Exploring Transformers for Ranking Portuguese Semantic Relations

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Abstract
We explored transformer-based language models for ranking instances of Portuguese lexico-semantic relations. Weights were based on the likelihood of natural language sequences that transmitted the relation instances, and expectations were that they would be useful for filtering out noisier instances. However, after analysing the weights, no strong conclusions were taken. They are not correlated with redundancy, but are lower for instances with longer and more specific arguments, which may nevertheless be a consequence of their sensitivity to the frequency of such arguments. They did also not reveal to be useful when computing word similarity with network embeddings. Despite the negative results, we see the reported experiments and insights as another contribution for better understanding transformer language models like BERT and GPT, and we make the weighted instances publicly available for further research.

Keywords: semantic relations, lexical patterns, transformer models, BERT, GPT

1. Introduction
Even though distributional semantics and deep learning are the current trend in Natural Language Processing (NLP), research on the automatic acquisition of semantic relations from large corpora and semi-structured sources has a long history, which, among others, lead to the development of several systems for Open Information Extraction from the Web (Etzioni et al., 2008), as well as large knowledge bases like DBPedia (Auer et al., 2007), YAGO (Tanon et al., 2020), or BabelNet (Navigli and Ponzetto, 2012). In opposition to distributional and neural language models, where words and sequences are represented by vectors of numbers, in the previous, relations are represented by triples of the kind \( \text{arg}_1 \text{related-to} \ \text{arg}_2 \), and are thus interpretable by humans. However, the automatic acquisition of relations can be a noisy process, and it is not always straightforward to discriminate between good extractions and those that are irrelevant or simply incorrect. To help with the latter, there has been work on computing the confidence of extractions, e.g., based on the occurrence of the relation arguments in a large collection of text (Cederberg and Widdows, 2003) (Downey et al., 2005) (Cimiano and Wenderoth, 2007).

On the other hand, the adoption of models based on transformers (hereafter, TLMs), like GPT (Brown et al., 2020) and BERT (Devlin et al., 2019), lead to unprecedented advances in a broad range of NLP tasks. Since the latter encode much linguistic and world knowledge, some authors (Petroni et al., 2019) (Haviv et al., 2021) show that, to some extent, they can be used as knowledge bases, e.g., when used to fill blanks in given text (see a recent review on the topic (AlKhamissi et al., 2022)). Furthermore, as it happens for traditional language models, TLMs can be used for computing the likelihood of given sequences of text. In principle, if given sequences express the target relation instances in natural language, this process could be seen as a shortcut for computing the confidence of such instances. This is what we explore in this paper, though focusing on the Portuguese language and in lexico-semantic relations, which are those one would expect to find in a dictionary or in a resource like WordNet (Fellbaum, 1998). The main contribution of this work is thus in the scope of the automatic creation of lexical knowledge bases. Our starting point is a set of relation instances obtained from ten lexical resources (PT-LKB), and two TLMs for Portuguese, one based on BERT and another on GPT. Since the instances have variable quality and utility, we aim at exploring the TLMs for ranking those instances according to their prototypicality. This would be useful for filtering out less useful (e.g., very specific) or incorrect relations. Inspired by earlier work on relation extraction, we construct sequences that transmit each instance and use the TLMs for computing their likelihood, based on the loss of the model. After this, we analyse the resulting weights, including their relationship to the number of resources each instance was obtained from, and by inspecting the top and bottom-ranked instances. Finally, we use PT-LKB with weights by different TLMs for answering similarity tests automatically. Our conclusions so far are that the new weights provide a new distinct dimension, which can be used to filter out some very specific relations. At the same time, we noted that they are very sensitive to the frequency of the relation arguments and do not lead to improvements in the computation of semantic similarity. Yet, in addition to the previous results, we see the reported insights as another contribution for better understanding TLMs and what we can do with them.

In the remainder of the paper, we overview related work on relation extraction and ranking; we describe the experimentation setup, focused on the weighting process; we give and discuss some insights on the re-
sults; and, before concluding, we report the performance of the weighted networks in similarity tests.

