LSTM : A Search Space Odyssey

IEEE Transactions on Neural Networks and Learning Systems, 2017

K. Greff et. al.

Presentation by

GIST College Physics Concentration Hanse Kim

Basic Information

Authors : K. Greff, et. al. 4

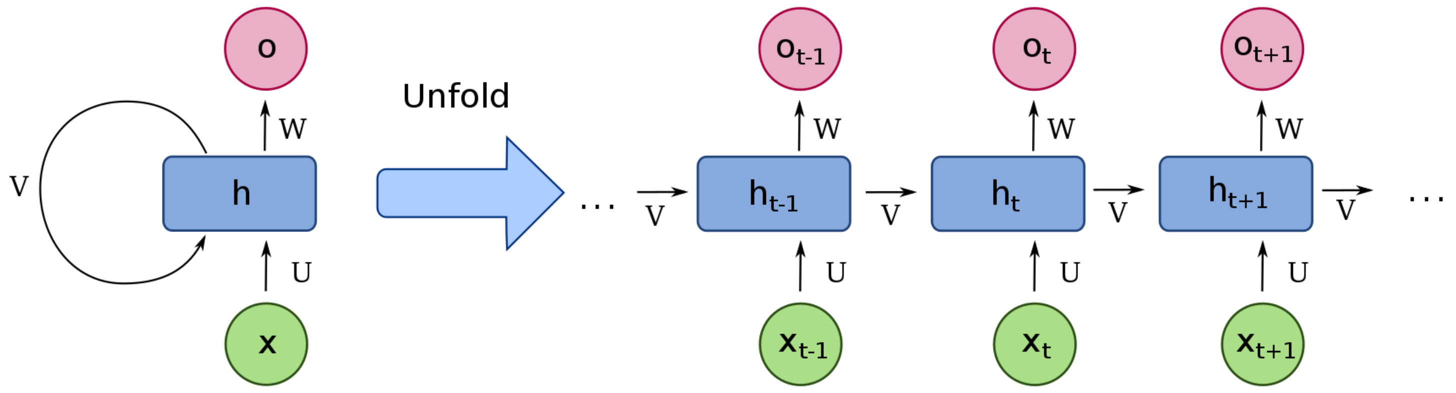
Journal : IEEE Transactions on Neural Networks and Learning Systems, 2017

