Artificial Intelligence for Text Analytics

国立臺北大學
National Taipei University

Text Classification and Sentiment Analysis

1121AITA05
MBA, IM, NTPU (M5265) (Fall 2023)
Tue 2, 3, 4 (9:10-12:00) (B3F17)

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2023-10-18

Syllabus

Week	Date	Subject/Topics
1	2023/09/13	Introduction to Artificial Intelligence for Text Analytics
2	2023/09/20	Foundations of Text Analytics: Natural Language Processing (NLP)
3	2023/09/27	Python for Natural Language Processing
4	2023/10/04	Natural Language Processing with Transformers
5	2023/10/11	Case Study on Artificial Intelligence for Text Analytics I
6	2023/10/18	Text Classification and Sentiment Analysis

Syllabus

Week	Date	Subject/Topics
7	2023/10/25	Multilingual Named Entity Recognition (NER)
8	2023/11/01	Midterm Project Report
9	2023/11/08	Text Similarity and Clustering
10	2023/11/15	Text Summarization and Topic Models
11	2023/11/22	Text Generation with Large Language Models (LLMs)
12	2023/11/29	Case Study on Artificial Intelligence for Text Analytics II

Syllabus

Week	Date	Subject/Topics
13	2023/12/06	Question Answering and Dialogue Systems
14	2023/12/13	Deep Learning, Generative AI, Transfer Learning, Zero-Shot, and Few-Shot Learning for Text Analytics
15	2023/12/20	Final Project Report I
16	2023/12/27	Final Project Report II

Text Classification and Sentiment Analysis

Outline

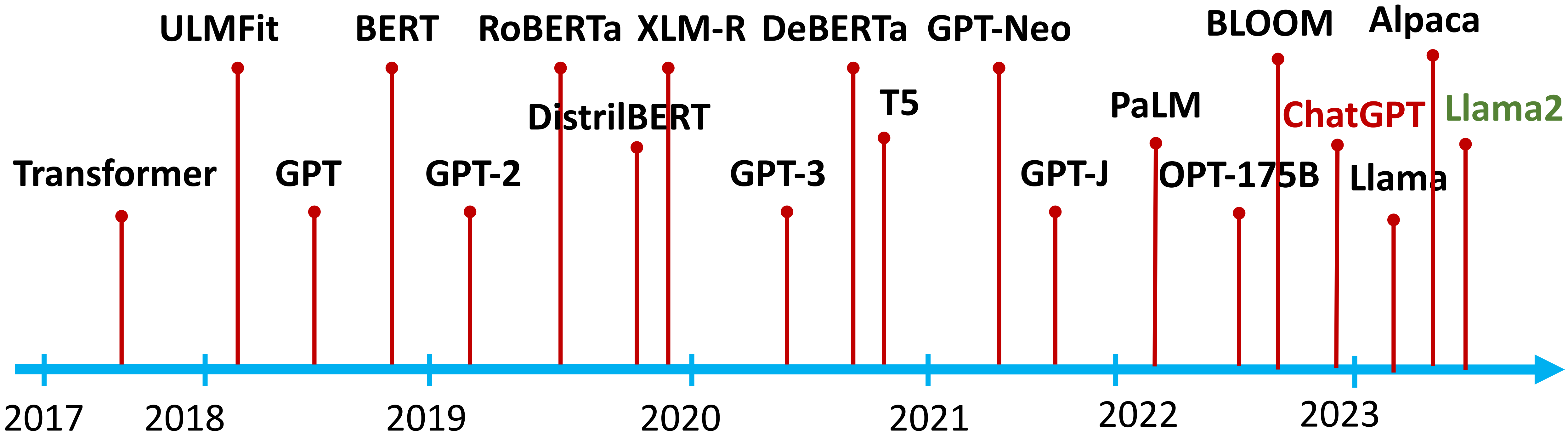
- Text Classification and Sentiment Analysis
  - Dataset
  - Tokenizer
  - Training a Text Classifier
  - Fine-Tuning Transformers

Text Classification (TC) Tasks

- **Sentiment Analysis**
- **News Categorization**
- **Product Categorization**
- **Topic Analysis**
  - Topic Classification: “customer support” or “ease of use”
- **Natural language inference (NLI)**
  - recognizing textual entailment (RTE)
  - entailment, contradiction, and neutral

Source: Shervin Minaee, Nal Kalchbrenner, Erik Cambria, Narjes Nikzad, Meysam Chenaghlu, and Jianfeng Gao (2021), "Deep learning--based text classification: a comprehensive review." ACM Computing Surveys (CSUR) 54, no. 3 (2021): 1-40.

The Transformers Timeline



Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.

Text Classification Datasets

Task	Dataset	Size	Dim.	Class Distribution					Density	Skewness
				# Classes	Minor	Median	Mean	Major		
Topic	DBLP	38,128	28,131	10	1,414	3,590	3,812	9,746	141	Imbalanced
	Books	33,594	46,382	8	1,226	4,534	4,199	4,934	269	Imbalanced
	ACM	24,897	48,867	11	63	2,041	2,263	6,562	65	Imbalanced
	20NG	18,846	97,401	20	628	984	942	999	96	Balanced
	OHSUMED	18,302	31,951	23	56	592	795	2,876	154	Imbalanced
	Reuters90	13,327	27,302	90	2	29	148	3,964	171	Extremely imbalanced
	WOS-11967	11,967	25,567	33	262	371	362	449	195	Balanced
	WebKB	8,199	23,047	7	137	926	1,171	3,705	209	Imbalanced
	TREC	5,952	3,032	6	95	1,148	992	1,344	10	Imbalanced
	WOS-5736	5,736	18,031	11	380	426	521	750	201	Balanced
Sentiment	SST1	11,855	9,015	5	1,510	2,242	2,371	3,140	19	Balanced
	pang_movie	10,662	17,290	2	5,331	5,331	5,331	5,331	21	Balanced
	MR	10,662	9,070	2	5,331	5,331	5,331	5,331	21	Balanced
	vader_movie	10,568	16,827	2	5,242	5,284	5,284	5,326	19	Balanced
	MPQA	10,606	2,643	2	3,312	5,303	5,303	7,294	3	Imbalanced
	Subj	10,000	10,151	2	5,000	5,000	5,000	5,000	24	Balanced
	SST2	9,613	7,866	2	4,650	4,806	4,806	4,963	19	Balanced
	yelp_reviews	5,000	23,631	2	2,500	2,500	2,500	2,500	132	Balanced
	vader_nyt	4,946	12,004	2	2,204	2,473	2,473	2,742	18	Balanced

Source: Washington Cunha, Felipe Viegas, Celso França, Thierson Rosa, Leonardo Rocha, and Marcos André Gonçalves (2023). "A Comparative Survey of Instance Selection Methods applied to NonNeural and Transformer-Based Text Classification." ACM Computing Surveys.

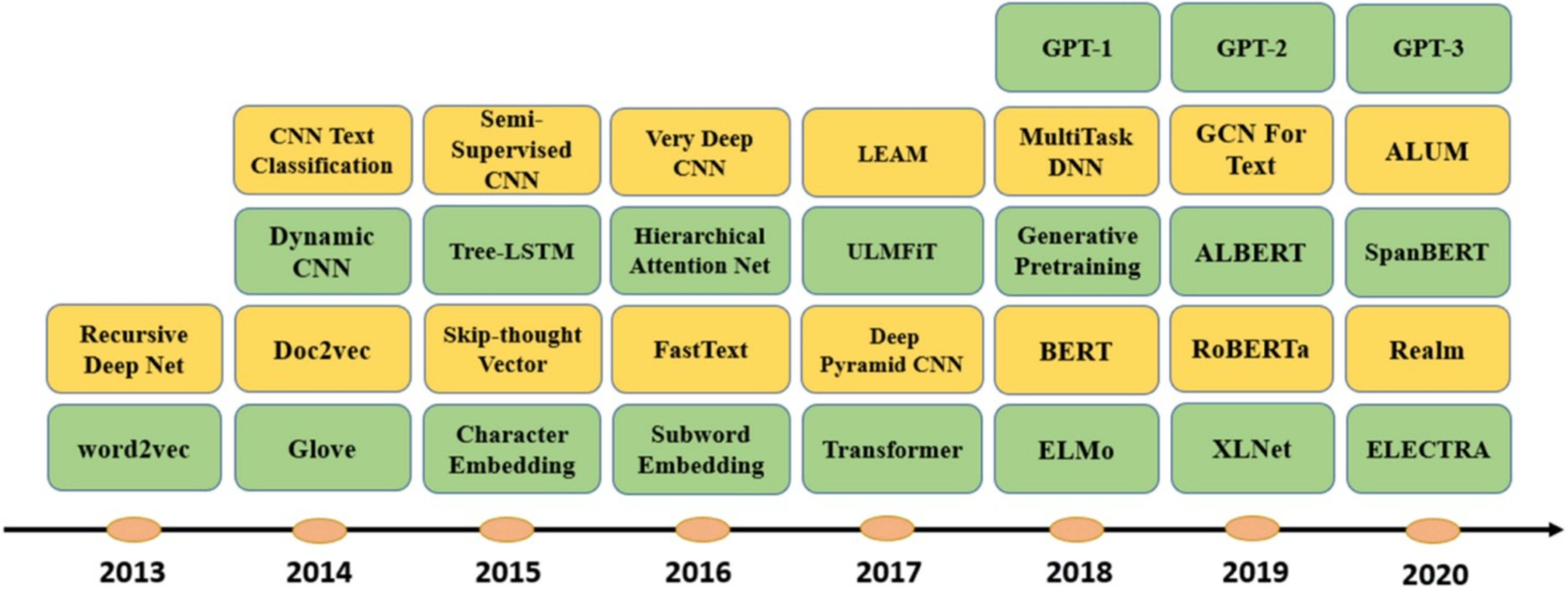
Text Classification Evaluation Metric MacroF1

Task	Dataset	RoBERTa	BART	XLNet	BERT	DistilBERT	ALBERT	MF+SVM	GPT2	TFIDF
Topic	DBLP	**81.4(0.5)** 🟡	**81.1(0.5)** 🟡	**81.4(0.6)** 🟡	**81.7(0.5)** 🟢	**81.0(0.6)** 🟡	77.3(1.0)	80.5(0.7)	78.9(0.8)	79.3(0.7)
	Books	87.2(0.6)	86.9(0.5)	87.3(0.4)	**89.5(0.2)** ▲	87.5(0.5)	84.6(0.8)	88.3(0.3)	85.4(0.7)	84.1(0.4)
	ACM	**70.3(1.4)** 🟡	**70.8(0.7)** 🟡	**69.9(0.9)** 🟡	**71.8(1.0)** 🟢	**70.1(1.0)** 🟡	66.2(1.9)	**70.3(1.0)** 🟡	67.6(1.2)	68.0(0.7)
	20NG	86.8(0.7)	87.4(0.9)	87.4(0.8)	85.4(0.5)	86.7(0.6)	76.9(1.2)	**90.7(0.6)** ▲	82.3(0.9)	89.1(0.7)
	OHSUMED	**77.8(1.2)** 🟢	**77.6(0.7)** 🟡	**77.6(1.0)** 🟡	**76.4(1.2)** 🟡	**76.2(0.7)** 🟡	66.1(4.8)	71.8(1.0)	74.5(0.8)	71.2(1.1)
	Reuters90	41.9(2.2)	42.2(2.1)	41.3(2.6)	40.2(2.8)	40.7(2.5)	41.0(2.6)	**48.4(2.6)** ▲	37.2(2.3)	31.9(3.2)
	WOS-11967	**86.8(0.4)** 🟡	**86.9(0.8)** 🟡	**87.0(0.7)** 🟢	85.5(0.7)	**86.0(0.7)** 🟡	76.8(1.1)	82.0(0.9)	81.5(0.9)	84.5(0.6)
	WebKB	**83.0(2.0)** 🟡	**83.0(1.7)** 🟡	**81.9(2.5)** 🟡	**83.2(2.1)** 🟢	**82.3(2.1)** 🟡	**80.3(1.4)** 🟡	71.6(2.4)	79.0(1.9)	72.9(2.1)
	TREC	**95.5(0.5)** 🟢	**95.5(0.8)** 🟡	**94.3(1.1)** 🟡	87.6(1.4)	**95.5(1.1)** 🟡	**93.5(1.4)** 🟡	67.4(1.5)	92.0(1.0)	68.3(2.0)
	WOS-5736	**90.5(0.9)** 🟢	**89.6(1.7)** 🟡	**90.2(0.9)** 🟡	**89.7(1.3)** 🟡	**89.2(0.9)** 🟡	86.7(1.3)	87.2(0.8)	83.8(0.5)	**90.4(0.7)** 🟡
Sentiment	SST1	**53.8(1.3)** 🟢	**52.8(1.0)** 🟡	**51.4(1.7)** 🟡	**51.6(1.2)** 🟡	48.9(1.1)	49.2(1.2)	28.2(0.7)	45.4(1.1)	29.6(0.8)
	pang_movie	**89.0(0.4)** 🟢	**88.1(0.5)** 🟡	**88.2(0.6)** 🟡	87.4(0.4)	85.2(0.6)	**82.9(4.2)** 🟡	33.4(0.1)	81.7(0.8)	77.0(1.0)
	MR	**89.0(0.7)** 🟢	**88.2(0.6)** 🟡	**86.4(3.3)** 🟡	**87.7(0.5)** 🟡	85.2(1.1)	84.9(1.2)	33.5(0.2)	81.6(0.8)	75.8(0.9)
	vader_movie	**91.3(0.5)** 🟢	**90.4(0.6)** 🟡	**90.5(0.4)** 🟡	88.2(0.7)	86.6(0.7)	85.4(1.6)	33.6(0.1)	85.0(0.5)	78.0(0.9)
	MPQA	**90.2(0.8)** 🟢	**90.1(0.7)** 🟡	88.6(0.5)	**89.1(0.7)** 🟡	88.5(0.6)	87.9(0.6)	76.9(0.6)	86.5(0.6)	78.3(0.7)
	Subj	**96.9(0.4)** 🟡	**96.8(0.4)** 🟡	**96.1(0.5)** 🟡	**97.0(0.3)** 🟢	**96.0(0.4)** 🟡	95.5(0.7)	90.0(0.7)	94.6(0.4)	89.1(0.6)
	SST2	**93.2(0.6)** 🟢	**92.8(0.5)** 🟡	92.1(0.4)	91.5(0.6)	89.6(0.5)	88.6(2.1)	79.2(0.8)	86.9(0.6)	79.0(0.7)
	yelp_reviews	**97.9(0.4)** 🟢	**97.5(0.4)** 🟡	**97.3(0.4)** 🟡	95.6(0.6)	95.6(0.6)	93.9(0.9)	33.5(0.2)	93.5(0.7)	94.7(0.8)
	vader_nyt	**85.3(0.6)** 🟡	**85.5(0.8)** 🟢	82.7(1.1)	80.7(0.9)	79.9(1.2)	76.9(1.8)	37.8(0.9)	74.9(1.8)	64.5(1.8)

(a) ▲: the classification approach is superior to *all others*; (b) 🟢: the classification approach presents the highest result in terms of absolute values, but there are statistical ties with *other approaches*; (c) 🟡: the classification approach is statistically equivalent to the best approach (marked with 🟢) in the dataset (line) considered.

Source: Washington Cunha, Felipe Viegas, Celso França, Thierson Rosa, Leonardo Rocha, and Marcos André Gonçalves (2023). "A Comparative Survey of Instance Selection Methods applied to NonNeural and Transformer-Based Text Classification." ACM Computing Surveys.

Deep learning models for text embedding and classification



Source: Shervin Minaee, Nal Kalchbrenner, Erik Cambria, Narjes Nikzad, Meysam Chenaghlu, and Jianfeng Gao (2021), "Deep learning--based text classification: a comprehensive review." ACM Computing Surveys (CSUR) 54, no. 3 (2021): 1-40.

Text Classification Models on Sentiment Analysis

Method	IMDB	SST-2	Amazon-2	Amazon-5	Yelp-2	Yelp-5
Naive Bayes [43]	-	81.80	-	-	-	-
LDA [214]	67.40	-	-	-	-	-
BoW+SVM [31]	87.80	-	-	-	-	-
*tf.*Δ *idf* [215]	88.10	-	-	-	-	-
Char-level CNN [50]	-	-	94.49	59.46	95.12	62.05
Deep Pyramid CNN [49]	-	84.46	96.68	65.82	97.36	69.40
ULMFiT [216]	95.40	-	-	-	97.84	70.02
BLSTM-2DCNN [40]	-	89.50	-	-	-	-
Neural Semantic Encoder [95]	-	89.70	-	-	-	-
BCN+Char+CoVe [217]	91.80	90.30	-	-	-	-
GLUE ELMo baseline [22]	-	90.40	-	-	-	-
BERT ELMo baseline [7]	-	90.40	-	-	-	-
CCCapsNet [76]	-	-	94.96	60.95	96.48	65.85
Virtual adversarial training [173]	94.10	-	-	-	-	-
Block-sparse LSTM [218]	94.99	93.20	-	-	96.73	
BERT-base [7, 154]	95.63	93.50	96.04	61.60	98.08	70.58
BERT-large [7, 154]	95.79	94.9	96.07	62.20	98.19	71.38
ALBERT [147]	-	95.20	-	-	-	-
Multi-Task DNN [23]	83.20	95.60	-	-	-	-
Snorkel MeTaL [219]	-	96.20	-	-	-	-
BERT Finetune + UDA [220]	95.80		96.50	62.88	97.95	62.92
RoBERTa (+additional data) [146]	-	96.40	-	-	-	-
XLNet-Large (ensemble) [156]	96.21	96.80	97.60	67.74	98.45	72.20

Source: Shervin Minaee, Nal Kalchbrenner, Erik Cambria, Narjes Nikzad, Meysam Chenaghlu, and Jianfeng Gao (2021), "Deep learning--based text classification: a comprehensive review." ACM Computing Surveys (CSUR) 54, no. 3 (2021): 1-40.

Classification Models on News Categorization, and Topic Classification

	News Categorization			Topic Classification	
Method	AG News	20NEWS	Sogou News	DBpedia	Ohsumed
Hierarchical Log-bilinear Model [221]	-	-	-	-	52
Text GCN [107]	67.61	86.34	-	-	68.36
Simplfied GCN [108]	-	88.50	-	-	68.50
Char-level CNN [50]	90.49	-	95.12	98.45	-
CCCapsNet [76]	92.39	-	97.25	98.72	-
LEAM [84]	92.45	81.91	-	99.02	58.58
fastText [30]	92.50	-	96.80	98.60	55.70
CapsuleNet B [71]	92.60	-	-	-	-
Deep Pyramid CNN [49]	93.13	-	98.16	99.12	-
ULMFiT [216]	94.99	-	-	99.20	-
L MIXED [174]	95.05	-	-	99.30	-
BERT-large [220]	-	-	-	99.32	-
XLNet [156]	95.51	-	-	99.38	-

Source: Shervin Minaee, Nal Kalchbrenner, Erik Cambria, Narjes Nikzad, Meysam Chenaghlu, and Jianfeng Gao (2021), "Deep learning--based text classification: a comprehensive review." ACM Computing Surveys (CSUR) 54, no. 3 (2021): 1-40.

Classification Models on Natural Language Inference (NLI)

	SNLI	MultiNLI	
Method	Accuracy	Matched	Mismatched
Unigrams Features [208]	71.6	—	—
Lexicalized [208]	78.2	—	—
LSTM encoders (100D) [208]	77.6	—	—
Tree-based CNN [61]	82.1	—	—
biLSTM Encoder [209]	81.5	67.5	67.1
Neural Semantic Encoders (300D) [95]	84.6	—	—
RNN-based Sentence Encoder [224]	85.5	73.2	73.6
DiSAN (300D) [81]	85.6	—	—
Decomposable Attention Model [92]	86.3	—	—
Reinforced Self-Attention (300D) [177]	86.3	—	—
Generalized Pooling (600D) [93]	86.6	73.8	74.0
Bilateral multi-perspective matching [41]	87.5	—	—
Multiway Attention Network [87]	88.3	78.5	77.7
ESIM + ELMo [4]	88.7	72.9	73.4
DMAN with Reinforcement Learning [225]	88.8	88.8	78.9
BiLSTM + ELMo + Attn [22]	—	74.1	74.5
Fine-Tuned LM-Pretrained Transformer [6]	89.9	82.1	81.4
Multi-Task DNN [23]	91.6	86.7	86.0
SemBERT [155]	91.9	84.4	84.0
RoBERTa [146]	92.6	90.8	90.2
XLNet [156]	—	90.2	89.8

Source: Shervin Minaee, Nal Kalchbrenner, Erik Cambria, Narjes Nikzad, Meysam Chenaghlu, and Jianfeng Gao (2021), "Deep learning--based text classification: a comprehensive review." ACM Computing Surveys (CSUR) 54, no. 3 (2021): 1-40.

General Language Understanding Evaluation (GLUE) benchmark

GLUE Test results

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**91.1**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**81.9**

MNLI: Multi-Genre Natural Language Inference
QQP: Quora Question Pairs
QNLI: Question Natural Language Inference
SST-2: The Stanford Sentiment Treebank
CoLA: The Corpus of Linguistic Acceptability
STS-B:The Semantic Textual Similarity Benchmark
MRPC: Microsoft Research Paraphrase Corpus
RTE: Recognizing Textual Entailment

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

ChatGPT and fine-tuned BERT-style models on GLUE benchmark

Method	CoLA	SST-2	MRPC		STS-B		QQP		MNLI		QNLI	RTE	GLUE
	Mcc.	*Acc.*	*Acc.*	*F1*	*Pear.*	*Spea.*	*Acc.*	*F1*	*m.*	*mm.*	*Acc.*	*Acc.*	avg.
BERT-base	56.4	88.0	90.0	89.8	83.0	81.9	80.0	80.0	82.7	82.7	84.0	70.0	79.2
BERT-large	62.4	96.0	92.0	91.7	88.3	86.8	88.0	88.5	82.7	88.0	90.0	82.0	85.4
RoBERTa-base	61.8	96.0	90.0	90.6	90.2	89.1	84.0	84.0	84.0	88.0	92.0	78.0	84.7
RoBERTa-large	65.3	96.0	92.0	92.0	92.9	91.1	90.0	89.4	88.0	90.7	94.0	84.0	87.8
ChatGPT	56.0	92.0	66.0*	72.1*	80.9	72.4*	78.0	79.3	89.3*	81.3	84.0	88.0*	78.7

MNLI: Multi-Genre Natural Language Inference
QQP: Quora Question Pairs
QNLI: Question Natural Language Inference
SST-2: The Stanford Sentiment Treebank
CoLA: The Corpus of Linguistic Acceptability
STS-B:The Semantic Textual Similarity Benchmark
MRPC: Microsoft Research Paraphrase Corpus
RTE: Recognizing Textual Entailment

Source: Qihuang Zhong, Liang Ding, Juhua Liu, Bo Du, and Dacheng Tao (2023). "Can chatgpt understand too? a comparative study on chatgpt and fine-tuned bert." arXiv preprint arXiv:2302.10198.

ChatGPT with Advanced Prompting Strategies

Method	CoLA	SST-2	MRPC		STS-B		QQP		MNLI		QNLI	RTE	GLUE
	Mcc.	*Acc.*	*Acc.*	*F1*	*Pear.*	*Spea.*	*Acc.*	*F1*	*m.*	*mm.*	*Acc.*	*Acc.*	avg.
BERT-base	56.4	88.0	90.0	89.8	83.0	81.9	80.0	80.0	82.7	82.7	84.0	70.0	79.2
RoBERTa-large	65.3	96.0	**92.0**	**92.0**	**92.9**	**91.1**	**90.0**	89.4	88.0	**90.7**	**94.0**	84.0	87.8
ChatGPT	56.0	92.0	66.0	72.1	80.9	72.4	78.0	79.3	**89.3**	81.3	84.0	88.0	78.7
Standard few-shot prompting (Brown et al., 2020)													
-w/ 1-shot	52.0	96.0	66.0	65.3	87.4	87.0	84.0	83.3	80.0	78.7	84.0	80.0	78.5
-w/ 5-shot	60.2	**98.0**	76.0	77.8	89.0	86.9	90.0	89.8	82.7	84.0	88.0	86.0	83.8
Zero-shot CoT (Kojima et al., 2022)													
-w/ zero-shot CoT	64.5	96.0	78.0	76.6	87.1	87.8	80.0	80.8	86.7	89.3	86.0	90.0	83.7
Manual few-shot CoT (Wei et al., 2022b)													
-w/ 1-shot CoT	60.8	94.0	82.0	83.2	89.1	88.7	84.0	82.6	85.3	84.0	88.0	**92.0**	84.3
-w/ 5-shot CoT	**68.2**	96.0	82.0	81.6	90.0	90.2	86.0	85.1	85.3	86.7	90.0	**92.0**	86.2

Source: Qihuang Zhong, Liang Ding, Juhua Liu, Bo Du, and Dacheng Tao (2023). "Can chatgpt understand too? a comparative study on chatgpt and fine-tuned bert." arXiv preprint arXiv:2302.10198.

