An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling

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14 January 2020

Presented by Lucian M. Sasu, Ph.D.
ML Reading Group, 14 January 2021

https://arxiv.org/pdf/1803.01271.pdf

Outline

Metadata

- Venue: CoRR, https://arxiv.org/pdf/1803.01271.pdf, 2018
- Authors' affiliations:
  - ML Department, Carnegie Mellon University
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- Visibility:
  - 906 citations as reported by Semantic Scholar
  - 155 highly influential – Semantic Scholar
  - 1022 citations — Google Scholar
- Pytorch code by paper's authors: https://github.com/locuslab/TCN

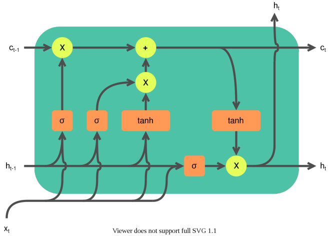
Aims and findings

- traditionally, a sequence modeling task is solved through recurrent neural networks (LSTM, GRU)
- at the moment of writing, some conv-based networks obtained state of the art results in audio synthesis, language modeling, machine translation
- paper's target: empirical evaluation of convolutional and recurrent architectures on RNNs benchmark tasks
- approach: Temporal Convolutional Networks (TCNs)
- in-depth analysis of memory retention of TCNs: longer memory than RNNs

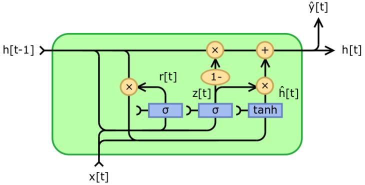
Outline

Background: RNNs

- RNNs: a vector of learned hidden states is propagated through time
- vanilla RNNs – difficult to train
- current architectures: Long Short Term Memory (LSTM) and Gated Recurrent Units (GRU) networks



(a) LSTM cell; source



(b) GRU cell; source

Figure 1: LSTM and GRU cells

Background: RNNs

- multiple empirical studies for recurrent networks: which is the best?
  - tests with tens of thousands of architectures
  - not trivial to find architectures better than LSTMs
  - models post–LSTM are often surpassed by classical LSTMs
  - variants and hybridizations with other techniques: Convolutional LSTM, Quasi–RNN, dilated RNNs

Background: TCNs

- Temporal Convolutional Networks (TCNs): "a simple descriptive term for a family of architectures"
- features:
  1. causal convolutions, no leakage from future to past
  2. can take a sequence of any length and produce a sequence of same length
  3. no gating mechanisms
  4. bonus: hints on how to build very long effective history sizes
  5. simpler than other CNN–based nets
- *not to be confused with [1]*

Background: Sequence modeling in TCNs

- input: input sequence $x_0, \ldots, x_T$
- associated output: sequence $y_0, \ldots, y_T$
- causal constraint is satisfied: value y_t is predicted based on $x_0, \ldots, x_t$ and not on $x_{t+1}, \ldots, x_T$
- training goal: find a network $f : \mathcal{X}^{T+1} \rightarrow \mathcal{Y}^{T+1}$, that produces the mapping $\hat{y}_0, \ldots, \hat{y}_T = f(x_0, \ldots, x_T)$ s.t. f minimizes a certain loss function (NLL, MSE, ...)
- such a topic is also covered by atoregressive prediction, but fall outside machine translation, which may peek into the future

Background: Sequence modeling in TCNs

- 1 dimensional fully convolutional network architecture [2]
- the same output length is obtained through padding with zeros;
- each hidden layer and output layer have the same length as the input

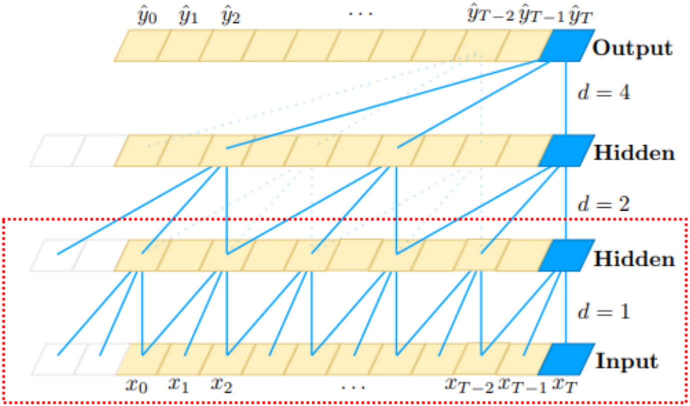


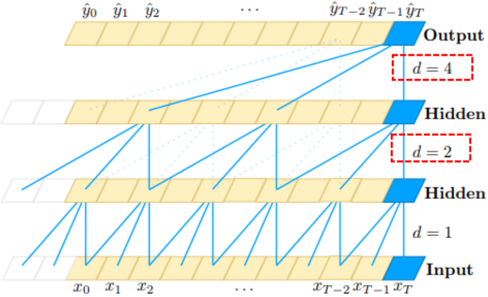
Figure 2: 1D fully convolutional, padding at the left, non–dilated convolution.
Source: [3]

