Text Classification

Alfan F. Wicaksono
Fakultas Ilmu Komputer, Universitas Indonesia

Credits

Information Retrieval Text Book, Chapter 13

CS276: Information Retrieval & Web Search, Chris Manning & Pandu Nayak, Stanford U.

Text Classification

- **Text mining** adalah bidang yang fokus untuk ekstraksi pengetahuan atau informasi terstruktur dari data tekstual yang tidak terstruktur.
- **Text classification** adalah salah satu task di bidang **text mining**.

f(Minggu lalu saya menginap di hotel Y dua malam. Ternyata kualitasnya tidak seperti yang saya bayangkan. Lantai tidak bersih, kasur berdebu, dan penjaga hotelnya agak cuek. **) = C**

Buatlah sebuah **classification function**!

C = {positif, negatif}

Text Classification for IR

- Word segmentation (Is the white space between two letters **a word boundary or not**?
- **Language classification**: identifying language of a document
- The automatic **detection of spam pages** (which then are not included in the search engine index).
- The automatic **detection of sexually explicit content** (which is included in search results only if the user turns an option such as **SafeSearch off**).

Text Classification for IR

- Text Classification dapat digunakan untuk **memperbaiki kualitas SERP** yang dihasilkan sistem.
  - Fungsi **score(Q, D)** dapat bergantung dengan topik/class dari dokumen (misal untuk **diversifikasi hasil**).
  - Dokumen pada SERP dapat dikategorikan berdasarkan topik: **sport, economics, politics, …** untuk meningkatkan **user experience**.

- **Query Classification**
  - Klasifikasi "**intent**" dari sebuah query.

Query Intent Classification

- Dalam konteks **medical IR**, klasifikasi sebuah query ke salah satu dari kelas berikut: **diagnosis, treatment plan, disease description, …**

- **Query:** "Ada noda hitam di kulit dan gatal. Saya sakit apa ya kira-kira?" **--> "diagnosis"**

- **Query:** "Kalau lelah dan pusing selama 2 hari berturut-turut, saya harus bagaimana ya dok?" **--> "treatment plan"**

Rule-Based Classifiers

- This method requires **experts** who carefully refine rules over time.
- However, building and maintaining these rules are expensive.
- For example,

Rule Antecedent -> Class Label rule nya manual

"finance" ^ "interest" ^ … -> Economics

"football" ^ "injury" ^ "motogp" ^ … -> Sports

Supervised Learning of Classification

- The rules are data-driven!
- Conventional Models -> requires **hand-crafted features**
  - Naïve Bayes
  - K-Nearest Neighbor
  - Logistic Regression
  - …
- Deep Learning Models -> the features can be automatically extracted
  - Recurrent Neural Networks
  - **BERT**: Bi-directional Encoder Representation from Transformers
  - …

fitur nya otomatis

rulenya manual

Multinomial Naïve Bayes

MNB, urutan tidak dipertimbangkan. Sedangkan frekuensi dipertimbangkan

Document representation?

f(Minggu lalu saya menginap di hotel Y dua malam. Ternyata kualitasnya tidak seperti yang saya bayangkan. Lantai tidak bersih, kasur berdebu, dan penjaga hotelnya agak cuek. **) = C**

Buatlah sebuah **classification function**!

C = {positif, negatif}

Multinomial Naïve Bayes

Bag-of-Words

$$\mathbf{f}\left(\begin{array}{l}\text{minggu: }\mathbf{1}\\ \text{tidak: }\mathbf{2}\\ \text{lantai: }\mathbf{1}\\ \text{cuek: }\mathbf{1}\\ \ldots\end{array}\right) = \mathbf{C}$$

Buatlah sebuah **classification function**!

C = {positif, negatif}

Multinomial Naïve Bayes

naive: kemunculan kata dianggap independen

Probabilitas bahwa dokumen **d** merupakan dokumen yang berasal dari kelas **c** adalah:

Tugas: Cari c yang memaksimalkan $P(c|d)$!

$$P(c|d) \propto P(c) \prod_{i=1}^{n_d} P(t_i|c)$$

$d = [t_1, t_2, t_3, \ldots, t_{n_d}]$ are tokens in **d** that are part of **Vocabulary**

$P(t_i|c)$ Conditional probability of term **t** occurring **at position i** in a document of class **c**

$P(c)$ Prior probability of a document occuring in class **c**

$$\hat{P}(c) = \frac{N_c}{N}$$

The number of documents in class **c**

Total number of documents in corpus

the number of occurrences of term ***t*** in training documents from class ***c***, including multiple occurrences of a term in a document.

$$\hat{P}(t|c) = \frac{T_{c,t} + 1}{\sum_{t' \in V} T_{c,t'} + |V|}$$

Banyaknya term di Vocab

Multinomial Naïve Bayes

▶ Table 13.1 Data for parameter estimation examples.

	docID	words in document	in $c = China$?
training set	1	Chinese Beijing Chinese	yes
	2	Chinese Chinese Shanghai	yes
	3	Chinese Macao	yes
	4	Tokyo Japan Chinese	no
test set	5	Chinese Chinese Chinese Tokyo Japan	?

jadi kalau kita predik ini, apakah ini yes atau no.

