Paper Reading

Learning Discourse-level Diversity for Neural Dialog Models using Conditional Variational Autoencoders, ACL 2017

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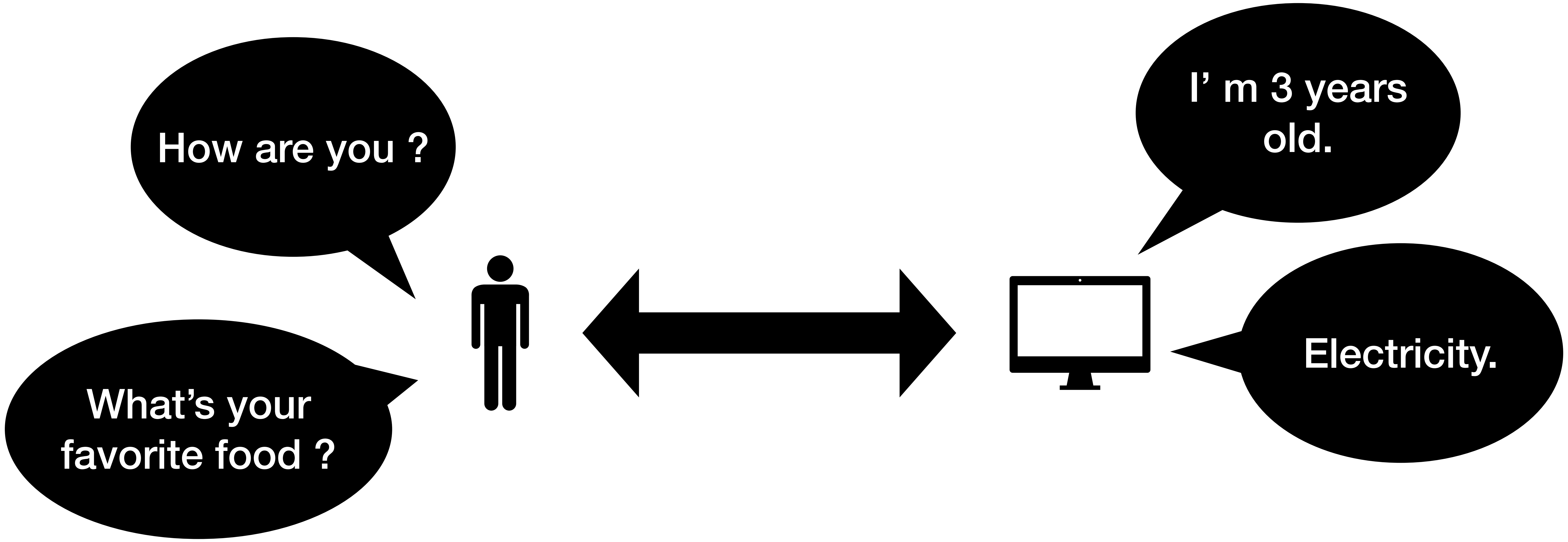
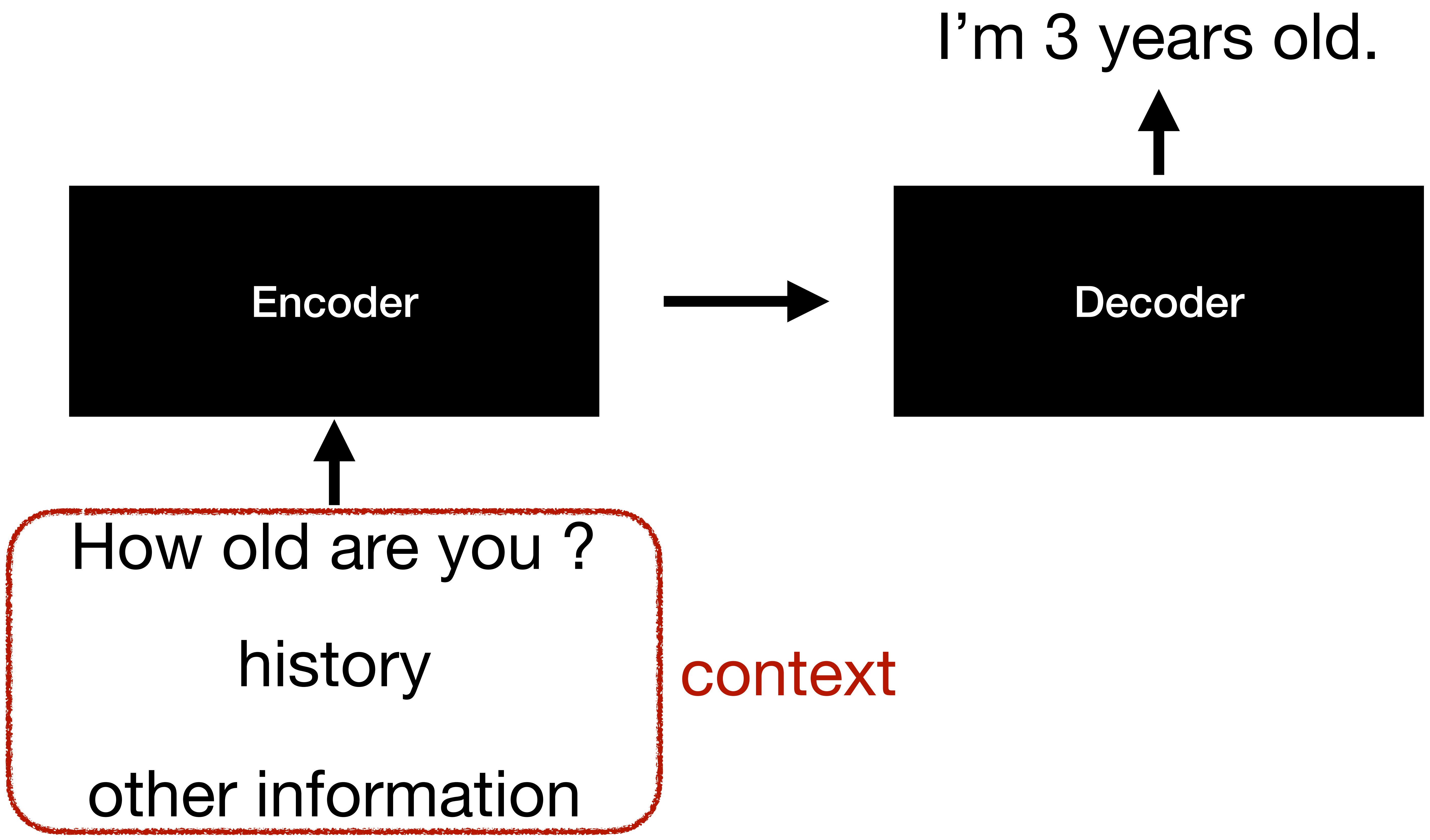
Dialog model ?

