Deep Learning para series temporales

Part I

Introduction

Máster
Deep Learning

POLITÉCNICA
UNIVERSIDAD POLITÉCNICA DE MADRID

Máster
Deep Learning

Presentation

Introduction

Máster
Deep Learning

Proffessors

- Víctor Rodríguez Fernández
  victor.rfernandez@upm.es

- María Inmaculada Santamaría Valenzuela
  mi.santamaria@upm.es

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).

Máster Deep Learning

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

Máster Deep Learning

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

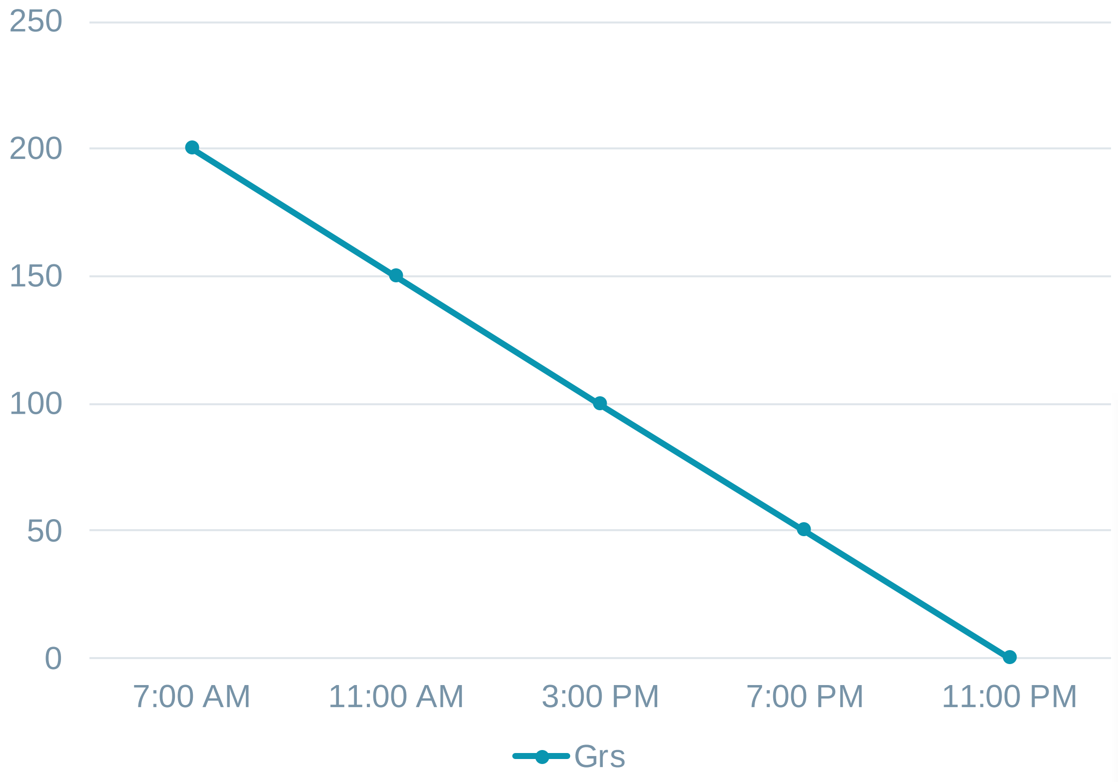
Máster Deep Learning

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**

Máster Deep Learning

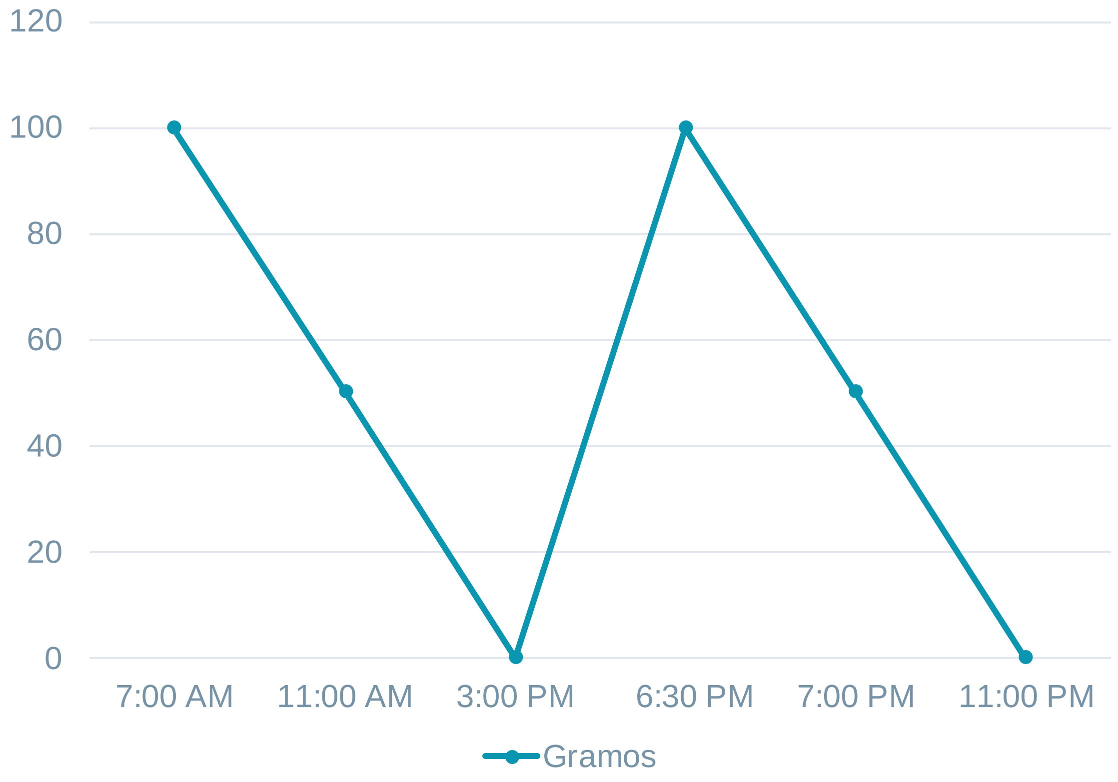
A first time series



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?

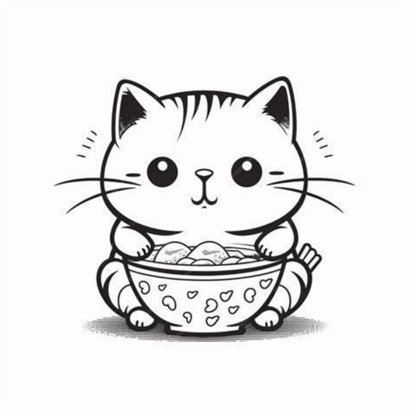
?

A first time series

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

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**

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



Máster Deep Learning

A first time series

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

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**

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

Use a predefined widely used class

pandas -> DataFrame / Series

numpy -> np.ndarray

torch -> tensor

Máster Deep Learning

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

Máster Deep Learning

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
Comatibility	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

