# Transfer learning with Transformer networks

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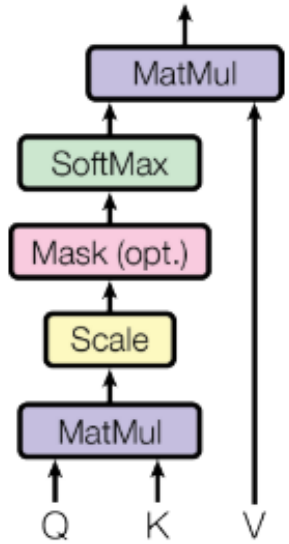
# Neural network architectures for NLP

MLP, CNN, dilated CNN, RNN (LSTM / GRU), Tranformer

# Attention mechanisms

## Scaled Dot-Product Attention

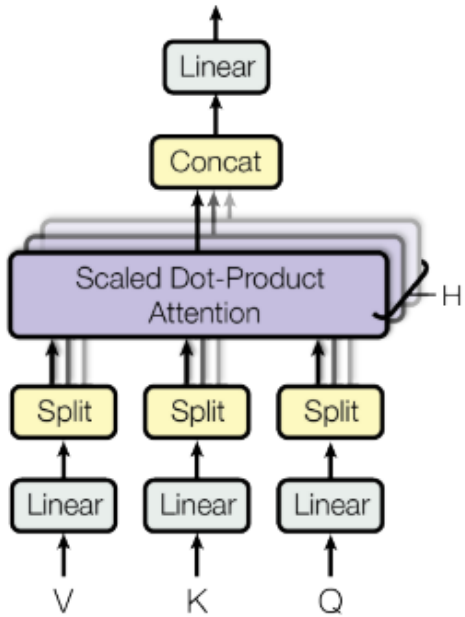



$Q$ is the query vector, $K$ is the key vector and $V$ value vector.

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

# Attention mechanisms

## Multi-Head Attention

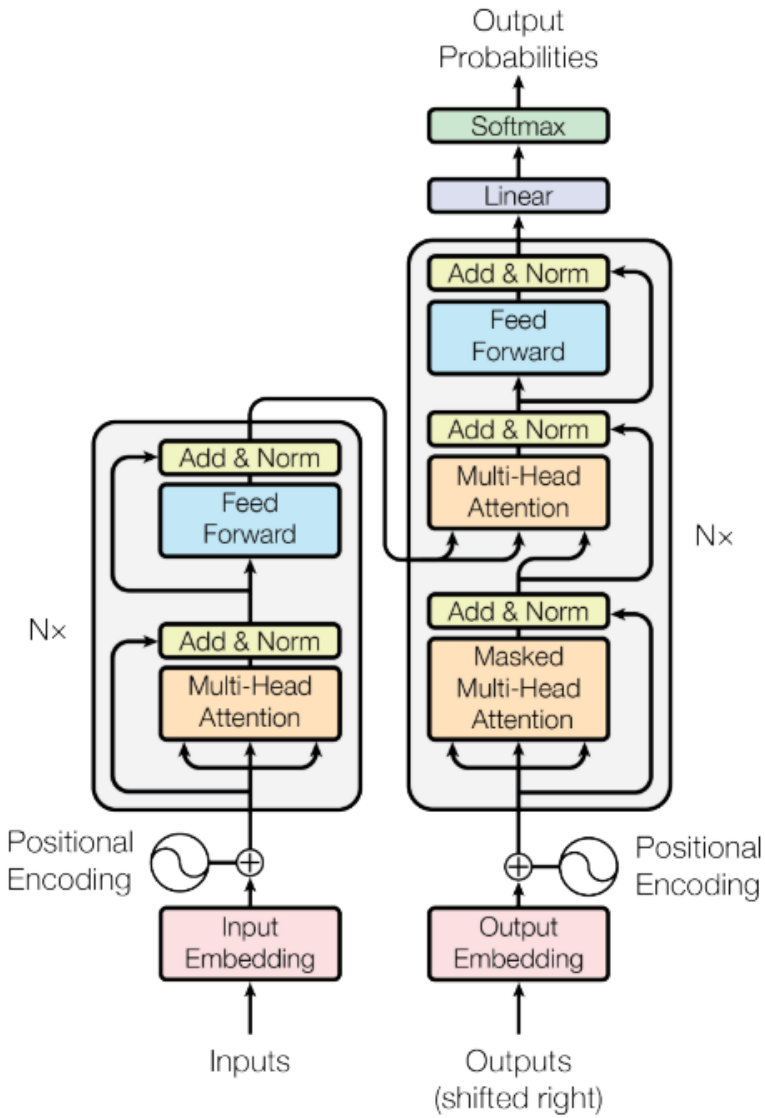



$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)$$
$$\text{where} \quad \text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

where the projections $W_i^Q$, $W_i^K$ and $W_i^V$ are parameter matrices.

