

Thesis update - 29/01/2024

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Sciences



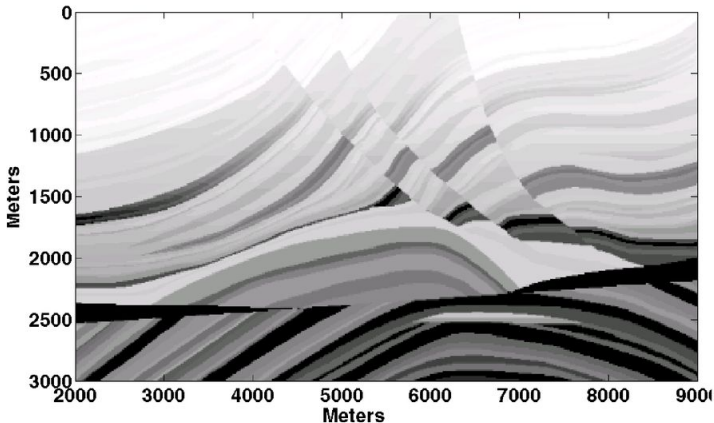
1. Introduction
2. Regression problem
3. Features
4. Studied methods
5. Analysis on polar coordinates
6. What about adding noise ?



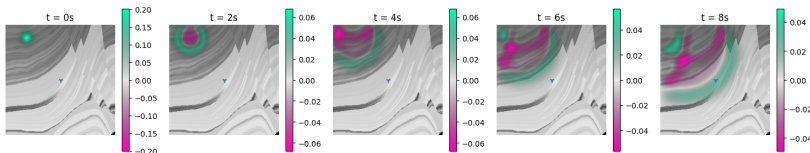
- ▶ Problem defined
 - ▶ Given the propagation of a wave through a heterogeneous field, retrieve the wave epicenter
- ▶ Data defined
 - ▶ Acoustic Wave Equation: $\frac{d^2 u}{dt^2} = c^2(x, y) \left(\frac{d^2 u}{dx^2} + \frac{d^2 u}{dy^2} \right)$
 - ▶ The *heterogeneous* part appears since c is a (non-linear) spatial function $c(x, y)$.
 - ▶ I use the *Marmousi*¹ field (see figure 1)

¹Brougois, A. & Bourget, M. & Lailly, P. & Poulet, M. & Ricarte, Patrice & Versteeg, Roelof. (1990). Marmousi, model and data. 10.3997/2214-4609.201411190.

Marmousi Velocity Model



- ▶ Data defined
 - ▶ Acoustic Wave Equation: $\frac{d^2 u}{dt^2} = c^2(x, y) \left(\frac{d^2 u}{dx^2} + \frac{d^2 u}{dy^2} \right)$ on the Marmousi velocity field
 - ▶ No standard synthetic dataset exists
 - ▶ Solved with Devito², a finite-differences computing library specialized for geophysical applications
 - ▶ Can be interrogated from chosen *Interrogators* (see blue cross on figure 2) that outputs a time series of the amplitude at this spatial point



Example of wave propagation

²Louboutin, Mathias & al. (2019). Devito (v3.1.0): An embedded domain specific language for finite differences and geophysical exploration.

- ▶ Data defined
 - ▶ Acoustic Wave Equation: $\frac{d^2 u}{dt^2} = c^2(x, y) \left(\frac{d^2 u}{dx^2} + \frac{d^2 u}{dy^2} \right)$ on the Marmousi velocity field
 - ▶ Multiple interrogators can be used to simulate an *array of seismometers* (see https://github.com/pascaltribel/PyAWD/blob/main/examples/example_interrogators.mp4)
 - ▶ Each interrogator yields synthetic data similar to the one accessible in STEAD³ which allows real-life testing

³Mousavi, S. Mostafa & Sheng, Yixiao & Weiqiang, Zhu & Beroza, Gregory. (2019). STanford EArthquake Dataset (STEAD): A Global Data Set of Seismic Signals for AI. IEEE Access. PP. 1-1. 10.1109/ACCESS.2019.2947848.

