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2018

Forecasting Customer Demand with Deep Neural Networks

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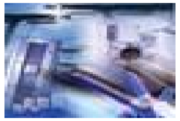
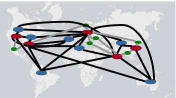
Neural Networks @ Siemens


Demand Forecasting


Load Forecasts for DB Energie

eMeter
Forecasting Smart Meters

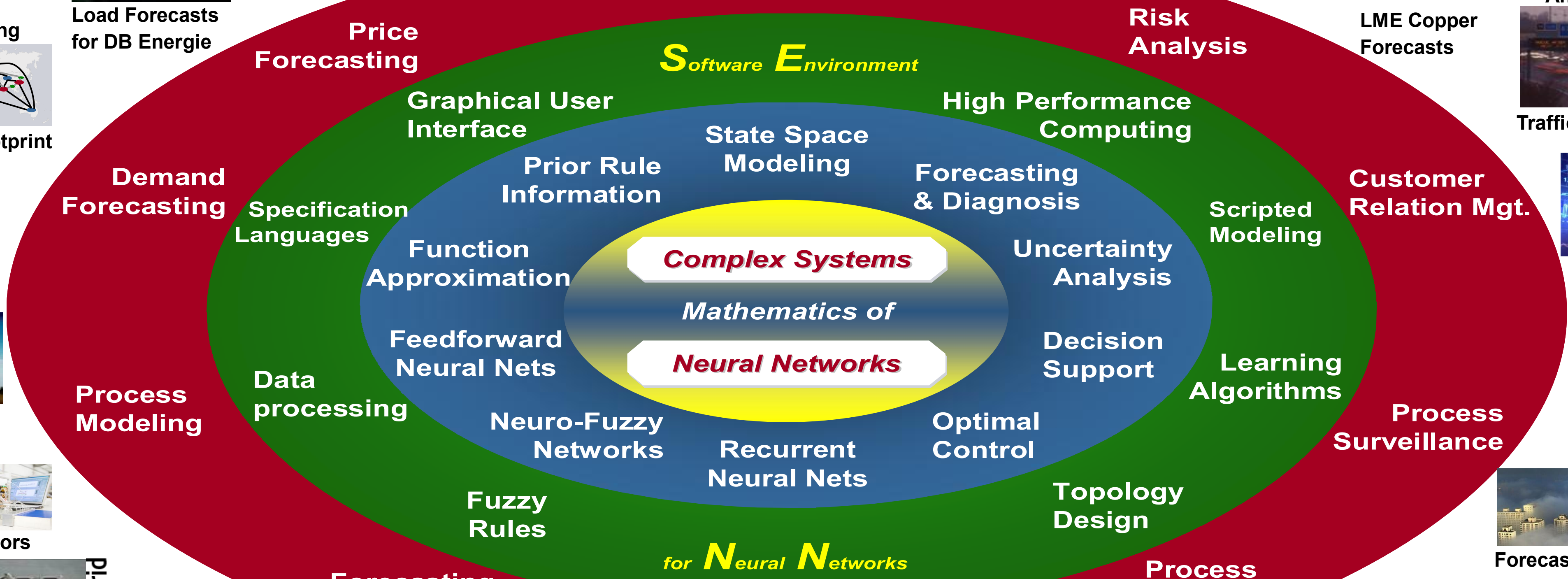

Global Footprint Simulator


Wind Turbines


Soft Sensors

Forecasting Transfer Losses


Solar Power



EEX
EUROPEAN ENERGY EXCHANGE
Energy Price Forecasts


LME Copper Forecasts

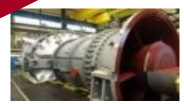

Clinical Trial Analysis


Traffic Forecasting


Credit Scoring

Quality Surveillance


Forecasting Emissions


Gas Turbine Analysis


Failure Detection

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Agenda

- Forecasting Customer Demand: Problem Setting & Test Set-up
- Forecast Models: Focus on Neural Networks
- Model comparison and benchmarking
- From forecasting to decision making (planning)

Forecasting Customer Demand at the Geräte-Werk Erlangen (GWE)

Problem Setting:

- Predict the customer demand for products for **the next year** in weekly time buckets (i.e. 52 forecasts)
- Forecast objects are so-called MLFBs (fine granularity, e.g. a product with a specific configuration). We have about **1100 active MLFBs**
- Forecasts should be used for production planning and material sourcing
- A **fully automated forecast and planning process** should be established

Test Set-Up

- We predict the customer demand under “real-world-conditions” (so-called backtest)
- Test horizon:

Training data (used to develop the forecast models)	Model Genaralization (Test Data)
10/2012 – 09/2017	10/2017 – 09/2018

- We measure the performance in terms of absolute error in pieces and the standard deviation of the error over the forecast objects

Model Inputs

- Calendar effects
  - WeekOfMonth
  - WeekOfQuarter
  - WeekOfYear

- Work days per week
- German public holidays

- Customer demand on preferred delivery date. Data is available from 2011 to 2018 (daily bookings weeks)

- Macroeconomic data: Business climate of the top 10 customer sectors and top 5 regions (both monthly data).

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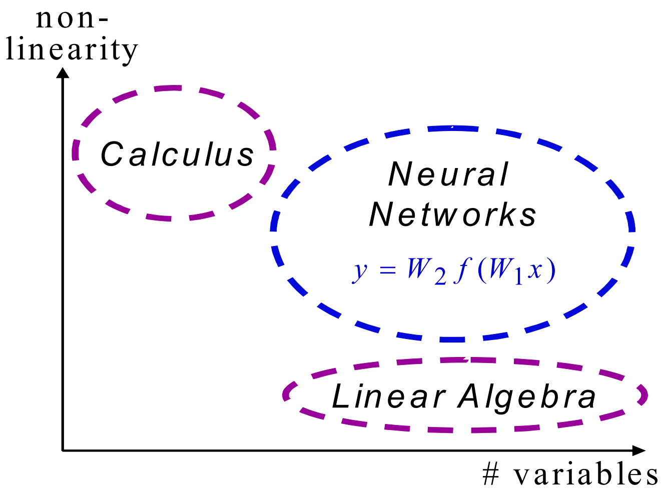
Mathematical Neural Networks in Nonlinear Regression



Existence Theorem:

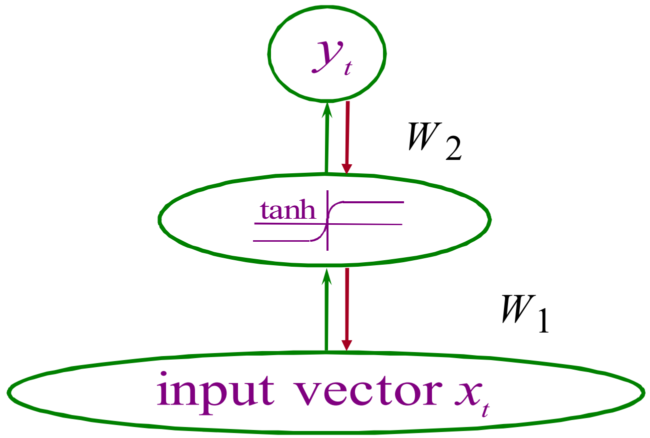
(Hornik, Stinchcombe, White 1989)

3-layer neural networks can approximate any continuous function on a compact domain.

Based on data identify an input-output relation

$$y = W_2 f(W_1 x)$$

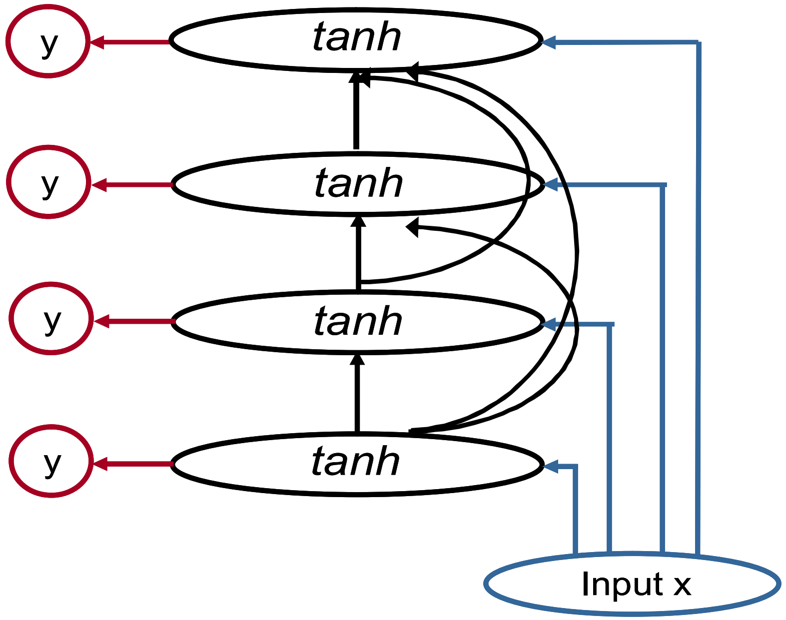
$$\sum_{t=1}^{T} (y_t - y_t^d)^2 \rightarrow \min_{W_1, W_2}$$



