



GROUP No.: 11

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AUTOMATIC ABSTRACT GENERATION USING LSTMs

INTRODUCTION

❖ Abstract

- Summarizes major aspects of a research article



Objective of the research
problem(s) investigated



Methodolgy employed to solve
the problem



**Results & their
interpretations**

WHY USE LSTM?

1 Scientific Articles have Long-Term Dependencies

Additionally, as described in Section 5 we apply a MERT tuning step after training using the DUC-

2 Summarization using LSTMs shown to work better than other summarizing methods

Model	ROUGE-1	DUC-2004	
		ROUGE-2	ROUGE-L
IR	11.06	1.67	9.67
PREFIX	22.43	6.49	19.65
COMPRESS	19.77	4.02	17.30
W&L	22	6	17
TOPIARY	25.12	6.46	20.12
MOSES+	26.50	8.13	22.85
ABS	26.55	7.06	22.05
ABS+	28.18	8.49	23.81
REFERENCE	29.21	8.38	24.46

Model	Encoder	Perplexity
KN-Smoothed 5-Gram	none	183.2
Feed-Forward NNLM	none	145.9
Bag-of-Word	enc ₁	43.6
Convolutional (TDNN)	enc ₂	35.9
Attention-Based (ABS)	enc ₃	27.1

3 Summarizing long documents using LSTMs unexplored

CHALLENGES INVOLVED

1 Scientific Articles are **too long to be processed** for current GPUs using **LSTMs**

2 Each scientific article contains **new ideas, approaches and results**

3 **Good quality, large-scale datasets** required

4 **Unique structure of Scientific Articles** needs a different modelling

DATASET

❖ [arXiv.org](https://arxiv.org)

- Online repository of e-prints of scientific articles

❖ [Crawled LaTeX Sources](#) of articles in following fields:

- Information Retrieval (**cs.IR**)
- Computation and Language (**cs.CL**)
- Machine Learning (**cs.LG**)
- Artificial Intelligence (**cs.AI**)

