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TREND ANALYSIS IN AI RESEARCH OVER TIME USING NLP TECHNIQUES

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ABSTRACT

Eemeli Saari: Trend Analysis in AI Research over time Using NLP Techniques
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The dramatic rise in the number of publications in machine learning related studies poses a challenge for companies and new researchers when they want to focus their resources effectively. This thesis aims to provide an automatic pipeline to extract the most relevant trends in the machine learning field. I applied unsupervised topic modeling methods to discover research trends from full NIPS conference papers from 1987 to 2018. By comparing the Latent Dirichlet Allocation (LDA) topic model with a model utilizing semantic word vectors (sHDP), it was shown that the LDA performed better in both quality and coherence. Using the LDA, 50 topics were extracted and interpreted to match the key concepts in the conference publications. The results revealed three distinct eras in the NIPS history as well as the steady shift away from the neural information processing roots towards deep learning.

Keywords: natural language processing, NLP, topic modeling, word embedding, trend analysis, scientometric study

The originality of this thesis has been checked using the Turnitin OriginalityCheck service.

PREFACE

This thesis was written as a part of Bachelor of Science program in the spring 2019. Selecting this subject for my work from a variety of other interesting subjects was due to my pre-existing interest towards Natural Language Processing. First and foremost, I would like to thank my instructor Nataliya Strokina for all the support and advice throughout the spring as well as Assistant Professor Okko Räsänen for his helpful comments and interest towards the work. I also would like to thank my other half for all the patience along the way.

Tampere, 5th June 2019

Eemeli Saari

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LIST OF SYMBOLS AND ABBREVIATIONS

BERT	Bidirectional Encoder Represen-tations from Transformers
BRNN	Bidirectional Recurrent Neural Network
CBOW	Continuous Bag-of-word
GAN	Generative Adversial Network
GPU	Graphical Processing Unit
HDP	Hierarchical Dirichlet Processes
JSD	Jensen-Shannon Divergence
KLD	Kullback-Leibler Divergence
LDA	Latent Dirichlet Allocation
LSA	Latent Semantic Analysis
LSTM	Long Short-Term Memory
MAP	Maximum A Posterior
nHDP	nested Hierarchical Dirichlet Processes
NIPS	Neural Information Processing Systems
NLP	Natural Language Processing
NNLM	Neural Net Language Model
PDF	Portable Document Format
PMI	Pointwise Mutual Information
RNN	Recurrent Neural Network
SGNS	Skip-Gram Negative Sampling
sHDP	spherical Hierarchical Dirichlet Processes
SVD	Singular Value Decomposition
SVM	Support-Vector Machine
θ	Topic distribution

vMF	von Mises-Fisher
ψ	Word distribution

1 INTRODUCTION

Available information in the world has grown exponentially since the introduction of the world wide web [1]. This phenomena is seen in different research domains as an increase in the number of publications yearly and as an acceleration in the development of research in general. In the field of machine learning and artificial intelligence particularly, the acceleration has made the overall image of the current trends fuzzy. This has lead to a problem for new researchers and companies when they want to invest their time and resources efficiently.

The Natural Language Processing (NLP) offers a set of tools capable of deriving knowledge from large collections of text data. Topic modeling [2] is one area of interest in the NLP research which focuses on the automatic discovery of hidden structures in texts. The method attempts to describe a collection of text documents as a collection of word topics using statistical methodology. Topic models have been applied to various tasks such as detecting suspicious e-mails [3], Twitter content classification [4], and clustering scientific papers [5]. Though powerful in many tasks, the statistical approach of topic models is often limited to semantic structures found in the natural language. To represent these structures efficiently a number of word embedding methods have been introduced [6][7][8][9]. These methods leverage the learned semantic structures from the data to various tasks such as machine translation [10] and sentiment analysis [11]. Topic modeling has also seen improvements when combined with word vector representations [12].

The main purpose of this thesis is to provide a pipeline for automatic topic discovery and analysis using the state-of-the-art tools. In this work I aim to apply the pipeline for unsupervised scientometric study to detect trends in machine learning over the years. Using the knowledge mined in this way I will hope to discover some of the latent paths and directions in the field. Unlike most research that involves scientific paper abstracts, I will use full publications as data. Secondary aim for this study is to detect and compare the impacts of combining word representations with topic modeling.

Chapter 2. introduces the related works on different topic, word representations models and combinatory models, as well as topic modeling over time. Chapter 3. presents the proposed pipeline and the used methods in detail. Chapter 4. introduces the data and the results for the conducted trend analysis study, and final Chapter 5. presents the results and future improvements.

2 PRIOR RELATED WORK

Most of the modern approaches in NLP are based on the distributional hypothesis [13] that words occurring in the same context tend to have similar meanings. This hypothesis lays the foundation for machine learning and pattern recognition in the computational linguistics and natural language processing.

2.1 Topic Modeling

Latent Dirichlet Allocation (LDA) [14] is the most commonly used topic modeling method that aims to find a set of latent topics from a given corpora. The objective of the LDA is to represent each document in the corpora as a probability distribution over topics. Each topic distribution is composed of probability distribution over all words in the vocabulary. From these distributions one can observe high probability words and derive understanding of each document content. The algorithm of the LDA model is generative and can be trained in batches with large datasets. This enables the model to generalize to the previously unseen documents. However, the task to infer the word and topic probabilities while iterating is intractable, as there exists multiple random variables. As the answer, the authors of LDA applied the Variational inference [15]. Other methods such as Gibbs sampling [16] are also widely used. LDA can be described as a general statistic model meaning that it can be applied to various fields with differing data other than text [17]. LDA is based on the probabilistic Latent Semantic Analytics (pLSA) [18] and has been described as Maximum A Posterior (MAP) estimation for the LDA model [19].

Capturing informative high level topics from text data is not limited to the LDA model. Since the process of using LDA often defaults to model selection and hyperparameter optimization, some nonparametric alternative elaborations have been proposed. One of these methods is HDP (Hierarchical Dirichlet Processes) [20] that uses Bayesian Dirichlet process [21] to extend the LDA in topic modeling tasks. The performance of the HDP model matched the best performance of the LDA without any model selection required. More recent elaboration nHDP [22] attempts to answer the inference scalability problem of topic models for very large datasets. This method composes the text efficiently as topic hierarchies, resulting in a tree-structure representation. The nonparametric nature of HDP models is advantageous in various autonomous tasks where the prior knowledge of the data can be unknown or when the resources limit the model selection.

Most topic modeling methods operate on discrete word types with integer numbers representing each word. Thus the methods ignore most of the semantic information that can be found from the text. To take the semantics of the language into account methods like Gaussian LDA [23] and sHDP [24] combine word embeddings with topic modeling. Both methods report better topic coherence overall related to LDA by using word2vec [25] for word embedding extraction. The basic idea of the Gaussian LDA is that Euclidean distance between word embeddings correlate with semantic similarities and thus justifies the use of Gaussian parameterization. The sHDP authors argue that the Euclidean distance as a metric combined with Gaussian assumptions is not enough to leverage the semantic correlations between words, and that the use of cosine distance would be the appropriate approach. In sHDP each word is seen as a point in unit sphere, and vMF (von Mises-Fisher) distribution [26] is utilized to model the topic distributions. The authors of sHDP report that that their method is both faster and better at producing coherent topics. However, it is worth noting that the word coherence is measured by comparing how often two measures occur together using PMI (Pointwise Mutual Information) [27]:

$$\mathrm{PMI}(w_i, w_j) = log \frac{p(w_i, p_j)}{p(w_i)p(w_j)} \tag{2.1}$$

It has been shown that the PMI correlates well with the human judgement on topic quality [28] providing a good basis for model selection. Although widely used, it should be noted that human evaluation is always needed to determine the quality of the topics.

2.2 Word Embedding

The ability to represent words and capture meaningful syntactic and semantic information of language [29] has made pre-trained word vectors a key component in modern NLP. A number of methods have been used in the past to learn word embeddings from simple N-Gram models [30] to statistical count base Latent Semantic Analysis (LSA) [31]. Modern methods utilize both shallow [25] and deep [8][9] neural networks to train the embeddings from large collections of data. The main idea of these models is to leverage learned semantic feature vectors to downstream tasks such as question answering and document classification.

