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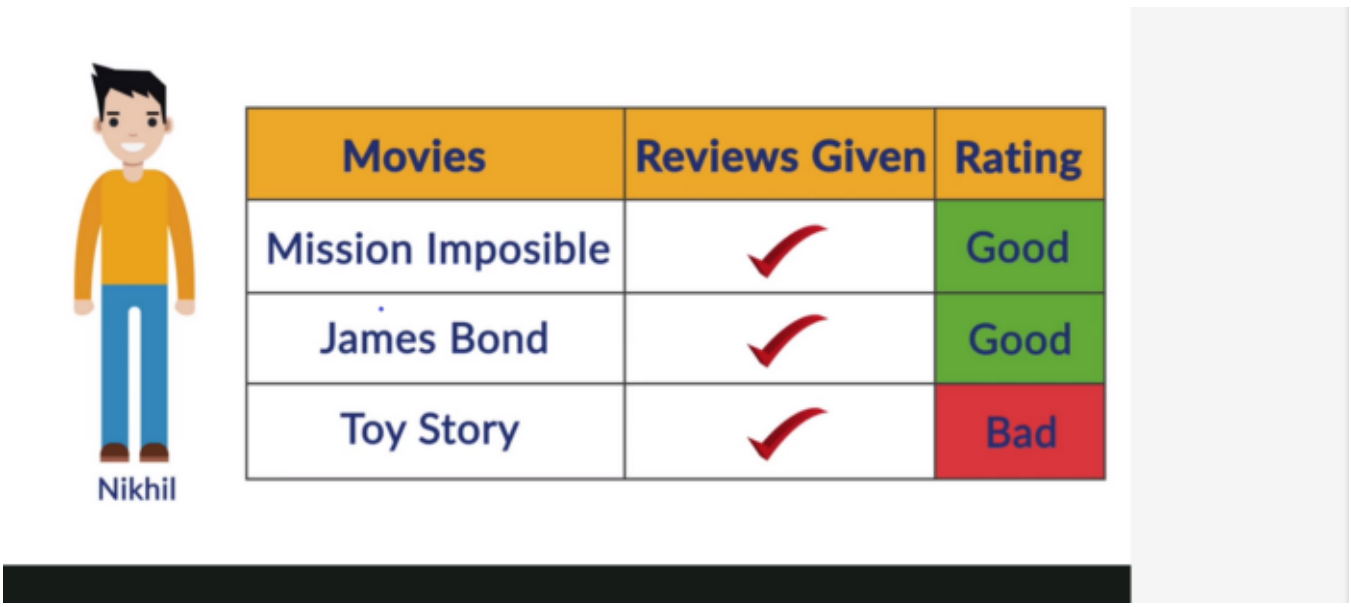
# Content-Based Recommendation System

Description and implementation with Python

Bindhu Balu Oct 16, 2019 · 6 min read ★

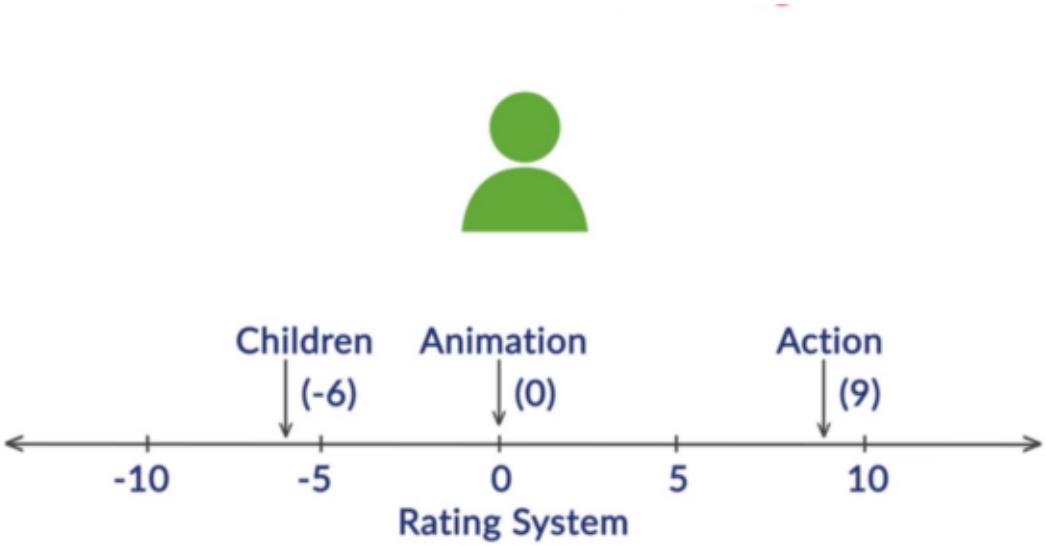
One popular technique of recommendation/recommender systems is **content-based filtering.** Content here refers to the content or attributes of the products you like. So, the idea in content-based filtering is to tag products using certain keywords, understand what the user likes, look up those keywords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

