Deep learning and inverse problems for geosteering applications

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Geosteering Inverse Problem: Background

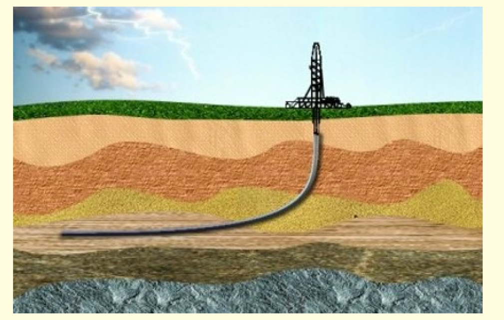


Figure: The schema of directional drilling. (www.amerexco.com)

- **Geosteering** is a key technique in directional drilling. It could be divided into two phases:
  - **Logging**: analyze the collected data.
  - **Drilling**: use the analysis results to adjust the well trajectory.

Geosteering Inverse Problem with a 3-layer Model

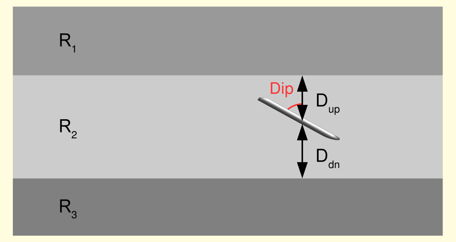


Figure: Directional drilling schema for an example of 3-layer model.

- The earth model are formulated by geophysical parameters.
  - R is resistivities.
  - $\mathrm{D_{up}}$ and $\mathrm{D_{dn}}$ are boundaries.
  - Dip is the dip angle (assumed to be fixed).
- The observed measurements are collected by the receiving antennas.

Common Solution to Geosteering Inverse Problem

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \mathcal{L}(\mathbf{x}) = \arg\min_{\mathbf{x}} \|\mathbf{y} - \mathcal{F}(\mathbf{x})\|_2^2 + \lambda\mathcal{R}(\mathbf{x}). \quad (1)$$

- The forward problem is of the form $\mathbf{y} = \mathcal{F}(\mathbf{x})$, where
  - $\mathbf{x} \in \mathbb{R}^5$ is earth model parameters including 3 resistivities and 2 boundaries.
  - $\mathbf{y} \in \mathbb{R}^{92}$ is observed measurements collected by logging tool.
  - $\mathcal{F} : \mathbb{R}^5 \mapsto \mathbb{R}^{92}$ is an EM forward model function defined by Maxwell Equations.
- Since $\mathcal{F}$ could produce synthetic measurements, (1) could be solved by minimizing the loss function $\mathcal{L}$, i.e. a synthetic error with a regularization term $\mathcal{R}(\mathbf{x})$.
- In deterministic methods [1, 2], $\mathbf{x}$ is optimized by calculating the gradient of $\mathcal{L}$.

$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}} = 2\left(\mathbf{y} - \mathcal{F}(\mathbf{x})\right)\frac{\partial \mathcal{F}}{\partial \mathbf{x}} + \lambda\frac{\partial \mathcal{R}}{\partial \mathbf{x}}. \quad (2)$$

- (2) is used to calculate first-order gradient, where
  - $\partial\mathcal{F}/\partial\mathbf{x} \in \mathbb{R}^{92\times 5}$ is the *Jacobian* matrix.
  - $\partial\mathcal{R}/\partial\mathbf{x} \in \mathbb{R}^5$ is the gradient of regularization term.

Challenges for Logging

Table: Different logging methods.

	On ground	Underground
Data Amount	Inadequate	Adequate
Computation	Fast	Slow
Memory	Large	Small

- Two logging methods in practice:
- On ground method.
  - Process data on the ground.
  - Need to wait until the data gets transmitted back.
  - Data is not enough but hardware is powerful.
  - Use optimization method.
- Underground method.
  - Process data with devices underground.
  - Do not need to wait for data transmission.
  - All data is available but hardware is limited by underground environmental conditions.
  - Use lookup table as a surrogate.

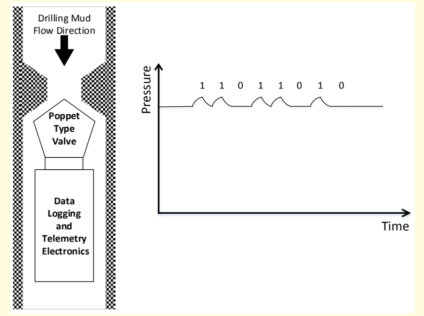


Figure: Positive purse pressure wave, used for data transmission, is with a very slow transmission rate.