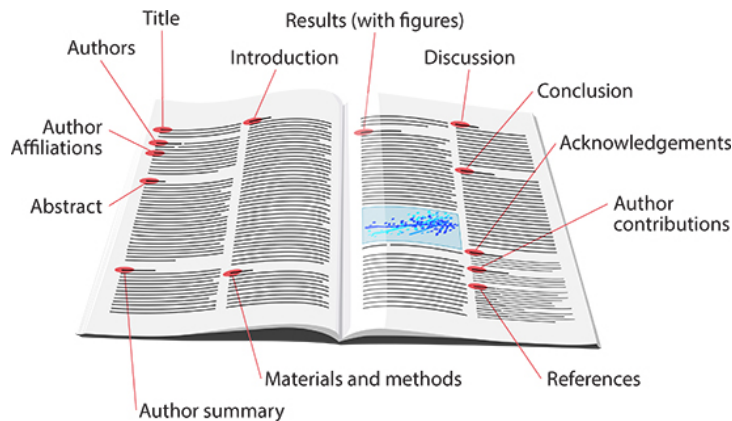


❖ **Size of the Dataset:** 16,780 articles

GENERAL APPROACH



Processed & Marked



Generate Representation

Reduced Length

Abstractive Summarization using LSTMs

Final Summary/
Abstract



PREPROCESSING

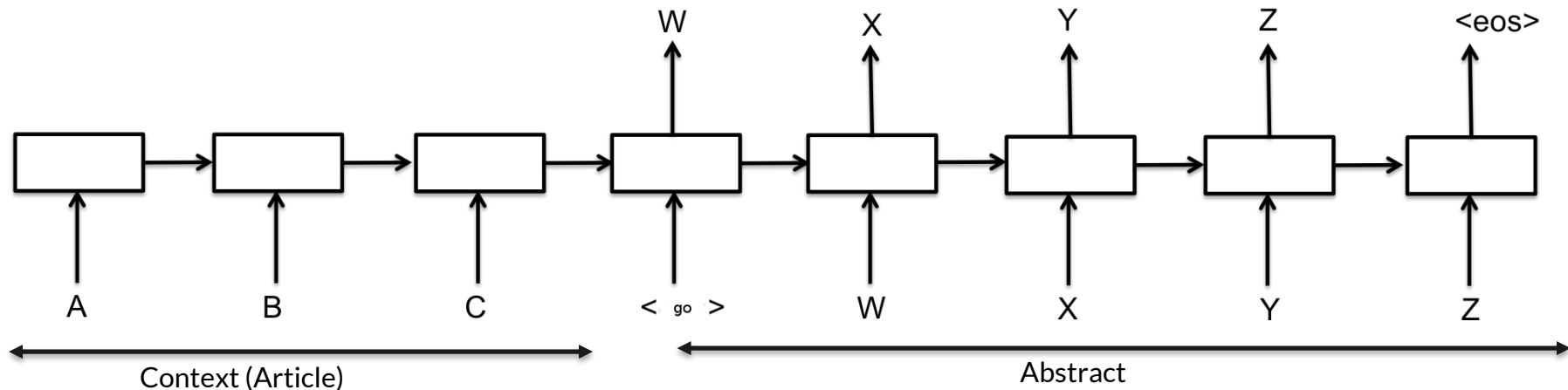
❖ `pylatexenc`

- Python library for parsing LaTeX to generate text

❖ Modifications

- 1 Sections and Subsections of article were identified and marked
- 2 Figures, Tables and Mathematical Equations were replaced by representative tokens
- 3 Obtained Structure was converted to LSTM input format

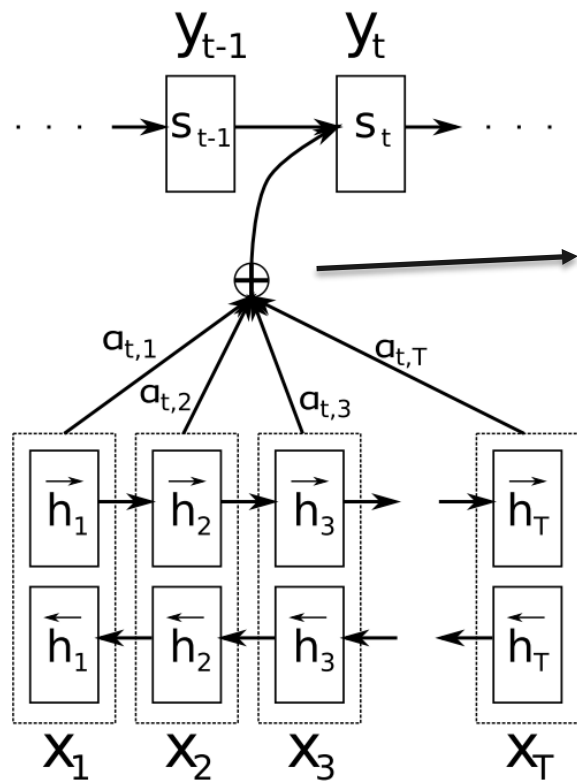
Sequence to Sequence Model



❖ Consists of two recurrent neural networks (RNNs):

- **Encoder:** Processes the input -> Sentences in the article or its Representation
- **Decoder:** Generates the output -> Abstract

ATTENTION MECHANISM



Output of encoder module as an additional conditioning input to Decoder

- Condition the RNN by a convolutional attention-based encoder

❖ Advantage:

- Informs the decoder **which part of the input sentence it should focus on** to generate the next word
- Both Decoder and Encoder are jointly trained on the data set.

TAKE 1: Using Extractive Summary

❖ Reduce length using Extractive Summarization :

- Lex-Rank
- C-Lex-Rank
- Text-Rank
- Luhn
- Edmundson
- LSA
- Sum-Basic



Extractive Summary
of 2000 words



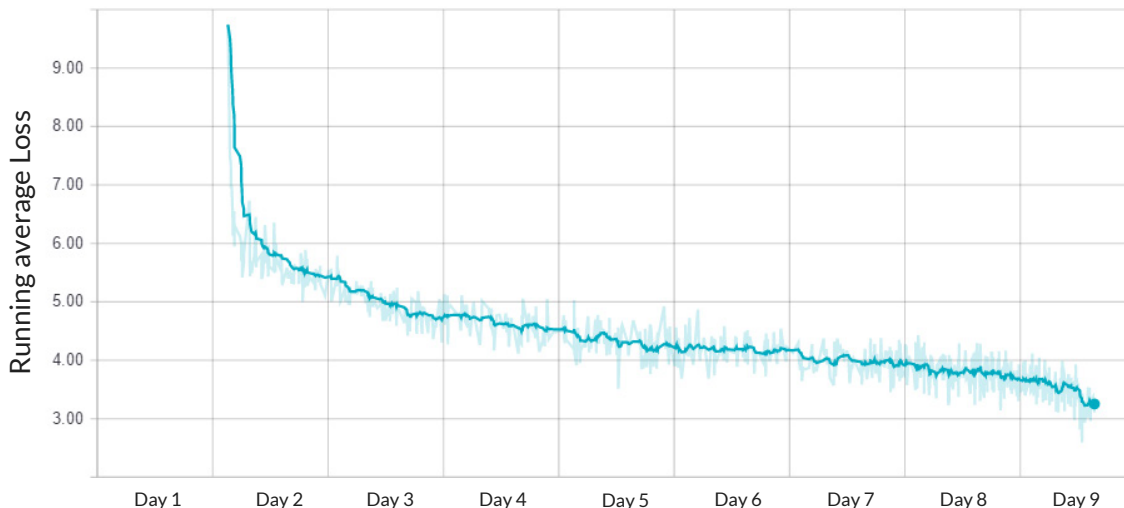
Sequence to Sequence
Model with Attention
Mechanism



