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SNAP4CITY

KM4CITY

Time Series Forecasting 4 Smart City Applications

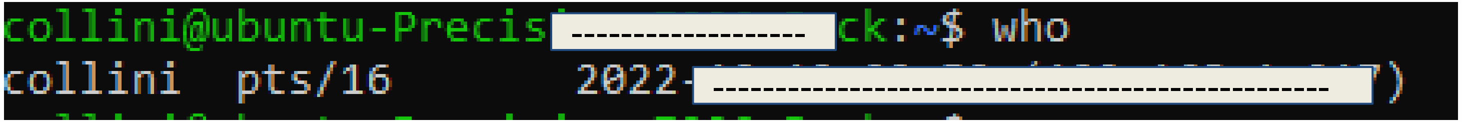
Enrico Collini

Lecture Schedule (with me)

- 8/11 (Today!)
  - Time Series Basics
  - Road to Time Series Forecasting
  - Deepening into Time Series Preparation for AI
    - Short-Term Prediction of Bikes Availability on Bike-Sharing Stations
    - Long Term Predictions of Yearly NO2 in the Florence Metropolitan Area
    - Short-Term Prediction of City Vehicle Flow via Convolutional Deep Learning
- 22/11 …:
  - **Workshop Hands On Data Analytics using Snap4City in Python!**
  - Retreive Data from Snap4City Open APIs
  - Data Analytic Node-Red Python Container
  - Data Analytics MyKpi + Monitoring Dashboard

Node-RED

python™



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collini@ubuntu-Precis[redacted]ck:~$ who
collini   pts/16        2022-[redacted])
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almost 2 years

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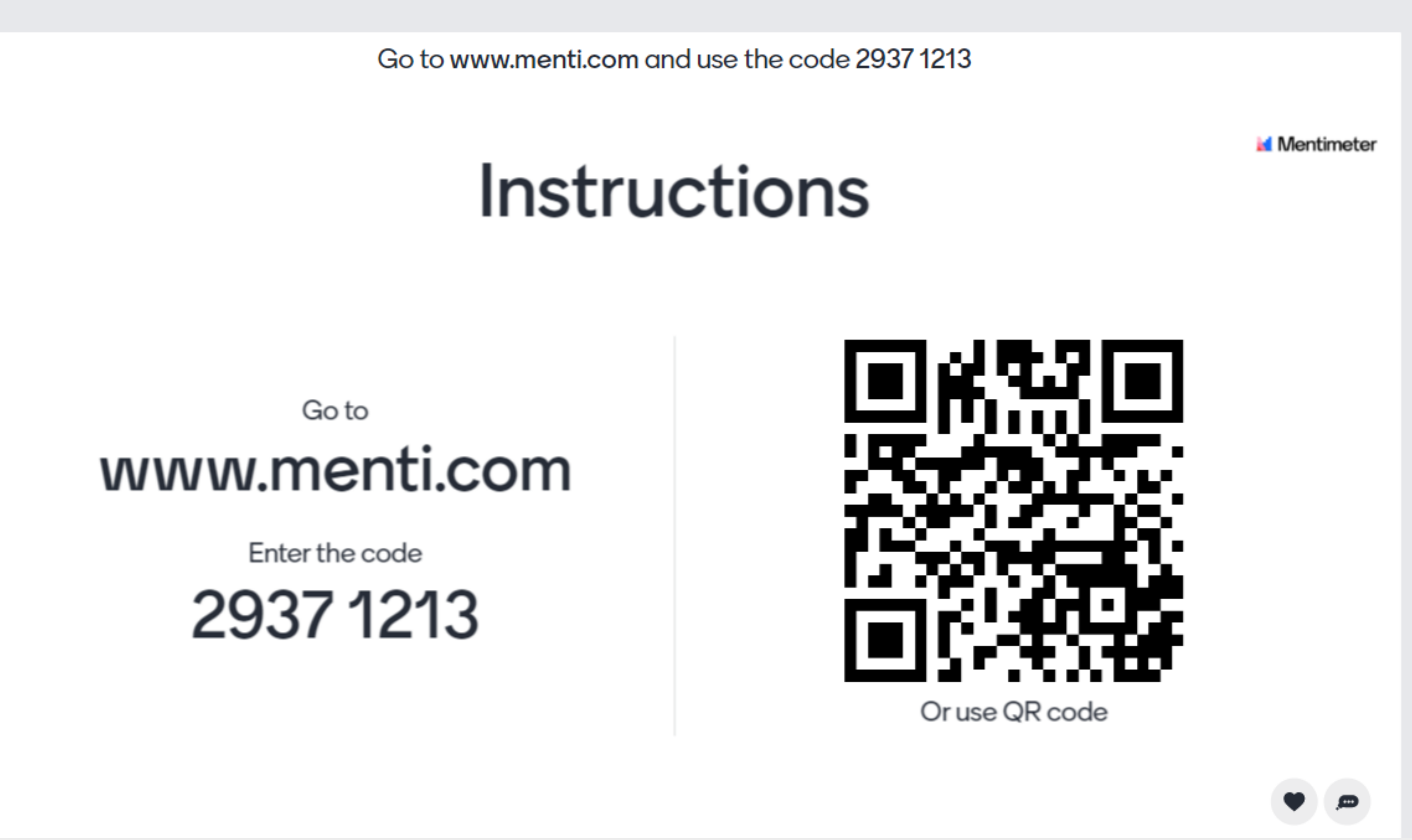
Enrico Collini

AI Smart City solutions Research Fellow at Distributed System and Internet Technologies Lab (DISIT), Università Degli Studi di Firenze

start 2nd year

UNIVERSITÀ DI PISA

DOTTORATO NAZIONALE IN INTELLIGENZA ARTIFICIALE



Go to www.menti.com and use the code 2937 1213

Instructions

Go to

www.menti.com

Enter the code

2937 1213

Or use QR code

Time Series Basics

- What is time series Data?
- What can you do with time series analysis (TSA)
- Stepladder to conduct a great time series analysis… with examples

What is Time Series Data

- A collection of observations obtained through repeated measurements of time

- Each instant represents a **timestep**
  - Days - Hours - Minutes

    ! this defines the time-granularity

- And the **attributes** are the values associated with that time

Quiz!

Introduced the definition of Time-Series Data what example comes into your mind of this type of data?

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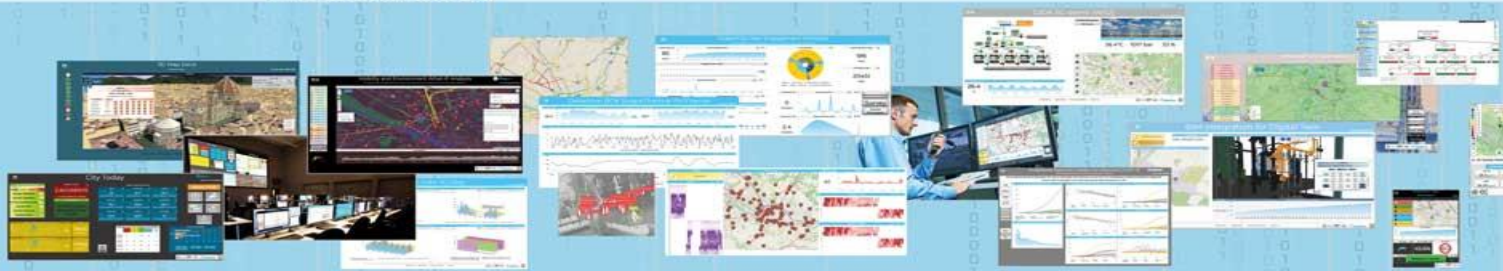
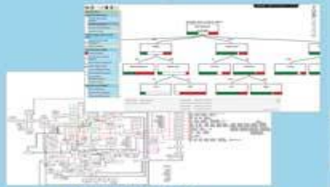
www.snap4city.org

Tools for rapid implementation of sustainable Smart Solutions and Decision Support Systems



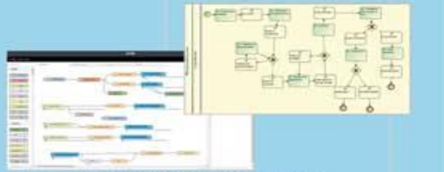
DASHBOARDS AND APPS - CONTROL ROOMS - DECISION SUPPORT SYSTEMS - WHAT-IF ANALYSIS - VISUAL ANALYTICS

PREDICTION - ANOMALY DETECTION - ENVIRONMENTAL MODEL - 3D MODEL
KPI - SIMULATION - EARLY WARNING - SYNOPTIC - DIGITAL TWIN - VIRTUAL REALITY

