Machine Learning in 4D Seismic Interpretation: Monitoring the Reservoir

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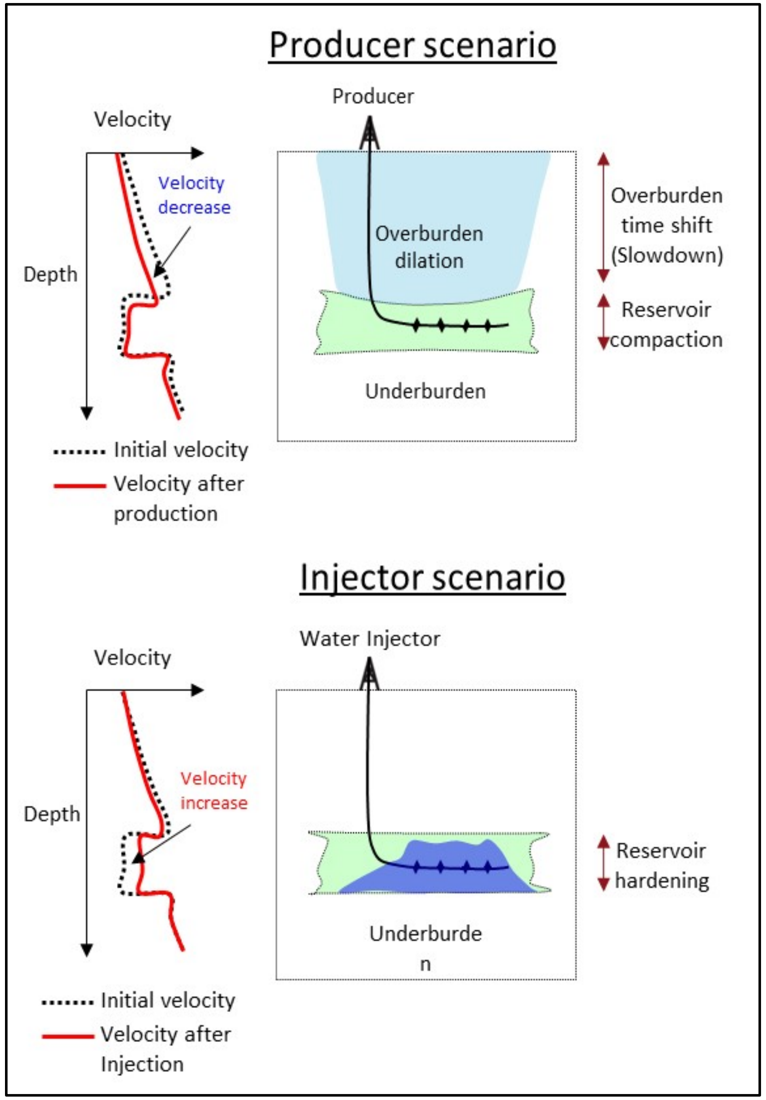
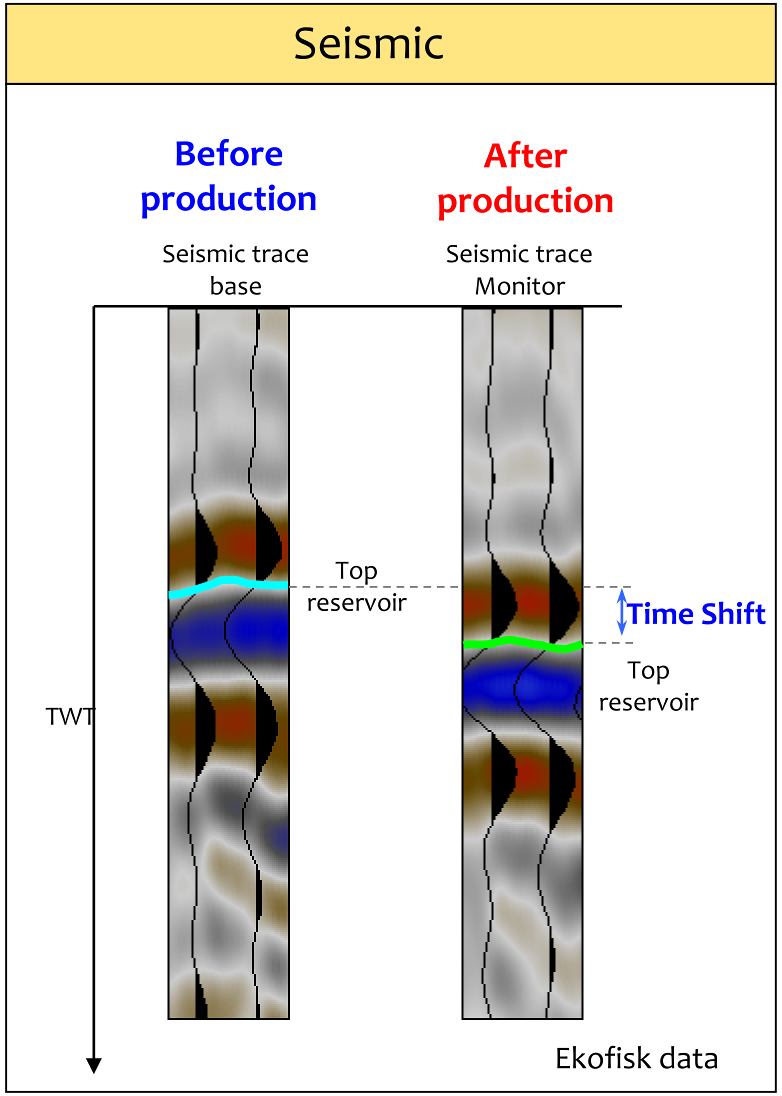
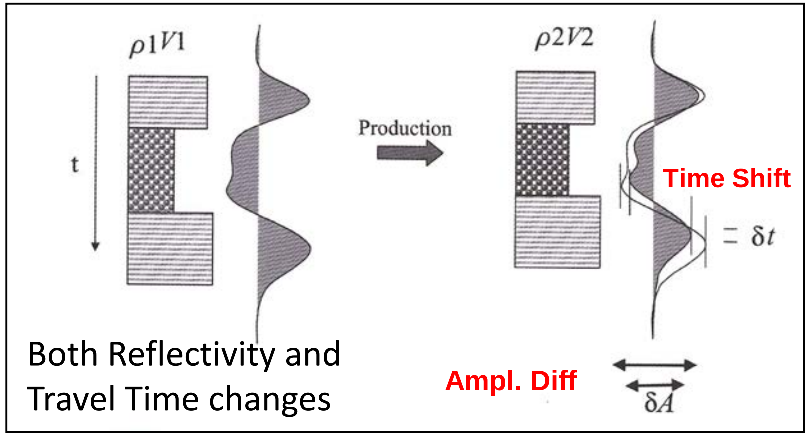
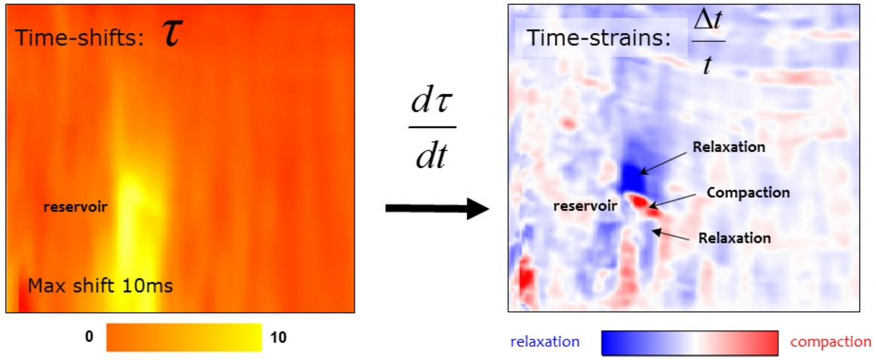
Basic Seismic Measurement: Time Delay & Amp Diff









after Rickett *et. al.*, SEG, New Orleans, 2006

Motivation

- **Objective:** Ability to reliably and efficiently interpret 4D reservoir property changes directly from joint usage of multiple attributes and multiple seismic surveys to impact
  - Reservoir management decisions
  - Well Planning
  - Reservoir Model Updating – impacts Long Range Planning and Forecasting

- **Challenges:**
  - Current 4D interpretation – requires simulation and rock physics models (modeling workflows)
  - 4D Seismic Inversion Difficult
  - Qualitative $\rightarrow$ Semi Quantitative interpretation
  - Linear workflows currently used for a very non-linear dynamic problem

