LLM 101

NCI Training

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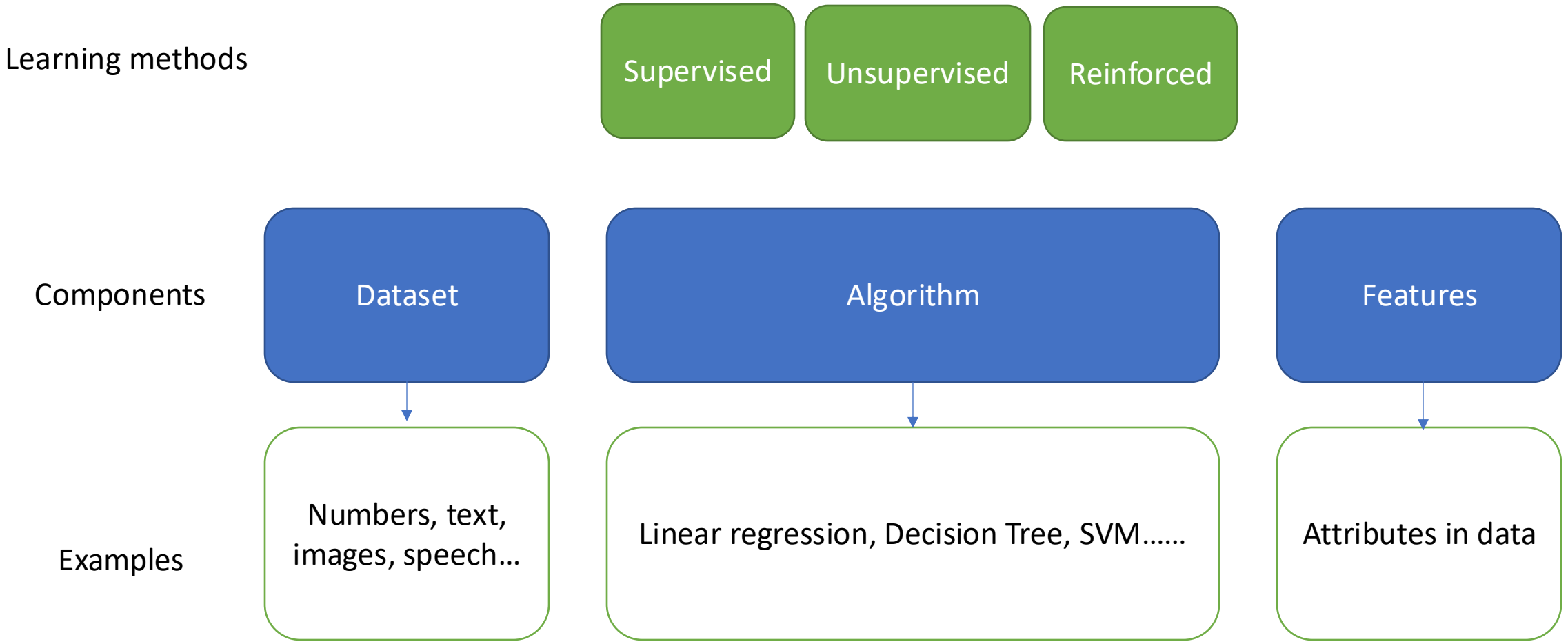
Outline

