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# Evaluation of the Latent Dirichlet Allocation for Modeling News Topics of Nusantara Capital City

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## Abstract.

**Purpose:** Acquiring research on the examination of news topic modeling pertaining to the Nusantara capital city in national mass media coverage becomes challenging. This study not only covered topic modeling of Nusantara Capital City, but also evaluated the LDA model for topic analysis to ensure its appropriate use by future researchers.

**Methods/Study design/approach:** The data used in this study is news about the Nusantara capital city. The data was taken from Indonesian online mass media, namely Detik and Kompas. The data used was 1050 from Detik, and 448 from Kompas. This research was conducted through experiments on several LDA parameters such as the number of documents, max\_features, and the number of topics. The main library used comes from Scikit Learn. It is important to make sure the libraries used in the program code will affect the results due to the algorithms used.

**Result/Findings:** The greater the volume of data and maximum features, the longer the computation time. Models require additional time to evaluate extensive data and increased features. The number of epochs necessary for convergence generally escalates with an increase in data volume and feature count, signifying a rise in model complexity. The greater the quantity of data and features, the more negative the log-likelihood value becomes, and the perplexity similarly tends to rise. This suggests that models were increasingly challenging to predict precise outcomes as the number of variables and data expands. The log-likelihood convergence increased with the number of iterations; however, the needed iterations may vary based on the model's complexity and the data included. Establishing the convergence threshold is crucial. This study employed threshold values as 1e-2 (0.01), to ascertain whether log-likelihood changes were deemed insufficient, necessitating the cessation of the training procedure. The algorithm employed to update the model parameters influences the rate of convergence. Certain algorithms may converge more rapidly than others when compared to Gibbs sampling and online variational Bayes.

**Novelty/Originality/Value:** This research is the initial research on topic modeling. As follow-up research of LDA model evaluation, Dynamic Topic Modeling (DTM) can be a very relevant and interesting topic. If this study focuses on the evaluation of LDA that is static, then the next study can provide an additional dimension by analyzing how the topic changes over time, which the LDA model cannot reach.

**Keywords:** LDA, IKN, model evaluation, log-likelihood, perplexity

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## INTRODUCTION

The ratification of the Draft Law on the Nusantara Capital City (IKN) into Law (UU) by the House of Representatives of the Republic of Indonesia and the government was carried out on January 18th, 2022. The day is an important milestone in the development of the Indonesian nation. Thus, Indonesia will have a new Nusantara Capital City to replace the city of Jakarta. The relocation of the IKN has several interests both in terms of economy [1], [2], traffics [3], overpopulation, and administrative efficiency [4], as well as other complex interests [4], [5]. In terms of economic importance, in accordance with Indonesia's vision 2045, the nation's economy will be part of the world's top five in 2045. The estimated GDP per capita in 2025 is US\$ 23,119. Thus, Indonesia needs economic transformation to achieve Indonesia's Vision 2045 [6]. Economic transformation requires support for the utilization of human resources, infrastructure, regulatory simplification, and bureaucratic reform starting from 2020-2024 so that industrial down streaming is supported. The relocation of the IKN is expected to be able to support and encourage the economic transformation.

Previous studies have extensively examined IKN. These studies generally discuss the sentiment analysis of IKN using various models such as Support Vector Machine [7], Orange application [8], [9], Naïve Bayes [10], [11], Long Short-Term Memory (LSTM) [12], [13] and word2vec [12], Feature Selection [14] and other research. Research related to topic modeling was [9] which found that there were topics such as hajj

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54 funds, the topic of the younger generation, the topic of local wisdom, the topic of tourism, and environmental topics related to the transfer of the IKN on Twitter. Nonetheless, acquiring research on the examination of news topic modeling pertaining to the Nusantara capital city in national mass media coverage becomes challenging. According to [15] the national mass media has a central role in conveying information and shaping public opinion regarding the relocation project of the archipelago's capital city. This study not only covered topic modeling, but also evaluated the model for topic analysis to ensure its appropriate use by future researchers or the government.

