SMAI Project Report - Team 40

Multi-Factor Duplicate Question Detction in Stack Overflow

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Abstract

This report details our implementation of the paper titled "Multi-Factor Duplicate Question Detection in Stack Overflow" by Y. Zhang et al. The objective of the paper is to create and train a model that is able to take a new question from a user as an input, compute certain weighted measures and give a list of k questions that are most similar to the input question. The similarity between two questions is calculated by using four distinct parameters, that are used in computing the measures, that stem from the four components in a stack overflow question - Title, Description, Tags and Topics. The similarity score is calculated and then used as a metric for ranking and creating the output list. We implement the model using Python due to its extensive library support. We also train and test the model on a smaller dataset due to hardware limitations, however the model has the same architecture and hence, should scale well. We conclude by showing results and listing some limitations.

Introduction and Motivation

Stack Overflow is an online platform for people to ask questions regarding specific subjects. Due to its massive popularity and userbase, the platform faces far too many questions a day, and a lot of them could be classified as duplicates. A human would take unimaginably long to go through the entire database and flag each question as a duplicate, and duplicates will not be answered quickly either, as people get tired of answering the same questions. Clearly, the manual approach is unfeasible and has many flaws, and a better solution is required. This is where the paper "Multi-Factor Duplicate Question Detection in Stack Overflow" by Y. Zhang et al. comes in. The paper proposes a model that is able to take a new question from a user as an input, compute certain weighted measures and give a list of k questions that are most similar to the input question. The similarity score is calculated and then used as a metric for ranking and creating the output list. The model is trained on a dataset of 1.5 million questions, and is able to give a list of 10 similar questions in less than 1 second. The model is implemented using Python due to its extensive library support. We also train and test the model on a smaller dataset due to hardware limitations, however the model has the same architecture and hence, should scale well. We conclude by showing results and listing some limitations.

Dataset

The dataset for the predictor is taken from Stack Exchange Data Explorer for Superuser. A set of 20,000 questions are taken along with 8811 past question and duplicate pairs.

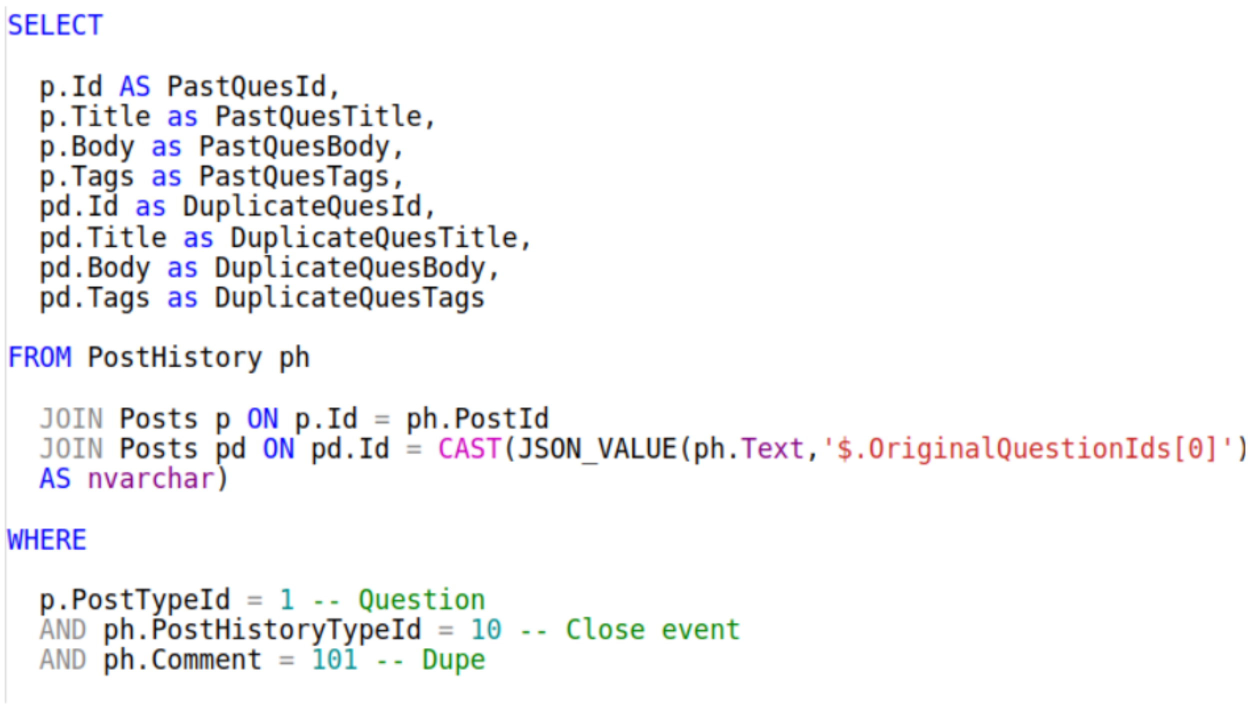
For every question four fields are taken into consideration, namely Question ID, Title, Tags and Body.

