



ITMO UNIVERSITY

Saint Petersburg, Russia

Methods and models for multivariate data analysis

Lecture 1. A bit about time (theory).

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SPb
29.11.2022

Agenda

- What exactly stationarity is?
- Why is non-stationary processes are differ?
- Markov processes
- Impulse processes



Life without non-stationarity

✓ Reminder: two stationarity definitions

- “Strong” – no time at all – stationary as a bus station

If $X_t = (x_1, \dots, x_n, t)$ – random process, F_X – distribution function, then

$$\forall \tau \in \mathbb{R} \quad F_X(x_1, \dots, x_n, t) = F_X(x_1, \dots, x_n, t + \tau) = F_X(x_1, \dots, x_n)$$

- “Weak” – only with several parameters

$$m_X(t) = m_X(t + \tau) = \text{const} \text{ – nonstationarity in ML}$$

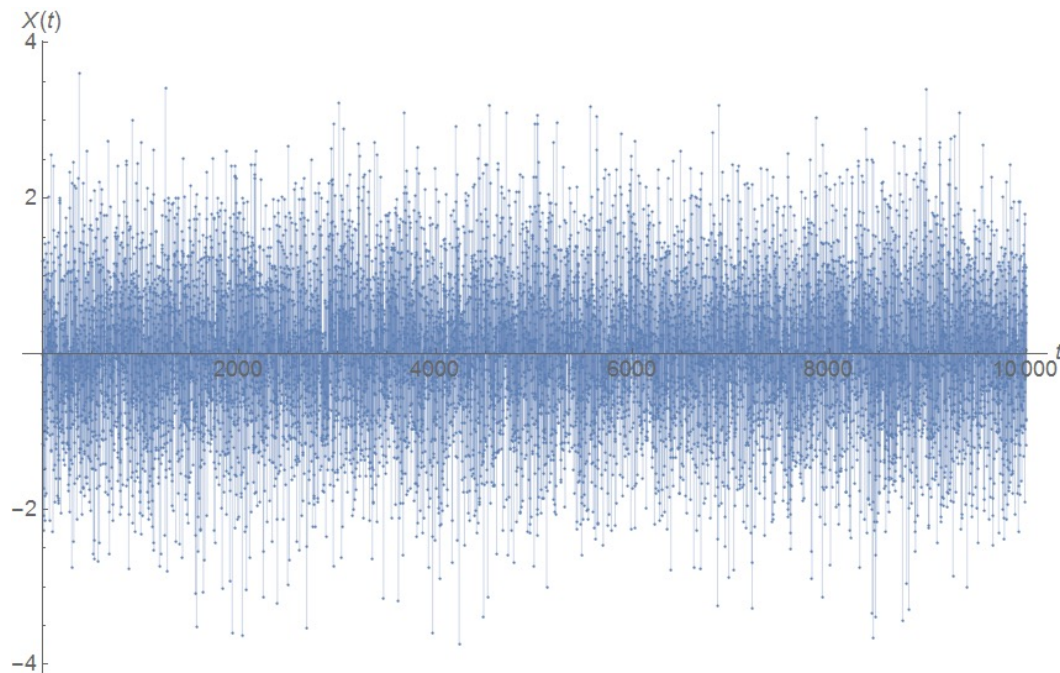
$$C_X(t_1, t_2) = C_X(\tau)$$

Weak > Strong (there are more weak stationary processes than strong ones)

Reminder: stationary RP example

✓ White noise –

Can one say, that stationarity roughly is the oscillation near zero (some constant)?



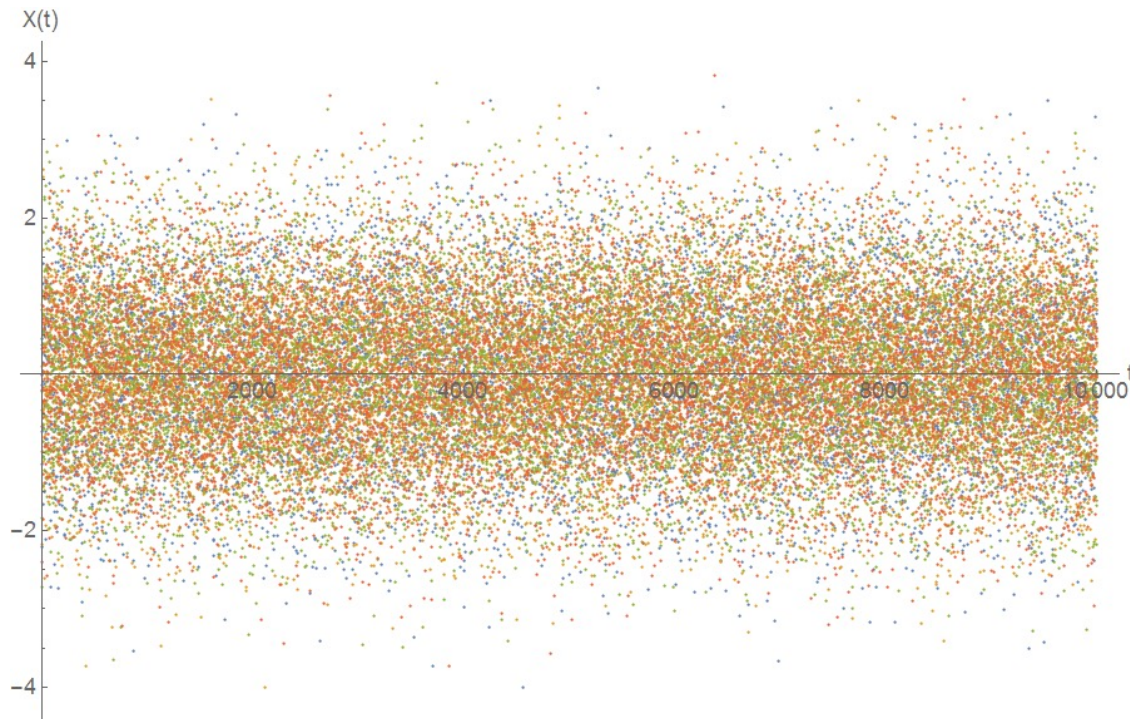
Reminder: What exactly stationarity is?