NN imply a **Correspondence** of **Equations**, **Architectures**, **Local Algorithms**.

Deep Feed-Forward Neural Networks

The extended net acts as a hierarchical filter



Forward path: feeding the inputs to all intermediate layers avoids a loss of the input information.

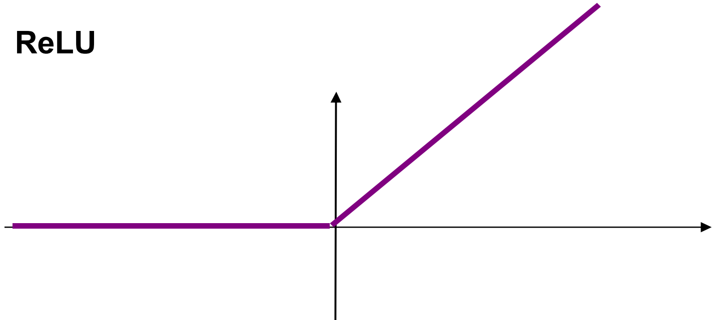
Backward path: learning is not only applied to the final target but to all intermediate layers.

The learning is improved if we use backward false in the hidden backbone (hidden → hidden connections learn, but transfer no error flow)

We can add information highways to spread information (faster) across the network

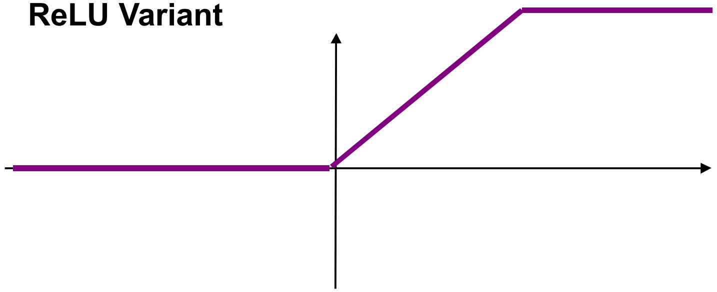
Rectified Linear Unit (ReLU, Alternative Basis Function)

