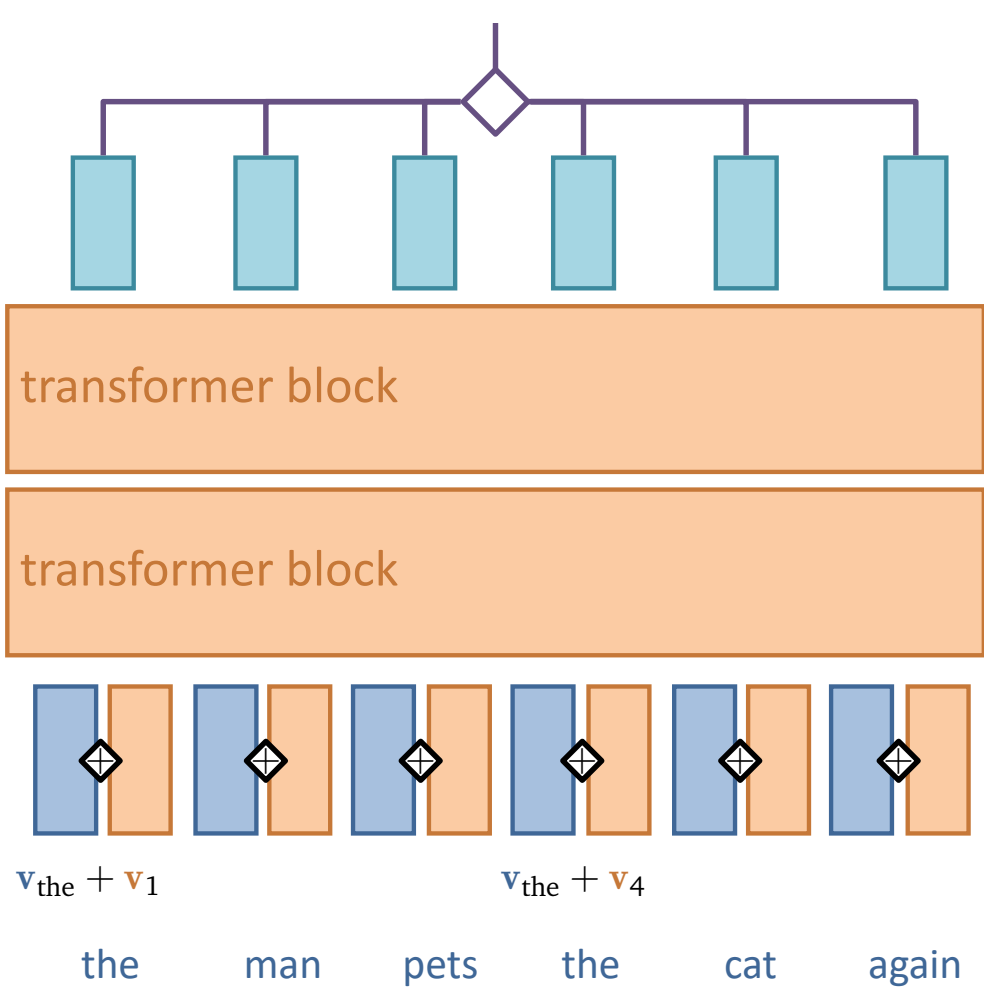


# Attention and sequential structure

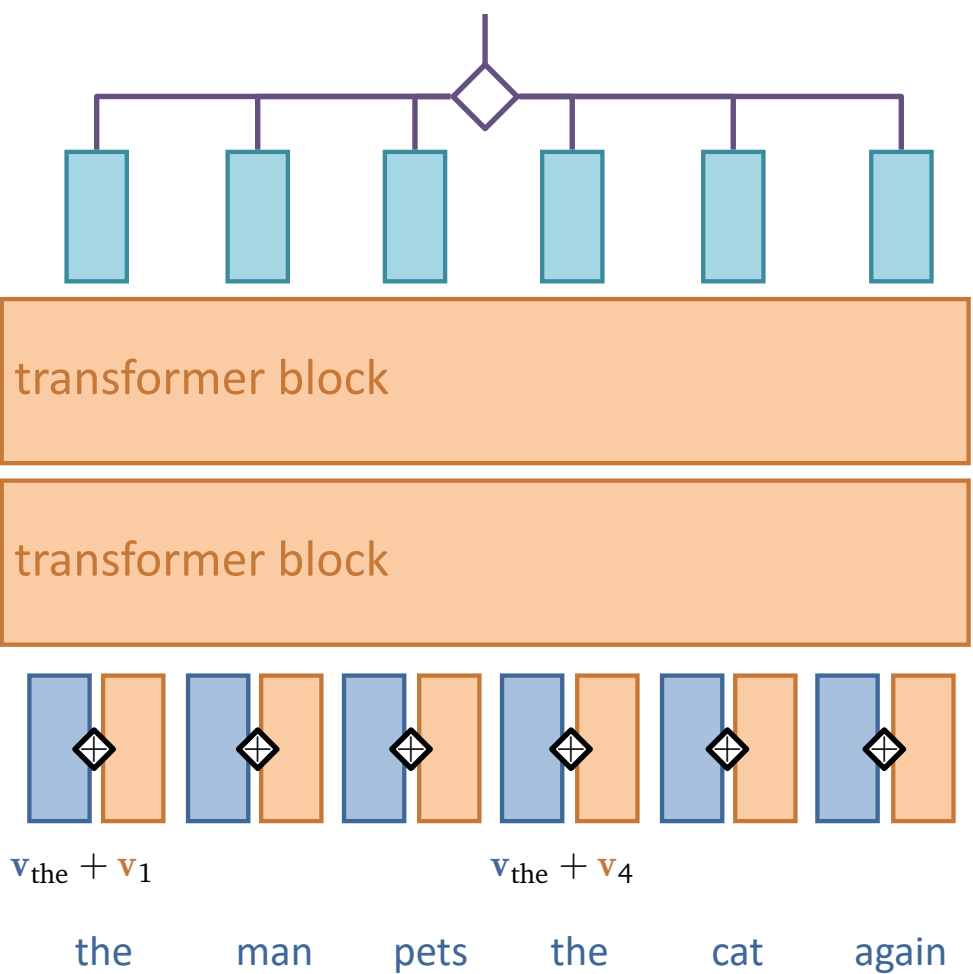
## Position Embeddings

- Conceptually simple