✓ White noises –

(four realizations)

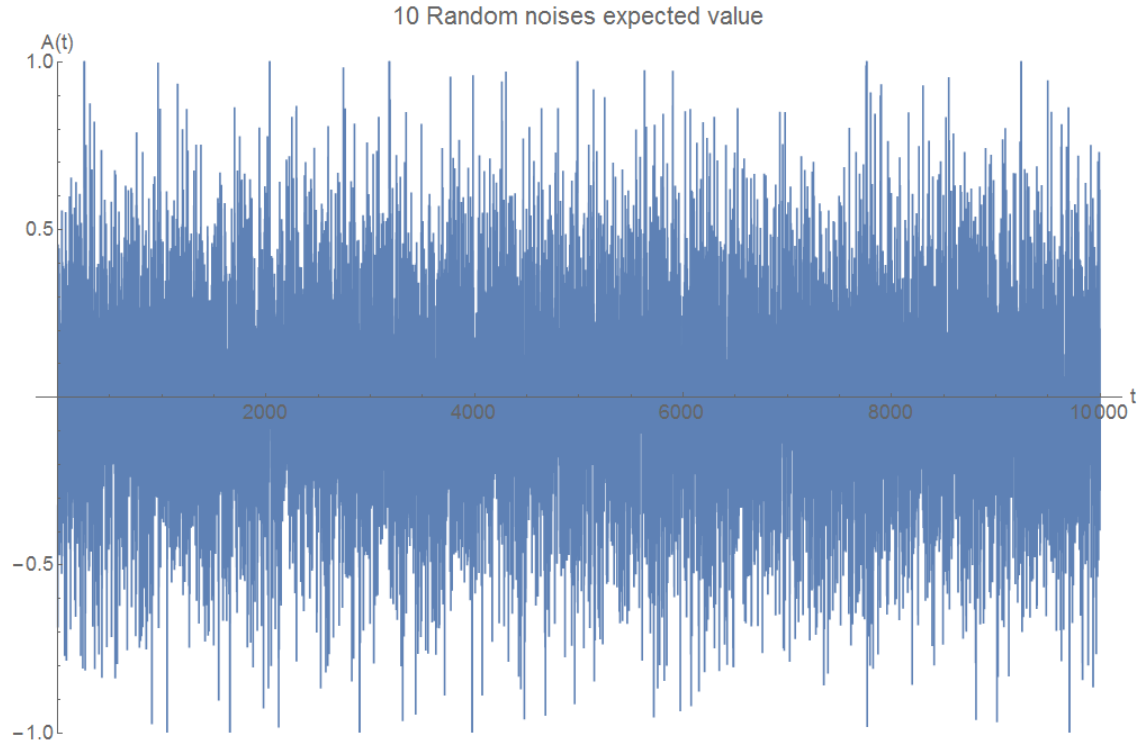
Let's pretend that we measure something four times in a row and at every time point we get four measures.

Is it still oscillating near zero?
Can you say what 'near zero' exactly is?

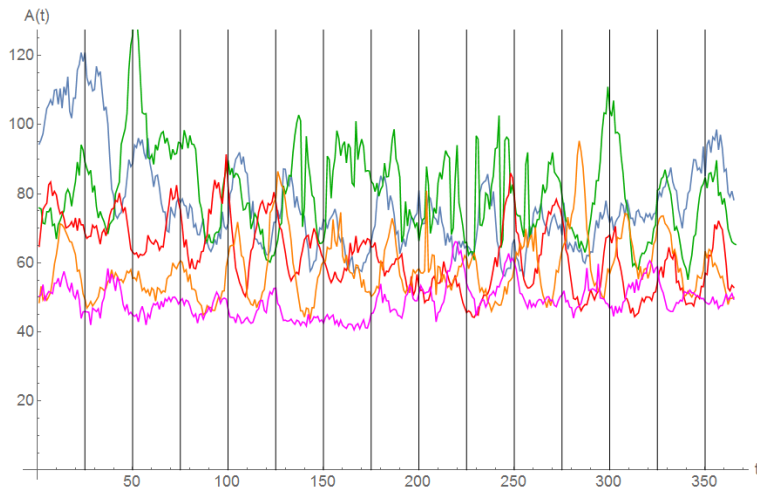


Reminder: stationary RP example

- Usually we use ‘weak’ non-stationarity and want to prove roughly $m_x(t) = \text{const}$
- What if we try to do that directly and make 10,20,...,3000 white noise experiments?
- Where is my $m_x(t) = 0$?
- (Can you measure air temperature for 3000 years?)

