AI Department

TGIF

Talk is cheap? Show me the code...

2020-03-26 4:30PM

分享题目：自然语言处理与对抗学习

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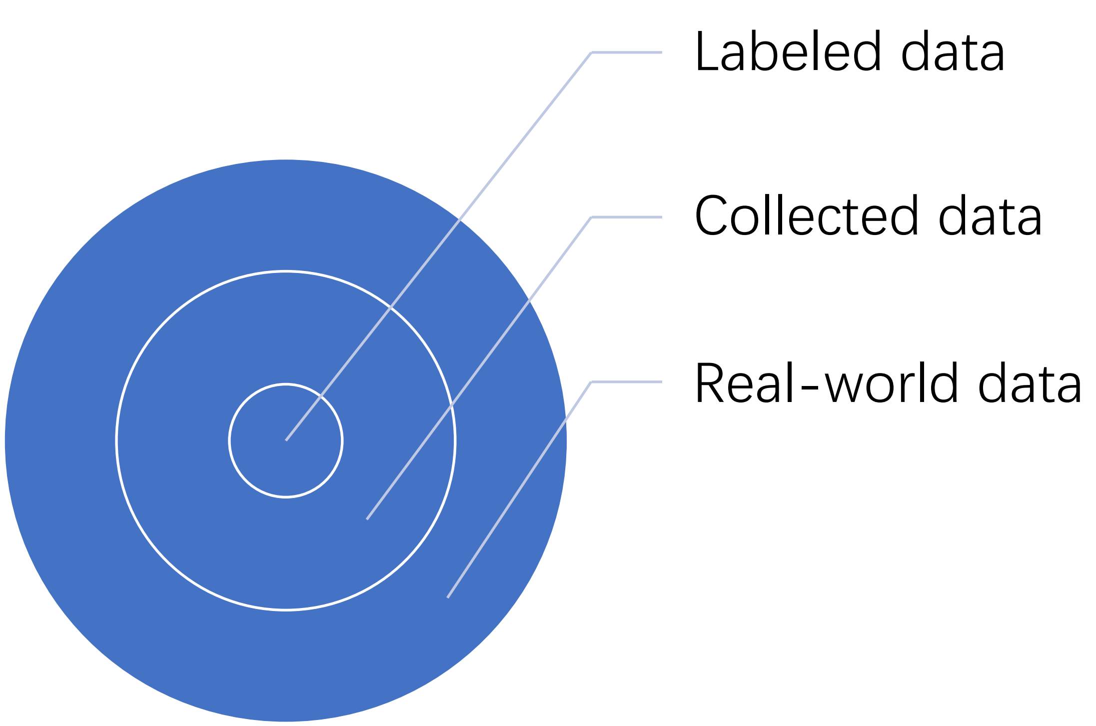
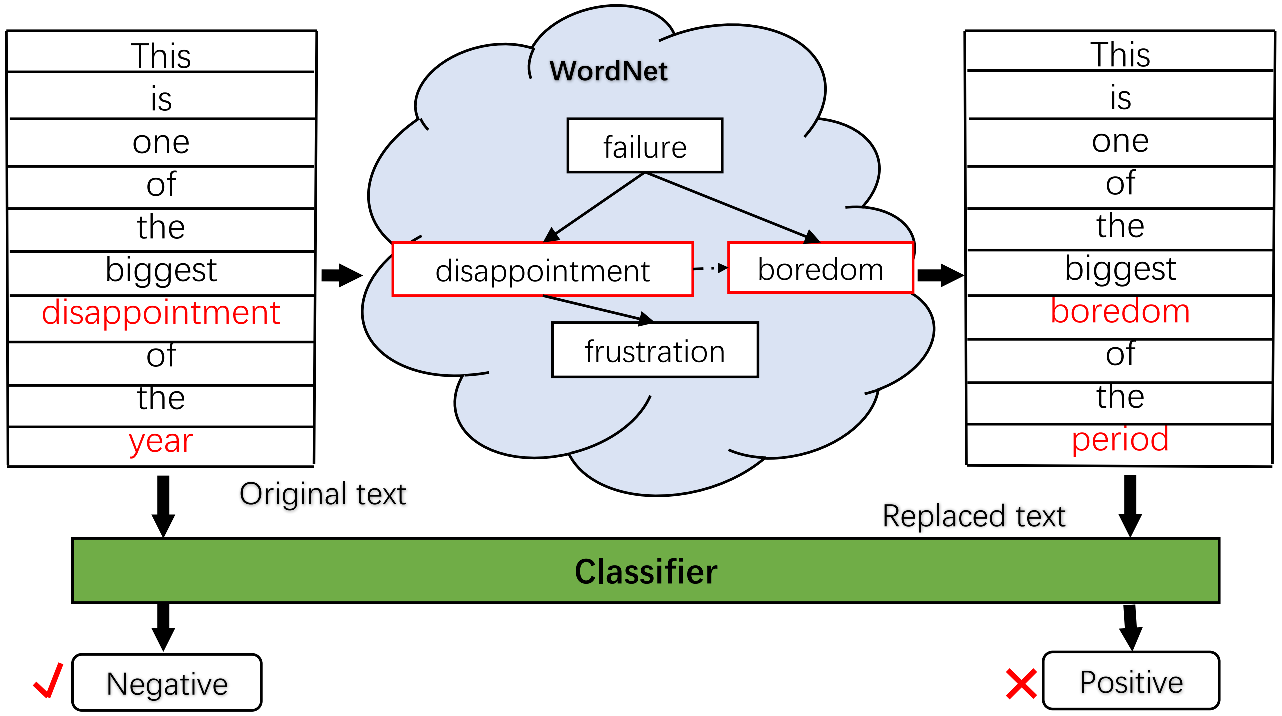
来自机构：北京大学