V = {Chinese, Beijing, Shanghai, Macao, Tokyo, Japan}

Example 13.1: For the example in Table 13.1, the multinomial parameters we need to classify the test document are the priors $\hat{P}(c) = 3/4$ and $\hat{P}(\overline{c}) = 1/4$ and the following conditional probabilities:

smoothing

P(Chinese | c = china)

$$
\begin{aligned}
\hat{P}(\text{Chinese}|c) &= (5+1)/(8+6) = 6/14 = 3/7 \\
\hat{P}(\text{Tokyo}|c) = \hat{P}(\text{Japan}|c) &= (0+1)/(8+6) = 1/14 \\
\hat{P}(\text{Chinese}|\overline{c}) &= (1+1)/(3+6) = 2/9 \\
\hat{P}(\text{Tokyo}|\overline{c}) = \hat{P}(\text{Japan}|\overline{c}) &= (1+1)/(3+6) = 2/9
\end{aligned}
$$

Multinomial Naïve Bayes

▶ **Table 13.1** Data for parameter estimation examples.

	docID	words in document	in $c = China$?
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	2	Chinese Chinese Shanghai	yes
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	4	Tokyo Japan Chinese	no
test set	5	Chinese Chinese Chinese Tokyo Japan	?

$$\hat{P}(c|d_5) \propto 3/4 \cdot (3/7)^3 \cdot 1/14 \cdot 1/14 \approx 0.0003.$$
$$\hat{P}(\overline{c}|d_5) \propto 1/4 \cdot (2/9)^3 \cdot 2/9 \cdot 2/9 \approx 0.0001.$$

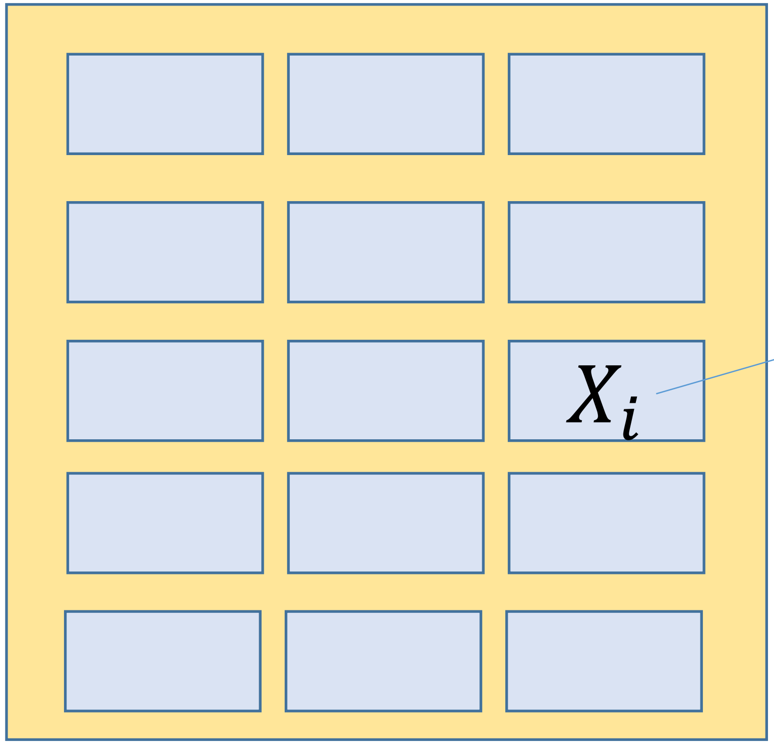
Thus, the classifier assigns the test document to $c = China$. The reason for this classification decision is that the three occurrences of the positive indicator Chinese in d_5 outweigh the occurrences of the two negative indicators Japan and Tokyo.

Apa Maksud Multinomial?

Bayangkan sebuah dokumen **d** terdiri dari $\mathbf{n_d}$ slot kosong.

masing-masing kotak sebenarnya categorical. CUman kalau kita consider semua (the whole kotak kuning), ini multinomial

$$d = [X_1, X_2, X_3, \ldots, X_{n_d}]$$



Di setiap posisi, ada **categorical random variable** $\mathbf{X_i}$ yang akan diisi secara acak oleh salah satu term di vocabulary (yang merepresentasikan kelas **c**).

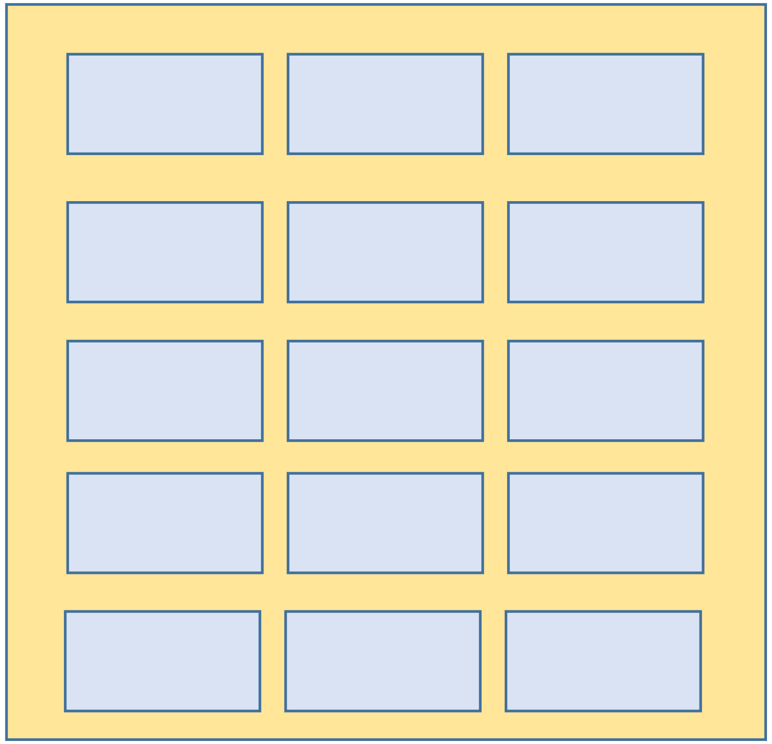
$$X_i \sim Cat(p_1, p_2, \ldots, p_{|V|}; \boldsymbol{c})$$