Predictive learning algorithms that represent words as continuous vectors have been shown to outperform some of the traditional count-based methods [32]. The main advantage comes from the ability of the embeddings to represent meaningful semantic relationships in encoded vector space. In this space analogy such as "Helsinki is to Stockholm as Finland is to Sweden" should be encoded in the equation

$$Helsinki - Stockholm = Finland - Sweden$$

Vector space also enables the query for similarity estimates. For example Euclidean distance is a metric which is shown to correlate semantic similiarities between two word embeddings. Word2vec authors also used cosine similarity to find nearest neighbors in the word vector space.

Skip-Gram model and Continuous Bag-of-Words (CBOW) model provided in Google's word2vec are commonly used methods for learning word embeddings. Both models use an architecture similar to the feedforward Neural Net Language Model (NNLM) [33]. The feedforward NNLM architecture consists of input, projection, hidden and softmax output layer. Skip-Gram model and CBOW model remove the non-linear hidden layer from NNLM and share the projection layer with all of the words, meaning that the word vectors are averaged. The principle for word2vector models is to stream the data window around a pivot word. In this way the model learns which words appear in similar context, unlike the NNLM which learns what words predict the pivot word. The Skip-Gram model and CBOW model differ in the learning objective. Skip-Gram model, in short, attempts to predict the surrounding context words around target word, whereas CBOW model predicts the target word based on the surrounding context. Word2vec models can also replace the softmax layer with efficient negative sampling layer to speed up the learning process.

The word2vec models have had multiple variations over the years. The most notable and widely used one is the Standford's GloVe [7] model that takes advantage of the global count-based statistics from the target corpora. This count-based method utilizes the global matrix factorization that has roots all the way back to the LSA [31]. LSA decomposes large matrices to capture statistical information from the corpora using SVD (Singular Value Decomposition) [34]. GloVe utilizes a similiar approach to LSA by composing co-occurrence matrices in both the local window and the global context. These co-occurrence matrices are used to form a set of probabilities for a word to appear in a given context. Then the model is trained to optimize the log mean squared error between the predicted probabilities and the observed probabilities. Interestingly the GloVe model is very similar to the word2vec skip-gram model that implicitly decomposes co-occurance matrix when streaming over windows of words [35].

The current state-of-the-art method for word embedding models is Bidirectional Encoder Representations from Transformers (Bert) [9] that uses a powerful Transformer architecture [36] to embed both sentences and words from corpora. BERT attempts to directly solve a polysemous word problem that a word such as "*apple*" may have meanings depending on whether it appears in the context of information technology or in agriculture. Models like ELMo [8] solve this problem by training the Bidirectional Recurrent Neural Network (BRNN) [37] with LSTM layers [38] to predict target word based on both previous and future context. BERT utilizes the cloze procedure [39] during the training where words from sentences are masked at random. This forces the model to consider the entire context simultaneously, which the authors report as one of the main factors for the outperformance of the model in various benchmark tests. BERT was designed to be used as a pre-trained base for domain specific transfer learning tasks, for example, data mining for biomedical texts [40].

2.3 Topic Modeling over time

Topic models are used to capture the low-dimensional statistical information about the structure of the data and thus not explicitly model the temporal relationships between topics. This causes the standard topic models such as LDA to suffer in terms of topic quality with datasets that usually have been collected over time. For example, in the case of Wikipedia, corpora the data might contain edits over a vastly different timescales and even outdated language and knowledge.It is desirable to detect these types of data features for many high-end tasks such as trend analysis where evolution of topics over time offers valuable information. Standard LDA needs to be extended to fully capture the topic evolution over time.

The time dimension can be taken into account for topic models in two modeling frameworks. The joint framework integrates the time domain directly into the process of topic modeling. One of the methods utilizing this is Topics over time [41] where time is taken into account by applying continuous distribution over timestamps. Topic over time model can thus capture the locality of given topics in time. Discretization of time is used in dynamic topic model [42] where one applies the Markov assumption that the state of topics changes in time. Non-joint approach is usually more flexible since it does not require radical adjustments to the existing models. The process of non-joint topic modeling is usually done using post hoc analysis. The process consists of fitting the topic model with time-unaware data and then aggregating the results for each time period [16]. This process relies on the assumption that the topics are static and the assumption does not distinguish whether the meaning or occurrence of the topic has changed.

Topic models applied to timeseries data have offered valuable information in various different domains. One of these domains has been scientometrics where mostly quantitative methods have been applied to study the citations as graph, and to conclude the importance of the given paper or article. This, however does not take into account the difference between research domains, and thus topic models have been applied to study these properties with more detail. For example the history of ideas [43] has been studied in conference publications where the the authors were able to detect rise and fall of topics over time. One of the key outcomes from this study was the observation that different conferences were converging over time to cover the same topics. Trends have also been studied in different research domains. Also one study focusing on the trends in transportation research journals found similarities between different journals and was able to cluster journals using topic modelling over time [44].

3 METHODS

This chapter explains the methods used in the trend analysis pipeline. The sections are divided into three subsections that are applied to the preprocessed data: Building the word representation vectors, topic modeling and interpreting the topics over time. All the steps in the pipeline are treated as scikit-learn API [45] transformers. In this way the pipeline can be built with different steps providing a robust system. Preprocessing steps are described in detail in Chapter 4.

3.1 Topic modeling methods

3.1.1 Latent Dirichlet Allocation

Latent Dirichlet Allocation (LDA) [14] is a Bayesian probabilistic model of a corpus D. The basic idea of the model is that each document d in corpus is a mixture over latent topics z, and each topic is characterized by a distribution over words w_n in the vocabulary V. LDA assumes the following generative process for each $d \in D$

1. Choose the length of documents $N \sim \text{Poisson}(\xi)$.
2. Choose the topic proportion $\theta \sim Dir(\alpha)$
3. For each word $w_n \in N$:
   (a) Choose a topic $z_n \sim Multinomial(\theta)$
   (b) Choose a word w_n from $P(w_n|z_d, \beta)$, a multinomial probability conditioned on the topic z_n.

Here the notation Dir is the Dirichlet distribution function and $Multinomial$ is the Multinomial distribution function. The parameter α marks the topic Dirichlet prior and β marks the word Dirichlet prior. Several simplification assumptions are made for the basic LDA model. The parameter N drawn from the Poisson assumption is not needed and the N is thus often marked as the length of the document. Dimensionality k of the Dirichlet distribution that determines the topic z dimension is assumed to be known and fixed. Since the model also uses a finite vocabulary V, the word probabilities are parameterized by a $k \times V$ matrix β. Using the matrix notation probability of the ith word in a given document is described as

$$P(w_i) = \sum_{j=1}^{k} P(w_i|z_i = j)P(z_i = j) \tag{3.1}$$

where i stands for ith row and j stands for jth column of matrix β. The task of the model is then to obtain an estimate for β that gives high probability to the words that appear in the corpus. The corpus D is analyzed by examining the posterior distribution of β, topic proportion θ and the topic assignment z in the documents. However, the posteriors cannot be computed directly and is therefore estimated. In the generative model the estimation problem transforms into maximizing the equation

$$P(d|\alpha, \beta) = \int P(\theta|\alpha)P(d|\beta, \theta), d\theta \tag{3.2}$$

where β is the hidden parameter to be estimated. The LDA model is shown graphically in Figure 3.1.

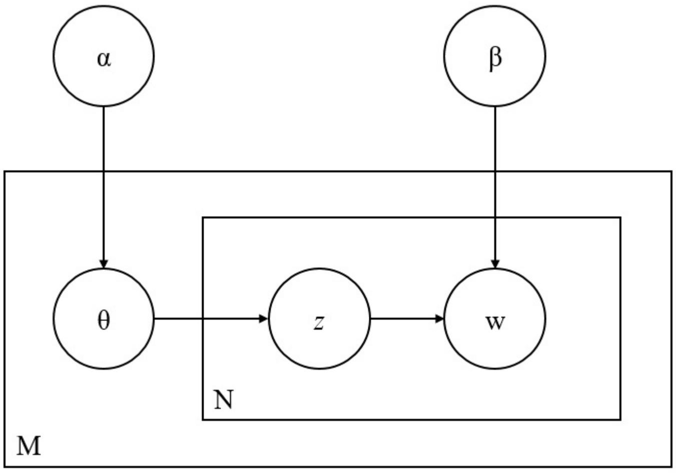


Figure 3.1. *Graphical representation of LDA model. The box M represents documents and N the choice of topic and word within the document.*

The estimation problem in the LDA is an inferential problem over parameter β. This thesis uses the LDA model provided by *gensim*[46] that utilizes the online implementation of the LDA [47]. In the online version of the LDA, the Variational inference is applied to single documents in a streaming manner. Other proposed inference methods include Gipps sampling and Markov Chain Monte Carlo (MCMC) [16].

