Eliciting Rich Positive Emotions in Dialogue Generation

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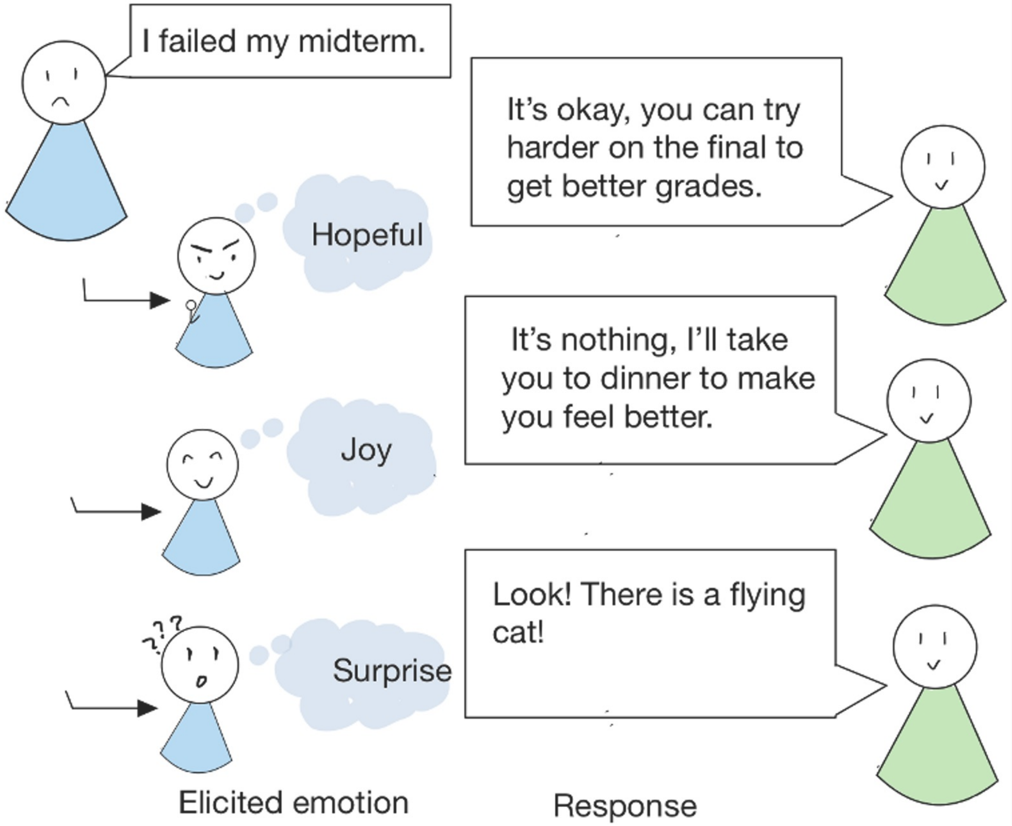
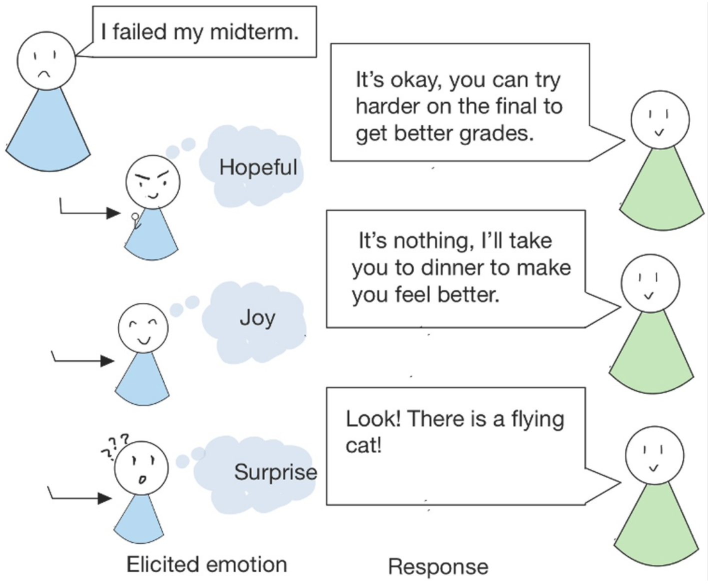
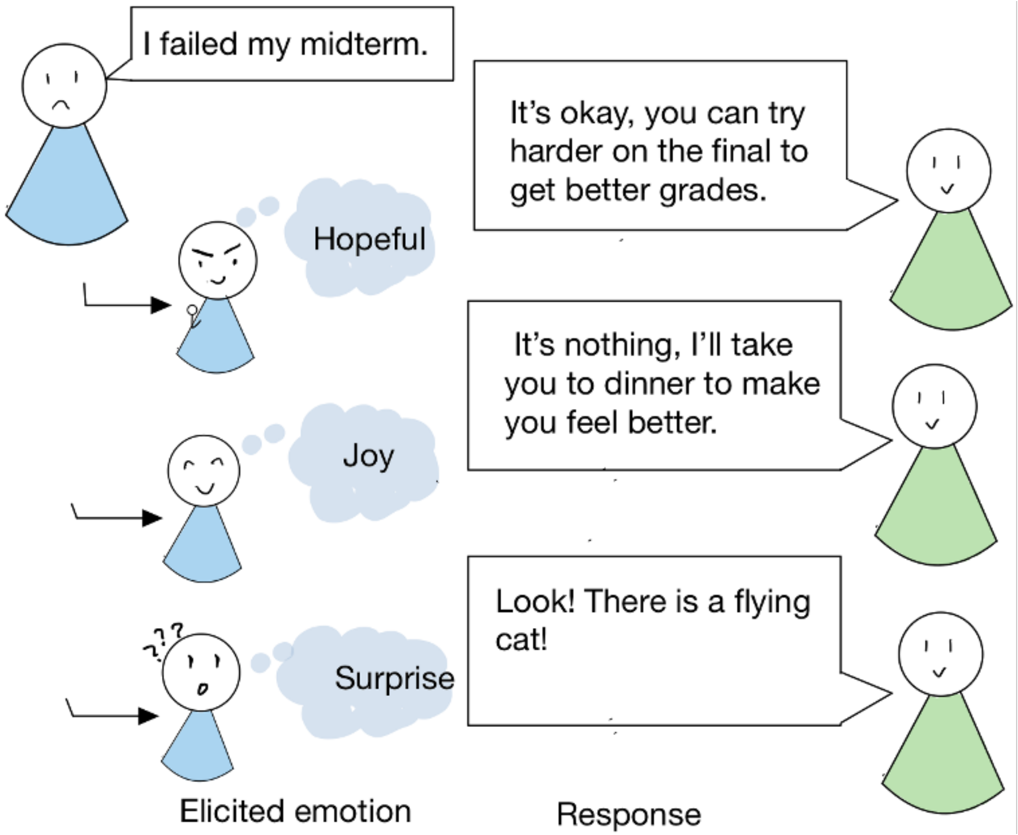