- $\mathbf{P_j}$ adalah probabilitas term **j** muncul dan mengisi $\mathbf{X_i}$.
- **V** adalah himpunan semua term di Vocabulary
- $\sum_j p_j = 1$

Apa Maksud Multinomial?

Bayangkan sebuah dokumen **d** terdiri dari $\mathbf{n_d}$ slot kosong.

$$d = [X_1, X_2, X_3, \ldots, X_{n_d}]$$



$$P(d|c) = P\left(X_1 = t_1, X_2 = t_2, \ldots, X_{n_d} = t_{n_d} | c\right)$$

$$= \prod_{i=1}^{n_d} P(X_i = t_i | c)$$

Conditional Independence Assumption
Kemunculan suatu term di sebuah posisi tidak dipengaruhi kemunculan term di posisi lain.

dengan kata lain,

$$\boldsymbol{P(d|c) \sim Multinomial(n_d, p_1, \ldots p_{|V|}; c)}$$

Apa Maksud Multinomial?

Ingat-ingat kembali. **Multinomial vs Categorical Dist.**

Jika Y_i adalah random variable yang menyatakan berapa kali nomor i muncul pada n buah percobaan, vektor $\boldsymbol{Y} = (Y_1, \dots, Y_k)$ mengikuti **distribusi multinomial** dengan parameter n dan $(p_1, \dots, p_k)$; dengan p_i adalah probabilitas nomor n muncul pada **sebuah** percobaan.

$$\boldsymbol{P}(\boldsymbol{Y_1} = y_1, \dots, \boldsymbol{Y_k} = y_k) = \underbrace{\frac{n!}{y_1! \dots y_k!}} p_1^{y_1} \dots p_k^{y_k}$$

$$\boldsymbol{n} = \boldsymbol{y_1} + \boldsymbol{y_2} + \cdots + \boldsymbol{y_k}$$

Term ini diabaikan pada perhitungan **P(d|c)** sebelumnya. Mengapa?

Apa Maksud Multinomial?

Ingat-ingat kembali. **Multinomial vs Categorical Dist.**

Jika X adalah random variable bisa bernilai salah satu dari $\{\mathbf{1}, \mathbf{2}, \dots, \boldsymbol{k}\}$, dengan $P(X = i) = p_i$; X dikatakan mengikuti distribusi **Categorical**.

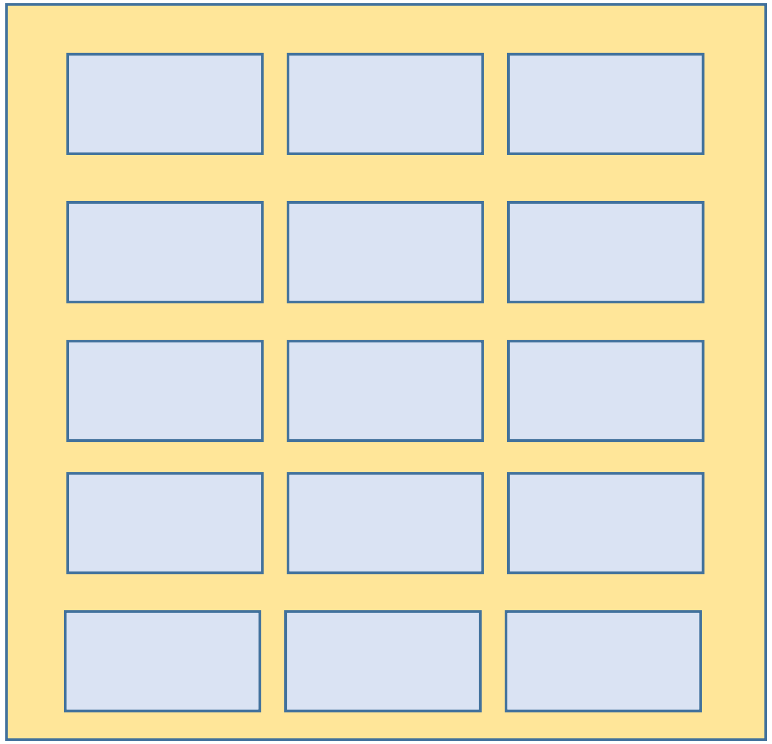
Sayangnya, istilah **"multinomial"** dan **"categorical"** sering kabur, khususnya di bidang *machine learning* & *natural language processing*.

