A Heuristic Robust Approach for Real Estate Valuation in Areas with Few Transactions

FIG Working Week 2017

Surveying the world of tomorrow –

From digitalisation to augmented reality

Helsinki – 31 May 2017

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Founded by DFG Deutsche Forschungsgemeinschaft

Motivation

- Real estate valuation:
  - Based on statistical evaluation of purchase cases
  - Data are heterogeneous and dispersion is large
  - Data contain often outliers

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- Areas with few transactions:
  - Only 20 to 30 purchase prices are available
  - Number of observations is too small for classical outlier detection

    => Detection of outliers in these data is a challenge

Aims and Methodological Approach

- **The focus of this research**

  Robust estimation of market values with a data-driven model in areas with few transactions

- **Aims of the evaluation process**

  Find the best estimation approach to deal with outliers in areas with few transactions

- **Methodological approach**

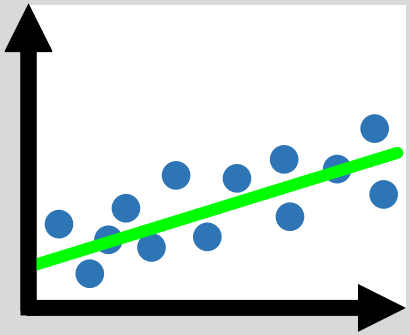
  Comparison of the results of different robust estimation approaches by means of Closed-Loop-Simulation

Source: bennettca.co.nz

Researched Estimation Approaches

Multiple Linear Regression

- Assumption: $e_i \sim N(0, \sigma^2)$
- Method of least square
- Is not robust



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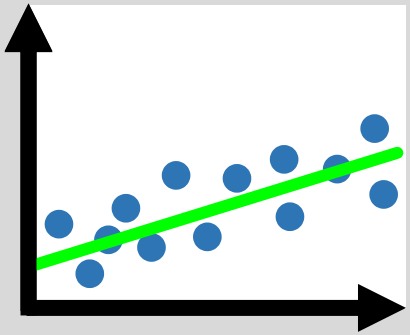
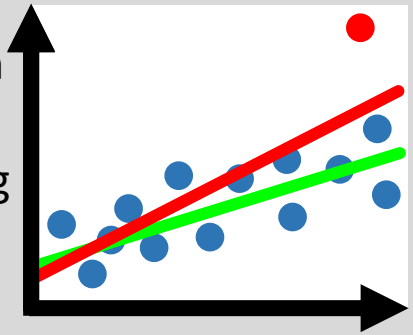


Data Snooping

- Regression approach
- Outlier detection by hypothesis testing



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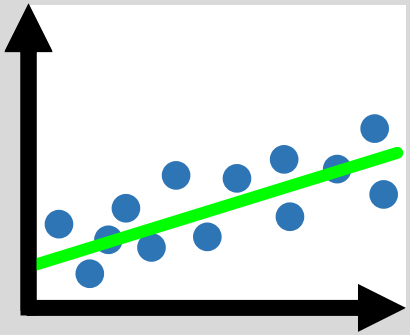

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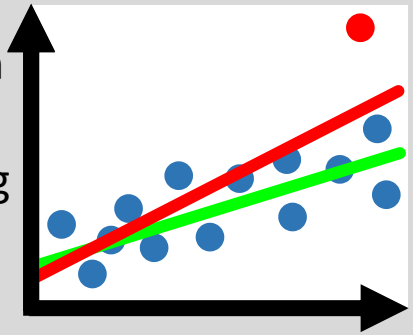
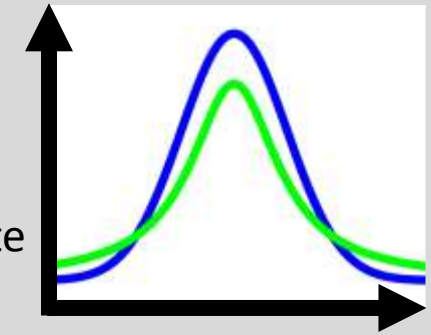


