

Lecture 5

Recommender Systems

Personalization, Collaborative Filtering & Content-based recommendation

COMP 474/6741, Winter 2024

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

René Witte
Department of Computer Science
and Software Engineering
Concordia University

1 Introduction

- Modeling Users
- Netflix Recommendations

2 Collaborative Filtering

- Introduction
- Computing with Words
- Item Recommendation
- Items Related to other Items
- Items of Interest to a User
- Relevant Users for an Item
- Semantic User Profiles
- Evaluation

3 Content-based Recommendations

- Motivation
- TF*IDF weighting
- Term Vector Space Model
- Summary

4 Notes and Further Reading

Introduction

- Modeling Users
- Netflix Recommendations

Collaborative Filtering

- Introduction
- Computing with Words
- Item Recommendation
- Items Related to other Items
- Items of Interest to a User
- Relevant Users for an Item
- Semantic User Profiles
- Evaluation

Content-based Recommendations

- Motivation
- TF*IDF weighting
- Term Vector Space Model
- Summary

Notes and Further Reading

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Slides Credit

Includes slides by Christopher D. Manning, Prabhakar Raghavan and
Hinrich Schütze [MRS08]

- Copyright © 2008 Cambridge University Press

Recommender Systems and Collaborative Filtering

René Witte



amazon.ca

Hello **Rene Witte**. We have [recommendations](#) for you. ([Not Rene?](#))

[Rene's Store](#) | [Deals Store](#) | [Gift Certificates](#)

[Shop All Departments](#)

Search

[Your Store](#) | [Page You Made](#) | [Recommended For You](#) | [Rate These Items](#) | [Improve Your Recommendation](#)

Rene, Welcome to Your Amazon.ca (If you're not René Witte, [click here.](#))

Today's Recommendations For You

Here's a daily sample of items recommended for you. Click here to [see all recommendations.](#)

Page 1 of 44



[Clean Code: A Handbook of Ag...](#) (Paperback) by Robert C. Martin

★★★★★ (7) CDN\$ 39.43

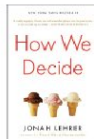
[Fix this recommendation](#)



[Why Does E=mc2?: \(And Why Should We...](#) (Paperback) by Brian Cox

★★★★★ (2) CDN\$ 14.44

[Fix this recommendation](#)



[How We Decide](#) (Paperback) by Jonah Lehrer

★★★★★ (10) CDN\$ 13.68

[Fix this recommendation](#)



[ANSI Common LISP](#) (Paperback) by Paul Graham

★★★★★ (18) CDN\$ 96.95

[Fix this recommendation](#)

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Collecting User Interactions

René Witte



[Introduction](#)

[Modeling Users](#)

[Netflix Recommendations](#)

[Collaborative Filtering](#)

[Introduction](#)

[Computing with Words](#)

[Item Recommendation](#)

[Items Related to other Items](#)

[Items of Interest to a User](#)

[Relevant Users for an Item](#)

[Semantic User Profiles](#)

[Evaluation](#)

[Content-based Recommendations](#)

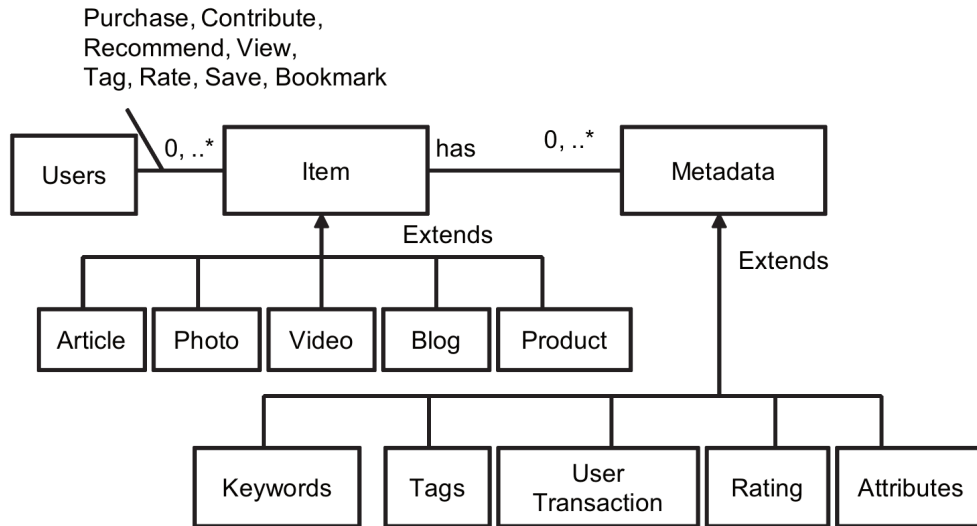
[Motivation](#)

[TF*IDF weighting](#)

[Term Vector Space Model](#)

[Summary](#)

[Notes and Further Reading](#)



Copyright 2009 by Manning Publications Co., [Ala09]

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

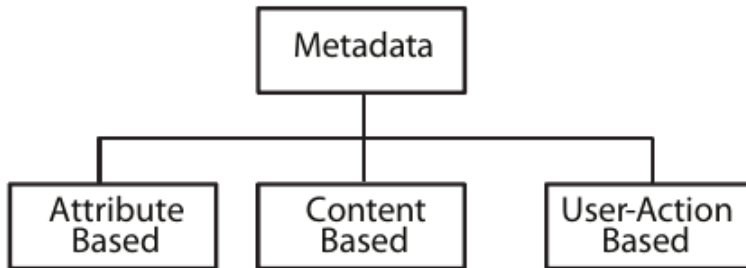
Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading



Copyright 2009 by Manning Publications Co., [Aia09]

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

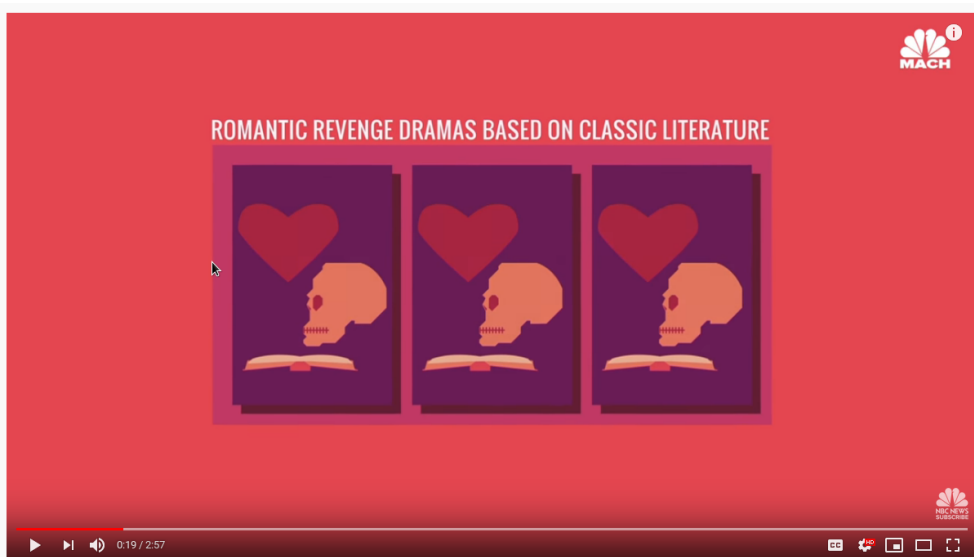
Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading



Why Netflix's Algorithm Is So Binge-Worthy | Mach | NBC News

<https://www.youtube.com/watch?v=nq2QtatuF7U>

1 Introduction

2 Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

3 Content-based Recommendations

4 Notes and Further Reading

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Making Recommendations

René Witte



Given Information about a User...

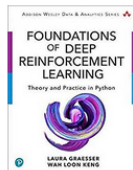
... we want to be able to have a system

- recommending items (books, movies, music, photos, videos, etc.)
- find users interested in a new item
- find similar items, based on interests of *other* users

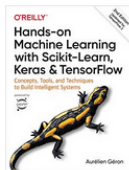
Customers who bought this item also bought



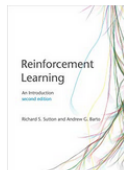
Hands-On Unsupervised
Learning Using Python:
How to Build Applied...
Ankur A. Patel
★★★★☆ 2
Paperback
CDN\$55.67



Foundations of Deep
Reinforcement Learning:
Theory and Practice in...
Laura Graesser
★★★★★ 1
Paperback
CDN\$48.59



Hands-On Machine
Learning with Scikit-Learn,
Keras, and TensorFlow...
Aurélien Géron
★★★★★ 13
Paperback
CDN\$69.16



Reinforcement Learning:
An Introduction
Richard S. Sutton
★★★★★ 9
Hardcover
CDN\$86.18



Practical Time Series
Analysis: Prediction with
Statistics and Machine...
Aileen Nielsen
★★★★☆ 1
Paperback
CDN\$42.60

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Introduction

Modeling Users
Netflix Recommendations

Collaborative Filtering

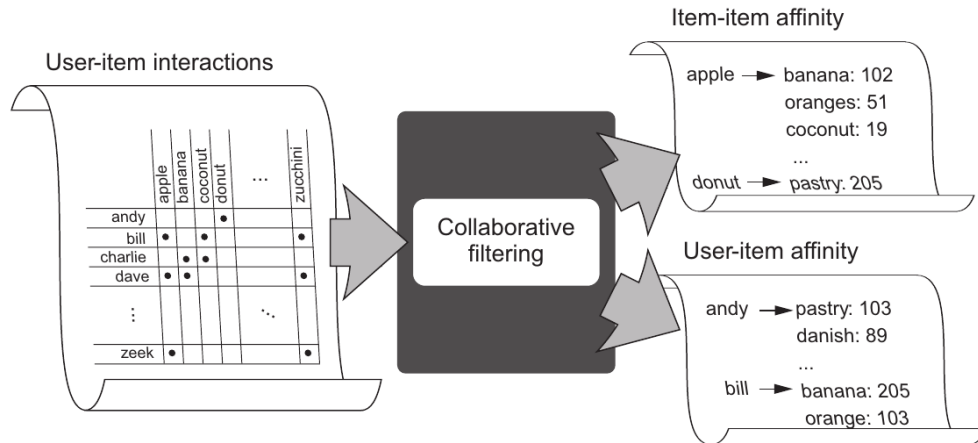
Introduction

Computing with Words
Item Recommendation
Items Related to other Items
Items of Interest to a User
Relevant Users for an Item
Semantic User Profiles
Evaluation

Content-based Recommendations

Motivation
TF*IDF weighting
Term Vector Space Model
Summary

Notes and Further Reading



Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Date	User	Item
2015-01-24 15:01:29	Allison	Tunisia Sadie dress
2015-01-26 05:13:58	Christina	Gordon Monk stiletto
2015-02-18 10:28:37	David	Ravelli aluminum tripod
2015-03-17 14:29:23	Frank	Nikon digital camera
2015-03-26 18:11:01	Christina	Georgette blouse
2015-04-06 21:50:18	David	Canon 24 mm lens
2015-04-15 10:21:44	Frank	Canon 24 mm lens
2015-04-15 21:53:25	Brenda	Tunisia Sadie dress
2015-07-26 08:08:25	Elise	Nikon digital camera

Vectors

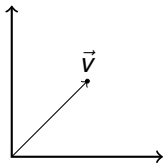
A vector \vec{v} is an element of a **vector space**.

