Simulation of Oil Well Pseudo Logs
using a Neural Network with Ultrafast Learning

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Outline

- Develop **faster learning algorithms** for neural nets
- Develop methodology to **determine the confidence limits of results** predicted by neural network models
- Obtain **best estimates** for network model parameters
  - consistently combine experimental data (sensor measurements) with model output
- Significantly **reduce** the **uncertainties** underlying decision processes based on learning
- Apply new methodology to characterization of oil fields

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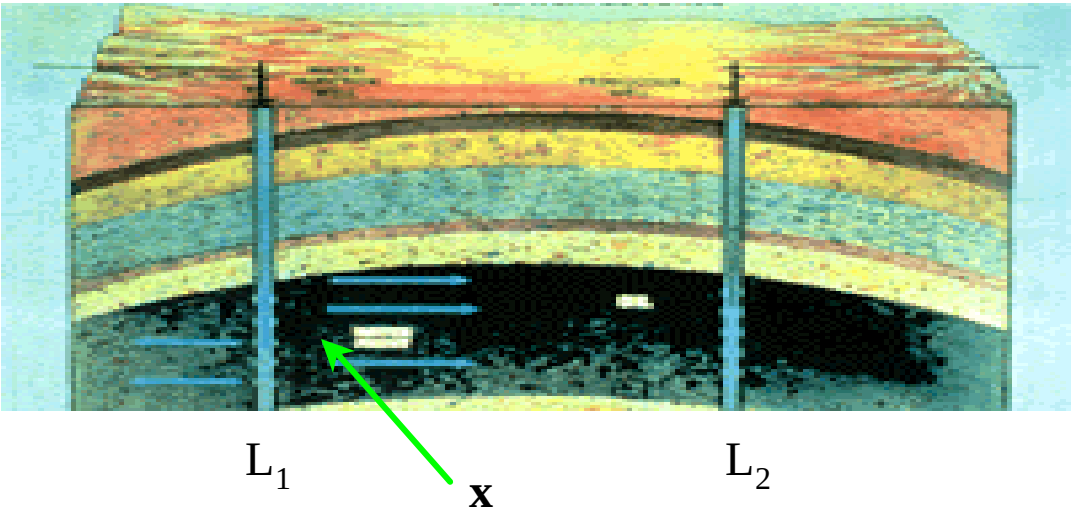
Artificial Neuromorphic Systems

Learning

Neural nets provide efficient solutions to challenging problems in pattern recognition, signal analysis, and real-time control of complex systems.

At the heart of such advances lies the development of very efficient methodologies for learning



Challenges

- systematic treatment of **uncertainty**
- very **slow learning** for systems of realistic size
- convergence to **local minima** of error function

Oil Field Characterization

- **Goal: given** detailed log data from L_1 and L_2 and seismic survey data between wells, **estimate** subsurface properties at **x**
- But, how much confidence can one place in such network predictions obtained from sensor data corrupted by uncertainty ?

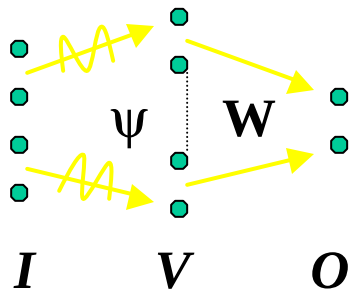
Learning

Development of neural learning algorithms is generally based upon the minimization of an energy–like neuromorphic error function

- pioneering contributions of Grossberg, Werbos, Hopfield
- **gradient-based techniques** have provided the main computational mechanism for the optimization process
  - excessive training times for large networks
- considerable efforts have been devoted by many groups to
  - speed up rate of convergence
    e.g., Barhen & Zak, *IEEE Computer*, 22, 67-76 (1989)
  - compute more efficiently gradients
    e.g., Barhen & Toomarian, *Appl. Math. Lett.*, **3**, 13-18 (1990)
    e.g., Toomarian & Barhen, *U.S Patent No.* 5,930,781 (July 1999)
- novel approaches based on **linear algebraic methods** pioneered by Biegler-König and Bärman
  e.g., Barhen & Protopopescu, *Neural Process. Lett.*, **11**, 113-129 (2000)

DeepNet

ARCHITECTURE



Feedforward flow

- I nodes input layer
- V nodes virtual layer
- O nodes output layer

K cluster patterns

Inputs: W_{KI}
Outputs: $\mathbf{R}_{KO}$

Synaptic interconnections

$\mathbf{W}_{VO}$ linear

ψ

nonlinear

Approach

Training Data

- given L training patterns $\{W_{LI}, \mathbf{R}_{LO}\}$
  - define K clusters: $I \cap K \cap L$: $\{W_{KI}, \mathbf{R}_{KO}\}$
- compute nominal uncertainties for each cluster