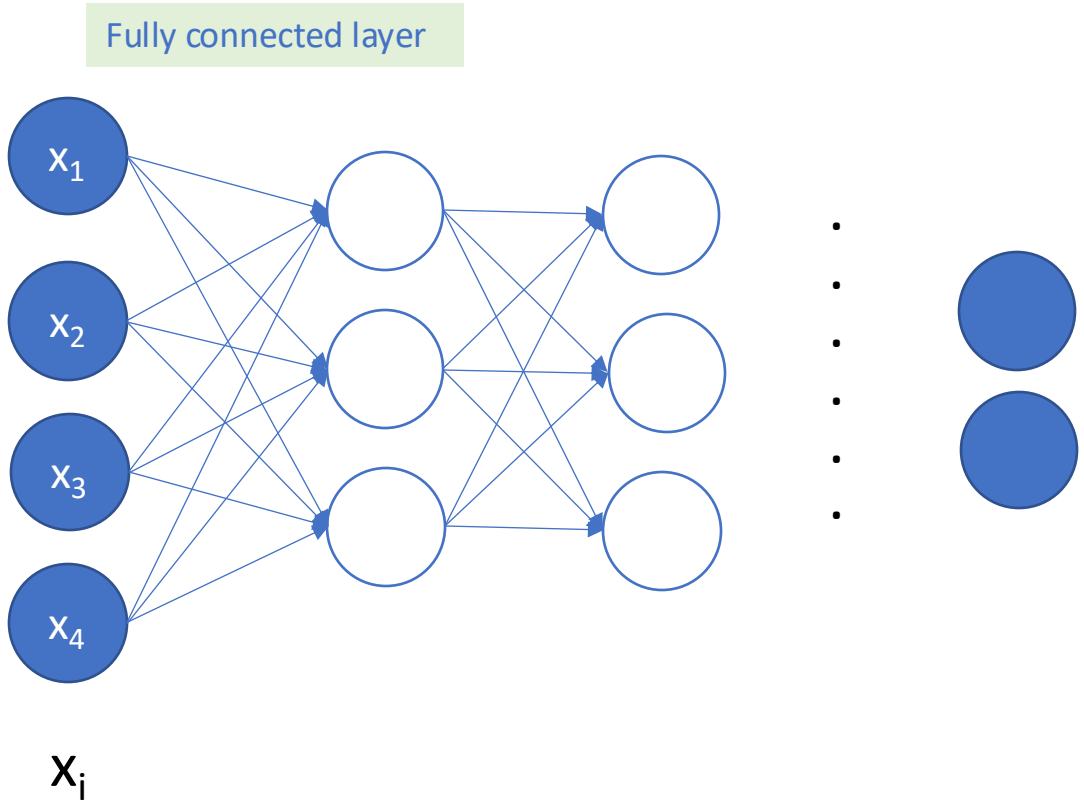
- Introduction to Machine Learning and Deep Learning
- Text Processing
- Transformers