Emotions

Love	Anger
Joy	Sadness
Surprise	Fear

Source: Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data,” Springer, 2nd Edition,

Example of Opinion: review segment on iPhone

"I bought an iPhone a few days ago.

It was such a nice phone.

The touch screen was really cool.

The voice quality was clear too.

However, my mother was mad with me as I did not tell her before I bought it.

She also thought the phone was too expensive, and wanted me to return it to the shop. … "

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

Example of Opinion: review segment on iPhone

"(1) I bought an iPhone a few days ago.

(2) It was such a nice phone.

(3) The touch screen was really cool.

(4) The voice quality was clear too.

+Positive Opinion

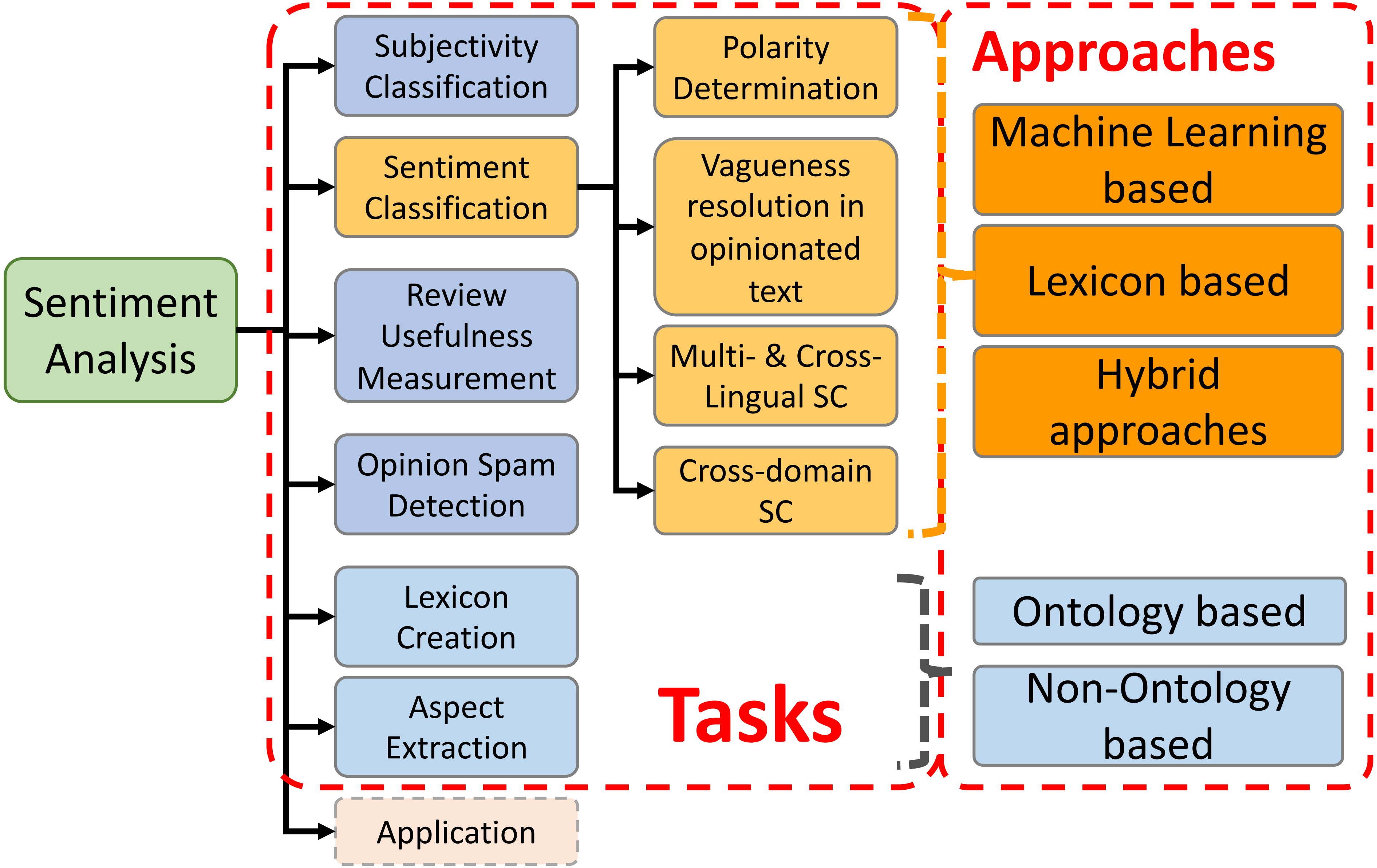
(5) However, my mother was mad with me as I did not tell her before I bought it.

(6) She also thought the phone was too expensive, and wanted me to return it to the shop. … "

-Negative Opinion

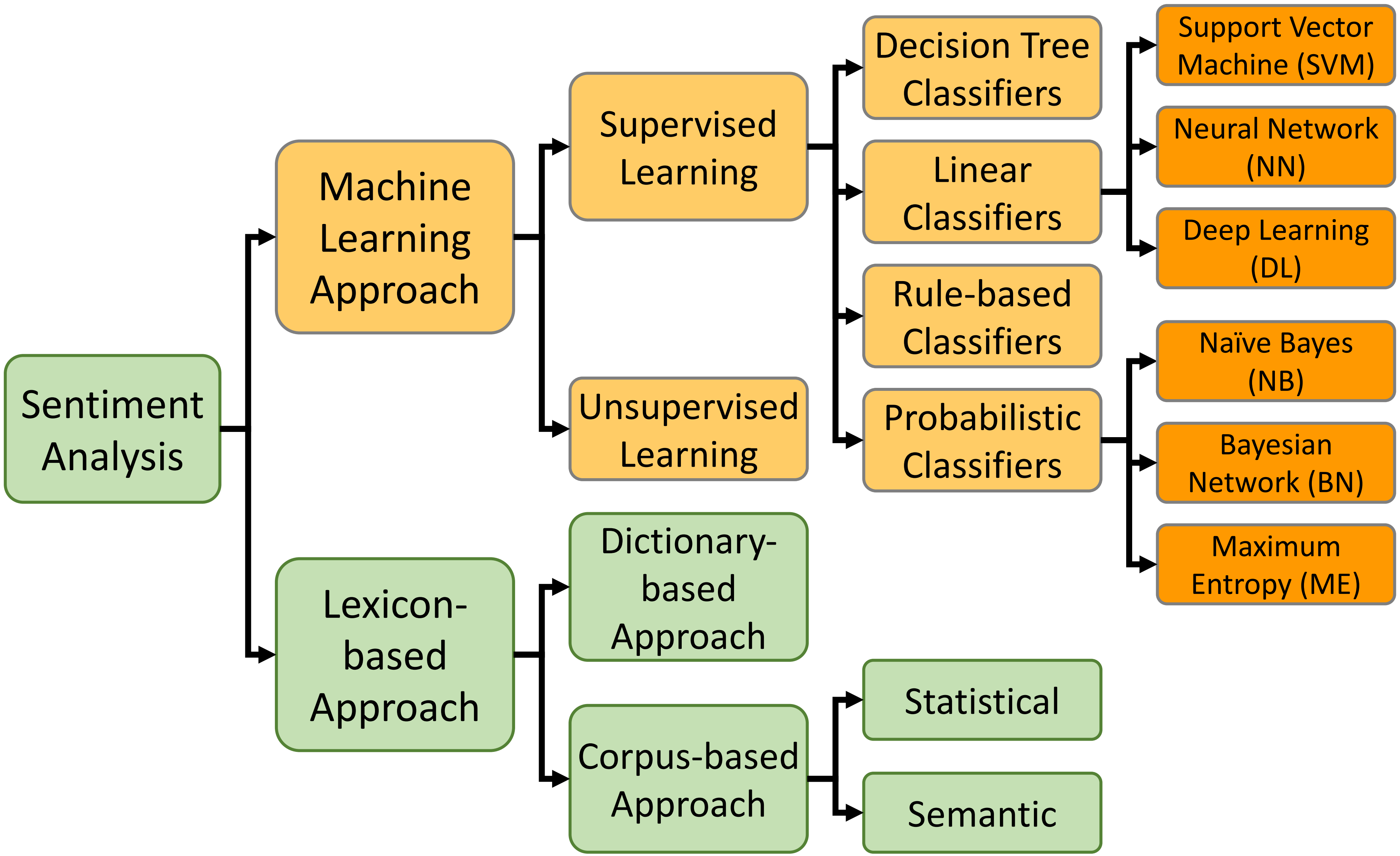
Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

Sentiment Analysis



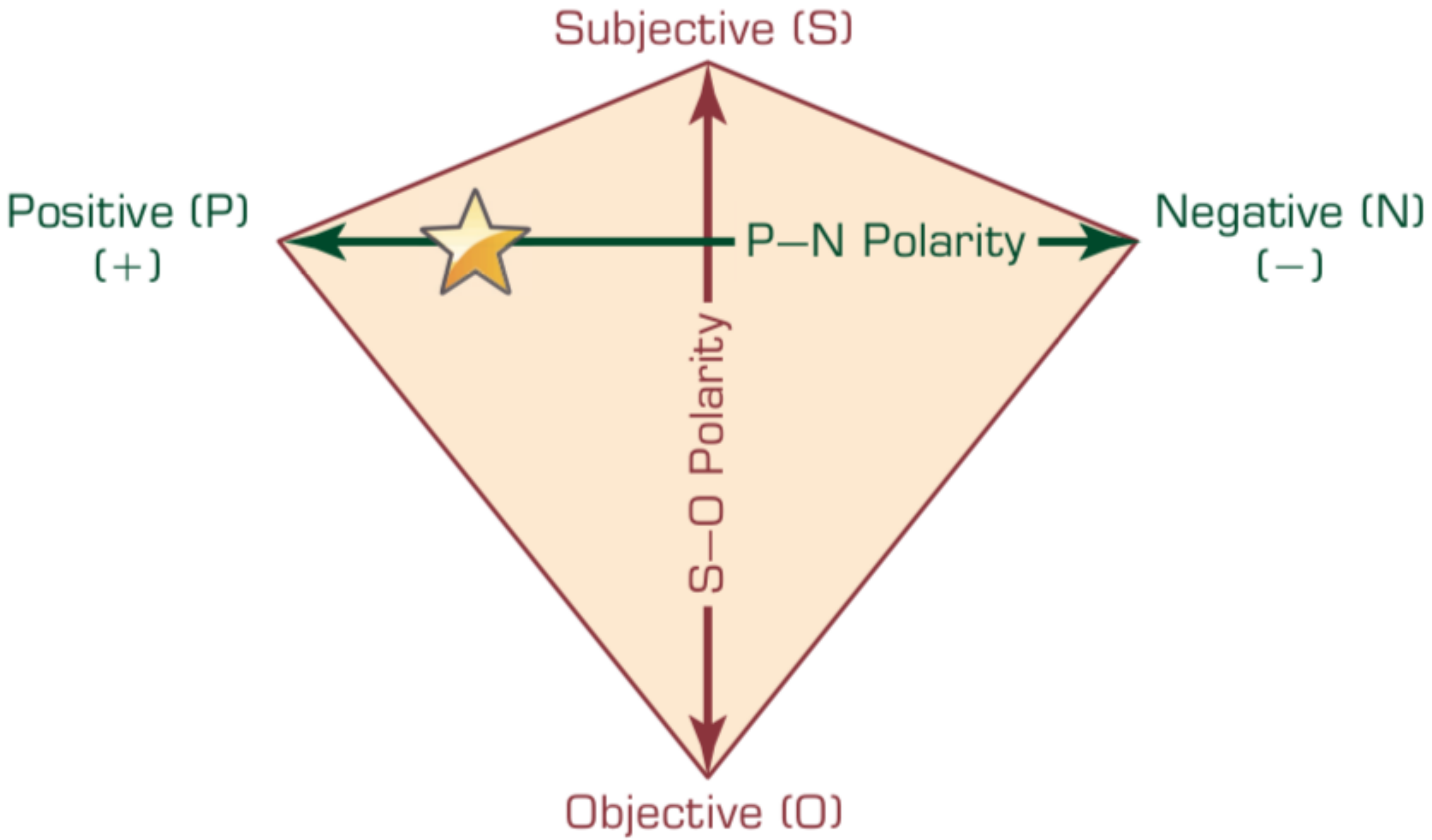
Source: Kumar Ravi and Vadlamani Ravi (2015), "A survey on opinion mining and sentiment analysis: tasks, approaches and applications." Knowledge-Based Systems, 89, pp.14-46.

Sentiment Classification Techniques



Source: Jesus Serrano-Guerrero, Jose A. Olivas, Francisco P. Romero, and Enrique Herrera-Viedma (2015), "Sentiment analysis: A review and comparative analysis of web services," Information Sciences, 311, pp. 18-38.

P–N Polarity and S–O Polarity Relationship



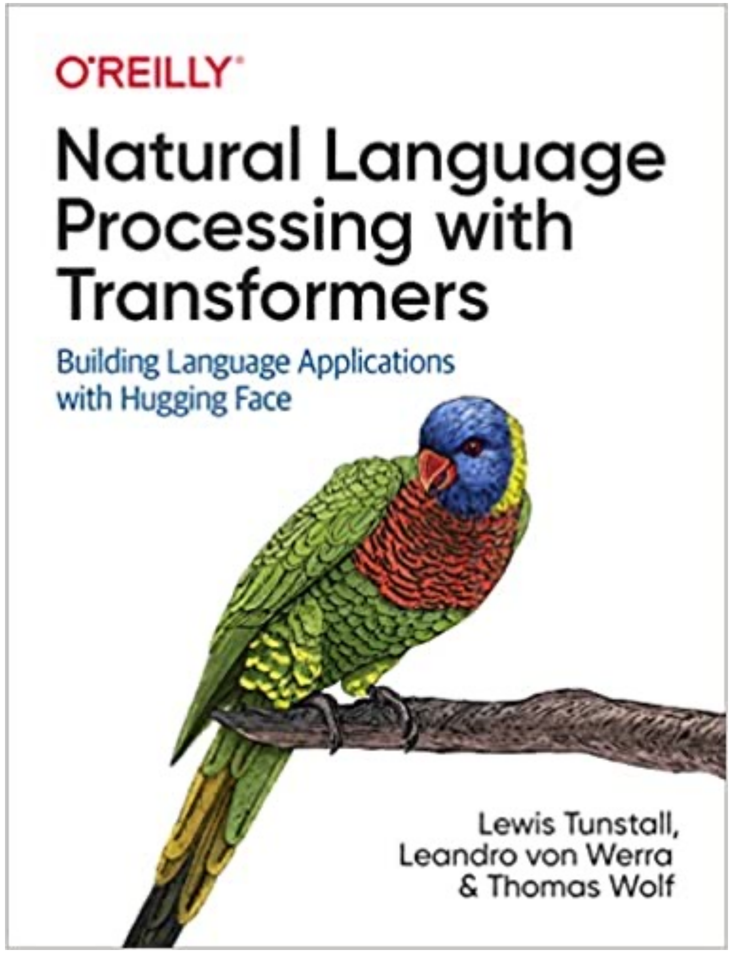
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022),

Natural Language Processing with Transformers:

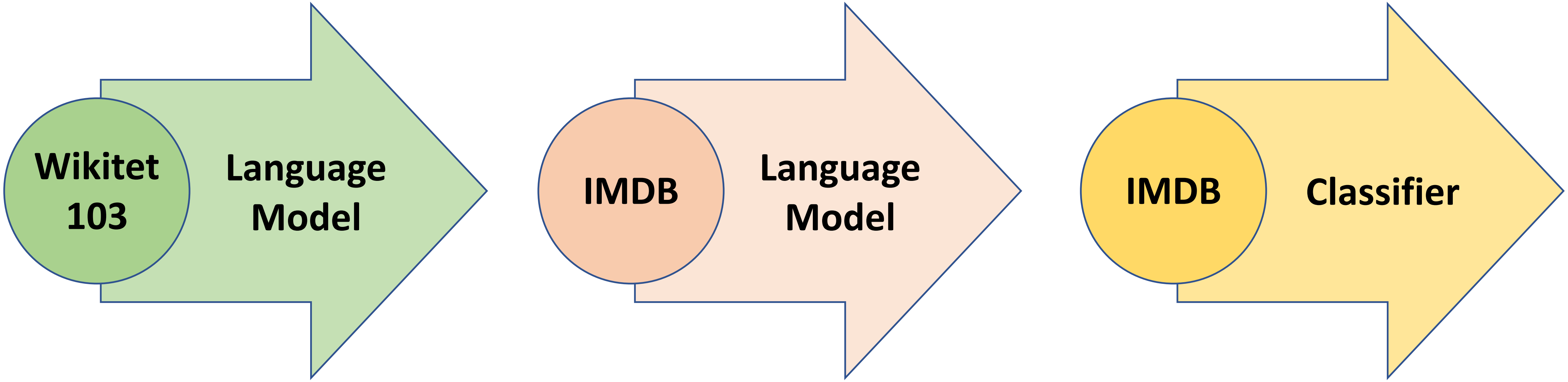
Building Language Applications with Hugging Face,

O'Reilly Media.



Source: https://www.amazon.com/Natural-Language-Processing-Transformers-Applications/dp/1098103246

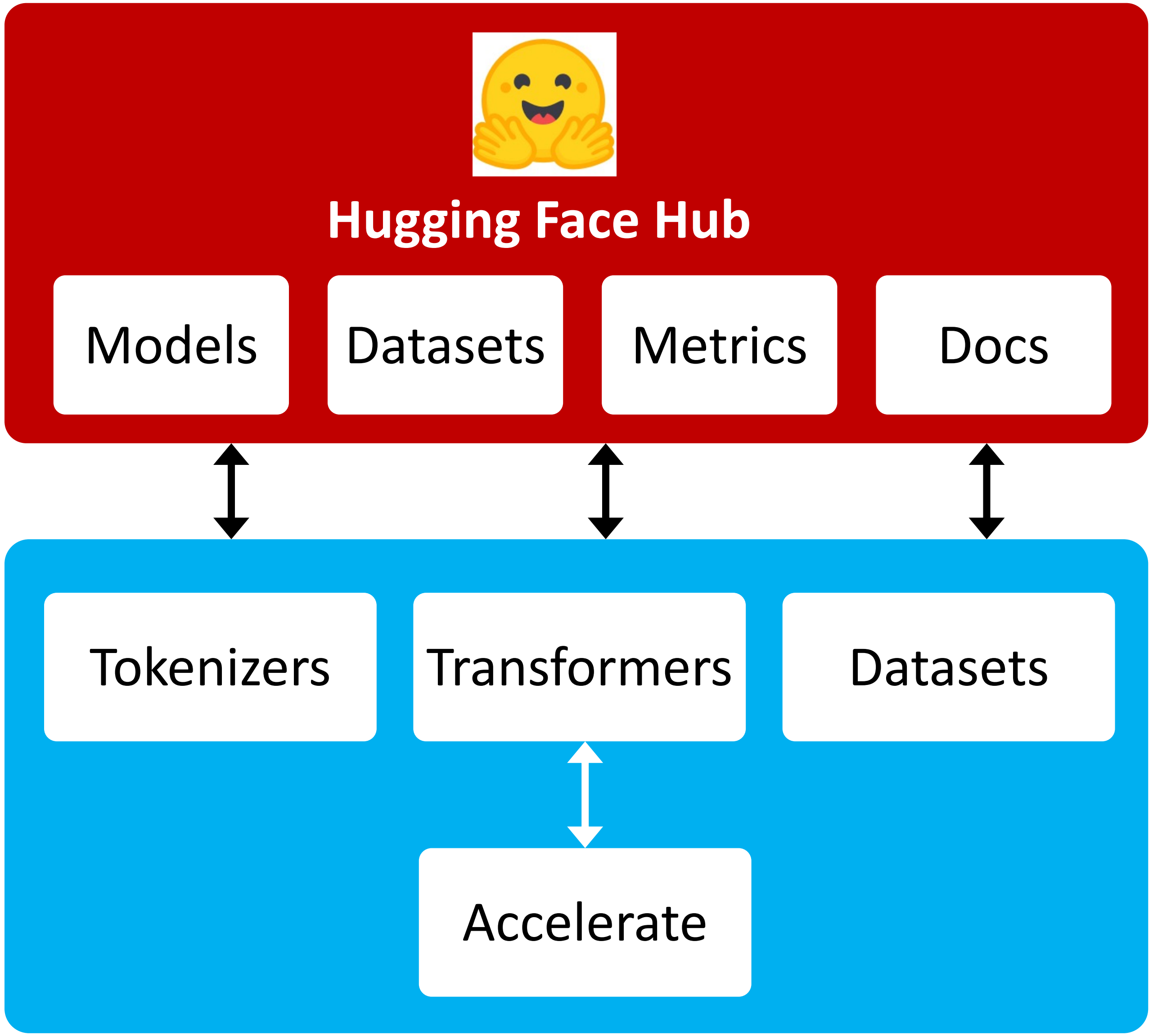
ULMFiT: 3 Steps
Transfer Learning in NLP



1. Pretraining **2. Domain adaptation** **3. Fine-tuning**

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.

An overview of the Hugging Face Ecosystem



Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.