Apa Maksud Multinomial?

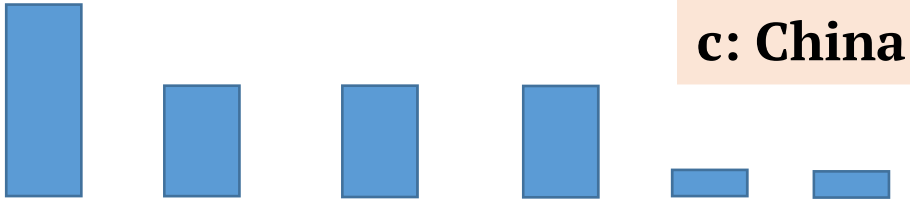
Banyaknya token pada dokumen d

Bayangkan sebuah dokumen **d** terdiri dari $\mathbf{n_d}$ slot kosong.

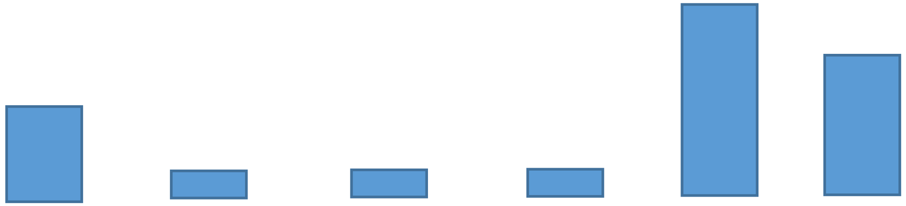
$$d = [X_1, X_2, X_3, \dots, X_{n_d}]$$



c: China



V = {Chinese, Beijing, Shanghai, Macao, Tokyo, Japan}

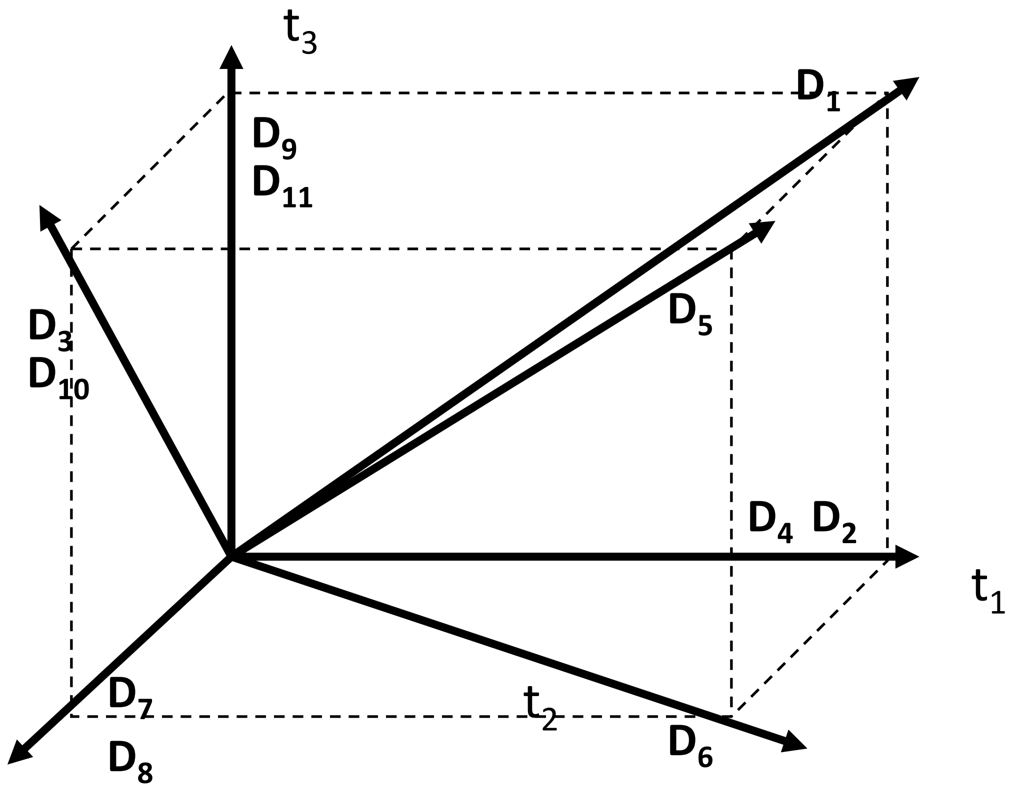


V = {Chinese, Beijing, Shanghai, Macao, Tokyo, Japan}

c: Not-China

Vector Space Representation

- Setiap dokumen adalah sebuah vektor.
- Satu komponen di vektor adalah untuk sebuah kata.



Vector Space Representation

Yang terkenal dan fundamental:

Term Frequency – Inverse Document Frequency (**TF-IDF**)

Document 1: halo selamat selamat pagi
Document 2: halo pagi pagi
Document 3: halo apa kabar kabar kabar

Beberapa contoh perhitungan TF:

$$tf("apa", D_3) = 1/5$$

$$tf("kabar", D_3) = 3/5$$

$$tf("halo", D_3) = 1/5$$

$$tf("halo", D_2) = 1/3$$

$$tf("pagi", D_2) = 2/3$$

Vector Space Representation

Yang terkenal dan fundamental:

Term Frequency – Inverse Document Frequency (**TF-IDF**)

Document 1: halo selamat selamat pagi
Document 2: halo pagi pagi
Document 3: halo apa kabar kabar kabar

Banyaknya dokumen di corpus

$$idf(word) = \log \frac{N}{n_{word}}$$

Banyaknya dokumen yang mengandung **word**

Contoh perhitungan IDF:

$$idf("halo") = \log \frac{3}{3} = 0$$

$$idf("kabar") = \log \frac{3}{1} = 0.47$$

$$idf("pagi") = \log \frac{3}{2} = 0.18$$

Perhitungan IDF bersifat konstan per corpus. Tidak bergantung dengan dokumen tertentu.