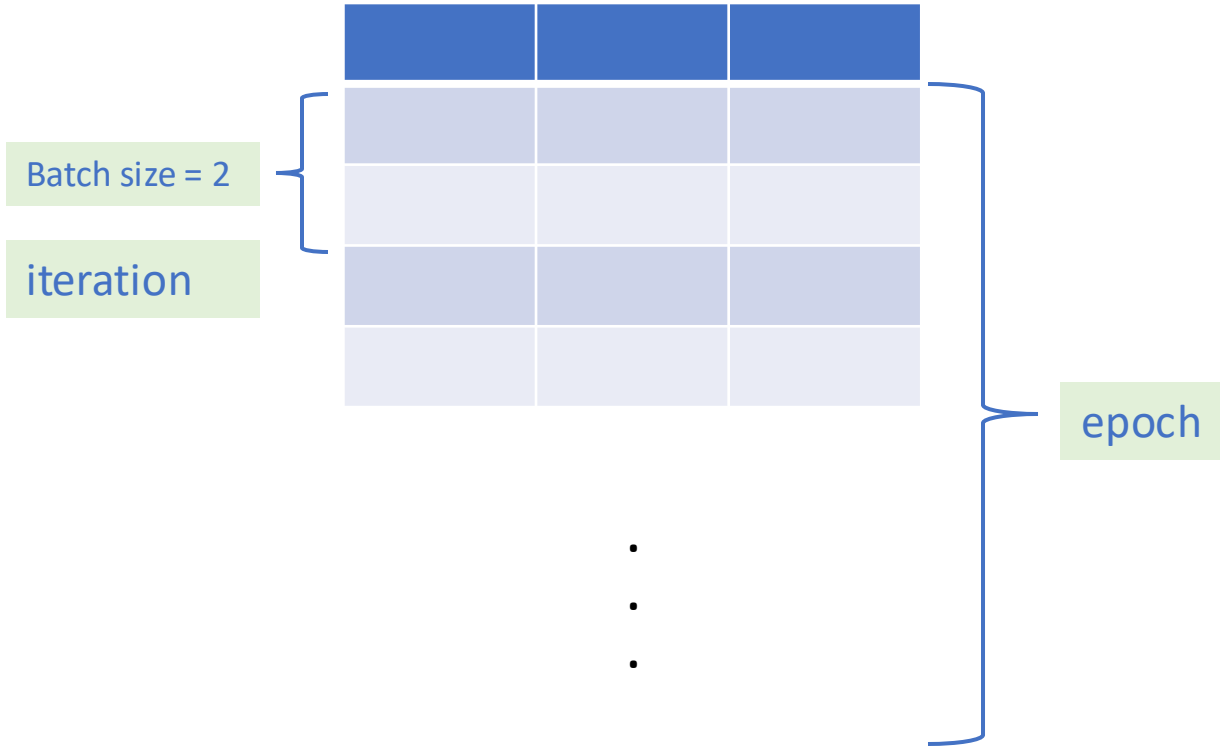
Machine learning

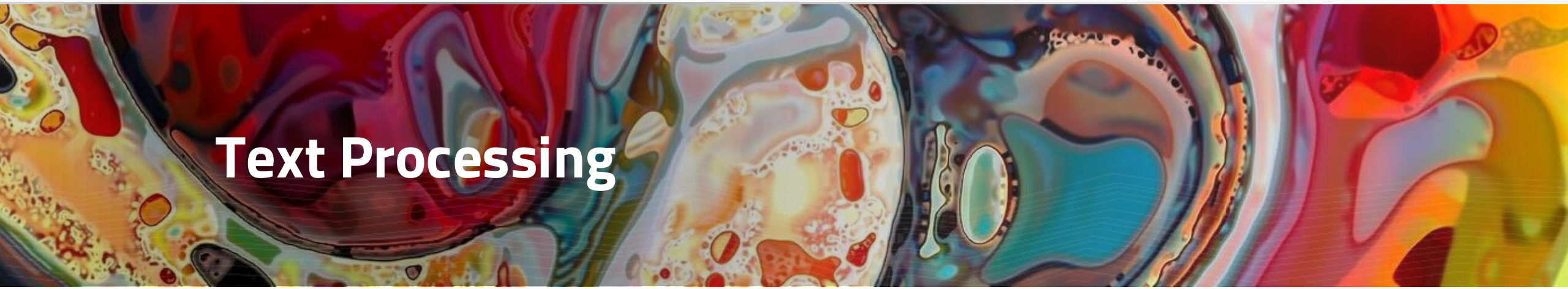


Deep Learning…

And more data!

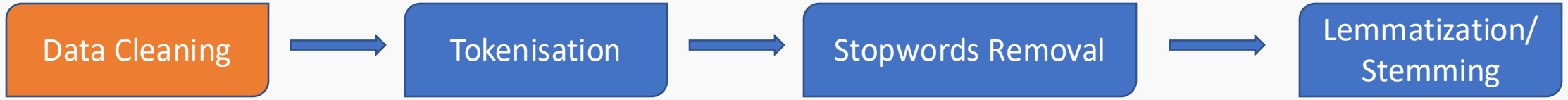






Text Processing

- Text cleaning
- Co-occurance
- Word2vec
  - CBOW

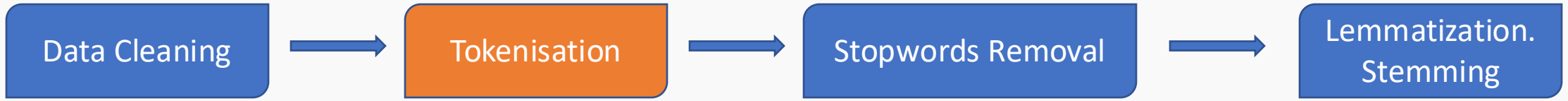


- Data structure
- Data source
- Common dirty strings:
  - HTML tags
  - Human typos
  - Data encoding
  - Punctuations

➢"A touching movie!!\n It is full of emotions and wonderful acting\n\n\n.
 I could have sat through it a second time."

