



Content-Based Recommendation System

Description and implementation with Python



Bindhu Balu · Follow

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One popular technique of recommendation/recommender systems is **content-based filtering**. Content here refers to the content or attributes of the products you like. So, the idea in content-based filtering is to tag products using certain keywords, understand what the user likes, look up those keywords in the database and recommend different products with the same attributes.

Example: Movie recommendation to a Netflix User by profile name Nikhil

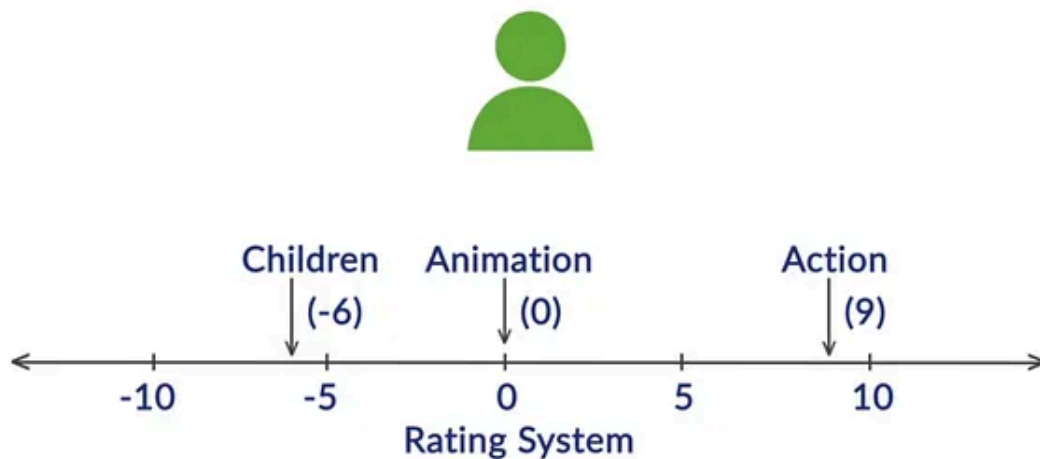


Nikhil

Movies	Reviews Given	Rating
Mission Impossible	✓	Good
James Bond	✓	Good
Toy Story	✓	Bad

Assume Nikil has given Good ratings to movies like Mission Impossible and James Bond which are tagged as “Action” Genre and gave a bad rating to the movie “Toy Story” which is tagged as “Children” Genre.

Now we will create a User Vector for Nikhil based on his 3 ratings :



On a rating scale of -10 to 10, since Nikhil loves Action movies, we assign value of 9 to “Action”, Nikhil hasn't watched any Animation movies, we assign 0 to “Animation” and since Nikhil has given bad reviews for movies with Children genre — we assign ‘-6 ‘ to “Children”.

So user Vector for Nikhil is (9, 0, -6) in order of (Action, Animation, Children).

Toy story	Nikhil	Star wars
↓	↓	↓
Item vector	User vector	Item vector
↓	↓	↓
(0, 1, 1)	(9, 0, -6)	(1, 0, 0)
$0 \times 9 + 1 \times 0 + 1 \times -6$		$9 \times 1 + 0 \times 0 + -6 \times 0$
$0 + 0 + -6$		$9 + 0 + 0$
-6		9

The item vector for movie “Toy Story” is (0,1,1) and the movie “Star Wars” is (1,0,0) in order of (Action, Animation, Children).

We now need to make dot product of two 2-D vectors — Item vector and User Vector

Dot product of 2-d vectors

$$v_1 = (x_1, y_1)$$

$$v_2 = (x_2, y_2)$$

$$v_1 \cdot v_2 = x_1x_2 + y_1y_2$$

Accordingly, the dot product of “Toy Story” is -6 and that of “Star Wars” is 9.

Hence “Star Wars” will be recommended to Nikhil — which also matches our intuition that Nikhil likes Action movies and dislikes Children movies.

In a similar manner — we can calculate the dot products of all the item vectors of all the movies in-store and recommend top 10 movies to Nikhil

Python Implementation of Content-Based Recommendation:

Link to download Input data(CSV file) and python code :

BindhuVinodh/Content-based-recommendation

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Loading the data

```
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import linear_kernel
ds = pd.read_csv("/home/nikita/Downloads/sample-data.csv")
```

Creating a TF-IDF Vectorizer

The **TF*IDF algorithm** is used to weigh a keyword in any document and assign the importance to that keyword based on the number of times it appears in the document. Put simply, the higher the TF*IDF score (weight), the rarer and more important the term, and vice versa.

