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Multi-System Identification for Efficient Knowledge Transfer with Factored Tensor Recurrent Neural Networks

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Introduction

- $(n+1)$ similar dynamical systems $\mathbf{S}_1,\ldots,\mathbf{S}_{n+1}$
- Sufficient observations from $\mathbf{S}_1,\ldots,\mathbf{S}_n$, few from $\mathbf{S}_{n+1}$
- Goal: Learn state transition function for $\mathbf{S}_{n+1}$
- Approach:
  - Transfer learning through parameter transfer
  - Exploiting similarity between $\mathbf{S}_1,\ldots,\mathbf{S}_{n+1}$

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System Identification

- Initial state: s_1
- Action sequence: $a_1, \ldots, a_t$
- Successor state sequence: $s_2, \ldots, s_{T+1}$
- Learn: $s_2, \ldots, s_{T+1} = f(s_1, a_1, \ldots, a_T)$

$$L(\hat{s}_{2,\ldots,T+1}, s_{2,\ldots,T+1}) = \frac{1}{2T} \sum_{t=1}^{T} \left\| s_{t+1} - \hat{s}_{t+1} \right\|_2^2$$

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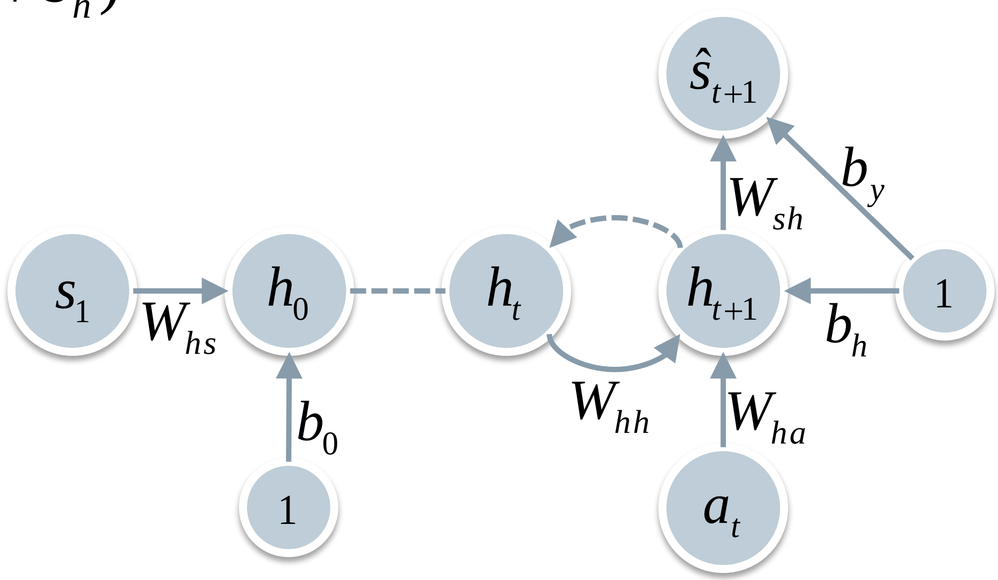
System Identification with Recurrent Neural Networks

$$h_0 = W_{hs} s_1 + b_0$$

$$h_{t+1} = \tanh(W_{ha} a_t + W_{hh} h_t + b_h)$$

$$\hat{s}_{t+1} = W_{sh} h_t + b_s$$



Multi-System Identification for Efficient Knowledge Transfer with Factored Tensor Recurrent Neural Networks

