Deep Temporal-Recurrent-Replicated-Softmax for Topical Trends over Time

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Abstract

Dynamic topic modeling facilitates the identification of topical trends over time in temporal collections of unstructured documents. We introduce a novel unsupervised neural dynamic topic model known as Recurrent Neural Network-Replicated Softmax Model (RNN-RSM), where the discovered topics at each time influence the topic discovery in the subsequent time steps. We account for the temporal ordering of documents by explicitly modeling a joint distribution of latent topical dependencies over time, using distributional estimators with temporal recurrent connections. Applying RNN-RSM to 19 years of articles on NLP research, we demonstrate that compared to state-of-the-art topic models, RNN-RSM shows better generalization, topic interpretation, evolution and trends. We also propose to quantify the capability of dynamic topic model to capture word evolution in topics over time.

1 Introduction

Topic Detection and Tracking (Allan et al., 1998) is an important area of natural language processing to find topically related ideas that evolve over time in a sequence of text collections and exhibit temporal relationships. The temporal aspects of these collections can present valuable insight into the topical structure of the collections and can be quantified by modeling the dynamics of the underlying topics discovered over time.

Problem Statement: We aim to generate temporal topical trends or Automatic Overview Time-lines (AOT) of topics for a time sequence collection of documents. This involves the following three tasks in dynamic topic analysis framework: (1) Topic Structure Detection (TSD): Identifying the main topics in the document collection.
(2) Topic Evolution Detection (TED): Detecting the emergence of a new topic and recognizing how it grows or decays over time (Allan, 2002).
(3) Temporal Topic Characterization (TTC): Identifying the characteristics for each of the main topics in order to track the words’ usage (keyword trends) for a topic over time i.e. topical trend analysis for word evolution (Fig[1] Left).

Probabilistic static topic models, such as Latent Dirichlet Allocation (LDA) (Blei et al., 2003) and its variants (Wang and McCallum, 2006; Hall et al., 2008; Gollapalli and Li, 2015) have been investigated to examine the emergence of topics from historical documents. Another variant known as Replicated Softmax (RSM) (Salakhutdinov and Hinton, 2009) have demonstrated better generalization in log-probability and retrieval, compared to LDA. While it is challenging to generalize static topic models to the dynamic setting, Blei and Lafferty (2006) developed a LDA based dynamic topic model (DTM) to capture the evolution of topics in a time sequence collection of documents; however these state space models do not explicitly capture the topic popularity and usage of specific terms over time and are limited to a fixed number of global topics (see also section 4 for a more in-depth discussion). We propose a family of probabilistic time series models with distributional estimators to explicitly model the dynamics of the underlying topics, introducing temporal latent topic dependencies (Fig[1] Right).

To model temporal dependencies in high dimensional sequences, such as polyphonic music, the temporal stack of RBMs (Smolensky, 1986; Hin...
have been investigated to model complex distributions. The Temporal RBM (Taylor et al. 2007) and (Sutskever and Hinton 2007), Recurrent Temporal RBM (RTRBM) (Sutskever et al. 2008) and RNN-RBM (Boulanger-Lewandowski et al. 2012) show success in modeling the temporal dependencies in such symbolic sequences. We inspire to build neural dynamic topic model called RNN-RSM to model document collections over time and learn temporal topic correlations.

We consider RSM for TSD and introduce the explicit latent topical dependencies for TED and TTC tasks. Fig[1] illustrates our motivation, where temporal ordering in document collection \( \mathbf{V}(t) \) at each time step \( t \), is modeled by conditioning the latent topic \( \mathbf{h}(t) \) on the sequence history of latent topics \( \mathbf{h}(0), ..., \mathbf{h}(t-1) \), accumulated with temporal lag. Each RSM discovers latent topics, where the introduction of a bias term in each RSM via the time-feedback latent topic dependencies enables to explicitly model topic evolution and specific topic term usage over time. The temporal connections and RSM biases allow to convey topical information and model relation among the words, in order to deeply analyze the dynamics of the underlying topics. We demonstrate the applicability of proposed RNN-RSM by analyzing 19 years of scientific articles from NLP research.

The contributions in this work are:

1. Introduce an unsupervised neural dynamic topic model based on recurrent neural network and RSMs, known as RNN-RSM to explicitly model discovered latent topics (evolution) and word relations (topic characterization) over time.