Python string functions
Regular expression – Regex

➢"A touching movie It is full of emotions and wonderful acting I could have sat through it a second time"



- "A touching movie It is full of emotions and wonderful acting I could have sat through it a second time"

Python string functions
Libraries: Nltk, WordNet, Spacy …

- ["a", "touching", "movie", "it", "is", "full", "of", "emotions", "and", "wonderful", "acting", "I", "could", "have", "sat", "through", "it", "a", "second", "time"]

- ["a", "touching", "movie", "it", "is", "full", "of", "emotions", "and", "wonderful", "acting", "I", "could", "have", "sat", "through", "it", "a", "second", "time"]

Python string functions (customization)
Libraries: Nltk, WordNet, Spacy …

- ["touching", "movie", "full", "emotions", "wonderful", "acting", "have", "sat", "second", "time"]

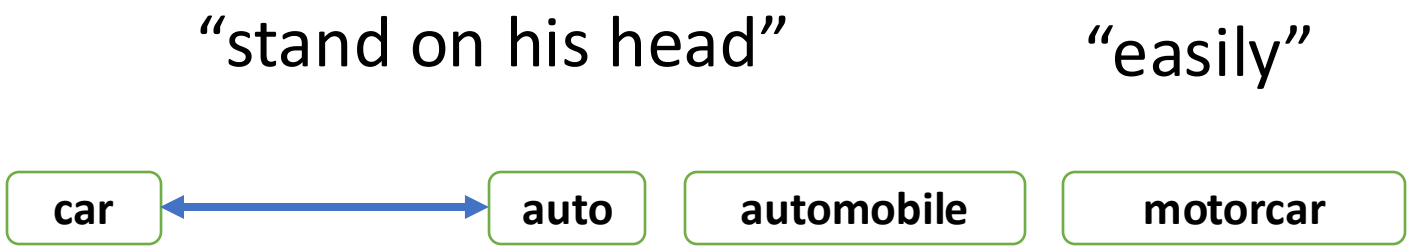
- ["touching", "movie", "full", "emotions", "wonderful", "acting", "have", "sat", "second", "time"]

Libraries: Nltk, WordNet, Spacy …

- ["touching", "movie", "full", "emotions", "wonderful", "acting", "have", "sait", "second", "time"]
- ["touching", "movie", "full", "emotions", "wonderful", "acting", "have", "sait", "second", "time"]

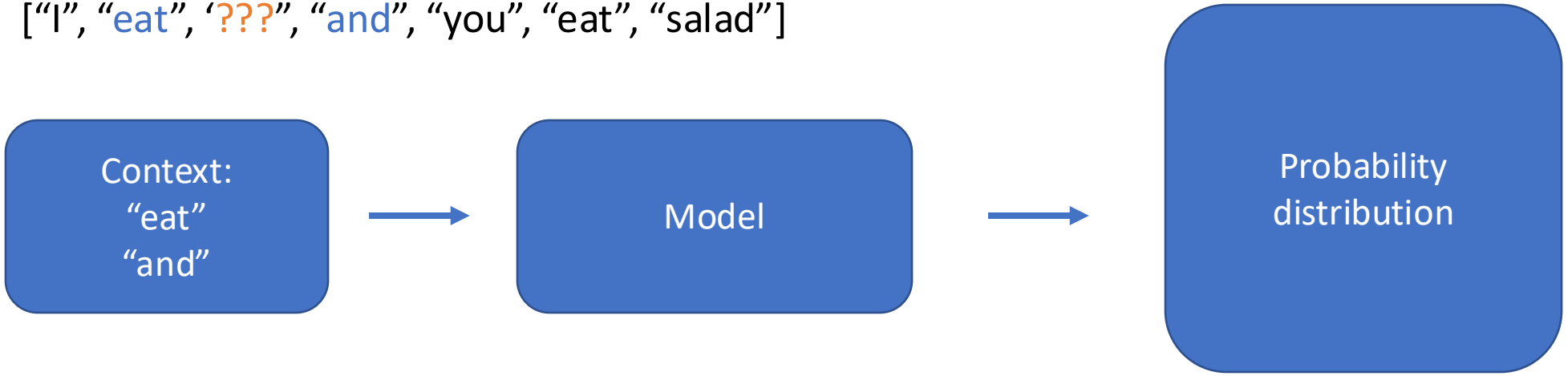
How to represent words so that computer can understand?