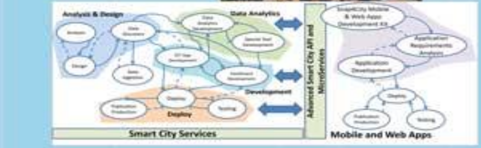


EXPERT SYSTEM
KNOWLEDGE BASE
STORAGE

BIG DATA ANALYTICS
EXPLAINABLE ARTIFICIAL INTELLIGENCE
BUSINESS INTELLIGENCE
MACHINE LEARNING



DATA FLOWS, DATA DRIVEN
WORKFLOWS, MICROSERVICES
PARALLEL DISTRIBUTED PROCESSING



METHODOLOGIES
LIVING LABS
COURSES AND COMMUNITY
DEVELOPMENT TOOLS

BEEP
BEEP

POLLUTION
ECOLOGY

Time Series Data - continued

- Are time series data just data with a time-field in your data-set?
  … sort of

Considering the following **Scenario: Web Application**

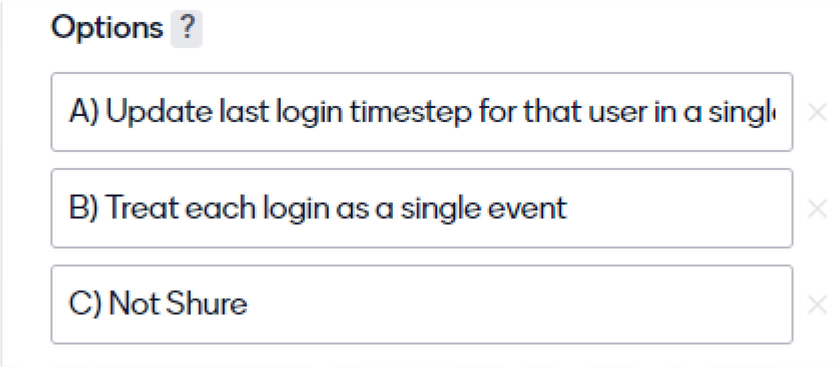
Imagine you maintain a web application. You have been asked to analyse when a new user logs in

a) When a new user logs in, you may just update a “last_login” timestep for that user in a single row

b) Or, you treat each login as a separate event

……. Quiz!

Which Option Would You Choose



Options ?

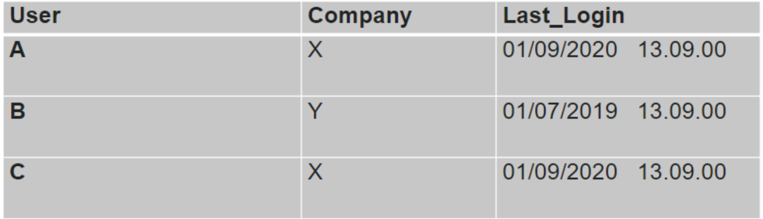
A) Update last login timestep for that user in a singl

B) Treat each login as a single event

C) Not Shure

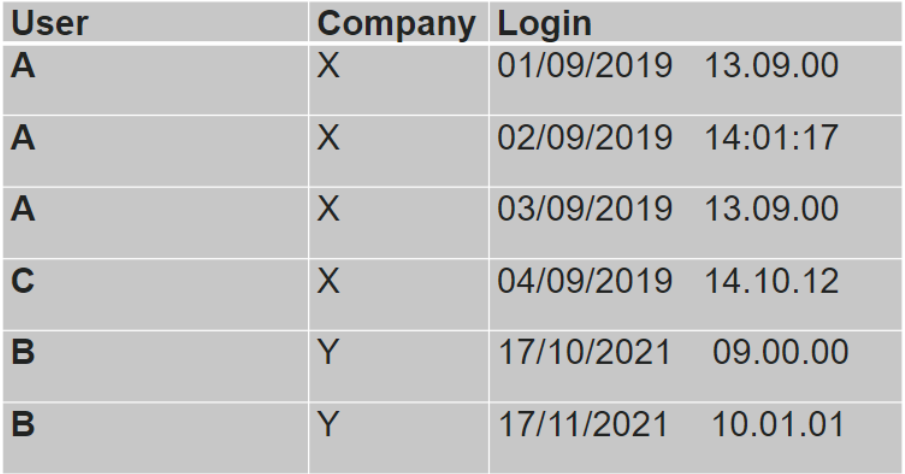
Which option would you choose

- Option A



User	Company	Last_Login
A	X	01/09/2020 13.09.00
B	Y	01/07/2019 13.09.00
C	X	01/09/2020 13.09.00

- Option B



User	Company	Login
A	X	01/09/2019 13.09.00
A	X	02/09/2019 14:01:17
A	X	03/09/2019 13.09.00
C	X	04/09/2019 14.10.12
B	Y	17/10/2021 09.00.00
B	Y	17/11/2021 10.01.01

Time Series Data in Summary

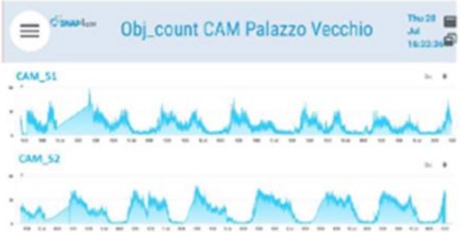
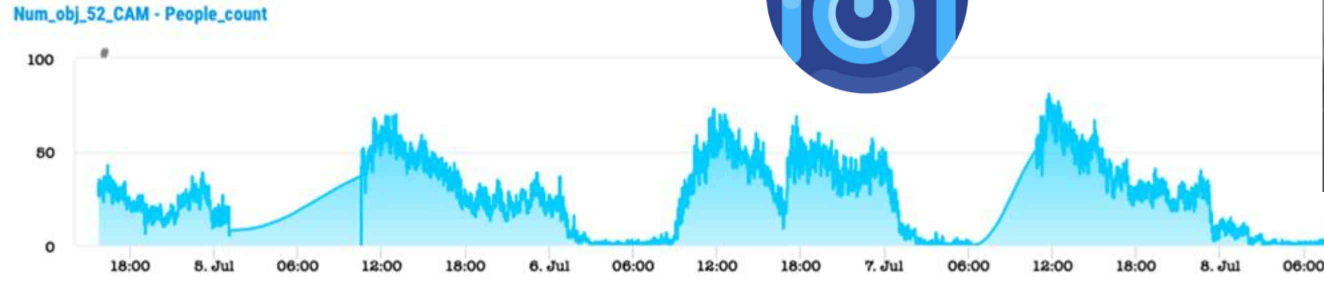


FIGURE 11. Monitoring Dashboard of people counting in Piazza Della Signoria, Florence

- Almost all data is recorded as a new entry
- The data typically arrives in time order
- Time-intervals can be **regular** (metrics) or irregular (events)



Time Series Data Analysis (TSA)

What can you do with time-series data?

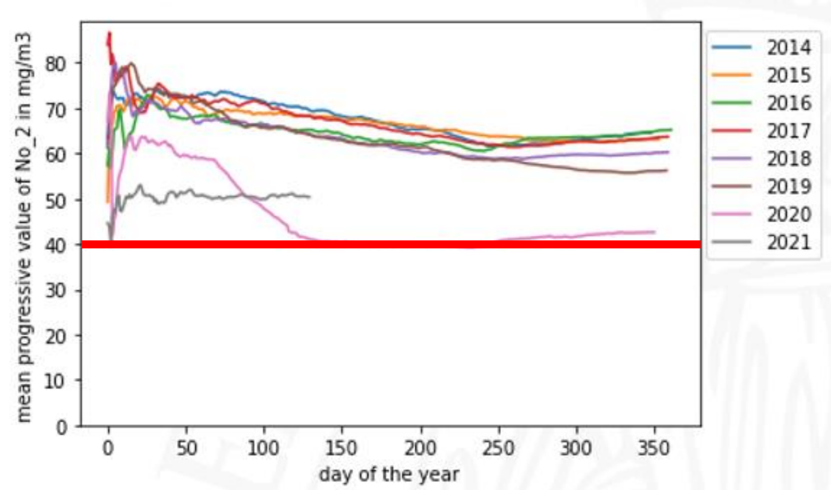
Analyze change (past - present -future)

3 main analysis types:

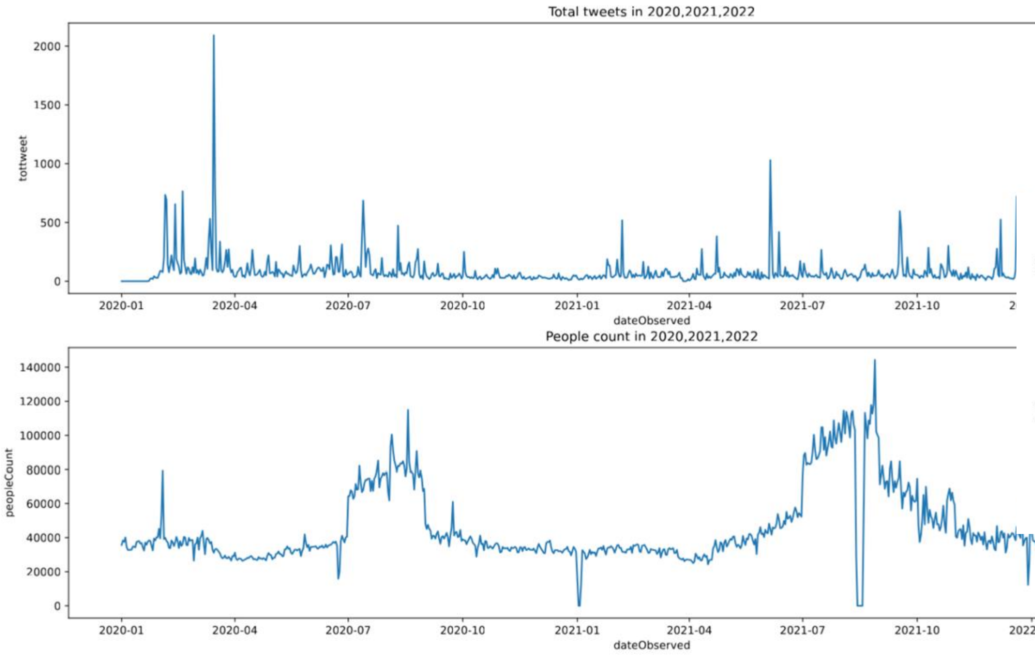
A) Access the impact of a single event (descriptive)
B) Study casual pattern i.e the effect of variables rather than events
C) Forecast Future Values of a Time-Series using the previous values of one series (or also values from others) (prediction)