Vector Space Representation

Yang terkenal dan fundamental:

Term Frequency – Inverse Document Frequency (**TF-IDF**)

Document 1: halo selamat selamat pagi
Document 2: halo pagi pagi
Document 3: halo apa kabar kabar kabar

$$tfidf(\text{"halo"}, D_1) = tf(\text{"halo"}, D_1)\ x\ idf(\text{"halo"}) = 1\ x \log\frac{3}{3} = 0$$

$$tfidf(\text{"pagi"}, D_2) = tf(\text{"pagi"}, D_2)\ x\ idf(\text{"pagi"}) = \frac{2}{3}\ x \log\frac{3}{2} = 0.12$$

$$tfidf(\text{"pagi"}, D_1) = tf(\text{"pagi"}, D_1)\ x\ idf(\text{"pagi"}) = \frac{1}{4}\ x \log\frac{3}{2} = 0.04$$

Vector Space Representation

Yang terkenal dan fundamental:

Term Frequency – Inverse Document Frequency (**TF-IDF**)

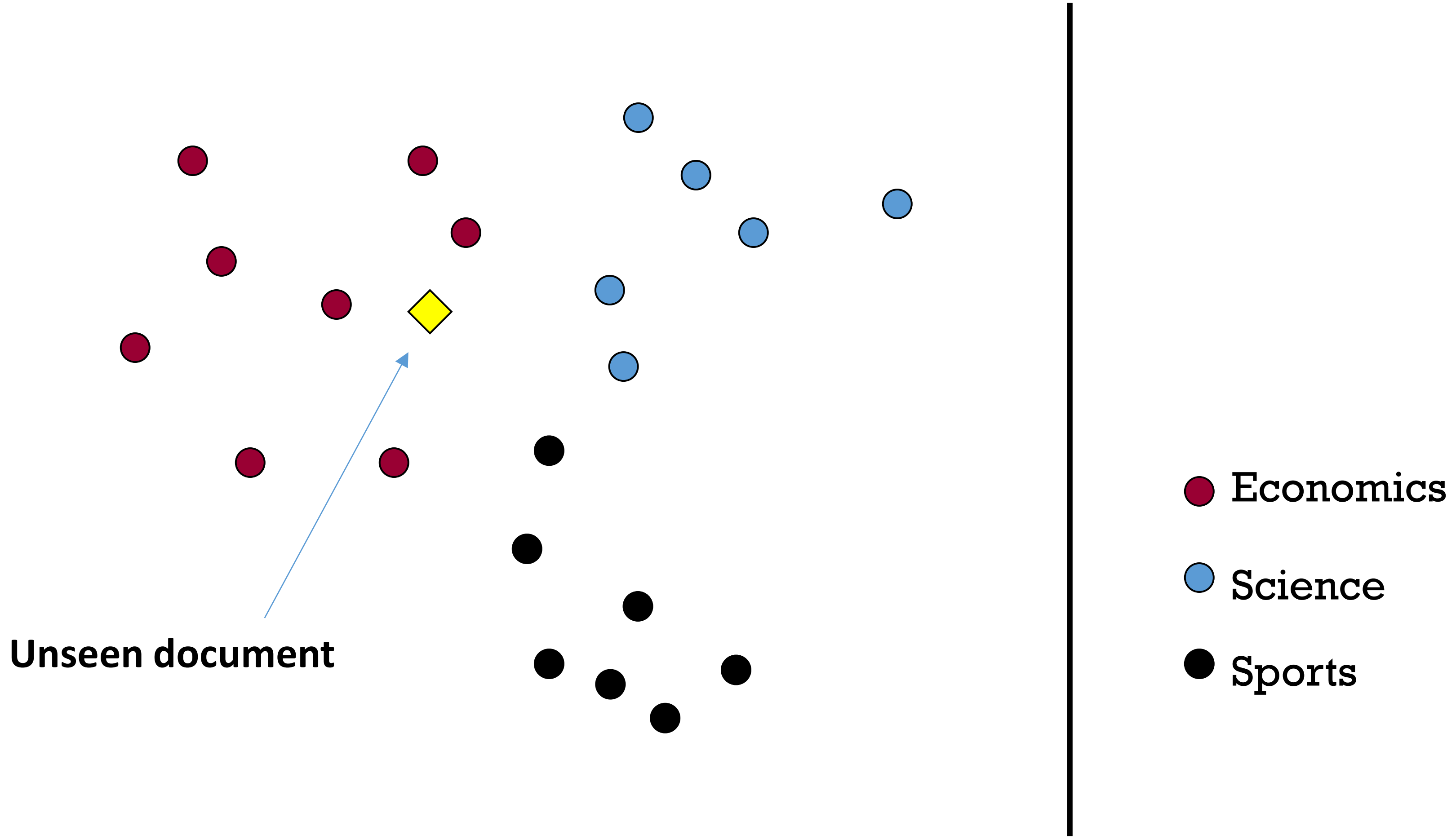
Document 1: halo selamat selamat pagi
Document 2: halo pagi pagi
Document 3: halo apa kabar kabar kabar

	halo	**selamat**	**pagi**	**apa**	**kabar**
Document 1	**0**	**0.24**	**0.04**	**0**	**0**
Document 2	**0**	**0**	**0.12**	**0**	**0**
Document 3	**0**	**0**	**0**	**0.1**	**0.29**

