Neural Networks dependence on time

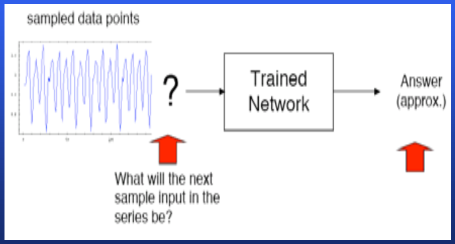
Topic 8

Note: lecture notes by Bob Keller (Harvey Mudd College, CA) are used

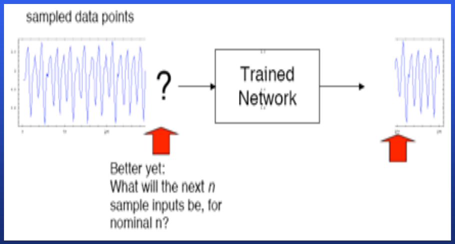
Main idea: include time dynamics into NN models

- So far NN have been a combinational input pattern presented at once
- How to include into the models time?
- We want to consider cases where network inputs and learned behaviour can include functions of time

Example: Time series or problems of future prediction



Example: Time series or problems of future prediction

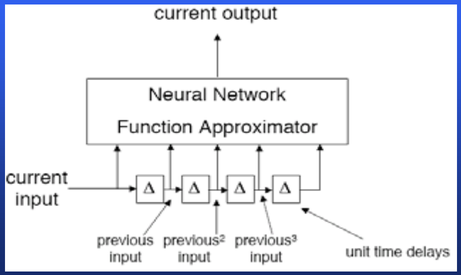


sampled data points
?
Trained Network
Better yet: What will the next *n* sample inputs be, for nominal n?

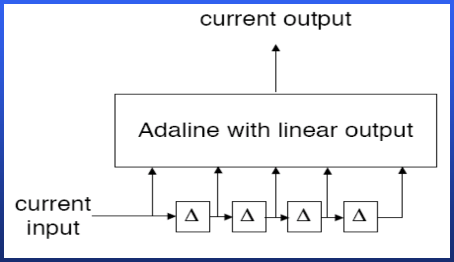
Applications

Signal processing
Sun-spot prediction
Predict the degradation of the ozone layer
Market analysis

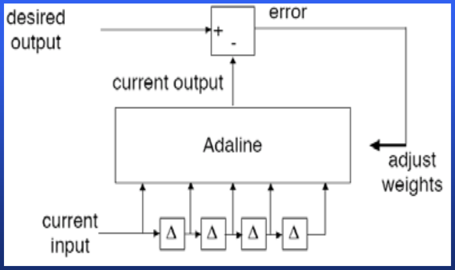
Learning to mimic



Example: Adaline Mimic



Example: Training Adaline Mimic



Training Adaline Mimic

- Recall the Adaline training rule:
  Δ**W** = η . (desired - actual output) . **input**
- Here input vector is the current input, along with all the delayed inputs (one per weight)
- An Adaline is trained to mimic a specific input-output behavior.
- The output is an attenuated version of the input.
- When subsequently presented with the input, the output is observed and the error computed.

Applications in training: Matlab

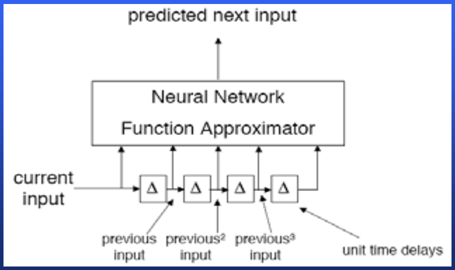
% DEFINE THE NETWORK
% NEWLIN generates a linear network.
% We will use a learning rate of 0.5, and two
% delays in the input. The resulting network will predict the next value of the target signal using the last two values of the input.
- lr = 0.5;
- delays = [0 1];
- net = newlin(minmax(cat(2,P{:})),1,delays,lr);

