



Topic oriented Summarization using Transformer based Encoder Decoder model

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DialogSum Challenge: Summarizing Real-Life Scenario Dialogues^[1]

- Challenge – Given a piece of multi-turn dialogue text, generate a salient, concise, fluent and coherent summary
- Motivation - investigate the challenges in dialogue summarization.
- Dialogue – an important channel for achieving communication intents, different from monologic texts in nature
- Applications - chatbot and personal assistant.

Dialogue Text:

#Person1#: Why didn't you tell me you had a girlfriend?

#Person2#: Sorry, I thought you knew.

#Person1#: But you should tell me you were in love with her.

#Person2#: Didn't I?

#Person1#: You know you didn't.

#Person2#: Well, I am telling you now.

#Person1#: Yes, but you might have told me before.

#Person2#: I didn't think you would be interested.

#Person1#: You can't be serious. How dare you not tell me you are going to marry her?

#Person2#: Sorry, I didn't think it mattered.

#Person1#: Oh, you men! You are all the same.

Summary from Dataset:

#Person1#'s angry because **#Person2#** didn't tell **#Person1#** that **#Person2#** had a girlfriend and would marry her.

Topic from Dataset: have a girlfriend

Dataset Description



Public dataset - train, dev, test and hidden-test dataset^[2]



Train - (12,460), dev - (500) consist of single human annotated summary and short topic for each dialogue



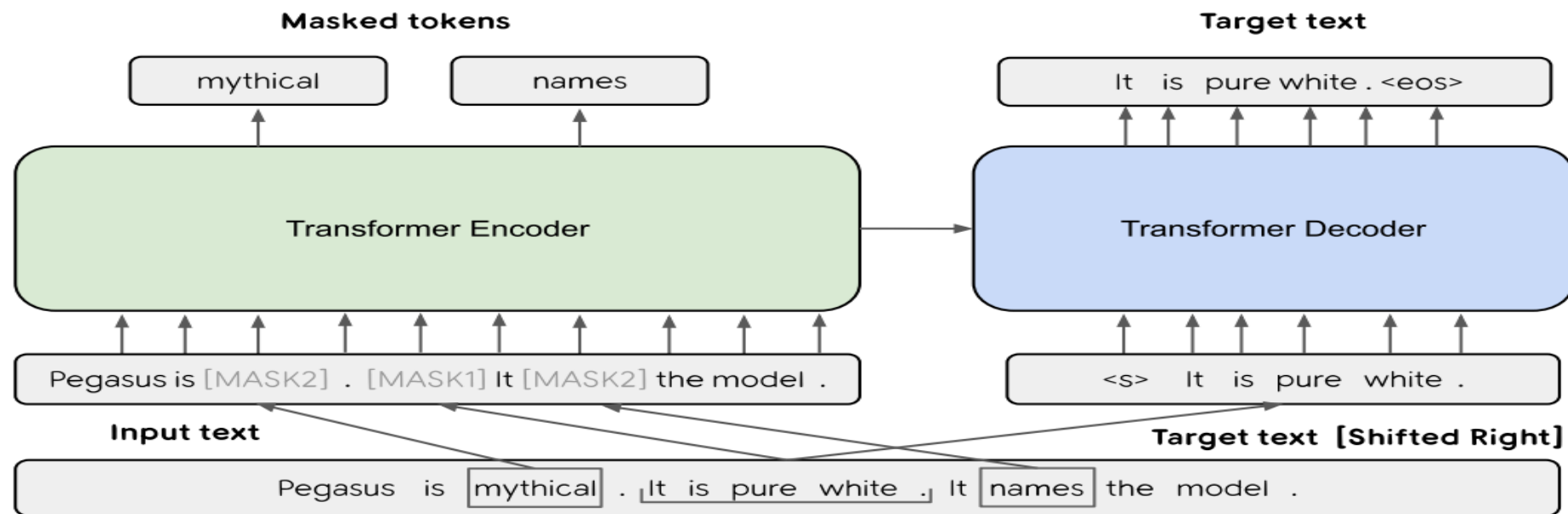
Test - (500) consists of 3 annotated summary and associated 3 short topic for each dialogue.



Hidden test - (100) dialogue and topics.

