1 INTRODUCTION
Ranking is the central part in information retrieval systems, and nowadays, many modern ranking algorithms tend to use machine learning to optimize the results. The conventional way to so-called "leaning-to-rank" has been trained from manually labelled data set, which consist with a set of documents judged as relevant or not to specific queries. Limited with the data set, it requires human annotations and usually becomes time consuming for the relevance model to adapt to changing user preference.

In this project, we propose an on-line learning-to-rank method to resolve this problem. This on-line system utilizes users’ interactive feedback in real time, automatically adapts and improves the ranking results with less or no reliance on labelled data. Based on the on-going work from Dr. Wang’s group, which focuses on learning to recommend scientific literature, we propose the implementation of a on-line learning-to-rank system to improve the ranking for literature search engine according to users’ feedback.

2 RELATED WORK
Thousands of work have been done in previous to optimize the ranking system for search engine. However, there has not been many large-scale implementations, especially on-line learning-to-rank systems that attract users other than their research participants. [2] presented a method that utilized users’ click-through data, which implies the links clicked in presented ranking and query, to train and improve the ranking model. While this design effectively addressed the bias problem of documents ranks and the experiments results outperformed Google, the query size and the number of users are limited. [3] proposed learning algorithms that took the fact that relevance of different documents are independent and trade off between exploration and exploitation in multi-armed bandit algorithm into account. Nevertheless, its evaluation was still limited to 20 users and lacked empirical evaluations with real users and documents. In [1], the authors explored the use of Support Vector Machines for learning text classifiers. It identified particular properties of learning with text data and showed why SVMs were suitable for this kind of task. While SVM was shown to be an effective method, its experiment was only concerned with offline training, and the dataset was still limited to Reuters-21578 and Ohsumed corpus data set.
In this project, our group tends to implement the ranking model initially trained with SVM, and the implementation of sustainable web service differentiate our strategy from previous ones, which is able to continuously and automatically fine-tune its ranking model by applying feedback from users differentiate our implementation.

3 METHOD

As mentioned before, this project is based on the on-going project from professor Wang’s research group, which focuses on learning search engine for scientific literature. The literature (documents) is crawled from Web of Science’s search results. Under the assumption that the search results from Web of Science are reasonably correct, we first train our initial model offline through binary classification with the ranks of given queries and random queries extracted from Web of Science. Specifically, the binary classification is assumed to be a SVM ranking model.

The essence of this project is to implement the on-line update of the ranking model based on the feedback. Users’ feedback can take many forms. In this project, we will first implement the system’s user interface for web environment to gather users’ feedback, which also helps to collect different forms of the feedback for on-line learning. The click-through data of documents, cursor highlighting and cursor tracking and other forms of user behavior tracking can all be considered as users’ feedback, among which we will first consider to implement the click-through data. Based on the feedback, the system will re-train the model to give more weight to some specific features to the query.

Once the feedback collection and ranking model adaptation are successfully implemented, the system will automatically improve its ranking model as users querying the system for a given period of time.

4 PERFORMANCE EVALUATION

To evaluate the effectiveness of user feedback, we will compare the performance of the ranking models with and without learning from user feedback. The initial results crawled from Web of Science will serve as the ranking baseline, against which the on-line learning ranking model will compared. Interleave test will be conducted to completely measure the relative satisfaction in users’ needs.

REFERENCES