Citations : 2982

- RNNs and LSTM
- Variants of LSTM
- Analysis of LSTM

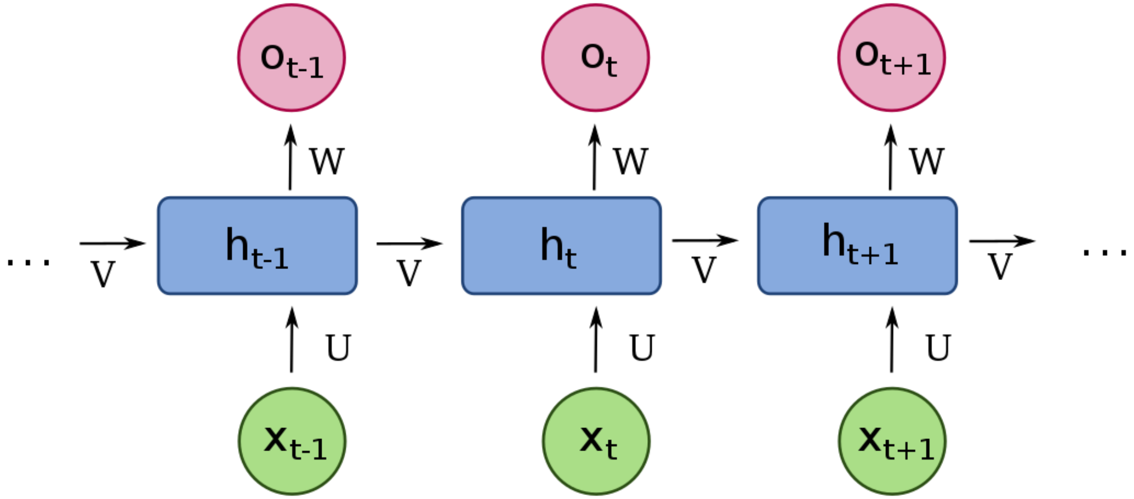
Introduction : RNNs

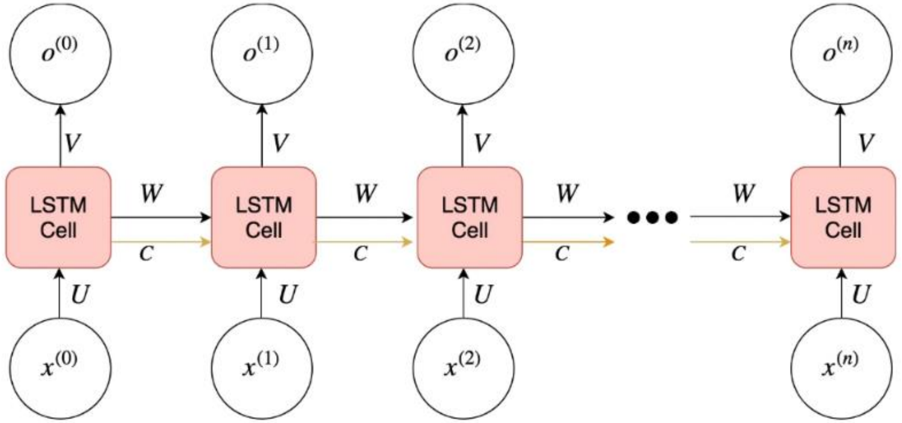
- RNN : Recurrent Neural Networks
  - NN that can input/output sequences of vectors of variable length
  - Internal state of previous events (memory) used in processing
  - FFNN hidden nodes connected along ‘temporal sequence’
- Applications of RNN
  - Time series : Stock market predictions, cryptocurrency
  - NLP : Translation, sentiment analysis



Introduction : Problems of RNNs

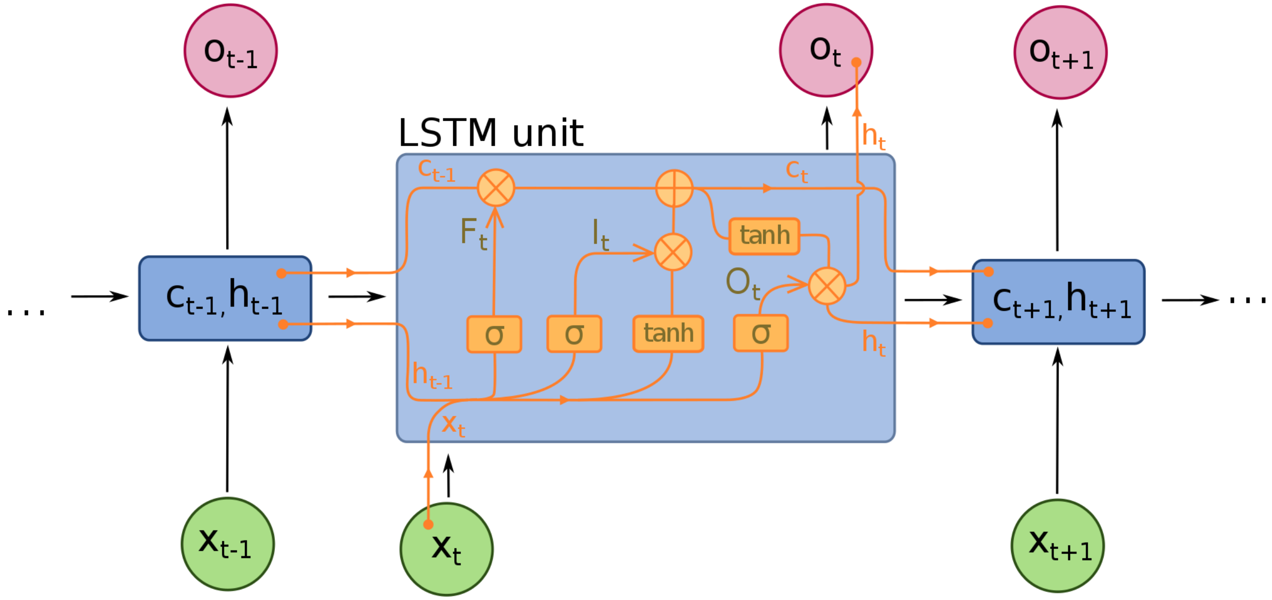
- Vanishing Gradient Problem
  - Problem more prominent than in DNNs; same weight V used over all hidden layers
- Skip Connections
  - Reduced rate of parameter vanishing
  - Layers that influence each other are independent from others; acts like DNN
- Gated Recurrent Networks
  - Leaky Recurrent Parameters
  - Set parameter for each time step; new parameter for network to design
  - GRU, LSTM etc.





