Exploratory topic modeling with distributional semantics

Samuel Rönnqvist
Turku Centre for Computer Science – TUCS
Department of Information Technologies
Åbo Akademi University, Finland
sronnqvi@abo.fi

Abstract
As we continue to collect and store textual data in a multitude of domains, we are regularly confronted with material whose largely unknown thematic structure we want to uncover. With unsupervised, exploratory analysis, no prior knowledge about the content is required and highly open-ended tasks can be supported. In the past few years, probabilistic topic modeling has emerged as a popular approach to this problem. Nevertheless, the representation of the latent topics as aggregations of semi-coherent terms limits their interpretability and level of detail.

This paper presents an alternative approach to topic modeling that maps topics as a network for exploration, based on distributional semantics using learned word vectors. From the granular level of terms and their semantic similarity relations global topic structures emerge as clustered regions and gradients of concepts. Moreover, the paper discusses the visual interactive representation of the topic map\footnote{Topic mapping code and demo available at \url{http://samuel.ronnqvist.fi/topicMap}/} which plays an important role in supporting its exploration.

Keywords: topic modeling, distributional semantics, visual analytics

1 Introduction
Following the increase in digitally stored and streamed text, the interest for computational tools that aid in organizing and understanding written content at a large scale has soared. Natural language processing and machine learning techniques demonstrate strength in their feats of handling the challenging intricacies of human language to extract information and in their aptitude for scanning big data sets. However, while we can model what information is likely to be interesting, humans alone are capable of a deeper understanding that involves evaluating information against a wide and diverse body of knowledge in nuanced ways, which motivates a focus on human-computer interaction and visual analytics in text mining \cite{17}.

1 Topic mapping code and demo available at \url{http://samuel.ronnqvist.fi/topicMap/}
This paper concerns analysis of text by means of exploratory topic modeling, by which I emphasize the exploratory use of models that convey topic structure. To this end, I put forward a new method for topic modeling based on distributional semantics using continuous word vector representations, for the construction of models called topic maps. On the one hand, the focus is set explicitly on unsupervised learning to allow maximum coverage in terms of domain and language without need for adaption, while taking advantage of recent advances in word vector training by neural networks. On the other hand, the role of the human user is acknowledged as an important part of the analysis process as the one who understands and explores the modeling results; therefore, visual interactive presentation is discussed as part of the contribution alongside map construction and perceived as equally important to exploratory topic modeling.

Probabilistic topic modeling [4] is a family of machine learning algorithms for uncovering thematic structure in text documents that are widely used, and applicable both for exploratory analysis of topics and as a discrete dimensionality reduction method in support of other learning tasks. Based on co-occurrence of terms in documents, probabilistic topic modeling extracts a number of latent topics. In the seminal algorithm, Latent Dirichlet Allocation (LDA), the number of topics to infer is given as a parameter. Assuming that each document may discuss a mixture of topics, it attempts to isolate coherent topics. Each topic is defined as a probability distribution over terms, where the terms collectively carry the meaning of the latent topic. While LDA and many of its variations are theoretically solid and rest on an interpretation-friendly probabilistic basis, issues of interpretability are nevertheless commonplace and well recognized [6]. First, the unsupervised modeling offers no guarantees that the topic division is semantically meaningful; some topics may seem similar and hard to distinguish, whereas others turn out very specific. These issues may be mitigated by selecting appropriate parameters, including the number of topics in the case of LDA. Second, the terms within topics may appear semantically incoherent and confusing to a human. Various efforts have been made to improve coherence (e.g., [15] [14]), yet for humans to form an understanding of what a topic signifies based on a set of weighted terms, interpretation inevitably involves a certain cognitive load, only increased by the iterative task of contrasting topics against each other to grasp the broader picture.

