Text classification
for take-home midterm exam preparation

(Common) Text classification pipeline

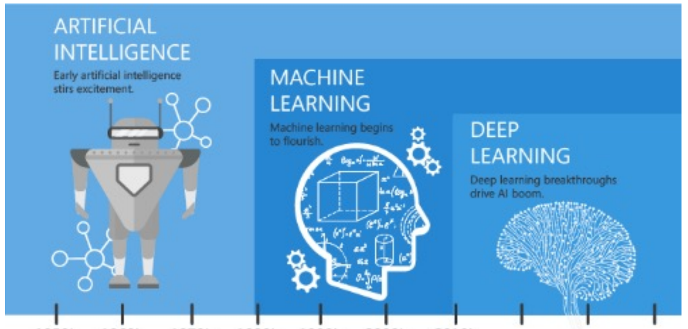
1) Data preparation → 2) Document representation → 3) Supervised learning model

NBC Nightly News @nbcnightlynews Following
America's #1 evening news broadcast. Tweets by @newsdel & @braddjaffy. Join us on Facebook http://facebook.com/nbcnightlynews

NBC News @NBCNews Following
A leading source of global news and information for more than 75 years. Have a news tip or question? Ask @rozzy, @lou_dubois, @jbaiata or @anthonyquintano.

CNN Breaking News @cnnbrk Following
CNN.com is among the world's leaders in online news and information delivery.

Comments	Good	Like	Hate	Sentiment
Tweet1	7	8	0	😁
Tweet2	1	0	10	😡
Tweet3	2	9	1	😁

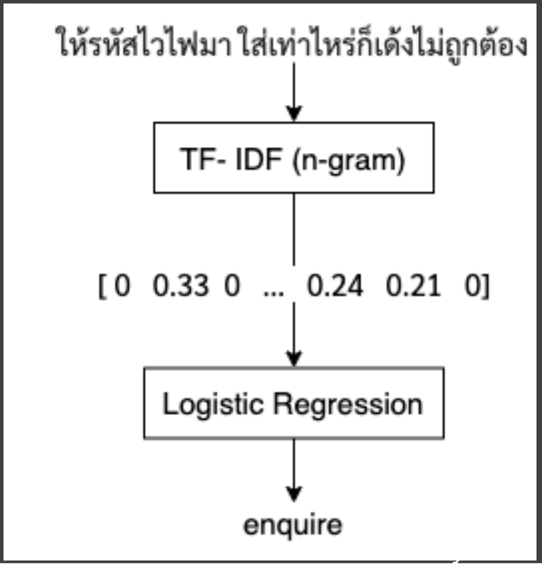


ARTIFICIAL INTELLIGENCE
Early artificial intelligence stirs excitement.
MACHINE LEARNING
Machine learning begins to flourish.
DEEP LEARNING
Deep learning breakthroughs drive AI boom.
1950's
1960's
1970's
1980's
1990's
2000's
2010's

Since an early flush of optimism in the 1950's, smaller subsets of artificial intelligence - first machine learning, then deep learning, a subset of machine learning - have created ever larger disruptions.

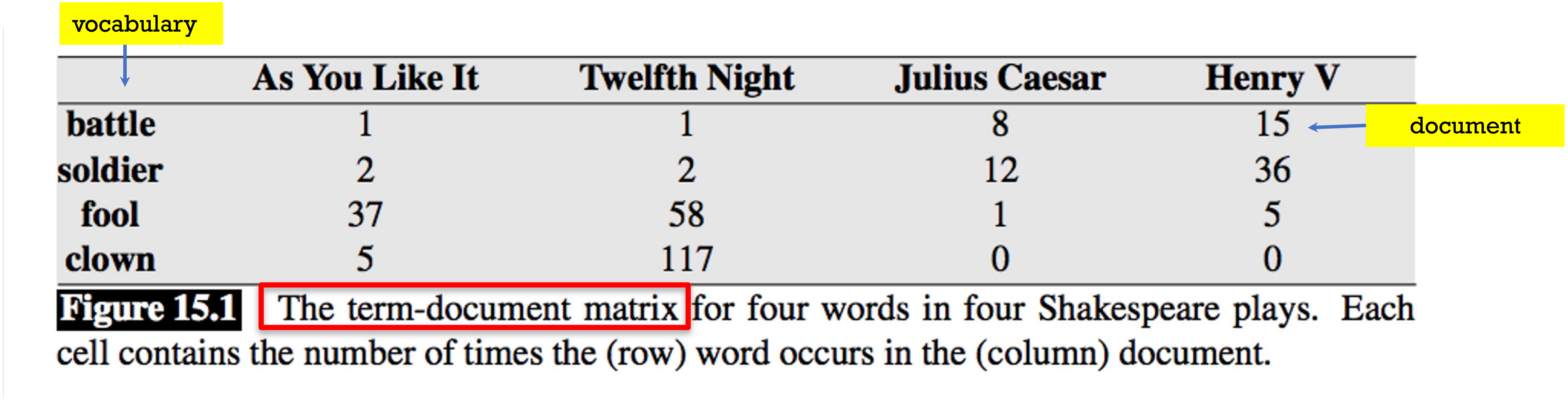
Part1: Traditional Approach

TF-IDF + Classifier



Sparse representation: Term Frequency (TF)

- Each row represents a word in the vocabulary and term-document matrix
- Each column represents a document.


vocabulary
document

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
clown	5	117	0	0

Figure 15.1 The term-document matrix for four words in four Shakespeare plays. Each cell contains the number of times the (row) word occurs in the (column) document.