Introduction : LSTM

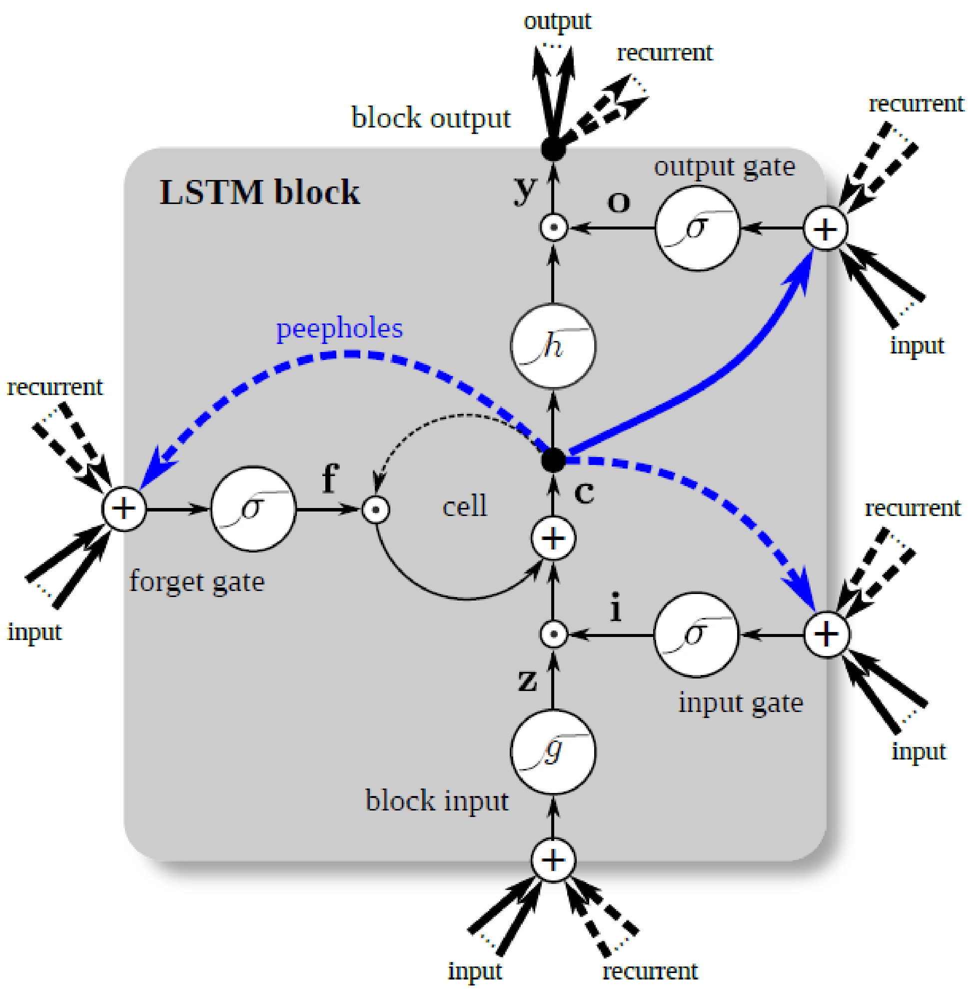
- LSTM
  - Most popular variant of GRN
  - Memory cell & Gating Units
- LSTM Unit, Cell State
  - Value passed between LSTM units
  - Each cell can decide to reset it, write to it, or read from it
  - Explicitly expressed in forms of ‘gates’; Forget, Input, Output



Introduction : Vanilla LSTM

- Vanilla LSTM
  - Peephole connections
  - Full BPTT

$$
\begin{aligned}
\bar{\mathbf{z}}^t &= \mathbf{W}_z\mathbf{x}^t + \mathbf{R}_z\mathbf{y}^{t-1} + \mathbf{b}_z \\
\mathbf{z}^t &= g(\bar{\mathbf{z}}^t) && \textit{block input} \\
\bar{\mathbf{i}}^t &= \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} + \mathbf{p}_i \odot \mathbf{c}^{t-1} + \mathbf{b}_i \\
\mathbf{i}^t &= \sigma(\bar{\mathbf{i}}^t) && \textit{input gate} \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} + \mathbf{p}_f \odot \mathbf{c}^{t-1} + \mathbf{b}_f \\
\mathbf{f}^t &= \sigma(\bar{\mathbf{f}}^t) && \textit{forget gate} \\
\mathbf{c}^t &= \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t && \textit{cell} \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} + \mathbf{p}_o \odot \mathbf{c}^t + \mathbf{b}_o \\
\mathbf{o}^t &= \sigma(\bar{\mathbf{o}}^t) && \textit{output gate} \\
\mathbf{y}^t &= h(\mathbf{c}^t) \odot \mathbf{o}^t && \textit{block output}
\end{aligned}
$$



