Tensor-Train Recurrent Neural Networks for Video Classification by Yang et al.

IFT6760A Class Presentation

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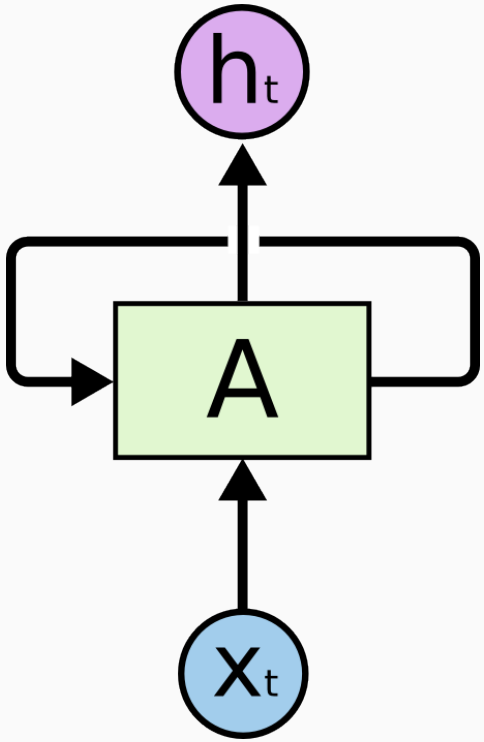
Problem

- Recurrent Neural Networks (RNN) are very successful for sequence modeling
- But are difficult to train for very high dimensional inputs due to large input-hidden weight matrix
- E.g. Input video frame of size $160x120x3$ $(57,600$ features) would require **5,760,000** weights for a hidden layer of 100 neurons.



Possible Approaches

- CNN-RNN model: CNN extracts compact representation and RNN learns temporal information.
  - Impractical for large video datasets.

[1] Donahue et al. (2015), and Srivastava et al. (2015)
[2] Donahue et al. (2015), Ng et al. (2015), and Sharma et al.

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- Focus on the CNN, and constrain the sequence length of the RNN[1]:
  - Cannot scale to long videos.

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- CNN-RNN model: CNN extracts compact representation and RNN learns temporal information.
  - Impractical for large video datasets.
- Focus on the CNN, and constrain the sequence length of the RNN[1]:
  - Cannot scale to long videos.
- Use embeddings from pretrained CNN as input[2]
  - Not trained end-to-end, suboptimal parameters
  - CNNs are pretrained on image datasets, which can be of totally different nature than video frames

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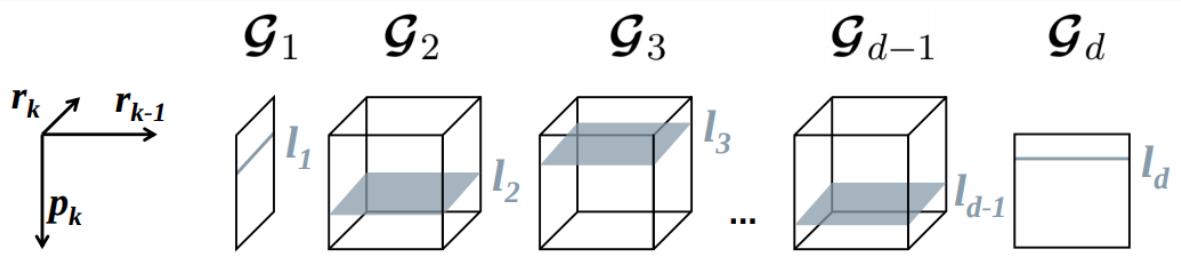
Proposed Solution

- Reduce the number of parameters in input-to-hidden layer by factorizing the Weight matrix using Tensor-Train decomposition
  (a) Allows the use of raw pixels as the input to the RNN
  (b) Can be easily trained end-to-end
  (c) Captures the correlation between spatial and temporal patterns, as the input-to-hidden and hidden-to-hidden are trained jointly



