

Norges miljø- og biovitenskapelige universitet Digitalisering på Ås

Institutt for datavitenskap

DAT121 Introduction to data science

- 3 Regression basics
- 3.4 Influence diagrams
- 3.5 Residual quantities
- 3.6 Time series

DAT121

23. august 2023

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4 9 2 0

2. root mean

What is our uncertainty in regression?

Fit a):

		OLS Re	egression Re	esults		
Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:		(Least Squar on, 06 Dec 20 10:55 nonrobu	res F-stat 021 Prob (:39 Log-Li 11 AIC: 7 BIC: 3	ared: R-squared: istic: F-statist: kelihood:	ic):	0.799 0.713 9.265 0.00781 -95.687 199.4 201.0
	coef	std err	t	P> t	[0.025	0.975]
const x1 x2 x3	-2.342e+05 7.821e+04 -8367.3711 297.8664	1.79e+05 5.49e+04 5558.872 185.111	-1.311 1.424 -1.505 1.609	0.231 0.198 0.176 0.152	-6.56e+05 -5.17e+04 -2.15e+04 -139.851	2.08e+05
Omnibus: Prob(Omni Skew: Kurtosis:		0.2):	2.877 1.069 0.586 4.04e+05

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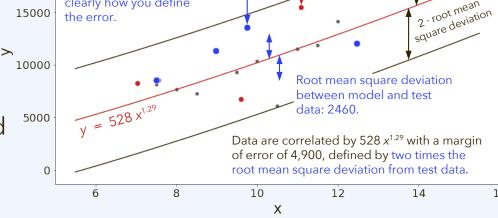
Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly [2] The condition number is large, 4.04e+05. This might indicate that there are strong multicollinearity or other numerical problems.

> There was the deviation that new single data points would be expected to have from the regression.

There was the uncertainty with which we can give the coefficients of the regression.

training dataset A data validation Good practice: Always 20000 data test make a statement about data the error. Always state clearly how you define 15000 the error.



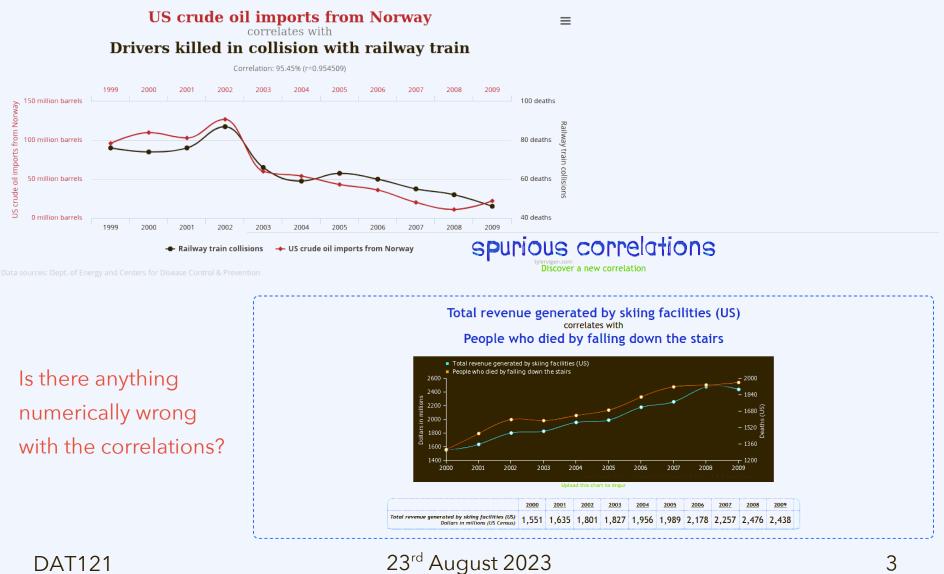
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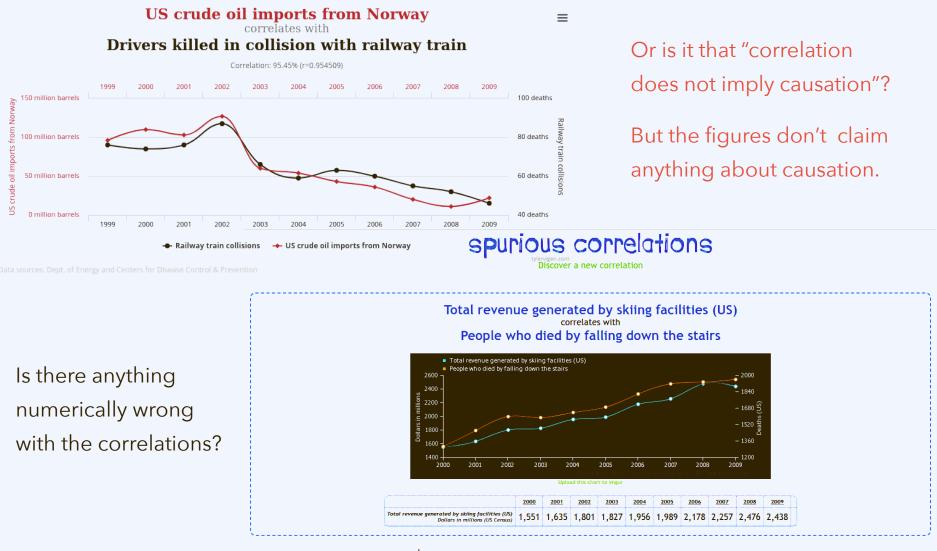


