Robust model aggregation

for production forecasting of oil and gas

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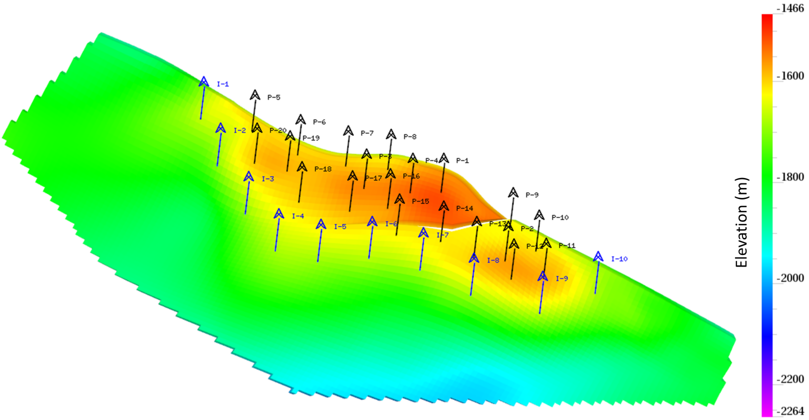
Problem: production forecasting of oil and gas

Keywords and objectives:

Lightening the computational burden of fluid-flow simulations by performing history-matching on the outputs of fixed models rather than updating candidate models with many parameters

The Brugge field (synthetic but realistic data)

Reference: Peters et al. (2010), SPE 119094



Can be decomposed into millions of grid blocks, in which petrophysical properties are unknown (= a model)

Classical approach:

Fluid-flow equations (and simulators) relate

- the production characteristics of the field (pressure, oil and water rates, etc.) over time
- to the model (to the petrophysical properties)

One may thus learn the model based on

- estimates of the petrophysical properties (using some past measurements)
- constraints of closeness of their associated production characteristics to those actually observed over time

This is computationally heavy:

At each time step, many fluid-flow simulations must be performed (many models are tested)

Our approach:

The Brugge data set comes with 104 geological models
(their petrophysical properties were chosen in some way)

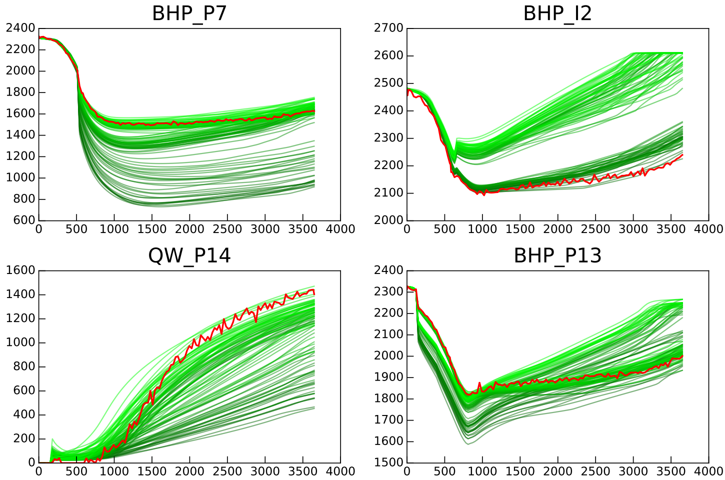
We reweigh their production forecasts over time depending on past performance

That is, we perform history-matching on the outputs of the models, not on their inputs

Advantages and disadvantages

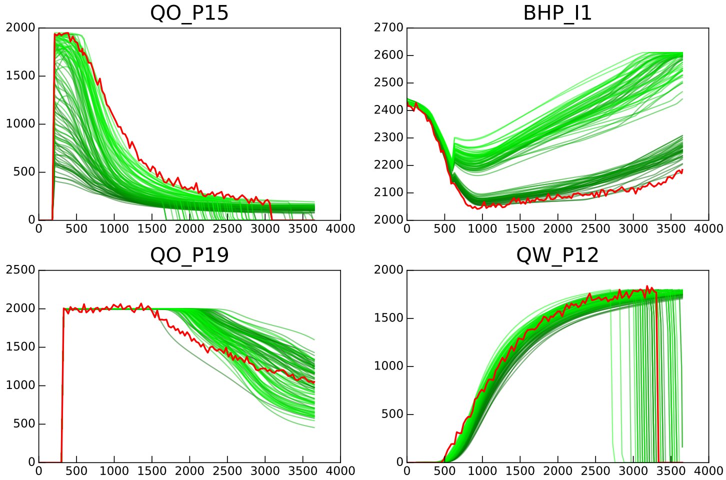
- Computationally very efficient
- Theoretical guarantees of good accuracy, without any stochastic assumption on the data
- No construction of an underlying geological model (= no interpretation)

