Personalization and Recommendation of web pages using Semi-Supervised Approach

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April 1, 2014

OVERVIEW

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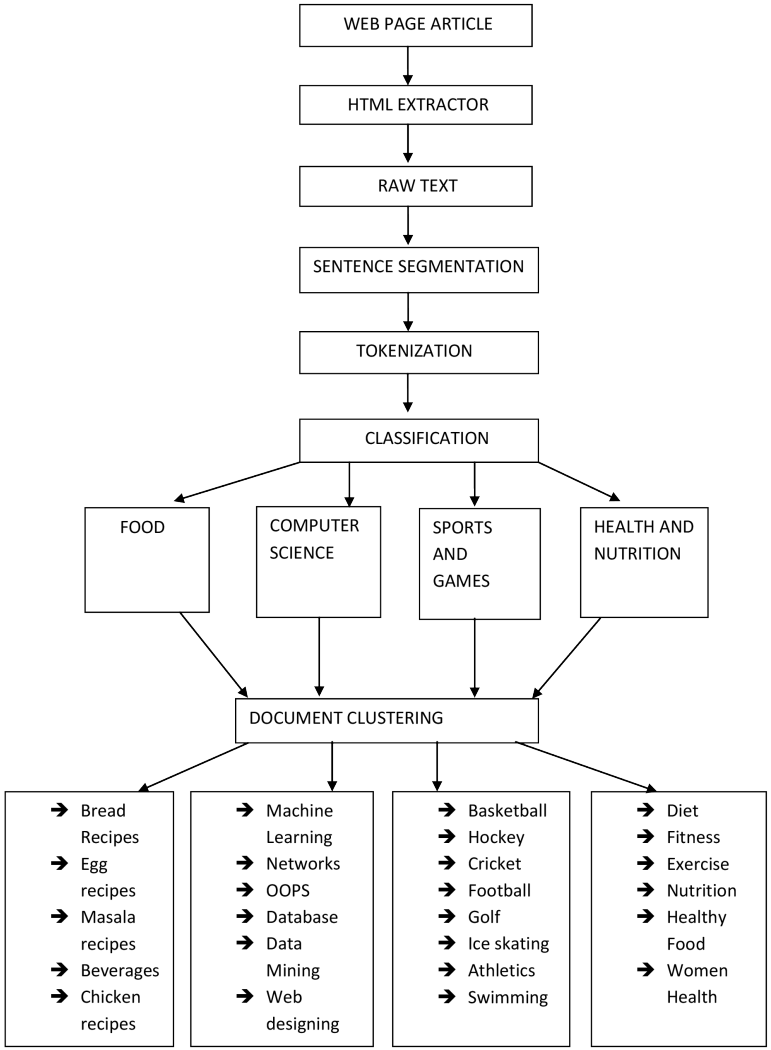
Introduction

- Due to large volume of unstructured data in the web there rises a necessity to categorize and structure the documents
- Document classification is the task of labeling documents with a set of predefined thematic categories.
- Document clustering is an unsupervised approach which groups similar articles together in one cluster

Proposed System



Proposed System

- A Semi-supervised method is proposed to address the problem of personalization and recommendation.
- Document classification and Document clustering methods are combined to achieve this.
- A real time web-application is developed which pools in web articles according to users more specific interest from various websites.

Module Split-Up

Training the classifier

- Features are extracted from the documents.
- The classifier is trained over the various pre-defined categories.
- Classifier uses logistic regression algorithm.

Document Pre-Proessing

- The web page document in the form of a raw HTML format is parsed and content is extracted
- The extracted content is processed by removing stop words and stemming to root form.

Module Split-Up

Document Classification

- The trained classifier returns a set of probability for all the pre-defined categories for the test document
- The categorized document are then further clustered together to find sub-categories

Document Clustering

- Clustering is done with the help of Incremental clustering algorithm .
- This algorithm makes use of similarity and distance metric in order to find the correlation distance between two documents.

Methods

Document Classification

- HTML tags removal
- Feature Extraction
- Logistic Regression

Document Clustering

- Incremental Clustering Algorithm
- Cosine Similarity
- TF-IDF
- Pearson Correlation

Document Classification

- HTML Tags Removal
  - The web page document which is in the form of a raw HTML format is parsed.
  - All the HTML tags are removed from the HTML document using a Python-Goose wrapper.

