BIG BIRD AND XLNET

Jonah Winninghoff

THESIS

Two text summarizations are compared using specific metrics and a timer.

- Transferred Learnings: Big Bird and XLNet Transformers
- Metrics: Recall-Oriented Understudy for Gisting Evaluation (ROUGE)
- Timer with CPU 1.6 GHZ

THESIS

Two text summarizations are compared u

Transferred Learnings: Big Bird

Metrics: Recall-Oriented Under

Timer with CPU 1.6 GHZ

BUT SO WHAT?

The Transformers has self-attention expensive to compute especially for longer sequence.

The Google Research team attempts to solve this using block sparsity.

Their mathematical assessment shows that this approach reduces this quadratic dependency to linear dependency in time or memory term, which is skeptical.

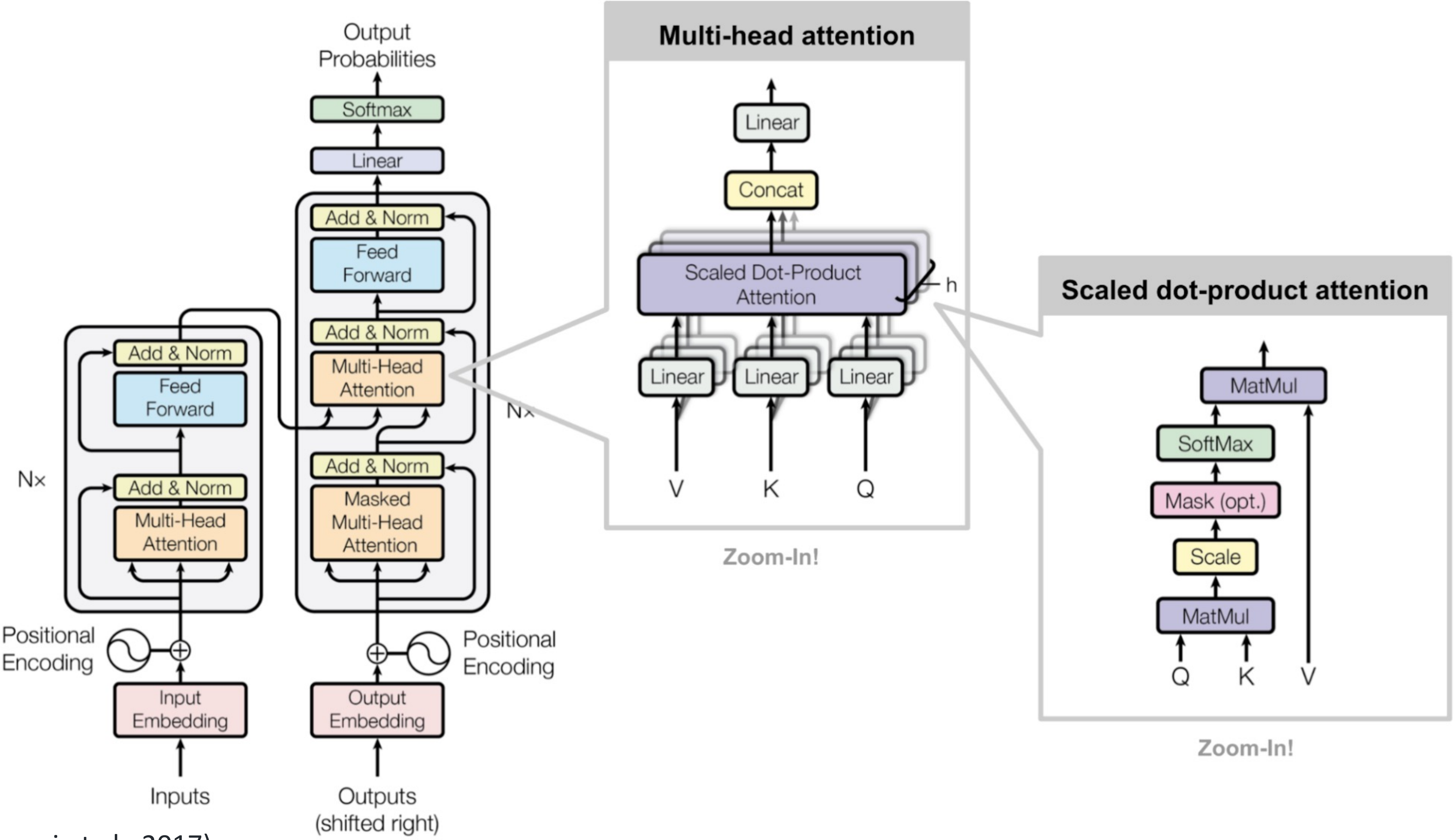
OUTLINE

- Describe Transformers and Big Bird architectures
- Explain method, dataset, and research questions
- Share actionable insights and future research ideas

