Artificial Intelligence for Text Analytics

NTPU
國立臺北大學
National Taipei University

Deep Learning, Generative AI, Transfer Learning, Zero-Shot, and Few-Shot Learning for Text Analytics

1121AITA10
MBA, IM, NTPU (M5265) (Fall 2023)
Tue 2, 3, 4 (9:10-12:00) (B3F17)

https://meet.google.com/miy-fbif-max

aws educate | Cloud Ambassador
2020 Cohort

aws academy Accredited Educator
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aws certified Solutions Architect Associate

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2023-12-20

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

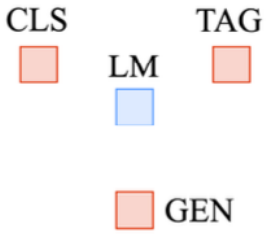
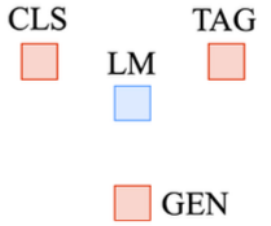
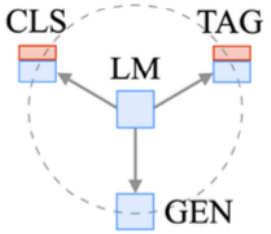
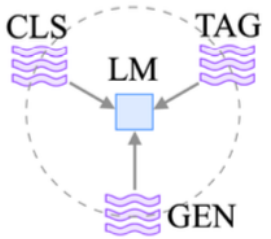
Week	Date	Subject/Topics
13	2023/12/06	Question Answering and Dialogue Systems
14	2023/12/13	Self-learning
15	2023/12/20	Deep Learning, Generative AI, Transfer Learning, Zero-Shot, and Few-Shot Learning for Text Analytics
16	2023/12/27	Final Project Report I
17	2024/01/03	Final Project Report II
18	2024/01/10	Self-learning

Deep Learning, Generative AI, Transfer Learning, Zero-Shot, and Few-Shot Learning for Text Analytics

Outline

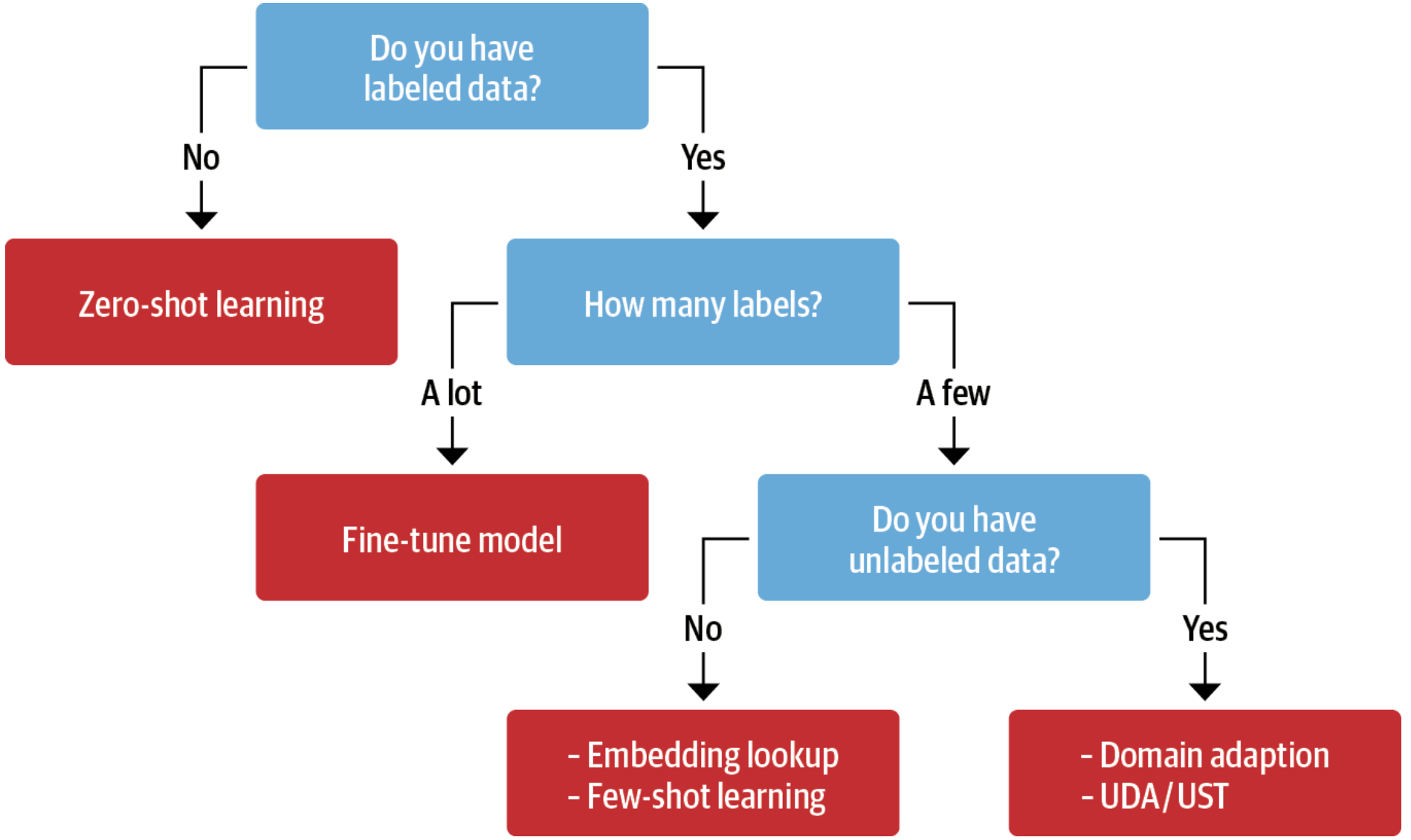
- Deep Learning
  - Generative AI
    - Pre-train, Prompt, and Predict (Prompting)
  - Transfer Learning
    - Pre-training, Fine-Tuning (FT)
- Few-Shot Learning (FSL)
  - Meta Learning: Learn to Learn
- One-Shot Learning (1SL)
- Zero-Shot Learning (0SL)(ZSL)

Four Paradigms in NLP (LM)

Paradigm	Engineering	Task Relation
a. Fully Supervised Learning (Non-Neural Network)	Feature (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
Transfer Learning: Pre-training, Fine-Tuning (FT) c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	
GAI: Pre-train, Prompt, and Predict (Prompting) d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	

Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

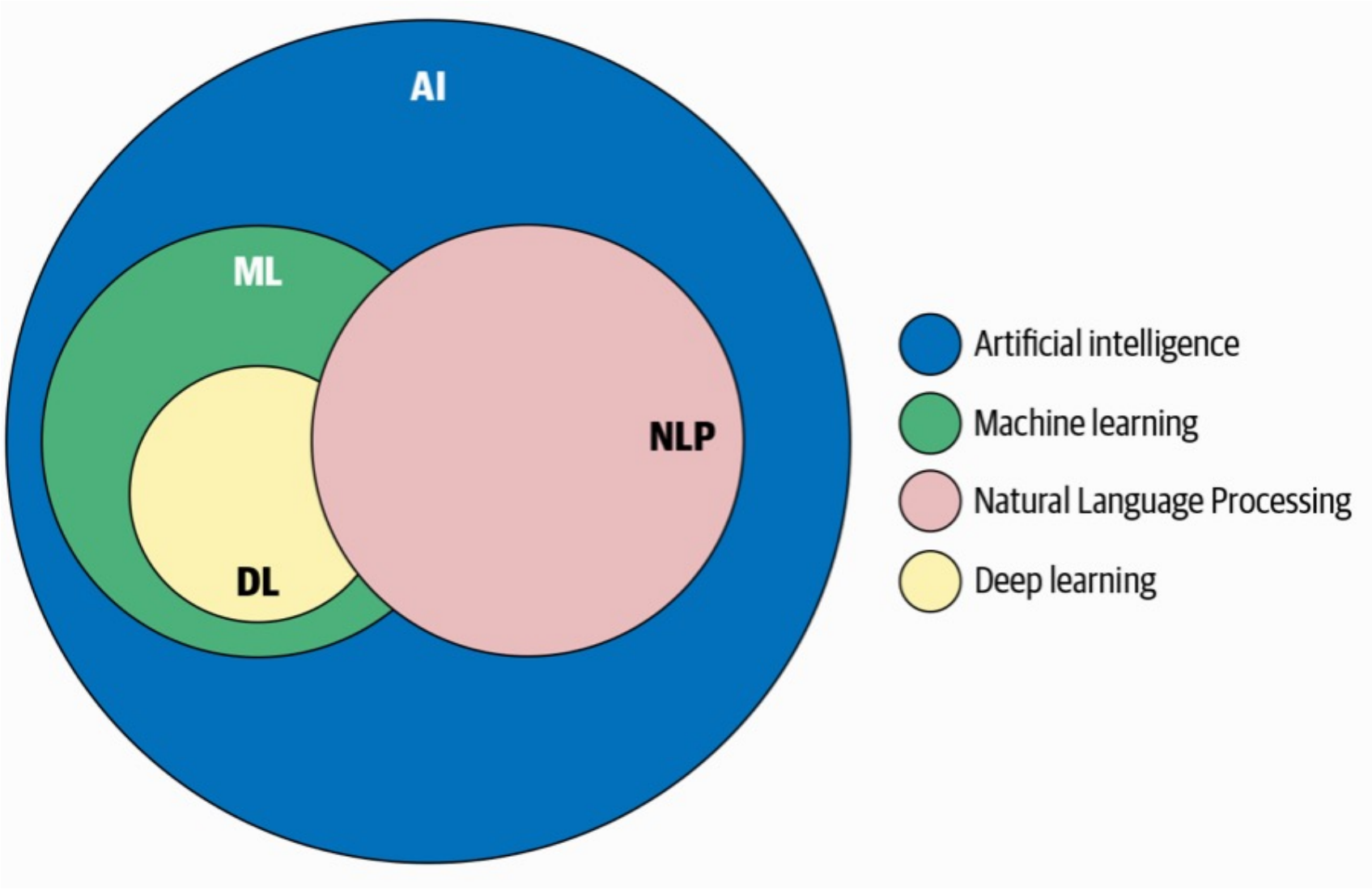
Transfer Learning, Fine-tuning, Few-shot learning



Unsupervised Data Augmentation (UDA)
Uncertainty-aware Self-Training (UST)

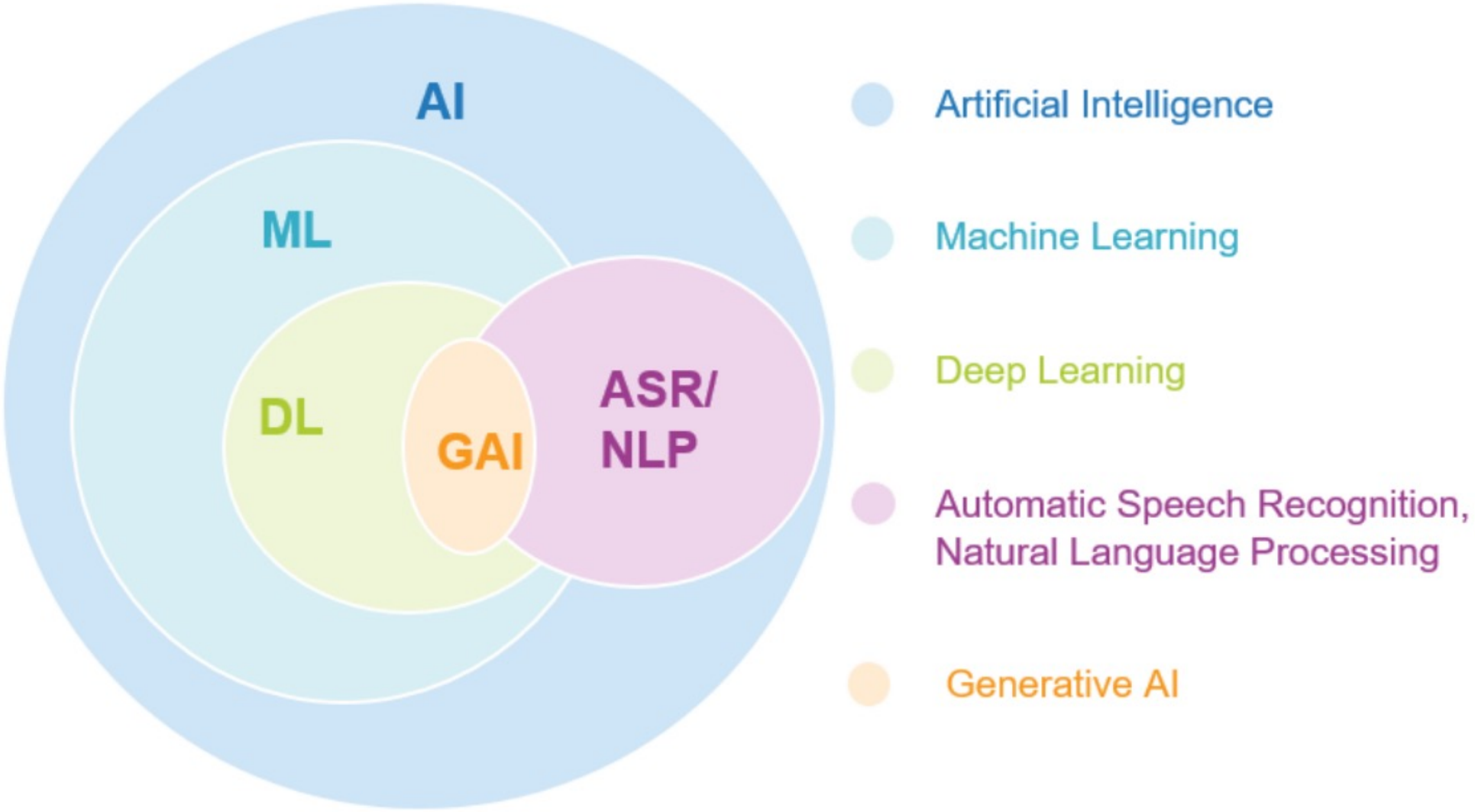
Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.

AI, NLP, ML, DL



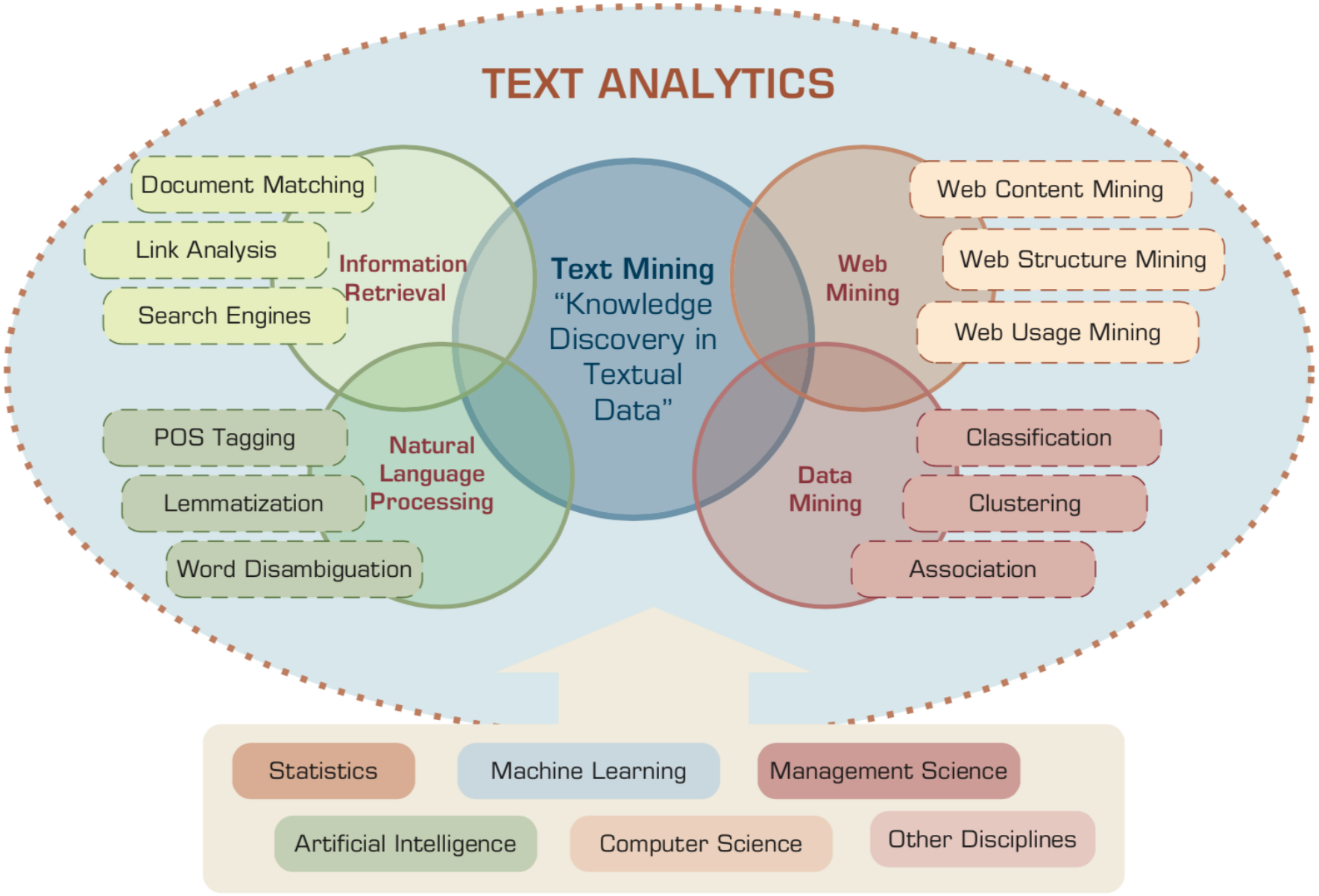
Source: Sowmya Vajjala, Bodhisattwa Majumder, Anuj Gupta (2020), Practical Natural Language Processing: A Comprehensive Guide to Building Real-World NLP Systems, O'Reilly Media.

Generative AI



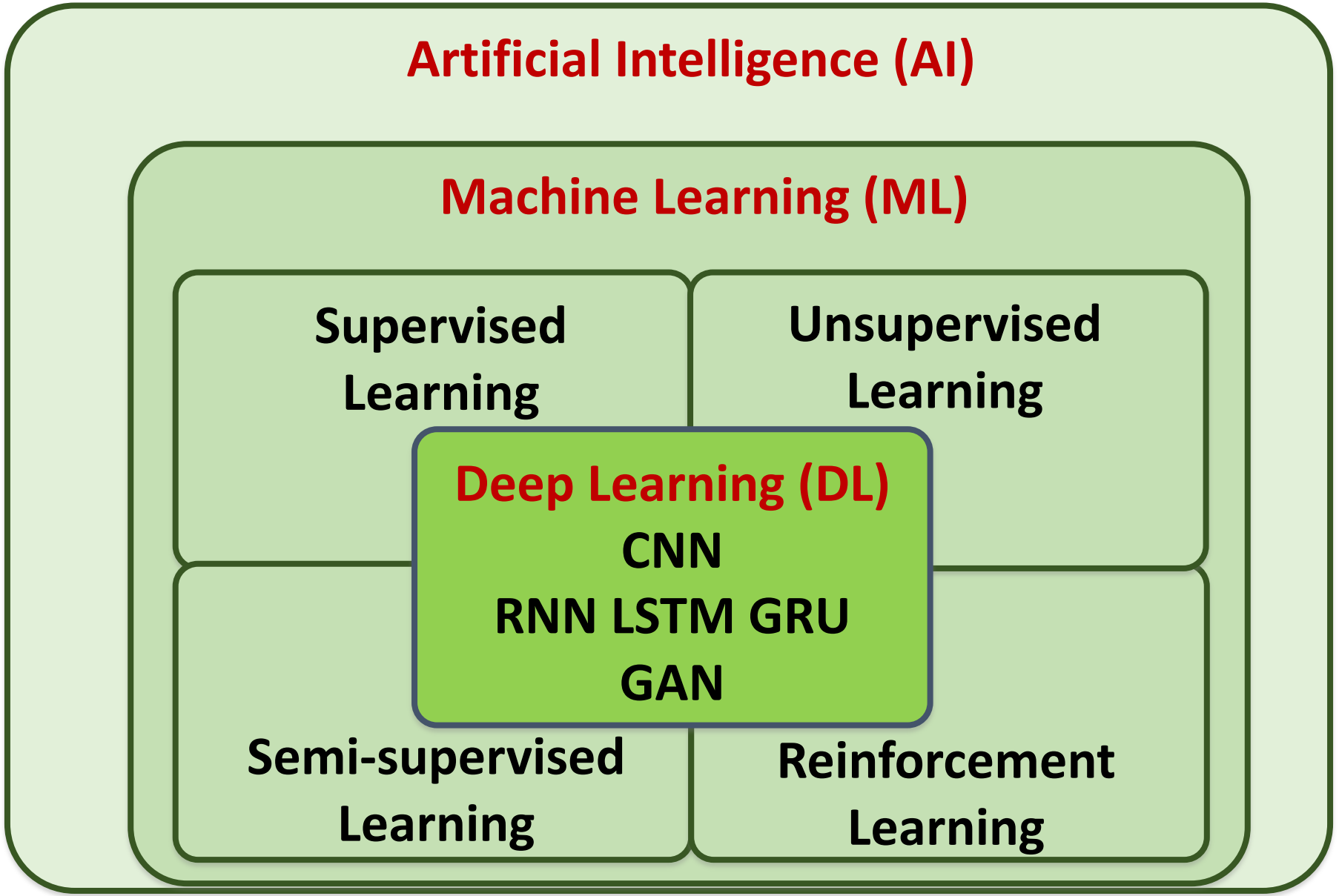
Source: Jeong, Cheonsu. "A Study on the Implementation of Generative AI Services Using an Enterprise Data-Based LLM Application Architecture." arXiv preprint arXiv:2309.01105 (2023).

Text Analytics and Text Mining



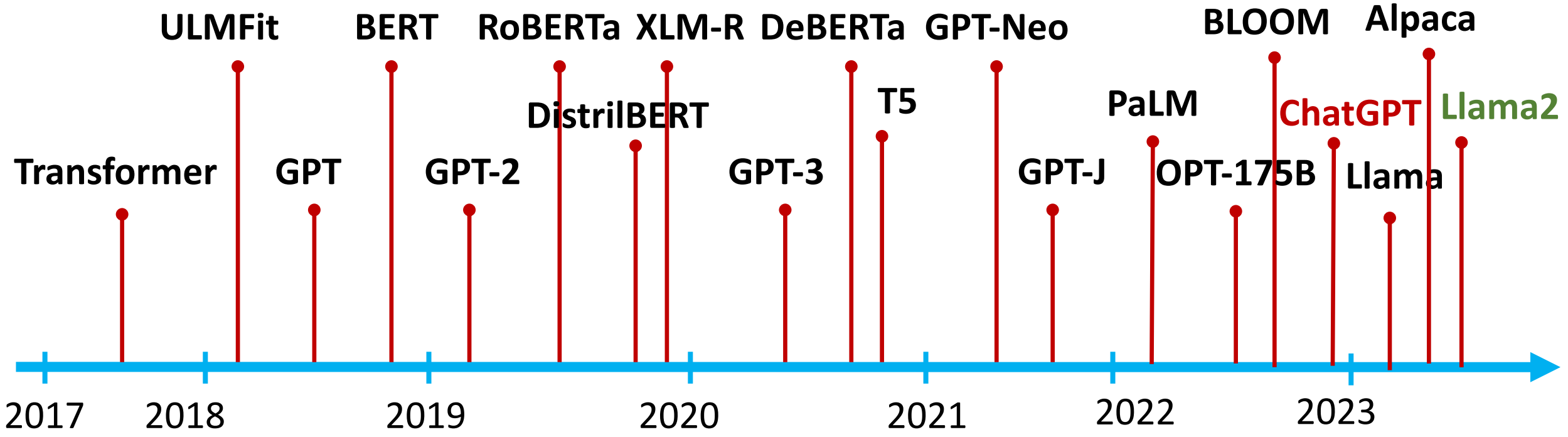
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

AI, ML, DL



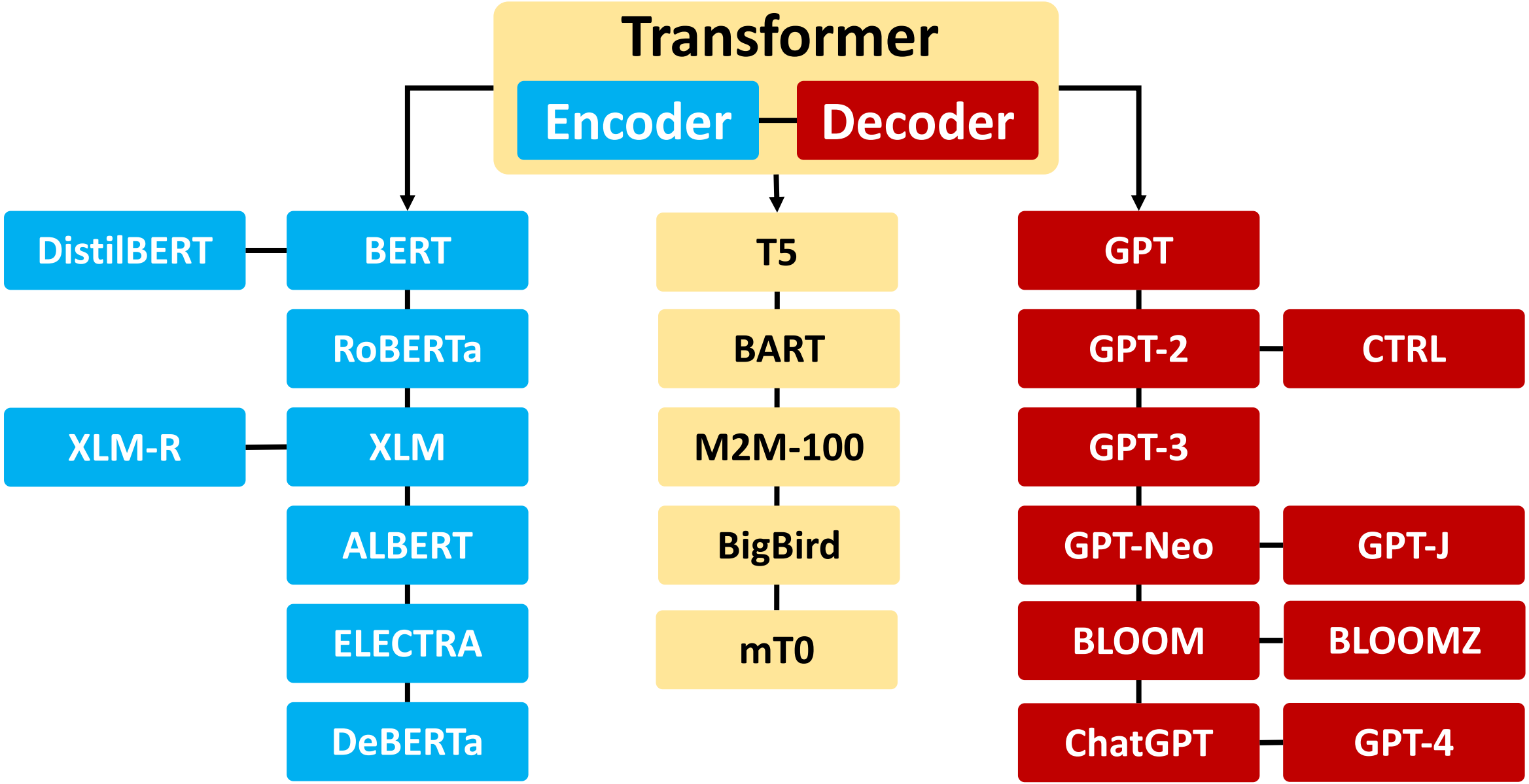
Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/deep_learning.html

The Transformers Timeline



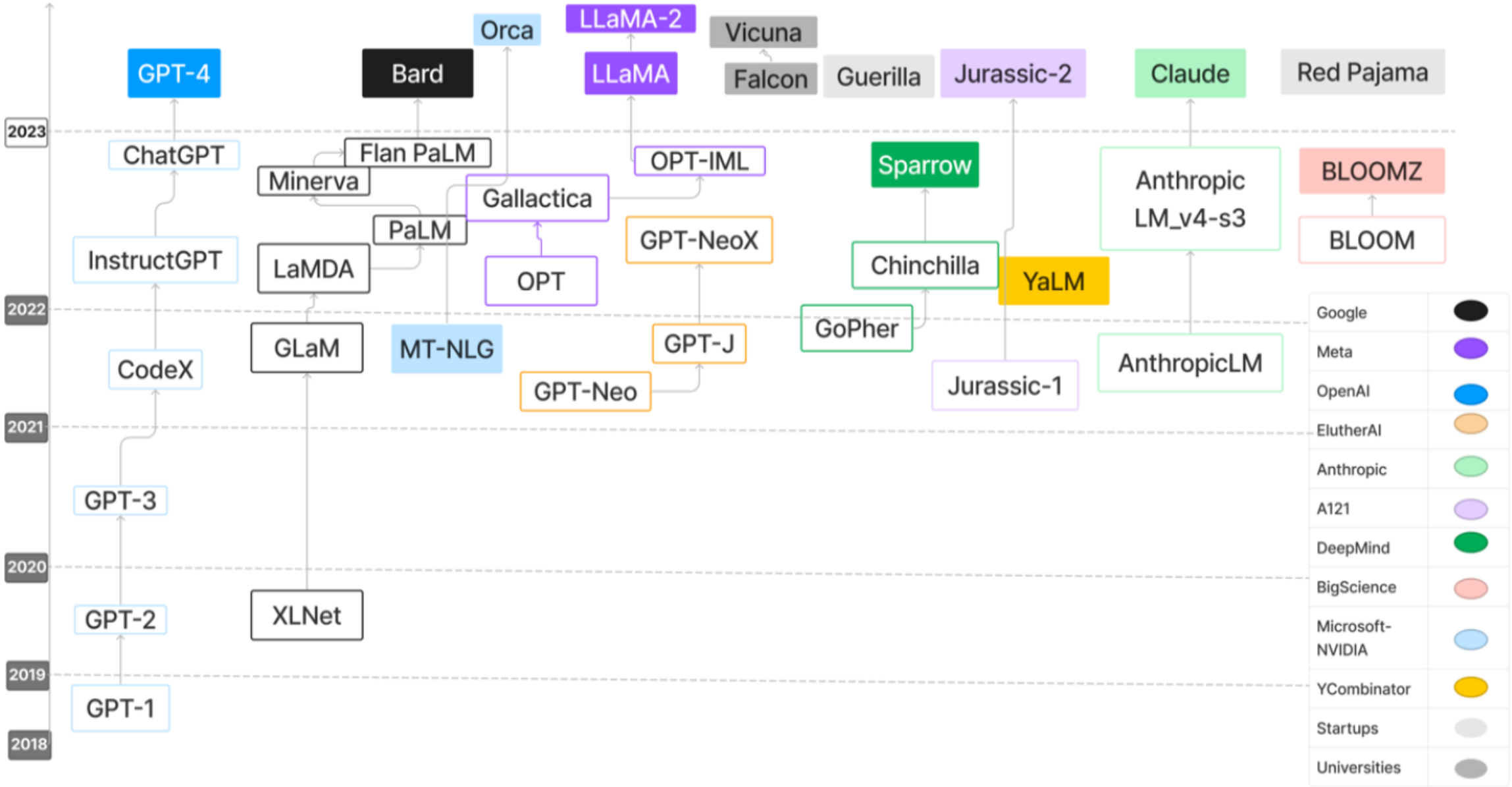
Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.

Transformer Models



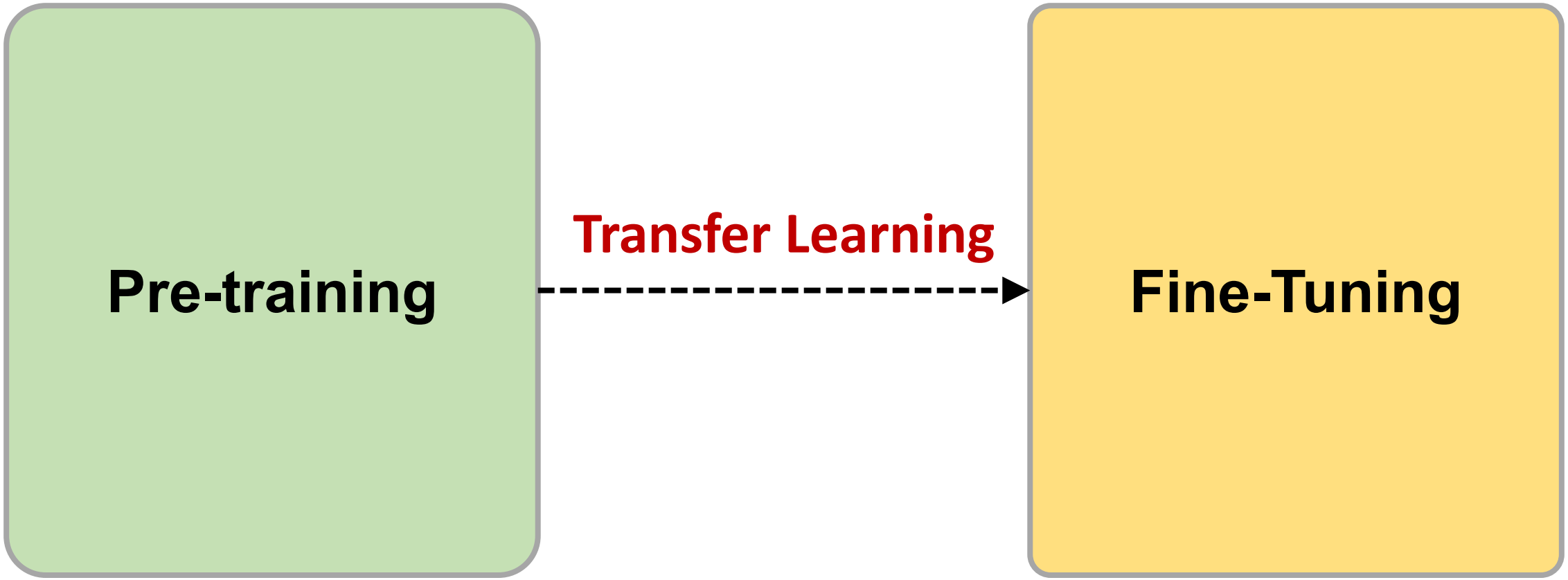
Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.

Large Language Models (LLMs)



Source: Hadi, Muhammad Usman, Rizwan Qureshi, Abbas Shah, Muhammad Irfan, Anas Zafar, Muhammad Bilal Shaikh, Naveed Akhtar, Jia Wu, and Seyedali Mirjalili. "Large language models: a comprehensive survey of its applications, challenges, limitations, and future prospects." Authorea Preprints (2023).

