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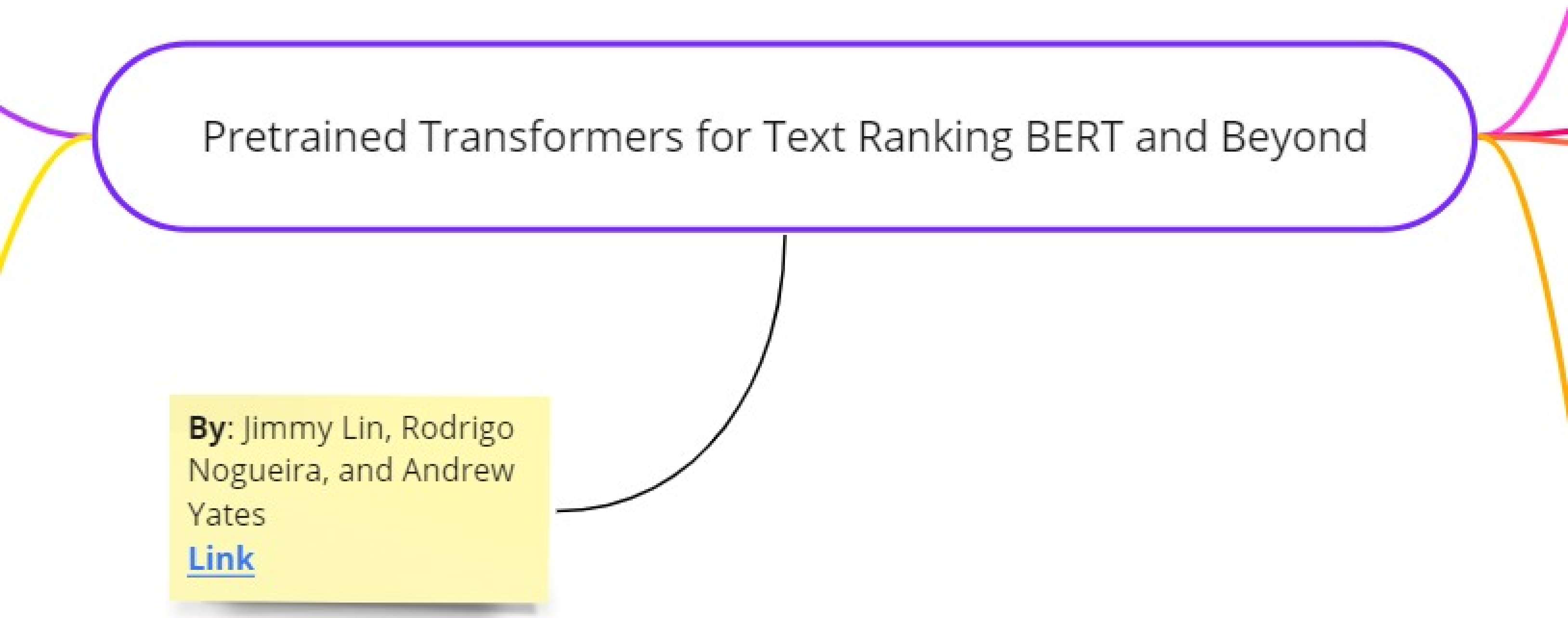
Article Presentation

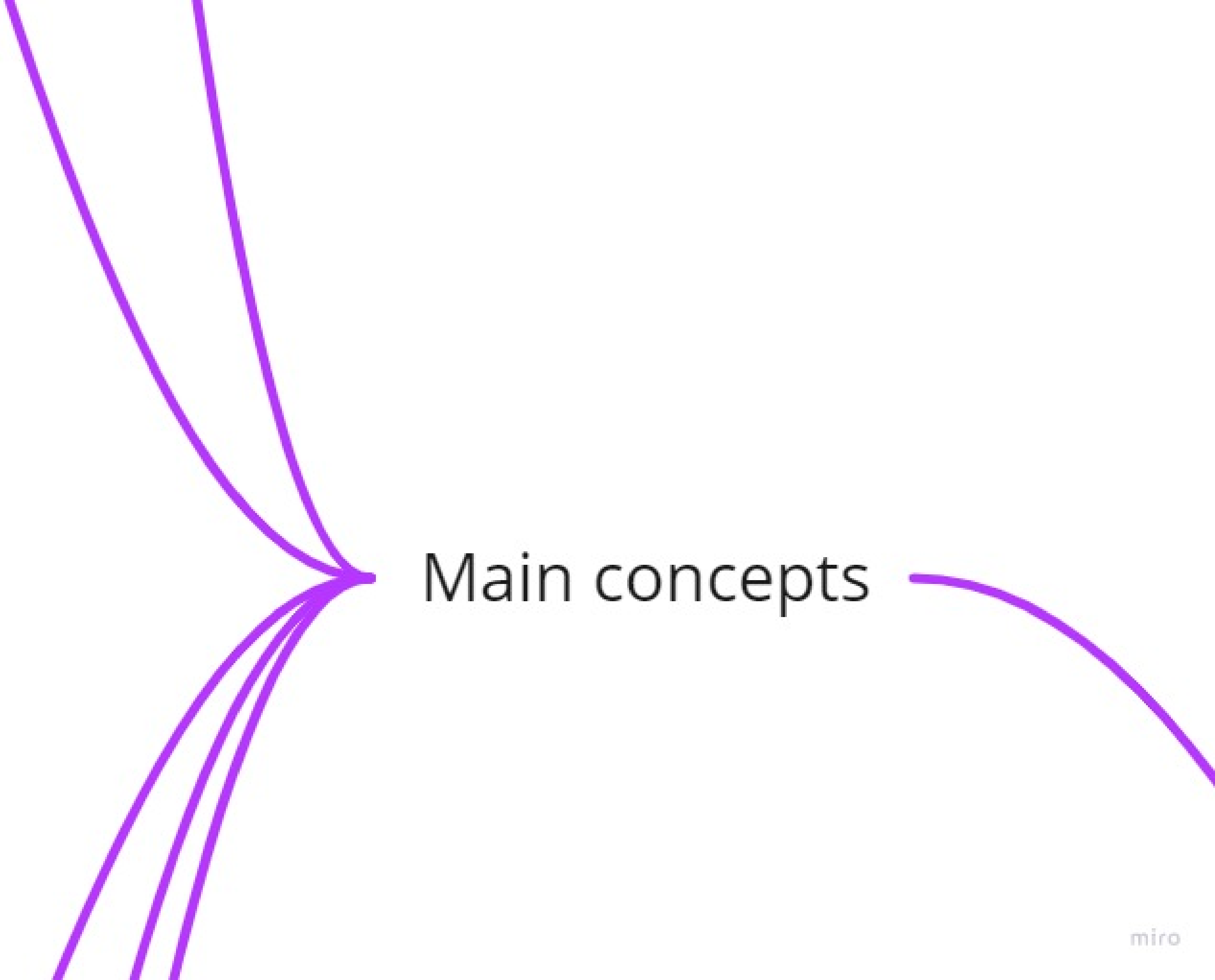
IA368DD_2023S1: Deep Learning aplicado a Sistemas de Buscas

