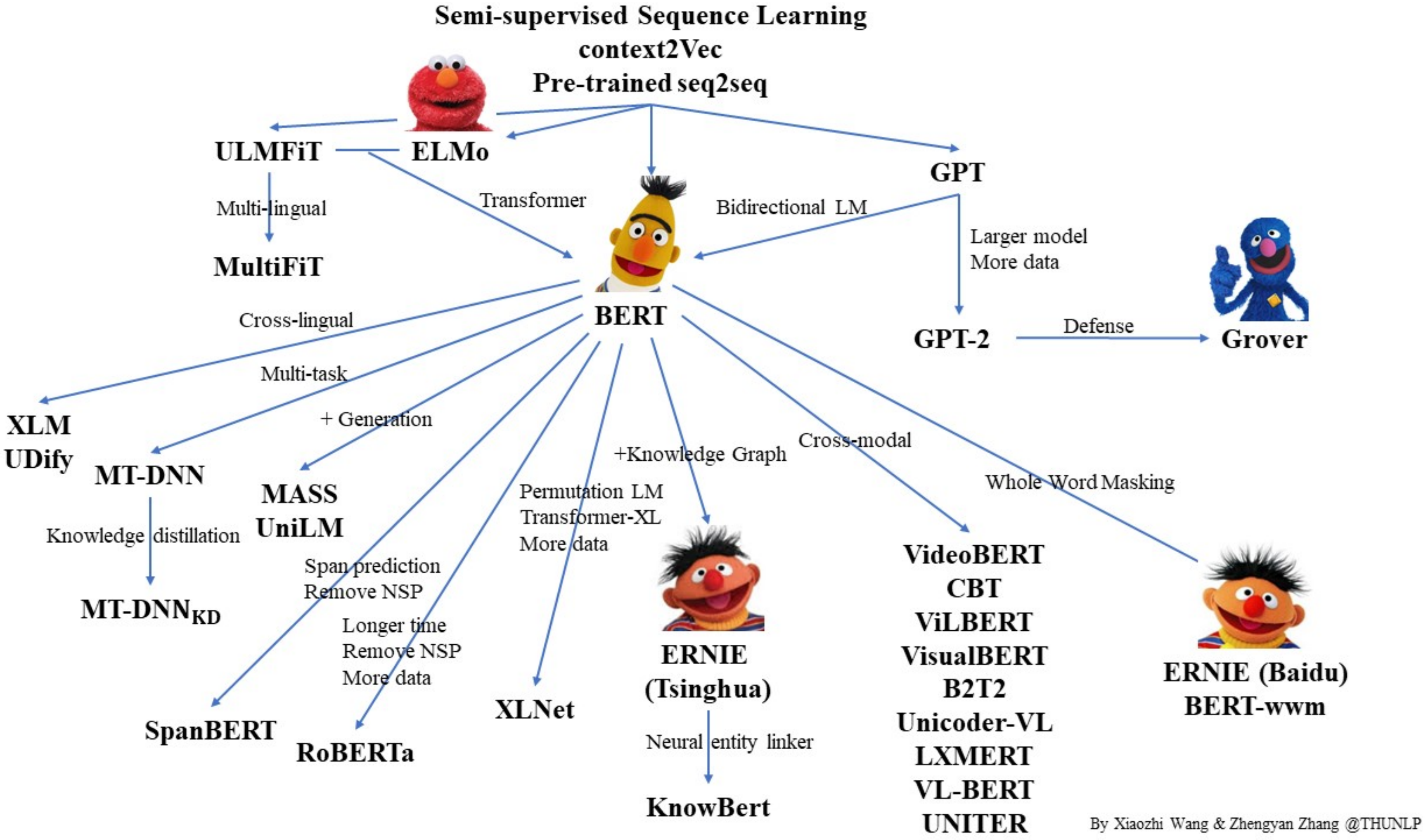
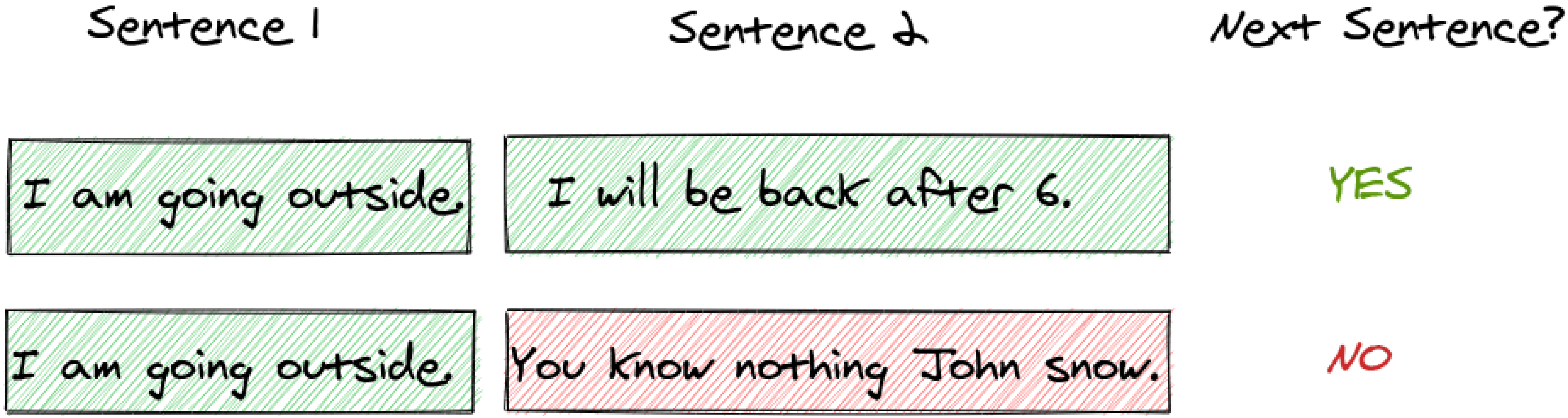
Advanced Pre-training for Language Models


