Selecting Priors for Latent Dirichlet Allocation

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***Abstract*—Latent Dirichlet Allocation (LDA) has gained much attention from researchers and is increasingly being applied to uncover underlying semantic structures from a variety of corpora. However, nearly all researchers use symmetrical Dirichlet priors, often unaware of the underlying practical implications that they bear. This research is the first to explore symmetrical and asymmetrical Dirichlet priors on topic coherence and human topic ranking when uncovering latent semantic structures from scientific research articles. More specifically, we examine the practical effects of several classes of Dirichlet priors on 2000 LDA models created from abstract and full-text research articles. Our results show that symmetrical or asymmetrical priors on the document–topic distribution or the topic–word distribution for full-text data have little effect on topic coherence scores and human topic ranking. In contrast, asymmetrical priors on the document–topic distribution for abstract data show a significant increase in topic coherence scores and improved human topic ranking compared to a symmetrical prior. Symmetrical or asymmetrical priors on the topic–word distribution show no real benefits for both abstract and full-text data.**

I. Introduction

Global research efforts have led to an ever-increasing amount of scientific output. Combined with the digitalization of scientific archives, this increase is threatening to overwhelm today's scientists trying to keep track of and identify relevant literature [1]. Consequently, scientists need new tools and algorithms for browsing these collections in a structured way, particularly as topics within articles, which are the ideas contained within articles that can be shared among similar articles, cannot always be detected through traditional keyword searches [2]. Probabilistic topic models such as latent Dirichlet allocation (LDA) [3] and probabilistic latent semantic indexing (pLSI) [4] are machine-learning algorithms used to automatically uncover underlying semantic structures, such as themes or topics, in large collections of documents. These underlying semantic structures can subsequently be used to categorize, summarize, and annotate large document collections in a purely unsupervised fashion.

LDA, although the simplest topic model, has received much attention from machine-learning researchers and has been adopted and extended in many ways. LDA is a three-level hierarchical Bayesian model that models documents as discrete distributions over K latent topics, and every topic is modeled as a multinomial distribution over the fixed vocabulary. Uncovering latent thematic structures proceeds through posterior inference of the latent variables given the observed words. Apart from its applicability to text, LDA has proven useful to other types of data, such as image [5], video [6], and audio [7].

As a conjugate prior to the multinomial distribution, LDA uses a Dirichlet prior to simplify posterior inference. Typically, these priors and related hyperparameters are set to be symmetrical, assuming that *a priori* all topics have equal probability to be assigned to a document and all words have an equal chance to be assigned to a topic. The reasons for choosing symmetrical priors, compared to asymmetrical priors, are not explicitly stated and are often implicitly assumed to have little or no practical effect [8]. However, hyperparameters can have a significant effect on the achieved accuracy for various inference techniques, such as Gibbs sampling, variational Bayes, or collapsed variational Bayes [9]. In fact, inference methods have relatively similar predictive performance when the hyperparameters are optimized, thereby explaining away most differences between them.

Little research has examined the effects of Dirichlet priors on the quality of generated topics. Among the few, Wallach *et. al.* [8] demonstrated that using an asymmetric Dirichlet prior on the document–topic distribution shows significant performance gains concerning the likelihood of held-out documents. However, the likelihood correlates negatively with human interpretability [10], which is often considered the gold standard for topic quality. Consequently, researchers have proposed topic coherence measures [11]–[14], a proxy for topic quality that shows improved correlation with human topic ranking data. The underlying idea of topic coherence is rooted in the distributional hypothesis of linguistics [15]—namely, words with similar meanings tend to occur in similar contexts. This paper is the first to explore the practical effects of several classes of Dirichlet priors on the coherence of generated topics. More specifically, we study topic coherence for the combinations of symmetrical and asymmetrical priors on the document–topic distribution, as well as the topic–word distribution, when uncovering latent topics with LDA. In addition, topics are ranked by a domain expert on interpretability, providing a qualitative analysis of topic quality for different classes of Dirichlet priors in addition to a quantitative measure. Such analyses can provide valuable guidance to researchers utilizing LDA tools such as Mallet and Gensim [16] to uncover topical structures from scientific articles [17]–[21] and unknowingly leaving hyperparameters set to default (i.e. symmetrical).

II. Background

A. Latent Dirichlet Allocation

LDA is a generative probabilistic topic model that aims to uncover latent semantic structures from a set of documents, D. LDA models documents as discrete distributions over K latent topics, and every topic is modeled as a discrete distribution over the fixed vocabulary. As a result, LDA captures the heterogeneity of ideas prevailing in a document collection and can be viewed as a mixed membership model [22]. The underlying latent semantic structure is expressed by topics β, topic proportions θ, and topic assignments z and includes hidden variables that LDA posits into the corpus. However, β, θ, and z are unobserved, and the goal is to determine them from the observed variables (i.e. the words within the documents). LDA's structure allows the observed variables to interact with structured distributions of a hidden variable model [23]. Learning the hidden variables can be achieved by inferring the posterior distribution of the latent variables given the observed documents. The interaction between latent and observed variables is manifested in the generative process behind LDA, the imaginary random process in which we assume the documents come from and are based on probabilistic sampling rules. The generative process is described as follows:

1) For every topic $k = \{1, ..., K\}$
    a) draw a distribution over the vocabulary V, $\beta_k \sim \text{Dir}(\eta)$
2) For every document d
    a) draw a distribution over topics, $\theta_d \sim \text{Dir}(\alpha)$ (i.e. per-document topic proportion)
    b) for each word w within document d
        i) draw a topic assignment, $z_{d,n} \sim \text{Mult}(\theta_d)$, where $z_{d,n} \in \{1, ..., K\}$ (i.e. per-word topic assignment)
        ii) draw a word $w_{d,n} \sim \text{Mult}(\beta_{z_{d,n}})$, where $w_{d,n} \in \{1, ..., V\}$

