MetaSumPerceiver

3rd August 2024

Need for fact-checking

1. AI-generated content is increasing. LLMs subject to hallucinations
2. Fact-checking manually is laborious

Multi-modality & Summarization

1. Summarization from all types of input (image, text, audio.. etc) is needed
2. Claim-specific summarization is more important for fact checking

Assessment

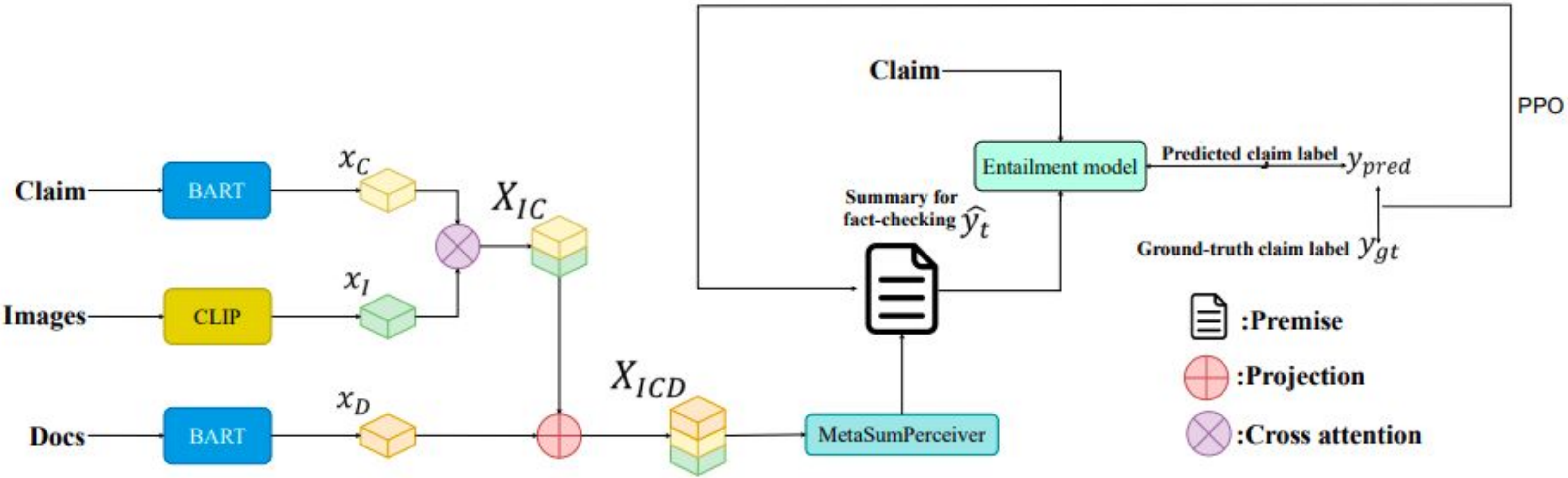
1. Entailment (given premise-hypothesis text fragments, can one be inferred from another)
2. MSP aims to generate the premise for a specific claim from a pool of multimodal data.

Contribution

1. Multi-News-Fact-Checking (claims and their entailment labels)

Perceiver (high-dim data → latents by iterative cross attention)
BART (Encoder & Decoder, trained as denoiser)
CLIP (Maps images and text embeddings)

Xc (NxD), Xd (MxD) where N, M num of tokens
Xi (KxD) where K is num of tokens
Xic cross attention (represents claim specific images) → Here Q comes from claim, KV comes from image
Xicd is projection of Xic & Xd (all the input data in latent space) → Input to summarization model



Multi-News-Fact-Checking dataset

1. Dataset required must have claims whose facts are drawn from multiple documents along with the entailment label of each claim
2. Created using LLama 2 to generate claims based on Multi-News dataset

Initial training

Initially only the perceiver model is trained with the summarization model to create summaries given multi-modal input. i.e only y^t is compared with ground truth summaries y^i

Fine-tuning

Summarization model is fine-tuned using an entailment model to generate summaries relevant to the claims. i.e y_pred is compared with y_gt.

y_pred is the prediction of entailment value between summary created by summarization model and the claim.
y_gt is the ground truth of entailment value between summary created by summarization model and the claim

This training is done using feedback with reinforcement learning (instead of human, it is the entailment model) using PPO