- **Data Analytics Opportunity:**
  - Directly estimate reservoir property change maps
  - Data driven workflows
  - Multidimensional data integration

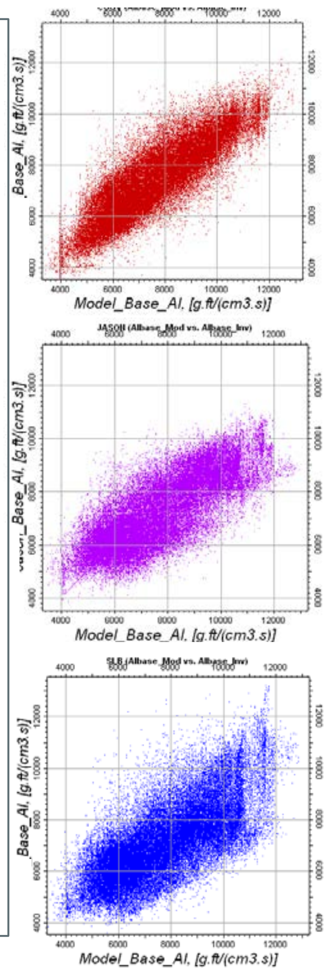
4D Pre-stack inversion

Synthetic dataset benchmarking

Vendor	Algorithm Type	Inputs	Outputs	Reservoir Properties Inversion	Joint 4D Inversion	Joint Amp & Time Shift
Contractor 1	Joint 4D Inversion, Prestack	Angle Stacks, Wavelets, LFM	ΔAI, ΔPR, Timeshifts, 4DLFM	Rock Physics template Compaction	Multiple vintages	intra-reservoir only
Contractor 2	3D Inversion + Differencing, 4D Inversion Prestack	Angle Stacks, Wavelets, LFM	ΔAI, ΔPR, Timeshifts, 4DLFM	Rock physics template Compaction – maybe	Yes	No
Contractor 3	Joint 4D Inversion, Prestack	Angle Stacks, Wavelets, LFM	ΔAI, ΔPR, Timeshifts, 4DLFM	Rock Physics template Compaction	Multiple vintages	No

3D Acoustic Impedance
(Inversion vs. True)

Inverted



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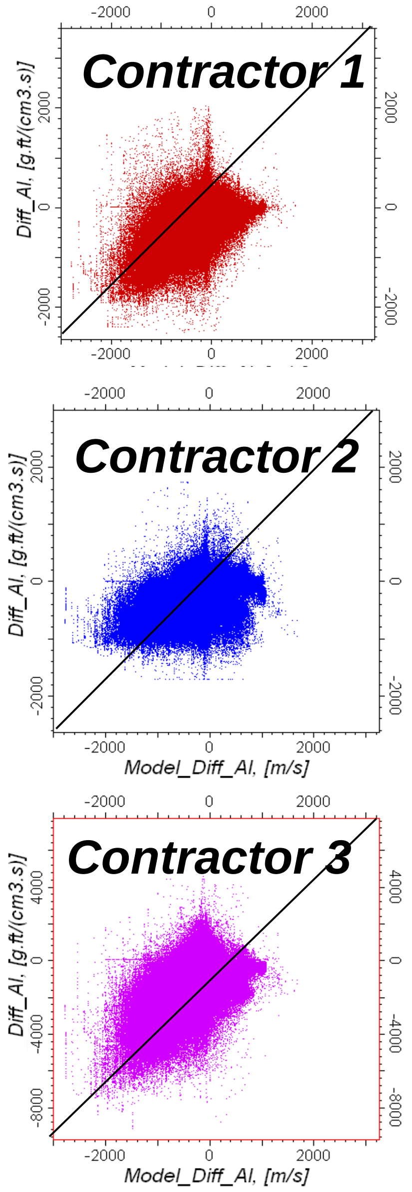
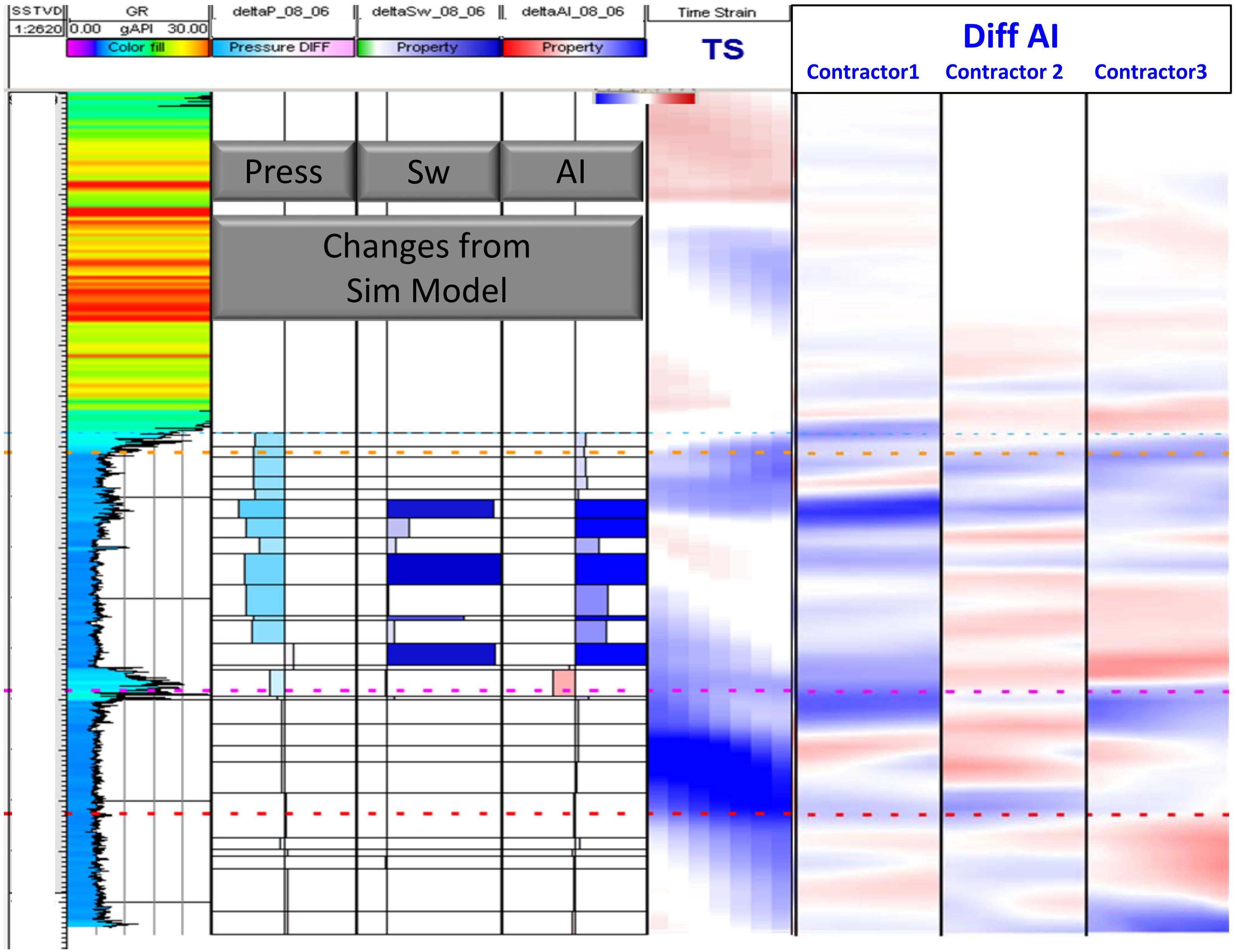
4D Synthetic Model Inversion: Δ (Acoustic Impedance) – Model vs. Inversion Results





Complexity of 4D Interpretation: Seismic sensitivity *(Prestack Integration required)*

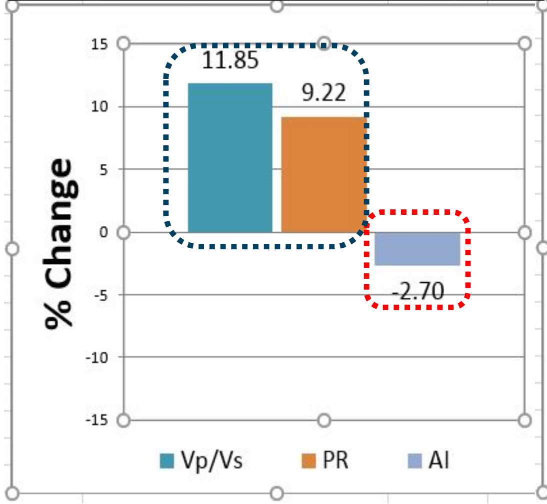
Complex Reservoir Property Changes

Reservoir Changes	Pressure	Sw	Sg	Compaction	Net effect on Vp
@producers	↓	↑	↑	Yes	↑ or ↓
@injectors	↑	↑	↓	Yes	↑ or ↓

