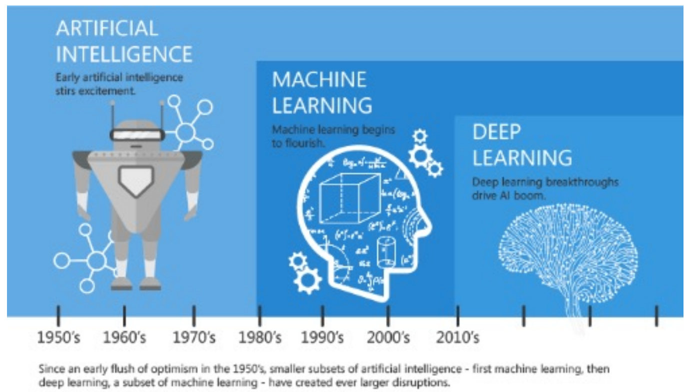
Text Classification

One of the ideas for your project

(Common) Text classification pipeline

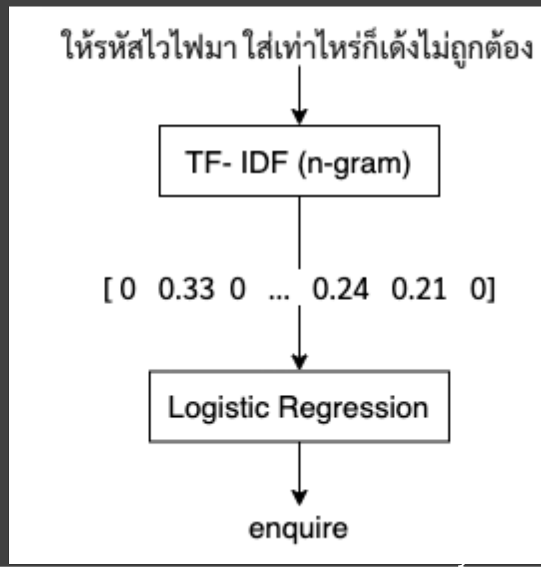
1) Data preparation → 2) Document representation → 3) Supervised learning model

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



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

	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

document

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.

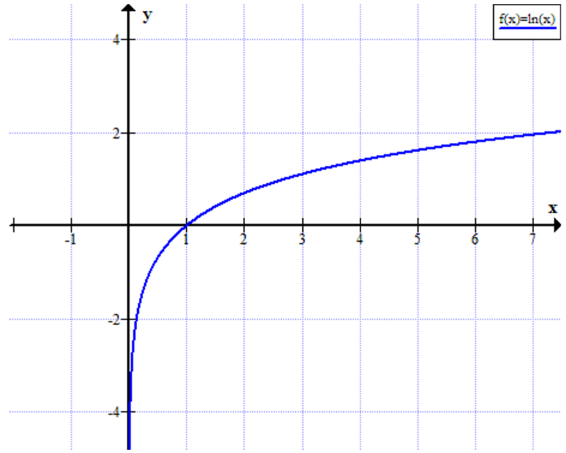
Reference: Jurafsky, Dan, and James H. Martin. Speech and language processing. 3rd edition draft, https://web.stanford.edu/~jurafsky/slp3/, August 2017

Sparse representation: TF-IDF

Need for normalization in TF

Doc1
cat = 5/10

Doc2
cat = 50/1000



- Term Frequency (TF) – per <u>each</u> 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 (<u>all</u> 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
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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.LogisticRe`

`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.

