

# **Geodatenanalyse I: Monte Carlo Methoden**

#### Kathrin Menberg



### Stundenplan



	08:30 – 12:30 Uhr	13:30 – 17:30 Uhr
Montag	Tag 1 / Block 1	Tag 1 / Block 2
Dienstag	Tag 2 / Block 1	Tag 2 / Block 2
Mittwoch	Tag 3 / Block 1	Tag 3 / Block 2
Donnerstag	Tag 4 / Block 1	Tag 4 / Block 2
Freitag	Tag 5 / Block 1	Tag 5 / Block 2

- **▶ 2.7 Monte Carlo Methoden**
- 2.8 Grundlagen der Sensitivitätsanalyse
- ▶ 2.9 Fortgeschrittene Sensitivitätsanalyse

#### Lernziele Block 2.7



#### Am Ende der Stunde werden die Teilnehmer:

- mit dem Prinzip von Unsicherheiten und statistischen Zufallsexperimenten vertraut sein.
- ... einen Überblick über Methoden für (Pseudo-)
   Zufallsexperimente haben.
- ... einfache Monte Carlo Simulationen in Python durchführen und auswerten können.

#### Unsicherheiten



"Nothing is certain, but our ignorance." (unbekannt)

Welche "Unsicherheiten" fallen Euch in Bezug auf Geodatenanalyse ein?

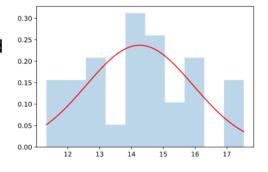
#### **Arten von Unsicherheit**



- Aleatorisch (aleatoric)
  - statistische Unsicherheit
  - Unbestimmbare Größen, die in wiederholten Experimenten variieren
  - Komplexe Prozesse, die nicht erfassbar sind
  - USW.



- Systematische Unsicherheit
- ► Größen, die in Experimenten nicht gemessen wurden.
- Vereinfachungen in numerischen Modellen
- Usw.



#### **Quellen von Unsicherheiten**



- Daten, Parameter
  - Messfehler, Messgenauigkeit
  - Szenarien
- Modelle
  - Annahmen (Randbedingungen usw.)
  - Vernachlässigte Prozesse
  - Auflösung, bzw. Diskretisierung
  - Numerische Fehler, Approximation
- Modellierer
  - Bedienungsfehler, Eingabefehler
- und viele mehr...

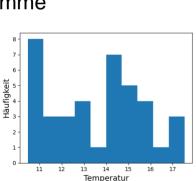


Ohmer et al. (2021)

# Visualisierung von Unsicherheiten



- Fehlerbalken
- Balkendiagramme
- Histogramme
- Boxplots
- Violinen Diagramme
- Schwarmplot
- u.v.m.

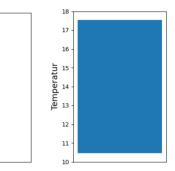


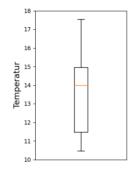
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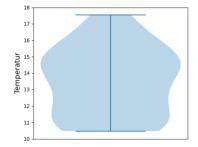
Temperatur 13

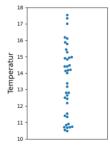
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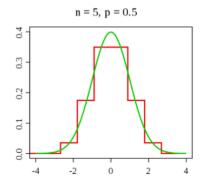


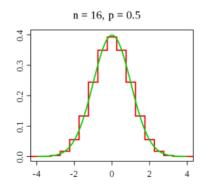
#### **Zentraler Grenzwertsatz**

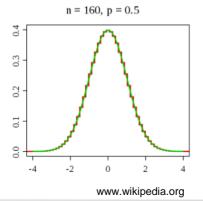


- engl. central limit theorem
- Für  $n \to \infty$  nähert sich die empirische Verteilungsfunktion  $Z_n$ der Standardnormalverteilung  $\Phi(z)$ 
  - ▶ Konvergenz gegen  $\Phi(z)$

$$\lim_{n \to \infty} P(Z_n \le z) = \Phi(z)$$







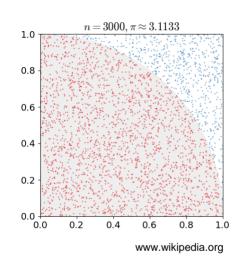
#### **Monte Carlo Simulation**



- Ziele (Beispiele)
  - Approximation von irrationalen Zahlen
  - Verteilungseigenschaften von Zufallsvariablen
  - Nachbildung komplexer Prozesse (z.B. Wetter- und Klimaphänomene)

#### Prinzip:

- mögliche Inputs definieren
- 2. zufällige Inputs anhand einer Wahrscheinlichkeitsfunktion generieren
- 3. <u>deterministische</u> Berechnung mit den Inputs durchführen
- 4. Ergebnisse zusammenfassen



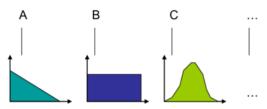
#### **Monte Carlo Simulation**



Input data & parameters

1.

