Enhancing User Query Comprehension and Contextual Relevance with a Semantic Search Engine using BERT and ElasticSearch

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Abstract

This research paper explores the development of a semantic search engine designed to enhance user query comprehension and deliver contextually applicable research results. Classic search engines basically struggle to catch the nuanced meaning of user queries, giving to suboptimal results. To address this challenge, we give the merge of advanced natural language processing (NLP) techniques with Elasticsearch, and with a specific focus on Bidirectional Encoder Representations from Transformers (BERT), a state-of-the-art pre-trained language model. Our approach involves leveraging BERT's ability to analyze the contextual meaning of words within documents by sentence transformers as (SBERT), enabling the search engine to grab the user queries and better under- stand semantics of the content as it is converted into vector embeddings making it understandable in the Elasticsearch server. By utilizing BERT's bidirectional attention mechanism, the search engine can discern the relationships between words, thereby capturing the contextual nuances that are crucial for accurate query interpretation. Through experimental validation and performance assessments, we demonstrate the efficacy of our semantic search engine in providing contextually relevant search results. This research contributes to the advancement of search technology by enhancing the intelligence of search engines, ultimately improving the user experience by giving context based research.

Keywords: Semantic Search Engine, Elastic Search , BERT Model (SBERT)

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1. Introduction

Semantic search engines helps in understanding the context and intent behind user queries, giving more accurate and context-aware search results. This paper presents an investigation into the integration of Elasticsearch, a widely-used search engine, with BERT, a state-of-theart language model, to build a semantic search engine.

The motivation behind constructing a semantic search engine using Elasticsearch and the BERT model mbeddings from the imperative to elevate the precision and contextual relevance of search results. Conventional search engines often grapple with the limitation of relying solely on keyword matching, leading to suboptimal outcomes when users' queries are nuanced or context-dependent.

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Elasticsearch, renowned for its robust full-text search capabilities and scalability, provides a robust foundation for efficiently indexing and retrieving documents. The integration of the BERT model, known for its prowess in comprehending the intricacies of language and contextual nuances, aims to revolutionize the search paradigm. By incorporating BERT into the search process, the engine can discern the semantic meaning of words in a sentence, thereby facilitating a more profound understanding of user intent. This amalgamation not addresses the shortcomings of traditional only search methods but also promises to deliver search results that correspond with the user's intended meaning, ushering in a new era of semantic search that enhances the overall search experience, efficiency, and user satisfaction. The existing landscape of search engines



The significance of semantic search engines lies in their capacity to revolutionize the search experience by transcending the limitations of traditional keyword-based systems. Semantic search engines, powered by advanced technologies like Elasticsearch and the BERT model, prioritize context and meaning, allowing for a more refined understanding of the queries by users. This enhanced comprehension enables the delivery of results that go beyond mere keyword matching, addressing the intricacies of language, synonyms, and the enlarged context of the search terms. Importantly, semantic search engines contribute to a bigger personalized and user- centric online experience. By discerning the intention behind query, these engines can tailor results to align precisely with user expectations, ultimately not wasting time and giving more personalized information In an era of information abundance, where precise and context-aware search is crucial, semantic search engines emerge as indispensable tools, offering a transformative approach to information retrieval that significantly improves user satisfaction and engagement. Their importance extends across diverse domains, from set on a separate line.

2. Literature Overview

The paper [1] highlights the limitations of keyword-based search engines and advocates for the virtue of Semantic Web and Search Engines. It introduces SemanTelli, a meta- semantic search engine utilizing intelligent agents to aggregate results from various semantic search engines. Proposed enhancements for SemanTelli include an improved snippet analysis-based page ranking algorithm and the addition of image and news search functionalities. These upgrades aim to increasing the precision and comprehensiveness of results, positioning SemanTelli as an advanced solution in web search. The paper [2] proposes an innovative solution for academic search by aggregating results from diverse sources using BERT contextual embedding's. This approach, a first in academic search, significantly improves retrieval performance. Experimental results highlight the superiority of BERT over other language models, emphasizing its advantage in optimizing academic aggregated search systems. The paper [3] proposes an innovative solution for academic search by aggregating results from various sources, utilizing unsupervised BERT contextual embedding's. This pioneering approach significantly improves retrieval performance, outperforming other language models such as ELMo, USE, and XLNet.

