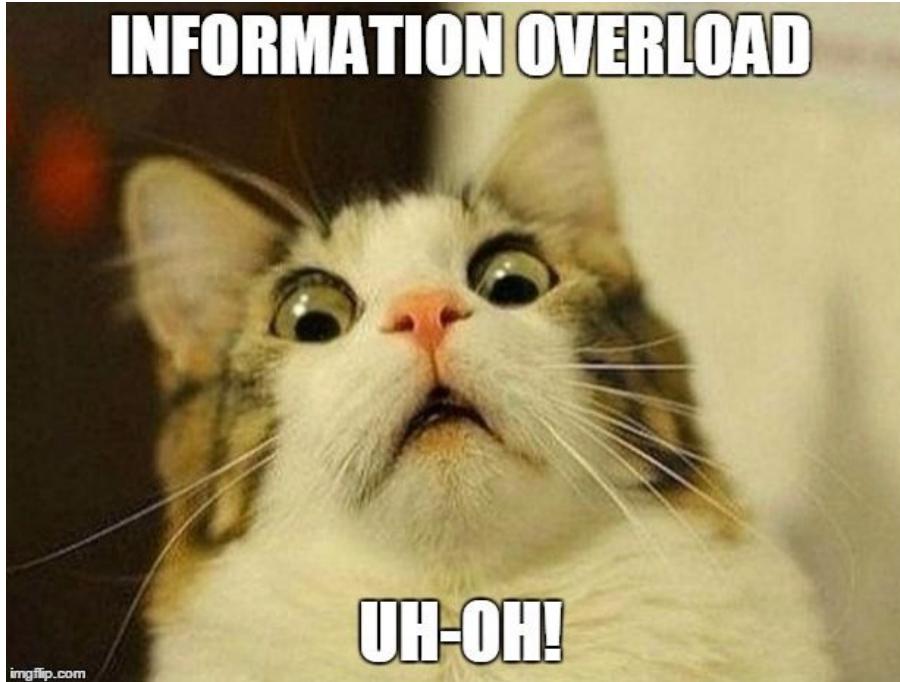
Recommendations are everywhere...

The image is a collage of screenshots from different websites and platforms illustrating various recommendation systems:

- Netflix:** Shows recommendations for TV shows like "Sherlock" based on interest in "DreamWorks Spooky Stories: Volume 2".
- Amazon:** Shows a sidebar titled "Customers who bought this item also bought" featuring books like "R for Data Science" and "Python Data Science Handbook".
- LinkedIn:** Shows recommendations for companies like IBM and Microsoft.
- YouTube:** Shows a "Recommended" section with video thumbnails for Michio Kaku, Stanford University's Recommender Systems course, and a lecture by Siraj Raval on the Mathematics of Machine Learning.
- Google:** Shows the "People also ask" section with questions like "What is the best programming language for machine learning?" and "What is a machine learning model?".
- Ford Motor Company:** Shows a recommendation for the "Ford Motor Company Automotive" page.
- J.P. Morgan:** Shows a recommendation for the "J.P. Morgan Financial Services" page.
- XYZAL Allergy 24HR:** Shows an advertisement for XYZAL Allergy 24HR with a "GET YOUR FREE SAMPLE" button.



