UNIVERSITY OF BIRMINGHAM

School of Computer Science
College of Engineering and Physical Sciences

MSc. Project

Analysing news articles about Russia's war on Ukraine using Latent Dirichlet Allocation based topic modelling

Submitted in conformity with the requirements
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Nelson Quintanilla Castro
Student ID: 2291960
Supervisor: Dr Mohammed Bahja

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Table of Abbreviations

- LDA – Latent Dirichlet Allocation
- API – Application Programming Interface
- NLTK – Natural Language Toolkit

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1 Overview

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1.1 Abstract

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1.2 Acknowledgements

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2 Introduction

The ongoing conflict between Russia and Ukraine is a topic of pivotal importance not only for the protagonist's regions but also for the whole world. This war is already causing many negative economic, political, and social consequences on a different scale for many countries (Caldara et al. 2022). As a result, this has become of paramount concern for governments and, subsequently for all types of media.

This is why there is currently a tremendous amount of information that has been generated about the Russo-Ukrainian conflict and there is no systematic way to analyse this corpora to examine what is currently happening regarding this conflict, to discover the main themes contained within it, and possibly draw conclusions about it.

At the same time, it is not humanly possible to read and study large quantities of articles with this thematic in a short period of time. To do this, experts in machine learning have created probabilistic topic modelling, a collection of several algorithms which are used to identify and interpret sizeable sets of documents that contain topical information. We can use topic modelling to identify the primary ideas that run through a sizable and otherwise unstructured collection of papers. We can arrange the collection in accordance with the themes found by applying topic modelling (Blei 2012).

For the purpose of this work, latent dirichlet allocation (LDA) is going to be the topic modelling algorithm of choice. A collection of texts can be broken down into their key topics using LDA, where a topic is defined as a probability distribution over a vocabulary (Blei n.d.).

A set number of topics are proposed by LDA, and it is assumed that each document in a collection of documents reflects a combination of those themes. Under these presumptions, probabilistic inference techniques identify an embedded theme structure in a document collection. LDA offers a technique to easily summarise, peruse, and search huge document collections with this structure (Blei et al. 2010).

The main motivation of this work is to capture the main themes or topics that can be found on news articles available on the internet that cover events related to Rusia's war on Ukraine. This represents an important topic to study because there is a need to derive insightful information from this vast amount of news about the war that are being generated in mass all over the world.

Furthermore, it is of utter importance to observe and detect significant patterns that are being communicated to the general public through news articles so we can predict consequences of the current state of the situation on the short term such as the economical, political, and social impact on human lives.

In this paper we provide an analysis of news articles retrieved from The Guardian newspaper that cover events related to the Russian invasion of Ukraine by utilising LDA based topic modelling with the purpose of obtaining abstract topics within a corpora of news articles. We also offer a way to assess the effectiveness and outcomes of our model. Additionally, we present the validation of our model by comparing it against human judgement. In order to allow others to duplicate our findings, we have also made our data sets publicly available. Further to this, we use pyLDAvis to interpret the topics obtained by our model in a more comprehensible and visual way. This software offers a global view of the topics and how they differ from one another while also enabling a close examination of the terms most closely associated with each specific topic (Sievert & Shirley 2014).

The structure of this paper is as follows. In section 3 we examine the most recent studies in this field. In Section 4 we present the specifics of our approaches, including a description of data extraction, preprocessing, parameter tuning of our model, and evaluation metrics implemented. We provide our findings and engage in a discussion in Section 5. The discussion is presented in part 6, and our conclusion is presented in section 7.

3 Literature Review

3.1 Subsection

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3.2 Subsection

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4 Methodology

In this section we explain the steps we took in order to build and prepare our dataset, the model generation and parameter tuning process, methods of evaluation for our model, and lastly visualisation and interpretation of our resulting topics. The Figure 1 summarises the method we just mentioned.

