argument similarity

Jan Milde jmilde@uni-potsdam.de

Kuan Yu kuanyu@uni-potsdam.de

Liubov Karpova lkarpova@uni-potsdam.de

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main idea

- following Luise Schricker 2018
- construct a representation for arguments
- hierarchical agglomerative clustering
- evaluate with adjusted rand index and v-measure

evaluation data

- reason and stance dataset (Hasan and Ng 2014)
- 4 topics (abortion, gay rights, obama, marijuana)
- 2 stances for each topic (pro & con)
- 56 reason classes, 5–9 for each stance

gay rights

pro	con
`normal`	`abnormal`
`religion`	`religion`
`born`	`gay_problems`
...	...

examples

- right_denied

I believe that they should be able to because it is their right. Just like we have the right to marry one another they should be able to

- right_denied

yes they should they are humas to and if you love some on so much you get married and live together

examples

```
There are only two (2) sexes created by God,
the male and the female gender.
An individual is given by God a "free choice".
Homosexuality is a person's personal choice,
so why forbid them in exercising their right?  9
```

- right_denied

```
Homosexuality is a person's personal choice,
so why forbid them in exercising their right?  9
```

- born

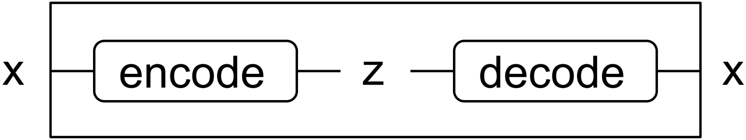
```
Homosexuality is a person's personal choice,
```

training data

- IBM debater datasets, claim sentences search 1.49 million sentences
- google research datasets (reddit) $9\,473$ threads comprised of $116\,347$ comments
- internet argument corpus

vae

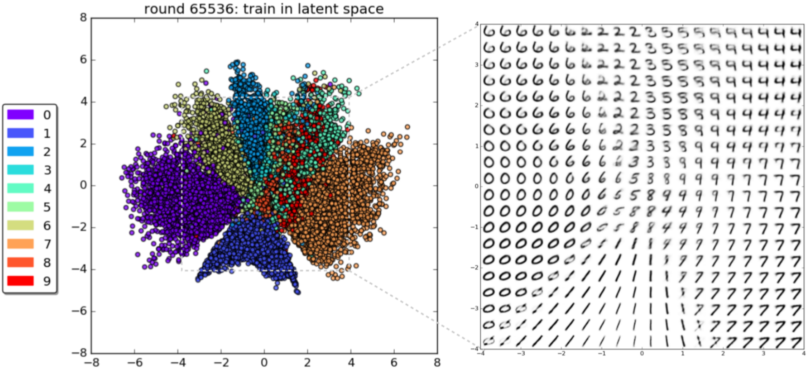
- variational autoencoder (Kingma and Welling 2013)



- trained by maximizing the variational lowerbound
- learns a disentangled latent representation

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

vae on mnist



source

vae for texts

- learning sentences Bowman et al. (2015) comparisons (Cífka et al. 2018)
- learning discourse-level diversity (Zhao, Zhao, and Eskenazi 2017)
- learning topic model (Srivastava and Sutton 2017) dirichlet vae (Xiao, Zhao, and Wang 2018)
- learning semantic space (Jang, Seo, and Kang 2018)
- target-level sentiment analysis (Xu and Tan 2018)
- abstractive sentence summarization (Schumann 2018)

our model

- gated recurrent units (Cho et al. 2014)
- encoder: 3 stacked bidirectional
- decoder: 3 unidirectional
- model dimension: 512
- latent dimension: 1024
- vocabulary size: 8192
- input-ouput embedding sharing (Press and Wolf 2016)

vocabulary

- sentencepiece for segmentation (Kudo 2018)

```
_argument ation _mining
_argument at ion _mining
_argument ation _ min ing
_argument ation _mini ng
_argument a tion _mining
```

homotopy

```
We are linguists.
We are lingagists.
We are sheurges.
We are ribisms.
We are ribisms or bankers.
We are sheors Islamism?).
We are ensity controlie's.
We are unsheational ismelists.
We are compathation/thsuence.
We are computational linguists.
```

classification

- sentence-level reason classification
- baseline and J3 from Hasan and Ng (2014)

topic	baseline	J3	ours
abortion	32.7	39.5	34.4
gayRights	23.3	31.4	34.8
marijuana	28.7	35.1	36.0
obama	19.5	25.1	20.6