Student: Marcus Vinícius Borela de Castro

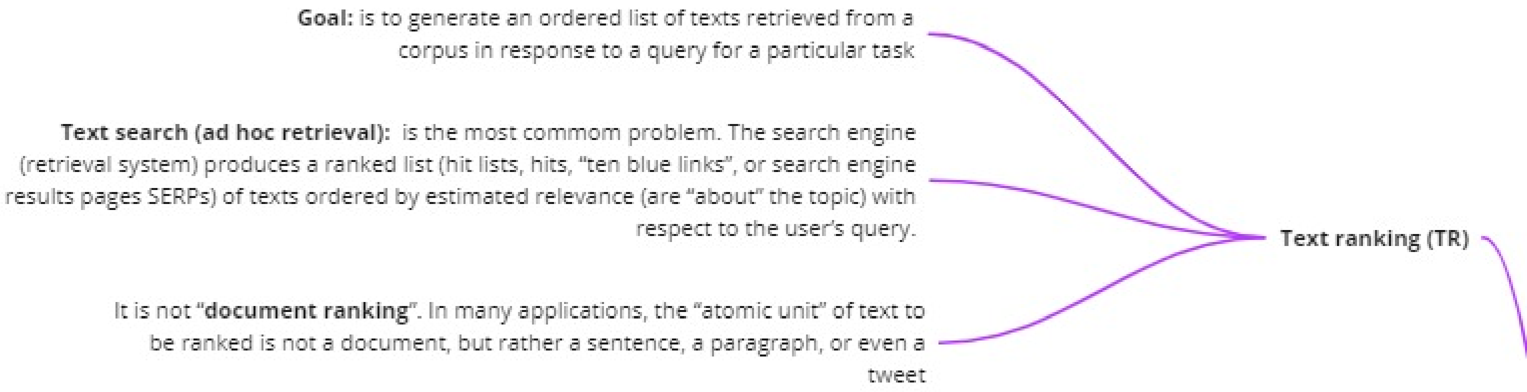


Pretrained Transformers for Text Ranking BERT and Beyond

By: Jimmy Lin, Rodrigo Nogueira, and Andrew Yates
Link



Main concepts

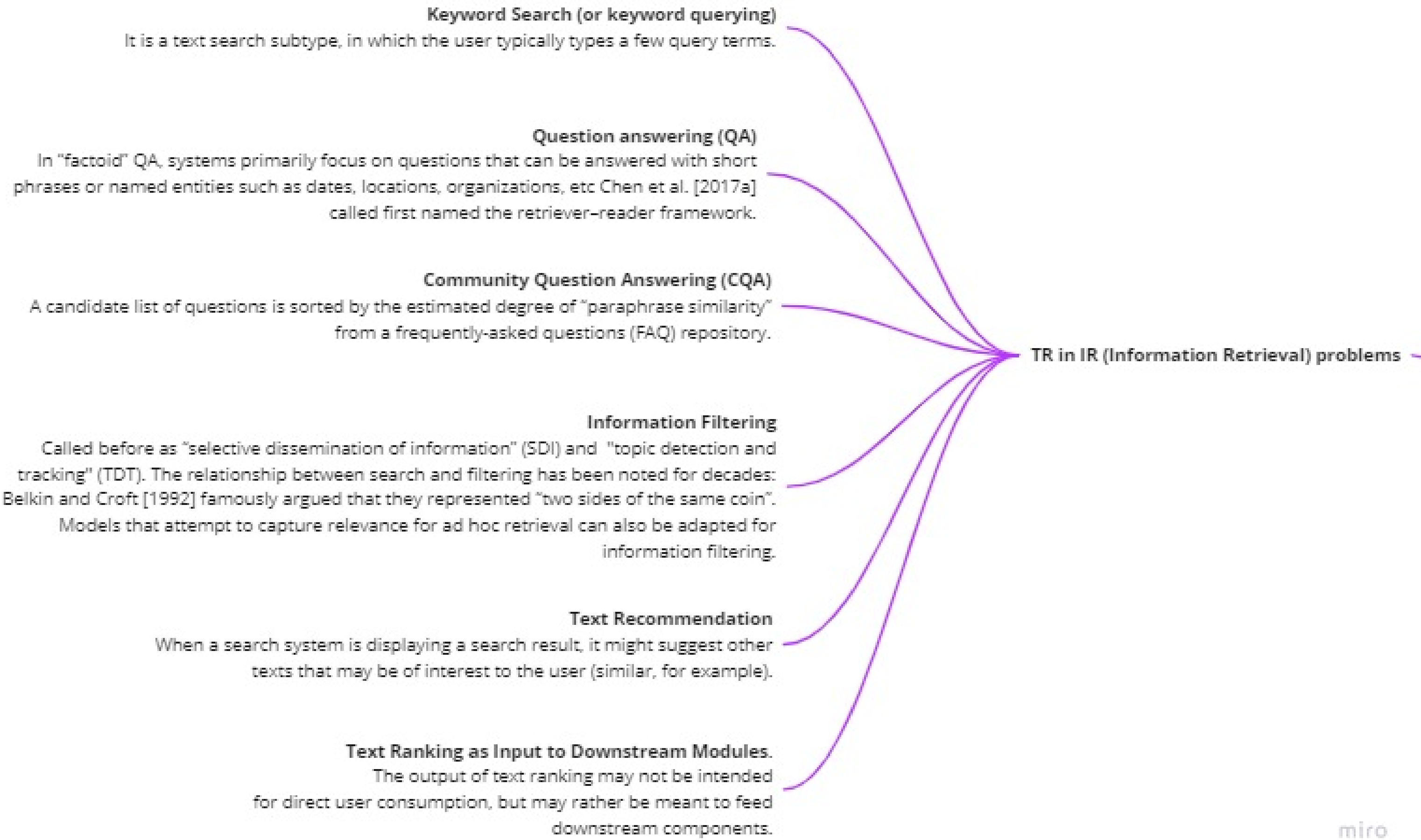


Text ranking (TR)

Goal: is to generate an ordered list of texts retrieved from a corpus in response to a query for a particular task

Text search (ad hoc retrieval): is the most commom problem. The search engine (retrieval system) produces a ranked list (hit lists, hits, "ten blue links", or search engine results pages SERPs) of texts ordered by estimated relevance (are "about" the topic) with respect to the user's query.

