Deep Learning para series temporales

Part I

Introduction

Presentation

Introduction

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Evaluation

Develop a project

- **Option I**: Develop a project within an open challengue.
- **Option II**: Develop your own project (previously asking teachers to confirm the proposal is adequated).

Contents

Part I: Introduction

Why am I here?

Part II: Preprocessing and analysis

ETL + First observations

Part III: Classification

Labelling time series

Part IV: Segmentation & Clustering

Identifying long-term behaviours

Part V: Forecasting

Predicting the future

Part VI: Other Deep Learning tasks

What more can we do?

What are time series?

Identify temporal data

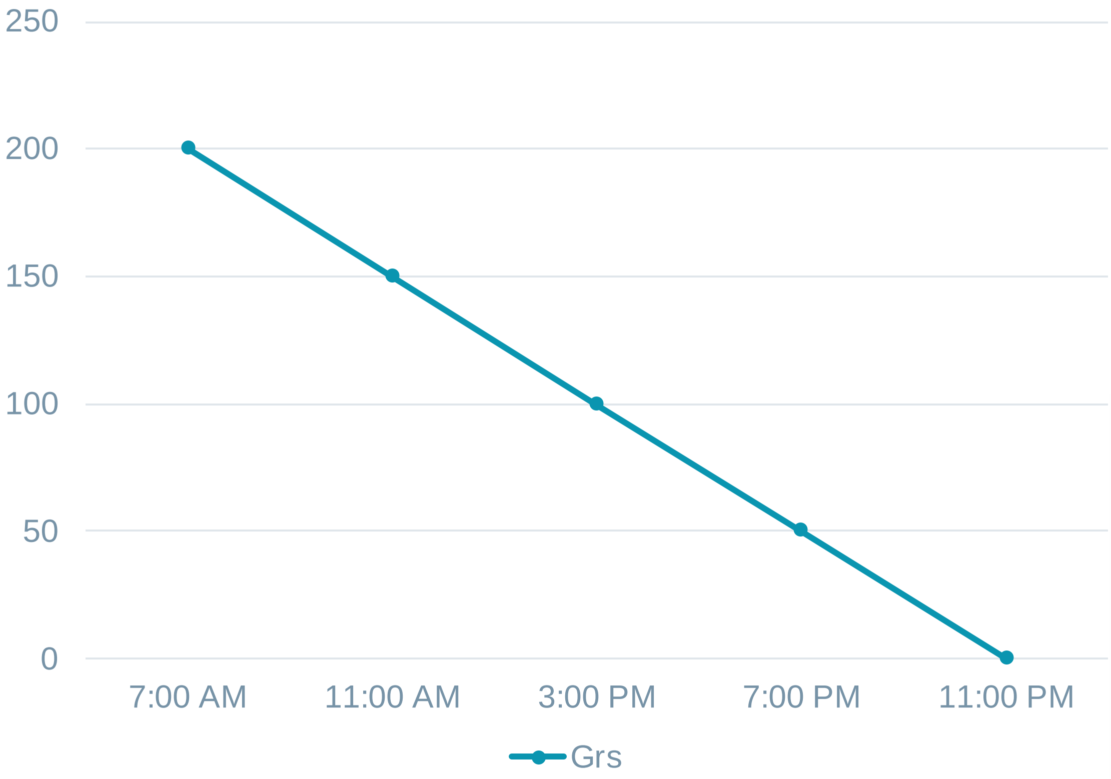
What are time series?

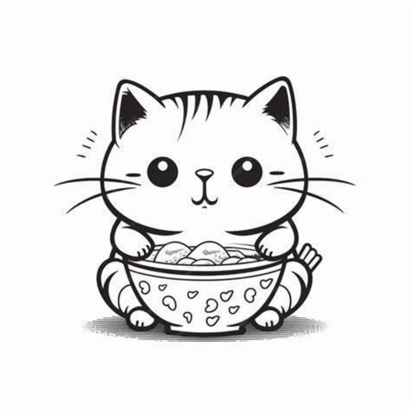
- **Meals**: kilocalories, grams, …
- **Airport**: planes departs, number of passengers waiting
- **Weather**: temperatura readings
- **Finance**: stock prices
- **Retail**: sales data
- **Sports**: goals per minute

A first time series with refill

Time	Available food (gr)
7:00 AM	**200**
11:00 AM	**150**
03:00 PM	**100**
07:00 PM	**50**
11:00 PM	**0**

