



# NEWS RECOMMENDER SYSTEM

Natural Language Processing

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# NEWS RECOMMENDER SYSTEM

News recommender system adalah sistem untuk melakukan proses rekomendasi berita berdasarkan kemiripan dari berita yang pernah dibaca dan topik dari berita sebelumnya



# PROSES YANG DILAKUKAN



## KEYWORD EXTRACTION

Setiap token pada berita akan dilabeli menjadi keyword atau bukan keyword. Output berupa

- kata kunci dari input
  - berita



## TOPIC CLASSIFICATION

List keyword akan dimasukkan ke dalam model klasifikasi untuk mengubah masukan keyword berita menjadi label topik

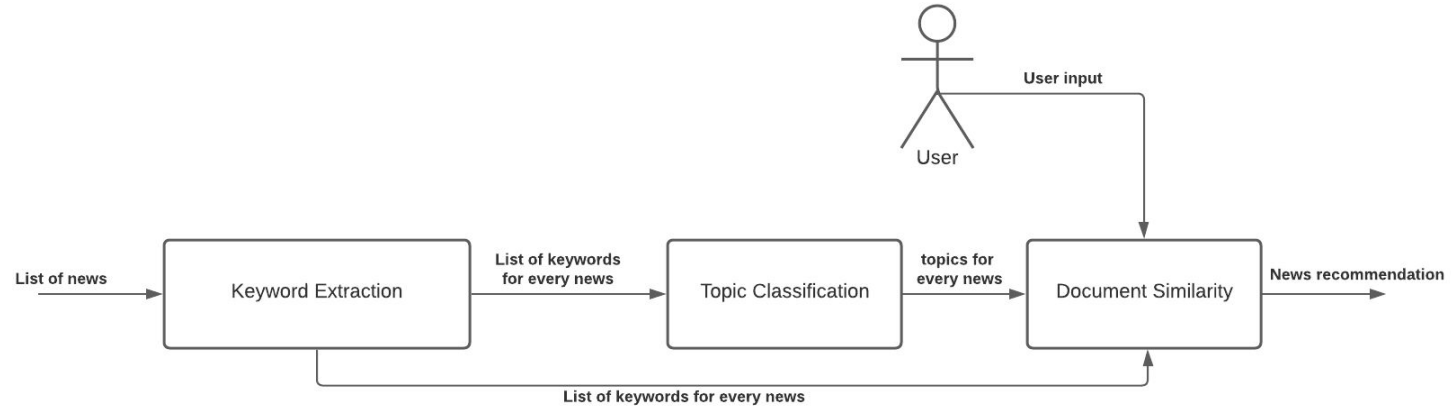


## DOCUMENT SIMILARITY

Kata kunci dari tiap berita yang diperoleh dari keyword extraction akan digunakan untuk memodelkan kemiripan dokumen berita lainnya yang berada dalam satu topik

menghasilkan rekomendasi berita





# KOMPONEN DALAM NRS



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# PIPELINE 1

## KEYWORDS EXTRACTION

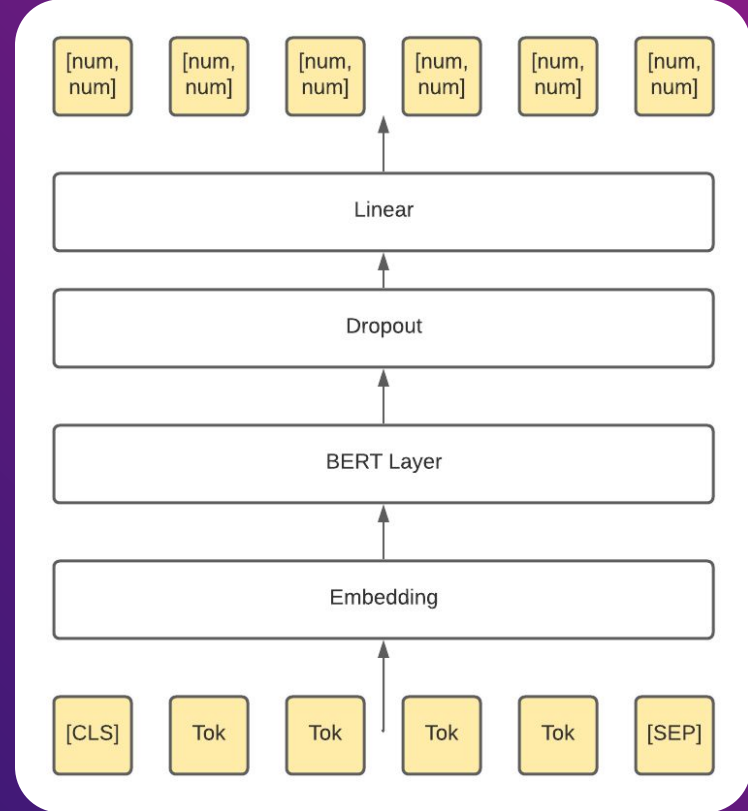
Proses mengekstrak keyword dari berita



# ARSITEKTUR UMUM

Arsitektur model yang digunakan adalah model berbasis BERT yang dipasang fully connected layer pada layer setelah layer attention (layer attention terletak setelah layer embedding) yang menghasilkan nilai untuk setiap token berupa list dua angka, yaitu untuk kelas 0 (bukan keyword) dan kelas 1 (keyword).