3.1.2 Spherical Hierarchical Dirichlet Processes

Spherical Hierarchical Dirichlet Processes (sHDP) [24] is based on the HDP. Instead of the LDA, the sHDP model assumes a non-fixed collection of topics z that are shared across the documents d in the corpus C. Using the normalized N dimensional word vector representations the topics are represented by topic centers $\mu_z \in^N$. The model assumes the word vectors as normalized, thus the topic center μ_k can be seen as directions on a unit sphere. The model defines the likelihood of the topic z for word w_k

$$f(w_k; \mu_z, \kappa_z) = \exp(\kappa_z \mu_z^T w_{dn}) C_N(\kappa_z) \tag{3.3}$$

where the von Mises-Fisher (vMF) probability function is used and κ_z is the concentration of the topic z. The model captures semantic similarity between topic and words in the log-likelihood of the vMF since the $\mu_z^T w_{dn}$ is equal to cosine distance that is used to compare word vectors as well. The factor C_N is the normalization constant used in the vMF [48]

$$C_N(\kappa_z) := \frac{\kappa_z^{N/2-1}}{(2\pi)^{N/2} I_{N/2-1}(\kappa_z)} \tag{3.4}$$

sHDP processes the documents in a generative way which is similar to how the LDA process. Topic z_{dw} is selected for the word w of document d from $z_{dw} \sim \text{Multinomial}(\pi_d)$. Using the Dirichlet Process to draw $\pi_d \sim \text{DP}(\alpha, \beta)$ which enables the model to estimate the number of topics from the data. Differing from LDA, the sHDP draws the parameter β from the stick-breaking distribution [21] $\beta \sim \text{GEM}(\gamma)$ where γ is the concentration parameter. Graphical representation for sHDP model is shown in Figure 3.2. Inference in the model for latent variables is done using Stochastic Variational Mean-field Inference (SVI) [49]. This enables the model to process documents in batches making it appropriate for large-scale settings. One can observe that the automatic HDP-based approach has some drawbacks. For example, the number of latent variables the model needs to infere is significantly larger compared to LDA.

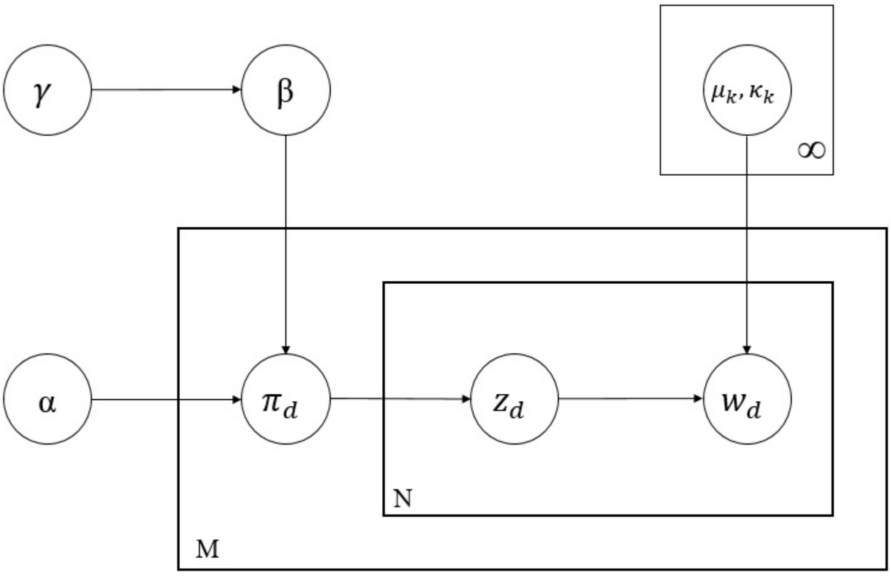


Figure 3.2. *Simplified graphical representation of sHDP model [24]. The model assumes M documents in the corpus with N words and countably infinite topics represented by (μ_k, κ_k).*

3.2 Word Representation

The first step of the pipeline is to compute the word representations for the vocabulary of words V. This can be done as a separate step by training with larger dataset or by training sequentially as part of the pipeline. Continuous Bag-of-word model [25] is selected for the single purpose of providing the word vectors as features for the topic modeling method.

The training objective for the CBOW model is to predict target word w_t given a set of context words $\{w_{t-n}, w_{t-n-1}, ..., w_{t+n-1}, w_{t+n}\}$ where the n is the window size. The model consists of the input, projection, hidden and output layers. Fixed vocabulary size V and hidden layer size of N is assumed. Figure 3.3 illustrates the architecture of the CBOW model.

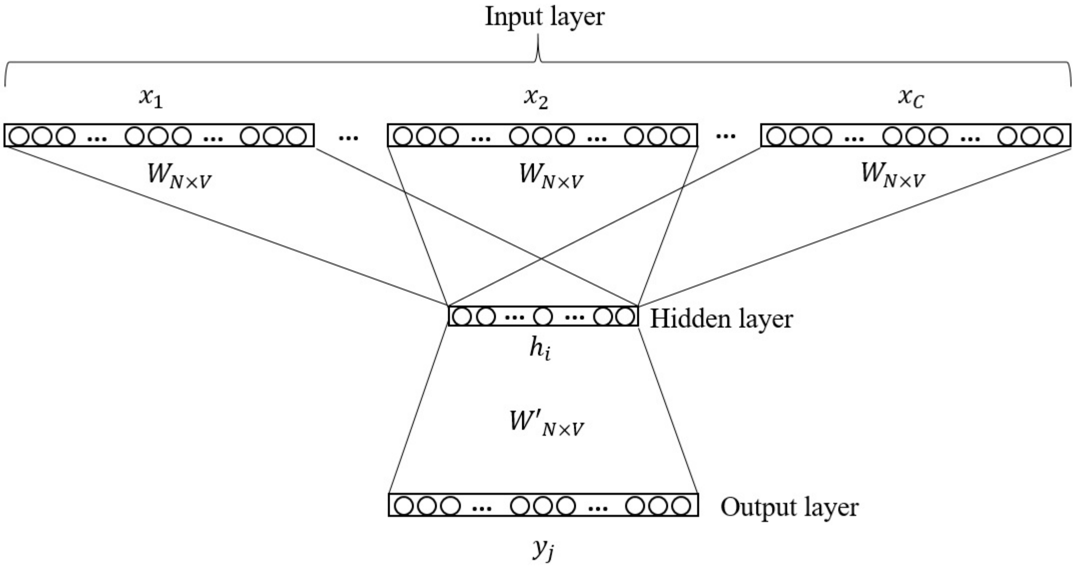


Figure 3.3. *Continuous Bag-of-word model.*

The input words are represented as one-hot encoded V size vectors $\{x_1, x_2, ...x_C\}$ where C is the number of words in the context. For the given context word $w_k \in V$, the one-hot encoded vector's unit will have one out of V units 1 and 0 otherwise. The weights between the input layer and the output layer are represented by $V \times N$ matrix W. This matrix contains N dimensional vector representations v_w of the associated word of the input layer on each row. The projection layer takes the input vectors of the input context and averages them. Computing the hidden layer output is thus

$$h = \frac{1}{C} W^T (x_1 + x_2 + ... + x_C) \tag{3.5}$$

which essentially copies the kth row for each input vector word from the matrix W and therefore the equation is reduced to

$$h = \frac{1}{C} (v_{w_1} + v_{w_2} + ... + v_{w_C}) \tag{3.6}$$

The weights of hidden layer to the output layer is represented as $N \times V$ matrix W'. With the weights W' the score u_j is computed for each word in the vocabulary V with

$$u_j = {v'_{w_j}}^T h \tag{3.7}$$

where the v'_{w_j} is the jth column of the weight matrix W'. Then softmax is applied to obtain the posterior distribution of words for all the input vector words w_j from formula

$$P(w_j | w_I) = \frac{\exp({v'_{w_j}}^T v'_{w_I})}{\sum_{j'=1}^{V} \exp({v'_{w'_j}}^T v'_{w_I})} \tag{3.8}$$

which is the training objective for the model to maximize. This process is represented with given loss function for the output layer y_j

$$E = -\text{log} P(w_O | w_{I,1}, ..., w_{I,C}) \tag{3.9}$$

where the w_O is the actual observed word and y_j is the output layer. This is computed with formula

$$E = -v'_{w_O} \cdot h + \log \sum_{j'=1}^{V} \exp({v'_{w_j}}^T \cdot h) \tag{3.10}$$

In the training process both weights W and W' are updated [50]. The training becomes computationally more efficient, if for example, hierarchical softmax or the negative sampling are applied instead of the standard softmax function.