- For example, $\vec{v} \in \mathbb{R}^n$ with

$$\vec{v} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^n$$

Visualization

We can visualize vectors, e.g., in 2D:



Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based

Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further

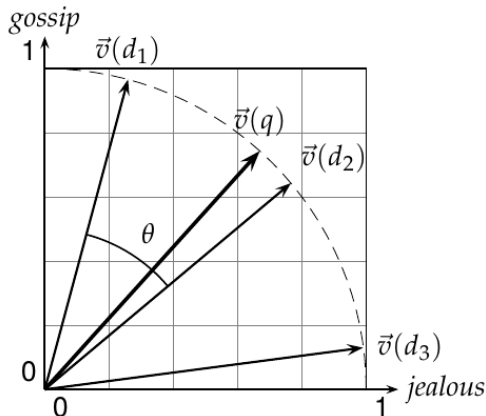
Reading

So what?

Vectors of words, users, products, ...

We can represent (users, documents, products) as vectors, e.g., using the count of tags or the weight of words. This is called a **vector space model**.

- Vector operations on entities, e.g., to compute their **similarity**



Copyright 2008 by Cambridge University Press, [MRS08]

Movies as Vectors

René Witte



Introduction

Modeling Users
Netflix Recommendations

Collaborative Filtering

Introduction

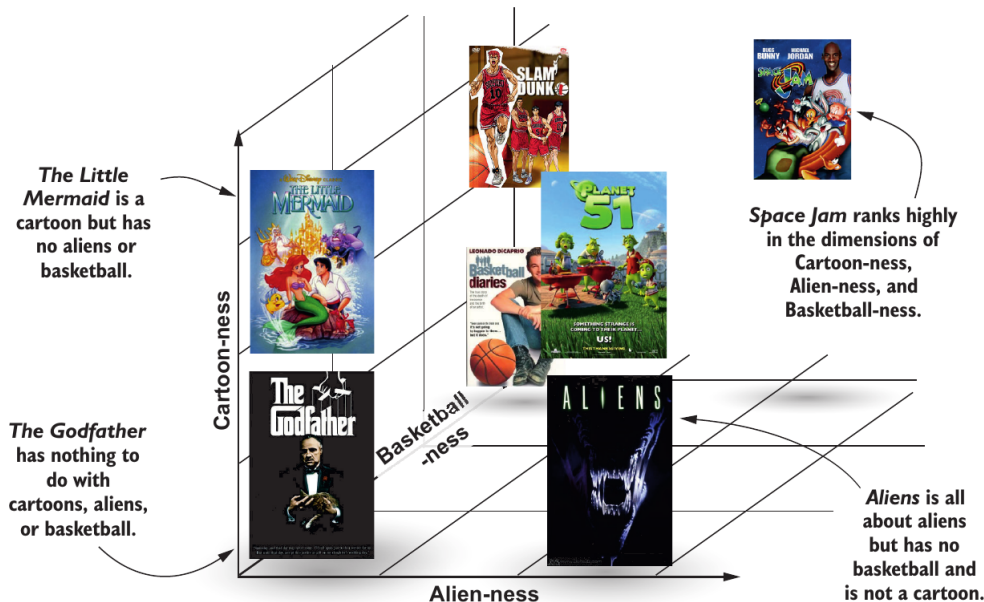
Computing with Words

Item Recommendation
Items Related to other Items
Items of Interest to a User
Relevant Users for an Item
Semantic User Profiles
Evaluation

Content-based Recommendations

Motivation
TF*IDF weighting
Term Vector Space Model
Summary

Notes and Further Reading



How do we compute the length of a vector?

- A vector can be (length-) normalized by dividing each of its components by its length – here we use the L_2 norm: $\|x\|_2 = \sqrt{\sum_i x_i^2}$
- This maps vectors onto the unit sphere ...
- ... since after normalization: $\|x\|_2 = \sqrt{\sum_i x_i^2} = 1.0$
- As a result, longer and shorter vectors (more/fewer tags) have weights of the same order of magnitude.

→ **Worksheet #4: Tasks 1, 2**

How do we formalize vector space similarity?

