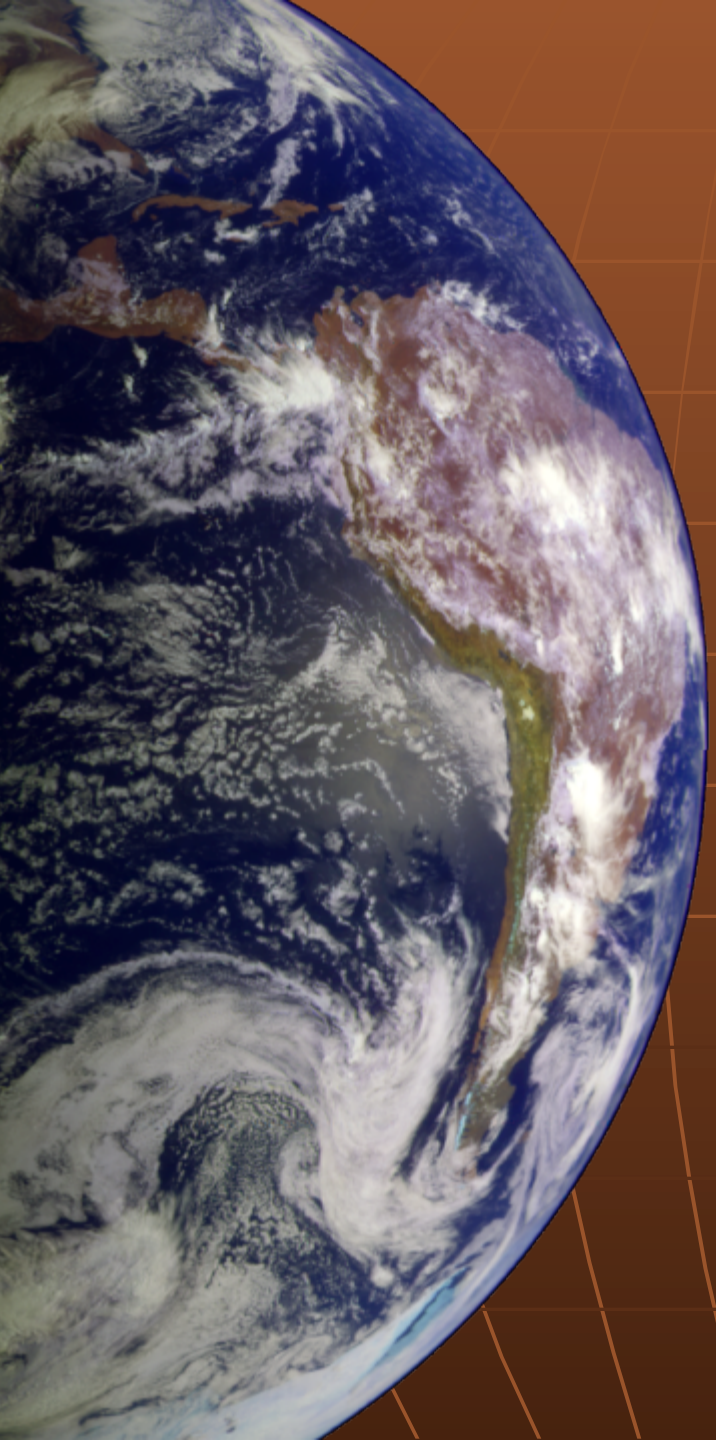

UT-AUSTIN EDGER FORUM

Application of new Monte Carlo method for inversion of prestack seismic data

Yang Xue
Advisor: Dr. Mrinal K. Sen

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Overview

- Motivation
- Introduction
  - Bayes theorem
  - Stochastic inference methods
- Methodology

  Greedy annealed importance sampling (GAIS)
- Application of GAIS on seismic inversion
  - Example 1: HRS demo data
  - Example 2: China data set
- Conclusions

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Motivation

- Goal: estimate a log of rock properties as a function of two-way vertical travel time or depth
- Problem: limited wells
- Purpose of seismic inversion: derive a pseudo-log to fill in the gaps between wells

Geophysical inversion has non unique solutions

⇨ Derive models with uncertainties

Introduction

Posterior pdf | Likelihood | Prior pdf

Bayes theorem: $$P(\boldsymbol{x}|\boldsymbol{d}) = \frac{P(\boldsymbol{d}|\boldsymbol{x})P(\boldsymbol{x})}{P(d)}$$

$$E(\boldsymbol{x}) = (\boldsymbol{d} - \mathrm{g}(\boldsymbol{x}))^T \boldsymbol{C}_D^{-1} (\boldsymbol{d} - \mathrm{g}(\boldsymbol{x}))$$

$$P(\boldsymbol{d}|\boldsymbol{x}) \propto \exp(-E(\boldsymbol{x}))$$

Draw samples from Prior distribution → Stochastic inference methods → Samples in Posterior distribution

$$\langle \boldsymbol{x} \rangle = \sum \boldsymbol{x} P(\boldsymbol{x}|\boldsymbol{d})$$

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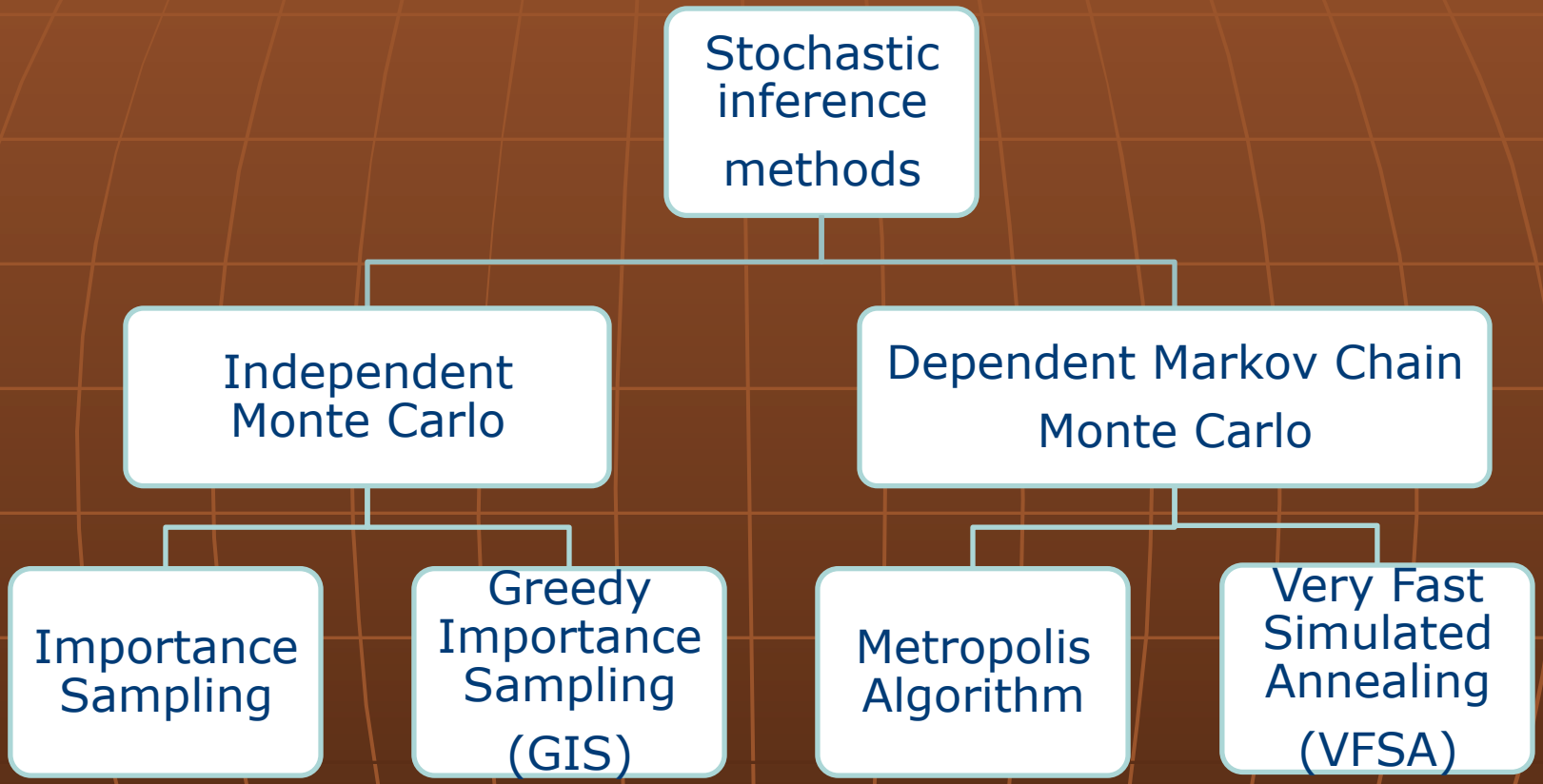
Introduction