36 Topic modeling is a process that aims to identify and group topics in a large set of text documents automatically. This is important because the increasingly abundant text data often contains scattered information and is difficult to interpret manually. With topic modeling, users can obtain a summary of the topics or themes contained in the document, so that the data analysis process becomes more efficient [16]. The most used algorithm for topic modeling is Latent Dirichlet Allocation (LDA), which works by grouping words in documents that have statistical similarities to form a specific topic [17], [18].

5  
4 LDA assumes that each document is a mixture of several topics, and each topic is a distribution of specific words. In the LDA model, each word in the document is selected based on a topic-dependent multinomial distribution, which allows this model to identify patterns and correlations between words [19]. Although LDA has been shown to be effective in finding latent topics in text data, this model has its drawbacks. Because the training is unsupervised, the results obtained need to be evaluated to ensure the quality of the topics produced [20].

Evaluation of topic models such as LDAs is carried out to determine whether the model is reliable and provides meaningful representation of topics. There are several evaluation methods used, including: (a) Intrinsic Evaluation: Includes an assessment of topic coherence or internal quality of the topic produced. Topic coherence can measure how consistent words are in a topic, usually through techniques such as the eyeball model or the top N words [21]. (b) Extrinsic Evaluation: Focuses on applying the model to a specific task, such as text classification, to assess how well the model solves the task [22].

17 Topics in LDA topic modeling are unique because they are based on probabilistic representations. Since the LDA model is unsupervised and still equipped with hyperparameters, it is necessary to evaluate that the model has produced the right results. In this study, in addition to looking at the quality of coherence, it is also important to pay attention to other metrics, such as metrics that measure convergence speed as well as parameters that affect computational time. Understanding these factors helps in refining the model and optimizing the use of topic modeling in various applications, such as sentiment analysis, document grouping, and text classification. This study aims to explore the evaluation metrics for LDA, especially related to topic coherence and computational time, which have important implications in the development of automated text analysis systems.

## METHODS

35 This study applied the LDA model with libraries from Scikit-learn. The organization produces libraries that are the result of community projects, which are made up of a group of people from all over the world. The library of Scikit-learn used in this study is mainly decomposition, especially LatentDirichletAllocation. The library uses the Bayesian Online Variational algorithm [23]. The model was evaluated using log-likelihood and perplexity. The output is in the form of topics in the document, and the words that make up each topic. The research conducted as follows:

23 LDA models can be run by using several libraries such as: "LatentDirichletAllocation" from Scikit-learn to create and train LDA models. The "CountVectorizer" library from Scikit-learn to convert text documents into word matrices. The "matplotlib" library is for visualization of results such as log-likelihood and perplexity, and the "numpy" library is for numerical calculations. At the document preprocessing stage, using a collection of news containing the word Ibu Kota Nusantara (IKN). This collection of news was obtained from online news in Indonesia, namely Detik and Kompas. The vectorization stage uses the "CountVectorizer" function to transform the news document into a term-document matrix representation, where each column represents a word, and each row represents a document. There are several parameters that are set (fine tuning) to affect the results, namely *max\_features*, *max\_df*, and *min\_df* [24].

22  
40 Max\_features parameter was used to limit the number of unique words to be used, which helps limit the complexity of the model. In this study, several experiments were carried out on the size of the max\_features parameters. A size of max\_features start from 1000 to 3000, then means that the CountVectorizer will only

retain the 1000 to 3,000 features of the most frequently occurring words (words or terms) based on their frequency of occurrence throughout the corpus [23]. These features will be selected from all the words found in the document. By limiting the number of features to specific number of words, it reduces the complexity and dimension of the text representation that the LDA model will use. The model will only use the words that are considered the most important or appear most frequently in the corpus, which are most likely more relevant to determine the topic than the words that appear very rarely. The `max_df` parameter was set to 0.95, which means that words that appear in more than 95% of documents will be ignored [23] because they are considered uninformative (e.g., common words such as "and", "in", "which", "to" and so on). The `min_df` parameter was set at 2. Words that appear in fewer than two documents will be ignored or removed from the feature set. In other words, words that appear in only one document will be removed, as they are considered too specific to that document and do not contribute enough to the overall analysis.

