

Portuguese Word Embeddings: Evaluating on Word Analogies and Natural Language Tasks

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Abstract. *Word embeddings have been found to provide meaningful representations for words in an efficient way; therefore, they have become common in Natural Language Processing systems. In this paper, we evaluated different word embedding models trained on a large Portuguese corpus, including both Brazilian and European variants. We trained 31 word embedding models using FastText, GloVe, Wang2Vec and Word2Vec. We evaluated them intrinsically on syntactic and semantic analogies and extrinsically on POS tagging and sentence semantic similarity tasks. The obtained results suggest that word analogies are not appropriate for word embedding evaluation instead task-specific evaluations may be a better option; Wang2Vec appears to be a robust model; the increase in performance in our evaluations with bigger models is not worth the increase in memory usage for models with more than 300 dimensions.*

1. Introduction

Natural Language Processing (NLP) applications usually take words as basic input units; therefore, it is important that they be represented in a meaningful way. In recent years, *word embeddings* have been found to efficiently provide such representations, and consequently, have become common in modern NLP systems. They are vectors of real valued numbers, which represent words in an n -dimensional space, learned from large non-annotated corpora and able to capture syntactic, semantic and morphological knowledge.

Different algorithms have been developed to generate embeddings [Bengio et al. 2003, Collobert et al. 2011, Mikolov et al. 2013, Ling et al. 2015, Lai et al. 2015, *inter alia*]. They can be roughly divided into two families of methods [Baroni et al. 2014]: the first is composed of methods that work with a co-occurrence word matrix, such as Latent Semantic Analysis (LSA) [Dumais et al. 1988], Hyperspace Analogue to Language (HAL) [Lund and Burgess 1996] and Global Vectors (GloVe) [Pennington et al. 2014]. The second is composed of predictive methods, which try to predict neighboring words given one or more context words, such as Word2Vec [Mikolov et al. 2013].

Given this variety of word embedding models, methods for evaluating them becomes a topic of interest. [Mikolov et al. 2013] developed a benchmark for embedding evaluation based on a series of analogies. Each analogy is composed of two pairs of words

that share some syntactic or semantic relationship, e.g., the names of two countries and their respective capitals, or two verbs in their present and past tense forms. In order to evaluate an embedding model, applying some vectorial algebra operation to the vectors of three of the words should yield the vector of the fourth one. A version of this dataset translated and adapted to Portuguese was created by [Rodrigues et al. 2016].

However, in spite of being popular and computationally cheap, [Faruqui et al. 2016] suggests that word analogies are not appropriate for evaluating embeddings. Instead, they suggest using task-specific evaluations, i.e., to compare word embedding models on how well they perform on downstream NLP tasks.

In this paper, we evaluated different word embedding models trained on a large Portuguese corpus, including both Brazilian and European variants (Section 2). We trained our models using four different algorithms with varying dimensions (Section 3). We evaluated them on the aforementioned analogies as well as on POS tagging and sentence similarity, to assess both syntactic and semantic properties of the word embeddings (Section 4). Section 5 revises recent studies evaluating Portuguese word embeddings. The contributions of this paper are: i) to make a set of 31 word embedding models publicly available¹ as well as the script used for corpus preprocessing and embedding evaluations²; and ii) an intrinsic and extrinsic evaluation of word embedding models, indicating the lack of correlation between performance in syntactic and semantic analogies and syntactic and semantic NLP tasks.

2. Training Corpus

We collected a large corpus from several sources in order to obtain a multi-genre corpus, representative of the Portuguese language. We rely on the results found by [Rodrigues et al. 2016] and [Fonseca and Aluisio 2016], which indicate that the bigger a corpus is, the better the embeddings obtained, even if it is mixed with Brazilian and European texts. Table 1 presents all corpora collected in this work.

2.1. Preprocessing

We tokenized and normalized our corpus in order to reduce the vocabulary size, under the premise that vocabulary reduction provides more representative vectors. Word types with less than five occurrences were replaced by a special UNKNOWN symbol. Numerals were normalized to zeros; URL's were mapped to a token URL and emails were mapped to a token EMAIL.