(Southey and Shuurmans 2002)

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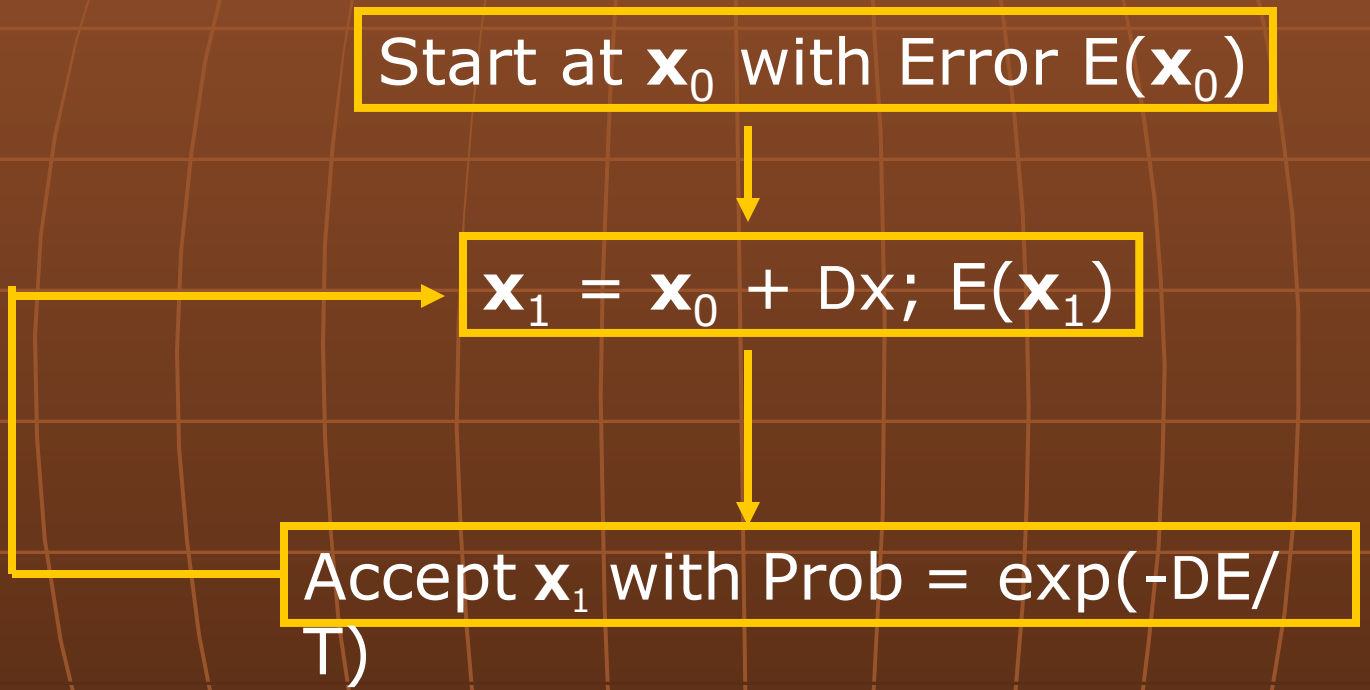
Introduction

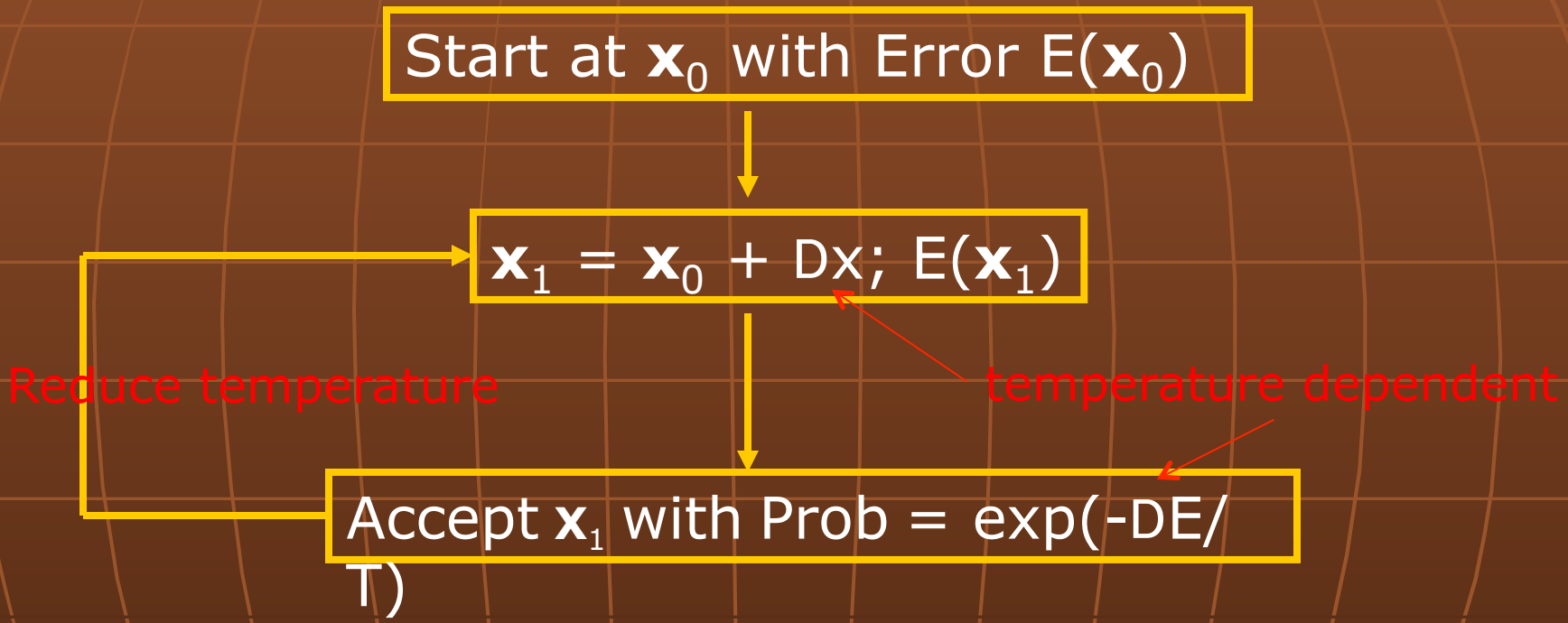
Metropolis-Hastings



Weigh each model with probability and then evaluate the integrals to estimate the marginal PPD, posterior mean, covariance and correlation matrices

Introduction

Very Fast Simulated Annealing



Weigh each model with probability and then evaluate the integrals to estimate the marginal PPD, posterior mean, covariance and correlation matrices

Introduction

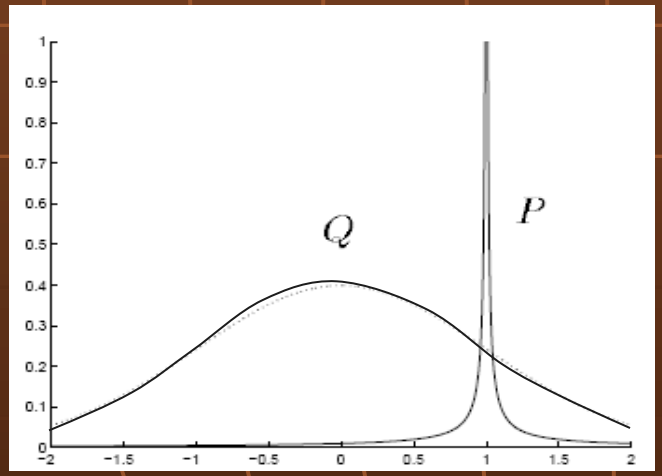
Importance Sampling

- Draw samples from prior distribution Q, assign weights $w_i = P/Q$, estimate expectation:

$$E_{P(x)} f(x) = \sum_{i=1}^{i=n} f(x_i) w(x_i) / n$$

- Problem:

  Q misses high probability regions of P



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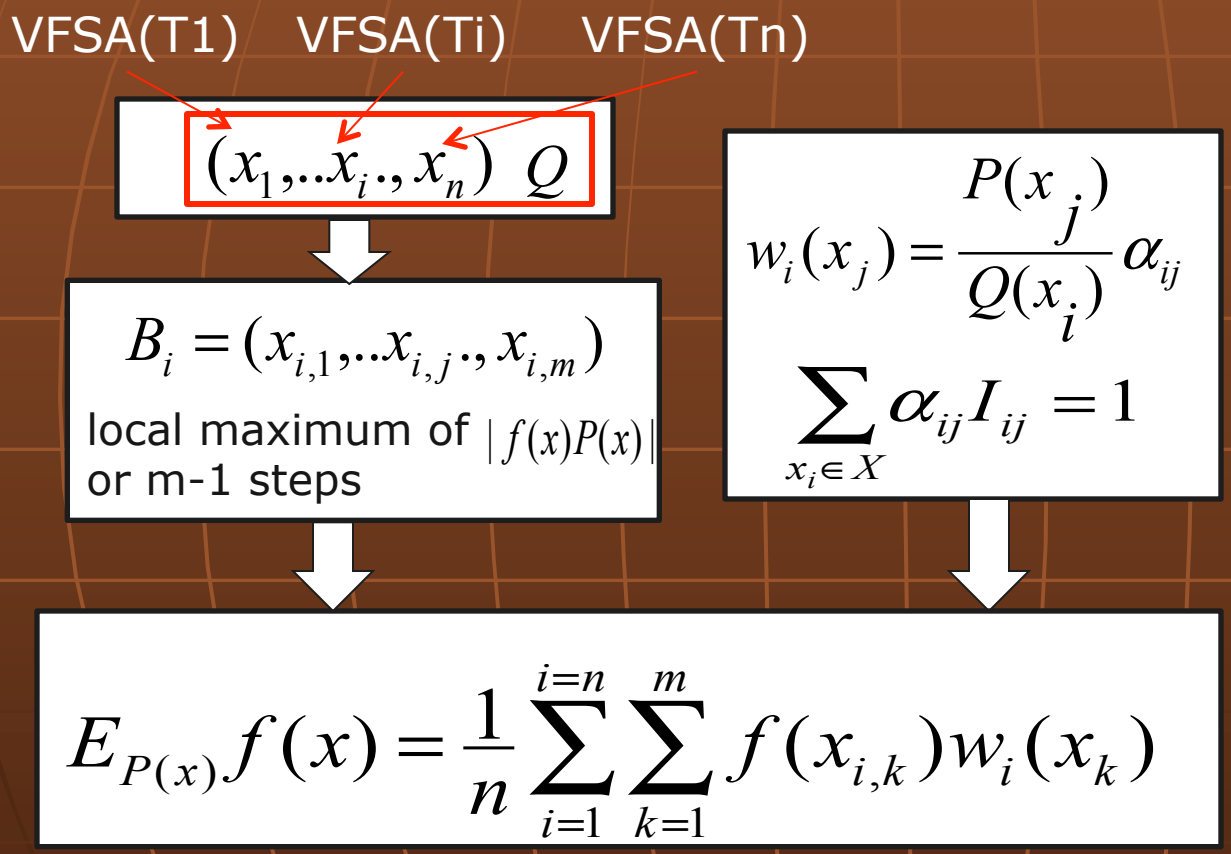
Stochastic inference methods

Methods	Algorithm	Acceptance Rule	Pros and cons
Metropolis Algorithm	Updating sample using Markov Chain	Change of misfit ΔE	Accurate estimation, Computationally slow
Very Fast Simulated Annealing	Updating sample using Markov Chain, prior distribution temperature dependent	Change of misfit ΔE	Fast, biased estimation of uncertainties due to continuous change of proposal distribution with iterations
Importance Sampling	Randomly drawing samples from prior distribution	All accepted, but weighted $w = \frac{P(\mathbf{x})}{Q(\mathbf{x})}$	Fails, if prior distribution Q miss high probability region of posterior distribution P

Methodology

Greedy Importance Sampling - GIS



(Southey and Shuurmans 2002)

- Methodology:
  - Greedy search for important region of ***X***
  - Each independent block contains one or two important points from ***X***
- Advantages:
  - Minimized variance while maintaining unbiasedness

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Methodology

Greedy Annealed Importance Sampling - GAIS

- Generate fractal initial model (Srivastava and Sen, 2010)
- Employ multiple VFSA with different starting temperatures and a small number of iterations
- Starting from the best fit model of each VFSA, greedy search important region

$$(\pm\Delta Zp, \pm\Delta Zs), (\mp\Delta Zp, \mp\Delta Zs)$$

- Summation of all weighted samples

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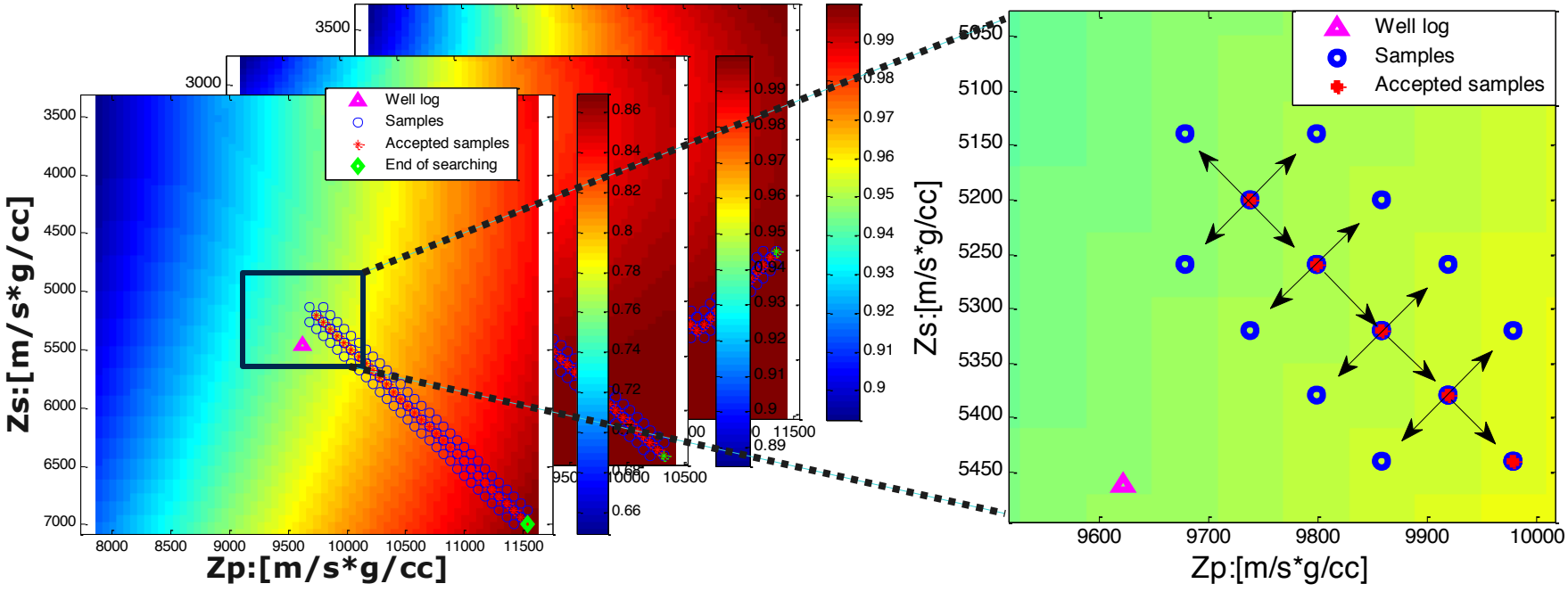
Methodology