Robust Bayesian Approach

- Replace normal likelihood by student distribution
- Markov Chain Monte Carlo (MCMC)



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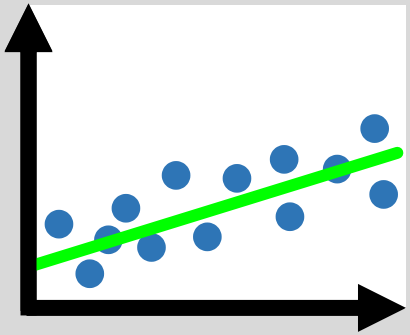

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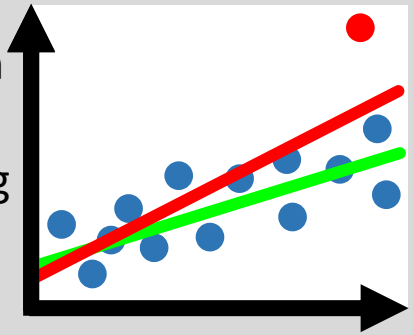

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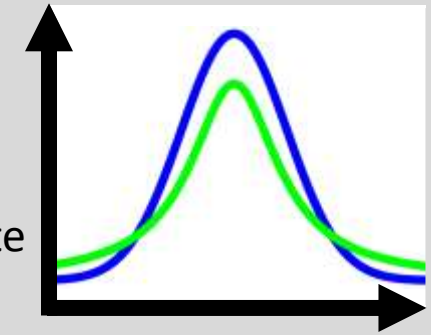
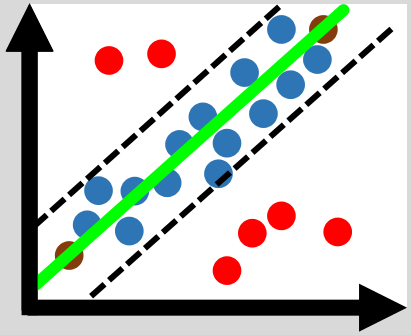


Random Sample Consensus Set (RANSAC)