- Easy to implement
- Adds set of learnable parameters
- Maximum context length at test time limited to max sequence length in training set
- Embedding quality diminishes (in theory) with  $t$



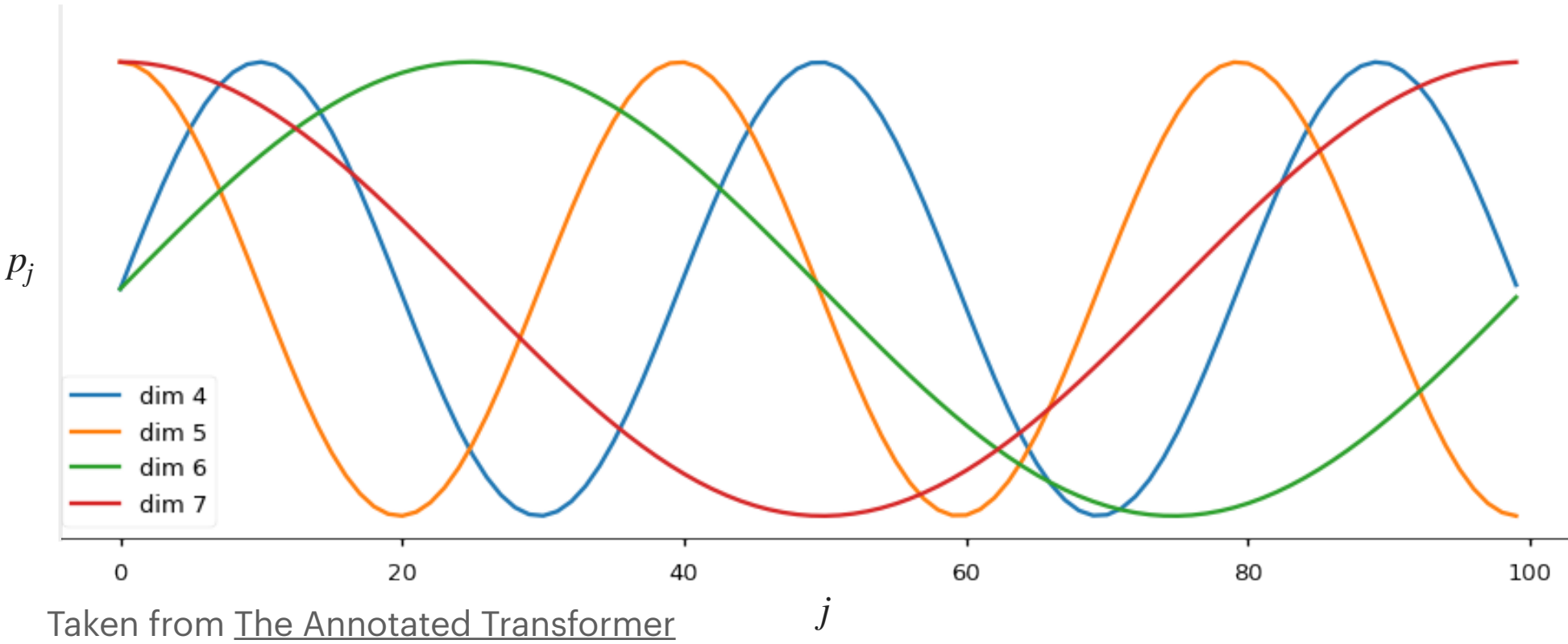
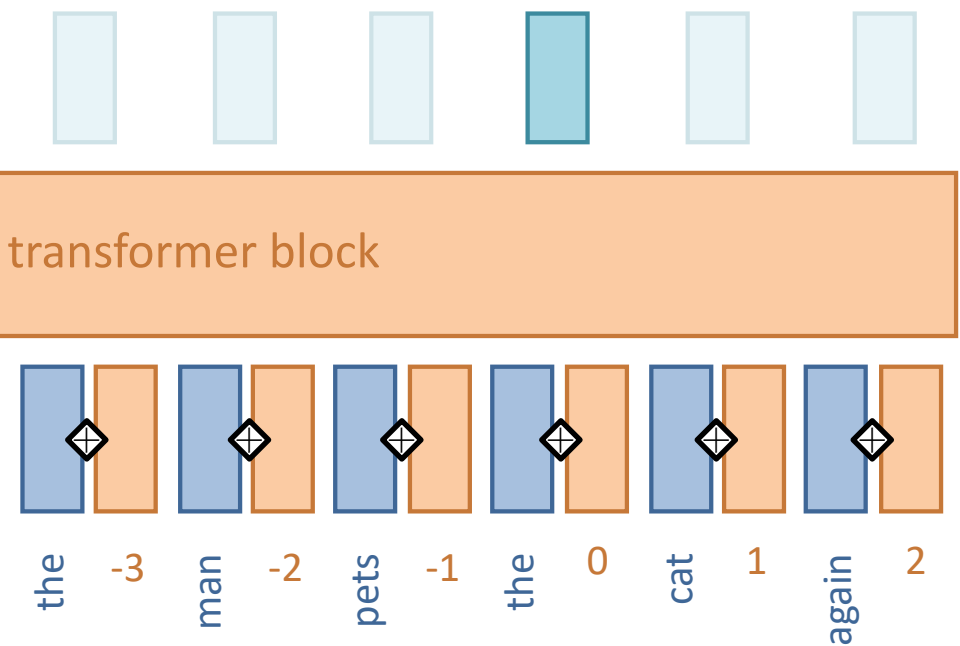
## Position encodings

