

# Semantic Annotation of Documents

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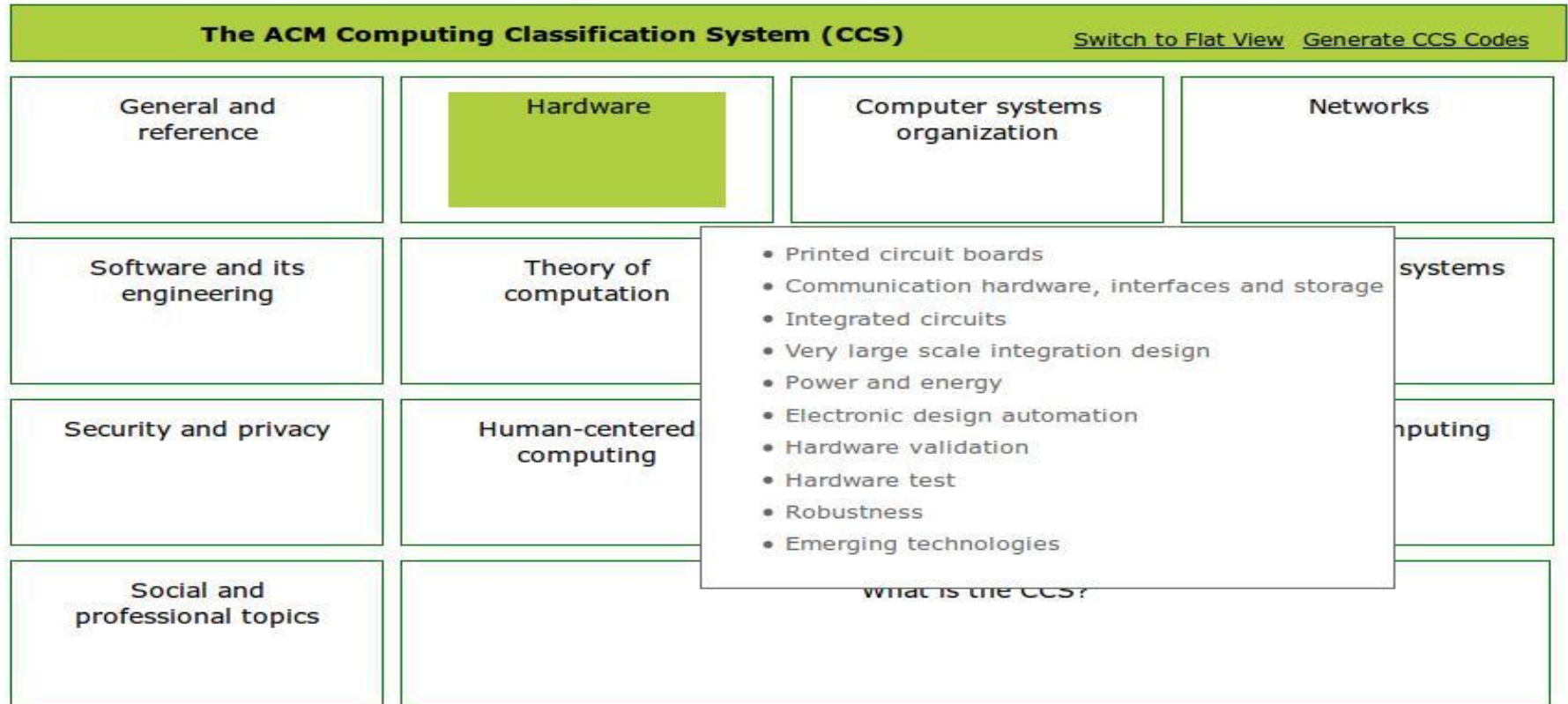
# Problem Statement

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.

