Time series prediction

- Given measurements of a time series x(k) at time points k,k-1,k-2,k-3,…,k-n, find an estimate $\hat{x}(k+1)$ of x(k+1).

- Applications in macroeconomics, finance, meteorology, geology, health care etc.

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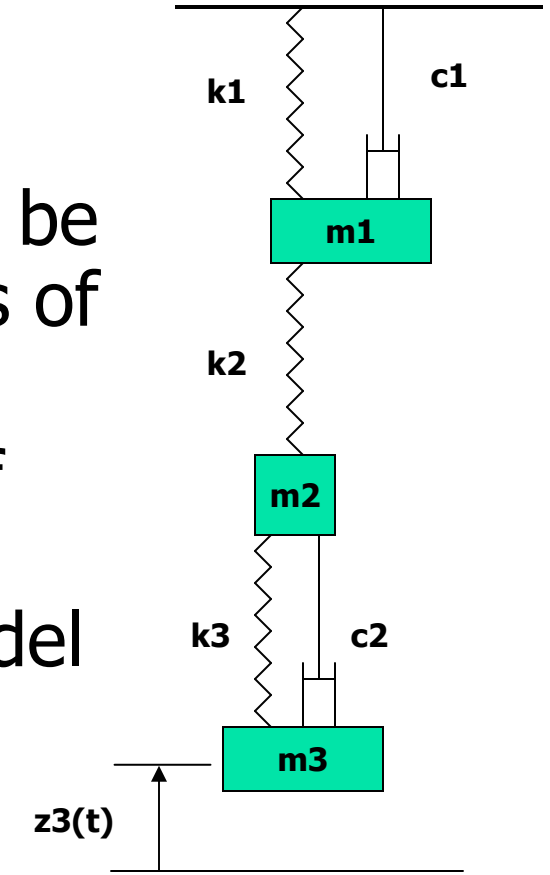
Model-based prediction

- In many cases, e.g. mechanical systems, a model of the system can often be generated. All that need to be determined then are the parameters of the model.
- In other cases, e.g. for prediction of weather, financial data etc., it is generally difficult to find a good model of the system => use e.g. ANN.



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Data set example

DJIA1971_1974
4 1

0.543400	0.576571	0.538600	0.536514	0.452657
0.576571	0.538600	0.536514	0.452657	0.430314
0.538600	0.536514	0.452657	0.430314	0.445771
0.536514	0.452657	0.430314	0.445771	0.516886
0.452657	0.430314	0.445771	0.516886	0.594714
0.430314	0.445771	0.516886	0.594714	0.607857
0.445771	0.516886	0.594714	0.607857	0.602857
0.516886	0.594714	0.607857	0.602857	0.594914
0.594714	0.607857	0.602857	0.594914	0.540886
0.607857	0.602857	0.594914	0.540886	0.554229
0.602857	0.594914	0.540886	0.554229	0.554029
0.594914	0.540886	0.554229	0.554029	0.499571
0.540886	0.554229	0.554029	0.499571	0.435343

