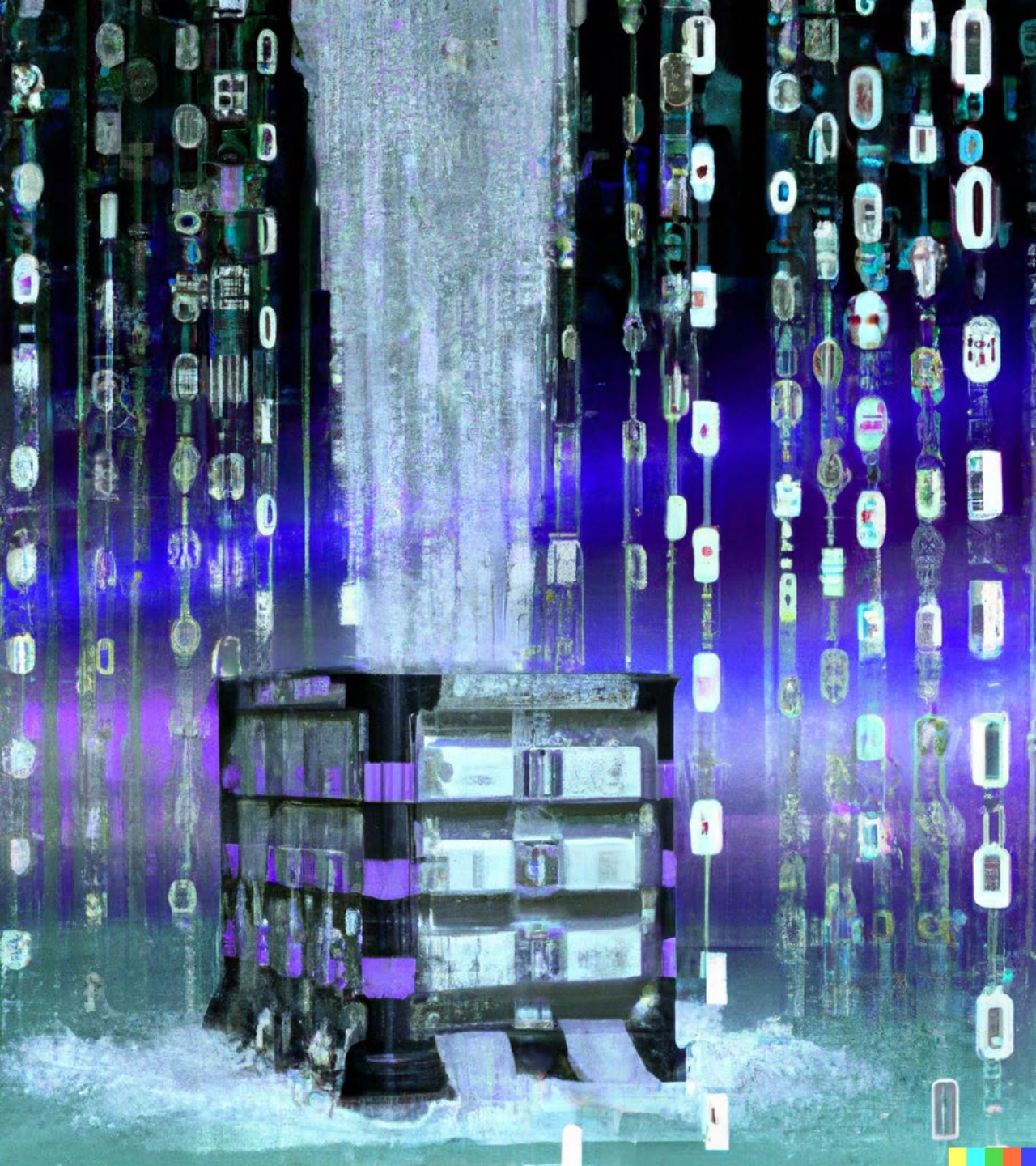




Transformers in Language and Vision

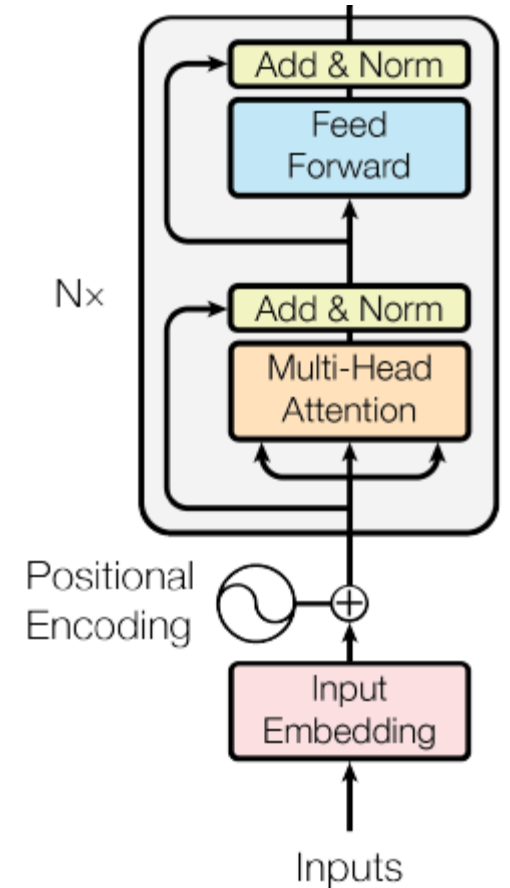
Applied Machine Learning
Derek Hoiem

Self-attention, in simple words

1. Project the input token values into query, key, and value vectors using (linear) weight matrices
2. Using keys and queries, compare each input token to all the tokens (including itself) to get a similarity score
3. Replace the input values with a similarity-weighted sum of all values

Transformers: general data processors

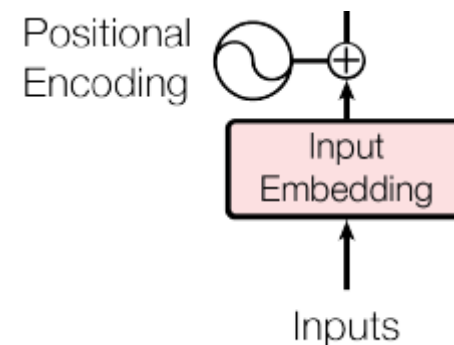
- **Input tokens can represent anything:** image patches, text tokens, audio, controls, etc.
- Invariant to order of tokens: **add positional embedding** to distinguish pos/type of input
- **Transformer block:**
 - Apply multi-head attention
 - Apply 2-layer MLP with ReLU to each token separately
 - Residual and layer norm (over all tokens) after each
- Can stack any number of transformer blocks



Positional encodings

- Transformer processing does not depend on position of token
 - This is kind of similar to convolution, as each “patch” or token vector is processed independently, but no overlap between patches
 - But to compare between tokens, relative position may be important
- Sinusoidal encoding (on right) is such that a dot product between encodings corresponds to positional similarity
- Learned or even fixed random encodings also work similarly in practice

$$PE_{(pos, 2i)} = \sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos, 2i+1)} = \cos(pos/10000^{2i/d_{\text{model}}})$$



Remember from last class

Sub-word tokenization based on byte-pair encoding is an effective way to turn natural text into a sequence of integers

Chair is broken →
ch##, ##air, is, brok##, ##en

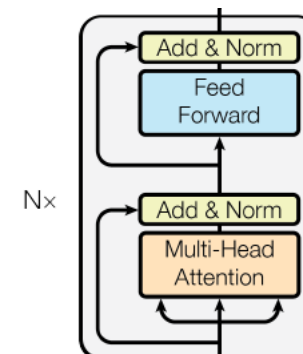
Learned vector embeddings of these integers model the relationships between words

**Paris – France
+ Italy = Rome**

Attention is a general processing mechanism that regresses or clusters values

Input (k,q,v)	iter 1	iter 2	iter 3	iter 4
1.000	1.497	1.818	1.988	2.147
9.000	8.503	8.182	8.012	7.853
8.000	8.128	8.141	8.010	7.853
2.000	1.872	1.859	1.990	2.147

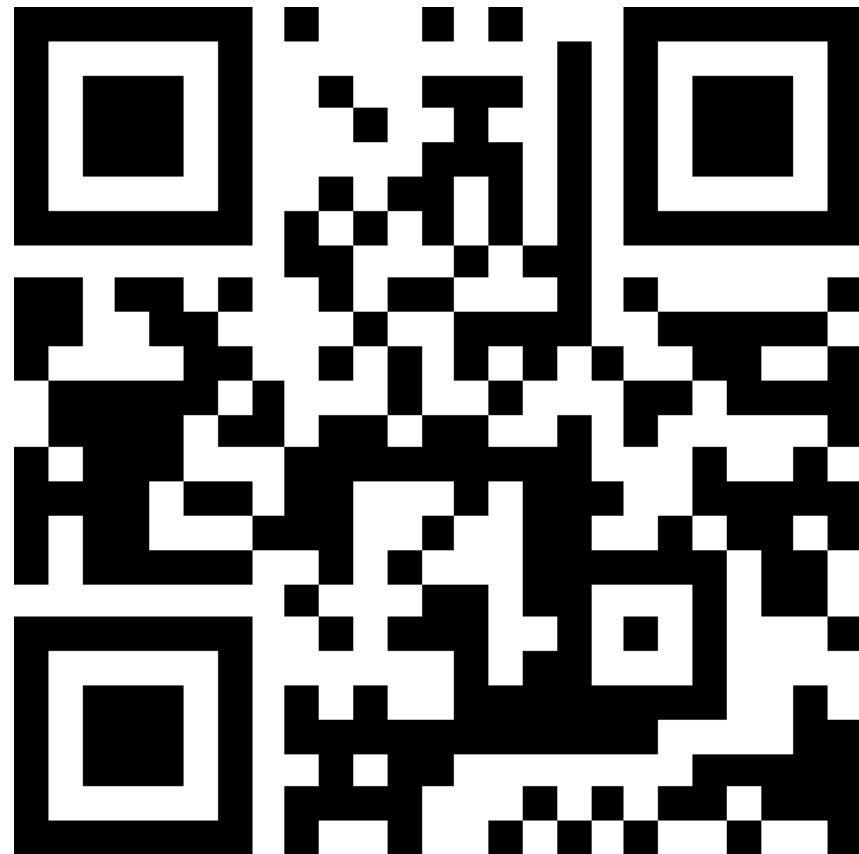
Stacked transformer blocks are a powerful network architecture that alternates attention and MLPs