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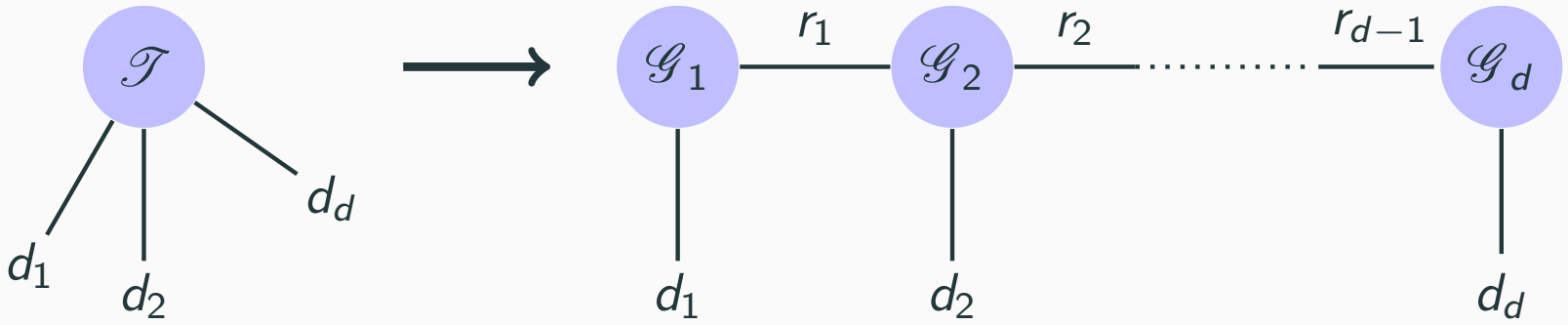
5. This work extended the work of Novikov et al. (2015) and used TT decomposition to factorize the input-to-hidden mapping in RNN, so as to succeed in using RNNs with videos.

TT-train factorization

For $\mathscr{T} \in \mathbb{R}^{d_1 \times d_2 \times \cdots \times d_d}$:

