UNSUPERVISED MACHINE LEARNING FOR ARCHIVAL COLLECTIONS: Possibilities and limits of topic modeling and word embedding

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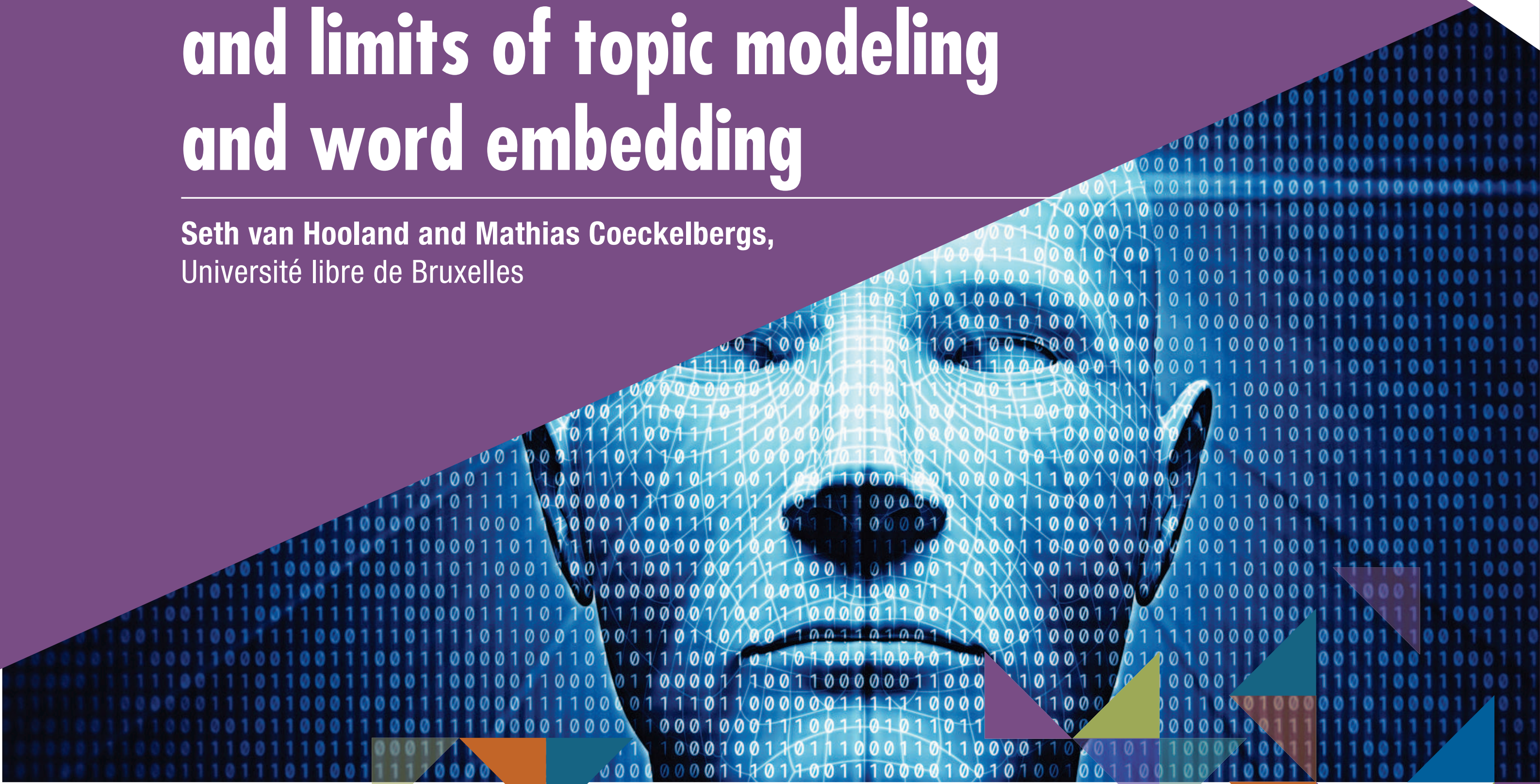