% ADAPTING THE LINEAR NEURON
% ADAPT simulates adaptive linear neurons. It takes the initial network, an input signal, and a target signal, and filters the signal adaptively. The output signal and the error signal are returned, along with new network.
% Adapting begins...please wait...
- [net,y,e]=adapt(net,P,T);

On-line training

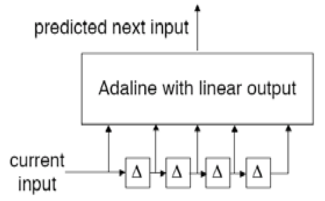
- The Adaline Predictor can be trained **during operation**.
- At each time step, one set of weight modifications can be made.
- After a transient, the network learns to mimic the desired behavior.

How to learn to predict?

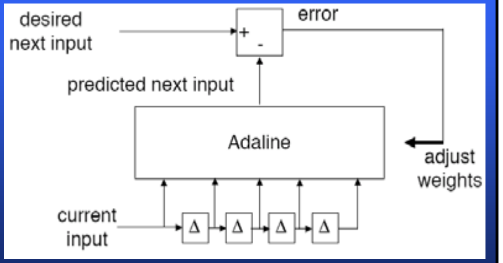


Example: Adaline predictor

The predictor is like a mimic, where the next input is what is to be mimicked.

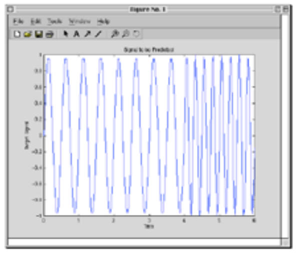


Example: Adaline predictor training



Example: Adaline predictor training

signal to be predicted (2 sine waves of different frequencies)



Example: Adaline predictor training

% DEFINING A WAVE FORM

% TIME1 and TIME2 define two segments of time.

- time1 = 0:0.05:4; % from 0 to 4 seconds, steps of .05
- time2 = 4.05:0.024:6; % from 4 to 6 seconds, steps of .05

% TIME defines all the time steps of this simulation.

- time = [time1 time2]; % from 0 to 6 seconds

% T defines a signal which changes frequency once:

- T = con2seq([sin(time1*4*pi) sin(time2*8*pi)]);

% The input P to the network is the same as the target.

% **The network will use the last five values of the target to predict the next value.**

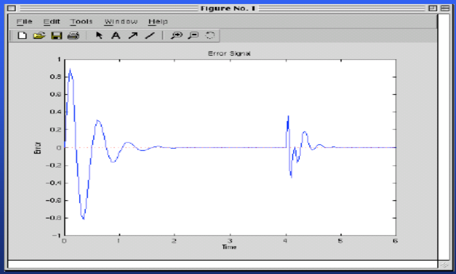
Example: Adaline predictor training

% NEWLIN generates a linear network.

% We will use a learning rate of 0.1, and five delays in the input. The resulting network will predict the next value of the target signal using the last five values of the target.

- lr = 0.1;
- delays = [1 2 3 4 5];
- net=newlin(minmax(cat(2,P{:})),1,delays,lr);

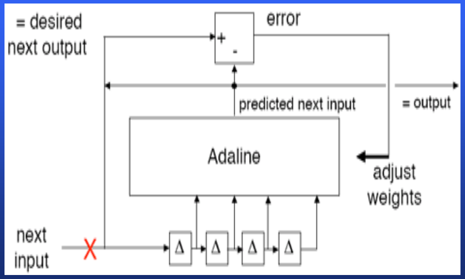
Error = target - output



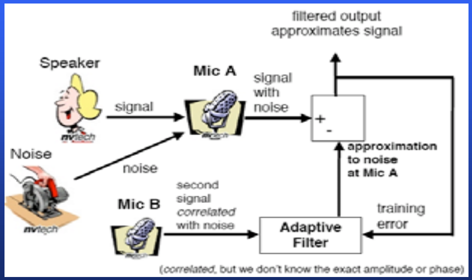
Once the network has been trained

- It can use its own output as the next input.
- That is, it can “run free”, predicting the full output **sequence.**
- Since the output was only an approximation, the accuracy of the predicted output will deteriorate with time.

