

# Advanced Time Series

## Lecture 1:

# Introduction to time series

Gleb Ivashkevich

# whoami

## Gleb Ivashkevich

doing deep learning - time series,  
satellite imagery

PhD in theoretical physics

6 years in academia doing  
numerical simulations

7 years in data science and  
machine learning





datarythmics **effimly**

data driven manufacturing efficiency

# Our TA



## Anatoly Bardukov

doing image similarity search in  
Yandex

applied math from HSE

back/front-end, data engineering





SpaceX Aims to Launch Satellite on Used Rocket Early Monday:  
[ca.news.yahoo.com](https://ca.news.yahoo.com)  
SpaceX Aims to Launch Satellite on Used ...  
Пожаловаться

X 37b ракета Фалькон  
Запуск ракеты Россия

Открыть 2048x1365

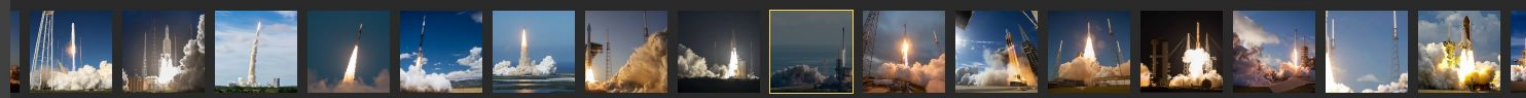
Похожие Отправить

Связанные картинки



Беспринципные – смотреть 1 серию! Неприличные истории о приличных людях в новой комедии. Только на КиноПоиск HD!

Перейти Яндекс.Директ



# What is ATS about?

Time series are **sequences**.

- all the sequential **deep learning** blocks can be applied (RNN, CNN, combinations, etc.)
- **various problems:** forecasting, classification, event prediction
- **mental image** of time series problems - how to select parameters, architectures, etc.

# What ATS is not about?

- AR, VAR, ARIMA, etc.
- specific domains
- econometrics
- financial time series

But we will **overview** the classical stuff. And will use it to build **intuition**.

# You should attend if...

**... most of the following is true:**

- you have some basic experience with classical time series approaches
- know how to read research papers
- have some understanding of deep learning in general and RNN and CNN in particular
- have no problems at all with Python stack (especially PyTorch)



# How do we check prerequisites

- **qualification** homework
- Pandas time series functionality + PyTorch
- **10 days to submit** (deadline is 24:00 Feb 3)
- at least **5 points out of 7**
- **individual** submissions

# Course logistics

**6 lectures, 3 hours each, Google classroom**

- slides + notebook(-s)
- 4 homeworks (in pairs)
- 2 paper reviews + 2 paper implementations
- manual grading
- Slack

# Course structure

## Intro + 4 topics:

- TS **forecasting**: RNNs<sup>(various)</sup>
- TS **classification**: CNN<sup>(various)</sup> and combined<sup>(RNN+CNN)</sup> models
- **TTE prediction**: DL models for predictive maintenance, survival analysis
- TS **representation learning**: VAMPnets, autoencoders<sup>(various)</sup>

# Course structure

Power consumption  
Weather  
Sales  
Traffic

## Forecasting

AR models  
RNNs  
Probabilistic forecasts

# ATS

Activity data (inertial sensors)  
Sound  
Medical signals

## Classification

Dilated/causal convolutions  
CNNs and hybrid models  
Attention mechanism  
Segmentation

