WORD EMBEDDINGS IN ROMANIAN FOR THE RETAIL BANKING DOMAIN

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Abstract. *Word embeddings are a considerable improvement in Natural Language Processing and Deep Learning research fields as a result of their effectiveness for representing textual data in form of fixed-length dense vectors. Currently, domain general pre-trained word embeddings such as Word2Vec and FastText are available in Romanian language. Retail banking domain is a context-sensitive field similar to financial or legal domains where people are using specific terms that are having particular meaning in that specific context. The main goal is to capture retail banking context in order to perform Sentiment Analysis tasks on retail banking reviews in Romanian language. Therefore, this research paper introduces a domain-specific word embeddings called RoBankingFastVec for representing textual data in Romanian language from retail banking field based on online resources such as Wikipedia, retail banking newspapers and books. A research framework is proposed in order to properly conduct the implementation of the retail banking domain-specific word embeddings. The word vectors are obtained by training a FastText model using Skip-gram architecture. By exploring embedding space, the word vectors are evaluated through different tasks related to word embeddings such as Clustering, Similarity, Analogy, Mismatching.*

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1. Introduction

Word embeddings known as distributed word representations or word vectors have been proposed as an alternative method for representing textual data in feature vectors [1]. Word embeddings can be seen as a Natural Language Processing (NLP) method which is based on a set of techniques of language modeling and feature learning to encode documents, sentences or words from a vocabulary to fixed-length dense vectors of real numbers. In simple terms, word embeddings are a word representation as a vector with dimensions corresponding to the words in the vocabulary and whose values are generated through feature engineering or most recently, unsupervised learning.

One of the most popular word embeddings models implemented by Google is Word2Vec [2]. Word2Vec was proposed for a better representation of word vectors so that the words similarity is captured more meaningfully by reducing the word vectors dimensionality. The idea behind Word2Vec is that instead of considering the words frequency, a classifier is learning how to do a prediction. Hence, Word2Vec is a predictive model that learns embeddings through a one hidden layer neural network of variable size by using a predefined number of words before and after a target word (the window size). A large corpus of textual data is given as input to Word2Vec and after learning process, Word2Vec produces a set of word vectors in a low dimensional vector space that are consistent with the context. Recently, Facebook implemented a word embeddings model called FastText [3] as an evolution of Word2Vec for enriching word vectors with sub-word information in the prediction model. Word embeddings such as Word2Vec or FastText could be applied on the own training dataset if there are enough data to be given as input. If the amount of training dataset is limited, available pre-trained word embeddings could be used as transfer learning methods to improve the accuracy of the model. Facebook released FastText pre-trained word embeddings that were trained on Wikipedia for 90 languages [3], including Romanian. In addition, Facebook released a year later another version of FastText pre-trained word embeddings, trained on Common Crawl and Wikipedia [4]. Another pre-trained word embeddings in Romanian can be found at [5] and [6]. These pre-trained word embeddings are generic, domain-general being hard to capture domain-specific particularities. In dynamic environments such as financial, legal or retail banking, people are using domain-related terms having a specific meaning in that context. The context plays an important role in sentiment analysis tasks in order to classify the sentiment in an accurate way. Therefore, several studies proposed domain-specific word embeddings. For instance, a domain-specific word embeddings in financial field that outperformed the domain-general Word2Vec embeddings has been proposed in [7]. In this paper, RoBankingFastVec based on FastText model, word embeddings for the retail banking domain in Romanian language, are proposed and evaluated. Textual data is collected from several online resources specific to retail banking domain in Romanian language yielding a corpus of **323.097** of Romanian words. The quality of the proposed word embeddings is evaluated using different tasks related to word embeddings such as Clustering, Similarity, Analogy, and Mismatching.

2. Research Framework for development of RoBankingFastVec

A research framework composed by four stages is proposed to develop RoBankingFastVec, word embeddings in Romanian language specific to retail banking context in order to be further used in sentiment analysis tasks of reviews in Romanian language. The research framework is composed by the following stages: Data Sources Identification, Data Sources Aggregation, Training Process and Exploration of the embedding space. These stages are described in the following sub-sections.