Further reading: <http://nlp.seas.harvard.edu/annotated-transformer/>

Q1

<https://tinyurl.com/AML441-L19>

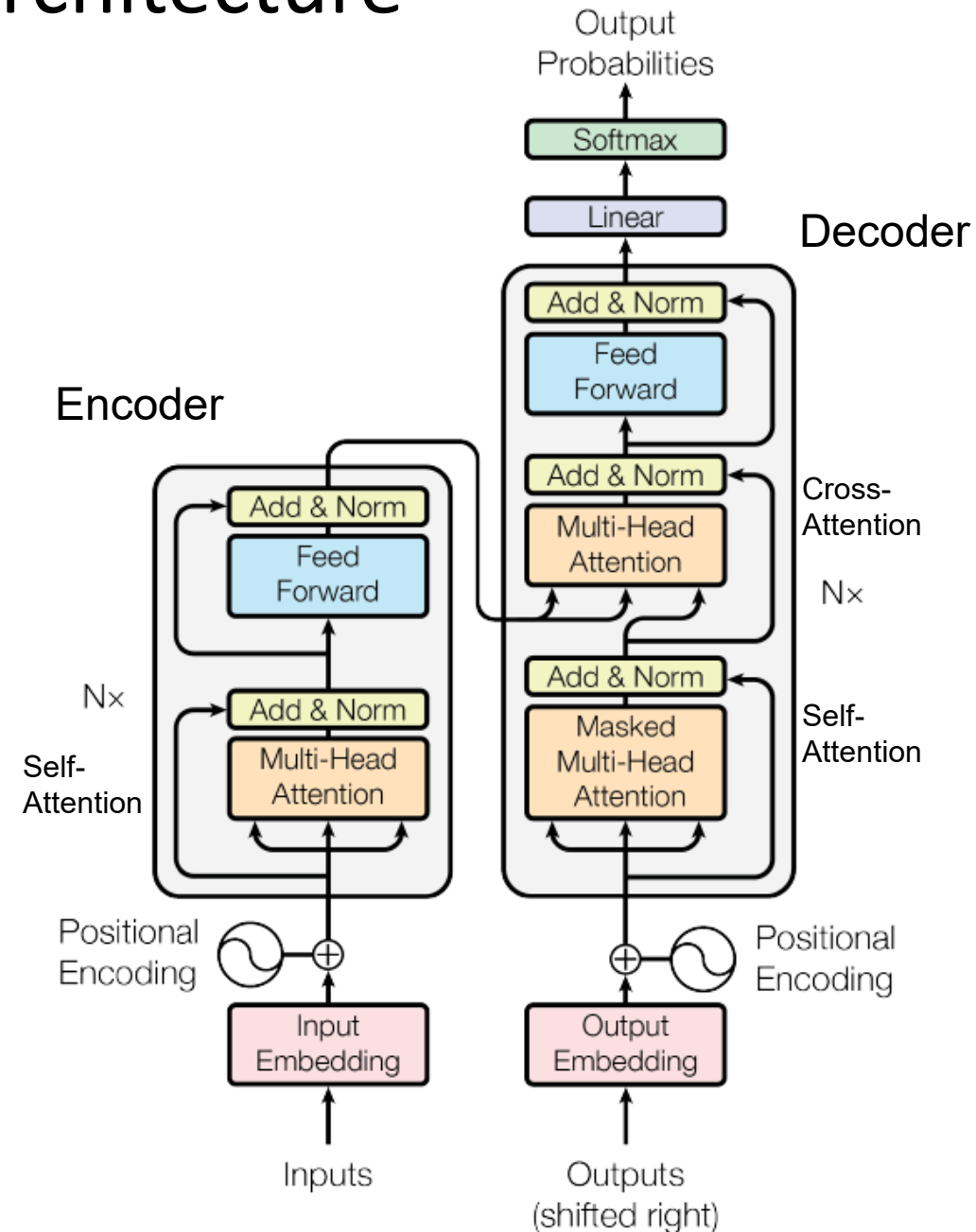


Today's Lecture

- Language Transformer architecture
- BERT: Large Language Model
- ViT (Vision Transformer): Image classification
- CNN vs Transformer comparison
- Unified-IO: Sequence-to-sequence vision-language

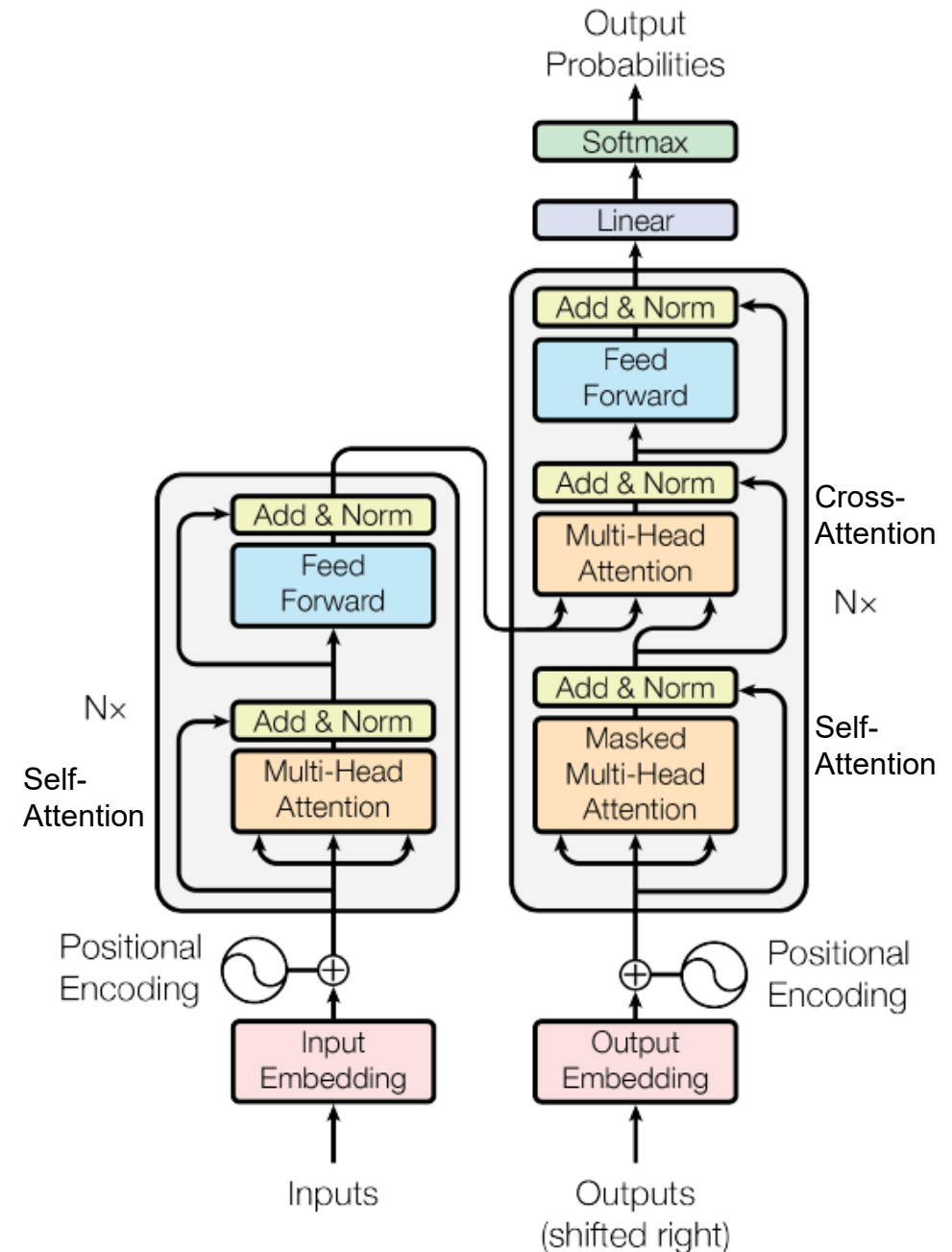
Language Transformer: Complete Architecture

- WordPiece tokens (integers) are mapped to learned 512-d vectors
- Positional encoding added to each vector
- N=6 transformer blocks applied to input
- Until <EOS> is output:
 - Process input + output so far
 - Output most likely word (after more attention blocks and linear model)
- Encoder/decoder architecture for sequence to sequence tasks



Application to Translation

- English-German
 - 4.5M sentence pairs
 - 37K tokens
- English-French
 - 36M sentences
 - 32K tokens
- Base models trained on 8 P100s for 12 hours
- Big models (2x token dim, 3x training steps) trained for 3.5 days
- Adam optimizer: learning rate ramps up for 4K iterations, then down
- Regularization: drop-out, L2 weight, label smoothing