- ▶ Data defined
 - ▶ Acoustic Wave Equation: $\frac{d^2 u}{dt^2} = c^2(x, y) \left(\frac{d^2 u}{dx^2} + \frac{d^2 u}{dy^2} \right)$ on the Marmousi velocity field, with multiple interrogators
 - ▶ Stored in a PyTorch dataset for ML convenience
 - ▶ Hosted on GitHub and PyPI with multiple notebooks for presenting the tool

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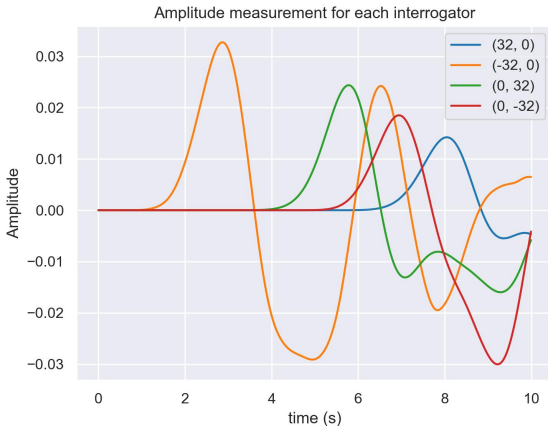


- ▶ Given i interrogators, and simulations of AWD initially centered in (x_0, y_0) lasting t seconds, solved with FD with a time step Δt , the problem is to find a mapping $F(i \times t\Delta t) \rightarrow (x_0, y_0)$. The criteria of evaluation are the *NMSE*, the memory and the time of computation.
- ▶ Hypotheses
 - ▶ The field of propagation is the same for all the simulation (it is region-specific)
 - ▶ Waves are acoustic but not elastic (the medium of propagation is not elastic)
 - ▶ Only one wave is propagating at a time (no P and S waves)
 - ▶ The medium of propagation is static in time
- ▶ Why is it important ?
 - ▶ Computing the epicenter of such waves can help in finding the sources of earthquakes, explosions, and other phenomena producing waves

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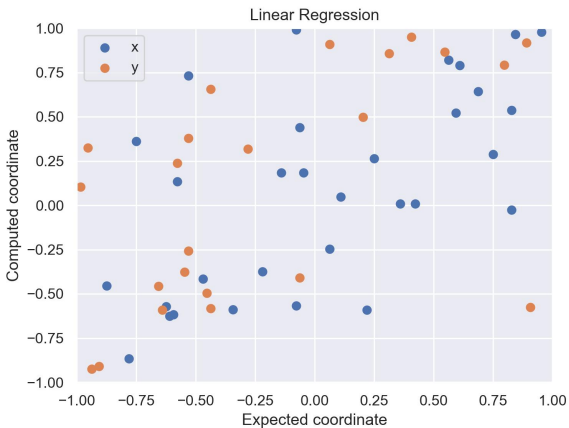
- ▶ Example of input data: the amplitude measurement for each of the interrogators for the whole duration of the experiment
- ▶ Expected output: $[-23/64 \ -50/64]$



3. Features

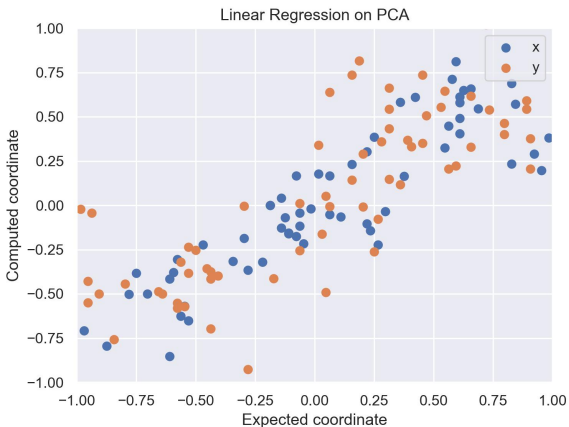
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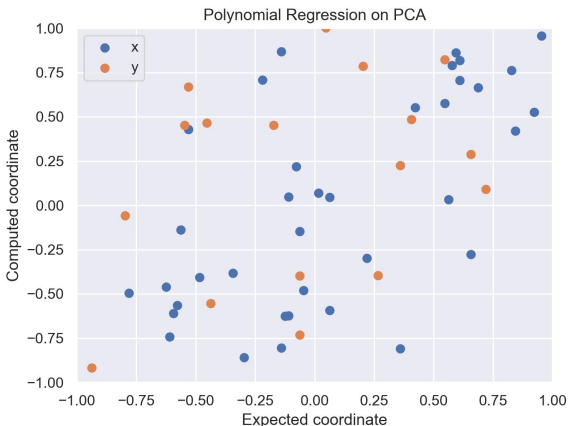
Linear Regression

