Generic resources are what you need: Style transfer tasks without task-specific parallel training data

Huiyuan Lai, Antonio Toral, Malvina Nissim
CLCG, University of Groningen / The Netherlands

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Text style transfer

Rephrasing a given text in the desired style while preserving its original content.

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Formality Transfer

Informal:
no different between ages if the mind is near to eachother

↔

Formal:
There is no difference between ages if the intellect is similar.

Style	Meaning	Topic
≠	=	=

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Rephrasing a given text in the desired style while preserving its original content.

Formality Transfer

Informal:
no different between ages if the mind is near to eachother

↔

Formal:
There is no difference between ages if the intellect is similar.

Polarity Swap

Negative:
bad service in these areas and really ruined our visit.

↔

Positive:
good service in these areas and really made our visit.

	Style	Meaning	Topic
Formality Transfer	≠	=	=
Polarity Swap	≠	≠	=

Dataset

Formality Transfer

Polarity Swap

DATASET	STYLE	PAIRED			UNPAIRED	
		Train	Valid	Test	Train	Valid
GYAFC	Informal	51,967	2,788	1,332	N/A	N/A
	Formal	51.967	2,247	1,019	N/A	N/A
YELP	Negative	N/A	N/A	500	177,218	2,000
	Positive	N/A	N/A	500	266,041	2,000

Evaluation

- Style Strength: pre-trained style classifier
- Content Preservation: BLEU

  - Learnable Metrics —BLEURT, COMET

- Overall: the harmonic mean (HM) of style accuracy and BLEU.

Generic resources

- General-purpose pre-trained seq2seq model—BART
- Paraphrasing data—PARABANK 2
- WordNet, SentiWordNet

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  A large pre-trained model helps preserve content (Lai et al 2021, Thank you BART!)

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  We can teach the model the basic task of re-writing independently of the task (so also with no or little task-specific data)

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- WordNet, SentiWordNet

  The general lexical resources can help to create synthetic pairs for polarity swap

Paraphrases

Text 1:
I guess I've always been pretty good with words.

Text 2:
I think narrating has always been my strong suit.

Paraphrases

Paraphrases

<u>Text 1:</u>
I guess I've always been pretty good with words.

<u>Text 2:</u>
I think narrating has always been my strong suit.