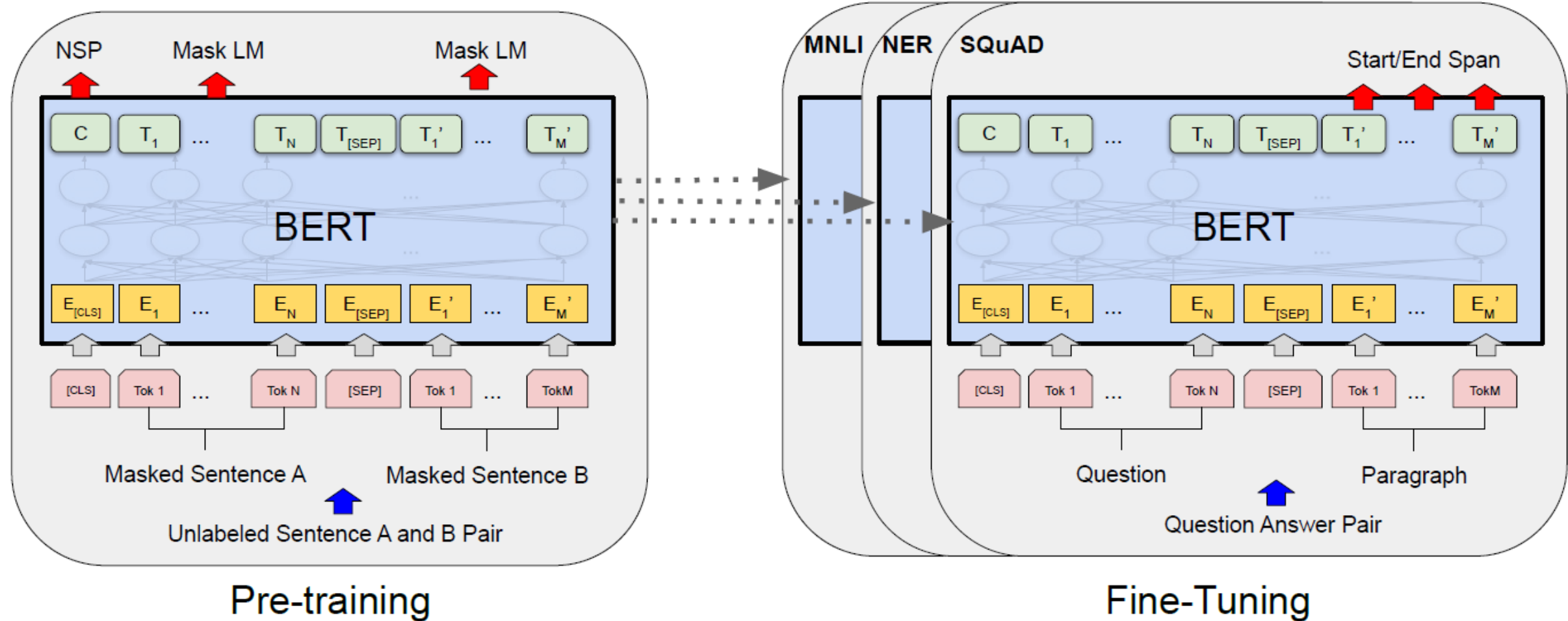


Results

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	41.29	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$3.3 \cdot 10^{18}$	
Transformer (big)	28.4	41.8	$2.3 \cdot 10^{19}$	

BERT (Devlin et al. 2019)



Why is BERT worth knowing?

(100K+ citations)

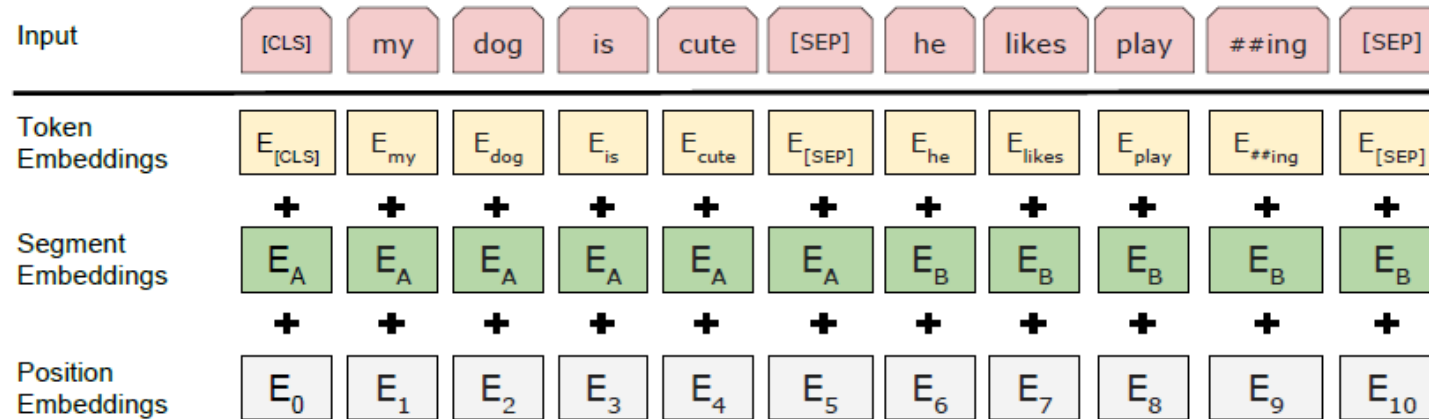
BERT is a significant breakthrough in NLP

- One of the first LLMs
- Transformer-based architecture
- Pre-training on large amounts of text data via masking objective
- Fine-tuned to achieve SotA for many tasks
- Still widely used

Overview of BERT

- Uses standard transformer blocks, encoder only
 - Base: 12 layers, 768-dim, 12 heads; 110M parameters
 - Large: 24 layers, 1024-dim, 16 heads; 340M parameters
- WordPiece: 30K tokens
 - Special [CLS] and [SEP] tokens
 - Positional and sentence embeddings
- Pre-trained with masked language modeling (MLM) and next sentence prediction
- Fine-tuned for other tasks

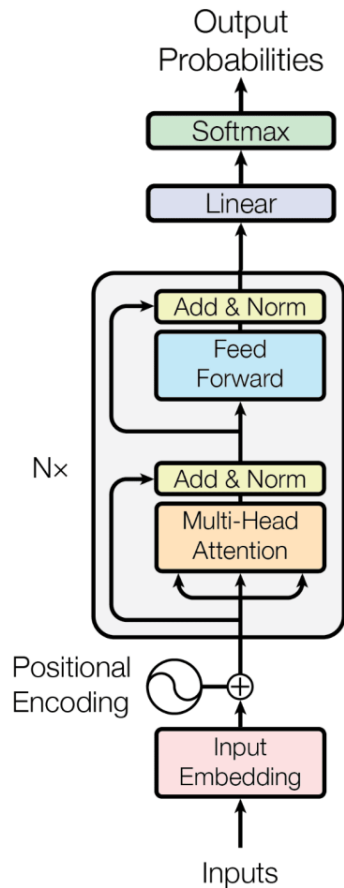
BERT: Input representation



- WordPiece: 30K tokens
 - Special tokens
 - [CLS] at start to encode sentence summary
 - [SEP] to separate sentences or question and answer
 - Positional and sentence embeddings

“Encoder-only” and “Decoder-only” architectures

Encoder-only (e.g. BERT): Each token attends to all input tokens (**bidirectional**). May output a single vector (CLS) or one per token.



Decoder-only (e.g. GPT): Each token attends to only the preceding tokens (**causal**) and outputs a prediction of the next token.

