

## Neural Paraphrase Generation with Stacked Residual LSTM Networks





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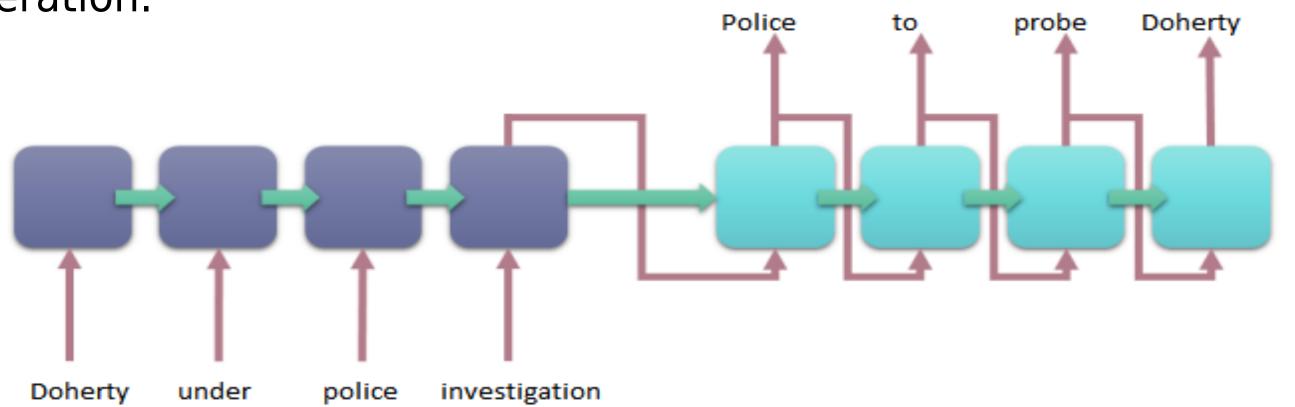
a baby sitting on top of a motorcycle

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### Problem Definition

Paraphrasing, the task of expressing the same meaning in different possible ways, is an important subtask in various Natural Language Processing (NLP) applications such as question answering, information extraction, information retrieval, summarization and natural language generation.



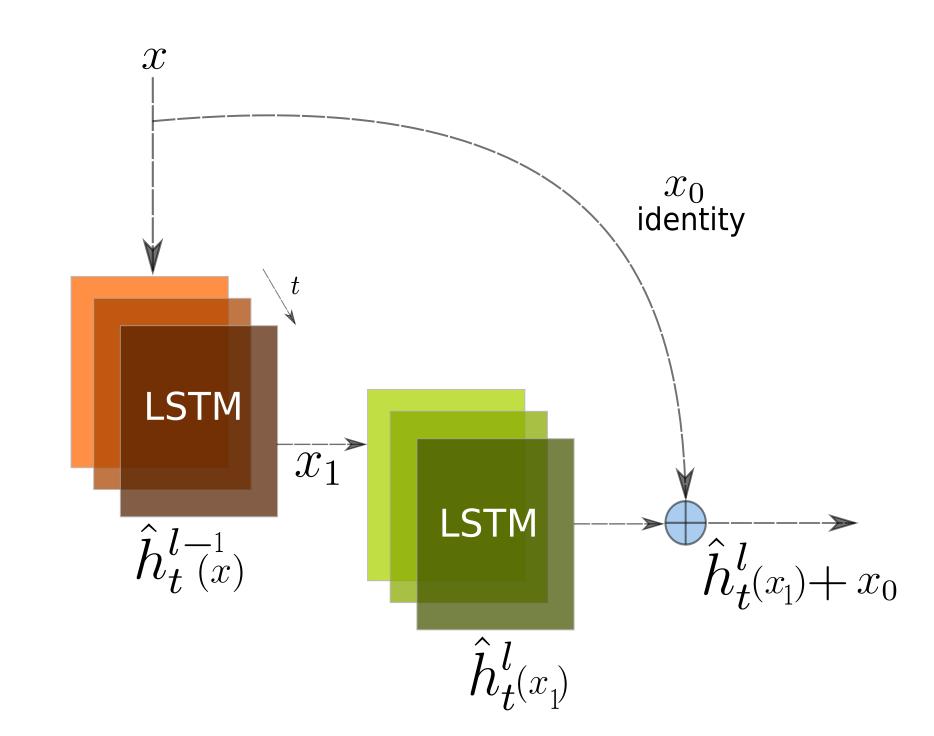
- Conventional paraphrase generation methods either leverage handwritten rules and thesauri-based alignments, or use statistical machine learning principles.
- To the best of our knowledge, this work is the first to explore deep learning models for paraphrase generation.
- Our primary contribution is a stacked residual LSTM network, where we add residual connections between LSTM layers. This allows for efficient training of deep LSTMs.
- Our model outperforms sequence to sequence, attention-based, and bidirectional LSTM models on BLEU, METEOR, TER, and greedy embedding.

