Assessing Exploration Risk for Geothermal Wells

Bernhard Kübler

14 July 2014
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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\[ P \propto TQ \]

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Problems

- 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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  1. Confidence and prediction intervals (estimation risk)
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# Classification of Techniques

## 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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[Chiles, Delfiner (2013)], [Demyanov (2013)], [Kanevskii et al. (2009)],...
Data – Map
Histograms

- **Temperatur**
  - Frequency vs. Temperature (°C)

- **Gradient**
  - Frequency vs. Gradient [K/km]

- **Fließrate**
  - Frequency vs. Flow Rate [l/s]

- **Absenkung**
  - Frequency vs. Subsidence [m]
Temperature and depth
Projections of the gradient
Projektions of the flow rate
Lagged Scatter Plot of the flow rate
Variograms

Gradient (brown), flow rate (blue)

London, 07/14/2014 11
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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Implicit kernel transformation

Gaussian RBF kernel

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

\( \epsilon \)-insensitive loss function (soft margin loss)

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

Hyperparameters
- $\epsilon$: Sensitivity parameter of the loss function
- $C$: Regularization
- $\sigma$: 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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[Karatzoglou et al. (2006)]
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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Measures of goodness
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Validation results

- Gradient instead of temperature
- SVR only

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<th>Flow rate</th>
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<tr>
<td>SVR</td>
<td>4.6</td>
<td>30.0</td>
</tr>
<tr>
<td>MKR</td>
<td>4.4</td>
<td>32.3</td>
</tr>
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<td>Kriging</td>
<td>4.8</td>
<td>32.2</td>
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<td>Linear</td>
<td>4.8</td>
<td>34.2</td>
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<tr>
<td>arithm. mean</td>
<td>4.7</td>
<td>31.7</td>
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## Uncertainty Analysis

### Intervals
- Confidence interval
- Prediction interval

### Bootstrap
- basic
- studentized
- wild

[Davison, Hinkley (1997)]
Uncertainty Analysis

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[Davison, Hinkley (1997)]
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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