LANGUAGE RECOGNITION USING RANDOM INDEXING

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ABSTRACT
Random Indexing is a simple implementation of Random Projections with a wide range of applications. It can solve a variety of problems with good accuracy without introducing much complexity. Here we demonstrate its use for identifying the language of text samples, based on a novel method of encoding letter n-grams into high-dimensional Language Vectors. Further, we show that the method is easily implemented and requires little computational power and space. As proof of the method’s statistical validity, we show its success in a language-recognition task. On a difficult data set of 21,000 short sentences from 21 different languages, we achieve 97.8% accuracy, comparable to state-of-the-art methods.

1 INTRODUCTION
As humans who communicate through language, we have the fascinating ability to recognize unknown languages in spoken or written form, using simple cues to distinguish one language from another. Some unfamiliar languages, of course, might sound very similar, especially if they come from the same language family, but we are often able to identify the language in question with very high accuracy. This is because embedded within each language are certain features that clearly distinguish one from another, whether it be accent, rhythm, or pitch patterns. The same can be said for written languages, as they all have features that are unique. Recognizing the language of a given text is the first step in all sorts of language processing, such as text analysis, categorization, translation and much more.

As popularized by Shannon (1948), most language models use distributional statistics to explain structural similarities in various specified languages. The traditional method of identifying languages consists of counting individual letters, letter bigrams, trigrams, tetragrams, etc., and comparing the frequency profiles of different text samples. As a general principle, the more accurate you want your detection method to be, the more data you have to store about the various languages. For example, Google’s recently open-sourced program called Chromium Compact Language Detector uses large language profiles built from enormous corpora of data. As a result, the accuracy of their detection, as seen through large-scale testing and in practice, is near perfect (McCandless (2011)).

High-dimensional vector models are popular in natural-language processing and are used to capture word meaning from word-use statistics. The vectors are called semantic vectors or context vectors.
Ideally, words with a similar meaning are represented by semantic vectors that are close to each other in the vector space, while dissimilar meanings are represented by semantic vectors far from each other. Latent Semantic Analysis is a well-known model that is explained in detail in Landauer & Dumais [1997]. It produces 300-dimensional (more or less) semantic vectors from a singular value decomposition (SVD) of a matrix of word frequencies in a large collection of documents.

An alternative to SVD, based on Random Projections, was proposed by Papadimitriou et al. and Kaski [1998]. Random Indexing (Kanerva et al. [2000]; Sahlgren [2005]) is a simple and effective implementation of the idea. It has been used in ways similar to Mikolov et al.’s Continuous Bag-of-Words Model (KBOW; Mikolov & Dean [2013]) and has features similar to Locality-Sensitive Hashing (LSH) but differs from them in its use of high dimensionality and randomness. With the dimensionality in the thousands (e.g., \( D = 10,000 \))—referred to as “hyperdimensional”—it is possible to calculate useful representations in a single pass over the dataset with very little computing.

In this paper, we will present a way of doing language detection using Random Indexing, which is fast, highly scalable, and space efficient. We will also present some results regarding the accuracy of the method, even though this will not be the main goal of this paper and should be investigated further.

2 RANDOM INDEXING

Random Indexing stores information by projecting data onto vectors in a hyperdimensional space. There exist a huge number of different, nearly orthogonal vectors in such a space (Kanerva [1988], p. 19). This lets us combine two such vectors into a new vector using well-defined vector-space operations, while keeping the information of the two with high probability. In our implementation of Random Indexing, we use a variant of the MAP (Multiply, Add, Permute) coding described in Levy & Gayler (2009) to define the hyperdimensional vector space. Vectors are initially taken from a \( D \)-dimensional space (with \( D = 10,000 \)) and have an equal number of randomly placed 1s and \(-1\)s. Such vectors are used to represent the basic elements of the system, which in our case are the 26 letters of the alphabet and the (ASCII) Space. These vectors for letters are sometimes referred to as their Random Labels.

The binary operations on such vectors are defined as follows. Elementwise addition of two vectors \( A \) and \( B \), is denoted by \( A + B \). Similar, elementwise multiplication is denoted by \( A \ast B \). A vector \( A \) will be its own multiplicative inverse, \( A \ast A = I \), where \( I \) is the \( D \)-dimensional identity vector consisting of only 1s. Cosine angles are used to measure the similarity of two vectors. It is defined as \( \cos(A, B) = |A' \ast B'| \), where \( A' \) and \( B' \) are the normalized vectors of \( A \) and \( B \), respectively, and \(|C|\) denotes the sum of the elements in \( C \).