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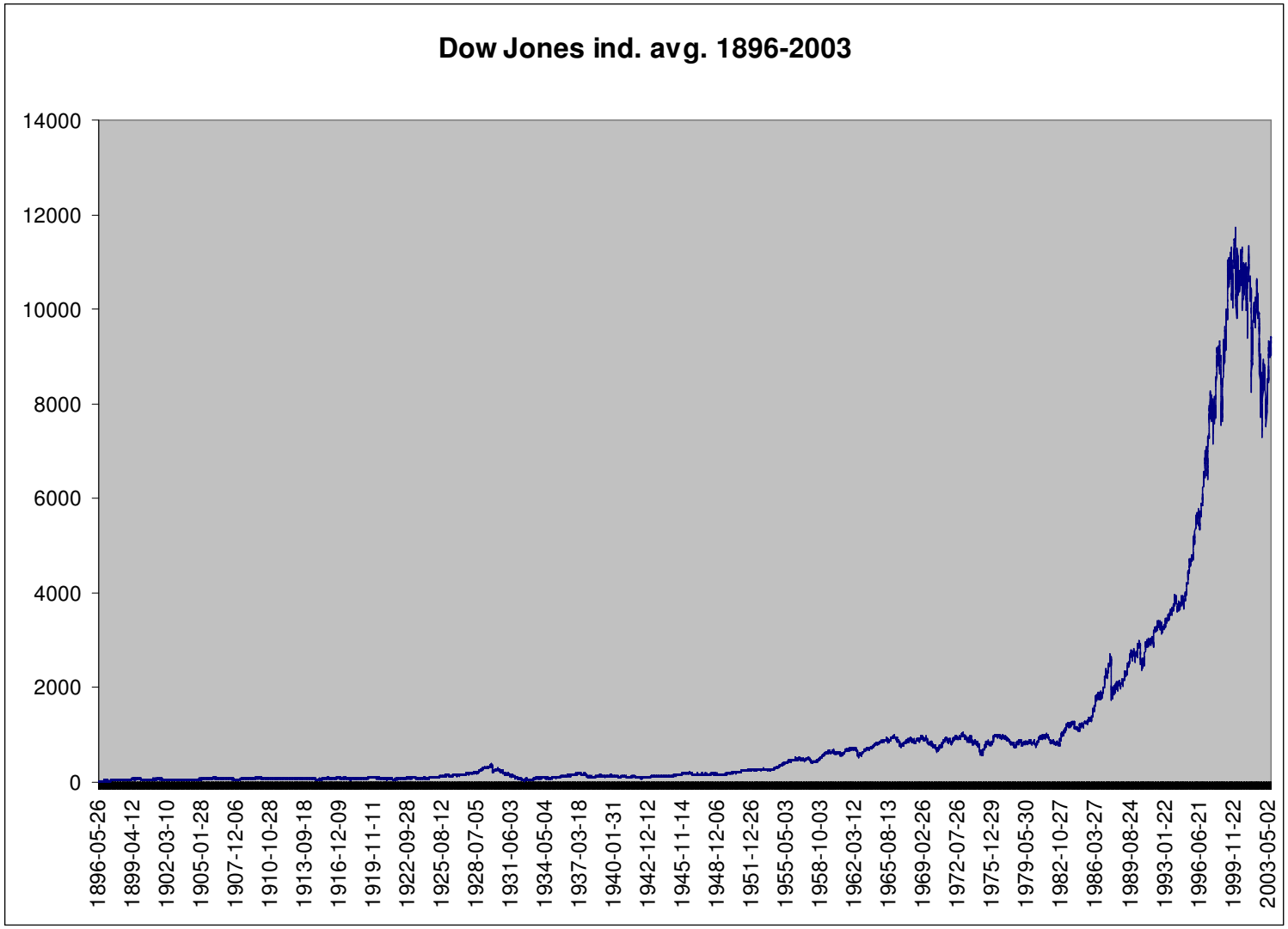