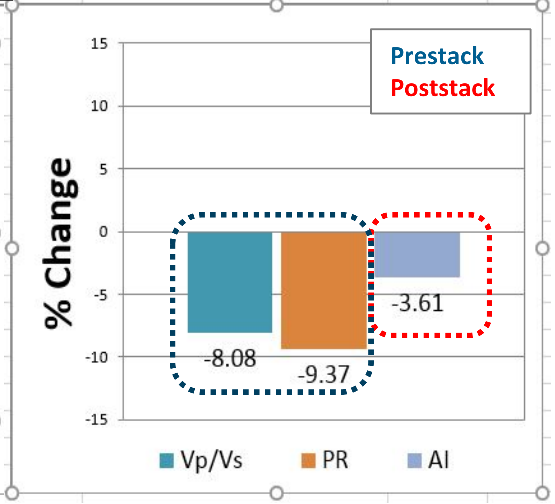
Property	Increase	Decrease
Pressure	Softening	Hardening
Sw	Hardening	Softening
Sg	Softening	Hardening

Prestack Seismic for P/Sat discrimination

Injection: P up, Sw up



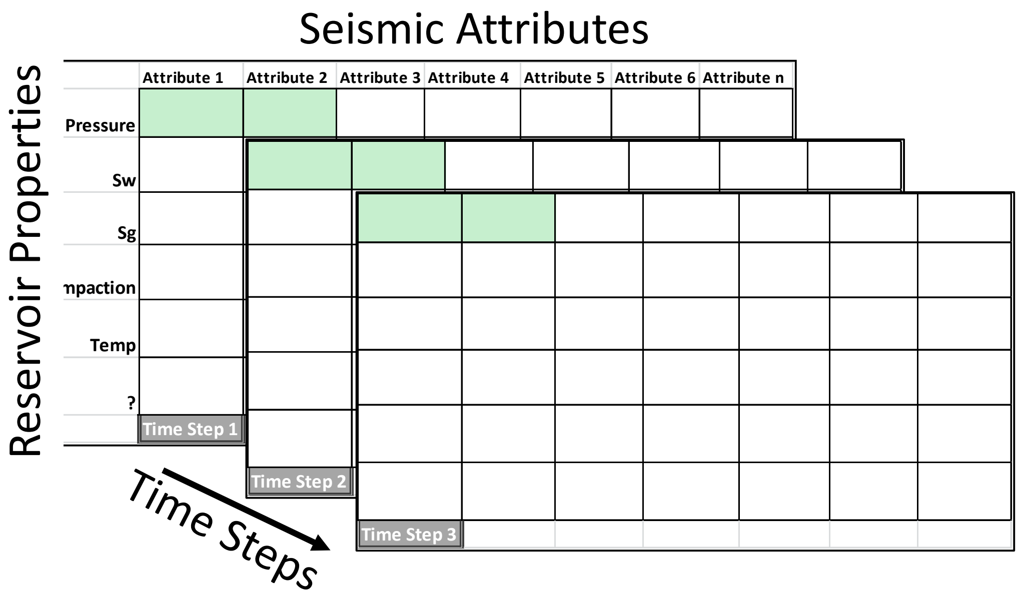
Production: P down, Sg up



- **Attributes typically used**
  - **4D stack amp**
  - **Time Strain**

- **Integration of prestack data is critical for pressure/saturation discrimination**

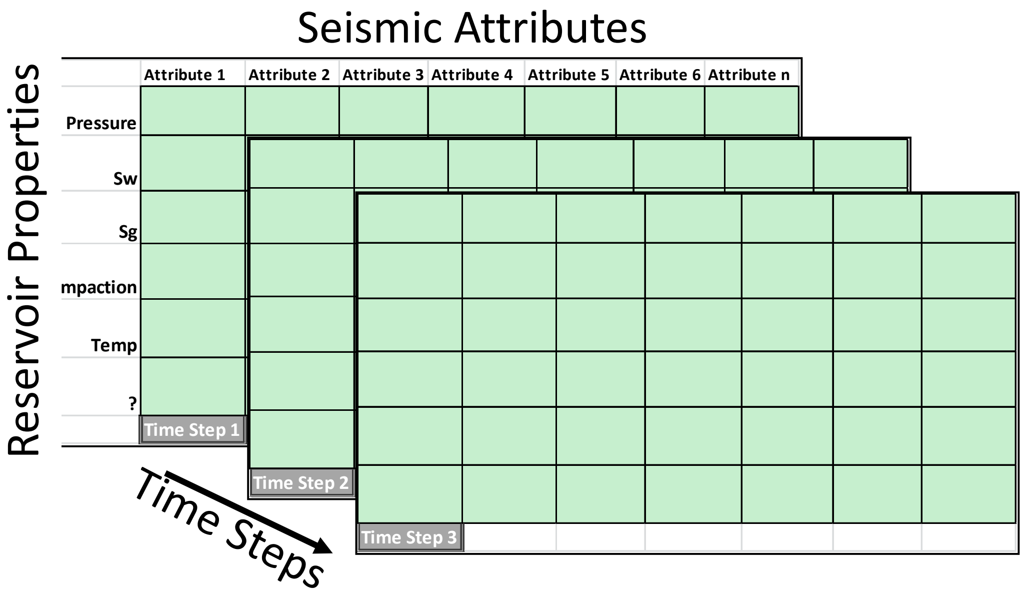
Seismic sensitivity to reservoir property changes makes 4D seismic assisted reservoir management possible



Technical Challenges

Predictive Analytics

Efficiency Challenges



Current: 4D Model Based Workflow

4D Attributes → **Manual Interpretation** / **Qualitative** → ΔPr, ΔSw ΔSg, ΔCp

- **Manual Interpretation 1-time step at a time**
- **Uses Simulation and RP Models**
- **Lack of repeat logs for RP calibration**

Predictive Analytics

Proposed: Data Driven Analytics Workflow

3D+ 4D Post Stack + Prestack All time steps → ***Direct Prediction*** / ***Simultaneous Quantitative*** → ΔPr, ΔSw ΔSg, ΔCp

- **Solution consistent with all available data**
- **Utilizes embedded physics in the data**
- **Uses property change from Sim model @ wells**

Dynamic Reservoir Property Prediction: 4D Analytics Workflow

Prediction Target: 4D pressure, saturations, temperature and compaction changes

Step1: CREATE INPUT MAP DATA

Feasibility

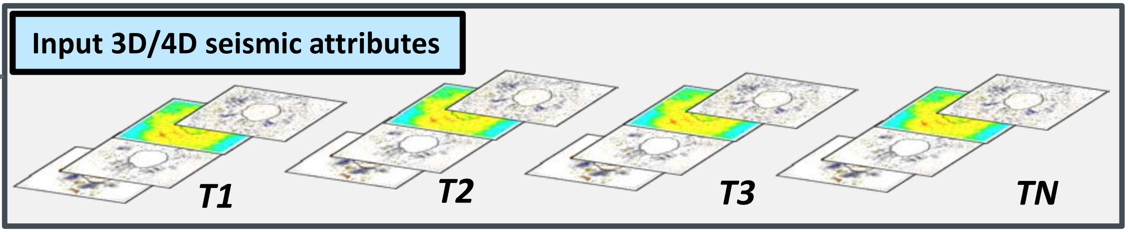
success case

Field Data

Simulation Model

RPM

4D Synthetic attributes

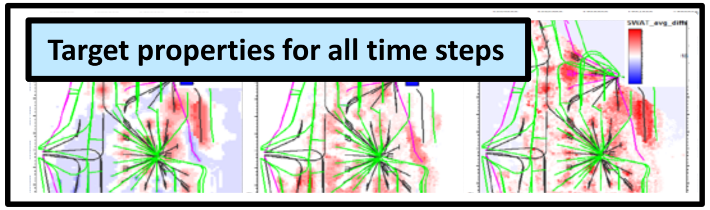


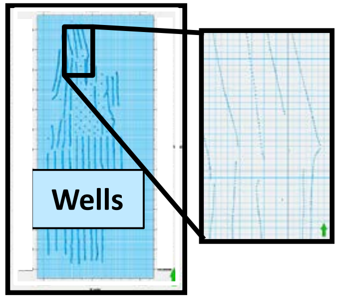
Step2: SELECT INPUT AND TARGET DATA AT WELLS