ReLU

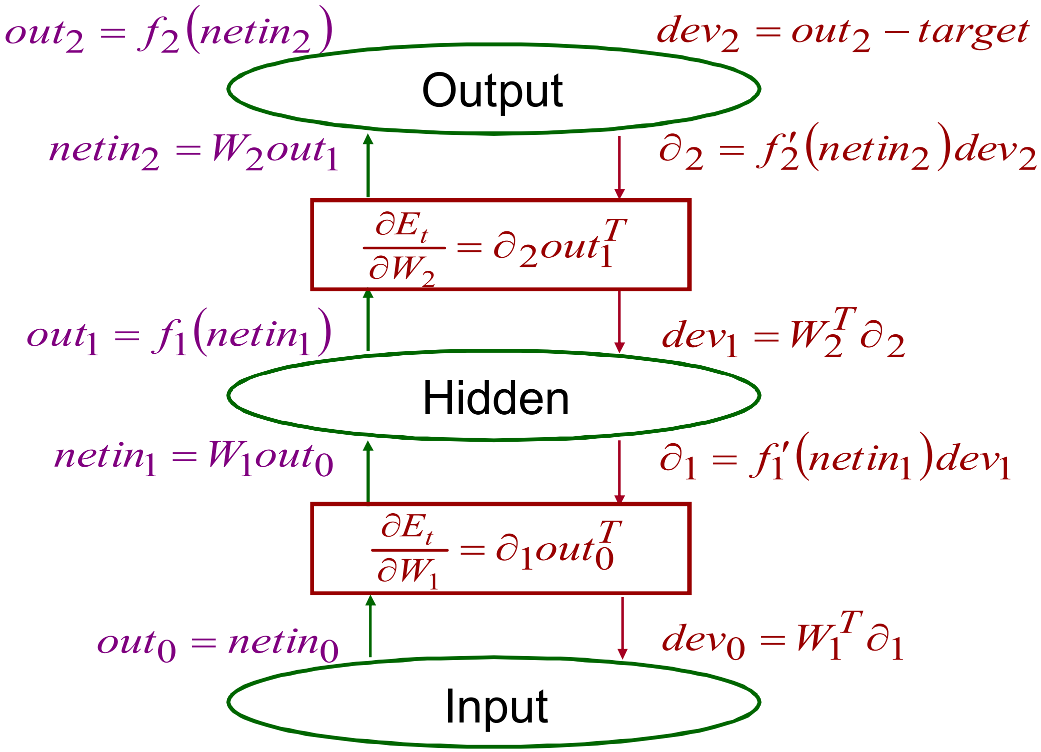


For x>0, the error flow is not squeezed
For x<0, we have no error flow anymore.
For x=0 the function is not differentiable.

ReLU Variant

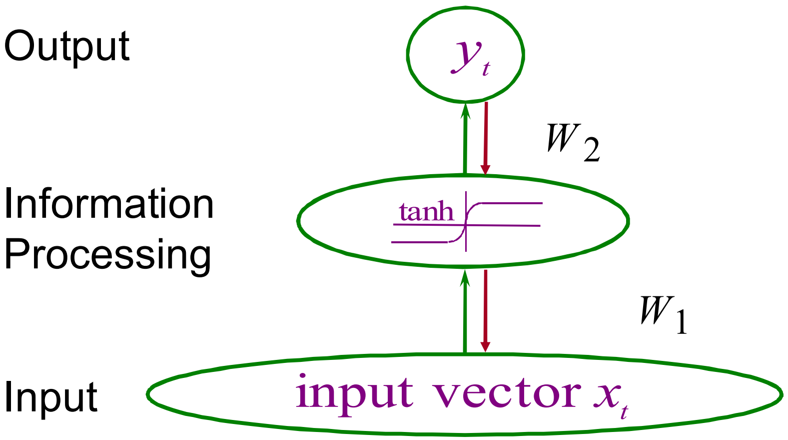


Squashing functions differ in their impact on the backpropagation algorithm.



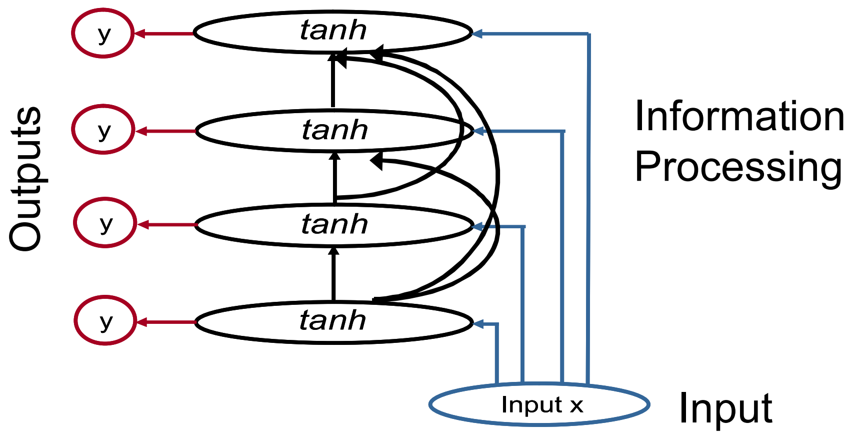
Deep Neural Networks and Deep Learning

Standard 3-Layer Neural Networks



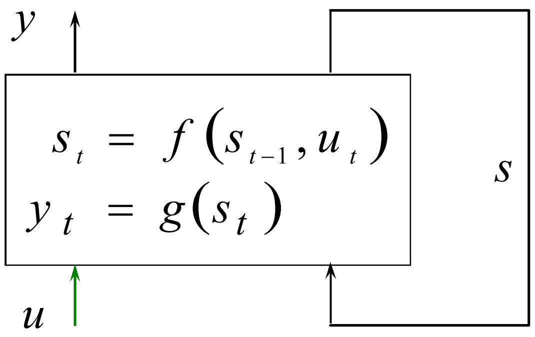
- Non-linear regression approach and universal function approximator
- All tasks are solved by a single information processing layer. Tends to overfit the data