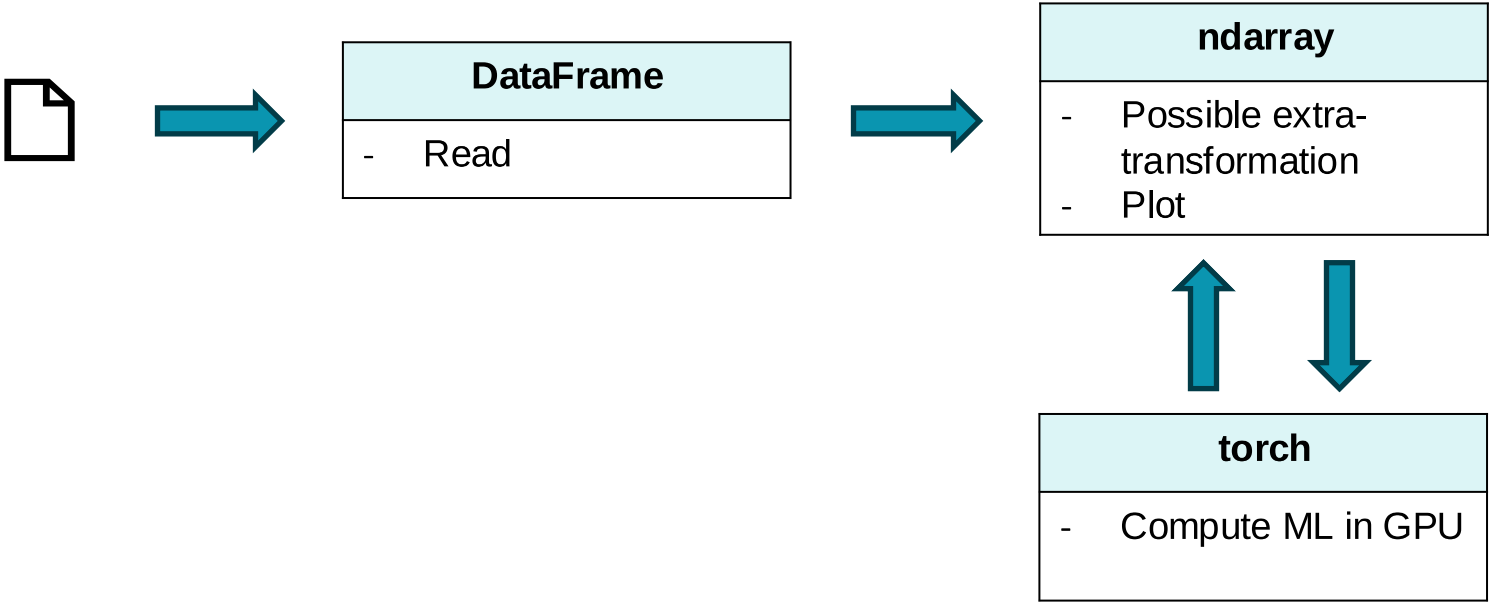
ndarray

- Transformations
  - normalization
  - Categorization
  - feature engenieering
- Analysis
- Plot

DataFrame

- Write

Possible workflow



Máster Deep Learning

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)

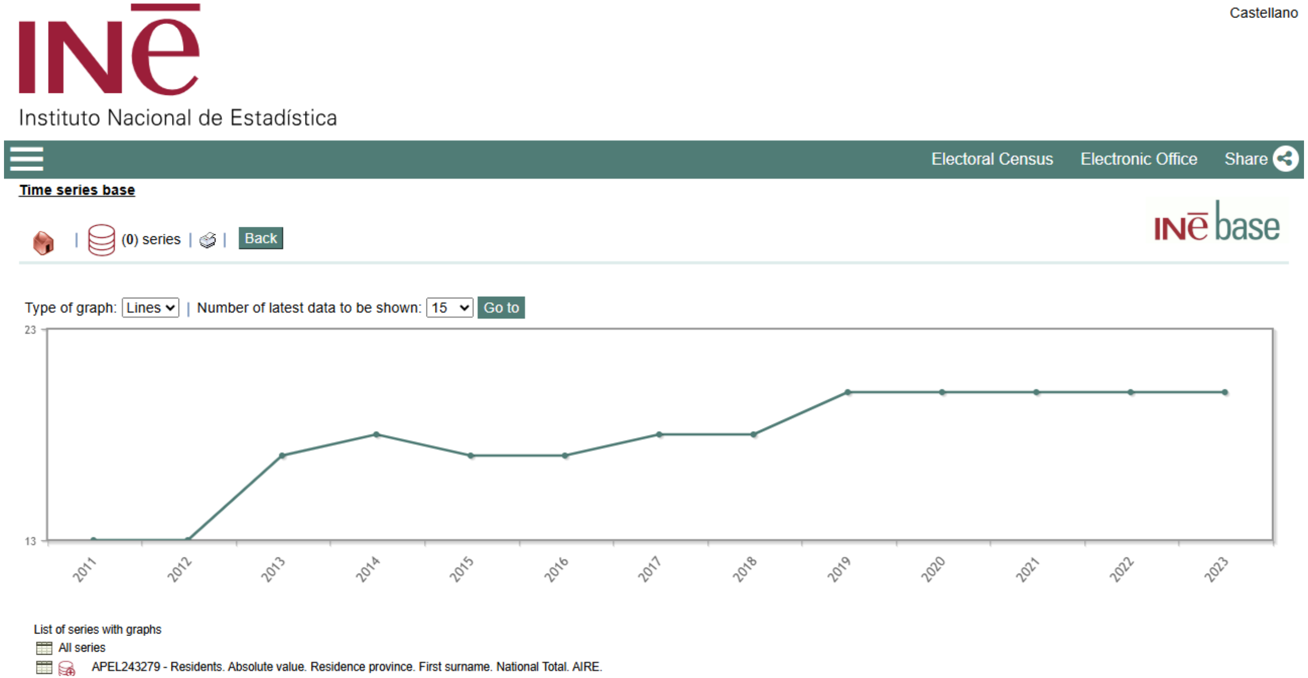
In the next lesson we will see

- 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



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

Other time series examples

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

Máster Deep Learning

Other time series examples

zenodo

Search records... Communities My dashboard

MONASH University Monash Time Series Forecasting Repository

Published June 11, 2020 | Version 3

Dataset Open

Solar Dataset (10 Minutes Observations)

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

Show affiliations

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?