Jadi, representasi vector dari Document 1 adalah $d = \langle 0,0.24,0.04,0,0 \rangle$

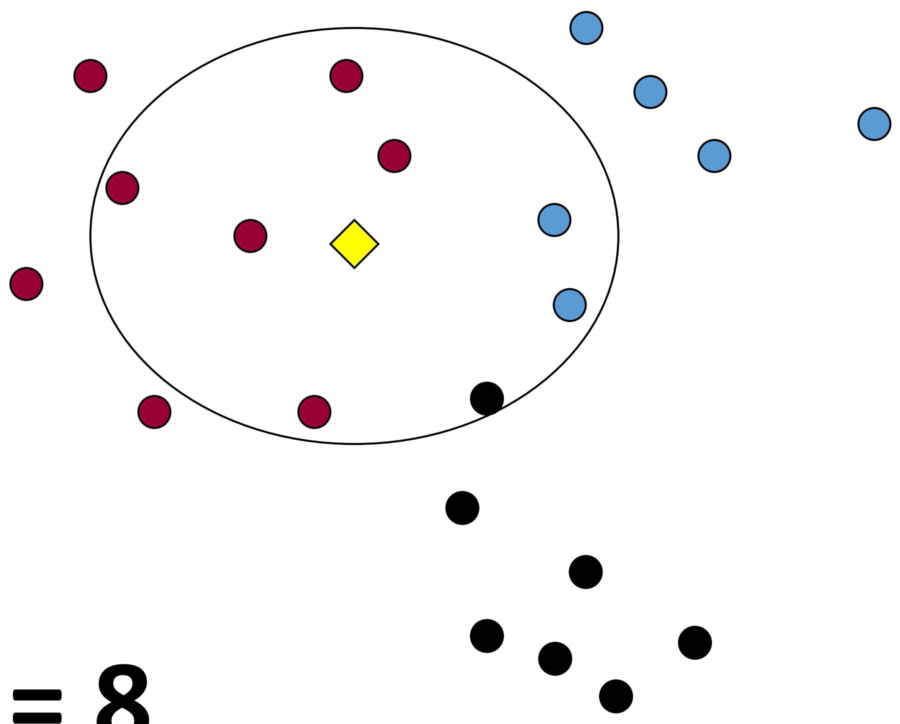
K-Nearest Neighbor Classification

Proses klasifikasi ditentukan oleh **K** tetangga terdekat.



K-Nearest Neighbor Classification

Proses klasifikasi ditentukan oleh **K** tetangga terdekat.



K = 8

P(Economics|◇) = 5/8

P(Science|◇) = 2/8

P(Sports|◇) = 1/8

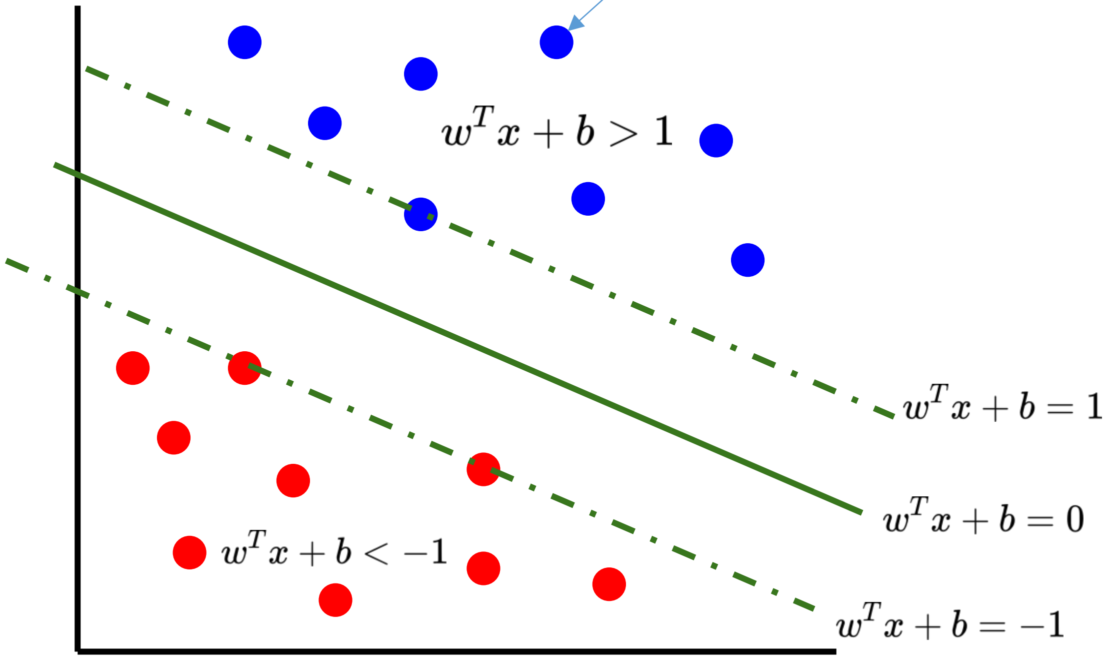
- Economics
- Science
- Sports

Other Models

Setelah mendapatkan representasi vector dari suatu dokumen (TF-IDF atau yang lainnya), kita juga bisa menggunakan model konvensional yang lain:

- Support Vector Machine
- Logistic Regression
- ...

