Final Report

Paper Name: Multi-Factor Duplicate Question Detection in Stack Overflow

TEAM NUMBER: 24 **Project ID:** 26

Team Name: Hyperplane Scavengers

Team members: Gurkirat Singh, Anmol Agarwal, Shrey Gupta, Pratyush Pratap Priyadarshi

Mentor Name: Sireesha

Important Links:	2
Dataset Curation	2
Preprocessing	2
Cleaning Title, Body and Tags attributes	2
Title	2
Body	2
Removal of Stopwords, Stemming, Tokenization	2
DupPredictor Model	3
Results	3
Paper Results	3
Recall-rate@k	3
Research Question 1: How good is DupPredictor over its 4 individual components?	4
Why did we do it?	4
How did we do it?	4
What result did we get?	4
Research Question 2: Effect of Varying Number of Training Questions	4
Why did we do it?	4
How did we do it?	4
What result did we get?	4
Research Question 3: Does DupPredictor estimate the 4 weights of its 4 constituent components well?	5
Why did we do it?	5
How did we do it?	5
What result did we get?	5
STATS AND ERROR ANALYSIS	6
How many times did the duplicate questions have a common tag with their parents	
Ablation study error analysis	7
Further Exploration	12
Jaccard coefficient as a similarity metric	12
Why did we do it?	12
How did we do it?	12
What result did we get?	12
Re-ranking using BERT embeddings	12
Why did we do it?	12
How did we do it?	12
What result did we get?	12
Website to view the working of our model	13
Work Distribution	13
Limitations	14
Size of training and testing set	14
Estimation of parameters	14
Bert Training	14

Important Links:

- CodeBase: Link
- All files used for training and testing model: Link
- All precomputed scores: Link
- Bert embedding scores: <u>Link</u>
- All computed parameters: <u>Link</u>

Dataset Curation

- We first downloaded the large MSR dataset but it didn't have all the files so we used the official StackOverflow dump of 2021 and filtered it to make sure we considered data only till 2012.
- Unusual result obtained while replicating the claims made in the paper: We used the same approach as proposed by the authors
 of finding duplicates by looking for a [Duplicate] label at the end of the title but we found only 2 duplicate posts out of a total of 2
 Million posts. We even tried regex searching for a variety of variations in a string like [DUplicate], [duplicate] but that got the
 same result.
- Finally on the basis of online literature and some StackOverflow posts we were able to find the stack exchange data dump which contained the StackOverflow data until 2021 (link to data dumps: <u>Link</u>). We found a file **PostLinks.xml** containing all the duplicate relationships between questions.

Database Creation

- Initially, we were using JSON to save and load data, but we soon realized that it was not the best way as it was becoming a
 bottleneck because of memory issues, sorting, and random access.
- We used a Postgres Database to save our data and use it for further processing.
- Later we also pushed our score to it to use for visualizations and error analysis.

Preprocessing

Cleaning Title, Body and Tags attributes

Title

- To maintain uniformity across all the titles we converted everything to lowercase.
- We removed the [Duplicate] word written anywhere in the Title.

Body

- The body contained any extra information like
- We removed all HTML tags and data inside the <code> tag as it does not add any value.

Removal of Stopwords, Stemming, Tokenization

After doing preliminary cleaning of title and body attributes to reduce noise in the text, we do additional preprocessing steps to get a cleaner and less noisy text:

- 1. We replace all multi spaces, tabs, and newlines with a single white space
- 2. The text had content like "C++ is an OOP language", where the "" HTML tag is not an actual part of the question. As a result, we remove **all the HTML tags** while preserving the content between them. But for the "<code>" tag, we remove the content within the tags as well.
- 3. All the punctuation except "#" is removed to compensate for unnecessary full stops, code blocks, and different grammatical practices. "#" is left as coding languages such as **C**# are considered unique and should not be confused with the language C. As many computer science doubts are asked on the StackOverflow platform for many languages, paying special attention to these languages becomes crucial. After this, the text is tokenized by splitting on all whitespace to get individual tokens
- 4. We then stem all the individual tokens to get their root form and reduce the size of the vocab dictionary
- 5. We also remove common English stopwords. For this, we create a *stopwords.py* file that removes words that are frequent in all the English language and thus would prevent unnecessary similarity and give more focus on the specific words.
- 6. These tokenized texts are stored in JSON files to prevent recomputation as they run extremely slow.

DupPredictor Model

Bag of words model and Cosine Similarity

On the basis of the tokenized text, we created a bag of word embeddings for components involved in the pipeline. On the basis of this bag of words representation, the cosine similarity is used to measure the closeness b/w the two vectors which are used in the estimation of the parameters of the greedy composer.

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

LDA Model

We used the LDA topic modelling to get the probability distribution of each post. We concatenate the title and body of each post to create the final text string as many specific keywords are present in the title and the words present in the title of one post may be present in the body of another post. This allows us to get the general trend of the conversation of the post.