Setelah itu, kita akan mencari nilai terbesar dari keduanya untuk menentukan kelas dari masing-masing token.



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# EKSPERIMEN

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# PERBANDINGAN METODE

Eksperimen yang dilakukan adalah dengan mengganti pretrained bert model yang dipakai yaitu bert-based-uncased dan distilbert-base-uncased. Juga mengganti jumlah epoch dari training

# HASIL EKSPERIMEN

distilbert-base-uncased

==== Epoch 1 / 4 =====

Training...

Batch	40	of	276.	Elapsed:	0:00:53.
Batch	80	of	276.	Elapsed:	0:01:46.
Batch	120	of	276.	Elapsed:	0:02:39.
Batch	160	of	276.	Elapsed:	0:03:31.
Batch	200	of	276.	Elapsed:	0:04:24.
Batch	240	of	276.	Elapsed:	0:05:17.

Average training loss: 0.30  
Training epoch took: 0:06:04

Running Validation...

Accuracy: 0.96  
Validation Loss: 0.27  
Validation took: 0:00:16

==== Epoch 2 / 4 =====

Training...

Batch	40	of	276.	Elapsed:	0:00:53.
Batch	80	of	276.	Elapsed:	0:01:45.
Batch	120	of	276.	Elapsed:	0:02:38.
Batch	160	of	276.	Elapsed:	0:03:31.
Batch	200	of	276.	Elapsed:	0:04:24.
Batch	240	of	276.	Elapsed:	0:05:16.

Average training loss: 0.26  
Training epoch took: 0:06:04

Running Validation...

Accuracy: 0.97  
Validation Loss: 0.26  
Validation took: 0:00:16

# HASIL EKSPERIMEN

distilbert-base-uncased

=====  
Epoch 3 / 4  
=====

Training...

Batch	40	of	276.	Elapsed:	0:00:53.
Batch	80	of	276.	Elapsed:	0:01:46.
Batch	120	of	276.	Elapsed:	0:02:38.
Batch	160	of	276.	Elapsed:	0:03:31.
Batch	200	of	276.	Elapsed:	0:04:24.
Batch	240	of	276.	Elapsed:	0:05:17.

Average training loss: 0.24

Training epoch took: 0:06:04

Running Validation...

Accuracy: 0.92

Validation Loss: 0.25

Validation took: 0:00:16

=====  
Epoch 4 / 4  
=====

Training...

Batch	40	of	276.	Elapsed:	0:00:53.
Batch	80	of	276.	Elapsed:	0:01:46.
Batch	120	of	276.	Elapsed:	0:02:38.
Batch	160	of	276.	Elapsed:	0:03:31.
Batch	200	of	276.	Elapsed:	0:04:24.
Batch	240	of	276.	Elapsed:	0:05:17.

Average training loss: 0.22

Training epoch took: 0:06:04

Running Validation...

Accuracy: 0.87

Validation Loss: 0.26

Validation took: 0:00:16

---

# HASIL EKSPERIMEN

distilbert-base-uncased

```
Training complete!  
Total training took 0:25:18 (h:mm:ss)
```

```
Size:          253 MB (265.729.799 bytes)
```

# HASIL EKSPERIMEN

bert-base-uncased

=====  
Epoch 1 / 4  
=====

Training...

Batch	40	of	276.	Elapsed: 0:01:38.
Batch	80	of	276.	Elapsed: 0:03:16.
Batch	120	of	276.	Elapsed: 0:04:55.
Batch	160	of	276.	Elapsed: 0:06:33.
Batch	200	of	276.	Elapsed: 0:08:11.
Batch	240	of	276.	Elapsed: 0:09:49.

Average training loss: 0.29  
Training epoch took: 0:11:17

Running Validation...

Accuracy: 0.98  
Validation Loss: 0.27  
Validation took: 0:00:29

=====  
Epoch 2 / 4  
=====

Training...

Batch	40	of	276.	Elapsed: 0:01:38.
Batch	80	of	276.	Elapsed: 0:03:16.
Batch	120	of	276.	Elapsed: 0:04:54.
Batch	160	of	276.	Elapsed: 0:06:33.
Batch	200	of	276.	Elapsed: 0:08:11.
Batch	240	of	276.	Elapsed: 0:09:49.

Average training loss: 0.25  
Training epoch took: 0:11:17

Running Validation...

Accuracy: 0.98  
Validation Loss: 0.26  
Validation took: 0:00:29

# HASIL EKSPERIMEN

bert-base-uncased

=====  
Epoch 3 / 4  
=====

Training...

Batch	40	of	276.	Elapsed: 0:01:38.
Batch	80	of	276.	Elapsed: 0:03:16.
Batch	120	of	276.	Elapsed: 0:04:54.
Batch	160	of	276.	Elapsed: 0:06:32.
Batch	200	of	276.	Elapsed: 0:08:10.
Batch	240	of	276.	Elapsed: 0:09:48.

Average training loss: 0.23

Training epoch took: 0:11:16

Running Validation...

Accuracy: 0.95

Validation Loss: 0.26

Validation took: 0:00:28

=====  
Epoch 4 / 4  
=====

Training...

Batch	40	of	276.	Elapsed: 0:01:36.
Batch	80	of	276.	Elapsed: 0:03:13.
Batch	120	of	276.	Elapsed: 0:04:49.
Batch	160	of	276.	Elapsed: 0:06:26.
Batch	200	of	276.	Elapsed: 0:08:02.
Batch	240	of	276.	Elapsed: 0:09:38.

