Unsupervised Probabilistic Text Generation

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CMPUT463/563 Lab Session

Advertisements

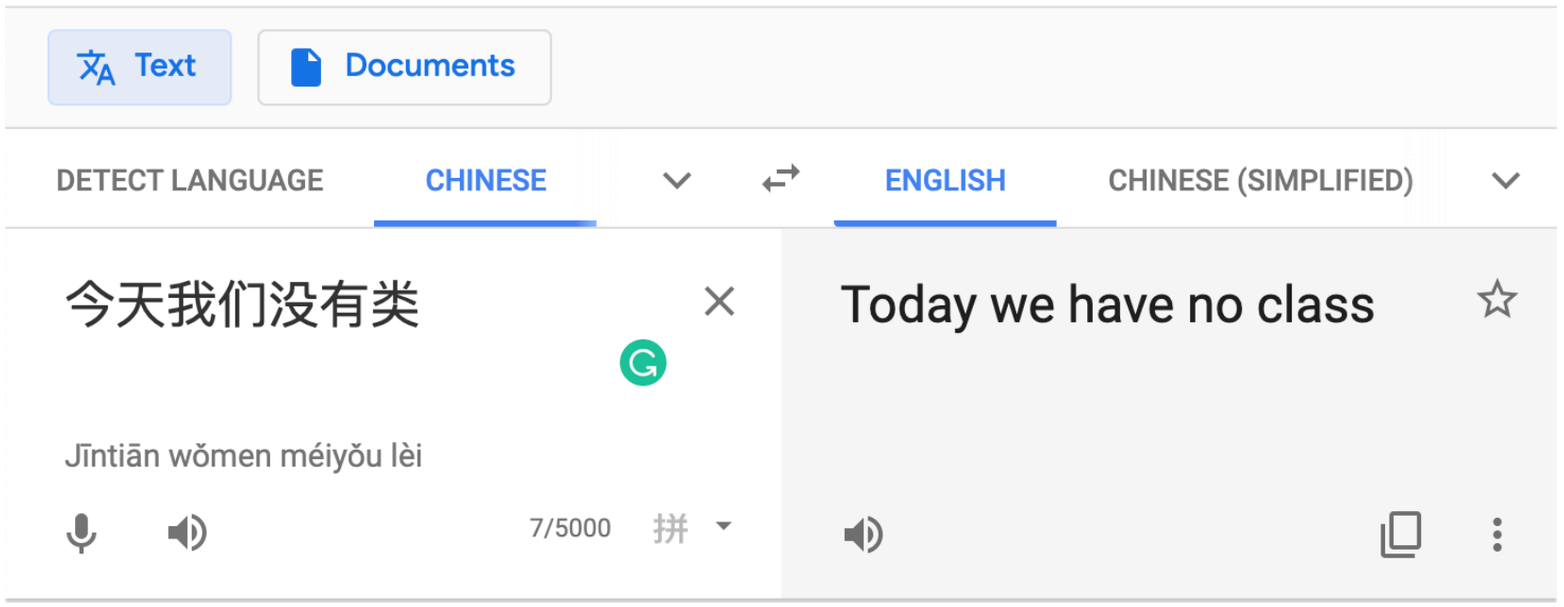
- Lili Mou is accepting all-level students
  - URA, MSc, PhD, postdoc
  - A typical path for URAs/MSc

    (466 course project →) Individual Study 499 → RAship
- Previous achievements
  - CMPUT499 (F20) → URA (W+S21) → CIKM'21
  - CMPUT499 (W21) → URA (S21) → EMNLP'21 (Findings)

amii UNIVERSITY OF ALBERTA

Why NLG is interesting?

- Industrial applications
  - Machine translation
  - Headline generation for news
  - Grammarly: grammatical error correction



https://translate.google.com/

Why NLG is interesting?

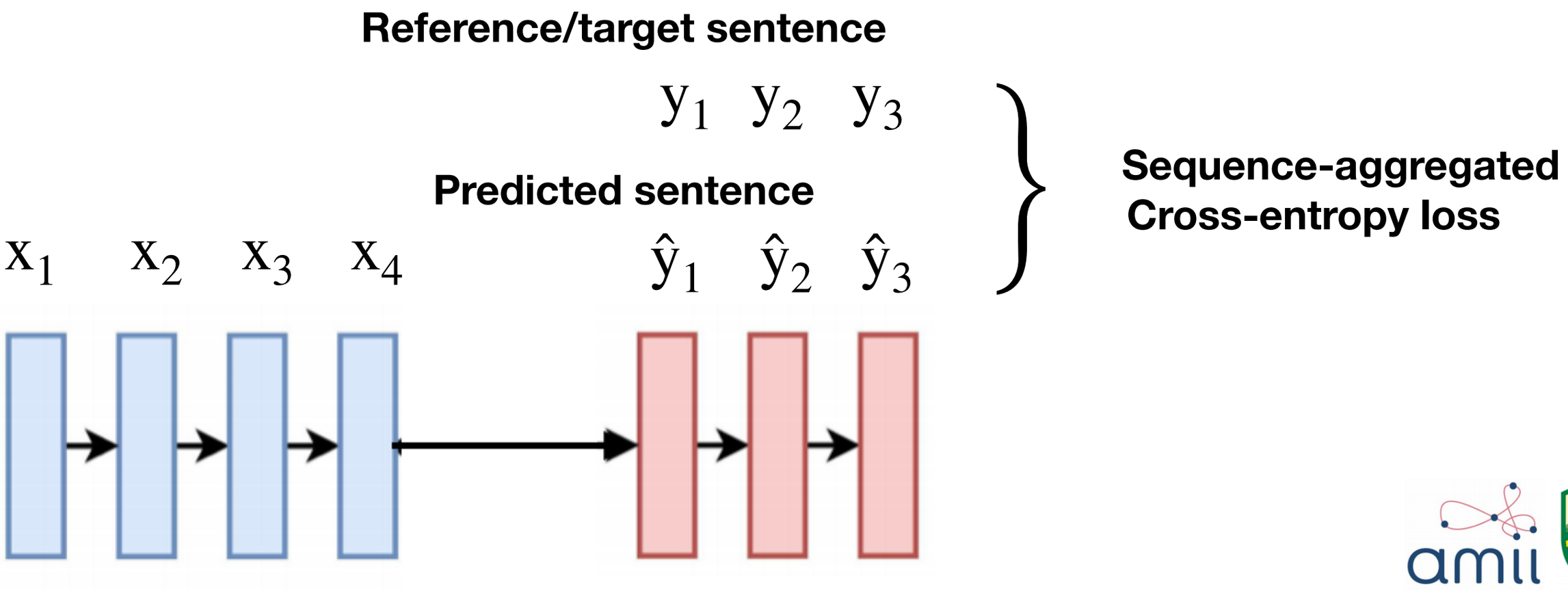
- Industrial applications
  - Machine translation
  - Headline generation for news
  - Grammarly: grammatical error correction
- Scientific questions
  - Non-linear dynamics for long-text generation
  - Discrete “multi-modal” distribution

Supervised Text Generation

Sequence-to-sequence training

Training data = $\{(\mathbf{x}^{(m)}, \mathbf{y}^{(m)})\}_{m=1}^{M}$

known as a *parallel corpus*



Unsupervised Text Generation

- Data = $\{\mathbf{x}^{(m)}\}_{m=1}^{M}$

- Important to **industrial applications**
  - Startup: No data
  - Minimum viable product

- Scientific interest

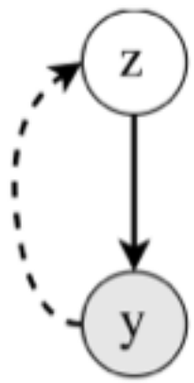
Key Ideas

- Data = $\{\mathbf{x}^{(m)}\}_{m=1}^{M}$
- Model a probabilistic distribution of data $P(\mathbf{x})$
  - Indirectly in the latent space z
  - Directly in the sentence space $\mathbf{x}$

Sampling in the latent space

Latent Space Modeling

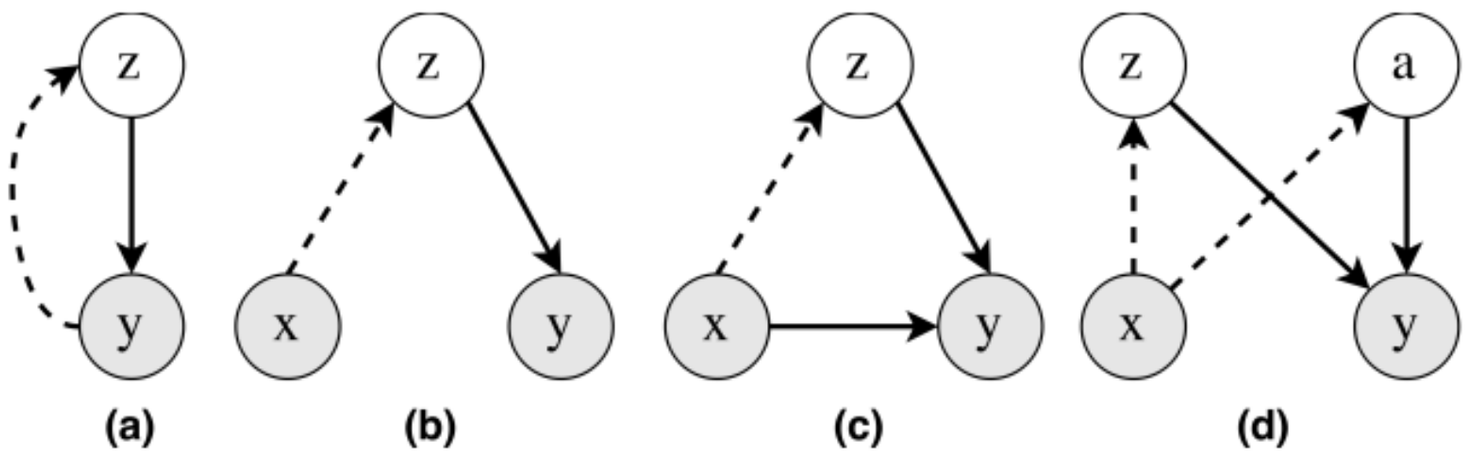
- Generation: $Z \rightarrow Y$, Recognition $Y \rightarrow Z$
  - Z: latent factors that control the generation
  - Y: the generated text