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Why does this feel wrong to us?



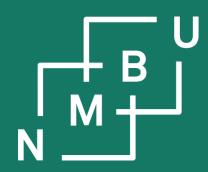
Why does this feel wrong to us?



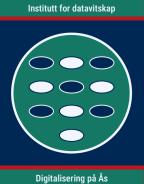
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3 Python basics

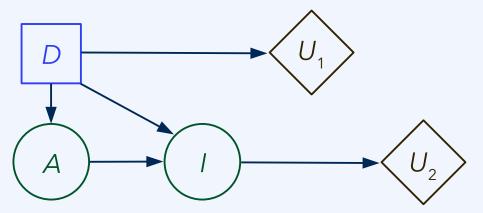
3.4 Influence diagrams



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Influence diagrams

Influence diagrams (also: decision networks) visualize how different quantities are connected to each other in a decision-making process.



(Example based on Barber,¹ Fig. 7.6)

D: Should I work on a doctorate?

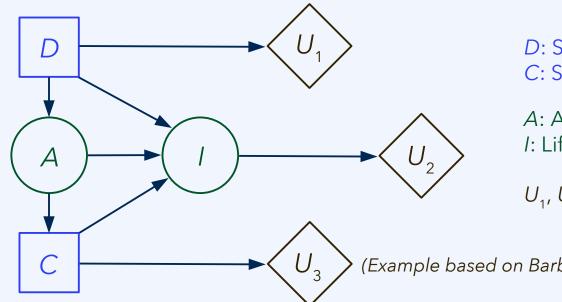
A: Academic recognition measure I: Life income

 U_1 , U_2 : Contributions to utility.

Influence diagrams



Influence diagrams (also: decision networks) visualize how different quantities are connected to each other in a decision-making process.



D: Should I work on a doctorate? C: Should I found a consultancy?

A: Academic recognition measure *I*: Life income

 U_1, U_2, U_3 : Contributions to utility.

(Example based on Barber,¹ Fig. 7.6)

Observation: An **influence diagram visualizes a process** by which quantities are evaluated. For it to represent a valid process, it **must not contain cycles**.

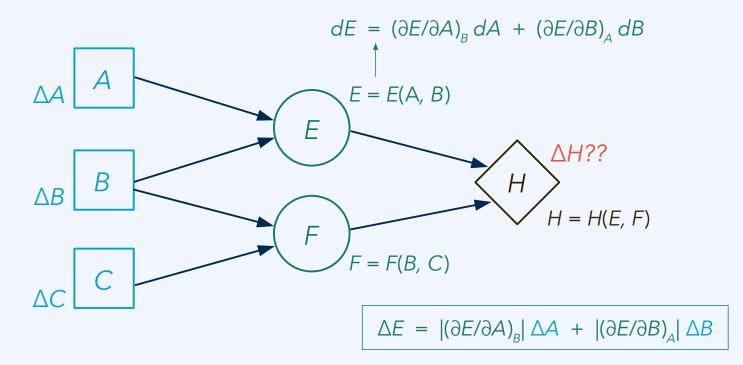
¹D. Barber, *Bayesian Reasoning and Machine Learning*, Cambridge Univ. Press, **2012**.



