Genetic Programming for Reservoir Modeling and Characterization

Ruben Nunes

TÉCNICO LISBOA

CERENA

The Economist explains

Explaining the world, daily

Previous | Next | Latest The Economist explains | All latest updates

The Economist explains

Why firms are piling into artificial intelligence

Mar 31st 2016, 23:45 BY A.E.S.

SPONSOR CONTENT STEPHEN F. DEANGELIS, ENTERRA SOLUTIONS

MACHINE LEARNING: BANE OR BLESSING FOR MANKIND?

SHARE

SHARE 128

TWEET

BRANDON KEIM SCIENCE 04.02.09 3:09 PM

COMPUTER PROGRAM SELF-DISCOVERS LAWS OF PHYSICS

CADE METZ BUSINESS 05.27.15 1:00 PM

'DEEP LEARNING' WILL SOON GIVE US SUPER-SMART ROBOTS

NG TO dismiss the notion of highly

The Economist | World politics | Business & finar

Artificial intelligence

Rise of the machines

Artificial intelligence scares people—excessiv

May 9th 2015 | From the print edition

TÉCNICO LISBOA

CERENA

The Economist explains

Explaining the world, daily

Previous | Next | Latest The Economist explains | All latest updates

The Economist explains

Why firms are piling into artificial intelligence

Mar 31st 2016, 23:45 BY A.E.S.

SPONSOR CONTENT STEPHEN F. DEANGELIS, ENTERRA SOLUTIONS

MACHINE LEARNING: BANE OR BLESSING FOR MANKIND?

SHARE

SHARE 128

TWEET

SCIENCE 04.02.09 3:09 PM

COMPUTER PROGRAM SELF-DISCOVERS LAWS OF PHYSICS

NG TO dismiss the notion of highly

The Economist | World politics | Business & finar

CADE METZ BUSINESS 05.27.15 1:00 PM

'DEEP LEARNING' WILL SOON GIVE US SUPER-SMART ROBOTS

Artificial intelligence

Rise of the machines

Artificial intelligence scares people—excessiv

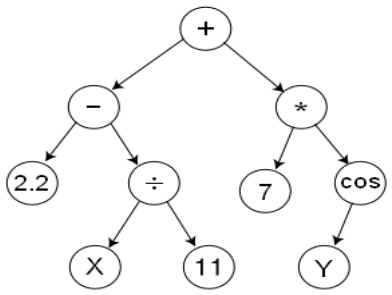
May 9th 2015 | From the print edition

Method

- We are using Symbolic Regression, a subset of Genetic Programming.
- We try to explain/predict our data using functions
- Simpler functions are prefered, when their explanatory power is the same.

Symbolic Regression

- Models to be evaluated are functions, here represented in a tree structure



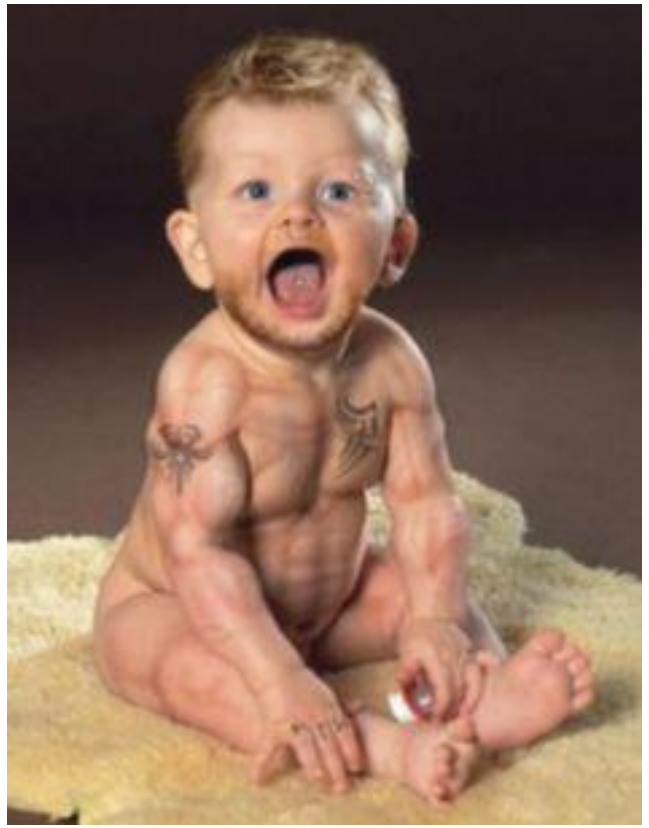
$$\left(2.2 - \left(\frac{X}{11}\right)\right) + \left(7 * \cos(Y)\right)$$

- We can generate random functions and evaluate them, but this is inefficient. We need something else…

Genetic Algorithms

- Models are evaluated, models with bad fitness are discarded.
- Higher fitness models are used as a base for new model generation
- Generation to generation, the fitness of the entire population will increase


BARBELL
45



So Symbolic Regression is…?