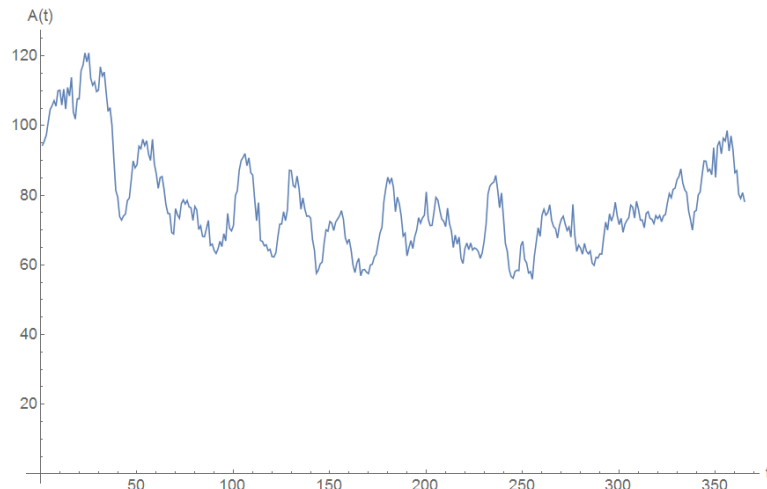


Two time series approaches



"Stochastic" - to study the distribution of different realizations at the same point in time (suitable if you have a lot of time and diligence)

vs



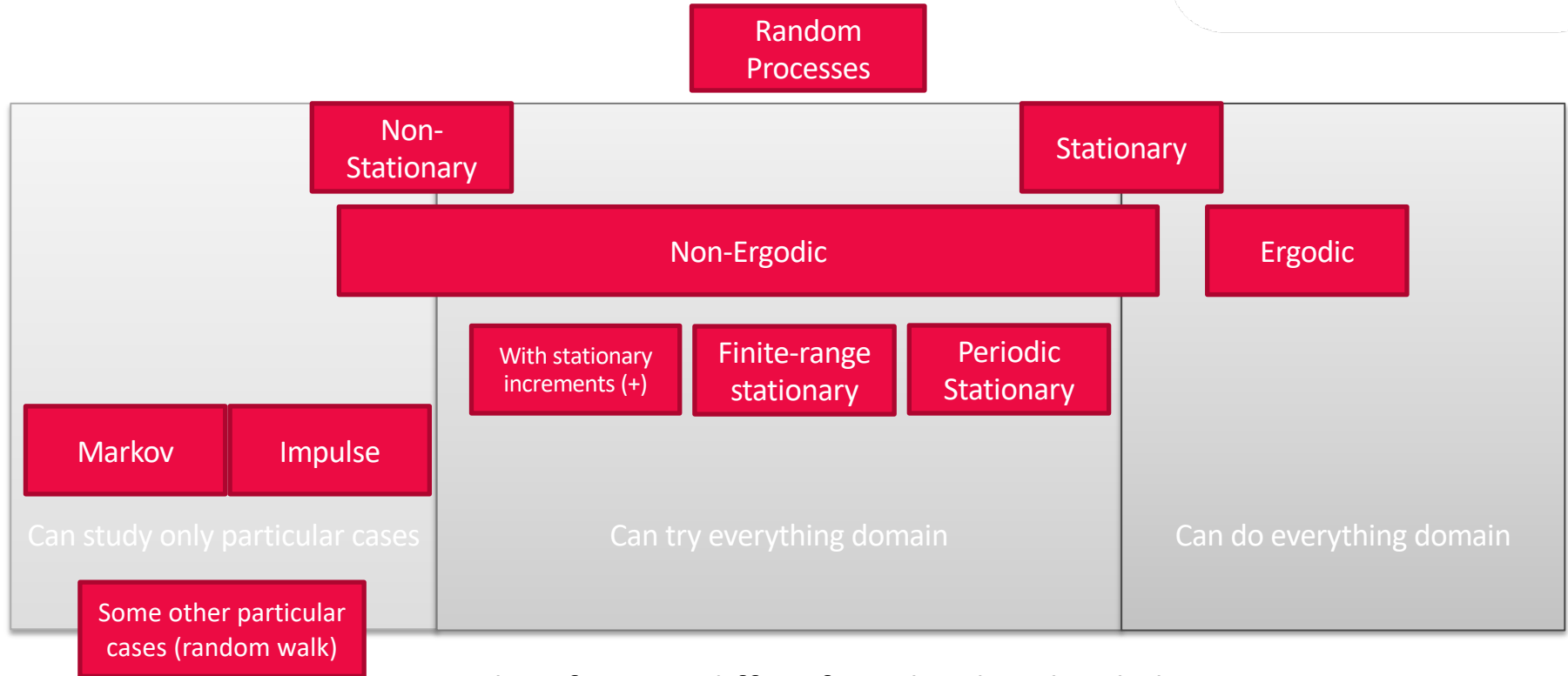
"Functional"- to study each implementation separately (we often have no other choice)



Life without time dependency

Divide et empera – divide and rule

(Time series classification)



- Classification differs from book to book, better not to even try to classify random processes

Why we don't like time-dependence?

- ✓ Every process can be written as $y_t = T(t) + S(t) + \varepsilon_t$
 - $T(t)$ is for trend
 - $S(t)$ is for seasonal component (low-frequency component)
 - ε_t is for random (stationary) noise (high-frequency component)
- ✓ Main trouble is $T(t)$, there is no solid answer what $T(t)$ actually is
- ✓ If $T(t)$ is somehow estimated, then $S(t)$ is “smoothed” $S(t) + \varepsilon_t$
- ✓ ε_t seems to be the white noise, there is no more troubles (?)