Information from a pair of vectors \( A \) and \( B \) is stored and utilized in a single vector by exploiting the summation operation. That is, the sum of two separate vectors naturally preserves unique information from each vector because of the mathematical properties of the hyperdimensional space. To see this, note that \( \cos(A, A) = 1 \), while for all \( B \neq A \), \( \cos(A, B) < 1 \). The cosine of two random, unrelated vectors tend to be close to 0. Because of this, the vector \( B \) can easily be found in the vector \( A + B \): \( \cos(B, A + B) \) differs significantly from 0.

For storing sequences of vectors, we use a random (but fixed throughout all our computations) permutation operation \( \rho \) of the vector coordinates. Hence, the sequence A-B-C, is stored as the vector \( (\rho((\rho A) \ast B)) \ast C = \rho P A \ast \rho B \ast C \). This efficiently distinguishes the sequence A-B-C from, say, A-C-B. This can be seen from looking at their cosine (here \( c \) is the normalization factor):

\[
\begin{align*}
V_1 &= \rho P A \ast \rho B \ast C \\
V_2 &= \rho P A \ast \rho C \ast B \\
\Rightarrow \cos(V_1, V_2) &= c \cdot |(\rho P A \ast \rho B \ast C) \ast (\rho P A \ast \rho C \ast B)| \\
&= c \cdot |\rho P A \ast \rho P A \ast \rho B \ast \rho P C \ast C \ast B| \\
&= c \cdot |\rho P (A \ast A) \ast (B \ast C) \ast (B \ast C)| \\
&\approx c \cdot (0)
\end{align*}
\]

since a random permutation \( \rho V_1 \) of a random vector \( V_1 \) is uncorrelated to \( V_2 \).
2.1 Making and Comparing of Text Vectors

We use the properties of hyperdimensional vectors to extract certain properties of text into a single vector. Kanerva (2014) shows how Random Indexing can be used for representing the contexts in which a word appears in a text, into that word’s context vector. We show here how to use a similar strategy for recognizing a text’s language by creating and comparing Text Vectors: the Text Vector of an unknown text sample is compared for similarity to precomputed Text Vectors of known language samples—the latter are referred to as Language Vectors.

Simple language recognition can be done by comparing letter frequencies of a given text to known letter frequencies of languages. Given enough text, a text’s letter distribution will approach the letter distribution of the language in which the text was written. The phenomenon is called an “ergodic” process in Shannon (1948), as borrowed from similar ideas in physics and thermodynamics. This can be generalized to using letter blocks of different sizes. By a block of size \( n \), we mean \( n \) consecutive letters in the text so that a text of length \( m \) would have \( m - n + 3 \) blocks. When the letters are taken in the order in which they appear in the text, they are referred to as sequences (of length \( n \)) or as \( n \)-grams.

As an example, the text “a brook” gives rise to the tetragrams “–a–b”, “a–br”, “–bro”, “broo”, “rook”, and “ook–” (here “–” stands for Space). The frequencies of such letter blocks can be found for a text and compared to known frequencies for different languages. For texts in languages using the Latin alphabet of 26 letters (plus Space), like English, this would lead to keeping track of \( 27^4 = 531,441 \) different tetragram frequencies. For arbitrary alphabets of \( l \) letters, there would be \((l + 1)^n\) \( n \)-grams to keep track of. These numbers grow quickly as the block size \( n \) increases.

The Random Indexing approach for doing language recognition is similar. A text’s Text Vector is first calculated by running over all the blocks of size \( n \) within the text and creating an \( n \)-Gram Vector for each. An \( n \)-Gram Vector is created for the sequence of letters as described earlier. As an example, if we encounter the block “grab”, its vector is calculated by performing \( ppG + ppR + pA + B \), where \( G \), \( R \), \( A \) and \( B \) are the Random Labels for \( g \), \( r \), \( a \), and \( b \)—they are random \( D \)-dimensional vector with half 1s and half -1s and they remain constant.