Why it's necessary





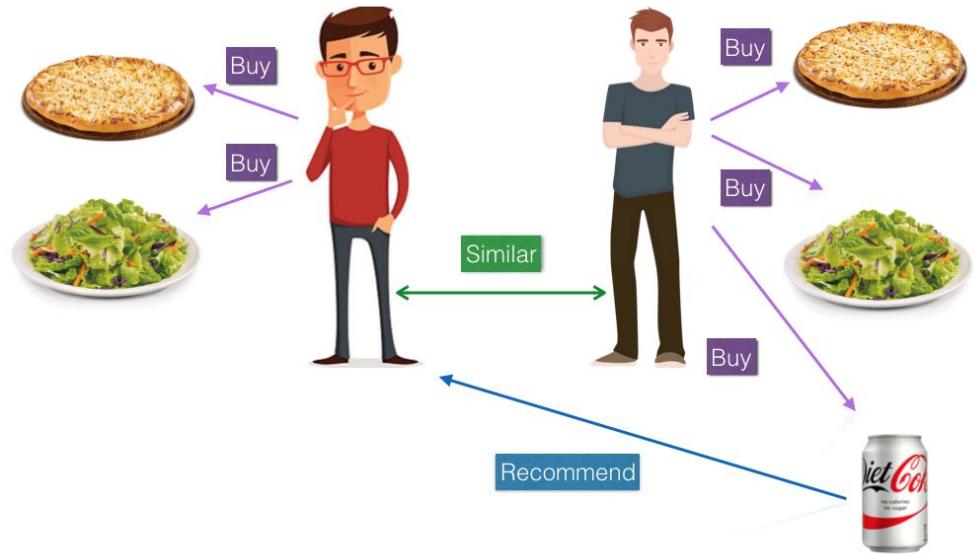
Two Ways to Approach This Problem...

1. Collaborative Filtering
2. Content-Based Filtering



Collaborative Filtering

Idea: Recommend items to customer x rated highly by similar customers to customer x.





Steps: Collaborative Filtering

Step 1: Find the neighborhood of users that “similar” (i.e. share similar likes and dislikes).



Step 2: Make a prediction



Step 3: Make a business decision



Example: Let's go to the movies!



Example: Let's go to the movies!





Example: Let's go to the movies!



| | Greatest Showman | Jumanji | Love, Simon | Black Panther | Coco | The Circle | The Big Sick | Similarity |
|-------|------------------|---------|-------------|---------------|------|------------|--------------|------------|
| John | | 5 | 1 | 5 | | | 3 | ? |
| Eric | 5 | 3 | 2 | | | 4 | | ? |
| Matt | | 4 | | 1 | 3 | 1 | | ? |
| Dylan | 5 | 2 | 5 | | 5 | | | ? |



Example: Let's go to the movies!



| | Greatest Showman | Jumanji | Love, Simon | Black Panther | Coco | The Circle | The Big Sick | Similarity |
|-------|------------------|---------|-------------|---------------|------|------------|--------------|------------|
| John | | 5 | 1 | 5 | | | 3 | ? |
| Eric | 5 | 3 | 2 | | | 4 | | ? |
| Matt | | 4 | | 1 | 3 | 1 | | ? |
| Dylan | 5 | 2 | 5 | | 5 | | | ? |
| David | | ??? | 2 | 4 | | 3 | 4 | ? |





Step 1: Find Similar Users

- **Step 1a:** Define measure of similarity.
- **Step 1b:** Calculate similarity measure between user and all other users.
- **Step 1c:** Rank and choose top N.