The queries to get the dataset for duplicate questions are as follows:

To find duplicate questions we are checking if the question has been closed and checking if the reason for closing was 'Duplicate' (i.e ph.Comment = 101).

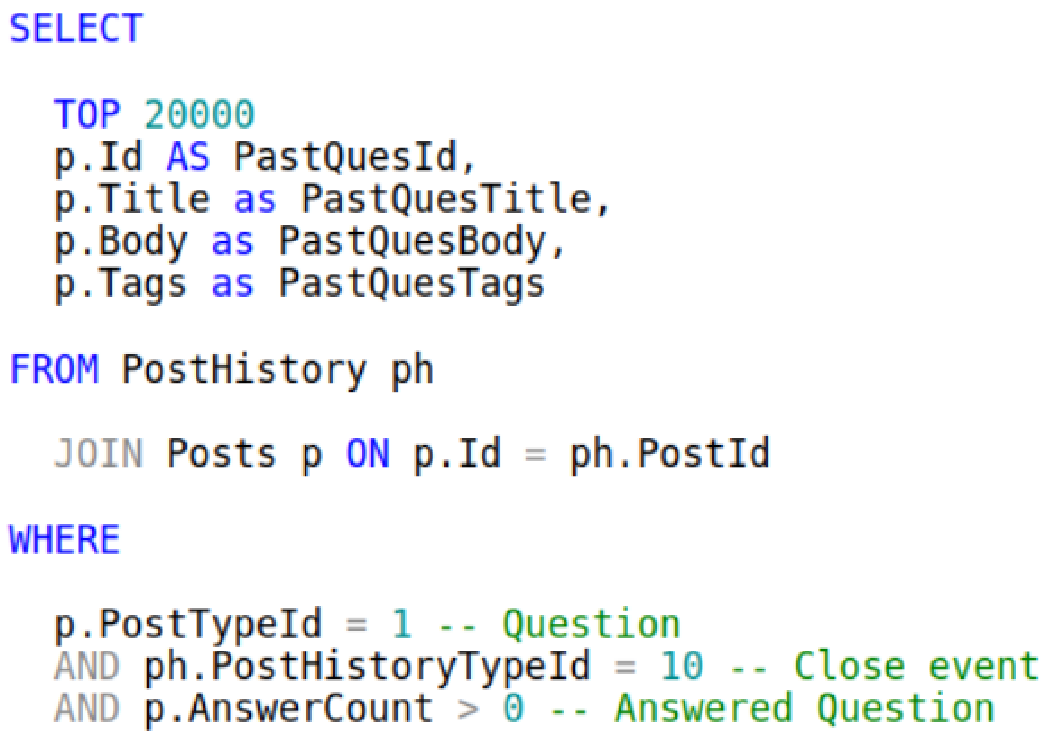
To get the main dataset of past questions, we run the following queries.

The questions we obtain are shown below.