1. INTRODUCTION

From the detection of cancer to self-driving cars: if we may believe media such as the *New York Times*, artificial intelligence (AI) and machine learning techniques have the potential to automate a wide range of societal challenges[1]. Given enough content to analyze and practice on as a training set, algorithms can develop statistical models to replace decision-making ordinarily perceived as requiring human intelligence, such as driving a car in traffic or interpreting an X-ray scan. Commercial vendors, but also computer scientists, are currently waving the magic wand of statistics and machine learning to make sense of large volumes of non-structured archives. More and more data scientists are being hired to tap into content and metadata scattered across shared drives and legacy applications to discover trends and outliers for business intelligence. In this context, archivists can "function as a partner in the analytic process, providing information about data's location, and improving the visual analyst's understanding and trust of data through explaining their context of creation, the history of their structure and semantics and their chain of custody" (Lemieux, 2014).

However, a lot of misunderstandings and false hope circulate among the archives and records management community on how we can use machine learning as a community[2]. This paper therefore wishes to give practitioners a better understanding of both the possibilities and limits of automation by focusing on two specific methods within the family of machine learning techniques: topic modeling (TM) and word embedding (WE). These machine learning methods are extensively used within digital humanities projects for the analysis of large non-structured corpora. The archival community is increasingly confronted with large volumes of non- or poorly structured content sitting on file servers with little to no metadata. As will be demonstrated in the case study, TM and WE allow results to be obtained relatively quickly, which then can be a trigger for thinking about the implementation of a linked data policy to create subject-based access spanning diverse holdings or to experiment with more complex and resource-intensive machine learning methods in regard to auto-classification.

In order to clarify some of the current confusion and vagueness regarding machine learning and automation, the first half of the paper develops a typology of the different approaches which have been in use for decades to automate particular aspects within the lifecycle of information. The latter half of the paper then focuses on a more detailed description of both TM and WE. In order to make the introduction to these techniques as pragmatic as possible, TM and WE are illustrated based on examples from an experimental case study on an archival corpus of the European Commission. The paper ends with ideas on how the results of TM and WE can be used as a stepping stone towards more subject-based access of large volumes of non-structured archives with the help of linked data.

2. AUTOMATING WHAT AND HOW?

Despite the ubiquitous usage of terms such as machine learning, semantic web or linked data, the archival literature has not yet provided much guidance on how these various approaches differ and how they might interact. The NARA

Directive's Automated Electronic Records Management Report/Plan has been a landmark document, acknowledging the necessity to embed automation as an essential aspect within a records management strategy[3]. The report distinguishes five different approaches to automation: no automation (manual management), rules-based automation, business process- and workflow-oriented automation, modular re-usable records management tools and auto-categorization.

The report provides a much-needed overview of the urgency of automation. However, NARA's typology mixes methods (manual, rules-based), implementation (modular re-usable records management tools) and functionalities (auto-categorization).

In order to clarify what automation methods can be used for what type of functionality, the next two sections will present an overview of how two different strands from computer science have the potential to make significant contributions to the archival community:

- **Rules:** based on an abstract model of the content and its application domain, decisions on content can be automated. NARA's Capstone approach to email is a simple example of this: from the moment someone reaches a certain position within the hierarchy of an organization, his or her email is automatically captured, for example.

- **Statistics:** based on an analysis of the content itself, making use of either supervised or non-supervised machine learning techniques. Auto-classification tools to categorize email as having business value or not, based on a training set, is a typical example of supervised machine learning.

Both approaches have their advantages and limitations, which will be pointed out. This article will focus on a presentation of machine learning, which falls into the "statistics" category. On the terrain, both rules and statistics can be combined, as will be discussed towards the end of the article.

2.1 DEFINING RULES: THE ROAD FROM ARTIFICIAL INTELLIGENCE TO RULES ENGINES AND LINKED DATA

Ever since the 1960s, the artificial intelligence community has developed methods to represent knowledge and algorithms which can infer new knowledge from a pre-defined set of rules. Rules-based systems require that the user define rules, so that the software can infer what to do in a certain situation. The danger of this approach is that if the rules miss a scenario, noise is generated as output, requiring ever more rules to be able to describe every possible scenario. In the 1980s, this strand of research culminated in the creation of the then-called expert systems. This type of software consisted of knowledge bases or ontologies containing a large amount of facts and statements connected by making use of formal logic. The drawback of this approach is the lack of adaptability: the system can only function based on the information it has. This implies that these systems can only be operational within well-delimited specialized application domains, such as a specific medical discipline. Also, the cost of creating and maintaining the rules tends to be prohibitive.