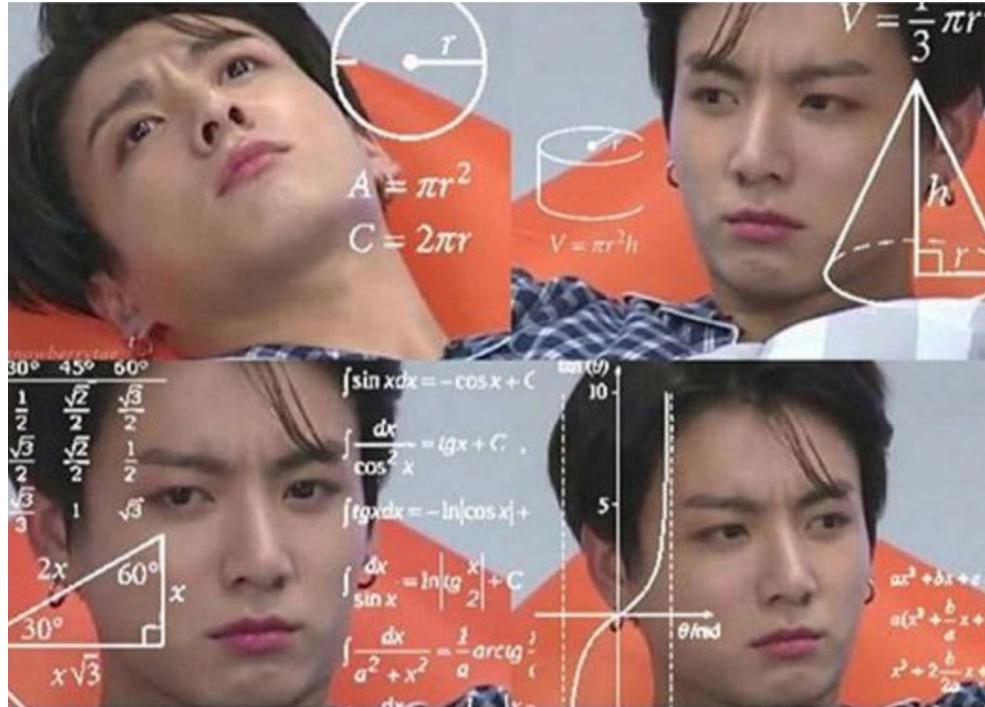


Step 1a: Define Measure of Similarity

THOUGHTS?



Step 1a: Define Measure of Similarity





Step 1a: Define Measure of Similarity

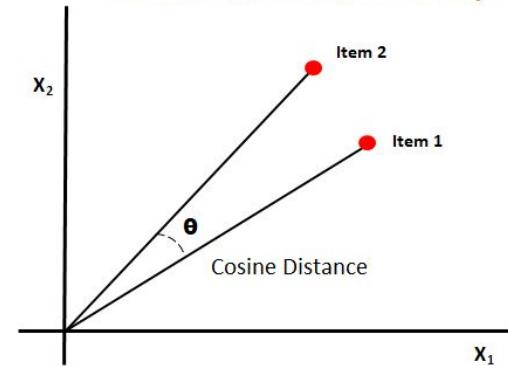
Cosine Similarity

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}}$$

Pearson Correlation

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}$$

Cosine Distance/Similarity





Step 1b: Calculate Similarity



| | Greatest Showman | Jumanji | Love, Simon | Black Panther | Coco | The Circle | The Big Sick | Similarity |
|-------|------------------|---------|-------------|---------------|------|------------|--------------|-------------|
| John | | 5 | 1 | 5 | | | 3 | 0.70 |
| Eric | 5 | 3 | 2 | | | 4 | | 0.47 |
| Matt | | 4 | | 1 | 3 | 1 | | -0.14 |
| Dylan | 5 | 2 | 5 | | 5 | | | -0.21 |
| David | | ??? | 2 | 4 | | 3 | 4 | 1 |



Step 1c: Rank and Choose Top N (N=2)



| | Greatest Showman | Jumanji | Love, Simon | Black Panther | Coco | The Circle | The Big Sick | Similarity |
|-------|------------------|---------|-------------|---------------|------|------------|--------------|-------------|
| John | | 5 | 1 | 5 | | | 3 | 0.70 |
| Eric | 5 | 3 | 2 | | | 4 | | 0.47 |
| David | | ??? | 2 | 4 | | 3 | 4 | 1 |



Step 2: Make a Prediction



How can we use the neighborhood of similar users to make a prediction?

| | Greatest Showman | Jumanji | Love, Simon | Black Panther | Coco | The Circle | The Big Sick | Similarity |
|-------|------------------|---------|-------------|---------------|------|------------|--------------|-------------|
| John | | 5 | 1 | 5 | | | 3 | 0.70 |
| Eric | 5 | 3 | 2 | | | 4 | | 0.47 |
| David | | ??? | 2 | 4 | | 3 | 4 | 1 |