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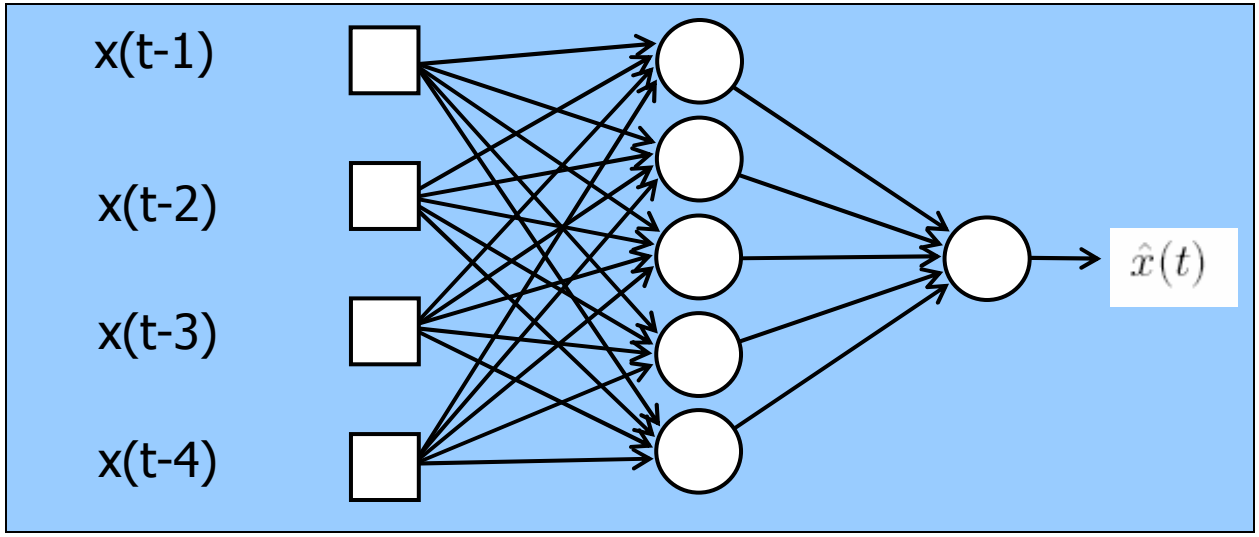
Using FFNN for prediction

- Common method:

  FFNN + backpropagation



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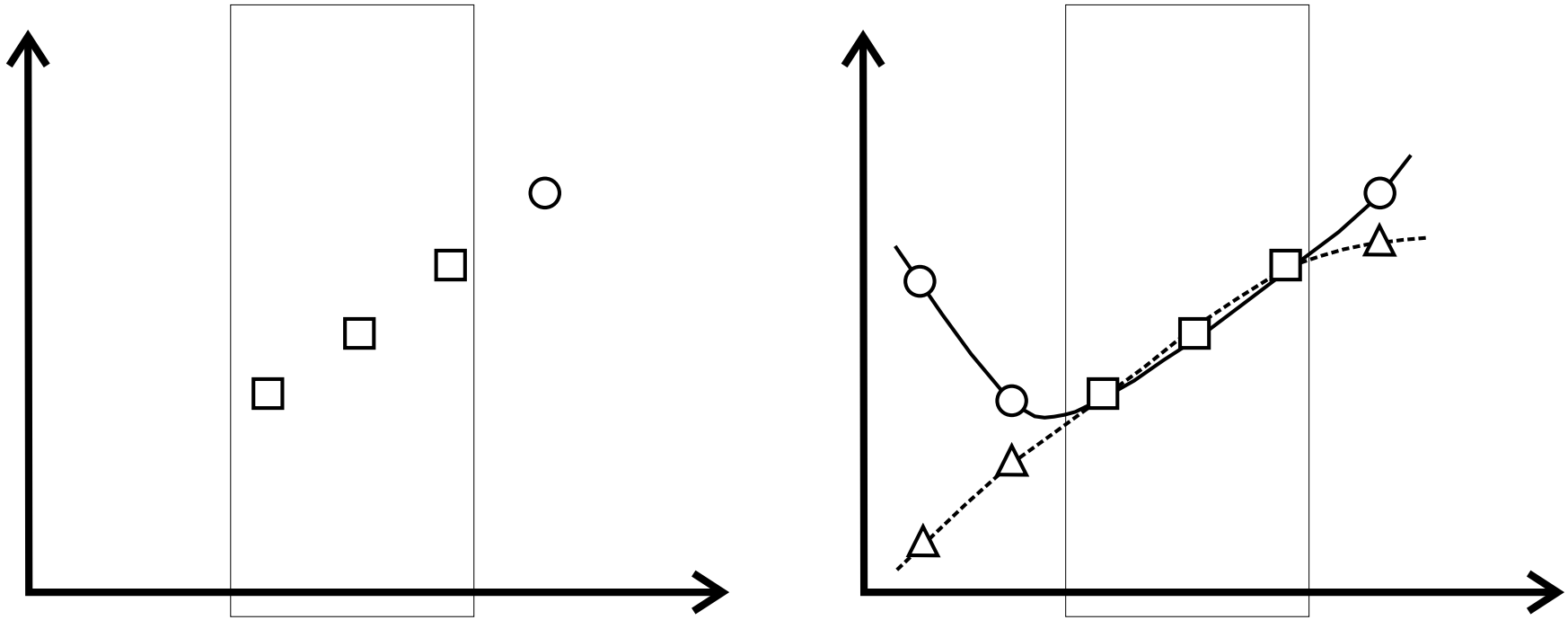
Problem: no dynamic memory



