

TSAH DU: Charter & Law Open Source Expert System, Vector Representation of Meaning for Judicial Searches

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ABSTRACT

Non weaponizable research the sort of Law and Market requires caution and broadcasting easy to use interfaces. Market for us is being still stabilized for a broad and stable theoretical common fortune of all participants. Effective and broad access to Law however is described in this paper; To be distributed and used without cost: <https://github.com/savethebeesandseeds/tsahdu>

1. Introduction

The natural exercise of caution that comes with intelligence advice those who do advanced Mathematics an assertive guide not to risk a weaponizable tool. Laws sort a encyclopedic strength, this prerogative aims to reduce the barrier of knowledge and reduce the price of legal advice, this tool on perpetuity free and with open access. The method serves to consult the state of Law and the state of Jurisprudence, given a Text describing a situation; Tsahdu is a modern search engine dedicated to Law. Implementation is limited to the Severn Constitution and all the Severn Codes of Conduct of the Republic of Colombia.

2. Mathematical Background

Used basis are, real numbers: \mathbb{R} , integers: \mathbb{Z} . To represent a phrases in Human language: \mathbb{W} . And a reference in a document of Law: \mathbb{Q} . Here a scalar v is specified to be real if $\mathbb{R}v$ and a p -dimensional real vector is defined as: $\mathbb{R}^p V$. Multiple vectors are grouped like Tensors, m grouped vectors is defined as $\mathbb{R}^p V^m$. Reference to a *document of Law* discriminates n individual Articles $\mathbb{W}\mathcal{A}^n$.

Following a static transformation $\phi(\cdot)$ each article is represented by a dense vector:


$$\phi(\mathbb{W}\mathcal{A}^n) = \mathbb{R}^d V^n. \quad (1)$$


Where \mathbf{V} is known as Embedding (in common transformation models $d = 384$), $\mathbb{W}\mathcal{A}$ are Article Paragraphs of varying length up to $s = 512$ words long, n is a positive integer $^+\mathbb{Z}$ specifying the article index.

Considering any paragraph or phrase is transformed into a dense vector $\{\mathcal{A}^n \rightarrow \mathbf{V}^n\}$, a document of Law is understood as a dense Matrix $\mathbb{R}^n \times \mathbb{R}^d \mathbf{M}$ of size $n \times d$. Any article larger than $s = 512$ words is fragmented and averaged in vector space.

The aforementioned transformation to vector space $\phi(\cdot)$ is done using Natural Language Transformers Models¹, on what is known as a Sentence Transformer². Whereby two sentences are alike if their vector representation is alike.

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¹<https://huggingface.co/>

²<https://huggingface.co/sentence-transformers/>

3. An Expert System for the Law

Search engines can be very complex, mixing multiple searching methods; this expert system uses only the comparison in vector space.

A citizen needing advice of Law will query a description paragraph $\mathbb{W}\mathcal{U}$, the expert system will consider the query transformation $\phi(\mathbb{W}\mathcal{U})$ and compare it against the matrix of Law \mathbf{M} . Rows most similar with the user query are returned as a reference of Law, note that every row in \mathbf{M} has associated a specific reference of Law \mathbb{Q} , e.g. article number n in chapter q , title u and document z , this is $\mathbb{Q} : \langle z, u, q, n \rangle$.

Regex expressions are used to separate Articles, discriminate references. There is generally one Constitution and many Laws compiled in documents known as Codes. Robots automates the downloading and updating of those .pdf documents, further automation extracts the text content of the document and generates regular .txt files; Finally using regular Expressions (regex) the full text is separated into individual articles with their associated reference. This has been proven very stable for Colombian Law.

4. An Expert System for Jurisprudence

These are Court sentences and resolutions, serves an enormous advantage to the exercise of a Judge and required to provide a proper trial.

Defining a reference to a sentence of a Court dictum on *Jurisprudence* searches requires the same vector approach $\phi(\cdot)$ but a different indexing of phrases, as the division by articles is only found in documents of Law. To generalize the technique across different type of documents, the role of n is changed to the role of ρ . Where ρ is a positive integer $^+\mathbb{Z}$ know as the document extension count, it varies from document to document as different documents has different sizes — for example, $\rho = 100$ implies a document was fragmented into 100 phrases. Creating, for every document a matrix $\mathbb{R}^{\rho \times \mathbb{R}^d} \mathbf{M}$.