## Dataset and Models

<b>Dataset</b>	Training	Test	Vocabulary Size
PPDB WikiAnswers MSCOCO	4,826,492 4,826,492 331,163	20,000 20,000	38,279 50,000 30,332
	Datas	set details	
Models		Referen	ce
Sequence to Set With Attention Bi-directional Residual LSTN	n LSTM	(Bahdan (Graves	ger et al., 2014) au et al., 2015) et al., 2013) posed model
Models			

- Words were represented as one-hot vector
- Each model trained for 10 epochs
- Dropout of 50% was applied on LSTM layers
- Number of LSTM units was 512 for all models and all layers
- Training time : 36 hours for WikiAnswers and PPDB (Titan X, Theano) : 14 hours for MSCOCO
- Perplexity was used as training loss
- Beam search used for generating samples

#### tacked Residual LSTM



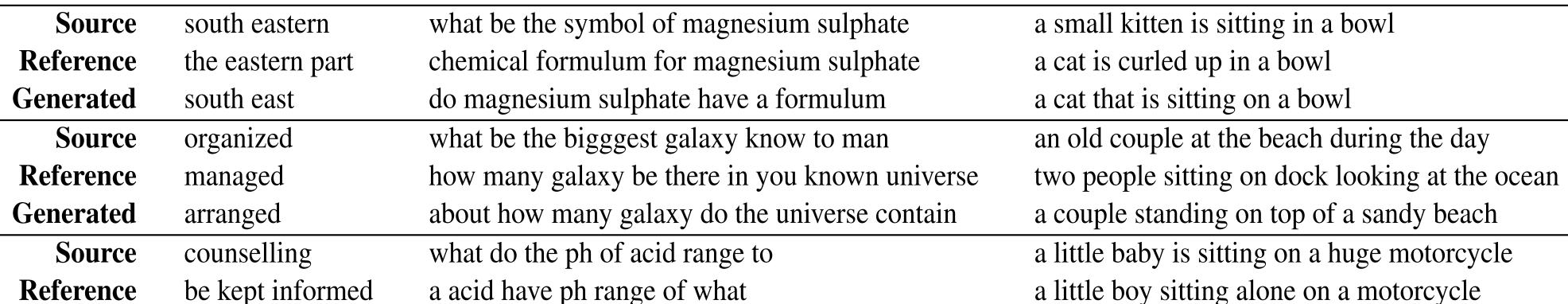
$$\hat{\boldsymbol{h}}_{t}^{(l)} = f_{h}^{l}(\boldsymbol{h}_{t}^{(l-1)}, \boldsymbol{h}_{t-1}^{(l)}) + x_{l-n}$$

- $oldsymbol{h}_t^l$  hidden state at layer l at time step t
- $\mathcal{X}$  input to layer i + 1
- $_{-}$   $n^{^{t}}$  # layers to skip between residual connection. Figure shows n=2
- Addition of residual connection does not add any learnable parameters

