ENHANCING CLUSTER LABELLING USING WIKIPEDIA

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Introduction

What is the need of Document Clustering?

- Organize data in manageable forms

How the Clusters should be ?

  - Documents with in cluster are as similar as possible
  - Documents from different clusters should be dissimilar

And then Cluster Labeling

How it is done?

- Applying statistical techniques for feature selection
- “important” terms that best represent the cluster topic

Why there is a need of another system?

- Keywords or phrases fails to provide a meaningful label
- It represent different aspects of the topic underlying the cluster
- A good label may not occur directly in the text

Cluster labeling using JSD

ODP category	Top-5 JSD important terms
Bowling	bowl, bowler, lane, bowl center, league
Buddhism	Buddhist, Buddhism, Buddha, Zen, dharma
Ice Hockey	hockey, nhl, hockey league, coach, head coach
Electronics	voltage, high voltage, circuit, laser, power supply
Tennis Players	Wimbledon, tennis, defeat, match today, Wta
Christianity	church, catholic, ministry, Christ, grace

ODP- Open Directory Project
JSD- Jensen-Shannon Divergence

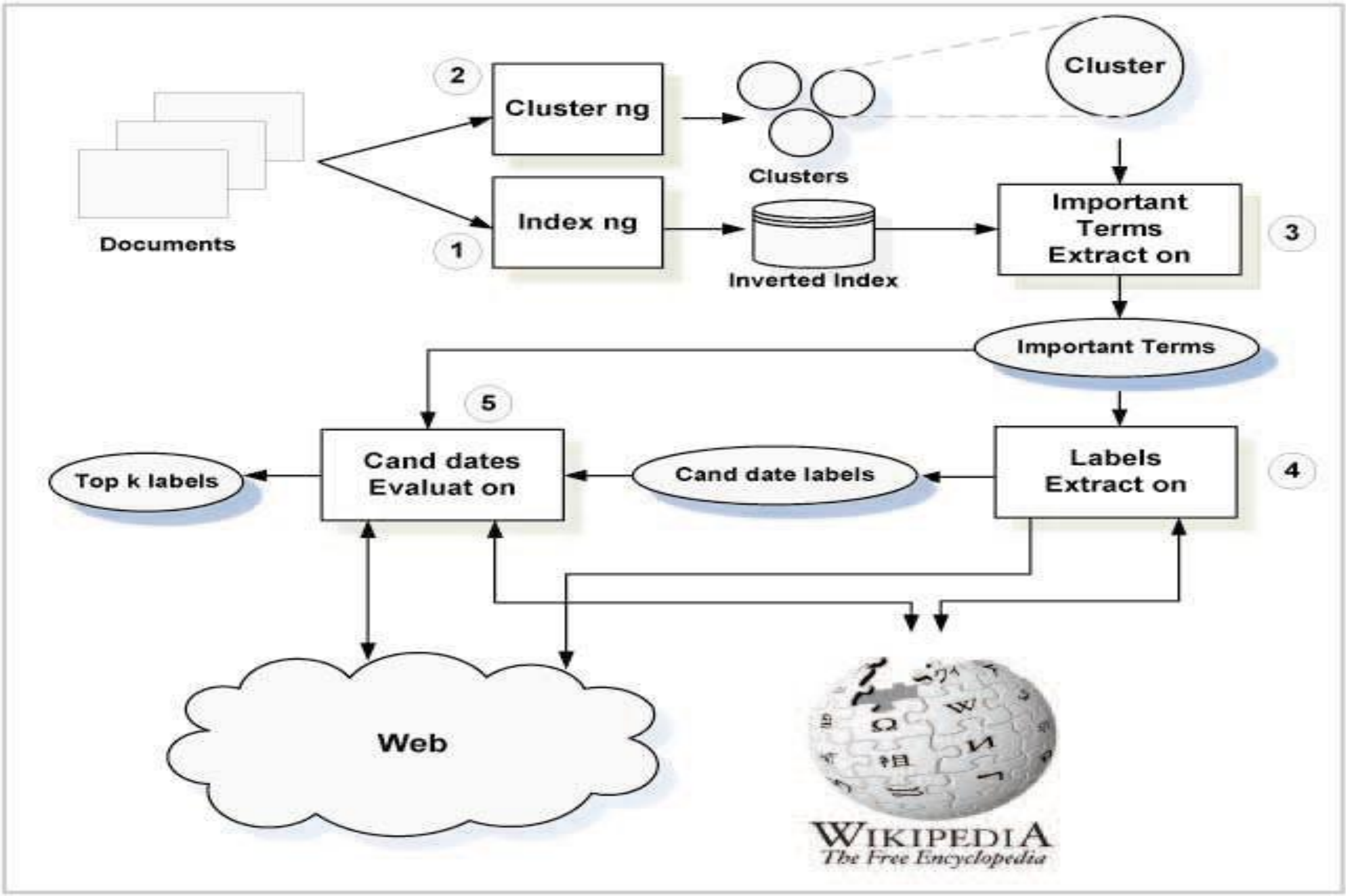
Approach

1. Extracts the most important terms from the documents
2. Find relevant Wikipedia pages
3. The categories and titles (meta-data) are candidates and In addition all important terms from documents also candidates
4. Evaluation by several judges
5. Top ranked candidate as cluster labels

Lists of top-5 important terms extracted using Wikipedia

ODP category	Top-5 JSD important terms	Top-5 Labels Using Wikipedia Enhancement
Bowling	bowl, bowler, lane, bowl center, league	Bowls, Bowling, Bowling (cricket), Bowling organizations, Bowling competitions
Buddhism	Buddhist, Buddhism, Buddha, Zen, dharma	Buddhism, History of Buddhism, Buddhism by country,Tibetan Buddhism, Buddhists
Ice Hockey	hockey, nhl, hockey league, coach, head coach	Ice hockey, Ice hockey leagues, Hockey prospects, Canadian ice hockey coaches, National Hockey League
Electronics	voltage, high voltage, circuit, laser, power supply	Electronics, Power electronics, Diodes, Power supplies,Electronics terms
