KOREA UNIVERSITY

DSBA Transformer survey paper study

# A Survey of Transformers

## #2: Attention – Sparse Attention

arXiv preprint


DSBA
Data Science & Business Analytics

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02

# 발표 목차

Contents

# 02 Taxonomy of Transformers

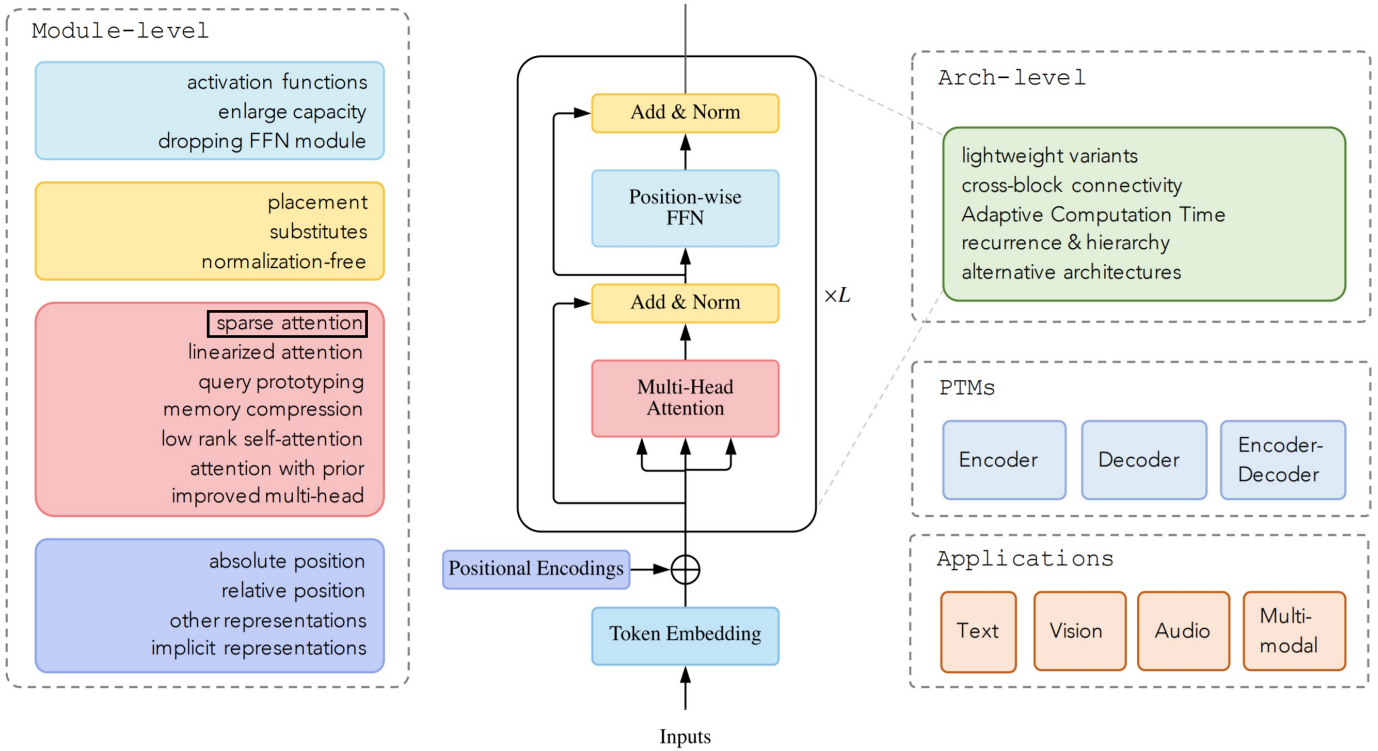
## Transformer Variants

Vanilla Transformer에서 수많은 Variant들이 파생

- Module-Level
- Architecture-Level
- Pretraining-Methods
- Applications

★ 색깔별 Matching

이 중, Module-Level 〉 Attention 〉 Sparse Attention을 살펴볼 것이다!



# 02 Attention

Attention은 매우 중요하지만, 문제가 있다.

**Self-Attention은 Transformer의 중요한 역할을 하지만, 두 가지 문제 발생**

- Complexity: Self Attention의 Complexity ($O(T^2 \cdot D)$)는 문장이 길어지면 Bottleneck이 된다.
- Structural Prior: Input에 대한 어떤 Structural Bias도 없다 (장점인 동시에 단점)

**이를 해소하기 위한 Attention Mechanism의 발전은 다음과 같다.**

- Sparse Attention

  Attention에 Sparsity Bias(Structural Bias)를 추가하여 Complexity 감소
- Linearized Attention
- Prototype and Memory Compression
- Low-rank Self-Attention
- Attention with Prior
- Improved Multi-Head Mechanism

# 02 Attention

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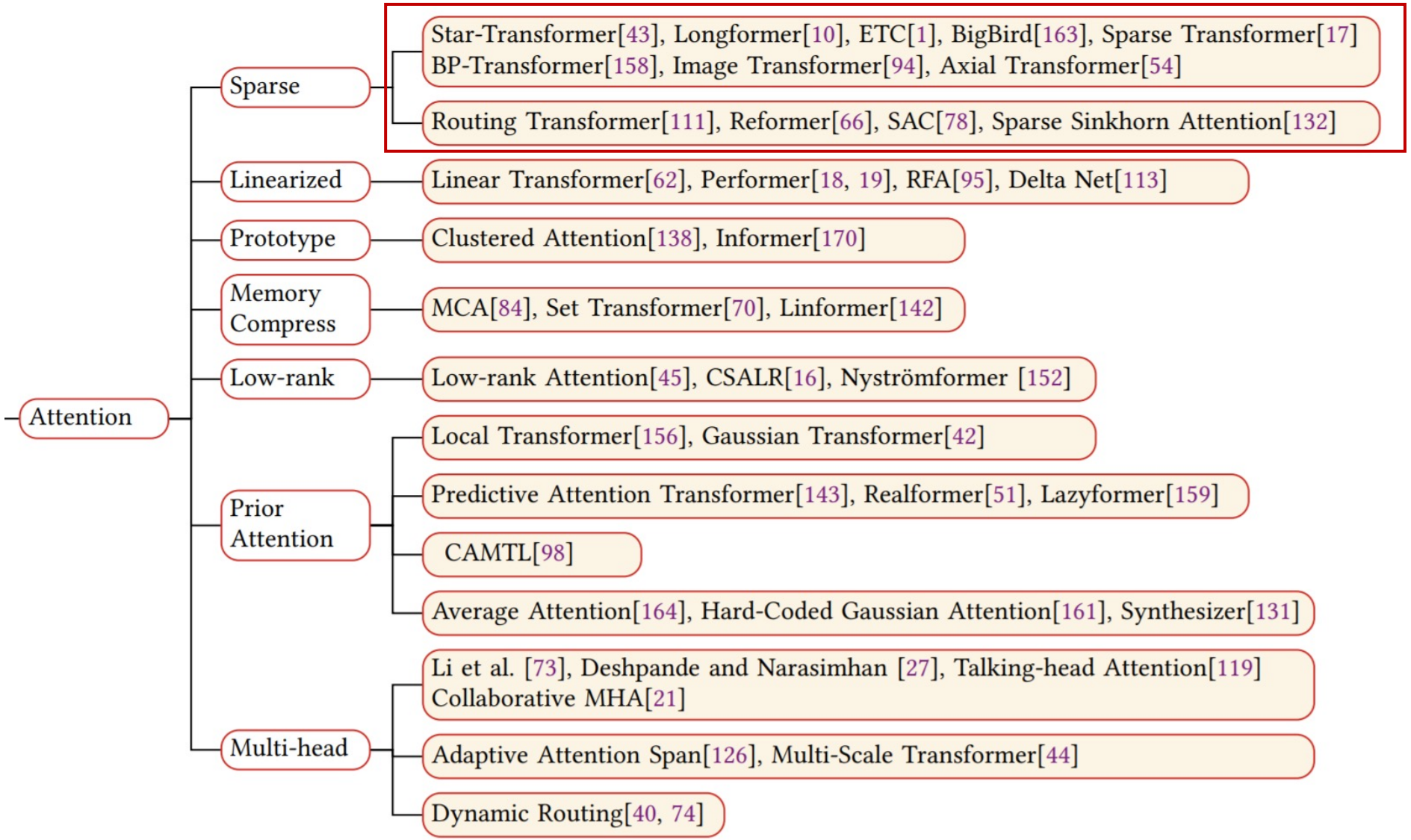


# 02 Sparse Attention

## Overview

Sparse Attention (2021.07 기준)

- Position Based Sparse Attention
  - Atomic Sparse Attention
  - Compound Sparse Attention (여러 Atomic Sparse Attention이 모여 구성)
    - Star Transformer (NAACL, 2019, 87회 인용)
    - Longformer (2020, 258회 인용 / AllenAI)
    - ETC (EMNLP, 2020, 24회 인용 / Google Research)
    - BigBird (NeurIPS, 2020, 139회 인용 / Google Research)
    - Sparse Transformer (2019, 353회 인용 / OpenAI)
  - Extended Sparse Attention (Atomic 혼합 대신 새로운 관점 또는 Non-Text Dataset)
    - BP-Transformer (2019, 24회 인용 / AWS AI Lab)
    - Image Transformer (ICML, 2018, 448회 인용)
    - Axial Transformer (2019, 59회 인용 / Google Brain)
- Content-Based Sparse Attention (Query와 Key Token의 유사도를 통한 Attention)
  - Reformer (ICLR, 2020, 360회 인용 / Google Research)
  - Routing Transformer (TACL, 2020, 66회 인용 / Google Research)
  - Sparse Adaptive Connection, Sparse Sinkhorn Attention

