

Text Style Transfer Dissection

: Deeper understanding on Text Style Transfer

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Problem Statement

Problem Statement

1. What do we want from Conversational AI?



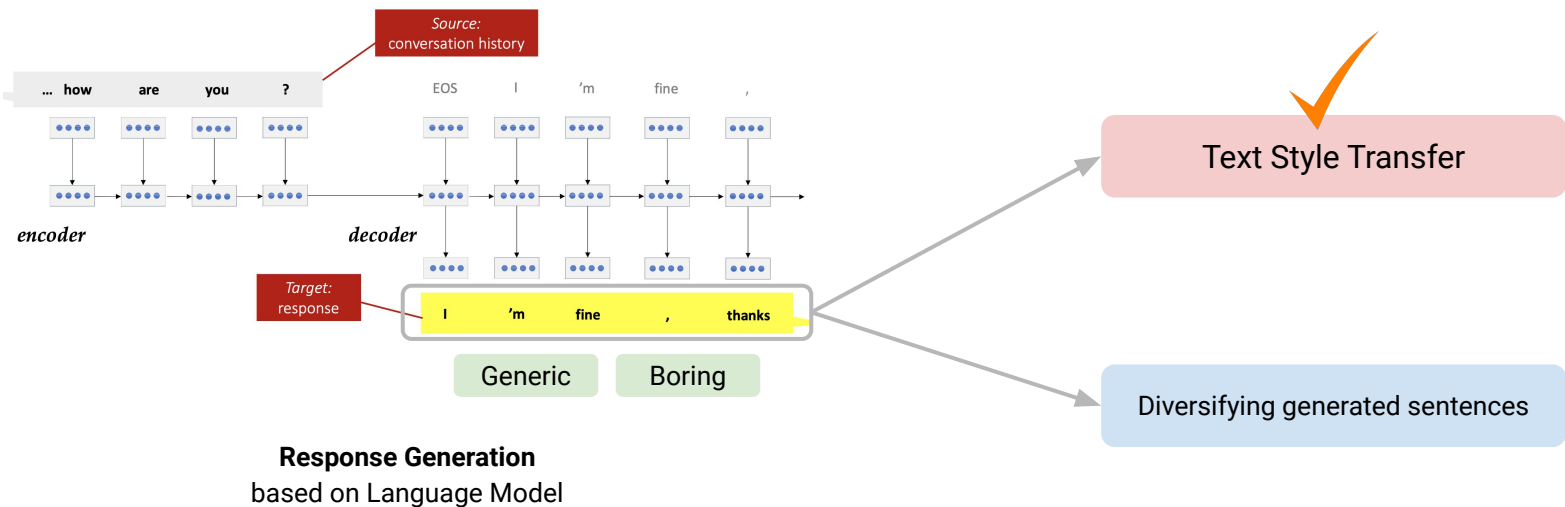
Samantha of <Her>



Jarvis of <Ironman>

Problem Statement

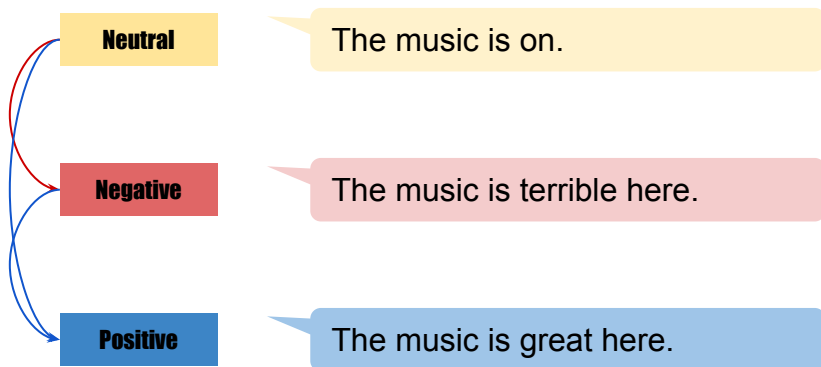
2. Limitation of Language Model



The general language model still produces **boring** and **generic** responses

Problem Statement

3. Text Style Transfer



LIMITATION



with **Style of Text**

Pos/Neg

Formality

Text style transfer refers to the study of changing the `style' of an input sentence while preserving the `content', overall information included in the sentence.