Factored Tensor RNN

$$z \in \{e_1, \dots, e_{|I|}\} \qquad I = \{1, \dots, \#\text{systems}\}$$

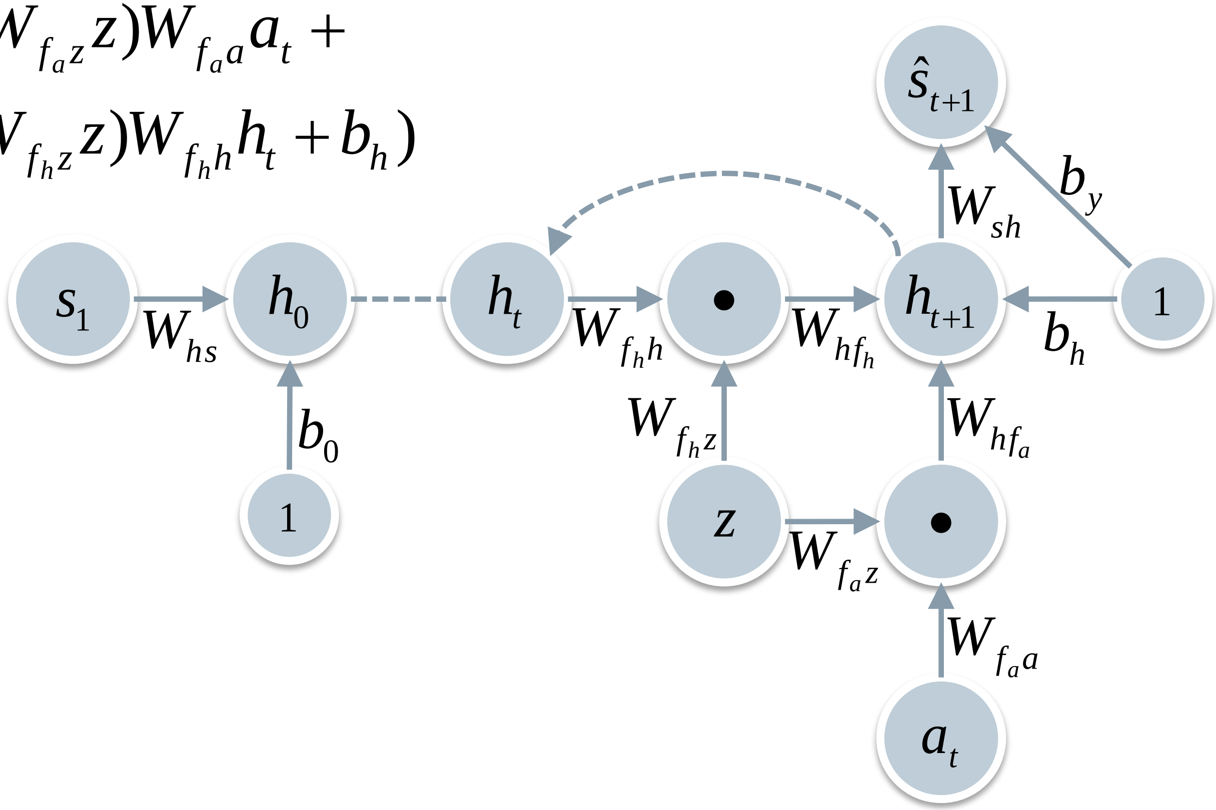
W_{vuz} = W_{vf} W_{fz} W_{fu}

Factored Tensor RNN

$$h_0 = W_{hs} s_1 + b_0$$

$$h_{t+1} = \tanh(W_{hf_a} \operatorname{diag}(W_{f_a z} z) W_{f_a a} a_t + W_{hf_h} \operatorname{diag}(W_{f_h z} z) W_{f_h h} h_t + b_h)$$