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



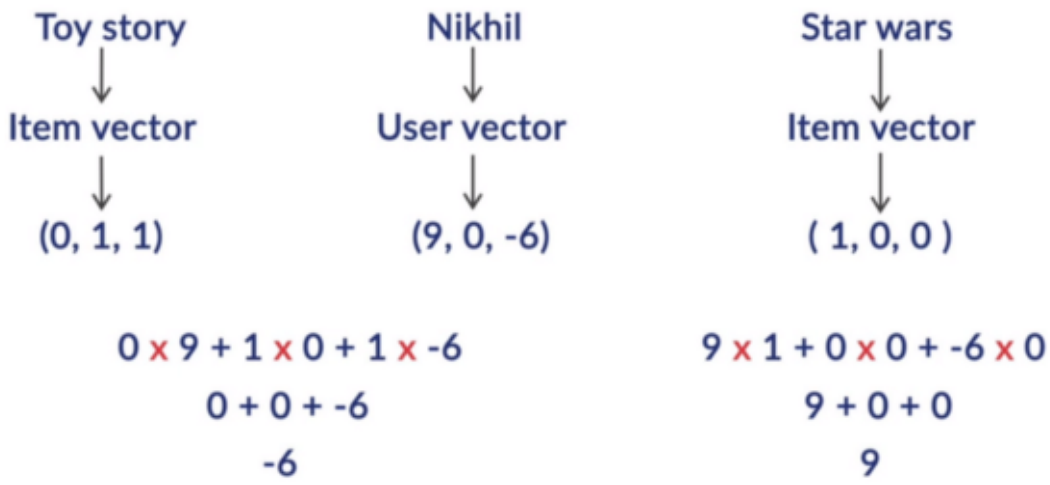
which is tagged as “Chil

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

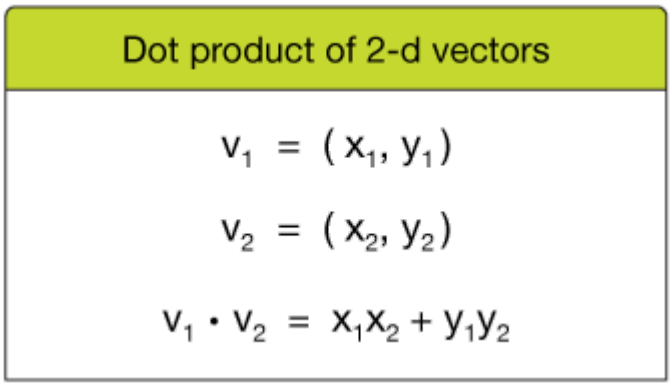



On a rating scale of -10 to 10, since Nikhil loves Action movies, we assign value of 9 to “Action”, Nikhil hasn't watched any Animation movies, we assign 0 to “Animation” and since Nikhil has given bad reviews for movies with Children genre — we assign ‘-6 ‘ to “Children”.

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



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




Accordingly, the dot product of “Toy Story” is -6 and that os “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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github.com

## 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")
```

importance to that keyw ppears 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) = (Number of times term t appears in a document) / (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(Total number of documents / Number of documents with
term t 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'])
```

add no significant value nce 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)
```

```
Recommending 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!
Recommending 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

- **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.

Data Science Machine Learning Artificial Intelligence Recommender Systems

Recommendation System