Problem Statement

4. What do we think about “style” of text

STYLE
of text



“ I won’t say I’m the
baddest,
or portray that role,
but I’m in the Top Two,
and my father’s gettin’
old.”

Hip hop



Love song



Problem Statement

5. Research Questions



To generate a more abstract style of sentences

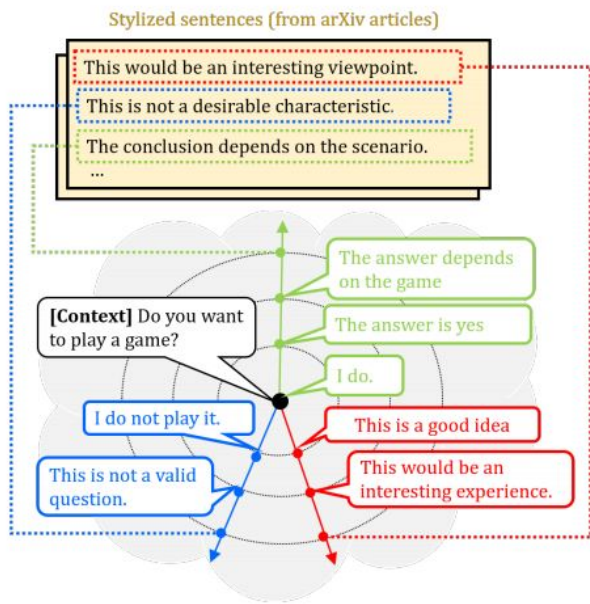
To explore how the model understands style and content.

Related Work

Related Work

1. Structuring Latent Spaces for Stylized Response Generation

([Gao et al., 2019](#))



They designed '**StyleFusion**' which maps the sentences of the general dataset(e.g. Reddit) and the stylized dataset(e.g. script of drama character) into the same latent space



Stylizes an input sentence with the closest style sentence.

Related Work

2. Domain Adaptive Text Style Transfer

([Li et al., 2019](#))

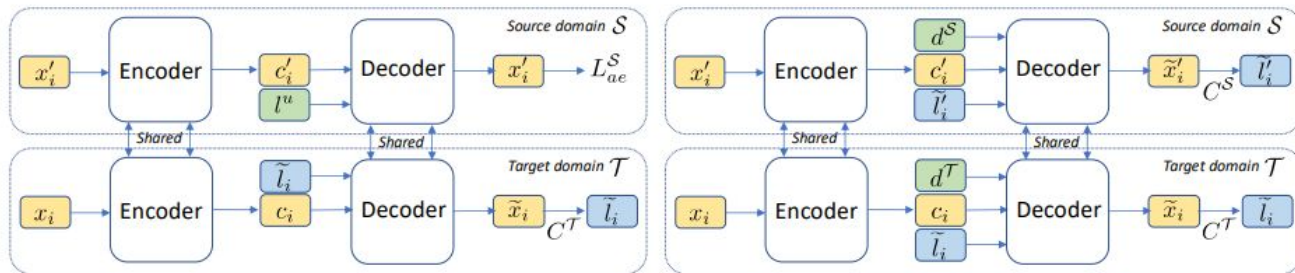


Figure 1: Illustration of the proposed **DAST-C** (left) and **DAST** (right) model. DAST-C learns the generic content information through L_{ae}^S on massive source domain data with unknown style l^u . For DAST, d^T , d^S and C^T , C^S denote domain vectors and domain-specific style classifiers, respectively. Better looked in color.