Then, we tokenized the text relying on whitespaces and punctuation signs, paying special attention to hyphenation. Clitic pronouns like “machucou-se” are kept intact. Since it differs from the approach used in [Rodrigues et al. 2016] and their corpus is a subset of ours, we adapted their tokenization using our criteria. We also removed their Wikipedia section, and in all our subcorpora, we only used sentences with 5 or more tokens in order to reduce noisy content. This reduced the number of tokens of LX-Corpus from 1,723,693,241 to 714,286,638.

¹Available at nilc.icmc.usp.br/embeddings.

²Available at github.com/nathanshartmann/portuguese_word_embeddings.

Corpus	Tokens	Types	Genre	Description
LX-Corpus [Rodrigues et al. 2016]	714,286,638	2,605,393	Mixed genres	A huge collection of texts from 19 sources. Most of them are written in European Portuguese.
Wikipedia	219,293,003	1,758,191	Encyclopedic	Wikipedia dump of 10/20/16
GoogleNews	160,396,456	664,320	Informative	News crawled from GoogleNews service
SubIMDB-PT	129,975,149	500,302	Spoken language	Subtitles crawled from IMDb website
G1	105,341,070	392,635	Informative	News crawled from G1 news portal between 2014 and 2015.
PLN-Br [Bruckschen et al. 2008]	31,196,395	259,762	Informative	Large corpus of the PLN-BR Project with texts sampled from 1994 to 2005. It was also used by [Hartmann 2016] to train word embeddings models
Literacy works of public domain	23,750,521	381,697	Prose	A collection of 138,268 literary works from the Domínio Público website
Lacio-web [Aluisio et al. 2003]	8,962,718	196,077	Mixed genres	Texts from various genres, e.g., literary and its subdivisions (prose, poetry and drama), informative, scientific, law, didactic technical
Portuguese e-books	1,299,008	66,706	Prose	Collection of classical fiction books written in Brazilian Portuguese crawled from Literatura Brasileira website
Mundo Estranho	1,047,108	55,000	Informative	Texts crawled from Mundo Estranho magazine
CHC	941,032	36,522	Informative	Texts crawled from Ciência Hoje das Crianças (CHC) website
FAPESP	499,008	31,746	Science Communication	Brazilian science divulgation texts from Pesquisa FAPESP magazine
Textbooks	96,209	11,597	Didactic	Texts for children between 3rd and 7th-grade years of elementary school
Folhinha	73,575	9,207	Informative	News written for children, crawled in 2015 from Folhinha issue of Folha de São Paulo newspaper
NILC subcorpus	32,868	4,064	Informative	Texts written for children of 3rd and 4th-years of elementary school
Para Seu Filho Ler	21,224	3,942	Informative	News written for children, from Zero Hora newspaper
SARESP	13,308	3,293	Didactic	Text questions of Mathematics, Human Sciences, Nature Sciences and essay writing to evaluate students
Total	1,395,926,282	3,827,725		

Table 1. Sources and statistics of corpora collected.

3. Embedding Methods

In this section, we describe the four methods we used to train 31 word embedding models: GloVe, Word2Vec, Wang2Vec, and FastText.

The Global Vectors (GloVe) method was proposed by [Pennington et al. 2014], and obtained state-of-the-art results for *syntactic* and *semantic* analogies tasks. This method consists in a co-occurrence matrix M that is constructed by looking at context words. Each element M_{ij} in the matrix represents the probability of the word i being close to the word j . In the matrix M , the rows (or vectors) are randomly generated and trained by obeying the equation $P(w_i, w_j) = \log(M_{ij}) = w_i w_j + b_i + b_j$, where w_i and w_j are word vectors, and b_i and b_j are biases.

Word2Vec is a widely used method in NLP for generating word embeddings. It has two different training methods: (i) *Continuous Bag-of-Words (CBOW)*, in which the model is given a sequence of words without the middle one, and attempts to predict it; (ii) *Skip-Gram*, in which the model is given a word and attempts to predict its neighboring words. In both cases, the model consists of only a single weight matrix (apart from the word embeddings), which results in a fast log-linear training able to capture *semantic*

information [Mikolov et al. 2013].

