# Deep Learning for Text 2

## Applied Text Mining

Ayoub Bagheri

### Recap: RNN in Python

```
embedding_dim = 100
model = Sequential()
model.add(layers.Embedding(vocab_size, embedding_dim, input_length=maxlen))
model.add(layers.LSTM(100, dropout=0.2, recurrent_dropout=0.2))
model.add(layers.Dense(10, activation='relu'))
model.add(layers.Dense(5, activation='softmax'))
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 100, 100)          3811100
_________________________________________________________________
lstm (LSTM)                  (None, 100)               80400
_________________________________________________________________
dense (Dense)                (None, 10)                1010
_________________________________________________________________
dense_1 (Dense)              (None, 5)                 55
=================================================================
Total params: 3,892,565
Trainable params: 3,892,565
Non-trainable params: 0
```

### Lecture plan

1. Convolutional Neural Networks
2. Transformers
3. BERT

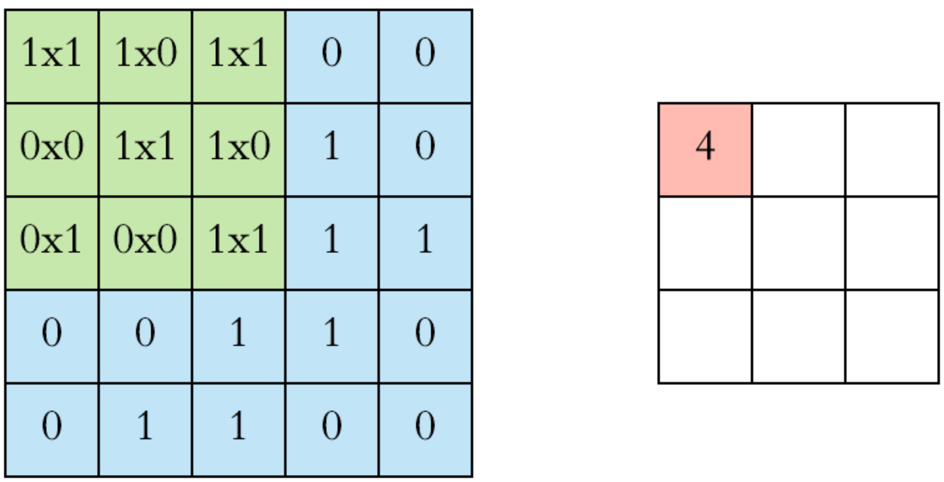
### Convolutional Neural Network (CNN)

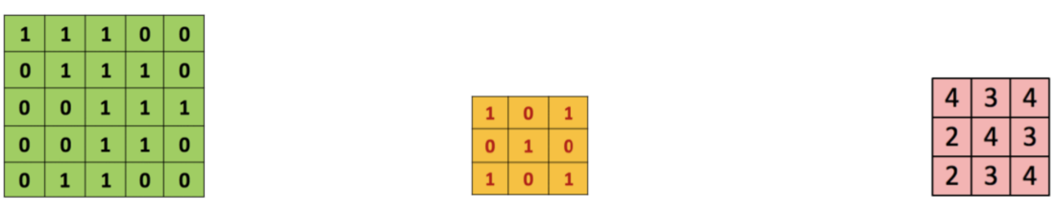
- Intuition: Neural network with specialized connectivity structure
  - Stacking multiple layers of feature extractors, low-level layers extract local features, and high-level layers extract learn global patterns.
- There are a few distinct types of layers:
  - **Convolution Layer**: detecting local features through filters (discrete convolution)
  - **Pooling Layer**: merging similar features

## Convolution layer

- The core layer of CNNs
- Convolutional layer consists of a set of filters
- Each filter covers a spatially small portion of the input data
- Each filter is convolved across the dimensions of the input data, producing a multidimensional **feature map**.
- As we convolve the filter, we are computing the dot product between the parameters of the filter and the input.
- **Deep Learning algorithm**: During training, the network corrects errors and filters are **learned**, e.g., in Keras, by adjusting weights based on **Stochastic Gradient Descent**, **SGD**.
- The key architectural characteristics of the convolutional layer is **local connectivity** and **shared weights.**

