

A Practical Approach for Few Shot Learning with SetFit for Scaling Up Search and Relevance Ranking on a Large Text Database



About me



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CEO of N2VEC

PhD in Artificial Intelligence (NLP)

+17 Years of experience in R&D

+ 8 Years of working experience in NLP

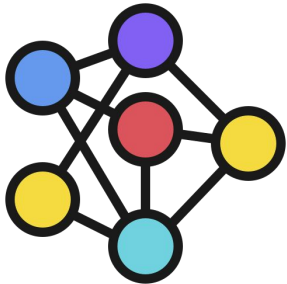


Find the information you need from the company documents with **[n2vec]**

About N2VEC



We developed a Search API for Documents or knowledge database



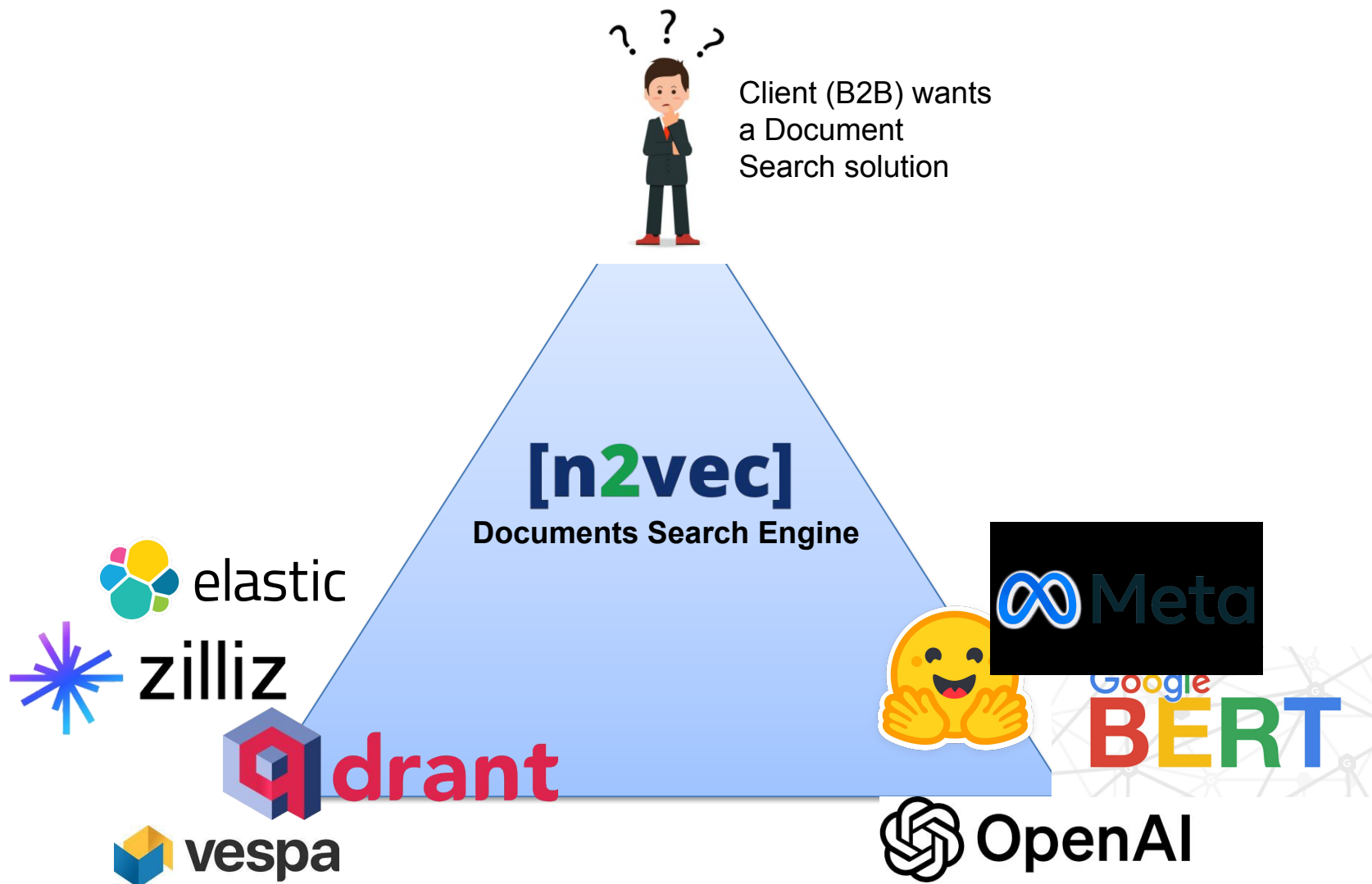
Our API uses Vector Databases and BERT for searching and ranking



