## **PROJECT 1**

Goal: Hybrid machine learning and inverse modeling for gas leakage detection based on observational data

- > Characterizing gas source strength  $(q_s)$ , properties (v, D) and locations
- Reconstructing gas concentration profile in time and space

**Results:** Reduced the cost of monitoring and number of detectors

Partnership: Australian National Low Emissions Coal Research & Development, Canberra, Australia

Methods: Machine learning, Inverse Modeling, K-means and genetic algorithm clustering, Web scraping, Non-negative matrix factorization, Non-linear least square minimization, Analytical solution





 $\frac{\partial C}{\partial t} + v \frac{\partial C}{\partial z} = D \frac{\partial^2 C}{\partial z^2}$  $V_n(t)$ : Observational data (1)  $N_{\rm s}$ : Number of sources N: Number of detectors  $W_s = q_s$ (2.a) (2.b)  $H_s(t) = \frac{C_0}{2} \left[ erfc\left(\frac{z-vt}{2\sqrt{Dt}}\right) + exp\left(\frac{vz}{D}\right) erfc\left(\frac{z+vt}{2\sqrt{Dt}}\right) \right]$  $0 = \sum_{n=1}^{N} \sum_{t=1}^{T} \left( V_n(t) - \sum_{s=1}^{N_s} W_s H_s(t) \right)^{\frac{1}{2}}$ 

A non-linear least square procedure, Levenberg–Marquardt algorithm, is used for minimization of cost function 0 which gives the optimal properties for the gas source. Python and



Fig 4. Temperature gradient profile in 1000 m of a monitoring well and different clusters derived from K-means and genetic algorithm.

## **PROJECT 2**

### PROJECT 3

#### Goal: Reservoir monitoring data management

Results: Draw meaningful insights from 370 Gb of data.

- Reduced the time and cost of data processing.
- Fully interactive visualizations and reservoir surveillance based on the real-time data

Partnership: Hilcorp Energy Company

**Methods:** C++ source code was developed to process temporal variance of the data, Data-quality management, Data cleansing, Data sampling, streaming and visualization



Fig 1. Pressure evolution in five wells.

**Goal:** Detection of salt precipitation based on time-lapse well log data in injection and monitoring wells.

**Results:** A novel approach was developed based on cross-wavelet transformation

Partnership: U.S. Department of Energy

**Methods:** Fractal analysis, Cross-wavelet transformation, Monte Carlo simulation, Exploratory data analysis, Petrophysical data interpretation, Matlab toolboxes



Fig 2. Time-lapse petrophysical data. a) Gamma ( $\gamma$ ) ray log, b) Porosity ( $\phi$ ), c) Sigma ( $\Sigma$ ), d) Probability distribution of porosity and e) Sigma. Injection interval is shown in gray on gamma log. Yellow color indicates the intervals with salt buildup.



Fig 3. Time-lapse cross-wavelet coherence between porosity and Sigma. Top: The connections between  $\phi$  and  $\Sigma$  for 2009 (a), 2010 (b) and 2014 (c). The thick black contours encloses the 5% significance level against red noise which indicates the notable coherence regions between  $\phi$  and  $\Sigma$ . Bottom: Phaseangle histograms between  $\phi$  and  $\Sigma$  at regions enclosed by thick black counters.

# **PROJECT 4**

## PHD RESEARCH

Goal: Stochastic Seismic Inversion Using Tensorflow

**Results:** A fast, GPU-based stochastic seismic inversion tool

**Method:** Tensorflow-gpu, python, Texas advanced computing center (and AWS)

I am presenting this work in 2019 Rice Oil & Gas HPC Conference

http://rice2019oghpc.rice.edu/program/



Seismic data denoising using curvelet transformation

Analyzing petrophysical data using wavelet transformation

GPU-based pore-scale simulation of evaporation, salt precipitation and reaction in porous media

Molecular dynamic simulation of nucleation of salt crystals in clay minerals

Personal projects:

My personal website hosted by AWS (Html, CSS, Java, D3.js, JSON):

http://www.hdashtian.com

PhD research:

http://hdashtian.com/research.html

Some cool data visualization:

http://hdashtian.com/levyflight.html

http://hdashtian.com/realnetwork.html