Injectors

Producers

Data sampling and QC

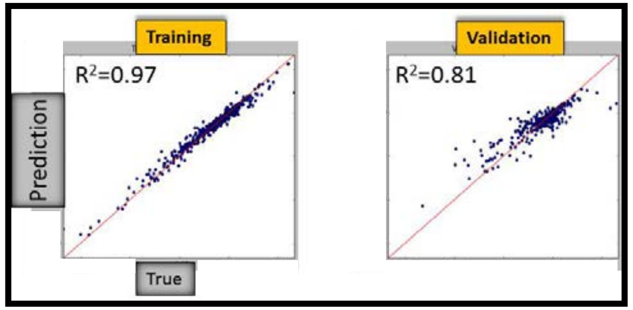




Step3: TRAINING AND VALIDATION

For field data application:

- **Assumption:** Sim model is sufficiently matched at the wells
- Detail QC required to assess outliers



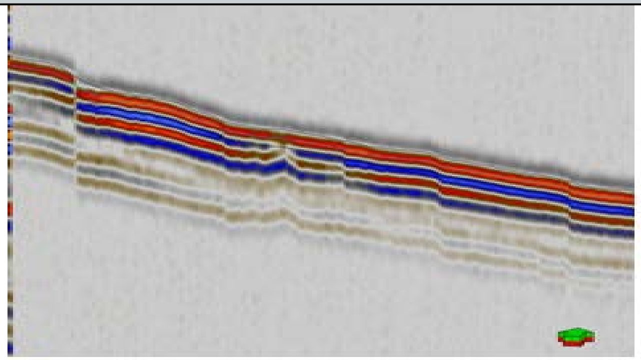
Step4: PREDICTION

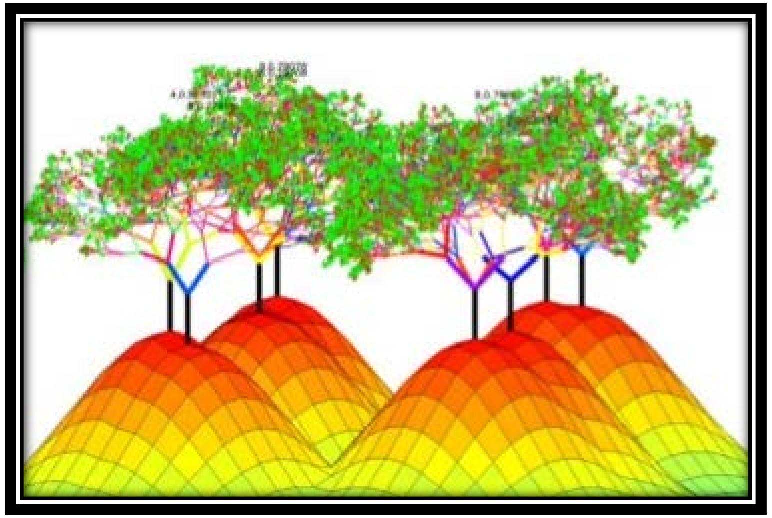
Onshore Conventional Field: Synthetic Study

Experiment Outline:

- ❑ Forward model 4D synthetic seismic based on a dynamic reservoir simulation model
- ❑ Assume knowledge of **predictors** (elastic/seismic attributes) & **targets** (pressures , saturations) at wells: ground truth
- ❑ Train and validate multiple supervised learning algorithms (random forest, neural nets, …)
- ❑ Test sensitivities:
  - Type of predictor
  - Reservoir stratigraphy
  - Noise

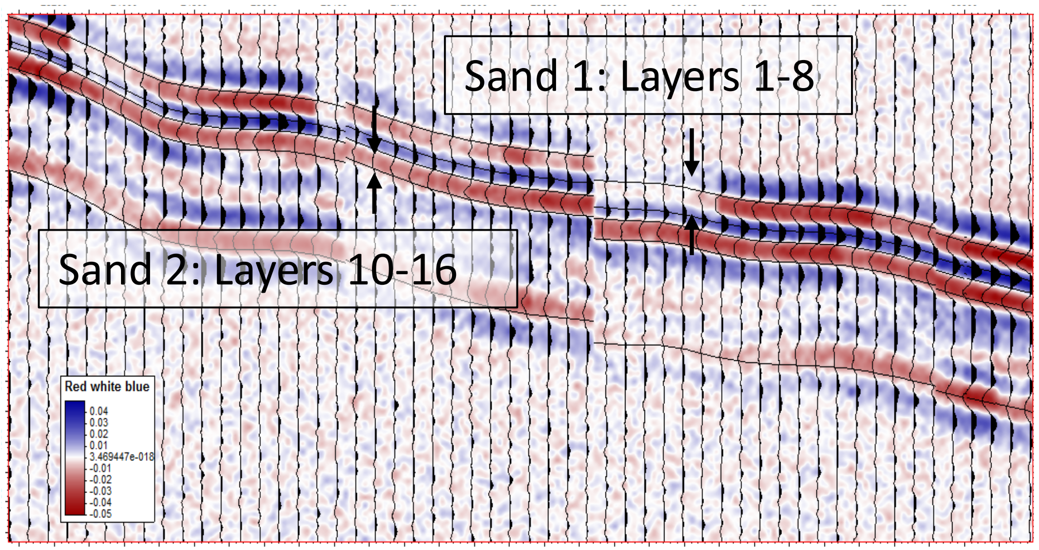
Forward Modeled Synthetic Seismic

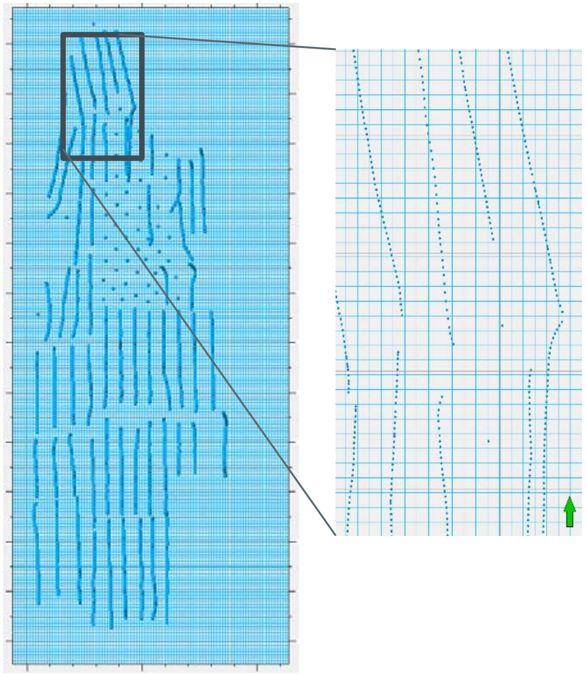




Horizon Based Attributes

- Synthetic seismic generated from the sim model
- Target attributes **(ΔSw, ΔSg, ΔP)** related to seismic attributes
  a) 4D Elastic properties **(acoustic impedandance, shear impedance, Vp/Vs, time strain)**
  b) 4D Seismic attributes **(stack, gradient and intercept quadrature amplitudes, seismic time strain,…)**
- Maps extracted and averaged over the sand intervals:





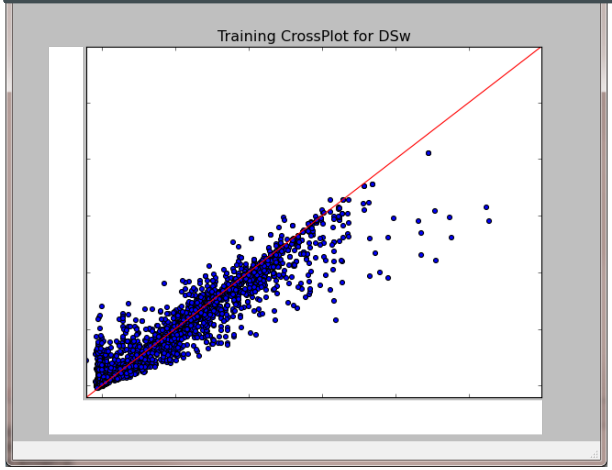
Well points extracted 100 ft intervals

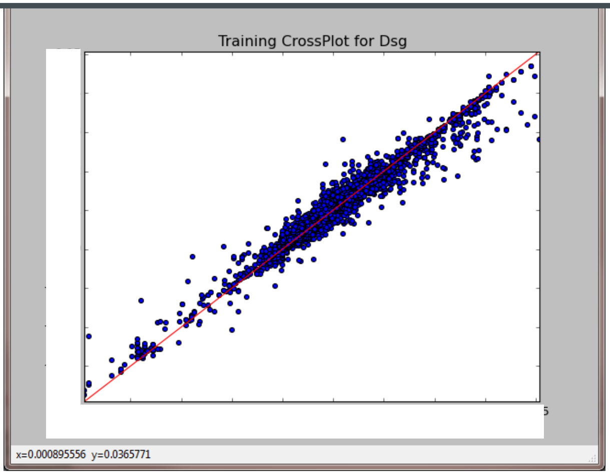
Noise Sensitivity: Training & Validation