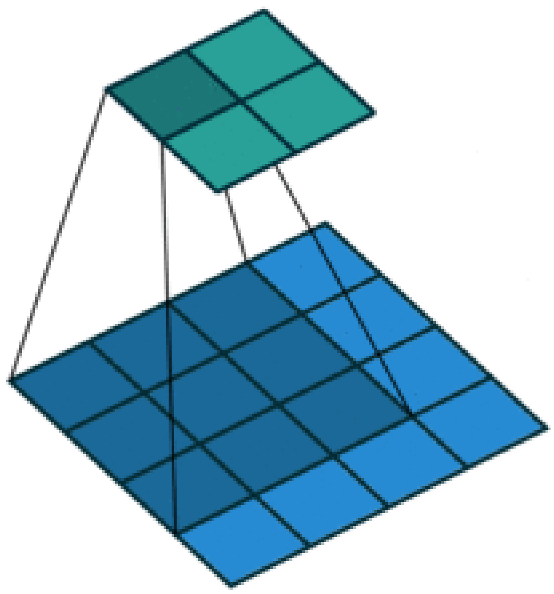
## Convolution without padding



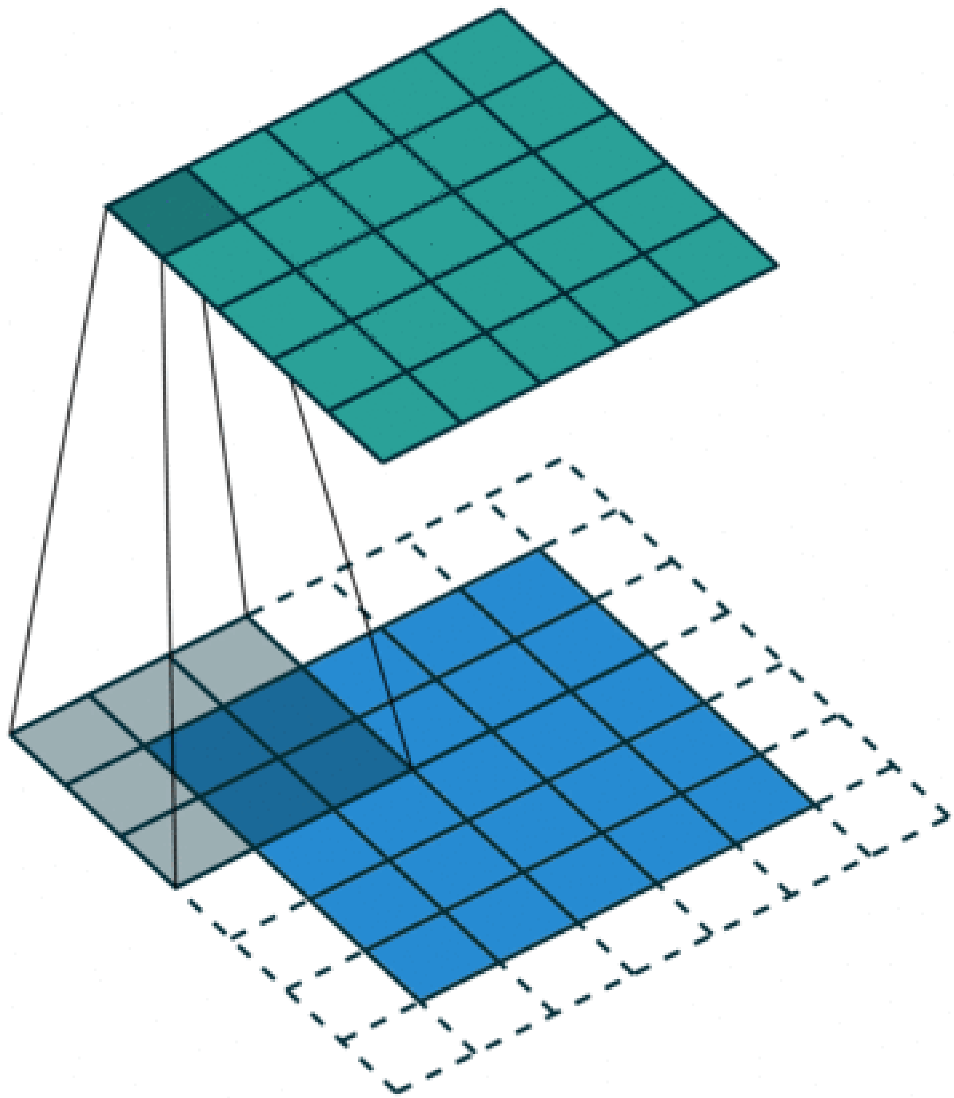




5x5 input. 3x3 filter/kernel/feature detector. 3x3 convolved feature/ activation map/feature map

## Convolution with padding



4x4 input. 3x3 filter. Stride = 1. 2x2 output.