It is not "**document ranking**". In many applications, the "atomic unit" of text to be ranked is not a document, but rather a sentence, a paragraph, or even a tweet



TR in IR (Information Retrieval) problems

Keyword Search (or keyword querying)
It is a text search subtype, in which the user typically types a few query terms.

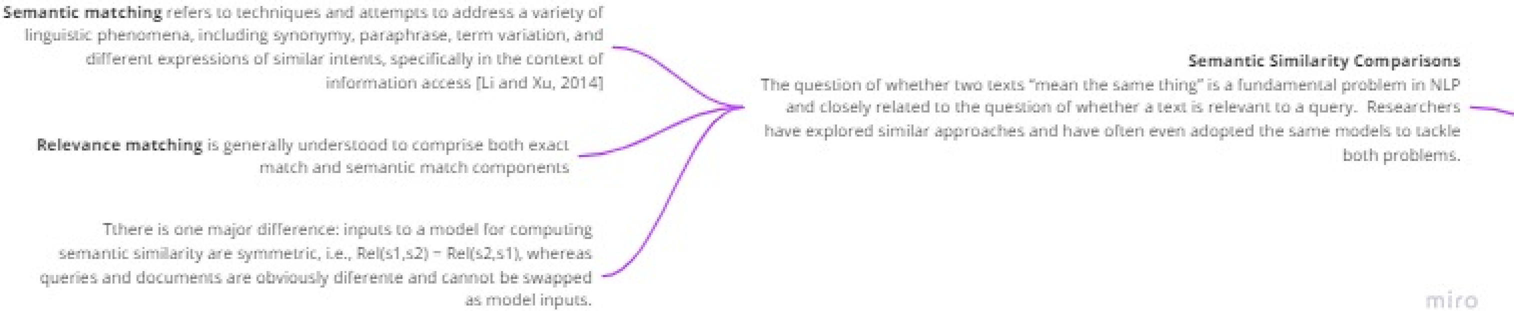
Question answering (QA)
In "factoid" QA, systems primarily focus on questions that can be answered with short phrases or named entities such as dates, locations, organizations, etc Chen et al. [2017a] called first named the retriever–reader framework.

Community Question Answering (CQA)
A candidate list of questions is sorted by the estimated degree of "paraphrase similarity" from a frequently-asked questions (FAQ) repository.