The complexity of developing and applying ontologies on a large scale across application domains has been illustrated by the difficulties of implementing the Semantic Web vision. Promoted by Tim Berners-Lee from 2001 onwards, the Semantic Web seeks to make information on the Web machine-readable by formalizing the meaning of data published on the Web through the use of the RDF data model and supporting ontologies. Due to the difficulty of implementing complex ontologies on a large scale, in 2006 Berners-Lee reformulated his vision to accommodate a more structured Web in a more pragmatic manner by rebranding the Semantic Web as the sum of linked data[4]. Throughout the 20th and 21st centuries, the library community has always been more advanced than the archival community in its level of data interoperability and technological developments. Therefore, it is interesting for archivists to observe how librarians have been implementing the linked data paradigm. For example, the Library of Congress has invested considerable effort in promoting Bibframe, a format which should allow the conversion of MARC files into RDF. Despite major efforts over the last few years, there is still no international consensus within the library world on the relevance and feasibility of the endeavor, due to the complexity of natively creating and maintaining very large volumes of data in RDF. The complexity of developing and applying ontologies is reflected in the efforts the archival community has made recently to gently head out into the linked data territory. ICA has initiated the Records in Context (RiC) project, which aims to package the semantics of pre-existing ICA standards such as ISAD(G) and ISAAR(CDF) into one global ontology. An extensive comment on this project is outside the scope of this article, but Ross Spencer correctly points out the complexity of the approach by referring to the 73 potential record-to-record relationships (Spencer, 2017). The W3C's initiative under the name Architypes offers another approach, in the sense that the project tries to re-use existing mark-up from Schema.org and to limit the development of new definitions to a strict minimum. These are very much ongoing efforts and, for the time being, one cannot claim that there is one widely accepted manner of translating traditional archival finding aids into the linked data realm.

2.2 RELYING ON STATISTICS: MACHINE LEARNING

In the last two decades, we have seen a rise in not only the amount of data available and the volume of documents, but also in the variety of data types, complexity of sources and unstructuredness of information. This shift in the landscape has led to the rules-based methods which thrived in the 20th century becoming outdated at best and often even obsolete in the context of the surge of big data, leading Guruswamy to designate them "dinosaurs in the big data world"[5]. Hence, we see a shift from knowledge-driven methods to data-driven methods, which means that traditional rules are in general left behind, leaving room for statistical systems trying to find structure in the wealth of information available today. The tremendous advantage compared to the previous rules-based approach is that there is no need to develop an a priori model of an application domain, which is then used to apply the rules. Chris Andersons framed this change of paradigm boldly by stating that "with enough data, the numbers speak for themselves"[6].

When introducing machine learning algorithms, an important distinction has to be made between so-called supervised and unsupervised methods. Unlike the analogy with raising children, namely that first you develop methods of supervising them before they can acquire their own unsupervised methods of coping with the world, it is not the case that supervised methods would be prior to unsupervised ones in the development of machine learning. It is difficult to state where exactly machine learning practices have taken off, but many place it with Hebb's theory (Hebb, 2005), published originally in 1949, explaining the adaptation of neurons in the brain during a learning process. Hebb describes an unsupervised process, known by the adage "cells that fire together wire together", which directly emphasizes one of the main characteristics of unsupervised methods, namely their bottom-up generation of results, whereby it is not known a priori which form the results will take. By contrast, for supervised methods we have to first give correct examples as training input, thereby determining the structure of the output in the number of categories we assign the input data to. It is therefore that one of the most important tasks of supervised learning is classification into a priori-designed categories, whereas that of unsupervised methods is clustering data together without knowing in advance what these clusters will represent. This makes unsupervised methods, among which topic modeling is one of the most prevalently used series of algorithms for textual data, suitable for dealing with large amounts of unknown data, to assist with tasks such as information retrieval or summarization. At the same time, it is evident that, since no "correct examples" are given to an unsupervised learning algorithm, evaluating the results is difficult, which will also become clear throughout the examples this article will present later on.