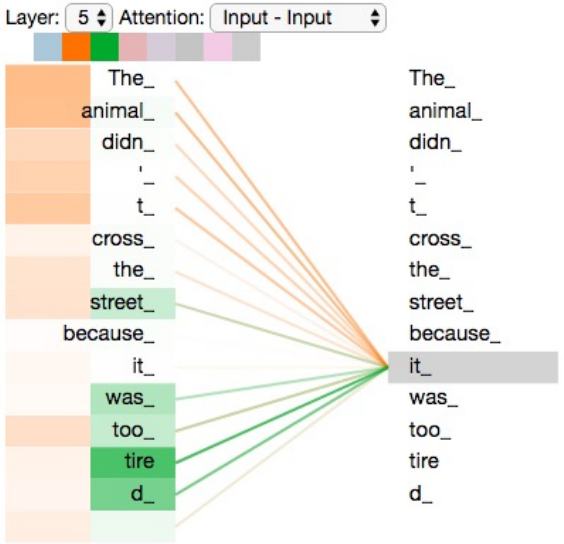
# 02 Sparse Attention

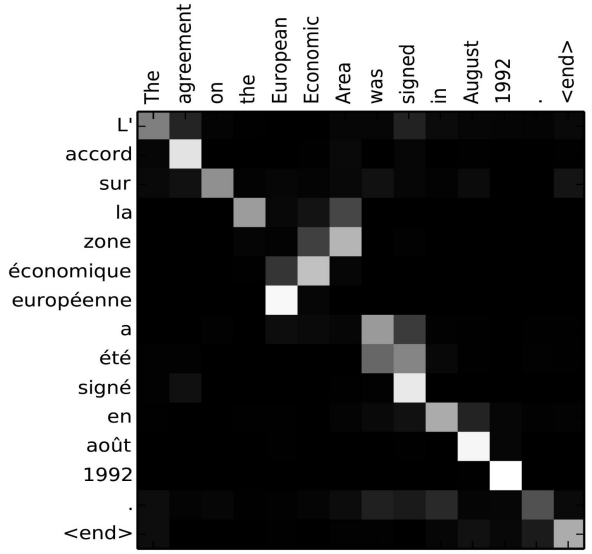
Vanilla Transformer Attention도 사실상 Sparse하다.

**Vanilla Transformer Attention Matrix는 사실상 Sparse하다?**

→ Attention은 훈련 뒤에는 볼 대상만 보게 된다.

→ 그럼 애초에 **Structural Bias**를 부여하여, Query-Key Pair 개수를 제한하자!




$$\hat{\mathbf{A}}_{ij} = \begin{cases} \mathbf{q}_i \mathbf{k}_j^\top & \text{if token } i \text{ attends to token } j, \\ -\infty & \text{if token } i \text{ does not attend to token } j, \end{cases}$$

Attend하지 않는 대상은 Memory에 담지도 않는다.

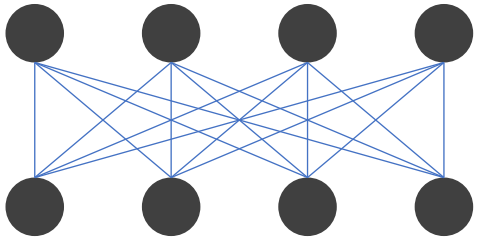
# 02 Sparse Attention

Transformer에 대한 Graph적 해석

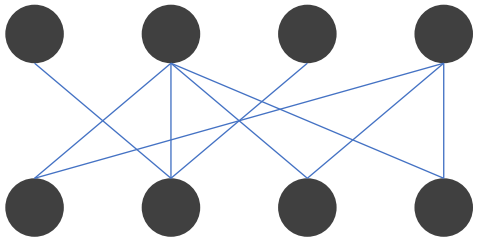
Vanilla Transformer Attention ⇒ Complete Bipartite Graph

Sparse Attention ⇒ Sparse Graph

Complete Bipartite Graph

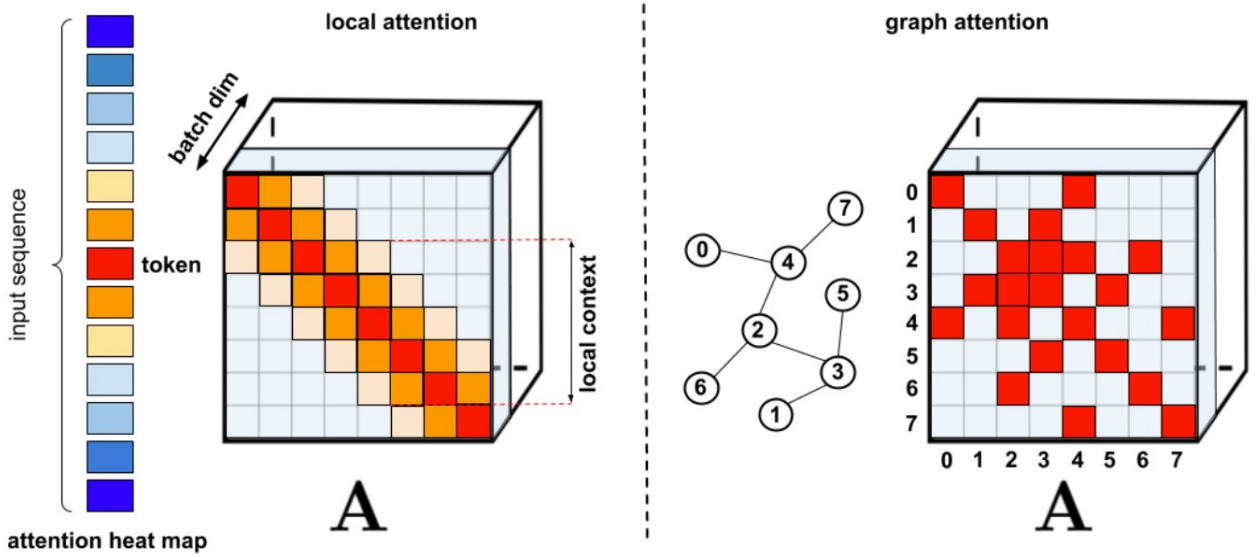


Sparse Graph



Sparse Attention ≈ Graph Neural Network

Graph Sparsification




Standard sparsification techniques. **Left:** Example of a sparsity pattern, where tokens attend only to other nearby tokens. **Right**: In Graph Attention Networks, tokens attend only to their neighbors in the graph, which should have higher relevance than other nodes. See Efficient Transformers: A Survey for a comprehensive categorization of various methods.

# 02 Sparse Attention

공통점

## Sparse Attention의 공통 주장

- **Computational Cost**: 문장이 길어질수록, Attention에 필요한 비용이 크다.

  Input Length에 **Quadratic**하게 증가하는 비용 대신에, **Linear**하게 증가하도록 만드는 것이 목적

$$O(n^2) \rightarrow O(n)$$

- **Long Range Dependency**: 긴 문장에는 Transformer를 적용하기 힘들다 (+Cost 문제)

  Global Attention을 통해 Long Range Dependency 해소

## Sparse Attention 효과

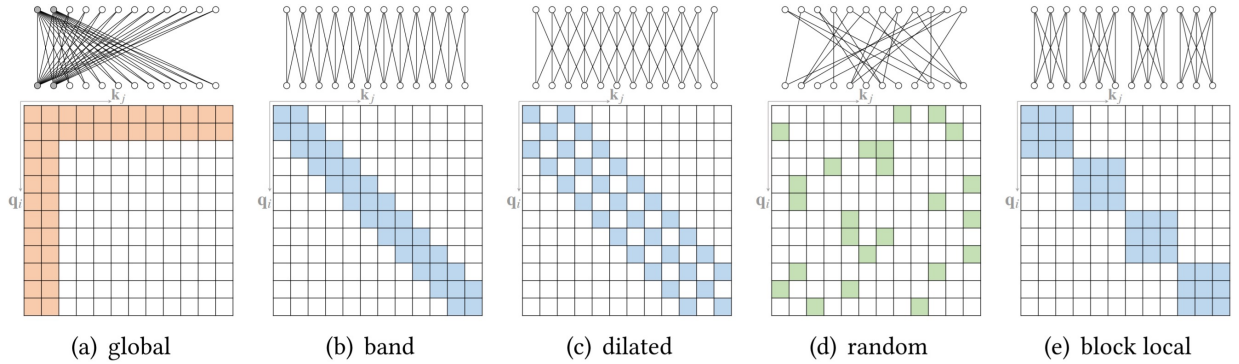
- 비용 / Dependency를 감소 시키면 512 Token보다 더 긴 문장을 Input으로 활용할 수 있다.

  Input 문장을 길게 만들면, Downstream Task에 사용되는 단서가 많아진다.

  Downstream Task로 QA & 문서 요약이 많이 사용 (단서 증폭 효과를 살피기 위하여)
- Sparse Attention은 Long Input이 사용되는 Encoder에 적용된다.