Any highly structured TS

## Representation

VAMPnets  
AEs

Equipment data  
Earthquakes and other physical signals

## TTE prediction

Survival models  
interpretability

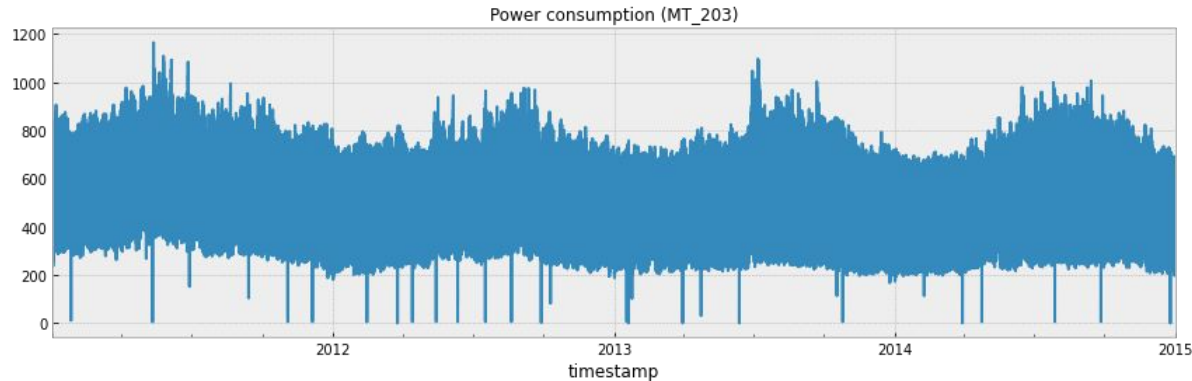
# Time series basics: time domain



# Power consumption

## Electricity load [dataset](#)

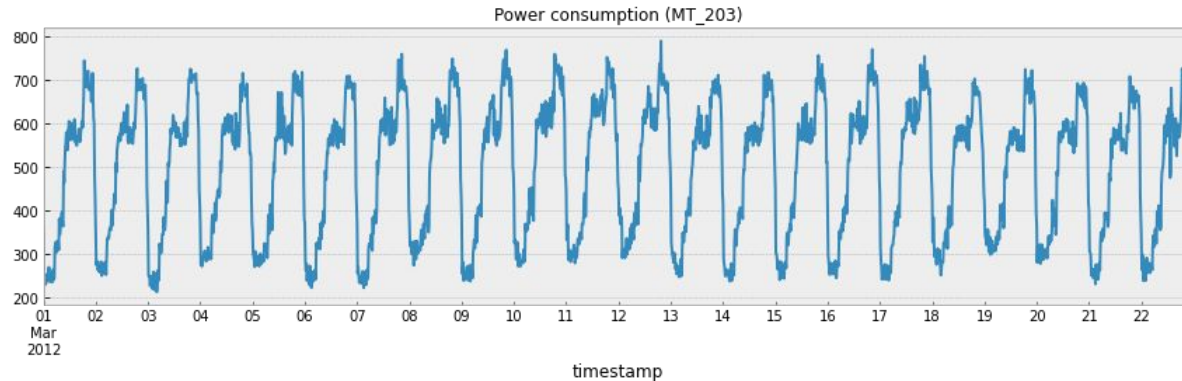
- 370 individual households
- 15 minutes sampling interval



# Power consumption

## Electricity load [dataset](#)

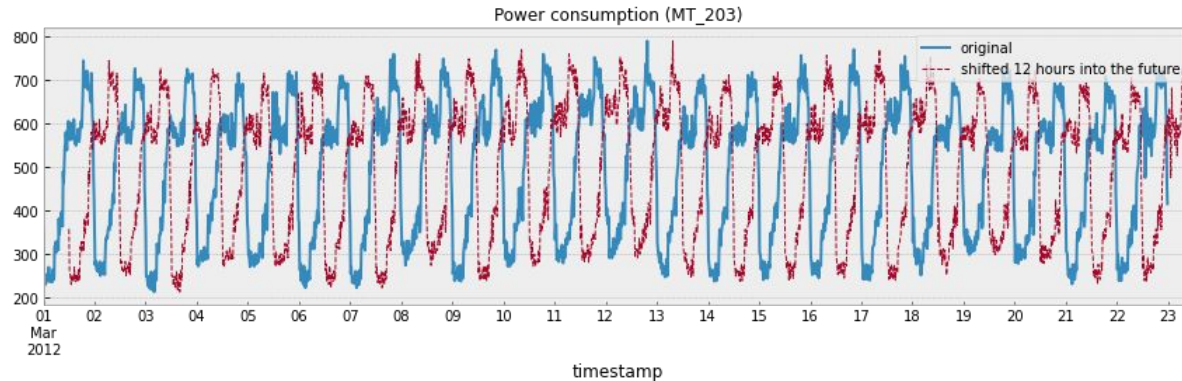
- 370 individual households
- 15 minutes sampling interval