Over the last few years, the archives and records management community has almost exclusively experimented with supervised machine learning methods. For the past few years, large software vendors, such as OpenText for example, have been offering auto-classification tools that can automatically sort documents into predesigned categories. The software offers easy-to-use interfaces allowing records managers to select a test corpus, perform the manual classification of documents into a limited number of categories and then check the quality of the auto-classification based on sampling. However, vendors do not provide any benchmarking studies or clear methods to assess the quality of their tools in an objective manner. Vellino and Alberts published a recent and very detailed study on the possibilities and limits of automatically appraising email (Vellino, 2016; Hengchen, 2016). The article underlines the need to formalize the organizational context by conducting semi-structured interviews and cognitive inquiries, followed by a data analysis. Based on this input, an abstract classification model was built, consisting of two top-level categories: emails with and without business value, further divided into 13 sub-categories. This study makes it very clear that the application of auto-classification requires substantial efforts and is not as straightforward as vendors suggest.

As the application of supervised machine learning is not as straightforward as many believe, this article aims to highlight the possibilities of two unsupervised machine learning methods for archival holdings: topic modeling (TM) and word embedding (WE). The term unsupervised is used because the process does not involve any pre-trained corpus. Let us first introduce topic modeling (TM), which has gained momentum over the last few years within the digital humanities to explore and interpret very large corpora of full-text documents (Klein, 2015). This generative probabilistic model clusters a determined number of keywords extracted from a document collection together in so-called topics. An example of a topic (topic 33 from our results) based on the archival holdings of the EC, which we will present in a moment, is the following cluster of ten terms:

Gas fuel energy electricity coal power
nuclear supply industry production

Upon reading the cluster of keywords, we understand that the subset of documents from our corpus with this topic probably address how the EC dealt with the usage and supply of energy resources. This example demonstrates the power, but also one of the problematic aspects of TM, namely the interpretation of the topics. As (Chang, 2009) has indicated, it is difficult to present objective standards to monitor which interpretations of the topic model are valid and which are not. The interpretational difficulty arises from the fact that it is psychologically attractive for humans to give a meaningful interpretation to a list of words they are presented with. Even when given several clear cases – which are often cherry-picked – we can see that a strong interpretation is sometimes possible, but it is difficult to discern where the grey area of interpretation is located. This results from an interpretational difficulty inherent in topic models, namely that we would like to find they represent concepts hidden within the text. Although we know that the clusters of keywords are merely a representation of their occurrence within the document collection, we expect them to correspond to clear-cut concepts. This is due to the distributional hypothesis within the field of linguistic semantics, which states that the meaning of a word is determined by the company it keeps. Expressed differently, this hypothesis understands words which occur in the same documents to have a semantic relatedness. In practice, topics are often difficult to interpret, as they cannot be mapped easily to one single concept, but rather as a combination of two or more concepts.

In contrast to topic models, which allow us to understand how documents are related to one another based on identified topics, word embedding (WE) is used to understand how words are related to one another semantically. The term was popularized by Mikolov's seminal paper (Mikolov, 2013) describing

Word2Vec, an online, freely available toolkit to either train WE on a corpus, or to use their pre-trained word vectors based on the Google Press corpus. Through a statistical analysis of a massive corpus, one can determine for example that the terms London and England have the same relation to one another as, for example, Paris and France. The algorithm is agnostic of the semantics of the relationship, just allowing us to monitor how these terms interact with one another in vector space, enabling semantic relationships like the aforementioned "is capital of" to be extracted. Due to the vectorial representation of these words, we can answer questions like "what is the capital of France?" by simply starting with the vector for "London", subtracting the vector for "England" and adding the vector for "France". The corresponding vector should lie closest to "Paris", hence answering our question correctly. Examples from an experimental case study will now demonstrate how an original method has been designed to apply WE to the results of TM, allowing the archival community to leverage the usage of unsupervised machine learning for archival holdings. Within this paper, the authors wish to give a global introduction and overview of the possibilities and limits of different machine learning methods for the archival community, without going into the details of a large-scale evaluation of the results.

