AST-Trans: Code Summarization with Efficient Tree-Structured Attention

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2. Background

Code Summarization/Code Comment Generation

```
float relu(float x){
    return x < 0 ? 0 : x
}
```
code

source code

return 0 if x<0, else return x itself.

summary

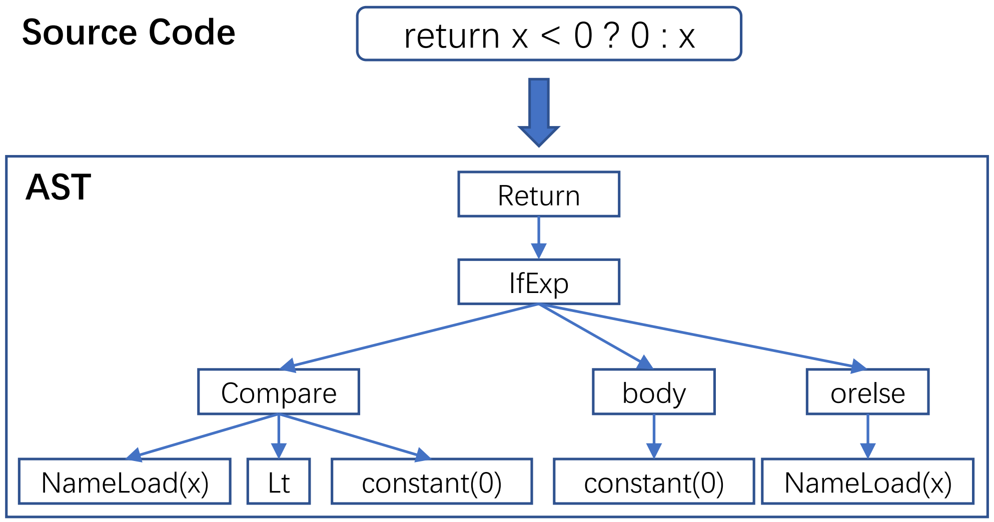
natural language description

Input	Method	Model
Code	split code into tokens	RNN[1] , Transformer[2]
Abstract Syntax Tree(AST)	use tree-based model or GNN	Tree-LSTM[3]
Linearized AST	convert AST to sequence • Pre-order Traversal(POT) • Structure-based Traversal(SBT) • Path Decomposition(PD)	LSTM[4] , Code2Seq[5]

3. Motivation

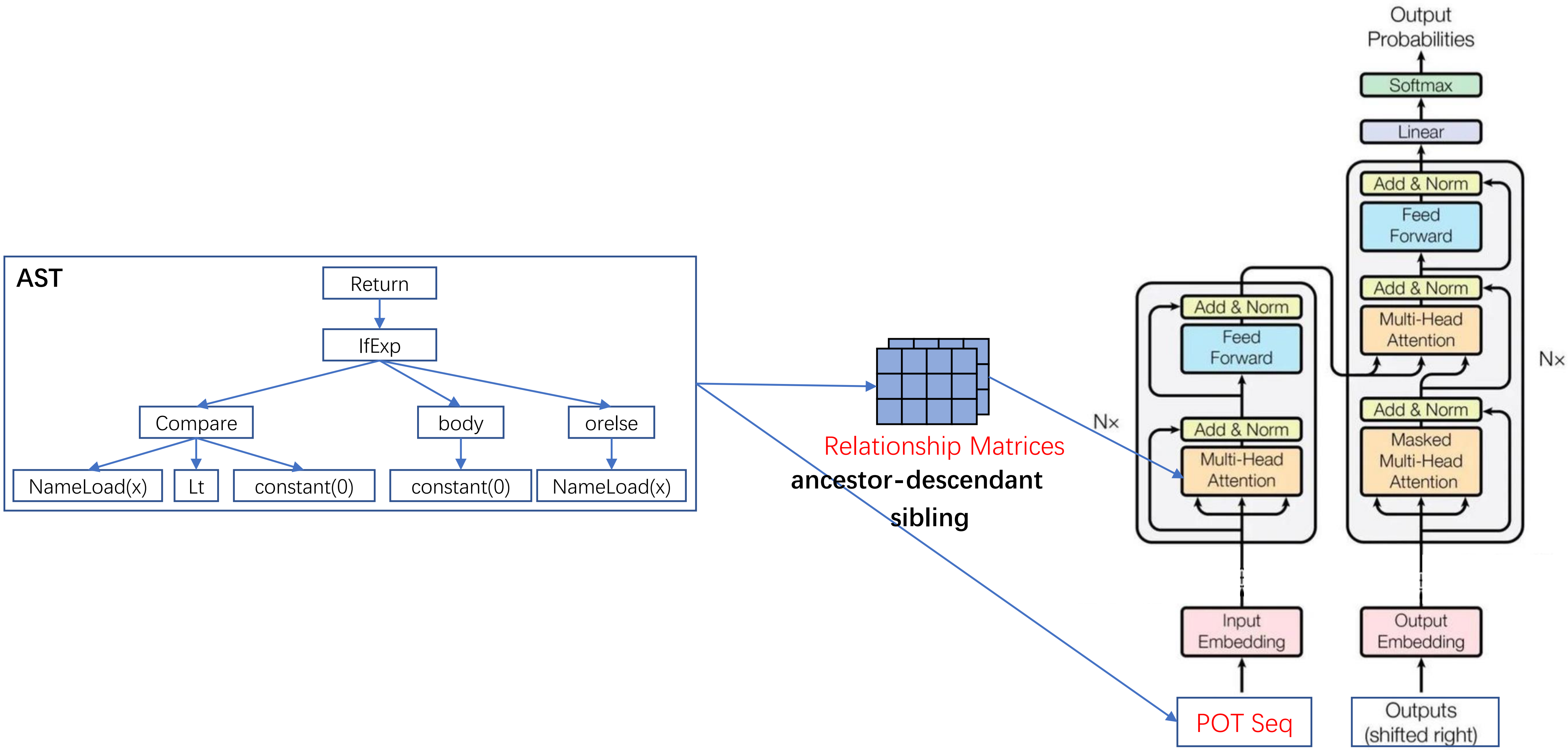
The length of **linearized AST** is much longer than **source code**