2. Related Work

Interest in the automatic acquisition of semantic relations from text has grown especially since the transition to the so-called Web 2.0, which enabled virtually anyone to publish content, resulting in large quantities of text easily accessible. Much related work is inspired by Hearst (1992), where a set of lexico-syntactic patterns was proposed for extracting hyponymy instances that could be used for enriching knowledge bases like WordNet (Fellbaum, 1998). Yet, to minimise human intervention and increase the quantity of extracted relations, automatic procedures were proposed, e.g., based on distant (Snow et al., 2005) or weak supervision (Pantel and Pennacchiotti, 2006), either focused on a closed set of relation types, or following the paradigm of Open Information Extraction (OIE) (Etzioni et al., 2008), where virtually every possible relation is extracted. By broadening the set of considered patterns, which can be learned automatically, such approaches lead to more but also noisier extractions. Therefore, some works focused on scoring extractions according to their reliability, which enabled to increase precision by filtering out some unreliable extractions. A straightforward approach is based on the semantic similarity of the relation arguments (Cederberg and Widdows, 2003) or other co-occurrence measures (Cimiano and Wenderoth, 2007), computed from corpora or using a Web search engine. This however does not consider the relation itself. For that, the actual patterns where the arguments occur have to be considered (Pantel and Pennacchiotti, 2006; Costa et al., 2011). And here, besides the number of times the arguments were found with one of the target patterns, redundancy has shown to be an important cue, i.e., instances extracted from different sources or using different patterns should be more reliable.

Considering the previous, a probabilistic model was developed (Downey et al., 2005), and measures were proposed for combining simple co-occurrence with the occurrence in target patterns (Bollegala et al., 2007). As it happened for other NLP tasks, the state-of-the-art on relation extraction from text currently relies on deep learning, where the task is either framed as a sequence labelling — e.g., based on bidirectional LSTM networks (Stanovsky et al., 2018); or on transformers like BERT (Ro et al., 2020) — or a generation problem — e.g., an LSTM encoder-decoder that generates relation instances from given sentences (Cui et al., 2018), with training examples bootstrapped from a more traditional OIE system (Mausam, 2016); or a BART model, pre-trained in sentences from Wikipedia abstracts and entailed Wikidata relations (Cabot and Navigli, 2021).

The previous are all supervised approaches, trained specifically for relation extraction. An alternative is to acquire relation instances from pre-trained language models, including static word embeddings — e.g., unsupervisedly (Chang et al., 2018), or supervisedly, based on a set of analogies (Drozd et al., 2016) — or TLMs — e.g., starting with a small number of patterns and seeds (Bouraoui et al., 2020), or based on predefined lexical patterns (Petroni et al., 2019), to some extent similar to those used for relation extraction from corpora.

Specifically for Portuguese, there are several OIE systems, most of which based on rules that consider the part-of-speech tags and dependency parsing (Glauber et al., 2019) or chunking (Sena and Claro, 2020), and, more recently, neural approaches (Cabrall et al., 2022). There is also recent work on the acquisition of lexico-semantic relations from static word embeddings (Goncalo Oliveira et al., 2020), hyponyms (Paes, 2021) and other relations from BERT (Goncalo Oliveira, 2022). Also for Portuguese, instances of lexico-semantic relations have been acquired from several lexical resources, and weighted according to redundancy, i.e., the intuition is that more reliable and useful an instance is, the more resources it is in (Goncalo Oliveira, 2018).

3. Experimentation

We aim at exploiting Portuguese TLMs for ranking instances of Portuguese lexico-semantic relations acquired from ten lexical resources, hereafter PT-LKB (Goncalo Oliveira, 2018). The previous resources include wordnets and thesauri, some of which created (semi-)automatically, and dictionaries, where relation instances were extracted automatically from. Therefore, those instances have variable utility and contain a portion of incorrect extractions as well, i.e., they go from widely accepted prototypical instances (e.g., tree hypernym-of oak) to others very specific (e.g., cd_store place-of elvis_presley_cd; give_to_girlfriend purpose-of kitty) or with underspecified / incomplete (e.g., possessive said-about to_make) or incorrect (e.g., various causes contest) arguments. They are currently weighted according to the number of resources they were obtained from (hereafter, Res weight). This may help to filter out some undesirable instances, but they are limited to discrete values in the 1-10 interval and to the contents of the resources, which may not reflect how language is actually used. An alternative would be to adopt some of the approaches enumerated in Section 2 where instances are scored according to occurrences of their arguments on the Web. Yet, we see TLMs as a potential shortcut for the future: they are trained in large quantities of text and encode knowledge about language and its usage.

