Deep Learning para series temporales

Part II

Preprocessing and Analysis

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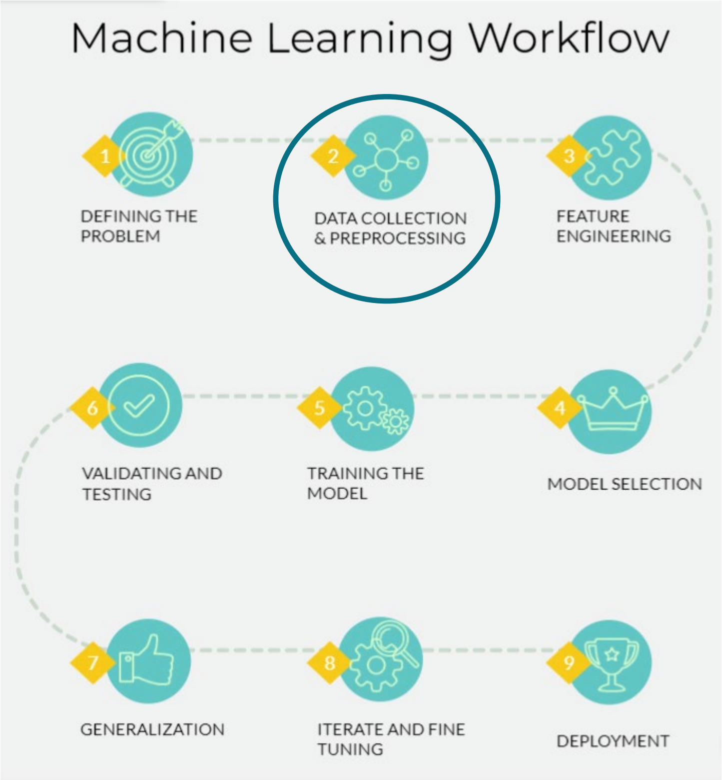
Contents

ETL

Preprocess the data

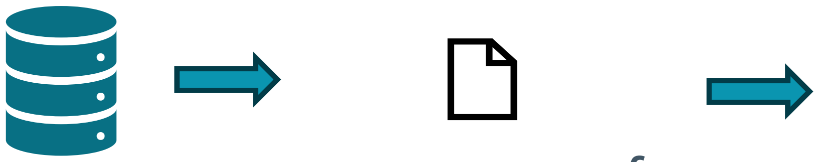
ML Workflow



https://www.linkedin.com/pulse/data-collection-preprocessing-dr-john-martin-5kj3f/

ETL (Extract + Transform + Load)

- Extract



.csv, .txt, .tsf

DataFrame

ETL (Extract + Transform + Load)

- Transform

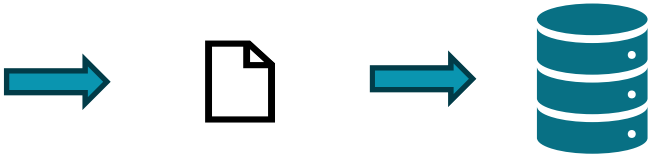
DataFrame & ndarray

Analyze ⇄ Transform as needed

ETL (Extract + Transform + Load)

- Load

DataFrame



Extract

Get & Open de data

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Extract

- **Files**: owned folder
- **Database**: SQL, Cassandra, MongoDB, PostgretSQL, Weight and Biases
- **Specific webpages**: Kaggle, zenodo, INE, HuggingFace
- **Other's datasets**: Github, GoogleDrive, e-mail, personal webpage

Extract

- Extract

Extract

In this step we want to get a first touch with the time series data

- Take a look to the file… What types of data does the file contains? What variables do we want to analyze?
- Take a look to the variables, plot them
  - Problems with the scale? Fix it if the variates are in different scales so you can read the information correctly.
- Take a profile from the data to get a little nearer to its information.

Extract

Let's take a look to the following dataset:

https://www.kaggle.com/datasets/uysalserkan/fault-induction-motor-dataset

- Take a look to the file... What types of data does the file contains? What variables do we want to analyze?

Extract

The database is composed by several CSV (Comma-Separated Values) files, each one with 8 columns, one column for each sensor, according to:

- **Col 1**: tachometer signal that allows to estimate rotation frequency
- **Cols 2-4**: underhang bearing accelerometer (axial, radiale tangential direction)
- **Cols 5-7**: overhang bearing accelerometer (axial, radiale tangential direction)
- **Col 8**: microphone

Extract

Se lleva un rato la descarga, dejarles en algún enlace público que puedan hacer wget un 20% del dataset...

Al variables are double, so we can analyze of all them

Dataset
To begin we need a dataset to have an available time series.

Activity 1:

Step 1: Download the MetroPT3 dataset
https://archive.ics.uci.edu/dataset/791/metropt+3+dataset

Step 2: Create a jupyter notebook to begin working

Step 3: Use pandas to load

```
import pandas as pd
pd.read_csv('MetroPT3(AirCompressor).csv')
```

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Extract | EDA (Exploratory Data Analysis) | Plot

- Take a look to the variables, plot them
- Plot variables by group
- Plot the first variable of each group toguether
  - Problems with the scale? Fix it if the variates are in different scales so you can read the information correctly.
- Take a profile from the data to get a little nearer to its information.

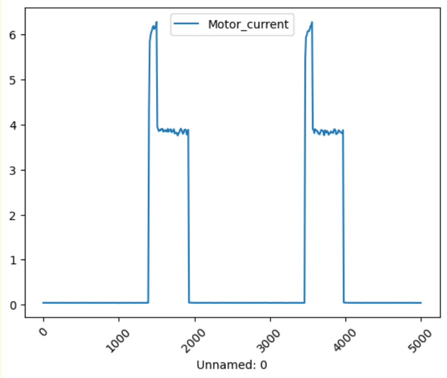
EDA

Visualize the information contained in the dataset

Activity 2:

Visualize a variable. Example for “Motor_current”.

```
ax = dataset.loc[:500].plot(x='Unnamed: 0',y='Motor_current')
ax.set_xticklabels(ax.get_xticklabels(), rotation=45)
```



Try other variables!

Extract | EDA | Profile

- Take a profile from the data to get a little nearer to its information.