Where K is the numbers of topics, V is the vocabulary size, and α and η are the Dirichlet hyperparameters that affect the smoothing of topic proportions within documents and words within topics, respectively. The joint distribution of all the hidden and observed variables becomes:

$$\begin{aligned} p(\beta_K, \theta_D, z_D, w_D | \alpha, \eta) = \quad & \prod_{k=1}^{K} p(\beta_K | \eta) \prod_{d=1}^{D} p(\theta_d | \alpha) \\ & \prod_{n=1}^{N} p(z_{d,n} | \theta_d) p(w_{d,n} | z_{d,n}, \beta_{d,k}) \end{aligned} \tag{1}$$

To learn the distribution of the hidden variables, we invert the generative process and fit the hidden variables onto the observed words. The hidden structure is thus described by the posterior distribution of the latent variables given the observed words:

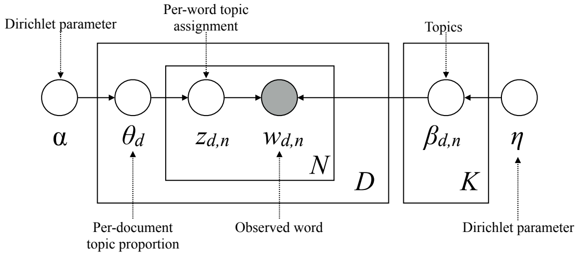


Fig. 1. LDA represented as a graphical model.

$$p(\beta_K, \theta_D, z_D | w_D, \alpha, \eta) = \frac{p(\beta_K, \theta_D, z_D, w_D | \alpha, \eta)}{p(w_D | \alpha, \eta)} \tag{2}$$

$$p(w_D | \alpha, \eta) = \int_{\beta_K} \int_{\theta_D} p(w_d | \alpha, \eta) \tag{3}$$

However, the posterior is intractable to compute [3] due to the evidence as expressed in (3). The solution is to approximate the posterior using inference techniques. Once inference is complete, the posterior distribution reveals the latent structure of the documents expressed by topics β, topic proportions θ, and topic assignments z.

B. Coherence Scores

Measures such as predictive likelihood on held-out data [24] have been proposed to evaluate the quality of generated topics. However, such measures correlate negatively with human interpretability [10], making topics with high predictive likelihood less coherent from a human perspective. Consequently, researchers have proposed topic coherence measures, which are a qualitative approach to automatically uncover the coherence of topics [11]–[14]. Topics are considered to be coherent if all or most of the words (e.g. a topic's top-N words) are related. Topic coherence measures aim to find measures that correlate highly with human topic evaluation, such as topic ranking data obtained by, for example, word and topic intrusion tests [10]. Human topic ranking data are often considered the gold standard and, consequently, a measure that correlates well is a good indicator for topic interpretability. A recent study by Röder *et. al.* [14] systematically and empirically explored the multitude of topic coherence measures and their correlation with available human topic ranking data; new coherence measures obtained by combining existing elementary elements were also examined. The researchers' systematic approach revealed a new unexplored coherence measure, which they labeled C_V, to achieve the highest correlation with all available human topic ranking data. This study adopts the C_V coherence measure for calculating topic coherence, with a detailed description of the calculations behind this measure described below.

The calculation of C_V starts with the segmentation of the topic's top-N words into pairs of word subsets, $S_i = (W', W^*)$, where $W' \in W$, $W^* \in W$, and W consists of the topic's top-N most probable words. More formally, a pair S is defined as $S = \{(W', W^*) | W' = \{w_i\}; w_i \in W; W^* = W\}$. For example, if $W = \{w_1, w_2, w_3\}$, then one pair might be $S_i = (W' = w_1), (W^* = w_1, w_2, w_3)$. Such segmentation measures the extent to which the subset W^* supports or conversely undermines the subset W' [25]. The support between word subsets of a pair $S_i = (W', W^*)$ is calculated with a confirmation measure ϕ. C_V uses an indirect confirmation measure that considers not only the words within a pair, but also all words in W. A direct confirmation measure, such as difference, ratio, and likelihood measure, could place a low probability on high-support but low-frequency pairs. An indirect confirmation measure overcomes this by pairing every subset with W, thereby increasing the semantic support of supporting pairs. Word subsets are now represented as context vectors [11], such as $\vec{v}(W')$ by pairing them to all words in W, as exemplified in (4). The relatedness between context vectors and words in W is calculated by normalized pointwise mutual information (NPMI), as shown in (5).

$$\vec{v}(W') = \left\{ \sum_{w_i \in W'} \text{NPMI}(w_i, w_j)^\gamma \right\}_{j=1,\ldots,|W|} \tag{4}$$

$$\text{NPMI}(w_i, w_j)^\gamma = \left(\frac{\log \frac{P(w_i, w_j) + \epsilon}{P(w_i) \cdot P(w_j)}}{-\log(P(w_i, w_j) + \epsilon)} \right)^\gamma \tag{5}$$

Given our running example of $W = \{w_1, w_2, w_3\}$, we obtain the context vector for w_1 as $\vec{w_1} = \{\text{NPMI}(w_1, w_1)^\gamma, \text{NPMI}(w_1, w_2)^\gamma, \text{NPMI}(w_1, w_3)^\gamma\}$, with the constant ϵ to prevent logarithms of zero, and γ to place more weight on higher NPMI values.