Examples of model outputs and observations (1/2)



BHP = pressure at the bottom of the hole; QW = water flow rate; QO = oil flow rate
P = producer well; I = injection well; the numbers index the wells

Examples of model outputs and observations (2/2)



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How to combine the outputs

For a given well and a given production characteristic:

We denote by $m_{j,s}$ the model forecasts and by y_s the observed measurements, $s \leqslant t-1$, that occurred prior to a given step t

We pick weights $w_{j,t}$ based on this past and aggregate the forecasts

$$\widehat{y}_t = \sum_{j=1}^{104} w_{j,t} m_{j,t}$$

which we later compare to the observed measurement y_t

Algorithmic question: how to pick the weights?

Theoretical question: what guarantees of performance?

Exponentially weighted averages (EWA): learning parameter $\eta > 0$,

$$w_{j,t} = \frac{\exp\left(-\eta \sum_{s=1}^{t-1} (y_s - m_{j,s})^2\right)}{\sum_{k=1}^{K} \exp\left(-\eta \sum_{s=1}^{t-1} (y_s - m_{k,s})^2\right)} .$$

Ridge regression: regularization factor $\lambda > 0$,

$$(w_{1,t}, \ldots, w_{K,t}) \in \mathop{\arg\min}_{(v_1,\ldots,v_K)\in\mathbb{R}^K} \left\{ \lambda \sum_{j=1}^{K} v_j^2 + \sum_{s=1}^{t-1} \left(\hat{y}_s - \sum_{j=1}^{K} v_j \, m_{j,s} \right)^2 \right\}$$

Lasso regression: replace the regularization above by $\lambda \sum_{j=1}^{K} |v_j|$

Performance guarantees for EWA and Ridge (not Lasso yet):

- No stochastic modeling, guarantees for all individual sequences
- Mimic the performance of (at least) the best model

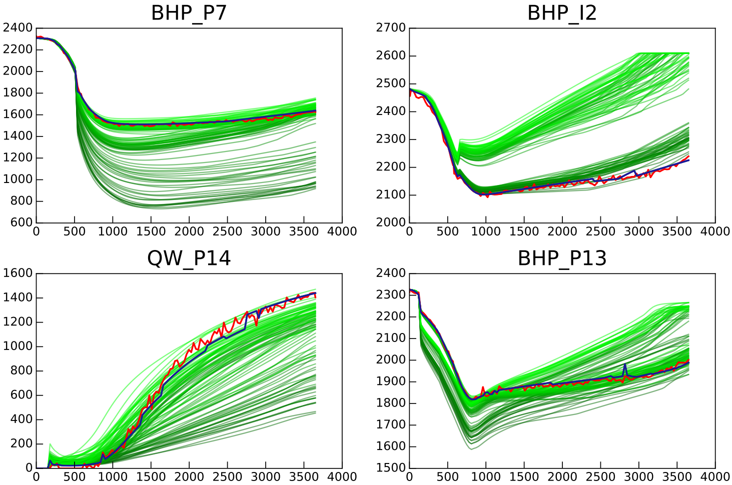
For all bounded sequences of forecasts $m_{j,t}$ and observed production characteristics y_t,

RMSE of algorithm $\leqslant$ RMSE of best model + small “regret”

$$\sqrt{\frac{1}{T}\sum_{t=1}^{T}\bigl(\hat{y}_t - y_t\bigr)^2} \leqslant \min_{j=1,\ldots,104} \sqrt{\frac{1}{T}\sum_{t=1}^{T}(m_{j,t} - y_t)^2} + O\bigl(T^{-1/4}\bigr)$$