Example of a Deep Neural Network



- Multi-level information processing: Enrichment of the information flow by multiple hidden-to-hidden and input-to-hidden connections
- Multiple outputs (same task) enrich the learning

Dynamical Systems and Recurrent Neural Networks (RNN)



$$s_t = f(s_{t-1}, u_t)$$
$$y_t = g(s_t)$$

$$s_t = \tanh(As_{t-1} + Bu_t)$$ state transition

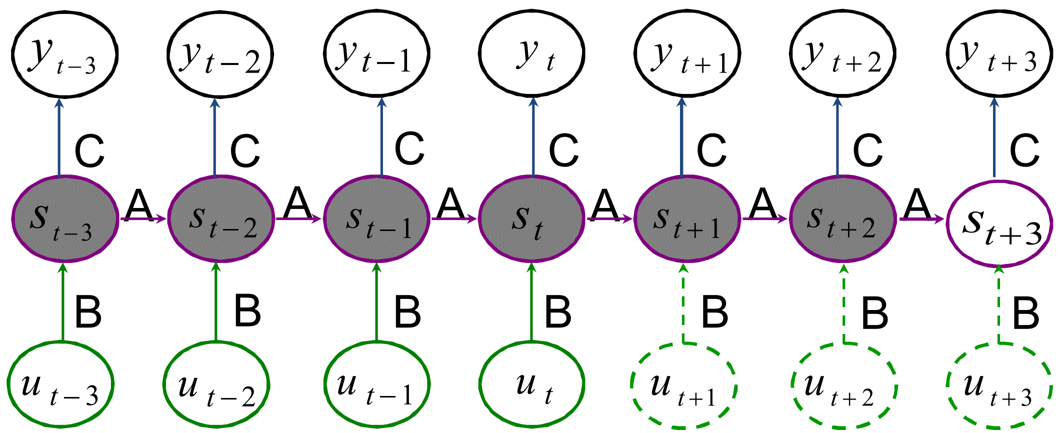
$$y_t = Cs_t$$ output equation

$$\sum_{t=1}^{T} (y_t - y_t^d)^2 \to \min_{A,B,C}$$ identification

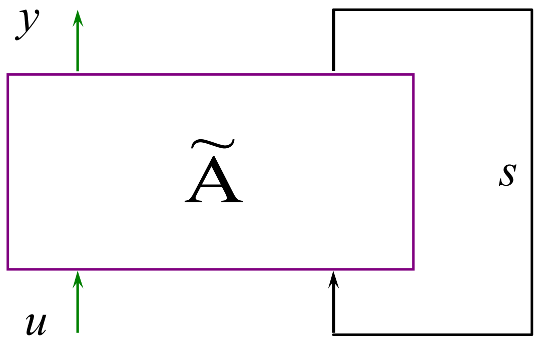
Finite unfolding in time transforms time into a spatial architecture. We assume, that x_t=const in the future.

The analysis of open systems with RNNs allows a decomposition of the autonomous & external driven part.