Stationarity check – I

(Know thy enemy - 101)

- Unit root test
 - Build autoregression model $y_t = a_1 y_{t-1} + a_2 y_{t-2} + \dots + a_p y_{t-p} + \varepsilon_p$
 - Build characteristic polynomial $m^p + a_1 m^{p-1} + \dots + a_{p-1} m + a_p$
 - If roots have property $\forall i \text{ } abs(m_i) < 1$, then process is stationary
 - Otherwise in most cases $\exists i \text{ } abs(m_i) = 1$ (there could be more than one such i)

In the second case, the process is nonstationary (generally speaking, weakly stationary). Moreover, the number of such roots $\#i$ is very important for further analysis.

If $\#i = 1$ then $\Delta y_t = y_{t+1} - y_t$ is stationary, and so on, if $\#i = 2$ then $\Delta \Delta y_t = \Delta^2 y_t = \Delta y_{t+1} - \Delta y_t$ is stationary.

Processes with this property are called integral with order of n where $n = \#i$

Stationarity check – II

(Advanced know thy enemy)

- $\#i$ helps one to determine $T(t)$
 - If $\#i = 1$ then trend could be chosen as linear
 - If $\#i > 1$ then linear trend is not fully descriptive, one should use polynomial of order at least of $\#i$
- There is no problem to use higher order polynomials
- So, trend $T(t)$ is often considered as a polynomial (linear) part
- What if $abs(m) > 1$?
 - Explosive process
 - In most cases we say, that choice of experiment setup/model is inappropriate

Si fecisti, nega – commit crime and deny it

(Why you should remove trend beforehand)



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- ✓ Non-constant trend is shifting the expected value
 - It has an effect on correlation function analysis
- ✓ Trend $T(t)$ and Seasonal component $S(t)$ have effect on spectrum (it follows from Wiener-Khinchin theorem)
 - It has effect on a spectral analysis (shifting)
 - We have to filter spectrum – we lose information

Life without Markov processes

- ✓ Simplest definition of Markov property can be defined in case of discrete state space $S = \{s_1, \dots, s_n\}$ and discrete time $T=N$
 - $P(X_n = x_n | X_{n-1} = x_{n-1}, \dots, X_0 = x_0) = P(X_n = x_n | X_{n-1} = x_{n-1})$
 - Future depends only on a current moment, not on a past moments
 - No matter how agent has reached current state, probability of next state depends only on a current state
- ✓ There is also common definition for a continuous state space and time, but the main idea is the same as above

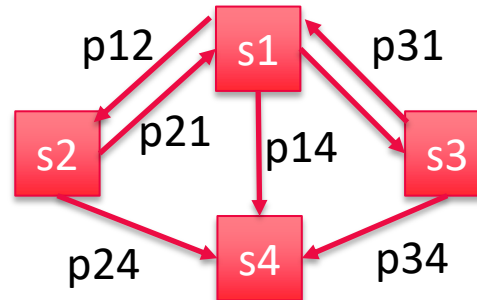
Markov chain - I

- ✓ System with discrete state space and discrete time with Markov property is called Markov's chain

- ✓ Markov's chain is fully defined by transition matrix $P = \begin{pmatrix} p_{11} & \dots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \dots & p_{nn} \end{pmatrix}$
and initial state distribution $p(0) = (p_1(0), \dots, p_n(0))$

- ✓ We can also draw a scheme

$$\sum_{i=1}^n p_{ji} = 1$$



Markov chain - II

- ✓ Let's introduce some numbers

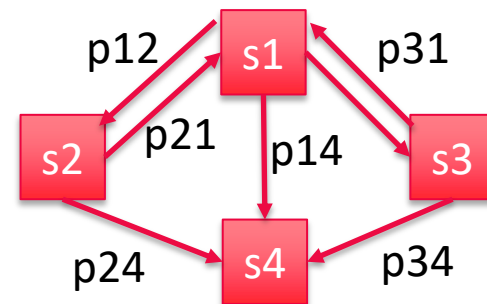
$$P = \begin{pmatrix} 0.7 & 0.2 & 0.2 & 0 \\ 0.1 & 0.6 & 0 & 0 \\ 0.1 & 0 & 0.5 & 0 \\ 0.1 & 0.2 & 0.3 & 1 \end{pmatrix}$$

- ✓ $p(0) = (1, 0, 0, 0)$

$$p(1) = P(p(0))^T = (0.7, 0.1, 0.1, 0.1)$$

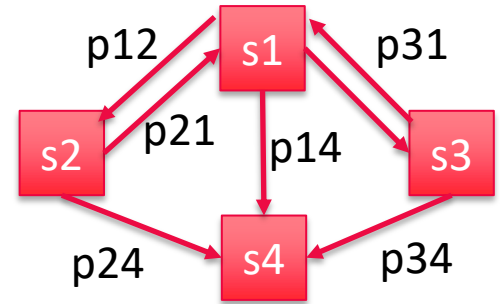
$$p(k) = P^k(p(0))^T$$

- ✓ From scheme is seen that $p(k) \rightarrow (0, 0, 0, 1)$ as $k \rightarrow \infty$
- ✓ Can we achieve it numerically?



✓ Can we achieve it numerically?