Vektor dari sebuah dokumen



Classical ML vs Deep Learning

Predicted label: Positive

Learn mapping from features to labels

Classifiers: kNN, SVM, LogReg, …

Feature Engineering (by human)

Hand-designed Feature Extractor (TF-IDF, Part-of-Speech, Bigrams, …)

beratnya di feature extractor ini. Karena bisa bigram, atau any conditional misalnya hasAdjective, etc.

Representation

Buku ini sangat menarik dan penuh manfaat

Classical ML vs **Deep Learning**

Predicted label: Positive

Learn mapping from features to labels — **Classifiers**

ini bkn deep learning, melainkan hanya classifier aja)

Feature yang lebih high-level — **Very High-Level Representation**

Feature high-level — **High-Level Representation**

Feature sederhana — **Representation**

deep learning untuk extract fitur (yg warna kuning).

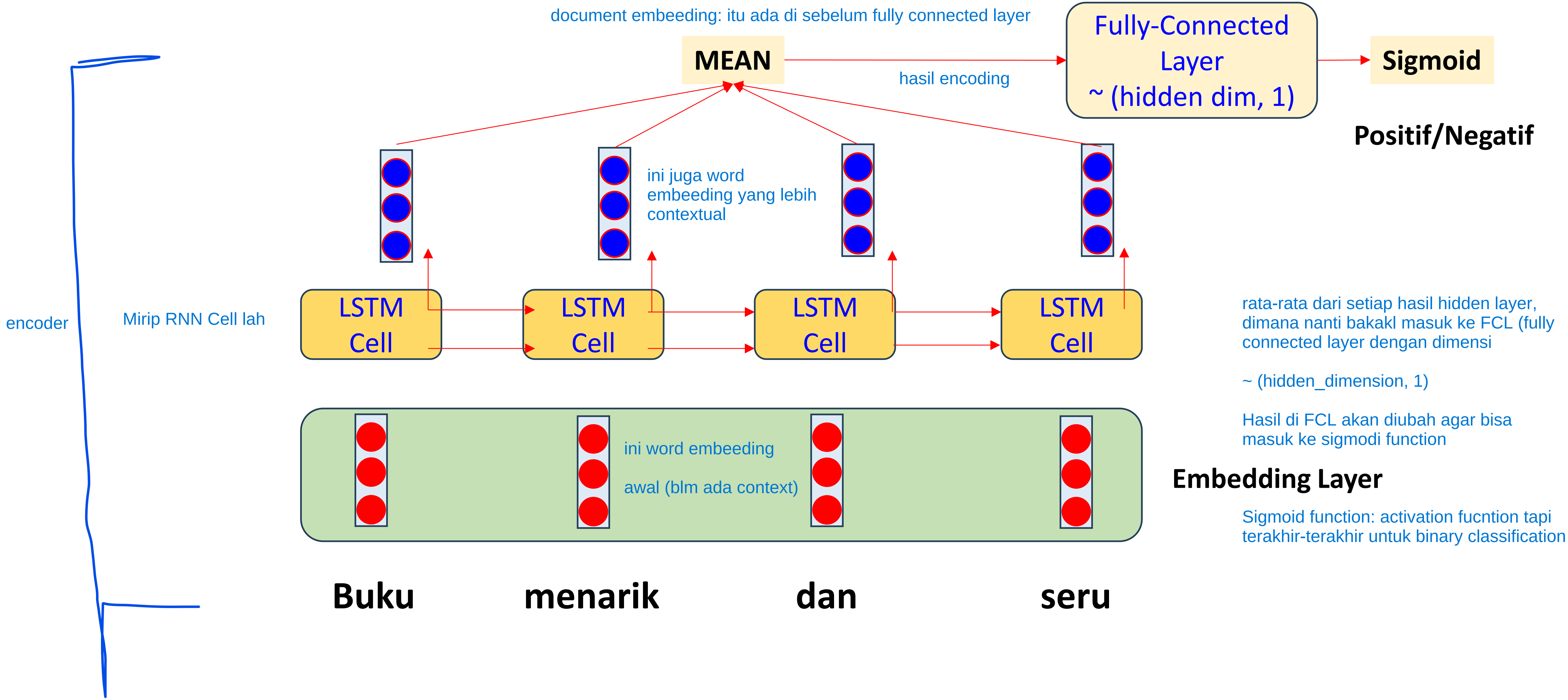
Automatic Feature Extraction

Feature Engineering is not needed.

kelemahan deep learning; kita gk tau makna dari layer-layer ditengah itu apa. (blackbox)