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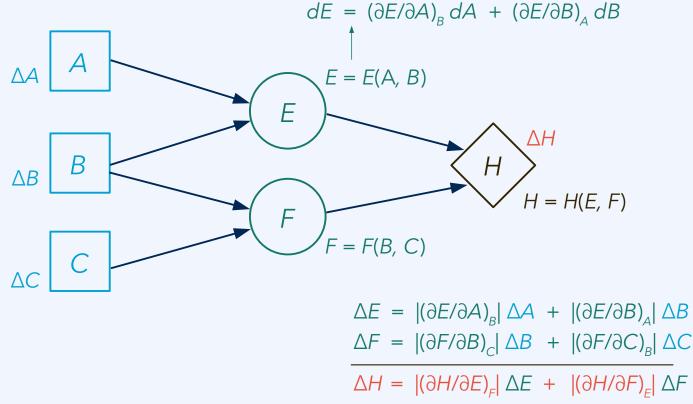
Linear uncertainty propagation

Idea: Treat the propagated uncertainty as analogous to a total differential.



Linear uncertainty propagation

Idea: Treat the propagated uncertainty as analogous to a total differential.



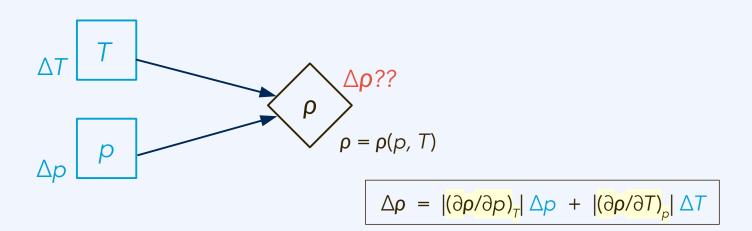
Advantages:

- Simple calculus that can be applied to complicated influence diagrams.
- No need to resolve backward, e.g., we don't need to find H(A, B, C).

Linear uncertainty propagation: "Nice" example

We are given information on the thermodynamic state of pure liquid water:

- Temperature given as $T = 280 \text{ K} \pm 3 \text{ K}$
- Pressure given as p = 1 MPa ± 0.1 MPa



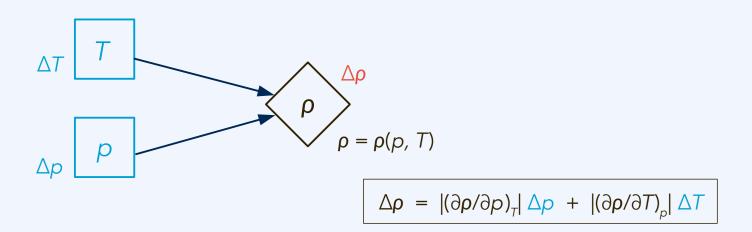
What is the uncertainty in the density of the water?

 $\rho = \rho(\rho, T) \pm \Delta \rho(\rho, \Delta \rho, T, \Delta T)$

Linear uncertainty propagation: "Nice" example

We are given information on the thermodynamic state of pure liquid water:

- Temperature given as $T = 280 \text{ K} \pm 3 \text{ K}$
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What is the uncertainty in the density of the water?

 $\rho = 55.521 \text{ mol } I^{-1} \pm \Delta \rho$ $(\partial \rho / \partial p)_{\tau} = 0.0275 \text{ mol } I^{-1} \text{ MPa}^{-1}$ $(\partial \rho / \partial T)_{\rho} = -0.0025 \text{ mol } I^{-1} \text{ K}^{-1}$

Limitations of the method

Influence diagrams supply the inductive reasoning with **helpful domain knowledge**. But they are limited to saying what quantities depend on what other quantities – they do not directly describe *how*, even if we know it.

There are also **limitations** to the method of **linear uncertainty propagation**. In practice these can cause a major risk of making potentially serious mistakes:

- The approximation as *linear* may not be warranted, which can make the *uncertainty appear smaller* than it actually is.
 Characteristic example: Potential energy of a harmonic oscillator.
- When there are diamonds in the diagram, relying on intermediate variables can make the uncertainty appear greater than it actually is.
 Typical example: Subtraction of a large number from a similar one.
- Non-trivial interaction between variables. (Not rare in decision making.)

