BIDIRECTIONAL AND AUTO-REGRESSIVE TRANSFORMER (BART) FOR INDONESIAN ABSTRACTIVE TEXT SUMMARIZATION

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Abstract

Automatic summarization technology is developing rapidly to reduce reading time and obtain relevant information in Natural Language Processing technology research. There are two main approaches to text summarization: abstractive and extractive. The challenge of abstractive summarization results is higher than abstractive because abstractive summarization produces new and more natural words. Therefore, this research aims to produce abstractive summaries from Indonesian language texts with good readability. This research uses the Bidirectional and Auto-Regressive Transformer (BART) model, an innovative Transformers model combining two leading Transformer architectures, namely the BERT encoder and GPT decoder. The dataset used in this research is Liputan6, with model performance evaluation using ROUGE evaluation. The research results show that BART can produce good abstractive summaries with ROUGE-1, ROUGE-2, and ROUGE-L values of 37.19, 14.03, and 33.85, respectively.

Keywords: Abstractive summarization, BART, Natural Language Processing, Transformers

1. Introduction

In the current digital era, the internet has become an important source of information for society. This information continues to grow over time, this can make information users increasingly confused in choosing the information they want to read (Laksana et al., 2022). One piece of information that will continue to increase is news content. Online news content can provide the latest information on various topics, from politics, economics, to entertainment. A very large explosion of information can make it increasingly difficult for readers to understand all the information at one time. Reading all the news at one time will take a lot of time, besides this news text is not written briefly but is written in long form (Laksana et al., 2022). Therefore, to overcome this problem is to provide a summary of the news to make it easier for readers to understand the content of the news.

Text summarization is one way to solve the problem of news texts that are too long. Text summarization aims to represent long documents by summarizing information so that it can be easily understood by readers (Abualigah et al., 2020; El-Kassas et al., 2021; Joshi et al., 2019). Text summarization can be implemented in two methods, namely extractive and abstractive. Extractive text summarization is an approach where the system selects existing pieces of text from the source text and combines them into a summary (Moratanch & Chitrakala, 2017; Rahimi et al., 2017; Shirwandkar & Kulkarni, 2018; Zhong et al., 2020), while abstractive text summarization is an approach where the system produces a summary that not only matches existing phrases, but also creates new phrases to convey the essence of the text more concisely (Kasture et al., 2014; Moratanch & Chitrakala, 2016; Rush et al., 2015).

Abstractive summarization for Indonesian text involves generating concise summaries by interpreting and rephrasing the original content, aiming to capture the essence of the document like a human would (Dewi & Widiastuti, 2022; Laksana et al., 2022). This approach is crucial in handling the information overload on the internet, especially for under-resourced languages like Indonesian (Wijayanti et al., 2021). Various techniques, such as Dual Encoding models and BERT pre-trained models, have been explored to enhance abstractive summarization in Indonesian, with evaluations based on ROUGE values to measure the quality of the summaries (Huda et al., 2022; N. Lin et al., 2022). There is a lot of previous research related to text summarization, one of which is research conducted, including Indonesian text summarization research which succeeded in building the IndoSum news portal dataset, then developed by research which produced the largest automatic summarization dataset currently, namely Liputan6, this research uses IndoBERT for extractive and abstractive summarization (Kurniawan & Louvan, 2018; Koto et al., 2020). Other research, regarding abstractive automatic text summarization of Indonesian language news using the BERT method with the IndoSum dataset (Halim et al., 2022). The results of this research for abstractive summarization produced the best F1-Score values for ROUGE-1 of 57.17, ROUGE-2 of 51.27, and ROUGE-L of 55.20, as well as ROUGE-1 of 84.46, ROUGE-2 of 83.21, and

ROUGE-L amounting to 83.40 in the extractive method.

Based on the presentation of several previous studies, there is still potential for further development of text summarization using other transformer models. In his research, Halim suggested using other transformer models such as OpenAI, Generative Pre-training Transformer (GPT), A Lite BERT (ALBERT), and BART. Therefore, this research will use the BART transformer model with an abstractive method to summarize text. The purpose of this research is to determine the performance of the BART model in its application for text summarization and how it compares with the transformer model that has been used previously.