2. Demonstrate better generalization (log-probability and time stamp prediction), topic interpretation (coherence), evolution and characterization, compared to the state-of-the-art.

3. As far as we know, it is the first work in dynamic topic modeling using undirected stochastic graphical models and deterministic recurrent neural network to model collections of different-sized documents over time, within the generative and neural network framework.

2 The RNN-RSM model

RSM (Fig[2] Left) models are a family of different-sized Restricted Boltzmann Machines (RBMs) that models word counts by sharing the same parameters with multinomial distribution over the observable i.e. it can be interpreted as a single multinomial unit (Fig[2] Middle) sampled as many times the document size. This facilitates in dealing with the documents of different lengths.

The proposed RNN-RSM model (Fig[2] Right) is a sequence of conditional RSMs such that at any time step \( t \), the RSM’s bias parameters \( b_v(t) \) and \( b_h(t) \) depend on the output of a deterministic RNN with hidden layer \( u(t-1) \) in the previous time step, \( t-1 \). Similar to RNN-RBM (Boulanger-Lewandowski et al. 2012), we constrain RNN hidden units \( (u(t)) \) to convey temporal information, while RSM hidden units \( (h(t)) \) to model conditional distributions. Therefore, parameters \( (b_v(t), b_h(t)) \) are time-dependent on the sequence history at time \( t \) (via a series of conditional RSMs) denoted by \( \theta(t) \equiv \{ \hat{V}(t), u^{(t)} | r < t \} \), that captures

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1 code and data are released at dummy-url

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2 Notations: \( \hat{U} = \{U_1\}_{n=1}^{N} \); \( U \): 2D-Matrix; \( l \): vector; \( U/l \): Upper/lower-case; Scalars in unbold
temporal dependencies. The RNN-RSM is defined by its joint probability distribution:

\[ P(\vec{h}, \vec{u}) = P(\{\vec{V}^{(t)}, \vec{h}^{(t)}\}_{t=1}^{T}) = \prod_{t=1}^{T} P(\vec{V}^{(t)}, \vec{h}^{(t)}|\vec{G}^{(t)}) \]

where \( \vec{G}^{(t)} = \{\vec{V}^{(t)}\} \) and \( \vec{h}^{(t)} = h^{(1)} \ldots h^{(T)} \). Each \( h^{(t)} \in \{0,1\}^F \) be a binary stochastic hidden topic vector with size \( F \) and \( \vec{V}^{(t)} = \{\vec{V}_n^{(t)}\}_{n=1}^{N} \) be a collection of \( N \) documents at time step \( t \). Let \( \vec{V}_n^{(t)} \) be a \( K \times D_n^{(t)} \) observed binary matrix of the \( n \)th document in the collection where, \( D_n^{(t)} \) is the document size and \( K \) is the dictionary size over all the time steps. The conditional distribution (for each unit in hidden or visible) in each RSM at time step, is given by softmax and logistic functions:

\[
P(v_{n,i}^{(t)} = 1|h^{(t)}) = \frac{\exp(b_{v,i}^{(t)} k_{n,i}^{(t)} + \sum_{j=1}^{F} h_{j} W_{v,j}^{(t)})}{\sum_{k=1}^{K} \exp(b_{v,k}^{(t)} k_{n,k}^{(t)} + \sum_{j=1}^{F} h_{j} W_{v,j}^{(t)})}
\]

where \( P(v_{n,i}^{(t)} = 1|h^{(t)}) \) and \( P(h^{(t)}) = 1|\vec{V}_n^{(t)} \) are conditional distributions for \( i \)th visible \( v_{n,i}^{(t)} \) and \( j \)th hidden unit \( h_{j} \) for the \( n \)th document at time step \( t \). \( v_{n,i}^{(t)} \) is sampled \( D_n^{(t)} \) times with identical weights connected to binary hidden units, resulting in multinomial visibles, therefore the name Replicated Softmax. The conditional across layers are factorized as: \( P(V_n^{(t)} | h^{(t)}) = \prod_{n=1}^{N} P(v_{n,i}^{(t)} | h^{(t)}) \) and \( P(h^{(t)} | \vec{V}_n^{(t)}) = \prod_{j=1}^{F} P(h_j | \vec{V}_n^{(t)}) \).