We are based near São Paulo, Brazil

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N2VEC in the ecosystem



Find the information you need from the company documents with **[n2vec]**

The Problem



Handling data with few labels...



SetFit



Few-shot Fine tuning of Sentence Transformers



Competitive results compared to GPT and others



Light and fast to train (you can train in your laptop)



Multilingual support

SetFit

Efficient Few-Shot Learning Without Prompts

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Abstract

Recent few-shot methods, such as parameter-efficient fine-tuning (PEFT) and pattern exploiting training (PET), have achieved impressive results in label-scarce settings. However, they are difficult to employ since they are subject to high variability from manually crafted prompts, and typically require billion-parameter language models to achieve high accuracy. To address these shortcomings, we propose SETFIT (Sentence Transformer Fine-tuning), an efficient and prompt-free framework for few-shot fine-tuning of Sentence Transformers (ST). SETFIT works by first fine-tuning a pretrained ST on a small number of

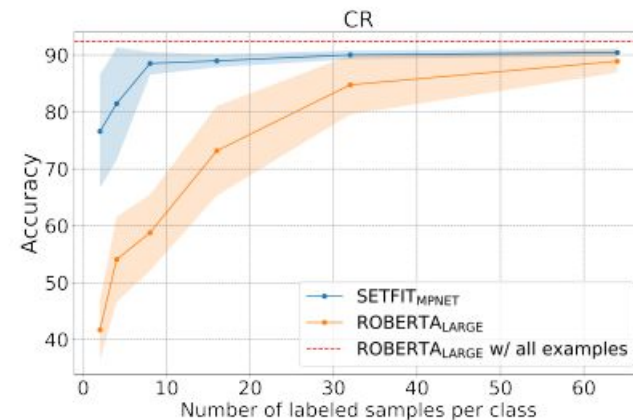
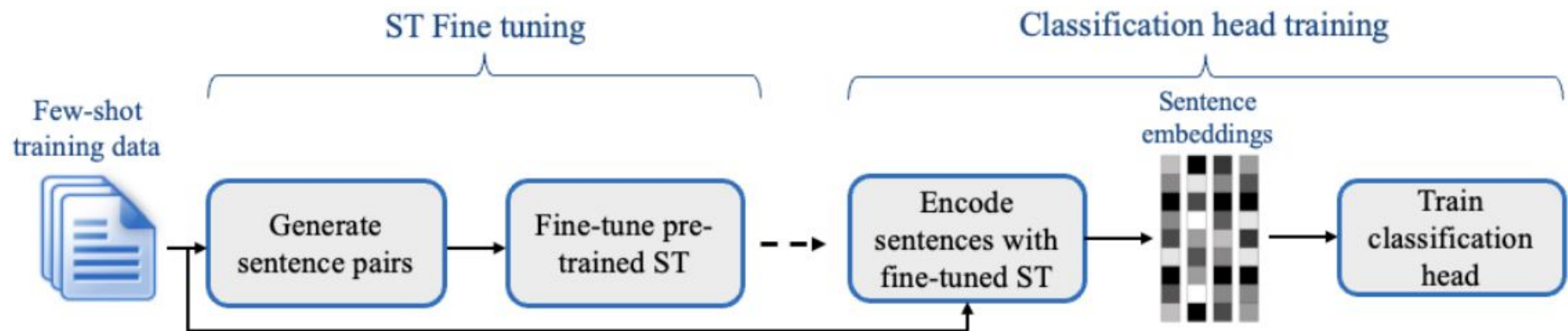


Figure 1: Compared to standard fine-tuning, SETFIT is more sample efficient and exhibits less variability when trained on a small number of labeled examples.