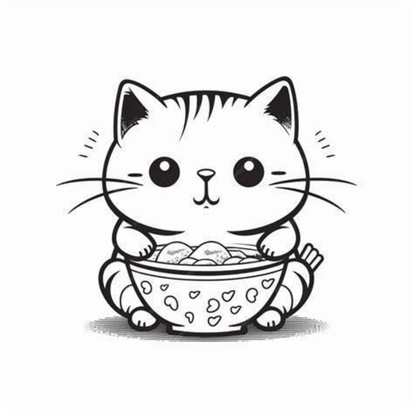
A first time series



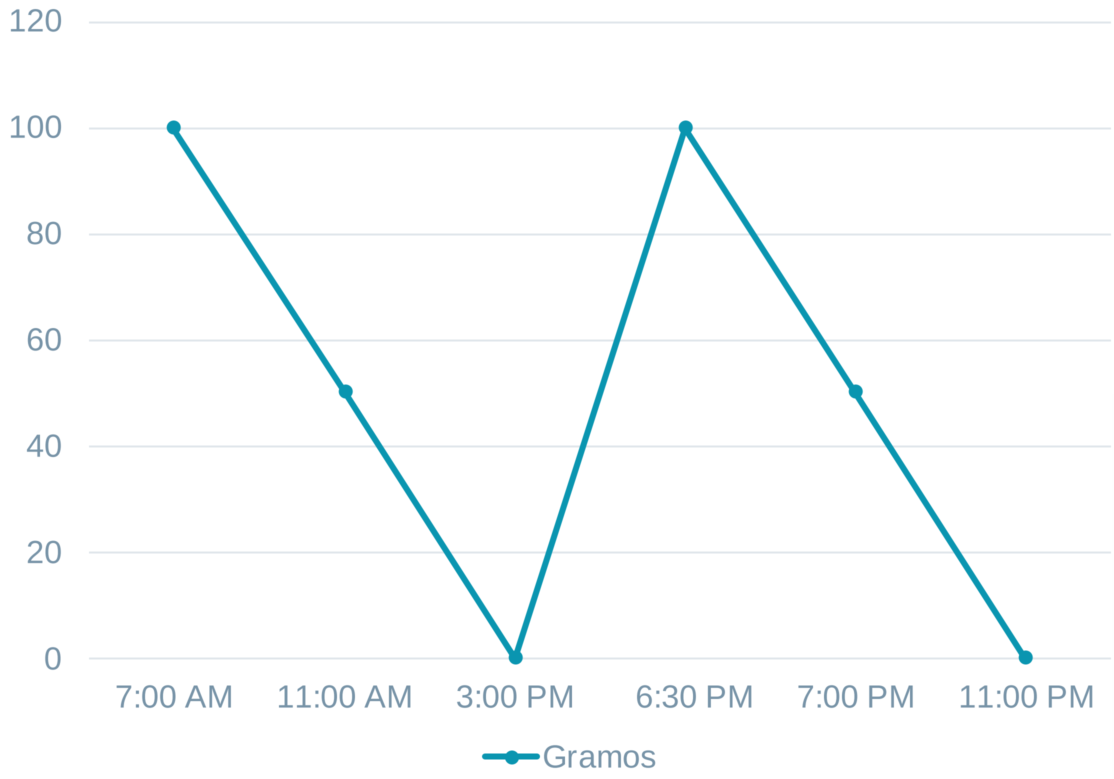


A first time series with refill

Time	Available food (grs)
7:00 AM	**100**
11:00 AM	**50**
03:00 PM	**0**
06:30 PM	**100**
07:00 PM	**50**
11:00 PM	**0**



A first time series with refill



Stop: What charasteristics makes data be a time series?

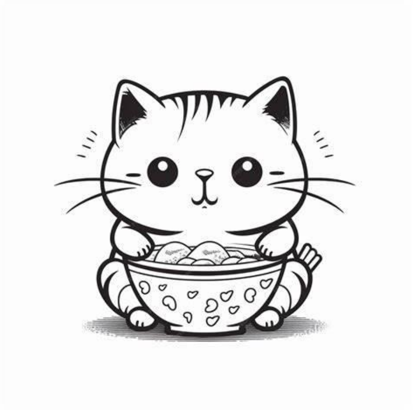
?

A first time series

Time	Available food (gr)
7:00 AM	**100**
11:00 AM	**50**
03:00 PM	**0**
06:30 PM	**100**
07:00 PM	**50**
11:00 PM	**0**

Ordered time sequence
$t0 < t1 < t2 < t3 < t4 < t5$

Time	Data
t0	**Dato (valor real) 1**
t1	**Dato 2**
t2	**Dato 3**
t3	**Dato 4**
t4	**Dato 5**
t5	**Dato 6**

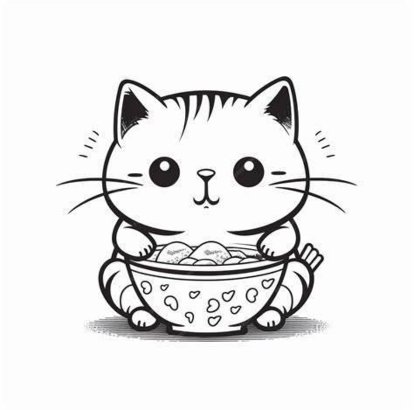


A first time series

Time	Cantidad de comida restante (gramos)
7:00 AM	**100**
11:00 AM	**50**
03:00 PM	**0**
06:30 PM	**100**
07:00 PM	**50**
11:00 PM	**0**

Variate to analize
Real values (1, 0.1, -0.27, …)

Time	Data
t0	**Data 1** ↓
t1	**Data 2** ↓
t2	**Data 3** ↓
t3	**Data 4** ↓
t4	**Data 5** ↓
t5	**Data 6**

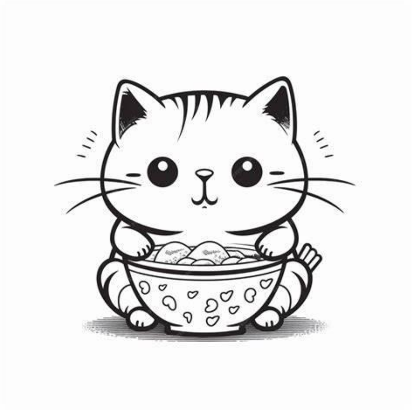


A first time series

Each data associated to one timestamp as an index

Time	Cantidad de comida restante (gramos)
7:00 AM	← 100
11:00 AM	← 50
03:00 PM	← 0
06:30 PM	← 100
07:00 PM	← 50
11:00 PM	← 0

Index	Data
t0	← **Dato 1**
t1	← **Dato 2**
t2	← **Dato 3**
t3	← **Dato 4**
t4	← **Dato 5**
t5	← **Dato 6**



What datatypes in python can we use for storing a time series?

?