4. Studied methods



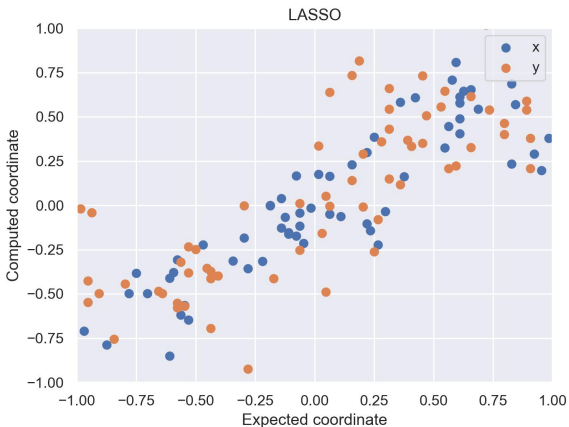
Linear Regression on PCA (features: 64)

4. Studied methods



Polynomial Regression on PCA (degree: 3, features: 64)

4. Studied methods

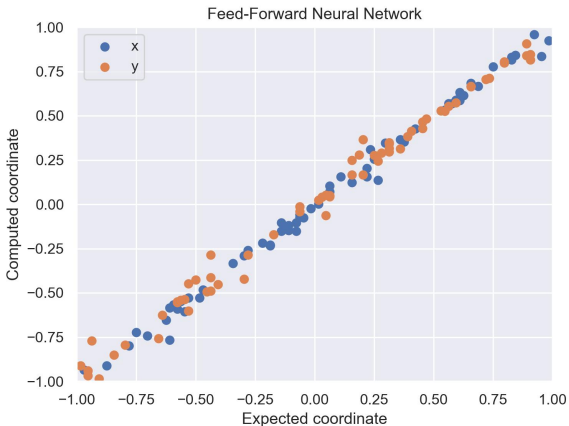


LASSO ($\alpha = 0.00001$)

4. Studied methods



Benchmark of the statistical methods



Non-convolutional FFN

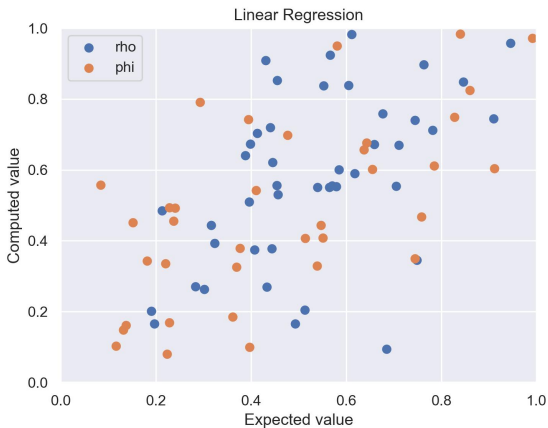
4. Studied methods

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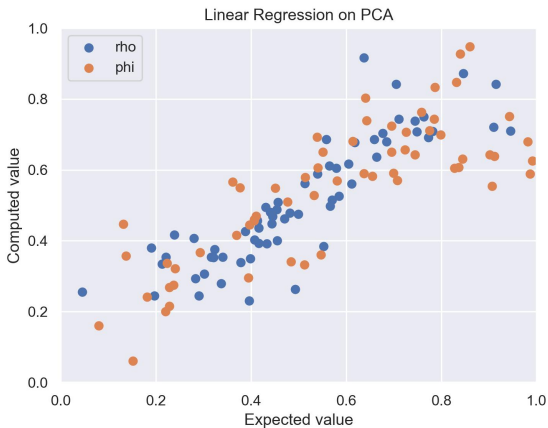
- ▶ We evaluate the methods on the same data, but where the Cartesian coordinates output are mapped to polar coordinates where the distance and the angle are normalized to $[0, 1]$
- ▶ The NMSE are computed with the transformed back outputs to Cartesian coordinates to be able to compare