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Extract | EDA | Analysis

- Check if the data is evenly spaced
- Take a look to the histogram
- Identify persistence with autocorrelation plot
- Use the lag plot to visualize autocorrelation
- Check periodogram plot
- Check pase plot
- Check calendar plots

--- Aquí no entiendo la mitad. Revisar y poner paso a paso ---

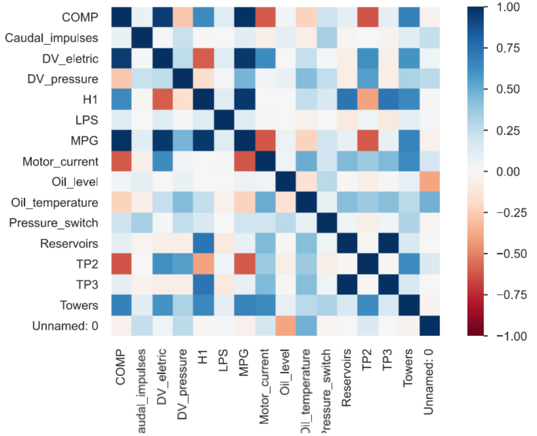
Data profiling

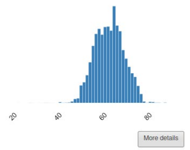
Time series can be examined through traditional EDA techniques

Activity 3:

Install and run ydata_profiling

```
!pip install ydata_profiling
from ydata_profiling import ProfileReport
profile = ProfileReport(dataset.sample(10000))
profile.to_file('report.html')
```





Oil_temperature
Real number (ℝ)

Distinct	1216	Minimum	21.4
Distinct (%)	12.2%	Maximum	88.1
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	62.656032	Memory size	156.2 KiB

Statistics | Histogram | Common values | Extreme values

Quantile statistics

Minimum	21.4
5-th percentile	52.2
Q1	57.8
median	62.75
Q3	67.15
95-th percentile	73.6
Maximum	88.1
Range	66.7
Interquartile range (IQR)	9.35

Descriptive statistics

Standard deviation	6.5750331
Coefficient of variation (CV)	0.10493855
Kurtosis	0.24527593
Mean	62.656032
Median Absolute Deviation (MAD)	4.675
Skewness	-0.070206527
Sum	626560.32
Variance	43.231061
Monotonicity	Not monotonic

Transform

Analyze and preprocess the data

Transform | Example 1 | Non evenly -> 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

Transform | Example 1 | Non evenly -> 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

Units: h, min

Spaces:
4h | 3h 30 min **=** 240 m | 210 min

Greatest common divisor:

$$\gcd(240, 190) = \gcd(2^4 \cdot 3 \cdot 5, 2*3*5*7) =$$
$$= 2*3*5 = 30$$

=> The biggest space we can use to fit both space sizes is **h = 30 min**

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Transform | Example 1 | Non evenly -> evenly spaced

Time	Available food (grs)	Time	Available food (grs)	Time	Available food (grs)	Time	Available food (grs)
07:00 AM	**100**	10:00 AM	**Unknown**	01:10 PM	**Unknown**	04:00 PM	**Unknown**
07:30 AM	**Unknown**	10:30 AM	**Unknown**	01:30 PM	**Unknown**	04:30 PM	**Unknown**
08:00 AM	**Unknown**	11:00 AM	**50**	02:00 PM	**Unknown**	05:00 PM	**Unknown**
08:30 AM	**Unknown**	11:30 AM	**Unknown**	02:30 PM	**Unknown**	05:30 PM	**Unknown**
09:00 AM	**Unknown**	00:00 AM	**Unknown**	03:00 PM	**0**	06:00 PM	**Unknown**
09:30 AM	**0**	00:30 PM	**Unknown**	03:30 PM	**Unknown**	06:30 PM	**100**

Evenly spaced 30 min

Transform | Example 1 | Non evenly -> evenly spaced

Time	Available food (grs)	Time	Available food (grs)
07:00 PM	**Unknown**	10:30 PM	**Unknown**
07:30 PM	**Unknown**	10:30 PM	**Unknown**
08:00 PM	**Unknown**	11:00 PM	**0**
08:30 PM	**Unknown**		
09:00 PM	**100**		
09:30 PM	**50**		

Length:

Evenly spaced 30 min

Transform | Example 1 | Non evenly -> evenly spaced

Time	Available food (grs)	Time	Available food (grs)
07:00 PM	**Unknown**	10:30 PM	**Unknown**
07:30 PM	**Unknown**	10:30 PM	**Unknown**
08:00 PM	**Unknown**	11:00 PM	**0**
08:30 PM	**Unknown**		
09:00 PM	**100**		
09:30 PM	**50**		

Evenly spaced 30 min

Length:

7AM -> 11 AM => 16 h

=> 32 timestamps of 30 min

Length: 32

How do we apply this change in python?

?

Transform | Example 1 | Non evenly -> evenly spaced

- Create an pd.DataFrame with index
- Add the previous data to its position within the index

Now we got the evenly spaced...
What problem do we have?

?

Transform | Example 1 | What problem do we have?

- We have a lot of "unknown" values.
- What will pandas have done with them at creating the dataset?
- How can we control the value in those place?
- In this case, … do we know the values?
- What about the multivariate version... could we fill any of the columns with real data based on the known information?

Missing data - Imputation

Transform | Example 1 | Missing data - Imputation

- In the multivariate version, in the column "Refilled food (grs)" we know exactly the hours we filled the bowl, thus we can just use '0' at the unknown timestamps.

- In the 'Eaten food (grs)' or 'Available food (grs)' we don't know if the cat have eaten between timestamps, so, we must take a decision.

Transform | Missing data - Imputation

Definition: Imputation

Replacing missing values (MVs) with an arbitrary value to fill the empty timestamps.

The most similar to the real time series, the better we are doing.

Transform | Missing data - Imputation

- Use 'NaN' in the unknown positions.
- Constant (eg. use '0' for the unknown positions).
- Statistics: Mean/mode/median of the time series.

Transform | Missing data - Imputation

- Use 'NaN' in the unknown positions.
  - The same as doing nothing
- Constant (eg. use '0' for the unknown positions).
  - Usually skews the value distribution
- Statistics: Mean/mode/median of the time series.
  - Bad for high variance variables

Transform | Missing data - Imputation

- LOCF: Last Observation Carried Forward (makes sense?)
- NOCB: Next Observation Carried Backward (makes sense?)
- Rolling statistics: mean/mode/median across a *time window*

Transform | Missing data - Imputation

- LOCF: Last Observation Carried Forward (makes sense?)
  - Biases the time series if non-stationary
- NOCB: Next Observation Carried Backward (makes sense?)
  - Same as LOCF
- Rolling statistics: mean/mode/median across a *time window*
  - Adjusting window size is non-trivial, bad for large MV gaps

Transform | Missing data - Imputation

- Lineal interpolation
- Spline (polynomical) interpolation
- Additive/multiplicative/mixed decomposition

Transform | Missing data - Imputation

- Lineal interpolation
  - Assumes linearity in observations
- Spline (polynomical) interpolation
  - Assumes the variable is smooth without many perturbations
- Additive/multiplicative/mixed decomposition
  - Assumes non-relevant noise

Transform | Missing data - Imputation

- IA – based (Imputation): RNN, K-NN, Miss Forest
  - Much more computionally expensive than the alternatives
- Other methods:
  - Regression
  - Multiple imputation: create various imputated dataset and combine them in some way
  - Inverse probability weighting
  - ARIMA/SARIMA: approximate through statistics
  - Matrix completion

Transform | Missing data - Definitions

Definition: missing data

Missing value related to a timestamp in a timeseries.