Store time series in python

- List
- Set
- Tuple
- Dictionary
- String
- Array
- Make a class

Store time series in python

- List
- ~~Set~~
  - Does not allow repeated values
- ~~Tuple~~
  - I am not going to write 10K elements 1 by 1 as a tuple to define my series. And you cannot append or shorten it for preprocessing.
- Dictionary
- ~~String~~
  - If I am going to work with data, I don't want a string with the data: I want the data
- Array
- Make a class

Store time series in python

- List
- ~~Set~~
- ~~Tuple~~
- Dictionary
- ~~String~~
- Array
- Make a class

Use a predefined widely used class

pandas -> DataFrame / Series

numpy -> np.ndarray

torch -> tensor

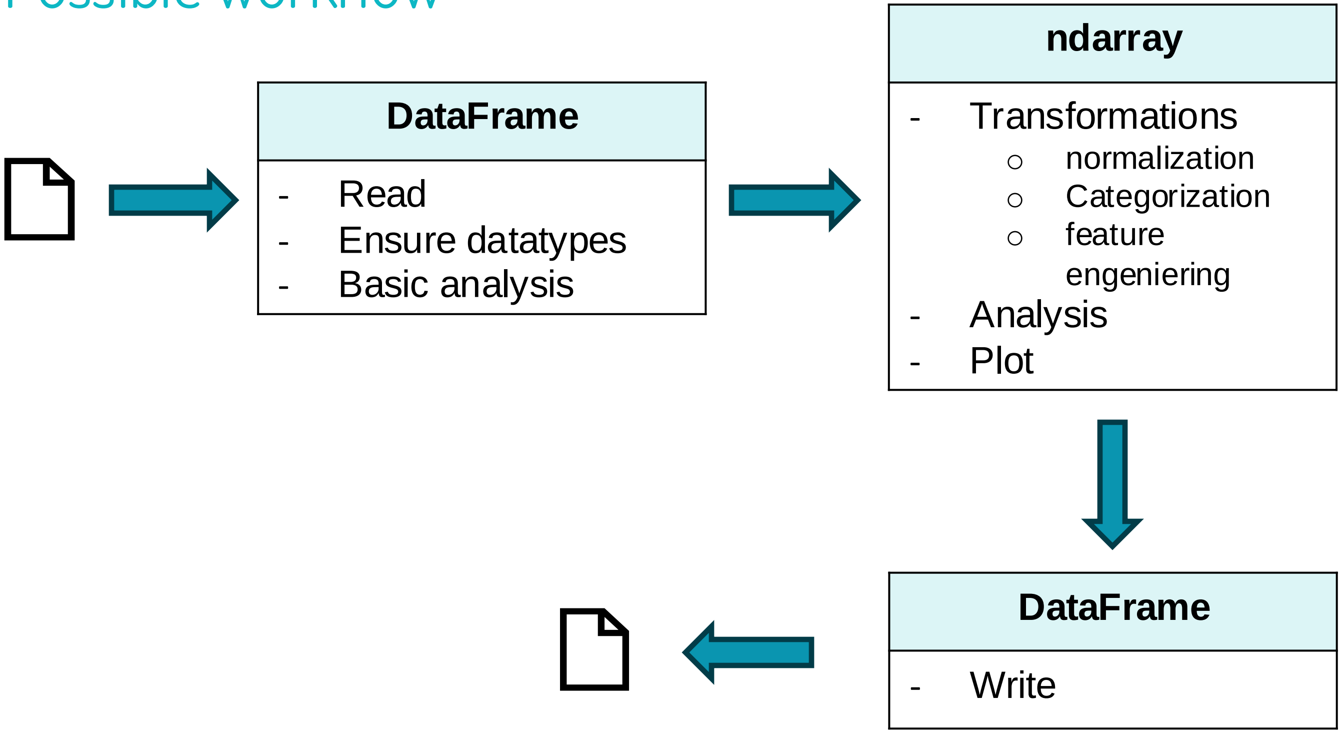
A first time series with refill

	np.ndarray	torch.tensor	pd.Series	pd.DataFrame
Allow saving 1 time series	**yes**	**Yes**	**Yes**	**Yes**
Allos saving > 1 columns time series	**yes**	**Yes**	**No**	**Yes**
Allow indexing	**Yes**	**Yes**	**Yes**	**Yes**
Has index	**No**	**No**	**Yes**	**Yes**
Compute in GPU or CPU	**CPU**	**CPU/GPU**	**CPU**	**CPU**

A first time series with refill

	np.ndarray	torch.tensor	pd.Series	pd.DataFrame
Mathematic operations	Advanced	Advanced. Optimized for Machine Learning	Basic	Basic
Used for	• Scientific / statistics calculations • Generating time series	• Deep Learning. Training in GPU	Tabular data, 1 column time series	• Tabular data • Multiple column time series • Usefull for reading and storing time series. • Easy conversion with ndarray and tensor
Optimized for	Vectorized numerical operations	High performance computing with auto-diferentiation	Reading / storing single series data	• Reading(/storing time series • Tabular data analysis
Compatibility	High with tensors and DataFrames	High with np.ndarray	Easy conversion to/from DataFrames	Easy conversion to/from np.ndarray