Information Filtering
Called before as "selective dissemination of information" (SDI) and "topic detection and tracking" (TDT). The relationship between search and filtering has been noted for decades: Belkin and Croft [1992] famously argued that they represented "two sides of the same coin". Models that attempt to capture relevance for ad hoc retrieval can also be adapted for information filtering.

Text Recommendation
When a search system is displaying a search result, it might suggest other texts that may be of interest to the user (similar, for example).

Text Ranking as Input to Downstream Modules.
The output of text ranking may not be intended for direct user consumption, but may rather be meant to feed downstream components.



Semantic matching refers to techniques and attempts to address a variety of linguistic phenomena, including synonymy, paraphrase, term variation, and different expressions of similar intents, specifically in the context of information access [Li and Xu, 2014]

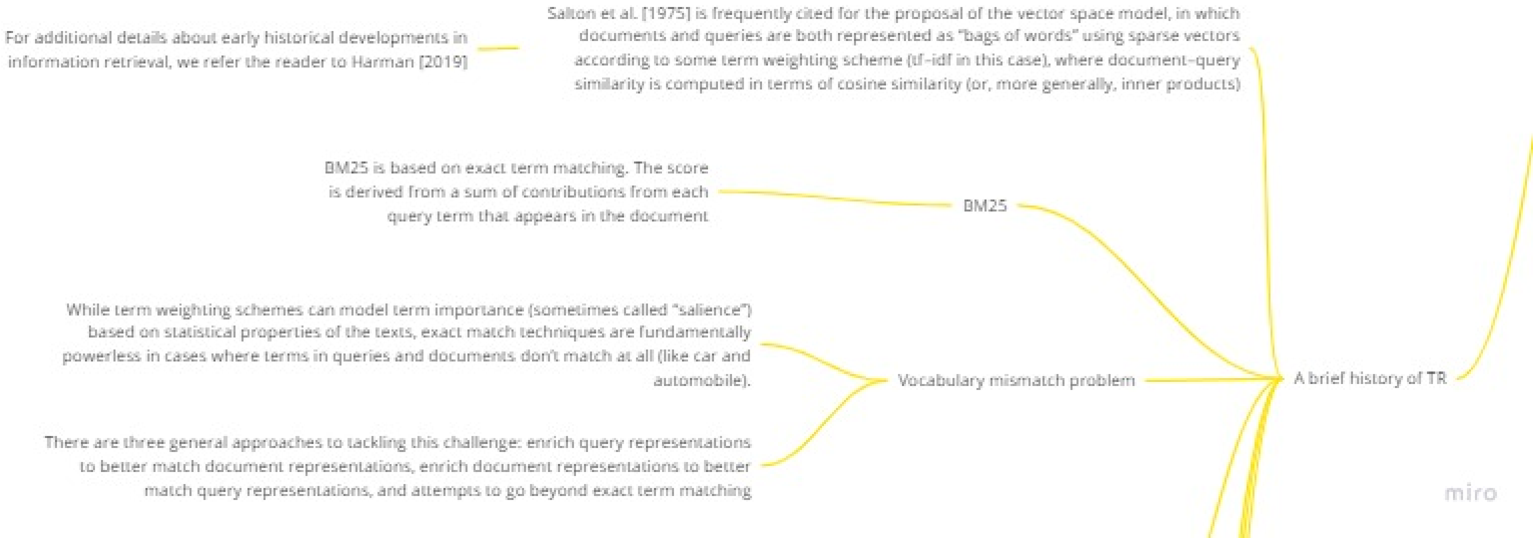
Relevance matching is generally understood to comprise both exact match and semantic match components

Tthere is one major difference: inputs to a model for computing semantic similarity are symmetric, i.e., Rel(s1,s2) = Rel(s2,s1), whereas queries and documents are obviously diferente and cannot be swapped as model inputs.

Semantic Similarity Comparisons

The question of whether two texts "mean the same thing" is a fundamental problem in NLP and closely related to the question of whether a text is relevant to a query. Researchers have explored similar approaches and have often even adopted the same models to tackle both problems.

A brief history of TR



A brief history of TR

Salton et al. [1975] is frequently cited for the proposal of the vector space model, in which documents and queries are both represented as "bags of words" using sparse vectors according to some term weighting scheme (tf-idf in this case), where document-query similarity is computed in terms of cosine similarity (or, more generally, inner products)

For additional details about early historical developments in information retrieval, we refer the reader to Harman [2019]