Transform | Missing data - Definitions

Definition: Types of missing data

Missing

- **Completely at random (MCAR)**
  - Random positions
- **At random (MAR):**
  - Random distribution related to other variable values
- **Not at random (MNAR):**
  - Related to events

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Transform

- LOCF: Last Observation Carried Forward (makes sense?)
  - Biases the time series if non-stationary
- NOCB: Next Observation Carried Backward (makes sense?)
  - Same as LOCF
- **Rolling statistics**: mean/mode/median across a ***time window***
  - Adjusting window size is non-trivial, bad for large MV gaps

Time window

Transform | Time window | Subsequence

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Definition: Subsequence

If $x^m = \{x_0, \ldots, x_m\}$ is a time series, a time window is a subsequence

$$x^{(k,n)} = \left\{x_{t_k}, \ldots, x_{t_{k+n-1}}\right\}$$

$$k, n > 0; \; k + n - 1 < m$$

Transform | Time window | Subsequence II

Definition: Subsequence II

If $x: [1, m] \cap (\mathbb{N} \cup \{0\}) \rightarrow \mathbb{R}$ is a time series, a time window is a restriction

$$x\Big|_{[k,n]\cap(\mathbb{N}\cup\{0\})}$$

$$k, n \ > \ 0; \ k + n - 1 \ < \ m$$

Transform | Time window | Time window

Definition: Time window

A time window is a subsequence of a time series, typically smaller in relation to the length of the series, used to compute derived features or perform analyses on the series.

Commonly, these extra features allow us to better understand patterns within the time series.

Extra feature: rolling mean, mean of two variates

Feature == variate

Transform | Time window | Classification
Sliding window |

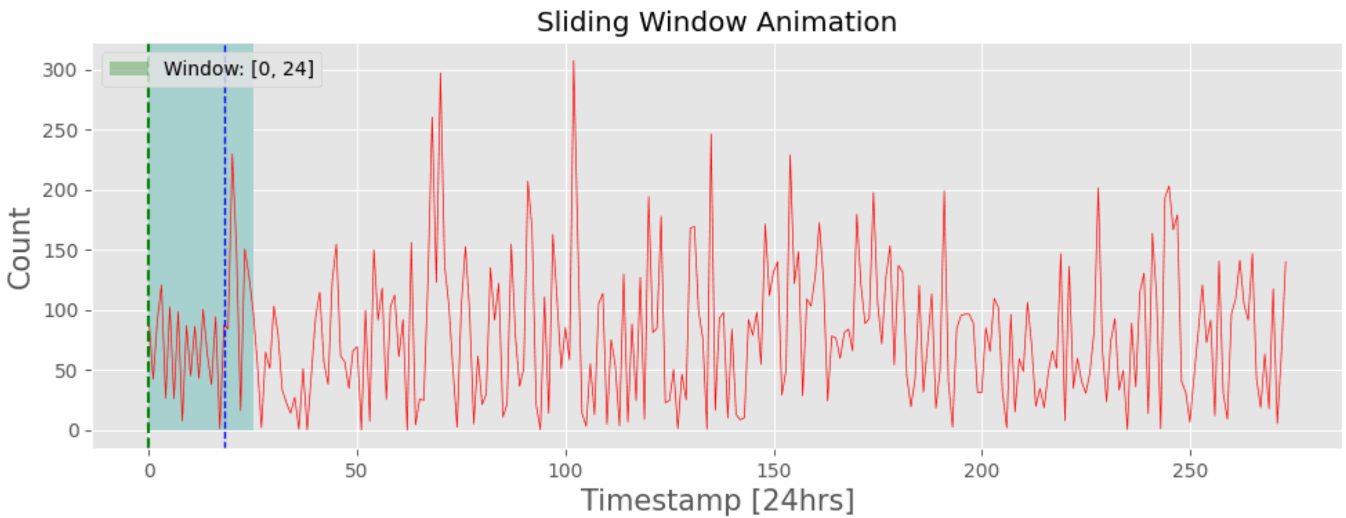
- Sliding window
- Tumbling window
- Rolling window
- Expanding window

Transform | Time window | Classification
Sliding window |

- **Sliding window**
  - $\{x^{(k+i \cdot stride, n)} \mid i \in \left[0, \frac{m-n-k}{stride}\right]\}$
  - **Fixed-size** window that moves through the time series in **steps** of an specific given ‘**stride**’ size.
  - ARIMA, AI-based (MVP)
- Tumbling window
- Rolling window
- Expanding window