Possible workflow



DataFrame

- Read
- Ensure datatypes
- Basic analysis

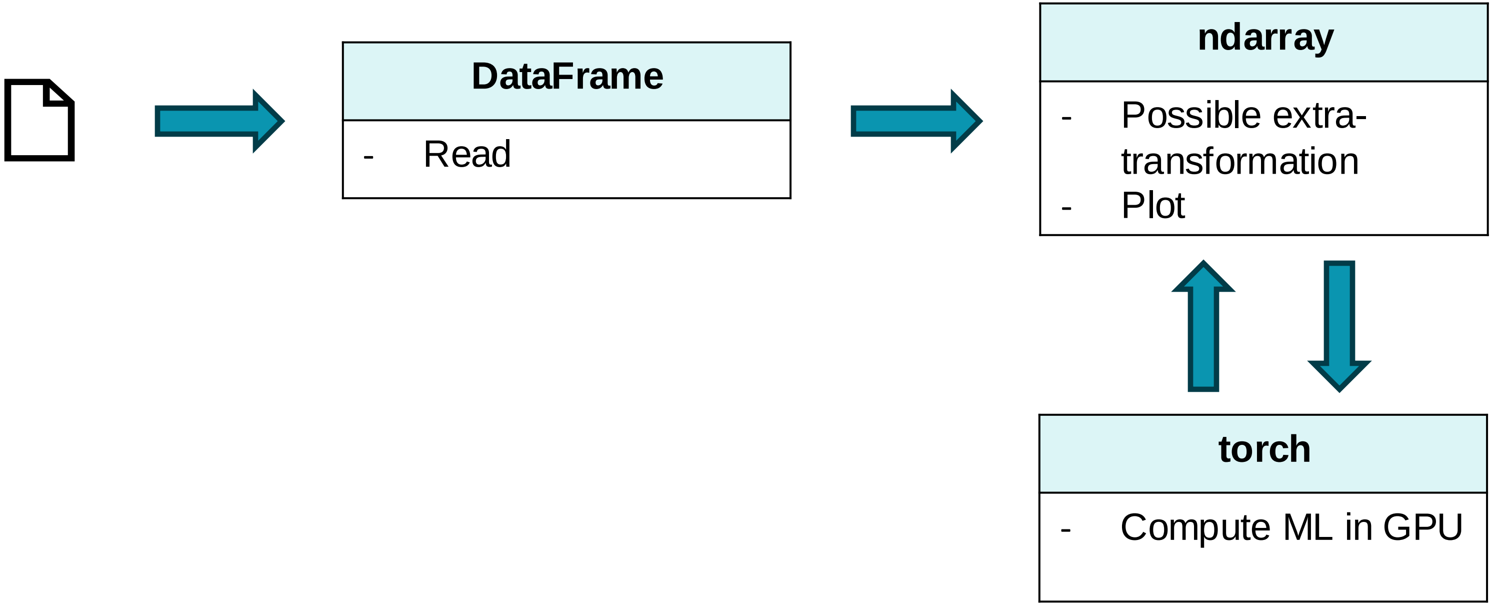
ndarray

- Transformations
  - normalization
  - Categorization
  - feature engeniering
- Analysis
- Plot

DataFrame

- Write

Possible workflow



DataFrame

- Read

ndarray

- Possible extra-transformation
- Plot

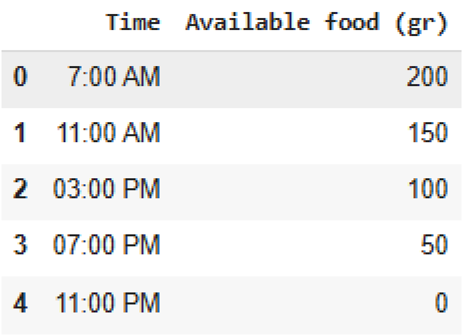
torch

- Compute ML in GPU

Store time series in python

```
raw_data_9 = pd.DataFrame({
    "Time": ["7:00 AM", "11:00 AM", "3:00 PM", "7:00 PM", "11:00 PM"],
    "Available food (gr)": raw_data
})

display(raw_data_9.head())
```



	Time	Available food (gr)
0	7:00 AM	200
1	11:00 AM	150
2	03:00 PM	100
3	07:00 PM	50
4	11:00 PM	0

- Index: 0, 1, 2…
- Column names: “Time”, “Available food (gr)”
- Column values:
  - “7:00 AM”, “12:00 AM”, …
  - 200, 150, …

Store time series in python

```
# Index
<pd.DataFrame>.index

# Columns names
<pd.DataFrame>.columns

# Values by column name
<pd.core.series.Series>.values
<pd.DataFrame>[<column name (str)>].values

# Values by column position
<pd.DataFrame>.iloc[:,<column number>].values

# Values by row position
<pd.DataFrame>.iloc[<row number>, :].values
```

Store time series in python

- We focus on float data (the most used in time series analysis)

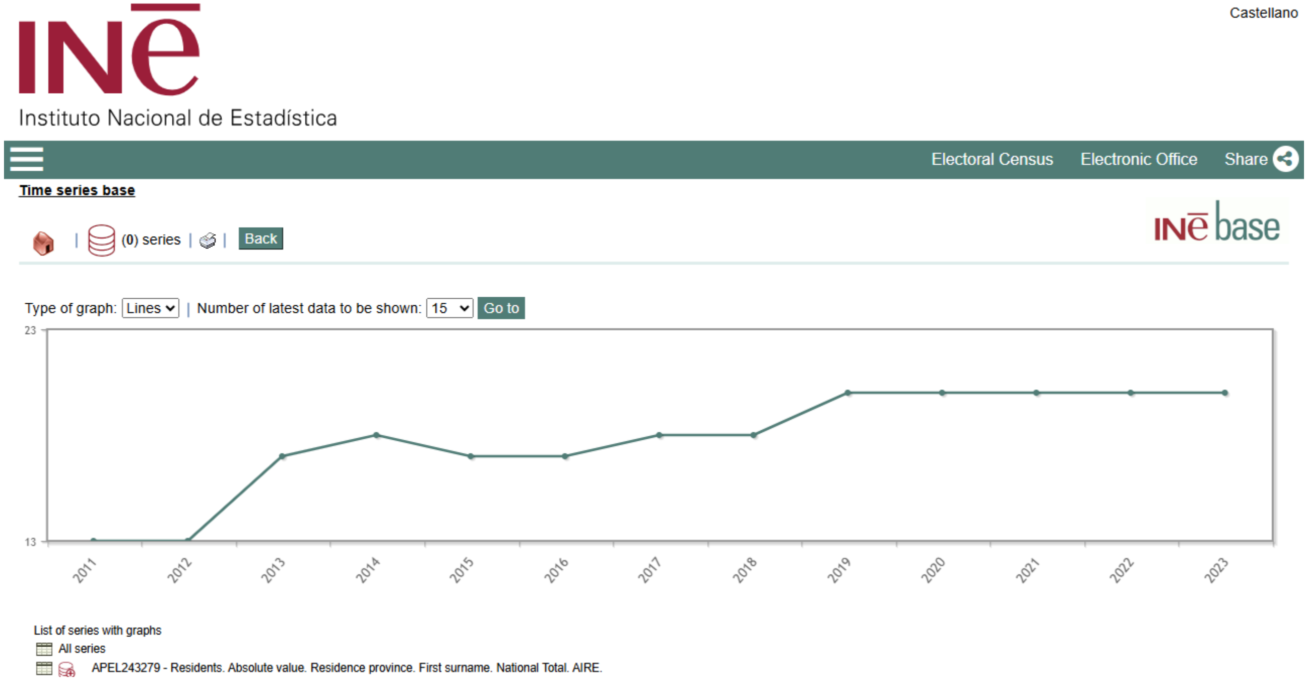
In the next lesson we will see

- How to preprocess data (ETL)
  - How to make the time be the index of the time series

What other time series can we check?

