Probabilistic Neural Networks (PNN)

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1. OBJECTIVE

Probabilistic Neural Networks (PNN) is a nonlinear transform which uses known properties as an input to predict a target property. PNN are commonly available in commercial quantitative interpretation packages; however, its implementation can sometimes be obscure. Thus we developed our own PNN implementation. In this work, we analyze how to train and apply the neural network, by predicting a porosity log in well data from Diamond M Field, TX.

2. PROBABILISTIC NEURAL NETWORKS

The Probabilistic Neural Networks (PNN) is an interpolation method which uses a neural network for its application (Hampson et. al., 2001). PNN was proposed by Donald Specht in 1990, who stated that different mathematical operations can be organized in different layers. In addition, instead of a sigmoid function, in PNN a Gaussian distribution is used as activation function (Specht, 1990).

$$e = (v - \hat{v})^2 \qquad e \text{----> Error}$$

$$\hat{v} = \frac{\sum_{i=1}^{N} v_i \, e^{-\sum_{m=1}^{2} \frac{(Input_m - Training_{im})^2}{\sigma^2}}}{\sum_{i=1}^{N} e^{-\sum_{m=1}^{2} \frac{(Input_m - Training_{im})^2}{\sigma^2}}}$$

$\hat{v}$ ----> Predicted Value
σ ----> Smoothing Parameter

$$corr_{1,2} = \frac{cov(1,2)}{\sigma_1 \sigma_2}$$

$corr$----> Pearson's correlation coefficient

Attribute #1	Attribute #2	Target Property
$Training_{11}$	$Training_{12}$	v_1
$Training_{21}$	$Training_{22}$	v_2
$Training_{31}$	$Training_{32}$	v_3
•	•	•
•	•	•
•	•	•
$Training_{N1}$	$Training_{N2}$	v_N

Attributes
$[Input_1 \quad Input_2]$

Figure 1. Basic design of a Probabilistic Neural Network (Modified from Hampson et. al., 2001)

3. GEOLOGICAL BACKGROUND

Diamond M Field is located in Scurry County, TX, approximately 80 mi northeast of Midland, Texas. The trend is part of the Horseshoe Atoll Reef Complex, an arcuate chain of reef mounds, made of mixed types of bioclastic debris that accumulated during the Late Paleozoic in the Midland basin (Vest, 1970). The massive carbonates presented in the Atoll are separated by correlative shale beds (Davogustto, 2010) .