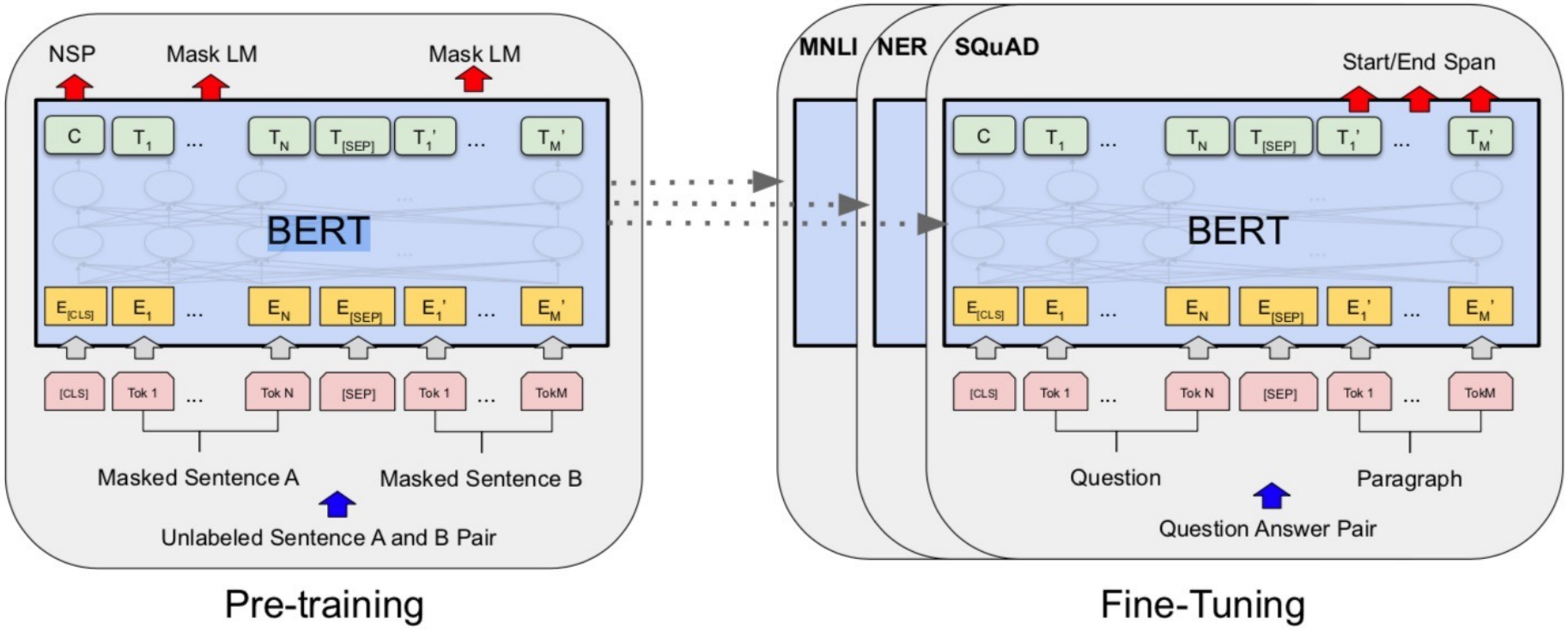
Transfer Learning



BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT (Bidirectional Encoder Representations from Transformers)

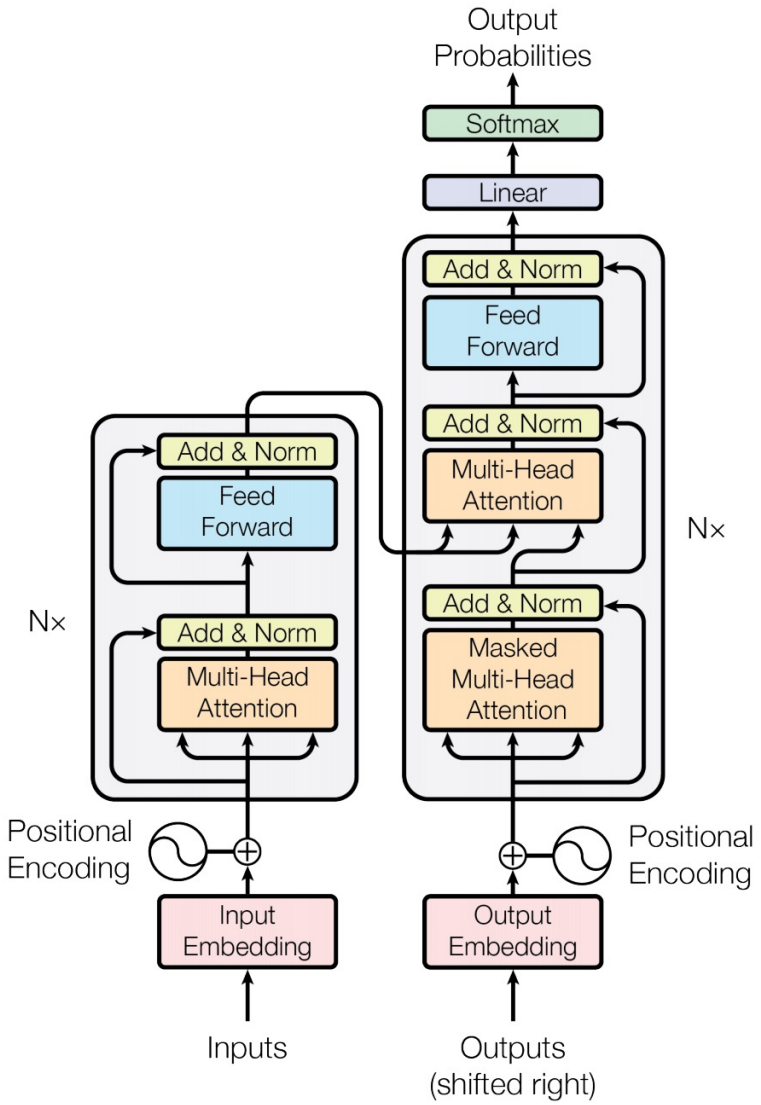
Overall pre-training and fine-tuning procedures for BERT



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.

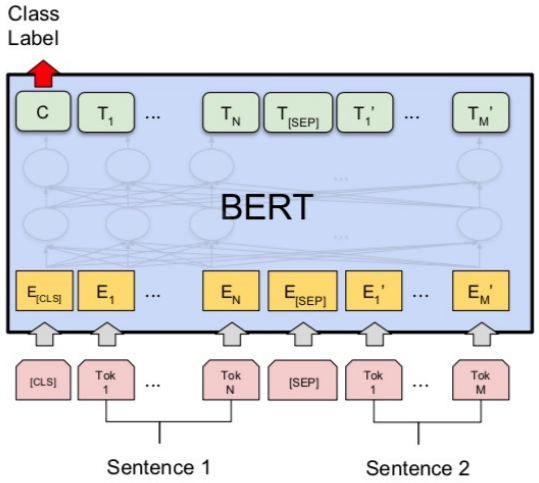
Transformer (Attention is All You Need)

(Vaswani et al., 2017)

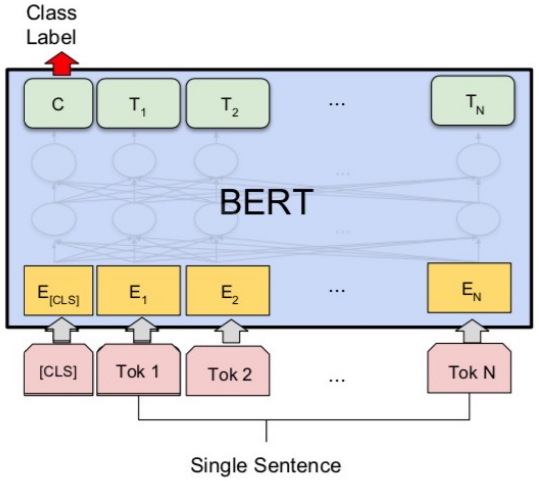


Source: Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." In *Advances in neural information processing systems*, pp. 5998-6008. 2017.

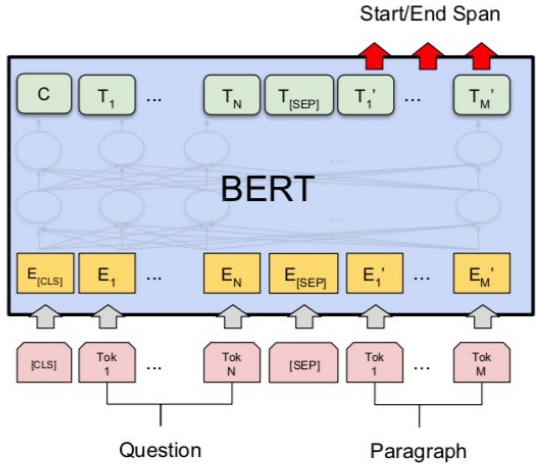
Fine-tuning BERT on Different Tasks



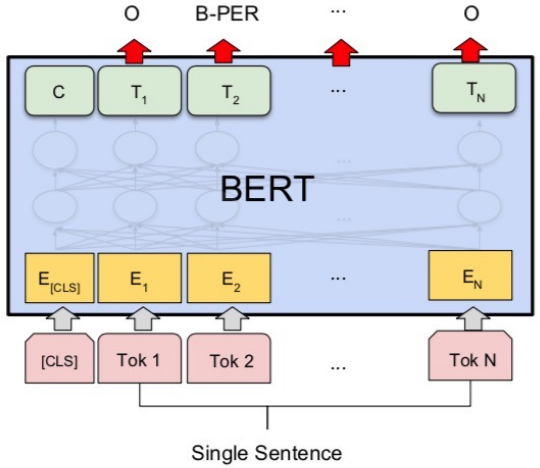
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



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



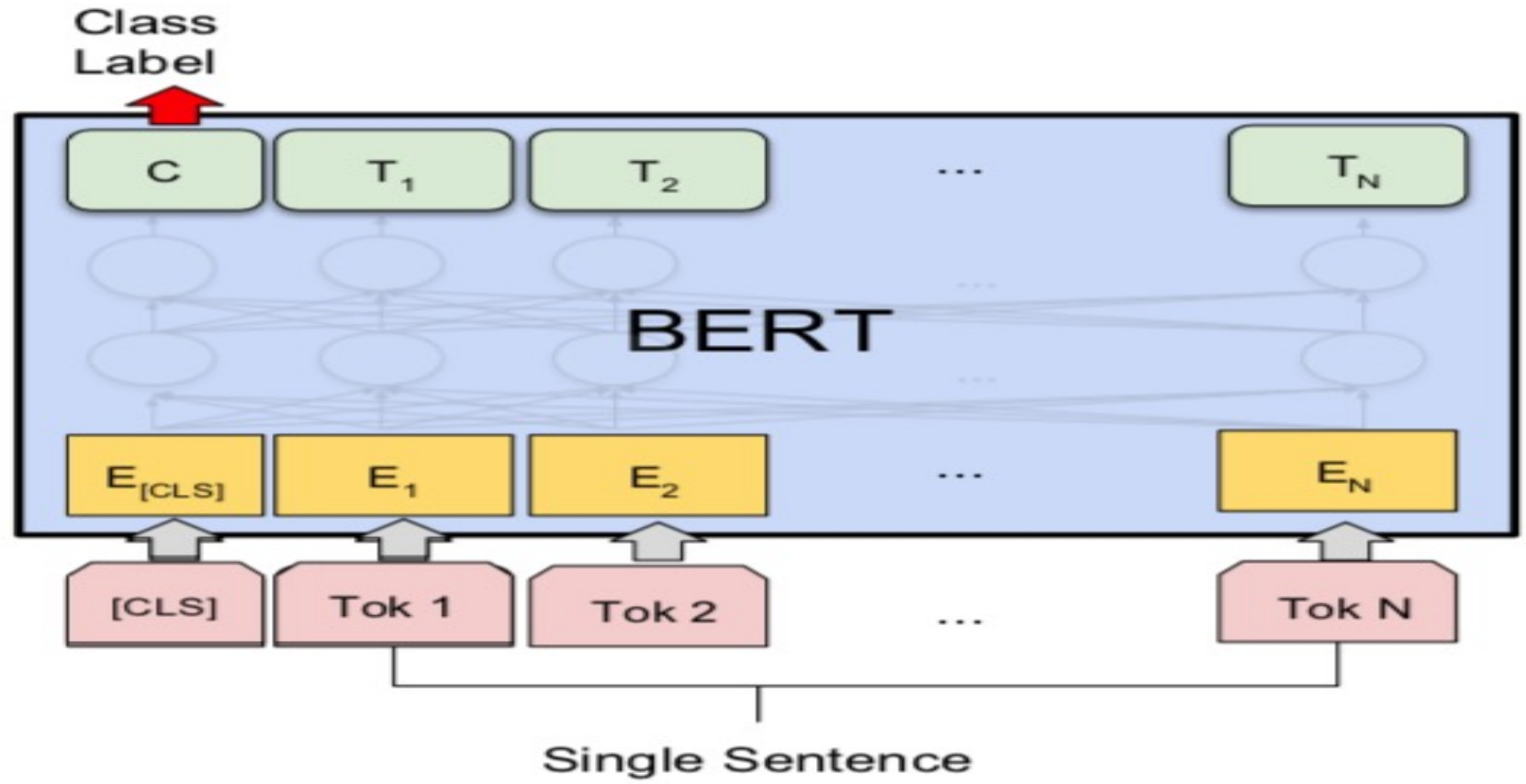
(c) Question Answering Tasks: SQuAD v1.1



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

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



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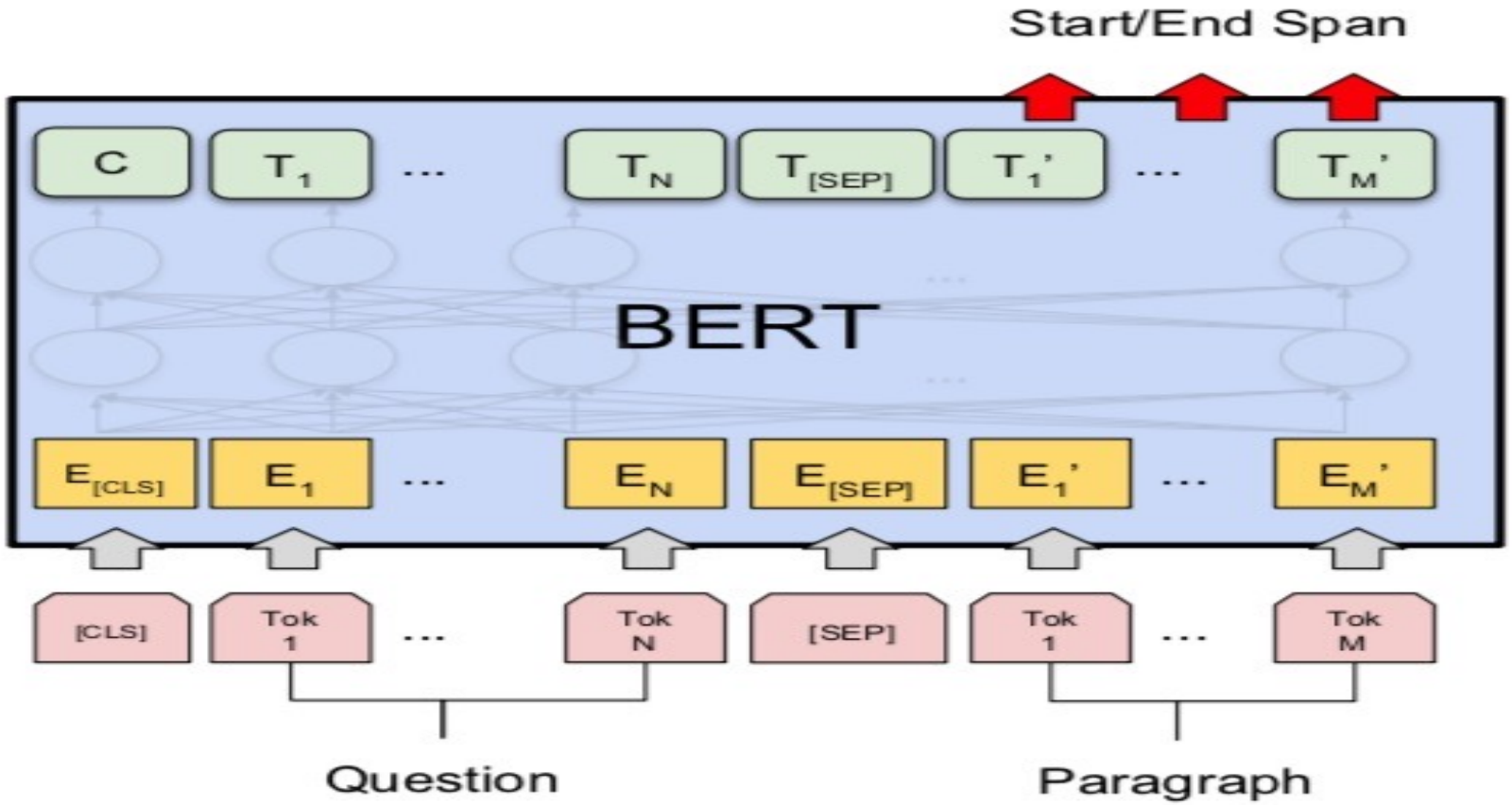
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

Fine-tuning BERT on Question Answering (QA)



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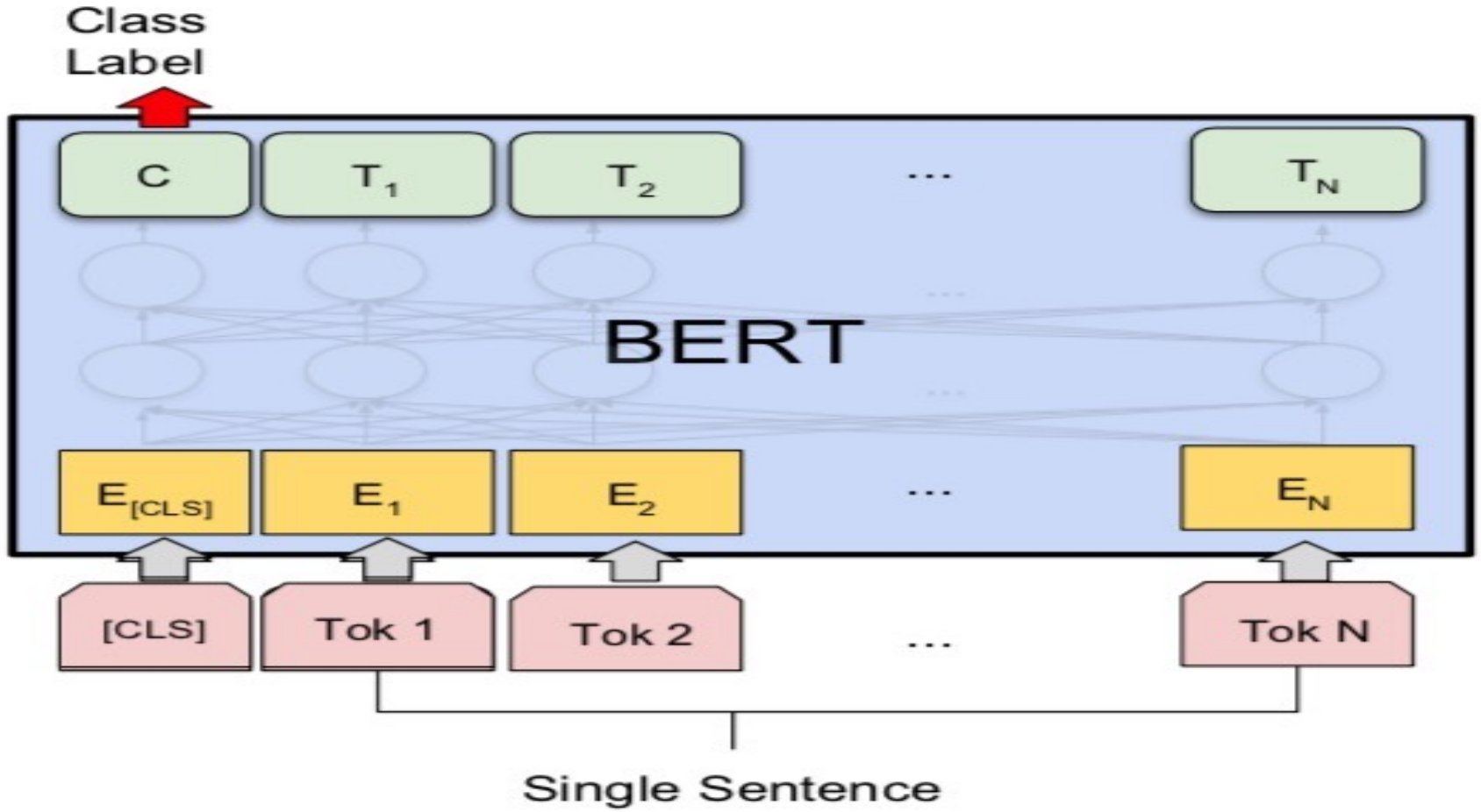
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

Fine-tuning BERT on Dialogue

Intent Detection (ID; Classification)



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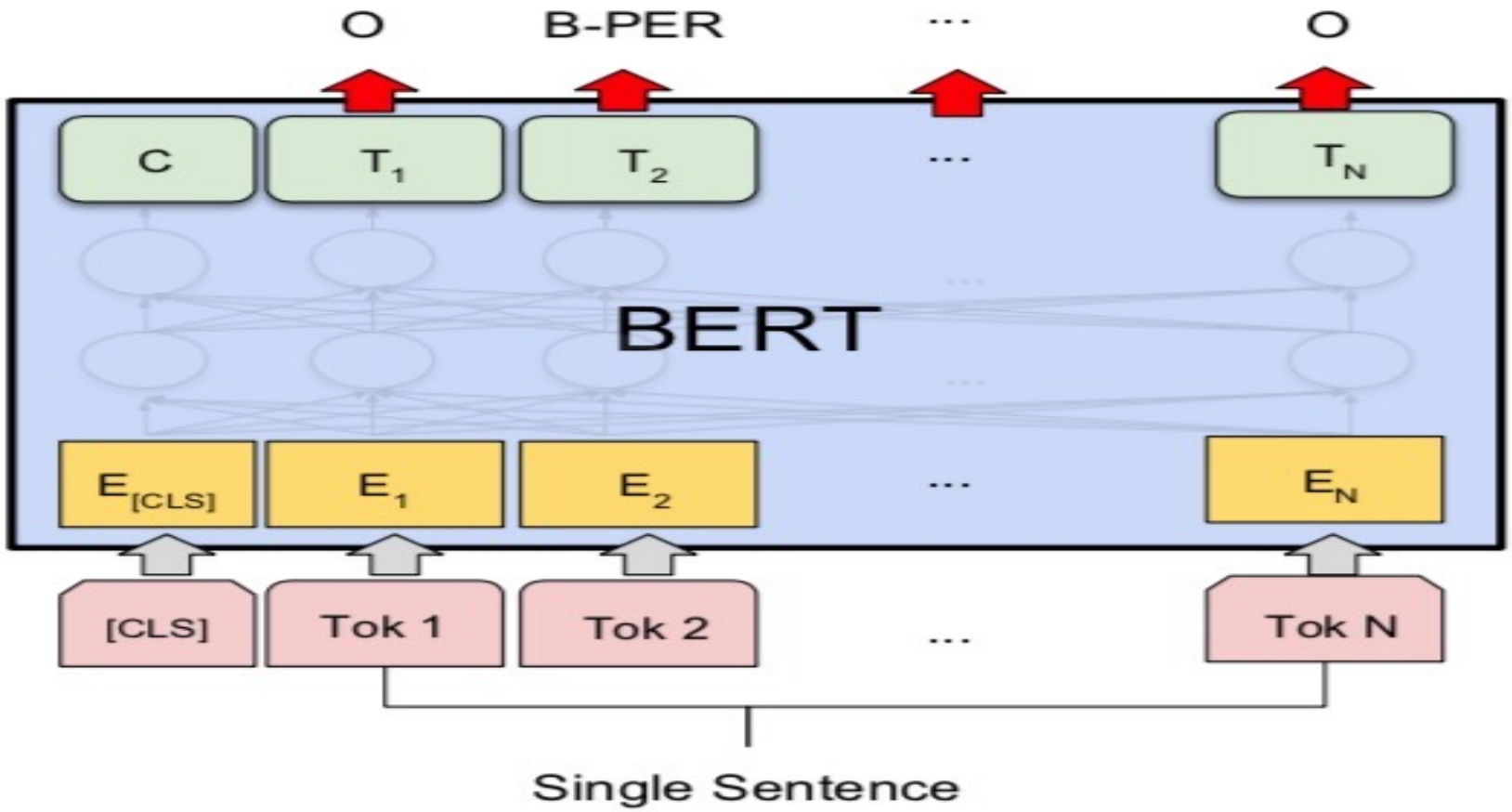
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

Fine-tuning BERT on Dialogue

Slot Filling (SF)

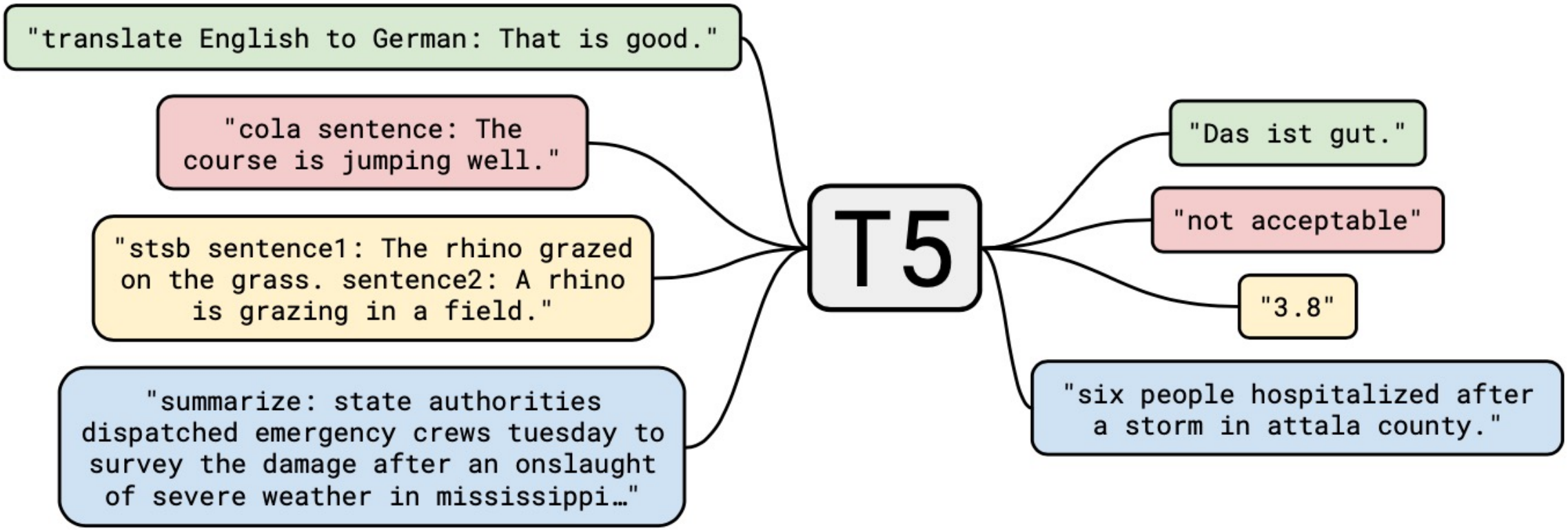


(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

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.

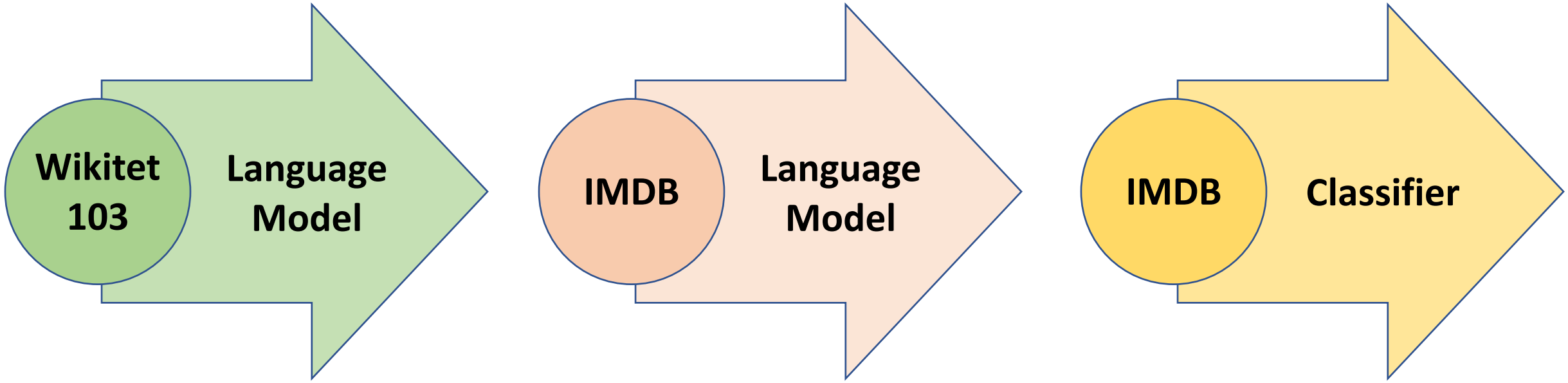
T5

Text-to-Text Transfer Transformer



Source: JColin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu (2019). "Exploring the limits of transfer learning with a unified text-to-text transformer." arXiv preprint arXiv:1910.10683 (2019).

ULMFiT: 3 Steps
Transfer Learning in NLP

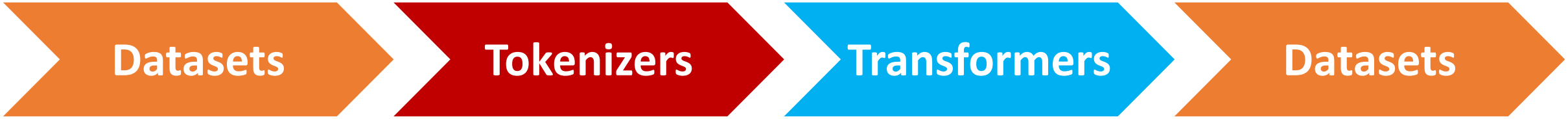


1. Pretraining
2. Domain adaptation
3. Fine-tuning

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

A typical pipeline for training transformer models

with the Datasets, Tokenizers, and Transformers libraries



Load and process datasets

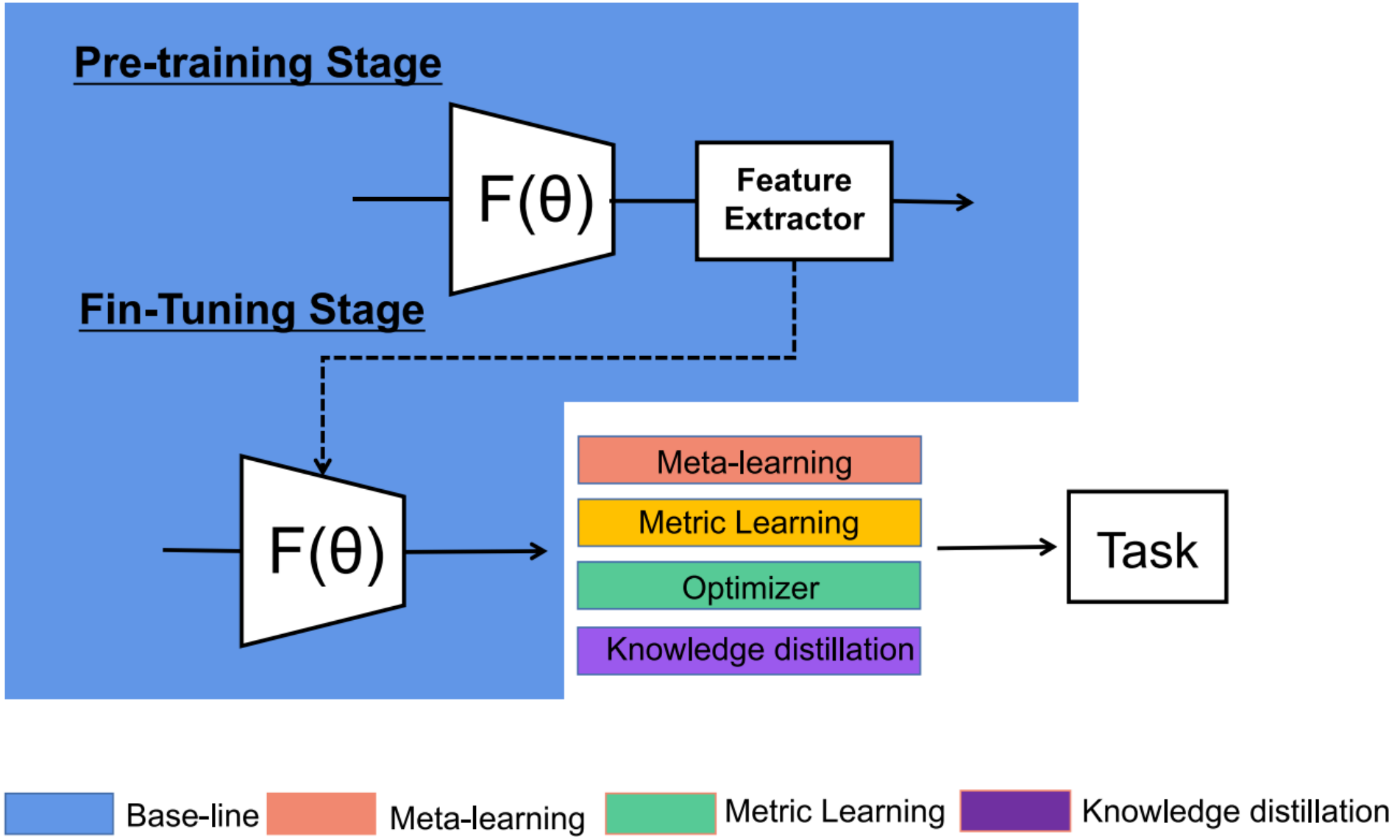
Tokenize input texts

Load models, train and infer

Load metrics evaluate models

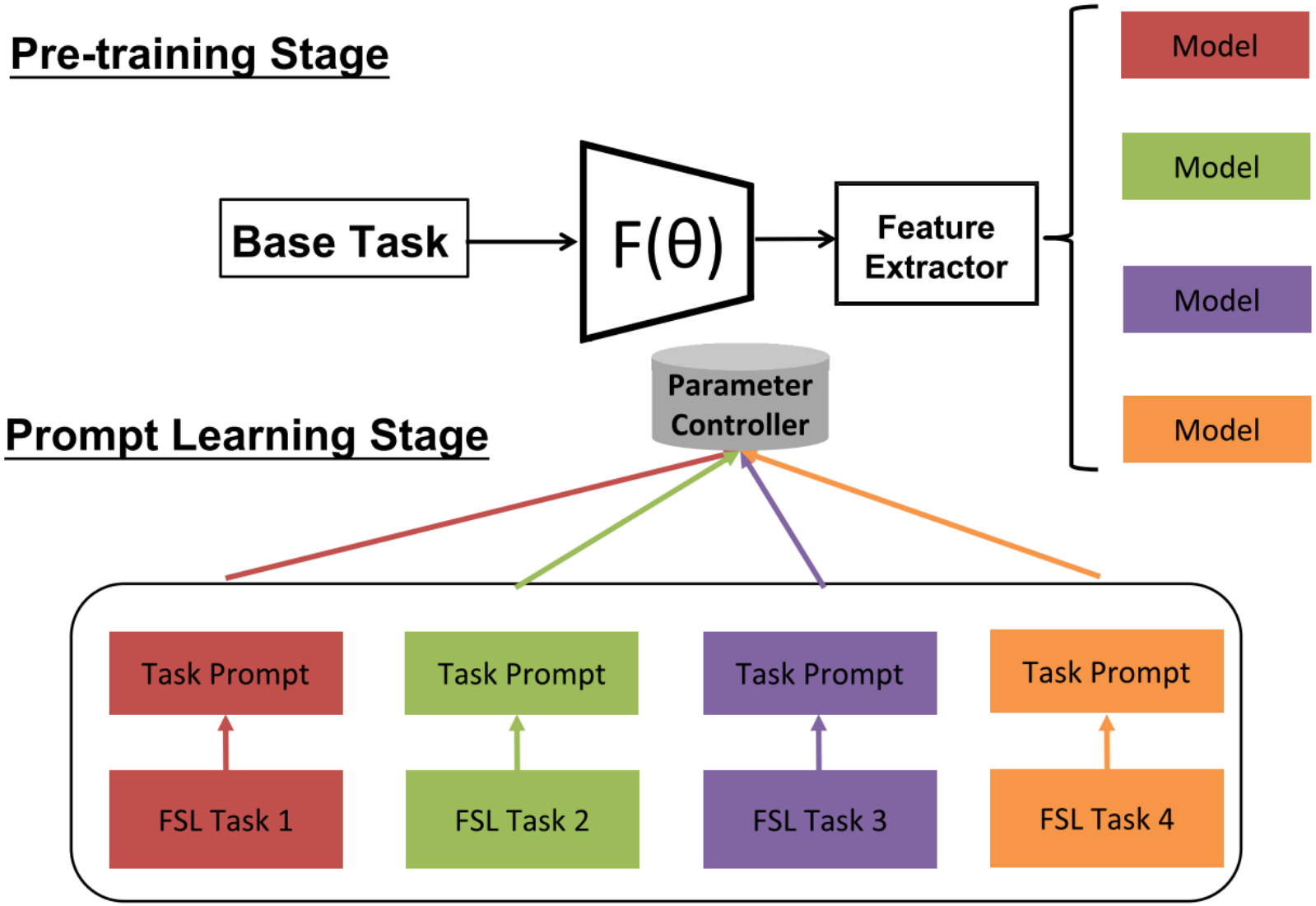
Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
https://github.com/nlp-with-transformers/notebooks

Transfer Learning



Source: Yisheng Song, Ting Wang, Puyu Cai, Subrota K. Mondal, and Jyoti Prakash Sahoo. (2023) "A comprehensive survey of few-shot learning: Evolution, applications, challenges, and opportunities." ACM Computing Surveys (2023).

