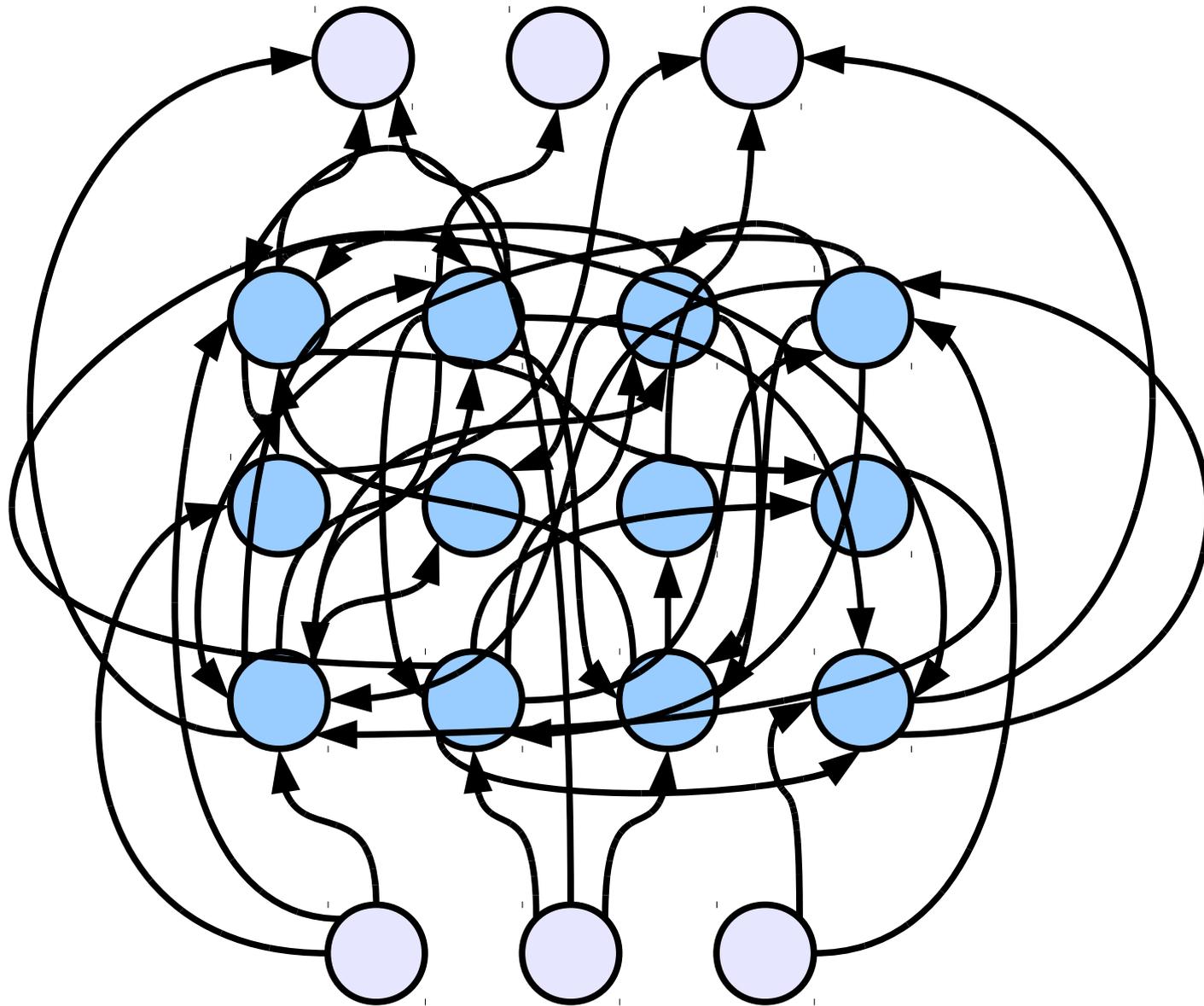


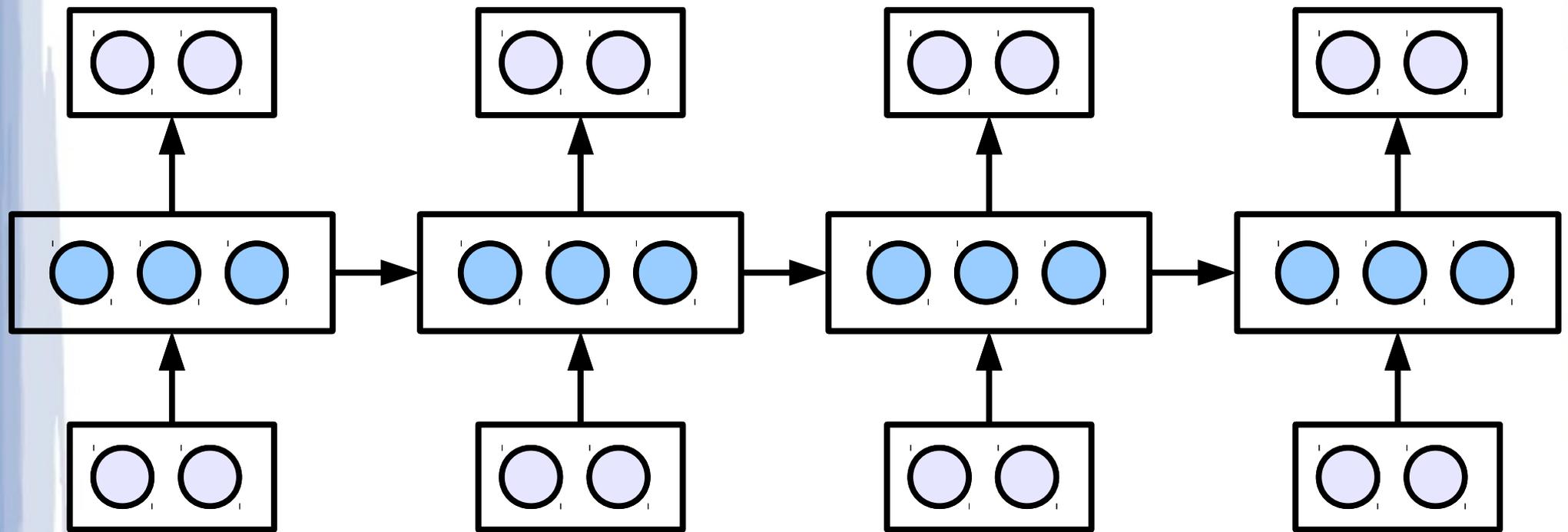
Generating text with Recurrent Neural Networks