Mathematically [don't worry it's easy :)],

Each word or term has its respective TF and IDF score. The product of the TF and IDF scores of a term is called the TF*IDF weight of that term.

The **TF (term frequency)** of a word is the number of times it appears in a document. When you know it, you're able to see if you're using a term too often or too infrequently.

$TF(t) = (\text{Number of times term } t \text{ appears in a document}) / (\text{Total number of terms in the document}).$

The **IDF (inverse document frequency)** of a word is the measure of how significant that term is in the whole corpus.

$IDF(t) = \log_e(\text{Total number of documents} / \text{Number of documents with term } t \text{ in it}).$

$$w_{x,y} = tf_{x,y} \times \log \left(\frac{N}{df_x} \right)$$

TF-IDF
Term x within document y

$tf_{x,y}$ = frequency of x in y
 df_x = number of documents containing x
 N = total number of documents

In Python, scikit-learn provides you a pre-built TF-IDF vectorizer that calculates the TF-IDF score for each document's description, word-by-word.

```
tf = TfidfVectorizer(analyzer='word', ngram_range=(1, 3), min_df=0,
stop_words='english')
tfidf_matrix = tf.fit_transform(ds['description'])
```

Here, the `tfidf_matrix` is the matrix containing each word and its TF-IDF score with regard to each document, or item in this case. Also, stop words are simply words that add no significant value to our system, like 'an', 'is', 'the', and hence are ignored by the system.

Now, we have a representation of every item in terms of its description. Next, we need to calculate the relevance or similarity of one document to another.

Calculating Cosine Similarity

```
cosine_similarities = linear_kernel(tfidf_matrix, tfidf_matrix)
results = {}
for idx, row in ds.iterrows():
    similar_indices = cosine_similarities[idx].argsort()[:-100:-1]
    similar_items = [(cosine_similarities[idx][i], ds['id'][i]) for i
in similar_indices]
    results[row['id']] = similar_items[1:]
```

Here we've calculated the cosine similarity of each item with every other item in the dataset, and then arranged them according to their similarity with item `i`, and stored the values in `results`.

Making a recommendation

So here comes the part where we finally get to see our recommender system in action.

```
def item(id):
    return ds.loc[ds['id'] == id]['description'].tolist()[0].split(' -')[0] # Just reads the results out of the dictionary.
def recommend(item_id, num):
    print("Recommending " + str(num) + " products similar to " +
item(item_id) + "...")
    print("-----")
    recs = results[item_id][:num]
    for rec in recs:
        print("Recommended: " + item(rec[1]) + " (score:" +
str(rec[0]) + ")")
```

Here, we just input an `item_id` and the number of recommendations that we want, and voilà! Our function collects the `results[]` corresponding to that `item_id`, and we get our recommendations on the screen.



Results

Here's a glimpse of what happens when you call the above function.

```
recommend(item_id=11, num=5)
```

```
Recommend 10 products similar to Relax fit organic ctn jeans-shor...
-----
Recommended: Relax fit organic ctn jeans-reg (score:0.8908101955877065)
Recommended: Relax fit organic ctn jeans-long (score:0.8866113828050025)
Recommended: Reg fit organic ctn jeans-short (score:0.507668259865595)
Recommended: Reg fit organic ctn jeans-long (score:0.48801052800273903)
Recommended: Reg fit organic ctn jeans-reg (score:0.48488884889129785)
Recommended: Custodian pants (score:0.1925730494862419)
Recommended: Shop pants (score:0.18030173682681883)
Recommended: Shop pants (score:0.1733375276479681)
Recommended: Custodian pants (score:0.1710311820622527)
Recommended: Inga shorts (score:0.17023045978100093)
```

Recommendations similar to organic cotton jeans-shorts

```
done!
Recommend 5 products similar to Baby sunshade top...
-----
Recommended: Sunshade hoody (score:0.2133029602108501)
Recommended: Baby baggies apron dress (score:0.10975311296284813)
Recommended: Runshade t-shirt (score:0.09988151262780706)
Recommended: Runshade t-shirt (score:0.09530698241688194)
Recommended: Runshade top (score:0.08510550093018401)
```

Recommendations similar to baby sunshade top

Advantages of Content-Based Filtering

- **User independence:** The content-based method only has to analyze the items and a single user's profile for the recommendation, which makes the process less cumbersome. Content-based filtering would thus produce more reliable results with fewer users in the system.
- **Transparency:** Collaborative filtering gives recommendations based on other unknown users who have the same taste as a given user, but with content-based filtering, items are recommended on a feature-level basis.
- **No cold start:** As opposed to collaborative filtering, new items can be suggested before being rated by a substantial number of users.