Probabilities of single words $p(w_i)$ or the joint probability of two words $p(w_i, w_j)$ can be estimated using a Boolean document calculation—that is, the number of documents in which (w_i) or (w_i, w_j) occurs, divided by the total number of documents. The Boolean document calculation, however, ignores the frequencies and distances of words. C_V incorporates a Boolean sliding window calculation in which a new virtual document is created for every window of size s when sliding over the document at a rate of one word token per step. The probabilities $p(w_i)$ and $p(w_i, w_j)$ are subsequently calculated from the total number of virtual documents. In contrast to the Boolean document calculation, the Boolean sliding window calculation tries to capture the word token proximity to some degree.

The indirect confirmation measure $\phi_{S_i}(\vec{u}, \vec{w})$ is obtained by calculating the cosine vector similarity between all context vectors $\vec{v}(W') \in \vec{u}$ and $\vec{v}(W^*) \in \vec{w}$ of a pair $S_i = (W', W^*)$, as shown in (6).

$$\phi_{S_i}(\vec{u}, \vec{w}) = \frac{\sum_{i=1}^{|W|} u_i \cdot w_i}{\|\vec{u}\|_2 \cdot \|\vec{w}\|_2} \tag{6}$$

Finally, the arithmetic mean of individual confirmation measures is used to arrive at an overall topic coherence score.

III. Methods

A. Dataset

We compare the influence of Dirichlet hyperparameters on two datasets containing scientific research articles related to the domain of *fisheries*. The first dataset, DS_1, contains all full-text research articles published by the journal *Canadian Journal of Fisheries and Aquatic Sciences* and the journal *ICES Journal of Marine Science* from 1996 to 2016, with $D = 8,012$ documents, vocabulary size of $V = 203,248$, a total of $N = 29,469,919$ words, and on average 3,678 words per document. The second dataset, DS_2, contains only abstract data from the journal *Canadian Journal of Fisheries and Aquatic Sciences*, with $D = 4,417$, $V = 14,643$, $N = 481,168$, and 109 words on average per document. Both journals are domain-specific (i.e. fisheries) journals, but employ a wide scope of research directives related to the biological, ecological, and socio-ecological aspects of fisheries.

The domain of fisheries includes a multitude of knowledge production approaches, from mono- to transdisciplinary. Biologists, oceanographers, mathematicians, computer scientists, anthropologists, sociologists, political scientists, economists, and researchers from many other disciplines contribute to the body of knowledge of fisheries, together with non-academic participants such as decision makers and stakeholders. Within the domain of fisheries, research into text analytics techniques has only been applied in a number of cases (e.g. [26]–[28]).

These journals were chosen for several reasons. First, a fisheries domain expert was available to rank the topics manually. Second, domain-specific journals, in contrast to generic journals such as *Nature*, *Science*, or *PLOS ONE*, increase generalizability to other domain-specific journals that are often the subject of study when uncovering topical structures from scientific publications, such as research performed within the field of computational linguistics [29] or neural information processing systems (NIPS) [20], thereby making our results applicable to such approaches. Finally, the two journals have the highest frequency of publication output within the analyzed period compared to all other fisheries journals.

Words that were part of a standard list of stop words ($n = 153$), single-occurrence words, and words occurring in $\geq 90\%$ of the documents (e.g. *fish*, *analysis*, *research*) were removed. The removal of the top 90% of words serves as an estimate to prevent frequently occurring words from dominating all topics. All documents were tokenized and represented as bag-of-word features. Apart from grouping lowercase and uppercase words, no normalization method (e.g. stemming or lemmatization) was applied to reduce inflectional and derivational forms of words to a common base form. Stemming algorithms can be overly aggressive and could result in unrecognizable words that reduce interpretability when labeling the topics. Stemming might also lead to another problem: It cannot be deduced whether a stemmed word comes from a verb or a noun [30]. As human topic ranking was part of our topic quality evaluation, interpretability was considered to be highly important.

TABLE I
NOTATION OF DIRICHLET CLASSES. α = DOCUMENT-TOPIC DISTRIBUTION, η = TOPIC-WORD DISTRIBUTION

Abbreviation	α	η
AA	Asymmetric	Asymmetric
AS	Asymmetric	Symmetric
SA	Symmetric	Asymmetric
SS	Symmetric	Symmetric

B. Dirichlet Hyperparameters

Hyperparameter α controls the shape of the document–topic distribution, whereas η controls the shape of the topic–word distribution. A large α leads to documents containing many topics, and a large η leads to topics with many words. In contrast, small values for α and η result in sparse distributions: documents containing a small number of topics and topics with a small number of words. In essence, the hyperparameters α and η have a smoothing effect on the multinomial variables θ and β, respectively. Four different classes or combinations of Dirichlet priors are explored, as listed in Table I, in which we follow a similar notation (i.e. AA, AS, SA, SS) as described in [8].