- Thesaurus
- Co-occurrence
- **word2vec**
- **CBOW**



Word2vec – a prediction problem

["I", "eat", '???', "and", "you", "eat", "salad"]

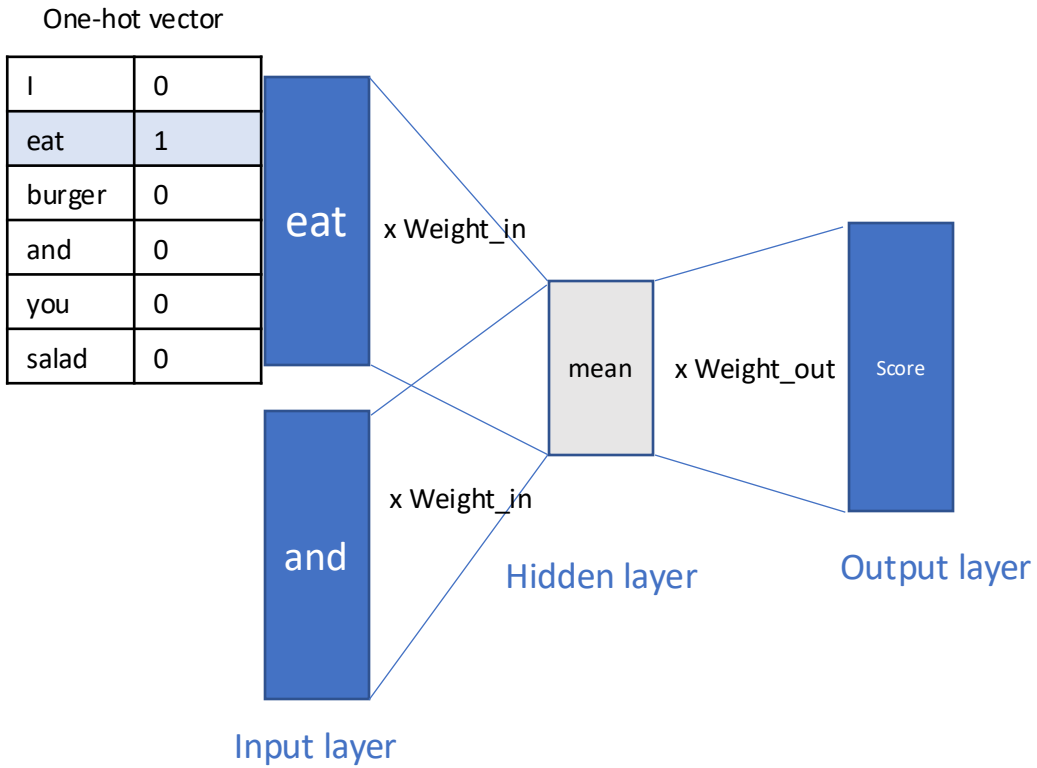


- One-hot vector:

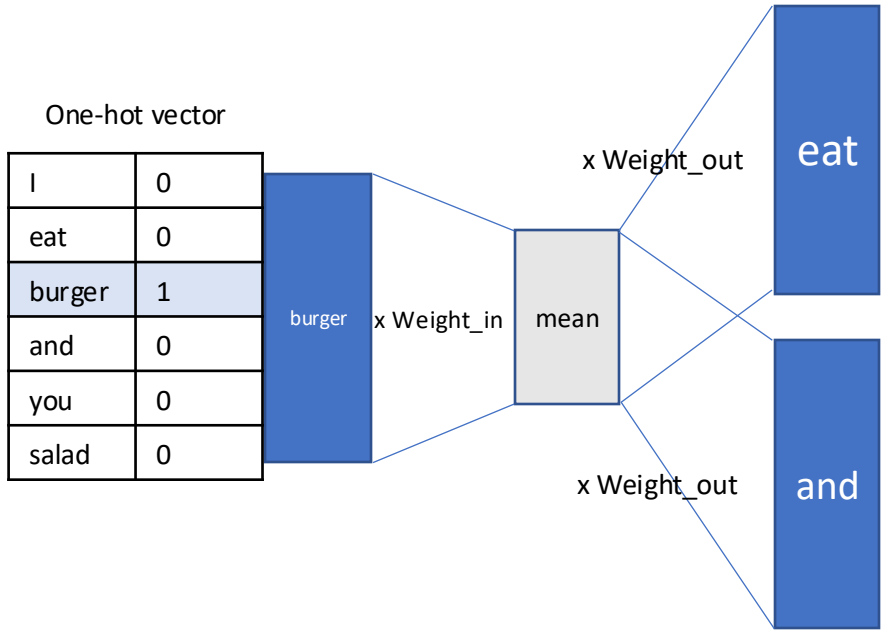
ID	Word	I	eat	burger	and	you	salad
2	eat	0	1	0	0	0	0