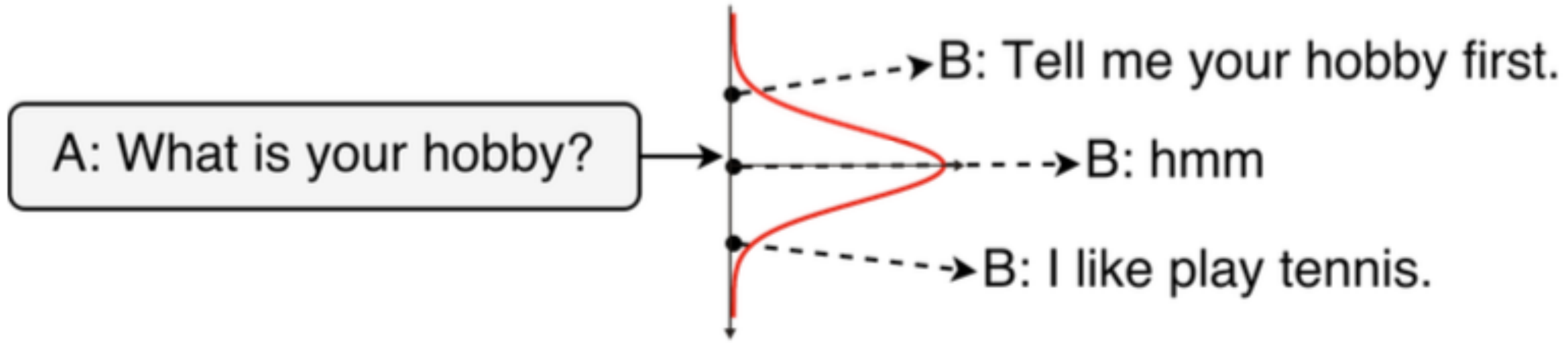


Baseline



A neural conversational model, Vinyals O, Le Q. , 2015 ICML Workshop

Problem



one-to-many

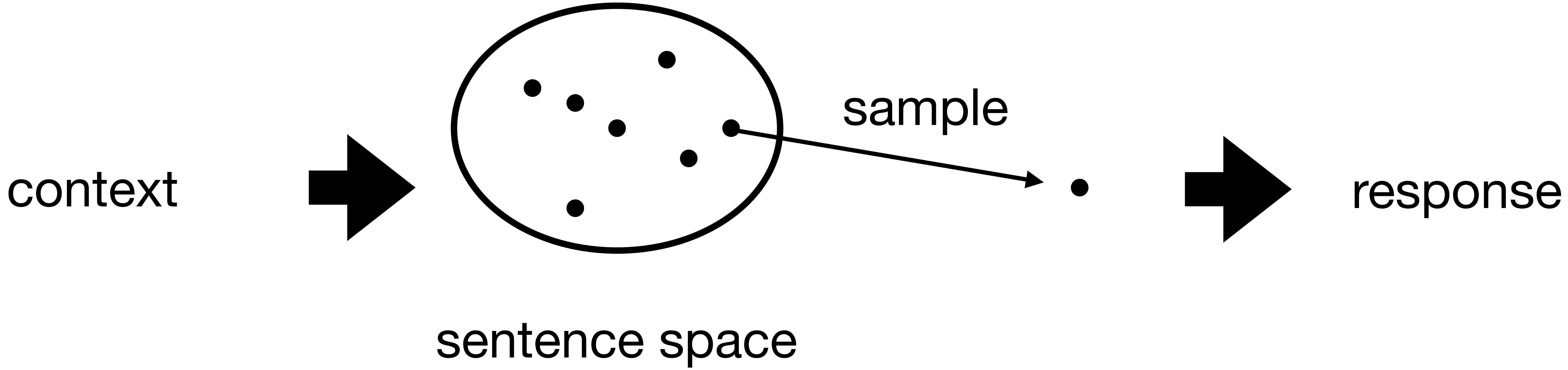
Seq2Seq:

The model tends to generate safe answers, like:

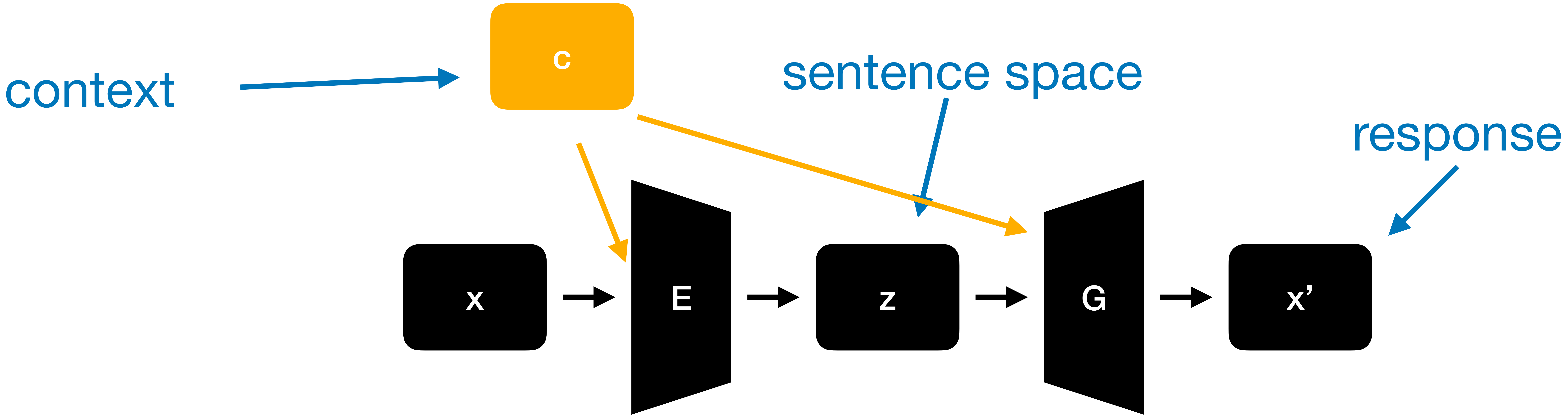
I don’t know.[1]