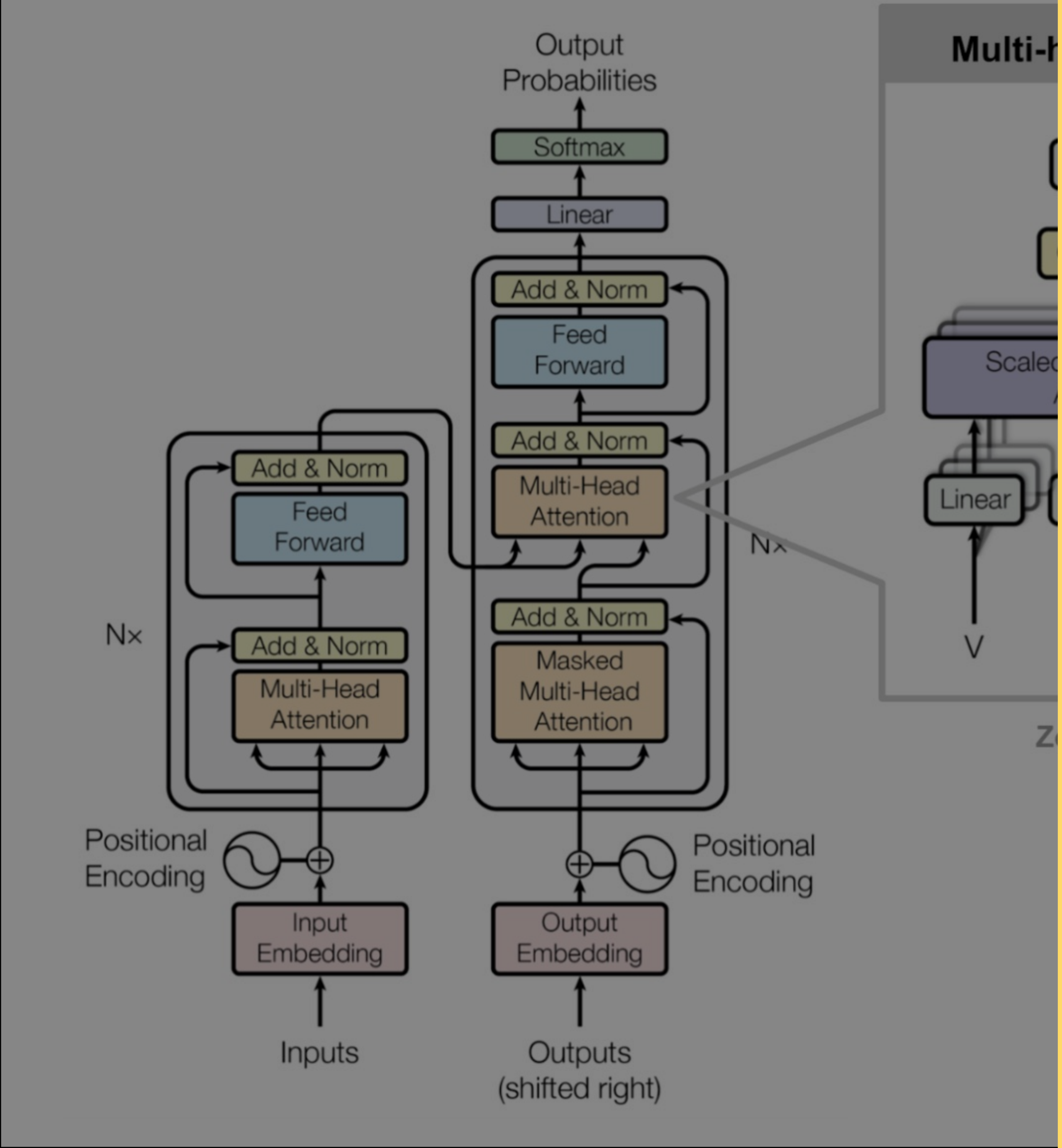
sing specific metrics and a timer.

and XLNet Transformers

study for Gisting Evaluation (ROUGE)



(Vaswani et al., 2017)



TRANSFORMERS ARCHITECTURE

The representation of encoder is the word embedding of X (x_1, …, x_n), such as article text.

The representation of decoder is the word embedding of Z (z_1, …, z_n), such as ground-truth summary.

Multi-head attention contains *head*$_i$ that contains attention.

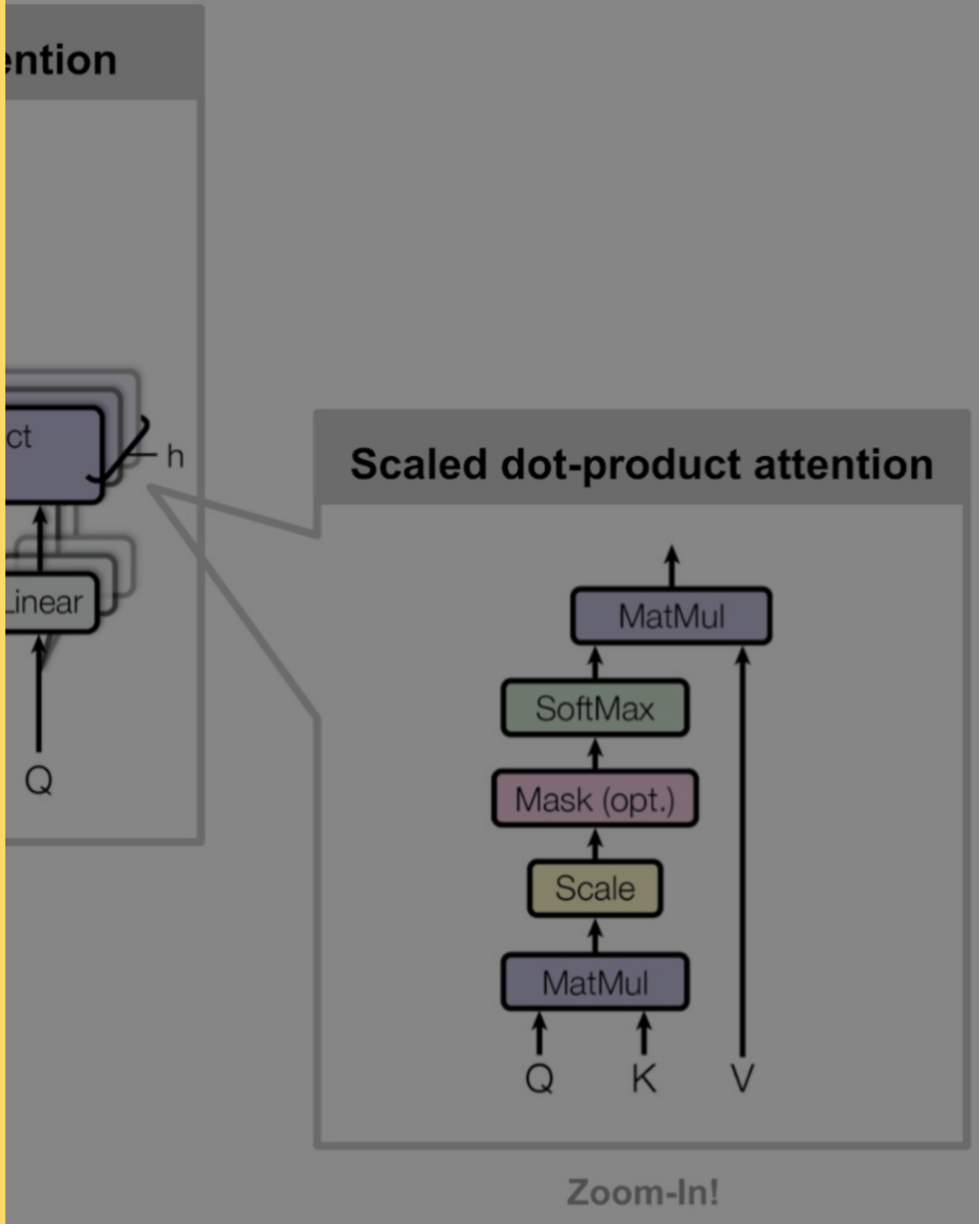
FORMULAS:

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

$$head_i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right)$$

$$MultiHead(Q,K,V) = Concat(head_i,\ldots, head_h)$$

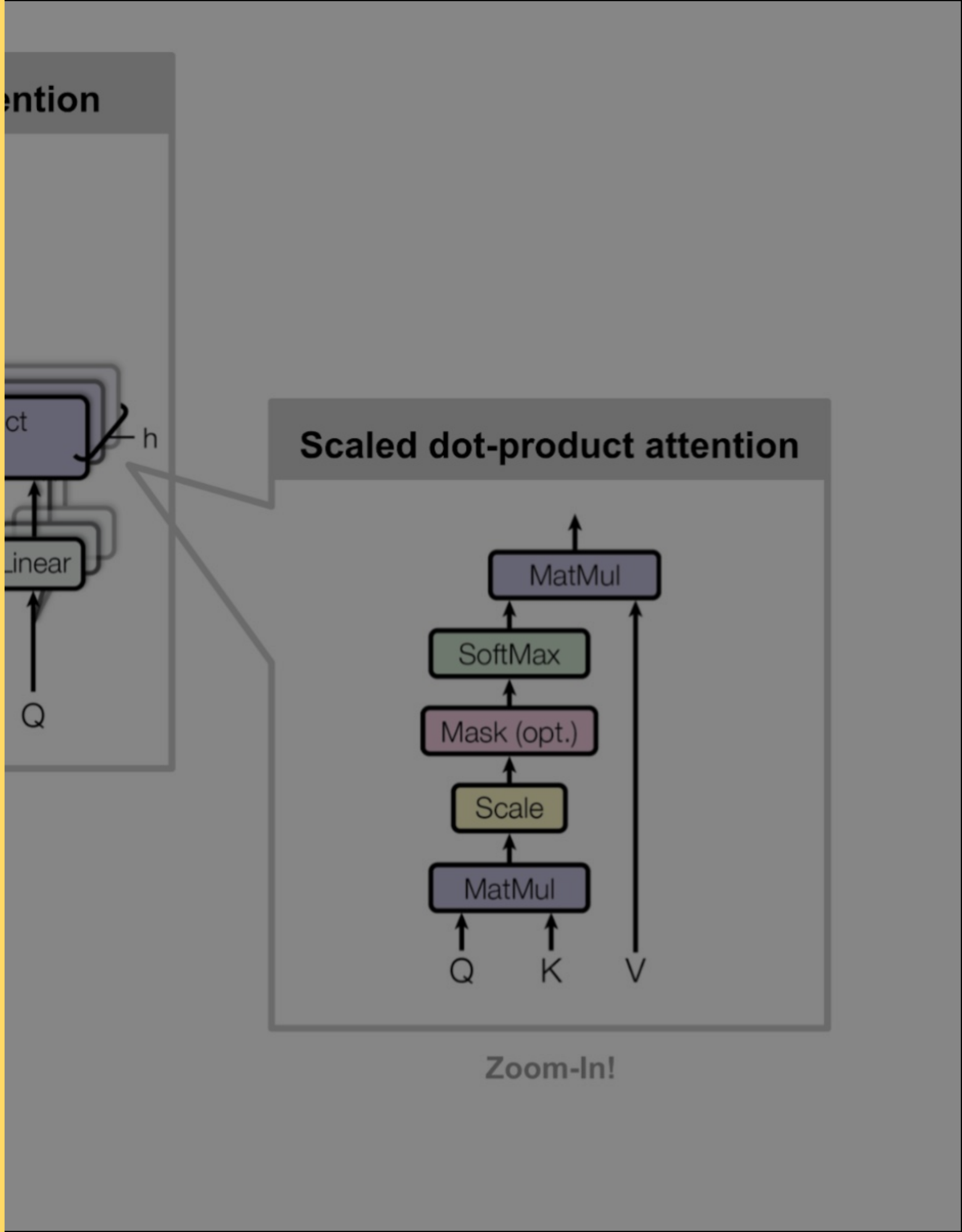
Q = a matrix of queries
K = a matrix of keys
V = a matrix of values (or weights)
W = a matrix of weights
d_k = dimensionality of key