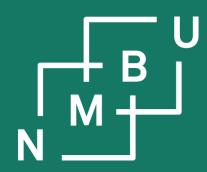
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Limitations of the method

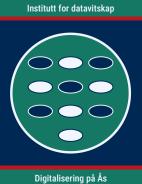
Influence diagrams supply the inductive reasoning with helpful domain knowledge. But they are limited to saying what quantities depend on what other quantities – they do not directly describe *how*, even if we know it.

There are also limitations to the method of linear uncertainty propagation. In practice these can cause a major risk of making potentially serious mistakes:

- The approximation as *linear* may not be warranted, which can make the *uncertainty appear smaller* than it actually is.
 Characteristic example: Potential energy of a harmonic oscillator.
 Remedy: Keep higher-order terms; only neglect them if you know it is OK!
- When there are diamonds in the diagram, relying on intermediate variables can make the uncertainty appear greater than it actually is.
 Typical example: Subtraction of a large number from a similar one.
 Remedies: a) Accept; b) avoid diamonds; c) expand in original variables.
- Non-trivial interaction between variables. (Not rare in decision making.)
 Remedies: Multicriteria and sampling methods (e.g., Monte Carlo).



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3 Python basics

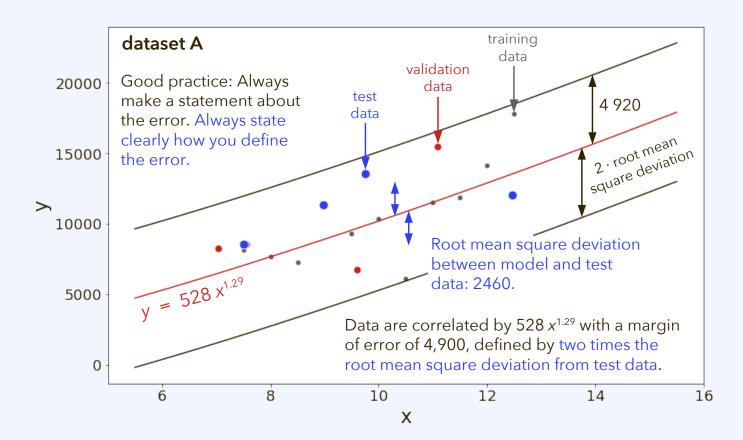
3.4 Influence diagrams3.5 <u>Residual quantities</u>

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Residual with respect to a model

Other ways of using a residual w.r.t. to a model, e.g., a model from regression:

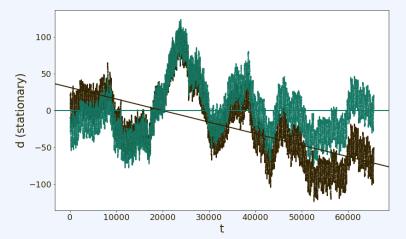
• We can express the **level of confidence or uncertainty** for a **model** from the **magnitude of the residual**, as we implicitly did in the last lecture:



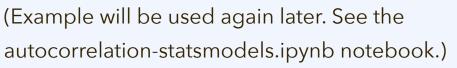
Residual with respect to a model

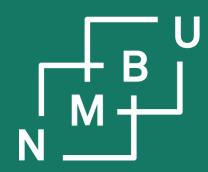
Other ways of using a residual w.r.t. to a model, e.g., a model from regression:

- We can express the **level of confidence or uncertainty** for a **model** from the **magnitude of the residual**, as we implicitly did in the last lecture.
- We can establish a **hierarchy of models**, with each new model approximating that what remains as a residual after the previous ones.
- Remove some undesired behaviour or bias before further analysing data.
 - Always document such steps very clearly, or you are engaging in fraud!

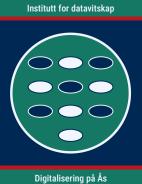


Black: Data with a tendency downward. Green: Residual w.r.t. the linear regression.