Semi-supervised Sequence Learning
context2Vec
Pre-trained seq2seq
ULMFiT
ELMo
GPT
Multi-lingual
MultiFiT
Transformer
Bidirectional LM
BERT
Larger model
More data
GPT-2
Defense
Grover
Cross-lingual
Multi-task
+ Generation
XLM
UDify
MT-DNN
MASS
UniLM
Knowledge distillation
MT-DNN$_{KD}$
Span prediction
Remove NSP
Longer time
Remove NSP
More data
SpanBERT
RoBERTa
Permutation LM
Transformer-XL
More data
XLNet
+Knowledge Graph
ERNIE
(Tsinghua)
Neural entity linker
KnowBert
Cross-modal
VideoBERT
CBT
ViLBERT
VisualBERT
B2T2
Unicoder-VL
LXMERT
VL-BERT
UNITER
Whole Word Masking
ERNIE (Baidu)
BERT-wwm
By Xiaozhi Wang & Zhengyan Zhang @THUNLP

Pre-Training Objectives

- Pre-training with abundantly available data
- Use Self-Supervised Learning
- GPT: Language Modeling
  - Predict next word given left context
- Word2Vec, BERT, RoBERTa: Masked Language Modeling
  - Predict missing word given a certain context

Next Sentence Prediction (NSP)



https://amitness.com/2020/02/albert-visual-summary/

Train the CLS and SEP tokens

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

Strategy used in BERT but shown to be ineffective in RoBERTa

Sentence Order Prediction (SOP)

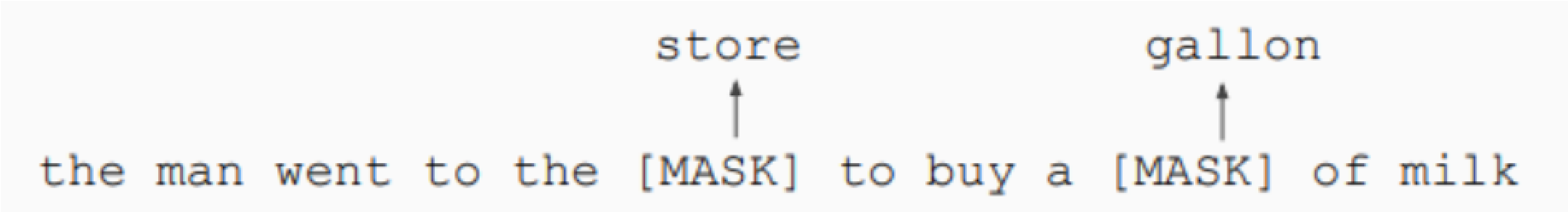
- NSP primarily requires topic-prediction
- SOP can be used to focus on inter-sentence coherence (ALBERT)

Input = [CLS] the man went to [MASK] store [SEP] he bought a gallon [MASK] milk [SEP]
Label = CorrectOrder

Input = [CLS] he bought a gallon [MASK] milk [SEP] the man went to [MASK] store [SEP]
Label = InCorrectOrder

Masking Strategy in BERT

- Mask 15% of the input tokens



- Problem 1: Assumes that the MASK tokens are independent of each other
- Problem 2: [MASK] tokens never appear during fine-tuning

Masking Strategy in BERT

- Mask 15% of the input tokens

- 80% of the time: Replace the word with the [MASK] token, e.g., my dog is hairy → my dog is [MASK]

