Recurrent Neural Networks

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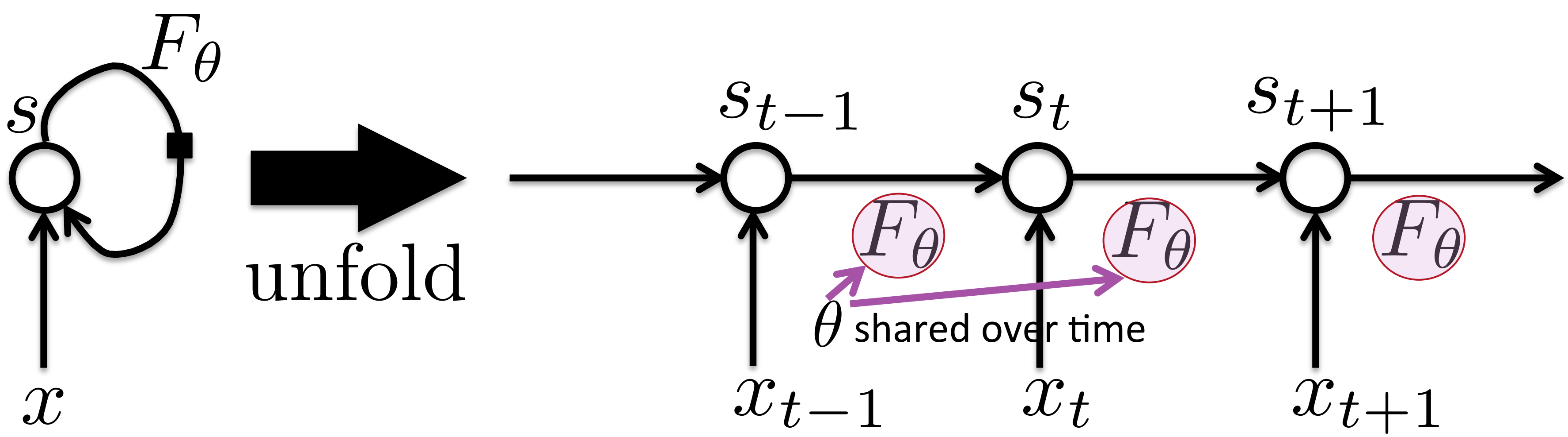
Recurrent Neural Networks

- Selectively summarize an input sequence in a fixed-size state vector via a recursive update

$$s_t = F_\theta(s_{t-1}, x_t)$$

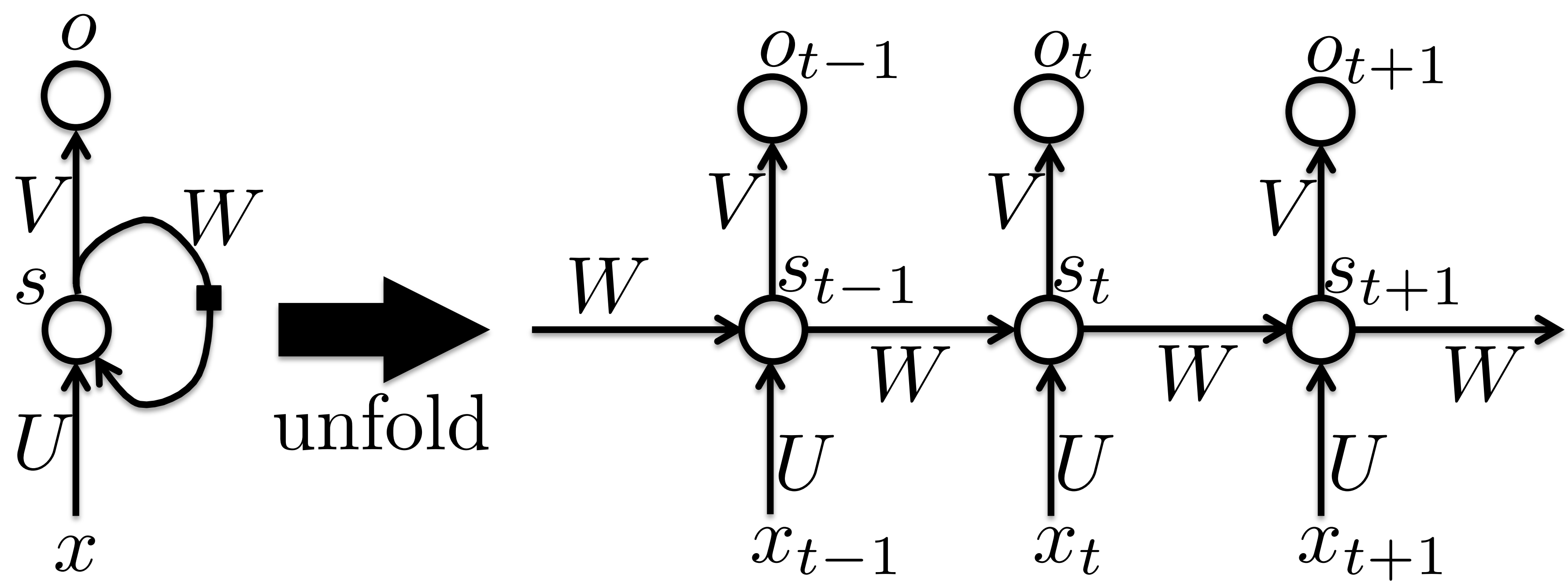


$$s_t = G_t(x_t, x_{t-1}, x_{t-2}, \ldots, x_2, x_1)$$

➔ **Generalizes naturally to new lengths not seen during training**

Recurrent Neural Networks

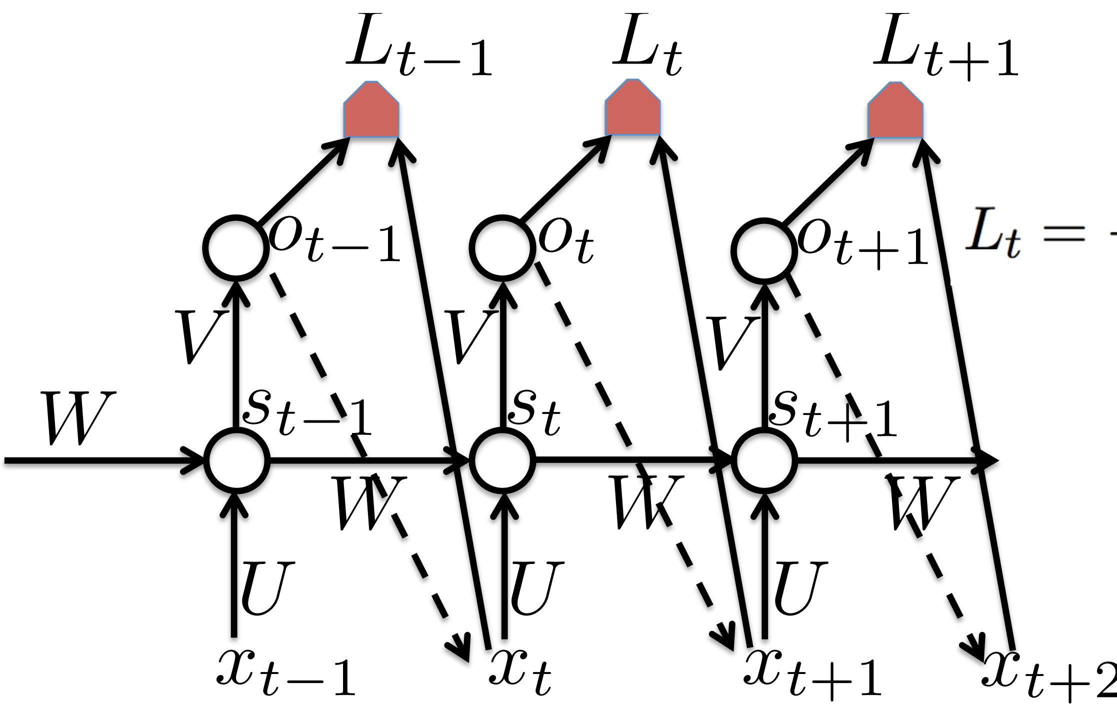
- Can produce an output at each time step: unfolding the graph tells us how to back-prop through time.



Generative RNNs

- An RNN can represent a fully-connected **directed generative model**: every variable predicted from all previous ones.

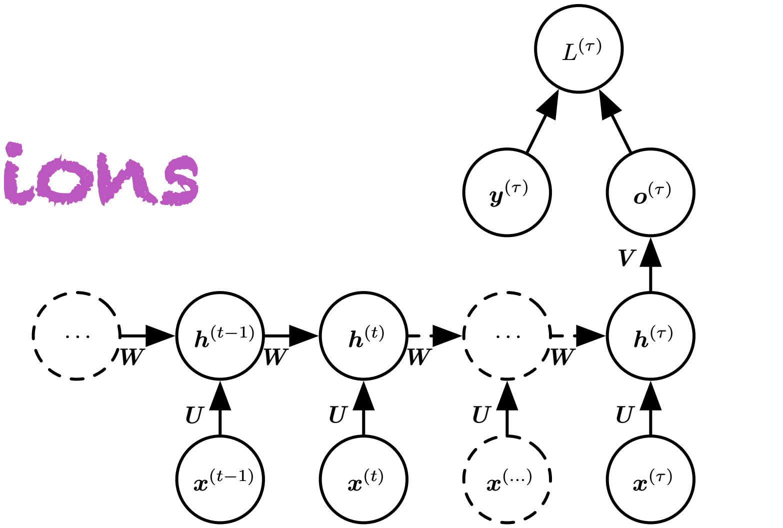
$$P(\mathbf{x}) = P(x_1, \ldots x_T) = \prod_{t=1}^{T} P(x_t | x_{t-1}, x_{t-2}, \ldots x_1)$$



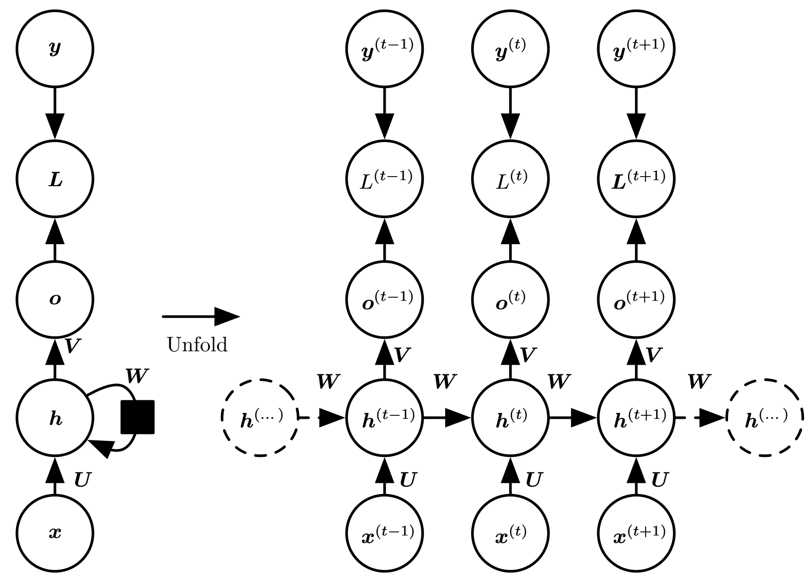
$$L_t = -\log P(x_t | x_{t-1}, x_{t-2}, \ldots x_1)$$

Conditional Distributions

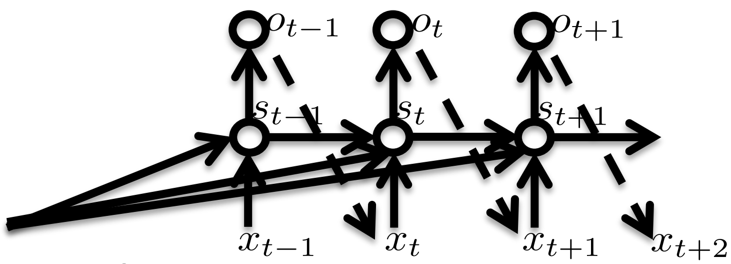
- Sequence to vector



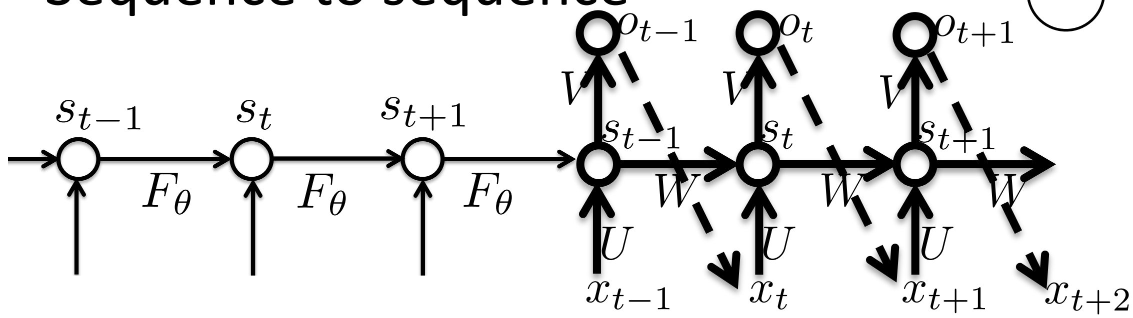
- Sequence to sequence of the same length, aligned