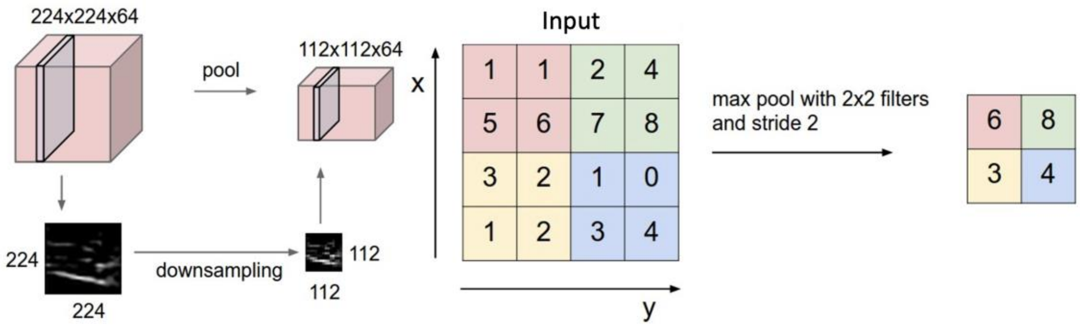


5x5 input. 3x3 filter. Stride = 1. 5x5 output.

https://github.com/vdumoulin/conv_arithmetic

## Pooling layer

- Intuition: to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network, and hence to also control overfitting
- Pooling partitions the input image (or documents) into a set of non-overlapping rectangles (n-grams) and, for each such sub-region, outputs the maximum value of the features in that region.




## Pooling (down sampling)

| | | | |
|---|---|---|---|
| 2 | 2 | 4 | 4 |
| 2 | 4 | 8 | 4 |
| 4 | 4 | 4 | 1 |
| 6 | 10 | 3 | 4 |

Max pooling

| | |
|---|---|
| 4 | 8 |
| 10 | 4 |

Mean Pooling

| | |
|---|---|
| 2.5 | 5 |
| 6 | 3 |

- The new size after pooling!

## Convolutional neural network

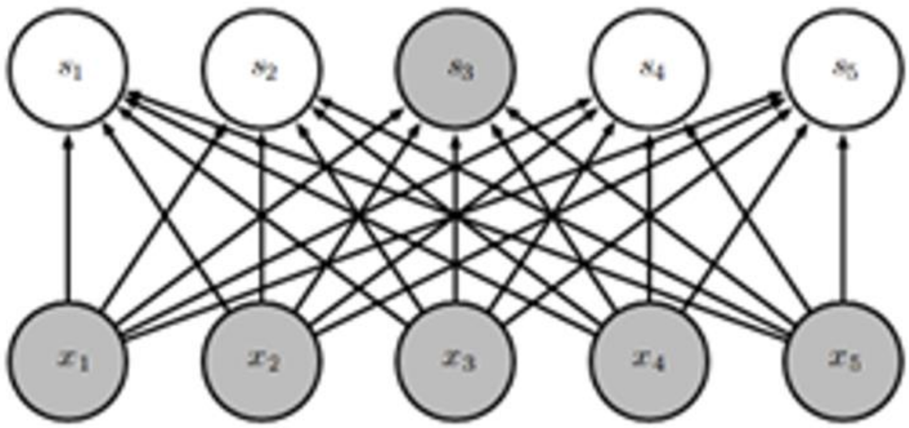
For processing data with a **grid-like** or array topology:

- 1-D convolution: text data, sequence data, time-series data, sensor signal data
- 2-D convolution: image data
- 3-D convolution: video data

## Other layers

- The convolution, and pooling layers are typically used as a set. Multiple sets of the above layers can appear in a CNN design.