VARIATIONS IN TAKE 1

❖ No. of Words in Extractive Summary:

- Computationally expensive to use large number of words (2000)



- Instead use a small extractive summary (250 words)

EXAMPLE OUTPUTS 1

Actual Abstract

the machine learning community adopted the use of null hypothesis significance testing (nhst) in order to ensure the statistical validity of results . many scientific fields however realized the shortcomings of frequentist reasoning and in the most radical cases even banned its use in publications . we should do the same : just as we have embraced the bayesian paradigm in the development of new machine learning methods , so we should also use it in the analysis of our own results .

- ROUGE-1: 0.334
- ROUGE-2: 0.076
- ROUGE-L: 0.204
- **Drawback:** Small Extractive summary misses out a lot of information

LSTM Generated

boltzmann media (resnets) have recently achieved places on challenging computer vision tasks . we introduce resnet in resnet (rir) : a deep architecture that generalizes resnets and standard cnns and is easily implemented with no computational overhead . rir consistently improves performance over resnets , outperforms architectures with similar amounts of augmentation on cifar-## , and establishes a new state-of-the-art on cifar-### .

TAKE 2: Paragraph Embeddings

❖ Para2Vec:

- **Unsupervised Learning of continuous representations for larger blocks of text, such as sentences, paragraphs or entire documents**

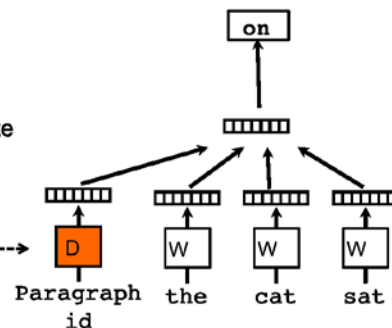


Separate Sections

Classifier

Average/Concatenate

Paragraph Matrix



Paragraph embeddings for each section

SUMMARY

Sequence to Sequence
Model with Attention
Mechanism

EXAMPLE OUTPUTS 2

Actual Abstract

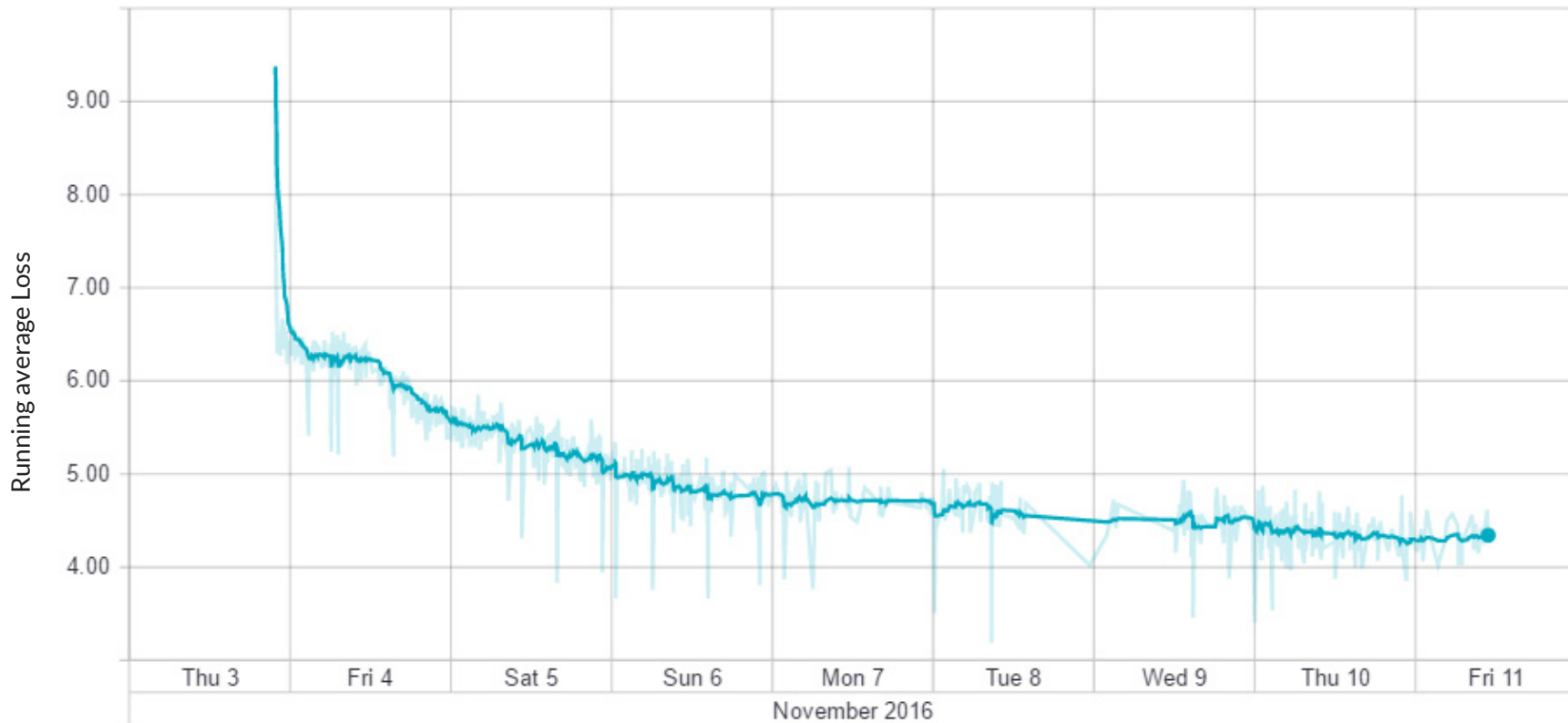
we present an approach of learning multi-sense word embeddings relying both on monolingual and bilingual information . our model consists of an encoder , which uses monolingual and bilingual context (i.e . a parallel sentence) to choose a sense for a given word , and a decoder which predicts context words based on the chosen sense . the two components are estimated jointly . we observe that the word representations induced from bilingual data outperform the