Tennis Players	Wimbledon, tennis, defeat, match today, Wta	Tennis Players, Tennis terminology, Tennis tournaments,2002 in tennis, 2000 in tennis
Christianity	church, catholic, ministry, Christ, grace	Christianity, Christian denominations, Non-denominational Christianity, Christian theology, Christianity in Singapore

General Framework



1. Indexing

- Parsed, tokenized and represented as term vectors
- Term weights are determined by **tf-idf**
- Indexed by generating a search index
- Lucene to generate a search index such that **tf** and **idf** value of each term **t** can be quickly accessed

2. Clustering

- It creates coherent clusters
- Given the input as collection of documents D, It returns a set of document clusters

  $$C = \{C_1, C_2, \ldots, C_n\}$$

- A cluster is represented by the centroid of the cluster's documents
- The weights of the terms in centroid is slightly modified

$$w(t,C) = ctf(t,C) \cdot cdf(t,C) \cdot idf(t)$$

where

$$ctf(t,C) = \frac{1}{|C|} \sum_{d \in C} tf(t,d)$$

Cdf (t,c)= log(n(t,c)+1)

Where n(t,c) is the document frequency of t in C

3. Important terms extraction

- Given a cluster $C \in \mathcal{C}$s input
- And to find a list of terms T(C) =(t_1, t_2,…,t_k)
- Term T(C) is that which best separates the cluster's documents from the entire collection
- Jensen-Shannon Divergence (JSD) is used to measure the distance between the cluster C and the entire collection for a set of terms
- Each term is scored according to their JSD distance
- The top scored terms are selected as Cluster important terms

4. Label extraction

- Given the important terms T(C)
- And to extract candidate labels for cluster C
- Two types
  1. Use directly **top-k important terms**
  2. Use this **top-k important terms** to execute a query **q** against **Wikipedia index**
- The result is a list of documents D(q)
- Documents title and categories are considered as potential candidate cluster labels L(C)

5. Candidate label evaluation

- Done by several judges

- Given the input for judges are L(C) and T(C)

- Two judges
  1. MI judge
  2. SP judge

- The scores of all judges are then aggregated and the label with highest score returned