While biases of RSM depend on the output of RNN at previous time steps, that allows to propagate the estimated gradient at each RSM backward through time (BPTT). The RSM biases and RNN hidden state \( \vec{u}^{(t)} \) at each time step \( t \) are given by:

\[
b_v^{(t)} = b_v + W_{uv} u^{(t-1)} \\
b_h^{(t)} = b_h + W_{uh} u^{(t-1)} \tag{1}
\]

\[
\vec{u}^{(t)} = \tanh(b_u + W_{uv} u^{(t-1)} + W_{vu} \sum_{n=1}^{N} \vec{v}_n^{(t)}) \tag{2}
\]

where \( W_{uv}, W_{uh} \) and \( W_{vu} \) are weights connecting RNN and RSM portions (Figure 2). \( b_u \) is the bias of \( u \) and \( W_{uu} \) is the weight between RNN hidden units. \( \vec{v}_n^{(t)} \) is a vector of \( \hat{v}_n^{(t)} \) (denotes the count for the \( k \)th word in \( n \)th document). \( \sum_{n=1}^{N} \vec{v}_n^{(t)} \) refers to the sum of observed vectors across documents at time step \( t \) where each document is represented as-

\[
\textbf{Algorithm 1 Training RNN-RSM with BPTT}
\]

**Input:** Observed visibles, \( \vec{V} = \{\vec{V}_u^{(t)}, \vec{V}_h^{(t)}\} \)

**RNN Parameters:** \( \theta = \{W_{uh}, W_{uh}, W_{uv}, W_{uu}, b_v, b_h, b_u, \vec{u}^{(0)}\} \)

1. Propagate \( \vec{u}^{(t)} \) in RNN portion of the graph using eq 2
2. Compute \( b_v^{(t)} \) and \( b_h^{(t)} \) using eq 1
3. Generate negatives \( \vec{V}^{(t)} \) using k-step Gibbs sampling.
4. Estimate the gradient of the cost \( C \) w.r.t. parameters of RSM \( W_{uh}, b_v^{(t)}, b_h^{(t)} \) and biases \( (b_v, b_h, b_u) \).
5. Compute gradients (eq 7 w.r.t. RNN connections \( W_{uv}, W_{uv}, W_{vu}, u^{(t)} \) and biases \( b_v, b_h, b_u \).
6. **Goto step 1 until stopping criteria**

\[
\hat{v}_n^{(t)} = [\hat{v}_n^{(t)}]_{k=1}^{K} \quad \text{and} \quad \hat{v}_n^{(t)} = \sum_{i=1}^{F} v_{n,i}^{(t)} \tag{3}
\]

where \( v_{n,i}^{(t)} = 1 \) if visible unit \( i \) takes on \( k \)th value.

In each RSM, a separate RBM is created for each document in the collection at time step \( t \) with \( D_n^{(t)} \) softmax units, where \( D_n^{(t)} \) is the count of words in the \( n \)th document. Consider a document of \( D_n^{(t)} \) words, the energy of the state \( \{\vec{V}_n^{(t)}, \vec{h}^{(t)}\} \) at time step, \( t \) is given by-

\[
E(\vec{V}_n^{(t)}, \vec{h}^{(t)}) = - \sum_{j=1}^{F} \sum_{k=1}^{K} h_{j} W_{v,j}^{(t)} \hat{v}_n^{(t)} - \sum_{k=1}^{K} \hat{v}_n^{(t)} b_{v,k}^{(t)} - D_n^{(t)} \sum_{j=1}^{F} b_{h,j} h_{j} \]