Reference: Jurafsky, Dan, and James H. Martin. Speech and language processing. 3rd edition draft, https://web.stanford.edu/~jurafsky/slp3/, August 2017

Sparse representation: TF-IDF

Need for normalization in TF

Doc1
cat = 5/10

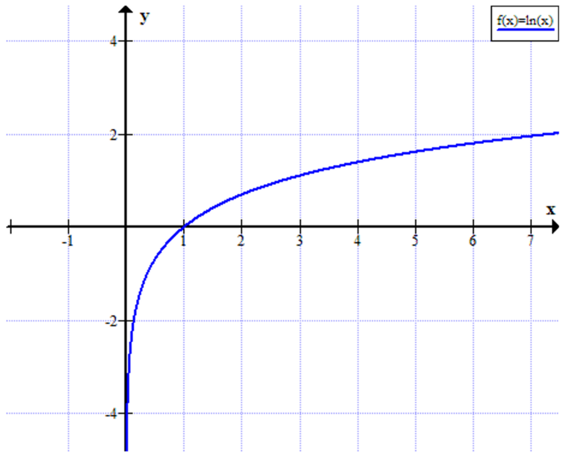
Doc2
cat = 50/1000

- Term Frequency (TF) – per each document

$$TF(w) = \frac{\text{Frequency of word } w \text{ in } \boxed{\text{a document}}}{\text{Total number of words in } \boxed{\text{the document}}}$$

- Inverse Document Frequency (IDF) – per corpus (all documents)

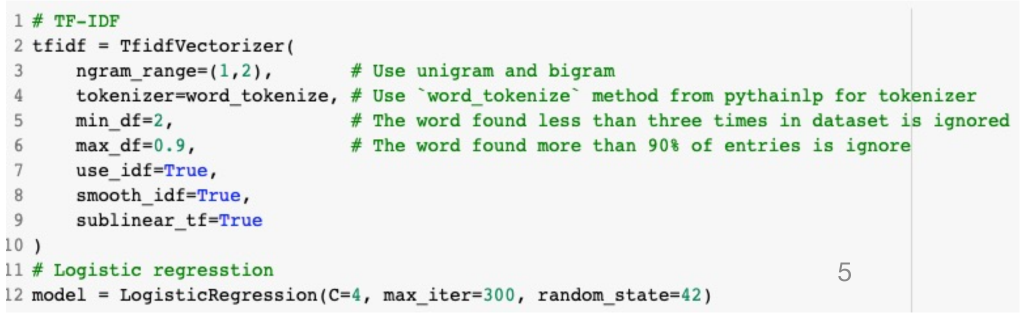
$$IDF(w) = \log_e\left(\frac{\text{Total number of documents}}{\text{Number of documents that contain word } w}\right)$$



penalty score
i.e., a, an, the

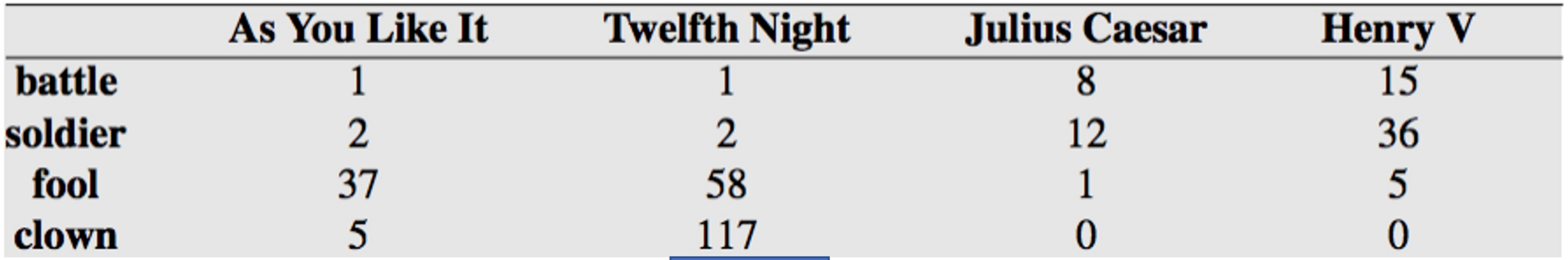
- TF-IDF

$$TFIDF(w) = TF(w) * IDF(w)$$


```
# TF-IDF
tfidf = TfidfVectorizer(
    ngram_range=(1,2),        # Use unigram and bigram
    tokenizer=word_tokenize, # Use `word_tokenize` method from pythainlp for tokenizer
    min_df=2,                 # The word found less than three times in dataset is ignored
    max_df=0.9,               # The word found more than 90% of entries is ignore
    use_idf=True,
    smooth_idf=True,
    sublinear_tf=True
)
# Logistic regresstion
model = LogisticRegression(C=4, max_iter=300, random_state=42)
```

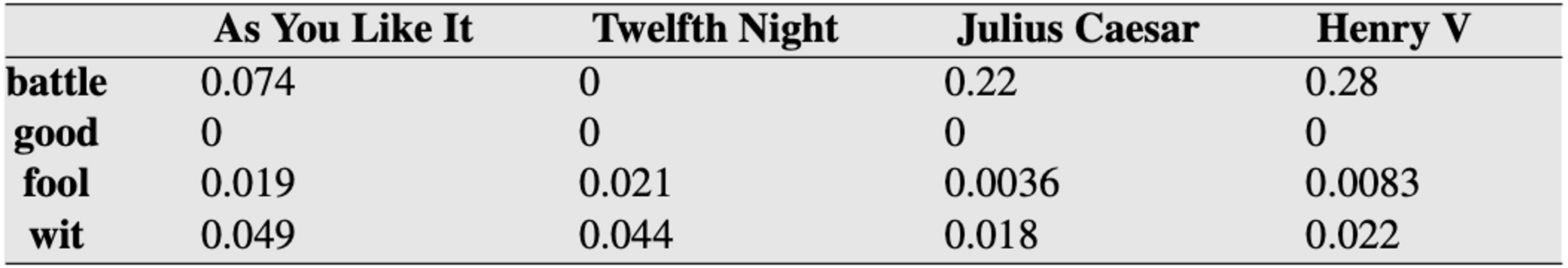
Sparse representation: TF-IDF (cont.)