?

Other time series examples



Time series base

(0) series | Back

Type of graph: Lines | Number of latest data to be shown: 15 Go to

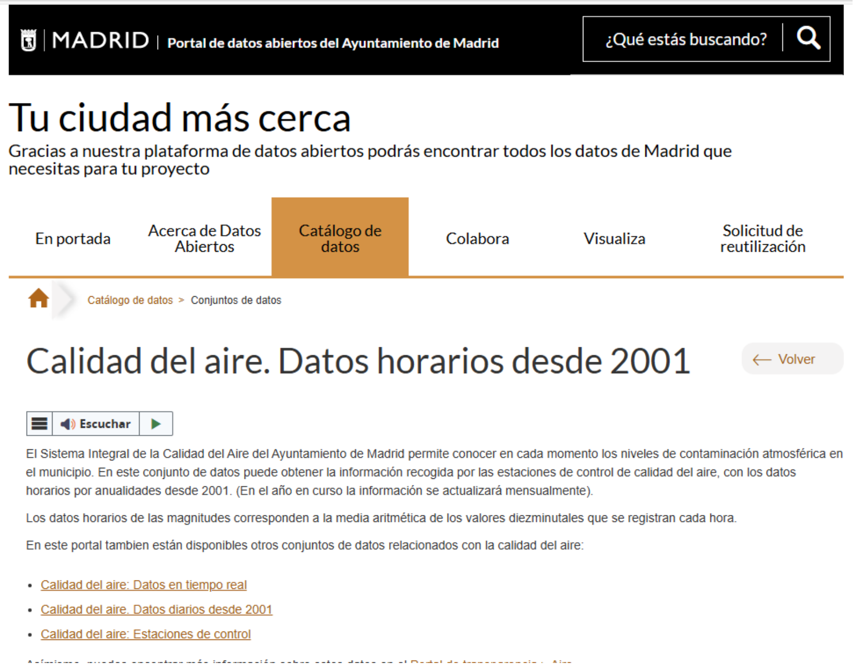
List of series with graphs

All series

APEL243279 - Residents. Absolute value. Residence province. First surname. National Total. AIRE.

https://ine.es/consul/serie.do?s=136-243279&L=1

Other time series examples


MADRID | Portal de datos abiertos del Ayuntamiento de Madrid
¿Qué estás buscando?
En portada
Acerca de Datos Abiertos
Catálogo de datos
Colabora
Visualiza
Solicitud de reutilización
Catálogo de datos > Conjuntos de datos
← Volver
Escuchar

Tu ciudad más cerca

Gracias a nuestra plataforma de datos abiertos podrás encontrar todos los datos de Madrid que necesitas para tu proyecto

Calidad del aire. Datos horarios desde 2001

El Sistema Integral de la Calidad del Aire del Ayuntamiento de Madrid permite conocer en cada momento los niveles de contaminación atmosférica en el municipio. En este conjunto de datos puede obtener la información recogida por las estaciones de control de calidad del aire, con los datos horarios por anualidades desde 2001. (En el año en curso la información se actualizará mensualmente).

Los datos horarios de las magnitudes corresponden a la media aritmética de los valores diezminutales que se registran cada hora.

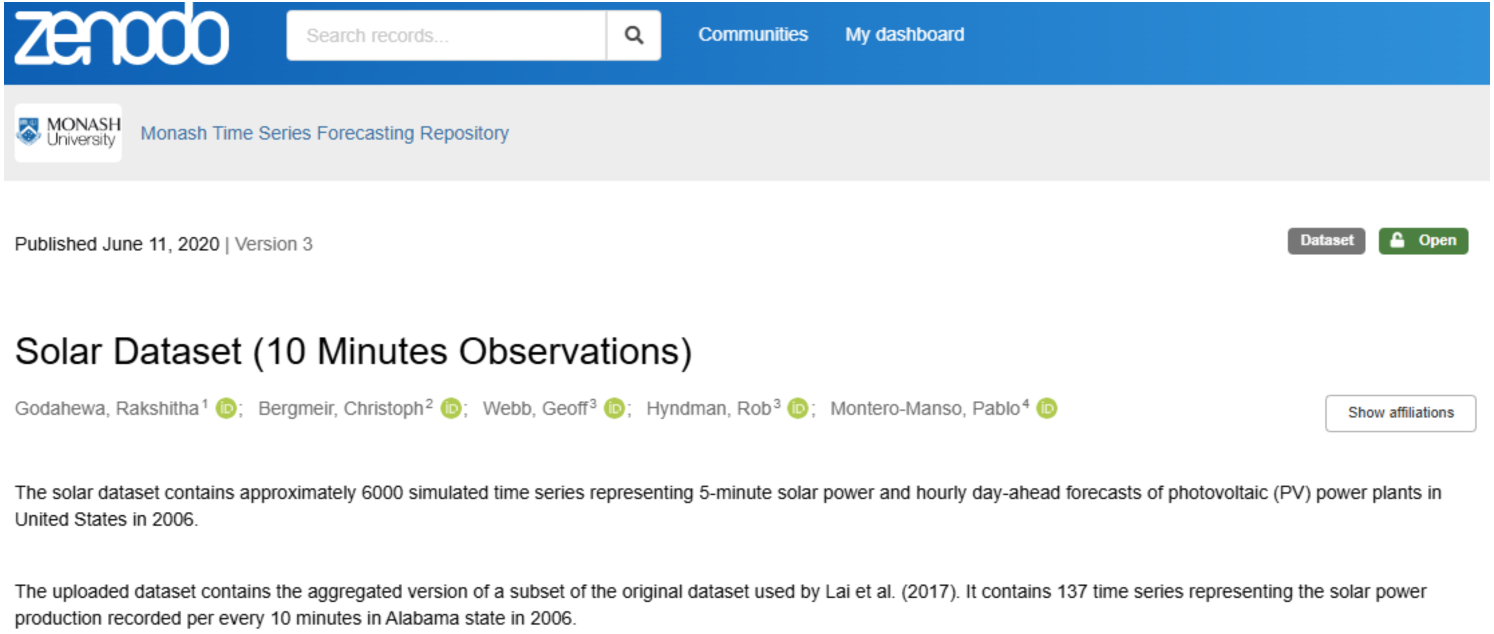
En este portal tambien están disponibles otros conjuntos de datos relacionados con la calidad del aire:

- Calidad del aire: Datos en tiempo real
- Calidad del aire. Datos diarios desde 2001
- Calidad del aire: Estaciones de control

Asímismo, puedes encontrar más información sobre estos datos en el Portal de transparencia - Aire

Calidad del aire. Datos horarios desde 2001 - Portal de datos abiertos del Ayuntamiento de Madrid

Other time series examples



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Solar Dataset (10 Minutes Observations)

Godahewa, Rakshitha[1]; Bergmeir, Christoph[2]; Webb, Geoff[3]; Hyndman, Rob[3]; Montero-Manso, Pablo[4]

The solar dataset contains approximately 6000 simulated time series representing 5-minute solar power and hourly day-ahead forecasts of photovoltaic (PV) power plants in United States in 2006.

The uploaded dataset contains the aggregated version of a subset of the original dataset used by Lai et al. (2017). It contains 137 time series representing the solar power production recorded per every 10 minutes in Alabama state in 2006.

[Solar Dataset (10 Minutes Observations) (zenodo.org)]

Other time series examples

- Residents / year
  https://ine.es/consul/serie.do?s=136-243279&L=1
- Air quality data values / hour
  Calidad del aire. Datos horarios desde 2001 - Portal de datos abiertos del Ayuntamiento de Madrid
- Solar power / 10 minutes
  Solar Dataset (10 Minutes Observations) (zenodo.org)
- ECG in High Intensity Exercise Dataset
  ECG in High Intensity Exercise Dataset (zenodo.org)
- Crop yield prediction
  Crop Yield Prediction Dataset (kaggle.com)

Applications in your work / real world?

?

Other time series examples

- Solved incidences/tickets per hour
- Trading
- Stock of products in a shop
- Available memory / execution time

Real-world uses

- Electronic health record (pulsus paradoxus)
- Human activity recognition (HAR using spartphone)
- Cibersecurity (intrusion detection -> attack prediction)
- Aerospace engineering (methods & applications for flight)
- Weather forecasting (kaggle's long-term dataset)

How/where can I get data from?

?

Real-world uses

- Own data:
  - Machines
  - person making actions
  - smartwatch
- Synthetic datasets
  - Toy (Stumpy): mSTAMP (MSTUMP) Toy Data · TDAmeritrade/stumpy Wiki · GitHub
- Databases
  - Kaggle, Google Dataset Search, Ine, private datasets

A bit of theory

Basic definitions

Number of variates

Univariate (1 feature)

Time	Available food (grs)
7:00 AM	**100**
11:00 AM	**50**
03:00 PM	**0**
06:30 PM	**100**
07:00 PM	**50**
10:00 PM	**0**

Multivariate (> 1 feature)

Time	Refilled food (grs)	Eaten food (grs)
7:00 AM	**100**	**0**
11:00 AM	**0**	**50**
03:00 PM	**0**	**50**
06:30 PM	**100**	**0**
07:00 PM	**0**	**50**
10:00 PM	**0**	**50**

Number of variates

Toy dataset

Index	T1	T2	T3
0	**0.565117**	**0.637180**	**0.741822**
1	**0.493513**	**0.629415**	**0.739731**
2	**0.469350**	**0.539220**	**0.718757**
3	**0.444100**	**0.577670**	**0.730169**
4	**0.373008**	**0.570180**	**0.752406**

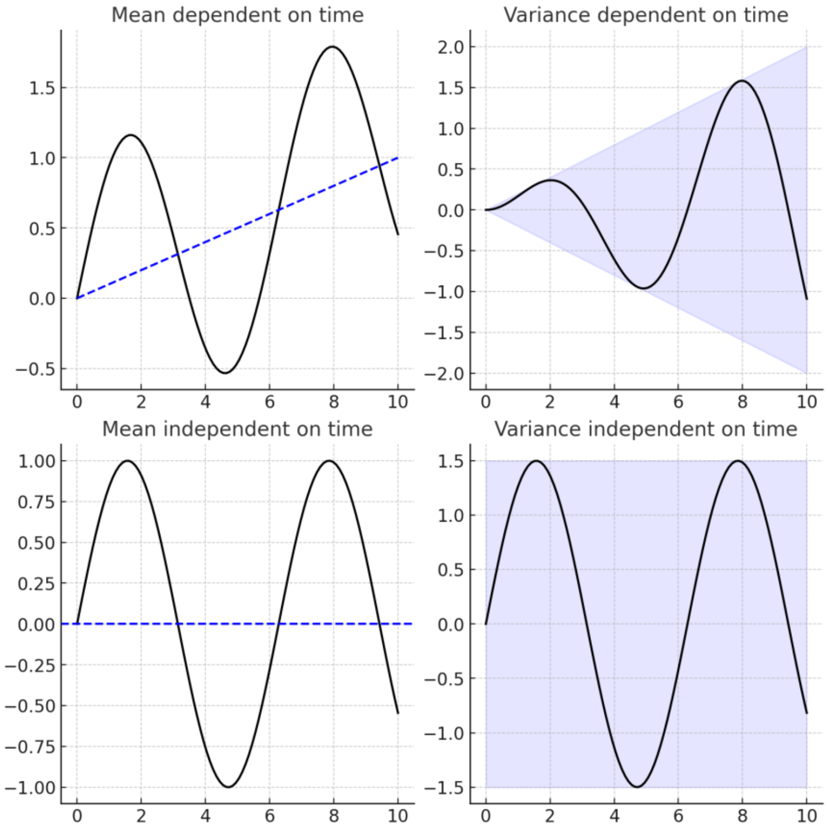
Tourist number

Date (Unicode format)	Tourist number (total turist number visiting the island)
33604	**8414**
33635	**9767**
33664	**13805**
33695	**12987**
33725	**32190**