Variational Training

$$\log p_{\boldsymbol{\theta}}(\boldsymbol{y}^{(n)}) \geq \mathbb{E}_{\boldsymbol{z}\sim q_{\boldsymbol{\phi}}(\boldsymbol{z}|\boldsymbol{y}^{(n)})}\left[\log\left\{\frac{p_{\boldsymbol{\theta}}(\boldsymbol{y}^{(n)},\boldsymbol{z})}{q_{\boldsymbol{\phi}}(\boldsymbol{z}|\boldsymbol{y}^{(n)})}\right\}\right]$$

$$= \underbrace{\mathbb{E}_{\boldsymbol{z}\sim q_{\boldsymbol{\phi}}(\boldsymbol{z}|\boldsymbol{y}^{(n)})}\left[\log p_{\boldsymbol{\theta}}(\boldsymbol{y}^{(n)}|\boldsymbol{z})\right]}_{\text{Reconstruction}} - \underbrace{\mathrm{KL}\left(q_{\boldsymbol{\phi}}(\boldsymbol{z}|\boldsymbol{y}^{(n)})\|p(\boldsymbol{z})\right)}_{\text{KL penalty}} \triangleq \mathcal{L}^{(n)}(\boldsymbol{\theta},\boldsymbol{\phi})$$

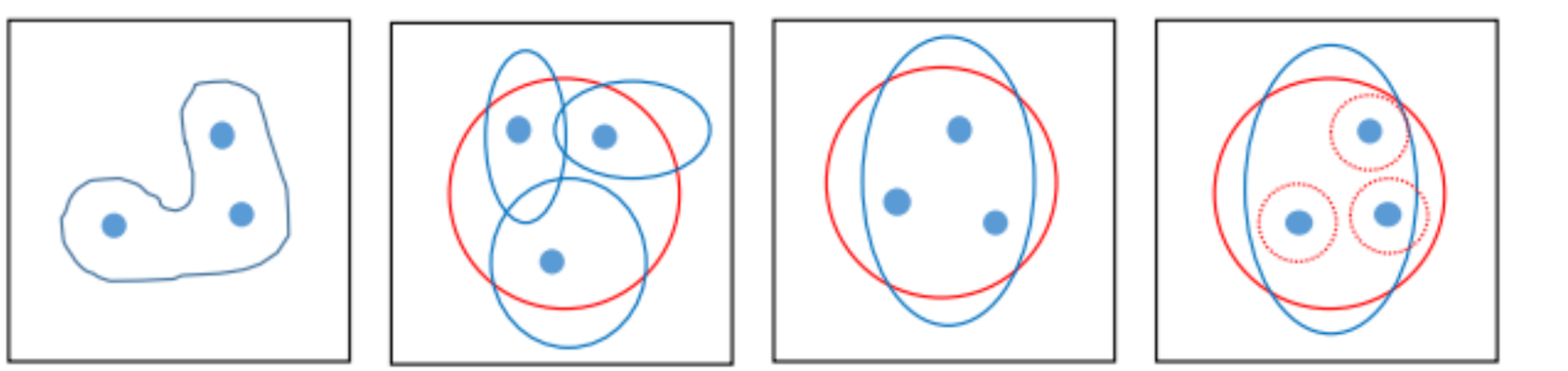


Autoencoder Menagerie

$$\log p_{\boldsymbol{\theta}}(\boldsymbol{y}^{(n)}) \geq \mathbb{E}_{\boldsymbol{z}\sim q_{\boldsymbol{\phi}}(\boldsymbol{z}|\boldsymbol{y}^{(n)})}\left[\log\left\{\frac{p_{\boldsymbol{\theta}}(\boldsymbol{y}^{(n)},\boldsymbol{z})}{q_{\boldsymbol{\phi}}(\boldsymbol{z}|\boldsymbol{y}^{(n)})}\right\}\right]$$

$$= \mathbb{E}_{\boldsymbol{z}\sim q_{\boldsymbol{\phi}}(\boldsymbol{z}|\boldsymbol{y}^{(n)})}\left[\log p_{\boldsymbol{\theta}}(\boldsymbol{y}^{(n)}|\boldsymbol{z})\right] - \mathrm{KL}\left(q_{\boldsymbol{\phi}}(\boldsymbol{z}|\boldsymbol{y}^{(n)})\|p(\boldsymbol{z})\right) \triangleq \mathcal{L}^{(n)}(\boldsymbol{\theta},\boldsymbol{\phi})$$

KL collapse to 0



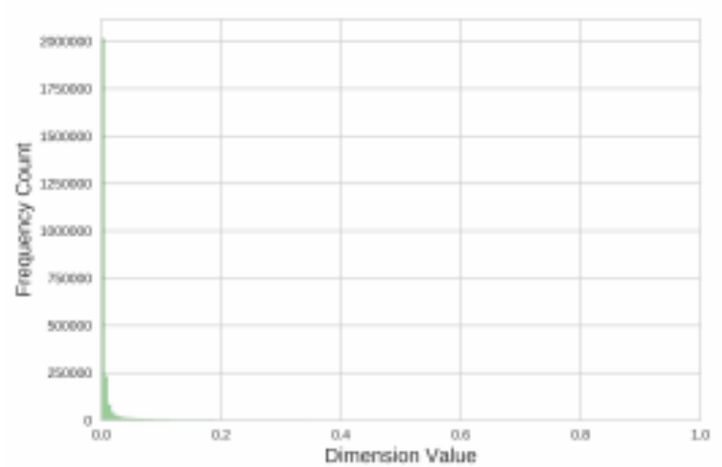
(a) DAE (b) VAE (c) WAE (d) WAE + aux loss

Wasserstein Autoencoder

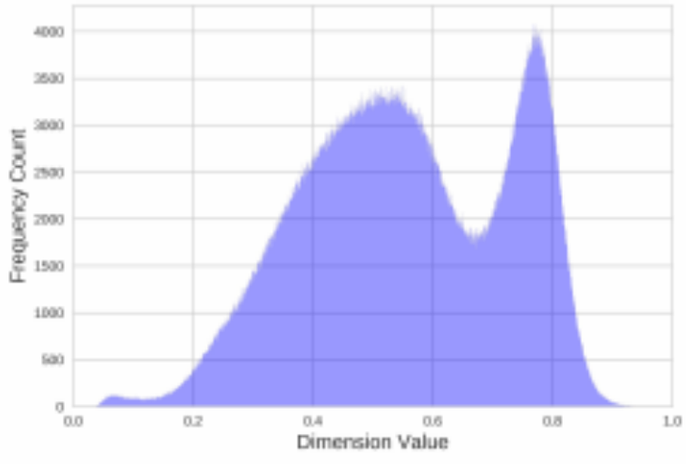
$$q(\boldsymbol{z}) \overset{\text{def}}{=} \sum_{\mathbf{x}} q(\boldsymbol{z}|\mathbf{x}) p_{\mathcal{D}}(\mathbf{x}) \overset{\text{set}}{=} p(\boldsymbol{z})$$

Stochasticity collapse

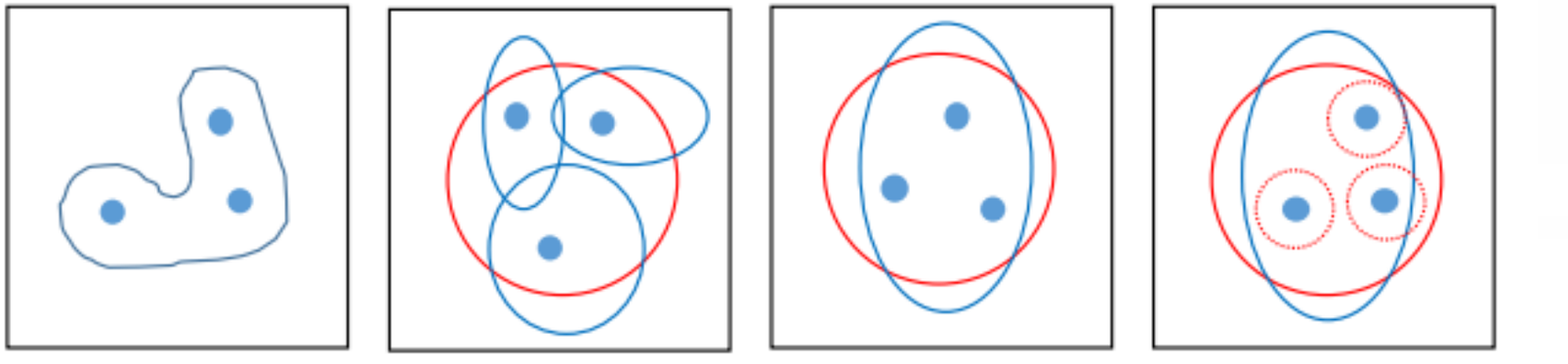
Theorem 1. *Suppose we have a Gaussian family* $\mathcal{N}(\boldsymbol{\mu}, \operatorname{diag} \boldsymbol{\sigma}^2)$*, where* $\boldsymbol{\mu}$ *and* $\boldsymbol{\sigma}$ *are parameters. The covariance is diagonal, meaning that the variables are independent. If the gradient of* $\boldsymbol{\sigma}$ *completely comes from sample gradient and* $\boldsymbol{\sigma}$ *is small at the beginning of training, then the Gaussian converges to a Dirac delta function with stochastic gradient descent, i.e.,* $\boldsymbol{\sigma} \to \mathbf{0}$*. (See Appendix A for the proof.)* □