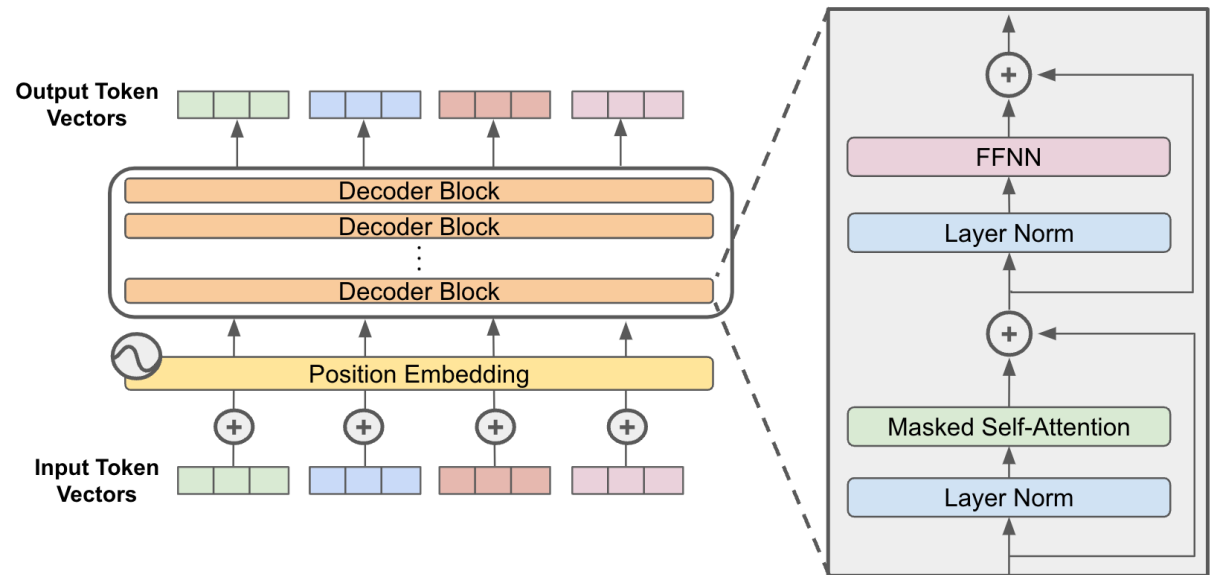
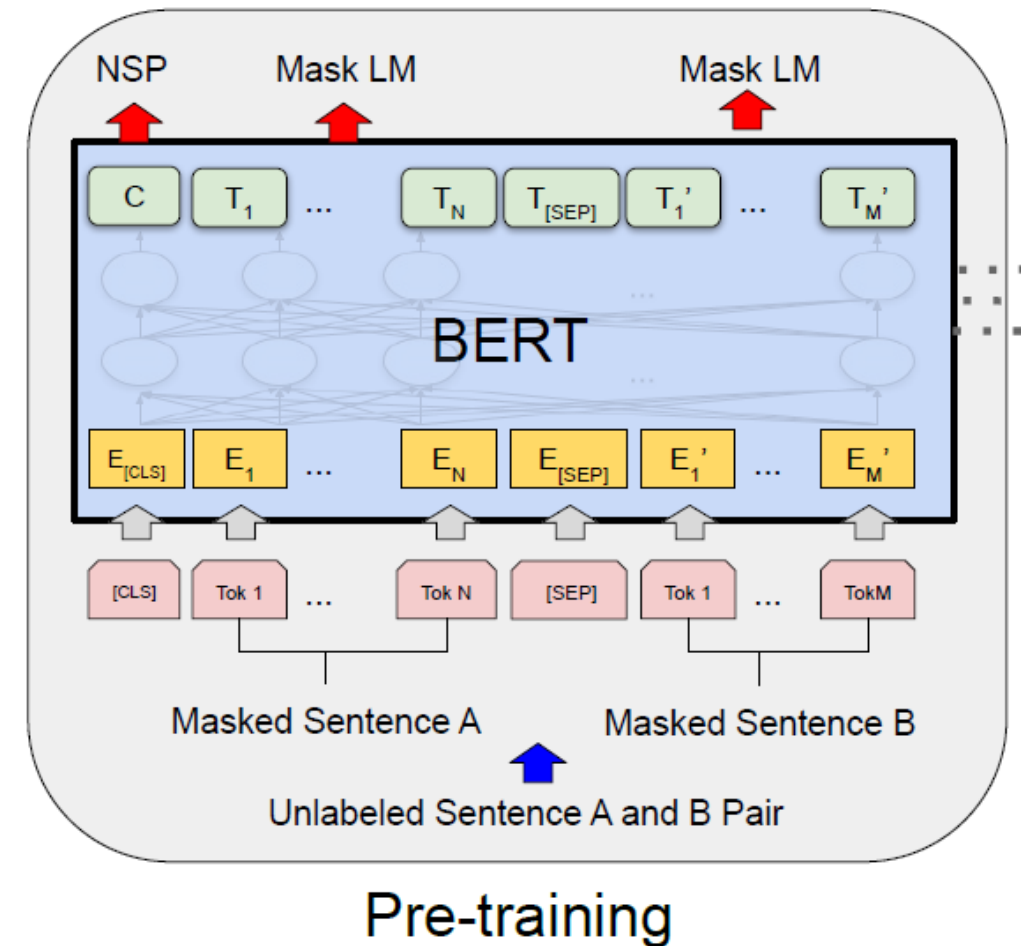


Figure: <https://cameronrwolfe.substack.com/p/decoder-only-transformers-the-workhorse>

Pre-training with masked language modeling (MLM)

- Randomly select 15% of text tokens to be “masked” and predicted by based on surrounding tokens
- Masked tokens are replaced by
 - [MASK] token (80% of the time)
 - Random token (10%)
 - Unchanged token (10%)
- Only masked tokens are predicted

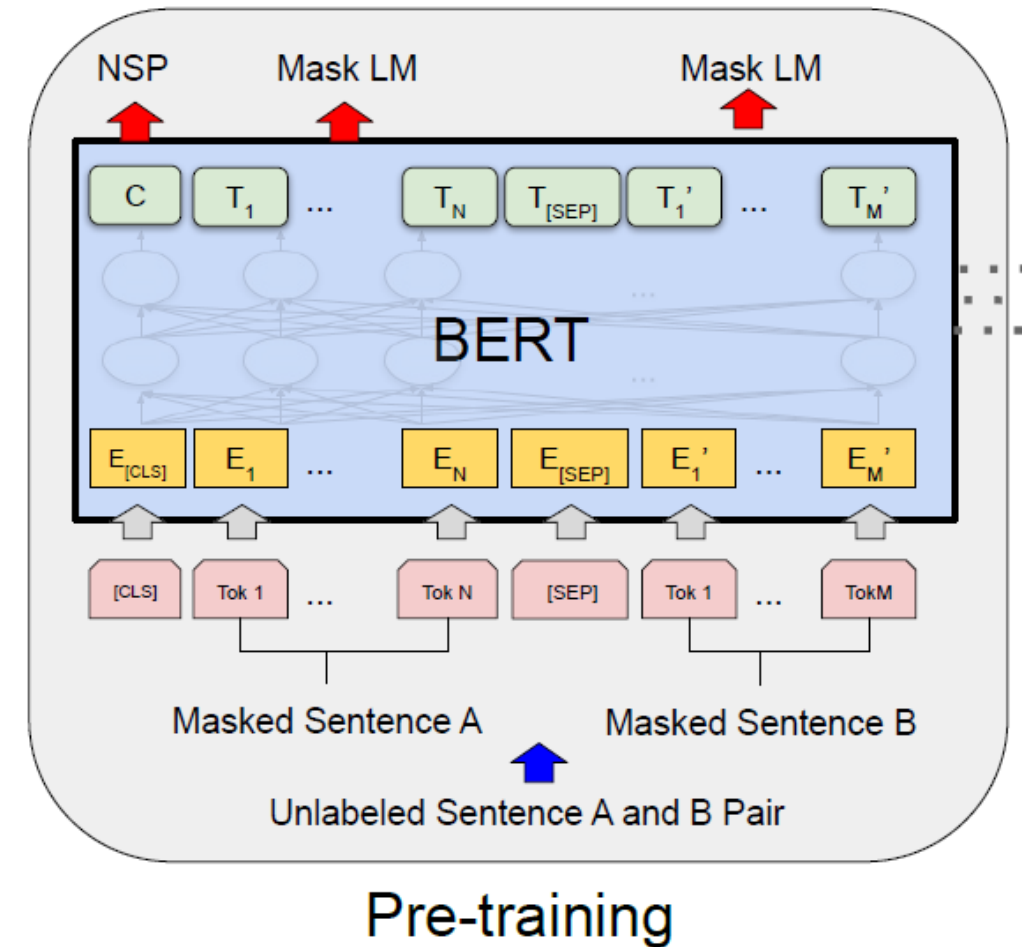


Masking
example:

[cls] **My** dog is **cute** [sep] He **likes** play ##ing [sep]
[cls] **[MASK]** dog is **grave** [sep] He **likes** play ##ing [sep]

Pre-training with next sentence prediction

- Input is two sentences A and B
- Replace B with a random sentence 50% of the time
- Predict whether B is the original sentence or not (via [CLS] token)



Pre-training and fine-tuning

- Pre-train on MLM and NSP tasks
 - BooksCorpus: 800M words
 - English Wikipedia: 2.5B words
 - Important to use full documents, not just shuffled sentences
 - BERT_{BASE} trained on 16 TPU chips; BERT_{LARGE} on 64 chips; 4 days each
- Fine-tune on each task, takes a few hours on a GPU
 - Paraphrasing
 - Entailment
 - Question answering
 - ...

BERT results

SQuAD: question answering dataset

GLUE: General Language Understanding Evaluation – many tasks

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	Average -
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	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
BERT _{BASE}	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
BERT _{LARGE}	86.7/85.9	72.1	92.7	94.9	60.5	86.5	89.3	70.1	82.1

System	Dev		Test	
	EM	F1	EM	F1
Top Leaderboard Systems (Dec 10th, 2018)				
Human	-	-	82.3	91.2
#1 Ensemble - nlnet	-	-	86.0	91.7
#2 Ensemble - QANet	-	-	84.5	90.5
Published				
BiDAF+ELMo (Single)	-	85.6	-	85.8
R.M. Reader (Ensemble)	81.2	87.9	82.3	88.5
Ours				
BERT _{BASE} (Single)	80.8	88.5	-	-
BERT _{LARGE} (Single)	84.1	90.9	-	-
BERT _{LARGE} (Ensemble)	85.8	91.8	-	-
BERT _{LARGE} (Sgl.+TriviaQA)	84.2	91.1	85.1	91.8
BERT _{LARGE} (Ens.+TriviaQA)	86.2	92.2	87.4	93.2

Table 2: SQuAD 1.1 results. The BERT ensemble is 7x systems which use different pre-training checkpoints and fine-tuning seeds.

Table 1: GLUE Test results, scored by the evaluation server (<https://gluebenchmark.com/leaderboard>). The number below each task denotes the number of training examples. The “Average” column is slightly different than the official GLUE score, since we exclude the problematic WNLI set.⁸ BERT and OpenAI GPT are single-model, single task. F1 scores are reported for QQP and MRPC, Spearman correlations are reported for STS-B, and accuracy scores are reported for the other tasks. We exclude entries that use BERT as one of their components.