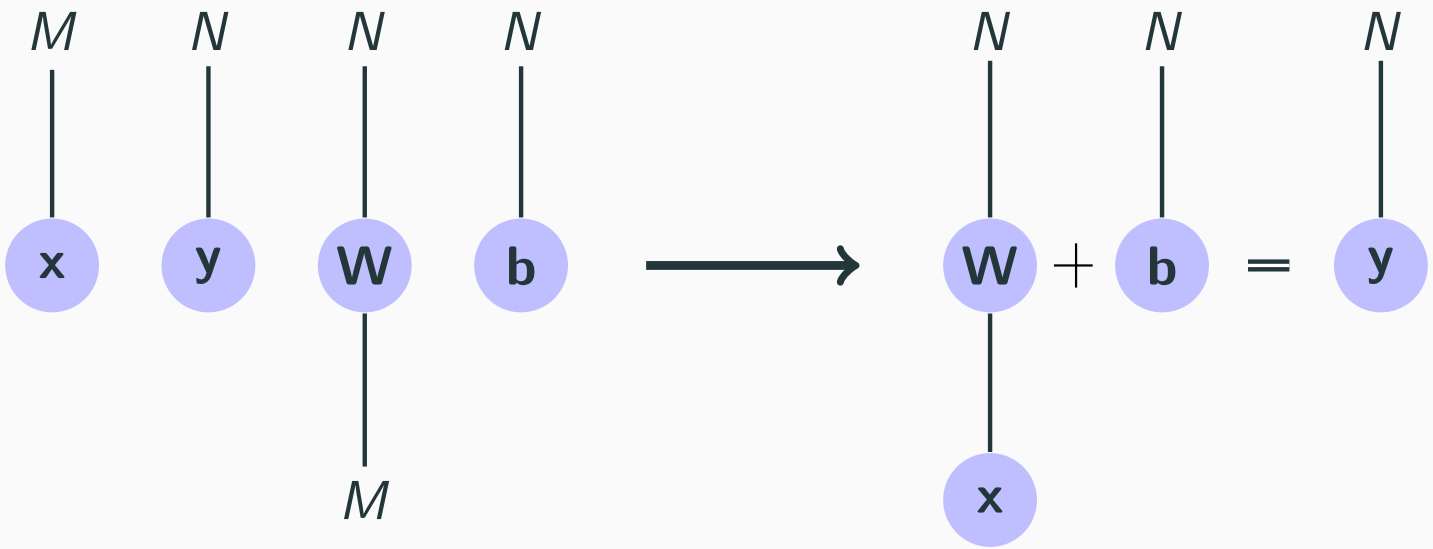


Where $r_1, r_2, \cdots, r_{d-1}$ are the TT-ranks (r_0 and r_d are always 1)

TT-MLP

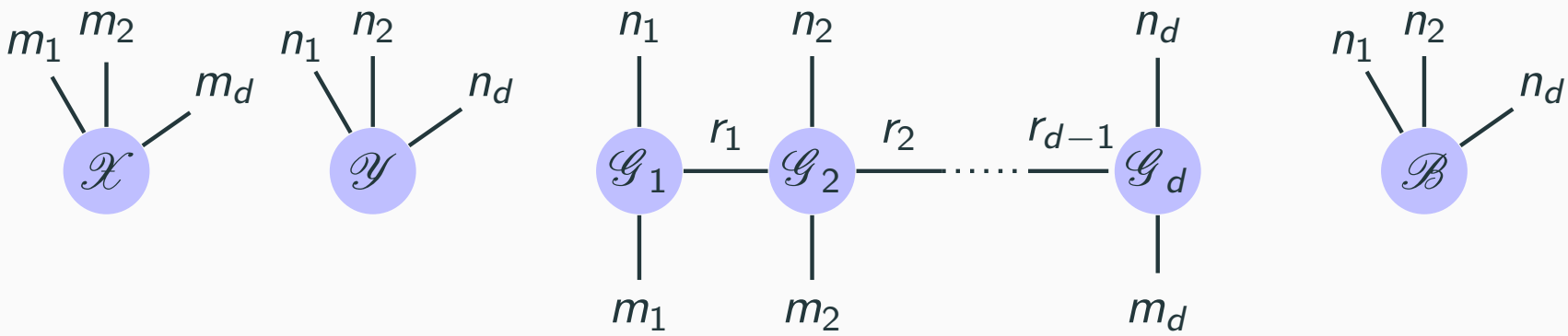
Before reshaping and TT, input $\mathbf{x} \in \mathbb{R}^M$, output $\mathbf{y} \in \mathbb{R}^N$, weights $\mathbf{W} \in \mathbb{R}^{M \times N}$, biases $\mathbf{b} \in \mathbb{R}^N$:

$$\mathbf{x}\mathbf{W} + \mathbf{b} = \mathbf{y}$$



TT-MLP

After reshaping and TT, $\mathscr{X} \in \mathbb{R}^{m_1 \times m_2 \times \cdots \times m_d}$, $\mathscr{Y} \in \mathbb{R}^{n_1 \times n_2 \times \cdots \times n_d}$, $\mathscr{W} \in \mathbb{R}^{(m_1 \times n_1) \times (m_2 \times n_2) \times \cdots \times (m_d \times n_d)}$, $\mathscr{B} \in \mathbb{R}^{n_1 \times n_2 \times \cdots \times n_d}$



