

Multi-attribute Text Style Transfer

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<https://qdata.github.io/deep2Read>

Outline

- 1 Introduction
- 2 Approach
- 3 Related Work
- 4 Evaluation and Experiments
- 5 Discussion and Takeaways

- Style transfer - change text attribute while preserving semantic meaning
- Previous methods
 - Supervised - use labeled data and sequence-to-sequence models
 - Unsupervised - latent representations with adversarial loss
- This paper - Style transfer via Back-translation (Unsupervised)
 - Multiple attributes transfer
 - Back-translation instead of adversarial loss
 - Empirical results for lack of disentanglement strength

Back-translation

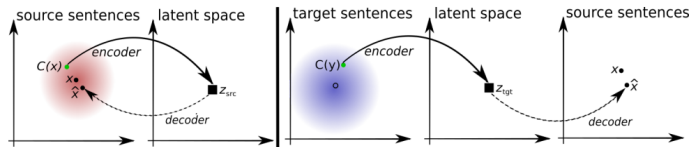


Figure: Source to target translation via sequence to sequence models

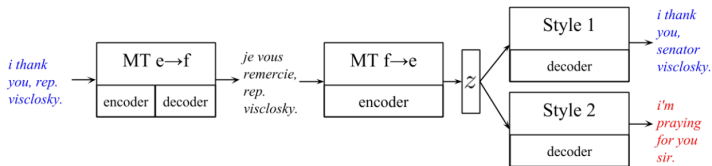


Figure: Style transfer via back-translation

Input and System Diagram

- Input text x , corrupted text x_c , original label y , required label \hat{y} , style transferred text \hat{x}
- Four step approach for complete style transfer

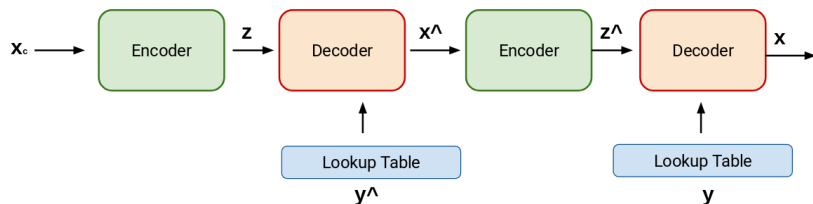


Figure: Architecture Diagram

Step by Step Procedure

- 1 Encode x into latent representation z : $x \rightarrow z$
- 2 Conditionally decode z into \hat{x} by adding \hat{y} : $z + \hat{y} \rightarrow \hat{x}$
- 3 Encode \hat{x} into latent representation \hat{z} : $\hat{x} \rightarrow \hat{z}$
- 4 Conditionally decode \hat{z} into x by adding y : $\hat{z} + y \rightarrow x$

$$\mathcal{L} = \sum_{(x,y) \sim \mathcal{D}} -\log p_d(x|e(x_c), y) + \lambda \sum_{(x,y) \sim \mathcal{D}, \tilde{y} \sim \mathcal{Y}} -\log p_d(x|e(d(e(x), \tilde{y})), y)$$

Figure: Loss function for the model

Related Work

DAR (Delete and Retrieve)

- Comparison system for style transfer
- Uses template based and neural models for style transfer

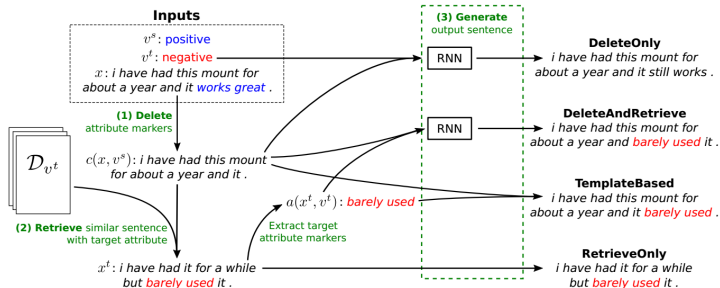


Figure: DAR Model

	Sentiment		Gender		Category				
	Positive	Negative	Male	Female	American	Asian	Bar	Dessert	Mexican
SYelp	266,041	177,218	-	-	-	-	-	-	-
FYelp	2,056,132	639,272	1,218,068	1,477,336	904,026	518,370	595,681	431,225	246,102
Amazon	64,251,073	10,944,310	-	-	26,208,872	14,192,554	25,894,877	4,324,913	4,574,167
Social Media Content	7,682,688	17,823,468	14,501,958	18,463,789	12,628,250	65+			

Table 3: The number of reviews for each attribute for different datasets. The *SYelp*, *FYelp* and the Amazon datasets are composed of 443k, 2.7M and 75.2M sentences respectively. Public social media content is collected from 3 different data sources with 25.5M, 33.0M and 20.2M sentences for the *Feeling*, *Gender* and *Age* attributes respectively.