- $p_j(k) = \sum_{i=1}^n p_i(k-1)p_{ij}(k)$
- Stationary mode is not dependent on k
- $p_j = \sum_{i=1}^n p_i p_{ij}$, with property $\sum_{i=1}^n p_{ji} = 1$
- $p_j \sum_{i=1}^n p_{ji} = \sum_{i=1}^n p_i p_{ij}$
- $p_j p_{jj} + \sum_{i=1}^n p_{ji} p_j = p_j p_{jj} + \sum_{i=1}^n p_i p_{ij}, i \neq j$
- $\sum_{i=1}^n p_{ji} p_j = \sum_{i=1}^n p_i p_{ij}, i \neq j$ – if this equation has the solution, then stationary mode exists
- Actually, solution of equation above is not unique, one should add norm equation $\sum_{i=1}^n p_i = 1$



- ✓ Transition matrix is now function of time

$$P(t) = \begin{pmatrix} \lambda_{11}(t) & \dots & \lambda_{1n}(t) \\ \vdots & \ddots & \vdots \\ \lambda_{n1}(t) & \dots & \lambda_{nn}(t) \end{pmatrix}$$

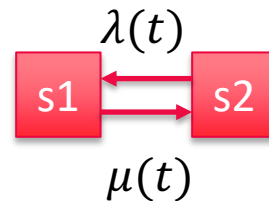
- ✓ Without proof, there are Kolmogoroff equations for stationary mode (now it is the system of ordinary differential equations, ODE)

$$\frac{dp_i(t)}{dt} = \sum_{j=1}^n p_j(t) \lambda_{ji}(t) - p_i(t) \sum_{j=1}^n \lambda_{ij}(t), i = 1, n$$

- ✓ Initial conditions have the form $p_i(0) = p_i, i = 1, n$
- ✓ In this case we need norm equation $\sum_{i=1}^n p_i(t) = 1, t \geq 0$

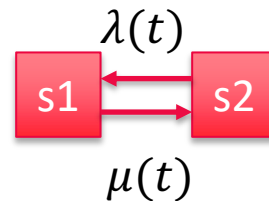
✓ Simple example

- $p_1'(t) = p_2(t)\mu(t) - p_1(t)\lambda(t)$
- $p_2'(t) = p_1(t)\lambda(t) - p_2(t)\mu(t)$
 $p_1(t) + p_2(t) = 1$
- With $p_2(t) = 1 - p_1(t)$ we obtain one differential equation
 $p_1'(t) + (\lambda(t) + \mu(t))p_1(t) = \mu(t)$
- Let simplify it a bit more $\lambda(t) = \lambda, \mu(t) = \mu$
- $p_1'(t) + (\lambda + \mu)p_1(t) = \mu$



Continuous time - III

- ✓ $p_1'(t) + (\lambda + \mu)p_1(t) = \mu$
- ✓ $p_1'(t) = \mu - (\lambda + \mu)p_1(t)$
- ✓ $\frac{1}{\lambda + \mu} \frac{d(\lambda + \mu)p_1(t) - \mu}{(\lambda + \mu)p_1(t) - \mu} = dt$
- ✓ $-\frac{1}{\lambda + \mu} \log(\mu - (\lambda + \mu)p_1(t)) = t$
- ✓ $p(t) = \frac{\mu}{\lambda + \mu} + \exp(-t(\lambda + \mu))C$
- ✓ Let $p(0) = 1$, then $p(t) = \frac{\mu}{\lambda + \mu} + \exp(-t(\lambda + \mu)) \frac{\lambda}{\lambda + \mu}$
- ✓ Equation has the stationary mode $p = \frac{\mu}{\lambda + \mu}, t \rightarrow \infty$



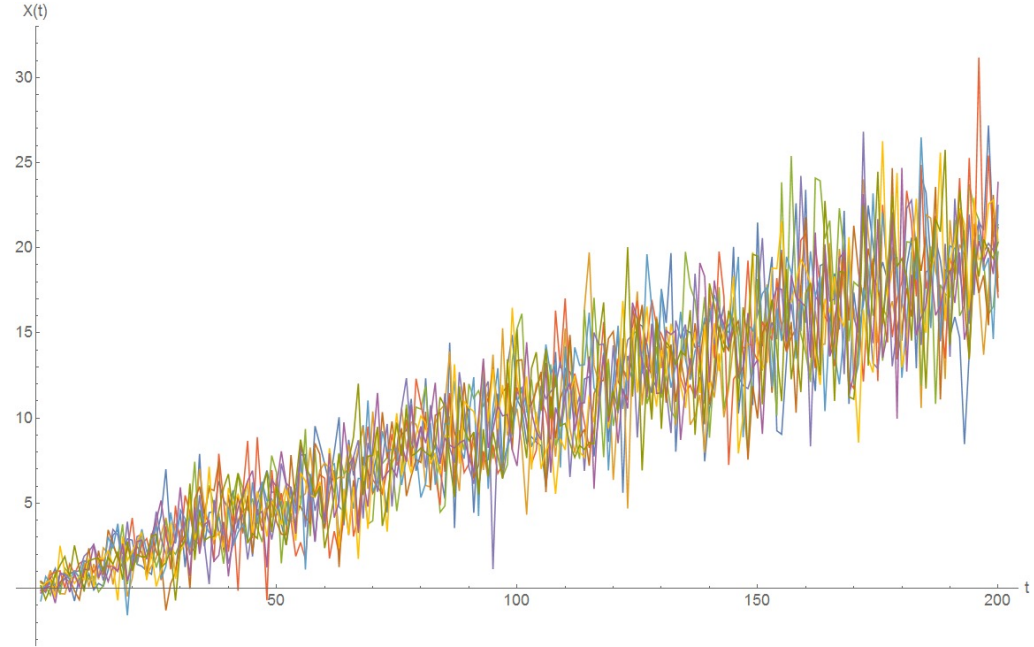
- ✓ General Markov process (with continuous time and state space) is defined by differential equation with stochastic right part $\xi(\mathbf{X}, t)$

$$\mathbf{X}'(t) = F(\mathbf{X}, t) + \xi(\mathbf{X}, t)$$

- ✓ In this case we have to integrate stochastic function $\xi(\mathbf{X}, t)$, which is of course not so easy process
- ✓ There are two definitions of stochastic integrals: Ito and Stratonovich integrals