A typical pipeline for training transformer models

with the Datasets, Tokenizers, and Transformers libraries

Datasets	Tokenizers	Transformers	Datasets
Load and process datasets	Tokenize input texts	Load models, train and infer	Load metrics evaluate models

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

NLP with Transformers

```
!git clone https://github.com/nlp-with-transformers/notebooks.git
%cd notebooks
from install import *
install_requirements()
```

```
from utils import *
setup_chapter()
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Text Classification

```
text = """Dear Amazon, last week I ordered an Optimus Prime action figure \
from your online store in Germany. Unfortunately, when I opened the package, \
I discovered to my horror that I had been sent an action figure of Megatron \
instead! As a lifelong enemy of the Decepticons, I hope you can understand my \
dilemma. To resolve the issue, I demand an exchange of Megatron for the \
Optimus Prime figure I ordered. Enclosed are copies of my records concerning \
this purchase. I expect to hear from you soon. Sincerely, Bumblebee."""
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

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Optimus Prime figure I ordered. Enclosed are copies of my records concerning \
this purchase. I expect to hear from you soon. Sincerely, Bumblebee."""
```

```
from transformers import pipeline
classifier = pipeline("text-classification")
```

```
import pandas as pd
outputs = classifier(text)
pd.DataFrame(outputs)
```

	label	score
0	NEGATIVE	0.901546

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Text Classification

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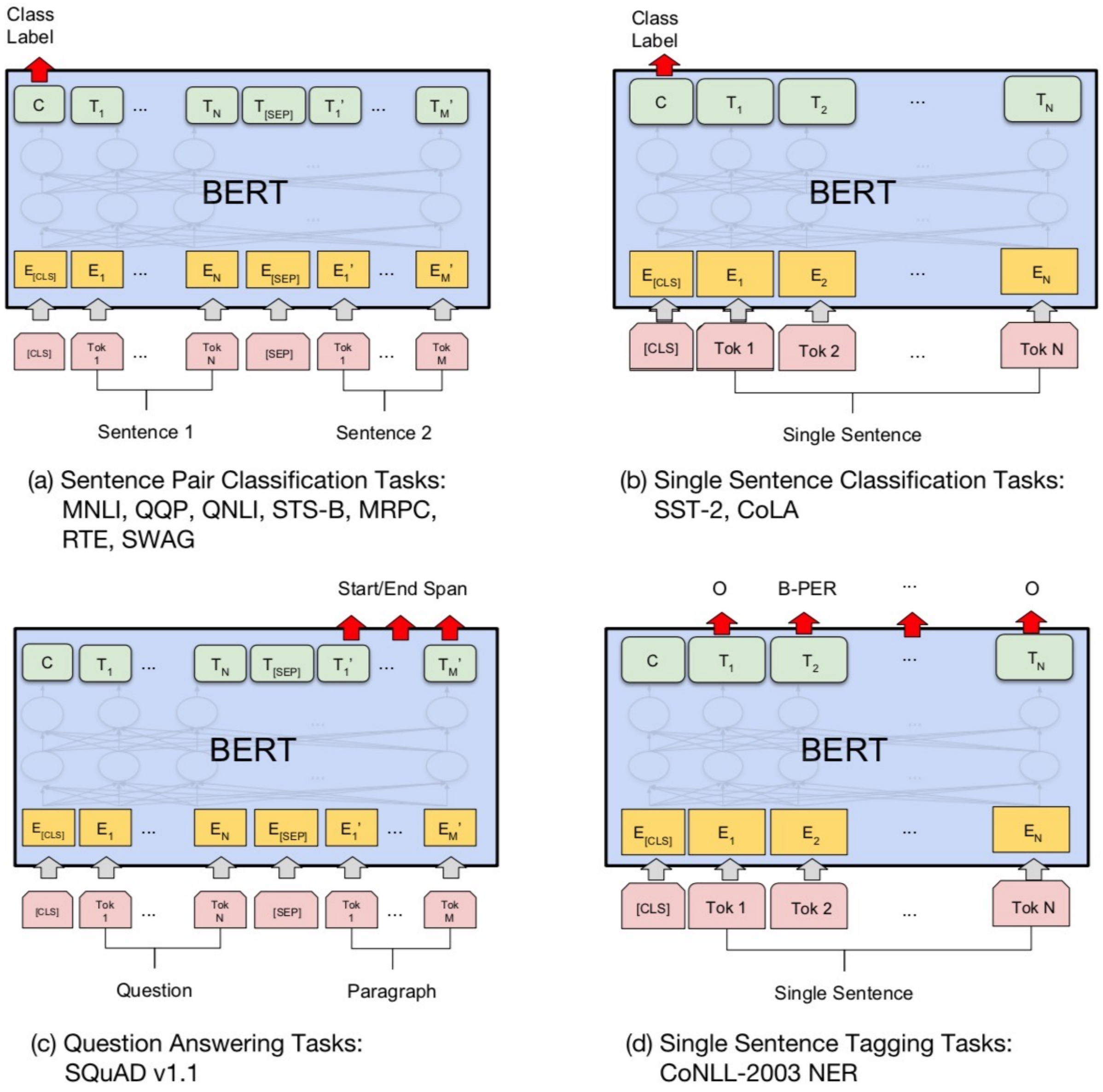
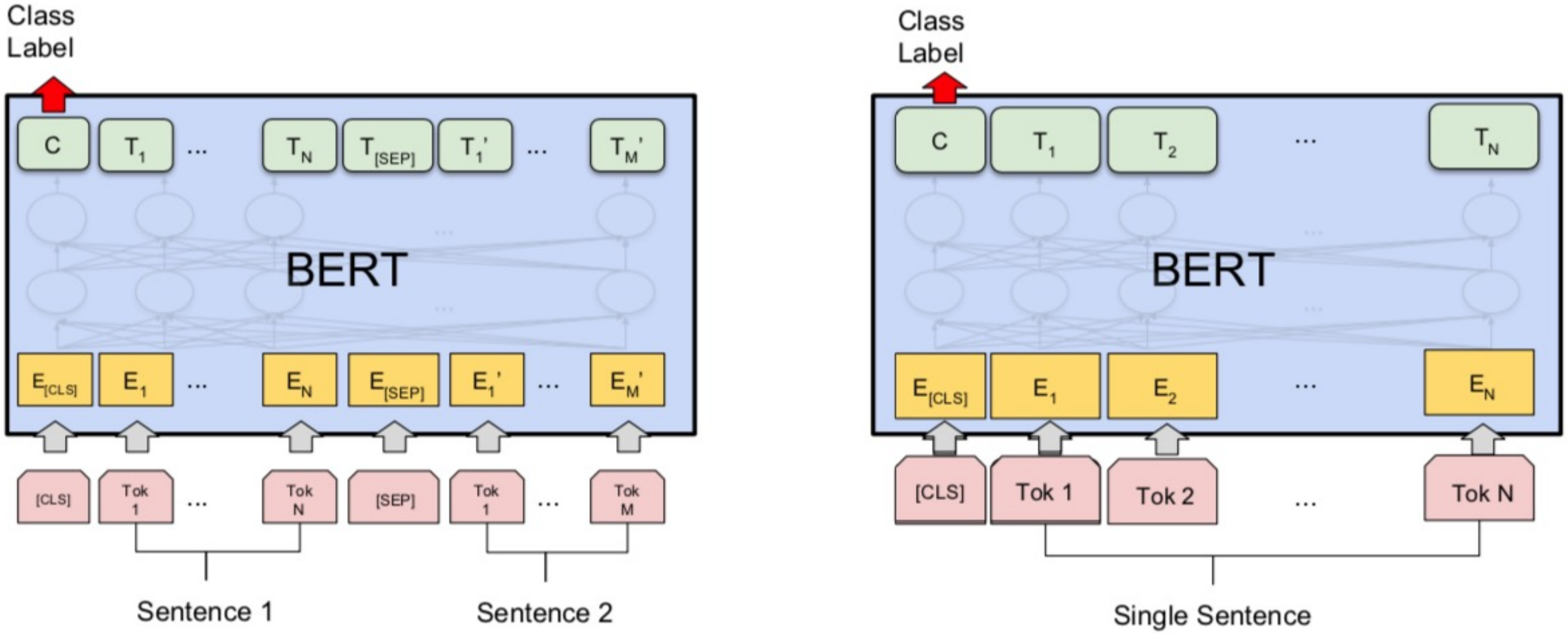
Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Fine-tuning BERT on NLP Tasks



Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

BERT Sequence-level tasks

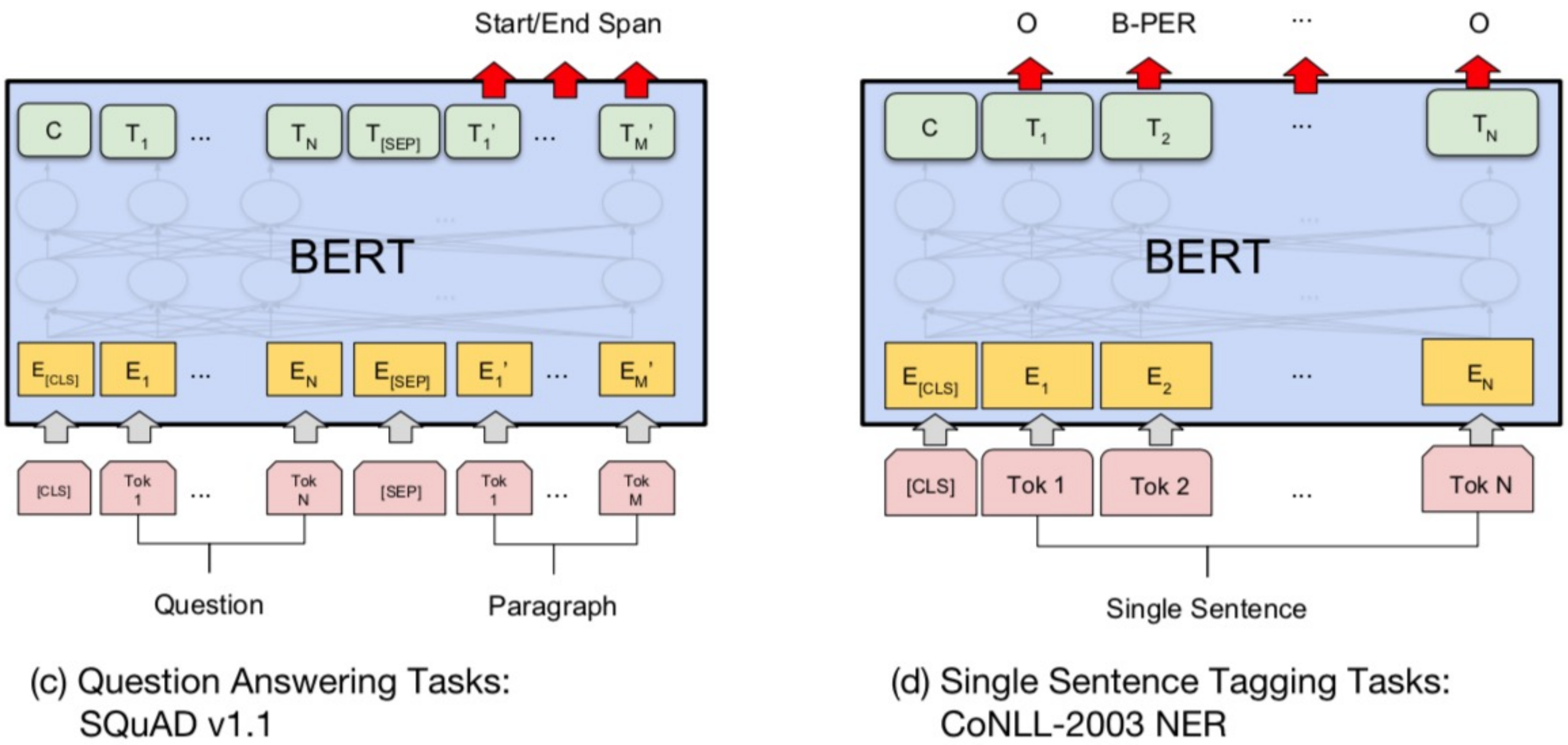


(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

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

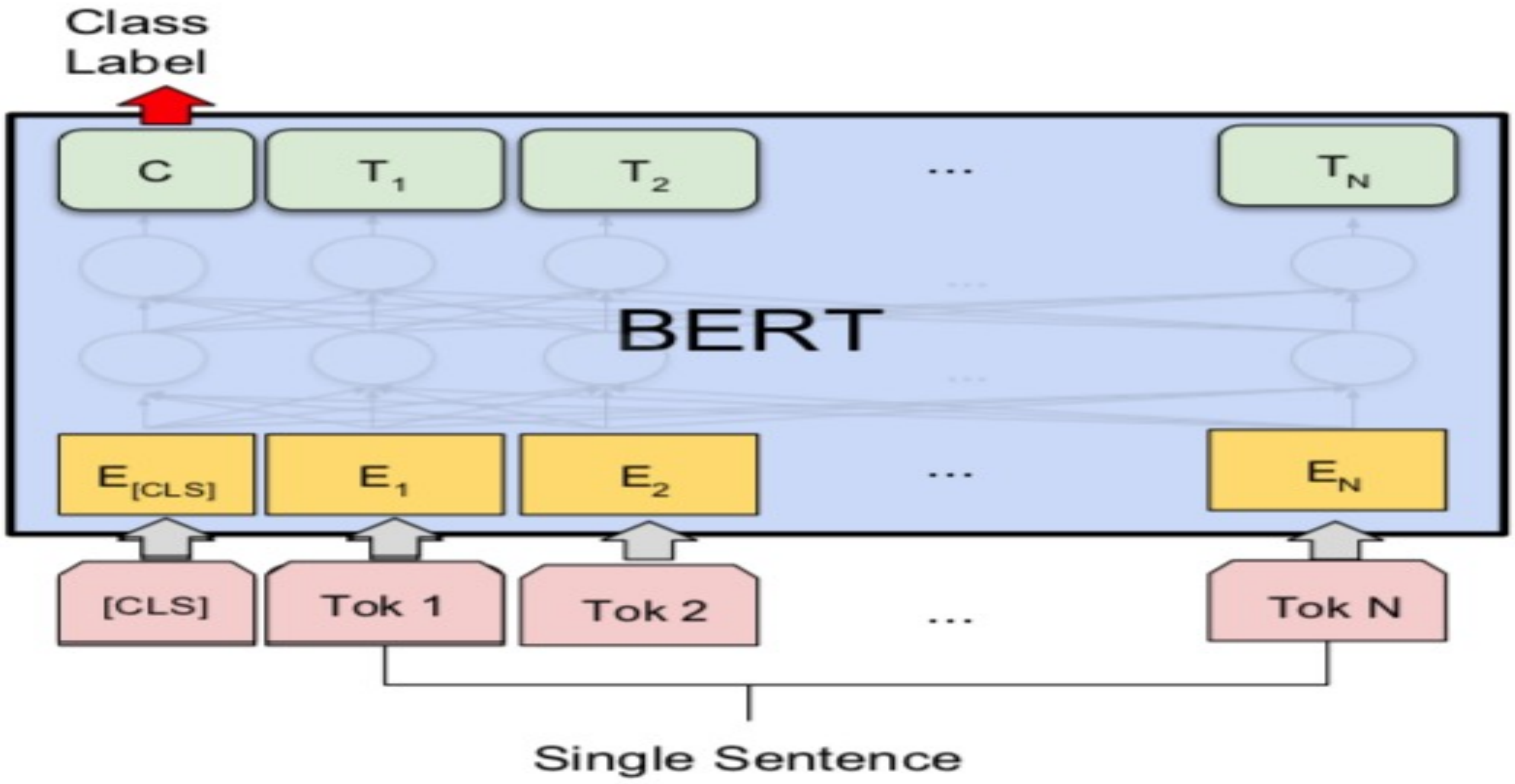
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

BERT Token-level tasks



Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

Sentiment Analysis: Single Sentence Classification



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

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

Character Tokenization

```
text = "Tokenizing text is a core task of NLP."
tokenized_text = list(text)
print(tokenized_text)
```

```
['T', 'o', 'k', 'e', 'n', 'i', 'z', 'i', 'n', 'g', ' ', 't', 'e', 'x', 't', ' ',
'i', 's', ' ', 'a', ' ', 'c', 'o', 'r', 'e', ' ', 't', 'a', 's', 'k', ' ', 'o',
'f', ' ', 'N', 'L', 'P', '.']
```

```
token2idx = {ch: idx for idx, ch in enumerate(sorted(set(tokenized_text)))}
print(token2idx)
```

```
{' ': 0, '.': 1, 'L': 2, 'N': 3, 'P': 4, 'T': 5, 'a': 6, 'c': 7, 'e': 8, 'f': 9,
'g': 10, 'i': 11, 'k': 12, 'n': 13, 'o': 14, 'r': 15, 's': 16, 't': 17, 'x': 18,
'z': 19}
```

```
input_ids = [token2idx[token] for token in tokenized_text]
print(input_ids)
```

```
[5, 14, 12, 8, 13, 11, 19, 11, 13, 10, 0, 17, 8, 18, 17, 0, 11, 16, 0, 6, 0, 7,
14, 15, 8, 0, 17, 6, 16, 12, 0, 14, 9, 0, 3, 2, 4, 1]
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Word Tokenization

```
text = "Tokenizing text is a core task of NLP."
tokenized_text = text.split()
print(tokenized_text)
```

```
['Tokenizing', 'text', 'is', 'a', 'core', 'task', 'of', 'NLP.']
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Subword Tokenization

```
from transformers import AutoTokenizer
model_ckpt = "distilbert-base-uncased"
tokenizer = AutoTokenizer.from_pretrained(model_ckpt)
```

```
text = "Tokenizing text is a core task of NLP."
encoded_text = tokenizer(text)
print(encoded_text)
```

```
{'input_ids': [101, 19204, 6026, 3793, 2003, 1037, 4563, 4708, 1997, 17953, 2361,
1012, 102], 'attention_mask': [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]}
```

```
tokens = tokenizer.convert_ids_to_tokens(encoded_text.input_ids)
print(tokens)
```

```
['[CLS]', 'token', '##izing', 'text', 'is', 'a', 'core', 'task', 'of', 'nl',
'##p', '.', '[SEP]']
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Subword Tokenization

```
print(tokenizer.convert_tokens_to_string(tokens))
```

```
[CLS] tokenizing text is a core task of nlp. [SEP]
```

```
tokenizer.vocab_size
```

```
30522
```

```
tokenizer.model_max_length
```

```
512
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Tokenizing the Whole Dataset

```python
def tokenize(batch):
      return tokenizer(batch["text"], padding=True, truncation=True)
```

```python
print(tokenize(emotions["train"][:2]))
```

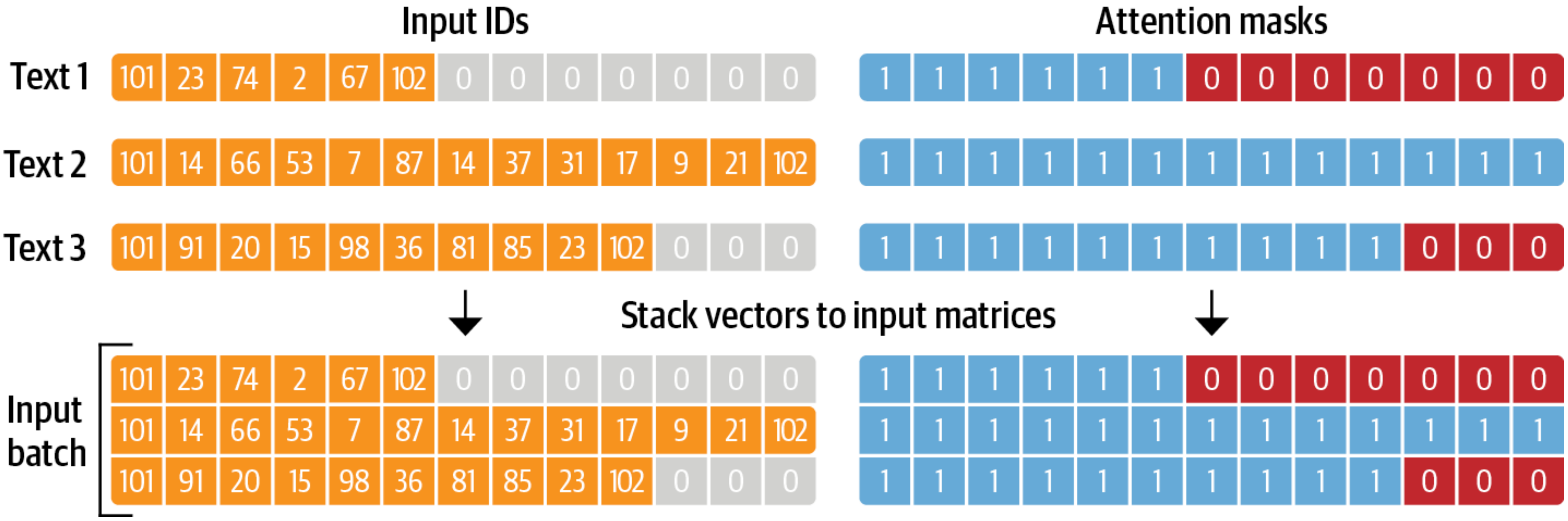
```
{'input_ids': [[101, 1045, 2134, 2102, 2514, 26608, 102, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0], [101, 1045, 2064, 2175, 2013, 3110, 2061,
20625, 2000, 2061, 9636, 17772, 2074, 2013, 2108, 2105, 2619, 2040, 14977,
1998, 2003, 8300, 102]], 'attention_mask': [[1, 1, 1, 1, 1, 1, 1, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0], [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]]}
```

```python
tokens2ids = list(zip(tokenizer.all_special_tokens,
tokenizer.all_special_ids))
data = sorted(tokens2ids, key=lambda x : x[-1])
df = pd.DataFrame(data, columns=["Special Token", "Special Token ID"])
df.T
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

From Text to Tokens

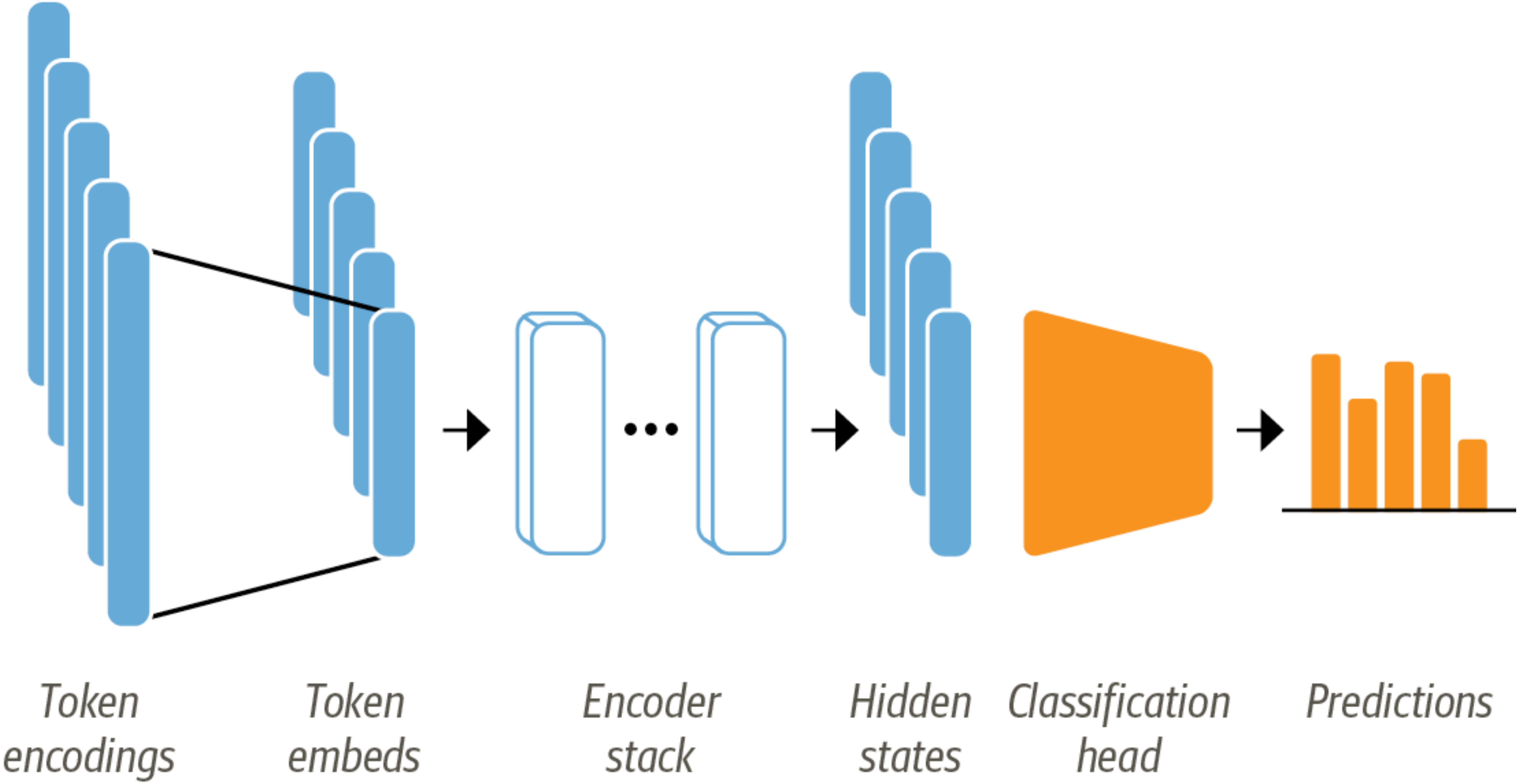
For each batch, the input sequences are padded to the maximum sequence length in the batch; the attention mask is used in the model to ignore the padded areas of the input tensors



Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Training a Text Classifier

The architecture used for sequence classification with an encoder-based transformer ; it consists of the model's pretrained body combined with a custom classification head



Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
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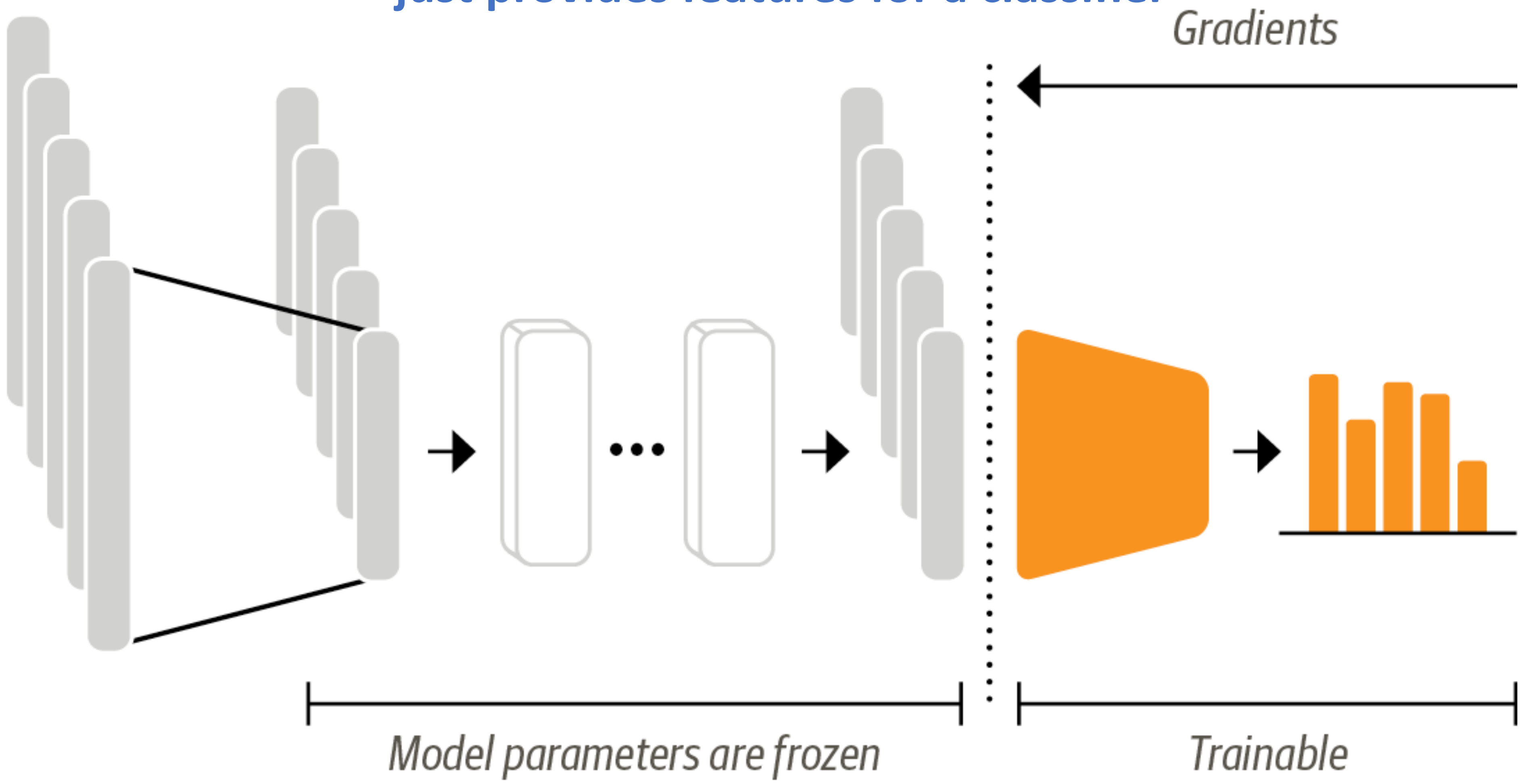
Transformers as Feature Extractors

In the feature-based approach, the DistilBERT model is frozen and just provides features for a classifier



Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
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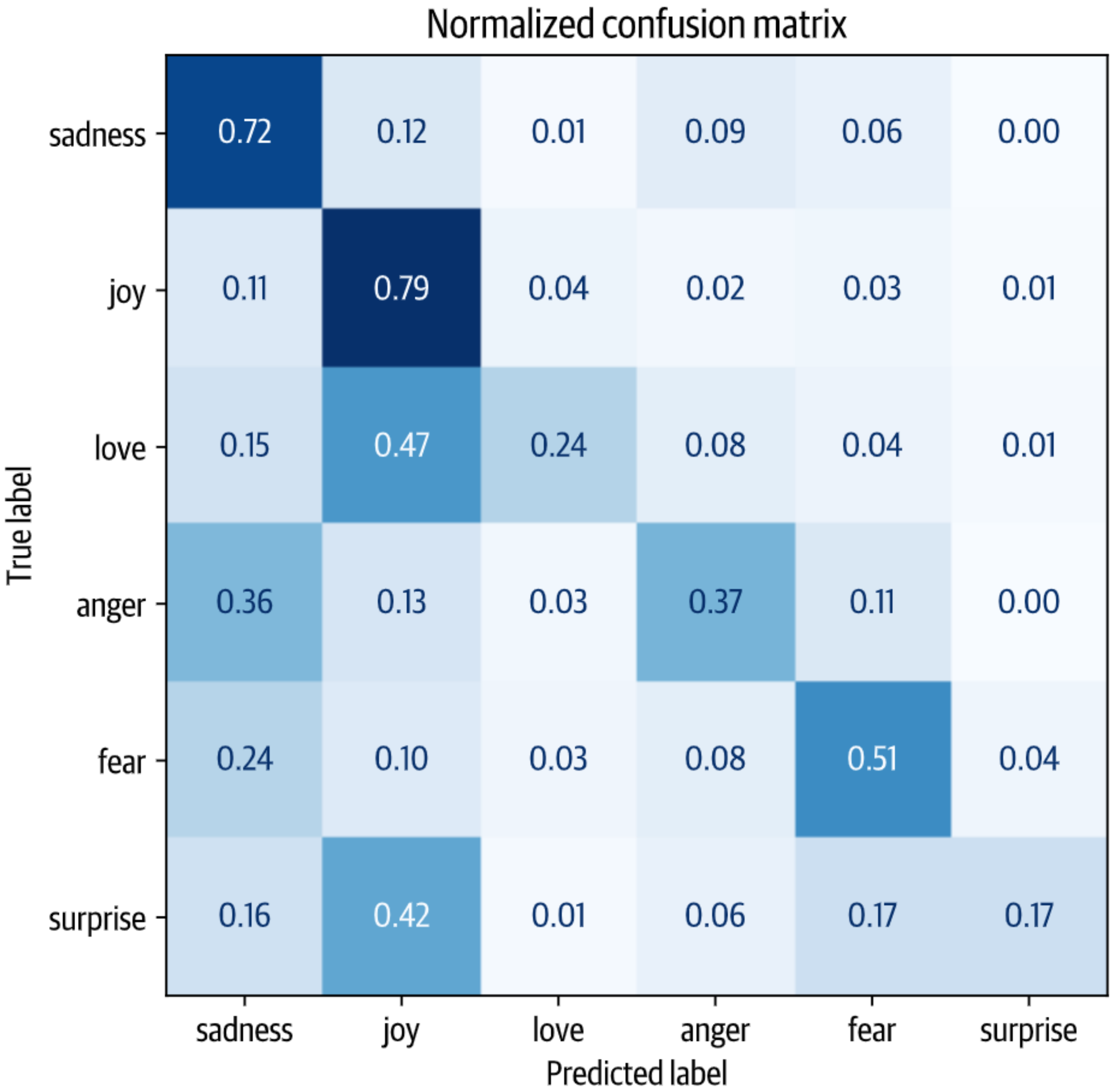
Training a Simple Classifier

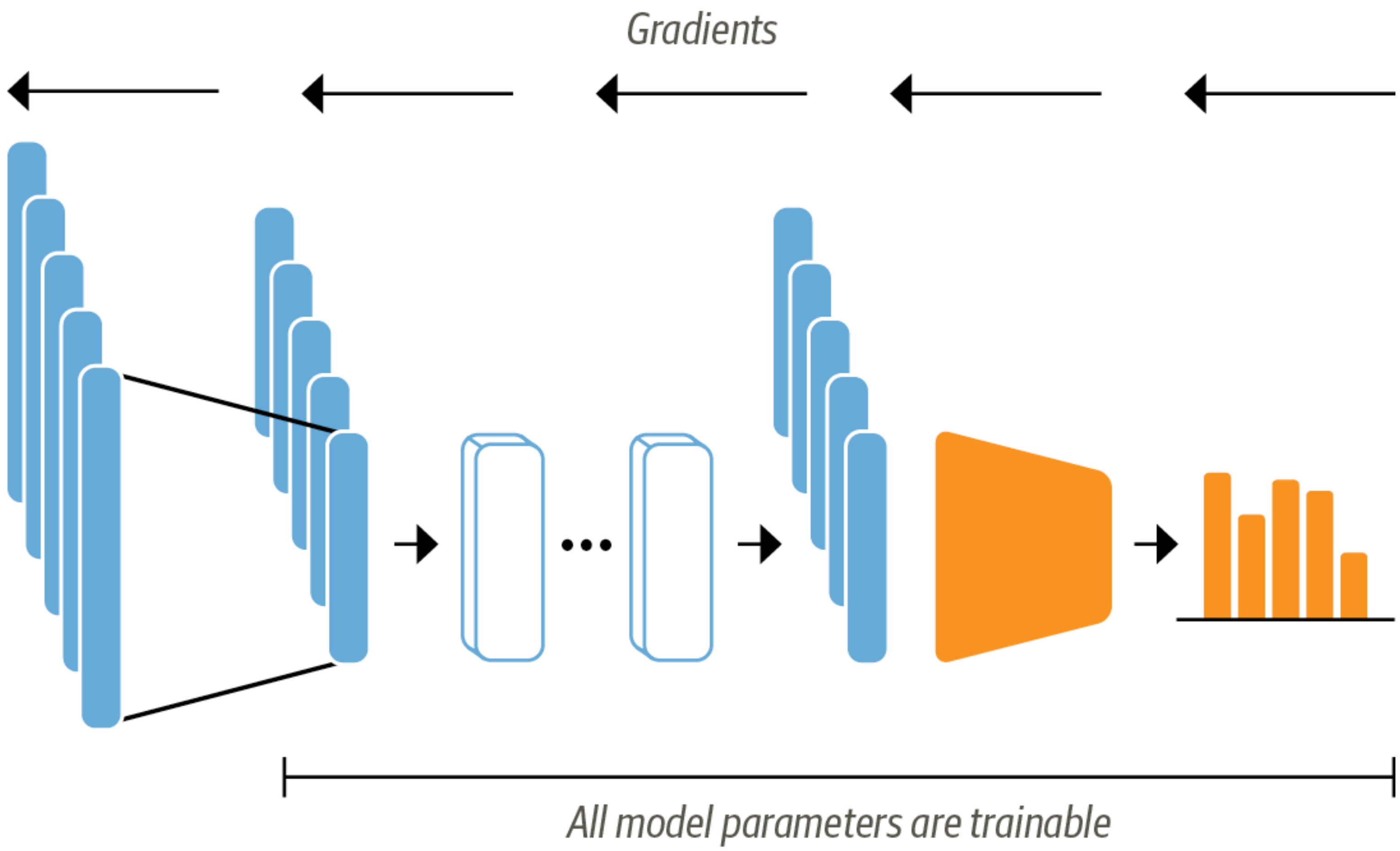


True label \ Predicted label	sadness	joy	love	anger	fear	surprise
sadness	0.72	0.12	0.01	0.09	0.06	0.00
joy	0.11	0.79	0.04	0.02	0.03	0.01
love	0.15	0.47	0.24	0.08	0.04	0.01
anger	0.36	0.13	0.03	0.37	0.11	0.00
fear	0.24	0.10	0.03	0.08	0.51	0.04
surprise	0.16	0.42	0.01	0.06	0.17	0.17

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Fine-Tuning Transformers

When using the fine-tuning approach the whole DistilBERT model is trained along with the classification head



Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Fine-Tuning Transformers
Loading a pretrained model

```
from transformers import AutoModelForSequenceClassification

num_labels = 6
model = (AutoModelForSequenceClassification
         .from_pretrained(model_ckpt, num_labels=num_labels)
         .to(device))
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Defining the performance metrics

```
from sklearn.metrics import accuracy_score, f1_score

def compute_metrics(pred):
     labels = pred.label_ids
     preds = pred.predictions.argmax(-1)
     f1 = f1_score(labels, preds, average="weighted")
     acc = accuracy_score(labels, preds)
     return {"accuracy": acc, "f1": f1}
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Train the model

```
from huggingface_hub import notebook_login

notebook_login()
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Train the model

```python
from transformers import Trainer, TrainingArguments

batch_size = 64
logging_steps = len(emotions_encoded["train"]) // batch_size
model_name = f"{model_ckpt}-finetuned-emotion"
training_args = TrainingArguments(output_dir=model_name,
                    num_train_epochs=2,
                    learning_rate=2e-5,
                    per_device_train_batch_size=batch_size,
                    per_device_eval_batch_size=batch_size,
                    weight_decay=0.01,
                    evaluation_strategy="epoch",
                    disable_tqdm=False,
                    logging_steps=logging_steps,
                    push_to_hub=True,
                    log_level="error")
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Train the model

```
from transformers import Trainer

trainer = Trainer(model=model, args=training_args,
        compute_metrics=compute_metrics,
        train_dataset=emotions_encoded["train"],
        eval_dataset=emotions_encoded["validation"],
        tokenizer=tokenizer)
trainer.train();
```

[500/500 01:48, Epoch 2/2]

Epoch	Training Loss	Validation Loss	Accuracy	F1
1	0.840900	0.327445	0.896500	0.892285
2	0.255000	0.220472	0.922500	0.922550

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Train the model

```
preds_output =
trainer.predict(emotions_encoded["validation"])
```

```
preds_output.metrics
```