MNLI: whether a sentence entails, contradicts, or is unrelated to another

QQP: whether two sentences are semantically equivalent

QNLI: question answering

SST-2: positive or negative sentiment

CoLA: whether sentence is grammatically correct

STS-B: sentence similarity score

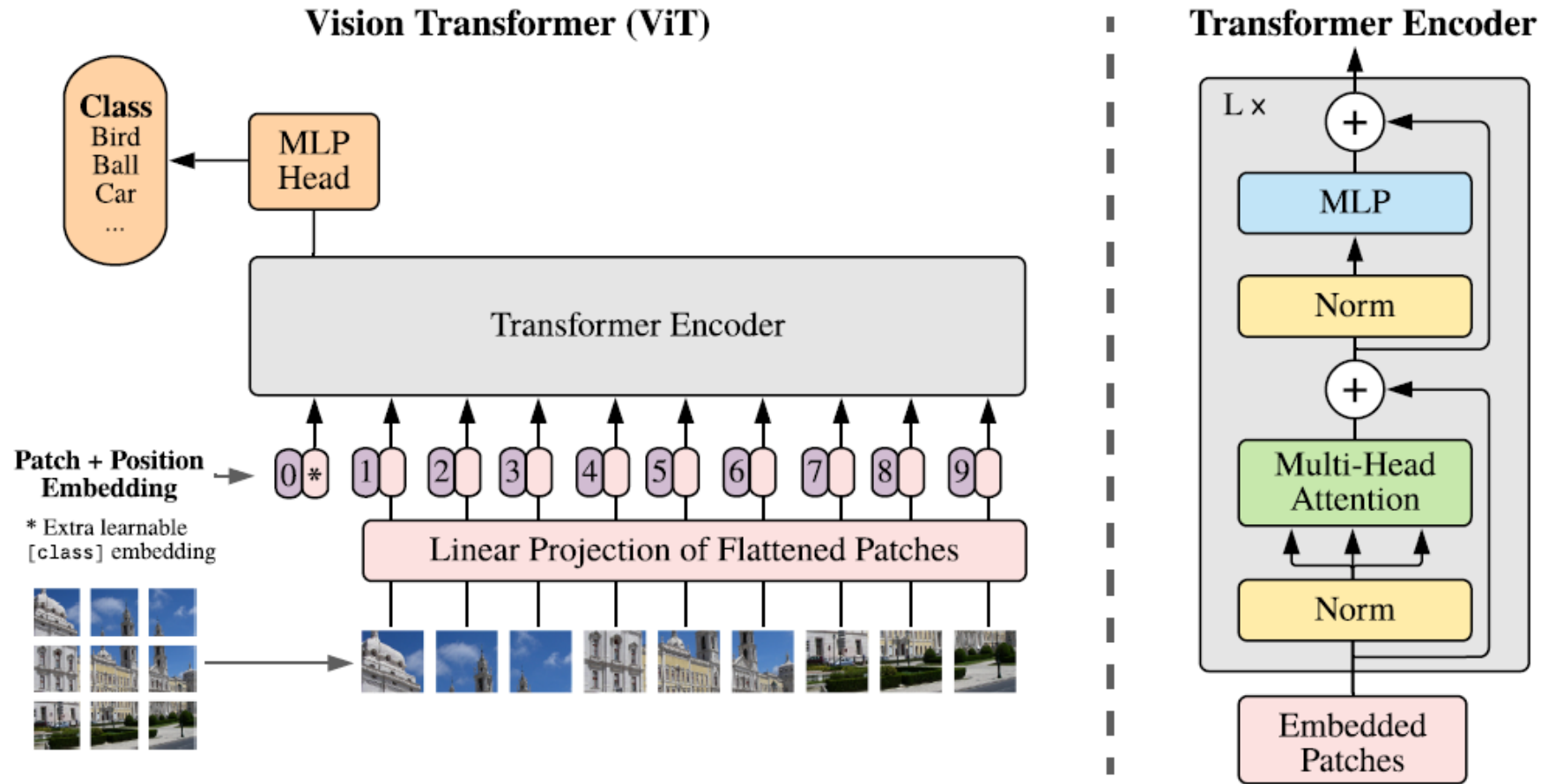
MRPC: whether one sentence paraphrases another

RTE: whether a sentence entails a hypothesis

Key Take-aways from BERT

- Bi-directional masked language modeling is highly effective pre-training
 - Does not require supervision
 - Learns general representations
- Same idea has been adopted for vision, but with much higher masking ratio (~80% of patches masked)

ViT: Vision Transformers (Dosovitskiy et al. 2021)

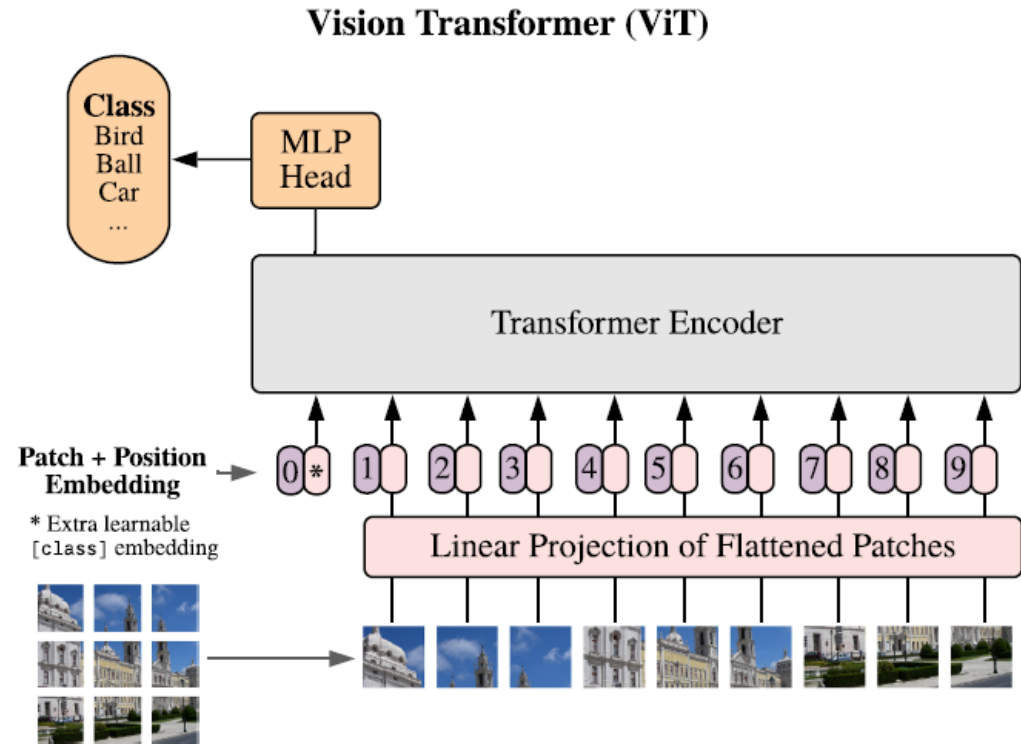


Why is ViT worth knowing about? (33K citations)

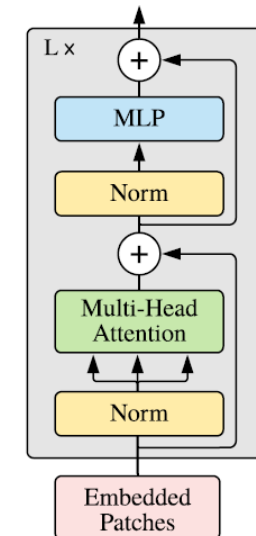
1. Shows that the same exact Transformer blocks can be used for vision, paving the way for multimodal processing
2. Transformers work as well as CNNs but are more computationally efficient
3. Vision and language are easier to combine using transformers

ViT Overview

- Image is divided into patches (e.g., 16x16)
- Each patch projects into a fixed length vector
- Positional encoding added to each patch
- Extra [CLS] token to encode image summary
- Multiple layers of standard transformer (same as for language)
- For classification, final prediction is linear layer applied to [class] token



Transformer Encoder



	Different size models, same pretraining		Same model, different pretraining dataset		Big convolutional networks	
	Ours-JFT (ViT-H/14)	Ours-JFT (ViT-L/16)	Ours-I21k (ViT-L/16)	BiT-L (ResNet152x4)	Noisy Student (EfficientNet-L2)	
ImageNet	88.55 ± 0.04	87.76 ± 0.03	85.30 ± 0.02	87.54 ± 0.02	88.4/88.5*	
ImageNet ReaL	90.72 ± 0.05	90.54 ± 0.03	88.62 ± 0.05	90.54	90.55	
CIFAR-10	99.50 ± 0.06	99.42 ± 0.03	99.15 ± 0.03	99.37 ± 0.06	—	
CIFAR-100	94.55 ± 0.04	93.90 ± 0.05	93.25 ± 0.05	93.51 ± 0.08	—	
Oxford-IIIT Pets	97.56 ± 0.03	97.32 ± 0.11	94.67 ± 0.15	96.62 ± 0.23	—	
Oxford Flowers-102	99.68 ± 0.02	99.74 ± 0.00	99.61 ± 0.02	99.63 ± 0.03	—	
VTAB (19 tasks)	77.63 ± 0.23	76.28 ± 0.46	72.72 ± 0.21	76.29 ± 1.70	—	
TPUv3-core-days	2.5k	0.68k	0.23k	9.9k	12.3k	
	\$30K		\$120K			

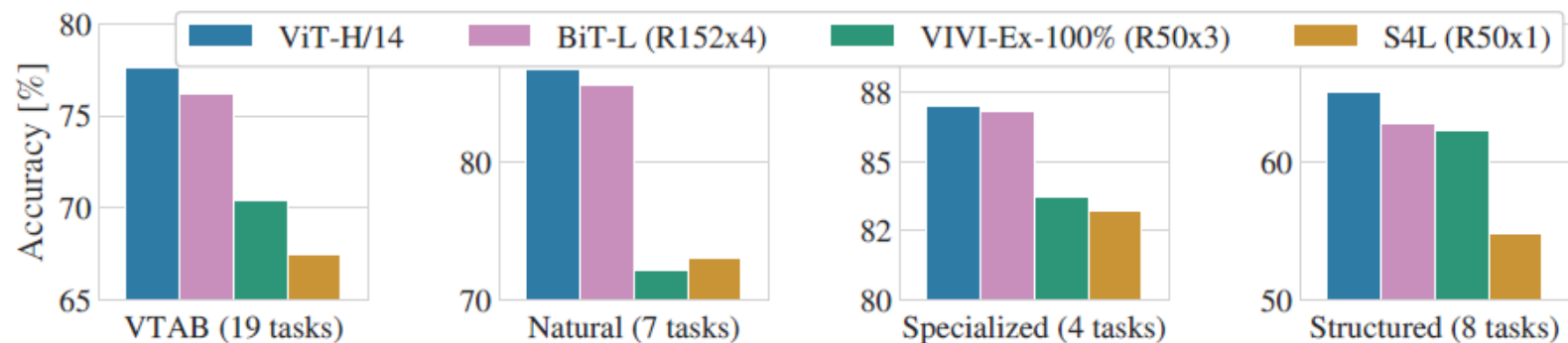


Figure 2: Breakdown of VTAB performance in *Natural*, *Specialized*, and *Structured* task groups.