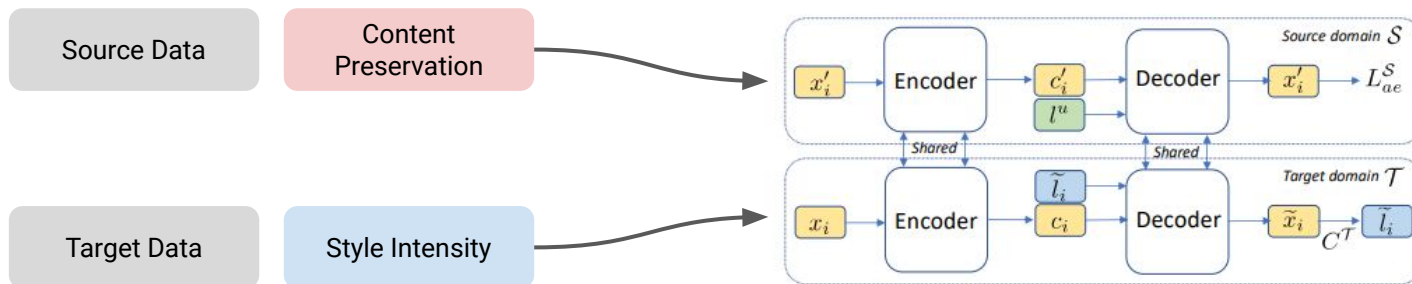
Autoencoder to maintain content resiliency of the source domain,
and apply **style classifier** to force meaningful style information into the model