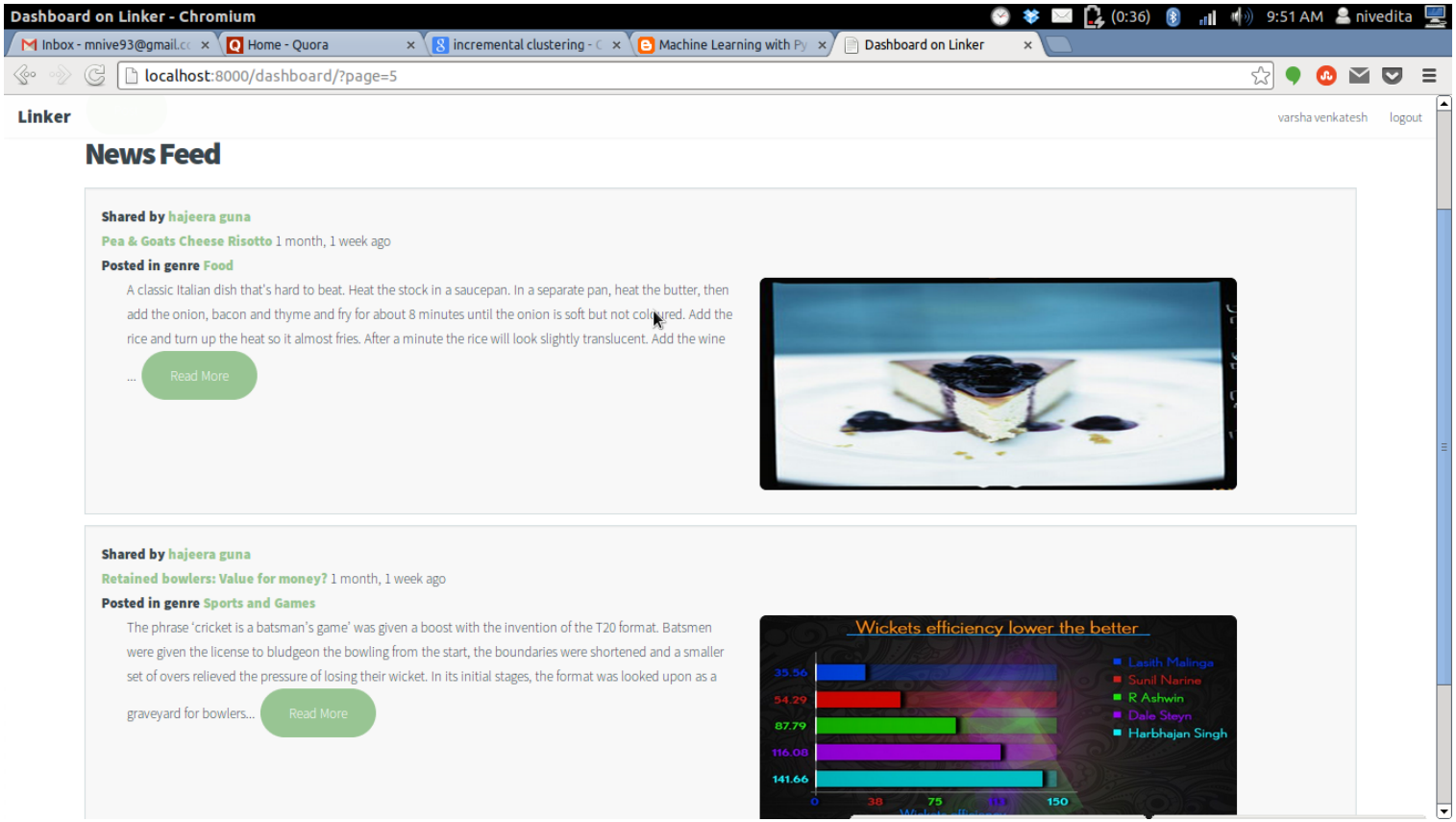
```
def parse_url(url):
 print url
 g = Goose()
 article = g.extract(url=url)
 print article.title
 print article.cleaned_text
 if article.title:
    if(len(article.cleaned_text)>200):
        return article.cleaned_text
```

Document Classification

- Feature Extraction
  - The document is pre-processed by removing stop words from the document and stemming the word to its root form.
  - After pre-processing unique features are selected from the document by using bi-grams.
- Logistic Regression
  - Logistic regression is used for predicting the outcome of a categorical dependent variable.
  - It is based on one or more predictor variables.