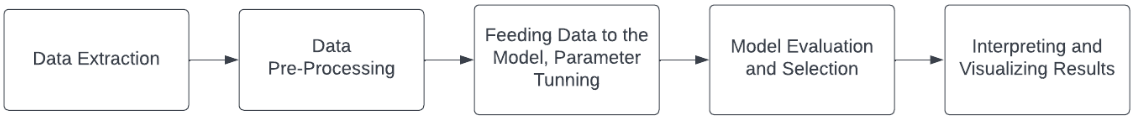
Data Extraction
Data Pre-Processing
Feeding Data to the Model, Parameter Tunning
Model Evaluation and Selection
Interpreting and Visualizing Results

Figure 1: *Diagram that summarises steps taken during the development of our work.*

4.1 Data Extraction

To obtain a significantly large dataset of reliable news articles related to the Russian invasion of Ukraine we decided to use The Guardian digital newspaper. The reasoning behind this decision is because The Guardian is one of the most trusted newspapers in the UK and Europe in terms of objective journalism (Matsa et al. 2018). Additionally, they provide The Guardian – Open Platform, which is their public web service or application programming interface (API) that provides free access to all of the content that the Guardian produces, organised by tags and sections (*theguardian / open platform - documentation / overview* n.d.). This is specially useful in our case because we need to filter the news to reduce noise in our data and have articles relevant to the ongoing conflict between Russia and Ukraine.

To narrow-down the retrieval of the articles, we requested published data between the 2nd of February of 2022 (day in which Russia invaded Ukraine) and the 31st of August of 2022. Additionally, we created a function to interact with the API and retrieve news articles filtered by search term and section. This is to avoid obtaining non relevant news; for instance, we used the section ”world” to point to data classified in this category and not other categories such as ”sports” or ”lifestyle”. Furthermore, we used 2 search terms: Ukraine and Russia. We obtained 2 different datasets corresponding to the mentioned search terms. After that, we merged both datasets and removed duplicates that could have existed in both to avoid redundancy. We also removed non pertinent articles that contained information about topics not related the conflict.

The resulting dataset is a json containing a list of 2275 news articles with their id, title of the article, body of the article, and url to read the article on the web. Such dataset is available in the repository included in Section 8 so it can be used for future research or work.

4.2 Data Pre-Processing

Before feeding the data to our model it is required to prepare the data (Jacobi et al. 2016).

Following is a detailed description of the processes we took when completing the analysis for our case study.

4.2.1 Dataset Relevant Features

Before starting pre-processing the data we display important features from our dataset, such as the number of articles to be used and the average word count per article. This is just to have a rough idea of the length of each document we are using for the purposes of training our model. In our case, we have a total of 2275 news articles and an average of 864 words per article.

4.2.2 Normalisation and Tokenisation

A topic model does not analyse documents directly; rather, it employs a so-called document–term matrix that is derived from the documents. This matrix displays the frequency for each term (word) in each document (Jacobi et al. 2016). The initial step in the creation of this matrix is normalisation and tokenisation, for which each page is converted into a list of lowercase words, ignoring short and long words.

4.2.3 Stop Word Removal

Stop words are the words in a stop list that are filtered out prior to processing natural language data (text) due to their insignificance (Rajaraman & Ullman 2011).

We compared three standard lists of stop words from extensively used libraries for machine learning applications: Natural Language Toolkit (NLTK) (Bird n.d.), scikit-learn (Pedregosa et al. n.d.), and spaCy (Honnibal & Montani 2017). There is a file dedicated to do this comparison on our repository included in Section 8. However, it is worth mentioning that our final decision was to merge the lists of stop words since this leads to better results in terms of removing words that are not adding any meaning, for instance "but", "end", and "the".

4.2.4 Lemmatisation

Lemmatisation is an important part of the preprocessing of the data. It reduces all words to their "lemma" by the use of a lexicon and regular conjugation rules. Thus, lemmatization reduces "is" and "were" to their respective lemma (to be) "be" (Jacobi et al. 2016). There is also another technique called stemming which removes the endings of the words leaving just the "stems". Using the commonly employed Porter stemming algorithm, for instance, "weaknesses" becomes "weak" while "failures" and "failure" both become "failur" (Jacobi et al. 2016).

In our case lemmatisation was preferred over stemming because it produced better results as compared to stemming which sometimes returned words that were missing letters at the end and therefore did not exist in the English dictionary.

For the analysis presented here we used the lemmatiser from spaCy (Honnibal & Montani 2017) which which assigns tokens' base forms using criteria derived from part-of-speech tags (POS).