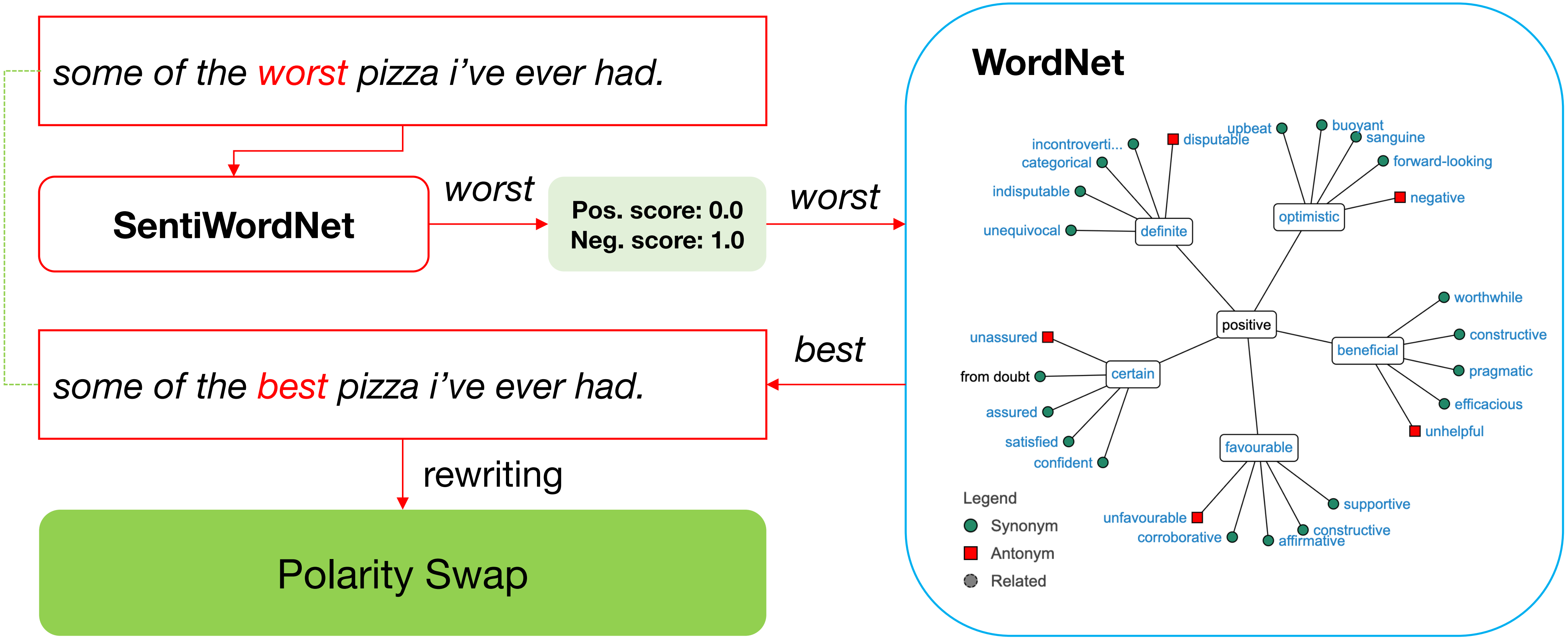
rewriting

Formality Transfer √

Polarity Swap ?

they are **not** exactly the same task!

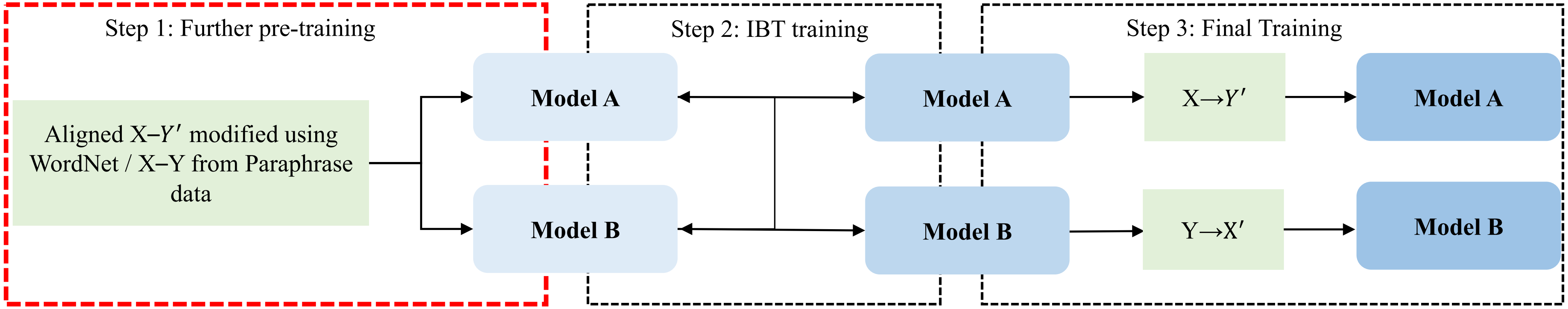
SentiWordNet and WordNet



This procedure creates synthetic pairs!