(a) $\lambda_{\text{KL}} = 0$

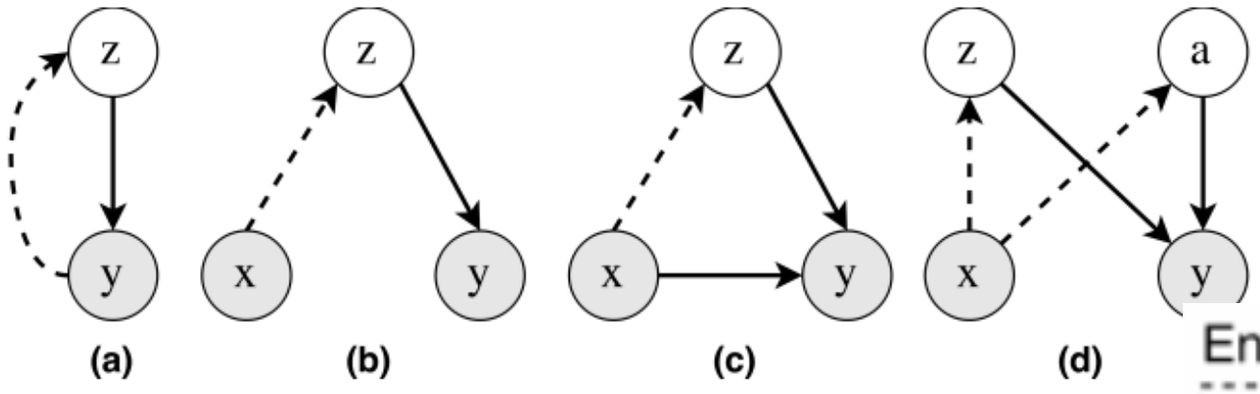


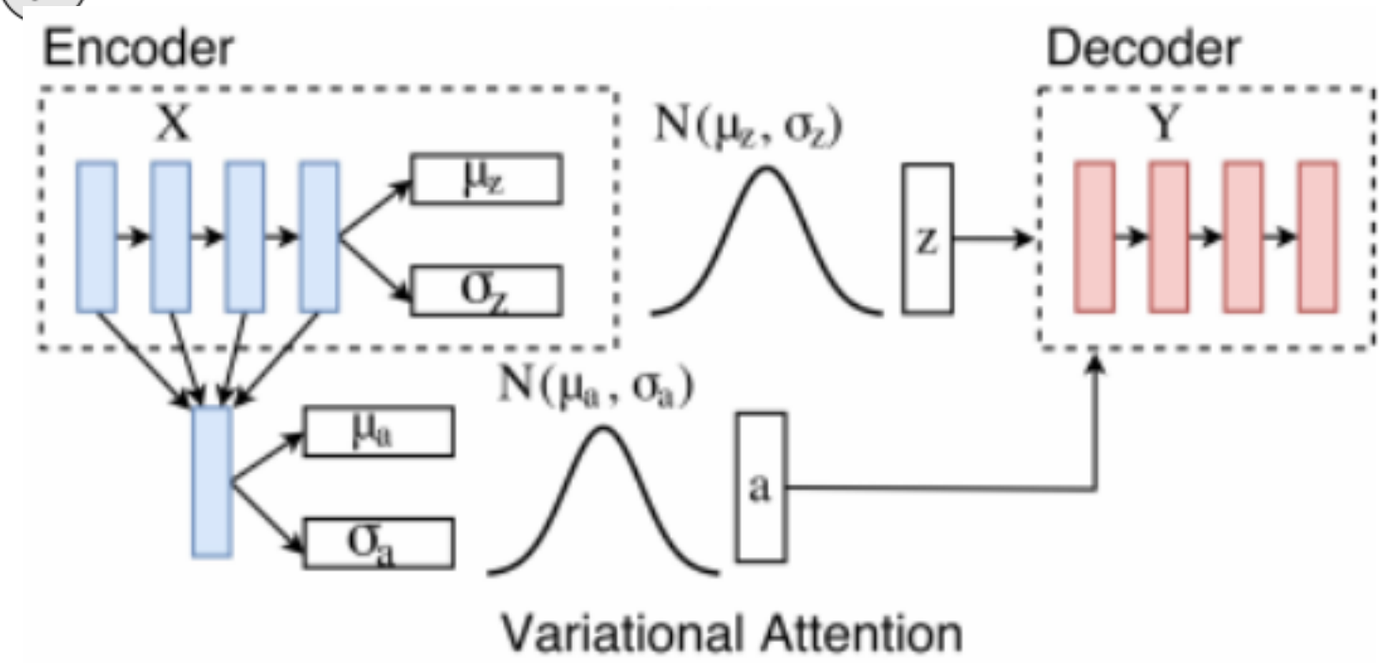
(b) $\lambda_{\text{KL}} = 0.01$



(a) DAE (b) VAE (c) WAE (d) WAE + aux loss

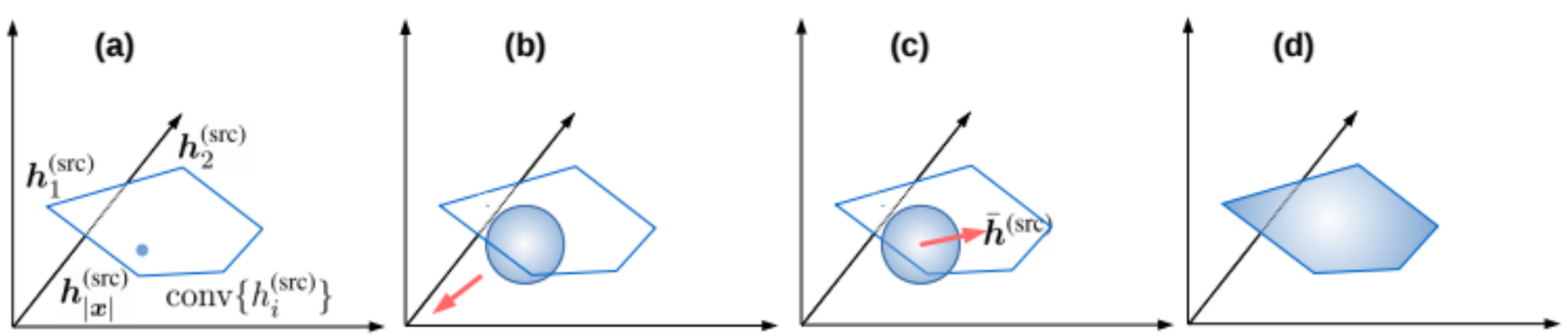
Variational Encoder-Decoder





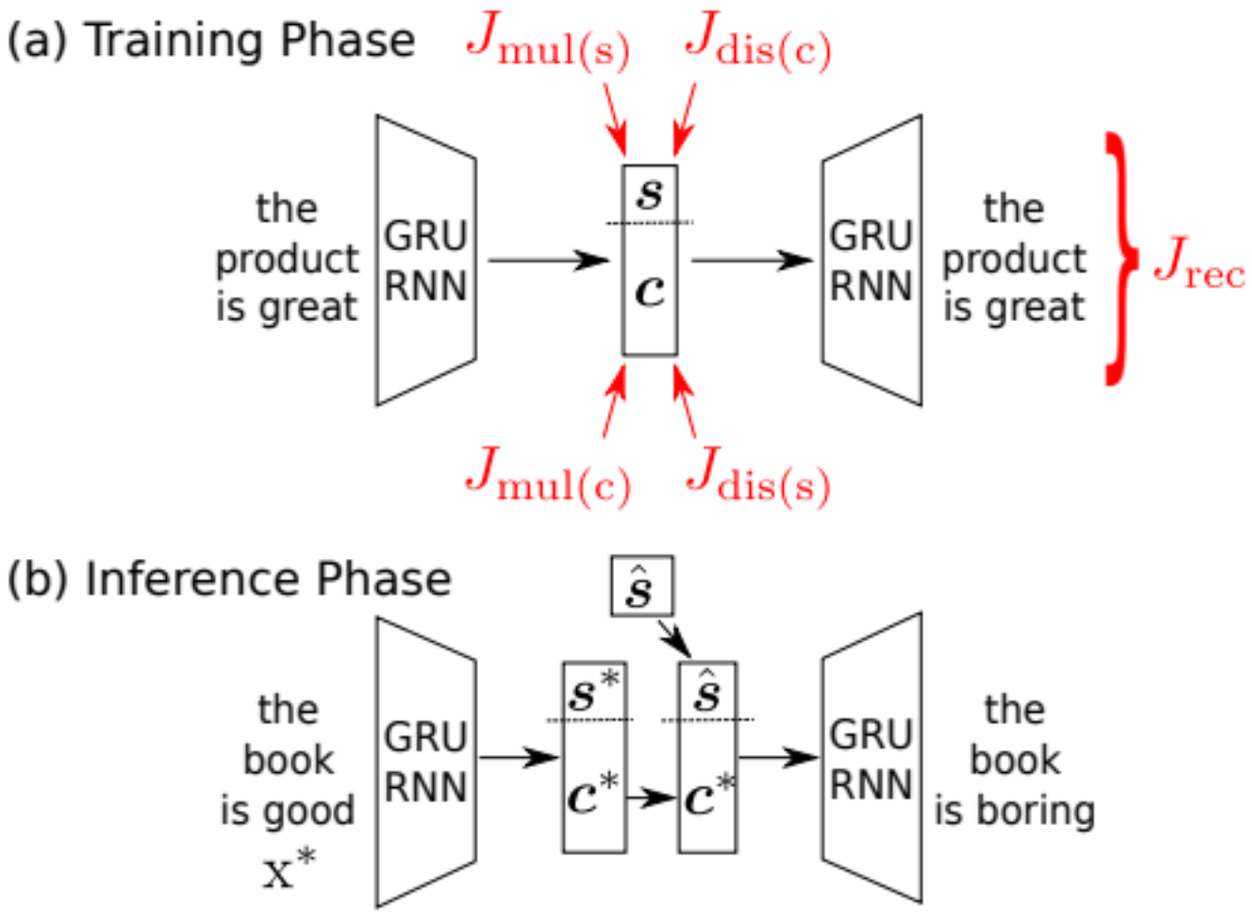
Bypassing mechanism

$$\mathcal{L}_j^{(n)}(\boldsymbol{\theta}, \boldsymbol{\phi}) = \mathbb{E}_{\boldsymbol{z},\boldsymbol{a}\sim q_{\boldsymbol{\phi}}(\boldsymbol{z},\boldsymbol{a}|\boldsymbol{x}^{(n)})}\left[\log p_{\boldsymbol{\theta}}(\boldsymbol{y}^{(n)}|\boldsymbol{z},\boldsymbol{a})\right] - \mathrm{KL}\left(q_{\boldsymbol{\phi}}(\boldsymbol{z},\boldsymbol{a}|\boldsymbol{x}^{(n)})\|p(\boldsymbol{z},\boldsymbol{a})\right)$$
$$= \mathbb{E}_{\boldsymbol{z}\sim q_{\boldsymbol{\phi}}^{(z)}(\boldsymbol{z}|\boldsymbol{x}^{(n)}),\boldsymbol{a}\sim q_{\boldsymbol{\phi}}^{(a)}(\boldsymbol{a}|\boldsymbol{x}^{(n)})}\left[\log p_{\boldsymbol{\theta}}(\boldsymbol{y}^{(n)}|\boldsymbol{z},\boldsymbol{a})\right]$$
$$- \mathrm{KL}\left(q_{\boldsymbol{\phi}}^{(z)}(\boldsymbol{z}|\boldsymbol{x}^{(n)})\|p(\boldsymbol{z})\right) - \mathrm{KL}\left(q_{\boldsymbol{\phi}}^{(a)}(\boldsymbol{a}|\boldsymbol{x}^{(n)})\|p(\boldsymbol{a})\right)$$



Applications

- Controlled generation



Latent Space	Yelp		Amazon	
	DAE	VAE	DAE	VAE
None (majority guess)	0.60		0.51	
Content space ($\boldsymbol{c}$)	0.66	0.70	0.67	0.69
Style space ($\boldsymbol{s}$)	0.97	0.97	0.82	0.81
Complete space ($[\boldsymbol{s}; \boldsymbol{c}]$)	0.97	0.97	0.82	0.81

Table 1: Classification accuracy on latent spaces.