A) Access the impact of a single event

		EU Air Quality Directives		
Pollutant	Averaging period	Objective	Concentration	Comments
$PM_{2.5}$	24-hour	Target value		
$PM_{2.5}$	Annual	Limit value	25 µg/m^3	
$PM_{2.5}$	Annual	Indicative limit value	20 µg/m^3	
PM_{10}	24-hour	Limit value	50 µg/m^3	Not to be exceede
PM_{10}	Annual	Limit value	40 µg/m^3	
O_3	Max. daily 8-hour mean	Target value	120 µg/m^3	Not to be exceede (averaged over 3 y
O_3	Max. daily 8-hour mean	Long-term objective	120 µg/m3	
O_3	8-hour	Target value		
O_3	Peak season [a]	Target value		
NO_2	Hourly	Limit value	200 µg/m^3	Not to be exceede
NO_2	Annual	Limit value	40 µg/m^3	
NO_2	24-hour	Target value		
SO_2	Hourly	Limit value	350 µg/m^3	Not to be exceeded on more than 24 hours/year
SO_2	24-hour	Limit value	125 µg/m^3	Not to be exceeded on more than 3 days/year
CO	Max. daily 8-hour mean	Limit value	10 mg/m^3	
CO	24-hour	Target value		



B) Study casual pattern i.e the effect of variables rather than events



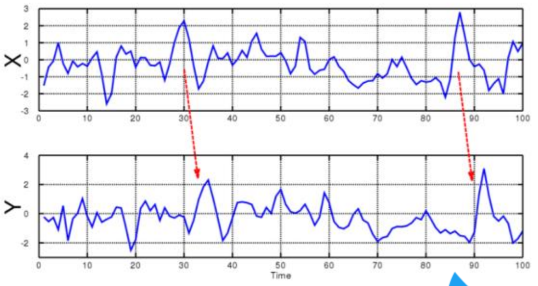
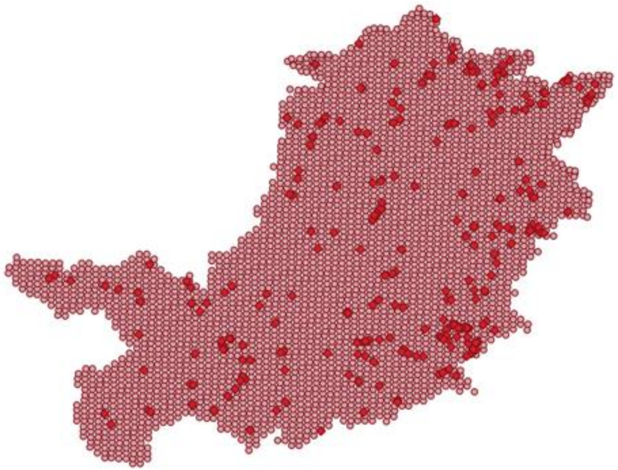


Image Source: https://en.wikipedia.org/wiki/Granger_causality

C) Forecast Future Values of a Time-Series



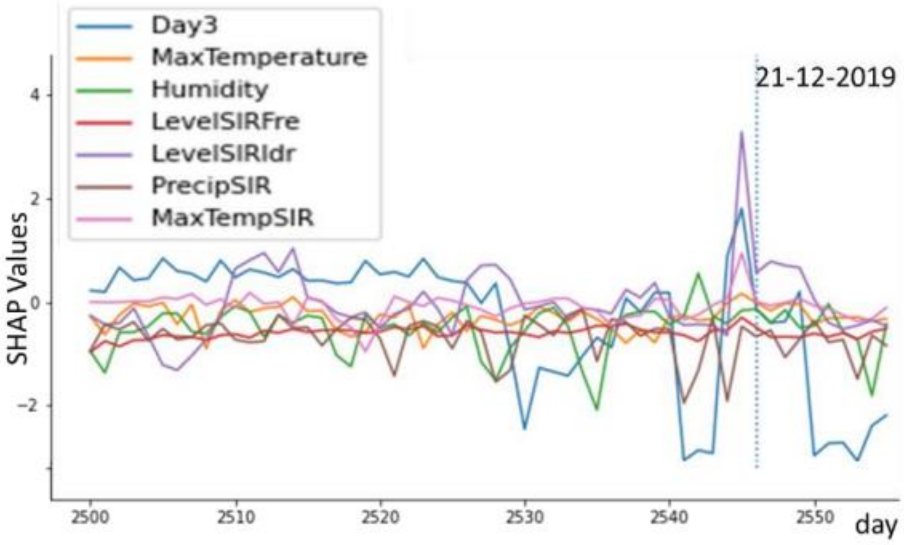
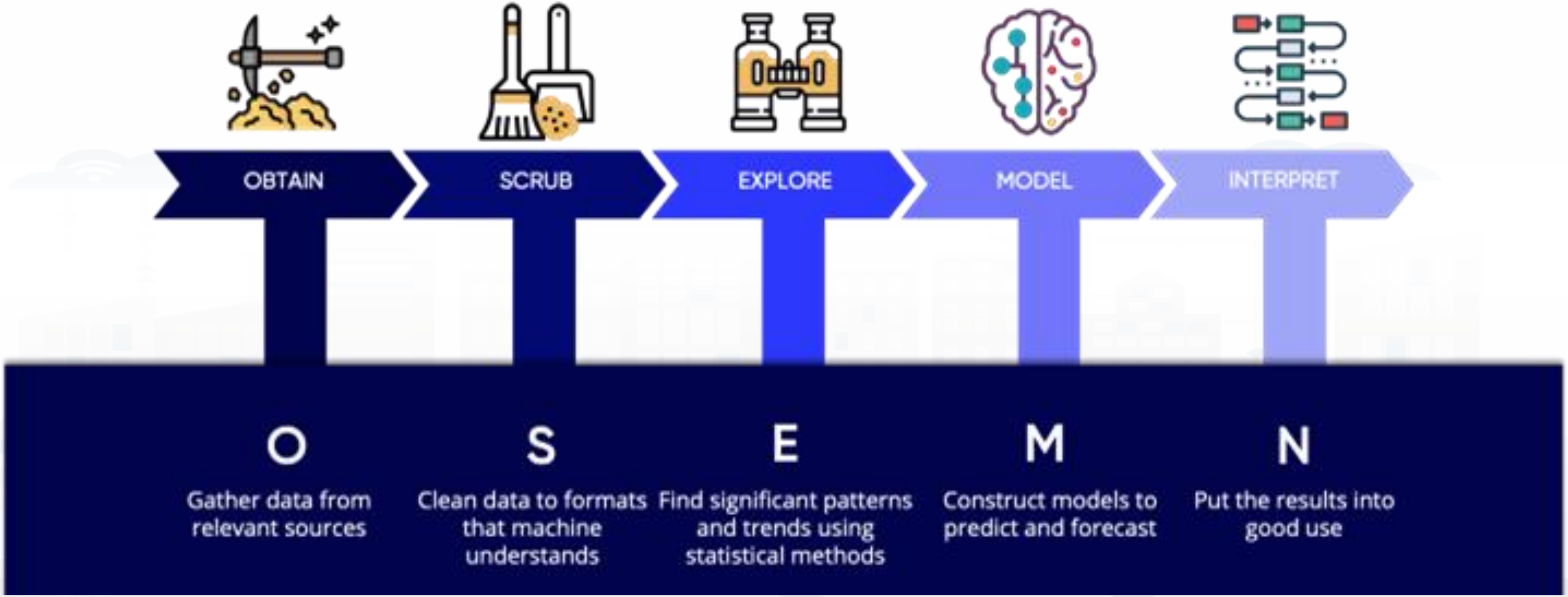


FIGURE 11. Time trend of SHAP values of most relevant features around the landslide event of 21-12-2019: values estimated by using data collected in the neighboring area of the event.

Stepladder to conduct a great time series analysis



O — Gather data from relevant sources

S — Clean data to formats that machine understands

E — Find significant patterns and trends using statistical methods

M — Construct models to predict and forecast

N — Put the results into good use

In which part of the OSEMN pipeline data analysts will spend the majority of their time?

In which part of the OSEMN pipeline data analysts will spend the majority of their time?