Thoughtful visual representation of the topic structure and terms can ease the task (see, e.g., [18] [7]), but I argue that in many cases it is more meaningful to choose to operate from the level of individual terms that represent concrete concepts and their bilateral semantic similarity relations. A discrete division of topics is practical in many use cases, but is somewhat unnatural for exploratory purposes, and mere aggregation of terms inevitably leads toward less interpretable abstractions. Instead, it is more fitting to allow for a topic structure to emerge as a global property from the local semantic similarity relations among terms. Such a semantic network allows the human user to flexibly identify topics as regions through proper visualization, while the network also supports
quantitative analysis such as community detection \cite{9} (overlapping clustering, which handles ambiguous terms) to identify discrete topics.

The following section introduces the method for building the semantic network model, the topic map, whereas Section 3 discusses its visualization, and Section 4 reports on experiments conducted to demonstrate the mapping method, followed by some concluding remarks.

2 Building the topic map

Distributional semantics models the meanings of words based on their contexts, namely the surrounding words in a sentence, according to the aphorism “you shall know a word by the company it keeps” \cite{8}. While modeling has traditionally been based on counting of context words, recent approaches that work by learning to predict words instead have been highly successful \cite{1}. A popular way of representing the semantics is by vectors, e.g., through projection \cite{19} or later through neural network training. \cite{4}. Lately, Mikolov et al. \cite{13} have shown how neural networks can be efficiently used to train semantic models based on corpora at the scale of billions of words, in order to achieve very high semantic accuracy. Their continuous skip-gram model is a neural network trained to predict context words based on the center word, using a single hidden layer. Through supervised training, the network optimizes its hidden layer weights, which results in the learned array of hidden nodes providing fixed-length vector representations of word semantics, i.e., word vectors. The word vectors embed words into a semantic space that supports measuring similarities among words by their vectors (e.g., by cosine similarity), as well as other vector arithmetic operations (e.g., addition and subtraction for regularities prediction).

For the purpose of modeling the general topic composition of corpora, I use the neural network skip-gram method to model word-level semantic similarity, and from pairwise relations let the broader topic structure emerge. Whereas the focus in word vector training generally is to approximate the semantics of language in general, which can be achieved by training on large and diverse enough text, the idea is here to explicitly model the semantics of the language in one’s corpus alone. The model then reflects how words relate in the discourse of the corpus rather than elsewhere. Thereby, the discrepancies between the word similarities presented by the model and the observers own, more general understanding and less data-informed expectation of how the words relate, constitute telltales of the thematic nature of the underlying text. (Kulkarni et al. use word vectors accordingly to study linguistic change in English over time. \cite{11}) For topic modeling to be meaningful, it naturally needs to work for corpora far smaller than billions of words. As will be demonstrated in Section 4, skip-gram models can learn usefully accurate word vectors on much smaller data sets, too.

Apart from semantic similarity, the topic map incorporates term frequencies, used to represent the prevalence of terms in the corpus, and in combination with their semantic neighborhood provide a sense of the overall importance of sections of the map, reflecting the prevalence of specific concepts or topics. Probabilistic
Algorithm 1 Topic map construction (in: tokens, V, C, E, N, P, L; out: net)

# Word vector training
model = Word2Vec(tokens, vector_size=V, context_size=C, epochs=E)

# Network construction
for i1 in range(0, N-1):
    for i2 in range(i1+1, N):
        t1, t2 = top_N_terms[i1], top_N_terms[i2]
        net.add_link(t1, t2, weight=model.similarity(t1, t2))

# Network pruning
threshold = percentile([link.weight for link in net.links], P)
for node in net.nodes:
    cap = sorted(net.links[node], key=lambda link: link.weight)[-1*L].weight
    for link in net.links[node]:
        if link.weight < max(cap, threshold):
            net.remove_link(link)
ws = [link.weight for link in net.links]
for link in net.links:
    net.links[link].weight = (link.weight-min(ws)) / (max(ws)-min(ws))

topic modeling similarly uses topic-wise probability distributions over terms to represent their degree of importance within the topic.

Using the word vector model and term counts, a semantic network that constitutes the topic map can be constructed according to Algorithm 1 as described in the following. First, the text of a corpus is processed and tokenized into meaningful and well normalized terms. Then, the map is constructed through the following two main steps.

