Enhancing the Dependency Mechanism of RoBERTa

Natural Language Processing:

EDM-RoBERTa

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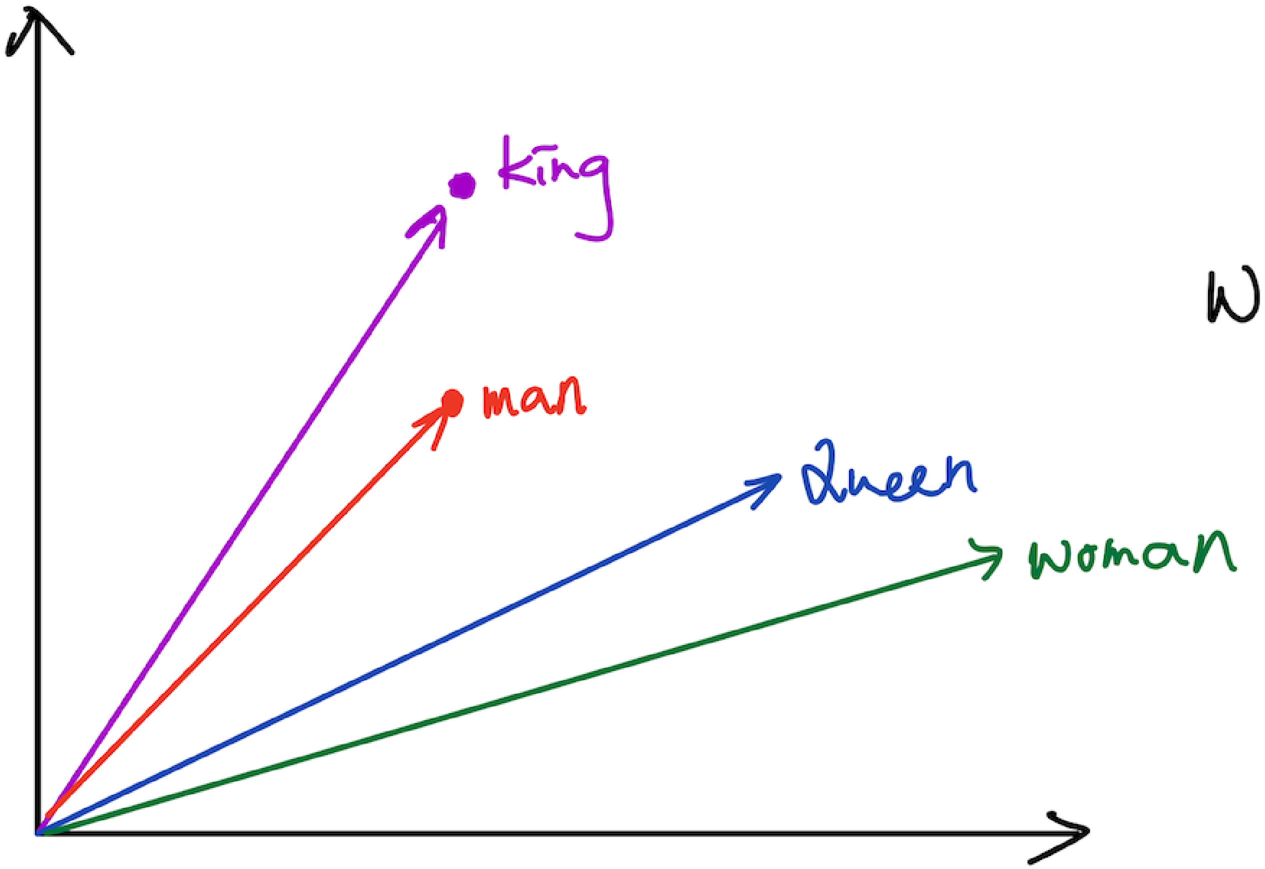
EDM-RoBERTa: Enhancing the Dependency Mechanism of RoBERTa

- **Learning Language Representations: Word Vectors (Word Embeddings)**



Word Vectors

General Language Model

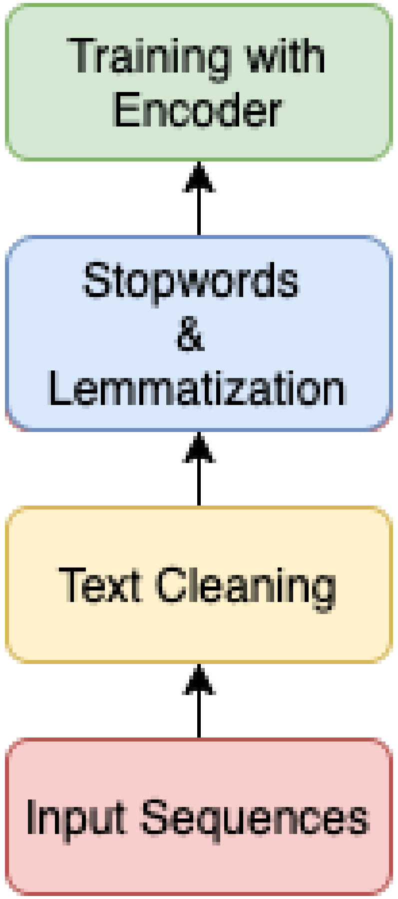
Goal: Build a general language model to process with natural language.