2. Research Methods

Text summarization is a technique of summarizing long documents into a more concise version that is easier for readers to understand (Joshi et al., 2019). This technique is part of Natural Language Processing (NLP), where computers are taught to understand and process human language (Zhang & Liu, 2018). NLP technology allows the system to understand the structure, syntax, and meaning of the source text. There are two approaches to text summarization, namely extractive and abstractive. Extractive summarizes text by selecting and rearranging complete phrases from the source text, while abstractive summarizes text by creating a new summary with semantic and syntactic understanding. This section presents the dataset, BART method, and measurement methods that will be used to produce an abstract summary of Indonesian language texts.

2.1 Research Flow

The research process encompasses the sequential steps undertaken by the researcher from the inception to the conclusion of the study. The specific stages of the research are depicted in Figure 1.

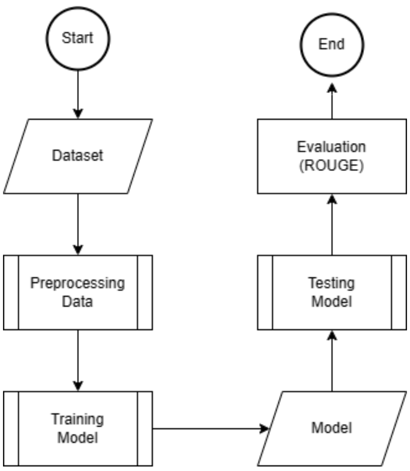

Figure 1. Research Flow

2.2 Liputan6 Dataset

The data used in this research is the Liputan6 dataset which was first introduced as a large-scale collection of Indonesian language news article data, consisting of 193,883 news article data (Koto et al., 2020). The Liputan6 dataset is divided into two types of tests, namely the Canonical variant and the more abstract Xtreme variant. The canonical variant contains a manually generated text summary, while the Xtreme variant contains an automatically generated text summary. This division allows researchers to evaluate the performance of abstract text models at different levels of abstraction. Table 1 presents the distribution of Canonical and Xtreme data contained in the Liputan6 dataset.

Table 1. Statistics for Canonical and Xtreme variants on the Liputan6 dataset (Koto et al., 2020)

Variant	#Doc		
	Train	Dev	Test
Canonical	193,883	10,972	10,972
Xtreme	193,883	4,948	3,862

2.3 Bidirectional and Auto-Regressive Transformers (BART)

Bidirectional and Auto-Regressive Transformers (BART) is an innovative Transformer model that combines two leading Transformer architectures, namely the Bidirectional Encoder Representations from Transformers (BERT) encoder and the Generative Pre-trained Transformer (GPT) decoder (Lewis et al., 2019). BART's advantage lies in its ability to produce bidirectional text output, combining context from left to right and right to left. This capacity produces more coherent and meaningful text than traditional Transformer models.

BART falls into the category of generative models in the fields of Natural Language Processing (NLP) and Machine Learning (ML). This model is based on the Transformer architecture which has proven its success in various NLP tasks, such as text summarization, machine translation, and natural language generation. Combining the BERT encoder and GPT decoder in BART results in a powerful and versatile model. The BERT encoder allows BART to better understand sentence context, while the GPT decoder allows it to produce text that flows naturally and fits the context.

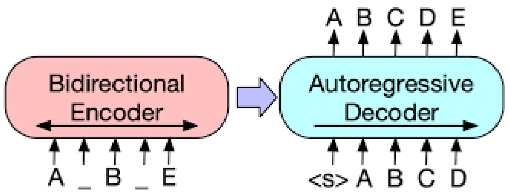

Figure 2. BART Mechanism

The BART mechanism in Figure 2 receives input in the form of text which is converted into tokens, then these tokens will be embedded into vector representation. Then, the encoder will process the vector representation of the input tokens and generate a hidden representation for each token. After that, the decoder will process the hidden representation and produce output tokens auto-regressively. The output of BART is a token that represents the translated or summarized text.

