Intelligent Semantic Web Search

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I. INTRODUCTION

A vast majority of information has shifted online, web search has become one of the most important tools these days. However, just the possibility of having access to a humongous amount of data present online is not enough, if you are not able to extract relevant information. The ability to search across multitudes of web pages has advanced a lot but the ability to search intelligently and semantically is still relatively new. Users may not necessarily be well aware of the accurate keywords required to be used for giving them correct results. Therefore, a more lenient approach is required to provide relevant results to the users instead of a strict keyword search approach. In this project, we try to obtain the results of a web search query in a way that is not restricted to a strict keyword search. Thus, we title this type of search as an *Intelligent Semantic Web Search*.



Fig. 1. Keyword based web search

II. USAGE SCENARIO

The intelligent and semantic web search is the next step towards making the user experience more seamless. This application can be integrated wherever a feature for user search is needed. For example, search engines, word meaning lookup on a website. This application can also be modified to integrate intelligence to semantic code search, for finding a specific piece of code in a huge project or code base or even online.

III. SPECIAL FEATURES OF APPLICATION

The most special feature of the application is what we emphasize as the semantic search. The semantic search feature will empower the user to search what they want without exactly remembering the words or keywords for it. The feature will help in displaying the relevant results even in the absence

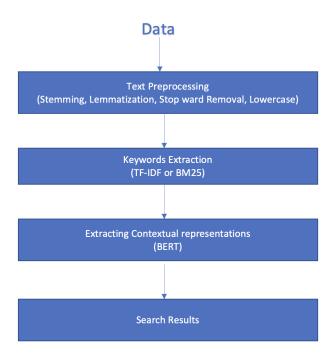


Fig. 2. Intelligent semantic web search

of precise keywords as well. The feature is relatively recent and unorthodox from traditional tools. Search becomes easier by identifying entities and mapping unstructured data thereby removing the reliance on specific terminologies or precise memory/recall.

IV. METHODOLOGY

Our intelligent semantic web search consists of two phases: Text Pre-processing and Contextual Representation Extraction.

A. Text Pre-processing

The user query needs to be pre-processed first before proceeding with the task of searching. Our text-pre-processing techniques will include converting the query text into lowercase, stemming, lemmatization and finally stop words and punctuations removal(using the list of most common stop words available).

B. Contextual Representation Extraction

We will be extracting contextual representation in order to get the core meaning of the query which user intends to search for. Getting the core meaning helps in getting similar words which might mean the same thing as the query and lead to actual results which the user is searching for. Contextual representation extraction have been achieved by obtaining embeddings and finally extracting similarity using advanced models like BERT. We use a variant of the BERT model called Sentence-BERT or SBERT for this task as it does not require training from scratch and can produce results faster.

V. IMPLEMENTATION

A. Dataset

Datasets of different resources such as GeeksforGeeks, NY Times, Medium and covid-19 aritcles published on Kaggle were used. The original datasets had several columns such as authors, date of publication, title, content. We used only title and content columns for our project.

B. Data Pre-processing

To make our data diverse we gathered data from different resources such as geeks for geeks, NY Times News, Medium and covid-19 articles. We performed preprocessing to refine our datasets.

The datasets were loaded into a Pandas dataframe and following forms of text pre-processing techniques were used to polish the datasets:

• Removing duplicates

```
df_1 = df_1.drop_duplicates()
df_2 = df_2.drop_duplicates()
df_3 = df_3.drop_duplicates()
df_4 = df_4.drop_duplicates()
df_5 = df_5.drop_duplicates()
```

Fig. 3. Text Pre-processing: Removing Duplicate values

• Dropping NAN values

```
df_1 = df_1.loc[:,:].dropna(axis=1)
df_2 = df_2.loc[:,:].dropna(axis=1)
df_3 = df_3.loc[:,:].dropna(axis=1)
df_4 = df_4.loc[:,:].dropna(axis=1)
df_5 = df_5.loc[:,:].dropna(axis=1)
```

Fig. 4. Text Pre-processing: Dropping NAN values

 Removal of unrequited columns such as 'published date', 'author', 'category', 'filename'

```
df_5 = df_5.drop(columns = ['category', 'filename'], axis = 1)
df_5.head()
```

Fig. 5. Text Pre-processing: Dropping additional columns

The last step was done on the basis of general observation that the published date, authors, URLs of an article would not lead to any significant improvement in the extraction of semantic similarity. Hence, it was decided to drop such columns from the dataset.