- A genetic algorithm
- Optimizing functions that explain the data
- Selecting the simplest possible from those

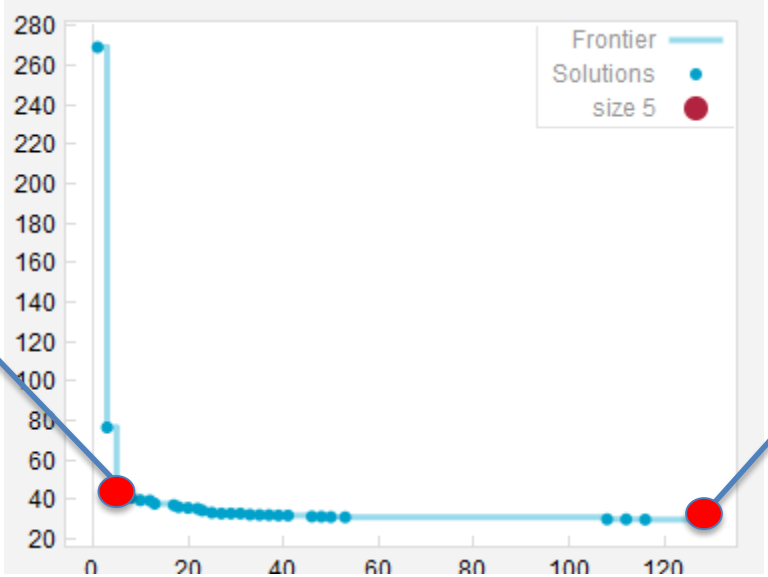
Velocity prediction:

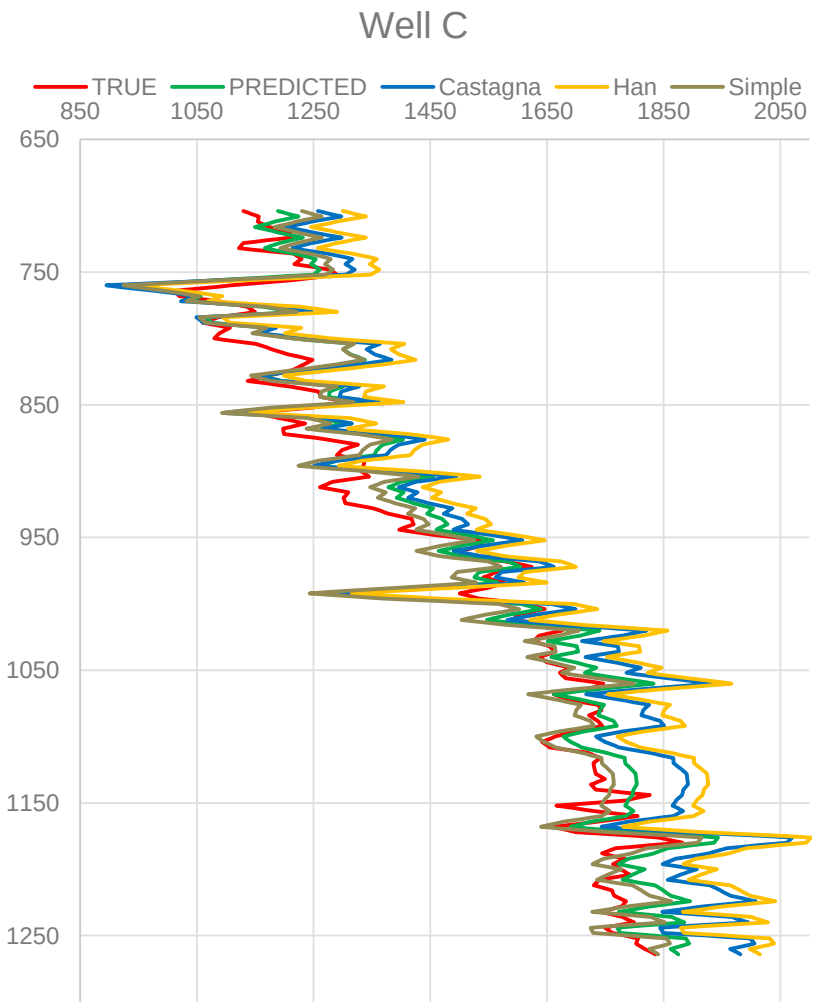
- S-wave information is normally scarcer than P-wave information.
- We can discover empirical relations, locally valid on the field scale.
- Known equations can be used as starting points
- The same is valid for other petrophysical properties.
- Vs prediction using Vp and TWT
- Two wells training, two wells testing

