GRID LSTM

A UNIFIED EXTENSION OF LSTM TO DEEP NETWORK

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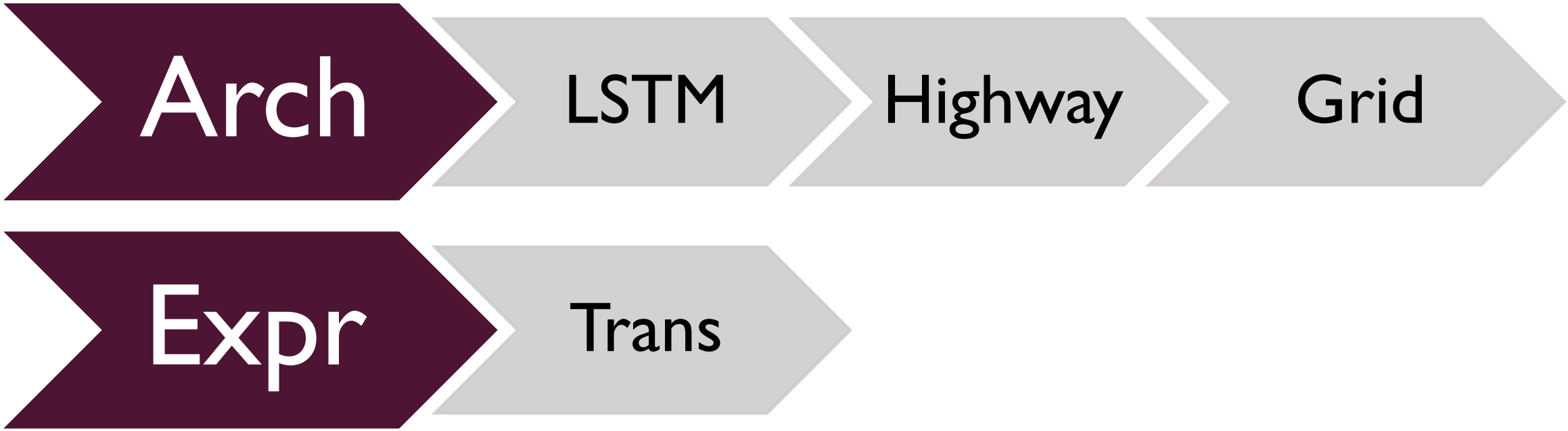
ROADMAP



RECAP LSTM

$$g^u = \sigma(W^u H) \quad \text{input gate}$$

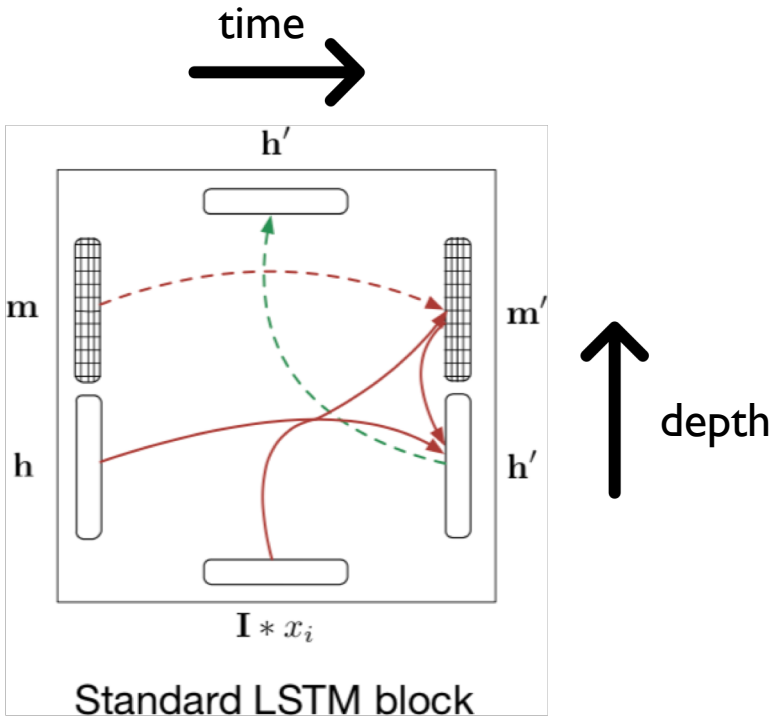
$$g^f = \sigma(W^f H) \quad \text{forget gate}$$