- After a few sets, the output is typically sent to one or two **fully connected layers**.
  - A fully connected layer is a ordinary neural network layer as in other neural networks.
  - Typical activation function is the sigmoid function.
  - Output is typically class (classification) or real number (regression).



## Other layers

- The final layer of a CNN is determined by the research task.
- Classification: Softmax Layer

$$P(y = j|\mathbf{x}) = \frac{e^{w_j \cdot x}}{\sum_{k=1}^{K} e^{w_k \cdot x}}$$

  - The outputs are the probabilities of belonging to each class.
- Regression: Linear Layer

$$f(\mathbf{x}) = \mathbf{w} \cdot \mathbf{x}$$

  - The output is a real number.

What hyperparameters do we have in a CNN model?

# CNN for Text

## CNN

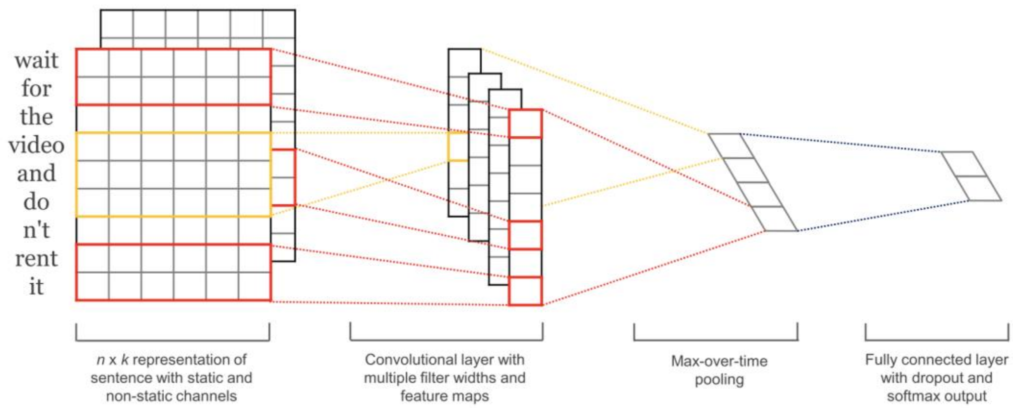
Main CNN idea for text:

Compute vectors for n-grams and group them afterwards

Example: “Utrecht summer school is in Utrecht” compute vectors for:

Utrecht summer, summer school, school is, is in, in Utrecht, Utrecht summer school, summer school is, school is in, is in Utrecht, Utrecht summer school is, summer school is in, school is in Utrecht, Utrecht summer school is in, summer school is in Utrecht, Utrecht summer school is in Utrecht

## CNNs for sentence classification




*Kim, Y. "Convolutional Neural Networks for Sentence Classification", EMNLP (2014)*

sliding over 3, 4 or 5 words at a time

https://arxiv.org/pdf/1408.5882.pdf

## Data sets (1)

- **MR**: Movie reviews with one sentence per review. Classification involves detecting positive/negative reviews (Pang and Lee, 2005). url: https://www.cs.cornell.edu/people/pabo/movie-review-data/
- **SST-1**: Stanford Sentiment Treebank—an extension of MR but with train/dev/test splits provided and fine-grained labels (very positive, positive, neutral, negative, very negative), re-labeled by Socher et al. (2013). url: https://nlp.stanford.edu/sentiment/
- **SST-2**: Same as SST-1 but with neutral reviews removed and binary labels.
- **Subj**: Subjectivity dataset where the task is to classify a sentence as being subjective or objective (Pang and Lee, 2004).

## Data sets (2)

- **TREC**: TREC question dataset—task involves classifying a question into 6 question types (whether the question is about person, location, numeric information, etc.) (Li and Roth, 2002). url: https://cogcomp.seas.upenn.edu/Data/QA/QC/

- **CR**: Customer reviews of various products (cameras, MP3s etc.). Task is to predict positive/negative reviews (Hu and Liu, 2004). url: https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html

- **MPQA**: Opinion polarity detection subtask of the MPQA dataset (Wiebe et al., 2005). url: https://mpqa.cs.pitt.edu/corpora/mpqa_corpus/