Average training loss: 0.21

Training epoch took: 0:11:05

Running Validation...

Accuracy: 0.89

Validation Loss: 0.26

Validation took: 0:00:28

---

# HASIL EKSPERIMEN

bert-base-uncased

```
Training complete!  
Total training took 0:46:49 (h:mm:ss)
```

```
Size:          415 MB (435.889.030 bytes)
```



---

# ANALISIS HASIL EKSPERIMEN

Dari hasil eksperimen melakukan keyword extraction, dapat disimpulkan beberapa hal:

1. Perbandingan akurasi antara model yang menggunakan pretrained bert-based model dan distilbert-based tidak terlalu berbeda
2. Training untuk keduanya hanya perlu dilakukan sampai epoch kedua. Setelah epoch kedua, nilai loss dari validasi akan bertambah dan nilai akurasi dari validasi juga akan berkurang
3. Waktu yang diperlukan untuk melakukan fine-tuning bert-based model mencapai dua kali lipat distilbert-based model
4. Ukuran model sekaligus tokenizer yang dihasilkan oleh bert-based model dua kali lipat distilbert-based model





# 02

# PIPELINE 2

## TOPIK KLASIFIKASI

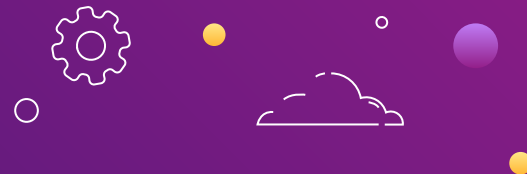


Proses melakukan klasifikasi topik berita





# PROSES TOPIK KLASIFIKASI



## 1. PREPROCESSING

Melakukan preprocessing dataset input



## 3. EVALUASI

Melakukan evaluasi metrik untuk setiap model dan memilih model terbaik untuk prediksi

## 2. TRAIN MODEL

Menggunakan TFIDF, Fine-Tuning BERT, KERAS, Word2Vec untuk memodelkan klasifikasi



## 4. PREDIKSI

Melakukan prediksi terhadap inputan keyword dari berita untuk diprediksi menjadi topik hasil klasifikasi



# PREPROCESSING

## 1. Tokenisasi

Melakukan tokenisasi dari sentence menjadi token/kata

## 2. Stop Word Removal

Menghapus token yang berupa stop word

```
841      ['dominici', 'back', 'lacklustr', 'franc', 'wi...
1748    ['id', 'theft', 'surg', 'hit', 'u', 'consum', ...
2118    ['blair', 'press', 'u', 'climat', 'toni', 'bla...
1174    ['realli', 'divid', 'parti', 'gap', 'labour', ...
1502    ['iran', 'budget', 'seek', 'state', 'sell', 'o...
      ...
1033    ['labour', 'eu', 'propaganda', 'taxpay', 'subs...
1731    ['crossrail', 'link', 'get', 'go', 'ahead', '£...
763     ['share', 'rise', 'new', 'man', 'utd', 'offer'...
835     ['rock', 'star', 'su', 'ex', 'girlfriend', 'mo...
1653    ['file', 'swapper', 'readi', 'new', 'network',...
Name: tokenized_text, Length: 1780, dtype: object
```

## 3. Number Eraser

Menghapus token yang termasuk angka

## 4. Stemming

Mengubah token menjadi kata hasil stem

## 5. Lemmatization

Mengubah token kata menjadi kata dasarnya

## 6. Encoding

Melakukan encoding terhadap kategori dari label topik



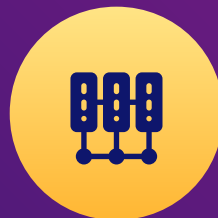
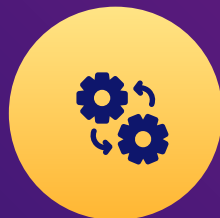


# TRAIN MODEL (EKSPERIMEN)



## TFIDF - SHALLOW ALGO

Melakukan TFIDF kemudian menggunakan Decision Tree, XGBoost, SVM, Multinomial Naive Bayes, Random Forrest

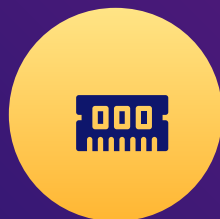


## FINE-TUNING BERT

Menggunakan model BERT-base multilingual dan distill-BERT

## KERAS MODEL

Menggunakan keras model dan keras layer berupa dense, activation berupa relu dan softmax



## WORD2VEC

Melakukan embedding terhadap kata kemudian membuat model deep learningnya dengan layer input, embedding, attentional, lstm, dense, dan output