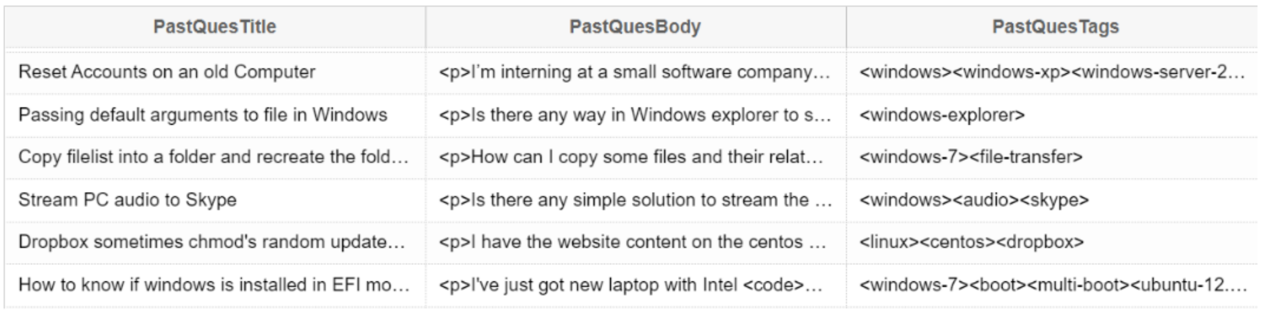
```sql
SELECT

  p.Id AS PastQuesId,
  p.Title as PastQuesTitle,
  p.Body as PastQuesBody,
  p.Tags as PastQuesTags,
  pd.Id as DuplicateQuesId,
  pd.Title as DuplicateQuesTitle,
  pd.Body as DuplicateQuesBody,
  pd.Tags as DuplicateQuesTags

FROM PostHistory ph

  JOIN Posts p ON p.Id = ph.PostId
  JOIN Posts pd ON pd.Id = CAST(JSON_VALUE(ph.Text,'$.OriginalQuestionIds[0]')
  AS nvarchar)

WHERE

  p.PostTypeId = 1 -- Question
  AND ph.PostHistoryTypeId = 10 -- Close event
  AND ph.Comment = 101 -- Dupe
```

Figure 1: Query to get the duplicate questions and their originals



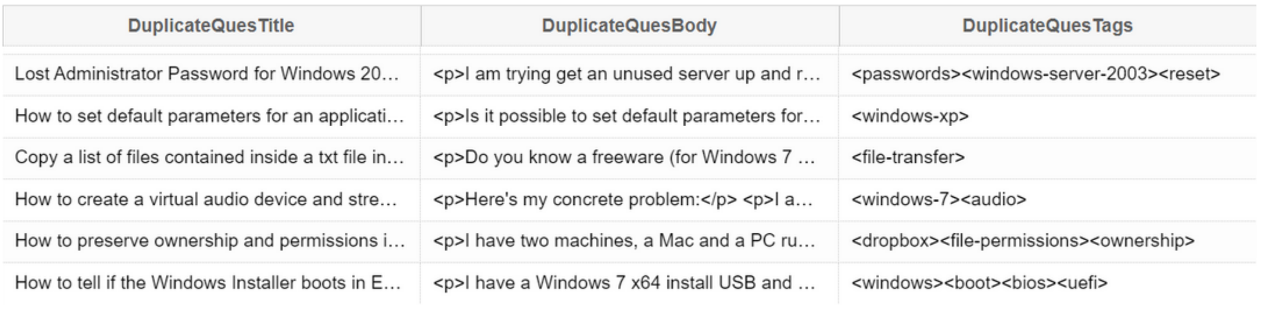
```sql
SELECT

  TOP 20000
  p.Id AS PastQuesId,
  p.Title as PastQuesTitle,
  p.Body as PastQuesBody,
  p.Tags as PastQuesTags

FROM PostHistory ph

  JOIN Posts p ON p.Id = ph.PostId

WHERE

  p.PostTypeId = 1 -- Question
  AND ph.PostHistoryTypeId = 10 -- Close event
  AND p.AnswerCount > 0 -- Answered Question
```