A text’s Text Vector is now obtained from summing the \( n \)-Gram Vectors for all the blocks in the text. This is still an \( D \)-dimensional vector and can be stored efficiently. Language Vectors are made in exactly the same way, by making Text Vectors from samples of a known language and adding them into a single vector. Determining the language of an unknown text is done by comparing its Text Vector to all the Language Vectors. More precisely, the cosine angle measure \( d_{\cos} \) between a language vector \( X \) and an unknown text vector \( V \) is defined as follows:

\[
d_{\cos}(X, V) = \frac{X \cdot V}{|X||V|} = \frac{\sum_{i=1}^{D} x_i v_i}{\sqrt{\sum_{j=1}^{D} x_j^2 \sum_{k=1}^{D} v_k^2}}
\]

If the cosine angle is high (close to 1), the block frequencies of the text are similar to the block frequencies of that language and thus, the text is likely to be written in the same language. Hence, the language that yields the highest cosine is chosen as the system’s prediction/guess.

2.2 Complexity

The outlined algorithm for Text Vector generation can be implemented efficiently. For generating a vector for an \( n \)-gram, \( n - 1 \) vector additions and permutations are performed. This takes time \( O(n \cdot D) \). Looping over a text of \( m \) letters, \( O(m) \) \( n \)-Gram Vectors must be created and added together. This clearly implies an \( O(n \cdot D \cdot m) \) implementation. This can be improved to \( O(D \cdot m) \) by noting that most of the information needed for creating the \( n \)-Gram Vector for the next block is already contained in the previous \( n \)-Gram Vector, and can be retrieved by removing the contribution from the letter that is now no longer in the block.

Say we have the \( n \)-Gram Vector \( A = \rho^{(n-1)} V_1 \ast \rho^{(n-2)} V_2 \ast \ldots \ast \rho V_{n-1} \ast V_n \) for block number \( i \), and now want to find the \( n \)-Gram Vector \( B \) for block \( i + 1 \). We remove from \( A \) the vector \( \rho^{(n)} V_1 \) by multiplying with its inverse (which is the vector itself), which we can do in \( O(D) \) time since \( \rho^{(n-1)} \) is just another (pre-calculated) permutation. Then we permute the result once using \( \rho \) and multiply
that with the Letter Vector $V_{n+1}$ for the new letter in the block. This gives us the new $n$-Gram Vector

$$B = \rho(\rho^{(n-1)}V_1 \ast A) \ast V_{n+1}$$
$$= \rho(\rho^{(n-2)}V_2 \ast \ldots \ast \rho V_{n-1} \ast V_n) \ast V_{n+1}$$
$$= \rho^{(n-1)}V_2 \ast \ldots \ast \rho^{(2)}V_{n-1} \ast \rho V_n \ast V_{n+1}$$

and so we can create $n$-Gram Vectors for arbitrary size blocks without adding complexity. In practice it means that the text is processed in a single pass at about a 100,000 letters a second on a laptop computer.

3 Experimental Results

The algorithm outlined above was implemented by Joshi & Halseth (2014), and used to create Language Vectors for 23 languages. Texts for the Language Vectors were taken from Project Gutenberg (Hart) where it is available in a number of languages, and from the Wortschatz Corpora (Quastoff et al. (2006)) where large numbers of sentences in selected languages can be easily downloaded. Each Language Vector was based on about 100,000 bytes of text. Computing of the Language Vectors corresponds to training the system and took about 1 second per language on a laptop computer.

Intuitively, Language Vectors within a language family should be closer to each other than vectors for unrelated languages. Indeed, the hyperdimensional Language Vectors roughly cluster in this manner, as seen in Figure 1.

To get an idea of how well the actual detection algorithm works, we tested the Language Vectors’ ability to identify text samples from the Europarl Parallel Corpus, described in Nakatani. This corpus includes 21 languages with 1,000 samples of each, and each sample is a single sentence.

Table 1 shows the result for $n$-gram sizes from 1 to 5 ($n = 1$ is the equivalent of comparing letter histograms). With tetragrams we were able to guess the correct language with 97.8% accuracy. Even when incorrect, the system usually chose a language from the same family, as seen from Table 2.

It is worth noting that 10,000-dimensional Language Vectors are keeping track of 531,441 possible tetragrams and easily accommodate pentagrams and beyond if needed. The method should be explored further, as explained in the Future Work section.
Table 1: Percentage of sentences correctly identified as a function of \( n \)-gram size.

| \( n \) | Detection success |
|-------|------------------|
| 1     | 74.9             |
| 2     | 94.0             |
| 3     | 97.3             |
| 4     | 97.8             |
| 5     | 97.3             |

Table 2: The confusion matrix of language detection using 10,000-dimensional Language Vectors based on letter trigrams. Each row corresponds to the correct label and each column is the predicted label for the Europarl corpus detection test. The entry \((i,j)\) is the number of sentences (out of a 1,000) that language \( j \) was guessed for language \( i \). A high value diagonal shows the very high accuracy.