- We preprocessed the combined text string to get tokens of each text string. And this information is stored in the database to prevent repetitive preprocessing of the same text in later steps. Error handling was taken care of and the created dictionary was saved in case of any error as it took a lot of time for this to run.
- On the basis of this dictionary, we create the bag of word representations of each preprocessed representation. Using these Bag Of Word representations, we create the LDA Model with K = 100 topics using the Gensim LDAMulticore Library which allows multiprocessing of the LDAModel creation and thus saving time.
- Finally, on the basis of the LDA model, we created the topic distribution of each post and stored it into JSON (and later into the database) to be used for cosine similarity in the composer.

Greedy Composer

• All the parameters are then fine-tuned using a greedy approach. For each iteration, one parameter is chosen and increased in step sizes of 0.05. On the basis of each parameter set created we calculate the weighted composer sum for each duplicate question with all the questions which came before it and store the top K questions which are done using a max heap

$$Composer_{nq}(oq) = \alpha \times TitleSim_{nq}(oq) +$$

$$\beta \times DesSim_{nq}(oq) +$$

$$\gamma \times TopicSim_{nq}(oq) +$$

$$\delta \times TagSim_{nq}(oq).$$

- On the basis of these top K "plausible" questions which the duplicate question can be the duplicate of, we calculate the evaluation metric.
- On the basis of the obtained score from the evaluation criteria, we get to take the best set of params which are finally reported as the best params according to our training dataset
- After calculating all the individual components, a final score was calculated by taking a weighted sum of all the components using 4 parameters (alpha, beta, gamma and delta). For each question, we calculate the final similarity with all the posts that came before it and store it for fine-tuning the parameters later.

Results

Paper Results

The authors of the paper were interested in answering a few questions about the performance of the DupPredictor Model. We try to replicate these findings with our own dataset and the DupPredictor Model which we have trained.

Recall-rate@k

To evaluate the performance of DupPredictor the authors used the following evaluation metric:

$$recall - rate@k = \frac{N_{detected}}{N_{total}}$$

Where $N_{detected}$ is the number of duplicate questions whose masters (i.eOriginal questions that are posted earlier in Stack Overflow) appear in the list of top-K questions (by DupPredictor), while N_{total} is the total number of duplicate questions used for testing.

Research Question 1: How good is DupPredictor over its 4 individual components?

Why did we do it?

To prove the novelty of the method, we needed to measure the performance of the composite DupPredictor model over its 4 individual components.

How did we do it?

To measure this, we compute recall-rate@10 and recall-rate@20 of DupPredictor when it is applied to the StackOverflow question dataset. We compare these recall rates, with the recall rates achieved using solely the title, body, topic and tag similarity components.

What result did we get?

From the table below we can observe that DupPredictor outperforms the 4 components in terms of recall-rate@10 by 69.69%,180%, 600% and 100% respectively. Similarly for recall-rate@20, we can see that the combined model outperforms the 4 components by 54.76%, 150%, 364.28% and 91.17% respectively.

DupPredictor achieves great improvements over its individual components and thus we can observe the novelty in combining multiple sources of information for duplicate detection.

Algorithm	Recall Rate@10	Improvement (%)
DupPredictor	0.56	0.0
Title similarity	0.33	69.69
Description similarity	0.2	180
Topic similarity	0.08	600
Tag similarity	0.28	100

Algorithm	Recall Rate@20	Improvement (%)
DupPredictor	0.65	0.0
Title similarity	0.42	54.76
Description similarity	0.26	150
Topic similarity	0.14	364.28
Tag similarity	0.34	91.17

Research Question 2: Effect of Varying Number of Training Questions

Why did we do it?

We needed to check whether changing the number of questions in training has drastic effects on the prediction performance.

How did we do it?

To measure this, we trained the model over 2 training set sizes, the first 100 and 300 questions. The test set consisted of the questions whose rank lie between 300 and 400 when all the duplicate questions are sorted according to their creation date. They were tested on the same testing set for uniformity. We measured the recall-rate@10 and recall-rate@20 to check our hypothesis.

What result did we get?

We observe that the composer learns different parameters for both training sets and sometimes their relationship (inequality) also changes, but overall the trend remains the same. Title and body similarity is given more preference followed by tags similarity and lastly topic similarity.

Trained on first	Alpha (Title)	Beta (Body)	Delta (Tags)			
		K = 10				
100	0.5	0.5	0.0454	0.45		
300	1.0	0.6	0.3	0.6		
K = 20						
100	0.4	0.5	0.13738	0.1992		
300	0.9	0.85	0.3153	0.3		

On the basis of the results, we can also observe that the model trained on the first 300 questions is able to generalize more on unseen data but the performance difference is extremely negligible. This means that the model is able to learn and tune its parameters even on a lesser amount of data.

Trained on first	Recall@10 Training	Recall@10 Testing	Recall@20 Training	Recall@20 Testing
100	0.74	0.55	0.78	0.62
300	0.67	0.56	0.74	0.65

Why did we do it?

DupPredictor estimated the 4 weights using a greedy random restart approach tuning one parameter at a time instead of using an optimization strategy to minimize loss as in traditional ML models. We wanted to know if these estimated parameters are accurate and well predicted.

How did we do it?

In order to analyze the performance, we randomly generate 50 sets of weights of alpha, beta, gamma and delta to compute the weighted score in the composer. The recall-rate@10 and recall-rate@20 are measured on the 100 questions test set for these 50 sets of weights and the results are compared to the best parameters generated by DupPredictor on training with the first 300 duplicate questions.