C. Data Augmentation

After pre-processing the datasets, we concatenated 300 rows from all the datasets to form the final dataset. We used this data to train our model.

```
final_data = pd.concat([df_1[:300], df_2[:300], df_3[:300], df_4[:300], df_5[:300]])
```

Fig. 6. Data Augmentation

D. Model

We have used two different approaches to generate results for our semantic search. In the first approach we have used a pre-trained model of SBERT and in the second approach we trained the model on our custom dataset for adapting the pre-trained model to our dataset.

1) Pre-trained Model: We have used a variation of the BERT model, Sentence Bert aka SBERT model, for extracting inferences and semantic meaning from the texts of the articles. The process requires to first generate the word embeddings of the texts. The embeddings are then used for determining the semantic similarity between the articles and the searched query. We have used cosine similarity for the task of determining semantic similarity between the articles and the search query provided by the user.

```
sentences = df['headline_text'].values.tolist()
model = SentenceTransformer('bert-base-nli-mean-tokens')
sentence_embeddings = model.encode(sentences)
```

Fig. 7. Pre-trained Model execution

2) Trained Model: We have used a similar approach to the original SBERT model for training. We have generated embeddings of the titles and the contents. We have then proceeded to calculate the dot scores of the embeddings. We have used dot scores because it is optimal for asymmteric semantic textual similarity. The dot scores are between the titles and the contents. This has been done to simulate the task of calculating scores between a short search query and the dataset. The dot scores have also been calculated for each title with all contents in order to augment the training data. The final number of rows have been limited to 80000 due to constraint of resources.

```
# Get embeddings of desired columns and dataframe
def get_embed(df, columns, model):
embed_df = pd.Oataframe(columns-columns)

for col in columns:
    sentences = df(col].values.tolist()
    colname = col="rimbed"
    embed_df.drop(columns-columns, axis=1)
    return embed_df

embed_df .drop(columns-columns, axis=1)

return embed_df

embed_df .get_embed(df, ['title', 'content'], model)

embed_df .get_embed(df, ['title', 'content'], model)
```

Fig. 8. Trained Model Embeddings Generation

```
# Calculate similarity scores based on desired metric

def get_similarity(similarity, embed_df):
    sim_df = pd.DutaFrame(columns=['titleEmbed', 'contentEmbed', 'dot'])

i=0
    for title in embed_df['titleEmbed']:
        for content in embed_df['contentEmbed']:|
        sim_df.at[i, 'titleEmbed'] = title
        sim_df.at[i, 'contentEmbed'] = content
        if similarity == "dot':
        sim_df.at[i, ismilarity] = float(util.dot_score([title], [content])[0])
        ellf similarity == "cosine":
        sim_df.at[i, similarity] = float(util.cos_sim([title], [content])[0])
        i += 1
        if i > 800000:
        break
        return sim_df

dot_df = get_similarity("dot", embed_df)
```

Fig. 9. Trained Model Semantic Score Calculation

```
# Compiling training dataset
train_examples = []

ctr = 0

for index, row in dot_df.iterrows():
    input = Input:cample(texts=[row[0], row[1]], label = row[2]) # texts = [title, content], label = (dot/cosine)score
    if ctr%2 = 0:
        train_examples.append(input)
        ctr += 1

train_dataset = SentencesDataset(train_examples, model)
train_dataloader = DataLoader(train_examples, shuffle=True, batch_size=16)
train_loss = losses.CosineSimilaritytoss(model)

#Tune the model
model.fit(train_objectives=[(train_dataloader, train_loss)], epochs=1, warmup_steps=100, output_path=model_save_path)
```

Fig. 10. Trained Model Training

VI. RESULTS

A. Processed Data

After executing the data pre-processing steps mentioned above, the resultant dataset is as shown below. The SBERT model chosen to generate embeddings and contextual representations and the model training is executed on this dataset.