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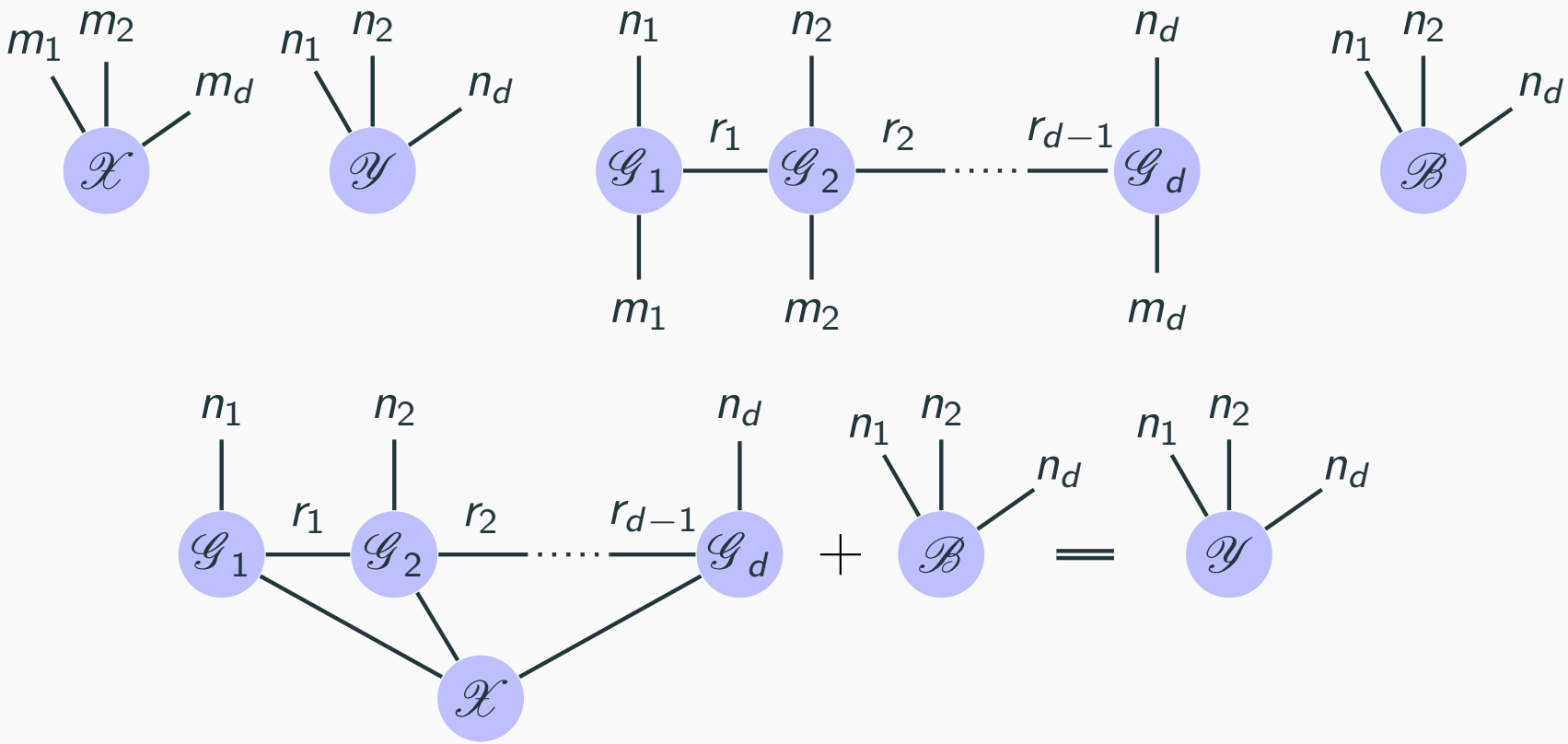
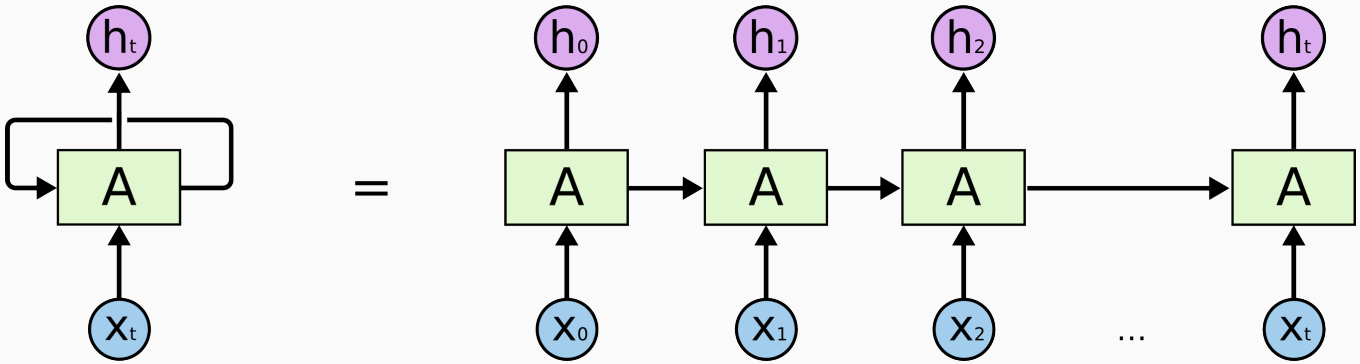