What result did we get?

We observe that the parameters generated by DupPredictos using its simplistic approach outperform all the randomly generated weights on both metrics.

alpha	beta	gamma	delta	recall-rate@10	recall-rate@20
0.9	0.85	0.3152	0.3	0.56	0.64
0.89	0.0687	0.29	0.2593	0.53	0.62
0.8118	0.5148	0.6062	0.3224	0.53	0.61
0.2605	0.88	0.6911	0.08	0.36	0.45
0.1749	0.4582	0.7276	0.0998	0.36	0.45

For the full results table, you can refer to this link: Results CSV

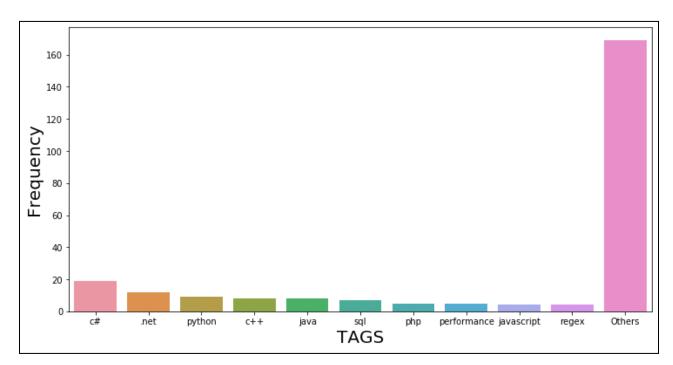
On the basis of these results, we can infer the following properties:

- Some randomly generated parameters perform very similarly to the parameters estimated by the DupPredictor model however NONE of the models outperforms DupPredictor. For example, the weights of the 2nd best model are very close to the weights predicted by DupPredictor, but it gives very little weight to the body of a question and hence it underperforms DupPredictor.
- Generally speaking, models with weights following the general relationship alpha ≥ beta ≥ delta ≥ gamma and alpha close to 1
 perform the best which supports our findings as well.
- The worst performing models give too little attention to the title or too much attention to the topic causing them to miss out on important information or focus on misleading information heavily respectively.

ERROR ANALYSIS AND BASIC STATISTICS

TOTAL NUMBER OF QUESTIONS CONSIDERED = 83,350

What tags were present the most in duplicate questions?



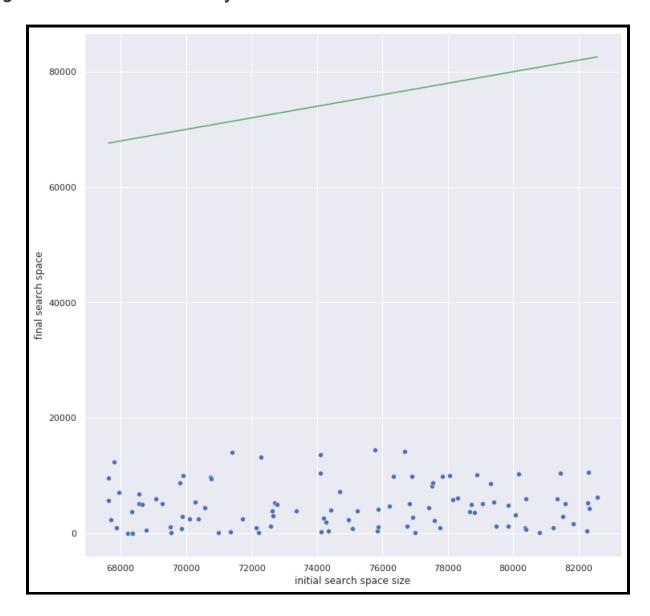
How many times did the duplicate questions have a common tag with their parents?

- Out of 100 elements in the test set, 94 of the questions had at least one tag common with their duplicates.
- The 6 cases where there was no common tag between the original question and its duplicates.

 441910
 476993
 495244

 450924
 495018
 513315

• This clearly indicates that **reducing the search space** based on whether the candidate duplicate has any common tags with the question Q would be highly beneficial to reduce the time needed to find a duplicate **without compromising on performance**. In the figure below, x: initial search space & y: search space size after pruning. As one will be able to see in the result, the performance increases on a pruned search space, thus **benefiting in both time and accuracy**.

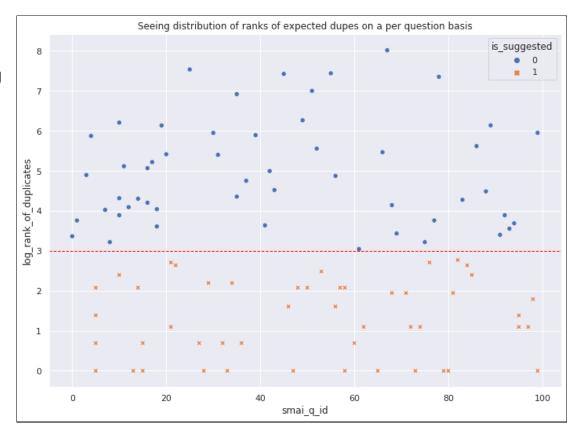


SUMMARY OF ABLATION STUDY SCORES (at Recall@20)