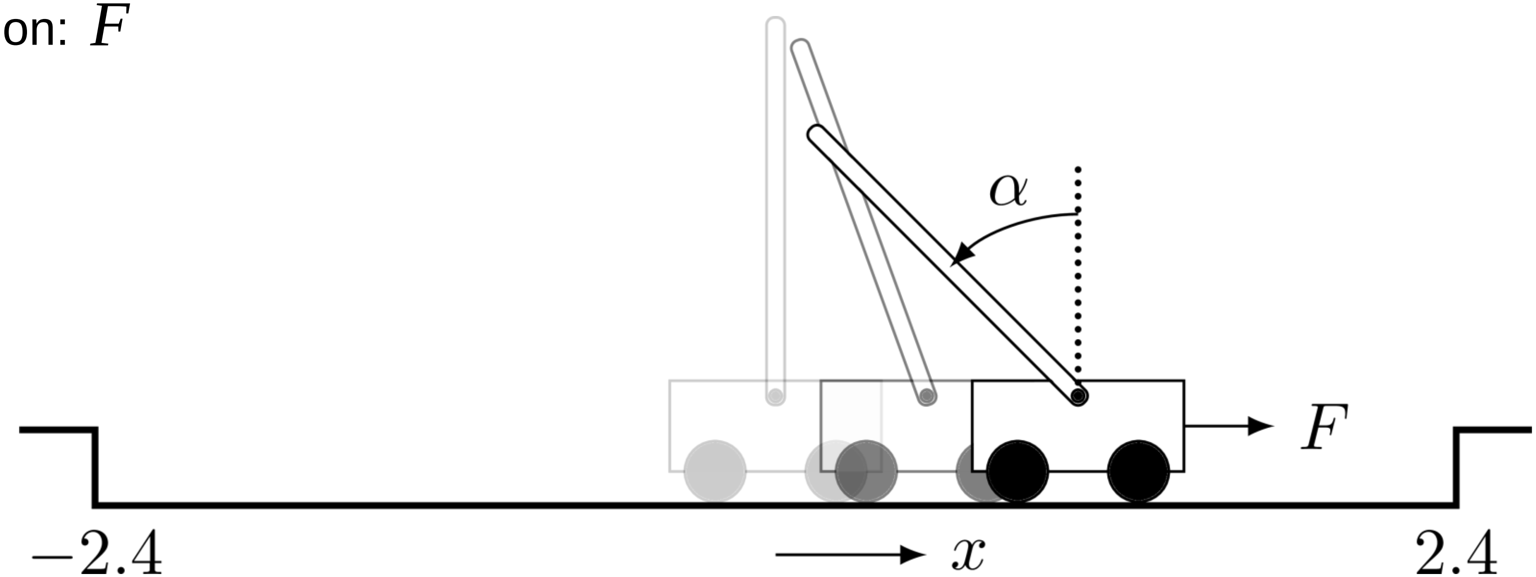
$$\hat{s}_{t+1} = W_{sh} h_t + b_s$$



Experiments – Cart-Pole

State: $(x, \dot{x}, \alpha, \dot{\alpha}) \longrightarrow (x, \dot{x}, \cos(\alpha), \sin(\alpha), \dot{\alpha})$

Action: F



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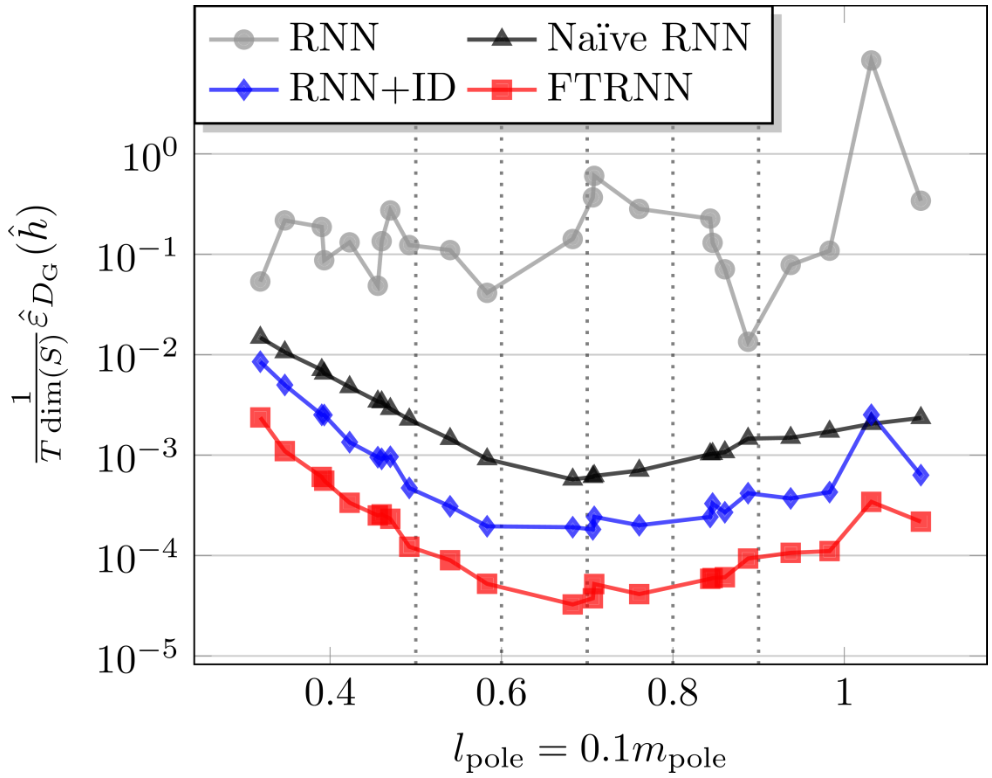
Experiments – Cart-Pole