The initialization of the LDA model was carried out through several stages. Once the document is converted into a word matrix, the LDA model was initialized using the "LatentDirichletAllocation" library from Scikit-learn. The main parameters in the initialization stage were `n_components`, `learning_method`, and `max_iter`. `n_components` parameter is used to determine the number of topics you want to find. In this study, `n_components` set at 10. So, the result of the model is 10 news topics. The `learning_method` parameter in this study was set to be "online". This means that the LDA model uses Bayesian variational online algorithms to process data in small batches. `max_iter` parameter is used to determine the number of iterations to train the model (Scikit Learn, 2024). This research used a `max-iter` of 7400. The hyperparameters in this study, namely alpha and beta, were set according to the default value of Scikit-learn, which is  $1/n\_components$ . Alpha is the parameter of the previous Dirichlet form for the distribution of topics per document, while beta will control the distribution of words per topic [25].

The training stage of the LDA model was carried out by running the training process by calling the function "lda.fit()" on the word matrix (the result of "CountVectorizer"). During the training, log-likelihood and perplexity calculations were also performed to evaluate the model's performance. Log-likelihood is a measure of how well the model describes the data. The higher the log-likelihood, the better the model is at capturing the data structure. Perplexity is another metric that is often used to evaluate the quality of LDA models, and it usually decreases as log-likelihood increases. Lower perplexity values indicate better models [26] When log-likelihood converges, the perplexity will also stop changing or reach the optimal value. Both are indicators that the model has reached an equilibrium point so it does not require longer training. After the model is trained, the process of extracting the topics and words that appear most often in each topic is carried out. Each topic consists of a collection of words with a certain probability of occurrence.

## RESULT AND DISCUSSION

### Model Evaluation based on Log-likelihood dan Perplexity.

Log-likelihood is a measure used in statistics to assess how well a probabilistic model predicts the data observed. It is based on the likelihood or "match" model, which measures the probability that the observed data (e.g., News in Latent Dirichlet Allocation/LDA) is generated by the model used. In other words, likelihood measures how likely it is that the data is given certain model parameters.

The log-likelihood in LDA is formulated as the sum of the log-likelihood of each document. For each document, likelihood was calculated based on the distribution of topics per document and the distribution of words per topic learned by the model.

In simple terms, the log-likelihood is calculated using the following formula [27]:

$$\text{Log - likelihood} = \sum_{d=1}^D \log P(W_d | \theta_d, \phi) \quad (1)$$

Equation (1) describe as  $D$  is the number of documents in the corpus.  $W_d$  is a collection of words in a document  $d$ . Furthermore,  $\theta_d$  is the topic distribution for  $d$  (topic distribution) documents. The  $\phi$  parameter is the word distribution for each topic. Finally  $P(W_d | \theta_d, \phi)$  is the probability that the document  $d$  is generated from the distribution of the topic  $\theta_d$  and the distribution of  $\phi$  words.

4 Tabel 1 shows the results of the evaluation of the document. The evaluation was carried out through several experiments on news documents about the IKN in two national mass media, Detik and Kompas. The experiments were carried out by trying several combinations of max\_features and n-components. This experiment is to see the computational time to achieve the convergent log-likelihood condition, the number of iterations to the convergent log-likelihood of the convergence, the magnitude of the log-likelihood and perplexity in the last iteration. To further explain the ability of the LDA model to find the right topic, experiments were carried out up to a maximum of 7400 iterations.

Table 1. The experiment of number of documents, max-features, n-components

News Source	Number of documents	Max-features	n-components	Compute time	Number epoch of convergence	Log-Likelihood at last iteration	Perplexity at last iteration
Detik	1050	1000	10	54 min 59 sec	2748	-989389,36453	409,540963
Detik	1050	2000	10	46 min 31 detik	2246	-1264029,571543	700,3040484
Detik	1050	3000	10	1 hr 40 min	3786	-1417555,14344	936,524625
Kompas	448	1000	10	19 min 28 sec	2096	-423467,26324	653,712141
Kompas	448	1500	10	16 min 16 sec	1811	-498486,85924	989,198198
Kompas	448	2000	40	41 min 2 sec	7389	-589774,22501	991,137198

Based on Table 1, an analysis was obtained regarding the changes in the "max-features" parameter and the Number of Data/Documents that affect the computing time, convergence, log-likelihood, and perplexity in the model.