Transform | Time window | Classification
Sliding window II

- Data: [1,2,3,5,8,13, …]
- Stride: 6 | m = 25

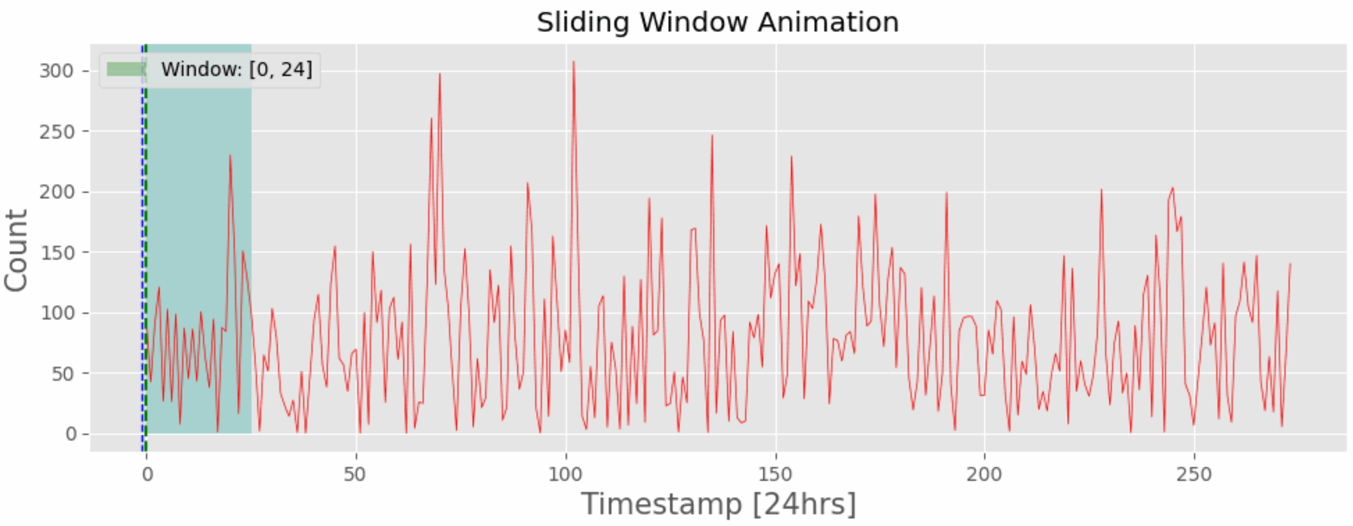


k	Timestamps (train)
0	$\{t_0, t_1, \dots, t_{24}\}$
1	$\{t_6, t_7, \dots, t_{30}\}$
2	$\{t_{12}, t_{13}, \dots, t_{36}\}$
3	$\{t_{18}, t_1, \dots, t_{42}\}$
4	$\{t_{24}, t_1, \dots, t_{48}\}$

https://stackoverflow.com/questions/76836503/how-can-reproduce-animation-for-rolling-window-over-time

Transform | Time window | Classification
Sliding window III

- Data: [1,2,3,5,8,13, ...]
- Stride: 25 | m = 25

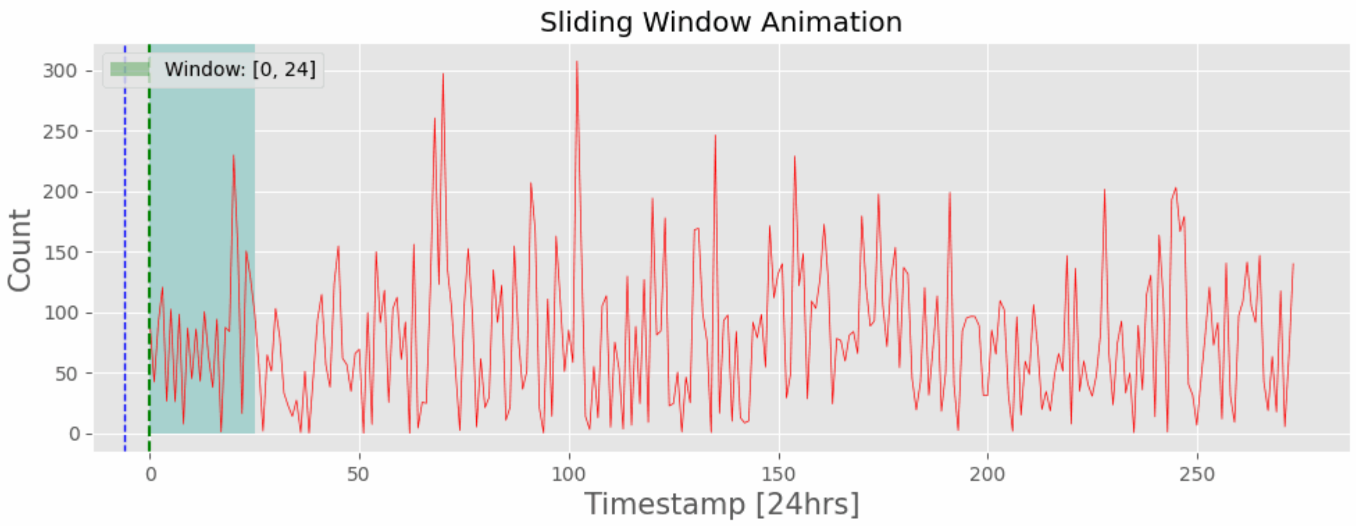


k	Timestamps (train)
0	$\{t_0, t_1, \dots, t_{24}\}$
1	$\{t_6, t_7, \dots, t_{30}\}$
2	$\{t_{12}, t_{13}, \dots, t_{36}\}$
3	$\{t_{18}, t_1, \dots, t_{42}\}$
4	$\{t_{24}, t_1, \dots, t_{48}\}$

https://stackoverflow.com/questions/76836503/how-can-reproduce-animation-for-rolling-window-over-time

Transform | Time window | Classification
Sliding window IV

- Data: [1,2,3,5,8,13, …]
- Stride: 30 | m = 25



k	Timestamps (train)
0	$\{t_0, t_1, \dots, t_{24}\}$
1	$\{t_6, t_7, \dots, t_{30}\}$
2	$\{t_{12}, t_{13}, \dots, t_{36}\}$
3	$\{t_{18}, t_1, \dots, t_{42}\}$
4	$\{t_{24}, t_1, \dots, t_{48}\}$

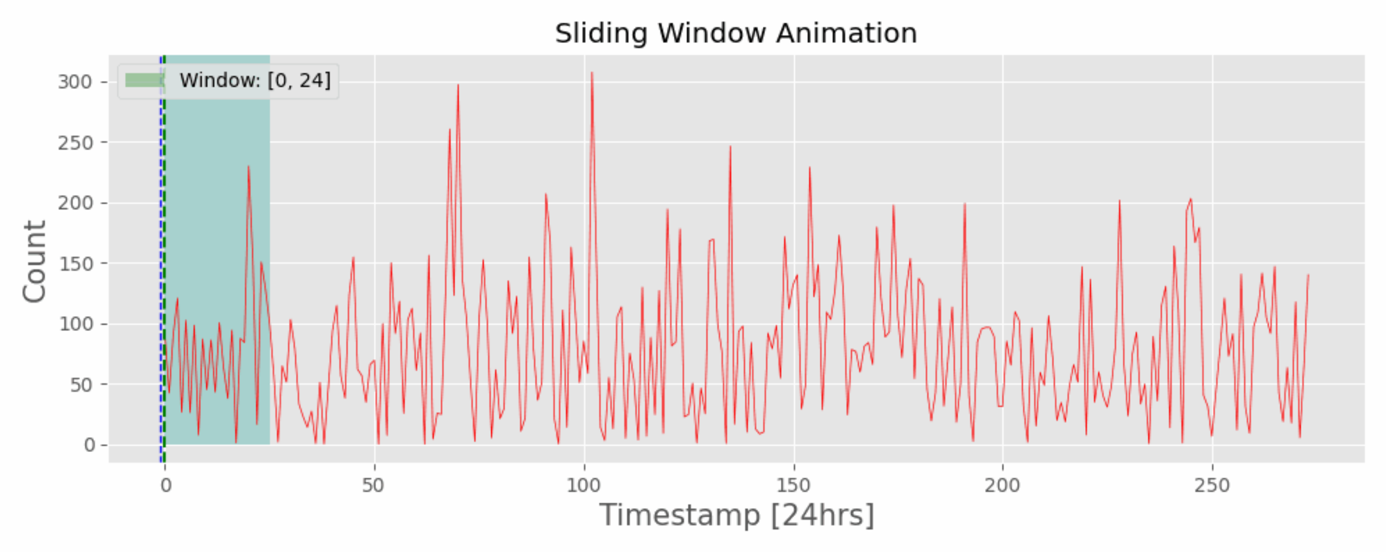
https://stackoverflow.com/questions/76836503/how-can-reproduce-animation-for-rolling-window-over-time