Figure: Dataset Statistics

Results

Model	Accuracy	BLEU	PPL
Fader/StyleEmbedding (Fu et al., 2017)	18%	16.7	56.1
MultiDecoder (Fu et al., 2017)	52%	11.3	90.1
CAE (Shen et al., 2017)	72%	6.8	53.0
Retrieval (Li et al., 2018)	81%	1.3	7.4
Rule-based (Li et al., 2018)	73%	22.3	118.7
DeleteOnly (Li et al., 2018)	77%	14.5	67.1
DeleteAndRetrieve (Li et al., 2018)	79%	16.0	66.6
Fader (Ours w/o backtranslation & attention)	71%	15.7	35.1
Ours	87%	14.6	26.2
Ours	85%	24.2	26.5
Ours	74%	31.2	49.8

Figure: Comparison with Benchmark Methods

	Fluency	Content	Sentiment
DAR (Li et al. (2018))	3.33 (1.39)	3.16 (1.43)	64.05%
Ours	4.07 (1.12)	3.67 (1.41)	69.66%
Human (Li et al. (2018))	4.56 (0.78)	4.01 (1.25)	81.35%

Figure: Evaluation Criterias

Qualitative Results

Attribute Transfer

Positive ↔ Negative (Yelp)	
Positive	frozen hot chocolate with peanut butter cups = amazing. i'll be back for some food next time!
Negative	frozen hot chocolate with peanut butter ? horrible. i'll stick with the coffee shop next door!
Negative	one word: underwhelming. save your money and find the many restaurants in vegas that offers a real experience.
Positive	one word: delicious. save room for the best and most authentic indian food in vegas.
Asian ↔ Mexican (Yelp)	
Asian	best thai food i've ever had in the us. great duck specials on monday.. best yellow curry fried rice..
Mexican	best mexican food i've ever had in my life. great guacamole on the side.. best carnitas tacos i have ever had..
Mexican	awesome carne asada! try the papa verde with steak! it's delicious and the portions are great!
Asian	awesome orange chicken! try the orange chicken with the spicy sauce! it's delicious and the portions are great!
Male ↔ Female (Yelp)	
Male	good food. my wife and i always enjoy coming here for dinner. i recommend india garden.
Female	good food. my husband and i always stop by here for lunch. i recommend the veggie burrito.
Female	we are regulars here... me n my husband just gorge on these freaking amazing donuts!!!! loved it
Male	we are regulars here... every time we come here she loves the new york style pizza!!!!!!

Figure: Attribute Transfer Results

Qualitative Results

Multiple Attributes

Sentiment	Category	Input / Generations
Amazon		
Positive	Movies	exciting new show. john malkovich is superb as always. great supporting cast. hope it survives beyond season 1
Positive	Books	exciting new book. john grisham is one of the best. great read. hope he continues to write more.
Negative	Books	nothing new. john grisham is not as good as his first book. not a good read.
Positive	Clothing	awesome new watch. fits perfectly. great price. great quality. hope it lasts for a long time.
Negative	Clothing	horrible. the color is not as pictured. not what i expected. it is not a good quality.
Positive	Electronics	works great. the price is unbeatable. great price. great price. hope it lasts for a long time.
Negative	Electronics	worthless. the picture is not as clear as the picture. not sure why it is not compatible with the samsung galaxy s2.
Positive	Movies	exciting new show. john goodman is great as always. great supporting cast. hope it continues to end.
Negative	Movies	horrible. the acting is terrible. not worth the time. it's not worth the time.
Positive	Music	awesome new album. john mayer is one of the best. great album. hope he continues to release this album.
Negative	Music	horrible. the songs are not as good as the original. not worth the price.
Yelp		
Negative	Dessert	the bread here is crummy, half baked and stale even when "fresh." i won't be back.
Positive	American	the burgers here are juicy, juicy and full of flavor! i highly recommend this place.
Negative	American	the bread here is stale, dry and over cooked even though the bread is hard. i won't be back.
Positive	Asian	the sushi here is fresh, tasty and even better than the last. i highly recommend this place.
Negative	Asian	the noodles here are dry, dry and over cooked even though they are supposed to be "fresh." i won't be back.
Positive	Bar	the pizza here is delicious, thin crust and even better cheese (in my opinion). i highly recommend it.
Negative	Bar	the pizza here is bland, thin crust and even worse than the pizza, so i won't be back.
Positive	Dessert	the ice cream here is delicious, soft and fluffy with all the toppings you want. i highly recommend it.
Negative	Dessert	the bread here is stale, stale and old when you ask for a "fresh" sandwich. i won't be back.

Figure: Multiple Attributes

Qualitative Results

Another Attribute Transfer

Relaxed → Annoyed	
Relaxed	Wow! Sitting on my sister's patio, a glass of wine, and glorious music! Hmmm!
Annoyed	Wow! Sitting on my sister's patio, a glass of wine, and the neighbors are out! Geez!
Relaxed	Nothing like a few 🍷🥂 after a long productive day!!
Annoyed	Nothing like a flat tire 🚗 after a long day at work!!
Relaxed	I decided it was time for a little chill time with my people tonight, I Missed them! Plus I need a break. 🍷🥂🎵
Annoyed	I thought I was sleeping for a little while at the end of the week, I'm done! Plus I need a nap. 😴♀️😡😡😡😡
Relaxed	Rain = Sleepy! Love the sound of rain on my tin roof. 🌧️💧 FYI: Tomorrow is FRIDAY!
Annoyed	Rain = Mad! The sound of rain on my tin roof. 🌧️🌧️ Rain is overrated!
Relaxed	Yay!! A quick pedicure before I pick up the little angel from school! 🧖‍♀️
Annoyed	Yay!! A week before I pick up the little bastard from school! FML
Relaxed	Had an amazing day driving around. The sea, the woods, just great. 👍
Annoyed	Had an amazing day driving around. The weather, the roads are delayed, and the traffic is closed. 🚗

Figure: Attribute Transfer

- Rule based methods still work much better than neural methods (Retrieve only from DAR)
- Back-translation a better alternative to adversarial loss in text domain
- Adding extra knowledge in neural models help
- What happens when you combine DAR and this paper's approach (explicit constrained style transfer)?
- Awesome paper!