**Word vector training.** Given the main parameters, vector size (V) and context size (C), word vectors are trained on term sequences by the method of Mikolov et al. (word2vec). Vector size determines the dimensionality of the semantic space and is customarily in the range of 50 to 1000, where higher dimensionality allows for a finer model given enough data. The size of the word context to consider is typically about 5-10 words, but for the current task even contexts up to 25 words have proved satisfactory. Training in multiple epochs (E) (e.g., 3-10) tends to improve the quality of the model noticeably, especially with little data available.

**Network construction.** Once the vectors have been trained, we can use the model to measure similarity of pairs of terms. The most frequent terms in the corpus are picked for comparison, preferably excluding stopwords. Typically in the range 100-1000, the number of unique terms to include (N) defines the maximum level of detail in the topic map and limits the computational complexity of building it. For each pair, the cosine similarity between their vectors \( \text{sim}(t_1, t_2) = \mathbf{v}(t_1) \cdot \mathbf{v}(t_2) \), with unit vectors, is computed and stored.

**Network pruning.** As only similar terms are meaningful to relate and as we seek to build a network that is neither too dense and cluttered nor too sparse and disconnected, the pairs with highest similarity scores are retained as links between the term nodes. With varying sizes of the vector and corpora, the
similarity scores vary considerably as well. Thus, filtering of pairs is performed by a threshold defined as a percentile of all scores stored \((P)\), typically at the 97-99th percentile, which makes the parameter’s effect more stable. Moreover, an upper bound on number of links per term \((L)\) helps reduce cluttering density due to general terms that may measure as very similar to many terms. Typical cap values are 8-15 links per term. All links are finally weighted according to its normalized similarity score, as a standard measure of link strength \((w' \in [0, 1])\).

In order to optimize parameter selection the quality of the topic maps must be evaluated. While the exploratory task ultimately calls for qualitative evaluation, semantic prediction accuracy will be used for initial guidance in word vector training, which is the more computationally demanding step. The evaluation method and data, borrowed from Mikolov et al., measures syntactic and semantic regularities such as “man is to woman as king is to queen”, “Athens is to Greece as Baghdad is to Iraq” and “code is to coding as dance is to dancing”, where accuracy in predicting the last word is evaluated. Measuring how well the model approximates general English, the relative performance on this task can help to rule out models that are too simple and produce suboptimal maps because they lack ability to appropriately model the semantics. The highest accuracy, however, does not necessarily provide the best topic map, as its quality relies on a balance between specificity and generality of its relations. The experiments in Section 4 illustrate this further.

Apart from local link accuracy, the network should ideally show good structure in terms of how broader clusters emerge, too. This is highly dependent on both calibration of the network parameters and how the network is analyzed. The experiments in this paper focus on visual analysis based on force-directed layouting, in which case desirable network structures contain some degree of clustering into coherent and meaningful regions, without excessive cross-linking between terms in different clusters to avoid overlaps. The network construction parameters \((P, L, N)\) may be adjusted to optimize the readability of the map, which in practice can be done instantaneously while visualizing the network. Hence, optimization of the word vector parameters is the more cumbersome groundwork that begets good maps, and evaluation of accuracy helps by reducing the search space.

### 3 Visualizing the topic map

Exploration of complex models such as topic models calls for presentations that provide as much detail as meaningfully possible. The most information-dense mode of communication is visualization, whereas interactivity helps expand the space of information that can be presented intelligibly on a finite screen. The visual analytics paradigm [10] embraces visual interactive interfaces as they offer a means of communication that is both rich and reactive, thus, helping users in making sense of models and data. Visualization of the topic map incorporates Shneiderman’s visual information-seeking mantra, “overview first, zoom and filter, then details-on-demand” [20], by providing both overview of a corpus and
a scaffold for exploration of its details. Visualization of the two main aspects of
the map, term frequencies and word vectors, is discussed in the following, as well
as their combination into a visual topic map.