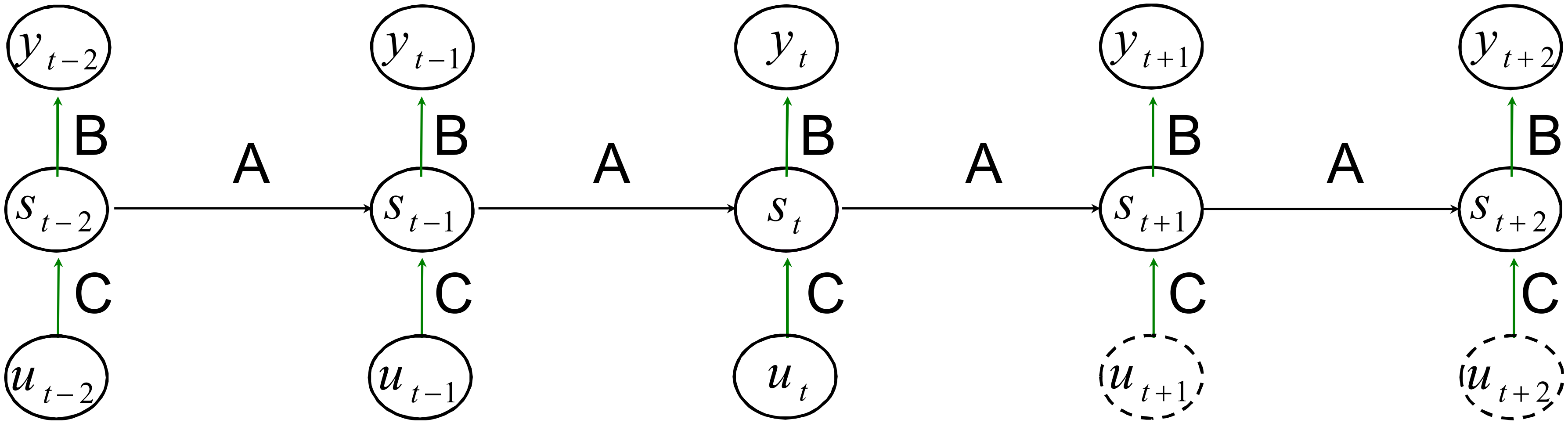
Long-term predictability depends on a strong autonomous subsystem.



Echo State Neural Networks



In echo state networks we have large state space with a fixed, sparse transition matrix A and matrix C for incorporating the inputs. We learn a linear filter B.



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Causal & Retro-Causal Neural Networks (CRCNN)

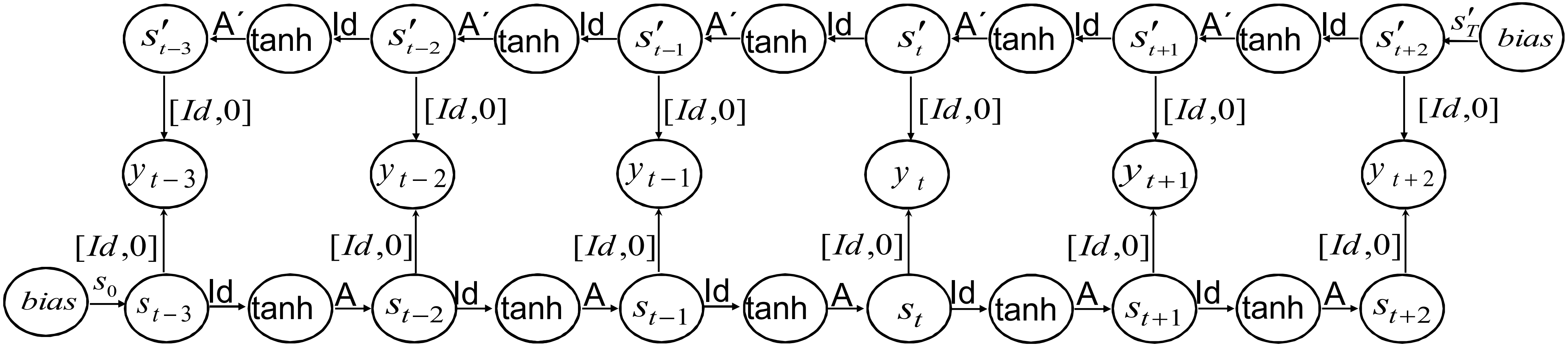
- We explain observations by a symmetric superposition of causal & retro-causal subnets.
- Both subnets are universal learners, but the more appropriate branch learns faster and reduces the error flow of the opposite branch.
- In non-unique optimization, we have to have attention on the path to the optimum!!!