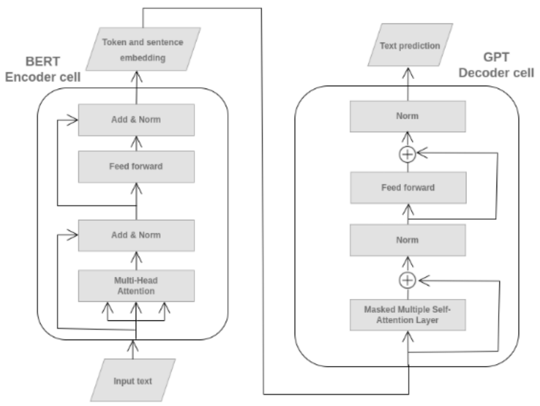

Figure 3. BART single encoder-decoder network architecture

As shown in Figure 3, the architecture of BART consists of a GPT decoder cell and a BERT encoder cell (shashwatswain, 2023). The multi-head attention in each encoder cell processes tokenized raw text; additional pre-processing (such as lowercase, stemming, stopword removal, etc.) is done based solely on the task at hand. Instead of learning the encoding from the mask BERT Encoder cell, the GPT decoder cell receives the masked embedding from the BERT Encoder cell. It passes it to multiple independent masked attention blocks. These blocks follow the same architecture as the multi-head attention block but operate sequentially rather than simultaneously. This layer learns to decode masked embeddings into semantically coherent tokens by considering multiple parallel embeddings of the input text that are masked at different levels.

2.4 Recall-Oriented Understudy for Gisting Evaluation (ROUGE)

ROUGE is one of the metrics commonly used to evaluate the quality of automatically generated text summaries. In this evaluation, the summary produced by the system is compared with the reference summary (gold summary) created by humans, which is the quality standard for the text being summarized (Ng & Abrecht, 2015). ROUGE was chosen for summary evaluation because it has become a standard and widely used in various studies. Two variants of ROUGE were used, namely ROUGE-N and ROUGE-L. ROUGE-N measures recall based on n-grams, while ROUGE-L focuses on the longest common subsequence (C. Y. Lin, 2004). ROUGE-N is used to measure informativeness, namely how much information is similar between the summary produced by the system and the reference summary. Meanwhile, ROUGE-L assesses fluency, looking at how smoothly and in line the word order in the resulting summary is compared to the reference summary (C. Y. Lin, 2004).

ROUGE-N measures the similarity between a machine-generated summary and a gold standard summary by calculating the percentage of n-grams in common. n-gram is a sequence of N consecutive words in a text. Commonly used N values are 1 (ROUGE-1) and 2 (ROUGE-2) (Yuliska & Syaliman, 2020). Equation (1) shows how to calculate ROUGE-N.

$$ROUGE - N = \frac{p}{q} \tag{1}$$

Where, p is the number of n-grams that are the same as the gold standard summary and the text of the machine's summarization results, while q is the number of n-grams in the gold standard summary.

ROUGE-L is a text summary evaluation metric that measures the similarity of the longest word sequence between a machine-generated text summary and a gold standard summary (Yuliska & Syaliman, 2020). ROUGE-L calculation uses equation (2) (Yuliska & Syaliman, 2020). ROUGE-L calculation uses equation (2).

$$ROUGE - L = \frac{LCS}{m} \tag{2}$$

Where LCS is the longest common subsequence and m is the number of words in the gold standard summary

3. Result and Discussion

This section presents research results starting from dataset collection, pre-processing, model building, and model evaluation.

3.1 Text Pre-processing

The pre-processing stage in this research aims to overcome the weaknesses of unstructured data which can hinder model performance. Data pre-processing helps prepare data so that it is easier for the model to understand and process, thereby increasing the efficiency, accuracy, and quality of the resulting summaries.

There are several tasks carried out during this stage, namely tokenization to break the text into smaller units that are easier for the model to process. Next, truncation to ensure all inputs have consistent lengths. After tokenization and truncation, there is the extracting information stage where important information needs to be extracted from the processed text to train the model, and finally there is the preparing input decoder stage which focuses on preparing the input sequence for the decoder part of the model.

3.2 BART Modeling

At this stage, after the data has been processed through the pre-processing stage, the data is ready to be used in the BART model to produce an abstract summary. The BART model and dataset that have been processed then enter the training process. This dataset is divided into two parts, namely training data and test data. The AdamW algorithm was chosen as the optimizer to optimize model performance during training (Yao et al., 2021). AdamW was chosen for its good performance, with modified weight decay to improve training stability and speed (Gkouti et al., 2024). The training process takes place over several epochs, during which the model learns patterns and relationships in the training data to produce accurate summaries.

