DEEP LEARNING

Lecture 8: Language Model

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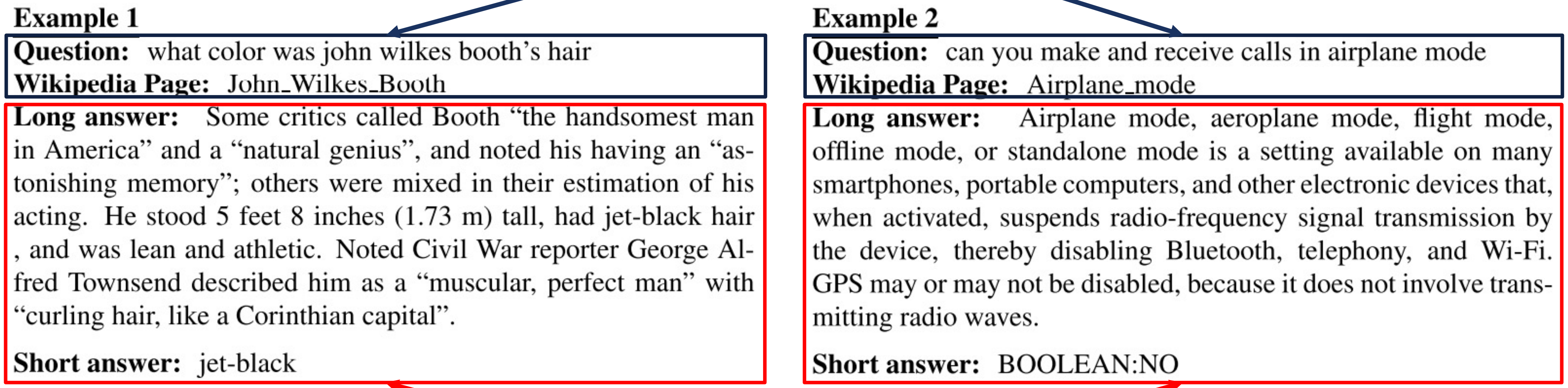
Question answering

Input



Example 1

Question: what color was john wilkes booth's hair

Wikipedia Page: John_Wilkes_Booth

Long answer: Some critics called Booth "the handsomest man in America" and a "natural genius", and noted his having an "astonishing memory"; others were mixed in their estimation of his acting. He stood 5 feet 8 inches (1.73 m) tall, had jet-black hair , and was lean and athletic. Noted Civil War reporter George Alfred Townsend described him as a "muscular, perfect man" with "curling hair, like a Corinthian capital".

Short answer: jet-black

Example 2

Question: can you make and receive calls in airplane mode

Wikipedia Page: Airplane_mode

Long answer: Airplane mode, aeroplane mode, flight mode, offline mode, or standalone mode is a setting available on many smartphones, portable computers, and other electronic devices that, when activated, suspends radio-frequency signal transmission by the device, thereby disabling Bluetooth, telephony, and Wi-Fi. GPS may or may not be disabled, because it does not involve transmitting radio waves.

Short answer: BOOLEAN:NO

Prediction

Source: Kwiatkowski, Tom, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein et al. "Natural questions: a benchmark for question answering research." Transactions of the Association for Computational Linguistics 7 (2019): 453-466.

NLP Tasks using Language Model

- Textual Entailment (TE) or Natural Language Inference (NLI)

Relationship		Premise & Hypothesis
Entailment	Premise:	This church choir sings to the masses as they sing joyous songs from the book at a church.
	Hypothesis:	The church is filled with song.
Neutral	Premise:	This church choir sings to the masses as they sing joyous songs from the book at a church.
	Hypothesis:	The church has cracks in the ceiling.
Contradict	Premise:	This church choir sings to the masses as they sing joyous songs from the book at a church.
	Hypothesis:	A choir singing at a baseball game.

Image source: Sha, Lei, Baobao Chang, Zhifang Sui, and Sujian Li. "Reading and thinking: Re-read lstm unit for textual entailment recognition." In Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers, pp. 2870-2879. 2016.

NLP Tasks using Language Model

- Sentiment analysis

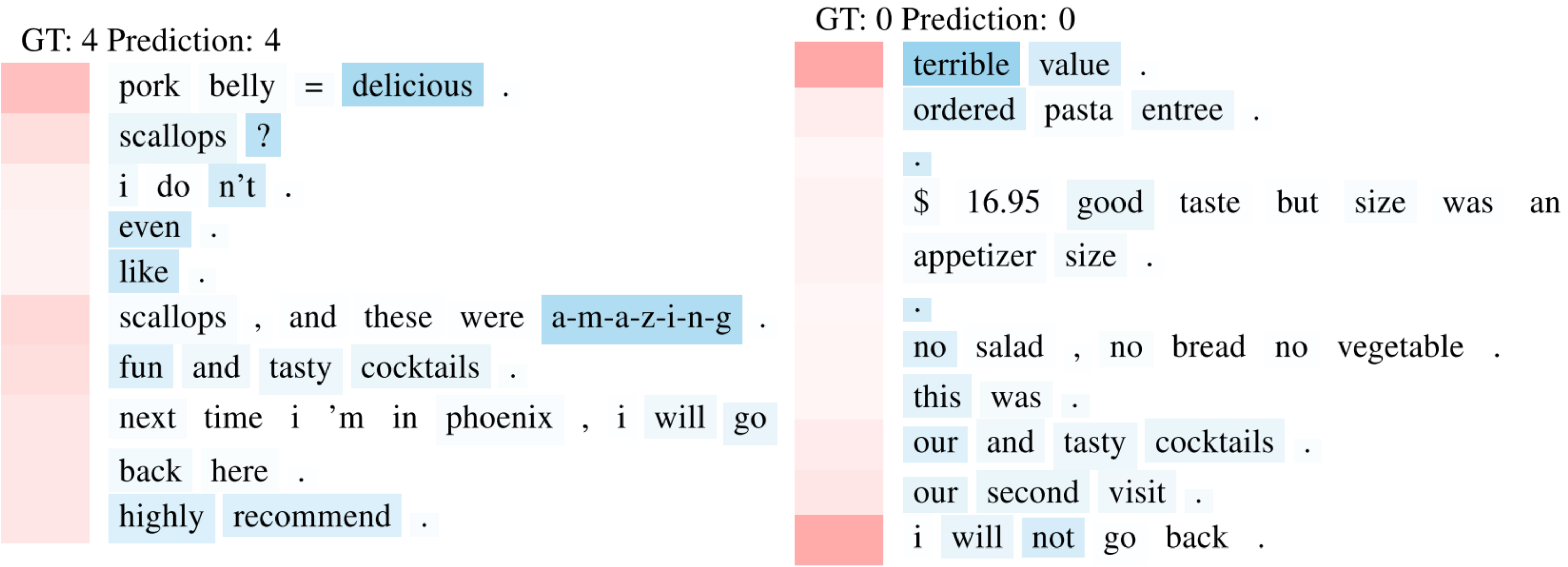


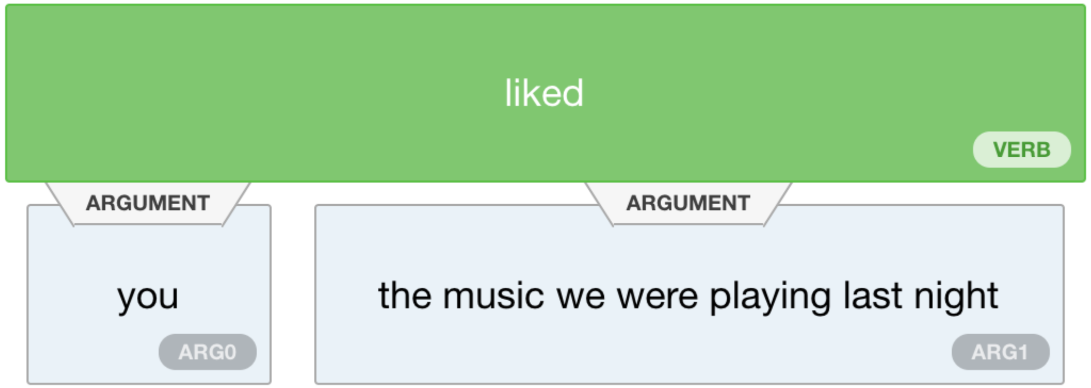
Image source: Yang, Zichao, Diyi Yang, Chris Dyer, Xiaodong He, Alex Smola, and Eduard Hovy. "Hierarchical attention networks for document classification." In Proceedings of the 2016 conference of the North American chapter of the association for computational linguistics: human language technologies, pp. 1480-1489. 2016.

NLP Tasks using Language Model

Semantic role labeling

Verb 1 of 4: **liked**

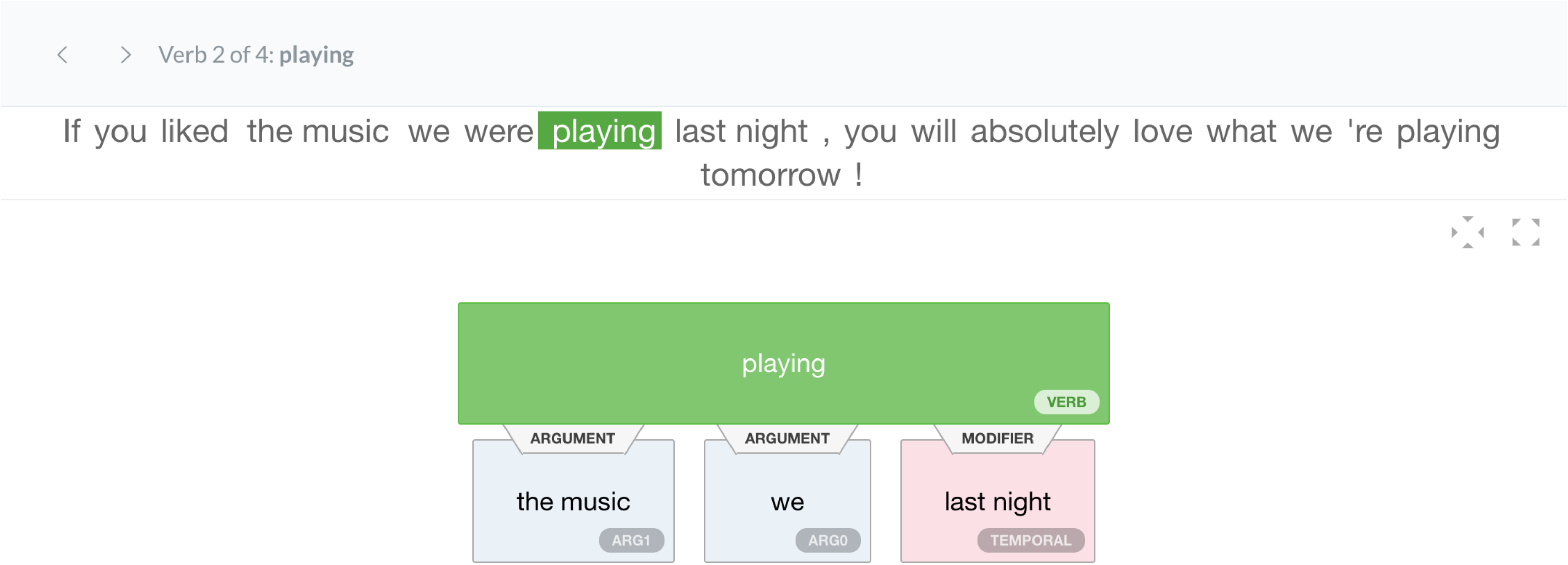
If you liked the music we were playing last night , you will absolutely love what we 're playing tomorrow !



Source: https://demo.allennlp.org/semantic-role-labeling/MjQ1MjQxOA==

NLP Tasks using Language Model

- Semantic role labeling



Source: https://demo.allennlp.org/semantic-role-labeling/MjQ1MjQxOA==

NLP Tasks using Language Model

- Coreference resolution

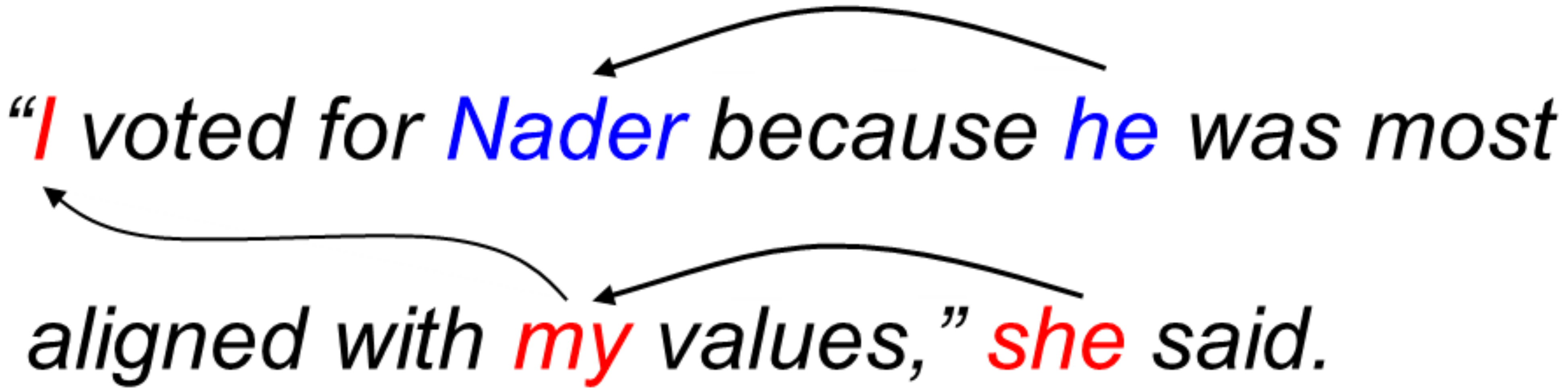


Image source: https://nlp.stanford.edu/projects/coref.shtml#:~:text=Coreference%20resolution%20is%20the%20task,question%20answering%2C%20and%20information%20extraction.

NLP Tasks using Language Model

- Named entity recognition (NER)

contentSkip to site indexPoliticsSubscribeLog InSubscribeLog InToday's PaperAdvertisementSupported ORG byF.B.I. Agent Peter Strzok PERSON , Who Criticized Trump PERSON in Texts, Is FiredImagePeter Strzok, a top F.B.I. GPE counterintelligence agent who was taken off the special counsel investigation after his disparaging texts about President Trump PERSON were uncovered, was fired. CreditT.J. Kirkpatrick PERSON for The New York TimesBy Adam Goldman ORG and Michael S. SchmidtAug PERSON . 13 CARDINAL , 2018WASHINGTON CARDINAL — Peter Strzok PERSON , the F.B.I. GPE senior counterintelligence agent who disparaged President Trump PERSON in inflammatory text messages and helped oversee the Hillary Clinton PERSON email and Russia GPE investigations, has been fired for violating bureau policies, Mr. Strzok PERSON 's lawyer said Monday DATE .Mr. Trump and his allies seized on the texts — exchanged during the 2016 DATE campaign with a former F.B.I. GPE lawyer, Lisa Page — in PERSON assailing the Russia GPE investigation as an illegitimate "witch hunt." Mr. Strzok PERSON , who rose over 20 years DATE at the F.B.I. GPE to become one of its most experienced counterintelligence agents, was a key figure in the early months DATE of the inquiry.Along with writing the texts, Mr. Strzok PERSON was accused of sending a highly sensitive search warrant to his personal email account.The F.B.I. GPE had been under immense political pressure by Mr. Trump PERSON to dismiss Mr. Strzok PERSON , who was removed last summer DATE from the staff of the special counsel, Robert S. Mueller III PERSON . The president has repeatedly denounced Mr. Strzok PERSON in posts on

Image source: https://towardsdatascience.com/named-entity-recognition-and-classification-with-scikit-learn-f05372f07ba2

NLP Tasks using Language Model

- Text summarization

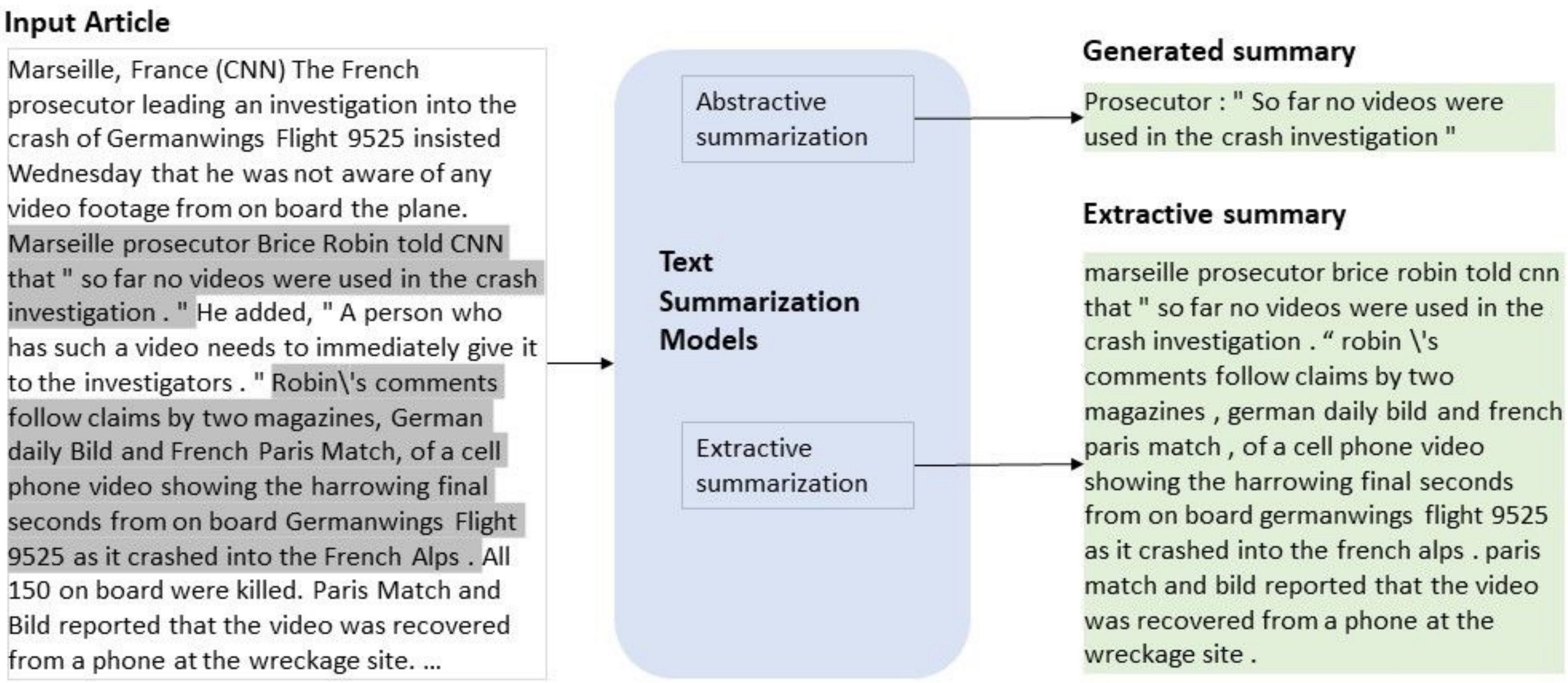


Image source: https://techcommunity.microsoft.com/t5/ai-customer-engineering-team/bootstrap-your-text-summarization-solution-with-the-latest/ba-p/1268809

NLP Tasks using Language Model

- Machine translation

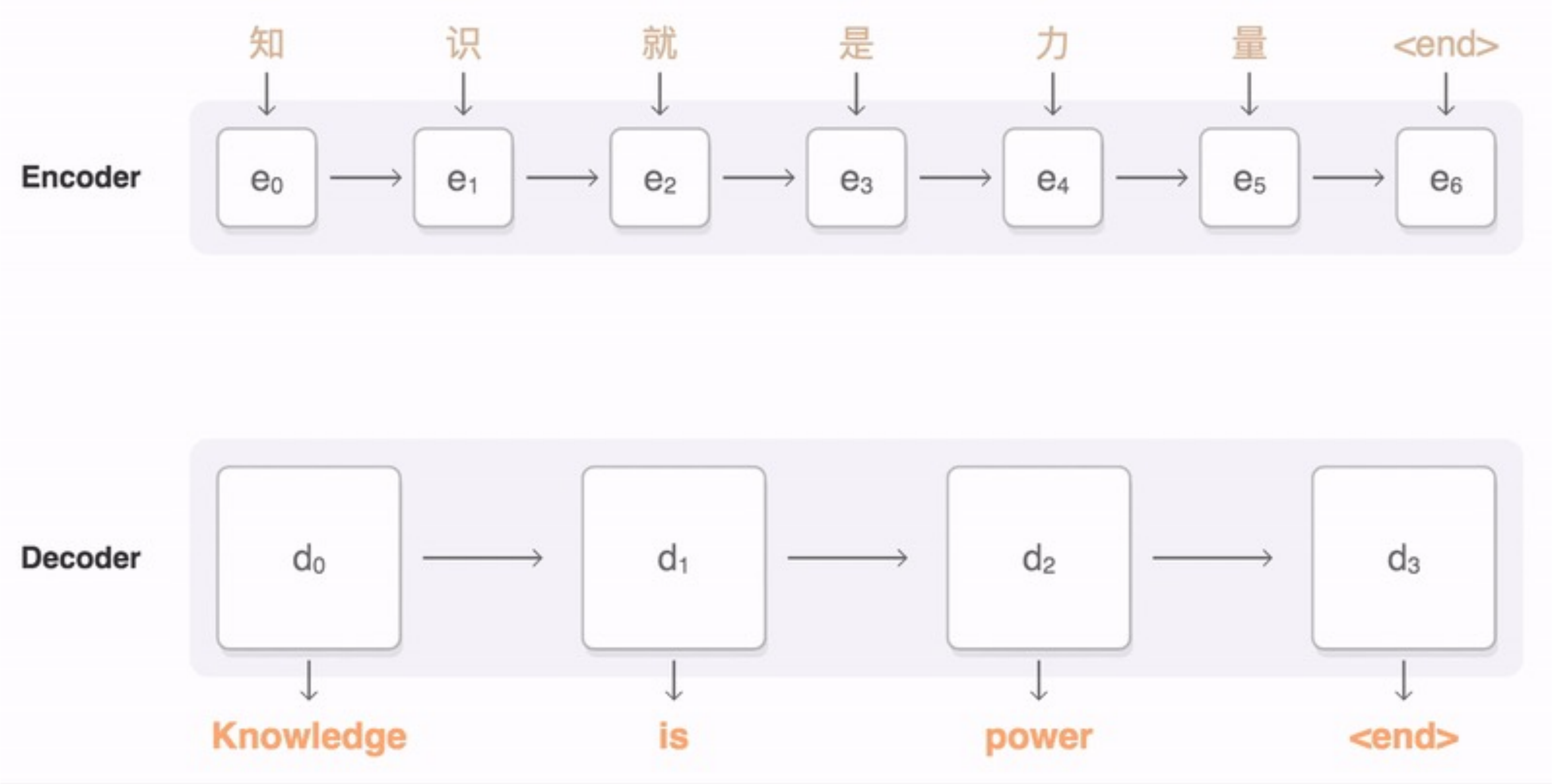
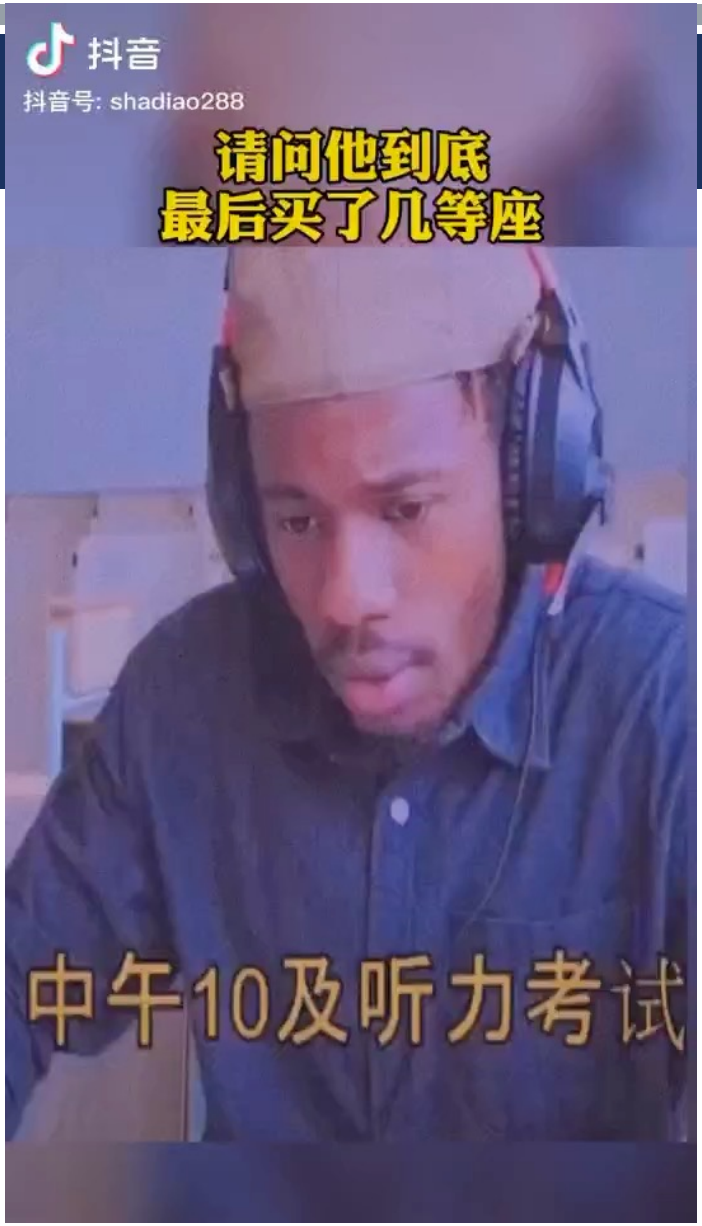


Image source: https://google.github.io/seq2seq/

NLP

- "NLP is the crown jewel of Artificial Intelligence".
- It is very hard to make AI understand underlying meaning of human language.
  - Among lots of problems, ambiguity is one of NLP's nightmares.