Approach

Approach

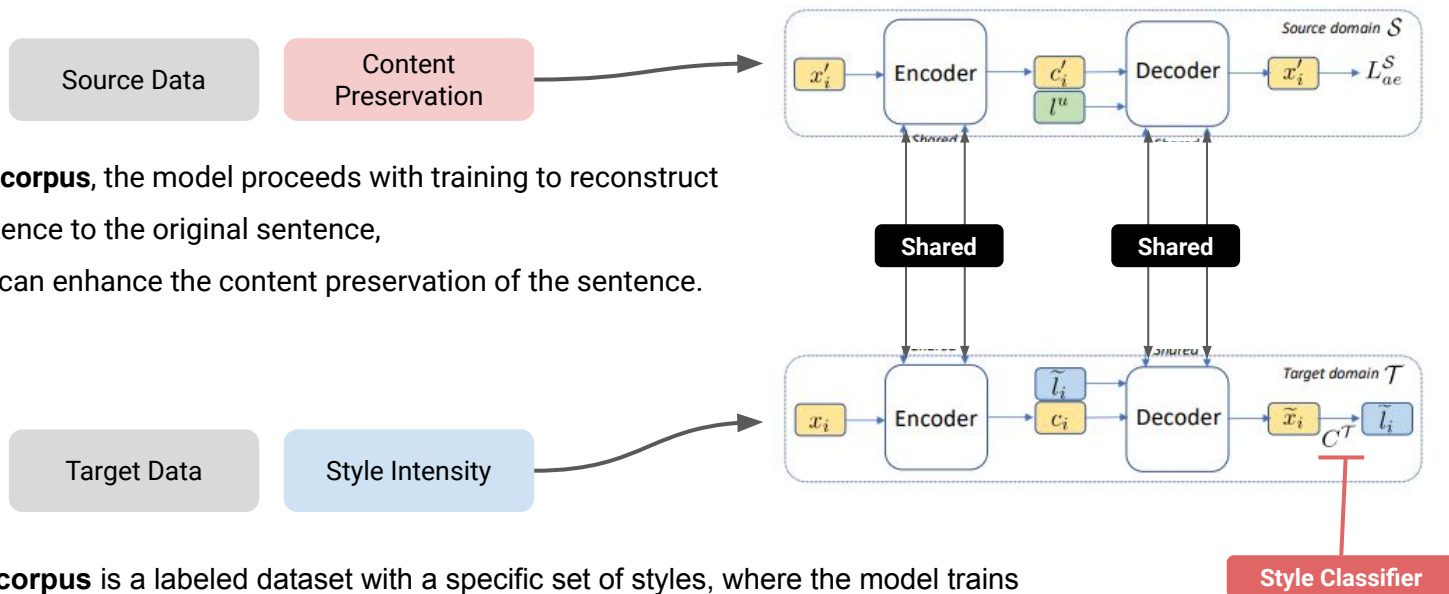
1. Research Questions

1. The range of style in a text
2. Which part should the model consider for preserving the content



Approach

2. Replication paper

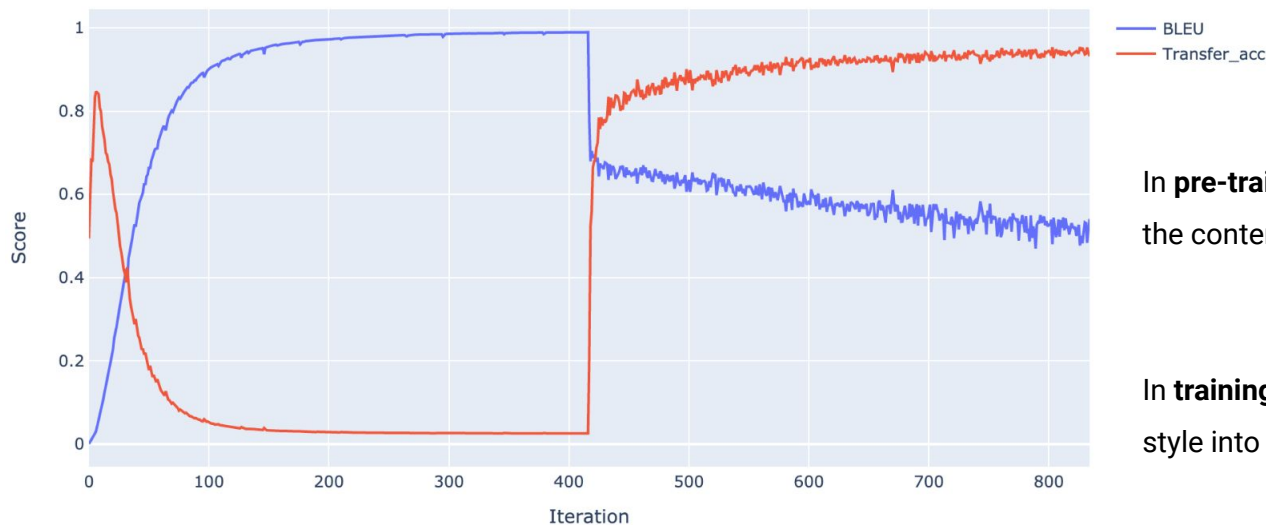


In the **source corpus**, the model proceeds with training to reconstruct the input sentence to the original sentence,
This process can enhance the content preservation of the sentence.

In the **target corpus** is a labeled dataset with a specific set of styles, where the model trains to change one style sentence to another style.
The style of the changed sentence can be verified using the pre-trained style classifier.

Approach

3. Preliminary Study



In **pre-training** phase, the model learns to preserve the content of the massive source sentence

In **training** phase, the model is trained to change the style into the opposite style

Pre-Training

Training

Approach

3. Preliminary Study

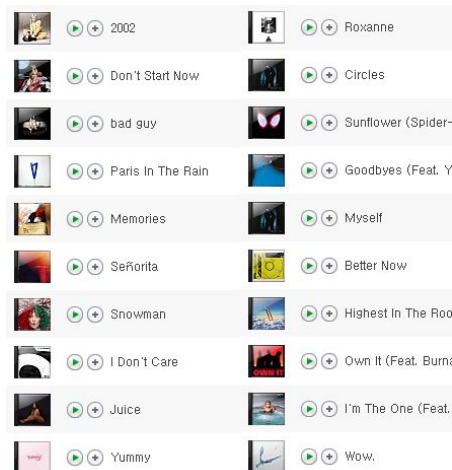
Model	Input (negative)	Transferred sentence (negative-to-positive)
DASTC	service was slow, disinterested skip this place and stay on the strip I would give this review negative stars service was lacking , waitress didn't know the menu	service was delicious, satisfying delicious this place and stay on the strip I definitely give perfect review terrific stars service was delicious , waitress did blast know the menu
Metaphor	swimming in the grease from the beef topping	refreshing in the inside from the beef topping
Model	Input (positive)	Transferred sentence (positive-to-negative)
DASTC	just tried their food, it was amazing! prices are great and the food was excellent very clean and attentive and also very quick very good lunch, service, and atmosphere we really enjoy everything we've had here	just tried their food, it was terrible! prices are awful and the food was disappointing very clean and outdated and also very disappointing very low lunch, service, and atmosphere we really left everything we've had here