Symmetrical priors are often the default setting for LDA tools such as Mallet and Gensim and assume a priori that each of the K topics has an equal probability of being assigned to a document while each word has an equal chance of being assigned to a topic. For the symmetrical prior α, the hyperparameter is a vector with the value $1/K$, where K is the number of topics. The symmetrical prior η has a scalar parameter with the value $1/V$, where V is the size of the vocabulary (full-text data $DS1 = 203,248$, and abstract data $DS_2 = 14,643$). For the asymmetrical priors, we utilize an iterative learning process to approximate the hyperparameters from the data; estimation is required as no exact closed form solution exists. Estimating hyperparameters can be used to increase model quality, and their values can reveal specific properties of the corpus: α for the distinctiveness in underlying semantic structures and η for the group size of commonly co-occurring words [31]. Several methods for hyperparameter estimation exist, such as gradient ascent, fixed point iteration, and Newton-Raphson method. Estimating the Dirichlet parameter α aims to maximize $p(D|\alpha)$ by maximizing the log likelihood function of the data D, with $\log \bar{p}_k$ being the observed sufficient statistics (the following is analogous to that of η).

$$F_{(\alpha)} = \log p(D|\alpha) = N \log\Gamma(\sum_k a_k) - N \sum_k \log \Gamma(a_k) + N \sum_k (a_k - 1) \log \bar{p}_k \quad \text{with} \log \bar{p}_k = \frac{1}{N} \log p_{i,k} \tag{7}$$

This study adopts the Newton-Rapson [32] method that provides a quadratic converging method for parameter estimation. Given an initial value for α, parameters are iteratively updated to arrive at an asymmetrical Dirichlet distribution learned from the data.

C. Creating LDA Models

LDA models were created for four different classes of priors on α and η, as listed in Table I. For each class of priors, LDA models were produced by varying the number of topics parameter $K = \{1, ..., 50\}$ and repeating the process five times; one class resulted in 250 LDA models. The same approach was performed on both datasets: DS_1 for abstract data and DS_2 for full-text data. A total of 2000 different LDA models were created. Given that our datasets focus on fisheries only, making them homogeneous in nature, a small number of topics is expected—typically around 10 to 20 given the scope and aims of the selected journals.

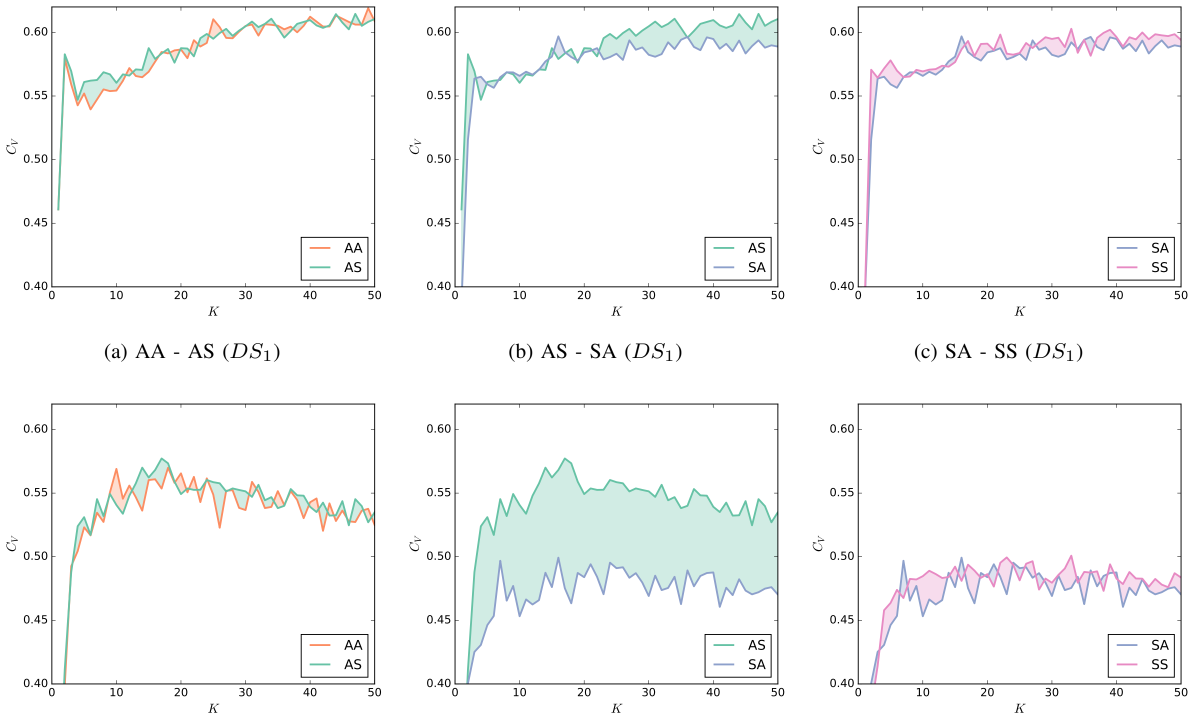
The Python library Gensim [16] was used to create LDA models. Posterior inference approximation is performed with online variational Bayes (VB) as proposed by Hoffman *et. al.* [33]. Online VB is based on an online stochastic optimization process and produces similar or improved [33] and faster [34] LDA models compared to its batch variant. The Newton-Raphson process of iteratively learning asymmetrical Dirichlet priors can conveniently be incorporated into online LDA in linear time.

D. Topic Coherence

The coherence of topics was calculated using the C_V coherence measure as described in detail in Section II-B. The segmentation of the topic's top-N words and subsequent calculation of confirmation are calculated for $N = 15$, pairing every top 15 word with every other top 15 word and calculating their semantic support within the corpus. $N = 15$ was chosen, in contrast to, for example, $N = 10$ [11], as no stemming or lemmatization was applied; with $N = 10$, several words with the same base form were among the top 10 words (e.g. *sample*, *sampling*), so analyzing the top 10 words would effectively mean analyzing fewer than 10 distinct words. The constant ϵ for NPMI calculations (see (5)) avoids logarithms of zero and acts as a smoothing factor. This value is set to a very small number, 10^{-12}, as proposed by Stevens *et. al.* [12]; the coherence measure is highly dependent on the smoothing constant, and a very small value significantly reduces the scores for unrelated words compared to, for example, $\epsilon = 1$ [35]. The γ constant for NPMI calculations is set to 1 (see (4)) to place equal weights on all NPMI values. In contrast to $\gamma = 2$ [11], $\gamma = 1$ produced a higher correlation with human topic ranking data [14]. The sliding window s for the Boolean sliding window calculation is set to 110 [14].