Lexical-Based Adversarial Reinforcement Training for Robust Sentiment Classification (EMNLP 2019)

- Training data is limited
- Real-world data is unlimited
  - Noises, diverse phrases



Lexical-Based Adversarial Reinforcement Training for Robust Sentiment Classification (EMNLP 2019)



Sensitive to little perturbation

Lexical-Based Adversarial Reinforcement Training for Robust Sentiment Classification (EMNLP 2019)

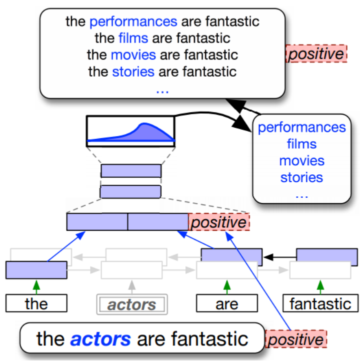
SST-2	Classifier (RNN)	Classifier (CNN)	LexicalAT (RNN)	LexicalAT (CNN)
Test Set	80.61	80.62	81.60	81.58
RNN-Attacking Set	69.91	65.62	76.44	73.70
CNN-Attacking Set	68.81	68.04	74.62	76.28
SST-5	**Classifier (RNN)**	**Classifier (CNN)**	**LexicalAT (RNN)**	**LexicalAT (CNN)**
Test Set	40.54	40.81	41.99	41.67
RNN-Attacking Set	35.16	35.43	38.73	38.91
CNN-Attacking Set	34.98	36.60	37.65	38.96
RT	**Classifier (RNN)**	**Classifier (CNN)**	**LexicalAT (RNN)**	**LexicalAT (CNN)**
Test Set	75.85	75.85	76.12	76.22
RNN-Attacking Set	69.05	68.78	71.44	70.61
CNN-Attacking Set	62.90	61.89	69.88	71.17

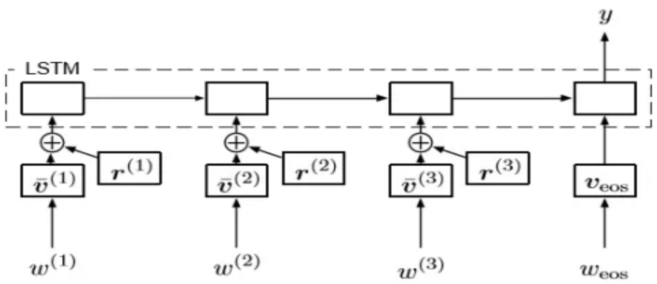
Performance drops largely

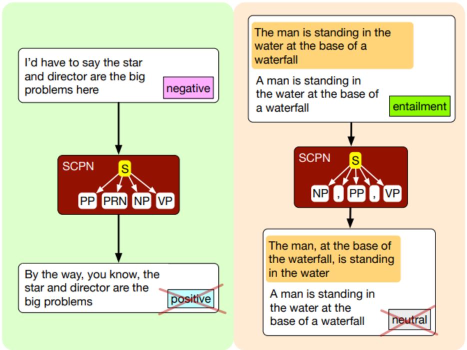
Lexical-Based Adversarial Reinforcement Training for Robust Sentiment Classification (EMNLP 2019)