- Vector to sequence

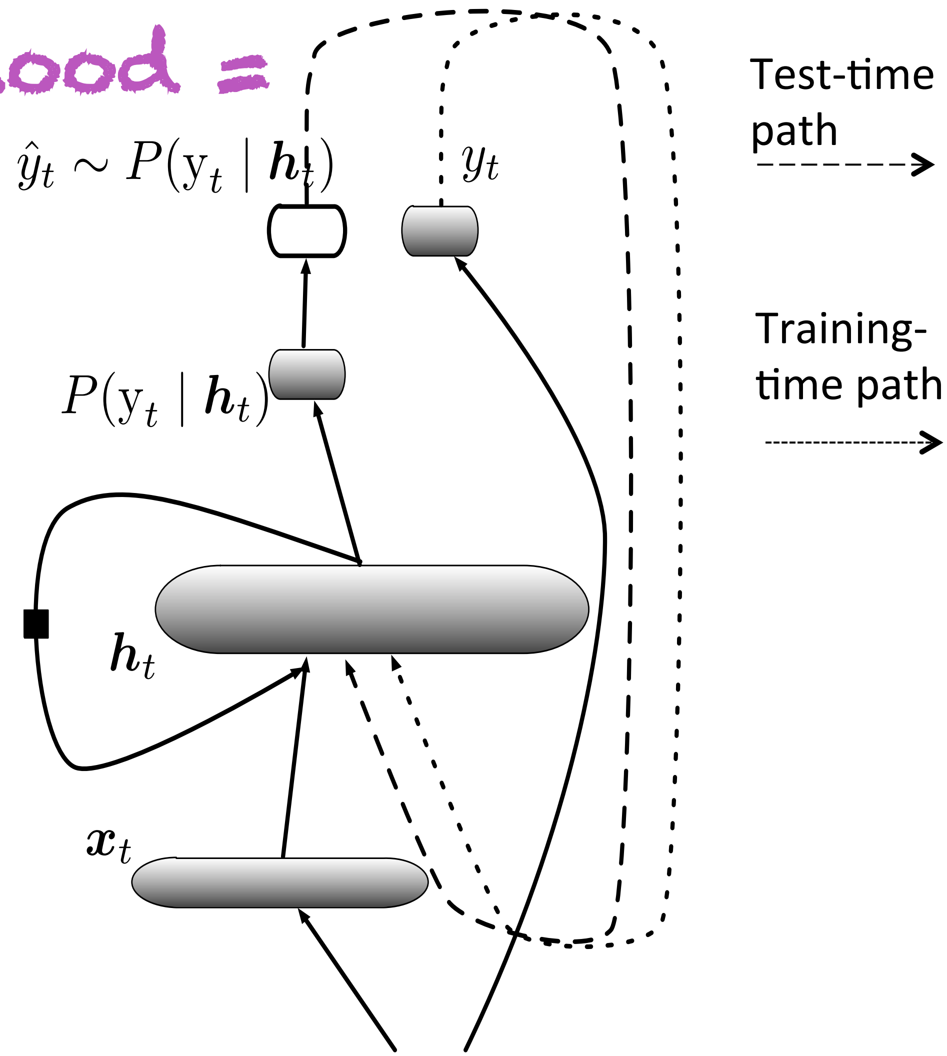


- Sequence to sequence



Maximum Likelihood = Teacher Forcing

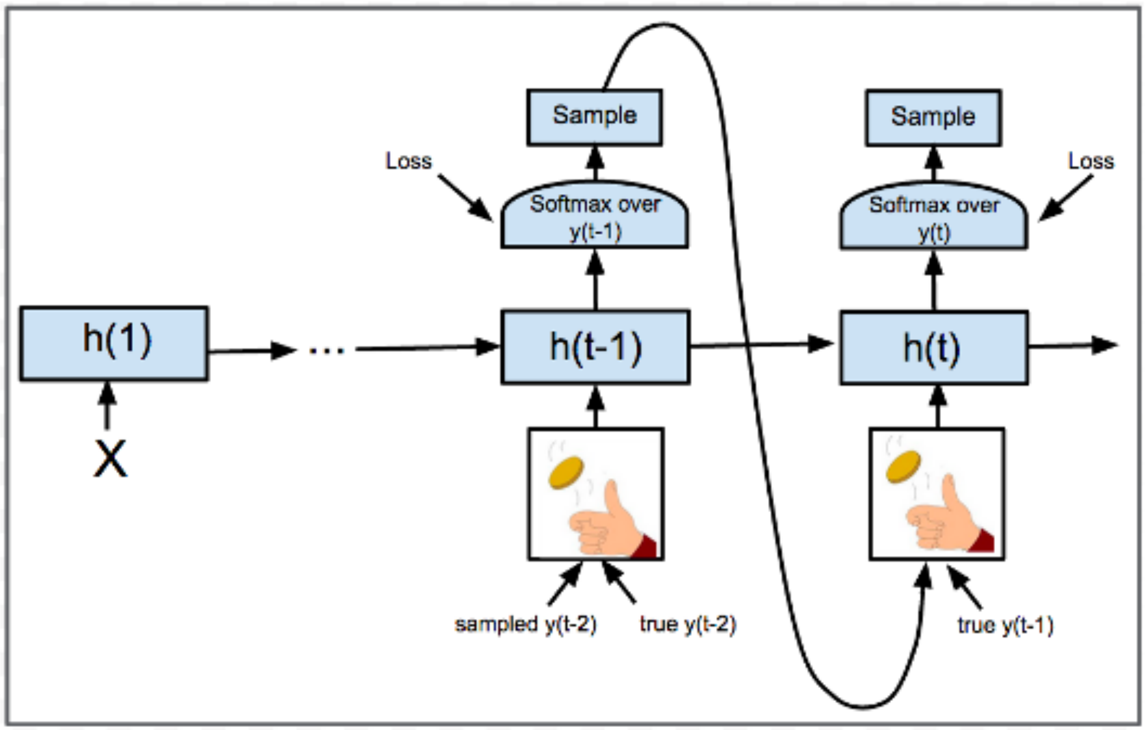
- During training, past *y* in input is from training data
- At generation time, past *y* in input is generated
- Mismatch can cause ”compounding error”



$(\boldsymbol{x}_t, y_t)$: next input/output training pair

Ideas to reduce the train/generate mismatch in teacher forcing

- Scheduled sampling *(S. Bengio et al, NIPS 2015)*



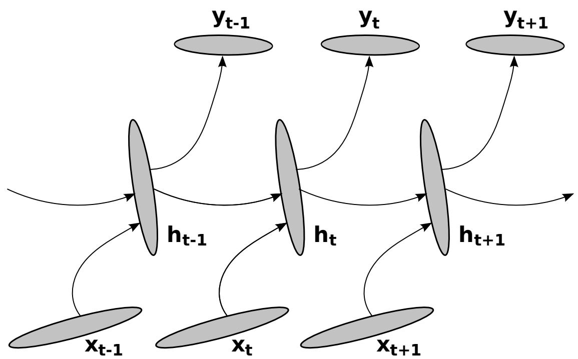
Related to
SEARN (Daumé et al 2009)
DAGGER (Ross et al 2010)

Gradually increase the probability of using the model's samples vs the ground truth as input.

- Backprop through open-loop sampling recurrence & minimize long-term cost (but which one? GAN would be most natural → Professor Forcing)

Increasing the Expressive Power of RNNs with more Depth

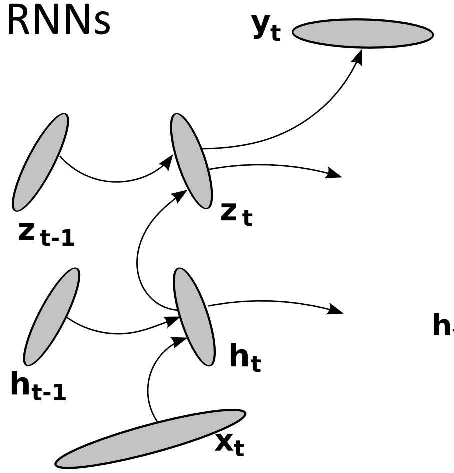
- ICLR 2014, *How to construct deep recurrent neural networks*

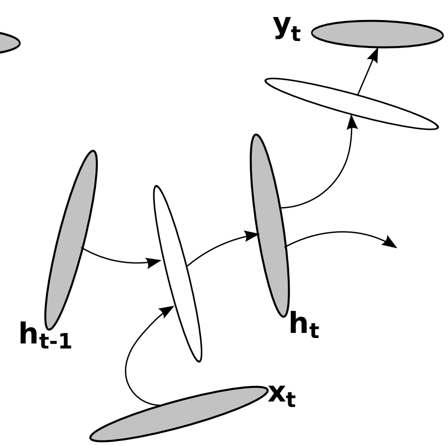


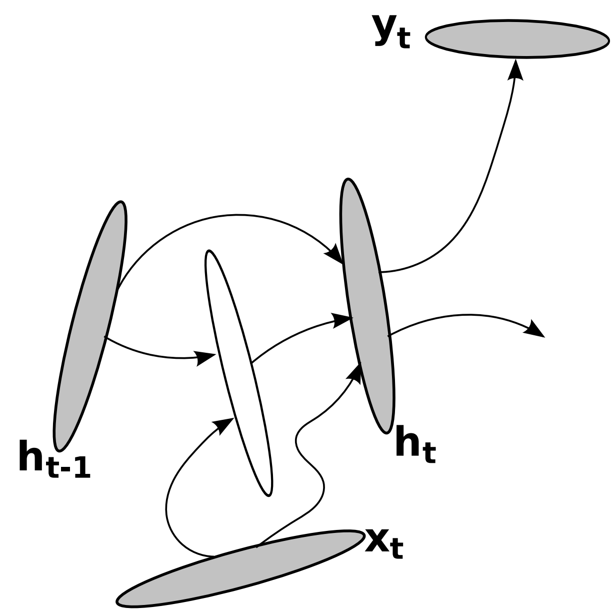
Ordinary RNNs

+ deep hid-to-out
+ deep hid-to-hid
+deep in-to-hid

+ stacking



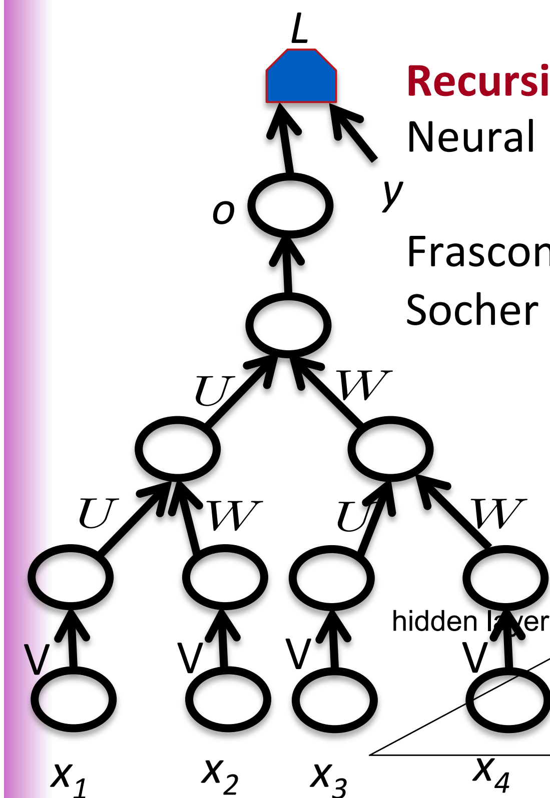




+ skip connections for creating shorter paths

Bidirectional RNNs, Recursive Nets, Multidimensional RNNs, etc.

- The unfolded architecture needs not be a straight chain

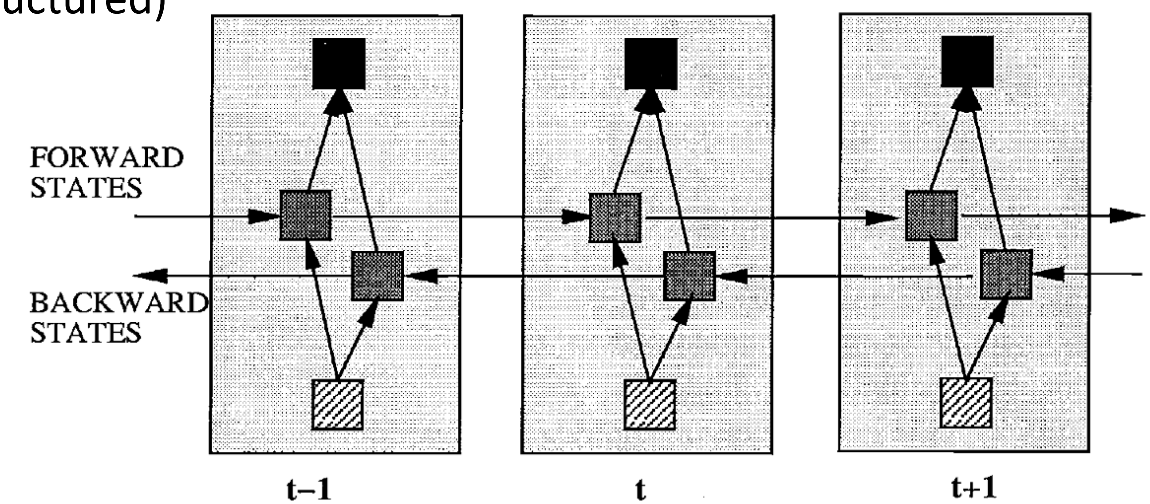


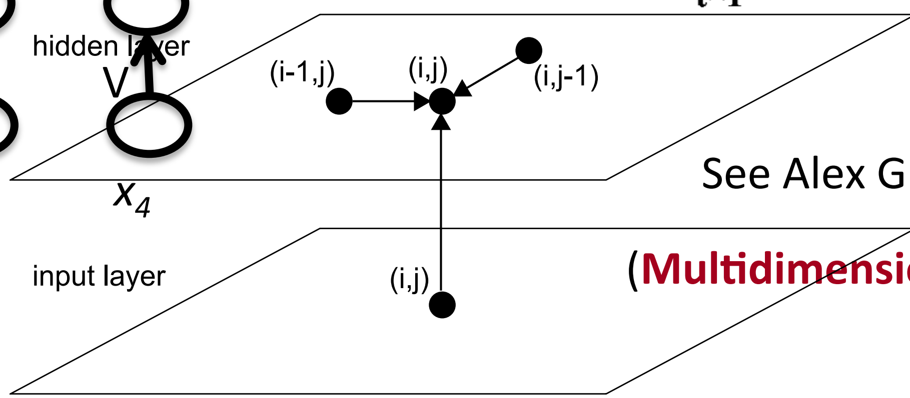
Recursive (tree-structured) Neural Nets:

Frasconi et al 97

Socher et al 2011

Bidirectional RNNs (Schuster and Paliwal, 1997)





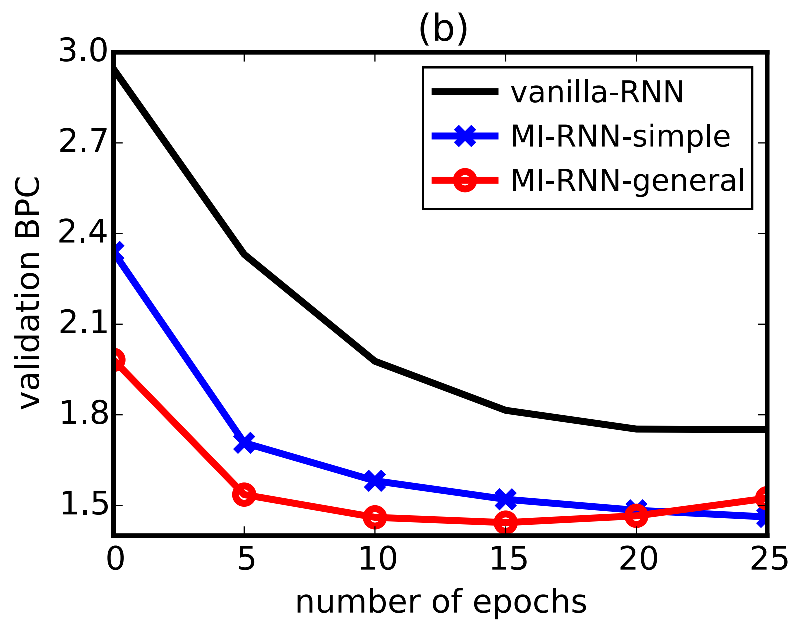
See Alex Graves's work, e.g., 2012

(**Multidimensional** RNNs, Graves et al 2007)

Multiplicative Interactions

(Wu et al, 2016, arXiv:1606.06630)

- Multiplicative Integration RNNs:
  - Replace
$$\phi(\mathbf{W}\boldsymbol{x} + \mathbf{U}\boldsymbol{z} + \mathbf{b})$$
  - By
$$\phi(\mathbf{W}\boldsymbol{x} \odot \mathbf{U}\boldsymbol{z} + \mathbf{b})$$
  - Or more general:



$$\phi(\boldsymbol{\alpha} \odot \mathbf{W}\boldsymbol{x} \odot \mathbf{U}\boldsymbol{z} + \boldsymbol{\beta}_1 \odot \mathbf{U}\boldsymbol{z} + \boldsymbol{\beta}_2 \odot \mathbf{W}\boldsymbol{x} + \boldsymbol{b})$$

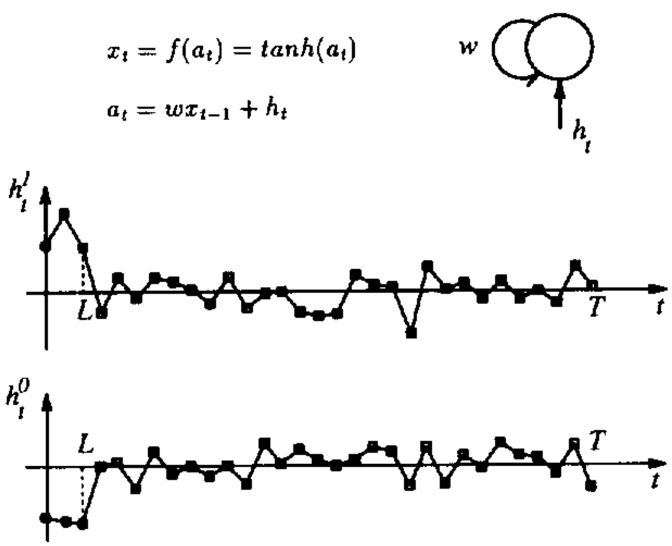
Learning Long-Term Dependencies with Gradient Descent is Difficult

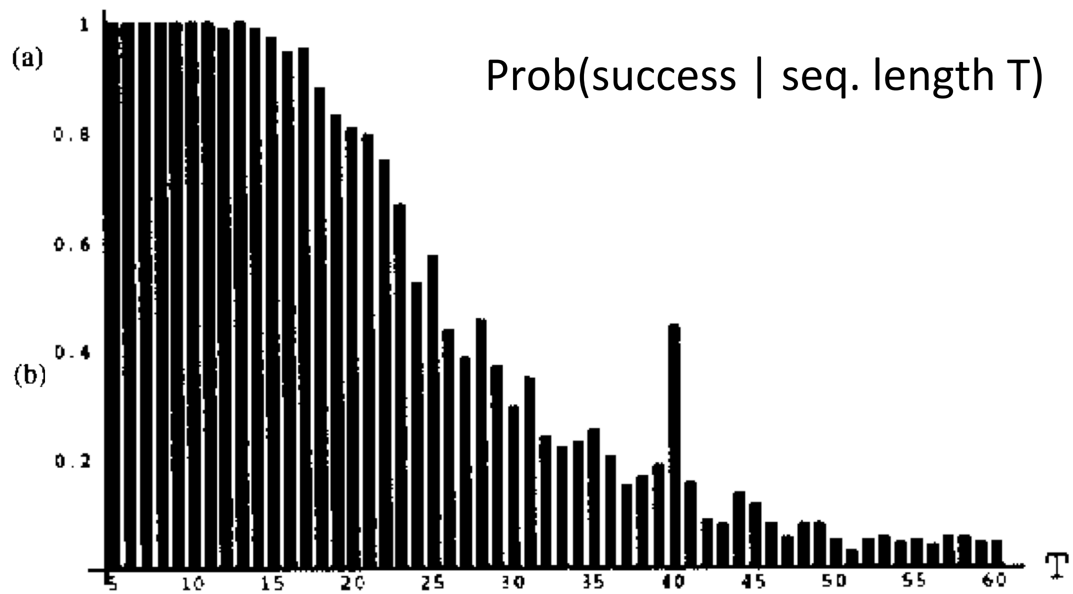
  

Y. Bengio, P. Simard & P. Frasconi, IEEE Trans. Neural Nets, **1994**

Simple Experiments from 1991 while I was at MIT

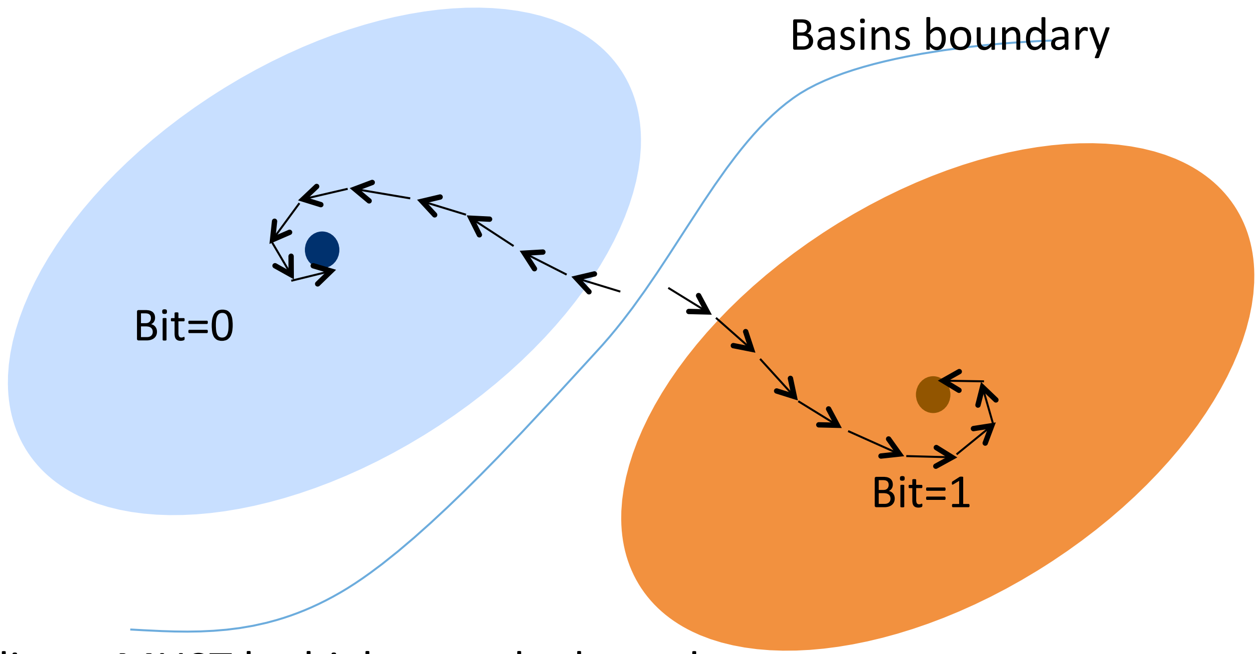
- 2 categories of sequences
- Can the single tanh unit learn to store for T time steps 1 bit of information given by the sign of initial input?





How to store 1 bit? Dynamics with multiple basins of attraction in some dimensions

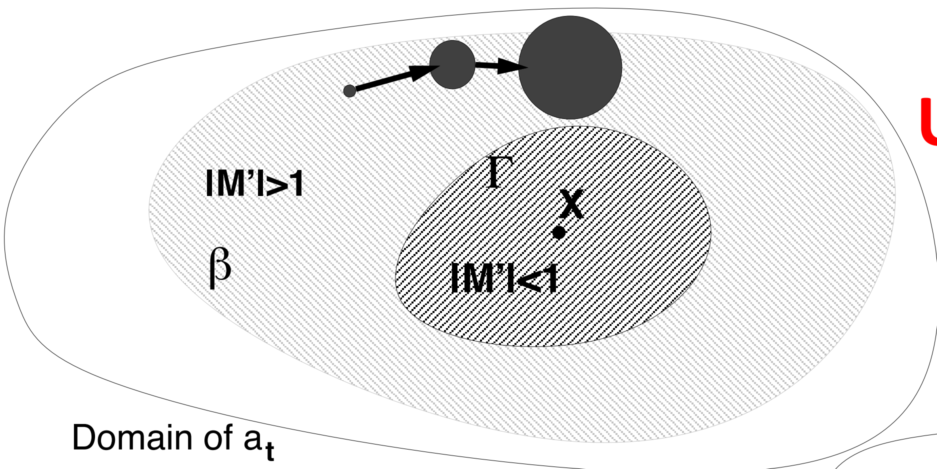
- Some subspace of the state can store 1 or more bits of information if the dynamical system has multiple basins of attraction in some dimensions



Note: gradients MUST be high near the boundary

Robustly storing 1 bit in the presence of bounded noise

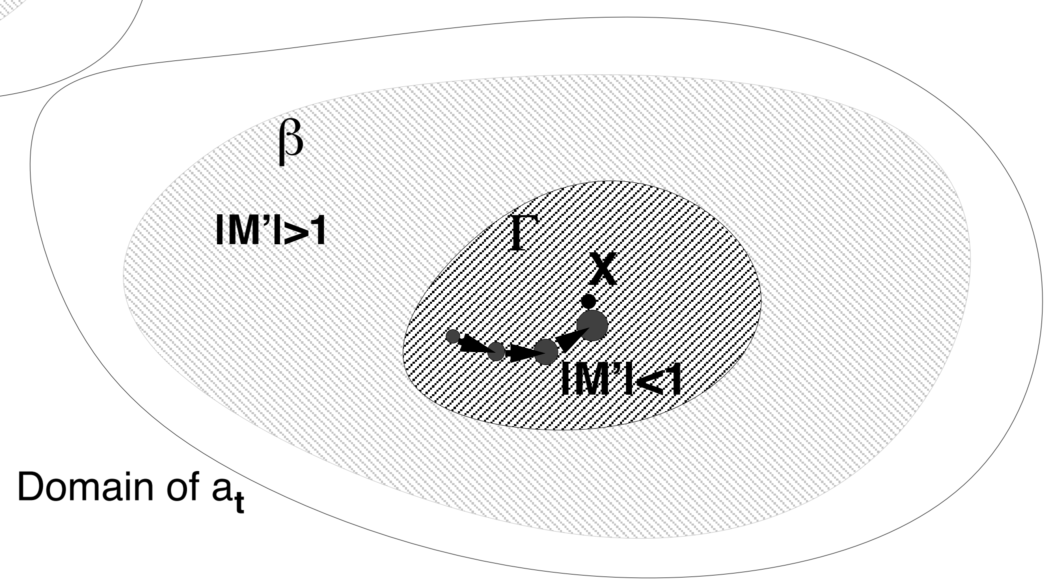
- With spectral radius > 1, noise can kick state out of attractor