$s_t = A \tanh(s_{t-1}) \quad , s_0$ causal transition

$s'_t = A' \tanh(s'_{t+1}) \quad , s'_T$ retro transition

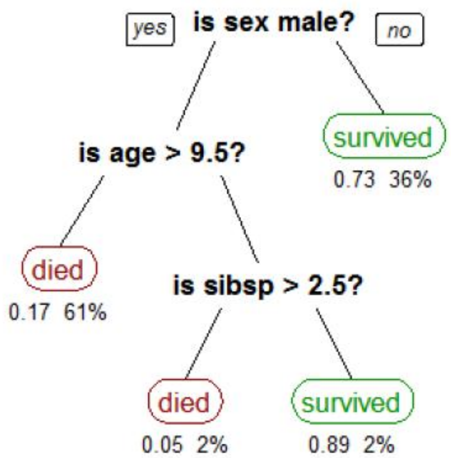
$y_t = [Id, 0] s_t + [Id, 0] s'_t$ output equation

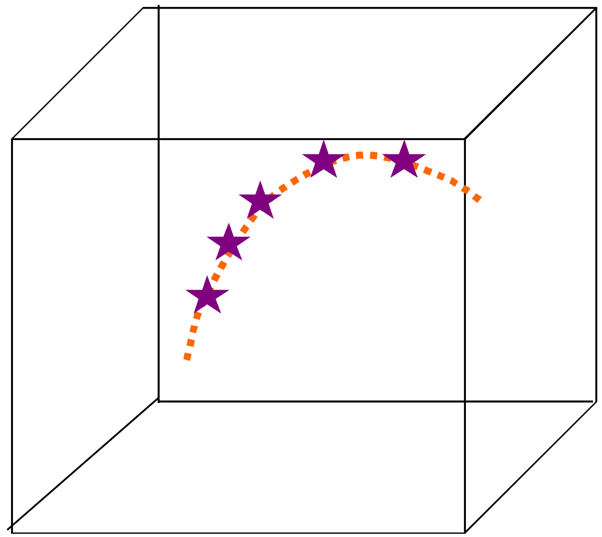
$\sum_{t=1}^{T} (y_t - y_t^d)^2 \rightarrow \min_{A, s_0, A', s'_T}$ identification



Additional Benchmarks

- Random Forests incorporating gradient boosting
- Support vector machines (SVM)





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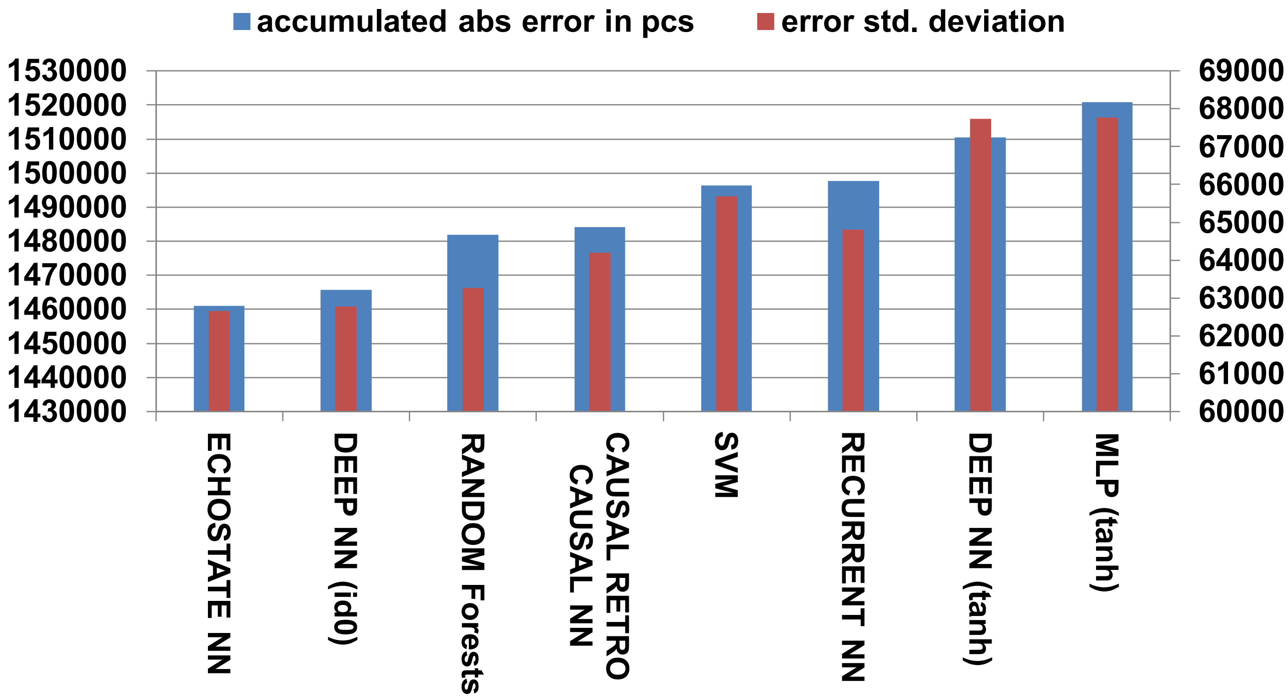
Model comparison and benchmarking