# 02 Position-based Sparse Attention

## Atomic Sparse Attention




### Atomic Sparse Attention의 종류

- **Global Attention**

  Attention의 Long Range Dependency를 완화하기 위해, Global Node를 설정하여 모든 노드를 Attend

- **Band Attention (Sliding Window Attention / Local Attention)**

  언어의 Locality를 반영하기 위하여, 근접한 이웃 노드들에 대해서만 Attend

- **Dilated Attention**

  Dilated CNN과 같이 Computation은 같지만 더 넓은 Receptive Field를 위해 한 칸씩 띄운 Band Attention

- **Random Attention**

  인접하지 않은 단어들에 대한 상호작용을 반영하기 위하여 각 Query에서 랜덤으로 Attend

- **Block Local Attention**

  문장을 여러 non-overlapping query block으로 나누고 해당 Block내에서만 Attention 적용

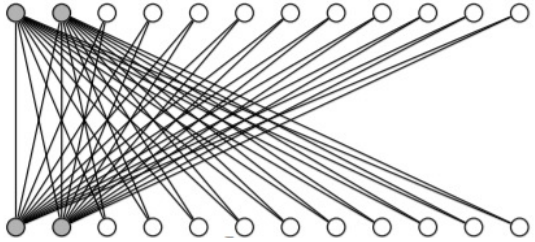
# 02 Position-based Sparse Attention

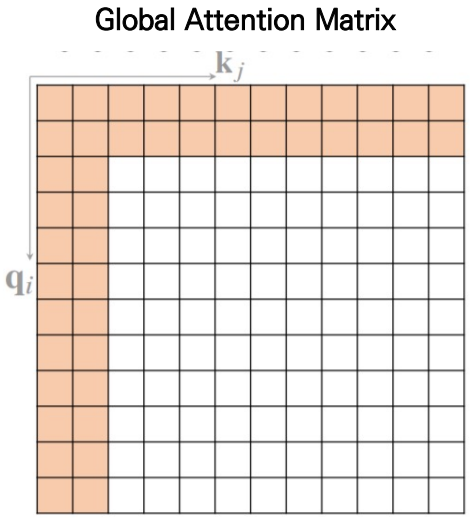
## Atomic Sparse Attention

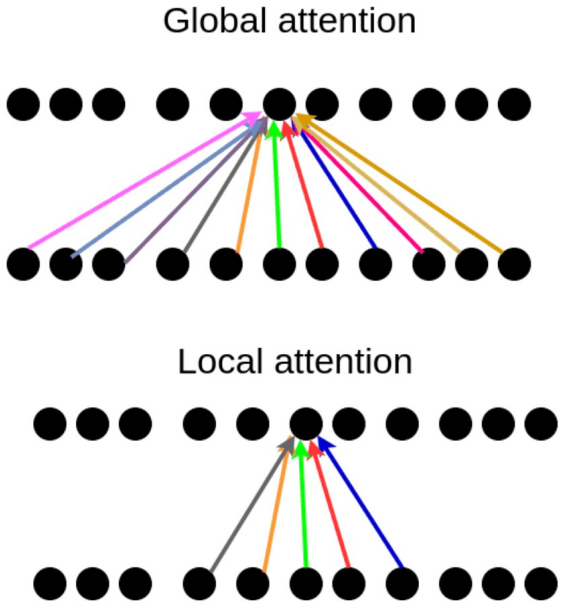
- **Global Attention**

  Attention의 Long Range Dependency를 완화하기 위해, Global Node를 설정하여 모든 노드를 Attend

  *모든 노드를 Attend한다는 의미와 다르다.*





# 02 Position-based Sparse Attention

## Atomic Sparse Attention

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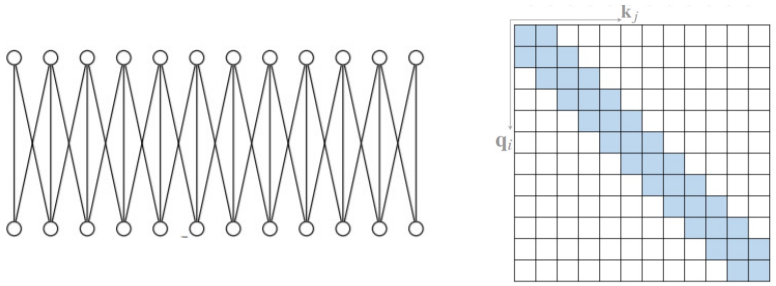


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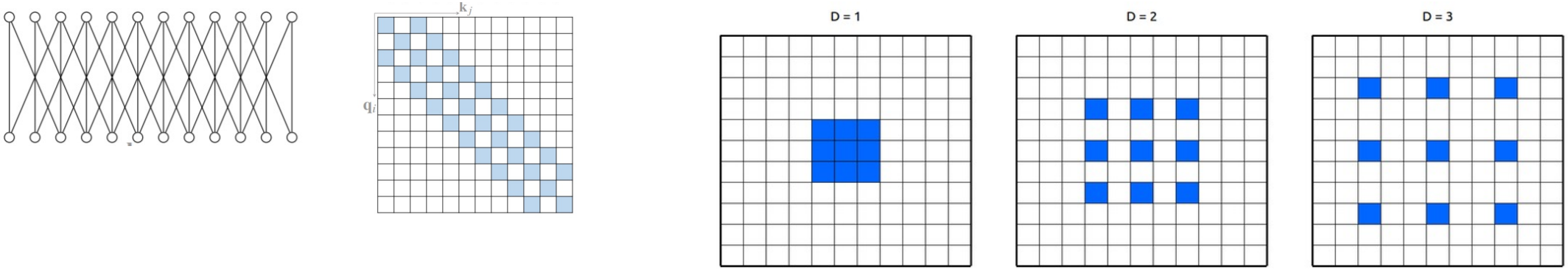

# 02 Position-based Sparse Attention

## Atomic Sparse Attention

- **Random Attention**

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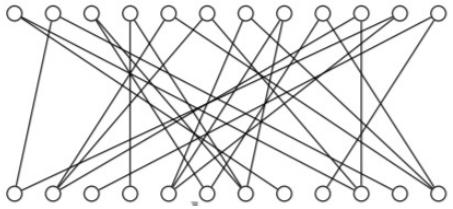

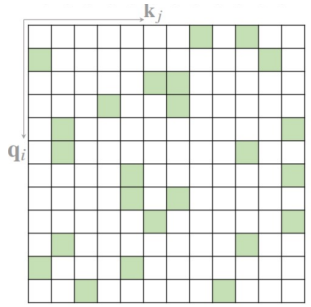


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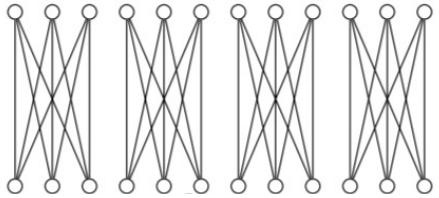
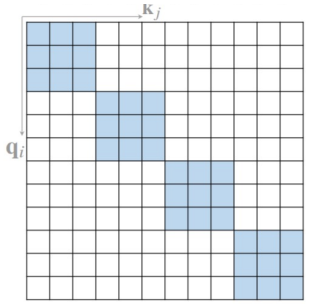
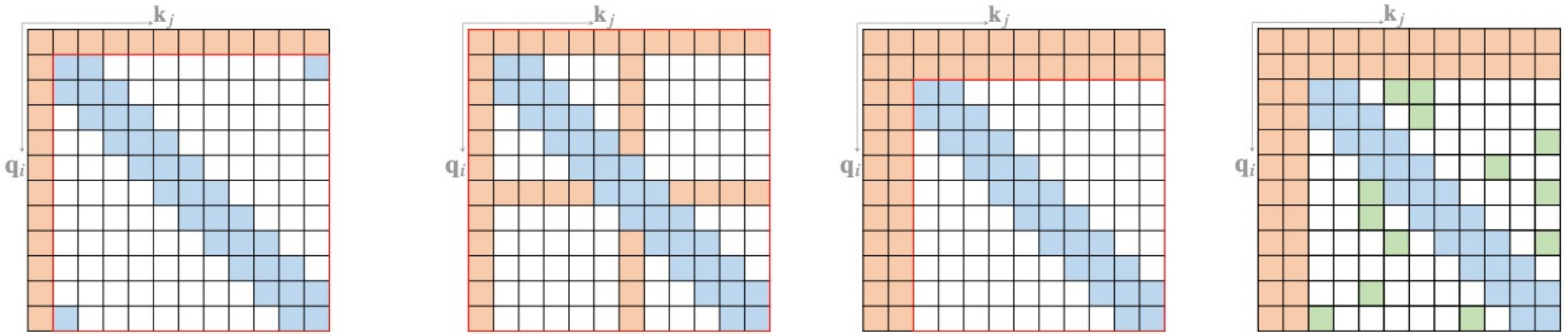




# 02 Compound Sparse Attention

Atomic Sparse Attention의 Combination




(a) Star-Transformer (b) Longformer (c) ETC (d) BigBird

Star-Transformer: Band Attention + Global-Node Attention

Longformer: Band Attention + Dilated Attention + (Internal) Global-Node Attention

Extended Transformer Construction: Band Attention + (External) Global-Node Attention

BigBird: Band Attention + Global-Node Attention + Random Attention

# 02 Compound Sparse Attention

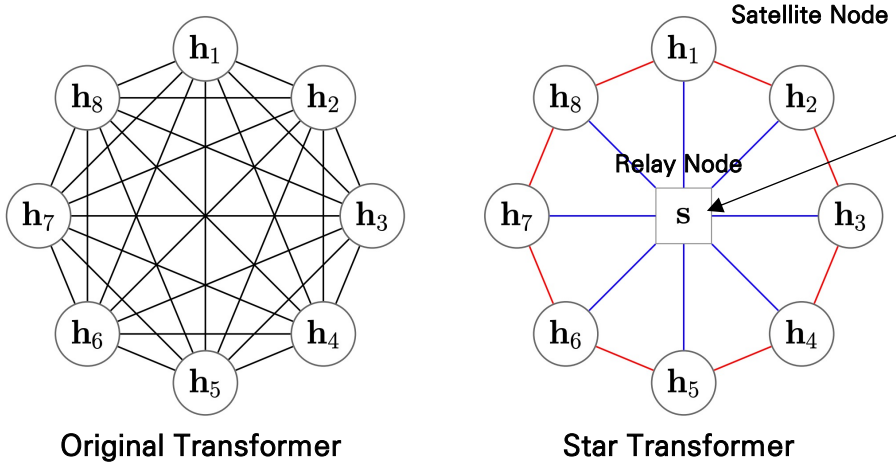
Star Transformer (NAACL, 2019, 87회 인용)