E. Human Topic Ranking

A fisheries domain expert manually ranked the topics by inspecting the topic's top 15 most probable words together with the document titles and a selection of the document



(a) AA - AS (DS_1)

(b) AS - SA (DS_1)

(c) SA - SS (DS_1)

(d) AA - AS (DS_2)

(e) AS - SA (DS_2)

(f) SA - SS (DS_2)

Fig. 2. A comparison of calculated C_V topic coherence for all classes of priors (i.e. AA, AS, SA, SS). Coherence scores represent mean scores from five runs for $K = \{1, ..., 50\}$. $DS_1 = 8,012$ full text articles and $DS_2 = 4,417$ abstracts. The comparison of AA to SA, AA to SS, and AS to SS are not shown as they show a similar trend with the comparison of AS to SA for both datasets.

contents. The domain expert is affiliated with the leading competence institution for fishery and aquaculture in Norway. As topic coherence scores are also obtained from the topic's top 15 words, the manual ranking of the top 15 words allows for equal comparison between the two proposed assessments. The domain expert was asked to provide a label for each topic that best captures the semantics of the top 15 words. In addition, the domain expert was asked to rank the topics concerning semantically correct or, conversely, incorrect words. An incorrect word could be a wrong fisheries domain-related word that does not match the topic label and, thus, does not fit with the semantics of the majority of right words. For example, in cases where most of the topic words resemble the fish species *cod*, an incorrect domain-related word might refer to a different kind of species. Furthermore, incorrect terms may refer to noise terms (i.e. words that serve a grammatical or syntactical purpose only). Topics are subsequently ranked by the number of right terms concerning all of the top 15 words. High-quality topics have $\geq$ 90% correct words, medium-quality topics have $\geq$ 80% but $<$ 90% correct words, and low-quality topics have $<$ 80% correct words.

IV. Results

A. Topic Coherence

The coherence scores for the prior classes AA, AS, SA, and SS obtained from 8,012 full-text research articles (DS_1) and 4,417 abstracts (DS_2) are displayed in Fig. 2. The score represents the mean coherence score from all five runs for each value of k. A visual inspection of Figs. 2a–2c (full-text data) shows that similar coherence scores are obtained for AA and AS (Fig. 2a), with both sharing an asymmetrical prior over α but a different prior over η. Similar results are obtained when comparing SA and SS (Fig. 2c), sharing a symmetrical prior over α and a different prior over η. Thus, varying η, while maintaining a similar prior over α, shows no real difference in obtained coherence score. A slightly increased coherence is obtained for an asymmetrical prior over α (Fig. 2b) for $k > 20$. Other combinations explored (e.g. AA–SA, AA–SS, and AS–SS) show similar results.

Figs. 2d–2f show coherence scores for LDA models obtained from abstract data (DS_2). AA–AS (Fig. 2d) show that different priors over η, while maintaining the same asymmetrical prior over α, result in similar coherence scores. Similarly, a symmetrical prior over α (Fig. 2f) with different priors over η shows no real differences in topic coherence. However, a large difference in coherence is obtained when varying the priors over α (Fig. 2e), with an asymmetrical α showing improved coherence over a symmetrical α. For DS_2, priors over α, in contrast to results from DS_1, show higher coherence scores for all values of k. Moreover, varying priors over η for DS_1 and DS_2 have a negligible effect on obtained coherence scores.