2.1. Data Sources Identification

In this stage, several online resources that contain retail banking related text were identified including websites in Romanian language from banks and financial institutions, newspapers, blogs and Wikipedia pages with specific to retail banking context. In addition, a financial banking education book which contains a relevant number of retail banking related words was considered as identified data source. Interviews, redactors or analysts opinions were not considered for extraction. Online resources considered for extraction are presented in Table 1.

Table 1. Identified data sources

Data Source	<i>Wikipedia Domain: Retail Banking Romanian language</i>	<i>Banks and Financial institutions websites and BNR</i>	<i>Finzoom</i>	<i>Conso</i>	<i>Vreau credit</i>	<i>BugetulFamiliei</i>	<i>Efin</i>	<i>Manualul Practic pentru utilizatorul de servicii financiare</i>
Number of words	113760	82917	20323	24877	8451	8901	7564	56.304

2.2. Data Sources Aggregation

After data sources identification, the next stage is related to data sources aggregation. The first step is to extract the relevant retail banking text in Romanian language from identified data sources. Using Scrapy as framework for data extraction, several web scrapers were created for performing the data extraction yielding a corpus of **323.097** Romanian words related to retail banking context stored in a CSV file.

2.3. Training Process

This stage is composed by two steps: corpus preprocessing and the model configuration.

2.3.1. Corpus Preprocessing

In this step, several tasks for cleaning the text from the corpus are performed. In most cases, in Romanian online resources, diacritics are omitted. Several websites don't use diacritics in their text, even most popular websites such as the Citi bank website¹. Hence, the first step in preprocessing the text from the corpus is to remove Romanian special characters which are refereed as diacritics. Then numbers, symbols, spaces and non-ASCII characters were eliminated. In addition, a lemmatization function was implemented in order to preserve the relative meaning of words when building the word embeddings.

2.3.2. Model Configuration

Obtaining quality-based word embeddings mainly depends on configuration of model parameters. For training RoBankingFastVec, the FastText model proposed by [3] is chosen following the implementation supported by Python library, Gensim [8]. FastText model is based on a neural network of one hidden layer that takes as input the data corpus and provides as output produces a set of word vectors of real numbers. To capture the context and to create meaningful semantic relationships between words, FastText model requires several parameters as input that are essential as directly influence the output. The FastText parameters configuration are detailed in Table 2. The architecture model chosen to train the FastText model for obtaining RoBankingFastVec word embeddings was Skip-gram that works better for smaller corpuses [9]. RoBankingFastVec receives as input the given corpus and learns embeddings by starting with an initial set of embeddings with random then shifting and take the embeddings of words that occurs nearby in texts according to the model configuration parameters. The dimension of the context window influences directly the semantic relationships of words. Using shorter context windows will generate similar words whilst larger context windows will generate topically related words. A good example of this aspect can be found in [13].

¹ <http://www.citibank.ro/romania/>

Table 2. FastText Configuration Model Parameters

FastText Parameter Gensim ²	Description	Value
sentences	Corpus in form of tokenized text.	Corpus composed by 323.097 Romanian words
size	Size of the hidden layer which determines the dimension of the dense output vector.	100
window	Context window used for collecting words counts.	10
sg	Option for choosing the architecture model between CBOW and Skip-gram. The default value is set to 0 for training a CBOW, 1 is for Skip-gram.	1
min_count	rare words from the corpus that are ignored for the training process.	5
sample	Down sampling of words	1e-2
iter	Number of epochs over the samples used to train the model	100

2.4. Exploration of the embedding space

For performing Natural Language Processing and Sentiment Analysis tasks, the quality of the word embeddings is essential. The previous stages were dedicated to build RoBankingFastVec and this stage evaluates the quality of the generated word embeddings in Romanian language for retail banking domain. There is not a quantitative baseline criterion for evaluating the quality of word embeddings. Even so, in literature, various intrinsic or extrinsic methods have been proposed for word embeddings quality evaluation such as: POS tagging, analogy, similarity and sentiment classification [10]. In this paper, for assessing the quality of the semantic relationships between retail banking-specific concepts different tasks related to word embeddings such as Clustering, Similarity, Analogy, and Mismatching, are used.