A common way to process the word vectors for other tasks is to normalize them. For this a commonly used Euclidean norm l^2 is used which is defined for word vector x of size N as [51]

$$|x| = \sqrt{\sum_{k=1}^{N} |x_k|^2} \tag{3.11}$$

3.3 Over time

The topic distributions are measured over time in a post hoc way. Models are trained without the time dimension and topics are computed for each document independently. Similar approach to [44] is taken by grouping the documents by year and averaging the distributions over year. For a topic distribution θ_k^t, at timestep t and topic k is defined as

$$\theta_k^t = \frac{\sum_{d=1}^{N} \theta_{dk} \Pi(t_d = t)}{\sum_{d=1}^{N} \Pi(t_d = t)} \tag{3.12}$$

where $\Pi(e) = 1$ if e is true and 0 otherwise. The topic distribution θ^t can be thus seen as a signature for given time t. This information over time is further refined to find rising and falling topics with the equation

$$r_k = \frac{\sum_{t=1897}^{2002} \theta_k^t}{\sum_{t=2003}^{2018} \theta_k^t} \tag{3.13}$$

where the higher r_k value indicates a falling topic. The topic distribution signatures can be used to find similarities between different years t_i and t_j. The similarity between two time windows d_{t_i,t_j} is found using Jensen-Shannon distance [52], namely

$$d_{t_i,t_j} = \sqrt{\mathrm{JSD}(\theta^{t_i}, \theta^{t_j})} \tag{3.14}$$

where JSD is known as Jensen-Shannon divergence which is used to quantify the difference between two distributions θ and θ'

$$\mathrm{JSD}(\theta^{t_i}, \theta^{t_j}) = \frac{1}{2}\mathrm{KLD}(\theta^{t_i}, \overline{\theta}) + \frac{1}{2}\mathrm{KLD}(\theta^{t_j}, \overline{\theta}) \tag{3.15}$$

where the $\overline{\theta} = \frac{1}{2}(\theta + \theta')$. The KLD used in the JSD is Kullback-Leibler divergen [53] and is define as

$$\mathrm{KLD}(\theta, \theta') = \sum_{k=1}^{K} \theta_k \mathrm{log} \frac{\theta_k}{\theta'_k} \tag{3.16}$$

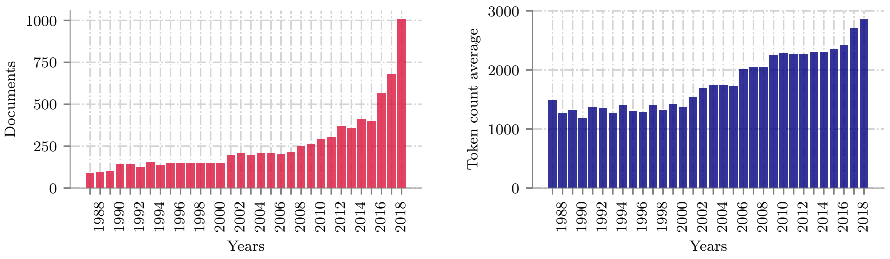
for any given distribution θ. Using this metric allows different time periods t to be explored by applying hierarchical clustering similar to [44] where different journals were compared.

4 TREND ANALYSIS

4.1 Data

Scientific conferences are often considered to represent the current state-of-the-art in scientific development. Related studies analysing the trends in the conferences have used information from abstracts as a proxy to the whole article [43]. This has been justified by the assertion that abstract contains enough keywords about the document and thus represents the overall research theme well [54]. However, in this thesis I expect some of the latent trends to be missed if only the abstracts are used. For example, the studies and methods cited in the sections covering related works and methods could contain some valuable information.

Neural Information Processing Systems Conference (NIPS) is a conference for machine learning and computational neuroscience and is held at high prestige amongst researchers. For this thesis, proceeding papers from years 1987 to 2018 were scraped from the website[1] using the *Beautifulsoup*[2]. PDF documents were then converted to raw text format using *pdftotext*[3], and those documents which were corrupted by the conversion process were removed manually. The number of documents collected was 8233 and the yearly results are shown in Figure 4.1a. A similar observation in the study on transportation field [44] can be seen as the number of papers have increased rapidly.



(a) *Document counts.*

(b) *Token counts.*

Figure 4.1. *Number of documents and average token count from NIPS between 1987 and 2018 processed dataset.*

The preprocessing of the documents was done using a parsing module found in the *gensim* [46]. The process included parsing tags, punctuations, multiple whitespaces, numeric values as well as removing the words under three characters long, and the common stopwords. Words that appeared in less than 20 documents and in more than 75% of the documents overall were also removed. Lastly the parsed documents were split with whitespace into discrete token vectors. With the preprocessed data a dictionary of $V = 18513$ words was built. I chose to exclude the stemming and lemmatization from the preprocess as they were not used in the other trend analysis papers either [44][54]. The results for average parsed token counts yearly are shown in Figure 4.1b.

[1] `https://papers.nips.cc/`
[2] `https://www.crummy.com/software/BeautifulSoup/`
[3] `https://www.xpdfreader.com/`

4.2 Word Embedding

One aim of this thesis was to investigate the impact of using the word embeddings as part of the topic modeling. The word vector model was trained from scratch with NIPS documents from 1987 to 2018. For this experiment I chose the CBOW model provided in *gensim* with default hyperparameters. Window size was set to 15 with the target embedding vector length 50, and word vectors were normalized using Formula 3.11 according to the original sHDP paper [24].

4.3 Model

First, I experimented with the sHDP[4] to see whether or not the promised higher PMI score would transfer well into the trend analysis task. Preprocessed token vectors were transformed into Bag-of-Word representations where each token was assigned a integer label, and the number of token occurrences from the document were counted. For the sHDP model, counts were replaced with the words vector representations using the CBOW model. The sHDP was trained with both default hyperparameters and experimented with lower α and γ values. The sHDP implementation was able to reach a maximum of 60 topics until unstable results occurred.

Next, multiple LDA models were trained using *gensim* to compare the results with sHDP. The LDA models were trained with $N = 50$ topics and different α values. Parameter $\alpha = 50/N = 1$, where N is the number of topics, was first chosen since it is suggested for general analysis [16]. Smaller value of $\alpha = 5/N = 0.1$ was also used as it has been argued to lead to more sparse topic distributions [44]. The model was also trained using *auto* α feature provided in *gensim*. In this way model computes the optimal α for each mini-batch while training. Measure of topic coherence was calculated using Equation 2.1. with the same corpus as a reference. Using the same corpora as reference one can estimate the model's capability to capture most of the information better for the purpose of trend analysis. Coherence metric for different models are listed in Table 4.1.