- **Previous work**
  - Data augmentation based approaches
    - Random noise
    - Increase syntactic diversity
  - Adversarial training based approaches
- **Challenges**
  - **Rely on human knowledge**
  - **Low semantic diversity**

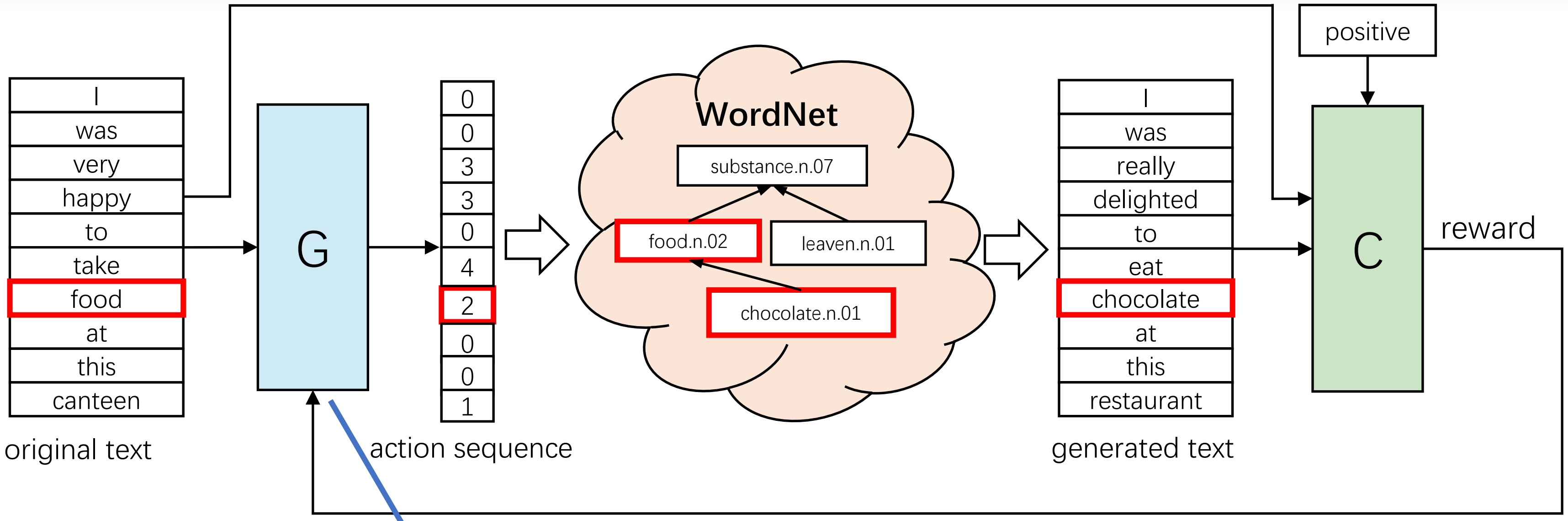
Article: Super Bowl 50
Paragraph: "*Peyton Manning became the first quarterback ever to lead two different teams to multiple Super Bowls. He is also the oldest quarterback ever to play in a Super Bowl at age 39. The past record was held by John Elway, who led the Broncos to victory in Super Bowl XXXIII at age 38 and is currently Denver's Executive Vice President of Football Operations and General Manager. Quarterback Jeff Dean had jersey number 37 in Champ Bowl XXXIV.*"
Question: "*What is the name of the quarterback who was 38 in Super Bowl XXXIII?*"
Original Prediction: John Elway
Prediction under adversary: Jeff Dean







Lexical-Based Adversarial Reinforcement Training for Robust Sentiment Classification (EMNLP 2019)