SetFit for Classification problems



SetFit Fine tuning and training blocks (extracted from the original article)



SetFit – Generate Sentence pairs

Original data

X	y
[0.1, 0.2, 0.3]	A
[0.4, 0.5, 0.6]	B
[0.1, 0.3, 0.3]	A
[0.1, 0.5, 0.6]	A
[0.4, 0.4, 0.6]	C

Positive triplets

X1	X2	Y
[0.1, 0.2, 0.3]	[0.1, 0.3, 0.3]	1
[0.1, 0.3, 0.3]	[0.1, 0.5, 0.6]	1

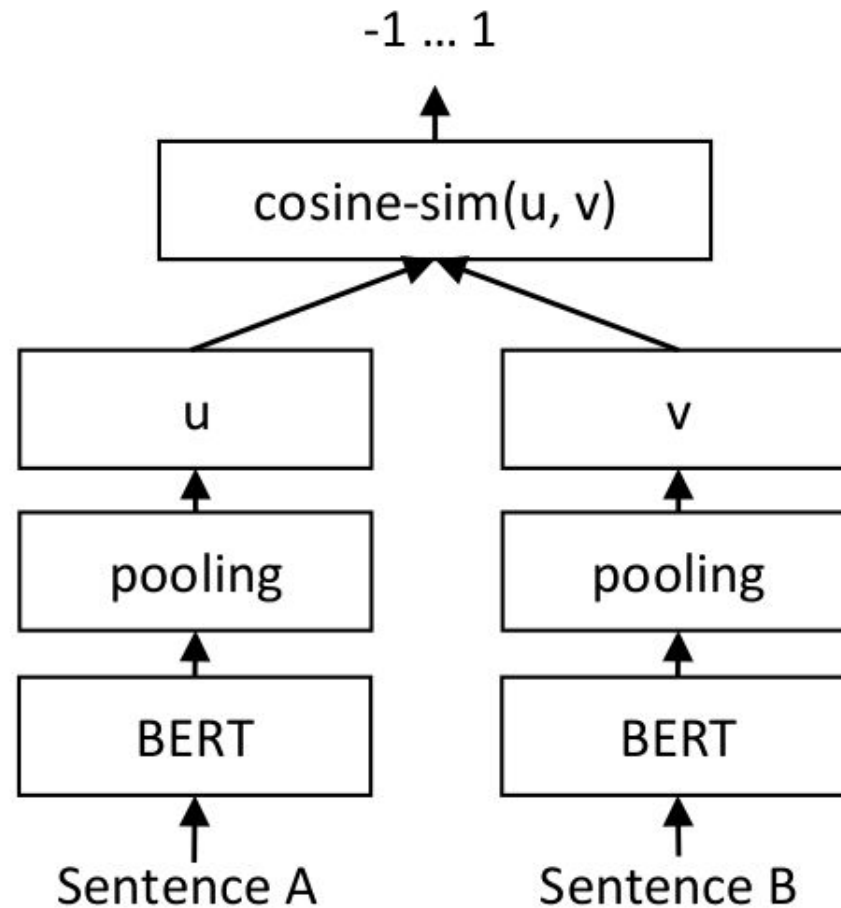
Negative triplets

X1	X2	Y
[0.1, 0.2, 0.3]	[0.4, 0.4, 0.6]	0
[0.1, 0.3, 0.3]	[0.4, 0.5, 0.6]	0

Total: $K(K-1) / 2$



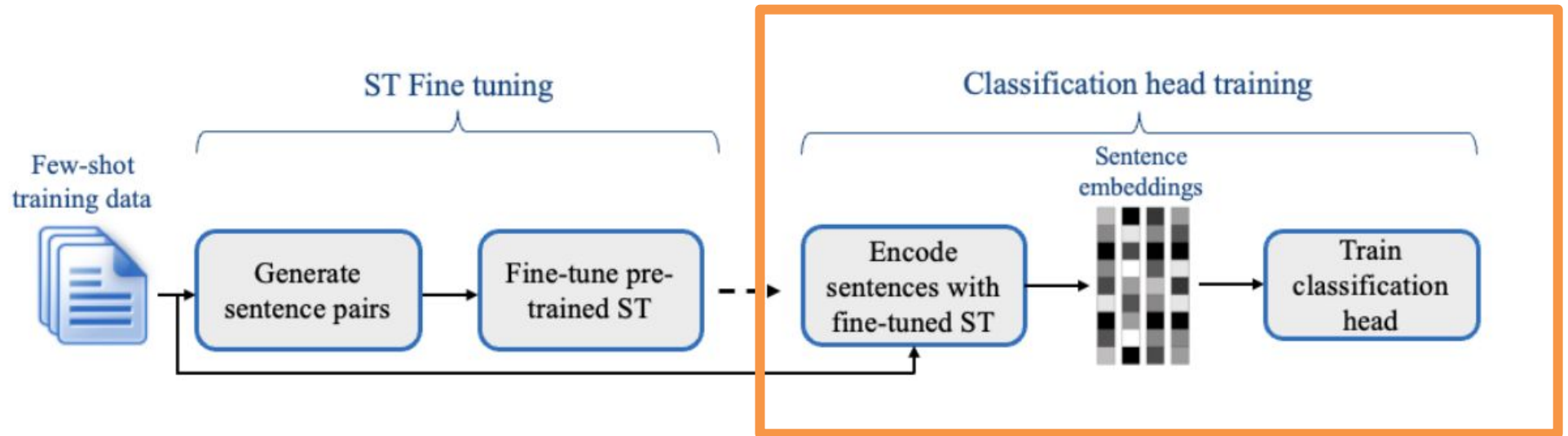
SetFit – Sentence Transformers



Reference: <https://www.sbert.net/docs/training/overview.html>



SetFit for Classification Problems



SetFit Fine tuning and training blocks (extracted from the original article)



SetFit - results

Method	SST-5	AmazonCF	CR	Emotion	EnronSpam	AGNews	Average [†]
$ N = 8^*$							
FINETUNE	33.5 _{2.1}	9.2 _{4.9}	58.8 _{6.3}	28.7 _{6.8}	85.0 _{6.0}	81.7 _{3.8}	43.0 _{5.2}
PERFECT	34.9 _{3.1}	18.1 _{5.3}	81.5 _{8.6}	29.8 _{5.7}	79.3 _{7.4}	80.8 _{5.0}	48.7 _{6.0}
ADAPET	50.0 _{1.9}	19.4 _{7.3}	91.0 _{1.3}	46.2 _{3.7}	85.1 _{3.7}	85.1 _{2.7}	58.3 _{3.6}