Model	Coherence (*PMI*)	
LDA($\alpha = 0.1$)	0.176	
LDA($\alpha = 1$)	0.126	*default*
LDA($\alpha = auto$)	**0.408**	
sHDP($\alpha = 1, \gamma = 2$)	0.176	*default*
sHDP($\alpha = 0.1, \gamma = 1.5$)	**0.212**	
sHDP($\alpha = 0.1, \gamma = 2$)	0.210	

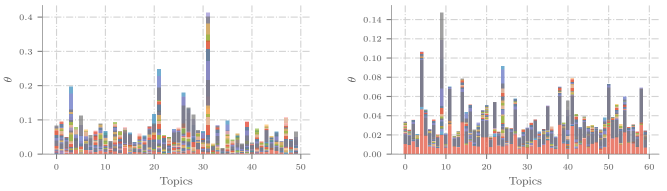
Table 4.1. *Average topic coherence for LDA and sHDP with different hyperparameters.*

Surprisingly, the utilization of word vectors in sHDP did not yield the best results. This difference might be explained by two factors. First, the automatic α tuning for LDA was able to estimate the best parameter for this data, whereas sHDP might have provided more generally coherent topics. This assumption is backed by the sHDP authors usage of Wikipedia corpus as reference when measuring PMI [24]. The importance of estimating a good α for the data is observed in Figure 4.2. where a dramatic bias is noticed towards some years where α is not tuned automatically. The other factor is the unstable nature of sHDP implementation where the iteration increase led to major memory issues and complete training failures.

4.4 Results and Analysis

This section focuses on describing and interpreting the results found from NIPS papers between 1987 and 2018. I chose the best performing LDA model to analyze document-topic distributions θ and word distribution ψ. The methods introduced in Section 3.3. were applied to detect occurring trends in the corpora over time.

[4] `https://github.com/Ardavans/sHDP`



(a) *LDA($\alpha = auto$)* ***(b)*** *sHDP($\alpha = 0.1, \gamma = 1.5$)*

Figure 4.2. *Topic distributions for NIPS 1987-2018 corpora. Each color represents one year's portion of overall topic distribution.*

4.4.1 Discovering Topics

The aim of the topic model is to provide a high level description of the target corpora. To fetch results from the model, the word distributions ψ_k for every topic k were drawn. Then the statistical structure of the word distributions were used to infer the content of each topic. Each topic was assigned a label manually by accounting the top words with highest probability ψ_{kn} where the $n = 10$. The results for the words and labels for topics are listed in Table 4.2. The resulting topics for the best performed sHDP model are listed in appendix Table A.1. The sHDP model topics are not labeled and contain only the top $n = 10$ words.

One can observe a diverge range of different research domains and methods applied in machine learning research from the labeled topics in Table 4.2. The topics focus on machine learning and on research in general, and no overall generic topics arise similar to ones in the previous studies [44]. However, more generic topics for machine learning overall are observed. For example, Topic-12 ("class, classification, detection, classes, classifier, recognition, rate, pattern, classifiers, test") and Topic-19 ("label, classification, labels, examples, class, classifier, margin, labeled, supervised, classifiers") both consist of commonly used vocabulary in machine learning studies.

Interestingly the model is able to infer methods both popular in the past and in current research. For example, the Topic-1 ("kernel, kernels, svm, support, operator, machines, machine, hilbert, regression, approximation") represents the Support-Vector Machines popularized and widely used throughout the early 2000s Support-vector networks [55]. An example of the more recent method is Topic-5 ("generative, latent, attention, image, samples, dataset, trained, preprint, generated, generation") that is interpreted to cover the Generative Adversarial Network (GAN) [56]. GAN's paper were originally introduced in NIPS 2014 conference making it one of the top topics of interest because of the rapid adaptation in the field.

The topics captured using LDA and sHDP differ in both coverage and in detail. For example, the sHDP Topic-9 ("pages, press, intelligence, thank, david, society, john, van, hinton, editors, williams, verlag, kaufmann, martin, comments") covers mostly names and concepts that commonly appear at the end of publications making it useless for the trend analysis task. This is one side effect also noted in the research [23][24] and is mainly the product of the names appearing often in the same context. Some similar topics are also observed where the both are be interpreted to mean the same abstract concept. Looking at the content of LDA, Topic-7 ("reward, action, agent, actions, reinforcement, environment, agents, exploration, goal, planning") and sHDP Topic-17 ("goal, control, world, strategy, partially, environment, reinforcement, policy, exploration, reward, intrinsic, game, expectations, agent, rewards"), both can be seen to represent Reinforcement Learning (RL). Even though the topics cover the same concept, LDA prioritizes words such as "reward, action, agent" that are more general, whereas sHDP "goal, control, world" words are more contextually related.

4.4.2 Topic Distribution over time

In this section I apply Equation 3.12. to study temporal trends for each topic. The results for the topic distribution yearly is shown in Figure 4.3. Observing the areas as they shrink and grow in size over time, one can see that some topics such as Hidden Units and Neurology were relevant in the earliest NIPS conferences. Contrasting to this, the topics covering Upper Confidence Bound

Topic-14	**Approximation**	theorem approximation polynomial properties proof definition continuous property condition positive
Topic-47	**Bayesian**	bayesian prior noise posterior covariance uncertainty likelihood priors variance processes
Topic-8	**Belief Propagation**	energy belief inference propagation factor message graphical field map variable
Topic-12	**Classification**	class classification detection classes classifier recognition rate pattern classifiers test
Topic-36	**Clustering**	clustering cluster clusters means points partition spectral centers partitioning sets
Topic-24	**Cost Optimization**	search cost active user query greedy items selection users optimization
Topic-43	**Datasets**	features feature dataset datasets accuracy table test score validation classification
Topic-32	**Distance metrics**	distance metric similarity causal nearest neighbor distances pairwise euclidean neighbors
Topic-20	**Distributed computing**	memory distributed communication parallel bit bits code binary precision size
Topic-34	**Domain Adaptation**	target domain source adaptation domains sources shift targets transfer distributions
Topic-16	**Entropy**	entropy divergence mutual measure ensemble measures log compression distributions maximum
Topic-25	**Estimations**	estimation estimator estimate variance estimates estimators rate statistics density estimating
Topic-6	**Face Images**	image images face pixel shape pixels vision matching recognition pose
Topic-17	**Filters**	filter filters basis natural coding sparse coefficients ica representation reconstruction
Topic-40	**Gamification**	game strategy expert strategies equilibrium experts utility price best play
Topic-5	**Generative Adversarial Network**	generative latent attention image samples dataset trained preprint generated generation
Topic-27	**Grandient optimization**	gradient optimization convergence stochastic descent convex step rate update iteration
Topic-2	**Graphs**	graph graphs edge edges nodes node structure degree connected directed
Topic-45	**Human/Subjects**	human subjects decision trial trials subject experiment task cognitive behavior
Topic-49	**Image segmentation**	image segmentation map cvpr vision semantic maps scale proposed detection
Topic-15	**Inference**	inference log variational latent posterior likelihood approximate approximation bound stochastic
Topic-19	**Labels**	label classification labels examples class classifier margin labeled supervised classifiers
Topic-11	**Loss/Predict**	loss prediction risk regression predictions structured output predict predictor predicted
Topic-44	**Markov Models**	sequence states sequences markov transition hidden dynamic series processes length
Topic-39	**Matrix factorization**	rank matrices low norm entries decomposition column columns factorization spectral
Topic-41	**Mixture models**	mixture likelihood distributions density log conditional parameter estimation components mixtures
Topic-10	**Motion/Video**	motion video position frame flow tracking direction frames motor trajectory
Topic-31	**Hidden Units**	units output hidden weights unit weight net inputs generalization layer
Topic-21	**Neurology**	cells cell activity brain cortex visual spatial cortical connections patterns
Topic-35	**Neurons/Synapses**	neurons neuron spike synaptic firing synapses spikes spiking rate rule
Topic-46	**Objects**	object objects visual scene features view categories category recognition representation
Topic-33	**Optimization**	optimization solution constraints convex constraint max objective min dual solutions
Topic-23	**Principal Component Analysis**	pca projection component subspace principal components eigenvalues covariance dimensionality vectors
Topic-37	**Policy learning**	policy reinforcement policies mdp decision action states control iteration reward
Topic-28	**Recurrent layers**	layer layers trained architecture output recurrent hidden weights size architectures
Topic-7	**Reinforcement learning**	reward action agent actions reinforcement environment agents exploration goal planning
Topic-4	**Rules/Knowledge**	rules rule knowledge program probabilistic representation question language variable reasoning
Topic-1	**Support-Vector Machine**	kernel kernels svm support operator machines machine hilbert regression approximation
Topic-48	**Samples**	sample samples test hypothesis size complexity testing empirical distributions tests
Topic-22	**Sampling**	sampling gibbs carlo sample monte samples chain mcmc markov inference
Topic-3	**Signal/Frequency**	signal frequency noise signals circuit phase analog chip output channel
Topic-0	**Sparse/Regression**	sparse regression regularization sparsity norm selection regularized recovery group penalty
Topic-13	**Speech Recognition**	speech recognition speaker alignment audio segment segments hmm acoustic signal
Topic-30	**Stimulus/Response**	stimulus response population responses neurons spike stimuli rate fig noise
Topic-29	**Surface Model**	local points global manifold region regions grid locally dimension surface
Topic-9	**System Dynamics**	control dynamics feedback group groups real interaction dynamical interactions simulation
Topic-18	**Topic modeling/NLP**	word words topic language text context semantic corpus vectors latent
Topic-38	**Transfer Learning**	task tasks multi transfer multiple learn shared related specific knowledge
Topic-42	**Tree structures**	tree node nodes trees structure hierarchical level root parent hierarchy
Topic-26	**Upper Confidence Bound**	bound log theorem bounds lemma lower proof setting upper bounded