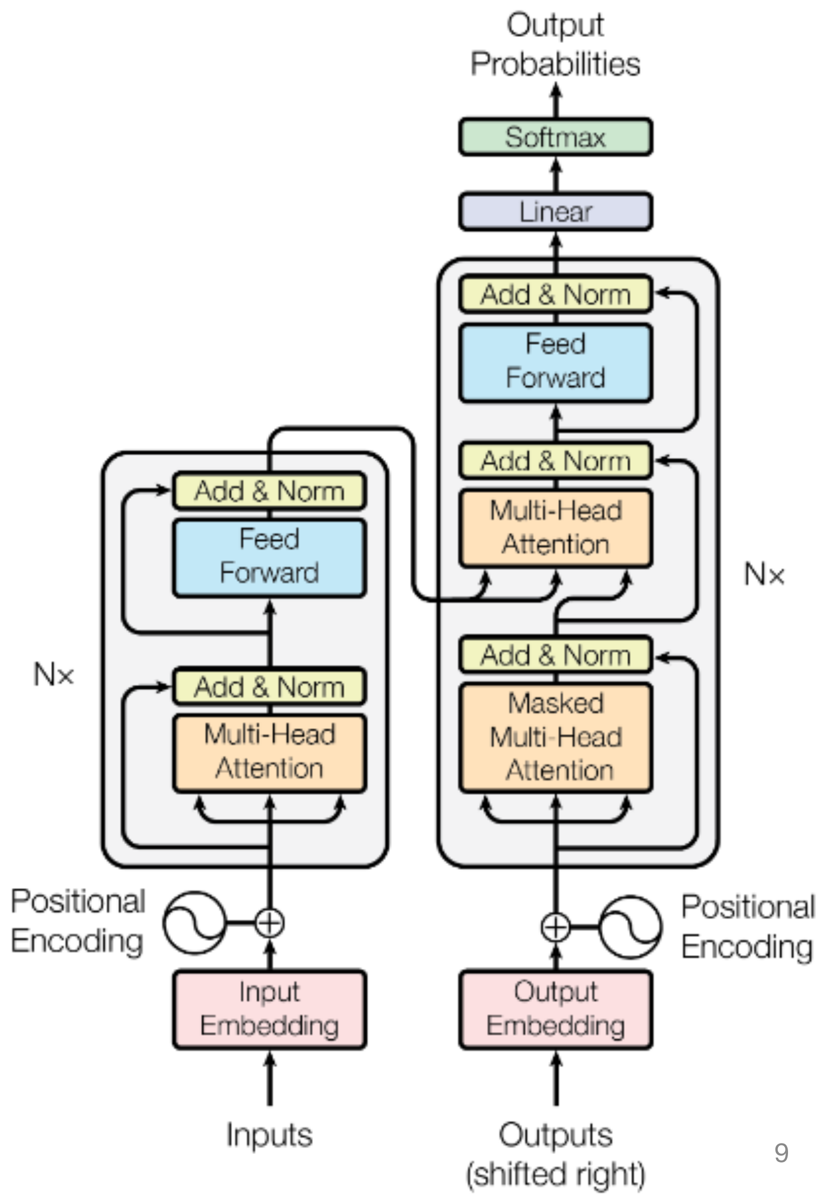
New in version 0.19: l1 penalty with SAGA solver (allowing 'multinomial' + L1)

Part2: Transformer-based models

Transformer-based models

Transformer

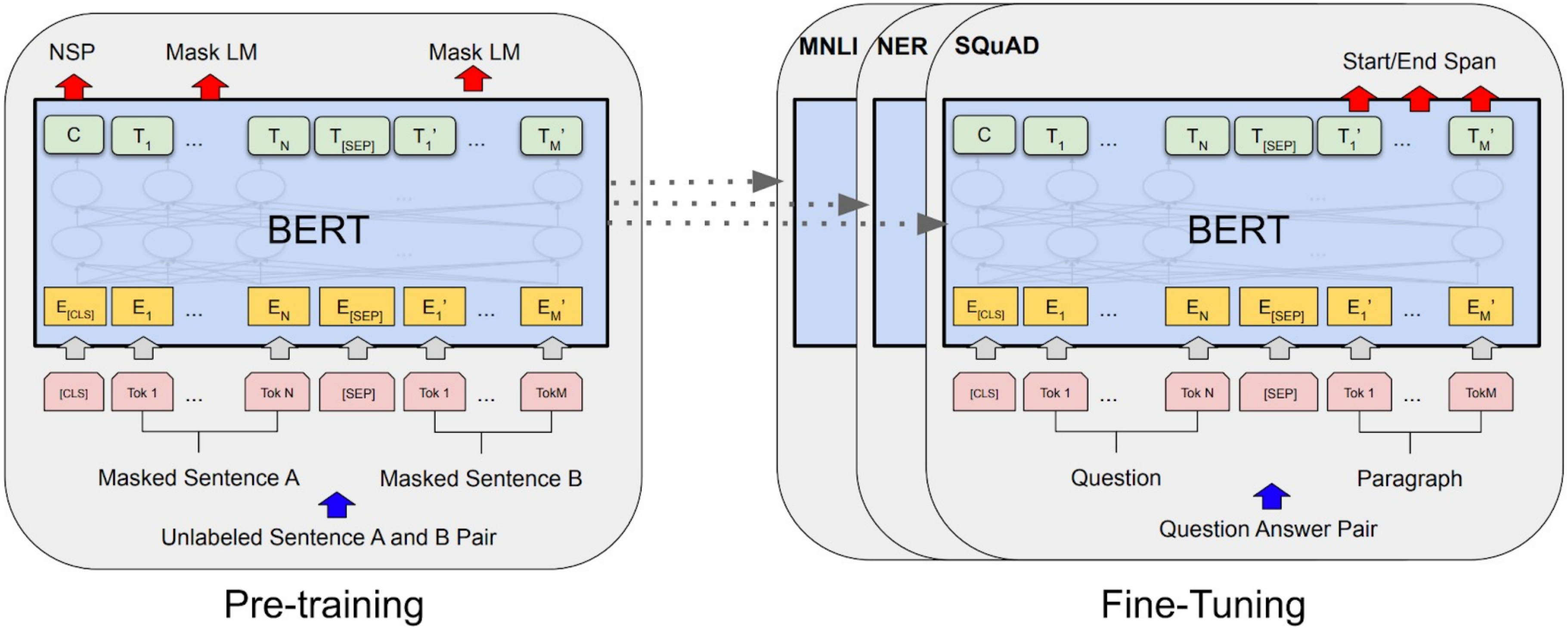
- A model based on attention mechanism
  - Gaining popularity in many application domain (NLP, speech, vision, bioinformatics, Reinforcement learning, Recommendation systems, etc.)