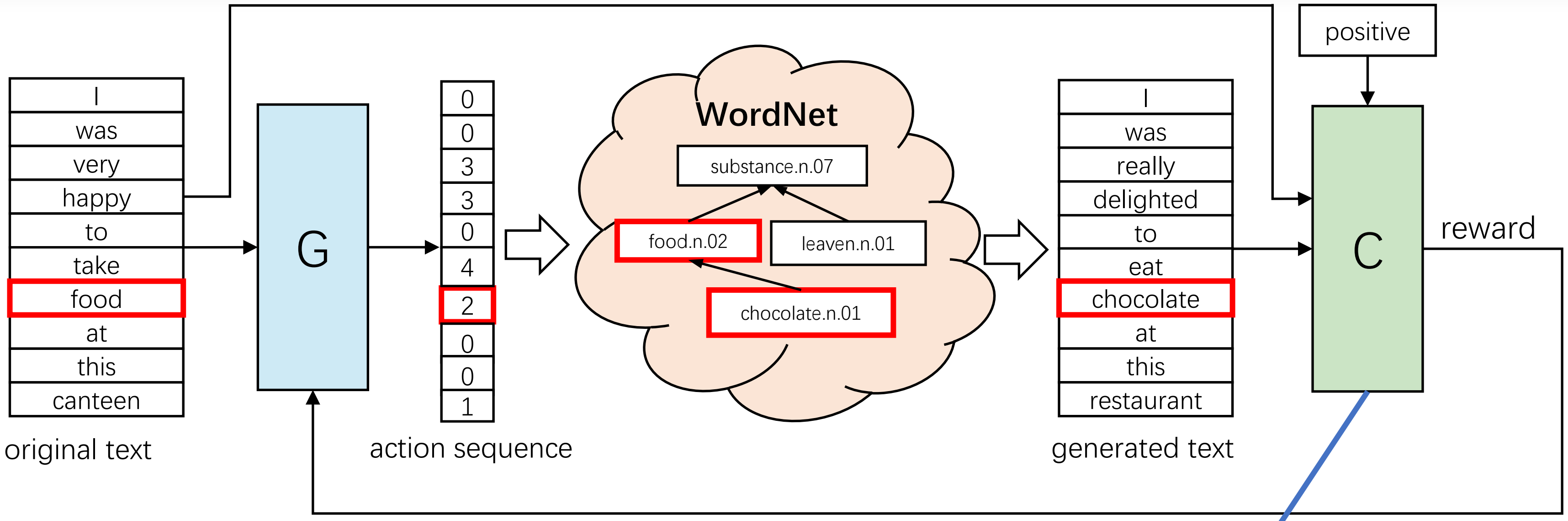


Action Type

0	no replacement
1	replacing with a superior word
2	replacing with a subordinate word
3	replacing with a synonym
4	replacing with its neighbor word

Generate attacking examples to confuse the classifier

Lexical-Based Adversarial Reinforcement Training for Robust Sentiment Classification (EMNLP 2019)