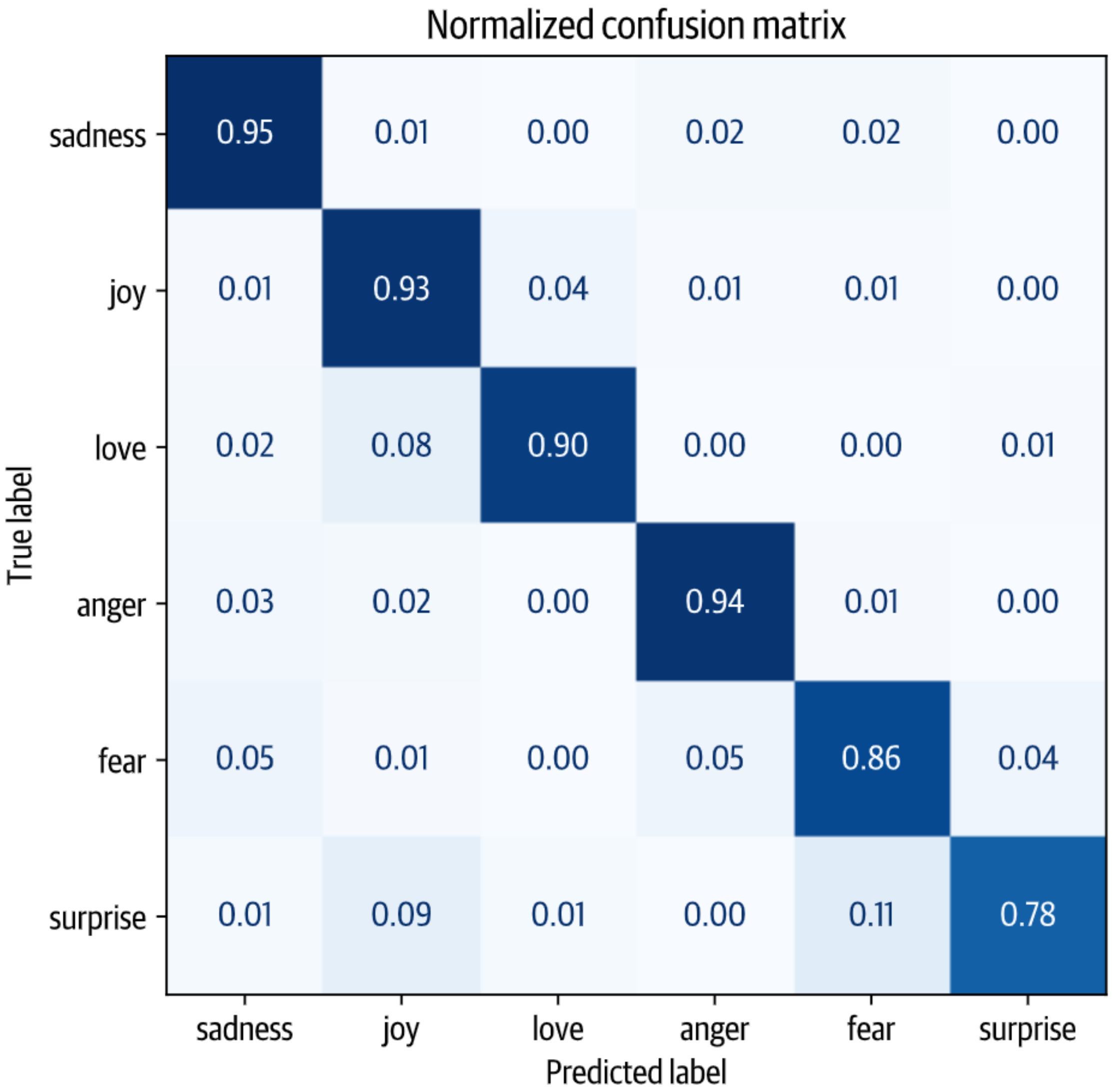
```
{'test_loss': 0.22047173976898193, 'test_accuracy': 0.9225, 'test_f1':
0.9225500751072866, 'test_runtime': 1.6357, 'test_samples_per_second':
1222.725, 'test_steps_per_second': 19.564}
```

```
y_preds = np.argmax(preds_output.predictions, axis=1)
```

```
plot_confusion_matrix(y_preds, y_valid, labels)
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

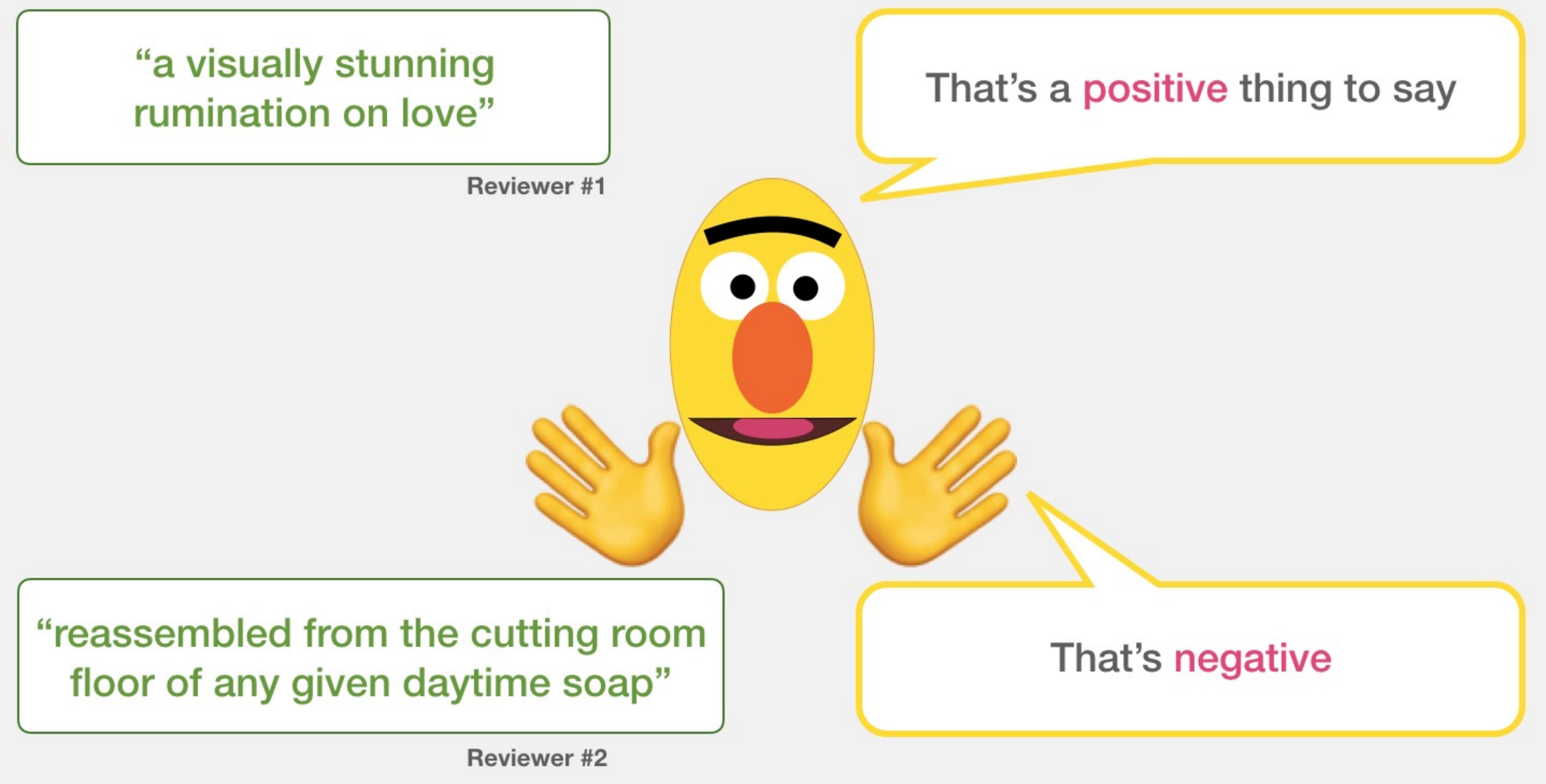
Fine-Tuning Transformers



Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

A Visual Guide to Using BERT for the First Time

(Jay Alammar, 2019)



Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Sentiment Classification: SST2
Sentences from movie reviews

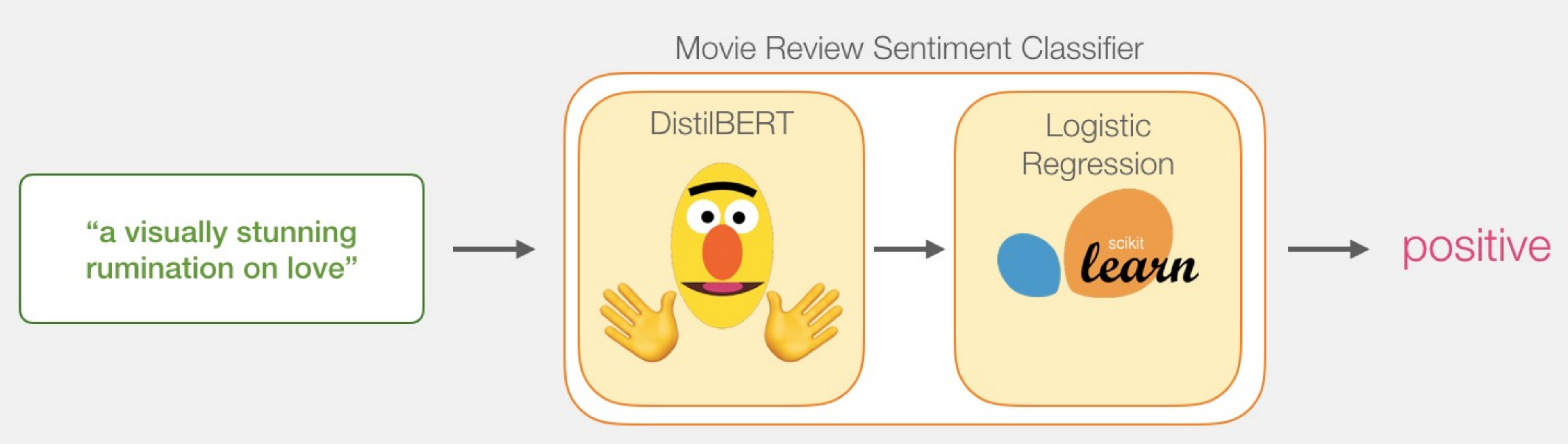
sentence	label
a stirring , funny and finally transporting re imagining of beauty and the beast and 1930s horror films	1
apparently reassembled from the cutting room floor of any given daytime soap	0
they presume their audience won't sit still for a sociology lesson	0
this is a visually stunning rumination on love , memory , history and the war between art and commerce	1
jonathan parker 's bartleby should have been the be all end all of the modern office anomie films	1

Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time,
http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Movie Review Sentiment Classifier

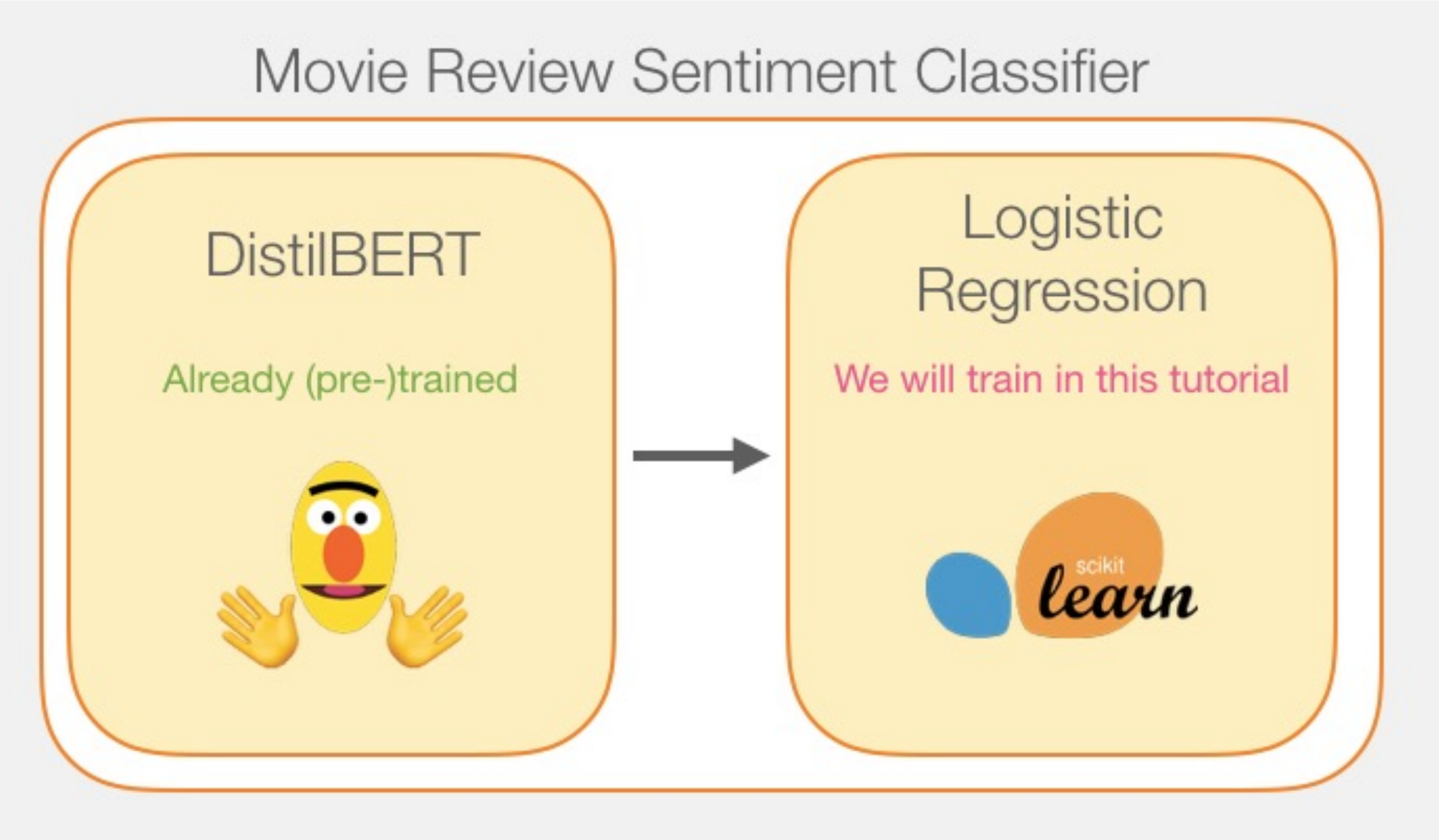
Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Movie Review Sentiment Classifier



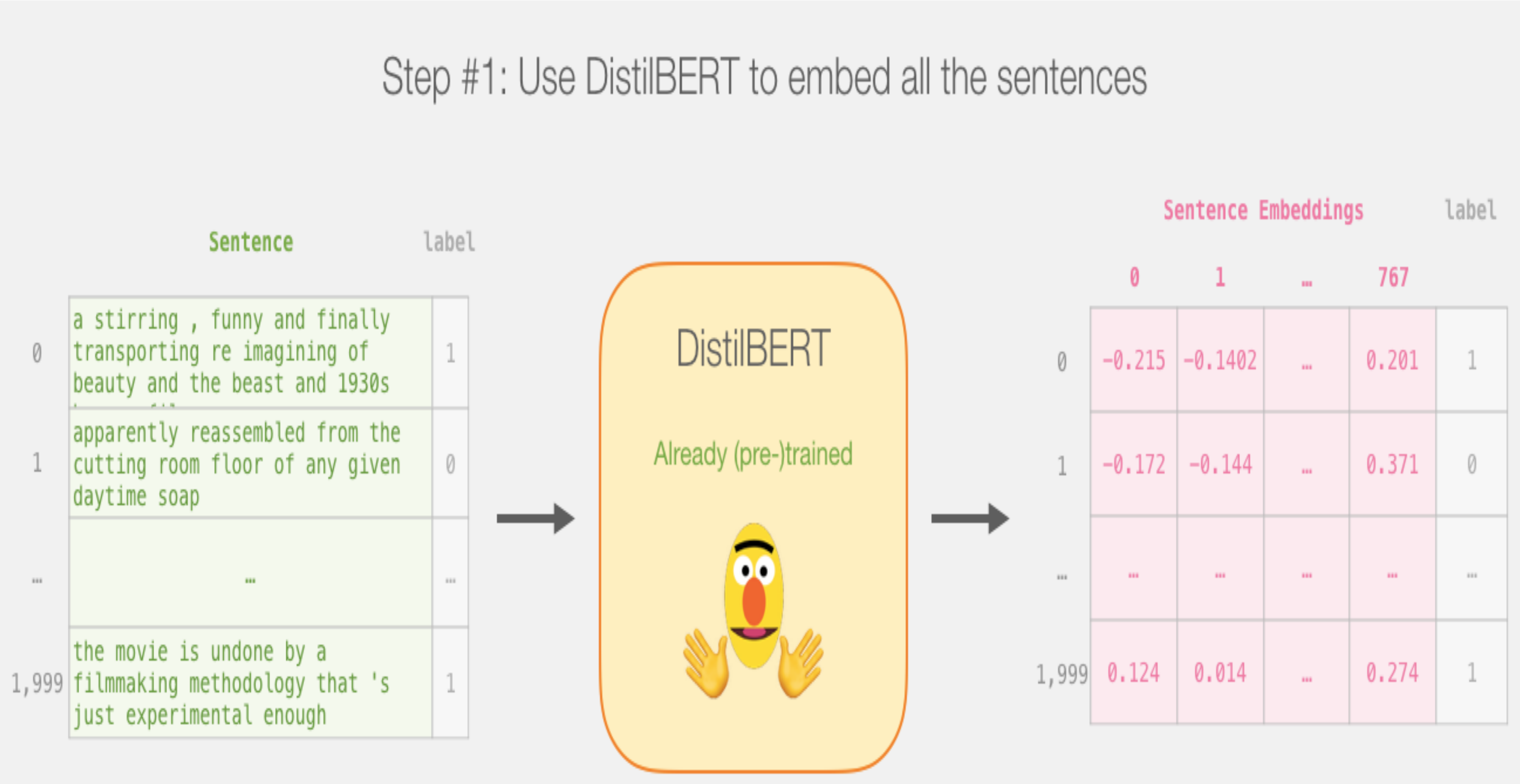
Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time,
http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Movie Review Sentiment Classifier
Model Training



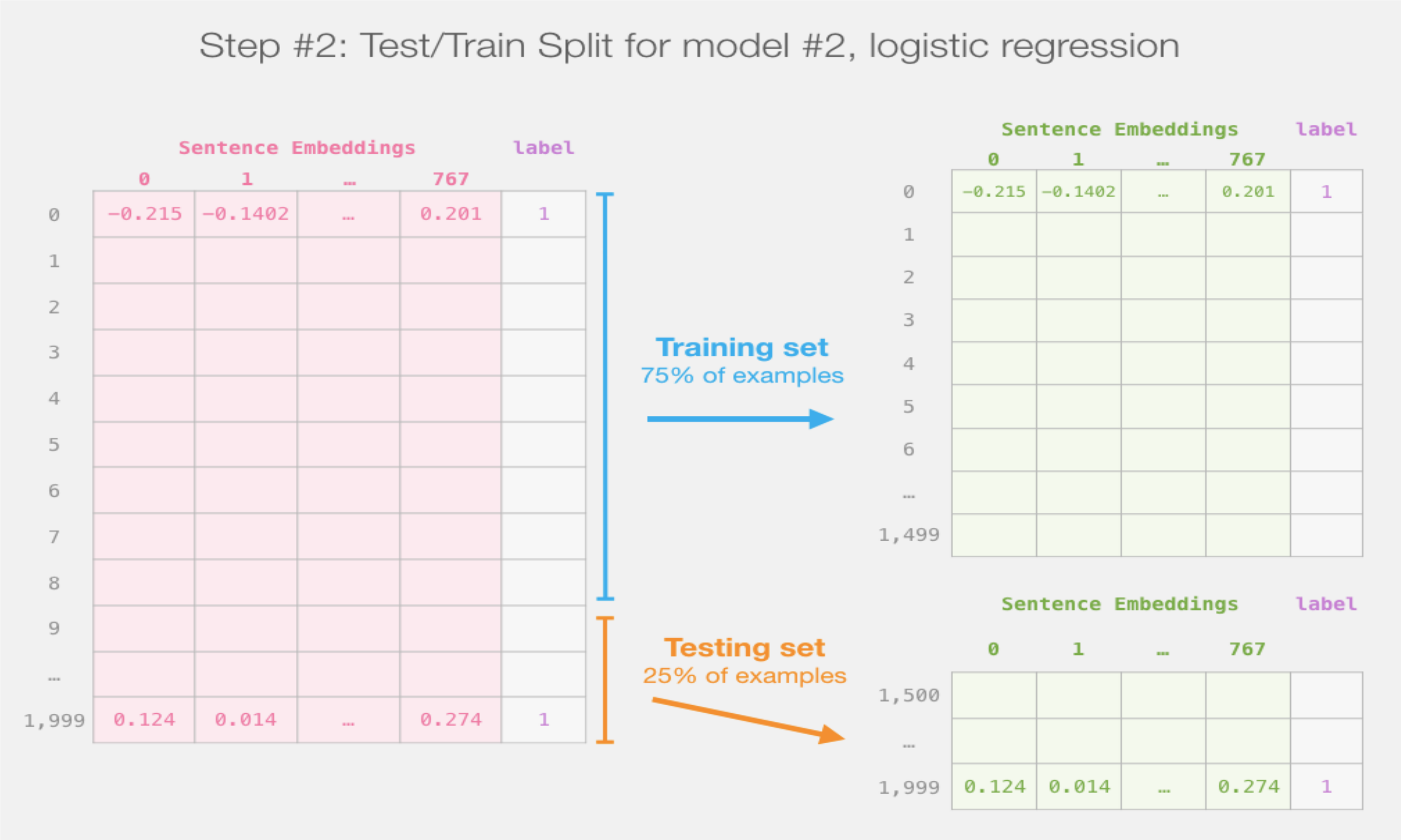
Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Step # 1 Use distilBERT to Generate Sentence Embeddings



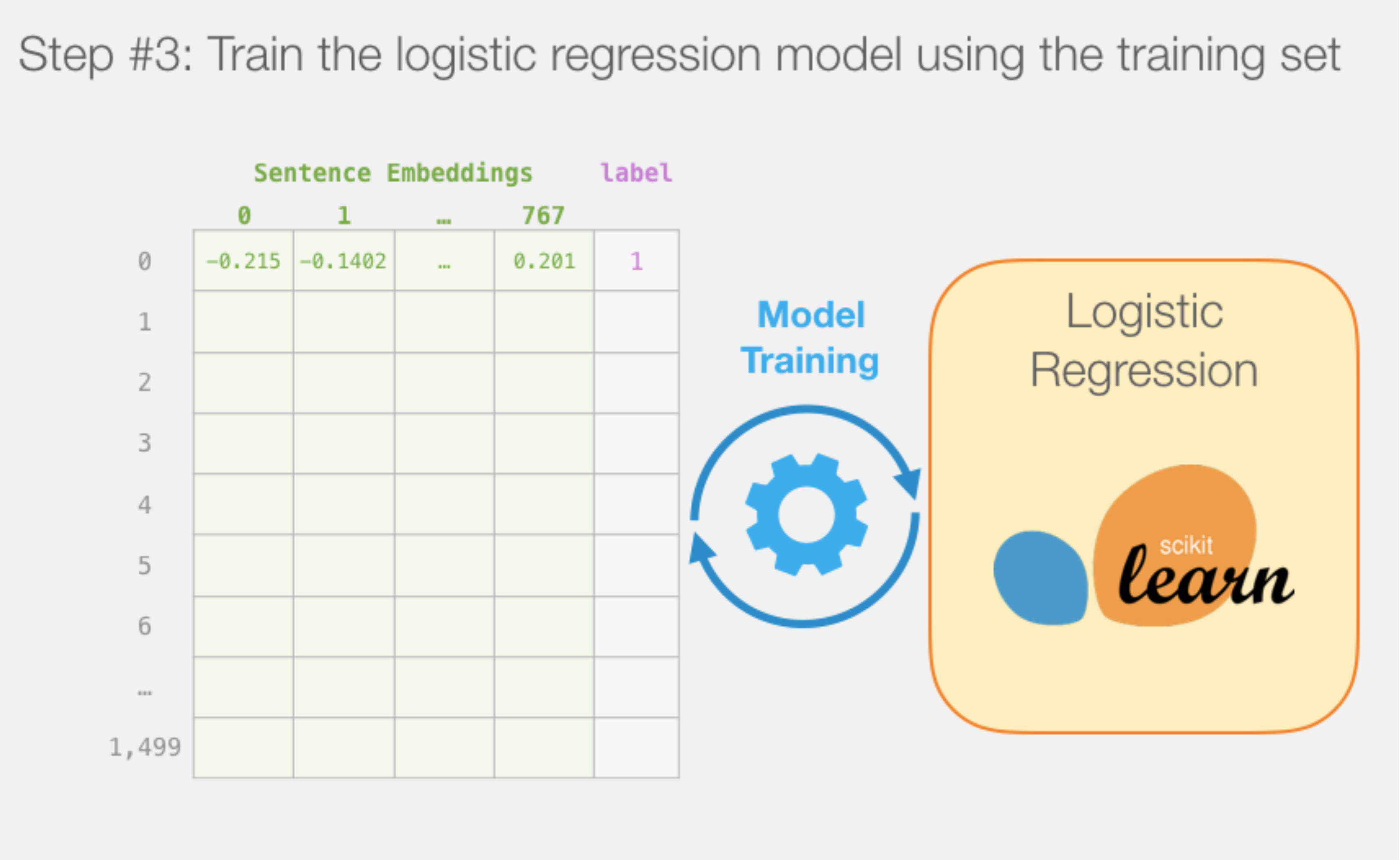
Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Step #2:Test/Train Split for Model #2, Logistic Regression



Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Step #3 Train the logistic regression model using the training set

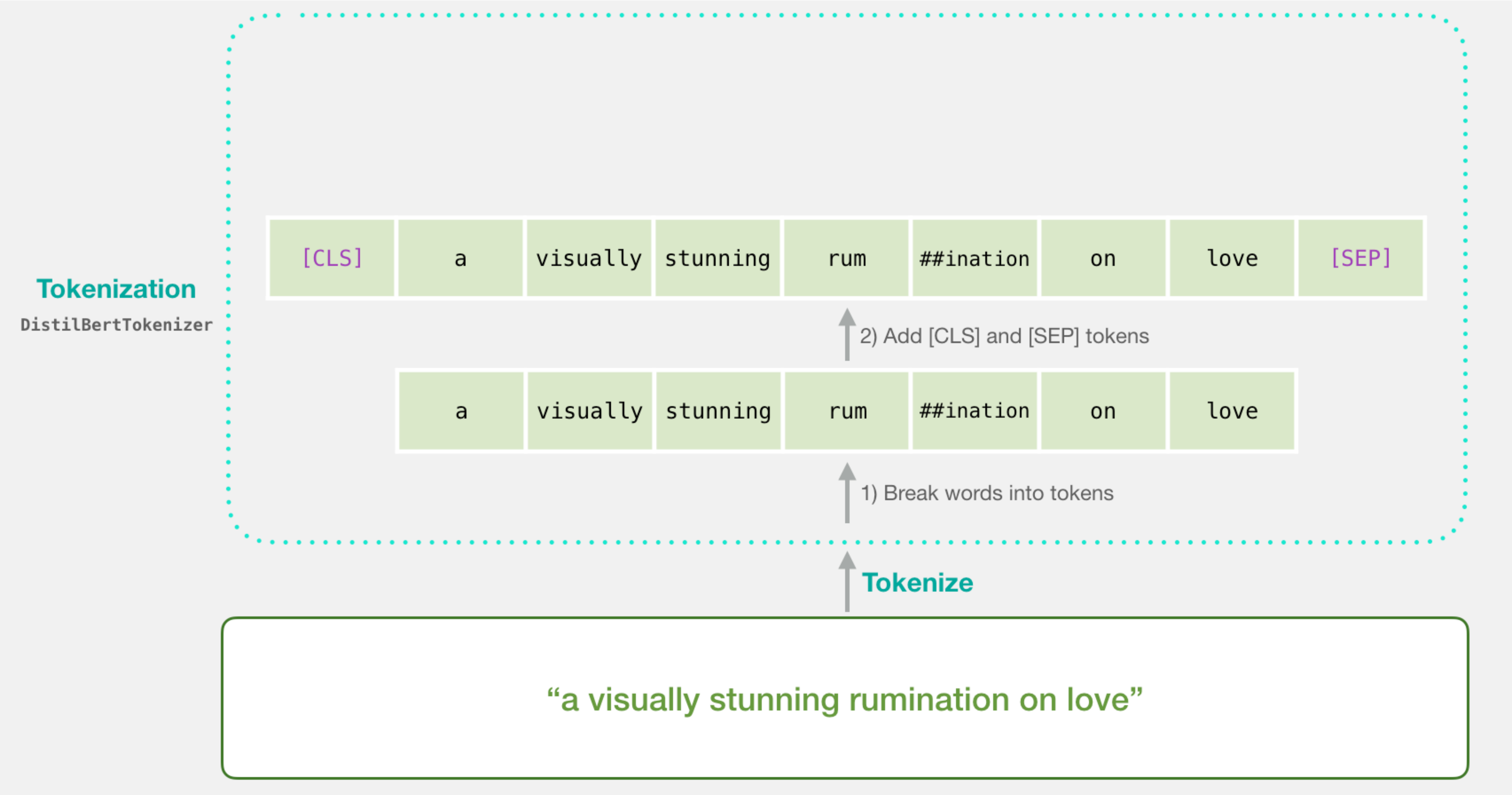


Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Tokenization

[CLS] a visually stunning rum ##ination on love [SEP]

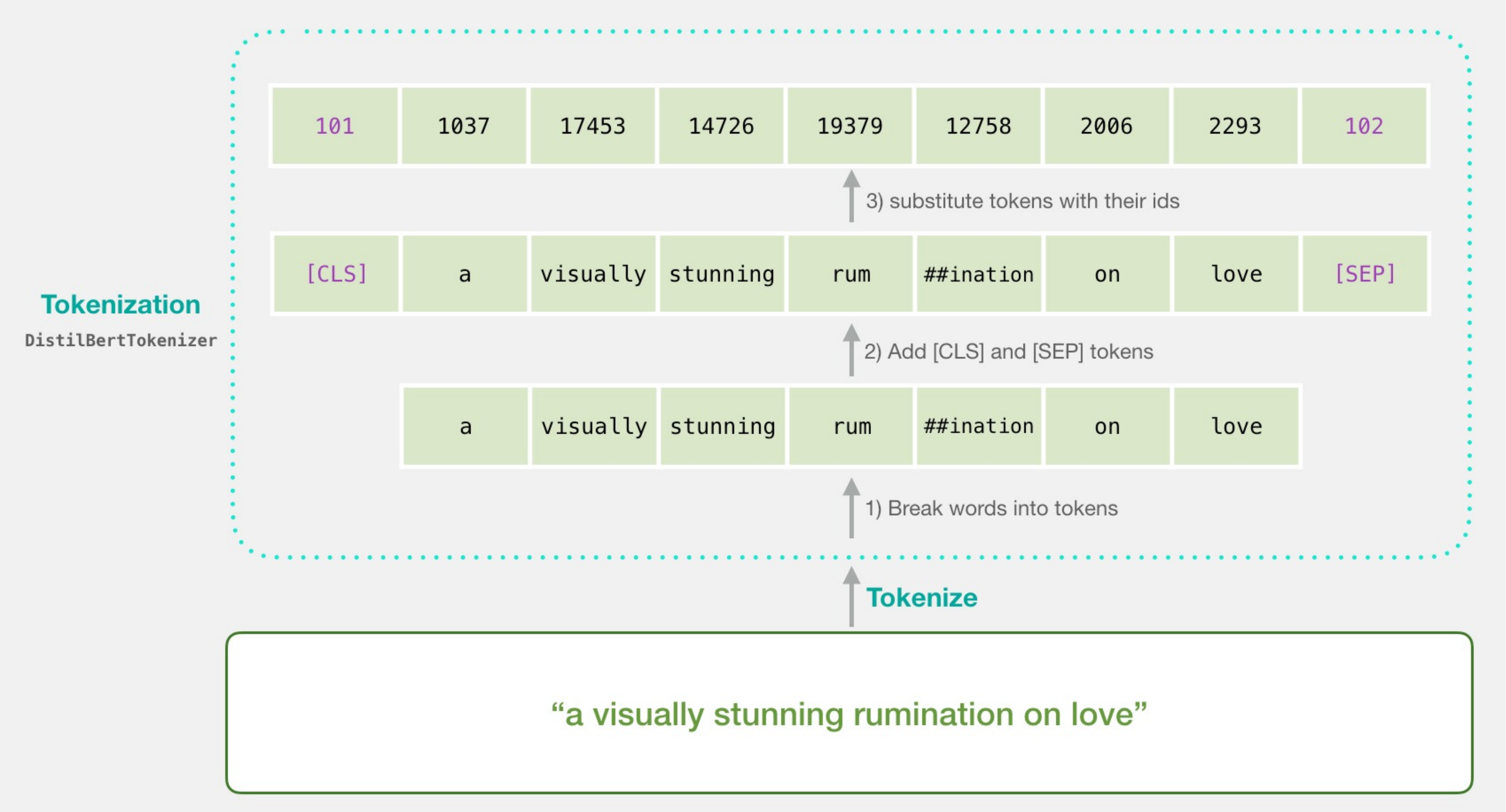
a visually stunning rumination on love



Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

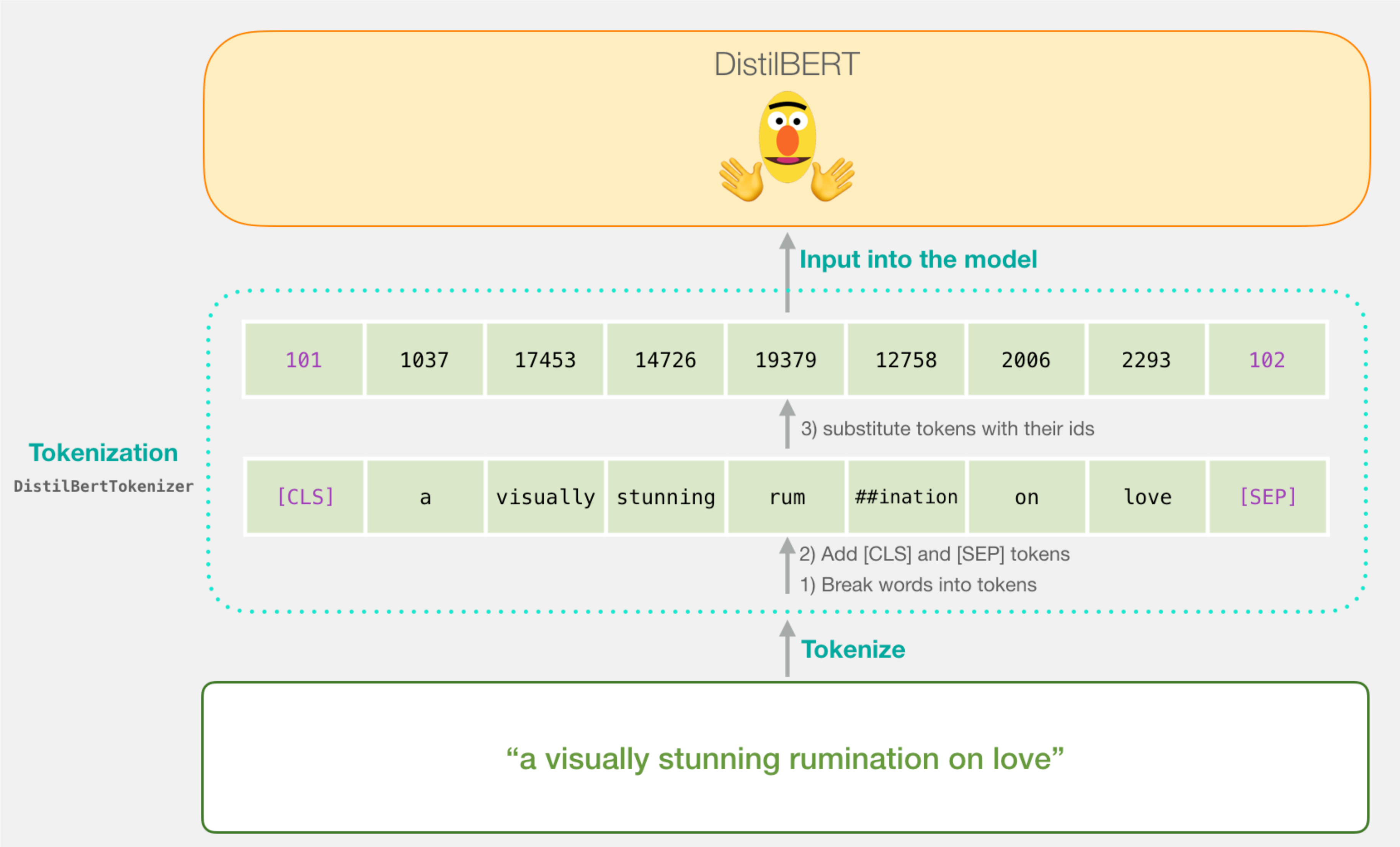
Tokenization