## Star Transformer

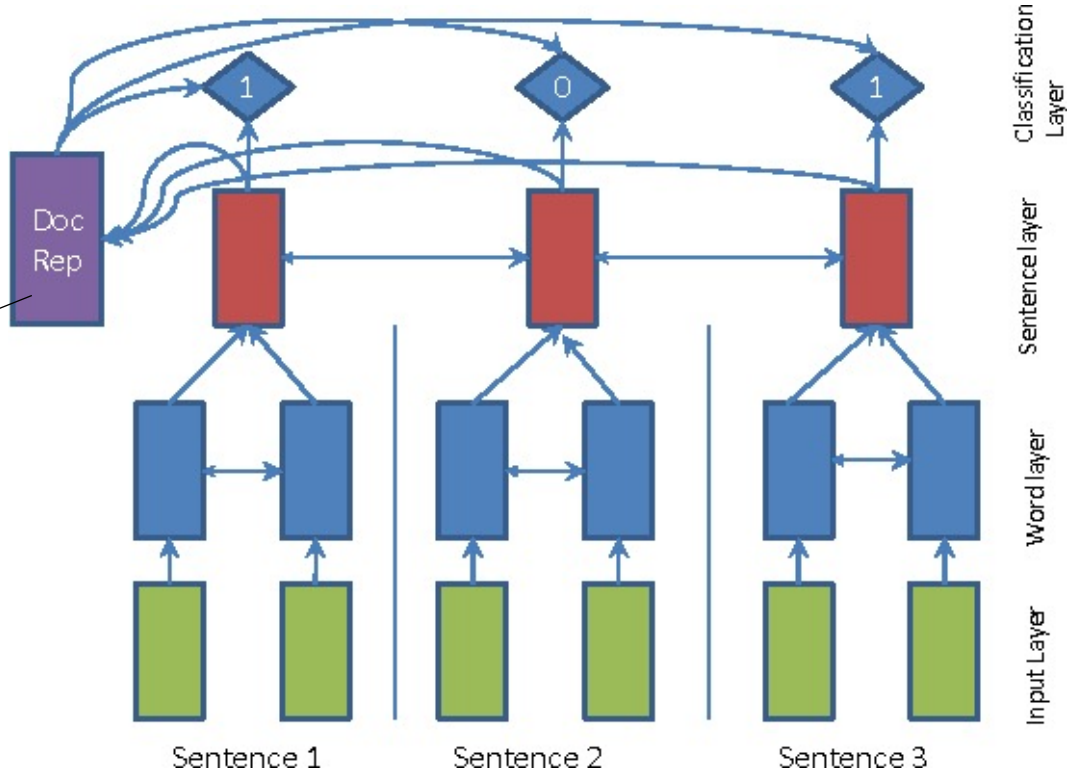
Band Attention + Global-Node Attention

**Text Inputs**

$$h_1, h_2, h_3, \dots, h_8$$




## SummaRuNNer




Global Attention〉 Radical Connections: Relay Node – Satellite Node ≈ Document Representation

Band Attention 〉 Ring Connections: Satellite Node – Satellite Node

# 02 Compound Sparse Attention

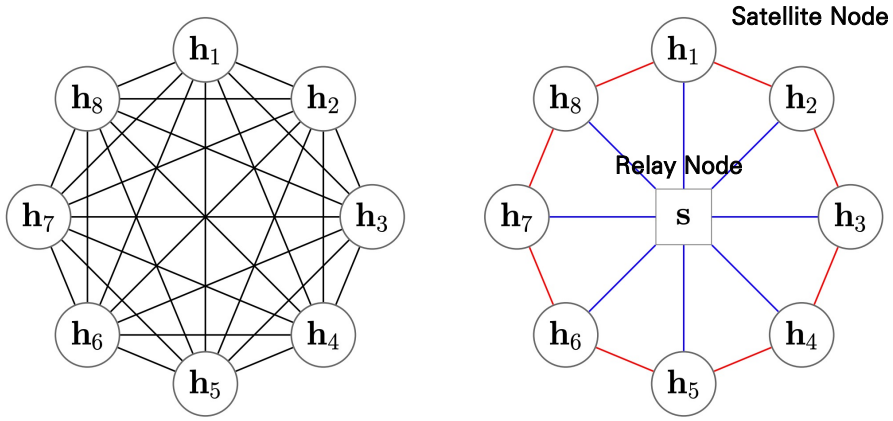
Star Transformer (NAACL, 2019, 87회 인용)

## Star Transformer

## Band + Global Attention

**Text Inputs**

$$h_1, h_2, h_3, \dots, h_8$$

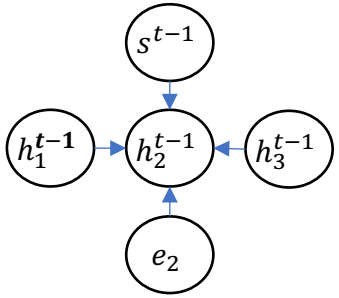



Original Transformer

Star Transformer

Radical Connections: Relay Node – Satellite Node

Ring Connections: Satellite Node – Satellite Node




절차

1. Satellite Node의 Update

   $C_i^t = [h_{i-1}^{t-1}; h_i^{t-1}; h_{i+1}^{t-1}; e^i; s^{t-1}]$

   $C_i^t$에 포함된 요소들로만 Attention 구성

   $h_i^t = MultiAtt(h_i^{t-1}, C_i^t)$

   $h_i^t = LayerNorm(ReLU(h_i^t))$

2. Relay Node의 Update

   Update된 Satellite Node ($H^t$)들에 대한 Multi-head Att.

   $s^t = MultiAtt(s^{t-1}, [s^{t-1}; H^t])$

   $s^t = LayerNorm(ReLU(s^t))$

## Implications

⇒ Band Attention과 Global Attention이 상호작용한다.

⇒ Original Transformer Complexity: $O(n^2 d)$

Star Transformer (ring conn): $O(5nd)$

Star Transformer (radical conn): $O(nd)$

⇒ Relay Node를 활용한 분류 Task 진행

# 02 Compound Sparse Attention

Star Transformer (NAACL, 2019, 87회 인용)

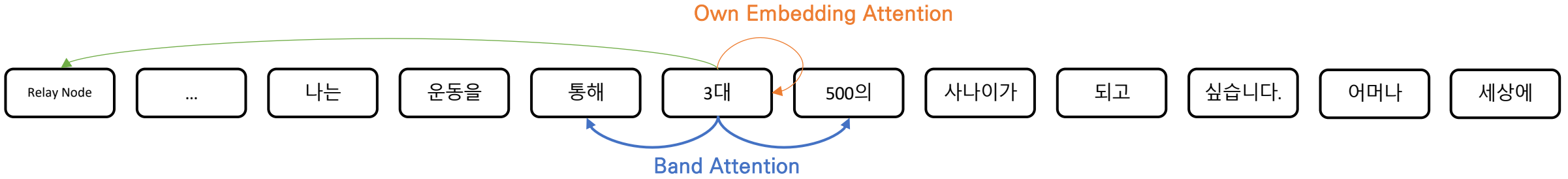
## Star Transformer

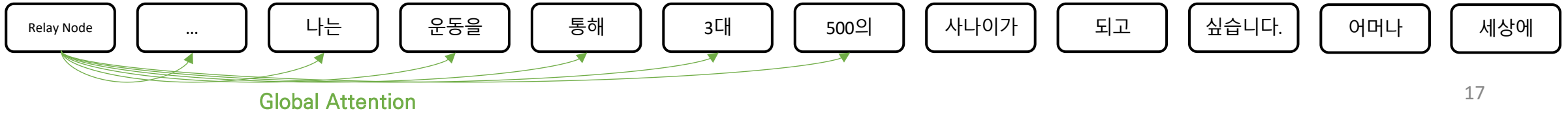
## [Discussion]

Attention이 Value에 어떻게 적용되는지 좀 더 자세하게 표현이 필요

Original Attention


Star Transformer Attention (Satellite Node / Relay Node Update)



# 02 Compound Sparse Attention

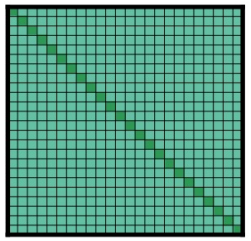
Longformer (2020, 258회 인용 / AllenAI)

## Longformer

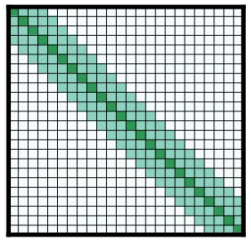
Band Attention + Dilated Attention + (Internal) Global-Node Attention

Long Sequence를 다루기 위한 Transformer (512 token 제한 벗어나고자 함)

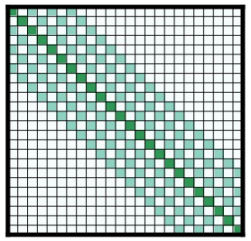
- LongFormer Attention을 통해 Self-Attention 보완
- Transformer의 Encoder 성능 향상 용이 아닌, Seq2Seq 성능 향상 용도



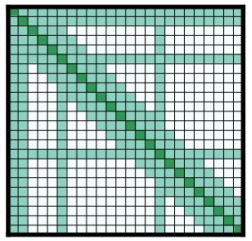
(a) Full $n^2$ attention



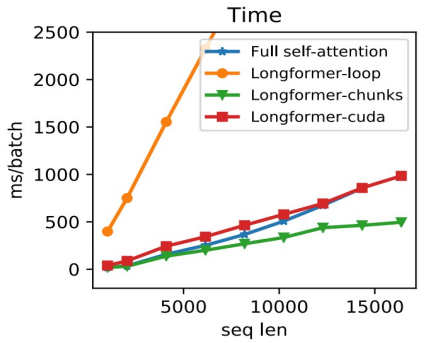
(b) Sliding window attention

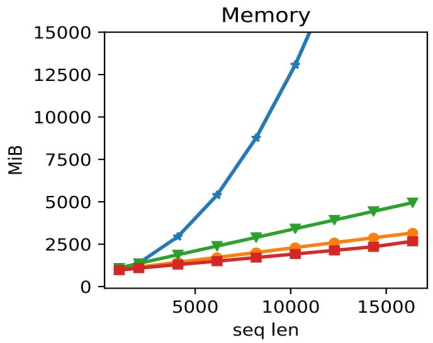


(c) Dilated sliding window



(d) Global+sliding window

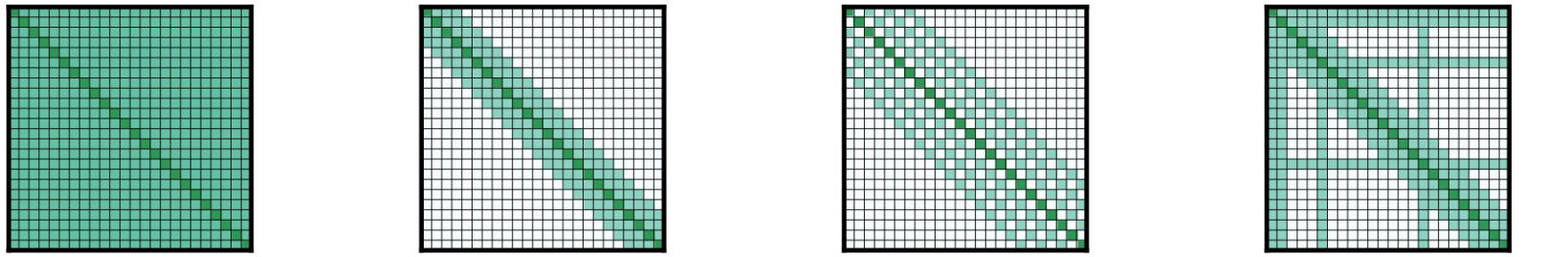



| | QA | | | Coref. | Classification | |
|---|---|---|---|---|---|---|
| Model | WikiHop | TriviaQA | HotpotQA | OntoNotes | IMDB | Hyperpartisan |
| RoBERTa-base | 72.4 | 74.3 | 63.5 | 78.4 | 95.3 | 87.4 |
| Longformer-base | **75.0** | **75.2** | **64.4** | **78.6** | **95.7** | **94.8** |