René Witte



Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

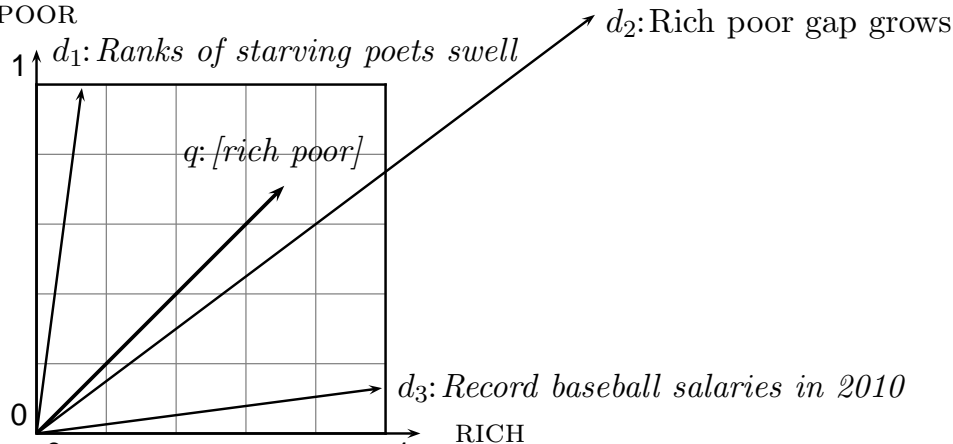
Notes and Further Reading

Computing the similarity

- First cut: (negative) distance between two points
- (= distance between the end points of the two vectors)
- Euclidean distance?
- Euclidean distance is a bad idea . . .
- . . . because Euclidean distance is **large** for vectors **of different lengths**.

Why Euclidian distance is a bad idea

POOR



The Euclidean distance of \vec{q} and \vec{d}_2 is large although the distribution of terms in the query q and the distribution of terms in the document d_2 are very similar.

René Witte



[Introduction](#)

[Modeling Users](#)

[Netflix Recommendations](#)

[Collaborative Filtering](#)

[Introduction](#)

[Computing with Words](#)

[Item Recommendation](#)

[Items Related to other Items](#)

[Items of Interest to a User](#)

[Relevant Users for an Item](#)

[Semantic User Profiles](#)

[Evaluation](#)

[Content-based](#)

[Recommendations](#)

[Motivation](#)

[TF*IDF weighting](#)

[Term Vector Space Model](#)

[Summary](#)

[Notes and Further Reading](#)

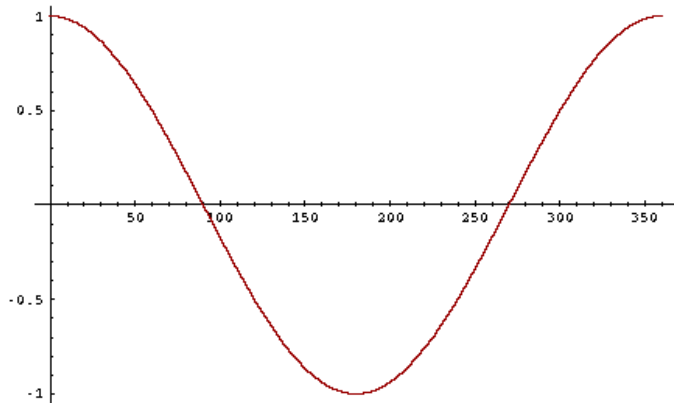
Comparing vectors

The following two notions are equivalent:

- Compare item vectors according to the **angle** between them, in decreasing order
- Rank item vectors according to **cosine**(item₁, item₂) in increasing order

Cosine is a monotonically decreasing function of the angle for the interval $[0^\circ, 180^\circ]$

Cosine



René Witte



Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Computing similarity

For normalized vectors, the cosine is equivalent to the dot product or scalar product:

$$\cos(\vec{q}, \vec{d}) = \vec{q} \cdot \vec{d} = \sum_i q_i \cdot d_i$$

(if both \vec{q} and \vec{d} are length-normalized)

→ **Worksheet #4: Task 3**

Simple Tag-based Recommendation

Collaborative tagging gives rise to simple recommender approaches:

- show other items (products, photos, videos, music) that were tagged similar by other users
- exploited in many e-commerce/social networking web sites

Tags Customers Associate with This Product ([What's this?](#))

Click on a tag to find related items, discussions, and people.

[tagging](#) (20)[metadata](#) (16)[folksonomy](#) (15)[information](#)[architecture](#) (11)[social software](#) (7)[findability](#) (6)[ia](#) (4)[social media](#) (4)[semantic web](#) (3)[interaction design](#) (2)[See all 28 tags...](#)

Search Products Tagged with



> [See most popular Tags](#)

Your tags: [Add your first tag](#)

Collaborative Filtering

Finding related content

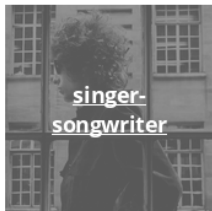
When **multiple users** tag the **same resource**, content can be discovered based on the most frequent tags (example: Last.fm).