final_data[1:100]		
	title	content
1	if you've tasted 21/52 of these international	food I if you've tasted 21/52 of these interna
2	16 twenties vs. thirties tweets that are so ac	16 twenties vs. thirties tweets that are so ac
3	the 19 most tone-deaf things celebrities have \dots	celebrity I the 19 most tone-deaf things celeb
4	if you're bored, try matching these disney pri	tv and movies I if you're bored, try matching \dots
5	kendall jenner responded to a fan who suggeste	kendall jenner responded to a fan who suggeste

Fig. 11. Processed Data

B. Embedding Vectors generated by SBERT model

After running the pre-trained SBERT model, the embedding vectors generated from the articles are as shown below in the snapshot.

Fig. 12. Embedding Vectors generated from pre-trained model

C. Output

To compare both the models we input six search queries to each model to find the most semantically related articles using the cosine similarity score. The outputs after searching the respective queries in each model have been shown below along with the respective queries and the snapshots:

```
Semantic Search Results in pre-trained models

--------------

Query: Employees are upset

Top 8 most similar news headlines:

Kristen Bell And Dax Shepard Said They're "At Each Other's Throats" In Isolation, And Things Got Awk (Cosine Score: 8.5916)

Abnormalities of serum and plasma components in patients with multiple sclerosis Qualitative and qua (Cosine Score: 8.4731)

Kim Kardashian Dragged Kendall And Kourtney's Lack Of Work Ethic In A Comment That Caused Their Huge (Cosine Score: 8.4731)

He 'ticking Dudget' Taing the US The budget proposals laid out by the administration of US Preside (Cosine Score: 8.4391)

Blockchain is not only crappy technology but a bad vision for the futureBlockchain is not only crapp (Cosine Score: 8.4391)

Alterations in Pulmany Function Following Respiratory Viral Infection Repiratory Viral Illness is (Cossine Score: 8.4391)

3 People Wan Are Having a Hay Maypyy where I'me Stuck Indoors Than Youl8 People Wan Are Having a Hay George Score: 4.4731)
```

Fig. 13. Pre-trained model output of Query:"Employees are upset"

Fig. 14. Pre-trained model output of Query:"Difficult time"

Fig. 15. Pre-trained model output of Query:"crickt sprts"

Fig. 16. Pre-trained model output of Query:"actrss brkup"

Fig. 17. Pre-trained model output of Query:"global warming impact"

Fig. 18. Pre-trained model output of Query:"Moderate impact on economy"

Semantic Search Results after training:

Query: employees are upset

Top 8 most smill are mose headlines:

Top 8 most smill are mose headlines:

Heart Employees Said The Company 15 "Porting Lines at Risk" as Social Distancing Rules Aren't Reing F (Cosine score: 0.9987)

If You Don't Pass This Youth Quit, You'll be Endoardasself You Don't Pass This Youth Quit, You'll be (Cosine score: 0.9986)

If You Don't Pass This Youth Quit, You'll be Endoardasself You Don't Pass This Youth Quit, You'll be (Cosine score: 0.9986)

There Self-Employed Morkers Yeel Japored by the Government's Coronavirus Financial Support Packagedin (Cosine score: 0.9986)

The People No Yee Senting A Navy, Manyy Morse Time Stuck Indoors Than You's Repole No Yee Having A Life (Cosine score: 0.9986)

The Yee You In the Top Self of the Post Creative People Into Navi Cosine Society (Cosine score: 0.9986)

Can Ne Guess Your Age Based On Your Plans For Tomorrow/Community | Yee You In the Top Self o (Cosine score: 0.9986)

Fig. 19. Trained model output of Query:"Employees are upset"

Query: difficult time

Top 8 most similar news headlines:

Minimum number of letters needed to make a total of noiven an integer n and let a = 1, b = 2, c = 3, (Cosine score: 0.9989)
Você sabe um pais para cada letra do alfabeto?você sabe um pais para cada letra do alfabeto? | A úni (Cosine score: 0.9989)
Você sabe um pais para cada letra do alfabeto? (Lougha (Corine score: 0.9989)
(Cosine score: 0.9989)

(Cosine score: 0.9989)