General Markov process

- ✓ Main idea is to consider motion as $X(t) = x_0 + \mu t + \sigma\sqrt{t}\varepsilon$
- ✓ Then $dx \sim \mu dt + \sigma\varepsilon\sqrt{dt}$ - Wiener equation
- ✓ We are not able to integrate it directly

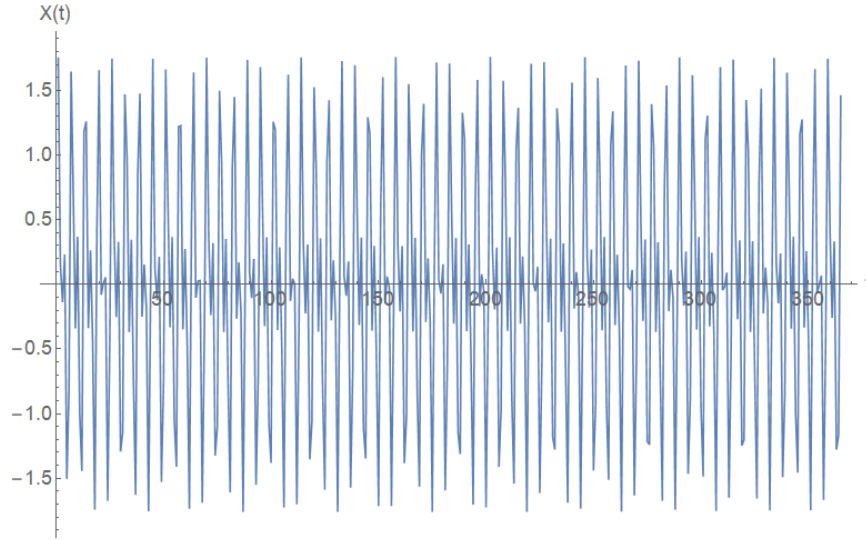


A lot of random walk

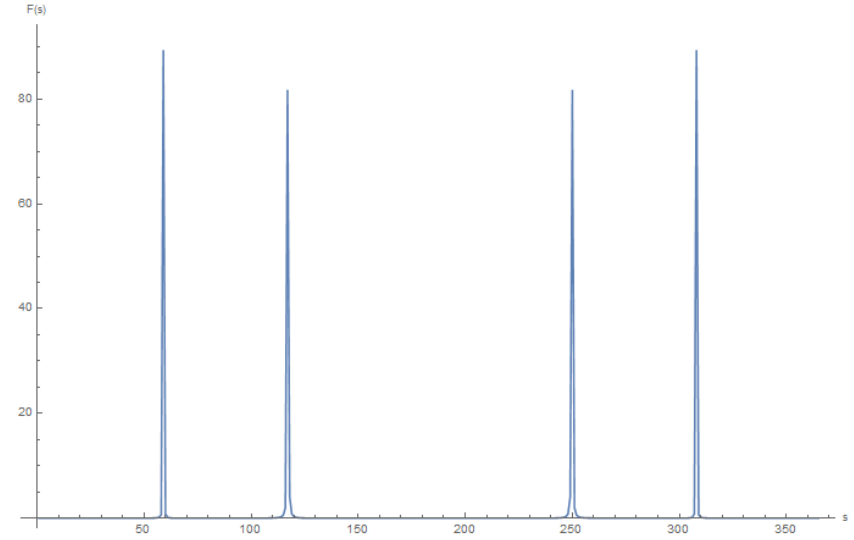


Life without wavelets

Impulse processes - I

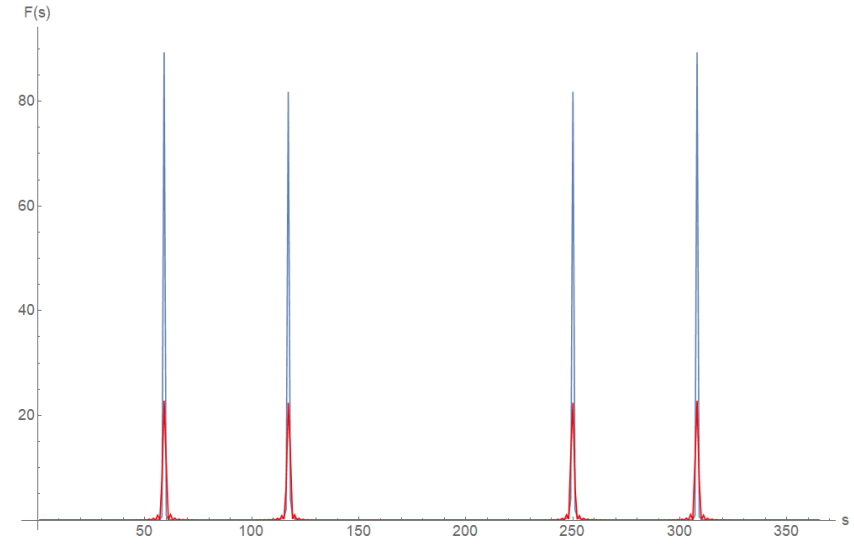
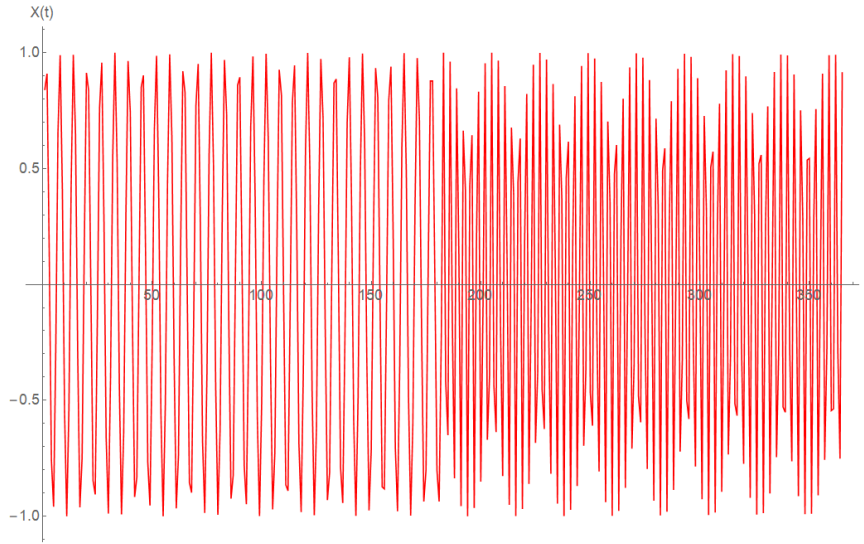


- Plot $\sin(t) + \sin(2t)$



- Fourier transform

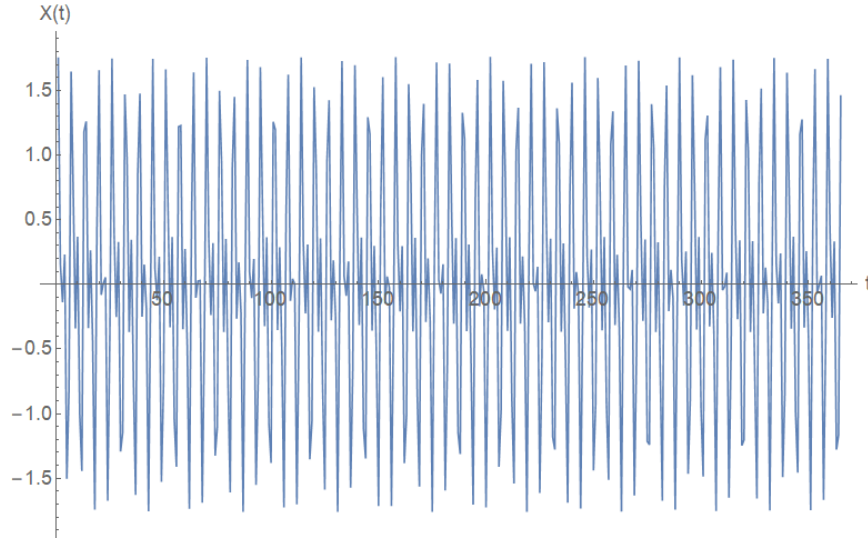
Impulse processes - II



