THE DEVELOPER'S CONFERENCE 2016

Track: Data Science

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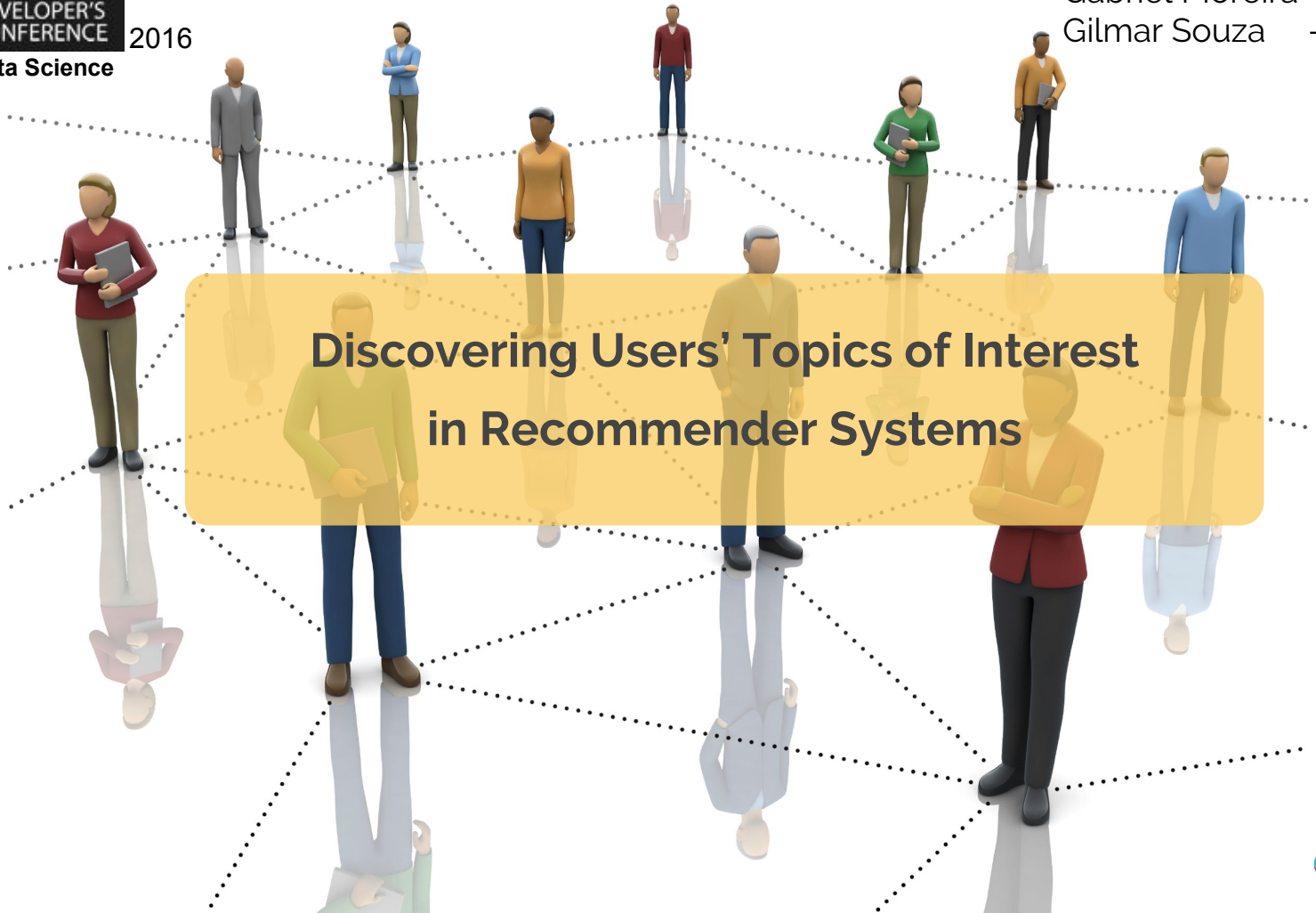


Discovering Users' Topics of Interest in Recommender Systems

ciandt.com

Agenda

- Recommender Systems
- Topic Modeling
- Case: Smart Canvas - Corporative Collaboration
- Wrap up

Recommender Systems

An introduction

Life is too short!

Social recommendations

Recommendations by interaction

"A lot of times, people don't know what they want until you show it to them."

Steve Jobs

"We are leaving the Information Age and entering the Recommendation Age.".

Cris Anderson, "The long tail"

Recommendations are responsible for...

amazon.com

38% of sales

NETFLIX

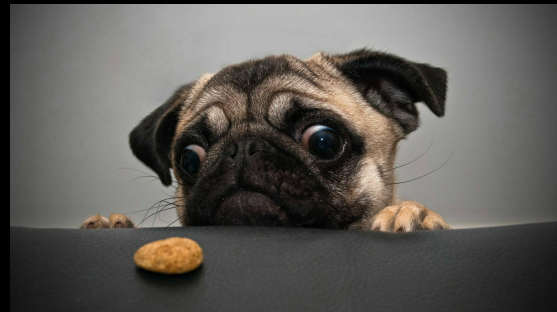
2/3 movie rentals

Google news

38% of top news visualization

What else may I recommend?

products
tags
professionals
courses
musics
movies
jobs
books
papers
girlfriends
investiments
restaurants
videos
dressing



What can a Recommender Systems do?

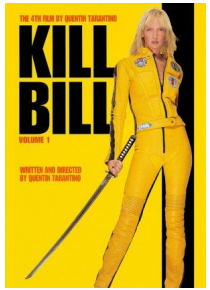
Recommendation
Given a user, produce an ordered list matching the user needs

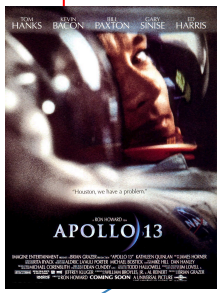
Prediction
Given an item, what is its relevance for each user?

How it works

Content-Based Filtering

Similar content (e.g. actor)





Likes

Recommends

Content-Based Filtering

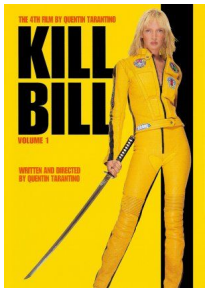
Advantages

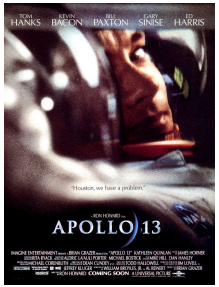
- Does not depend upon other users
- May recommend new and unpopular items
- Recommendations can be easily explained

Drawbacks

- Overspecialization
- May not recommend to new users
  May be difficult to extract attributes from audio, movies or images

User-Based Collaborative Filtering





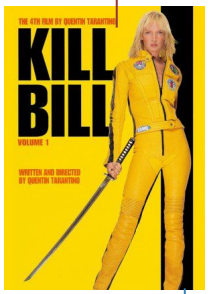
Likes

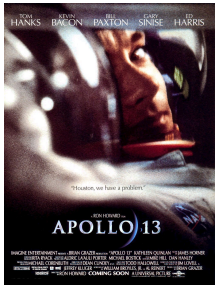
Recommends

Similar interests

Item-Based Collaborative Filtering

Who likes A also likes B





Likes

Likes

Likes

Recommends

Collaborative Filtering

Advantages

- Works to any item kind (ignore attributes)

Drawbacks

- Cannot recommend items not already rated/consumed
- Usually recommends more popular items
- Needs a minimum amount of users to match similar users (*cold start*)

Hybrid Recommender Systems

Some approaches

Composite
Iterates by a chain of algorithm, aggregating recommendations.

Weighted
Each algorithm has as a weight and the final recommendations are defined by weighted averages.

UBCF Example (Java / Mahout)

```
User,Item,Rating1,
15,4.0
1,16,5.0
1,17,1.0
1,18,5.0
2,10,1.0
2,11,2.0
2,15,5.0
2,16,4.5
2,17,1.0
2,18,5.0
3,11,2.5
```

input.csv

```
// Loads user-item ratings
1 DataModel model = new FileDataModel(new File("input.csv"));
// Defines a similarity metric to compare users (Person's correlation coefficient)
2 UserSimilarity similarity = new PearsonCorrelationSimilarity(model);
// Threshold the minimum similarity to consider two users similar
3 UserNeighborhood neighborhood = new ThresholdUserNeighborhood(0.1, similarity,
model);
// Create a User-Based Collaborative Filtering recommender
4 UserBasedRecommender recommender = new GenericUserBasedRecommender
5 (model, neighborhood, similarity);
// Return the top 3 recommendations for userId=2
6 List recommendations = recommender.recommend(2, 3);
```

User-Based Collaborative Filtering example (Mahout)