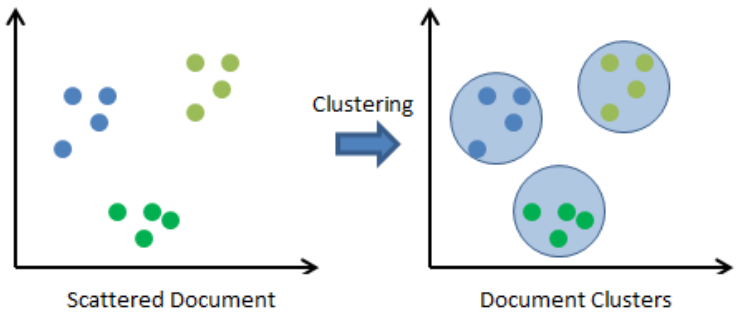
Personalized user feed

- The user feed is customized to suit the user's particular interests thus filtering out web pages that does not appeal to the user.
- This is achieved with the help of classification methods which assigns a category to the web page thus helping to generate a personalized feed.



Document Clustering

- Clustering can be considered the most important unsupervised learning problem deals with finding a structure in a collection of unlabeled data.



- Two or more objects belong to the same cluster if they are close according to a given distance (in this case geometrical distance).

Document Clustering

- Incremental Clustering Algorithm
  - Incremental Clustering algorithm is implemented due to the dynamic nature of the web documents.
  - In Incremental clustering the documents are clustered using a pair wise similarity.
  - If the pair wise similarity falls below a particular threshold,the documents are clustered together
  - Threshold is calculated by finding out the average between highest and lowest pair wise similarity.