	CP1	CP2	CP3	CP4	CP5	CP6
pole length (*)	0.50	0.6	0.7	0.8	0.9	U(0.3,1.1)
pole mass	0.1·(*)	0.1·(*)	0.1·(*)	0.1·(*)	0.1·(*)	0.1·(*)
$\|D_T\|$	10 000	10 000	10 000	10 000	10 000	156
$\|D_V\|$	5000	5000	5000	5000	5000	78
$\|D_G\|$	–	–	–	–	–	100 000

Experiments – Cart-Pole



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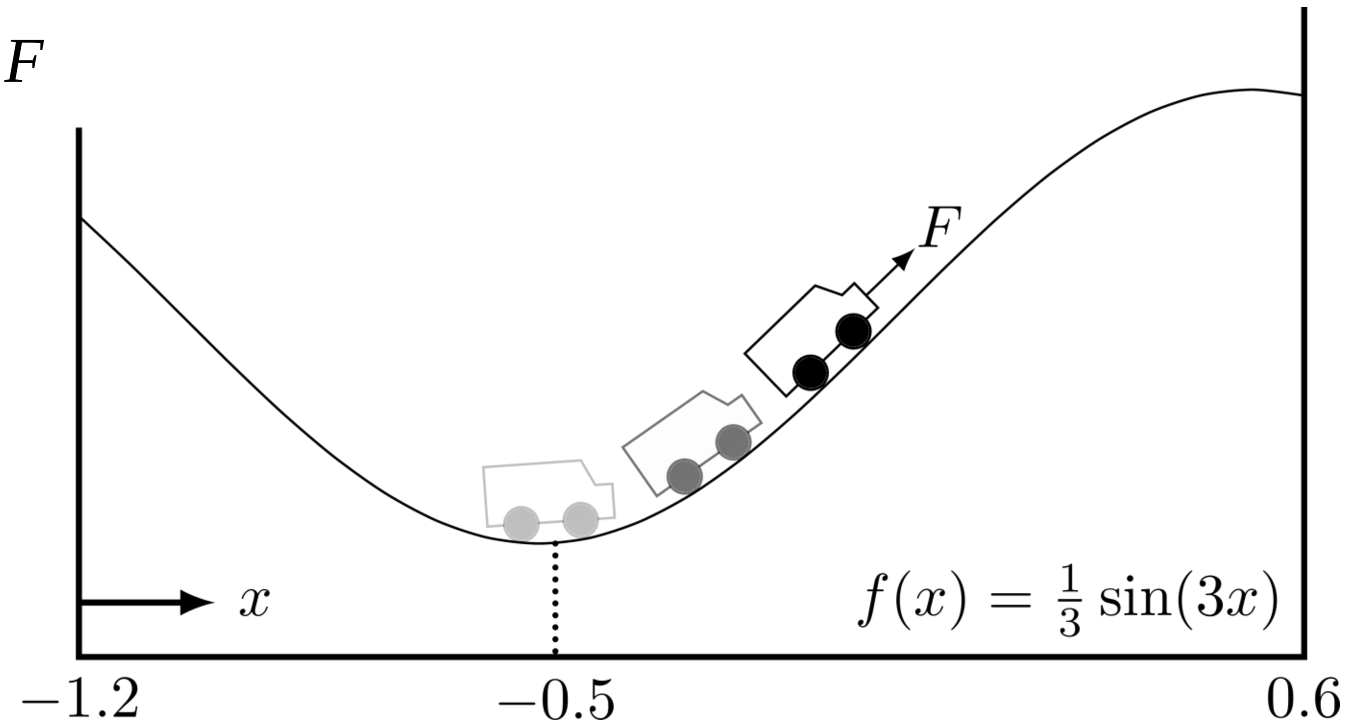
Experiments – Mountain Car