Challenges

- Diverse Interactive patterns between speakers as well as inherent topic drifts
- A frequent coreference and ellipsis make dialogue difficult to understand.
- Linguistic phenomena make dialogues difficult to encode using ordinary representation learning technologies.
- Objective summary requires summary from an observer's perspective
- Dialogue actions at the pragmatic level – It not only summarizes what the speakers are saying but also what they are doing



The base architecture of PEGASUS [3]. Both GSG and MLM are applied simultaneously in this example.

Variants –

- PEGASUS_{BASE} – 12 layers and H=768
- PEGASUS_{LARGE} – 16 layers and H=1024

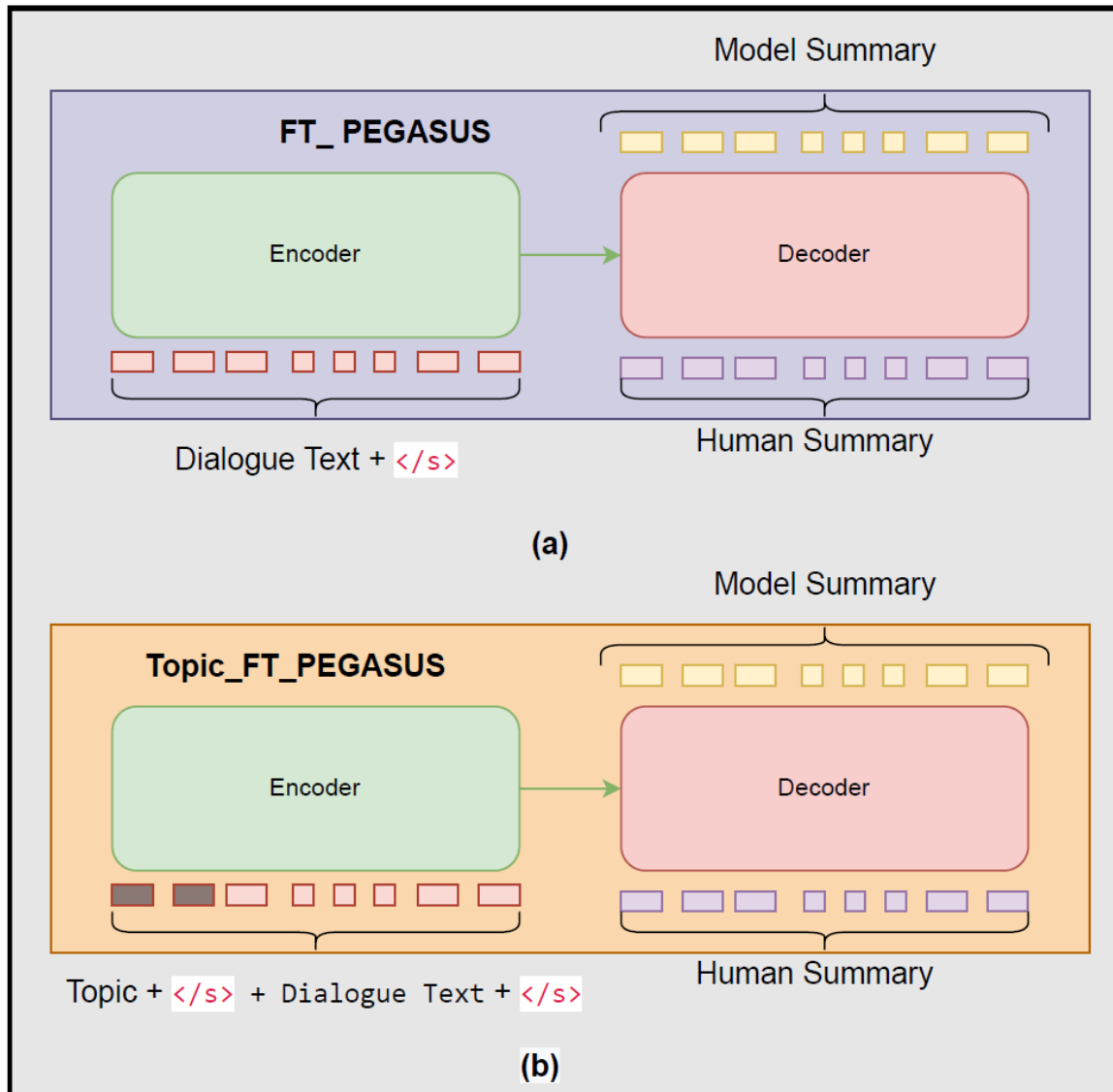
Pre-training

Corpora – C4 & HugeNews

Objectives –

- Masked Language Model (MLM)
- Gap Sentence Generation (GSG)