Figure 2: Query to get the past questions



PastQuesTitle	PastQuesBody	PastQuesTags
Reset Accounts on an old Computer	<p>I'm interning at a small software company…	<windows><windows-xp><windows-server-2…
Passing default arguments to file in Windows	<p>Is there any way in Windows explorer to s…	<windows-explorer>
Copy filelist into a folder and recreate the fold…	<p>How can I copy some files and their relat…	<windows-7><file-transfer>
Stream PC audio to Skype	<p>Is there any simple solution to stream the …	<windows><audio><skype>
Dropbox sometimes chmod's random update…	<p>I have the website content on the centos …	<linux><centos><dropbox>
How to know if windows is installed in EFI mo…	<p>I've just got new laptop with Intel <code>…	<windows-7><boot><multi-boot><ubuntu-12.…

Figure 3: Past questions obtained



DuplicateQuesTitle	DuplicateQuesBody	DuplicateQuesTags
Lost Administrator Password for Windows 20…	<p>I am trying get an unused server up and r…	<passwords><windows-server-2003><reset>
How to set default parameters for an applicati…	<p>Is it possible to set default parameters for…	<windows-xp>
Copy a list of files contained inside a txt file in…	<p>Do you know a freeware (for Windows 7 …	<file-transfer>
How to create a virtual audio device and stre…	<p>Here's my concrete problem:</p> <p>I a…	<windows-7><audio>
How to preserve ownership and permissions i…	<p>I have two machines, a Mac and a PC ru…	<dropbox><file-permissions><ownership>
How to tell if the Windows Installer boots in E…	<p>I have a Windows 7 x64 install USB and …	<windows><boot><bios><uefi>

Figure 4: Duplicate questions obtained

All have 4 fields: Title, Body, Tags, ID We have 8000 past and duplicate question pairs, along with 20000 top questions. All of them will not be used purely because of hardware constraints. We will be using 150 past and duplicate question pairs as suggested in the paper, along with 5000 top questions for training the model.

Implementation

Our implementation follows closely with the implementation provided in the paper. The flowchart below summarizes our approach.

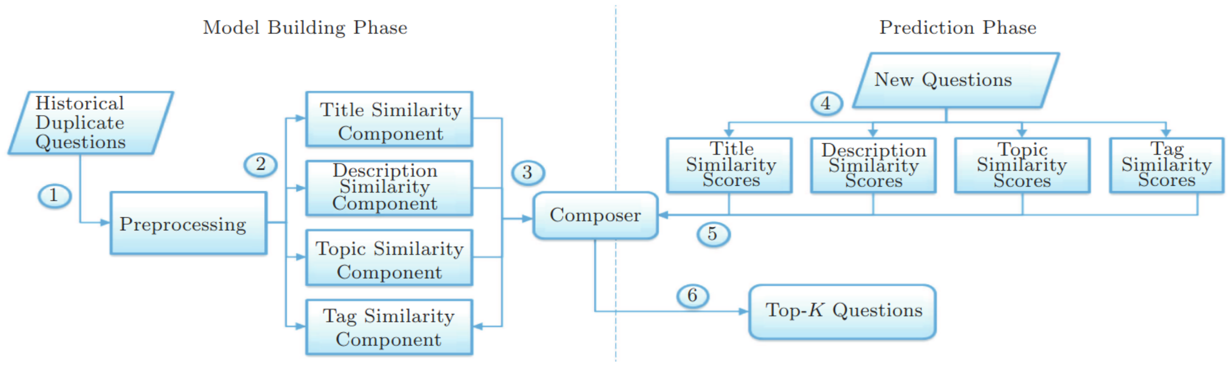


Figure 5: Overall framework

We first train the model on the dataset as we are required to and obtain the parameters. We then store the parameters in a file, after which we only read the weights from the file and use them to compute the similarity between two questions. This is done to save time and avoid retraining the model every time we want to predict the similarity between two questions. The model on average runs in around 13 seconds with the weights given, however it took about an hour to train entirely with the specified dataset sizes. The trained parameters are stored in `trained_params.txt`. We have used the `tqdm` library to show the progress of the model when run with a new input question, and to give the user a real-time estimate of the amount of time it would take for the code to run.