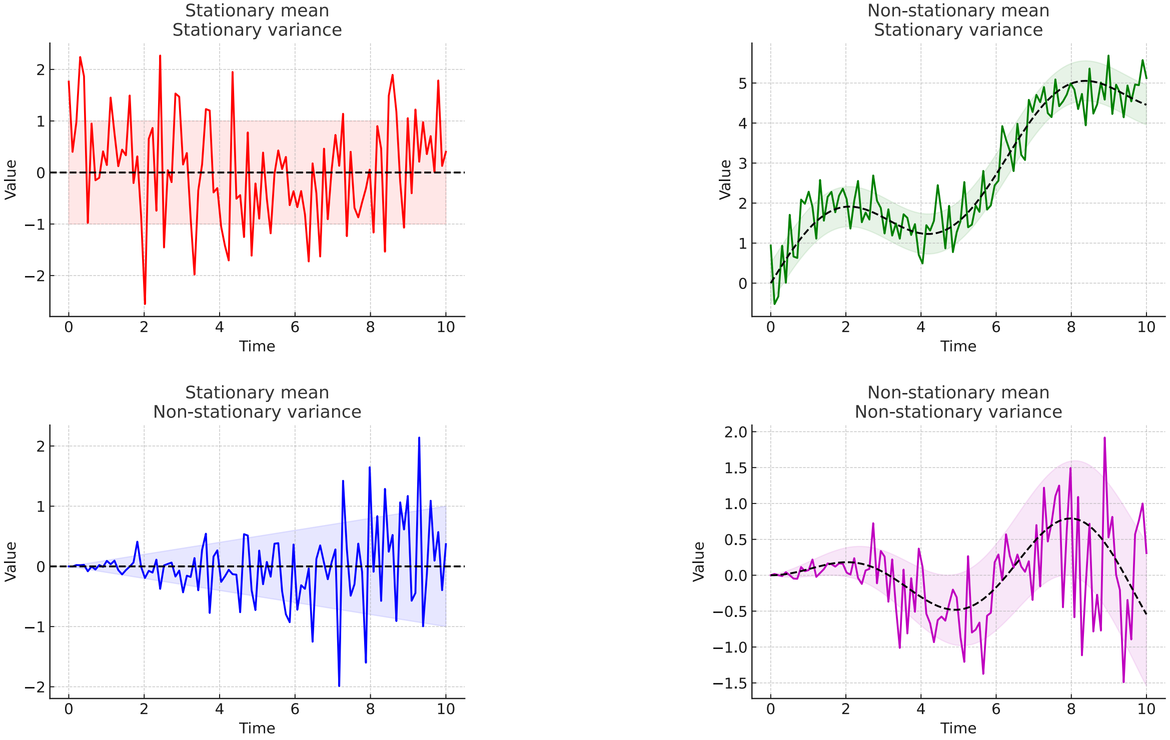
Tourist Numbers Univariate Forecasting Dataset (kaggle.com)

Stationarity

A stationary time series *mean* and *variance* doesn’t change.



Stationarity


Stationary mean Stationary variance

Non-stationary mean Stationary variance

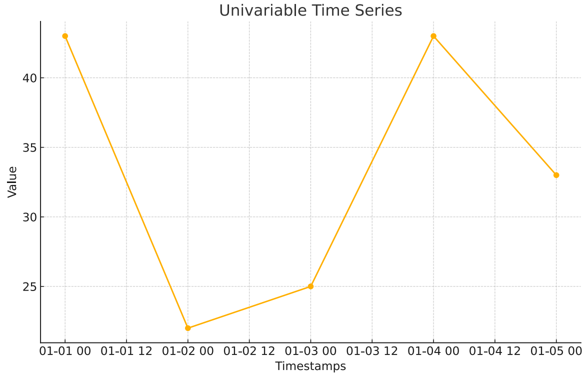
Stationary mean Non-stationary variance

Non-stationary mean Non-stationary variance

Length

Number of timestamps

Timestamps	Value
2023-01-01	**43**
2023-01-02	**22**
2023-01-03	**25**
2023-01-04	**43**
2023-01-05	**33**

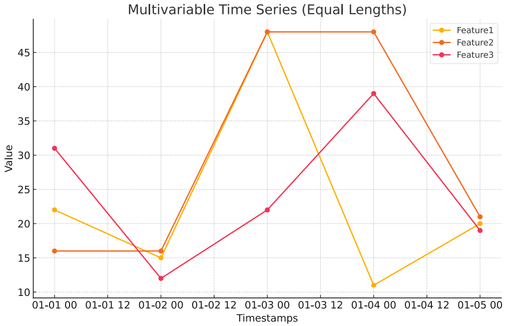


length ?

Length

And… multivariate?

Timestamps	V1	V2	V3
2023-01-01	**16**	**25**	**41**
2023-01-02	**46**	**47**	**42**
2023-01-03	**36**	**47**	**26**
2023-01-04	**40**		**42**
2023-01-05	**15**		**20**

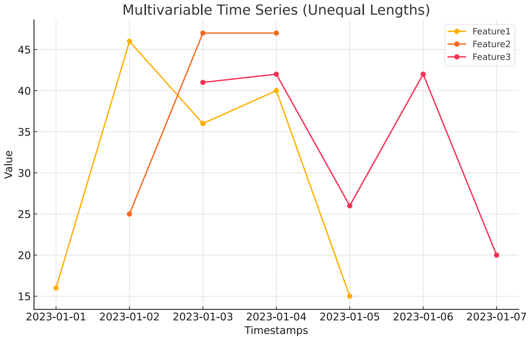


length ?

Length

And…
multivariate?

