

# TENSORFLOW 2.0 QUESTION ANSWERING

**Identify the answers to real user questions about  
Wikipedia page content**

# PROJECT GOALS

1. Develop a model that defines the answers to the questions
2. The score of the predictions must be at least a baseline equal to 0.21
3. Depending on the question it is necessary to distinguish between short and long answers to questions

Kaggle:



# DATASET

The contents of dataset:

- Text
- List of long answers
- Question text
- Annotations

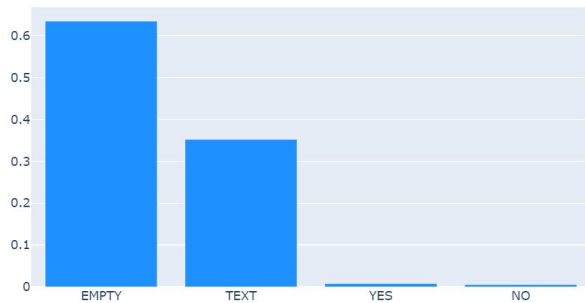
	document_text	long_answer_candidates	question_text	annotations	document_url	example_id
0	Email marketing - Wikipedia<H1> Email marketi...	[{'start_token': 14, 'top_level': True, 'end_t...	which is the most common use of opt-in e-mail ...	[{'yes_no_answer': 'NONE', 'long_answer': {'st...	<a href="https://en.wikipedia.org/w/index.php?title=Em...">https://en.wikipedia.org/w/index.php?title=Em...</a>	5655493461695504401
1	The Mother (How I Met Your Mother) - wikiped...	[{'start_token': 28, 'top_level': True, 'end_t...	how i.met your mother who is the mother	[{'yes_no_answer': 'NONE', 'long_answer': {'st...	<a href="https://en.wikipedia.org/w/index.php?title=Th...">https://en.wikipedia.org/w/index.php?title=Th...</a>	5328212470870865242

# MAIN FINDINGS (EXECUTIVE SUMMARY)

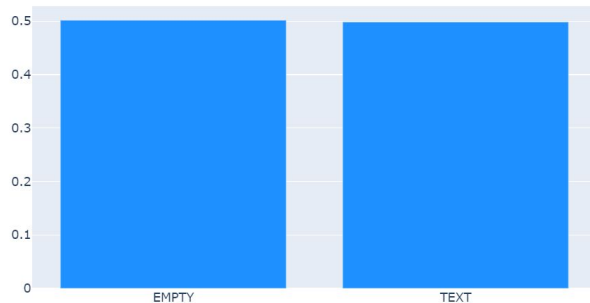
**If successful, this challenge will help spur the development of more effective and robust QA systems**

- About 40 percent of the questions have short answers
- About 50 percent of the questions have long answers

Short Answer Distribution



Long Answer Distribution



# APPROACH

Using the sinusoidal distance, the search was carried out for answers with the highest search.

The cosine distance was considered. If the score was less than 0.15, then it was believed that there was no long answer.

The cosine distance between you and B is defined as  $1 - \frac{u \cdot v}{||u||_2 ||v||_2}$ .