5. Considerations of Implementation

Law recommendation is a sensible topic, an online open service requires an explicit caution note specifying a check statement: "this is not a professional advice of law".

The colossal body of Jurisprudence and the monumental size of Law, require computational efficiency of implementation a high performance programming language is recommended. Robotic Web Process Automation is probably required to scrap and update Web documents. Transformers Networks are downloaded pretrained for the idiom or matching tongue, further fine tuning is recommended.

The sensibility of the topic involve require the Transformer Network be trained properly, on a mistake in a case of Law the developers intend to show good faith by maximizing likelihood.

.pdf documents are better stored as .txt files, not every .pdf document has a straightforward way to transform into a .txt, sometimes software known as optical character recognition is required.

6. Vector Representation of a Phrase

Law is very well written, but natural language is not precise; The challenge for English is the same challenge for Spanish, they have not a straightforward analytical representation $f(\cdot) : \mathbb{W} \rightarrow \mathbb{R}^x$. Best I know how is Deep Learning Transformers $\phi(\cdot) : \mathbb{W} \rightarrow \mathbb{R}^d$, as a way to formulate Text (\mathbb{W}) as a precise numeric abstraction (\mathbb{R}).

A high goal for the sciences of language is to construct and agree on an analytical transformation of idioms to vectors, an orthogonal language would serve Humanity with great progress, but it is proven to be very hard, justice is mixed with poetry and without extensive context science seems like fantasy.

Until a transformation is discovered and accord on, best we can do is to use Deep Neural Networks, generally known as Text Input Transformers Neural Architecture; Where a specific Layer inside the Deep model is

used to represent the Input Phrase as a Vector of embedding.

For English Language: *all-MiniLM-L12-v2*³ with a vector size $d = 384$.

For Spanish Language: *sentence_similarity_spanish_es*⁴ with a vector size $d = 768$.

There are Transformers for other languages; English Model performs better than Spanish. With a sufficient corpus of Law one can fine train these Models to better perform.

7. Stable Embedding

These are some marginal operations to better represent the embedding vector: $\mathbb{R}^d \mathbf{V}$. It be useful for the vector to be normalized, two types of normalization are consider:

$$\mu_1 - \text{normalization} := \mathbb{R}^d \mathbf{V} = \frac{1}{\mathbb{R}\mu_1} \cdot \mathbb{R}^d \mathbf{V}, \quad \text{where : } \mathbb{R}\mu_1 = \sum_{i=1}^d \mathbb{R} \mathbf{V}_i \quad (2)$$

$$\mu_2 - \text{normalization} := \mathbb{R}^d \mathbf{V} = \frac{1}{\mathbb{R}\mu_2} \cdot \mathbb{R}^d \mathbf{V}, \quad \text{where : } \mathbb{R}\mu_2 = \sum_{i=1}^d \text{abs}(\mathbb{R} \mathbf{V}_i) \quad (3)$$

$$\mu_3 - \text{normalization} := \mathbb{R}^d \mathbf{V} = \frac{1}{\mathbb{R}\mu_3} \cdot \mathbb{R}^d \mathbf{V}, \quad \text{where : } \mathbb{R}\mu_3 = \sqrt{\sum_{i=1}^d (\mathbb{R} \mathbf{V}_i)^2} \quad (4)$$

Where (\cdot) is the element-wise multiplication.

From now on, unless otherwise mention assume \mathbf{V} and all the rows in \mathbf{M} are $\mu_3 - \text{normalized}$, this is the standard way to normalize a vector.

8. Average vector

A policy for dealing with long phrases is superposition of rolling overlapping windows of phrase segments averaged in vector space. The superposition of multiple (m) vectors outputs a vector:

$$\mathbb{R}^d \text{Avg}(\mathbf{V}^m) = \frac{1}{m} \cdot \sum_{i=1}^m \mathbb{R}^d \mathbf{V}^{(i)} \quad (5)$$

Where (\cdot) is the element-wise multiplication, and Σ sums vectors.