Preprocessing

The questions that were retrieved from stack exchange data explorer were first processed into a workable form. The following steps were taken to preprocess the data.

First, using inbuilt Python libraries, the questions were converted from HTML to text and any links in the question were removed. The questions were also tokenized.

After tokenising, we use the gensim library to remove stopwords. Stop words are commonly occurring words like ‘a’, ‘and’, ‘the’, which do not add a contextual meaning to the sentence. These words are removed as they do not help in differentiating between questions.

The questions are also stemmed using the Porter Stemmer algorithm (part of the gensim library) as recommended by the paper. Stemming is the process of reducing words to their root form. For example, ‘running’ and ‘runs’ can be reduced to ‘run’.

Similarity Scores

For each known duplicate question, we compare it with every other question. We compute four similarity scores based on the following parameters for each of these pairs; Title, Tags, Description, and Topic Similarity.

After preprocessing, each component is represented as a bag of words, for example, $TitleBag_n$ and $TitleBag_m$. We then take the union of these bags to eliminate duplicates and create a set: $TitleBag_u$.

We then use vector space modelling to represent the two titles as vectors as follows:

$$TitleVec_m = (wt_{m,1}, wt_{m,2}, ...wt_{m,v})$$

Where the $wt_{m,q}$ is the relative term frequency of the qth word in the mth question’s title, which is computed as follows:

$$wt_{m,q} = \frac{n_{m,q}}{\sum_i n_{q,i}}$$

Where $n_{m,q}$ is the term frequency of the qth word in the mth question’s title.

We then compute the similarity between two titles by calculating the cosine similarity of their vectors. The same process is used to calculate scores for tag and description.

$$TitleSim(TitleVec_m, TitleVec_n) = \frac{TitleVec_m \cdot TitleVec_n}{|TitleVec_m||TitleVec_n|}$$

The denominator is the magnitude of the vector, which is the square root of the sum of the squares of the elements of the vector.

$$|TitleVec_m| = \sqrt{\sum_i wt_{m,i}^2}$$

To calculate the topic similarity scores we use a topic model: LDA (Latent Dirichlet Allocation). We input the preprocessed title and descriptions of the questions to the LDA model and generate the topic distributions of each question.

A topic distribution for a question, d, can be represented as follows:

$$T_d = (p_{d,1}, p_{d,2} ... p_{d,t})$$

Where each $p_{d,i}$ represents the probability that question d belongs to that topic.We then use these vector to compute the cosine similarity score (using the same method as title).

We have used Python's gensim library to train the LDA and get the topic distributions. We have used 50 topics for the LDA model.

Composer

Training

The composer is where the model, consisting of the four parameter weights, is trained. This is done in the following steps:

1. Calculate all 4 similarity scores for every duplicate question and question pair
2. Initialise all 4 weights to a random number in [0,1].
3. Take the first weight α, vary it starting at 0 in increments of 0.01.
4. Evaluate the composer score for every duplicate question (d) and question (q) pair according to the expression:

$$Composer\ Score = \alpha TitleSim_d(q) + \beta TagSim_d(q) + \gamma DescSim_d(q) + \delta TopicSim_d(q)$$

5. Evaluate the evaluation criterion (Taken to be the $recall - rate$@20 like the paper) of the model.
6. If EC score is better than the previous best, then update the current best value of the weight to the present value.
7. Do the same for β, γ, δ.
8. This is one iteration.
9. Do this for multiple iterations.
10. For every weight, the value with highest EC score across iterations is chosen as the final trained weight.

Recall-Rate@20 Given by

$$\frac{N_{detected}}{N_{total}}$$

Where $N_{detected}$ is the number of duplicate questions whose masters (i.e., original questions that are posted earlier in Stack Overflow) appear in the list of top-20 questions and $N_{total} $ is the total number of duplicate questions used for testing.

Prediction

For every new query question, we calculate the composer score with every other question. The questions corresponding to the top 20 composer scores are displayed as the final output.