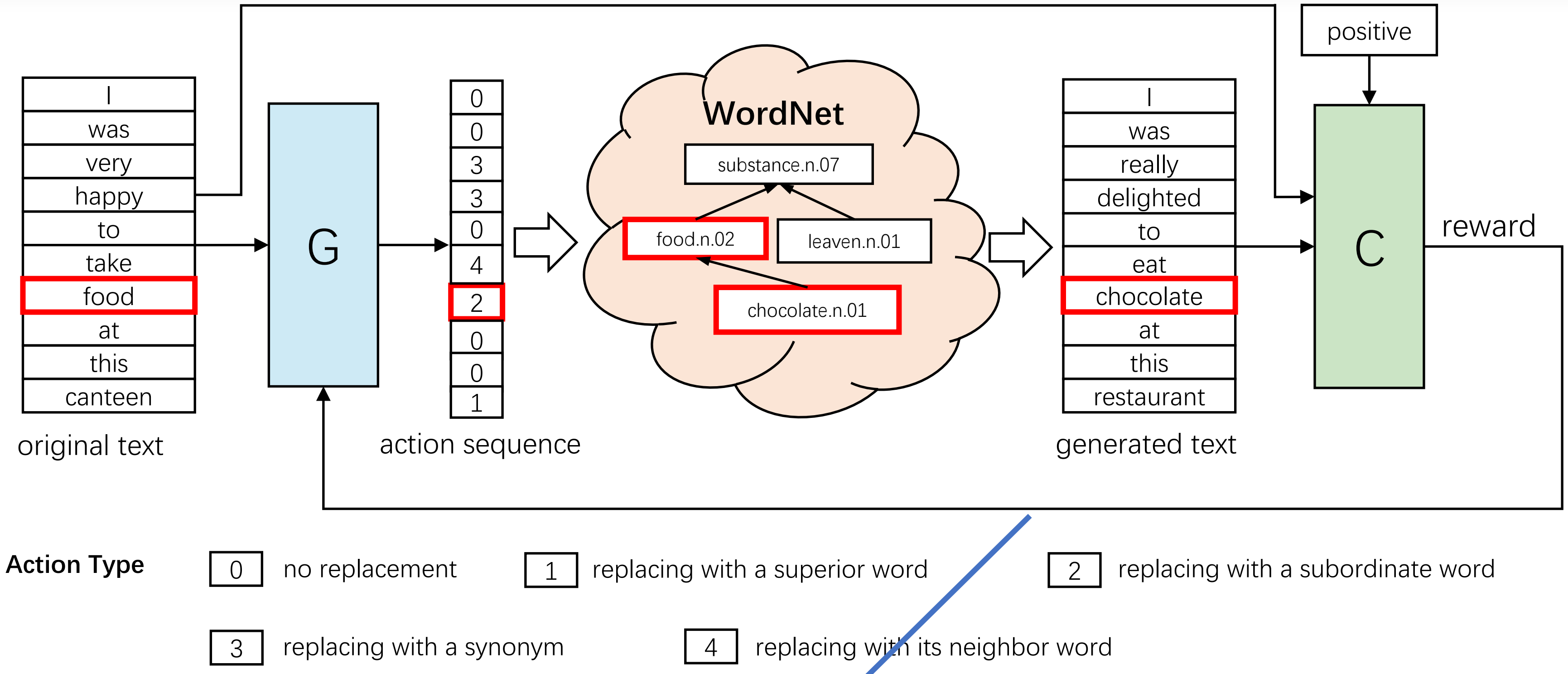


Action Type

0	no replacement	1	replacing with a superior word
2	replacing with a subordinate word	3	replacing with a synonym
4	replacing with its neighbor word		

Learn to classify attacking examples

Lexical-Based Adversarial Reinforcement Training for Robust Sentiment Classification (EMNLP 2019)



$$r(\hat{a}) = logp_C(y|x;\emptyset) - logp_C(y|\hat{x};\emptyset)$$

Return the reward of the generated examples

Lexical-Based Adversarial Reinforcement Training for Robust Sentiment Classification (EMNLP 2019)

- **Dataset**
  - Four sentiment classification tasks
- **Classifier**
  - CNN, RNN, BERT

Dataset	#Class	Avg. #w	Train	Dev	Test
SST2	2	19	6,920	872	1,821
SST5	5	18	8,544	1,101	2,210
RT	2	21	8,608	964	1,089
Yelp	5	89	100,000	10,000	10,000

Table 3: Dataset statistics. "Class" is the number of pre-defined labels. "Avg. #w" is the average word number in the input text. "Train", "Dev", and "Test" represent the sizes of the training set, the development set, and the test set.

Lexical-Based Adversarial Reinforcement Training for Robust Sentiment Classification (EMNLP 2019)

Test set

Approach	SST-2	SST-5	RT	Yelp
RNN(our implemented)	80.61	40.54	75.85	60.94
RNN (Kobayashi, 2018)	80.30	40.20	*	*
+SynDA (Zhang et al., 2015)	80.20	40.50	*	*
+ConDA (Kobayashi, 2018)	80.10	41.10	*	*
+VAT (Miyato et al., 2017)	81.16	37.38	75.94	59.69
+LexicalAT (proposed)	**81.60**	**41.99**	**76.12**	**61.18**