For this purpose, we exploit two TLMs, namely BERT (Devlin et al., 2019) and GPT (Radford et al., 2019). Relation instances in PT-LKB are in Portuguese but, for the sake of simplicity, we use rough translations in these examples.
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3.1. Models
Two TLMs were used in this work, both available through the Hugging Face transformers library,
BERTimbau (Souza et al., 2020) (base), a BERT
model pretrained for Portuguese; and GPorTuguese-2,
a GPT2 for Portuguese, more precisely, GPT2-small
fine-tuned with 1GB of text in Portuguese.
These models are significantly different, but they are both based on the transformer architecture. So, af-
ter loading them, the likelihood of a sequence of text
can be approximated by the exponential of the loss of
the model for its tokens, which is what we do. For
BERT, however, it is advisable that the special tokens
[CLS] and [SEP] are added respectively to the be-
inning and to the end of the sequence. A similar
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y
3.2. Relations
PT-LKB contains 938,846 instances, represented by
arg-1 related-to arg-2, where arg-1 and
arg-2 are Portuguese words and related-to is
the name of a relation type. Several types of lexico-
semantic relations are covered and their distribution is
highly imbalanced. In this work, we focus only on the
16 types for which there are at least 5,000 instances,
which accounts for 862,693 instances, about 92% of all
the instances. These are illustrated in Table [1] where
we include the original name of the relation, in Por-
tuguese, followed by an English translation including
the part-of-speech (PoS) of the expected arguments, the
number of available instances, and an example, also in
Portuguese (original) and English. Note that the names
of the relation types consider not only the meaning of
the relation, but also the PoS of its arguments. This
means that, for instance, there are four types of syn-
onymy, respectively between nouns (n), verbs (v), ad-
jectives (adj) and adverbs (adv).
3.3. Lexical Patterns
For each of the considered relation types, we hand-
crafted a set of templates based on lexical patterns that
transmit these relations, illustrated in Table [2] where
A1 and A2 are to be replaced by the first and the sec-
ond argument of the instance, respectively. This means
that, for each instance (e.g., árvore hiperonoimo_de
carvalho), weights are computed from the loss of the
models, given each sequence obtained with the tem-
plates for the relation type (e.g., ‘árvore é hiperonoimo
de carvalho’, ‘carvalho ou outra árvore’, ‘carvalho é
um tipo de árvore’).
For some relations (synonymy, hypernymy, part-of,
purpose-of), we selected the top-performing patterns
in previous work (Gonçalo Oliveira, 2022), where
BERTimbau was used for discovering instances by pre-
dicting masked tokens. When the top-3 contained a
group of very similar patterns, we only used the first,
skipped the others, and used the following patterns.
This happened, for instance, for patterns that only dif-
f ered in the gender of a determiner, and means that,
as in previous work (Paes, 2021), determiners will
do not be inflected according to the gender of the argu-
ments (e.g., ‘outro’ for HIPERONIMO_DE or ‘uma’ for
FINALIDADE_DE). Empirically, we also noted that this
only had a minor impact in the (relative) computed
scores, while enabling to broaden the variability in the
used patterns. For the remaining relations, we tried to
consider patterns that would typically be used to trans-
mit each relation. Yet, as in some cases it would be
virtually impossible to select patterns that always trans-
mit the relation, we also used patterns that were simply
compatible with the relation. We did this while trying
to use different enough patterns, i.e., covering different
constructions.
Once the loss is computed for all resulting sequences,
each relation instance will have six new weights, i.e.,
three for each pattern times the two models (BERT and
GPT). Yet, as the patterns used for different relations
are significantly different, the computed scores are not
comparable. Therefore, we decided to compute the log-
arithm of these scores and normalise them to the 0–10
interval, the same of Res, but with continuous values.

