Mixing syntagmatic and paradigmatic information for concept detection

Louis Chartrand

Abstract
In the last decades, philosophers have begun using empirical data for conceptual analysis, but corpus-based conceptual analysis has so far failed to develop, in part because of the absence of reliable methods to automatically detect concepts in textual data. Previous attempts have shown that topic models can constitute efficient concept detection heuristics, but while they leverage the syntagmatic relations in a corpus, they fail to exploit paradigmatic relations, and thus probably fail to model concepts accurately. In this article, we show that using a topic model that models concepts on a space of word embeddings (Hu and Tsujii, 2016) can lead to significant increases in concept detection performance, as well as enable the target concept to be expressed in more flexible ways using word vectors.

Introduction
Conceptual analysis has, in one form or another, long been a staple of philosophical methodology (Beaney 2018). When considered as a method, conceptual analysis often requires the input of empirical data, be it in the form of perceptual data, like philosophical intuitions (Pust 2000), or in other measurable forms. In the last decades, philosophers have begun performing experiments to get a grasp of human’s conceptual behaviour and reactions in order to get a more precise understanding of fundamental concepts like KNOWLEDGE, JUSTICE or RESPONSIBILITY. However, these methods are limited, as controlling for variables forces experimenters to put participants in somewhat unnatural situations and create studies with low ecological validity.

Other voices have suggested that concepts could fruitfully be studied in textual corpora (Meunier, Biskri, and Forest 2005; Bluhm 2013; Andow 2016; Chartrand 2017). They argue that methods based on the distributional hypothesis, and that hail from subfields such as natural language processing, text mining and corpus linguistics, could shed light on at least some of the concepts that are objects of philosophical scrutiny.
However, these methods are not well-tuned to philosophical conceptual analysis, as they usually rely heavily on keywords as an indicator of the presence of a concept. While concepts are often associated to words—indeed, even in philosophical discussions, we usually use words as tags for concepts—words are usually associated to more than one concept, and the one that is expressed in any instance is determined by the context. Conversely, concepts can be expressed in a variety of ways. Not only can two or more words or word compounds express the same concept, but concepts don’t always attach to words: they can be present in a sentence thematically, or because of an inference that one must make when decoding the sentence. For conceptual analysts who would like their idea of a concept to be representative of all its various uses, this can be an important problem.

The first problem can often be circumvented with a judicious choice of corpus, as controlling the context can often control the sense a word will espouse. As a result, recent work on concept detection has focused on the second problem in a bid to detect where a concept is expressed without the word it is most associated with (Pulizzotto et al. 2016; Chartrand et al. 2016; Chartrand, Cheung, and Bouguessa 2017). While these efforts have yielded promising results, these methods still rely on the identification of a concept with a word in order both for modelling the constitution of higher-level discursive entities (like topics or narratives) and for representing the queried concept.

This assumption is problematic in at least two ways. On the one hand, these higher-level entities are not composed of words, but of concepts. There is thus the worry that representing them as composed of words makes for an imprecise model. Another concern is with the word-sense ambiguity: a single word may refer to two different concepts, depending on its pragmatic and textual context. One way textual data analysts have dealt with this problem has been to tailor corpora to fit their needs, and choose corpora where the concepts they are interested in happen to be unambiguously associated to a word or a word expression.

Our hypothesis is that these two concerns can be addressed by representing concepts not as words or word expressions, but coordinates on a word embedding space—or, to be more precise, \( n \)-dimensional vectors whose semantic properties are determined by their distances to other \( n \)-dimensional vectors that represent words and concepts from a text corpus. In other words: representing concepts as such enable us (1) to make a better model of higher-level entities like topics, which in turn translates in better performances in concept detection and (2) to formulate queries when concepts do not perfectly match with a word or word expression in the corpus.

To test this hypothesis, we employ Hu’s and Tsujii’s (2016) Latent Concept Topic Model (LCTM) to construct processing chains for concept detection. The LCTM constructs topics as distributions over concepts, which are coordinates in a word embedding space, making for a model that is more theoretically coherent with (Chartrand no date) than previous concept detection models. The processing chains can then be applied to a corpus (in this case, decisions from the Québec
Court of Appeal, as in Chartrand, Cheung, and Bouguessa 2017) and tested against human annotations.

In section , we review the relevant literature. We give an overview of the state of the art in topic modelling and word embeddings, and then review hybrid models. In section section , we formulate the concept detection task and explain how the annotations forming the gold standard are gathered. In section , we describe the underlying model and functioning of LCTM, and how it links with the theory that underlies the concept detection task. In sections and , the experiments and their application are described, and in section , we review the results, which are discussed in section section .

**Previous work**

From the beginning, topic models have tried to model concepts as an underlying dimension of the text: latent semantic indexing (Deerwester et al. 1990) described documents in terms of latent “concepts”. However, by the end of the 90s, Hofmann (1999) described the latent variables in his probabilistic latent semantic indexing as “class variables”, and Blei, Ng, and Jordan (2003) called them “topics” in his latent Dirichlet allocation (LDA) model. Gabrilovich and Markovitch (2007) resurrected the idea of a latent semantic dimension as a concept by forming representations from Wikipedia articles, but their reported success seems to hail from a mere size effect rather than Wikipedia’s grouping of discourse under labels (Gottron, Anderka, and Stein 2011).

While there are numerous variations, the topic models that are well-known in the natural language processing community treat topics as a mixture of variables that are of the same kind, that influence word occurrences in the same way, and that thus have a priori the same role in shaping discourse. Once learned, they capture the syntagmatic relations between words. Words are syntagmatically close when they participate in the same discourse units—in other words, when they are neighbours, or when they tend to come together.

Word embeddings, on the other hand, tend to capture paradigmatic relations. Words are paradigmatically close when they tend to have the same neighbours. As a result, they tend to have similar roles in discourse, and therefore be synonyms or antonyms. Word embeddings evolved from language models in the early 2000s (Bengio et al. 2003), but were then too computationally expensive to be applied to large corpora. Collobert and Weston (2008), followed by Mikolov and colleagues (Mikolov, Chen, et al. 2013; Mikolov, Sutskever, et al. 2013), found ways to get the computing cost down, opening the way for word embeddings to become an essential part of the natural language processing toolkit.