# TFIDF SHALLOW ALGORITMA



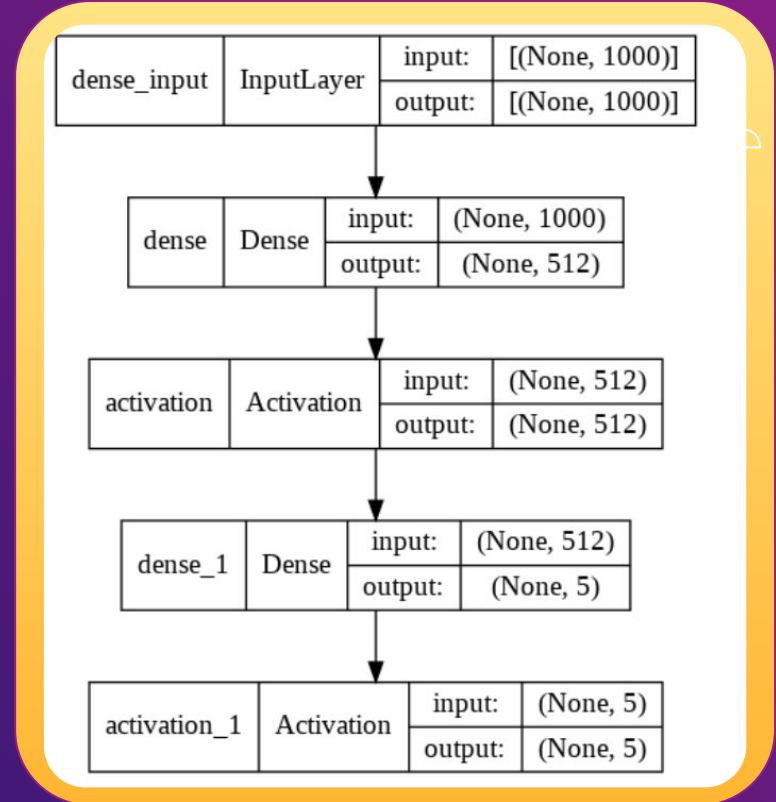
VARIABLE	AKURASI	PRESISI	RECALL	F1 SCORE
Decision Tree Learning	86%	85%	85%	85%
XGBoost	96%	96%	96%	96%
SVM	96%	95%	97%	96%
Multinomial Naive Bayes	98%	97%	97%	97%
Random Forest Classifier	97%	97%	97%	97%



# KERAS SEQ MODEL

Keras sequential model adalah model yang dibentuk dengan tumpukan lapisan di mana setiap lapisan memiliki tepat satu tensor input dan satu tensor output.

Layer yang digunakan adalah layer input, dense layer, activation pertama dengan relu, dense layer lagi, dan activation kedua menggunakan softmax





# KERAS MODEL

Hasil akurasi mencapai 99.7%

```
Epoch 1/2  
54/54 [=====] - 3s 8ms/step - loss: 0.4303 - accuracy: 0.8770 - val_loss: 0.1054 - val_accuracy: 0.9607  
Epoch 2/2  
54/54 [=====] - 0s 5ms/step - loss: 0.0360 - accuracy: 0.9944 - val_loss: 0.0717 - val_accuracy: 0.9719
```

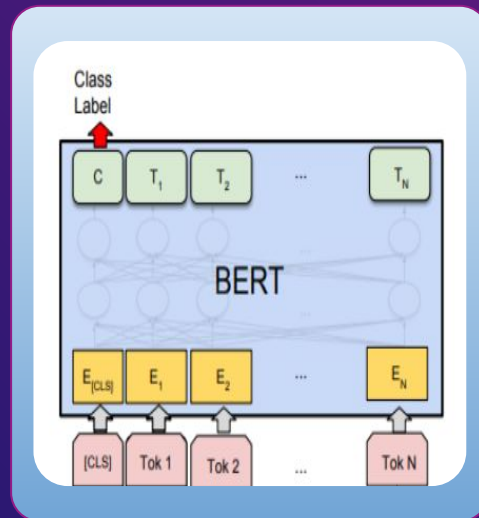
```
60/60 [=====] - 0s 3ms/step - loss: 0.0202 - accuracy: 0.9972  
Test accuracy score: 0.9971910119056702  
Test loss score: 0.02018641121685505
```



# FINE TUNING BERT

Fine tuning BERT adalah melakukan training model bert pada input dataset dari model BERT yang sudah dilatih sebelumnya dengan dataset yang besar.

Fine tuning bert dilakukan dengan menyesuaikan representasi input sebelum dimasukkan ke pretrained model dan menambahkan satu untrained output layer untuk dilatih kembali ke task spesifik



## Layer Embedding

```
bert.embeddings.word_embeddings.weight (119547, 768)
bert.embeddings.position_embeddings.weight (512, 768)
bert.embeddings.token_type_embeddings.weight (2, 768)
bert.embeddings.LayerNorm.weight (768,)
bert.embeddings.LayerNorm.bias (768,)
```

## Transformer Pertama

```
bert.encoder.layer.0.attention.self.query.weight (768, 768)
bert.encoder.layer.0.attention.self.query.bias (768,)
bert.encoder.layer.0.attention.self.key.weight (768, 768)
bert.encoder.layer.0.attention.self.key.bias (768,)
bert.encoder.layer.0.attention.self.value.weight (768, 768)
bert.encoder.layer.0.attention.self.value.bias (768,)
bert.encoder.layer.0.attention.output.dense.weight (768, 768)
bert.encoder.layer.0.attention.output.dense.bias (768,)
bert.encoder.layer.0.attention.output.LayerNorm.weight (768,)
bert.encoder.layer.0.attention.output.LayerNorm.bias (768,)
bert.encoder.layer.0.intermediate.dense.weight (3072, 768)
bert.encoder.layer.0.intermediate.dense.bias (3072,)
bert.encoder.layer.0.output.dense.weight (768, 3072)
bert.encoder.layer.0.output.dense.bias (768,)
bert.encoder.layer.0.output.LayerNorm.weight (768,)
bert.encoder.layer.0.output.LayerNorm.bias (768,)
```