This research was conducted to determine the performance of abstractive summarization on Indonesian language texts using the BART model. The dataset used is coverage6, and the model used for training is facebook/bart-large-cnn. Therefore, testing or evaluation will be carried out to determine the performance and evaluation results of the model training.

In the model training process, there are several settings in the hyperparameters used, namely learning rate, batch size, and epochs. The learning rate tested was 0.0001, with a per-device train batch size of 8 and a per-device evaluation batch size of 4. The number of epochs tested was 5. Additionally, warmup steps were set to 500, weight decay to 0.01, logging steps to 100, and model checkpoints were saved every 6,250 steps.

The evaluation process is similar to the training process, but the model is not trained but is used to calculate the loss (error rate) on the evaluation dataset. This loss is used as an indicator of model performance, showing whether the model is getting better at producing accurate summaries. Evaluation aims to prevent overfitting, which is a condition where the model focuses too much on the training data and cannot produce a good summary of new data. After the model is created, the testing process will continue to determine the performance of the model that has been trained. Figure 4 shows the training loss of BART model.

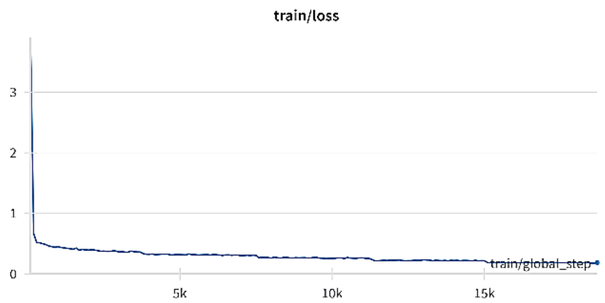

Figure 1. Training loss

3.3 ROUGE Evaluation

This research uses ROUGE-1, ROUGE-2, and ROUGE-L valuations which are commonly used for automatic text summarization research. The results of the evaluation of the trained BART model are in Table 2 and Figure 5. Based on the ROUGE evaluation results, we can see that BART has good results for Xtreme Liputan6 data with an f1 score of 37.19 for ROUGE-1 and 33.85 for ROUGE-L, while ROUGE-2 has a value of 14.03.

Table 2. ROUGE evaluation result

Score	Evaluasi ROUGE		
	ROUGE-1	ROUGE-2	ROUGE-L
Recall	52.28	21.92	48.07
Precision	29.16	10.41	26.39
F1-Score	37.19	14.03	33.85

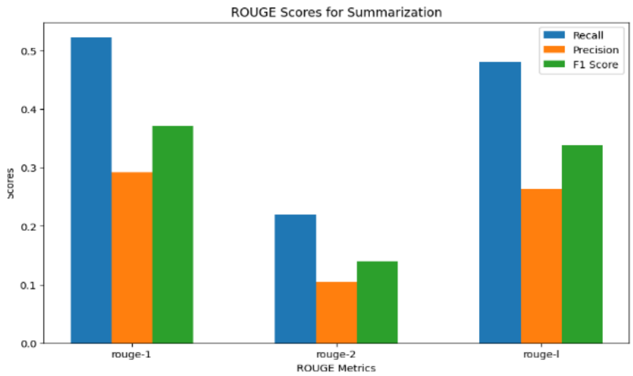

Figure 2. Recall, precision, and F1 score of ROUGE

There have been several previous studies regarding text summarization using Liputan6 as a dataset for abstractive summarization with Xtreme test data, including mBERT (Koto et al., 2020), IndoBERT (Koto et al., 2020), BERT2BERT (Fahluzi, 2024), and Pegasus (Widjaja, 2023). The selection of this dataset becomes a benchmark reference for assessing the performance of models trained on the same dataset. This research presents the results of evaluating the performance of the Indonesian language abstractive summarization model based on the Liputan6 dataset.

Based on the results of model comparisons in previous research presented in Table 3, BART has better results than mBERT and BERT2BERT based on the evaluation of ROUGE-1, ROUGE-2, and ROUGE-L, and better than IndoBERT based on the evaluation results of ROUGE-1 and ROUGE-L. Meanwhile, compared to Pegasus, BART has better summary results based on ROUGE-L evaluation. These results show that overall, BART can be a good model choice for summarizing Indonesian texts in abstractive form. An example of the abstractive summary results produced by BART can be seen in Table 4.

