Adversarially Regularized Autoencoders

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Training Deep Latent Variable Models

Two dominant approaches

- **Variational inference**: bound $\log p_\theta(\mathbf{x})$ with the evidence lower bound (ELBO) and find a variational distribution that approximates the posterior $\implies$ Variational Autoencoders (VAE)
- **Implicit density methods**: Avoid dealing with the likelihood directly and learn a discriminator that distinguishes between real/fake samples $\implies$ Generative Adversarial Networks (GAN)

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Training GANs for natural language is hard because the loss is not differentiable with respect to the generator

GAN: Problem

Possible solutions

- Use policy gradient techniques from reinforcement learning (Yu et al. 2017, Lin et al. 2017)
  - unbiased but high variance gradients
  - need to pre-train with MLE
- Consider a "soft" approximation to the discrete space (Rajeswar et al. 2017, Shen et al. 2017):
  - e.g. with the Gumbel-Softmax distribution (Maddison et al. 2017, Jang et al. 2017)
  - hard to scale to longer sentences/larger vocabulary sizes

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Our Work

Adversarially Regularized Autoencoders (ARAE)

- Learns an autoencoder that encodes discrete input into a continuous space and decode from it.
- Adversarial training in the continuous space at the same time

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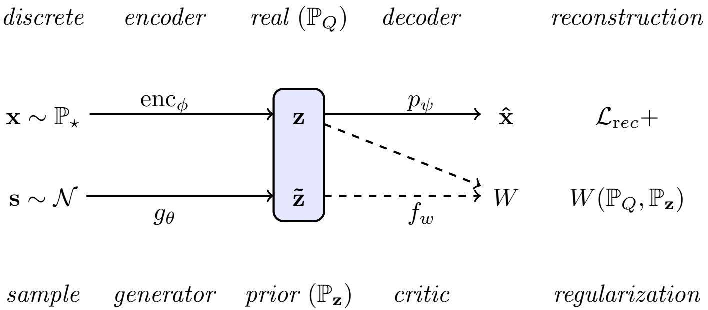
Adversarially Regularized Autoencoders



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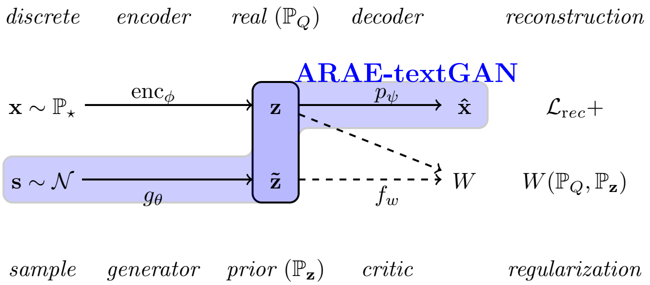
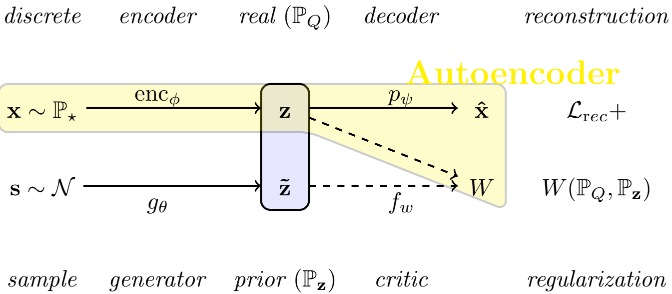


- In Corollary 1, we proved the equivalency of training ARAE and a latent variable model using the prior distribution, **in the discrete case**.
- Text generation
- Latent space manipulation: interpolation / vector arithmetic

Adversarially Regularized Autoencoders



- Semi-supervised learning
- Unaligned style transfer

Adversarially Regularized Autoencoders: experiments

New metric: **Reverse perplexity**, w/ normally used **Forward perplexity**

- Generate **synthetic** training data from generative model
- Train a RNN language model on generated data
- Evaluate perplexity, $PPL = \exp(-\frac{1}{N}\sum_{i=1}^{N} \log p(\mathbf{x}^{(i)}))$ on **real** data
- Captures mode-collapse (vs regular PPL)
- Baselines
    - Autoregressive model: RNN language model
    - Autoencoder without adversarial regularization
    - Aversarial Autoencoders with no standalone generator (mode-collapse, Reverse PPL 980)
    - Unable to train VAEs on this dataset

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Adversarially Regularized Autoencoders

Data for Training LM	Reverse PPL
Real data	27.4
Language Model samples	90.6
Autoencoder samples	97.3
ARAE samples	82.2

(Lower perplexity means higher likelihood)

ARAE: Unaligned Style Transfer

Transfer Sentiment

- Train a classifier on top of the code space:
  $classifer(\mathbf{c}) =$ probability $\mathbf{c}$ is a positive sentiment sentence
- The encoder is trained to **fool** the classifier
- To transfer sentiment:
  - Encode sentence to get code $\mathbf{c}$
  - Switch the sentiment label, concatenate with $\mathbf{c}$
  - Generate using the concatenated vector

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ARAE: Unaligned Style Transfer

Cross-AE: State-of-the-art model from Shen et al. 2017

	Positive ⇒ Negative
Original	great indoor mall .
ARAE	no smoking mall .
Cross-AE	terrible outdoor urine .
Original	it has a great atmosphere , with wonderful service .
ARAE	it has no taste , with a complete jerk .
Cross-AE	it has a great horrible food and run out service .
Original	we came on the recommendation of a bell boy and the food was amazing .
ARAE	we came on the recommendation and the food was a joke .
Cross-AE	we went on the car of the time and the chicken was awful .

ARAE: Unaligned Style Transfer

Cross-AE: State-of-the-art model from Shen et al. 2017

	Negative ⇒ Positive
Original	hell no !
ARAE	hell great !
Cross-AE	incredible pork !
Original	small , smokey , dark and rude management .
ARAE	small , intimate , and cozy friendly staff .
Cross-AE	great , , , chips and wine .
Original	the people who ordered off the menu did n't seem to do much better .
ARAE	the people who work there are super friendly and the menu is good .
Cross-AE	the place , one of the office is always worth you do a business .

ARAE: Unaligned Style Transfer

Automatic Evaluation

Model	Transfer	BLEU	PPL	Reverse PPL
Cross-Aligned AE	77.1%	17.75	65.9	124.2
ARAE	81.8%	20.18	27.7	77.0

Human Evaluation

Model	Transfer	Similarity	Naturalness
Cross-Aligned AE	57%	3.8	2.7
ARAE	74%	3.7	3.8

(Similarity/Naturalness scores are between [1,5], 5 being best)

ARAE: Unaligned Style Transfer

Topic Transfer from Yahoo! Answers Dataset

Science	what is an event horizon with regards to black holes ?
Music	what is your favorite sitcom with adam sandler ?
Politics	what is an event with black people ?
Music	do you know a website that you can find people who want to join bands ?
Science	do you know a website that can help me with science ?
Politics	do you think that you can find a person who is in prison ?
Politics	republicans : would you vote for a cheney / satan ticket in 2008 ?
Science	guys : how would you solve this question ?
Music	guys : would you rather be a good movie ?

ARAE: Conclusion

- Introduced a simple method for training a GAN for text by performing generation/discrimination in a continuous code space
- A (somewhat) successful text-GAN instatiation
- Can do unaligned style transfer through training an additional classifier (much exciting work in this area: Shen et al. 2017, Prabhumoye et al. 2018)

ARAE: Open source

All our code is available at: https://github.com/jakezhaojb/ARAE.

Poster: #58