# 02 Compound Sparse Attention

Longformer (2020, 258회 인용 / AllenAI)



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

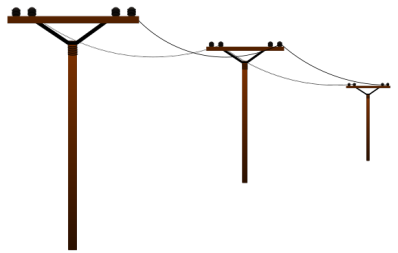
**Attention Pattern: Transformer Layer의 일반적인 특성 반영**

**Local Attention**

- Lower Layer: Local Information → Sliding Window Attention (낮은 층에서는 문장의 지엽적인 정보를 인코딩한다).
- Higher Layer: Higher-level representation → Dilated Sliding Window Attention (높은 층에서는 문장의 더 넓은 정보를 인코딩한다).

**Global Attention**

- Sliding Window와 Dilated Sliding Window Attention은 [CLS] Token과 같이 Task Specific Representation을 구성할 수 없다.
- [CLS] token과 같이 단 하나만 사용하는 것이 아니라, 선택된 위치에 복수 개 삽입 (like 전봇대)

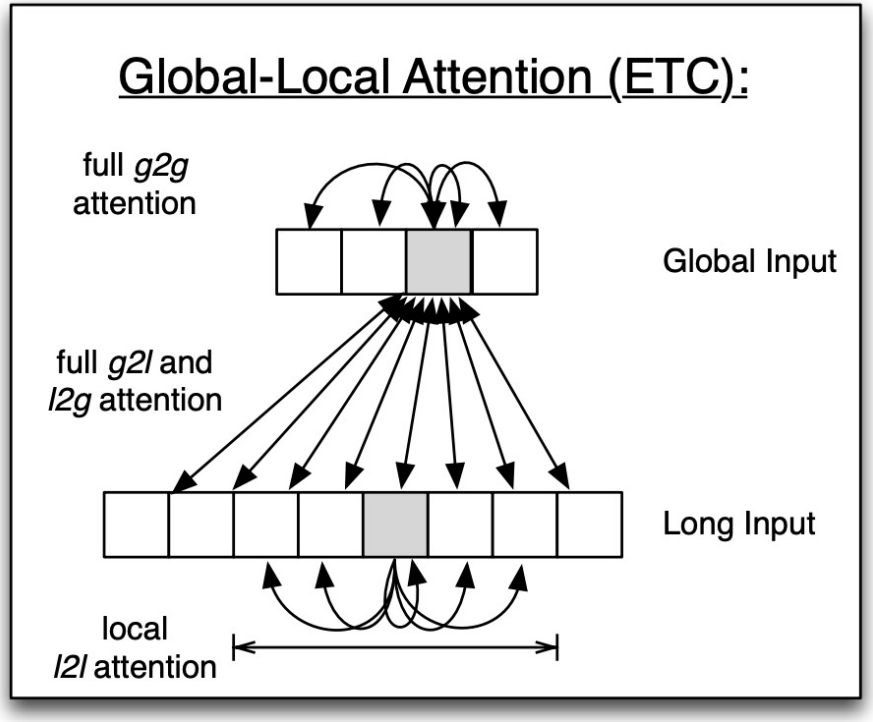


# 02 Compound Sparse Attention

ETC: Encoding Long and Structured Inputs in Transformers (EMNLP, 2020, 24회 인용 / Google Research)

## Extended Transformer Construction

Band Attention + (External) Global-Node Attention




## Key Ideas

- **Global-Local Attention**

  Global Node를 통해 전체 문장의 Attention을 계산

  Local Attention을 통해 인접 Token들 간의 Attention 계산

- **Relative Position Representations**

  문서 내 문장 내에서 단어의 상대적 위치를

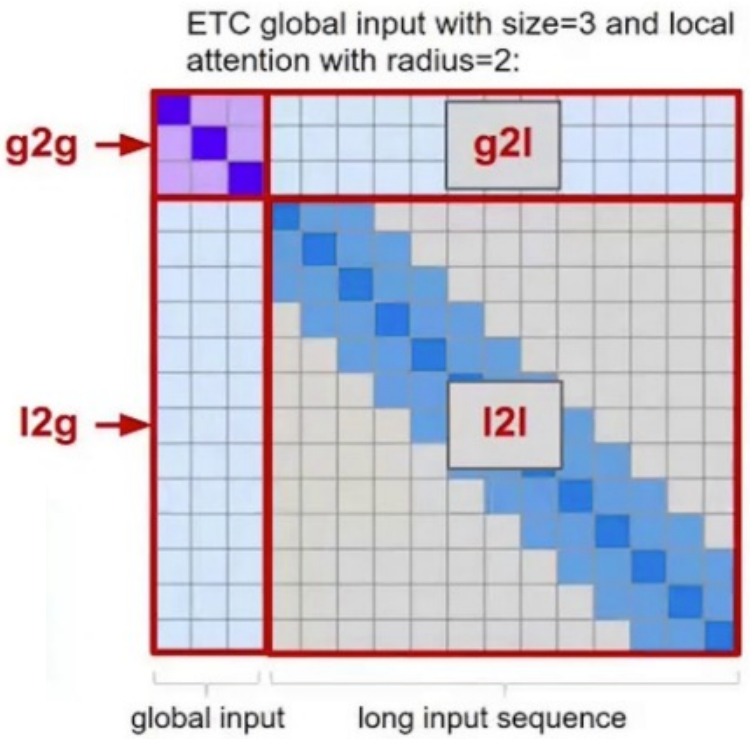
  Position Encoding에 반영한다.

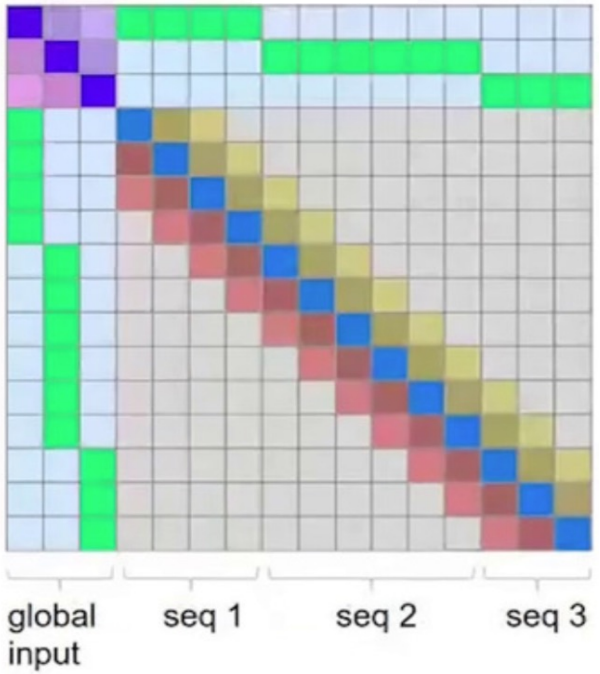


참고자료: https://slideslive.com/38938951/etc-encoding-long-and-structured-inputs-in-transformers

# 02 Compound Sparse Attention

ETC: Encoding Long and Structured Inputs in Transformers (EMNLP, 2020, 24회 인용 / Google Research)




Global Node 하나마다 하나의 문장 Attend

색깔 별로 Relative Positional Encoding

[Discussion]

QA Task에서는 Question과 Text의 Seperation이 중요



참고자료: https://slideslive.com/38938951/etc-encoding-long-and-structured-inputs-in-transformers

# 02 Compound Sparse Attention

BigBird (NeurIPS, 2020, 139회 인용 / Google Research)

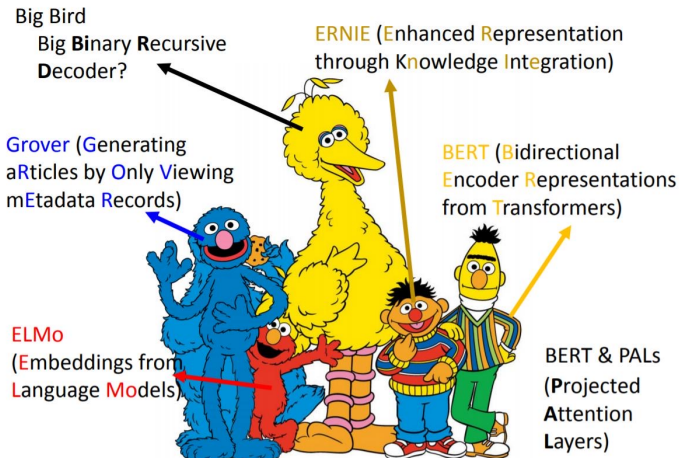
## BigBird

Band Attention + Global-Node Attention + Random Attention

## Question

- Sparse Attention이 원래 Attention의 성능과 동일할 수 있는가?
- 더 적은 Inner-product로 Full Quadratic Self-Attention의 성능을 보존할 수 있는가?