Wang2Vec is a modification of Word2Vec made in order to take into account the lack of word order in the original architecture. Two simple modifications were proposed in Wang2Vec expecting embeddings to better capture *syntactic* behavior of words [Ling et al. 2015]. In the *Continuous Window* architecture, the input is the concatenation of the context word embeddings in the order they occur. In *Structured Skip-Gram*, a different set of parameters is used to predict each context word, depending on its position relative to the target word.

FastText is a recently developed method [Bojanowski et al. 2017] in which embeddings are associated to character n-grams, and words are represented as the summation of these representations. In this method, a word representation is induced by summing character n-gram vectors with vectors of surrounding words. Therefore, this method attempts to capture *morphological* information to induce word embeddings.

4. Evaluation

In order to evaluate the robustness of the word embedding models we trained, we performed intrinsic and extrinsic evaluations. For the intrinsic evaluation, we used the set of syntactic and semantic analogies from [Rodrigues et al. 2016]. For extrinsic evaluation, we chose to apply the trained models on POS tagging and sentence similarity tasks. The tasks were chosen deliberately since they are linguistically aligned with the sets of analogies used in the first evaluation. POS tagging is by nature a morphosyntactic task, and although some analogies are traditionally regarded as *syntactic*, they are actually morphological — for example, suffix operations. Sentence similarity is a semantic task since it evaluates if two sentences have similar meaning. It is expected that the models which achieve the best results in (morpho-)syntactic analogies also do so in POS tagging, and the same is true for semantic analogies and semantic similarity evaluation. We trained embeddings with the following dimensions: 50, 100, 300, 600 and 1,000. Because Wang2Vec’s implementation suffers from the vanishing gradient problem for high dimension matrices, it was not possible to train its CBOW models for 600 and 1,000 dimensions.

4.1. Intrinsic evaluation

We evaluated our embeddings in the syntactic and semantic analogies provided by [Rodrigues et al. 2016]. The benchmark contains five types of semantic analogy: (i) common capitals and countries, (ii) all capitals and countries, (iii) currency and countries, (iv) cities and states, and (v) family relations. Moreover, nine types of syntactic analogy are also represented: adjectives and adverbs, opposite adjectives, base adjectives and comparatives, base adjectives and superlatives, verb infinitives and present participles, countries and nationalities (adjectives), verb infinitives and past tense forms, nouns in plural and singular, and verbs in plural and singular. Since our corpus is composed of both Brazilian (PT-BR) and European (PT-EU) Portuguese, we also evaluated the models in the test sets for both variants, following [Rodrigues et al. 2016].

Table 2 shows the obtained results for the intrinsic evaluation. On average, GloVe was the best model for both Portuguese variants. The model which best performed on syntactic analogies was FastText, followed by Wang2Vec. This makes sense since FastText is a morphological model, and Wang2Vec uses word order, which provides some minimal

Embedding Models		Size	PT-BR			PT-EU			
			Syntactic	Semantic	All	Syntactic	Semantic	All	
FastText	CBOW	50	35.2	4.2	19.6	35.2	4.6	19.8	
		100	45.0	6.1	25.5	45.1	6.4	25.7	
		300	52.0	8.4	30.1	52.0	9.1	30.5	
		600	52.6	5.9	29.2	52.4	6.5	29.4	
		1,000	50.6	4.8	27.7	50.4	5.4	27.9	
	Skip-Gram	50	36.8	18.4	27.6	36.5	17.1	26.8	
		100	50.8	30.0	40.4	50.7	28.9	39.8	
		300	58.7	32.2	45.4	58.5	31.1	44.8	
		600	55.1	24.3	39.6	55.0	23.9	39.4	
		1,000	45.1	14.6	29.8	45.2	13.8	29.4	
GloVe	50	28.7	13.7	27.4	28.5	12.8	27.7		
	100	39.7	28.7	34.2	39.9	26.6	33.2		
	300	45.8	45.8	46.7	45.9	42.3	46.2		
	600	42.3	48.5	45.4	42.3	43.8	43.1		
	1,000	39.4	45.9	42.7	39.8	42.5	41.1		
Wang2Vec	CBOW	50	28.4	9.2	18.8	28.4	8.9	18.6	
		100	40.9	26.2	33.5	40.8	24.4	32.6	
		300	49.9	40.3	45.1	50.0	36.9	43.5	
	Skip-Gram	50	30.6	12.2	21.3	30.6	11.5	21.0	
		100	43.9	22.2	33.0	44.0	21.2	32.6	
		300	53.3	33.9	42.8	53.4	32.3	43.6	
		600	52.9	35.0	43.9	53.0	33.2	43.1	
		1,000	47.3	33.2	40.2	47.6	30.9	39.2	
	Word2Vec	CBOW	50	9.8	2.2	6.0	9.7	1.9	5.8
			100	16.2	3.6	9.9	16.0	3.5	9.7
300			24.7	4.6	23.9	24.5	4.5	23.6	
600			25.8	5.2	23.1	25.4	5.1	22.9	
1,000			26.2	4.9	22.9	26.2	4.5	22.7	
Skip-Gram		50	17.0	5.4	11.2	16.9	4.8	10.8	
		100	25.2	8.0	16.6	24.8	7.4	16.1	
		300	33.0	15.6	29.2	32.2	14.1	29.8	
		600	35.6	20.0	33.4	35.3	17.6	33.5	
		1,000	34.1	21.3	32.6	33.6	18.1	31.9	