Disadvantages of Content-Based Filtering

- **Limited content analysis:** If the content doesn't contain enough information to discriminate the items precisely, the recommendation itself risks being imprecise.
- **Over-specialization:** Content-based filtering provides a limited degree of novelty since it has to match up the features of a user's profile with available items. In the case of item-based filtering, only item profiles are created and users are suggested items similar to what they rate or search for, instead of their past history. A perfect content-based filtering system may suggest nothing unexpected or surprising.

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
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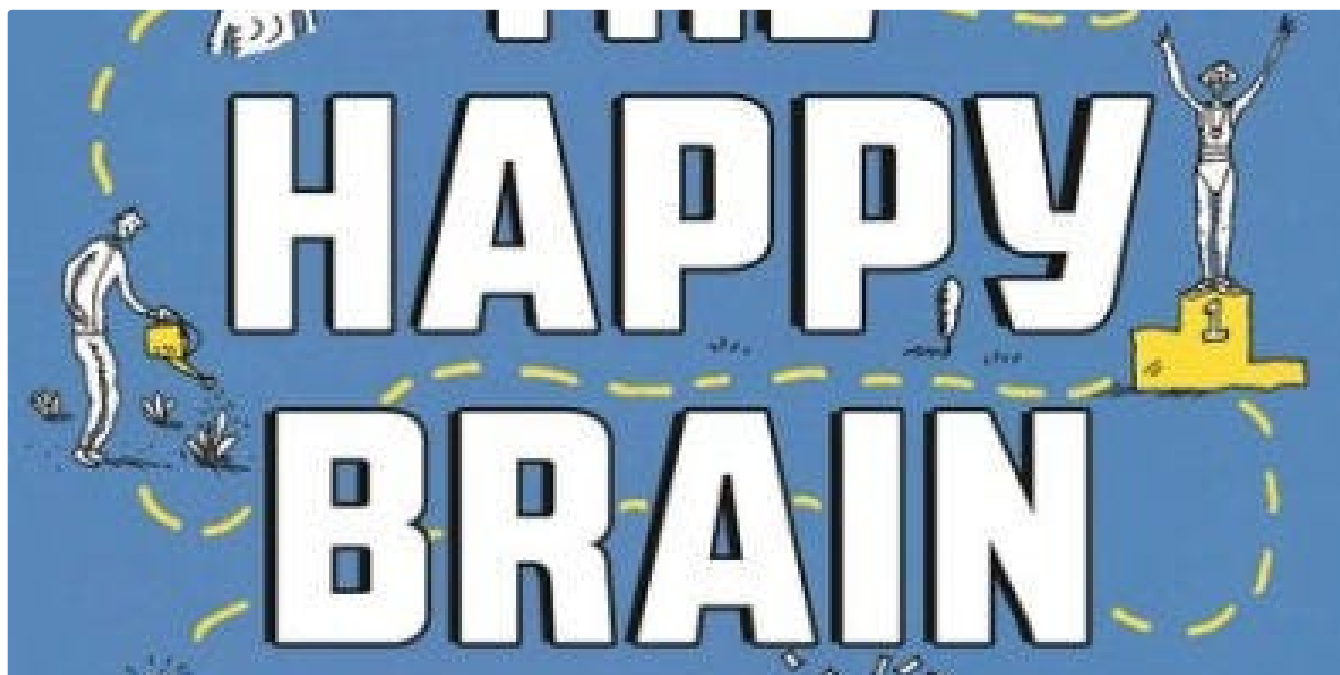