Computational Model

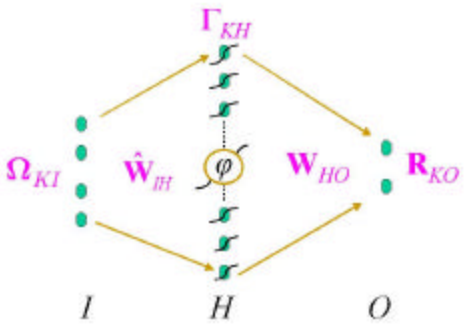
$$\mathbf{R}_{KO} = M\ (W_{KI}, \mathbf{W}_{VO})$$

Unique feature

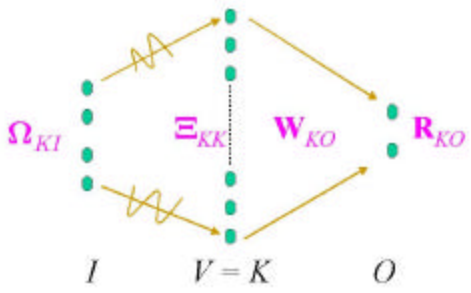
- virtual layer connected to input layer via non-linear ψ transform (**nonlinear weights**)
- ψ maps W_{KI} into nonsingular matrix X_{KK}

$$X_{KK} = \Box\ (W_{KI})$$

DeepNet



$$T_{KO} = \rho^{-1}(R_{KO})$$



BKB Network

- $P_{KO} = G_{KH}\, W_{HO}$
- the learning algorithm minimizes the norm $\boxed{\wedge}\, T_{KO} - P_{KO}\, \boxed{\wedge}$
- since G_{KH} **not known**, one sweeps backwards, using initial W_{HO} guess

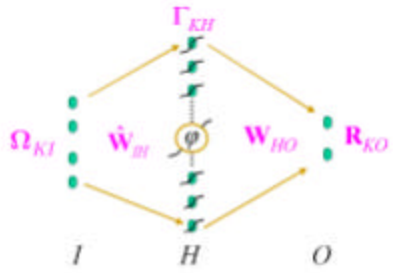
  $G_{KH}\, W_{HO} = T_{KO} = G_{KH}\, R_{HH}\, R^{-1}_{HH}\, W_{HO}$
- renormalization matrix R_{HH} introduced to satisfy sigmoid constraints at HL

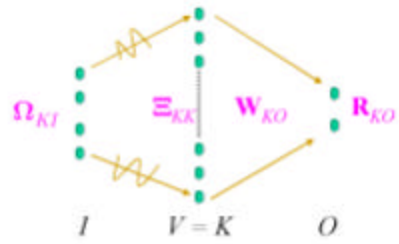
DeepNet

- $P_{KO} = X_{KK}\, W_{KO}$
- the learning algorithm minimizes the norm $\boxed{\wedge}\, T_{KO} - P_{KO}\, \boxed{\wedge}$
- solves the system

  $$T_{KO} = X_{KK}\, W_{KO}$$
- since T_{KO} and X_{KK} are known, we can compute W_{KO} by SVD of X_{KK}

DeepNet





BKB Network

- solve for $\hat{\mathbf{W}}_{IH}$ the system

$$\Omega_{KI}\,\hat{\mathbf{W}}_{IH} = j^{-1}(\Gamma_{KH}\mathbf{R}_{HH})$$

- inversion of W_{KI} introduces an unavoidable loss of accuracy, since $K \square I$

- forward sweep yields $\mathbf{P}_{KO}$

$$\mathbf{P}_{KO} = j\,(\Omega_{KI}\,\hat{\mathbf{W}}_{IH})\mathbf{R}_{HH}^{-1}\mathbf{W}_{HO}$$

DeepNet

- in *virtual* layer architecture the matrix X is nonsingular

$$\mathbf{X}_{KK}^{(i)}(k,l) = 1 - \frac{\left|\mathrm{w}_k^{(i)} - \mathrm{w}_l^{(i)}\right|}{D^{(i)}}$$