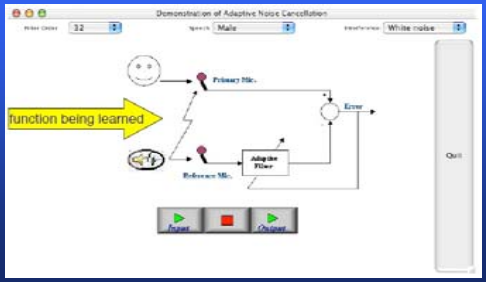
Free – running mode



Noise-Reduction Scenario Filter Learns to Predict the Noise


filtered output approximates signal
Speaker
signal
Mic A
signal with noise
+
-
approximation to noise at Mic A
Noise
noise
Mic B
second signal *correlated* with noise
Adaptive Filter
training error
(*correlated*, but we don't know the exact amplitude or phase)

ANC Audio Demo from Ariz. State Univ. http://www.eas.asu.edu/~dsp/grad/anand/java/ANC/ANC.html

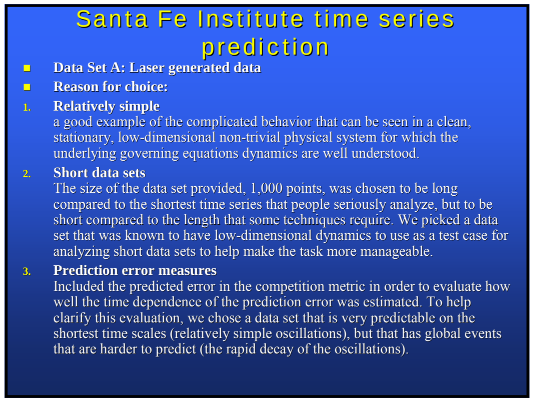


Filters

- Classical filters don’t adapt (Lowpass / Highpass / Bandpass) filters
- Adaptive filters adapt
- LMS filter (least-mean-squared)
- RLS filter (recursive least squares, based on pseudo-inverse, not as stable)
- Kalman filter (based on a stochastic state space model)
- Filter form is also called a **FIR** (Finite Impluse Response) filter.
- In statistics, it is called an **MA** (Moving Average) filter.

Santa Fe Institute time series prediction

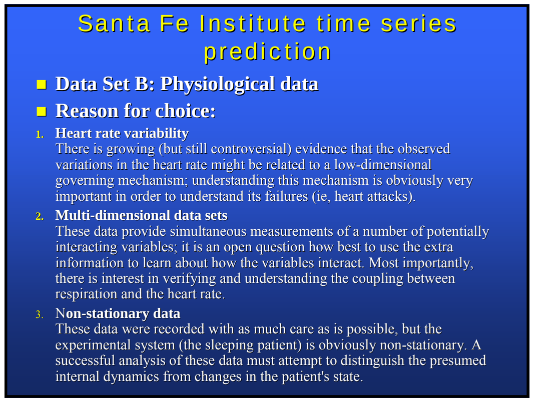
- Available at http://www-psych.stanford.edu/~andreas/Time-Series/SantaFe.html
- **contains descriptions of the 6 data sets (A, B, C, D, E and, F) that were used in the Santa Fe Competition, directed by Neil Gershenfeld (now at MIT's Media Lab) and Andreas Weigend (now at NYU's Stern School of Business).**
- The competition is described in the 650 page book ($58 at amazon.com) *Time Series Prediction: Forecasting the Future and Understanding the Past.* A. S. Weigend and N. A. Gershenfeld, eds. Reading, MA: Addison-Wesley, 1994.
- The information distributed through ftp on the Internet in 1991, and html-ized in 1994.