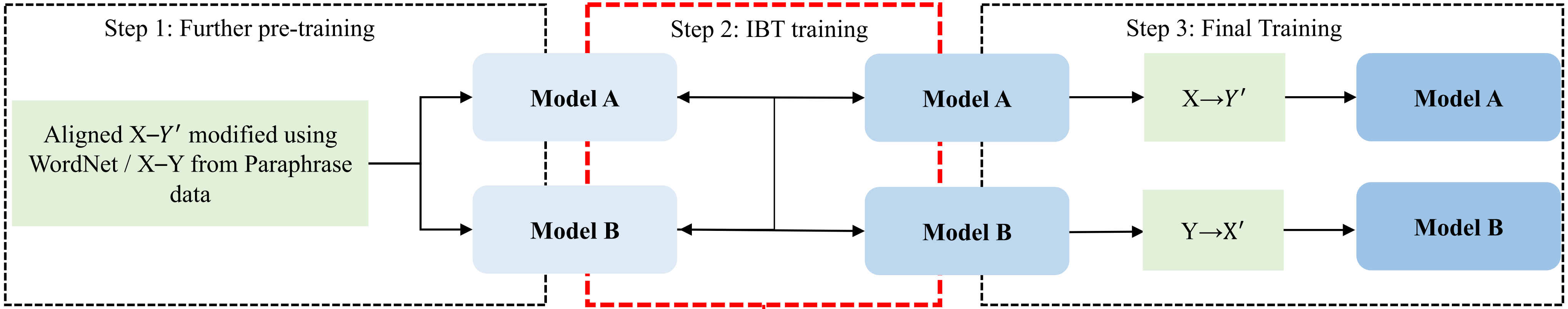
Our Pipeline

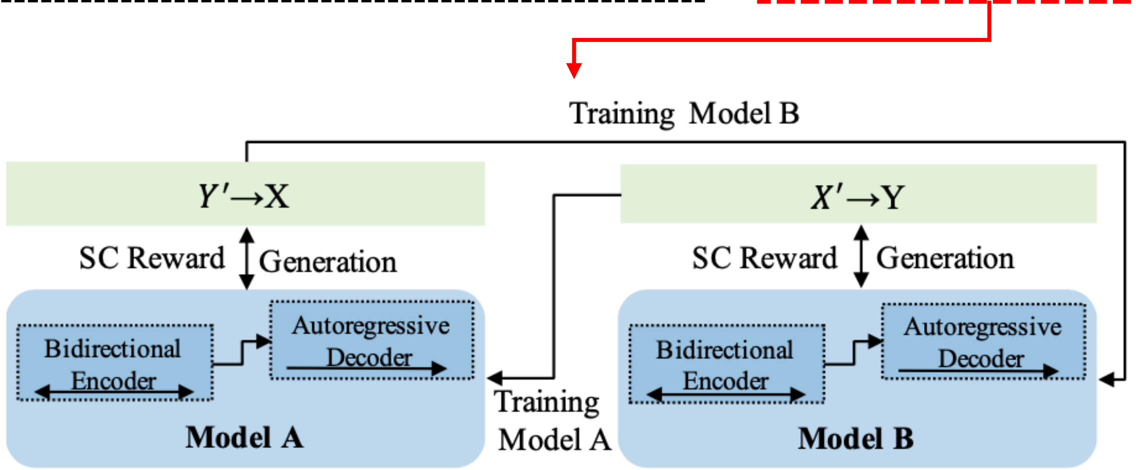
General overview of our pipeline



1) Second phase of pre-training using paraphrases and the WordNet-derived synthetic pairs.