Model description	Training Recall@20	Test R	Mean rank of highest ranked duplicate		Best ra dupl	nk of a icate		ank of a icate	Parameters	
		Without Pruning	With pruning	Without Pruning			With pruning		With pruning	
K=20 with all components	0.74	0.65	0.68	175.84	99.9	1	1	2365	1359	[0.9, 0.85, 0.31, 0.3, 0.0]
K =20 with all components except Title Similarity	0.61	0.53	0.53	454	287	1	1	12366	4048	[0, 0.85, 0.35, 0.64, 0.0]
K =20 with all components except Topic Similarity	0.733	0.61	0.61	229	160	1	1	3691	3613	[0.2, 0.19, 0, 0.07, 0.0]
K =20 with all components except Body Similarity	0.707	0.61	0.62	214	120	1	1	4058	1972	[1.0, 0, 0.45, 0.6, 0.0]
K =20 with all components except Tags Similarity	0.67	0.51	0.62	540	122	1	1	25818	3177	[0.9, 0.8, 0.1, 0, 0.0]
K=20 with all components + Jaccard Coeff included	0.763	0.65	0.67	105	78	1	1	2054	1197	[0.45, 0.35, 0.25, 0.29, 1.0]

Some insights based on the table above and the detailed analysis in the next section

- Pruning the search space is able to improve results and is quicker computationally
- The most significant increase in results after pruning was in the case where tag similarity was discarded. This was as pruning based on tags does a job similar to tag similarity.
- As per the ablation study, the most significant parts for detection seem to be "title" and the "tags".
- With moderators strictly enforcing titles to be precise and accurate, "title similarity" seems to be a great indicator.
- TAGS become important as it helps in restricting search to relevant languages and technologies. Eg: a question regarding retrieval queries on MySQL is likely to be similar in body and title when compared to the same question wrt MongoDB. However, the two questions being different tagged is what is allowing the model to successfully differentiate between the two.
- In the adjoining figure, x: question id; y: rank of one of the expected duplicates. Since a question can have more than one expected duplicate, there may be multiple dots on the same vertical line. The red line depicts the threshold (20) beyond which questions are not suggested. Clearly, for some questions, one of the duplicates



ALL 4 components (title + body + tags + topics) involved

In general, the 0.68% accuracy seems decent.

Params: [0.9, 0.85, 0.3125, 0.3] i.e. high importance to title and body text

• qid for whom we want a duplicate: 441529

• Link to qid: LINK

Actual best candidate: 263400
 scores: [0.51, 0.11, 0.5, 0.4]
 final score: 0.85 | rank 68

• Chosen best candidate: 34505

o Scores: [0.5, 0.5, 0.7, 1]

o final score: 1.4287 | rank: 1

• We see that the q_chosen beats q_expected in all 4 criteria.

• **Conclusion:** The model is misled by the use of common words like "objects" and "hash function" in q_asked and q_chosen. Even though q_expected is clearly a better match; but the model fails to capture the fact that the q_asked is actually discussing an algorithm and naively allots q_chosen as the higher score (despite it being very different) just because of common words. This can be improved by considering synonyms or word embedding such that phrases like "intelligently built" etc can be linked to words like "algorithm".

[ON PRUNED SEARCH SPACE] Distribution of ranks of expected duplicate questions --- Mean rank:102 80 --- Median rank:7 70 --- Threshold:20 60 50 40 30 20 10 200 400 1000 1200 1400 Ranks