Santa Fe Institute time series prediction

- **Data Set A: Laser generated data**
- **Reason for choice:**

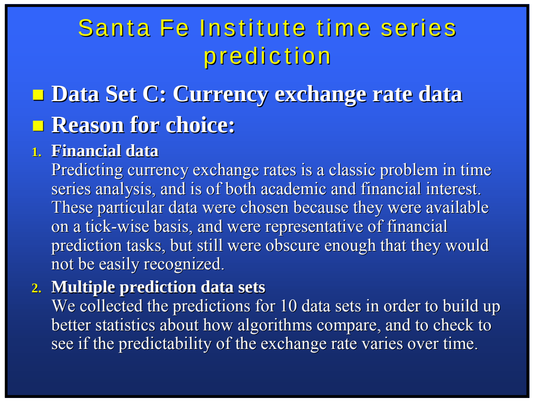
1. **Relatively simple**
   a good example of the complicated behavior that can be seen in a clean, stationary, low-dimensional non-trivial physical system for which the underlying governing equations dynamics are well understood.
2. **Short data sets**
   The size of the data set provided, 1,000 points, was chosen to be long compared to the shortest time series that people seriously analyze, but to be short compared to the length that some techniques require. We picked a data set that was known to have low-dimensional dynamics to use as a test case for analyzing short data sets to help make the task more manageable.
3. **Prediction error measures**
   Included the predicted error in the competition metric in order to evaluate how well the time dependence of the prediction error was estimated. To help clarify this evaluation, we chose a data set that is very predictable on the shortest time scales (relatively simple oscillations), but that has global events that are harder to predict (the rapid decay of the oscillations).



Santa Fe Institute time series prediction

- **Data Set B: Physiological data**
- **Reason for choice:**

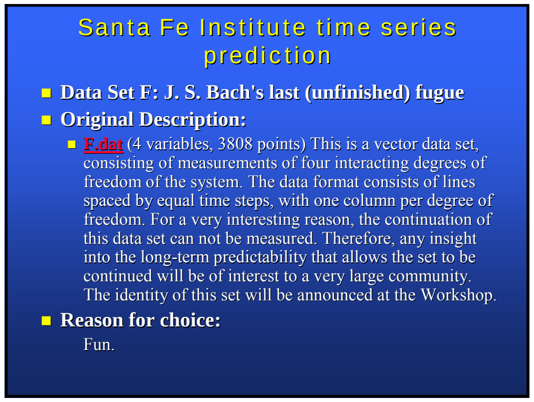
1. **Heart rate variability**
   There is growing (but still controversial) evidence that the observed variations in the heart rate might be related to a low-dimensional governing mechanism; understanding this mechanism is obviously very important in order to understand its failures (ie, heart attacks).
2. **Multi-dimensional data sets**
   These data provide simultaneous measurements of a number of potentially interacting variables; it is an open question how best to use the extra information to learn about how the variables interact. Most importantly, there is interest in verifying and understanding the coupling between respiration and the heart rate.
3. **Non-stationary data**
   These data were recorded with as much care as is possible, but the experimental system (the sleeping patient) is obviously non-stationary. A successful analysis of these data must attempt to distinguish the presumed internal dynamics from changes in the patient's state.



Santa Fe Institute time series prediction

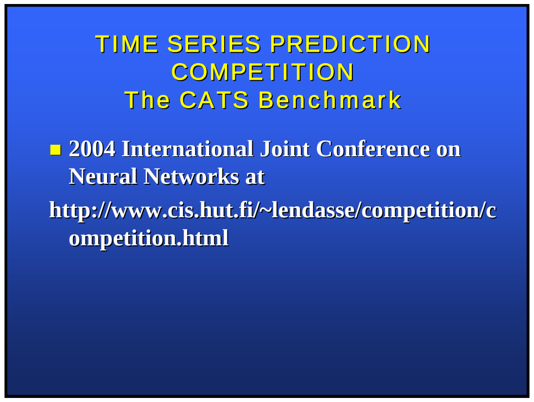
- **Data Set C: Currency exchange rate data**
- **Reason for choice:**

1. **Financial data**
   Predicting currency exchange rates is a classic problem in time series analysis, and is of both academic and financial interest. These particular data were chosen because they were available on a tick-wise basis, and were representative of financial prediction tasks, but still were obscure enough that they would not be easily recognized.
2. **Multiple prediction data sets**
   We collected the predictions for 10 data sets in order to build up better statistics about how algorithms compare, and to check to see if the predictability of the exchange rate varies over time.