$$g^o = \sigma(W^o H) \quad \text{output gate}$$

$$c = \tanh(W^c H) \quad \text{modulated input}$$

$$m := g^f \odot m + g^u \odot c \quad \text{update memory}$$

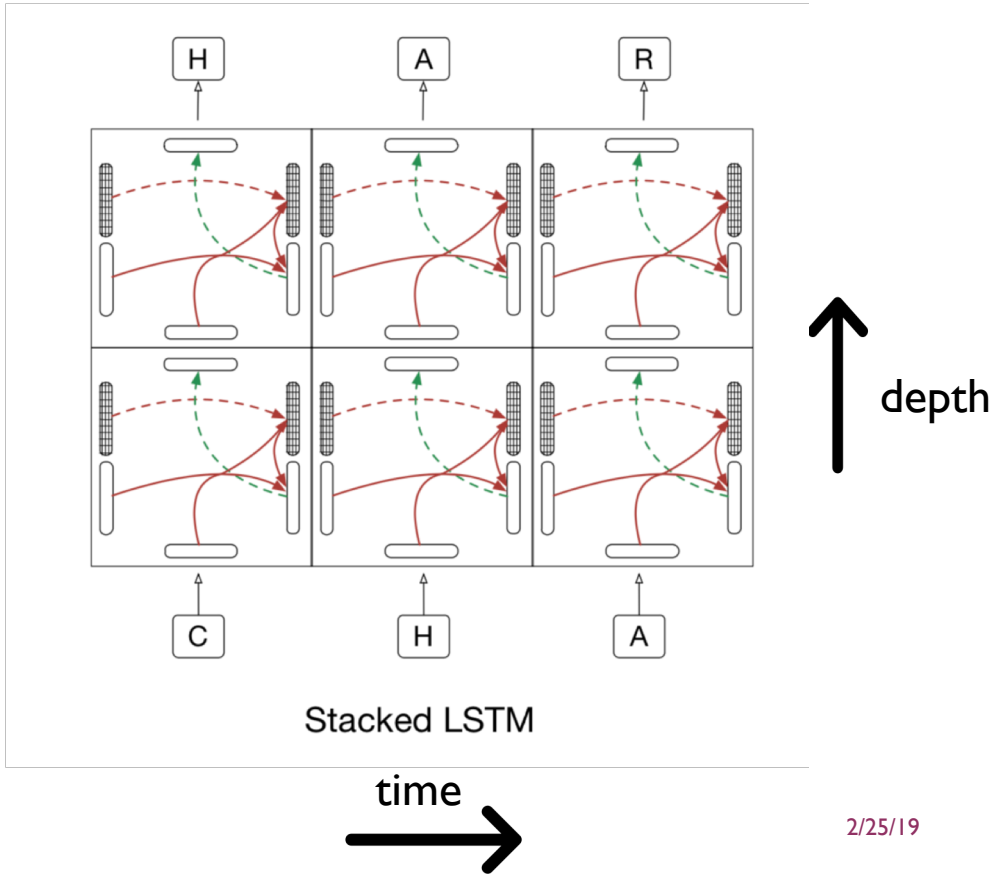
$$h := \tanh(g^o \odot m) \quad \text{output new hidden}$$



No sigmoid-like function when updating memory.
Therefore no vanishing gradient in time axis.