Table 2. Intrinsic evaluation on syntactic and semantic analogies.

syntactic knowledge. In semantic analogies, the model which best performed was GloVe, followed by Wang2Vec. GloVe is known for modeling semantic information well and Wang2Vec potentially captures semantics because it uses word order. The position of a negation word in a sentence can totally change its semantics. If this negation is shuffled in a bag of words (Word2Vec CBOW), sentence semantic is diluted.

All CBOW models, except for the Wang2Vec ones, achieved very low results in semantic analogies, similarly to the results from [Mikolov et al. 2013]. Wang2Vec CBOW differs from traditional CBOW in that it takes word order into account, and then we can speculate that an unordered bag-of-words is not able to capture a word’s semantics so well.

We exemplify with our best (GloVe) and worst (Word2Vec CBOW) models using 600 dimensions. Dealing with the well known analogy “king to queen”, in Portuguese “rei - homem + mulher \approx rainha”, our best model produced “rainha” as the most similar embedding (0,62 cosine similarity) and our worst model produced “esposa” (0,50 cosine similarity) with “rainha” in the 7th place (0,41 cosine similarity).

4.2. Extrinsic Evaluation

In this section we describe the experiments performed on POS tagging and Semantic Similarity tasks.

POS Tagging

POS tagging is a very suitable NLP task to evaluate how well the embeddings capture morphosyntactic properties. The two key difficulties here are: i) correctly classifying words that can have different tags depending on context; and ii) generalizing to previously unseen words. Our experiments were performed with the nlpnet POS tagger³ using the revised Mac-Morpho corpus and similar tagger configurations to those presented by [Fonseca et al. 2015] (20 epochs, 100 hidden neurons, learning rate starting at 0.01, capitalization, suffix and prefix features). We did not focus on optimizing hyperparameters; instead, we set a single configuration to compare embeddings.

Table 3 presents the POS accuracy results⁴. As a rule of thumb, the larger the dimensionality, the better the performance. The exception is the 1,000 dimensions Word2Vec models, which performed slightly worse than those with 600. GloVe and FastText yielded the worst results, and Wang2Vec achieved the best. GloVe’s poor performance may be explained by its focus on semantics rather than syntax, and FastText’s performance was surprising in that despite its preference for morphology, something traditionally regarded as important for POS tagging, it yielded relatively poor results. Wang2Vec resulted in the best performance – actually, its 300 dimension Skip-Gram model was superior to Word2Vec’s 1000 model.

Embedding Models			Size	Accuracy	Embeddings model			Size	Accuracy
FastText	CBOW		50	91.18%	GloVe			50	93.13%
			100	92.57%				100	93.72%
			300	93.86%				300	94.76%
			600	93.86%				600	95.23%
			1000	94.27%				1,000	95.57%
	Skip-Gram		50	93.15%	Word2Vec	CBOW		50	95.00%
			100	93.78%				100	95.27%
			300	94.82%				300	95.58%
			600	95.25%				600	95.65%
			1000	95.49%				1,000	95.62%
Wang2Vec	CBOW		50	95.33%	Word2Vec	Skip-Gram		50	94.79%
			100	95.59%				100	95.18%
			300	95.83%				300	95.66%
	Skip-Gram		50	95.07%				600	95.82%
			100	95.57%				1,000	95.81%
			300	95.89%					
			600	95.88%					
			1,000	95.94%					

Table 3. Extrinsic evaluation on POS tagging.