# Power consumption

## Temporal structure?

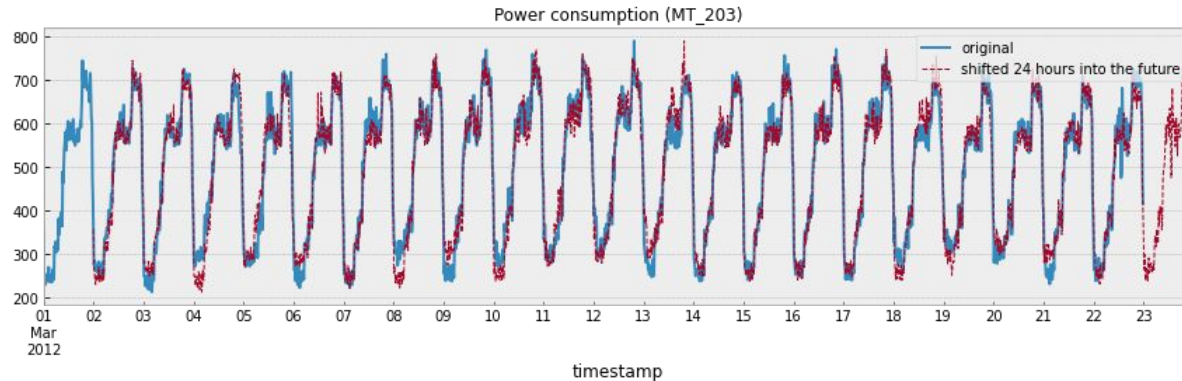
- shift the data: 12 hours



# Power consumption

## Temporal structure?

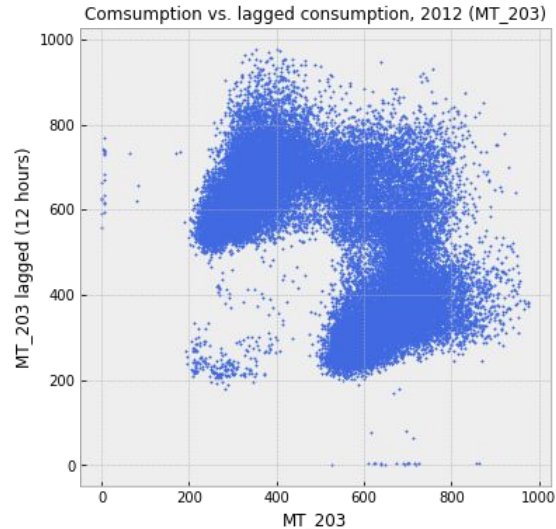
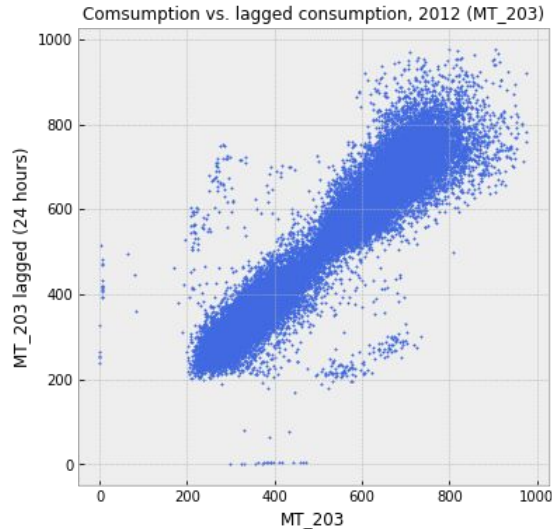
- shift the data: 24 hours