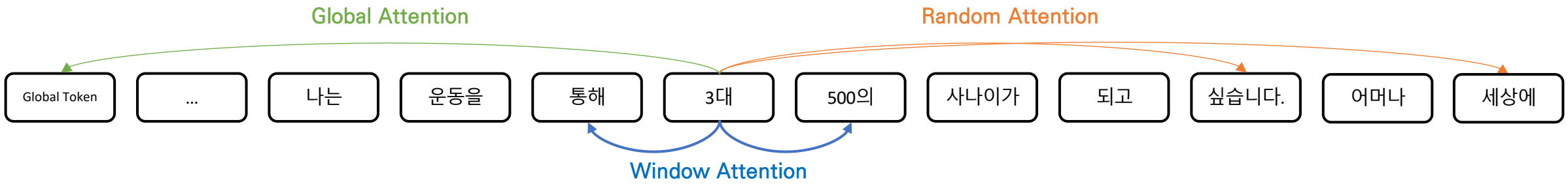
⇒ Sparsity를 생성하면서도 최대한 Full Attention Model과 유사한 성능을 만들고자 한다.

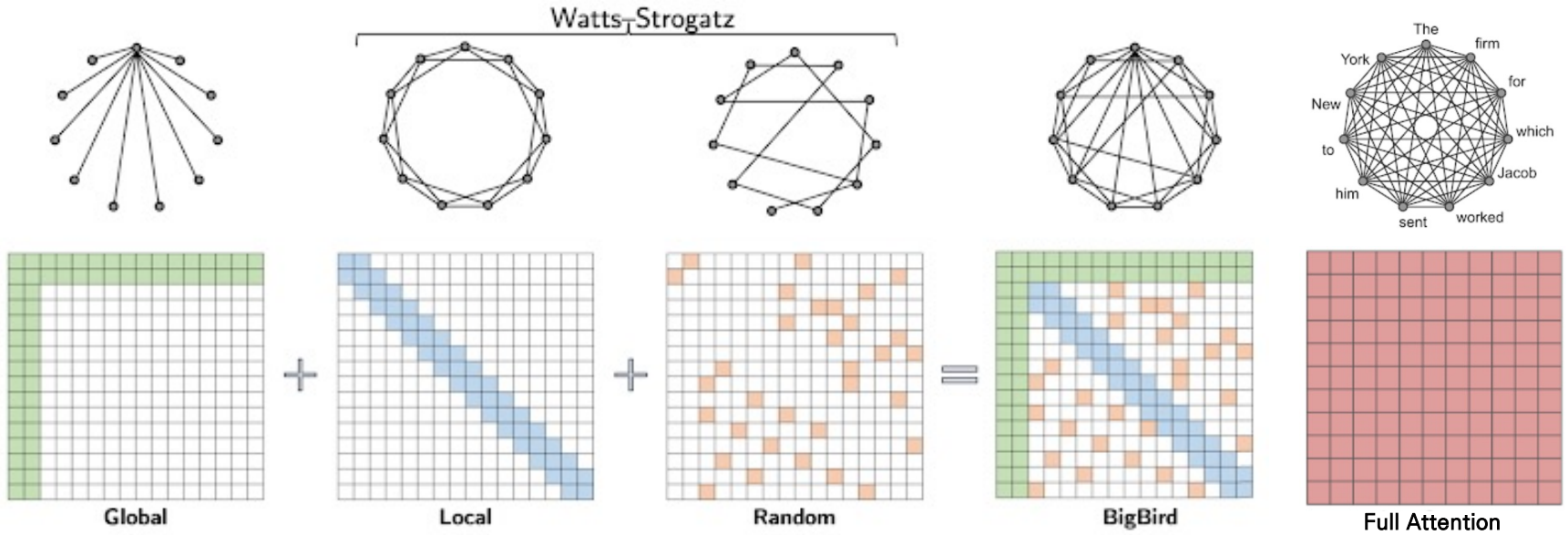


# 02 Compound Sparse Attention

BigBird (NeurIPS, 2020, 139회 인용 / Google Research)

## BigBird's Attentions

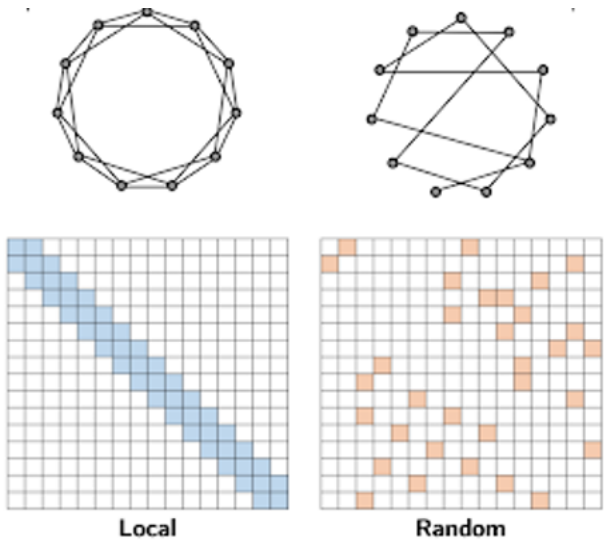


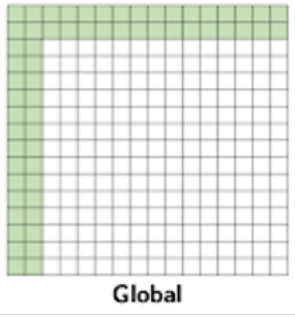




참고: https://ai.googleblog.com/2021/03/constructing-transformers-for-longer.html

# 02 Compound Sparse Attention

BigBird (NeurIPS, 2020, 139회 인용 / Google Research)




- **Random Attention (Random Blocks) ≈ Graph Sparsification Problem**

  Graph Theory에서 Random Graph는 Complete Graph를 잘 근사하기 때문에,

  Full Attention Graph를 Random Graph로 치환해도 문제가 없다.

  (Erdos-Renyi model, Spectral Graph Theory)

- **Local Attention (Local Window)**

  Linguistic Structure를 반영하기 위해 인접한 Token에 대한 Attention이 필요하다.

**실험 결과**

**Random Blocks와 Local Window만으로는 BERT에 상응하는 성능을 달성할 수 없었음.**

- **Global Attention (Global Tokens)**

  **〉 BIGBIRD-ITC (기존 Corpus에 존재하는 Token들 중 Global Token을 지정)**

  **ex) "global" 이라는 특정 Token을 사용**

  **〉 BIGBIRD-ETC (문장에 [CLS]와 같은 Global Token 추가)**

# 02 Compound Sparse Attention

BigBird (NeurIPS, 2020, 139회 인용 / Google Research)

## Results

BigBird의 Sparse Attention으로 더 긴 길이의 문장을 Transformer에 적용 가능 → DownStream Task의 성능

- Basic Masked Language Modeling을 통해 더 좋은 Representation을 학습할 수 있었는지
- QA Task에서 긴 문장의 Input이 정답을 유도할 수 있는 더 많은 Evidence를 제공하는지
- 문서 요약에서 512 token보다 더 긴 문장의 효과를 볼 수 있는 지

를 실험을 통해 보이고자 한다.

## Encoder-Decoder Task Setup

- Sparse Attention을 Encoder에만 적용
- Encoder Input이 Decoder Output보다 높은 수준으로 차이가 있기 때문에,
  Decoder에서는 Full Attention을 사용한다. (Input Median Len: 3000이상 / Decoder Median Len: 200)

# 02 Compound Sparse Attention

BigBird (NeurIPS, 2020, 139회 인용 / Google Research)

## 문서 요약 ROUGE Score

| | Model | Arxiv | | | PubMed | | | BigPatent | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L |
| Prior Art | SumBasic [68] | 29.47 | 6.95 | 26.30 | 37.15 | 11.36 | 33.43 | 27.44 | 7.08 | 23.66 |
| | LexRank [25] | 33.85 | 10.73 | 28.99 | 39.19 | 13.89 | 34.59 | 35.57 | 10.47 | 29.03 |
| | LSA [97] | 29.91 | 7.42 | 25.67 | 33.89 | 9.93 | 29.70 | - | - | - |
| | Attn-Seq2Seq [85] | 29.30 | 6.00 | 25.56 | 31.55 | 8.52 | 27.38 | 28.74 | 7.87 | 24.66 |
| | Pntr-Gen-Seq2Seq [77] | 32.06 | 9.04 | 25.16 | 35.86 | 10.22 | 29.69 | 33.14 | 11.63 | 28.55 |
| | Long-Doc-Seq2Seq [20] | 35.80 | 11.05 | 31.80 | 38.93 | 15.37 | 35.21 | - | - | - |
| | Sent-CLF [81] | 34.01 | 8.71 | 30.41 | 45.01 | 19.91 | 41.16 | 36.20 | 10.99 | 31.83 |
| | Sent-PTR [81] | 42.32 | 15.63 | 38.06 | 43.30 | 17.92 | 39.47 | 34.21 | 10.78 | 30.07 |
| | Extr-Abst-TLM [81] | 41.62 | 14.69 | 38.03 | 42.13 | 16.27 | 39.21 | 38.65 | 12.31 | 34.09 |
| | Dancer [31] | 42.70 | 16.54 | 38.44 | 44.09 | 17.69 | 40.27 | - | - | - |
| Base | Transformer | 28.52 | 6.70 | 25.58 | 31.71 | 8.32 | 29.42 | 39.66 | 20.94 | 31.20 |
| | + RoBERTa [76] | 31.98 | 8.13 | 29.53 | 35.77 | 13.85 | 33.32 | 41.11 | 22.10 | 32.58 |
| | + Pegasus [107] | 34.81 | 10.16 | 30.14 | 39.98 | 15.15 | 35.89 | 43.55 | 20.43 | 31.80 |
| | BIGBIRD-RoBERTa | 41.22 | 16.43 | 36.96 | 43.70 | 19.32 | 39.99 | 55.69 | 37.27 | 45.56 |
| Large | Pegasus (Reported) [107] | 44.21 | 16.95 | 38.83 | 45.97 | 20.15 | 41.34 | 52.29 | 33.08 | 41.75 |
| | Pegasus (Re-eval) | 43.85 | 16.83 | 39.17 | 44.53 | 19.30 | 40.70 | 52.25 | 33.04 | 41.80 |
| | BIGBIRD-Pegasus | **46.63** | **19.02** | **41.77** | **46.32** | **20.65** | **42.33** | **60.64** | **42.46** | **50.01** |

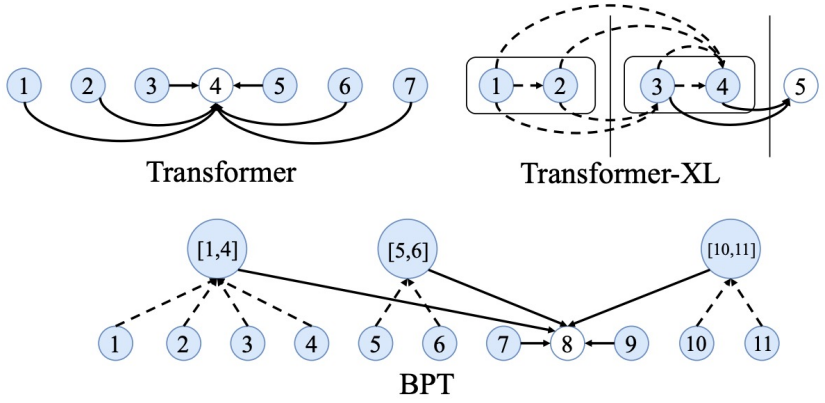
Table 4: Summarization ROUGE score for long documents.