## Datasets' statistics

| **Data** | $c$ | $l$ | $N$ | $\lvert V\rvert$ | $\lvert V_{pre}\rvert$ | *Test* |
|---|---|---|---|---|---|---|
| MR | 2 | 20 | 10662 | 18765 | 16448 | CV |
| SST-1 | 5 | 18 | 11855 | 17836 | 16262 | 2210 |
| SST-2 | 2 | 19 | 9613 | 16185 | 14838 | 1821 |
| Subj | 2 | 23 | 10000 | 21323 | 17913 | CV |
| TREC | 6 | 10 | 5952 | 9592 | 9125 | 500 |
| CR | 2 | 19 | 3775 | 5340 | 5046 | CV |
| MPQA | 2 | 3 | 10606 | 6246 | 6083 | CV |

Table 1: Summary statistics for the datasets after tokenization. $c$: Number of target classes. $l$: Average sentence length. $N$: Dataset size. $|V|$: Vocabulary size. $|V_{pre}|$: Number of words present in the set of pre-trained word vectors. *Test*: Test set size (CV means there was no standard train/test split and thus 10-fold CV was used).

## CNN variations

- **CNN-rand**: Our baseline model where all words are randomly initialized and then modified during training.
- **CNN-static**: A model with pre-trained vectors from `word2vec`. All words—including the unknown ones that are randomly initialized—are kept static and only the other parameters of the model are learned.
- **CNN-non-static**: Same as above but the pre-trained vectors are fine-tuned for each task.
- **CNN-multichannel**: A model with two sets of word vectors.

## Similar words

| | Most Similar Words for | |
|---|---|---|
| | Static Channel | Non-static Channel |
| ***bad*** | *good* | *terrible* |
| | *terrible* | *horrible* |
| | *horrible* | *lousy* |
| | *lousy* | *stupid* |
| ***good*** | *great* | *nice* |
| | *bad* | *decent* |
| | *terrific* | *solid* |
| | *decent* | *terrific* |
| ***n't*** | *os* | *not* |
| | *ca* | *never* |
| | *ireland* | *nothing* |
| | *wo* | *neither* |
| ***!*** | *2,500* | *2,500* |
| | *entire* | *lush* |
| | *jez* | *beautiful* |
| | *changer* | *terrific* |
| ***,*** | *decasia* | *but* |
| | *abysmally* | *dragon* |
| | *demise* | *a* |
| | *valiant* | *and* |

## Results

| Model | MR | SST-1 | SST-2 | Subj | TREC | CR | MPQA |
|---|---|---|---|---|---|---|---|
| CNN-rand | 76.1 | 45.0 | 82.7 | 89.6 | 91.2 | 79.8 | 83.4 |
| CNN-static | 81.0 | 45.5 | 86.8 | 93.0 | 92.8 | 84.7 | **89.6** |
| CNN-non-static | **81.5** | 48.0 | 87.2 | 93.4 | 93.6 | 84.3 | 89.5 |
| CNN-multichannel | 81.1 | 47.4 | **88.1** | 93.2 | 92.2 | **85.0** | 89.4 |
| RAE (Socher et al., 2011) | 77.7 | 43.2 | 82.4 | – | – | – | 86.4 |
| MV-RNN (Socher et al., 2012) | 79.0 | 44.4 | 82.9 | – | – | – | – |
| RNTN (Socher et al., 2013) | – | 45.7 | 85.4 | – | – | – | – |
| DCNN (Kalchbrenner et al., 2014) | – | 48.5 | 86.8 | – | 93.0 | – | – |
| Paragraph-Vec (Le and Mikolov, 2014) | – | **48.7** | 87.8 | – | – | – | – |
| CCAE (Hermann and Blunsom, 2013) | 77.8 | – | – | – | – | – | 87.2 |
| Sent-Parser (Dong et al., 2014) | 79.5 | – | – | – | – | – | 86.3 |
| NBSVM (Wang and Manning, 2012) | 79.4 | – | – | 93.2 | – | 81.8 | 86.3 |
| MNB (Wang and Manning, 2012) | 79.0 | – | – | **93.6** | – | 80.0 | 86.3 |
| G-Dropout (Wang and Manning, 2013) | 79.0 | – | – | 93.4 | – | 82.1 | 86.1 |
| F-Dropout (Wang and Manning, 2013) | 79.1 | – | – | **93.6** | – | 81.9 | 86.3 |
| Tree-CRF (Nakagawa et al., 2010) | 77.3 | – | – | – | – | 81.4 | 86.1 |
| CRF-PR (Yang and Cardie, 2014) | – | – | – | – | – | 82.7 | – |
| $SVM_S$ (Silva et al., 2011) | – | – | – | – | **95.0** | – | – |