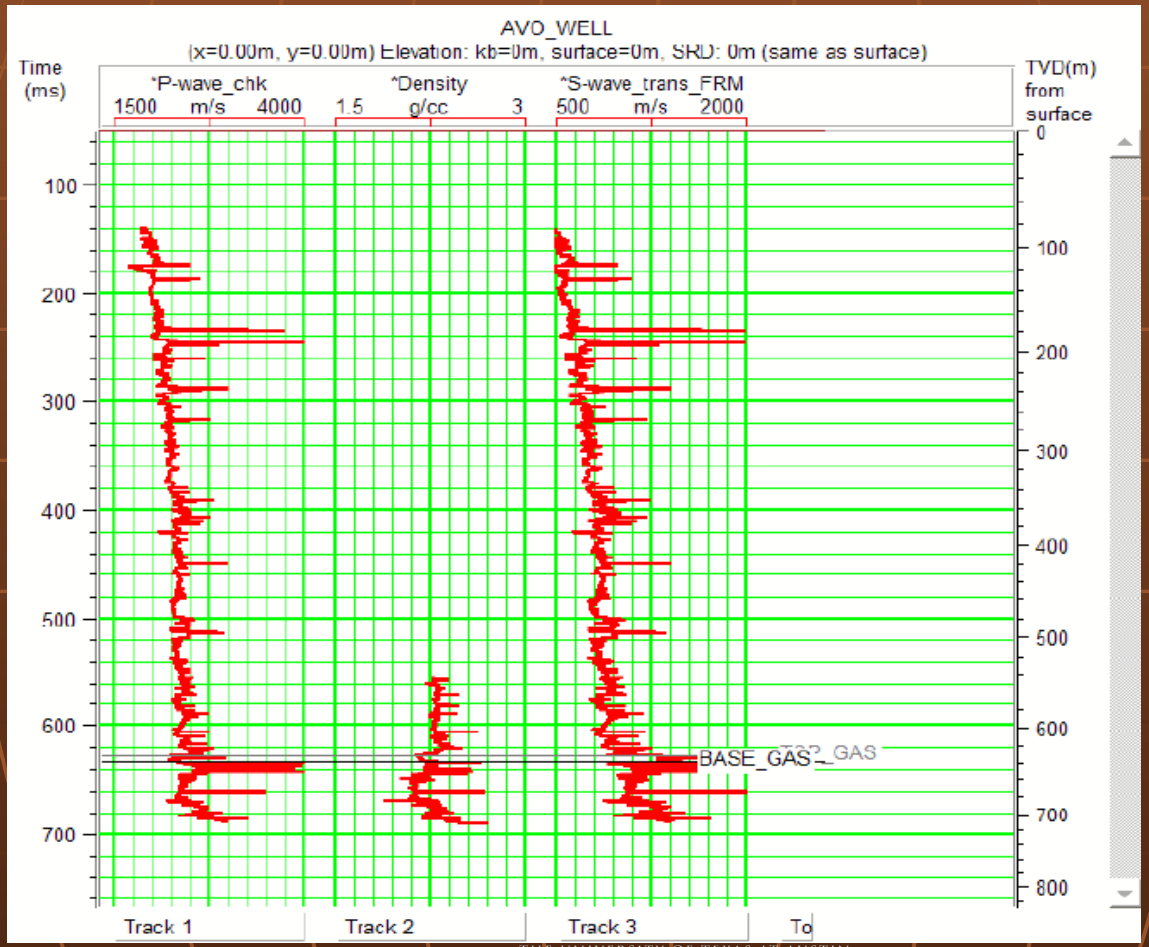
Visualization of Greedy Search



Marginal probability map of one layer at the well location with multiple runs of VFSA (left box) and zoom in (right). GIS searches within the high probability area step by step. At each step, we compare the importance of the square's ends, whose middle point is our starting point and choose the most important end as a new starting point. Calculation of gradient matrix can also provide the direction of search.

Application of GAIS

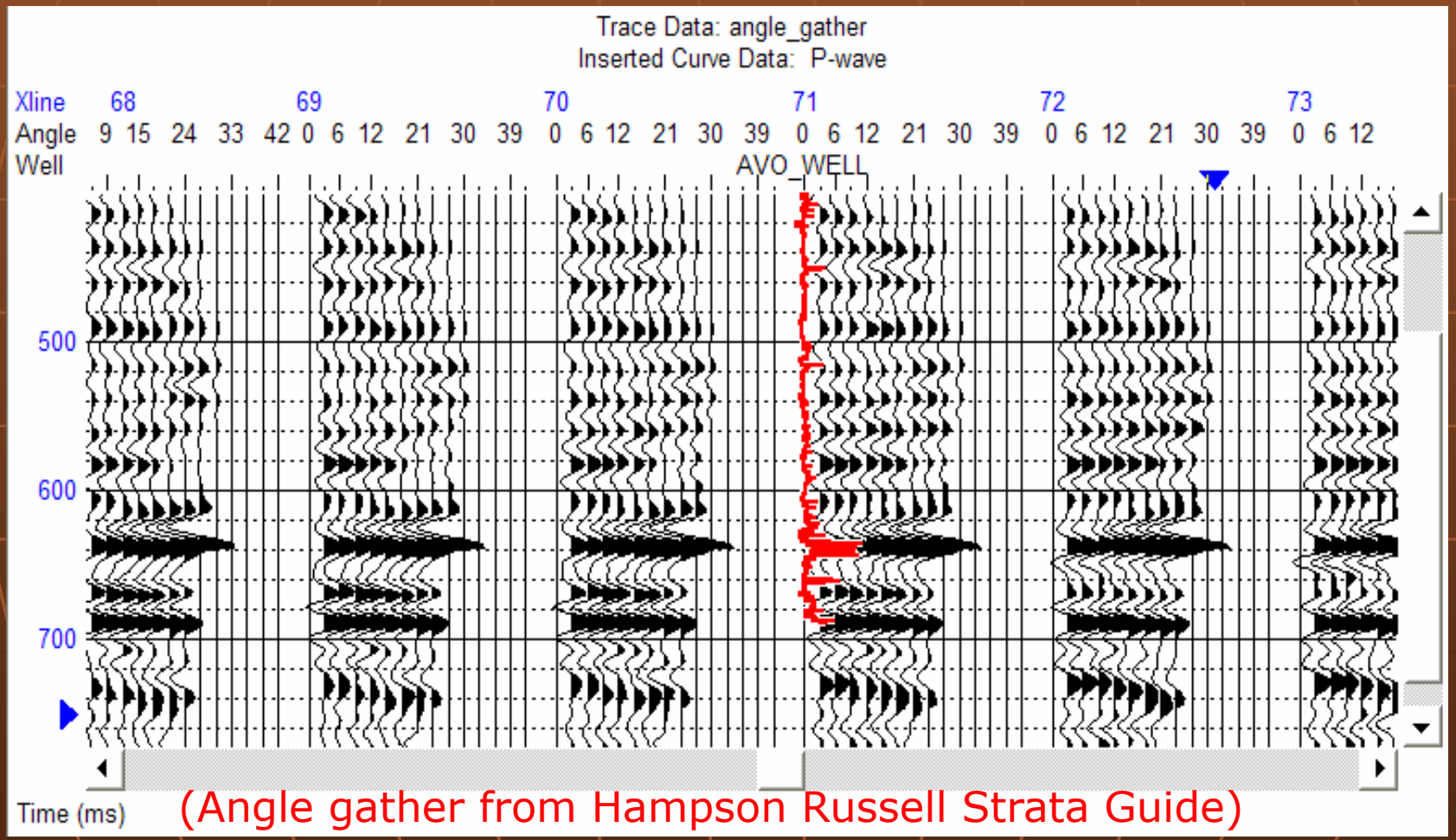
Example 1: HRS demo data (prestack seismic)



Well logs plot from Hampson Russell Strata Guide

Application of GAIS

Example 1: HRS demo data (prestack seismic)



(Angle gather from Hampson Russell Strata Guide)