Approach	SST-2	SST-5	RT	Yelp
CNN(our implemented)	80.62	40.81	75.85	60.77
CNN (Kobayashi, 2018)	79.50	41.30	*	*
+SynDA (Zhang et al., 2015)	80.00	40.70	*	*
+ConDA (Kobayashi, 2018)	80.80	**42.10**	*	*
+VAT (Miyato et al., 2017)	*	*	*	*
+LexicalAT (Proposed)	**81.58**	41.67	**76.22**	**61.86**

Approach	SST-2	SST-5	RT	Yelp
BERT(our implemented)	92.60	55.07	88.57	66.76
+SynDA (Zhang et al., 2015)	*	*	*	*
+ConDA (Kobayashi, 2018)	*	*	*	*
+VAT (Miyato et al., 2017)	*	*	*	*
+LexicalAT (proposed)	**93.03**	**55.38**	**88.68**	**67.50**

Adversarial set

SST-2	Classifier (RNN)	Classifier (CNN)	LexicalAT (RNN)	LexicalAT (CNN)
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Large improvement

Lexical-Based Adversarial Reinforcement Training for Robust Sentiment Classification (EMNLP 2019)

■ Conclusion

- Current data-driven models tend to over-fit to training data.
- We propose a lexical-based adversarial reinforcement training approach, LexicalAT, to improve the generalization ability of text understanding models.
- To the best of our knowledge, it is the first work of combining a knowledge base and adversarial learning.

DP-GAN: A Cross-Entropy Based Generative Adversarial Network for Diversified Text Generation (EMNLP 2018)

Input: *One of my favorite places to eat.*
MLE: *Service is great.*
PG-BLEU: *Service is always good.*
SeqGAN: *Love the chicken and waffles. Service is always great.*
DP-GAN: *Love the fact that they have a large selection of food. Service is always great and the food is always fresh. I've been to this place a few times and have never been disappointed.*

Input: *Excellent service, clean, nice ambience.*
MLE: *Food is very good.*
PG-BLEU: *Food is very good.*
SeqGAN: *Food is very good.*
DP-GAN: *I had the chicken and beef and it was delicious. Food is good and the service is great. I would recommend this place to anyone who wants to eat here.*

Current approaches tend to generate "boring" text

Input: *I brought friends – seven of them – who'd never been to a Bar Louie before.*
MLE: *Food was mediocre, but the service was great. I will not be returning.*
PG-BLEU: *Food was terrible. Wouldn't recommend this place to anyone.*
SeqGAN: *Food was just okay. I wouldn't recommend this place.*
DP-GAN: *Ordered a chicken salad with a side of fries, and it was just ok. Food was good, but the service was slow. I had to ask for a refill on my drink, and the bartender was rude. I wouldn't recommend this place to anyone.*

Input: *I don't think it's too spicy, so i add a little hot curry spice to the sauce.*
MLE: *It's great for cooking. I have to say, I'm not sure if it is the same.*
PG-BLEU: *Love it!*
SeqGAN: *Love it! Love this stuff. I have used it for years and it is very good.*
DP-GAN: *I've tried many different brands of hot sauces but this one is the best. I've also used it in soups and stews. I also like that it is organic and has a great flavor.*

Challenge in Generation: Heavy-Tailed Patterns

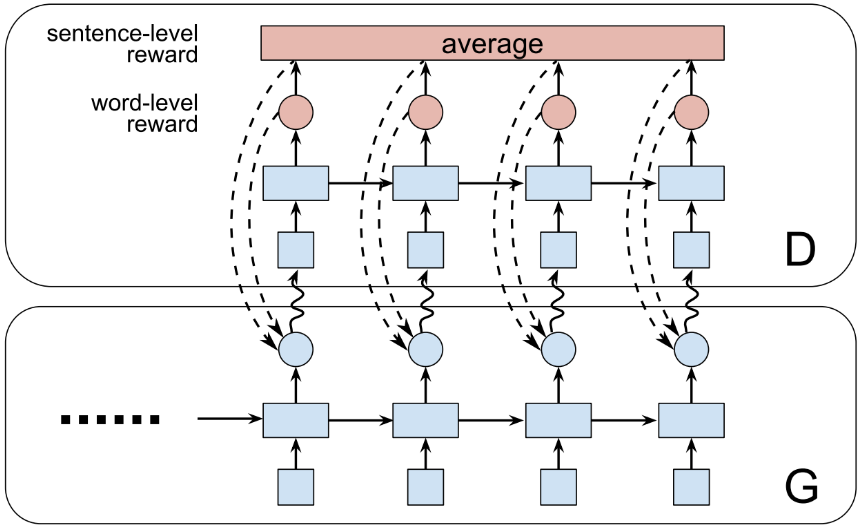
词	真实文本频率	生成文本频率
the	4.2%	7.1%
and	3.2%	4.6%
was	1.5%	5.3%

