Semantic Annotation of Documents

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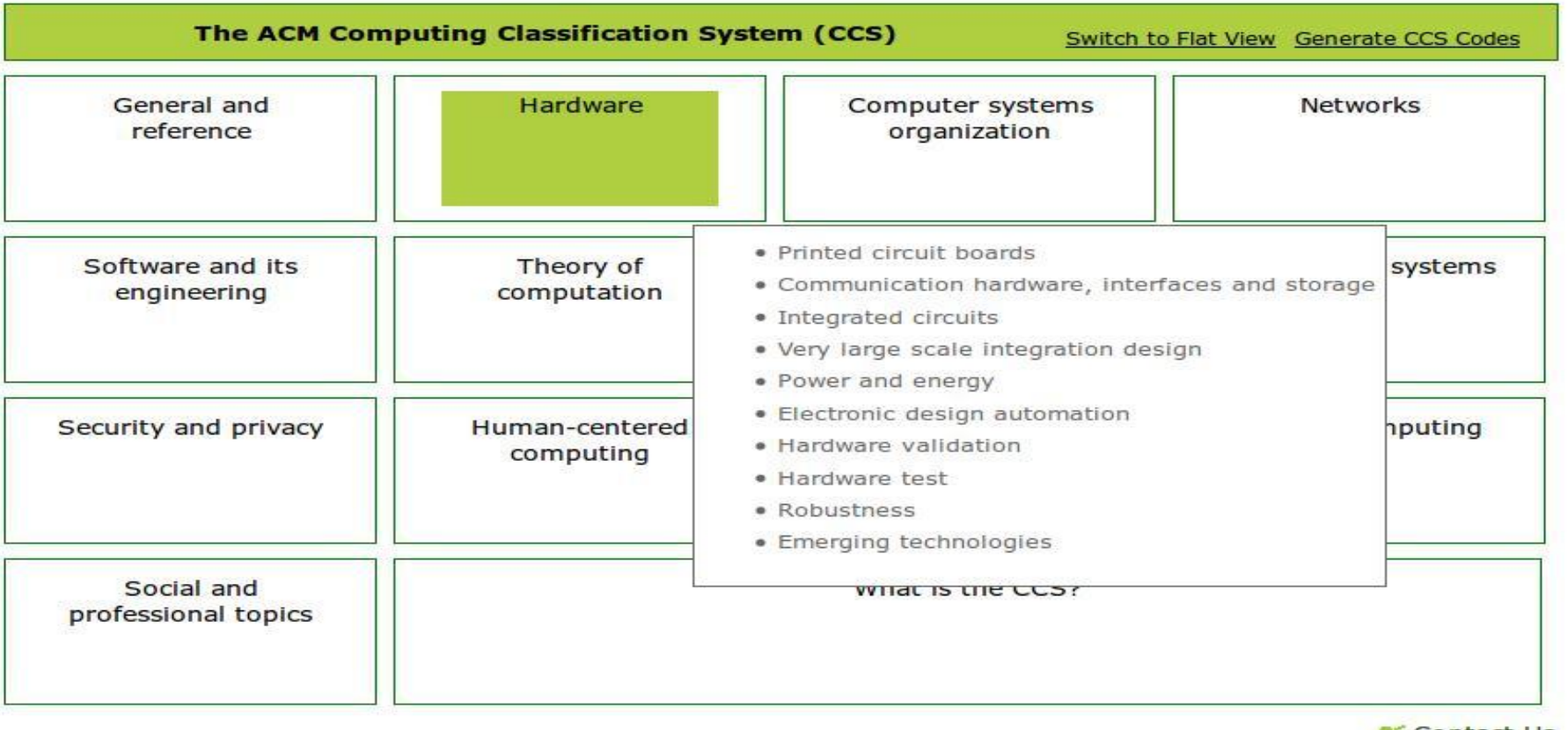
Problem Statement

Annotation of title and abstract of research paper to 2012 ACM classification categories.

The 2012 ACM Computing Classification System has been developed as a poly-hierarchical ontology that can be utilized in semantic web applications. It plays a key role in the development of a people search interface in the ACM Digital Library to supplement its current traditional bibliographic search.

The complete classification tree can be found here.

Snapshot of ACM Classification Tree



Dataset Overview

1. A private dataset of the SIEL lab of IIIT-Hyderabad. Fields:
    a. Title
    b. Author
    c. Country of authors
    d. Year of publication
    e. Conference
    f. Categories
    g. Abstract (For few research papers)
2. Wiki Dataset : For all the acm categories a dataset was build having the summary of the wikipedia page (The First section of the wikipedia document).
3. Dblp dataset : For initial tasks, this dataset was used to train the lda model. Though this was not used for the final proposition of the model.