BM25

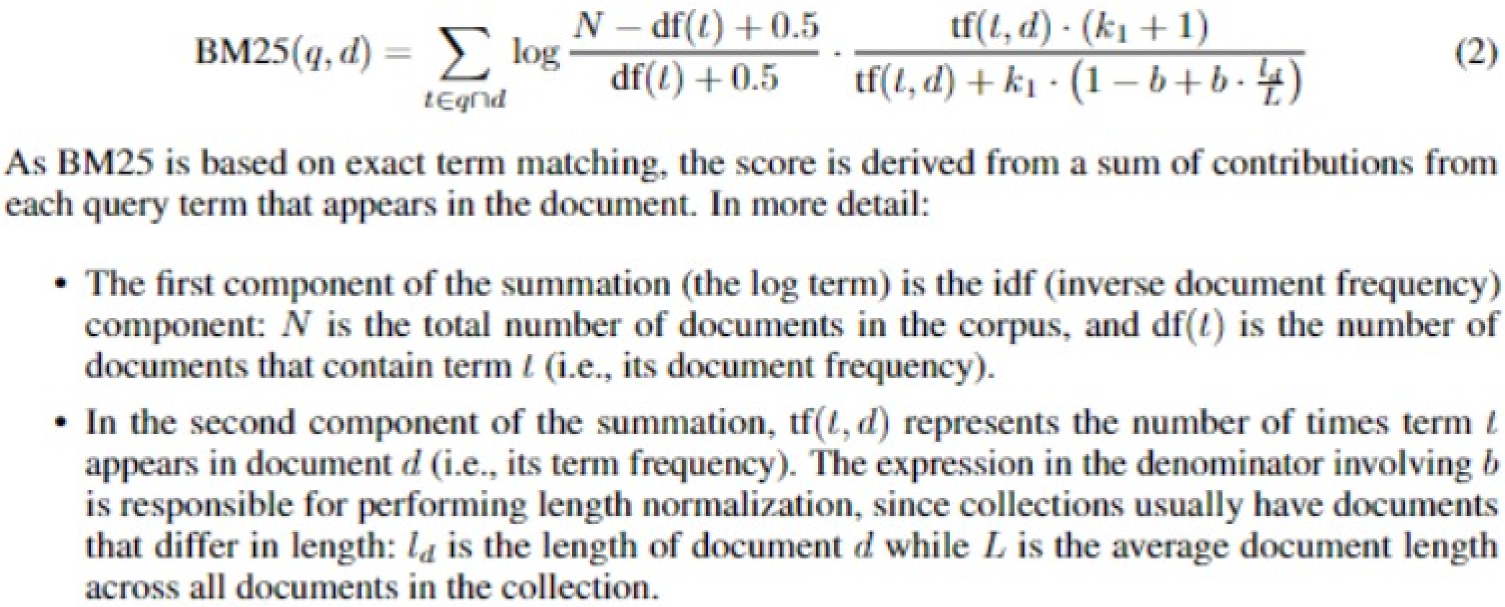
BM25 is based on exact term matching. The score is derived from a sum of contributions from each query term that appears in the document

Vocabulary mismatch problem

While term weighting schemes can model term importance (sometimes called "salience") based on statistical properties of the texts, exact match techniques are fundamentally powerless in cases where terms in queries and documents don't match at all (like car and automobile).

There are three general approaches to tackling this challenge: enrich query representations to better match document representations, enrich document representations to better match query representations, and attempts to go beyond exact term matching

BM25 formula



$$\mathrm{BM25}(q,d) = \sum_{t \in q \cap d} \log \frac{N - \mathrm{df}(t) + 0.5}{\mathrm{df}(t) + 0.5} \cdot \frac{\mathrm{tf}(t,d) \cdot (k_1 + 1)}{\mathrm{tf}(t,d) + k_1 \cdot \left(1 - b + b \cdot \frac{l_d}{L}\right)} \qquad (2)$$

As BM25 is based on exact term matching, the score is derived from a sum of contributions from each query term that appears in the document. In more detail:

- The first component of the summation (the log term) is the idf (inverse document frequency) component: N is the total number of documents in the corpus, and $\mathrm{df}(t)$ is the number of documents that contain term t (i.e., its document frequency).
- In the second component of the summation, $\mathrm{tf}(t,d)$ represents the number of times term t appears in document d (i.e., its term frequency). The expression in the denominator involving b is responsible for performing length normalization, since collections usually have documents that differ in length: l_d is the length of document d while L is the average document length across all documents in the collection.

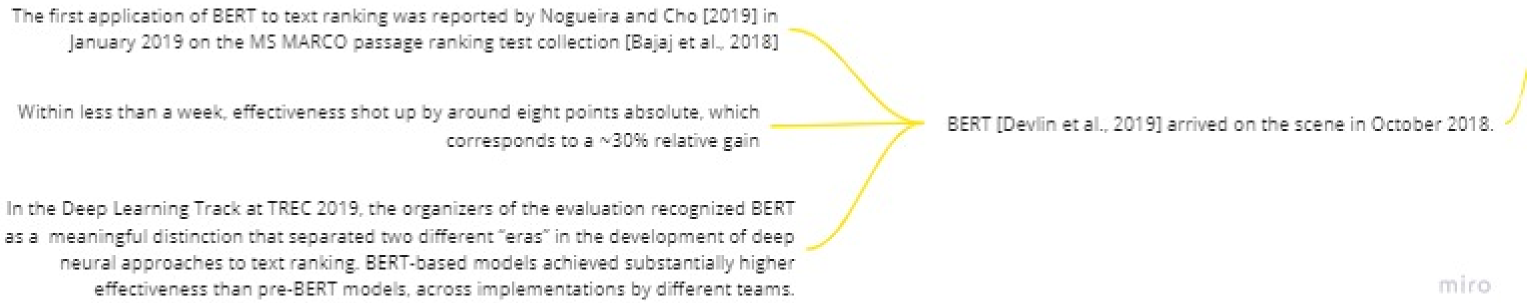
A provocative and historical question

Under this limited data condition, studies showed thet most of the neural ranking methods were unable to beat the keyword search baseline

With BERT, though, everything changed, nearly overnight, as many researchers quickly demonstrated that with pretrained transformer models, large amounts of relevance judgments were not necessary to build effective models for text ranking.