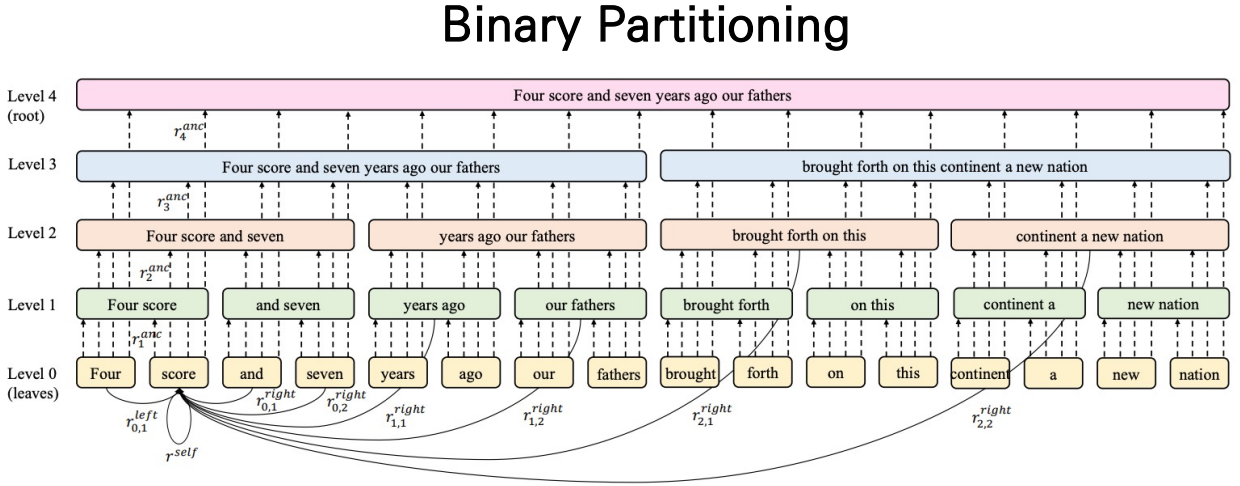
## QA Task Exact Match

| Model | HotpotQA | | | NaturalQ | | TriviaQA | | WikiHop |
|---|---|---|---|---|---|---|---|---|
| | Ans | Sup | Joint | LA | SA | Full | Verified | MCQ |
| HGN [26] | **82.2** | 88.5 | **74.2** | - | - | - | - | - |
| GSAN | 81.6 | 88.7 | 73.9 | - | - | - | - | - |
| ReflectionNet [32] | - | - | - | 77.1 | **64.1** | - | - | - |
| RikiNet-v2 [61] | - | - | - | 76.1 | 61.3 | - | - | - |
| Fusion-in-Decoder [39] | - | - | - | - | - | 84.4 | 90.3 | - |
| SpanBERT [42] | - | - | - | - | - | 79.1 | 86.6 | - |
| MRC-GCN [87] | - | - | - | - | - | - | - | 78.3 |
| MultiHop [14] | - | - | - | - | - | - | - | 76.5 |
| Longformer [8] | 81.2 | 88.3 | 73.2 | - | - | 77.3 | 85.3 | 81.9 |
| BIGBIRD-ETC | 81.2 | **89.1** | 73.6 | **77.8** | 57.9 | **84.5** | **92.4** | **82.3** |

# 02 Extended Sparse Attention

BP-Transformer (2019, 24회 인용 / AWS AI Lab)




## BP-Transformer

- **Binary Partitioning**을 통해 문장을 Graph의 형태로 나타낸다.

  Binary Partitioning: 문장을 재귀적으로 나누어 단일 Token이 될 때 까지 나눈다.
- Graph Self Attention을 통해 Representation을 Update

## Edge Construction

- Affiliated Edges: Span Node에 대하여 포함되어 있는 Token들과 모두 연결 (Hierarchical Linguistic Structure 반영)
- Contextual Edges: 모든 이웃 Token을 Edge로 연결하지 않고, 상위 Span Node들을 연결

  파라미터 $k$ 를 통해 Layer별 몇 개의 노드와 연결할 지 결정

# 02 Content-based Sparse Attention

위치 기반이 아닌, Token의 내용 기반

**Content Based Sparse Attention의 목적**

- 모든 Query-Key Pair에 대하여 내적을 실시하지 않고, 최대 내적 값을 갖는 Key값 탐색
- 가장 유사한 Content들 간의 Attention으로 Sparse Attention을 달성하고자 한다.

- 유사한 Content Search Algorithm: Maximum Inner Product Search(MIPS) problem

  MIPS = $argmax_{k \in K}(q^T k)$

- (Exact) MIPS를 근사하기 위한 여러 전략이 있으며, Transformer에서는
  - Locality-Sensitive Hasing(LSH): Reformer
  - Nearest Neighbor Search(NNS): Routing Transformer

# 02 Content-based Sparse Attention

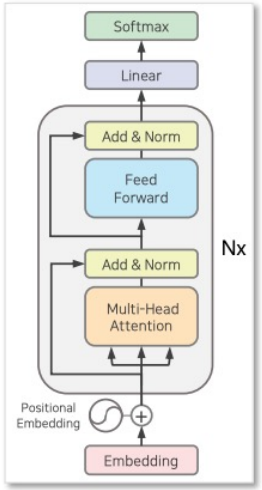
Reformer (ICLR, 2020, 356회 인용 / Google Research)

## Reformer: The Efficient Transformer → Transformer의 극한의 효율을 달성하고자 한다.

### Main Idea

Memory ≈ 모델깊이 × 모델넓이 × 문장길이 × Batch

- Transformer 모델에서 Memory 효율적으로 사용하는 방법
  1. ~~모델깊이, 모델넓이, 문장길이 줄이기~~
  2. ~~Batch size를 줄이기~~
  3. 메모리에 저장되는 중간결과물 줄이기




| Attention Layer 개선 | Residual Block 개선 | Feedforward Layer 개선 |
|---|---|---|
| 쓸모 없는 Attention을 줄일 수 있도록 LSH Attention 적용 | 중간 값 저장없이 역전파 할 수 있는 Reversible Network 구조 적용 | 계산하는 단위를 나누어 메모리를 사용할 수 있는 Chunking 적용 |
| 문장길이 | 모델깊이 | 모델넓이 |
| 필요 없는 연결 제거 | 메모리 저장 구조 변경 | 단계별로 메모리 사용 |

DSBA 연구실 김정희 석사과정의 자료가 가장 우수하여 그대로 사용하고자 함

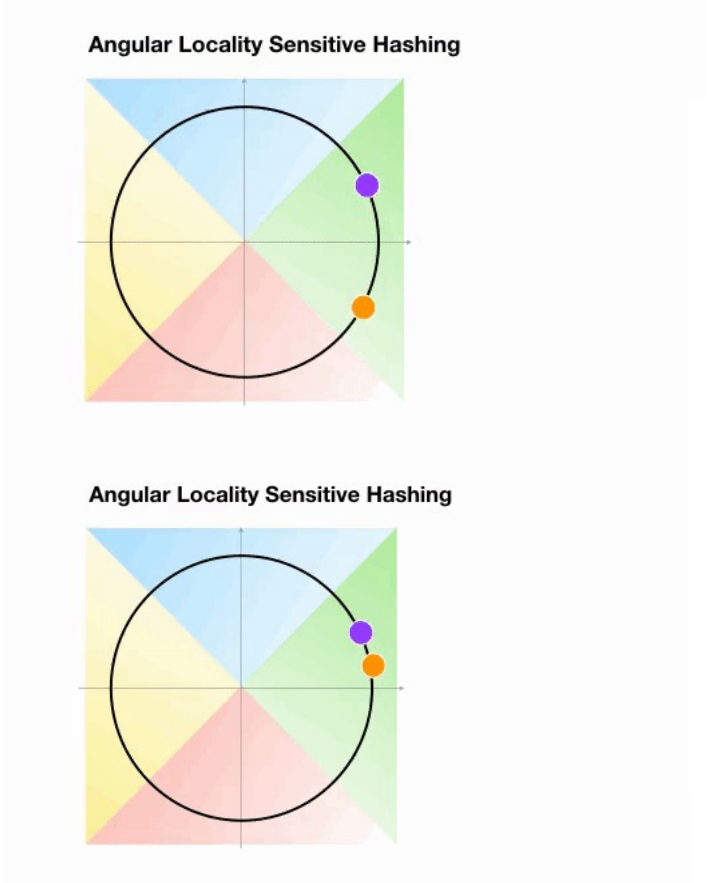
참고자료: http://dsba.korea.ac.kr/seminar/?mod=document&pageid=1&keyword=reformer&uid=385