---

1For a more thorough account of syntagmatic and paradigmatic relations in the context of distributional semantics, cf. Sahlgren (2008). Cf. also pages ??-?? of the present thesis.

2Antonyms are nearly identical except on one semantic dimension, on which they are opposites. This is why they typically have very similar roles in discourse and sentences.
Given the popularity of topic models and the word embedding boom that followed word2vec (Mikolov, Chen, et al. 2013), it is no wonder that many attempts to combine them have been made. Several of them (Nguyen et al. 2015; C. Li et al. 2016; Hu and Tsujii 2016; Wang et al. 2017; Le and Lauw 2017; Li et al. 2018; Peng et al. 2018; Zhang, Feng, and Liang 2019) aim at making topic models that work well with short documents like tweets, where too few words are employed (sparsity problem). Others target the problem of homonymy/polysemy (Liu et al. 2015; Law et al. 2017), seek more interpretable topics (Potapenko, Popov, and Vorontsov 2017; Zhao et al. 2018), or aim at exploiting complementary representations (S. Li et al. 2016; Moody 2016; Bunk and Krestel 2018). Often word embeddings are simply seen as a means to make a more realistic model (Das, Zaheer, and Dyer 2015; Batmanghelich et al. 2016; Hu and Tsujii 2016; X. Li et al. 2016; Xun et al. 2017).

For example, there is a lineage of models that can be seen as attempts to see how word embeddings fit in the generative story behind probabilistic topic models. Das et al.'s Gaussian LDA (2015) replaces the word-over-topic distribution of the LDA with coordinates on the word embedding space. A word’s probability given a topic associated with such coordinates are then inferred from the corresponding word embedding’s proximity using the Gaussian distribution. Batmanghelich et al. (2016) starts from the Gaussian LDA and replaces the Gaussian distribution with the von Mises-Fisher (vMF) distribution, which is a probability distribution over angles centered on a vector. Hu and Tsujii (2016) and X. Li et al. (2016) both choose not to identify topics to coordinates or vectors on the word embeddings space, but rather model topics as constituted by such objects. In the former, topics are distributed over these objects (which are called “concepts”), and word probabilities are inferred from concepts using a Gaussian distribution, while the latter identifies topics as complex von Mises-Fisher mixtures over a determined number of bases. Bunk and Krestel (2018) go for a middle-ground position, where words are both influenced by typical LDA-style topics and GLDA-style vector-topics that are situated in the word embeddings space. Perhaps more interestingly, they report no advantage in using mixture models or vMF distributions over simple GLDA-style gaussian distributions, at least in terms of topic coherence and word intrusion tasks.

Perhaps because it is specifically tailored for the needs of philosophical conceptual analysis, few attempts have been made so far at addressing the concept detection task (Chartrand et al. 2016; Pulizzotto et al. 2016; Chartrand, Cheung, and Bouguessa 2017). These papers emphasize the inadequacy of using keywords to recall text segments where a concept is expressed, but their models still use words as stand-ins for concepts both for articulating queries and for modelling the concept-topic relationship.

This inadequacy calls for alternate models. However, given the large variety of existing topic models, we might not have to create a new one. Chartrand (no date) argues that higher-level discourse entities (which can arguably be modelled by LDA-style topics) are constructed from concepts rather than words, topic
models that use the word embedding space to model concepts over which topics are distributed. This suggests that topics models where topics are distributed over concepts (rather than words) in the word embedding space (Hu and Tsujii 2016; X. Li et al. 2016) are more likely to accurately represent topics and their structure. One can hope that such a representation of concepts and their association with topics will yield better results on the concept detection task.

The concept detection task

As Haslanger (2012) argues, philosophical conceptual analysis can pursue different aims. In some cases, the goal is to represent the concept that we (collectively) have as we possess it. We can call this a conceptualistic conceptual analysis. In other cases, the idea is to represent the concept as it functions: this would be a functionalistic conceptual analysis. In the case of a concept that represents something, this means that our objective here is to represent the concept so as to reflect its referent rather than our common account of it. For instance, if the function of the concept is to refer to dolphins, then it would not matter if most of us thought of dolphins as fish or if we thought that they have wings: a proper functionalist analysis would still represent dolphins as wingless aquatic mammals. Finally, we make an ameliorative conceptual analysis when the goal of the analysis is to produce a concept that better fulfills the role it plays in discourse, knowledge or society.

This diversity in purpose, however, branches from common grounds. Firstly, there is a sense in which conceptual analysis always is ameliorative, as the representation it aims to make is itself a new concept, meant to play (most often) new roles, if only in philosophical conversations. Secondly, no matter our purpose, it ought to start with an understanding of how this concept functions in its community’s discourses and ways of life. Therefore, conceptual analysis demands a thorough picture of a concept’s usage, which is where natural language processing can lend a hand.

This thorough picture demands that we be able to capture a concept in as large a variety of uses as possible. While NLP can only be of help when it comes to observing discourse, it is important to include, as much as possible, all ways by which a concept is employed in discourse. As argued by Chartrand (no date), much like words bind together to form sentences, concepts bind together to form higher-level entities that are reproduced in a community. These entities can be themes, narratives, arguments, etc. To understand such a higher-level entity, one needs to understand all of its components—therefore, a concept is always present when a topic or a narrative is expressed. However, a concept might not be present in the form of the word that, in proper context, we most readily associate with it (say the word “dolphin” for the concept DOLPHIN). It might present itself in the form of an anaphor (“it”, “them”), an hypernym (“the animal”) or a description (“these long-nosed swimmers”). It might also
be implicitly present within a hidden premise, as part of a piece of information that can be inferred from the text, as part of the background knowledge that we access in order to understand what is being communicated, or even as the object about which we are implicitly talking about. Being present in different ways in discourse often means that a concept is employed differently and, therefore, has different roles. As a result, it is important that a concept detection algorithm be able to capture the different ways a concept is present in the text.