As approaches based on deep learning (before BERT) required large amounts of training data, Lin [2018] posed the provocative question, asking if neural ranking models were actually better than "traditional" keyword-matching techniques in the absence of vast quantities of training data?

Bert era - the correct answer

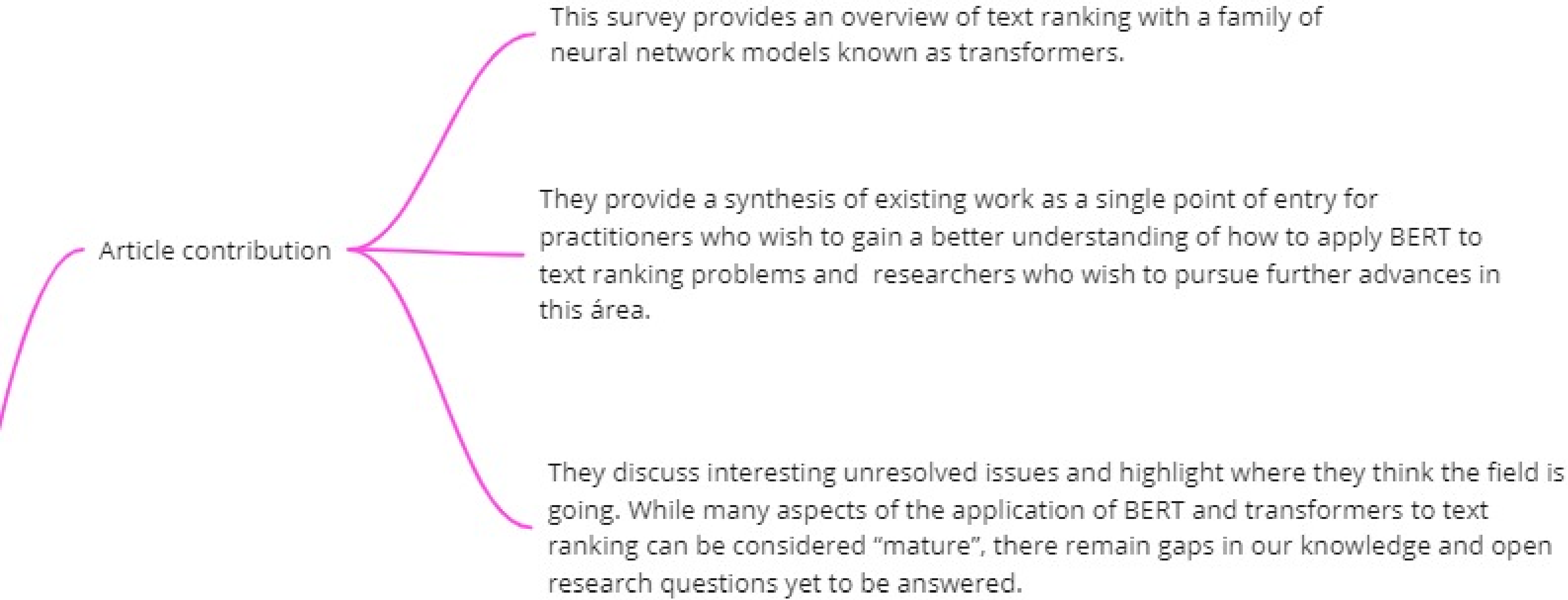


The first application of BERT to text ranking was reported by Nogueira and Cho [2019] in January 2019 on the MS MARCO passage ranking test collection [Bajaj et al., 2018]

Within less than a week, effectiveness shot up by around eight points absolute, which corresponds to a ~30% relative gain

In the Deep Learning Track at TREC 2019, the organizers of the evaluation recognized BERT as a meaningful distinction that separated two different "eras" in the development of deep neural approaches to text ranking. BERT-based models achieved substantially higher effectiveness than pre-BERT models, across implementations by different teams.

BERT [Devlin et al., 2019] arrived on the scene in October 2018.

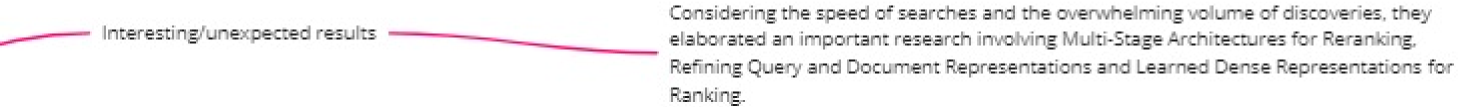


Article contribution

This survey provides an overview of text ranking with a family of neural network models known as transformers.