Table 4.2. *Top 10 words and interpreted topics in alphabetical order.*

and Generative Adversarial Network are topics that have seen rise in popularity in recent years. As expected the more general topics such as Topic-14 about approximation is steadily represented in the overall trend figure. Similar behavior is not observed for sHDP from Figure A.1. as the distributions are much smoother.

I categorized the topics into two categories, namely rising and falling using Equation 3.13. The results for the rising topics are shown in Figure 4.4 and the falling topics in the Figure 4.5. The trend curve for each topic distributions is visualized using moving one-dimensional Gaussian filter with $\sigma = 2$ [57]. The topic trends are in different scales and though one topic might seem to gain momentum independently, it still might be irrelevant in the relative sense.

The rising topics contain some of the widely known popular methods such as Recurrent layers, Transfer learning and GAN. Examples of more generic methods that have RIsen the most are topics covering concepts such as Matrix factorization and Inference. The rise in three similar topics covering Optimization, Cost Optimization and Gradient Optimization is also notable. These observations are in line with the general trends on the current research areas, as it often culminates to the optimization of existing research to produce state-of-the-art results. More interestingly the LDA model is able to detect some of the more complex trends in the research. For example the

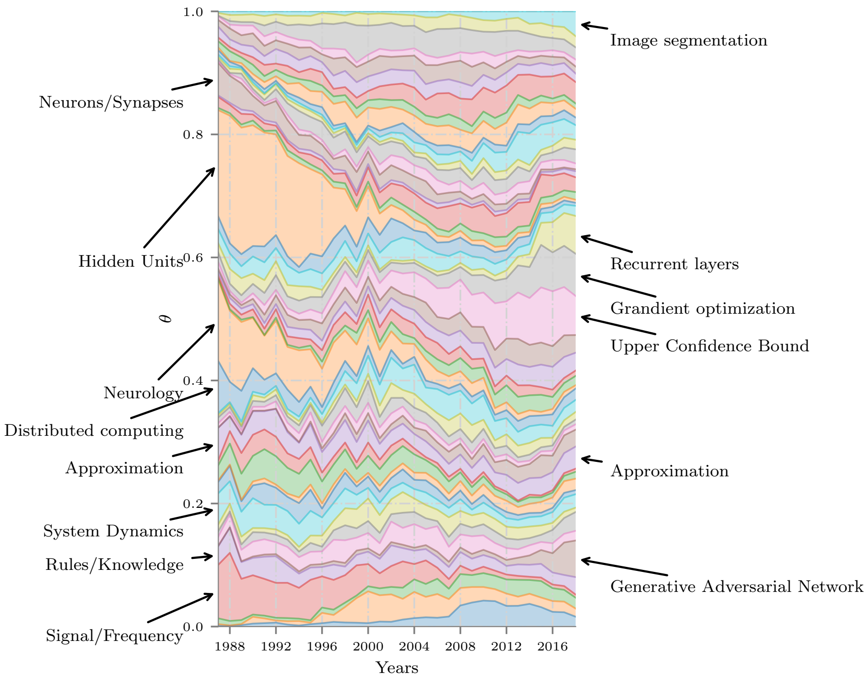


Figure 4.3. *Yearly topic distributions for LDA model. Topics are shown in ascending order from the first (bottom) to the last (top).*

Recurrent Neural Networks (RNN) were studied in the late 1980s [58] and the method did not have many applications until technical advancements of 2010s. The rise and fall of the popularity of the SVM methods was also captured by the model.

The falling topics are mostly concepts related to neural information processing side of the conference. For example, topics covering Neurology and Neurons/Synapses have seen dramatic fall in coverage. Surprisingly, topics covering more classical signal processing and machine learning concepts like Signal/Frequency and Hidden Units have also seen a similar fall. In general this indicates the shift in focus of the NIPS conference away from the neural information and signal processing to pure machine learning focused conference. Interestingly the fall of some application fields such as Speech Recognition and Face Images topics can also be seen. However, it is worth noting that the resulted trends are affected by the rise of number of publications, thus exposing the topics relevant in the past to inflation.

The hierarchical clustering is applied to yearly topic distributions using Equation 3.16. as metric and Python library *scipy* [59] with average method as parameter. Yearly topic distributions alongside the clusters are shown in Figure 4.6. From this representation, the eras and turning points in the NIPS conferences can be highlighted. The heatmap representation of the topic yearly distributions also highlights important phenomena. For example, Topics-3 (Signal/Frequency) and Topic-21 (Neurology) are dominant topics from the early conferences whereas Topics-26 (Upper Confidence Bound) and Topic-29 (Surface Model) represent the most recent topics.

Figure 4.6. represents three major cluster eras: 1987-1995 (green), 1996-2012 (red) and 2013-2018 (cyan). These eras present the general advancements in the machine learning field. The earliest cluster from 1987 to 1995 is interpreted as the era for earliest neural networks and the theories inspired from the neurology. The second from 1996 to 2012 represents the era of learning algorithms and the last and the current era from 2013 to 2018 covers the deep learning. The turning point from current to present is mostly explainable by the popularization of the GPU computation.