Step 2: Make a Prediction



Take an average or a weighted average:

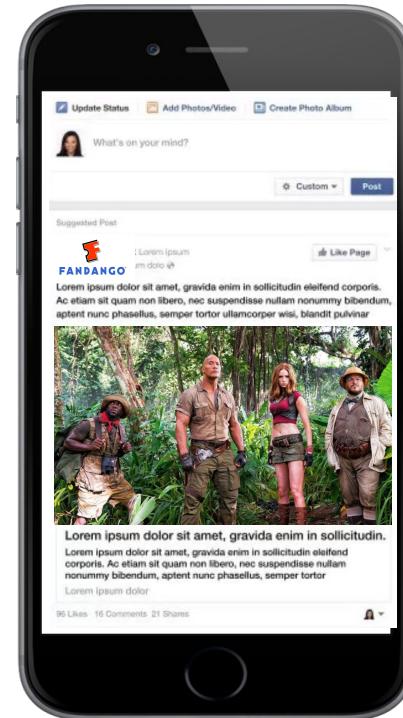
$$\text{average} = \frac{5 + 3}{2} = 4$$

$$\text{weighted average} = \frac{0.7 * 5 + 0.47 * 3}{0.7 + 0.47} = 4.19$$





Step 3: Make a Business Decision





Advantages

1. Cross-domain recommendations
2. More diversified recommendations



Disadvantages

1. Bias towards popular products
2. Need information on other users
3. Work best when there is a large user space
4. Cold-start problem



Content-Based Filtering

Idea: Recommend items to customer x similar to items rated highly by customer x





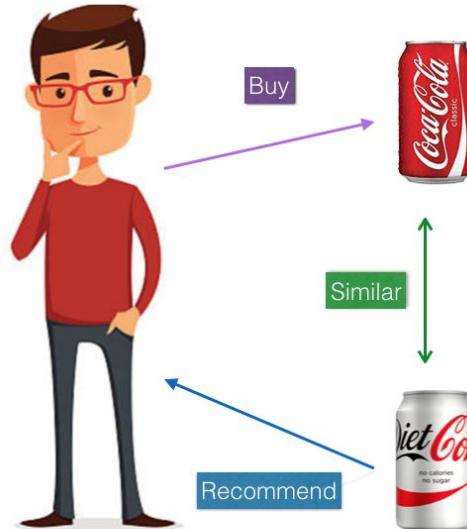
Steps: Content-Based Filtering

Step 1: Define Item Profiles

Step 2: Define User Profiles

Step 3: Calculate Similarity

Step 4: Rank and Recommend



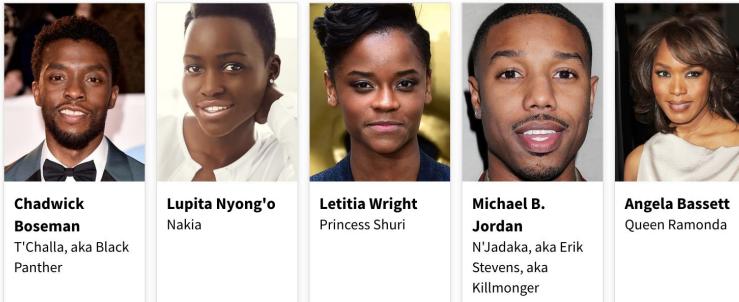
Step 1: Define Item Profiles

A profile is just a set of features. For movies:

- Actors
- Director
- Genre
- Overview
- Etc.

For articles:

- Topics or words in the articles



| | |
|----------------------------|----------------------------------------------------------------------------|
| Status | Released |
| Release Information | January 29, 2018 PG-13 Premiere |
| Original Language | English |
| Runtime | 2h 14m |
| Budget | \$200,000,000.00 |
| Revenue | \$1,211,644,236.00 |
| Homepage | https://marvel.com/... |
| Genres | ACTION ADVENTURE FANTASY SCIENCE FICTION |



Step 1: Define Item Profiles

How does all of the text get translated into recommendations??