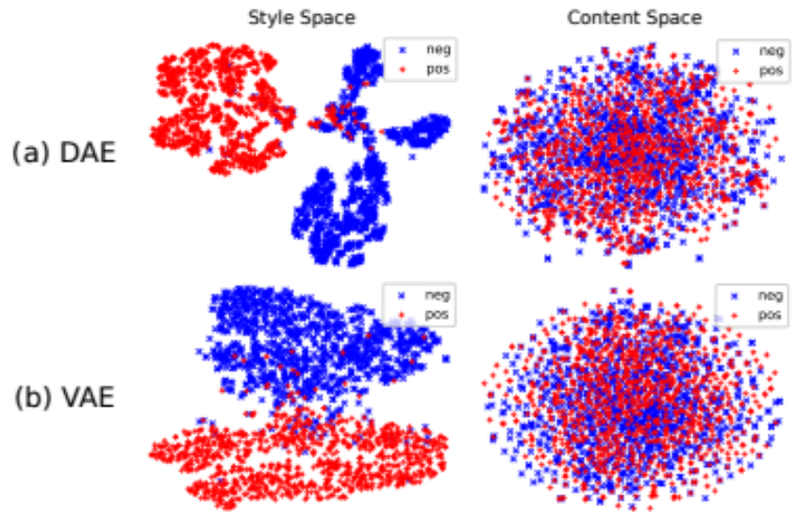


Figure 2: t-SNE plots of the disentangled style and content spaces on Yelp (with all auxiliary losses).

Applications

Original (Positive)	DAE Transferred (Negative)	VAE Transferred (Negative)
the food is excellent and the service is exceptional	the food was a bit bad but the staff was exceptional	the food was bland and i am not thrilled with this
the waitresses are friendly and helpful	the guys are rude and helpful	the waitresses are rude and are lazy
the restaurant itself is romantic and quiet	the restaurant itself is awkward and quite crowded	the restaurant itself was dirty
great deal	horrible deal	no deal
both times i have eaten the lunch buffet and it was outstanding	their burgers were decent but the eggs were not the consistency	both times i have eaten here the food was mediocre at best
Original (Negative)	**DAE Transferred (Positive)**	**VAE Transferred (Positive)**
the desserts were very bland	the desserts were very good	the desserts were very good
it was a bed of lettuce and spinach with some italian meats and cheeses	it was a beautiful setting and just had a large variety of german flavors	it was a huge assortment of flavors and italian food
the people behind the counter were not friendly whatsoever	the best selection behind the register and service presentation	the people behind the counter is friendly caring
the interior is old and generally falling apart	the decor is old and now perfectly	the interior is old and noble
they are clueless	they are stoked	they are genuinely professionals

Table 5: Examples of style transferred sentence generation.

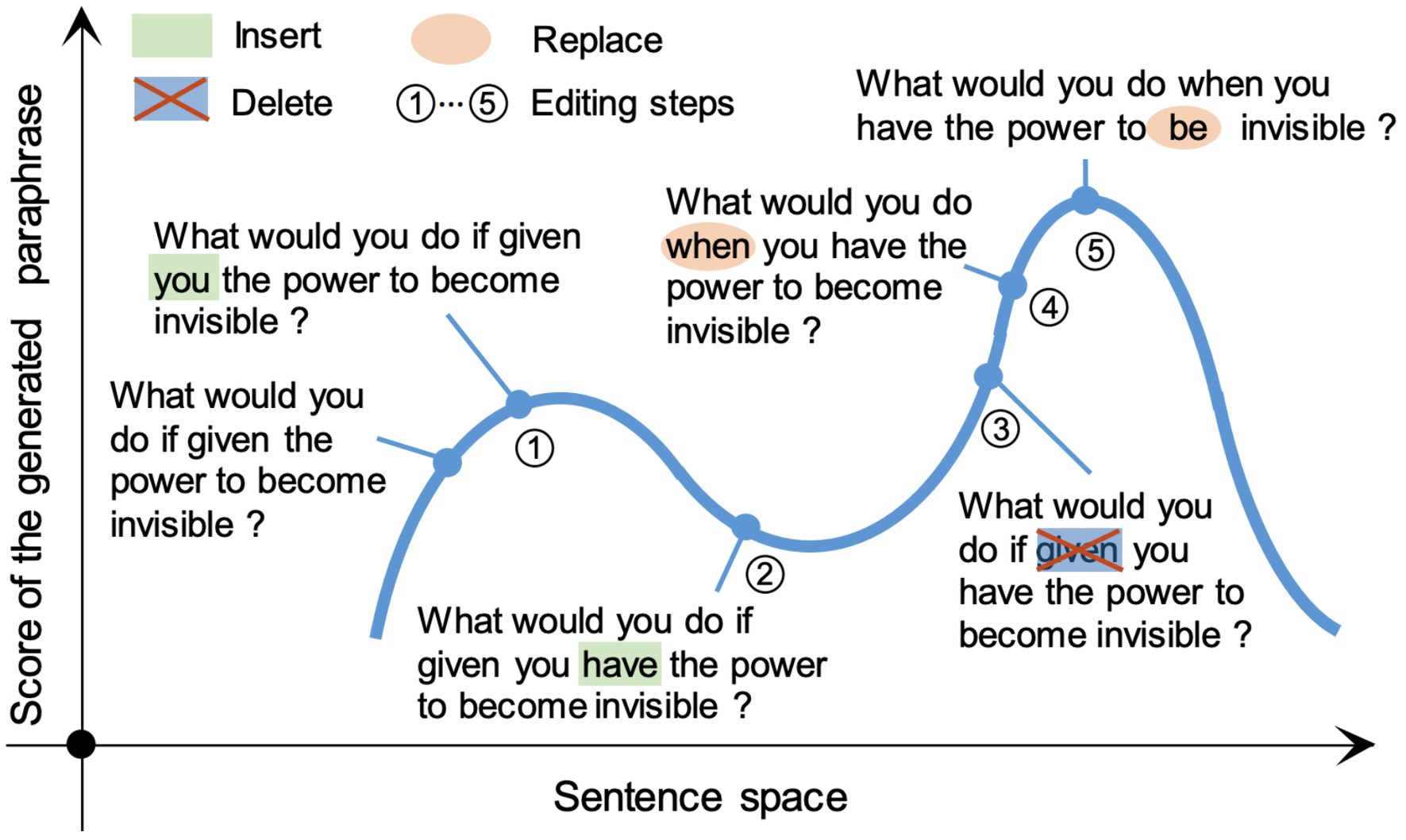
Applications

Semantic and Syntactic Providers		Syntax-Transfer Output	
Ref$_{syn}$:	There is an apple on the table.	**VAE**:	The man is in the kitchen.
Ref$_{sem}$:	The airplane is in the sky.	**DSS-VAE**:	There is a airplane in the sky.
Ref$_{syn}$:	The shellfish was cooked in a wok.	**VAE**:	The man was filled with people.
Ref$_{sem}$:	The stadium was packed with people.	**DSS-VAE**:	The stadium was packed with people.
Ref$_{syn}$:	The child is playing in the garden.	**VAE**:	There is a person in the garden.
Ref$_{sem}$:	There is a dog behind the door.	**DSS-VAE**:	A dog is walking behind the door.

Sampling and search in the sentence

General Framework

- **Search objective**
  - Scoring function measuring text quality
- **Search algorithm**
  - Currently we are using stochastic local search



Scoring Function

- **Search objective**
  - Scoring function measuring text quality

$$s(\mathbf{y}) = s_{LM}(\mathbf{y}) \cdot s_{Semantic}(\mathbf{y})^{\alpha} \cdot s_{Task}(\boldsymbol{y})^{\beta}$$

  - Score-induced probability

$$P(\mathbf{y}) = \frac{s(\mathrm{y})}{\sum_{\mathrm{y}'} s(\mathbf{y}')}$$

- Language fluency
- Semantic coherence
- Task-specific constraints

Scoring Function

- Search objective
  - Scoring function measuring text quality

$$s(\mathbf{y}) = s_{LM}(\mathbf{y}) \cdot s_{Semantic}(\mathbf{y})^{\alpha} \cdot s_{Task}(\mathbf{y})^{\beta}$$

- **Language fluency**
  - Language model estimates the “probability" of a sentence

$$\overleftrightarrow{\mathrm{PPL}}(\mathbf{y}) = \sqrt[2|\mathbf{y}|]{\prod_{i}^{|\mathbf{y}|} \frac{1}{p_{\overrightarrow{\mathrm{LM}}}(y_i|\mathbf{y}_{<i})} \prod_{i}^{|\mathbf{y}|} \frac{1}{p_{\overleftarrow{\mathrm{LM}}}(y_i|\mathbf{y}_{>i})}}.$$

$$s_{LM}(\mathbf{y}) = \mathrm{PPL}(\mathbf{y})^{-1}$$

- Semantic coherence
- Task-specific constraints

Scoring Function

- Search objective
  - Scoring function measuring text quality

$$s(\mathbf{y}) = s_{LM}(\mathbf{y}) \cdot s_{Semantic}(\mathbf{y})^{\alpha} \cdot s_{Task}(\boldsymbol{y})^{\beta}$$

- Language fluency
- **Semantic coherence**

$$s_{semantic} = \text{normalize}[\cos(\boldsymbol{e}(\mathbf{y}), \boldsymbol{e}(\mathbf{x}))]$$

- Task-specific constraints

Scoring Function

- Search objective
  - Scoring function measuring text quality

$$s(\mathbf{y}) = s_{LM}(\mathbf{y}) \cdot s_{Semantic}(\mathbf{y})^{\alpha} \cdot s_{Task}(\mathbf{y})^{\beta}$$

- Language fluency
- Semantic coherence

- **Task-specific constraints**
  - Paraphrasing: lexical dissimilarity with input
  - Summarization: length budget