MI(Mutual Information) judge

- It scores each candidate by the average **pointwise mutual information (PMI)** with respect to a given external textual corpus
- The average PMI reflects the **semantic distance** of the label from the cluster content
- Labels closer to the cluster content are preferred

MI(Mutual Information) judge

- Given the input is L(C), T(C) and a corpus (Google n-grams)
- Given a candidate label $l \in \mathcal{L}(C)$, the following score is assigned to l:

$$\mathtt{MI}(l, \mathcal{T}(C)) = \sum_{t \in \mathcal{T}(C)} \mathtt{PMI}(l, t|corpus) \times \omega(t)$$

Where $\omega(t)$ denotes the relative importance of important term t in T (C)

- The PMI between two terms is measured by:

$$\mathtt{PMI}(l, t|corpus) = \log\left(\frac{Pr(l, t|corpus)}{Pr(l|corpus) \times Pr(t|corpus)}\right)$$

- The probability of a term is approximated by the maximum likelihood estimation

$$Pr(x|corpus) = \frac{\#(x|corpus)}{\#(corpus)}$$

SP(Score Propagation) judge

- It scores each candidate label with respect to the scores of the documents in the result set associated with that label
- Given $l \in \mathcal{L}(C)$, the score propagation from D(q) to l, weight for l is represented as,

$$\omega(l) = \sum_{d \in \mathcal{D}(q) : l \in d} \frac{score(d)}{n(d)}$$

n(d) - number of candidate labels extracted from document d

- scoring of label keywords

$$\omega(kw) = \sum_{l \in \mathcal{L}(C) : kw \in l} \omega(l)$$

- Each candidate label is scored by the average score from its keywords

$$\mathrm{SP}(l|\mathcal{D}(q)) = \frac{1}{n(l)} \sum_{kw \in l} \omega(kw)$$

n(l) -number of l's unique keywords

Score Aggregation

- The final stage is to aggregate the scores from the different judges for each label
- Each candidate label is scored using a linear combination of the judge (J_1, …J_m) scores

$$\mathtt{score}(l|C) = \sum_{i=1}^{m} \beta_i J_i(l|C)$$

Where $\sum_i \beta_i = 1$

- Finally the set of top-k scored candidates are recommended for cluster labeling

Experiments

Data Collection

Two data collections

I. 20 News Groups (20NG) data collection
   - Newsgroup documents that were manually classified into 20 different categories
   - Each category includes 1,000 documents, so totally 20,000 documents

II. Open Directory Project(ODP)
   - Randomly selected 100 different categories from the ODP hierarchy
   - Example categories include, among others, sub-categories of the top level ODP categories such as Ceramic Art and Pottery
   - From each category randomly selected up to 100 documents, so totally 10,000 documents

Evaluation and Experimental setup

- Given a collection of clusters, and the parameter k
- The system proposes up to k labels for each cluster

Evaluation of system's performance :