Model	Layers	Hidden size D	MLP size	Heads	Params
ViT-Base	12	768	3072	12	86M
ViT-Large	24	1024	4096	16	307M
ViT-Huge	32	1280	5120	16	632M

Table 1: Details of Vision Transformer model variants.

Information is integrated
among distant patches

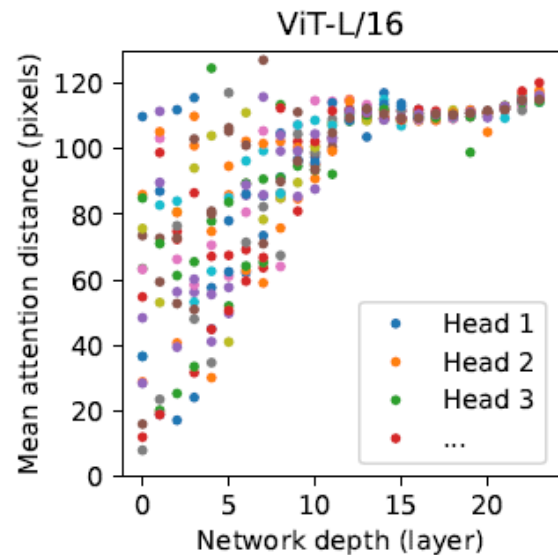
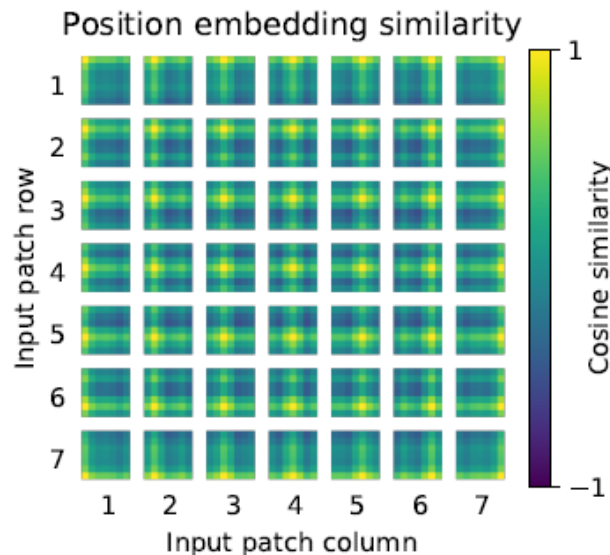
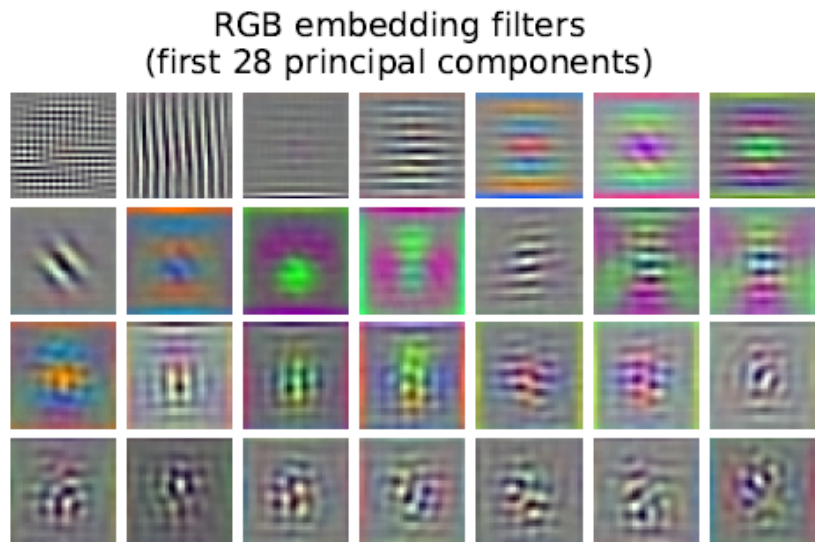
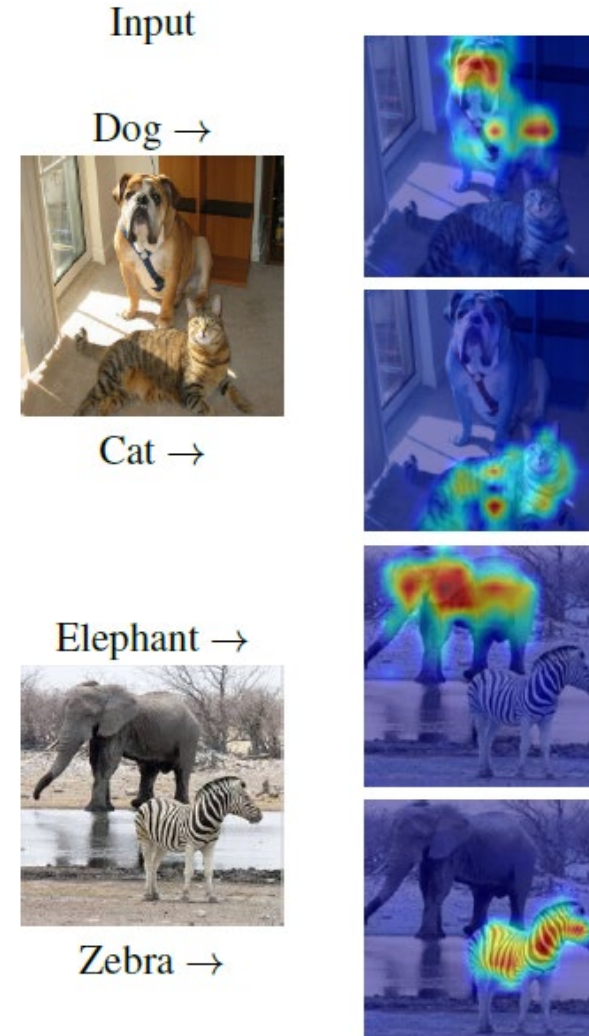
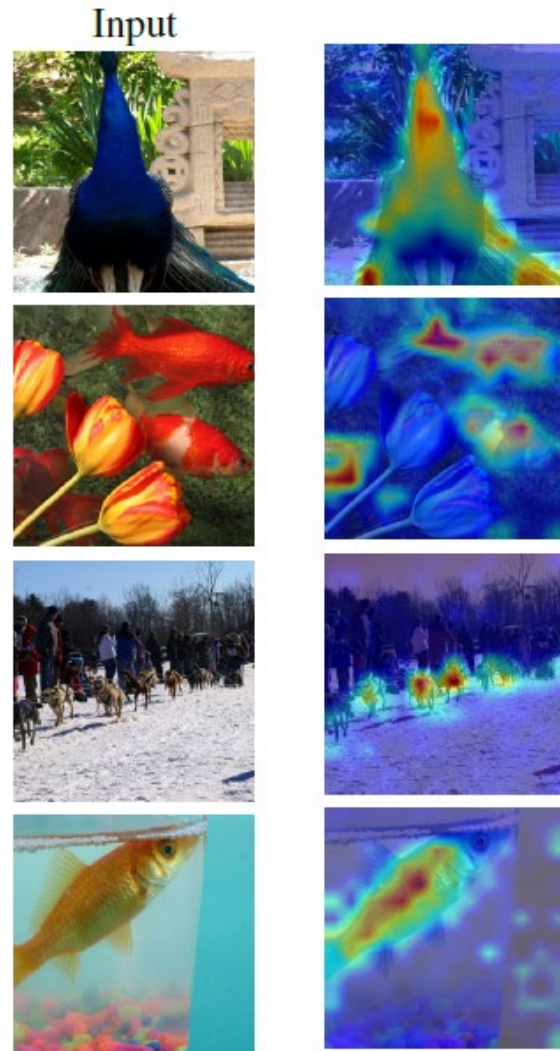


Figure 7: **Left:** Filters of the initial linear embedding of RGB values of ViT-L/32. **Center:** Similarity of position embeddings of ViT-L/32. Tiles show the cosine similarity between the position embedding of the patch with the indicated row and column and the position embeddings of all other patches. **Right:** Size of attended area by head and network depth. Each dot shows the mean attention distance across images for one of 16 heads at one layer. See Appendix D.7 for details.