Search Algorithm

- Observations:
  - The output closely resembles the input
  - Edits are mostly local
  - May have hard constraints

- Thus, we mainly used **local stochastic search**

Search Algorithm

(stochastic local search)

Start with $\mathbf{y}_0$ # an initial candidate sentence

Loop within budget at step t:

$\mathbf{y}' \sim \text{Neighbor}(\mathbf{y}_t)$ # a new candidate in the neighbor

Either reject or accept $\mathbf{y}'$

If accepted, $\mathbf{y}_t = \mathbf{y}'$, or otherwise $\mathbf{y}_t = \mathbf{y}_{t-1}$

Return the best scored $\mathbf{y}_*$

Search Algorithm

Local edits for $\mathbf{y}' \sim \text{Neighbor}(\mathbf{y}_t)$

- General edits
  - Word deletion
  - Word insertion
  - Word replacement

$$p(w_*|\cdot) = \frac{f_{\text{sim}}(\mathbf{x}_*, \mathbf{x}_0) \cdot f_{\text{exp}}(\mathbf{x}_*, \mathbf{x}_0) \cdot f_{\text{flu}}(\mathbf{x}_*)}{Z},$$

$$Z = \sum_{w_* \in \mathcal{W}} f_{\text{sim}}(\mathbf{x}_*, \mathbf{x}_0) \cdot f_{\text{exp}}(\mathbf{x}_*, \mathbf{x}_0) \cdot f_{\text{flu}}(\mathbf{x}_*),$$

Gibbs in Metropolis

- Task specific edits
  - Reordering, swap of word selection, etc.

Search Algorithm

Example: Metropolis—Hastings sampling

Start with $\mathbf{y}_0$ # an initial candidate sentence

Loop within budget at step t:

$\mathbf{y}' \sim \text{Neighbor}(\mathbf{y}_t)$ # a new candidate in the neighbor

Either reject or accept $\mathbf{y}'$

$$A(\mathrm{x}'|\mathrm{x}_{t-1}) = \min\{1, A^*(\mathrm{x}'|\mathrm{x}_{t-1})\}$$

$$A^*(\mathrm{x}'|\mathrm{x}_{t-1}) = \frac{\pi(\mathrm{x}')g(\mathrm{x}_{t-1}|\mathrm{x}')}{\pi(\mathrm{x}_{t-1})g(\mathrm{x}'|\mathrm{x}_{t-1})}$$

If accepted, $\mathbf{y}_t = \mathbf{y}'$, or otherwise $\mathbf{y}_t = \mathbf{y}_{t-1}$

Return the best scored $\mathbf{y}_*$

Ning Miao, Hao Zhou, Lili Mou, Rui Yan, Lei Li. CGMH: Constrained sentence generation by Metropolis-Hastings sampling. In AAAI, pages 6834--6942, 2019.

Search Algorithm

Example: Simulated annealing

Start with $\mathbf{y}_0$ # an initial candidate sentence

Loop within budget at step t:

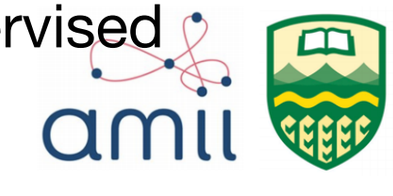
$\mathbf{y}' \sim \text{Neighbor}(\mathbf{y}_t)$ # a new candidate in the neighbor

Either reject or accept $\mathbf{y}'$ $p(\text{accept}|\mathrm{x}_*, \mathrm{x}_t, T) = \min\left(1, e^{\frac{f(\mathrm{x}_*)-f(\mathrm{x}_t)}{T}}\right)$

If accepted, $\mathbf{y}_t = \mathbf{y}'$, or otherwise $\mathbf{y}_t = \mathbf{y}_{t-1}$

Return the best scored $\mathbf{y}_*$

Xianggen Liu, Lili Mou, Fandong Meng, Hao Zhou, Jie Zhou, Sen Song. Unsupervised paraphrasing by simulated annealing. In ACL, pages 302--312, 2020.



Search Algorithm

Example: Hill climbing

Start with $\mathbf{y}_0$ # an initial candidate sentence

Loop within budget at step t:

$\mathbf{y}' \sim \text{Neighbor}(\mathbf{y}_t)$ # a new candidate in the neighbor

Either reject or accept $\mathbf{y}'$ whenever $\mathbf{y}'$ is better than $\mathbf{y}_{t-1}$

If accepted, $\mathbf{y}_t = \mathbf{y}'$, or otherwise $\mathbf{y}_t = \mathbf{y}_{t-1}$

Return the best scored $\mathbf{y}_*$

Raphael Schumann, Lili Mou, Yao Lu, Olga Vechtomova, Katja Markert. Discrete optimization for unsupervised sentence summarization with word-level extraction. In ACL, 2020.

Applications

Paraphrase Generation

Input	Reference
Which is the best training institute in Pune for digital marketing ?	Which is the best digital marketing training institute in Pune ?

Could be useful for various NLP applications

- E.g., query expansion, data augmentation

Paraphrase Generation

- Search objective
  - Fluency
  - Semantic preservation
  - Expression diversity
    - The paraphrase should be different from the input

$$s_{exp}(\mathbf{y}_*, \mathbf{x}) = 1 - \mathrm{BLEU}(\mathbf{y}_*, \mathbf{x})$$

BLEU here measures the *n*-gram overlapping

- Search algorithm
- Search space
- Search neighbors

Xianggen Liu, Lili Mou, Fandong Meng, Hao Zhou, Jie Zhou, Sen Song. Unsupervised paraphrasing by simulated annealing. In ACL, pages 302--312, 2020.

Paraphrase Generation

- Search objective
  - Fluency
  - Semantic preservation
  - Expression diversity
    - The paraphrase should be different from the input

$$s_{exp}(\mathbf{y}_*, \mathbf{x}) = 1 - \mathrm{BLEU}(\mathbf{y}_*, \mathbf{x})$$

BLEU here measures the *n*-gram overlapping

- Search algorithm: Simulated annealing
- Search space: the entire sentence space with $\mathbf{y}_0$ = input $\mathbf{x}$
- Search neighbors
  - Generic word deletion, insertion, and replacement
  - Copying words in the input sentence

Text Simplification

Input	Reference
In 2016 alone, American developers had spent 12 billion dollars on **constructing** theme parks, <u>according to a Seattle based reporter.</u>	American developers had spent 12 billion dollars in 2016 alone on **building** theme parks.

Could be useful for

- education purposes (e.g., kids, foreigners)
- for those with dyslexia

Key observations

- Dropping phrases and clauses
- Phrase re-ordering
- Dictionary-guided lexicon substitution

Text Simplification

Search objective

- Language model fluency (discounted by word frequency)
- Cosine similarity
- Entity matching
- Length penalty
- Flesh Reading Ease (FRE) score [Kincaid et al., 1975]

Search operations

Dhruv Kumar, Lili Mou, Lukasz Golab, Olga Vechtomova. Iterative edit-based unsupervised sentence simplification. In ACL, pages 7918--7928, 2020.

Text Simplification

Search objective

- Language model fluency (discounted by word frequency)
- Cosine similarity
- Entity matching
- Length penalty
- Flesh Reading Ease (FRE) score [Kincaid et al., 1975]

Search operations

- Dictionary-guided substitution (e.g., WordNet)
- Phrase removal
- Re-ordering

} with parse trees

Text Summarization

Input	Reference
The *world's biggest miner* ***bhp billiton*** *announced tuesday it was* ***dropping*** *its controversial hostile* ***takeover bid*** *for rival* ***rio tinto*** *due to the state of the global economy*	bhp billiton drops rio tinto takeover bid

Key observation

- Words in the summary mostly come from the input
- If we generate the summary by selecting words, we have

```
bhp billiton dropping hostile bid for rio tinto
```

Text Summarization

- Search objective
  - Fluency
  - Semantic preservation
  - A hard length constraint

$$f_{\text{LEN}}(\mathbf{y}; s) = \begin{cases} 1, & \text{if } |\mathbf{y}| = s, \\ -\infty, & \text{otherwise.} \end{cases}$$

(Explicitly controlling length is not feasible in previous work)

- Search space
- Search neighbor
- Search algorithm

Raphael Schumann, Lili Mou, Yao Lu, Olga Vechtomova, Katja Markert. Discrete optimization for unsupervised sentence summarization with word-level extraction. In ACL, pages 5032--5042, 2020.

Text Summarization

- Search objective
  - Fluency
  - Semantic preservation
  - A hard length constraint

$$f_{\text{LEN}}(\mathbf{y}; s) = \begin{cases} 1, & \text{if } |\mathbf{y}| = s, \\ -\infty, & \text{otherwise.} \end{cases}$$

(Explicitly controlling length is not feasible in previous work)

- Search space with only feasible solutions

$$|\mathscr{V}|^{|\mathbf{y}|} \Longrightarrow \begin{pmatrix} |\mathbf{x}| \\ s \end{pmatrix}$$

- Search neighbor: swap only

- Search algorithm: hill-climbing

Experimental Results

Research Questions

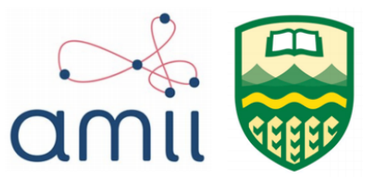
- General performance
- Greediness vs. Stochasticity
- Search objective vs. Measure of success

General Performance

Paraphrase generation

		Quora				Wikianswers			
	Model	iBLEU	BLEU	Rouge1	Rouge2	iBLEU	BLEU	Rouge1	Rouge2
Supervised	ResidualLSTM	12.67	17.57	59.22	32.40	22.94	27.36	48.52	18.71
	VAE-SVG-eq	15.17	20.04	59.98	33.30	26.35	32.98	50.93	19.11
	Pointer-generator	16.79	22.65	61.96	36.07	31.98	39.36	57.19	25.38
	Transformer	16.25	21.73	60.25	33.45	27.70	33.01	51.85	20.70
	Transformer+Copy	17.98	24.77	63.34	37.31	31.43	37.88	55.88	23.37
	DNPG	**18.01**	**25.03**	**63.73**	**37.75**	**34.15**	**41.64**	**57.32**	**25.88**
Supervised + Domain-adapted	Pointer-generator	5.04	6.96	41.89	12.77	21.87	27.94	53.99	20.85
	Transformer+Copy	6.17	8.15	44.89	14.79	23.25	29.22	53.33	21.02
	Shallow fusion	6.04	7.95	44.87	14.79	22.57	29.76	53.54	20.68
	MTL	4.90	6.37	37.64	11.83	18.34	23.65	48.19	17.53
	MTL+Copy	7.22	9.83	47.08	19.03	21.87	30.78	54.10	21.08
	DNPG	10.39	16.98	56.01	28.61	25.60	35.12	56.17	23.65
Unsupervised	VAE	8.16	13.96	44.55	22.64	17.92	24.13	31.87	12.08
	Lag VAE	8.73	15.52	49.20	26.07	18.38	25.08	35.65	13.21
	CGMH	9.94	15.73	48.73	26.12	20.05	26.45	43.31	16.53
	UPSA	12.03	18.21	59.51	32.63	24.84	32.39	54.12	21.45