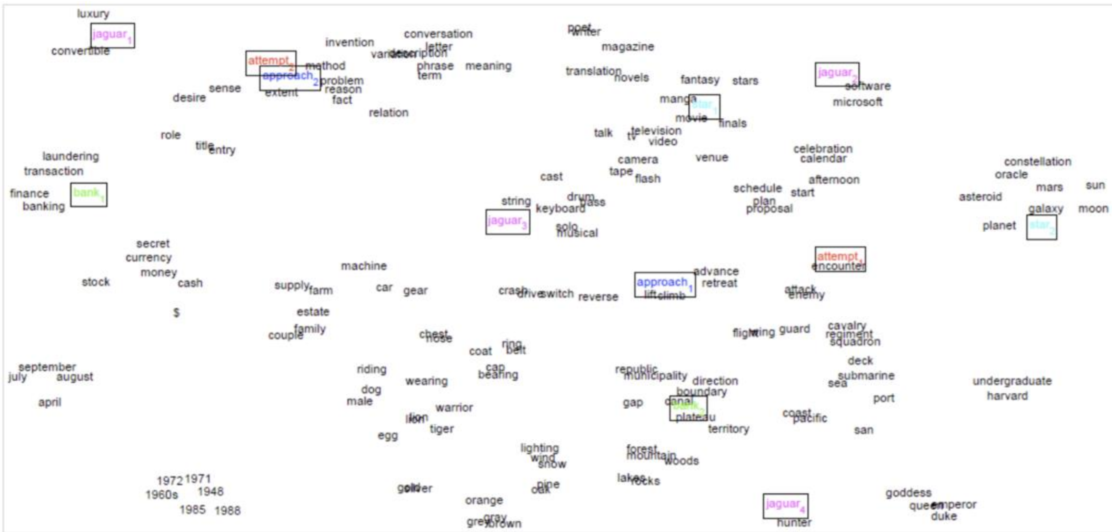
## CNN with Keras in Python

```
model = Sequential()
model.add(layers.Embedding(vocab_size, embedding_dim, input_length=maxlen))
model.add(layers.Conv1D(128, 5, activation='relu'))
model.add(layers.GlobalMaxPooling1D())
model.add(layers.Dense(10, activation='relu'))
model.add(layers.Dense(5, activation='sigmoid'))
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 100, 100)          3811100
_________________________________________________________________
conv1d (Conv1D)              (None, 96, 128)           64128
_________________________________________________________________
global_max_pooling1d (Global (None, 128)               0
_________________________________________________________________
dense_4 (Dense)              (None, 10)                1290
_________________________________________________________________
dense_5 (Dense)              (None, 5)                 55
=================================================================
Total params: 3,876,573
Trainable params: 3,876,573
Non-trainable params: 0
```