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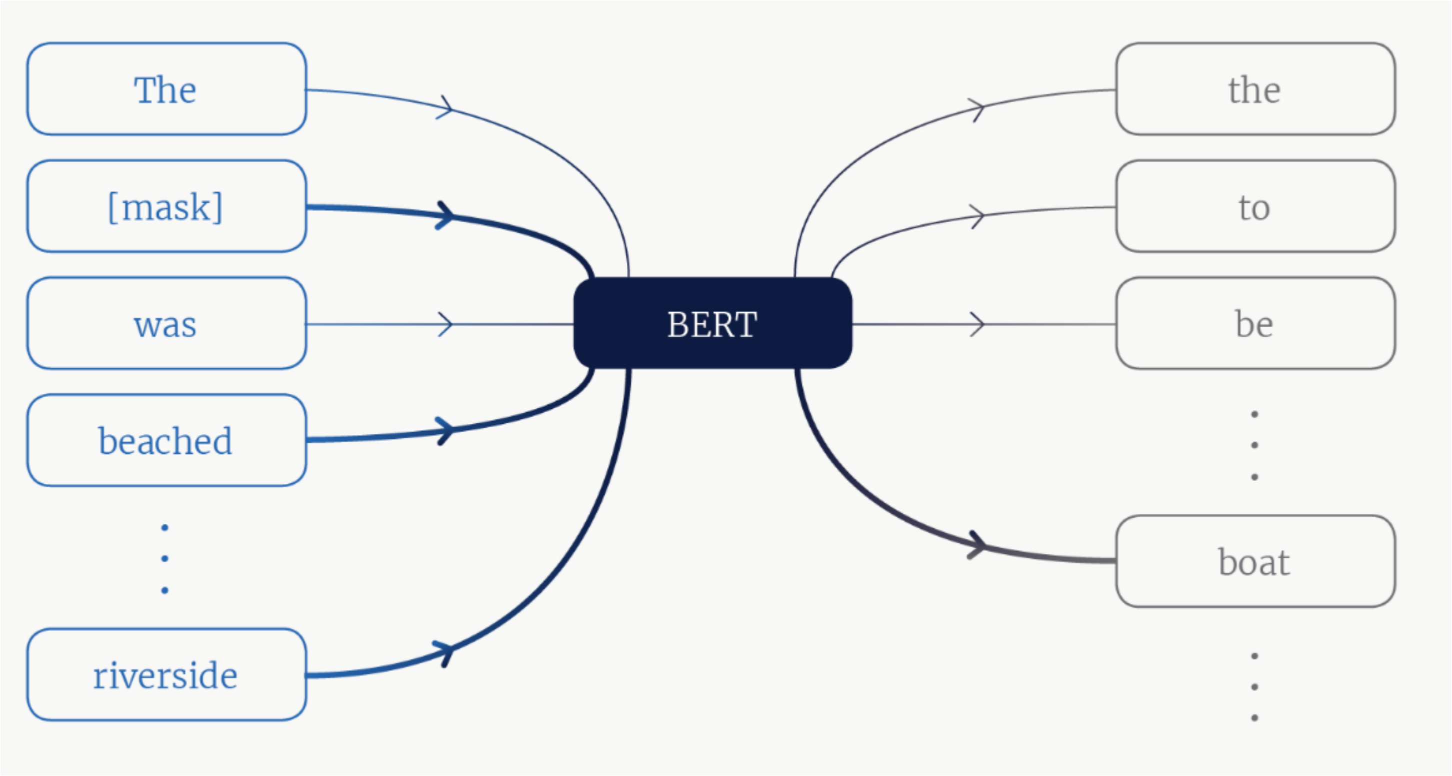
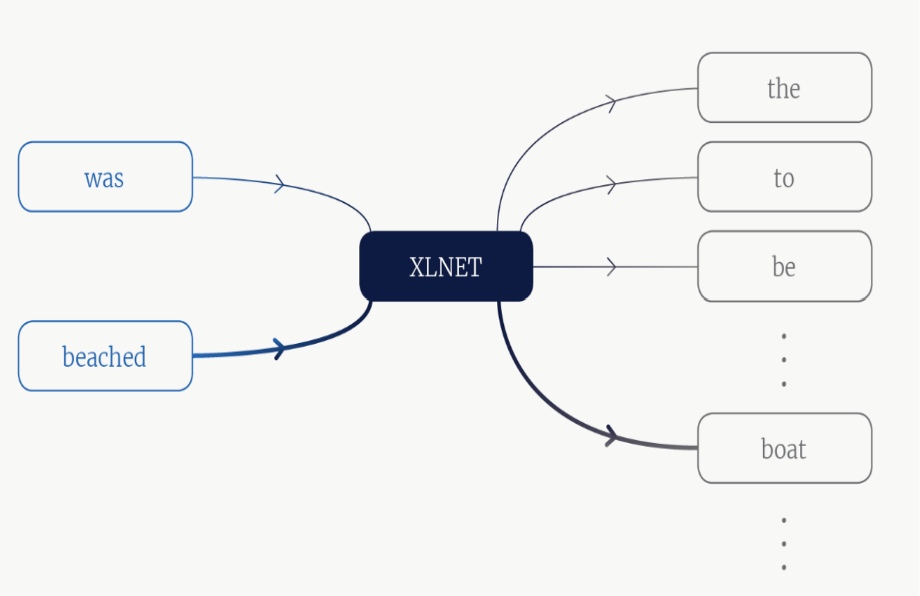
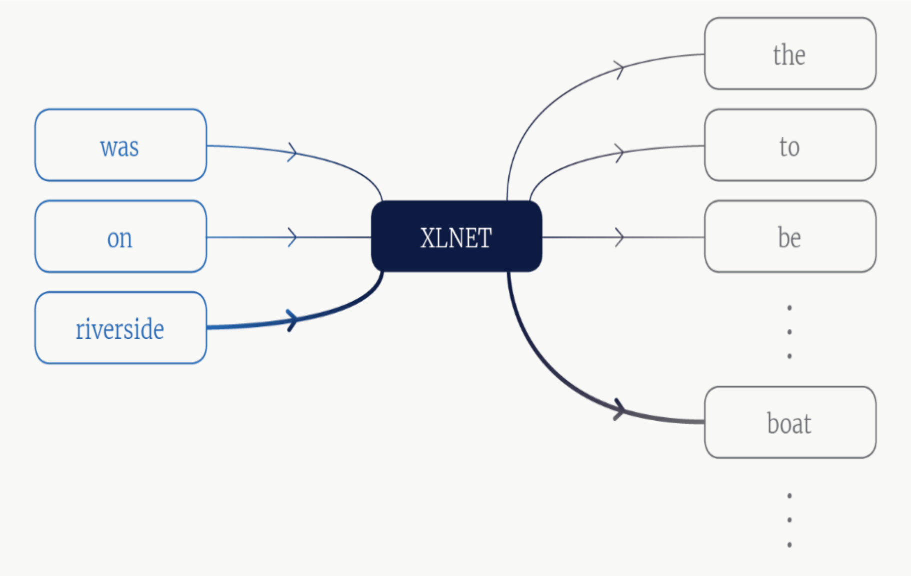
- 10% of the time: Keep the word unchanged, e.g., my dog is hairy → my dog is hairy.



The boat was beached on the riverside

Permutation Modeling using XLNET





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Approximate Computation Time

ULMFit	1 GPU day
ELMo	40 GPU days
BERT	450 GPU days
XLNet	2000 GPU days

Granularity of Masking

- BERT chooses word-pieces but this is sub-optimal
- Philammon → Phil ##am ##mon
- Not much information to be gained by predicting at word piece level

Granularity of Masking

- BERT-wwm (whole word masking): Always mask entire word
- BERT: Phil ##am [MASK] was a great singer
- BERT-wwm: [MASK] [MASK] [MASK] was a great singer

SpanBERT

- [MASK] Delhi, the Indian Capital is known for its rich heritage.
- Easier to predict “New”, given that we already know Delhi
- Instead of masking individual words, mask contiguous spans
- [MASK] [MASK], the Indian Capital is known for its rich heritage.