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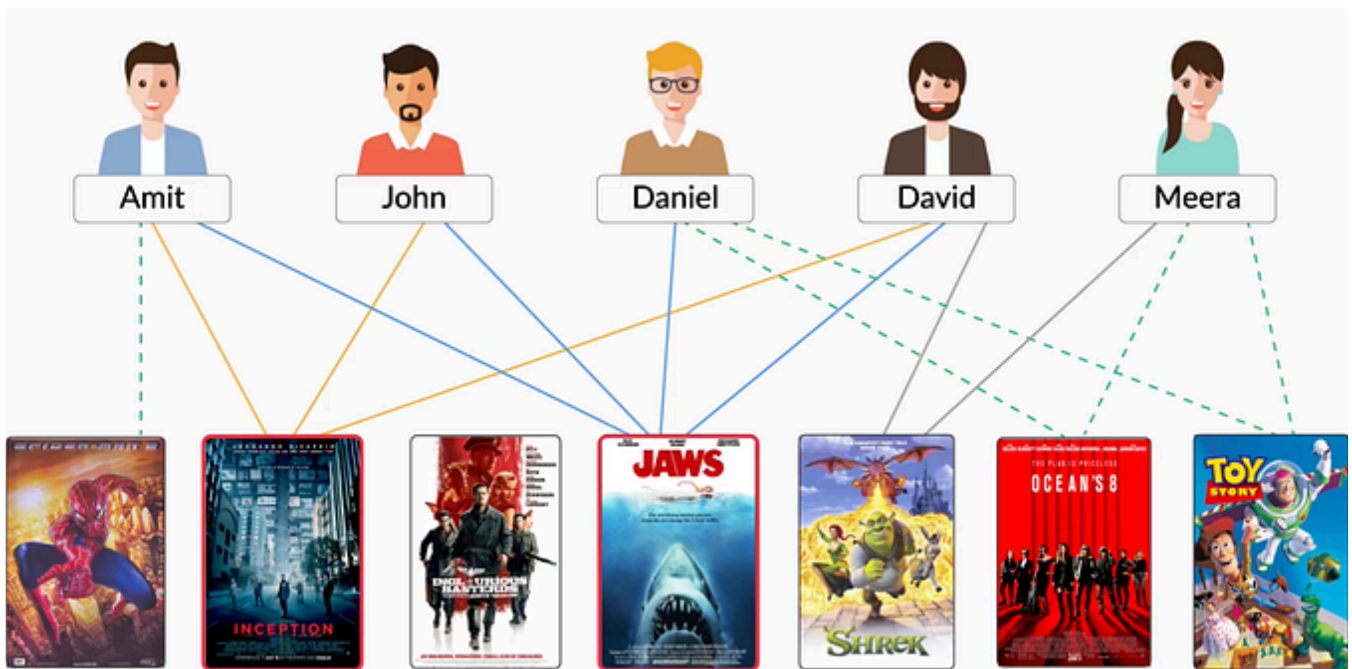
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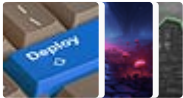
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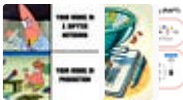


