MISTRALMODELSTUDY

Longformer

SLIDING WINDOW ATTENTION(SWA)

Longformer: The Long-Document Transformer

2024.01.09.

CONTENTS

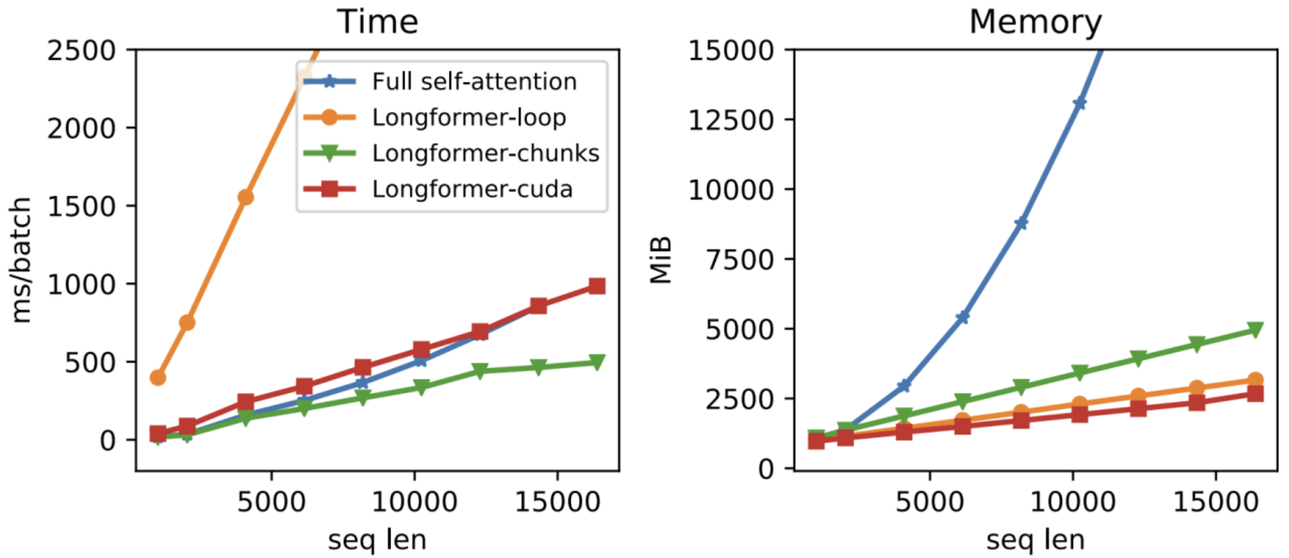
목차

Longformer의 등장 배경

긴 문서에 대한 효율적 처리 필요

기존 트랜스포머 기반 모델들의 셀프 어텐션 연산은
시퀀스 길이에 따른 계산, 메모리가 제곱으로 증가

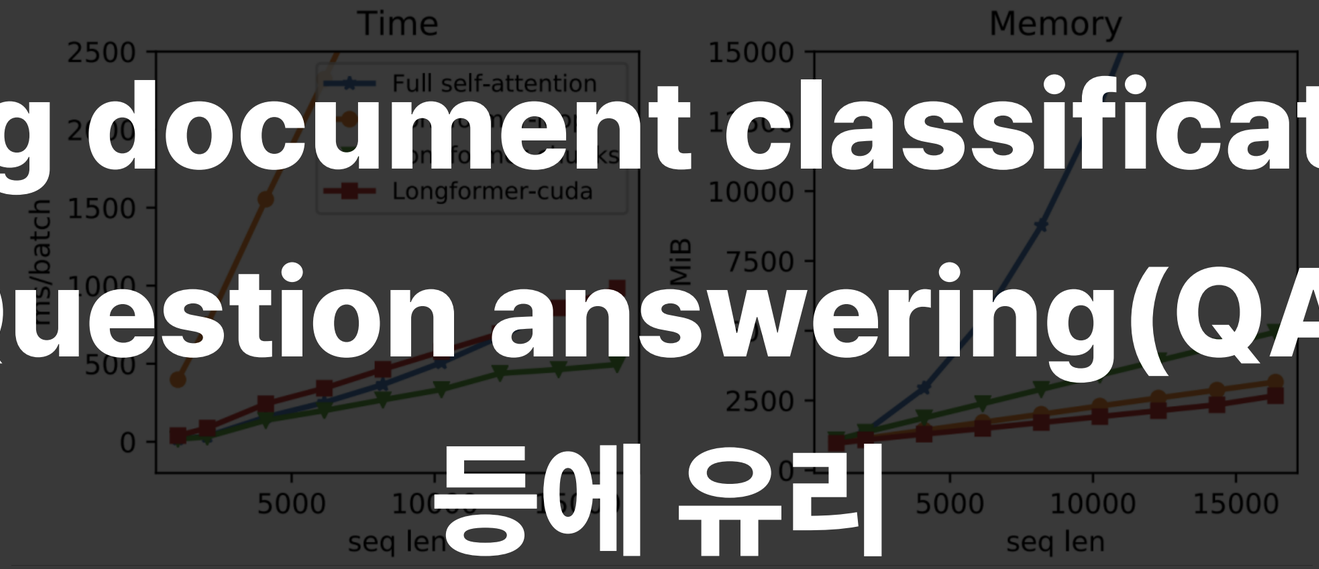
Longformer의 등장 배경



시퀀스 길이에 "선형적으로"