Among the most popular forms of text visualization are word clouds, which
are simple yet useful. Their main property, representing word importance by
size, is powerful because it utilizes a preattentively recognized visual variable,
i.e., relative word importance is recognized effortlessly and without requiring
focused attention, in parallel across the field of vision at the early stage of the
human visual system [21]. While word clouds have received some criticism re-
lating to other properties such as the (dis)organization of words, studies have
sought improvement and in terms of readability evaluated various approaches
such as clustered [12] and semantic word clouds [2] that impose some semanti-
cally meaningful organization of words. However, so far none of the approaches
have used distributional semantics, which offers advantages by being arguably
more specific than tried clustering approaches, and unsupervised as opposed to
database approaches.

By contrast, a common approach to visualizing word vectors is to plot words
according to their two-dimensional projections by PCA (or other multidimen-
sional scaling methods), which achieves a basic form of semantic organization,
albeit easily cluttered at the center. While word clouds commonly place words
as closely as possible, regarding order or not, projection uses planar distance
to communicate the degree of semantic similarity (a spatial visual metaphor)
as well as ordering. Nevertheless, projection into two dimensions is bound to
produce overlap between semantically unrelated sets of words, which motivates
the visualization of semantic relations by drawn line connections that is more
explicit [16]. For visualization of the topic map network, I propose to use a force-
directed layout (a projection method) that optimizes word positions explicitly
based on semantic relations present in the network model, rather than the whole
word vector model. In particular, the D3 force algorithm [5] is suitable as it can
counter overlap of terms (by node charge) to preserve readability, even when
they are densely connected. It can also run in real time to allow for interac-
tive adjustment of positions which lets the user explore multiple local optima of
positioning.

The visual topic map lends from word clouds the word sizing relative to their
corpus frequency, and uses force-directed layouting to organize the map seman-
tically. Drawing the network of words, the strength of each link is encoded by
opacity, which makes more explicit the relative importance of individual links,
and together with the emergent density of links it provides an aggregate impres-
sion of the varying density of the map.

Interactive exploration of the map is enabled foremost by zoom/pan capa-
bilities, which in a very direct way allows more terms to be displayed, and high-
lighting of links of specific terms. The filtering of terms by frequency can be
responsive to the level of zoom to seamlessly provide more detail on demand.
The percentile filter used to construct the network can be relaxed if the visual
interface can counter the added complexity, and the number of terms can be
increased accordingly. Hence, the scalability of the topic map visualization depends largely on interaction design. The semantic network of frequent terms also functions as a canvas for other types of information, such as mapping of local term neighborhoods and relational information, touched upon in Section 5.

4 Experiments

The topic map will be demonstrated and tested using two different corpora. The first corpus is a sample of news articles from Reuters (U.S. online edition) containing 23k articles and 9.2M words (167k unique) and the other is a collection of financial patent application abstracts from the U.S. Patent and Trademark Office comprising 14k abstracts and 1.7M words (20k unique). In accordance with the exploratory aim of this article, a topic map is trained and visualized for each corpus as discussed above, in hope of gaining insight into the thematic composition of each (see Fig. 1 and 2). The most prevalent terms representing concrete concepts are displayed and their semantic similarity relations provide organization that portray topics implicitly as regions and gradients between them.

The experiment starts by selecting the parameters for word vector training, guided by quantitative accuracy and qualitative assessment of the map (as discussed in Section 2). Having exhaustively tested various settings, their relationship can be described as follows. With a fixed context size of 15 for the Reuters corpus, accuracy reaches a plateau from vector sizes 200 to 500 (on average at 17%, with $E=3$), decreasing afterwards. Meanwhile, at a given vector size, accuracy tends to asymptotically approach a limit with increased context size. Qualitatively, the best network structure appears to result from settings where accuracy is close to the limit but context size is kept moderate.

The experiments show that the map is surprisingly robust with respect to the training parameters, producing largely comprehensible results even at vector sizes of 25 or 600 and context sizes of 5 and 50 respectively. Nevertheless, the quality of the Reuters map is noticeably best at vector sizes 200-400 and context sizes 10-20, where larger contexts benefit from larger vectors. Simpler models produce networks with smaller regions that are tightly clustered, but result in either few or arbitrary connections between regions, depending on the threshold ($P$). Networks from complex models have similar problems, although the strong connections tend to be very specific and semantically accurate, which explains their good testing performance.