- Heuristic approach
- Search the model with the most observations



Strategy of the Investigation

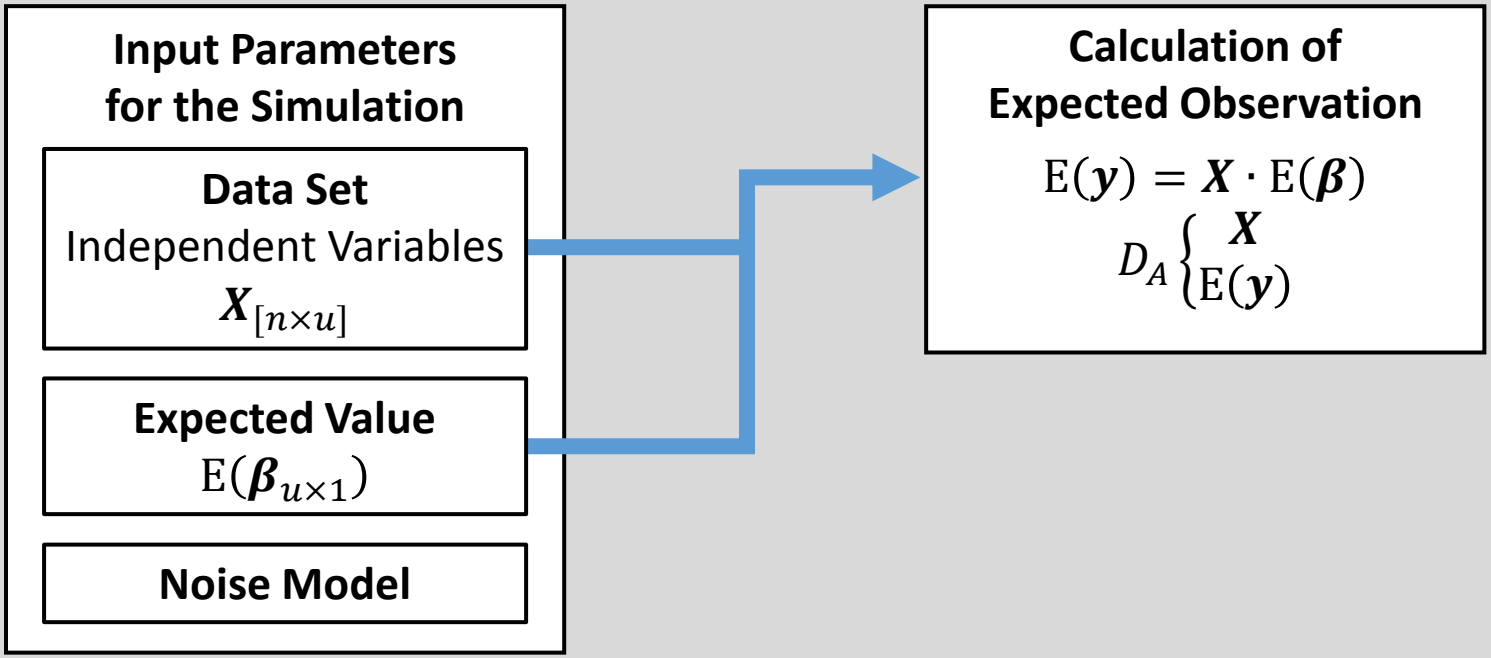
Input Parameters for the Simulation

Data Set
Independent Variables
$\boldsymbol{X}_{[n\times u]}$

Expected Value
$\mathrm{E}(\boldsymbol{\beta}_{u\times 1})$

Noise Model

Strategy of the Investigation



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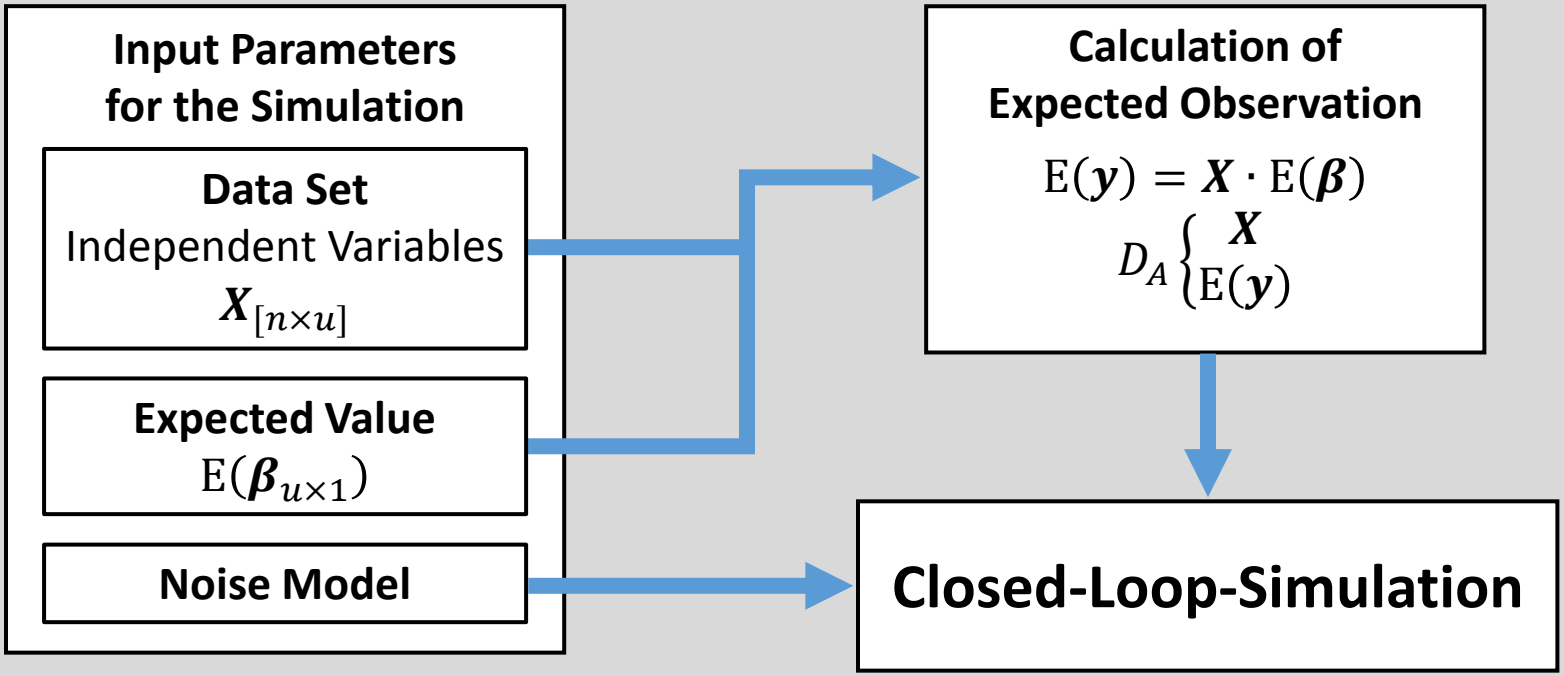