[1]Li J, Galley M, Brockett C, et al. A diversity-promoting objective function for neural conversation models, NAACL 2016

Solution



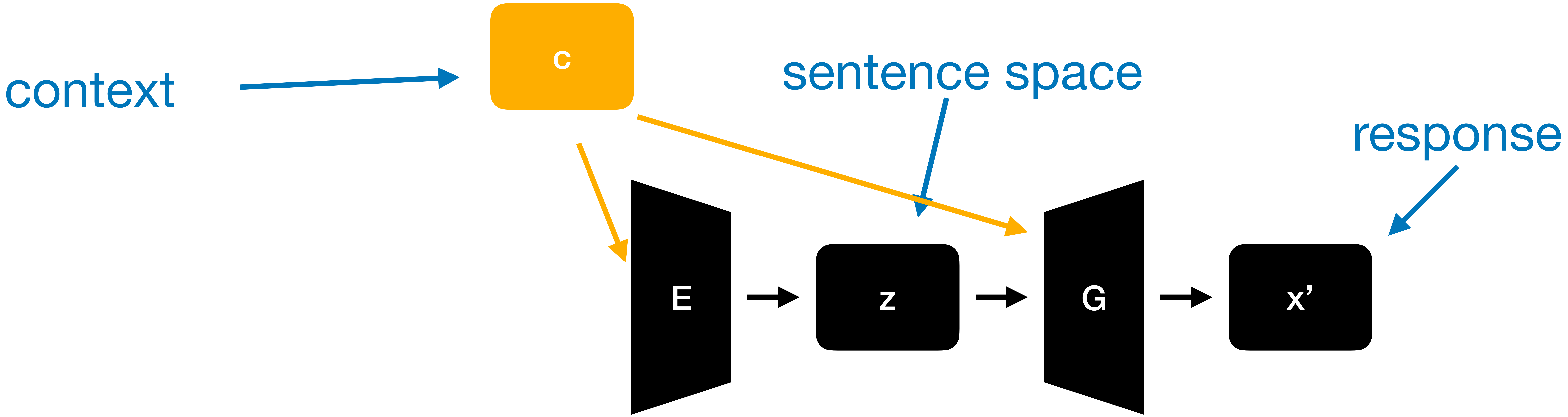
CVAE for Dialog Generation: Training



$$\log P(x) - \mathcal{D}[Q(z\,|\,x)\|P(z\,|\,x)] = E_{z\sim Q}[\log P(x\,|\,z)] - \mathcal{D}[Q(z\,|\,x)\|P(z)]$$

$$\log P(x\,|\,c) - \mathcal{D}[Q(z\,|\,x,c)\|P(z\,|\,x,c)] = E_{z\sim Q(x,c)}[\log P(x\,|\,z,c)] - \mathcal{D}[Q(z\,|\,x,c)\|P(z\,|\,c)]$$