Related Work



- Emotion in Generation
- Emotion Elicitation
  - statistical response generator (Hasegawa et al., 2013)
  - Hierarchical Recurrent Encoder Decoder model (Serban et al.,2016) extended with a separate layer of emotion modules (Lubis et al., 2018)
  - encoder-decoder adversarial model with two discriminators to increase emotion-awareness or empathetic dialogue generation (Li et al., 2020)
- Style Transfer
  - control text over multiple styles in generation while preserving the original content
  - Using Variational Autoencoder (VAE) and wake-sleep learning procedure (Fu et al., 2018;Tikhonov et al., 2019; Fei et al., 2020)
- Conditional Variational Autoencoder
  - CVAE is an extension of VAE, which has been used for dialogue generation (Chen et al., 2019) by introducing a latent variable to capture discourse-level variations (Zhao et al., 2017).

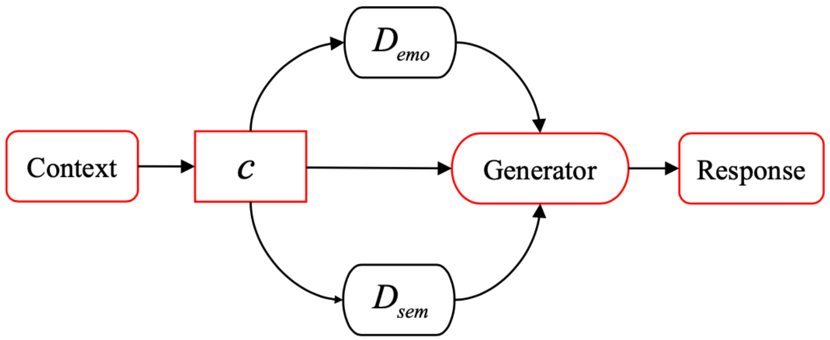
Motivations



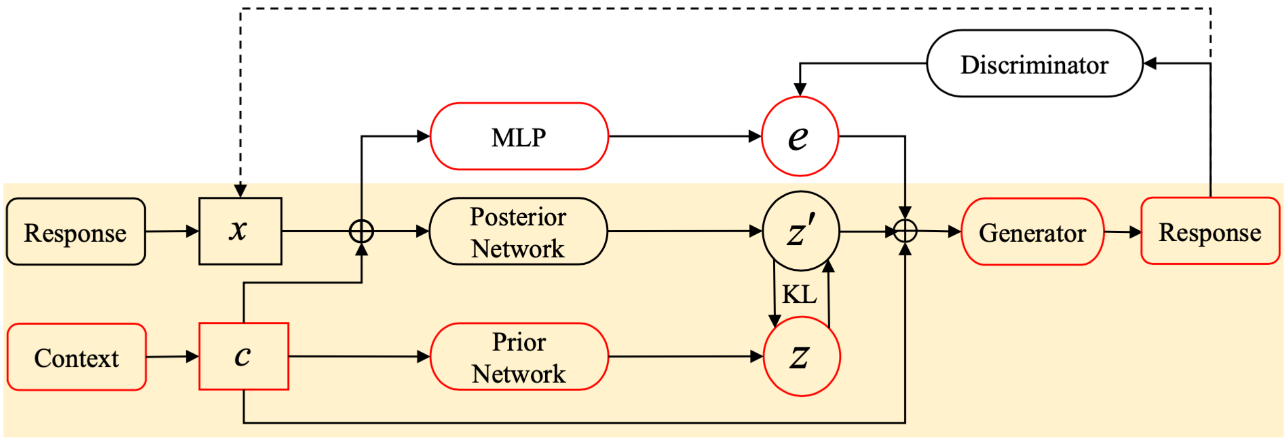
- Key factors to a conversation (in human communication theory):
  - **intentionality** (intention of speakers) and **effectiveness** (effects of conversations)
  - both exhibited by emotions.

- Current work on emotion elicitation focuses on positive sentiment.
- However, positive sentiment can include more fine-grained emotions such as “*Hopeful*”, “*Joy*” and “*Surprise*”, which can further serve to deepen the model's understanding of **effect**, if not **intention**.
- Small-scale human-annotated datasets, which limit the capacity of eliciting various emotions.

Model Comparison



(a) Baseline mode: EmpDG



(b) Our EE-CVAE model.

Single emotion category

Multiple emotion categories

- The latent variable e is used to control the generation of the response
- The latent variable z is separated from e to fully capture the elicited emotions

Model Detail

- CVAE for Dialogue Generation (yellow background)

- Adding Emotion Elicitation Function
- augment CVAE with a latent variable e, which is used to control the generation of a response together with the unstructured variable

$$\begin{aligned}\mathcal{L}_{\mathrm{VAE}}(\theta,\phi) =& \mathbf{E}_{q_\phi(z|c,x)q_\phi(e|c,x)}[\log p_\theta(x|z,c,e)] \\ &- \mathrm{KL}(q_\phi(z|c,x)\|p_\theta(z|c)) \\ &\leq \log p(x|c),\end{aligned}$$