Concept detection is thus distinct from more traditional information retrieval problems: here, it is not relevance that is sought, but presence. The challenge is not to find the most relevant passages for the expression of a concept, but to find all text segments where it is present. It is also different from such problems as word-sense extraction or ontology learning because concepts need not be associated with words.

Models

As mentioned in section 2, there are considerations which lead us to hypothesize that, for concept detection, models that represent concepts in their generative story are more likely to reflect the topic structure in such a way that it can be leveraged for concept detection. Perhaps more interestingly, explicit modelling of concepts (as opposed to simply leveraging word embedding data to direct the learning process) makes it possible to formulate queries using word combinations, which can help disambiguate the query (e.g. bank – river might yield the concept of BANK as this place where we make financial transaction) or make it possible to look for new concepts.

This leaves us with the LCTM (Latent Concept Topic Model, Hu and Tsujii 2016) and MvTM (Mix von Mises-Fisher Topic Model, X. Li et al. 2016) models. However, the MvTM makes counter-intuitive assumptions concerning the availability of concepts for constituting topics. There are two variants to the MvTM: the “disjoint bases” variant (MvTM_d), in which topic mixtures are made from bases that cannot be shared with other topics, and the “overlapping bases” variant (MvTM_o) where topic mixtures are partly made from bases that can be shared with other topics. If bases were meant to model concepts, then we would expect all of them to be shared by many topics. According to the authors, this serves to prevent identical topics from emerging, but language is too fluid to afford such a restriction: no theme, narrative or argument ever has had exclusive rights to a concept. As a result, LCTM seems like the better alternative.

The LCTM is an evolution of the LDA (Blei, Ng, and Jordan 2003) and GLDA (Das, Zaheer, and Dyer 2015) models, all three of which are probabilistic graphical

---

3This is also why topic models based on word embeddings are, in this context, a superior solution to algorithms that use concept databases, such as Tang et al. (2018), or algorithms that model concepts simply as latent variables, as El-Arini, Fox, and Guestrin (2012).
models. This is to say that they rely on a generative model, which represents an abstract hypothesis of how a text is constructed and structured.

**LDA**

In the LDA model, topics are represented by two variables: a multinomial distribution over documents ($\theta$), and multinomial distribution over words ($\phi$). These distributions are designed to be sampled from the conjugate Dirichlet priors with parameters $\alpha$ and $\beta$ respectively. In Blei’s (Blei, Ng, and Jordan 2003) account, model uses this generative process, which assumes a corpus $D$ of $M$ documents each of length $N_i$:

- Draw $\theta_i \sim \text{Dirichlet}(\alpha)$, where $i \in \{1 \ldots M\}$, the topic distribution for document $i$
- Draw $\phi_k \sim \text{Dirichlet}(\beta)$, where $k \in \{1 \ldots K\}$, the word distribution for topic $k$
- For each of the word positions $i,j$, where $j \in \{1,\ldots,N_i\}$, and $i \in \{1,\ldots,M\}$:
  - Draw a topic $z_{i,j} \sim \text{Multinomial}(\theta_i)$.
  - Draw a word $w_{i,j} \sim \text{Multinomial}(\phi_{z_{i,j}})$.

**GLDA**

With their GLDA model, Das, Zaheer, and Dyer (2015) replace $\phi_k$ with a covariance $\Sigma_k$ and coordinates to a point that acts as its distribution’s mean $\mu_k$. The covariance $\Sigma_k$ is sampled from an inverse Wishart distribution, and the mean $\mu_k$ is sampled from a normal distribution centered at zero ($\mu$). Thus, GLDA’s generative story goes like this:

- For each topic $k \in \{1 \ldots K\}$
  - Draw a topic covariance $\Sigma_k \sim \mathcal{W}^{-1}(\Psi, \nu)$
  - Draw a topic mean $\mu_k \sim \mathcal{N}(\mu, \frac{1}{\kappa} \Sigma_k)$
- For each document $i \in \{1 \ldots M\}$
  - Draw a topic distribution $\theta_i \sim \text{Dirichlet}(\alpha)$
- For each word $w \in \{1 \ldots N_i\}$
  - Draw a topic $z_w \sim \text{Multinomial}(\theta_i)$
  - Draw a word vector $v_w \sim \mathcal{N}(\mu_{z_w}, \Sigma_{z_w})$ (the chosen word is the one whose word embedding is closest to $v_w$)

**Word embeddings**

Word embeddings have developed as a way of representing the semantic information of words in a corpus (paradigmatic relations in particular), and they are employed as such in the LCTM model.
Word embeddings tap in the power of term-term cooccurrence vectors. A term-term cooccurrence matrix is a $N \times N$ matrix $M$, where $N$ is the number of word types in a corpus, and where the value of each cell $w_{i,j}$ is equal to the number of times the $i$th and $j$th cooccur within a window of $k$ words. A cooccurrence vector $v_i$ is the $i$th row of matrix $M$ and corresponds to the $i$th word. Cooccurrence vectors whose cosine distance are small are typically semantically close in the sense that they are often synonyms or antonyms. In other words, they are paradigmatically related.

Because term-term cooccurrence vectors tend to be very large, especially in big corpora, there is an incentive to compress them to make them more manageable through dimensionality reduction. Thus, words are associated with a $k$-dimensional vector, where $k$ is an arbitrary number, typically between 50 and 300.

Dimensionality reduction can be achieved by many means. So-called “count” methods (Baroni, Dinu, and Kruszewski 2014; Pennington, Socher, and Manning 2014) use methods such as singular value decomposition and matrix factorization to reduce weighted count vectors (weighting schemes include positive pointwise mutual information and local mutual information). Meanwhile “predict” methods (Bengio et al. 2003; Collobert and Weston 2008; Mikolov, Chen, et al. 2013; Mikolov, Sutskever, et al. 2013) set up neural networks that simultaneously learn to predict a word from its a small context window and learn vector representations for each word type.