4.2.5 Transforming the documents in a vectorised form (Bag of Words Representation)

4.2.6 Pre-Processed Data information

4.3 Model Training and Parameter Tunning

4.3.1 Training Multiple Models for different values of 'Number of Topics' Parameter

4.3.2 Choice of Stop Word List

4.3.3 Addition of Custom Words to the Stop Word List

4.3.4 Change of function to train the model

4.4 Model Evaluation and Selection

4.4.1 Visualising topic models

4.4.2 Using trained models on sample of documents

4.4.3 Model Perplexity and Coherence

4.4.4 Coherence

4.4.5 Perplexity

4.4.6 Human Judgement

4.4.7 Word intrusion

4.4.8 Topic intrusion

4.5 Topics Interpretation and Visualisation

5 Results

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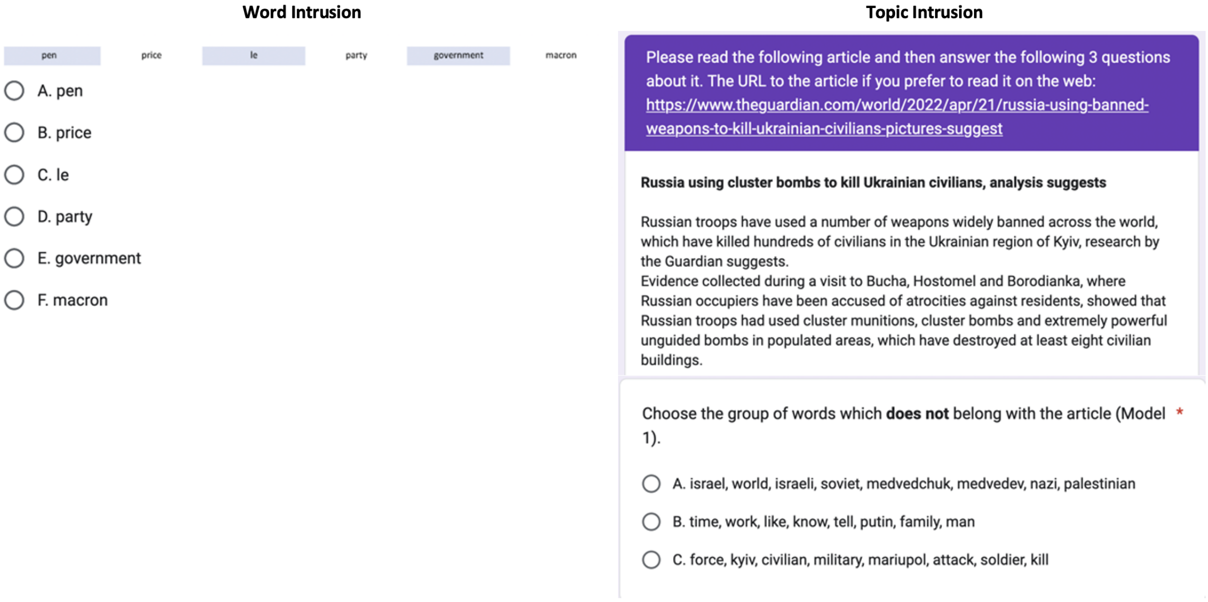
Experiment	Model	Correct Answers	Total Answers	Ratio
Word intrusion	Model 1	13	50	0.260
	Model 2	10	50	0.200
	Model 3	14	50	0.280
Topic Intrusion	Model 1	16	30	0.533
	Model 2	17	30	0.567
	Model 3	13	30	0.433

Table 1: *Results: word intrusion and topic intrusion experiments*



Word Intrusion

pen price le party government macron

○ A. pen

○ B. price

○ C. le

○ D. party

○ E. government

○ F. macron

Topic Intrusion

Please read the following article and then answer the following 3 questions about it. The URL to the article if you prefer to read it on the web: https://www.theguardian.com/world/2022/apr/21/russia-using-banned-weapons-to-kill-ukrainian-civilians-pictures-suggest

Russia using cluster bombs to kill Ukrainian civilians, analysis suggests

Russian troops have used a number of weapons widely banned across the world, which have killed hundreds of civilians in the Ukrainian region of Kyiv, research by the Guardian suggests.
Evidence collected during a visit to Bucha, Hostomel and Borodianka, where Russian occupiers have been accused of atrocities against residents, showed that Russian troops had used cluster munitions, cluster bombs and extremely powerful unguided bombs in populated areas, which have destroyed at least eight civilian buildings.