Table 3. Comparison Model

Model	F1 Score of ROUGE		
	R1	**R2**	**RL**
BART (Proposed Model)	37.19	14.03	**33.85**
IndoBERT (Koto et al., 2020)	34.59	15.10	31.19
mBERT (Koto et al., 2020)	33.26	13.82	30.12
BERT2BERT (Fahluzi, 2024)	34.48	14.58	27.36
Pegasus (Widjaja, 2023)	**38.27**	**20.22**	31.26

Table 4. The example of abstractive summaries that generated by BART model

Article I	*Liputan6.com, Jakarta: Tentara Nasional Indonesia hendaknya benar-benar profesional. TNI juga harus berada di atas seluruh kekuatan politik yang ada. Demikian permintaan mantan Presiden Partai Keadilan Sejahtera Hidayat Nur Wahid, di sela-sela Munas PKS, Sabtu (19/6), di Jakarta. TNI adalah alat negara yang harus netral dan berada di atas seluruh kekuatan politik yang ada. Ini untuk menjaga keamanan teritorial dan keutuhan Negara Kesatuan Republik Indonesia, kata Hidayat, seperti ditulis Antara. Menurut Hidayat…*
Reference Summary	*Dalam sebuah Munas PKS di Jakarta, mantan Presiden PKS, Hidayat Nur Wahid, menyerukan agar Tentara Nasional Indonesia (TNI) tetap profesional dan netral. Dia menegaskan bahwa TNI harus berada di atas segala kekuatan politik untuk menjaga keamanan teritorial dan keutuhan Negara Kesatuan Republik Indonesia (NKRI).*
Generated Summary	*Mantan Presiden PKS Hidayat Nur Wahid menegaskan tentara nasional Indonesia harus berada di atas seluruh kekuatan politik yang ada untuk menjaga keamanan teritorial dan keutuhan Negara Kesatuan Republik Indonesia.*
Article II	*Liputan6.com, Jakarta: Presiden Joko Widodo (Jokowi) meresmikan Bendungan Kuningan di Kabupaten Kuningan, Jawa Barat, pada hari ini, Rabu (10/5/2024). Bendungan ini merupakan salah satu proyek infrastruktur strategis nasional yang diharapkan dapat membantu mengatasi kekeringan di musim kemarau, khususnya di wilayah Jawa Barat. Bendungan…*
Reference Summary	Presiden Jokowi meresmikan Bendungan Kuningan di Jawa Barat dengan harapan dapat membantu atasi kekeringan, meningkatkan produktivitas pertanian, dan mendorong pertumbuhan ekonomi. Bendungan ini memiliki kapasitas tampung 15 juta meter kubik, merupakan yang terbesar di Jawa Barat, dan menghabiskan dana Rp 2,2 triliun. Jokowi meminta pemerintah daerah dan masyarakat untuk menjaga dan memelihara bendungan ini.
Generated Summary	Presiden Joko Widodo meresmikan Bendungan Kuningan, salah satu proyek infrastruktur strategis nasional yang diharapkan dapat meningkatkan produktivitas pertanian dan mendorong pertumbuhan ekonomi.
Article III	*CNN Indonesia, Jakarta: Kementerian Kesehatan (Kemenkes) melaporkan bahwa kasus Covid-19 di Indonesia terus menunjukkan tren penurunan dalam beberapa pekan terakhir. Pada hari ini, Kamis (11/5/2024), Kemenkes mencatat terdapat 4.500 kasus baru Covid-19, yang merupakan angka terendah sejak Februari 2024. Meskipun kasus Covid-19 terus menurun, Kemenkes…*
Reference Summary	*Kasus Covid-19 di Indonesia terus menurun, Kemenkes minta masyarakat tetap waspada dan disiplin prokes, terus lakukan 3T untuk tekan penularan. Kemenkes catat 4.500 kasus baru Covid-19 hari ini, terendah sejak Februari 2024. Kemenkes targetkan 100.000 tes Covid-19 per hari dan lacak kontak erat pasien positif.*
Generated Summary	*Kementerian Kesehatan mencatat, pada hari ini, terdapat 4.500 kasus baru Covid-19 yang merupakan angka terendah sejak Februari 2024. Masyarakat diminta waspada dan disiplin untuk menerapkan 3T penularan.*
Article IV	*detikcon, Surabaya: Gempa bumi berkekuatan 5,1 mengguncang Kabupaten Jember, Jawa Timur, pada hari ini, Kamis (11/5/2024), pukul 13.20 WIB. Pusat gempa bumi ini berada di 22-kilometer barat daya Jember dengan kedalaman 10 kilometer. Gempa bumi ini tidak menimbulkan tsunami, namun beberapa bangunan di wilayah Jember mengalami kerusakan. Badan Meteorologi…*
Reference Summary	*Gempa bumi berkekuatan 5,1 guncang Jember, Jawa Timur, tidak ada tsunami, beberapa bangunan rusak, BMKG minta masyarakat waspada dan ikuti informasi dari pihak berwenang.*
Generated Summary	*Gempa bumi berkekuatan 5,1 mengguncang Kabupaten Jember, Jawa Timur, pagi tadi. Beberapa bangunan di kawasan tersebut mengalami kerusakan. Masyarakat diimbau untuk tetap waspada dan tidak panik.*
Article	*Kompas.com, Jakarta: Stadion Gelora Bung Tomo, Surabaya, bergemuruh dengan sorak sorai para pendukung Tim Nasional Indonesia U-19 pada Kamis (11/5/2024) sore. Garuda Muda baru saja menyelesaikan pertandingan terakhir Grup A Piala AFF U-19 2024 dengan hasil gemilang, mengalahkan Vietnam dengan skor 2-1. Kemenangan ini…*
Reference Summary	*Timnas Indonesia U-19 berhasil lolos ke babak semifinal Piala AFF U-19 2024 setelah mengalahkan Vietnam dengan skor 2-1. Garuda Muda akan berhadapan dengan Thailand di babak semifinal. Pertandingan melawan Vietnam berlangsung sengit, dengan Timnas Indonesia U-19 membuka skor terlebih dahulu melalui gol Arkhan Fikri, kemudian disamakan oleh Vietnam, dan akhirnya Ronaldo Kwateh mencetak gol penentu kemenangan. Timnas Indonesia U-19 menunjukkan mentalitas juara dan pantang menyerah di sepanjang turnamen ini. Dukungan penuh dari para suporter menjadi kekuatan tambahan bagi Garuda Muda. Mari kita dukung Timnas Indonesia U-19 untuk meraih mimpi mereka, yaitu membawa pulang trofi Piala AFF U-19 2024 ke Indonesia!*
Generated Summary	*Timnas Indonesia U-19 membuka skor pada menit ke-35 melalui gol tendangan bebas melengkung dari Arkhan Fikri. Di babak semifinal, mereka akan berhadapan dengan Thailand, juara grup.*