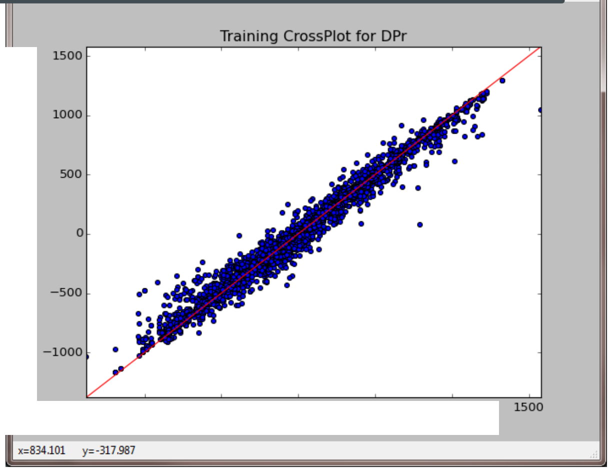
S/N=0 Synthetic

Training

ΔSw	ΔSg	ΔPressure



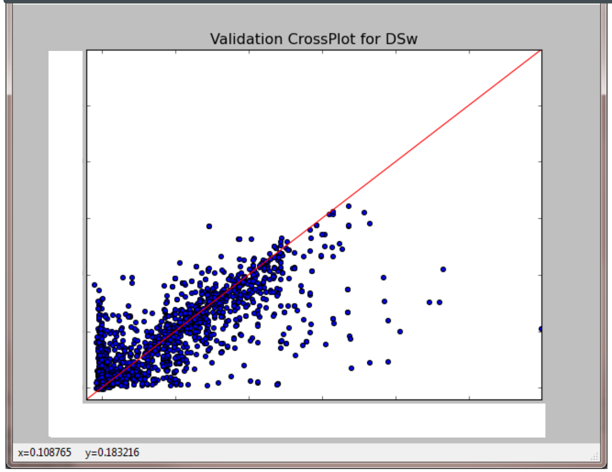


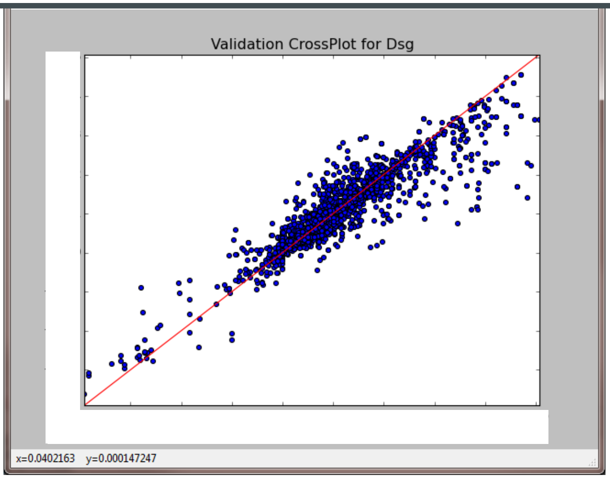


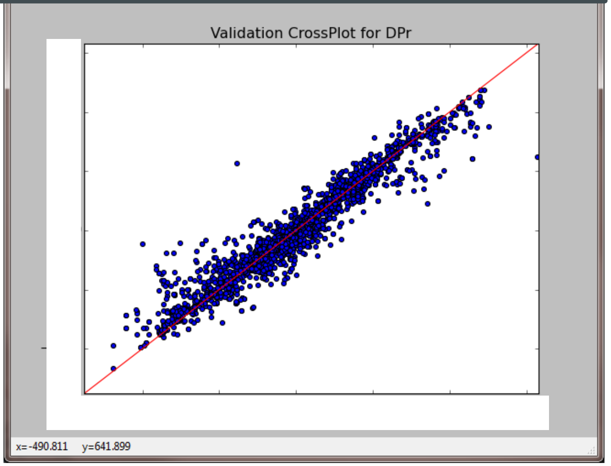
Median importance of variables:
'stack' = 0.129
'grad' = 0.633
'intercept' = 0.129
't strain' = 0.110