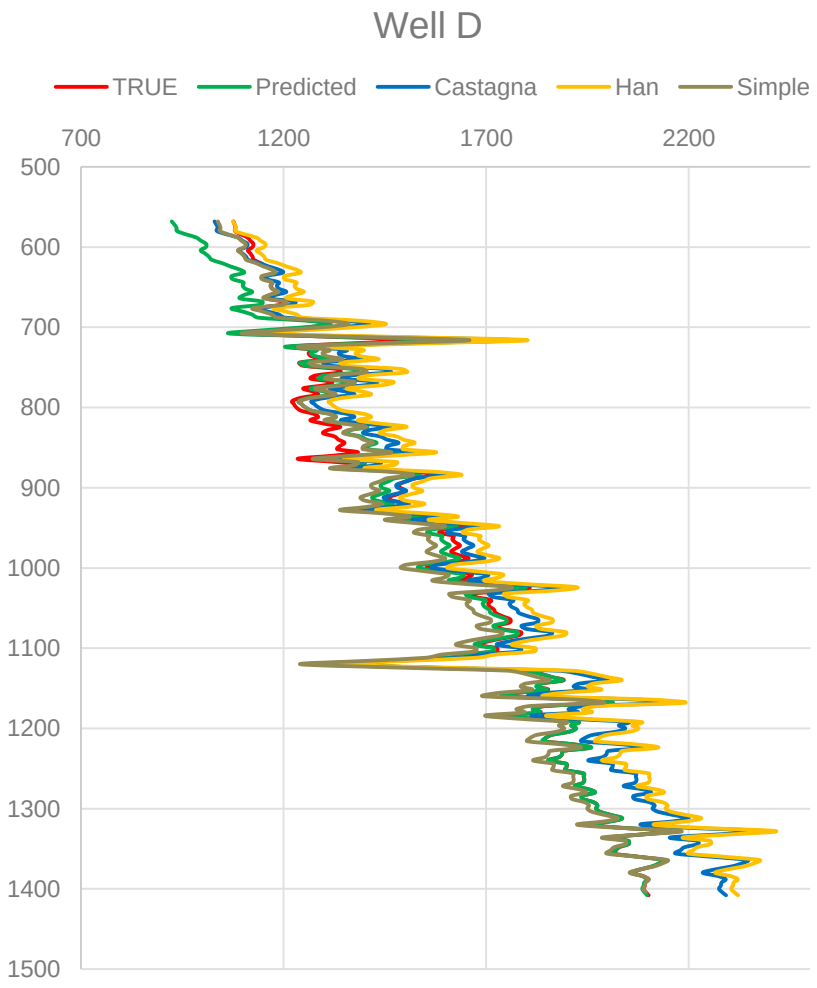
Selecting models

$V_s = 0.6615397 V_p - 495.6991379$

$V_s = 730.66786 - 2.20672T - 3.8 \times 10^4 TV_p - 6.5 \times 10^4 T^2 + 2.2 \times 10^4 V_p^2 + 4.56 \times 10^{-11} T^3 V_p - 3.02 \times 10^{-12} V_p^4$



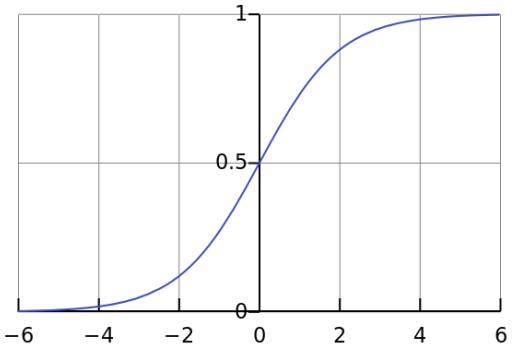

Well C
TRUE
PREDICTED
Castagna
Han
Simple
850
1050
1250
1450
1650
1850
2050
650
750
850
950
1050
1150
1250


Well D
TRUE
Predicted
Castagna
Han
Simple
700
1200
1700
2200
500
600
700
800
900
1000
1100
1200
1300
1400
1500

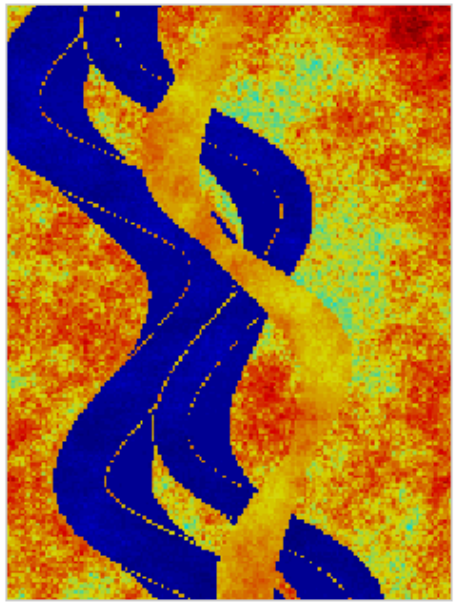
Facies classification:

- Stanford VI - One layer tested.
- 32 wells (50 % data training 50% testing).
- The method generates a continuous function with domain $[-\infty, +\infty]$.
- We must “squash” these values with a function to obtein a 0/1 classification.
- This also works as a classification uncertainty surrogate.

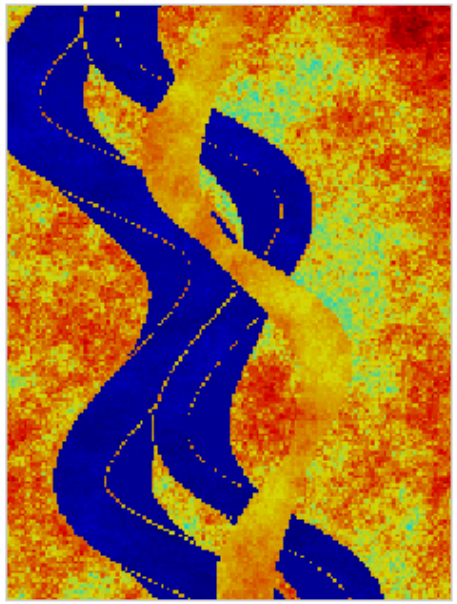
$$f(x) = \frac{L}{1 + e^{-k(x - x_0)}}$$