[1] https://huggingface.co/transformers/
[2] https://huggingface.co/pierreguillou/
gpt2-small-portuguese
*After experimenting with and without [CLS] and
[SEP], we decided to always add them.
### Table 1: Lexical patterns indicating lexicosemantic relations.

| Relation Name | Pattern | Instances | Example |
|---------------|---------|-----------|---------|
| SINOI NIMO_Q_DE | A₁ é o mesmo que A₂ | 155,224 | pedente – mendigo (beggar, mendicant) |
| SINOI NIMO_Q.REACT | A₁ é sinônimo de A₂ | 127,779 | apagar – pegar (grab, catch) |
| SINOI NIMO_ADJ.DE | A₁ é adj sinônimo de A₂ | 92,028 | porventura – talvez (perhaps, possibly) |
| HIPERONIMO.DE | A₁ é hipérionimo de A₂ | 6,583 | aove – carvalho (tree, oak) |
| HIPERONIMO.ACCEAO.DE | A₁ é hipérionimo de A₂ | 204,860 | alterar – modificar (change, modify) |
| PARTE.DE | A₁ é parte de A₂ | 19,109 | degrau – escada (step, stairs) |
| PARTE.DE_ALGO. | A₁ é parte de A₂ | 5,675 | força – robusto (strength, robust) |
| MEMBRO.DE | A₁ é membro de A₂ | 12,626 | carta – baralho (card, deck) |
| FINALENDE.DE | A₁ é o mesmo que A₂ | 23,587 | fumar – charuto (smoke, cigar) |
| FAZ.É.ÇOM | A₁ é o mesmo que A₂ | 8,547 | conduto – cano (conduction, pipe) |
| ACCEAO.QUE.CUSA | A₁ por causa de A₂ | 12,137 | poupas – poupança (save, savings) |
| LOCAL.ORG.EM.DE | A₁ é o mesmo que A₂ | 18,454 | ecuadoriano – ecuadoriano (ecuador, ecuadorian) |
| DIZ.É.ÇO.QUE | A₁ diz-se que A₂ | 2,389 | dependente – depende (dependable, depend) |
| DIZ.É.ÇO.ÆRE | A₁ diz-se de A₂ | 22,385 | netico – mito (mythical, myth) |
| PROPRIEDADE.ÈMELHANÇA. | A₁ é semelhança A₂ | 16,206 | adjacente – próximo (adjacent, close) |

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Furthermore, we combine the scores of the patterns for each model, which results in four additional weights: the maximum of the three weights and their average, for each model. These final changes are illustrated in Tables 3 and 4, where example instances are respectively shown with the originally computed weights (exponential of the loss) and after normalisation plus computation of the combined weights. Res stands for the number of resources the instance was obtained from, Bn stands for the nth pattern for BERT, Gm for the nth pattern for GPT. In Table 3 Mx(x) stands for the maximum of the x patterns and Av(x) for the average of the x patterns.

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4. Insights

After weighting all the instances, we try to get some conclusions on the utility of this process. First, we analyse how comparable the new weights were to the previous Res weight, based on the number of resources. Then, we check to what extent the instances with the higher weights are actually better (i.e., more prototypical) than those with lower weights.

4.1. Weight Correlation

To better understand the relation between different weights, the Pearson correlation was computed for all pairs of weights. The higher the correlation, the stronger the linear relationship between the weights. For instance, a high correlation between Res and any other weight would mean that the transformers could be used to simulate redundancy / the presence in different resources, and were thus an alternative to the previous weight, e.g., in the typical case when there are not many lexical resources available. A lower correlation would mean that they are measuring something completely different, either reflecting the gap between relations in lexical resources versus relations actually used in language, or just because the weights do not have the expected meaning. Moreover, given the similarity of the approach and of the models, it is expected that the weights by BERT are correlated with those by GPT.