Also: fixed network structure if backpropagation is used – the chosen structure can turn out not to be optimal.

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Using RNN for prediction

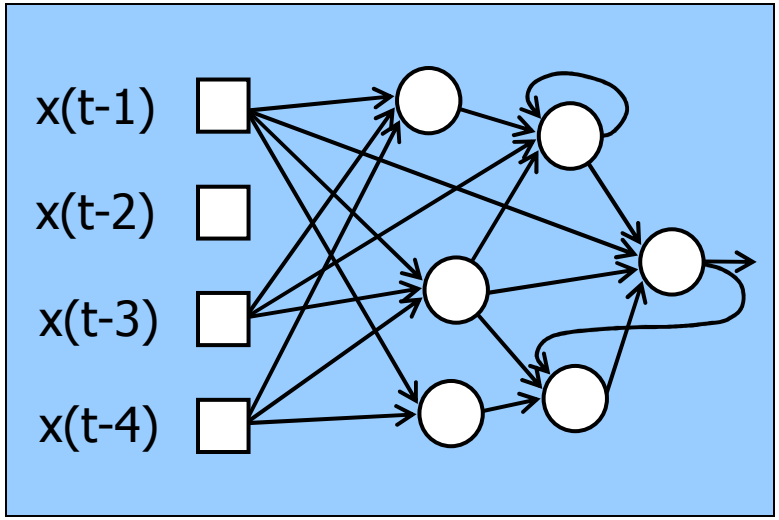
- Both problems can be solved if instead an RNN is used.

- Additional problems:

  (1) Signal flow through the RNN

  (2) Setting the structure

  (3) Training



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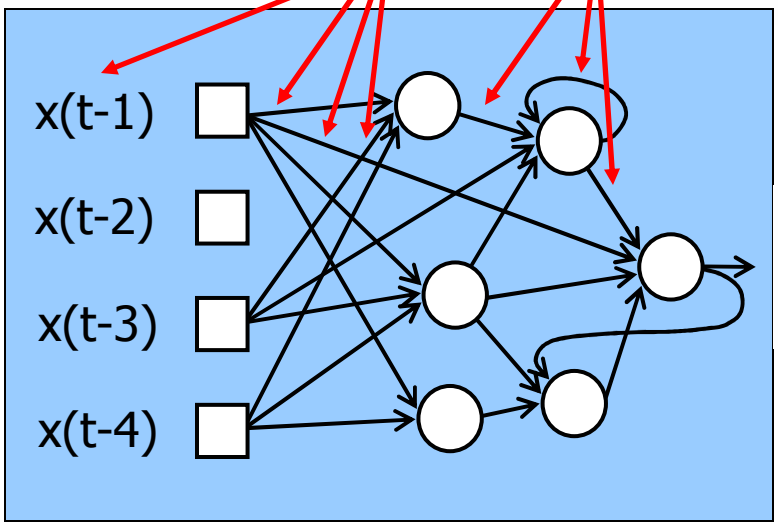
Using RNN for prediction