Validation

ΔSw	ΔSg	ΔPressure





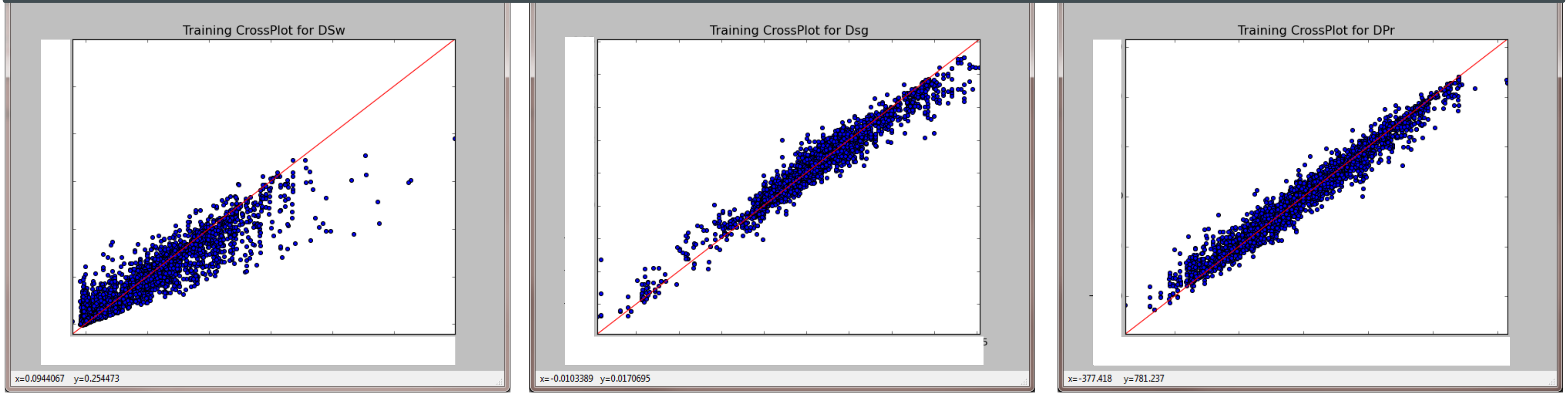


Noise Sensitivity: Training & Validation

S/N=12 Synthetic

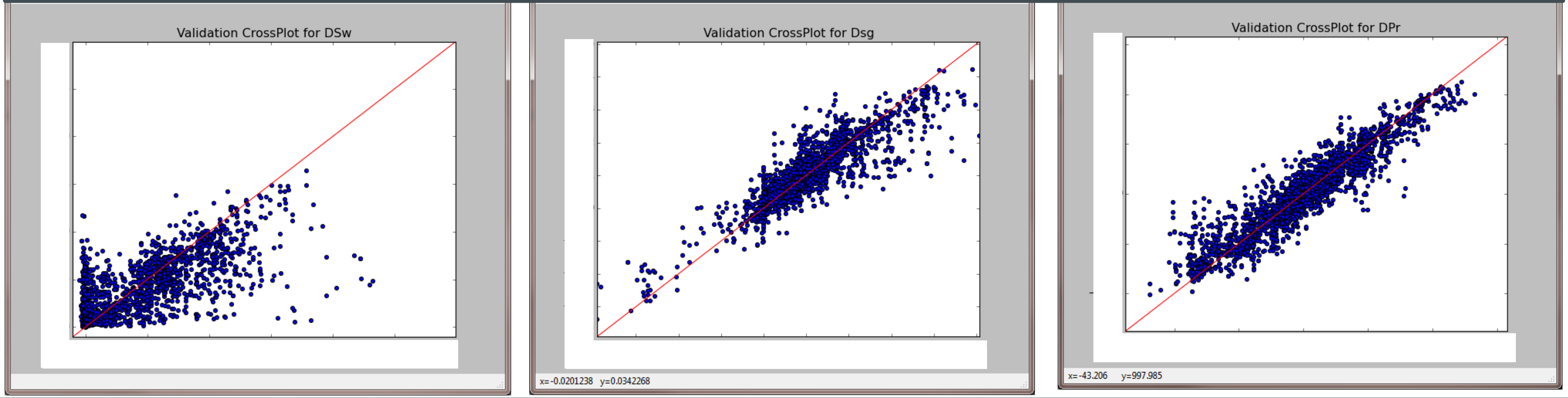
Training

ΔSw	ΔSg	ΔPressure



Validation

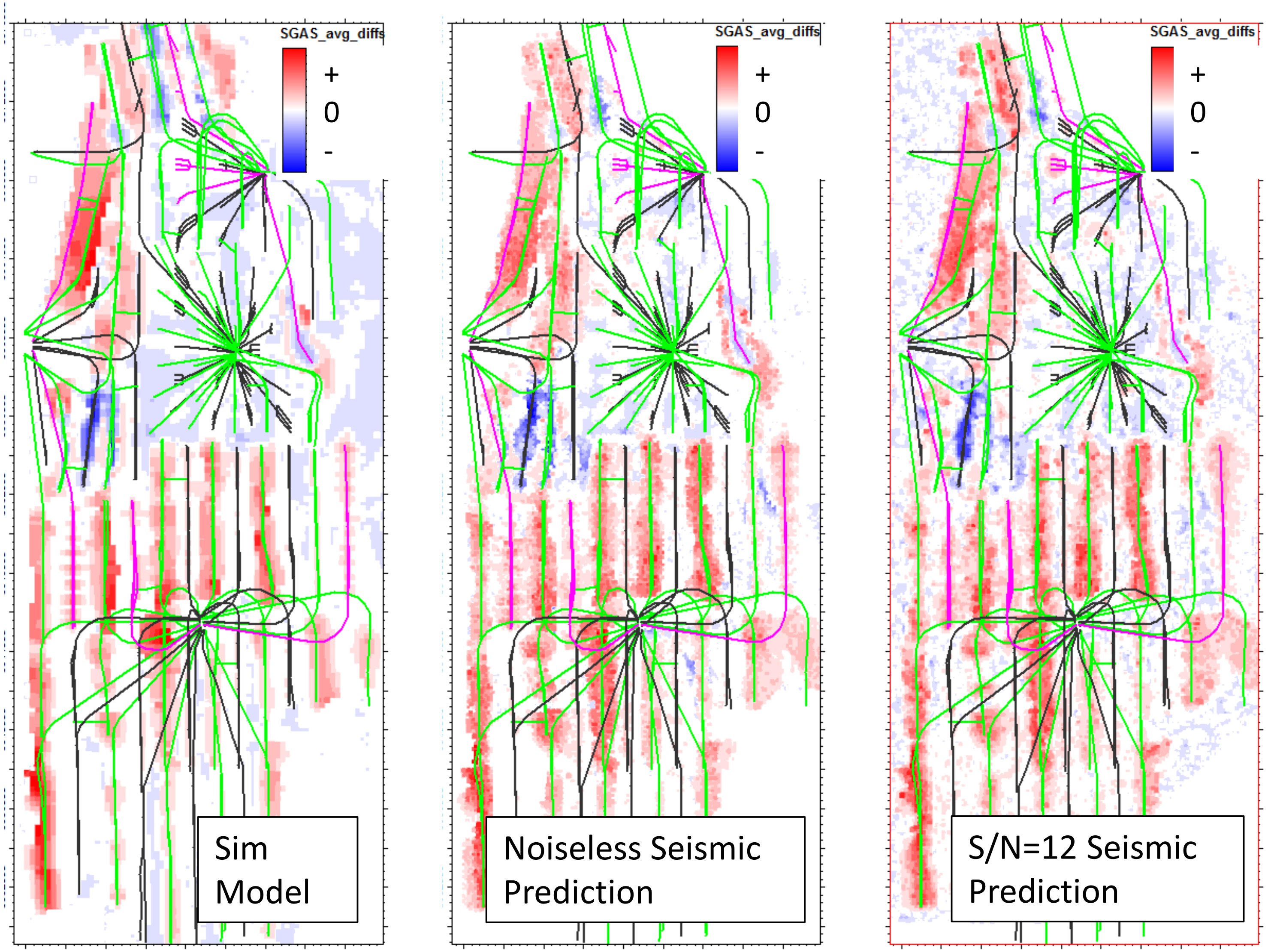
ΔSw	ΔSg	ΔPressure

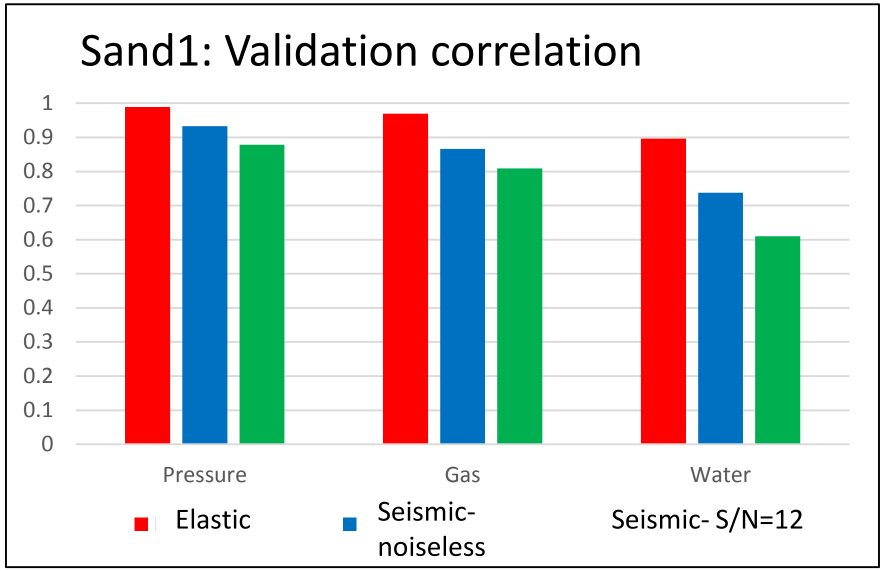


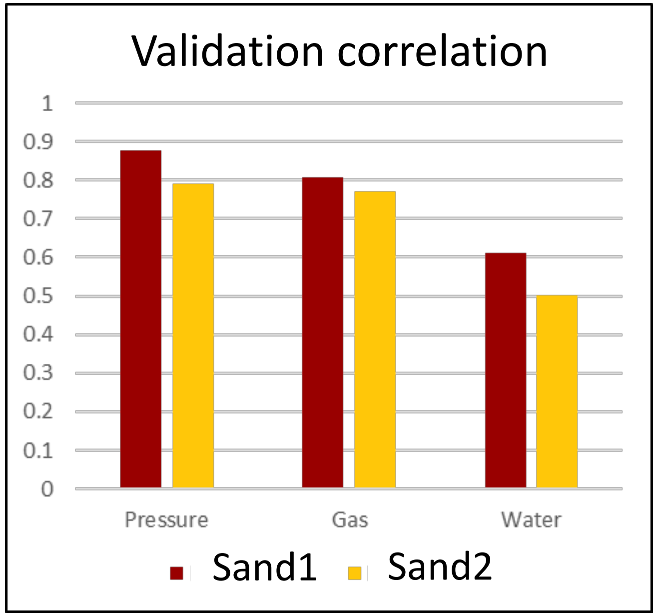
Median importance of variables:
'stack' = 0.177
'grad' = 0.516
'intercept' = 0.163
't strain' = 0.144