11  
46 First, the influence of the number of data/documents: documents with a total of 1050 take longer compared to data or documents totaling 448. This is natural because the more data is processed, the longer the computing time will take. The number of epochs needed to achieve convergence tends to be greater in data totaling 1050 compared to data totaling 448. Log-likelihood values for larger data (1050) tend to be more negative, indicating that the model is trying harder to adapt to more complex data. Meanwhile, perplexity values also tended to be lower at 1050 data than at 448 data, suggesting that the model was better able to predict larger data than smaller data.

Second, the effect of Max-Features on the same amount of data is 1050: With a fixed number of data (1050), increasing the number of max-features from 1000 to 3000 increases the compute time. In this study, from 54 minutes 59 seconds (1000 features) to 1 hour 40 minutes (3000 features). This indicates that the more features are considered, the more complex the model will be and the longer it will take to calculate it. The number of epochs required for convergence varies, but generally increases with the increasing number of features. This indicates that the model needs more iterations to adapt to more complex features. Log-likelihood tends to be increasingly negative with an increase in the number of max-features. This can mean that the model has more parameters to optimize so it tends to give more negative probabilities. Meanwhile, the perplexity value is also increasing, which suggests that with more features, it is increasingly difficult for the model to make accurate predictions.

41 Third, the effect of Max-Features on smaller data, i.e. 448: on smaller data (448), the increase in max-features from 1000 to 2000 still shows an increase in compute time, although not as large as the 1050 data. The increase from 1000 to 2000 max-features increases the compute time from 19 minutes 28 seconds to 41 minutes 2 seconds. The number of epochs for convergence increased quite significantly from 2096 (1000 features) to 7389 (2000 features), suggesting that the model required more iterations to adapt to a larger number of features. Log-likelihood is getting more negative with the increase in max-features, suggesting that the addition of features adds to the complexity of the model. The perplexity value also increases with the increase in max-features, which indicates that the accuracy of the model's predictions decreases.

Figure 1 and Figure 2 show the log-likelihood and perplexity sequentially in the news documents about the IKN in the Detik media.