Table 4: Example instances and their weights after normalisation and combination.

| Instance | Res | B1 | B2 | B3 | G1 | G2 | G3 | Mx(B) | Av(B) | Mx(G) | Av(G) |
|----------|-----|----|----|----|----|----|----|-------|-------|-------|-------|
| fim do SINONIMO_ADJ DE concluido | 3   | 26.19 | 49.29 | 53.02 | 138.16 | 165.2 | 413.67 |
| cozer FINALIDADE_DE panela | 2   | 16.43 | 44.17 | 23.45 | 160.67 | 476.8 | 158.56 |
| sonar PARTE_DE submarino | 1   | 48.39 | 70.93 | 49.13 | 4802.38 | 706.29 | 14161.6 |

4.2. Weight Meaningfulness

As previously discussed, having no correlation does not necessarily mean that the new weights are not useful for identifying the best relations, but that they capture a different dimension than Res. For additional insights, we inspected the top and bottom-weighted instances, looking for a trend. In the bottom, we found mostly instances with long multiword expressions as argu-
Table 5: Pearson correlation between different weights for different relations.

| Relation               | MxB(B) | Av(B) | MxG(B) | AvG(B) |
|------------------------|--------|-------|--------|--------|
| SÍNÓNIMO _N.DE         | 0.99   | 0.99  | -0.33  | -0.64  |
| SINÓNIMO _V.DE         | 0.98   | 0.98  | -0.86  | -0.92  |
| SINÓNIMO _ADV.DE       | 0.94   | 0.91  | -0.76  | -0.65  |
| HIPERONIMO _DE         | 0.82   | 0.82  | -0.23  | -0.28  |
| HIPERONIMO _ACAO.DE    | 0.99   | 0.99  | -0.69  | -0.75  |
| PARTE.DE               | 0.98   | 0.98  | -0.90  | -0.95  |
| PARTE.DE _ALGO.COM_PROP| 0.56   | 0.64  | 0.01   | 0.06   |
| MEMBRO.DE              | 0.72   | 0.70  | 0.97   | 0.98   |
| FINALIDADE.DE          | 0.82   | 0.86  | -0.67  | -0.82  |
| FAZ _SE.COM            | 0.97   | 0.96  | 0.47   | 0.16   |
| ACCAO _QUE_CAUSA       | 0.88   | 0.82  | 0.99   | 0.03   |
| LOCAL_ORIGEM.DE        | 0.92   | 0.92  | 0.94   | 0.93   |
| DIZ _SE.DO.QUE         | 0.90   | 0.88  | 0.37   | -0.02  |
| PROPRIEDADE_SEMELHANTE_A | 0.94  | 0.94  | 1.00   | 1.00   |

Table 6: Pearson correlation between average weights and Res, for different relations.

| Relation               | 1      | 2      | 3      | 4      | 5      | 6      | 7      | 8      | 9      |
|------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| SÍNÓNIMO _N.DE         | 3.86±1.0 | 3.97±0.9 | 4.05±0.9 | 4.12±0.9 | 4.20±0.8 | 4.26±0.8 | 4.28±0.8 | 4.41±0.7 |
| SINÓNIMO _V.DE         | 4.09±0.9 | 4.11±0.9 | 4.24±0.9 | 4.27±0.9 | 4.33±0.9 | 4.36±0.9 | 4.41±0.9 | 4.57±0.8 | 4.63±0.7 |
| HIPERONIMO _DE         | 3.78±0.8 | 3.87±0.8 | 3.92±0.8 | 3.95±0.8 | 4.04±0.8 | 4.15±0.9 | 4.16±0.8 | 4.21±0.8 | 4.12±0.0 |
| HIPERONIMO _ACAO.DE    | 4.83±1.1 | 5.03±1.1 | 5.28±1.1 | 5.53±1.0 | 5.77±1.0 | 5.99±1.2 | 5.78±1.4 | 5.54±0.8 |
| PARTE.DE               | 4.21±1.1 | 4.45±1.0 | 4.47±0.9 | 4.61±0.9 | 4.76±0.9 | 4.94±0.7 |
| MEMBRO.DE              | 4.00±1.2 | 5.21±1.3 | 5.49±1.2 | 5.81±1.0 |
| FINALIDADE.DE          | 4.18±1.3 | 5.35±1.3 | 5.09±1.3 | 6.49±1.7 | 5.09±0.0 |
| FAZ _SE.COM            | 4.25±1.2 | 4.19±1.1 | 4.44±1.0 |
| ACCAO _QUE_CAUSA       | 3.95±1.1 | 4.66±1.1 | 5.06±0.9 | 4.82±0.9 |
| LOCAL_ORIGEM.DE        | 3.97±1.0 | 4.34±1.0 | 4.53±1.1 | 4.65±0.8 |
| DIZ _SE.DO.QUE         | 4.41±1.2 | 4.61±1.0 | 4.61±0.9 |
| DIZ _SE.SOBRE          | 3.47±1.1 | 3.23±0.9 | 3.52±1.0 | 4.01±1.1 |
| PROPRIEDADE_SEMELHANTE_A | 3.70±1.3 | 4.52±1.5 | 4.70±0.8 |