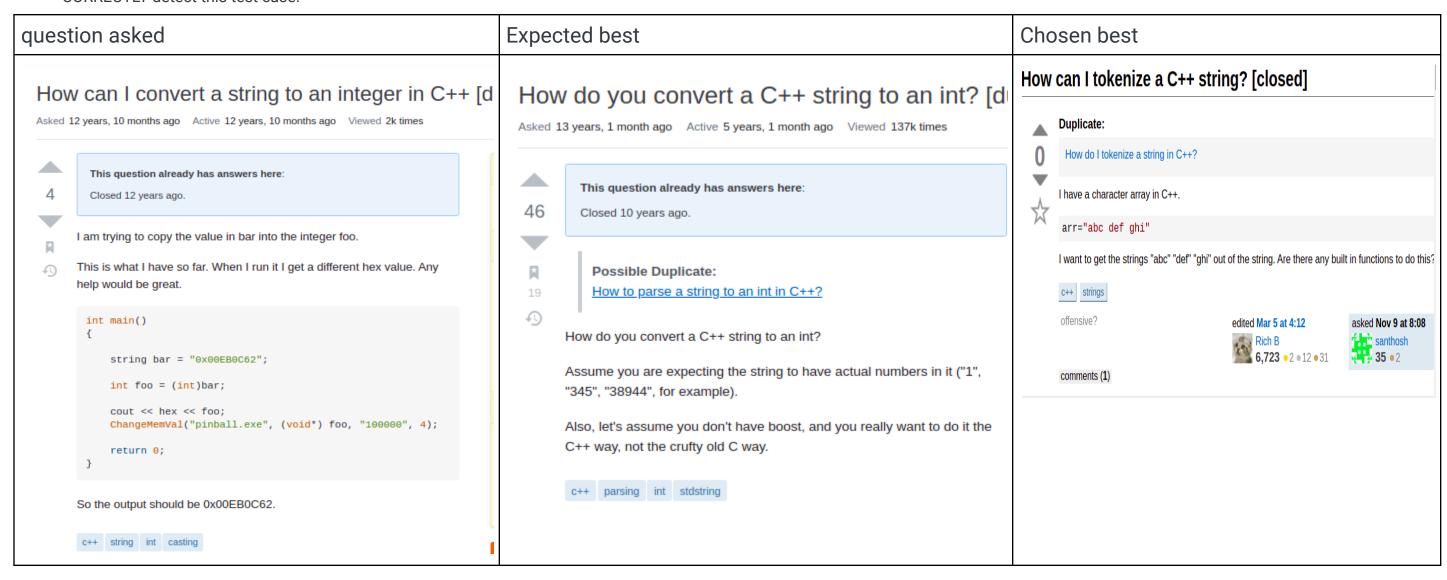
juestion asked	n asked Expected best		
How do you implement GetHashCode() on objects? [duplicate] Asked 12 years, 10 months ago Active 12 years, 10 months ago Viewed 2k times This question already has answers here:	What is the best algorithm for overriding GetHashCode? Asked 13 years, 1 month ago Active 1 month ago Viewed 252k times	Is Object.GetHashCode() unique to a reference or a value? Asked 13 years, 3 months ago Active 6 years, 2 months ago Viewed 8k times The MSDN documentation on Object.GetHashCode(). The Overflow Bit The Overfl	
Closed 12 years ago. Podcast 39 democratizi Puplicate: What is the best algorithm for an overridden System.Object.GetHashCode? Featured on Me	In .NET, the GETHAShCode method is used in a lot of places throughout the .NET base class libraries. Implementing it properly is especially important to find items quickly in a collection or when determining equality.	describes 3 contradicting rules for how the method should work. 1. If two objects of the same type represent the same value, the hash function must return the same constant value for either object. Podcast 397 democratizing the hash function must return the same constant value for either object.	
If you've written an object with a variety of data-members, how do you intelligently implement GetHashCode()? One developer told me he just XORs (^ operator) the Hash of relevant data-fields, but I am unconvinced this is a "best-practices" implementation. Reducing tl Upcoming I **Two B or not and Bharge** Community collectives I	Is there a standard algorithm or best practice on how to implement Gethashcode for my custom classes so I don't degrade performance?	2. For the best performance, a hash function must generate a random distribution for all input. 3. The hash function must return exactly the same value regardless of any changes that are made to the object. Rules 1 & 3 are contradictory to me.	
If I had my way, there would be functions Object.CombineHashes(Object[]), and/or Object.CombineHashes(int[]) to help intelligently build hashes of complex objects. The constructive benchmark How would you write these functions? Hot Meta Posts 32 Is this ques 7 Constructive benchmark 30 Is it frowner.	Share Edit Follow edited Sep 18 '19 at 17:55 poke 325k • 64 • 498 • 558	Does Object.GetHashCode() return a unique number based on the value of an object, or the reference to the object. If I override the method I can choose what to use, but I'd like to know what is used internally if anyone knows. The Meta Posts 32 Is this quest 7 Constructive benchmarking the benchmarking the constructive benchmark the constructive benchma	
c# .net	asked Nov 4 '08 at 20:53 bitbonk 46.7k • 35 • 177 • 271	30 Is it frowned a word or ev	

ALL components (Except Title Similarity) involved

In general, the 0.53% accuracy WITHOUT using the title is reasonable.

Params: [0, 0.85, 0.35, 0.64] i.e. without the title, the content now shifts attention to TAGS.

- qid for whom we want a duplicate: 508191 | Link to qid: LINK
- Actual best candidate: 200090
 - $\circ\quad$ scores: [0.67 , 0, 0.95 , 0.5]
 - o final score: 0.65 | rank 62
- Chosen best candidate: 275733
 - o Scores: [0.4, 0.129, 0.88, 0.7]
 - o final score: 0.87 | rank: 1
- q_chosen beats q_expected in "body_score" which has a high weightage of 0.85.
- **Conclusion:** Due to removal of title, q_expected loses out. Also, because the body in q_asked is almost entirely empty (since we remove the code before inputting to model), there are hardly any words in the "filtered body" of q_asked to give any meaningful insights for matching. However, since the coefficient for the body is high, q_chosen overtakes q_expected. The model where title similarity exists is able to CORRECTLY detect this test case.



ALL components (Except Description Similarity) involved

In general, the 0.62% accuracy WITHOUT using the body shows that BODY does not play a major role in helping the detector...

Params: [1, 0, 0.5, 0.6] with emphasis on TITLE and TAGS.