The qualitatively optimal models in between strike a balance between, on the one hand, semantic accuracy that provides a map of meaningful connections and, on the other hand, generality by connecting parts of the map through more abstract but still helpful term relations. Hence, measured accuracy provides fundamental guidance in learning a model that handles the language well, but the map then benefits from a slight regularizing or smoothing effect achieved by using a simpler model than the quantitatively optimal. While large vectors and contexts combined can achieve maximum accuracy (about 22% for the Reuters
Fig. 1. Topic map of financial news articles, interactive version available at: [http://samuel.ronnqvist.fi/topicMap/]

Fig. 2. Topic map of financial patent abstracts
corpus), it does not seem productive to surpass contexts of about 25 words,
and given a limited context size, it is motivated to choose a vector size towards
the beginning of the accuracy plateau. The number of training epochs has a
strong effect on accuracy, e.g., the settings $V=400$, $C=15$ and $E=\{1, 3, 5\}$ give
accuracies 7.3, 16.7 and 19.1, but the two latter cases do not show any notable
qualitative difference for the Reuters data.

The topic map in Fig. 1 was produced with the settings $V=250$, $C=12$, $E=5$, $N=500$, $P=\cdot95$ and $L=12$ (accuracy 17.6%, training time 14.5 min on 4
cores). It depicts the topic landscape of the Reuters financial news corpus by
its most frequent terms excluding stop words (including automatically detected
bi-gram phrases). The similarity threshold set at the 98.5th percentile provides
an appropriate degree of connectivity. The cap on links per term helps improve
readability especially in the dense region surrounding the terms business and
technology. The map uncovers an uneven distribution of terms, where smaller
concentrations highlight cliques of terms (e.g., president, ceo, etc. down left)
that represent a rather distinct general concept. Larger concentrated regions
form to highlight a broader topic division of the corpus, the three main regions
broadly reflecting discourse on business-related activities, realized performance
and expected performance.

The map in Fig. 2 similarly illustrates the lay of specific concepts and more
general topics as they occur in the set of patent abstracts. A few themes can
be identified, such as payment systems, telecommunications, trading, portfolio
management and patent-specific language. The map includes 350 terms and links
for the top 2% most similar pairs. As the patent corpus is much smaller the vector
size was reduced according to vocabulary size heuristically by $V = 2 \frac{|\text{vocab}_1|}{|\text{vocab}_2|}$
to $V=85$, context size was kept at 12 not to reduce the already scarce data and
training was run in 10 epochs (training time 3.2 min on 4 cores).

To conclude the evaluation of the generated topic maps, I compare the news
corpus against a benchmark obtained by LDA (results for the patent corpus are
similar but omitted due to space constraints). The same preprocessing of the text
is used as above, and the topics are modeled with standard parameter settings
into 8 topics. Each topic is presented by their top-10 terms according to the topic-
term probability distributions, as the most direct way of presenting the model.
Stop words are excluded to make the results more informative. While several
methods have been proposed that rerank terms to better support interpretation
of the topics (cf. [22][7][18]), no such method seems to have been unanimously or
widely adopted. The obtained topics are:

Topic 0: million, net, quarter, year, financial, income, company, share, operating, total
Topic 1: securities, class, relevant, number, options, option, price, form, code, relevant security
Topic 2: company, shares, fitch, fund, rating, share, ratings, information, financial, available
Topic 3: u.s, bank, new, company, financial, government, state, group, year, years
Topic 4: first, people, world, new, patients, home, years, health, year, games
Topic 5: company, information, new, services, business, market, products, forward-looking
    statements, technology, solutions
Topic 6: q2 2014, jul amc, call, company, 29 jul, corp, earnings conf, jul bmo, trust, share
Topic 7: percent, year, million, billion, market, u.s, sales, shares, growth, down
For some topics it is possible to discern a latent meaning, while others prove hard to interpret. For instance, Topics 0 and 7 appear to relate to realized financial performance, but it is difficult both to form a more detailed explanation of them and to distinguish logically between them. As mentioned in Section 1, recognizing a distinct topic from an aggregate of terms is challenging, as is the task of understanding how multiple topics relate. While the topic map includes many of the same frequent terms, its natural, semantic organization makes it easier to view and grasp the overall topic composition and scope. Local neighborhoods of the map tend to be more coherent than LDA topics, and the relation between different sections of the map is made more explicit. While exploration of LDA topic models can be supported by meaningful presentation (e.g., [7,18]), the topic map’s alternative way of approaching topic modeling remains well motivated for exploration.