UNSTABLE

- Not so with radius<1

CONTRACTIVE
→ STABLE



Storing Reliably → Vanishing gradients

- Reliably storing bits of information requires spectral radius<1
- The product of T matrices whose spectral radius is < 1 is a matrix whose spectral radius converges to 0 at exponential rate in T

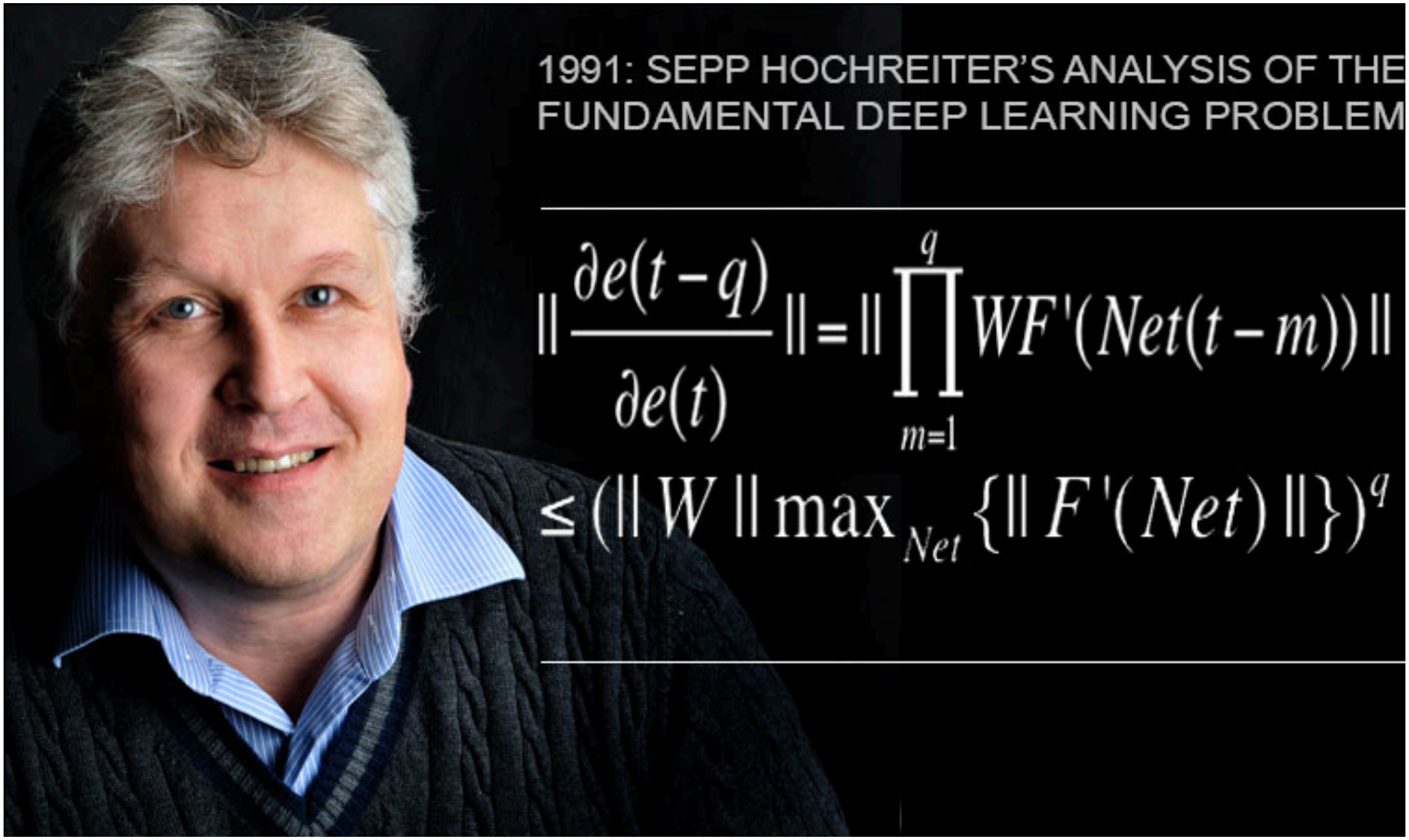
$$L = L(s_T(s_{T-1}(\ldots s_{t+1}(s_t, \ldots))))$$

$$\frac{\partial L}{\partial s_t} = \frac{\partial L}{\partial s_T} \frac{\partial s_T}{\partial s_{T-1}} \cdots \frac{\partial s_{t+1}}{\partial s_t}$$

- If spectral radius of Jacobian is < 1 → propagated gradients vanish

Vanishing or Exploding Gradients

- Hochreiter's 1991 MSc thesis (in German) had independently discovered that backpropagated gradients in RNNs tend to either vanish or explode as sequence length increases



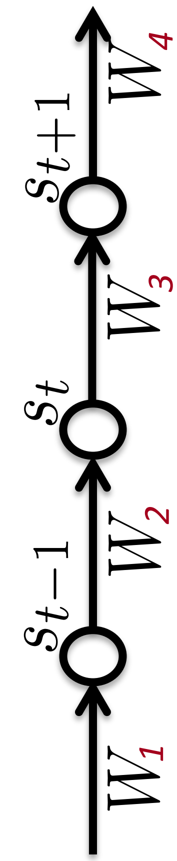
Why it hurts gradient-based learning

- Long-term dependencies get a weight that is exponentially smaller (in T) compared to short-term dependencies

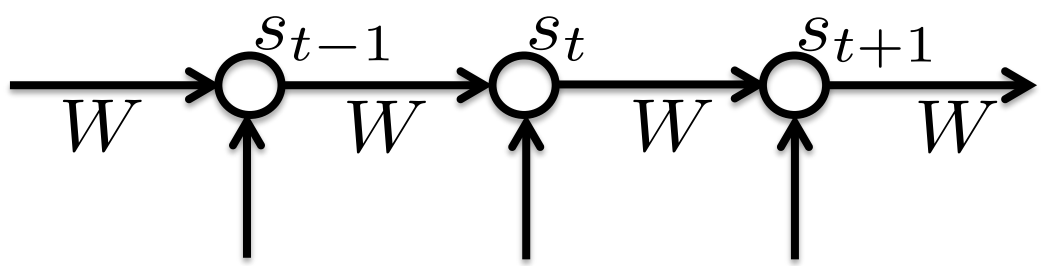
$$\frac{\partial C_t}{\partial W} = \sum_{\tau \le t} \frac{\partial C_t}{\partial a_\tau} \frac{\partial a_\tau}{\partial W} = \sum_{\tau \le t} \frac{\partial C_t}{\partial a_t} \frac{\partial a_t}{\partial a_\tau} \frac{\partial a_\tau}{\partial W}$$

Becomes exponentially smaller for longer time differences, when spectral radius < 1

Vanishing Gradients in Deep Nets are Different from the Case in RNNs



- If it was just a case of vanishing gradients in deep nets, we could just rescale the per-layer learning rate, but that does not really fix the training difficulties.



- Can't do that with RNNs because the weights are shared, & total true gradient = sum over different "depths"

$$\frac{\partial C_t}{\partial W} = \sum_{\tau \leq t} \frac{\partial C_t}{\partial a_\tau} \frac{\partial a_\tau}{\partial W} = \sum_{\tau \leq t} \frac{\partial C_t}{\partial a_t} \frac{\partial a_t}{\partial a_\tau} \frac{\partial a_\tau}{\partial W}$$

To store information robustly the dynamics must be contractive

- The RNN gradient is a product of Jacobian matrices, each associated with a step in the forward computation. To store information robustly in a finite-dimensional state, the dynamics must be contractive [Bengio et al 1994].

$$L = L(s_T(s_{T-1}(\ldots s_{t+1}(s_t, \ldots))))$$
$$\frac{\partial L}{\partial s_t} = \frac{\partial L}{\partial s_T} \frac{\partial s_T}{\partial s_{T-1}} \cdots \frac{\partial s_{t+1}}{\partial s_t}$$

Storing bits robustly requires e-values<1

- Problems:
  - e-values of Jacobians > 1 → *gradients explode*
  - **or e-values < 1 → *gradients shrink & vanish***
  - or random → variance grows exponentially

Gradient clipping

RNN Tricks

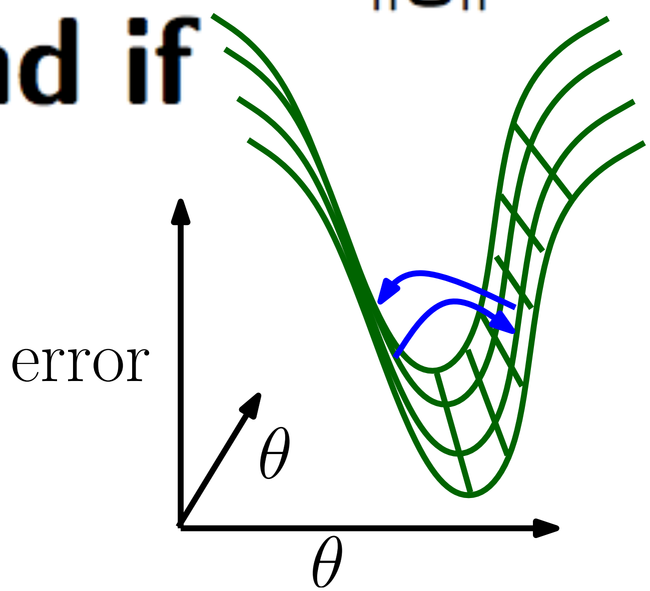
(Pascanu, Mikolov, Bengio, ICML 2013; Bengio, Boulanger & Pascanu, ICASSP 2013)

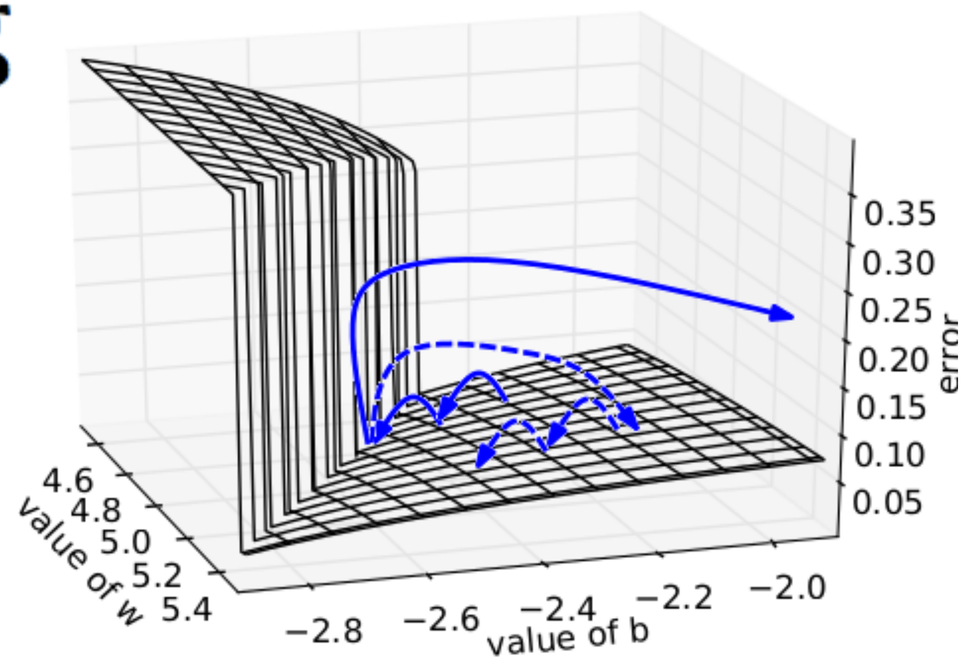
- Clipping gradients (avoid exploding gradients)
- Leaky integration (propagate long-term dependencies)
- Momentum (cheap 2nd order)
- Initialization (start in right ballpark avoids exploding/vanishing)
- Sparse Gradients (symmetry breaking)
- Gradient propagation regularizer (avoid vanishing gradient)
- Gated self-loops (LSTM & GRU, reduces vanishing gradient)

Dealing with Gradient Explosion by Gradient Norm Clipping

(Mikolov thesis 2012;
Pascanu, Mikolov, Bengio, ICML 2013)

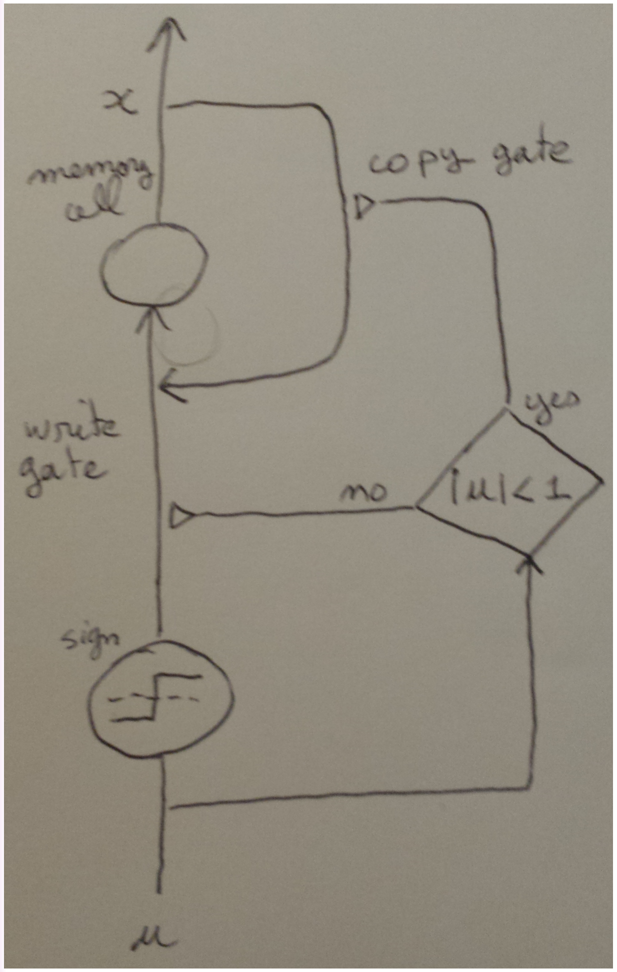
$$
\begin{aligned}
&\hat{\mathbf{g}} \leftarrow \frac{\partial \mathit{error}}{\partial \theta} \\
&\textbf{if } \ \|\hat{\mathbf{g}}\| \geq \mathit{threshold} \ \textbf{ then} \\
&\quad \hat{\mathbf{g}} \leftarrow \frac{\mathit{threshold}}{\|\hat{\mathbf{g}}\|}\hat{\mathbf{g}} \\
&\textbf{end if}
\end{aligned}
$$