Source: douyin

Outlines

- Word2vec
- Transformer
- BERT
- GPT

WORD2VEC

Meaning of a Word

- How can computer know the meaning of a word?
- Use e.g. WordNet, a thesaurus containing lists of synonym sets and hypernyms ("is a" relationships).

Synonym (同义词) of "good"

```
from nltk.corpus import wordnet as wn
poses = { 'n':'noun', 'v':'verb', 's':'adj (s)', 'a':'adj', 'r':'adv'}
for synset in wn.synsets("good"):
    print("{}: {}".format(poses[synset.pos()],
          ", ".join([l.name() for l in synset.lemmas()])))
```

```
noun: good
noun: good, goodness
noun: good, goodness
noun: commodity, trade_good, good
adj: good
adj (sat): full, good
adj: good
adj (sat): estimable, good, honorable, respectable
adj (sat): beneficial, good
adj (sat): good
adj (sat): good, just, upright
…
adverb: well, good
adverb: thoroughly, soundly, good
```

Hypernyms (上位词) of "panda"

```
from nltk.corpus import wordnet as wn
panda = wn.synset("panda.n.01")
hyper = lambda s: s.hypernyms()
list(panda.closure(hyper))
```

```
[Synset('procyonid.n.01'),
Synset('carnivore.n.01'),
Synset('placental.n.01'),
Synset('mammal.n.01'),
Synset('vertebrate.n.01'),
Synset('chordate.n.01'),
Synset('animal.n.01'),
Synset('organism.n.01'),
Synset('living_thing.n.01'),
Synset('whole.n.02'),
Synset('object.n.01'),
Synset('physical_entity.n.01'),
Synset('entity.n.01')]
```


Code source: Lecture 1, cs224n

Meaning of a Word

Problems of using dictionary library:

- Great as a resource but missing slight difference between words.
  - e.g. “proficient” is listed as a synonym for “good”. This is only correct in some contexts.
- Different meanings depending on the context.
- Missing new meanings of words, or new created words.
  - e.g., badass, lmao, skr, kiki…
  - Impossible to keep up-to-date!
- Requires human labor to create and adapt.

Meaning of a Word

- In traditional NLP, we regard words as discrete symbols.
- Words can be represented by one-hot vectors:

Cat: [0,0,0,0,0,0,…,1,0,0]

Dog: [1,0,0,0,0,0,…,0,0,0]

Car: [0,0,0,0,1,0,…,0,0,0]

- The length of the vector equals to the size of the corpus (e.g. 500,000).
- Problem: the distance between any pair of words are 1, except itself.
  - There is no natural notion of similarity for one-hot vectors.
- Solution: learn to encode similarity in the vectors themselves.

Word Vectors

- Build a dense vector for each word, chosen so that it is similar to vectors of words that appear in similar contexts.
  - Word vectors are sometimes called word embeddings or word representations. They are a distributed representation.
- Word vectors with small distance have the close meaning.

Cat:	[0.1,0.7,0.9,0.1,0.1]
Dog:	[0.2,0.7,0.8,0.2,0.1]
Car:	[0.9,0.1,0.5,0.6,0.8]

  - Usually hundreds of dimensions.
- However, there is no label to train these word embeddings in a supervised manner.
  - It is impossible to label the similarity between any two words.

Contextual Information

- Distributional semantics: words that are used and occur in the same contexts tend to purport similar meanings.
  - "A word is characterized by the company it keeps" was popularized by J. R. Firth, an English linguist, in the 1950s.
- When a word w appears in a text, its context is the set of words that appear nearby (within a fixed-size window).
- Use the many contexts of w to build up a representation of w.

…government debt problems turning into	***banking***	*crises as happened in 2009…*
…saying that Europe needs unified	***banking***	*regulation to replace the hodgepodge…*
…India has just given its	***banking***	*system a shot in the arm…*

"Banking" is represented by its context words

Image source: Lecture 1, cs224n

Word2vec

Distributed representations of words and phrases and their compositionality
T Mikolov, I Sutskever, K Chen… - Advances in neural …, 2013 - proceedings.neurips.cc
… We show how to train **distributed representations** of **words** and phrases with the Skip-gram model and demonstrate that these **representations** exhibit linear structure that makes precise …
☆ Save 99 Cite Cited by 41093 Related articles All 53 versions

Idea:

- Every word in a fixed vocabulary is represented by a dense vector.
- Go through each position t in the text, which has
  - a center word c,
  - context words o.
- Use the similarity of the word vectors for c and o to calculate the probability of c given o (or vice versa).
- Keep adjusting the word vectors to maximize this probability.

Word2vec

- The authors proposed Skip-gram model to train word vectors.
- Given the center word c, predict the context words o.

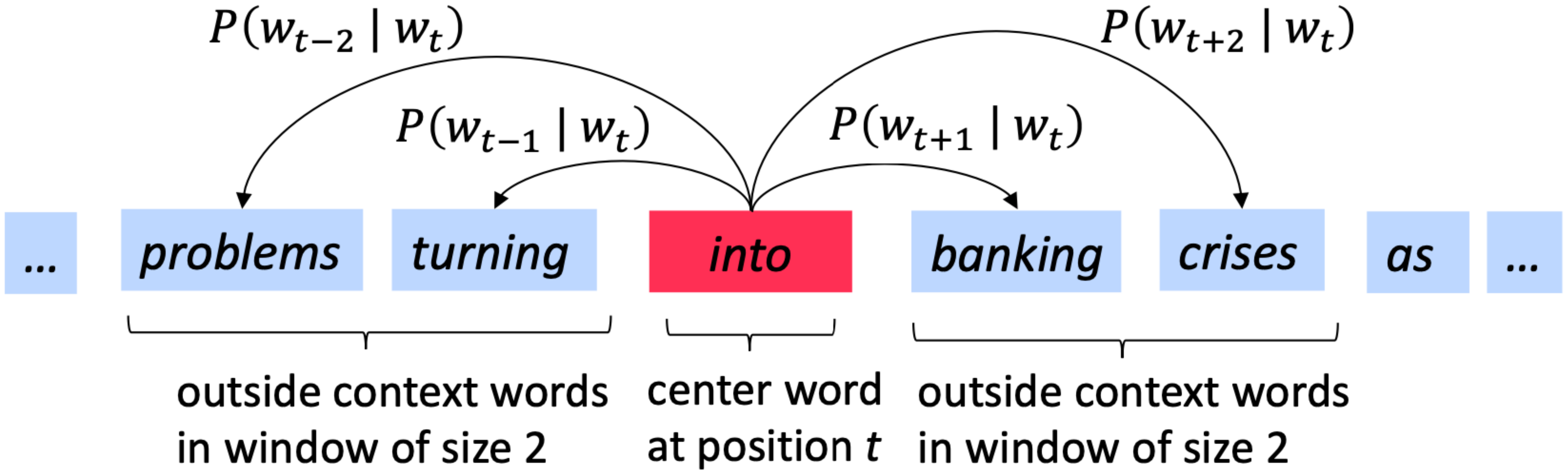


Image source: Lecture 1, cs224n

- The objective function $J(\theta)$ is the negative log likelihood:

$$J(\theta) = -\frac{1}{T}\log L(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\le j\le c, j\ne 0} \log p\left(w_{t+j}\middle|w_t;\theta\right).$$

Predict context

Given center

- The probability is calculated by:

$$p(o|c) = \frac{\exp(\boldsymbol{w}_o'^{T}\boldsymbol{w}_c)}{\sum_{u\in V}\exp(\boldsymbol{w}_u'^{T}\boldsymbol{w}_c)}.$$

It is nothing but inner product with softmax.

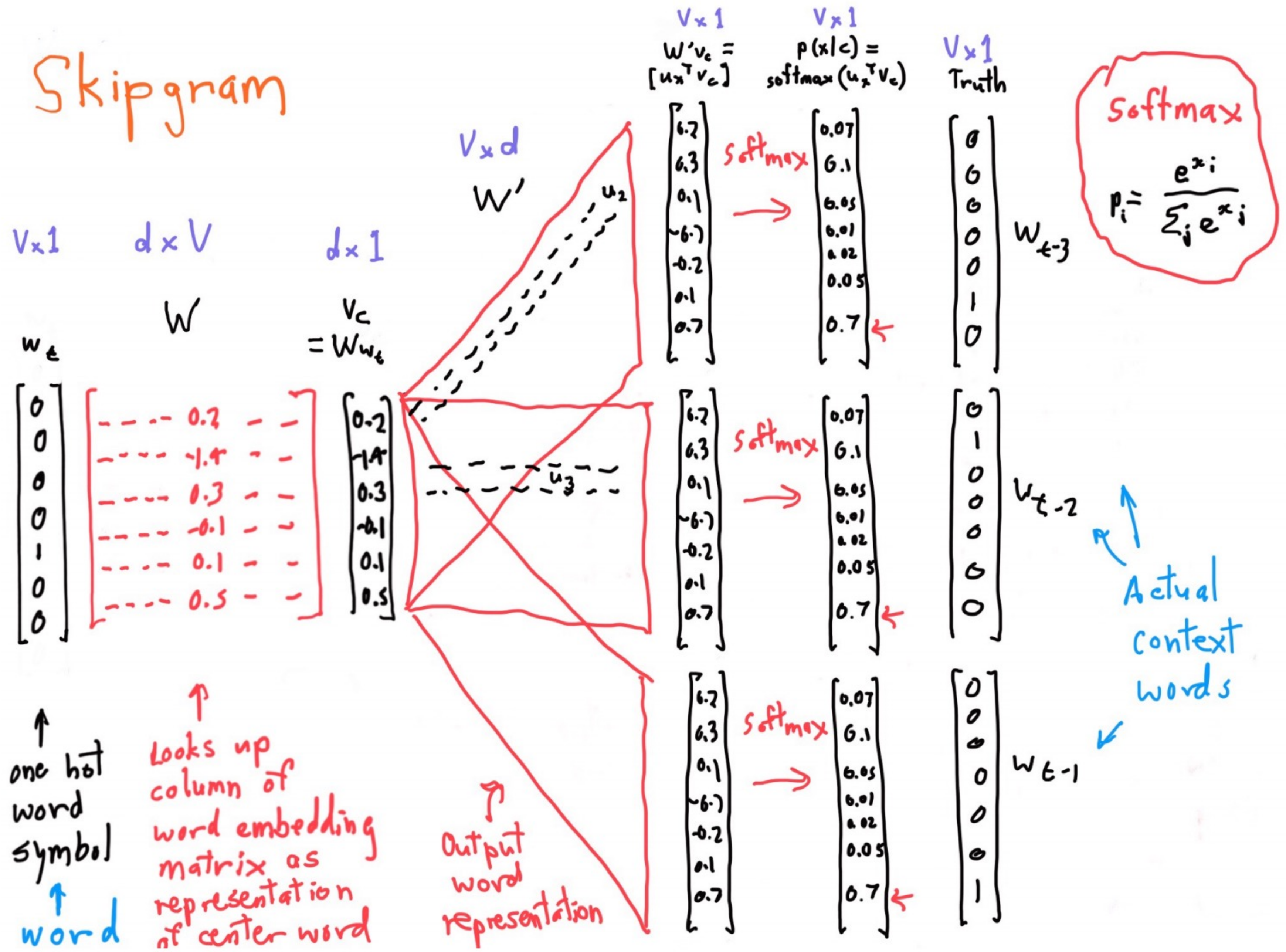


Image source: Lecture 2, cs224n

Word2vec

- The learnable representation is called embedding.
- What is the difference between embedding and feature/ representation?
  - Feature / representation is produced by learnable parameters, but embeddings themselves are learnable parameters.

Negative Sampling

- The probability is calculated by:

$$p(o|c) = \frac{\exp(\boldsymbol{w}_o'^T \boldsymbol{w}_c)}{\sum_{u \in V} \exp(\boldsymbol{w}_u'^T \boldsymbol{w}_c)}.$$

- Every time, we calculate the similarity between word embedding of c and all $u \in V$.
  - It is computational cost is very high.
- We can simply sample a few random samples as the negative samples for training.

Word2vec

- We can also use the context words to predict the center word. This model is called CBOW (Continuous Bag of Words).

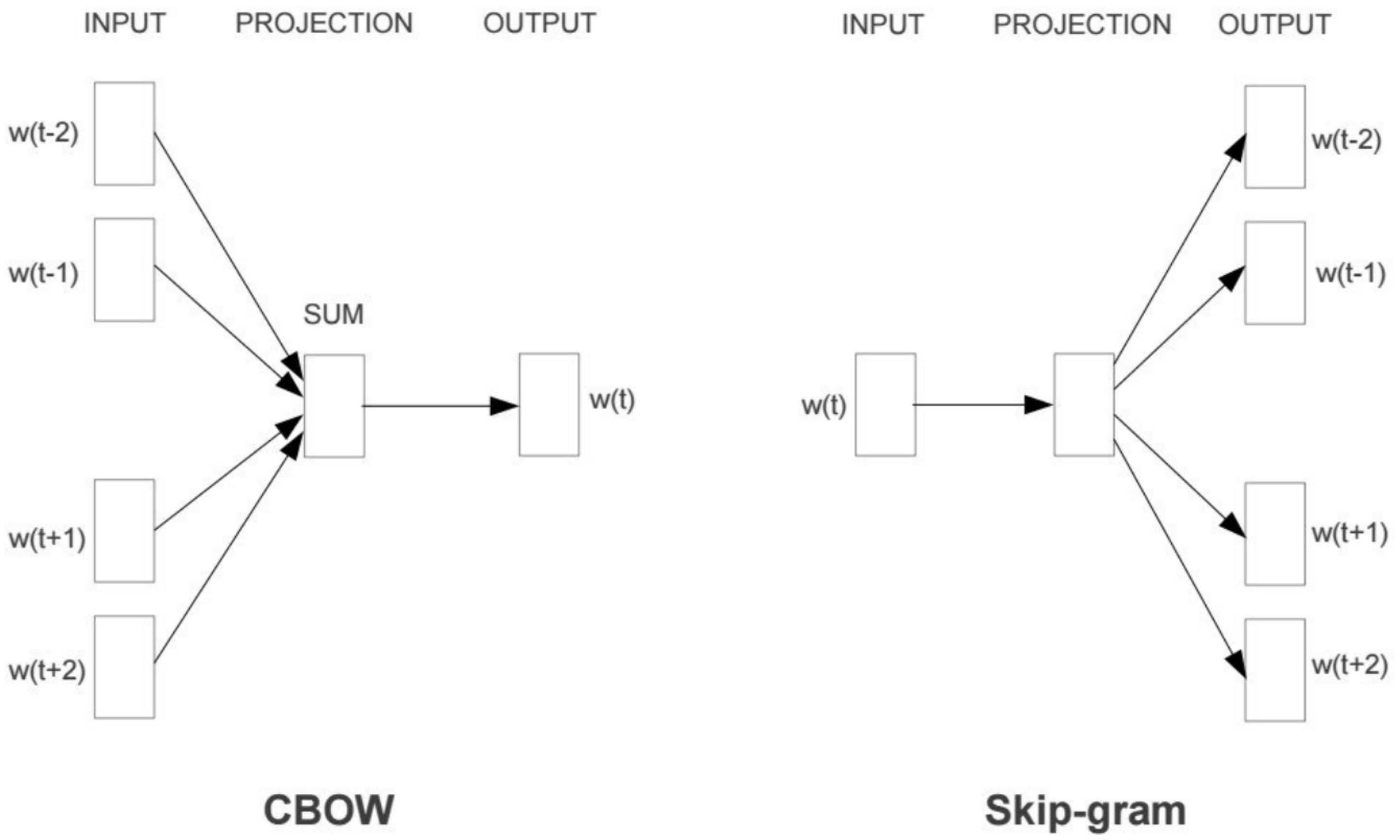
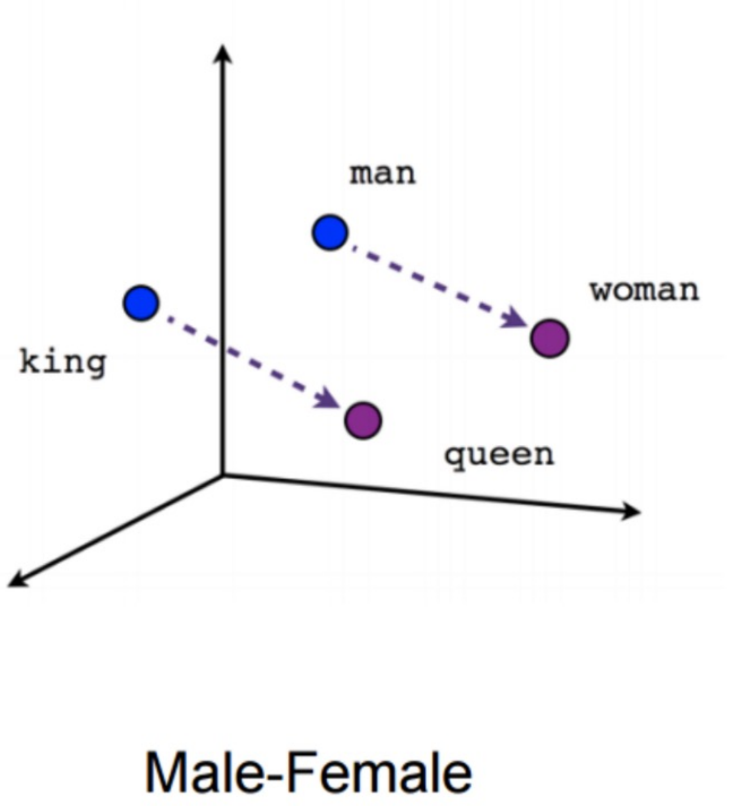


Image source: https://mubaris.com/posts/word2vec/

- By using word vectors, we can "calculate their meaning":

$$w['\text{king}'] \approx w['\text{queen}'] - w['\text{woman}'] + w['\text{man}']$$



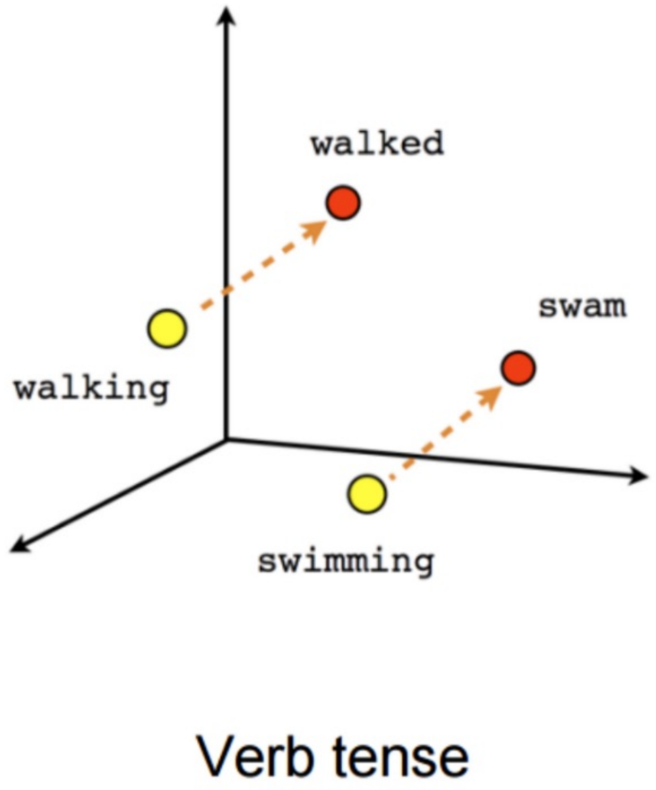


Image source: https://medium.com/@khulasaandh/word-embeddings-fun-with-word2vec-and-game-of-thrones-ea4c24fcf1b8

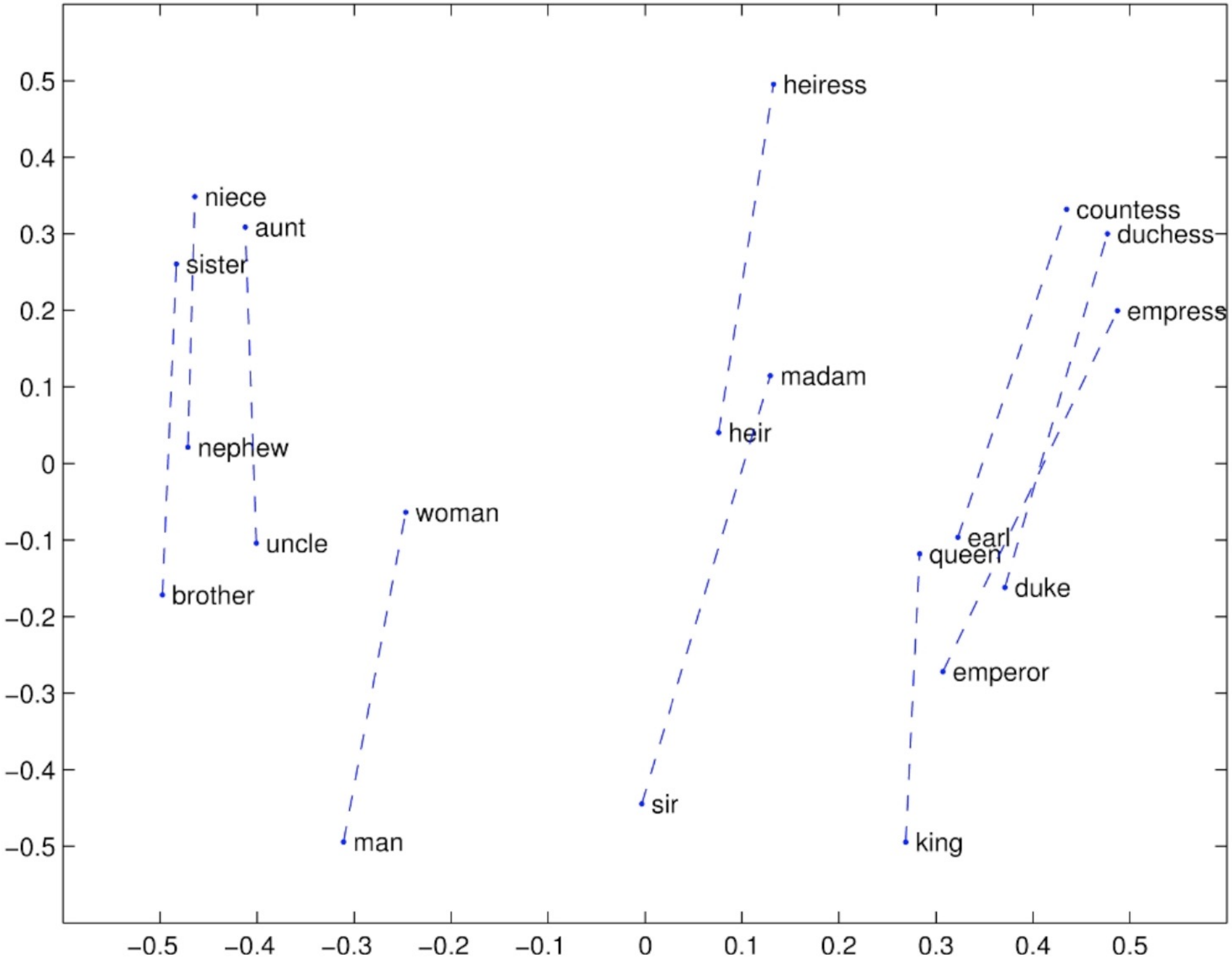
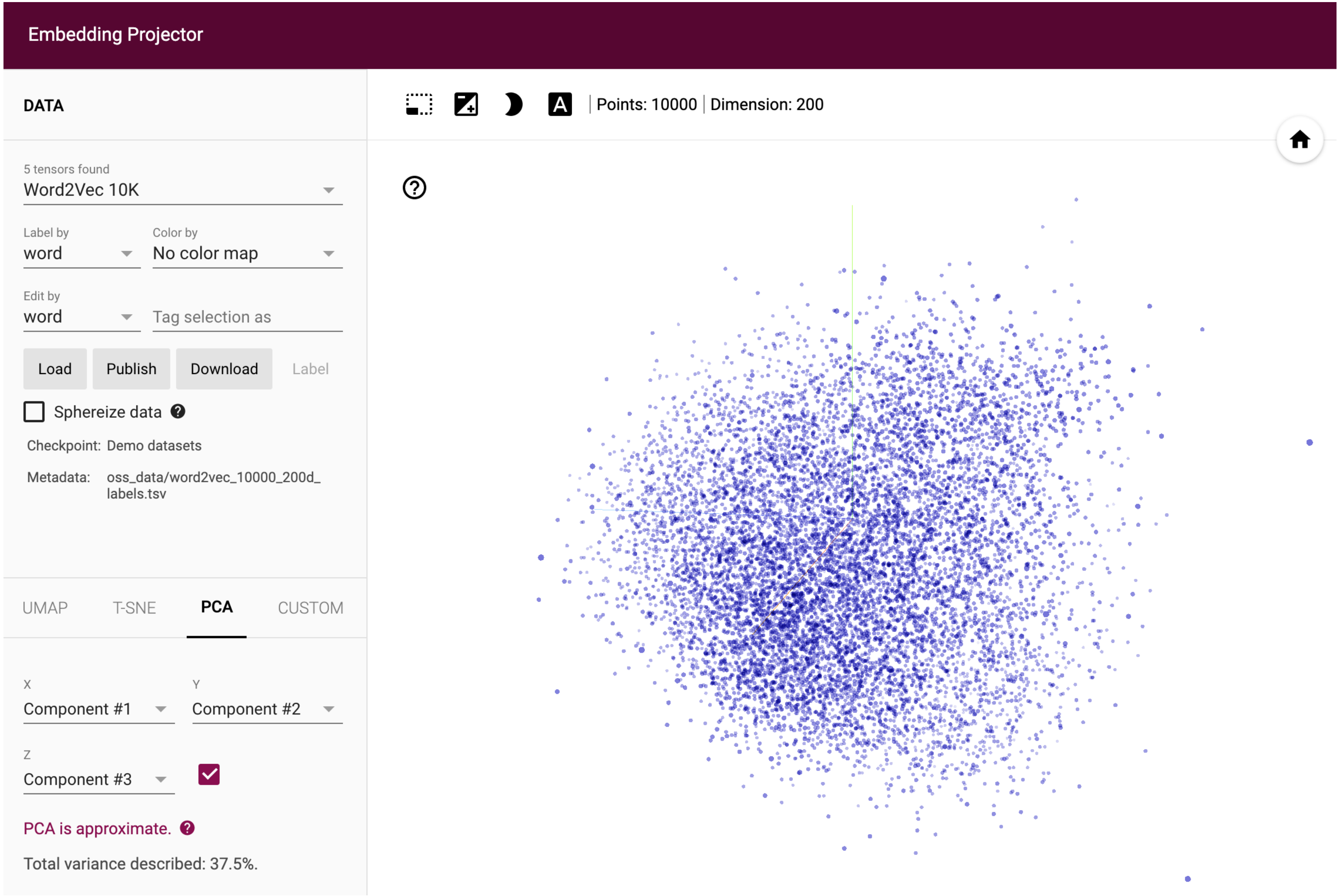