Transform | Time window | Classification
Sliding window VI: Tumbling window I

- **Sliding window**
- **Tumbling window**
  - $\{x^{(k+i\cdot stride,n)} \mid i \in \left[0, \frac{m-n-k}{stride}\right]\}, n = stride$
  - $\{x^{(k+i\cdot n,n)} \mid i \in \left[0, \frac{m-k}{n} - 1\right]\}$
  - **Fixed-size** window that moves through the time series in **steps** of an specific given 'stride' size.
- Rolling window
- Expanding window

Transform | Time window | Classification
Sliding window VII: Tumbling window II

- Data: [1,2,3,5,8,13, …]
- Stride: 25 | m = 25



k	Timestamps (train)
0	$\{t_0, t_1, \ldots, t_{24}\}$
1	$\{t_6, t_7, \ldots, t_{30}\}$
2	$\{t_{12}, t_{13}, \ldots, t_{36}\}$
3	$\{t_{18}, t_1, \ldots, t_{42}\}$
4	$\{t_{24}, t_1, \ldots, t_{48}\}$

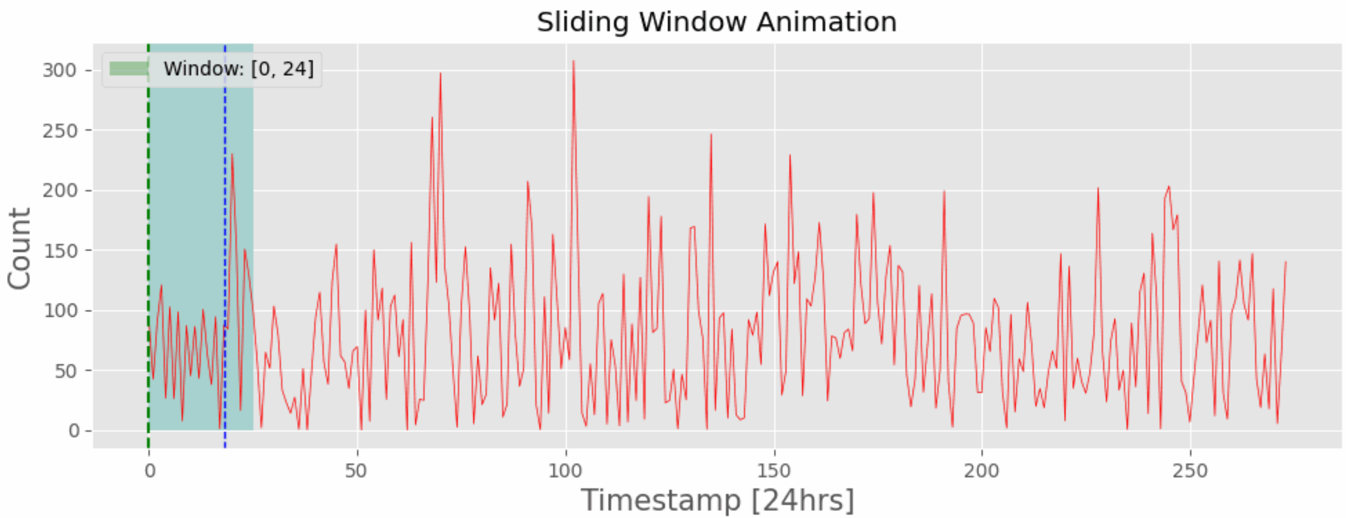
https://stackoverflow.com/questions/76836503/how-can-reproduce-animation-for-rolling-window-over-time

Transform | Time window | Classification
Sliding window VII: Rolling window I

- **Sliding window**
- Tumbling window
- **Rolling window**
  - $\{x^{(k+i\cdot stride,n)} \mid i \in \left[0, \frac{m}{stride} - n - k + 1\right]\}, stride < n$
  - Sliding window with overlap: each window includes part of the previews window
  - Rolling statistics (rolling mean), time series smoothing
- Expanding window

Transform | Time window | Classification
Sliding window VIII: Rolling window II

- Data: [1,2,3,5,8,13, …]
- Stride: 6 | m = 25



k	Timestamps (train)
0	$\{t_0, t_1, \dots, t_{24}\}$
1	$\{t_6, t_7, \dots, t_{30}\}$
2	$\{t_{12}, t_{13}, \dots, t_{36}\}$
3	$\{t_{18}, t_1, \dots, t_{42}\}$
4	$\{t_{24}, t_1, \dots, t_{48}\}$