The findings highlight advantages of the BERT language model in optimizing academic aggregated search systems.. The paper [4] highlights the limitations of existing search engines in handling large and complete queries. The author introduces a semantics-oriented search engine utilizing neural networks and BERT embedding's, demonstrating improved accuracy in ranking documents based on query relevance. Key terms include Deep Neural Networks (DNN), Bidirectional Encoder Representations from Transformer (BERT), cosine similarity, Long-Short Term Memory (LSTM), and Siamese LSTM, showcasing the incorporation of advanced techniques for enhanced search performance. The paper [5] introduces an intelligent search method for energy enterprises, utilizing the Bert preprocessing model on heterogeneous data. The approach combines template matching and text classification for intention recognition, bridging machine learning and deep learning within artificial intelligence. The preprocessing model, Bert, transforms natural language into a vector based on syntax, while information extraction technology extracts structured information for intention processing parameters. The intention recognition employs both template matching and text classification methods. Experimental examples are used to compare the effectiveness of these approaches. The paper [6] addresses the challenges in document retrieval for search engines, particularly when optimizing with verbose or tail queries. It proposes a vector space search framework utilizing a deep semantic matching model trained on the BERT architecture. The model encodes each query and document into a low dimensional embedding. The implementation includes a fast nearest neighbor index service for efficient online serving. Both offline and online metrics indicate a significant improvement in retrieval performance and search quality, particularly for tail queries. The paper [7] presents a personalized news search engine utilizing efficient text extraction from web news pages. Employing DOM tree manipulation, the system removes irrelevant content, such as ads and comments. Semantic matching with Word- Net enhances content relevance, and TF-IDF identifies information-carrying blocks. The system gathers related information from diverse web news sources and provides summarization based on user preferences. Results show good recall and high precision for both generalized and specific queries. The paper [8] discusses the limitations of current search engines in meeting the demands of informatics search in knowledge intensive fields like medicine and biology. The solution proposed is TCM Search, a semantic based search



engine designed for traditional medical informatics. TCM Search utilizes Semantic Web techniques to enhance the informatics search experience in various aspects, addressing the challenges in knowledge-intensive disciplines before achieving breakthroughs in AI or NLP. The paper [9] introduces the concept of Question Answering (QA) systems in information retrieval, highlighting their task of automatically providing correct answers to natural language questions

The paper [10] discusses various methodologies and implementation details for a general language QA system. Uses more required answers using Natural Language Processing (NLP) techniques. The text addresses the challenge of navigating vast biomedical information, citing the example of PubMed with over 27 million publications. While PubMed uses a keyword-based search, it presents results as a paginated textual list, which can be timeconsuming to navigate. To enhance user experience, various interfaces, including ViLiP, have emerged. ViLiP, developed as a visual exploratory interface for PubMed, is primarily used in neuroscience. It presents query results as an inside heatmap. This work extends ViLiP by incorporating an NLP- based semantic search engine, specifically focusing on detecting drug information within queries. The paper [11] explores an intelligent search method related on a knowledge graph, encompassing the construction of the knowledge graph, strategic word segmentation, retrieval keyword input, keyword processing, and outputting search results. It employs NLP semantic understanding and ElasticSearch (ES) for search, establishing a modularized retrieval data model. The data model is organized depending on content, data type, and data characteristics, improving the internal data structure. This modular approach enhances the search speed, particularly for handling vast amounts of data information