Visualizing transformer (Chefer et al. 2021)

Visualizations for overall and class-specific feature importance



CNNs vs. Transformers

- **CNNs** encode position as an index in the feature map. **Transformers** do not care about index order but encode positional embeddings
 - Surprisingly, even when positional embeddings are not used, transformer models still work well
- **CNNs** encode a bias that nearby pixels are most related. **Transformers** enable combining information from distant patches, with positional embedding providing a weak prior to consider nearby patches
 - CNNs can only use information in neighboring pixels/cells, but the receptive field (pixel area considered) grows larger as network gets deeper
- In practice, CNNs and Transformers perform similarly for pure vision tasks, but Transformers are faster to train
 - Hybrids are possible, e.g. apply shallow CNN before first patch embedding
- Transformers operate on “tokens”, which is very general and can be applied to any modality

Q2-4

<https://tinyurl.com/AML441-L19>

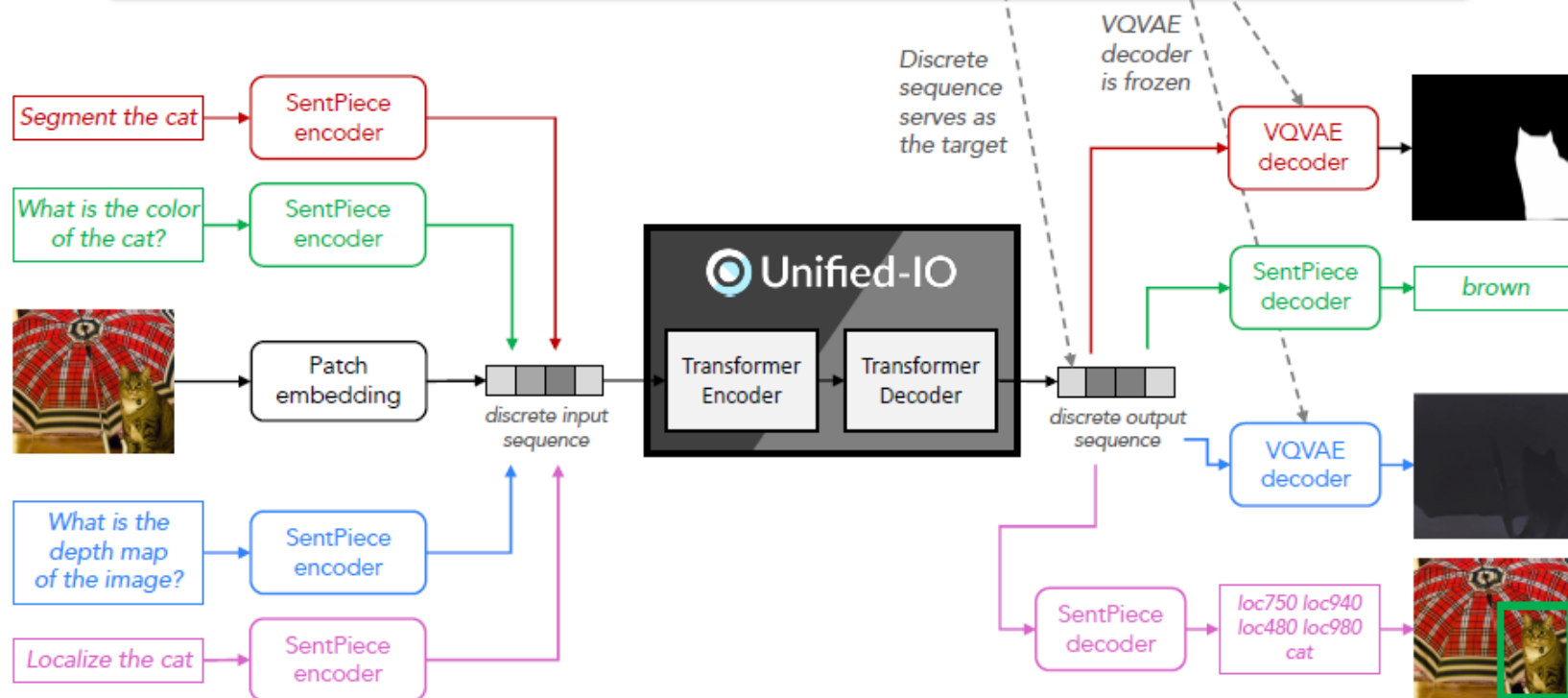
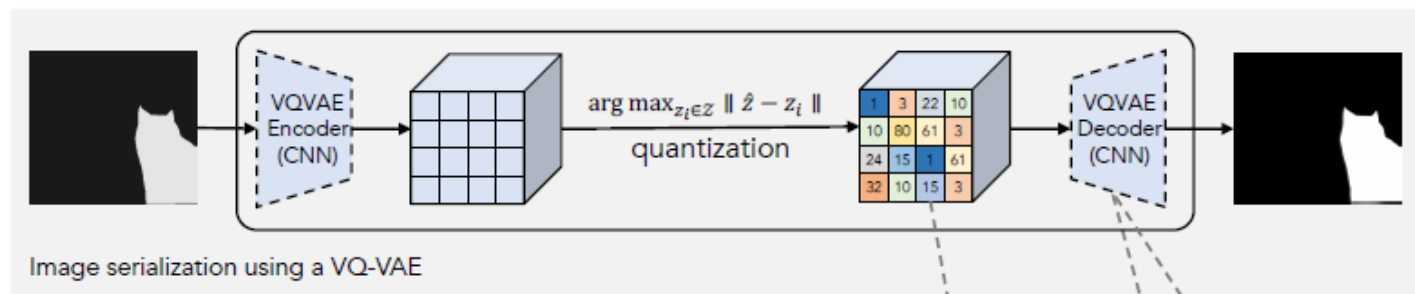


Unified-IO: <text, image> to <text, image> (Lu et al. 2022)

3B parameters

Pre-train on masked text and image completion for text, images, and image/caption pairs

Multitask training on 80 datasets



Unified-IO (June 2022)

<https://unified-io.allenai.org/>

Vision tasks

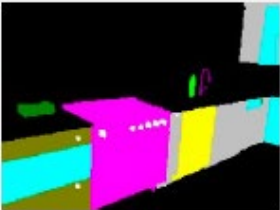
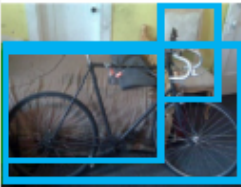
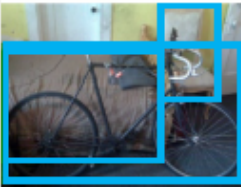
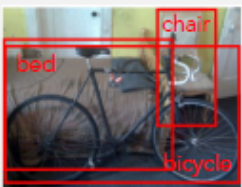
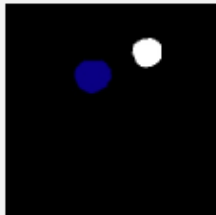
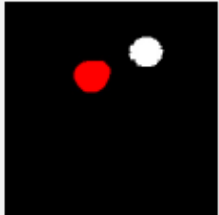
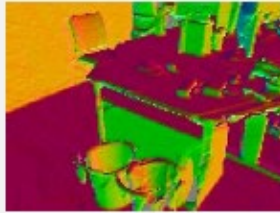
- Image synthesis from text / inpainting / segmentation
- Image/object classification
- Object detection, segmentation, keypoint estimation
- Depth/normal estimation

Vision-language tasks

- VQA, image/region captioning, referring expressions comprehension, relationship detection

NLP tasks

- Question answering
- Text classification

SEG BASED IMAGE GENERATION	What is the complete image? Segmentation color: "white: knob, silver: cupboard, olive: drawer, lime ..."  	TRUTH 	PREDICTION 
OBJECT DETECTION	What objects are in the image?  Viz loc100 loc745 loc495 loc991 chair loc293 loc100 loc753 loc763 bed loc262 loc103 loc841 loc1096 bicycle	TRUTH 	PREDICTION  * text outputs omitted for brevity
OBJECT SEGMENTATION	What is the segmentation of "apple"? 	TRUTH 	PREDICTION 
SURFACE NORMAL ESTIMATION	What is the surface normal of the image? 	TRUTH 	PREDICTION 
QUESTION ANSWERING	context: Uptake of O₂ from the air is the essential purpose of respiration, so oxygen supplementation is used in medicine. Treatment not only increases oxygen levels in the patient's blood.... question: What medical treatment is used to increase oxygen uptake in a patient?	TRUTH oxygen supplementation	PREDICTION oxygen supplementation

Often performs similarly or better than SotA single-task models

	<i>NYUv2</i>	<i>ImageNet</i>	<i>Place365</i>	<i>VQA_{v2}</i>	<i>OkVQA</i>	<i>A-OkVQA</i>	<i>VizWizQA</i>	<i>VizWizGround</i>	<i>Swig</i>	<i>SNLI-VE</i>	<i>VisComet</i>	<i>Nocaps</i>	<i>COCO</i>	<i>COCO</i>	<i>MRPC</i>	<i>BoolQ</i>	<i>SciTail</i>
Split	val	val	val	test-dev	test	test	test-dev	test-std	test	val	val	val	val	test	val	val	test
Metric	RMSE	Acc.	Acc.	Acc.	Acc.	Acc.	Acc.	IOU	Acc.	Acc.	CIDEr	CIDEr	CIDEr	CIDEr	F1	Acc	Acc
Unified SOTA	UViM 0.467	- -	- -	- -	Flamingo 57.8	- -	Flamingo 49.8	- -	- -	- -	- -	- -	- -	- -	T5 92.20	PaLM 92.2	- -
UNIFIED-IO _{SMALL}	0.649	42.8	38.2	57.7	31.0	24.3	42.4	35.5	17.3	76.5	-	45.1	80.1	-	84.9	65.9	87.4
UNIFIED-IO _{BASE}	0.469	63.3	43.2	61.8	37.8	28.5	45.8	50.0	29.7	85.6	-	66.9	104.0	-	87.9	70.8	90.8
UNIFIED-IO _{LARGE}	0.402	71.8	50.5	67.8	42.7	33.4	47.7	54.7	40.4	86.1	-	87.2	117.5	-	87.5	73.1	93.1
UNIFIED-IO _{XL}	0.385	79.1	53.2	77.9	54.0	45.2	57.4	65.0	49.8	91.1	21.2	100.0	126.8	122.3	89.2	79.7	95.7
Single or fine-tuned SOTA	BinsFormer 0.330	CoCa 91.00	MAE 60.3	CoCa 82.3	KAT 54.4	GPV2 38.1	Flamingo 65.7	MAC-Caps 27.3	JSL 39.6	OFA 91.0	SVT 18.3	CoCa 122.4	- -	OFA 145.3	Turing NLR 93.8	ST-MOE 92.4	DeBERTa 97.7