TF



	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
clown	5	117	0	0

TF-IDF

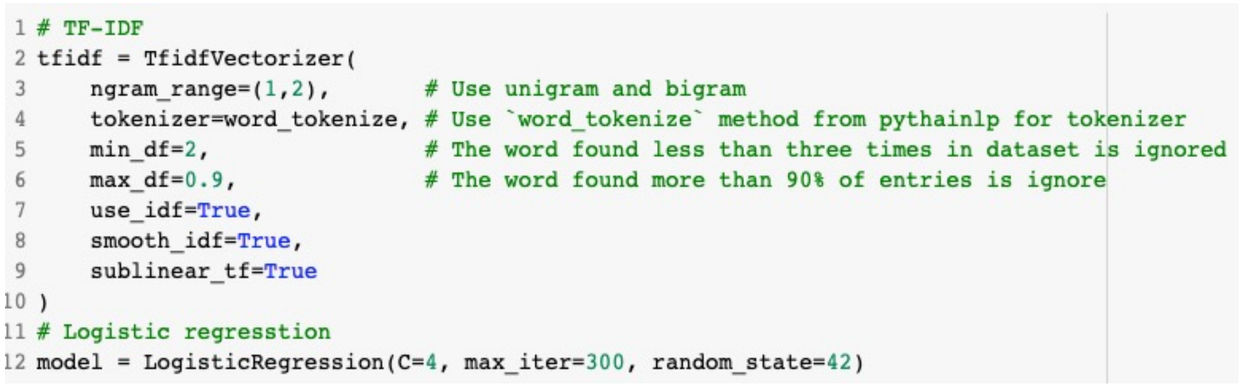


	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	0.074	0	0.22	0.28
good	0	0	0	0
fool	0.019	0.021	0.0036	0.0083
wit	0.049	0.044	0.018	0.022

Reference: Jurafsky, Dan, and James H. Martin. Speech and language processing. 3rd edition draft, https://web.stanford.edu/~jurafsky/slp3/6.pdf, Feb 2020

What classifier?