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

BERT

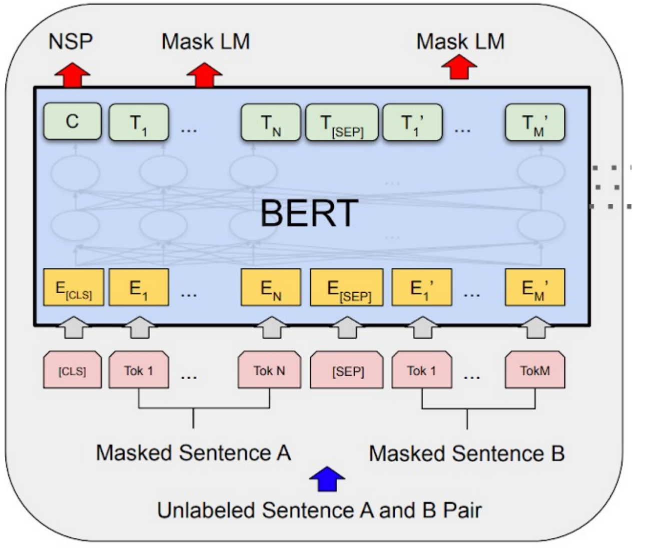
- Pretrained language model based on transformers
  - Can be used in many NLP tasks



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

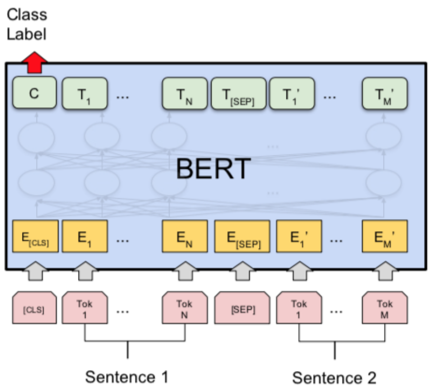
Pre-training BERT

- 1) Predicting masked words in a sentence
  - The quick brown fox jumps over the [MASK]
  - Variants: predict correct word or not, predict swapped words, etc.
- 2) 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