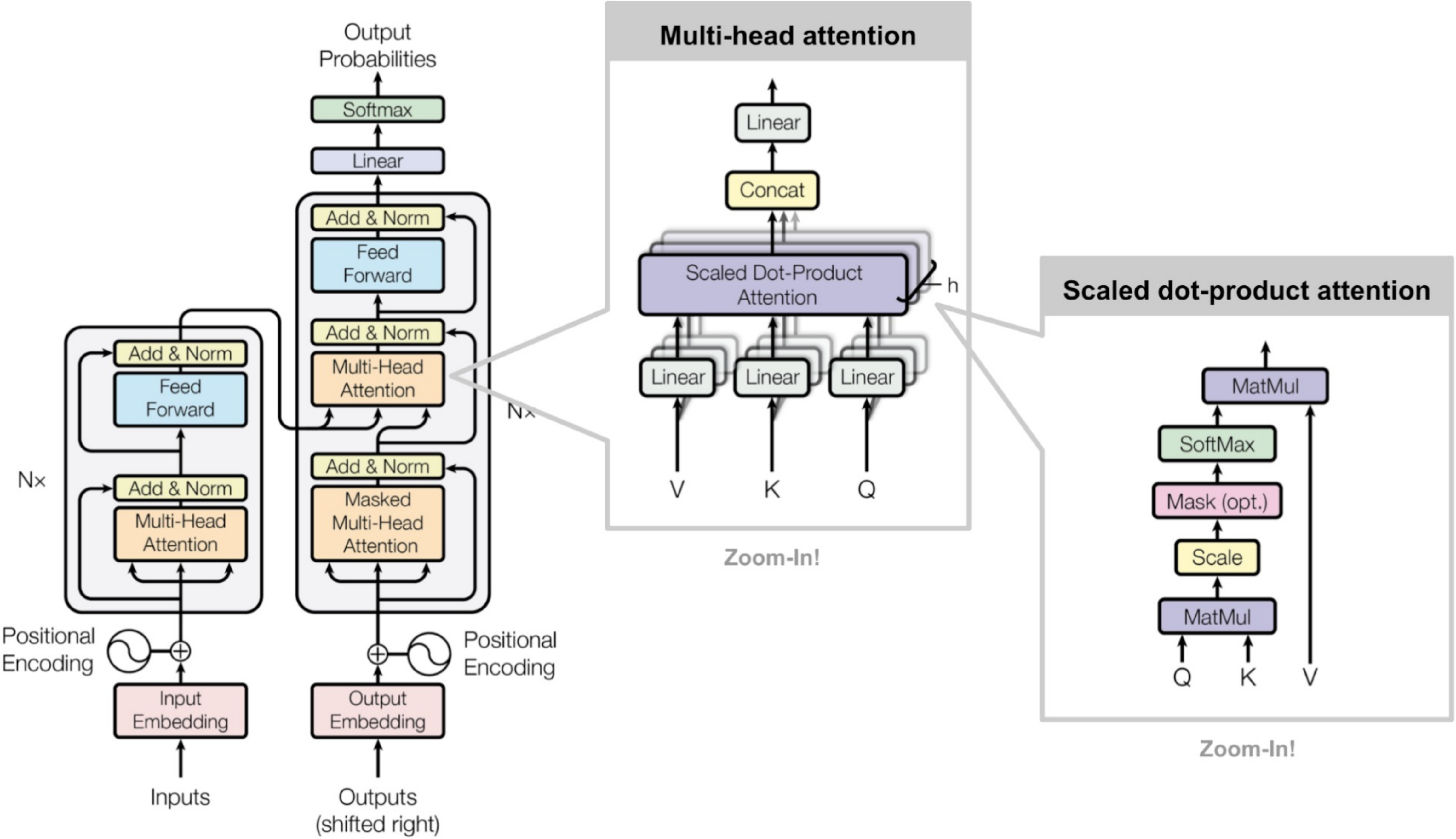


XLNET

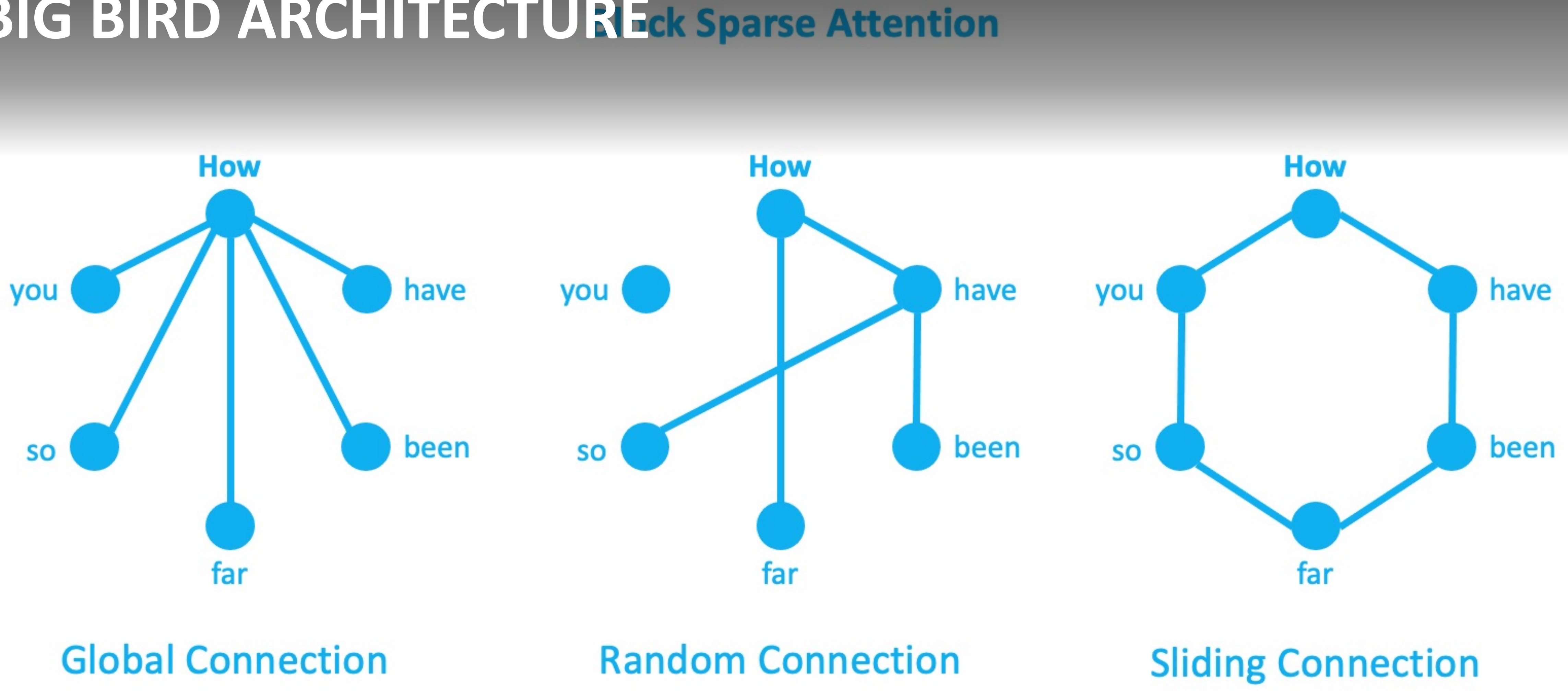
For this research, the XLNet is in use. This model is different by maximum log likelihood of the sequence *wrt* permutation being in used.