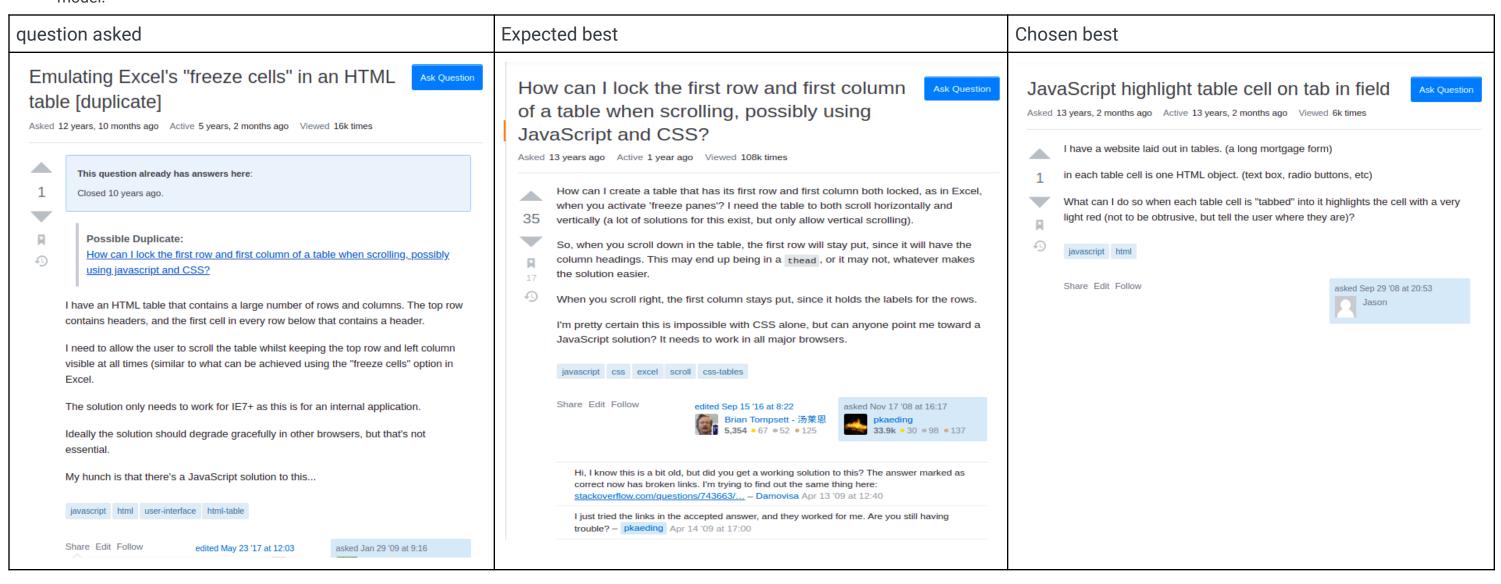
• qid for whom we want a duplicate: 490973 | Link to qid: LINK

• Actual best candidate: 296020

scores: [0.15, 0.6, 0.7, 0.4]final score: 0.8 | rank 42

Chosen best candidate: 150606
 Scores: [0.36, 0.26, 0.65, 0.7]
 final score: 1.11 | rank: 1

• Conclusion: The question wants an answer on how to FREEZE cells in EXCEL using HTML/CSS. Q_chosen gives an answer which is **NOT EVEN REMOTELY related** to EXCEL. ILearly, the model fails to capture the "excel" factor and hence, blunders. The BODY of q_expected and q_ask match to a large extent to give a score of 0.6. But since coeff for body score is ZERO in this model, the test case gets misdetected by the model.

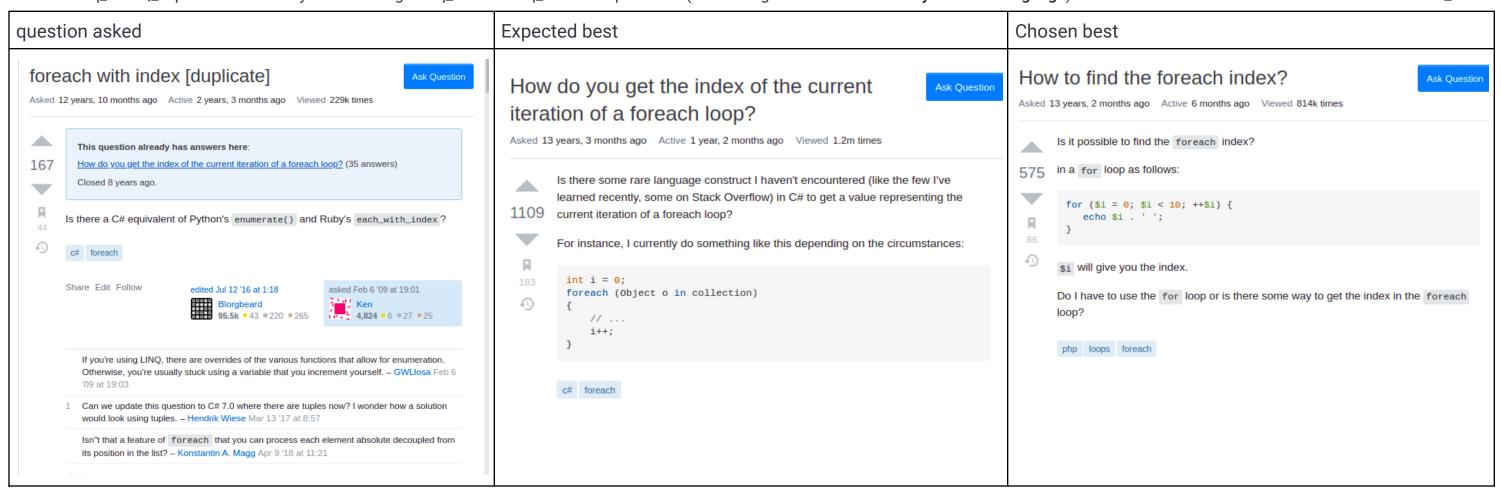


ALL components (Except TAGS Similarity) involved

In general, the accuracy without using tags is 0.51%. But in the pruned search space, tags are automatically taken care of and hence, leads to an accuracy of 0.62% (very minor drop) when tags are not considered.