Knowledge Masking Strategies in ERNIE

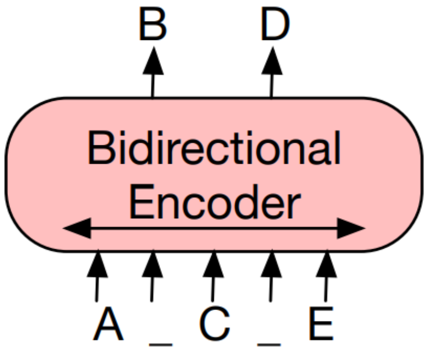
Sentence	Harry	Potter	is	a	series	of	fantasy	novels	written	by	British	author	J.	K.	Rowling
Basic-level Masking	[mask]	Potter	is	a	series	[mask]	fantasy	novels	[mask]	by	British	author	J.	[mask]	Rowling
Entity-level Masking	Harry	Potter	is	a	series	[mask]	fantasy	novels	[mask]	by	British	author	[mask]	[mask]	[mask]
Phrase-level Masking	Harry	Potter	is	[mask]	[mask]	[mask]	fantasy	novels	[mask]	by	British	author	[mask]	[mask]	[mask]

ERNIE 2.0

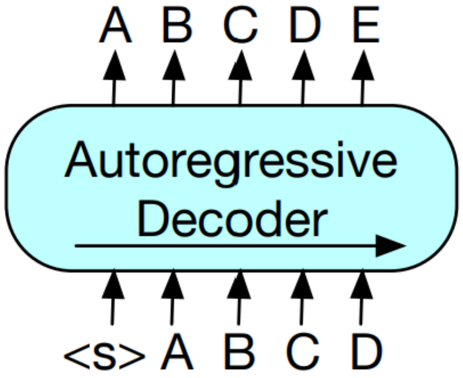
- Word-Level Pre-training:
  - Capitalization Prediction Task
  - Token-Document Relation Prediction Task (Frequency)
- Sentence-Level Pre-training:
  - Sentence Reordering Task
  - Sentence Distance Task
- Semantic-Level Pre-training:
  - Discourse Relation Task
  - IR Relevance Task