Assumed
distributions

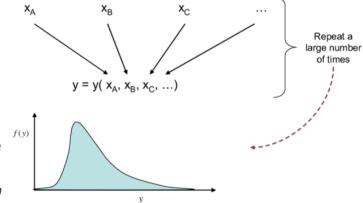




**2.** Take random sample

Obtain model output

Repeat process a large number of times to generate output distribution



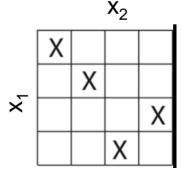
Henderson & Bui 2005

#### Generieren von Zufallswerten

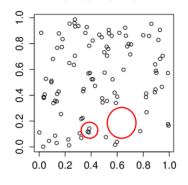


- einfache Zufallswerte (random values)
  - z.B. in Python über numpy.random

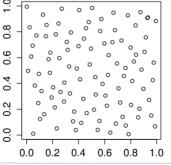
- "near-random" Zufallswerte
  - Latin Hypercube sampling
  - Orthogonal sampling
  - Sobol Sequenzen



#### Random Uniform



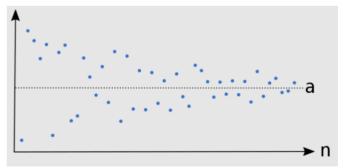
#### **LH Sampling**



### Wie groß muss n sein?



- ▶ Konvergenz gegen unbekanntes  $\Phi(z)$
- ▶ 1. Option: n richtig hoch ansetzen (z.B. 10<sup>7</sup>)
  - lange Rechenlaufzeiten!
- ▶ 2. Option: n schrittweise erhöhen und Ergebnisse beobachten



# **Übung 2.7: Monte-Carlo Methoden**



- Bestimmung der Unsicherheit von biologischen Abbauraten in einem kontaminierten Aguifer
  - Monte Carlo Simulation für das analytische Modell in Eq. (6):

$$\lambda = \frac{\Delta \delta^{13} C \cdot k_f \cdot i}{\varepsilon \cdot s \cdot n_e}$$

- Angaben zu Parametern in Tab. 1
- Brunnen G10m G30u
- Aufgaben in Jupyter Notebook: geodatenanalyse\_1-2-7



natural attenuation (MNA) at such field sites.

The contamination of the subsurface due to leaking point sources from industrial plants is a widespread issue and often requires extensive long term monitoring and remediation (Schwarzenbach et al., 2010). A common example for such incidences is the release of coal tar and creosote constituents into the subsurface. Most of the latter occur as dense on-aqueous phase liquids (DNAPL). Once they enter the subsurface, these liquids typically seep through unsaturated and saturated sones of the aquifer until reaching a natural barrier, such as impermeable or lowpermeable soils or geological layers, where they tend to accumulate and nigrate in groundwater flow direction (e.g. D'Affonseca et al., 2008a). When it comes to monitoring and remediation, biodegradation is often considered as an appropriate remediation strategy in the form of monitored natural attenuation (MNA) at such sites (e.g. Blum et al., 2007, 2011; Marcus and Schaal, 2010). The qualitative and quantitative proof of biodegradation is crucial for a successful implementation of

During the last decades stable compound-specific isotope analysis (CSIA) has been established as the major method for assessing the occurrence of biodegradation in contaminated aquifers (e.g. Sturchis (bio-)chemical reactions degrading organic contaminants are accompanied by isotope fractionation according to the kinetic isotope effect Blaner, 2010). A large number of studies exist showing the potential of CSIA. Thus, one can assess the fate of organic pollutants (Meckenstock et al., 2004; Braeckevelt et al., 2012), differentiate between multiple source sones (Hunkeler et al., 2004), or reveal transformation mechaniome and pathways via multi isotope analysis (Elener et al., 2005). However, the concept of CSIA also have some challenges and limitations: It struggles when concentrations of organic contaminants are low and therefore only tap the full potential at highly polluted field sites (Schmidt et al., 2004). Furthermore, field applicability suffers from factors that potentially influence observable isotope shifts, namely imited bioavailability (Branchevelt et al., 2012), and physical processes

Median biodegradation rate constants for o-xylene ranging between 0.08 and 0.22 a<sup>-1</sup> were estimated. By using tracer-based groundwater dating in these two wells, hydraulic conductivities could be also estimated, which are in a similar range as k-values derived from sieve analysis, a pumping test and a calibrated groundwater flow model. These results clearly demonstrate the applicability of tracer-based groundwater dating for the determination of in situ hydraulic conductivities in aquifers without numning contaminated groundwater. Finally, a sensitivity analysis is performed using a Monte Carlo simulation. These results indicate high sensi assumed effective porosity for the estimation of the hydraulic conductivity and the selected isotone enrichment

the main limitations of the novel combined isotone approach for a successful implementation of monitore

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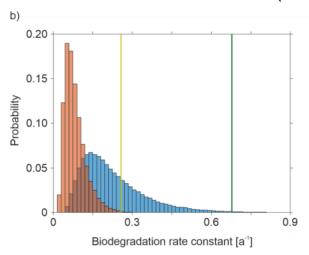
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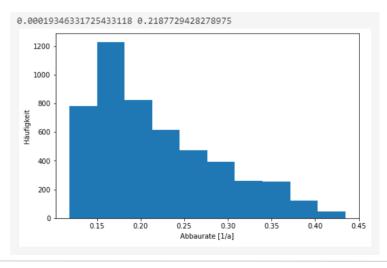
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# Aufgabenbesprechung

► Monte Carlo Simulation (Würth et al. 2021, Abb. 3)





#### Literatur



- Bättig (2017): Angewandte Datenanalyse, 2. Aufl., Springer Spektrum
- Gelman et al. (2014): Bayesian Data Analysis, 2nd Ed., CRC **Press**
- Würth et al. (2021): Quantifying biodegradation rate constants of o-xylene by combining compound-specific isotope analysis and groundwater dating. Journal of Contaminant Hydrology, 238, 103757