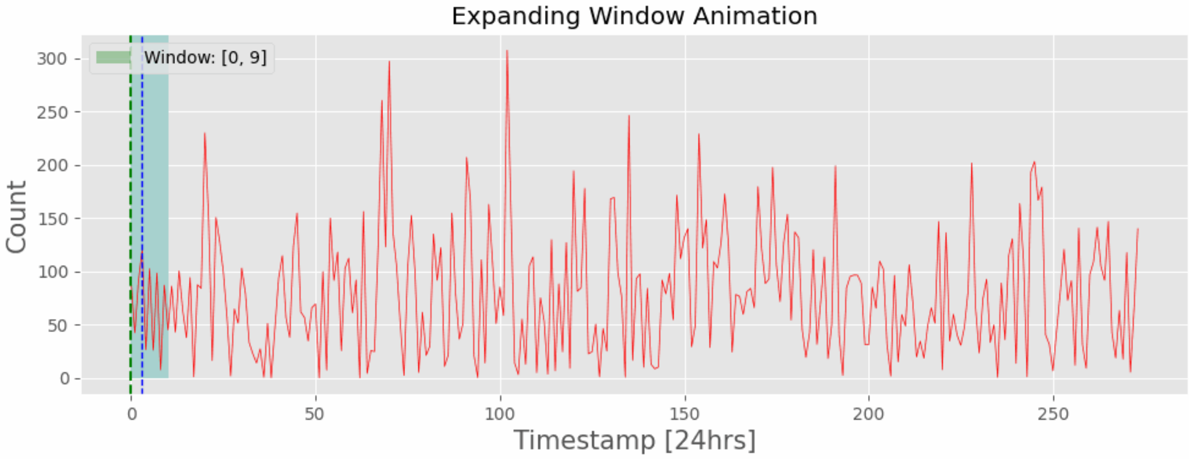
https://stackoverflow.com/questions/76836503/how-can-reproduce-animation-for-rolling-window-over-time

Transform | Time window | Classification
Expanding window I

- Sliding window
- Tumbling window
- Rolling window
- **Expanding window**
  - $\{x^{(k,n+i\cdot\Delta)} \mid i \in \left[0, \frac{m-n-k}{\Delta}\right]\}$
  - Each window expands the previous one a Δ size.
  - Financial forecasting, cumulative statistics

Transform | Time window | Classification
Expanding window II

- Data: [1,2,3,5,8,13, …]
- Delta: 6 | m = 25



k	Timestamps (train)
0	$\{t_0, t_1, \dots, t_9\}$
1	$\{t_0, t_1, \dots, t_{15}\}$
2	$\{t_0, t_1, \dots, t_{21}\}$
3	$\{t_0, t_1, \dots, t_{27}\}$
4	$\{t_0, t_1, \dots, t_{33}\}$

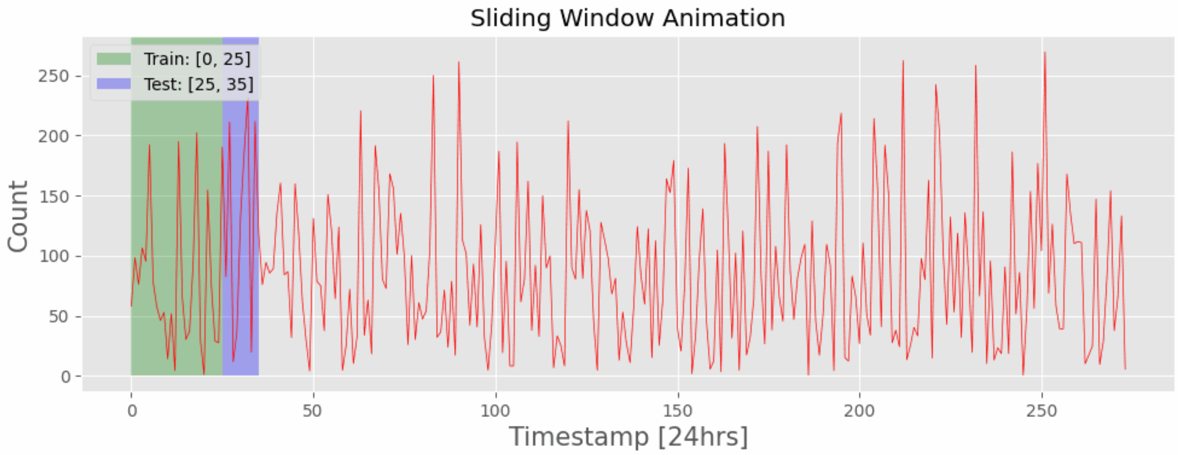
https://stackoverflow.com/questions/76836503/how-can-reproduce-animation-for-rolling-window-over-time

If we are splitting the dataset for a AI model into train + test +validation. How should the preprocessing look look like?

?

Transform | Time windows | AI-based methods

- Data: [1,2,3,5,8,13, …]
- Stride: 6 | m_train = 25 | m_test = 10



k	Timestamps (train)	Timestamps (test)
0	$\{t_0, t_1, \dots, t_{24}\}$	$\{t_{25}, t_{26}, \dots, t_{34}\}$
1	$\{t_6, t_7, \dots, t_{30}\}$	$\{t_{31}, t_{32}, \dots, t_{40}\}$
2	$\{t_{12}, t_{13}, \dots, t_{36}\}$	$\{t_{37}, t_{38}, \dots, t_{46}\}$
3	$\{t_{18}, t_1, \dots, t_{42}\}$	$\{t_{43}, t_{44}, \dots, t_{52}\}$
4	$\{t_{24}, t_1, \dots, t_{48}\}$	$\{t_{49}, t_{50}, \dots, t_{58}\}$

https://stackoverflow.com/questions/76836503/how-can-reproduce-animation-for-rolling-window-over-time

Activity 4:

Step 1: We need missing values to impute

```
mv_dataset = dataset.mask(np.random.random(dataset.shape) < .01, other=pd.NA)
```

Step 1.5: Plot the variable with missing values

Step 2: Rolling mean imputation

```
mv_dataset['Oil_temperature'].fillna(mv_dataset['Oil_temperature'].rolling(window=100).mean())
```

Step 3: Compare the variable with/ without missing values

Is this impute method adequate? Why?

Making data “similar”

Transform | Making similar

Having similar data in terms of

- Scale (range of values)
- Distribution

makes easier reducing the data with both classical an AI techniques

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Transform | Making similar | Normalization

- **Normalization / Min-max scaling**
  - Scale values to an specific range $[r_{min}, r_{max}]$
  - Used for having same scale in all data.
  - Used when the features have different scales and no specif distribution is needed
    - RRNN, k-NN

Transform | Making similar | Normalization

- **Normalization**
  - $[0,1] \rightarrow x_{norm} = \frac{x - \min(x)}{\max(x) - \min(x)}$
  - $[-1,1] \rightarrow x_{norm} = 2 \cdot \frac{x - \min(x)}{\max(x) - \min(x)} - 1$
  - $[0,1] \rightarrow x_{norm} = (r_{max} - r_{min}) \cdot \frac{x - \min(x)}{\max(x) - \min(x)} + r_{min}$

Transform | Making similar | Standarization

- **Standarization**
  - Fix value to have mean = 0 and standard deviation = 1
  - Used for having same mean and deviation in all features
  - Used when data must follow a normal distribution
    - SVM – Support Vector Machine
    - PCA – Principal Component Analysis
    - Logistic regression