Prompt Learning



Source: Yisheng Song, Ting Wang, Puyu Cai, Subrota K. Mondal, and Jyoti Prakash Sahoo. (2023) "A comprehensive survey of few-shot learning: Evolution, applications, challenges, and opportunities." ACM Computing Surveys (2023).

Few-Shot Learning (FSL)
Typical Scenarios

- **Acting as a test bed for learning like human**
- **Learning for rare cases**
- **Reducing data gathering effort and computational cost**

Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

- **Few-Shot Learning (FSL) is a sub-area in machine learning.**
- **Machine Learning Definition**
  - **A computer program is said to learn from experience E with respect to some classes of task T and performance measure P if its performance can improve with E on T measured by P.**
    - Example: Image classification task (T), a machine learning program can improve its classification accuracy (P) through E obtained by training on a large number of labeled images (e.g., the ImageNet data set).

Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Machine Learning

task T	experience E	performance P
image classification [73]	large-scale labeled images for each class	classification accuracy
the ancient game of Go [120]	a database containing around 30 million recorded moves of human experts and self-play records	winning rate

Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

- **Few-shot Learning (FSL) is a type of machine learning problems (specified by E, T, and P), where E contains only a limited number of examples with supervised information for the target T.**
  - **Existing FSL problems are mainly supervised learning problems.**
  - **Few-shot classification learns classifiers given only a few labeled examples of each class.**
    - image classification
    - sentiment classification from short text
    - object recognition

Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

- **Few-shot classification learns a classifier h, which predicts label y_i for each input x_i.**
- **Usually, one considers the *N-way-K-shot* classification, in which D_{train} contains $I = KN$ examples from N classes each with K examples**

Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

- **Few-Shot Learning (FSL)**
  - $K = 10 \sim 100$ **examples**
- **One-Shot Learning (1SL)**
  - $K = 1$ **example**
- **Zero-Shot Learning (0SL)(ZSL)**
  - $K = 0$

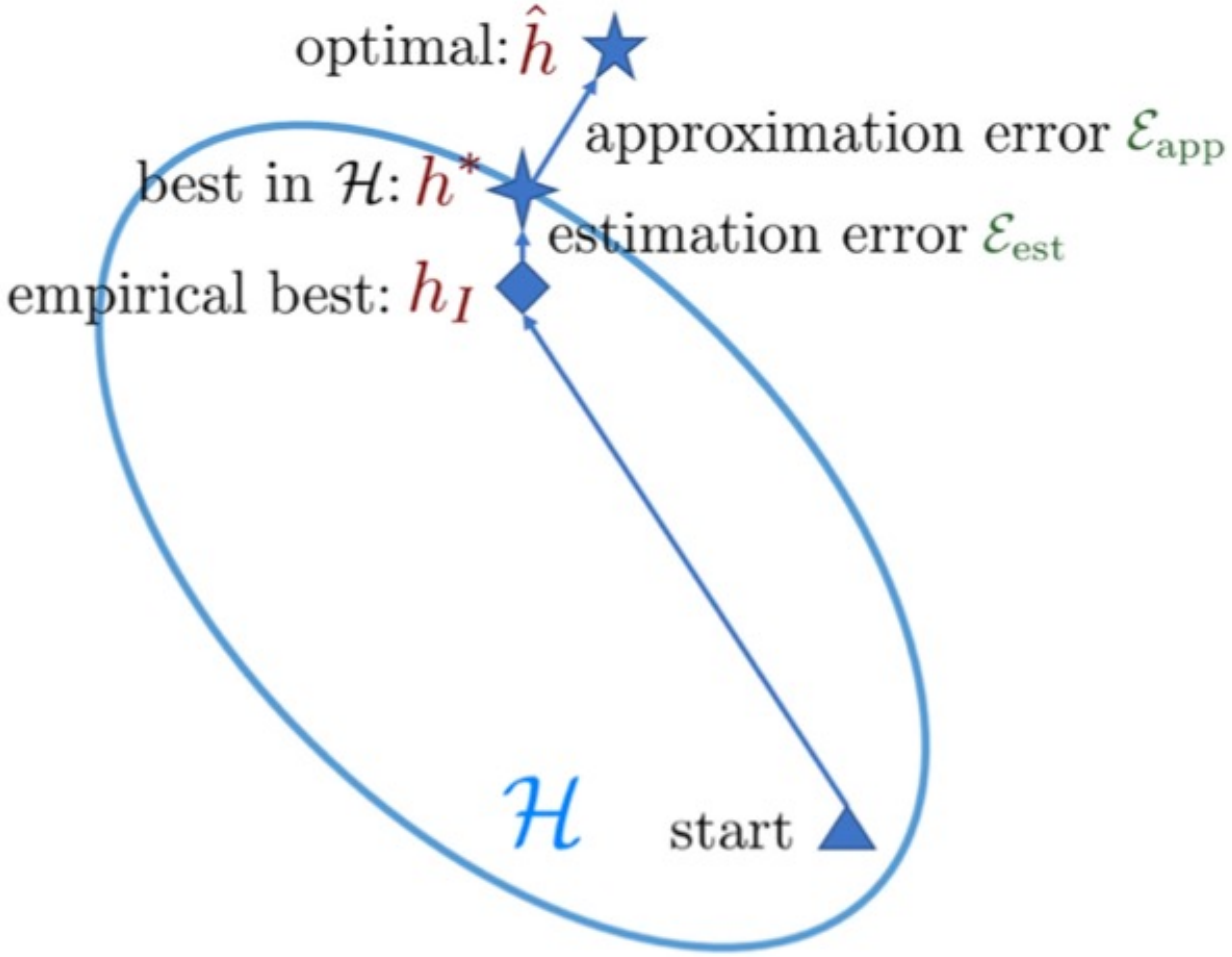
Few-Shot Learning (FSL)

task T	experience E		performance P
	supervised information	prior knowledge	
character generation [76]	a few examples of new character	pre-learned knowledge of parts and relations	pass rate of visual Turing test
drug toxicity discovery [4]	new molecule's limited assay	similar molecules' assays	classification accuracy
image classification [70]	a few labeled images for each class of the target T	raw images of other classes, or pre-trained models	classification accuracy

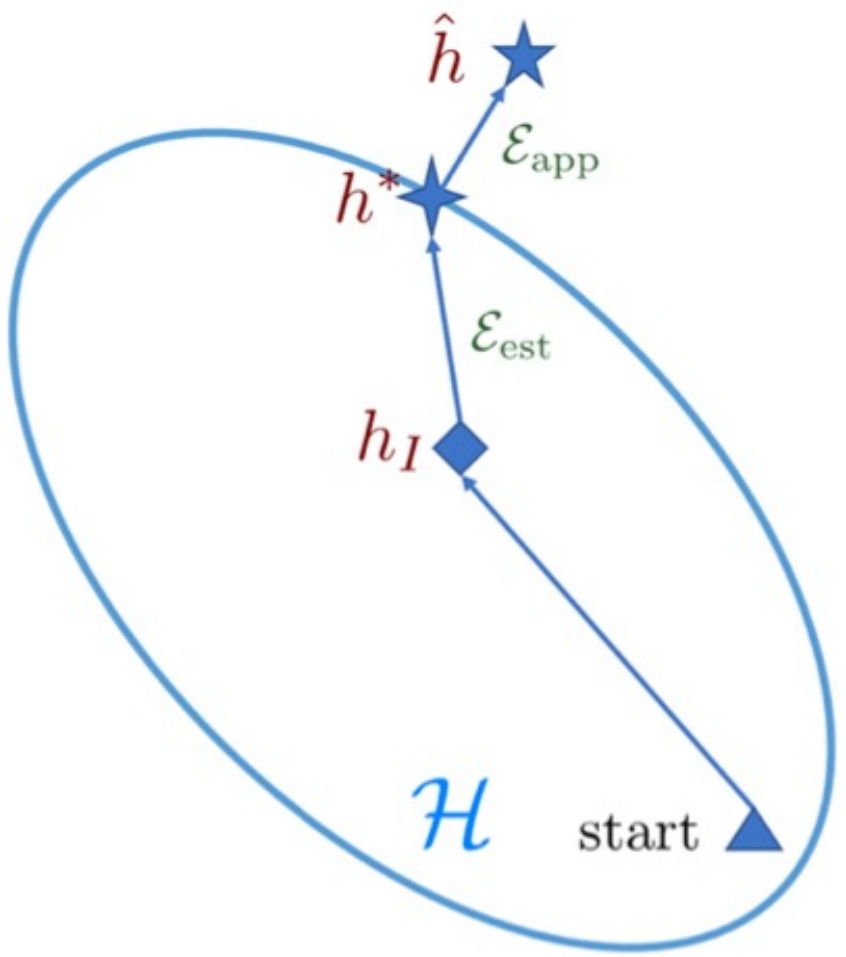
Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

Comparison of learning with sufficient and few training samples



(a) Large I

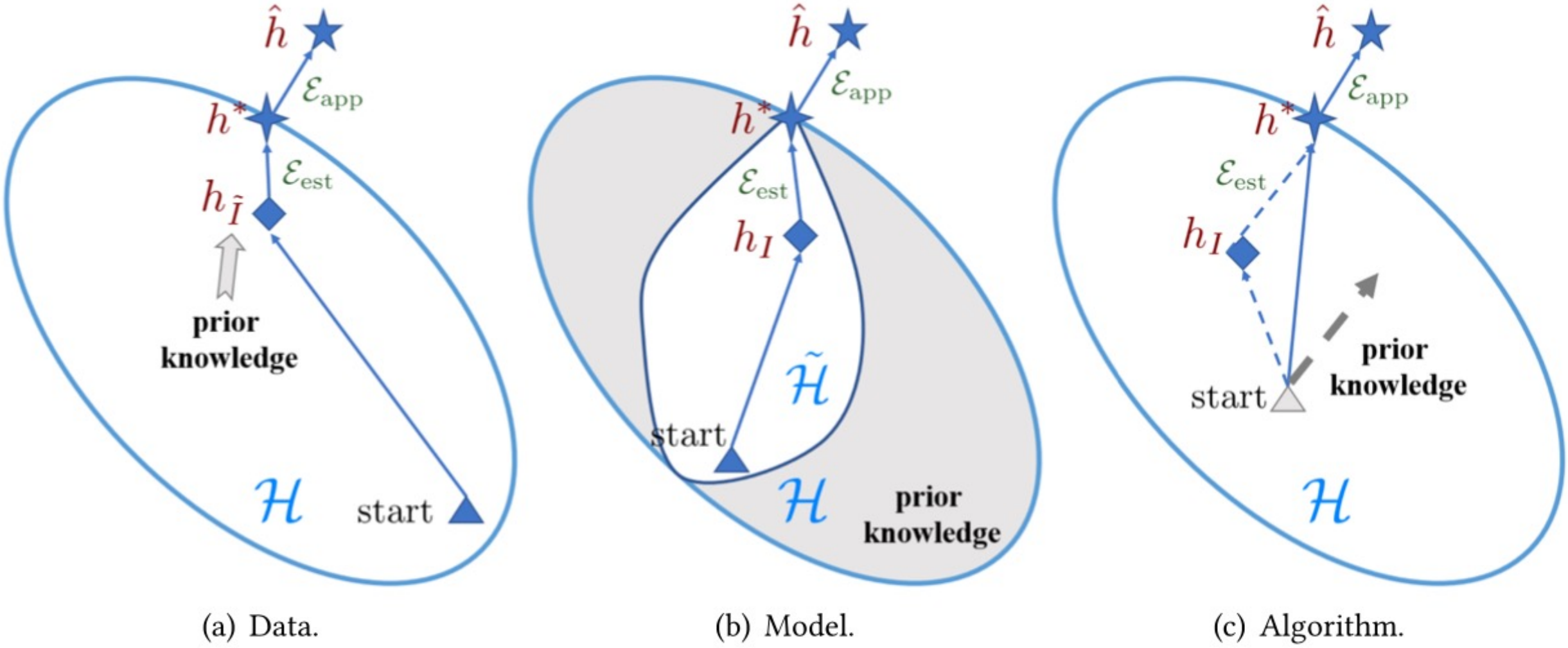


(b) Small I

Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

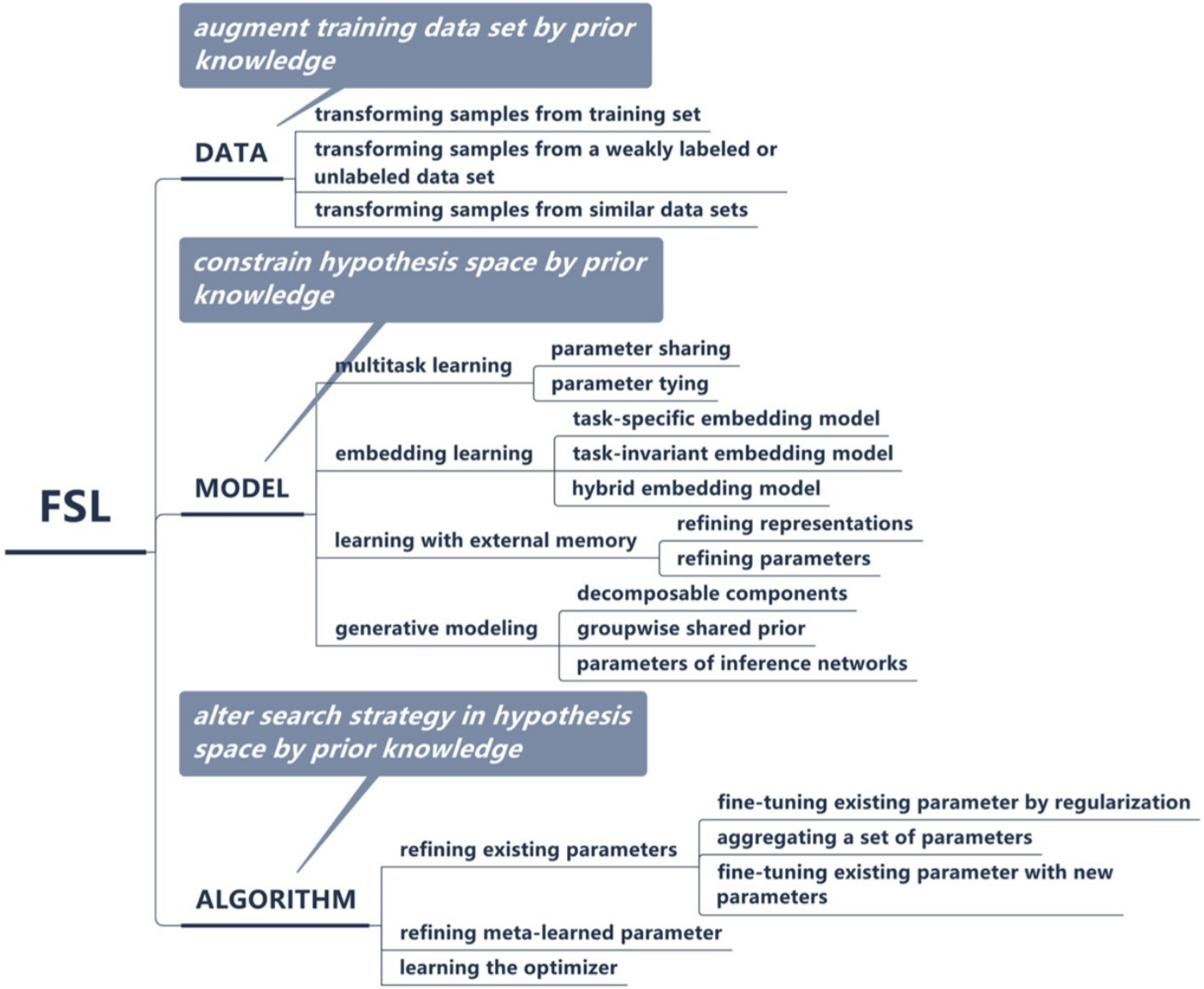
Different perspectives on how FSL methods solve the few-shot problem



Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

A taxonomy of FSL methods



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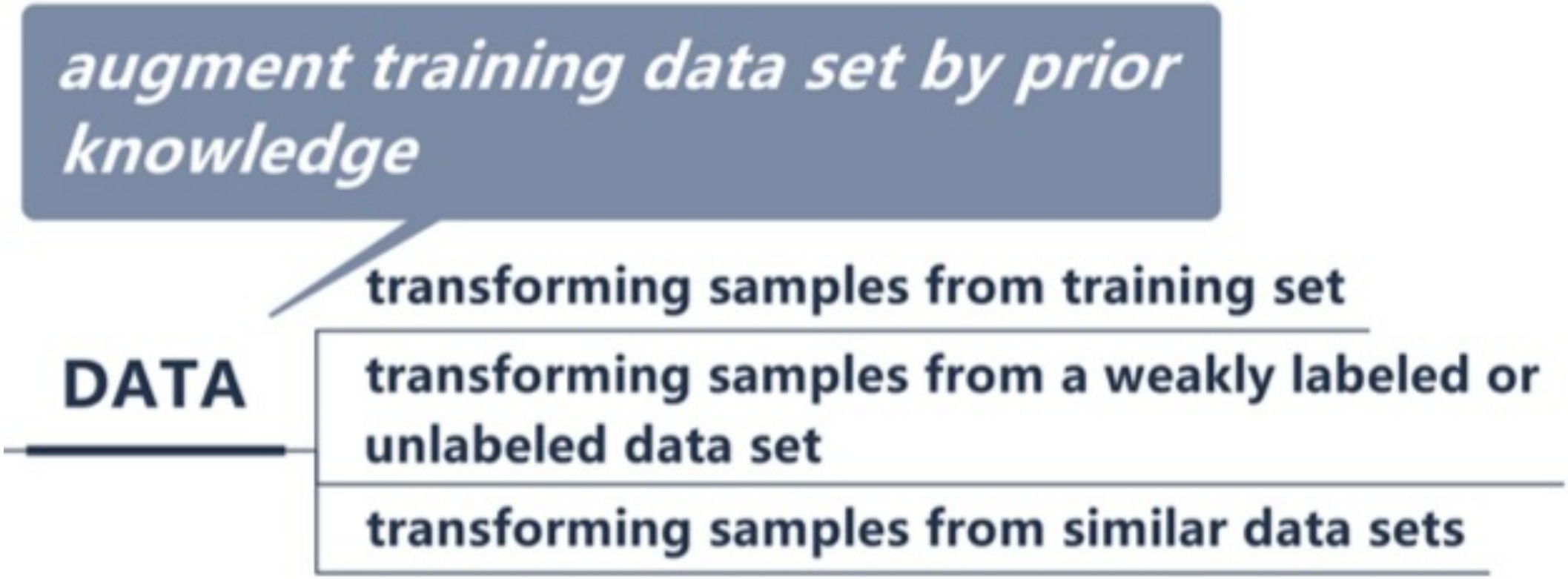
Few-Shot Learning (FSL)



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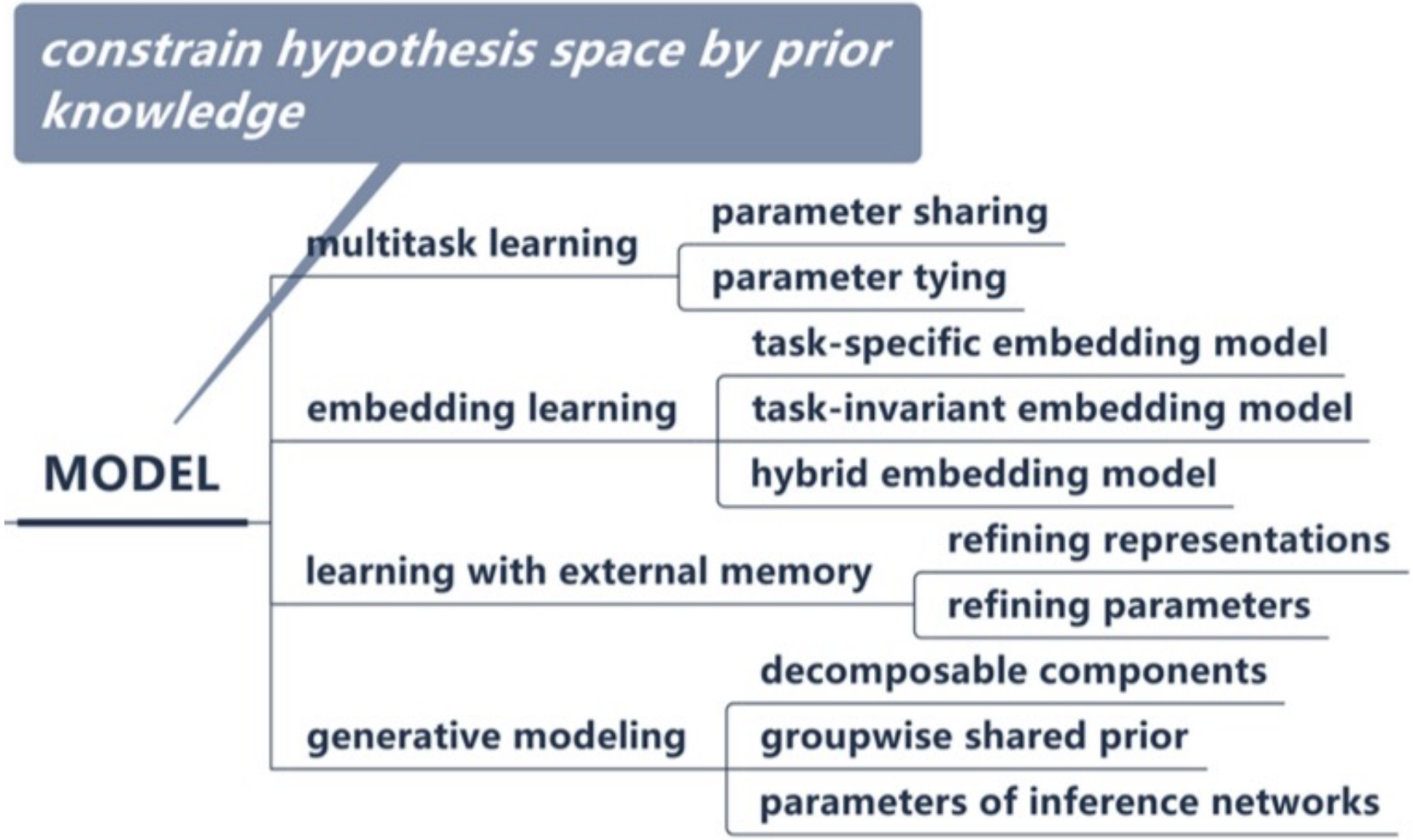
Few-Shot Learning (FSL)



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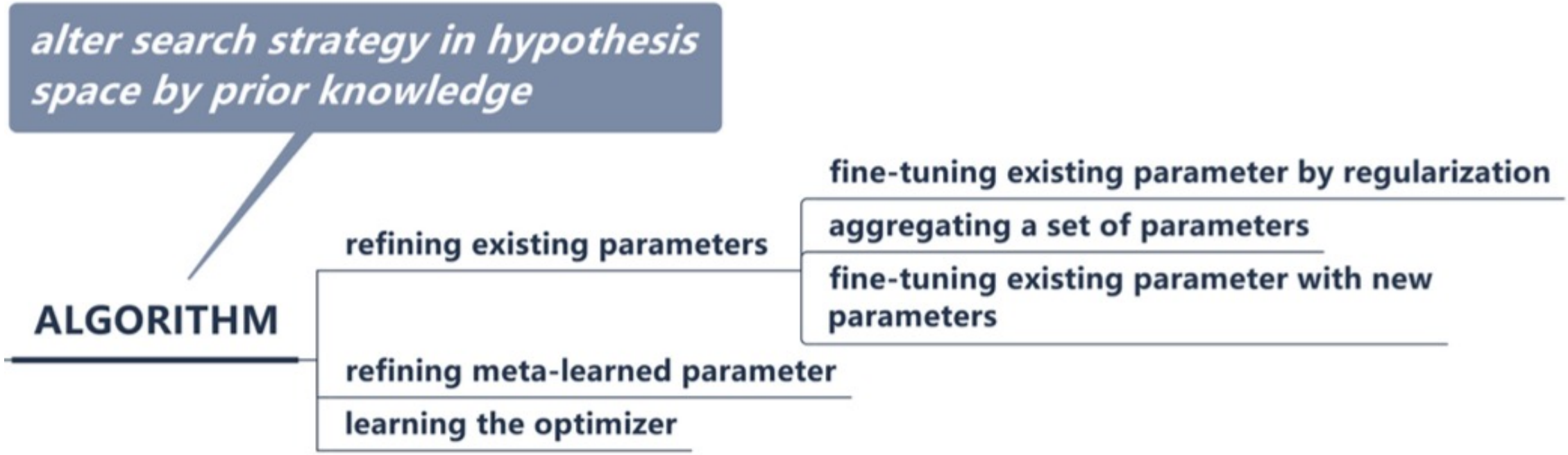
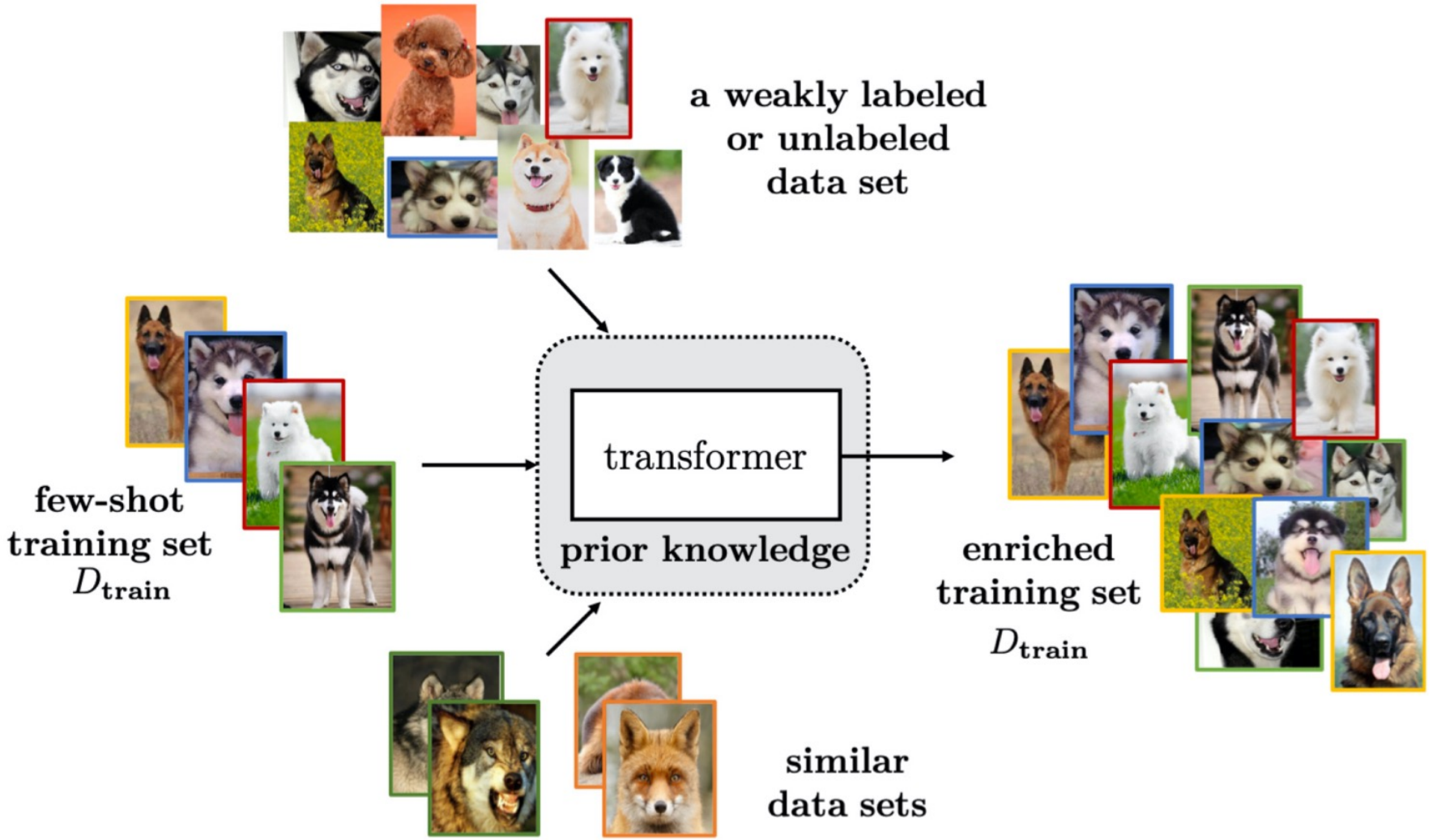
Few-Shot Learning (FSL)



Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

Solving the FSL problem by data augmentation



Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

Characteristics for FSL Methods Focusing on the Data Perspective

category	input (x, y)	transformer t	output $(\tilde{x}, \tilde{y})$
transforming samples from D_{train}	original (x_i, y_i)	learned transformation function on x_i	$(t(x_i), y_i)$
transforming samples from a weakly labeled or unlabeled data set	weakly labeled or unlabeled $(\bar{x}, -)$	a predictor trained from D_{train}	$(\bar{x}, t(\bar{x}))$
transforming samples from similar data sets	samples $\{(\hat{x}_j, \hat{y}_j)\}$ from similar data sets	an aggregator to combine $\{(\hat{x}_j, \hat{y}_j)\}$	$(t(\{\hat{x}_j\}), t(\{\hat{y}_j\}))$

The transformer $t(\cdot)$ takes input (x, y) and returns synthesized sample $(\tilde{x}, \tilde{y})$ to augment the few-shot D_{train}.

Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

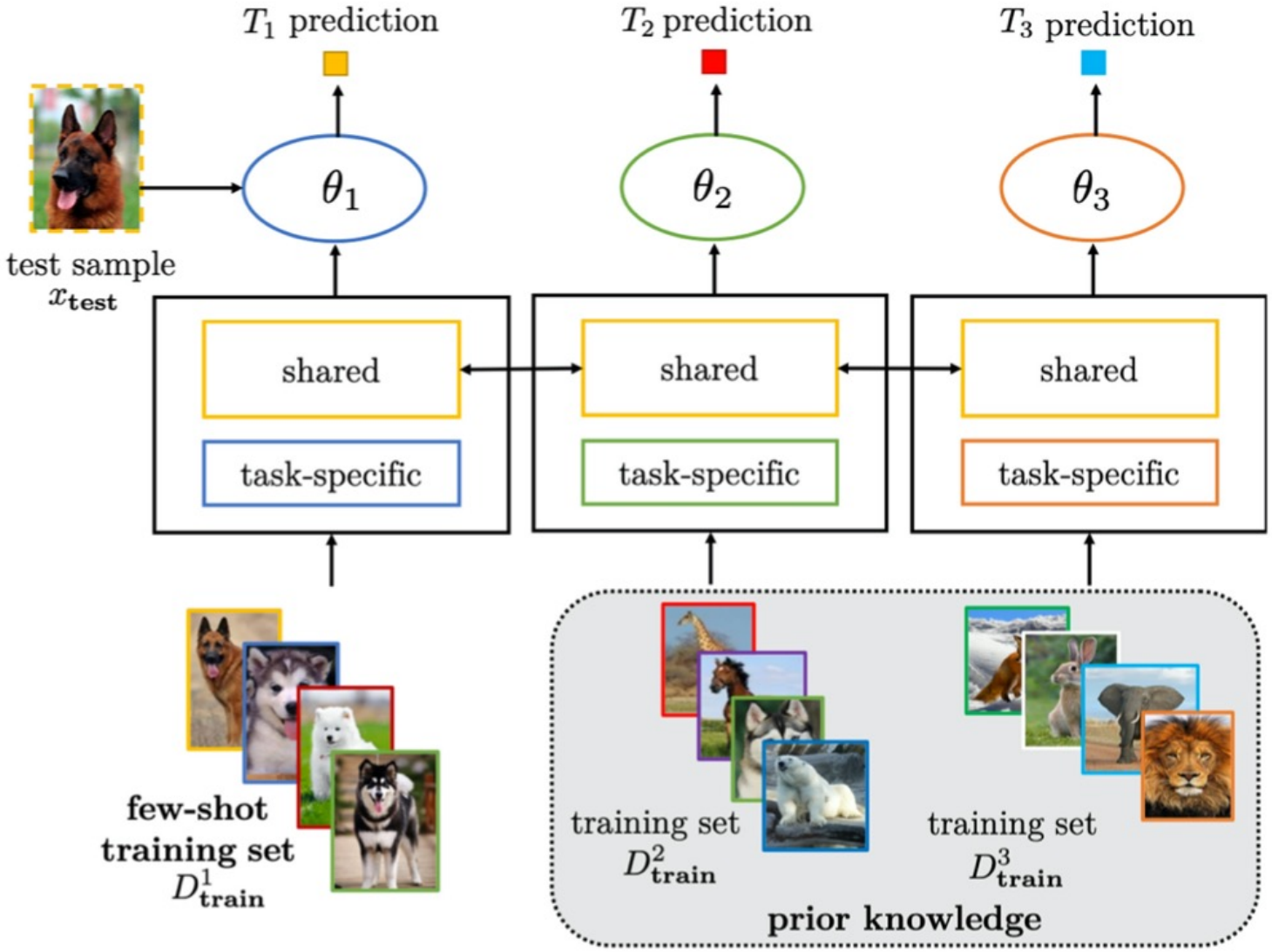
Characteristics for FSL Methods Focusing on the Model Perspective

strategy	prior knowledge	how to constrain $\mathcal{H}$
multitask learning	other T's with their data sets D's	share/tie parameter
embedding learning	embedding learned from/together with other T's	project samples to a smaller embedding space in which similar and dissimilar samples can be easily discriminated
learning with external memory	embedding learned from other T's to interact with memory	refine samples using key-value pairs stored in memory
generative modeling	prior model learned from other T's	restrict the form of distribution

Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

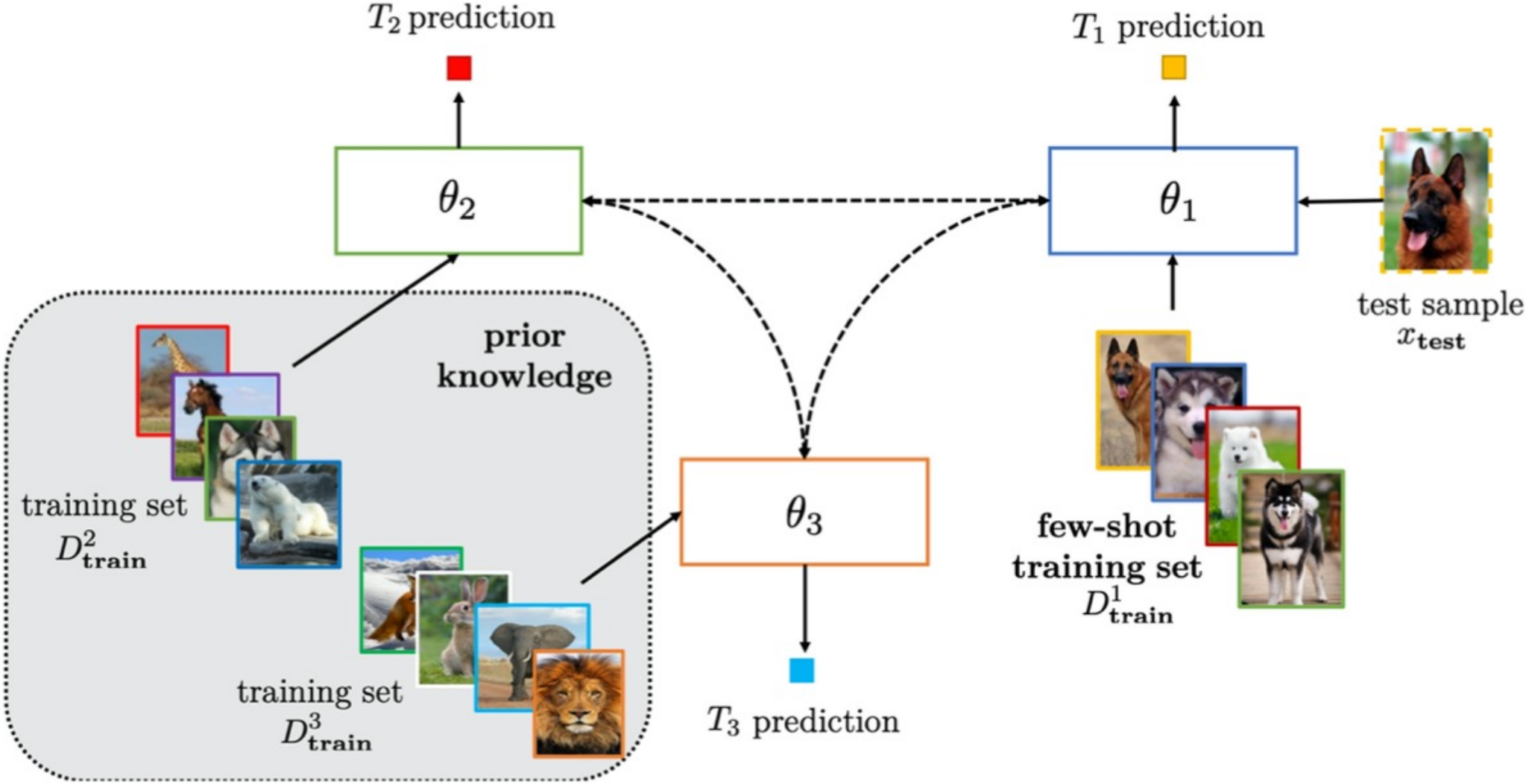
Solving the FSL problem by multitask learning with parameter sharing



Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

Solving the FSL problem by multitask learning with parameter tying



Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

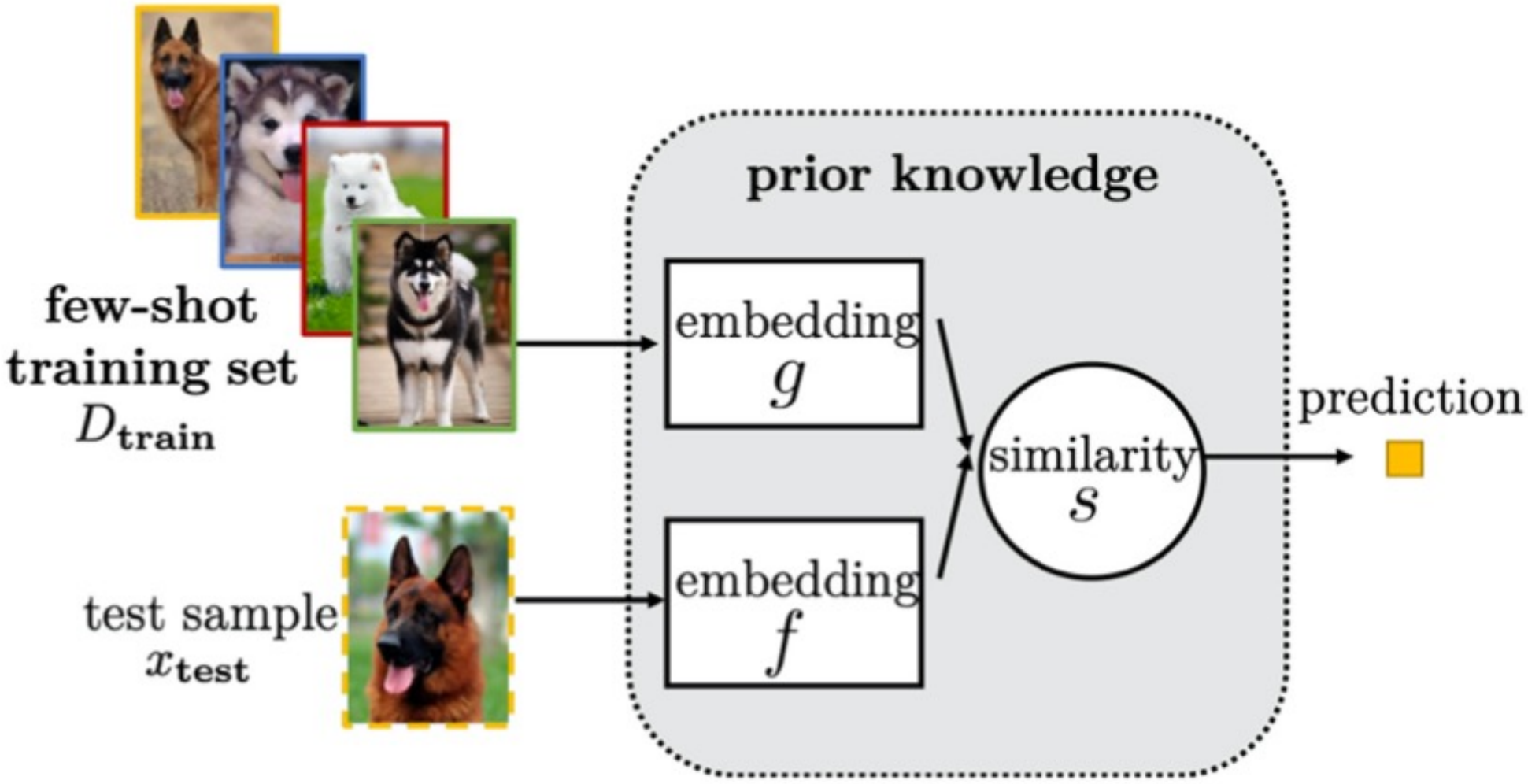
Characteristics of Embedding Learning Methods

category	method	embedding function f for x_{test}	embedding function g for D_{train}	similarity measure s
task-specific	mAP-DLM/SSVM[130]	CNN	the same as f	cosine similarity
task-invariant	class relevance pseudo-metric [36]	kernel	the same as f	squared ℓ_2 distance
	convolutional siamese net [70]	CNN	the same as f	weighted ℓ_1 distance
	Micro-Set[127]	logistic projection	the same as f	ℓ_2 distance
	Matching Nets [138]	CNN, LSTM	CNN, biLSTM	cosine similarity
	resLSTM [4]	GNN, LSTM	GNN, LSTM	cosine similarity
	Active MN [8]	CNN	biLSTM	cosine similarity
	SSMN [24]	CNN	another CNN	learned distance
	ProtoNet [121]	CNN	the same as f	squared ℓ_2 distance
	semi-supervised ProtoNet[108]	CNN	the same as f	squared ℓ_2 distance
	PMN [141]	CNN, LSTM	CNN, biLSTM	cosine similarity
	ARC [119]	LSTM, biLSTM	the same as f	-
	Relation Net [126]	CNN	the same as f	-
	GNN [115]	CNN, GNN	the same as f	learned distance
	TPN [84]	CNN	the same as f	Gaussian similarity
	SNAIL [91]	CNN	the same as f	-
hybrid	Learnet [14]	adaptive CNN	CNN	weighted ℓ_1 distance
	DCCN [162]	adaptive CNN	CNN	-
	R2-D2 [13]	adaptive CNN	CNN	-
	TADAM [100]	adaptive CNN	the same as f	squared ℓ_2 distance

Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

Solving the FSL problem by task-invariant embedding model



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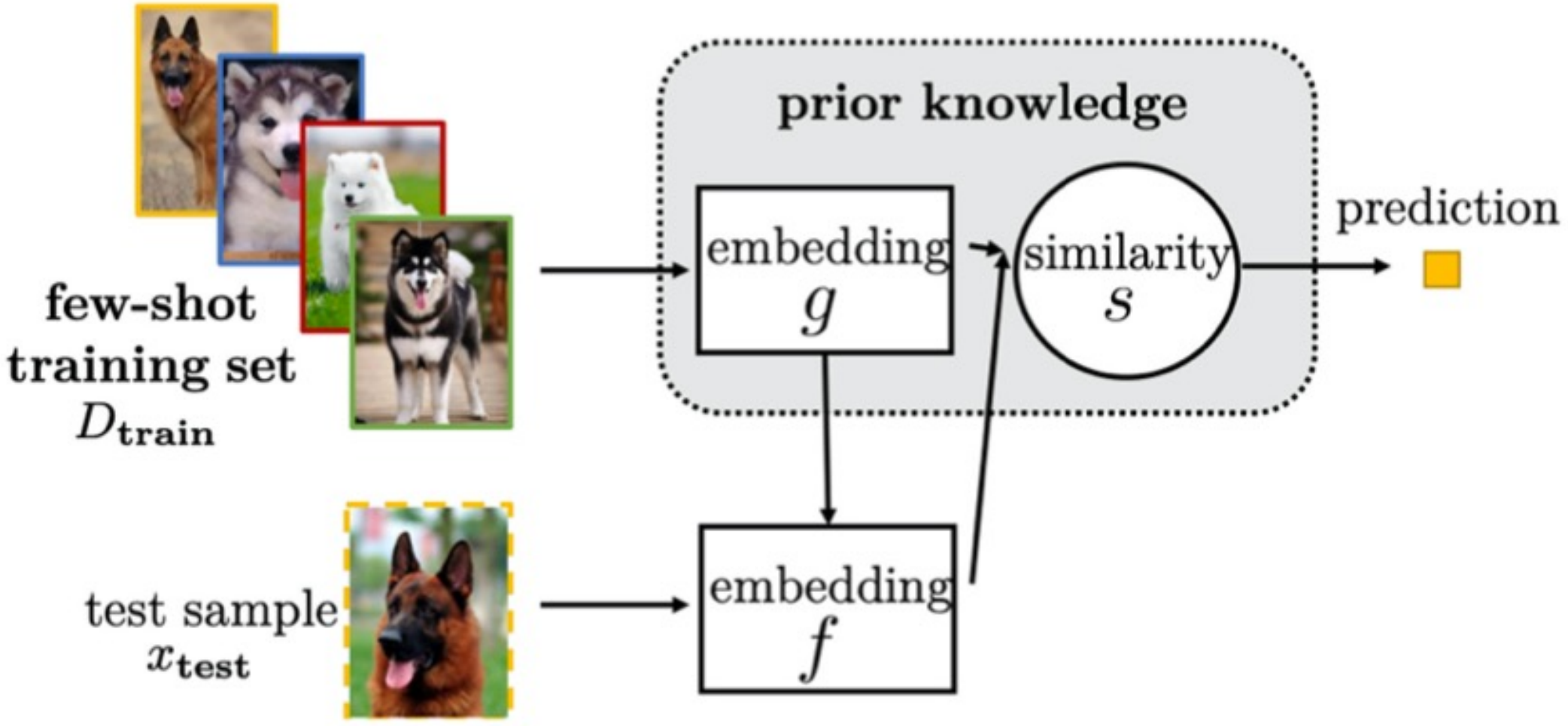
Few-Shot Learning (FSL)

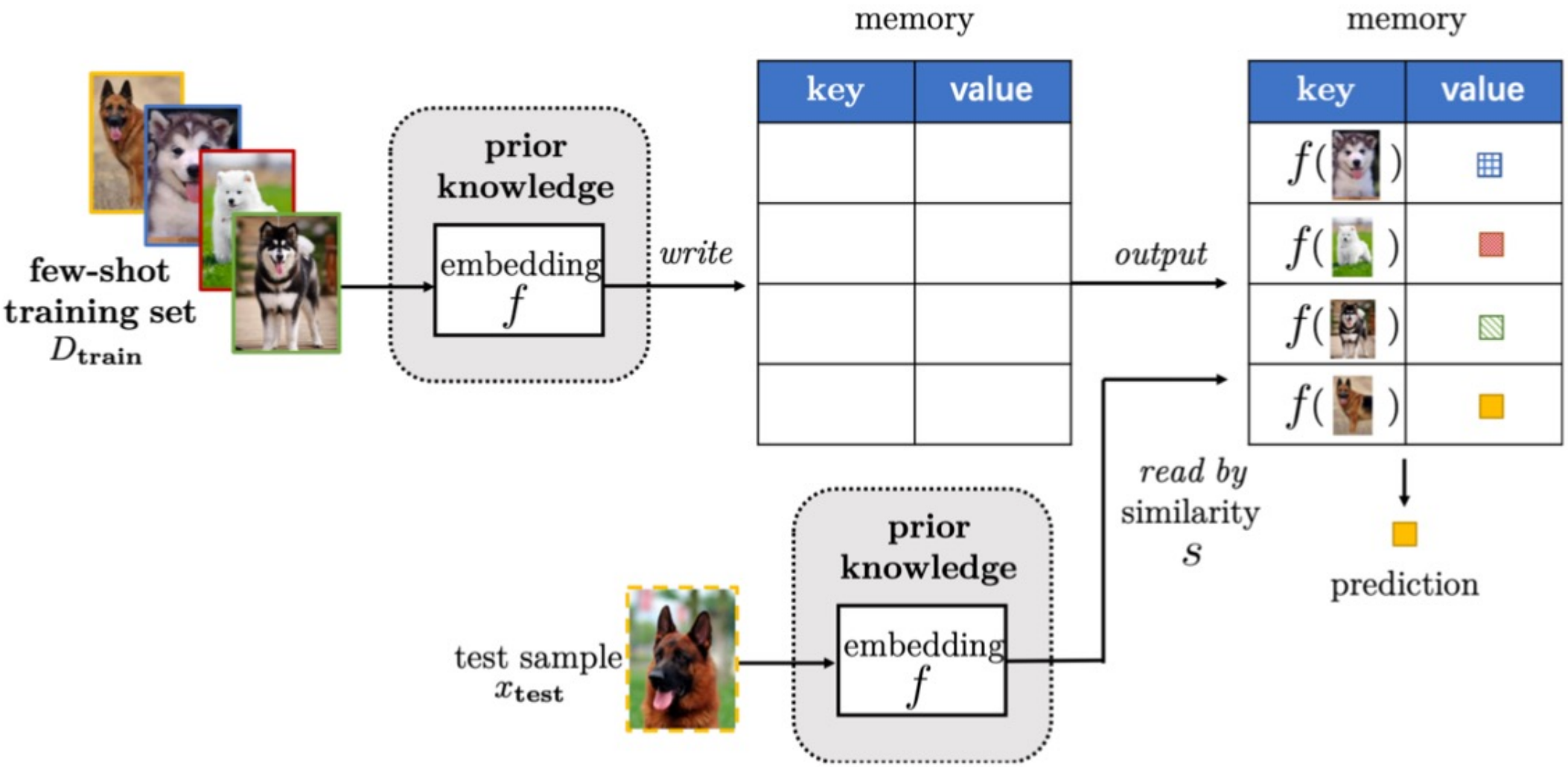
Solving the FSL problem by hybrid embedding model



Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

Solving the FSL problem by learning with external memory



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Few-Shot Learning (FSL)

Characteristics of FSL Methods

Based on Learning with External Memory

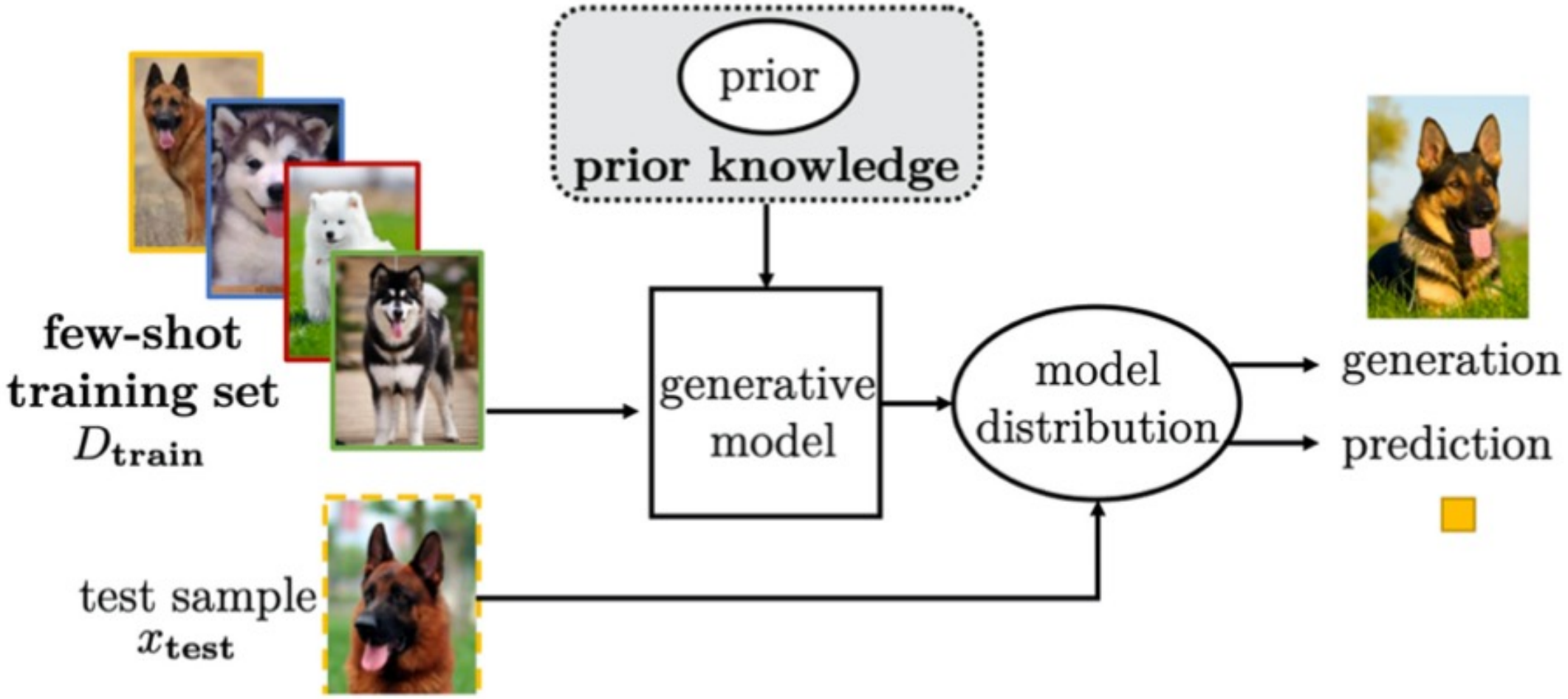
category	method	memory M		similarity s
		key M_{key}	value M_{value}	
refining representations	MANN [114]	$f(x_i, y_{i-1})$	$f(x_i, y_{i-1})$	cosine similarity
	APL [104]	$f(x_i)$	y_i	squared ℓ_2 distance
	abstraction memory [149]	$f(x_i)$	word embedding of y_i	dot product
	CMN [164]	$f(x_i)$	y_i, age	dot product
	life-long memory [65]	$f(x_i)$	y_i, age	cosine similarity
	Mem2Vec [125]	$f(x_i)$	word embedding of y_i, age	dot product
refining parameters	MetaNet [96]	$f(x_i)$	fast weight	cosine similarity
	CSNs [97]	$f(x_i)$	fast weight	cosine similarity
	MN-Net [22]	$f(x_i)$	y_i	dot product

Here, f is an embedding function usually pre-trained by CNN or LSTM.

Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

Solving the FSL problem by generative modeling



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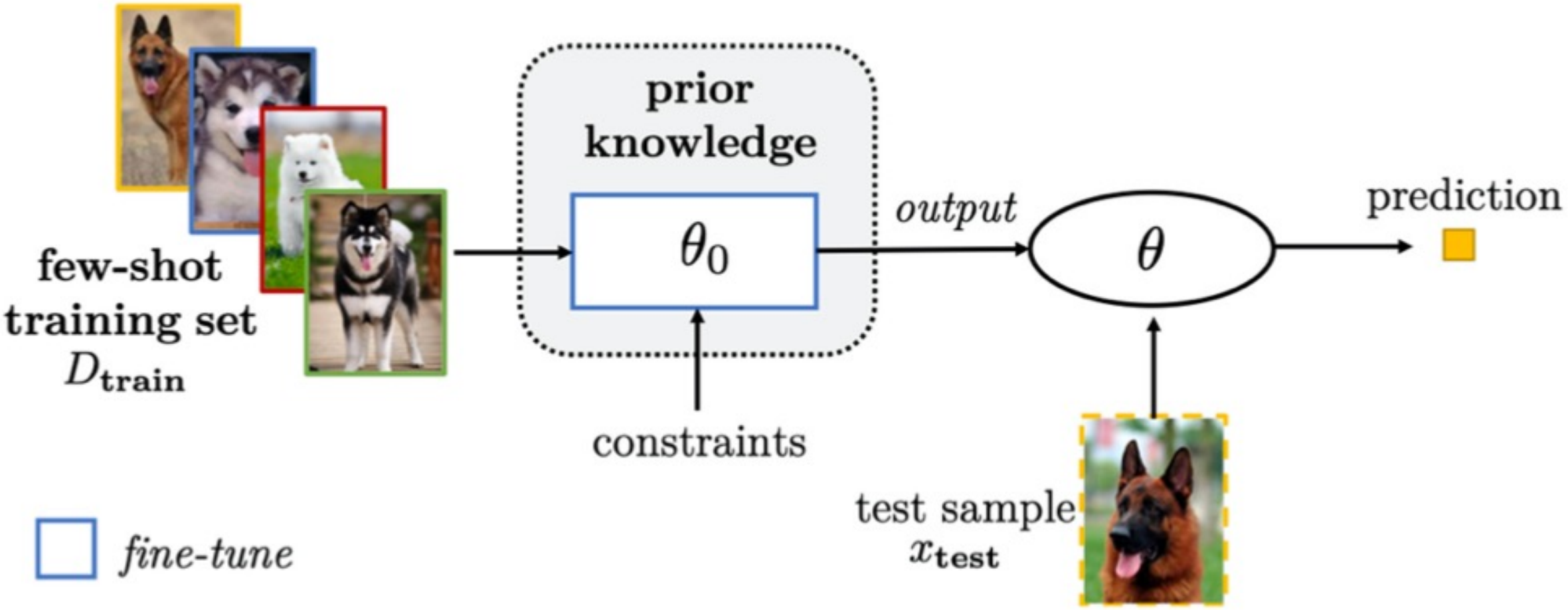
Few-Shot Learning (FSL)

Solving the FSL problem by fine-tuning existing parameter θ_0 by regularization



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Few-Shot Learning (FSL)

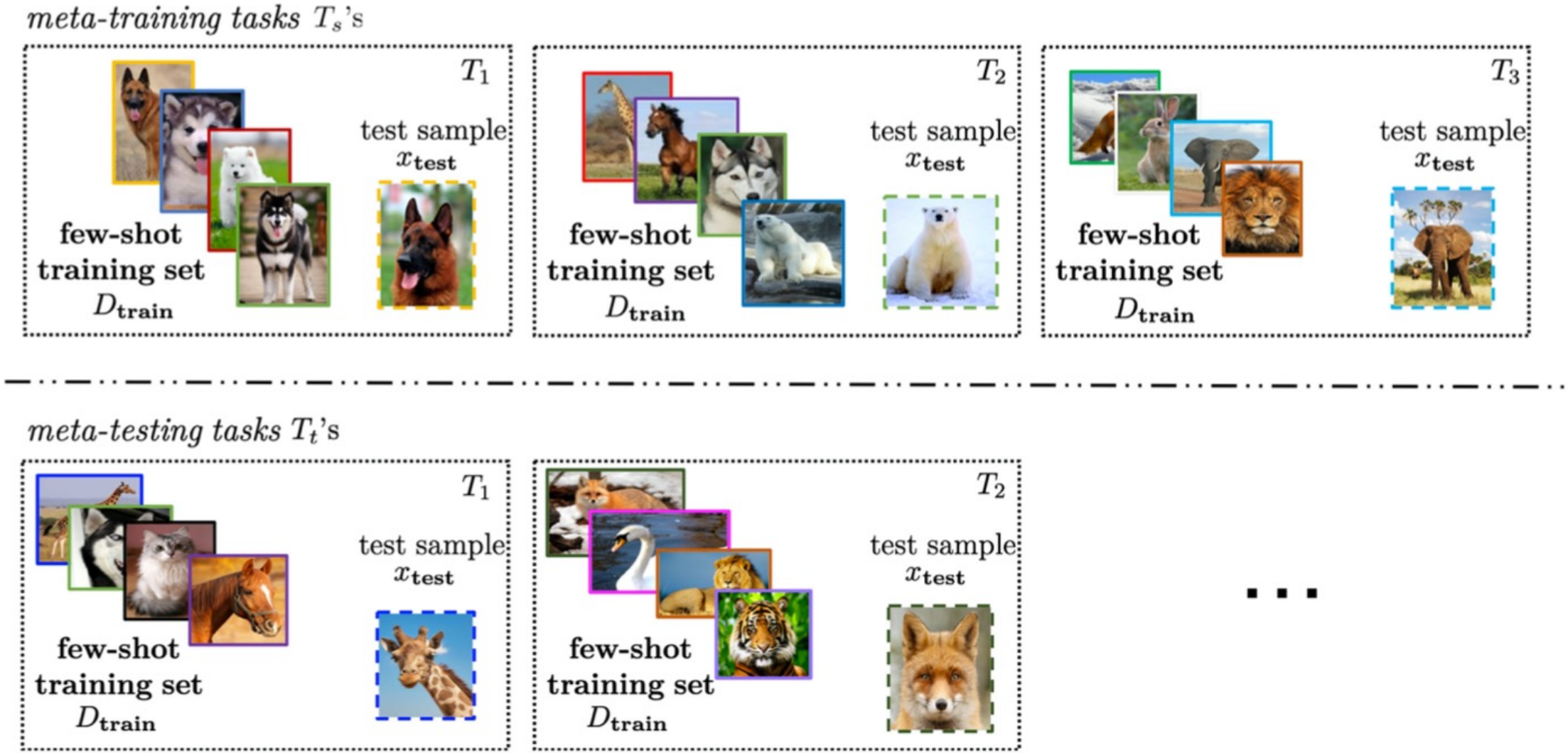
Characteristics for FSL Methods Focusing on the Algorithm Perspective

strategy	prior knowledge	how to search θ of the h^* in $\mathcal{H}$
refining existing parameters	learned θ_0	refine θ_0 by D_{train}
refining meta-learned parameters	meta-learner	refine θ_0 by D_{train}
learning the optimizer	meta-learner	use search steps provided by the meta-learner

Source: Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni (2020). "Generalizing from a few examples: A survey on few-shot learning." ACM computing surveys (csur) 53, no. 3 (2020): 1-34.

Few-Shot Learning (FSL)

Solving the FSL problem by meta-learning



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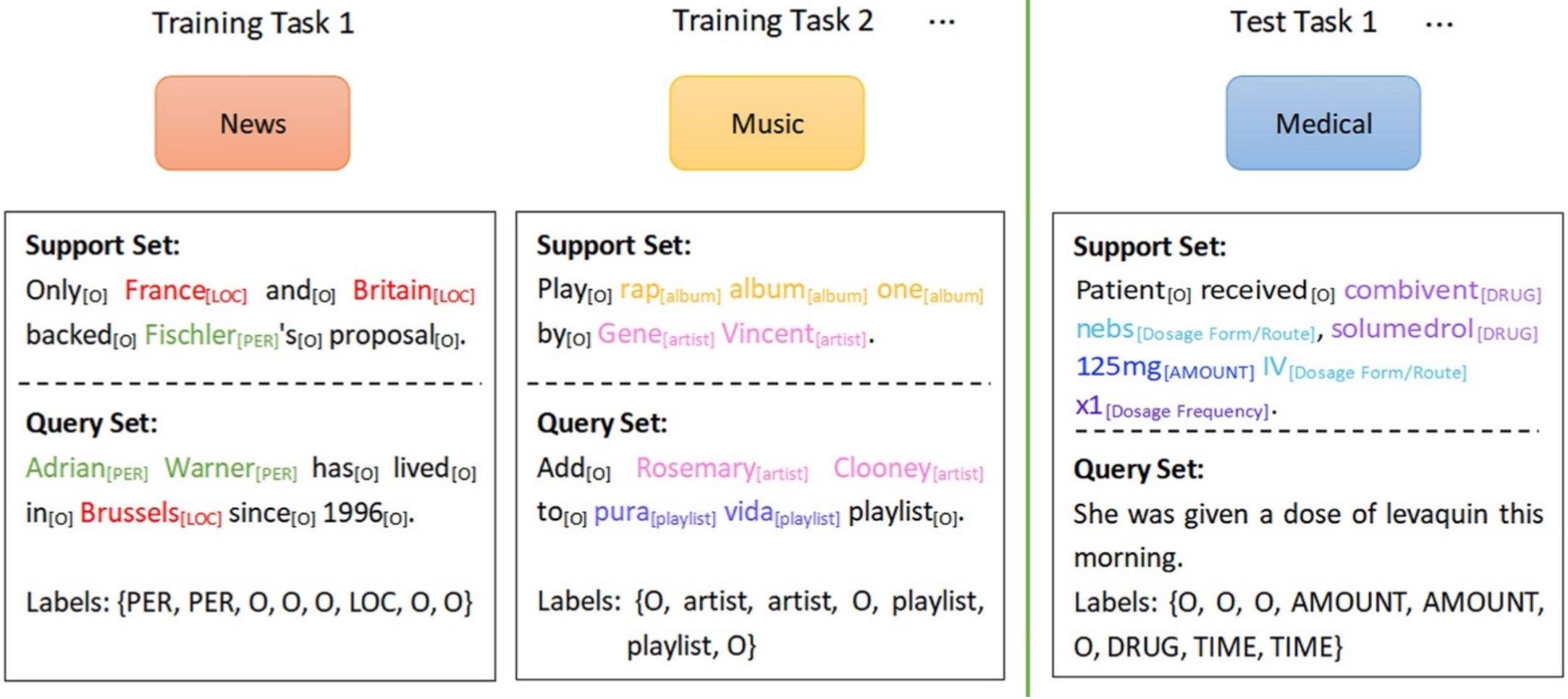
Few-Shot Learning (FSL)

Meta-learning

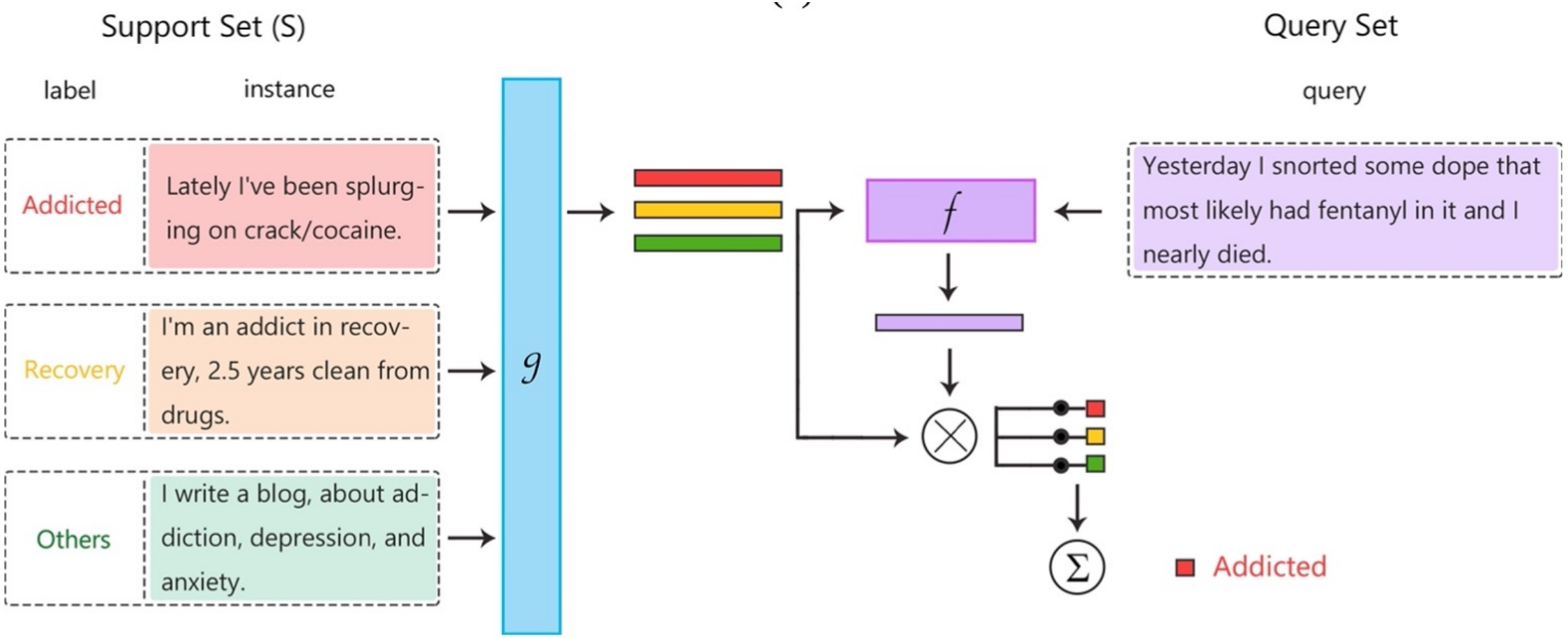
Each task mimics the few-shot scenario, and can be completely non-overlapping.
Support sets are used to train; query sets are used to evaluate the model



Source: Yao Ge, Yuting Guo, Yuan-Chi Yang, Mohammed Ali Al-Garadi, and Abeed Sarker (2022). "Few-shot learning for medical text: A systematic review." arXiv preprint arXiv:2204.14081 (2022).