- **Hard to learn :** encoding SBT underperforms encoding source code when using Transformer[2]
- **Significant computational overhead :** quadratically with the sequence length in Transformer

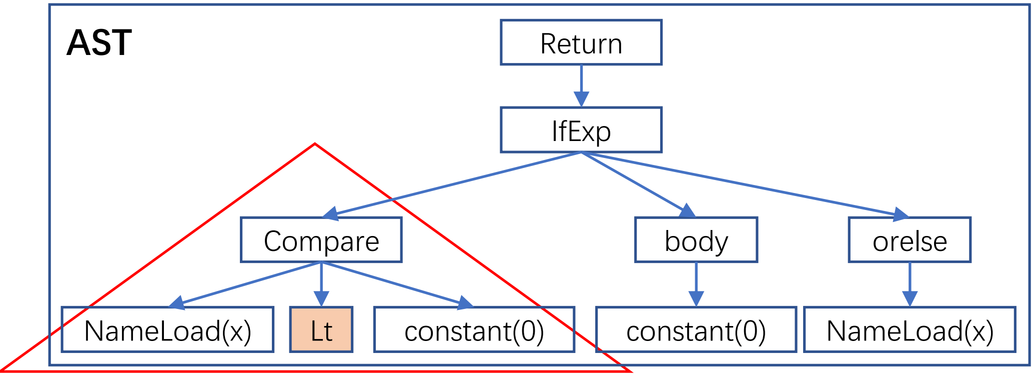


Methods	Linearized AST sequence
POT	Return IfExp Compare NameLoad(x) Lt constant(0) body constant(0) orelse NameLoad(x)
SBT	(Return (IfExp (Compare (constant(0)) constant(0) (Lt) Lt (NameLoad(x)) NameLoad(x)) Compare (body (constant(0)) constant(0)) body (orelse (NameLoad(x)) NameLoad(x)) orelse) IfExp) Return
PD	Path1: Path1: Lt Compare constant(0) Path2: NameLoad(x) Compare constant(0) Path3: Path3: constant(0) Compare IfExp body constant(0) ...