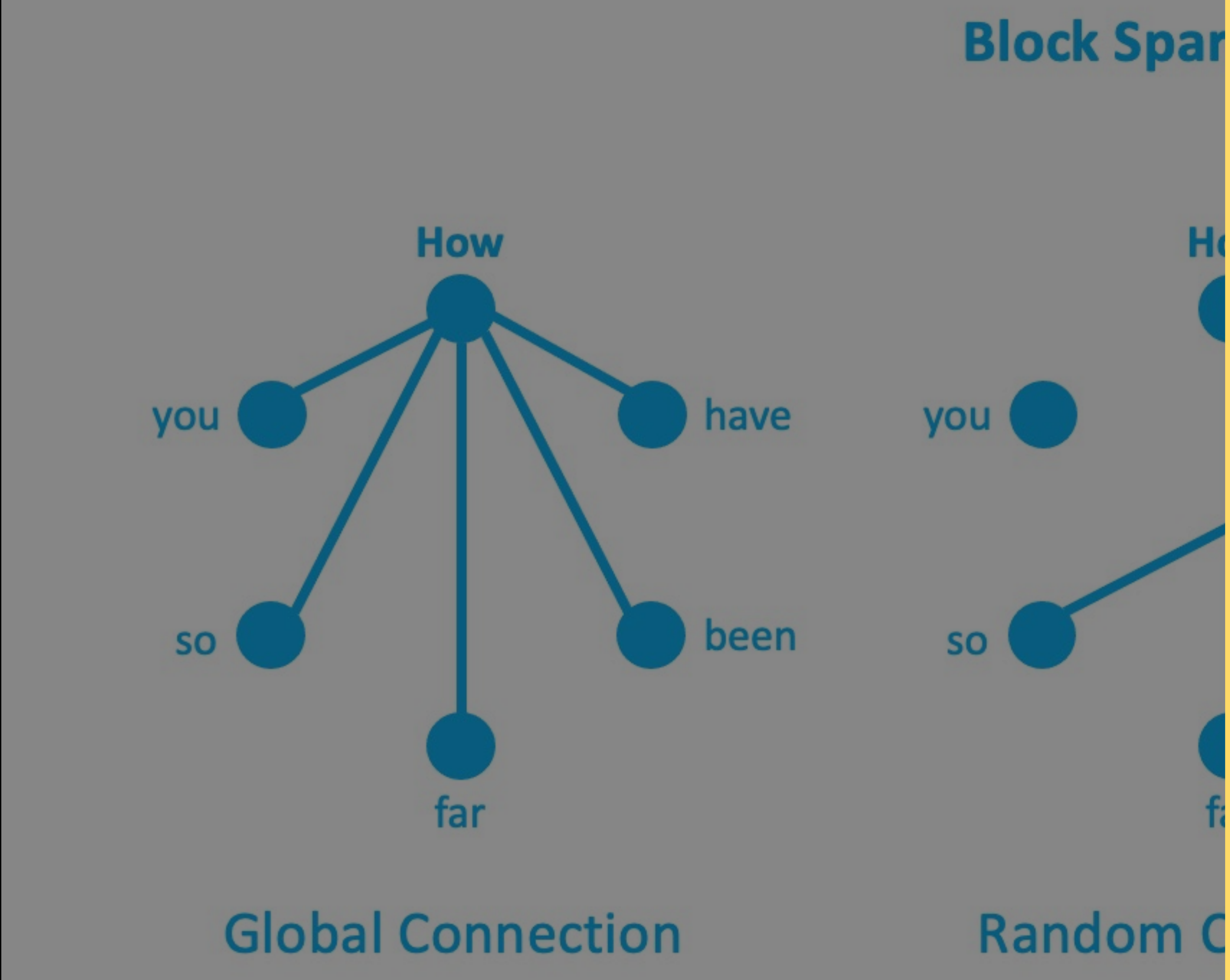
The fundamental of the model remains same.




Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Nx
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Nx
Positional Encoding
Positional Encoding
Input Embedding
Output Embedding
Inputs
Outputs (shifted right)
Multi-head attention
Linear
Concat
Scaled Dot-Product Attention
h
Linear
Linear
Linear
V
K
Q
Zoom-In!
Scaled dot-product attention
MatMul
SoftMax
Mask (opt.)
Scale
MatMul
Q
K
V
Zoom-In!

BIG BIRD ARCHITECTURE





BLOCK SPARSITY

The concept of sliding and global connections is not novel but what is new is random connection.

Perhaps, the Google Research team develops the random connection based on CLT and LLN.

For example, predicted summaries become more consistent when sequence length is longer.

But this comes with the price of no theoretical guarantees.

METHOD

- Partial NLP data science pipeline and Randomized Controlled Trials (RCTs)
- Variables: article, actual abstract, predicted abstract, word counts for each, and type of model.
- Target variables: time per predicted abstract (in seconds), ROUGE-1 F1 score, ROUGE-2 F1 score, and ROUGE-L F1 score

METHOD

Partial NLP data science pipe

Variables: article, actual abs
each, and type of model.

Target variables: time per pr
score, ROUGE-2 F1 score, anc

ROUGE-N

ROUGE-N F1-score is a measure of model accuracy based on a number of matching n-grams between predicted and ground-truth summaries.

For example, ROUGE-1 means a number of matching unigram.

ROUGE-1 means a number of matching the longest common subsequence (LCS).

DATASET

The arXiv journals prepared by TensorFlow is in use, which contains *article_id*, *article_text*, and *actual abstract text*.

Three subsets: testing (6,658 entities), training (119,924 entities), and validation (6,633 entities) sets.

70.8% of tokens in article texts matches NLTK dictionaries while 62.05% in abstract text matches these dictionaries

ine and Randomized Controlled Trials (RCTs)

tract, predicted abstract, word counts for

redicted abstract (in seconds), ROUGE-1 F1
ROUGE-L F1 score

DATASET

For this research, validation set is in use. This set is unseen, technically.

Why?

- Big Bird model is pretrained with Wikipedia dataset.
- XLNet model is pretrained with several datasets other than arXiv.

Random sampling for this set to predict is 110 in total for each model. This data collection takes two days.

ine and Randomized Controlled Trials (RCTs)

