Optimizing Search Efficiency: Exploring Differentiable Search Index Models for Information Retrieval

Information Retrieval

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Introduction

Motivation

- The efficacy of IR systems in providing pertinent document rankings in response to user queries is paramount
- Traditional IR systems commonly employ an index-then-retrieve pipeline (not always the most efficient approach!)
- Alternative approaches like the Differentiable Search Index (DSI) aim to integrate indexing and retrieval processes into a unified model. By doing so, they offer the potential for more seamless and efficient document ranking in response to user queries.

Problems

- **Sequential nature of traditional IR methods:** Indexing occurs first, followed by retrieval
  → Latency issues, especially when dealing with large datasets or in real-time search scenarios
- **Struggle with handling dynamic or evolving datasets:** The index becomes outdated over time
  → Stale search results and diminish the user experience
- **Futile optimization efforts:** Improvements made in one stage may not directly benefit the other
  → Limit the system's ability to adapt and improve over time.

Goal

- Inspired by the Differentiable Search Index concept, our goal is to merge these traditionally separate stages and developing a unified model, designated as 'f', utilizing a sequence-to-sequence architecture, which handles user queries ('q') and employs an auto-regressive approach to generate relevant document IDs.

Dataset

The MS MARCO dataset → Pre-built index provided by **Pyserini** library

1 Building Resources

- **documents (dictionary):** document ID (docid) as key, a dictionary with field 'raw’ (containing the raw text as string) as value
- **queries (dictionary):** query ID as key , a dictionary with field 'raw' (containing the raw text as string) and 'docids_list' (containing the list of correlated document IDs) as value

2 Computing Word2Vec Embeddings for queries and documents

- Using the trained Word2Vec model (on corpus data, containing all the processed ’raw’ data
- **Processed ’raw’ data:** Converted to lowercase, tokenized, and stopwords and punctuation removed (+ Stemming & Lemmatization)
- **Created 2 types of embeddings for each query/document:** emb, obtained as the average of the embeddings of all words, and first_L_emb, obtained by concatenating the embeddings of the first MAX_TOKENS words

3 Creating Datasets for Siamese Models

- **Pairwise Dataset (query, document, relevance):**
  → Designed for pairwise learning, where each sample consists of a query paired with a document
- **Triplet Dataset (query, doc+, doc-):**
  → Designed for triplet learning, where each sample comprises a query along with a positive and a negative document for training

Dataset

Example of Pairwise/Triplet Datasets

4 Creating Datasets for Sequence-to-Sequence (seq2seq) Models

- **Document Dataset (encoded document, encoded docid):**
  → Designed to facilitate training Seq2Seq models by providing documents as input sequences
- **Retrieval Dataset (encoded query, encoded docid):**
  → Designed for Seq2Seq models used in retrieval tasks. It pairs documents with corresponding queries for training

Documents and queries encodings are computed using the **T5-small tokenizer**, and we choose to pick the first **L=32** tokens for representing the documents, and the first **L=9** for representing the queries.

Example of Document/Retrieval Datasets

Siamese Neural Network: SNN-Convolutional

Siamese Neural Network: Neural network architecture that consists of two identical subnetworks, which have the same architecture and share the same parameters (weights)

→ Learn the similarity or dissimilarity between pairs of inputs (Differential learning approach)

1 Convolutional Siamese Neural Network (using Word2Vec embeddings)

Steps:

- **Changing Dataset Return Type:** The dataset pairs_dataset return type is modified to 'emb' (Word2Vec embeddings)
- **Initializing Siamese Network (Parameters):**

  input_size: Set to the dimensionality of Word2Vec embeddings

  conv_channels: The number of channels for convolutional layers
- **Training the Model (Parameters):**

  pairs_dataset, siamese_net, max_epochs, batch_size, split_ratio, etc.