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3 Python basics

- 3.4 Influence diagrams
- 3.5 Residual quantities
- <u>3.6</u> <u>Time series</u>

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Time series in Python

Methods for time series from pandas are summarized in the Python for Data Analysis book, Chapter 11 (https://wesmckinney.com/book/time-series):



In [254]: close_px["AAPL"].rolling(250).mean().plot()

Figure 11.4: Apple price with 250-day moving average

Time series in Python

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https://www.statsmodels.org/stable/tsa.html

https://www.statsmodels.org/stable/examples/index.html#time-series-analysis

;; ;	statsmodels 0.14.0	Stable -	Q Search

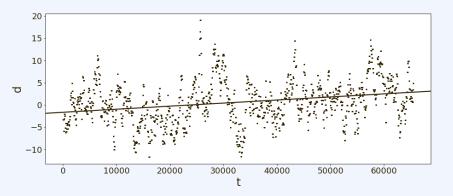
statsmodels 0.14.0						
Installing statsmodels						
Getting started						
User Guide	`					
Background						
Regression and Linear Models						
Time Series Analysis	`					
Time Series analysis tsa						
Descriptive Statistics and Tests	3					
Estimation	;					

Time Series analysis tsa

statsmodels.tsa contains model classes and functions that are useful for time series analysis.
Basic models include univariate autoregressive models (AR), vector autoregressive models (VAR) and univariate autoregressive moving average models (ARMA). Non-linear models include
Markov switching dynamic regression and autoregression. It also includes descriptive statistics for time series, for example autocorrelation, partial autocorrelation function and periodogram, as well as the corresponding theoretical properties of ARMA or related processes. It also includes methods to work with autoregressive and moving average lag-polynomials. Additionally, related statistical tests and some useful helper functions are available.

Autocorrelation of time series data

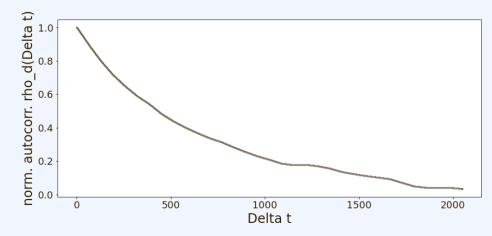
Time series data are **autocorrelated**. This means that *data points taken at times close to each other cannot be regarded as independent* items of information.



Assume we are given time series data d(t):

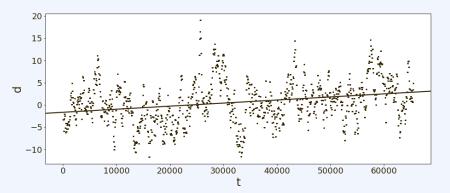
autocorrelation $R(\Delta t) = \langle d(t) d(t + \Delta t) \rangle$ autocovariance $\langle [d(t) - \langle d \rangle] [d(t + \Delta t) - \langle d \rangle] \rangle$

Often **normalized** by Var(d) to yield $\rho(\Delta t)$.