- ROUGE-1: 0.475
- ROUGE-2: 0.158
- ROUGE-L: 0.307

LSTM Generated

to address this paper , we propose a novel method for learning translation , which is able to learn the word of words in a sequence of words . we show that our approach can be used to be used to improve the performance of words in the context of words . our results show that our method can be used to improve the performance of words in the context of words.

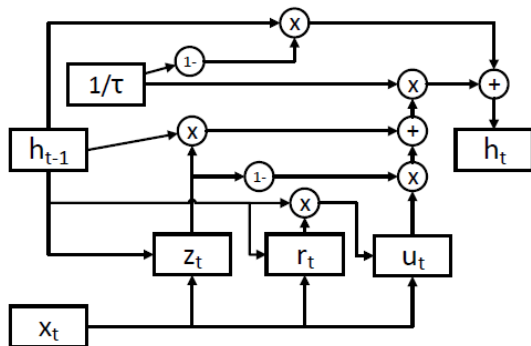
Paragraph Embeddings Status



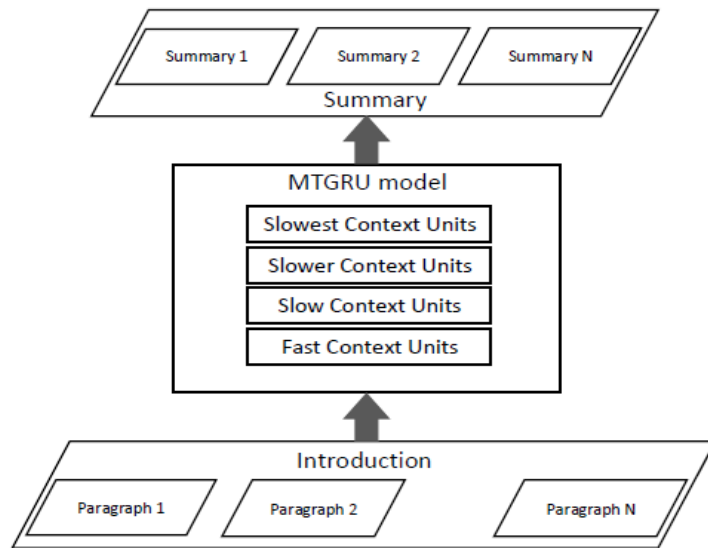
TAKE 3: Multiple Timestamp Gated Recurrent Unit

❖ Temporal Hierarchies to Sequence to Sequence Model:

- Apply a timescale constant at the end of a GRU
- Adds another constant gating unit which modulates the mixture of past and current hidden states.



MT-GRU Unit



MT-GRU Summarization Approach

Conclusion

- Novel attempt to summarize long scientific articles using LSTMs
- Proposed 2 abstractive summarization approaches:
 - **Extractive Summarization** followed by **Seq2Seq Model**
 - Utilizing **Paragraph Embeddings**
- **LSTMs have potential** to work for long documents but **require more computational power**

Future Work

- Use a **larger and richer dataset** for the problem
- Utilize better **computational resources**
- Make changes to the proposed models to make it more **robust**

THANK YOU !



"Ms. Jones, there are a number of big questions here to see you. They say they won't leave until they have some answers."