Conference version (1993) of the 1994 paper by the same authors had a predecessor of GRU and targetprop

(The problem of learning long-term dependencies in recurrent networks, Bengio, Frasconi & Simard ICNN'1993)



IV. A TRAINABLE FLIP-FLOP

- Flip-flop unit to store 1 bit, with gating signal to control when to write

$$x_{t+1} = f(x_t, u_t)$$

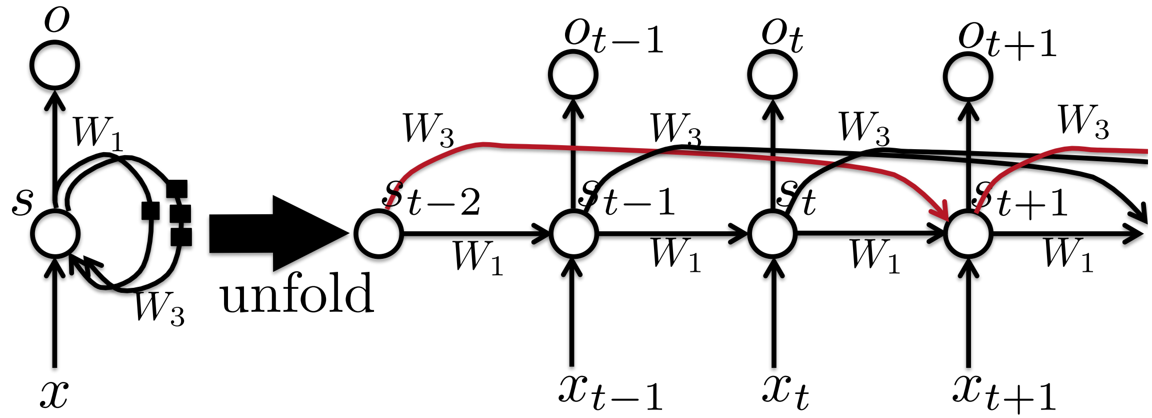
$$f(x,u) = \left| \begin{array}{ll} 1 & \text{if } |u|<1 \text{ and } x \geq 0 \\ & \text{or if } u \geq 1 \\ -1 & \text{otherwise} \end{array} \right. \quad (8)$$

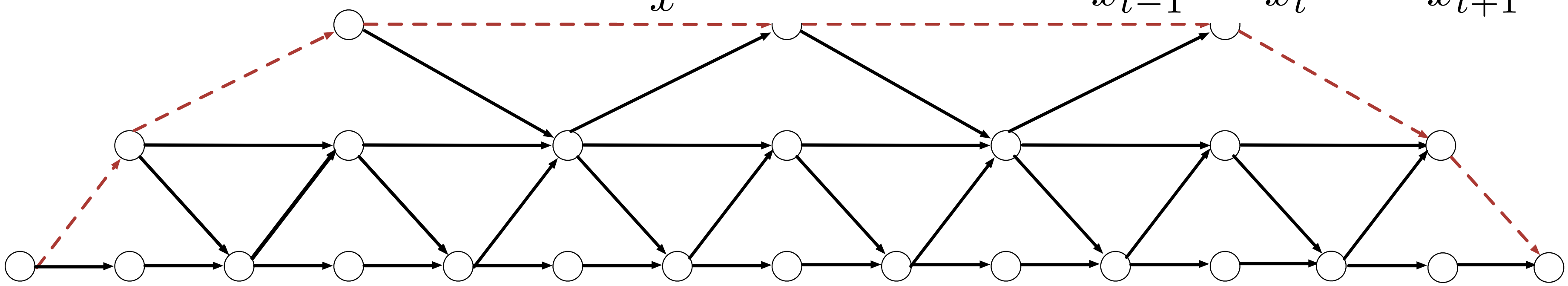
- Pseudo-backprop through it by a form of targetprop

$$\Delta x(\Delta f, u) = \left| \begin{array}{ll} \Delta f & \text{if } |u|<1 \\ 0 & \text{otherwise} \end{array} \right. \quad (11)$$

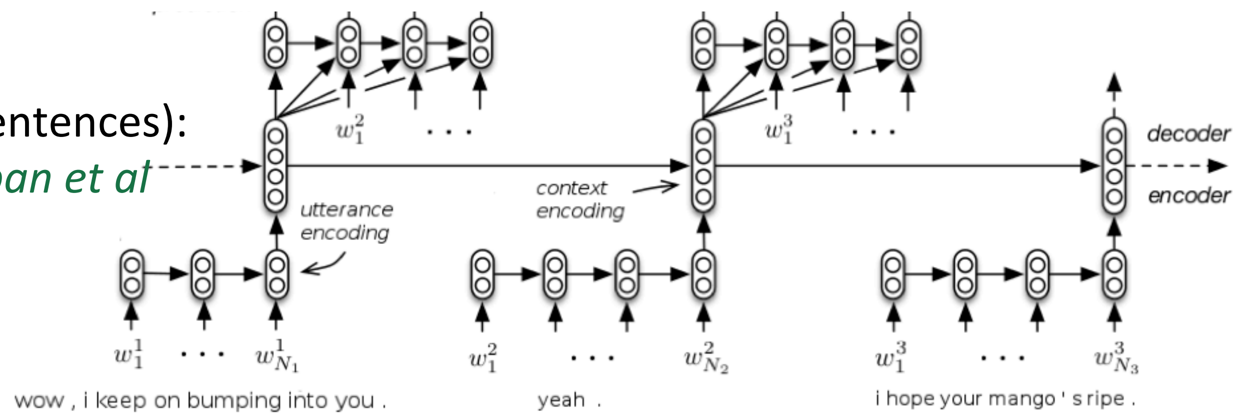
Delays & Hierarchies to Reach Farther

- Delays and multiple time scales, *Elhihi & Bengio NIPS 1995, Koutnik et al ICML 2014*
- *How to do this right?*
- *How to automatically and adaptively do it?*





Hierarchical RNNs (words / sentences): *Sordoni et al CIKM 2015, Serban et al AAAI 2016*

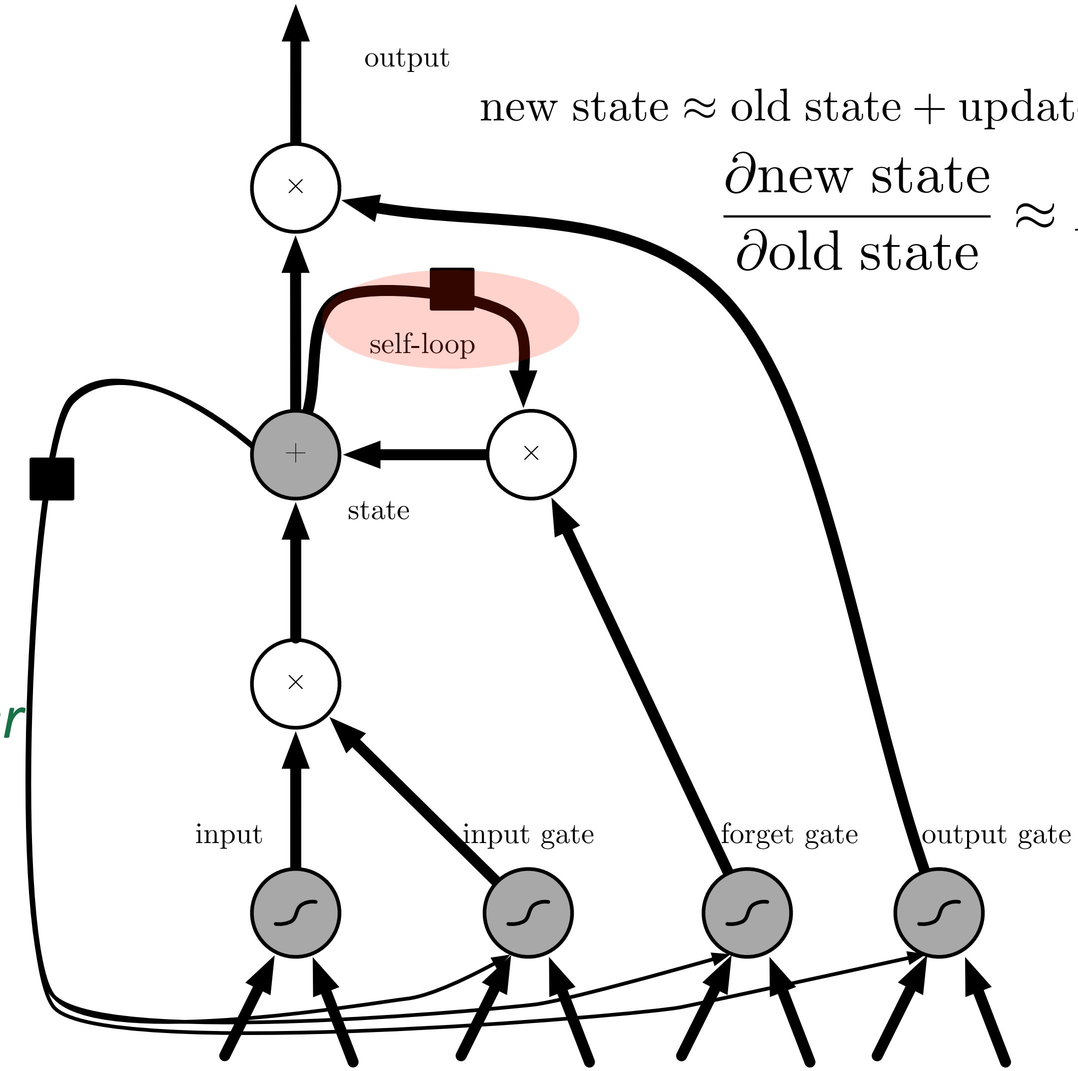


Fighting the vanishing gradient: LSTM & GRU

(Hochreiter 1991); first version of the LSTM, called Neural Long-Term Storage with self-loop

- Create a path where gradients can flow for longer with a self-loop
- Corresponds to an eigenvalue of Jacobian slightly less than 1
- LSTM is now **heavily used** *(Hochreiter & Schmidhuber 1997)*
- GRU light-weight version *(Cho et al 2014)*

LSTM: (Hochreiter & Schmidhuber 1997)

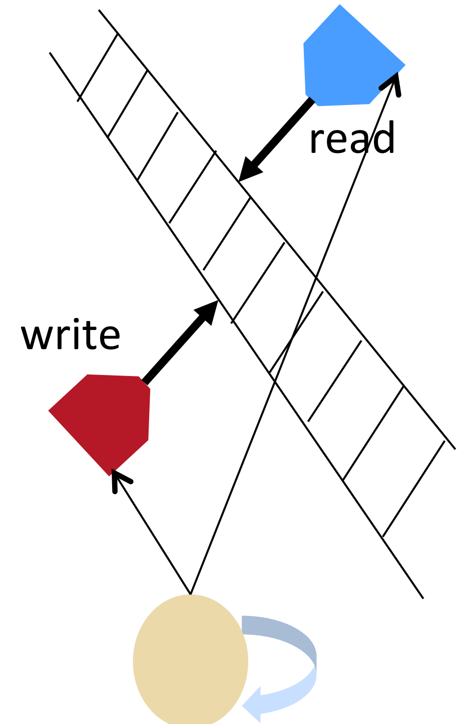


$$\text{new state} \approx \text{old state} + \text{update}$$

$$\frac{\partial \text{new state}}{\partial \text{old state}} \approx I$$

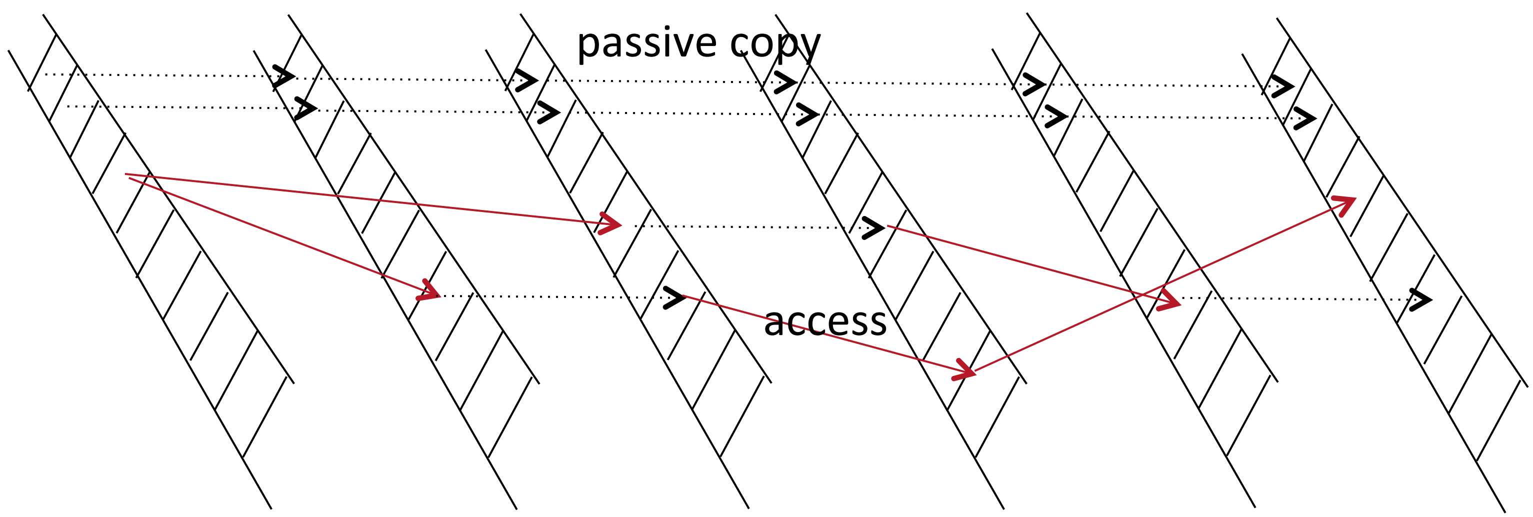
Fast Forward 20 years: Attention Mechanisms for Memory Access