# Power consumption

## Temporal structure?

- shift the data: 12, 24 hours

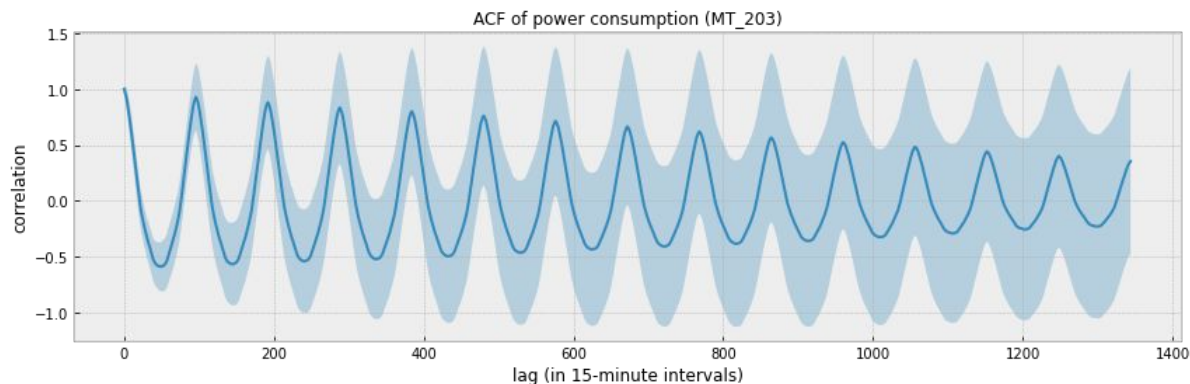




# Autocorrelation function

## Temporal structure?

- calculate correlations at different shifts:  
**autocorrelation function (ACF)**



# Autocorrelation function

Temporal structure?

- calculate correlations at different shifts:  
**autocorrelation function** (ACF)

$$ACF(\tau) = C(y(t)y(t - \tau))$$

# Autocorrelation function

**ACF:**

- quick assessment of signal temporal structure
- correlation length -> model parameters

$$ACF(\tau) = C(y(t)y(t - \tau))$$

# Modeling

## Modeling ideas:

- use some AR-alike classical model
- use some RF, gradient boosting, provide lags explicitly
- **recurrent** model (modified?)