4. AST-Trans —— Overall Architecture



4. AST-Trans—— Relationship Matrices



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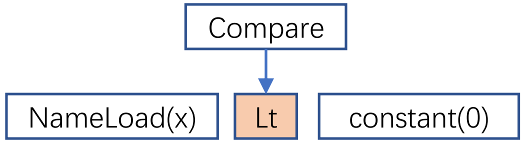
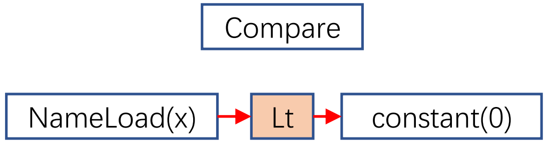


Ancestor-descendant relationship



Sibling relationship

In AST, children nodes are orderd

$$A_{ij} = \begin{cases} \mathbf{SPD}(i,j) & \text{if } |\mathbf{SPD}(i,j)| \le P \\ \infty & \text{otherwise} \end{cases}$$

$$S_{ij} = \begin{cases} \mathbf{SID}(i,j) & \text{if } |\mathbf{SID}(i,j)| \le P \\ \infty & \text{otherwise} \end{cases}$$

P: max distance

SPD(i,j) : Shorted Path Distance between node i and j

SID(i,j) : horizontal SIbling Distance between node i and j

$A_{ij} = -A_{ji}$ and $S_{ij} = -Sji$

	Compare	NameLoad(x)	Lt	constant(0)
Compare	0	1	1	1
NameLoad(x)	-1	0	∞	∞
Lt	-1	∞	0	∞
constant(0)	-1	∞	∞	0

$\{A_{ij}\}$

	Compare	NameLoad(x)	Lt	constant(0)
Compare	0	∞	∞	∞
NameLoad(x)	∞	0	1	∞
Lt	∞	-1	0	1
constant(0)	∞	∞	-1	0

$\{S_{ij}\}$

P=1

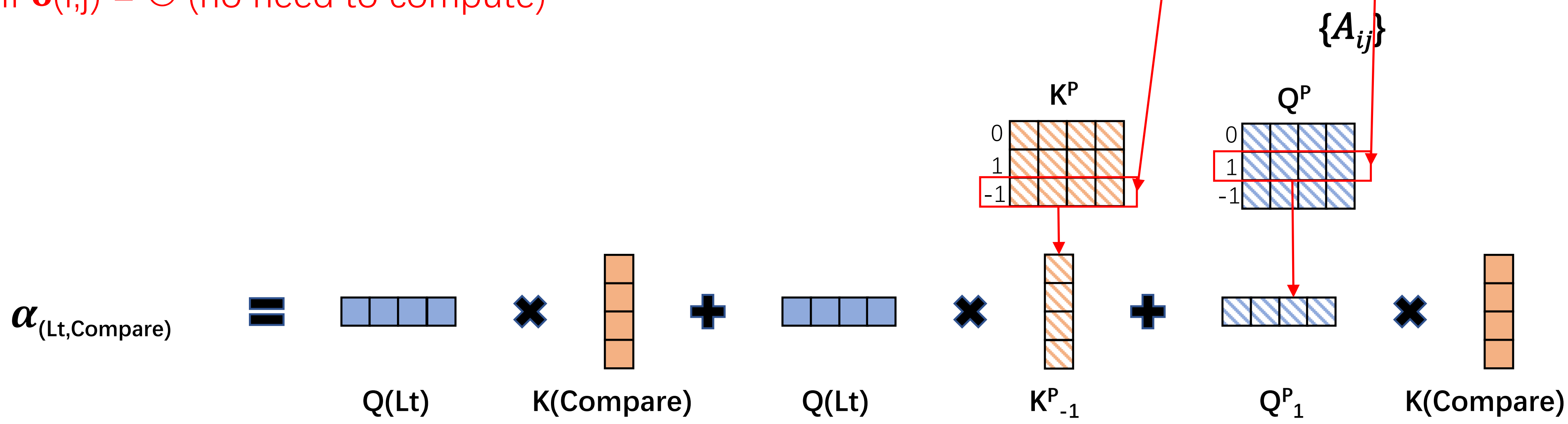
4. AST-Trans—— Tree-Structured Attention

Disentangled Attention[6]

$$\tilde{\alpha}_{i,j} = \underbrace{Q(x_i)K(x_j)^\top}_{\text{content-to-content}} + \underbrace{Q(x_i){K^P_{\delta(i,j)}}^\top}_{\text{content-to-position}} + \underbrace{Q^P_{\delta(j,i)}K(x_j)^\top}_{\text{position-to-content}}$$