- Signal flow: use continuous-time dynamics

$$\tau_i \dot{y}_i + y_i = \sigma\left(b_i + \sum_j w_{ij}^{\mathrm{IN}} I_j + \sum_j w_{ij} y_j\right), \quad i = 1, \ldots, n$$



$$e_{\mathrm{RMS}} = \sqrt{\frac{1}{N-L+1}\sum_{j=L}^{N}(\hat{X}(j) - X(j))^2}$$

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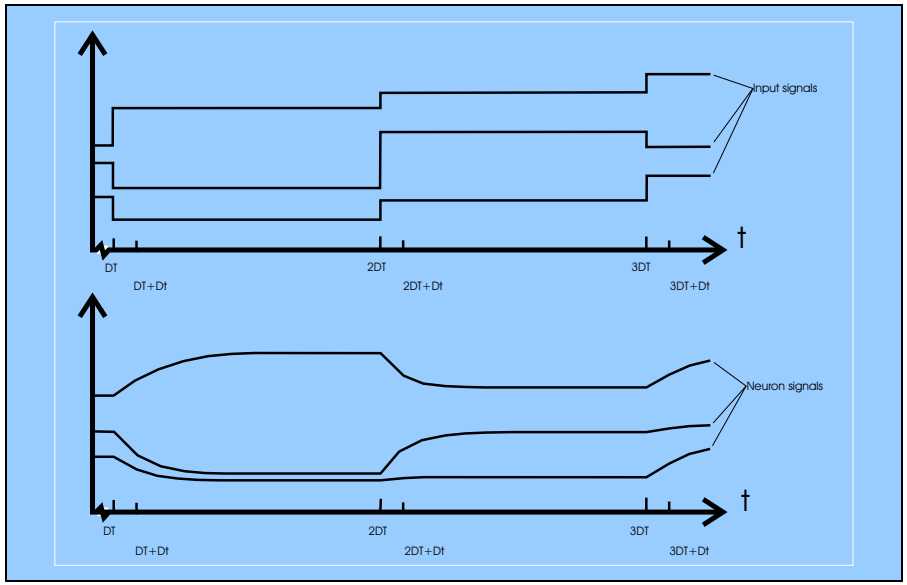
Using RNN for prediction

- The continuous-time dynamics unfolds (within the RNN) between successive inputs



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Using EA for generating RNN

- Problem: slow to evolve from scratch (if arbitrary network structure is allowed)

- Solution: First generate an FFNN using backpropagation, *then* apply an EA (starting from the FFNN), to generate an RNN.