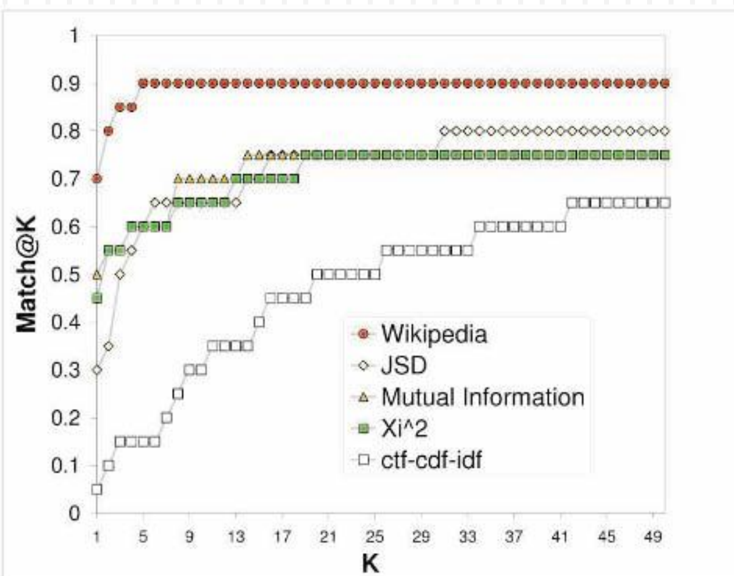
- Two methods were used

I. **Match@K**
The relative number of clusters for which at least one of the top-k labels is correct.

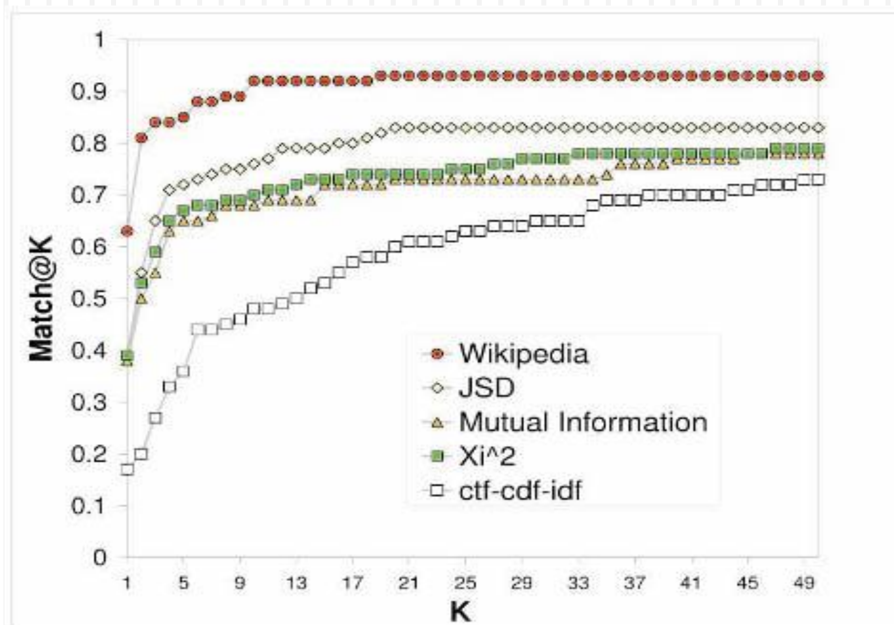
II. **Mean Reciprocal Rank (MRR@K)**
Given an ordered list of k proposed labels for a cluster, the reciprocal rank is the inverse of the rank of the first correct label, or zero if no label in the list is correct. The MRR@K is the average of the reciprocal ranks of all clusters.