T-FEW 3B	55.0 _{1.4}	19.0 _{3.9}	92.1 _{1.0}	57.4 _{1.8}	93.1 _{1.6}	–	63.4 _{1.9}
SETFIT _{MPNET}	43.6 _{3.0}	40.3 _{11.8}	88.5 _{1.9}	48.8 _{4.5}	90.1 _{3.4}	82.9 _{2.8}	62.3 _{4.9}
$ N = 64^*$							
FINETUNE	45.9 _{6.9}	52.8 _{12.1}	88.9 _{1.9}	65.0 _{17.2}	95.9 _{0.8}	88.4 _{0.9}	69.7 _{7.8}
PERFECT	49.1 _{0.7}	65.1 _{5.2}	92.2 _{0.5}	61.7 _{2.7}	95.4 _{1.1}	89.0 _{0.3}	72.7 _{1.9}
ADAPET	54.1 _{0.8}	54.1 _{6.4}	92.6 _{0.7}	72.0 _{2.2}	96.0 _{0.9}	88.0 _{0.6}	73.8 _{2.2}
T-FEW 3B	56.0 _{0.6}	34.7 _{4.5}	93.1 _{1.0}	70.9 _{1.1}	97.0 _{0.3}	–	70.3 _{1.5}
SETFIT _{MPNET}	51.9 _{0.6}	61.9 _{2.9}	90.4 _{0.6}	76.2 _{1.3}	96.1 _{0.8}	88.0 _{0.7}	75.3 _{1.3}
$ N = Full^{**}$							
FINETUNE	59.8	80.1	92.4	92.6	99.0	93.8	84.8

Table 2: SETFIT performance score and standard deviation compared to the baselines across 6 test datasets for three training set sizes $|N|$. *Number of training samples per class. **Entire available training data used. †The AGNews dataset is excluded from the average score to enable fair comparison with T-FEW (which has AGNews in its training set). *The inputs of SST-5 (but not its labels) appeared in T-FEW’s training set, as part of Rotten Tomatoes dataset.