- Inability to effectively discriminate between relevant and random documents, assigning high similarity scores to irrelevant documents

	MAP		nDCG		Precision@10		Recall@1000	
	Train	Test	Train	Test	Train	Test	Train	Test
CNN-SNN	0.1181	0.0500			0.0399	0.0100	0.3900	0.5

Siamese Neural Network: SNN-Attention

2 Siamese-Attention-Net Transformer (using token embeddings)

- **Attention network:** Designed to identify the highest correlations amongst words within a sentence, assuming that it has learned those patterns from the training corpus
- This enables learning representations based on token-level information (capture dependencies regardless of their distance in the input sequence.)
- Generates a relevance score using cosine similarity

Steps:

- **Changing Dataset Return Type to Token Embeddings:** The return type of the dataset pairs_dataset is adjusted to 'first_L_emb' (embeddings of first L tokens) - Use the stack of the first MAX_TOKENS embeddings (first_L_emb) of queries and documents
- **Initializing Siamese Transformer Network (Parameters):**
  embedding_size (total): Set to the product of EMBEDDING_SIZE and MAX_TOKENS
- **Training the Model (Parameters):** pairs_dataset, siamese_transformer, max_epochs, batch_size, split_ratio, etc.

- This model also struggles to distinguish relevant documents from random ones, frequently attributing high scores to both

	MAP		nDCG		Precision@10		Recall@1000	
	Train	Test	Train	Test	Train	Test	Train	Test
SNN-Att	0.0999	0.0			0.01	0.0	0.08	0.0499

Siamese Neural Network: SNN-Contrastive

3 Siamese Lightning module using embeddings (Contrastive Learning Approach with Triplet Loss)

- **Triplet loss function:** The network learns by comparing a set of three inputs: an anchor image, a positive image (similar to the anchor), and a negative image (dissimilar to the anchor). The goal is to bring the anchor and positive image embeddings closer while pushing the negative embedding further away.

Steps:

- **Changing Dataset Return Type to Embeddings:** The return type of the dataset `triplets_dataset` is adjusted to 'emb' (embeddings)
- **Initializing Siamese Lightning Module (Parameters):**
  input_size: Set to the dimensionality of embeddings (EMBEDDING_SIZE)
  margin: Defines the margin for the triplet loss function
  arch_type: Specifies the architecture type, set to 'linear'
- **Training the Model (Parameters):** triplets_dataset, siamese_lightning_module, max_epochs, batch_size, split_ratio, etc.

- This method, by leveraging the principles of contrastive learning, showed notable effectiveness over previous baselines and effectively discerns between similar and dissimilar query-document pairs

	MAP		nDCG		Precision@10		Recall@1000	
	Train	Test	Train	Test	Train	Test	Train	Test
SNN-Cons	0.2725	0.1706			0.1659	0.1599	0.7319	0.666

DSI Transformer-Based Model

1 Sequence-to-Sequence Model

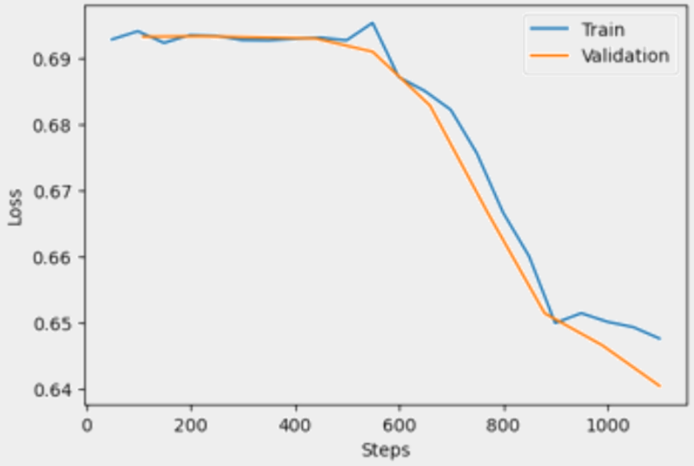
Model's architecture: A transformer-based encoder-decoder that involves three transformer layers for each component. Encoder plays the role of indexing, in which the model has to acquire the documents knowledge to map every document to its related docid. Meanwhile, the decoder is tasked with retrieval, generating the complete target sequence from a given query. Ranking is conducted according to semantic similarity.