2.4.1. Clustering

Word with similar meaning are grouped nearby in the vector space. Visualization of embedding space allows to verify if the words with similar meaning in the context of retail banking are grouped nearby each other by forming clusters. The embeddings space can be visualized by using T-SNE (acronym of t-distributed stochastic neighbor embedding visualization algorithm) [11]. For exemplification, considering two words ‘dobanda’ (Romanian translation of English word ‘interest’) and ‘comision’ (translation of English word ‘comission’), the similar Romanian words (top 5 words) in meaning from words ‘dobanda’, and ‘comision’ are grouped and the similar words in meaning are also close together in the RoBankingFastVec word embeddings space.

2.4.2. Similarity

Cosine similarity metric or dot product is a widely used metric for exploring the similarity of words from the embeddings space. To determine the cosine similarity, a query is performed to the trained model in order to return the 5 words closest. For return the top 5 words similar in meaning to “dobanda” (from English “interest rate”), the following query was executed:

ft_model.wv.most_similar(positive=['dobanda'])

² <https://radimrehurek.com/gensim/models/fasttext.html>

The results of this query are presented in Table 3.

Table 3. Top 5 words closet to 'dobanda' (cosine distance)

Words closest to "dobanda"	Cosine distance
fixa (Translation from English "fix")	.73
rata (Translation from English "credit rate")	.72
lunar (Translation from English "monthly")	.66
variabila (Translation from English "variable")	.66
credit (Translation from English "loan")	.60

As illustrated, RoBankingFastVec model even if it is composed by only raw textual data and it was trained in an unsupervised way, RoBankingFastVec managed to learn different semantic relationship between words in retail banking context. Also, for the out-of-vocabulary words, the model can adapt and make correct semantic correlations.

2.4.3. Analogy

In natural language processing, word pairs are often used. Word analogies are word pairs with semantic meaning [12] which can be determined using vector offset method [2]. For instance, the vector operation of words: Science + Art - Tesla = Michelangelo. This means that the Michelangelo is determined by measuring how closer the vector is to the operation of word pairs. Considering two words pairs P_1 composed by vectors w_1 and w_2 and pair P_2 composed by vectors v_1 and v_2 , table 4 illustrates how word analogies are organized within embedding space by RoBankingFastVec.

Table 4. Word analogies for RoBankingFastText

$\vec{w_1}$	$\vec{w_2}$	$\vec{v_1}$	$\vec{v_2}$
dobanda (interest)	credit (loan)	comision(commission)	card (card)
polita (policy)	viata (life)	credit (loan)	ipotekar (real estate)
card (card)	posesor (owner)	asigurare (insurance)	asigurat (insurant)

2.4.4. Mismatching

The aim of the mismatching task is to test the model if it's able to discriminate between different retail banking concepts. In other words, the model should be able to identify from a list of words the word which is not related to that list. To perform this type of query, the model is calculating in the embedding space the cosine similarity for each word in the list and all other words and returns an average result. The word which has the lowest cosine distance value is considered as a no-matching word. Table 5 shows the responses of the RoBankingFastVec model to the mismatching queries.

Table 5. Mismatching queries for RoBankingFastVec model

List of words	Response
moneda, dobanda, rata, fixa, variabila	moneda
asigurare, prima, polita, viata, bacnota	bacnota
comision, taxa, cost, fngcimm, perceput	fngcimm

3. Conclusions

Word embeddings are a powerful representation of textual data widely used in Natural Language Processing and Deep Learning research fields. This research paper presented RoBankingFastVec, a domain-specific word embeddings for retail banking field from online sources in Romanian language. These custom word embeddings are available on GitHub³.

The research framework proposed for generating RoBankingFastVec is presented. Textual data specific to retail banking context is extracted from several online resources yielding a corpus of **323.097** of Romanian retail-banking specific words. RoBankingFastVec is trained following FastText implementation based on skip-gram architecture. The quality of the trained embeddings was evaluated through different tasks and the results showed that the RoBankingFastVec encode meaningful semantically relationships in retail banking domain.

So far, in the current literature, there have not been proposed word embeddings for retail-banking in Romanian language. In the future, RoBankingFastVec will be used as a transfer learning method in sentiment analysis tasks of retail banking reviews in Romanian language.

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³ <https://github.com/irina-raicu/custom-word-embeddings>