Timestamps	V1	V2	V3
2023-01-01	**22**	**16**	**31**
2023-01-02	**15**	**16**	**12**
2023-01-03	**48**	**48**	**22**
2023-01-04	**11**	**48**	**39**
2023-01-05	**20**	**21**	**19**



length ?

Spacing

4h
4h
4h
4h

Time	Available food (gr)
7:00 AM	**200**
11:00 AM	**150**
03:00 PM	**100**
07:00 PM	**50**
11:00 PM	**0**

Evenly spaced

4h
4h
3h 30 min
30 min
4h

Time	Available food (grs)
7:00 AM	**100**
11:00 AM	**50**
03:00 PM	**0**
06:30 PM	**100**
07:00 PM	**50**
11:00 PM	**0**

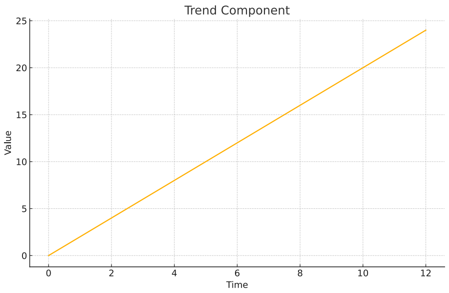
Non evenly spaced

Classical (additive) decomposition

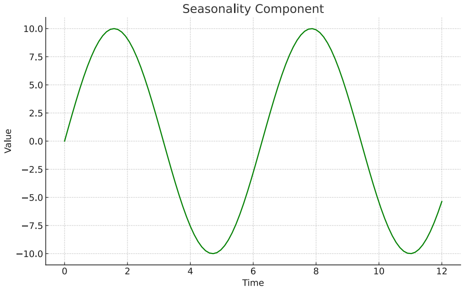
$$x(t) = T(t) + S(t) + I(t)$$

- x(t): time series “x” data at index position “t”
- T: trend component.
- S: seasonality component
- I: Irregular/noise/random component

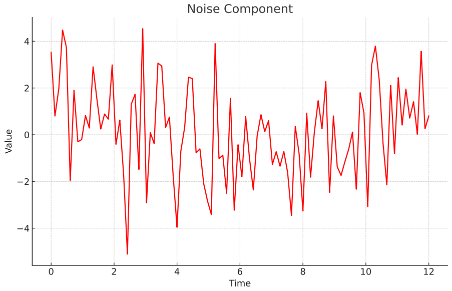
Classical (additive) decomposition



+



+

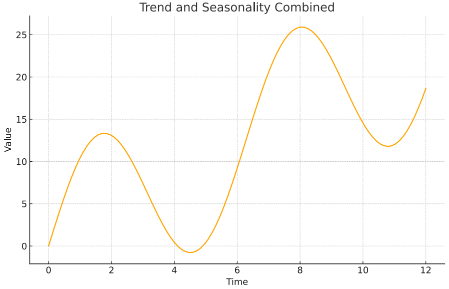


T

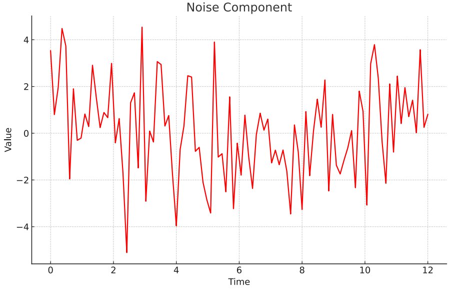
S

I

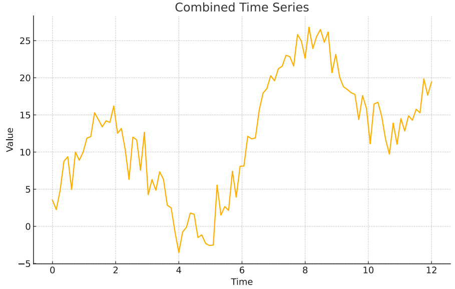
Classical (additive) decomposition


Trend and Seasonality Combined

+


Noise Component

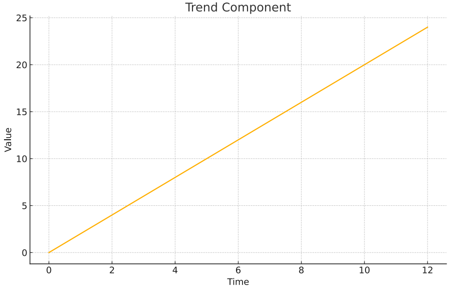
=

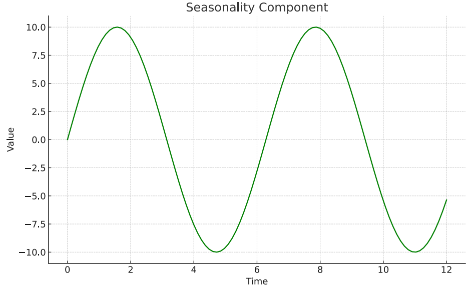

Combined Time Series

T+S

I

X(t)


Trend Component


Seasonality Component

By hand

?

By hand: check learned

- Check cat dataset length (both datasets)
- Plot two univariate time series: one stationary, one non-stationary
- Mark in those series which would be the length
- Plot a multivariate time series with same lengths
- Plot a multivariate time series with different lengths

Google Collab

01_Introduction.ipynb

?

Summary

Summary of the lesson

What this we just learned?

- What is a time series
- Where can we get time series from
- Types of time series
- The problem of evenly/non-evenly distribution
- Lenth
- Classical (additive decomposition): trend, seasonality, irregular/noise

Google Collab

01_Introduction_exercies.ipynb

?

What is the next step?

- Given a time series…
  - How to Extract + Transform + Load the data
  - Basic EDA (Exploratory Data Analysis)
  - Preprocessing techniques (upgrading ETL)

To be continued...

Questions? mi.santamaria@upm.es

Deep Learning para series temporales

Part I

Introduction

Máster
Deep Learning

POLITÉCNICA
UNIVERSIDAD
POLITÉCNICA
DE MADRID

Máster
Deep Learning