확장되는 어텐션 메커니즘 도입

Longformer의 등장 배경



Long document classification, Question answering(QA) 등에 유리

시퀀스 길이에 "선형적으로" 확장되는 어텐션 메커니즘 도입

Longformer's attention mechanism

Local windowed attention

주로 문맥 표현을 구축하는 데 사용

+

Global attention

예측을 위한 전체 시퀀스 표현을 구축하는 데 사용

Longformer's attention mechanism

Windowed local-context self-attention

모델이 입력 시퀀스 내의 각 토큰이
주변의 특정 범위 내 토큰들과만 상호작용하도록 제한

+

Global attention

모델이 전체 입력 시퀀스에 걸쳐
중요한 토큰들에 주목하게 함

Time and memory complexity

The original Transformer model

$O(n^2)$

*n: input sequence length

Time and memory complexity

The original Transformer model

수천 개 이상의 토큰을 포함하는
문서 처리에서 어려움을 겪음

*n: input sequence length

KEY POINT

Longformer

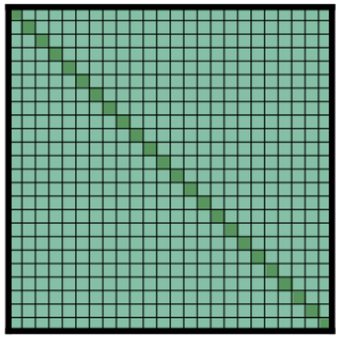
Sparsify

일부 "중요한"
토큰 쌍에만
어텐션 적용

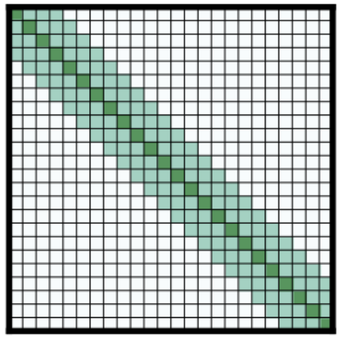
Attention Pattern

입력 시퀀스와
"선형적"으로 확장되어
긴 시퀀스에 대해 효율적

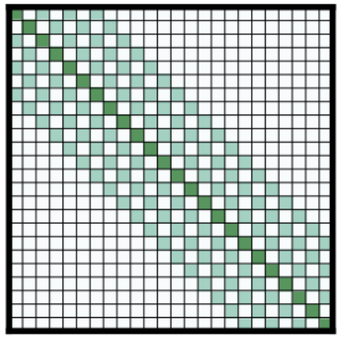
Attention pattern



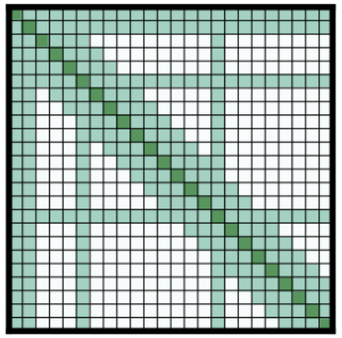
(a) Full n^2 attention



(b) Sliding window attention



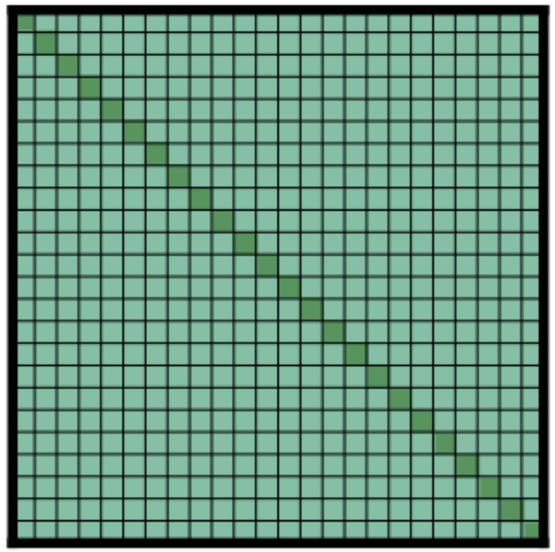
(c) Dilated sliding window



(d) Global+sliding window

Attention pattern

Full self-attention pattern



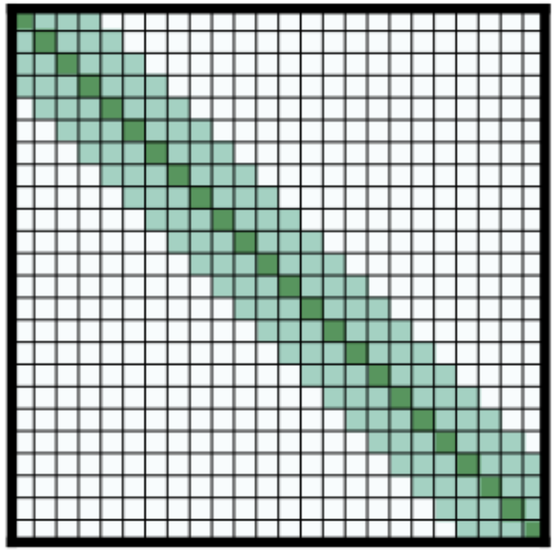
(a) Full n^2 attention

- 모든 토큰 쌍 간의 어텐션 계산