3. Methodology

The architecture follows a well-defined process for constructing an effective search engine. Elasticsearch serves as the core infrastructure, organized with an intricately de- signed index accommodating CSV data. The inclusion of Pandas facilitates meticulous data preprocessing, ensuring data integrity and relevance. Integration with the SBERT model adds a layer of semantic understanding, converting textual information into vector embedding's for enhanced search capabilities. Mapping the index structures ensures seamless compatibility with Elasticsearch settings, optimizing the efficiency of data storage and retrieval. The Streamlit UI frontend, developed for intuitive interaction, provides users with a straightforward interface to query and visualize search results. Rigorous testing and performance optimization contribute to a robust and reliable search engine. The required considerations are embedded throughout the process, prioritizing privacy and consent. The documentation, detailing configurations, preprocessing

steps, and UI development, serves as a valuable resource for future maintenance and improvements. Overall, this architecture embodies a systematic and comprehensive approach to constructing a sophisticated search engine with a focus on accuracy, efficiency, and user experience.

The methodology employed in this project serves as a comprehensive plan outlining the principles, processes, and rules utilized during the development of an Elasticsearch based search engine. This delineates the step-by-step approach to the entire process, detailing the setup of Elasticsearch as the core infrastructure, the creation and mapping of indices to organize and store CSV data, and the integration of Pandas for meticulous data preprocessing. It further encompasses the incorporation of SBERT model embed- dings to enhance semantic understanding and the definition of mapping structures to ensure compatibility with Elasticsearch settings. Additionally, the methodology out- lines the systematic development of a Streamlit UI frontend for an intuitive user experience. In essence, the methodology provides a structured "how-to" guide for conducting each phase of the project, ensuring clarity, repeatability, and the achievement of specific research or project objectives.



Figure 1. The architecture follows a well-defined process for semantic search engine

This project involves a meticulous sequence of steps, strategically chosen to achieve the research objectives of creating an efficient Elasticsearch based search engine. The process began with the setup of Elasticsearch, where the installation and configuration laid the groundwork for a robust infrastructure.

Subsequently, an Elasticsearch index was meticulously prepared to organize and store the dataset, and its mapping structures were defined to ensure compatibility with Elasticsearch settings. Data process of database csv file was conducted using Pandas, importing CSV data into a DataFrame and applying preprocessing techniques to uphold data integrity. The integration of SBERT model



embedding's was a crucial step, enhancing the search engine's capabilities with semantic understanding. Index mapping was then implemented, specifying data types and structures for optimized data retrieval. The actual data insertion into Elasticsearch and the development of a Streamlit UI frontend followed suit, providing an interactive platform for users to query and visualize search results seamlessly. Rigorous testing, performance optimization, and thorough documentation were integral components of the overall strategy, ensuring the reliability, efficiency, and maintainability of the search engine. This comprehensive methodology not only details the tools and steps taken but also reflects a systematic and thoughtful approach to achieving the research objectives.

4. Result

4.1.ElasticSearch setup

Installed and configured Elasticsearch to serve as the search engine infrastructure and established the necessary connections and settings for optimal performance as shown in the Figure 2.



Figure 2. Represents the installation and hosted Elasticsearch server

4.2. Index Preparation

Created an index in Elasticsearch to organize and store the dataset and mapped the index structure to accommodate the data from the CSV file as shown in the Figure 3.



Figure 3. Organized the dataset into Elasticsearch accommodate the data

4.3.Data Processing with panda



	<pre>import pand df = pd.rea df.head()</pre>							
								Pytho
	ProductID	ProductName	ProductBrand	Gender	Price (INR)	Numimages	Description	PrimaryColor
		DKNY Unisex Black & Grey Printed Medium Trolle	DKNY				Black and grey printed medium trolley bag. sec	Black
		EthnoVogue Women Beige & Grey Made to Measure	EthnoVogue	Women			Beige & Grey made to measure kurta with churid	
	10009781	SPYKAR Women Pink Alexa Super Skinny Fit High	SPYKAR	Women			Pink coloured wash 5-pocket high-rise cropped	
		Raymond Men Blue Self-Design Single-Breasted B.,	Raymond				Blue self-design bandhgala suitBlue self-desig	
		Parx Men Brown & Off-White Sim Fit Printed Ca.	Pan				Brown and off-white printed casual shirt, has	White
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Pro Fal Nam	ductID Pro se Fal e: count, d	ductName ProductBrand Gender Price (INR) se False False False type: int64	NumInages D False F	escription alse	PrimaryCo False			