Máster Deep Learning

Transform | Making similar | Other

- **Robut scaling**: using percentile values
  - $x_{scaled} = \frac{x-Q1}{Q3-Q1}$
  - Less affected by outliers
- **Logaritmic scaling**: logarithm
  - $x_{scaled} = \log(x+1)$
  - Large differences in scale (economics)

Transform | Making similar | Other

- **Quantile normalization**: align different distribution quantiles
- Steps:
    - Order values from upper to lwer
    - Compute the mean of each position of the quantile
    - Replace values by the mean
  - Bioinformatics, genetics

Transform | Making similar | Other scaling

A	B
5	7
8	6
12	10

pos	A
0	5
1	8
2	12

pos	B
0	6
1	7
2	10

pos	mean
0	5,5
1	7,5
2	11

A	B
5,5	7,5
7,5	5,5
11	11

Transform | Making similar | Other

- **MaxAbs scaling**: scale by absolute máximum per feature
- Scales in [-1,1]
- $x_{scaled} = \frac{x}{\max(|x|)}$
- Useful for:
  - Data with positive and negative models where wee need to preserve the sign: finances
  - Models sensitive to relative magnitudes that do no require centering (e.g. mean = 0): Lasso, ElasticNets, NN
  - Sparse data. Does not alter the structure. Sparse matrices (Word frequencies)
  - Preserve relative proportions: signal processing

Transform | Making similar | Other

- **Rolling <...>**
  - Make the operation within sliding windows
- **Expanding <...>**
  - Make the operation withing expanding windows
- **Seasonal <...>**
  - Makes the operation for specific time sizes (eg. yearly)

Stationarity, Seasonality and Trend

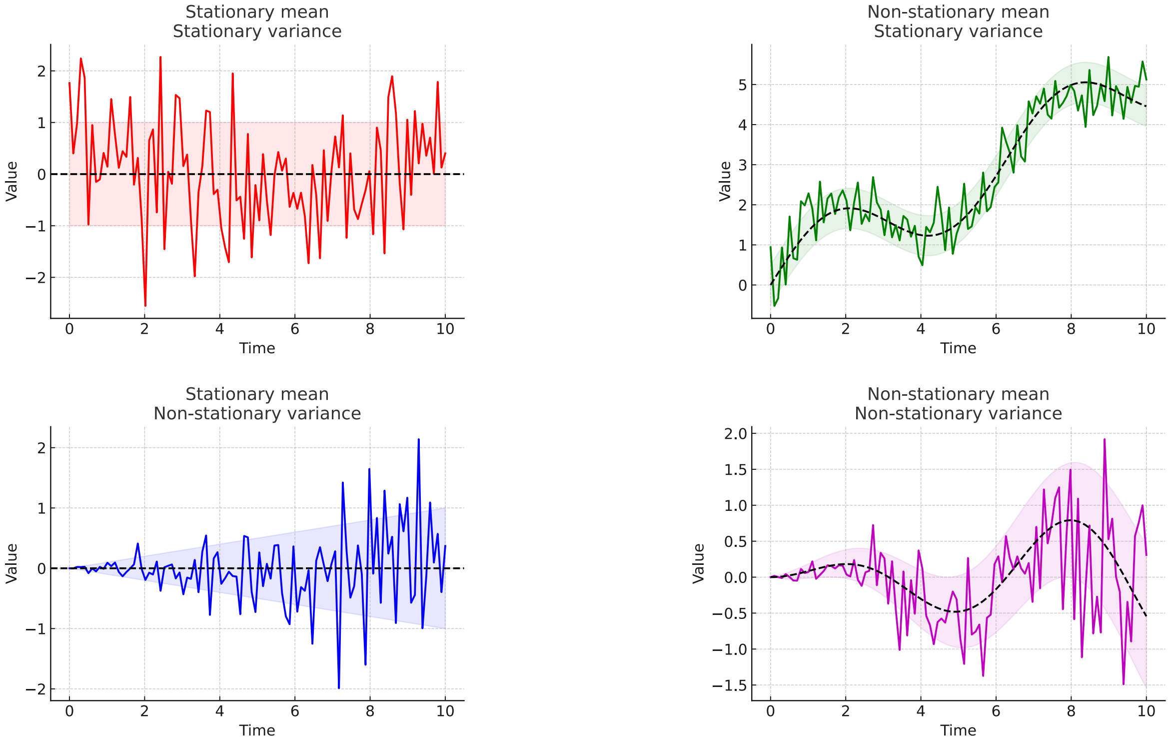
Transform | Stationarity

- **Qualitative**
  - Plot and check
- **Quantitative**
  - Get mean and standard deviation from random sliding windows
- **Statistical analysis**
  - Check through statistical analysis wether the time series is stationary or not

Transform | Stationarity

- **Qualitative**
  - Plot and check
- Quantitative
  - Get mean and standard deviation from random sliding windows
- Statistical analysis
  - Check through statistical analysis wether the time series is stationary or not

Transform | Stationarity | Qualitative



Transform | Stationarity

- Qualitative
  - Plot and check
- **Quantitative**
  - Get mean and standard deviation from random sliding windows
- Statistical analysis
  - Check through statistical analysis wether the time series is stationary or not

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Transform | Stationarity | Qualitative

- **Mean stationarity**
  - Look for trends: any upward/downward tren?
  - Non-stationary data often show a trend,
  - Stationary data fluctuates around a constant mean.
- **Variance stationarity**
  - Non-stationary data may show increasing or decreasing variance over time
- **Auxiliar plots:** use the time series decomposition to get the trend plot for easier analysis (if not that clear)

Transform | Quantitative

- Get mean and standard deviation from random sliding windows
  - Select representative window sizes: for example, computing Fourier predominant frequencies
  - Generate sliding window of those size in random positions
  - Compute mean and standard deviation

Transform | Quantitative

- If mean and deviation are ~constant between windows, the time series should be stationary
- Big changes between the values may indiquate seasonality, trends or non-variance-stationary

Transform | Stationarity

- Qualitative
  - Plot and check
- Quantitative
  - Get mean and standard deviation from random sliding windows
- **Statistical analysis**
  - Check through statistical analysis wether the time series is stationary or not

Transform | Statistical analysis

- **Augmented Dickey-Fuller (ADF) Test**
  - Tests for the presence of a unit root
- **Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test**
  - Tests for stationarity around a deterministic trend
- **Philips-Perron (PP) Test**
  - Similar to the ADF test, but adjusts for heteroscedasticity (variance on errors) and autocorrelation (dependency on past values) in the data.