Few-Shot Learning (FSL)

Matching networks



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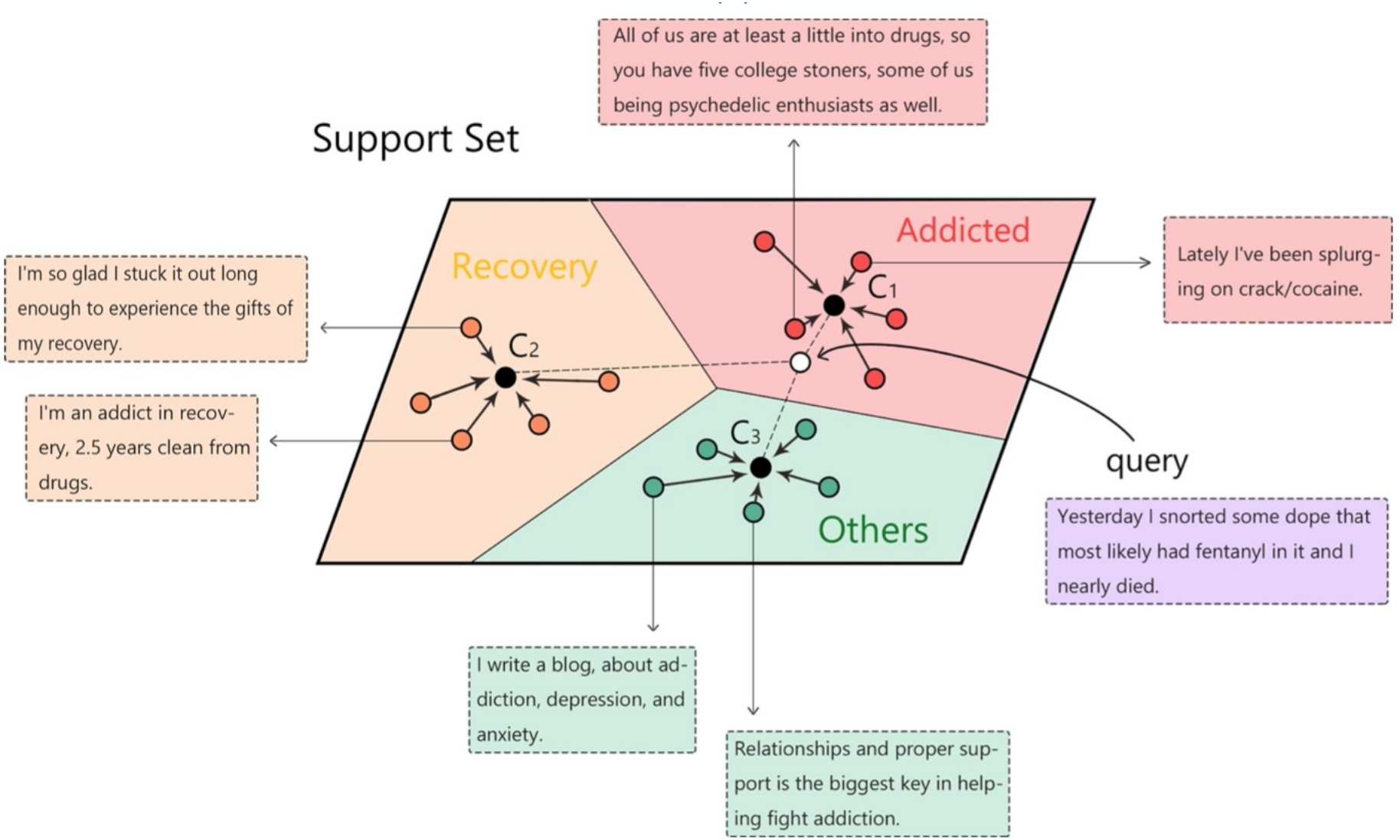
Few-Shot Learning (FSL)

Prototypical network



Source: Yao Ge, Yuting Guo, Yuan-Chi Yang, Mohammed Ali Al-Garadi, and Abeed Sarker (2022). "Few-shot learning for medical text: A systematic review." arXiv preprint arXiv:2204.14081 (2022).

Few-Shot Learning (FSL) for medical text

Study	Year	Data source	Research aim	Size of training set	Number of entities / classes	Entity type of training domain	Entity type of test domain
Alicia Lara-Clares and Ana Garcia-Serrano[44]	2019	MEDDOCAN shared task dataset[45]	NER	500 clinical cases, with no reconstruction	29	Clinical	Clinical
Ferré et al.[46]	2019	BB-norm dataset from the Bacteria Biotope 2019 Task[47]	Entity Normalization	Original dataset with no reconstruction and zero-shot	Not mentioned *	Biological	Biological
Hou et al.[48]	2020	Snips dataset[49]	Slot Tagging (NER)	1-shot and 5-shot	7	Six of Weather, Music, PlayList, Book (including biomedical), Search Screen (including biomedical), Restaurant and Creative Work.	The remaining one
Sharaf et al.[50]	2020	ten different datasets collected from the Open Parallel Corpus (OPUS)[51]	Neural Machine Translation (NMT)	Sizes ranging from 4k to 64k training words (200 to 3200 sentences), but reconstructed	N/A †	Bible, European Central Bank, KDE, Quran, WMT news test sets, Books, European Medicines Agency (EMEA), Global Voices, Medical (ufal-Med), TED talks	Bible, European Central Bank, KDE, Quran, WMT news test sets, Books, European Medicines Agency (EMEA), Global Voices, Medical (ufal-Med), TED talks
Lu et al.[52]	2020	MIMIC II[22] and MIMIC III[23], and EU legislation dataset[53]	Multi-label Text Classification	5-shot for MIMIC II and III, 50-shot for EU legislation	MIMIC II: 9 MIMIC III: 15 EU legis-lation: 5	Medical	Medical

Source: Yao Ge, Yuting Guo, Yuan-Chi Yang, Mohammed Ali Al-Garadi, and Abeed Sarker (2022). "Few-shot learning for medical text: A systematic review." arXiv preprint arXiv:2204.14081 (2022).

Few-Shot Learning (FSL) for medical text

Study	Year	Data source	Research aim	Size of training set	Number of entities / classes	Entity type of training domain	Entity type of test domain
Lu et al.[80]	2021	Constructed and shared a novel dataset [††] based on Weibo for the research of few-shot rumor detection, and use PHEME dataset[81]	Rumor Detection (NER)	For the Weibo dataset: 2-way 3-event 5-shot 9-query; for PHEME dataset: 2-way 2-event 5-shot 9-query	Weibo: 14 PHEME: 5	Source posts and comments from Sina Weibo related to COVID-19	Source posts and comments from Sina Weibo related to COVID-19
Ma et al.[82]	2021	CCLE, CERES-correctedCRISPR gene disruption scores, GDSC1000 dataset, PDTC dataset and PDX dataset[‡‡]	Drug-response Predictions	1-shot, 2-shot, 5-shot and 10-shot	N/A[†]	Biomedical	Biomedical
Kormilitzin et al.[83]	2021	MIMIC-III[23] and UK-CRIS datasets[30,31]	NER	25%, 50%, 75% and 100% of the training set, with no reconstruction	7	Electronic health record	Electronic health record
Guo et al.[84]	2021	Abstracts of biomedicalliteratures (from relation extraction task of BioNLP Shared Task 2011 and 2019[47]) and structured biological datasets	NER	100%, 75%, 50%, 25%, 0% of training set, with no reconstruction	Not mentioned *	Biomedical entities	Biomedical entities
Lee et al.[85]	2021	COVID19-Scientific[86], COVID19-Social[87] (fact-checked by journalists from a website called Politi-fact.com), FEVER[88] (Fact Extraction and Verification, generated by altering sentences extracted from Wiki-pedia to promote research onfact-checking systems)	Fact-Checking (close to Text Classification)	2-shot, 10-shot and 50-shot	Not mentioned *	Facts about COVID-19	Facts about COVID-19

Source: Yao Ge, Yuting Guo, Yuan-Chi Yang, Mohammed Ali Al-Garadi, and Abeed Sarker (2022). "Few-shot learning for medical text: A systematic review." arXiv preprint arXiv:2204.14081 (2022).

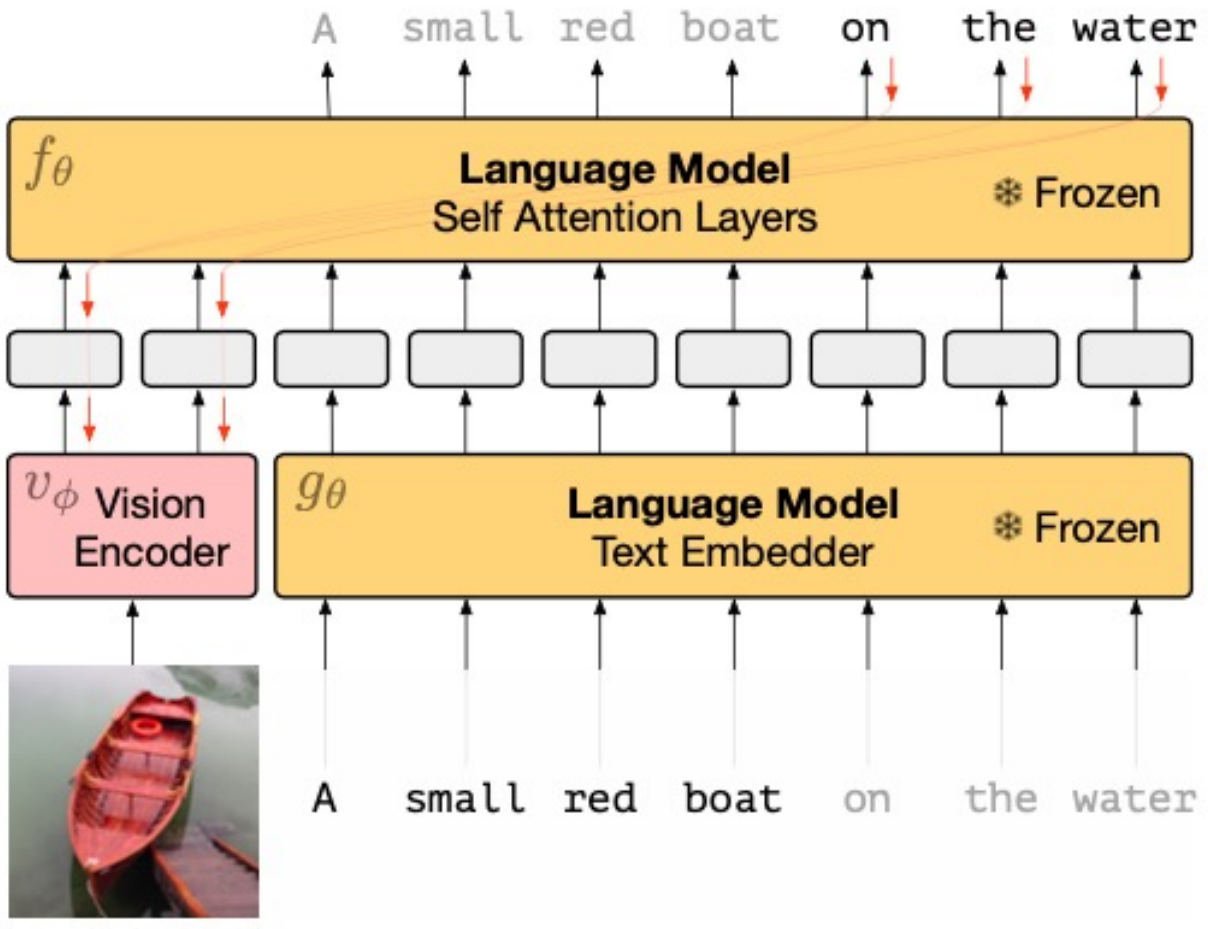
Multimodal Few-Shot Learning with Frozen Language Models

Curated samples with about five seeds required to get past well-known language model failure modes of either repeating text for the prompt or emitting text that does not pertain to the image.

These samples demonstrate the ability to generate open-ended outputs that adapt to both images and text, and to make use of facts that it has learned during language-only pre-training.

Source: Maria Tsimpoukelli, Jacob L. Menick, Serkan Cabi, S. M. Eslami, Oriol Vinyals, and Felix Hill (2021). "Multimodal few-shot learning with frozen language models." Advances in Neural Information Processing Systems 34 (2021): 200-212.

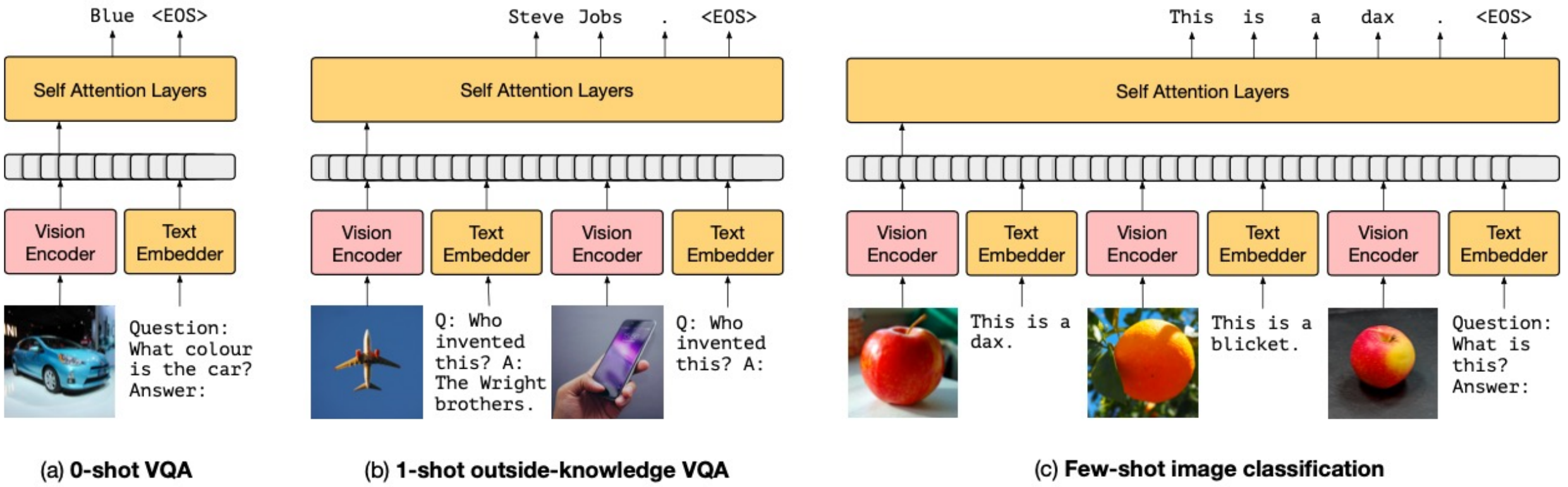
Multimodal Few-Shot Learning with Frozen Language Models



Gradients through a frozen language model's self attention layers are used to train the vision encoder.

Source: Maria Tsimpoukelli, Jacob L. Menick, Serkan Cabi, S. M. Eslami, Oriol Vinyals, and Felix Hill (2021). "Multimodal few-shot learning with frozen language models." Advances in Neural Information Processing Systems 34 (2021): 200-212.

Multimodal Few-Shot Learning with Frozen Language Models



Inference-Time interface for *Frozen*. The figure demonstrates how we can support (a) visual question answering, (b) outside-knowledge question answering and (c) few-shot image classification via in-context learning.

Source: Maria Tsimpoukelli, Jacob L. Menick, Serkan Cabi, S. M. Eslami, Oriol Vinyals, and Felix Hill (2021). "Multimodal few-shot learning with frozen language models." Advances in Neural Information Processing Systems 34 (2021): 200-212.

Multimodal Few-Shot Learning with Frozen Language Models

Examples of (a) the Open-Ended miniImageNet evaluation (b) the Fast VQA evaluation.

Source: Maria Tsimpoukelli, Jacob L. Menick, Serkan Cabi, S. M. Eslami, Oriol Vinyals, and Felix Hill (2021). "Multimodal few-shot learning with frozen language models." Advances in Neural Information Processing Systems 34 (2021): 200-212.

GPT-3: Language Models are Few-Shot Learners

Language Models are Few-Shot Learners

Tom B. Brown* Benjamin Mann* Nick Ryder* Melanie Subbiah*

Jared Kaplan† Prafulla Dhariwal Arvind Neelakantan Pranav Shyam

Girish Sastry Amanda Askell Sandhini Agarwal Ariel Herbert-Voss

Gretchen Krueger Tom Henighan Rewon Child Aditya Ramesh

Daniel M. Ziegler Jeffrey Wu Clemens Winter

Christopher Hesse Mark Chen Eric Sigler Mateusz Litwin Scott Gray

Benjamin Chess Jack Clark Christopher Berner

Sam McCandlish Alec Radford Ilya Sutskever Dario Amodei

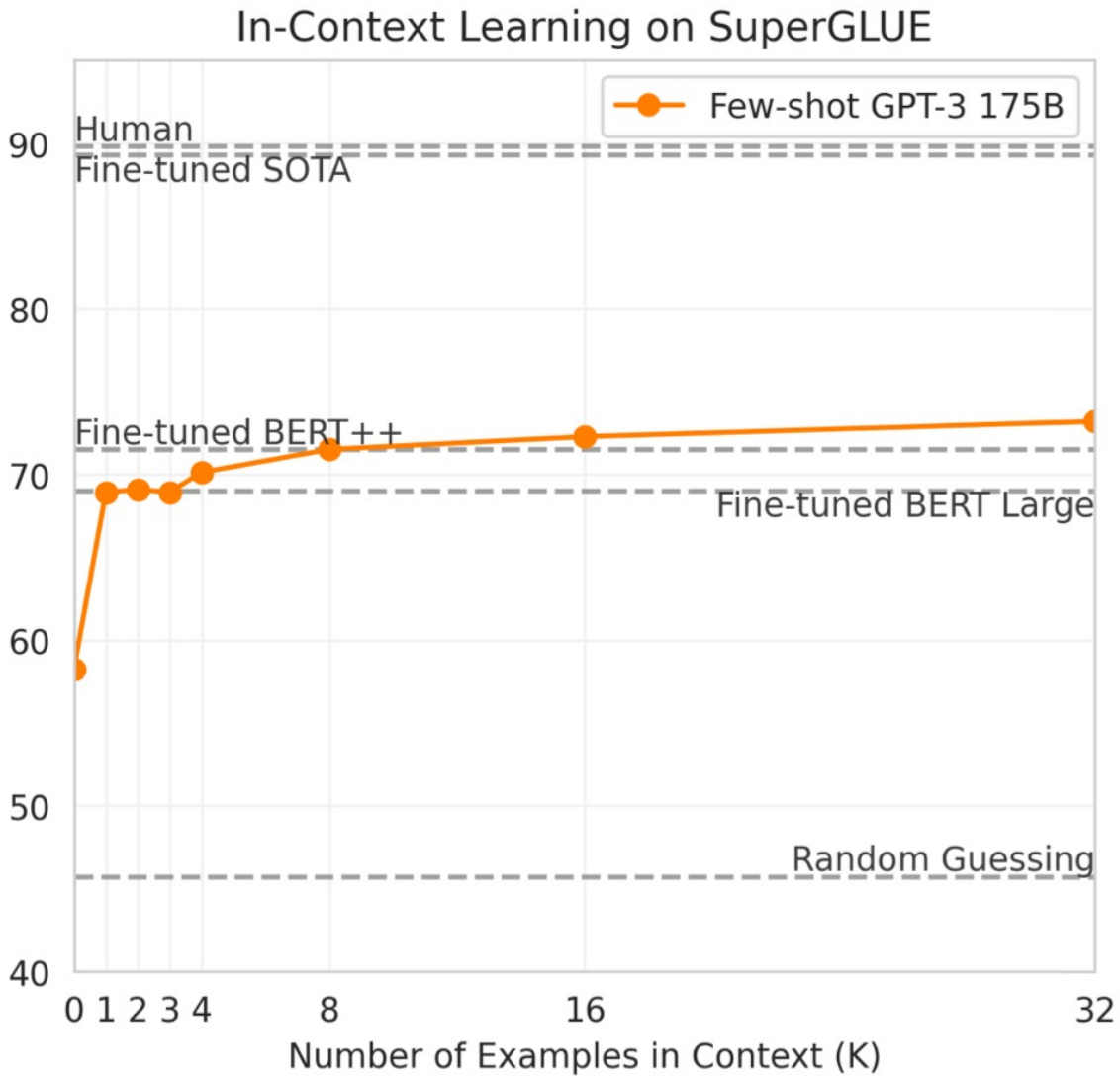
This work was funded by **OpenAI**.
All models were trained on **V100** GPU's on part of a high-bandwidth cluster provided by Microsoft.

Source: Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. (2020) "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901

GPT-3: Language Models are Few-Shot Learners

Source: Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. (2020) "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901

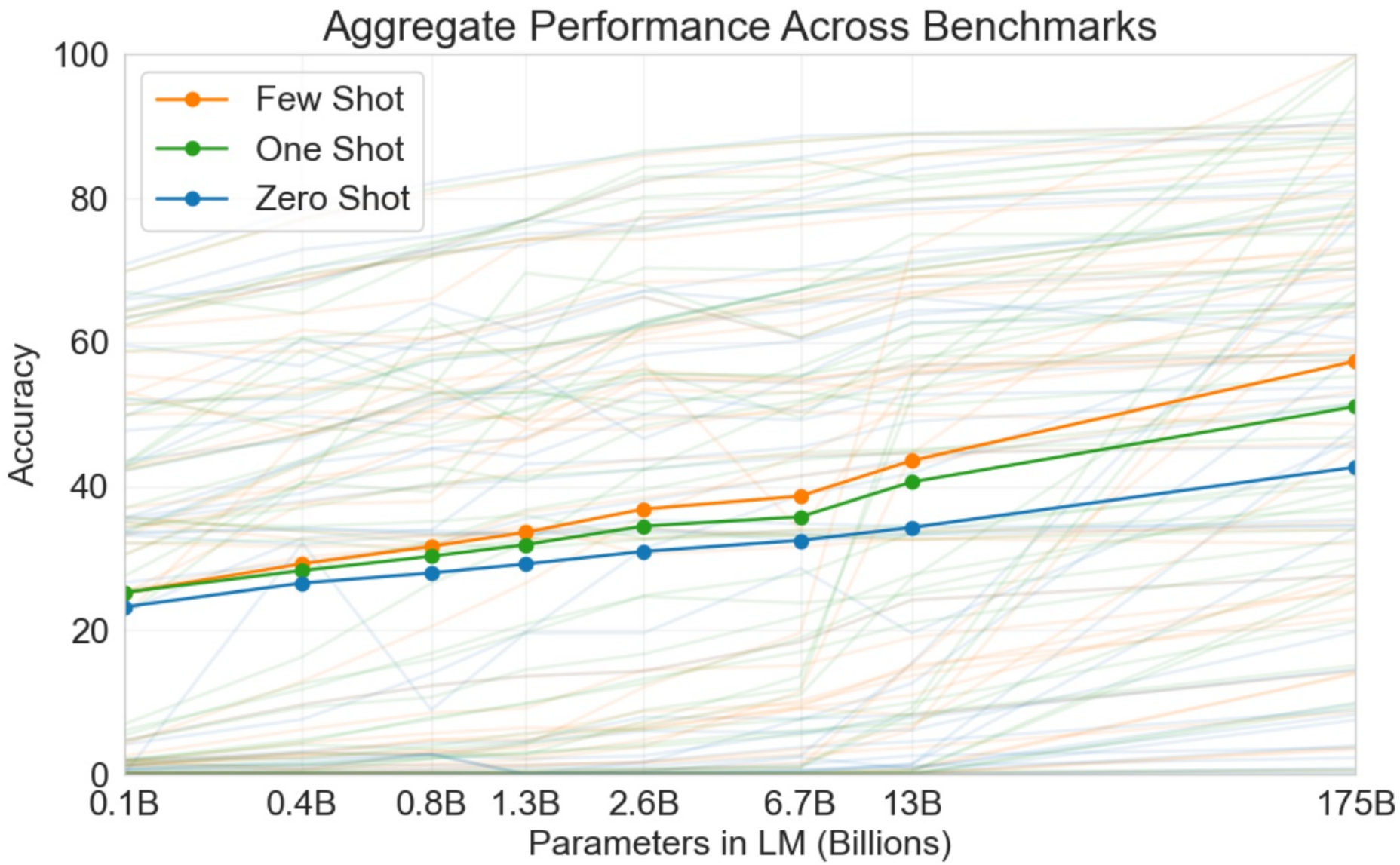
GPT-3: Language Models are Few-Shot Learners



Performance on SuperGLUE increases with model size.
A value of K = 32 means that our model was shown 32 examples per task, for 256 examples total divided across the 8 tasks in SuperGLUE.

Source: Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. (2020) "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901

GPT-3: Language Models are Few-Shot Learners



Source: Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. (2020) "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901

GPT-3: Language Models are Few-Shot Learners

Performance on cloze and completion tasks.

Setting	LAMBADA (acc)	LAMBADA (ppl)	StoryCloze (acc)	HellaSwag (acc)
SOTA	68.0[a]	8.63[b]	**91.8**[c]	**85.6**[d]
GPT-3 Zero-Shot	**76.2**	**3.00**	83.2	78.9
GPT-3 One-Shot	**72.5**	**3.35**	84.7	78.1
GPT-3 Few-Shot	**86.4**	**1.92**	87.7	79.3

GPT-3 significantly improves SOTA on LAMBADA while achieving respectable performance on two difficult completion prediction datasets.

Source: Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. (2020) "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901

GPT-3: Language Models are Few-Shot Learners

Results on three Open-Domain QA tasks

Setting	NaturalQS	WebQS	TriviaQA
RAG (Fine-tuned, Open-Domain) [LPP+20]	**44.5**	**45.5**	**68.0**
T5-11B+SSM (Fine-tuned, Closed-Book) [RRS20]	36.6	44.7	60.5
T5-11B (Fine-tuned, Closed-Book)	34.5	37.4	50.1
GPT-3 Zero-Shot	14.6	14.4	64.3
GPT-3 One-Shot	23.0	25.3	**68.0**
GPT-3 Few-Shot	29.9	41.5	**71.2**

GPT-3 is shown in the few-, one-, and zero-shot settings, as compared to prior SOTA results for closed book and open domain settings.
TriviaQA few-shot result is evaluated on the wiki split test server.

Source: Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. (2020) "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901

GPT-3: Language Models are Few-Shot Learners

GPT-3 results on a selection of QA / RC tasks.

Setting	ARC (Easy)	ARC (Challenge)	CoQA	DROP
Fine-tuned SOTA	**92.0**[a]	**78.5**[b]	**90.7**[c]	**89.1**[d]
GPT-3 Zero-Shot	68.8	51.4	81.5	23.6
GPT-3 One-Shot	71.2	53.2	84.0	34.3
GPT-3 Few-Shot	70.1	51.5	85.0	36.5

CoQA and DROP are F1 while ARC reports accuracy.
See the appendix for additional experiments. a[KKS+20] b[KKS+20] c[JZC+19] d [JN20]

Source: Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. (2020) "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901

GPT-3: Language Models are Few-Shot Learners

Setting	En→Fr	Fr→En	En→De	De→En	En→Ro	Ro→En
SOTA (Supervised)	**45.6**[a]	35.0 [b]	**41.2**[c]	40.2[d]	**38.5**[e]	**39.9**[e]
XLM [LC19]	33.4	33.3	26.4	34.3	33.3	31.8
MASS [STQ+19]	37.5	34.9	28.3	35.2	35.2	33.1
mBART [LGG+20]	-	-	29.8	34.0	35.0	30.5
GPT-3 Zero-Shot	25.2	21.2	24.6	27.2	14.1	19.9
GPT-3 One-Shot	28.3	33.7	26.2	30.4	20.6	38.6
GPT-3 Few-Shot	32.6	39.2	29.7	40.6	21.0	39.5

Few-shot GPT-3 outperforms previous unsupervised NMT work by 5 BLEU when translating into English reflecting its strength as an English LM.

Source: Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. (2020) "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901

GPT-3: Language Models are Few-Shot Learners

Performance of GPT-3 on SuperGLUE compared to fine-tuned baselines and SOTA

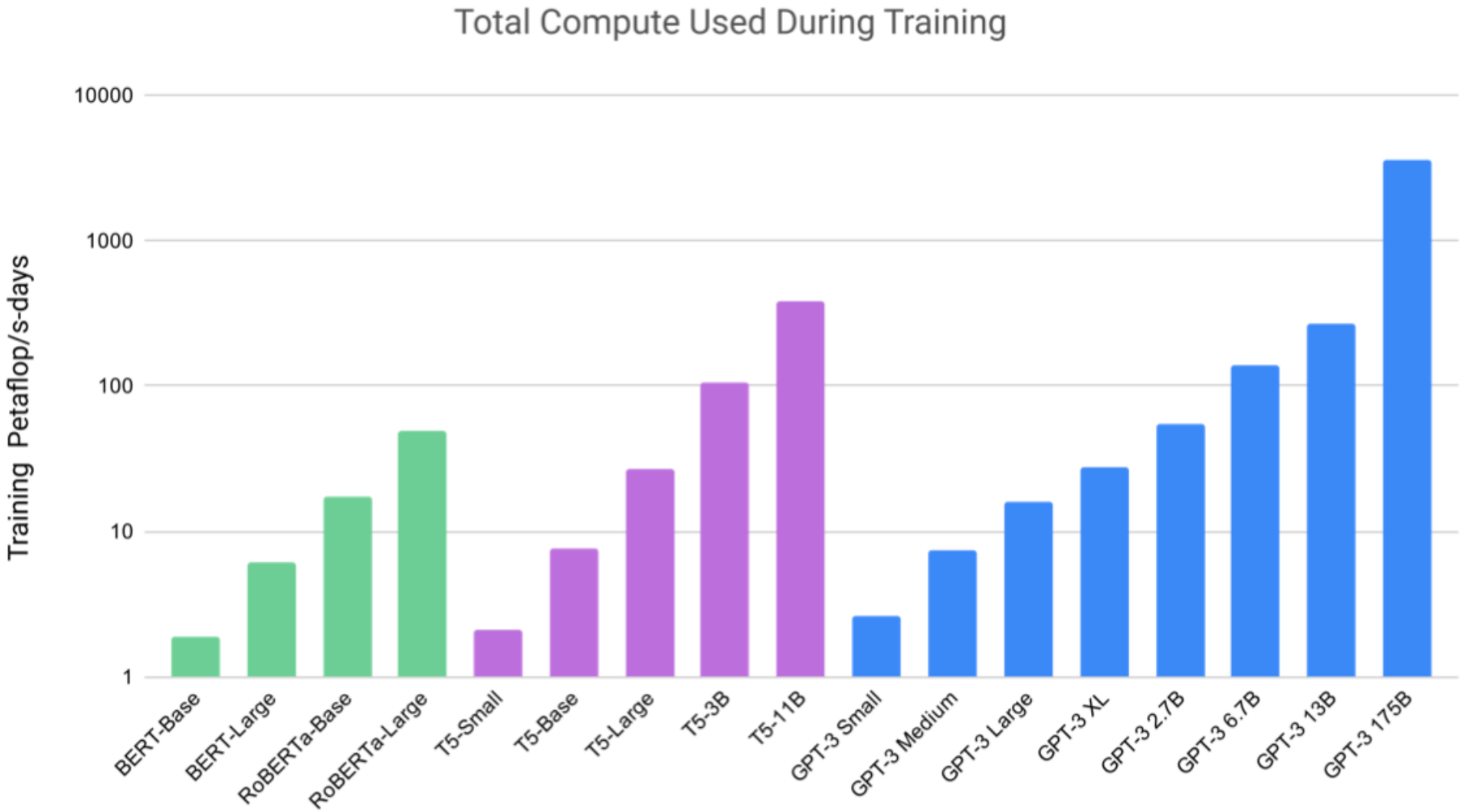
	SuperGLUE Average	BoolQ Accuracy	CB Accuracy	CB F1	COPA Accuracy	RTE Accuracy
Fine-tuned SOTA	**89.0**	**91.0**	**96.9**	**93.9**	**94.8**	**92.5**
Fine-tuned BERT-Large	69.0	77.4	83.6	75.7	70.6	71.7
GPT-3 Few-Shot	71.8	76.4	75.6	52.0	92.0	69.0

	WiC Accuracy	WSC Accuracy	MultiRC Accuracy	MultiRC F1a	ReCoRD Accuracy	ReCoRD F1
Fine-tuned SOTA	**76.1**	**93.8**	**62.3**	**88.2**	**92.5**	**93.3**
Fine-tuned BERT-Large	69.6	64.6	24.1	70.0	71.3	72.0
GPT-3 Few-Shot	49.4	80.1	30.5	75.4	90.2	91.1

GPT-3 few-shot is given a total of 32 examples within the context of each task and performs no gradient updates.

Source: Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. (2020) "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901

GPT-3: Language Models are Few-Shot Learners



GPT-3 3B is almost 10x larger than RoBERTa-Large (355M params),
both models took roughly 50 petaflop/s-days of compute during pre-training

Source: Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. (2020) "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901

GPT-3: Language Models are Few-Shot Learners

Human accuracy in identifying whether short (~200 word) news articles are model generated

	Mean accuracy	95% Confidence Interval (low, hi)	t compared to control (p-value)	"I don't know" assignments
Control (deliberately bad model)	86%	83%–90%	-	3.6 %
GPT-3 Small	76%	72%–80%	3.9 (2e-4)	4.9%
GPT-3 Medium	61%	58%–65%	10.3 (7e-21)	6.0%
GPT-3 Large	68%	64%–72%	7.3 (3e-11)	8.7%
GPT-3 XL	62%	59%–65%	10.7 (1e-19)	7.5%
GPT-3 2.7B	62%	58%–65%	10.4 (5e-19)	7.1%
GPT-3 6.7B	60%	56%–63%	11.2 (3e-21)	6.2%
GPT-3 13B	55%	52%–58%	15.3 (1e-32)	7.1%
GPT-3 175B	52%	49%–54%	16.9 (1e-34)	7.8%

This table compares mean accuracy between five different models, and shows the results of a two-sample T-Test for the difference in mean accuracy between each model and the control model (an unconditional GPT-3 Small model with increased output randomness).