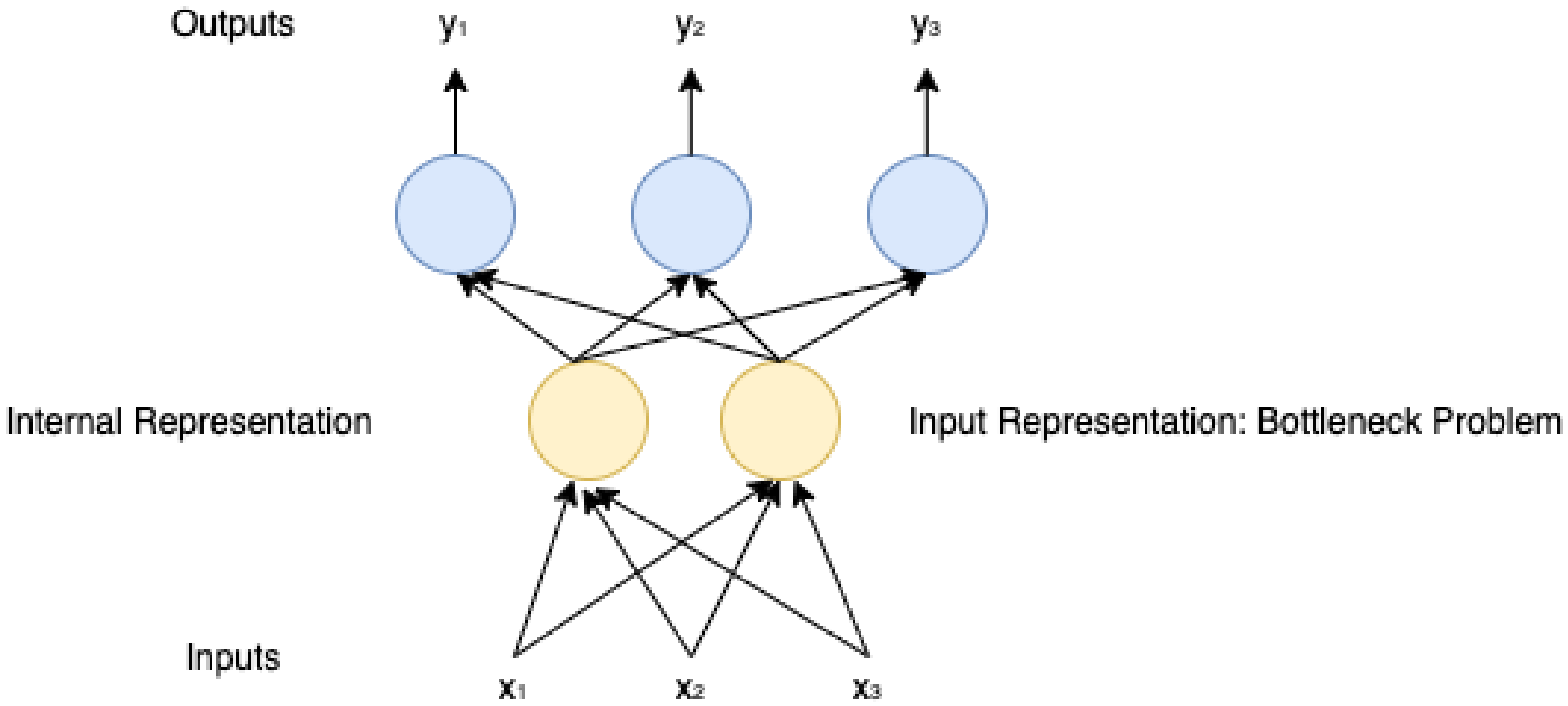
The model can be adapted to different NLP tasks by transfer learning.

Transfer Learning: Pre-train and fine-tune the language model.