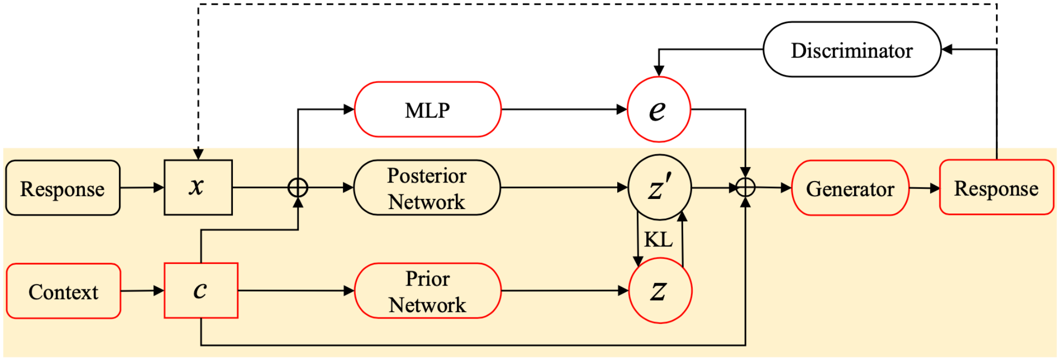
- a discriminator D is used to force the generator to produce coherent emotions

$$\mathcal{L}_{\mathrm{Attr},e}(\theta) = \mathbb{E}_{p(z)p(e)}\left[\log q_D\left(e \mid \widetilde{G}_\tau(z,e)\right)\right]$$

- Similarly, the variational encoder is reused to separate unrelated attributes from e by forcing them to be fully captured by z. It can be considered as another discriminator E :

$$\mathcal{L}_{\mathrm{Attr},z}(\theta) = \mathbb{E}_{p(z)p(e)}\left[\log q_E\left(z \mid \widetilde{G}_\tau(z,e)\right)\right].$$

- Combining, we have $\min \mathcal{L}_G = \mathcal{L}_{\mathrm{VAE}} + \lambda_e \mathcal{L}_{\mathrm{Attr},e} + \lambda_z \mathcal{L}_{\mathrm{Attr},z}$