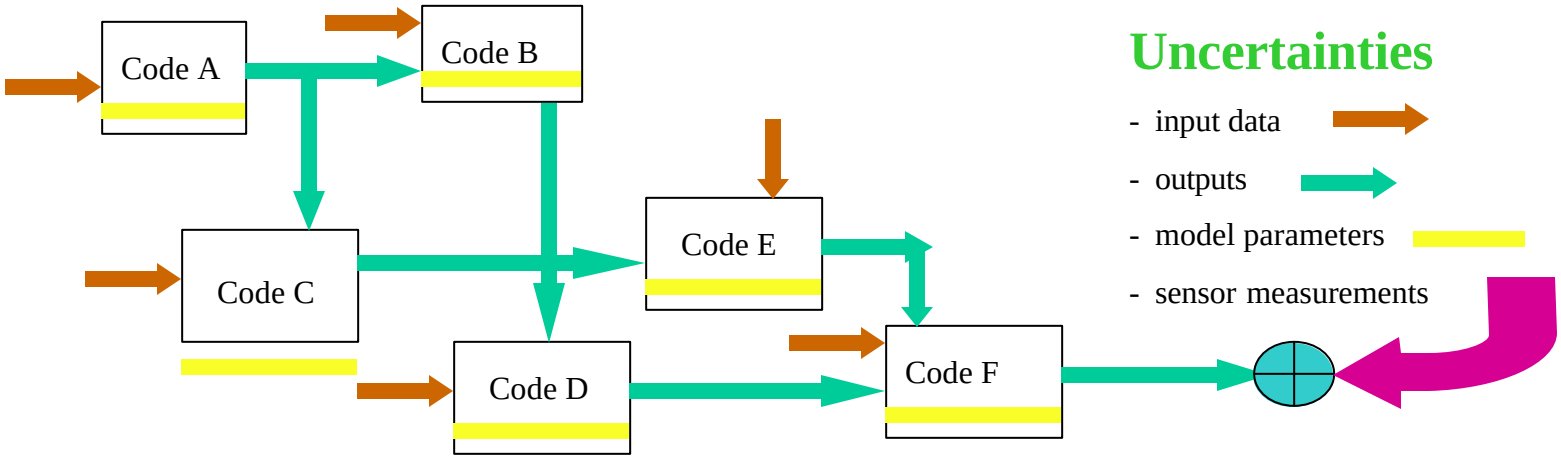
$$\det(\mathbf{X}_{KK}) = \prod_{i=1}^{I}\left(\frac{1}{2}\prod_{k=1}^{K-1}\frac{2u^{(i)}(k)}{D^{(i)}}\right) > 0$$

➔ new ***DeepNet*** methodology enables **accurate ultrafast** (***single iteration***) **learning**

Learning under Uncertainty

Motivation

How much confidence should be placed in decisions obtained on the basis of predictions from complex mathematical and / or physical models embedded in complex code systems?



The methodology we are developing has two primary goals:

- determine ***confidence limits*** of ***neural net – predicted*** results
- consistently ***combine*** sensor measurements with computational results
  - obtain ***best estimates*** of model parameters
  - ***reduce uncertainties*** in estimates

Critical Requirements
for Learning under Uncertainty

We seek techniques based upon model **sensitivities** that enable robust learning and efficient error estimation from a neural network

Such methods should incorporate five **key capabilities**

- guarantee that no ***important effects*** are overlooked
  ➔ *full set of* ***sensitivities***
- fast processing of large data sets
  ➔ *efficient computation of sensitivities*
- systematic treatment of ***nonlinearities***
- inclusion, where relevant, of ***time dependence*** *inputs, model parameters, responses*
- comprehensive method for **combining experimental** (i.e., **sensor**) **data** and **model results**; goal is to ***reduce the uncertainties***

J. Barhen and V. Protopopescu, in *DARS*, **4**, 403-413, Springer (2000)

F. Aminzadeh and J. Barhen, *Comp. & Geosci.*, **26**, 869-875 (2000)

F. Aminzadeh and J. Barhen, *Petrol. Sci. & Eng.*, **24**, 49-56 (1999)

NOGA

Sensitivities

- provide a systematic way to **propagate uncertainties** in complex, non stationary, nonlinear models

$$S^{?\mu}_{ni} = \P q^{?}_{n} / \P a^{\mu}_{i}$$

system parameters: $\mathbf{a} = \{\mathbf{W}, z\}$

network computed responses: $\mathbf{q} = \rho(\mathbf{p})$

experimental response: $\mathbf{r}$

- determine and **rank** the **importance** of parameters and input data to computed quantities of interest (*system responses*)
- computed using **adjoint operator** methods or automatic differentiation codes for recurrent nets
- nominal ***uncertainties*** quantified in terms of **covariance matrices** $C_{\mathbf{aa}} = \langle D\mathbf{a}\, D\mathbf{a}^{t} \rangle$