- Neural Turing Machines *(Graves et al 2014)*
- and Memory Networks *(Weston et al 2014)*
- Use a content-based attention mechanism *(Bahdanau et al 2014)* to control the read and write access into a memory
- The attention mechanism outputs a softmax over memory locations



Large Memory Networks: Sparse Access Memory for Long-Term Dependencies

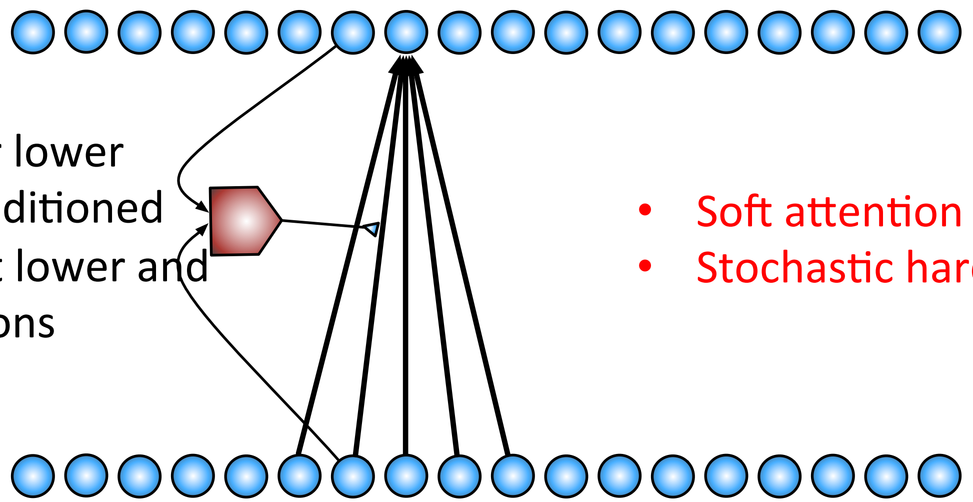
- Memory = part of the state
- Memory-based networks are special RNNs
- A mental state stored in an external memory can stay for arbitrarily long durations, until it is overwritten (partially or not)
- Forgetting = vanishing gradient.
- Memory = **higher-dimensional state**, avoiding or reducing the need for forgetting/vanishing



Attention Mechanism for Deep Learning

(Bahdanau, Cho & Bengio, ICLR 2015; Jean et al ACL 2015; Jean et al WMT 2015; Xu et al ICML 2015; Chorowski et al NIPS 2015; Firat, Cho & Bengio 2016)

- Consider an input (or intermediate) sequence or image
- Consider an upper level representation, which can choose « where to look », by assigning a weight or probability to each input position, as produced by an MLP, applied at each position



- Soft attention (backprop) vs
- Stochastic hard attention (RL)

End-to-End Machine Translation with Recurrent Nets and Attention Mechanism

(Bahdanau et al ICLR 2015, Jean et al ACL 2015, Gulcehre et al 2015, Firat et al 2016)

- Reached the state-of-the-art in one year, from scratch

(a) **English→French (WMT-14)**

	NMT(A)	Google	P-SMT
NMT	32.68	$30.6^{\star}$	
+Cand	33.28	–	$\mathbf{37.03}^{\bullet}$
+UNK	33.99	32.7°	
+Ens	**36.71**	$\mathbf{36.9}^{\circ}$	

(b) **English→German (WMT-15)**

Model	Note
24.8	Neural MT
24.0	U.Edinburgh, Syntactic SMT
23.6	LIMSI/KIT
22.8	U.Edinburgh, Phrase SMT
22.7	KIT, Phrase SMT

(c) **English→Czech (WMT-15)**

Model	Note
18.3	Neural MT
18.2	JHU, SMT+LM+OSM+Sparse
17.6	CU, Phrase SMT
17.4	U.Edinburgh, Phrase SMT
16.1	U.Edinburgh, Syntactic SMT

Google-Scale NMT Success

(Wu et al & Dean, Nature, 2016)

- After beating the classical phrase-based MT on the academic benchmarks, there remained the question: will it work on the very large scale datasets like used for Google Translate?
- Distributed training, very large model ensemble
- Not only does it work in terms of BLEU but it makes a killing in terms of human evaluation on Google Translate data

Table 10: Side-by-side scores on production data

	PBMT	GNMT	Human	Relative Improvement
English $\rightarrow$ Spanish	3.594±1.58	5.031±1.09	5.140±1.04	93%
English $\rightarrow$ French	3.518±1.70	5.032±1.22	5.215±1.03	89%
English $\rightarrow$ Portuguese	3.675±1.64	4.856±1.29	4.973±1.17	91%
English $\rightarrow$ Chinese	2.457±1.48	4.154±1.42	4.580±1.26	80%
Spanish $\rightarrow$ English	3.410±1.65	4.921±1.16	4.930±1.12	99%
French $\rightarrow$ English	3.639±1.63	5.000±1.07	5.016±1.09	99%
Portuguese $\rightarrow$ English	3.471±1.74	5.029±1.05	5.040±1.03	99%
Chinese $\rightarrow$ English	1.994±1.47	3.884±1.37	4.334±1.20	81%

Pointing the Unknown Words

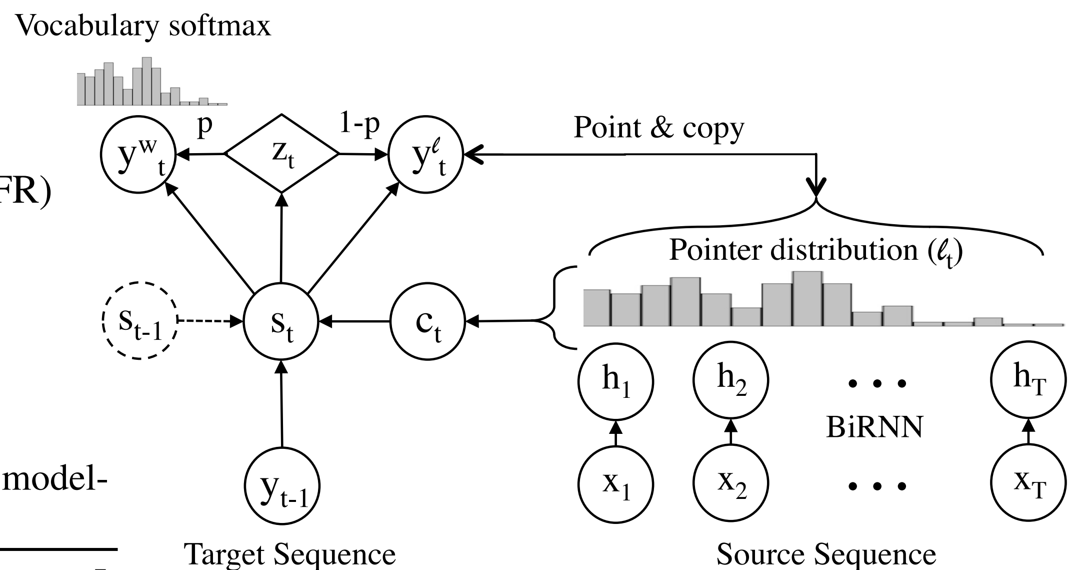
Gulcehre, Ahn, Nallapati, Zhou & Bengio ACL 2016
Based on 'Pointer Networks', Vinyals et al 2015

The next word generated can either come from vocabulary or is copied from the input sequence.

French: Guillaume et Cesar ont une voiture bleue a Lausanne.

Copy Copy Copy

English: Guillaume and Cesar have a blue car in Lausanne.



Machine Translation

Table 5: Europarl Dataset (EN-FR)

	BLEU-4
NMT	20.19
NMT + PS	**23.76**

Table 3: Results on Gigaword Corpus for modeling UNK's with pointers in terms of recall.

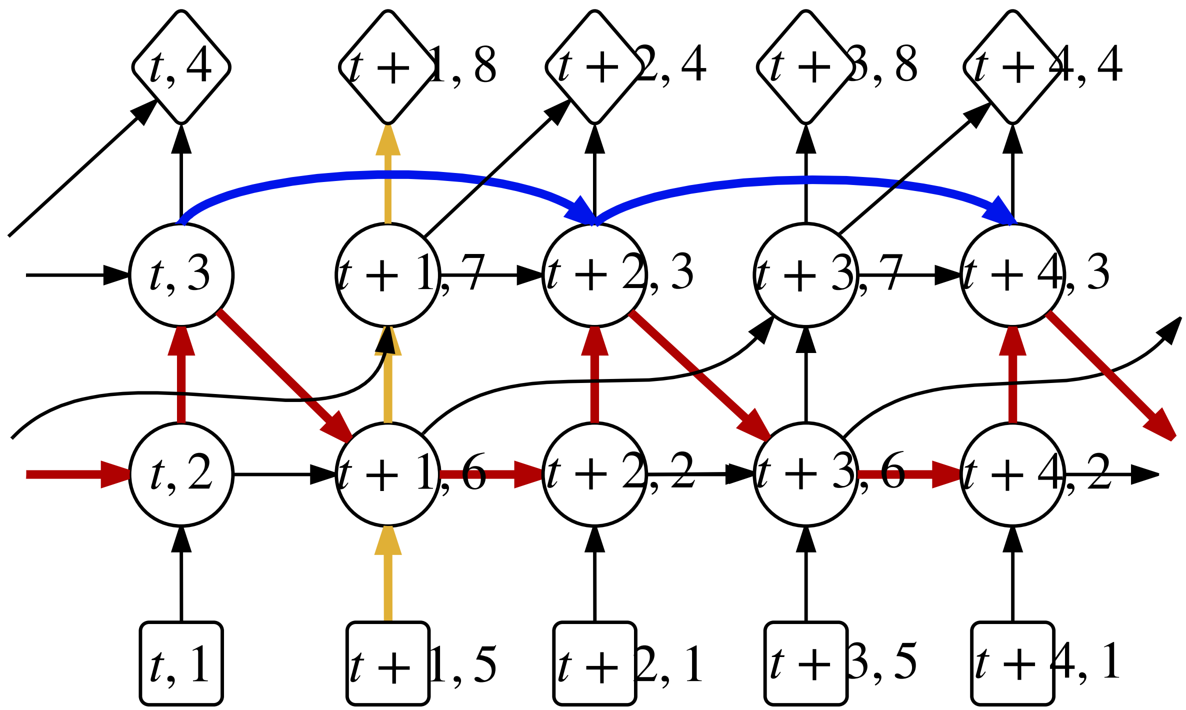
	Rouge-1	Rouge-2	Rouge-L
NMT + lvt	36.45	17.41	33.90
NMT + lvt + PS	**37.29**	**17.75**	**34.70**

Text summarization

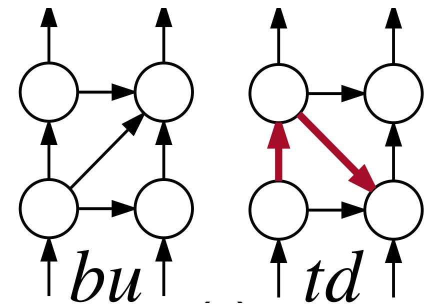
Designing the RNN Architecture

(Architectural Complexity Measures of Recurrent Neural Networks
Zhang et al 2016, arXiv:1602.08210)

- **Recurrent depth**: max path length divided by sequence length
- **Feedforward depth**: max length from input to nearest output
- **Skip coefficient**: shortest path length divided sequence length



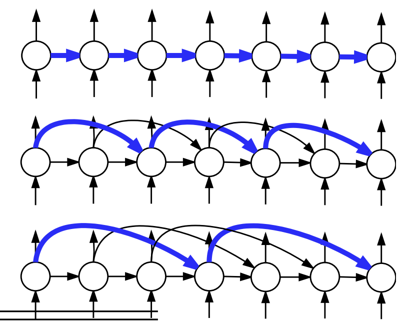
It makes a difference



- Impact of change in recurrent depth

DATASET	MODELS\ARCHS	*sh*	*st*	*bu*	*td*
PennTreebank	*tanh* RNN	1.54	1.59	1.54	**1.49**
text8	*tanh* RNN-SMALL	1.80	1.82	1.80	**1.77**
	tanh RNN-LARGE	1.69	1.67	1.64	**1.59**
	LSTM-SMALL	1.65	1.66	1.65	**1.63**
	LSTM-LARGE	1.52	1.53	1.52	**1.49**