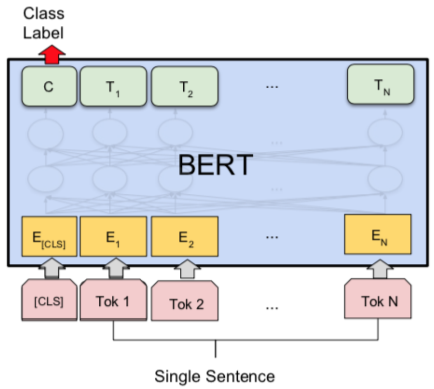


Pre-training

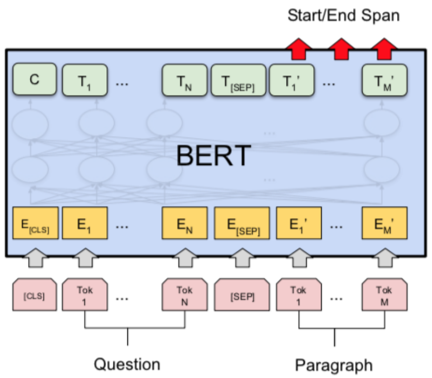
Downstream tasks with BERT



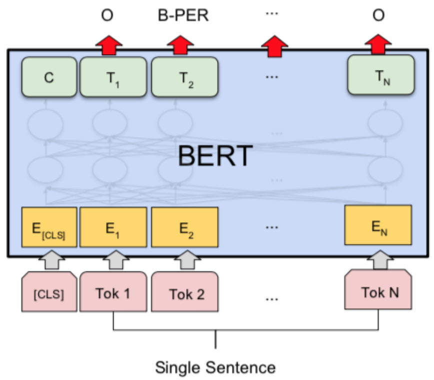
(a) Sentence Pair Classification Tasks:
MNLI, QQP, QNLI, STS-B, MRPC,
RTE, SWAG



(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) [Facebook AI, 2019]

- 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

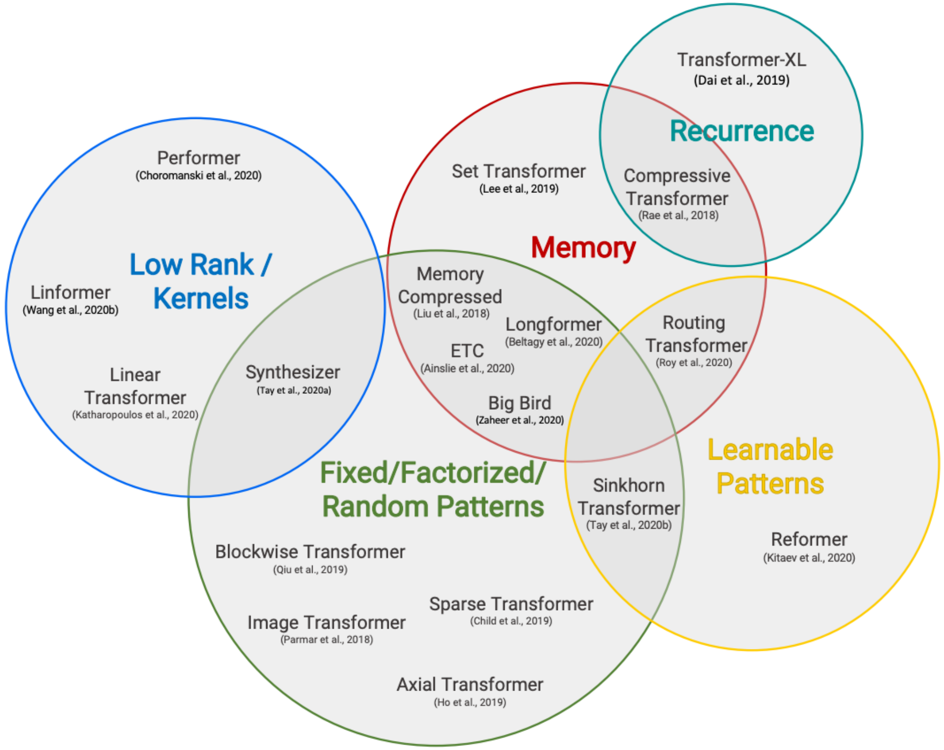
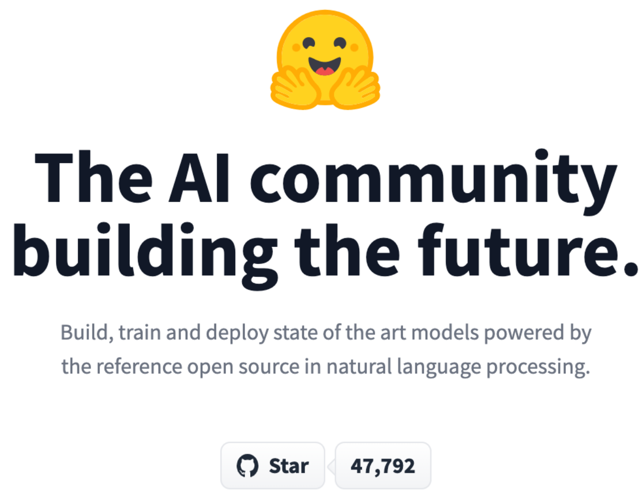


Figure 2: Taxonomy of Efficient Transformer Architectures.