Technical Approach and Models

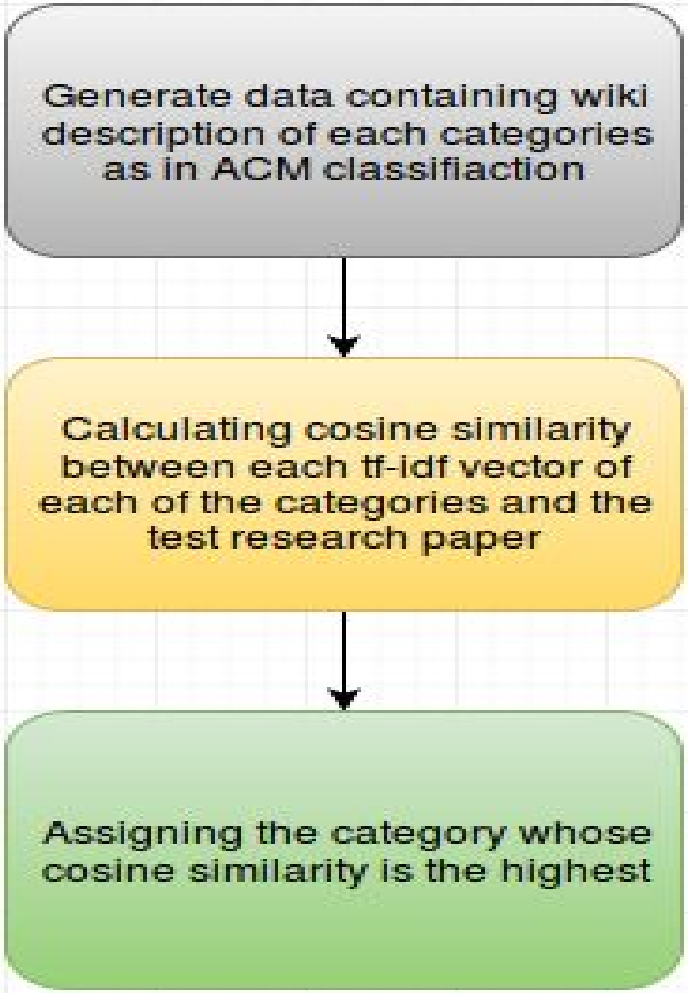
Multiple approaches were tried for the given problem

1) Cosine similarity
2) Latent Dirichlet Allocation
3) Labeled LDA + Doc2vec

Approach 1 : Cosine Similarity

Intuition Behind The Approach:

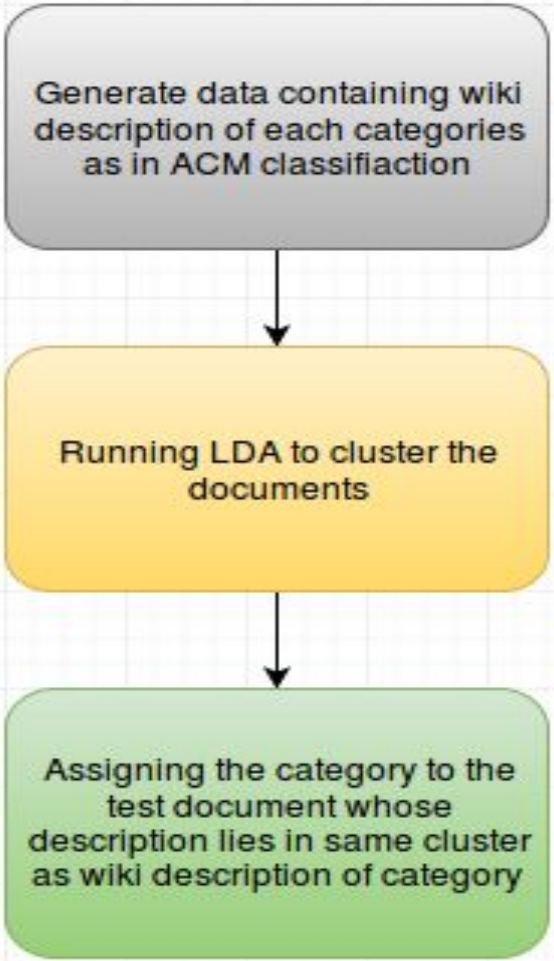
Title and abstract paper generally contain words contained in the description of the categories so finding the cosine similarity of the tf-idf vector of the title + abstract and all the categories and assigning the closest one became our first approach.