General overview of our pipeline



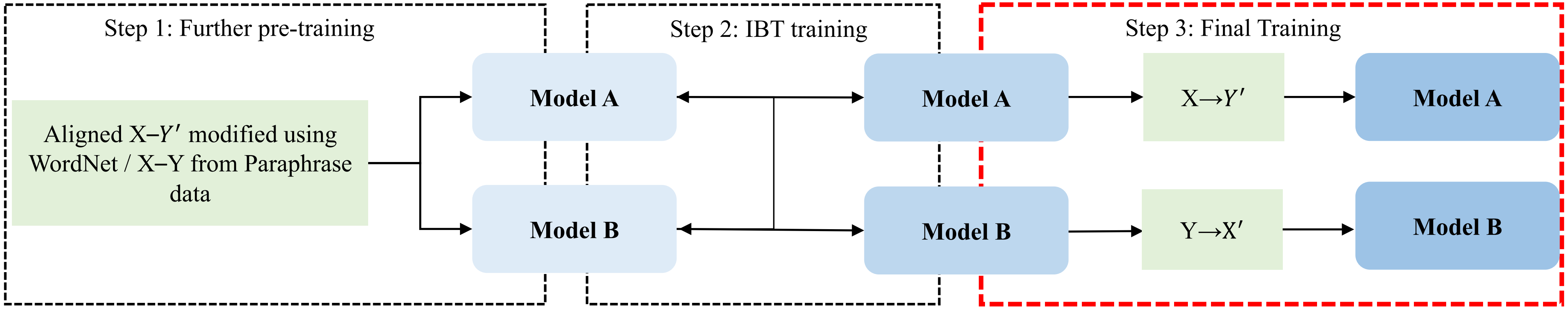


General overview of IBT training

2) Iterative back-translation (IBT) training

- BLEU-/BLEURT-based reward: Content
- Style classification based reward: Style

General overview of our pipeline



3) Fine-tuning BART with high quality pairs, with all reward strategies

- BLEURT – Content Preservation
- Style Classifier – Style Strength

Experiments

Step 1- Paraphrase-based pre-training

DATASET	GYAFC (FORMALITY TRANSFER)					YELP (POLARITY SWAP)				
MODEL	BLEURT	COMET	BLEU	ACC	HM	BLEURT	COMET	BLEU	ACC	HM
M0: Original BART	-0.116	0.242	0.414	0.333	0.369	-0.388	-0.146	0.309	0.022	0.041
STEP 1: Further pre-training										
M1.1: Further pre-training using whole dataset	0.012	0.209	0.420	0.357	0.386	-0.412	-0.282	0.179	0.040	0.065
M1.2: Further pre-training using subset	0.011	0.225	0.441	0.693	0.539	-0.347	-0.178	0.247	0.166	0.199
M1.3: Further pre-training using synthetic data	-	-	-	-	-	-0.321	-0.074	0.326	0.189	0.239
STEP 2 [illegible]T + Rewards										
M2.1: IBT + all rewards with M0	[illegible]	0.292	0.507	0.836	0.631	-0.229	-0.017	0.298	0.826	0.438
M2.2: IBT + all rewards with [illegible]	[illegible]	0.318	0.553	**0.932**	**0.694**	-0.176	0.026	0.295	0.853	0.438
M2.3: IBT + all reward[illegible]	[illegible]	-	-	-	-	-0.246	-0.035	0.302	0.884	0.450
M2.4: M2.2 except [illegible]	[illegible]	[illegible]	0.552	0.929	0.693	-0.187	0.001	0.285	0.860	0.428
M2.5: M2.2 except B[illegible]	[illegible]	[illegible]	0.551	0.925	0.691	**-0.149**	0.031	0.295	0.784	0.429
M2.6: M2.2 except SC0	[illegible]	**0.321**	0.544	0.928	0.686	-0.195	-0.016	0.286	0.881	0.432
M2.7: M2.2 except SC1	0.039	0.318	0.555	0.873	0.679	-0.176	0.039	**0.331**	0.500	0.398
STEP 3: Offline training (Model used: original BART + Rewards)										
M3.1: training pairs generated with M2.2 (GYAFC) / M2.3 (YELP)	0.030	**0.321**	**0.560**	0.904	0.692	-0.183	**0.046**	0.316	**0.887**	**0.466**
M3.2: training pairs are subset of paraphrase data (same as in M1.2)	0.012	0.229	0.455	0.783	0.576	-0.338	-0.221	0.215	0.457	0.292

Using paraphrase data
benefits more formality
transfer than polarity swap

Step 2- IBT training

Further pre-training significantly improves performance on formality transfer.