Image source: Lecture 2, cs224n



Source: http://projector.tensorflow.org/

Word2vec

- In essence, Word2vec uses supervised manner to train word vectors.
  - The center word is the input, the context words are its labels.

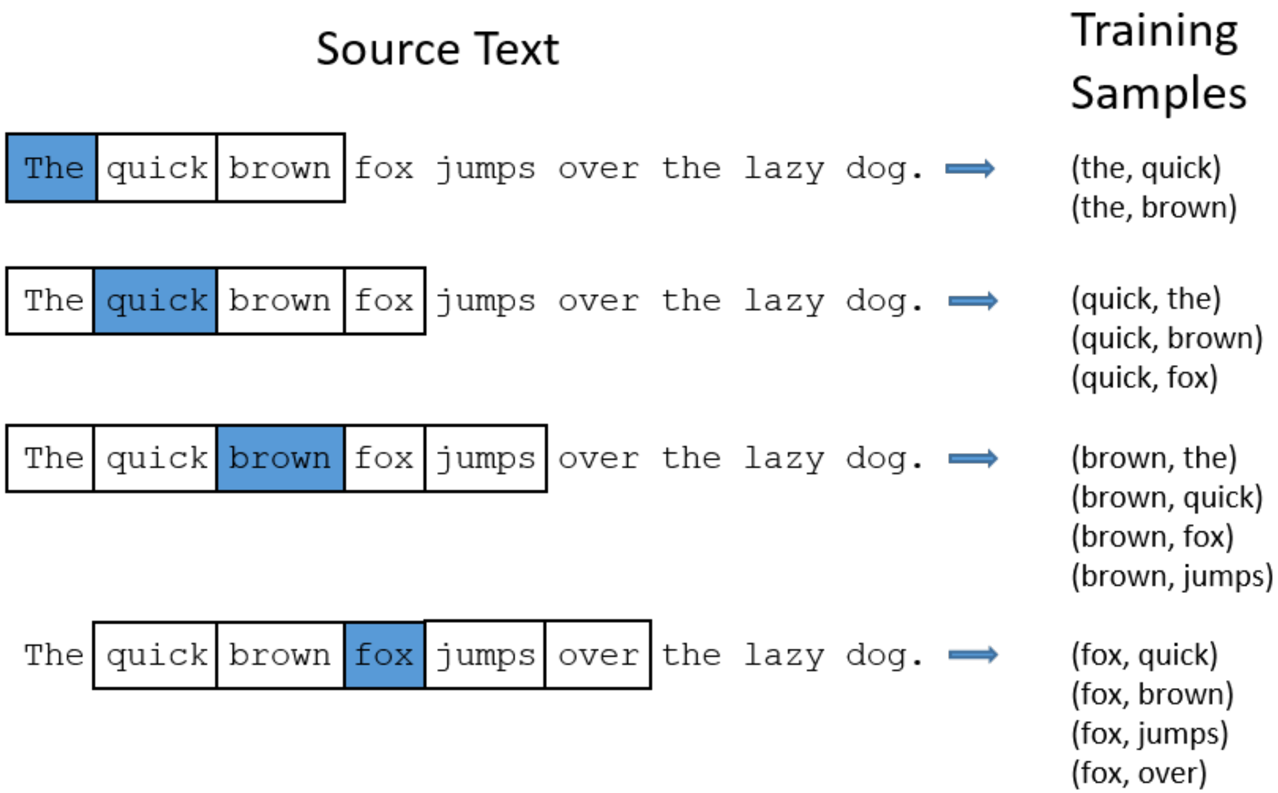
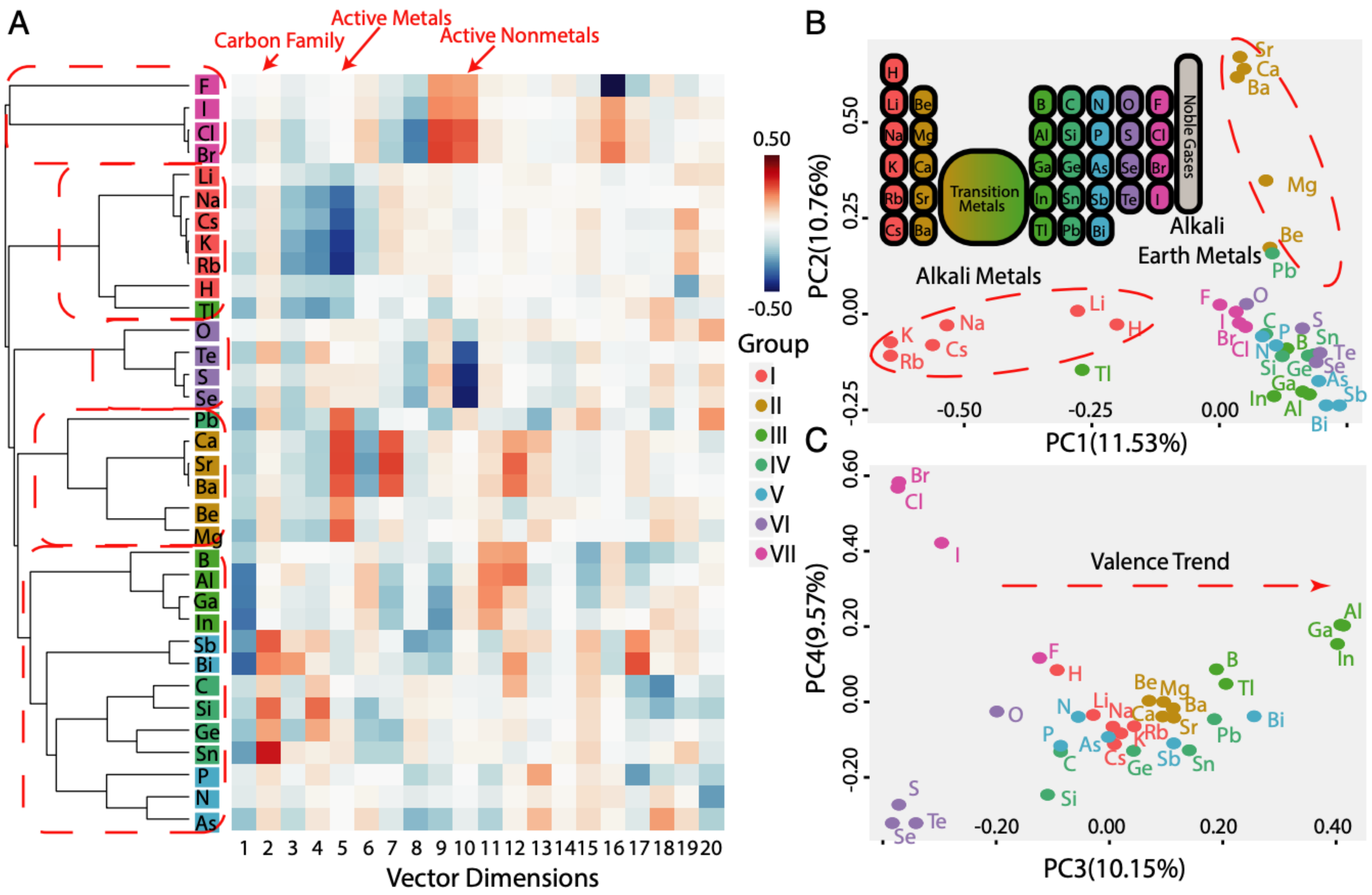


Image source: https://mubaris.com/posts/word2vec/

XXX2vec

- Follow this idea, any pair frequently occur in a set can be represented by a vector:
  - Recommender system: item2vec, user2vec.
  - Graph: node2vec, edge2vec.
  - Social media: tweet2vec, emoji2vec.
  - Bioinformatics: protein2vec, dna2vec.
  - Chemistry: molecule2vec, atom2vec.
  - Finance: stock2vec, fund2vec, company2vec.
- For more xxx2vec, check here.

Atom2vec



厦門大學信息学院（特色化示范性软件学院）
School of Informatics Xiamen University (National Characteristic Demonstration Software School)
厦门大学 计算机科学与技术系
Department of Computer Science and Technology, Xiamen University

Image source: Zhou, Quan, Peizhe Tang, Shenxiu Liu, Jinbo Pan, Qimin Yan, and Shou-Cheng Zhang. "Learning atoms for materials discovery." Proceedings of the National Academy of Sciences 115, no. 28 (2018): E6411-E6417.

Emoji2vec

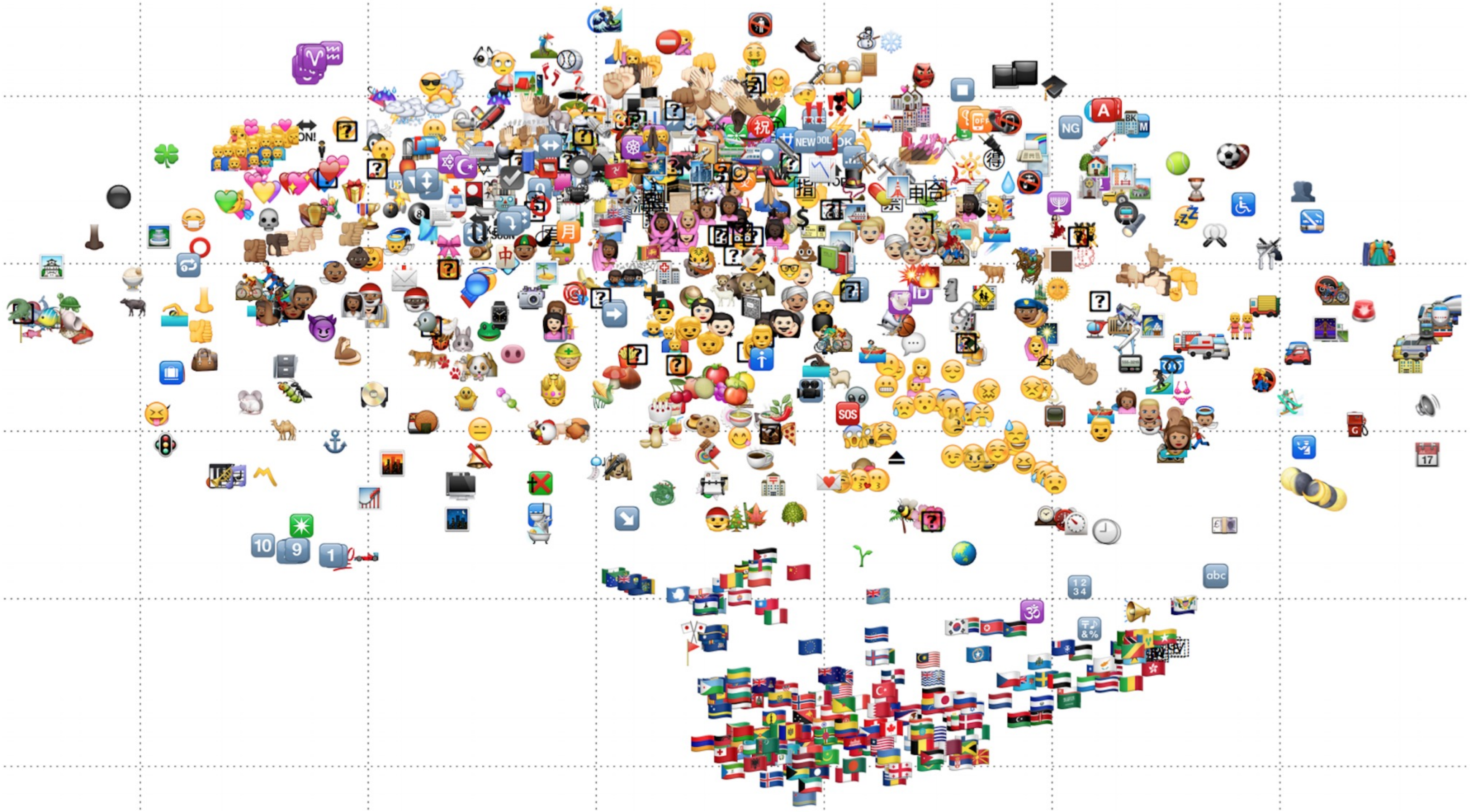


Image source: Eisner, Ben, Tim Rocktäschel, Isabelle Augenstein, Matko Bošnjak, and Sebastian Riedel. "emoji2vec: Learning emoji representations from their description." arXiv preprint arXiv:1609.08359 (2016).

Train Word2vec by PyTorch

- Use `nn.Embedding` for embedding loop-up.

```
word_to_ix = {"hello": 0, "world": 1}
embeds = nn.Embedding(2, 5)  # 2 words in vocab, 5 dimensional embeddings
lookup_tensor = torch.tensor([word_to_ix["hello"]], dtype=torch.long)
hello_embed = embeds(lookup_tensor)
print(hello_embed)
```

```
tensor([[ 0.6614,  0.2669,  0.0617,  0.6213, -0.4519]],
       grad_fn=<EmbeddingBackward>)
```


Code is modified from https://pytorch.org/tutorials/beginner/nlp/word_embeddings_tutorial.html

```python
EMBEDDING_DIM = 10
# We will use Shakespeare Sonnet 2
test_sentence = """When forty winters shall besiege thy brow,
And dig deep trenches in thy beauty's field,
Thy youth's proud livery so gazed on now,
Will be a totter'd weed of small worth held:
Then being asked, where all thy beauty lies,
Where all the treasure of thy lusty days;
To say, within thine own deep sunken eyes,
Were an all-eating shame, and thriftless praise.
How much more praise deserv'd thy beauty's use,
If thou couldst answer 'This fair child of mine
Shall sum my count, and make my old excuse,'
Proving his beauty by succession thine!
This were to be new made when thou art old,
And see thy blood warm when thou feel'st it cold.""".split()

# we should tokenize the input, but we will ignore that for now
# build a list of tuples.
# Each tuple is ([ word_i-2, word_i-1, word_i+1, word_i+2 ], target word)

context_tuple_list = [(test_sentence[i + 2],
                       [test_sentence[i], test_sentence[i + 1],
                        test_sentence[i + 3], test_sentence[i + 4]])
                        for i in range(len(test_sentence) - 4)]

# print the first 3, just so you can see what they look like
print(context_tuple_list[:3])

vocab = set(test_sentence)
word_to_ix = {word: i for i, word in enumerate(vocab)}
```

```
[('winters', ['When', 'forty', 'shall', 'besiege']), ('shall', ['forty',
'winters', 'besiege', 'thy']), ('besiege', ['winters', 'shall', 'thy', 'b
row,'])]
```

Code is modified from https://pytorch.org/tutorials/beginner/nlp/word_embeddings_tutorial.html

```python
class SkipGramLanguageModeler(nn.Module):

    def __init__(self, vocab_size, embedding_dim):
        super(SkipGramLanguageModeler, self).__init__()
        self.embeddings = nn.Embedding(vocab_size, embedding_dim)
        self.linear = nn.Linear(embedding_dim, vocab_size)

    def forward(self, inputs):
        embeds = self.embeddings(inputs).view((1, -1))
        out = self.linear(embeds)
        log_probs = F.log_softmax(out, dim=1)
        return log_probs


losses = []
loss_function = nn.NLLLoss()
model = SkipGramLanguageModeler(len(vocab), EMBEDDING_DIM)
optimizer = optim.SGD(model.parameters(), lr=0.001)
```


Code is modified from https://pytorch.org/tutorials/beginner/nlp/word_embeddings_tutorial.html

```python
for epoch in range(10):
    total_loss = 0
    for target, context_list in context_tuple_list:
        for context in context_list:

            # Step 1. Prepare the inputs to be passed to the model (i.e, t
            # into integer indices and wrap them in tensors)
            context_idxs = torch.tensor(word_to_ix[context], dtype=torch.l

            # Step 2. Recall that torch *accumulates* gradients. Before pa
            # new instance, you need to zero out the gradients from the ol
            # instance
            model.zero_grad()

            # Step 3. Run the forward pass, getting log probabilities over
            # words
            log_probs = model(context_idxs)

            # Step 4. Compute your loss function. (Again, Torch wants the
            # word wrapped in a tensor)
            loss = loss_function(log_probs, torch.tensor([word_to_ix[targe

            # Step 5. Do the backward pass and update the gradient
            loss.backward()
            optimizer.step()

            # Get the Python number from a 1-element Tensor by calling ten
            total_loss += loss.item()
    print(total_loss)
    losses.append(total_loss)
```

```
2106.0324614048004
2099.963498353958
2093.969718694687
2088.050463914871
2082.2050607204437
2076.4329063892365
2070.7334401607513
2065.10606575012
2059.550250291824З
2054.065470457077
```

Code is modified from https://pytorch.org/tutorials/beginner/nlp/word_embeddings_tutorial.html

Word Representation

- Originally, we basically had only one representation of words:
  - E.g. Word2vec, GloVe, fastText.
- These have two problems:
  - Always the same representation for a word regardless of the context in which a word token occurs.
  - We just have one representation for a word, but words have different aspects, including semantics, syntactic behavior, and register /connotations.

ELMo

Deep contextualized word representations
ME Peters, M Neumann, M Iyyer, M Gardner… - arXiv preprint arXiv …, 2018 - arxiv.org
We introduce a new type of deep contextualized word representation that models both (1) complex characteristics of word use (eg, syntax and semantics), and (2) how these uses vary across linguistic contexts (ie, to model polysemy). Our word vectors are learned functions of …
Cited by 4902 Related articles All 18 versions

- Combine pre-trained word token vectors or contextual word vectors.
- Learn word token vectors using long contexts not context windows (here, whole sentence, could be longer).
- Learn a deep bidirectional language model (biLM) and use all its layers in prediction.

ELMo

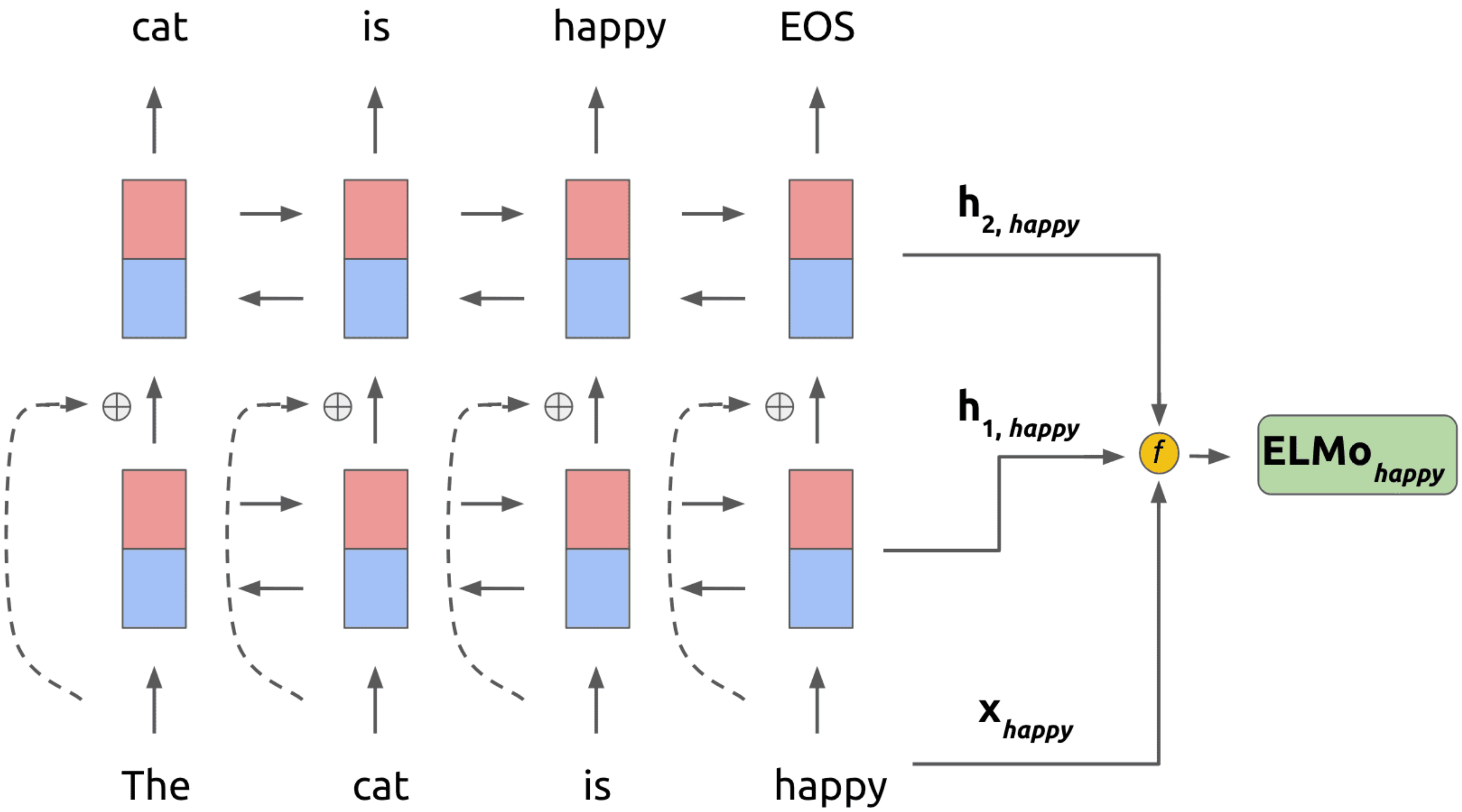


Image source: https://www.mihaileric.com/posts/deep-contextualized-word-representations-elmo/