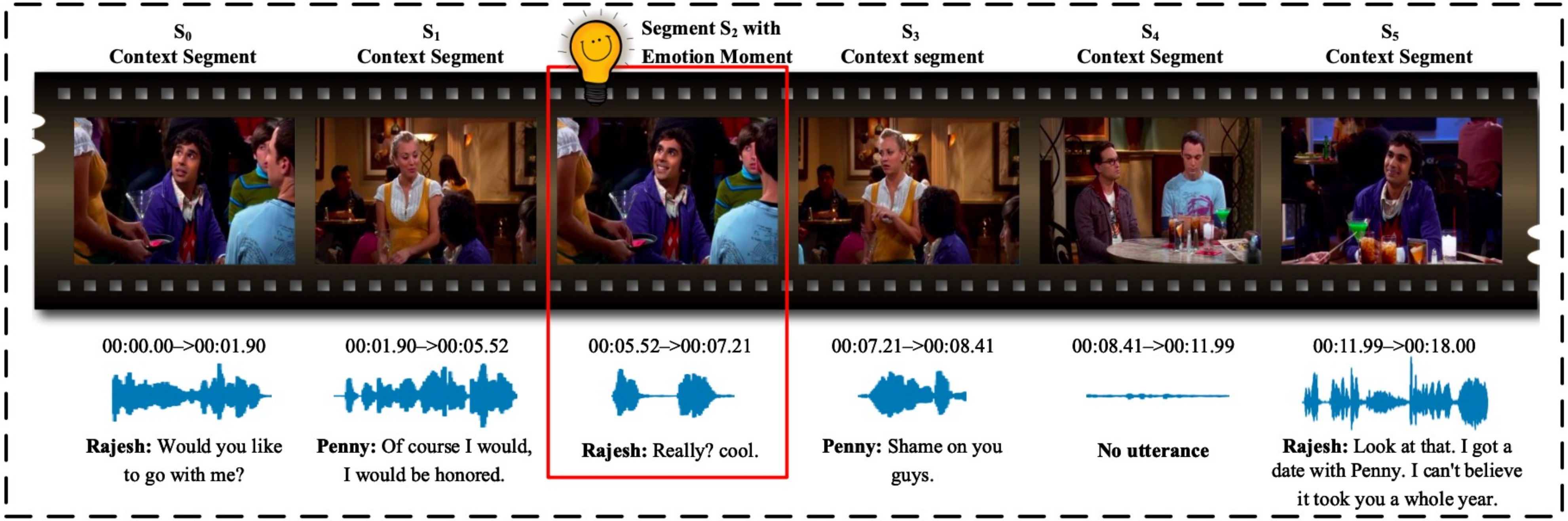


(b) Our EE-CVAE model.

Training illustration of our model. Red components are used for testing. CVAE in yellow background. Dashed arrow denotes a discriminator.

Dataset

- Reconstructed the multi-modal MEmoR dataset to fit our emotion elicitation task and conducted human evaluation to validate the usability in a single modality. (annotator agreement of 80% accuracy (Cohen's = 0.491))
- The reconstructed corpus has 22,732 utterances
  - ➢ Split the data in training (18,943), dev (1,894), and test (1,894).
- Pretrain: we use more than 200k utterances from the Friends and Open Subtitles datasets

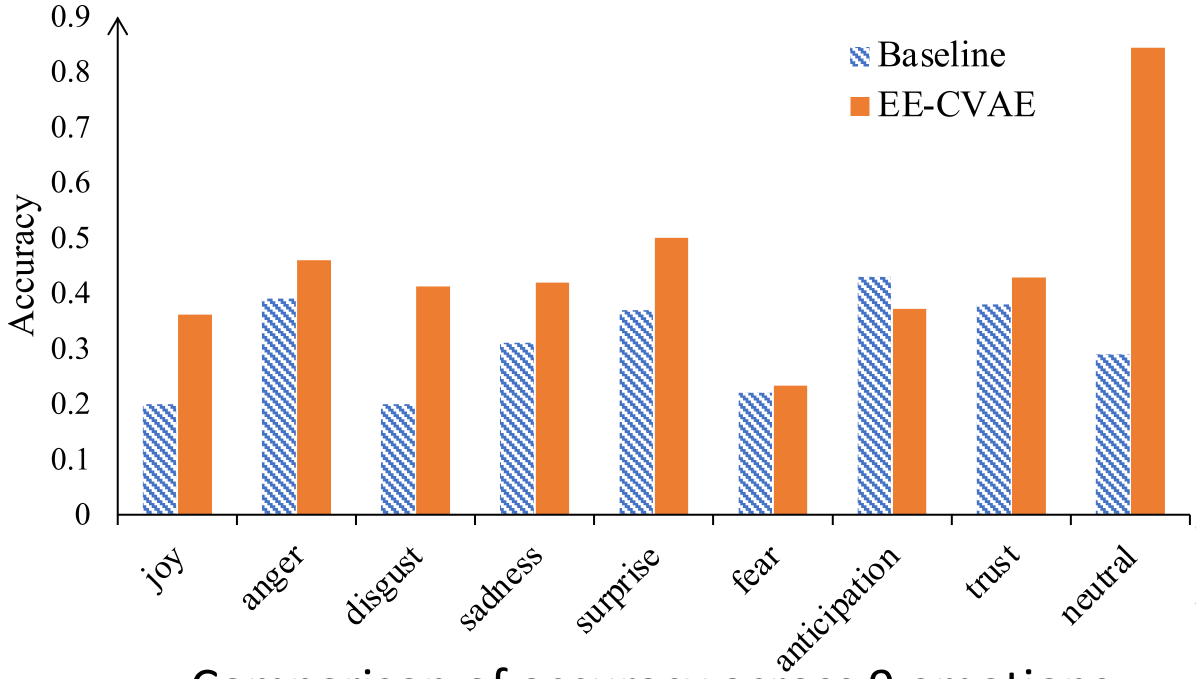


Results

1. The quality of the repones has been improved, from the comparison of PPL and Avg.len
2. The accuracy of the emotion in generated response has significantly improved during manual evaluation
3. Pretraining is effective in improving the quality of generation in both models
4. The Effect of Modeling Negative Emotions: Using all emotions in pretraining and finetuning produces the best performance in eliciting positive emotions.

