Abstract

English. In this work we analyze the performances of two of the most used word embeddings algorithms, skip-gram and continuous bag of words on Italian language. These algorithms have many hyper-parameter that have to be carefully tuned in order to obtain accurate word representation in vectorial space. We provide an accurate analysis and an evaluation, showing what are the best configuration of parameters for specific tasks.

Italiano. In questo lavoro analizziamo le performances di due tra i più usati algoritmi di word embedding: skip-gram e continuous bag of words. Questi algoritmi hanno diversi iperparametri che devono essere impostati accuratamente per ottenere delle rappresentazioni accurate delle parole all'interno di spazi vettoriali. Presentiamo un'analisi accurata e una valutazione dei due algoritmi mostrando quali sono le configurazioni migliori di parametri per applicazioni specifiche.

1 Introduction

The distributional hypothesis of language, set forth by Firth (1935) and Harris (1954), states that the meaning of a word can be inferred from the contexts in which it is used. Using the co-occurrence of words in a large corpus, we can observe for example that the contexts in which client is used are very similar to those in which customer occur, while less similar to those in which waitress or retailer occur. A wide range of algorithms have been developed to exploit these properties. Recently, one of the most widely used method in many natural language processing (NLP) tasks is word embeddings (Bengio et al., 2003; Mikolov et al., 2010; Mikolov et al., 2013). It is based on neural network techniques and has demonstrated to capture semantic and syntactic properties of words taking as input raw texts without other sources of information. It represents each word as a vector such that words that appear in similar contexts are represented with similar vectors (Collobert and Weston, 2008; Mikolov et al., 2013). The dimensions of the word are not easily interpretable and, with respect to explicit representation, they do not correspond to specific concepts.

In this work we seek to explore the relationships by generating word embedding for over 40 different parameterizations of the continuous bag-of-words (CBOW) and the skip-gram (SG) architectures, since as shown in Levy et al. (2015) the choice of the hyper-parameters heavily affect the construction of the embedding spaces. The main difference among the two architectures is that CBOW tries to predict a word given its context while SG tries to predict the context given a word.

Specifically our contributions include:

• **Word embedding.** The analysis of how different hyper-parameters can achieve different accuracy levels in relation recovery tasks (Mikolov et al., 2013).

• **Morpho-syntactic and semantic analysis.** Word embeddings have demonstrated to capture semantic and syntactic properties, we compare two different objectives to recover relational similarities for semantic and morph-syntactical tasks.

• **Qualitative analysis.** We investigate problematic cases.

2 Related works

The interest that word embedding models have achieved in the NLP international community has
recently been confirmed by the increasing number of studies that are adapting these algorithms in languages different from English (Al-Rfou et al., 2013). One of the first examples is the Polyglot project that produced word embedding for 117 languages. They demonstrated the utility of word embedding, achieving, in a part of speech tagger task, performances competitive with the state-of-the-art methods in English. Attardi et al. (2014) have done the first attempt to introduce word embedding in Italian obtaining similar results. They have shown that, using word embedding, they obtained one of the best accuracy levels in a named entity recognition task.

However, these optimistic results are not confirmed by more recent studies. Indeed the performance of word embedding are not directly comparable in the accuracy test to those obtained in the English language. For example, Attardi and Simi (2014) combining the word embeddings in a dependency parser have not observed improvements over a baseline system not using such features. Berardi et al. (2015) found a 47% accuracy on the Italian versus 60% accuracy on the English. The results may be a sign of a higher complexity of Italian with respect to English as we will see section 4.1.

Similarly, recent work that trained word embeddings on tweets have highlighted some criticalities. One of these aspects is how the morphology of a word is opaque to word embeddings. Indeed, the relatedness of the meaning of a lemma’s different word forms, its different string representations, is not systematically encoded. This means that in morphologically rich languages with long-tailed frequency distributions, even some word embedding representations for word forms of common lemmata may become very poor (Kim et al., 2016).

For this reason, some recent contributions on Italian tweets have tried to capture these aspects. Tamburini (2016) trained SG on a set of 200 million tweets. He proposed a PoS-tagging system integrating neural representation models and a morphological analyzer, exhibiting a very good accuracy. Similarly, Stemle (2016) proposes a system that uses word embeddings and augments the WE representations with character-level representations of the word beginnings and endings.