State: $(x, \dot{x})$

Action: F



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Experiments – Mountain Car

	MC1	MC2	MC3	MC4	MC5	MC6
gravity	0.0010	0.0015	0.0020	0.0025	0.0030	U(0.0005,0.005)
$\|D_T\|$	10 000	10 000	10 000	10 000	10 000	156
$\|D_V\|$	5000	5000	5000	5000	5000	78
$\|D_G\|$	–	–	–	–	–	100 000

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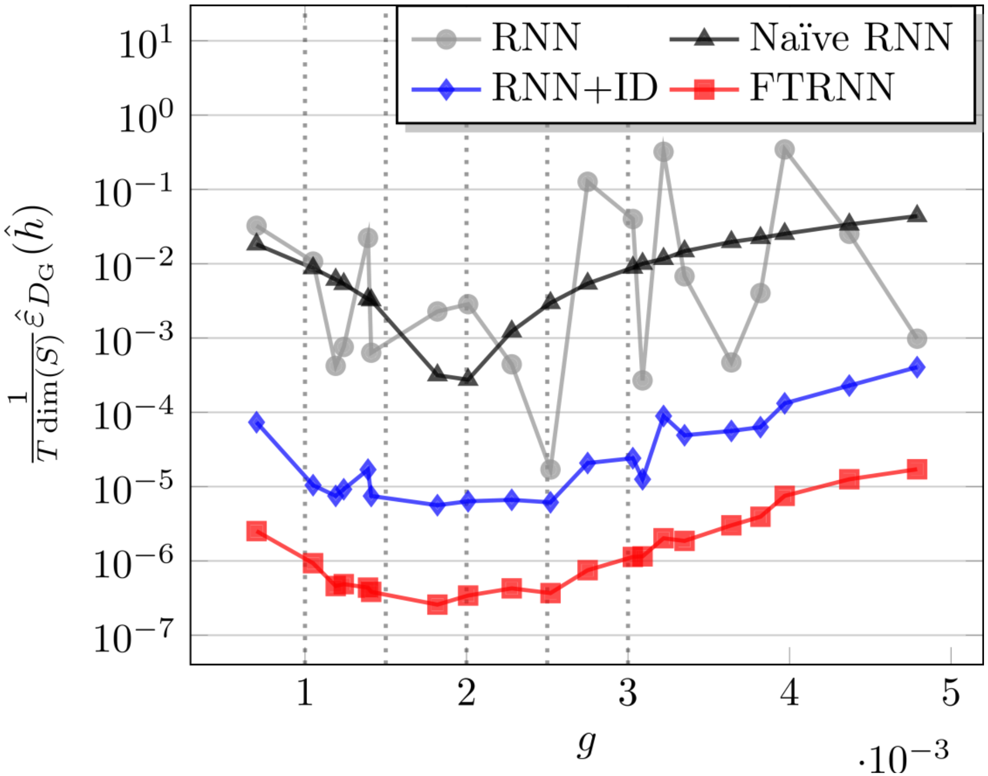
Experiments – Mountain Car



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Conclusion

- Factored Tensor RNN is a new approach for system identification through transfer learning
- FTRNN was consistently superior to other considered RNN-based approaches on the CP and MC simulations