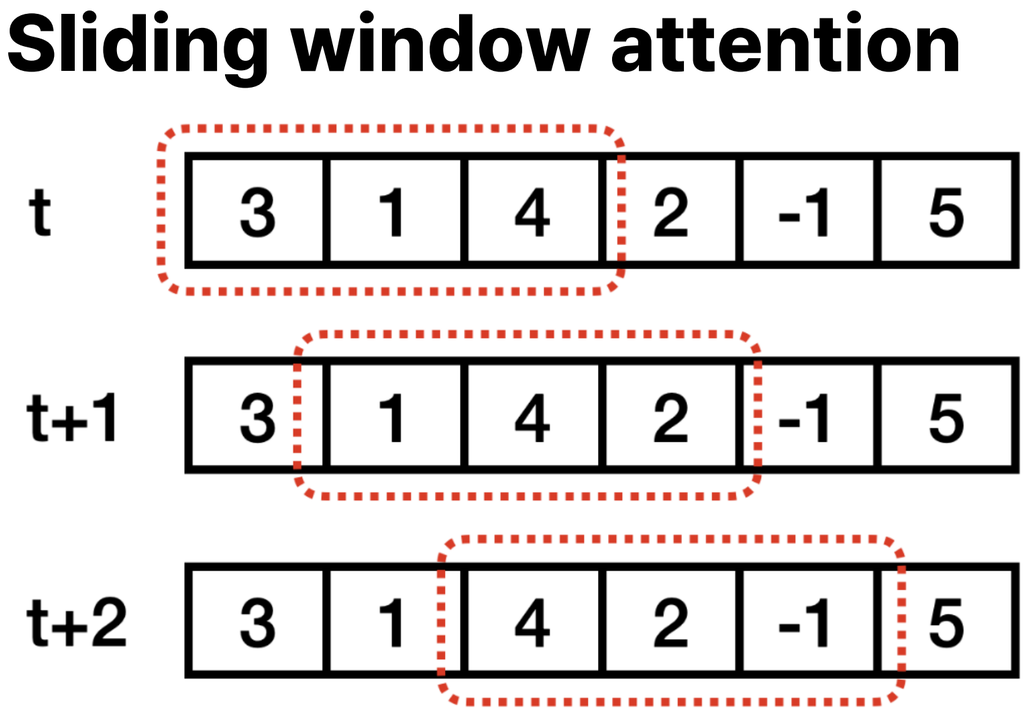
- computation complexity
  : $O(n^2)$

*n: input sequence length

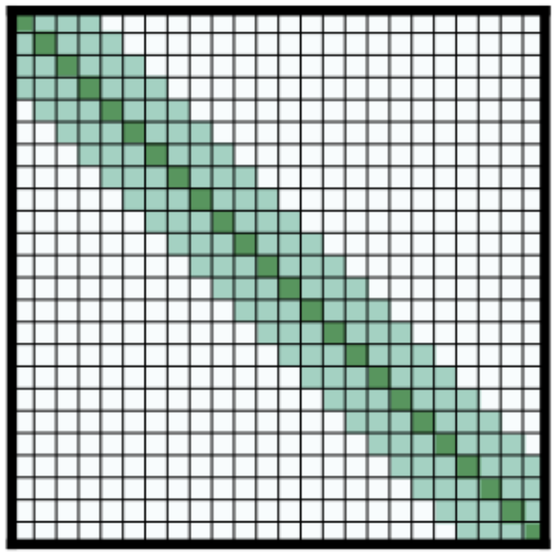
Attention pattern



(b) Sliding window attention



Attention pattern



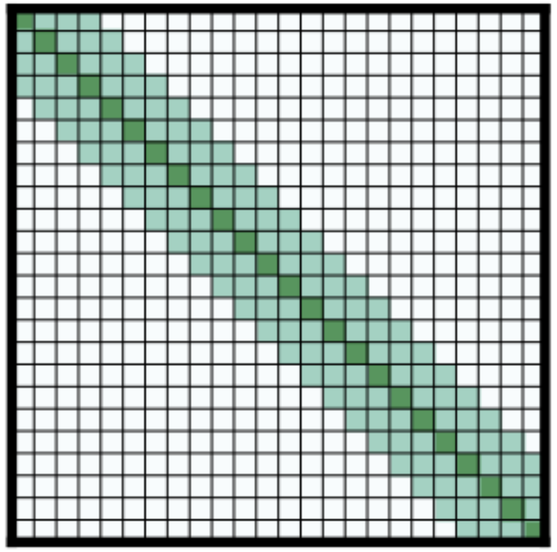
(b) Sliding window attention

Sliding window attention

- 고정된 window size 'w'가 주어졌을 때,
  각 토큰들은 양옆에 1/2w 토큰에 주의를 기울임
- window attention을 여러 층에
  쌓아 올림으로써 큰 수용 영역 형성
- 최상위 층은 모든 입력 위치에 접근 가능
- 전체 입력에 걸친 정보를 통합한 표현을
  구축할 수 있는 능력을 갖추게 됨

Attention pattern

Sliding Window Attention



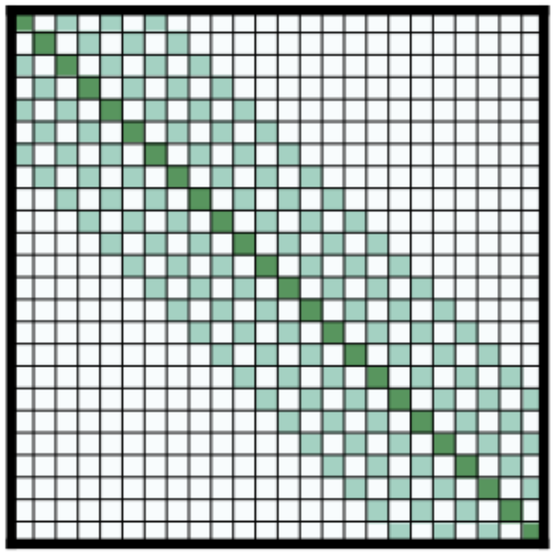
(b) Sliding window attention

- computation complexity
  : O(n x w)