Is coisas para ta ajudar a sobreviver a um dia de chuvaShopping | 16 coisas para te ajudar a sobrevi (Cosine score: 0.9989)
O principe Charles, 71, testou positivo para (Cosine score: 0.9989)

O principe Charles, 71, testou positivo para (Cosine score: 0.9989)

(Cosine score: 0.9989)

Responda essas perguntas sobre personalidade e diremos quão velha é a sua almaResponda essas pergunt (Cosine score: 0.9989)

24 Fotos impressionantes da Itália antes e depois de ser submetida ao confinamento24 Fotos impressio (Cosine score: 0.9989)

Fig. 20. Trained model output of Query:"Difficult time"

VII. CONCLUSION

We have compared the performances of SBERT model with our custom trained SBERT model for semantic web search. While our custom trained SBERT model retrieves human perceivable better results for most of the input search queries. There is a comparable performance when a search query consists of any typos. In case there exists any typos in the search query, both models returned results of languages other than english. Thus bringing a shortcoming in sight in the pre-

Query: crickt sprts

Top 8 most similar news headlines:

16 coisas para te ajudar a sobreviver a um dia de chuvaShopping | 16 coisas para te ajudar a sobrevi (Cosine score: 0.9997)

Você sabe um país para cada letra do alfabeto?você sabe um país para cada letra do alfabeto? | A úni (Cosine score: 0.9997)

Croque monsieur grandão-Croque monsieur grandão | Im clâssiro francês! | publicado March 20, 2020, 19 (Cosine score: 0.9997)

People Are Sharing Their Unpopular Beauty Opinions And Whew, ChildPeople Are Sharing Their Unpopular (Cosine score: 0.9997)

18 People Who Are Hawing A May, Mayyyy Norse Time Stuck Indoors Than Youls People Who Are Hawing A W (Cosine score: 0.9997)

17 Memes That Are Seared In Your Memory If You Were On Tumblr In 20117 Memes That Are Seared In You (Cosine score: 0.9997)

19 Dinge, die du nur verstebst, wend um tit Kazten aufgewachen bistip Dinge, die du nur verstebst, wend um tit Kazten aufgewachen bistip Dinge, die du nur verstebst, wend um tit Kazten aufgewachen bistip Dinge, die du nur verstebst, wend um tit Kazten aufgewachen bistip Dinge, die du nur verstebst, wend um tit Kazten aufgewachen bistip Dinge, die du nur verstebst, wend um tit Kazten aufgewachen bistip Dinge, die du nur verstebst, wend um tit Kazten aufgewachen bistip Dinge, die du nur verstebst, wend um tit Kazten aufgewachen bistip Dinge, die du nur verstebst, wend um tit Kazten aufgewachen bistip Dinge, die du nur verstebst, wend um tit Kazten aufgewachen bistip Dinge, die du nur verstebst.

Semantic Search Results after training:

Fig. 21. Trained model output of Query:"crickt sprts"

Fig. 22. Trained model output of Query:"actrss brkup"

Query: global warming impact

Top 8 most similar news headlines:

Eleven Reasons To Be Excited About The Future of TechnologyIn the year 1820, a person could expect t (Cosine score: 0.9965)
10 Days That Changed Britain: 'Heated' Debate Between Scientists Forced Boris Johnson To Act On Coro: (Osine score: 0.9965)
14 is coming, and it will be boring - Denny vrandečic - Mediumi was asked about my opinion on this (Cosine score: 0.9960)
16 is Lab Told Oprah the Believes The Cornovarius Is The bund's Response to 'Damage' By Humansceleb (Cosine score: 0.9960)
16 is Lab Told Oprah the Believes The Cornovarius Is The bund's Response to 'Damage' By Humansceleb (Cosine score: 0.9960)
16 is Lab Tolis son'd economy' The soaring cost of oil has hit global economic growth, although wo (Cosine score: 0.9960)
26 Everyday IA - Louis Rosenfeld - MediumA few days ago, Cennydd Bowles gently trolled many of us thusl (Cosine score: 0.9969)

Fig. 23. Trained model output of Query:"global warming impact"

Fig. 24. Trained model output of Query:"Moderate impact on economy"

trained model, SBERT.

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