## Layer Output

```
bert.pooler.dense.weight (768, 768)
bert.pooler.dense.bias (768,)
classifier.weight (5, 768)
classifier.bias (5,)
```



# FINE TUNING BERT

## BERT-Base Multilingual (dengan 36 epoch)

Melakukan Validation Accuracy: 0.91 Validation took: 0:00:04		precision	recall	f1-score	support
===== Epoch 14 / 15 ===== Melakukan Training Batch 40 of 45. Elapsed: 0:00:45.  Average training loss: 0.00 Training epoch took: 0:00:50	tech	0.92	0.91	0.91	97
	business	0.97	0.90	0.94	81
	sport	0.88	0.91	0.89	75
Melakukan Validation Accuracy: 0.88 Validation took: 0:00:04	entertainment	0.98	0.96	0.97	112
	politics	0.86	0.94	0.90	80
===== Epoch 15 / 15 ===== Melakukan Training Batch 40 of 45. Elapsed: 0:00:45.  Average training loss: 0.00 Training epoch took: 0:00:50	accuracy			0.93	445
	macro avg	0.92	0.92	0.92	445
Melakukan Validation Accuracy: 0.90 Validation took: 0:00:04	weighted avg	0.93	0.93	0.93	445

# FINE TUNING BERT

## Distill BERT-based uncase (dengan 60 epoch)

===== Epoch 49 / 50 =====					
Average training loss: 0.00			precision	recall	f1-score
Training epoch took: 0:00:48					support
Melakukan Validation					
Accuracy: 0.95		tech	0.94	0.93	0.93
Validation took: 0:00:04		business	0.96	0.93	0.94
===== Epoch 49 / 50 =====		sport	0.91	0.93	0.92
Melakukan Training		entertainment	0.98	1.00	0.99
Batch 40 of 45. Elapsed: 0:00:43.		politics	0.94	0.94	0.94
Average training loss: 0.00					
Training epoch took: 0:00:48					
Melakukan Validation					
Accuracy: 0.93		accuracy			0.95
Validation took: 0:00:04		macro avg	0.95	0.94	0.95
===== Epoch 50 / 50 =====		weighted avg	0.95	0.95	0.95
Melakukan Training					
Batch 40 of 45. Elapsed: 0:00:43.					
Average training loss: 0.00					
Training epoch took: 0:00:48					

# WORD2VEC

Word2Vec adalah metode embedding word yang berguna untuk merepresentasikan kata-kata menjadi sebuah vektor dengan panjang N.

Layer (type)	Output Shape	Param #	Connected to
input_11 (InputLayer)	[(None, 15)]	0	[]
embedding_10 (Embedding)	(None, 15, 300)	5933700	['input_11[0][0]']
permute_9 (Permute)	(None, 300, 15)	0	['embedding_10[0][0]']
dense_26 (Dense)	(None, 300, 15)	240	['permute_9[0][0]']
attention (Permute)	(None, 15, 300)	0	['dense_26[0][0]']
multiply_8 (Multiply)	(None, 15, 300)	0	['embedding_10[0][0]', 'attention[0][0]']
bidirectional_18 (Bidirectional)	(None, 15, 30)	37920	['multiply_8[0][0]']
bidirectional_19 (Bidirectional)	(None, 30)	5520	['bidirectional_18[0][0]']
dense_27 (Dense)	(None, 64)	1984	['bidirectional_19[0][0]']
dense_28 (Dense)	(None, 5)	325	['dense_27[0][0]']
Total params: 5,979,689			
Trainable params: 45,989			
Non-trainable params: 5,933,700			

Word2Vec menggunakan neural network untuk mendapatkan vektor tersebut. Arsitektur Word2vec hanya terdiri dari layer input, hidden layer, dan layer output.

Pada arsitektur ini maka kita menggunakan layer input, layer embedding, layer attentional (yang terdiri dari layer permute, layer dense dengan activation softmax, layer permute lagi), kemudian 2 layer bidirectional LSTM, dan 2 layer dense (dengan activation pertama adalah relu dan kedua adalah softmax)



```

▶ trained = model_w2v.fit(x=x_train_w2v, y=y_train_oh, batch_size=256,
                           epochs=20, shuffle=True,
                           validation_split=0.3)