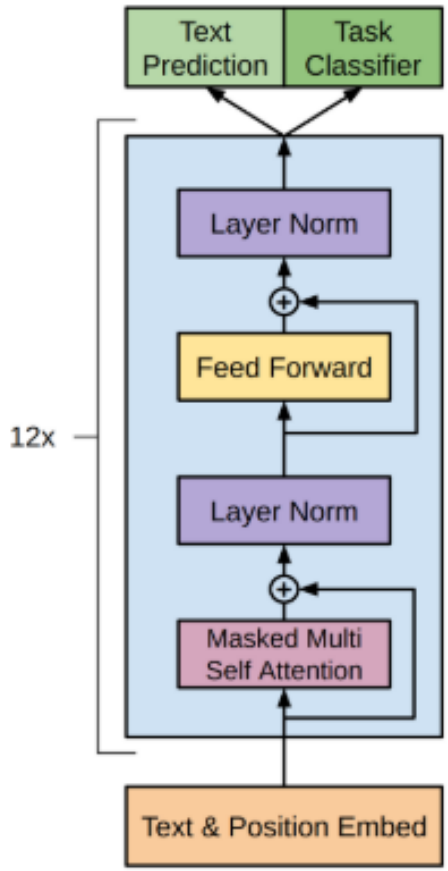
# Transformer network

## Original transformer



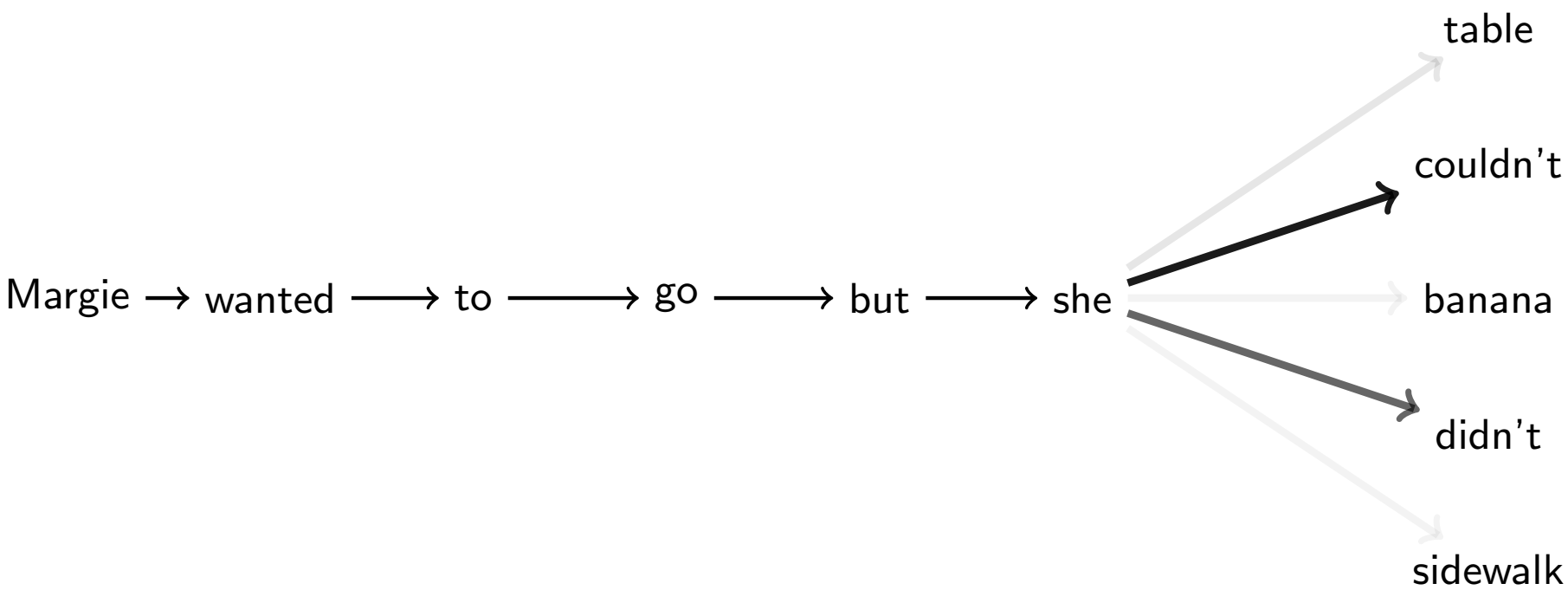
# Transformer network

## OpenAI multi-layer decoder



# Pre-training task

## Language modeling



# Results on standard datasets

New state of the art on the following tasks:

- Textual Entailment
  - SNLI 89.3 → 89.9
  - MNLI Matched 80.6 → 82.1
  - MNLI Mismatched 80.1 → 81.4
  - SciTail 83.3 → 88.3
  - QNLI 82.3 → 88.1
- Semantic Similarity
  - STS-B 81.0 → 82.0
  - QQP 66.1 → 70.3
- Reading Comprehension
  - RACE 53.3 → 59.0
- Commonsense Reasoning
  - ROCStories 77.6 → 86.5
  - COPA 71.2 → 78.6
- Linguistic Acceptability
  - CoLA 35.0 → 45.4
- Multi-Task Benchmark
  - GLUE 68.9 → 72.8

# References


- Vaswani, Ashish, et al. "Attention is all you need." Advances in Neural Information Processing Systems. 2017.
- Radford, Alec, et al. "Improving language understanding by generative pre-training." URL Article pdf link Blog post (2018).
- Devlin, Jacob, et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805 (2018).