Training the Model

To train the model, we run it on all the data we obtained from the data explorer, to get the best weights as specified in the paper. The `main.py` file has commented lines that can be uncommented to retrain with different parameters, after changing the size literals of the dataset in the `parse.py` file.

Testing the Model

To test the model, we simply run `main.py`, which then calls the `prediction.py` file. The user is then prompted to enter a question, its tags and its description, which are then preprocessed and used to calculate scores with all questions in the dataset we have at hand. The top 20 questions (ranked according to their similarity score as calculated by the composer) are then displayed to the user along with their universal question ID from stack overflow. The user can then go through these questions and check if there is a match. THe software is simply suggestive in this manner.

Interface

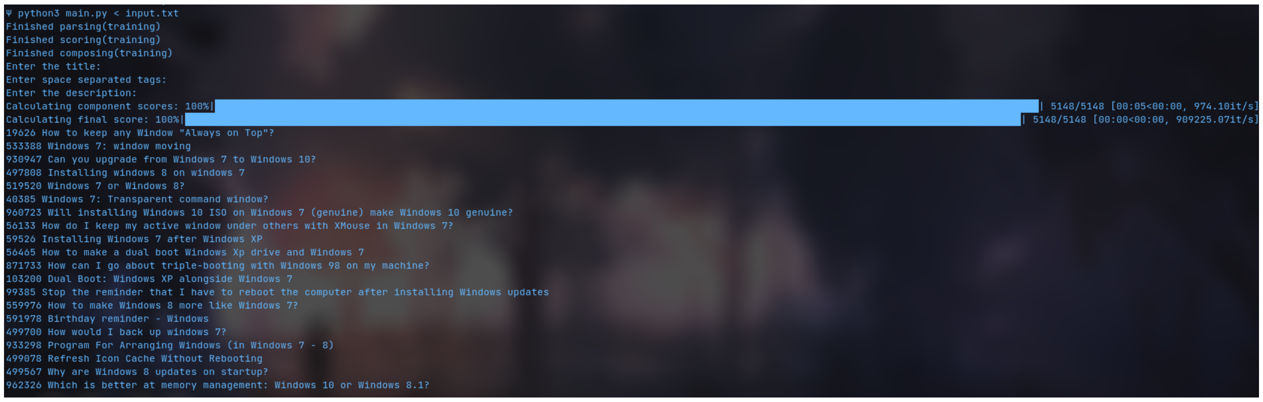
The interface of our software is a simple CLI, that accepts three inputs from the user. Testing can be done by the two default question files provided in the repository which are in `input.txt` and `input2.txt`, which can be redirected when running the code. The output is displayed in the terminal itself.