Params: [0.9, 0.8, 0.1, 0] with emphasis on TITLE and BODY.

- qid for whom we want a duplicate: 521687 | Link to qid: LINK
- Actual best candidate: 43021
 - scores: [0.5, 0.08, 0.35, 1]final score: 0.77 | rank 28
- Chosen best candidate: 141108
 - Scores: [0.8, 0.25, 0.64, 0.4]final score: 0.999 | rank: 1
- **Conclusion:** q_ask is concerned with foreach in C#. Q_expected is related to foreach in C# but q_chosen is related to foreach in PHP. Both of them are not filtered as both of them have the "foreach" tag common with q_ask. Q_expected has exactly the same tags as q_asked but q_chosen is predicted (even though it **deals with a totally different language**). This is due to the zero value of coefficients of TAGS_SCORE.



Further Exploration

We attempted to further improve the best results obtained using the methodology proposed in the paper. For improving accuracy we mainly experiment with 2 techniques: Increasing the number of features while calculating the composer score and further improving the predictions of the greedy composer with the help of NLP in the hopes of capturing the semantic and lexical meaning of the questions.

Jaccard coefficient as a similarity metric

Why did we do it?

Our hypothesis was that since the **composer is treating each of its similarities as separate entities**, it might miss cases where some words that are present in the title for one question may be present in another section for another question. To incorporate these cases inside the model we used the Jaccard coefficient.

How did we do it?

We combined the processed title, body and tags as a single bag of words for all the questions. Then we computed the Jaccard score between each duplicate question and a question candidate of being the master of the duplicate question.

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

What result did we get?

We trained on the first 300 questions including the fifth parameter as Jaccard similarity.

alpha	beta	gamma	delta	Jaccard	recall-rate@20 Training	recall-rate@20 Testing
0.45	0.35	0.25	0.2941	1.0	0.763	0.65

We found that the composer predicts Jaccard to be a very important parameter (with a value of 1) while predicting a candidate question to be a duplicate's master. One reason for this might be that the Jaccard score looks at each entity i.e. title, body & tags together in a holistic view thereby providing much more information about the pairs in consideration. We can also state that the Jaccard score somewhat represents the title, body and tags similarity components together.

But we observe that the testing recall does not increase significantly. From this, we can conclude that, generally, all the three entities are disjoint and do not provide any significant extra information when combined together.

Re-ranking using BERT embeddings

Why did we do it?

After Jaccard, we felt that increasing the number of features more would only increase the complexity of the model and will not improve results significantly. Also applying a computationally heavy approach like embeddings generation using Word2Vec, or BERT is **not feasible for fast training and training time will take a hit**. In this scenario, reranking only the smaller pruned rank list created using DupPredictor is easier and much more computationally feasible.

How did we do it?

The DupPredictor was initially trained on the first 300 duplicate questions (Best Params reported above). For each duplicate question, we calculate the **top 30 predictions on the basis of the parameters estimated from the DupPredictor Model.** The actual master questions which have not been predicted in the **top 30** were then appended at the end of the predictions list and this list is the initial ranking list for a duplicate according to DupPredictor.

Now, the title and body texts are cleaned and then Bert embeddings are calculated for each text phrase using a pre-trained hugging face transformer. For reranking the questions, the weighted cosine similarity metric is calculated using the formula as described below:

$$BertScore = \alpha \times CosineSim(BERT(Q1_{Title}), BERT(Q2_{Title})) + \beta \times CosineSim(BERT(Q1_{Body}), BERT(Q2_{Body}))$$

Here Q1 and Q2 represent the candidate and duplicate questions for which we calculate the BERT embeddings. The weights alpha and beta for calculating this score are found on the basis of observations and the findings from the DupPredictor model. Thus, we set the value of α = **0.6** and β = **0.5** giving more weight to the title (DupPredictor gives more weightage to Title generally). Finally, all the predictions are re-ranked using this newly calculated BertScore.

What result did we get?

We observe that re-ranking on the basis of BERT embeddings helps the model a lot.