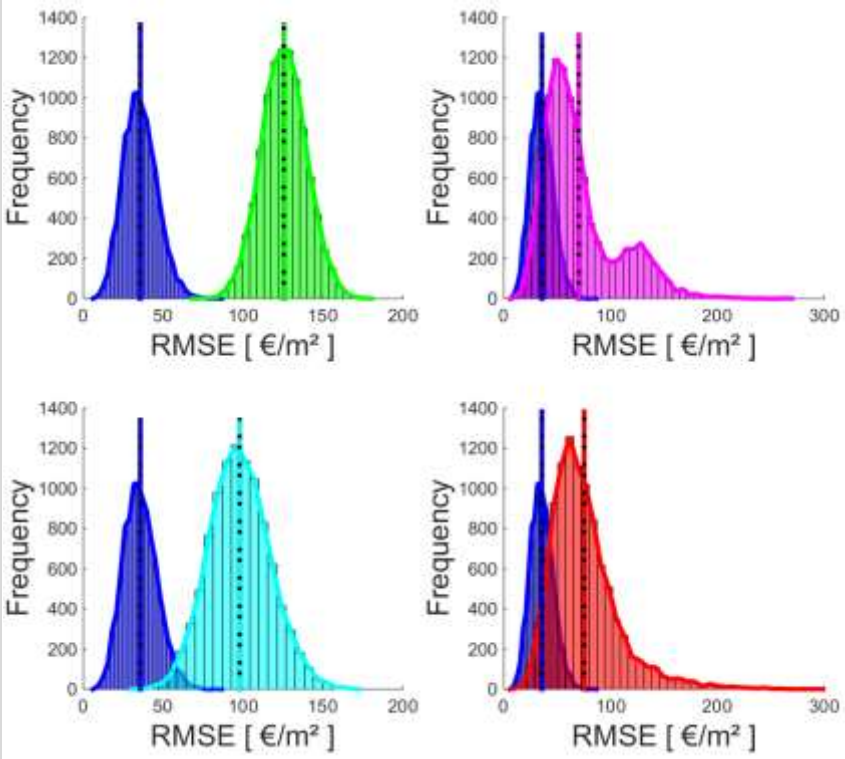


Closed-Loop-Simulation

- Benefit
  - The expected results are known
  - Position of outliers are known
  - Noise distribution is known, e. g. mixture distribution
- Procedure
  - Two scenarios:
    - Submarket with 100 purchases
    - Submarket with 30 purchases
  - Repetition of one scenario 100.000 times
  - Calculation of the Root Mean Square Error (RMSE) between adjusted and expected observations