Recurrent Neural Networks

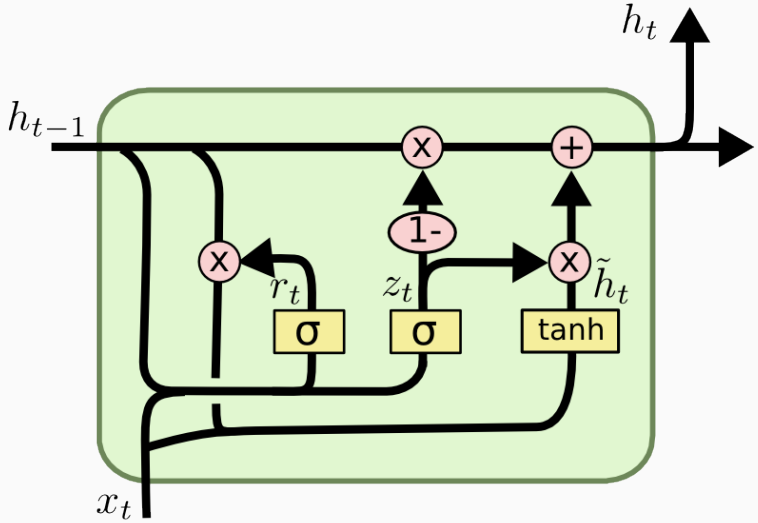


In a simple RNN, the cell A is defined as:

$$h^{[t]} = \tanh(\mathbf{W}\mathbf{x}^{[t]} + \mathbf{U}\mathbf{h}^{[t-1]} + \mathbf{b})$$

Gated Recurrent Unit (GRU)

- In practice, A is typically a GRU (or LSTM cell).
- For GRU:



$$r^{[t]} = \sigma(\mathbf{W}^r \mathbf{x}^{[t]} + \mathbf{U}^r \mathbf{h}^{[t-1]} + \mathbf{b}^r)$$
$$z^{[t]} = \sigma(\mathbf{W}^z \mathbf{x}^{[t]} + \mathbf{U}^z \mathbf{h}^{[t-1]} + \mathbf{b}^z)$$
$$\tilde{\mathbf{h}}^{[t]} = \tanh(\mathbf{W}^d \mathbf{x}^{[t]} + \mathbf{U}^d (r^{[t]} * \mathbf{h}^{[t-1]}) + \mathbf{b}^d)$$
$$\mathbf{h}^{[t]} = (1 - z^{[t]}) * \mathbf{h}^{[t-1]} + z^{[t]} * \tilde{\mathbf{h}}^{[t]}$$

Tensor-Train GRU (TT-GRU)

- We replace the input-to-hidden layer connection with a Tensor-Train layer (TTL)

$$
\begin{aligned}
r^{[t]} &= \sigma(\mathit{TTL}(\mathbf{W}^r, \mathbf{x}^{[t]}) + \mathbf{U}^r \mathbf{h}^{[t-1]} + \mathbf{b}^r) \\
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\end{aligned}
$$