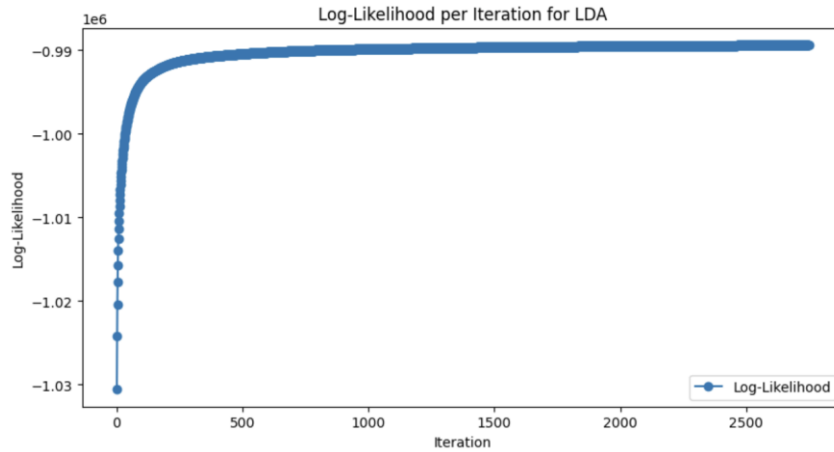


Figure 1. Log-Likelihood on data from Detik.com

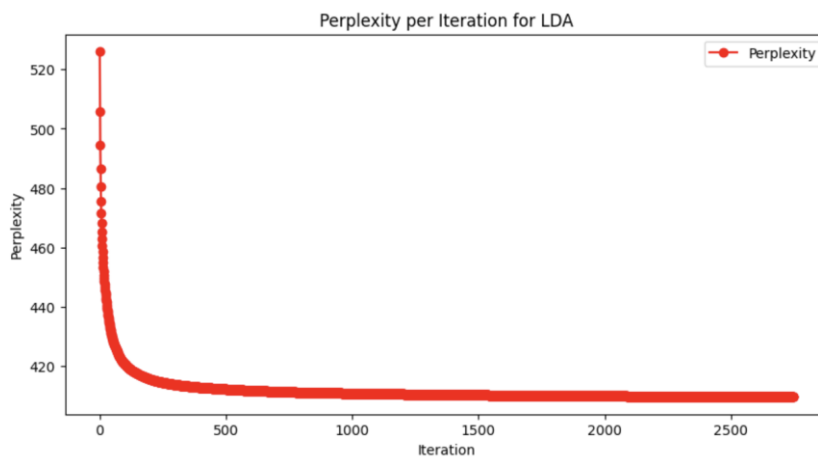


Figure 2. Perplexity on data from Detik.com

An experiment was also carried out on IKN news data in Kompas.com with the number of documents or news about IKN as many as 448. The parameter condition of the number of topics is 10, the number of features is 1500, then the log-likelihood and perplexity are obtained as shown in Figure 3 and Figure 4.

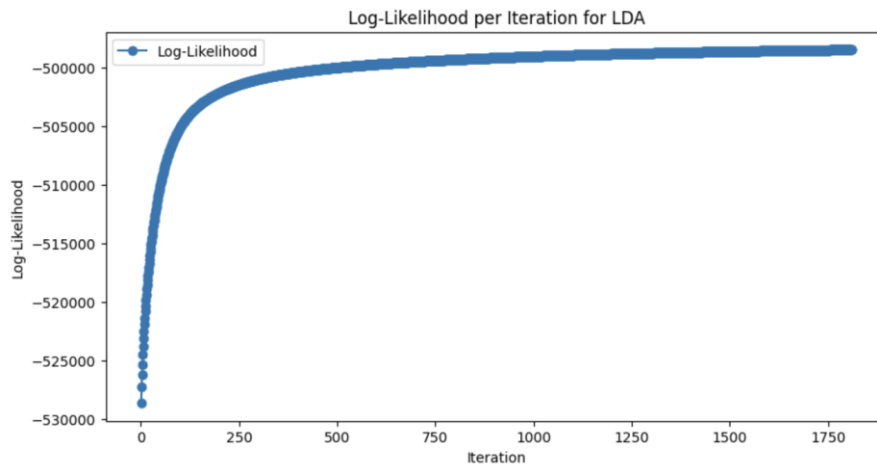


Figure 3. Log-Likelihood on data from Kompas.com

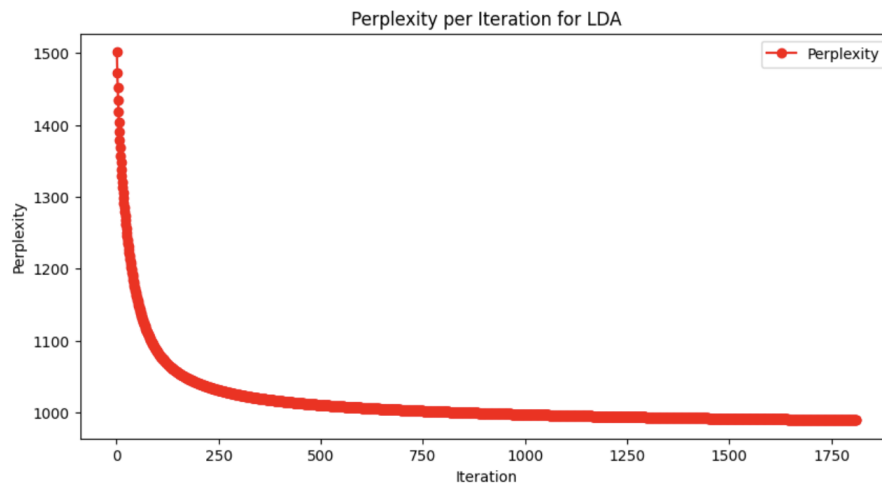


Figure 4. Perplexity on data from Kompas.com

The experiment led to discussion that are convergent log-likelihood is a state in which log-likelihood (i.e., a measure of how well a probabilistic model explains data) stops changing significantly after a certain number of iterations in the model training process. In the context of a model such as Latent Dirichlet Allocation (LDA), log-likelihood is measured at each iteration, and the goal is to maximize this value. Figure 1, Figure 2, Figure 3, Figure 4 meet the expectation that when the log-likelihood increases (towards zero), then the perplexity value decreases, which indicates that the model is getting better at predicting the words in the document. A high log-likelihood (closer to zero) generally indicates that the model has a good ability to adjust to the data it has been trained on, while a low perplexity indicates that the model has good generalization ability for new data. Perplexity is often used in the evaluation of LDA models on test data to see if the model is overfitting or not. If the perplexity is high, it means that the model is having trouble predicting new data, which could indicate overfitting.