Observe that the bias terms on hidden units are scaled up by document length to allow hidden units to stabilize when dealing with different-sized documents. The corresponding energy-probability relation in the energy-based model is-

\[
P(V_n^{(t)}) = \frac{1}{Z^{(t)}} \sum_{h^{(t)}} \exp(-E(V_n^{(t)}, h^{(t)})) \tag{4}
\]

where \( Z^{(t)} = \sum_{\{h^{(t)}\}} \sum_{\{V^{(t)}\}} \exp(-E(V_n^{(t)}, h^{(t)})) \) is the normalization constant. The lower bound on the log likelihood of the data takes the form:

\[
\ln P(V_n^{(t)}) \geq \sum_{h^{(t)}} Q(h^{(t)} | V_n^{(t)}) \ln P(V_n^{(t)}, h^{(t)}) + H(Q) \\
= \ln P(V_n^{(t)}) - KL(Q(h^{(t)} | V_n^{(t)})) || P(h^{(t)} | V_n^{(t)})
\]

where \( H(\cdot) \) is the entropy functional and \( Q \) is the approximating posterior. Similar to Deep Belief Networks [Hinton et al. 2006], adding an extra layer improves lower bound on the log probability of data, we introduce the extra layer via RSM biases that propagates the prior via RNN connections. The dependence analogy follows-

\[
E(V_n^{(t)}, h^{(t)}) \propto \frac{1}{b_v^{(t)}} \text{and} \quad E(V_n^{(t)}, h^{(t)}) \propto \frac{1}{b_h^{(t)}}
\]
\[
\ln P(V^{(t)}_n) \propto \ln \frac{1}{E[V^{(t)}_n | V^{(t)}]}; \ln P(\hat{V}^{(t)}_n) \propto \ln P(\{\hat{V}^*_n\}_{t<\tau})
\]

Observe that the prior is seen as the deterministic hidden representation of latent topics and injected into each hidden state of RSMs, that enables the likelihood of the data to model complex temporal densities i.e. heteroscedasticity in document collections (\(\mathbb{D}\)) and temporal topics (\(\mathbb{H}\)).

**Gradient Approximations:** The cost in RNN-RSM is: \(C = \sum_{t=1}^{T} C_t = \sum_{t=1}^{T} -\ln P(\hat{V}^{(t)}_n)\)

Due to intractable \(Z\), the gradient of cost at time step \(t\) w.r.t. (with respect to) RSM parameters are approximated by k-step Contrastive Divergence (CD) [Hinton 2002]. The gradient of the negative log-likelihood of a document collection \(\{V^{(t)}_n\}_{n=1}^{N(\tau)}\) w.r.t. RSM parameter \(W_{vh}\).

\[
\frac{1}{N^{(\tau)}} \sum_{n=1}^{N^{(\tau)}} \partial \ln P(V^{(t)}_n) = \frac{1}{N^{(\tau)}} \sum_{n=1}^{N^{(\tau)}} \frac{\partial \hat{V}(V^{(t)}_n)}{\partial W_{vh}} - \frac{\partial \ln Z^{(t)}}{\partial W_{vh}}
\]

\[
= \mathbb{E}_{P_{data}(V^{(t)}_n, h^{(t)}_t)} \left[ \frac{\partial \hat{V}(V^{(t)}_n)}{\partial W_{vh}} \right] - \mathbb{E}_{P_{model}(\hat{V}(V^{(t)}_n))} \left[ \frac{\partial \hat{V}(V^{(t)}_n)}{\partial W_{vh}} \right]
\]

\[
\approx \frac{1}{N^{(\tau)}} \sum_{n=1}^{N^{(\tau)}} \frac{\partial \hat{V}(V^{(t)}_n)}{\partial W_{vh}} - \frac{\partial \hat{V}(V^{(t)}_n)}{\partial W_{vh}}
\]



For the single-layer RNN-RSM, the BPTT recurrence relation for \(0 \leq t < T\) using eq \(2\) follows-

\[
\frac{\partial C_t}{\partial b_{h_t}} = W_{uv} \frac{\partial C_{t+1}}{\partial b_{h_{t+1}}} u^{(t+1)} + W_{hh} \frac{\partial C_{t+1}}{\partial b_{h_{t+1}}} + W_{uv} \frac{\partial C_{t+1}}{\partial b_{v_{t+1}}}
\]

\[
\frac{\partial C_t}{\partial b_{v_t}} = W_{uv} \frac{\partial C_{t+1}}{\partial b_{v_{t+1}}} u^{(t+1)} + W_{uv} \frac{\partial C_{t+1}}{\partial b_{v_{t+1}}}
\]

where \(u^{(t)}\) being a parameter of the model and \(\frac{\partial C_T}{\partial b_{v_T}} = 0\). The estimated gradients w.r.t. RSM biases are back-propagated via hidden-to-bias parameters (eq \(1\)) to compute gradients w.r.t. RNN connections \(\{W_{hh}, W_{uv}, W_{vu}, W_{uu}\}\) and biases \(\{b_{h}, b_{v}\}\).