TRANSFORMER

Image source: https://www.ebay.com/p/1054996955

XXX is All You Need

Attention is all you need ???
A Vaswani, N Shazeer, N Parmar… - Advances in neural …, 2017 - proceedings.neurips.cc
… to attend to **all** positions in the decoder up to and including that position. **We need** to prevent … **We** implement this inside of scaled dot-product **attention** by masking out (setting to −∞) …
☆ Save 99 Cite Cited by 94235 Related articles All 62 versions

[PDF] Attention **is all you need**
A Vaswani, N Shazeer, N Parmar… - Advances in neural …, 2017 - papers.nips.cc
The dominant sequence transduction models are based on complex recurrent orconvolutional neural networks in an encoder and decoder configuration. The best performing such models also connect the encoder and decoder through an attentionm …
☆ 99 Cited by 30000 Related articles All 28 versions

Rezero **is all you need**: Fast convergence at large depth
T Bachlechner, BP Majumder, HH Mao… - arXiv preprint arXiv …, 2020 - arxiv.org
Deep networks often suffer from vanishing or exploding gradients due to inefficient signal propagation, leading to long training times or convergence difficulties. Various architecture designs, sophisticated residual-style networks, and initialization schemes have been shown …
☆ 99 Cited by 61 Related articles All 3 versions

Diversity **is all you need**: Learning skills without a reward function
B Eysenbach, A Gupta, J Ibarz, S Levine - arXiv preprint arXiv:1802.06070, 2018 - arxiv.org
Intelligent creatures can explore their environments and learn useful skills without supervision. In this paper, we propose DIAYN ('Diversity **is All You Need**'), a method for learning useful skills without a reward function. Our proposed method learns skills by …
☆ 99 Cited by 398 Related articles All 4 versions

Hopfield networks **is all you need**
H Ramsauer, B Schäfl, J Lehner, P Seidl… - arXiv preprint arXiv …, 2020 - arxiv.org
We introduce a modern Hopfield network with continuous states and a corresponding update rule. The new Hopfield network can store exponentially (with the dimension of the associative space) many patterns, retrieves the pattern with one update, and has …
☆ 99 Cited by 70 Related articles All 7 versions

Proving the lottery ticket hypothesis: Pruning **is all you need**
E Malach, G Yehudai… - International …, 2020 - proceedings.mlr.press
The lottery ticket hypothesis (Frankle and Carbin, 2018), states that a randomly-initialized network contains a small subnetwork such that, when trained in isolation, can compete with the performance of the original network. We prove an even stronger hypothesis (as was also …
☆ 99 Cited by 60 Related articles All 4 versions

Rethinking few-shot image classification: a good embedding **is all you need**?
Y Tian, Y Wang, D Krishnan, JB Tenenbaum… - Computer Vision–ECCV …, 2020 - Springer
The focus of recent meta-learning research has been on the development of learning algorithms that can quickly adapt to test time tasks with limited data and low computational cost. Few-shot learning is widely used as one of the standard benchmarks in meta-learning …
☆ 99 Cited by 194 Related articles All 7 versions

Image augmentation **is all you need**: Regularizing deep reinforcement learning from pixels
I Kostrikov, D Yarats, R Fergus - arXiv preprint arXiv:2004.13649, 2020 - arxiv.org
We propose a simple data augmentation technique that can be applied to standard model-free reinforcement learning algorithms, enabling robust learning directly from pixels without the need for auxiliary losses or pre-training. The approach leverages input perturbations …
☆ 99 Cited by 130 Related articles All 6 versions

15 keypoints **is all you need**
M Snower, A Kadav, F Lai… - Proceedings of the IEEE …, 2020 - openaccess.thecvf.com
Pose-tracking is an important problem that requires identifying unique human pose-instances and matching them temporally across different frames in a video. However, existing pose-tracking methods are unable to accurately model temporal relationships and …
☆ 99 Cited by 6 Related articles All 5 versions

Depthwise convolution **is all you need** for learning multiple visual domains
Y Guo, Y Li, L Wang, T Rosing - … of the AAAI Conference on Artificial …, 2019 - ojs.aaai.org
There is a growing interest in designing models that can deal with images from different visual domains. If there exists a universal structure in different visual domains that can be captured via a common parameterization, then we can use a single model for all domains …
☆ 99 Cited by 39 Related articles All 11 versions

Diffusion **is all you need** for learning on surfaces
N Sharp, S Attaiki, K Crane, M Ovsjanikov - arXiv preprint arXiv …, 2020 - arxiv.org
We introduce a new approach to deep learning on 3D surfaces such as meshes or point clouds. Our key insight is that a simple learned diffusion layer can spatially share data in a principled manner, replacing operations like convolution and pooling which are complicated …
☆ 99 Cited by 6 Related articles All 3 versions

Source: Google Scholar

Transformer

- Recurrent models typically factor computation along the symbol positions of the input and output sequences.
  - i.e. either forward or backward.
- It brings two problems:
  - Preclude parallelization within training examples.
  - Difficult to learn dependencies between distant positions.

Transformer

- Thoroughly abandoned RNN or CNN achitecture.
- Only use self-attention and feed forward neural network to model contextual information.
- Designed for machine translation by the encoder-decoder achitecture, but now widely used as a basic component of many NLP and CV tasks.

- From a high-level look, it is nothing but an encoder-decoder network.

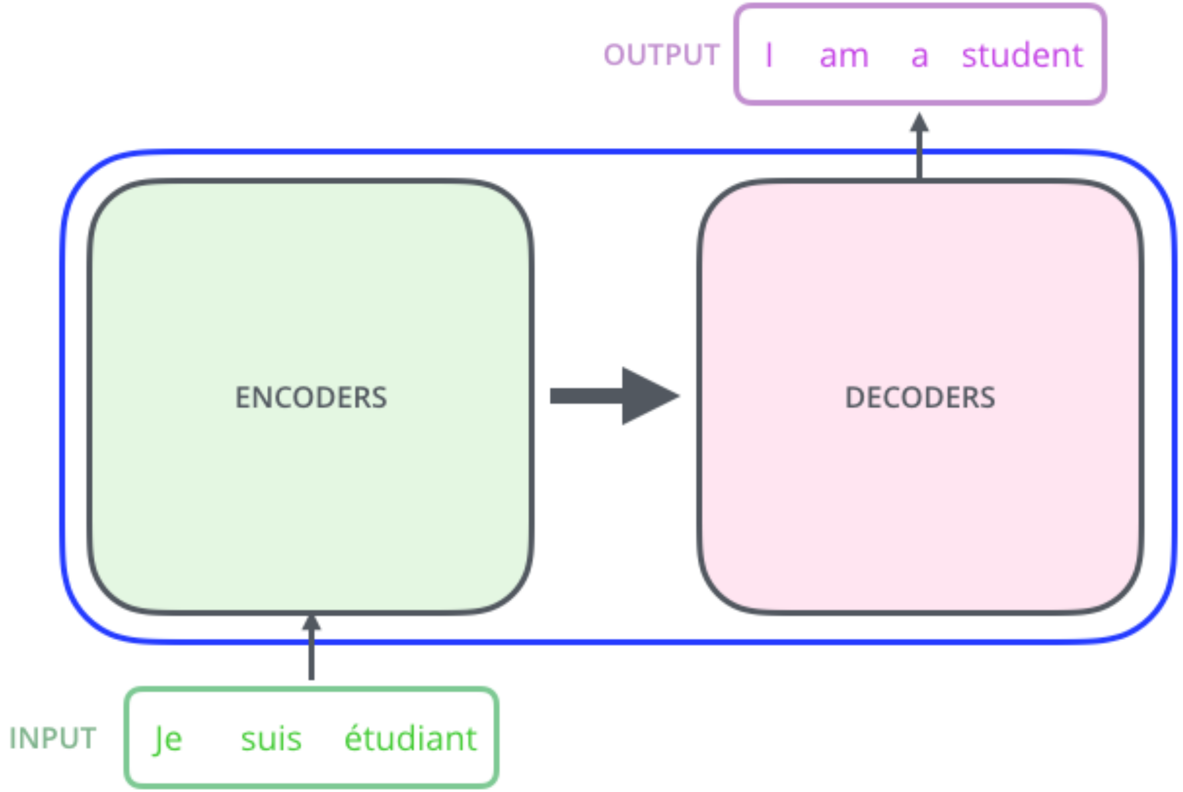


Image source: https://jalammar.github.io/illustrated-transformer/

Transformer

- The encoding component is a stack of encoders.
  - In the paper, it is 6.
- The decoding component is a stack of decoders of the same number.

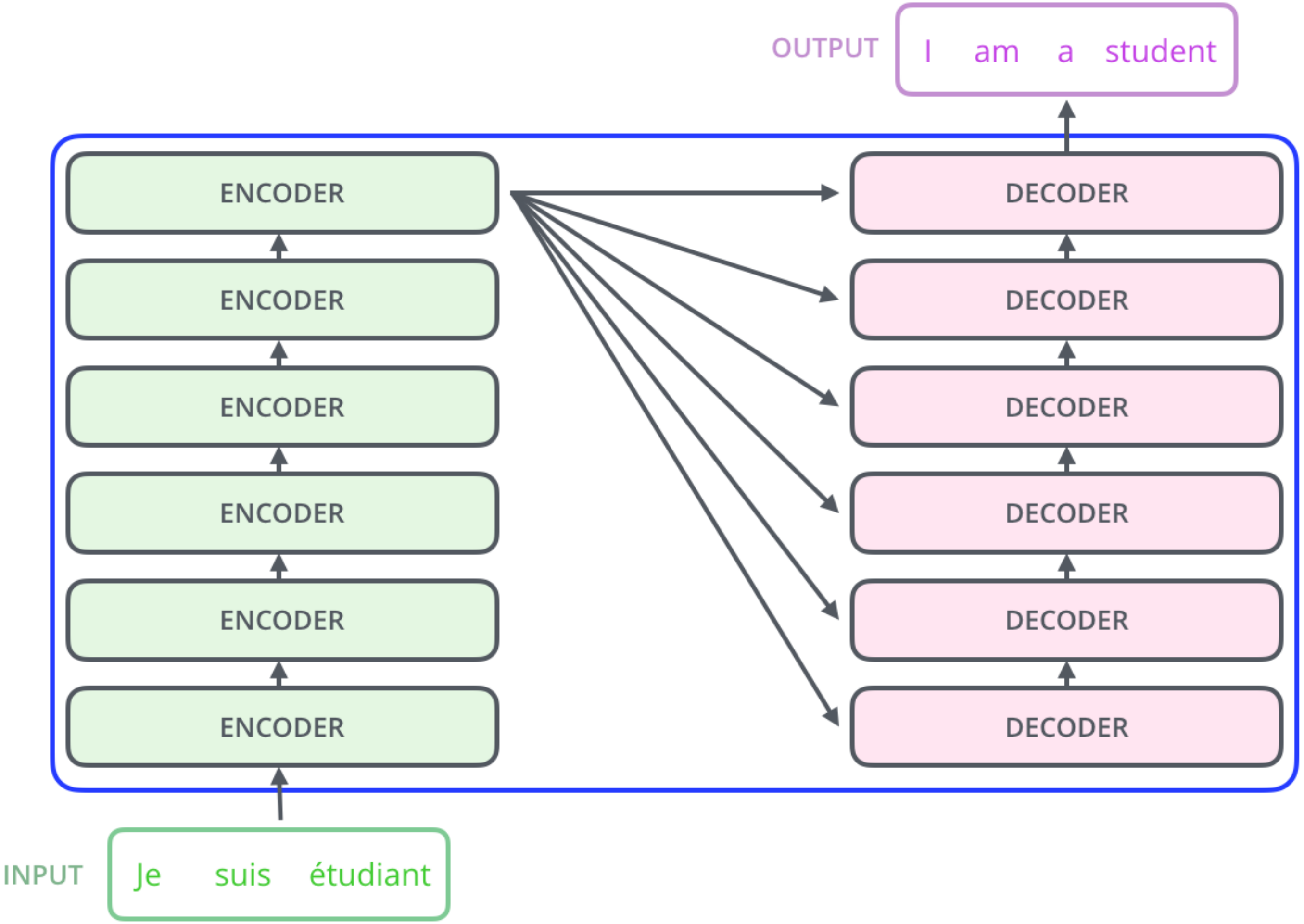


Image source: https://jalammar.github.io/illustrated-transformer/

Transformer

- Transformer keeps the encoder-decoder attention, but replace RNN layer by self-attention layer.

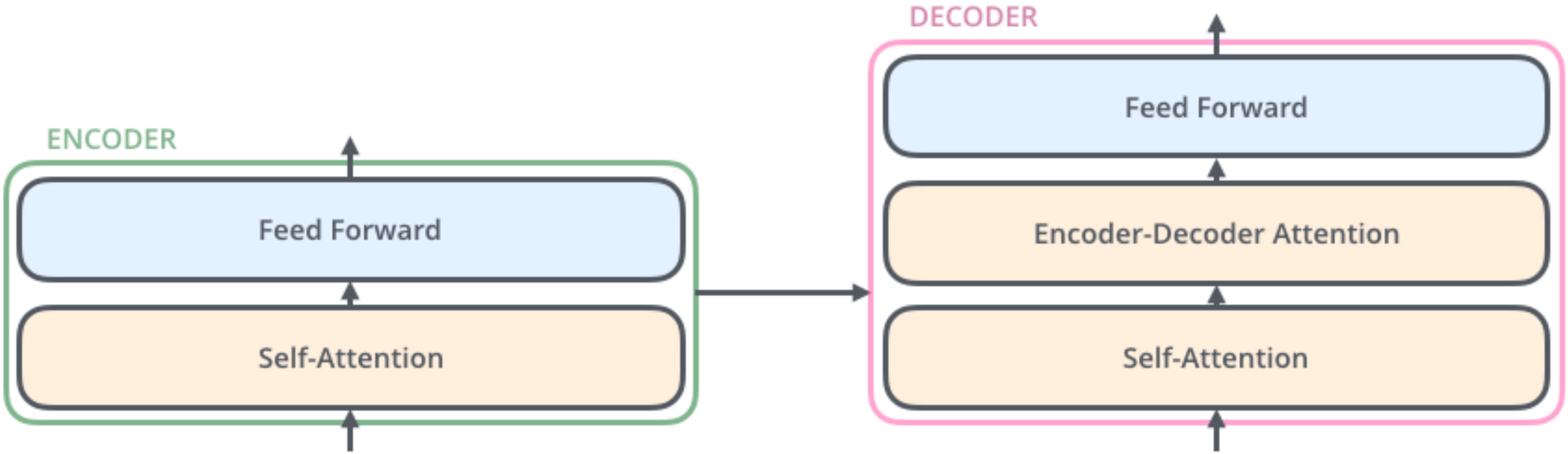


Image source: https://jalammar.github.io/illustrated-transformer/

Self-Attention

- As is the case in NLP applications in general, we begin by turning each input word into a vector using an embedding algorithm.
  - e.g. each word is embedded into a vector of size 512.

Image source: https://jalammar.github.io/illustrated-transformer/

Self-Attention

- Each embedding flows through each of the two layers of the encoder.
- There are dependencies between these paths in the self-attention layer.

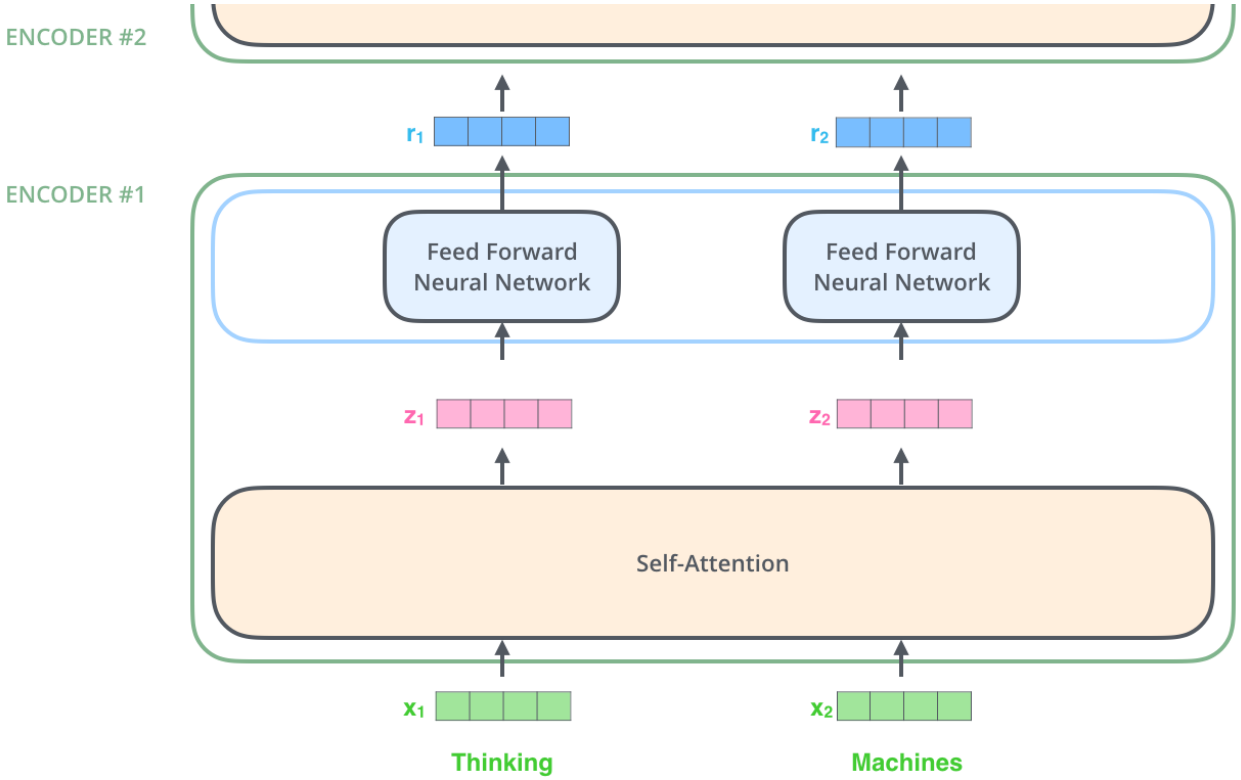


Image source: https://jalammar.github.io/illustrated-transformer/

Attention

Recall the encoder-decoder attention architecture:

- Use RNN to capture context information.
- Use attention to assign weights from the encoder hidden states to the decoder.

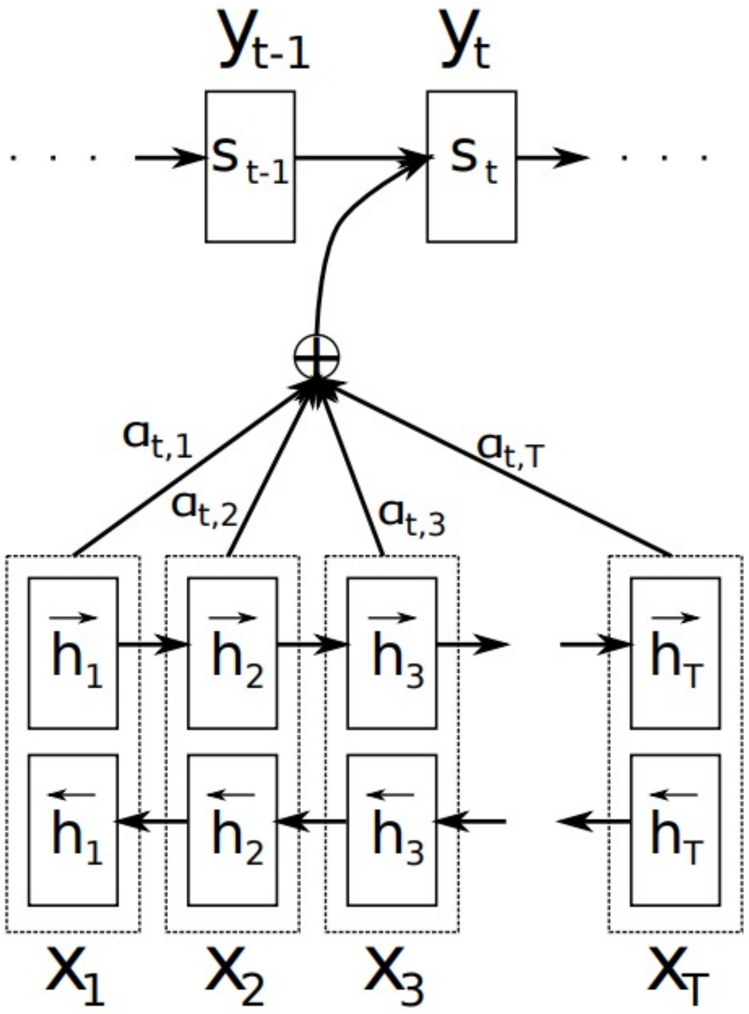


Image source: Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio. "Neural machine translation by jointly learning to align and translate." arXiv preprint arXiv:1409.0473 (2014).

Self-Attention

- Self-attention is the weighted representation of the target at place of itself.
- When the model is processing the word “it”, self-attention allows it to associate “it” with “animal”.
- RNN can also do this job, but the correlation highly depends on the distance.

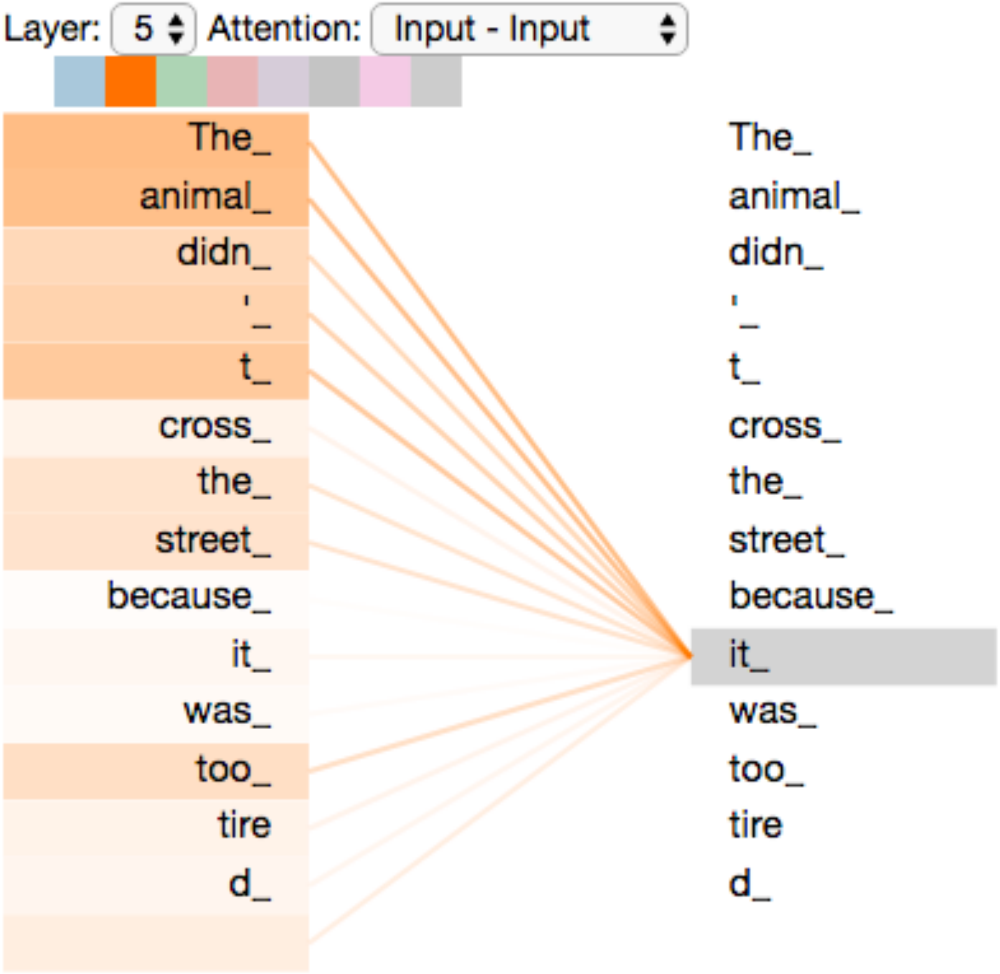


Image source: https://jalammar.github.io/illustrated-transformer/

Self-Attention

- So for each word vector, we transform it into a Query vector, a Key vector, and a Value vector.