- Compression rate

$$
r = \frac{\sum_{k=1}^{d} m_k n_k r_{k-1} r_k}{\prod_{k=1}^{d} m_k n_k}
$$

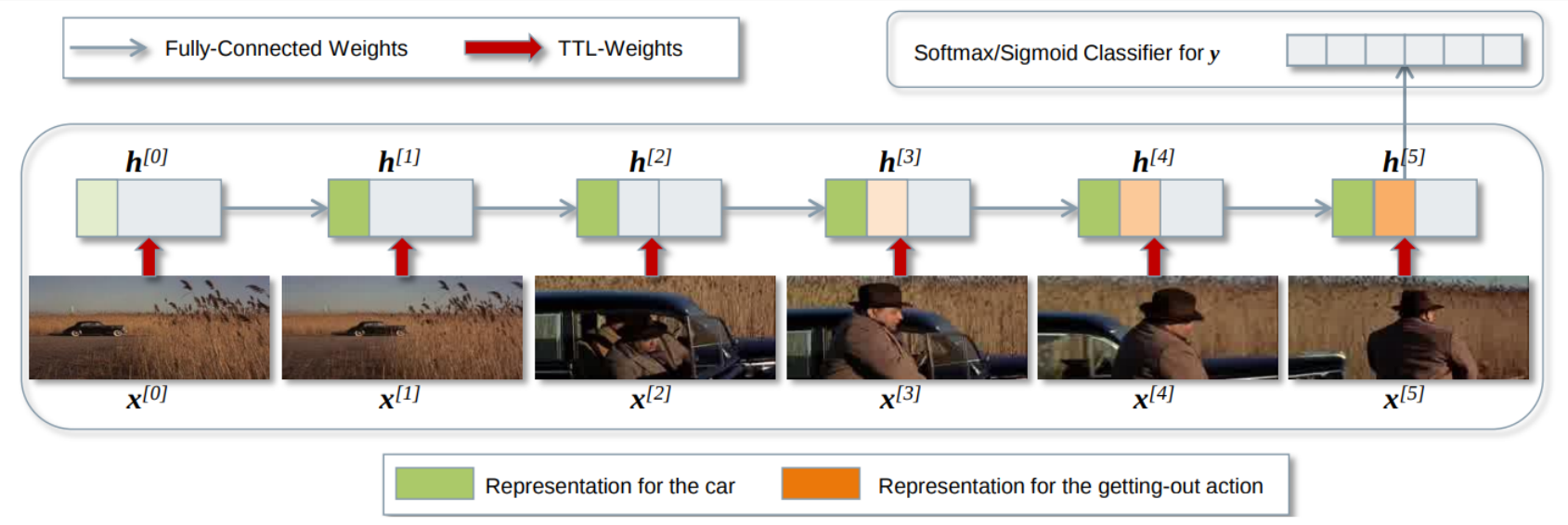
TT-GRU Implementation Trick

- Concatenate the gates as one output tensor.
- TT-GRU factorizes this tensor once, instead of factorizing each gate successively.
- Parallelizes computation and further reduces number of parameters

$$r^* = \frac{\sum_{k=1}^{d} m_k n_k r_{k-1} r_k + (c-1)(m_1 n_1 r_0 r_1)}{c. \prod_{k=1}^{d} m_k n_k}$$

where c is the number of TTLs

Video Classification



For a classification task (eg video classification):

$$P(y_i = 1 | \{x_i^{[t]}\}_{t=1}^{T_i}) = \phi(h_i^{[T_i]})$$

Compression with TT-RNNs

- Consider video frames of size $160x120x3 = 57,600$ pixels reshaped as $8x20x20x18$
- Hidden layer of size 256, reshaped as $4x4x4x4$

FC	TT-ranks	TTL	vanilla TT-LSTM	TT-LSTM	vanilla TT-GRU	TT-GRU
14,745,600	3	1,752	7,008	2,040	5,256	1,944
	4	2,976	11,904	3,360	8,928	3,232
	5	4,520	18,080	5,000	13,560	4,840

Figure 1: Number of parameters for the different settings

Experiment 1

UCF11 Dataset

- 1600 video clips
- 11 classes (basketball shooting, biking, diving, etc)