**LCTM**

With the LCTM, Hu and Tsujii (2016) act on the intuition that topics do not model the same kind of distributional similarity that are modeled with word embeddings. As they note, words that are topically close, like “neural” and “network” in a computer science corpus, will be far away on a word embedding space. This is why they see topics as distributed over other latent variables which they call concept and which are represented by coordinates in the word

---

4Classically, this meant a small window before the target word (Bengio et al. 2003; Collobert and Weston 2008) (this would be the classic “language model” paradigm), but Mikolov, Chen, et al. (2013) have introduced the Skip-gram model, where a word is used to predict the words immediately before and after it, within a small window, and the CBOW model, where the context words are used to predict the target word. These models have since then become the norm.

5While here “concept” is a technical term that refers to features of the LCTM, we believe this use is justified as this concept of CONCEPT can be argued to be an *explication* (in Carnap’s (1950) sense) of the concept of CONCEPT that is defended in Chartrand (no date). In other words, for the purpose of building an algorithm, it is a more precise, more explicit version of the latter concept, that retains some of its features and enables us to say something about the former. In particular, we assume that instantions of the technical sense of CONCEPT can tell us something about where, in the text corpus, corresponding instantiations of the non-technical sense of CONCEPT are mobilized. For example, if a technical concept, represented as coordinates in a word embedding space, has for corresponding lay concept the
embedding space. In other words, if a concept is active at a certain point in the
text, then the words whose word embeddings are close to the concept’s are more
likely to appear there.

The LCTM’s generative model goes like this, with $C$ being the number of
concepts in the model:

- For each topic $k \in \{1 \ldots K\}$
- Draw a topic concept distribution $\phi_k \sim \text{Dirichlet}(\beta)$
- For each concept $c \in \{1 \ldots C\}$
- Draw a concept vector $\mu_c \sim \mathcal{N}(\mu, \sigma_0^2 I)$
- For each document $i \in \{1 \ldots M\}$
- Draw a topic distribution $\theta_i \sim \text{Dirichlet}(\alpha)$
- For each word $w \in 1 \ldots N_i$
  - Draw a topic $z_w \sim \text{Multinomial}(\theta_i)$
  - Draw a concept $c_w \sim \text{Multinomial}(\phi_{z_w})$
  - Draw a word vector $v_w \sim \mathcal{N}(\mu_{c_w}, \Sigma_{z_w})$ (the chosen word is the one
    whose word embedding is closest to $v_w$)

![Plate models for LDA and LCTM](image)

**Figure 1: Plate models for LDA and LCTM**

The graphical model for LDA and LCTM are shown in figure 1.

In relation with the problem of word-sense ambiguity mentioned in section
section, it is interesting to note that the same word can be highly likely for
different concepts belonging to different topics, which themselves are associated
with whole documents. As such, the context of the document determines the
topics, and therefore the concept to which a word can be associated. In so
doing, the LCTM model can associate different concepts to the same word type
depending on the context of the document it is in, and can thus disambiguate
between different senses of a word.

A concept that we associate with the word “dolphin” (therefore, the lay concept DOLPHIN),
then we expect this technical concept to help us determine where the lay concept DOLPHIN
is mobilized.
Method

Inference

Given its relative simplicity and its efficiency, Gibbs sampling is by far the most popular method for learning the parameters of topic models that employ word embeddings. LCTM is no exception.

During the inference process, both concept and topic assignments for each word are sampled, using those two equations:

\[
p(z_w = k|c_w = c, z^{-w}, c^{-w}, v) \propto \left( \frac{n_{w,k} + \alpha_k}{n_{w,k} + \beta_c} \right) \cdot \frac{n_{w,k} + \beta_c}{\sum_{c' \in \{1...C\}} \beta_{c'}}
\]

(1)

\[
p(c_w = c|z_w = k, z^{-w}, c^{-w}, v) \propto \left( n_{c,w} + \beta_c \right) \cdot N(v_w | \mu_c, \sigma_c^2 I)
\]

(2)

Concept extension

Figure 2: Constructing a concept extension chain from an LCTM model.

Once the model has been learned, we have, for each word position, assignment to a concept and a topic, on top of information about its word type and document membership that was provided to the LCTM. Furthermore, we have vectors for
each concept and we had provided a vector for each word, all in the same word embeddings space.

Concept detection formally consists in a function that yields a set of documents from a query, which can be either a word type or a vector in the word embeddings space. From the information LCTM produces, there are a number of ways we could make such a function. For instance, we could find the concepts assigned to the query word, and then find all the documents where these concepts are assigned. But we could also find the word vector for this word, then retrieve the closest concept (in terms of cosine similarity), find the topics where it is assigned, then find the documents where these topics are assigned.

In order to represent the variety of ways a concept extension can be obtained, we use a special notation (cf. figure 2). “w”, “c”, “z” and “d” respectively mean “word”, “concept”, “topic” and “document”. Furthermore, “q” represents a query expressed in the form of a vector. Transitions are noted “E” or “A”: “xEy” means “get the y whose vector is closest to x’s vector” and “xAy” means “get all the y’s which are assigned to a word where x is also assigned”. Thus, the first example of the previous paragraph would be noted “wAcAd” and the second example would be “wEcAzAd”. Given the nature of concept detection, the first letter is always either “w” or “q”, and the last is always “d”.

While the number of possible ways we can get a concept extension using data from a LCTM model is potentially infinite, it makes no sense looping over concepts and topics. Therefore, given a word query, only 8 variations are possible: “wAcAd”, “wAcAzAcAd”, “wAcAzAd”, “wAzAcAd”, “wAzAd”, “wEcAd”, “wEcAzAcAd” and “wEcAzAd”. Given a word vector query, only three variations are available: “qEcAd”, “qEcAzAcAd” and “qEcAzAd”.

**Experimentation**

**Experiment 1**

The first part of our research hypothesis stated that modelling concepts in a topic model would lead to a generally better modelling of the text structure. This, in turn, should lead to better concept detection performance.