3. 3. EXPERIMENTAL CASE STUDY: ARCHIVES OF THE EUROPEAN COMMISSIONQ

When and how did environmental considerations start to influence agricultural policy development at the European Commission (EC)? What are the key documents to analyze the debate on nuclear energy production from the 1960s onwards? These are two examples of typical research questions historians might have regarding the archival holdings of the EC. In this context, the mass digitization of the EC's archives offers new and exciting possibilities to query and analyze the archival corpus in an automated manner. However, there is a large gap between the promises made by big data advocates, who rely on statistics to discover patterns and trends in large volumes of non-structured data, and how historians can actually derive value from automatically generated metadata to explore archives and find answers to their research questions. Currently, researchers can only perform full-text queries in order to make sense of this massive corpus, as illustrated in Figure 1. In the context of a research collaboration, the authors received a local copy of the corpus from the EC archives, allowing us to process and apply various machine learning methods.[7]

Figure 1. Search interface of the COM files of the EC archives, available at http://ec.europa.eu/historical_archives/archisplus/

3.1 DATA SET AND PREVIOUS WORK

The dataset, spanning a period ranging from 1958 to 1982, is multilingual: it contains documents in French, Dutch, German, Italian, Danish, English and Greek, as those were the then official languages of the what we now call the European Union. For this experimental case study, only the English corpus was taken into account, which represents a total number of 11,868 documents. In the context of the first exploratory study by Hengchen (Hengchen, 2016), latent Dirichlet allocation (LDA), which is the most popular TM algorithm, was applied to the corpus. As already mentioned, the dataset presents close to no metadata; apart from an XML file corresponding to each PDF and containing basic information such as a unique identifier, a creation date, the number of a reference volume and the language and title of the document, little additional information is given. There is no insight as to what the documents encompass in terms of topics and themes, which makes the dataset difficult for historians to use. In the context of this first exploratory study, the authors manually interpreted the topics, in order to attach a descriptor from the EUROVOC thesaurus. Figure

2 gives three examples of topics and the EUROVOC descriptors which were manually attached to the topics.

URI	label	tokens			
http://eurovoc.europa.eu/2965	agricultural aid	agricultural premium farms	areas directive production	aid number	measures eec
http://eurovoc.europa.eu/852	ECSC aid	coal industry measures	steel production community	ecsc iron	aid decision
http://eurovoc.europa.eu/1418	textile industry	fabrics crocheted products	textile fibres yarn	woven community	knitted agreement

Figure 2. Manual labeling of TM results with Eurovoc.

It is important to underline that the authors in this first exploratory study were unable to attach a label to around 30% of the topics, due to either the very general nature of the terms (*e.g. agreement community parties negotiations*) or the fact that the authors were unable to find a semantic link between the terms (*e.g. lights bmw brazil eec coffee*). For some topics, OCR noise resulting in terms such as *cf, ii or ir* was the main cause.

However, the manual labeling of topics with descriptors from the EUROVOC thesaurus is of course suboptimal. One of the key problems is the interpretation of the clusters of terms which form a topic. Throughout the examples, one can sense that, in the majority of cases, topics do not point to one clear concept, but are often a combination of concepts. This aspect makes the manual labeling process inherently subjective and troublesome. Ideally, one would also want to perform an automated reconciliation process, as described in (van Hooland, Verborgh, De Wilde, & Hercher, 2013). Unfortunately, the semantic heterogeneity of topics also constitutes a stumbling block for this process, as there is no way to indicate in the reconciliation process how the different concepts within a topic should be tackled separately.

3.2 LEVERAGING WE TO BETTER ANALYZE TM OUTCOMES

As we have learned from the state of the art, TM can be viewed as a method to learn more about the topics addressed in a large corpus of documents, whereas (pre-trained) WE can be seen as a general, vectorial representation of language itself, allowing us to understand the distance between words. In the context of his doctoral research, one of the authors designed an original methodology which brings together both sources of information[8]. As WE enables vectorial representations of language as a whole to be produced, this then allows us to estimate the semantic relatedness of terms found in the same topic. In other words, we wish to automate the identification of different concepts present in one topic.

We have found that two situations are present when applying word embedding to the results of topic modeling, which are dealt with in the following section. The results described below illustrate that some topics are used to mark a single concept, that is, topics as concepts, whereas others – and by far the largest amount of topics – are used to indicate a collocation of two or more concepts, which the paper will refer to as “topics as collocations”.