Tags

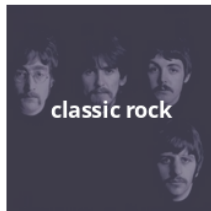
+ Add Tags



Including Bob Dylan, Johnny Cash and Iron & Wine



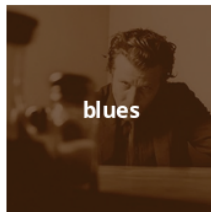
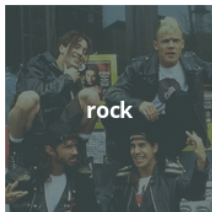
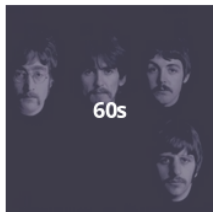
Including Bob Dylan, Tom Waits and Elliott Smith



Including The Beatles, Led Zeppelin and Pink Floyd



Including Bob Dylan, Jethro Tull and Neil Young



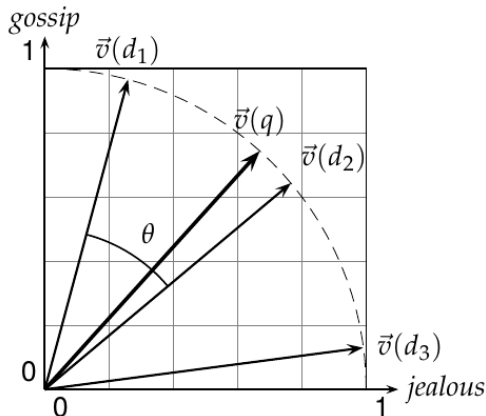
Recommendations based on tags

We can now exploit tags for a number of use cases:

- Recommend items related to other items
- Recommend items based on user's interest
- Find users interested in a new item

General Approach

- Represent users/items as (normalized) **term vectors**
- Compute **cosine similarity** between vectors; i.e., the **angle** between them (for normalized vectors, this is simply their **dot product**)



Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Simple point-to-point recommendation engine

- Create item vectors using raw count
- Normalize vectors
- Compute cosine similarity

Result is a similarity matrix

Personalization

- Item-to-item is the same for **all** users
- How can we recommend items for a **particular** user?

Solution: build user-specific similarity matrix

- Computation of vectors, normalization as before
- This time, we calculate the cosine similarity between a **user vector** and an **article vector**

→ **Worksheet #4: Tasks 4, 5**

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Recommending items to users

- New item comes in (blog post, photo, article, product, . . .)
- Which users would be interested in it?

Similar to before, compute similarity matrix between metadata of new item and metadata of users.

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

General issue in recommender system deployment

- New user \Rightarrow no user profile for recommendations
- New item \Rightarrow no user interactions for this item

No general solution...

Some strategies:

- Ask user for preferences during sign-up
- Recommend top- n items (e.g., currently most popular movies/songs/products)

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Semantic User Profiles

Idea: Use **vocabularies** instead of keywords in the vector representation of a user profile

Motivation

- **Semantic** recommendations (remember the “tree” example from Lecture #01)
- Open knowledge bases:
 - interoperable between applications
 - controlled by users, not corporations

Generic user modeling vocabularies

FOAF

- The most popular generic user model offering descriptions for basic user information
- No comprehensive classes for describing preferences or interests

GUMO

- A generic user model that offers several classes for users' characteristics
- Basic user dimensions like Emotional States, Characteristics and Personality

IntelLEO

- Several ontologies strongly focused on personalization
- Enables describing user and team modelling, preferences, tasks and interests

The \$1m Netflix Prize Competition (2009)

NETFLIX

Netflix Prize

COMPLETED

[Home](#) [Rules](#) [Leaderboard](#) [Update](#)

Leaderboard

Showing Test Score. [Click here to show quiz score](#)

Rank **Team Name** **Best Test Score** **% Improvement** **Best Submit Time**

Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos

1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22
3	Grand Prize Team	0.8582	9.90	2009-07-10 21:24:40
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31
5	Vandelay Industries I	0.8591	9.81	2009-07-10 00:32:20
6	Pragmatic Theory	0.8594	9.77	2009-06-24 12:06:56
7	BellKor in BigChaos	0.8601	9.70	2009-05-13 08:14:09
8	Dace	0.8612	9.59	2009-07-24 17:18:43
9	Feeds2	0.8622	9.48	2009-07-12 13:11:51
10	BigChaos	0.8623	9.47	2009-04-07 12:33:59
11	Opera Solutions	0.8623	9.47	2009-07-24 00:34:07

René Witte



[Introduction](#)

[Modeling Users](#)

[Netflix Recommendations](#)

[Collaborative Filtering](#)

[Introduction](#)

[Computing with Words](#)

[Item Recommendation](#)

[Items Related to other Items](#)

[Items of Interest to a User](#)

[Relevant Users for an Item](#)

[Semantic User Profiles](#)

[Evaluation](#)

[Content-based](#)

[Recommendations](#)

[Motivation](#)

[TF*IDF weighting](#)

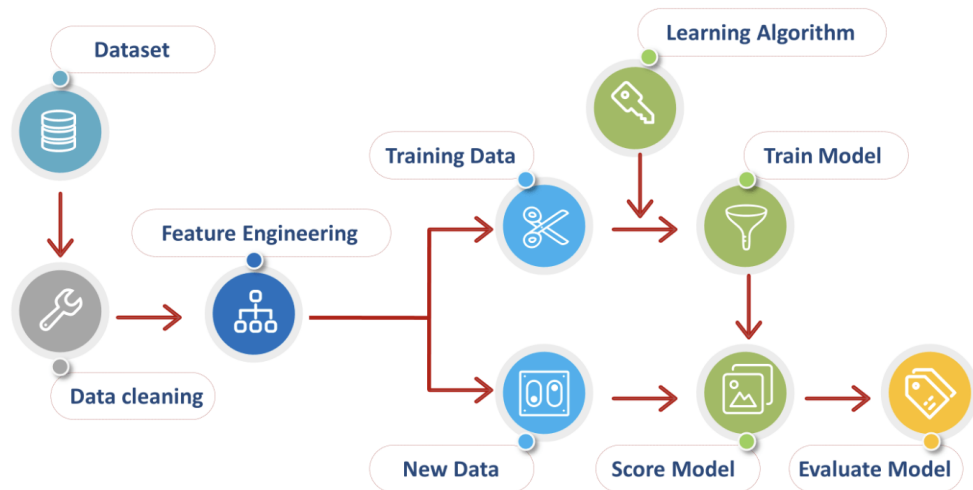
[Term Vector Space Model](#)