CVAE for Dialog Generation: Inference

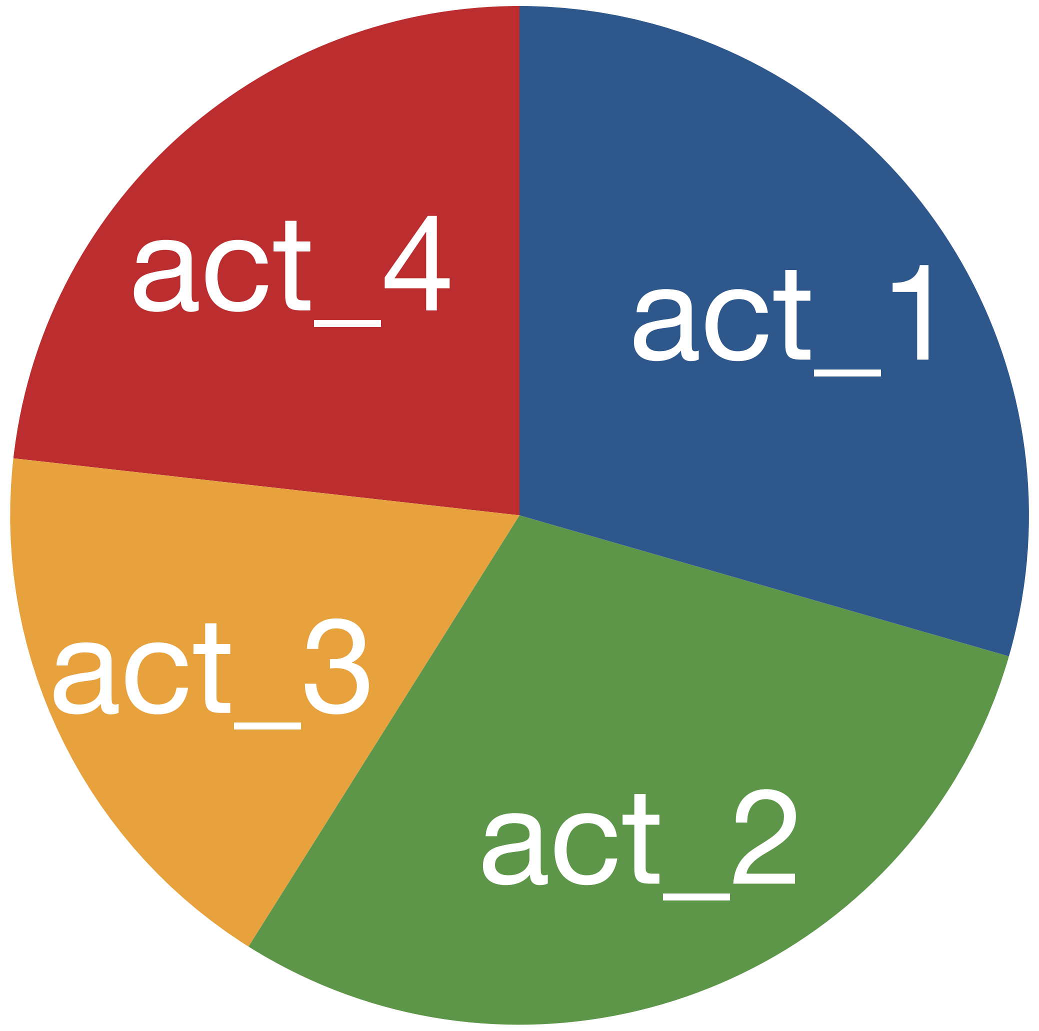


Knowledge-Guided CVAE (kgCVAE)

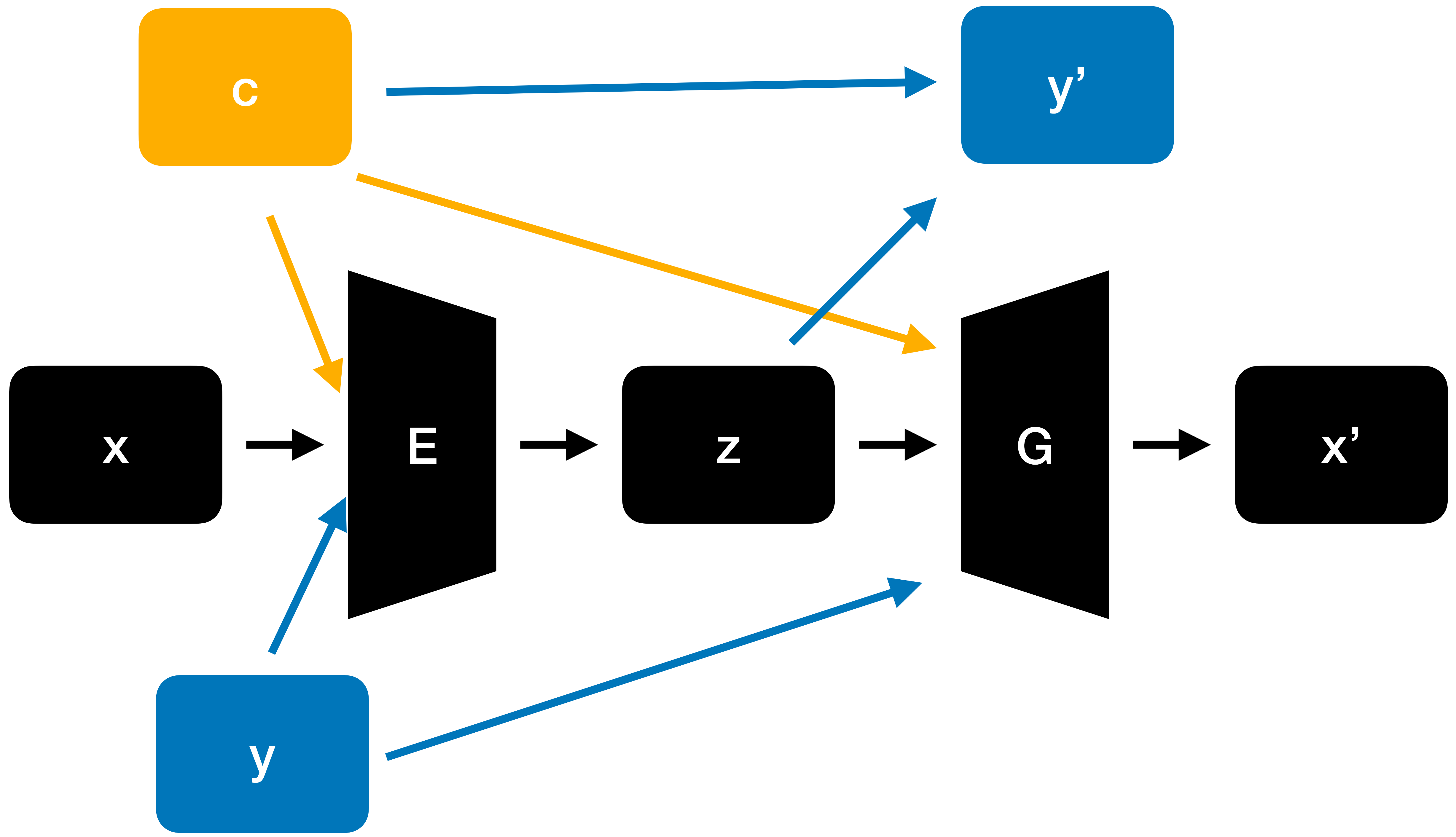
dialog act

context →

1. (non-understand) pardon
2. (statement) oh you're not going to have a curbside pick up here
3. (statement) okay I am sure about a recycling center
4. (yes-answer) yeah so