\[
\frac{\partial C}{\partial W_{uv}} = \sum_{t=1}^{T} \frac{\partial C_t}{\partial u(t)} u^{(t-1)T}
\]

\[
\frac{\partial C}{\partial W_{uu}} = \sum_{t=1}^{T} \frac{\partial C_t}{\partial u(t)} u^{(t-1)T}
\]

\[
\frac{\partial C}{\partial b_{h}} = \sum_{t=1}^{T} \frac{\partial C_t}{\partial b_{h(t)}} u^{(t-1)T}
\]

\[
\frac{\partial C}{\partial b_{v}} = \sum_{t=1}^{T} \frac{\partial C_t}{\partial b_{v(t)}} u^{(t-1)T}
\]

See **Training RNN-RSM with BPTT** in Algo \(1\)

### 3 Evaluation

#### 3.1 Dataset and Experimental Setup

We use the processed dataset [Gollapalli and Li 2015], consisting of EMNLP and ACL conference papers from the year 1996 through 2014 (Table 1). We combine papers for each year from the two venues to prepare the document collections over time. We use ExpandRank [Wan and Xiao 2008] to extract the top 100 keyphrases for each paper, including unigrams and bigrams. The dictionary size (K) and word count are 3390 and 5.19 M, respectively. For term-frequency, we count the occurrences of a term in its corresponding full text.

We evaluate RNN-RSM against static (RSM, LDA) and dynamic (DTM) topics models for topic and keyword evolution in NLP research over time. Individual 19 different RSM and LDA models are trained for each year, while DTM and RNN-RSM are trained over the years with 19 time steps,

[https://radimrehurek.com/gensim/models/dtmmodel.html](https://radimrehurek.com/gensim/models/dtmmodel.html)
Table 1: Number of papers from ACL and EMNLP conferences over the years

| Year | ACL | EMNLP | Total |
|------|-----|-------|-------|
| 1996| 58  | 15    | 73    |
| 1997| 73  | 24    | 97    |
| 1998| 250 | 15    | 265   |
| 1999| 83  | 15    | 98    |
| 2000| 70  | 14    | 84    |
| 2001| 177 | 36    | 213   |
| 2002| 112 | 29    | 141   |
| 2003| 134 | 21    | 155   |
| 2004| 134 | 29    | 163   |
| 2005| 307 | 28    | 335   |
| 2006| 204 | 28    | 232   |
| 2007| 214 | 15    | 229   |
| 2008| 243 | 75    | 318   |
| 2009| 270 | 132   | 402   |
| 2010| 349 | 115   | 464   |
| 2011| 227 | 164   | 391   |
| 2012| 398 | 125   | 523   |
| 2013| 331 | 149   | 480   |
| 2014| 1756| 140   | 1896  |

Table 2: Hyperparameters for RNN-RSM model

| Parameter      | Value(s) | Optimal |
|----------------|----------|---------|
| epochs         | 1000     | 1000    |
| CD iterations  | 15       | 15      |
| learning rate  | 0.1, 0.03, 0.001 | 0.001   |
| hidden size    | 20, 30, 50 | 30      |

Table 3: State-of-the-art Comparison: Generalization (PPL and Err), Topic Interpretation (COH) and Evolution (TTD).

| model   | PPL  | Err  | mean-COH | median-COH | TTD  |
|---------|------|------|----------|------------|------|
| DTM     | 32.5 | 8.10 | 0.1514   | 0.1379     | 0.084|
| RNN-RSM | 11.6 | 7.58 | 0.1620   | 0.1552     | 0.268|

3.2 Generalization in Dynamic Topic Models

Perplexity: We compute the average perplexity per word of document collections \( \overline{\text{PPL}} \) over time:

\[
\overline{\text{PPL}}(t) = \exp \left( -\frac{1}{T} \sum_{t=1}^{T} \frac{1}{N(t)} \sum_{r=1}^{N(t)} \log P(V(t)^{r}) \right)
\]

where \( T \) is the total time steps. \( N(t) \) is the number of documents in a collection \( \langle V(t) \rangle \) at time \( t \). Better models have lower perplexity values, suggesting less uncertainties about the documents.