?

Máster Deep Learning

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

Máster Deep Learning

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**

Máster Deep Learning

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**

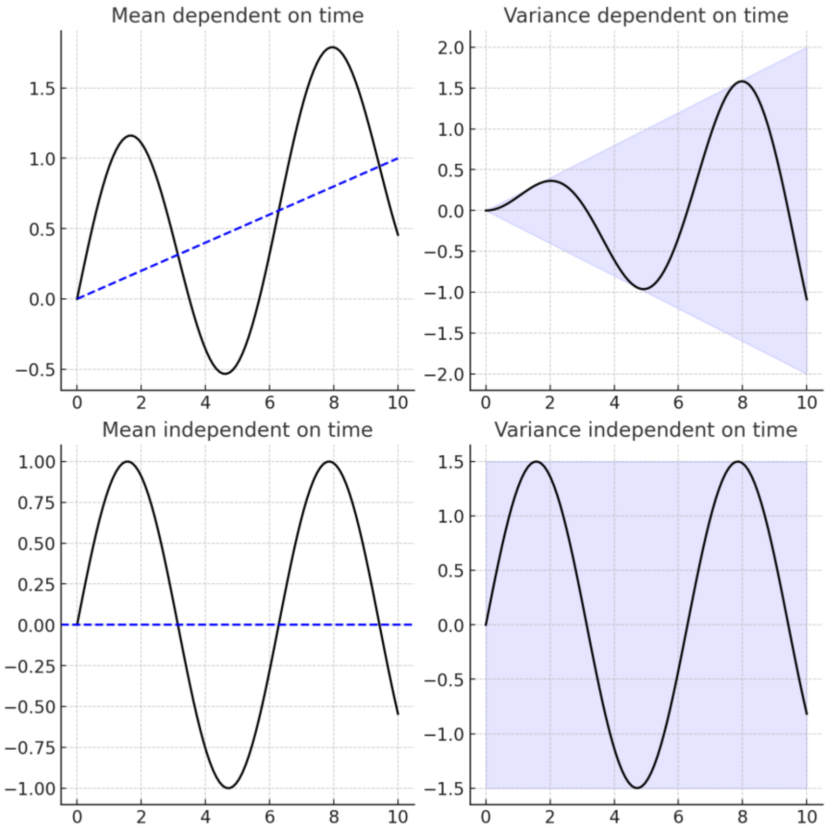
Tourist number

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

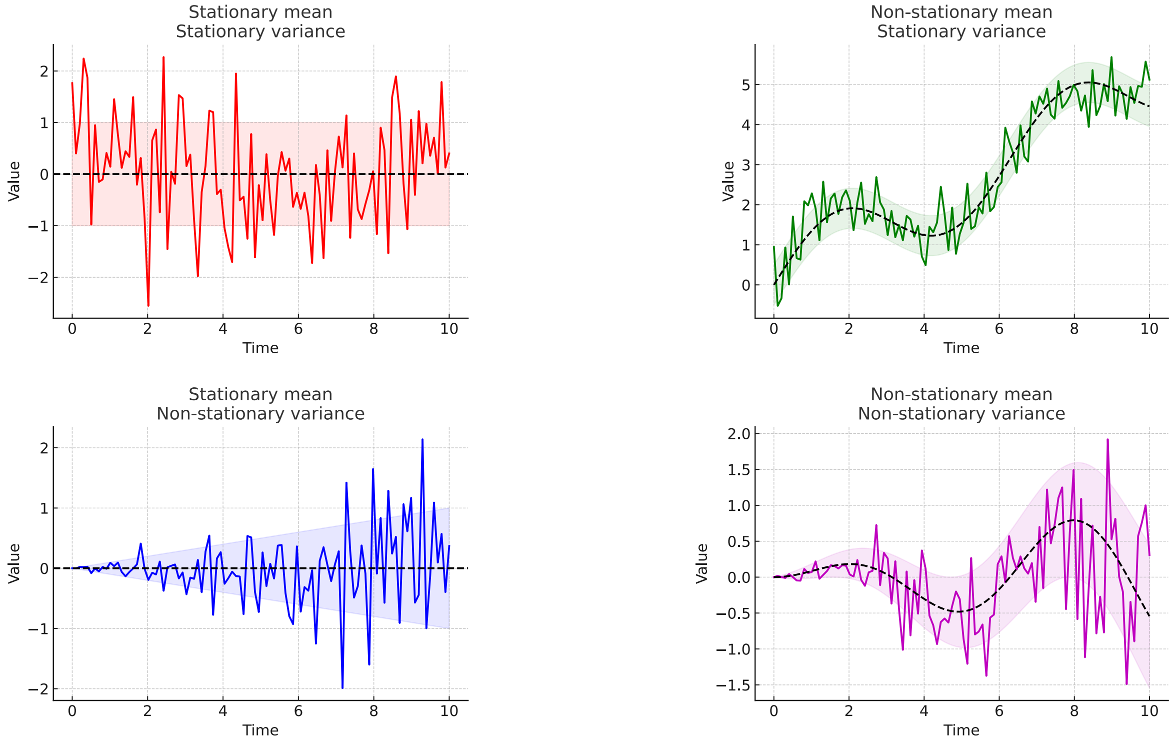
Tourist Numbers Univariate Forecasting Dataset (kaggle.com)

