

## SHOPPING RECOMMENDATION SYSTEM DESIGN BASED ON OPENAI EMBEDDINGS AND ELASTICSEARCH

The popularity of recommender systems grew recently due to several factors that include global COVID-2019 pandemic, invasion to Ukraine, and other offline destabilizing reasons. Shopping online is convenient, time saving, and sometimes also could provide additional safety.

Recommendation systems have seen significant evolution both domestically and internationally. They can be broadly categorized into a few main types: collaborative filtering, content-based, demographics-based, community-based, hybrid and deep learning-based recommendation systems. The development of Large Language Models (LLM) from OpenAI, Google, Microsoft allows us to build recommender systems that utilize semantic search and could pretend to be more humane than ever. Using vector representations of products using AI and ML methods is a promising approach to creating recommendations. This method allows you to represent products in a vector space, measuring the similarity between them based on vector distances. The most common methods that use vector representations include Word2Vec, matrix factorization, and recurrent neural networks (RNNs). Word2Vec provides the ability to capture semantic similarity, matrix factorization explores the hidden space for user and product, and RNNs take into account sequential context [1].

Methods based on vector representations have numerous advantages, including high accuracy, fast learning, and the ability to work with a variety of data types. However, unfortunately, they have their drawbacks, such as computational resource requirements, the need for a large amount of data, and the complexity of maintenance and customization. These limitations are important to consider when implementing methods based on vector representations to optimize recommender systems. This paper embarks on a deep exploration of OpenAI Embeddings [2] and recommendation algorithms based on cosine similarity between search request vector and existing products in Elasticsearch database. It entails the creation of a shopping recommendation system, underpinned by semantic search. The system utilizes test item data from existing datasets and self-generated items. The key advantages of this system are the absence of the need for manual model training and the speed of implementation

of such a recommendation system combined with the high quality of the resulting recommendations.

The shopping recommender system mainly includes two modules, one of which is a module for creating vectors based on product data and search query, and the other is a module for saving information into the Elasticsearch vector database and then using the built-in cosine similarity vector search function to obtain product recommendations. The relationship between the modules is shown in Fig. 1.

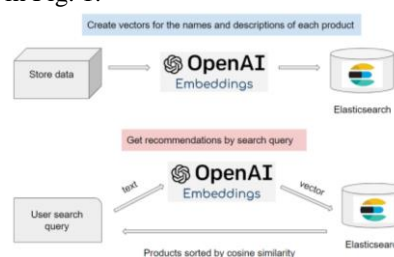


Fig. 1 Connection between system modules

Testing the implemented recommender system on the STS benchmark dataset [3] yielded impressive results, with a Pearson's correlation coefficient of 0.9121 and a Spearman's correlation coefficient of 0.9280. These high correlation values indicate a strong alignment between the predicted and actual recommendations, highlighting the effectiveness and accuracy of the recommender system in capturing relationships within the dataset.

### References

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