Explore demo of Unified IO 2 which extends to audio and multiple image inputs

<https://unified-io-2.allenai.org/>

HW 5

1. Applications of AI [30 pts]

Choose an application area (e.g. AI for agriculture, advertising, recommendation systems, self-driving cars/trucks, manufacturing, construction, home monitoring, virtual assistants), read at least two related media articles or papers, cite your sources, and answer the following questions:

1. How is AI used in that application area? What is the problem that AI is trying to solve, and what are the key AI/ML technologies involved? What are the technical challenges? (100+ words)
2. What is the actual or potential positive impact? Who is impacted? (50+ words)
3. What is the actual or potential negative impact? Who is impacted? (50+ words)

If you use media articles, they should be from highly respected sources, e.g. The Economist, Wall Street Journal, NY Times, Washington Post, Atlantic, MIT Technology Review. This will be graded as complete/incomplete. Any citation format is OK, as long as it clearly indicates the source, article title, and date of article.

2. Fine-tune ImageNet Model for Pets Classification [30 pts]

A convolutional neural network (CNN) is a type of deep learning artificial neural network commonly used for image processing tasks. In this section, you will load a pretrained network, finetune it for a new task, and evaluate it to achieve a good image classification accuracy on the **Oxford-IIIT Pet dataset**. The task is to classify the breed of cat or dog.

This code is worth understanding, but writing it all from scratch would be too much work for those new to deep network learning. So we have provided most of the code structure. Read it carefully and uncomment it as you go, where indicated. Your key steps are:

1. Load a pretrained ResNet34 and replace the last layer of the network so that the output dimension matches the number of Pet classes. See Mar 26 lecture. Include the printout of network structure and parameters in your report.
2. Set the learning rate and learning scheduler, train, and evaluate. You may need to modify the training settings to get a better performance. You can consider the data augmentation, learning rate, learning rate scheduler, and batch size. Attach the accuracy and loss plots for training_set and test_set, and report your best testing accuracy. You should be able to reach an accuracy of at least 90% within 10 epochs.

3. Zero-shot and Linear Probe using CLIP [40 pts]

CLIP (Contrastive Language-Image Pre-Training), developed by OpenAI, is a neural network trained on 400 million (image, text) pairs. CLIP encodes text and images into the same vector space, so that it can match images to text descriptions by encoding each and computing the dot product of the encodings. This enables zero-shot classification, i.e. assigning images to text labels from a dataset without training on that dataset. The following are some resources you may find useful for understanding CLIP and finishing your tasks in this homework.

- [GitHub Repo](#) (Make sure to look at this for examples of how to use CLIP)
- [Learning Transferable Visual Models From Natural Language Supervision](#) (paper)
- [CLIP Website](#)
- [Labels for Flowers 102 dataset \(json file\)](#)

The starter code includes sections for loading the Flowers 102 dataset, the CLIP model, and examples of usage. The code splits the data into a "train" and "test" (validation) set.

Your tasks are to use CLIP for a new classification task in three ways:

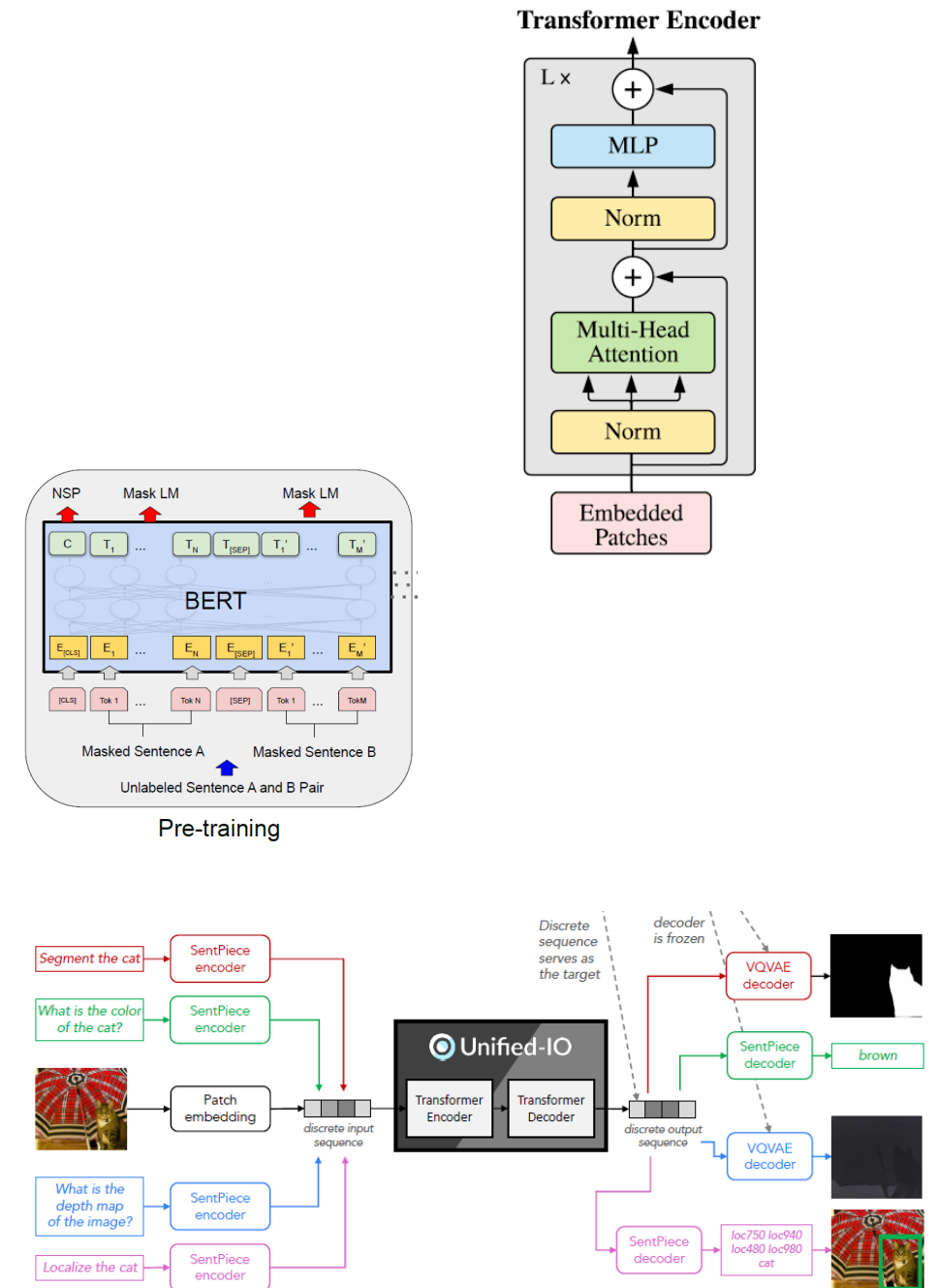
Zero-shot: Use pre-trained text and image representations to classify images. For zero-shot recognition (no training), text features are computed from the CLIP model for phrases such as "An image of <flower_name>, a type of flower" for varying <flower_name> inserts. Then, image features are computed using the CLIP model for an image, and the cosine similarity between each text and image is computed. The label corresponding to the most similar text is assigned to the image. We've included an example in the starter code. You'll get that working using a data loader, which enables faster batch processing; then, compute the accuracy over the test set. You should see top-1 accuracy (i.e. percent of times the highest confidence predicted label is correct) in the 60-70% range.

Linear probe: Often, it is possible to improve performance for a particular classification task by training a linear classifier on the model's features. This is called a "linear probe". We can do that by extracting the CLIP pre-trained image features and then training a linear logistic regression classifier. We do not use text features for the linear probe method. Train on the train set, and evaluate on the test set and report your performance. You can get top-1 accuracy in the 90-95% range. If you see accuracy in the 80's, try both normalizing and not normalizing the features.

Nearest neighbor: We can also extract pretrained CLIP features and apply a nearest neighbor classifier. You can use your own implementation of nearest neighbor or a library like sklearn or FAISS for this. Try $K=\{1, 3, 5, 7, 11, 21\}$. Report performance for best K on the test set. You should see top-1 accuracy in the 80-90% range.

Things to remember

- Transformers are general data processors, applicable to text, vision, audio, control, and other domains
- Pre-training to generate missing tokens in unsupervised text data learns a general model that can be fine-tuned
 - Same idea is also applicable to other domains
- Transformer architectures are state-of-art for vision and language individually
- Arguably, the biggest benefit of transformers is ability to combine information from multiple domains



Next class: Foundation Models

- CLIP
- GPT line of work