- the receptive field size at the top layer
  : l x w

*응용 프로그램의 요구에 따라 각 층에서 window size w를 다르게 설정 가능

Attention pattern



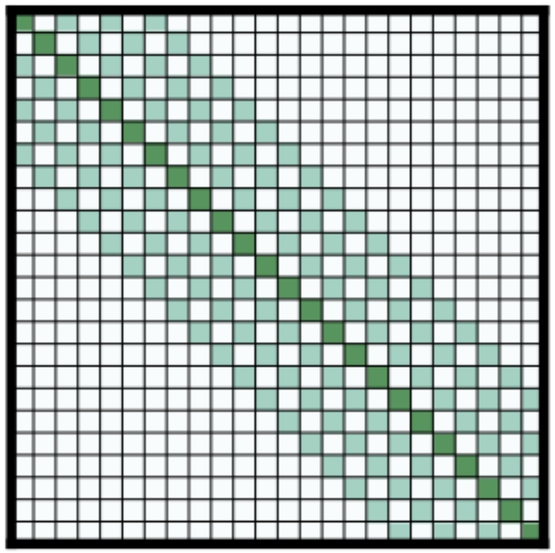
(c) Dilated sliding window

Dilated Sliding Window Attention

- receptive field는 늘리면서 계산량은 증가시키지 않게 하기 위한 확장(Dilated)
- gaps of size dilation 'd'
- multi-head attention에서, 각각 헤드에 대해 다른 dilated attention score를 적용해 계산 가능
- 일부 헤드는 dilation없이 가까운 토큰에만 집중, dilation이 있는 헤드는 긴 컨텍스트에 집중

Attention pattern

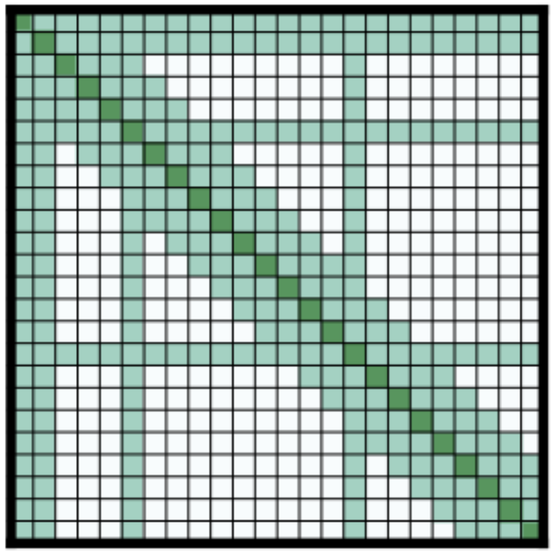
Dilated Sliding Window Attention



(c) Dilated sliding window

- the receptive field size
  : l x d x w

Attention pattern



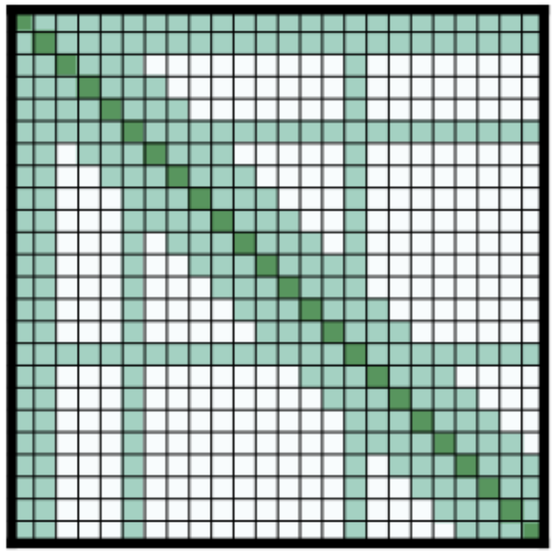
(d) Global+sliding window

Global Attention

- Sliding window attention과
  Dilated sliding window attention의 한계점
  : local context만 바라봄