# Contextual Word Embeddings & Transformers

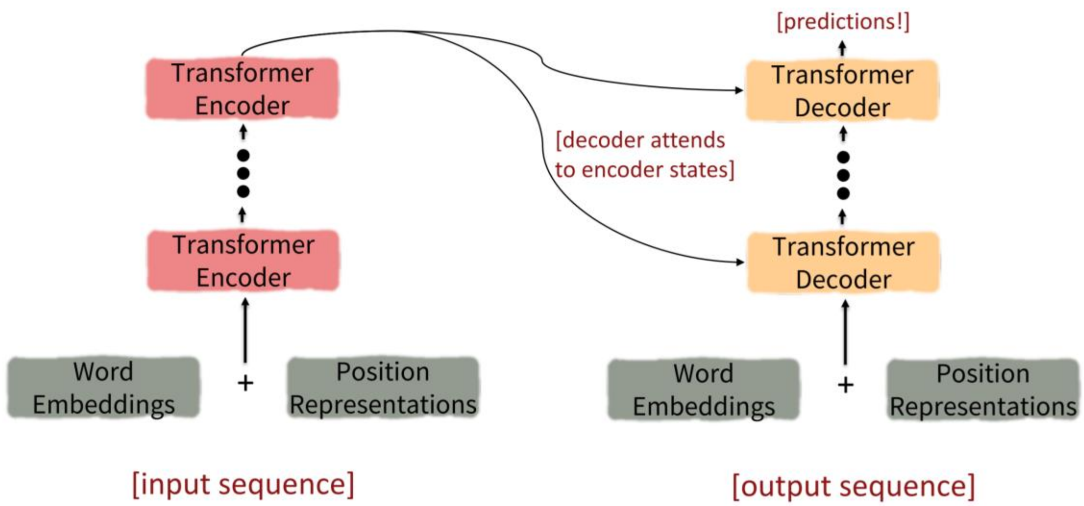
## Contextual Word Embeddings



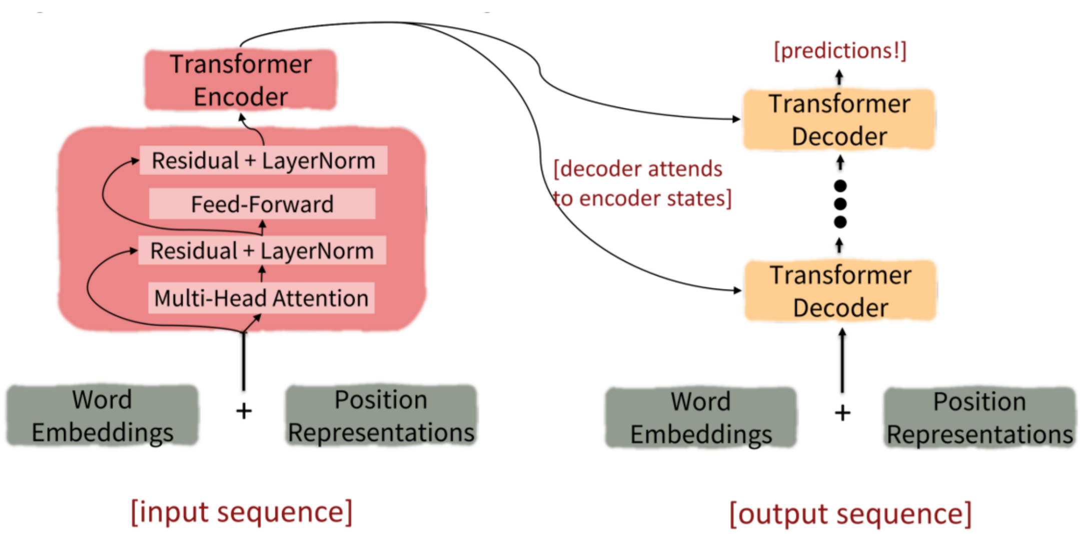

## Transformers

- A transformer adopts an encoder-decoder architecture.
- Transformers were developed to solve the problem of sequence transduction, or neural machine translation. That means any task that transforms an input sequence to an output sequence.
- More details on the architecture and implementation:
  - https://arxiv.org/abs/1810.04805
  - http://nlp.seas.harvard.edu/2018/04/03/attention.html
  - https://jalammar.github.io/illustrated-transformer/