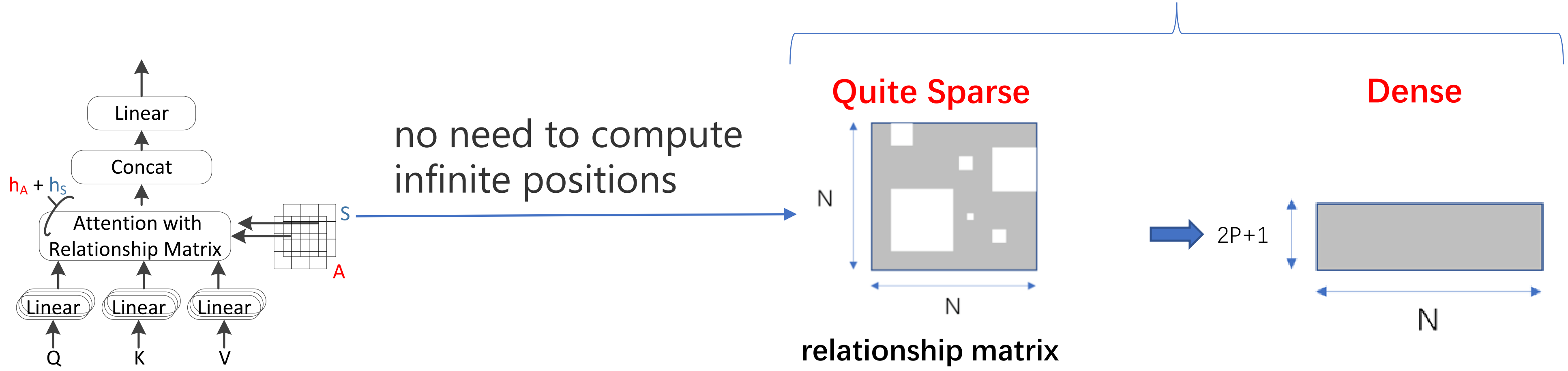
- K^P and Q^P are hype parameter matrices with shape (2P+1) X m
- $K^P_{\boldsymbol{\delta}(i,j)}$ is the $\delta(i, j)$-th row of K^P
- $\alpha_{i,j}$ = ∞ if $\boldsymbol{\delta}$(i,j) = ∞ (no need to compute)

	Compare	NameLoad(x)	Lt	constant(0)
Compare	0	1	1	1
NameLoad(x)	-1	0	∞	∞
Lt	-1	∞	0	∞
constant(0)	-1	∞	∞	0



5. Model Implementation

Gather with decomposed COO (GDC) Algroithm



GDC Algorithm:

1. Decompose the matrix
2. Reorder query and key context by col_index and row_index separately
3. Compute the attention scores

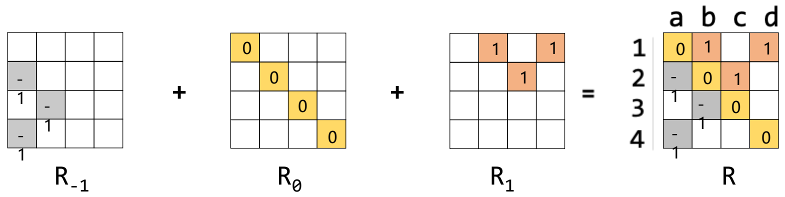
COO format

$$\begin{pmatrix} 5 & 0 & 0 & 0 \\ 0 & 8 & 0 & 0 \\ 0 & 0 & 3 & 0 \\ 0 & 6 & 0 & 0 \end{pmatrix}$$

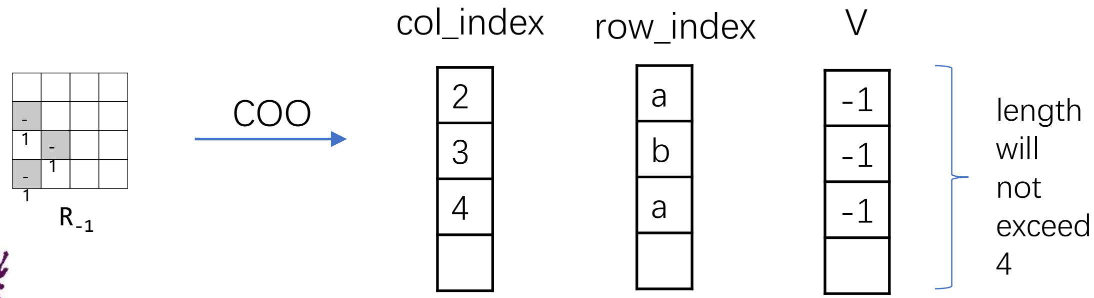
```
V         = [ 5 8 3 6 ]
COL_INDEX = [ 0 1 2 1 ]
ROW_INDEX = [ 0 1 2 3 ]
```