```

```

❏ Epoch 1/20
5/5 [=====] - 12s 723ms/step - loss: 1.6092 - accuracy: 0.2416 - val_loss: 1.6093 - val_accuracy: 0.2097
Epoch 2/20
5/5 [=====] - 1s 184ms/step - loss: 1.6086 - accuracy: 0.2416 - val_loss: 1.6091 - val_accuracy: 0.2097
Epoch 3/20
5/5 [=====] - 1s 185ms/step - loss: 1.6079 - accuracy: 0.2303 - val_loss: 1.6090 - val_accuracy: 0.2097
Epoch 4/20
5/5 [=====] - 1s 179ms/step - loss: 1.6074 - accuracy: 0.2303 - val_loss: 1.6090 - val_accuracy: 0.2097
Epoch 5/20
5/5 [=====] - 1s 179ms/step - loss: 1.6069 - accuracy: 0.2303 - val_loss: 1.6089 - val_accuracy: 0.2097
Epoch 6/20
5/5 [=====] - 1s 181ms/step - loss: 1.6065 - accuracy: 0.2303 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 7/20
5/5 [=====] - 1s 187ms/step - loss: 1.6060 - accuracy: 0.2303 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 8/20
5/5 [=====] - 1s 188ms/step - loss: 1.6055 - accuracy: 0.2303 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 9/20
5/5 [=====] - 1s 181ms/step - loss: 1.6050 - accuracy: 0.2303 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 10/20
5/5 [=====] - 1s 184ms/step - loss: 1.6046 - accuracy: 0.2303 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 11/20
5/5 [=====] - 1s 180ms/step - loss: 1.6042 - accuracy: 0.2255 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 12/20
5/5 [=====] - 1s 188ms/step - loss: 1.6038 - accuracy: 0.2239 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 13/20
5/5 [=====] - 1s 188ms/step - loss: 1.6038 - accuracy: 0.2239 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 14/20
5/5 [=====] - 1s 188ms/step - loss: 1.6038 - accuracy: 0.2239 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 15/20
5/5 [=====] - 1s 188ms/step - loss: 1.6038 - accuracy: 0.2239 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 16/20
5/5 [=====] - 1s 188ms/step - loss: 1.6038 - accuracy: 0.2239 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 17/20
5/5 [=====] - 1s 188ms/step - loss: 1.6038 - accuracy: 0.2239 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 18/20
5/5 [=====] - 1s 188ms/step - loss: 1.6038 - accuracy: 0.2239 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 19/20
5/5 [=====] - 1s 188ms/step - loss: 1.6038 - accuracy: 0.2239 - val_loss: 1.6088 - val_accuracy: 0.2097
Epoch 20/20
5/5 [=====] - 1s 188ms/step - loss: 1.6038 - accuracy: 0.2239 - val_loss: 1.6088 - val_accuracy: 0.2097

```

	precision	recall	f1-score	support
accuracy			0.22	445
macro avg	0.04	0.20	0.07	445
weighted avg	0.05	0.22	0.08	445

# HASIL WORD2VEC

Hasil eksperimen menunjukkan akurasi 22%. Sehingga model klasifikasi lebih baik menggunakan model lainnya





MENU

ANALYSIS

CONTACT

DATA ANALYSIS

03

# PIPELINE 3

## DOCUMENT SIMILARITY

Proses menentukan kemiripan antara beberapa berita





# PROCESS

## GET USER INPUT

Mengambil teks dari news yang dibaca user

01



02

## LOAD KEYWORDS

Membaca keywords hasil dari Keyword Extraction



03

## TRAIN MODEL

Train model menggunakan keywords hasil Keyword Extraction

04



## PREDICT

Mendapatkan document similarity

05



## RECOMMEND

Melakukan sorting hasil doc similarity dan hasil topic classification



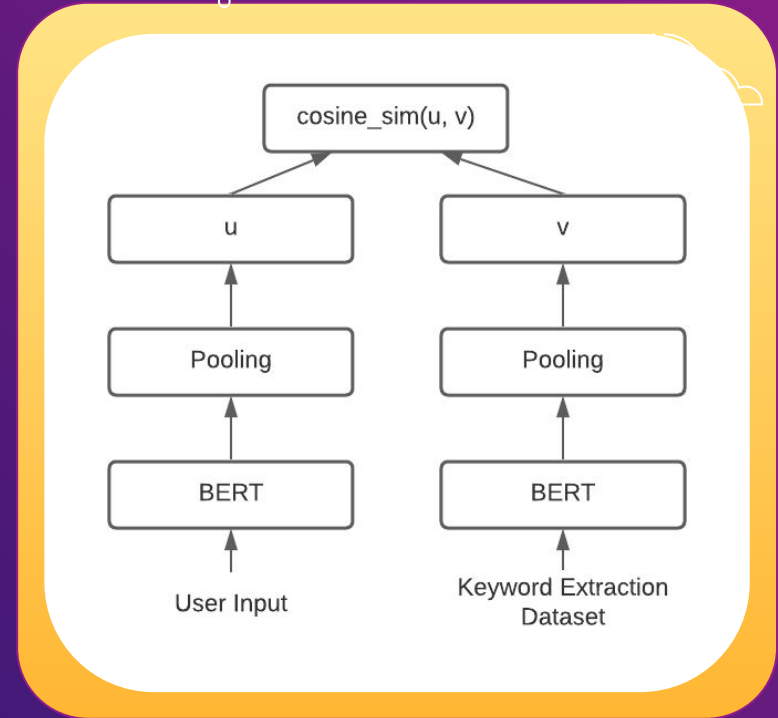
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# ARSITEKTUR

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# ARSITEKTUR

Arsitektur model yang digunakan adalah model transformer dengan pretrained-model BERT yang di-embed dengan data yang berasal dari *user input* dan *keyword extraction dataset*. Setelah itu, similarity dihitung dengan menggunakan *cosine\_similarity*





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# EKSPERIMEN

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# EKSPERIMEN

Eksperimen yang dilakukan adalah dengan mencoba model yang berbasiskan statistik yaitu TF-IDF, dan model yang menggunakan neural network yaitu word2vec dan Transformers. Model yang digunakan pada Transformers adalah sentence-transformers/all-MiniLM-L6-v2 dan sentence-transformers/paraphrase-mpnet-base-v2.

Untuk model TF-IDF dilakukan perbandingan variasi parameter min\_df pada TfidfVectorizer untuk mengabaikan kata-kata dengan frekuensi kurang dari threshold tertentu.