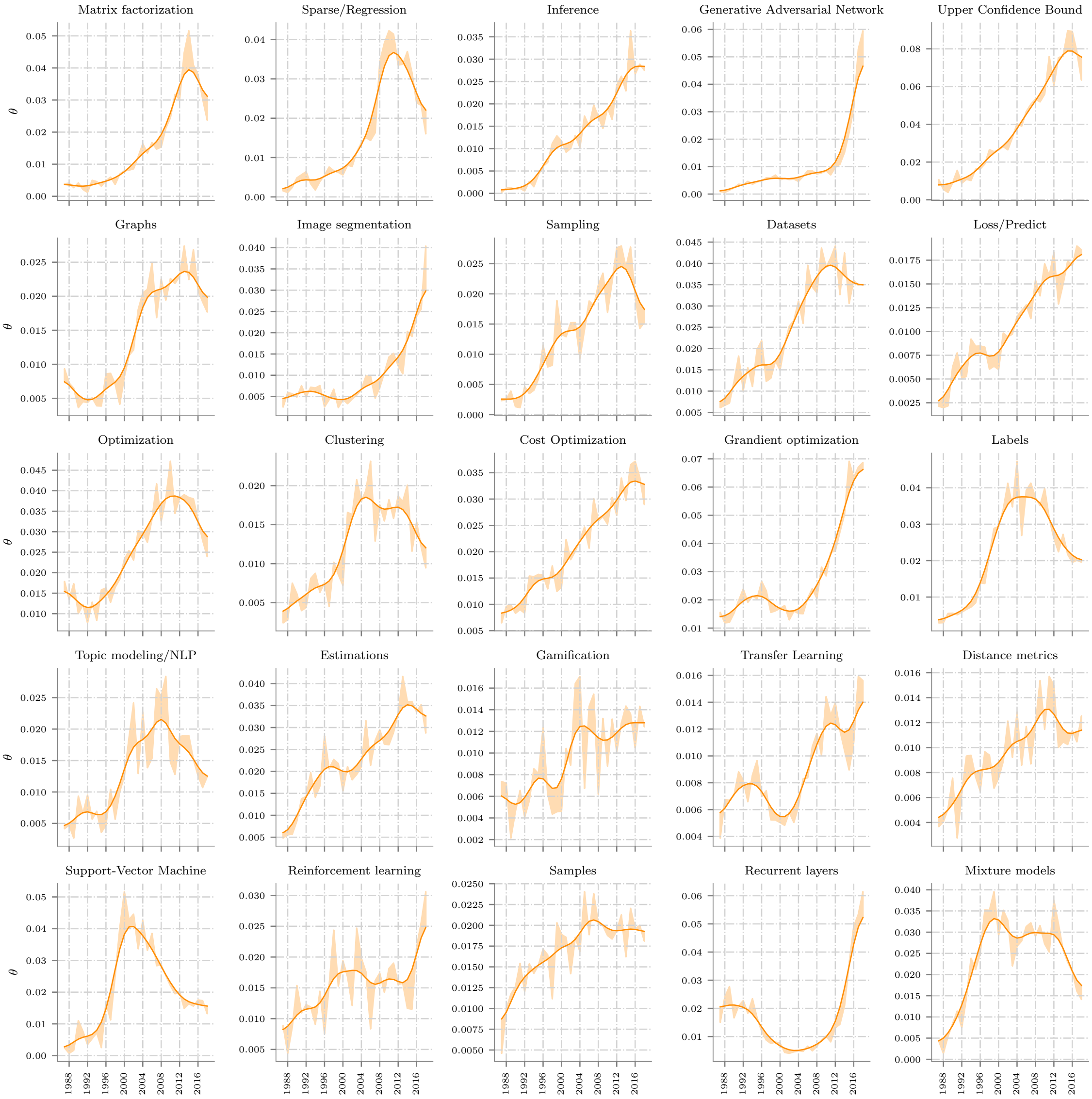


Figure 4.4. *Top 25 rising labeled topics from NIPS 1987-2018.*

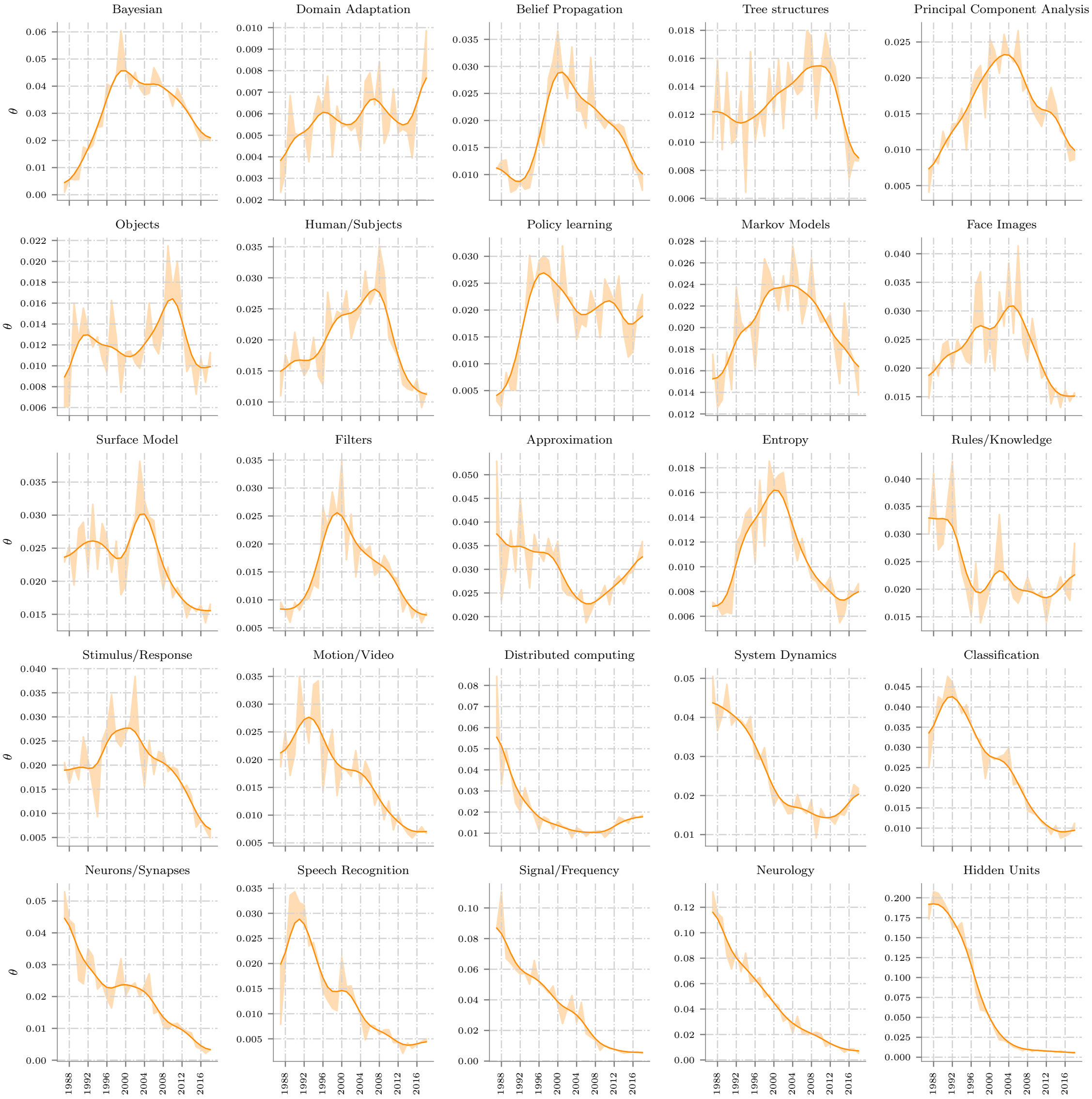


Figure 4.5. Bottom 25 falling labeled topics from NIPS 1987-2018.

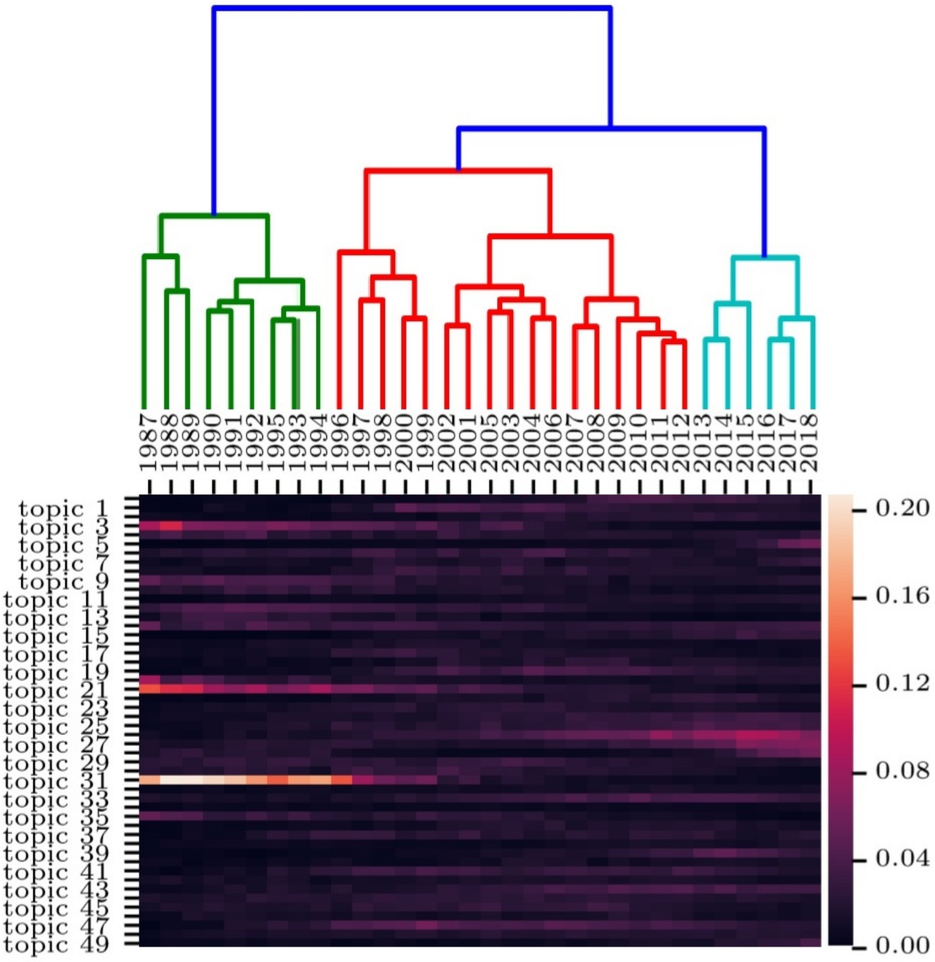


Figure 4.6. *Yearly topic distributions and similarities between years. Green marks the era of neuroscience, red marks the algorithmic era, and cyan represents the deep learning era.*

5 CONCLUSION

This thesis provided an overview of the current and past trends of NIPS conferences from 1987 to 2018. The topics found using the best performing model were easily interpretable and informative. Unfortunately, the topics presented in this thesis did not offer the latent information expected. However, the effectiveness of topic modeling methods as mining meaningful knowledge from large sets of unlabeled data is demonstrated.