Buku ini sangat menarik dan penuh manfaat

Contoh: LSTM for Text Classification



https://colab.research.google.com/drive/1bxDyuddrTqPi0d63icKTS--5Lmtw-kXy?usp=sharing

```python
import torch
import pandas as pd
import numpy as np

from collections import Counter
from torch import nn, optim
from torch.utils.data import DataLoader
```

https://colab.research.google.com/drive/1bxDyuddrTqPi0d63icKTS--5Lmtw-kXy?usp=sharing

```python
class Dataset(torch.utils.data.Dataset):
    def __init__(
        self, sequence_length, documents, labels,
    ):
        self.sequence_length = sequence_length
        self.words = self.load_words(documents)
        self.uniq_words = self.get_uniq_words()

        # id vocab mulai dari 1, bukan 0; 0 untuk [PAD]
        self.index_to_word = {(index + 1): word for index, word in enumerate(self.uniq
        self.word_to_index = {word: (index + 1) for index, word in enumerate(self.uniq
        self.index_to_word[0] = "[PAD]"
        self.word_to_index["[PAD]"] = 0

        self.labels = labels
        self.docs = []
        for doc in documents:
            self.docs.append(self.to_ids(doc))
```

https://colab.research.google.com/drive/1bxDyuddrTqPi0d63icKTS--5Lmtw-kXy?usp=sharing

```python
# continued ...

    def to_ids(self, doc):
        doc = [self.word_to_index[w] for w in self.tokenize(doc)]
        if len(doc) >= self.sequence_length:
            doc = doc[:self.sequence_length]
        else:
            doc += [0] * (self.sequence_length - len(doc))
        return doc

    def tokenize(self, text):
        return text.split(' ')

    def load_words(self, documents):
        text = ""
        for doc in documents:
          text += doc + " "
        return self.tokenize(text)
```

https://colab.research.google.com/drive/1bxDyuddrTqPi0d63icKTS--5Lmtw-kXy?usp=sharing

```python
# continued ...

    def get_uniq_words(self):
        word_counts = Counter(self.words)
        return sorted(word_counts, key=word_counts.get, reverse=True)

    def __len__(self):
        return len(self.docs)

    def __getitem__(self, index):
        return (
            torch.tensor(self.docs[index]),
            torch.tensor(self.labels[index]),
        )
```

https://colab.research.google.com/drive/1bxDyuddrTqPi0d63icKTS--5Lmtw-kXy?usp=sharing

```python
class LSTMNet(nn.Module):
    def __init__(self, vocab_size, embedding_dim, hidden_dim, output_dim):
        super(LSTMNet,self).__init__()
        # Embedding layer
        # padding_idx (int, optional) - If specified, the entries at padding_idx do
        # not contribute to the gradient; therefore, the embedding vector at
        # padding_idx is not updated during training, i.e. it remains as a fixed "pad"
        self.embedding = nn.Embedding(vocab_size, embedding_dim, padding_idx=0)

        # LSTM layer process the vector sequences
        self.lstm = nn.LSTM(embedding_dim, hidden_dim)

        self.fc = nn.Linear(hidden_dim, output_dim) # Dense layer to predict
        self.sigmoid = nn.Sigmoid() # Prediction activation function

    def forward(self, text):
        embedded = self.embedding(text)
        output, (hidden_state, cell_state) = self.lstm(embedded)
        output = torch.mean(output, dim=1)
        output = self.fc(output)
        output = self.sigmoid(output)
        return output
```

```python
def train(dataset, model, batch_size, max_epochs=400):
    model.train()

    dataloader = DataLoader(dataset, batch_size=batch_size)
    criterion = nn.BCELoss()
    optimizer = optim.Adam(model.parameters(), lr=0.001)

    for epoch in range(max_epochs):
        for batch, (x, y) in enumerate(dataloader):
            y_pred = model(x)
            loss = criterion(y_pred, y)
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()
            print({ 'epoch': epoch, 'batch': batch, 'loss': loss.item() })
```

https://colab.research.google.com/drive/1bxDyuddrTqPi0d63icKTS--5Lmtw-kXy?usp=sharing

```python
documents = ["buku bagus rapih cerdas dan menarik",
             "rumah rapih cantik dan bersih",
             "hotel kotor berisik dan bau",
             "kantin jorok kotor mahal dan panas"]
labels = [[1.], [1.], [0.], [0.]]

dataset = Dataset(8, documents, labels)
model = LSTMNet(len(dataset.index_to_word), 16, 16, 1)
train(dataset, model, 2, max_epochs=200)


# prediction
model.eval()

with torch.no_grad():
  sent = "hotel dan kantin rapih bersih menarik dan bagus"
  sent = torch.tensor([dataset.to_ids(sent)])
  print(model(sent))  # tensor([[0.6977]])
```

https://colab.research.google.com/drive/1bxDyuddrTqPi0d63icKTS--5Lmtw-kXy?usp=sharing

Poin Partisipasi: 300 Point

- Selain LSTM, bisa juga mengunakan Conv1D
- Gunakan implementasi Conv1D yang pernah dibuat di kuliah sebelumnya, dan gunakan layer tersebut untuk ekstraksi fitur teks, hingga akhirnya digunakan untuk klasifikasi di layer terakhir (fully-connected layer)