Dataset yang digunakan dalam eksperimen adalah dataset yang berasal dari:  
<https://www.kaggle.com/achintyatripathi/news-dataset-18920>

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# HASIL EKSPERIMEN (STATISTICAL)

TF-IDF, min\_df=0.25 (15 columns)

```
Article Read: Even as more than 150 million people are using dig...
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Recomendation 1: (IDX: 507), score: 0.8798349819335274 | Online advertising is a game of scale, but one att...
```

```
Recomendation 2: (IDX: 166), score: 0.8755319876279275 | LONDON, Aug 18 (Thomson Reuters Foundation) - Form...
```

```
Recomendation 3: (IDX: 926), score: 0.8747096090847626 | HONG KONG (Reuters) - Chinese online insurance tec...
```

```
Recomendation 4: (IDX: 7), score: 0.871895008547424 | Airmeet, a startup that offers a platform to host ...
```

```
Recomendation 5: (IDX: 469), score: 0.8614875812334784 | As Trump Visits Kenosha, Hundreds Gather Where Jac...
```

```
Recomendation 6: (IDX: 1292), score: 0.8549618479955363 | BRASILIA (Reuters) - Brazil's President Jair Bolso...
```

```
Recomendation 7: (IDX: 1454), score: 0.8549618479955363 | FILE PHOTO: Climate change activists demonstrate a...
```

```
Recomendation 8: (IDX: 1464), score: 0.8549618479955363 | FILE PHOTO: Climate change activists demonstrate a...
```

```
Recomendation 9: (IDX: 9), score: 0.8546135883744768 | Byju's has raised $500 million in a new financing ...
```

```
Recomendation 10: (IDX: 1226), score: 0.8533195048726804 | BRASILIA/MOSCOW (Reuters) - The Brazilian state of...
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# HASIL EKSPERIMEN (STATISTICAL)

TF-IDF, min\_df=0.1 (188 columns)

```
Article Read: Even as more than 150 million people are using dig...  
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```
Recomendation 1: (IDX: 177), score: 0.6145900956318281 | Indian food delivery startup Zomato has raised $62...
```

```
Recomendation 2: (IDX: 1091), score: 0.583970308827363 | Southeast Asia's leading property listing company ...
```

```
Recomendation 3: (IDX: 9), score: 0.5487703260742444 | Byju's has raised $500 million in a new financing ...
```

```
Recomendation 4: (IDX: 11), score: 0.5435676545074747 | Indian billionaire Mukesh Ambani's retail business...
```

```
Recomendation 5: (IDX: 7), score: 0.52496019034492 | Airmeet, a startup that offers a platform to host ...
```

```
Recomendation 6: (IDX: 176), score: 0.5159538061419459 | 3one4 Capital, a venture capital firm in India, to...
```

```
Recomendation 7: (IDX: 178), score: 0.5134475943083189 | Mumbai-based Eruditus, which works with top univer...
```

```
Recomendation 8: (IDX: 0), score: 0.4958957368213379 | Vodafone Idea, one of the largest telecom operator...
```

```
Recomendation 9: (IDX: 123), score: 0.4764466896482933 | NEW DELHI (Reuters) - India plans to significantly...
```

```
Recomendation 10: (IDX: 1086), score: 0.4743197003412171 | Point72 Ventures, the early-stage investment firm ...
```

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# HASIL EKSPERIMEN (STATISTICAL)

TF-IDF, min\_df=0.0 (588777 columns)

```
Article Read: Even as more than 150 million people are using dig...
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Recommendation 1: (IDX: 176), score: 0.057123252265082164 | 3one4 Capital, a venture capital firm in India, to...
Recommendation 2: (IDX: 9), score: 0.0501242050658371 | Byju's has raised $500 million in a new financing ...
Recommendation 3: (IDX: 7), score: 0.0486033162806363 | Airmeet, a startup that offers a platform to host ...
Recommendation 4: (IDX: 1), score: 0.04808100864680179 | At the beginning of the previous decade, Facebook ...
Recommendation 5: (IDX: 11), score: 0.04661801280603871 | Indian billionaire Mukesh Ambani's retail business...
Recommendation 6: (IDX: 8), score: 0.04240052932842192 | Since India enforced a lockdown across the country...
Recommendation 7: (IDX: 97), score: 0.04143247655591322 | And we're back! Today was part two of Y Combinator...
Recommendation 8: (IDX: 178), score: 0.03992847727515998 | Mumbai-based Eruditus, which works with top univer...
Recommendation 9: (IDX: 564), score: 0.03961769704900882 | Poland is becoming an important European tech ecos...
Recommendation 10: (IDX: 720), score: 0.03781986356587531 | Here's how you can get a second shot at Startup Ba...
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# HASIL EKSPERIMEN (NEURAL NETWORK)

## Word2Vec

Article Read: Even as more than 150 million people are using dig...

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Recommendation 1: (IDX: 264), score: 0.6808363199234009 | Aug 26 - The following are the details of Indian S...

Recommendation 2: (IDX: 113), score: 0.6790512204170227 | Aug 19 - The following are the details of Indian S...

Recommendation 3: (IDX: 62), score: 0.5325736403465271 | (Reuters) - A look at the key facts and records of...

Recommendation 4: (IDX: 1343), score: 0.5170466899871826 | FILE PHOTO: A view is seen from the Amazon Tall To...

Recommendation 5: (IDX: 214), score: 0.46485865116119385 | Sep 1 (OPTA) - Scoreboard at close of play of 3rd ...