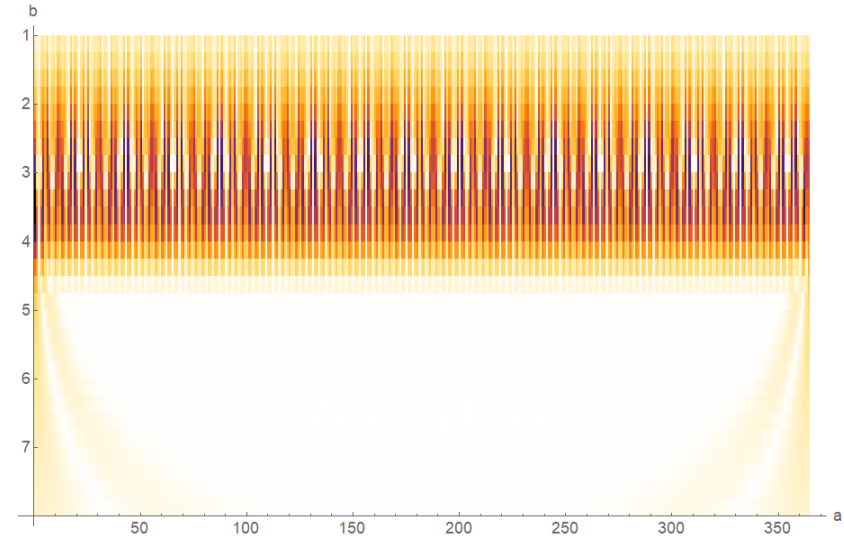
- Plot half $\sin(t)$, half $\sin(2t)$
- Fourier transform
- They are not so different in Fourier specter

- $W(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi^* \left(\frac{t-b}{a} \right) dt$ - wavelet transform
 a - scale parameter (frequency analogue)
 b - shift parameter
- $\psi(t)$ - wavelet
 $\int_{-\infty}^{\infty} \psi(t) dt = 0$ - main wavelet property
 $\int_{-\infty}^{\infty} \psi(t) t^m dt = 0$ - optional wavelet property
- Wavelet ignores linear (m degree polynomial, if optional property is fulfilled) trend
 - Still better to remove it