BLEU and ROUGE scores are automatic evaluation metrics based on references



General Performance

Text Summarization

	Model	Data			Len D	Rouge F1			Len O
		article	title	external		R-1	R-2	R-L	
	Lead-N-8	✓			8	21.39	7.42	20.03	7.9
A	*HC_article_8*	✓			8	23.09	7.50	21.29	7.9
	HC_title_8		✓		8	**26.32**	**9.63**	**24.19**	7.9
	Lead-N-10	✓			10	23.03	7.95	21.29	9.8
	Wang and Lee (2018)	✓	✓		-	27.29	10.01	24.59	10.8
	Zhou and Rush (2019)		✓	billion	-	26.48	10.05	24.41	9.3
B	*HC_article_10*	✓			10	24.44	8.01	22.21	9.8
	HC_title_10		✓		10	27.52	10.27	24.91	9.8
	HC_title+twitter_10		✓	twitter	10	28.26	10.42	25.43	9.8
	HC_title+billion_10		✓	billion	10	**28.80**	**10.66**	**25.82**	9.8
	Lead-P-50	✓			50%	24.97	8.65	22.43	14.6
	Fevry and Phang (2018)	✓		SNLI	50%	23.16	5.93	20.11	14.8
C	Baziotis et al. (2019)	✓			50%	24.70	7.97	22.14	15.1
	HC_article_50p	✓			50%	25.58	8.44	22.66	14.9
	HC_title_50p		✓		50%	**27.05**	**9.75**	**23.89**	14.9

General Performance

Text Simplification

Method	BLEU	SARI	Add	Delete	Keep	GM	FKGL	Len
Reference	100	70.13	-	-	-	83.74	3.20	12.75
Baselines								
Complex	21.30	2.82	-	-	-	7.75	8.62	23.06
Reduced-250	11.79	28.39	-	-	-	18.29	-0.23	14.48
Supervised Methods								
PBMT-R	18.1	15.77	3.07	38.34	5.90	16.89	7.59	23.06
Hybrid	14.46	28.61*	0.95*	78.86*	6.01*	20.34	4.03	12.41
EncDecA	21.68	24.12	2.73	62.66	6.98	22.87	5.11	16.96
Dress	23.2	27.37	**3.08**	71.61	7.43	25.2	4.11	14.2
Dress-Ls	24.25	26.63	3.21	69.28	7.4	25.41	4.21	14.37
DMass	11.92	31.06	1.25	84.12	7.82	19.24	3.60	15.07
S2S-All-FA	19.55	30.73	2.64	81.6	**7.97**	24.51	2.60	10.81
Edit-NTS	19.85	30.27*	2.71*	80.34*	7.76*	24.51	3.41	10.92
EncDecP	23.72	28.31	-	-	-	25.91	-	-
EntPar	11.14	**33.22**	2.42	**89.32**	7.92	19.24	1.34	7.88
Unsupervised Methods (Ours)								
Base	**27.22**	26.07	2.35	68.35	7.5	26.64	2.95	12.9
Base+LS	27.17	26.26	2.28	68.94	7.57	**26.71**	2.93	12.88
Base+RO	26.31	26.99	2.47	70.88	7.63	26.64	3.14	12.81
Base+LS+RO	26.21	27.11	2.40	71.26	7.67	26.66	3.12	12.81

General Performance

Human evaluation on paraphrase generation

Model	Relevance		Fluency	
	Mean Score	Agreement	Mean Score	Agreement
VAE	2.65	0.41	3.23	0.51
Lag VAE	2.81	0.45	3.25	0.48
CGMH	3.08	0.36	3.51	0.49
UPSA	**3.78**	0.55	**3.66**	0.53

General Performance

Examples

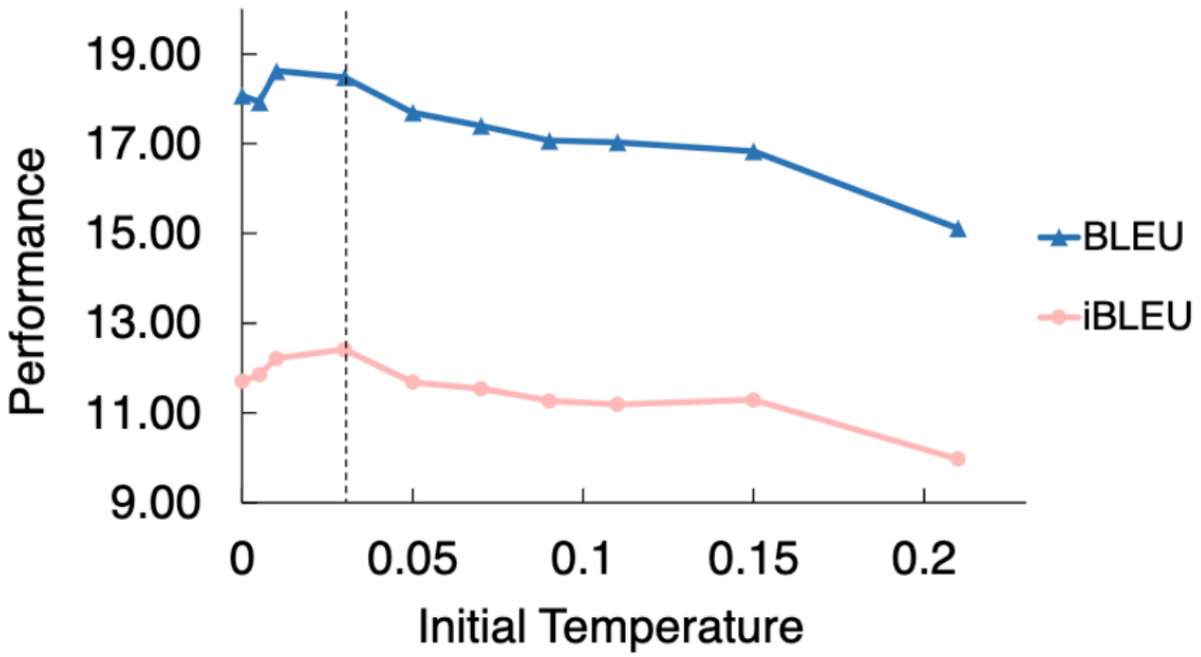
Input	VAE	Lag VAE	CGMH	UPSA
where are best places for spring snowboarding in the us?	where are best places for running in the world? (3.33)	where are best places for honeymoon year near the us? (2.33)	Where is best store for the snowboarding in the US? (3.67)	Where can I find the best places in the US for snowboarding? (4.67)
how can i become good in studies?	how can i have a good android phone? (2.33)	how can i become good students? (4.33)	how can i become very rich in studies? (4.00)	how should i do to get better grades in my studies? (4.33)
what are the pluses and minuses about life as a foreigner in singapore?	what are the UNK and most interesting life as a foreigner in medieval greece? (2.33)	what are the UNK and interesting things about life as a foreigner? (2.33)	what are the misconception about UNK with life as a foreigner in western? (2.33)	what are the mistakes and pluses life as a foreigner in singapore? (2.67)

Main conclusion

- Search-based unsupervised text generation works in a variety of applications
- Surprisingly, it does yield **fluent sentences**.

Greediness vs Stochasticity

Paraphrase generation



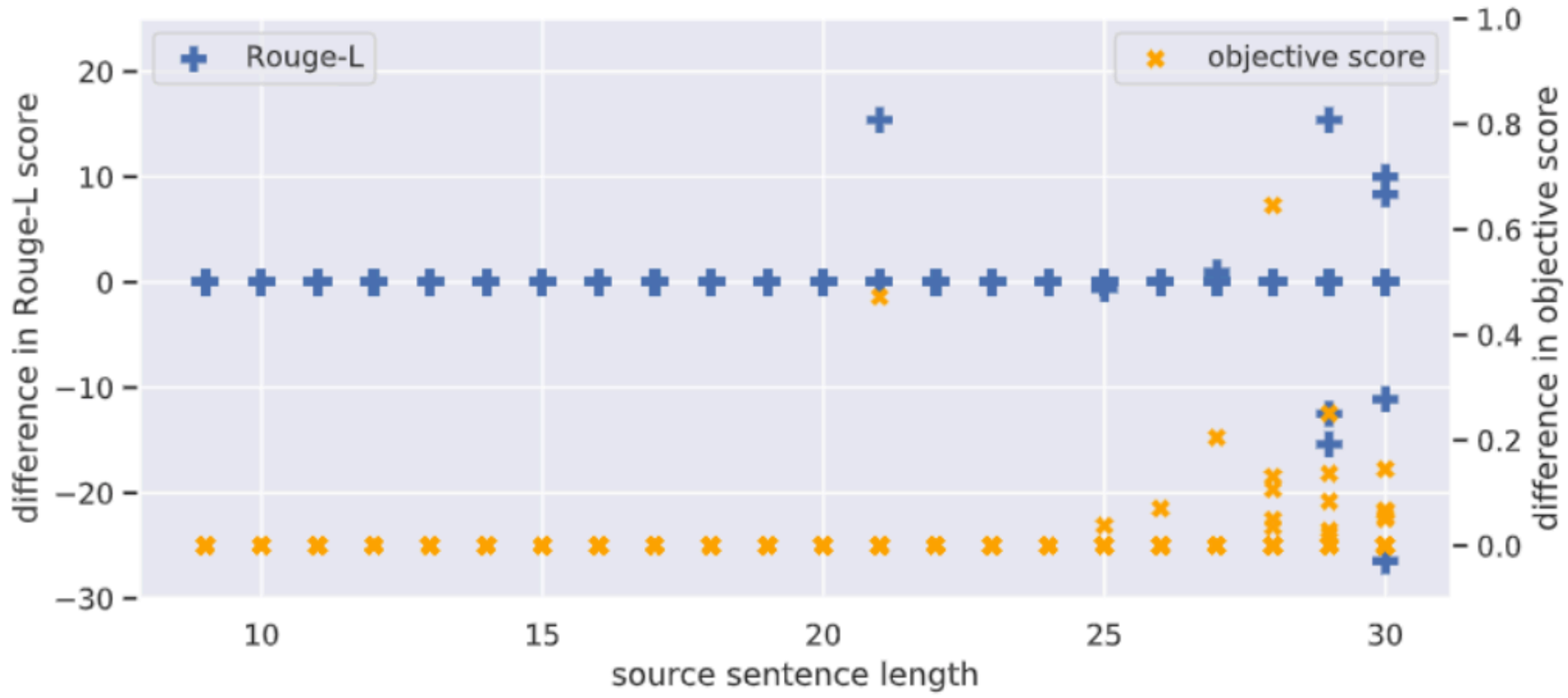
Line #	UPSA Variant	iBLEU	BLEU	Rouge1	Rouge2
1	UPSA	**12.41**	18.48	57.06	31.39
2	w/o $f_{\text{sim,key}}$	10.28	15.34	50.85	26.42
3	w/o $f_{\text{sim,sen}}$	11.78	17.95	57.04	30.80
4	w/o f_{exp}	11.93	21.17	59.75	34.91
5	w/o copy	11.42	17.25	56.09	29.73
6	w/o annealing	10.56	16.52	56.02	29.25