Frameworks - Recommender Systems

Java

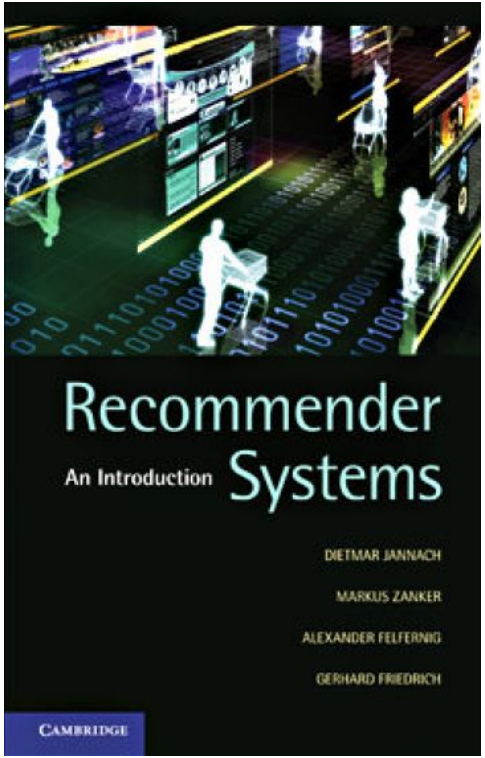
Python / Scala

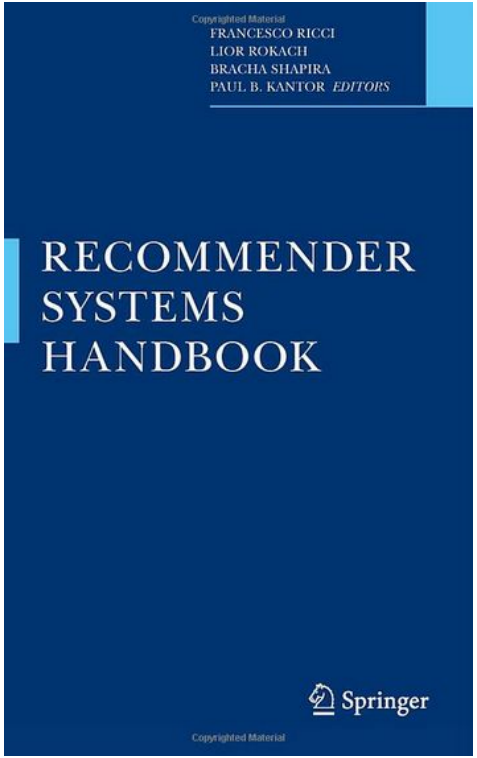
Python

Java

.NET

Books


Recommender Systems
An Introduction
DIETMAR JANNACH
MARKUS ZANKER
ALEXANDER FELFERNIG
GERHARD FRIEDRICH
CAMBRIDGE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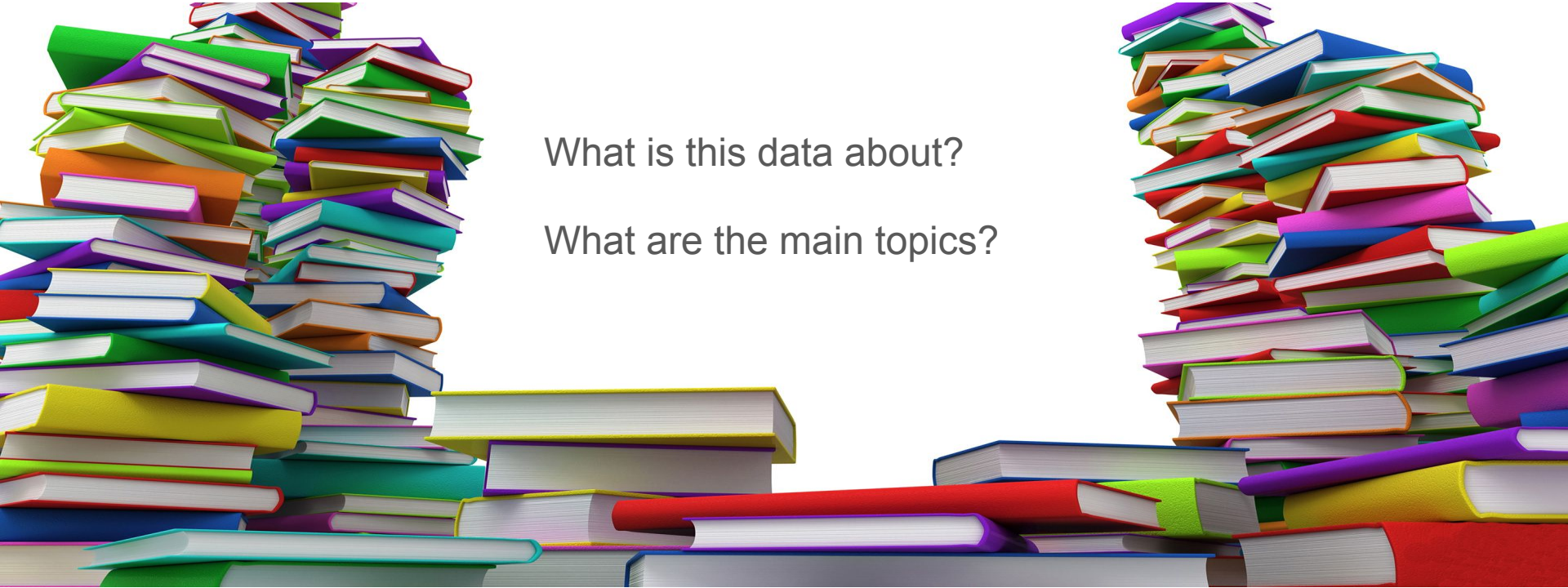
Topic Modeling

An introduction

Topic Modeling

A simple way to analyze topics of large text collections (corpus).

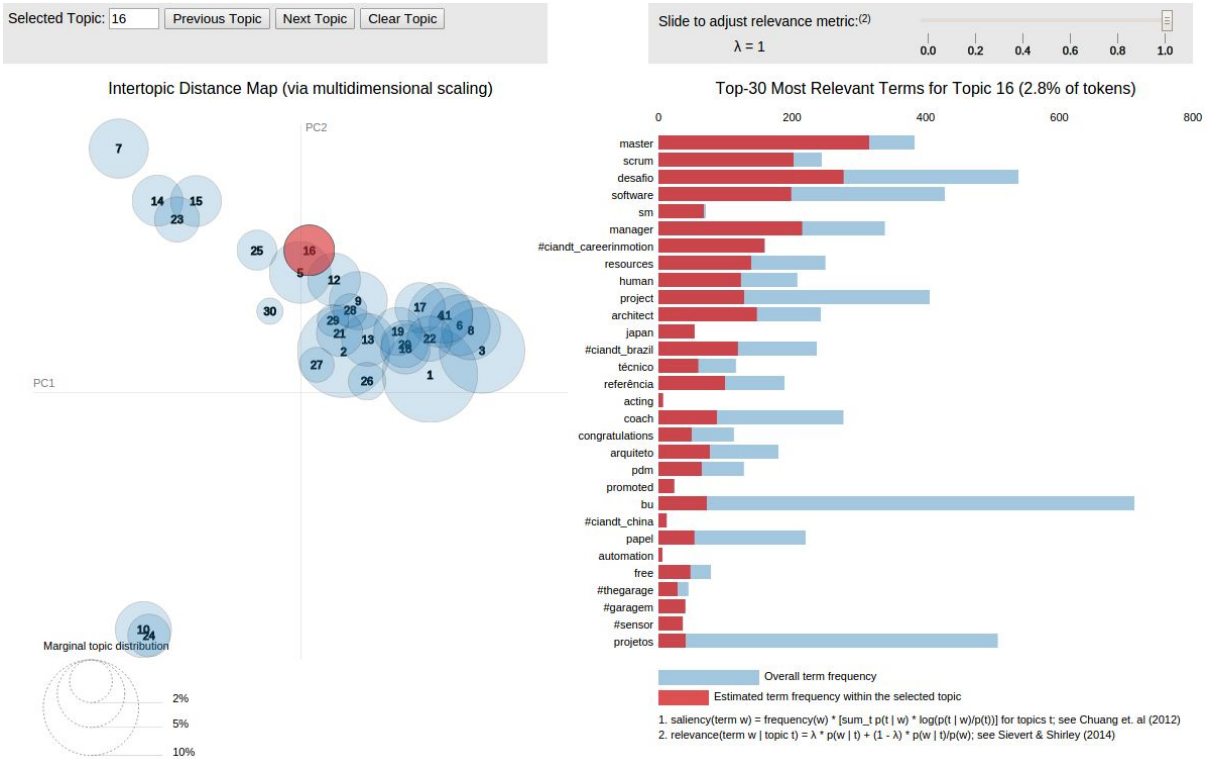


What is this data about?

What are the main topics?