MODEL	[illegible] TRANSFER)					YELP (POLARITY SWAP)				
	[illegible]	[illegible]	[illegible]	CC	HM	BLEURT	COMET	BLEU	ACC	HM
M0: Original BART	[illegible]	[illegible]	[illegible]	[illegible]	0.369	-0.388	-0.146	0.309	0.022	0.041
[illegible]										
M1.1: Further pre-training using whole dataset	[illegible]	[illegible]	[illegible]	[illegible]57	0.386	-0.412	-0.282	0.179	0.040	0.065
M1.2: Further pre-training using subset	[illegible]	[illegible]	[illegible]	0.693	0.539	-0.347	-0.178	0.247	0.166	0.199
M1.3: Further pre-training using synthetic data	-	-	[illegible]	-	-	-0.321	-0.074	0.326	0.189	0.239
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M2.2: IBT + all rewards with M1.2	**0.041**	0.318	0.553	**0.932**	**0.694**	-0.176	0.026	0.295	0.853	0.438
M2.3: IBT + all rewards with M1.3	-	-	-	-	-	-0.246	-0.035	0.302	0.884	0.450
M2.4: M2.2 except BLEURT	0.033	0.313	0.552	0.929	0.693	-0.187	0.001	0.285	0.860	0.428
M2.5: M2.2 except BLEU	**0.041**	0.320	0.551	0.925	0.691	**-0.149**	0.031	0.295	0.784	0.429
M2.6: M2.2 except SC0	0.024	**0.321**	0.544	0.928	0.686	-0.195	-0.016	0.286	0.881	0.432
M2.7: M2.2 except SC1	0.039	0.318	0.555	0.873	0.679	-0.176	0.039	**0.331**	0.500	0.398
STEP 3: Offline training (Model used: original BART + Rewards)										
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M3.2: training pairs are subset of paraphrase data (same as in M1.2)	0.012	0.229	0.455	0.783	0.576	-0.338	-0.221	0.215	0.457	0.292

Step 3- High-quality synthetic pairs

Model \ Dataset	GYAFC (Formality Transfer) BLEURT	COMET	BLEU	ACC	HM	YELP (Polarity Swap) BLEURT	COMET	BLEU	ACC	HM
M0: Original BART	-0.116	0.242	0.414	0.333	0.369	-0.388	-0.146	0.309	0.022	0.041
STEP 1: Further pre-training										
M1.1: Further pre-training using whole dataset	0.012	0.209	0.420	0.357	0.386	-0.412	-0.282	0.179	0.040	0.065
M1.2: Further pre-training using subset	0.011	0.225	0.441	0.693	0.539	-0.347	-0.178	0.247	0.166	0.199
M1.3: Further pre-training using synthetic data	-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	-0.074	0.326	0.189	0.239
STEP [illegible]										
M2.1: IBT + all rewards with M0	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.298	0.826	0.438
M2.2: IBT + all rewards with M1.2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.295	0.853	0.438
M2.3: IBT + all rewards with M1.3	-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.302	0.884	0.450
M2.4: M2.2 except BLEURT	0.033	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.001	0.285	0.860	0.428
M2.5: M2.2 except BLEU	**0.041**	0.320	0.551	0.925	[illegible]	[illegible]	0.031	0.295	0.784	0.429
M2.6: M2.2 except SC0	0.024	**0.321**	0.544	0.928	0.686	[illegible]	-0.016	0.286	0.881	0.432
M2.7: M2.2 except SC1	0.039	0.318	0.555	0.873	0.679	[illegible]	0.039	**0.331**	0.500	0.398
STEP 3: Offline training (Model used: original BART + Rewards)										
M3.1: training pairs generated with M2.2 (GYAFC) / M2.3 (YELP)	0.030	**0.321**	**0.560**	0.904	0.692	-0.183	**0.046**	0.316	**0.887**	**0.466**
M3.2: training pairs are subset of paraphrase data (same as in M1.2)	0.012	0.229	0.455	0.783	0.576	-0.338	-0.221	0.215	0.457	0.292

Model trained with high-quality synthetic pairs achieves the best performance on polarity swap.