Choose the group of words which **does not** belong with the article (Model 1). *

○ A. israel, world, israeli, soviet, medvedchuk, medvedev, nazi, palestinian

○ B. time, work, like, know, tell, putin, family, man

○ C. force, kyiv, civilian, military, mariupol, attack, soldier, kill

Figure 2: *Results*

5.1 Dataset

5.2 LDA model parameters

5.3 Experimental comparison between coherence and perplexity

5.3.1 Coherence

5.3.2 Dataset

5.4 Experimental comparison using human judgement

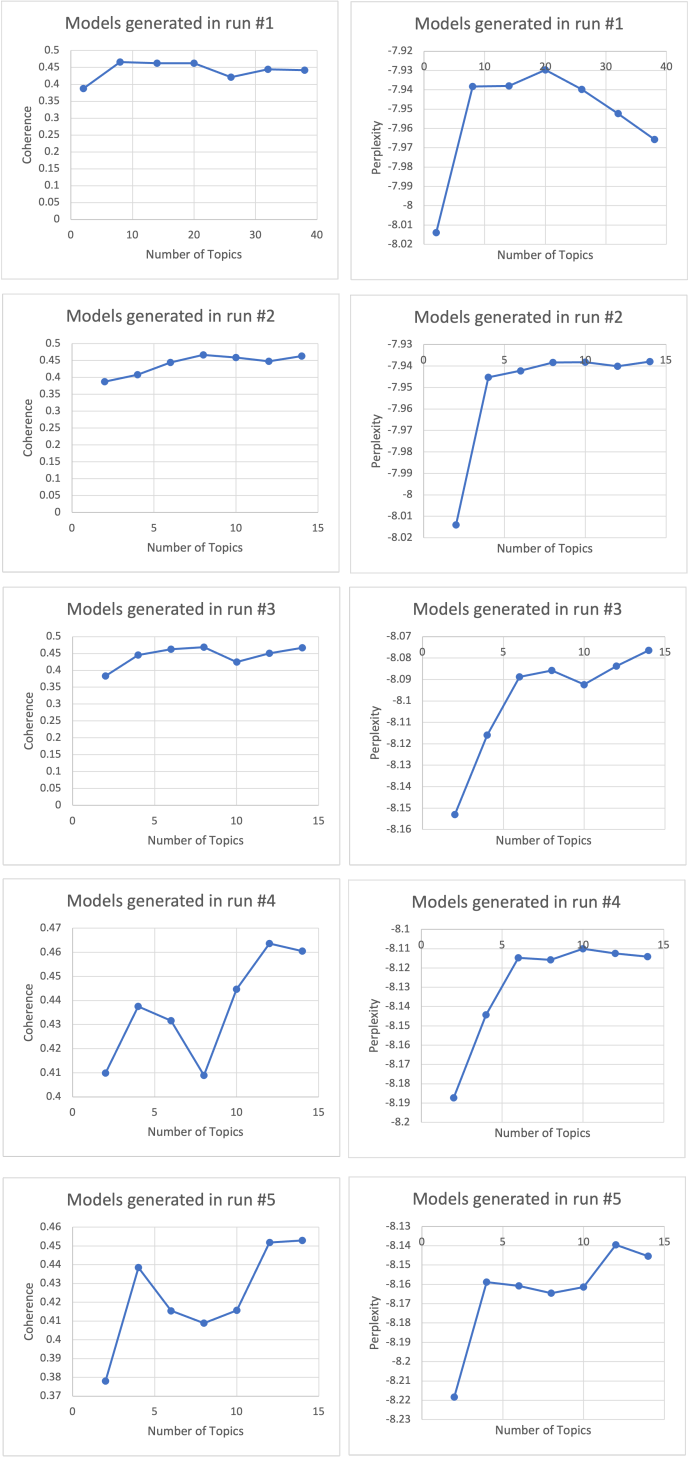


Figure 3: *Charts*

6 Discussion

6.1 Subsection

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6.1.1 Subsubsection

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7 Conclusion

7.1 Subsection

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8 Appendix One: Accompanying Archive and Instructions

8.1 Directory Structure

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8.2 Running the Provided Code

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