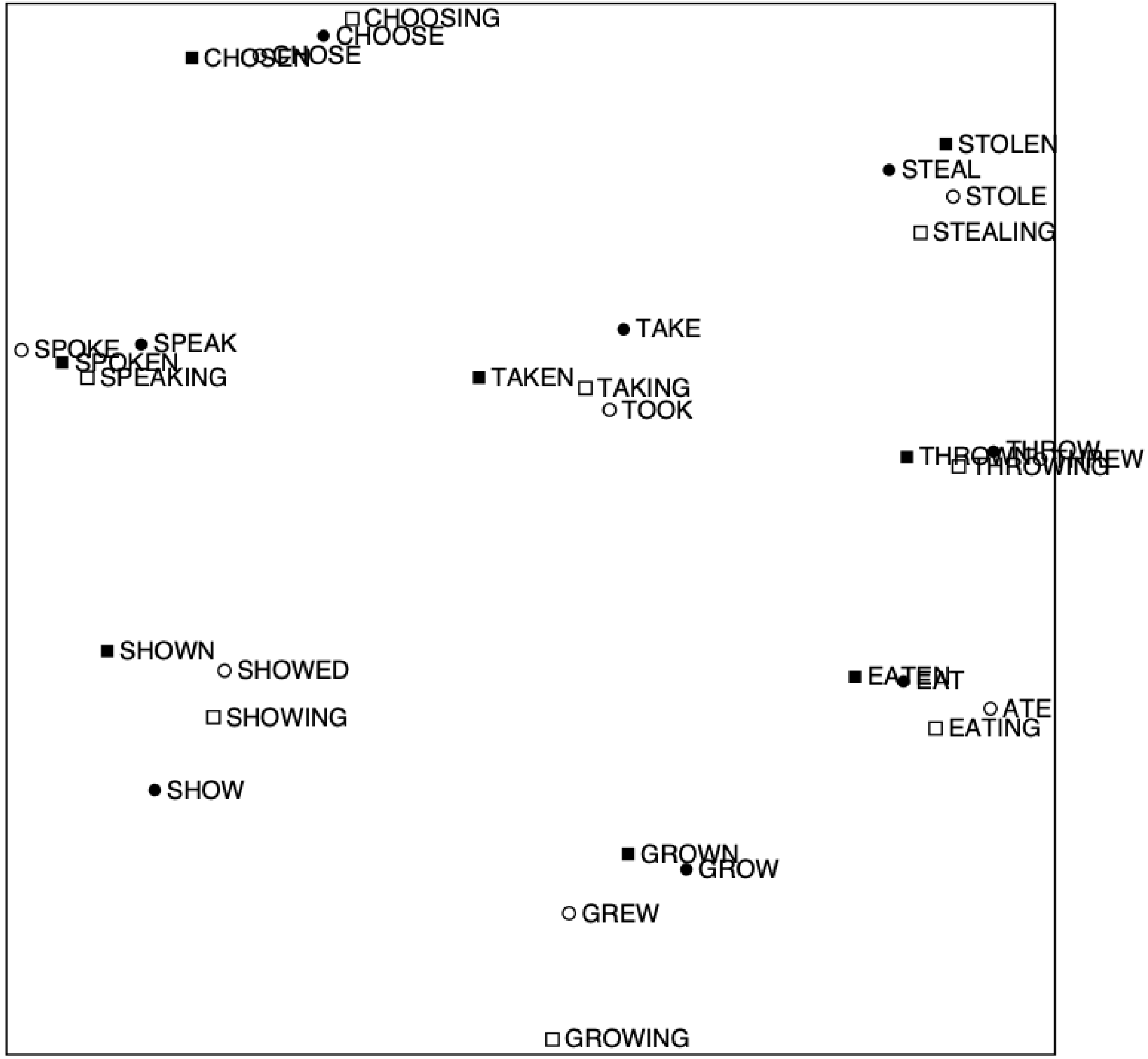
Conventional Language Model: Sequence to Sequence model **(Seq2Seq)**