Bayesian Inference

- **information fusion goal** is to combine consistently ***computational results and measurements***
- ***minimize a generalized Bayesian loss function with constraints***

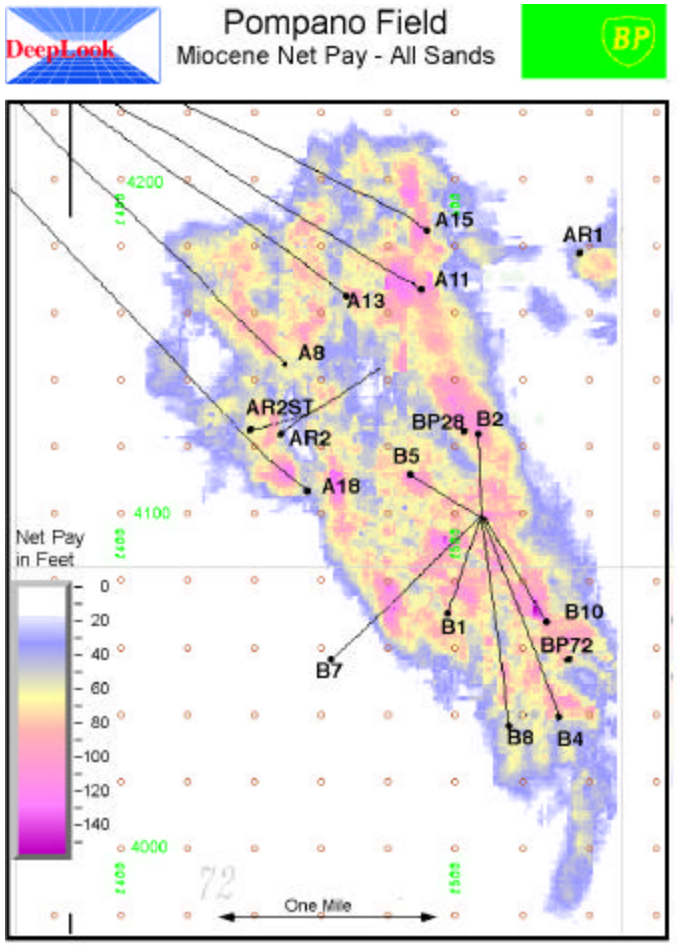
$$L = (\hat{\mathbf{q}} - \mathbf{r} \,|\, \hat{\mathbf{a}} - \mathbf{a} \,|\, Y) \begin{pmatrix} C_{\mathbf{rr}} & C_{\mathbf{ra}} & s \\ C_{\mathbf{ar}} & C_{\mathbf{aa}} & t \\ s & t & u \end{pmatrix}^{-1} \begin{pmatrix} \hat{\mathbf{q}} - \mathbf{r} \\ \hat{\mathbf{a}} - \mathbf{a} \\ \bullet \end{pmatrix} + l^{T} \mathbf{c}[\hat{\mathbf{a}}, \mathbf{a}, \hat{\mathbf{q}}, \mathbf{q}, \mathbf{r}, \ldots, \mathbf{S}, \ldots]$$

- optimization uses the inverse of the total covariance matrix as the **natural metric** of the calculational manifold
- solution of optimality equations yields **best estimates** for parameters and **reduced uncertainties**