Source: Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. (2020) "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901

GPT-3: Language Models are Few-Shot Learners

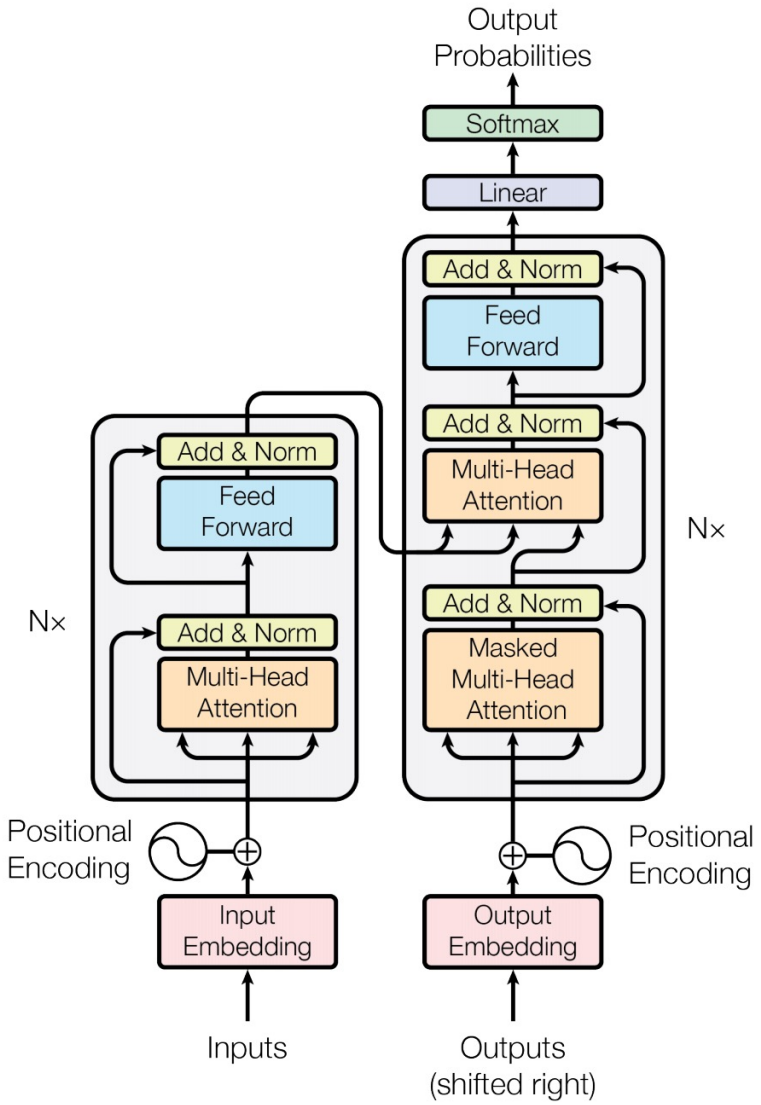
The GPT-3 generated news article that humans had the greatest difficulty distinguishing from a human written article (accuracy: 12%)

Title: United Methodists Agree to Historic Split
Subtitle: Those who oppose gay marriage will form their own denomination
Article: After two days of intense debate, the United Methodist Church has agreed to a historic split - one that is expected to end in the creation of a new denomination, one that will be "theologically and socially conservative," according to The Washington Post. The majority of delegates attending the church's annual General Conference in May voted to strengthen a ban on the ordination of LGBTQ clergy and to write new rules that will "discipline" clergy who officiate at same-sex weddings. But those who opposed these measures have a new plan: They say they will form a separate denomination by 2020, calling their church the Christian Methodist denomination.
The Post notes that the denomination, which claims 12.5 million members, was in the early 20th century the "largest Protestant denomination in the U.S.," but that it has been shrinking in recent decades. The new split will be the second in the church's history. The first occurred in 1968, when roughly 10 percent of the denomination left to form the Evangelical United Brethren Church. The Post notes that the proposed split "comes at a critical time for the church, which has been losing members for years," which has been "pushed toward the brink of a schism over the role of LGBTQ people in the church." Gay marriage is not the only issue that has divided the church. In 2016, the denomination was split over ordination of transgender clergy, with the North Pacific regional conference voting to ban them from serving as clergy, and the South Pacific regional conference voting to allow them.

Source: Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. (2020) "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901

Transformer (Attention is All You Need)

(Vaswani et al., 2017)

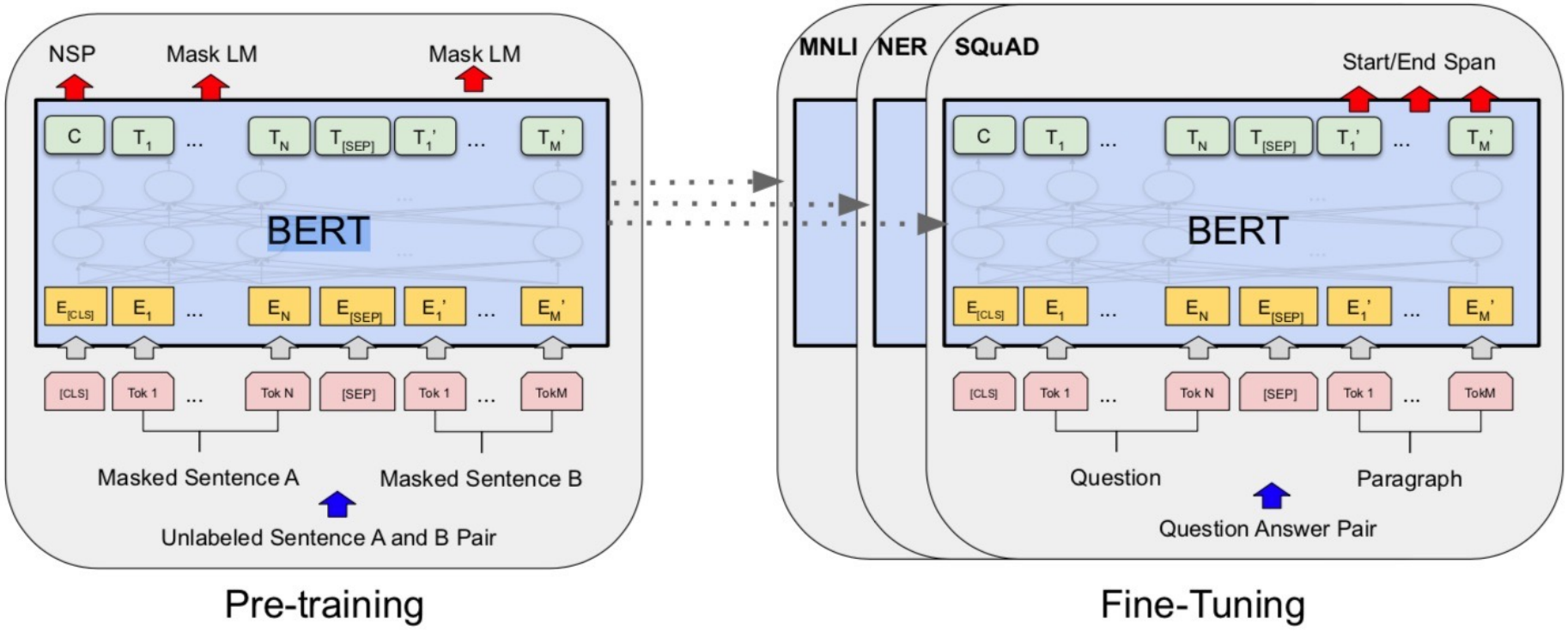


Source: Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." In *Advances in neural information processing systems*, pp. 5998-6008. 2017.

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT (Bidirectional Encoder Representations from Transformers)

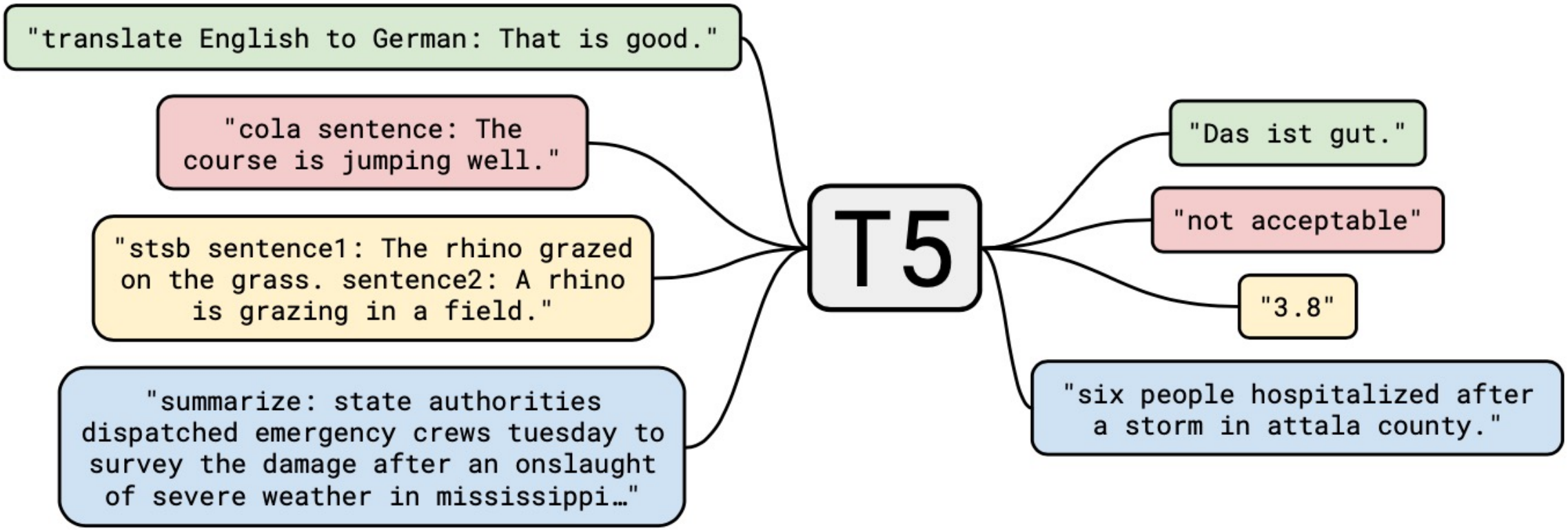
Overall pre-training and fine-tuning procedures for BERT



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.

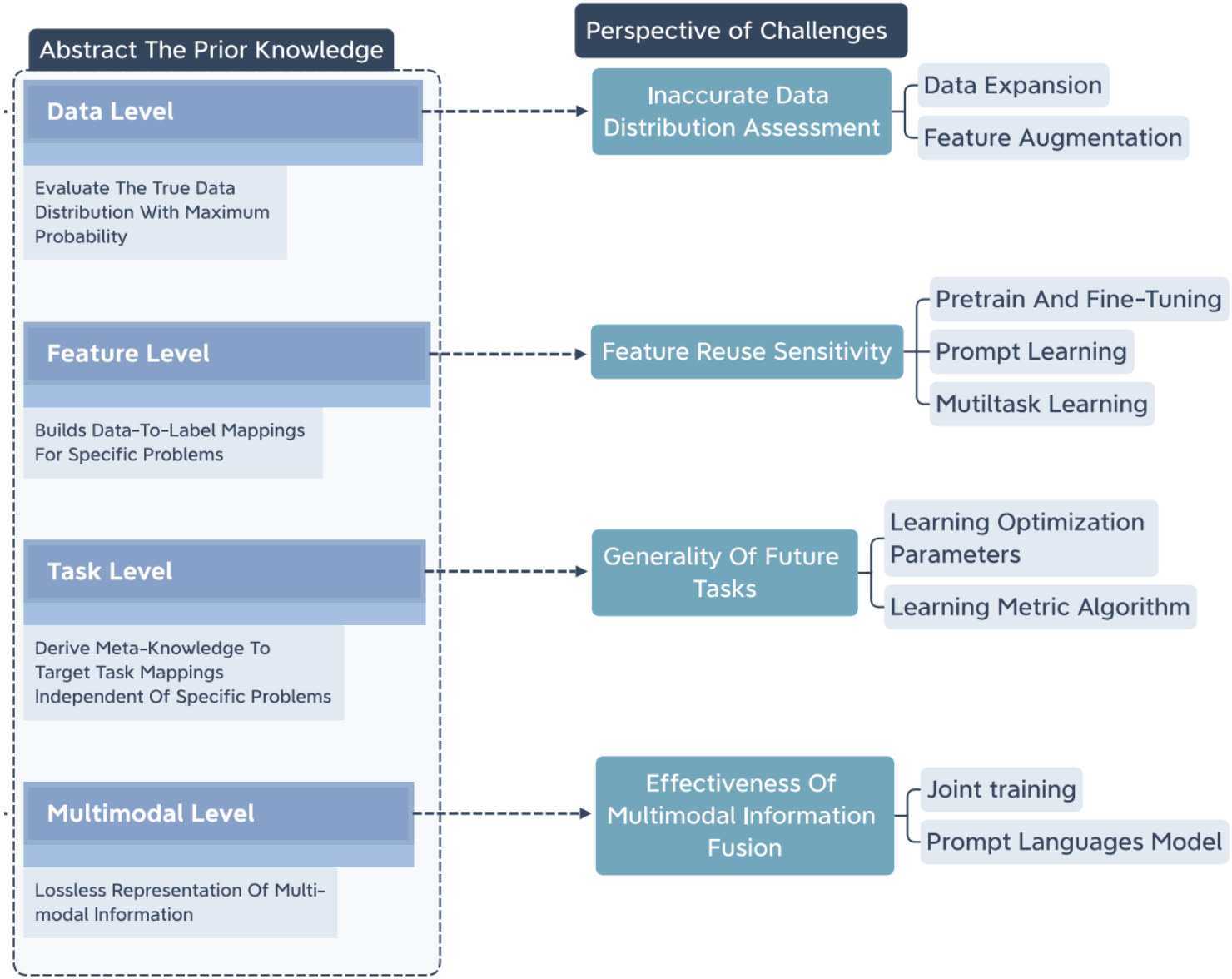
T5

Text-to-Text Transfer Transformer



Source: JColin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu (2019). "Exploring the limits of transfer learning with a unified text-to-text transformer." arXiv preprint arXiv:1910.10683 (2019).

Few-Shot Learning (FSL)



Source: Yisheng Song, Ting Wang, Puyu Cai, Subrota K. Mondal, and Jyoti Prakash Sahoo. (2023) "A comprehensive survey of few-shot learning: Evolution, applications, challenges, and opportunities." ACM Computing Surveys (2023).

Pre-training and Fine-tuning Methods

Method	Venue	Backbone	Parameters	Tricks		
				Refining Parameters	Knowledge distillation	Attention
Squad [101]	EMNLP'16	Logistic Regression	-	✓		
Attention is All you Need [102]	NIPS'17	Transformer	110M			✓
Baseline [92]	ICLR'19	Conv64F	0.22M			
Baseline++ [92]	ICML'19	Conv64F	0.22M		✓	✓
CAN [98]	NIPS'19	ResNet12	12.47M			✓
GLUE [103]	ICLR'19	ELMo	94M	✓		
RFS-distill [95]	ECCV'20	ResNet-12	12.47M		✓	
LEE et al. [104]	WPI'20	GPT-2	1500M	✓		
CTX [97]	NIPS'20	Transformer	110M		✓	
SKD [96]	CVPR'20	ResNet12	12.47M			✓
P-Transfer [93]	AAAI'21	ResNet-12	12.47M	✓		
BERT Fine-tuning [105]	CL'21	BERT	110M	✓		✓
COSOC [106]	NIPS'21	ResNet-12	12.47M			✓
P>M>F [100]	CVPR'22	ViT	307M			✓
ReFine [94]	CVPR'22	ResNet-10	9.86M	✓		

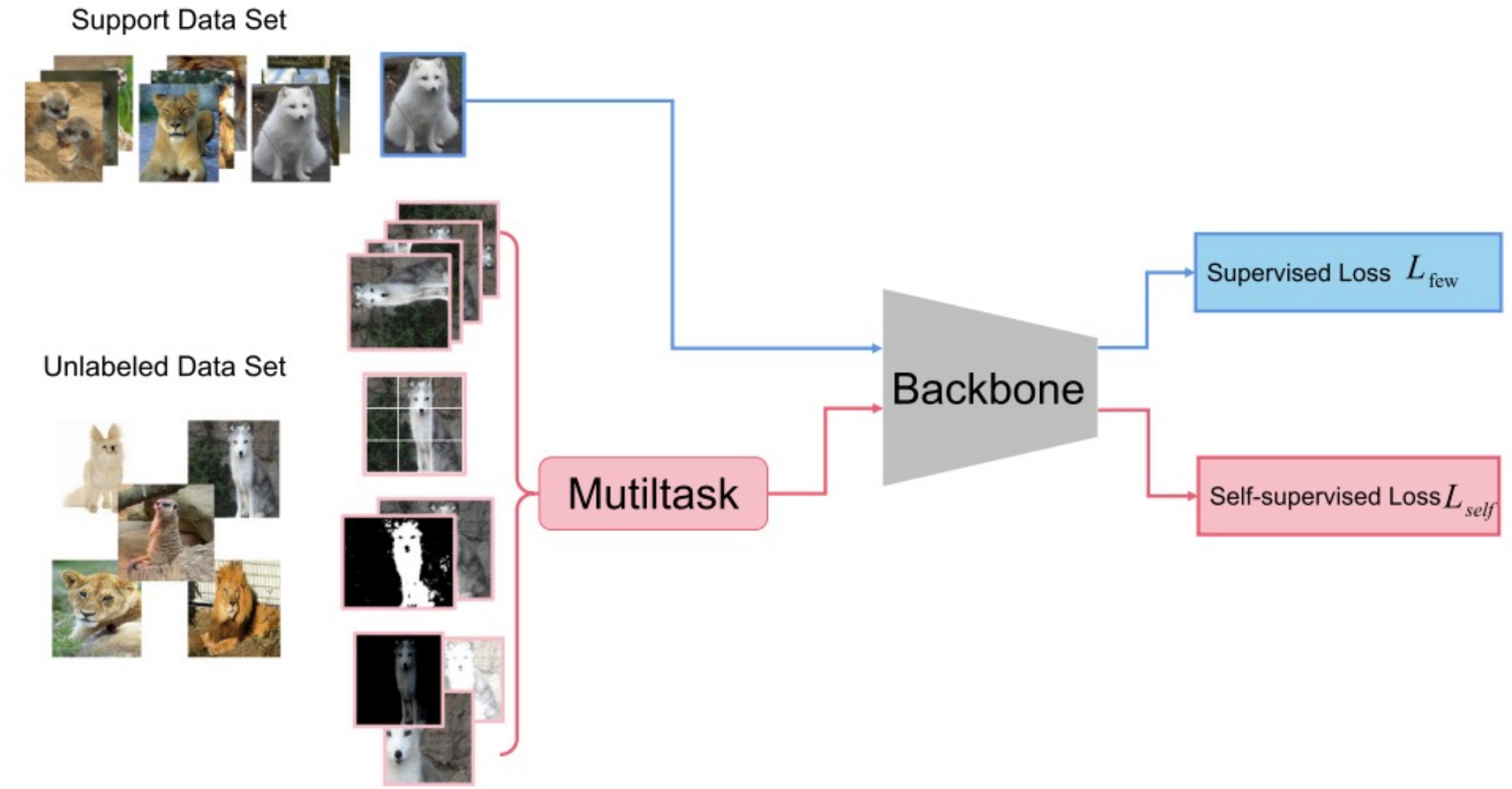
Source: Yisheng Song, Ting Wang, Puyu Cai, Subrota K. Mondal, and Jyoti Prakash Sahoo. (2023) "A comprehensive survey of few-shot learning: Evolution, applications, challenges, and opportunities." ACM Computing Surveys (2023).

Few-Shot Learning (FSL) Prompt Learning in Natural Language Processing

Method	Venue	Backbone	Type	Shape	Highlight
PT [110]	ACL'21	GPT-3	Manual prompt	Prefix Prompt	Combine input vector and prefix prompts
Brown [88]	NIPS'20	GPT-3	Manual Prompt	Prefix Prompt	Design task-related prompt
Petroni et al. [87]	EMNLP'19	BERT	Manual Prompt	Cloze-style	Use cloze-style prompt to learn prior knowledge
Cui et al. [107]	ACL-IJCNLP'21	BERT	Manual prompt	Cloze-style	Use cloze to construct tasks in entity classification
PET [112]	EACL'21	PLM	Manual Prompt	Cloze-style	Introduces fine-tuning and knowledge distillation
LPAQA [113]	MIT'20	LMS	Auto-Prompt	Cloze-style	Collect manual templates as template library
AutoPrompt [114]	ACL'20	MLMs	Auto-Prompt	Cloze-style	Automatically search template by collect prior prompt
LM-BFF [115]	ACL'21	GPT-3	Auto-Prompt	Cloze-style	Restore the span of the mask sentences
PT* [108]	ACL'21	GPT-2	Latent Prompt	Prefix Prompt	Add prefix ID in front of the input text
CP-Tuning [116]	ACL'22	PLMs	Latent Prompt	Prefix Prompt	Continuous prompt embedding instead of manually designed prompt
OptiPrompt [117]	NAACL'21	BERT	Latent Prompt	Cloze-style	Initialize with text prompt templates and fine-tuning
GPT understands [118]	Arxiv'21	GPTs	Latent Prompt	Prefix Prompt	Model output is regarded as hidden vector to optimize
PPT [119]	ACL'22	PLMS	Latent Prompt	Cloze-style	Add soft prompt during pre training

Source: Yisheng Song, Ting Wang, Puyu Cai, Subrota K. Mondal, and Jyoti Prakash Sahoo. (2023) "A comprehensive survey of few-shot learning: Evolution, applications, challenges, and opportunities." ACM Computing Surveys (2023).

Contrast Learning is involved in FSL multitask



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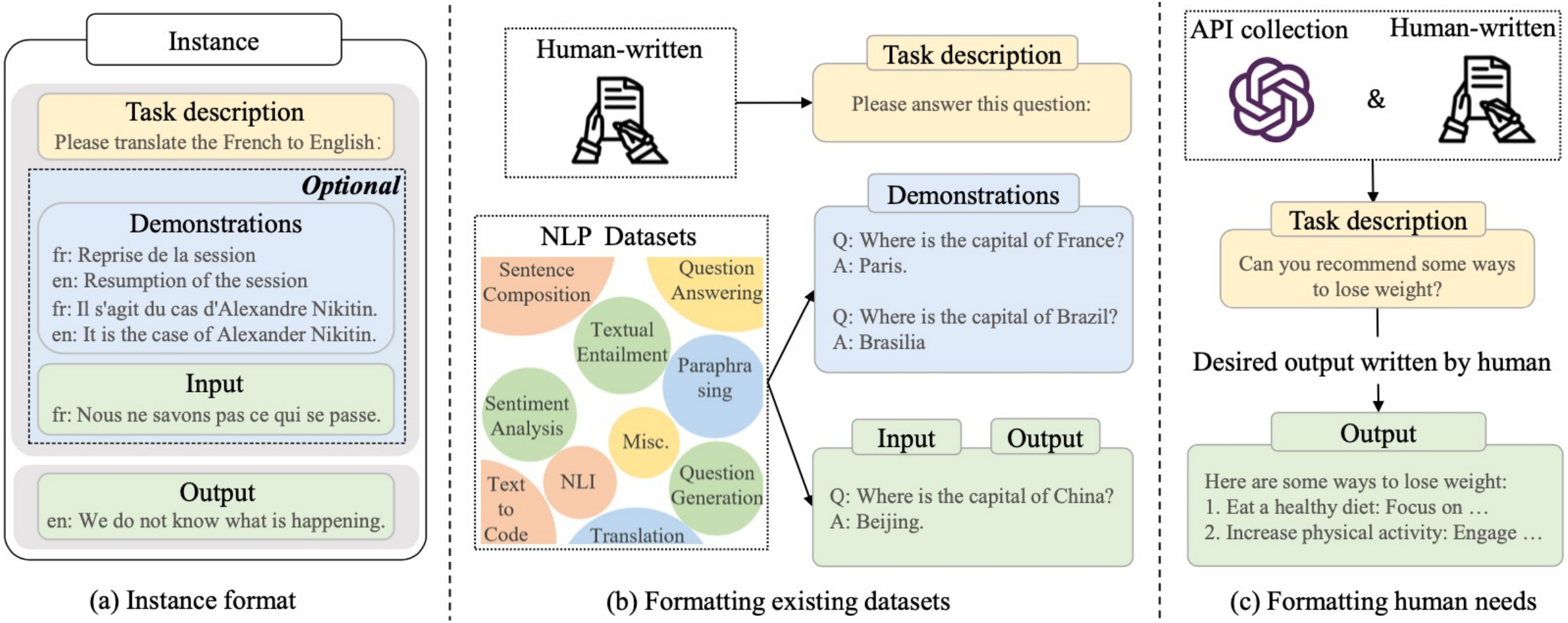
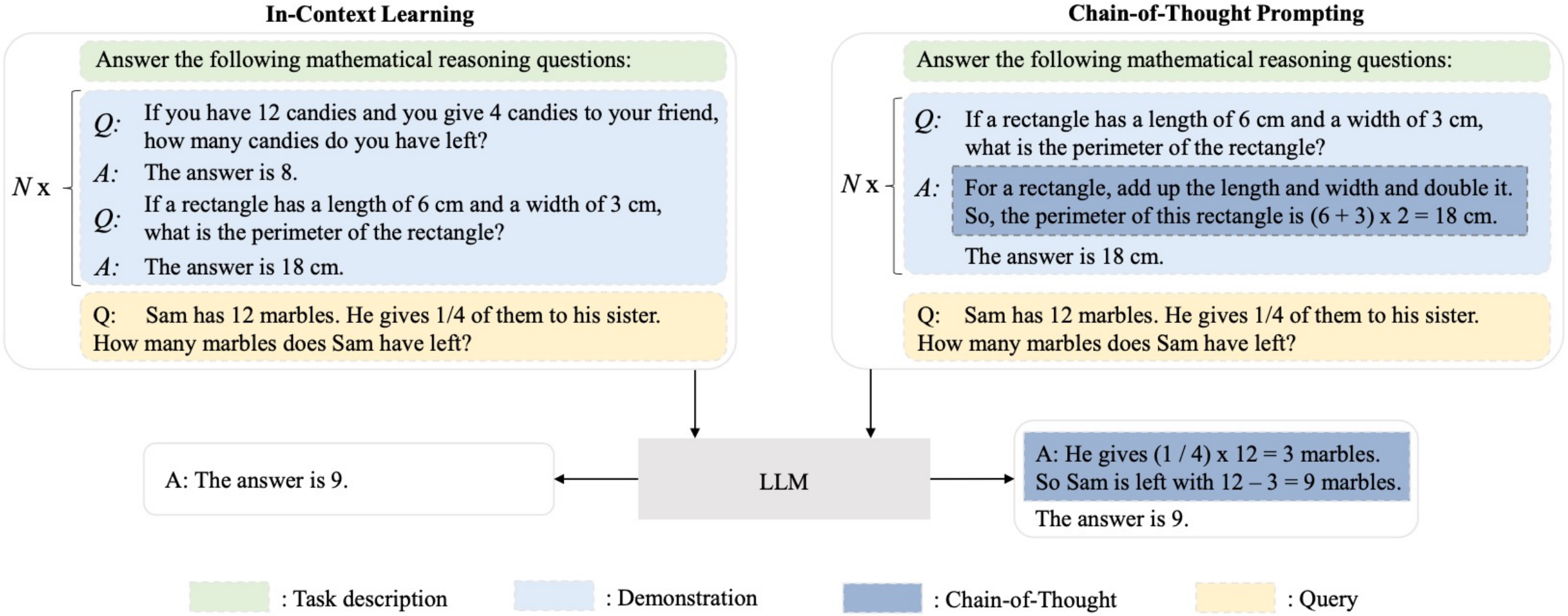
Instance Formatting and Two Different Methods for Constructing the Instruction-formatted Instances



Source: Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min et al. (2023) "A Survey of Large Language Models." arXiv preprint arXiv:2303.18223.

In-context Learning (ICL) and Chain-of-thought (CoT) Prompting

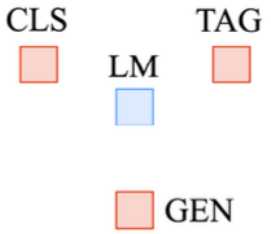
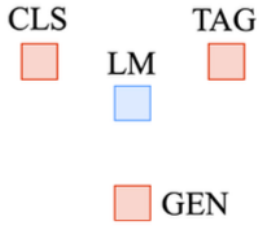
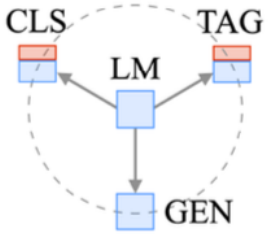
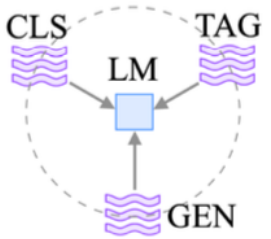


Source: Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min et al. (2023) "A Survey of Large Language Models." arXiv preprint arXiv:2303.18223.

Pre-train, Prompt, and Predict: Prompting Methods in Natural Language Processing (LLMs)

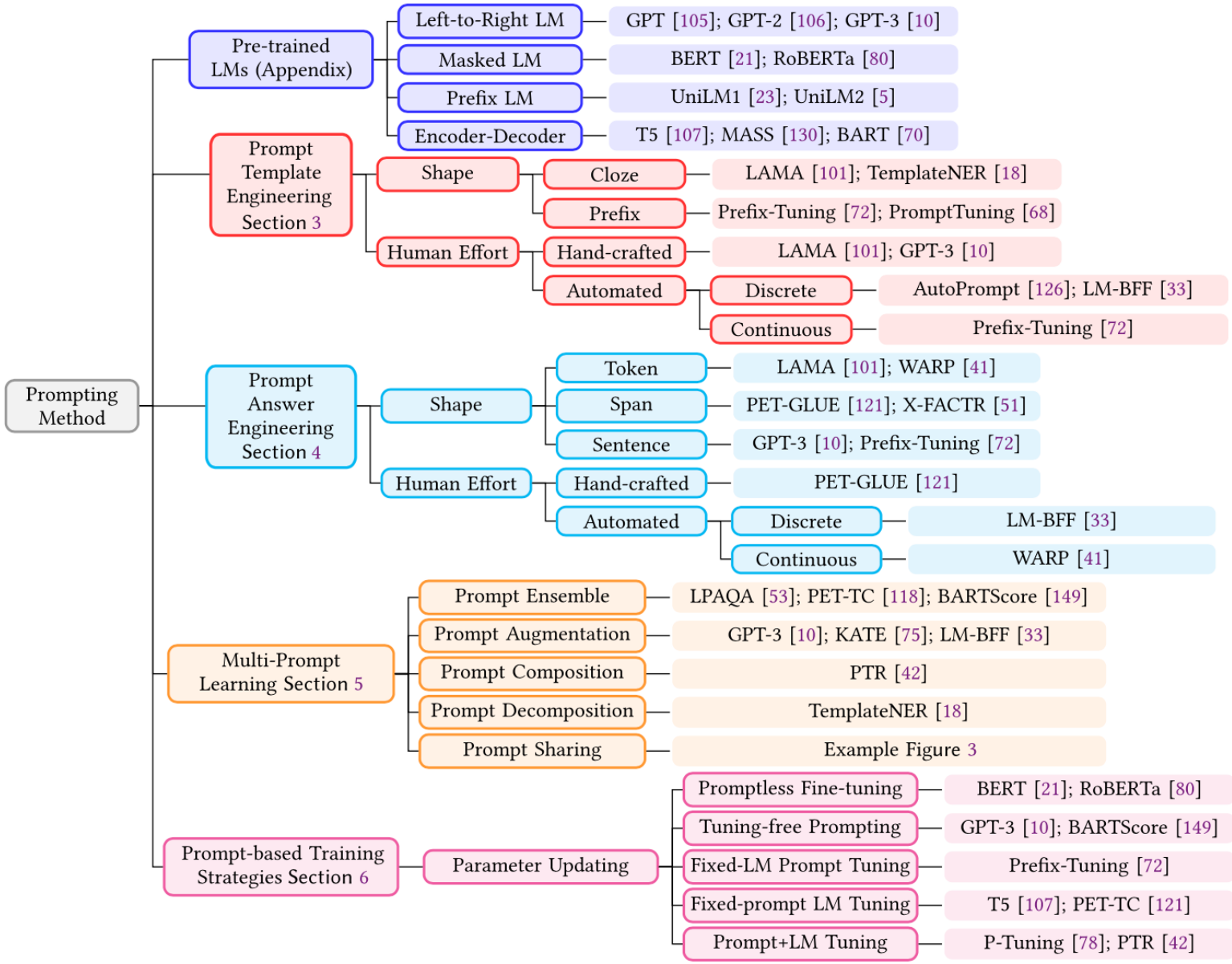
Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

Four Paradigms in NLP (LM)

Paradigm	Engineering	Task Relation
a. Fully Supervised Learning (Non-Neural Network)	Feature (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
Transfer Learning: Pre-training, Fine-Tuning (FT) c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	
GAI: Pre-train, Prompt, and Predict (Prompting) d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	

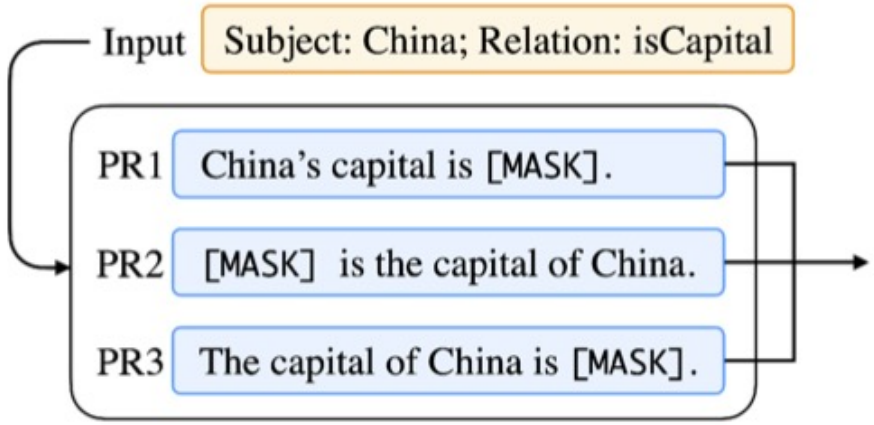
Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

Typology of Prompting Methods

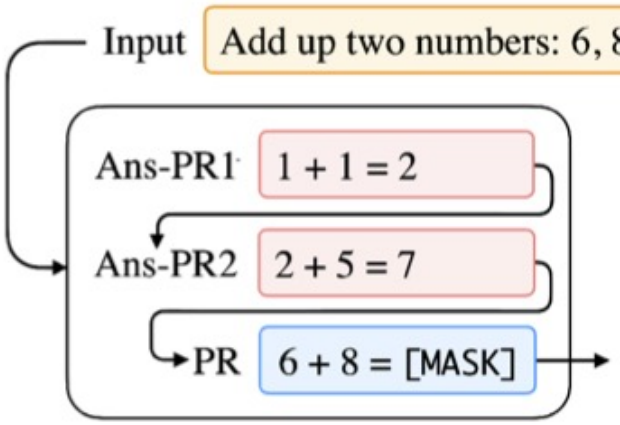


Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

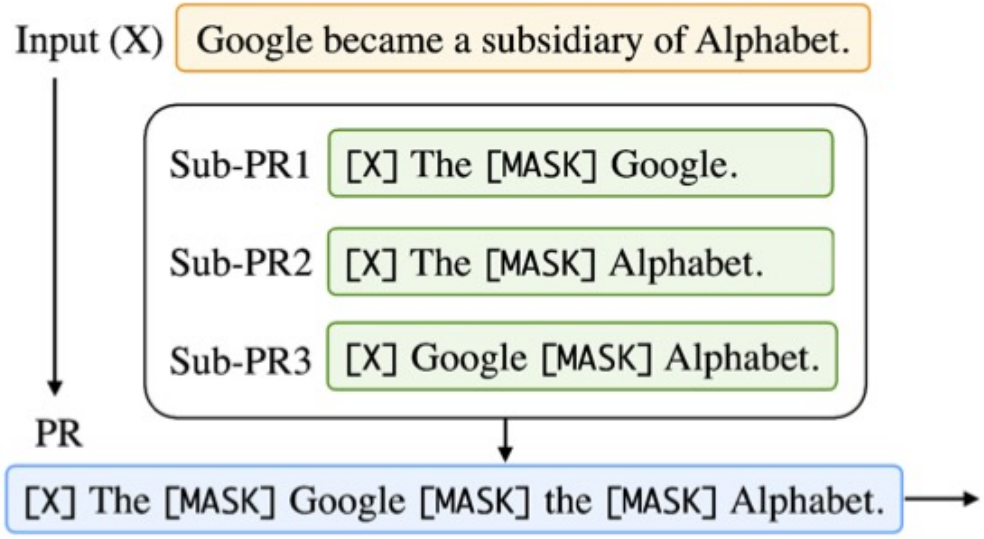
Different Multi-Prompt Learning Strategies



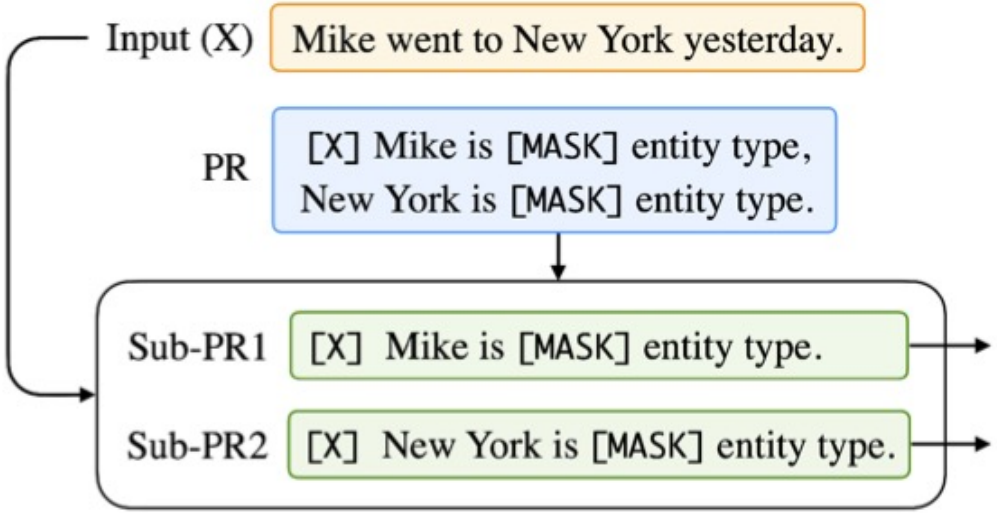
(a) Prompt Ensembling.