Command to run the software:

```
python3 main.py < input.txt
```

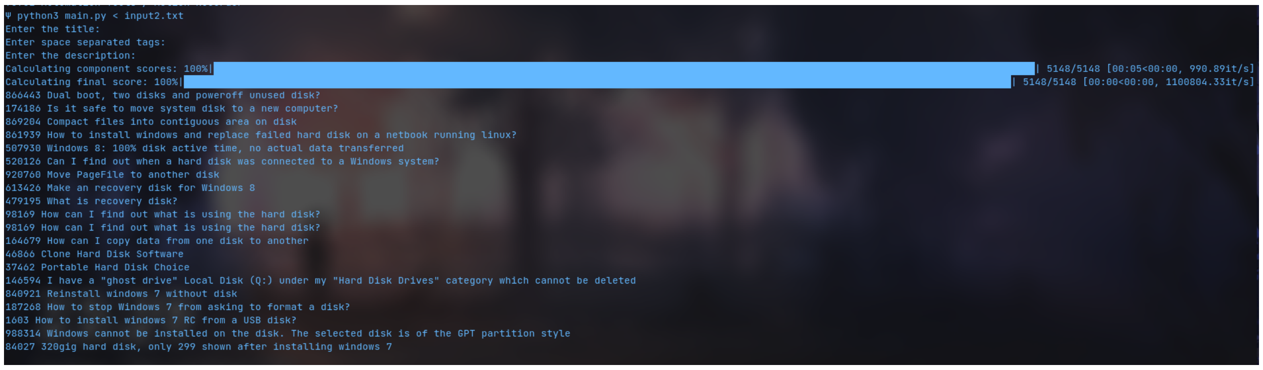
Results

The outputs for the two given input files are shown below. The weights are permanently stored after the training process in `trained_params.txt`, which is read by the `prediction.py` file.



```
Ψ python3 main.py < input.txt
Finished parsing(training)
Finished scoring(training)
Finished composing(training)
Enter the title:
Enter space separated tags:
Enter the description:
Calculating component scores: 100%|██████████| 5148/5148 [00:05<00:00, 974.10it/s]
Calculating final score: 100%|██████████| 5148/5148 [00:00<00:00, 909225.07it/s]
19626 How to keep any Window "Always on Top"?
533388 Windows 7: window moving
930947 Can you upgrade from Windows 7 to Windows 10?
497808 Installing windows 8 on windows 7
519520 Windows 7 or Windows 8?
40385 Windows 7: Transparent command window?
960723 Will installing Windows 10 ISO on Windows 7 (genuine) make Windows 10 genuine?
56133 How do I keep my active window under others with XMouse in Windows 7?
59526 Installing Windows 7 after Windows XP
56465 How to make a dual boot Windows Xp drive and Windows 7
871733 How can I go about triple-booting with Windows 98 on my machine?
103200 Dual Boot: Windows XP alongside Windows 7
99385 Stop the reminder that I have to reboot the computer after installing Windows updates
559976 How to make Windows 8 more like Windows 7?
591978 Birthday reminder - Windows
499700 How would I back up windows 7?
933298 Program For Arranging Windows (in Windows 7 - 8)
499078 Refresh Icon Cache Without Rebooting
499567 Why are Windows 8 updates on startup?
962326 Which is better at memory management: Windows 10 or Windows 8.1?
```

Figure 6: Output for `input.txt`



```
Ψ python3 main.py < input2.txt
Enter the title:
Enter space separated tags:
Enter the description:
Calculating component scores: 100%|██████████| 5148/5148 [00:05<00:00, 990.89it/s]
Calculating final score: 100%|██████████| 5148/5148 [00:00<00:00, 1100804.33it/s]
866443 Dual boot, two disks and poweroff unused disk?
174186 Is it safe to move system disk to a new computer?
869204 Compact files into contiguous area on disk
861939 How to install windows and replace failed hard disk on a netbook running linux?
507930 Windows 8: 100% disk active time, no actual data transferred
520126 Can I find out when a hard disk was connected to a Windows system?
920760 Move PageFile to another disk
613426 Make an recovery disk for Windows 8
479195 What is recovery disk?
98169 How can I find out what is using the hard disk?
98169 How can I find out what is using the hard disk?
164679 How can I copy data from one disk to another
46866 Clone Hard Disk Software
37462 Portable Hard Disk Choice
146594 I have a "ghost drive" Local Disk (Q:) under my "Hard Disk Drives" category which cannot be deleted
840921 Reinstall windows 7 without disk
187268 How to stop Windows 7 from asking to format a disk?
1603 How to install windows 7 RC from a USB disk?
988314 Windows cannot be installed on the disk. The selected disk is of the GPT partition style
84027 320gig hard disk, only 299 shown after installing windows 7
```

Figure 7: Output for `input2.txt`

The outputs are as expected, similar to the given input. The accuracy can be improved by training the model on more past questions to improve the weights.

Limitations

The model is limited by the dataset it trains on, and limiting it will greatly restrain its accuracy. It also suffers from bias in training the weights due to the order in which the weights are trained. This has been addressed in the paper by training the weights iteratively and by initialising all weights to random numbers at the beginning of each iteration, to help find the optimal set of weights.

Link to the GitHub Repository

https://github.com/KarthikL1729/DupPredictor-22

References

- Multi-Factor Duplicate Question Detection on Stack Overflow, 2015, Y. Zhang et al.