[Summary](#)

[Notes and Further](#)

[Reading](#)

General machine learning process



Introduction

Modeling Users
Netflix Recommendations

Collaborative Filtering

Introduction
Computing with Words
Item Recommendation
Items Related to other Items
Items of Interest to a User
Relevant Users for an Item
Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation
TF*IDF weighting
Term Vector Space Model
Summary

Notes and Further Reading

Measuring performance

- Is our fancy model better than giving out random recommendations?
- We need **metrics** to evaluate and compare the performance of different approaches against a **ground truth** (a.k.a. gold standard)

Precision and Recall

The **precision** provides a measure of the quality of the generated recommendations:

$$\text{precision} = \frac{\text{\#correct system recommendations}}{\text{\#all system recommendations}}$$

The **recall** indicates how many relevant recommendations were found by a system:

$$\text{recall} = \frac{\text{\#correct system recommendations}}{\text{\#all correct recommendations}}$$

Generally, there is a trade-off between precision and recall.

→ **Worksheet #4: Task 6**

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based

Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further

Reading

Precision at *cutoff k*

- Return a **ranked** list of recommendations (e.g., based on cosine similarity)
- Evaluate only **top-k** recommendations (e.g., top-10)

$$\text{precision@k} = \frac{1}{k} \cdot \sum_{c=1}^k \text{rel}(c),$$

where $\text{rel}(c)$ tells us if item at rank c was relevant (1) or not (0).

Intuitively...

The percentage of correct recommendations in the top- k .

Wait, what happened to *Recall*?

Well... in this application scenario, we don't really care (there are millions of potentially relevant items on Amazon or movies on Netflix)

→ **Worksheet #4: Task 7**

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based

Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further

Reading

Average Precision at N

If we recommend N items to a user, where there are at most m relevant items in $1 \dots N$,

$$AP@N = \frac{1}{m} \sum_{k=1}^N \text{precision}@k \cdot \text{rel}(k)$$

again, $\text{rel}(c)$ is 1 if the recommendation at rank c is relevant, 0 otherwise

Note

AP “rewards” (gives a higher score to) higher-ranked, correct recommendations

→ **Worksheet #4: Task 8**

MAP

- So far, everything was calculated for one user $u \in U$
- But we want to know how well the system works across all users
- Hence, average the AP for all users:

$$\text{MAP@N} = \frac{1}{|U|} \sum_{u=1}^{|U|} \text{AP@N}(u)$$

But wait, there's more...

- Accuracy, Sensitivity, F-measure, ...
- Non-binary ranked results (i.e., not just correct or wrong, but a *Likert-scale*):
Compute the *discounted cumulative gain* (DCG),

$$\text{DCG}_u = \text{rel}_1 + \sum_{c=2}^{|C|} \frac{\text{rel}_c}{\log_2 c}$$

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based

Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further

Reading

1 Introduction

2 Collaborative Filtering

3 Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

4 Notes and Further Reading

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Motivation

- So far, we build our model using vectors of concepts (e.g., tags, movie categories, etc.)
- What if we want to create recommendations based on the **content**
 - Movie description/summary
 - Blog post
 - News article
 - Research publication
 - ...

Approach

Same idea, but now we have to build vectors out of whole **documents**

- Basic idea of **information retrieval** (IR)
- Used in Internet **search engines**

Binary incidence matrix

René Witte



	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
ANTHONY	1	1	0	0	0	1	
BRUTUS	1	1	0	1	0	0	
CAESAR	1	1	0	1	1	1	
CALPURNIA	0	1	0	0	0	0	
CLEOPATRA	1	0	0	0	0	0	
MERCY	1	0	1	1	1	1	
WORSER	1	0	1	1	1	0	
...							

Each document is represented as a binary vector $\in \{0, 1\}^{|V|}$.

[from *Introduction to Information Retrieval*]

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Count matrix

René Witte



Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based

Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further

Reading

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
ANTHONY	157	73	0	0	0	1	
BRUTUS	4	157	0	2	0	0	
CAESAR	232	227	0	2	1	0	
CALPURNIA	0	10	0	0	0	0	
CLEOPATRA	57	0	0	0	0	0	
MERCY	2	0	3	8	5	8	
WORSER	2	0	1	1	1	5	
...							

Each document is now represented as a count vector $\in \mathbb{N}^{|V|}$.

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Bag of words model

- We do not consider the **order** of words in a document.
- *John is quicker than Mary and Mary is quicker than John* are represented the same way.
- This is called a **bag of words model**.

Term frequency tf

The term frequency $tf_{t,d}$ of term t in document d is defined as the **number of times that t occurs in d** .

Frequency in document vs. frequency in collection

- In addition, to term frequency (the frequency of the term in the document) . . .
- . . . we also want to use the frequency of the term **in the collection** for weighting and ranking.
- Rare terms are more informative than frequent terms.
 - Consider a term in the query that is **rare** in the collection (e.g., ARACHNOCENTRIC).
 - A document containing this term is very likely to be relevant.
 - → We want **high weights for rare terms** like ARACHNOCENTRIC.