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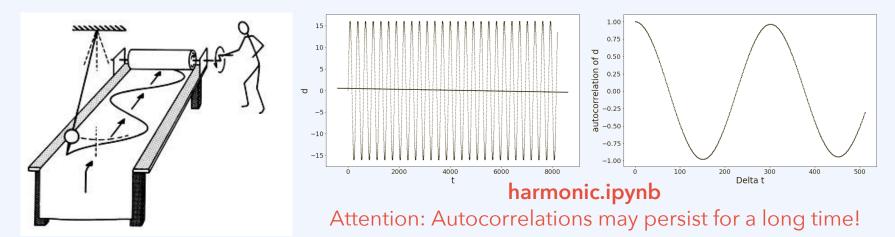
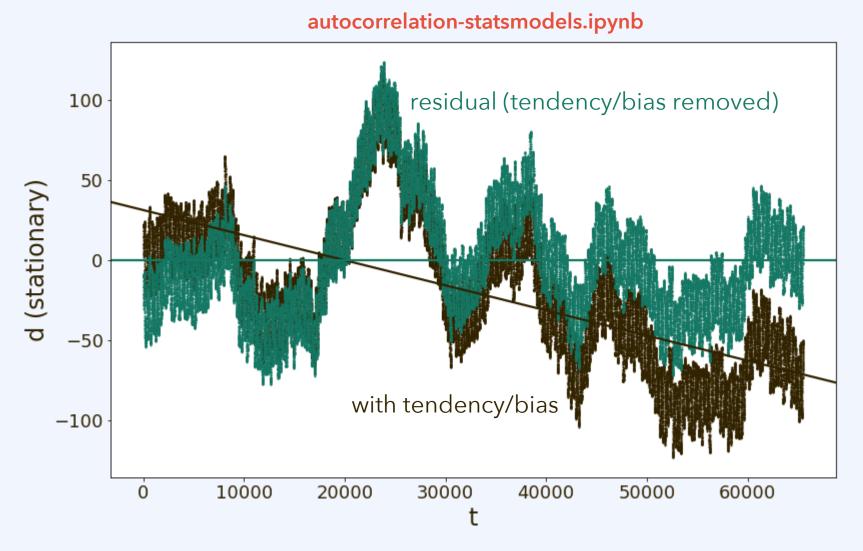
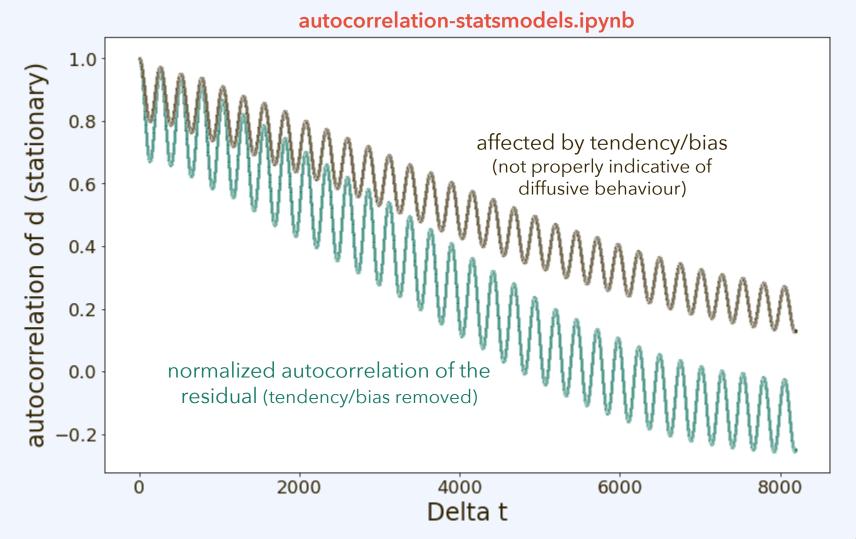


Figure: IOP, https://spark.iop.org/broomstick-pendulum-sinusoidal-motion. 21

Autocorrelation function (normalized autocovariance)



Autocorrelation function (normalized autocovariance)

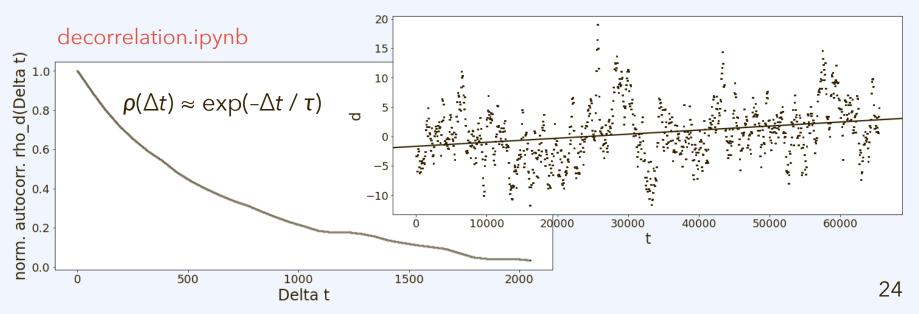


Decorrelation time

Our previously introduced approach to uncertainty estimation was based on:

- Some set of data that are representative of the phenomenon;
- Separation of data points into training, validation, and test data.
 - What would happen if we split the points into these three at random?

Different data points on a time series are not independent tests, they are correlated - this is exactly what is expressed by the autocorrelation function.

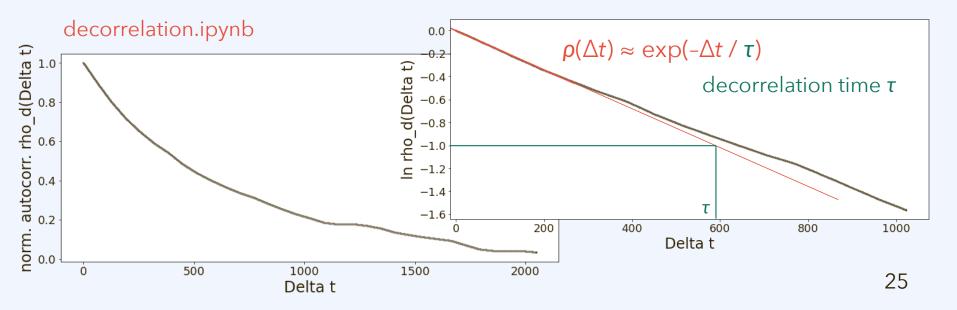


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Uncertainty in time series

Our previously introduced approach to uncertainty estimation was based on:

- Some set of data that are representative of the phenomenon;
- Separation of data points such that they are *decorrelated*.