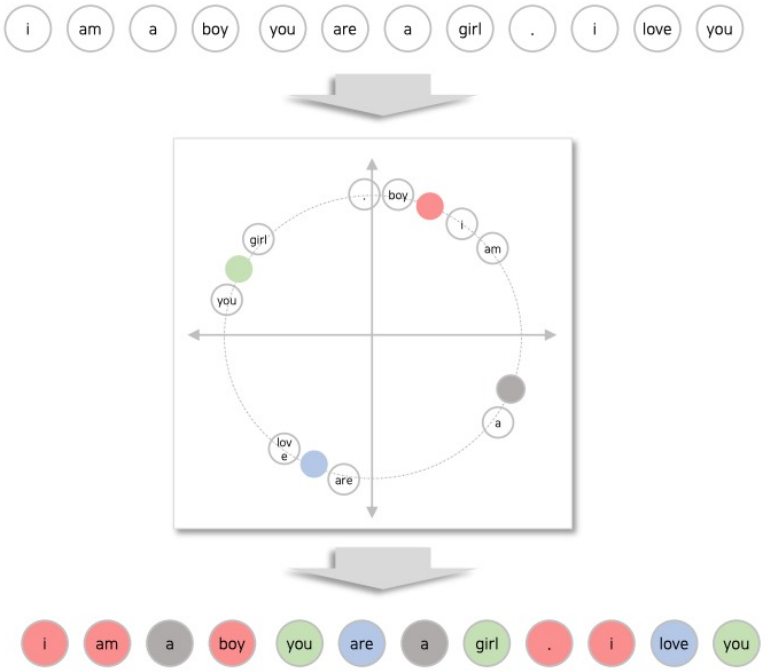
# 02 Content-based Sparse Attention

Reformer (ICLR, 2020, 356회 인용 / Google Research)

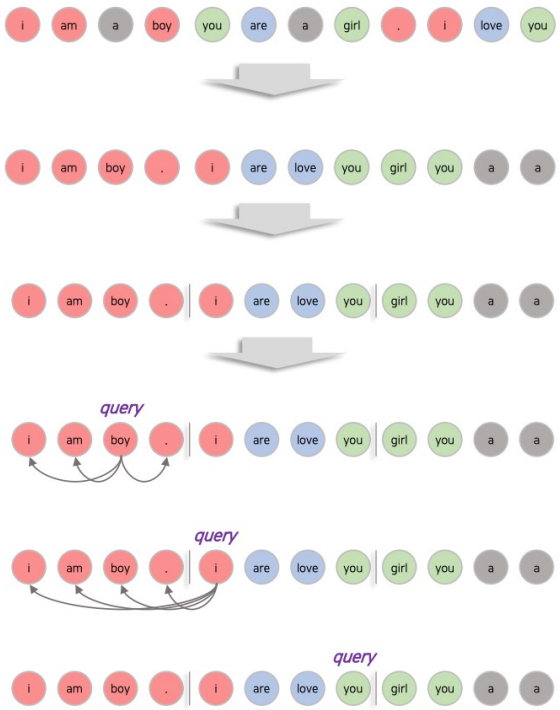
## Locality-Sensitive Hashing을 적용한 뒤, 같은 Hashing Bucket 내에서 Attention 적용

### Locality-Sensitive Hashing: Token들에 Hashing Bucket 할당




### LSH Attention




참고자료: http://dsba.korea.ac.kr/seminar/?mod=document&pageid=1&keyword=reformer&uid=385

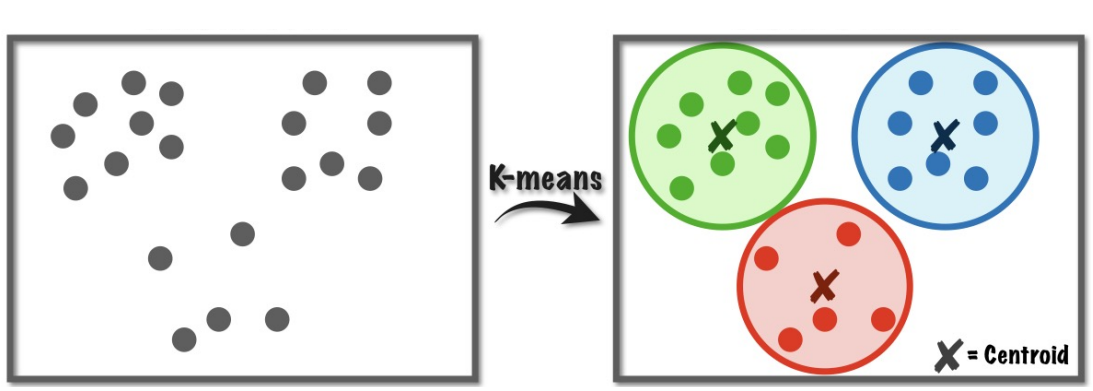
# 02 Content-based Sparse Attention

Routing Transformer (TACL, 2020, 66회 인용 / Google Research)

## Routing Transformer

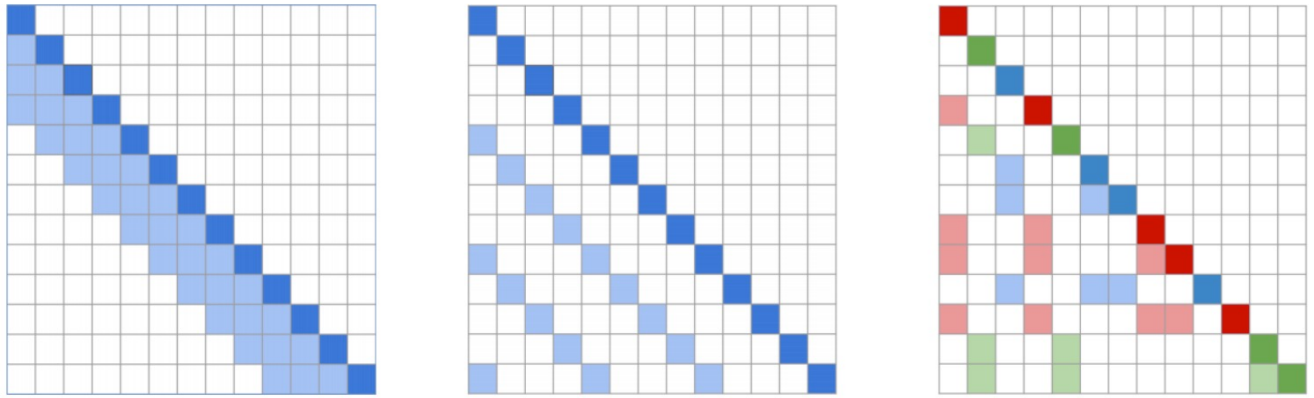
- Query가 Attention을 구할 대상인 Key들에게 Routed(연결)되어 대상이 제한된다.
- Maximum Inner Product Search (MIPS)를 근사하려는 목적에서 LSH보다 spherical k-means가 더 우수

### Query & Key K-Means




각 Token에 대한 K-Means를 통해 Clustering 진행

### Attention Matrix




(c)에서 같은 색깔 (Cluster)에 대해서만 Attention이 적용되는 것을 볼 수 있다.

# 02 Conclusion

## Sparse Attention 정리

**일반 Self-Attention은 Transformer의 중요한 역할을 하지만, 두 가지 문제 발생**

- Complexity: Self Attention의 Complexity ($O(T^2 \cdot D)$)는 문장이 길어지면 Bottleneck이 된다.
- Structural Prior: Input에 대한 어떤 Structural Bias도 없다 (장점인 동시에 단점)

**Vanilla Transformer Attention Matrix는 사실상 Sparse하다?**

→ Attention은 훈련 뒤에는 볼 대상만 보게 된다.

→ 그럼 애초에 **Structural Bias**를 부여하여, Query-Key Pair 개수를 제한하자!

**Sparse Attention의 공통 주장**

- **Computational Cost**: 문장이 길어질수록, Attention에 필요한 비용이 크다.
  Input Length에 **Quadratic**하게 증가하는 비용 대신에, **Linear**하게 증가하도록 만드는 것이 목적
  $$O(n^2) \rightarrow O(n)$$
- **Long Range Dependency**: 긴 문장에는 Transformer를 적용하기 힘들다 (+Cost 문제)
  Global Attention을 통해 Long Range Dependency 해소

**Sparse Attention 효과**

- 비용 / Dependency를 감소 시키면 512 Token보다 더 긴 문장을 Input으로 활용할 수 있다.
  Input 문장을 길게 만들면, Downstream Task에 사용되는 단서가 많아진다.
  Downstream Task로 QA & 문서 요약이 많이 사용 (단서 증폭 효과를 살피기 위하여)
- Sparse Attention은 Long Input이 사용되는 Encoder에 적용된다.

**Sparse Attention (2021.07 기준)**

- **Position Based Sparse Attention**
  - **Atomic Sparse Attention**
  - **Compound Sparse Attention (여러 Atomic Sparse Attention이 모여 구성)**
    - Star Transformer (NAACL, 2019, 87회 인용)
    - Longformer (2020, 258회 인용 / AllenAI)
    - ETC (EMNLP, 2020, 24회 인용 / Google Research)
    - BigBird (NeurIPS, 2020, 139회 인용 / Google Research)
    - Sparse Transformer (2019, 353회 인용 / OpenAI)
  - **Extended Sparse Attention (Atomic 혼합 대신 새로운 관점 또는 Non-Text Dataset)**
    - BP-Transformer (2019, 24회 인용 / AWS AI Lab)
    - Image Transformer (ICML, 2018, 448회 인용)
    - Axial Transformer (2019, 59회 인용 / Google Brain)
- **Content-Based Sparse Attention (Query와 Key Token의 유사도를 통한 Attention)**
  - Reformer (ICLR, 2020, 360회 인용 / Google Research)
  - Routing Transformer (TACL, 2020, 66회 인용 / Google Research)
  - Sparse Adaptive Connection, Sparse Sinkhorn Attention

# 02 Conclusion

## Sparse Attention 의문

1) 이렇게 좋은데 왜 기존 Transformer 대신 Default로 쓰지 아니한가?
2) QA / Text Summarization과 같이 Long Sequence가 필요한 Task에는 필요할 Attention이라고 생각
3) HuggingFace에 등록된 모델
    - Longformer
    - BigBird (+Pegasus)
    - Reformer