# Time series basics:

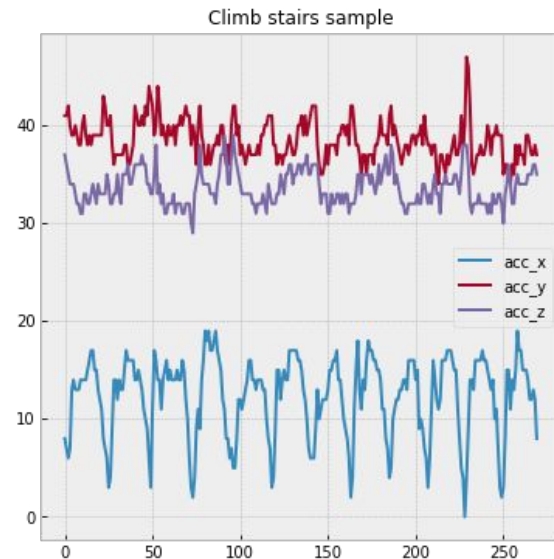
## frequency domain



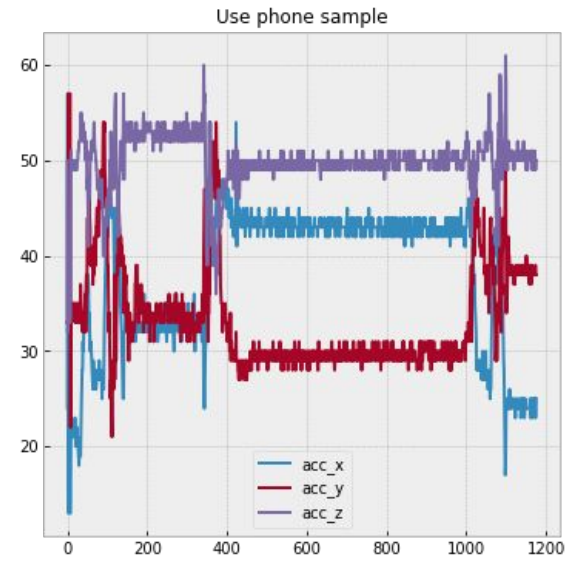
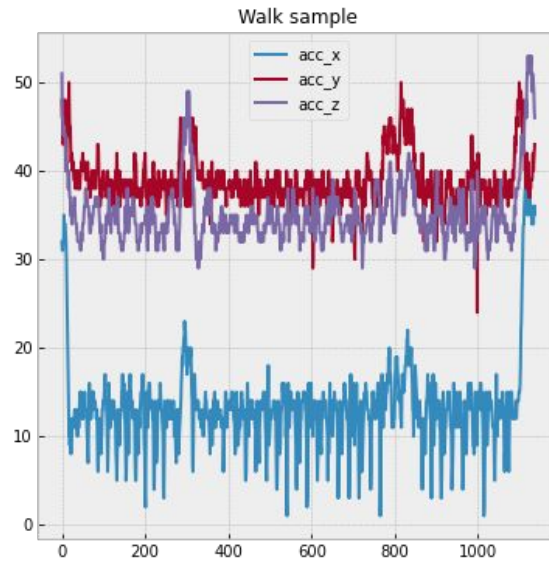
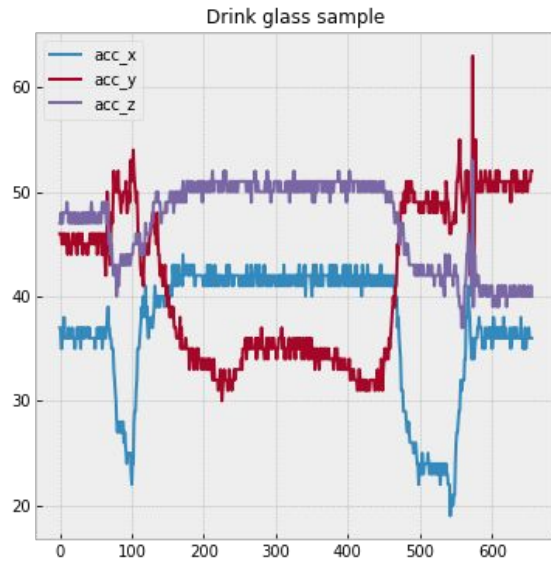
# Activity recognition

## ADL Recognition dataset

- multiple activities, short samples
- 50 Hz sampling rate



# Activity recognition



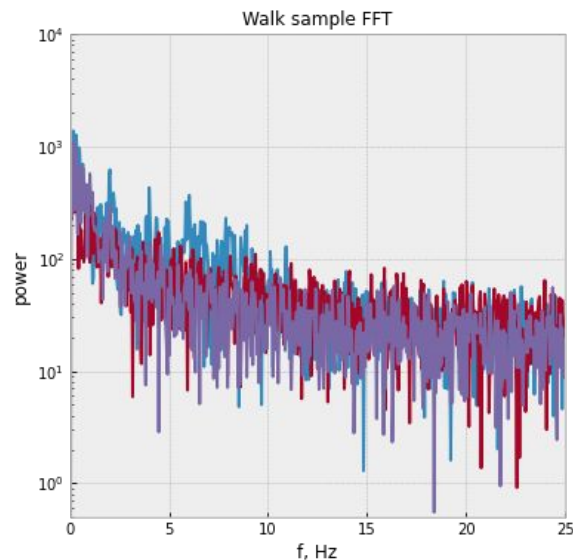
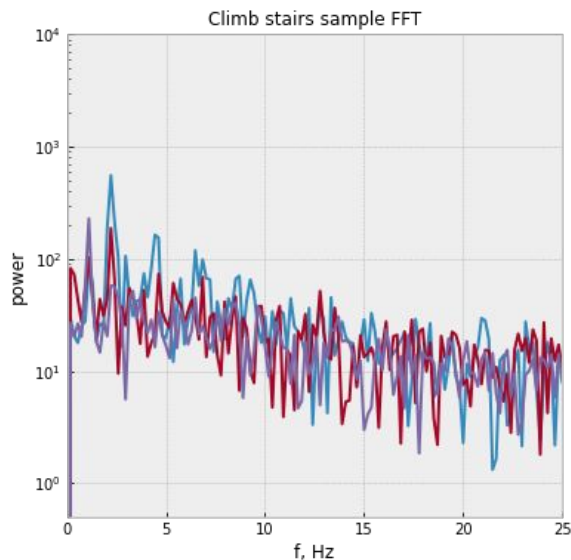
# Activity recognition