Once Δt exceeds 3τ , the normalized autocorrelation is small, $\rho(\Delta t) < 0.05$. We can *average over blocks* with size 3τ (or more) and then treat each of these **block averages** as independent data points.

Warning: This only works if the autocorrelation *actually is* decaying.

It will lead to mistakes where there is a strong correlation over long timespans, such as when analysing a periodic signal. If your data points are not really decorrelated, you can never treat them as independent items of information.

Uncertainty in time series

Our previously introduced approach to uncertainty estimation was based on:

- Some set of data that are representative of the phenomenon;
- Separation of data points such that they are *decorrelated*.

Once Δt exceeds 3τ , the normalized autocorrelation is small, $\rho(\Delta t) < 0.05$. We can *average over blocks* with size 3τ (or more) and then treat each of these **block averages** as independent data points. This is called **block averaging**.

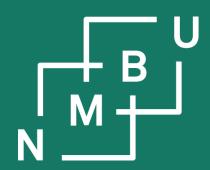
 $N_{\rm b}$ such blocks correspond to $N_{\rm b}$ -1 independent deviations from the mean.

Variance of the block averages: $\sigma_{b}^{2} = (N_{b} - 1)^{-1} \Sigma (B_{i} - \langle B \rangle)^{2}$

Uncertainty based on σ , where $\sigma = N_{\rm b}^{-1/2} \sigma_{\rm b}$ from central limit theorem

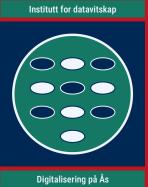
A rigorous theory of block averaging was developed by Flyvbjerg and Petersen¹ (which is therefore also called *Flyvbjerg-Petersen block averaging*).

¹H. Flyvbjerg, H. G. Petersen, J. Chem. Phys. **91**: 461-466, doi:10.1063/1.457480, **1989**.



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Conclusion





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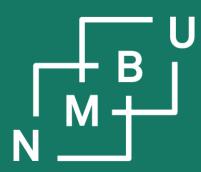
Glossary terms

Proposed glossary¹ terms:

- How do we best define them? Is the definition controversial?
- What is the best translation into Norwegian bokmål/nynorsk?
- Are there more key concepts that would require an agreed definition?



¹https://home.bawue.de/~horsch/teaching/dat121/glossary-en.html



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DAT121

24. august 2023

Schedule for DAT121 part 3

Monday, 21st August 2023

9.15 - 10.00 Q&A session

10.15 - 11.00 first lecture on regression

11.15 - 12.00 discussion and problem solving

Tuesday, 22nd August 2023

10.15 - 12.00 scheduling of group sessions and of the final presentations

Wednesday, 23rd August 2023

10.15 - 11.00 second lecture on regression

11.15 - 12.00 interest group sessions

Thursday, 24th August 2023

10.15 - 11.00 third lecture on regression11.15 - 12.00 discussion and problem solving

13.15 - 15.00 project work and tutorial

13.15 - 15.00 project work and tutorial

13.15 - 15.00 project work and tutorial

Schedule for DAT121 parts 4 and 5

Friday, 25th August 2023

10.15 – 11.00 lecture on good practice 11.15 – 12.00 **interest group sessions**

Monday, 28th August 2023

9.15 - 10.00 first multidimensionality lecture 13.15 - 15.00 project work and tutorial
10.15 - 10.?? Pangasia presentation in TF1-115
11.15 - 12.00 discussion and problem solving

Tuesday, 29th August 2023

9.15 – 10.00 Q&A session and discussion 13.15 – 15.00 project work and tutorial

10.15 - 11.00 second multidimensionality lecture

11.15 - 12.00 interest group sessions

13.15 - 15.00 project work and tutorial