To evaluate this proposition, we test all 8 methods for concept detection using LCTM as described in section . For comparison, we are also testing the “Online LDA-Top 30” and the “Gibbs sampling-Concrete Assignment” heuristics from Chartrand, Cheung, and Bouguessa (2017)[6] along with the keyword heuristic (recall all text segments where the query word is present). In this evaluation,

---

In this heuristic, words are associated to a topic if they are among the 30 words most likely to come up if this topic is activated. From this, we get the concept extension by recalling all the segments or documents in which any of the topics associated with the query word are activated.
concept extensions for 754 queries are computed and evaluated against gold standards using the Matthew correlation coefficient (MCC)\[7\]. All of these queries are formulated as a single word; when computing an extension from a chain that begins with “wE”, we employ the word embedding corresponding to the query word.

**Experiment 2**

The second part of our research hypothesis suggested that using a topic model like LCTM, that models concepts on the word embedding space, would allow us to formulate queries for concepts that are not adequately represented with a single word. To test this, we test 588 multiword expressions and represent them on the word embedding space. To do this, we exploit the compositional property of word embeddings, and represent these expressions as the sum of the vectors corresponding to the content words in the expression\[8\]. Because LCTM makes no assignment for multiword expressions, only the chains built for word vector queries—those beginning with “qE”—are available. They are compared with the keyword heuristic against a gold standard using the MCC.

**Corpus & pretreatment**

Our corpus is composed of 186,860 segments extracted from 5,229 French-language court decisions of the Quebec Court of Appeal. These decisions where all published between January 1, 2004 and December 31, 2014. Each segment corresponds to a numbered paragraph in this judgements, and each is parsed with a POS tagger\[9\]. Only verbs, nouns, adverbs and adjectives are kept. Furthermore, judges like to cite law articles, jurisprudence or doctrine in their judgements; these citations have been removed.

Prior to applying the concept detection chains, a word embedding matrix has been learned using gensim’s implementation of word2vec\[10\]. Vector size has been set to 100. The LCTM model was learned using Hu and Tsujii’s implementation\[11\] with the number of topics being 150 (same as in Chartrand, Cheung, and Bougessa 2017) and the number of concepts being 1,000. Two LDA models were used for comparison: one is learned using Hoffman’s Online LDA algorithm (2010), as implemented in gensim\[12\], the other is learned using Griffiths’ and Steyvers’

\[7\]Here, IR standard metrics for evaluation like accuracy and F1-measure are not employed because our gold standard represents an unusual set, where annotated concept-segment pairs are much more likely to be positive than randomly chosen concept-segment pairs. Cf. section .

\[8\]Unlike in English, where compound words are created merely by putting the words together, compound words in French often involve prepositions that further constrains how the semantic composition should be interpreted. For simplicity’s sake, we ignore this information here.

\[9\]http://www.cis.uni-muenchen.de/~schmid/tools/TreeTagger/

\[10\]https://radimrehurek.com/gensim/

\[11\]https://github.com/weihua916/LCTM

\[12\]https://radimrehurek.com/gensim/
Corpus annotations

A subset of our corpus was annotated using the same two-step method presented in Chartrand, Cheung, and Bougessa (2017):

1. Annotators were asked to read a text segment from the corpus, and then write down five concepts that were present in it—or, in other words, that contributed to what was being said.
2. Drawing from concepts obtained in step 1, segments were paired with six concepts. Annotators were asked to rate the concept’s presence from 1 to 4, 1 being completely absent and 4 being highly present. For our purpose, we consider that a concept is present if the annotator scores more than 1—the scale was employed to avoid a concept to be tagged as absent if it was weakly or very implicitly present. The scale was employed to avoid a concept to be tagged as absent if it was weakly or very implicitly present. The draw was tweaked so that, on average, annotators would generally be compelled to say that any given concept was present (2-4) roughly half of the time—this was to ensure that annotators would not be tempted to force a concept upon a segment to compensate for the fact that very little concept were marked as absent.

These annotations were done, on the one hand, by domain experts—jurists—and on the other hand by workers on the crowdsourcing site Crowdflower (which rechristened itself Figure 8 before the end of the study). The 9 expert jurists annotated 103 segments with 1,031 annotations. As for lay workers’ annotations, after screening for “spam” annotations (annotations that seemed random or did not seem to reflect an actual understanding), we were left with 3,240 annotations from 25 workers on 105 segments. While there was little overlap in the segment-concept pairs annotated by experts and non-experts, annotation patterns on the 130 pairs where there was overlap reveal that annotations of experts and non-experts correlate moderately (\(r_{MCC} = 0.32\)). In Experiment 1, performances were evaluated over 871 single-word concept tags used as queries (710 for non-experts and 201 for experts), and in Experiment 2, performances were evaluated over 588 multi-word expressions.

Results

Experiment 1

13Code available at https://gist.github.com/mblondel/542786
Table 1: Concept detection performance on single-word queries. Best scores in MCC and precision are emphasized in bold

|                | Non-experts MCC | Experts MCC |
|----------------|-----------------|-------------|
| Keyword        | 0.14            | 0.14        |
| LDA-Top30      | 0.37            | 0.34        |
| Gibbs LDA      | 0.22            | 0.23        |
| wAcAd          | 0.31            | 0.30        |
| wAcAzAcAd      | 0.08            | 0.12        |
| wAcAzAd        | 0.38            | 0.41        |
| wAzAcAd        | 0.10            | 0.15        |
| wAzAd          | 0.45            | 0.48        |
| wEcAd          | 0.14            | 0.18        |
| wEcAzAcAd      | 0.12            | 0.16        |
| wEcAzAd        | **0.46**        | 0.45        |

As table 1 illustrates, the “wAzAd” and “wEcAzAd” heuristics were the most performant of all, outperforming the leading LDA-Top30 method from Chartrand, Cheung, and Bouguessa (2017) by scores ranging from 0.07 to 0.14 against non-expert and expert annotations.

Other trends can also be observed. Firstly, chains ending in “cAd” do not fare well: their MCCs against non-expert annotations range from 0.10 to 0.31 (0.11 to 0.30 against expert annotations) while the chains ending with “zAd” have MCCs ranging from 0.38 to 0.46 (0.41 to 0.48 against expert annotations). In fact, only and all zAd-ending chains consistently outperformed LDA and keyword methods. Secondly, shorter chains tend to have better performance than longer chains ($r = -0.48, p < 0.001$ against non-experts, $r = -0.46, p < 0.001$ against experts).