```
tokenizer.encode("a visually stunning rumination on love",
                 add_special_tokens=True)
```



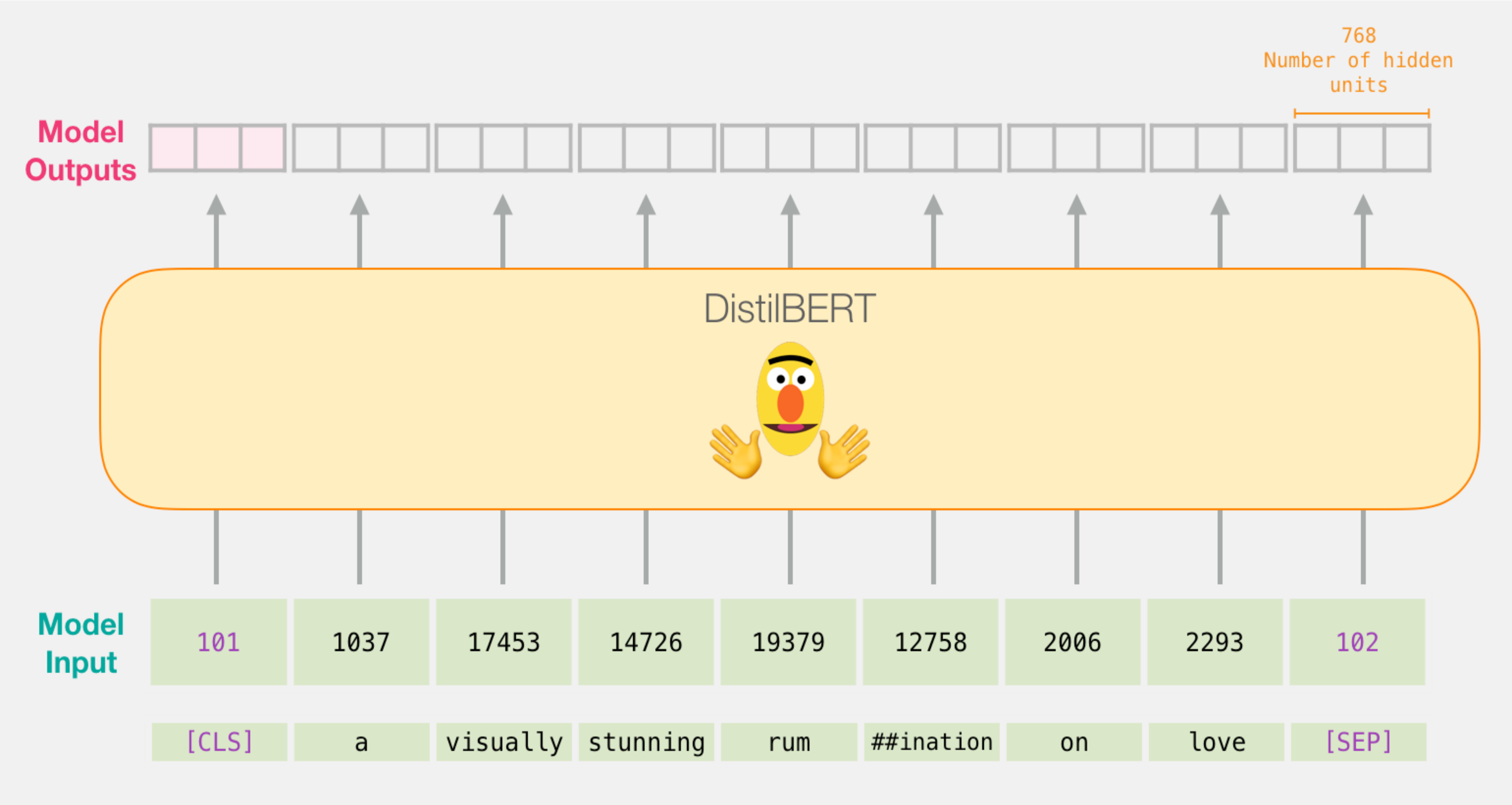
Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Tokenization for BERT Model



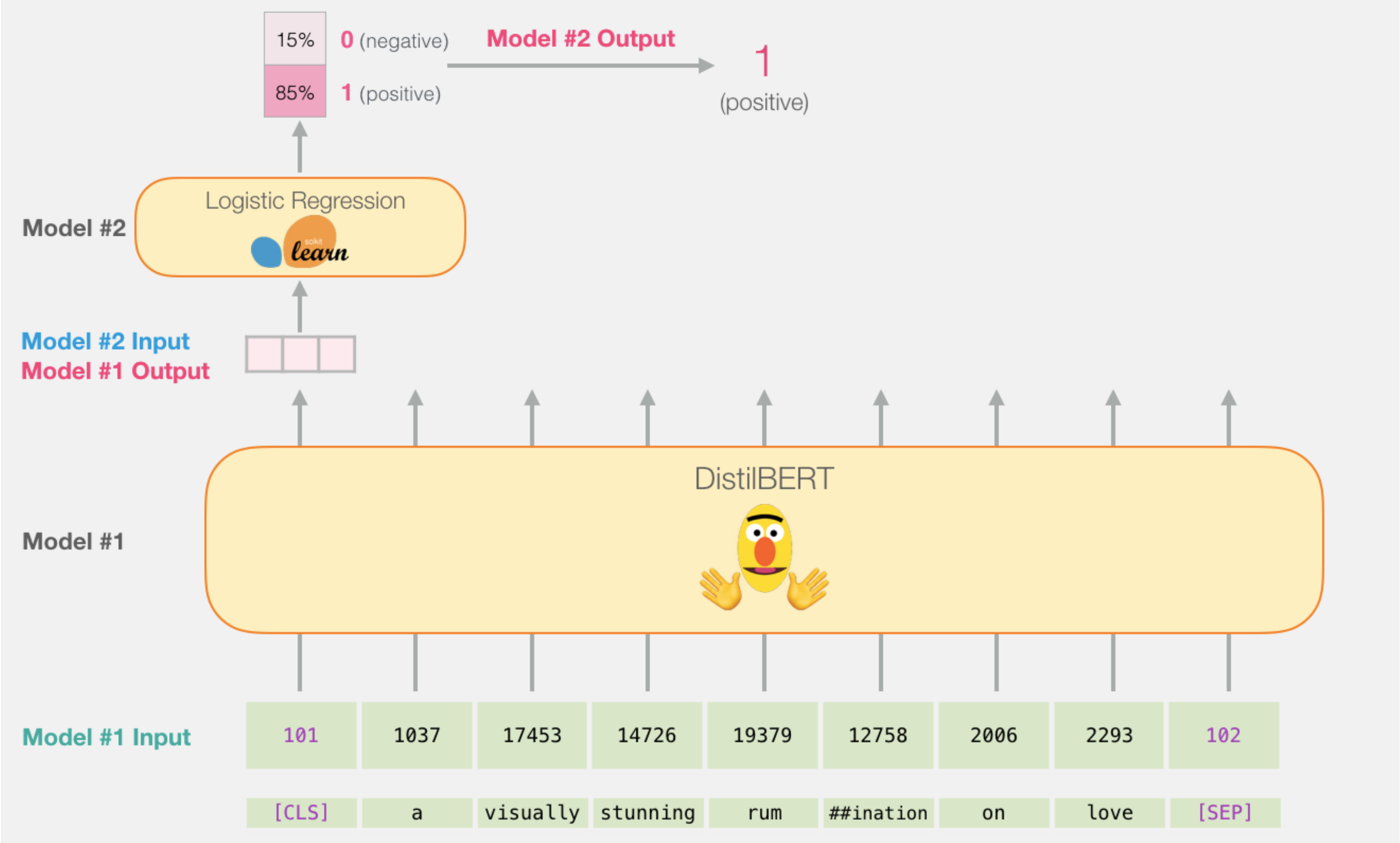
Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Flowing Through DistilBERT (768 features)



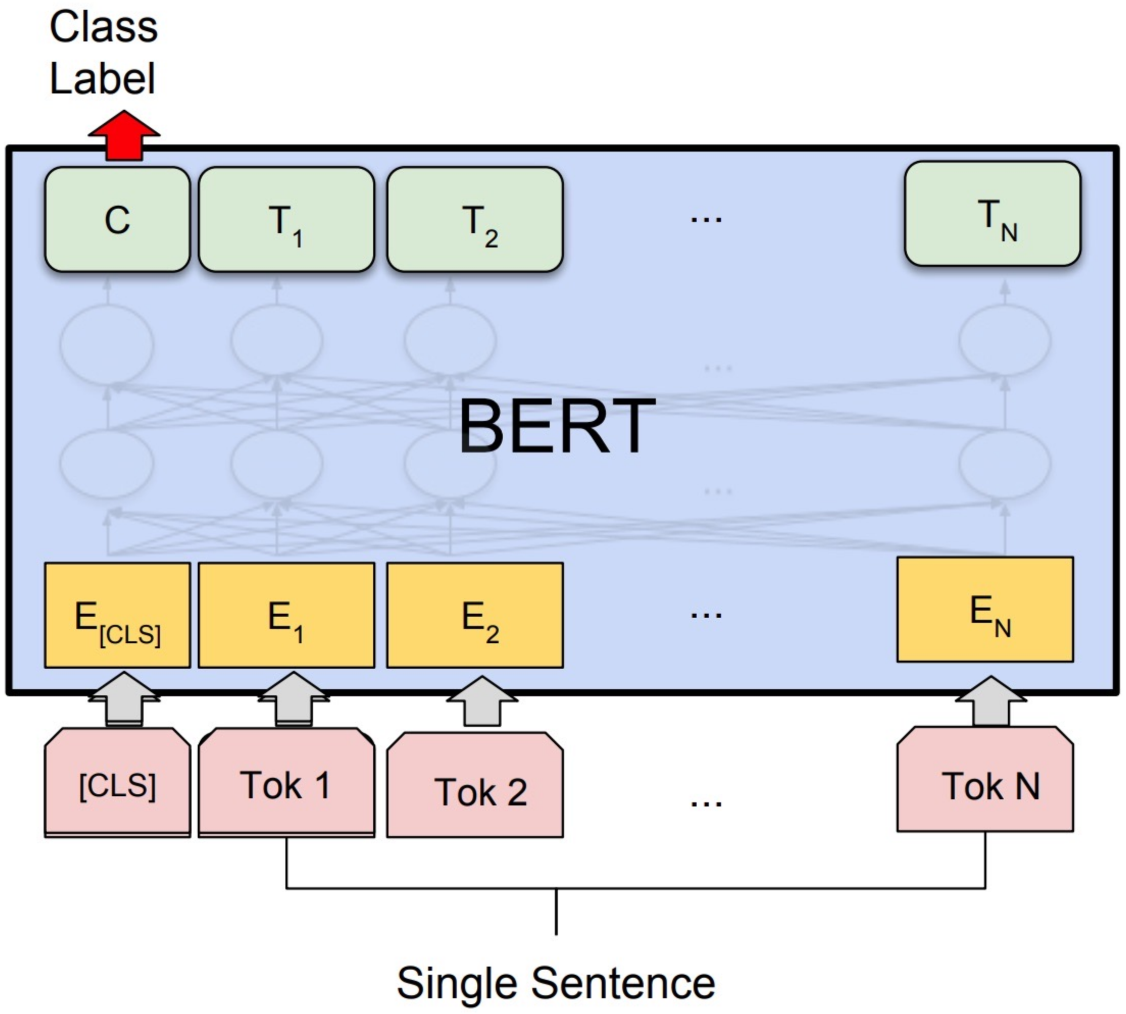
Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Model #1 Output Class vector as Model #2 Input



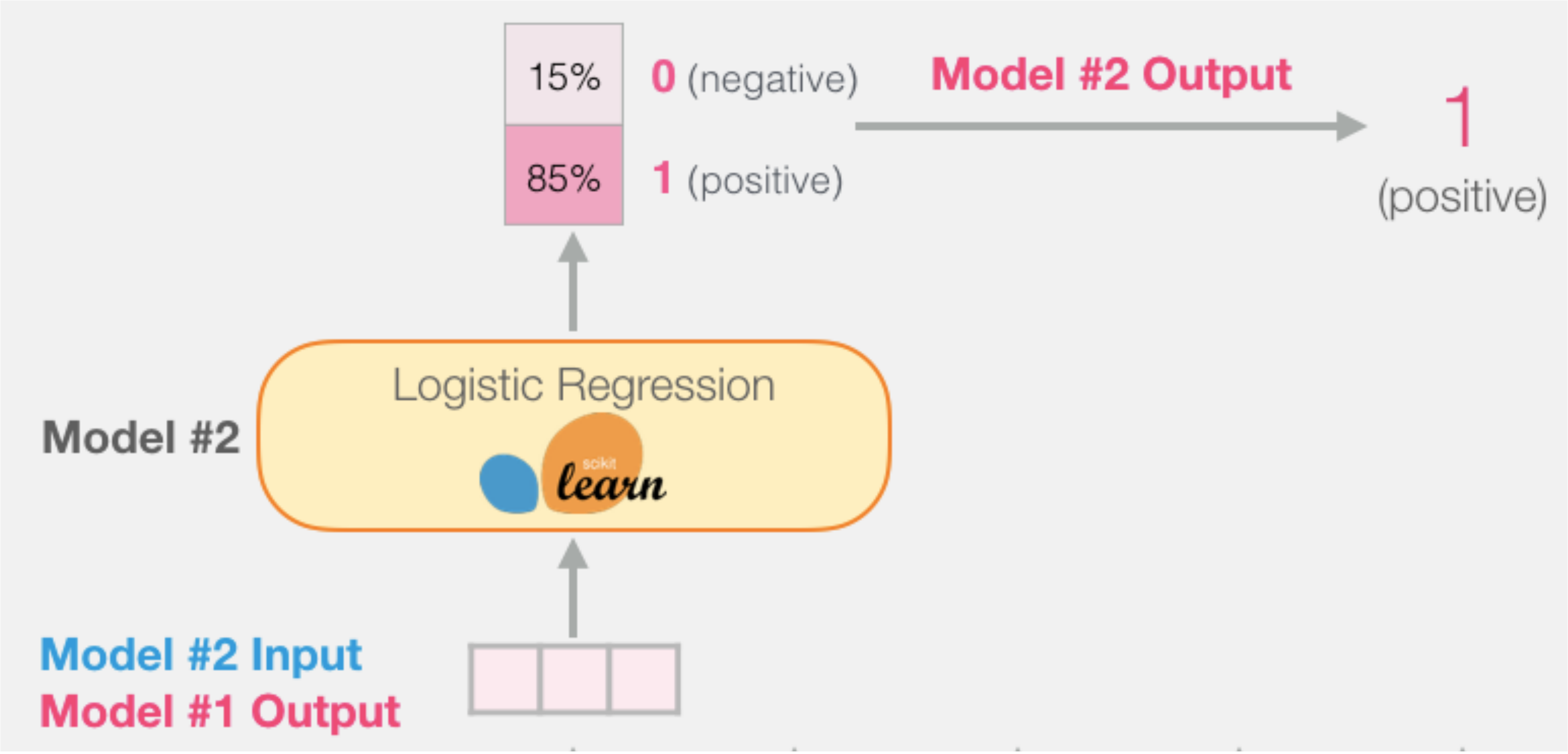
Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Fine-tuning BERT on Single Sentence Classification Tasks



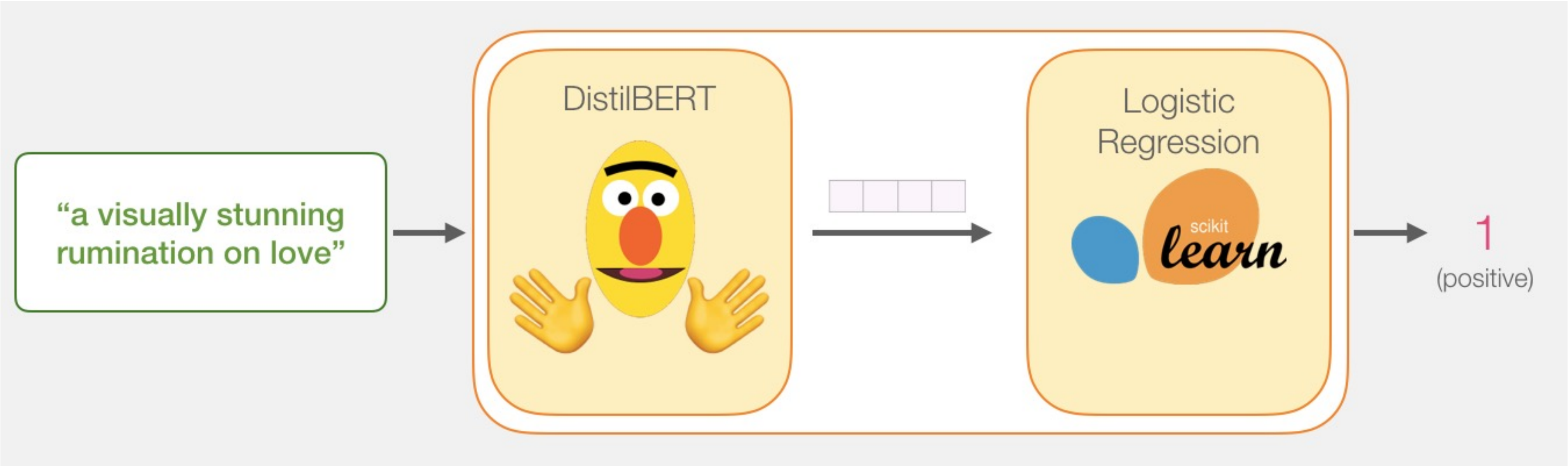
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

Model #1 Output Class vector as Model #2 Input



Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Logistic Regression Model to classify Class vector



Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time,
http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

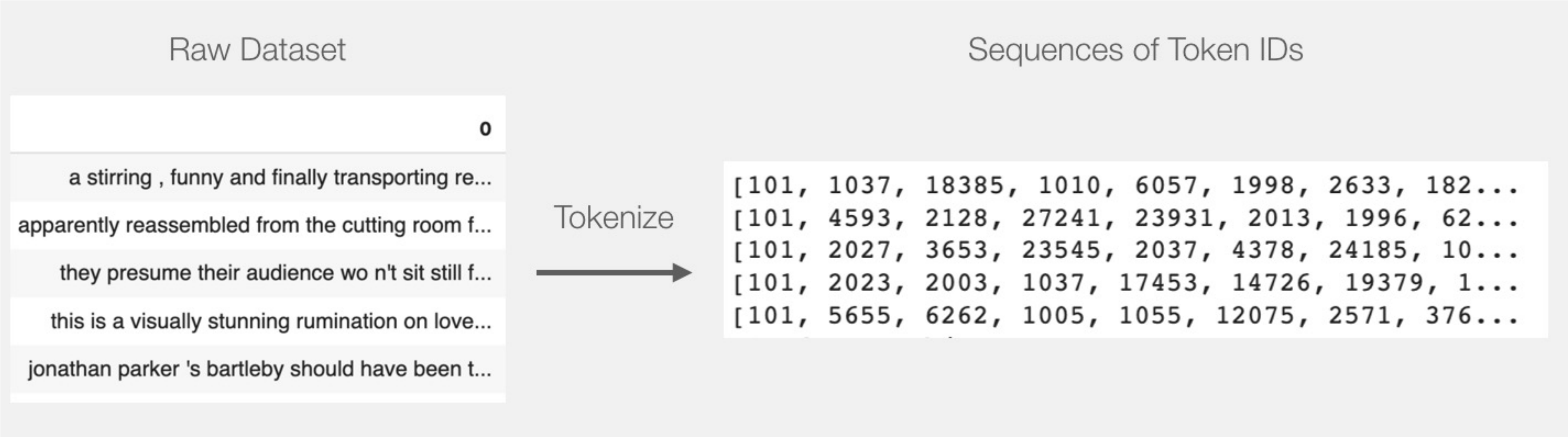
```
df = pd.read_csv('https://github.com/clairett/pytorch-sentiment-classification/raw/master/data/SST2/train.tsv', delimiter='\t', header=None)

df.head()
```

	0	1
0	a stirring , funny and finally transporting re...	1
1	apparently reassembled from the cutting room f...	0
2	they presume their audience wo n't sit still f...	0
3	this is a visually stunning rumination on love...	1
4	jonathan parker 's bartleby should have been t...	1

Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Tokenization