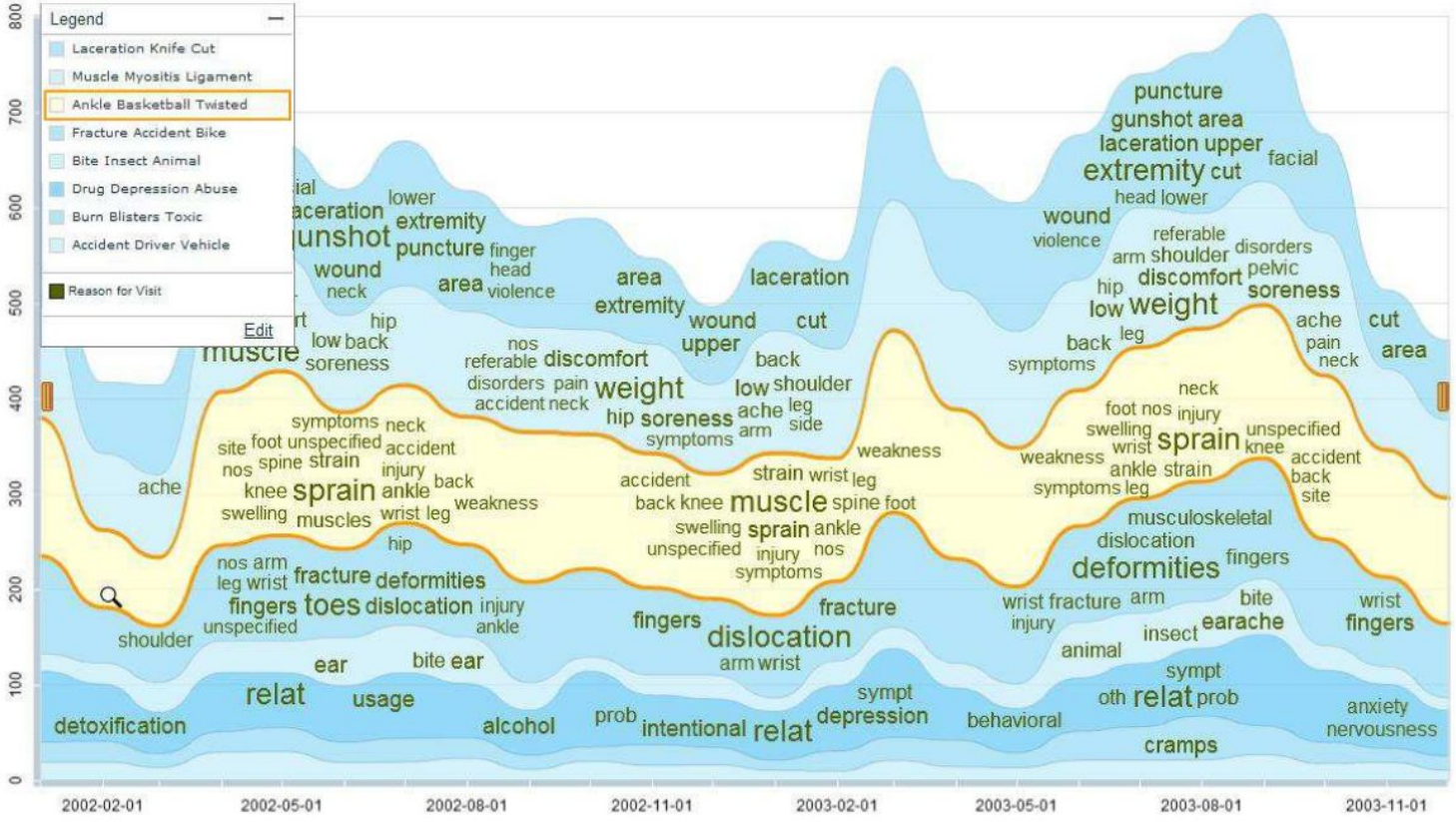
Topic

A *Cluster* of words that generally occur together and are related.



Example 2D topics visualization with [pyLDAviz]() (topics are the circles in the left, main terms of selected topic are shown in the right)

Topics evolution



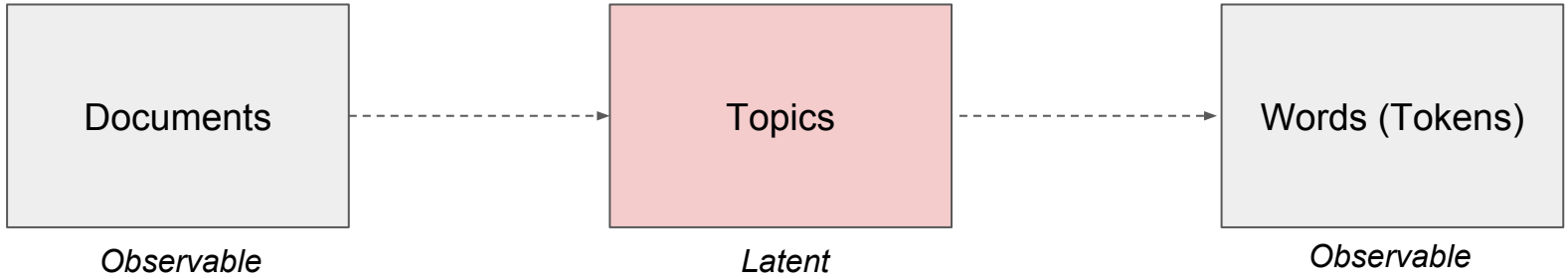
Visualization of topics evolution during across time

Topic Modeling applications

- Detect trends in the market and customer challenges of a industry from media and social networks.
- Marketing SEO: Optimization of search keywords to improve page ranking in searchers
- Identify users preferences to recommend relevant content, products, jobs, …

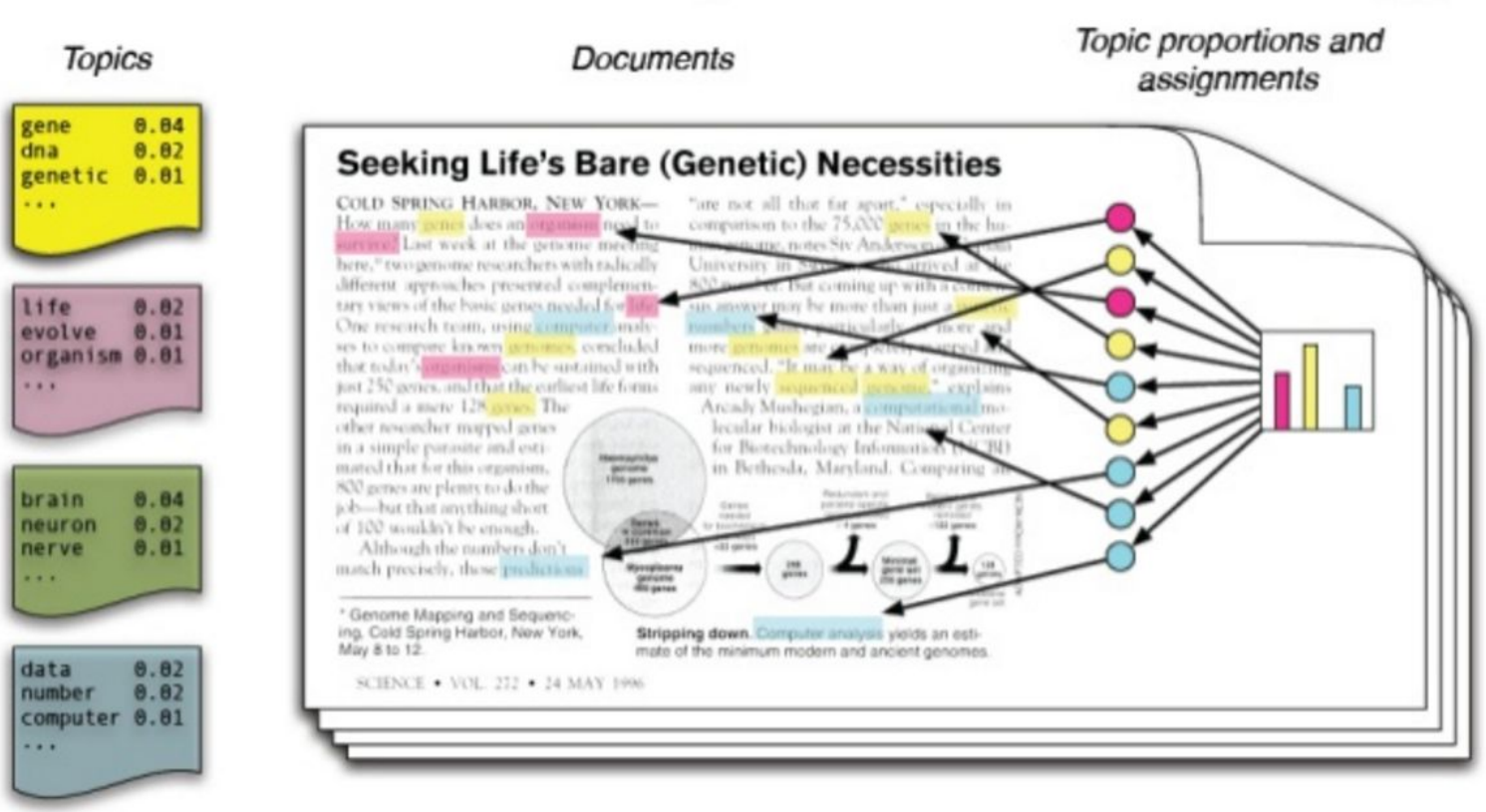
Topic Modeling

Unsupervised learning technique, which does not require too much effort on pre-processing (usually just Text Vectorization). In general, the only parameter is the number of topics (k).



- Documents are composed by many topics
- Topics are composed by many words (tokens)

Topics in a document



Topics example from NYT

Topic analysis (LDA) from 1.8 millions of New York Times articles

How it works

Text vectorization

Represent each document as a feature vector in the vector space, where each position represents a word (token) and the contained value is its relevance in the document.