Stationarity

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



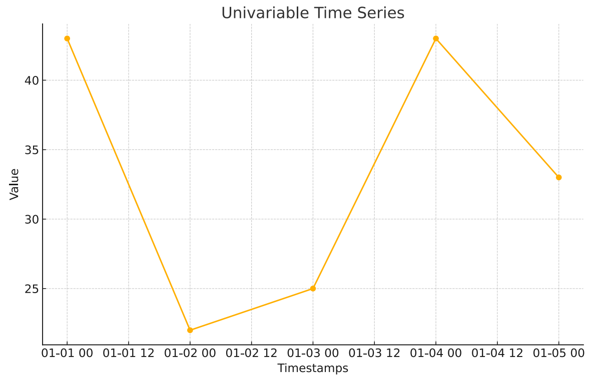
Stationarity



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**



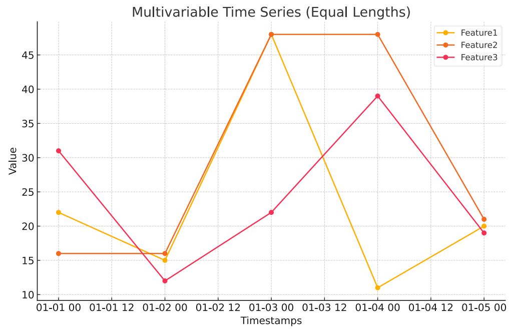
length ?

Length

Máster Deep Learning

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

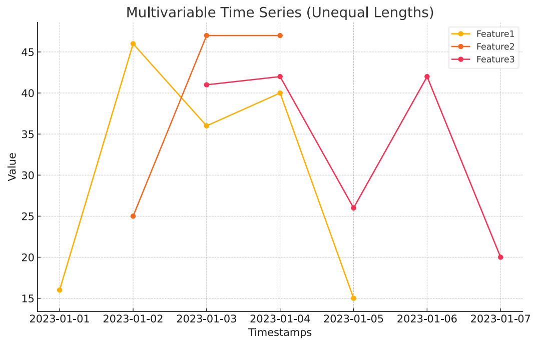


length ?

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 ?

Máster Deep Learning

Spacing

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

4h
4h
4h
4h

Evenly spaced

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**

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

Non evenly spaced

Papel y boli

?

Máster Deep Learning

Papel y boli

- Parte 1:
  - Pregunta evaluable: longitud del dataset del gato
  - Dibujar dos series temporales univariables (una estacionaria y otra no)
    - Pregunta evaluable: longitud de la serie temporal
    - Pregunta evaluable: estacionareidad
  - Dibujar serie temporal multivariable con las mismas longitudes
  - Dibujar serie temporal multivariable con distintas longitudes