✓	✓	✗	✗	✗
Obtain	Scrub	Explore	Model	Interpret

Obtain Data

For every data analysis of course you need… Data!

Obtaining data can be simple … Snap4City ServiceMap

But often requires:

- more than 1 data source (OpenData)
- feature engineering
- identify gaps in dataset regarding the analysis goal

Or in exploratory analysis:

- generate Synthetic Data to work on

https://www.snap4city.org/dashboardSmartCity/view/Gea.php?iddasboard=MzUxNQ==

VERY IMPORTANT

Best Practice **Fully Document** this process:

- data sources

Scrub Data

What is better to have:

Good Data with Bad AI models

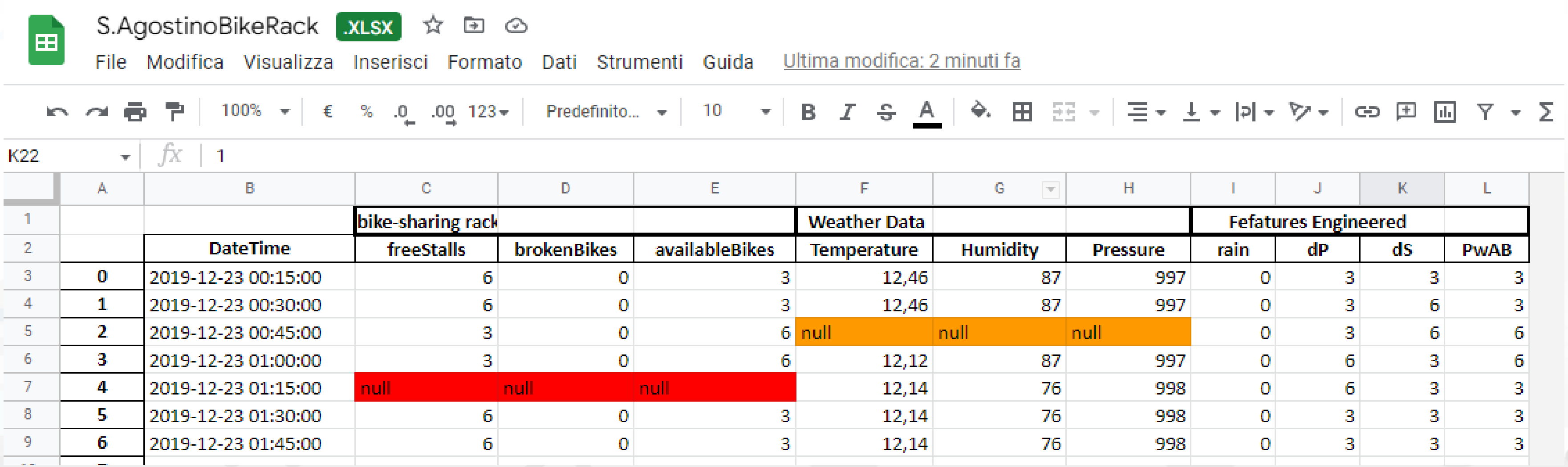
Bad Data with Good AI models

- Probably the MOST important technical component of the pipeline
- Good data is more important than any analysis method
- Go to Actions:
  - Time granularity casting
  - Handling Data missing - Imputation Strategies
  - “3” -> 3 string numbers??

- 5 PILLARS of Information Quality:
  - Complete
  - Accurate
  - Consistent
  - Validity
  - Timely

Scrub Data

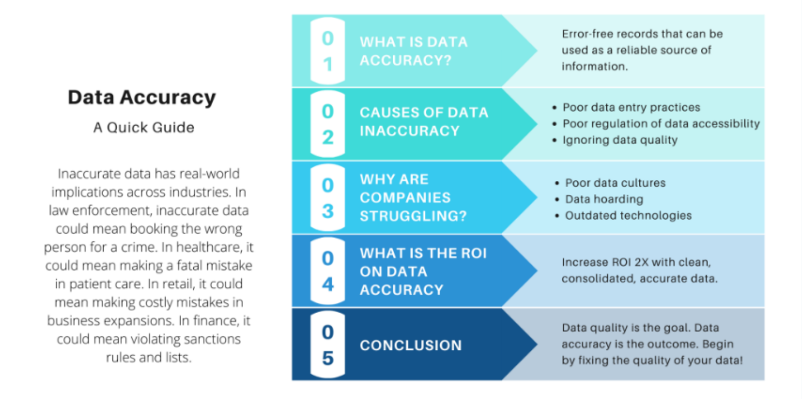
- 5 PILLARS of Information Quality:
  - **Complete**: are there any gaps in the data referring to the period selected from what was expected and on what was actually there
  - Accurate
  - Consistent
  - Validity
  - Timely



	A	B	C	D	E	F	G	H	I	J	K	L
1			bike-sharing rack			Weather Data			Fefatures Engineered			
2		DateTime	freeStalls	brokenBikes	availableBikes	Temperature	Humidity	Pressure	rain	dP	dS	PwAB
3	0	2019-12-23 00:15:00	6	0	3	12,46	87	997	0	3	3	3
4	1	2019-12-23 00:30:00	6	0	3	12,46	87	997	0	3	6	3
5	2	2019-12-23 00:45:00	3	0	6	null	null	null	0	3	6	6
6	3	2019-12-23 01:00:00	3	0	6	12,12	87	997	0	6	3	6
7	4	2019-12-23 01:15:00	null	null	null	12,14	76	998	0	6	3	3
8	5	2019-12-23 01:30:00	6	0	3	12,14	76	998	0	3	3	3
9	6	2019-12-23 01:45:00	6	0	3	12,14	76	998	0	3	3	3

Scrub Data

- 5 PILLARS of Information Quality:
  - Complete
  - **Accurate:** are the collected data correct / do they accurately represent what it should
  - Consistent
  - Validity
  - Timely



Data Accuracy

A Quick Guide

Inaccurate data has real-world implications across industries. In law enforcement, inaccurate data could mean booking the wrong person for a crime. In healthcare, it could mean making a fatal mistake in patient care. In retail, it could mean making costly mistakes in business expansions. In finance, it could mean violating sanctions rules and lists.

01 WHAT IS DATA ACCURACY? — Error-free records that can be used as a reliable source of information.

02 CAUSES OF DATA INACCURACY
- Poor data entry practices
- Poor regulation of data accessibility
- Ignoring data quality

03 WHY ARE COMPANIES STRUGGLING?
- Poor data cultures
- Data hoarding
- Outdated technologies

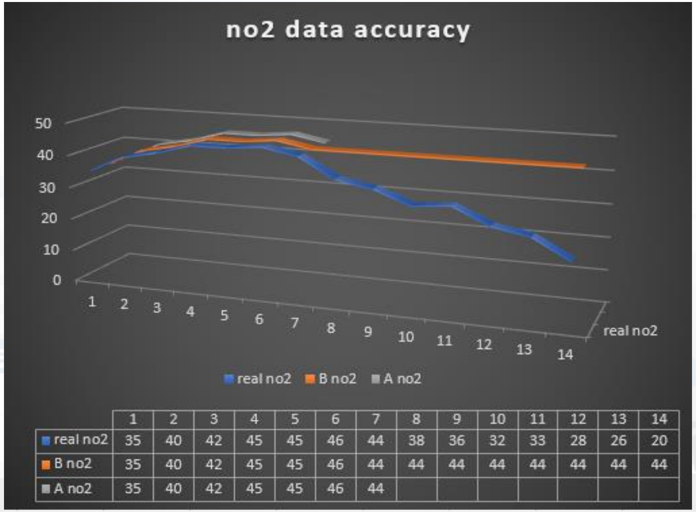
04 WHAT IS THE ROI ON DATA ACCURACY — Increase ROI 2X with clean, consolidated, accurate data.

05 CONCLUSION — Data quality is the goal. Data accuracy is the outcome. Begin by fixing the quality of your data!

Scenario: Data Acquisition… IoT environment sensor with air pollutants which solution would you implement considering that this sensor could break.

A) Node-Red Process that saves the last value of the sensor in a variable and every 5 minutes send the data

B) Every 5 minutes send the data if available



	1	2	3	4	5	6	7	8	9	10	11	12	13	14
real no2	35	40	42	45	45	46	44	38	36	32	33	28	26	20
B no2	35	40	42	45	45	46	44	44	44	44	44	44	44	44
A no2	35	40	42	45	45	46	44							

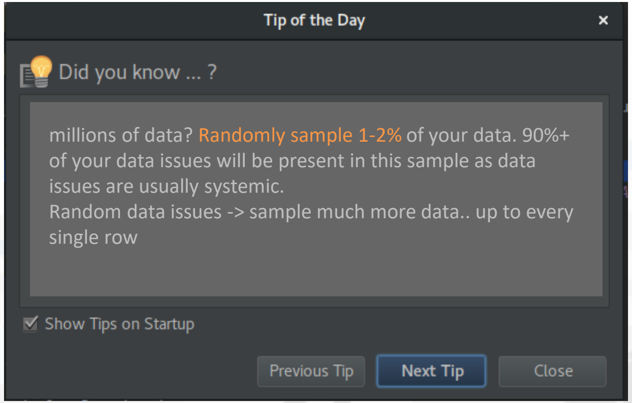
Scrub Data

- 5 PILLARS of Information Quality:
  - Complete
  - Accurate
  - **Consistent:** does the type of data align with the expected version of the data that should be coming in

    Validity: data really measure what is intended?