Table 7: Average weights for different relations and number of resources.

3Even though multword expressions have terms separated by underscores ("_"), before using them for computing weights, underscores were replaced by spaces.

The computed losses are not only sensitive to the relation top and bottom-weighted instances for specific values of Res. For illustrative purposes, Table 10 shows the instances in two resources (Res = 2) with top and bottom Av(B) weights. The bottom-weighted still include some instances with multword expressions, and mostly instances with very specific arguments. On the top-weighted, this judgement is harder to make, but quality is generally better, suggesting that the weights can indeed be useful for filtering out lower quality instances.

4.3. Argument Frequency vs Validity

While performing these experiments, we noted that the computed losses are not only sensitive to the relation...
they are transmitting, but also to the words used and their commonality, i.e., sequences that contain words that the TLM has seen more times will get higher weights. This may have a negative impact on the ideal weight attribution, because it makes it hard to discriminate between semantically-valid sentences and well-formed sentences that use frequent words. To illustrate this, we selected two relations with a fixed argument (‘x hypernym of animal’ and ‘wheel part-of x’), and one pattern for each, then instantiated with valid and invalid arguments. For illustrative purposes, we selected arguments with variable frequency in a corpus of Brazilian Portuguese (Berber Sardinha et al., 2009), the variant BERTTimbaux was pre-trained for, namely: cachorro (6,372), gato (6,586), esquilo (78), carro (90,500), moto (5,209), skate (1,564). Table 8 shows the exponential of the loss in BERTimbau base. For the valid arguments, relative weights seem to have some correlation with the frequency of their variable argument (e.g., cat and dog are more frequent than squirrel; car is more frequent than motorcycle and skate). However, even if invalid, when a very frequent word is used as the argument (e.g., car or cat), the weight is higher than for the less frequent valid argument (squirrel) or for all the valid arguments (car, motorcycle, skate).

Table 8: Top and bottom-weighted instances in only two resources.

| Relation | Top/Av(B) | Bottom/Av(B) |
|----------|-----------|--------------|
| SINONIMO | beira-cairel | mesa-de-cabeceira-mesinha-de-cabeceira |
| SINONIMO | cortar-foiçar | empenhar–empeionhentar |
| SINONIMO | instável-lável | infortunado–mal-afinado |
| SINONIMO | senhora-condessa | búfalo-búfalo-asíntico |
| HIPERONIMO | mover-depor | metanoforar-acomunmar |
| HIPERONIMO | salário-remendo | para-brisa-aeroplano |
| HIPERONIMO | esforço-campanha | porca-alferão-crociacede |
| HIPERONIMO | trata-precursor | tira-rocha-da-garrafa-saca-rolhas |
| HIPERONIMO | liquido-taiega | galanopunctura-agulha |
| HIPERONIMO | luar-livre | empenhar–empeionhamento |
| HIPERONIMO | estado-catarinense | freixo-de-espada-a-cinta-freixonita |
| HIPERONIMO | austríaco-áustria | peciníbrânquo-ter-brinqual-em-forma-de-pente |
| HIPERONIMO | auxiliar-áustria | mnemotécnico-mnemotecnia |

Table 9: Weights of sequences in BERTimbau base.