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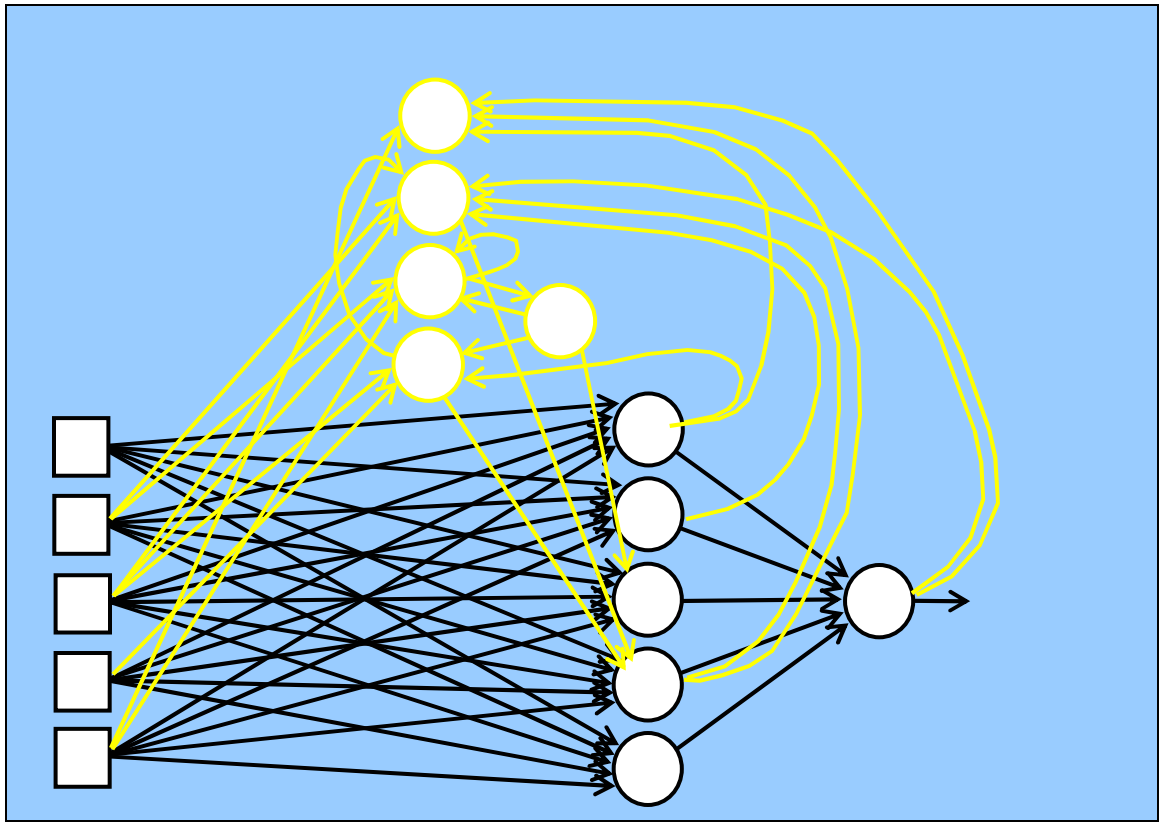
Illustration of the procedure



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Methods (summary)

(1) FFNN + Backpropagation

(2) EA + RNN (from random initiation)

(3) EA + RNN (from FFNN, generated using backpropagation)

(4) Naive predictor: $\hat{x}(t+1) = x(t)$

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Time series types

- Original series
- Difference series $x_{\mathrm{d}}(t) = x(t+1) - x(t)$
- Relative difference series $x_{\mathrm{d}}(t) = \dfrac{x(t+1) - x(t)}{x(t)}$

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Results (best predictors)

Series	FFNN	RNN (from random)	RNN (from FFNN)
USD-JPY	2.20%	1.93%	3.12%
USD-JPY (d)	2.42%	4.39%	4.01%
US unempl.	1.19%	5.50%	4.68%
US unempl. (d.)	2.04%	4.09%	4.12%
DJIA (r.d.)	5.08%	6.01%	6.00%

(All results shown were obtained on the *validation* data. The percentages indicate the improvements relative to a naive predictor, $\hat{x}(t+1) = x(t)$)

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Results: average and st.dev.

Series	FFNN	RNN (from random)	RNN (from FFNN)
USD-JPY	1.38% 1.15%	-2.15% 6.43%	2.37% 0.62%
USD-JPY (d)	1.68% 0.50%	2.64% 1.52%	3.44% 0.30%
US unempl.	-2.37% 2.21%	2.18% 1.84%	3.07% 0.71 %
US unempl. (d.)	0.44% 0.94%	3.33% 0.51%	3.74% 0.31%
DJIA (r.d.)	4.37% 0.47%	5.09% 0.50%	5.72% 0.16%

(Improvements are measured relative to a naive predictor, $\hat{x}(t+1) = x(t)$)

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Conclusions

- RNNs generated by EAs (either starting from a random initial population or an FFNN) consistently outperform FFNNs and naive predictors. Thus short-term memory appears to be crucial.
- The improvements compared to the naive predictor are rather small, but significant (and consistent).
- The method of first generating an FFNN and then evolving an RNN generates better results on average, an in *much shorter time* than evolution from a random initial population.