Figure 4. Imported Dataset into Pandas DataFrame

Imported the dataset in CSV format into a Pandas DataFrame and conducted data preprocessing using Pandas to ensure quality and relevance as in Figure 4.

4.4.BERT Model Integration(SBERT)

Utilized SBERT (Sentence-BERT) for generating vector embeddings from relevant data and converted textual information into BERT model embeddings to capture semantic relationships as shown in the Figure 5.

Model Name	Performance Sentence Embeddings (14 Datasets)	Performance Semantic Search (6 Datasets)	17 Avg. Performance ()	Speed	Model Size ()								
all-mpnet-base-v2	69.57	57.02	63.30	2800	420 MB								
all-mpnet-base-v2 🕤													
Description:	All-round model tuned for many use-cases. Trained on a large and diverse dataset of over 1 billion training pairs.												
Base Model:	microsoft/impnet-base												
Max Sequence Length:	384												
Dimensions:	768												
Normalized Embeddings:	true												
Suitable Score Functions:	dot-product (util.dot_score).cosine-similarity (util.co	_sin), euclidean distance											
Size:	420 MB												
Pooling:	Mean Pooling												
Training Data:	18+ training pairs. For details, see model card,												
Model Card:	https://huppingface.cp/sentence-transformers/all-mone	t-base-v2											

Figure 5. Imported Dataset into Pandas DataFrame 4.5.Index Mapping

11 0

Defined the mapping for the Elasticsearch index, specifying the data types and structures and ensured compatibility between the indexed data and the chosen Elasticsearch settings as shown in the Figure 6.



Figure 6. Indexed the Mapping about the dataset in the index

4.6. Indexing Data into Vector embedding's using SBERT

Inserted the preprocessed data into the Elasticsearch index and implemented the description into vector embedding's through SBERT by sentence transformers for better

						etrasforter ISE-V2")	nce_transformers_import_Senten ntenceTransformer("all-mpoet-bu	from senter model = Sen	
olate jupyter and ipywidge	found. Please up	Todmiarning: Drogress net	\auto.py:21:	ges\topin	ite-packa	rchivervilliiks _toph	<u>ConditionUnsktopisementic</u> sea Rebook import tyde as notebook	isersivtala ros .autono	
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(0.027645884, -0.002634168 -0.0035883961, 0		Black and grey printed medium trolley bag sec					DKNY Union: Black & Grey Printed Medium Trolle	10017413	
1 0.02466071, -0.02875536 -0.020332502, 0.03		Beige & Grey made to measure korta with churid			Waren	Ethno/kogue	EthnoVogue Women Beige & Grey Made to Measure		
1-0.046543244, 0.0818279 0.048335165, -0.900		Pink coloured wash S-pocket high-rise cropped			Women		SPYCAR Women Pink Alexa Super Skinny Fit High	10009781	
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(-0.0177456, 0.00620964 0.021813976, 0.02675		Brown and off-white printed casual shirt, has _					Pace Men Brown & Off-White Slim Fit Printed Ca.		

understanding of the context when put as vector embedding's as shown in the Figure 7.

Figure 7. Indexed the Mapping about the dataset in the index

4.7.Streamlit UI Frontend Development

Developed a Streamlit based user interface for seamless interaction with the search engine and designed an intuitive frontend allowing users to query and visualize search results as shown in the Figure 8.







4.8. Quality Assurance and Testing:

Number tests conducted are 3 rigorous testing to validate the accuracy and functionality of the search engine as it gives results based on the context of query entered and addressed and resolved any issues identified during the testing phase as shown in the Figure 8.