Word2vec

CBOW



Skip-gram



CBOW Result – Distributional Representation

- Weight_in matrix to represent words meaning
  - Syntax – plurals, past tenses…
  - Semantics
    - “king – men + women = queen”

```
[analogy] king:man = queen:?
 woman: 5.161407947540283
 veto: 4.928170680999756
 ounce: 4.689689636230469
 earthquake: 4.633471488952637
 successor: 4.6089653968811035
```

```
[analogy] take:took = go:?
 went: 4.548568248748779
 points: 4.248863220214844
 began: 4.090967178344727
 comes: 3.9805688858032227
 oct.: 3.9044761657714844
```

```
[analogy] car:cars = child:?
 children: 5.217921257019043
 average: 4.725458145141602
 yield: 4.208011627197266
 cattle: 4.18687629699707
 priced: 4.178797245025635
```

Language Model

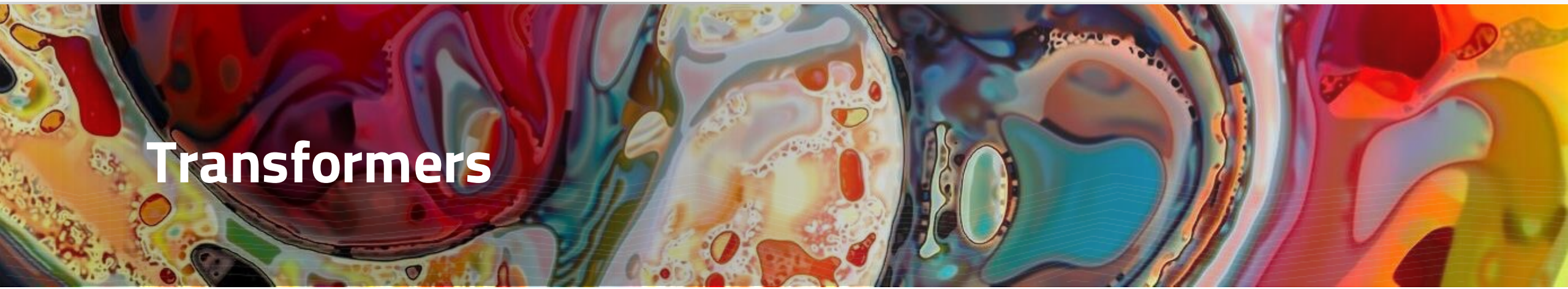
- Language model: the probability of a sequence of words.

$$P(w_1, \cdots, w_m) = P(w_m \,|\, w_1, \cdots, w_{m-1}) P(w_{m-1} \,|\, w_1, \cdots, w_{m-2})$$