MLE over-estimates highly frequent words

DP-GAN: A Cross-Entropy Based Generative Adversarial Network for Diversified Text Generation (EMNLP 2018)

Approach

- The generator G is responsible for generating text, which is based on a sequence-to-sequence structure.
- The discriminator D is a language model to encourage the generator to generate novel texts.
- Cross entropy as reward.



DP-GAN: A Cross-Entropy Based Generative Adversarial Network for Diversified Text Generation (EMNLP 2018)

Reward

- **Sentence-Level Reward**
  For a sentence y_t of K words, the reward at the sentence level is the averaged reward of each word: y_t

$$R(y_t) = -\frac{1}{K}\sum_{k=1}^{K} \log D(y_{t,k}|y_{t,<k})$$

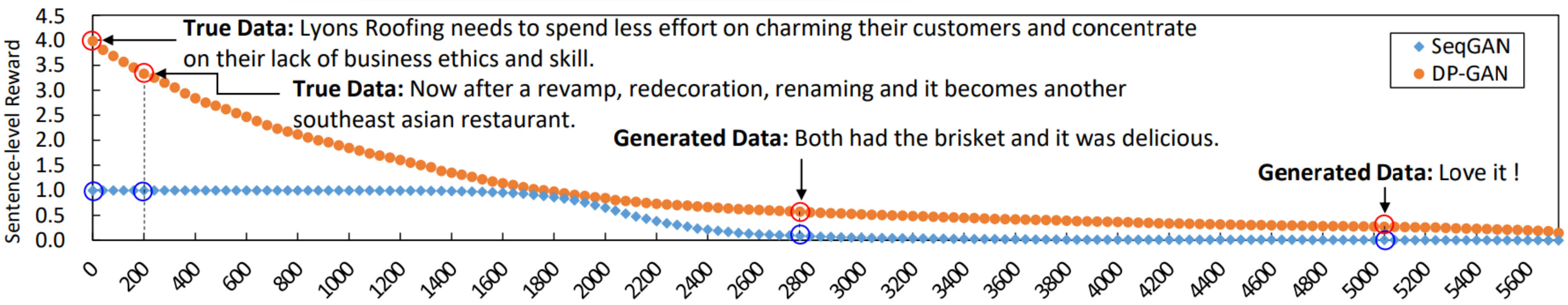
- **Word-Level Reward**
  Considering that the reward for different words in a sentence y_t should be different, we further propose to use the reward at the word level as follows:

$$R\left(y_{t,k}|y_{t,<k}\right) = -\log D(y_{t,k}|y_{t,<k})$$

DP-GAN: A Cross-Entropy Based Generative Adversarial Network for Diversified Text Generation (EMNLP 2018)

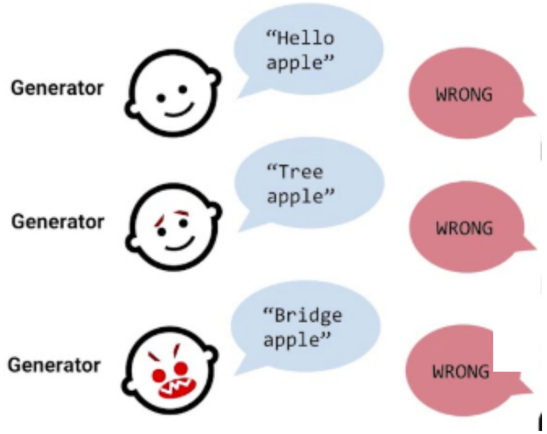
Why language model

- Without the saturation problem
- Each word has a reward
- Novel text gets high reward



DP-GAN: A Cross-Entropy Based Generative Adversarial Network for Diversified Text Generation (EMNLP 2018)