3.3 RESULTS

LLDA was applied to the English-based subcorpus, as described above. The full results can be analyzed on Github. Within the data set, three different color codes are used, which help to visualize the following different outcomes of WE on the TM results:

- Terms in orange indicate a topic which represents one single concept.

- Blue and red are used to indicate the first and the second concept in a topic consisting of two different concepts.

- Terms in light-blue are terms that do not indicate a clear link with the terms from the topic surrounding them.

Using the vectorial representations of the key words within a topic, we discover that some topics indicate a general concept, represented by terms displayed in orange. A good example can be found in topic 17, indicating territorial authority. Since within our corpus the authority of several living structures are discussed, we discover them as terms in our topic, showing semantic relatedness, namely “community”, “territory”, “national”, “country”, “state” and “states”. On the other hand, the different ways in which their authority can be discussed are found in the words scoring highest in the semantic coherence hierarchy, namely “authorities”, “legal”, “rights”, “authority”, “undertakings”, “directive”, “provisions”, “rules” and “law”. We remark in passing that the words “authorities” and “authority” are not ranked next to each other, which we would expect for words having the same lexeme. However, in this case it is clear that both words have a vastly different usage, given that “authority” indicates the power of judgment and action a person or body possesses, whereas “authorities” can refer to this power as well as the institutions of authority themselves, such as the police department or the jurisprudential body.

In some cases, we see that the semantic coherence of terms is attested, but it does not pinpoint a clear concept. For example, in topic 31, the WE clusters together all ten terms, which are “vocational”, “labor”, “education”, “employment”, “health”, “social”, “migrant”, “worker”, “work” and “working”. One can assume that the topic relates to the social security of migrant workers, but the documents clustered under this topic might also relate more to the impact of education on the employment of migrant workers, for example.

This analysis brings us to the possibility that a topic is the collocation of two concepts, the first one represented in blue and the second one in red. This situation is by far more common than topics representing only one concept, depicted in orange. These collocations indicate that an important relationship between those two concepts exists, since they are prevalent throughout the document collection. Some clear examples of these collocations are found in the data. For example, topic 30 brings together two concepts, namely those of industry and studies. Hence, documents which have a high score for this topic can be attributed a high probability of dealing with industry studies, assessing the progress of markets and work. First, our methodology clusters together industry-related terms “project”, “development”, “market”, “industry”, “industrial”, “system”, followed by the study-related terms “study”, “survey” “data” and “statistic”. The concept of industry can be found multiple times within the topics. For example, next to topic 30, which we have just explained, in topic 33 we find the terms “industry”, “supply” and “production”, constituting the industry concept, which is collocated with the resources concept, expressed through the words “gas”, “fuel”, “energy”, “electricity”, “coal”, “power”, and “nuclear”.

However, WE does not always manage to group together terms from a topic into one concept. This is for example the case with topic 27. There are two distinct concepts, the first one consisting of “price”, “market” and “product”, and the second one of “milk”, “sugar” and “wine”. Four terms are then displayed in light-blue, indicating terms which do not have a clear link with the terms from the topic which surrounds them: “production”, “quality”, “variety” and “marketing”.

Based on the examples analyzed, there are definitely cases where WE does deliver a clear added-value to interpret the outcomes from TM. How can this help archivists? In future work, we plan to experiment with a reconciliation process between the terms from the topics and the EUROVOC thesaurus. The fact that we can automatically divide one topic into two different concepts will allow us to increase the relevance of the reconciliation results, as we will not be forced to automatically assign one label to a topic which actually represents two different concepts.

4. 4. CONCLUSIONS AND FUTURE WORK

AWith the help of an experimental case study, this paper has given a global introduction to the automation of archival holdings in general and the usage of unsupervised machine learning techniques in particular. With the exponential growth of digitized full text from archival holdings, the archival community needs alternatives to the manual creation of metadata. In the current hype surrounding the use of machine learning, most attention within the archival world is focused on how supervised machine learning methods can be used for auto-classification purposes. However, as was underlined in this paper, this approach requires a vast amount of expertise and resources in order to define a test corpus and to fine-tune the process during an iterative progression of testing the results. This paper therefore explored the possibilities offered by non-supervised methods such as TM and WE, illustrated with a real-life case study based on digitized archival holdings of the EC.