Model	accumulated abs error in pcs	error std. deviation
ECHOSTATE NN	1461094	62651
DEEP NN (id0)	1465803	62768
RANDOM Forests	1481960	63263
CAUSAL RETRO CAUSAL NN	1484119	64194
SVM	1496393	65694
RECURRENT NN	1497693	64807
DEEP NN (tanh)	1510528	67733
MLP (tanh)	1520819	67777

Accumulated absolute error in pieces over 52 weeks and all products (MLFBs) on test data.

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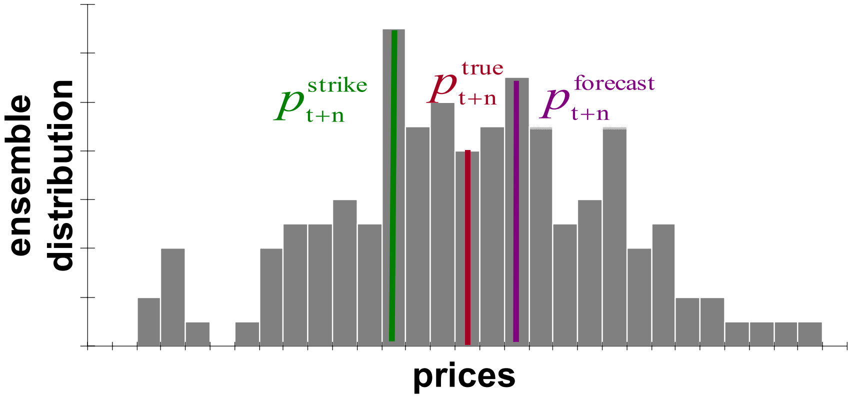
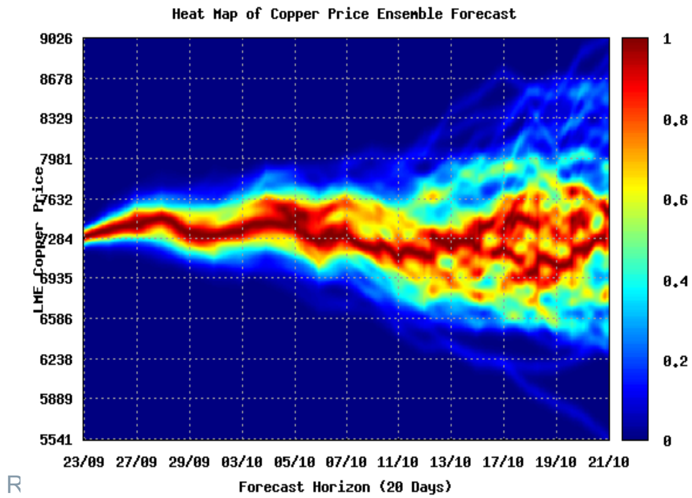
On Risk and Forecasting Uncertainty





Paradigms for the Computation of Uncertainty / Risk:

- **Volatility** as a risk measure implies a naive, constant forecast (a high frequency wave has high volatility without uncertainty).
- Backward **risk is the error between model and real-world**. Here distributional features of the risk depends on the chosen model.
- Forward risk can be estimated by an **ensemble forecast**: many models fit the past perfectly and still give diversifying forecasts.
- Risk is often not double-sided within the uncertainty distribution, e.g. unexpected gain or unexpected loss!

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Success requires multidisciplinary teams more than ever

Our vision to differentiate

Robotics

Data | **Smart Digital Solutions** | **Analytics**

Business

Digital Transformation: a team sport