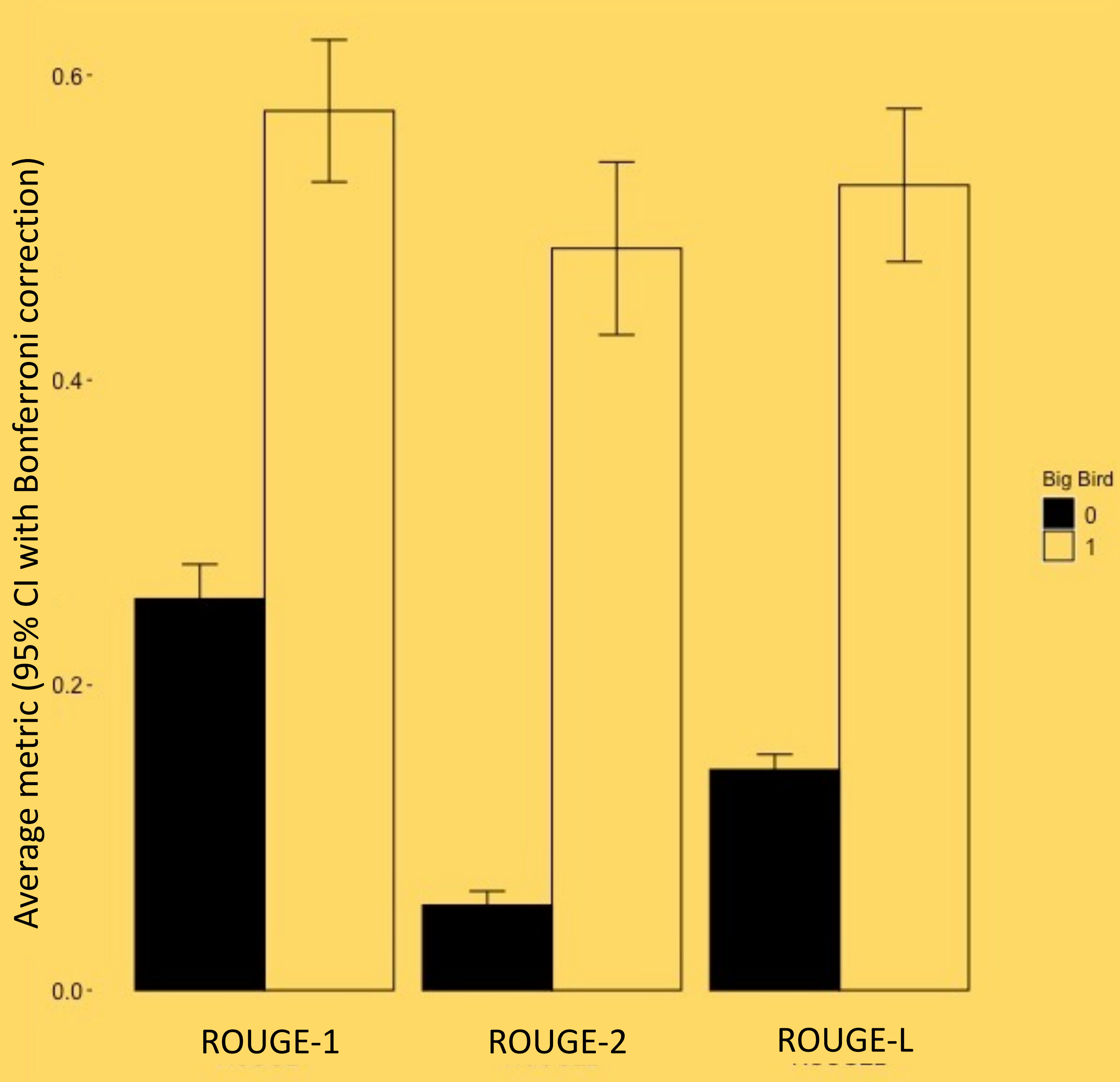
tract, predicted abstract, word counts for