Santa Fe Institute time series prediction

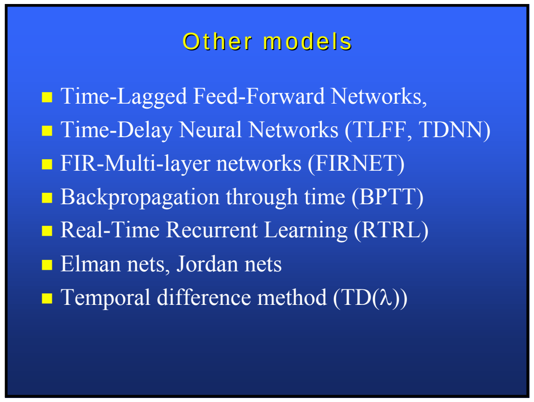
- **Data Set F: J. S. Bach's last (unfinished) fugue**
- **Original Description:**
  - F.dat (4 variables, 3808 points) This is a vector data set, consisting of measurements of four interacting degrees of freedom of the system. The data format consists of lines spaced by equal time steps, with one column per degree of freedom. For a very interesting reason, the continuation of this data set can not be measured. Therefore, any insight into the long-term predictability that allows the set to be continued will be of interest to a very large community. The identity of this set will be announced at the Workshop.
- **Reason for choice:**
  Fun.



TIME SERIES PREDICTION COMPETITION The CATS Benchmark

- **2004 International Joint Conference on Neural Networks at**

http://www.cis.hut.fi/~lendasse/competition/competition.html

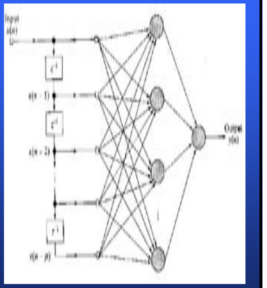


Other models

- Time-Lagged Feed-Forward Networks,
- Time-Delay Neural Networks (TLFF, TDNN)
- FIR-Multi-layer networks (FIRNET)
- Backpropagation through time (BPTT)
- Real-Time Recurrent Learning (RTRL)
- Elman nets, Jordan nets
- Temporal difference method (TD(λ))

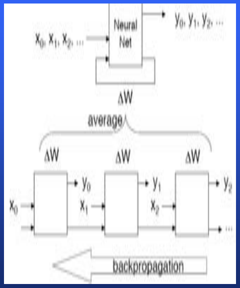
Time-lagged Feed-forward Networks (TLFF)

- An extension of the "Adaline" adaptive filter model
- Use an arbitrary feed-forward net (MLP) in place of the Adaline
- Train using ordinary backpropagation, analogous to LMS



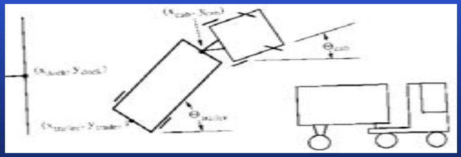
Backpropagation through time (BPTT)

- Unlike TLFF input samples are not kept in explicit delay
- Input fed sequentially into network .
- Training is **as if** the network were **unrolled** to accommodate the entire sequence of input samples.
- Only one set of weights is actually used in operation; the weight changes are **averaged** across stages to get the actual weight change