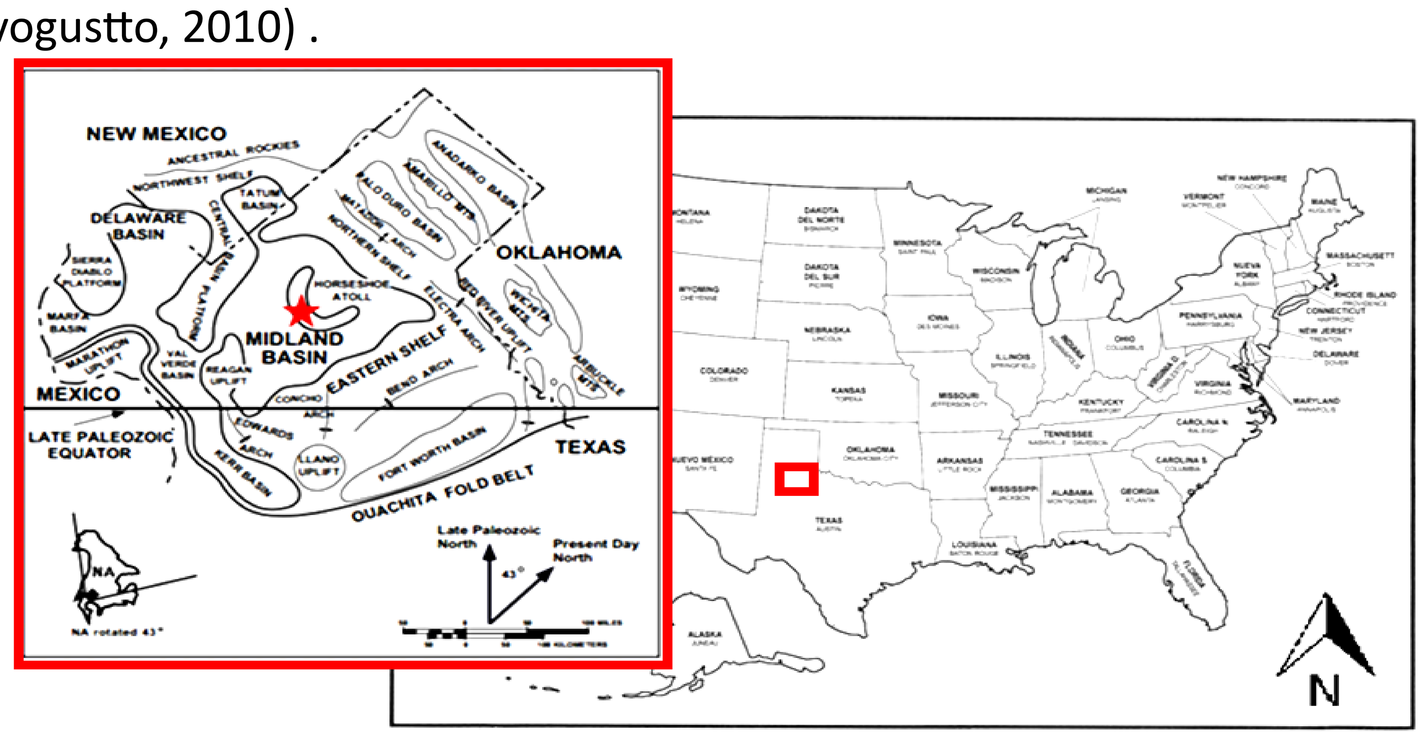

Figure 2. Location of Diamond M Field in the Midland Basin, Texas, USA. (Modified from Walker et. al., 1995)

4. PNN TRAINING

Wells: Garnet, Emerald, Topaz, Garnet. Cross-validation is used to train the neural network (Hampson et. al, 2001).

Logs used for prediction: Gamma Ray (GR), Resistivity (RD), Density (ρ) and Photoelectric Factor (PEFZ).

Zone of interest: 5500-6600 ft.