Application of GAIS

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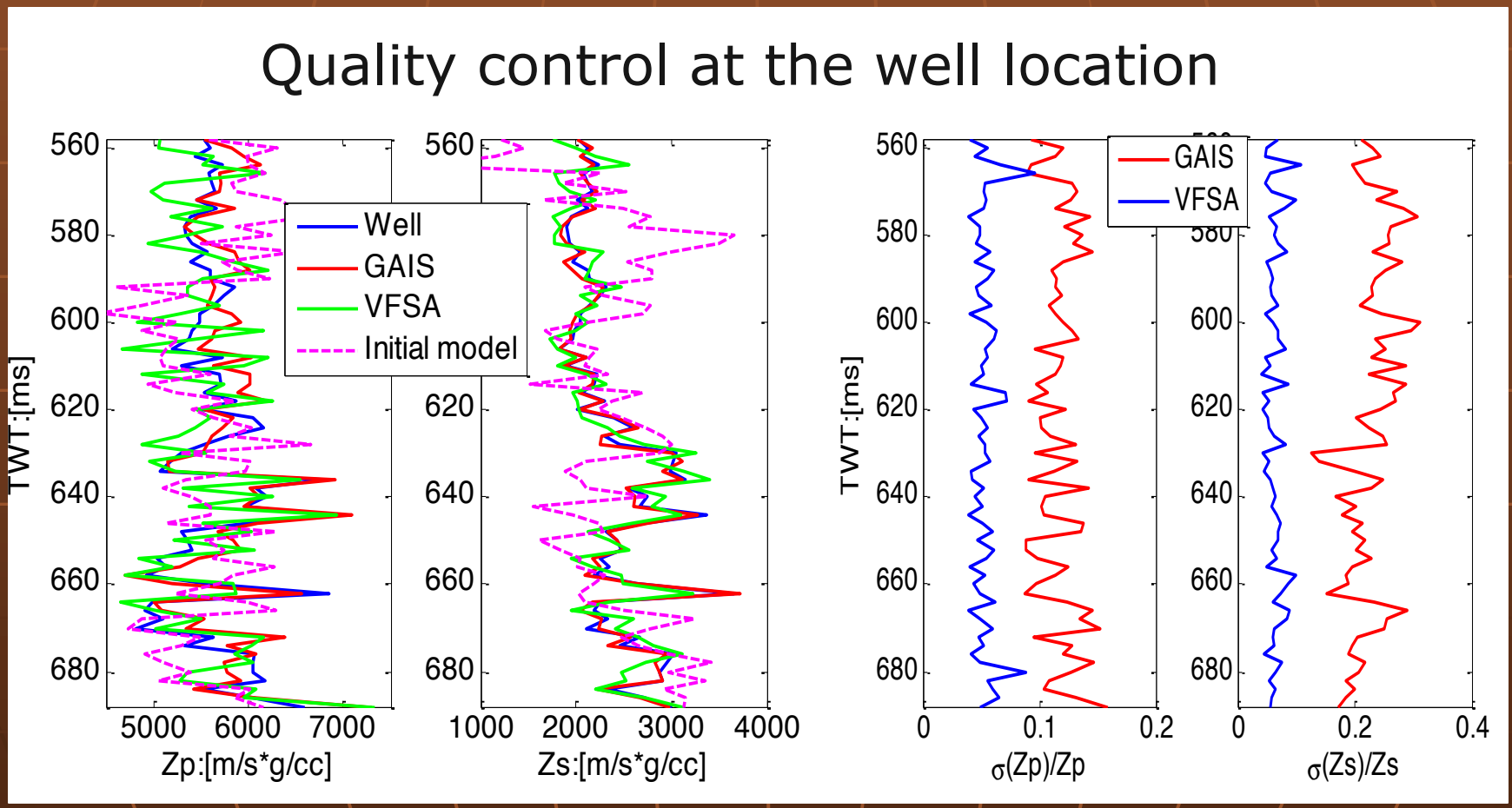

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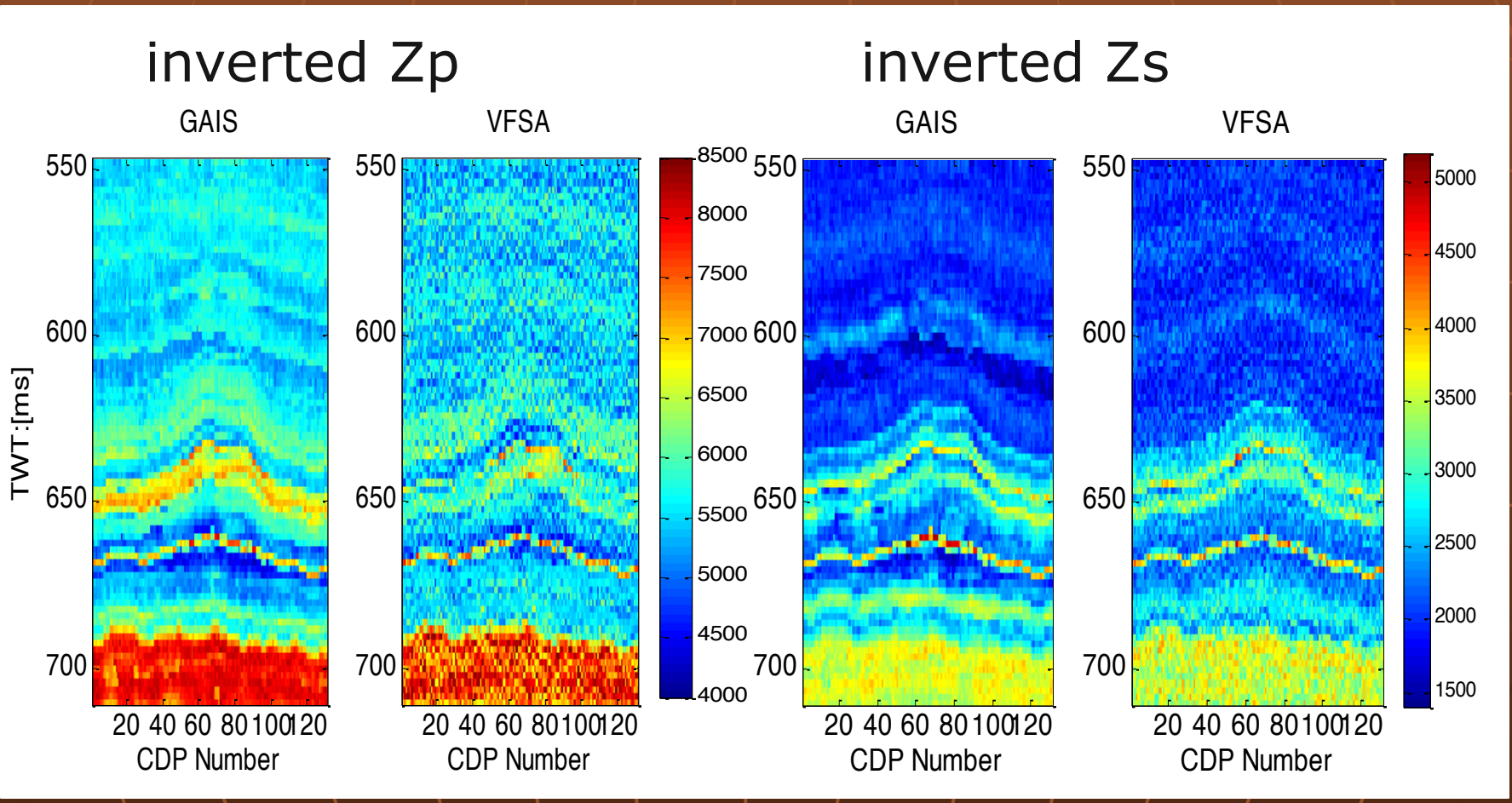