Rank	Method	Score	Size*
1	YIWISE	76.8	-
2	T-FEW 11B	75.8	11B
4	Human baseline	73.5	-
6	SETFIT _{ROBERTA}	71.3	355M
9	PET	69.6	235M
11	SETFIT _{MPNET}	66.9	110M
12	GPT-3	62.7	175B

Table 3: SETFIT compared to prominent methods on the RAFT leaderboard (as of Sept. 5, 2022). *Number of parameters.

Tables extracted from the original article

Could SetFit be Applied for Search Relevance?



Legal Research



Good precedents more chances to WIN!!!



Find the information you need from the company documents with **[n2vec]**

Legal Research



65% of lawyers spend most of their **TIME** doing **Legal Research**



75% of lawyers say **Legal Research** is the **HARDEST** task



Find the information you need from the company documents with **[n2vec]**

Our Legal Research Database



+ 60 million sentences extracted from legal decisions

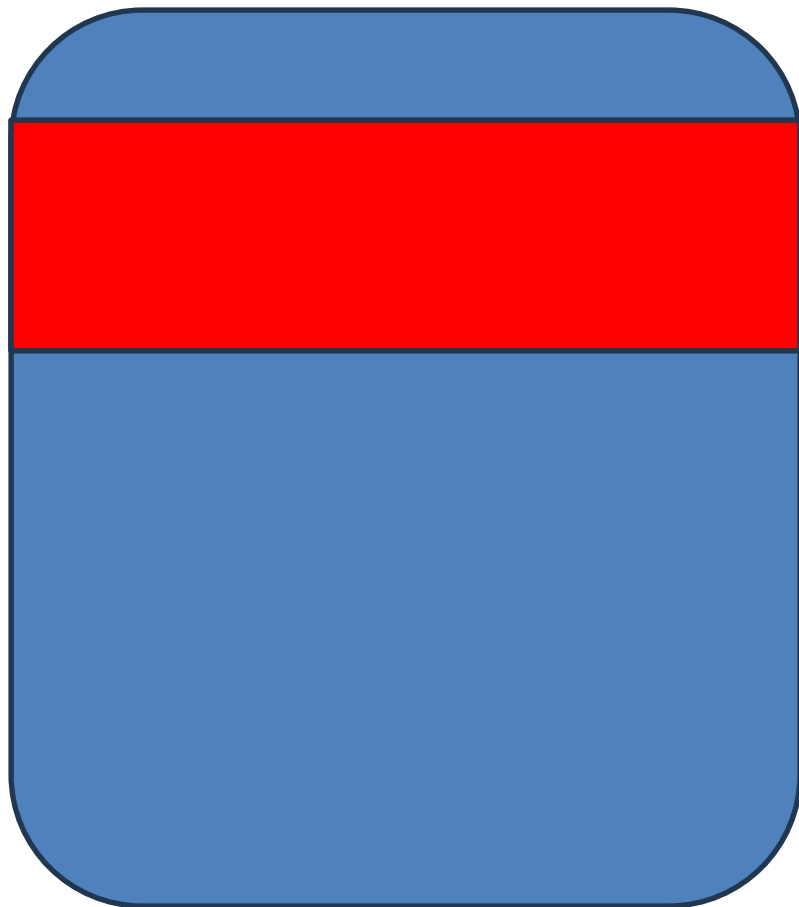


Precedents from 8 courts in Brazil



+ 7,800 results annotated by lawyers

First Step: Using SetFit for sentences Classification



A fraction of the dataset was labeled according to the theme (i.e. “traffic accident”, “consumer rights”, “health”)

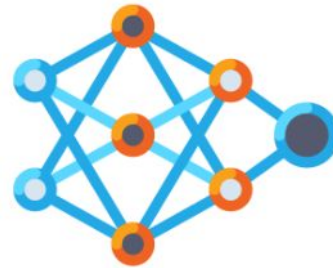
But too many classes with few labels each... (9K split in 138 classes)