We have observed that in these studies the authors used either the most common set-up of parameters gathered from the literature (Tamburini, 2016; Stemle, 2016; Berardi et al., 2015) or an arbitrary number (Attardi and Simi, 2014; Attardi et al., 2016). Despite the relevance given to these parameters in the literature (Goldberg, 2017) we have not seen studies that analyze the different strategies behind the possible parametrization. In the next section, we propose a model to deepen these aspects.

### 3 Italian word embeddings

Previous results on the word analogy tasks have been reported using vectors obtained with proprietary corpora (Berardi et al., 2015). To make the experiments reproducible, we trained our models on a dump of the Italian Wikipedia (dated 2017.05.01), from which we used only the body text of each article. The obtained texts have been lowercased and filtered according to the corresponding parameter of each model. The corpus consists of 994,949 sentences that result in 470,400,914 tokens.

The hyper-parameters used to construct the different embeddings for the SG and the CBOW models are: the size of the vectors ($dim$), the window size of the words contexts ($w$), the minimum number word occurrences ($m$) and the number of negative samples ($n$). The values that these hyper-parameters can take are shown in Table 1.

| .05em | HP | SG | CBOw |
|------|----|----|------|
| dim  | 200, 300, 400, 500 | 200, 300, 400, 500 |
| w    | 3, 5 | 2, 5 |
| m    | 1, 5 | 1, 5 |
| n    | 1, 5, 10 | 1, 5, 15 |

Table 1: Hyper-parameters

| Morphosyntactic | Semantic |
|-----------------|----------|
| adjective-to-adverb | capital-common-countries |
| opposite | capital-world |
| comparative | currency |
| superlative (assoluto) | city-in-state |
| present-participle (gerundio) | regione capoluogo |
| nationality-adjective | plural |
| past-tense | plural-verbs (3rd person) |
| plural | plural-verbs (1st person) |
| plural-verbs (1st person) | remote-past-verbs (1st person) |
| remote-past-verbs (1st person) | noun-masculine-feminine-singular |
| noun-masculine-feminine-singular | noun-masculine-feminine-plural |

Table 2: Relation types

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4 Evaluation

The obtained embedding spaces are evaluated on an word analogy task, using a enriched version of the Google word analogy test (Mikolov et al., 2013), translated in Italian by (Berardi et al., 2015). It contains 19,791 questions and covers 19 relations types. 6 of them are semantic and 13 morphosyntactic (see Table 2). The proportions of these two types of question is balanced as shown in Table 2.

To recover these relations two different methods are used: 3COSADD (Eq. 1) (Mikolov et al., 2013) and 3COSMUL (Eq. 2) (Levy et al., 2014) to compute vectors analogies:

\[
\text{3COSADD } \arg \max_{b \in V} \cos(b^*, b - a + a^*) \quad (1)
\]

\[
\text{3COSMUL } \arg \max_{b \in V} \frac{\cos(b^*, b)\cos(b^*, a^*)}{\cos(b^*, a) + \epsilon} \quad (2)
\]

These two measures try to capture different relations between word vectors. The idea behind these measures is to use the cosine similarity to recover the vector of the hidden word \(b^*\) that has to be the most similar vector given two positive and one negative word. In this way, it is possible to model relations such as queen is to king what woman is to man. In this case, the word queen \((b^*)\) is represented by a vector that has to be similar to king \((b)\) and woman \((a^*)\) and different to man \((a)\). The two analogy measures slightly differ in how they weight each aspect of the similarity relation. 3COSADD allow one sufficiently large term to dominate the expression (Levy et al., 2014). 3COSMUL achieves a better balance amplifying the small differences between terms and reducing the larger ones levy2014linguistic. As explained in Levy et al. (2014), we expect 3COSADD to be more accurate for solving syntactic analogies and 3COSMUL to over-perform 3COSADD in evaluating both the syntactic and the semantic tasks as it tries to normalize the strength of the relationships that the hidden term has both with the attractor terms and with the repellers term.