4 Future Work

Many adjustments can be made to improve the efficacy of Random Indexing on language detection. The results of this paper are based solely on letter trigrams and tetragrams. However, it is a simple matter to add into the Text Vectors single-letter frequencies and bigrams, for example. Also, the vector dimensionality can be reduced to several thousands without markedly affecting the results.
The arithmetic (algebra) of the operations with which Text Vectors are made—i.e., permutation, multiplication, and addition, and how they work together—make it possible to analyze the Language Vectors and find out, for example, what letters are most likely to follow “the”. (In English it would be the Space, but what is the next most likely?) Notice that we don’t need to contemplate such questions in advance and then design the data-gathering algorithm with that in mind. The information is in the vectors in a form that allows it to be retrieved with the arithmetic.

Because of the generality of Random Indexing on texts, any time series with a well-defined “alphabet” can be encoded using this scheme. In this way, we propose that our method can be used to do language detection in speech data, addressing our original problem.

5 Conclusion

We have described the use of Random Indexing to language identification. Random Indexing has been used in the study of semantic vectors since 2000 (Kanerva et al. (2000); Sahlgren (2005)), and for encoding problems in graph theory (Levy & Gayler (2009)), but only now for identifying source materials. It is based on simple operations on high-dimensional random vectors: on Random Labels with 0-mean components that allow weak signals to rise above noise as the data accumulate. The algorithm works in a single pass, in linear time, with limited memory, and thus is inherently scalable, and it produces vectors that are amenable to further analysis. The experiments reported in this paper were an easy task for a laptop computer.

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References

Hart, M. Project gutenberg. URL https://www.gutenberg.org.

Joshi, A. and Halseth, J.T. Github: Random indexing for languages python implementation, 2014. URL https://github.com/halseth/vs265_project_f14.

Kanerva, P. Sparse Distributed Memory. MIT Press, 1988.

Kanerva, P. Computing with 10,000-bit words. Proc. 52nd Annual Allerton Conference on Communication, Control, and Computing, 2014.

Kanerva, P., Kristoferson, J., and Holst, A. Random indexing of text samples for latent semantic analysis. pp. “1036”. Proc. 22nd Annual Conference of the Cognitive Science Society, 2000.

Kaski, S. Dimensionality reduction by random mapping: Fast similarity computation for clustering. Proc. IJCNN’98, International Joint Converence on Neural Networks, 1:413–418, 1998.

Landauer, T. and Dumais, S. A solution to plato’s problem: The latent semantic analysis theory of acquisition, induction and representation of knowledge. Psychology Review, 104(2):“211–240”, 1997.

Levy, S.D. and Gayler, R.W. lateral inhibition in a fully distributed connectionist architecture. Proceedings of the Ninth International Conference on Cognitive Modeling, 2009.

McCandless, M. Accuracy and performance of google’s compact language detector, 2011. URL http://blog.mikemccandless.com/2011/10/accuracy-and-performance-of-gogles.html

Mikolov, T., Corrado G. Chen K. and Dean, J. Efficient estimation of word representations in vector space. 2013. arXiv:1301.3781v3 [cs.CL] 7 Sep 2013, 12 pp.

Nakatani, S. langdetect is updated(added profiles of Estonian / Lithuanian / Latvian / Slovene, and so on. http://shuyo.wordpress.com/2011/09/29/langdetect-is-updated-added-profiles-of-estonian-lithuanian-latvian-slovene-and-so-on/. [Online; accessed 16-December-2014].
Papadimitriou, C.H., Raghavan, P., Tamaki, H., and Vempala, S. Latent semantic indexing: A probabilistic analysis. *Proc. 17th ACM Symp. on the Principles of Database Systems*, pp. 159–168.

Quastoff, U., Richter, M., and Biemann, C. Corpus portal for search in monolingual corpora. *Proceedings of the fifth international conference on Language Resources and Evaluation, LREC*, pp. 1799–1802, 2006.

Sahlgren, M. An introduction to random indexing. *Methods and Applications of Semantic Indexing Workshop at the 7th international conference on Terminology and Knowledge Engineering*, 2005.

Shannon, C.E. A mathematical theory of communication. *The Bell System Technical Journal*, 1948.

van der Maaten, L. Visualizing high-dimensional data using t-sne. *Journal of Machine Learning Research*, 9:2579–2605, 2008.