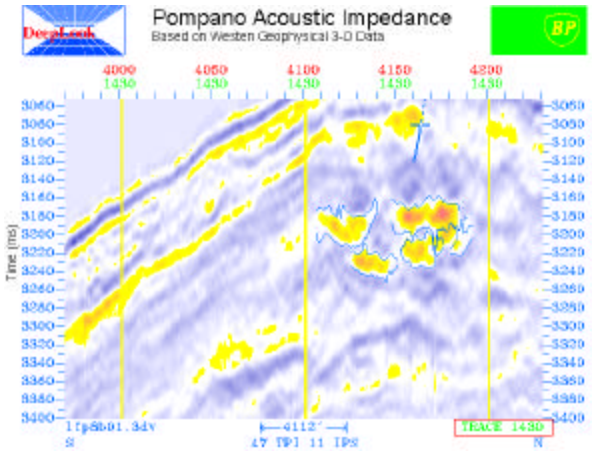
Oil Field Characterization

Framework

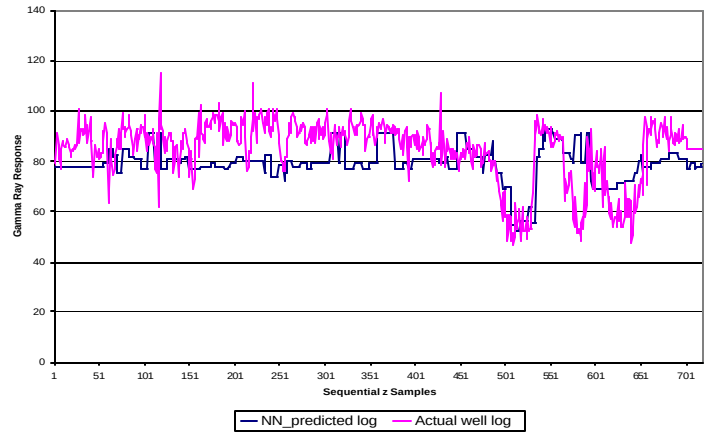
- Ability to predict location of remaining oil in neighborhood of existing production wells is of vital economic importance to petroleum industry
- **Neural nets** are used to capture the relationship between seismic survey data and well logs
- Avoid costly drilling of new wells
- Demonstrate capability of ***DeepNet*** to capture this extremely complex nonlinear relationship

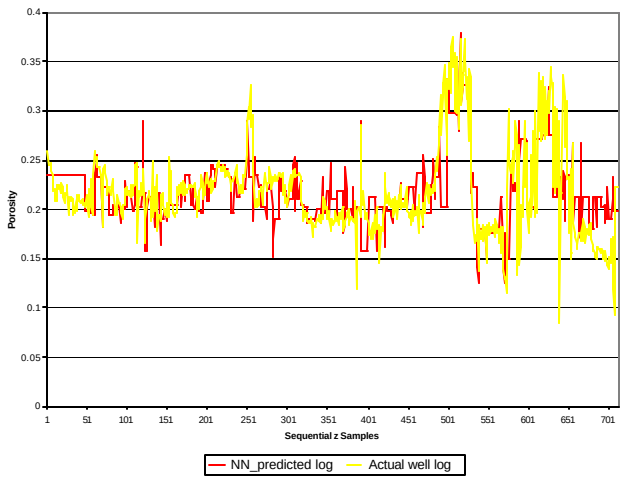


DeepNet Results

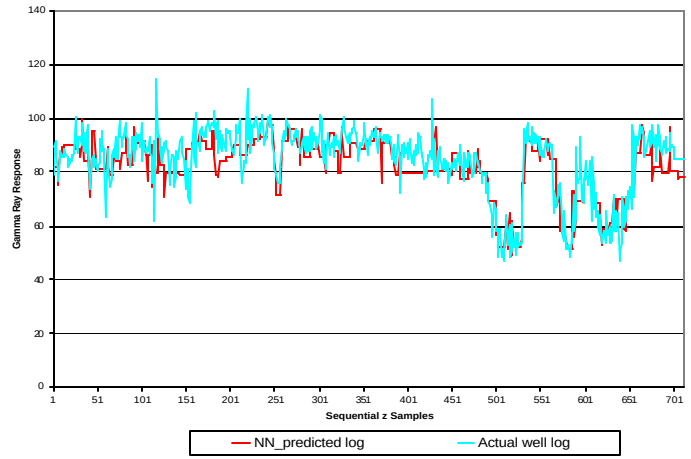


Prediction of best-estimates: **gamma ray** log.
Current state-of-art method (Nadaraya-Watson by Rao) Data: B10_5S (well B10)





DeepNet prediction of best-estimates: **porosity**
Data: B10_5S (well B10)



DeepNet prediction of best-estimates: **gamma ray**
Data: B10_5S (well B10)

Summary

We have developed new methods for neural net learning under uncertainty

- **ultrafast** (single iteration) ***DeepNet*** neural net learning code provides the computational framework for modeling
- **information fusion** module ***NOGA*** uses ***sensitivity matrices*** in conjunction with minimization of a constrained generalized Bayesian loss function to ***combine model prediction and experimental results***
- best-estimates for model parameters and ***reduced uncertainties***

DeepNet ☞ ***NOGA*** are providing **enabling capabilities** for several CESAR basic research activities

- prediction of pseudo-logs in the neighborhood of petroleum reservoir wells
- tracking in cooperating robots
- pattern classification using quantum dot arrays
- synchronization of arrays of lasers