Table II shows the coherence score values obtained from

TABLE II

COHERENCE SCORE VALUES AND ONE-WAY ANOVA TEST STATISTICS FOR DS_1 FOR $K = \{2, ..., 50\}$. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Num. Topics	**Mean**				**Std. dev.**				**ANOVA Statistics**							
K	$\bar{X}_{AA}$	$\bar{X}_{AS}$	$\bar{X}_{SA}$	$\bar{X}_{SS}$	s_{AA}	s_{AS}	s_{SA}	s_{SS}	f	p	$AA-AS$	$AA-SA$	$AA-SS$	$AS-SA$	$AS-SS$	$SA-SS$
2	0.580	**0.583**	0.516	0.571	0.037	0.021	0.055	0.004	3.237	0.0501						
3	0.559	**0.570**	0.564	0.564	0.026	0.020	0.021	0.035	0.108	0.9543						
4	0.543	0.547	0.565	**0.572**	0.014	0.016	0.020	0.020	2.554	0.0918						
5	0.552	0.561	0.559	**0.578**	0.013	0.010	0.025	0.013	1.788	0.1899						
6	0.539	0.562	0.556	**0.570**	0.014	0.011	0.021	0.007	3.298	0.0475*	**		**			
7	0.547	0.563	0.565	**0.565**	0.010	0.017	0.013	0.018	1.308	0.3063						
8	0.555	**0.569**	0.569	0.565	0.025	0.009	0.012	0.012	0.682	0.5761						
9	0.554	0.567	0.569	**0.571**	0.025	0.019	0.018	0.018	0.571	0.6419						
10	0.554	0.560	0.566	**0.569**	0.011	0.017	0.008	0.018	0.878	0.4732						
11	0.562	0.567	0.569	**0.571**	0.012	0.009	0.022	0.016	0.242	0.8660						
12	**0.572**	0.566	0.567	0.571	0.006	0.005	0.005	0.021	0.270	0.8462						
13	0.566	0.571	0.571	**0.574**	0.014	0.012	0.013	0.005	0.334	0.8006						
14	0.565	0.570	**0.577**	0.573	0.014	0.017	0.007	0.010	0.670	0.5828						
15	0.569	**0.588**	0.581	0.577	0.014	0.016	0.012	0.013	1.309	0.3061						
16	0.577	0.579	**0.597**	0.587	0.011	0.017	0.014	0.011	1.816	0.1848						
17	0.585	0.583	0.585	**0.593**	0.008	0.010	0.008	0.012	0.926	0.4508						
18	0.583	**0.587**	0.581	0.581	0.015	0.009	0.005	0.006	0.359	0.7837						
19	0.586	0.576	0.578	**0.591**	0.010	0.009	0.010	0.014	1.639	0.2200						
20	0.587	0.588	0.584	**0.591**	0.010	0.017	0.008	0.012	0.216	0.8840						
21	0.580	**0.587**	0.586	0.586	0.004	0.012	0.005	0.010	0.659	0.5890						
22	0.594	0.581	0.588	**0.598**	0.010	0.010	0.007	0.020	1.385	0.2834						
23	0.589	**0.595**	0.579	0.583	0.004	0.011	0.012	0.009	2.377	0.1082						
24	0.592	**0.599**	0.581	0.582	0.008	0.019	0.009	0.012	1.730	0.2010						
25	**0.610**	0.595	0.583	0.584	0.009	0.011	0.011	0.007	6.739	0.0038**		**	**			
26	**0.604**	0.599	0.578	0.592	0.008	0.015	0.014	0.013	3.162	0.0534						
27	0.596	**0.603**	0.594	0.588	0.009	0.013	0.008	0.010	1.471	0.2601						
28	0.595	**0.597**	0.586	0.592	0.008	0.008	0.009	0.015	0.812	0.5056						
29	0.601	**0.601**	0.588	0.596	0.008	0.005	0.014	0.017	1.038	0.4024						
30	**0.605**	0.605	0.582	0.595	0.012	0.007	0.007	0.006	6.342	0.0049**		**		**		
31	0.606	**0.608**	0.581	0.596	0.007	0.011	0.004	0.013	7.172	0.0029**		***		**		
32	0.597	**0.604**	0.583	0.588	0.010	0.004	0.005	0.009	6.359	0.0048**		**		***	**	
33	0.606	**0.607**	0.592	0.603	0.006	0.013	0.010	0.017	1.237	0.3290						
34	0.606	**0.611**	0.587	0.584	0.007	0.009	0.009	0.016	5.993	0.0061**		**	**	**	**	
35	**0.605**	0.603	0.594	0.594	0.014	0.010	0.005	0.011	1.269	0.3185						
36	**0.602**	0.596	0.596	0.582	0.007	0.012	0.004	0.006	5.398	0.0093**			**			
37	**0.604**	0.601	0.589	0.596	0.005	0.011	0.010	0.013	1.864	0.1764						
38	0.600	**0.607**	0.586	0.600	0.004	0.004	0.016	0.011	2.937	0.0650						
39	0.605	**0.608**	0.596	0.602	0.004	0.008	0.013	0.006	1.529	0.2453						
40	**0.612**	0.610	0.595	0.596	0.009	0.013	0.009	0.010	3.006	0.0612						
41	**0.608**	0.605	0.587	0.589	0.007	0.008	0.007	0.013	5.712	0.0074**		**	**	**		
42	**0.605**	0.604	0.591	0.596	0.005	0.010	0.015	0.007	1.605	0.2274						
43	0.605	**0.605**	0.585	0.594	0.015	0.010	0.006	0.014	2.664	0.0831						
44	0.613	**0.614**	0.594	0.600	0.009	0.010	0.007	0.011	4.600	0.0167*		**		**		
45	**0.611**	0.608	0.583	0.595	0.011	0.009	0.009	0.017	4.402	0.0194*		**		**		
46	**0.608**	0.602	0.589	0.599	0.009	0.009	0.009	0.007	3.502	0.0400*		**				
47	0.606	**0.615**	0.594	0.598	0.004	0.006	0.011	0.006	6.280	0.0051**	**		**	**	**	
48	**0.606**	0.605	0.588	0.597	0.007	0.007	0.007	0.008	5.384	0.0094**		**		**		
49	**0.619**	0.608	0.590	0.599	0.009	0.008	0.006	0.005	12.376	0.0002***		***	**	**		
50	0.609	**0.611**	0.589	0.594	0.006	0.007	0.010	0.010	6.225	0.0053**		**	**	**	**	

DS_1 for $k = \{2, ..., 50\}$, with $\bar{X}$ representing the mean coherence over 5 runs, s the standard deviation, and f and p the one-way ANOVA F-value and p-value, respectively. The last six columns show the post hoc significance thresholds for all six comparison of priors.

Table II reveals that significant differences are obtained starting from $k \geq 25$, although this does not hold for every $k \geq 25$. For $k < 25$, except for $k = 6$, no significant differences are obtained for combinations of priors; asymmetrical or symmetrical priors over α and η have no significant effect on topic coherence. However, the coherence score values for $k < 25$ show slightly higher values (shown in bold) for a symmetrical prior over α compared to an asymmetrical prior. In contrast, for $k \geq 25$, an asymmetrical prior over α shows higher coherence values compared to a symmetrical prior. For all k, where p is significant, SA–SS show no significance and AA–AS show significance only for $k = 6$ and $k = 47$; indicating the marginal importance of symmetrical or asymmetrical priors over η.