Model	TBBT - 9			
	PPL	**Avg. len**	**KL**	**Acc.**
EmpDG	667.4	8.7	-	
EmpDG_{pre}	462.2	9.2	-	0.290
Ours	196.4	14.3	25.9	
Ours_{pre}	91.5	13.2	14.0	0.448

Table 1: Results of models generation in comparison.



Comparison of accuracy across 9 emotions.

Sample generations

Context:Well, you be sure to let us know when you win the nobel prize for boysenberry.
Golden (anticipation): Hey. **EmpDG** (anticipation): yeah . **Ours** (joy): Oh , what a gentleman? **Ours** (trust): Wow , I really appreciate it.
Context: Aw, Amy, that was lovely. You know, this is fun. Let's do more. Someone else say something wonderful about me.
Golden (joy) Sheldon, I don't think everyone ... **EmpDG** (joy): What is great. **Ours** (joy) Oh, sure. Mmm. I told you, he's got too many. **Ours** (anticipation) And you.

The Effect of Modeling Negative Emotions

	Setting1	Setting2	Setting 3	Tie
Anticipation	.47	.32	.19	.02
Joy	.55	.215	.215	.02
Trust	.54	.17	.27	.02
All	.51	.25	.22	.02

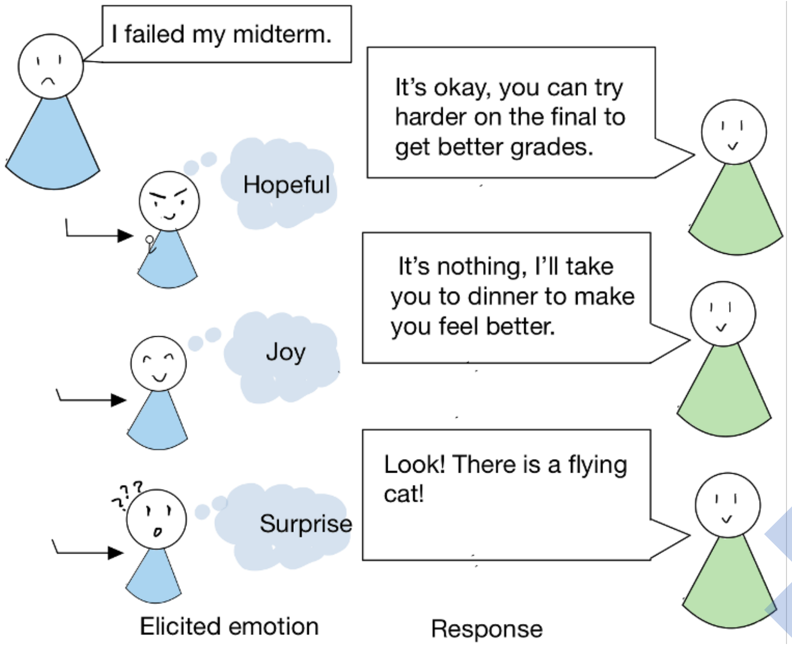
- Results comparing three settings with the percentage of times one model is considered the best when eliciting different positive emotions.

- Setting 1: modeling all emotions in pretraining and fine-tuning.
- Setting 2: modeling all emotions in pretraining, fine-tuning with only positive emotions.
- Setting 3: modeling only positive emotions in pretraining and fine-tuning.

- Using all emotions in pretraining and finetuning produces the best performance in eliciting positive emotions.

Conclusions and Future Directions

- Using **all** emotions in pretraining and finetuning produces the best performance in eliciting positive emotions.
- Results show the advantage of using a latent variable for **modeling rich emotions**, compared to hard-coding one emotion in a multi-encoder model.
- The effectiveness of our model in **pretraining**.



Future directions:
Our results show that rich emotion elicitation is a challenging task for current neural models, and there is a need for more effective few-shot learning.

Thank you! Questions?