In Law, Articles are grouped in Chapters, Chapters are grouped in Titles and all Titles make a Document. It is useful to know the average vector of an entire Chapter ($\mathbb{W}\mathcal{C}$), Title ($\mathbb{W}\mathcal{T}$) or Document ($\mathbb{W}\mathcal{D}$), and for long Articles also ($\mathbb{W}\mathcal{A}$). —the vector of it's member phrases average, and so on,

$$\begin{aligned} \mathbb{R}^d \phi(\mathbb{W}\mathcal{A}^n) &= \text{Avg}(\mathbf{V}^m), \quad \forall m \in \mathcal{A}^n, & \text{average vector over all phrases in the } n\text{th-article} \\ \mathbb{R}^d \phi(\mathbb{W}\mathcal{C}^q) &= \text{Avg}(\mathbf{V}^m), \quad \forall m \in \mathcal{C}^q, & \text{average vector over all phrases in the } q\text{th-chapter} \\ \mathbb{R}^d \phi(\mathbb{W}\mathcal{T}^u) &= \text{Avg}(\mathbf{V}^m), \quad \forall m \in \mathcal{T}^u, & \text{average vector over all phrases in the } u\text{th-title} \\ \mathbb{R}^d \phi(\mathbb{W}\mathcal{D}) &= \text{Avg}(\mathbf{V}^m), \quad \forall m. & \text{average vector over all phrases in the document} \end{aligned} \quad (6)$$

Those are meant to be simple formulas, but imply some considerations; let me explain by a simple example: Imagine a window size of $s = 2$ words and overlapping of size $g = 1$, the user inputs this phrase:

\mathbb{W} "Dogs chase Cats" $\rightarrow [\mathbb{W}$ "Dogs chase", \mathbb{W} "chase Cats"] = $[\mathbb{R}^d [2.0, 3.0, 1.0, \dots], \mathbb{R}^d [4.0, 5.0, 6.0, \dots]]$,

³<https://huggingface.co/sentence-transformers/all-MiniLM-L12-v2>

⁴https://huggingface.co/hiiamsid/sentence_similarity_spanish_es

\mathbb{W} "Dogs chase Cats" = \mathbb{R}^d [3.0, 4.0, 3.5, ...]

Since the phrase was too long, the overlapping window policy segmented the input phrase into two partial phrases. The result is the average vector, consider to think the embedding for the word in the middle \mathbb{W} "chase" was considered two times, this is not ideal.

If $s = 2$ and there is no overlap considered $g = 0$, contextual information might be broken:
 \mathbb{W} "Dogs chase Cats" \rightarrow [\mathbb{W} "Dogs chase", \mathbb{W} "Cats"] = [\mathbb{R}^d [2.0, 3.0, 1.0, ...], \mathbb{R}^d [1.0, 0.5, 9.0, ...]],
 \mathbb{W} "Dogs chase Cats" = \mathbb{R}^d [1.5, 1.75, 5.0, ...]

The two approaches yield different average vectors, this trade-off is hard to come-by.
 Values of $s = 512$ and $g = 64$, seem to work fine.

9. Dense Vectors Comparison

Be sure any vector \mathbf{V} is normalized in it self: $\mathbf{V} = \|\mathbf{V}^*\|^{-1} \cdot \mathbf{V}^*$ so that, $\sum_{j=1}^d V_j = 1$.
 Comparing two vectors, vector ($\mathbb{R}^d \mathbf{V}_a = a$) and ($\mathbb{R}^d \mathbf{V}_b = b$), these are some simple comparison formulas:

$$\begin{aligned}
 \text{Minkowski :} & \quad \left(\sum_{j=1}^d (a_j - b_j)^p \right)^{1/p} \\
 \text{Cosine :} & \quad \frac{\sum_{j=1}^d a_j \cdot b_j}{\sqrt{\sum_{j=1}^d (a_j)^2} \cdot \sqrt{\sum_{j=1}^d (b_j)^2}} \\
 \text{Dot - Product :} & \quad \sum_{j=1}^d a_j \cdot b_j
 \end{aligned} \tag{7}$$

Where $\mathbb{R}^d a_j$ and $\mathbb{R}^d b_j$ are the scalar components in the j index of the vectors $\mathbb{R}^d \mathbf{V}_a$ and $\mathbb{R}^d \mathbf{V}_b$ respectably. For Dot-Product and Cosine, the higher the value the better, for Minkowski the lower the value the better. Euclidean distance, arise from Minkowski where $p = 2$. However, the size for the dense vector is very high $d = 384$, the overall information from the upmost relevant dimensions might be opaqued given the vector size, to illustrate this let's view in the Figure 1 below:

About dense high dimensional vector comparison one might go beyond simple analytical formulas; to train a machine learning comparison schema, derive Principal Component Analysis or Relevance Vector Machines to reduce the d -dimensional of the vectors. Or describe optimization procedures, label or in anyway train a Model to compare vectors. For now the Euclidean distance suffice, on these sensible topics efforts rather help to construct analytical solutions, as it is hard to argue the validity of a solution involving deep compositional function approximations, like Neural Networks.