BPTT application

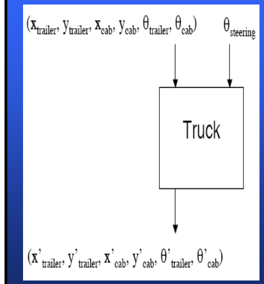
- Problem: Back up a truck so that (xtrailer,ytrailer)= (xdock, ydock),
  given initial values for (xtrailer, ytrailer,xcab, ycab, θtrailer, θcab)

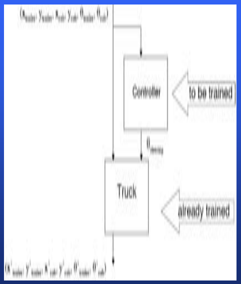


Training the track-backer

- The truck moves in small time increments Δ
- A neural net is first trained to mimic the truck backing using **real truck dynamics**.
- Given the current state at a time t (which includes the steering angle), the network learns to determine the next state (at time t +Δ)
- This is done by starting the truck in a random state, observing the error between what the network does and the dynamic model, and adjusting the weights.
- An error value is produced by comparing the desired final state with the goal.
- The error value is backpropagated through the controller-truck combination to adjust the controller's weights, using BPTT.

Truck-Controller simulation

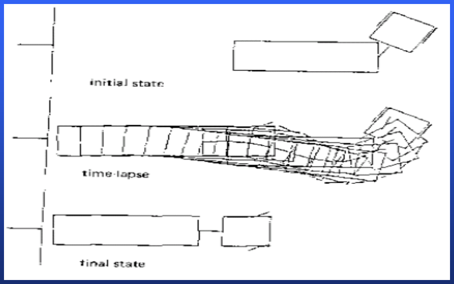

$(x_{trailer}, y_{trailer}, x_{cab}, y_{cab}, \theta_{trailer}, \theta_{cab})$
$\theta_{steering}$
Truck
$(x'_{trailer}, y'_{trailer}, x'_{cab}, y'_{cab}, \theta'_{trailer}, \theta'_{cab})$


$(x_{trailer}, y_{trailer}, x_{cab}, y_{cab}, \theta_{trailer}, \theta_{cab})$
Controller
to be trained
$\theta_{steering}$
Truck
already trained
$(x'_{trailer}, y'_{trailer}, x'_{cab}, y'_{cab}, \theta'_{trailer}, \theta'_{cab})$

Training

- 20,000 trials required to train
- 16 lessons of 1000-2000 each
- Initially truck positioned very close to dock and in a nearly-correct position, so controller could **learn easy tasks first**.
- Final MSE was 3% of truck length, angle 7 degrees

Simulations



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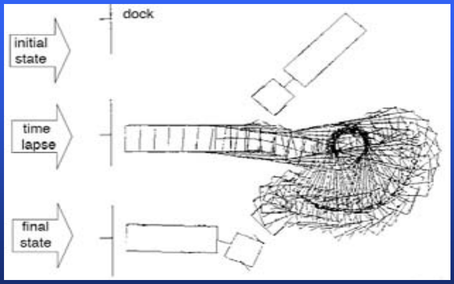

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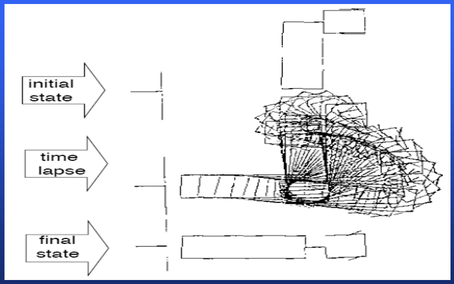

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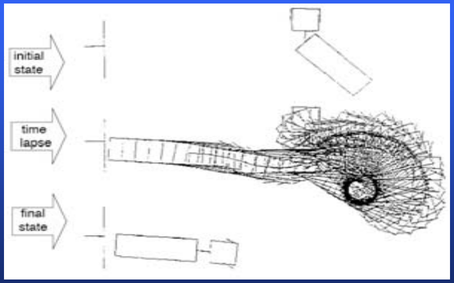
initial state
time lapse
final state