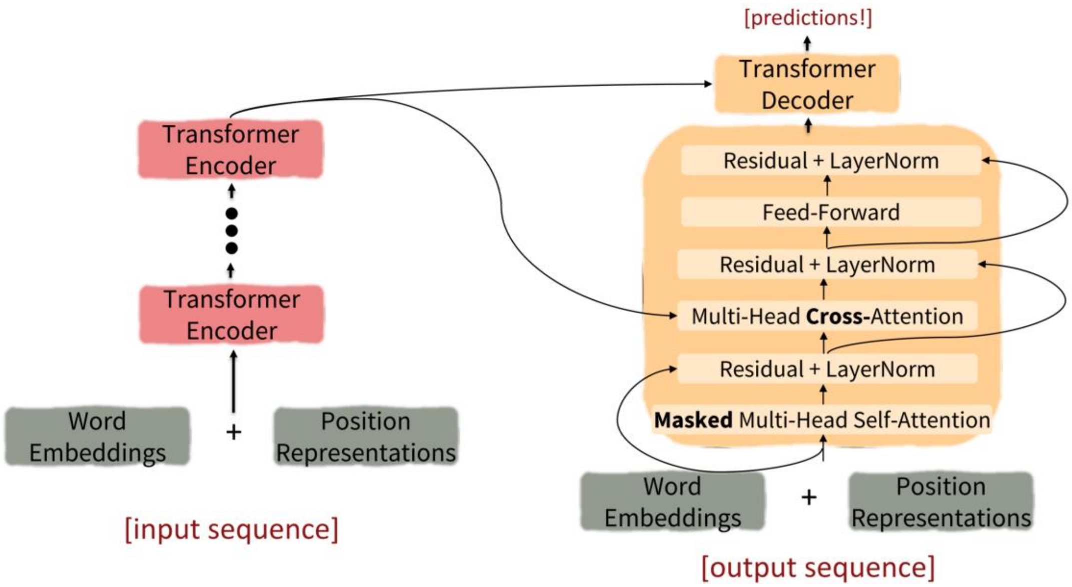
## The Transformer Encoder-Decoder




## The Transformer Encoder-Decoder



## The Transformer Encoder-Decoder




## Transformers

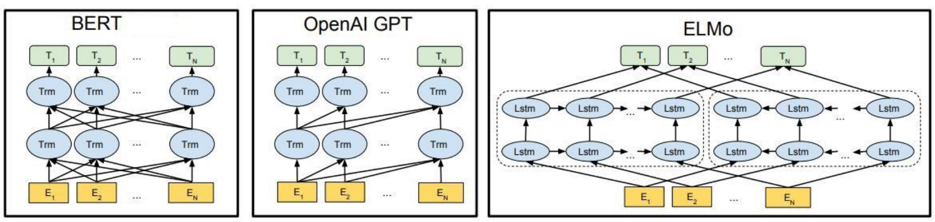



Figure 1: Differences in pre-training model architectures. BERT uses a bidirectional Transformer. OpenAI GPT uses a left-to-right Transformer. ELMo uses the concatenation of independently trained left-to-right and right-to-left LSTM to generate features for downstream tasks. Among three, only BERT representations are jointly conditioned on both left and right context in all layers.

## BERT: Bidirectional Encoder Representations from Tranformers

## BERT: Bidirectional Encoder Representations from Tranformers

## What kinds of things does pretraining learn?

There's increasing evidence that pretrained models learn a wide variety of things about the statistical properties of language:

*Talk to Transformer:* https://app.inferkit.com/demo

- Utrecht University is located in …

## Transformers

## Transformers

## Transformers

## What kinds of things does pretraining learn?

There's increasing evidence that pretrained models learn a wide variety of things about the statistical properties of language:

- **Basic arithmetic:** I was thinking about the sequence that goes 1, 1, 2, 3, 5, 8, 13, 21, …

## Transformers

## What kinds of things does pretraining learn?

There's increasing evidence that pretrained models learn a wide variety of things about the statistical properties of language:

- **Reasoning:** Garry went into the kitchen to make some tea. Standing next to Garry, Carrie pondered her destiny. Carrie left the …

## Transformers

## Transformers

## Transformers

## Transformers

- ChatGPT: https://chat.openai.com/
- Write with Transformer: https://transformer.huggingface.co/
- Talk to Transformer: https://app.inferkit.com/demo

- Transformer model for language understanding: https://www.tensorflow.org/text/tutorials/transformer

- Pretrained models: https://huggingface.co/transformers/pretrained_models.html

### ChatGPT (5-min exercise)

- Go to https://chat.openai.com/ and login

- How many hyperparameters has chatgpt-3 model been trained on?

- How many hyperparameters has chatgpt-4 model been trained on?

- What is the next generation NLP?

- Build a neural network model with an LSTM layer of 100 units in Keras. As before, the first layer should be an embedding layer, then the LSTM layer, a Dense layer, and the output Dense layer for the 5 news categories. Compile the model and print its summary.

- Can you make it functional keras?

## Summary

### Summary

- Convolutional Neural Networks

- Transformers

  - "Small" models like BERT have become general tools in a wide range of settings
  - GPT-3 has 175 billion parameters
- These models are still not well-understood

## Practical 7