In this thesis the LDA model outperformed the sHDP model in both topic coherence metrics and in the trend analysis task. This finding contradicts the previous results of sHDP [24]. The reasons for this finding can vary from both maturity of the implementation and the underlying theory behind the model. The sHDP implementation suffered from both memory problems and unstable parameter combinations. As stated in Chapter 4, these problems gave the LDA model unfair advantage for comparison. Furthermore, the relatively small size of data that was used to train the CBOW model might have led to poor resulting word representations. However, the underlying reason why sHDP performed relatively better on PMI metrics might relate to word2vec model's implicit approximation of PMI [35]. This might have led to the topics being seemingly better when measured with the PMI coherence metric, but in closer human observation might look meaningless and harder to interpret.

The topic models used in this work all relied on the slow CPU-powered computations. This limited the amount of data and experiments. Both LDA and sHDP models would most likely benefit from the inference computed using GPU. Additionally, the implementation of selecting the best α into other topic models could result in better topics overall. Further studies should be conducted to analyse trends in multiple different conferences. These studies could further give a deeper understanding on specialized conferences and wider range of trends. It is worth noting that while this thesis focused on the completely unlabeled text data, the scientific publications can be studied from the other scientometric point of views. Combining the citation numbers to the topic trends could give insight into the question why some papers are popular while others are not.

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A APPENDIX

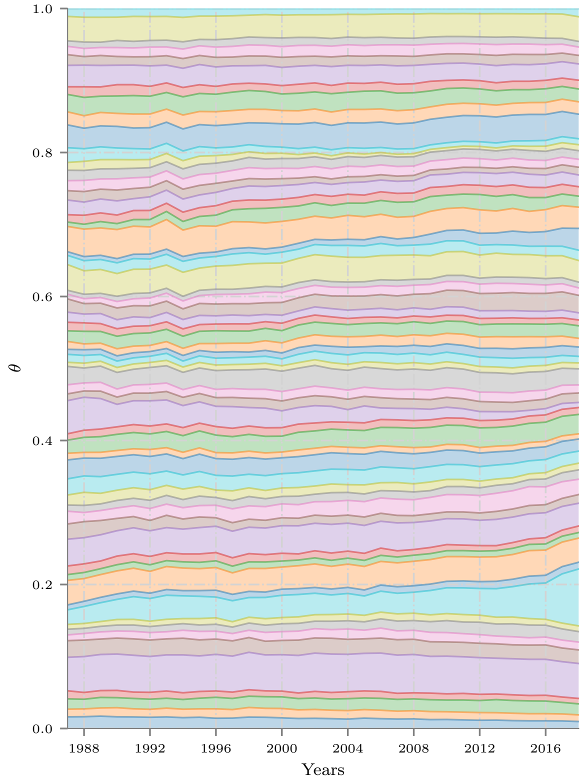

Figure A.1. *Yearly topic distributions for sHDP model. Topics are shown in ascending order from the first (bottom) to the last (top).*

Topic-0	behavior observation series observations highly field patterns equations differences dynamics
Topic-1	linear point points feature features finite kernel power nonlinear parametric
Topic-2	size terms computational log constant setting sample scale total times
Topic-3	local underlying global euclidean locally consistency geometric compact consequently lies
Topic-4	obtained provide obtain compute presented perform computed provides uses learn
Topic-5	like generated chosen current randomly initial choose run generate selected
Topic-6	classification pattern domain target cross label supervised labels classifier source
Topic-7	optimization solving regression applying convex formulation descent minimization constrained solved
Topic-8	search selection decision tree rules strategies carlo monte heuristic trees
Topic-9	pages press intelligence thank david society john van hinton editors
Topic-10	best optimal rate max convergence rates near guarantees strongly bayes
Topic-11	general applied proposed related previous approaches recent propose including study
Topic-12	single independent stochastic multi takes dependent independently dynamic followed sequential
Topic-13	position maps spatial frequency operation filter transform pixel convolutional resolution
Topic-14	result known fact cases requires observed means require required practice
Topic-15	distributed implementation parallel machines levels building communication software core seconds
Topic-16	functions solution version theorem min definition equation proof furthermore exists
Topic-17	goal control world strategy partially environment reinforcement policy exploration reward
Topic-18	human performing active encoding cognitive play reasoning observing concepts people
Topic-19	respectively multiple contains consists subset represented joint elements individual pair
Topic-20	fixed equal depends corresponds seen change consistent length determined depend
Topic-21	state sequence discrete taking states sequences deterministic action transition past
Topic-22	algorithms experiments standard compared finally comparison available compare table experimental
Topic-23	parameters distribution parameter class choice weights gradient weight context variance
Topic-24	nature evidence place brain neurons correlated activity biological cell responses
Topic-25	maximum loss objective distance finding minimum minimize minimizing normalized measures
Topic-26	structure properties noise assumption factor conditions constraints property condition assumptions
Topic-27	form space defined vector corresponding let assume define denote respect
Topic-28	real test sets samples dataset testing validation half evaluating fraction
Topic-29	complete graph structures nodes clustering matching graphical node edge graphs
Topic-30	question online black database user answer receives web decisions query
Topic-31	matrix vectors product matrices norm row essentially covariance rank symmetric
Topic-32	high better low good higher complex fast acknowledgments sufficient robust
Topic-33	representation signal sparse representations solutions code phase successfully signals precision
Topic-34	response expression energy predicting discovery identification differential link outcome medical
Topic-35	machine conference journal ieee proceedings advances international nips artificial springer
Topic-36	mean approximation estimate statistics estimation approximate estimates density estimating square
Topic-37	error lower bound accuracy upper generalization bounds risk absolute gap
Topic-38	possible particular way instead need efficient directly allows specific able
Topic-39	recognition image images vision visual object parts detection challenge objects
Topic-40	zhang wang jordan chen michael lee liu association lin yang
Topic-41	science edu supported department mit cambridge volume institute com grant
Topic-42	process gaussian variables variable distributions prior sampling inference likelihood probabilistic
Topic-43	step procedure end steps update iteration iterations entire sub updates
Topic-44	theory applications statistical application range empirical theoretical review mathematical conclusions
Topic-45	models training networks network prediction idea architecture wide manner ways
Topic-46	values examples positive line negative classes ones threshold region predictions
Topic-47	simple sum addition similarly special alternative weighted combination adaptive scheme
Topic-48	unit hidden fully layer outputs units layers activation residual feed
Topic-49	long memory turn forward longer propagation connections self path gradients
Topic-50	consider present follows described framework natural main details discussion focus
Topic-51	term difference knowledge effect advantage previously errors account regularization bias
Topic-52	average right left relative final overall correspond indicates fig indicate
Topic-53	problems task level hand tasks generally words text language jointly
Topic-54	larger smaller increases increase increasing observe likely clearly relatively especially
Topic-55	computation computing exactly exact efficiently programming computationally separate operations infinite
Topic-56	random probability zero true according expected measure support exp taken
Topic-57	dimensional components component basis generalized dimensions reduction largest dimensionality correlation
Topic-58	important additional future useful significant improve interesting practical improved limited
Topic-59	input output resulting original instance inputs program identity invariant transformation

Table A.1. *Top 10 words for sHDP($\alpha = 0.1, \gamma = 1.5$) topics.*