- Impact of change in skip coefficient



RNN($tanh$)	s = 1	s = 5	s = 9	s = 13	s = 21
MNIST	34.9	46.9	74.9	85.4	**87.8**
	s = 1	s = 3	s = 5	s = 7	s = 9
pMNIST	49.8	79.1	84.3	**88.9**	88.0

LSTM	s = 1	s = 3	s = 5	s = 7	s = 9
MNIST	56.2	**87.2**	86.4	86.4	84.8
	s = 1	s = 3	s = 4	s = 5	s = 6
pMNIST	28.5	25.0	60.8	62.2	**65.9**

Model	MNIST	pMNIST
iRNN[25]	97.0	≈82.0
uRNN[24]	95.1	91.4
LSTM[24]	**98.2**	88.0
RNN($tanh$)[25]	≈35.0	≈35.0
$s$tanh(s = 21, 11)	98.1	**94.0**

Architecture, s		(1), 1	(2), 1	(3), $\frac{k}{2}$	(4), k
MNIST	k = 17	39.5	39.4	54.2	**77.8**
	k = 21	39.5	39.9	69.6	**71.8**
pMNIST	k = 5	55.5	66.6	74.7	**81.2**
	k = 9	55.5	71.1	78.6	**86.9**

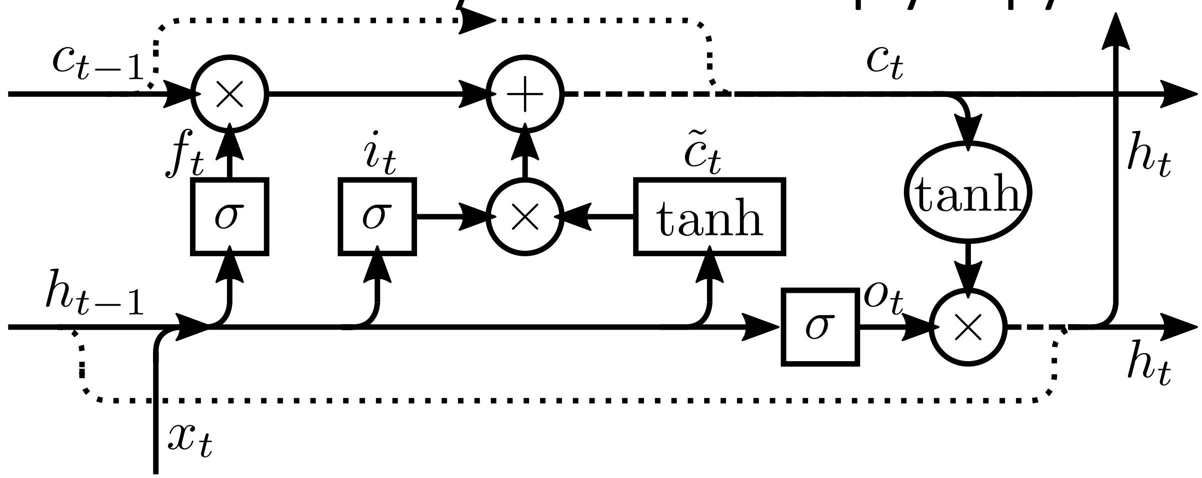
Table 2: Results for MNIST/pMNIST. **Top-left**: test accuracies with different s for $tanh$ RNN. **Top-right**: test accuracies with different s for LSTM. **Bottom**: compared to previous results. **Bottom-right**: test accuracies for architectures (1), (2), (3) and (4) for $tanh$ RNN.

Near-Orthogonality to Help Information Propagation

- Initialization to orthogonal recurrent W *(Saxe et al 2013, ICLR2014)*
- Unitary matrices: all e-values of matrix are 1 *(Arjowski, Amar & Bengio ICML 2016)*

$$\mathbf{W} = \mathbf{D}_3\mathbf{R}_2\mathcal{F}^{-1}\mathbf{D}_2\Pi\mathbf{R}_1\mathcal{F}\mathbf{D}_1$$

- Zoneout: randomly choose to simply copy the state unchanged

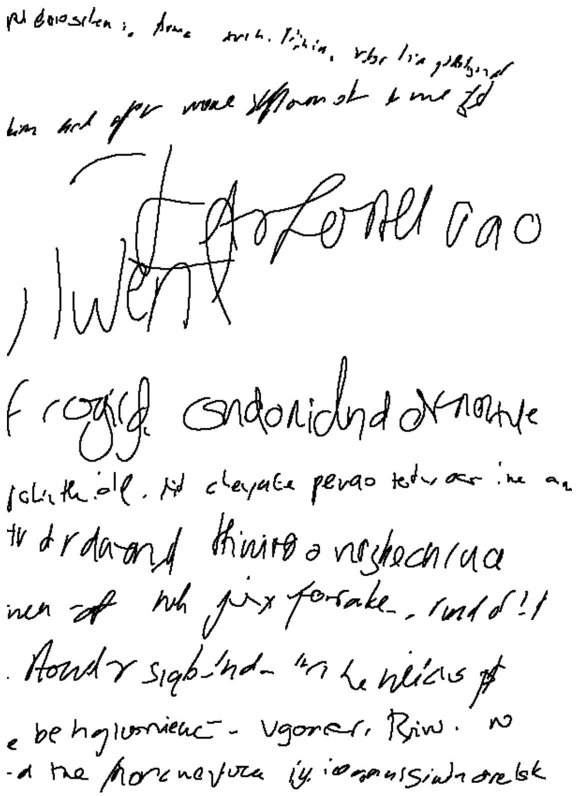


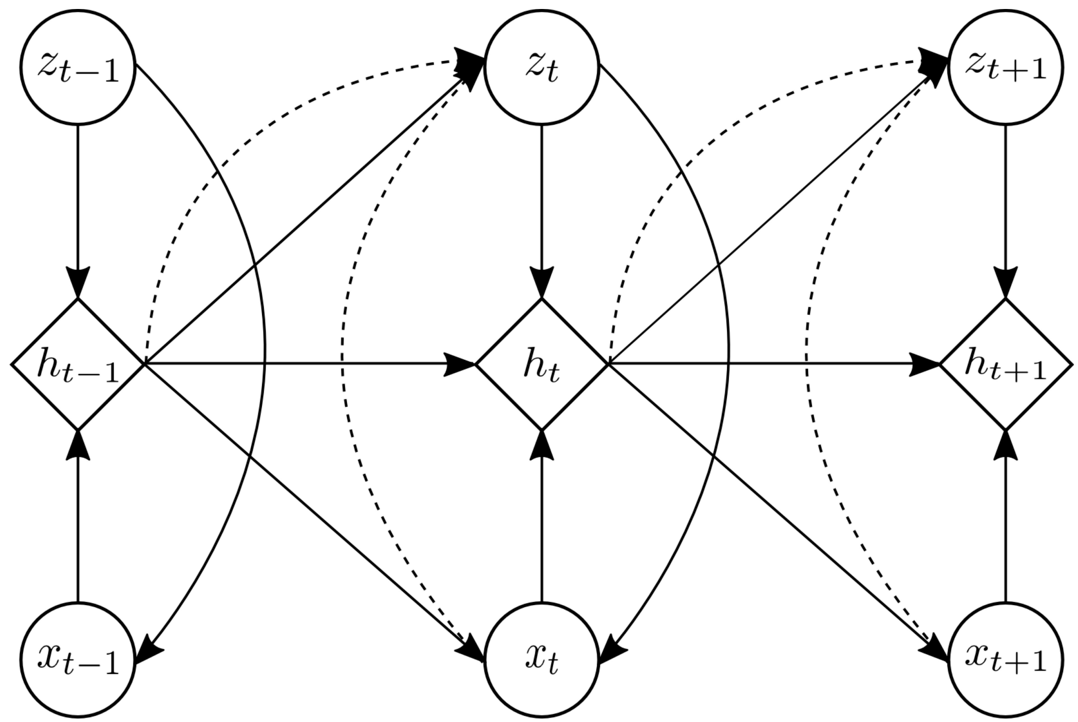
(Krueger et al 2016, submitted)

Variational Generative RNNs

Injecting higher-level variations / latent variables in RNNs

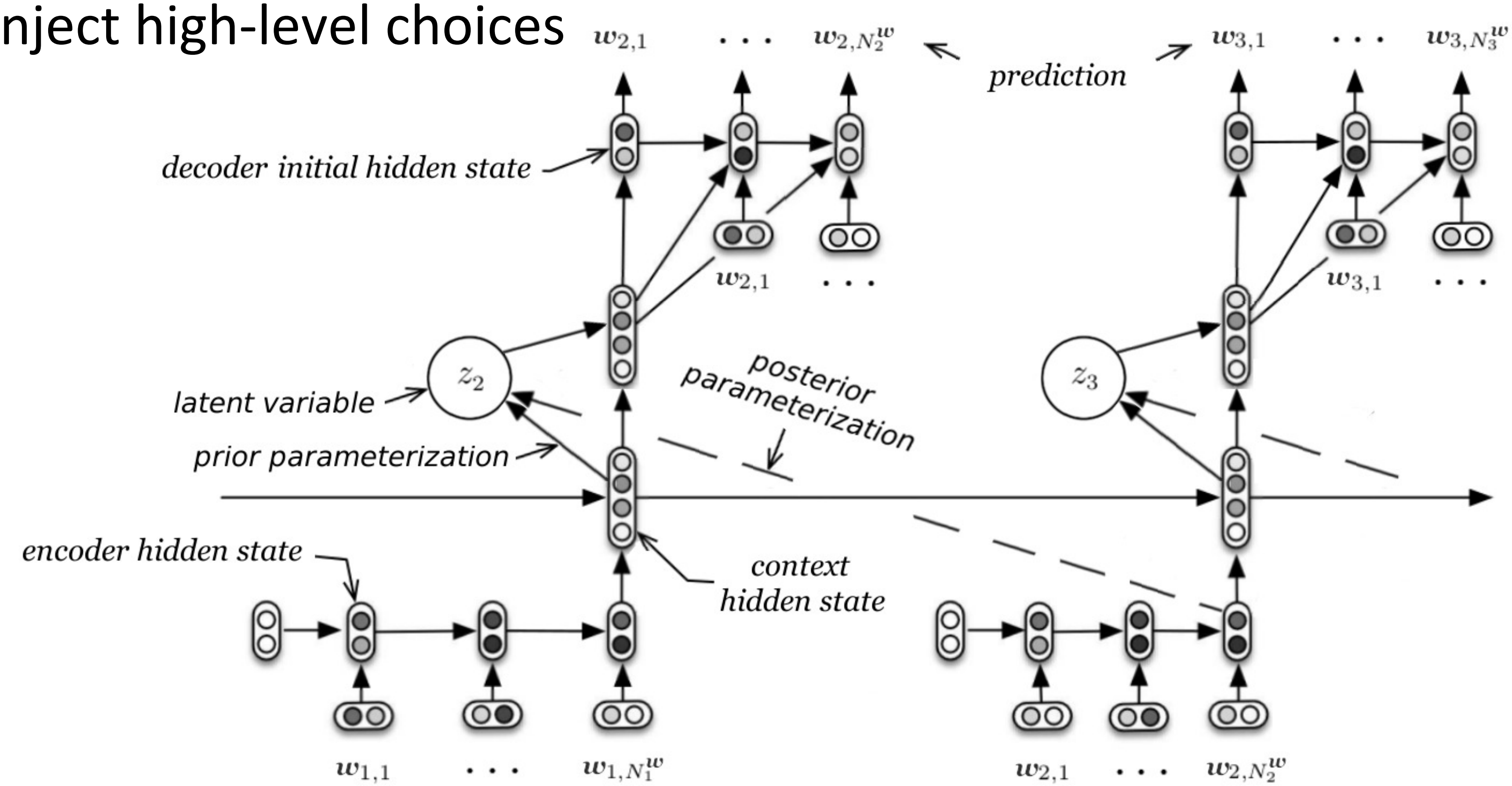
- *(Chung et al, NIPS'2015)*
- Regular RNNs have noise injected only in input space
- VRNNs also allow noise (latent variable) injected in top hidden layer; more « high-level » variability





Variational Hierarchical RNNs for Dialogue Generation (Serban et al 2016)

- Lower level = words of an utterance (turn of speech)
- Upper level = state of the dialogue
- Inject high-level choices



VHRNN Results – Twitter Dialogues

Table 1: Wins, losses and ties (in %) of the VHRED model against the baselines based on the human study on Twitter (mean preferences $\pm$ 90% confidence intervals)

	Short Contexts			Long Contexts		
Opponent	**Wins**	**Losses**	**Ties**	**Wins**	**Losses**	**Ties**
VHRED vs LSTM	32.3 ± 2.4	$\mathbf{42.5 \pm 2.6}$	25.2 ± 2.3	$\mathbf{41.9 \pm 2.2}$	36.8 ± 2.2	21.3 ± 1.9
VHRED vs HRED	$\mathbf{42.0 \pm 2.8}$	31.9 ± 2.6	26.2 ± 2.5	$\mathbf{41.5 \pm 2.8}$	29.4 ± 2.6	29.1 ± 2.6
VHRED vs TF-IDF	$\mathbf{51.6 \pm 3.3}$	17.9 ± 2.5	30.4 ± 3.0	$\mathbf{47.9 \pm 3.4}$	11.7 ± 2.2	40.3 ± 3.4

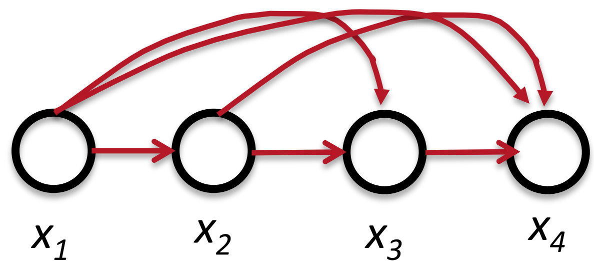
Table 2: Twitter examples for the neural network models. The $\rightarrow$ token indicates a change of turn.

