Controlling the Transition of Hidden States for Neural Machine Translation

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Outline

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Neural Machine Translation

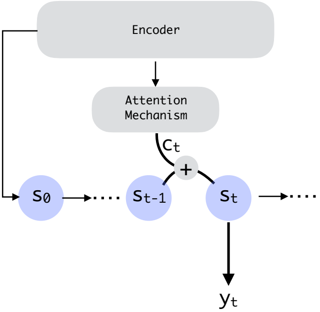
- Neural network-based methods show a promising trend in machine translation
- Generally, a neural machine translation (NMT) system adopts an *encoder-decoder* architecture with *attention mechanism* to model translating process

Recurrent Neural Network (RNN) based NMT

RNN-based NMT models with attention are widely deployed that deserves further study.

- Bi-directional encoder
- Uni-directional (left-to-right) decoder
- Encoder and decoder are bridged by attention

In this work, we focus on the RNN-based NMT model, especially its decoder part.



Recurrent Neural Network (RNN) based NMT

The NMT model

- is fed with a source sentence: $\langle x_1, ..x_i, ...\rangle \rightarrow \langle \boldsymbol{h}_1, ..\boldsymbol{h}_i, ...\rangle$
- does some **magics** with decoder **hidden states** step by step

$$\boldsymbol{s}_t = f(\boldsymbol{s}_{t-1}, y_{t-1}), \tag{1}$$

$$\boldsymbol{s}_0 = \text{summary}(\mathbf{h}). \tag{2}$$

- finally throws out a translated sentence: $\mathbf{s} \rightarrow \langle y_1, ..y_t, ...\rangle$

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We may ask..

What happens inside this so-called "black box"?
Why and how does it work?

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  - In each decoding step, the decoder hidden state is able to predict the rest untranslated Bag-of-Words (Weng et al., 2017)
  - The decoder hidden states should model past, present and future translation contents, which are varied according to the translation process (Zheng et al., 2018)

Preliminary Probing Experiment

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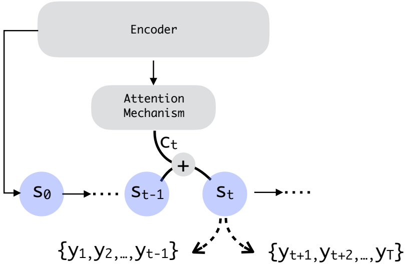
- we trained the word predictors while fixed all the parameters of the original NMT model
- we wanted to validate if the hidden states store the translated and untranslated BoW, extending the observations of Weng et al. (2017)

Bag-of-Word (BoW) Predictions

$$acc_{fw} = \frac{1}{T}\sum_{1}^{T}\sum_{w\in top_{(\text{T-t-1})}(P_t)} \frac{\mathbb{1}(w \in y_{>(t+1)})}{T-t-1}$$

	Acc.	ppl
Forward pred.	71%	5.1
Backward pred.	78%	4.6

Table 1: Statistics of BoW predictions.



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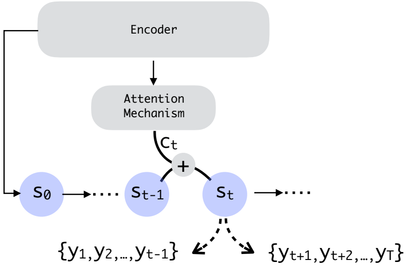

Figure 1: Illustration of BoW pred.

Each hidden state stores its backward directional contents (translated words) and forward directional contents (untranslated words).

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We suggest that

- The translations vary at different timesteps in accordance with the hidden states' transitions.
- The transitions play an important role in the RNN-based decoder, updating the span-level information of each hidden state.
- The difference between two hidden states should represent *lexicon-level* information of the current translation.

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So, we probably need

An explicit supervision to control the transition

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Predictive Constraint

For clarity, let us take $\{\boldsymbol{s}_{t-1}, \boldsymbol{s}_t\}$ and y_t for example.

- we denote $\boldsymbol{\Delta s}_t$ as the increment produced by the transition from $\boldsymbol{s}_{t-1}$ to $\boldsymbol{s}_t$.

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- the transition of two successive decoder hidden states should be predictive of the translation at current timestep.
  - $\boldsymbol{\Delta s}_t \approx y_t$,
  - we introduce a predictive constraint:

$$q(y_t|\boldsymbol{\Delta s}_t) = \mathrm{softmax}\big(\boldsymbol{E}(y_t)^\top \boldsymbol{W} \tanh(\boldsymbol{\Delta s}_t)\big), \tag{4}$$

where $\boldsymbol{W}$ is a learned matrix.

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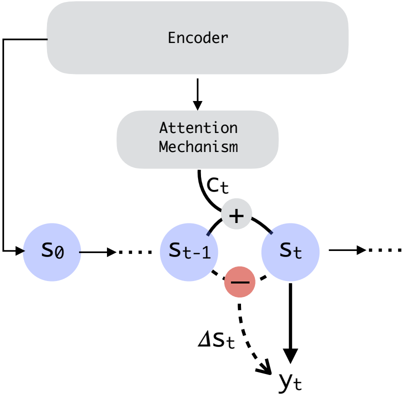

Figure 2: Illustration of proposed approach. Dotted lines denote the way to obtain the increment and predictive constraint.