We omitted a similar table for coherence score values obtained from DS_2 as, for all $k > 2$, the difference is significant ($p < 0.001$). These significant differences are caused by using

TABLE III
HUMAN TOPIC RANKING FOR DS_2 (ABSTRACT) ON $k = 17$ LDA MODEL

Class	High-quality	Medium-quality	Low-quality
AA	15/17 (88%)	2/17 (12%)	0/17 (0%)
AS	15/17 (88%)	2/17 (12%)	0/17 (0%)
SA	12/17 (70.5%)	4/17 (23.6%)	1/17 (5.9%)
SS	11/17 (64.7%)	6/17 (35.3%)	0/17 (0%)

an asymmetrical prior over α compared to a symmetrical prior. Where DS_1 shows mixed results between different priors over α, for DS_2, every combination of asymmetrical priors over α outperforms symmetrical priors over α.

B. Human Topic Ranking

The results of the fisheries domain expert's human topic ranking are shown in Table III. Human topic ranking was performed on DS_2 for $k = 17$ LDA models, which is the k-value that shows the best coherence score (via elbow method) and, simultaneously, the k-value with the largest difference amongst all prior classes ($f = 41.06$). A similar pattern as found for topic coherence scores can be identified (Figs. 2d–2f): AA and AS with an asymmetrical prior over α result in more high-quality (88%) topics compared to SA and SS with a symmetrical prior over α (70.5% and 64.7% high-quality topics). Both AA and AS perform similarly, indicating that priors over η have no effect on human topic ranking. Furthermore, SA and SS show similar lower human topic ranking, with three topics differently classified: SS has 77.5% of high-quality topics compared to 64.7% for SS, but simultaneously one low-quality topic. A two-dimensional inter-topic distance map for DS_2 with $k = 17$ is displayed in Fig. 3 for all classes of priors. This two-dimensional representation is obtained by computing the distance between topics [36] and applying multidimensional scaling [37]. It displays the similarity between topics concerning their probability distribution over words.

We omitted human topic ranking results for DS_1 as they show an equal number of high-quality and medium-quality topics for all classes of priors and for several arbitrarily chosen k-values ($k < 25$). These results are in line with topic coherence scores that show similar scores for all prior classes (see Figs. 2a–2c). An inspection of $k \geq 25$ LDA models (the point where significant differences between prior classes start) shows an increasing number of incorrect terms for LDA models with a symmetrical prior over α (SA and SS), compared to models with an asymmetrical prior over α.

V. DISCUSSION AND CONCLUSION

Our results show that an asymmetrical prior over α indicates increased topic coherence and topic ranking compared to a symmetrical prior. However, this particularly holds for the DS_2 dataset, the collection of 4,417 abstracts, and not necessarily for the DS_1 dataset, the collection of 8,012 full-text documents. Thus, selecting a different prior on α has large practical implications for datasets containing a smaller vocabulary size and being homogenous in nature. Symmetrical or asymmetrical priors over η show no real benefits regarding topic coherence and human topic ranking.

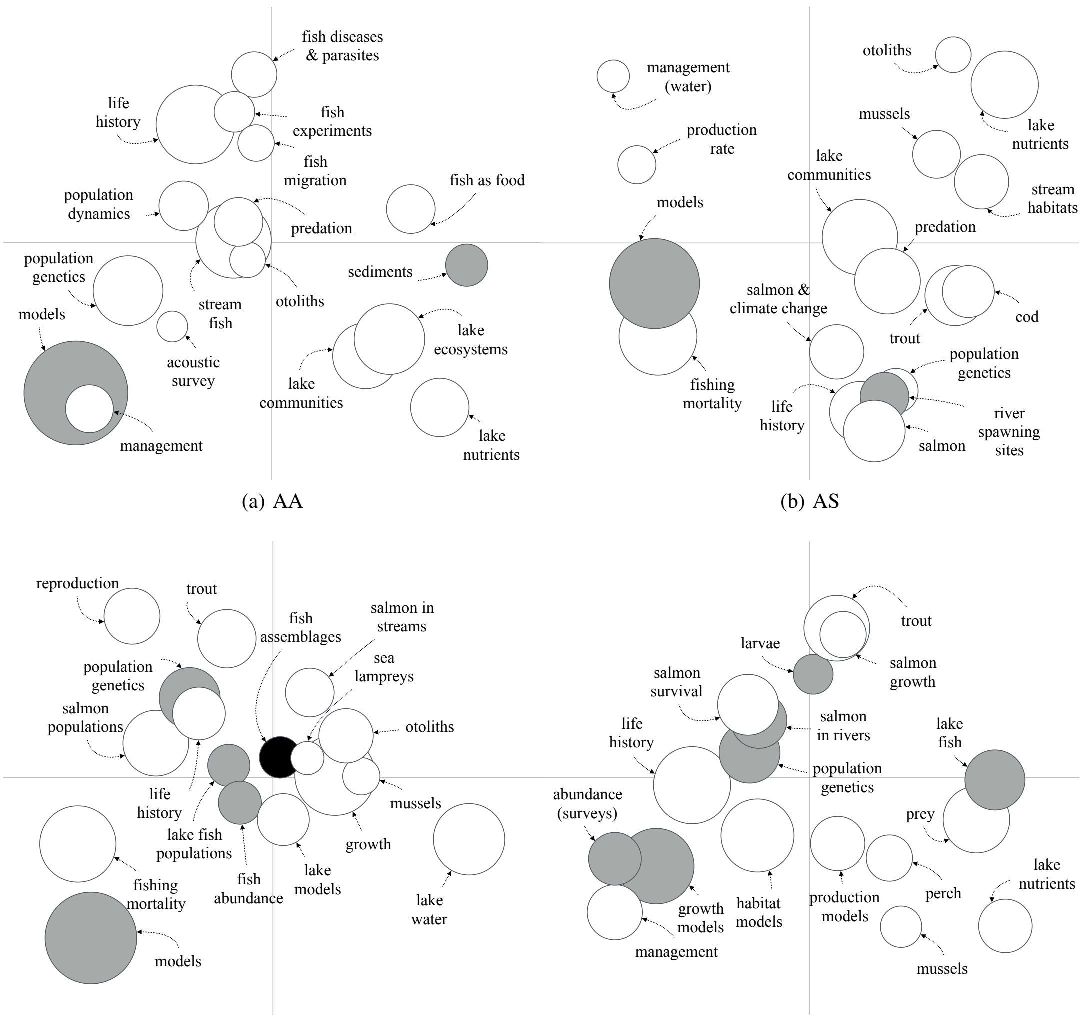
The results on DS_2 are in line with research performed by Wallach *et. al.* [8], which found that an asymmetrical prior over α shows improved likelihood of held-out data and that different priors over η show no real differences. However, our results on DS_1, the full-text dataset with significantly higher vocabulary size and an average number of words per document, found no difference for combinations of priors over α and η, making topic coherence and manual topic ranking less influenced by full-text data.