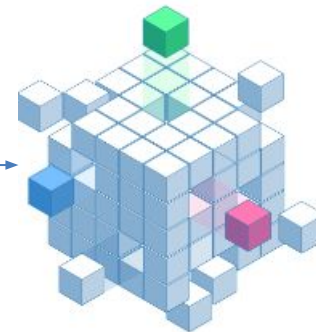
First Step: Using SetFit for sentences Classification

X1	X2	Y
[0.1, 0.2, 0.3]	[0.1, 0.3, 0.3]	1
[0.1, 0.3, 0.3]	[0.1, 0.5, 0.6]	1

X1	X2	Y
[0.1, 0.2, 0.3]	[0.4, 0.4, 0.6]	0
[0.1, 0.3, 0.3]	[0.4, 0.5, 0.6]	0



Fine tune
Sentence
Transformer

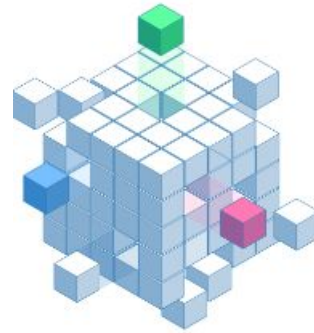


Fine-tuned
ST



Classifier

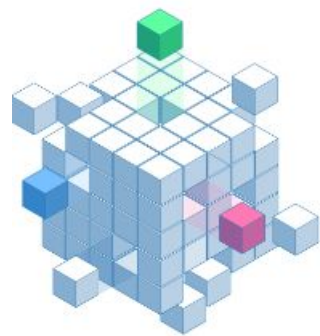
First Step: Using SetFit for sentences Classification



Fine-tuned
ST



Second Step: Fine tuning with queries/results

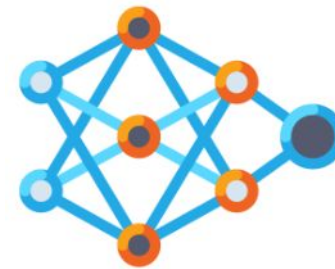


Fine-tuned ST

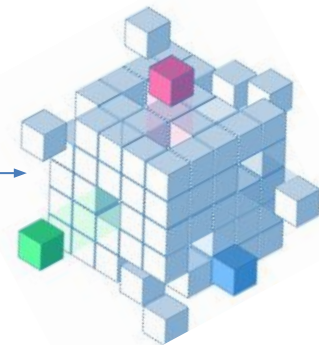
X1	X2	Y
[0.1, 0.2, 0.3]	[0.1, 0.3, 0.3]	1
[0.1, 0.3, 0.3]	[0.1, 0.5, 0.6]	1