5. Model Implementation

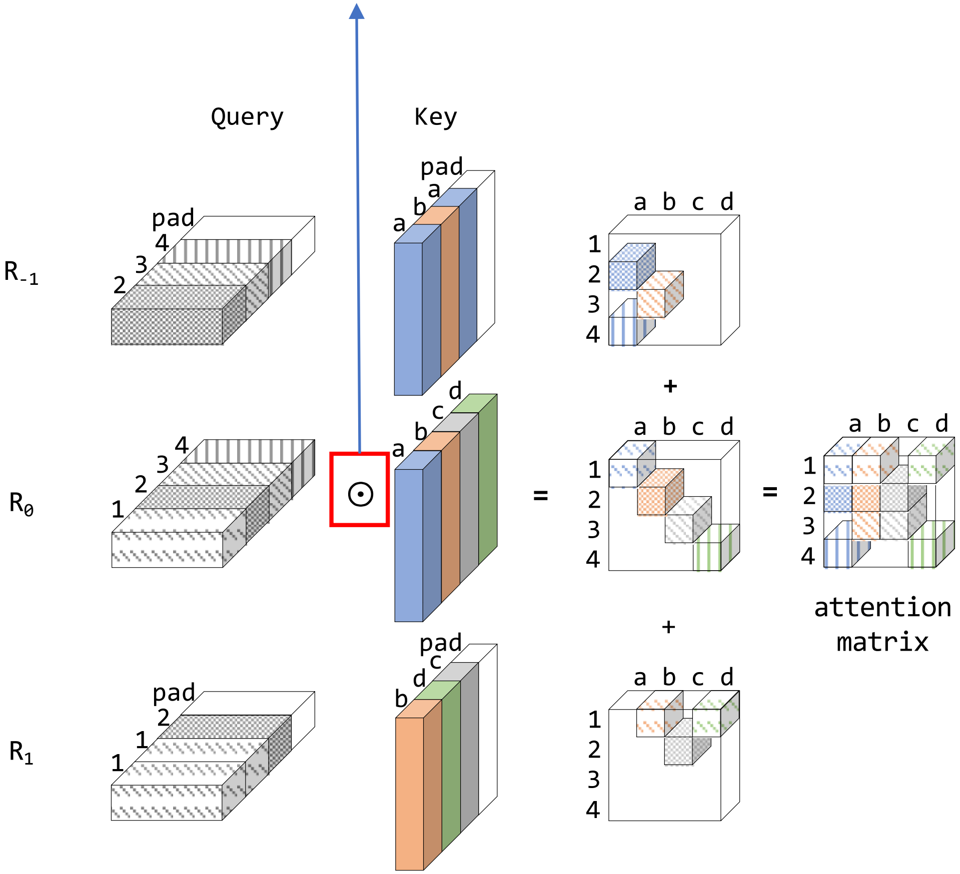
***Theorem**: the number of node pairs with the same distance length in relationship matrix will not exceed the size of the tree.*



1) **Decompose the matrix**: group node pairs with the same distance(value).



complexity: quadratically (matrix production) -> linearly(dot production)