To end the section, let me be simple about it; if every Article is transform into a Vector and a corpus of Law is a Matrix. A user input is transformed and compared against the matrix of Law \mathbf{M} , returning the references of Law corresponding to the rows indices with the lower distance.

10. Entropy, Information of the Vector Space

In this framework, Entropy of a Text Fragment is the Entropy of a Layer in a Natural Language Transformer Neural Network. This is to say, Entropy of a Text is for this framework the Entropy of the Embedding Vector.

Entropy might be in units of [Shannon] (or [bits]) if \log_2 is used, or in units of [nats] if \log_e . Let's use the [Shannon] terminology to share respect. Vector Space Entropy usefulness insights about the information of

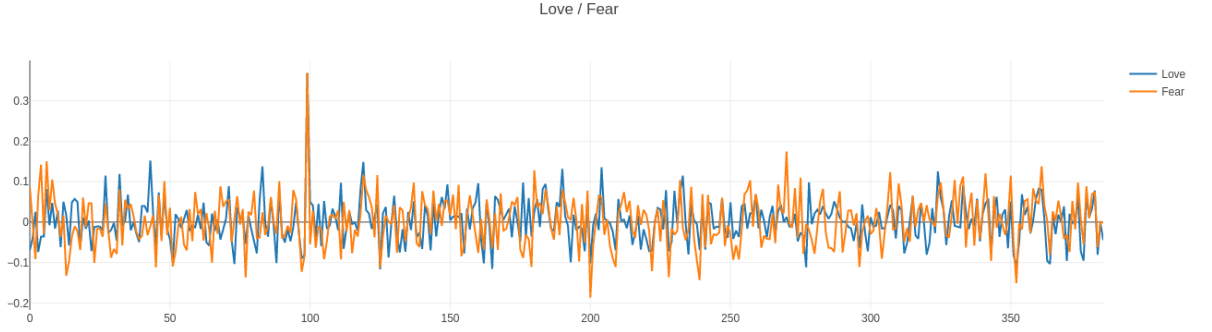


Figure 1: Embedding Vectors for the words **Love** and **Fear**, To be notice index 99 might be a flag for the Human emotion component. The numeric comparison yields are: Minkowski(p=1): 0.13416162, Minkowski(p=2): 1.0309231, Minkowski(p=3): 0.21693337, Minkowski(p=5): 0.19361636, Cosine: 0.4685991 [rad]. Dot-Product: 0.4685991. These two ideas are as expected fairly different, as the vectors are μ_3 – *normalized* the maximum possible distance using Minkowski(p=2) is 2.0.

a given fragment of Text depends on the method used to train the Transformer Network. Experiments for the used Transformer yield **not determinant results**.

A way to calculate Entropy of a Phrase in Vector Space is shown, requires three steps:

Calculate the Absolute Value for all the dimensions in the vector:

$$\mathbb{R}^d \mathbf{V}_j^* = \text{abs}(\mathbb{R}^d \mathbf{V}_j) \quad (8)$$

This way the Vector Space resembles a Discrete Distribution, and the Entropy or the Embedding uncertainty is:

$$\mathbb{R} \mathbf{H}_V = (-1) \cdot \sum_{j=1}^d \mathbf{V}_j^* * \log_2(\mathbf{V}_j^*) \quad [Shannon] \quad (9)$$

11. Documents, Titles, Chapters and Articles

There is an Average Vector for every Document, for every Title, Chapter and every Article.

12. Robotic Process Automation

13. Results

Implemented in Rustc Language for the Colombian Constitution and for all the Colombian Laws in the Republic (count 2359 as of 10/2022), a server to provide free access was mounted and hosted locally, using a Spanish Language Transformer `sentence_similarity_spanish_es` with a maximum phrase size of $s = 512$ words and overlapping of 64 Words, yielded the following example results:

14. Conclusions and outlook

The server is functional and mounted for the Colombian Law, Jurisprudence searches resulted too extensive to be solved and hosted on a home machine.

15. Acknowledgments

References