Recommendation 6: (IDX: 67), score: 0.4537274241447449 | Sep 13 (OPTA) - Scores from the LPGA Tour ANA Insp...

Recommendation 7: (IDX: 274), score: 0.45062702894210815 | Aug 30 (OPTA) - Scoreboard at close of play of 2nd...

Recommendation 8: (IDX: 832), score: 0.4493864178657532 | KIGALI (Reuters) - Rwandan President Paul Kagame d...

Recommendation 9: (IDX: 130), score: 0.44323742389678955 | Aug 25 (OPTA) - Scoreboard at close of play on the...

Recommendation 10: (IDX: 84), score: 0.4368095099925995 | Sep 12 (OPTA) - Scores from the European Tour Port...



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# HASIL EKSPERIMEN (NEURAL NETWORK)

Transformer - sentence-transformers/paraphrase-mpnet-base-v2 (768 dimensional dense vector space)

```
Article Read: Even as more than 150 million people are using dig...  
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```

```
Recomendation 1: (IDX: 6), score: 0.2762608230113983 | CashKaro, one of the leading cashback and coupon s...
```

```
Recomendation 2: (IDX: 9), score: 0.25234079360961914 | Byju's has raised $500 million in a new financing ...
```

```
Recomendation 3: (IDX: 176), score: 0.2384922057390213 | 3one4 Capital, a venture capital firm in India, to...
```

```
Recomendation 4: (IDX: 741), score: 0.29171955585479736 | As a business model, SaaS has expanded to epic siz...
```

```
Recomendation 5: (IDX: 8), score: 0.3042358160018921 | Since India enforced a lockdown across the country...
```

```
Recomendation 6: (IDX: 1086), score: 0.28184065222740173 | Point72 Ventures, the early-stage investment firm ...
```

```
Recomendation 7: (IDX: 1124), score: 0.29140838980674744 | Dawn Capital, the London-based VC that focuses on ...
```

```
Recomendation 8: (IDX: 890), score: 0.26587602496147156 | Apple is well known for picking up smaller startup...
```

```
Recomendation 9: (IDX: 740), score: 0.23904013633728027 | Once upon a time, fintech founders could pitch 10 ...
```

```
Recomendation 10: (IDX: 91), score: 0.24016138911247253 | More than 150 e-commerce and delivery companies gl...
```

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# HASIL EKSPERIMEN (NEURAL NETWORK)

Transformer - sentence-transformers/all-MiniLM-L6-v2 (384 dimensional dense vector space)

```
Article Read: Even as more than 150 million people are using dig...  
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```

```
Recomendation 1: (IDX: 566), score: 0.7232925431037607 | Investor interest in no-code, low-code apps and se...
```

```
Recomendation 2: (IDX: 176), score: 0.7168260677463922 | 3one4 Capital, a venture capital firm in India, to...
```

```
Recomendation 3: (IDX: 179), score: 0.7060372750709747 | Your startup is special and different, and you nee...
```

```
Recomendation 4: (IDX: 9), score: 0.6904699084050727 | Byju's has raised $500 million in a new financing ...
```

```
Recomendation 5: (IDX: 5), score: 0.683123557261046 | More than a third of small and medium-sized busine...
```

```
Recomendation 6: (IDX: 8), score: 0.6814406174305236 | Since India enforced a lockdown across the country...
```

```
Recomendation 7: (IDX: 498), score: 0.6803235459609738 | DNX Ventures, an investment firm that focuses on e...
```

```
Recomendation 8: (IDX: 733), score: 0.6703664729903799 | Nerdwallet, which provides resources for people lo...
```

```
Recomendation 9: (IDX: 499), score: 0.6695382917091338 | The CEO of Pan-African fintech unicorn Interswitch...
```

```
Recomendation 10: (IDX: 7), score: 0.6638006522966278 | Airmeet, a startup that offers a platform to host ...
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# ANALISIS HASIL EKSPERIMEN

1. Model dengan neural network (word2vec, transformers) memiliki nilai *cosine\_similarity* lebih baik daripada model TF-IDF.
2. Pada model dengan TF-IDF, semakin kecil nilai *min\_df*, nilai *cosine\_similarity* semakin kecil namun jumlah kolom semakin banyak. Pada *min\_df*=0.25, skor mencapai 0.879. Namun hanya terdapat 15 kolom/kata yang digunakan dalam prediksi.
3. Pada model transformer, model sentence-transformers/all-MiniLM-L6-v2 dengan 384 *dimensional dense vector space* menghasilkan nilai *cosine\_similarity* lebih baik daripada sentence-transformers/paraphrase-mpnet-base-v2 dengan 768 *dimensional dense vector space*



MENU

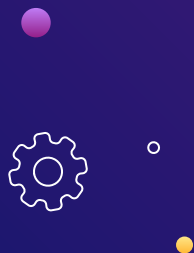
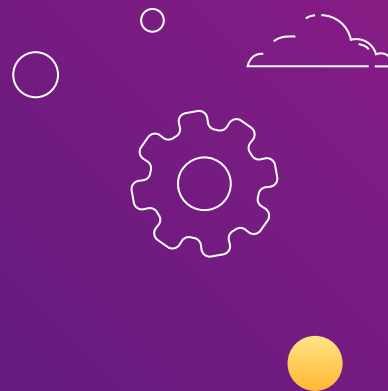
ANALYSIS

CONTACT

DATA ANALYSIS



DEMO





# THANKS!



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