Results of the Simulation

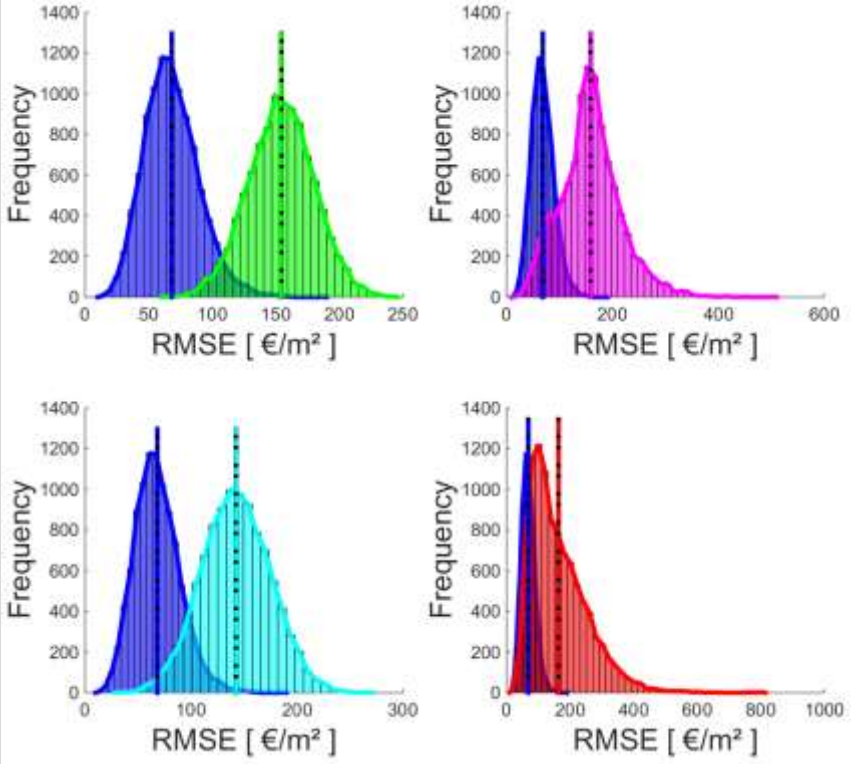
RMSE for 100 purchases



Estimation Approach	Mean [€/m²]	σ [€/m²]
Reference	36	11
Regression	126	14
Data Snooping	70	35
Robust Bayesian Approach	98	19
RANSAC	75	32

Results of the Simulation

RMSE for 30 purchases



Estimation Approach	Mean [€/m²]	σ [€/m²]
Reference	68	21
Regression	154	26
Data Snooping	159	57
Robust Bayesian Approach	143	32
RANSAC	163	89

Conclusion & Outlook

- Data Snooping and RANSAC provide results with good quality only in data sets with an adequate number of purchases
- Robust Bayesian approach has the greatest potential to deal with outliers in areas with few transaction
- In future studies:
  - Optimisation of the robust Bayesian approach to deal more efficiently with outliers
  - Combination of prior information like offer prices or expert knowledge with the available purchases by means of the Bayes theorem

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Many thanks for your attention!

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Input Parameters for the Simulation

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Expected Value
$\mathrm{E}(\boldsymbol{\beta}_{u\times 1})$

Noise Model

Data base are 260 purchases of detached houses. Following influence quantities are used:

- Living space [m²]
- Area of lot [m²]
- Standard land value [€/m²]
- Construction year [year]
- Equipping standard [without unit]

Strategy of the Investigation

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Noise Model

The estimated regression coefficients of the 260 purchases are used as expected values.

