Assessing Exploration Risk for Geothermal Wells

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14 July 2014

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Agenda

Motivation

Classification of Techniques

Data

Support Vector Machine Regression (SVR)

Uncertainty Analysis

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Power P

depends on temperature T and flow rate Q:

$$P \propto TQ$$

Success

- Flow rate exceeds given level Q_0 (at a certain drawdown)
- Temperature exceeds given level T_0

[Schulz et al. (2005)], [Schulz et al. (2007)]

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- Forecast *expected* flow rate and temperature
- Uncertainty analysis
  1. Confidence and prediction intervals (*estimation risk*)
  2. Estimate *quantiles* (cf. *Value at Risk* – VaR)

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Geomathematics

Seismics, gravimetry and geomagnetics

Deterministic methods

Splines, inverse distance weighting

Spatial statistics

- Kriging
- Simulation
- Machine Learning

[Chiles, Delfiner (2013)], [Demyanov (2013)], [Kanevski et al. (2009)],...

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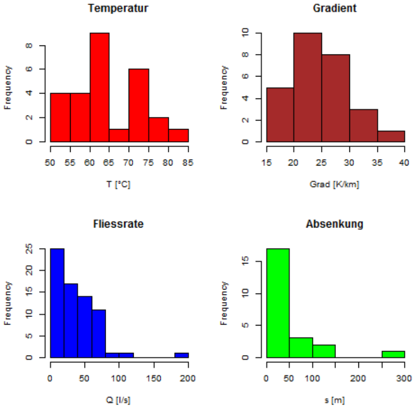
Data – Map

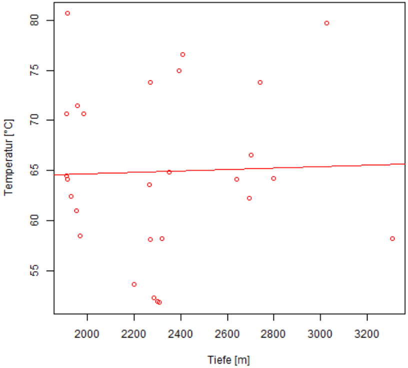

Hamburg
North German Basin
Berlin
Hanover
Cologne
Frankfurt
Upper Rhine Graben
South German
Molasse Basin
Munich

Histograms

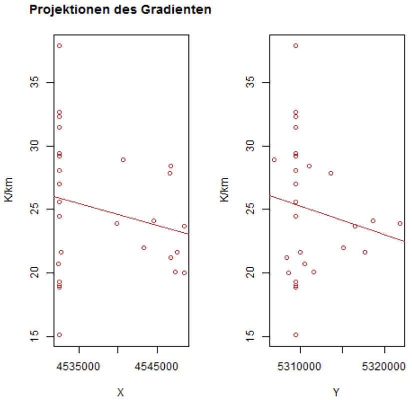


Temperatur
Frequency
0
2
4
6
8
50 55 60 65 70 75 80 85
T [°C]
Gradient
Frequency
0
2
4
6
8
10
15 20 25 30 35 40
Grad [K/km]
Fliessrate
Frequency
0
5
10
15
20
25
0 50 100 150 200
Q [l/s]
Absenkung
Frequency
0
5
10
15
0 50 100 200 300
s [m]