Transform | Statistical analysis

- Key values:

Test	p-value < 0,05	Null hypothesis (H_0):	Alternative hypothesis
ADF Test	Stationary	Non-stationary	Stationary
KPSS Test	Non-stationary	Stationary	Non-stationary
PP Test	Non-stationary	Non-stationary	X

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Transform | Statistical analysis | Expanded table

Test	Purpose	Speed	Python module	Notes/Alternatives
ADF Test	Detect unit roots	Moderate	statsmodels	Fails for heteroscedastic data. Sensitive to lag selection.
KPSS Test	Check trend	Moderate	statsmodels	Often used alongside ADF to confirm stationary
PP Test	Adjusts for heterosedasticity	Fast	statsmodels	Similar to ADF but robust to serial correlation and heteroscedasticity
Perron Test	Multiple structural breaks	Slow	Limited external libraries	Best for datasets with complex strutural changes
Dickey-Fuller GLS (DF-GLS)	Improved ADF with Generalized Least Squares (GLS) detrending	Moderate	statsmodels	Powerfull with small sample sizes or data with trends
Hurst Exponent	Long-term memory or tren persistence	Moderate	hurst	Classifies Mean-reverting / random walk / Trending

Transform | Statistical analysis | Expanded table

Test	Purpose	Speed	Python module	Notes/Alternatives
ADF-GLS Test	Combines ADF with GLS	Moderate	statsmodels	Effective when trends are present but subtle
Wavelet Analysis	Examines stationarity at different scales	Slow	pywt (wavelet transforms)	Useful for non-stationarity signals with localized variation (e.g. seismic data)

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Transform | Statistical analysis | Summary

Test	When to use	Strengths	Notes/Alternatives
ADF/KPSS/PP	General stationarity testing	Widely used, well documented	Sensitive to parameter tuning
Wavelet Analysis	Non-stationary signals with localized changes	Handles multi-scale analysis	Computationally intensive
Hurst exponent	Long-term detection	Hihlights persistence or mean-reversion	Less robust for short time series
ADF-GLS Test	When trends are present but subtle	More powerfull for small sample sizes	Combines ADF with GLS detrending
Perron Test	Multiple structural breaks	Handles structural changes in data	Limited external libraries, slower compared to others

Transform | Trend

- Trends and seasonality can affect model's convergence and results, it may be beneficial to remove it. How?

Transform | Trend

Method	Definition
Differencing	Substracting the observations from a previous time period
Decomposition	Breaking down the series into tren, seasonality, and residual components
Moving averages	Average over a sliding window
Polynomial fitting	Fitting a polynomial curve to the data and substract it
Trend filters	Using statistical tool to detect/remove trends
Log transformations	Applying logarithmic functions to remove exponential growth
Box-Cox transformations	Applying power transformations (mathematical transformations) to stabilize variance and make trends linear.

Transform | Trend

Method	Advantages	Disadvantages
Differencing	Simple, effective for removing trends	Can amplify noise; may lose interpretability of the data
Decomposition	Separate components clearly	Requires assumptions about the model (additive/multiplicative/mixed)
Moving averages	Smooths fluctuations, reduce noises	May remove important short-term patterns
Polynomial fitting	Handles non-linear trends effectively	Risk of overfitting; higher-degree polinomials can distort data
Trend filters	Effective for extracting smooth trends	Can be computionally expensive; parameters need fine-tuning
Log transformations	Stabilizes variance, simplifies multiplicative relationships	Non suitable for data with <= 0 values
Box-Cox transformations	Handles both tren and variance issues	Requires non-negative data; interpretation of transformed data is harder

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Transform | Trend

Method	Recommendations
Differencing	When trends are linear and the data is heavily autocorrelated
Decomposition	Ideal for datasets with clear seasonality or multiple components
Moving averages	Best for smooting noise in non-seasonal series with light trends
Polynomial fitting	Use for series with non-linear trends; limit polynomial degree to avoid overfitting
Trend filters	Use for economic or financial data with noisy trends
Log transformations	Use for exponential growth trends (e.g. population, financial data)
Box-Cox transformations	Use for data with heteroscedasticity and exponential trends

Transform | Seasonality

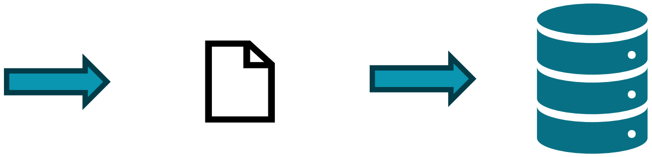
- Detect a seasonality period -> Remove seasonality
- Steps:
  - Plot the data: check the period of your target variable
  - Identify pattern period: hourly, daily, weekly
  - Treat seasons are ‘cyclical trends’
    - Differentiating: remove the value from a <insert detected period> before
    - Polynomial fitting: Fit a polynomial on a given season, later substract it from each <insert detect period>.

Load

Save the data

Load

DataFrame



Load

- **Files**: owned folder
- **Database**: SQL, Cassandra, MongoDB, PostgretSQL, Weight and Biases
- **Specific webpages**: Kaggle, zenodo, HuggingFace
- **Own datasets**: Github, GoogleDrive, personal webpage

Miscelaneous

Auxiliar material

Further reading

- Research paper: Survey: Time-series data preprocessing: A survey and an empirical analysis
- Example I: IMSL
- Example II: Medium
- Example III: Kaggle
- Example IV: Advanced missing data reconstruction. UCO: Time series data mining: preprocessing, analysis, segmentation and prediction. Applications
- Example V: Linkedin schema
- Example VI: Linkedin | Dr. John Martin – AI | ML | Newsletter

Further reading

- Paper | Missing data: A comparison of three popular methods of handling missing data: complete-case analysis, inverse probability weighting, and multiple imputaiton
- OpenAccess paper: Recurrent Neural Networks for Multivariate Time Series with Missing Values
- Light lectura on ADF: Machine Learning Plus
- Original paper of ADF: Rizwan Mushtaq

Practice datasets

- Tourism: Tourists night stances in Tenerife
- Normalization and standarization example: Machine Learning Mastery

Google Collab

02_preprocessing.ipynb

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Summary

Summary of the lesson

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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

02_preprocessing_exercises.ipynb

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What is the next step?

- Start with Deep Learning!
- Time series classification
  - How can we compare two time series and put them inside a cattegory?

To be continued...

Questions? mi.santamaria@upm.es

Deep Learning para series temporales

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Part II

Preprocessing and Analysis