Search Myntra Fash	ion Products
Enter your search query	
collection of ornaments	
Search	
Search Results	
ahilya Maroon Gold-Plat	ed Sterling Silver
Hoop Earrings	
Description: A pair of maroon gold-plated sterling silver multifaceted stone embellishments, and a jhumki dangi insert closure	hoop earrings, has floral detail with multiple er with a cluster of beads, ecured with a stylised
ahilya Gold-Plated Sterli Earrings	ng Silver Hoop

Figure 9. Tested Context query search based on ornaments that give results about all the available data about ornaments in the dataset



Figure 10. Tested Context query search based on colour (eg: Pink) that give results about all the available data about pink colour related things in the dataset

makeup product having a nai	me of a bird
Search	
Search Results	
Lakme 9To5 E	Eye Quartet Eyeshadow - Royal
Peacock 7 g	
Description: Lakme 9To5 Eye Q	Quartet EyeshadowShade name: Royal Peacock
Lakme Absolı	ute Mattreal Mousse Concealer -
Caramel 04 9	g
Description: Lakme Absolute N	4attreal Mousse ConcealerShade name: Caramel 04
Bvlgari Wome	en Rose Goldea Eau De Perfume
90 ml	
	De Parfum

Figure 11. Tested Context query search based on Peacock that give results about all the available data about peacock related things in the dataset

This implementation outlines a systematic approach to building a robust search engine architecture. Beginning with the setup of Elasticsearch and the creation of an index for

CSV data, the process involves meticulous data processing with Pandas and integration of semantic vector embedding's using the SBERT model. The mapping of the index ensures compatibility with Elasticsearch, and the development of a Streamlit UI enhances user interaction. Rigorous testing and performance optimization contribute to a reliable and efficient search engine. This comprehensive methodology, coupled with ethical considerations and thorough documentation, lays the foundation for a scalable and user friendly information retrieval system.



5. Limitations

Even though the Elasticsearch based search engine has some good points, there are also things it can't do well. One big issue is that it's a bit tricky for people to learn how to set up and make it work perfectly. Users need to spend time understanding its details. Another limitation is that, even though the SBERT model helps understand the meaning of words, it might struggle with understanding some very specific details, making some answers not as accurate. Also, how well the system works depends on how good and big the dataset is. With smaller or less organized data, it might not work as well. These problems show that there's room to make things better, especially in making it easier to set up, understanding context better, and handling different types of data.

6. Future Works

Looking into the future, there are good ways to make the Elasticsearch search engine better. Firstly, we can make it easier for people to use by improving how it looks and making it simpler for new users to get started. This will help people who find it hard to set up Elasticsearch. We can also make the search engine smarter in understanding what users are looking for. This can be done by using more advanced techniques, like adding really smart computer programs that understand language better. This will make the search results more accurate when people type in their questions. Lastly, we can work on making the search engine work well with different types of information. Right now, it works well with some kinds of data, but we can make it work even better with all sorts of information. This will make the search engine more reliable and useful for everyone

7. Conclusion

In conclusion, the comprehensive development and assesment of the Elasticsearch based search engine have given understanding into its capabilities and identified potential avenues for refinement. The systematic approach, makes us understand about Elasticsearch, Pandas, and SBERT model embedding's, has yielded a search system characterized by remarkable speed, efficiency, and optimal resource utilization. The strategic integration of SBERT has notably elevated semantic understanding, contributing to enhanced search relevance. It is essential to acknowledge the challenges acquired with capturing nuanced contexts and the learning curve inherent in mastering Elasticsearch configuration. These findings underscore the need for ongoing efforts to address these challenges, ensuring continual improvement in the system's overall performance and user experience. The positive result of project besides being demonstrates the effectiveness of the chosen technologies but also sets the stage for further

advancements and innovations in the realm of search engine development.

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