## Analysis

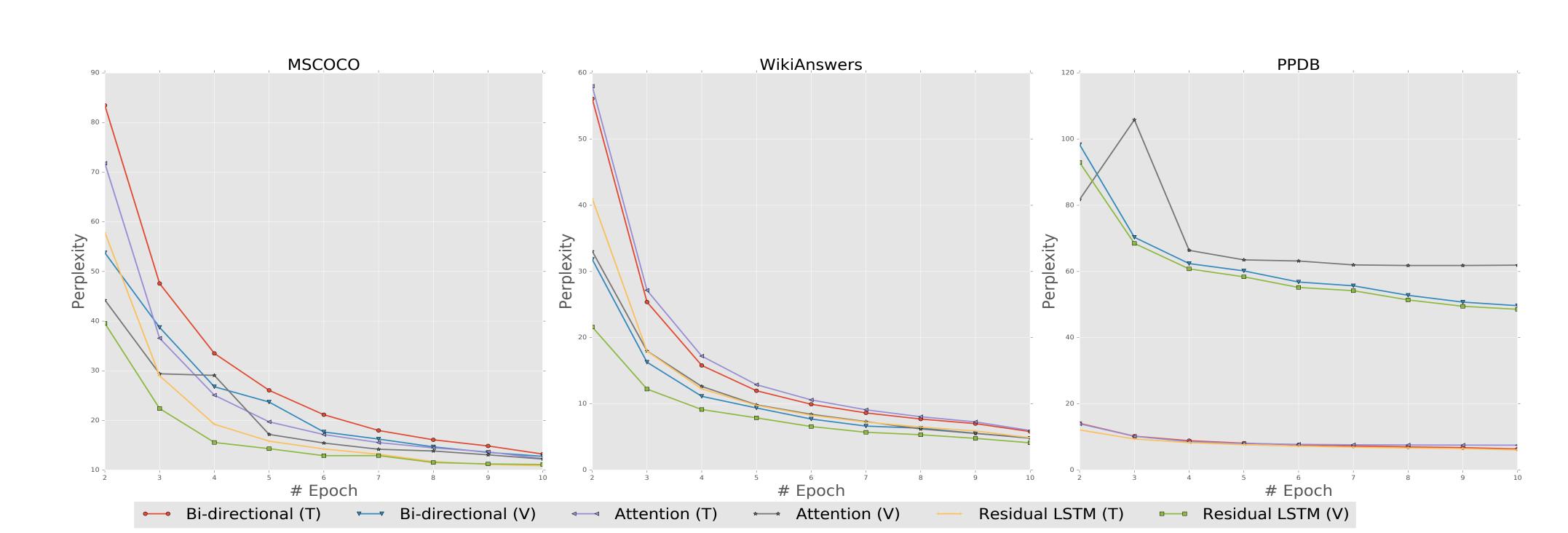
- Scores on various metrics vary across the datasets due to differences in sentence length and vocabulary.
- PPDB contains very short phrases and does not score well with metrics like BLEU and METEOR, which penalizes short phrases.
- Deeper LSTM always leads to better performance.
- Larger beam size always improves performance but only marginally
- Models exploit the dataset 'bias'. For example an OBJECT is mostly paraphrased with an OBJECT (eg. bowl, motorcycle). Shorter phrases generate shorter paraphrases.
- Perplexity does not incorporate reward "diversity", thus a better metric for paraphrase training and evaluation is required.
- Residual LSTM layers is useful for paraphrase generation, but it may not perform well for machine translation because not every word in a source sequence needs to be substituted for paraphrasing.
- Our work can be used to augment the datasets like MSCOCO used for image caption generation.
- We plan to explore memory networks to improve paraphrase generation.

# Training and Results WikiAnswers MSCOCO what be the symbol of magnesium sulphate chemical formulum for magnesium sulphate do magnesium sulphate have a formulum a cat is curled up in a bowl a cat that is sitting on a bowl



Example paraphrases generated using the 4-layer Residual LSTM with beam size 5.

how do acid affect ph



## Evaluation

			В	eam size = 5	Beam size = 10				
#Layers	Model	BLEU†	METEOR†	Emb Greedy†	TER↓	BLEU†	METEOR†	Emb Greedy†	TER↓
				PPDB					
2	Sequence to Sequence	12.5	21.3	32.55	82.9	12.9	20.5	32.65	83.0
	With Attention	13.0	21.2	32.95	82.2	13.8	20.6	32.29	81.9
4	Sequence to Sequence	18.3	23.5	33.18	82.7	18.8	23.5	33.78	82.1
	Bi-directional	19.2	23.1	34.39	77.5	19.7	23.2	34.56	84.4
	With Attention	19.9	23.2	34.71	83.8	20.2	22.9	34.90	77.1
	<b>Residual LSTM</b>	20.3	23.1	34.77	<b>77.</b> 1	21.2	23.0	34.78	77.0
				WikiAnswer	S				
2	Sequence to Sequence	19.2	26.1	62.65	35.1	19.5	26.2	62.95	34.8
	With Attention	21.2	22.9	63.22	37.1	21.2	23.0	63.50	37.0
4	Sequence to Sequence	33.2	29.6	73.17	28.3	33.5	29.6	73.19	28.3
	Bi-directional	34.0	30.8	73.80	27.3	34.3	30.7	73.95	27.0
	With Attention	34.7	31.2	73.45	27.1	34.9	31.2	73.50	27.1
	Residual LSTM	<b>37.0</b>	32.2	75.13	<b>27.0</b>	37.2	32.2	<b>75.19</b>	26.8
				MSCOCO					
2	Sequence to Sequence	15.9	14.8	54.11	66.9	16.5	15.4	55.81	67.1
	With Attention	17.5	16.6	58.92	63.9	18.6	16.8	59.26	63.0
4	Sequence to Sequence	28.2	23.0	67.22	56.7	28.9	23.2	67.10	56.3
	Bi-directional	32.6	24.5	68.62	53.8	32.8	24.9	68.91	53.7
	With Attention	33.1	25.4	69.10	54.3	33.4	25.2	69.34	53.8
	<b>Residual LSTM</b>	36.7	27.3	69.69	52.3	37.0	27.0	69.21	51.6

Evaluation results on PPDB, WikiAnswers, and MSCOCO (Best results are in bold).