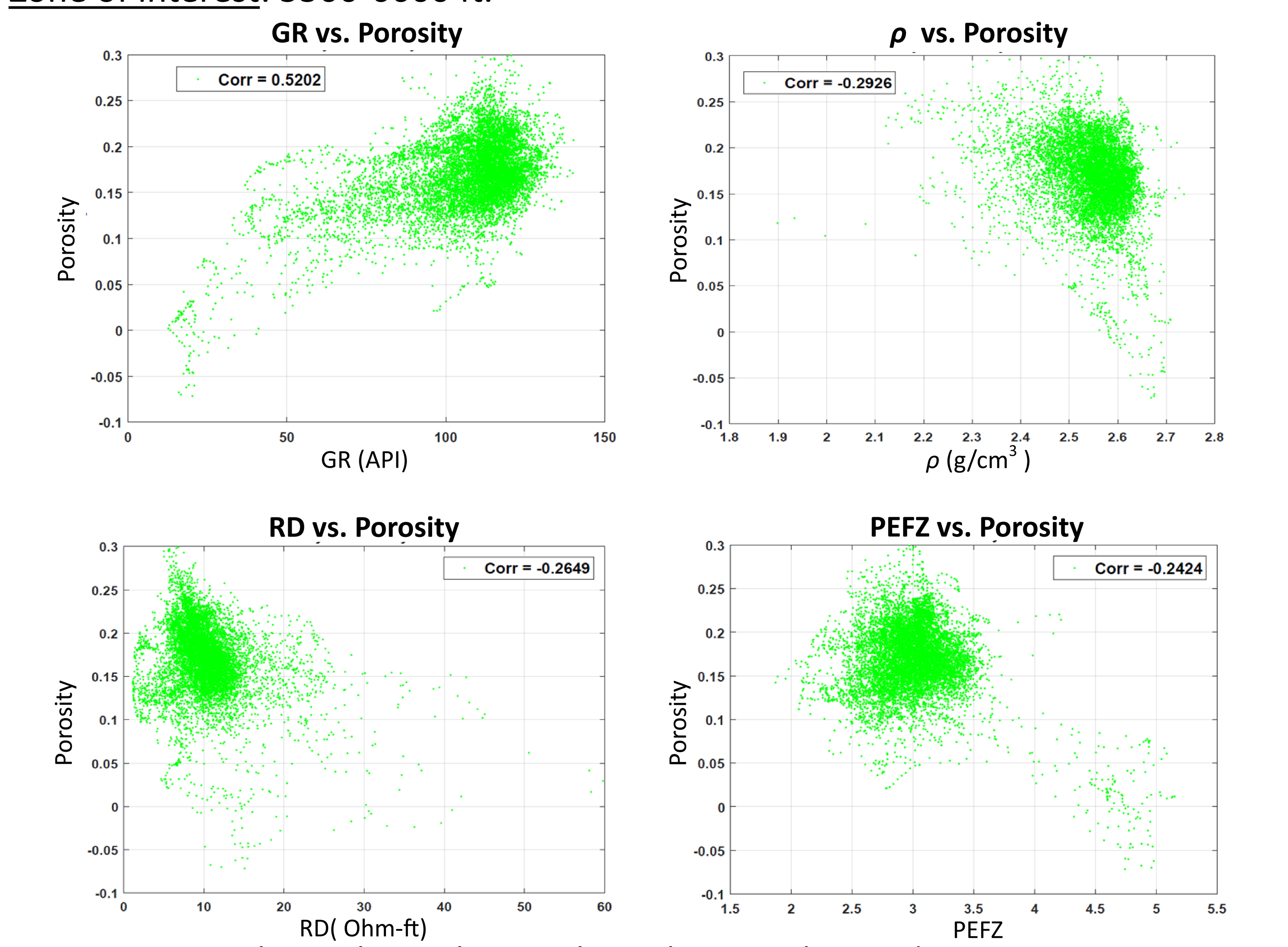

Figure 3: Cross-plots to know the correlation between logs and target property. Gamma Ray has the highest correlation with the porosity. Correlation was computed using Pearson's correlation coefficient.