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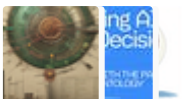
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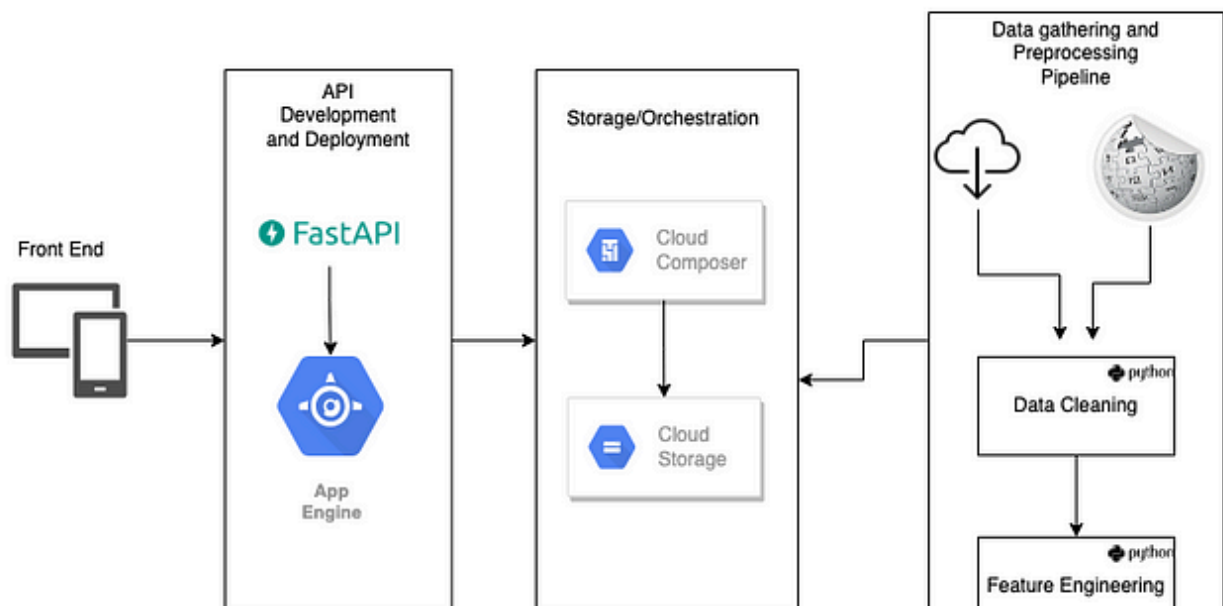
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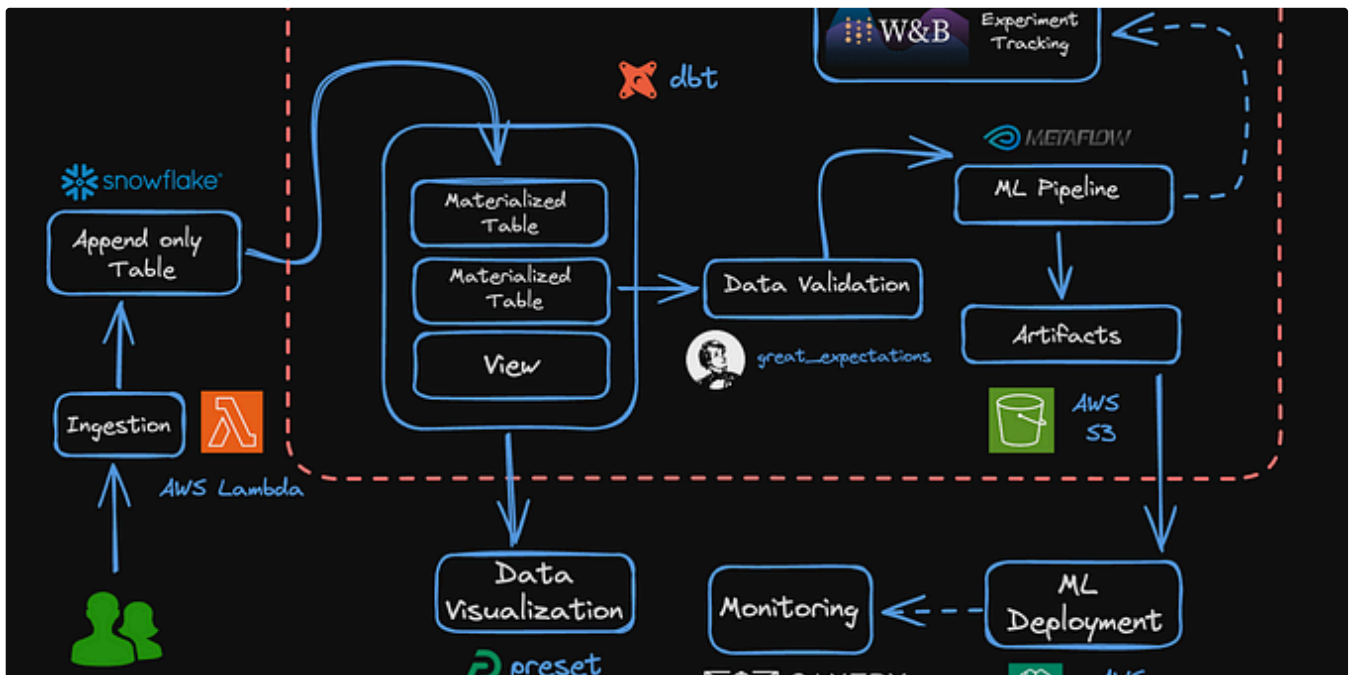


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