Ilya Sutskever
James Martens
Geoff Hinton

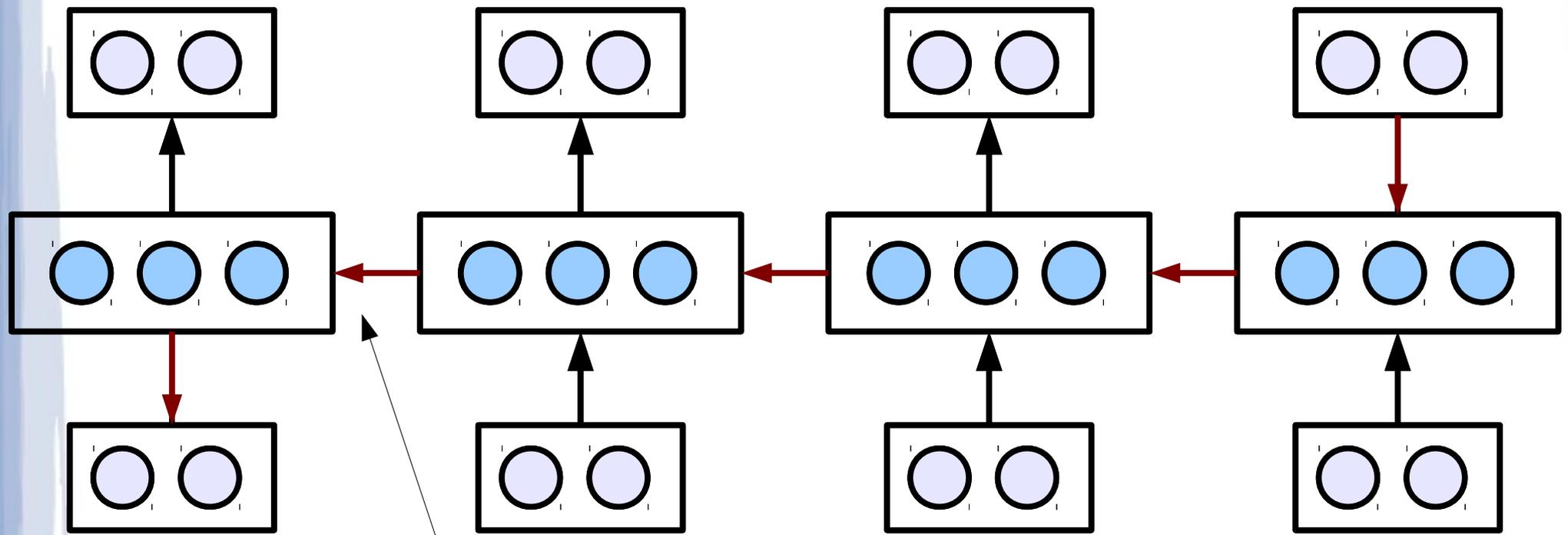
Recurrent Neural Networks



Recurrent Neural Networks



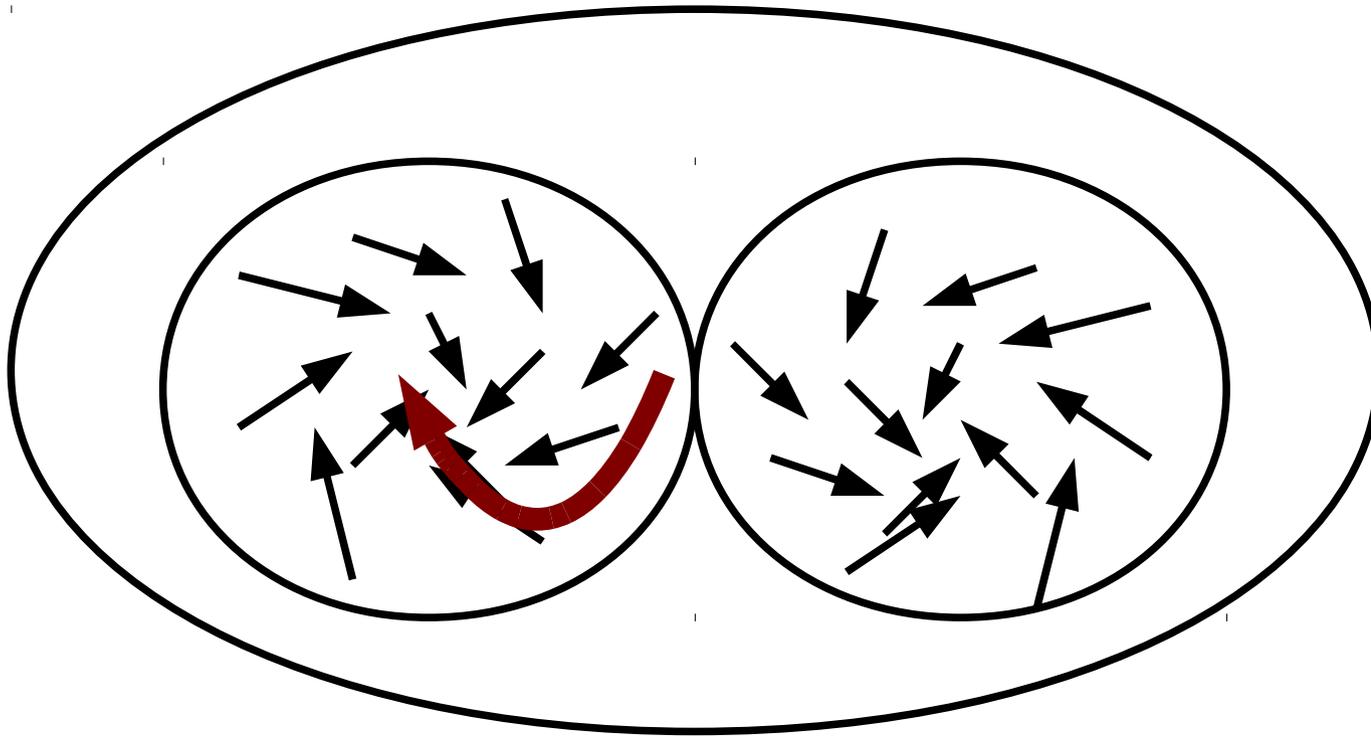
Backprop



Gradient decay / blowup

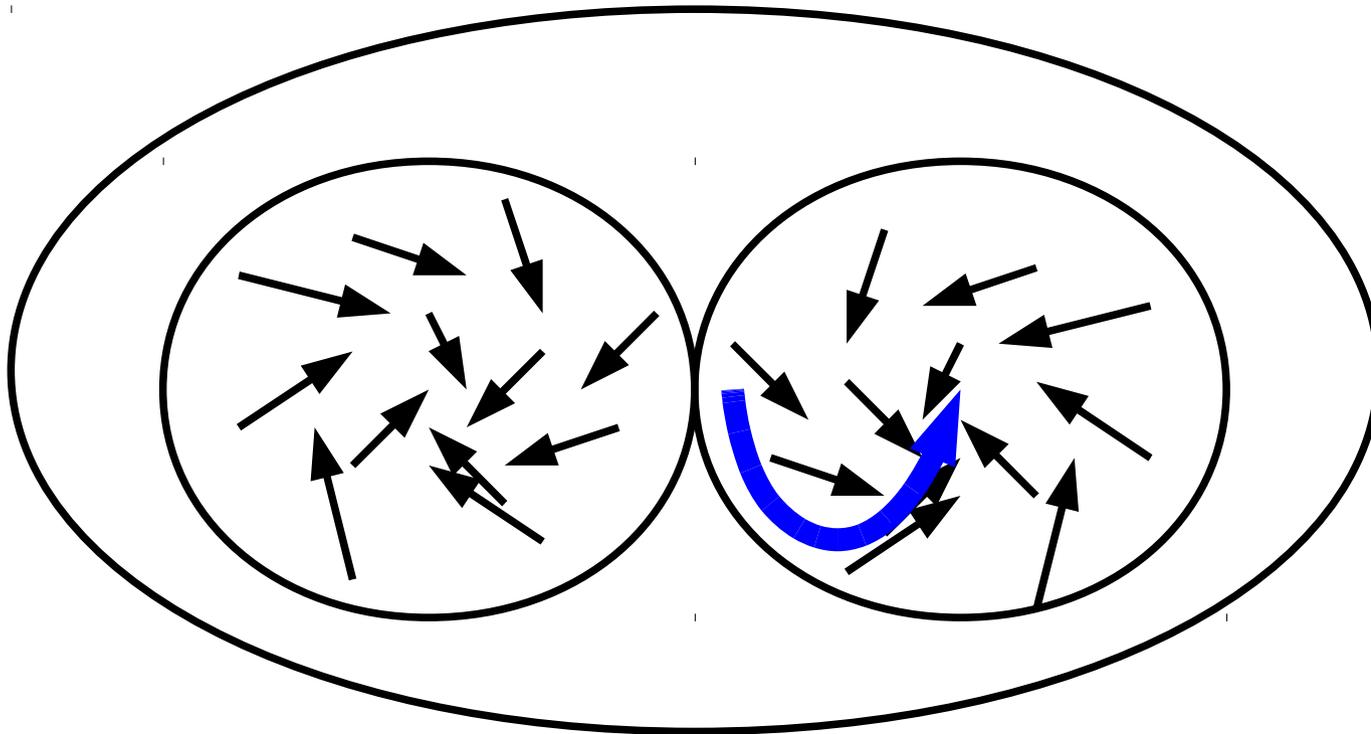
A source of the difficulty

- Tiny gradient



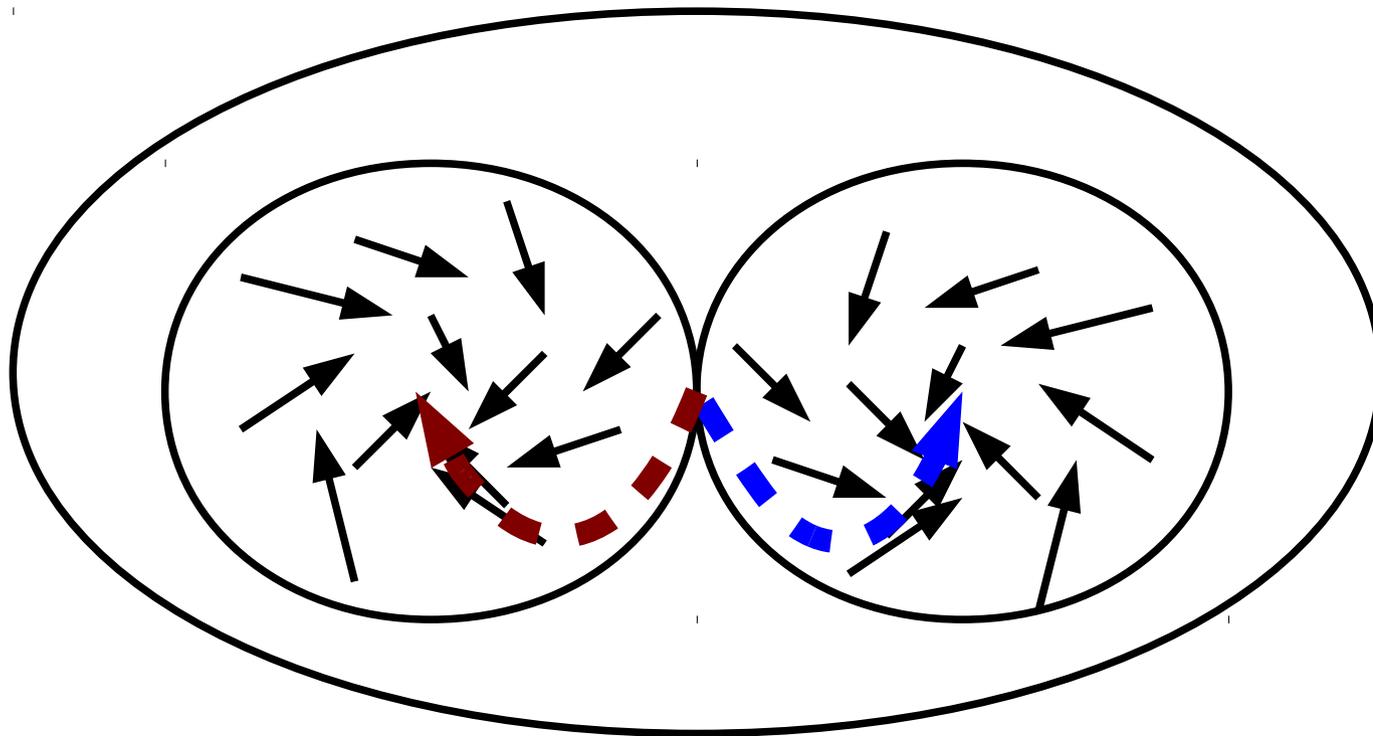
A source of the difficulty

- Tiny gradient



A source of the difficulty

- Giant gradient: instability



Hessian-Free optimization

- A practical large-scale 2nd order optimization technique
- It can optimize RNNs

Hessian-Free optimization

- A remarkable 2nd-order optimization technique
- Partially invert the curvature using linear Conjugate Gradient