where u and v (N,) are input arrays

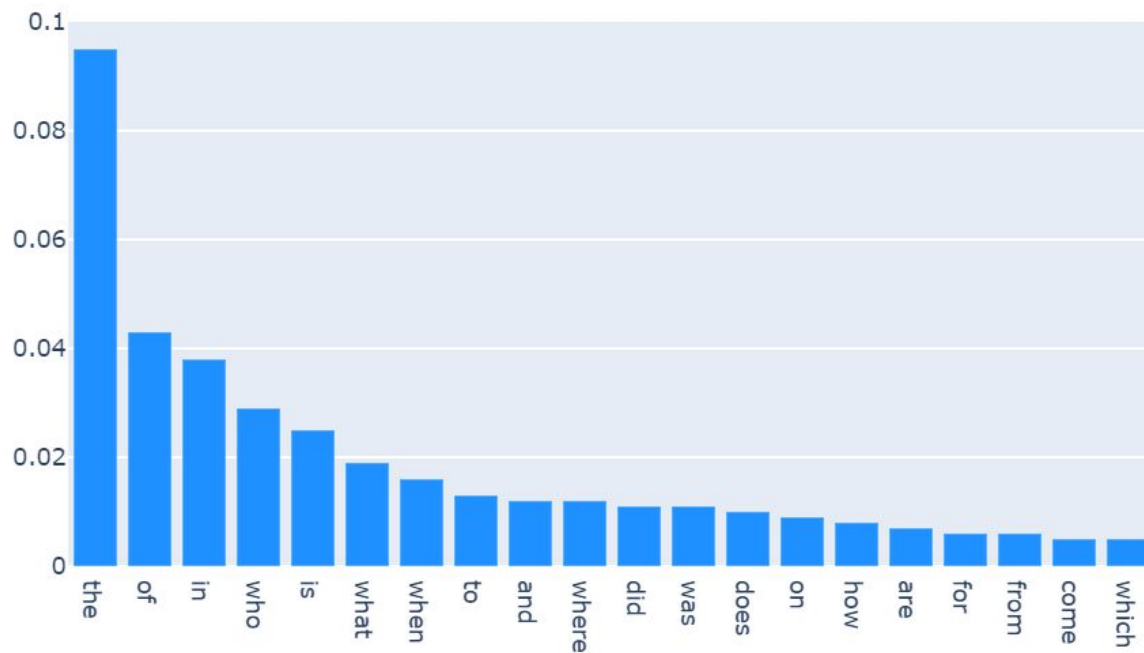
Python:

```
scipy.spatial.distance.cosine
```

```
scipy.spatial.distance.cosine (u, v, w = None)
```