How to Model the Transition Δs_t?

- Algebraic Subtraction
  - A general assumption: the decoding states form a shared latent representation space,
  - Get $\boldsymbol{\Delta s}_t$ by an algebraic subtraction

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- Parametric Subtraction
  - Apply the subtraction in a parametric manner
  - The subtrahend and minuend are first mapped by separate linear transformations $\boldsymbol{U}_1$ and $\boldsymbol{U}_2$, respectively

$$\boldsymbol{\Delta s}_t = \boldsymbol{U}_1 \boldsymbol{s}_t - \boldsymbol{U}_2 \boldsymbol{s}_{t-1} \tag{6}$$

Training

Give a training dataset $\{[\mathbf{x^{(m)}}, \mathbf{y^{(m)}}]\}_{m=1}^{M}$, we learn our model as follow:

- Sentence-level predictive constraint of the transitions

$$q_\gamma(\mathbf{y}) = \sum_{t}^{T} q(y_t | \boldsymbol{\Delta s}_t)$$

- Training objective

$$\mathcal{L}(\theta, \gamma) = \frac{1}{M} \sum_{m=1}^{M} \log P_\theta(\mathbf{y^{(m)}} | \mathbf{x^{(m)}}) + \log q_\gamma(\mathbf{y}^{(m)}) \tag{7}$$

Inference

- $\boldsymbol{\Delta s}_t$ is supposed to predict y_t,
- Use $P(y_t|y_{<t}) + q(y_t|\boldsymbol{\Delta s}_t)$ instead of $P(y_t|y_{<t})$ as the search score in testing phase

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This *re-scoring* strategy ensures the consistence of the objective of training and inference.

Outline

Settings

- Dataset
  - Chinese$\rightarrow$ English (Zh-En): NIST corpus, 1.6m
  - German $\leftrightarrow$ English (De-En & En-De): WMT2017 news translation task, 5.8m
- BPE for De-En and En-De,
- 30K vocabularies for Zh-En,
- Filter long sentence whose lengths are large than 80,
- 512-dims word embedding, 1024-dims hidden state,
- Use Adam with learning rate annealing for optimization.

Results on Zh-En

Model	MT03	MT04	MT05	Avg.	Δ
RNNSearch	37.95	40.80	36.06	38.27	-
Algebraic Subtraction	38.66	40.93	37.00	38.86	+0.59
Parametric Subtraction	39.07	41.23	37.35	39.22	+0.95
Algebraic Subtraction + Re-scoring	39.53	41.88	37.40	39.60	+1.33
Parametric Subtraction + Re-scoring	39.95	42.53	38.17	40.22	+1.95

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RNNSearch (BPE 32K)	40.59	41.65	37.73	40.00	-
Parametric Subtraction + Re-scoring	41.43	43.50	39.83	41.59	+1.60

Table 2: Case-insensitive BLEU on Zh-En translation task.

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Observations:

- Constraint on the transitions is effective
- Parametric constraint is better
- Re-scoring is useful and cheap to boost the performance

Results on De-En and En-De

Model	**De-En**		**En-De**	
	Dev	Test	Dev	Test
RNNSearch	32.0	27.8	28.3	23.3
Parametric Subtraction	32.2	28.7	29.6	23.6
Parametric Subtraction + re-scoring	32.9	29.1	30.6	24.1

Table 3: Case-sensitive BLEU on De-En and En-De Translation Tasks.

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Table 3: Case-sensitive BLEU on De-En and En-De Translation Tasks.

Observations:

- Our approach is effective across various language pairs,
- Our approach works well consistently on both words and sub-words (BPE) scenarios.

Analysis on Parameters and Speeds

Model	#Parameter	Speed	
		Training	Testing
RNNSearch	80M	42.59	2.05
Algebraic Subtraction	80.5M	37.91	2.03
Parametric Subtraction	82.5M	36.50	2.00
Parametric Subtraction + re-ordering	82.5M	36.55	1.72

Table 4: Statistics of parameters, training and testing speeds (sentences per second). **Note that** if we don't use re-scoring strategy, the newly added parameters will never be used in testing phase. i.e., it uses the same amount of parameters as the original NMT.

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Observations:

- Little increase of parameters
- Re-scoring strategy only lowers the testing speed slightly

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- The better we understand the model, the more inspirations we would find.

Simply applying re-scoring in testing helps a lot

- A better score function for the search-based decoding would be useful, which deserves further investigations.

Conclusion

Thanks!

Alexis Conneau, German Kruszewski, Guillaume Lample, Loïc Barrault, and Marco Baroni. 2018. What you can cram into a single vector: Probing sentence embeddings for linguistic properties.

Rongxiang Weng, Shujian Huang, Zaixiang Zheng, Xin-Yu Dai, and Jiajun Chen. 2017. Neural machine translation with word predictions. In *EMNLP 2017*.

Zaixiang Zheng, Hao Zhou, Shujian Huang, Lili Mou, Xinyu Dai, Jiajun Chen, and Zhaopeng Tu. 2018. Modeling past and future for neural machine translation. *TACL*, 6:145–157.