Pre-Trained Encoder-Decoder Models

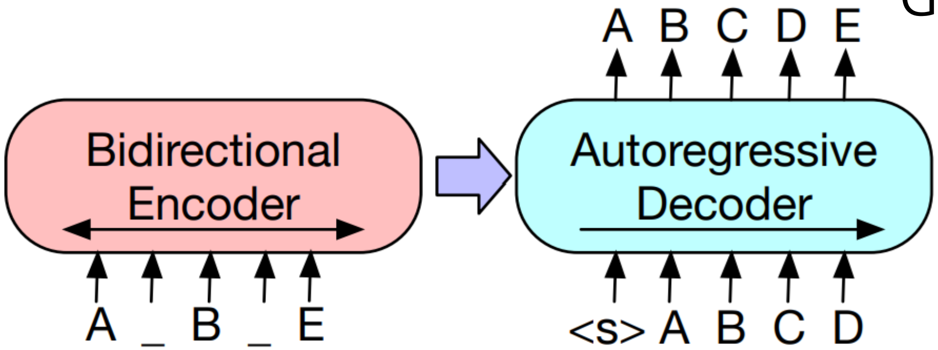
Pre-training Encoder-Decoder models



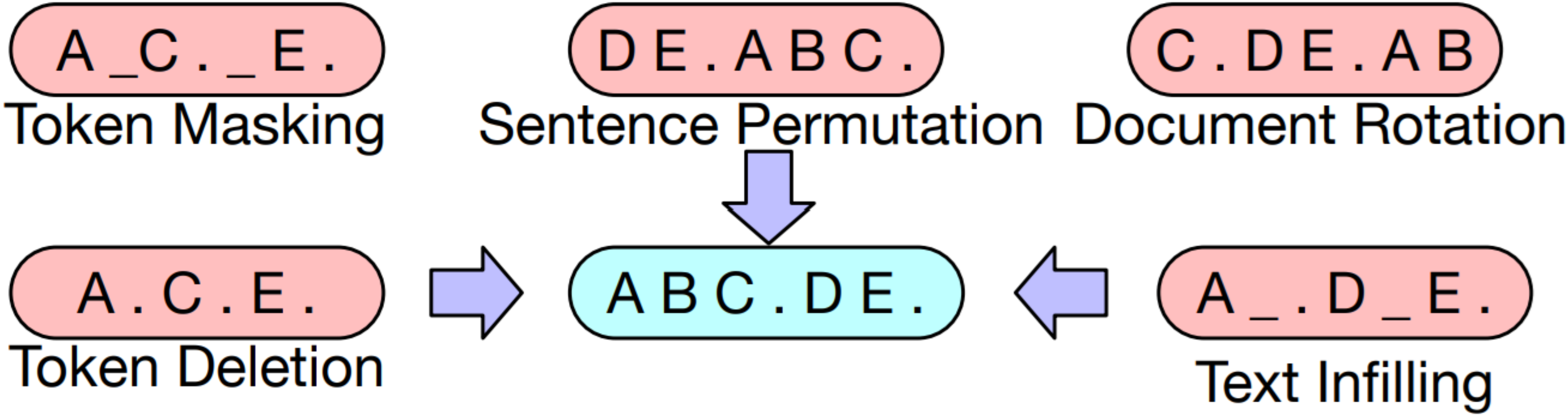
BERT



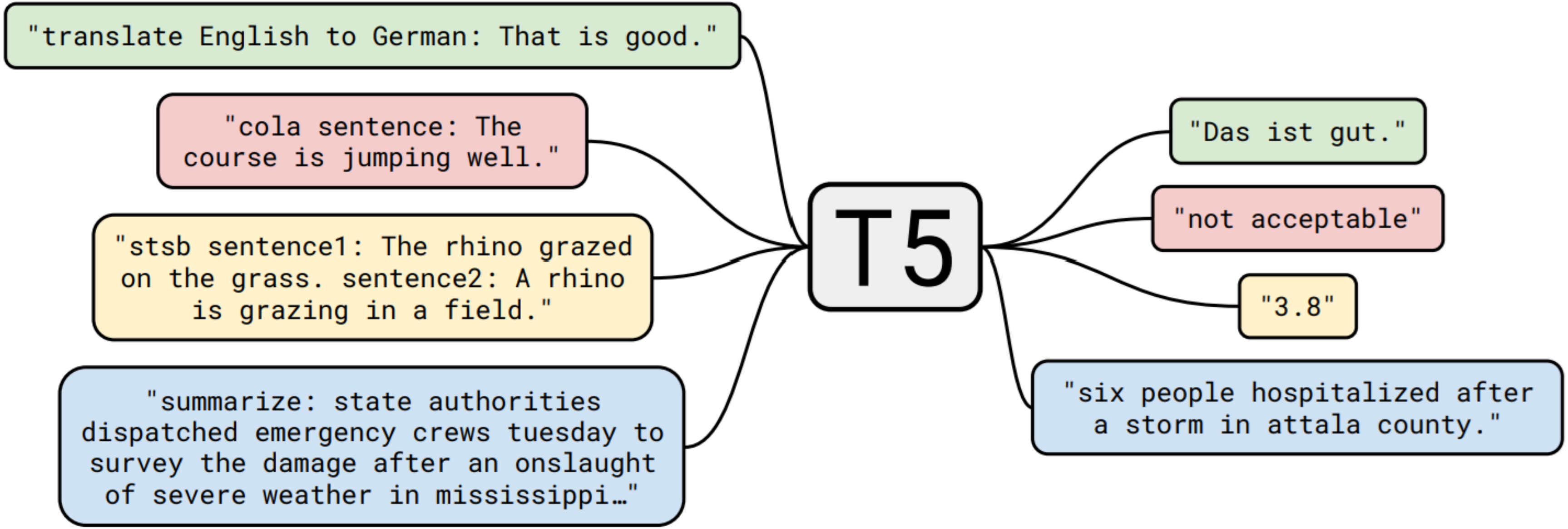
GPT



BART from Facebook



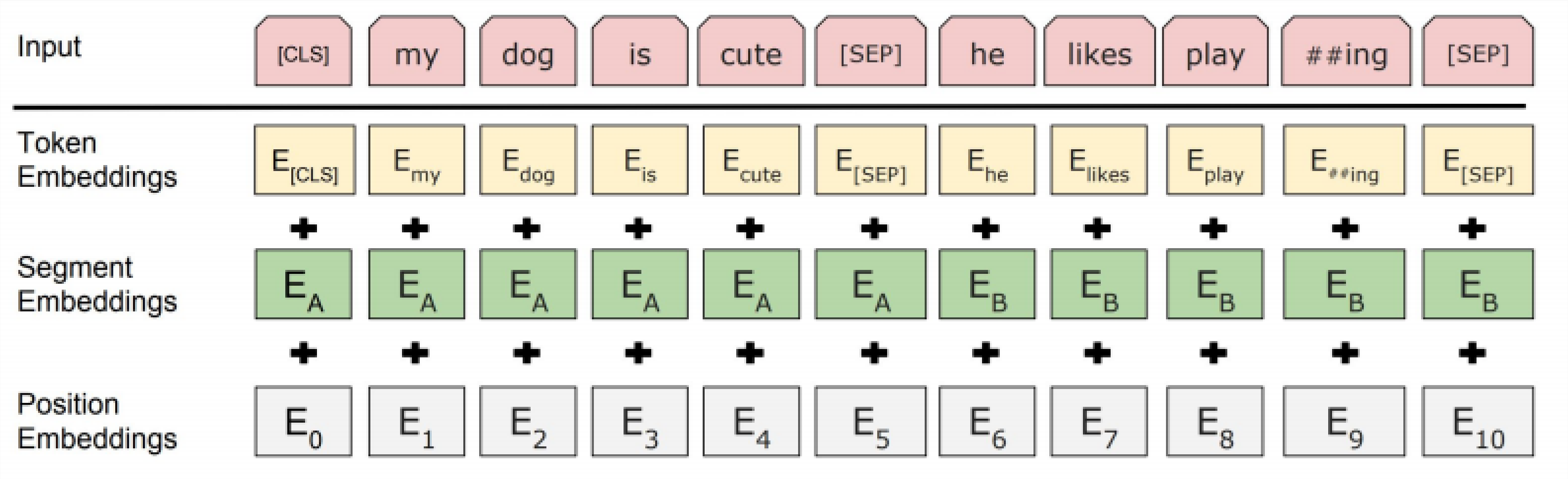
T5 from Google



T5: Unsupervised Pre-training Objectives

Objective	Inputs	Targets
Prefix language modeling	Thank you for inviting	me to your party last week .
BERT-style Devlin et al. (2018)	Thank you <M> <M> me to your party apple week .	*(original text)*
Deshuffling	party me for your to . last fun you inviting week Thank	*(original text)*
MASS-style Song et al. (2019)	Thank you <M> <M> me to your party <M> week .	*(original text)*
I.i.d. noise, replace spans	Thank you <X> me to your party <Y> week .	<X> for inviting <Y> last <Z>
I.i.d. noise, drop tokens	Thank you me to your party week .	for inviting last
Random spans	Thank you <X> to <Y> week .	<X> for inviting me <Y> your party last <Z>

Tokenization Strategies



- Use 30,000 WordPiece vocabulary on input.
- Each token is sum of three embeddings

Byte Pair Encoding (cs224n slides)

- Originally a compression algorithm:
  - Most frequent byte pair ↦ a new byte.