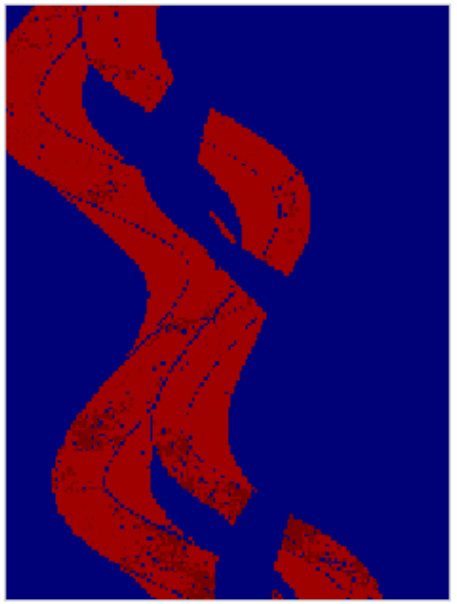


Vp to channel facies

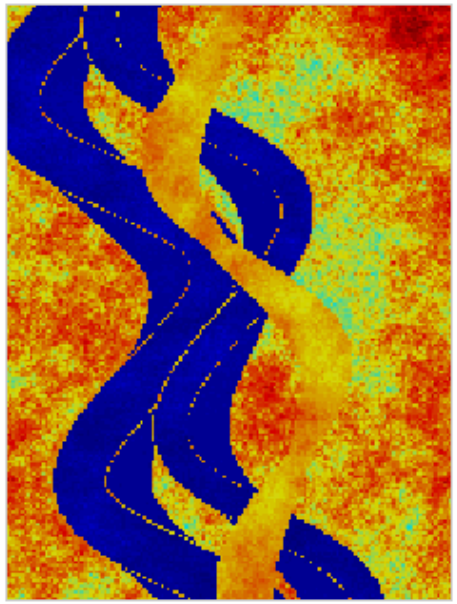


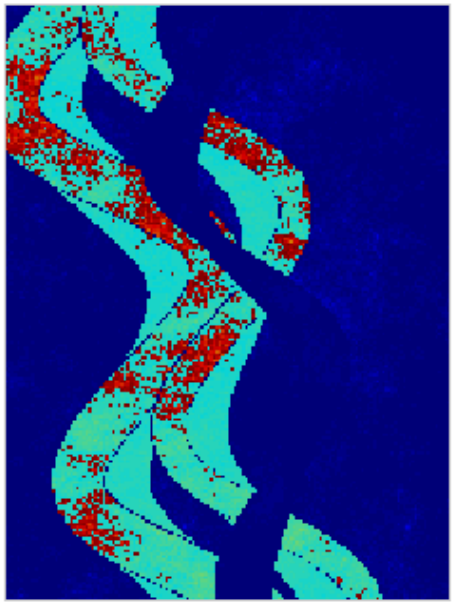
Vp to channel facies – complex model





A simpler model





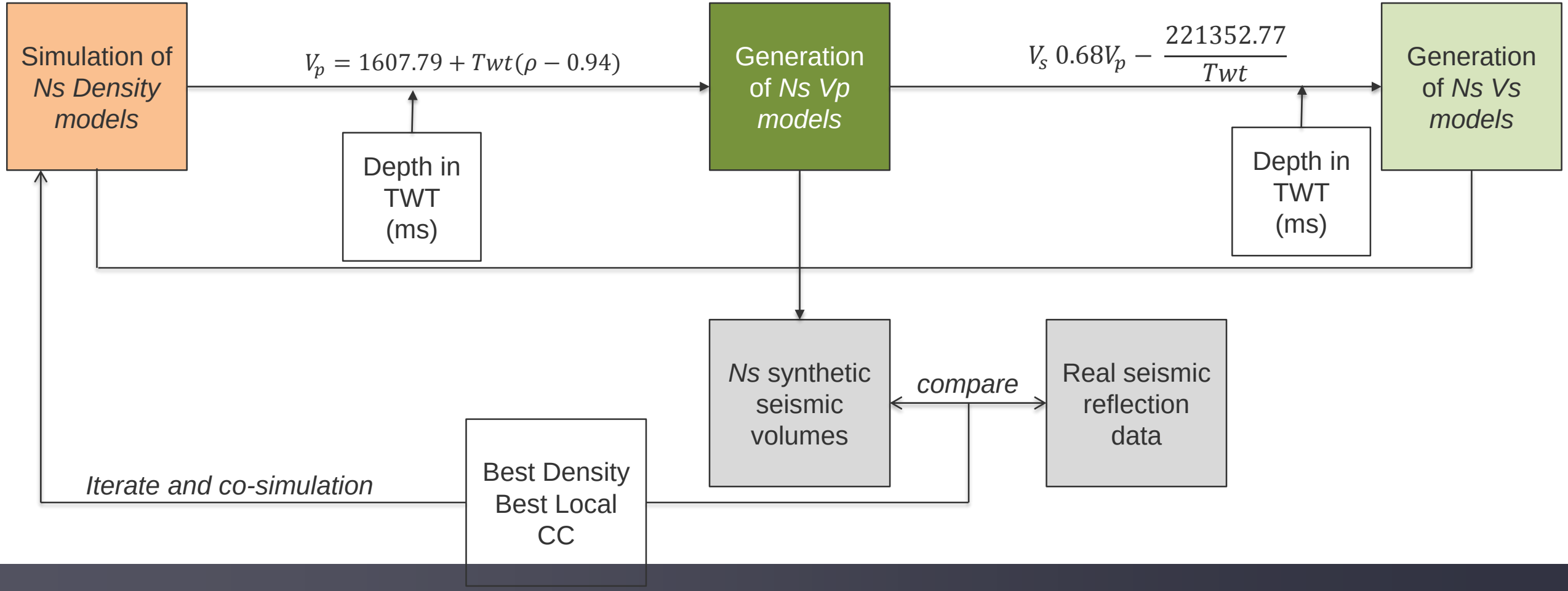
Geostatistical inversion with genetic programing