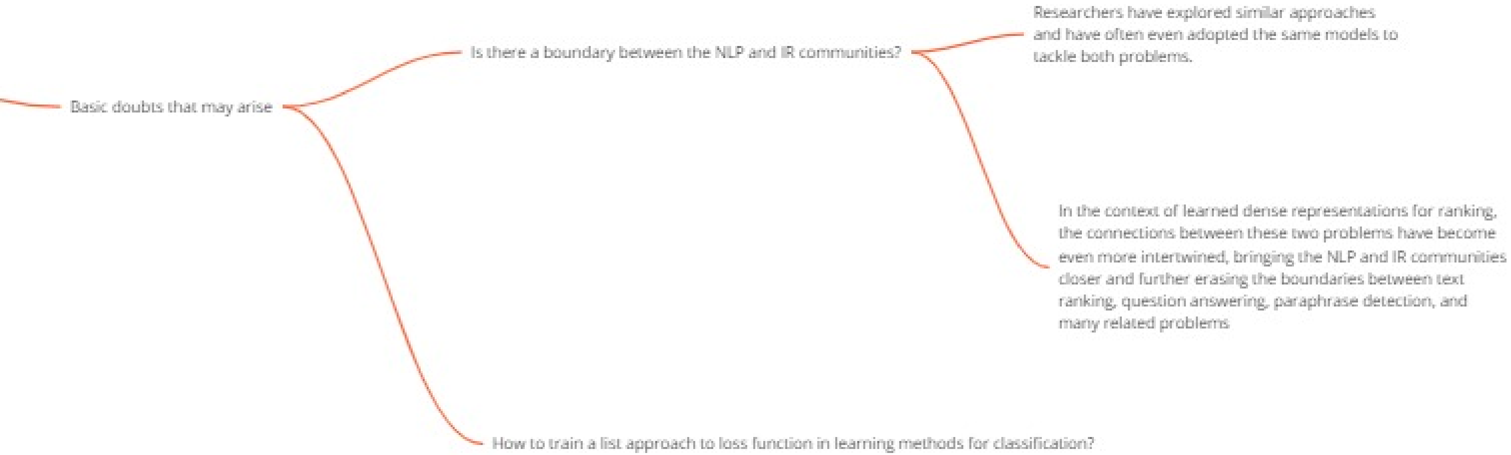
They provide a synthesis of existing work as a single point of entry for practitioners who wish to gain a better understanding of how to apply BERT to text ranking problems and researchers who wish to pursue further advances in this área.

They discuss interesting unresolved issues and highlight where they think the field is going. While many aspects of the application of BERT and transformers to text ranking can be considered “mature”, there remain gaps in our knowledge and open research questions yet to be answered.



Interesting/unexpected results

Considering the speed of searches and the overwhelming volume of discoveries, they elaborated an important research involving Multi-Stage Architectures for Reranking, Refining Query and Document Representations and Learned Dense Representations for Ranking.



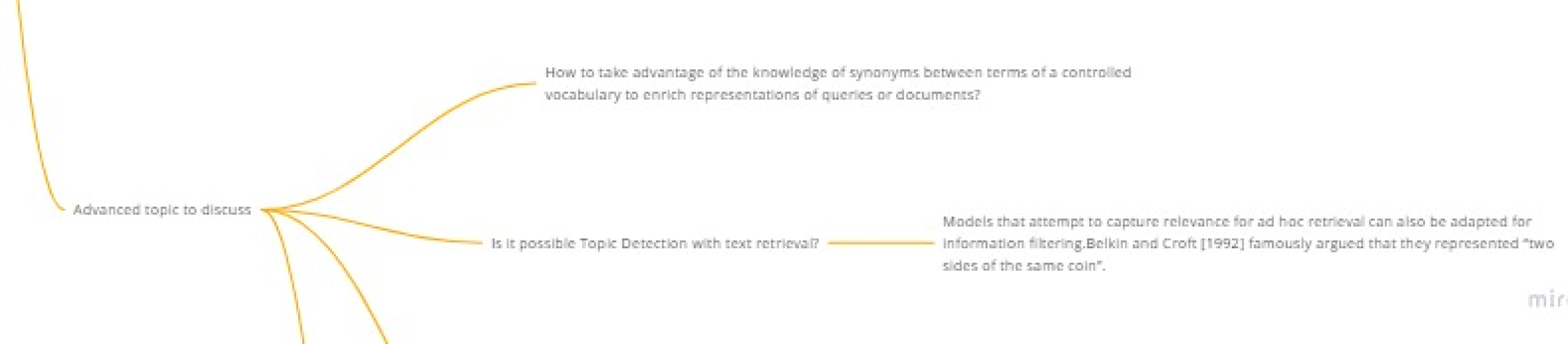
Basic doubts that may arise

Is there a boundary between the NLP and IR communities?

Researchers have explored similar approaches and have often even adopted the same models to tackle both problems.

In the context of learned dense representations for ranking, the connections between these two problems have become even more intertwined, bringing the NLP and IR communities closer and further erasing the boundaries between text ranking, question answering, paraphrase detection, and many related problems

How to train a list approach to loss function in learning methods for classification?