 - Only requires matrix-vector products
- Use the **exact** Hessian

$$H v = \frac{\nabla L(\theta + \epsilon v) - \nabla L(\theta - \epsilon v)}{2 \epsilon}$$

Conjugate Gradient

- Conjugate gradient optimizes quadratic functions

$$\frac{\delta^T B \delta}{2} + g^T \delta$$

- Only requires computing Bv products
- At step i , it finds the optimal solution in

$$\text{span}\{g, Bg, B^2g, \dots, B^{i-1}g\}$$

- Converges in N steps or less

Differences from Quasi-Newton methods

- Quasi-Newton: exact minimization on a very crude quadratic approximation
- Hessian-Free: partial minimization on an extremely rich quadratic approximation

Why is HF better than Nonlinear Conjugate gradient?

- Conjugate gradient strongly assumes that the function is quadratic
- Nonlinear CG is a hack: apply CG as is to a nonlinear function and hope for the best
- In contrast, the HF approach says: make the conditions where CG shines

Applying HF optimization to RNNs

- Essentially a straightforward application of Hessian-free optimization
- But it's important to use structural damping:
 - Normal damping asks the parameters to not change too much
 - Structural damping asks internal variables to not change too much

Structural damping

- Take our quadratic approximation, and add a nonlinear objective that doesn't want the hidden state sequence to change
- Then use a quadratic approximation of this term
 - Must do so for CG to be applicable
- The resulting can be obtained with no extra work!

Character-level language modelling

- RNNs were, until now, impossibly hard to optimize
- Hessian-Free optimization is really powerful and can optimize RNNs

Dataset	RNN	Memoizer
WIKI	1.60	1.66
NYT	1.49	1.48
ML	1.33	1.31

The 500-timesteps multiplication problem

- Shows that the Hessian-Free optimizer has little problem with Long-Term dependencies

← 10 timesteps →

0	0	1	0	0	0					0	1	0	0	0	0
0.2	0.4	0.1	0.8	0.5	0.7					0.2	0.1	0.8	0.3	0.3	0.1

← 500 timesteps →

- Cannot be solved without structural damping

Major application

- Train an RNN with 2000 units to predict the next character in Wikipedia