A symmetrical prior over α assumes that all topics have an equal probability of being assigned to a document. Such an assumption ignores that certain topics are more prominent in a document collection and, consequently, would logically have a higher probability to be assigned to a document. Conversely, specific topics are less common and, thus, not appropriately reflected with a symmetrical prior distribution. Logically speaking, an asymmetrical prior over α would capture this intuition and would, therefore, be the preferred choice. We have empirically shown that this intuition indeed results in significantly higher topic coherence and a better topic ranking for DS_2 and DS_1 for $k \geq 25$. For DS_1 with $k < 25$, the differences are not significant, although human topic ranking shows slightly better topics for the classes with an asymmetrical prior over α.

Concerning priors over η, we naturally want topic–word distributions to be different from each other so as to avoid conflicts between them. A symmetrical prior over η will reflect the power-law usage of words (i.e. some words occur in all topics) while simultaneously resolving ambiguity between topics with a few distinct word co-occurrences [8]. Therefore, symmetrical priors over η are the preferred choice. However, our empirical results indicate no real benefits when varying priors on η; the symmetrical prior shows slight, but still very marginal, overall improved coherence and ranking results for both datasets.

Human topic ranking was based on the presence of incorrect terms being part of the topic's 15 most probable words. A closer look into the reasons why topics are ranked lower reveals that all topics contain correct domain-related terms, but are only ranked lower due to the presence of so-called noise terms (e.g. *used*, *using*, *two*, *among*, *total*, *higher*, *within*, *great*, *large*, *high*, *significantly*). Lower-ranked topics contain a higher number of such terms and, as such, are classified as medium- or low-quality topics. Interestingly, none of the topics have incorrect domain-related terms that could refer to, for example, the biological, ecological, socio-ecological, or social aspects of fisheries. Topics uncovered from abstract data, combined with a symmetrical prior over α, are more prone to contain such noise terms. For full-text data, all classes of priors show an equal but low number of noise words.

A growing amount of research is utilizing LDA to uncover latent semantic structures from scientific research articles as a mean to discover topical trends and developments within a particular research area [17]–[21]. These approaches are



(a) AA

(b) AS

(c) SA

(d) SS

Fig. 3. A two-dimensional inter-topic distance map (via multidimensional scaling) for all classes of priors for DS_2 with $k = 17$. The surface of the node indicates the overall topic prevalence within the corpus. Color coding is used to indicate human topic ranking classification: white = high-quality, grey = medium-quality, and black = low-quality.

often characterized by (i) exploring one or several domain-specific journals, (ii) using abstract data, and (iii) using an open source tool such as Mallet or Gensim to perform LDA. Our approach touches upon all three characteristics; thus, we would recommend an asymmetrical prior over α and a symmetrical prior over η for optimal topic coherence and topic ranking.

Fig. 3 shows a visual representation of 17 latent topics for DS_2. We identify several overlapping topics (e.g. *otoliths*, *population genetics*) and several semantically related topics (e.g. *population dynamics* and *population genetics*; *lake nutrients* and *lake waters*). At the same time, we find several topics occurring in one of the prior classes that are absent in other prior classes. For instance, *fish diseases and parasites* occurs only in AA (Fig. 3a). One reason might be that manual topic labeling is limited by the subjectivity inherent in human interpretation [38]; indeed, an analysis of the topics by another domain expert could yield contradictory results. Another reason might be due to the probabilistic nature of LDA, where differences are merely a result of differences in sampling. Although such analysis is outside the scope of this research, it is an interesting directive for future research. Furthermore, the research performed by Wallach *et. al.* was applied on corpora related to patent, newsgroup and news data, whereas this paper analyzed scientific research articles. Future research might focus on different types of scientific articles, more broadly oriented journals, or other unexplored forms of textual data to gain more insights into the practical effects Dirichlet priors have on LDA's latent topics.

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