LSTM Variants

- One aspect each tuned
  - No peepholes
  - Full Gate Recurrence
    Recurrent connections between all gates

$$
\begin{aligned}
\bar{\mathbf{z}}^t &= \mathbf{W}_z \mathbf{x}^t + \mathbf{R}_z \mathbf{y}^{t-1} + \mathbf{b}_z \\
\mathbf{z}^t &= g(\bar{\mathbf{z}}^t) && \textit{block input} \\
\bar{\mathbf{i}}^t &= \mathbf{W}_i \mathbf{x}^t + \mathbf{R}_i \mathbf{y}^{t-1} + \mathbf{p}_i \odot \mathbf{c}^{t-1} + \mathbf{b}_i \\
\mathbf{i}^t &= \sigma(\bar{\mathbf{i}}^t) && \textit{input gate} \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f \mathbf{x}^t + \mathbf{R}_f \mathbf{y}^{t-1} + \mathbf{p}_f \odot \mathbf{c}^{t-1} + \mathbf{b}_f \\
\mathbf{f}^t &= \sigma(\bar{\mathbf{f}}^t) && \textit{forget gate} \\
\mathbf{c}^t &= \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t && \textit{cell} \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o \mathbf{x}^t + \mathbf{R}_o \mathbf{y}^{t-1} + \mathbf{p}_o \odot \mathbf{c}^t + \mathbf{b}_o \\
\mathbf{o}^t &= \sigma(\bar{\mathbf{o}}^t) && \textit{output gate} \\
\mathbf{y}^t &= h(\mathbf{c}^t) \odot \mathbf{o}^t && \textit{block output}
\end{aligned}
$$

NIG: No Input Gate: $\mathbf{i}^t = \mathbf{1}$

NFG: No Forget Gate: $\mathbf{f}^t = \mathbf{1}$

NOG: No Output Gate: $\mathbf{o}^t = \mathbf{1}$

NIAF: No Input Activation Function: $g(\mathbf{x}) = \mathbf{x}$

NOAF: No Output Activation Function: $h(\mathbf{x}) = \mathbf{x}$

CIFG: Coupled Input and Forget Gate: $\mathbf{f}^t = \mathbf{1} - \mathbf{i}^t$

NP: No Peepholes:

$$
\begin{aligned}
\bar{\mathbf{i}}^t &= \mathbf{W}_i \mathbf{x}^t + \mathbf{R}_i \mathbf{y}^{t-1} + \mathbf{b}_i \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f \mathbf{x}^t + \mathbf{R}_f \mathbf{y}^{t-1} + \mathbf{b}_f \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o \mathbf{x}^t + \mathbf{R}_o \mathbf{y}^{t-1} + \mathbf{b}_o
\end{aligned}
$$