    Timely: data should be received in order and depending on the application really fast!

datetime_mantainance	brand	model	…	price
2019-12-23 00:15:00	FIAT	500	…	200
2019-12-23 00:30:00	FERRARI	500	…	2500
2019-12-23 01:00:00	FIAT	PANDA	…	2180



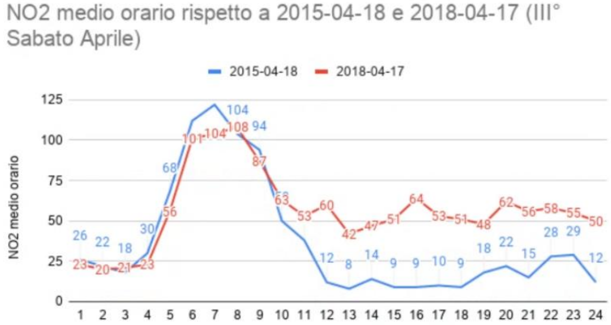
millions of data? Randomly sample 1-2% of your data. 90%+ of your data issues will be present in this sample as data issues are usually systemic.
Random data issues -> sample much more data.. up to every single row

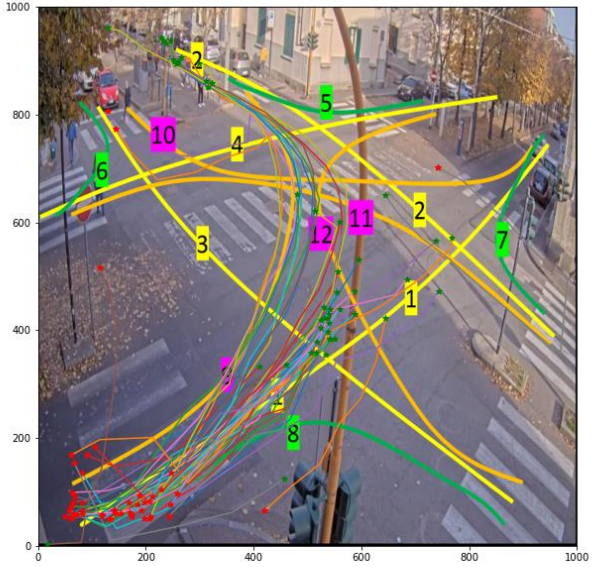
Explore

Exploratory Data Analysis:
-> Stats class will be handy
-> Does your data meet the assumptions of your intended analysis type

- Distributions
- Outliers
- Patterns / Trends
- Clustering

Visualize what you find for a bette understanding


NO2 medio orario rispetto a 2015-04-18 e 2018-04-17 (III° Sabato Aprile)



Model

Fortunately there are two main kinds of analysis:

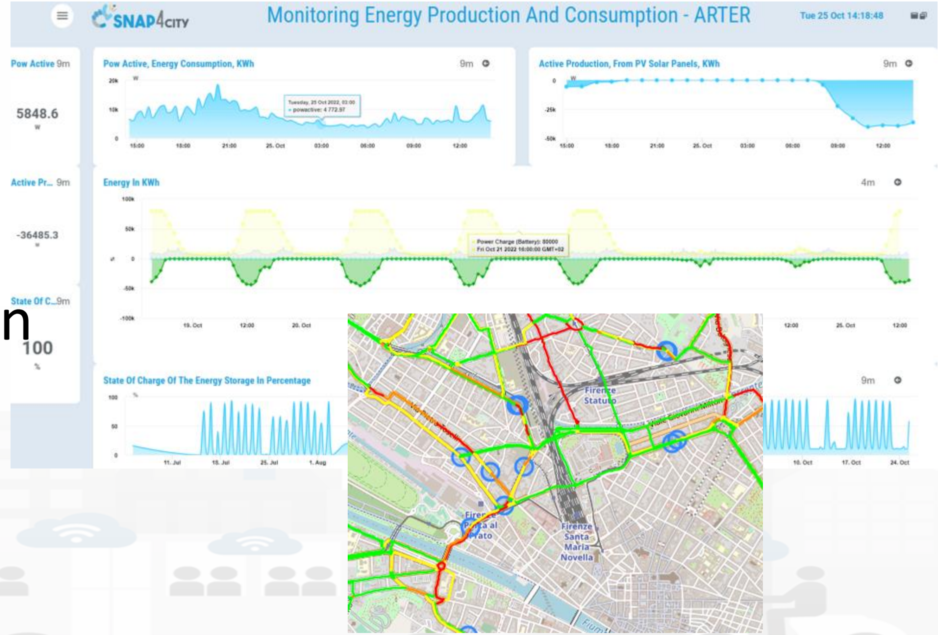
- Classification Problems
  - Focus on putting one data record into one of a set of groups

- Quantitative Prediction Problems
  - Based on the values recorded predict the value of some other variable of interest

Provide one example of a classification problem and one of a Prediciton problem based on time-series data in the context of Smart Cities

Interpret

- Finally using visualization and other techniques we will interpret the results.
  - Monitoring Dashboards
  - What-if-analysis tools
  - Web/Mobile Application
  - Edge device implementation
  - Early warning systems


SNAP4CITY
Monitoring Energy Production And Consumption - ARTER
Tue 25 Oct 14:18:48
Pow Active 9m
5848.6
Pow Active, Energy Consumption, KWh
Active Production, From PV Solar Panels, KWh
Active Pr... 9m
-36485.3
Energy In KWh
State Of C...9m
100
State Of Charge Of The Energy Storage In Percentage
Firenze Statuto
Firenze Porta al Prato
Firenze Santa Maria Novella

Time Series Basics

- What is time series Data?
- What can you do with time series analysis (TSA)
- Stepladder to conduct a great time series analysis… with examples

Road to Time Series Forecasting

– Time Series Characteristics
  - ● Mathematical formulation of Time Series
  - ● Autocorrelation
  - ● Seasonality
  - ● Stationarity
    - ○ Unit Roots gets in the way

➡ **Forecasting Methods Selection**

Mathematical Formulation of Time Series

Time Series is the set of several observations of a phenomenon with respect to time.

The observed phenomenon, called a **variable** Y , can be observed at given instants of time and it can be denoted with Y_t with $t = \{1, 2, 3, ..., T\}$ the time instant.

So a Time Series can be defined as follows: $Y = \{Y_1, Y_2, ..., Y_T\}$

For example, if one were to survey quarterly GDP in millions of euros at chain-linked values (reference year: 2000; raw data) from Q1 1981 to Q2 2008, one would have 110 observations, including:

Y_1 : GDP at the end of Q1 1981 (193,505);
Y_{12} : GDP at the end of Q4 1983 (215,584);
Y_{55} : GDP at the end of Q3 1994 (263,660).

Moments of Time Series can be defined as:

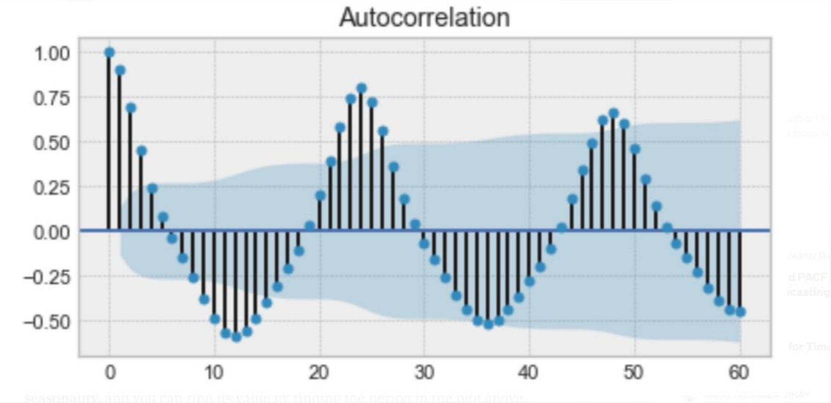
Mean $\mu_t = \mathbb{E}[Y_t]$
Variance $\sigma_t^2 = \mathbb{E}[(Y_t - \mu_t)^2]$
Autocovariance: $\gamma_{t,s} = \mathbb{E}[(Y_t - \mu_t)(Y_s - \mu_s)]$

$\mathbb{E}[X] = \sum_{i=1}^{\infty} x_i p_i .$ with Discrete uniform distribution

$$p_i = \frac{1}{T}$$

Time Series Characteristics

Autocorrelation is the similarity between observations as a function of the time lag between them.



Autocorrelation Function Plot (**ACF**)

- The first value and the 24th value have a high autocorrelation. Similarly, the 12th and 36th observations are highly correlated. This means that we will find a very similar value at every 24 units of time.