Findings:

- Greedy search ≺ Simulated annealing
- Sampling ≺ stochastic search

Search Objective vs. Measure of Success

Experiment: summarization by word selection



Comparing hill-climbing (w/ restart) and exhaustive search

- Exhaustive search does yield higher scores $s(\mathbf{y})$
- Exhaustive search does NOT yield higher measure of success (ROUGE)

Search and Learning for Unsupervised Text Generation

Jingjing Li, Zichao Li, Lili Mou, Xin Jiang, Michael Lyu, Irwin King. Unsupervised text generation by learning from search. In NeurIPS, 2020.

Main Disadvantages of Search

Low inference efficiency

- Hundreds of proposals and re-evaluations

Search could be noisy

- Objective is heuristically defined
- May be stuck at local optimum

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Low inference efficiency

- Hundreds of proposals and re-evaluations

Search could be noisy

- Objective is heuristically defined
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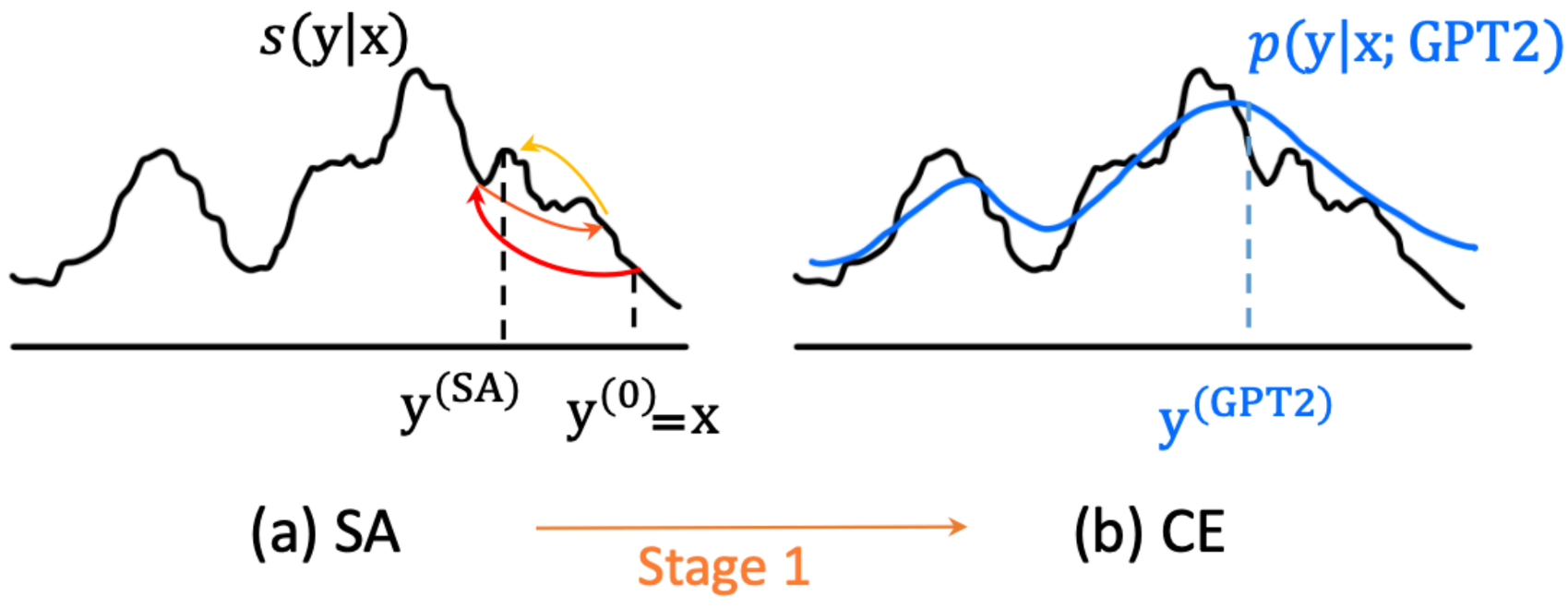
Our idea:

We can alleviate these issues by training a Seq2Seq model

Learning from Search

Stage 1: Cross-entropy training

▷ First-stage learning from search
for *an input* $\mathrm{x} \in X$ **do**
  $\mathrm{y}^{(\mathrm{SA})} = \mathrm{SA}(\mathrm{x}, \mathrm{x})$
    ▷ SA is detailed in Algorithm 2. In the first stage, SA starts with input x as the initial candidate
for *all epochs* **do**
  for *an input* x *with its SA output* $\mathrm{y}^{(SA)}$ **do**
    Fine-tune GPT2 by cross-entropy loss (4) with pseudo-reference $\mathrm{y}^{(\mathrm{SA})}$, conditioned on x



Learning from Search

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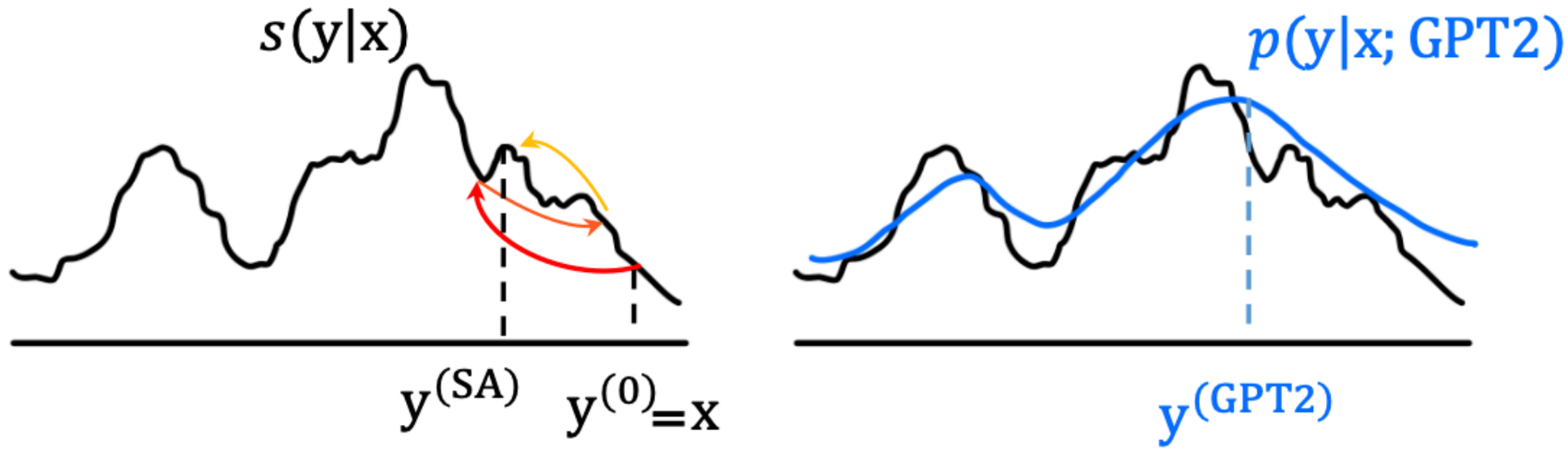
  for *an input* x *with its SA output* $\mathrm{y}^{(SA)}$ **do**
    Fine-tune GPT2 by cross-entropy loss (4) with pseudo-reference $\mathrm{y}^{(\mathrm{SA})}$, conditioned on x