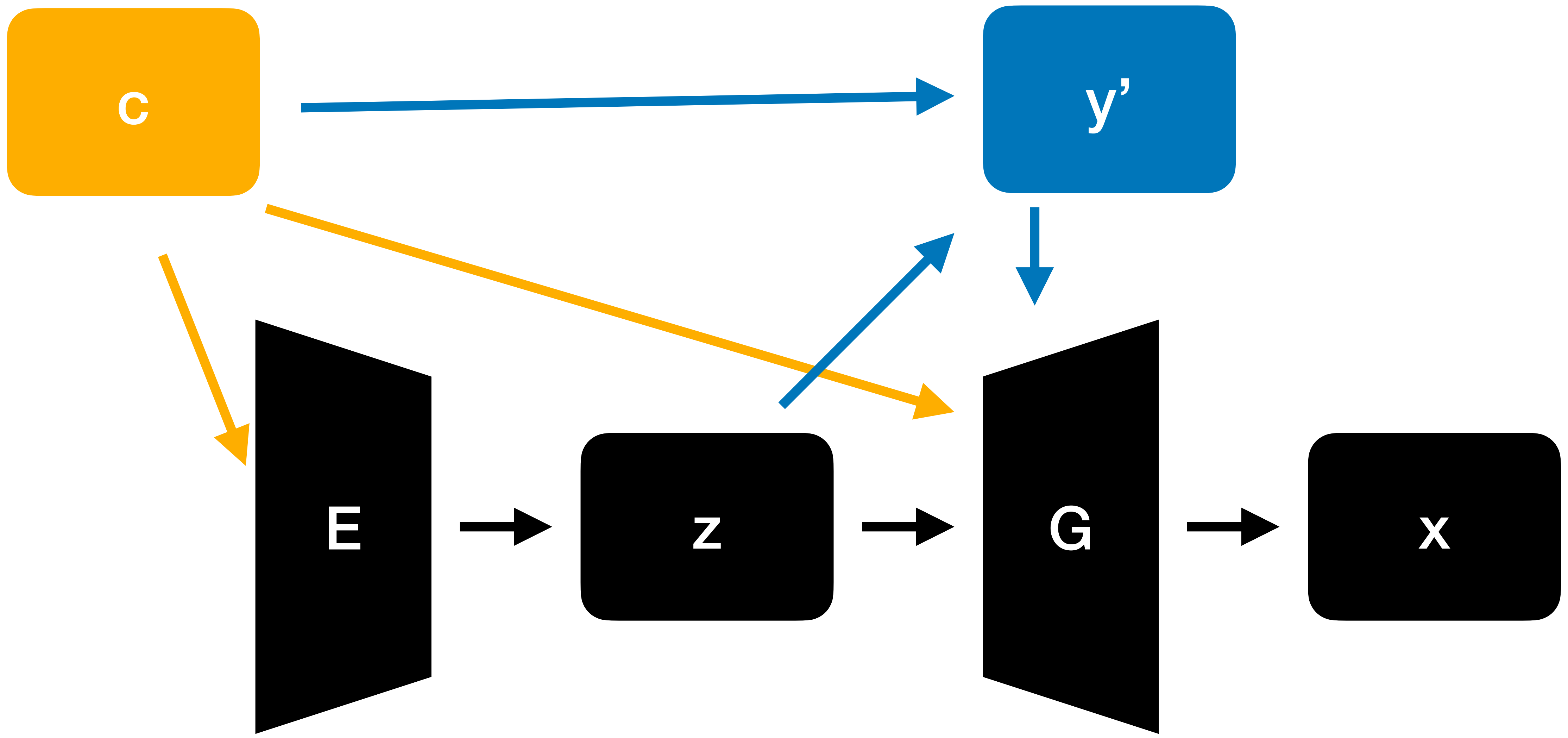
Knowledge-Guided CVAE (kgCVAE): Training



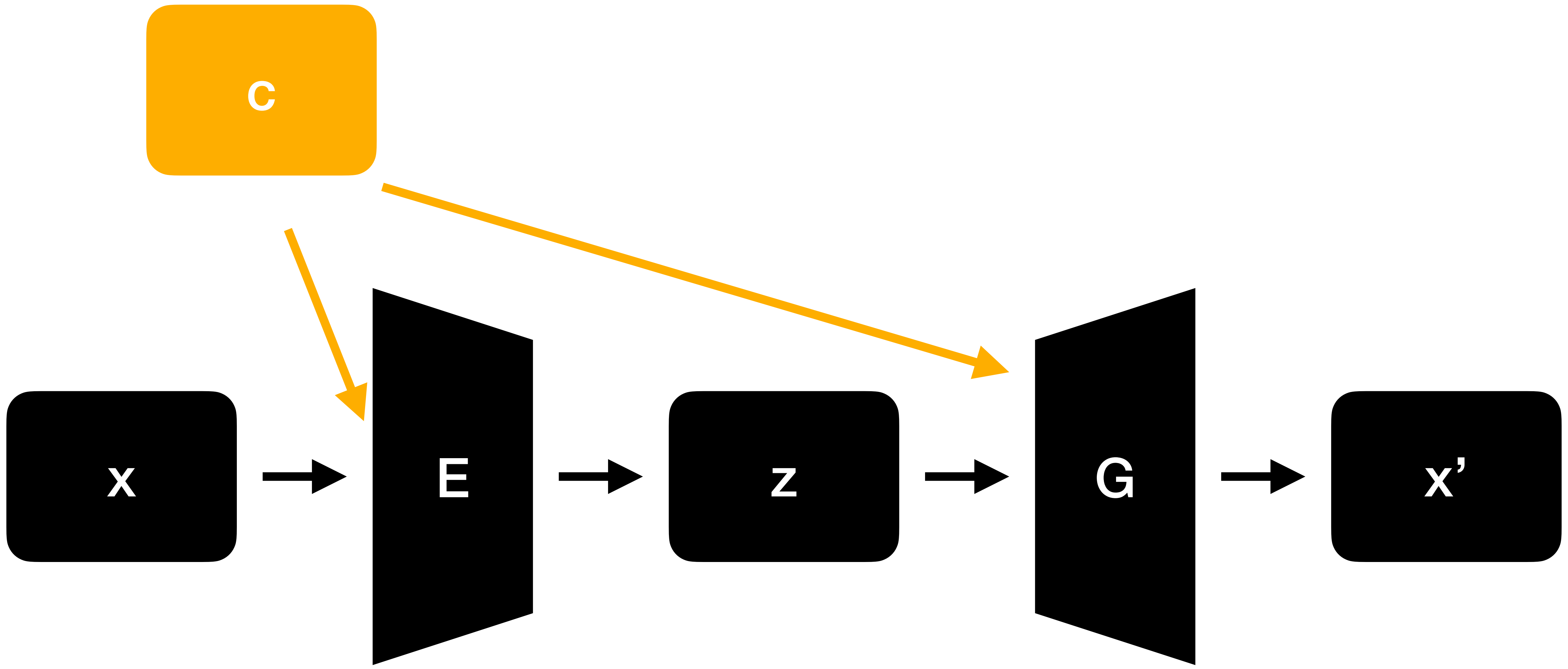
$$\mathscr{L}_{CVAE} = E_{z\sim Q(x,c)}[\log P(x|z,c)] - \mathscr{D}[Q(z|x,c)\|P(z|c)]$$