Performance Analysis between Distance Metrics

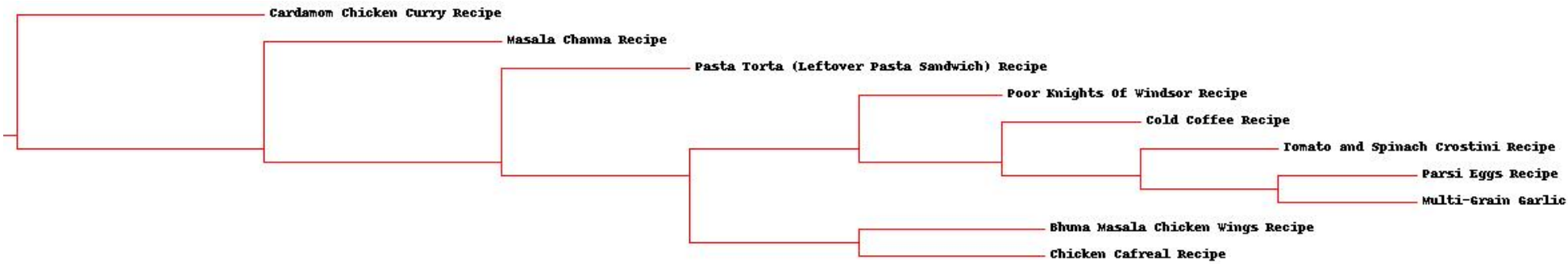


Figure: Euclidean distance with cosine similarity

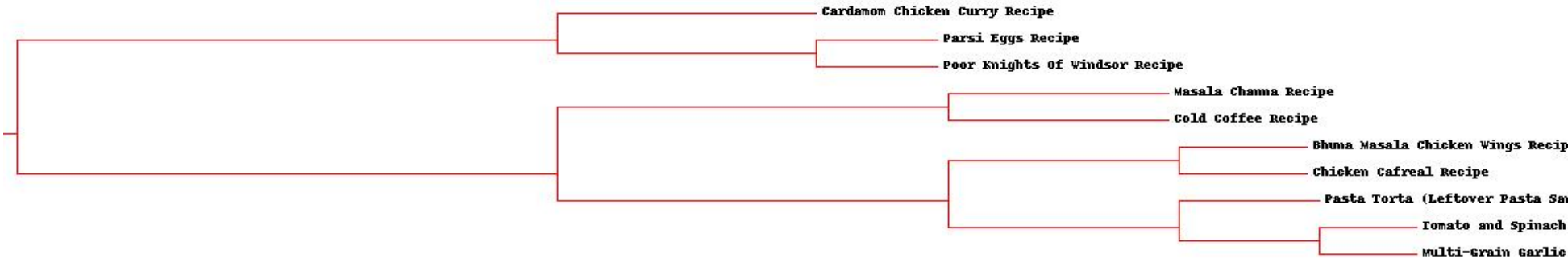


Figure: Hamming distance with cosine similarity

Performance Analysis between Distance Metrics

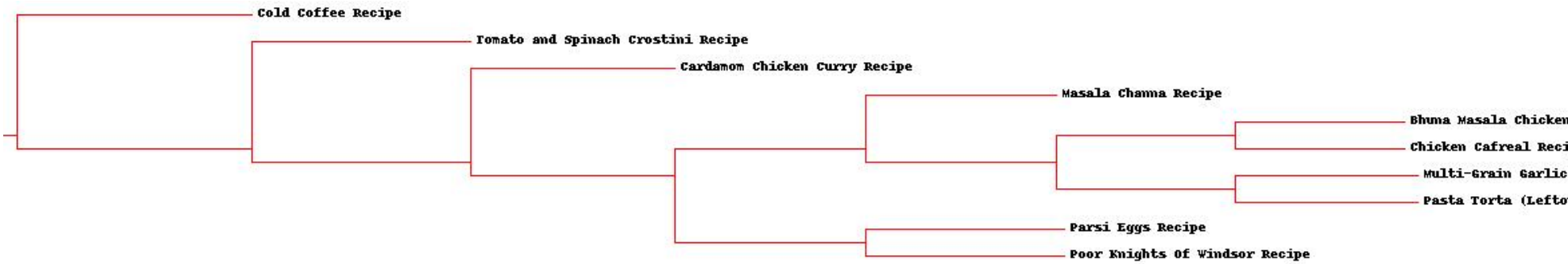


Figure: Tanamoto distance with cosine similarity

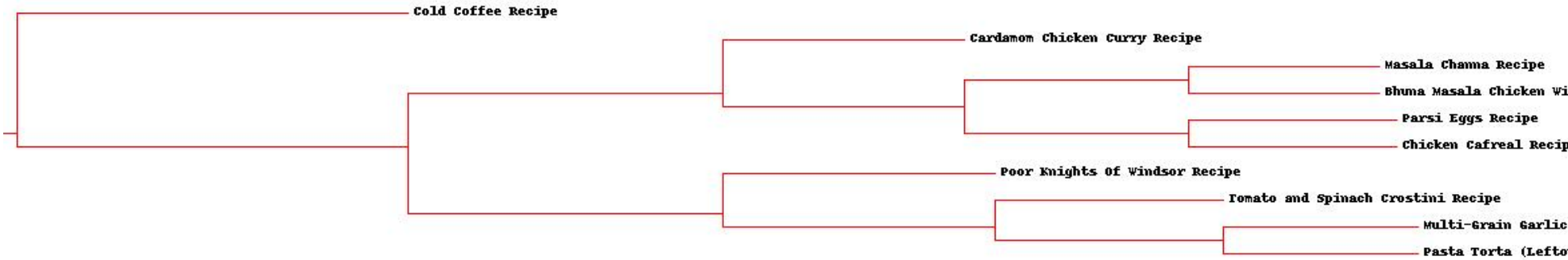


Figure: Pearson distance with cosine similarity

Document Clustering

- Cosine Similarity
  - This metric is frequently used when trying to determine similarity between two documents.
  - In this similarity metric, the attributes is used as a vector to find the normalized dot product of the two documents.

```
def cosim(v1, v2):
    dot_product = sum(n1 * n2 for n1,n2 in zip(v1, v2) )
    magnitude1 = sqrt (sum(n ** 2 for n in v1))
    magnitude2 = sqrt (sum(n ** 2 for n in v2))
    return dot_product / (magnitude1 * magnitude2)
```

Document Clustering

- TF-IDF
  - Term FrequencyInverse Document Frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus.

```
from nltk.corpus import stopwords
from math import log
from math import sqrt
def tfidf(alldocument):
   wc = {}
   idf = {}
   tot_tfidf = []
   for content in alldocument:
    temp = []
    normalizedoc = content.lower().split()
    for word in normalizedoc:
      if word not in stopwords.words('english') and len(word) >1:
          wc[word] = normalizedoc.count(word.lower()) / float(len(normalizedoc))
          count = 0
          for c in alldocuments:
             if word.lower() in c:
                count+=1
          if count > 0:
            idf[word] = 1 + log(float(len(alldocument))/count)
          else:
            idf[word] = 1
          temp.append(wc[word]*idf[word])
    tot_tfidf.append(temp)

   return tot_tfidf
```