```
tokenized = df[0].apply((lambda x: tokenizer.encode(x,
add_special_tokens=True)))
```



Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time,
http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

BERT Input Tensor

BERT/DistilBERT Input Tensor

Tokens in each sequence

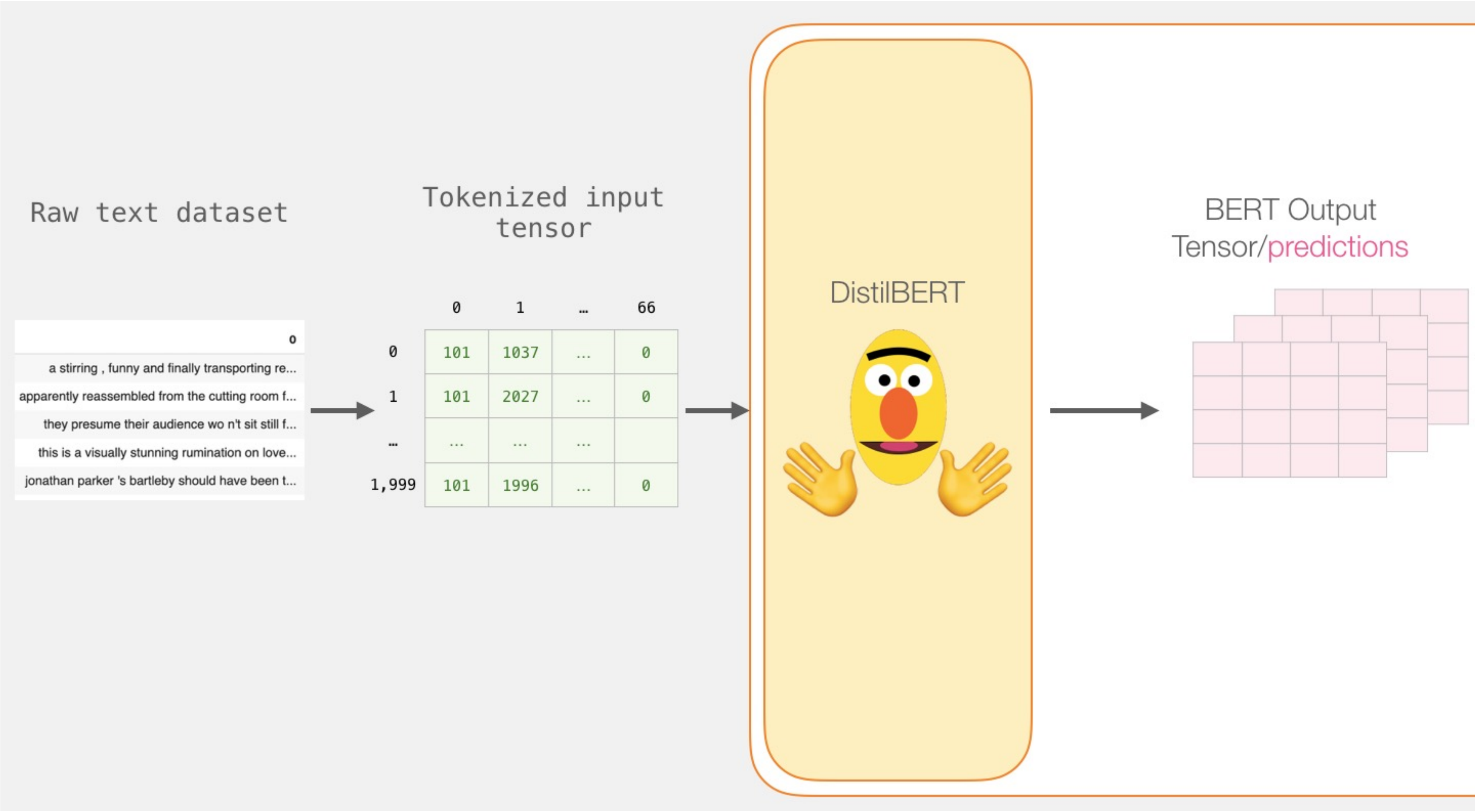
Input sequences (reviews)

	0	1	…	66
0	101	1037	...	0
1	101	2027	...	0
…	...	...	...	
1,999	101	1996	...	0

Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

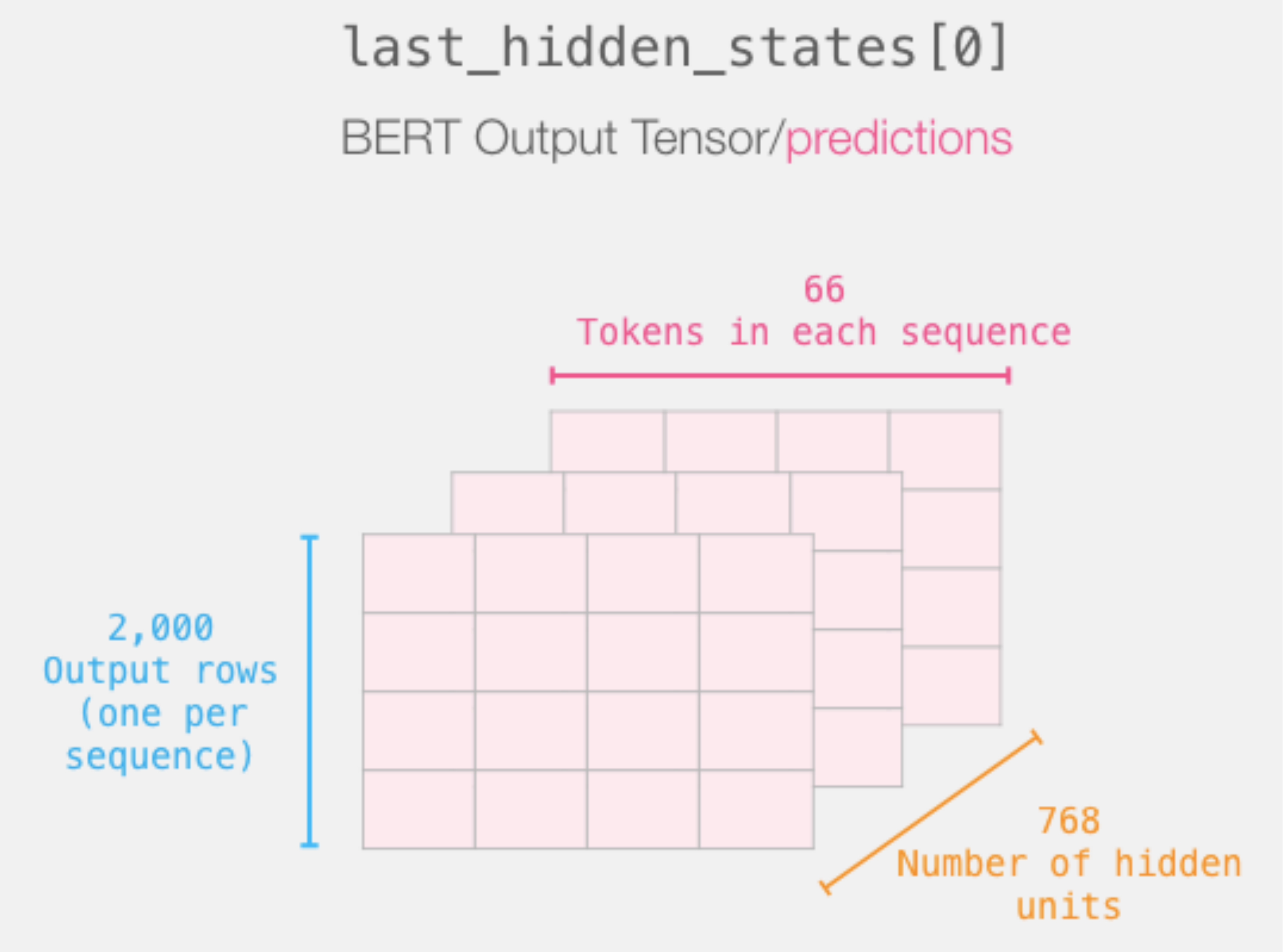
Processing with DistilBERT

```
input_ids = torch.tensor(np.array(padded))
last_hidden_states = model(input_ids)
```



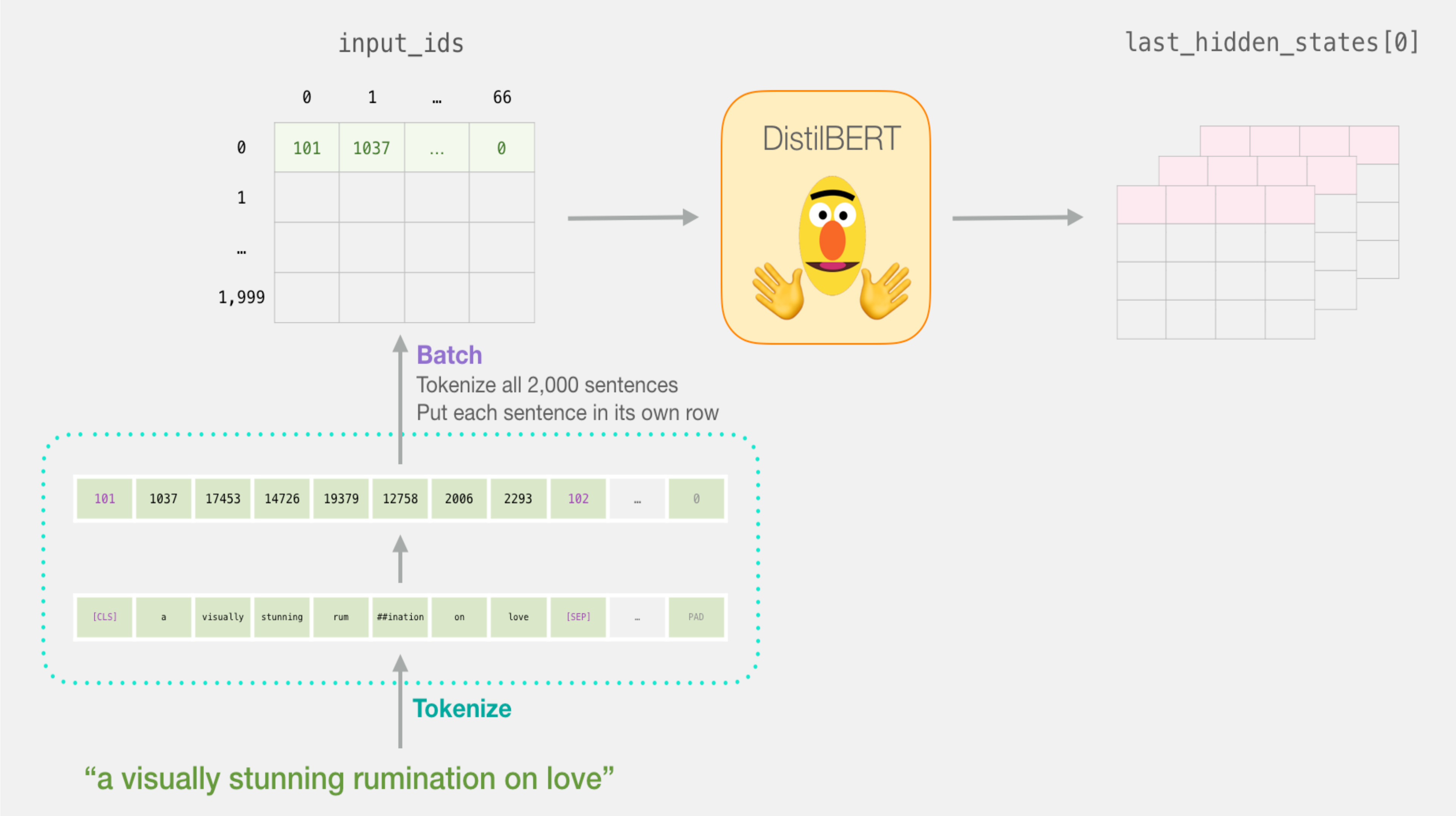
Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Unpacking the BERT output tensor



Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

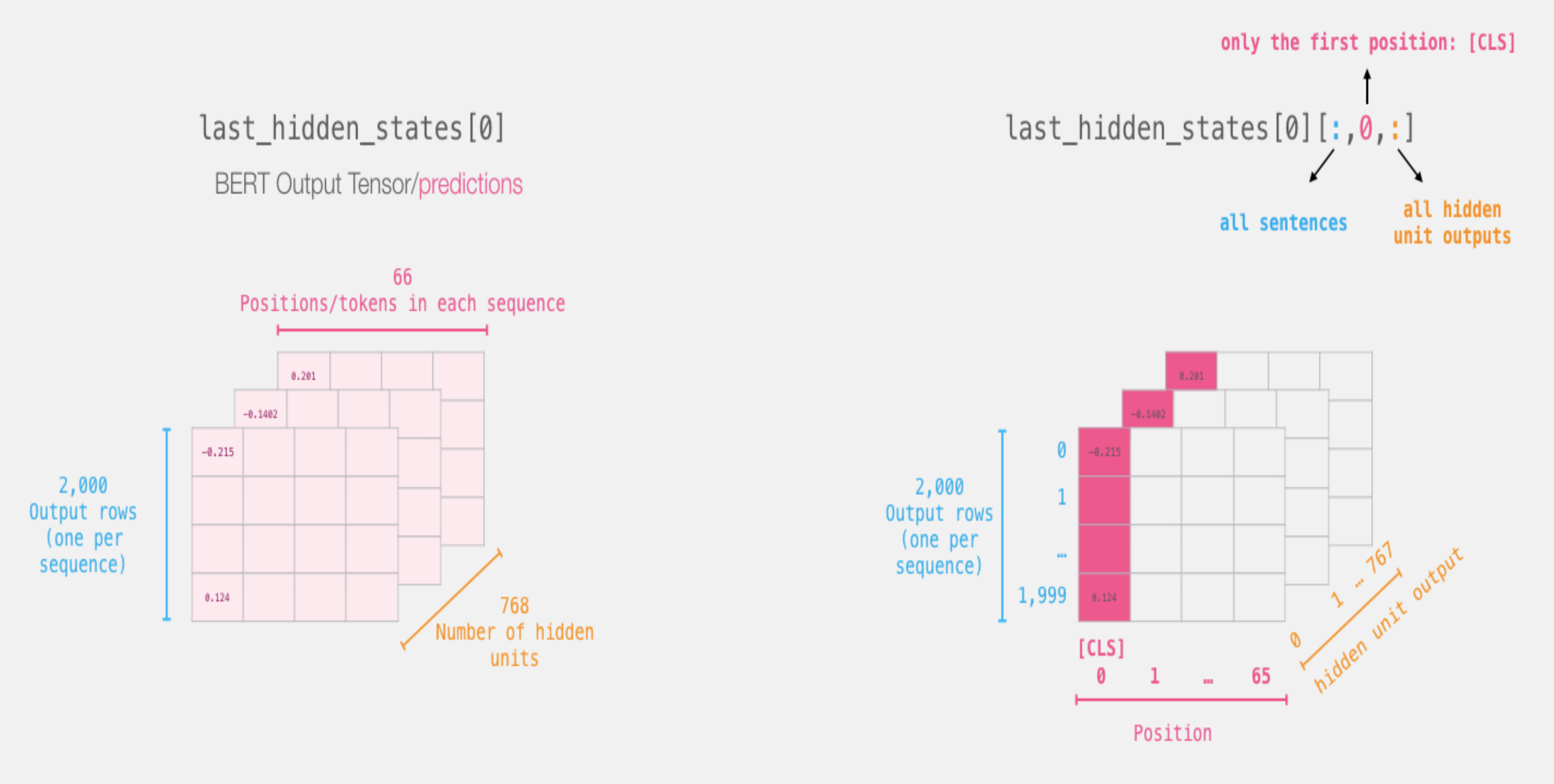
Sentence to last_hidden_state[0]



Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time,
http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

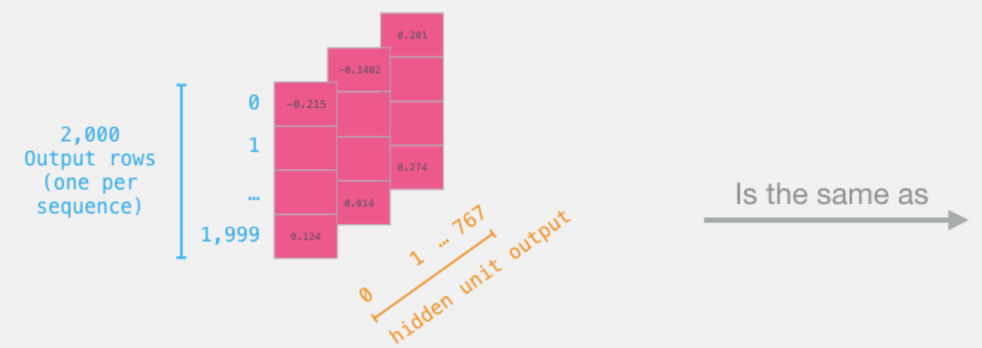
BERT's output for the [CLS] tokens

```
# Slice the output for the first position for all the
sequences, take all hidden unit outputs
features = last_hidden_states[0][:,0,:].numpy()
```



Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

The tensor sliced from BERT's output
Sentence Embeddings

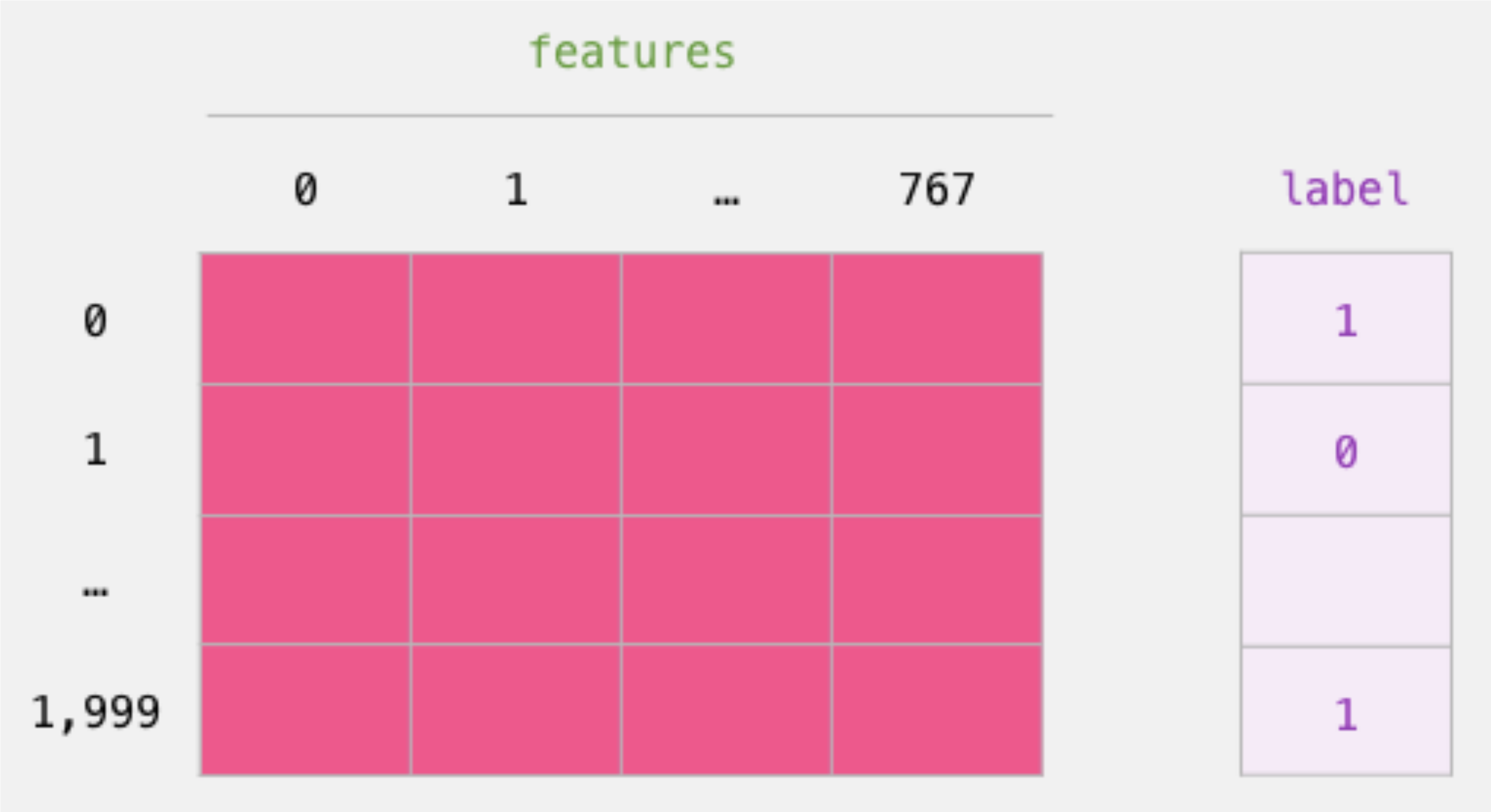


	0	1	…	767	label
0	-0.215	-0.1402	…	0.201	1
1					
2					
3					
4					
5					
6					
7					
8					
9					
…					
1,999	0.124	0.014	…	0.274	1

Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time,
http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

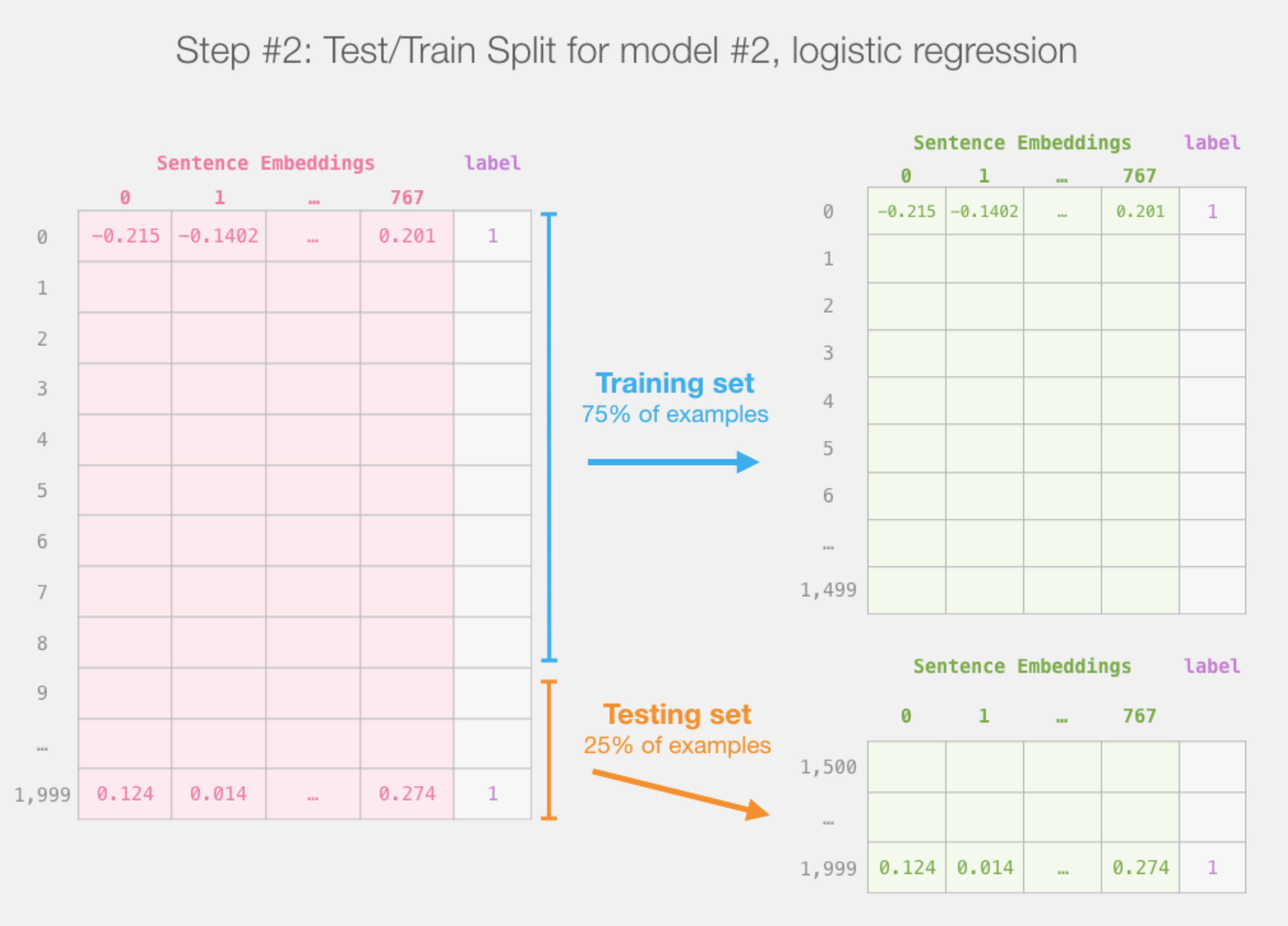
Dataset for Logistic Regression (768 Features)

The features are the output vectors of BERT for the [CLS] token (position #0)



Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time,
http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