Flowchart of Text Sequences Processing and Bottleneck Problem

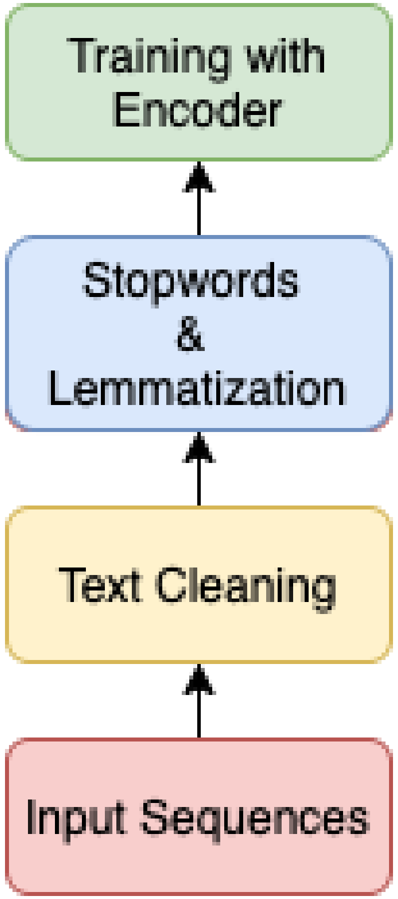


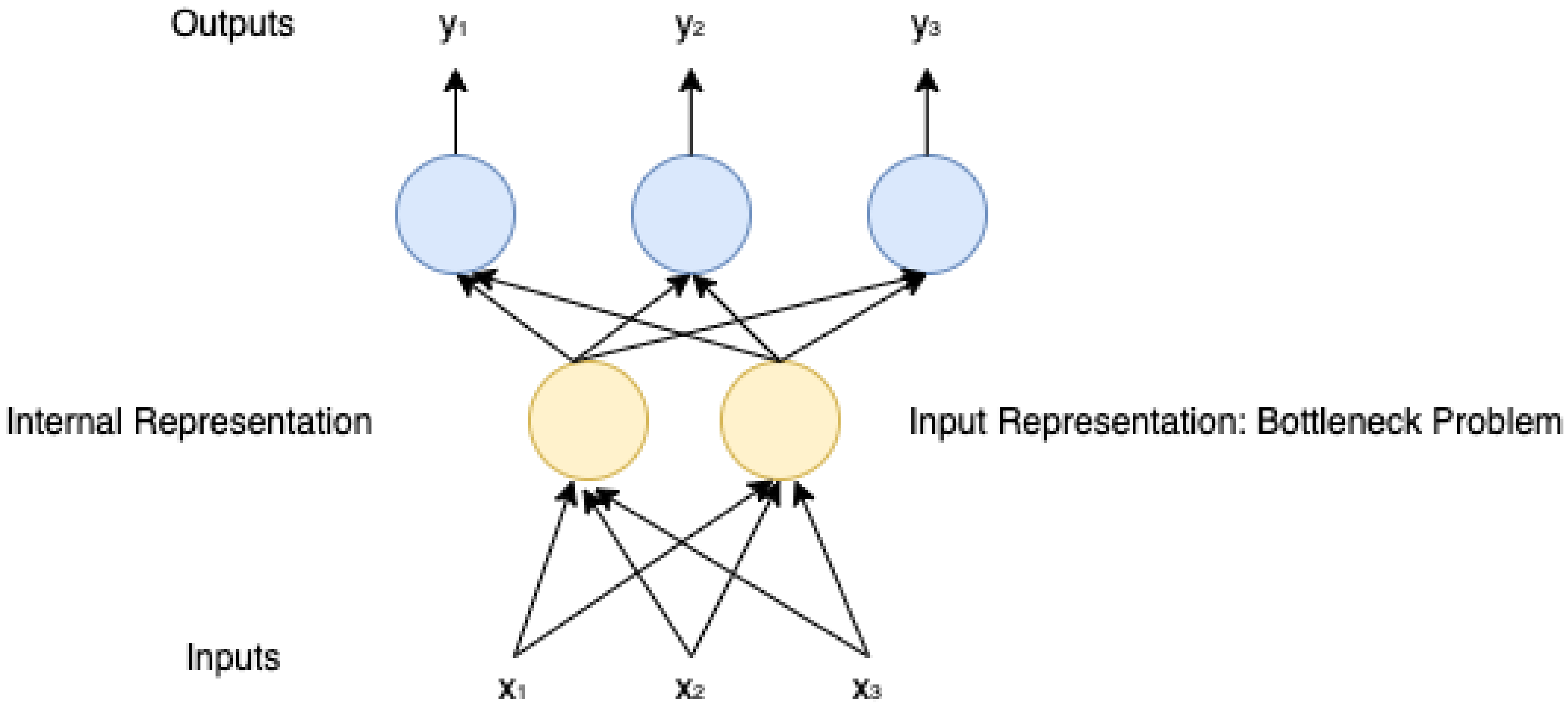


Syntactic Patterns Emerge in Word Vectors



Flowchart of Text Sequences Processing and Bottleneck Problem





Encoder-Decoder Structure

- **Natural Language Understanding (NLU) with Encoder: Sentiment Analysis, Named Entity Classification, etc.**

- **Natural Language Generation (NLG) with Decoder: Neural Machine Translation, Question Answering, etc.**

- **Context Vector: Causing "Bottleneck Problem"**

Encoder-Decoder Structure: Transformer-based Models

- **Models: BERT, RoBERTa, XLNet, DistilBERT**

  Bidirectional Encoder Representation from Transformers (**BERT**)
  Robustly optimized BERT approach (**RoBERTa**)