To provide a clearer and more detailed understanding of BART's capabilities in producing abstractive summaries, a specific example is presented in Table 4. This table showcases the comparison between the original article, the reference summary, and the summary generated by the BART model. Through this example, one can observe how BART goes beyond merely extracting information from the original article. Instead, it intelligently condenses and rephrases the content into a new, more concise summary. The generated summary demonstrates BART's ability to creatively manipulate language, presenting the core essence of the article in a shorter form, yet often distinct from the original text. Table 4 serves as a clear demonstration of BART's advanced abilities in the field of natural language processing, particularly in generating abstractive text summaries.

4. Conclusion

Conclusion This research successfully demonstrates the capability of the Bidirectional and Auto-Regressive Transformer (BART) model in generating high-quality abstractive summaries for Indonesian language texts. Utilizing the Liputan6 dataset and evaluating model performance using the ROUGE metric, the study finds that BART achieves ROUGE-1, ROUGE-2, and ROUGE-L scores of 37.19, 14.03, and 33.85, respectively. These results indicate that BART can produce summaries with good readability and coherence. When compared to other models such as mBERT, IndoBERT, BERT2BERT, and Pegasus, BART shows competitive performance, reinforcing its effectiveness in handling Indonesian text summarization tasks.

Future research can enhance the effectiveness and applicability of automatic summarization technologies, particularly for low-resource languages like Indonesian. Future research also can extend the research to include multilingual capabilities, allowing the model to handle and summarize texts in multiple languages. This would be particularly useful in multilingual societies and for comparative linguistic studies.

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