(b) Prompt Augmentation.



(c) Prompt Composition.



(d) Prompt Decomposition.

Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

Examples of Input, Template, and Answer for Different Tasks

Type	Task Example	Input ([X])	Template	Answer ([Z])
Text Classification	Sentiment	I love this movie.	[X] The movie is [Z].	great fantastic ...
	Topics	He prompted the LM.	[X] The text is about [Z].	sports science ...
	Intention	What is taxi fare to Denver?	[X] The question is about [Z].	quantity city ...
Text-span Classification	Aspect Sentiment	Poor service but good food.	[X] What about service? [Z].	Bad Terrible ...
Text-pair Classification	Natural Language Inference	[X1]: An old man with ... [X2]: A man walks ...	[X1]? [Z], [X2]	Yes No ...
Tagging	Named Entity Recognition	[X1]: Mike went to Paris. [X2]: Paris	[X1][X2] is a [Z] entity.	organization location ...
Text Generation	Summarization	Las Vegas police ...	[X] TL;DR: [Z]	The victim ... A woman ... ...
	Translation	Je vous aime.	French: [X] English: [Z]	I love you. I fancy you. ...
Regression	Textual Similarity	[X1]: A man is smoking. [X2]: A man is skating.	[X1] [Z], [X2]	Yes No ...

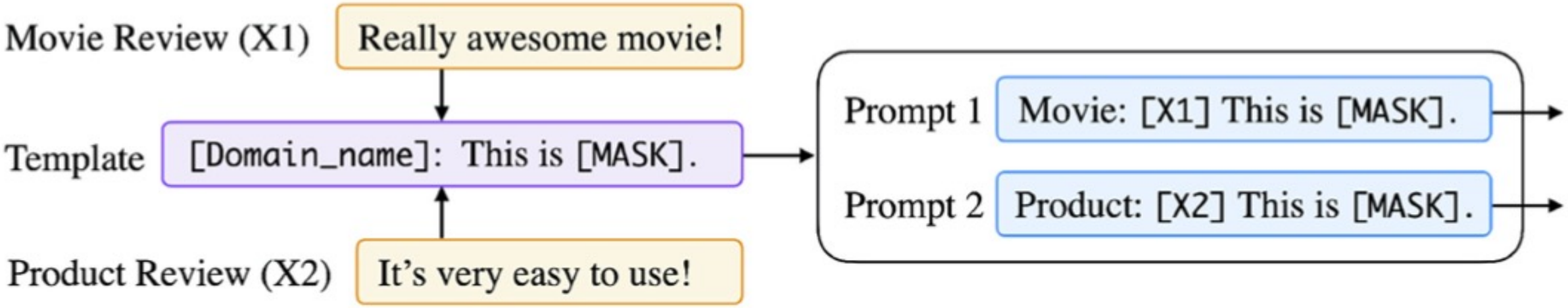
Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

Characteristics of Different Tuning Strategies

Strategy	LM Params	Prompt Params		Example
		Additional	Tuned	
Promptless Fine-tuning	Tuned	–		ELMo [97], BERT [20], BART [69]
Tuning-free Prompting	Frozen	✗	✗	GPT-3 [9], AutoPrompt [125], LAMA [100]
Fixed-LM Prompt Tuning	Frozen	✓	Tuned	Prefix-Tuning [71], Prompt-Tuning [67]
Fixed-prompt LM Tuning	Tuned	✗	✗	PET-TC [117], PET-Gen [118], LM-BFF [32]
Prompt+LM Fine-tuning	Tuned	✓	Tuned	PADA [5], P-Tuning [77], PTR [41]

Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

Multi-prompt Learning for Multi-task, Multi-domain, or Multi-lingual Learning



Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

GPT Prompt Engineering for Question Answering

- **Find the answer to the question from the given context.**
- **When the question cannot be answered with the given context, say "unanswerable".**
- **Just say the answer without repeating the question.**
- **Context: {context}**
- **Question:{question}**
- **Answer:**

Prompts and QA Inference For FLAN T5 Question Answering

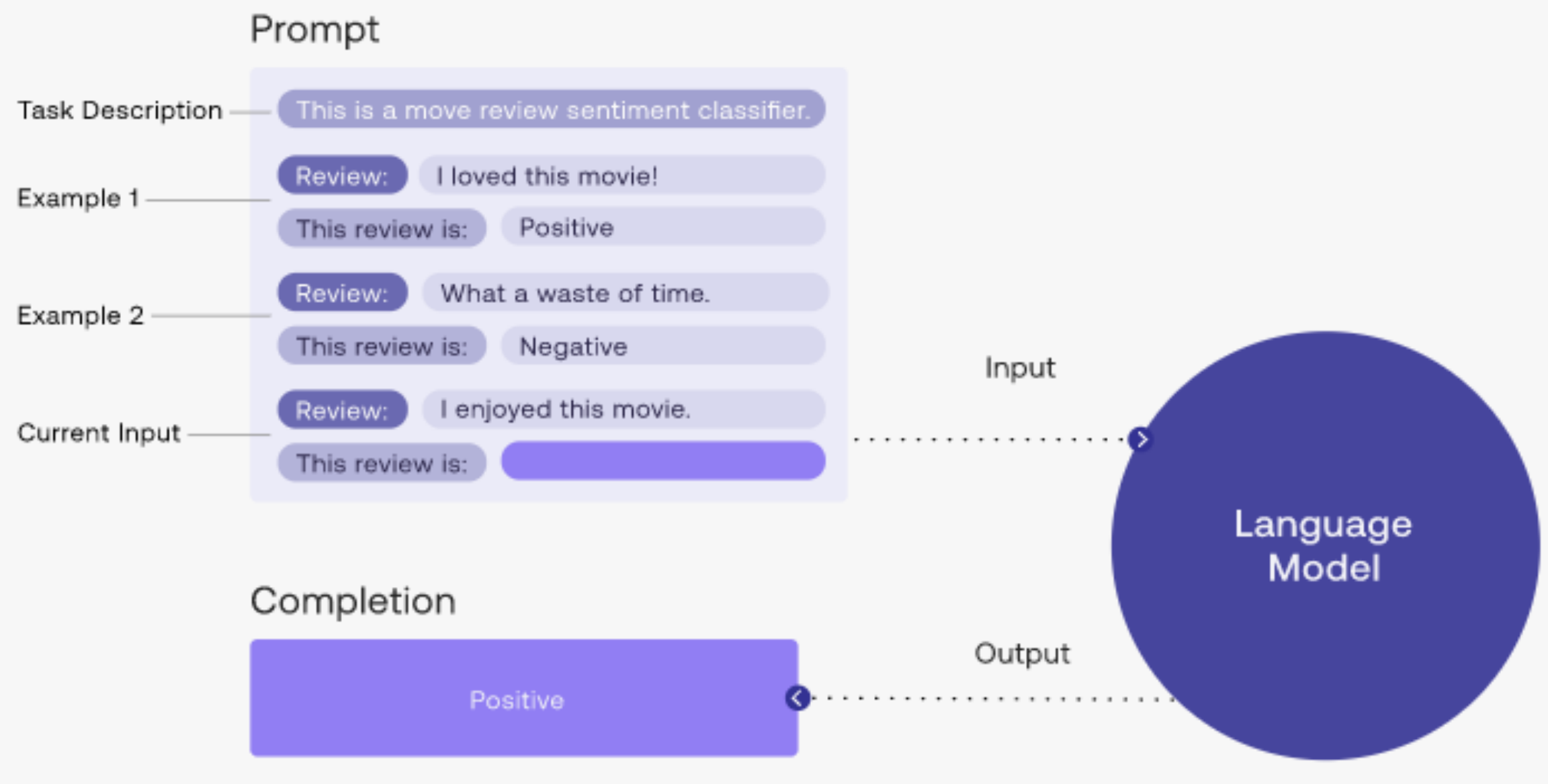
- **Prompts and QA Inference For FLAN T5, we follow [41] and use the following prompt:**
- **Context: {context}\nQuestion: {question}\nAnswer:**

- **Context: {context}**
- **Question: {question}**
- **Answer:**

Prompt Engineering

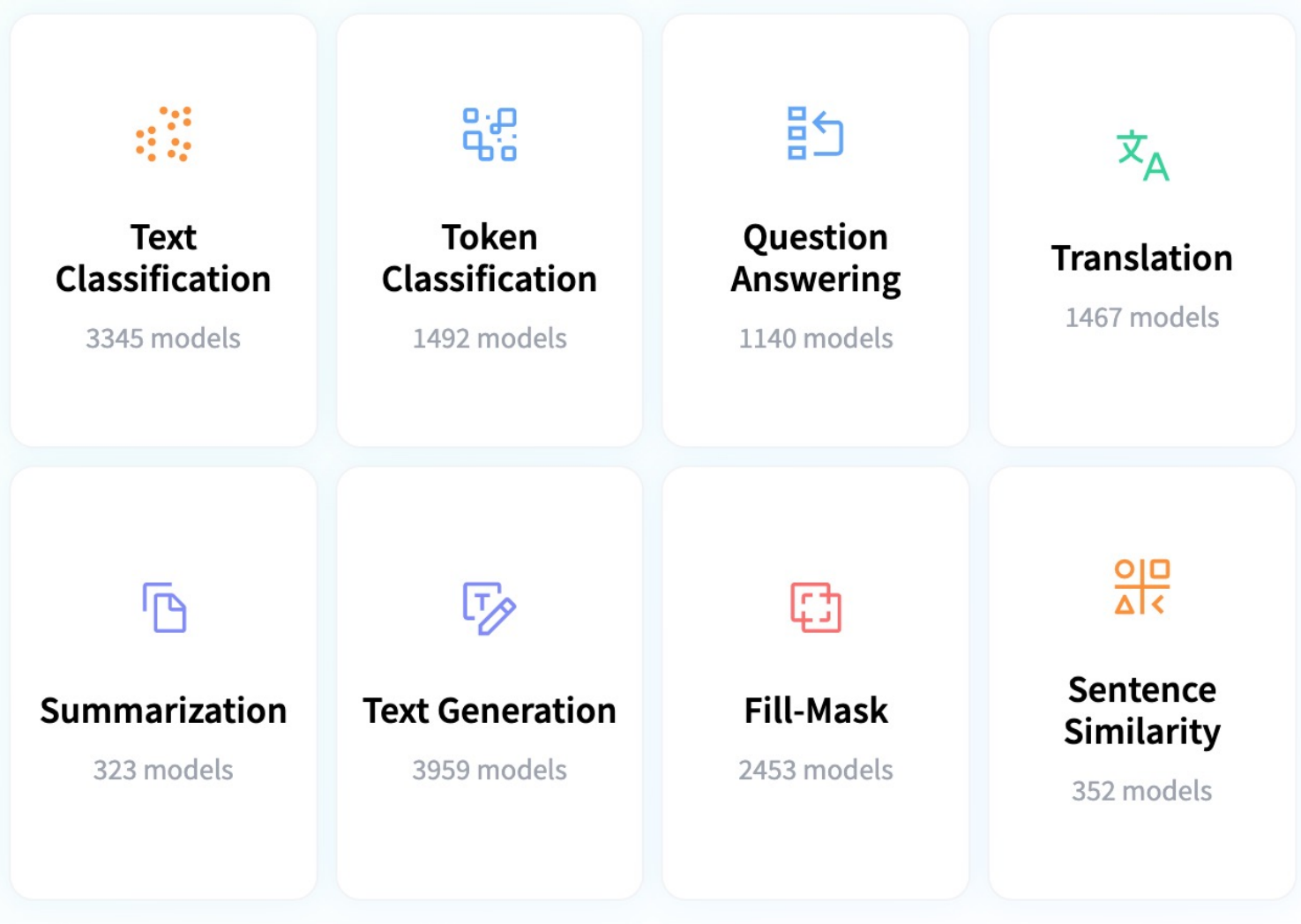
- **Prompts For FLAN models**
  - Longpre, S., Hou, L., Vu, T., Webson, A., Chung, H. W., Tay, Y., ... & Roberts, A. (2023). The flan collection: Designing data and methods for effective instruction tuning. *arXiv preprint arXiv:2301.13688*.
- **MNLI, NLI-FEVER, VitaminC:**
  - **"Premise: {premise}\n\nHypothesis: {hypothesis}\n\nDoes the premise entail the hypothesis?\n\nA yes\nB it is not possible to tell\nC no"**
- **ANLI:**
  - **"{context}\n\nBased on the paragraph above can we conclude that\"{hypothesis}\"?\n\nA Yes\nB It's impossible to say\nC No"**
- **SNLI:**
  - **"If \"{premise}\", does this mean that \"{hypothesis}\"?\n\nA yes\nB it is not possible to tell\nC no"**

Prompt Engineering with ChatGPT for NLP



Source: https://www.predera.com/blog/prompt-engineering-for-nlp-tasks

Hugging Face Tasks
Natural Language Processing



https://huggingface.co/tasks

NLP with Transformers Github

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Code Issues Pull requests Actions Projects Wiki Security Insights

main 1 branch 0 tags Go to file Code

lewtun Merge pull request #21 from JingchaoZhang/patch-3 ... ae5b7c1 15 days ago 71 commits

.github/ISSUE_TEMPLATE	Update issue templates	25 days ago
data	Move dataset to data directory	4 months ago
images	Add README	last month
scripts	Update issue templates	25 days ago
.gitignore	Initial commit	4 months ago
01_introduction.ipynb	Remove Colab badges & fastdoc refs	27 days ago
02_classification.ipynb	Merge pull request #8 from nlp-with-transformers/remove-display-df	26 days ago
03_transformer-anatomy.ipynb	[Transformers Anatomy] Remove cells with figure references	22 days ago
04_multilingual-ner.ipynb	Merge pull request #8 from nlp-with-transformers/remove-display-df	26 days ago
05_text-generation.ipynb	Merge pull request #8 from nlp-with-transformers/remove-display-df	26 days ago

About

Jupyter notebooks for the Natural Language Processing with Transformers book

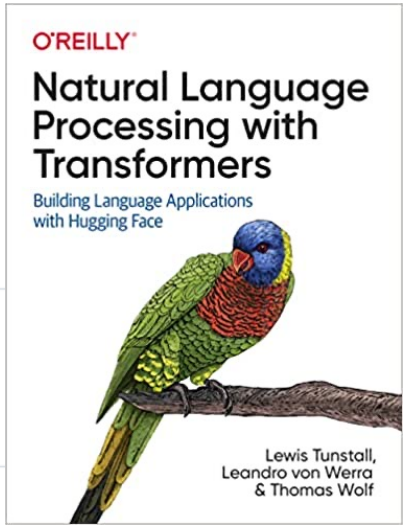
transformersbook.com/

Readme
Apache-2.0 License
1.1k stars
33 watching
170 forks

Releases

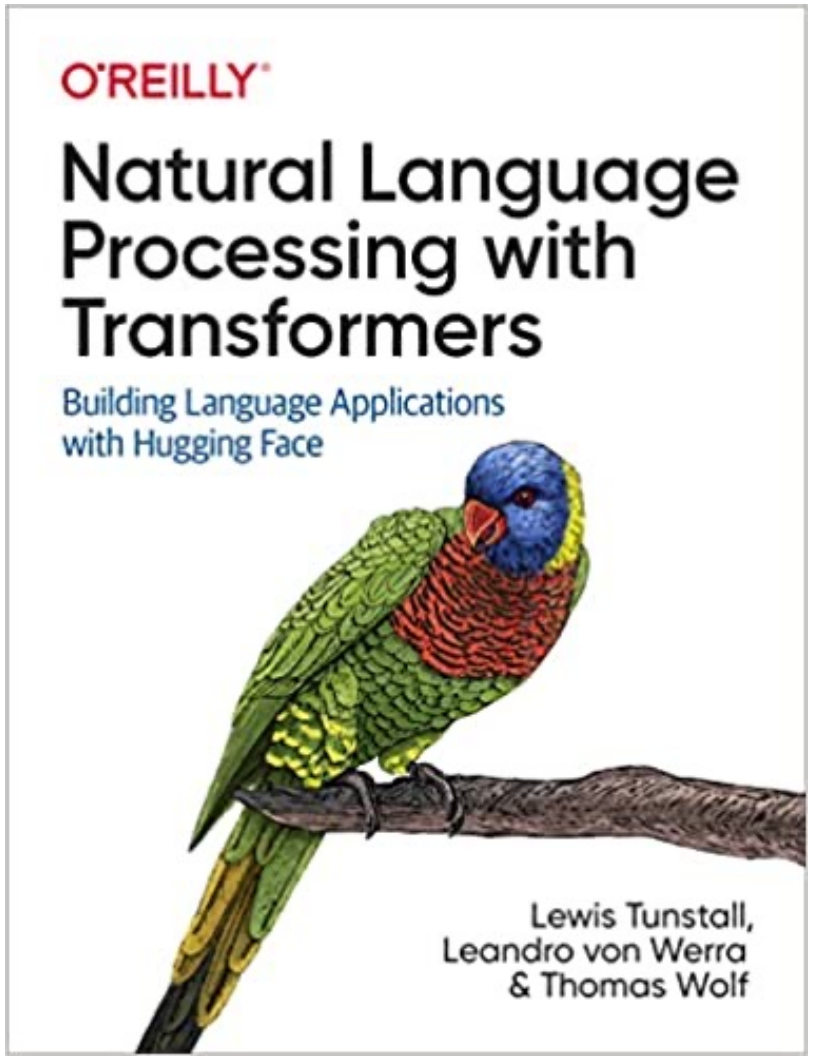
No releases published

Packages



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

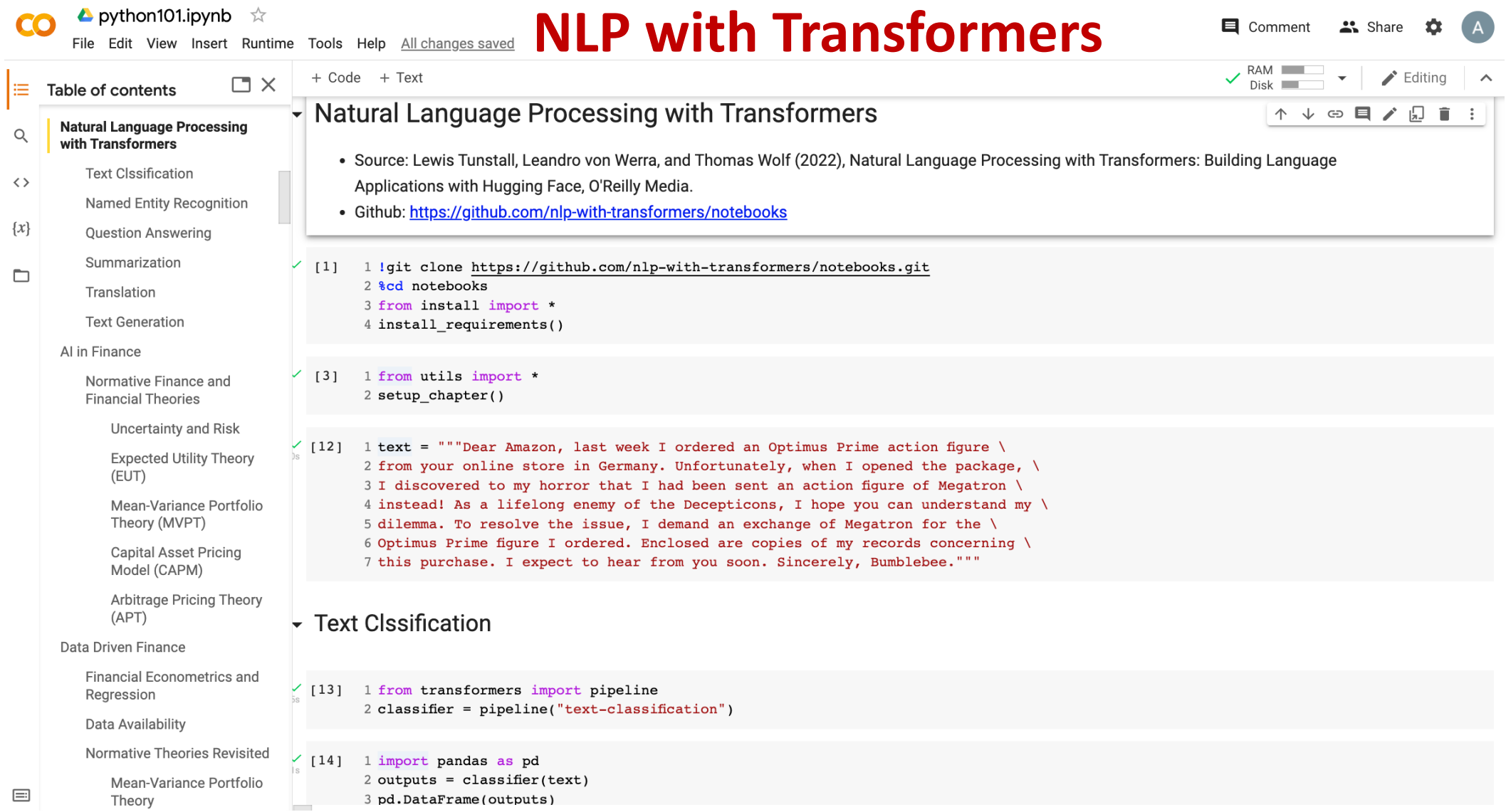
Nowadays, the GPUs on Colab tend to be K80s (which have limited memory), so we recommend using Kaggle, Gradient, or SageMaker Studio Lab. These platforms tend to provide more performant GPUs like P100s, all for free!

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

Python in Google Colab (Python101)

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

NLP with Transformers



https://tinyurl.com/aintpupython101

Python in Google Colab (Python101)

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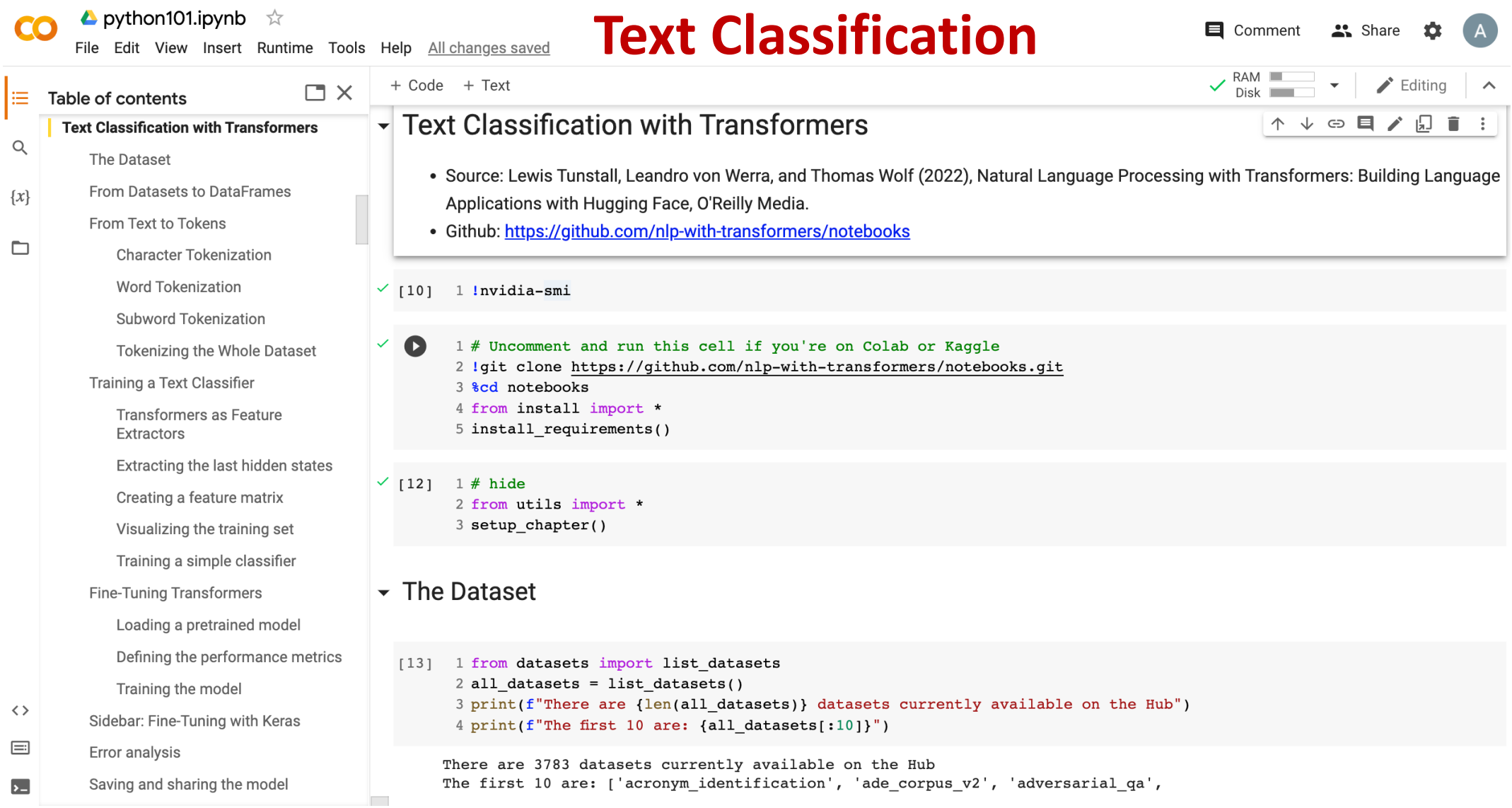

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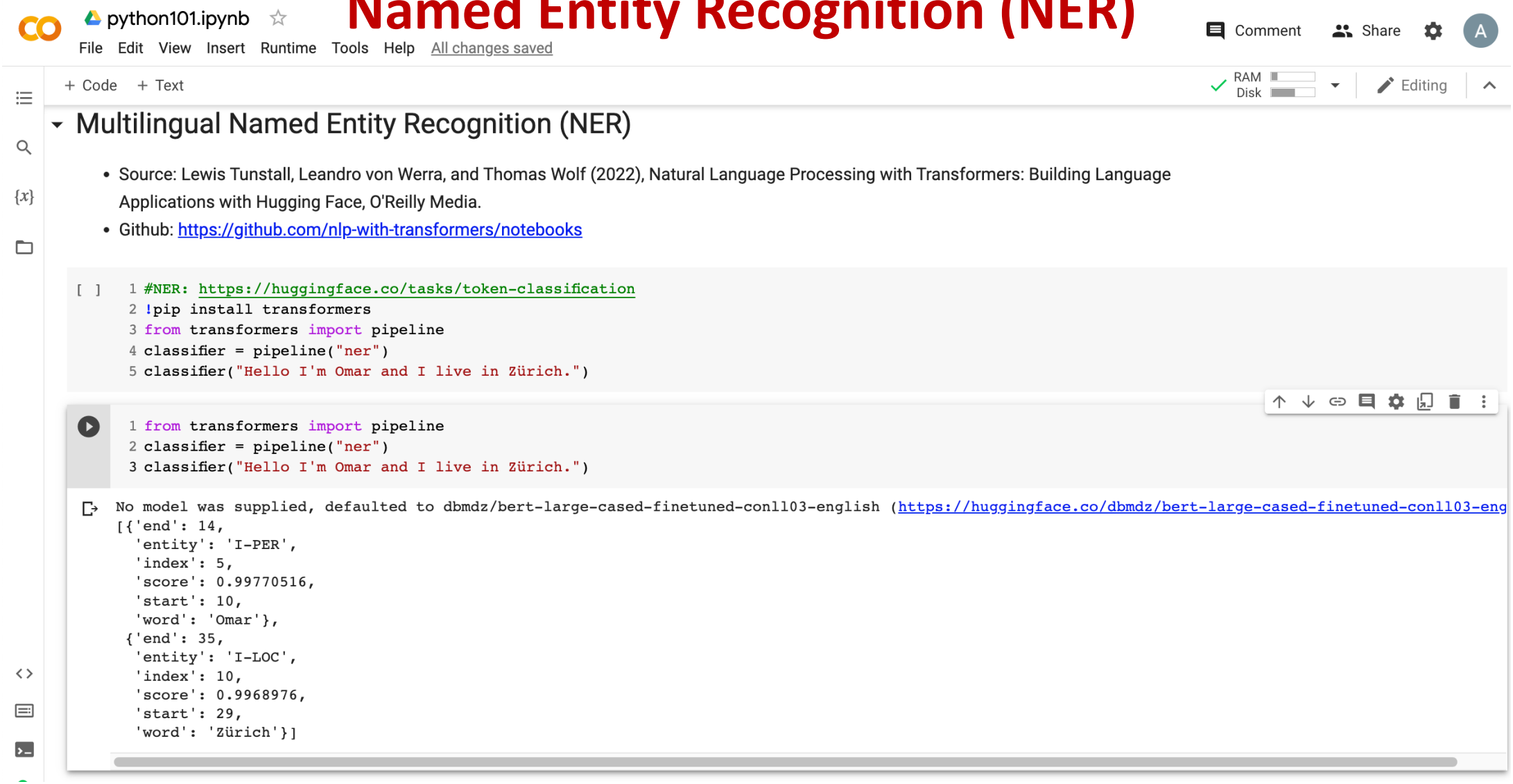
Named Entity Recognition (NER)



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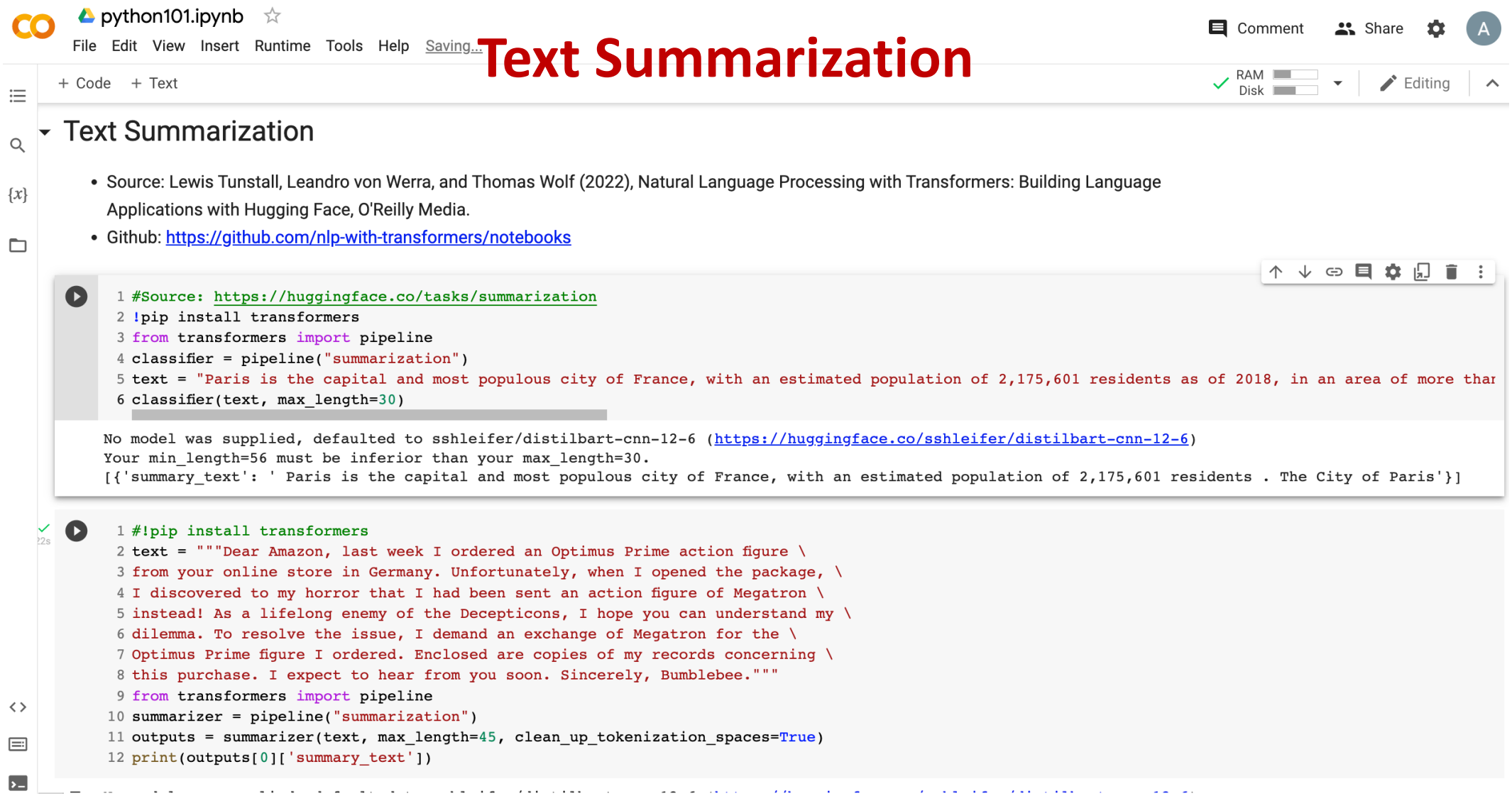