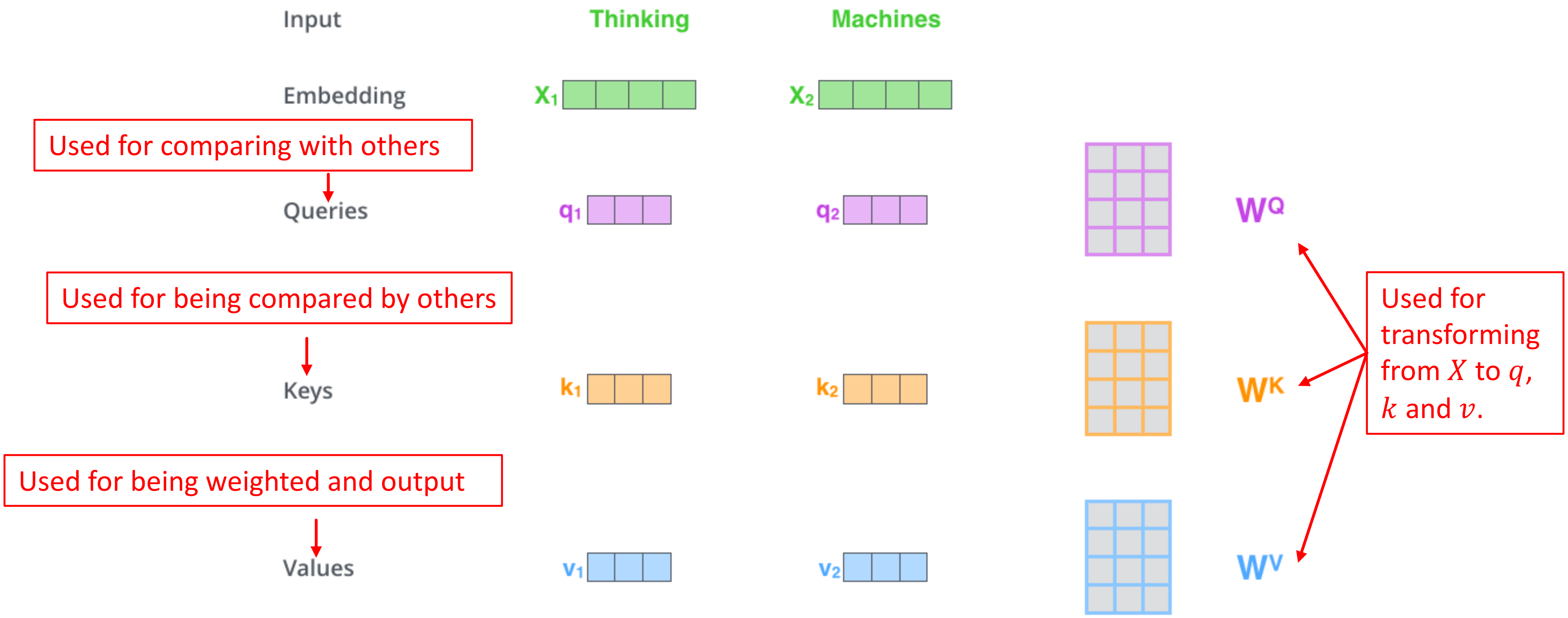


Image source: https://jalammar.github.io/illustrated-transformer/

Self-Attention

- Q and K are used to calculate attention weights, and V is used to apply those weights.
- Q is the vector for itself, and K is the vector for others.

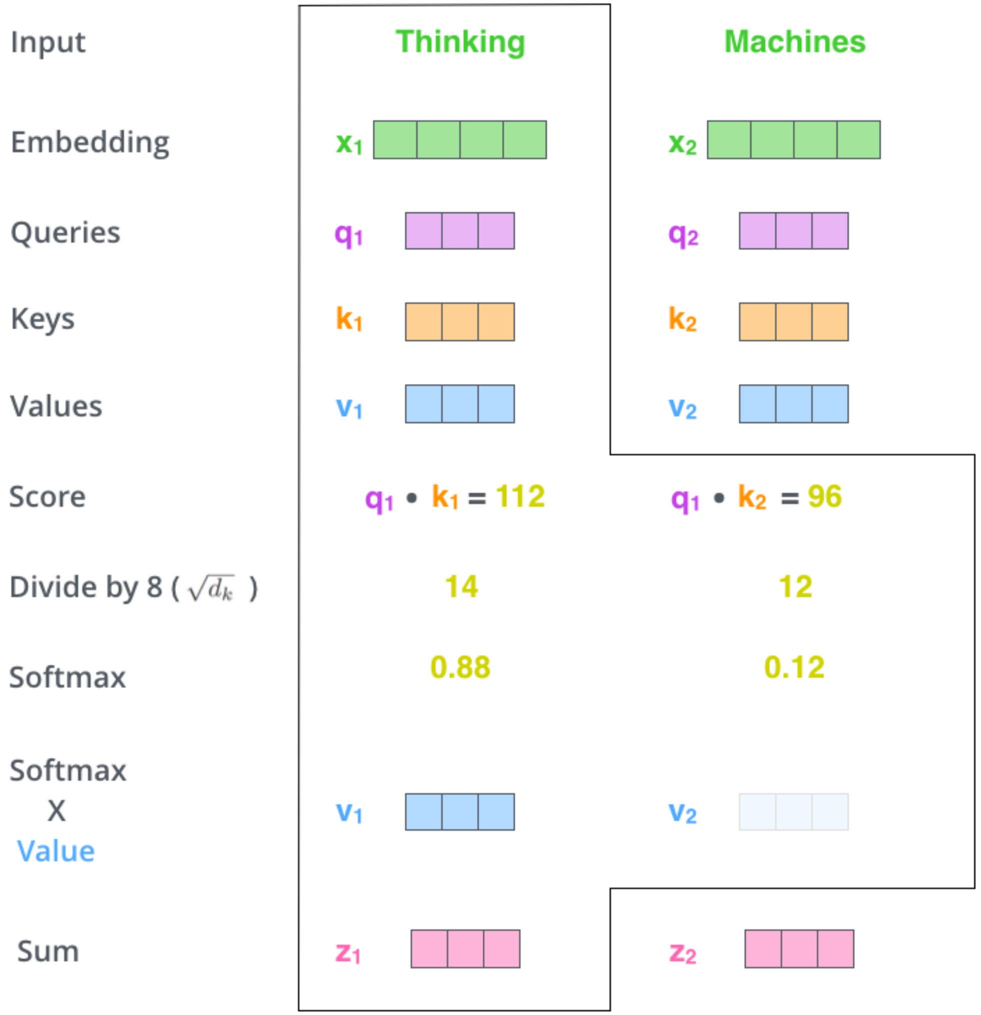
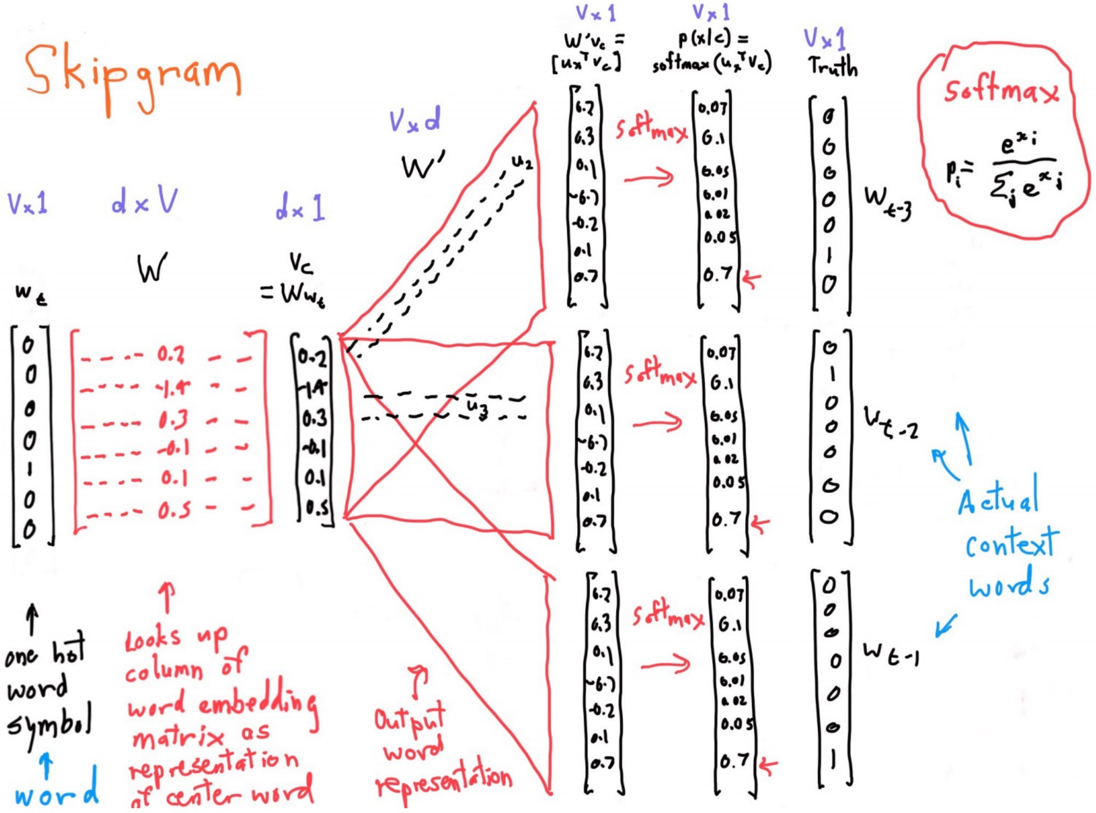


Image source: https://jalammar.github.io/illustrated-transformer/

Self-Attention

- Q and K represent central and context, which is similar to W and W' in Skipgram.



Self-Attention

- It is also called dot-product attention:

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

- When we calculate the self-attention representation, we put all words into matrix:

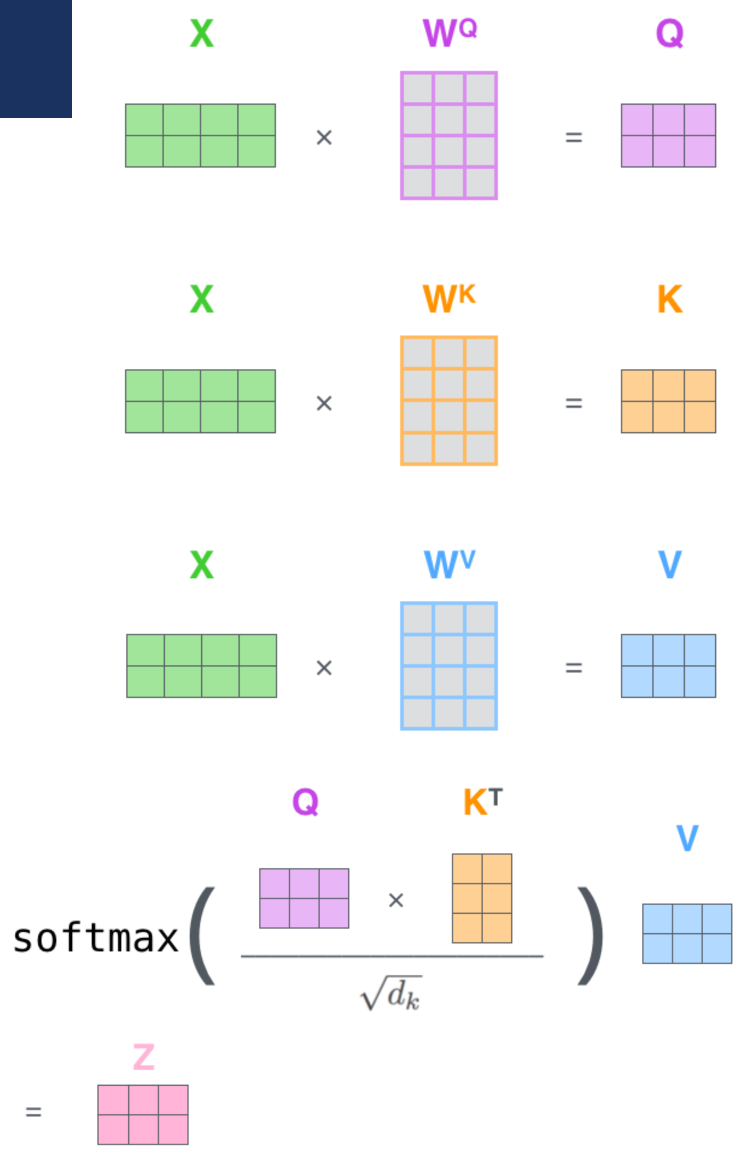


Image source: https://jalammar.github.io/illustrated-transformer/

Multi-Head Attention

- Multi-head attention expands the model's ability to focus on different positions.
- Each head uses different W^Q, W^K and W^V, which are randomly initialized.
- Different attention heads can be trained in parallel.

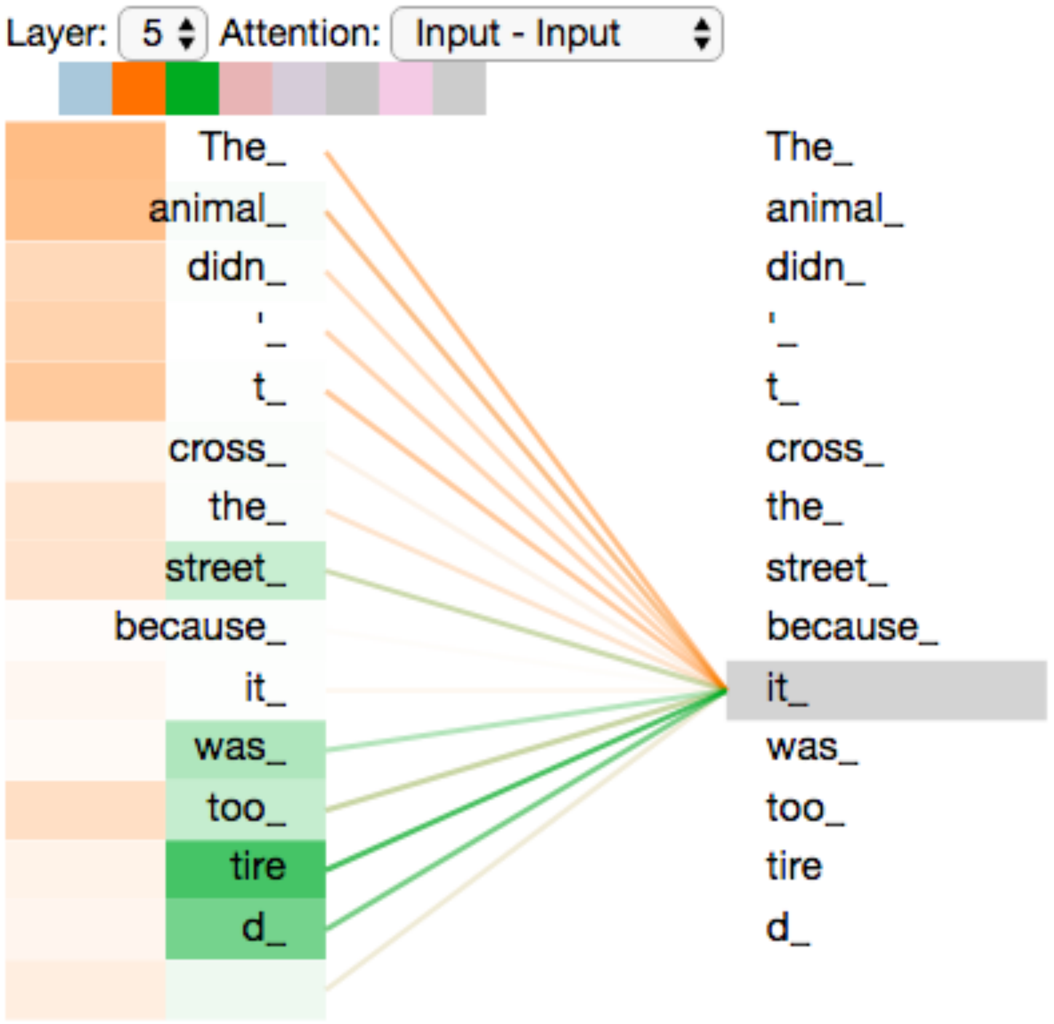


Image source: https://jalammar.github.io/illustrated-transformer/

Multi-Head Attention

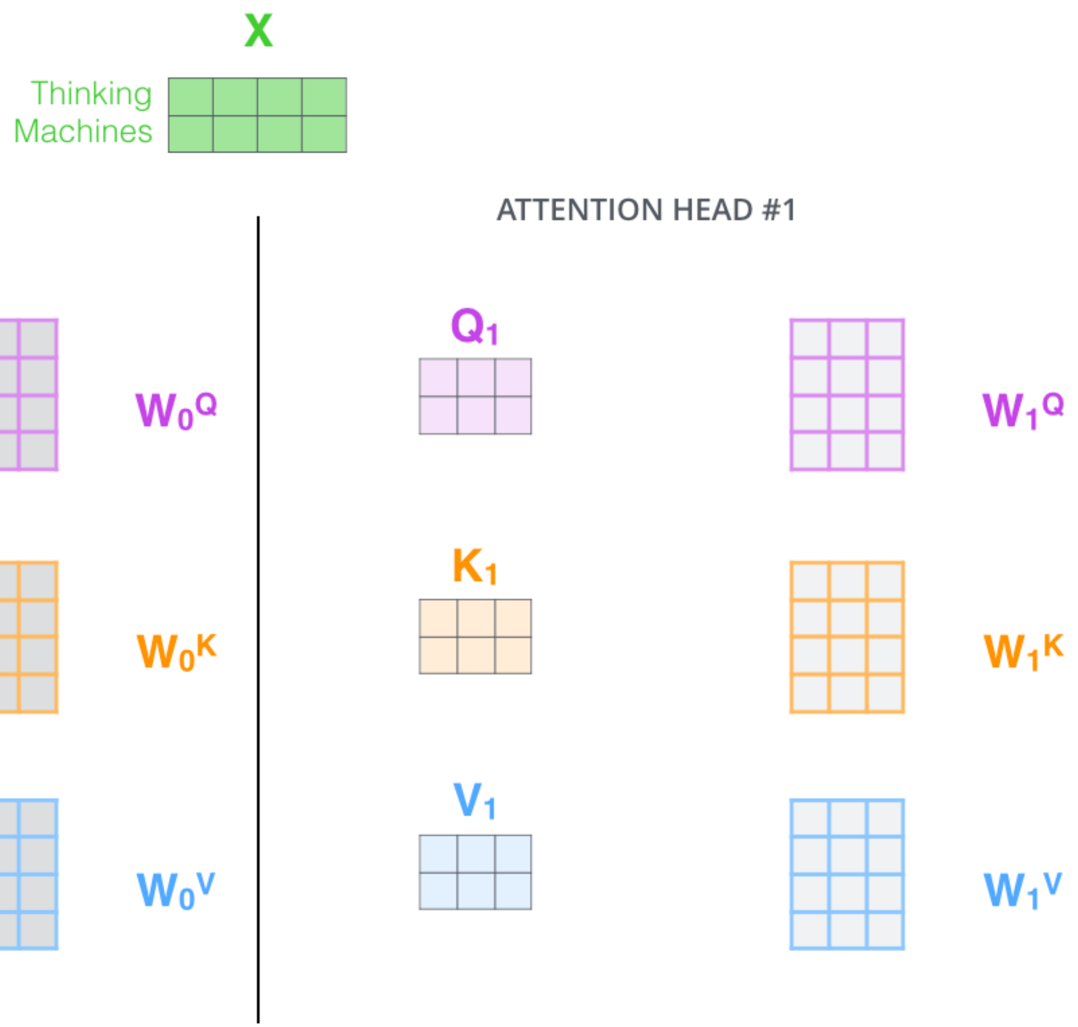


Image source: https://jalammar.github.io/illustrated-transformer/

Multi-Head Attention

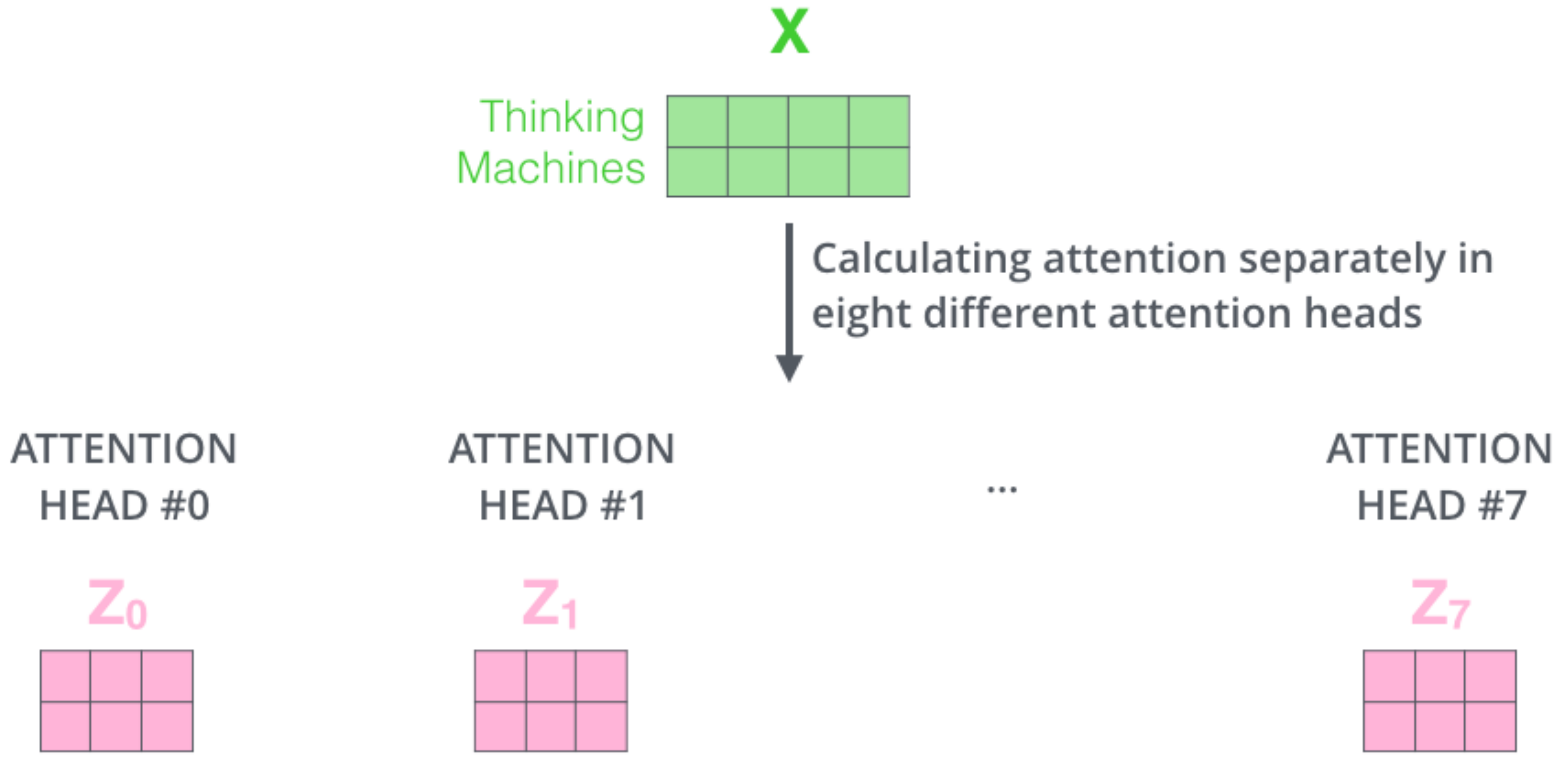


Image source: https://jalammar.github.io/illustrated-transformer/

Multi-Head Attention

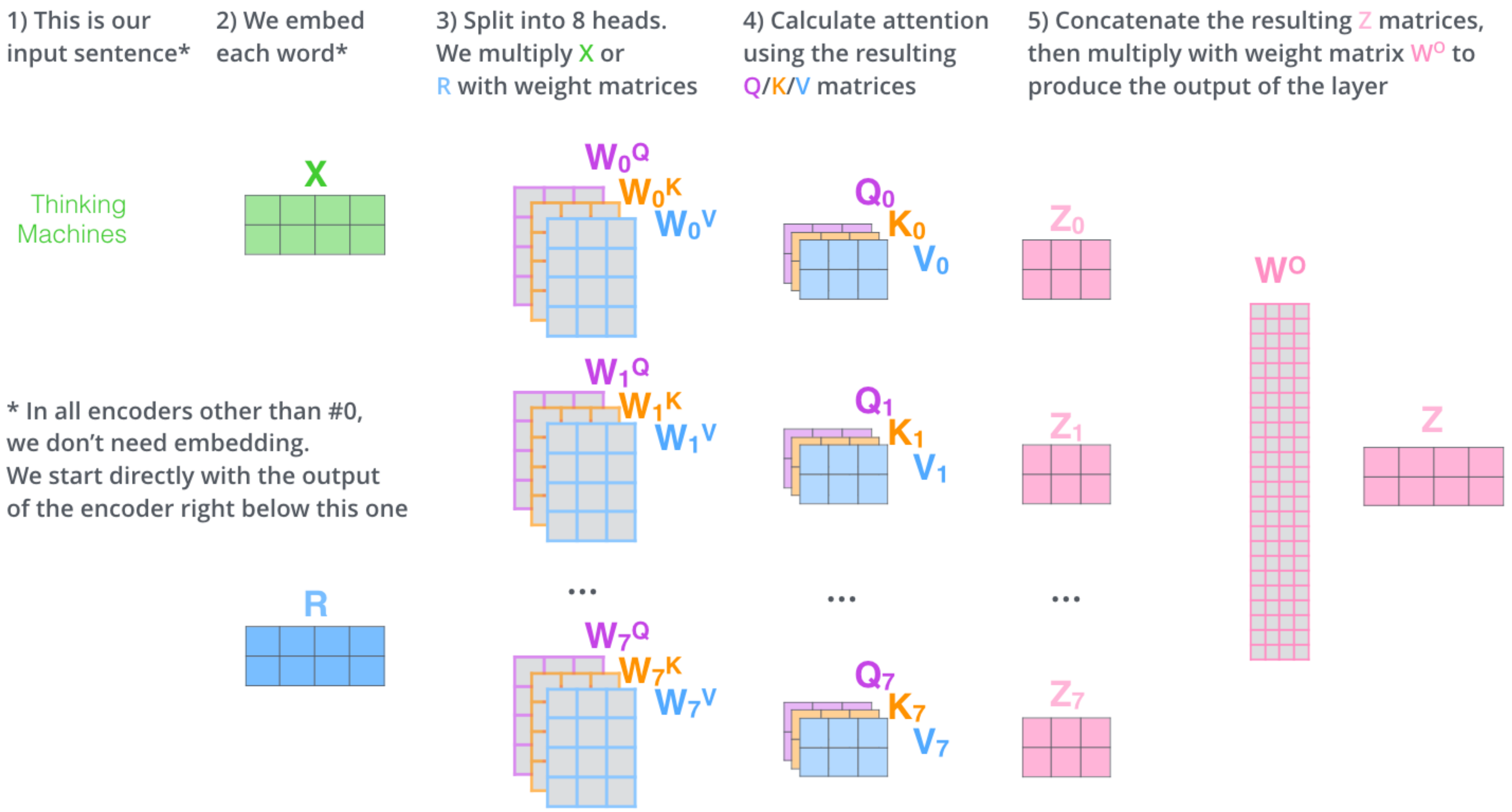


Image source: https://jalammar.github.io/illustrated-transformer/

Positional Encoding

- Now, one problem is that we lose the information about the relative or absolute position of the tokens in the sequence.
  - He likes this movie because it doesn‘t have an overhead history. -> Positive.
  - He doesn’t like this movie because it has an overhead history. -> Negative.
- Positional encoding helps the model determine the position of each word, or the distance between different words in the sequence.