Notice how the plot looks like sinusoidal function. This is a hint for seasonality, and you can find its value by finding the period in the plot above, which would give 24h

Understanding ACF Plots

We defined a Time Series as follows: $Y = \{Y_1, Y_2, ..., Y_T\}$

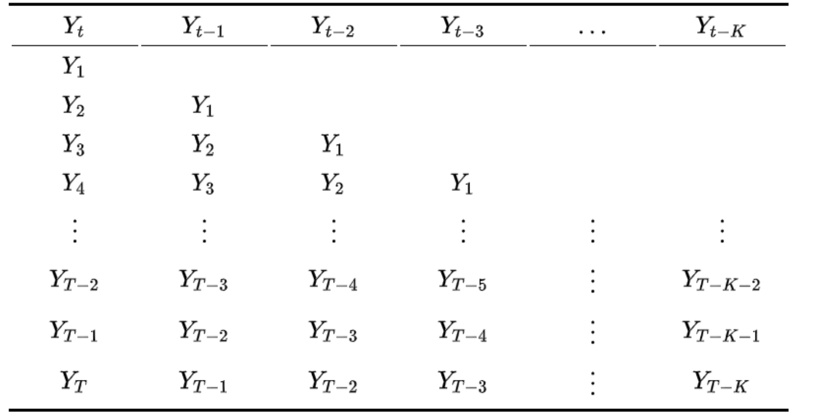
Lets now consider the delayed Time Series in a new variable $Z = Y_{t-k}$

Where k is the size of the lag. Setting $k = 3$,

if Y_a is the Italian GDP of 2007,

Z_a is the Italian GDP of 2004.

- To construct a correlogram, the correlations between the historical series and several lagged series of k periods are examined; for example, given the series. $Y_1, Y_2, Y_3, \ldots, Y_{T-2}, Y_{T-1}, Y_T$
- One ideally constructs a table like the following, where K indicates the maximum value of k:
- And the K correlations between the Yt-column and each of the Yt-k columns are examined.



Y_t	Y_{t-1}	Y_{t-2}	Y_{t-3}	$\ldots$	Y_{t-K}
Y_1					
Y_2	Y_1				
Y_3	Y_2	Y_1			
Y_4	Y_3	Y_2	Y_1		
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Y_{T-2}	Y_{T-3}	Y_{T-4}	Y_{T-5}	$\vdots$	Y_{T-K-2}
Y_{T-1}	Y_{T-2}	Y_{T-3}	Y_{T-4}	$\vdots$	Y_{T-K-1}
Y_T	Y_{T-1}	Y_{T-2}	Y_{T-3}	$\vdots$	Y_{T-K}

Understanding ACF Plots

- To construct a correlogram, the correlations between the historical series and several lagged series of k periods are examined; for example, given the series. $Y_1, Y_2, Y_3, \ldots, Y_{T-2}, Y_{T-1}, Y_T$
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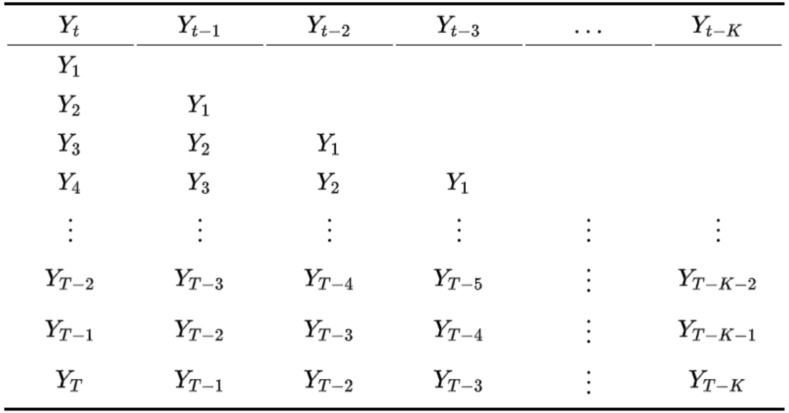


Y_t	Y_{t-1}	Y_{t-2}	Y_{t-3}	$\ldots$	Y_{t-K}
Y_1					
Y_2	Y_1				
Y_3	Y_2	Y_1			
Y_4	Y_3	Y_2	Y_1		
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Y_{T-2}	Y_{T-3}	Y_{T-4}	Y_{T-5}	$\vdots$	Y_{T-K-2}
Y_{T-1}	Y_{T-2}	Y_{T-3}	Y_{T-4}	$\vdots$	Y_{T-K-1}
Y_T	Y_{T-1}	Y_{T-2}	Y_{T-3}	$\vdots$	Y_{T-K}

The calculation is done by varying k from 1 to K and noting the correlation r between the columnY_t and the lagged variable column Y_{t-k}:

$$r_k = \frac{\sum_{t=K+1}^{T} (Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=K+1}^{T} (Y_t - \bar{Y})^2}$$

The autocovariance divided by the product of the standard deviations, i.e. the variance

Understanding ACF Plots

The calculation is done by varying k from 1 to K and noting the correlation r between the column Y_t and the lagged variable column Y_{t-k} :

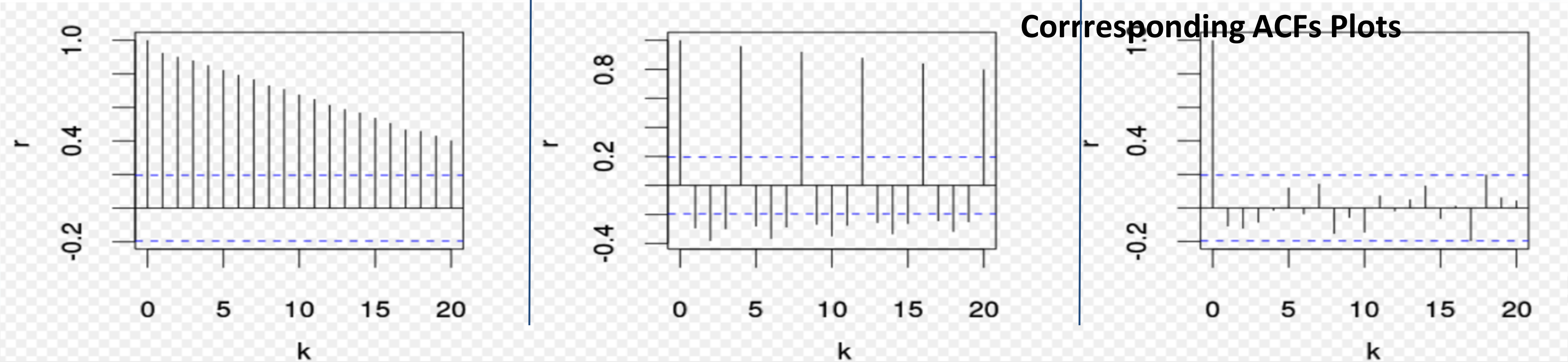
$$r_k = \frac{\sum_{t=K+1}^{T}(Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=K+1}^{T}(Y_t - \bar{Y})^2}$$

The autocovariance divided by the product of the standard deviations, i.e. the variance

Original Time Series characteristics

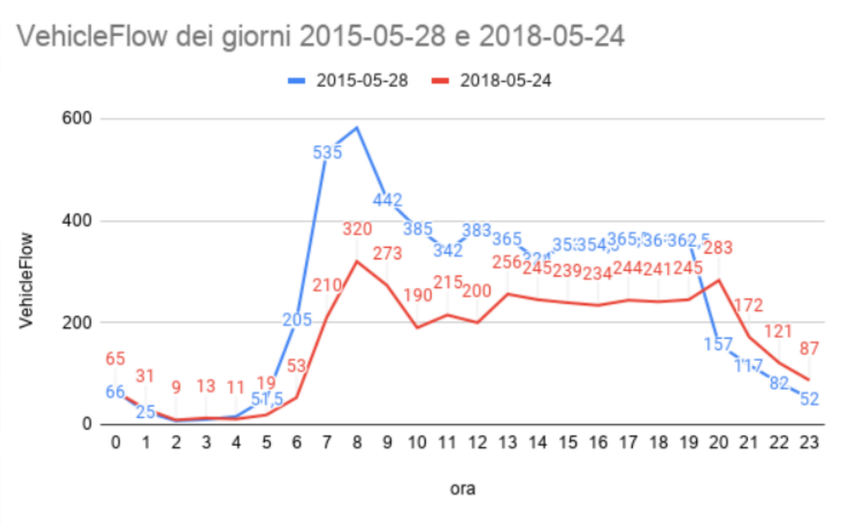
linear trend Behaviour	Seasonal component	Stochastic

Corrresponding ACFs Plots

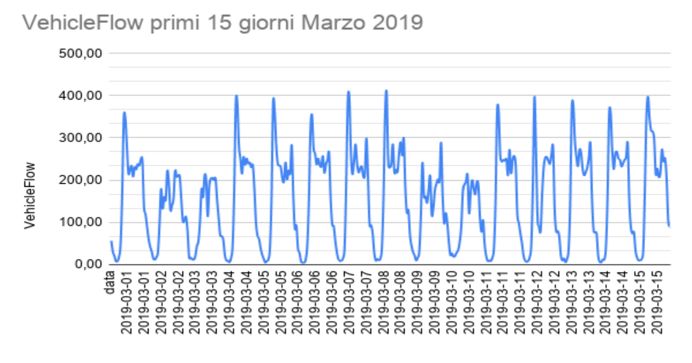


Time Series Characteristics

Seasonality refers to periodic fluctuations. For example, VehicleFlow is high during the day and low during night



Remember that seasonality can also be derived from an autocorrelation plot if it has a sinusoidal shape. Simply look at the period, and it gives the length of the season.