Semantic Similarity

ASSIN (*Avaliação de Similaridade Semântica e Inferência Textual*) [Fonseca et al. 2016] was a workshop co-located with PROPOR-2016. ASSIN made two shared-tasks available: i) semantic similarity; and ii) textual entailment. We chose the first one to evaluate our word embedding models extrinsically in a semantic task. ASSIN semantic similarity

³More info at nilc.icmc.usp.br/nlpnet/.

⁴Note that accuracies are well below those reported by [Fonseca et al. 2015]. The probable cause is that the embedding vocabularies used here did not have clitic pronouns split from verbs, resulting in a great amount of out of vocabulary words.

shared task required participants to assign similarity values between 1 and 5 to pairs of sentences. The workshop made training and test sets for Brazilian (PT-BR) and European (PT-EU) Portuguese available. [Hartmann 2016] obtained the best results for this task. The author calculated the semantic similarity of pairs of sentences training a linear regressor with two features: i) the cosine similarity between the TF-IDF of each sentence; and ii) the cosine similarity between the summation of the word embeddings of the sentences' words. We chose this work as a baseline for evaluation because we can replace its word embedding model with others and compare the results. Although the combination of TF-IDF and word embeddings produced better results than only using word embeddings, we chose to only use embeddings for ease of comparison. [Hartmann 2016] trained the word embedding model using Word2Vec Skip-Gram approach, with 600 dimensions, and a corpus composed of Wikipedia, G1 and PLN-Br. Only using embeddings, [Hartmann 2016] achieved 0.58 in Pearson's Correlation (ρ) and a 0.50 Mean Squared Error (MSE) for PT-BR; and 0.55 ρ and 0.83 MSE for PT-EU evaluation.

Table 4 shows the performance of our word embedding models for both PT-BR and PT-EU test sets. To our surprise, the word embedding models which achieved the best results on semantic analogies (see Table 2) were not the best in this semantic task. The best results were achieved by Wang2Vec Skip-Gram using 600 dimensions for PT-EU and using 1,000 dimensions for PT-BR. Wang2Vec also achieved the best results for POS tagging what shows its potential. Neither FastText nor GloVe models beat the baseline results achieved by [Hartmann 2016]. FastText poor results are expected since it has a morphological bias, but GloVe poor results are surprising since it achieved the best results in semantic analogies.

Embedding Models		Size	PT-BR		PT-EU	
			ρ	MSE	ρ	MSE
FastText	CBOW	50	0.36	0.66	0.34	1.05
		100	0.37	0.66	0.36	1.04
		300	0.38	0.65	0.37	1.03
		600	0.33	0.68	0.38	1.02
		1,000	0.39	0.64	0.41	0.99
	Skip-Gram	50	0.45	0.61	0.43	0.98
		100	0.49	0.58	0.47	0.94
		300	0.55	0.53	0.40	1.02
		600	0.40	0.64	0.40	1.01
		1,000	0.52	0.56	0.54	0.86
Wang2Vec	CBOW	50	0.53	0.55	0.51	0.89
		100	0.56	0.52	0.54	0.85
		300	0.53	0.55	0.51	0.89
	Skip-Gram	50	0.51	0.56	0.47	0.92
		100	0.54	0.54	0.50	0.89
		300	0.58	0.50	0.53	0.85
		600	0.59	0.49	0.54	0.83
		1,000	0.60	0.49	0.54	0.85

Embedding Models		Size	PT-BR		PT-EU	
			ρ	MSE	ρ	MSE
GloVe		50	0.42	0.62	0.38	1.01
		100	0.45	0.60	0.42	0.98
		300	0.49	0.58	0.45	0.95
		600	0.50	0.57	0.45	0.94
		1,000	0.51	0.56	0.46	0.94
CBOW		50	0.47	0.59	0.46	0.95
		100	0.50	0.57	0.49	0.91
		300	0.55	0.53	0.54	0.87
		600	0.57	0.51	0.55	0.86
		1,000	0.58	0.50	0.55	0.86
Word2Vec		50	0.46	0.60	0.43	0.97
		100	0.48	0.58	0.45	0.95
		300	0.52	0.56	0.48	0.93
		600	0.53	0.54	0.50	0.92
		1,000	0.54	0.54	0.50	0.91

Table 4. Extrinsic evaluation on Semantic Similarity task.