Log-likelihood convergence occurs when the log-likelihood value is stable, i.e. the difference between the log-likelihood in the  $n$ th iteration and the  $n+1$  iteration is small (smaller than the predefined threshold, i.e.  $1e-2$ ). At this point, it can be said that the models have converged. This indicates that the model has reached an optimal point, where updates to the model's parameters (such as topic distribution in the document and word distribution in topic) no longer result in a significant improvement in the model's fit to the data. Convergence shows that the model has "learned" from the data well [28]. When log-likelihood is already convergent, stopping further iterations is usually done, as continuing the iteration will not provide a significant benefit.

This study used Scikit-Learn, especially the LatentDirichletAllocation library. According to [23] the LDA model uses Bayesian variational optimization algorithms. The training process involved iterations where the model's parameters were updated at each step. Bayes' Online Variational algorithm makes it possible to break the process into small sizes (batches) [29], as well as perform parallel data processing [30]. This algorithm uses stochastic optimization, which is an optimization approach that uses only a portion of the data (or mini batch) of the entire document corpus in each iteration. Instead of processing the entire corpus at once, the algorithm only takes a small sample or subset of the document at each step. This method helps reduce computational time and allows for faster model updates.

#### Model Evaluation based on human judgement.

Often the easiest way to evaluate is to just look at the output of the model [31] Evaluating the quality of the model by examining the top words of each topic is the simplest way to see the quality of the model. Table 2 shows the distribution of words on each topic generated. The parameters in the results are max\_features = 1000 and n\_components = 10 with the total amount of detik.com data amounting to 1050.

Table 2. The comparison of topics generated in the first and last epoch on documents from Detik

First Epoch	Last Epoch (2748th)
Topic 0: ikn pembangunan gibran rp triliun jokowi kota indonesia presiden ibu	Topic 0: gibran prabowo ikn ganjar pembangunan cawapres program <b>pak</b> mahfud presiden
Topic 1: kota ikn bandara makassar tanah ibu masyarakat baik operasional <b>orang</b>	Topic 1: indonesia ekonomi jokowi ibu tahun masyarakat kota investasi kerja presiden
Topic 2: ikn jokowi nusantara groundbreaking proyek hotel investasi kota investor ibu	Topic 2: ikn nusantara jokowi hotel investor proyek groundbreaking investasi ibu pembangunan
Topic 3: indonesia tahun hari ekonomi ibu nasional kota rp <b>ma</b> sebesar	Topic 3: hari rp tahun kota jakarta biaya bangunan indonesia juta harga
Topic 4: ikn kota pembangunan nusantara bangunan ibu rumah dibangun indonesia gedung	Topic 4: ikn kota nusantara pembangunan lingkungan ibu kawasan bangunan otorita oikn
Topic 5: ikn asn kementerian kota pemerintah nusantara negara tahun ibu pindah	Topic 5: ikn asn pemerintah jakarta rp tahun triliun negara kota kementerian
Topic 6: pks ibu ganjar <b>mengatakan tetap</b> ikn kota jakarta prabowo nusantara	Topic 6: pks ibu kota jakarta undang <b>mengatakan tetap</b> ikn sohibul kampanye
Topic 7: jalan hari ikn tol kota listrik balikpapan kendaraan kawasan bus	Topic 7: ikn balikpapan kota kalimantan air jalan tol bandara km timur
Topic 8: kota ikn jakarta anies undang <b>baru</b> ibu indonesia pemerataan imin	Topic 8: kota ikn anies indonesia baru imin pembangunan cak membangun pemerataan
Topic 9: desember pembangunan ikn rusun negara juli masjid tower ibu pekerjaan	Topic 9: ikn pembangunan masjid kantor infrastruktur negara jokowi rumah pekerjaan Menteri

Table 2 shows that in the first iteration, the focus of the topic was more general, leading to the infrastructure and physical development aspects of the IKN. The role of political figures is not very prominent. In the 2748th iteration, some topics underwent an evolution with a greater emphasis on political issues and broader economic impacts. There are more mentions of political figures such as Gibran, Prabowo, Ganjar, and Mahfud, as well as details on investment and development costs. Overall, the 2748th iteration appears to be more specific, with more mature topics focused on more complex issues, such as politics, economics, and development costs. This shows that the model appears to have successfully constructed a topic that has a specific distribution of words on that topic.