Experiment 2

Table 2: Concept detection performance on compound word queries

|                | Non-experts MCC | Experts MCC |
|----------------|-----------------|-------------|
| keyword        | 0.33            | 0.20        |
| qEcAd          | 0.13            | 0.12        |
| qEcAzAcAd      | 0.17            | 0.15        |
| qEcAzAd        | **0.46**        | **0.46**    |

As table 2 shows, the performances of the “qEcAzAd” hold up with compound words, achieving similar MCCs as with single-word queries. The same can
probably be said for the “qEcAd” and “qEcAzAcAd” chains: while the former
does worse against expert annotations, and the latter does better against non-
expert annotations, it could only be indicative of noise in the data. The scores
of the keyword heuristic, on the other hand, have seen a significant uptick,
especially against non-expert annotations, where performance has more than
doubled.

Discussion

We made two claims about LCTM: (1) it makes for a better model of higher-level
entities like topics, which in turn translates in better performances in concept
detection and (2) it allows us to formulate queries when concepts do not perfectly
match with a word or word expression in the corpus.

Modelling and concept detection

Concerning the first claim, results from Experiment 1 seem to validate it, at
least on the surface, as three of the heuristics managed to provide us with better
concept detection performance than what had previously been achieved. These
three chains also were more correlated with experts and non-experts than experts
and non-experts annotations were correlated with each other.

Moreover, these results also suggest that the relationship between concepts
and the textual contexts in which they are present should not be understood
as a direct relation between words and concepts, but rather, is mediated by
higher-level entities like topics. Indeed, the most successful chains are those that
end by connecting those contexts (in our case, the textual segments) to topics
(i.e. they end with a “zAd” operation). This confirms theoretical intuitions that
we have expressed elsewhere (Chartrand et al. 2016; Chartrand, Cheung, and
Bouguessa 2017; Chartrand no date).

Furthermore, it seems like it is the quality of the model that drives the success
of the LCTM in comparison with the LDA, because when the same chain is used,
LCTM does a lot better. The “Gibbs LDA-Concrete Assignment” employs a
“wAzAd” chain, but with a LDA model learned using collapsed Gibbs sampling.
Similarly, the LCTM model is learned with an adapted collapsed Gibbs sampler.
Therefore, the only difference between those two methods lies in the model, and
yet LCTM’s “wAzAd” chain does more than twice as good as LDA’s.

Other factors are also likely at play—in particular, chain length may explain
why some chains are better than others. For instance, some chains seem to be
achieving excessive recall (“wAcAzAcAd”, “wAzAcAd” and “wEcAzAcAd” in
particular). This makes intuitive sense: the “xAy” operations all make it so that
for every x, there can be more than one y, as there usually is more than one
token of x in the corpus, and each token of x can be associated with a different
type of y. As a result, they end up overgenerating, and thus it is no wonder that they would perform poorly in terms of the MCC. The relative success of “wAcAd” compared with “wEcAd” seems to come from the opposite excess on the part of “wEcAd”: given that the “xEy” operation only select one y for every x, “wEcAd” only yields the segment assignations of single LCTM concept, which makes for a very restricted concept extension. On the other hand, with “wAcAd”, individual words are likely to be associated with various concepts. As a result, word queries passing through the “wAcAd” chain yield the extension of several concepts that are likely mobilized in the topics which mobilize the queried concept—as such, they approximate the extension of a chain that would use the topic extension like “wAzAd”. For the same reason, the “xEy” operation at the beginning of the “wEcAzAcAd” chain might neutralize some of this long-chain effect, which would explain why it does slightly better than “wAcAzAcAd”.

**Concept detection of multiword expressions**

Concerning the second claim, it derives strong evidence from the success of the “qEcAzAd” chain, which does as well on compound words as it did on single words. This sustained performance may be somewhat surprising, given that word embeddings composition is only an approximation of a multi-word expression’s meaning (e.g. Salehi, Cook, and Baldwin 2015). However, single words themselves are often ambiguous (especially when they are not chosen as research term, as is the case here); it is possible that composition alleviates this ambiguity as to counter-balance the imprecision it creates.

The relative success of the keyword heuristic on multiword expression compared to single-word queries might also have to do with ambiguity. In fact, most multiword expressions encountered among the annotation, like “arbitre amiable compositeur” (amiable compositeur arbitrator) and “témoignage d’expert” (expert testimony) belong to the technical juridical vocabulary. One can often find a precise definition for it at the beginning of a law or a contract, or a detailed discussion for its interpretation in the doctrine. Because jurists need to mitigate the risk of coming to different interpretations of the same words, it is perhaps more important than elsewhere to have technical concepts that are explicitly linked to a body of text that can be leveraged for interpretation. As a result, jurists have developed an habit of crafting expressions that can be linked to a concept as unambiguously as possible, and which are usually embedded in a set of words that can rarely be seen elsewhere. Not only are these concepts unambiguous, but often, the corresponding concept, being very technical, is also hard to mobilize without using the corresponding expression. The keyword heuristic thus employs expressions that have been refined for better precision and recall—hence its success.
Limitations

One of the motivations for employing LCTM was that it seemed like employing words as a stand-ins for concepts was too indirect a way to identify topics linked to said concept. One might have assumed that translating that query into a vector on a word embedding space would yield better results—but as we saw, one of the leading chains (“wAzAd”) doesn’t even leverage these representations. This might be because annotators themselves were determining concept presence from a word rather than a more direct expression of a concept. A fair test for determining the best way to formulate a concept query would likely require that annotators be given the task to identify the presence of concepts formulated in other ways than corresponding words or expression.

Another issue is that while testing for multiword expressions might give us a hint as to the capacity of our LCTM chains to detect concepts obtained from composition, it is not the most straightforward test for the success of concept detection. We can expect a conceptual analyst to compose concept representations to disambiguate a concept (e.g. MIND - OPINION to get the concept of MIND without contexts where “mind” is used to mean “opinion”, like “in my mind, . . .”) or to add or remove a dimension of interest to it (e.g. MIND + REASONING to study the mind as a reasoning tool). Using composition in such ways is very different to approximating a multiword expression, as is done in Experiment 2. While its success is a good omen, we need to replicate these results with tasks that are more in line with what conceptual analysts are really likely to do.