- Any classifier you like
- k-NN
- Naïve Bayes
- Logistic regression
- SVM
- Neural networks



```python
# TF-IDF
tfidf = TfidfVectorizer(
    ngram_range=(1,2),        # Use unigram and bigram
    tokenizer=word_tokenize, # Use `word_tokenize` method from pythainlp for tokenizer
    min_df=2,                 # The word found less than three times in dataset is ignored
    max_df=0.9,               # The word found more than 90% of entries is ignore
    use_idf=True,
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model = LogisticRegression(C=4, max_iter=300, random_state=42)
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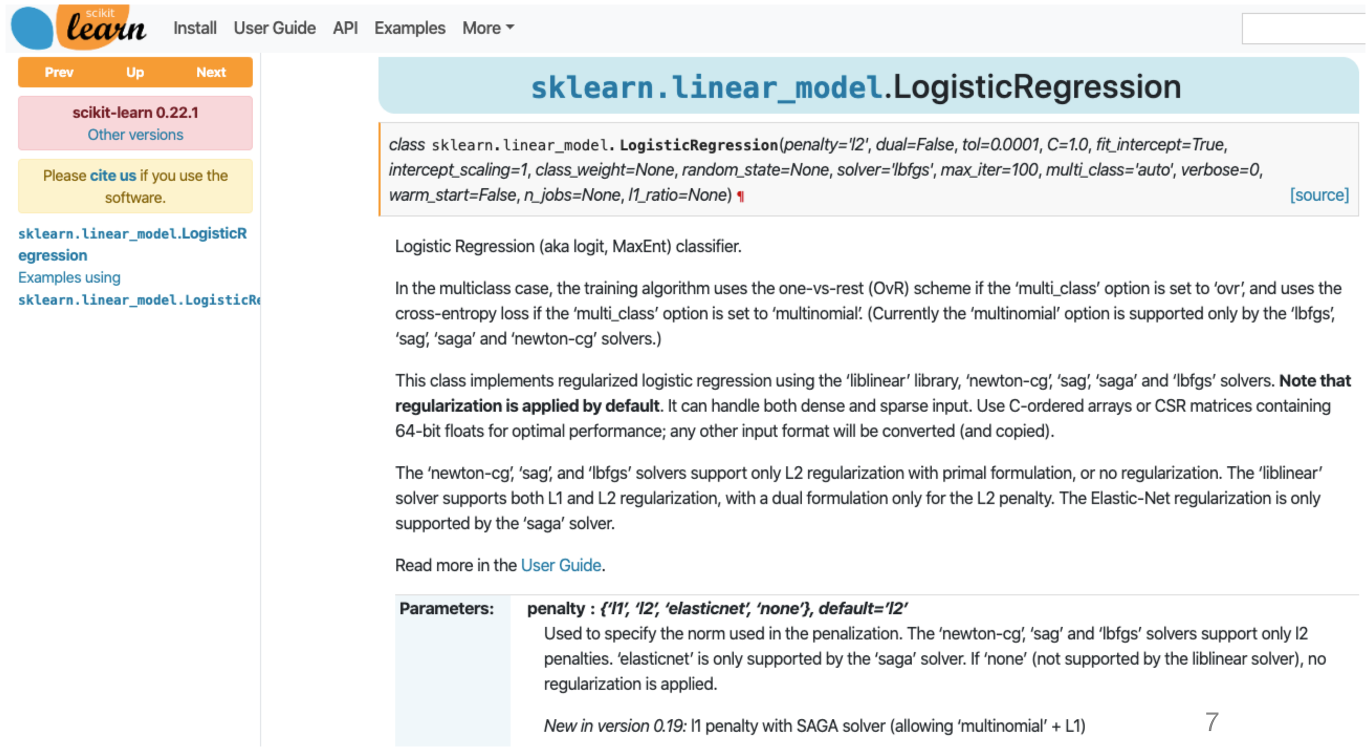


scikit learn
Install
User Guide
API
Examples
More
Prev
Up
Next
scikit-learn 0.22.1
Other versions
Please cite us if you use the software.
sklearn.linear_model.LogisticRegression
Examples using sklearn.linear_model.LogisticR

sklearn.linear_model.LogisticRegression

class sklearn.linear_model.**LogisticRegression**(*penalty='l2', dual=False, tol=0.0001, C=1.0, fit_intercept=True, intercept_scaling=1, class_weight=None, random_state=None, solver='lbfgs', max_iter=100, multi_class='auto', verbose=0, warm_start=False, n_jobs=None, l1_ratio=None*) ¶ [source]

Logistic Regression (aka logit, MaxEnt) classifier.

In the multiclass case, the training algorithm uses the one-vs-rest (OvR) scheme if the 'multi_class' option is set to 'ovr', and uses the cross-entropy loss if the 'multi_class' option is set to 'multinomial'. (Currently the 'multinomial' option is supported only by the 'lbfgs', 'sag', 'saga' and 'newton-cg' solvers.)