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



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

WangchanBERTa [VISTEC, 2021]

- WangchanBERTa is a Thai language model based on the RoBERTa-base architecture, comprising approximately 110 million parameters.
- This model was trained on a diverse Thai text dataset totaling 78.5 GB, sourced from Thai Wikipedia, news articles, social media posts, and other publicly available datasets.
- 4 versions of word tokenization:
  - spm - sentenpiece
  - newmm
  - syllable
  - sefr – Stacked Ensemble Filter and Refine for Word Segmentation
- Recommend: wangchanberta-base-att-spm-uncased

<table>
<tr><td>หน่วยคำ
(Word)</td><td>วันนี้|ฉัน|สั่ง|กิวด้ง|มา|ทาน|ที่|บ้าน</td></tr>
<tr><td>หน่วยคำย่อย
(Subword)</td><td>วันนี้|ฉัน|สั่ง|กิ|วด|◌้ง|มา|ทาน|ที่บ้าน
(SentencePiece; XLMR)</td></tr>
<tr><td>หน่วยพยางค์
(Syllable)</td><td>วัน|นี้|ฉัน|สั่ง|กิว|ด้ง|มา|ทาน|ที่|บ้าน</td></tr>
<tr><td>หน่วยตัวอักษร
(Character)</td><td>ว|◌ั|น|น|◌ี|◌้|ฉ|◌ั|น|ส|◌ั|◌่|ง|กิ|ว|ด|◌้|ง|ม|า|ท|า|น|ที่|◌ี|◌่|บ|◌้|า|น</td></tr>
</table>

https://airesearch.in.th/releases/wangchanberta-pre-trained-thai-language-model/

https://huggingface.co/airesearch

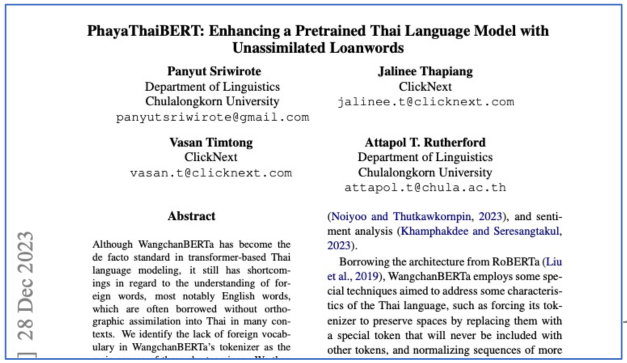
PhayaThaiBERT [Attapol, 2023]

- It addresses limitations found in previous models, such as WangchanBERTa, by expanding the vocabulary to include foreign terms, particularly English words commonly used in Thai contexts.

- Model Size: Approximately 277 million parameters, making it larger than WangchanBERTa's 110 million parameters.

- Training Data: Utilized a preprocessed and tokenized dataset totaling 156.5 GB, which is twice the size of the dataset used for WangchanBERTa. This extensive dataset includes a variety of sources to enhance the model's comprehension of diverse language patterns.

- Vocabulary Expansion: Enhanced by incorporating foreign vocabulary through a transfer from XLM-R's pretrained tokenizer, allowing for better tokenization of unassimilated loanwords and emojis.



PhayaThaiBERT: Enhancing a Pretrained Thai Language Model with Unassimilated Loanwords

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28 Dec 2023

Abstract

Although WangchanBERTa has become the de facto standard in transformer-based Thai language modeling, it still has shortcomings in regard to the understanding of foreign words, most notably English words, which are often borrowed without orthographic assimilation into Thai in many contexts. We identify the lack of foreign vocabulary in WangchanBERTa's tokenizer as the

(Noiyoo and Thutkawkornpin, 2023), and sentiment analysis (Khamphakdee and Seresangtakul, 2023).

Borrowing the architecture from RoBERTa (Liu et al., 2019), WangchanBERTa employs some special techniques aimed to address some characteristics of the Thai language, such as forcing its tokenizer to preserve spaces by replacing them with a special token that will never be included with other tokens, and normalizing sequences of more

https://huggingface.co/clicknext/phayathaibert

Appendix

Additional resources

- NLP course @ Chula 2025 version
  - https://www.youtube.com/watch?v=E28rC70ppLs&list=PLcBOyD1N1T-NSF5TATtlbuGgNjNfF07zl&index=7
  - https://github.com/ekapolc/NLP_2025