For held-out documents, we take 10 documents from each time step i.e. total 190 documents and compute perplexity for 30 topics. Fig 3d shows the comparison of average perplexity values for unobserved documents from DTM and RNN-RSM at each time step. See average perplexity over the time line (PPL) for held-out documents in Table 3.

Document Time Stamp Prediction: To further assess the dynamic topics models, we split
the document collections at each time step into 80-20% train-test, resulting in 1067 held-out documents. We predict the time stamp (dating) of a document by finding the most likely location over the time line. See the mean absolute error (Err) for the held-out in Table 4. Note, we do not use the time stamp as observables during training.

3.3 TSD, TED: Topic Evolution Over Time

**Topic Detection:** To extract topics from each RSM, we compute posterior $P(V^{(t)}|h_j = 1)$ by activating a hidden unit and deactivating the rest in a hidden layer. We extract the top 20 terms for every 30 topic set from 1996-2014, resulting in $|Q|_{max} = 19 \times 30 \times 20$ possible topic terms.

**Topic Popularity:** To determine topic popularity, we selected three popular topics (Sentiment Analysis, Word Vector and Dependency Parsing) in NLP research and create a set of key-terms (including unigrams and bigrams) for each topic. We compute cosine similarity of the key-terms defined for each selected topic and topics discovered by the topic models over the years. We consider the discovered topic that is the most similar to the key-terms in the target topic and plot the similarity values in Fig. 5a, 5b and 5c. Observe that RNN-RSM shows better topic evolution for the three emerging topics. LDA and RSM show topical locality in Fig. 5e attributed due to no correlation in topic dynamics over time, while in Fig. 5f DTM does not capture the evolution of topic Word Vector.

**Topic Drift (Focus Change):** To compute the topic focus change over the years, we first split the time period 1996-2014 into five parts: {1996, 2000, 2005, 2010, 2014}. The cosine similarity scores are computed between the topic sets discovered in a particular year and the years preceding it in the above set, for example the similarity scores between the topic-terms in (1996, 2000), (1996, 2005), (1996, 2010) and (1996, 2014), respectively. Fig. 5 shows that RNN-RSM shows higher convergence in topic focus over the years, compared to LDA and RSM. In RNN-RSM, the topic similarity is gradually increased over time, however not in DTM. The higher similarities in the topic sets indicate that new/existing topics and words do not appear/disappear over time.

We compute topic-term drift ($TTD$) to show the changing topics from initial to final year. $TTD = 1.0 - \text{cosineSimilarity}(Q^{(t)}, Q^{(t')})$ where $Q$ is the set of all topic-terms for time step $t$. Table 4 shows that $TTD$ (where $t=1996$ and $t'=2014$) are 0.268 and 0.084 for RNN-RSM and DTM, respectively. It suggests that the higher number of new topic-terms evolved in RNN-RSM, compared to DTM. Qualitatively, the Table 5 shows the topics observed with the highest and lowest cosine drifts in DTM and RNN-RSM.

In Fig. 5e and 5f, we also illustrate the temporal

| Drift   | Model (year)          | Topic Terms                                                                                       |
|---------|-----------------------|---------------------------------------------------------------------------------------------------|
| 0.20    | DTM (1996)            | document, retrieval, query, documents, information, search, information retrieval, queries, terms, words, system, results, performance, method, approach |
| 0.53    | DTM (2014)            | semantic, lexical, structure, syntactic, argument, frame, example, lexicon, information, approach, source, function, figure, verbs, semantic representation |
| 0.20    | RNN-RSM (1996)        | reordering, statistical machine, translation model, translations, arabic, word align, translation probability, word alignment, translation system, source word, ibm model, source sentence, english translation, target language, word segmentation |
| 0.53    | RNN-RSM (2014)        | input, inference, semantic representation, distributional models, lexical forms, space model, clustering algorithm, space models, similar word, frequent word, meaning representation, lexical acquisition, new algorithm, same context, multiple words, example, role labeling, language, learning, logical form, system, lexicon |