Weighting scheme

- Frequent terms are less informative than rare terms.
- Consider a term in the query that is **frequent** in the collection (e.g., GOOD, INCREASE, LINE).
- A document containing this term is more likely to be relevant than a document that doesn't ...
- ... but words like GOOD, INCREASE and LINE are not sure indicators of relevance.
- → **For frequent terms** like GOOD, INCREASE, and LINE, we want positive weights ...
- ... but **lower weights** than for rare terms.

Document Frequency (df)

- We want **high weights for rare terms** like ARACHNOCENTRIC.
- We want **low (positive) weights for frequent words** like GOOD, INCREASE, and LINE.
- We will use **document frequency** to factor this into computing the matching score.
- The document frequency is **the number of documents in the collection that the term occurs in**.

inverse document frequency (idf)

- df_t is the document frequency, the number of documents that t occurs in.
- df_t is an inverse measure of the **informativeness** of term t .
- We define the **idf weight** of a term t as follows:

$$idf_t = \log_{10} \frac{N}{df_t}$$

(N is the number of documents in the collection.)

- idf_t is a measure of the **informativeness** of the term.
- $[\log N/df_t]$ instead of $[N/df_t]$ to “dampen” the effect of idf
- Note that we use the log transformation for both term frequency and document frequency.

Calculation

Compute idf_t using the formula: $\text{idf}_t = \log_{10} \frac{1,000,000}{\text{df}_t}$ (example size $N = 1,000,000$)

term	df_t	idf_t
calpurnia	1	6
animal	100	4
sunday	1000	3
fly	10,000	2
under	100,000	1
the	1,000,000	0

Effect of idf on ranking

- idf affects the ranking of documents for **queries with at least two terms**.
- For example, in the query “arachnocentric line”, idf weighting **increases** the relative weight of ARACHNOCENTRIC and **decreases** the relative weight of LINE.
- idf has **little effect** on ranking for **one-term queries**.

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based

Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further

Reading

Computing tf-idf

The **tf-idf weight** of a term is the **product of its tf weight and its idf weight**:

$$w_{t,d} = (1 + \log \text{tf}_{t,d}) \cdot \log \frac{N}{\text{df}_t}$$

- Set to 0 if $\text{tf}_{t,d} = 0$
- Best known weighting scheme in information retrieval
- Note: the “-” in tf-idf is a hyphen, not a minus sign!
- Alternative names: tf.idf, tf x idf

Computation

Assign a tf-idf weight for each term t in each document d :

$$w_{t,d} = \begin{cases} (1 + \log \text{tf}_{t,d}) \cdot \log \frac{N}{\text{df}_t}, & \text{if } \text{tf}_{t,d} > 0 \\ 0, & \text{otherwise} \end{cases}$$

Effect

The tf-idf weight ...

- ... increases with the **number of occurrences** within a document (due to the term frequency)
- ... increases with the **rarity of the term** in the collection (due to the inverse document frequency)

→ **Worksheet #4: Task 9**

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based

Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Binary incidence matrix

René Witte



	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
ANTHONY	1	1	0	0	0	1	
BRUTUS	1	1	0	1	0	0	
CAESAR	1	1	0	1	1	1	
CALPURNIA	0	1	0	0	0	0	
CLEOPATRA	1	0	0	0	0	0	
MERCY	1	0	1	1	1	1	
WORSER	1	0	1	1	1	0	
...							

Each document is represented as a binary vector $\in \{0, 1\}^{|V|}$.

[from *Introduction to Information Retrieval*]

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based

Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further

Reading

Count matrix

René Witte



	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
ANTHONY	157	73	0	0	0	1	
BRUTUS	4	157	0	2	0	0	
CAESAR	232	227	0	2	1	0	
CALPURNIA	0	10	0	0	0	0	
CLEOPATRA	57	0	0	0	0	0	
MERCY	2	0	3	8	5	8	
WORSER	2	0	1	1	1	5	
...							

Each document is now represented as a count vector $\in \mathbb{N}^{|V|}$.

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Binary → count → weight matrix

René Witte



Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based

Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further

Reading

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
ANTHONY	5.25	3.18	0.0	0.0	0.0	0.35	
BRUTUS	1.21	6.10	0.0	1.0	0.0	0.0	
CAESAR	8.59	2.54	0.0	1.51	0.25	0.0	
CALPURNIA	0.0	1.54	0.0	0.0	0.0	0.0	
CLEOPATRA	2.85	0.0	0.0	0.0	0.0	0.0	
MERCY	1.51	0.0	1.90	0.12	5.25	0.88	
WORSER	1.37	0.0	0.11	4.15	0.25	1.95	
...							

Each document is now represented as a real-valued vector of tf-idf weights $\in \mathbb{R}^{|V|}$.

Documents as vectors

Each document is now represented as a real-valued vector of tf-idf weights $\in \mathbb{R}^{|V|}$

- So we have a $|V|$ -dimensional real-valued vector space.
- Terms are **axes** of the space.
- Documents are **points** or **vectors** in this space.
- Very high-dimensional: tens of millions of dimensions when you apply this to web search engines
- Each vector is very sparse – most entries are zero.