This class implements regularized logistic regression using the 'liblinear' library, 'newton-cg', 'sag', 'saga' and 'lbfgs' solvers. **Note that regularization is applied by default**. It can handle both dense and sparse input. Use C-ordered arrays or CSR matrices containing 64-bit floats for optimal performance; any other input format will be converted (and copied).

The 'newton-cg', 'sag', and 'lbfgs' solvers support only L2 regularization with primal formulation, or no regularization. The 'liblinear' solver supports both L1 and L2 regularization, with a dual formulation only for the L2 penalty. The Elastic-Net regularization is only supported by the 'saga' solver.

Read more in the User Guide.

Parameters: **penalty : *{'l1', 'l2', 'elasticnet', 'none'}, default='l2'***

Used to specify the norm used in the penalization. The 'newton-cg', 'sag' and 'lbfgs' solvers support only l2 penalties. 'elasticnet' is only supported by the 'saga' solver. If 'none' (not supported by the liblinear solver), no regularization is applied.

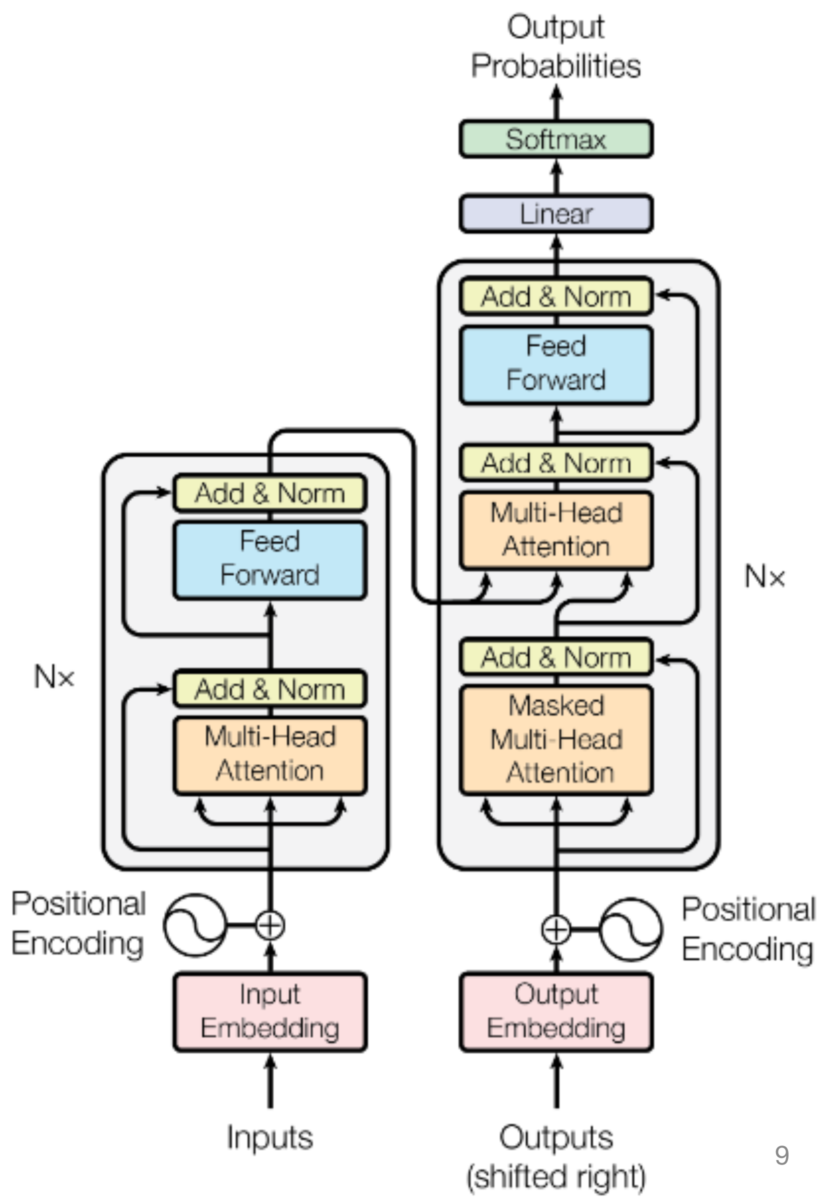
New in version 0.19: l1 penalty with SAGA solver (allowing 'multinomial' + L1)

Part2: Transformer-based models

Transformer-based models

Transformer

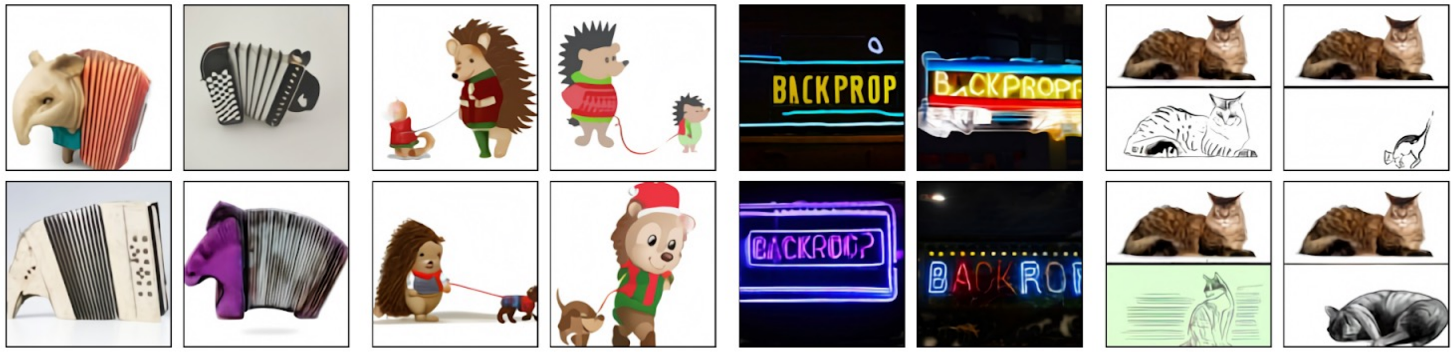
- A model based on attention mechanism
  - Gaining popularity in many application domain (NLP, speech, vision, bioinformatics, Reinforcement learning, Recommendation systems, etc.)



Attention is all you need 2017 https://arxiv.org/abs/1706.03762

Dall E

https://openai.com/blog/dall-e/



(a) a tapir made of accordion. a tapir with the texture of an accordion.

(b) an illustration of a baby hedgehog in a christmas sweater walking a dog

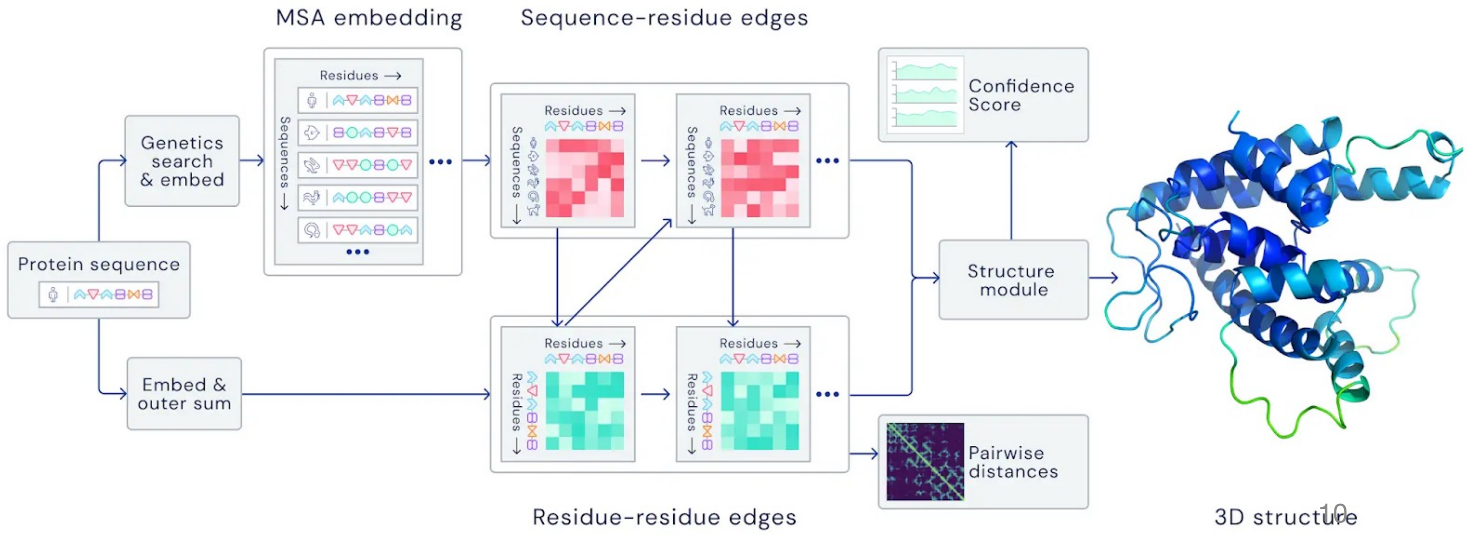
(c) a neon sign that reads "backprop". a neon sign that reads "backprop". backprop neon sign

(d) the exact same cat on the top as a sketch on the bottom