Underground Method Surrogate: Lookup Table

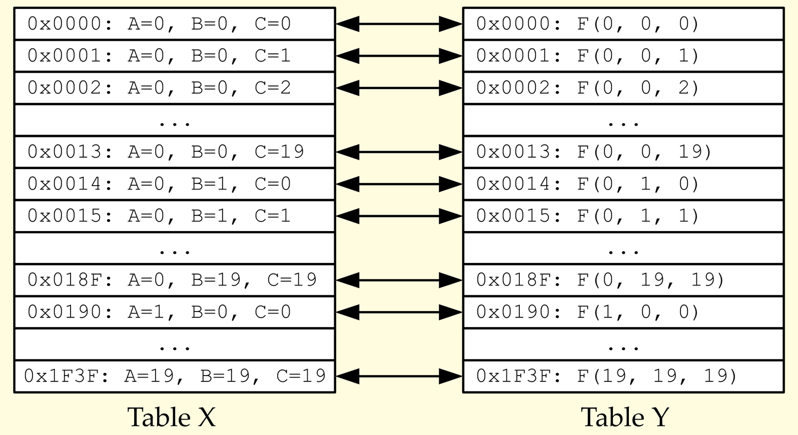


Figure: Lookup table method for fast estimation of the inversion.

- Construct table by pre-computing a lot of samples in the whole data space.
- Use the best-matched sample in the table to estimate a coarse solution.
- Drawbacks:
  - Large memory consumption and extremely coarse samples.
  - Both the computational cost and memory cost increase exponentially with the density of the table.

Our Proposed Surrogate: PhDNN

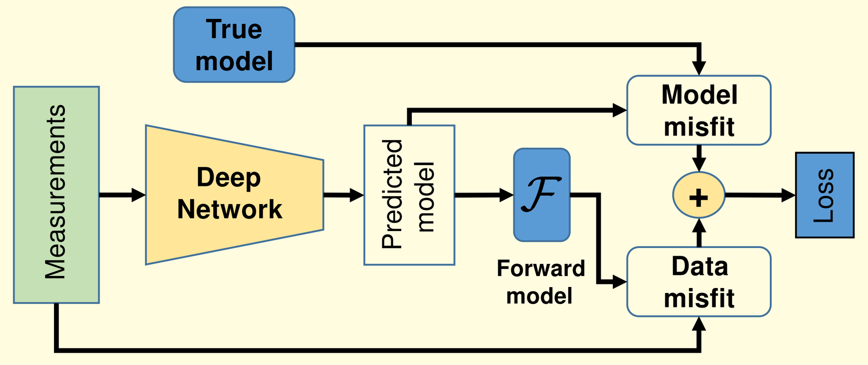


Figure: The physics-driven deep CNN (PhDNN) structure.

- The deep network is a 1D network which is adapted from VGG16 model. The model is trained by Adam optimizer [3].
- We have two contributions for this architecture.
  - Use 1D convolutional layers. Each layer composes of a convolution, an instance normalization [4] and a PReLu activation [5].
  - Use a physics-driven loss function:
    - A model misfit: $\|\mathbf{x} - \hat{\mathbf{x}}\|$.
    - A data misfit ($\|\mathbf{y} - \mathcal{F}(\hat{\mathbf{x}})\|$).

Computing Gradients for PhDNN – I

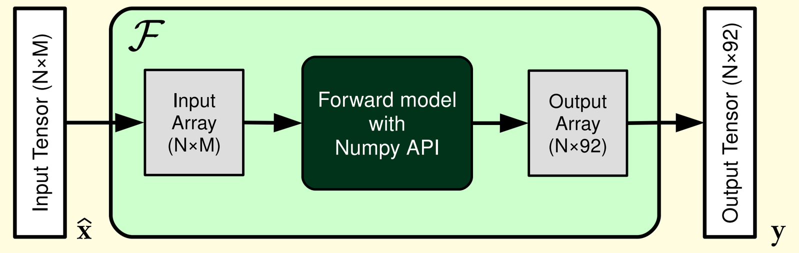


Figure: The implement of the forward model.

- The forward model function is highly nonlinear.
- In feed-forward process, the function could be viewed as a black box accepting earth model parameters ($\mathbf{x}$) and producing synthetic measurements ($\mathbf{y}$).

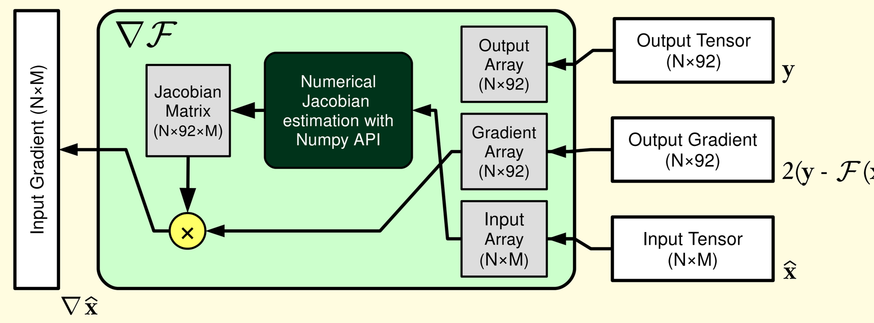


Figure: The implement of the back propagation of the forward model.