References: several papers of the 90s and early 2000s;
see the monograph by Cesa-Bianchi and Lugosi, 2006

Aggregated production forecasts with EWA (1/2)



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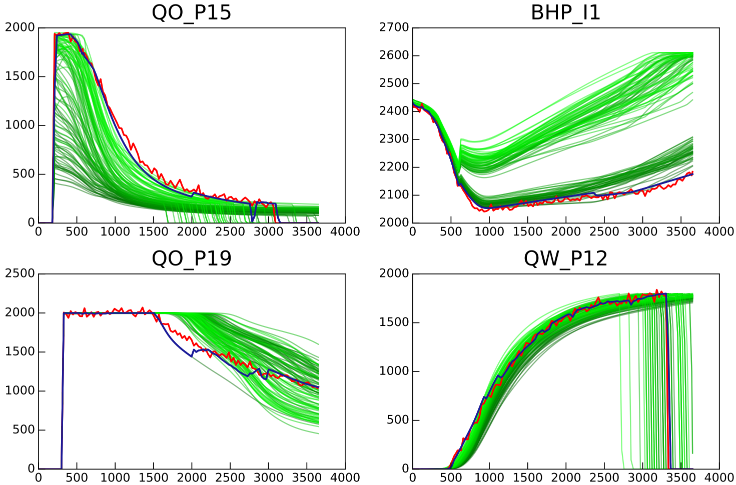
Aggregated production forecasts with EWA (2/2)



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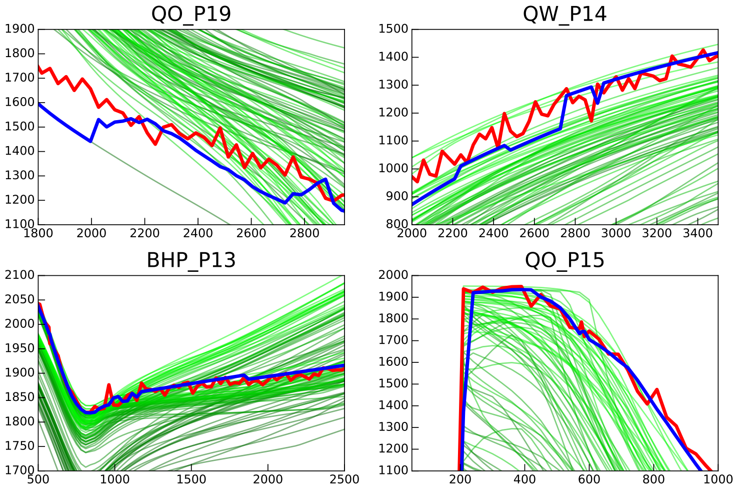
Aggregated production forecasts with EWA (zooming in)



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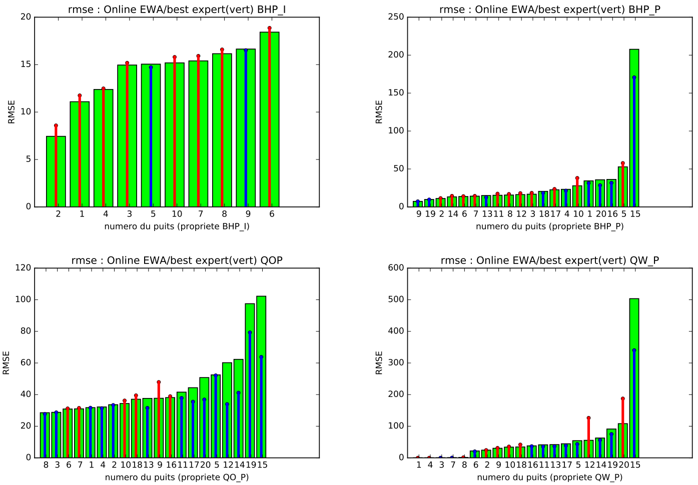
Overview of the performance of EWA (in red or blue) versus the best model for the well–production characteristic pair