- *BoW* (*Bag of words*)
- *TF-IDF* (*Term Frequency - Inverse Document Frequency*)

	D1	D2	D3	D4
linux	3	4	1	0
modem	4	3	0	1
the	3	4	4	3
clutch	0	1	4	3
steering	2	0	3	3
petrol	0	1	3	4

Document Term Matrix - Bag of Words

Text vectorization

TF-IDF - More "relevant" terms in a document are frequent terms in the document and rare in other documents

f_{ij} = frequency of term (feature) i in doc (item) j

$$TF_{ij} = \frac{f_{ij}}{\max_k f_{kj}}$$

n_i = number of docs that mention term i

N = total number of docs

$$IDF_i = \log \frac{N}{n_i}$$

TF-IDF score: $w_{ij} = TF_{ij} \times IDF_i$

Doc profile = set of words with highest **TF-IDF** scores, together with their scores

TF-IDF example with scikit-learn

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(max_df=0.5, max_features=1000,
                             min_df=2, stop_words='english')
tfidf_corpus = vectorizer.fit_transform(text_corpus)
```

tokens

	face	person	guide	lock	cat	dog	sleep	micro	pool	gym	...
	0	1	2	3	4	5	6	7	8	9	
D1		0.05					0.25				
D2	0.02			0.32					0.45		
...											

documents

TF-IDF sparse matrix example

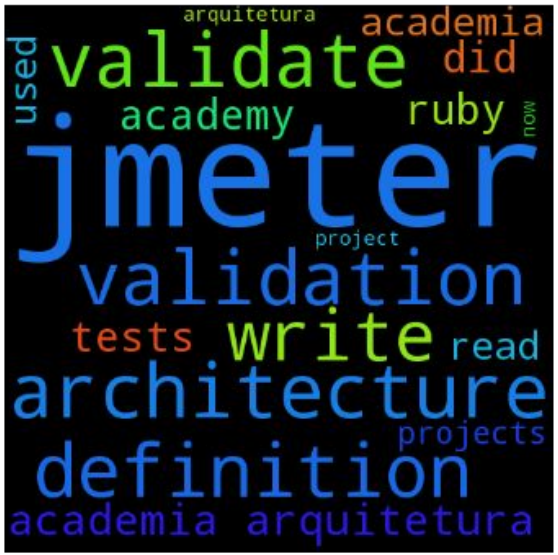
Text vectorization

Example

“Did you ever wonder how great it would be if you could **write** your **jmeter tests** in **ruby** ? This projects aims to do so. If you use it on your project just let me now. On the Architecture Academy you can read how jmeter can be used to **validate** your Architecture. **definition** | architecture **validation** | **academia** de **arquitetura**”

Relevant keywords (TF-IDF)

Tokens (unigrams and bigrams)	**Weight**
jmeter	0.466
architecture	0.380
validate	0.243
validation	0.242
definition	0.239
write	0.225
academia arquitetura	0.218
academy	0.216
ruby	0.213
tests	0.209



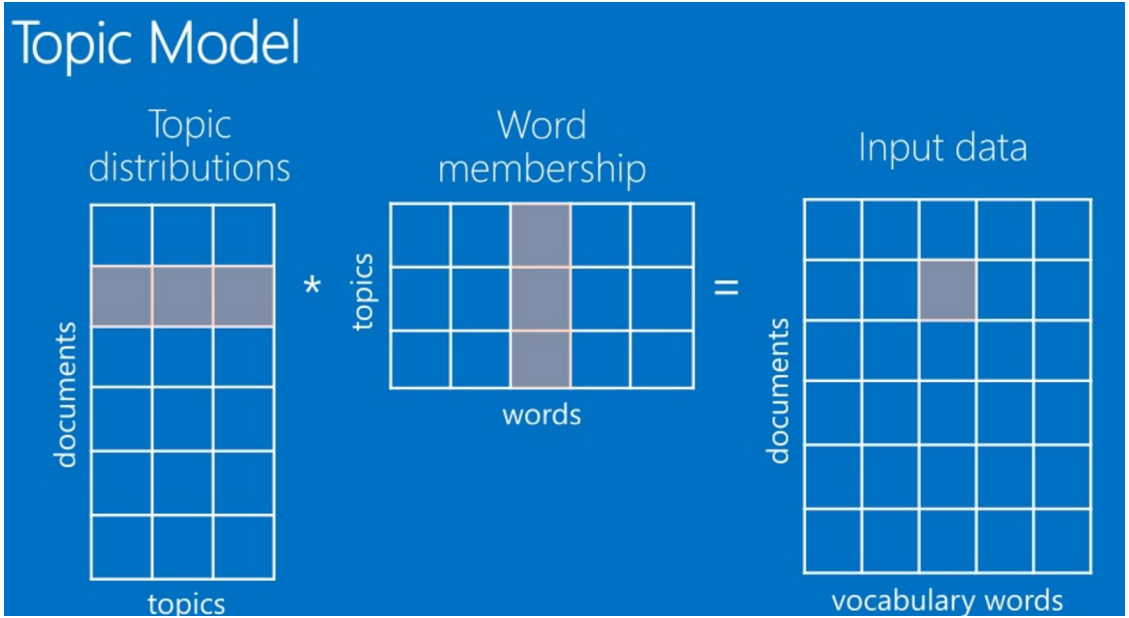
Text vectorization

Visualization of the average TF-IDF vectors of posts at Google+ for Work (CI&T)

See the more details about this social and text analytics at http://bit.ly/python4ds_nb

Main techniques

- ***Latent Dirichlet Allocation (LDA)*** -> Probabilistic
- ***Latent Semantic Indexing / Analysis (LSI / LSA)*** -> Matrix Factorization
- ***Non-Negative Matrix Factorization (NMF)*** -> Matrix Factorization



Topic Modeling example (Python / gensim)

```
1  from gensim import corpora, models, similarities
2  documents = ["Human machine interface for lab abc computer applications",
3               "A survey of user opinion of computer system response time",
4               "The EPS user interface management system", ...]
5  stoplist = set('for a of the and to in'.split())
6  texts = [[word for word in document.lower().split() if word not in stoplist] for document in documents]
7  dictionary = corpora.Dictionary(texts)
8  corpus = [dictionary.doc2bow(text) for text in texts]
9  tfidf = models.TfidfModel(corpus)
10 corpus_tfidf = tfidf[corpus]
11 lsi = models.LsiModel(corpus_tfidf, id2word=dictionary, num_topics=2)
12 corpus_lsi = lsi[corpus_tfidf]
13 lsi.print_topics(2)
```

Example of topic modeling using LSI technique

```
topic #0(1.594): 0.703*"trees" + 0.538*"graph" + 0.402*"minors" + 0.187*"survey" + ...
topic #1(1.476): 0.460*"system" + 0.373*"user" + 0.332*"eps" + 0.328*"interface" + 0.320*"response" + ...
```

Example of the 2 topics discovered in the corpus

Topic Modeling example (PySpark MLLib LDA)

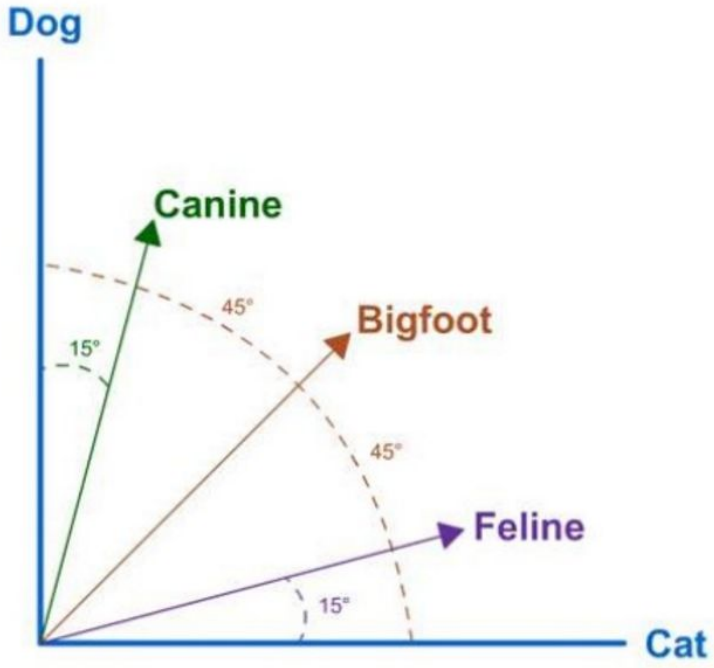
```
1  from pyspark.mllib.clustering import LDA, LDAModel
2  from pyspark.mllib.linalg import Vectors
3  # Load and parse the data
4  data = sc.textFile("data/mllib/sample_lda_data.txt")
5  parsedData = data.map(lambda line: Vectors.dense([float(x) for x in line.strip().split(' ')]))
6  # Index documents with unique IDs
7  corpus = parsedData.zipWithIndex().map(lambda x: [x[1], x[0]]).cache()
8  # Cluster the documents into three topics using LDA
9  ldaModel = LDA.train(corpus, k=3)
```

Sometimes simpler is better!

Scikit-learn topic models worked better for us than Spark MLlib LDA distributed implementation because we have thousands of users with hundreds of posts, and running scikit-learn on workers for each person was much quicker than running distributed Spark LDA for each person.

Cosine similarity

Similarity metric between two vectors is cosine among the angle between them



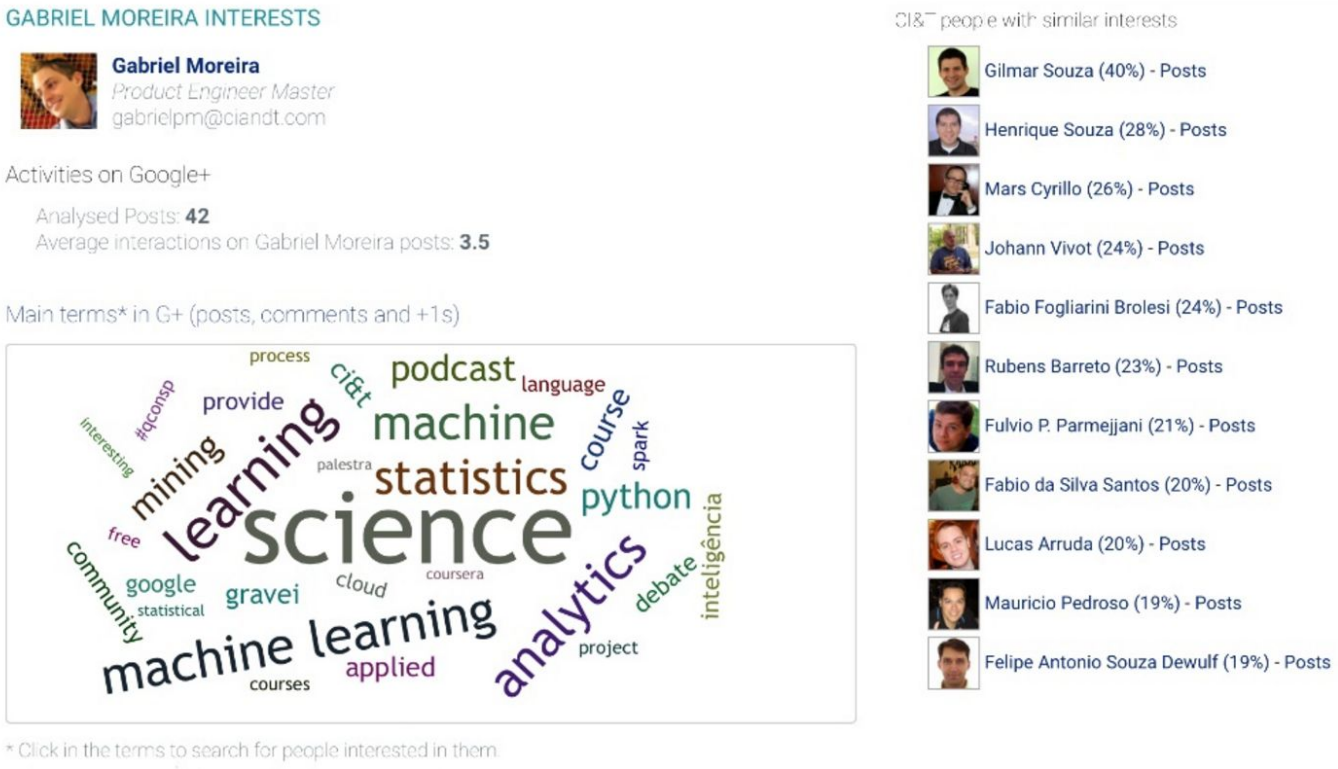
$$\vec{a} \cdot \vec{b} = \|\vec{a}\| \|\vec{b}\| \cos\theta$$

$$\cos\theta = \frac{\vec{a} \cdot \vec{b}}{\|\vec{a}\| \|\vec{b}\|}$$