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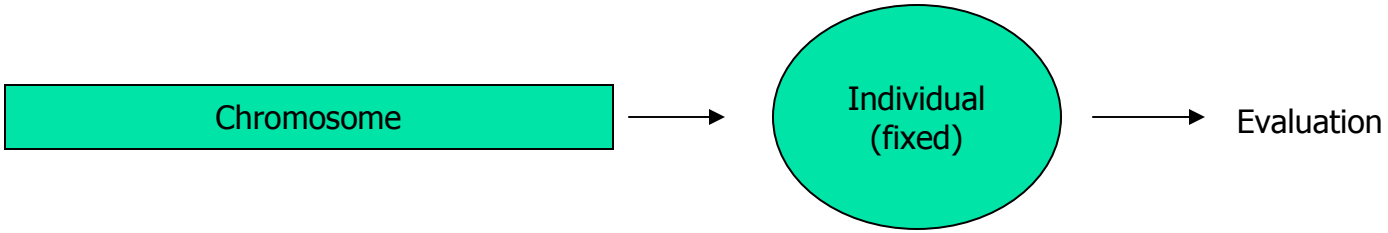
Evolution of learning rules in ANN

- Normal GA operation: fixed individual decoded from genome



- By contrast, biological organisms (even simple ones) are capable of *learning*.

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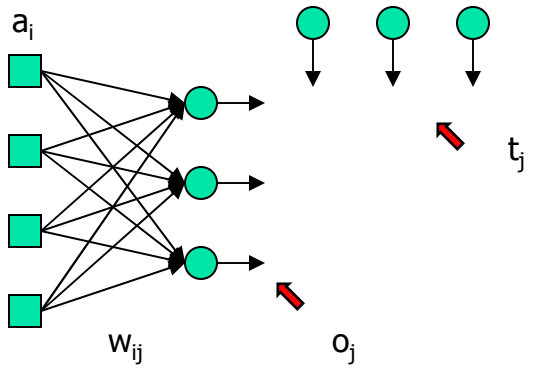
Evolution of learning rules in ANN

- An example of the evolution of learning: Chalmers (1990) http://citeseer.ist.psu.edu/chalmers90evolution.html
- Chalmers evolved learning rules for feedforward, single-layer neural networks



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Evolution of learning rules in ANN

- The delta rule:

$$\Delta w_{ij} = \eta(t_i - o_i)a_j$$

- Chalmers' representation:

$$\Delta w_{ij} = k_0(k_1 w_{ij} + k_2 a_j + k_3 o_i + k_4 t_i + k_5 w_{ij} a_j + k_6 w_{ij} o_i + k_7 w_{ij} t_j + k_8 a_j o_i + k_9 a_j t_i + k_{10} o_i t_i)$$

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Evolution of learning rules in ANN

- Encoding scheme:

11011 000 000 000 000 000 000 010 110 000

$k_0 = 2^{j-1}$ if $j > 0$, otherwise 0 (four last bits used for j ([0,15]), the first bit encodes the sign.

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Evolution of learning rules in ANN

- Rules were applied to networks with 2-7 inputs and one output.
- The rules encoded by the chromosomes were applied to a number of different input-output mappings
- The evolved best rules were essentially versions of the delta rule, e.g.

$$\Delta w_{ij} = 8(t_i - o_i)(a_j - 0.5)$$

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Evolution of learning rules in ANN

- More advanced example (multi-layer networks), see Radi and Poli (2002), http://citeseer.ist.psu.edu/radi02discovering.html

$$\Delta w_{ij}^{l}(s) = \begin{cases} F_o(w_{ij}^{l}, o_{jp}^{l}, t_{ip}, o_{ip}^{l+1}) & \text{for the output layer,} \\ F_h(w_{ij}^{l}, o_{jp}^{l}, o_{ip}^{l+1}, \varepsilon_{ip}^{l+1}) & \text{for the hidden layers} \end{cases}$$