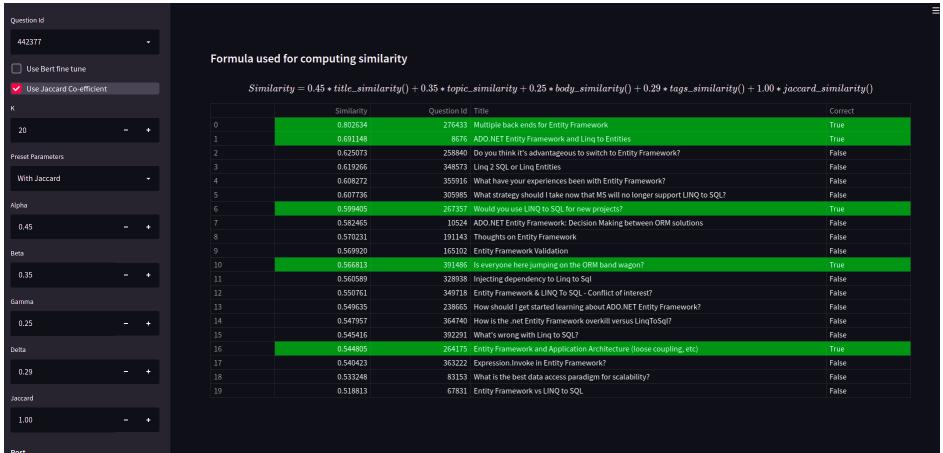
• Firstly, we improved the recall-rate@20 of the DupPredictor from 0.65 to 0.88 on the test set, which is a very significant improvement for quite minimal computation. From this, we can conclude that BERT's power to understand the semantic and lexical meaning of the sentences greatly helps to improve the quality of the predictions.

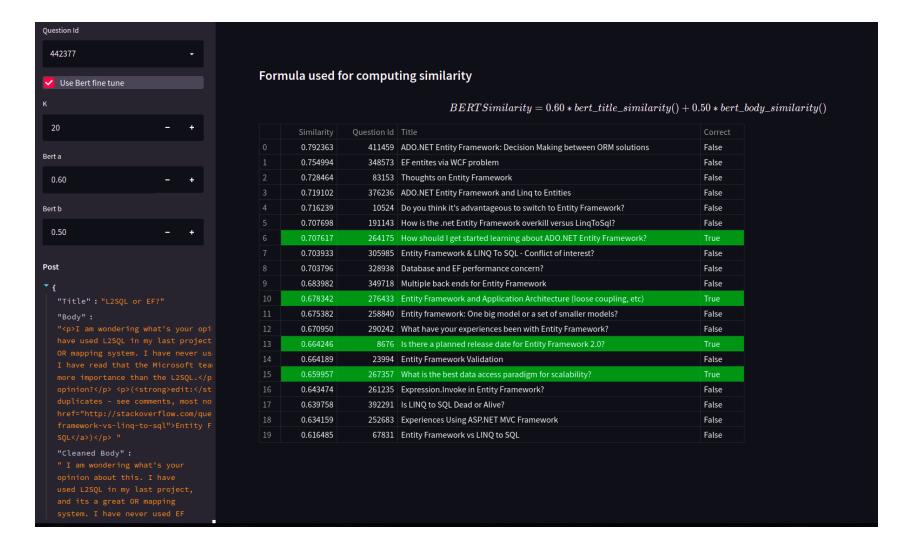
- Secondly, we observe that for **29** duplicate questions, we are able to improve the richness of the top 20 predictions by including **32** more correct candidate questions which were initially in the top 30 but not in the top 20 predictions.
- Surprisingly, we are also able to include **2** questions in the top 20 which were initially not even in the top 30.

Website to view the working of our model

We have created a website to easily understand the importance of each score/similarity and play around with the various parameters in the composer to understand how the ranking of the various candidate questions change.







Work Distribution

Member	Work
Anmol	Data Cleaning, Error Analysis on ablation results, Search Space Pruning, insights on fitting BERT in the pipeline
Gurkirat	Data Preprocessing, Database Handling and Sorting, Paper Experiments and Website Creation
Shrey	Data Preprocessing, Paper Experiments and Model, Ablation, Jaccard and BERT explorations
Pratyush	Data Preprocessing, Paper Experiments and Model, Ablation, Jaccard and BERT explorations

Limitations

All the limitations and the challenges we faced in the course of this project, mainly boil down to the computational limits of the process.

Size of training and testing set

The training and testing set size was extremely large.

Since we have to compute for every duplicate question the pairwise scores for all the questions that came before it, the number of pairwise scores to compute increases exponentially as we try to increase the number of duplicate questions. Currently, we have around 60,000 candidate questions per duplicate question in our training set (300 duplicate questions) and 80,000 candidate questions per duplicate question in the test set (100 duplicate questions).

The time taken to compute the scores for the training set (300 questions) came around 8 hours. And the time taken to compute scores for the test set (100 questions) was 5 hours since the test set had more even a more number of candidate questions per duplicate. From this trend, we can see that the compute time increases exponentially and using more questions becomes incredibly difficult.

Estimation of parameters

Even though we managed to estimate the majority of the parameters, since the procedure for estimation is greedy, it takes around 4 hours for each training. Therefore, we were unable to compute the parameters for recall@5.

Bert Training

Creating embeddings for each post in the training set using either Word2Vec or BERT was exceedingly compute-heavy as well. The estimated time for computing this was approximately 20 hours and consumed approximately 14GB of RAM making it impossible to run our laptops. **Even on ADA, we weren't able to allocate more than 4GB of RAM to a batch job** and the process kept on failing. Due to this, we weren't able to train using BERT and thus resorted to a re-ranking approach to reduce the question search space.

Due to these limitations, only one laptop was able to run the training steps making the entire process extremely sequential.