$$\cdots P(w_3 \,|\, w_1, w_2) P(w_2 \,|\, w_1) P(w_1)$$

$$= \prod_{t=1}^{m} P(w_t \,|\, w_1, \cdots, w_{t-1}) \quad ①$$

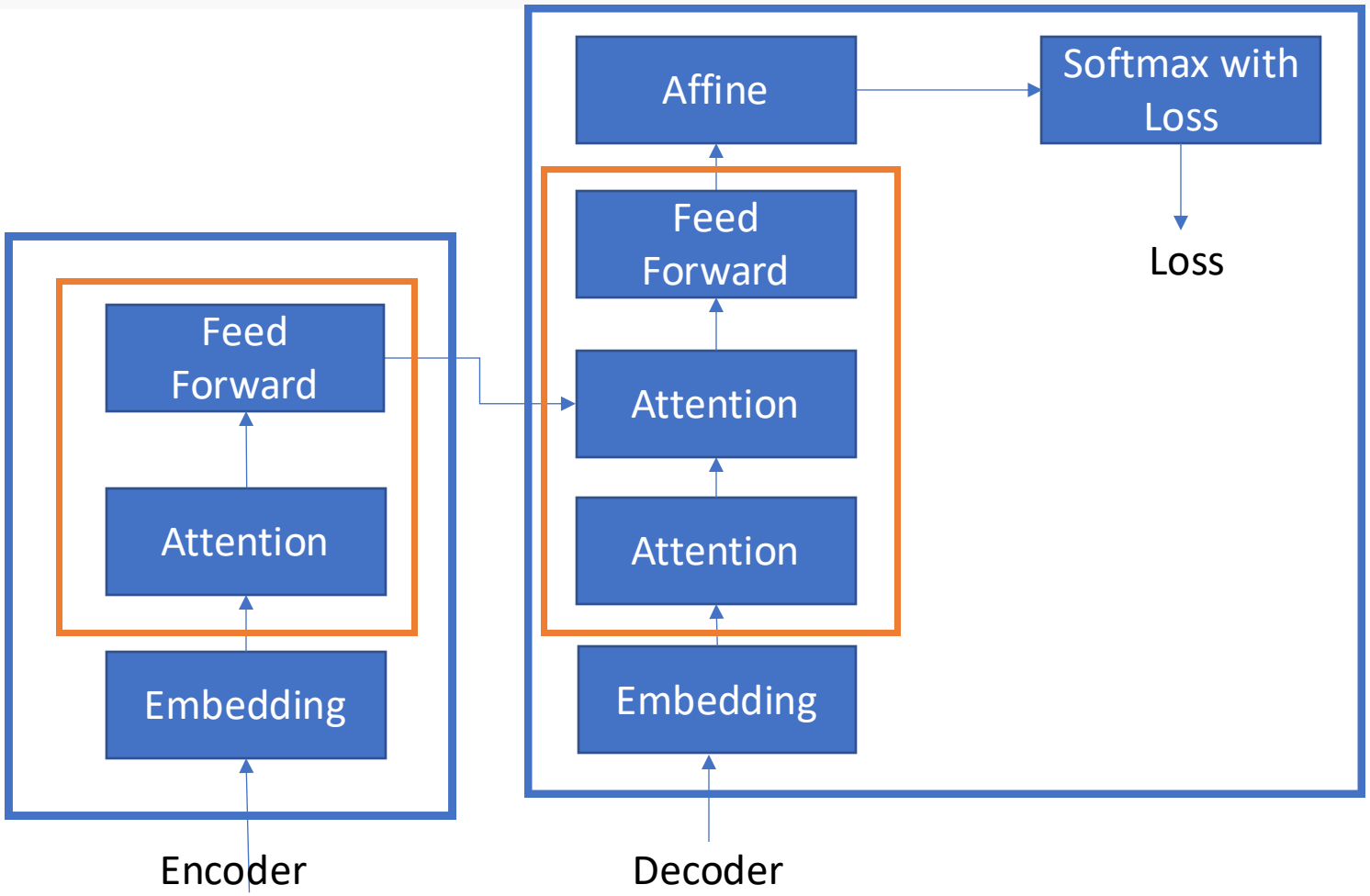
$$P(A,B) = P(A|B)P(B)$$



Transformers

- Transformer
- GPT
- Bert

Transformer – Attention without RNN



- Self-attention instead of LSTM layer
- Multi-head attention

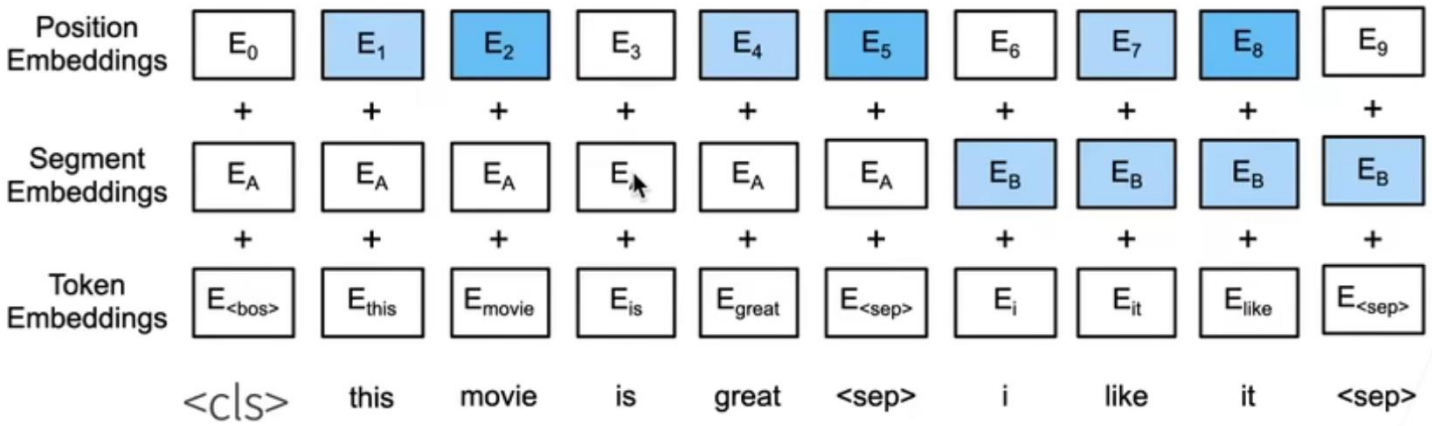
Depth repetition

Bert – NLP Model Based on Fine Tuning!

Bert – transformer without decoder

- Pre-trained model has extracted enough features
- Only need to replace output layer for a new task
- Original models in the paper:
  - Base: 12 (transformer encoder) blocks, hidden size = 768, 12 heads, 110M parameters
  - Large: 24 blocks, hidden size = 1024, 16 heads, 340M parameters
  - Trained on more than 3B words (whole Wikipedia and some books)

Bert

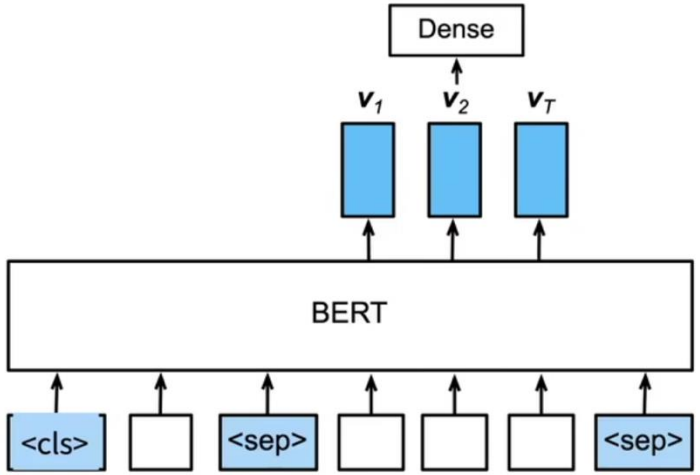


Pretraining:

- Masked language model - randomly mask some words in the sentence to predict
- Predict next sentence – 50% chance to select adjacent sentences as paired input, 50% chance to select random sentence pairs. Predict <cls> in output

1. Paired sentence input
2. Additional special tokens
3. Trainable position embedding

Bert – Q&A



Output:

- Token is the start of the answer
- Token is the end of the answer
- Neither

Fine tuning:
Increase the learning rate for output layer
Set some of the base layer parameters so finish training faster

References

- *Deep Learning from Scratch 2 © 2018 Koki Saitoh, O' Reilly Japan, Inc.*
- *Wu, Yonghui, et al. Google's neural machine translation system:Bridging the gap between human and machine translation[J]. arXiv preprint arXiv:1609.08144, 2016.*
- *https://www.youtube.com/watch?v=T05t-SqKArY&list=TLPQMjQxMDIwMjLirqQmTCjo-w&index=1*
- *https://www.youtube.com/watch?v=6ArSys5qHAU*


Questions ?

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