Optimizing σ: Exhaustive Search

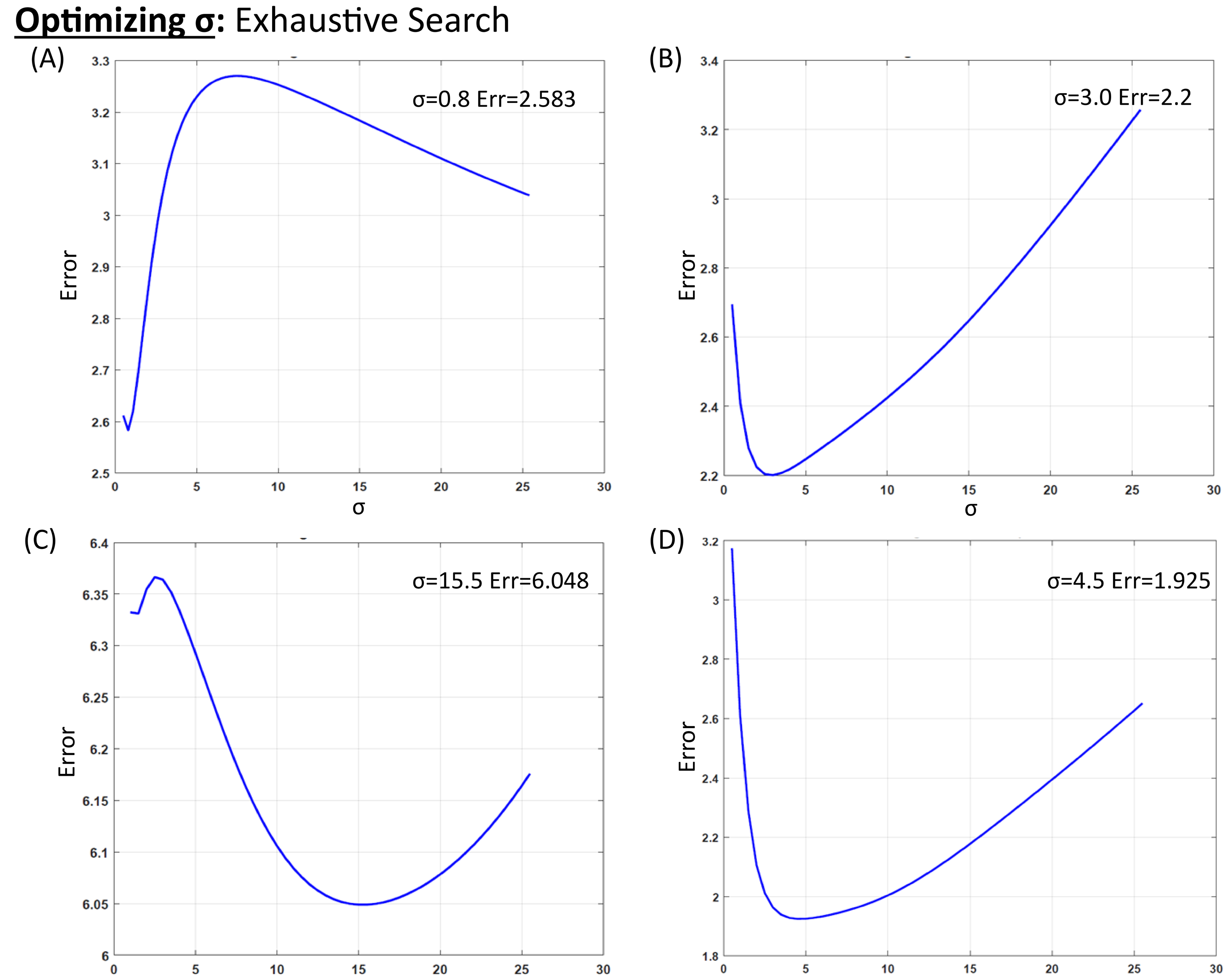

Figure 4: Determination of the optimal value of σ using exhaustive search and cross-validation. (A) Emerald (B) Garnet (C) Jade (D) Topaz. Using Emerald, Garnet and Jade as training to predict Topaz provides the minimum error.