4.1 Experimental results

The results of our evaluation are presented in Figure 1. The main trend that it is possible to notice is that accuracy increases as the number of dimensions of the embedded vectors increases. This indicates that Italian language benefits of a rich representation that can account for its rich morphology. Another important trend that emerges is the fact that the parameters have the same effect on both algorithms and that they perform very differently on all the tasks. CBOW has very low accuracy compared to SG. We can also see that the \(\text{dim}\) hyper-parameter is not correlated with the dimension of the vocabulary (model complexity) as one should expect. In fact, with increasing values of \(\text{dim}\) the accuracy increases whatever is the value of \(m\). This hyper-parameter heavily affects the vocabulary length (see table 4.1). However the \(\text{dim}\) hyper-parameter seems to be correlated only with the accuracy in the semantic tasks while the performances on the morpho-syntactic tasks seems not to have a big burst increasing the dimensionality.

With respect to the size of the context \((w)\) used to create the words representations we do not observe a clear difference between the 18 pairs both in the SG and in the CBOW. On the contrary a clear trend can be observed varying the \(n\) hyper-parameter, with \(n = 1\) the accuracy was significantly lower than the one we obtained with \(n = 5\) or \(n = 10\). Increasing the number of negative samples constantly increases the accuracy.

These results support also the claim put forward by (Levy et al., 2014) that the 3COSMUL method is more suited to recover analogy relations. In fact, we can see that on average the right bars of the plots are higher than the left.

4.2 Error analysis

Most of the recovery errors are due to vocabulary issues. In fact, many words of the test set have no correspondence in the developed embedding spaces. This is due to the low frequency of many words that are not in the training corpus or that have been removed from the vocabulary because of their (low) frequency. For this reason we kept the \(m\) hyper-parameter very low (e.g., 1 and 5), in counter-tendency with recent works that use larger corpora and then remove infrequent words setting \(m\) with high values (e.g., 50 or 100).

| \(m\) | 1 | 5 | Berardi |
|------|---|---|---------|
| 3  | 227.282 | 473.355 | 733.392 |

Table 3: Vocabulary length
Figure 1: Results as accuracy with different hyper-parameters ($y$ axis) using the 3CosAdd (left bar) and the 3CosMul (right bar) formula. The green part of the bars indicates the accuracy on the morphosyntactic task whereas the red one the accuracy on the semantic task. The + sign on each bar indicates the accuracy on the entire dataset. The upper row of the figure shows the results of the SG algorithm and the bottom row the results of CBOW. The last two bars of the SG plots indicates the results obtained using the vectors made available by (Berardi et al., 2015)

fact, with increasing value of $m$ the number of not given answers increases rapidly. It passes from 300 ($m = 1$) to 893 ($m = 5$).

Some of the words that are not present in the vocabulary with $m = 1$ include plural verbs (1st person), that probably are not used by a typical Wikipedia editor and remote past verbs (1st person), a tense that in recent years is disappearing from written and spoken Italian. Some of these verbs are:

- giochiamo
- zappiamo
- mescolai
- affiliamo
- implementai
- rallentiamo
- rallentai
- predissi

In (Berardi et al., 2015) the number of not given answer is 1,220. The accuracy of their embeddings, obtained using a larger corpus and using the hyper-parameters that perform well on English language, is always lower than those obtained with our setting, in both the morphosyntactic and the semantic tasks. This confirms that the regularization of the parameters is crucial for good representation of the embeddings, since the Berardi et al. (2015)’s model has been trained on a much larger corpus and for this should outperform ours. Furthermore, this model seems to have some tokenization problem. In fact, its vocabulary contains entries like:

- disco.ancora
- giocatori.”fonte”collegamenti
- campionato.tuttavia
- industriale.viene
tardi.sempre
televisione.fr

5 Conclusions

We have tested two word representation methods: SG and CBOW training them only on a dump of the Italian Wikipedia. We compared the results of the two models using 12 combinations of hyper-parameters.

We have adopted a simple word analogy test to evaluate the generated word embeddings. The results have shown that increasing the number of dimensions and the number of negative examples improve the performance of both the models.

These types of improvement seems to be beneficial only for the semantic relationships. On the contrary the syntactical relationship are negatively affected by the low frequency of many of its terms. This should be related to the morphological complexity of Italian. In the future it would be helpful to represent the spatial relationship regarding specific syntactical domain in order to evaluate the contribution of hyper-parametrization to syntactical relationship accuracy. Moreover future work will include the testing of these word embedding parametrizations in practical applications (e.g. analysis of patents’ descriptions and books’ corpora).

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