X1	X2	Y
[0.1, 0.2, 0.3]	[0.4, 0.4, 0.6]	0
[0.1, 0.3, 0.3]	[0.4, 0.5, 0.6]	0

Annotated triplets augmented by negative triplets



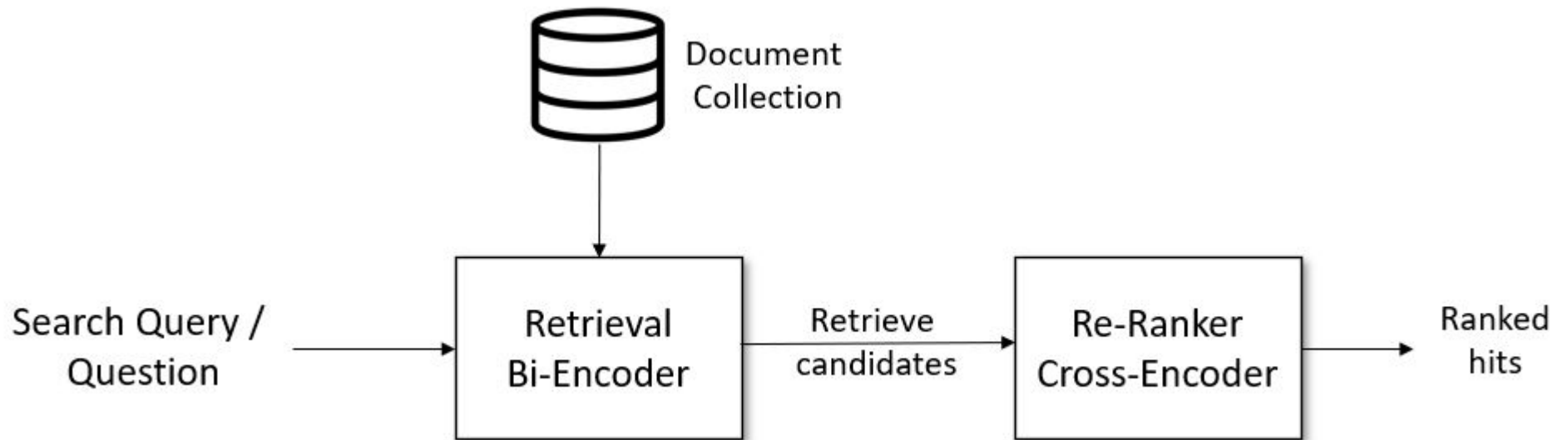
Fine tune Sentence Transformer



2nd Fine-tuned ST



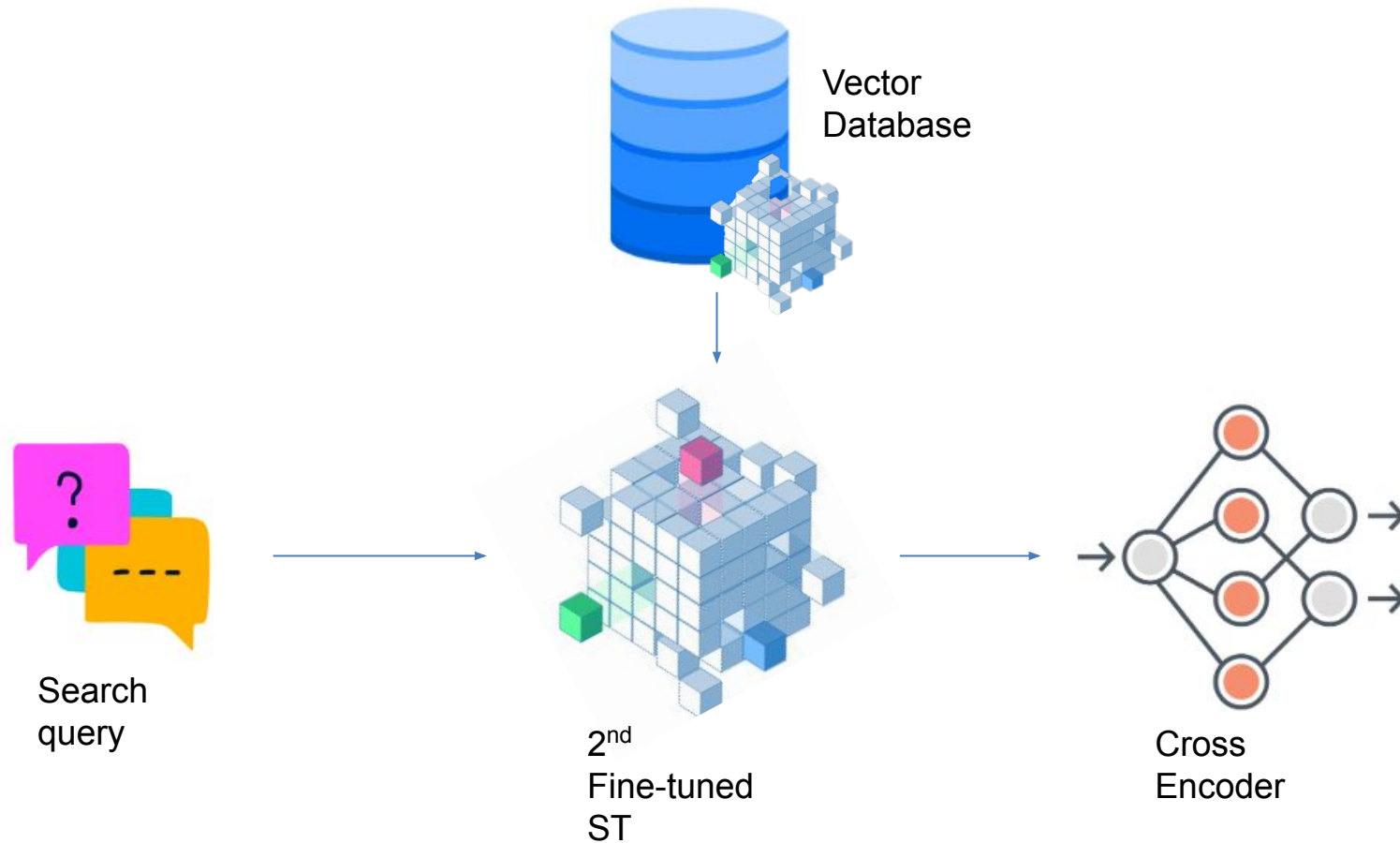
Third Step: Implement Search and Ranking