5 Discussion

My aim has been to introduce a new approach of using distributional semantics, specifically word vectors trained by neural networks, to explore topics in bodies of text. A problem commonly addressed by probabilistic topic modeling, this approach sets out to tackle it with finer granularity, by building a topic map bottom-up from concrete terms towards general topics, rather than forcing interpretation of implicit meaning among an explicit, but not necessarily coherent, set of topic terms. Distributional-semantic modeling provides meaningful word-to-word similarity relations and organization that is easy to navigate. In addition, I put forward a visualization design for the map that provides overview and means for linking to further details, thus supporting interactive exploration. As a network model, the map also supports quantitative network analysis, in particular community detection as a form of second-level clustering to provide explicit topics, which are useful in some cases. The topic map opens up to a range of possible extensions to be explored.

As the map provides a projection of the semantic space of a corpus, another interesting type of information is the relational, i.e., how different concepts are referenced together in text. Mapping such relations onto the topic map may lead to still more informative ways of summarizing the contents of texts. Document-level co-occurrence of terms used in probabilistic topic modeling represents a crude way of harnessing relational information to extract topic information, but it is likely beneficial to treat distributional word context similarity and word-to-word co-occurrence as separate aspects that both contribute toward summarizing the discourse of a corpus. Thus, the approach of constructing a topic map outlined in this paper should be seen as elementary to future extensions that among other things include sophisticated analysis of relations in text and powerful visual interactive interfaces to make the semantic space and its linked information readily browsable. The semantic network is the basic data structure, which can be meaningfully presented in many other ways as well, e.g.,
using more structured network layouts or non-graphical representation, possibly emphasizing search with a completely local focus rather than overview.

Studying immediate neighborhoods of specific terms may in fact be a desirable mode of exploration, which can be supported in other ways than described above. Rather than starting from the frequent term set, terms with the closest vectors can be searched. By recursively traversing the nearest neighbors of a term, a close-up view of its semantic context in the corpus is obtainable.

Vector similarity comparisons can also be performed with compound vectors that average two or a few word vectors, for instance, as a way to disambiguate a term (e.g., financial by financial+group, financial+results) or merge closely related terms (e.g., customer+customers). The latter could be applied to enhance the map by reducing term redundancy and thereby visual clutter, while joining their term counts. Another way to generalize across terms would be to smooth term counts to some extent among direct neighbors, in order to make the representation of prevalence of regions more congruent.

In this paper, word vectors and term frequencies were obtained from the same set of text, which may lead to problems of accuracy for the study of smaller sets of text (e.g., in the order of 10-100k rather than 1M words). It is possible to separate these, letting the word vectors be trained on a larger background corpus while counting terms on a smaller foreground set, as long as they are related in nature. For instance, the background corpus may consist of text from a single source over a certain period of time, while texts from smaller intervals during that period would be used as foreground corpora to allow for more specific study of varying term prevalence over time, still benefiting from a more robust semantic model.

As efficient word vector training with neural networks has opened up many new possibilities in natural language processing, I hope to introduce it for the purpose of exploring topics in masses of text by proposing a methodology for building and visualizing topic maps. Unsupervised word-level modeling of semantics offers very flexible and detailed means for analysis that deserve further study. The concluding discussion has outlined a few interesting future directions, and ultimately the utility of topic maps and their visual representations should be tested by how they support users’ understanding in a variety of real-world settings.

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