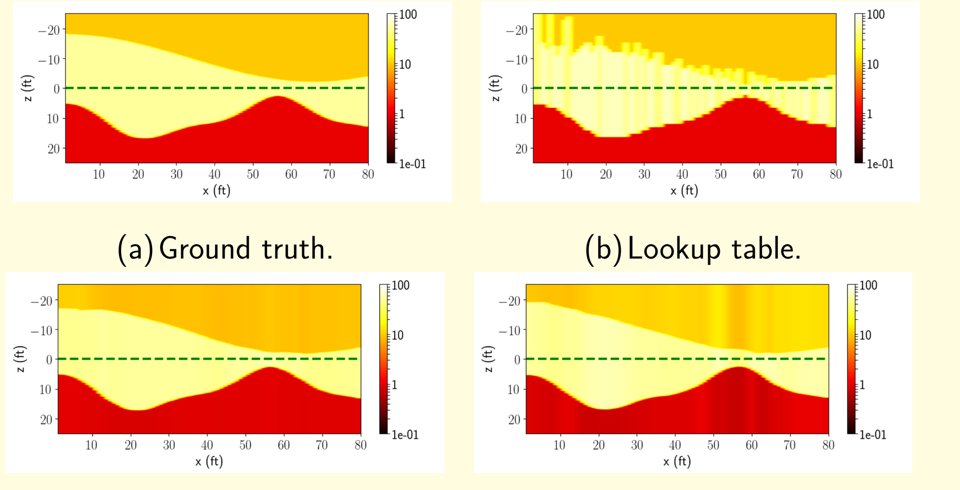
Computing Gradients for PhDNN – II

- In back-propagation process, The module accepts two inputs:
  - The current synthetic input of the forward model ($\hat{\mathbf{x}}$).
  - The gradient from the next layer ($2(\mathbf{y} - \mathcal{F}(\mathbf{x}))$).
- The gradient would be back-propagated to the previous layer in the deep network by using Jacobian matrix like (2).

Our Proposed Surrogate: Advantages – I

- The following performances are produced by a 2-core (i5) laptop without GPU.
- The network could be deployed for underground method.
  - The network is totally **feed-forward** and only requires **light computation** (about 0.3s for 80 points). The lookup table is slower (about 60s) while the optimization method is much slower (about 400s).
  - The network has a **small data size** (lower than 30MB) compared to a lookup table (about 1.6GB), which requires **lower memory consumption**.
- The network could make use of **all data** by taking advantage of underground method, while the optimization method could not.
- The network could get a far more **accurate prediction** compared to lookup table.
- The **computational cost** of the network **would not increase** with the data amount.

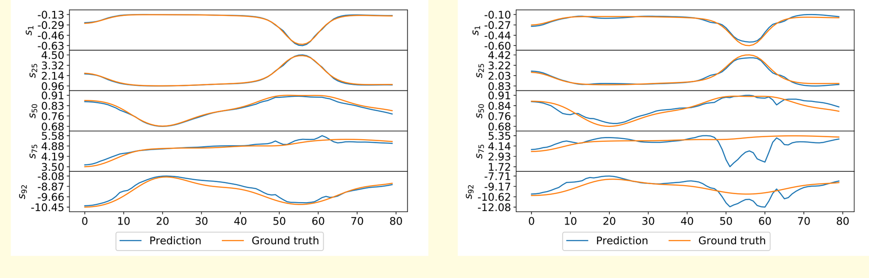
Results: Solution for Earth Model



(a) Ground truth. (b) Lookup table. (c) Proposed (PhDNN). (d) Data-driven Network.

Figure: The predicted earth model of an example, where the proposed network achieves better resistivity prediction compared to that of the conventional data-driven network.

Results: Synthetic Measurements



(a) Proposed (PhDNN). (b) Data-driven Network.

Figure: Some selected curves for the example, where the curves are picked from the synthetic measurements produced by the predicted earth model.

Results: Numerical Tests

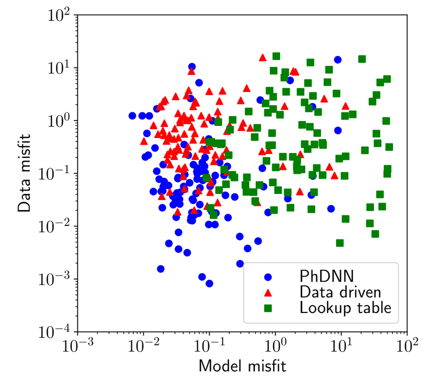


Figure: The numerical tests over compared methods.

- We generated 100 examples earth models like the shown one.
- $\boldsymbol{x}$ axis represents model misfit, and $\boldsymbol{y}$ axis represents data misfit.
- Compared to data-driven network, the proposed one could achieve the same model misfit but a better data misfit.

Acknowledgment

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