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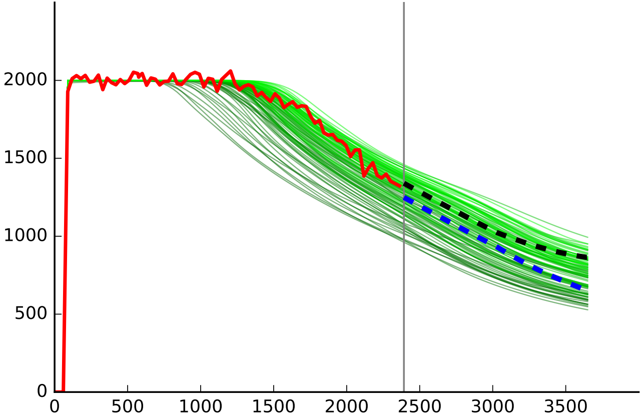
Can we provide interval forecasts?



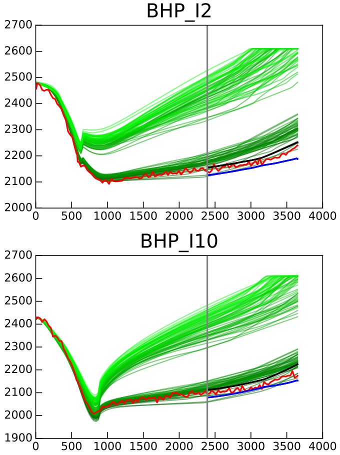
Standard request (and offer) with stochastic modelings.
Not so clear within the theory of individual sequences...

Our individual-sequences approach for interval forecasts

1. On the first part of the data set, $t = 1, \ldots, T$,
   when one-step ahead aggregated forecasts are provided
   - use the algorithms as explained above

2. On the second part of the data set, $t = T+1,\ T+2, \ldots$
   when interval forecasts are to be provided
   - The models still provide forecasts $m_{j,T+s}$ for $s \geqslant 1$
   - Consider all possible (bounded) continuations $y'_{T+1}, y'_{T+2}, \ldots$ of the observed characteristics
   - Deduce a series of aggregated forecasts $\widehat{y}'_{T+1}, \widehat{y}'_{T+2}, \ldots$
   - Obtain the intervals as the convex hulls of all these possible aggregated forecasts
   - Possibly enlarge them to take into account some noise (observed characteristics are measured with noise)

Interval forecasts with Ridge (1/3)



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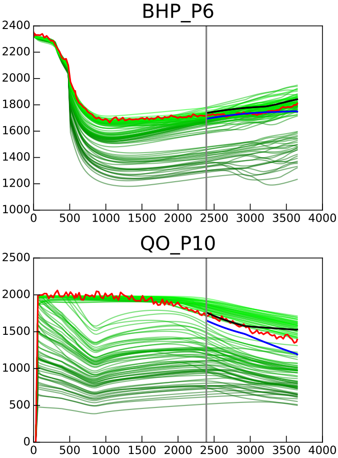
Interval forecasts with Ridge (2/3)



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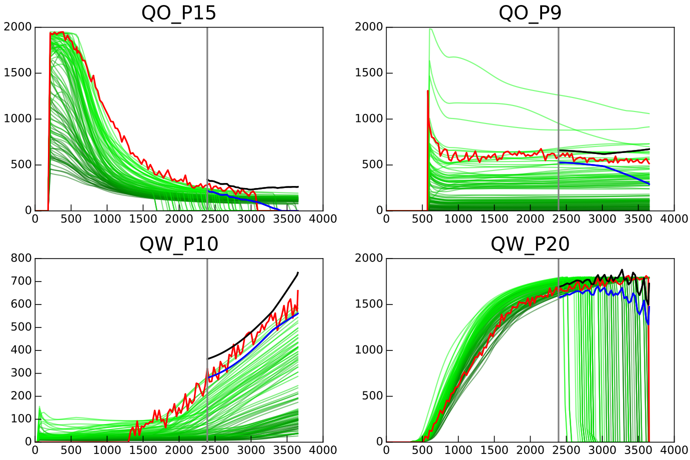
Interval forecasts with Ridge (3/3)



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An announcement for those who like real-world machine learning!

PGMO /IRSDI: call for projects in industrial data science

Team = academic members + industrial partner

Funding = 10-15 kE, for one year

Application = only 3-4 pages; deadline at May 14