Step 1: Define Item Profiles

How does all of the text get translated into recommendations??

Overview

King T'Challa returns home from America to the reclusive, technologically advanced African nation of Wakanda to serve as his country's new leader. However, T'Challa soon finds that he is challenged for the throne by factions within his own country as well as without. Using powers reserved to Wakandan kings, T'Challa assumes the Black Panther mantel to join with girlfriend Nakia, the queen-mother, his princess-kid sister, members of the Dora Milaje (the Wakandan "special forces"), and an American secret agent, to prevent Wakanda from being dragged into a world war.

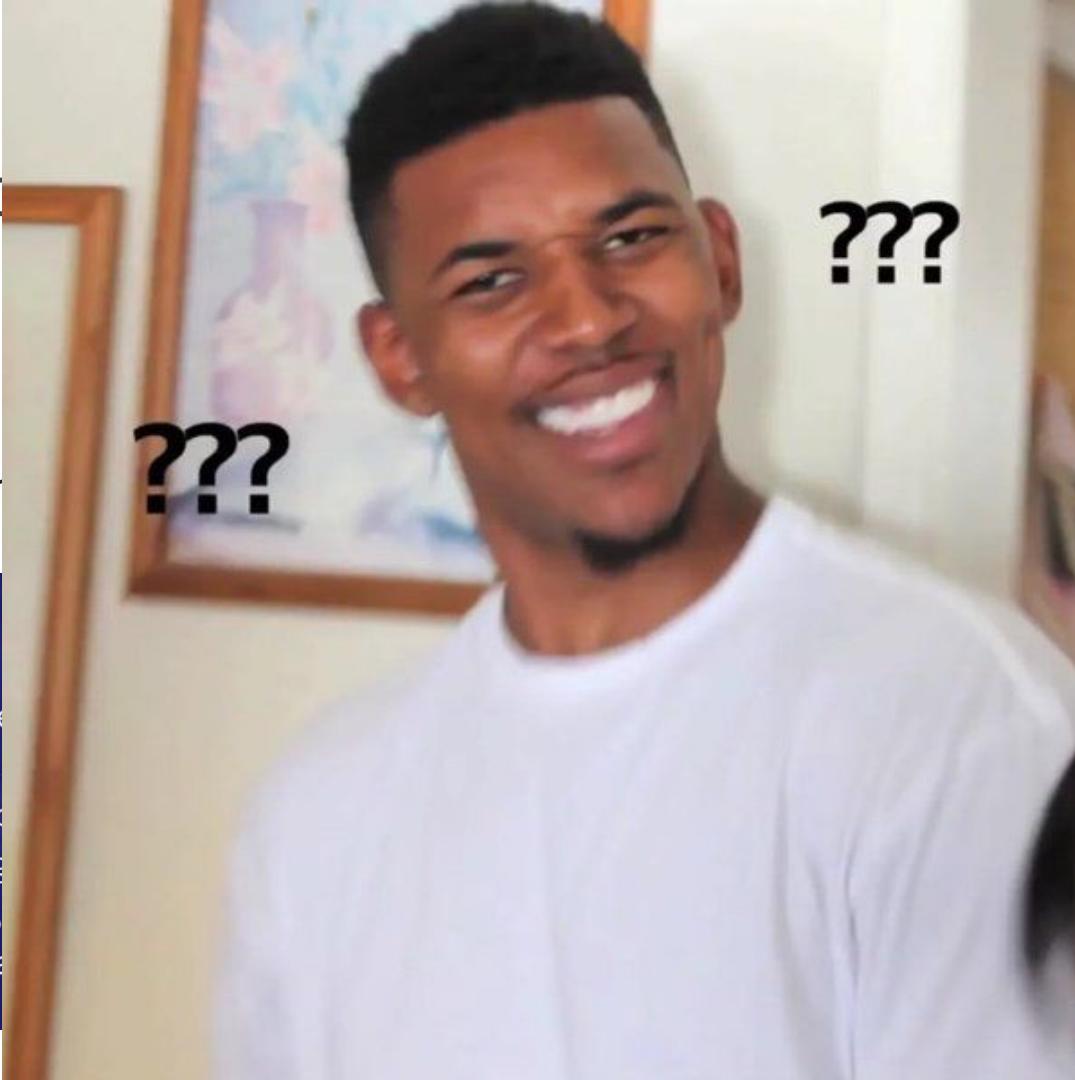


Step

How
recor

Overview

King T'Challa returns to Wakanda to compete for the throne before his Wakandan king, the queen-mother, and an American



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Understanding TF-IDF

What is TF-IDF?

TF-IDF stands for "Term Frequency, Inverse Document Frequency". It is a way to score the importance of words (or "terms") in a document based on how frequently they appear across multiple documents.

Intuitively...

- If a word appears frequently in a document, it's important. Give the word a high score.
- But if a word appears in many documents, it's not a unique identifier. Give the word a low score.