- **Challenge**
  - Broken generator
- **Solution**
  - Teacher forcing



Policy Gradient Training

Adversarial reinforcement training:

Initialize G_θ, D_ϕ with random weights θ, ϕ
Pre-train G_θ using MLE on a sequence dataset $\mathcal{D} = (X, Y)$
Generate samples using G_θ for training D_ϕ
Pre-train D_ϕ
N = number of training iterations
M = number of training generator
K = number of training discriminator
for each $i = 1, 2, ..., N$ **do**
    for each $j = 1, 2, ..., M$ **do**
        Generate a sequence $Y_{1:T} \sim G_\theta$
        Update generator via policy gradient
        Sample a sequence $Y_{1:T} \sim \mathcal{D}$
        Update generator parameters
    end for
    for each $j = 1, 2, ..., K$ **do**
        Generate samples using G_θ
        Train discriminator D_ϕ
    end for
end for

DP-GAN: A Cross-Entropy Based Generative Adversarial Network for Diversified Text Generation (EMNLP 2018)

- **Datasets**
  - Yelp Review Generation
  - Amazon Review Generation
  - Open Subtitles
- **Performance**
  - Human Evaluation
    - Highest rank
  - Automatic Evaluation
    - Longer sentences
    - More n-grams

	Model	Averaged Ranking
Yelp	MLE	1.89
	PG-BLEU	2.22
	SeqGAN	2.12
	DP-GAN	**1.51**
Amazon	MLE	1.93
	PG-BLEU	2.24
	SeqGAN	1.98
	DP-GAN	**1.50**
Dialogue	MLE	2.46
	PG-BLEU	2.40
	SeqGAN	2.17
	DP-GAN	**1.92**

Yelp	Token	Dist-1	Dist-2	Dist-3	Dist-S
MLE	151.2K	1.2K	3.9K	6.6K	3.9K
PG-BLEU	131.1K	1.1K	3.3K	5.5K	3.1K
SeqGAN	140.5K	1.1K	3.5K	6.1K	3.6K
DP-GAN(S)	**438.6K**	1.7K	7.5K	15.7K	10.6K
DP-GAN(W)	271.9K	2.8K	14.8K	29.0K	12.6K
DP-GAN(SW)	406.8K	**3.4K**	**22.3K**	**49.6K**	**17.3K**
Amazon	Token	Dist-1	Dist-2	Dist-3	Dist-S
MLE	176.1K	0.6K	2.1K	3.5K	2.6K
PG-BLEU	124.5K	0.6K	1.9K	3.5K	2.3K
SeqGAN	217.3K	0.7K	2.6K	4.6K	3.2K
DP-GAN(S)	**467.6K**	0.8K	3.6K	7.6K	7.0K
DP-GAN(W)	279.4K	1.6K	8.9K	18.4K	9.6K
DP-GAN(SW)	383.6K	**1.9K**	**11.7K**	**26.3K**	**13.6K**
Dialogue	Token	Dist-1	Dist-2	Dist-3	Dist-S
MLE	81.1K	1.4K	4.4K	6.3K	4.1K
PG-BLEU	97.9K	1.2K	3.9K	5.5K	3.3K
SeqGAN	83.4K	1.4K	4.5K	6.5K	4.5K
DP-GAN(S)	**112.2K**	1.5K	5.2K	8.5K	5.6K
DP-GAN(W)	79.4K	1.9K	7.7K	11.4K	6.0K
DP-GAN(SW)	97.3K	**2.1K**	**10.8K**	**19.1K**	**8.0K**

DP-GAN: A Cross-Entropy Based Generative Adversarial Network for Diversified Text Generation (EMNLP 2018)

- **Generated results**

Input: *One of my favorite places to eat.*
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DP-GAN: A Cross-Entropy Based Generative Adversarial Network for Diversified Text Generation (EMNLP 2018)

Conclusion

- We propose a new model, called DP-GAN, for diversified text generation, which assigns low reward for repeated text and high reward for novel and fluent text.
- We propose a novel language-model based discriminator that can better distinguish novel text from repeated text without the saturation problem.
- The experimental results on review generation and dialogue generation tasks show that our method can generate substantially more diverse and informative text than existing methods.