Approach 2 : Latent Dirichlet Allocation

Intuition Behind The Approach:

Topic modelling - a topic model is a type of statistical model for discovering the abstract "topics" that occur in a collection of documents.
We picked the most common topic modelling algorithm - Latent Dirichlet Allocation



Proposed Model : Labeled LDA + Doc2Vec

Intuition :

Accuracy can only be improved by supervised topic modelling i.e. by labelling the documents with topics and taking care of the semantic distance between the research paper and the categories.

References :

Labeled LDA: A supervised topic model for credit attribution in multi-labeled corpora - Stanford University (2009)

Distributed Representations of Sentences and Document - Google Inc. (2014)

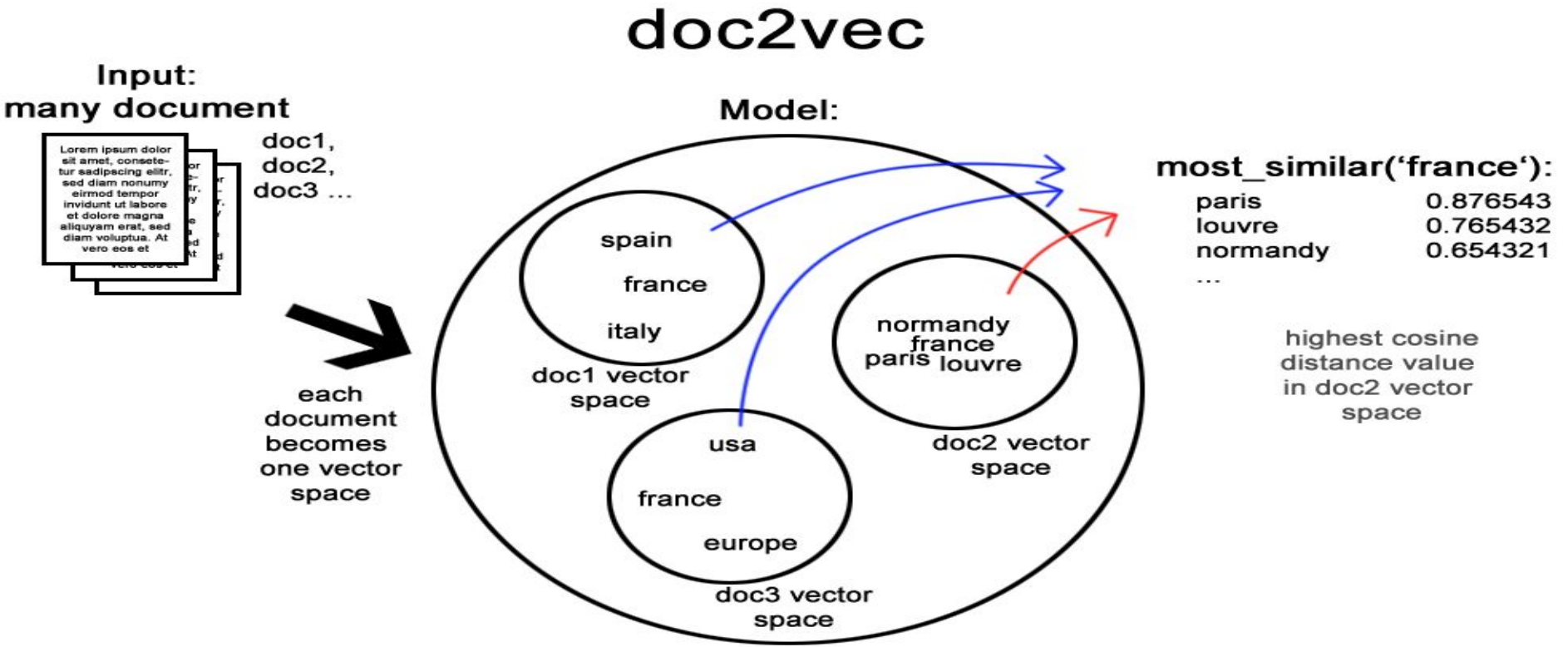
Labeled Latent Dirichlet Allocation

Labeled LDA is a probabilistic graphical model that describes a process for generating a labeled document collection. Like Latent Dirichlet Allocation, Labeled LDA models each document as a mixture of underlying topics and generates each word from one topic. Unlike LDA, L-LDA incorporates supervision by simply constraining the topic model to use only those topics that correspond to a document's (observed) label set.