$$\mathscr{L}_{kgCVAE} = E_{z\sim Q(x,c,y)}[\log P(x|z,c,y)] - \mathscr{D}[Q(z|x,c,y)\|P(z|c)] + \mathbf{E}_{z\sim Q(x,c,y)}[\log p(y|z,c)]$$

Knowledge-Guided CVAE (kgCVAE): Inference



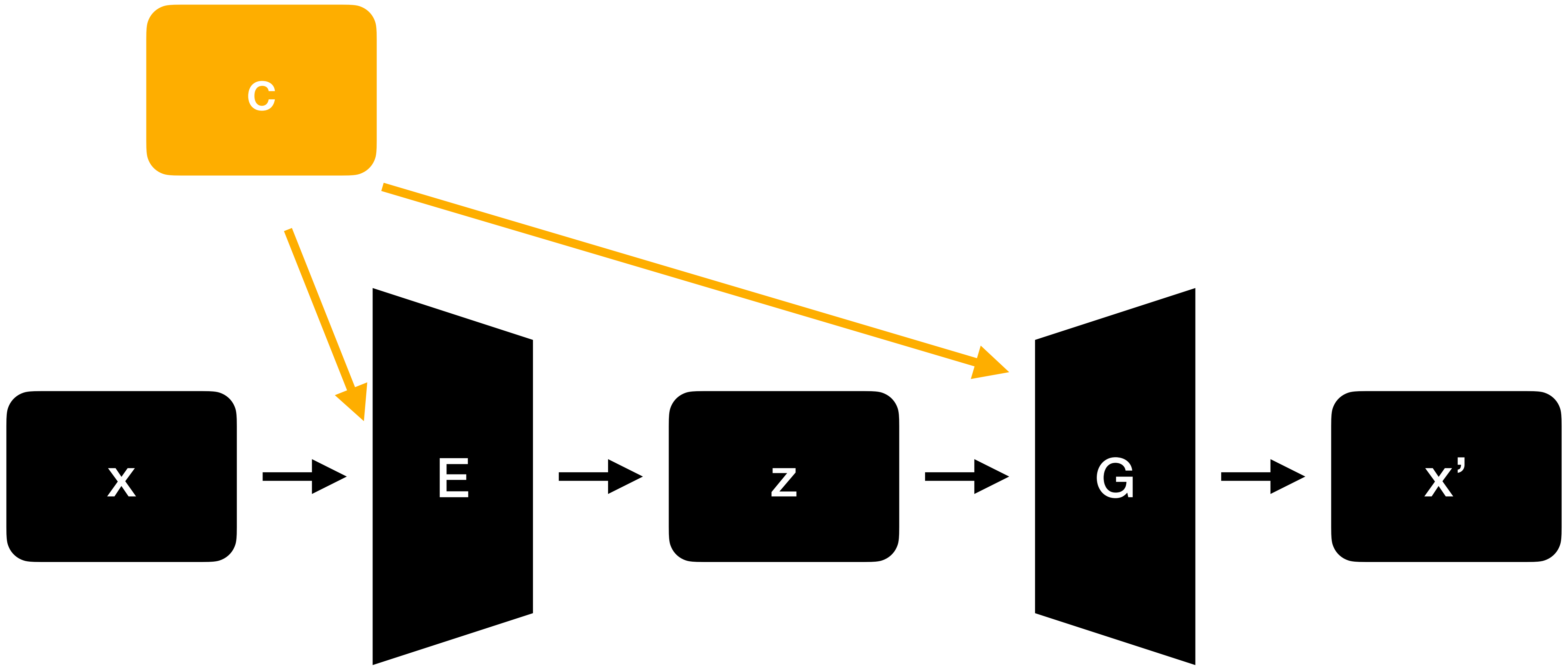
Optimization Challenges: vanishing latent variable problem



$$\mathscr{L} = E_{z\sim Q(x,c)}[\log P(x\,|\,z,c)] - \underbrace{\mathscr{D}[Q(z\,|\,x,c)\|P(z\,|\,c)]}_{0}$$

Bowman S R, Vilnis L, Vinyals O, et al. Generating sentences from a continuous space, CONLL 2016