Table 3 shows the results of topics and the distribution of topical words in documents/news in Kompas.com. The experimental parameters on the document are max\_features = 1000 and n\_components = 10 and the data totals 448 documents.

Table 3. The comparison of topics generated in the first and last epoch on documents from Kompas

First Epoch	Last Epoch (2096th)
Topic 0: tol jalan persen seksi infrastruktur kementerian danis segmen pembangunan kariangau	Topic 0: tol jalan danis pembangunan seksi proyek infrastruktur segmen kementerian kkt
Topic 1: pembangunan nusantara tahap infrastruktur kawasan presiden istana ibu air pekerjaan	Topic 1: pembangunan presiden bandara tahap istana persen proyek vvip nusantara infrastruktur
Topic 2: kalimantan tahun balikpapan lebaran april pertahanan kendaraan persen nusantara timur	Topic 2: balikpapan kendaraan tol samarinda mudik penumpang bandara lintas hari jalan
Topic 3: nusantara ibu oikn balikpapan pembangunan bambang otorita indonesia hotel baru	Topic 3: nusantara pembangunan oikn ibu indonesia otorita teknologi bambang lingkungan tahun
Topic 4: balikpapan persen kaltim kalimantan samarinda provinsi tni timur daerah tahun	Topic 4: balikpapan persen kaltim kalimantan <b>sebesar</b> pertumbuhan harga timur tahun inflasi
Topic 5: pembangunan ppu masyarakat warga kabupaten pemerintah nusantara tahun oikn ibu	Topic 5: ppu masyarakat warga kabupaten pembangunan sepaku oikn penajam tanah pemerintah
Topic 6: rp proyek triliun <b>sebesar</b> pt nusantara pembangunan miliar tahun ibu	Topic 6: rp triliun investasi miliar nusantara groundbreaking proyek tahun agung Bambang
Topic 7: investasi proyek agung industri groundbreaking suara timur teknologi balikpapan nusantara	Topic 7: proyek investasi balikpapan kalimantan timur industri tahun air bkpm rp
Topic 8: asn kementerian tower pembangunan rusun tanah investasi bkpm rp unit	Topic 8: asn jakarta nusantara ibu presiden menteri rusun <b>jokowi</b> tower jadi
Topic 9: rumah pembangunan nusantara menteri ibu rtjm unit persen pekerja konstruksi	Topic 9: rumah pembangunan konstruksi unit rtjm menteri pekerjaan pupr jabatan nusantara

16 The results of human observation show that the distribution of words on each topic in Table 3 shows that the results of iteration 1 and the last iteration (2096th) show a relatively relevant distribution of words. Each topic undergoes changes that reduce the appearance of common words, narrowing the topic to be more relevant to a specific context, such as transportation, economic growth, and the role of government in regional development.

## CONCLUSION

Based on the discussion lead us to conclusion as follows:

1. The larger the amount of data and max-features, the higher the computing time. Models need more time to process larger data and more features.
- 11 2. The number of epochs required to achieve convergence tends to increase as the amount of data and the number of features increases, indicating that the complexity of the model increases.
3. The more data and features, the more negative the log-likelihood value, and the perplexity also tends to increase. This indicates that models are becoming more difficult to predict accurate outcomes with an increase in the number of features and data.
- 50 4. The more iterations, the more likely log-likelihood to approach convergence, but depending on the complexity of the model and data, the number of iterations required can vary.
5. Setting the convergence threshold is very important. In this study, threshold values such as 1e-2 (0.01) were used to determine when log-likelihood changes were considered too small and the training process should be stopped.
6. The algorithm used to update the model parameters also affects the convergence speed. Some algorithms can be faster in achieving convergence than others compared to gibss and online variational bayes.

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