- baseline: logistic classifier based on ngram, dependency, frame-semantic, quotation, and positional features
- J3: joint density estimation (stance & reason) with reasons predicted for the preceding post
- ours: logistic classifier with latent representation (l2 cost = 0.001)

clustering: per topic

Topic	Our Model		Luise M.2	
	ARI	V-MSR	ARI	V-MSR
abortion	.02	.08	.14	.29
gayRights	.01	.04	.07	.18
marijuana	.01	.04	.16	.23
obama	.01	.09	.15	.34

- Luise: sum of pretrained CBOW embedding of filtered words
- Our Model: 292 dimensions of the latent representation picked out with a logistic classifier (l1 cost $= 0.1$)

clustering: per stance

Model	Measure	abortion		gayRights		marijuana		obama	
		con	pro	con	pro	con	pro	con	pro
Ours	ARI	.03	.02	.01	.01	.00	.01	.00	.01
	V-MSR	.04	.07	.02	.02	.05	.03	.06	.06
Luise	ARI	.20	.12	.06	.04	.05	.15	.15	.17
M.2	V-MSR	.27	.24	.13	.10	.12	.21	.26	.29

problems so far

- training data is very different from the evaluation data
  - clean vs messy
  - single sentence vs multiple sentences
- training method not suitable for the task
  - over 95% reconstruction accuracy, however
  - the task is not concerned with reconstructing sentences down to each piece
  - most info learned is irrelevant to the labels
- evaluation data not suitable for the task
  - labels too specific (ad hoc)
  - questionable labeling

what's next

- rethink project objective
  - analyze the learned representation, specifically its relevance to argument similarity
  - use the reason dataset for training to generate arguments
- clean the reason dataset
  - remove questionable instances
- training
  - try the other training datasets
  - train on whole texts instead of sentences
  - train with different source and target (sentecepiece samples, paraphrasing)

references I

Kingma, Diederik P and Max Welling (2013). "Auto-encoding variational bayes". In: *arXiv preprint arXiv:1312.6114*.

Cho, Kyunghyun et al. (2014). "Learning phrase representations using RNN encoder-decoder for statistical machine translation". In: *arXiv preprint arXiv:1406.1078*.

Hasan, Kazi Saidul and Vincent Ng (2014). "Why are you taking this stance? identifying and classifying reasons in ideological debates". In: *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 751–762.

Bowman, Samuel R et al. (2015). "Generating sentences from a continuous space". In: *arXiv preprint arXiv:1511.06349*.

Press, Ofir and Lior Wolf (2016). "Using the output embedding to improve language models". In: *arXiv preprint arXiv:1608.05859*.

references II

Srivastava, Akash and Charles Sutton (2017). "Autoencoding variational inference for topic models". In: *arXiv preprint arXiv:1703.01488*.

Zhao, Tiancheng, Ran Zhao, and Maxine Eskenazi (2017). "Learning discourse-level diversity for neural dialog models using conditional variational autoencoders". In: *arXiv preprint arXiv:1703.10960*.

Cífka, Ondřej et al. (2018). "Eval all, trust a few, do wrong to none: Comparing sentence generation models". In: *arXiv preprint arXiv:1804.07972*.

Jang, Myeongjun, Seungwan Seo, and Pilsung Kang (2018). "Recurrent Neural Network-Based Semantic Variational Autoencoder for Sequence-to-Sequence Learning". In: *arXiv preprint arXiv:1802.03238*.

references III

Kudo, Taku (2018). "Subword Regularization: Improving Neural Network Translation Models with Multiple Subword Candidates". In: *arXiv preprint arXiv:1804.10959*.

Schumann, Raphael (2018). "Unsupervised Abstractive Sentence Summarization using Length Controlled Variational Autoencoder". In: *arXiv preprint arXiv:1809.05233*.

Xiao, Yijun, Tiancheng Zhao, and William Yang Wang (2018). "Dirichlet Variational Autoencoder for Text Modeling". In: *arXiv preprint arXiv:1811.00135*.

Xu, Weidi and Ying Tan (2018). "Semi-supervised Target-level Sentiment Analysis via Variational Autoencoder". In: *arXiv preprint arXiv:1810.10437*.