Application of GAIS

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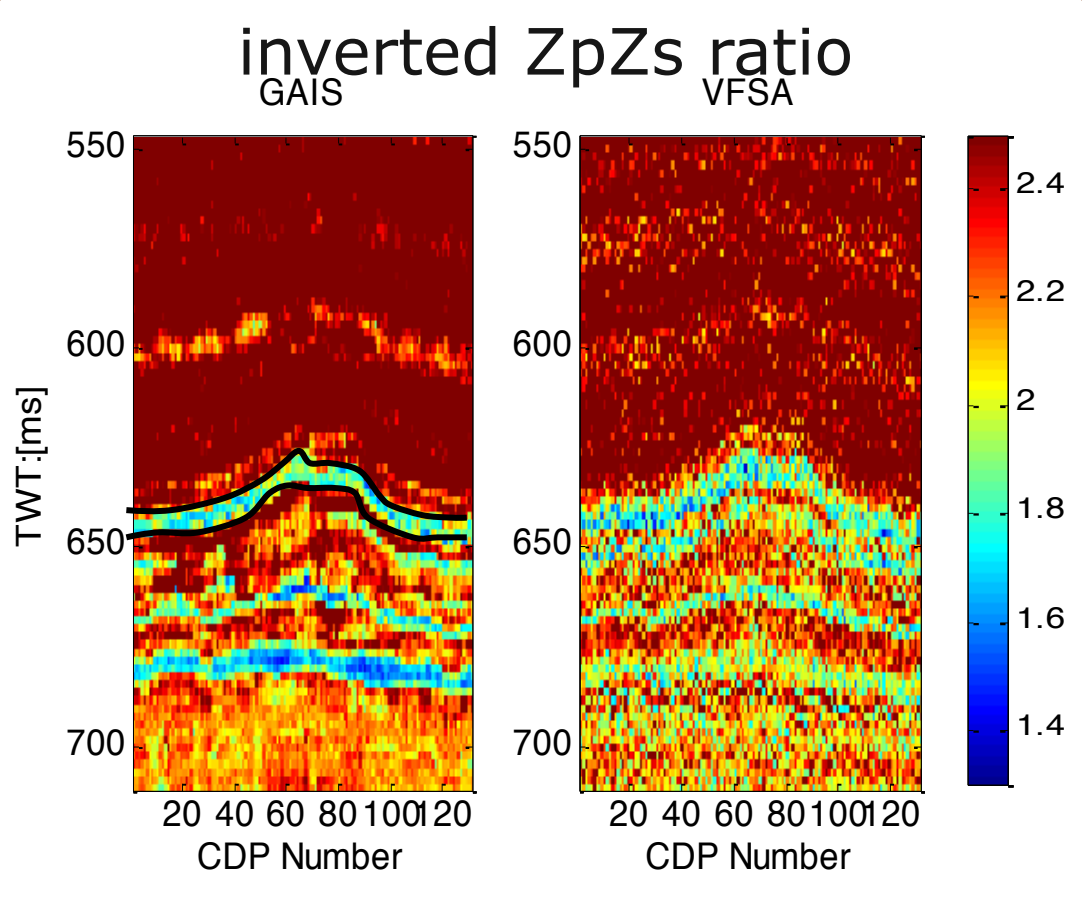
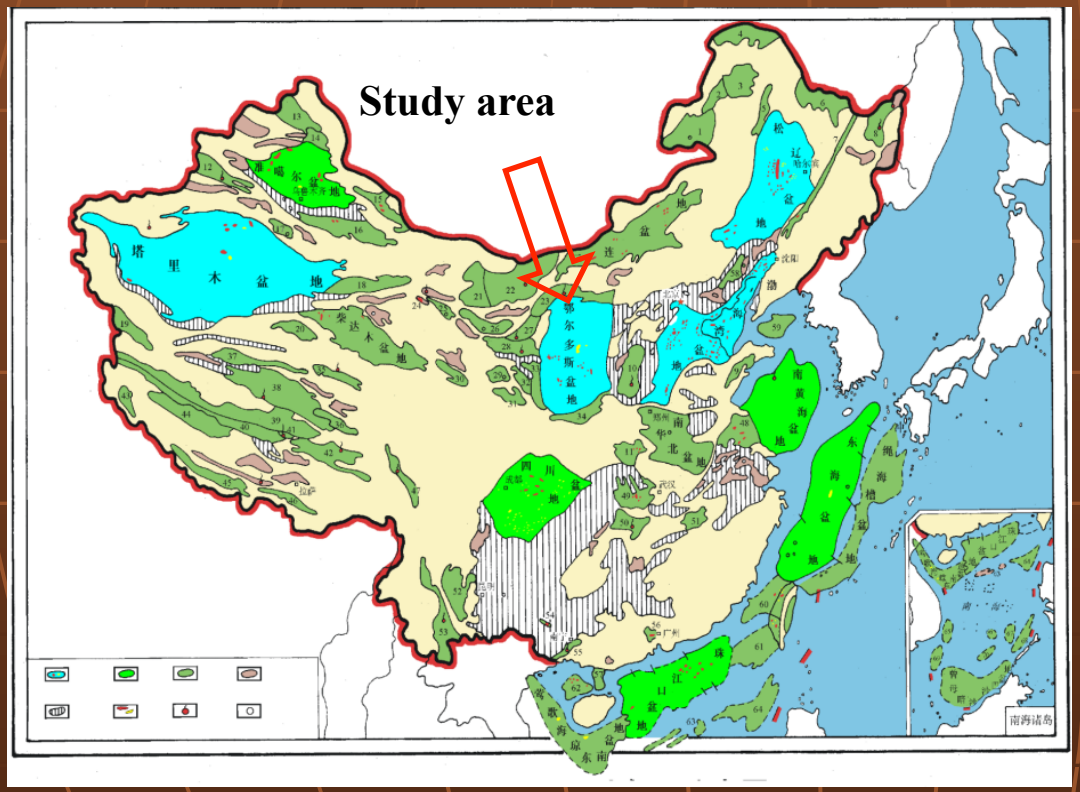


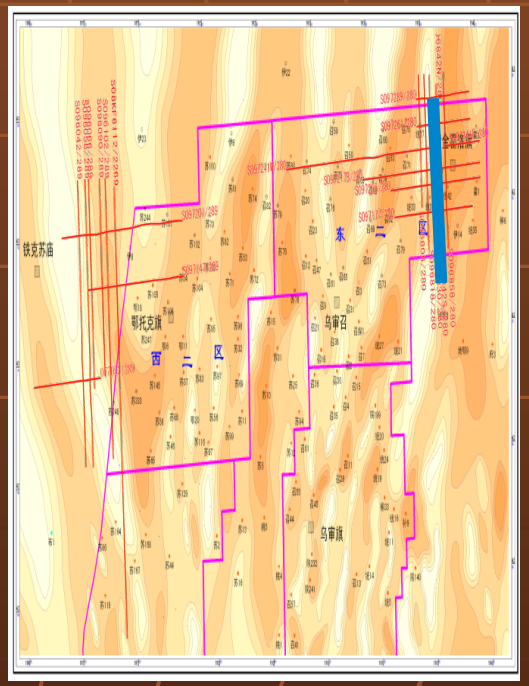
GAIS shows superior Performance than VFSA alone

Application of GAIS

Example 2: Ordos Basin, China (prestack seismic)



Zoomed study area



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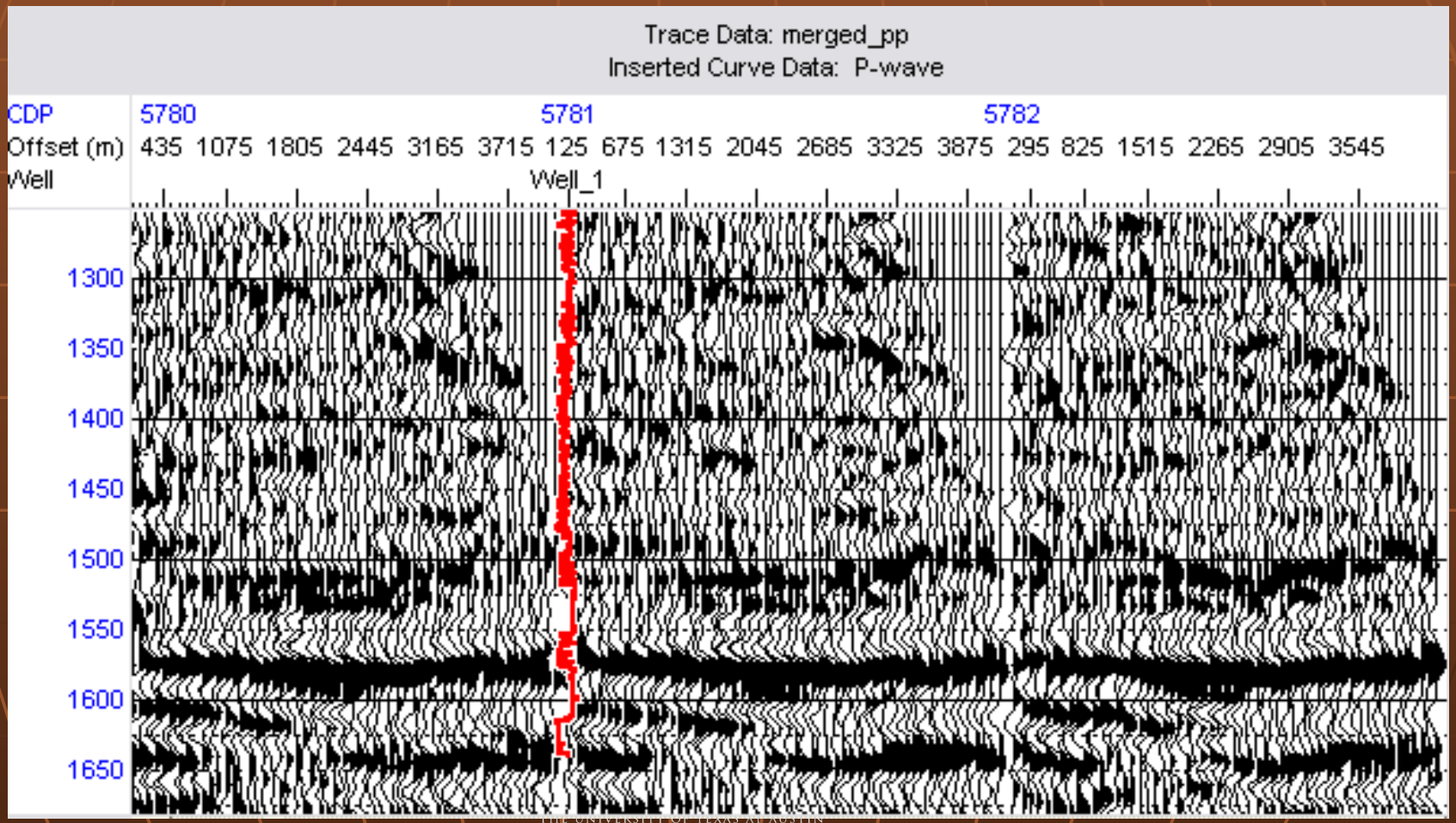
Application of GAIS