As the examples from the case study showcase, there are both reasons for enthusiasm and serious problem areas which underline the need for further work before archivists can actually start applying TM and WE on a large operational scale. Let us first start with the bad news. As already underlined in the existing literature from the computational linguistics domain, the interpretation of TM's results is complex and requires a manual analysis of how the various terms reflect a topic present in a large corpus. Also, the configuration of the k-parameter, the number of terms per topic and the terms included as stop words all have a big impact on the results. The currently available scientific literature does not offer a clear examination of how these parameters affect the results, which underlines the "black box" character of the use of these methods. However, there are also enough reasons for archivists to keep a close eye on machine learning methods. By using WE, this paper demonstrated how the complexity of interpreting the outcome of TM can be simplified, as WE can help to automatically identify the different concepts hiding within one topic. This method holds the potential to facilitate at a later stage the automated labeling of topics with headings from a controlled vocabulary. Also, importantly, the method is language independent and can be applied across a wide variety of application domains.

All in all, this paper underlines the semi-automated nature of applying machine learning techniques. At crucial stages of the process, archival experts still need to make strategic decisions and intervene manually. We can therefore conclude that automation is a tool, and not a replacement for professional archivists.

NOTES

1. See articles such as https://www.nytimes.com/2016/10/17/technology/ibm-is-counting-on-its-bet-on-watson-and-paying-big-money-for-it.html.
2. We use the terms information governance and archives and records management interchangeably throughout this paper. The debate regarding the definitions and the exact boundaries of each discipline is outside the scope of this paper, but automation has a role to play in each one.
3. For a full overview of the report, please consult https://www.archives.gov/records-mgmt/prmd/automated-erm.html.
4. For a more in-depth overview of the development of linked data, please consult "Linked data for libraries, archives and museums" by van Hooland and Verborgh (Facet, 2004).
5. See http://bigdata.teradata.com/US/Articles-News/Data-Science--Machine-Learning-Vs--Rules-Based-Systems/.
6. See https://www.wired.com/2008/06/pb-theory/.
7. The dataset has been created following Council Regulation (EEC, Euratom) No 354/83 of 1 February 1983 concerning the opening to the public of the historical archives of the European Economic Community and the European Atomic Energy Commun ity. The legal text and all its amendments are available at http://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1475395564392\&uri=CELEX\:31983R0354. After the signature of a Non-Disclosure Agreement (NDA), the MaSTIC research group of the Université Libre de Bruxelles obtained a 138.3-GB, 24,787-document corpus from the European Commission Archives.
8. Mathias Coeckelberghs is currently preparing an in-depth paper to present the usage of WE to interpret the results of TM.
9. The research results are available on https://github.com/MathiasCoeckelbergs/Concepts-

within-Topics.

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RESUM

L'enrenou que avui envolta l'aprenentatge automàtic ha provocat una nova onada d'esperança i entusiasme entre els arxivers, que fan servir algorismes per reduir el nombre d'intervencions manuals en la gestió i la valoració de grans volums de contingut no-estructurat. Els agents comercials promouen instruments ja preparats per a la classificació automàtica, però és tan fàcil integrar l'aprenentatge automàtic en un context de governança dels arxius i la informació com actualment s'assenyala en la premsa generalista i la bibliografia informàtica? D'altra banda, quina relació té l'aprenentatge automàtic amb el debat al voltant de l'ús de dades connectades per a les descripcions arxivístiques? En aquest article tenim l'objectiu d'aportar pragmatisme al debat sobre l'automatització de les descripcions arxivístiques tot oferint una descripció general de les possibilitats i els límits de l'aprenentatge automàtic des de la perspectiva arxivística. En l'àmbit de les humanitats digitals, dos mètodes han esdevingut considerablement populars: els models temàtics (MT) i els *word embeddings* (WE; representació de paraules com a vectors). En aquest article no només s'introdueixen aquests mètodes d'aprenentatge automàtic no-supervisat per al col·lectiu dels professionals de l'arxivística, sinó que també es demostra com es poden aprofitar els WE per interpretar els resultats dels MT d'una manera més efectiva, la qual cosa és una aportació innovadora. Per il·lustrar ambdós mètodes ens basem en un estudi de cas experimental dels fons digitalitzats de la Comissió Europea (CE).