Asymmetric KL ensures a smoother distribution

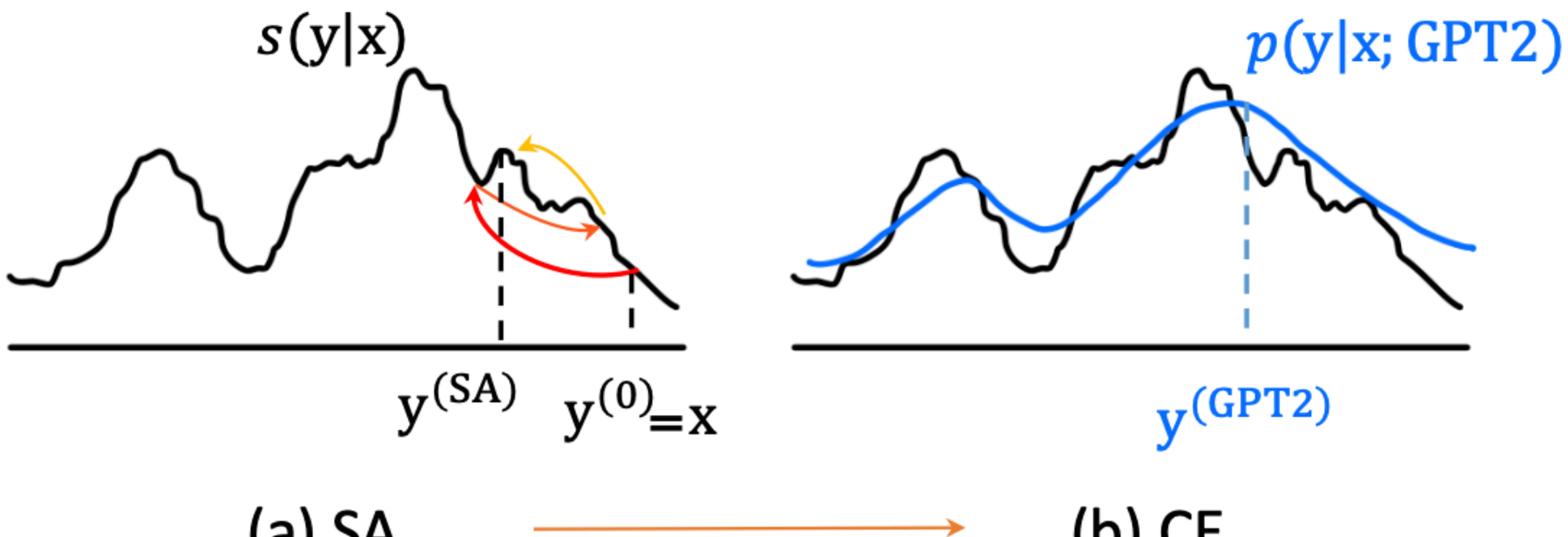


Learning from Search

Stage 1: Cross-entropy training

Pros: Training is efficient

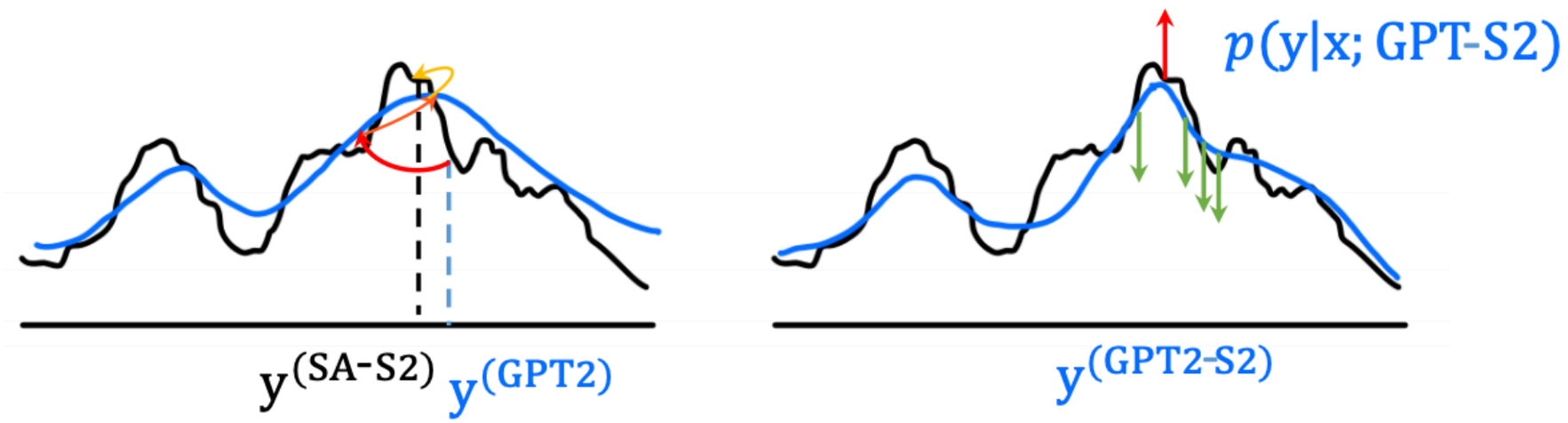
Cons: Only trained with positive samples



Learning from Search

Stage 2: Max-margin training

▷ Second-stage learning from search
for *all epochs* **do**
  for *an input* x **do**
    $Y^{(\text{GPT2})} = \text{BeamSearch}(\text{GPT2}(\text{x}))$ ▷ $Y^{(\text{GPT2})}$ is a set of output by beam search
    $\text{y}^{(\text{SA-S2})} = \text{SA}(\text{x}, \text{y}^{(\text{GPT2})})$ for some $\text{y}^{(\text{GPT2})} \in Y^{(\text{GPT2})}$
      ▷ In the second stage, SA starts with GPT2's output (any output in the beam is fine)
    $\widetilde{Y} = Y^{(\text{GPT2})} \cup \{\text{y}^{(\text{SA-S2})}\}$
    Fine-tune GPT2 with max-margin loss (5) with
      positive sample: $\text{y}^{+} = \text{argmax}_{\text{y} \in \widetilde{Y}}\, s(\text{y}|\text{x})$, and
      negative samples: $\widetilde{Y} \backslash \{\text{y}^{+}\}$



Experimental Results

Paraphrase generation

Methods	iBLEU	BLEU
Supervised		
RL-NN [32]	14.83	20.98
DAGGER† [7]	18.88	28.42
GPT2† [33]	19.19	26.92
Distant supervised		
Round-Trip MT (GPT2)† [11]	11.24	16.33
Round-Trip MT (Transformer)† [26]	14.36	20.85
Unsupervised		
VAE [3]	8.16	13.96
CGMH [28]	9.94	15.73
UPSA [23]	12.02	18.18
SA w/ PLM (Ours)†	14.52	21.08
TGLS (Ours)†	**17.48**	**25.00**

iBLEU is the main metric

Experimental Results

Style Transfer

Methods†	PPL↓	BLEU	Formality	H-mean	G-mean
Supervised					
LSTM-attn [35]	**23.42**	**69.36**	**87.39**	**77.34**	**77.85**
Unsupervised					
BackTrans [31]	183.7	1.23	31.18	2.37	6.13
StyleEmb [9]	114.6	8.14	12.31	9.80	10.01
MultiDec [9]	187.2	13.29	8.18	10.13	10.42
CrossAlign [38]	44.78	3.34	67.34	6.36	14.99
DelRetrGen [21]	88.52	24.95	56.96	34.70	37.69
Template [21]	197.5	43.45	37.09	40.02	40.14
UnsupMT [56]	55.16	39.28	66.29	49.33	51.02
DualRL [25]	66.96	54.18	58.26	56.15	56.18
TGLS (Ours)	**30.26**	**60.25**	**75.15**	**66.88**	**67.29**

Experimental Results

Ablation test

Methods	iBLEU	BLEU
SA	14.52	21.08
SA+CE	14.97	23.25
SA+CE+SA	15.41	21.48
SA+CE+SA+CE	15.70	21.70
SA+CE+SA+MM (full)	**17.48**	**25.00**

Experimental Results

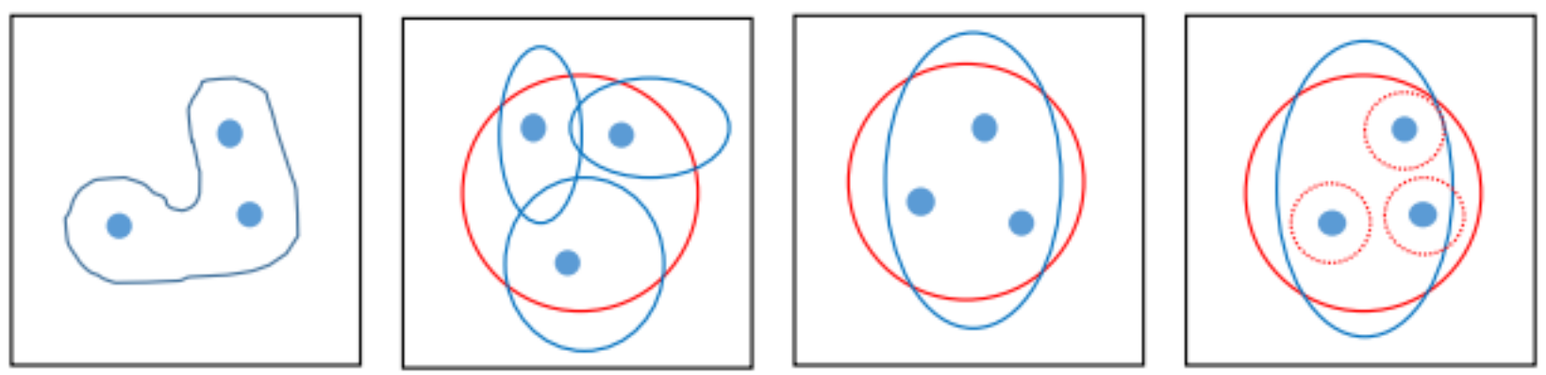
Efficiency analysis: 5—10x speedup

Methods	iBLEU	BLEU	Inference Time (sec/sample)
SA	14.52	21.08	5.46
SA+CE	14.97	23.25	0.06
SA+CE+SA	15.41	21.48	2.62
SA+CE+SA+CE	15.70	21.70	0.37
SA+CE+SA+MM (full)	**17.48**	**25.00**	0.43

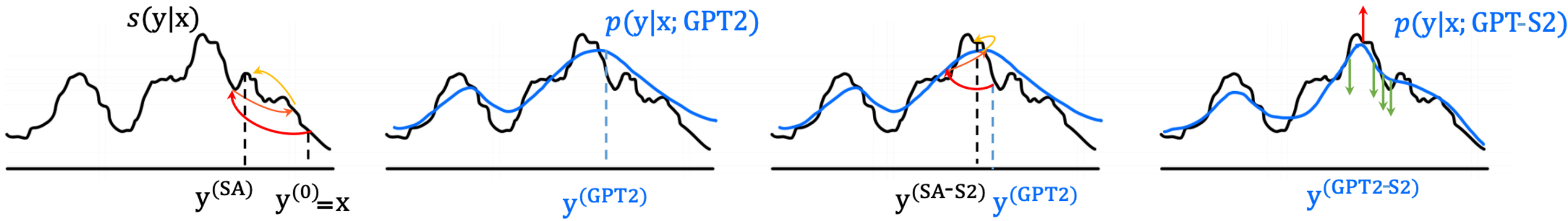
Conclusion

Conclusion

- Frameworks
  - Latent space sampling
  - Sentence space sampling and search



(a) DAE (b) VAE (c) WAE (d) WAE + aux loss



(a) SA → Stage 1 → (b) CE

(c) SA ↔ Stage 2 → (d) MM

Advertisements (Again)

- Lili Mou is accepting all-level students
  - URA, MSc, PhD, postdoc
  - A typical path for URAs/MSc

    (466 course project →) Individual Study 499 → RAship

- Previous achievements
  - CMPUT499 (F20) → URA (W+S21) → CIKM'21
  - CMPUT499 (W21) → URA (S21) → EMNLP'21 (Findings)

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Q&A

Thanks for listening!