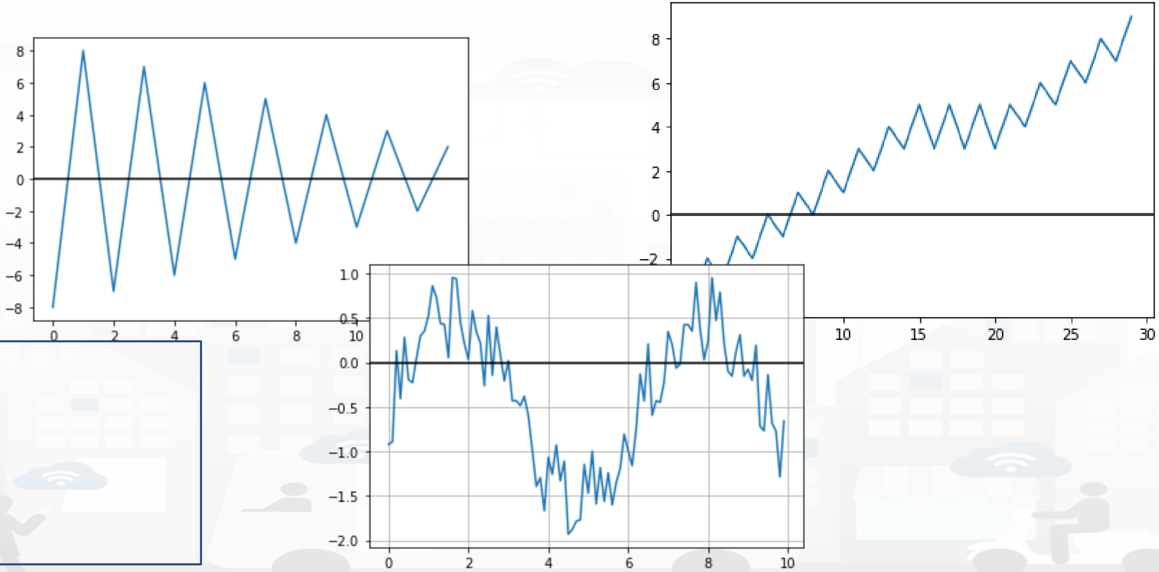


Time Series Characteristics

Stationarity is an important characteristic of time series that the majority of statistical forecasting techniques require. A time series is said to be stationary if its statistical properties do not change over time and there is not seasonality…

3 requirements:

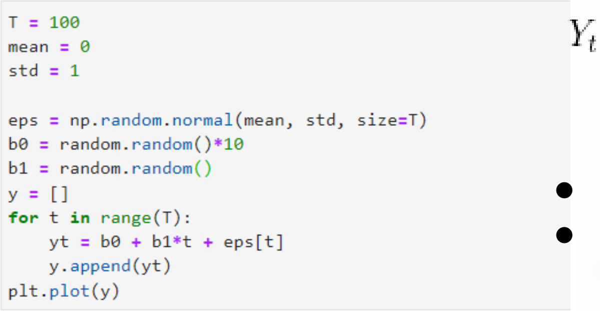
- μ const
- σ^2 const
- No Seasonality



How to check for stationarity:

1) Visually as we did
2) Global mean vs local mean ….
3) **Statistical Tests**

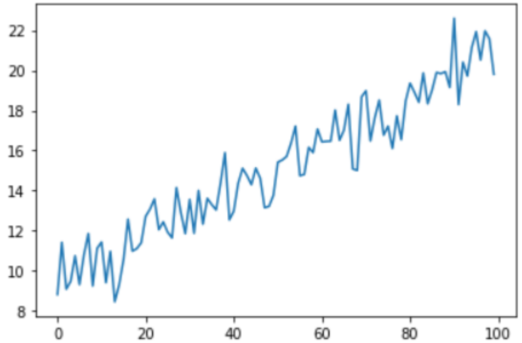
Making a Time Series Stationary



```
T = 100
mean = 0
std = 1

eps = np.random.normal(mean, std, size=T)
b0 = random.random()*10
b1 = random.random()
y = []
for t in range(T):
    yt = b0 + b1*t + eps[t]
    y.append(yt)
plt.plot(y)
```

```
[<matplotlib.lines.Line2D at 0x7faac0353cd0>]
```



$$Y_t = \underbrace{\beta_0 + \beta_1 t}_{\text{straight line}} + \underbrace{\epsilon_t}_{\text{white noise error N(0,k)}}$$

- ! not stationary but somewhat seems predictable...
- Lets define $D_t = Y_t - Y_{t-1} =$

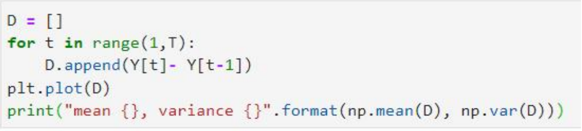
$$\beta_0 + \beta_1 t + \epsilon t - \beta_0 - \beta_1(t-1) + \epsilon_{t-1} =$$

$$\beta_1(t - t - 1) + \epsilon_t - \epsilon_{t-1} =$$

$$\underbrace{b_1}_{\text{const}} + \underbrace{(\epsilon_t - \epsilon_{t-1})}_{\text{indip vars}}$$

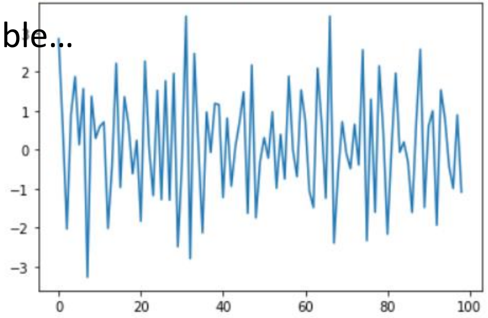
μ const b_1

σ^2 k^2 k^2 = 2k^2 const



```
D = []
for t in range(1,T):
    D.append(Y[t]- Y[t-1])
plt.plot(D)
print("mean {}, variance {}".format(np.mean(D), np.var(D)))
```

```
mean 0.15033575645472239, variance 2.1557327920738136
```

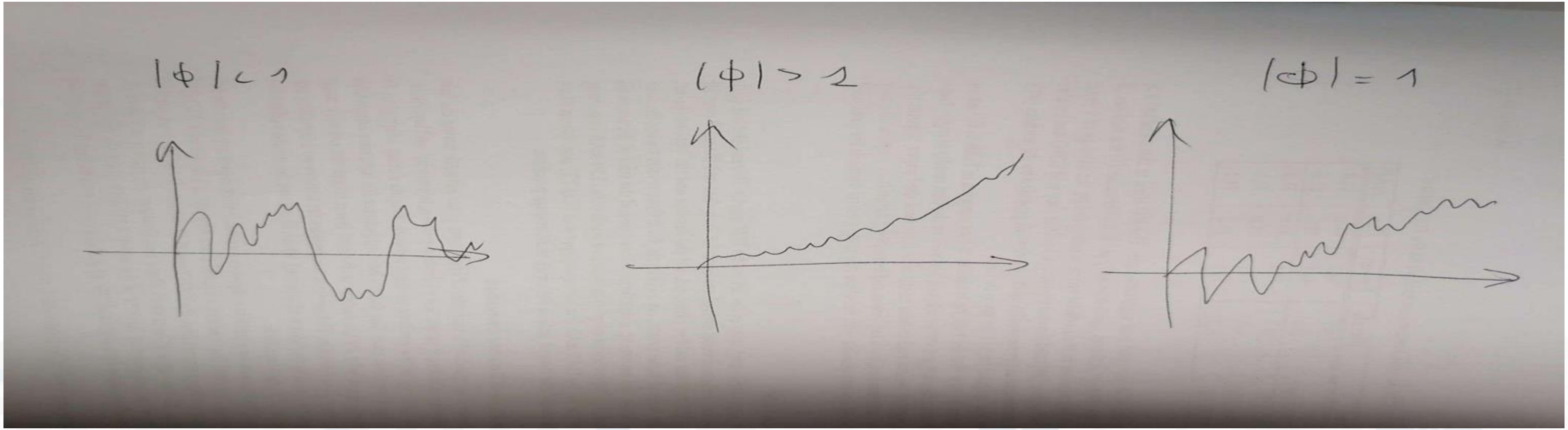


Transformations such as logarithms can help to stabilise the variance of a time series. **Differencing** can help stabilise the mean of a time series by removing changes in the level of a time series, and therefore eliminating (or reducing) trend and seasonality.

Unit Roots gets in the way! 😡

Why? If the time-series has a unit root it is not stationary!

And so you can't apply the stats forecasting techniques but you have to apply some transformations to eliminate this but in some cases you can't



Unit Roots gets in the way!