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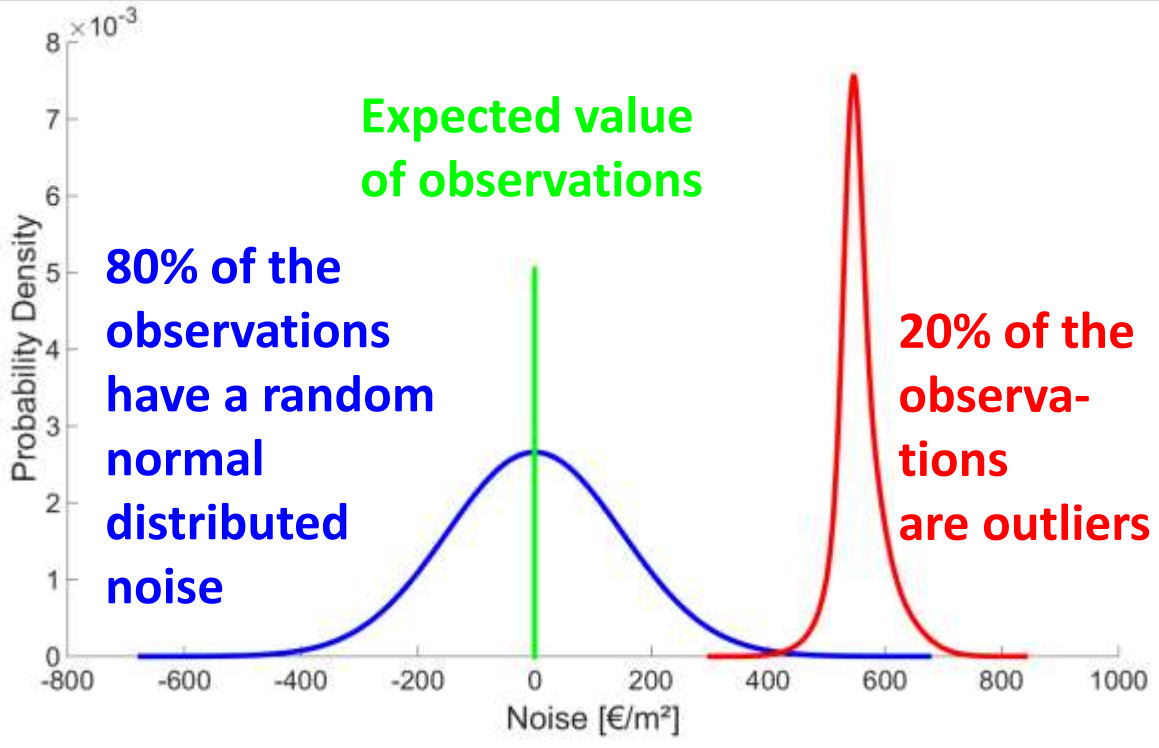
Noise Model



Closed-Loop-Simulation

Create Data Set 1

Create set $\boldsymbol{D}_R^{(j)}$ from set $\boldsymbol{D}_A^{(j)}$ by h times random drawing (e.g. h =30 purchases).

Create Observations 2

Create noise $\varepsilon^{(j)}$ with the noise model.

$$y_R^{(j)} = \mathrm{E}(\boldsymbol{y})_R^{(j)} + \varepsilon^{(j)}$$

Create Data Set without Outliers 3

Create set $\boldsymbol{D}_F^{(j)}$ from set $\boldsymbol{D}_R^{(j)}$ by removing all purchases with outliers.

Estimation 4

- Estimate $\widehat{\boldsymbol{\beta}}_l^{(j)}$ with l ={Regression, Data Snooping, robust Bayes, RANSAC, Reference}
- Calculate the Root Mean Square Error:

$$RMSE_l^{(j)} = \sqrt{\frac{1}{n_l}\sum_{i=1}^{n}\left(\left(\boldsymbol{X}_l^{(j)}\widehat{\boldsymbol{\beta}}_l^{(j)} - \mathrm{E}(\boldsymbol{y}_l)^{(j)}\right)^2\right)}$$

Iterations: $j = 1, \ldots, 100000$