edicted abstract (in seconds), ROUGE-1 F1

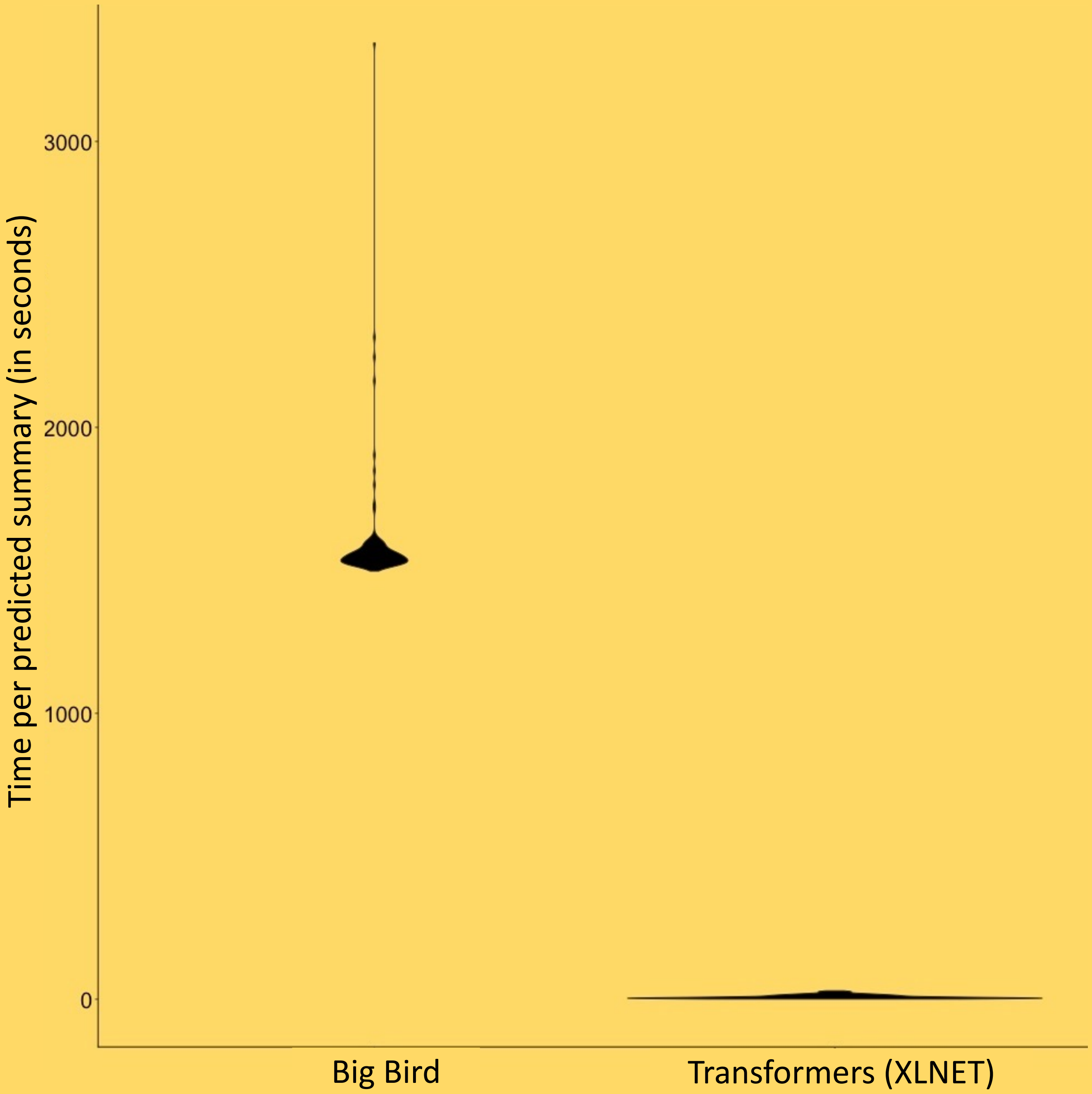
ROUGE-L F1 score

RESEARCH QUESTIONS

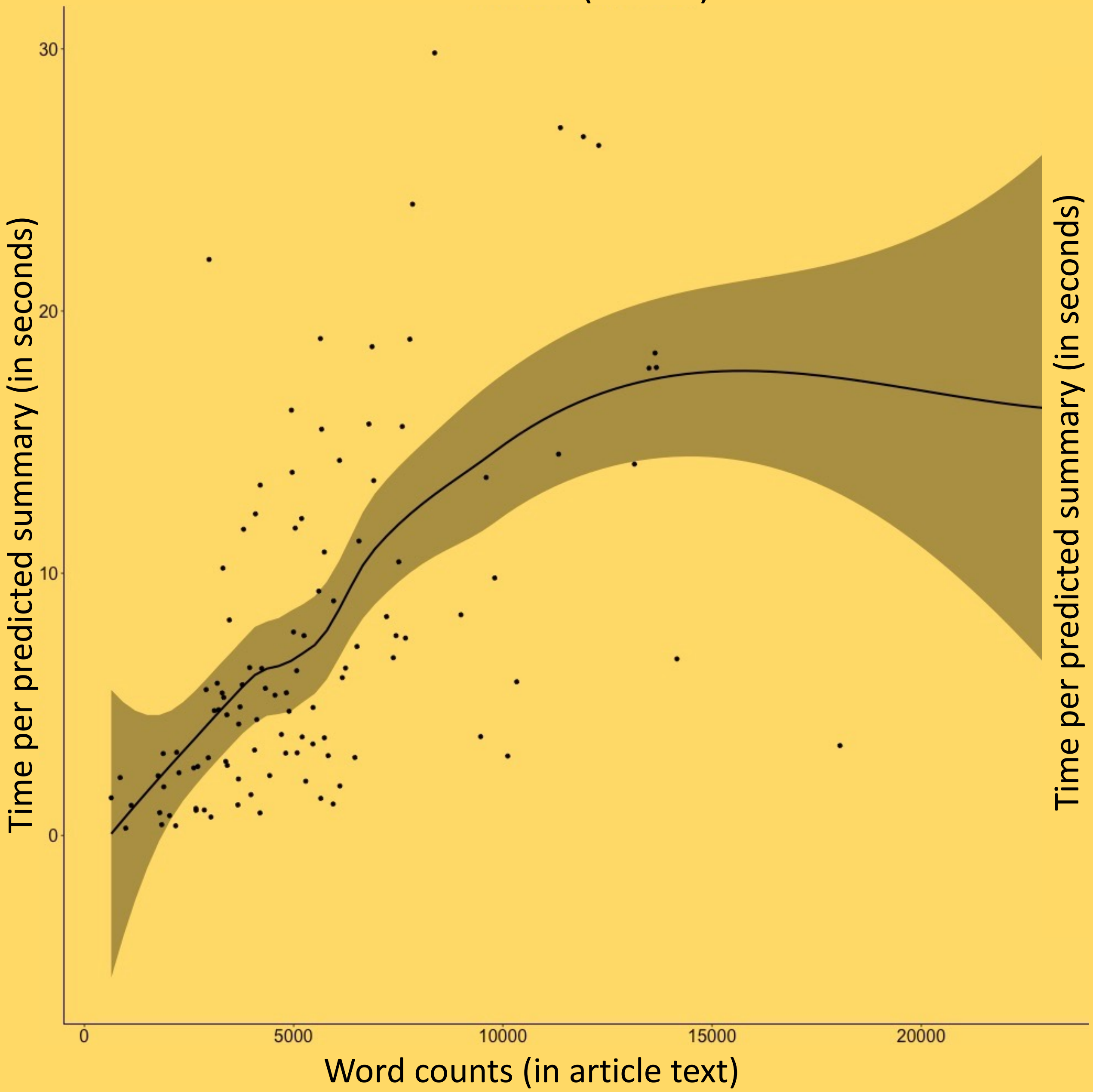
- Does the Big Bird model outperform XLNet model?
- Being compared with XLNet model, how fast Big Bird can produce each predicted summary?
- Does the Big Bird successfully reduce this quadratic dependency to linear dependency in sequence term?



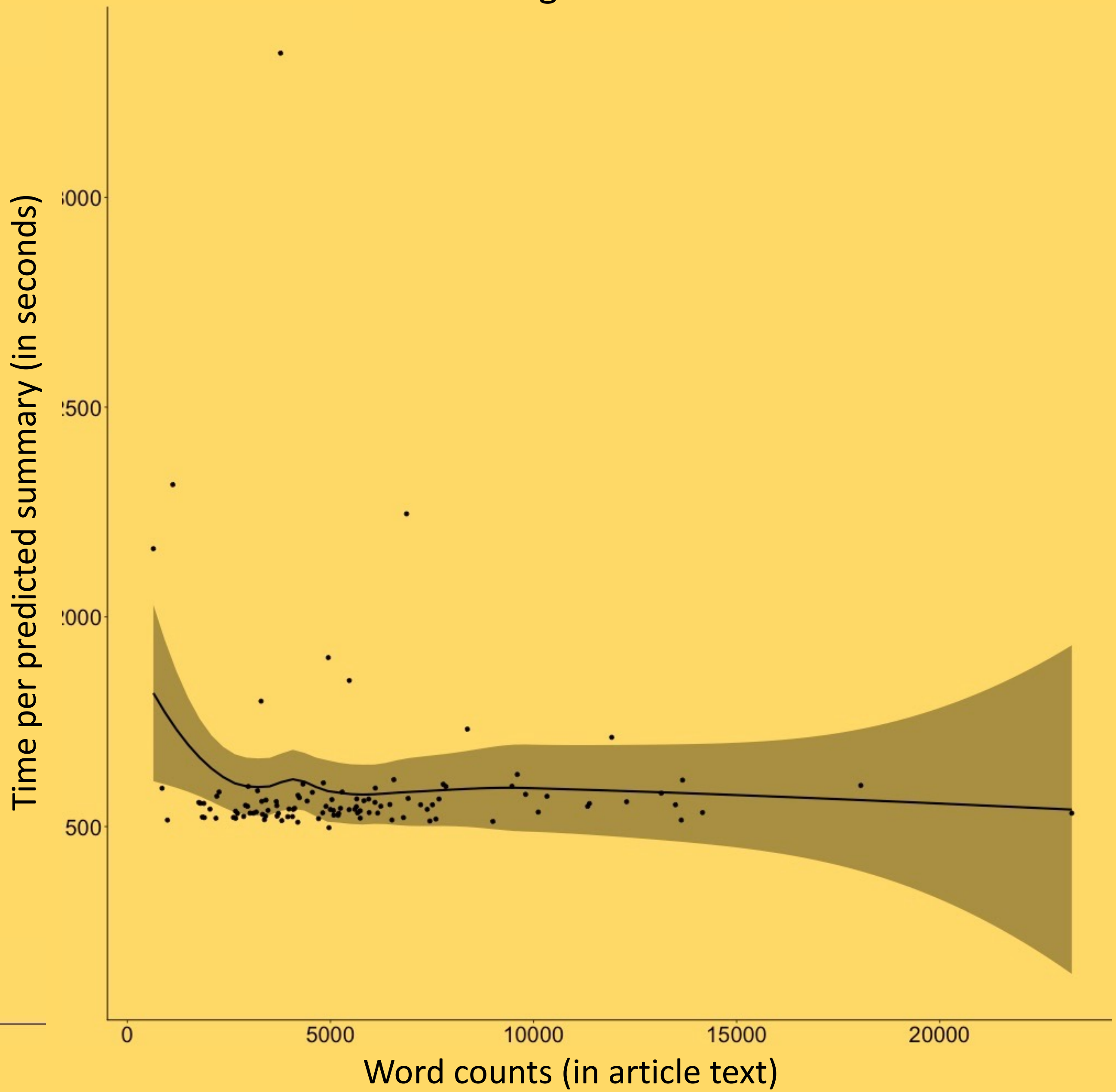
Average metric (95% CI with Bonferroni correction)
0.6
0.4
0.2
0.0
ROUGE-1
ROUGE-2
ROUGE-L
Big Bird
0
1