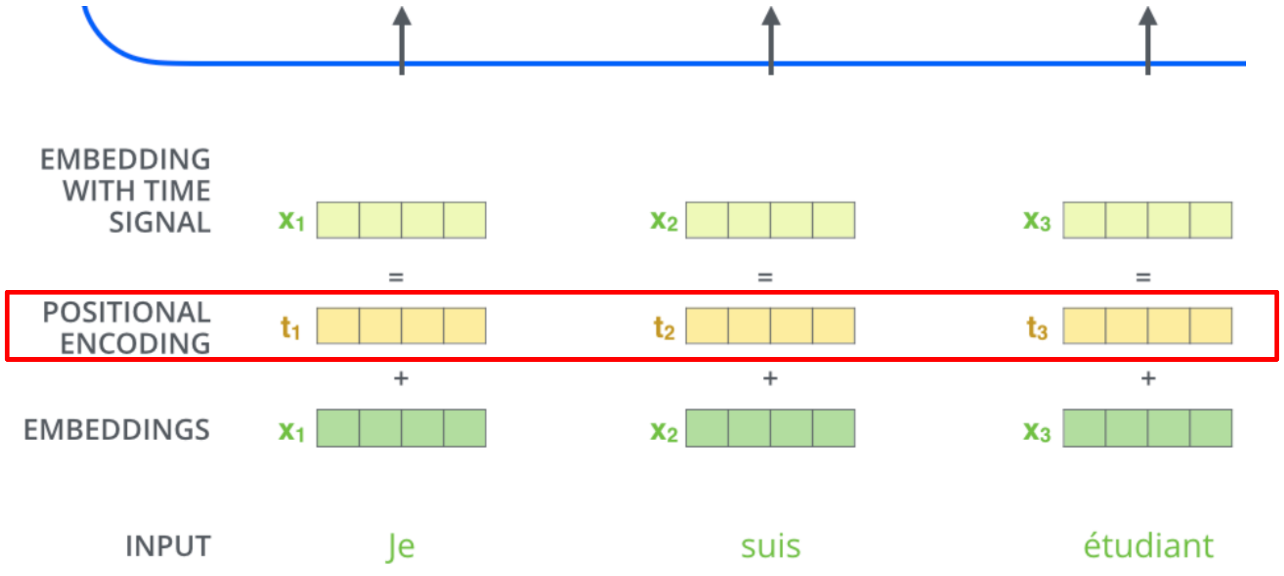


Image source: https://jalammar.github.io/illustrated-transformer/

Positional Encoding

- Positional encoding is fomulated as:

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

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

where pos is the position, i is the dimension index, d_{model} is word embedding dimension.

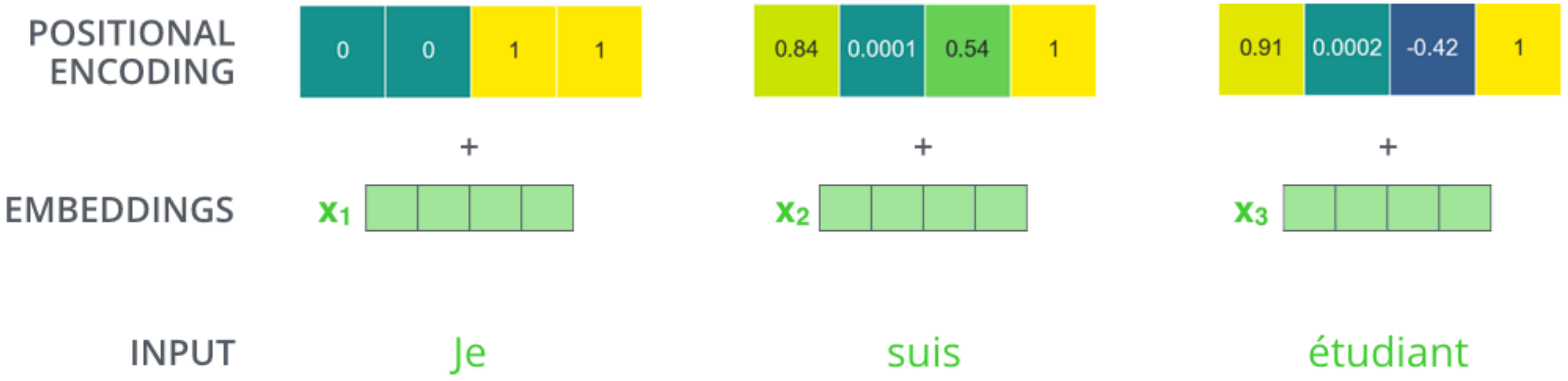


Image source: https://jalammar.github.io/illustrated-transformer/

Encoder-Decoder Architecture

- Residual connections are used in both encoder and decoder.
- In the decoder, the self-attention layer is only allowed to attend to earlier positions in the output sequence, which is called masked multi-head attention.
- In the encoder-decoder attention, only K and V from the encoder are used.

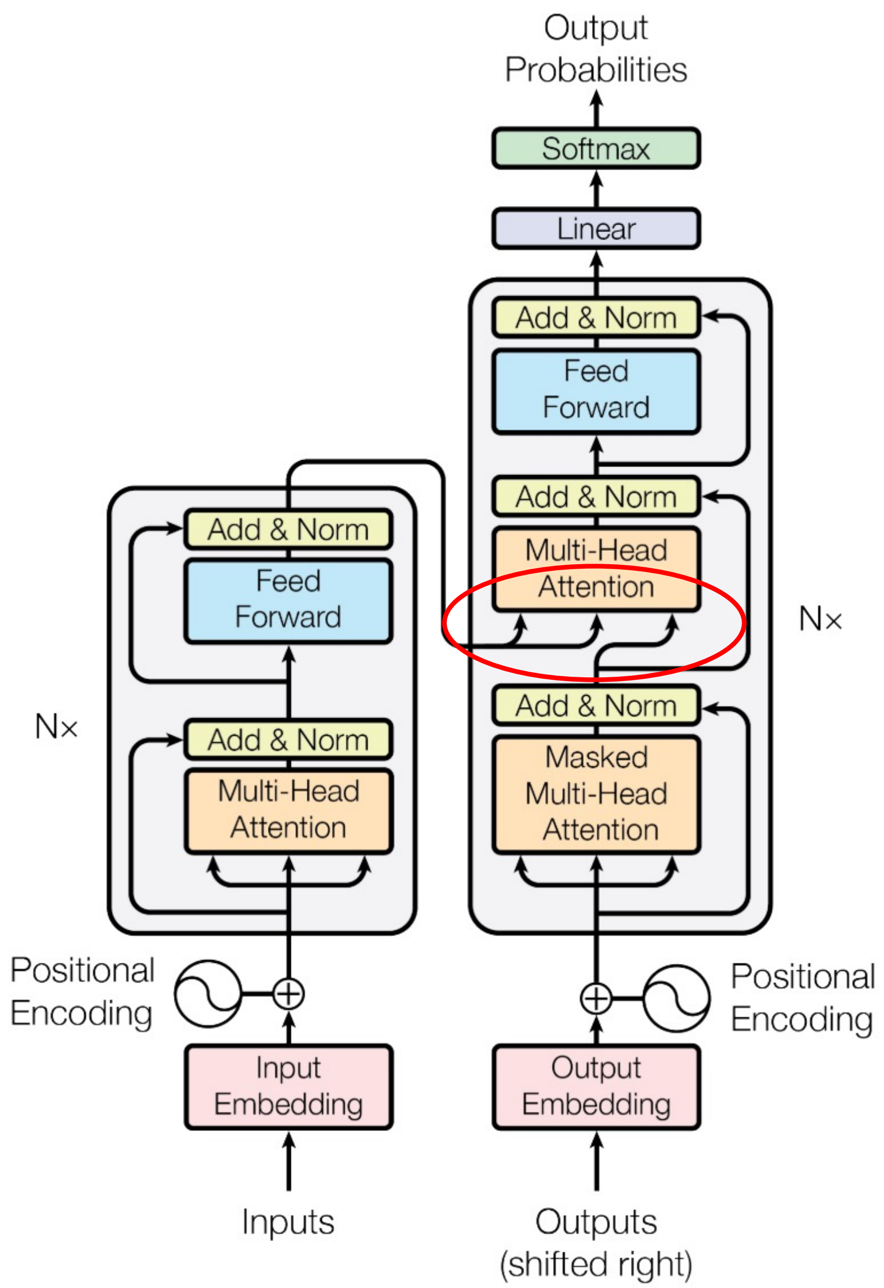


Image source: Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." In Advances in neural information processing systems, pp. 5998-6008. 2017.

Encoder-Decoder Architecture

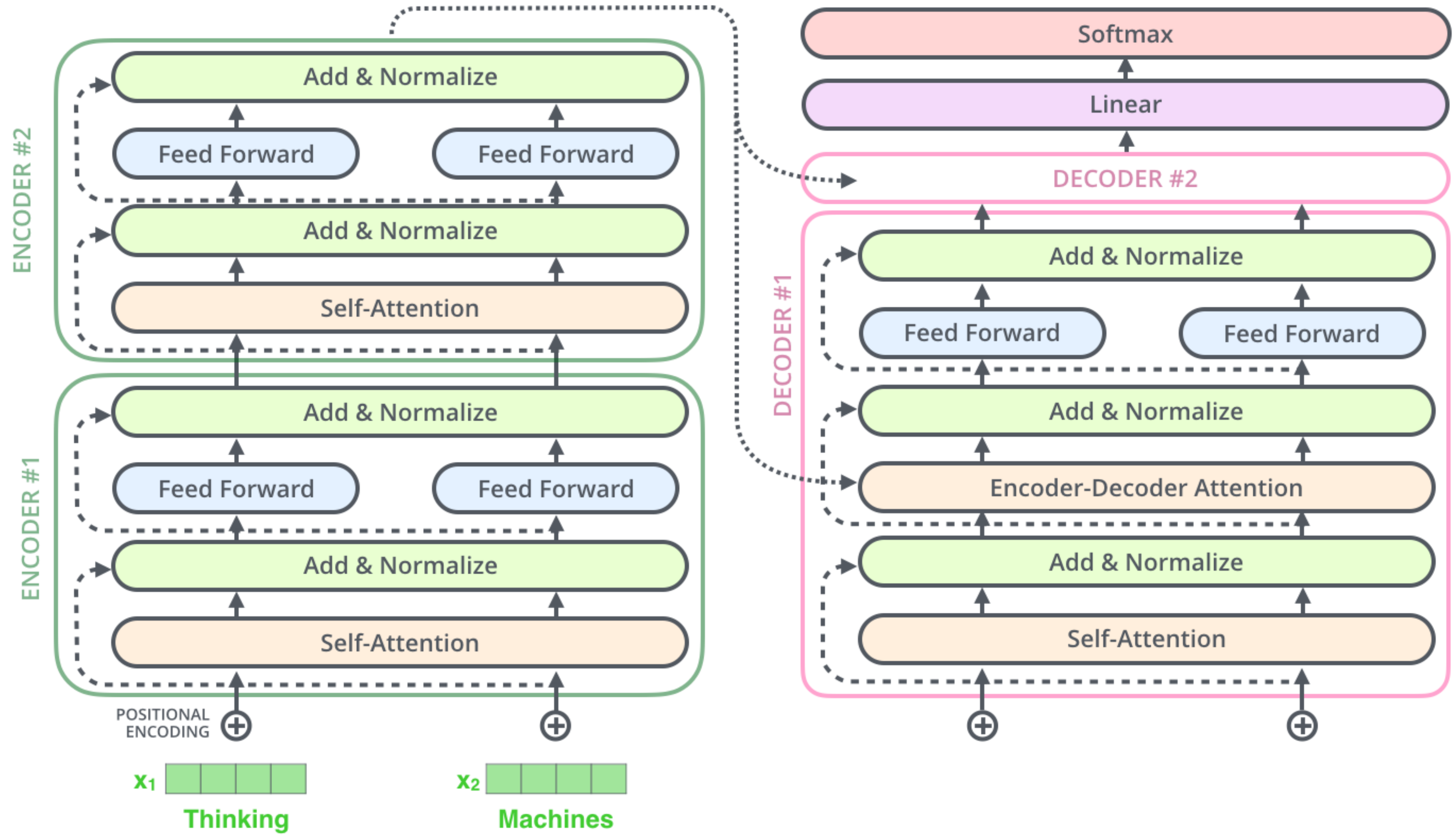
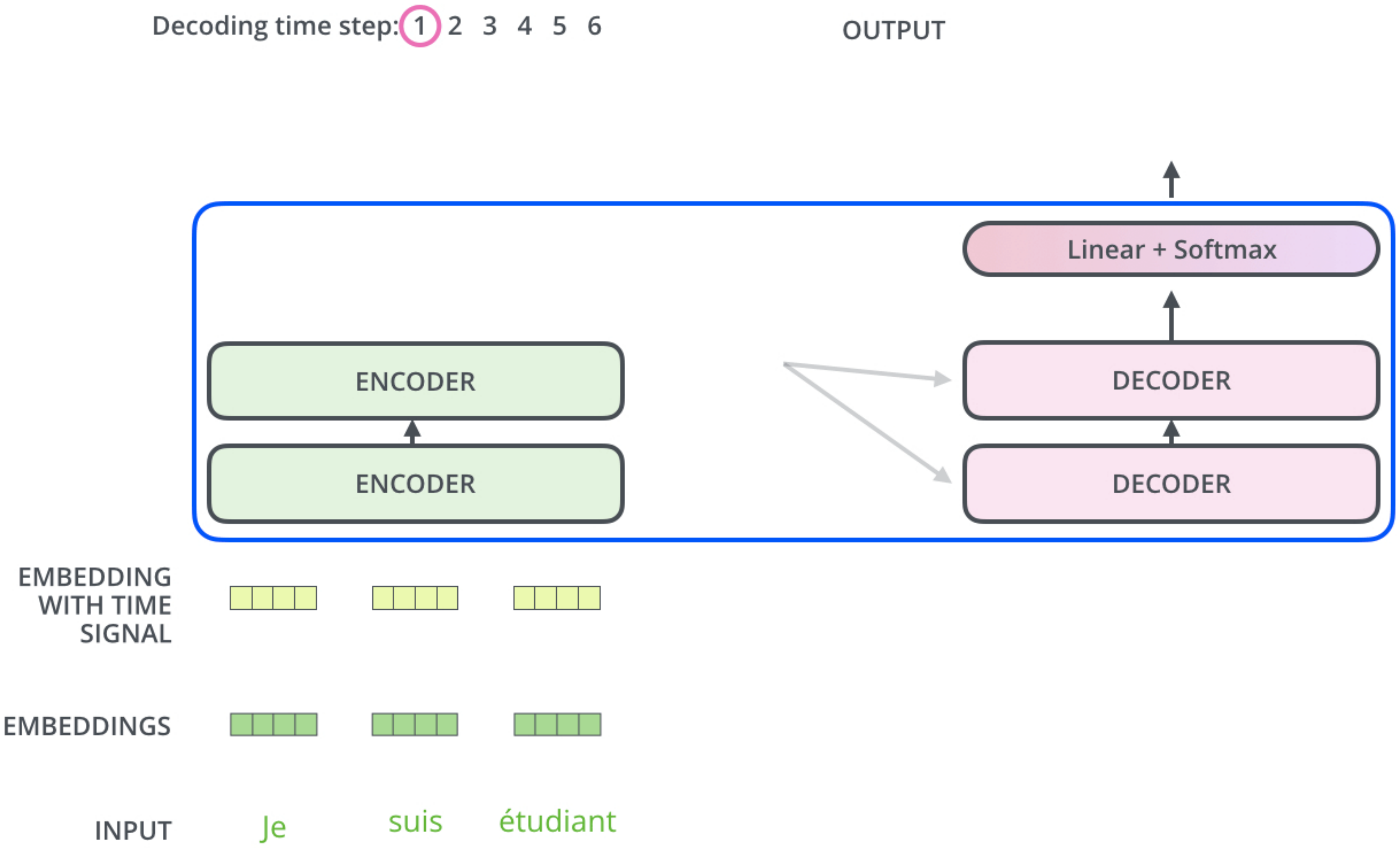


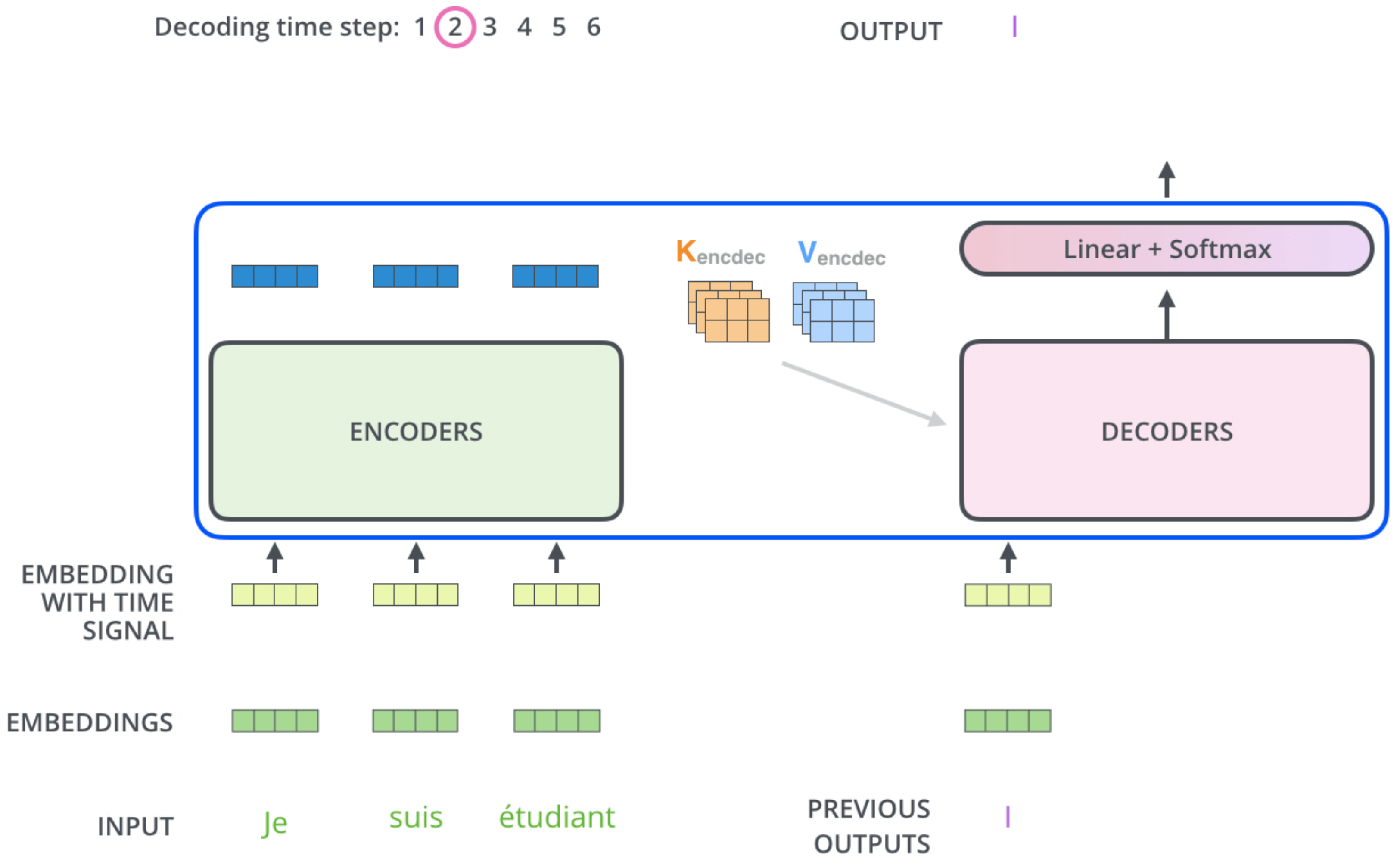
Image source: https://jalammar.github.io/illustrated-transformer/

Encoder-Decoder Architecture



https://jalammar.github.io/illustrated-transformer/

Encoder-Decoder Architecture



Vision Transformer

An image is worth 16x16 words: Transformers for image recognition at scale
A Dosovitskiy, L Beyer, A Kolesnikov… - arXiv preprint arXiv …, 2020 - arxiv.org
… directly to **images**, with the fewest possible modifications. To do so, we split an **image** into patches … only to small-resolution **images**, while we handle medium-resolution **images** as well. …
Save Cite Cited by 23476 Related articles All 12 versions

The Vision Transformer treats an input image as a sequence of patches, akin to a series of word embeddings generated by an NLP Transformer.

Image source: https://ai.googleblog.com/2020/12/transformers-for-image-recognition-at.html

Swin Transformer

Swin transformer: Hierarchical vision **transformer** using shifted windows
Z Liu, Y Lin, Y Cao, H Hu, Y Wei… - Proceedings of the …, 2021 - openaccess.thecvf.com
… **Transformer**, called **Swin Transformer**, that capably serves as a general-purpose backbone for computer vision. Challenges in adapting **Transformer** … a hierarchical **Transformer** whose …
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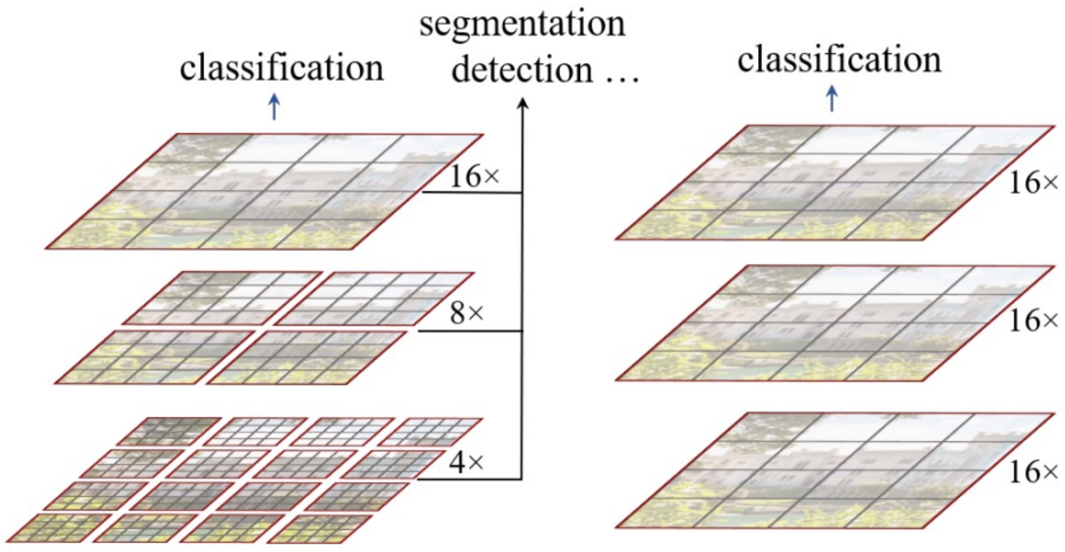
- Challenges in adapting Transformer from language to vision:

large variations in the scale of visual entities and the high resolution of pixels in images compared to words in text.