2) Reorder query and key context by col_index and row_index separately

3) Compute the attention scores

6. Results —— Compared with baselines

Methods	Input	Java			Python		
		BLEU (%)	METEOR (%)	ROUGE-L (%)	BLEU (%)	METEOR (%)	ROUGE-L (%)
CODE-NN[20]	Code	27.6	12.61	41.10	17.36	09.29	37.81
API+CODE[19]		41.31	23.73	52.25	15.36	08.57	33.65
Dual Model[53]		42.39	25.77	53.61	21.80	11.14	39.45
BaseTrans*[1]		44.58	29.12	53.63	25.77	16.33	38.95
Code-Transformer*[57]		45.74	29.65	54.96	30.93	18.42	43.67
Tree2Seq[11]	AST(Tree)	37.88	22.55	51.50	20.07	08.96	35.64
RL+Hybrid2Seq[51]		38.22	22.75	51.91	19.28	09.75	39.34
GCN*[22]		43.94	28.92	55.45	32.31	19.54	39.67
GAT*[50]		44.63	29.19	55.84	32.16	19.30	39.12
Graph-Transformer*[40]		44.68	29.29	54.98	32.55	19.58	39.66
Code2Seq*[4]	AST(PD)	24.42	15.35	33.95	17.54	08.49	20.93
Code2Seq(Transformer)*		35.08	21.69	42.77	29.79	16.73	40.59
DeepCom[18]	AST(SBT)	39.75	23.06	52.67	20.78	09.98	37.35
Transformer(SBT)*		43.37	28.36	52.37	31.33	19.02	44.09
AST-Trans(SBT)*		44.15	29.58	54.73	32.86	19.89	45.92
Transformer(POT)*	AST(POT)	39.62	26.30	50.63	31.86	19.63	44.73
AST-Trans		**48.29**	**30.94**	**55.85**	**34.72**	**20.71**	**47.77**

6. Results —— Complexity

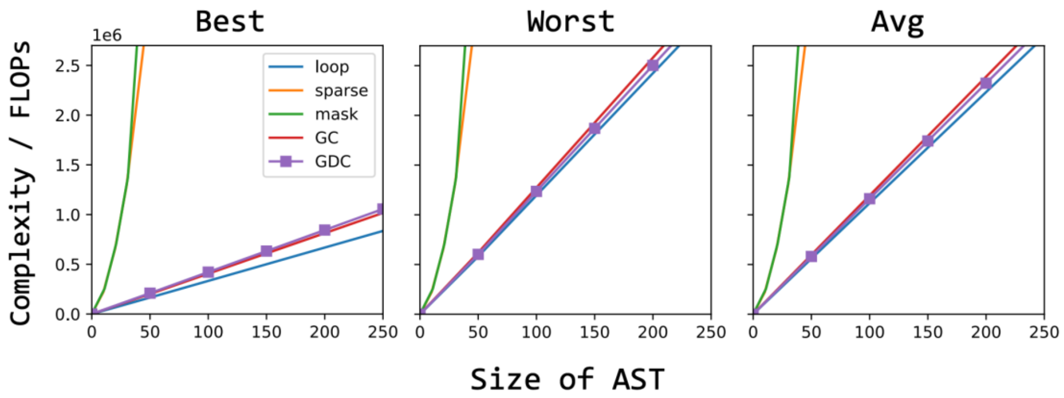


Figure 5: Theoretical complexity with $P = 5$, $m = 32$. loop has the lowest complexity but cannot be parallelized in practice.

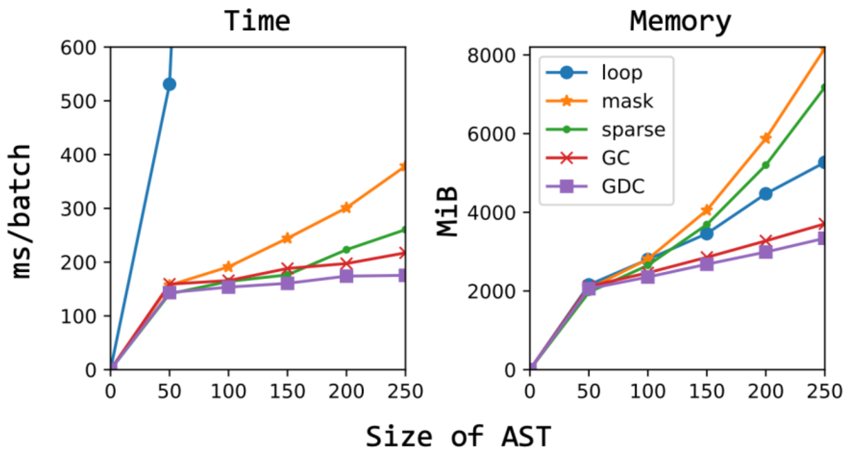


Figure 7: Runtime and memory cost of five implementations with batch size=16. The cost of the mask implementation is equal to the standard Transformer, which grows quadratically with the AST size.

Theoretical complexity

Runtime and memeory cost in GPU

Reference

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THANKS