[Table 1] Transferred sentences on IMDB movie review to Yelp dataset of the preliminary result, where **red** denotes negative term and **blue** denotes positive term

Approach

4. Approach

1. Effects of early stopping - Love & Hip hop lyrics dataset
2. Effects of pre-trained epoch - Love & Hip hop lyrics dataset
3. Effects of weights in style loss - Love & Hip hop lyrics dataset
4. Further experiment - Hillary & Trump twitter dataset



Love & Hip hop lyrics dataset

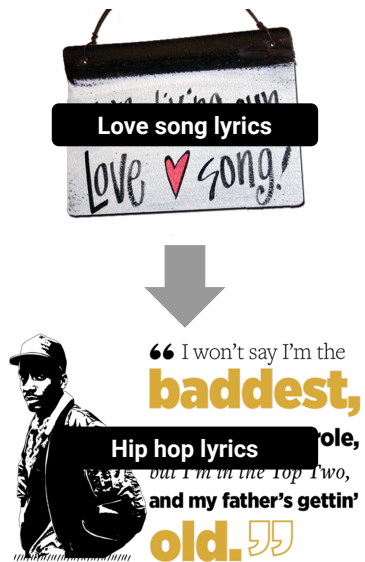


Trump & Hillary twitter dataset

Experiment

Experiment

1. Effects of early stopping



	Style	Lyrics
Input	love	and i swear by the moon and the stars in the sky i'll be there
early stopping	hip-hop	and i swear by the mc and the stars in the am i'll not stan
Last epoch	hip-hop	and i swear by the kick and the stars in the police i'll not stan
Input	love	every inch of your skin is a holy gray I have got to find
early stopping	hip-hop	every hip of your back is a holy hip I have got to find
Last epoch	hip-hop	every mcs of your back is a gangsta hip I have got to joint
Input	love	i never thought that you would be the one to hold my heart
early stopping	hip-hop	i never thought that you would be the one to ask joint plug
Last epoch	hip-hop	i never thought that you would be the one to jock swift swift
Input	love	if she changes her mind this is the first place she will go
early stopping	hip-hop	if she changes her mind this is the first place she can properly
Last epoch	hip-hop	if she because her mind this is the first place she police uhhuh

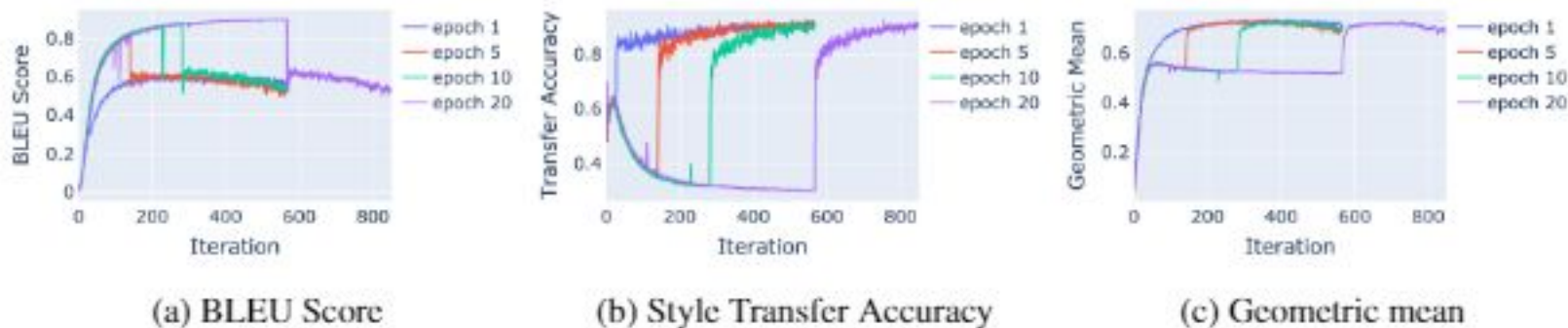
[Table 2] Results of text style transfer with song lyrics with early stopping or not