On the more technical side, the relative success of online variational Bayes compared to collapsed Gibbs sampling (which had already been established by Chartrand, Cheung, and Bouguessa 2017) suggests that LCTM might do even better with a different learning method. As such, it would likely be worthwhile to adapt learning online variational Bayes (Hoffman, Bach, and Blei 2010) or hybrid variational/Gibbs sampling inference (Welling, Teh, and Kappen 2012) to the LCTM model in order to learn better models.

Conclusion

This paper sought to improve on existing concept detection methods by modelling topics in a more theoretically appropriate way as constituted of concepts, and by enabling queries formulated in terms of coordinates on the word embedding space. It pursued this objective by constructing processing chains using LCTM models inferred from a court decision corpus using the method described by Hu and Tsujii (2016), and evaluated their performance against annotations by legal experts and lay people.

It was successful on both counts. On single-word queries, some of the chains
achieved higher performance than the previous leading method, and for reasons that seem to be due to the nature of the LCTM model. Queries formulated as compositions of word embeddings were also tested as approximation of multiword expressions and achieved equally high results, demonstrating that our method can also successfully be used with queries formulated as coordinates on the word embedding space.

**Acknowledgment**

This research was supported by the Social Sciences and Humanities Research Council of Canada and enabled in part by the support provided by WestGrid (http://www.westgrid.ca) and Compute Canada (www.computecanada.ca). The author also wishes to thank Marc Queudot, Mohamed Bouguessa and Jackie C.K. Cheung for their help and comments.

**References**

Andow, James. 2016. “Qualitative tools and experimental philosophy.” *Philosophical Psychology* 29 (8):1128–41.

Baroni, Marco, Georgiana Dinu, and Germán Kruszewski. 2014. “Don’t count, predict! A systematic comparison of context-counting vs. context-predicting semantic vectors.” In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 1:238–47.

Batmanghelich, Kayhan, Ardavan Saeedi, Karthik Narasimhan, and Sam Gershman. 2016. “Nonparametric spherical topic modeling with word embeddings.” *arXiv preprint arXiv:1604.00126*.

Beaney, Michael. 2018. “Analysis.” In *The Stanford Encyclopedia of Philosophy*, edited by Edward N. Zalta, Summer 2018. Metaphysics Research Lab, Stanford University.

Blei, David M., Andrew Y. Ng, and Michael I. Jordan. 2003. “Latent Dirichlet Allocation.” *Journal of machine learning research* 3 (Feb):1137–55.

Blei, David M., Andrew Y. Ng, and Michael I. Jordan. 2003. “Latent Dirichlet Allocation.” *Journal of machine Learning research* 3 (Jan):993–1022.

Blondel, Mathieu. 2010. “Latent Dirichlet Allocation in Python.” *Mathieu’s log*.[http://www.mblondel.org/journal/2010/08/21/latent-dirichlet-allocation-in-python/]

Bluhm, Roland. 2013. “Don’t Ask, Look! Linguistic Corpora as a Tool for Conceptual Analysis.” In *Was dürfen wir glauben?: Was sollen wir tun? Sektions-
beiträge des achten internationalen Kongresses der Gesellschaft für Analytische Philosophie e.V., edited by Migue Hoeltje, Thomas Spitzley, and Wolfgang Spohn, 7–15. DuEPublico.

Bunk, Stefan, and Ralf Krestel. 2018. “WELDA: Enhancing Topic Models by Incorporating Local Word Context.” In Proceedings of the 18th ACM/IEEE on Joint Conference on Digital Libraries, 293–302.

Carnap, Rudolf. 1950. Logical Foundations of Probability. Chicago: University of Chicago Press.

Chartrand, Louis. 2017. “La Philosophie Entre Intuition Et Empirie: Comment les Études du Texte Peuvent Contribuer À Renouveler la Réflexion Philosophique.” Artichaud Magazine 2017 (8 juin).

———. no date. “Similarity in conceptual analysis and concept as proper function.”

Chartrand, Louis, Jackie C. K. Cheung, and Mohamed Bouguessa. 2017. “Detecting Large Concept Extensions for Conceptual Analysis.” In Machine Learning and Data Mining in Pattern Recognition, 78–90. Lecture Notes in Computer Science. Springer, Cham.

Chartrand, Louis, Jean-Guy Meunier, Davide Pulizzotto, José López González, Jean-François Chartier, Ngoc Tan Le, Francis Lareau, and Julian Trujillo Amaya. 2016. “CoFiH: A heuristic for concept discovery in computer-assisted conceptual analysis.” In JADT 2016 : 13ème Journées internationales d’Analyse statistique des Données Textuelles. Vol. 1. Nice, France.

Collobert, Ronan, and Jason Weston. 2008. “A unified architecture for natural language processing: Deep neural networks with multitask learning.” In Proceedings of the 25th international conference on Machine learning, 160–67.

Das, Rajarshi, Manzil Zaheer, and Chris Dyer. 2015. “Gaussian Lda for topic models with word embeddings.” In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing, 1:795–804.

Deerwester, Scott, Susan T. Dumais, George W. Furnas, Thomas K. Landauer, and Richard Harshman. 1990. “Indexing by latent semantic analysis.” Journal of the American society for information science 41 (6):391–407.

El-Arini, Khalid, Emily B. Fox, and Carlos Guestrin. 2012. “Concept modeling with superwords.” arXiv preprint arXiv:1204.2523.

Gabrilovich, Evgeniy, and Shaul Markovitch. 2007. “Computing Semantic Relatedness Using Wikipedia-based Explicit Semantic Analysis.” In IJCAI 2007, Proceedings of the 20th International Joint Conference on Artificial Intelligence, Hyderabad, India, January 6-12, 2007, 1606–11.

Gottron, Thomas, Maik Anderka, and Benno Stein. 2011. “Insights into explicit semantic analysis.” In Proceedings of the 20th ACM international conference on
Information and knowledge management, 1961–4.