The Effectiveness of Using Wikipedia to Enhance Cluster Labeling

- Here four different feature selection methods also compared



20NG

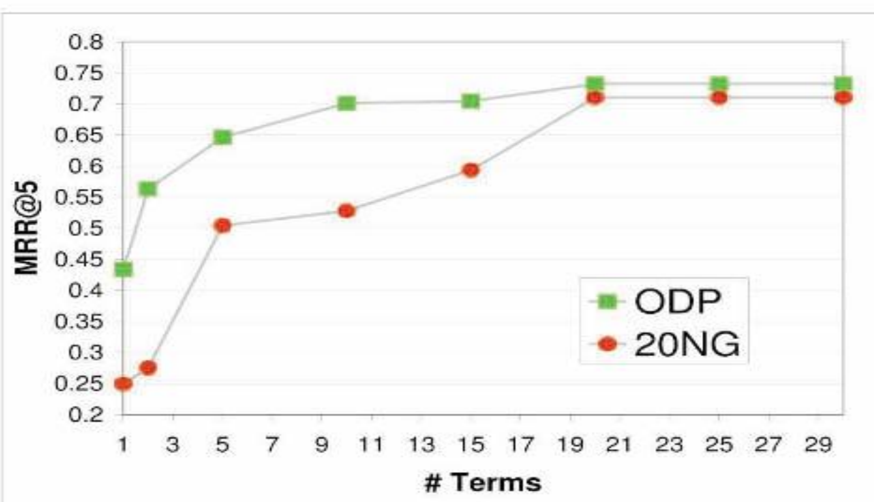


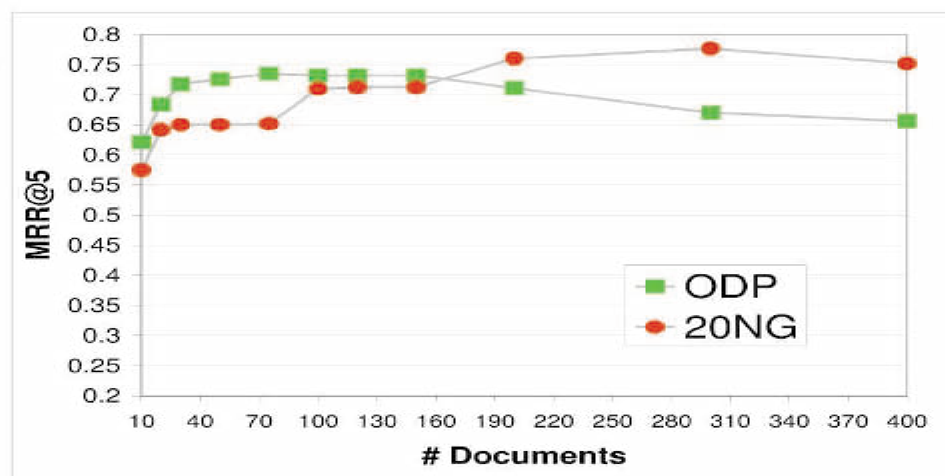
ODP

Candidate Labels Extraction

There are two significant parameters that can affect the quality of Wikipedia's labels:

I. The number of important terms that are used to query Wikipedia
II. The number of top scored results from which candidate labels are extracted