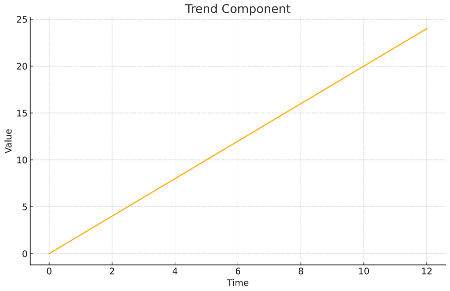
Classical (additive) decomposition

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

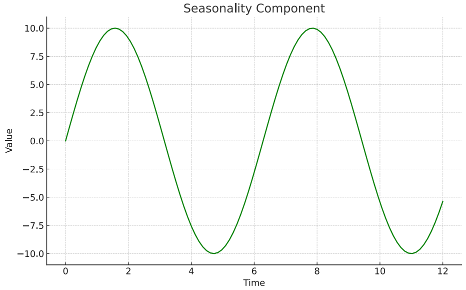
- x(t): time series “x” data at index position “t”
- T: trend component.
- S: seasonality component
- I: Irregular/noise/random component

Máster Deep Learning

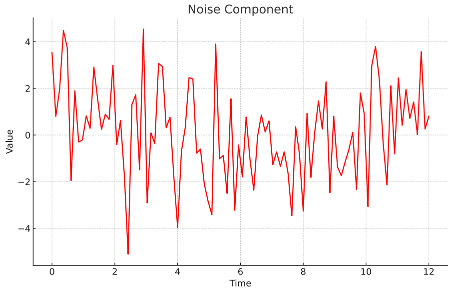
Classical (additive) decomposition



+



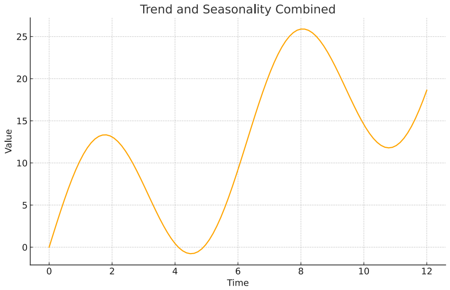
+



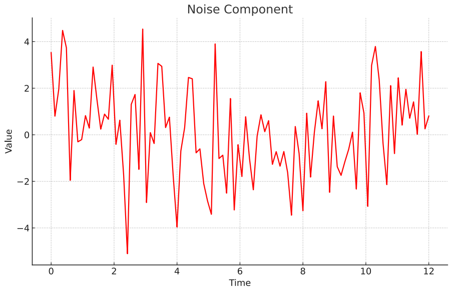
T S I

Máster Deep Learning

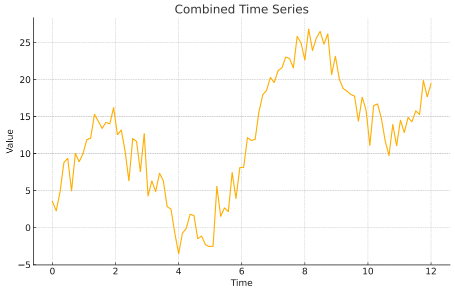
Classical (additive) decomposition



+



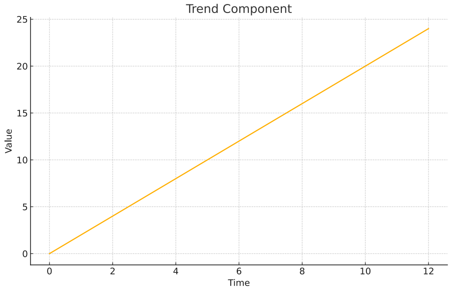
=

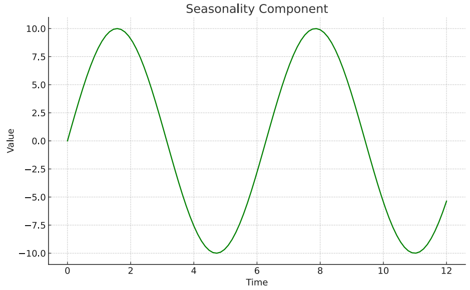


T+S

I

X(t)





Google Collab

01_Introduction_exercies.ipynb

?

Máster
Deep Learning

Google Collab

- Dar un código para generar series temporales con la descomposición clásica aditiva y pedir: (todas de largo 40)
  - Generar una serie temporal dada y explicar su estacionariedad o no.
  - Generar una serie temporal con:
    - Tendencia ascendente y sin ruido, con seasonalidad repetida cada 10 índices
    - Estacionaria respecto a la media

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

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

UNIVERSIDAD POLITÉCNICA DE MADRID

POLITÉCNICA

Máster Deep Learning