Map Predictions Time Step 1

Δ Sg Comparison

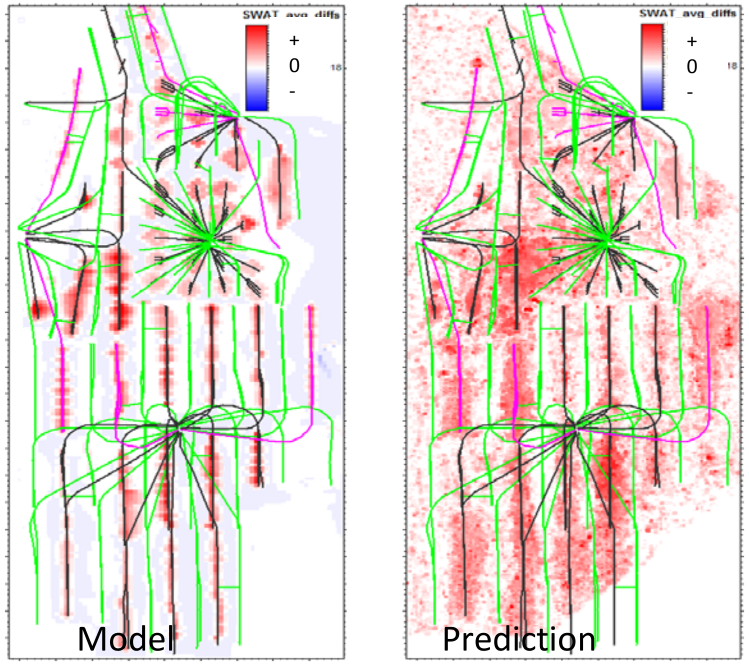




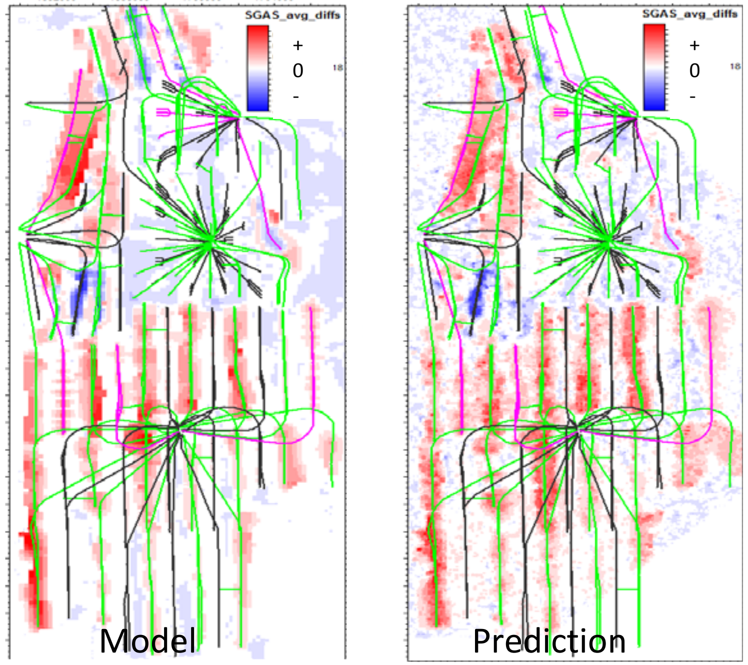


Synthetic Seismic – Prediction Maps: Time Step 1 changes Sand 1

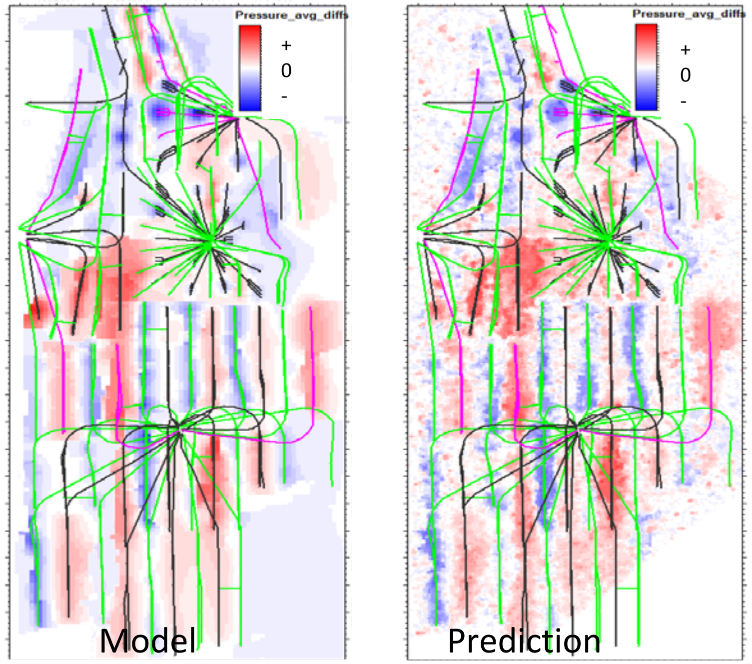
Δ Sw



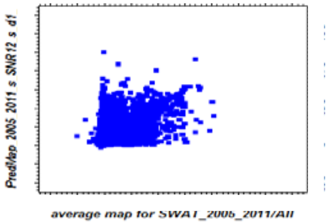
Δ Sg



Δ Pressure

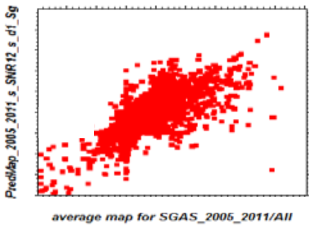


Prediction



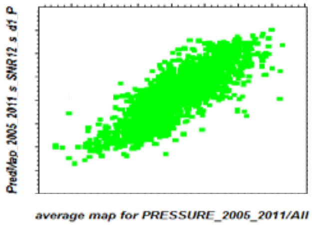
Model

Prediction



Model

Prediction



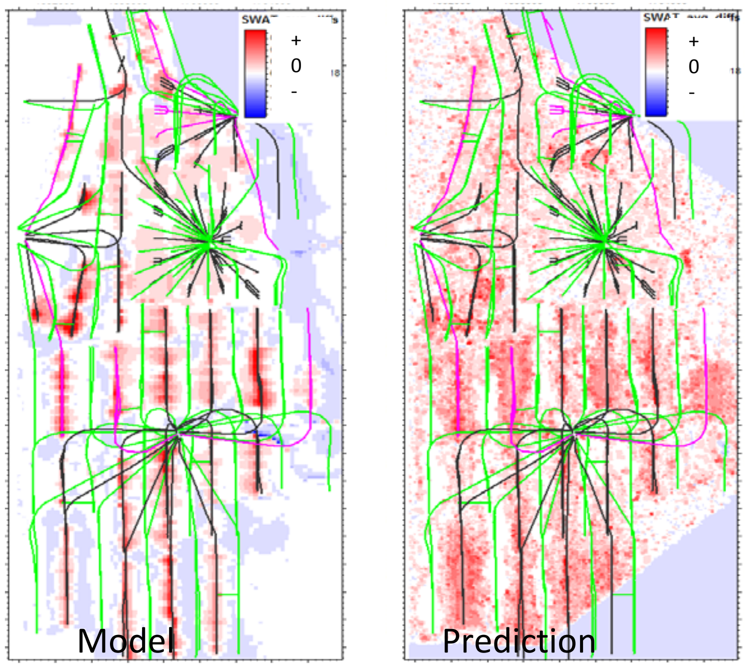
Model

Key Highlights:

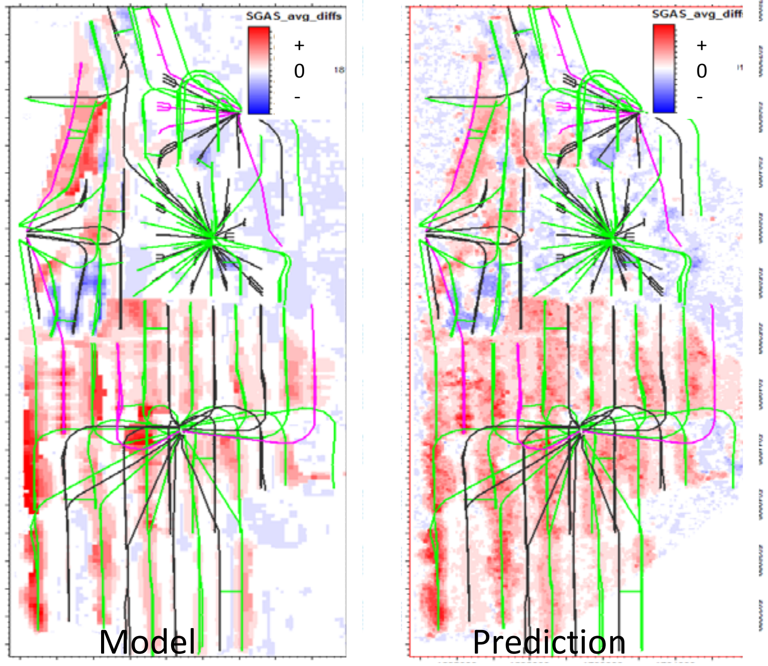
- Δ Pressure, Δ Sg excellent agreement
- Δ Sw noisy, sensitive only to larger changes
- Pre-stack input crucial