Experiment

2. Effects of pre-trained epoch

Pre-trained Epochs	Domain Acc.	Style Transfer Acc.	BLEU Score	Geometric Mean
1	0.9952	0.8676	0.5976	0.7201
5	0.9933	0.9043	0.5826	0.7258
10	0.9934	0.8613	0.6114	0.7257
20	0.9899	0.8567	0.6000	0.7169

[Table 3] Quantitative analysis results of generated sentences with variation of pre-trained epochs



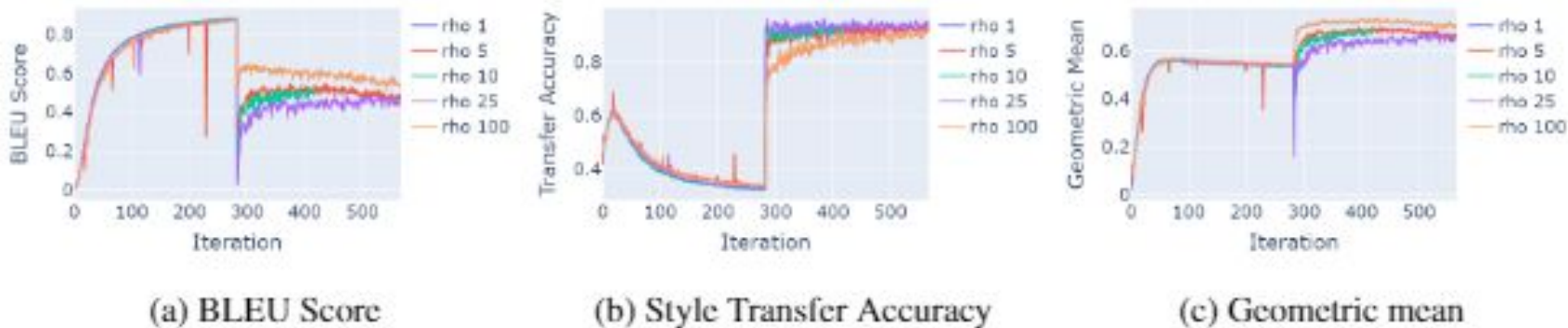
[Figure 1] BLEU score, style transfer accuracy and geometric mean graphs of generated sentences with variation of pre-trained epochs

Experiment

3. Effects of weights ρ in style loss

ρ	Domain Acc.	Style Transfer Acc.	BLEU Score	Geometric Mean
1	0.9923	0.8491	0.6119	0.7207
5	0.9950	0.9031	0.5101	0.6785
25	0.9925	0.9327	0.4274	0.6309
100	0.9585	0.9585	0.3871	0.6090

[Table 4] Quantitative analysis results of generated sentences with variation of value ρ



[Figure 2] BLEU score, style transfer accuracy and geometric mean graphs of generated sentences with variation of value ρ

Experiment

3. Effects of weights ρ in style loss

ρ	Lyrics	
	Input	and i swear by the moon and the stars in the sky ill be there
1	Early stop	and i swear by the moon and the short in the style ill be there
5	Early stop	and i swear by the rhythm and the stars in the suckers ill be there
25	Early stop	and i swear as the role and the stars in the cell not phase there
100	Early stop	and i swear by the moon and the stars in the jungle be street heard
	Input	every inch of your skin is a holy gray I have got to find
1	Early stop	every mcs of your brothers is a dandy uhh I have got to find
5	Early stop	every slick of your vocal is a few uncle I have got to find
25	Early stop	every stain of your skin is a sayin off I am got to find
100	Early stop	visiting livin of your skin is a old soul I have got to find
	Input	oh her eyes her eyes make the stars look like they are not shinin
1	Early stop	oh her eyes her eyes make the stars look like they are not
5	Early stop	oh she eyes her eyes make the o look like people are not
25	Early stop	o her can to bear make the stars look like they are not
100	Early stop	oh her eyes her eyes make the school look like they are not