Therefore, common words like "the" and "for", which appear in many documents, will be scaled down. Words that appear frequently in a *single* document will be scaled up.



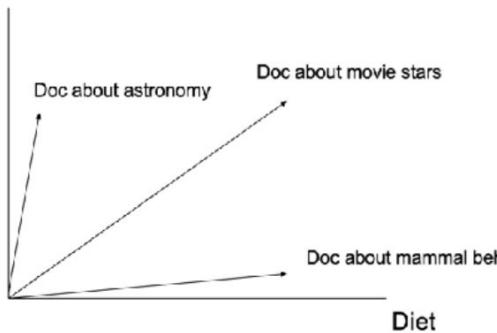
Understanding TF-IDF

How it works

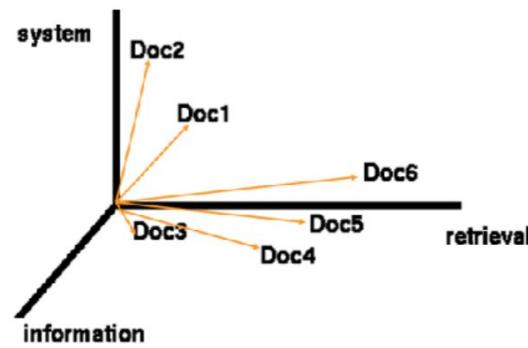
- Documents are represented as vectors in term space.
- Primary assumption of the Vector Space Model: Documents that are close together in space are similar in meaning.

2-D Space

Star



3-D Space





Understanding TF-IDF

How it works

- TF-IDF computes a weight which represents the importance of a term inside a document. It does this by comparing the frequency of usage inside an individual document as opposed to the entire dataset (a collection of documents).

Each row is a document

| | T_1 | T_2 | \dots | T_t |
|-------|----------|----------|---------|----------|
| D_1 | w_{11} | w_{21} | \dots | w_{t1} |
| D_2 | w_{12} | w_{22} | \dots | w_{t2} |
| : | : | : | | : |
| : | : | : | | : |
| D_n | w_{1n} | w_{2n} | \dots | w_{tn} |

Each column is a term

Each term is a feature



Understanding TF-IDF

Step 1 Frequency Matrix

TF (Term Frequency, Part 1): measures how frequently a term occurs in a document. Since every document is different in length, it is possible that a term would appear more often in a long document than a shorter one. Thus, the term frequency is often divided by the document length as a way of normalization.





