

Better Conversations by Modeling, Filtering, and Optimizing for Coherence and Diversity

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Introduction

- New GloVe-based measure of coherence (Coh) between dialogue context and generated response
- Filtering corpora using *Coh* to get more coherent & diverse training data
- New Generator based on conditional Variational Autoencoders (cVAE)
 - Coh used as latent variable
 - Novel Coh-based context gate to improve coherence & diversity while generating

Measure of Coherence

Coh = cosine similarity over averaged GloVe embeddings between context vs. response

Coh	Dialogue context	Response
≥0.9	yeah? ## you're new in	you call this a town?
	town, right?	
\geq 0.9	to find the president.	the president, he lives!
0.7-0.9	call your grandfather to pick	grandpa 's not here.
	me up.	
0.7-0.9	kitchen. ## definitely the	specifically the stove.
	kitchen.	
0.4-0.6	so the boy becomes a man	it's amazing.
0.4-0.6	can we stop at the drug	oh, uh, don't worry.
	store?	
<0.4	mag? ## thank you.	i'm going to go for a walk
<0.4	i dont want it. ## why ## ok	you want the car.

Our Model: cVAE + Context Gate

Enhancements over seq2seq model with attention:

- Conditioning on context generally: latent variable z
- Conditioning on *Coh* explicitly: latent variable *c*
- Context gate: balance between words generated so far & previous context



Training

Inference

Dialogue context x Prior Network $z' \rightarrow \phi$ $s \rightarrow \phi$ Decoder ϕ Response y

(a

Combined training objective:

- Generation loss (MLE): response should be close to ground truth
- Coherence loss: match coherence signal given by c
- Diversity loss (cVAE): responses should be diverse so they can reproduce *z*

Experiments

Evaluation metrics:

- BLEU: word overlap, *Coh*: coherence (GloVe-based)
- D-1, D-2, D-Sent: The proportion of distinct unigrams, bigrams, and sentences in the outputs

Model variants

- cVAE-XGate: our context gate
- cVAE-CGate: context gate variant of Tu et al. (2017)

Results – models trained on OST, evaluated on fOST (hardest)

Model	BLEU%	Coh	D-1%	D-2%	D-Sent%
Seq2seq	0.86	0.284	3.6	14.6	29.4
MMI (Li et al. 2015)	0.89	0.278	3.7	15.3	31.5
cVAE-CGate	2.25	0.422	5.4	28.2	81.0
cVAE-XGate	2.41	0.434	4.8	23.4	84.0

Generation output examples

• comparing MMI (B-MMI) and cVAE-XGate (B-XGT), B-GT is the ground truth response

Data and Pre-processing

- **OST**: OpenSubtitles corpus with automatic dialogue turn segmentation (Lison and Meena, 2016).
- **fOST**: OST + *Coh*-based filtering
 - Only data where Coh > 0.68, i.e. $> \overline{Coh} + 2 \cdot \sigma$

Dataset	Coh	D-1%	D-2%	D-Sent%
OST	0.390	14.3	57.9	83.8
fOST	0.801	15.5	62.9	89.3

Conclusions

- Explicity modelling & optimizing for coherence significantly improves dialogue response generation
- Our cVAE-based models consistently outperform competitive baselines

 Our cVAE-based models produce better responses even when trained on noisy, incoherent data

Code available at:

https://github.com/XinnuoXu/CVAE_Dial



	Dialogue context	Response
1	A: i have an audition at 4:00.	B-GT: you volunteered.
	B: apparently now i'm cooking dinner.	B-MMI: i don 't know.
	A: how did this all happen?	B-XGT: well, i'm going to have a dinner.
2	A: was it what you wanted?	B-GT: you like model planes?
	B: no.	B-MMI: i wanted to know.
	A: i wanted an airplane.	B-XGT: i wanted a helicopter.
3 E 4	A: great.	B-GT: yeah, a vanilla decaf latte.
	B: thanks so much.	B-MMI: no.
	A: vanilla decaf latte?	B-XGT: yeah , that 's a good coffee



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