Optimization Challenges: solution 1

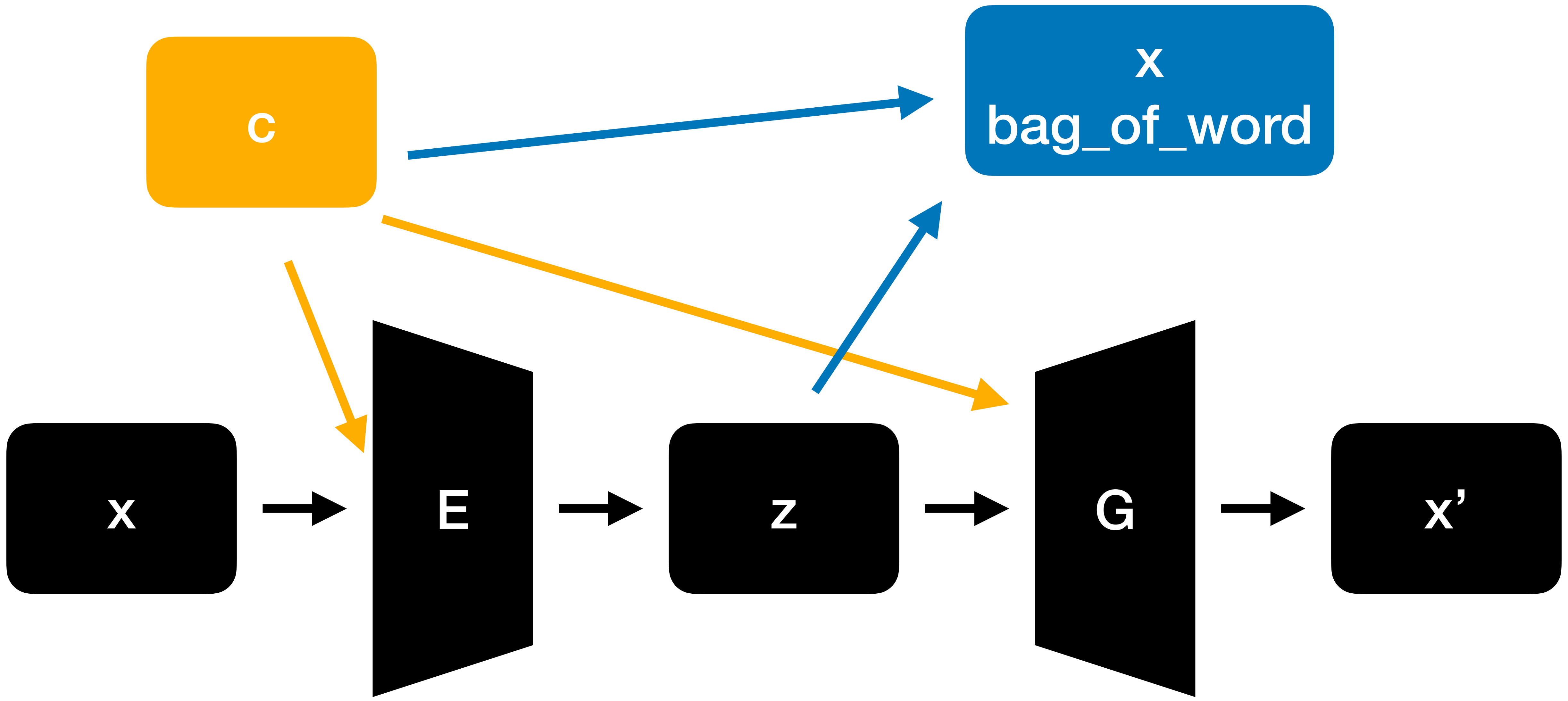


$$\mathscr{L} = E_{z \sim Q(x,c)}[\log P(x \mid z, c)] - \boxed{\lambda} \mathscr{D}[Q(z \mid x, c) \| P(z \mid c)]$$

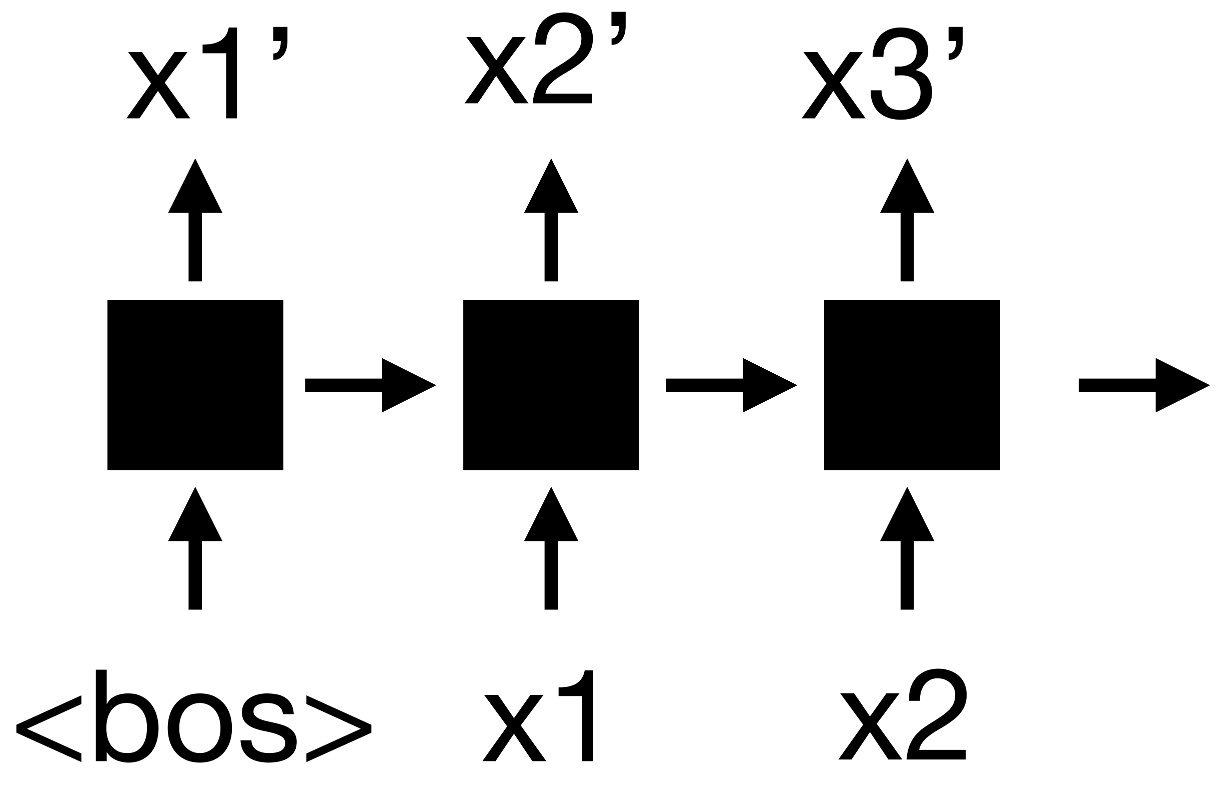
Bowman S R, Vilnis L, Vinyals O, et al. Generating sentences from a continuous space, CONLL 2016