- Captures the property of absolute position invariance which is desirable
- Conceptually and practically more complex; on the surface this results in  $(T-1)^2$  different inputs because each input will have  $T-1$  separate representations (there is a hack that turns this into  $2T-1$ )



## Relative position embeddings

- Captures the property of absolute position invariance which is desirable
- Like absolute position embeddings, limited in context length at inference
- Conceptually and practically more complex; on the surface this results in  $(T-1)^2$  different inputs because each input will have  $T-1$  separate representations (there is a hack that turns this into  $2T-1$ )



# BERT (2018)

## BERT

The most popular/used/studied Transformer model to date

30K citations [1]

Trained on Wikipedia and Book Corpus (~10K books)

Wordpiece embedding [2]

Non-causal, uses masked LM procedure for pretraining

340 M parameters in total

LM prediction head: 4 ReLU (D=4096)

LM training took 4 days on 64 TPU cores

$$D = 1024$$

$$N_H = 16$$

$$N_B = 24$$

$$T_{max} = 1024$$

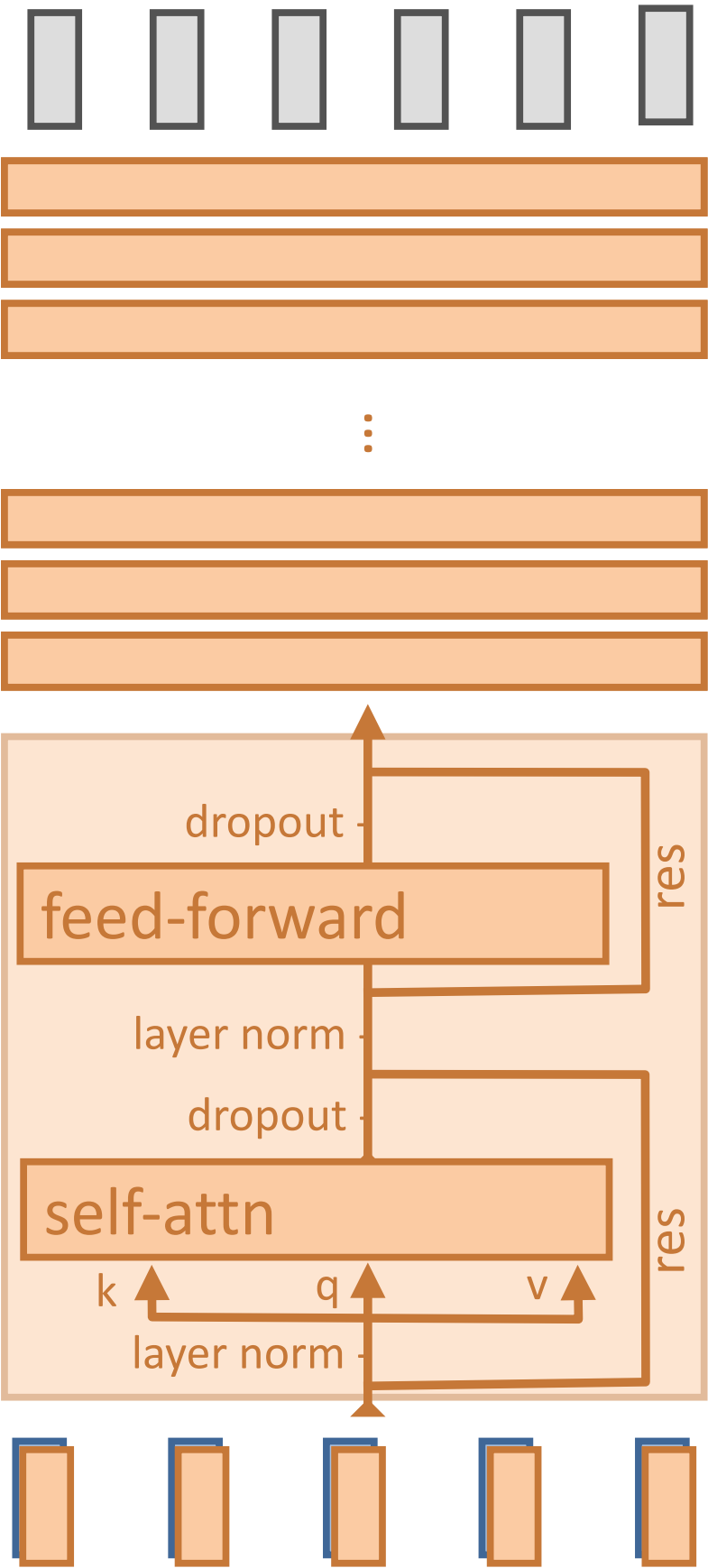


Figure taken from Bloem, 2020

Input	[CLS]	my	dog	is	cute	[SEP]	he	likes	play	##ing	[SEP]
Token Embeddings	E <sub>[CLS]</sub>	E <sub>my</sub>	E <sub>dog</sub>	E <sub>is</sub>	E <sub>cute</sub>	E <sub>[SEP]</sub>	E <sub>he</sub>	E <sub>likes</sub>	E <sub>play</sub>	E <sub>##ing</sub>	E <sub>[SEP]</sub>
	+	+	+	+	+	+	+	+	+	+	+
Segment Embeddings	E <sub>A</sub>	E <sub>A</sub>	E <sub>A</sub>	E <sub>A</sub>	E <sub>A</sub>	E <sub>A</sub>	E <sub>B</sub>	E <sub>B</sub>	E <sub>B</sub>	E <sub>B</sub>	E <sub>B</sub>
	+	+	+	+	+	+	+	+	+	+	+
Position Embeddings	E <sub>0</sub>	E <sub>1</sub>	E <sub>2</sub>	E <sub>3</sub>	E <sub>4</sub>	E <sub>5</sub>	E <sub>6</sub>	E <sub>7</sub>	E <sub>8</sub>	E <sub>9</sub>	E <sub>10</sub>

BERT Input Features [1]

Hyperparams				Dev Set Accuracy		
#L	#H	#A	LM (ppl)	MNLI-m	MRPC	SST-2
3	768	12	5.84	77.9	79.8	88.4
6	768	3	5.24	80.6	82.2	90.7
6	768	12	4.68	81.9	84.8	91.3
12	768	12	3.99	84.4	86.7	92.9
12	1024	16	3.54	85.7	86.9	93.3
24	1024	16	3.23	86.6	87.8	93.7

Ablation Study [1]

[1] Devlin et al., *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding* (2018), [2] Wu et al., *Google’s Neural Machine Translation System: Bridging the Gap between Human and Machine Translation* (2016)