```
from sklearn.metrics.pairwise import cosine_similarity
cosine_similarity(tfidf_matrix[0:1], tfidf_matrix)
```

Example with scikit-learn

People similarity



Example of relevant keywords for a person and people with similar interests

Frameworks - Topic Modeling

gensim
topic modelling for humans

Python

MALLET
machine learning for language toolkit

Java

Stanford Topic Modeling Toolbox (Excel plugin)
http://nlp.stanford.edu/software/tmt/tmt-0.4/

scikits learn
machine learning in Python

Spark

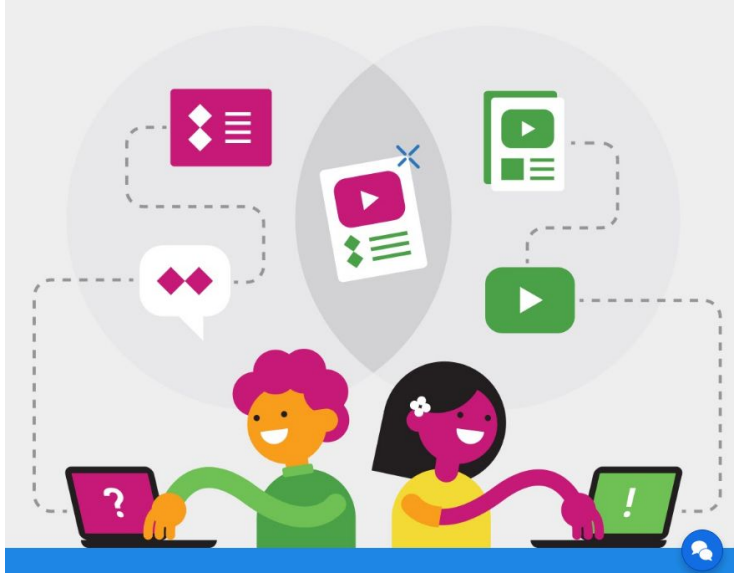
Python / Scala

Case

Smart Canvas©

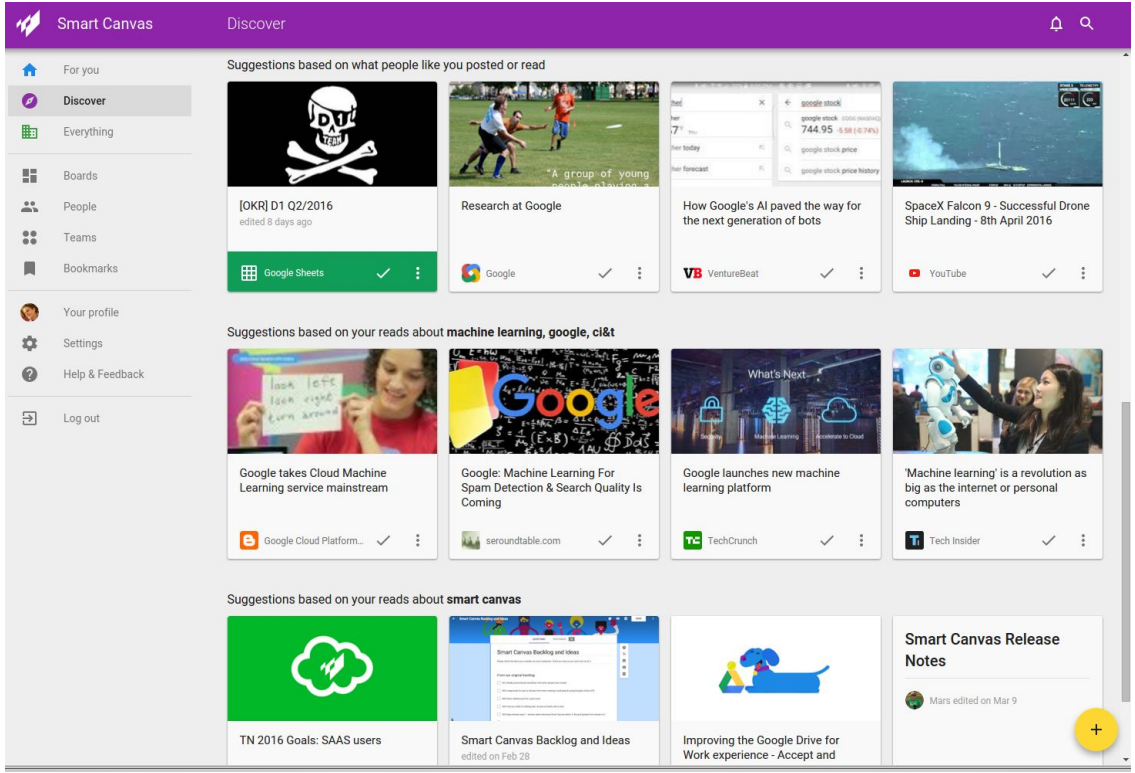
Corporate Collaboration

Powered by Recommender Systems and Topic Modeling techniques



http://www.smartcanvas.com/

Content recommendations

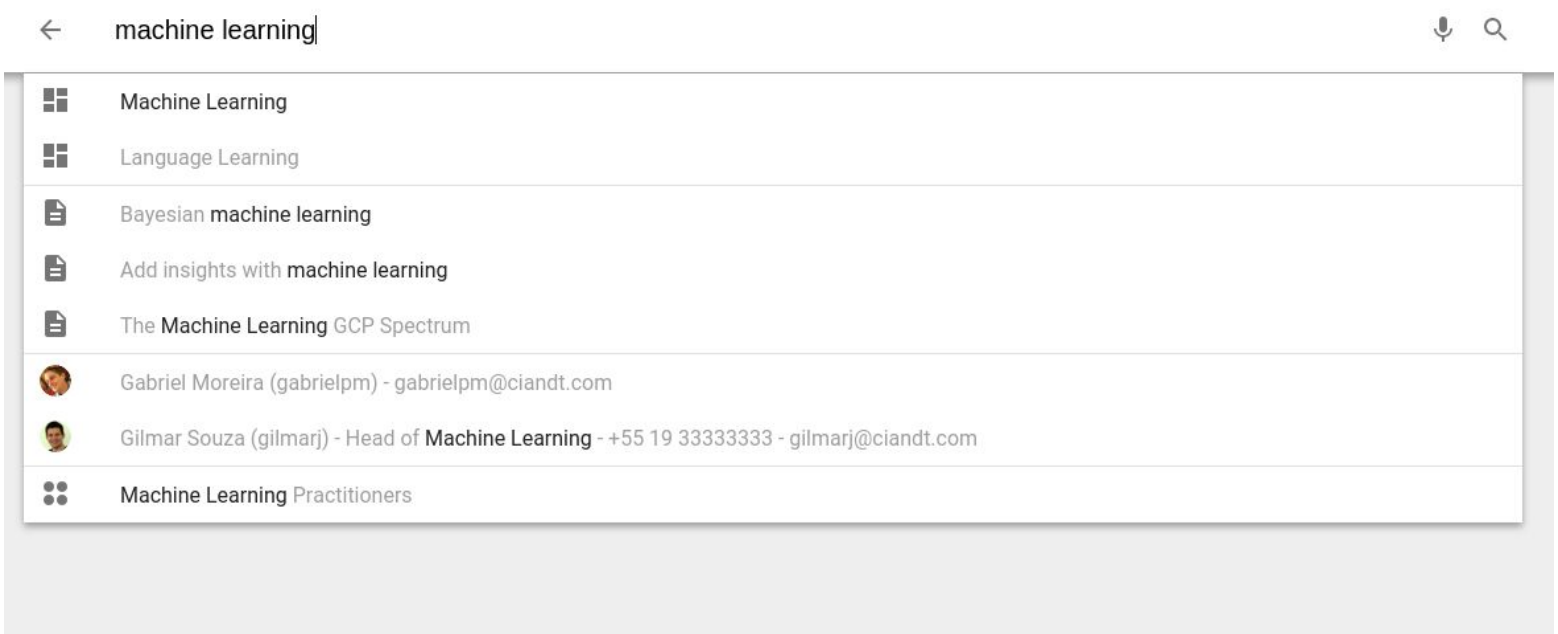


Discover channel - Content recommendations with personalized explanations, based on user's topics of interest (discovered from their contributed content and reads)

Person topics of interest

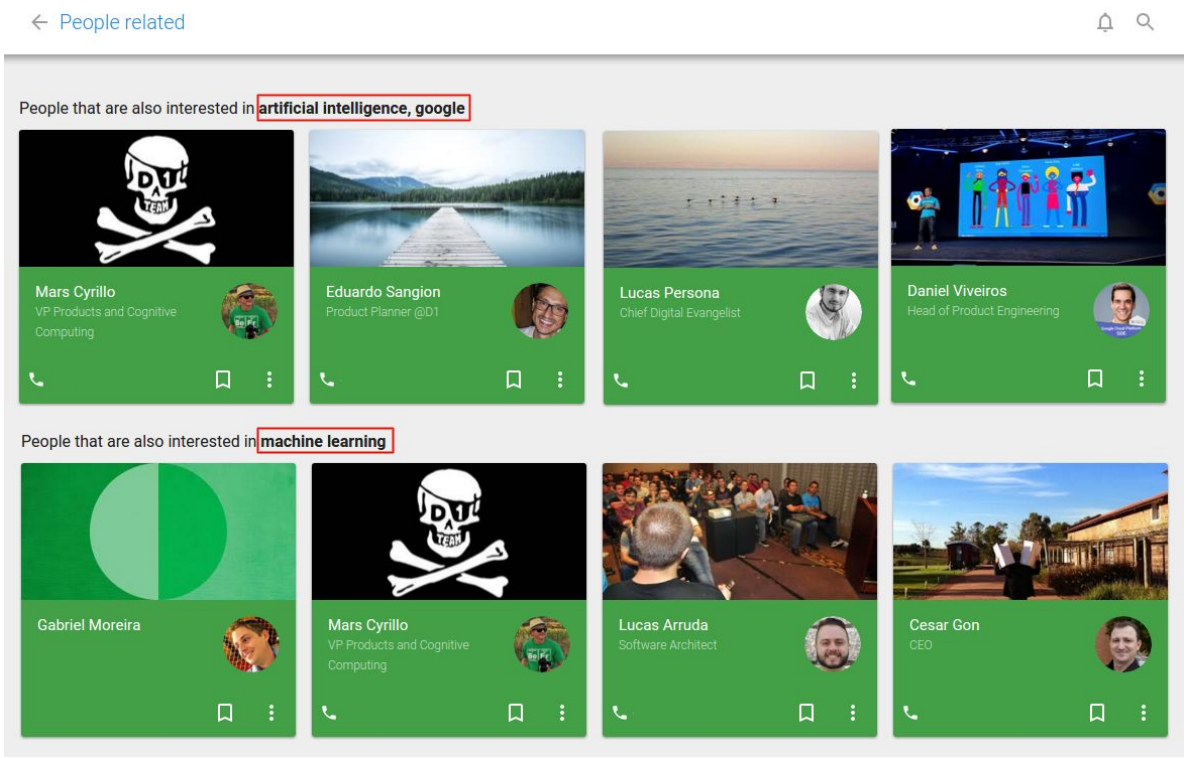
User profile - Topics of interest of users are from the content that they contribute and are presented as tags in their profile.