Griffiths, Thomas L., and Mark Steyvers. 2004. “Finding scientific topics.” Proceedings of the National academy of Sciences 101 (suppl 1):5228–35.

Haslanger, Sally. 2012. Resisting Reality: Social Construction and Social Critique. Oxford: Oxford University Press.

Hoffman, Matthew, Francis R. Bach, and David M. Blei. 2010. “Online learning for latent dirichlet allocation.” In advances in neural information processing systems, 856–64.

Hofmann, Thomas. 1999. “Probabilistic latent semantic analysis.” In Proceedings of the Fifteenth conference on Uncertainty in artificial intelligence, 289–96.

Hu, Weihua, and Jun’ichi Tsujii. 2016. “A latent concept topic model for robust topic inference using word embeddings.” In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), 2:380–86.

Law, Jarvan, Hankz Hankui Zhuo, Junhua He, and Erhu Rong. 2017. “LTSG: Latent Topical Skip-Gram for Mutually Learning Topic Model and Vector Representations.” CoRR abs/1702.07117.

Le, Tuan M. V., and Hady W. Lauw. 2017. “Semantic Visualization for Short Texts with Word Embeddings.” In Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI-17, 2074–80.

Li, Chenliang, Haoran Wang, Zhiqian Zhang, Aixin Sun, and Zongyang Ma. 2016. “Topic modeling for short texts with auxiliary word embeddings.” In Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval, 165–74.

Li, Shaohua, Tat-Seng Chua, Jun Zhu, and Chunyan Miao. 2016. “Generative topic embedding: a continuous representation of documents.” In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, 1:666–75.

Li, Ximing, Jinjin Chi, Changchun Li, Jihong Ouyang, and Bo Fu. 2016. “Integrating topic modeling with word embeddings by mixtures of vMFs.” In Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers, 151–60.

Li, Ximing, Ang Zhang, Changchun Li, Lantian Guo, Wenting Wang, and Jihong Ouyang. 2018. “Relational Biterm Topic Model: Short-Text Topic Modeling using Word Embeddings.” The Computer Journal.

Liu, Yang, Zhiyuan Liu, Tat-Seng Chua, and Maosong Sun. 2015. “Topical Word Embeddings.” In AAAI’15 Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence, 2418–24.

Meunier, Jean Guy, Ismail Biskri, and Dominic Forest. 2005. “Classification and
categorization in computer assisted reading and analysis of texts.” In *Handbook of categorization in cognitive science*, edited by Henri Cohen and Claire Lefebvre, 955–78. Elsevier.

Mikolov, Tomas, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. “Efficient estimation of word representations in vector space.” *arXiv preprint arXiv:1301.3781*.

Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg S. Corrado, and Jeff Dean. 2013. “Distributed representations of words and phrases and their compositionality.” In *Advances in neural information processing systems*, 3111–9.

Moody, Christopher E. 2016. “Mixing Dirichlet Topic Models and Word Embeddings to Make lda2vec.” *CoRR abs/1605.02019*.

Nguyen, Dat Quoc, Richard Billingsley, Lan Du, and Mark Johnson. 2015. “Improving topic models with latent feature word representations.” *Transactions of the Association for Computational Linguistics* 3:299–313.

Peng, Min, Qianqian Xie, Yanchun Zhang, Hua Wang, Xiuzhen Zhang, Jimin Huang, and Gang Tian. 2018. “Neural Sparse Topical Coding.” In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2332–40. Melbourne, Australia: Association for Computational Linguistics.

Pennington, Jeffrey, Richard Socher, and Christopher Manning. 2014. “Glove: Global vectors for word representation.” In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, 1532–43.

Potapenko, Anna, Artem Popov, and Konstantin Vorontsov. 2017. “Interpretable probabilistic embeddings: bridging the gap between topic models and neural networks.” In *Conference on Artificial Intelligence and Natural Language*, 167–80.

Pulizzotto, Davide, José A. Lopez, Jean-François Chartier Jean-Guy, Meunier1 Louis Chartrand1 Francis Lareau Tan, and Le Ngoc. 2016. “Recherche de «périsegments» dans un contexte d’analyse conceptuelle assistée par ordinateur: le concept d’«esprit» chez Peirce.” In *JEP-TALN-RECITAL 2016*. Vol. 2. Paris.

Pust, Joel. 2000. *Intuitions as Evidence*. New York: Routledge.

Sahlgren, Magnus. 2008. “The distributional hypothesis.” *Italian Journal of Disability Studies* 20:33–53.

Salehi, Bahar, Paul Cook, and Timothy Baldwin. 2015. “A word embedding approach to predicting the compositionality of multiword expressions.” In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 977–83.

Tang, Yi-Kun, Xian-Ling Mao, Heyan Huang, Xuwen Shi, and Guihua Wen. 2018. “Conceptualization topic modeling.” *Multimedia Tools and Applications*
Wang, Bo, Maria Liakata, Arkaitz Zubiaga, and Rob Procter. 2017. “A Hierarchical Topic Modelling Approach for Tweet Clustering.” In International Conference on Social Informatics, 378–90.

Welling, Max, Yee Whye Teh, and Hilbert Kappen. 2012. “Hybrid variational/Gibbs collapsed inference in topic models.” arXiv preprint arXiv:1206.3297.

Xun, Guangxu, Yaliang Li, Wayne Xin Zhao, Jing Gao, and Aidong Zhang. 2017. “A correlated topic model using word embeddings.” In Proceedings of the 26th International Joint Conference on Artificial Intelligence, 4207–13.

Zhang, Xianchao, Ran Feng, and Wenxin Liang. 2019. “Short Text Topic Model with Word Embeddings and Context Information.” In Recent Advances in Information and Communication Technology 2018, edited by Herwig Unger, Sunantha Sodsee, and Phayung Meesad, 55–64. Cham: Springer International Publishing.

Zhao, He, Lan Du, Wray Buntine, and Mingyuan Zhou. 2018. “Inter and Intra Topic Structure Learning with Word Embeddings.” In International Conference on Machine Learning, 5887–96.