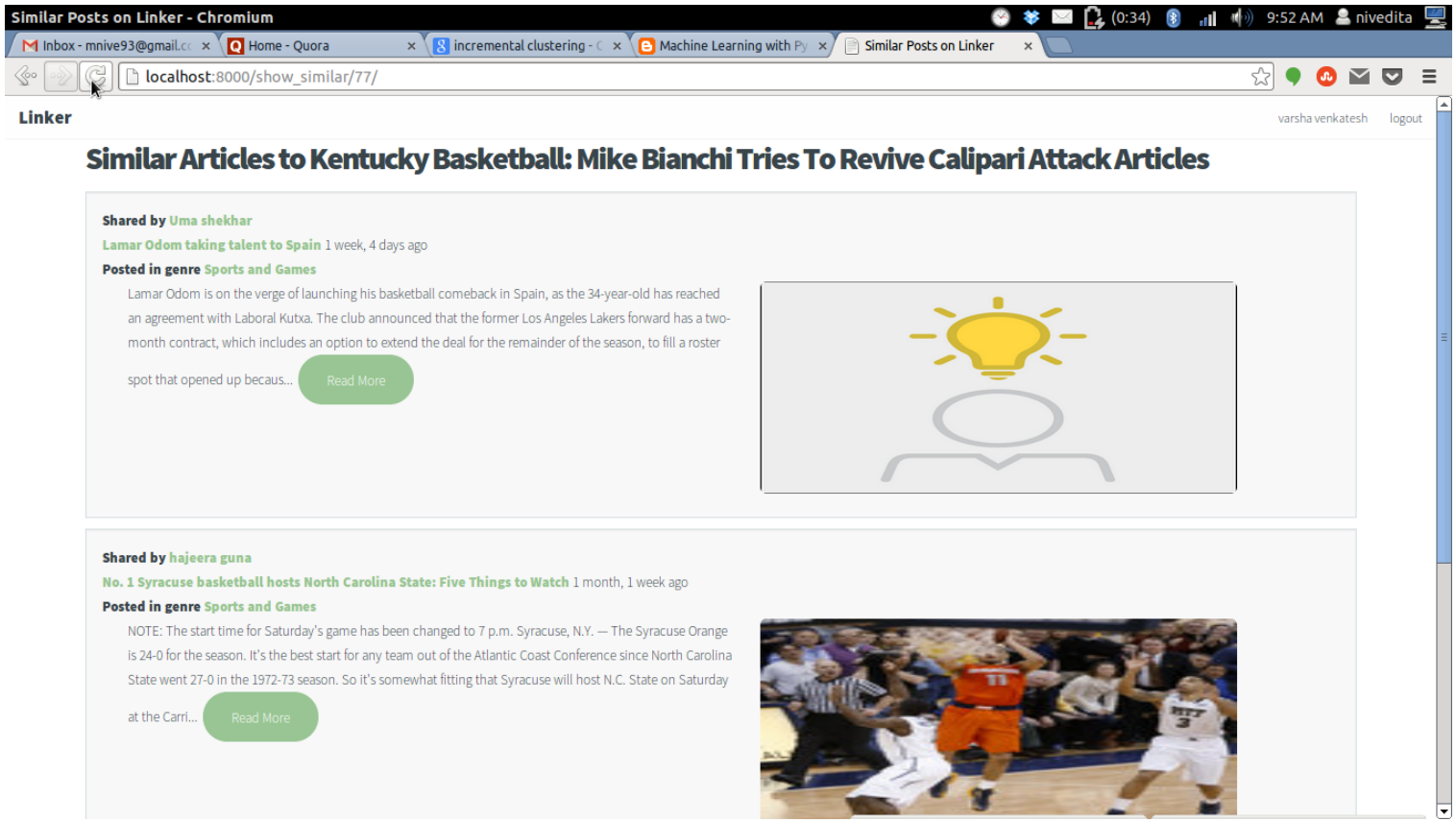
Document Clustering

- Pearson-Correlation
  - This metric measures how highly correlated are two variables and is measured from -1 to +1.

```
def pearson(v1,v2):
  # Simple sums
  sum1=sum(v1)
  sum2=sum(v2)

  # Sums of the squares
  sum1Sq=sum([pow(v,2) for v in v1])
  sum2Sq=sum([pow(v,2) for v in v2])

  # Sum of the products
  pSum=sum([v1[i]*v2[i] for i in range(len(v1))])

  # Calculate r (Pearson score)
  num=pSum-(sum1*sum2/len(v1))
  den=sqrt((sum1Sq-pow(sum1,2)/len(v1))*(sum2Sq-pow(sum2,2)/len(v1)))
  if den==0: return 0

  return 1.0-num/den
```

Recommendation of Similar Articles

- The user's specific interests are targeted by showing similar articles to a particular article.
- This is done with the help of clustering methods.



Conclusion

- We have finally developed a personalized dashboard for a user which streams web documents depending on the users interests .
- The classified documents are then further clustered together using an unsupervised algorithm which is used in identifying the users specific interests.
- The web application supports many concurrent users and the users can share their favourite posts simultaneously which can be viewed by other users depending upon the genre of the article.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