**Table 4:** Topics (top 15 words) with the highest and lowest drifts (cosine) observed in DTM and RNN-RSM models.

| Model (year) | Jobs                                                                 |
|--------------|-----------------------------------------------------------------------|
| DTM (2001)   | semantic frame, words models, discourse relation, parse cluster       |
| RNN-RSM (2001)| argument grammar, relations structure, query pos tag                  |
| DTM (2012)   | semantic structure, lexical dependency parsing, lexical argument      |
| RNN-RSM (1997)| parse trees, lexical parse trees, argument corpus retrieval cohereence logical form |

| COH | 0.268 | 0.284 | 0.064 | 0.071 |

**Table 5:** Topics with the highest and lowest coherence.
evolution (drift) in the selected topics by computing cosine similarity on their adjacent topic vectors over time. The topic vectors are selected similarly as in computing topic popularity. We observe better TED in RNN-RSM than DTM for the three emerging topics in NLP research. For instance, for the selected topic *Word Vector*, the red line in DTM (Fig 3H) shows no drift (for x-axis 00-05, 05-10 and 10-14), suggesting the topic-terms in the adjacent years are similar and does not evolve.

### 3.4 Topic Interpretability

Beyond perplexities, we also compute topic coherence ([Chang et al., 2009; Newman et al., 2009; Das et al., 2015]) to determine the meaningful topics captured. We use the coherence measure proposed by [Aletras and Stevenson (2013)](http://example.com) that retrieves co-occurrence counts for the set of topic words using Wikipedia as a reference corpus to identify context features (window=5) for each topic word. Relatedness between topic words and context features is measured using normalized pointwise mutual information (NPMI), resulting in a single vector for every topic word. The coherence (COH) score is computed as the arithmetic mean of the cosine similarities between all word pairs. Higher scores imply more coherent topics. We use Palmetto library to estimate coherence.

**Quantitative:** We compute mean and median coherence scores for each time step using the corresponding topics, as shown in Fig 5E and 5F. Table 3 shows mean-COH and median-COH scores, computed by mean and median of scores from Fig 5E and 5F, respectively. Observe that RNN-RSM captures topics with higher coherence.

**Qualitative:** Table 3 shows topics (top-10 words) with the highest and lowest coherence scores from DTM and RNN-RSM models.

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*github.com/earthquakesan/palmetto-py*

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### 3.5 TTC: Trending Keywords over time

We demonstrate the capability of RNN-RSM to capture word evolution (usage) in topics over time. We define: *keyword-trend* and *span*. The **keyword-trend** is the appearance/disappearance of the keyword in topic-terms detected over time, while the **span** is the length of the longest sequence of the keyword appearance in its keyword trend.

Let \( \hat{Q}_{model} = \{ Q_{model}^{(t)} \}_{t=1}^{T} \) be a set of set of topic-terms discovered by the *model* (LDA, RSM, DTM and RNN-RSM) over different time steps. Let \( Q^{(t)} \in \hat{Q}_{model} \) be the topic-terms at time step \( t \). The keyword-trend for a keyword \( k \) is a time-ordered sequence of 0s and 1s, as

\[
\text{trend}_t(Q) = [\text{find}(k, Q^{(t)})]_{t=1}^{T}
\]

where:

\[
\text{find}(k, Q^{(t)}) = \begin{cases} 1 & \text{if } k \in Q^{(t)} \\ 0 & \text{otherwise} \end{cases}
\]

And the span for a keyword \( k \) is given by:

\[
\text{span}_k(Q) = \text{length}([\text{longestOnesSeq}(\text{trend}_t(Q))])
\]

We compute keyword-trend and span for each keyword. \( \text{longestOnesSeq} \) refers to the length of the longest sequence of 1s in the keyword-trend. The keyword-trend and the span are computed using a library that determines the keyword’s presence in topics for each year.
term from the set of some popular terms. We define average-span for all the topic-terms appearing in the underlying topics discovered over the years,

$$\text{avg-span}(\hat{Q}) = \frac{1}{||\hat{Q}||} \sum_{k} \left( |k| \text{span}_{\hat{Q},k} | \in \hat{Q} \land k \in Q^{(t)} \right) \text{span}_k(Q^{(t)})$$

where $||\hat{Q}|| = \{ |k| \text{span}_{\hat{Q},k} \in \hat{Q} \land k \in Q^{(t)} \}$ is the count of unique topic-terms and $\text{span}_k(Q^{(t)})$ denotes the count of $k^{th}$ keyword.