```
labels = df[1]
train_features, test_features, train_labels, test_labels =
train_test_split(features, labels)
```



Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time,
http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Score Benchmarks
Logistic Regression Model
on SST-2 Dataset

```
# Training
lr_clf = LogisticRegression()
lr_clf.fit(train_features, train_labels)

#Testing
lr_clf.score(test_features, test_labels)

# Accuracy: 81%
# Highest accuracy: 96.8%
# Fine-tuned DistilBERT: 90.7%
# Full size BERT model: 94.9%
```

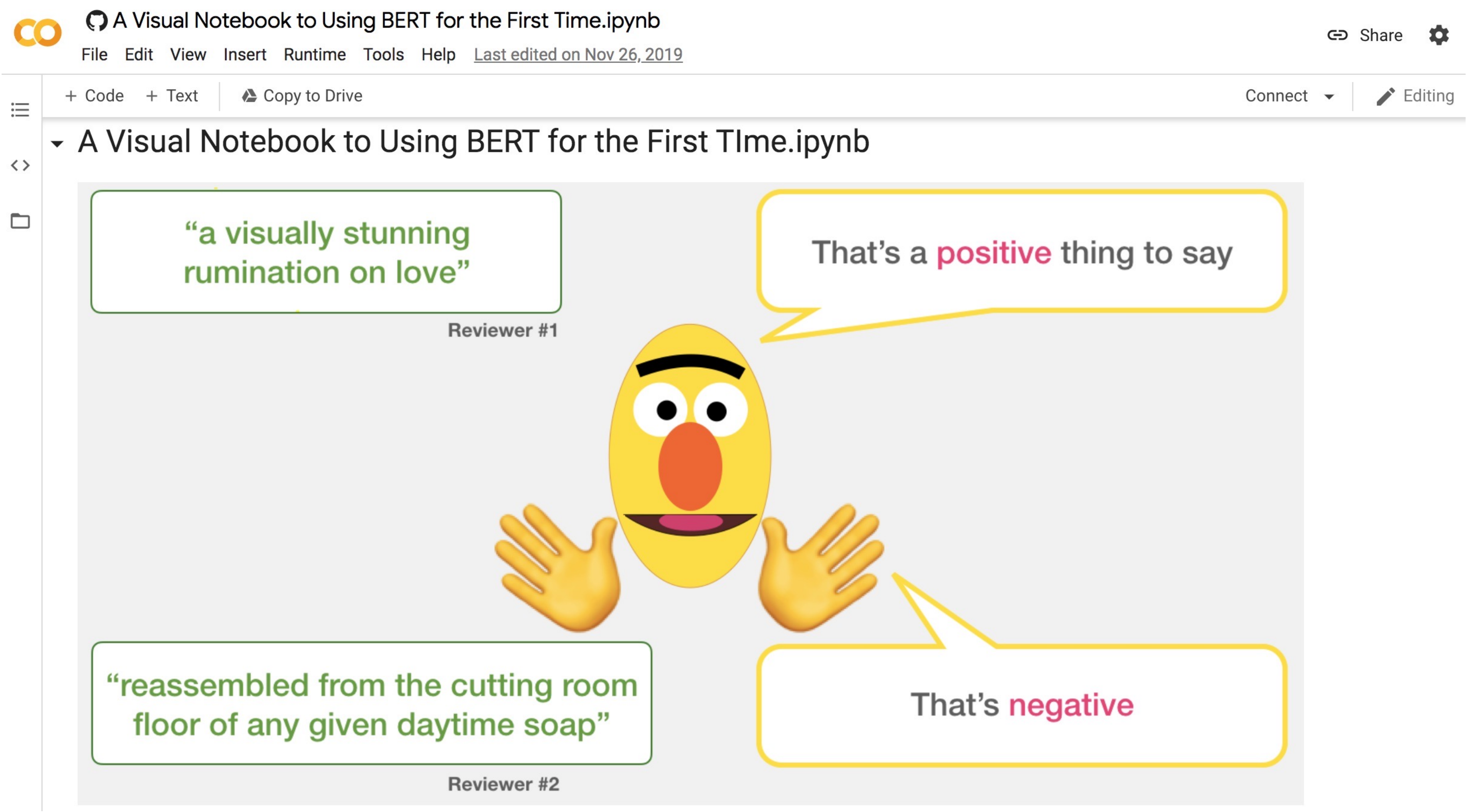
Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time,
http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

Sentiment Classification: SST2
Sentences from movie reviews

sentence	label
a stirring , funny and finally transporting re imagining of beauty and the beast and 1930s horror films	1
apparently reassembled from the cutting room floor of any given daytime soap	0
they presume their audience won't sit still for a sociology lesson	0
this is a visually stunning rumination on love , memory , history and the war between art and commerce	1
jonathan parker 's bartleby should have been the be all end all of the modern office anomie films	1

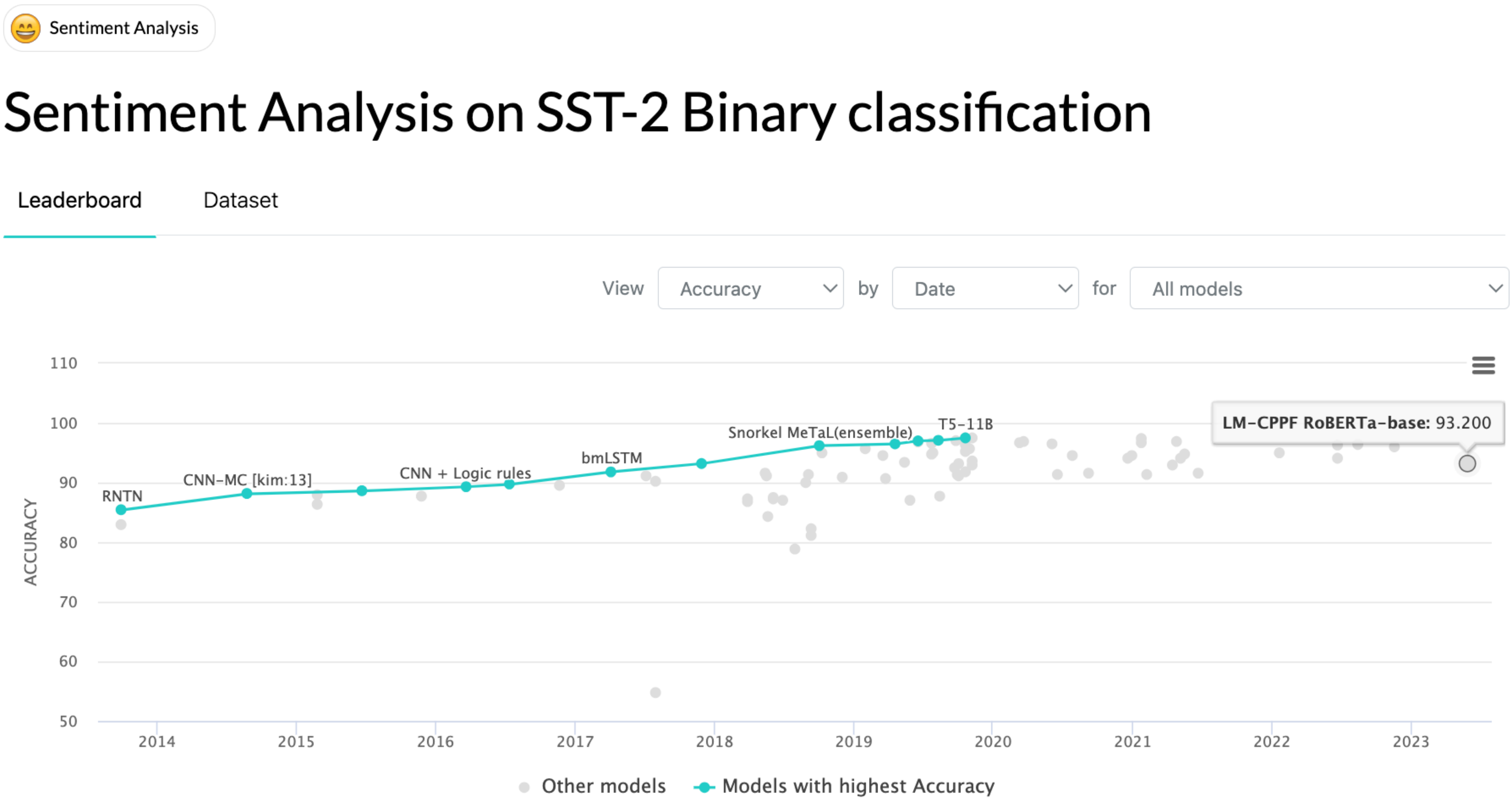
Source: Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/

A Visual Notebook to Using BERT for the First Time



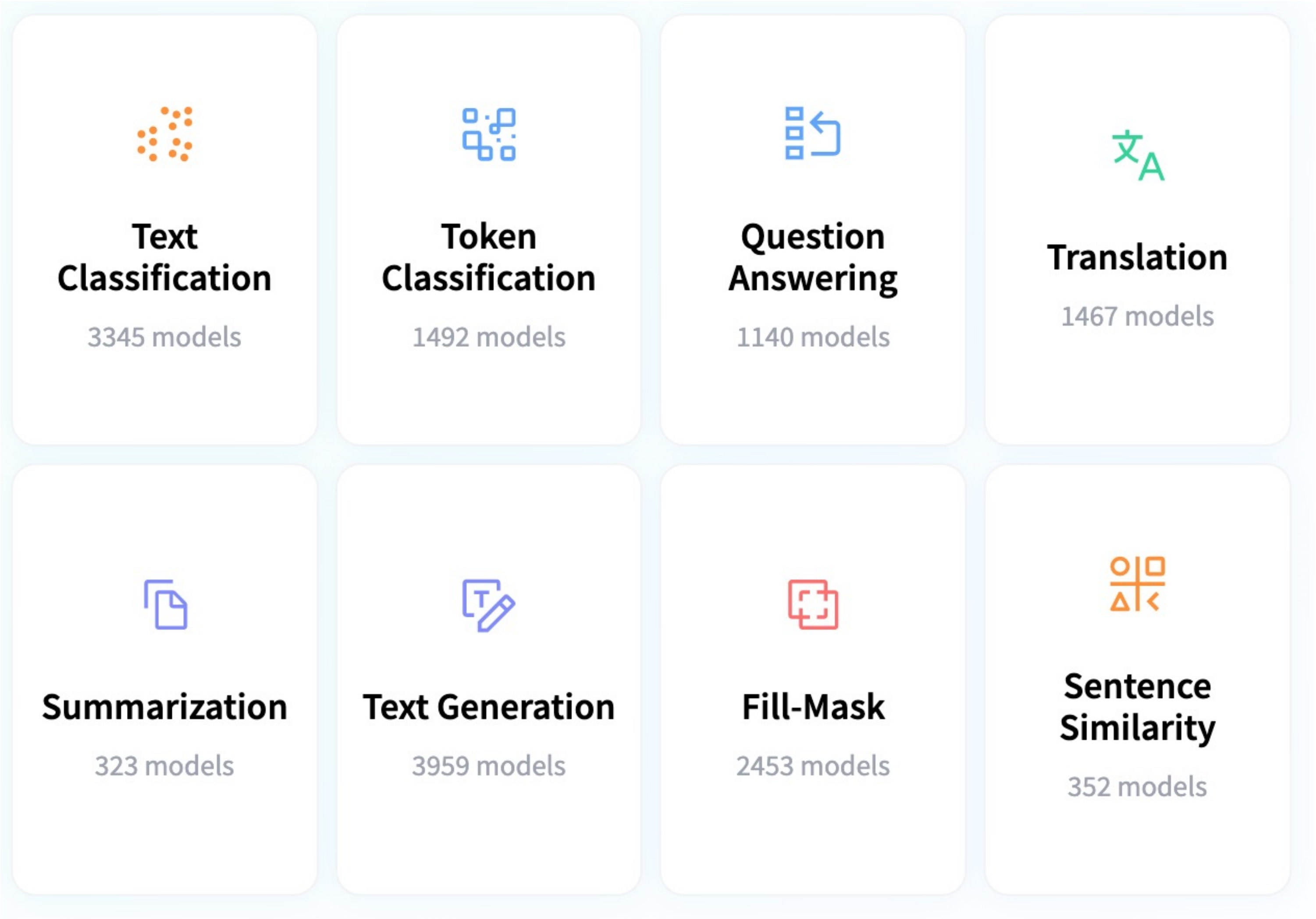
https://colab.research.google.com/github/jalammar/jalammar.github.io/blob/master/notebooks/bert/A_Visual_Notebook_to_Using_BERT_for_the_First_Time.ipynb

SOTA: Sentiment Analysis on SST-2 Binary classification



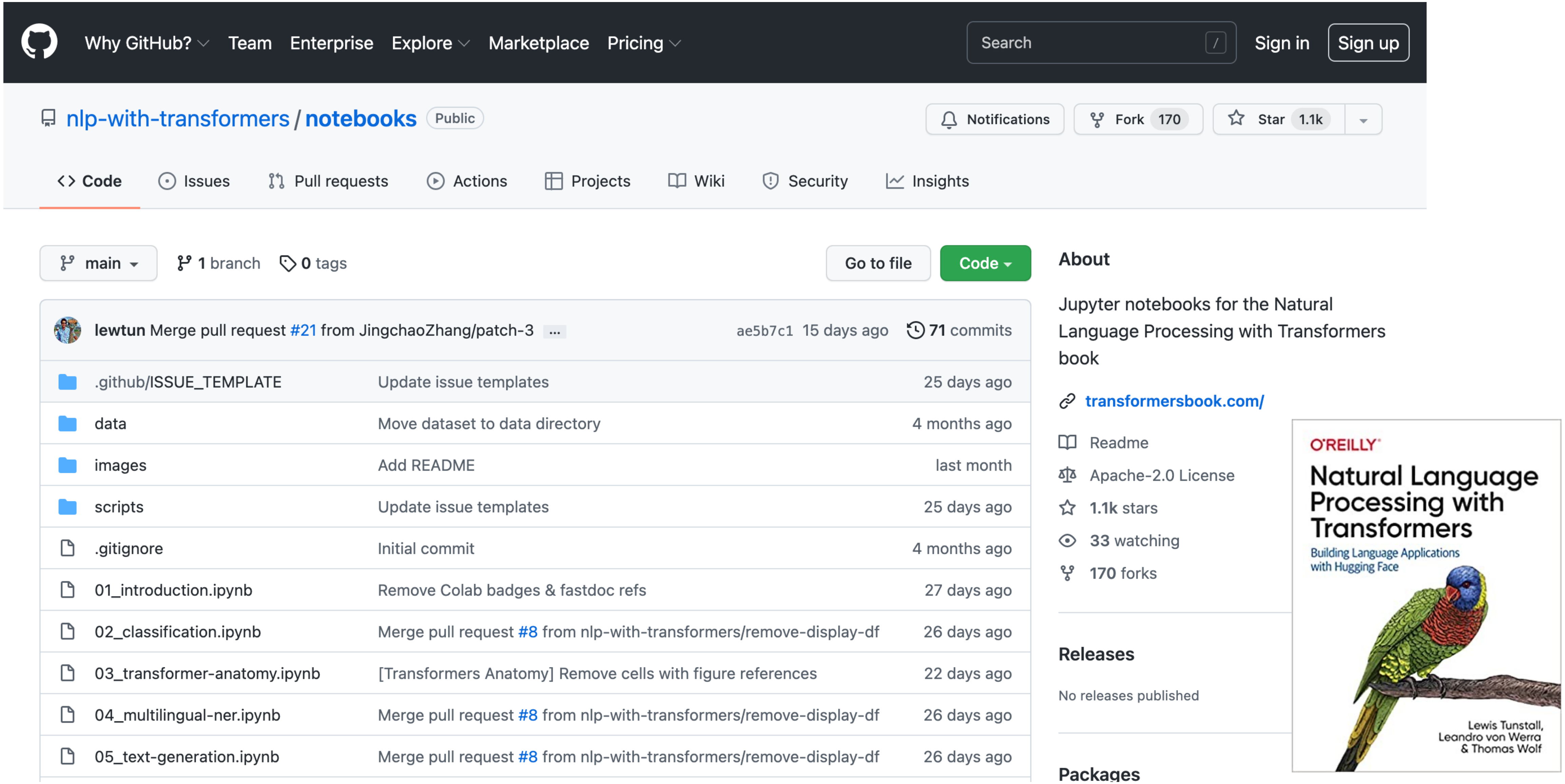
Source: https://paperswithcode.com/sota/sentiment-analysis-on-sst-2-binary

Hugging Face Tasks
Natural Language Processing



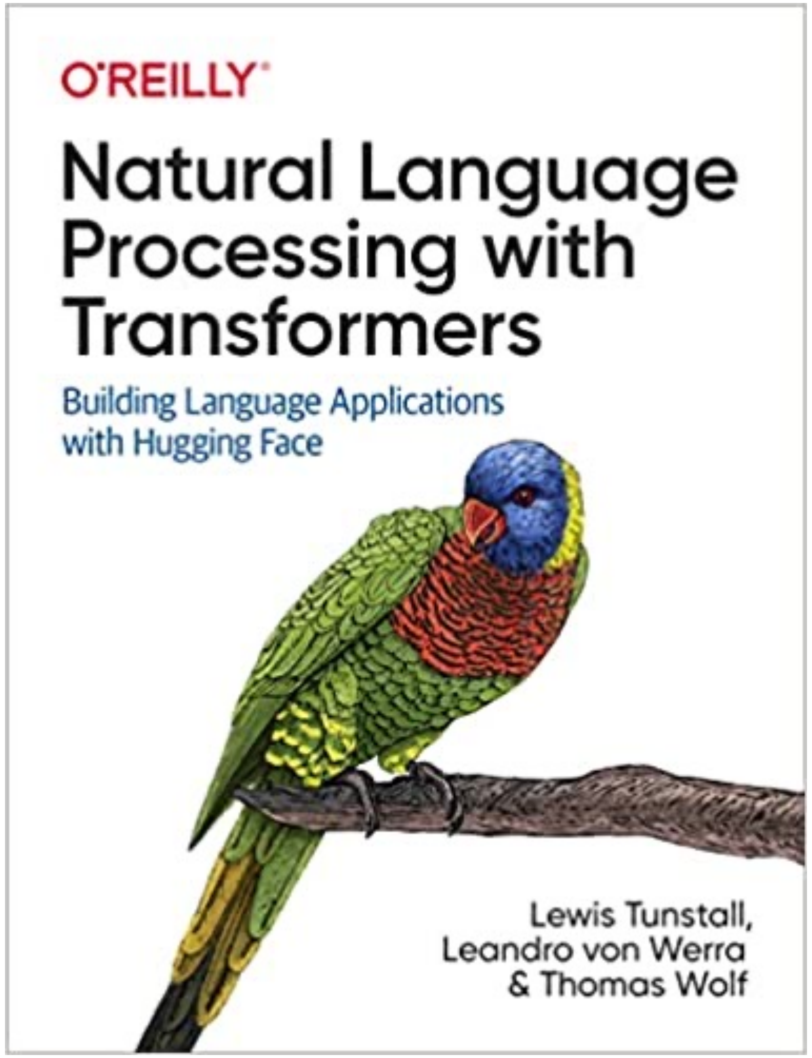
https://huggingface.co/tasks

NLP with Transformers Github



https://github.com/nlp-with-transformers/notebooks

NLP with Transformers Github Notebooks



Running on a cloud platform

To run these notebooks on a cloud platform, just click on one of the badges in the table below:

Chapter	Colab	Kaggle	Gradient	Studio Lab
Introduction	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Text Classification	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Transformer Anatomy	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Multilingual Named Entity Recognition	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Text Generation	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Summarization	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Question Answering	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Making Transformers Efficient in Production	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Dealing with Few to No Labels	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Training Transformers from Scratch	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Future Directions	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab

Nowadays, the GPUs on Colab tend to be K80s (which have limited memory), so we recommend using Kaggle, Gradient, or SageMaker Studio Lab. These platforms tend to provide more performant GPUs like P100s, all for free!

https://github.com/nlp-with-transformers/notebooks

Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT

python101.ipynb

File Edit View Insert Runtime Tools Help All changes saved

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Table of contents

+ Code + Text RAM Disk Editing

Natural Language Processing with Transformers

- Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
- Github: https://github.com/nlp-with-transformers/notebooks

[1]
```
!git clone https://github.com/nlp-with-transformers/notebooks.git
%cd notebooks
from install import *
install_requirements()
```

[3]
```
from utils import *
setup_chapter()
```

[12]
```
text = """Dear Amazon, last week I ordered an Optimus Prime action figure \
from your online store in Germany. Unfortunately, when I opened the package, \
I discovered to my horror that I had been sent an action figure of Megatron \
instead! As a lifelong enemy of the Decepticons, I hope you can understand my \
dilemma. To resolve the issue, I demand an exchange of Megatron for the \
Optimus Prime figure I ordered. Enclosed are copies of my records concerning \
this purchase. I expect to hear from you soon. Sincerely, Bumblebee."""
```

Text Clssification

[13]
```
from transformers import pipeline
classifier = pipeline("text-classification")
```

[14]
```
import pandas as pd
outputs = classifier(text)
pd.DataFrame(outputs)
```

https://tinyurl.com/aintpupython101

Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT

python101.ipynb

File Edit View Insert Runtime Tools Help All changes saved

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+ Code + Text RAM Disk Editing

Text Classification with Transformers

- Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
- Github: https://github.com/nlp-with-transformers/notebooks

[10]
```
!nvidia-smi
```

```
# Uncomment and run this cell if you're on Colab or Kaggle
!git clone https://github.com/nlp-with-transformers/notebooks.git
%cd notebooks
from install import *
install_requirements()
```

[12]
```
# hide
from utils import *
setup_chapter()
```

The Dataset

[13]
```
from datasets import list_datasets
all_datasets = list_datasets()
print(f"There are {len(all_datasets)} datasets currently available on the Hub")
print(f"The first 10 are: {all_datasets[:10]}")
```

```
There are 3783 datasets currently available on the Hub
The first 10 are: ['acronym_identification', 'ade_corpus_v2', 'adversarial_qa',
```

https://tinyurl.com/aintpupython101

Summary

- Text Classification and Sentiment Analysis
  - Dataset
  - Tokenizer
  - Training a Text Classifier
  - Fine-Tuning Transformers

References

- Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
- Denis Rothman (2021), Transformers for Natural Language Processing: Build innovative deep neural network architectures for NLP with Python, PyTorch, TensorFlow, BERT, RoBERTa, and more, Packt Publishing.
- Savaş Yıldırım and Meysam Asgari-Chenaghlu (2021), Mastering Transformers: Build state-of-the-art models from scratch with advanced natural language processing techniques, Packt Publishing.
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- Rajesh Arumugam (2018), Hands-On Natural Language Processing with Python: A practical guide to applying deep learning architectures to your NLP applications, Packt.
- Jake VanderPlas (2016), Python Data Science Handbook: Essential Tools for Working with Data, O'Reilly Media.
- Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805.
- Washington Cunha, Felipe Viegas, Celso França, Thierson Rosa, Leonardo Rocha, and Marcos André Gonçalves (2023). "A Comparative Survey of Instance Selection Methods applied to NonNeural and Transformer-Based Text Classification." ACM Computing Surveys.
- Qihuang Zhong, Liang Ding, Juhua Liu, Bo Du, and Dacheng Tao (2023). "Can chatgpt understand too? a comparative study on chatgpt and fine-tuned bert." arXiv preprint arXiv:2302.10198.
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- Jay Alammar (2018), The Illustrated Transformer, http://jalammar.github.io/illustrated-transformer/
- Jay Alammar (2019), A Visual Guide to Using BERT for the First Time, http://jalammar.github.io/a-visual-guide-to-using-bert-for-the-first-time/
- NLP with Transformer, https://github.com/nlp-with-transformers/notebooks
- Min-Yuh Day (2023), Python 101, https://tinyurl.com/aintpupython101