**ACF? Non-informative:** wrong “scale”

- FFT for the rescue

# Activity recognition

Power spectrum:



# Modeling

## Modeling ideas:

- use manual features (tsfresh) and some classical model
- **CNN** model (modified?)



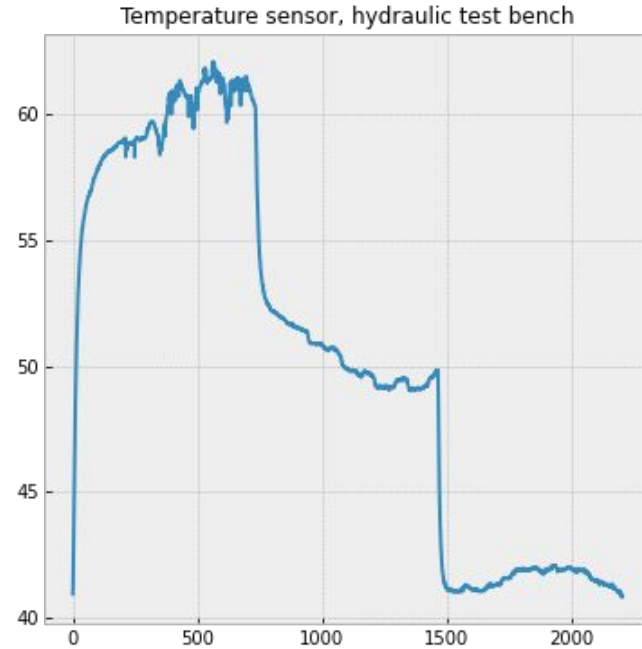
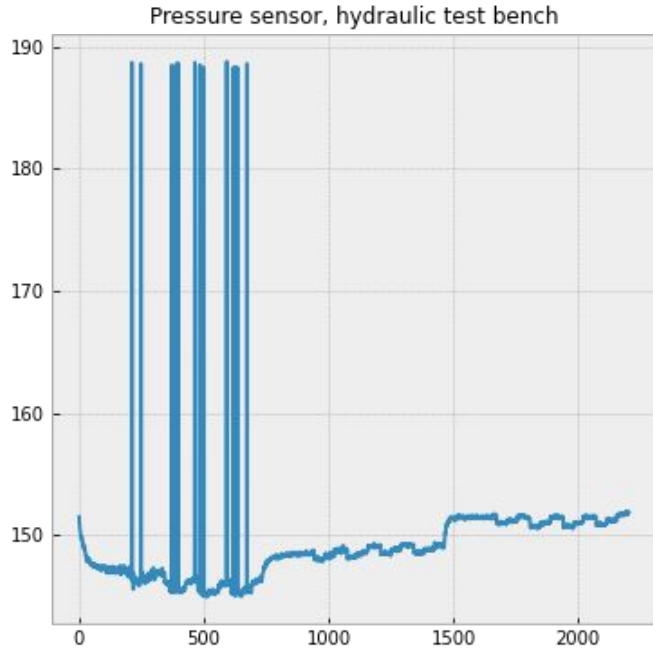
# Time series basics: other examples

# Industrial equipment

Condition monitoring of hydraulic systems [dataset](#)

- multiple sensors (temperature, pressure)
- 100 Hz sampling rate

# Industrial equipment



# Time series basics: tools

# Pandas

**Mostly for preprocessing:**

- datetime operations
- resampling, rolling
- shifts

# Cross-validation

**Random split cannot be applied to time series**

- use fixed split
- use rolling CV
- otherwise, autocorrelation will kill your model

questions?