Experiment 1

	Accuracy	# Parameters	Runtime
TT-MLP	0.427 ± 0.045	7,680	902s
GRU	0.488 ± 0.033	44,236,800	7,056s
LSTM	0.492 ± 0.026	58,982,400	8,892s
TT-GRU	$\mathbf{0.813 \pm 0.011}$	3,232	1,872s
TT-LSTM	0.796 ± 0.035	3,360	2,160s

Figure 2: Experimental results

Original: (Liu et al., 2009)	0.712
(Liu et al., 2013)	0.761
(Hasan & Roy-Chowdhury, 2014)	0.690
(Sharma et al., 2015)	**0.850**
Our best model (TT-GRU)	0.813

Figure 3: Comparison to state-of-the-art results

Experiment 2

Hollywood2 Dataset

- 1707 video clips from 69 movies
- 12 (non-exclusive) classes. E.g. answering the phone, driving, eating, fighting, etc

Experiment 2

	MAP	# Parameters	Runtime
TT-MLP	0.103	4,352	16s
GRU	0.249	53,913,600	106s
LSTM	0.108	71,884,800	179s
TT-GRU	0.537	2,944	96s
TT-LSTM	**0.546**	3,104	102s

Figure 4: Experimental results

Original: (Marszałek et al., 2009)	0.326
(Le et al., 2011)	0.533
(Jain et al., 2013)	0.542
(Sharma et al., 2015)	0.439
(Fernando et al., 2015)	**0.720**
(Fernando & Gould, 2016)	0.406
Our best model (TT-LSTM)	0.546

Figure 5: Comparison to state-of-the-art results

Experiment 3

YouTube Celebrities Face Data

- 1910 YouTube video clips
- 47 prominent individuals such as movie stars and politicians

Experiment 3

	Accuracy	# Parameters	Runtime
TT-MLP	0.512 ± 0.057	3,520	14s
GRU	0.342 ± 0.023	38,880,000	212s
LSTM	0.332 ± 0.033	51,840,000	253s
TT-GRU	$\mathbf{0.800 \pm 0.018}$	3,328	72s
TT-LSTM	0.755 ± 0.033	3,392	81s

Figure 6: Experimental results

Original: (Kim et al., 2008)	0.712
(Harandi et al., 2013)	0.739
(Ortiz et al., 2013)	**0.808**
(Faraki et al., 2016)	0.728
Our best model (TT-GRU)	0.800