- Global Attention의 보완
  : 긴 텍스트에 대한 task 효율적 처리

Attention pattern



(d) Global+sliding window

Global Attention

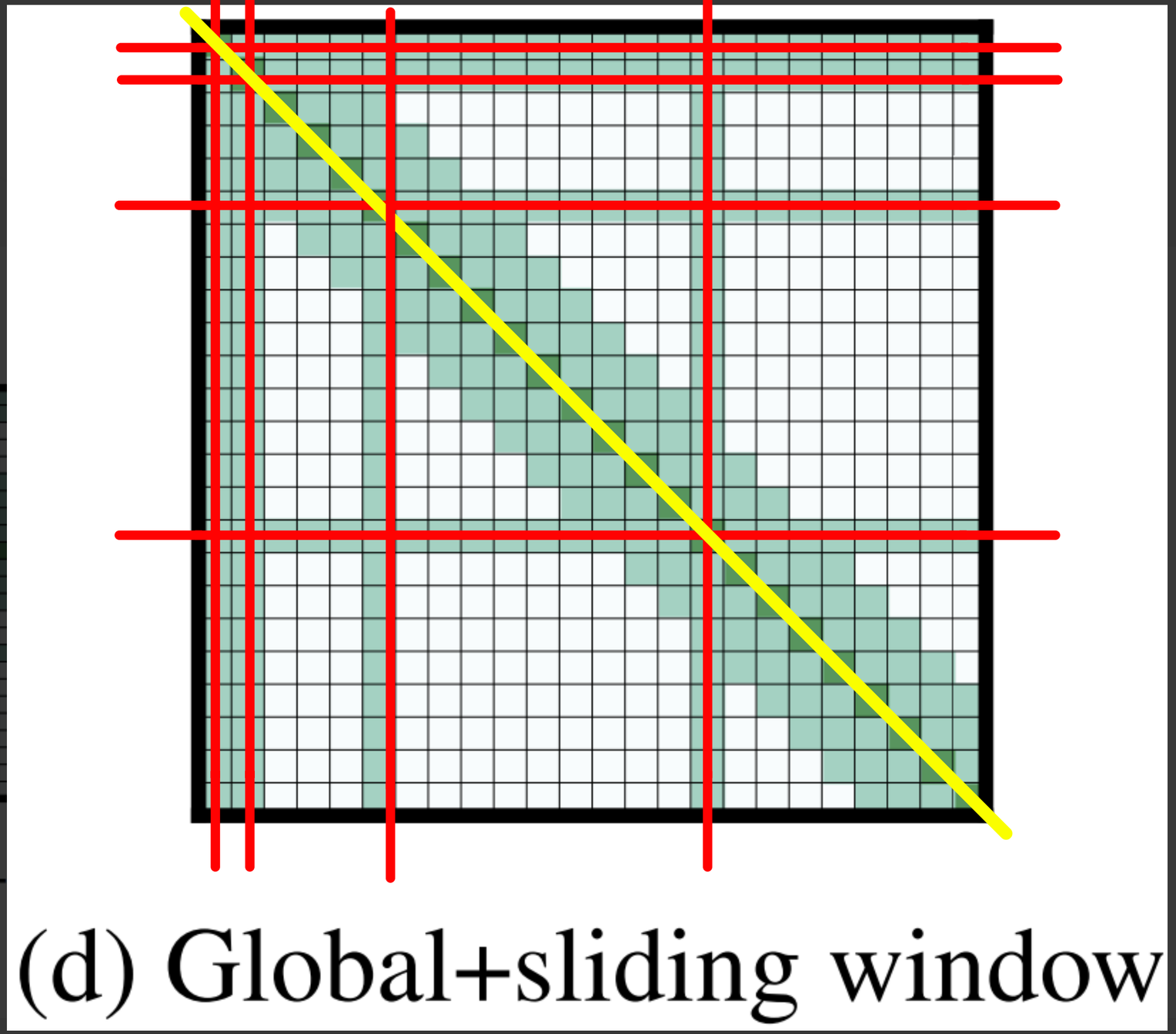
-BERT

- Classification: [CLS] 토큰에 global attention
- QA: 모든 질문 토큰에 global attention

- Global + sliding window 형태
  - Global: 전체 시퀀스에 걸쳐 다른 모든 토큰에 주의를 기울임
  - sliding window: 각 토큰의 로컬 컨텍스트를 포착