Two case studies:

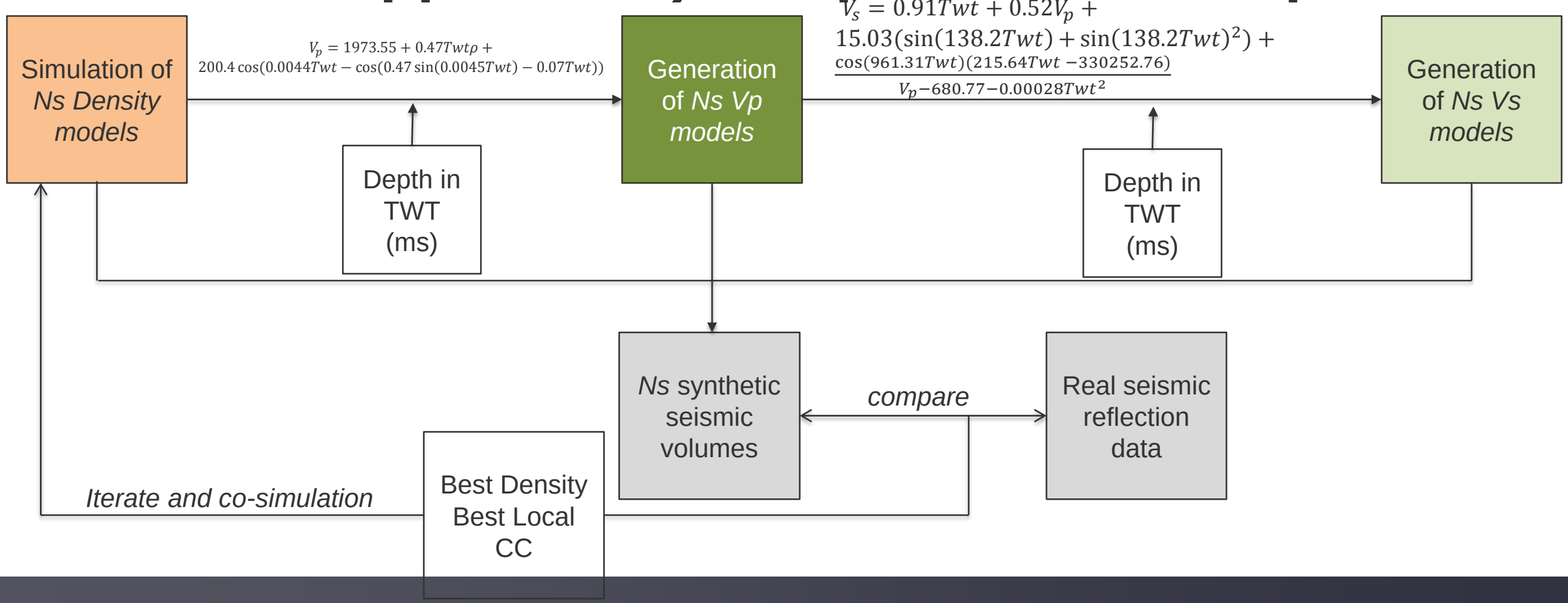
1) Simple relationship between density, Vp; and Vp, Vs

2) Complex relationship between density, Vp; and Vp, Vs

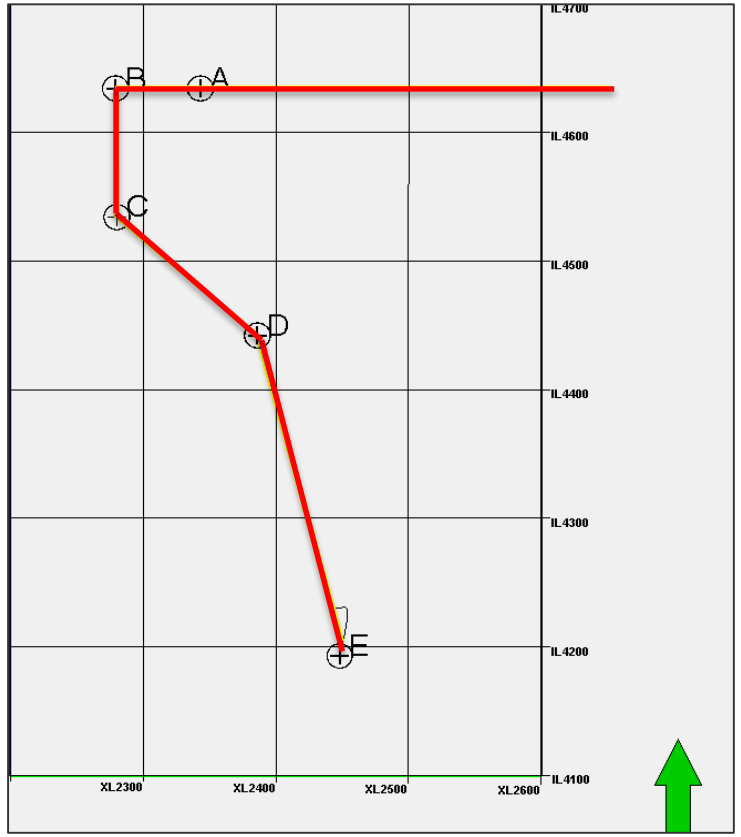
Inversion approach 1) simple relationship