Understanding TF-IDF

Step 1 Frequency Matrix

TF (Term Frequency, Part 1): measures how frequently a term occurs in a document. Since every document is different in length, it is possible that a term would appear more often in a long document than a shorter one. Thus, the term frequency is often divided by the document length as a way of normalization.

| Variants of term frequency (TF) weight | |
|----------------------------------------|----------------------------------------------------------------|
| weighting scheme | TF weight |
| binary | 0, 1 |
| raw count | $f_{t,d}$ |
| term frequency | $f_{t,d} / \sum_{t' \in d} f_{t',d}$ |
| log normalization | $1 + \log(f_{t,d})$ |
| double normalization 0.5 | $0.5 + 0.5 \cdot \frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$ |
| double normalization K | $K + (1 - K) \frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$ |



Understanding TF-IDF

Step 2: How to calculate weights?

IDF (Inverse Document Frequency, Part 2): measure of how unique a word is i.e. how infrequently the word occurs across all documents.





Understanding TF-IDF

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Variants of inverse document frequency (IDF) weight

| weighting scheme | IDF weight ($n_t = \{d \in D : t \in d\} $) |
|------------------------------------------|------------------------------------------------------------------|
| unary | 1 |
| inverse document frequency | $\log \frac{N}{n_t} = -\log \frac{n_t}{N}$ |
| inverse document frequency smooth | $\log \left(1 + \frac{N}{n_t} \right)$ |
| inverse document frequency max | $\log \left(\frac{\max_{\{t' \in d\}} n_{t'}}{1 + n_t} \right)$ |
| probabilistic inverse document frequency | $\log \frac{N - n_t}{n_t}$ |



Understanding TF-IDF

Putting it all together

$$w_{ik} = tf_{ik} * \log(N / n_k)$$

T_k = term k in document D_i

tf_{ik} = frequency of term T_k in document D_i

idf_k = inverse document frequency of term T_k in C

N = total number of documents in the collection C

n_k = the number of documents in C that contain T_k

$$idf_k = \log\left(\frac{N}{n_k}\right)$$



Understanding TF-IDF

Example

Example: Tagging Blog Posts

Step 1: Generate Scores for Each Document

Let's say you have a 100 word blog post with the word "JavaScript" in it 5 times. The calculation for the Term Frequency would be:



Next, assume your entire collection of blog posts has 10,000 documents and the word "JavaScript" appears at least once in 100 of these. The Inverse Document Frequency calculation would look like this:



To calculate the TF-IDF, we multiply the previous two values. This gives us the final score:





Understanding TF-IDF

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$$TF = 5/100 = 0.05$$

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To calculate the TF-IDF, we multiply the previous two values. This gives us the final score:





Understanding TF-IDF

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To calculate the TF-IDF, we multiply the previous two values. This gives us the final score:

$$TF-IDF = 0.05 * 2 = 0.1$$



Step 2: Define User Profiles

Explicit: Users rate items

Implicit: Looking at clicks etc

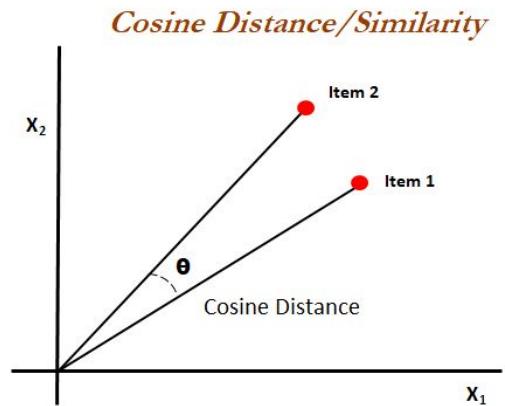


Step 3: Calculate Similarity

Cosine Similarity

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Where: A is the Item Profile and B is the User Profile





Advantages

1. Don't need data on other users
2. Able to recommend to users with unique tastes
3. Able to recommend new and unpopular items
4. Can give explanations



Disadvantages

1. Finding features can be hard (images, movies, music)
2. Overspecialization
3. Cold-start for new users