Searching people interested in topics / experts...



User discovered tags are searchable, allowing to find experts or people with specific interests.

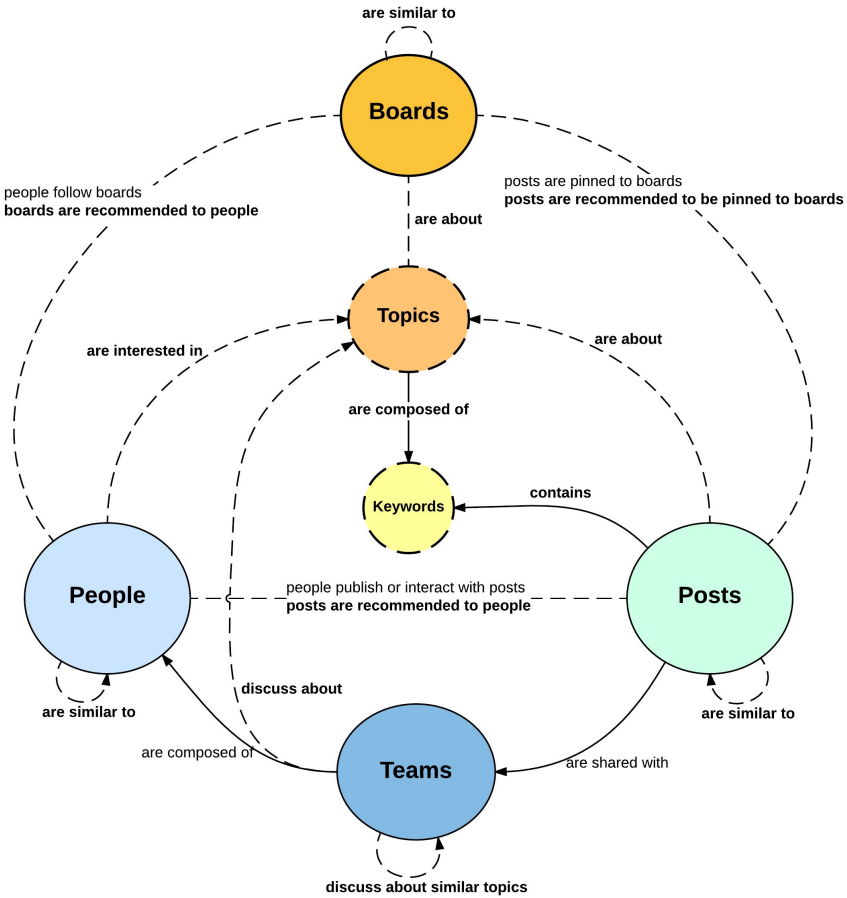
Similar people



People recommendation - Recommends people with similar interests, explaining which topics are shared.

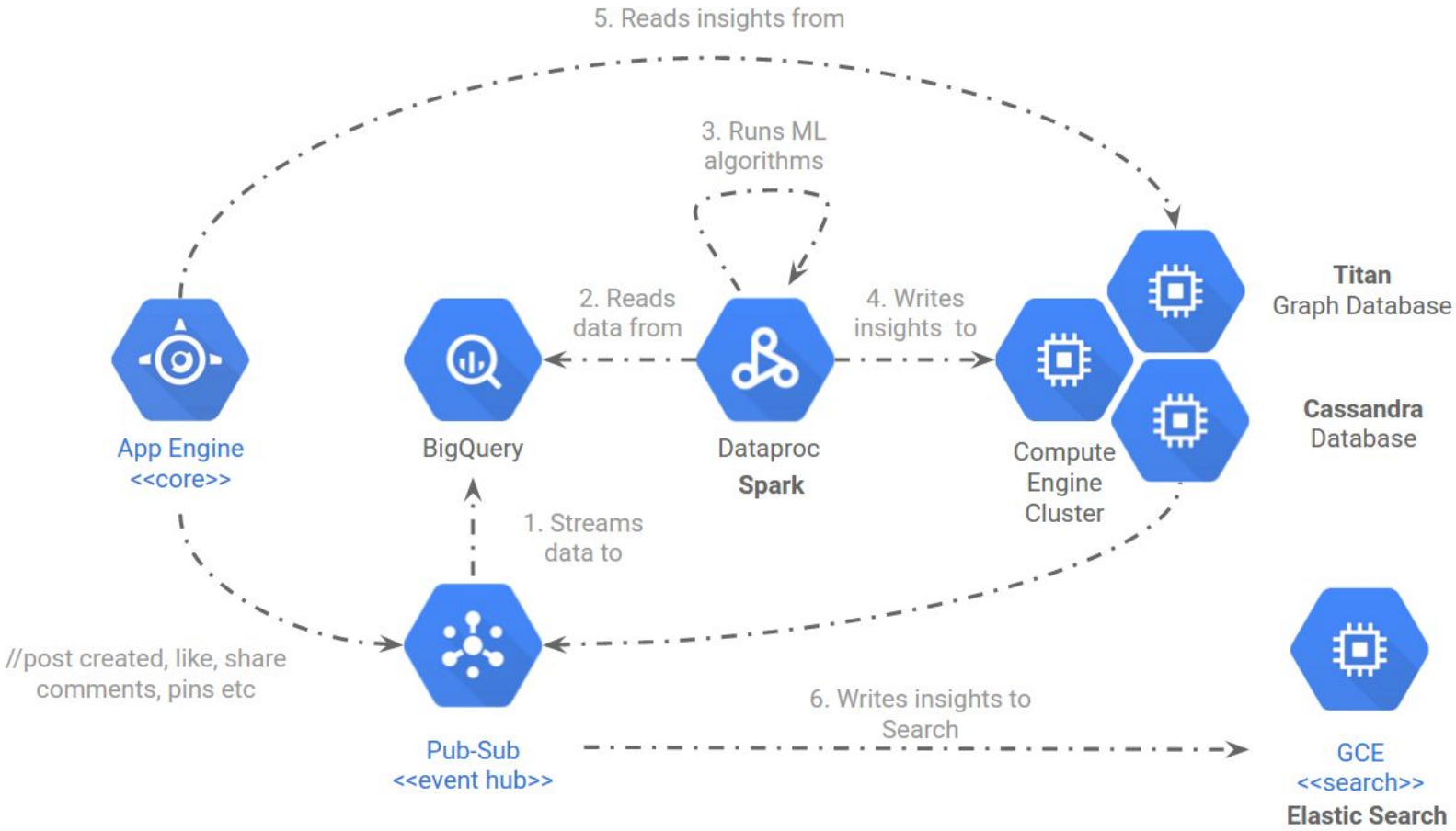
How it works

Collaboration Graph Model

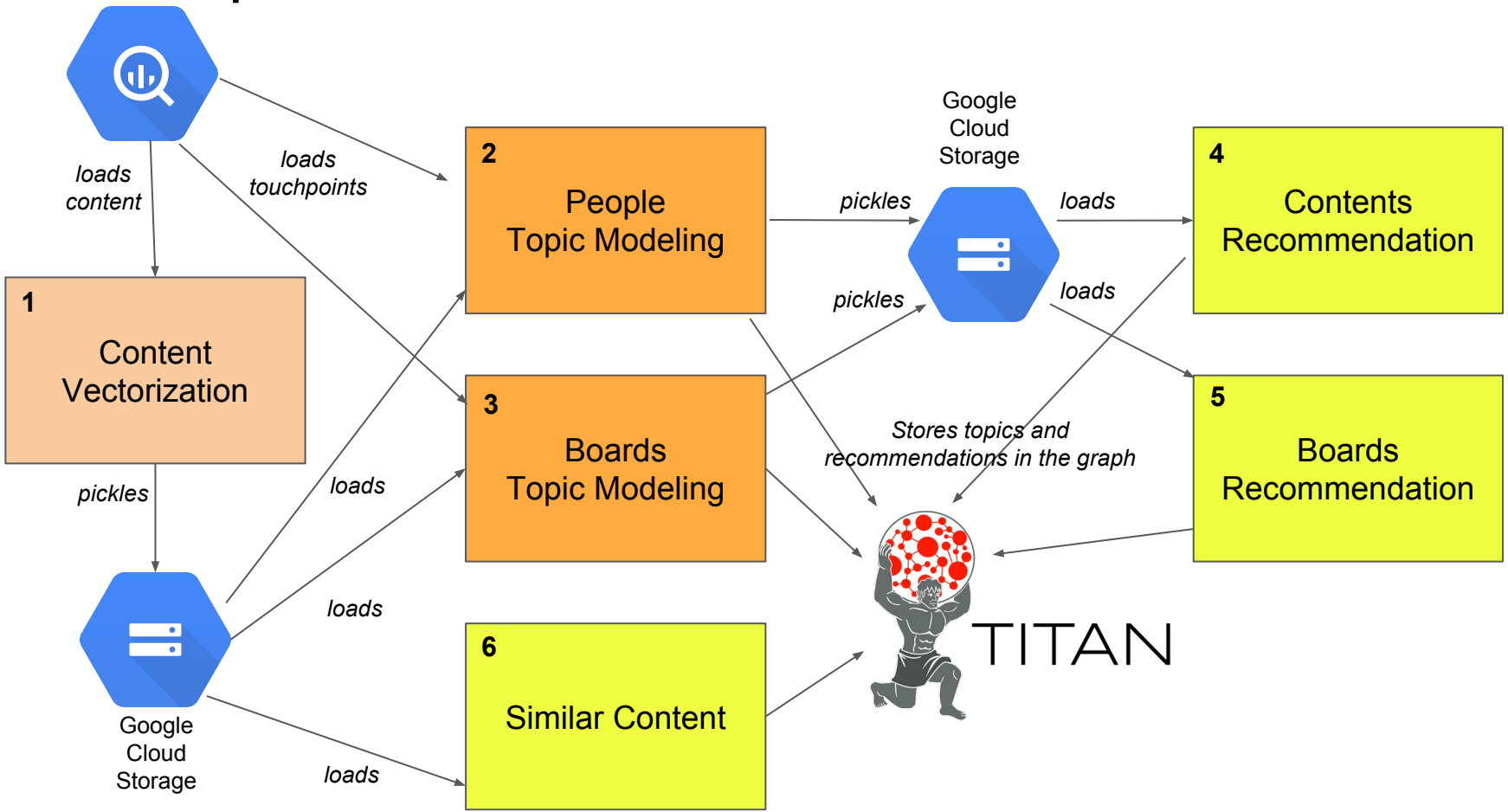


Smart Canvas © Graph Model: Dashed lines and bold labels are the relationships inferred by usage of RecSys and Topic Modeling techniques

Architecture Overview



Jobs Pipeline

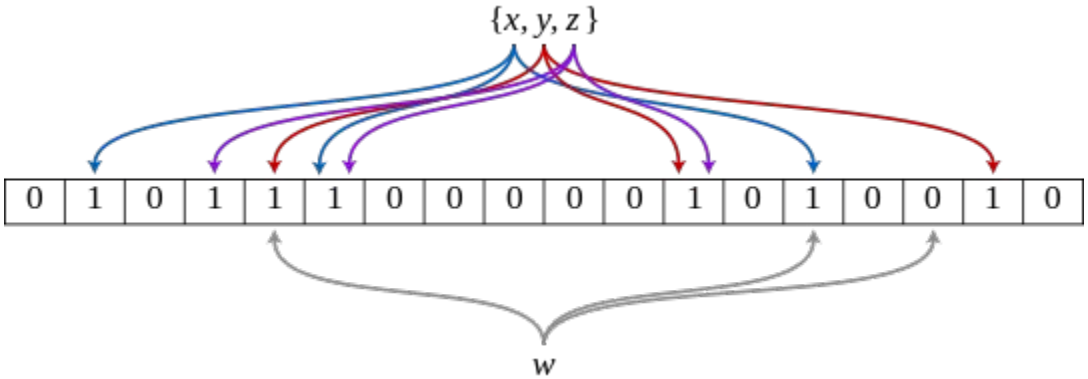


People Topic Modeling and Content Recommendations algorithm

1. Groups all touchpoints (user interactions) by person
2. For each person
   a. Selects contents user has interacted
   b. Clusters contents TF-IDF vectors to model (e.g. LDA, NMF, Kmeans) person' topics of interest (varying the k from a range (1-5) and selecting the model whose clusters best describe cohesive topics, penalizing large k)
   c. Weights clusters relevance (to the user) by summing touchpoints strength (view, like, bookmark, …) of each cluster, with a time decay on interaction age (older interactions are less relevant to current person interest)
   d. **Returns highly relevant topics** vectors for the person,labeled by its three top keywords
3. For each people topic
   a. Calculate the cosine similarity (optionally applying Pivoted Unique Pivoted Normalization) among the topic vector and content TF-IDF vectors
   b. **Recommends more similar contents** to person user topics, which user has not yet

Bloom Filter

- A space-efficient Probabilistic Data Structure used to test whether an element is a member of a set.
- False positive matches are possible, but false negatives are not.
- An empty Bloom filter is a bit array of m bits, all set to 0.
- Each inserted key is mapped to bits (which are all set to 1) by k different hash functions.



The set {**x,y,z**} was inserted in Bloom Filter. **w** is not in the set, because it hashes to one bit equal to 0

Bloom Filter - Example

Using **cross_bloomfilter** - Pure Python and Java compatible implementation
GitHub: http://bit.ly/cross_bf

In [4]:
```
#Max number of entries
BLOOM_CAPACITY = 100000;
#False positive error rate
BLOOM_ERROR_RATE = 0.005;