Steps:

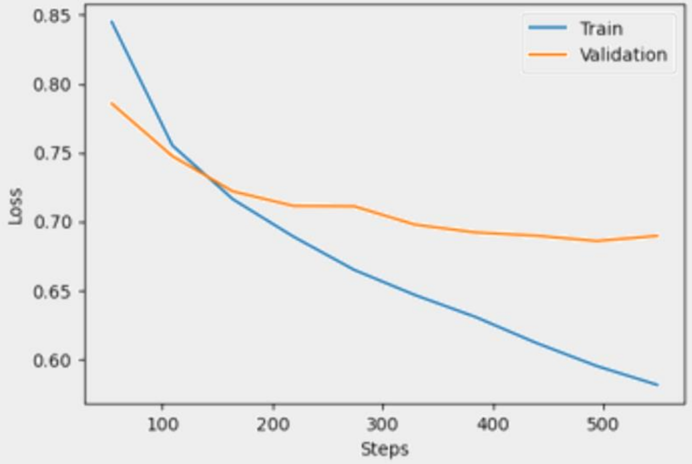
- **Initializing the sequence-to-sequence model (Parameters):**
  nlayers: Set the number of transformer layers for the encoder-decoder model
  nhead: The number of heads in the multihead attention models
  nhid: The dimension of the feedforward network model
  droupout: The dropout rate for each layer
- **Training the Model (Parameters):**
  tokenized_dataset, Transformer_module, max_epochs, batch_size, split_ratio, etc.
- This model can be a more generalizable one but needs more powerful computational racecourse for training.

	MAP		nDCG		Precision@10		Recall@1000	
	Train	Test	Train	Test	Train	Test	Train	Test
Seq-2-Seq		0.0165				0.0208		0.0208

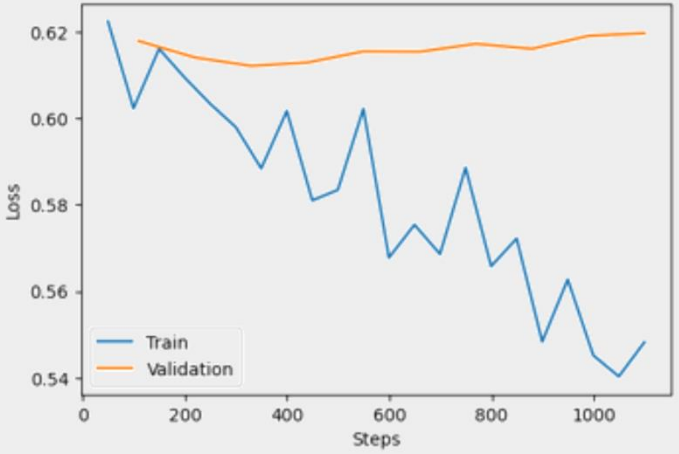
DSI Transformer-Based Model



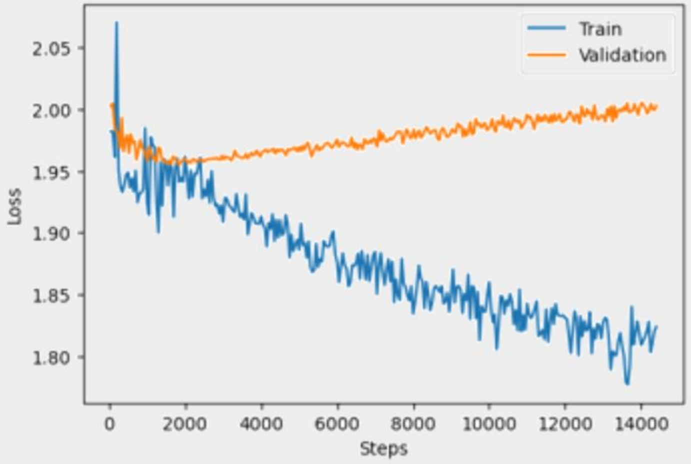
Siamese Network



Siamese-attention Network



Siamese-contrastive Network



Sequence-to-Sequence Model

Conclusion

Comparing the results

	MAP		nDCG		Precision@10		Recall@1000	
	Train	Test	Train	Test	Train	Test	Train	Test
CNN-SNN	0.1181	0.0500			0.0399	0.0100	0.3900	0.5
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Seq-2-Seq		0.0165				0.0208		0.0208

1 DSI can make the training process faster and needs less computational cost for IR tasks

→ But might not show better efficiency compared to index-then-retrieve approaches

2 Using sequence-to-sequence learning models can outperform classical self-supervised approaches (?)

Future Works

- If computational recourses available, we could evaluate the trained models using higher number of epochs
- A comprehensive compassion in terms of time, computational costs, scalability and efficiency between the developed models and other index-then-retrieve pipelines

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Thank You!