5. Answering Similarity Tests

In the previous section, we noted some positive insights from weights computed by TLMS, but also issues that made us unsure on their suitability, especially of the GPT-based weights. To get more on the utility of these weights, and on their advantages when compared to no weights or to simply using Res, we used them in a more objective task, for which a benchmark exists. This task was word similarity and our gold data were adaptations of well-known similarity tests to Portuguese, namely PT-65 (Granada et al., 2014), SimLex-999 and WordSim-353 (Querido et al., 2017), which contain pairs of Portuguese words and their semantic similarity or relatedness score, based on human judgements (e.g., pássaro grua 0.24 or menino rapaz 3.58). The goal was to exploit the network resulting from PT-LKB and the different weights for computing the similarity of every pair in the test, to finally assess the results with the Pearson correlation between the automatically-computed and the gold scores.

A similar approach to that of previous work (Gonçalo Oliveira, 2018) was followed: embeddings were learned from PT-LKB with node2vec (Grover and Leskovec, 2016), while considering the TLM weights, Res, and no weights. Node2vec represents node neighbourhoods in a d-dimensional feature space by applying a biased random walk procedure. We used its implementation available in the node2vec Python library and ran the algorithm with the following parameters: dimensions = 64, walk_length = 80.
num_walks = 10, window = 3, min_count = 1

After this process, each word in the network is represented as a numeric vector of size 64, and the similarity between two words can be given by the cosine of their vectors. So, the goal was to compare the performance of different embeddings in the considered similarity tests. Table 10 presents the Pearson correlations achieved by the embeddings learned for different weights. As it happens to other embedding methods, node2vec is not deterministic, meaning that each run for the same network may result in slightly different vectors. Therefore, for each considered weight, a total of five node2vec models were learned. This enabled us to compute the mean correlation and the standard deviation. We should add that pairs for which one of the arguments was not in the network were ignored (3.5%, 6.3% and 0, respectively in SimLex, WordSim and PT-65).

Coefficients in the table show that no network stood out and no significant improvements could be achieved with any of the weights. Not even with the Res weights when compared to no weights, which is contradictory to results reported in Gonçalo Oliveira (2018), and is possibly caused by minor differences in the experimentation setup (e.g., different implementation of node2vec, different window size, considered relation types and number of runs). So, in this scenario, the weights computed with the TLMs have shown to be no more useful than Res, based on the number of resources. However, results also suggest that the impact of the weight when embedding the network with node2vec is not enough for exposing the differences, and that this experiment was not the best for reaching strong conclusions. Alternative experiments will have to be devised in the future.

6. Conclusion

Inspired by early work on ranking automatically acquired relation instances from text, useful for discarding noisier extractions, we explored recent TLMs for a similar purpose, while avoiding to search directly on large corpora. We focused in Portuguese lexi-co-semantic relations and weighted the instances in PT-LKB, obtained from ten lexical resources. For each of the 16 relation types considered, three lexical patterns were handcrafted. TLMs for Portuguese were then used for computing the likelihood of the sequences resulting from instantiating the patterns with the relation instances. The latter scores were used as weights. Though not correlated with the number of resources the instances were obtained from, weights were lower for instances with very long and specific arguments, suggesting that weights computed like this can be used for filtering out noisier extractions. This may help in the selection of more prototypical relations from a large set, and be useful for the automatic creation of more reliable knowledge bases.

However, when used for computing semantic similarity, the new weights did not make a difference to using no weights. Towards stronger conclusions, alternative experiments will have to be made in the future. For instance, in the domain of semantic similarity, we may consider pre-discarding low-weighted instances, or try to consider the relation type in the process. Still, we should look for tasks where the impact of the weights is more noticeable. It would also be interesting to test a similar approach in alternative TLMs, not only for Portuguese, but for other languages. For that, in addition to the TLM and instances to weight, a small list of lexical patterns would have to be written for each target relation, which should be straightforward for most relations.

In the meantime, the weighted PT-LKB instances are available from https://github.com/NLP-CISUC/PT-LexicalSemantics/blob/master/Relations/triplos_pesados_norm.tsv.zip for anyone willing to use them and possibly complement our conclusions. Despite this negative result, we see the discussed insights as another contribution to better understanding TLMs, what linguistic knowledge they encode, and how we can leverage on it towards better language resources.

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