Figure 2. With varying degrees of reliability, our model appears to be able to combine distinct concepts in plausible ways, create anthropomorphized versions of animals, render text, and perform some types of image-to-image translation.

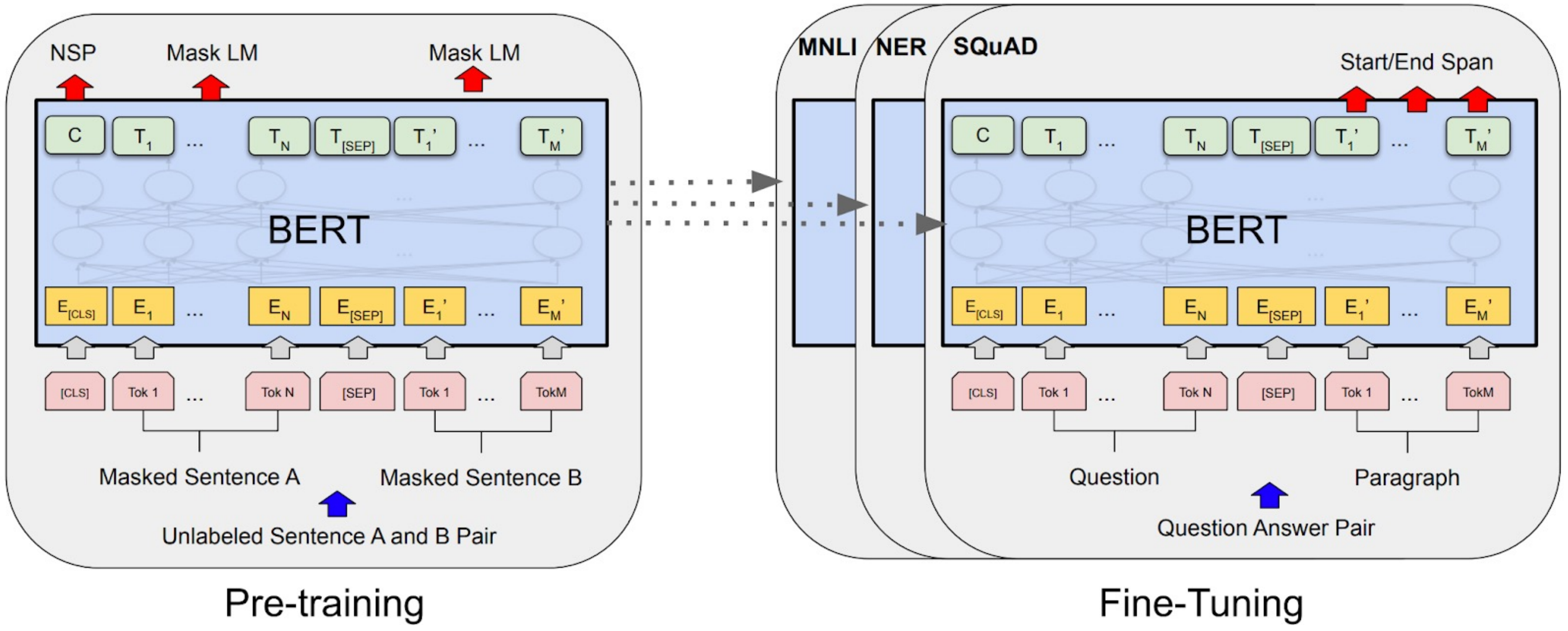
AlpheFold2

https://www.nature.com/articles/d41586-020-03348-4



BERT

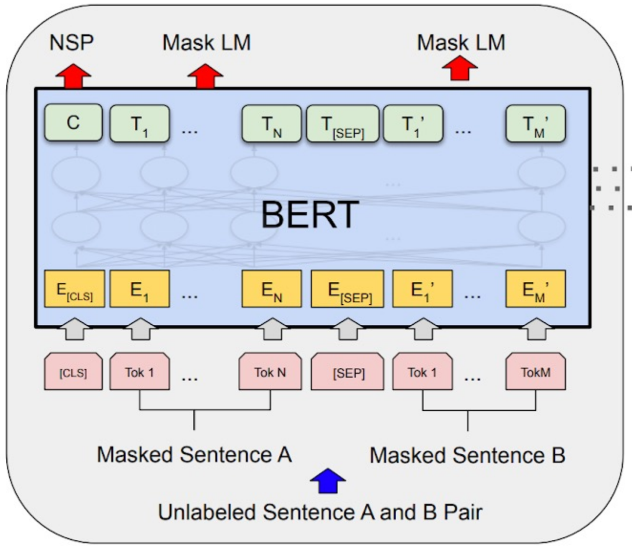
- Pretrained language model based on transformers
  - Can be used in many NLP tasks



BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, 2018 https://arxiv.org/abs/1810.04805

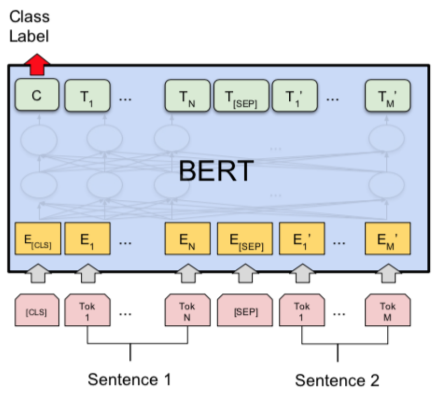
Pre-training BERT

- Predicting masked words in a sentence
  - The quick brown fox jumps over the [MASK]
  - Variants: predict correct word or not, predict swapped words, etc.
- Next sentence prediction
  - A: The cat is scared. B: It hides under the table.
  - A: The apple is on the table. B: It always rain.
  - Variants: sentence order prediction

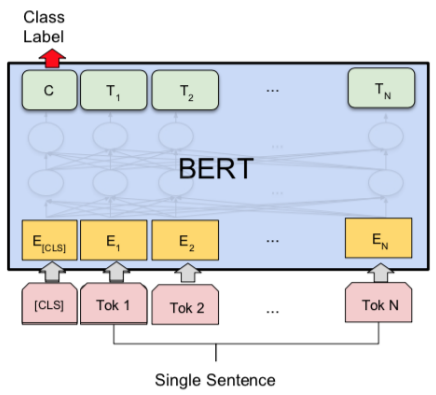


Pre-training

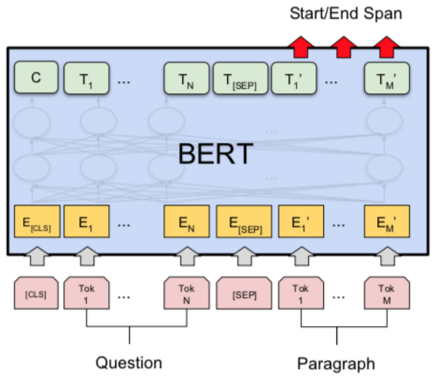
Downstream tasks with BERT



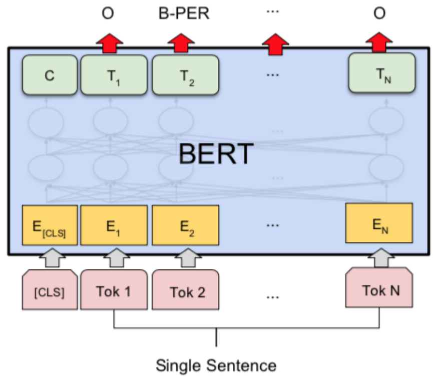
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



(b) Single Sentence Classification Tasks: SST-2, CoLA



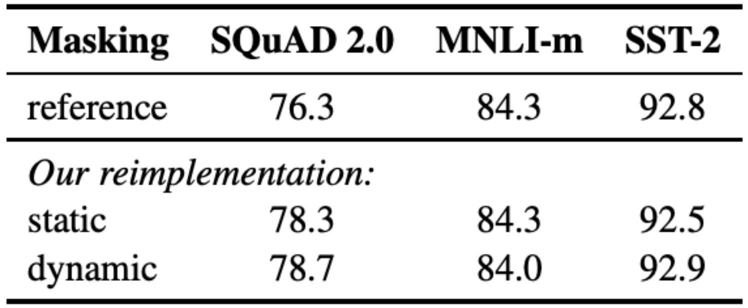
(c) Question Answering Tasks: SQuAD v1.1



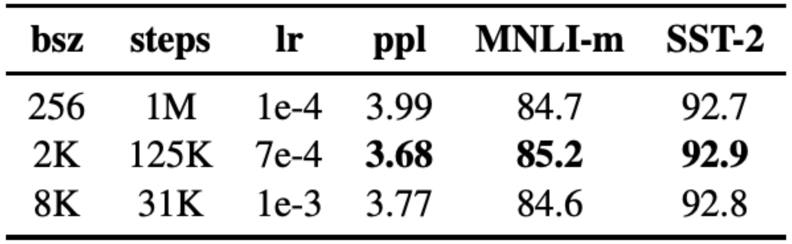
(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

ROBERTA (Robustly optimized BERT approach)

- A trick and tuning study
- Dynamic masking > static
- Next sentence prediction is removed



Masking	SQuAD 2.0	MNLI-m	SST-2
reference	76.3	84.3	92.8
Our reimplementation:			
static	78.3	84.3	92.5
dynamic	78.7	84.0	92.9



bsz	steps	lr	ppl	MNLI-m	SST-2
256	1M	1e-4	3.99	84.7	92.7
2K	125K	7e-4	**3.68**	**85.2**	**92.9**
8K	31K	1e-3	3.77	84.6	92.8