Example 2: Ordos Basin, China (prestack seismic)



Application of GAIS

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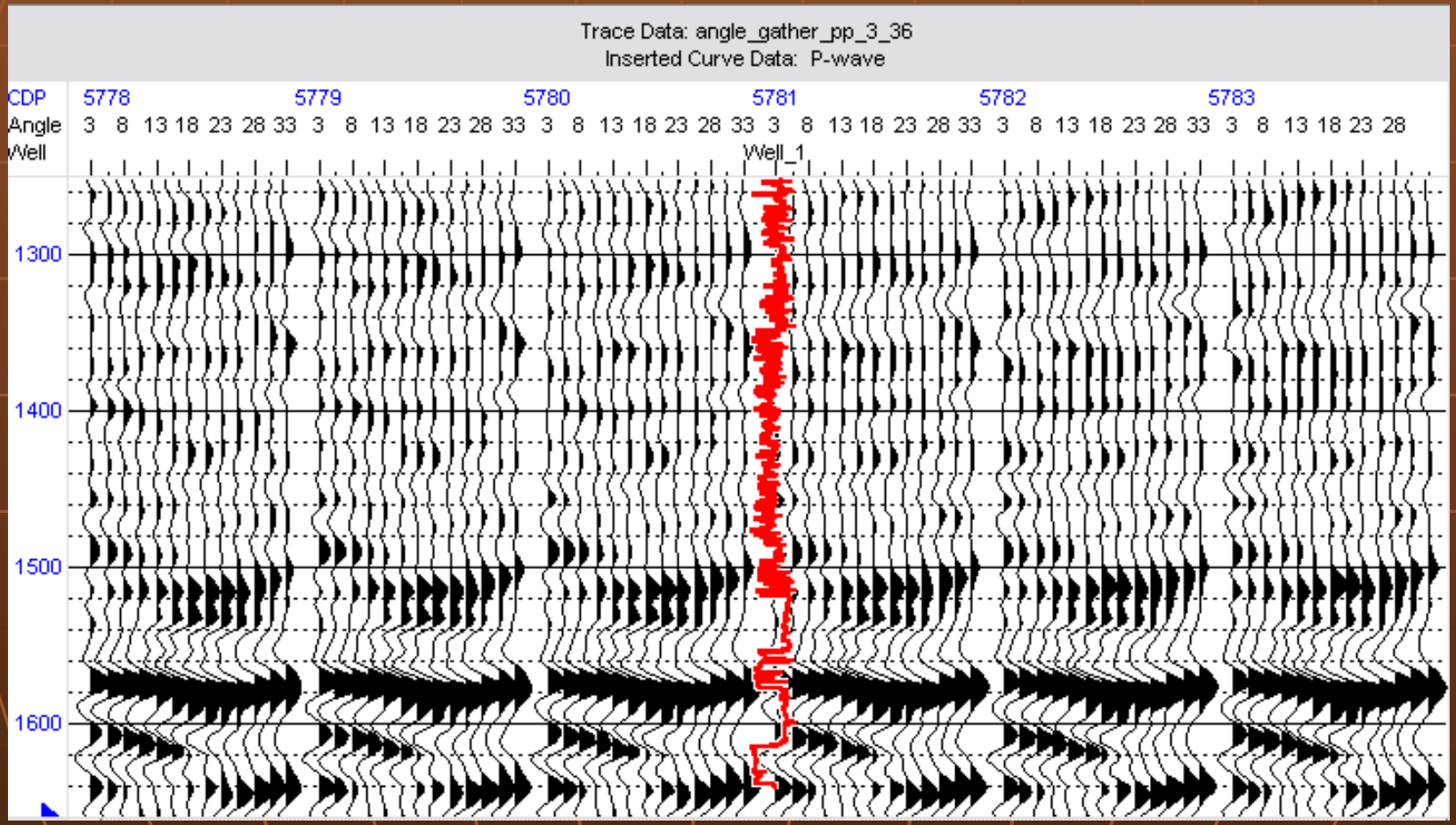

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Application of GAIS

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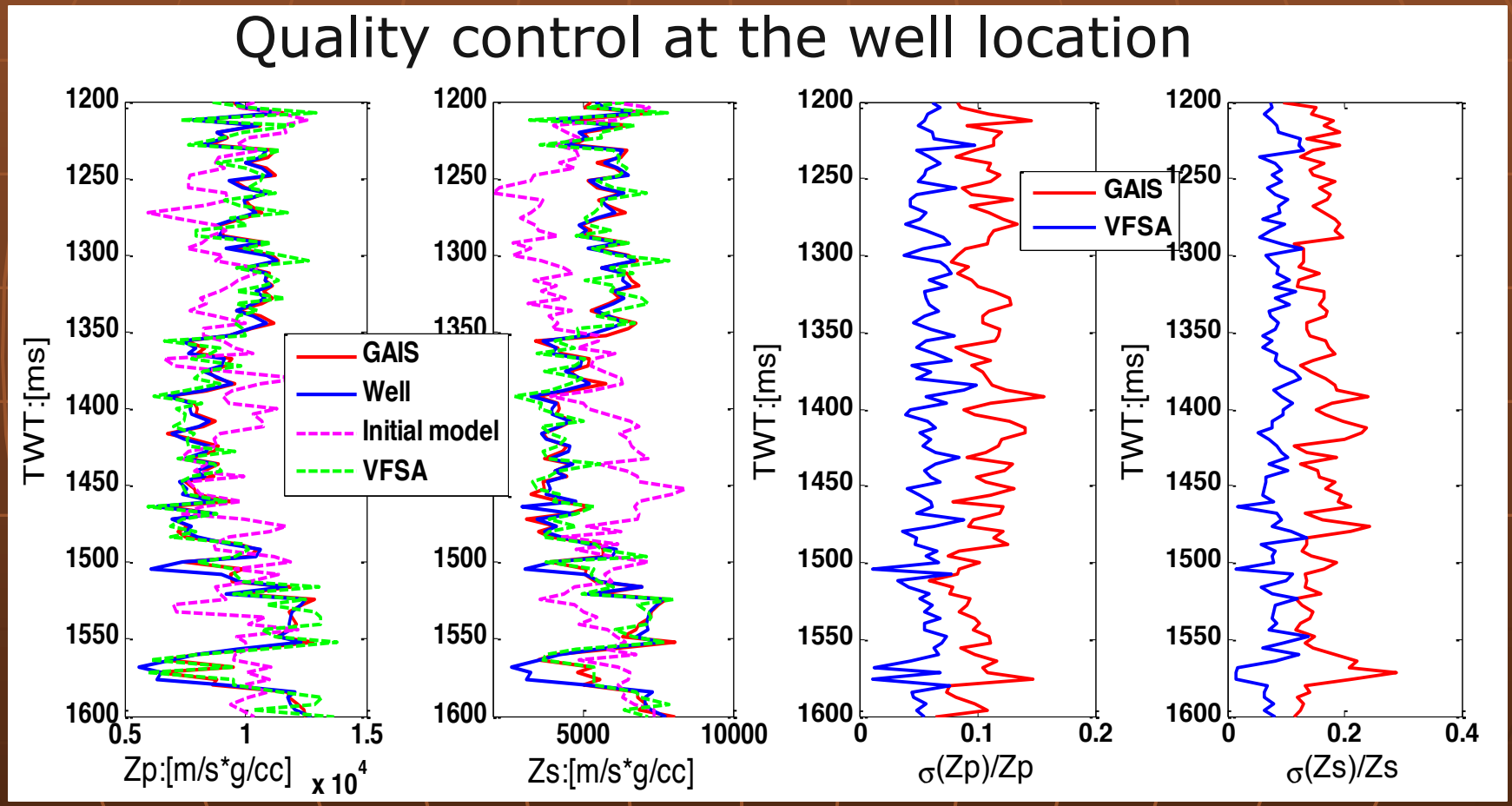