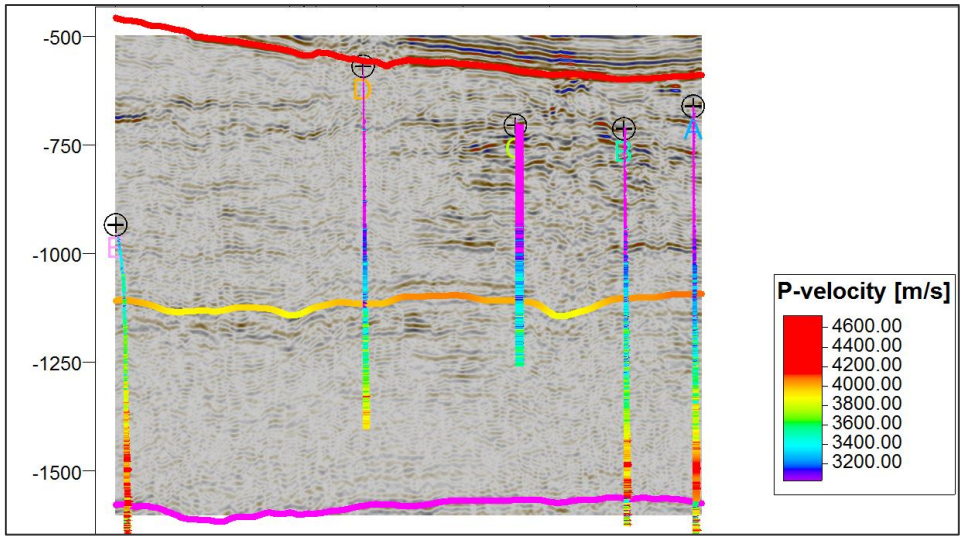
Inversion approach 2) complex relationship