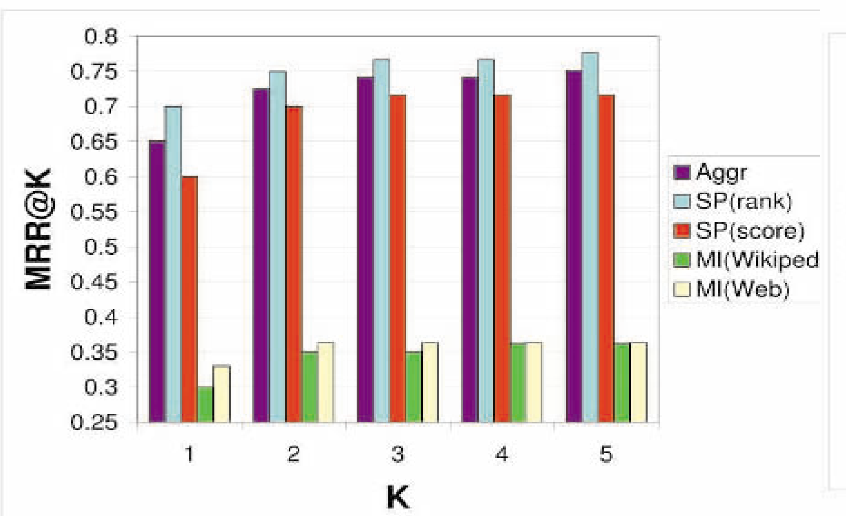




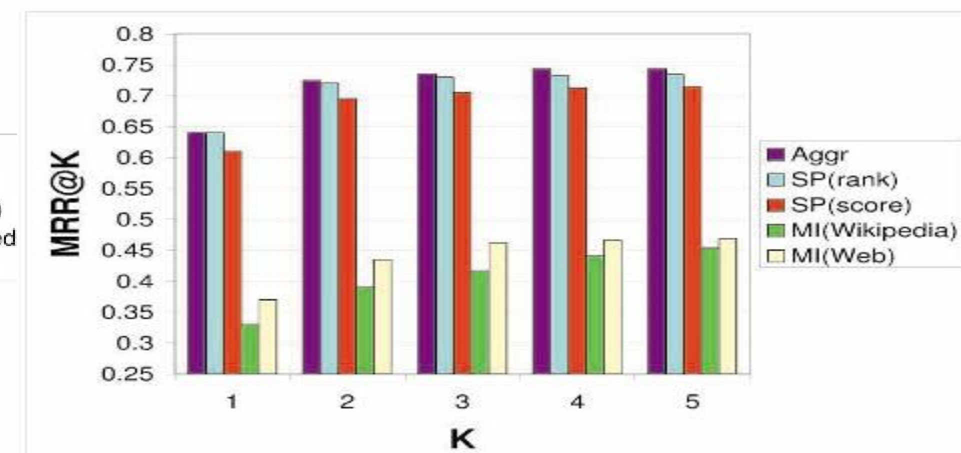
Evaluating judge Effectiveness

- Observations for all judges shows, as k increases (i.e., more cluster labels are proposed) the MRR score increases.

- Overall, among the four different judges, the SP(rank) judge performs the best.



20NG



ODP

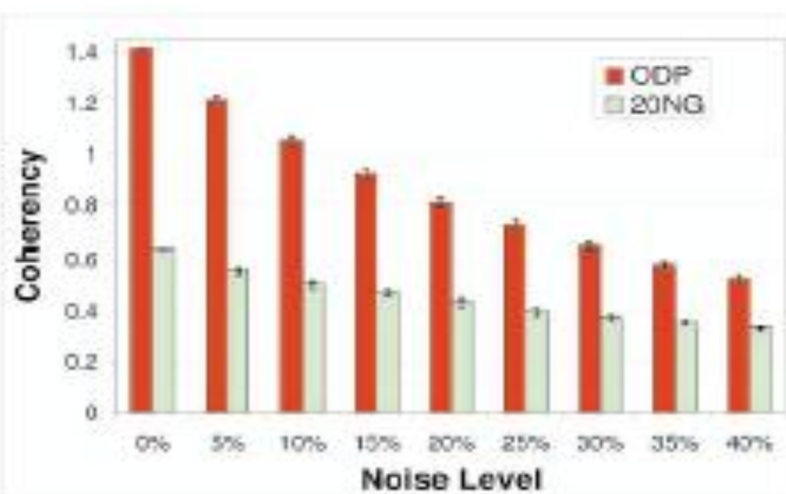
The Effect of Clusters' Coherency on Label Quality

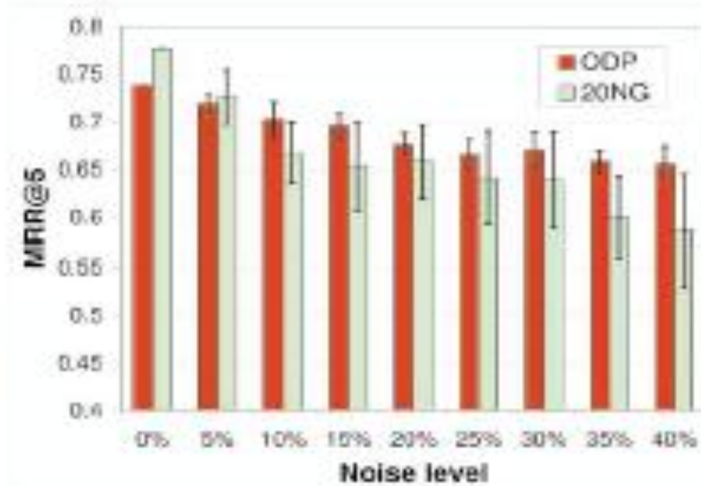
- A cluster of documents given to the labelling component is usually the corresponding result of the clustering algorithm used by the system.

$$coherency(\mathcal{C}) = \frac{\sum_{i=1}^{n} \frac{|C_i|}{|\mathcal{D}|} sim_{in}(C_i)}{sim_{out}(\mathcal{C})}$$

Testing on a noisy cluster

- For a noise level p(in[0,1]) of clusters, each document in one cluster have probability p to swap with document in other cluster





Conclusion

Advantages

- Cluster labeling can be enhanced by utilizing the Wikipedia knowledge-base
- A detailed evaluation is done all the phase of the Framework
- Evaluation results demonstrates the proposed system is robust and resiliency to noise

Disadvantages

- The topics which are not covered by Wikipedia may affect the system performance

Thank you!