- **Task: Sentiment Analysis**

- **Benchmark Datasets:**

  ✓ First GOP Debate Twitter Sentiment

  ✓ Tweets from verified users concerning stocks traded on the NYSE, NASDQ & SNP

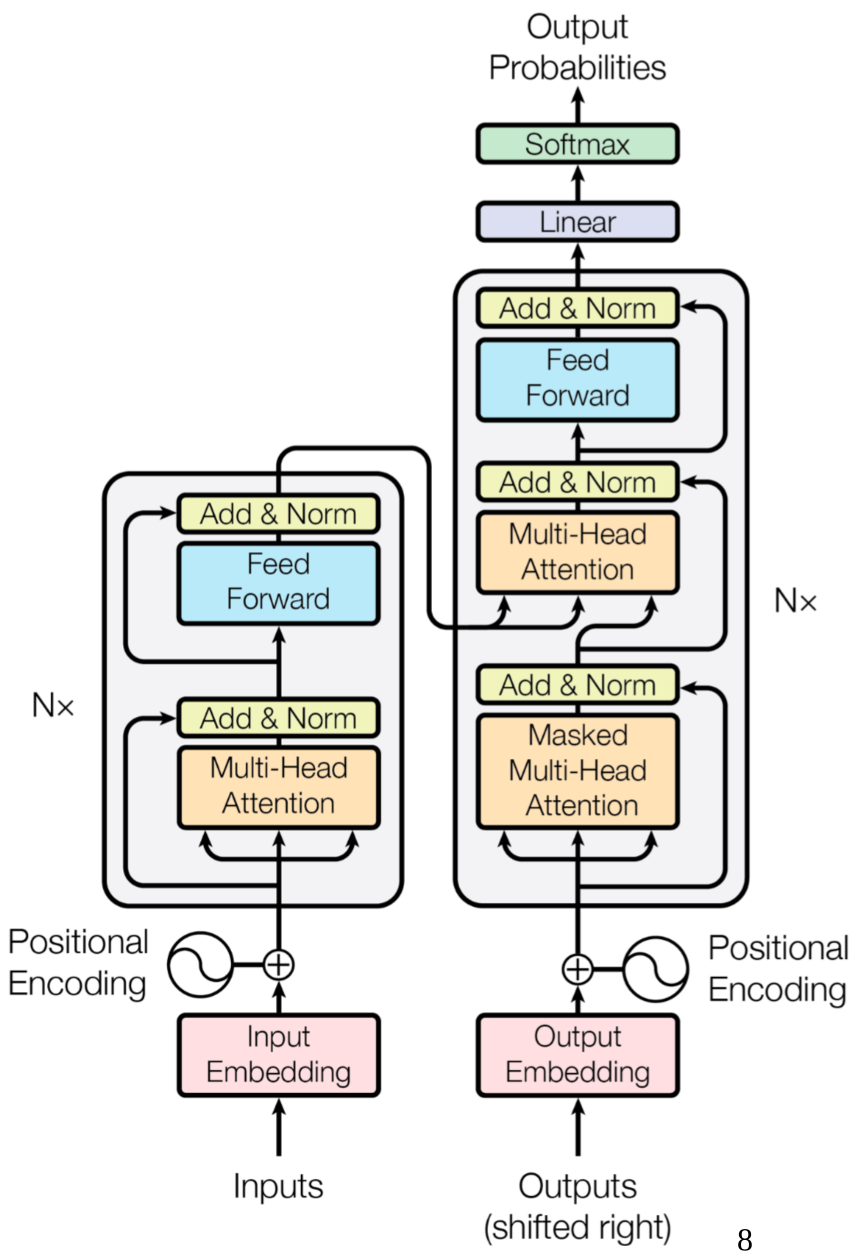
  ✓ SST-2: IMDb Movies Reviews

  ✓ SST-5: Rotten Tomatoes Movies Reviews

Structure: Transformer-based Models

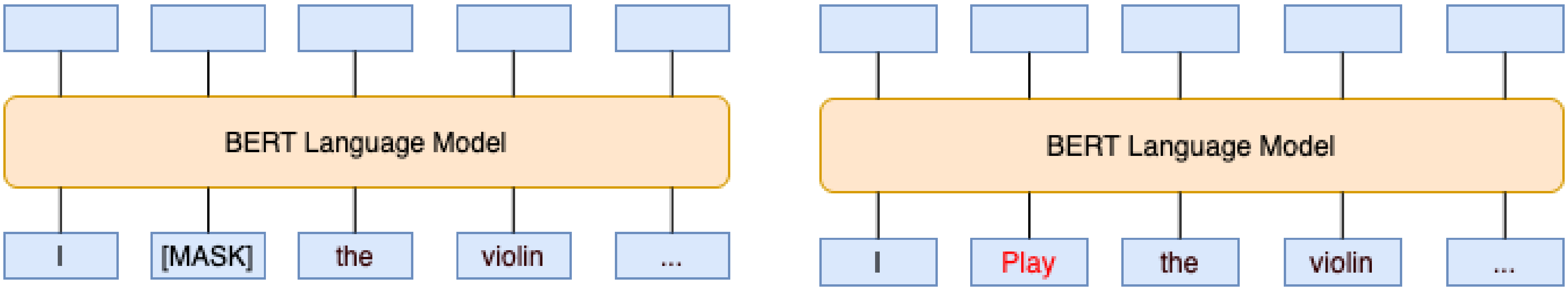
Pre-training approaches

- **BERT:** Maskd LM & Next Sentence Prediction
- **RoBERTa:**
  - Trained on **More Corpus (WikiText103, BookCorpus, CCNews)**
  - Trained with **Bigger batch sizes**



Masked Language (Masked LM)

- **Masked LM**



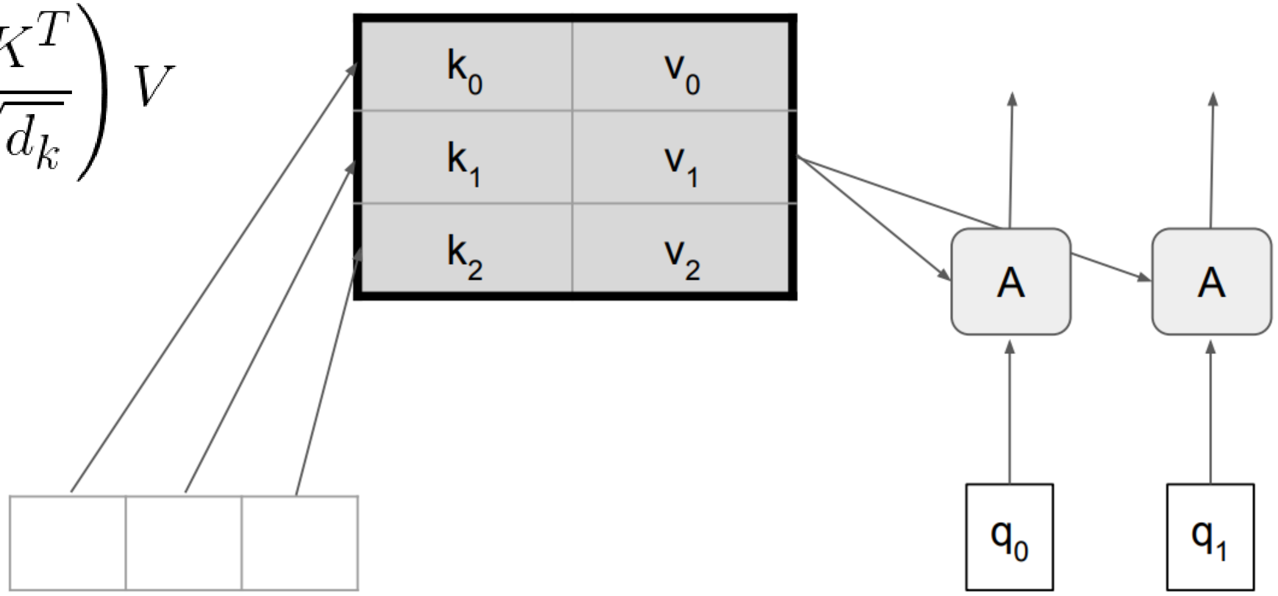
Next Sentence Prediction (NSP)