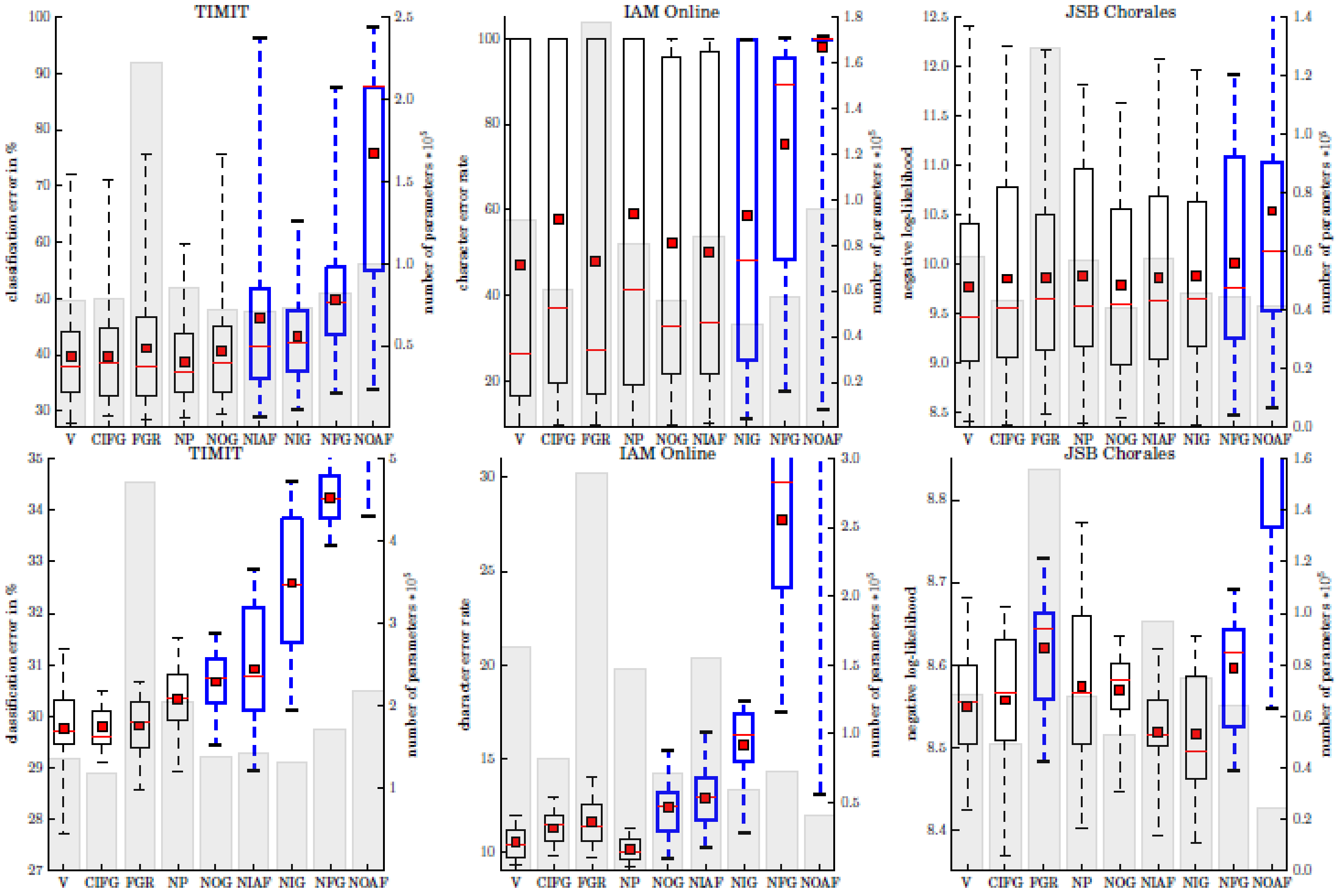
FGR: Full Gate Recurrence:

$$
\begin{aligned}
\bar{\mathbf{i}}^t = \mathbf{W}_i \mathbf{x}^t &+ \mathbf{R}_i \mathbf{y}^{t-1} + \mathbf{p}_i \odot \mathbf{c}^{t-1} + \mathbf{b}_i \\
&+ \mathbf{R}_{ii} \mathbf{i}^{t-1} + \mathbf{R}_{fi} \mathbf{f}^{t-1} + \mathbf{R}_{oi} \mathbf{o}^{t-1} \\
\bar{\mathbf{f}}^t = \mathbf{W}_f \mathbf{x}^t &+ \mathbf{R}_f \mathbf{y}^{t-1} + \mathbf{p}_f \odot \mathbf{c}^{t-1} + \mathbf{b}_f \\
&+ \mathbf{R}_{if} \mathbf{i}^{t-1} + \mathbf{R}_{ff} \mathbf{f}^{t-1} + \mathbf{R}_{of} \mathbf{o}^{t-1} \\
\bar{\mathbf{o}}^t = \mathbf{W}_o \mathbf{x}^t &+ \mathbf{R}_o \mathbf{y}^{t-1} + \mathbf{p}_o \odot \mathbf{c}^{t-1} + \mathbf{b}_o \\
&+ \mathbf{R}_{io} \mathbf{i}^{t-1} + \mathbf{R}_{fo} \mathbf{f}^{t-1} + \mathbf{R}_{oo} \mathbf{o}^{t-1}
\end{aligned}
$$

Evaluation

- Datasets
  - TIMIT : Speech corpus, acoustic modelling benchmark
  - IAM Online : Handwriting database, time series of pen movement
  - JSB Chorales : Next-step prediction for music
- Network Architecture
  - JSB Chorales : Single-layer LSTM
  - TIMIT, IAM Online : Bi-directional LSTM
- Hyperparametres evaluated by random search

Results & Discussion



Conclusion

- LSTM attempts to improve upon RNN
- Vanishing gradient solved by non-linear output activation function, forget gate; ability to ‘memorise’ and ‘forget’
- Empirical analysis backs the assertion

References

- Websites
  - https://en.wikipedia.org/wiki/Recurrent_neural_network