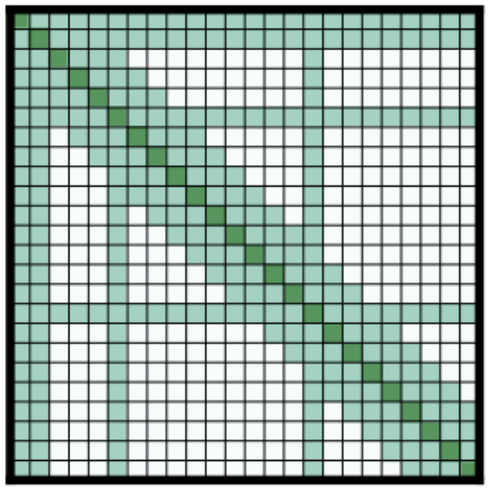
Global attention

(d) Global+



Sliding window attention pattern

Attention pattern



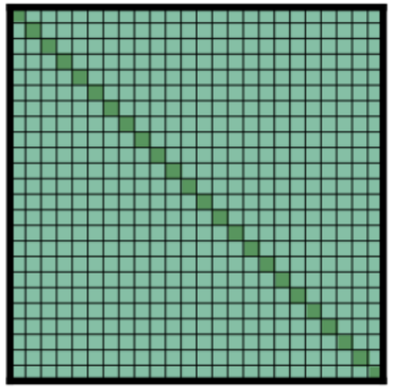
(d) Global+sliding window

Global Attention

- computation complexity
  : O(n)

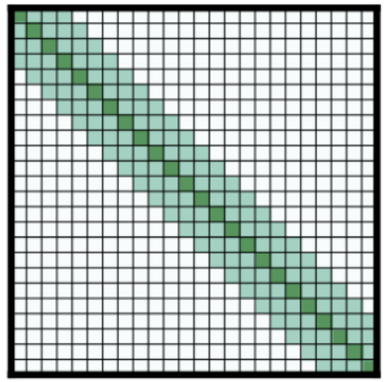
- 부연 설명
  - Global attnetion
    : 시퀀스 내 소수의 중요한 위치에만 적용
  - Local attention
    : 각 토큰의 주변에만 적용
  - 전체 시퀀스에 대한
    모든 토큰 쌍 간의 어텐션을 계산할 필요X

정리



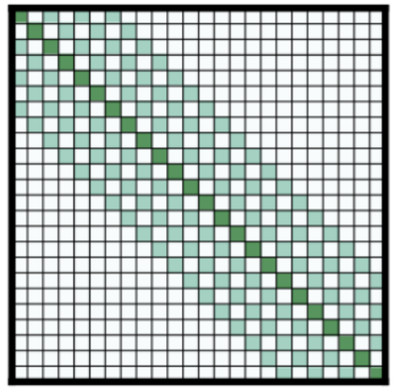
Full n^2 attention

모든 토큰 쌍 간의
어텐션을 계산함으로써
입력 시퀀스 길이에 따라
제곱되는 계산량과 메모리
$O(n^2)$



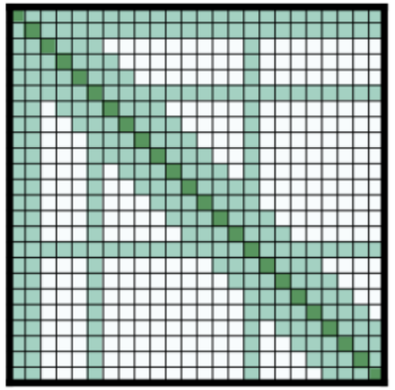
Sliding window

특정 토큰 앞뒤로
1/2w만큼의 토큰에
대해 어텐션 계산
O(n x w)



Dilated Sliding Window

모델이 입력 데이터의
근접한 부분에 있는
중요한 정보를 포착



Global attention

긴 텍스트에 대한
task 작업에 용이
O(n)

THANKS FOR WATCHING

E.O.D.