Optimization Challenges: solution 2

solution2:



global information



$$\mathscr{L} = E_{z \sim Q(x,c)}[\log P(x \mid z, c)] - \lambda \mathscr{D}[Q(z \mid x, c) \| P(z \mid c)] \quad + \mathscr{L}_{bow}$$

Bowman S R, Vilnis L, Vinyals O, et al. Generating sentences from a continuous space, CONLL 2016

Experiments: diversity

$$context \rightarrow golden : (r_1, \cdots, r_{M_C})$$

$$context \rightarrow predict : (h_1, \cdots, h_N)$$

generated responses

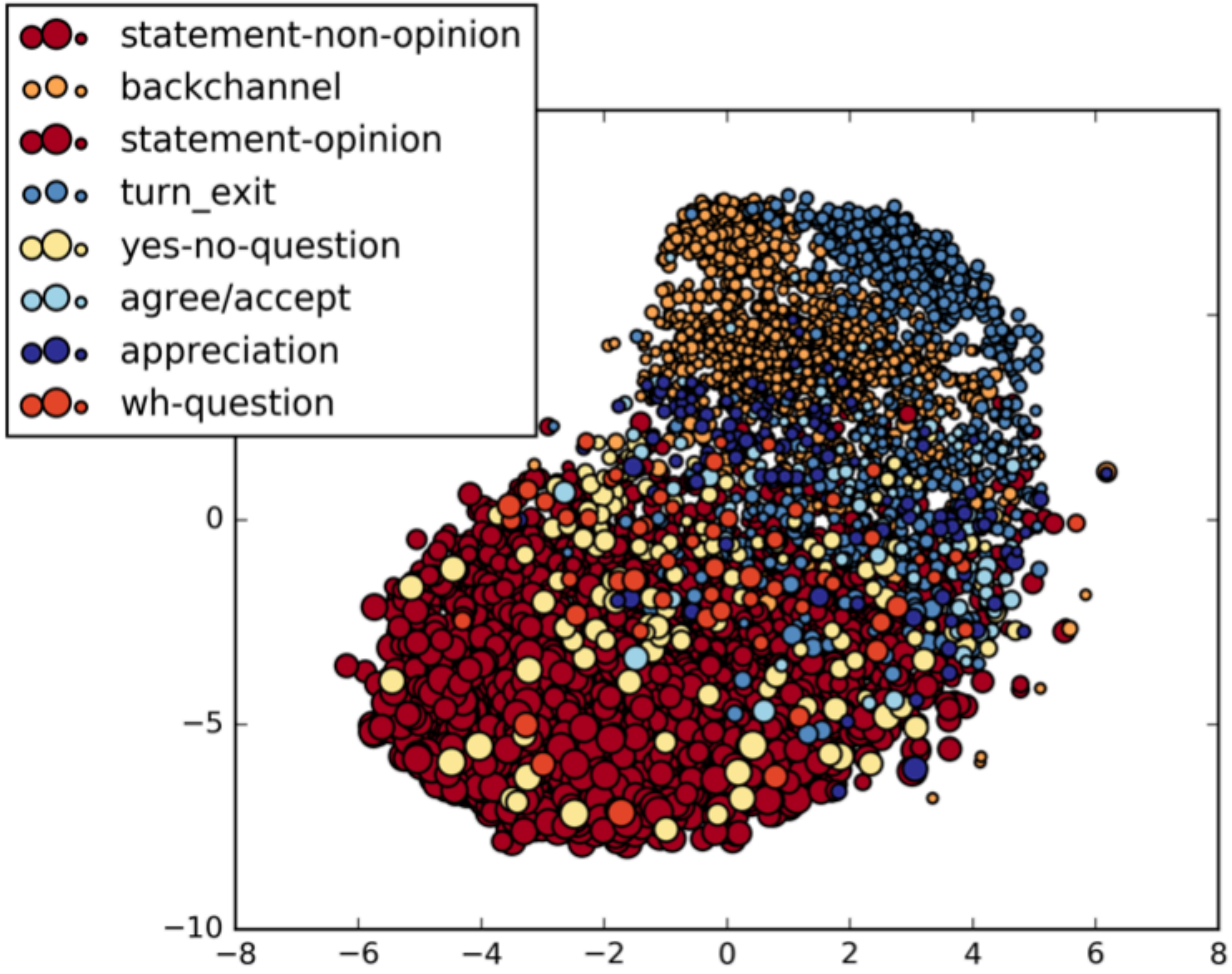
reference responses

$$\text{precision(c)} = \frac{\sum_{i=1}^{N} \max_{j \in [1, M_c]} d\left(r_j, h_i\right)}{N}$$

$$\text{recall(c)} = \frac{\sum_{j=1}^{M_c} \max_{i \in [1, N]} d\left(r_j, h_i\right))}{M_c}$$

Metrics	Baseline	CVAE	kgCVAE
perplexity (KL)	35.4 (n/a)	20.2 (11.36)	16.02 (13.08)
BLEU-1 prec	0.405	0.372	**0.412**
BLEU-1 recall	0.336	0.381	**0.411**
BLEU-2 prec	0.300	0.295	**0.350**
BLEU-2 recall	0.281	0.322	**0.356**
BLEU-3 prec	0.272	0.265	**0.310**
BLEU-3 recall	0.254	0.292	**0.318**
BLEU-4 prec	0.226	0.223	**0.262**
BLEU-4 recall	0.215	0.248	**0.272**
A-bow prec	0.951	0.954	**0.961**
A-bow recall	0.935	0.943	**0.944**
E-bow prec	**0.827**	0.815	0.804
E-bow recall	0.801	**0.812**	0.807
DA prec	**0.736**	0.704	0.721
DA recall	0.514	**0.604**	0.598

Experiments: z space



Experiments: bow loss

Model	Perplexity	KL cost
Standard	122.0	0.05
KLA	111.5	2.02
BOW	97.72	7.41
BOW+KLA	73.04	15.94

QA