Synthetic Seismic – Prediction Maps: Time Step 1 changes   Sand 2

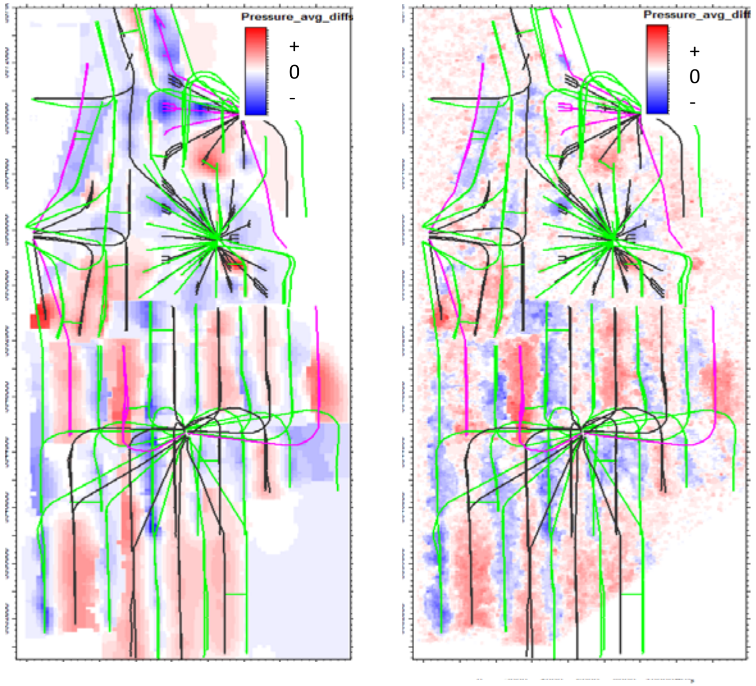
Δ Sw



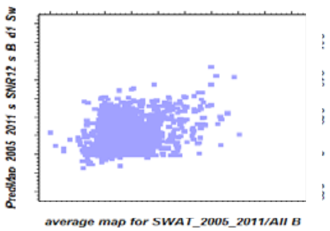
Δ Sg



Δ Pressure

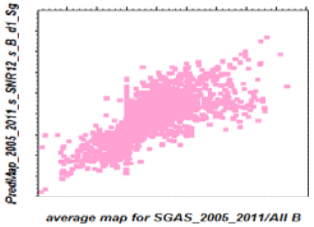


Prediction



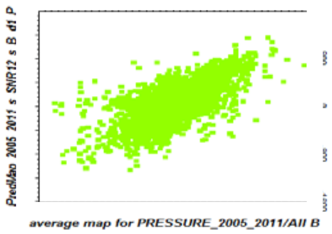
Model

Prediction



Model

Prediction



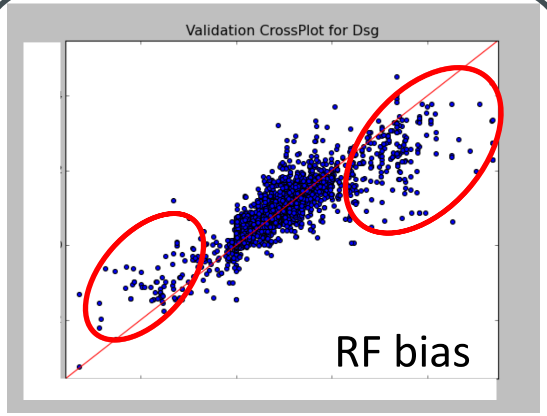
Model

Observations:

- Δ Pressure, Δ Sg still good
- Δ Sw limited sensitivity
- Interbed interference can be resolved

4D Synthetic Project Learnings

- Time-lapse seismic inverse problem solvable by ML regression algorithms:
  - Random Forest – stable, robust, best results
  - Gradient Boosted Trees – alleviates some RF shortcomings
  - Neural Nets – not as successful



- Map based analytics approach data driven
  - Avoids explicit need for a calibrated rock physics model
  - Simplifies vertical reservoir complexity (4D attributes can be augmented by 3D attributes, e.g. Impedances from inversion)
  - Predicted saturation and pressure differences directly constrain sim models

- Challenges:
  - Not a full volume based inversion (resolution issues) and depends on interpretation
  - Lack of 4D well data - crucial assumption about sim model being true at well locations

4D Predictive Analytics - Key Takeaways

- New data driven workflow for simultaneous 4D reservoir properties prediction

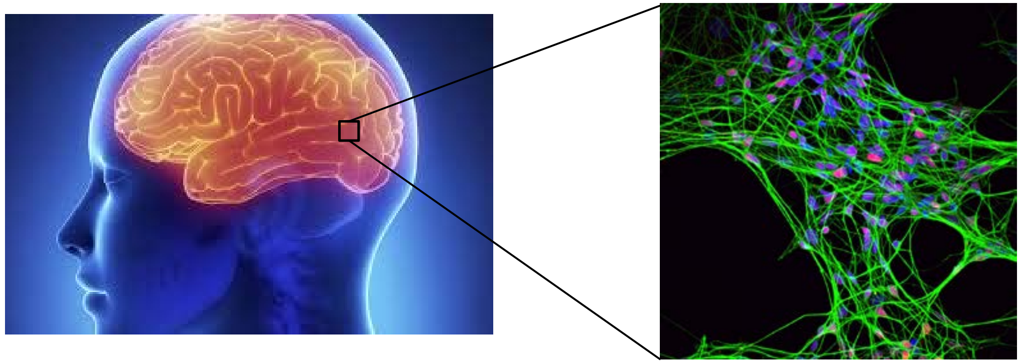
- Predictive Analytics is a key enabler for directly predicting (ΔP, ΔSw, ΔSg) using all 4D attributes and integrating prestack seismic

- Value to 4D interpretation workflows:
  - Efficiency and reduced cycle time for interpretation
  - Provides a common ground for revisiting 4D model updating workflows
  - Facilitates inter disciplinary integration (geophysics, reservoir engineering,…)

- Validation is critical

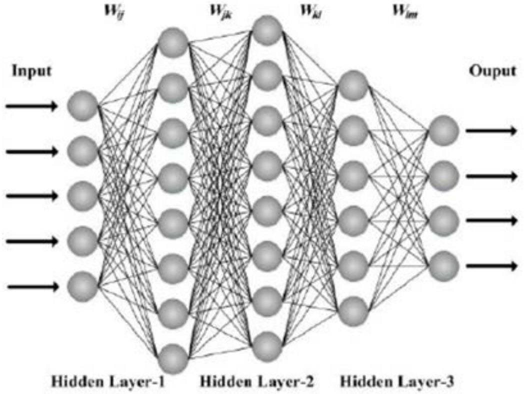
- Success of the feasibility projects have resulted in successful field data applications

Future: Deep Learning - Multi Layer Neural Networks



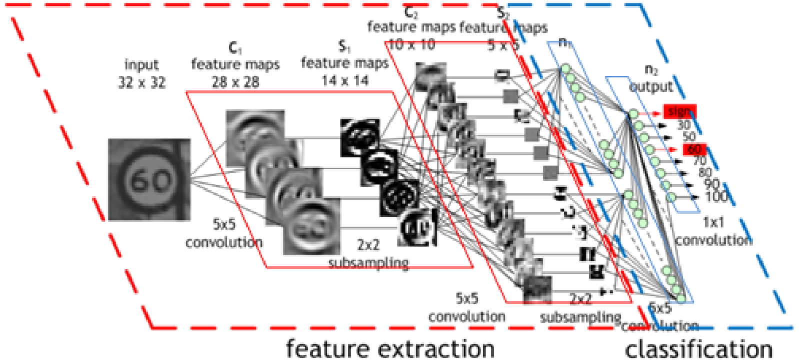
- Neural networks are loosely modeled after the highly interconnected cortical neurons and how they pass information from one to another (via charge buildup).
- **Intelligence** and **learning** are accomplished when neural pathways are strengthened by associating observations or other impulses with a specific result.

Multi-Layer Perceptron (MLP)



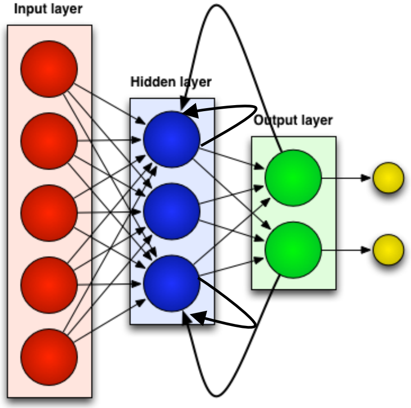
- Simplest form of neural net
- Everything is fully connected
- The weights of each connection are learned
- Universal extrapolators
- Excel in classification and regression

Convolutional Neural Net (CNN)



- Mainly used for classification
- Uses MLP at the end of the architecture
- A variety of features pertaining to the input are learned
- Computer vision is possible due to CNNs

Recurrent Neural Net (RNN)



- Used for classification or regression
- Outcomes are cycled back into the hidden layers to preserve information
- Useful for detecting patterns over time or other sequential data (i.e. speech recognition)
- Hard to train