RESUMEN

El actual revuelo en torno al aprendizaje automático ha provocado una nueva ola de esperanza y entusiasmo entre los archiveros, que usan algoritmos para reducir el número de intervenciones manuales en la gestión y la valoración de grandes volúmenes de contenido no estructurado. Los agentes comerciales promueven instrumentos ya preparados para la clasificación automática, pero: ¿es tan fácil integrar el aprendizaje automático en un contexto de gobernanza de archivos e información como actualmente se señala tanto en la prensa generalista como en la literatura informática? Por otra parte, ¿qué relación tiene el aprendizaje automático con el debate en torno al uso de datos conectados para las descripciones archivísticas? En este artículo tenemos por objetivo aportar pragmatismo al debate sobre la automatización de las descripciones archivísticas ofreciendo una descripción general de las posibilidades y los límites del aprendizaje automático desde una perspectiva archivística. En el ámbito de las humanidades digitales, dos métodos han ganado considerable popularidad: los modelos temáticos (MT) y las *word embeddings* (WE; 'representación de palabras como vectores'). En este artículo no solo se introducen estos métodos de aprendizaje automático no supervisado para el colectivo de los profesionales de la archivística, sino que también se demuestra cómo se pueden aprovechar las WE para interpretar los resultados de los MT de una manera más efectiva, lo cual es una aportación innovadora. Para ilustrar ambos métodos nos basamos en un estudio de caso experimental de los fondos digitalizados de la Comisión Europea (CE).

ABSTRACT

The current hype surrounding machine learning has spurred a new wave of hope and enthusiasm amongst archivists, who are relying on algorithms to reduce the amount of manual intervention in the management and appraisal of large volumes of non-structured content. Commercial players promote out-of-the-box tools for auto-classification, but is the integration of machine learning within an archival and information governance context as straightforward as it is currently presented in both the popular press and computer science literature? Also, how does machine learning relate to the discussion regarding the usage of linked data for archival descriptions? This paper aims to bring a sense of pragmatism to the debate on the automation of archival descriptions by giving an overview of both the possibilities and the limits of machine learning from an archival perspective. Two methods have gained substantial popularity within the digital humanities: topic modeling (TM) and word embedding (WE). This paper not only introduces these non-supervised machine learning methods to the archival community, but also demonstrates how WE can be leveraged to interpret the results of TM in a more meaningful manner, which is a novel contribution. Both methods are illustrated based on an experimental case study of digitized archival holdings of the European Commission (EC).

RÉSUMÉ

La forte médiatisation actuelle de l'apprentissage machine a fait naître de nouveaux espoirs et suscité beaucoup d'enthousiasme chez les archivistes, qui s'appuient sur des algorithmes pour réduire le nombre d'interventions manuelles lors de la gestion et de l'évaluation de gros volumes de contenus non structurés. Certaines entreprises proposent des outils clé en main pour la classification automatique, mais l'intégration de l'apprentissage machine dans un environnement d'archivage et de gouvernance de l'information est-il aussi simple que cela est actuellement présenté dans la presse grand public et la littérature de l'informatique ? Par ailleurs, comment l'apprentissage machine s'insère-t-il dans le cadre de la discussion sur l'utilisation du Web des données pour les descriptions d'archives ? Le présent article vise à contribuer au débat sur l'automatisation des descriptions d'archives avec pragmatisme en proposant un aperçu des possibilités autant que des limites de l'apprentissage machine appliqué à l'archivage. Deux méthodes ont énormément gagné en popularité dans le cadre des sciences humaines numériques : les modèles thématiques (topic modeling, TM) et le plongement lexical (word embedding, WE).
Après avoir présenté ces méthodes d'apprentissage machine non supervisé à la communauté des archivistes, le présent article démontre comment le plongement lexical peut être exploité pour interpréter les résultats d'un modèle thématique plus finement, ce qui constitue une contribution inédite. Les deux méthodes sont illustrées par une étude de cas expérimentale portant sur les archives numériques de la Commission européenne (CE).