In Fig 3 the keyword-trends indicate emergence (appearance/disappearance) of the selected popular terms in topics discovered in ACL and EMNLP papers over time. Observe that RNN-RSM captures longer spans for popular keywords and better word usage in NLP research. For example: Word Embedding is one of the top keywords, appeared locally (Fig 3) in the recent years. RNN-RSM detects it in the topics from 2010 to 2014, however DTM does not. Similarly, for Neural Language. However, Machine Translation and Language Model are globally appeared in the input document collections over time and captured in the topics by RNN-RSM and DTM. We also show keywords (Rule-set and Seed Words) that disappeared in topics over time.

Higher span suggests that the model is capable in capturing trending keywords. Table 6 shows the corresponding comparison of spans for the 13 selected keywords. The $\text{span}_{\hat{Q},k}$ for each keyword is computed from Fig 5. Observe that $||\hat{Q}||_{\text{DTM}} < ||\hat{Q}||_{\text{RNN-RSM}}$ suggests new topics and words emerged over time in RNN-RSM, while higher span values in RNN-RSM suggest better trends. Fig 6 shows how the word usage, captured by DTM and RNN-RSM for the topic Word Vector, changes over 19 years in NLP research. RNN-RSM captures the popular terms Word Embedding and Word Representation emerged for the topic.

### 4 Discussion: RNN-RSM vs DTM

**Architecture:** RNN-RSM treats document’s stream as high dimensional sequences over time and models the complex conditional probability distribution i.e. heteroscedasticity in document collections and topics over time by a temporal stack of RSMs (undirected graphical model), conditioned on time-feedback connections using RNN (Rumelhart et al. 1986). It has two hidden layers: $h$ (stochastic binary) to capture topical information, while $u$ (deterministic) to convey temporal information via BPTT that models the topic dependence at a time step $t$ on all the previous steps $\tau < t$. In contrast, DTM is built upon LDA (directed model), where Dirichlet distribution on words is not amenable to sequential modeling, therefore its natural parameters (topic and topic proportion distributions) for each topic are chained, instead of latent topics that results in intractable inference in topic detection and chaining.

**Topic Dynamics:** The introduction of explicit connection in latent topics in RNN-RSM allow new topics and words for the underlying topics to appear or disappear over time by the dynamics of topic correlations. As discussed, the distinction of $h$ and $u$ permits the latent topic $h^{(t)}$ to capture new topics, that may not be captured by $h^{(t-1)}$.

DTM assumes a fixed number of global topics and models their distribution over time. However, there is no such assumption in RNN-RSM. We fixed the topic count in RNN-RSM at each time step, since $W_{\vartheta h}$ is fixed over time and RSM biases turn off/on terms in each topic. However, this
is fundamentally different for DTM. E.g. a unique label be assigned to each of the 30 topics at any time steps $t$ and $t'$. DTM follows the sets of topic labels: $\{\text{TopicLabels}^{(t)}\}_{k=1}^{30} = \{\text{TopicLabels}^{(t')}\}_{k=1}^{30}$, due to eq (1) in [Blei and Lafferty (2006)] discussed in section 5 that limits DTM to capture new (or local) topics or words appeared over time. It corresponds to the keyword-trends (section 3.5).

**Optimization:** The RNN-RSM is based on Gibbs sampling and BPTT for inference while DTM employs complex variational methods, since applying Gibbs sampling is difficult due to the nonconjugacy of the Gaussian and multinomial distributions. Thus, easier learning in RNN-RSM.

5 Conclusion

We have proposed a neural temporal topic model known as RNN-RSM, based on probabilistic undirected graphical topic model RSM with time-feedback connections via deterministic RNN, to capture temporal relationships in historical documents. The experimental results have demonstrated that RNN-RSM shows better generalization (perplexity and time stamp prediction), topic interpretation (coherence) and evolution (popularity, drift) in scientific articles over time. We also introduced span to illustrate topic characterization.

In future work, we forsee to investigate learning dynamics in variable number of topics over time.

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