Replace bytes with character ngrams

(though, actually, some people have done interesting things with bytes)

Rico Sennrich, Barry Haddow, and Alexandra Birch. ***Neural Machine Translation of Rare Words with Subword Units****. ACL 2016.*
https://arxiv.org/abs/1508.07909
https://github.com/rsennrich/subword-nmt
https://github.com/EdinburghNLP/nematus

Byte Pair Encoding

- A word segmentation algorithm:
    - Though done as bottom up clusering
  - Start with a unigram vocabulary of all (Unicode) characters in data
  - Most frequent ngram pairs $\mapsto$ a new ngram

- A word segmentation algorithm:
  - Start with a vocabulary of characters
  - Most frequent ngram pairs ↦ a new ngram

Dictionary

5 l o w
2 l o w e r
6 n e w e s t
3 w i d e s t

Vocabulary

l, o, w, e, r, n, w, s, t, i, d

Start with all characters in vocab

- A word segmentation algorithm:
  - Start with a vocabulary of characters
  - Most frequent ngram pairs ↦ a new ngram

Dictionary

5	l o w
2	l o w e r
6	n e w **es** t
3	w i d **es** t

Vocabulary

l, o, w, e, r, n, w, s, t, i, d, **es**

Add a pair (e, s) with freq 9

- A word segmentation algorithm:
  - Start with a vocabulary of characters
  - Most frequent ngram pairs ↦ a new ngram

Dictionary

5	l o w
2	l o w e r
6	n e w **est**
3	w i d **est**

Vocabulary

l, o, w, e, r, n, w, s, t, i, d, es, **est**

Add a pair (es, t) with freq 9

- A word segmentation algorithm:
  - Start with a vocabulary of characters
  - Most frequent ngram pairs ↦ a new ngram

Dictionary

5	**lo** w
2	**lo** w e r
6	n e w est
3	w i d est

Vocabulary

l, o, w, e, r, n, w, s, t, i, d, es, est, **lo**

Add a pair (l, o) with freq 7

Byte Pair Encoding

- Have a target vocabulary size and stop when you reach it
- Do deterministic longest piece segmentation of words
- Segmentation is only within words identified by some prior tokenizer (commonly Moses tokenizer for MT)

- Automatically decides vocab for system
  - No longer strongly "word" based in conventional way

Wordpiece model

- Rather than char n-gram count, uses a greedy approximation to maximizing language model log likelihood to choose the pieces
- Add n-gram that maximally reduces perplexity
- [link1] and [link2] contain further details

Issues with Wordpiece tokenizers

- Handles “sub-words” but not “typos”
- Need to re-train for adding new languages
- Takes engineering effort to maintain

Character-level models

CANINE: Character-level Pre-trained Encoder

- Issues:
- Results in much longer sequence-lengths
- 143K unicode characters

- Down-sample input embeddings (Convolution)
- Hash functions to reduce embedding space

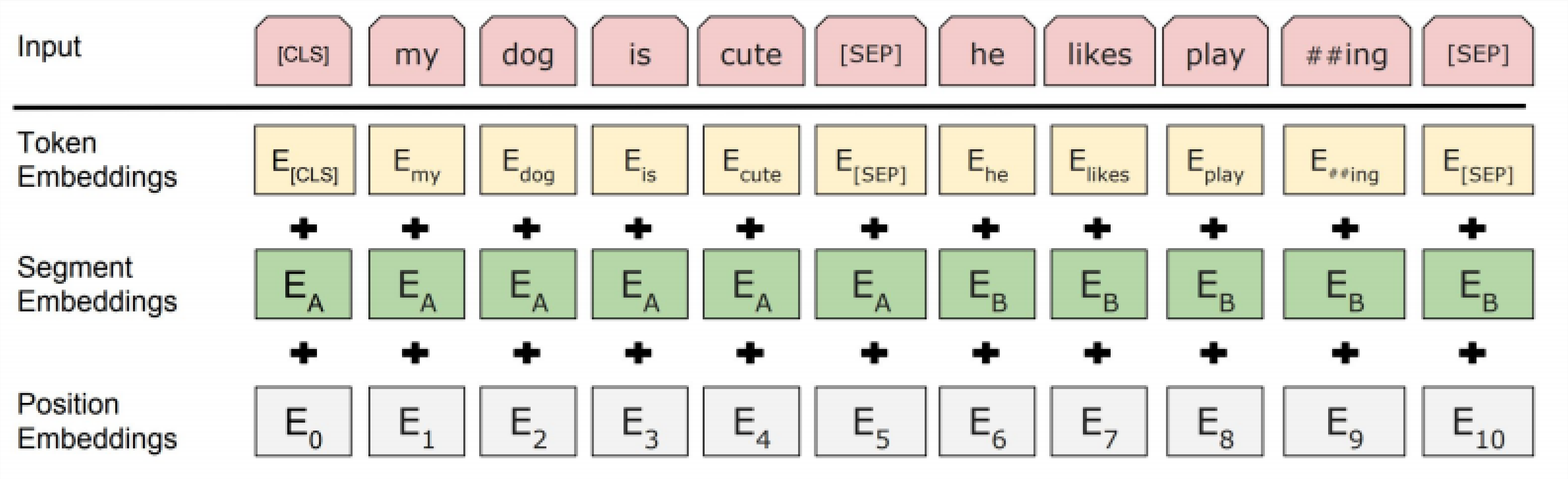
ByT5: Byte-level Seq2Seq

- Operate directly on byte-representations
  - Only 256 input embeddings!