RoBERTa: A Robustly Optimized BERT Pretraining Approach, 2019 https://arxiv.org/abs/1907.11692

Current BERTrends

- Transformers are notorious for requiring large resources
- Newer models focus on
  - Better size/compute
  - Longer context

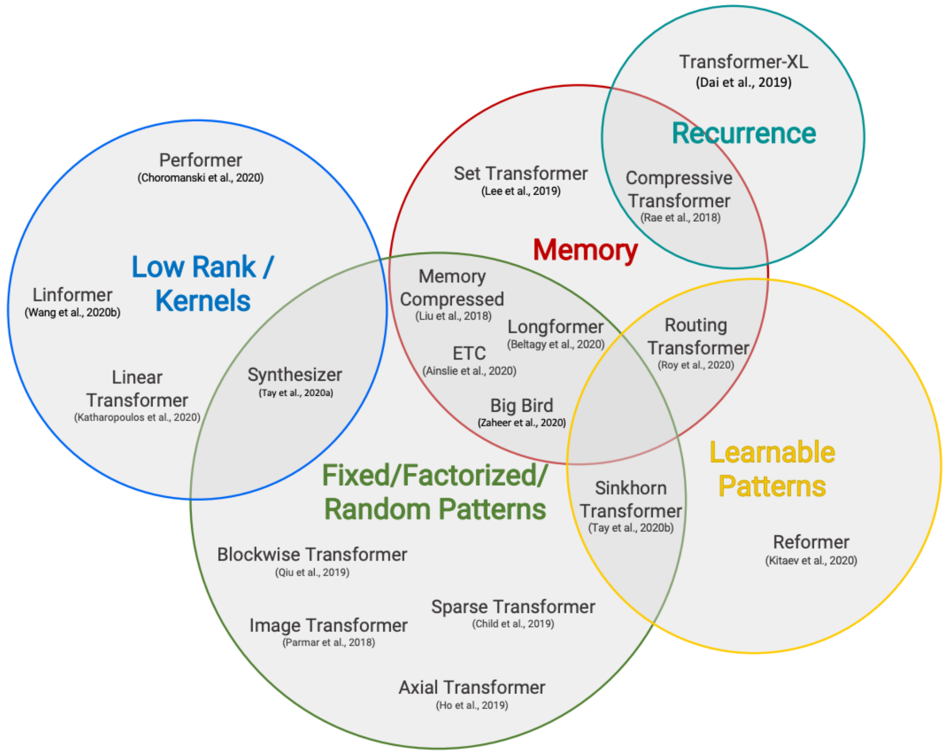
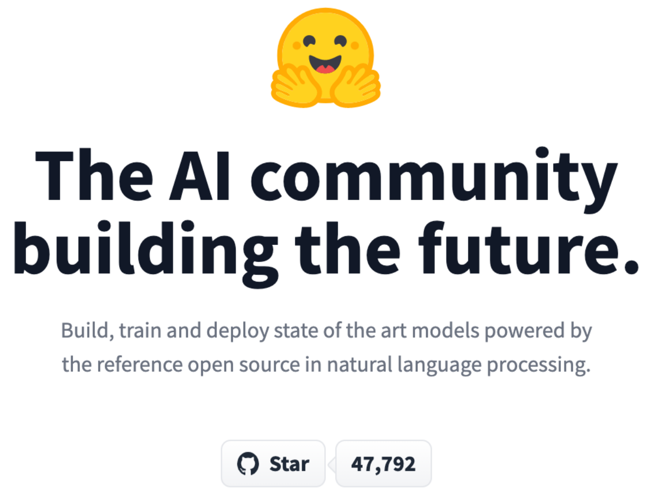

Transformer-XL (Dai et al., 2019)
Recurrence
Compressive Transformer (Rae et al., 2018)
Set Transformer (Lee et al., 2019)
Memory
Performer (Choromanski et al., 2020)
Low Rank / Kernels
Linformer (Wang et al., 2020b)
Linear Transformer (Katharopoulos et al., 2020)
Synthesizer (Tay et al., 2020a)
Memory Compressed (Liu et al., 2018)
Longformer (Beltagy et al., 2020)
ETC (Ainslie et al., 2020)
Big Bird (Zaheer et al., 2020)
Routing Transformer (Roy et al., 2020)
Learnable Patterns
Sinkhorn Transformer (Tay et al., 2020b)
Reformer (Kitaev et al., 2020)
Fixed/Factorized/ Random Patterns
Blockwise Transformer (Qiu et al., 2019)
Image Transformer (Parmar et al., 2018)
Sparse Transformer (Child et al., 2019)
Axial Transformer (Ho et al., 2019)

Figure 2: Taxonomy of Efficient Transformer Architectures.

Efficient Transformers: A Survey, 2020 https://arxiv.org/abs/2009.06732

Huggingface

- An opensource library for transformer-related models
- Has datasets, models, scripts, deployment solutions
- New official online course https://huggingface.co/course/chapter1



The AI community building the future.

Build, train and deploy state of the art models powered by the reference open source in natural language processing.

Pretrained BERT models (EN)

- 1. BERT-base-uncased (Google, 2018)
  - The original BERT model trained on uncased English text for general NLP tasks.
  - https://huggingface.co/bert-base-uncased
- 2. RoBERTa-base (Facebook, 2019)