bloom_filter = BloomFilter(BLOOM_CAPACITY, BLOOM_ERROR_RATE)
```

In [5]:
```
all_keys = get_random_keys(BLOOM_CAPACITY)
for key in all_keys:
    bloom_filter.add(key)
```

In [8]:
```
#Checks for keys existing in the set
errors = 0
for key in all_keys:
    if key not in bloom_filter:
        errors += 1

if errors > 0:
    print("Some included keys were not found in the Bloom Filter (false negatives)")
```

In [11]:
```
#Checks for keys not existing in the set
errors = 0
for key in all_keys:
    if (key+"DOES NOT EXISTS") in bloom_filter:
        errors += 1

error_rate = float(errors) / BLOOM_CAPACITY;
print(error_rate)
```

```
0.00511
```

Bloom Filter - Complexity Analysis

Ordered List

Space Complexity: O(n)

where *n* is the number of items in the set

Check for key presence

Time Complexity (binary search): O(log(n))

assuming an ordered list

Bloom Filter

Space Complexity: O(t * ln(p))

where *t* is the maximum number of items to be inserted and *p* the accepted false positive rate

Check for key presence

Time Complexity: O(k)

where *k* is a constant representing the number of hash functions to be applied to a string key

Example: For a list of 100,000 string keys, with an average length of 18 characters

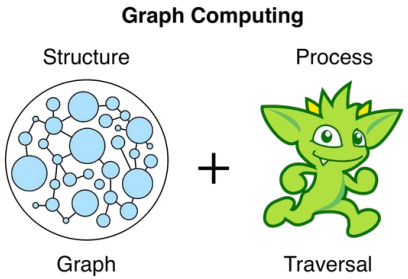
Key list size: 1,788,900 bytes

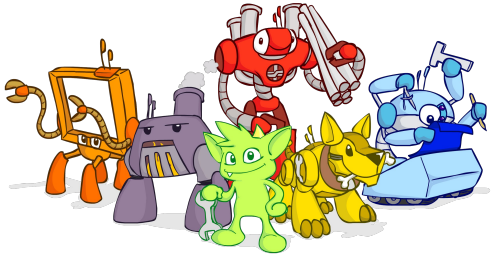
Bloom filter size: 137,919 bytes (false positive rate = 0.5%)

Bloom filter size: 18,043 bytes (false positive rate = 5%)

(and you can gzip it!)

TITAN





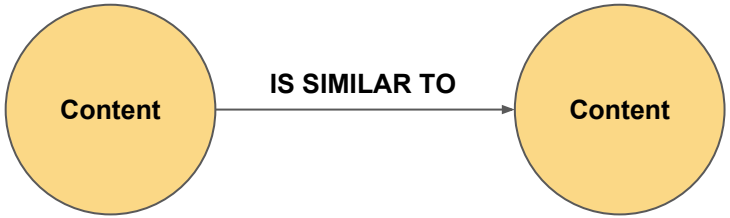
TinkerPop

- Distributed Graph Database
- Elastic and linear scalability for a growing data and user base
- Support for ACID and eventual consistency
- Backended by Cassandra or HBase
- Support for global graph data analytics, reporting, and ETL through integration with Spark, Hadoop, Giraph
- Support for geo and full text search (ElasticSearch, Lucene, Solr)
- Native integration with TinkerPop (Gremlin query language, Gremlin Server, ...)

Gremlin traversals

Querying similar contents

```
1  g.V().has('CONTENT','id', 'Post:123')
2  .outE('IS SIMILAR TO')
3  .has('strength', gte(0.1)).as('e').inV().as('v')
4  .select('e','v')
5  .map{['id': it.get().v.values('id').next(),
6          'strength': it.get().e.values('strength').next()]}
7  .limit(10)
```



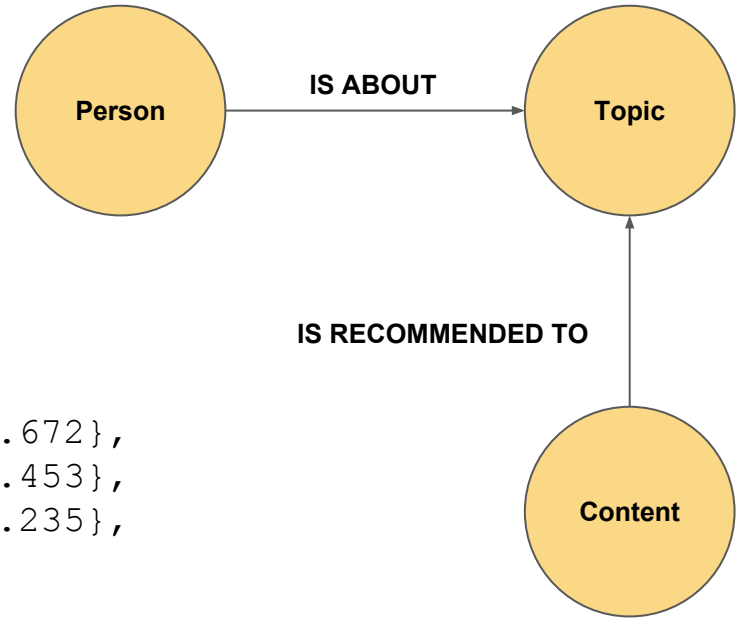
Example output:

```
[{'id': 'Post:456', 'strength': 0.672},
 {'id': 'Post:789', 'strength': 0.453},
 {'id': 'Post:333', 'strength': 0.235},
 ...]
```

Gremlin traversals

Querying recommended contents for a person

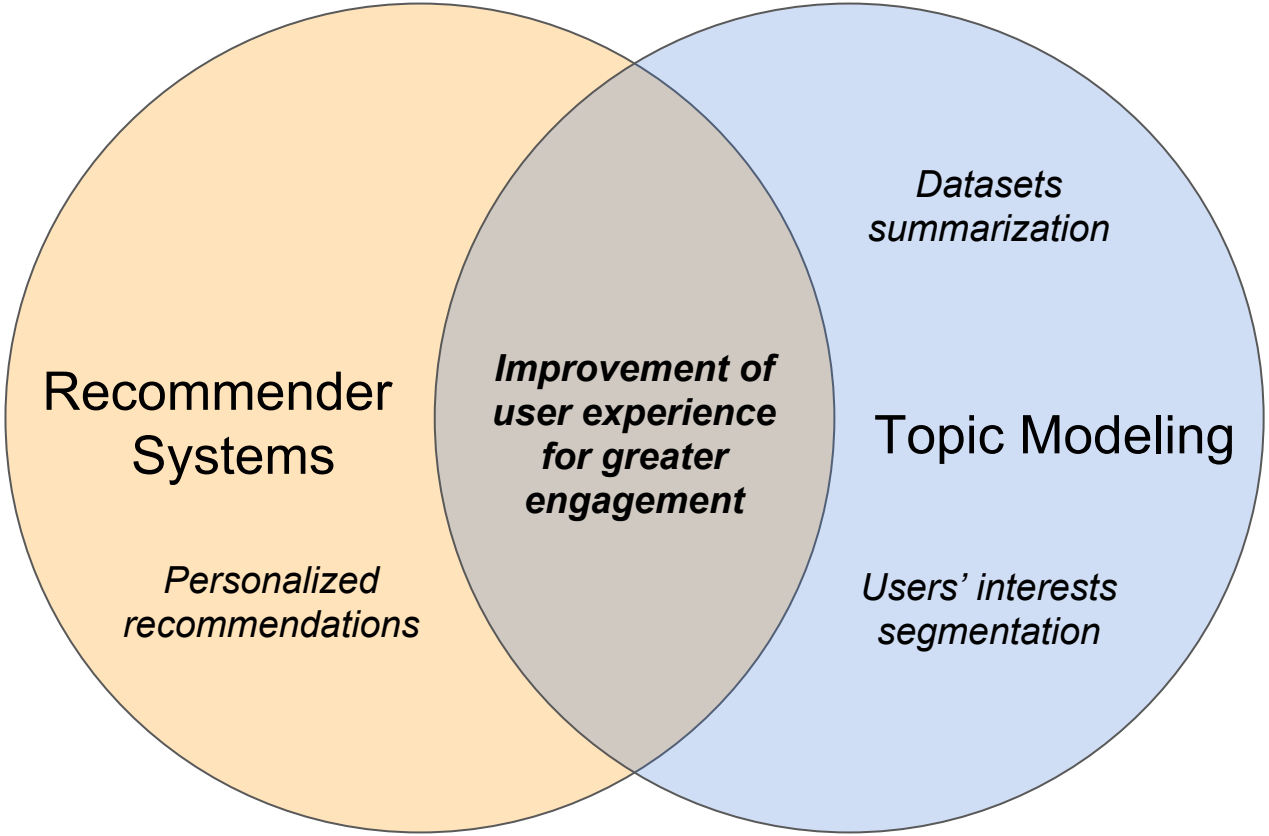
```
1 g.V().has('PERSON','id','Person:gabrielpm@ciandt.com')
2 .out('IS ABOUT').has('number', 1)
3 .inE('IS RECOMMENDED TO').filter{ it.get().value('strength') >= 0.1}
4 .order().by('strength',decr).as('tc').outV().as('c')
5 .select('tc','c')
6 .map{ ['contentId': it.get().c.value('id'),
7          'recommendationStrength': it.get().tc.value('strength') *
8                getTimeDecayFactor(it.get().c.value('updatedOn')) ] }
```



Example output:

```
[{'contentId': 'Post:456', 'strength': 0.672},
 {'contentId': 'Post:789', 'strength': 0.453},
 {'contentId': 'Post:333', 'strength': 0.235},
 ...]
```

Wrap up


Recommender Systems
Personalized recommendations
Improvement of user experience for greater engagement
Topic Modeling
Datasets summarization
Users' interests segmentation

Start building smarter, deeper connections and discover what you are missing inside your own organization, for free.

Smart Canvas

http://www.smartcanvas.com/

Discovering Users' Topics of Interest in Recommender Systems

Gabriel Moreira - @gspmoreira
Gilmar Souza - @gilmarsouza

ciandt.com