5. Related Work

The research on evaluating unsupervised word embeddings can be divided into intrinsic and extrinsic evaluations. The former relying mostly on word analogies (e.g. [Mikolov et al. 2013]) and measuring the semantic similarity between words (e.g. the WS-353 dataset [Finkelstein et al. 2002]), while extrinsic evaluations focus on practical

NLP tasks (e.g. [Nayak et al. 2016]). POS tagging, parsing, semantic similarity between sentences, and sentiment analysis are some commonly used tasks for this end.

To the best of our knowledge, only a few works attempted to evaluate Portuguese word embeddings. [Rodrigues et al. 2016] collected a corpus of Portuguese texts to train word embedding models using the Skip-Gram Word2Vec technique. The authors also translated the benchmark of word analogies developed by [Mikolov et al. 2013] and made it available for both Brazilian and European Portuguese. They report a 52.8% evaluation accuracy of their word embedding model in both syntactic and semantic analogies.

[Sousa 2016] investigated whether Word2Vec (CBOW and Skip-Gram) or GloVe performed best on the benchmark in [Rodrigues et al. 2016]. The author compiled a sample of texts from Wikipedia in Portuguese, searching for articles related to teaching, education, academics, and institutions. The best results were obtained using Word2Vec CBOW to train vectors of 300 dimensions. This model achieved an accuracy of 21.7% on syntactic analogies, 17.2% on semantic analogies and 20.4% overall.

[Fonseca et al. 2015] compared the performance of three different vector space models used for POS tagging with a neural tagger. They used Word2Vec Skip-Gram, HAL, and the neural method from [Collobert et al. 2011]; Skip-Gram obtained the best results in all tests.

Concerning the differences between embeddings obtained from Brazilian and European Portuguese texts, [Fonseca and Aluisio 2016] present an extrinsic analysis on POS tagging. They trained different embedding models; one with only Brazilian texts, one with only European ones and another with mixed variants; and trained neural POS taggers which were evaluated on Brazilian and European datasets. One of their findings is that, as a rule of thumb, the bigger the corpus in which embeddings are obtained, the better. Additionally, mixing both variants in the embedding generation did not decrease tagger performance in any of the POS test sets. This supports the hypothesis that a single, large corpus comprising Brazilian and European texts can be useful for most NLP applications in Portuguese.

6. Conclusions and Future Work

In this paper, we presented the word embeddings we trained using four different techniques and their evaluation. All trained models are available for download, as well as the script used for corpus preprocessing and evaluation. The results obtained from intrinsic and extrinsic evaluations were not aligned with each other, contrary to the expected. GloVe produced the best results for syntactic and semantic analogies, and the worst, together with FastText, for both POS tagging and sentence similarity. These results are aligned with those from [Faruqui et al. 2016], which suggest that word analogies are not appropriate for evaluating word embeddings. Overall, Wang2Vec vectors yielded very good performance across our evaluations, suggesting they can be useful for a variety of NLP tasks. Our results also suggest that the increase in performance is not worth the increase in memory usage for models with more than 300 dimensions. As future work, we intend to try different tokenization and normalization patterns, and also to lemmatize certain word categories like verbs, since this could significantly reduce vocabulary, allowing for more efficient processing. An evaluation with more NLP tasks would also be beneficial to our understanding of different model performances.