- Embeddings occupy 66% of T5-base

- “Unbalanced”-Seq2Seq
  - 6 layer encoder, 2 layer decoder (3:1)

Positional Embeddings



- Use 30,000 WordPiece vocabulary on input.
- Each token is sum of three embeddings

Absolute Positional Embeddings in BERT

- Transformer architecture suggested using sinusoidal embeddings
- BERT instead learnt absolute positional embeddings
- Fine tuned a randomly initialized embedding matrix
- Size: 512 * 768
- To reduce training time: 90% of the time trained with sequence size of 128

Relative Positional Embeddings

$$z_i = \sum_{j=1}^{n} \alpha_{ij}(x_j W^V) \qquad\qquad z_i = \sum_{j=1}^{n} \alpha_{ij}(x_j W^V + a_{ij}^V)$$

$$e_{ij} = \frac{(x_i W^Q)(x_j W^K)^T}{\sqrt{d_z}} \qquad\qquad e_{ij} = \frac{x_i W^Q (x_j W^K + a_{ij}^K)^T}{\sqrt{d_z}}$$

$$\left.\begin{aligned} a_{ij}^K &= w_{\mathrm{clip}(j-i,k)}^K \\ a_{ij}^V &= w_{\mathrm{clip}(j-i,k)}^V \\ \mathrm{clip}(x,k) &= \max(-k, \min(k, x)) \end{aligned}\right\} \text{RPE(j-i,k)}$$

Relative Positional Embeddings in T5

$$Att_{ij} = Q_i * K_j + RPE_{clip(j-i,128)}$$

Only 32 embeddings, scaled logarithmically

Long Input Transformers

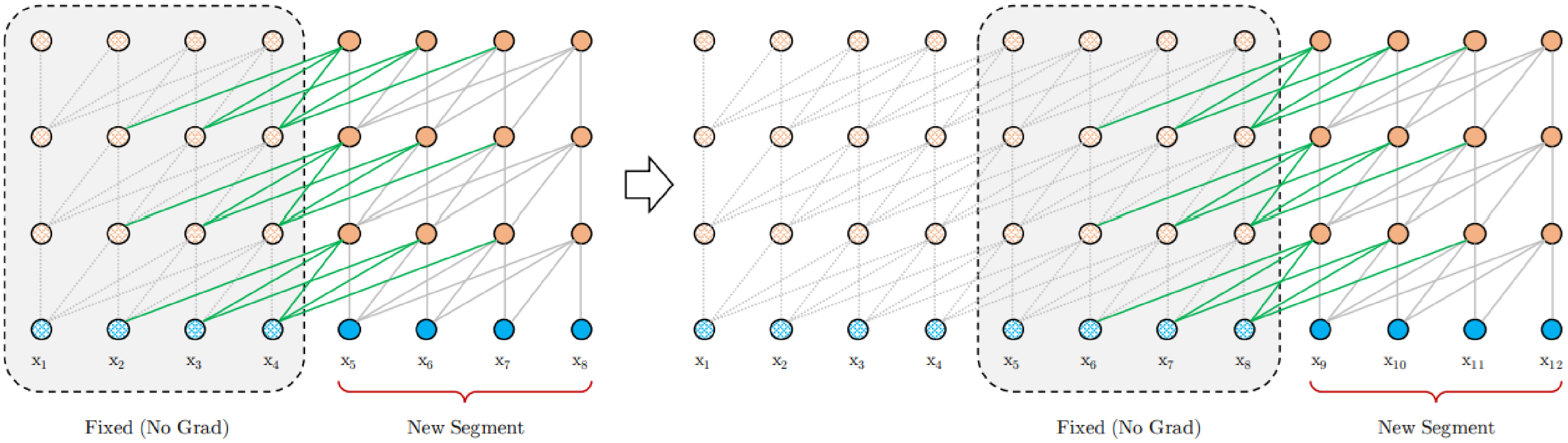
Attention in Transformers

- Every word attends over every other word
- $O(n^2)$ complexity, compared to $O(n)$ complexity of LSTM
- Inherently unscalable to long sequences

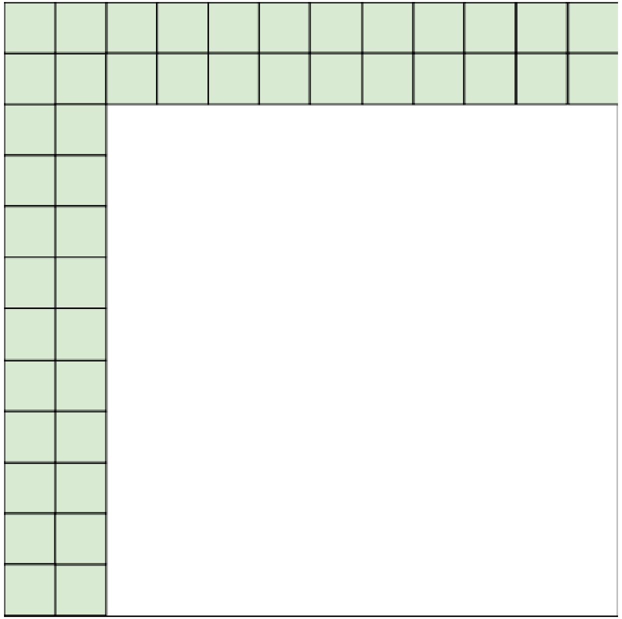
Transformer-XL: Recurrence in Transformers

- Chunk the text into segments
- Attend over current and previous segments
- Don’t pass gradient to previous segment
- Faster training and inference (1800x)