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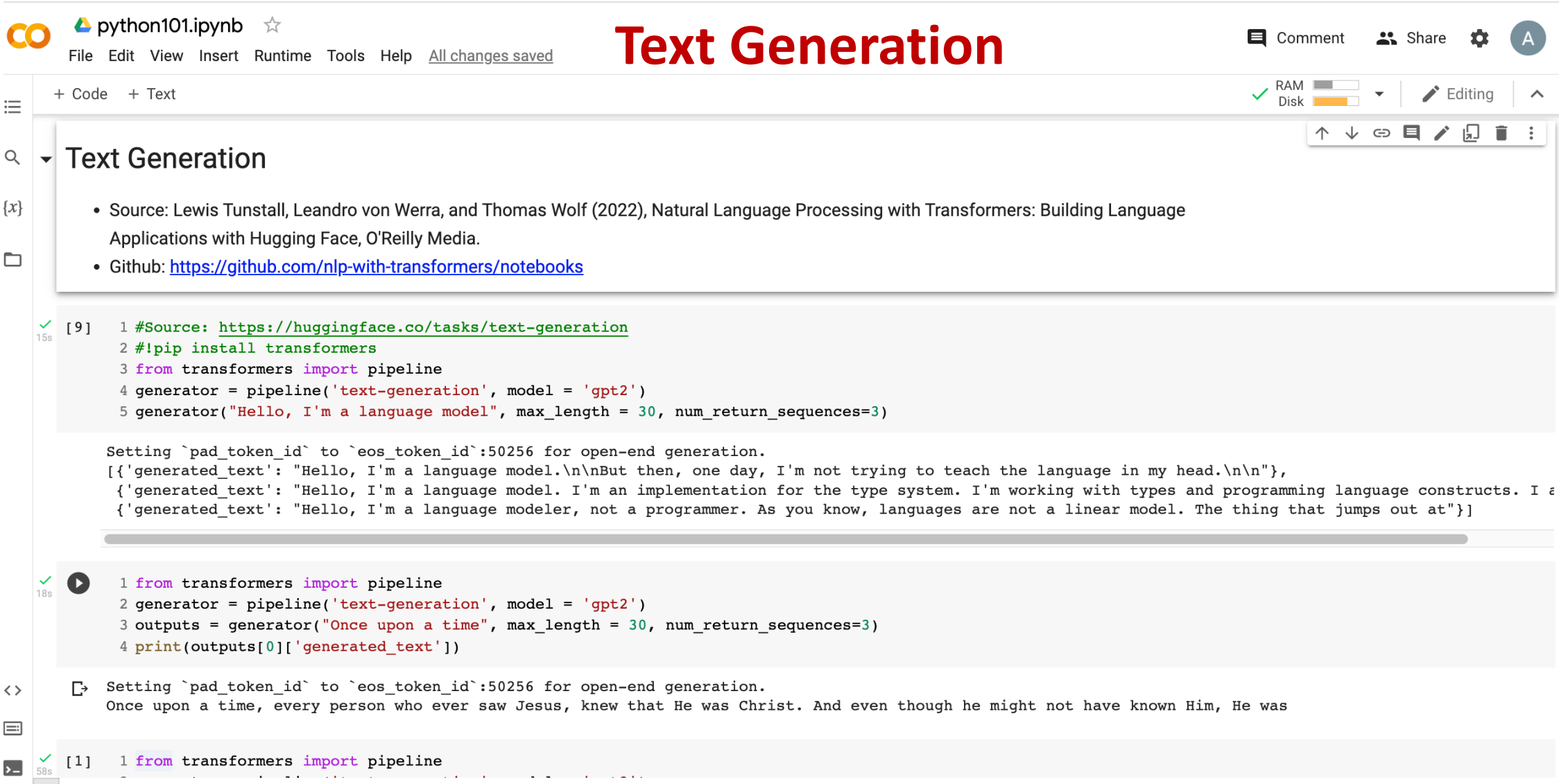

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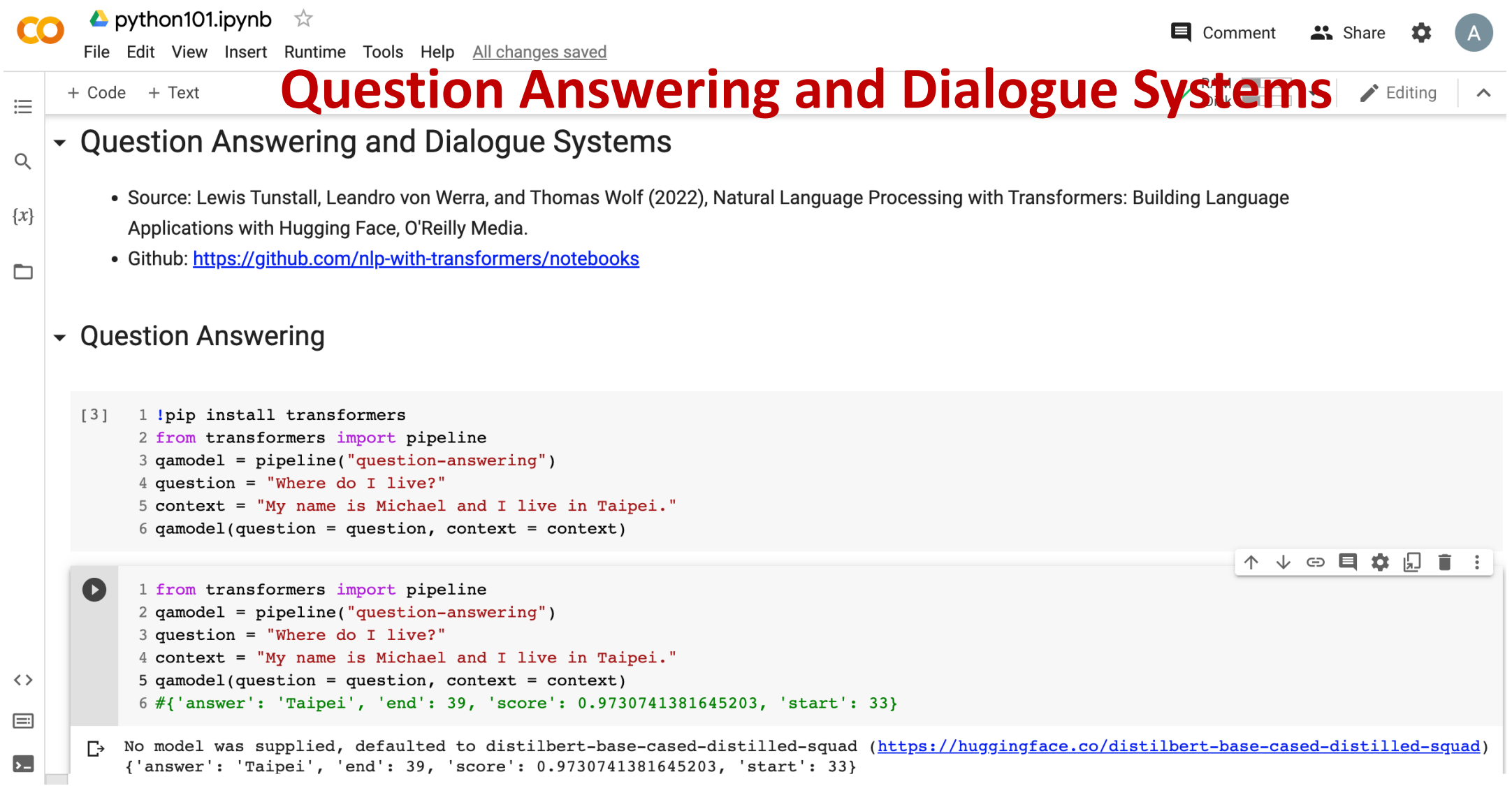

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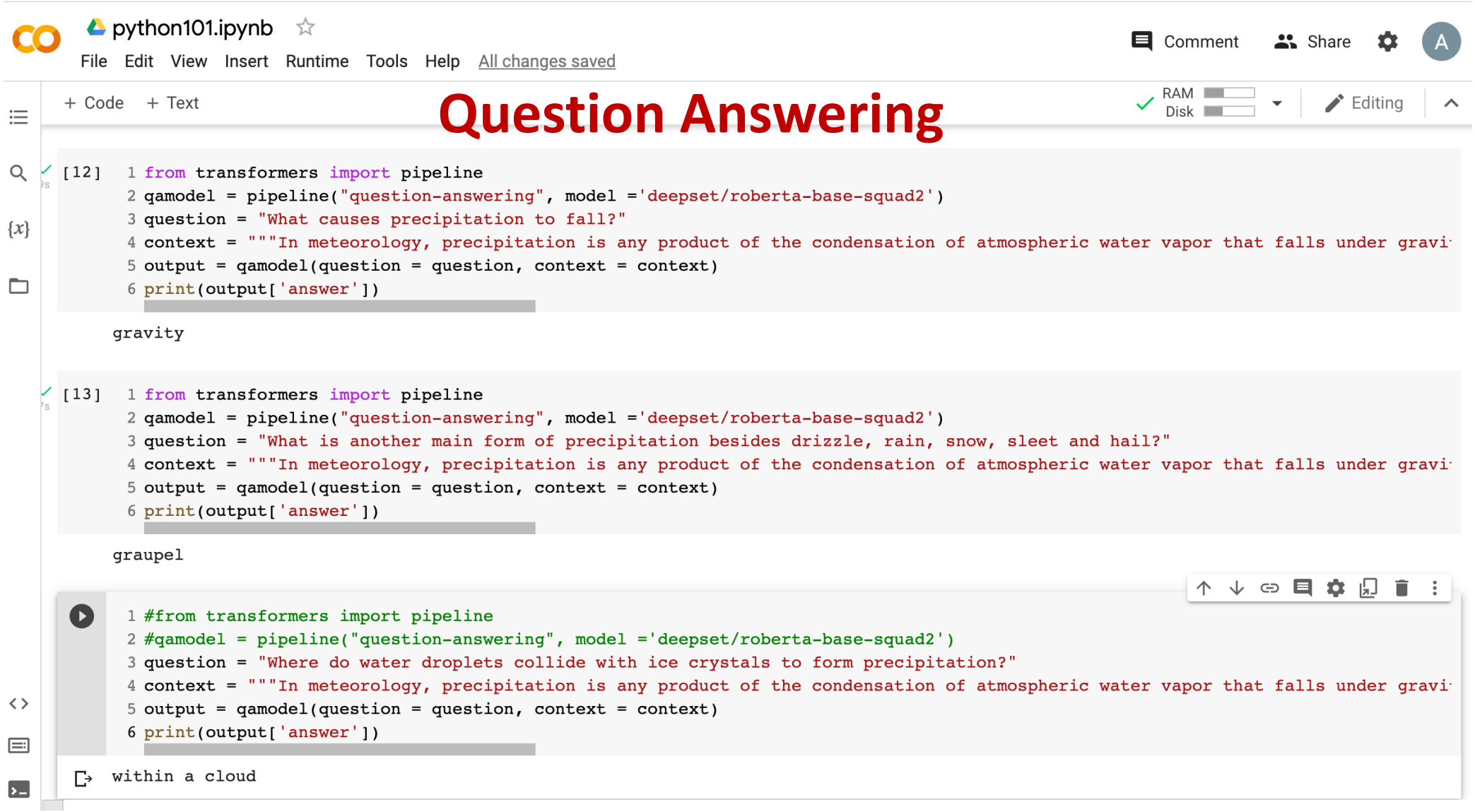

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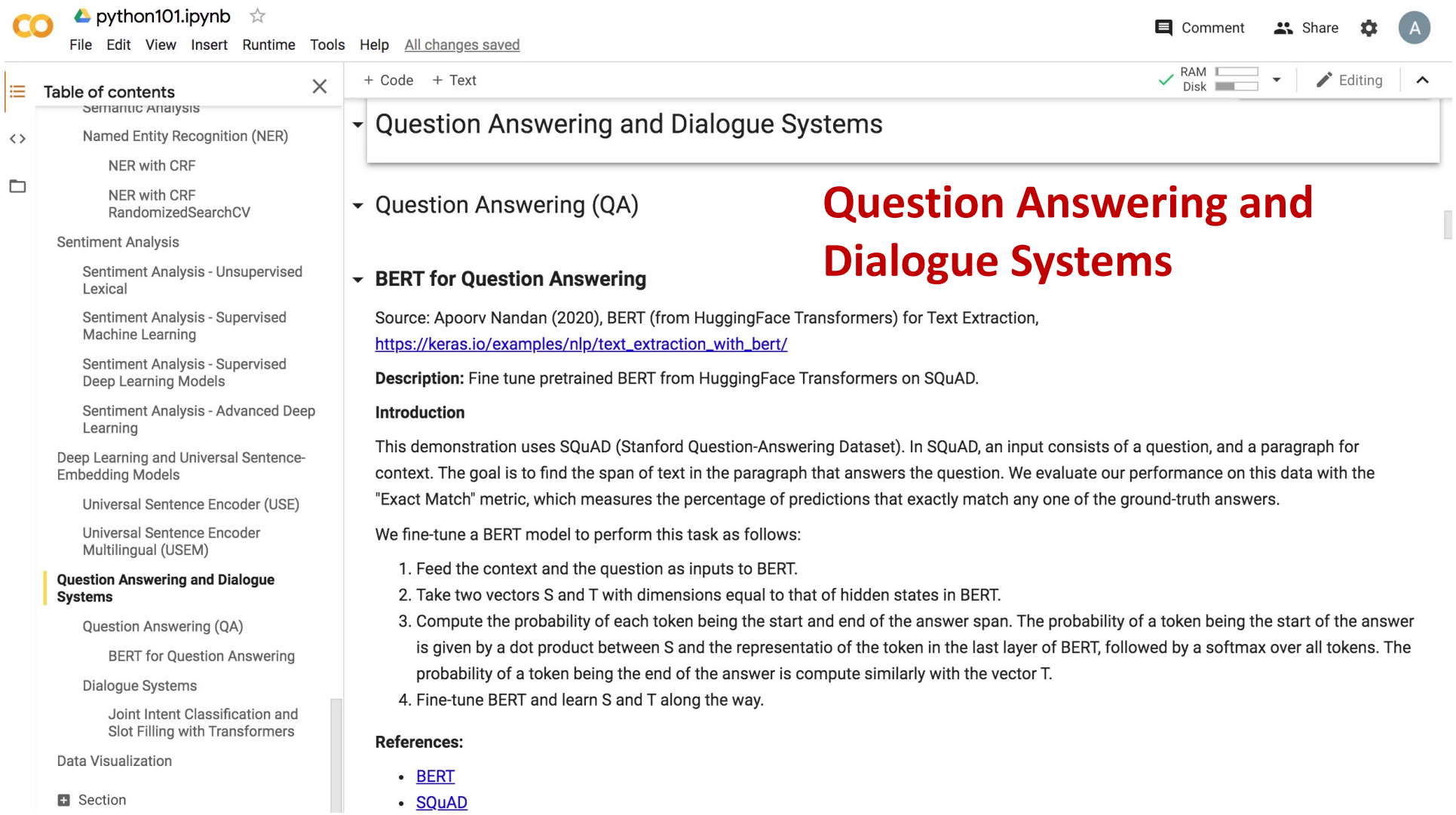

Question Answering and Dialogue Systems

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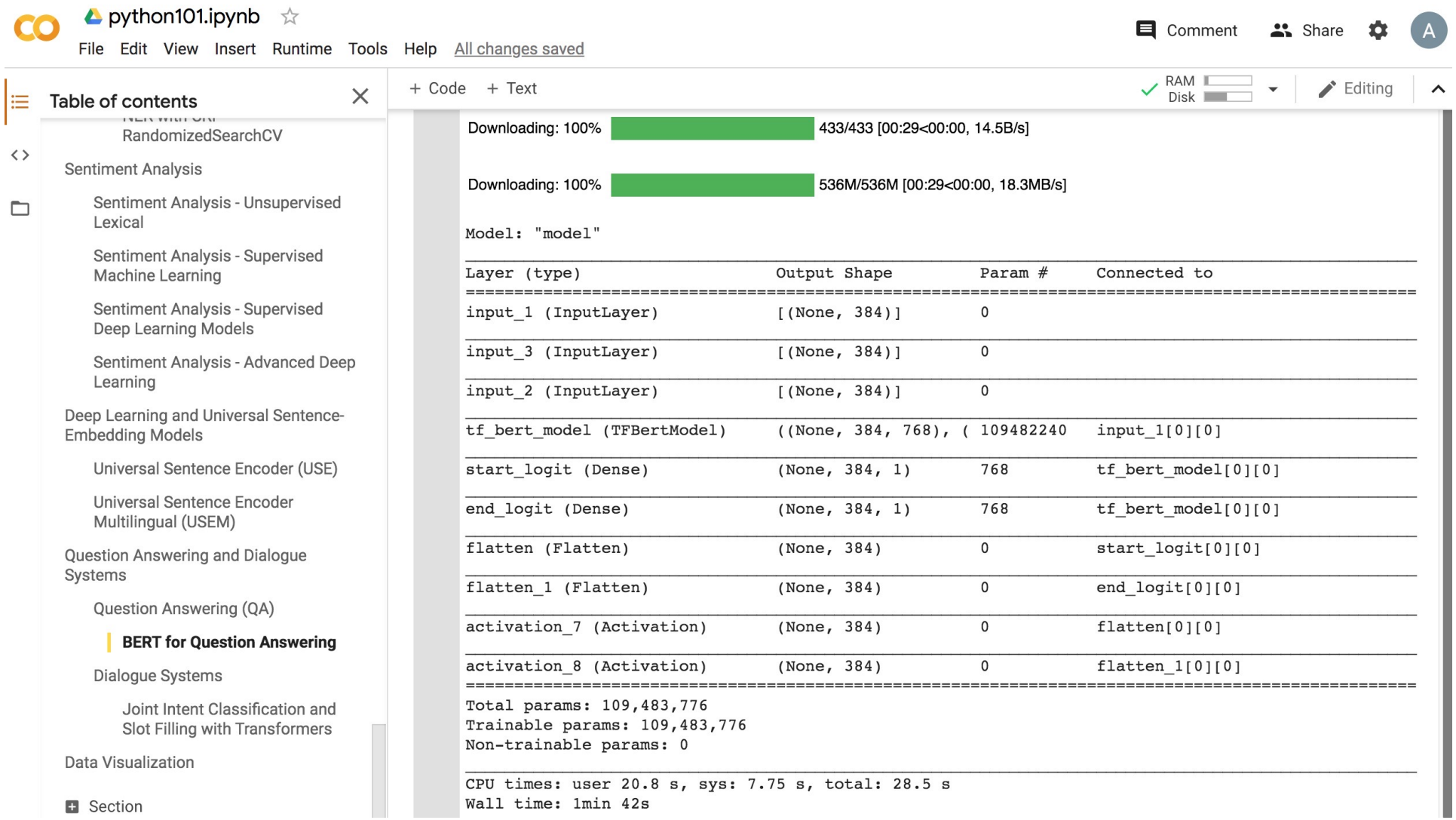

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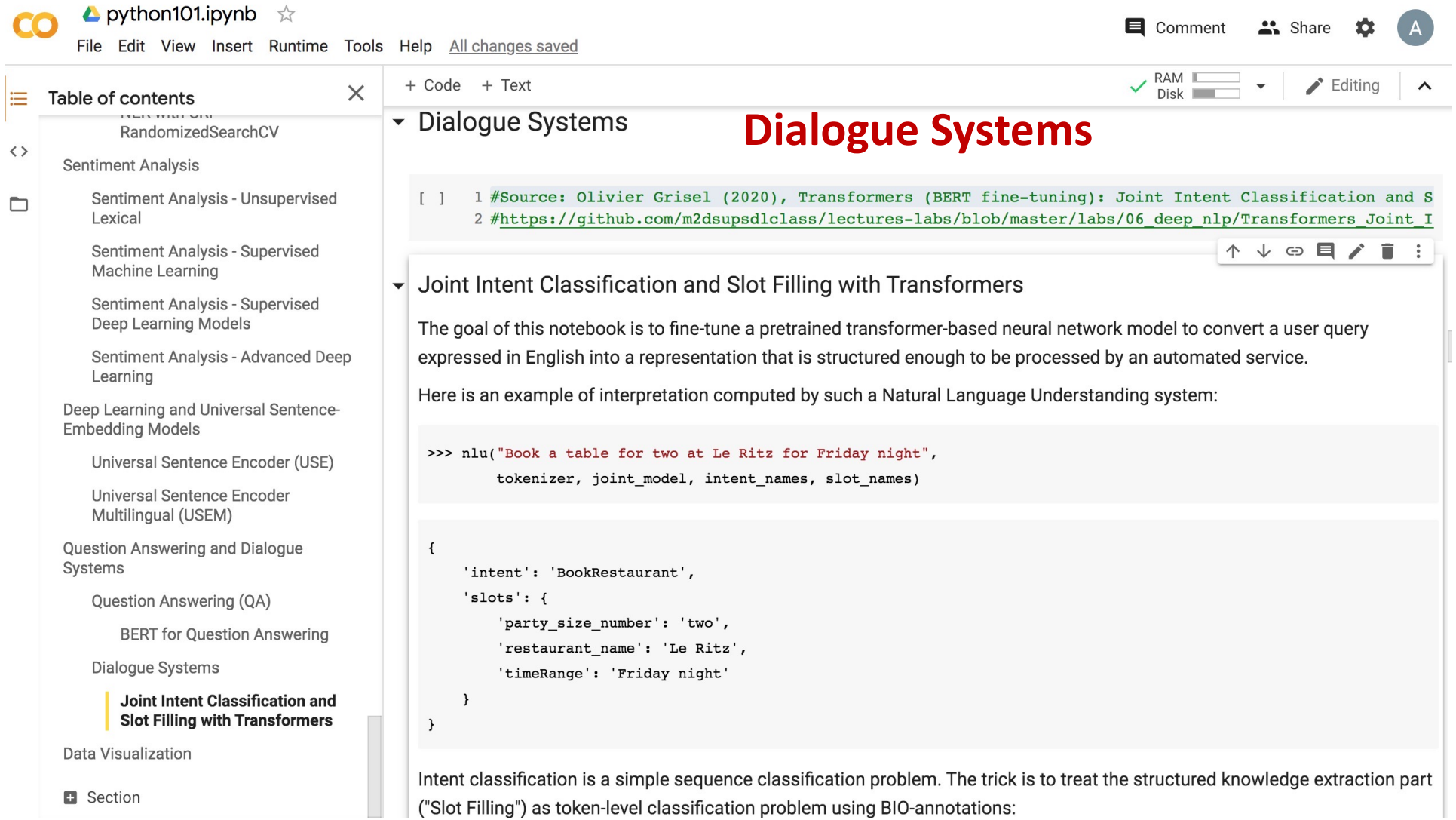

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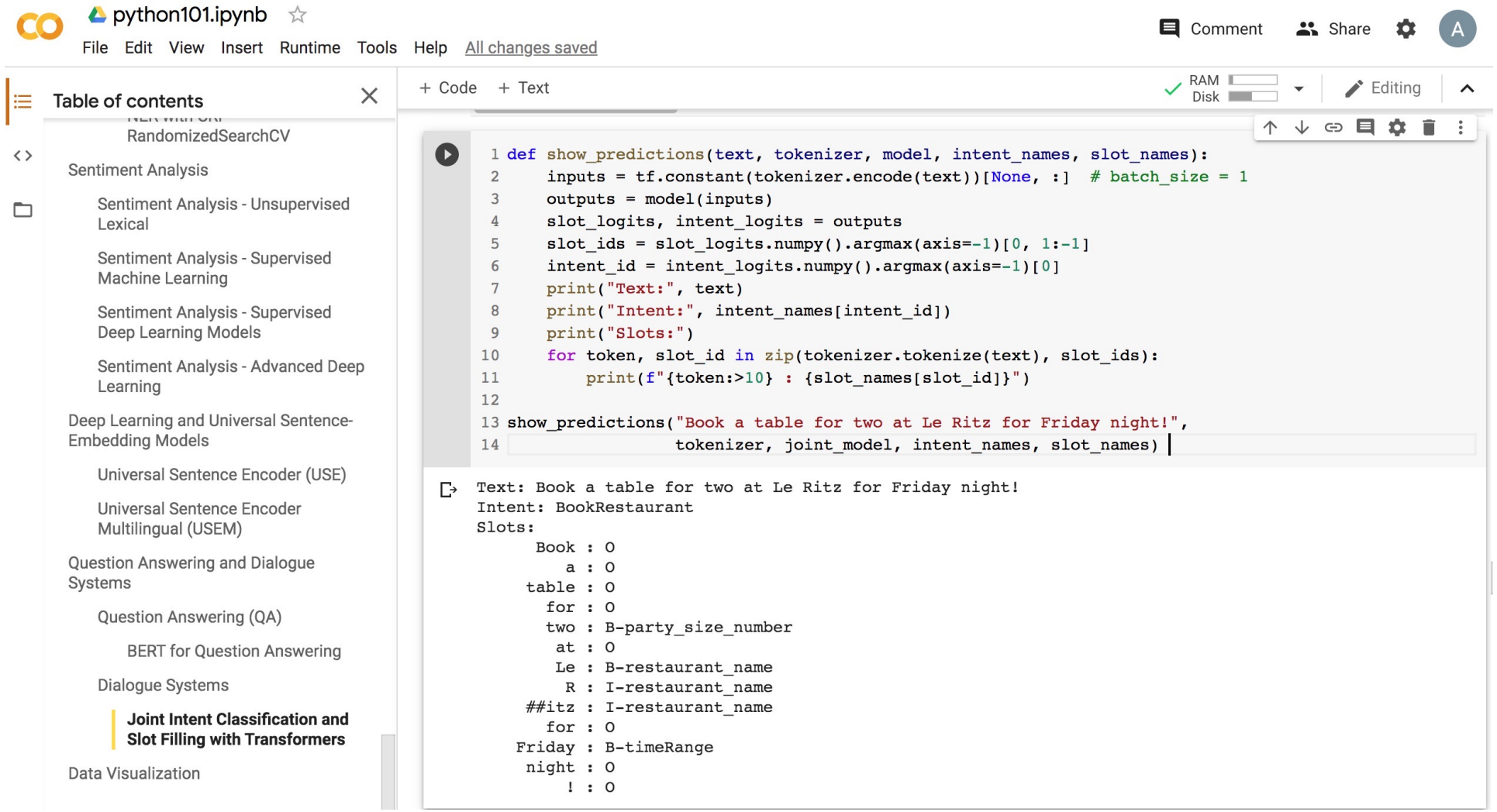

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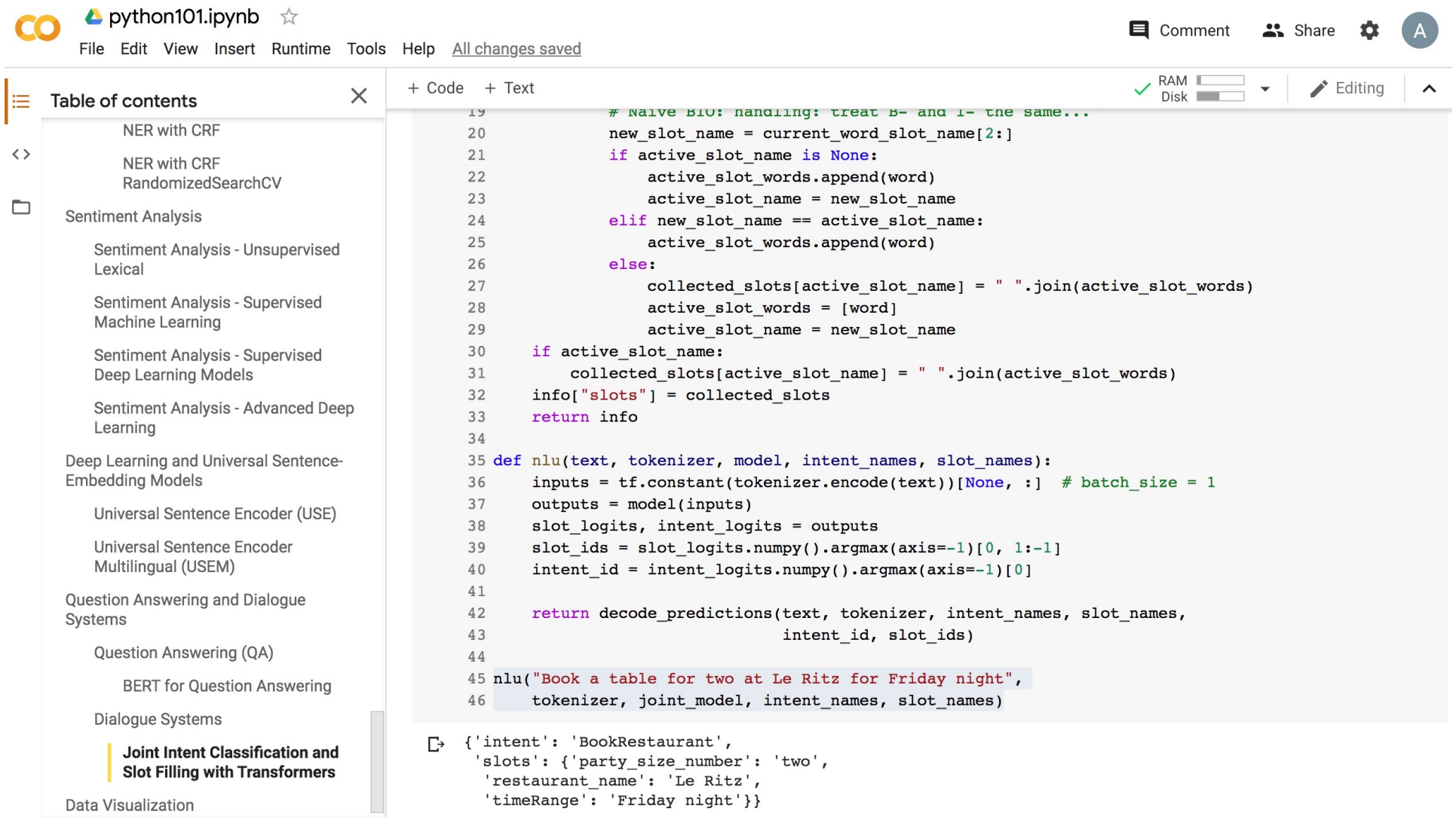

https://tinyurl.com/aintpupython101

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

Named Entity Recognition

```
ner_tagger = pipeline("ner", aggregation_strategy="simple")
outputs = ner_tagger(text)
pd.DataFrame(outputs)
```

	entity_group	score	word	start	end
0	ORG	0.879010	Amazon	5	11
1	MISC	0.990859	Optimus Prime	36	49
2	LOC	0.999755	Germany	90	97
3	MISC	0.556570	Mega	208	212
4	PER	0.590256	##tron	212	216
5	ORG	0.669692	Decept	253	259
6	MISC	0.498349	##icons	259	264
7	MISC	0.775362	Megatron	350	358
8	MISC	0.987854	Optimus Prime	367	380
9	PER	0.812096	Bumblebee	502	511

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

Question Answering

```
reader = pipeline("question-answering")
question = "What does the customer want?"
outputs = reader(question=question, context=text)
pd.DataFrame([outputs])
```

	score	start	end	answer
0	0.631292	335	358	an exchange of Megatron

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

Summarization

```
summarizer = pipeline("summarization")
outputs = summarizer(text, max_length=45, clean_up_tokenization_spaces=True)
print(outputs[0]['summary_text'])
```

```
Bumblebee 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.
```

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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```

```
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```
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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.
```

https://tinyurl.com/aintpupython101

Translation

```
translator = pipeline("translation_en_to_de",
                      model="Helsinki-NLP/opus-mt-en-de")
outputs = translator(text, clean_up_tokenization_spaces=True, min_length=100)
print(outputs[0]['translation_text'])
```

```
Sehr geehrter Amazon, letzte Woche habe ich eine Optimus Prime Action Figur aus
Ihrem Online-Shop in Deutschland bestellt. Leider, als ich das Paket öffnete,
entdeckte ich zu meinem Entsetzen, dass ich stattdessen eine Action Figur von
Megatron geschickt worden war! Als lebenslanger Feind der Decepticons, Ich
hoffe, Sie können mein Dilemma verstehen. Um das Problem zu lösen, Ich fordere
einen Austausch von Megatron für die Optimus Prime Figur habe ich bestellt.
Anbei sind Kopien meiner Aufzeichnungen über diesen Kauf. Ich erwarte, bald von
Ihnen zu hören. Aufrichtig, 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

Text Generation

```
from transformers import set_seed
set_seed(42) # Set the seed to get reproducible results
```

```
generator = pipeline("text-generation")
response = "Dear Bumblebee, I am sorry to hear that your order was mixed up."
prompt = text + "\n\nCustomer service response:\n" + response
outputs = generator(prompt, max_length=200)
print(outputs[0]['generated_text'])
```

```
Customer service response:
Dear Bumblebee, I am sorry to hear that your order was mixed up. The
order was completely mislabeled, which is very common in our online
store, but I can appreciate it because it was my understanding from this
site and our customer service of the previous day that your order was
not made correct in our mind and that we are in a process of resolving
this matter. We can assure you that your order
```

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 Generation

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.

Customer service response:
Dear Bumblebee, I am sorry to hear that your order was mixed up. The order was completely mislabeled, which is very common in our online store, but I can appreciate it because it was my understanding from this site and our customer service of the previous day that your order was not made correct in our mind and that we are in a process of resolving this matter. We can assure you that your order

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

Question Answering

```
!pip install transformers
from transformers import pipeline
qamodel = pipeline("question-answering")
question = "Where do I live?"
context = "My name is Michael and I live in Taipei."
qamodel(question = question, context = context)
```

```
{'answer': 'Taipei', 'end': 39, 'score': 0.9730741381645203, 'start': 33}
```

Question Answering

```
from transformers import pipeline
qamodel = pipeline("question-answering", model ='deepset/roberta-base-squad2')
question = "Where do I live?"
context = "My name is Michael and I live in Taipei."
output = qamodel(question = question, context = context)
print(output['answer'])
```

```
Taipei
```

https://tinyurl.com/aintpupython101

Text Generation with LLM (zephyr-7b-beta)

```
# Install transformers from source - only needed for versions <= v4.34
!pip install git+https://github.com/huggingface/transformers.git
!pip install accelerate
```

https://huggingface.co/HuggingFaceH4/zephyr-7b-beta

Text Generation with LLM (zephyr-7b-beta)

```
import torch
from transformers import pipeline

pipe = pipeline("text-generation",
model="HuggingFaceH4/zephyr-7b-beta",
torch_dtype=torch.bfloat16,
device_map="auto")
```

https://huggingface.co/HuggingFaceH4/zephyr-7b-beta

Text Generation with LLM (zephyr-7b-beta)

```
# We use the tokenizer's chat template to format each message - see
https://huggingface.co/docs/transformers/main/en/chat_templating
messages = [
            {
            "role": "system",
            "content": "You are a friendly chatbot who always responds in the style of a pirate",
            },
            {"role": "user", "content": "How many helicopters can a human eat in one sitting?"},
            ]
prompt = pipe.tokenizer.apply_chat_template(messages,
tokenize=False, add_generation_prompt=True)

outputs = pipe(prompt, max_new_tokens=256,
do_sample=True, temperature=0.7, top_k=50, top_p=0.95)
print(outputs[0]["generated_text"])
```

https://huggingface.co/HuggingFaceH4/zephyr-7b-beta

Text Generation with LLM (zephyr-7b-beta)

```
import torch
from transformers import pipeline

pipe = pipeline("text-generation", model="HuggingFaceH4/zephyr-7b-beta",
torch_dtype=torch.bfloat16, device_map="auto")

# We use the tokenizer's chat template to format each message - see
https://huggingface.co/docs/transformers/main/en/chat_templating
messages = [
            {
            "role": "system",
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add_generation_prompt=True)
outputs = pipe(prompt, max_new_tokens=256, do_sample=True, temperature=0.7,
top_k=50, top_p=0.95)
print(outputs[0]["generated_text"])
```

https://huggingface.co/HuggingFaceH4/zephyr-7b-beta

Summary

- Deep Learning
  - Generative AI
    - Pre-train, Prompt, and Predict (Prompting)
  - Transfer Learning
    - Pre-training, Fine-Tuning (FT)
- Few-Shot Learning (FSL)
  - Meta Learning: Learn to Learn
- One-Shot Learning (1SL)
- Zero-Shot Learning (0SL)(ZSL)

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