Generate data containing wiki description of each categories as in ACM classification

Calculating cosine similarity between each tf-idf vector of each of the categories and the test research paper

Assigning the category whose cosine similarity is the highest

# 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

Generate data containing wiki description of each categories as in ACM classification

Running LDA to cluster the documents

Assigning the category to the test document whose description lies in same cluster as wiki description of category

# 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.

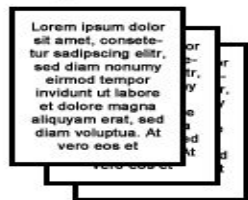
# Doc2Vec

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...)

## doc2vec

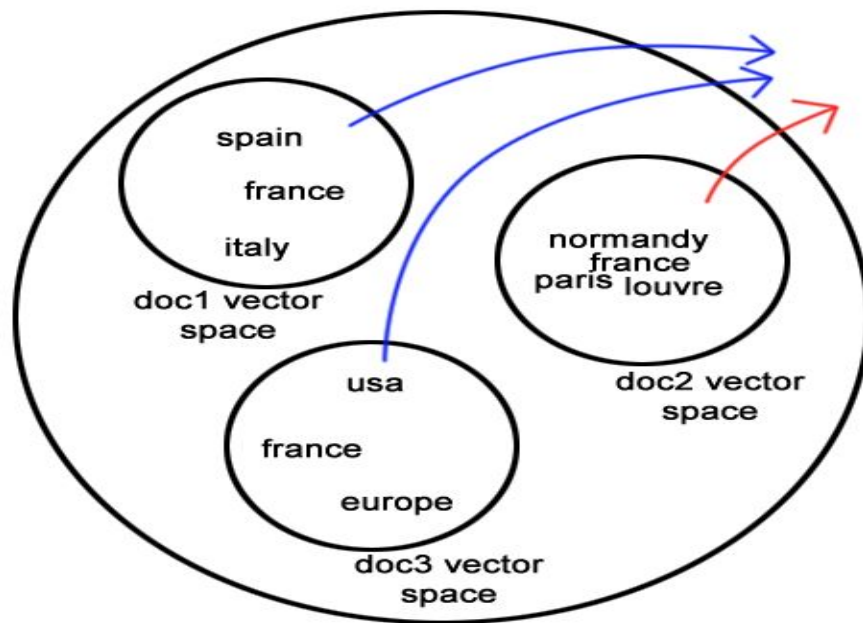
Input:  
many document



doc1,  
doc2,  
doc3 ...

each  
document  
becomes  
one vector  
space

Model:

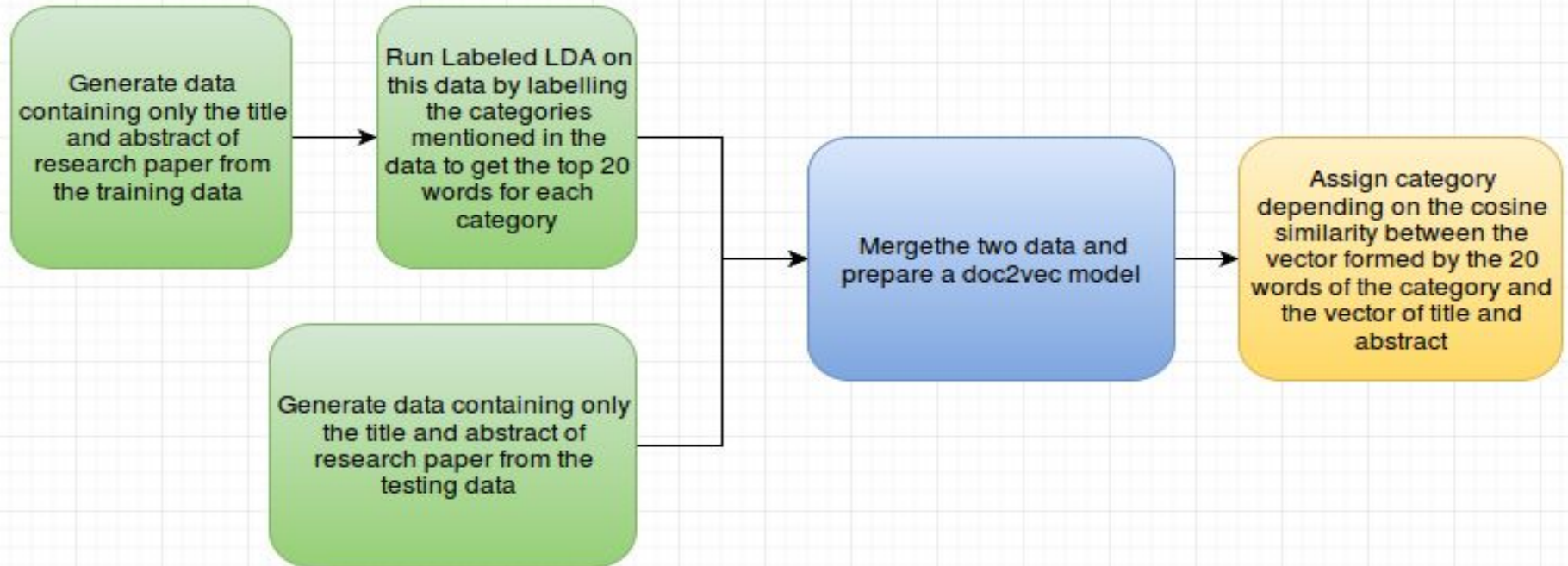


most\_similar('france'):

paris	0.876543
louvre	0.765432
normandy	0.654321
...	

highest cosine  
distance value  
in doc2 vector  
space

# Proposed Model



# MAP

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. 
$$\text{MAP} = \frac{\sum_{q=1}^Q \text{AveP}(q)}{Q}$$

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 the final model (approach 3), we are getting a MAP of 0.68 (68%).

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.

# Results Overview

## Categories used for classification :

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

## Training Dataset :

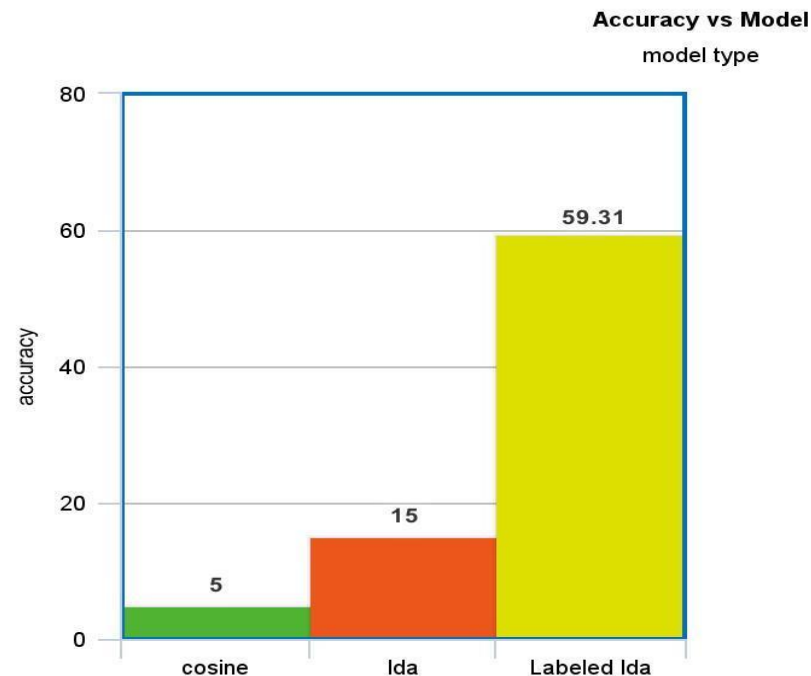
No. of research papers : 549

## Test Dataset:

No. of research papers : 51745

No. of research papers correctly classified : 36334

MAP score : 59.31 %



# Achievement of the project

With so less training data, we got a MAP of 59.31%.

Doc2Vec and Labeled LDA are responsible for such surprisingly good results.

The model will given even better results for good training set, provided labeled as the requirement of our model.