Context	**Response**
jamaica blood!! <url> → lol. yes [name]!. [name]! → what's poppin in toronto homie	**VHRED:** nothing much. just chillin. what's good with you? **LSTM:** something!!!!!!! **HRED:** something!!!!!!
whhhhhhyyyy is it suddenly cold in tallahassee today?? this is florida! how can i dream of the beach when my fingers are icey cold?? → sittin on deck in sun looking at lake travis in austin! enjoying day b4 birthday	**VHRED:** the sun is shining!!! **LSTM:** i know!!!!!!!!! **HRED:** something!!!!!!!
reaches for [name]! → - approaches him warily - hey there buddy. - swings him into the air - how you doin? → tilts his head and your wariness and reaches for your face [name].	**VHRED:** - looks up at you and smiles - you're so cute. - kisses your cheek - **LSTM:** - smiles - i'm fine thank you. how are you? **HRED:** - grins, looking at you as i look at you -
i think i want an ipad2. but i already have an ibook. want vs. need. → if you have an ibook. then you deserve an ipad!	**VHRED:** that's what i'm thinking. i'm going to buy a new one. **LSTM:** i want one!!!! **HRED:** i don't know what to do with it. i don't know what to do.
ah echt? dan anrtwoord ik volgende keer via twitter als je me smst. → haha doe maar p. goed bezig hoor myrthe d → goed bezig? die snap ik even niet p	**VHRED:** haha, ik heb er geen zin in de something, maar ik heb er geen something meer something **LSTM:** haha something something something **HRED:** something something something something something something something something
i love katie waissel more than like, anything in life. → i wanna c the show again! i need <number> meet her again! n i want a b-day tweet nxt week doubt that will happen x	**VHRED:** me too. i'm going to have to wait for her to come back. i'm so excited. **LSTM:** i'm sure she will. i'm sure she'll be fine. **HRED:** i'm sure she'll be fine, i'm sure she'll be fine.
my math teacher over here talkn bout nickels nd i'm tryna make big money i need to be in calculus → lol	**VHRED:** i need to go to the gym and get my hair done lol **LSTM:** lol **HRED:** how u been

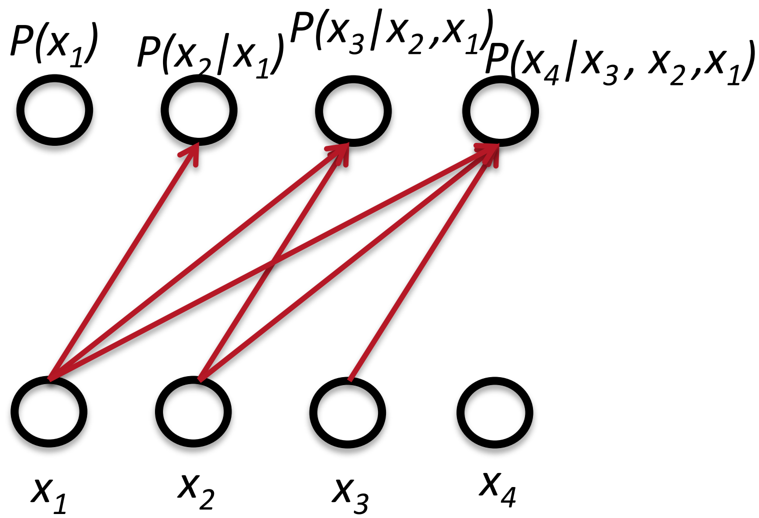
Other Fully-Observed Neural Directed Graphical Models

Neural Auto-Regressive Models

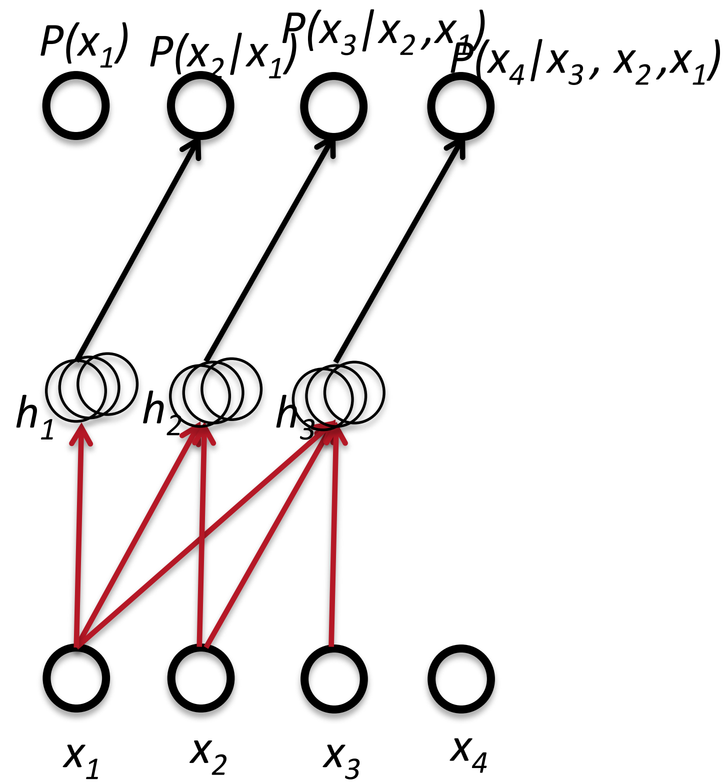
$$P(\mathbf{x}) = P(x_1, \ldots x_T) = \prod_{t=1}^{T} P(x_t | x_{t-1}, x_{t-2}, \ldots x_1)$$



- Decomposes the joint of a fully observed directed model in terms of conditionals
- Logistic auto-regressive: *(Frey 1997)*



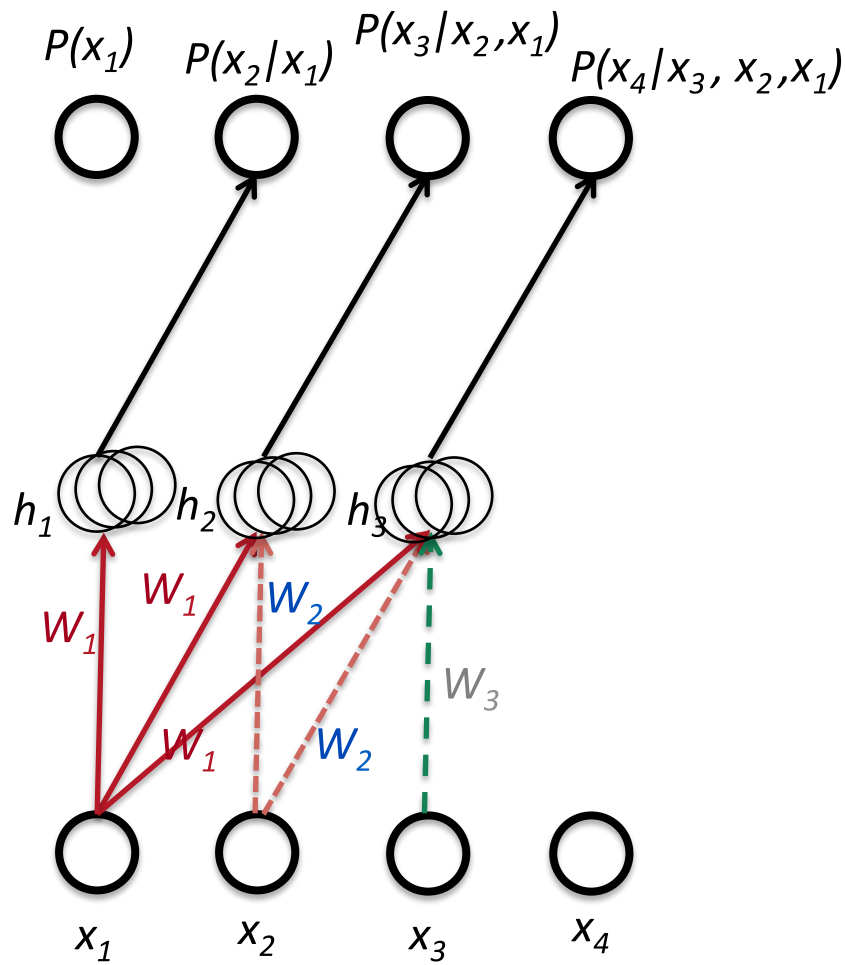
- First neural version: *(Bengio&Bengio NIPS'99)*



NADE: Neural AutoRegressive Density Estimator

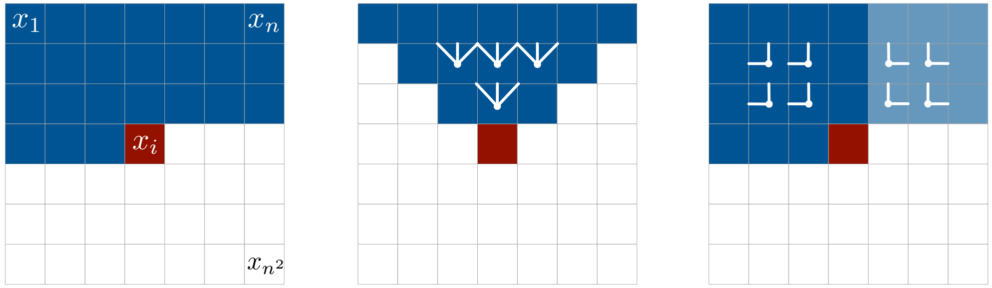
(Larochelle & Murray AISTATS 2011)

- Introduces smart sharing between some weights so that the different hidden groups use the same weights to the same input but look at more and more of the inputs.

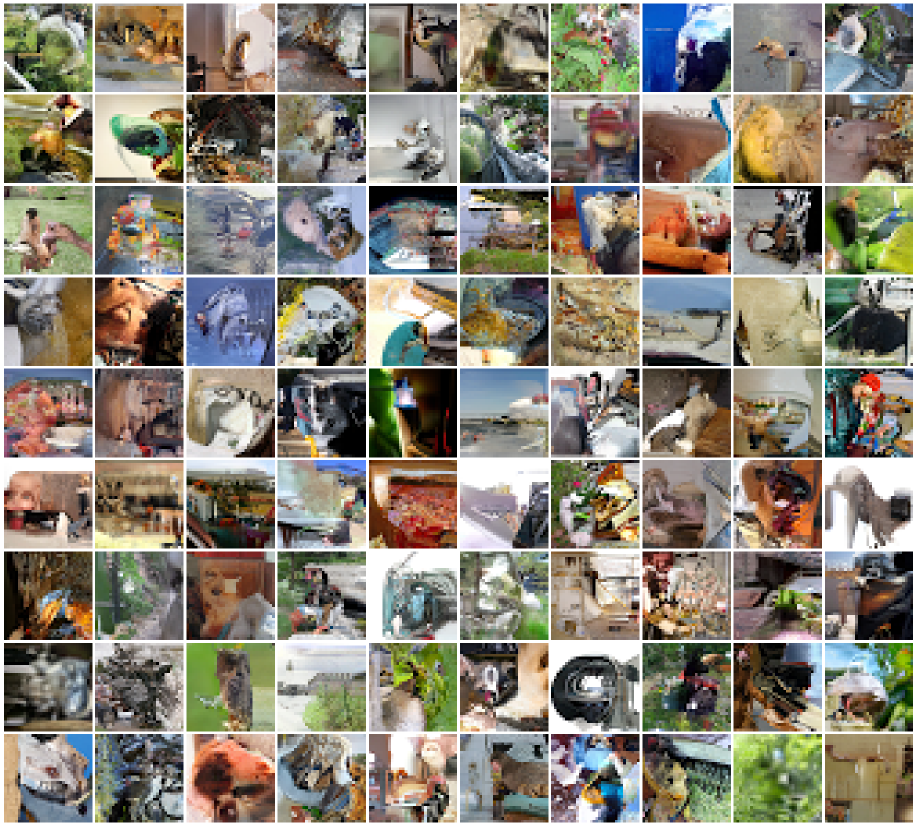


Pixel RNNs

(van den Oord et al ICML 2016, best paper)



- Similar to NADE and RNNs but for 2-D images
- Surprisingly sharp and realistic generation
- Gets texture right but not necessarily global structure



Forward Computation of the Gradient

- BPTT does not seem biologically plausible and is memory-expensive
- RTRL *(Real-Time Recurrent Learning, Williams & Zipser 1989, Neural Comp.)*
  - Practically useful: online learning, no need to store all the past states and revisit history backwards (which is biologically weird)
  - Compute the gradients forward in time, rather than backwards
    - Think about multiplying many matrices left-to-right vs right-to-left
  - **BUT** exact computation is O(nhidden x nweights) instead of O(nweights), to recursively compute dh(t)/dW ← all params
- Recently proposed, *approximate* the forward gradient using an efficient stochastic estimator (rank 1 estimator of dh/dW tensor) *(Training recurrent networks online without backtracking, Ollivier et al arXiv: 1507.07680)*

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