- **NSP**

Attention Mechanism

- **Scaled Dot-Product Self Attention**

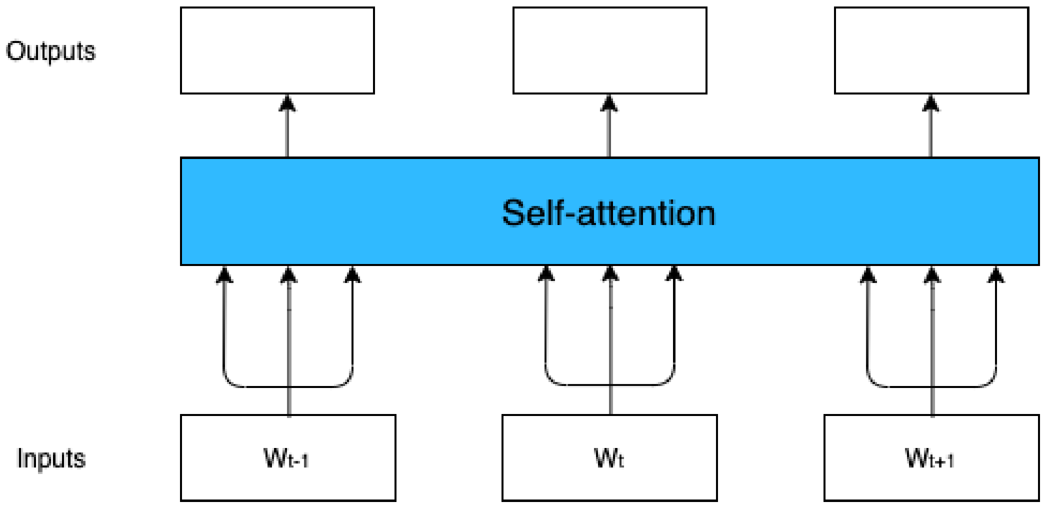
$$Attention\,(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



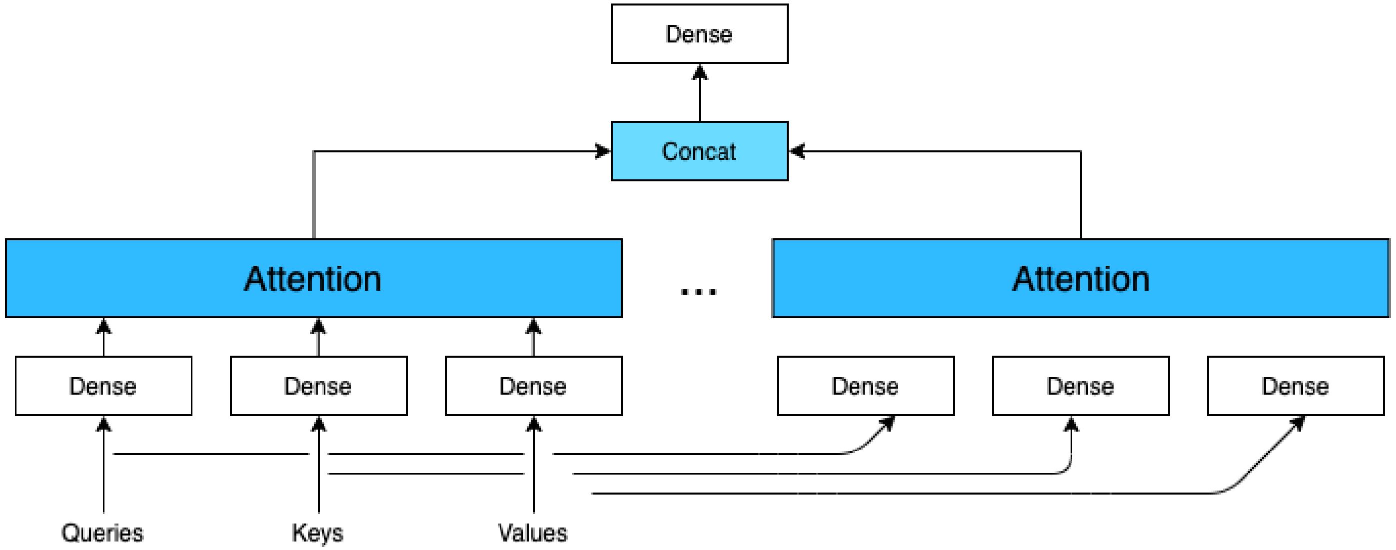
Attention Mechanism

- **Scaled Dot-Product Attention**

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

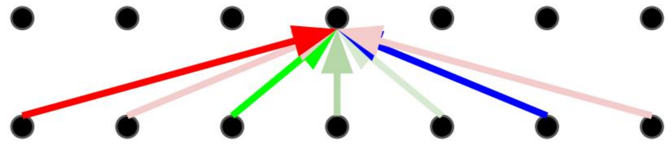


- **Multi-Headed Attention**



Attention Mechanism: The Fix – Multi-Headed Attention

- **Multi-Headed Attention**
  - Multiple attention layers (heads) in parallel (shown by different colors)
  - Each layer uses different linear transformations.
  - Different heads can learn different relationships.