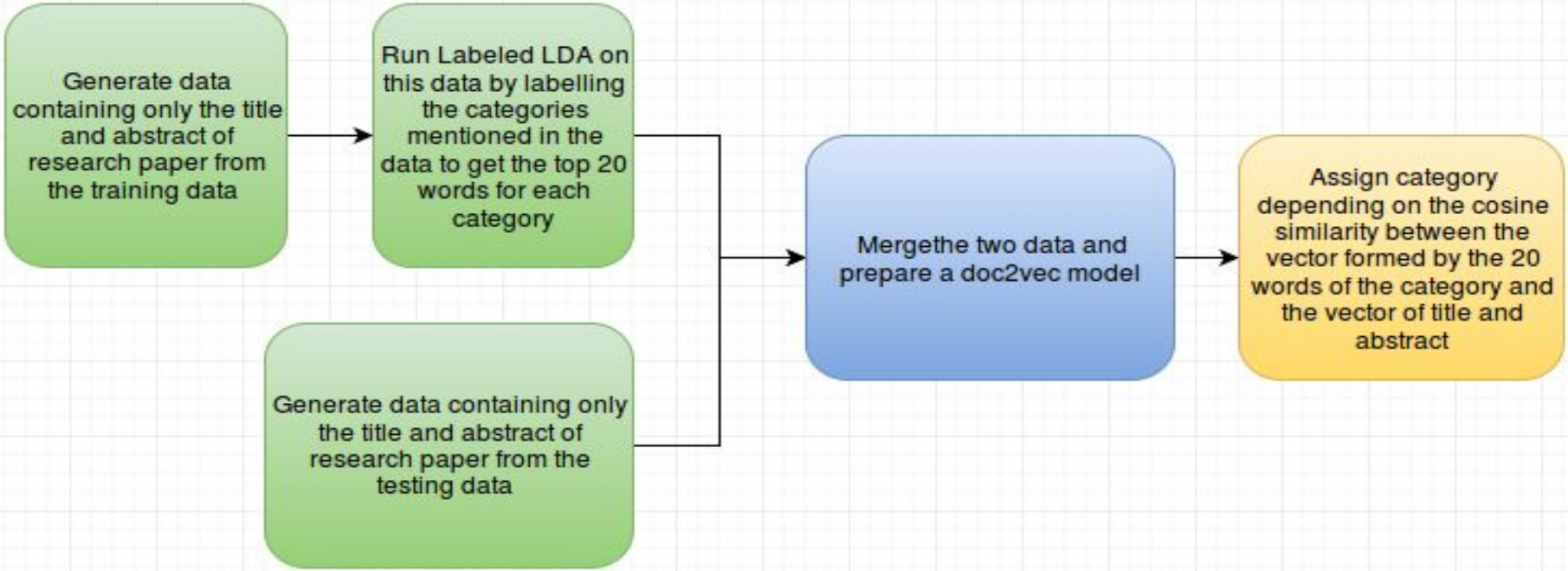
Doc2Vec

Doc2Vec is a tool provided by gensim that maps each sentences to a paragraph vector. Paragraph vector is an unsupervised framework that learns continuous distributed vector representations for pieces of texts. The texts can be of variable-length, ranging from sentences to documents. The name Paragraph Vector is to emphasize the fact that the method can be applied to variable-length pieces of texts, anything from a phrase or sentence to a large document.

Doc2Vec (continued...)



Proposed Model



Mean Average Precision

- For performance measure

Mean average precision for a set of queries is the mean of the average precision scores for each query.

where Q is the number of queries. $$\mathrm{MAP} = \frac{\sum_{q=1}^{Q} \mathrm{AveP(q)}}{Q}$$

In our work, the number of queries is the number of test documents and average precision is calculated by the definition: Average of the precision values at the points at which each relevant document is retrieved.

For only Doc2Vec model, **MAP = (0.2518) 25.18%**

For the final model (approach 3), we are getting a **MAP of 0.5931 (59.31%).**

We believe for our work and the data provided, this MAP is quite good. The results of such approaches depend a lot on the data.

NDCG (Normalized Discounted Cumulative Gain)

$$NDCG_n = \frac{DCG_n}{IDCG_n}$$

For only Doc2Vec **NDCG = 35.26%**

For the final approach, Doc2Vec + labeled LDA, **NDCG = 45.03%**

Results Overview

Categories used for classification :

Artificial - Intelligence, Databases, Computer-Vision, Information Retrieval and Other.

Training Dataset :

No. of research papers : 549

Test Dataset:

No. of research papers : 51745
No. of research papers correctly classified : 36334
MAP score : 59.31 %
NDCG score : 45.03%