1. RL on Perceiver
2. RL on Perceiver and Summarizer

Reinforcement learning with reward

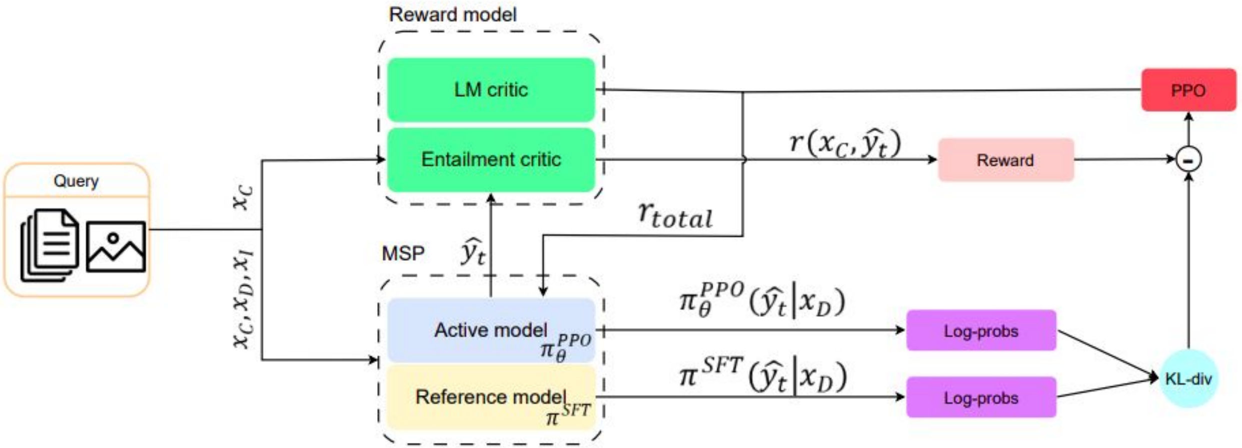
1. Reward = p_gt (entailment label) given the claim and the generated summary.
2. Primary objective is to maximize the likelihood that the generated summary for fact-checking contains the facts necessary for the model to predict the claim’s ground truth label.

Proximal Policy Optimization

1. Total reward: r - KL-div (comparing the likelihood of token sequences in the response with both the currently fine-tuned active model and a pre-trained reference model)
2. r also includes an LM critic which gives r_quality (clarity and conciseness)

$$r(x_C, \hat{y}_t) = P(y_{gt}|x_C, \hat{y}_t) -$$
$$0.5 * \Sigma_{y_{gt} \neq y_{pred}} P(y_{pred}|x_C, \hat{y}_t),$$

$$r_{total} = (r_{quality} + r(x_C, \hat{y}_t) -$$
$$\eta KL(\pi_\phi^{PPO}(\hat{y}_t|x_D), \pi^{SFT}(\hat{y}_t|x_D)))/2,$$



Results

1. Test on MOCHEG dataset
2. Fixed Entailment models (DeBERTAV3 and Llama 2)
3. LM Critic helps (concise summaries → better entailment scores)
4. Better with both text and image evidence

Setting	Accuracy (%)	Precision (%) Supported	Precision (%) Refuted	Precision (%) NEI	Recall (%) Supported	Recall (%) Refuted	Recall (%) NEI
MSP (Entail. critic) w/ Text Evidence → DeBERTAV3	43.7	79.2	66.9	**33.9**	40.5	30.6	25.8
MSP (Entail. critic) w/ Text + Img Evidence → DeBERTAV3	50.8	83.4	**69.3**	27.3	42.9	34.2	30.9
MSP (Entail. critic) w/ Text Evidence → Llama 2	46.7	80.4	68.1	31.5	37.2	35.4	31.5
MSP (Entail. critic) w/ Text + Img Evidence → Llama 2	**53.7**	**87.3**	60.3	32.4	**48.3**	**36.9**	**34.8**
MSP (Entail., LM critics) w/ Text Evidence → DeBERTAV3	40.2	77.3	63.4	**45.9**	38.2	35.7	28.4
MSP (Entail., LM critics) w/ Text + Img Evidence → DeBERTAV3	47.8	78.1	**67.5**	38.1	39.5	**37.5**	34.1
MSP (Entail., LM critics) w/ Text Evidence → Llama 2	49.3	81.5	65.2	37.4	39.7	31.5	35.7
MSP (Entail., LM critics) w/ Text + Img Evidence → Llama 2	**55.6**	**88.2**	57.5	39.6	**51.2**	32.4	**37.2**