Problems with Attention Mechanism

- **Too many heads -> Hard to process queries from multiple positions in parallel.**
- **Valid heads are unknown**
- **Processing with "Valid heads" problem:**

We propose EDM-RoBERTa to optimize the attention process

Optimization

- Single-headed Attention RNN (SHA-RNN)
  - **Boom Layer**

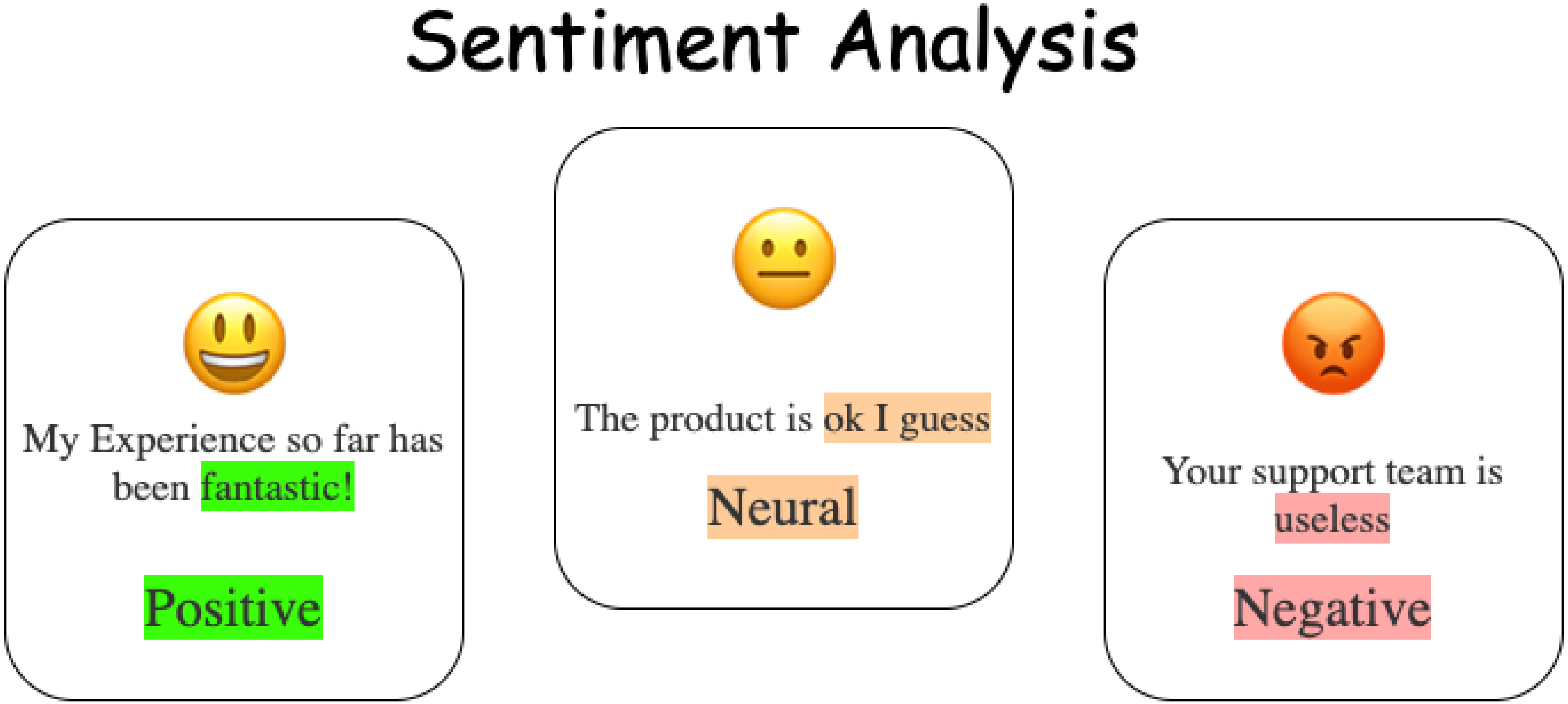
$$v \in \mathbb{R}^{H} \rightarrow \mu \in \mathbb{R}^{N \times H} \rightarrow \omega \in \mathbb{R}^{H}$$

  - **Activation Function:** Gaussian Error Linear Units (GELUs)

- Models: BERT, RoBERTa, DistilBERT, XLNet

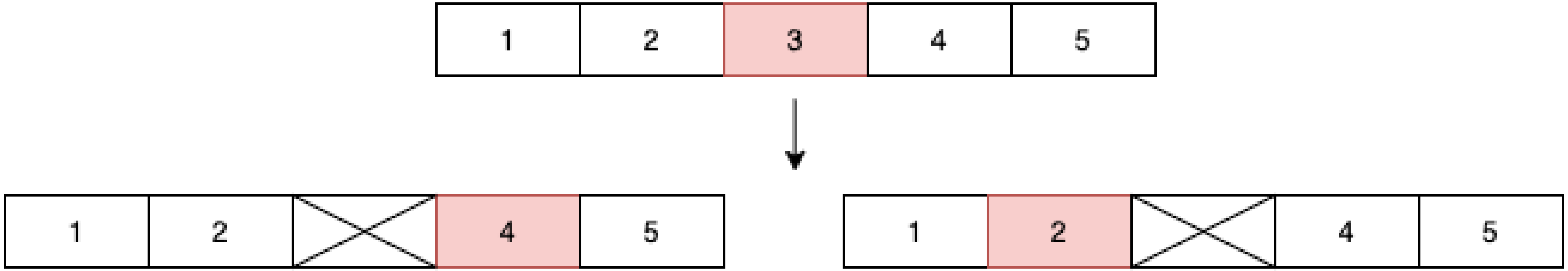
- **Solving the short-term dependency problem from Transformer-based Models**