5. PNN PREDICTION

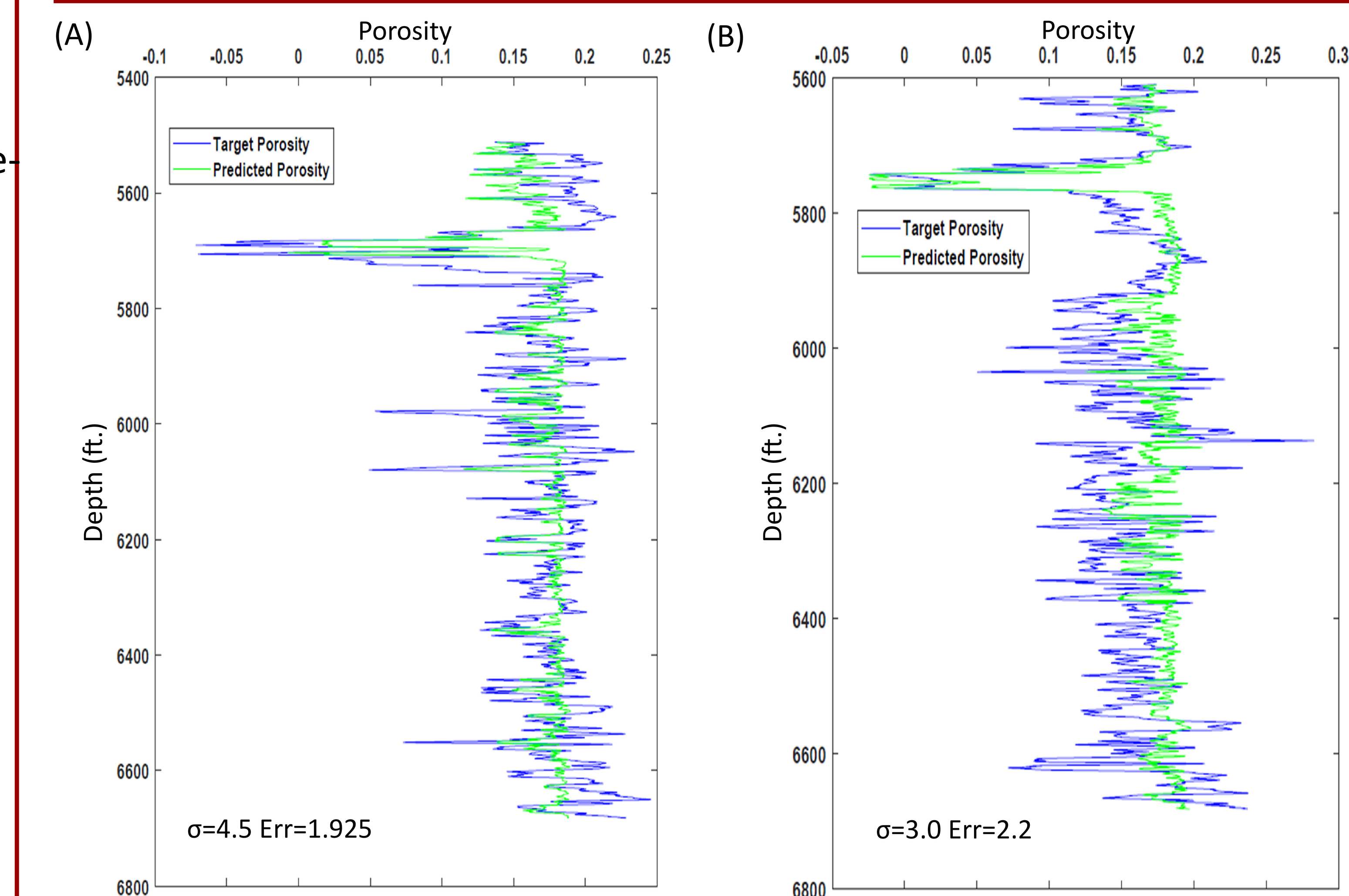

Figure 5: (A) PNN Prediction using Topaz as validation well. The predicted porosity follows correctly the behavior given by the target porosity. (B). PNN Prediction with Garnet as validation well. Note that the trends are similar, but that PNN overestimates the target values.

6. CONCLUSIONS AND FUTURE WORK

- PNN is a powerful technique to predict missing data using known properties as input.
- Computation time increases as more logs and a larger range of σ is used.

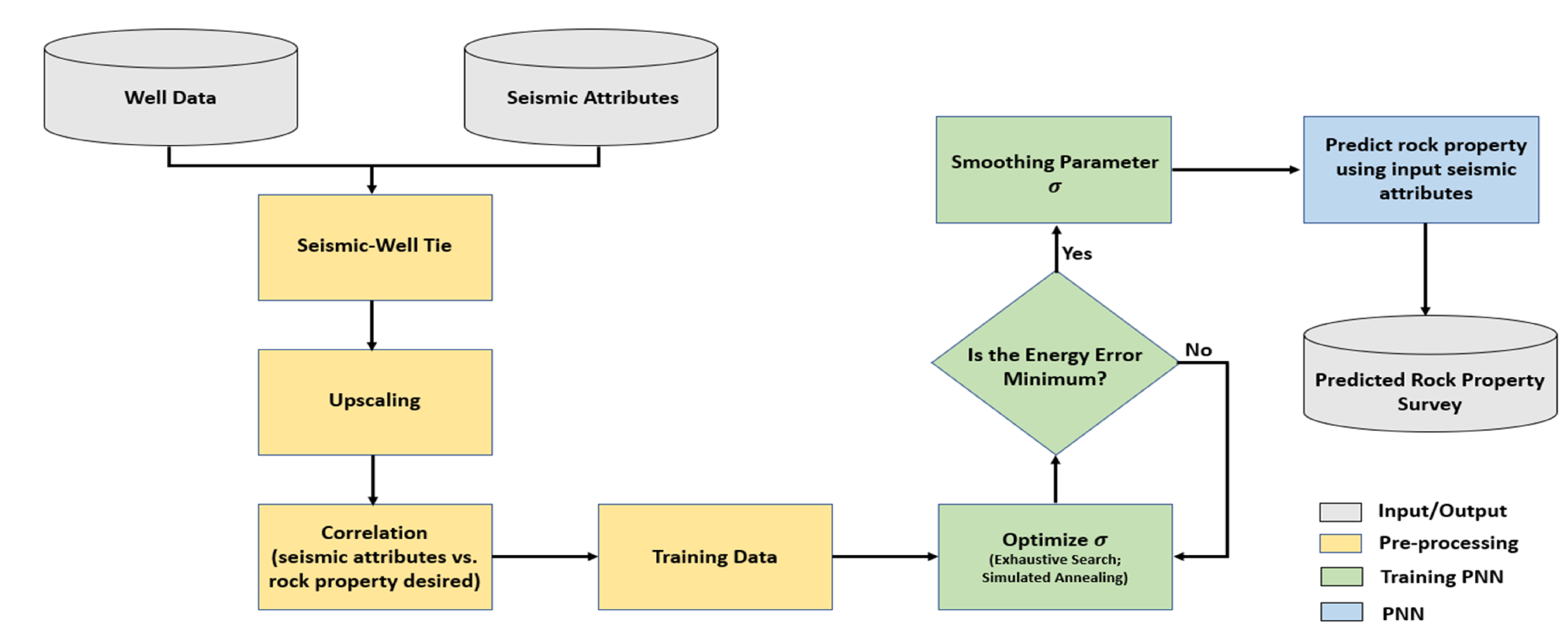

Figure 6: Workflow to implement probabilistic neural networks in order to predict reservoir properties using seismic attributes as input.

7. REFERENCES

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