Proposed Method – Topic_FT_PEGASUS



Sample Output

Dialogue Text

#Person1#: Who stands out in your mind as a man or woman of sound character?
#Person2#: If I think of famous people, I think of Abraham Lincoln.
#Person1#: He's the US president, who walked five miles just to give a lady her change, isn't he?
#Person2#: That's the one. He also was famous for never giving up on his goals.
#Person1#: That's right. He ran for office quite a few times before he was finally elected.
#Person2#: And I also admire him for his courage in fighting for equal rights.
#Person1#: He had great vision, didn't he?
#Person2#: And humility. I would have liked to meet him personally.

Topic – sound character

Model Summary

#Person1# and #Person2# talk about who stands out in their mind as a man or woman of sound character.

Human Summary

#Person1# and #Person2# are talking about Abraham Lincoln. They think he was a noble man.

Topic – famous people

Model Summary

#Person1# and #Person2# are talking about famous people. They admire Abraham Lincoln for his great vision, courage, and humility.

Human Summary

#Person2# admires Abraham Lincoln for his perseverance, courage and humility.

Topic – discuss Abraham Lincoln

Model Summary

#Person1# and #Person2# talk about Abraham Lincoln as a man or woman of sound character.

Human Summary

#Person1# and #Person2# talk about Abraham Lincoln and his glorious history. They both admire him.

Experiments and Results

Model	Average Score				Best Score			
	R1	R2	RL	B-S	R1	R2	RL	B-S
PT_PEGASUS	25.99	6.41	20.97	87.77	37.63	9.63	26.48	88.15
FT_PEGASUS	43.36	18.36	36.23	92.19	51.59	26.58	45.54	92.64
Topic_FT_PEGASUS	49.42	21.81	40.85	92.22	54.53	32.00	51.47	93.22

Evaluation results over the public test dataset.

Baselines

- PT_PEGASUS – pretrained PEGASUS_LARGE generate the summary using dialogue text as an input.
- FT_PEGASUS – fine-tuned PEGASUS_LARGE using DialogSum train and dev dataset with input dialogue text as input.

Evaluation Metric - ROUGE and BERTScore

Observations

- Fine-tuning helped the model to learn the linguistic phenomena of dialogues.
- Incorporating topics while fine-tuning allows the model to focus on different text segments centred around a given topic.

DialogSum Challenge Leaderboard

S.No.	Team	R1	R2	RL	BERTScore
1	GoodBai	49.66	26.03	48.44	91.69
2	UoT	49.75	25.15	46.50	91.76
3	IITP-CUNI	45.89	21.88	43.16	91.13
4	TCS_WITM_2022*	50.32	25.59	47.40	91.81

Evaluation Result on the Hidden Testset. Evaluated by the challenge organisers.

*evaluated the prediction topic-wise

Conclusions and Future Work

- Generate a topic-oriented summary using pre-trained abstractive model
- Shown that the PEGASUS can be fine-tuned using the proposed methodology.
- Proposed methodology performed significantly better than baselines.

Future work

- Incorporating nuances of dialogue, speech act theory etc.
- Propose a model that generate topic from dialogue

References

- [1] Yulong Chen, Yang Liu, and Yue Zhang. 2021b. Dialogsum challenge: Summarizing real-life scenario dialogues. In Proceedings of the 14th International Conference on Natural Language Generation, pages 308–313.
- [2] Yulong Chen, Yang Liu, Liang Chen, and Yue Zhang. 2021a. DialogSum: A real-life scenario dialogue summarization dataset. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 5062–5074, Online. Association for Computational Linguistics.
- [3] Jingqing Zhang, Yao Zhao, Mohammad Saleh, and Peter Liu. 2020. Pegasus: Pre-training with extracted gap-sentences for abstractive summarization. In International Conference on Machine Learning, pages 11328–11339. PMLR.



Thank You

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