Optimization: Sentimental Ambiguity



Optimization: Sentimental Ambiguity

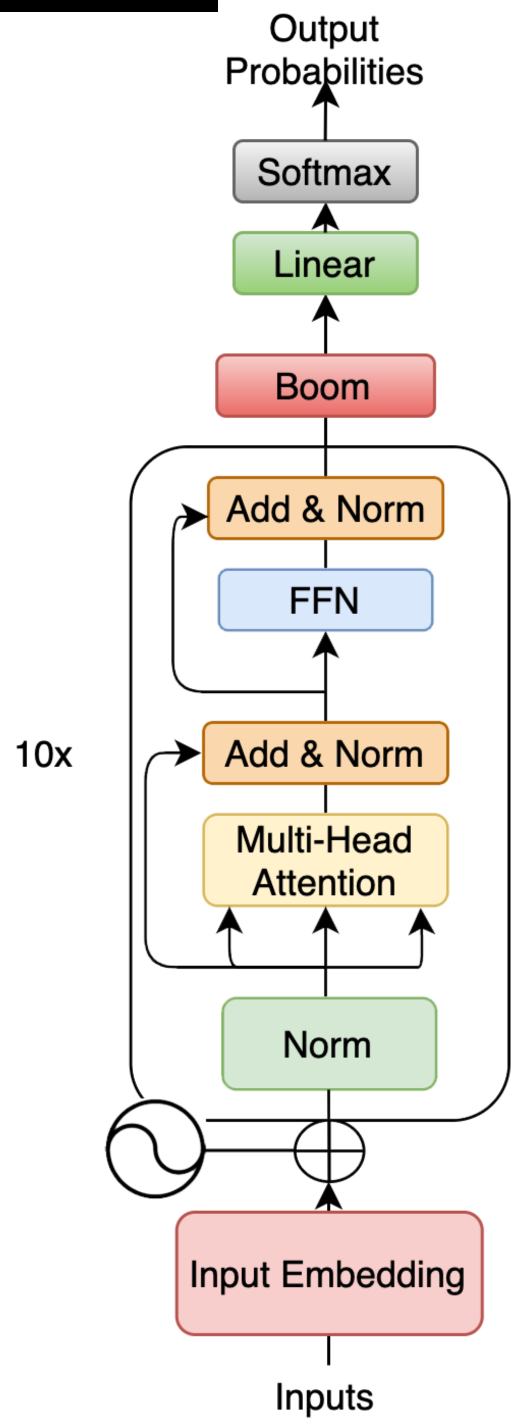
- Why using both two-dimensional and multi-dimensional sentiment analysis datasets to train EDM-RoBERTa ?
  - **Deal with the sentences with sentimental ambiguity**



Improved Learning Model: EDM-RoBERTa

- Choose the best-performed model: **RoBERTa**
- **Optimize the RoBERTa model with Boom Layer**

Enhancing the Dependency Mechanism of RoBERTa



Optimization: Statistics

Fine-tuning Transformer-based Models with IMDb Dataset

	Epoch	Accuracy	train loss	valid loss	error rates
$BERT_{LARGE}$	6	92.6	0.35	0.55	0.29
$RoBERTa_{LARGE}$	6	93.17	0.22	0.53	0.26
XLNet	6	89.53	0.28	0.69	0.37
DistilBERT	6	86.48	0.32	0.74	0.35
EDM-RoBERTa	6	94.76	0.27	0.49	0.2

Fine-tuning Transformer-based Models with Rotten Tomatoes Dataset

	Epoch	Accuracy	train loss	valid loss	error rates
$BERT_{LARGE}$	5	66.21	0.64	0.68	0.3
$RoBERTa_{LARGE}$	5	68.91	0.67	0.7	0.29
XLNet	5	62.83	0.73	0.79	0.38
DistilBERT	5	54.65	0.8	0.77	0.44
EDM-RoBERTa	5	76.18	0.64	0.62	0.26

EDM-RoBERTa: Enhancing the Dependency Structure of RoBERTa

- **Detailed parameters of EDM-RoBERTa**

EDM-RoBERTa (Enhance the Dependency Mechanism of RoBERTa)

bsz	steps	lr	ppl	SST-2	SST-5
256	1M	1.00E-05	3.83	92.6	74.57
2K	**125K**	**2.00E-04**	**3.61**	**94.76**	**76.18**
8K	31K	1.00E-03	3.72	92.1	74.31

Runtimes & Environments

Google Colaboratory Pro	**GPU:** NVIDIA Tesla V100-SXM2-16GB
	CPU: Intel Xeon(R) @2.00GHz **OS:** Ubuntu 18.04.5 LTS **RAM:** 32GB
MacBook Pro (16-inch Late 2019)	**GPU:** AMD Radeon Pro 5600M-8GB-HBM2
	CPU: Intel Core i9-9980HK @2.4GHz **Dual Boot OS:** Ubuntu 18.04.5 LTS with macOS Catalina 10.15.7 (19H2) **RAM:** 64GB
MacBook Pro (13-inch, M1, 2020)	**GPU & CPU:** Apple M1 Chip with 8-core CPU, 8-core GPU **NPU:** Apple M1 Chip with 16-core Neural Engine **Environments:** CreateML, Tensorflow-mac **RAM:** 16GB

Conclusions

We introduced a language representation model called EDM-RoBERTa.

EDM-RoBERTa is designed to improve the dependency mechanism, and fine-tune the whole model with sentiment analysis datasets.

Experiments and statistics show our proposed model successfully enhance the dependency mechanism on local context.

EDM-RoBERTa outperforms conventional pre-trained models, including Seq2Seq, BERT, RoBERTa, XLNet, and DistilBERT.