Goal: Query a dataset d to find similar items

Similar products, photos, movies, songs, ... to a given item q

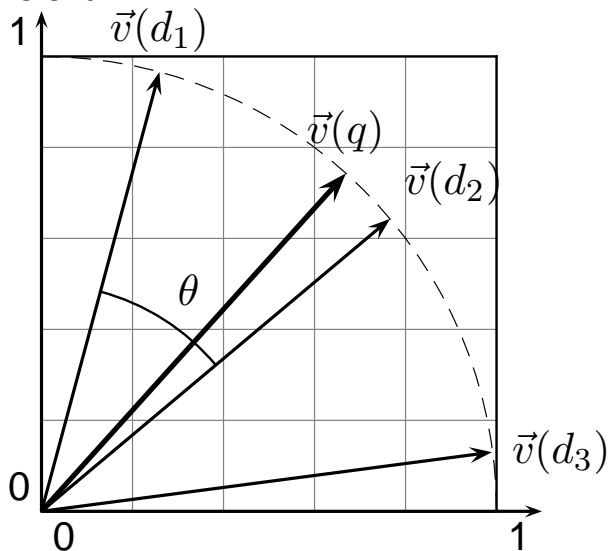
Solution: cosine similarity

$$\cos(\vec{q}, \vec{d}) = \text{SIM}(\vec{q}, \vec{d}) = \frac{\vec{q} \cdot \vec{d}}{|\vec{q}| |\vec{d}|} = \frac{\sum_{i=1}^{|V|} q_i d_i}{\sqrt{\sum_{i=1}^{|V|} q_i^2} \sqrt{\sum_{i=1}^{|V|} d_i^2}}$$

- q_i is the tf-idf weight of term i in the query.
- d_i is the tf-idf weight of term i in the document.
- $|\vec{q}|$ and $|\vec{d}|$ are the lengths of \vec{q} and \vec{d} .
- This is the [cosine similarity](#) of \vec{q} and \vec{d} or, equivalently, the cosine of the angle between \vec{q} and \vec{d} .

Cosine similarity illustrated

POOR



RICH

René Witte



Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Approach

- Represent all documents (movie descriptions, blog posts, research articles, ...) as a weighted tf-idf vector
- Compute the [cosine similarity](#) between the target vector and each document vector
- Rank documents with respect to the target
- Return the top k (e.g., $k = 10$) to the user

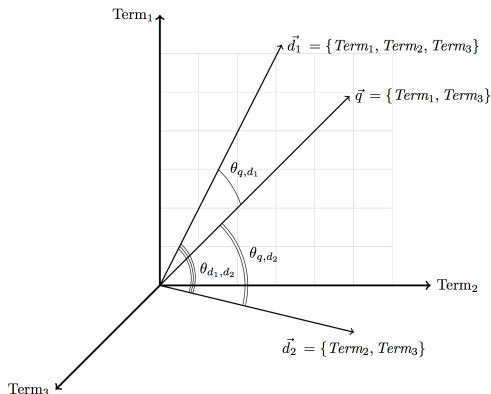
Vector Space Model

- A mathematical model to portray an n -dimensional space
- Entities are described by vectors with n coordinates in a real space \mathbb{R}^n
- Given two vectors, we can compute a similarity coefficient between them
- Cosine of the angle between two vectors reflects their degree of similarity

$$\text{tf} = 1 + \log(\text{tf}_{t,d}) \quad (1)$$

$$\text{idf} = \log \frac{N}{\text{df}_t} \quad (2)$$

$$\cos(\vec{q}, \vec{d}) = \frac{\sum_{i=1}^{|V|} q_i \cdot d_i}{\sqrt{\sum_{i=1}^{|V|} q_i^2} \cdot \sqrt{\sum_{i=1}^{|V|} d_i^2}} \quad (3)$$



Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading



CORE (JAVA)

SOLR

PYLUCENE

Ultra-fast Search Library and Server



Apache Lucene and Solr set the standard for search and indexing performance

Welcome to Apache Lucene

The Apache Lucene™ project develops open-source search software, including:

- [Lucene Core](#), our flagship sub-project, provides Java-based indexing and search technology, as well as spellchecking, hit highlighting and advanced analysis/tokenization capabilities.

DOWNLOAD

Apache Lucene 8.4.1

DOWNLOAD

Apache Solr 8.4.1

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

1 Introduction

2 Collaborative Filtering

3 Content-based Recommendations

4 Notes and Further Reading

Introduction

Modeling Users

Netflix Recommendations

Collaborative Filtering

Introduction

Computing with Words

Item Recommendation

Items Related to other
Items

Items of Interest to a User

Relevant Users for an Item

Semantic User Profiles

Evaluation

Content-based Recommendations

Motivation

TF*IDF weighting

Term Vector Space Model

Summary

Notes and Further Reading

Required

- [Ala09, Chapters 2, 3] (Recommendations)
- [MRS08, Chapter 8] (Evaluation)

Supplemental

- [MRS08, Chapter 6] (Vector Space Model, tf-idf)

- [Ala09] Satnam Alag.
Collective Intelligence in Action.
Manning, 2009.
<https://concordiauniversity.on.worldcat.org/oclc/314121652>.
- [MRS08] Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schütze.
Introduction to Information Retrieval.
Cambridge University Press, 2008.
<http://informationretrieval.org>.
- [TB16] Doug Turnbull and John Berryman.
Relevant Search.
Manning, 2016.
<https://concordiauniversity.on.worldcat.org/oclc/954339855>.