Notes on Vector Retrieval

Compiled by D. Gueorguiev, 10/18/2025, following Sebastian Bruch’s *“Foundations of Vector Retrieval”*

# Introductory Notes

A diagram of a number

AI-generated content may be incorrect.Let us consider a text document in English. Strip the document of grammar and word order and we end up with *a set* of words a.k.a. “bag of words” (BoW).

Figure: Vector representation of a piece of text by adopting BoW approach: a text document, when stripped of grammar and word order, is represented by a vector where each coordinate represents a term in our vocabulary and its value records the frequency of that term or represent some function of the frequency. The resulting vectors are *sparse* – that is , they have few non-zero coordinates.

Transformer-based models ([5], [6]) brought about vector representations that beyond the elementary formation above. The resulting vector representation is referred to as an *embedding*, instead of a “feature vector”, though the underlying concept is the same – an object is encoded as a real -dimensional vector, a point in .

Question: how the embedding of a text document differs from its representation as a frequency-based feature vector?

In the lexical BoW representation if a coordinate is non-zero, that implies that the corresponding term is present in the document and its value indicates its frequence-based feature. In the embedding representation our embedding algorithm *learns* to turn coordinates on or off and when a coordinate is turned on , its value must predict the significance of the corresponding term based on semantics and contextual information. For example, the absent synonyms of a present term may get a non-zero value, and terms that offer little discriminative power in the given context become 0 or close to it.

This idea has been explored by many recent embedding models such as those discussed in [7], [8], [9], [10], [11], [12], [13], and [14].

Similarity in vector space must imply similarity between objects. So, as we engineer features to be extracted from an object or design a protocol to learn a model to produce embeddings of data, we must choose the dimensionality of the target space (a subset of ) along with a distance function . Together, these define an inner product of metric space.

Consider the lexical representation of a text document where d is the size of the English vocabulary

# References

[1] [Foundations of Vector Retrieval, S. Bruch, 2024](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/Foundations_of_Vector_Retrieval_Bruch_2024.pdf)

[2] [Distributed Representations of Words and Phrases and their Compositionality, Thomas Mikolov et al, Google, 2013](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/embeddings/Distributed_Representations_of_Words%20and_Phrases_and_their_Compositionality_Mikolov_2013.pdf)

[3] [Efficient Estimation of Word Representations in Vector Space, Thomas Mikolov et al, Google, 2013](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/embeddings/Efficient_Estimation_of_Word_Representations_in_Vector_Space_Mikolov_2013.pdf)

[4] [GloVe: Global Vectors for Word Representation, Jeffrey Pennington et al, 2014](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/embeddings/GloVe-Global_Vectors_for_Word_Representation_Pennington_2014.pdf)

[5] [Attention is all you need, Ashish Vaswani, Google Brain, 2017](https://github.com/dimitarpg13/transformers_intro/blob/main/articles_and_books/Attention-is-all-you-need-NIPS-2017.pdf)

[6] [BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, Jacob Devlin et al, 2019](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/embeddings/BERT-Pre-training_of_Deep_Bidirectional_Transformers_for_Language_Understanding_Devlin_2019.pdf)

[7] [Sparterm: Learning term-based sparse representation for fast text retrieval, Y. Bai et al, 2020](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/SparTerm-Learning_Term-based_Sparse_Representation_for_Fast_Text_Retrieval_Bai_2020.pdf)

[8] [Splade: Sparse lexical and expansion model for first stage ranking, T. Formal et al, 2021](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/Splade-Sparse_lexical_and_expansion_model_for_first_stage_ranking_Formal_2021.pdf)

[9] [Fast Passage Re-ranking with Contextualized Exact Term Matching and Efficient Passage Expansion, S. Zhuang et al, 2021](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/Fast_Passage_Re-ranking_with_Contextualized_Exact_Term_Matching_and_Efficient_Passage_Expansion_Zhuang_2021.pdf)

[10] [Context-aware term weighting for first stage retrieval, Z. Dai et al, 2020](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/Context-Aware_Passage_Term_Weighting_For_First_Stage_Retrieval_sigir20-Zhuyun_Dai.pdf)

[11] [COIL: Revisit Exact Lexical Match in Information Retrieval with Contextualized Inverted List, L. Gao et al, CMU, 2021](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/COIL-revisit_exact_lexical_match_in_information_retrieval_with_contextualized_inverted_list_Gao_2021.pdf)

[12] [Learning Passage Impacts for Inverted Indexes, A. Mallia et al, NYU, 2021](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/Learning_Passage_Impacts_for_Inverted_Indexes_Mallia_2021.pdf)

[13] [From Neural Re-Ranking to Neural Ranking: Learning a Sparse Representation for Inverted Indexing, H. Zamani et al, U Mass Amherst, 2018](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/From_Neural_Re-Ranking_to_Neural_Ranking-Learning_a_Sparse_Representation_for_Inverted_Indexing_Zamani_UMassAmherst_2018.pdf)

[14] [A Few Brief Notes on DeepImpact, COIL, and a Conceptual Framework for Information Retrieval Techniques, J. Lin et al, 2021](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/A_Few_Brief_Notes_on_DeepImpact_COIL_and_a_Conceptual_Framework_for_Information_Retrieval_Techniques_Lin_2021.pdf)

[15] ["King - man + woman = queen" is fake news, Mike Cohen's substack blog, Oct 12, 2025](https://mikexcohen.substack.com/p/king-man-woman-queen-is-fake-news)

[] [Approximate Nearest Neighbors: Towards Removing the Curse of Dimensionality, Piotr Indyk et al, Stanford, 1998](https://github.com/dimitarpg13/vector_db_intro/blob/main/articles/Approximate_Nearest_Neighbors-Towards_Removing_the_Curse_of_Dimensionality_Indyk_1998)

[]

# Appendix

## Notes on SparTerm model for Learning Term-based Sparse Representation for Fast Text Retrieval

Text retrieval in response to natural language query is a core task for information retrieval systems. A popular approach to this problem adopts a two-stage pipeline where as a first stage an initial set of documents is retrieved from the document collection by a fast retriever, and then further re-ranked by more suitable re-ranker models.

The paper proposing SparTerm model and related algorithm is [7].

Question: Can we transfer the deep knowledge of the pretrained language model (PLM) to **Term**-based **Spa**rse representations, aiming to improve the representation capacity of BoW while keeping its advantages?

The proposed SparTerm comprises an importance predictor to predict the importance for each term in the vocabulary, and a gating controller to control the term activation. These two modules cooperatively ensure the sparsity and flexibility of the final text representation, which unifies the term-weighting and expansion in the same framework.