[Table 5] Results of text style transfer with song lyrics with different ρ

Experiment

4. Further experiment - Hillary & Trump twitter dataset

	Style	Sentence	
Input	Hillary	it took years but will be the year of the first woman POTUS great day to be an American woman	proponent
	Trump	it took years but will be the winner of the very presidential person my speech for very many the	
Input	Hillary	I want you to know that I see you and I am with you Hillary to the Latino community at	policy
	Trump	I want you to know that I am me today to me with I hope to the amazing amp	
Input	Hillary	if fighting for affordable child care and paid family leave is playing the woman card, then deal me	policy
	Trump	if fighting for jobs care than jobs is setting the opposite card then, will join me	
Input	Trump	the ratings for the republican national convention were very good	party
	Hillary	but for the final night my speech great thank you the ratings for the democratic congressional convention is also happening on my heart for this speech my democratic friend	
Input	Trump	this is why I would think the unions would support	proponent
	Hillary	this is why I would think the women would support	
Input	Trump	we are going to bring steel and manufacturing back to Indiana	policy
	Hillary	we are going to bring the community and build back to Indiana	

[Table 6] Results of text style transfer with Twitter data of Hillary and Trump

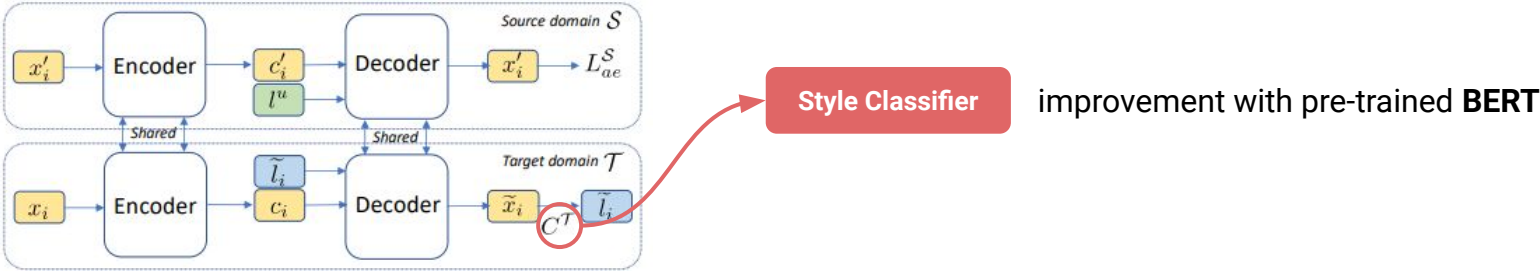
Discussion

Discussion

1. Improvement of the style classifier

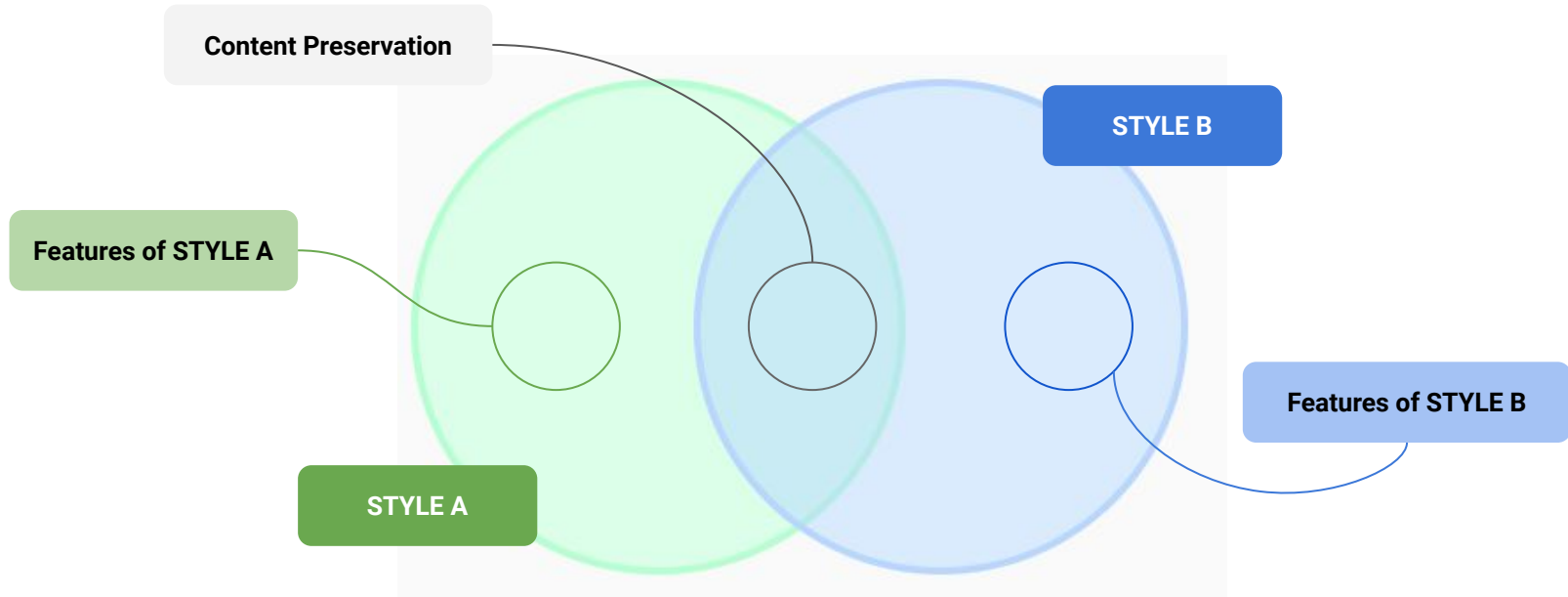
Target Dataset	Style set	Pre-trained style classifier accuracy
Yelp	positive, negative	0.9317
Lyrics	love song, hip hop	0.8701
Tweet	Trump, Hillary	0.8453

[Table 7] Pre-trained style classifier accuracy of models with different dataset



Discussion

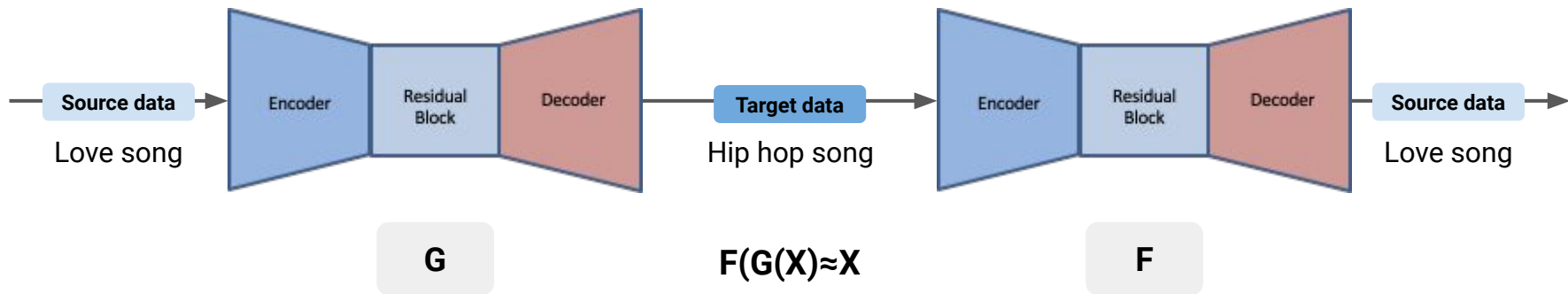
2. Differences in model styles and content recognition by data configuration



Model recognizes the **CONTENT to preserve** as the words which are not different between datasets while it regards to **STYLE** as the words which seem different apparently.

Discussion

3. Cycle consistency loss



Adding **cycle consistency loss** on our work
would promote the quality of the stylized sentences

THANK YOU