- Evolution in two stages: first evolve learning rules for the output layer, using standard backprop (SBP) for the hidden layer, and then evolving the rules for the hidden layer

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Evolution of learning rules in ANN

- Modified (compared to SBP) rules were found that outperformed SBP – see the paper for details. Example:

Vowel			
Algorithm	N	% of success	Std. Dev.
SBP	8	32	2.1
SBP	12	39	1.8
SBP	16	45	1.6
SBP	24	49	1.3
SBP	32	50	1.1
$NLR_o + NLR_h$	8	48	1.5
$NLR_o + NLR_h$	12	50	1.2
$NLR_o + NLR_h$	16	58	1.1
$NLR_o + NLR_h$	24	63	1.0
$NLR_o + NLR_h$	32	65	1.0

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Reconstruction of extinct animals in the computer

- ALIFE VI, 1998
  http://alife6.alife.org/abstracts/RE29.html
- The authors tried to recreate the motion patterns of an extinct (530 Myr) animal (*Anomalocaris*)

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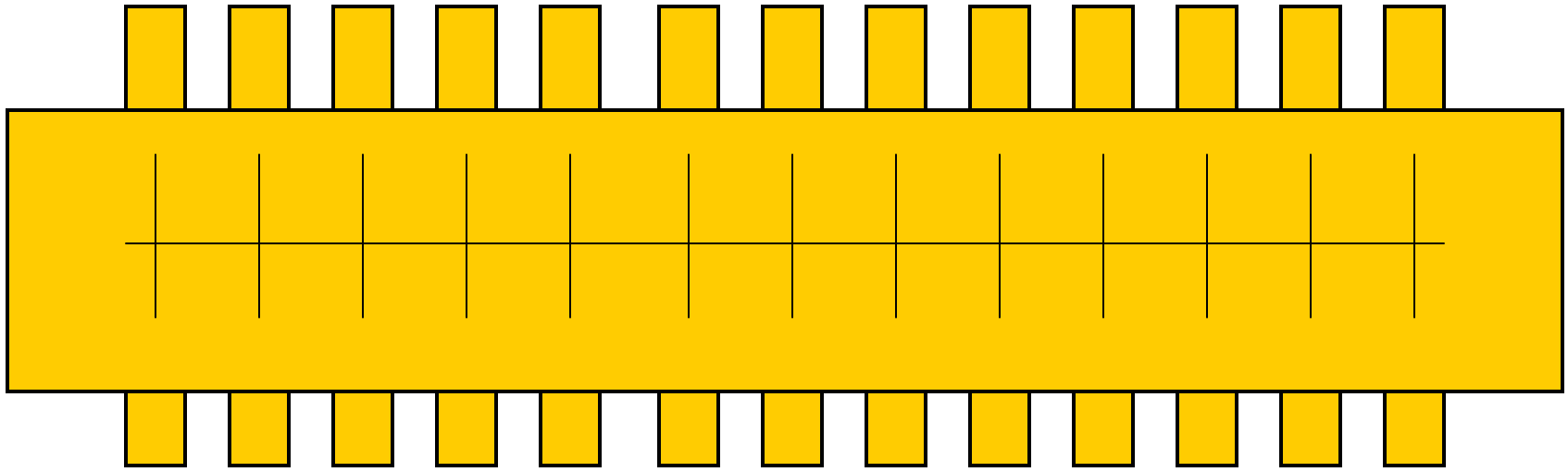
Reconstruction of extinct animals in the computer

- Representation of the body:



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Reconstruction of extinct animals in the computer

- The artificial animal moved in a simplified hydrodynamical model.
- The force in each joint varied according to a trigonometric rule.
- Fitness measure: Motion speed
- Wave-like swimming patterns (similar to those of a stingray) were found to be most efficient

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