Scalogram-I

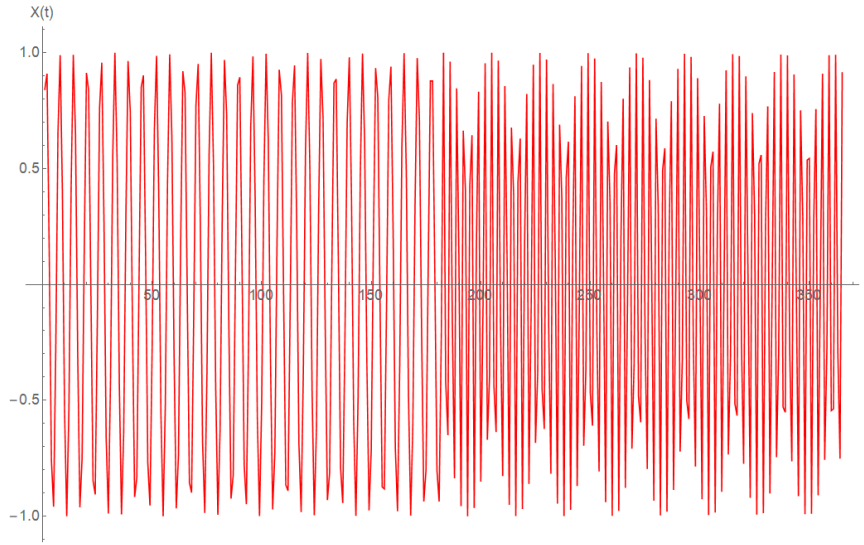


- Plot $\sin(t) + \sin(2t)$

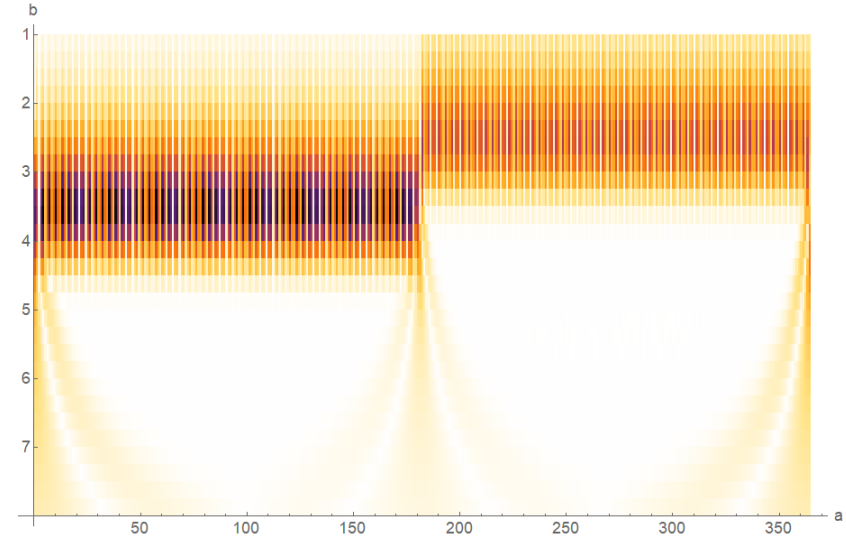


- Wavelet transform

Scalogram-II



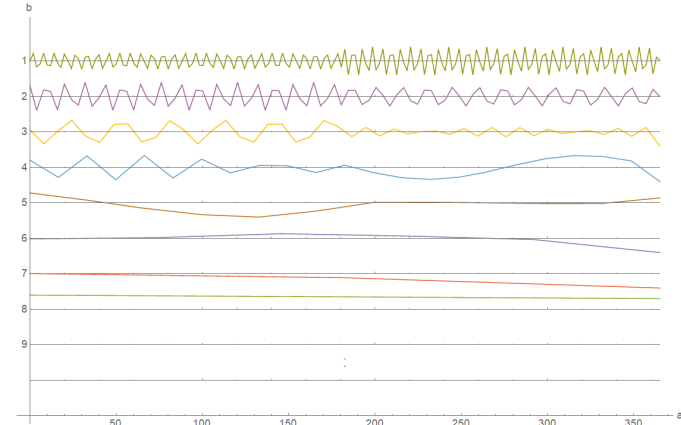
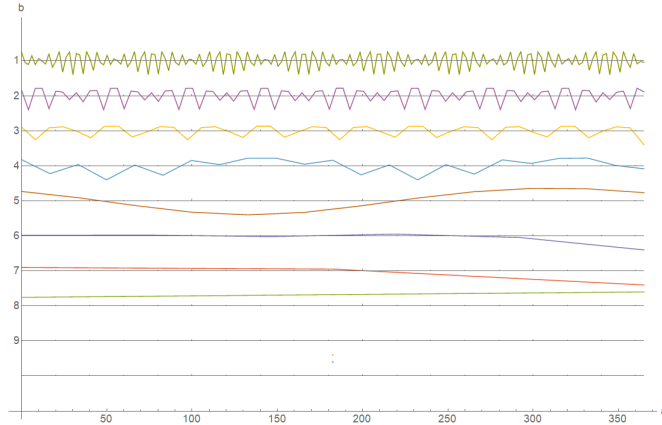
- Plot half $\sin(t)$, half $\sin(2t)$



- Wevalet transform
- They are different in wavelet specter

Wavelet transform

- Wavelet analysis is used in signal processing
- There are a lot of different wavelets with many applications
- Scalogram is difficult to interpret and is kind of art



- Discrete wavelet transform

Thanks for coming!

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