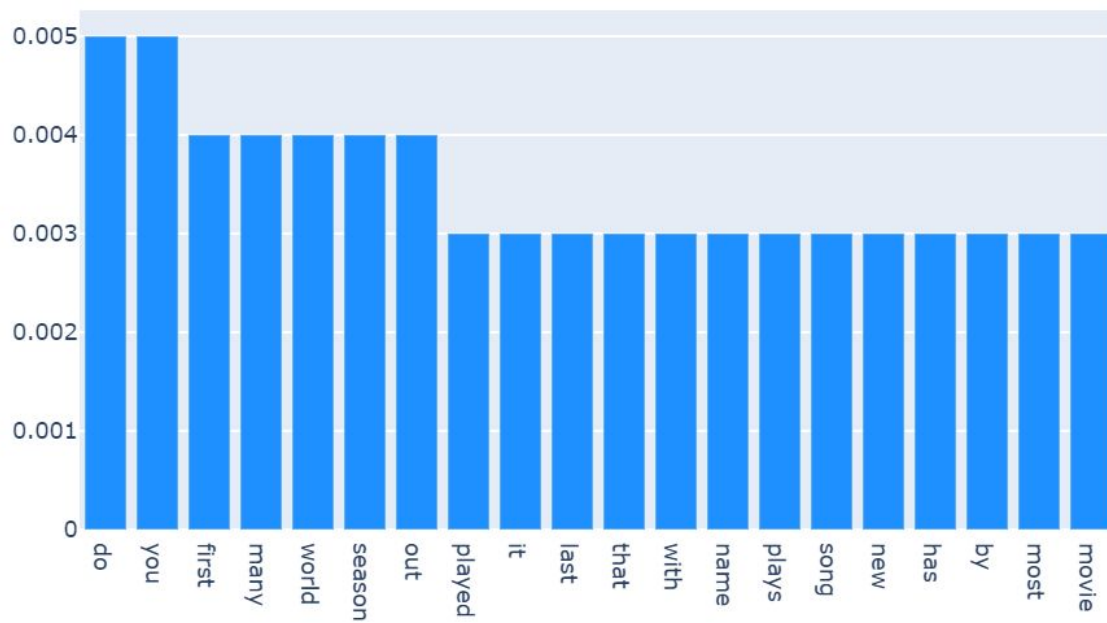
# KEY POINTS

Question Text Word Frequency Distribution



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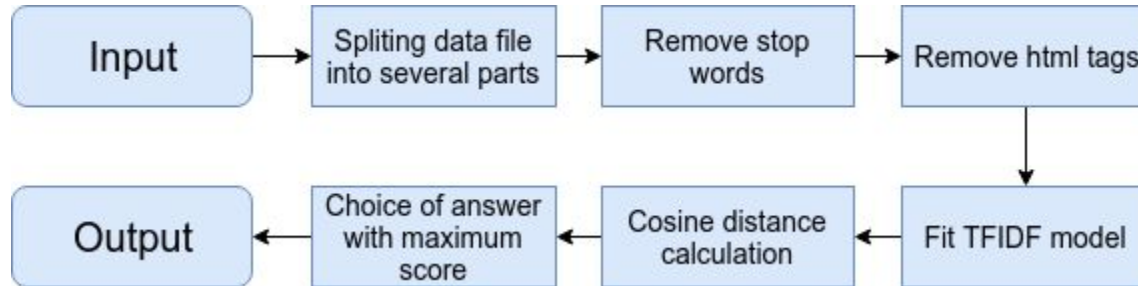
Question Text Word Frequency Distribution



# ALGORITHM DETAILS

Input data contained 600 sample texts. The output formed the indices of the most appropriate answer.

In the process of preparing the text, lemmatization and normalization algorithms were used.



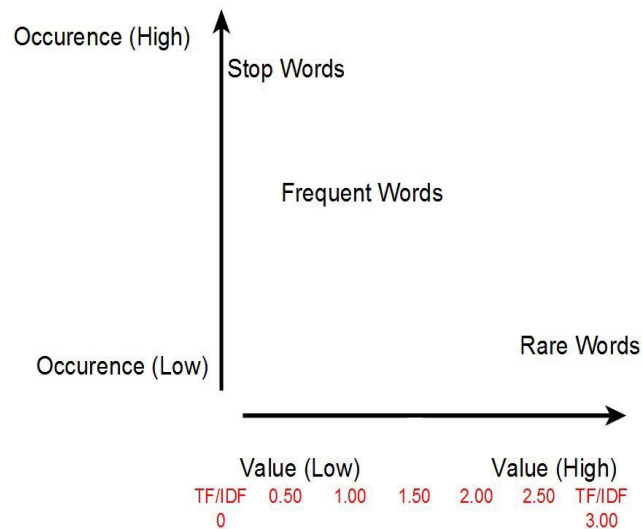


# MODEL DESCRIPTION

TF - is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus.

IDF - is the inverse frequency of documents. It measures directly the importance of the term.

The tf - idf value increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word. tf - idf is one of the most popular term-weighting schemes today.



$TFIDF \text{ score for term } i \text{ in document } j = TF(i, j) * IDF(i)$

where

$IDF = \text{Inverse Document Frequency}$

$TF = \text{Term Frequency}$

$$TF(i, j) = \frac{\text{Term } i \text{ frequency in document } j}{\text{Total words in document } j}$$


$$IDF(i) = \log_2 \left( \frac{\text{Total documents}}{\text{documents with term } i} \right)$$

and

$t = \text{Term}$

$j = \text{Document}$

# RESULT

525	且听风吟李狗嗨		0.23	2	14d
526	<b>iastapov17</b>		0.23	9	5d
527	<b>TF-Paris</b>		0.23	1	15h

# RECOMMENDATIONS

- If tag <P> contained the answer, it increased score
- Using BERT for word processing
- Choose the optimal number of n\_grams in TFIDF model

THANKS FOR YOUR ATTENTION

COMMAND 3+1

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