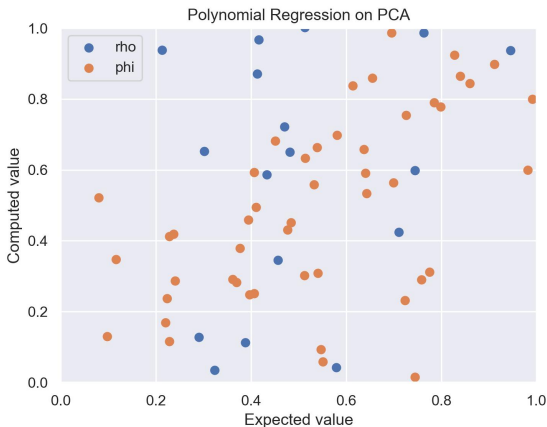
Linear Regression

5. Analysis on polar coordinates

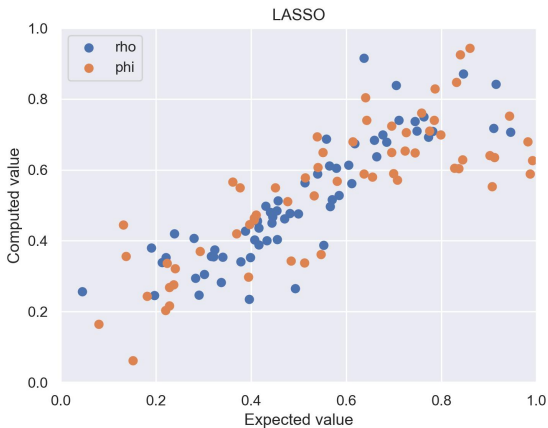


Linear Regression on PCA (features: 64)

5. Analysis on polar coordinates



Polynomial Regression on PCA (degree: 3, features: 64)

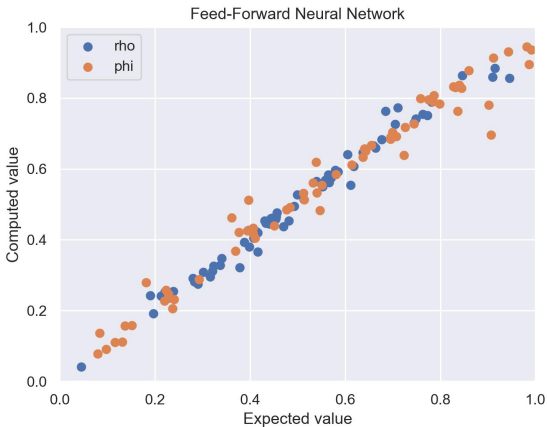


LASSO ($\alpha = 0.00001$)

5. Analysis on polar coordinates



Benchmark of the statistical methods



Non-convolutional FFN

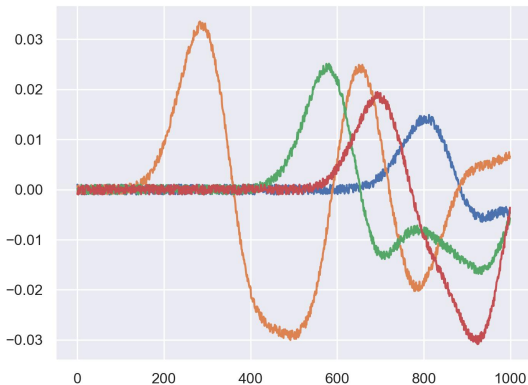
5. Analysis on polar coordinates

Model	NMSE	Time	NMSE x Time
LR	58.3462	0.29456	17.1868
LR (PC)	3.085930	0.302900	0.934730
LR PCA	0.330680	0.250970	0.082990
LR PCA (PC)	0.778870	0.257630	0.200660
PR PCA	82.243200	0.216110	17.774100
PR PCA (PC)	56.785100	0.215730	12.250400
LASSO	0.330190	0.035870	0.011840
LASSO (PC)	0.780670	0.010930	0.008530
FNN	0.00847	18.8223	0.15944
FNN (PC)	0.06450	16.6964	1.07708

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- ▶ We add uniform noise in the range $(-0.001, 0.001)$



Example of interrogators response with noise added
6. What about adding noise ?

- ▶ Now, among the statistical methods, LR performs the better
- ▶ FNN still has the best results, with no big lap with the clean signal (NMSE = 0.06450)
- ▶ Note that the NMSEs for LR PCA and LASSO are equal to the ones on clean signal (0.330680 and 0.330190)

Model	NMSE	Time	NMSE x Time
LR	0.23020	0.20626	0.04748
LR PCA	0.33167	0.26367	0.08745
PR PCA	1.17214	0.13107	0.15363
LASSO	0.33109	0.01891	0.00626
FNN	0.09919	36.3691	3.60781