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Application of GAIS

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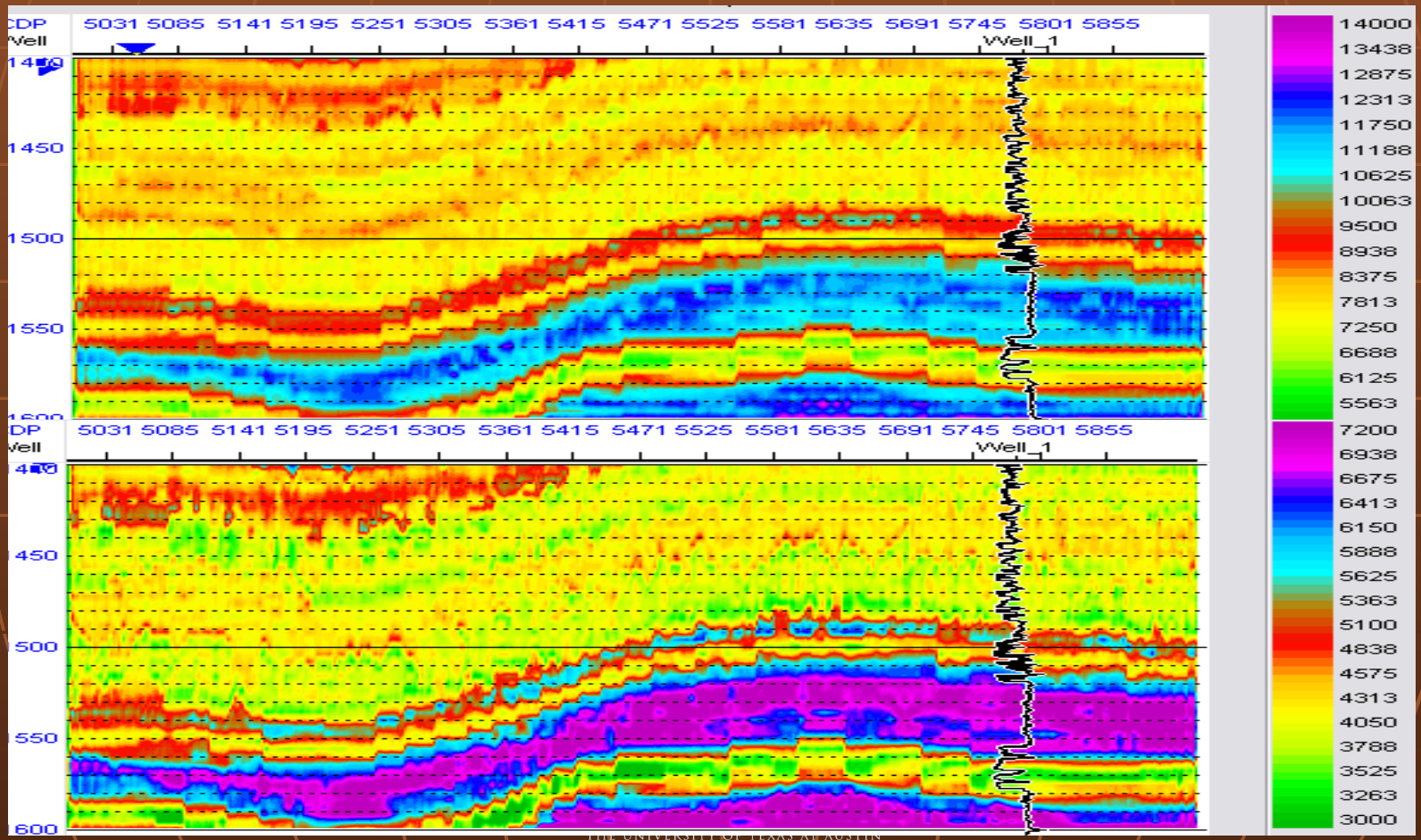

Application of GAIS

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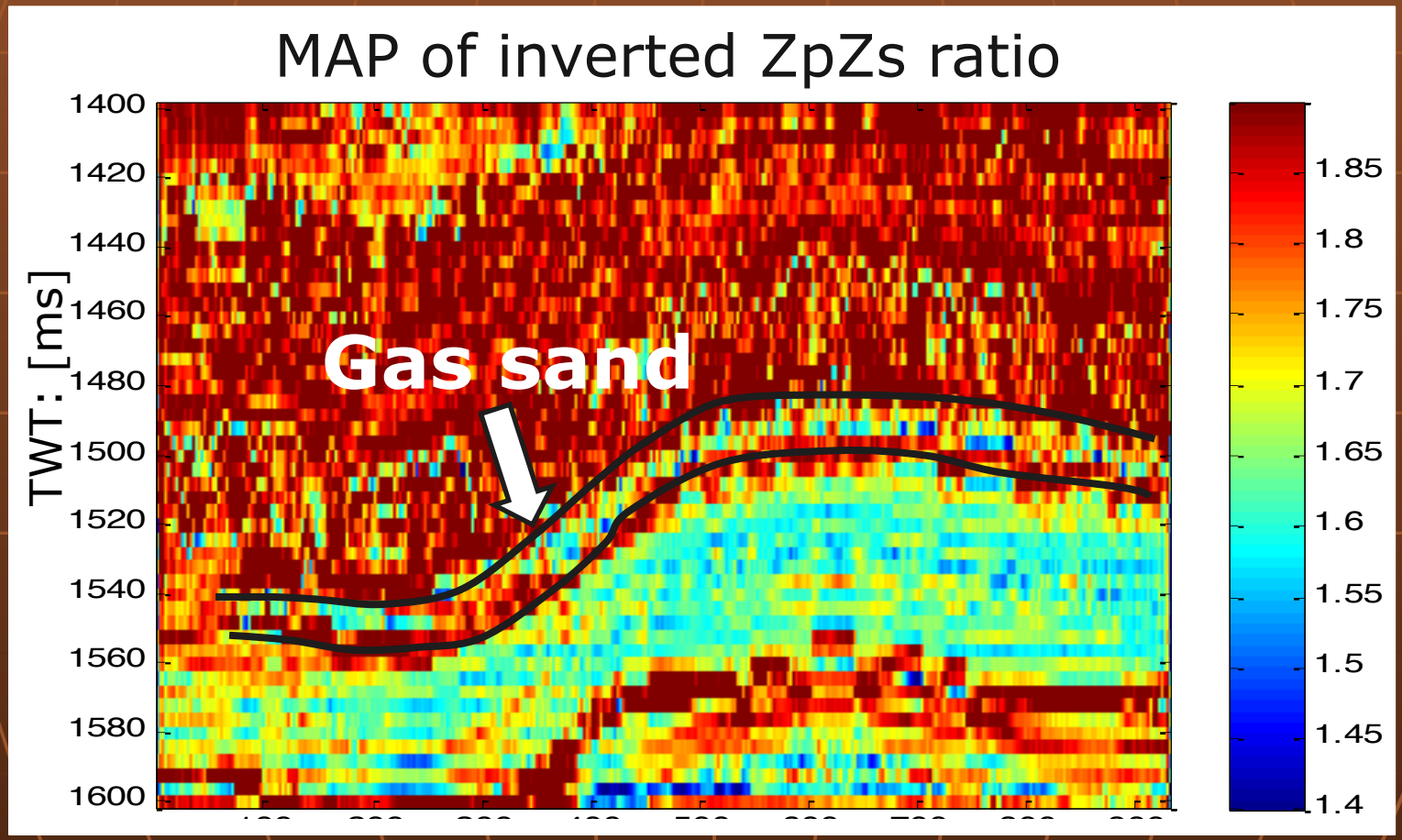

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Conclusion

- GAIS attempts to explore important regions starting with models that are close to the important regions already located by VFSA and estimates the expectation value very accurately.
- The example of pre-stack inversion demonstrates superior performance of GAIS compared to VFSA alone

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