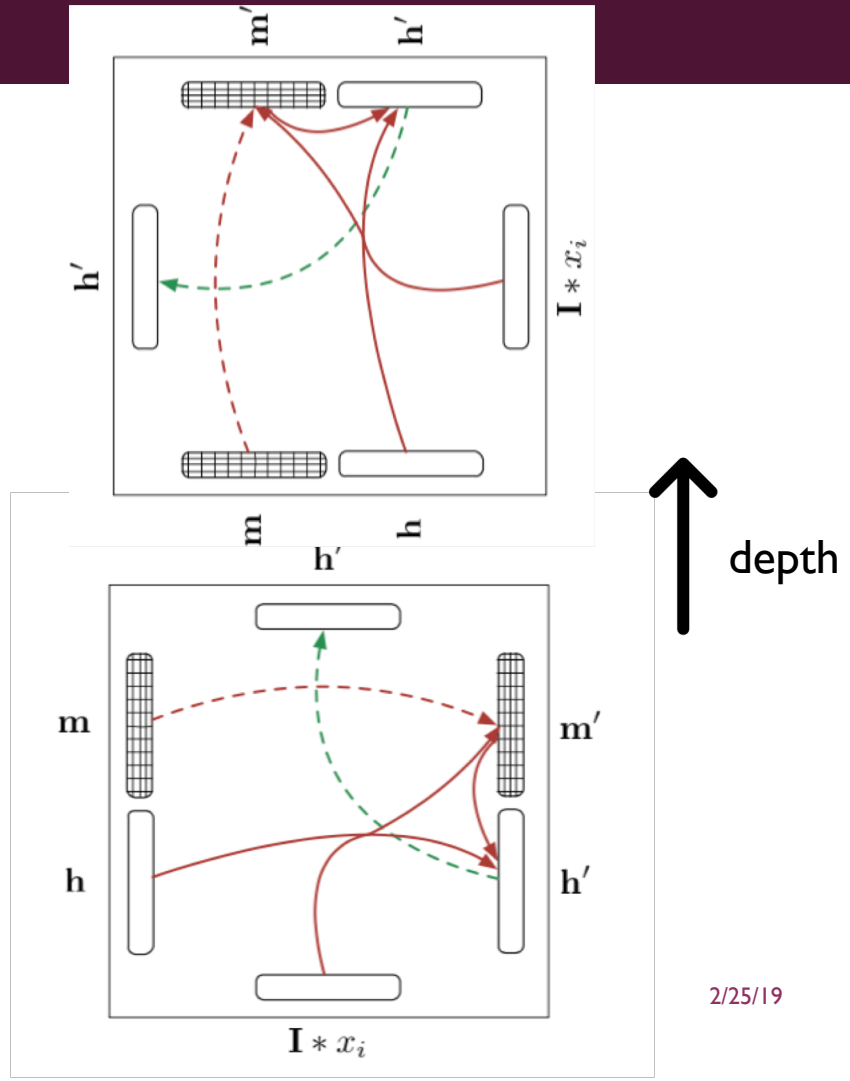
ADDING DEPTH TO LSTM

- A natural extension of LSTM is *Stacked LSTM*
- However, it loses the dynamic routing ability along depth axis
- The depth cannot be large to prevent vanishing gradient



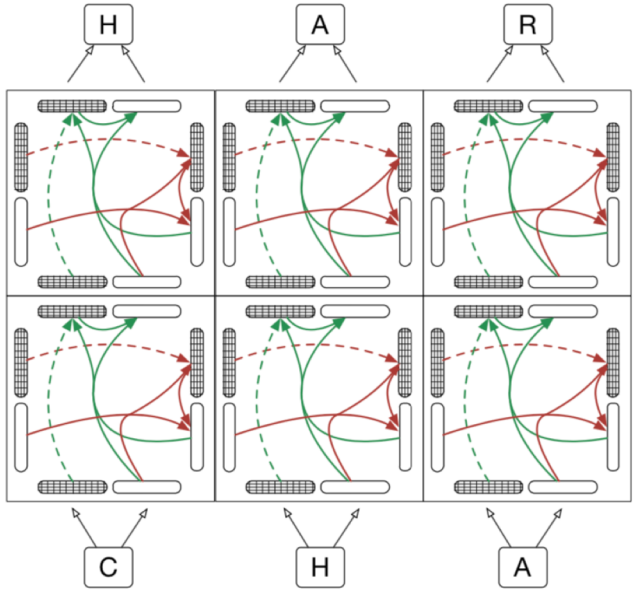
HIGHWAY NETWORK (APPROX.)

Applying LSTM to depth axis rather than time axis yields highway network.



GRID LSTM

- LSTM connection along any or all dimensions
- Inputs to any or all dimensions
- Each LSTM dimension maintains its own memory



2d Grid LSTM

TRICKS

- Evaluation order of each dimension (*Priority Dimensions*)
- Feedforward connection along some dimensions (*Non-LSTM Dimensions*)
- Weight sharing

EXPERIMENT: TRANSLATION

- Existing work: seq2seq (bottleneck problem) => attention
- 3D Grid LSTM in translation:

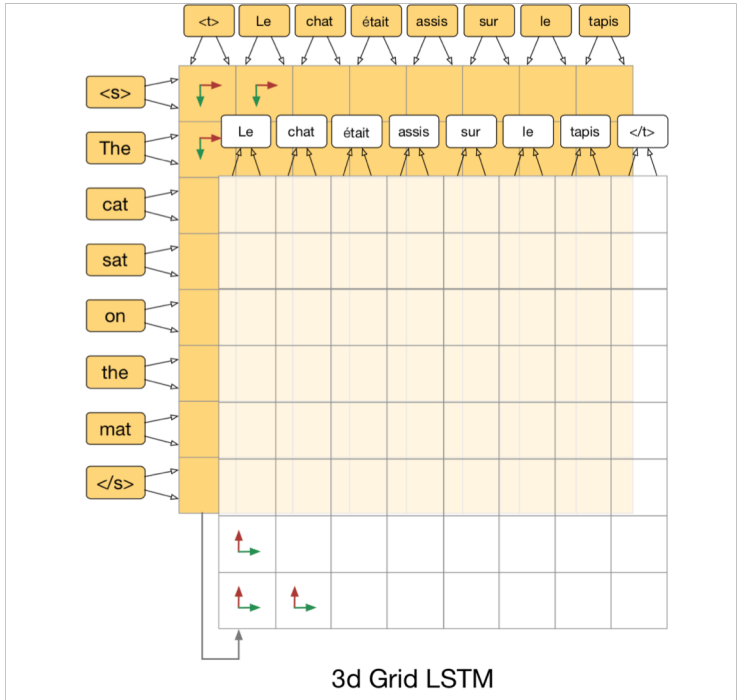


Figure 7: Illustration of the 3-LSTM neural translation model.

OPEN-END QUESTION

- What other applications of Grid LSTM you can think of?