  - An optimized version of BERT, trained with more data and using better training techniques for improved performance on various NLP tasks.
  - https://huggingface.co/roberta-base
- 3. DistilBERT-base-uncased (Hugging Face, 2019)
  - A smaller, faster version of BERT that retains 97% of its performance while being lighter and more efficient.
  - https://huggingface.co/distilbert-base-uncased
- 4. DeBERTa-v3-large (Microsoft, 2021)
  - An improved version of BERT and RoBERTa, using disentangled attention and enhanced mask decoding for better performance on classification tasks.
  - https://huggingface.co/microsoft/deberta-v3-large
- 5. ALBERT-base-v2 (Google, 2019)
  - A lighter, faster version of BERT with fewer parameters but excellent performance for text classification.
  - https://huggingface.co/albert-base-v2

Pretrained BERT models (TH)

- 1. PhayaThaiBERT (ClickNext, 2023)
  - A BERT-based model fine-tuned specifically for Thai language tasks, including text classification.
  - https://huggingface.co/clicknext/phayathaibert

- 2. wangchanberta-base-att-spm-uncased (VISTEC, 2021)
  - A Thai-specific RoBERTa model trained on a large Thai corpus using SentencePiece tokenizer.
  - https://huggingface.co/airesearch/wangchanberta-base-att-spm-uncased

- 3. mBERT (Multilingual BERT) (Google, 2018)
  - A multilingual BERT model trained on 104 languages, including Thai.
  - https://huggingface.co/bert-base-multilingual-cased

- 4. xlm-roberta-base (Facebook, 2019)
  - A multilingual model trained on 100 languages, including Thai, often performing well for Thai text classification.
  - https://huggingface.co/xlm-roberta-base

Appendix

Additional resources

- NLP course @ Chula 2023 version
    - https://www.youtube.com/playlist?list=PLcBOyD1N1T-OCVsj7sGMcMd8VQCNtk50i
    - https://github.com/ekapolc/NLP_2023