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References

- Aluísio, S. M., Pinheiro, G. M., Finger, M., Nunes, M. G. V., and Tagnin, S. E. (2003). The LacioWeb Project: Overview and Issues in Brazilian Portuguese Corpora Creation. In *Proceedings of Corpus Linguistics*, pages 14–21.
- Baroni, M., Dinu, G., and Kruszewski, G. (2014). Don’t count, predict! A systematic comparison of context-counting vs. context-predicting semantic vectors. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics*, volume 1, pages 238–247.
- Bengio, Y., Ducharme, R., Vincent, P., and Jauvin, C. (2003). A neural probabilistic language model. *Journal of machine learning research*, 3:1137–1155.
- Bojanowski, P., Grave, E., Joulin, A., and Mikolov, T. (2017). Enriching word vectors with subword information. *Transactions of the Association of Computational Linguistics*, 5:135–146.
- Bruckschen, M., Muniz, F., Souza, J., Fuchs, J., Infante, K., Muniz, M., Gonçalves, P., Vieira, R., and Aluísio, S. (2008). Anotação Lingüística em XML do Corpus PLN-BR. NILC–TR–09–08. Technical report, University of São Paulo, Brazil.
- Collobert, R., Weston, J., Bottou, L., Karlen, M., Kavukcuoglu, K., and Kuksa, P. (2011). Natural Language Processing (Almost) from Scratch. *Journal of Machine Learning Research*, 12:2493–2537.
- Dumais, S. T., Furnas, G. W., Landauer, T. K., Deerwester, S., and Harshman, R. (1988). Using latent semantic analysis to improve access to textual information. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 281–285. ACM.
- Faruqui, M., Tsvetkov, Y., Rastogi, P., and Dyer, C. (2016). Problems With Evaluation of Word Embeddings Using Word Similarity Tasks. In *Proc. of the 1st Workshop on Evaluating Vector Space Representations for NLP*.
- Finkelstein, L., Gabrilovich, E., Matias, Y., Rivlin, E., Solan, Z., Wolfman, G., and Ruppín, E. (2002). Placing search in context: The concept revisited. *ACM Transactions on Information Systems*, 20(1).
- Fonseca, E. and Aluisio, S. (2016). Improving POS Tagging Across Portuguese Variants with Word Embeddings. In *Proceedings of the Computational Processing of the Portuguese Language*, pages 227–232.
- Fonseca, E. R., Borges dos Santos, L., Crisculo, M., and Aluísio, S. M. (2016). Visão geral da avaliação de similaridade semântica e inferência textual. *Linguamática*, 8(2):3–13.
- Fonseca, E. R., Rosa, J. L. G., and Aluísio, S. M. (2015). Evaluating word embeddings and a revised corpus for part-of-speech tagging in portuguese. *Journal of the Brazilian Computer Society*.

- Hartmann, N. S. (2016). ASSIN Shared Task - Solo Queue Group: Mix of a Traditional and an Emerging Approaches. In *Avaliação de Similaridade Semântica e Inferência Textual (ASSIN), Propor Workshop*.
- Lai, S., Xu, L., Liu, K., and Zhao, J. (2015). Recurrent convolutional neural networks for text classification. In *AAAI*, volume 333, pages 2267–2273.
- Ling, W., Dyer, C., Black, A., and Trancoso, I. (2015). Two/too simple adaptations of word2vec for syntax problems. In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. Association for Computational Linguistics.
- Lund, K. and Burgess, C. (1996). Producing high-dimensional semantic spaces from lexical co-occurrence. *Behavior Research Methods, Instruments, & Computers*, 28(2):203–208.
- Mikolov, T., Chen, K., Corrado, G., and Dean, J. (2013). Efficient estimation of word representations in vector space. In *Proceedings of International Conference on Learning Representations Workshop (ICLR-2013)*.
- Nayak, N., Angeli, G., and Manning, C. D. (2016). Evaluating Word Embeddings Using a Representative Suite of Practical Tasks. In *RepEval Workshop*.
- Pennington, J., Socher, R., and Manning, C. D. (2014). Glove: Global vectors for word representation. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP-2014)*, 12:1532–1543.
- Rodrigues, J., António, B., Steven, N., and João, S. (2016). LX-DSemVectors: Distributional Semantics Models for Portuguese. In *Computational Processing of the Portuguese Language: 12th International Conference (PROPOR-2016)*. Springer International Publishing.
- Sousa, S. (2016). Estudo de Modelos de Word Embeddings. Monograph (Bacharel em Computação), UTFPR (Universidade Tecnológica Federal do Paraná), Paraná, Brazil.