Reference: <https://www.sbert.net/examples/applications/information-retrieval/README.html>



Third Step: Implement Search and Ranking



Results

ST + Cross Encoder

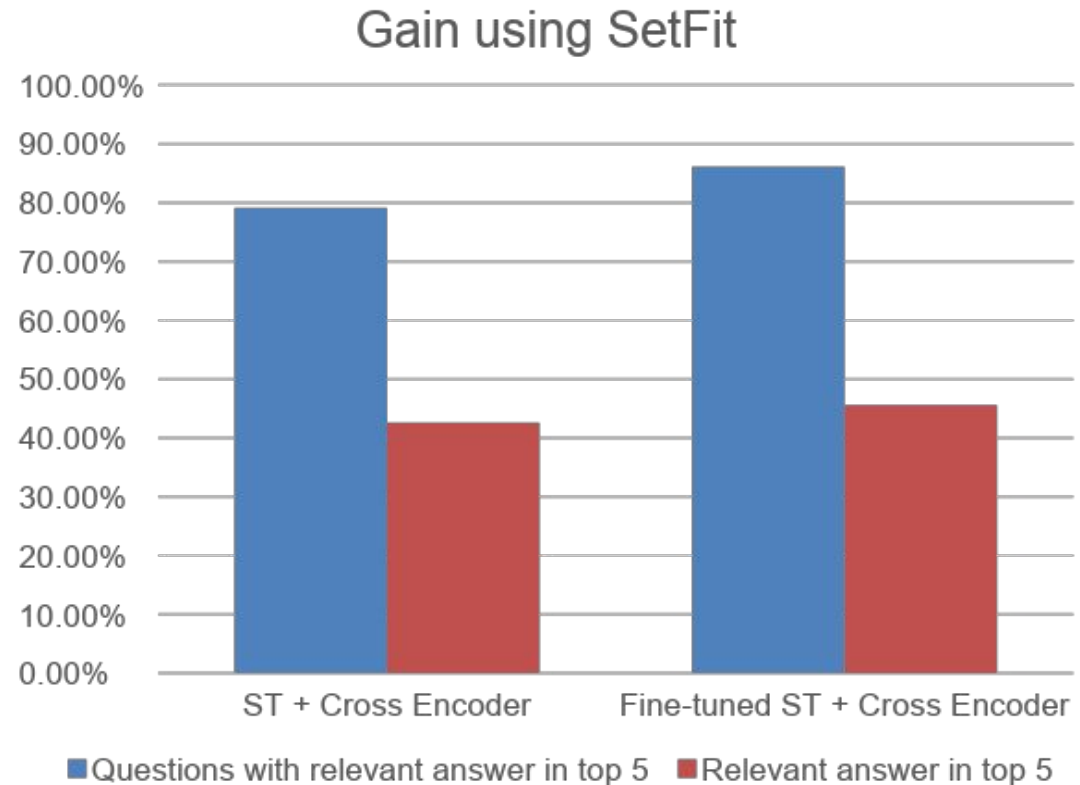
79.1% of questions with relevant answers in top 5

42.6% of relevant answers in top 5

Fine-tuned ST + CrossEncoder

86.1% of questions with relevant answers in top 5

45.6% of relevant answers in top 5



Acknowledgement



N2VEC Team:



Pedro Kim
Machine Learning
Engineer



Gustavo Sarti
Machine Learning
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Yara Campos
Data Engineer



Alfonso Guerra
Python SW Engineer



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