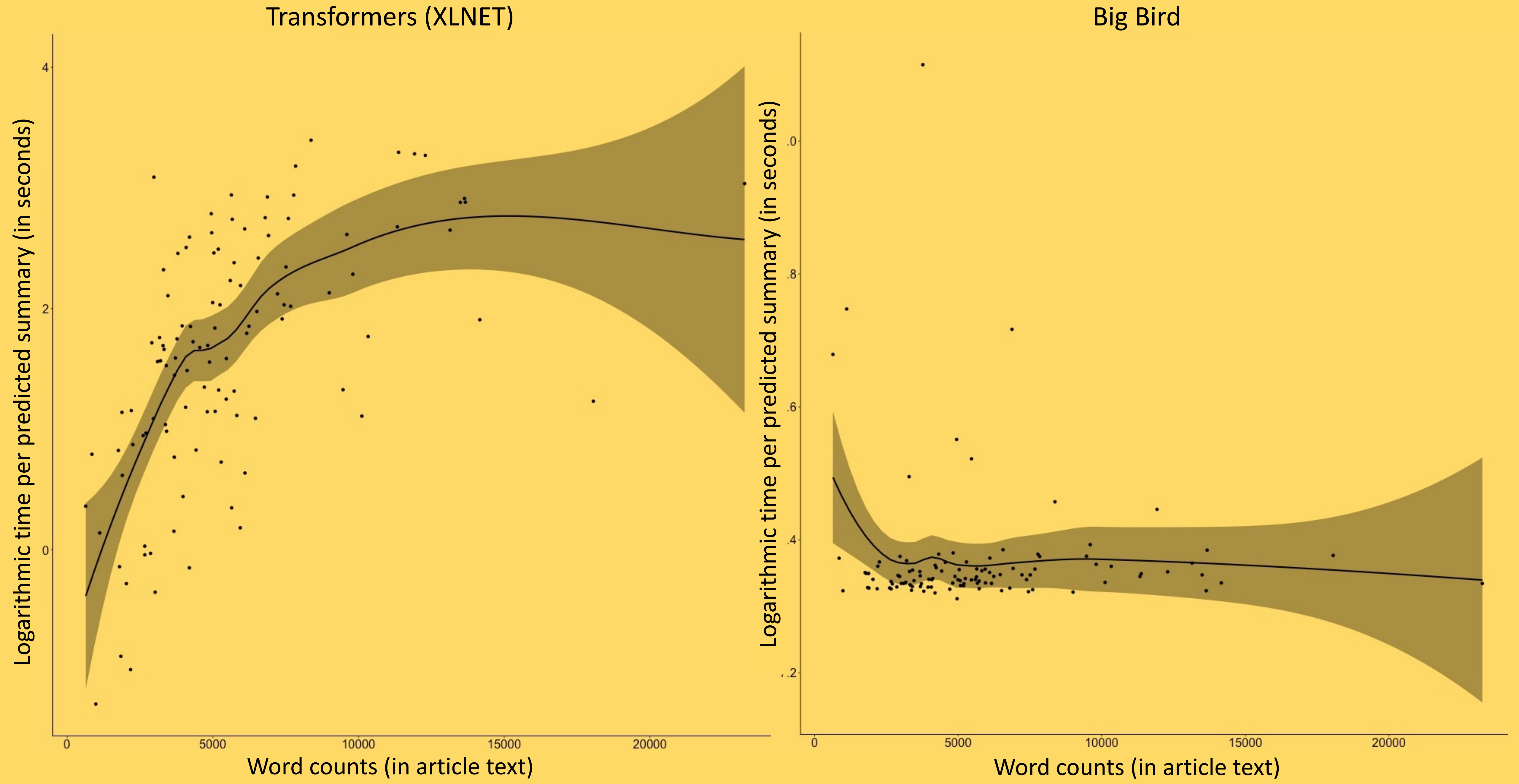

Time per predicted summary (in seconds)
3000
2000
1000
0
Big Bird
Transformers (XLNET)

Transformers (XLNET)



Big Bird





Transformers (XLNET)
Logarithmic time per predicted summary (in seconds)
4
2
0
0
5000
10000
15000
20000
Word counts (in article text)
Big Bird
Logarithmic time per predicted summary (in seconds)
.0
.8
.6
.4
.2
0
5000
10000
15000
20000
Word counts (in article text)

CONCLUSION AND FUTURE WORK

Big Bird model does better with predicting summary and successfully linearize self-attention. However, the speed of this model is 193.04 wpm by median.

The Big Bird algorithm is highly recommended for producing summaries as long as if the cloud environment is in use.

To address scalability and redundancy problems, Attention Free Transformer and Bayesian connection need to be tested with block sparsity.

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