(a) Swin Transformer (ours)

(b) ViT

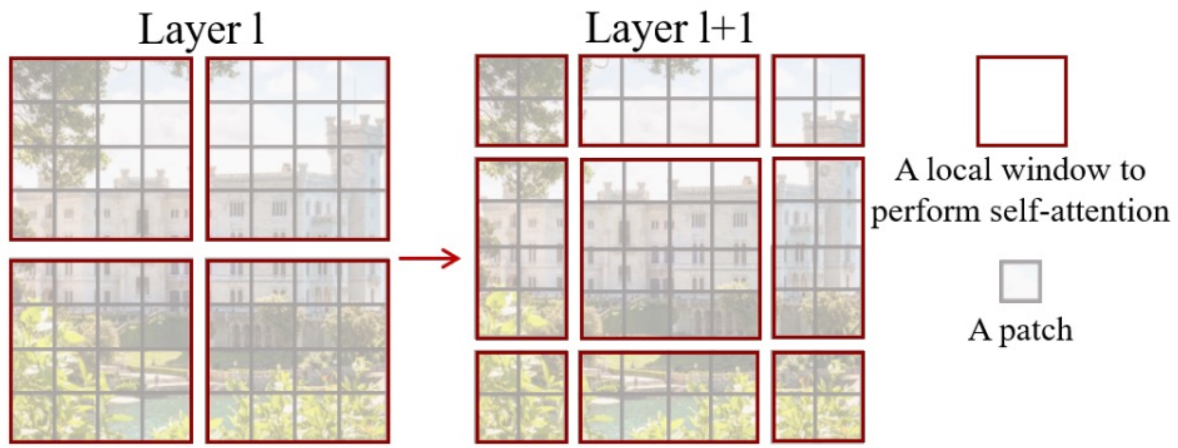
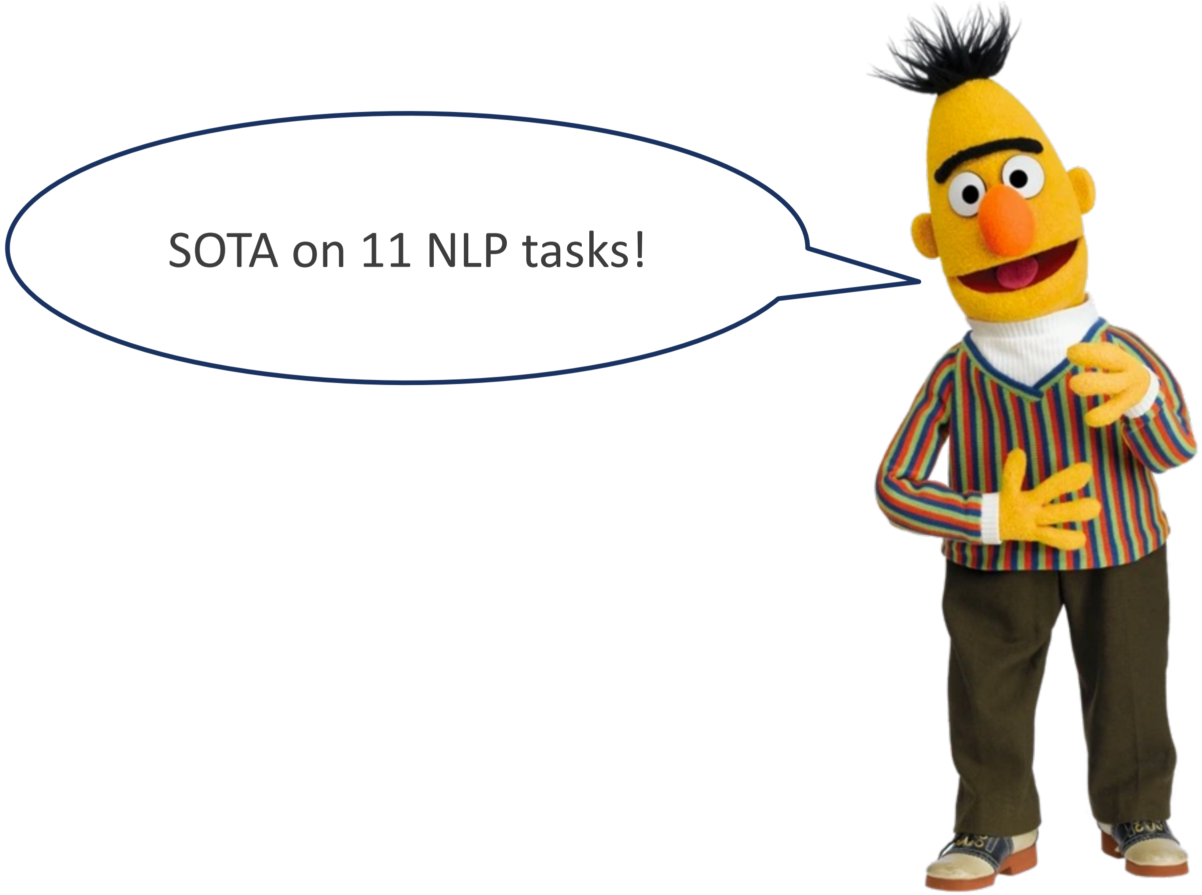


Image source: Liu, Ze, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. "Swin transformer: Hierarchical vision transformer using shifted windows." In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 10012-10022. 2021.



BERT

Image source: https://hero.fandom.com/wiki/Bert_(Sesame_Street)

BERT

Bert: Pre-training of deep bidirectional transformers for language understanding
J Devlin, MW Chang, K Lee, K Toutanova - arXiv preprint arXiv …, 2018 - arxiv.org
… We introduce **BERT** and its detailed implementation in this … For finetuning, the **BERT** model is first initialized with the pre-… A distinctive feature of **BERT** is its unified architecture across …
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- BERT is a pre-training framework using deep bidirectional transformers for language understanding.
- It uses the idea of self-supervised learning, rather than training on any specific NLP task.
- After we obtain the BERT pre-trained model, we can fine-tune it for a specific NLP task.

BERT Model Architecture

- BERT's model architecture is a multi-layer bidirectional Transformer encoder.
- The input is word embedding and output is context sensitive word representation.
  - Just like ELMo. But ELMo is a task-specific model, rather than a pre-trained model.

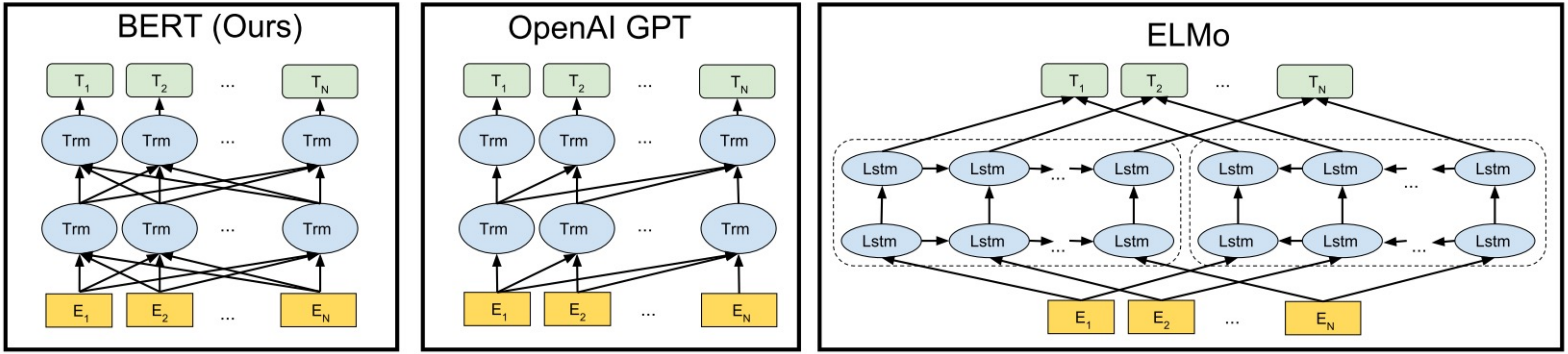


Image source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805 (2018).

Input representation

- Positional embeddings are learnable, rather than fixed magic number as in the Transformer paper.
- Each input sequence is a pair of sentences, separated by the token `[SEP]`. It adopted two learnable embeddings to each sentence.
- `[CLS]` is the a special classification embedding for the first token of every sequence.

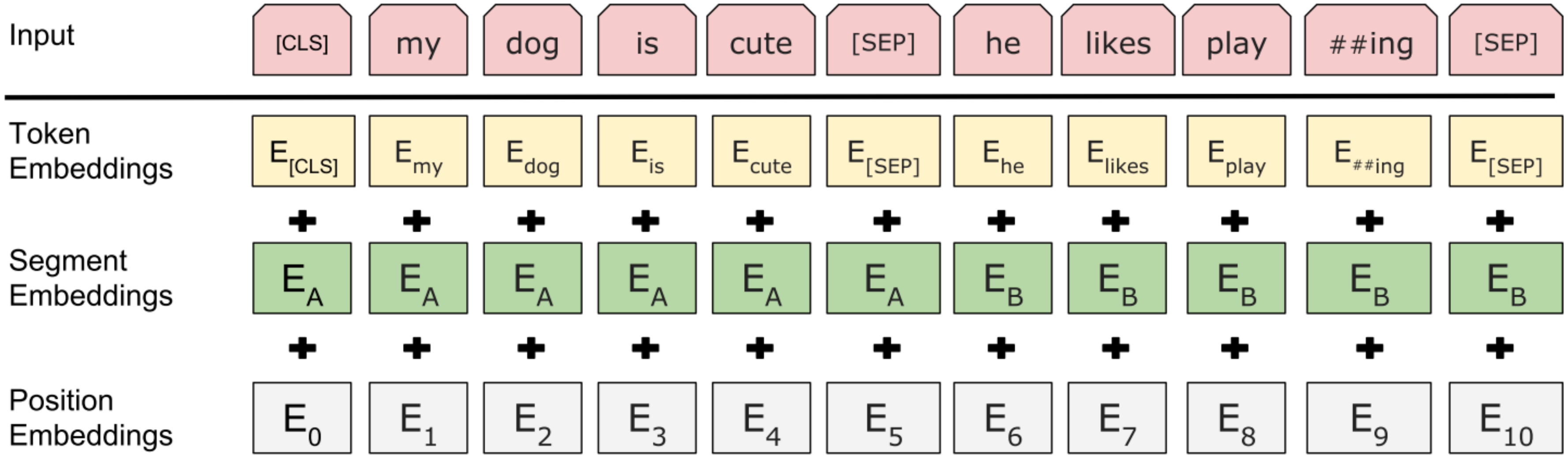


Image source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805 (2018).

Pre-Training Task 1: Masked LM

- Mask some percentage of the input tokens at random, and then predicting only those masked tokens.
- Use `[MASK]` token to replace 15% tokens randomly, and use the real token as the label to make it predict.
- Howerver, the `[MASK]` token is never seen during fine-tuning. The authors proposed the following strategy:
  - 80% of the time: Replace the word with the `[MASK]` token.
    - e.g., my dog is hairy → my dog is `[MASK]`.
  - 10% of the time: Replace the word with a random word.
    - e.g., my dog is hairy → my dog is apple.
  - 10% of the time: Keep the word unchanged. The purpose of this is to bias the representation towards the actual observed word.
    - e.g., my dog is hairy → my dog is hairy.

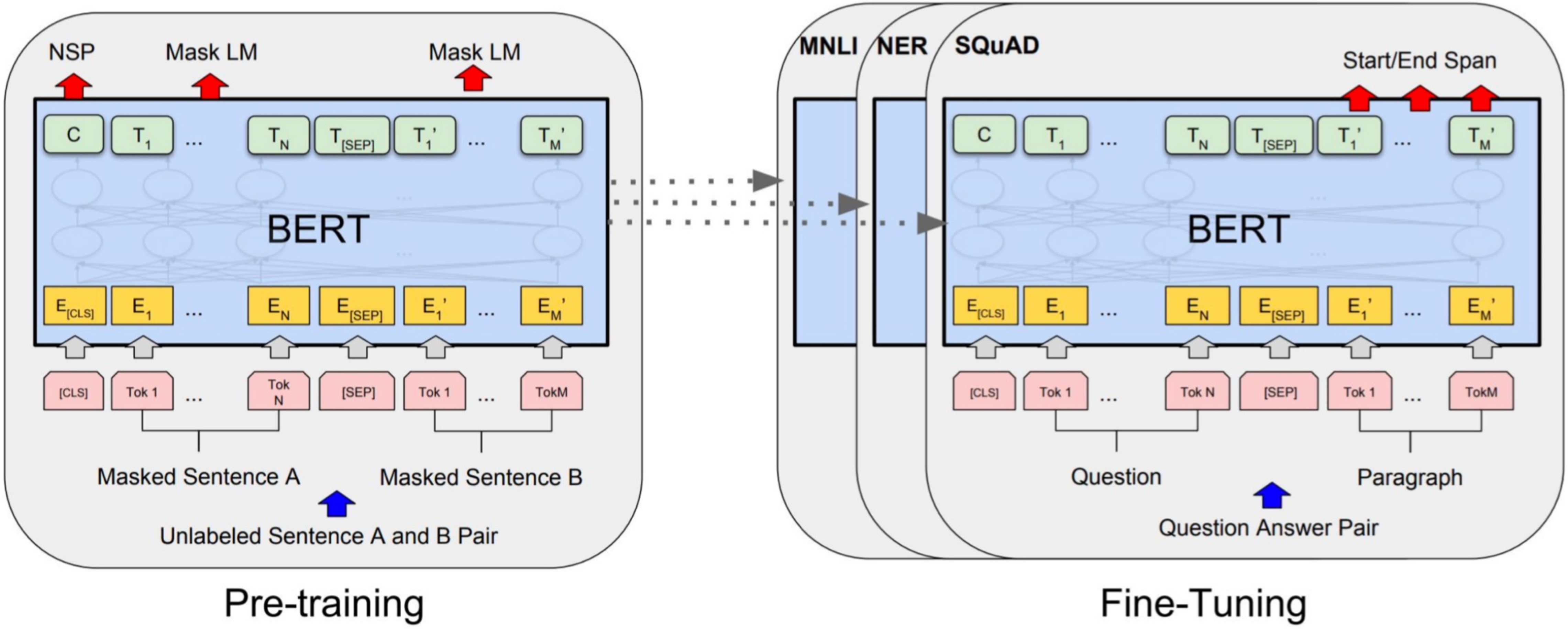
Pre-Training Task 2: Next Sentence Prediction

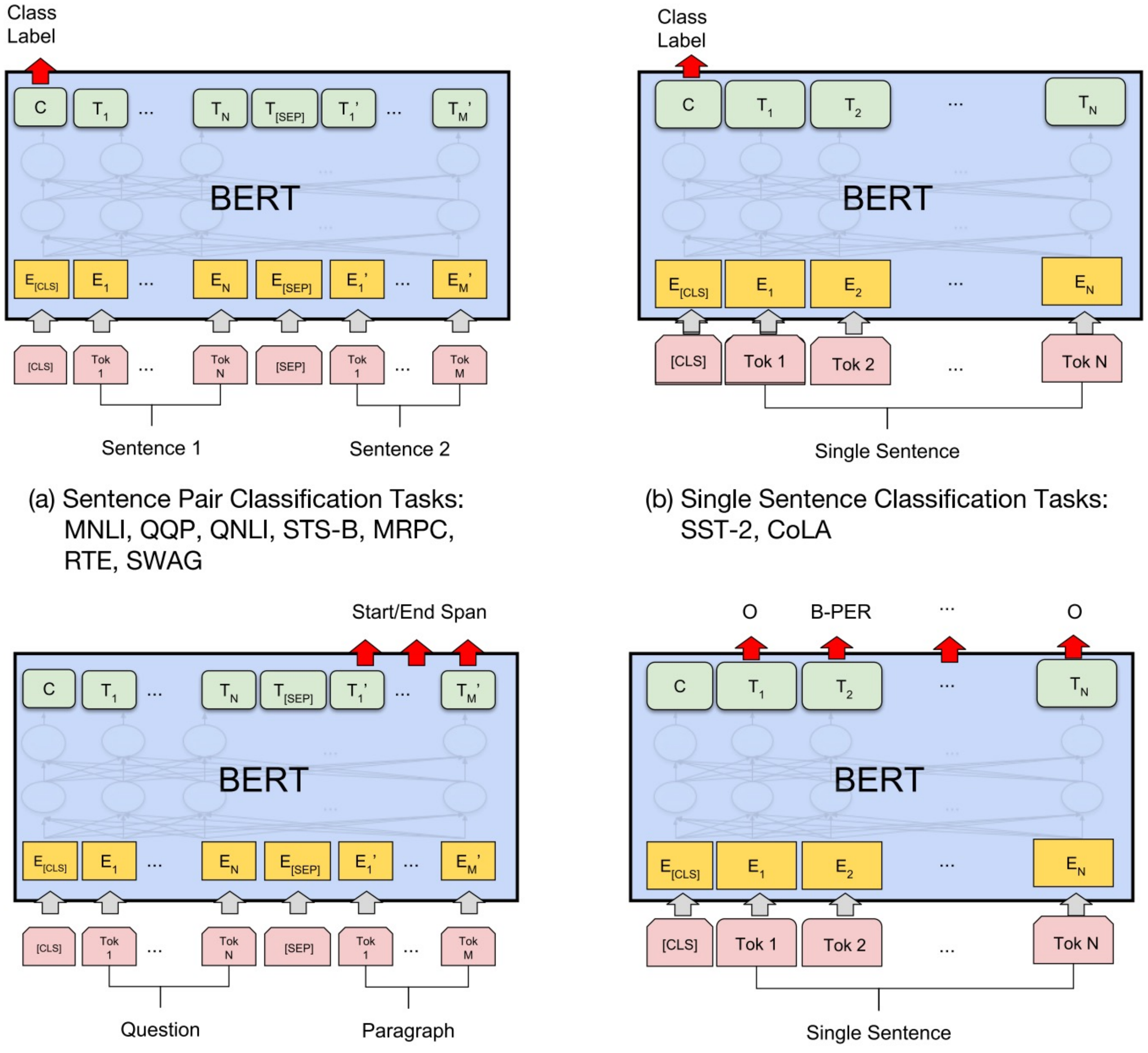
- Make the model understand the relationship between two text sentences.
- Choose the sentences A and B for each pre-training example.
  - 50% of the time B is the actual next sentence that follows A.
  - 50% of the time it is a random sentence from the corpus.
- Example:
  - Input = `[CLS] the man went to [MASK] store [SEP] he bought a gallon [MASK] milk [SEP]`

    Label = `IsNext`
  - Input = `[CLS] the man [MASK] to the store [SEP] penguin [MASK] are flight ##less birds [SEP]`

    Label = `NotNext`

Pre-Train and Fine-Tune





(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

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

GPT

BERT v.s. GPT

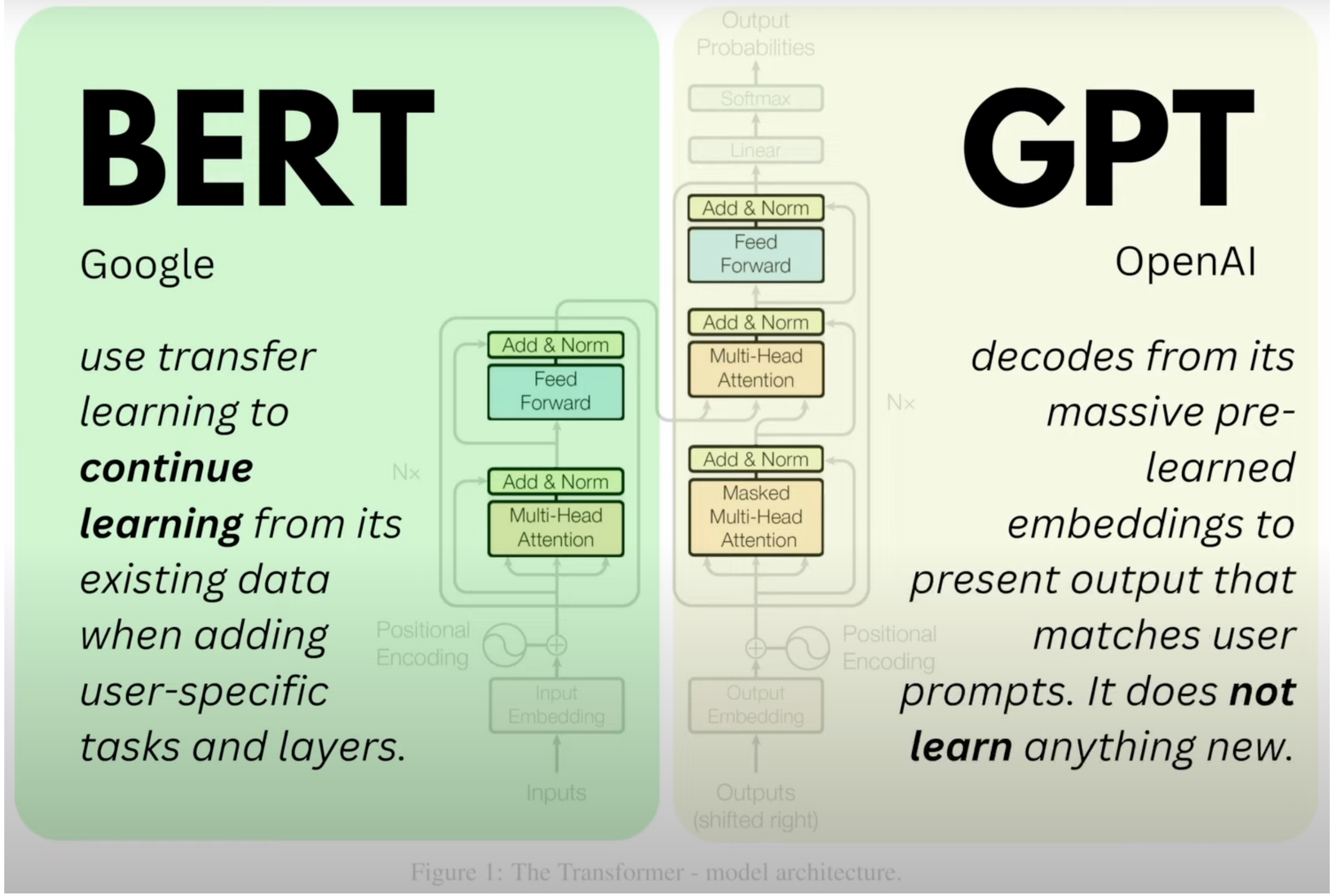


Image source: https://www.youtube.com/watch?v=ewjlmLQI9kc

History of GPT

OpenAI

GPT-1: Improving Language **Understanding** by Generative Pre-Training

Keyword: unsupervised pre-training, supervised fine-tuning, auxiliary objective

GPT-2: Language Models are Unsupervised **Multitask** Learners

Keyword: multi-task

GPT-3: Language Models are Few-Shot Learners

Keyword: few-shot, one-shot, zero-shot

InstructGPT: Training language models to follow instructions with human feedback

Keyword: instruct learning, **labeler-written prompts**, **reinforcement learning from human feedback**

ChatGPT: Optimizing Language Models for Dialogue

GPT-4

2018 2019 2020 2022.3 2022.11 2023 ?

past **new** **future**

Source: ChatGPT的过去、现在与未来, 冯骁骋, 哈尔滨工业大学/社会计算与信息检索研究中心

GPT-1

[PDF] **Improving language understanding** by generative pre-training

A Radford, K Narasimhan, T Salimans, I Sutskever - 2018 - mikecaptain.com

… on four types of **language understanding** tasks – natural **language** inference, question … architectures specifically crafted for each task, significantly **improving** upon the state of the art in 9 …

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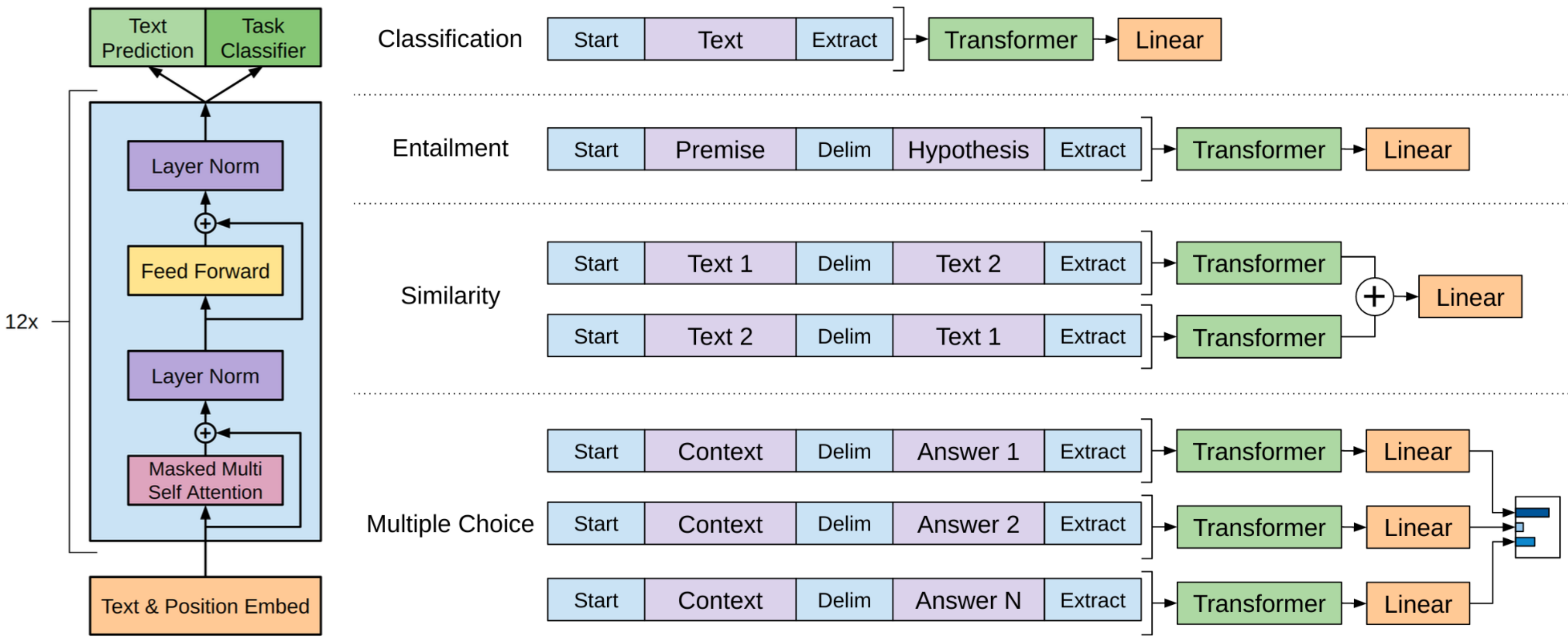

GPT Keyword: unsupervised pre-training, supervised fine-tuning, auxiliary objective

Image source: Radford, Alec, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. "Improving language understanding by generative pre-training." (2018).