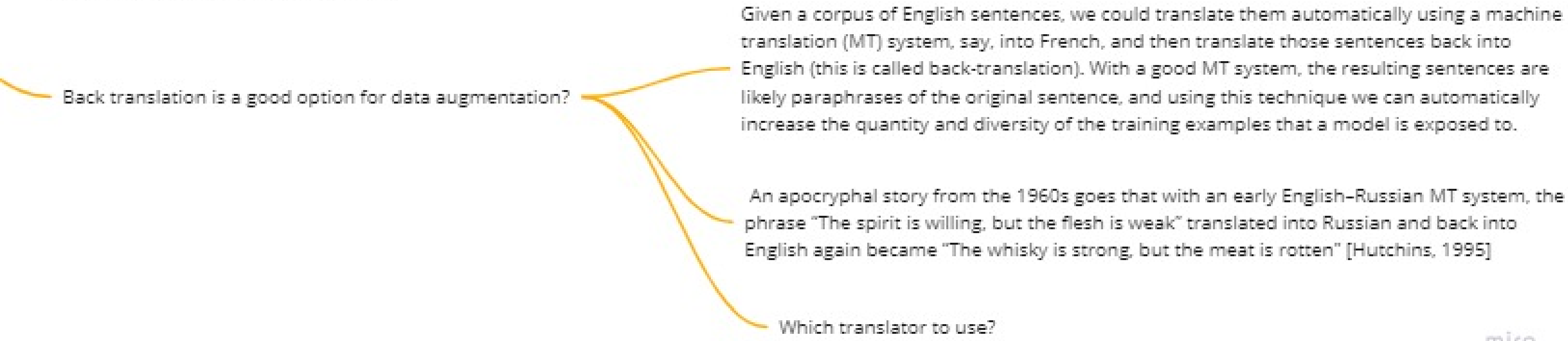
Advanced topic to discuss

How to take advantage of the knowledge of synonyms between terms of a controlled vocabulary to enrich representations of queries or documents?

Is it possible Topic Detection with text retrieval?

Models that attempt to capture relevance for ad hoc retrieval can also be adapted for information filtering.Belkin and Croft [1992] famously argued that they represented “two sides of the same coin”.

Advanced topic to discuss 3/4



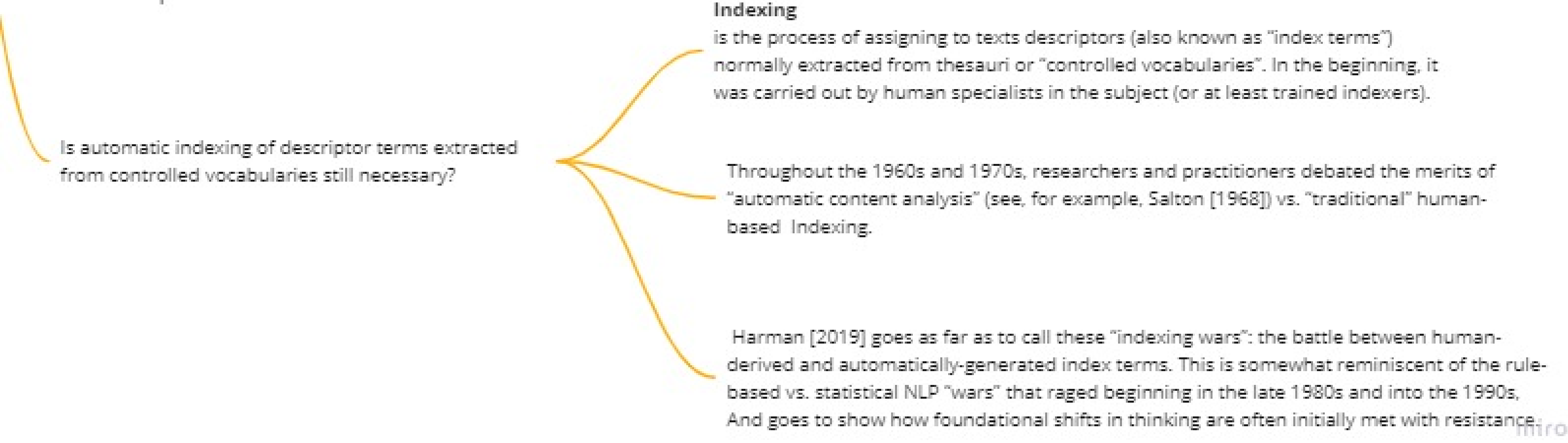
Back translation is a good option for data augmentation?

Given a corpus of English sentences, we could translate them automatically using a machine translation (MT) system, say, into French, and then translate those sentences back into English (this is called back-translation). With a good MT system, the resulting sentences are likely paraphrases of the original sentence, and using this technique we can automatically increase the quantity and diversity of the training examples that a model is exposed to.

An apocryphal story from the 1960s goes that with an early English–Russian MT system, the phrase "The spirit is willing, but the flesh is weak" translated into Russian and back into English again became "The whisky is strong, but the meat is rotten" [Hutchins, 1995]

Which translator to use?

Advanced topic to discuss 4/4



Is automatic indexing of descriptor terms extracted from controlled vocabularies still necessary?

Indexing
is the process of assigning to texts descriptors (also known as "index terms") normally extracted from thesauri or "controlled vocabularies". In the beginning, it was carried out by human specialists in the subject (or at least trained indexers).

Throughout the 1960s and 1970s, researchers and practitioners debated the merits of "automatic content analysis" (see, for example, Salton [1968]) vs. "traditional" human-based Indexing.

Harman [2019] goes as far as to call these "indexing wars": the battle between human-derived and automatically-generated index terms. This is somewhat reminiscent of the rule-based vs. statistical NLP "wars" that raged beginning in the late 1980s and into the 1990s, And goes to show how foundational shifts in thinking are often initially met with resistance.