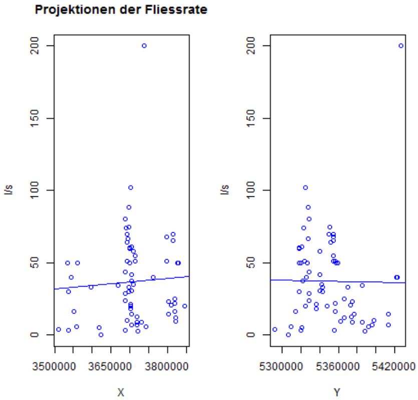
Temperature and depth



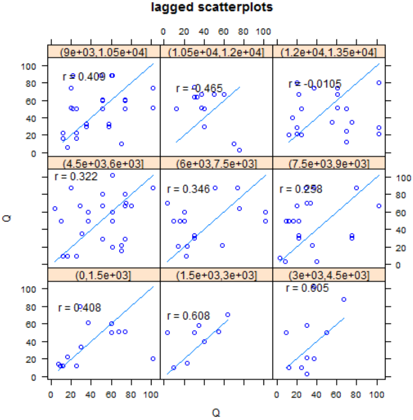
Projections of the gradient



Projektions of the flow rate



Lagged Scatter Plot of the flow rate



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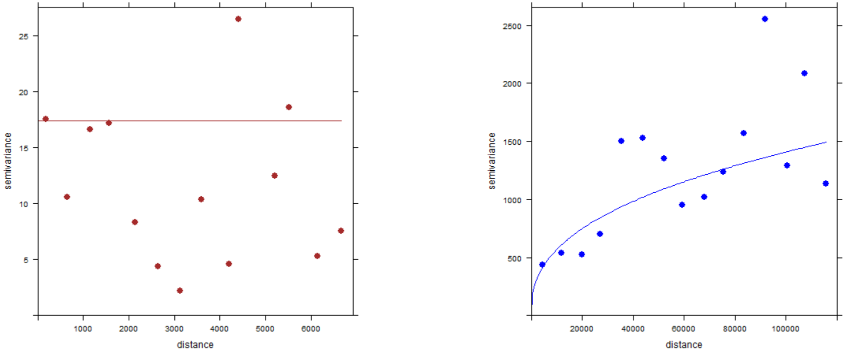
Variograms



Gradient (brown), flow rate (blue)

SVR

Features

- Nonparametric regression / model free learning
- No distribution assumptions
- Modelling complex, nonlinear phenomena
- Allows for ultrahighdimensional input data
- Allows for modelling multi-scale effects
- Good model calibration – no local optima
- Parameter sparsity – no variogram
- Robustness – high variability, sparse data
- Good generalization w.r.t. unseen data

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SVR

Implicit kernel transformation

Gaussian RBF kernel

$$k(x, x') = \langle \Phi(x), \Phi(x') \rangle = \exp(-\sigma \|x - x'\|^2)$$

ϵ-insensitive loss function (soft margin loss)

$$|\xi|_\epsilon := \begin{cases} 0 & , \quad \text{if} \quad |\xi| \leq \epsilon \\ |\xi| - \epsilon & , \quad \text{otherwise} \end{cases}$$

SVR

Hyperparameters

- ϵ: Sensitivity parameter of the loss function
- C: Regularization
- σ: Kernel width

Implementation in R

- `ksvm{kernlab}`
- Model choice
  - `tune.svm{e1071}` performs a *grid search*
  - `kpar = ''automatic''` adjusts kernel width
- Quantile regression: `kqr{kernlab}`

[Karatzoglou et al. (2006)]

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Validation scheme

Cross validation

- Partition data in a training and a test set
- Fit hyperparameters on training set (nested CV)
- Predict values for test set
- Calculate forecast error
- ... repeat this 100 times

Measures of goodness

- RMSE
- p-value (quantile regression)

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Validation results

- Gradient instead of temperature
- SVR only

	Gradient	Flow rate
SVR	4.6	30.0
MKR	4.4	32.3
Kriging	4.8	32.2
linear	4.8	34.2
arithm. mean	4.7	31.7

Uncertainty Analysis

Intervals

- Confidence interval
- Prediction interval

Bootstrap

- basic
- studentized
- wild

[Davison, Hinkley (1997)]

Uncertainty Analysis

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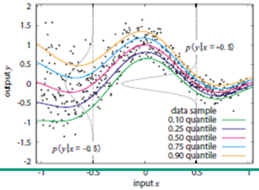
Uncertainty Analysis

(Kernel-)Quantile regression

- usually: conditional expectation
- here: conditional quantile
- 10%-quantile and 90%-quantile yield 80%-coverage interval

[Koenker (2005)], [Takeuchi et al. (2006)]



Summary

Limits of geostatistics

- Relevant predictors
- Sample size sufficiently large?
- Selection bias

Conclusions

- Integration of further predictors
- Enlarging sample size

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Support code 0325512C