Transformer-XL

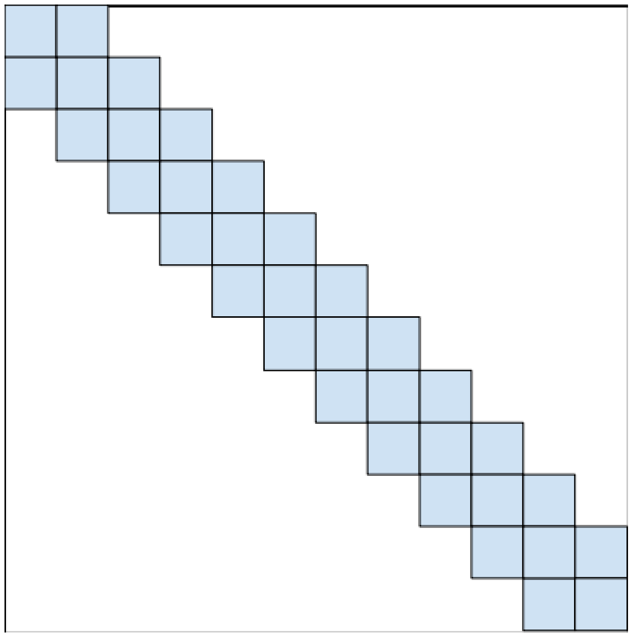


BigBird - Sparse Attention



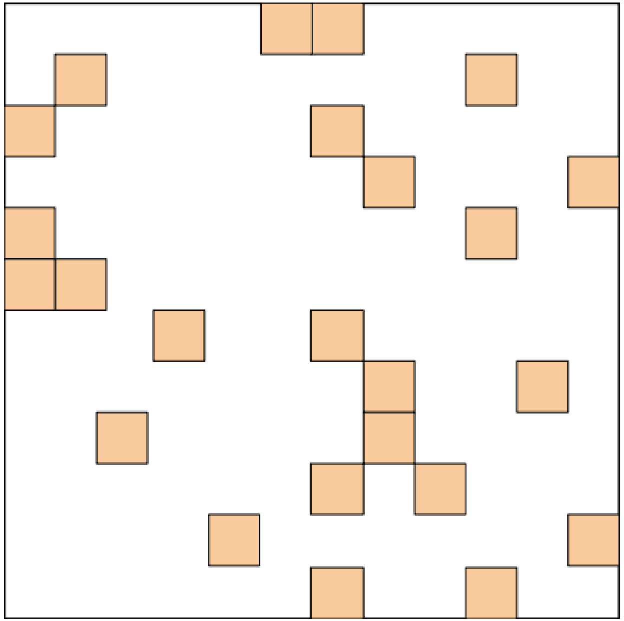
(c) Global Attention

BigBird - Sparse Attention



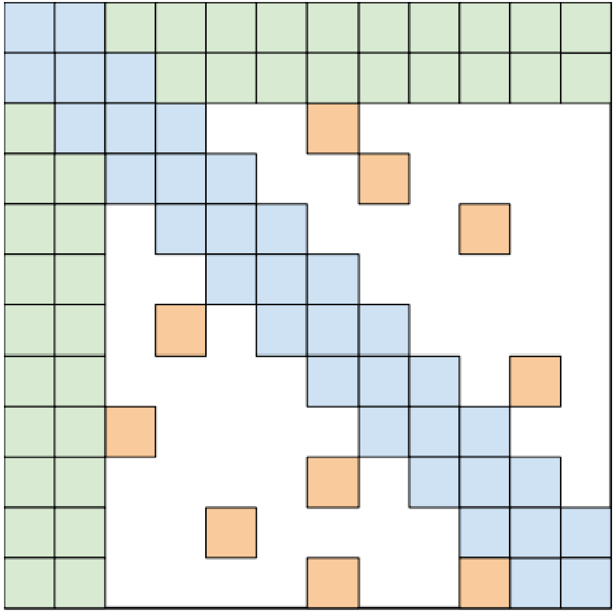
(b) Window attention

BigBird - Sparse Attention



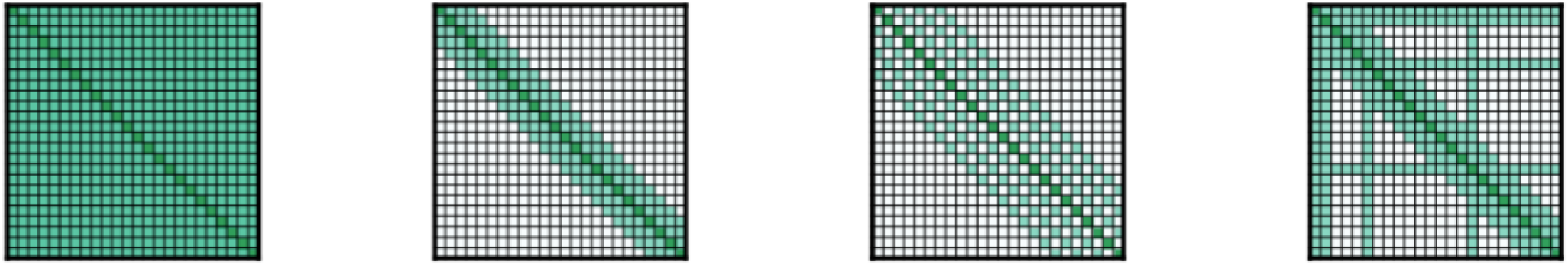
(a) Random attention

BigBird - Sparse Attention (8x faster)



(d) BIGBIRD

LongFormer



(a) Full n^2 attention (b) Sliding window attention (c) Dilated sliding window (d) Global+sliding window

Figure 2: Comparing the full self-attention pattern and the configuration of attention patterns in our Longformer.