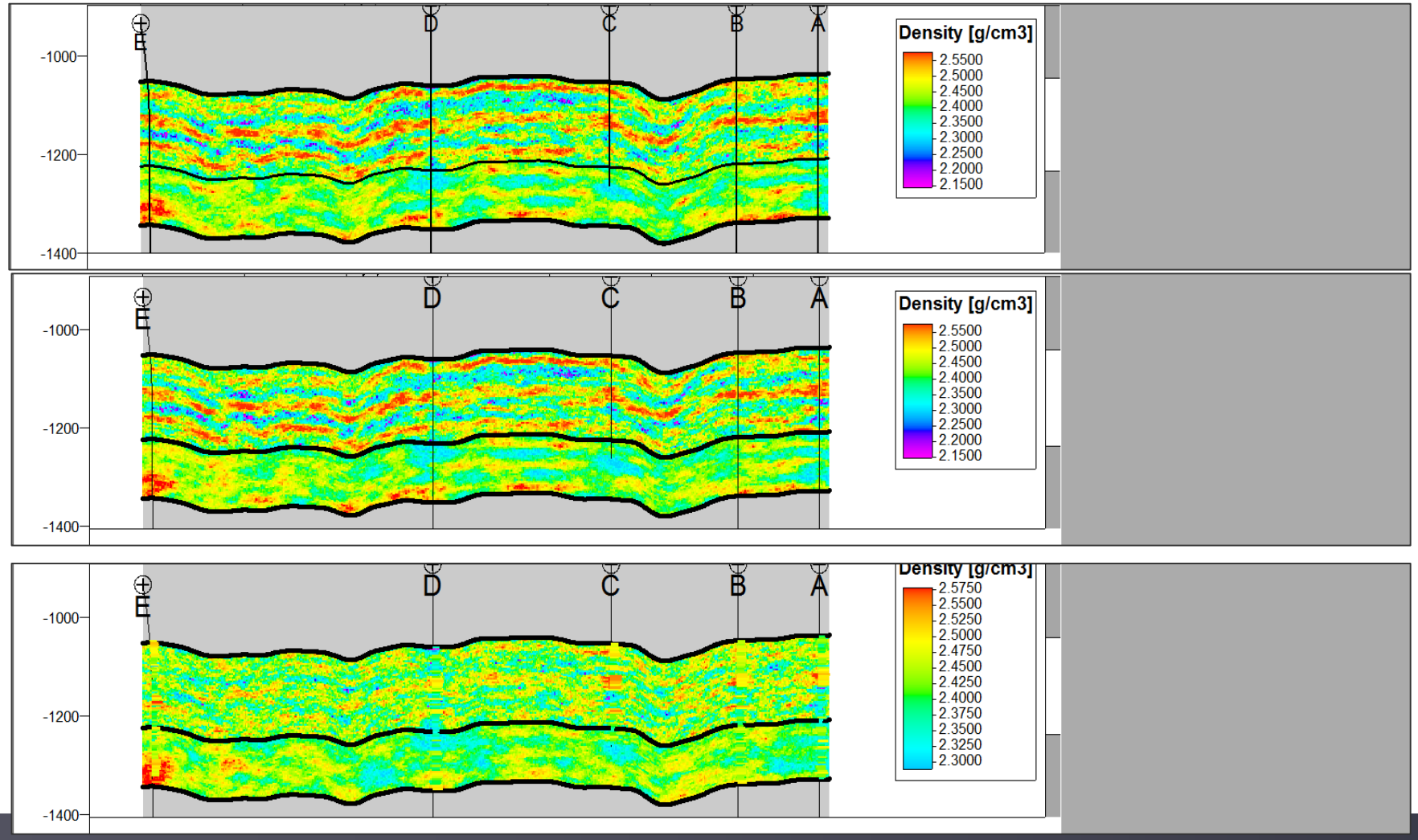


Dataset description



- Grid size: 399 x 599 x 73.
- 6 iterations → 32 models of **Density** simulated at each iteration
- All 5 wells
- Cell thickness in *k* = 4 ms

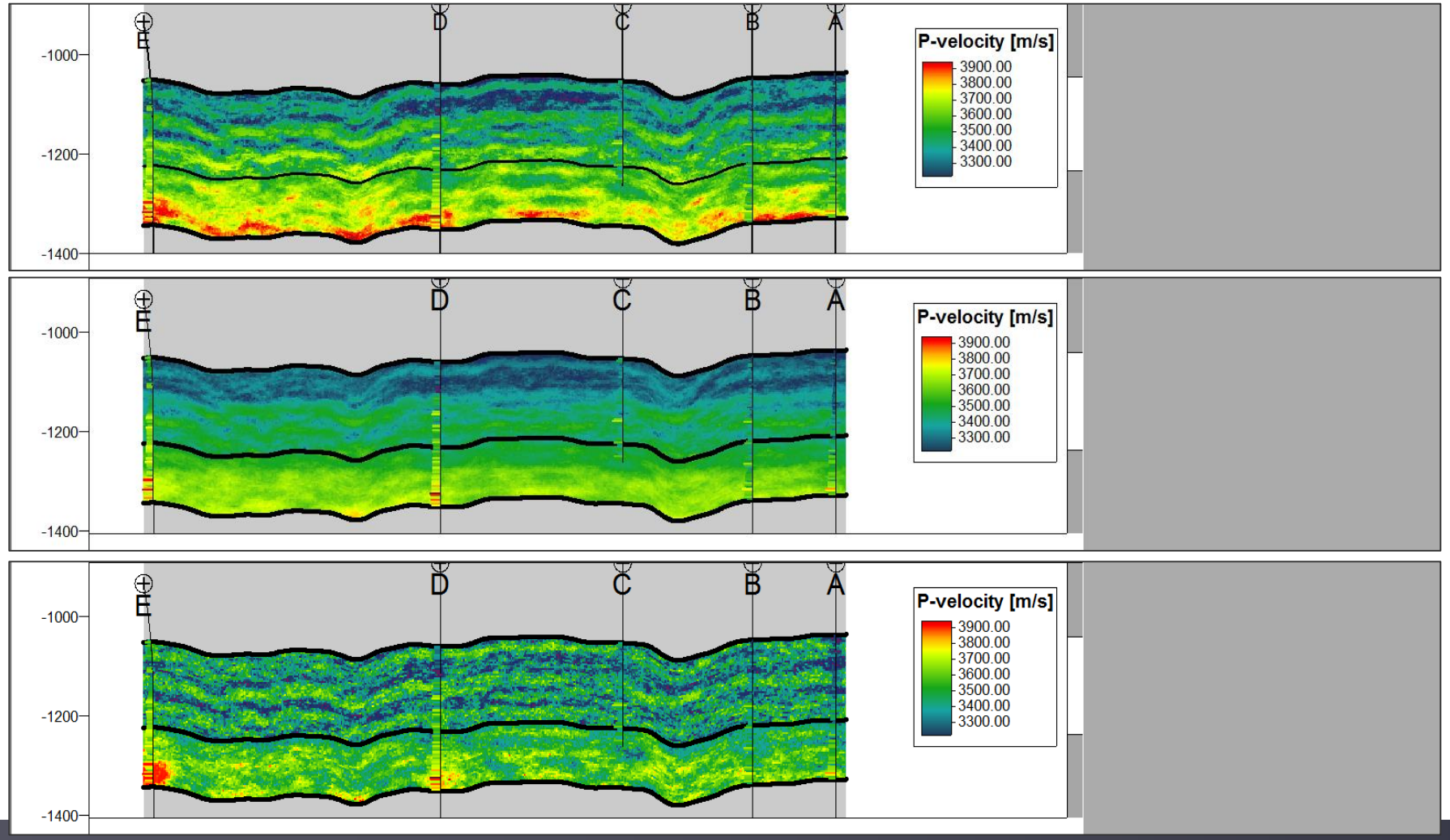




Simple approx.

Complex approx.