GPT-2

[PDF] **Language models** are **unsupervised** multitask learners
A Radford, J Wu, R Child, D Luan… - OpenAI …, 2019 - insightcivic.s3.us-east-1.amazonaws …
… We demonstrate that **language models** begin to learn these … , the answers generated by the **language model** reach 55 F1 on the … The capacity of the **language model** is essential to the …
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- Previously, NLP tasks, such as question answering, machine translation, reading com- prehension, and summarization, are typically approached with supervised learning on task-specific datasets.
- GPT-2 is trained on a new dataset of millions of webpages called WebText without any explicit supervision.

GPT-2

Ability: Zero-shot or one-shot：

- Zero-shot: use summarization as an example
  - Input: original text + “TL; DR”
  - Output: summary
- One-shot: use translation as an example
  - Input: “English sentence1 = French sentence1” + “English sentence2 = ”
  - Output: “French sentence2”

One-shot is not supervised information. It is not involved into the training process

GPT-3

Language models are few-shot learners

T Brown, B Mann, N Ryder… - Advances in neural …, 2020 - proceedings.neurips.cc

… up **language models** greatly improves task-agnostic, **few-shot** … GPT-3, an autoregressive **language model** with 175 billion … **language model**, and test its performance in the **few-shot** …

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- Pre-trained model with In-context learning (few-shot, one-shot, zero-shot) is becoming competitive with prior state-of-the-art fine-tuning approaches.

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

```
1  Translate English to French:     ← task description
2  cheese => ..................     ← prompt
```

One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

```
1  Translate English to French:     ← task description
2  sea otter => loutre de mer       ← example
3  cheese => ..................     ← prompt
```

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
1  Translate English to French:     ← task description
2  sea otter => loutre de mer       ← examples
3  peppermint => menthe poivrée
4  plush girafe => girafe peluche
5  cheese => ..................     ← prompt
```


Source: ChatGPT的过去、现在与未来, 冯骁骋, 哈尔滨工业大学/社会计算与信息检索研究中心

InstructGPT

Training language models to follow instructions with human feedback
L Ouyang, J Wu, X Jiang, D Almeida… - Advances in …, 2022 - proceedings.neurips.cc
… **InstructGPT**. In human evaluations on our prompt distribution, outputs from the 1.3B parameter **InstructGPT** model … Moreover, **InstructGPT** models show improvements in truthfulness and …
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- GPT-3 is good at in-context learning tasks, but these models are not aligned with their users.
  - Can only handle traditional NLP tasks, but not human interaction.
- Instruction Tuning
  - Unify tasks in the form of Prompts.
  - Fine-tune the language model.
  - The model can handle unseen tasks.

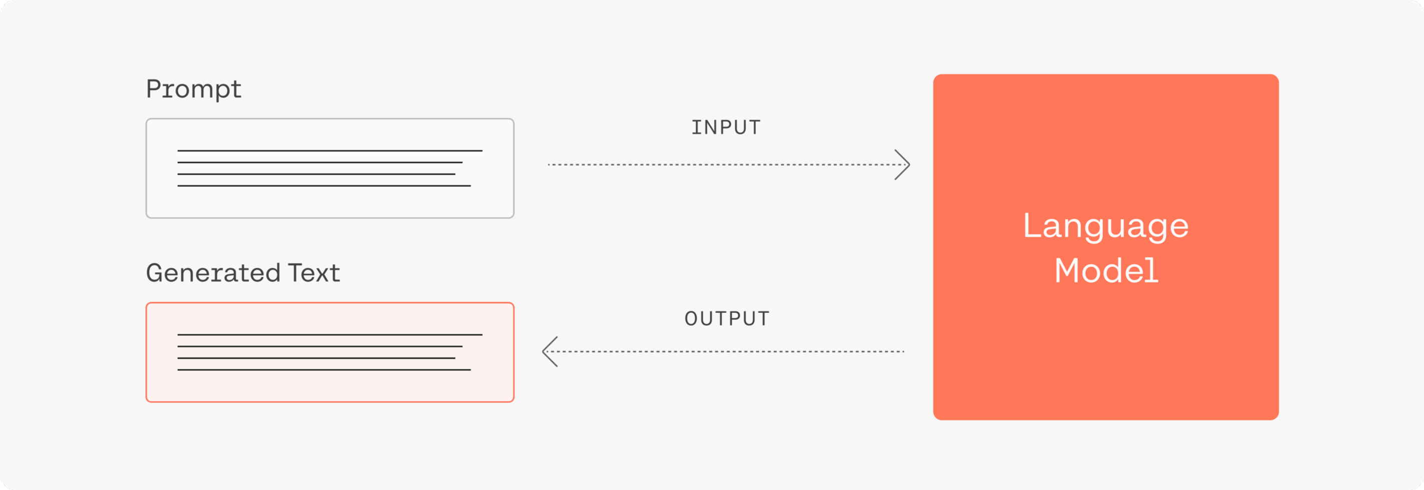


Image source: https://docs.cohere.com/docs/prompt-engineering

InstructGPT

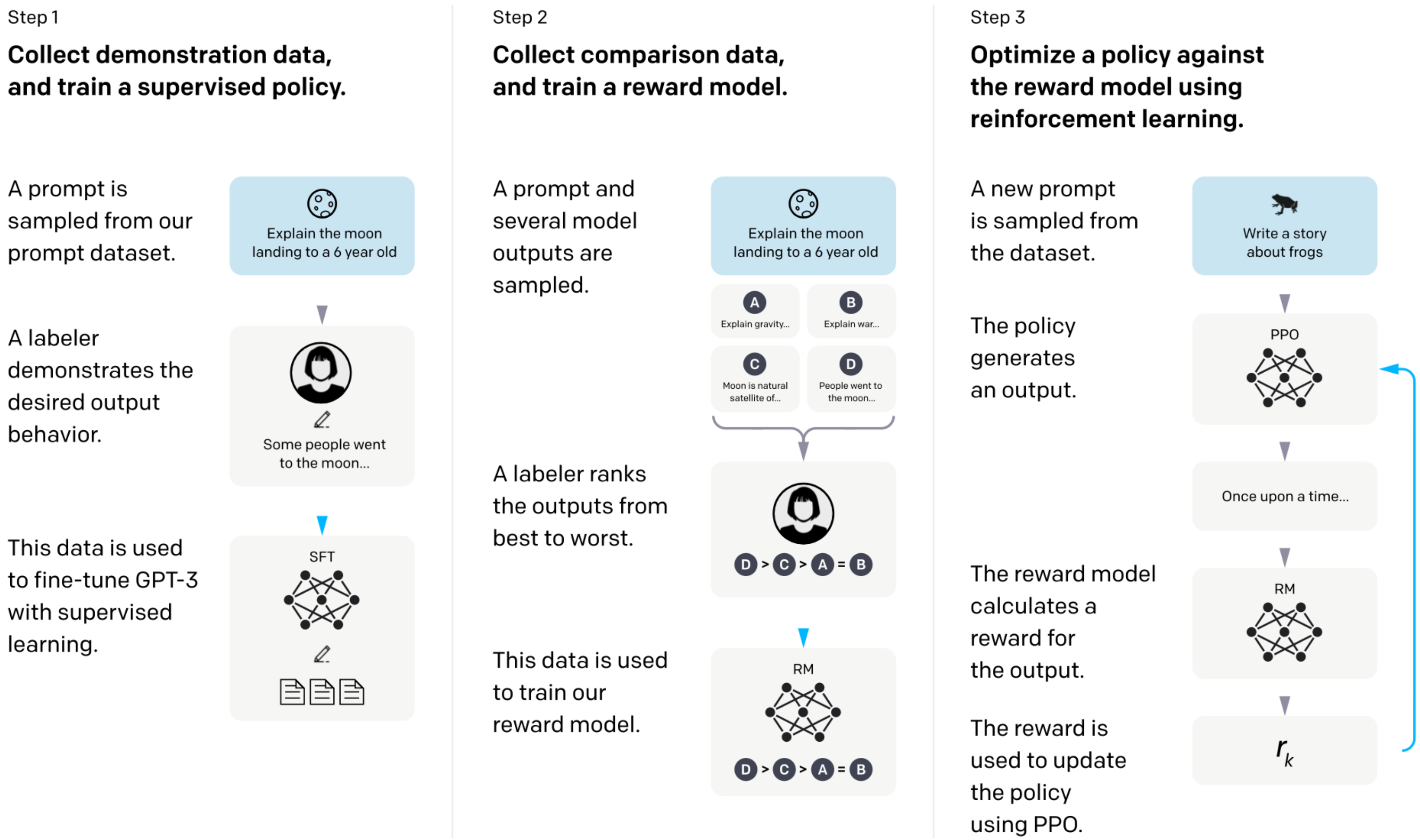


Image source: Ouyang, Long, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang et al. "Training language models to follow instructions with human feedback." Advances in Neural Information Processing Systems 35 (2022): 27730-27744.

ChatGPT v.s. InstructGPT

- ChatGPT can generate more detailed responses
  - This might stem from the annotators' preference for "more detailed responses" during the training reward model process => a preference for verbosity.
- ChatGPT excels more in multi-turn dialogue formats
  - This might be due to the multi-turn dialogue data annotated by the annotators during the instruction fine-tuning process.
- ChatGPT is better at capturing COT and long-term dependencies in multi-turn dialogues
  - This could be attributed to ChatGPT's initialization model.

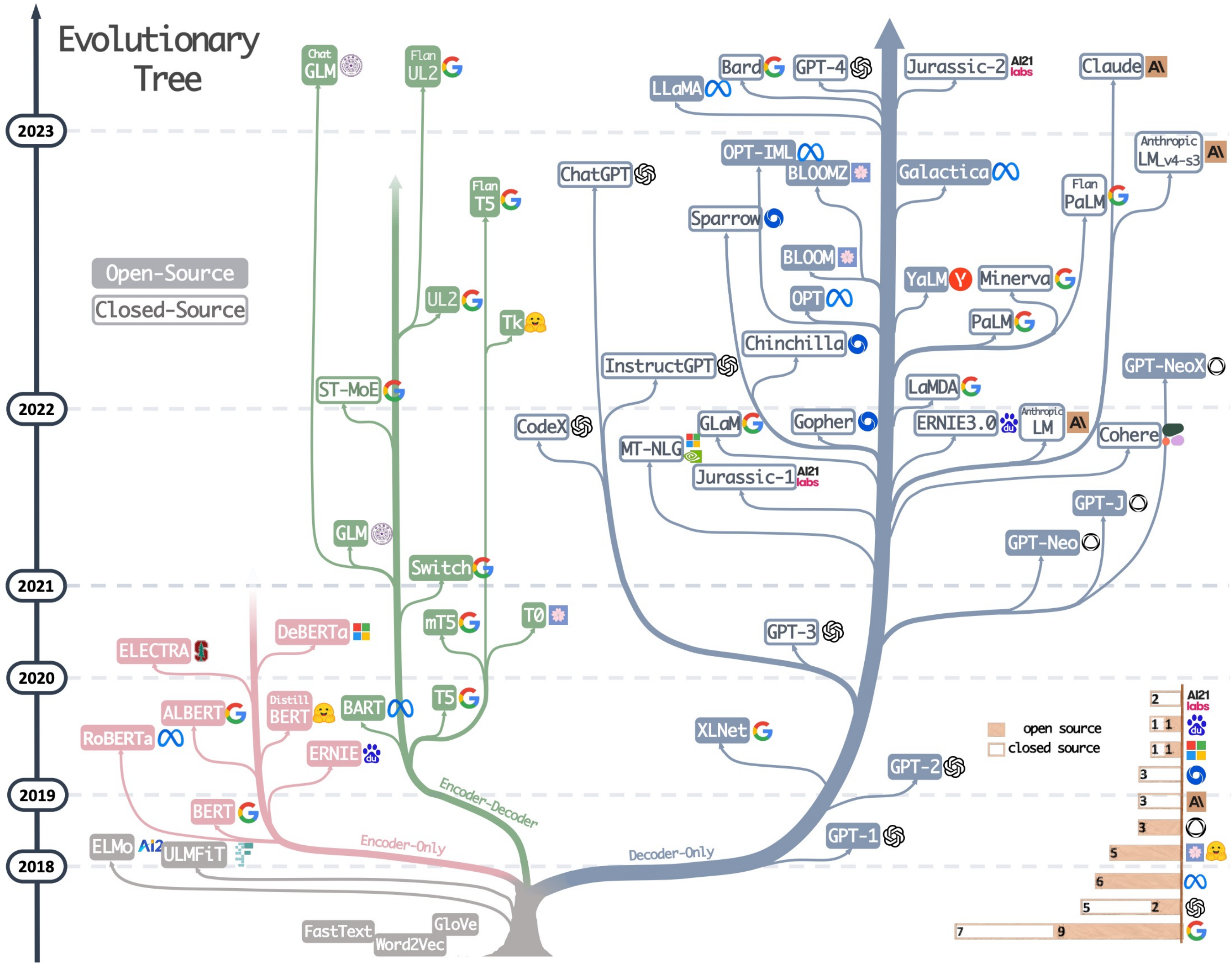
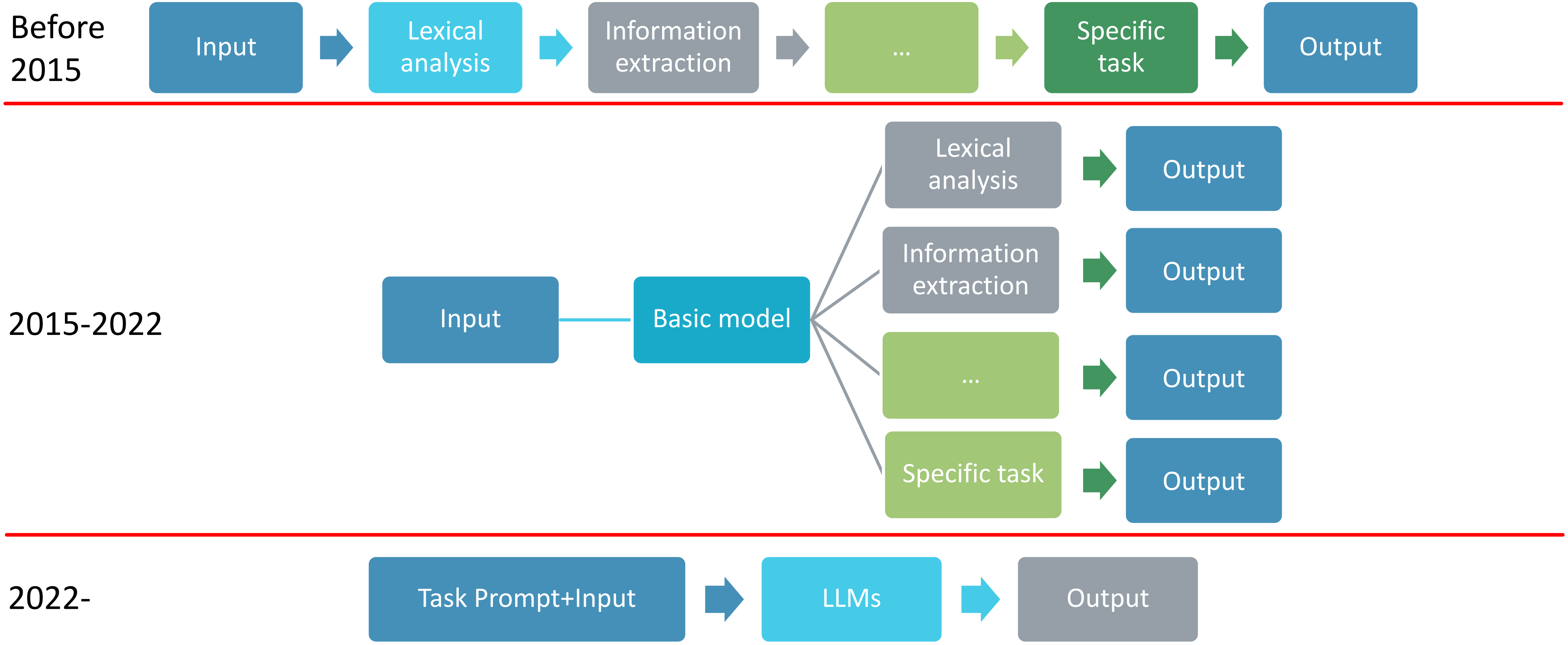
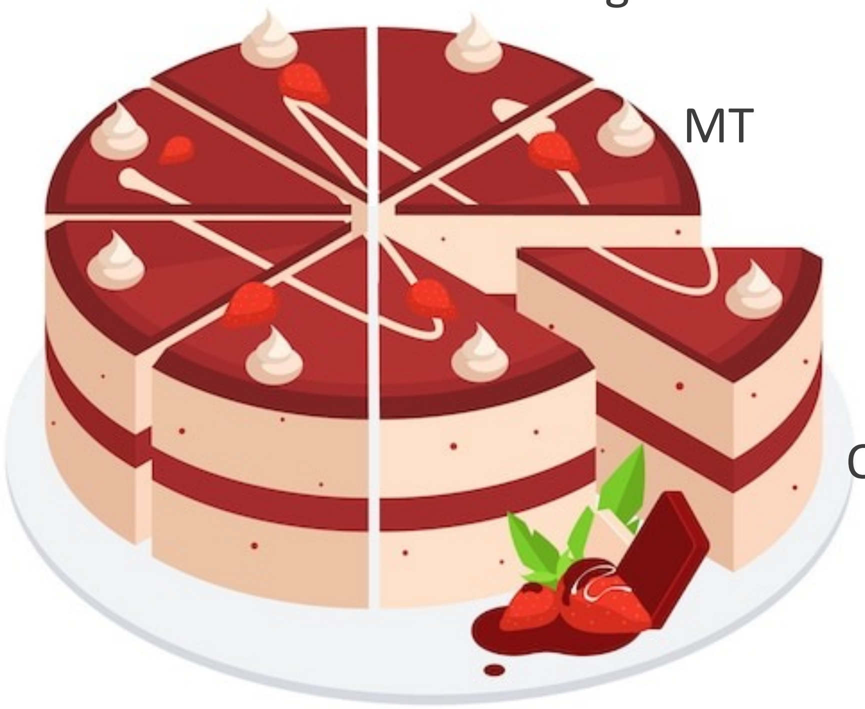


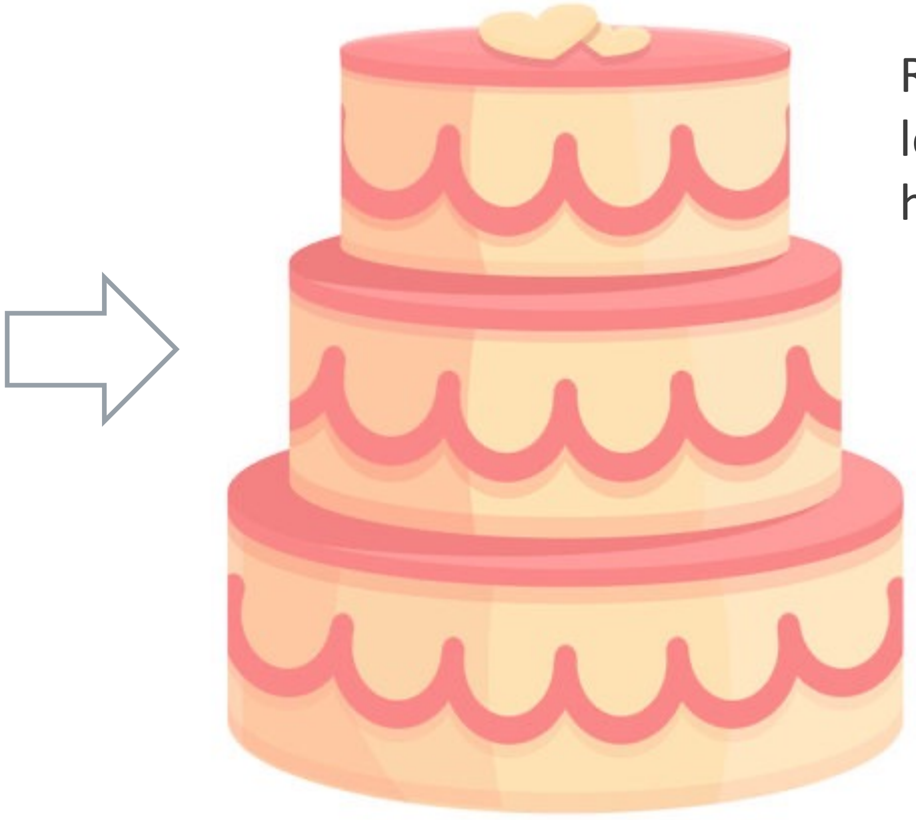
Image source: Yang, Jingfeng, Hongye Jin, Ruixiang Tang, Xiaotian Han, Qizhang Feng, Haoming Jiang, Bing Yin, and Xia Hu. "Harnessing the power of llms in practice: A survey on chatgpt and beyond." arXiv preprint arXiv:2304.13712 (2023).

Times of NLP Have Changed…



Times of NLP Have Changed...





Divided by task

Divided by process

Image source:大型语言模型的科学挑战, 邱锡鹏

Conclusion

After this lecture, you should know:

- Why do we need word embedding?
- How to generate xxx2vec?
- Why context information is important can how to incorporate it into word embedding?
- What is multi-head self-attention?
- What is a pre-trained language model and how to use it?

Suggested Reading

- Word2vec paper: Distributed representations of words and phrases and their compositionality
- ELMo paper: Deep contextualized word representations
- Transformer paper: Attention is all you need
- 李沐: Transformer论文逐段精读
- BERT paper: Bert: Pre-training of deep bidirectional transformers for language understanding
- Excellent Transformer tutorial with notebook
- Illustrated Transformer

Assignment 3

- Assignment 3 will be released soon. The deadline is 18:00, 20th November.

Thank you!

- Any question?
- Don't hesitate to send email to me for asking questions and discussion. ☺