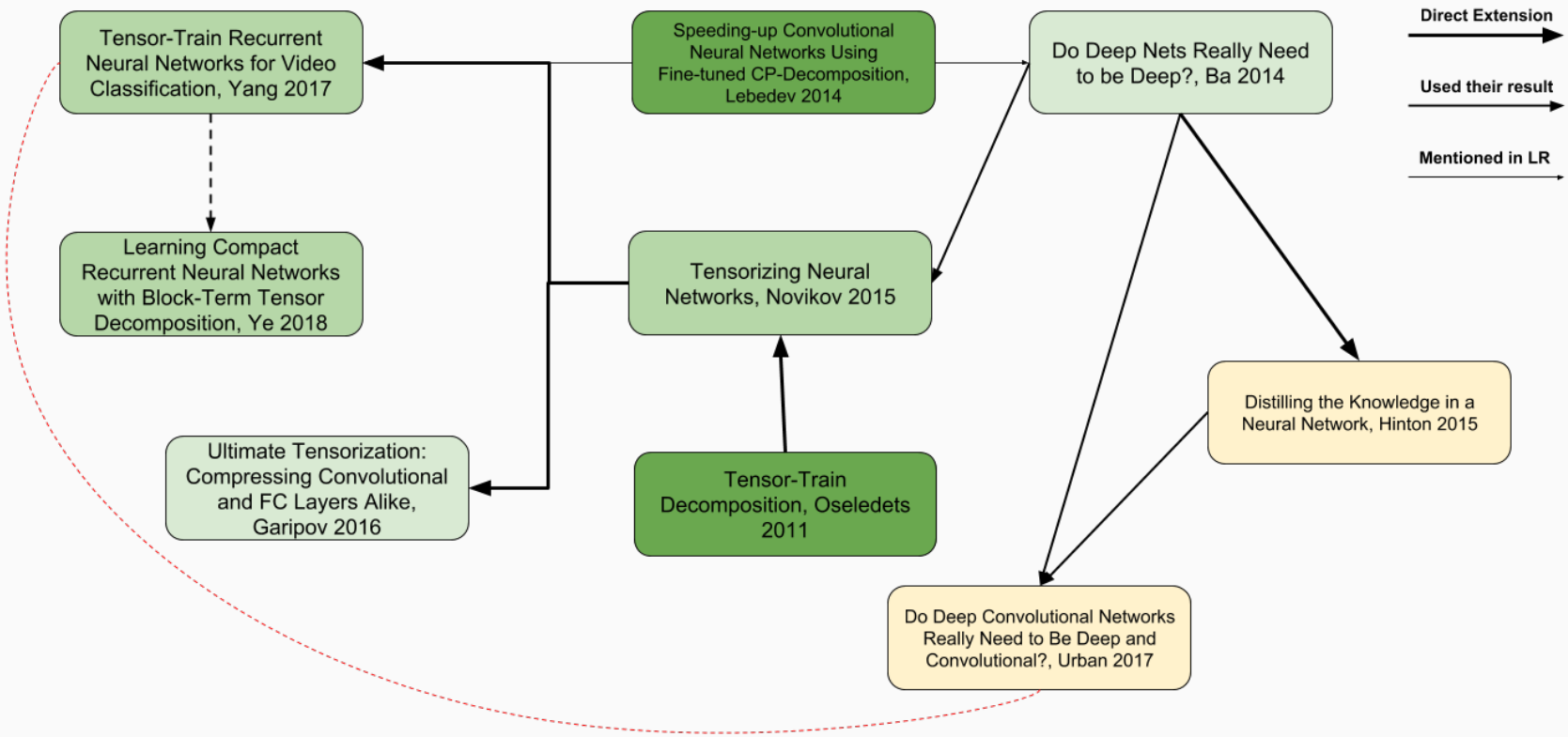
Figure 7: Comparison to state-of-the-art results

Summary

- Compressing input-hidden weights in RNN using TT factorization.
- Drastic reduction in number of parameters, still with competitive performance.
- Applicable to other kind of data, not just video.
- Ideas extend beyond RNN - MLP, CNNs as well.
- Other applications:
  - Deployment of DL models to smart devices.
  - Faster iteration in scientific process.

Questions?

Related Papers



References

J. Donahue, L. A. Hendricks, S. Guadarrama, M. Rohrbach, S. Venugopalan, K. Saenko, and T. Darrell. Long-term recurrent convolutional networks for visual recognition and description. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2625—-2634, 2015.

T. Garipov, D. Podoprikhin, A. Novikov, and D. Vetrov. Ultimate tensorization: compressing convolutional and fc layers alike. *arXiv preprint arXiv:1611.03214*, 2016.

V. Lebedev, Y. Ganin, M. Rakhuba, I. Oseledets, and V. Lempitsky. Speedingup convolutional neural networks using fine-tuned cpdecomposition. *arXiv preprint arXiv:1412.6553*, 2014.

References ii

J. Y.-H. Ng, M. Hausknecht, S. Vijayanarasimhan, O. Vinyals, R. Monga, and G. Toderici. Beyond short snippets: Deep networks for video classification. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4694—-4702, 2015.

A. Novikov, D. Podoprikhin, A. Osokin, and D. P. Vetrov. Tensorizing neural networks. *Advances in Neural Information Processing Systems*, pages 442—-450, 2015.

I. V. Oseledets. Tensor-train decomposition. *SIAM Journal on Scientific Computing*, 33:2295–2317, 2011.

S. Sharma, R. Kiros, and R. Salakhutdinov. Action recognition using visual attention.

N. Srivastava, E. Mansimov, and R. Salakhutdinov. Unsupervised learning of video representations using lstms. *CoRR, abs/1502.04681*, 2015.