Comparison with other systems

GYAFC (Formality Transfer)					
Model	BLEURT	COMET	BLEU	ACC	HM
Input Copy	-0.114	0.272	0.474	0.120	0.192
UnsuperMT (Zhang et al., 2018)	-0.665	-0.446	0.327	0.670	0.439
DualRL (Luo et al., 2019)	-0.589	-0.451	0.404	0.654	0.499
StyIns (Yi et al., 2020)	-0.395	-0.112	0.458	0.761	0.573
Zhou's (Zhou et al., 2020)	-0.454	-0.203	0.447	0.799	0.573
*TGLS (Li et al. (2020a); $0 \rightarrow 1$)	-	-	0.603	-	-
Ours (M2.2; lowercase)	**0.009**	**0.328**	**0.563**	**0.866**	**0.682**
Ours (M2.2; lowercase; $0 \rightarrow 1$)	-	-	**0.741**	-	-

Comparison with other systems

YELP (POLARITY SWAP)					
MODEL	BLEURT	COMET	BLEU	ACC	HM
Input Copy	-0.383	-0.139	0.312	0.019	0.036
Style-Transformer (Dai et al., 2019)	-0.469	-0.269	0.282	0.857	0.424
DualRL (Luo et al., 2019)	-0.385	-0.202	0.278	0.894	0.424
StyIns (Yi et al., 2020)	-0.576	-0.390	0.250	**0.924**	0.394
Zhou's (Zhou et al., 2020)	-0.270	-0.051	0.302	0.865	0.448
DGST (Li et al., 2020b)	-0.421	-0.240	0.268	0.781	0.399
Ours (M3.1)	**-0.183**	**0.046**	**0.316**	0.887	**0.466**
-			-		

Example outputs

MODEL	SENTENCE	BLEU	BLEURT	COMET	ACC
Source	So if you’re set on that, that’s the way to go!!	-			
M0	so if you’re set on that, that’s the way to go!!	0.417	0.175	0.568	0.000
M1.1	so if you want to do this, this is the way to go!	0.301	0.204	0.354	0.003
M1.2	If you want to do this, this is the way to go.	0.416	0.339	0.433	0.855
M2.1	So if you’re set on that, that is the way to go.	0.763	0.525	0.689	0.179
M2.2	So, if you are set on that, then that is the way to go.	**0.884**	0.456	0.722	**0.880**
M3.1	So if you are set on that, that is the way to go.	0.541	**0.941**	**0.734**	0.617
M3.2	If you’re on board, that’s the way to go.	0.352	0.200	0.311	0.552

if you’re set on that -> *if you want to do this* [thanks to paraphrases!]

Example outputs

MODEL	SENTENCE	BLEU	BLEURT	COMET	ACC
Source	the staff are all super friendly and on top of there jobs.		-		
M0	the staff are all super friendly and on top of there jobs.	0.163	-0.561	-0.169	0.000
M1.1	all the staff are very friendly and they're doing their jobs well.	0.107	-0.571	-0.301	0.003
M1.2	the staff are all super friendly and on top of each same jobs.	0.149	-0.662	-0.507	0.000
M1.3	the staff are all super unfriendly and on top of there jobs.	0.151	-0.239	0.095	**1.000**
M2.1	the staff are all super rude and on top of there jobs.	0.151	-0.513	0.048	**1.000**
M2.2	the staff are all super rude and on top of there jobs.	0.151	-0.513	0.048	**1.000**
M2.3	the staff are all super rude and on top of there jobs.	0.151	-0.513	0.048	**1.000**
M3.1	the staff are not super friendly or on top of there jobs.	**0.320**	**0.322**	**0.621**	**1.000**
M3.2	the staff are so friendly and they're doing their jobs.	0.148	-0.663	-0.326	0.001

on top of there jobs -> they're doing their jobs well [thanks to paraphrases!]

Thanks for your attention!

@HuiyuanLai @_atoral @MalvinaNissim @GroNlp

huiyuanlai.l@gmail.com

https://arxiv.org/pdf/2109.04543.pdf

Paper Link

https://github.com/laihuiyuan/Generic-resources-for-TST

Code Link