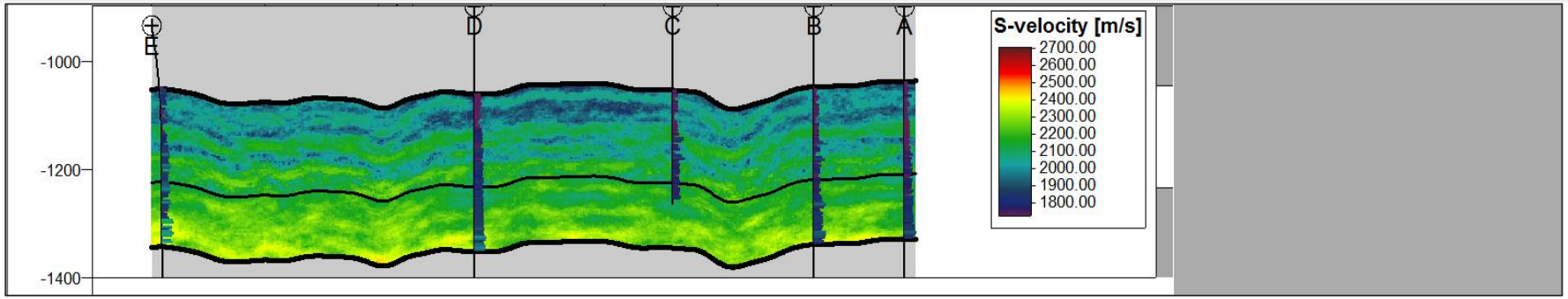
Geostats AVA



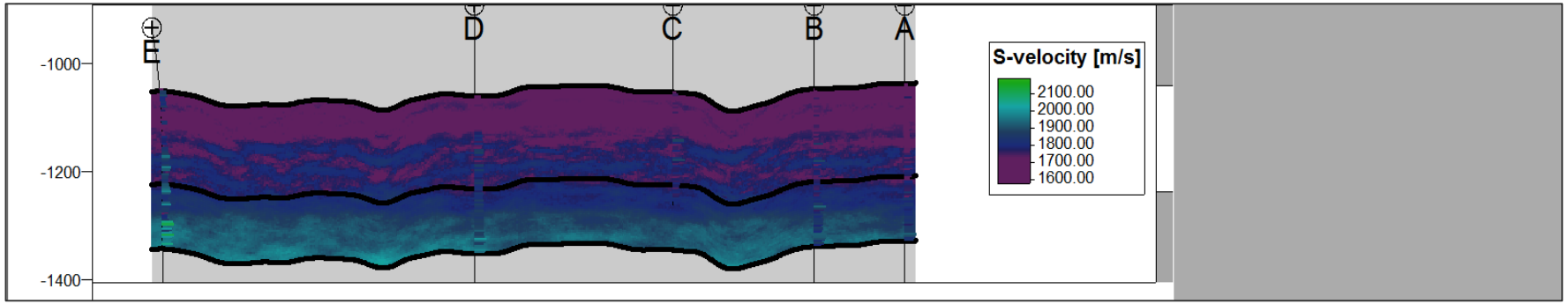
Simple approx.

Complex approx.

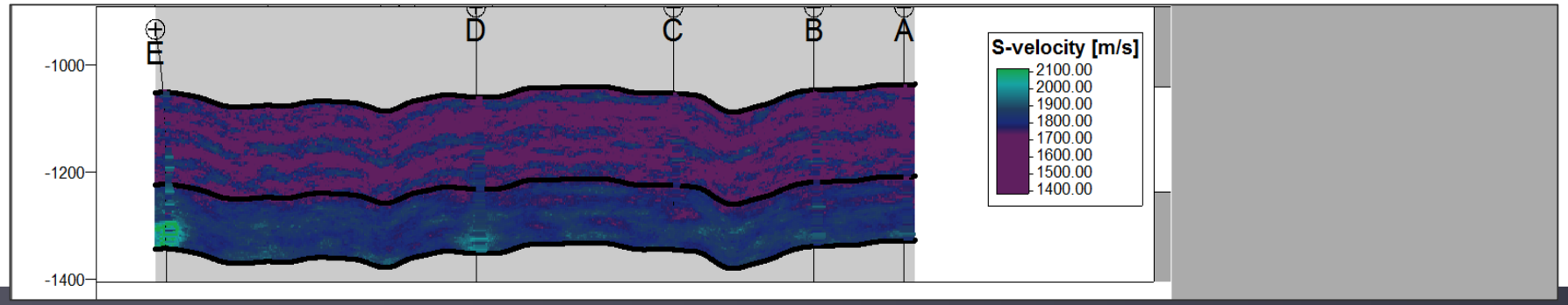
Geostats AVA



Simple approx.



Complex approx.



Geostats AVA

Conclusions

- Good results with 1/3 of computational effort.
- Other RPM's can be used – facies classification can also be integrated.
- Data driven approaches to rock physics are feasible.
- Properties predictions, are good quality, and fast.
- Applications of machine learning techniques have high potential: in exploration and modelling, since we now are in big data environments; also in production management, inserted in smart fields environments.

THANKS!

- To Nutonian for permission to use Eureqa software.
- To Schlumberger for permission to use Petrel software.

- To the audience.

- Any questions?

References

- Schmidt M., Lipson H. (2009) "Distilling Free-Form Natural Laws from Experimental Data," ***Science***, Vol. 324, no. 5923, pp. 81 - 85.
- Nunes R., Soares A., Azevedo L., Pereira P., Geostatistical seismic inversion with direct sequential simulation and co-simulation with multi-local distribution functions, Mathematical Geosciences, Accepted 2016.
- Soares, A. 2001. “Direct Sequential Simulation and Cosimulation.” Mathematical Geology 33 (8): 911–926.
- Mavko, G., Mukerji, T., & Dvorkin, J. (2003). *The rock physics handbook.* Cambridge University Press.