Background: Causal convolutions

- “causal”: no leackage from future into the past
- output at time t is obtained by convolving kernel and inputs at time $t, t-1, \ldots, t-k+1$ (here: for $d=1$)
- TCN = 1D FCN + causal convolution
- disadvantage: one needs a very large number of hidden layers or large kernels to process a long history

Background: Dilated convolutions

- looking deep in history: dilated convolutions
- results: exponentially large receptive fields



- formal: input $\mathbf{x} \in \mathbb{R}^n$, filter (kernel) $f : \{0, \ldots, k-1\} \rightarrow \mathbb{R}$, one defines dilated conv F on s as:

$$F(s) = (\mathbf{x} *_d f)(\mathbf{s}) = \sum_{i=0}^{k-1} f(i) \cdot \mathbf{x}_{s-d \cdot i} \tag{1}$$

Background: Dilated convolutions

- $d = 1 \Rightarrow$ regular convolution
- $d > 1 \Rightarrow$ larger range of receptive fields
- dilation increases exponentially with depth, $d = 2^i$, i being the index of the hidden layer
- result: there is at least one filter which touches each value of the input

Background: Residual connections, dropout

- residual connections [4] combine input $\mathbf{x}$ with its transformation $\mathcal{F}$; popular approach which improves results of DL architectures
- $o = Activation(\mathbf{x} + \mathcal{F}(\mathbf{x}))$

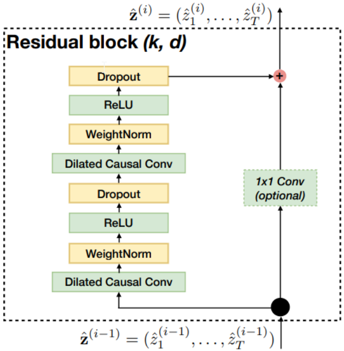


Figure 3: TCN residual block; source [3]

- dropout after each dilated convolution: a whole channel is zeroed out

TCN Advantages

- convs are parallel–friendly; a long sequence can be processed in parallel
- flexible receptive size: stacking more dilated layers, using larger dilation factors, increasing the filters size: about the same effect
- no vanishing/exploding gradients as in vanilla RNNs
- low memory requirement for training, unlike for partial results which feeds LSTM and GRU gates
- allows for variable length inputs, by sliding the kernel

TCN Disadvantages

- data storage during evaluation - the whole input sequence $x_0, \ldots, x_T$ must be maintained to build the estimation
- transfer learning might not work: a pretrained model with small k, d might be inappropriate for a problem where large history must be learned

Outline

Sequence Modeling Tasks

- adding problem
- sequential MNIST and P–MNIST
- copy memory
- JSB Chorales and Nottingham
- PennTreebank
- LAMBADA
- text8

Experimental setup and results

- quite the same TCN architecture used across experiments, with different depth of network and kernel size; exponential dilation $d = 2^i$
- recurrent networks: around the same number of parameters as TCN

Sequence Modeling Task	Model Size (≈)	Models			
		LSTM	GRU	RNN	**TCN**
Seq. MNIST (accuracy^h)	70K	87.2	96.2	21.5	**99.0**
Permuted MNIST (accuracy)	70K	85.7	87.3	25.3	**97.2**
Adding problem T=600 (loss$^\ell$)	70K	0.164	**5.3e-5**	0.177	**5.8e-5**
Copy memory T=1000 (loss)	16K	0.0204	0.0197	0.0202	**3.5e-5**
Music JSB Chorales (loss)	300K	8.45	8.43	8.91	**8.10**
Music Nottingham (loss)	1M	3.29	3.46	4.05	**3.07**
Word-level PTB (perplexity$^\ell$)	13M	**78.93**	92.48	114.50	88.68
Word-level Wiki-103 (perplexity)	-	48.4	-	-	**45.19**
Word-level LAMBADA (perplexity)	-	4186	-	14725	**1279**
Char-level PTB (bpc$^\ell$)	3M	1.36	1.37	1.48	**1.31**
Char-level text8 (bpc)	5M	1.50	1.53	1.69	**1.45**

Figure 4: Experimental results. Bold values on each line are the best.

- caveat: the canonical recurrent networks are not state of the art

Results

- adding problem: TCN has fastest convergence
- sequential MNIST and P–MNIST: better perfomance in convergence and final accuracy; outperforms state of the art
- copy memory: quick convergence; stress test for long sequences; TCN allows for much longer history, LSTM and GRU degenerate to random guessing
- JSB Chorales and Nottingham: better than canonic recurrent models, but under state of the art
- PennTreebank: for small datasets, LSTM wins; for larger ones, TCN is the best without extensive hyperparameter search
- LAMBADA: large ds, TCN wins; stress test for both local and non-local textual "understanding"
- text8: TCN beats canonical recurrent networks, but not SOTA

Outline

Conclusions

- dilated convolutions and residual connections might explain TCN performance; former CNNs did not work well in sequence tasks
- a clear winner when large history must be learned; under LSTM for short sequences
- small effort in hyperparameter tuning; see paper's supplementary material

Outline

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