## A Study on Emerging Topics Discovery by Text Minging

Team

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#### Step 1: Parsing and Rreprocessing of Raw Data

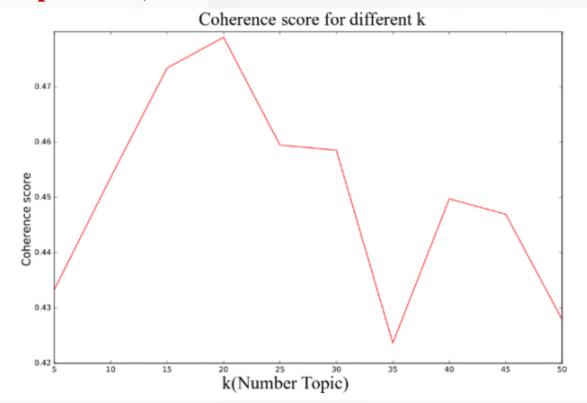
The XML data was parsed into CSV format with a total of 2,584 records. Then three fields of **the pubyear**, **title and abstract** were extracted into the CSV dataform and the text field was obtained by merging the title and abstract fields. Table1shows the basic format of the experimental data.

| Id   | Pubyear     | Text (title+abstract) |
|------|-------------|-----------------------|
| 1    | T1          | Text1                 |
| 2    | T2          | Text2                 |
| 3    | Т3          | Text3                 |
|      |             |                       |
| 2584 | $T_{\rm m}$ | Text <sub>n</sub>     |

NLTK toolkit was used in the data preprocessing of text field, including conversion of capitalization, removing of numbers and punctuation and filtering of pause words, to improve the accuracy and validity of topics recognition.

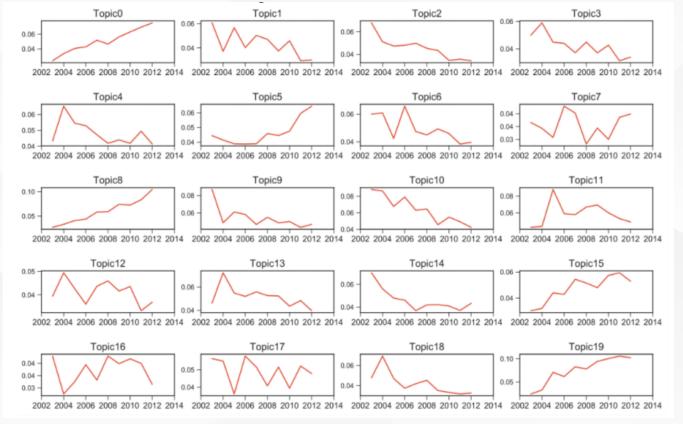
#### **Step 2: LDA Topic Recognition with Optimized Parameters**

Python's Gensim toolkit was used for topic recognition in the method. In the parameter optimization, the number of topics k was determined by calculating the consistence score of the topic model with alpha=50/k, beta=0.01. The consistency score gets its highest value when k = 20. Therefore, the topics number k = 20 was determined with alpha = 2.5, beta = 0.01.



#### **Step 3: Building of Topic Time Intervals**

Based on the results of the previous LDA topic recognition, the topic change time intervals data were further constructed with **the self-defined function def topic\_dis\_year()**. In order to observe the trend of the topic time intervals more intuitively and effectively, the topic time intervals line chart was drawn by using the Matplotlib toolkit.



### **Step 4: Emerging Topics Recognition**

BasedThe function def gram\_dis\_year() was defined to construct the 2-gram vocabulary time intervals data by extracting 2-gram vocabulary with NLTK tools. Next, the average growth rate of each 2-gram vocabulary in the past three years was calculated, and the top300 topic words were obtained through a sorting. Finally, the vocabulary of top300 topic words were mapped as a schedule to our emerging topics identification results.

| 4  | A    | В        | С           | D                               |
|----|------|----------|-------------|---------------------------------|
| 1  | rank | Topic-id | Topic words | emerging(2-gram)                |
| 2  | 1    | Topic8   | biology     | "synthetic biology", "biology a |
| 3  | 1    | Topic8   | synthetic   | "synthetic biology", "synthetic |
| 4  | 1    | Topic8   | engineere   | "metabolic engineere", "enginee |
| 5  | 1    | Topic8   | system      | "biological system", "genetic : |
| 6  | 1    | Topic8   | biological  | "biological system", "synthetic |
| 7  | 1    | Topic8   | genome      | "synthetic genome", "genome wid |
| 8  | 1    | Topic8   | assemle     |                                 |
| 9  | 1    | Topic8   | recent      |                                 |
| 10 | 1    | Topic8   | field       | "field synthetic"               |
| 11 | 1    | Topic8   | development | "development synthetic"         |
| 12 | 2    | Topic5   | enzyme      | "restriction enzyme"            |
| 13 | 2    | Topic5   | production  | "protein production"            |
| 14 | 2    | Topic5   | strain      | "coli strain"                   |
| 15 | 2    | Topic5   | substrate   | "substrate specificity"         |



# Thanks for your attention Q&A?