Why? If the time-series has a unit root it is not stationary!

And so you can't apply the stats forecasting techniques but you have to apply some transformations to eliminate this but in some cases you can't

Lets consider the most basic time series AR(1) model $A_t = \phi A_{t-1} + \epsilon t$

The time series is modeled as a lagged version of a time series multiplied by a coefficient ϕ

Focus on which values this can assume

$$A_t = \phi A_{t-1} + \epsilon t$$

$$= \phi(\phi A_{t-2} + \epsilon t - 1) + \epsilon t$$

$$= \phi^2 A_{t-2} + \phi \epsilon_{t-1} + \epsilon_t = \phi^2(\phi A_{t-3} + \epsilon_{t-2}) + \phi \epsilon_{t-1} + \epsilon_t$$

$$= \phi^3 A_{t-3} + \phi^2 \epsilon_{t-2} + \phi \epsilon_{t-1} + \epsilon_t$$

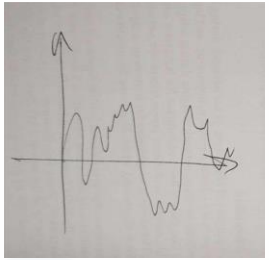
$$= \phi^t A_0 + \sum \phi^k \epsilon_{t-k}$$

$$E[A_t] = \phi E[A_{t-1}] = \phi^2 E[A_{t-2}] = \ldots = \phi^t a_0$$

$$Var(A_t) = \sigma^2[\phi^0 + \phi^2 + \ldots + \phi^{2(t-1))}]$$

Unit Roots gets in the way! 😠

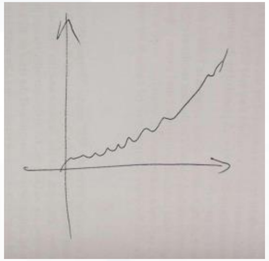
$|\phi| < 1$



$$E[A_t] \rightarrow 0$$

$$Var[A_t] \rightarrow \frac{\sigma^2}{1-\phi^2}$$

$|\phi| > 1$



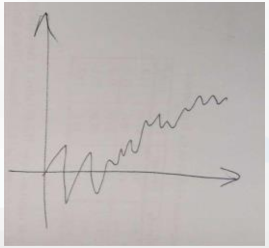
$E[A_t] \rightarrow$ 💣

$$E[A_t] = \phi E[A_{t-1}] = \phi^2 E[A_{t-2}] = ... = \phi^t a_0$$

$$Var(A_t) = \sigma^2[\phi^0 + \phi^2 + ... + \phi^{2(t-1))}]$$

Focus on which values this can assume **3 cases**

$|\phi| = 1$



A Time Series has a unit root if

$$\begin{tikzcd} & \phi = 1 \\ {|\phi| = 1} \arrow[ur] \arrow[dr] & \\ & \phi = -1 \end{tikzcd}$$

$E[A_t] = \pm a_0$ We are on track maybe it is stationary

$Var(A_t) = t\sigma^2$ No! as time passes variance increases!

Unit Roots gets in the way! 😀

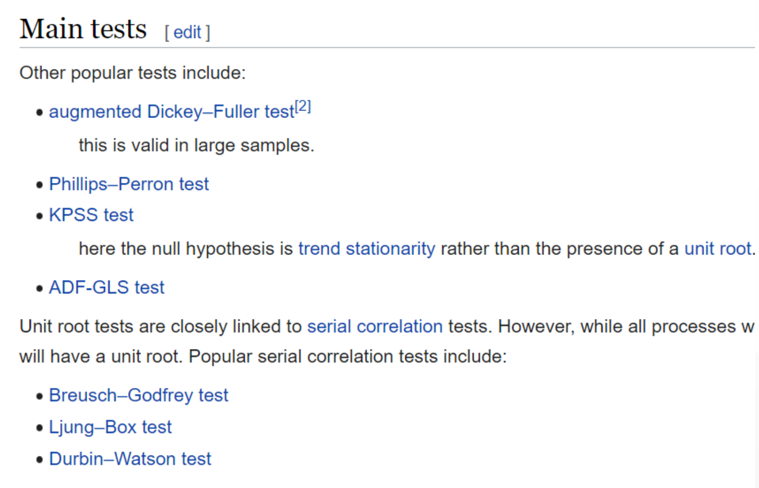
- Assumes that the Time Series in question is an AR(1)

$$Y_t = \beta_0 + \beta_1 t + \epsilon_t \longrightarrow Y_t = \beta_0 + \phi Y_{t-1} + \epsilon_t$$

Null Hypothesis Ho $\phi = 1$ <- unit root -> not stationary
Alternative Hypothesis H1 $\phi < 1$ <- not unit root -> stationary

Rejecting the null hypothesis means that the Series is stationary

There are multiple Stationarity tests based on this unit roots hypothesis



Main tests [edit]

Other popular tests include:

- augmented Dickey–Fuller test[2]
  this is valid in large samples.
- Phillips–Perron test
- KPSS test
  here the null hypothesis is trend stationarity rather than the presence of a unit root.
- ADF-GLS test

Unit root tests are closely linked to serial correlation tests. However, while all processes w will have a unit root. Popular serial correlation tests include:

- Breusch–Godfrey test
- Ljung–Box test
- Durbin–Watson test

Forecasting Methods Selection

Stationary Time Series

Short-term predictions

Works with not so long data history

Statistical Forecasting Techniques

Stationary & Not Stationary Time Series

Short-term predictions or Long-term Predictions

Needs more data to train the models

AI model development required

Road to Time Series Forecasting

– Time Series Characteristics
  - Mathematical formulation of Time Series
  - Autocorrelation
  - Seasonality
  - Stationarity
    - Unit Roots gets in the way

Forecasting Methods Selection

AI model development required

Deepening into Time Series Preparation for AI

Short-Term Prediction of Bikes Availability on Bike-Sharing Stations

with deepenings on

- In Depth Scenario
  - from simple data acquisition to time series with Snap4City platform
- In Depth Data Availability Analysis
  - Check on Information Quality pillars
  - Data Imputation
- Modelling Phase
  - Features and AI Architectures

Long Term Predictions of NO 2 Average Values via Deep Learning

with deepenings on

- Time Series Feature Selection for better AI predictive models
- Time Series in good use -> Monitoring Dashboard example

UNIVERSITÀ DEGLI STUDI FIRENZE

DINFO DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE

DISIT DISTRIBUTED SYSTEMS AND INTERNET TECHNOLOGIES LAB

SNAP4CITY

KM4CITY

Short-Term Prediction of Bikes Availability on Bike-Sharing Stations

Bike Sharing

- **Pros**:
  - Eco-friendly
  - Prevent traffic congestions
  - Reduce the probability of social contacts in public transports
  - Regular bikes or e-bikes
- **Problems**:
  - Irregular distribution of bikes on racks/areas
  - Difficulty of knowing in advance their status with a certain degree of confidence
    - available bikes at a specific bike-station
    - free slot for leaving the rented bike

 providing **PREDICTIONS** can be useful to improve quality of service

GOALS

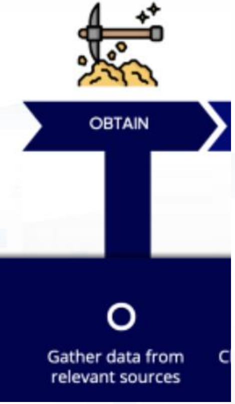
- Producing short-term 1h predictions of:
  (i) number of bikes available in bike-sharing systems stations,
  (ii) free slots.
- Identify the best solution among different AI/ML Techniques.
- Understand which are the most relevant features for the predictive model

Scenario

- The solution and its validation have been performed by using data collected in bike-stations
  - in the cities of **Siena** and **Pisa (Tuscany, Italy)**,
  - in the context of **Sii-Mobility National Research Project on Mobility and Transport**
  - **exploiting Snap4City Smart City IoT infrastructure**

- The data exploited referred to 15 stations in Siena and 24 in Pisa.
  - the status of each station is registered every 15 minutes

In Depth Scenario

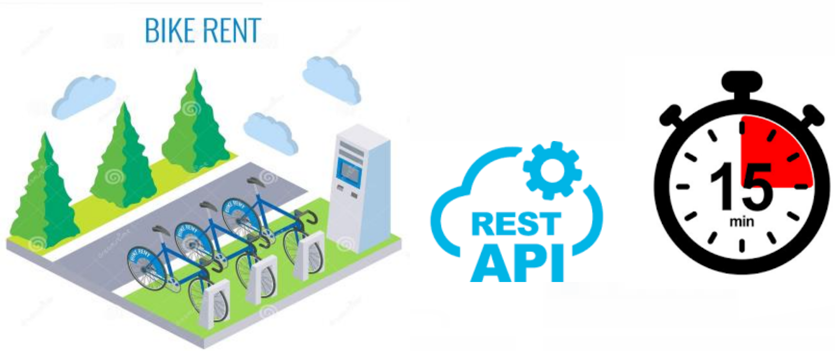


https://www.bicincitta.com/

REST API

- number of bikes available
- the total capacity of the rack
- the number of broken bikes

In Depth Scenario



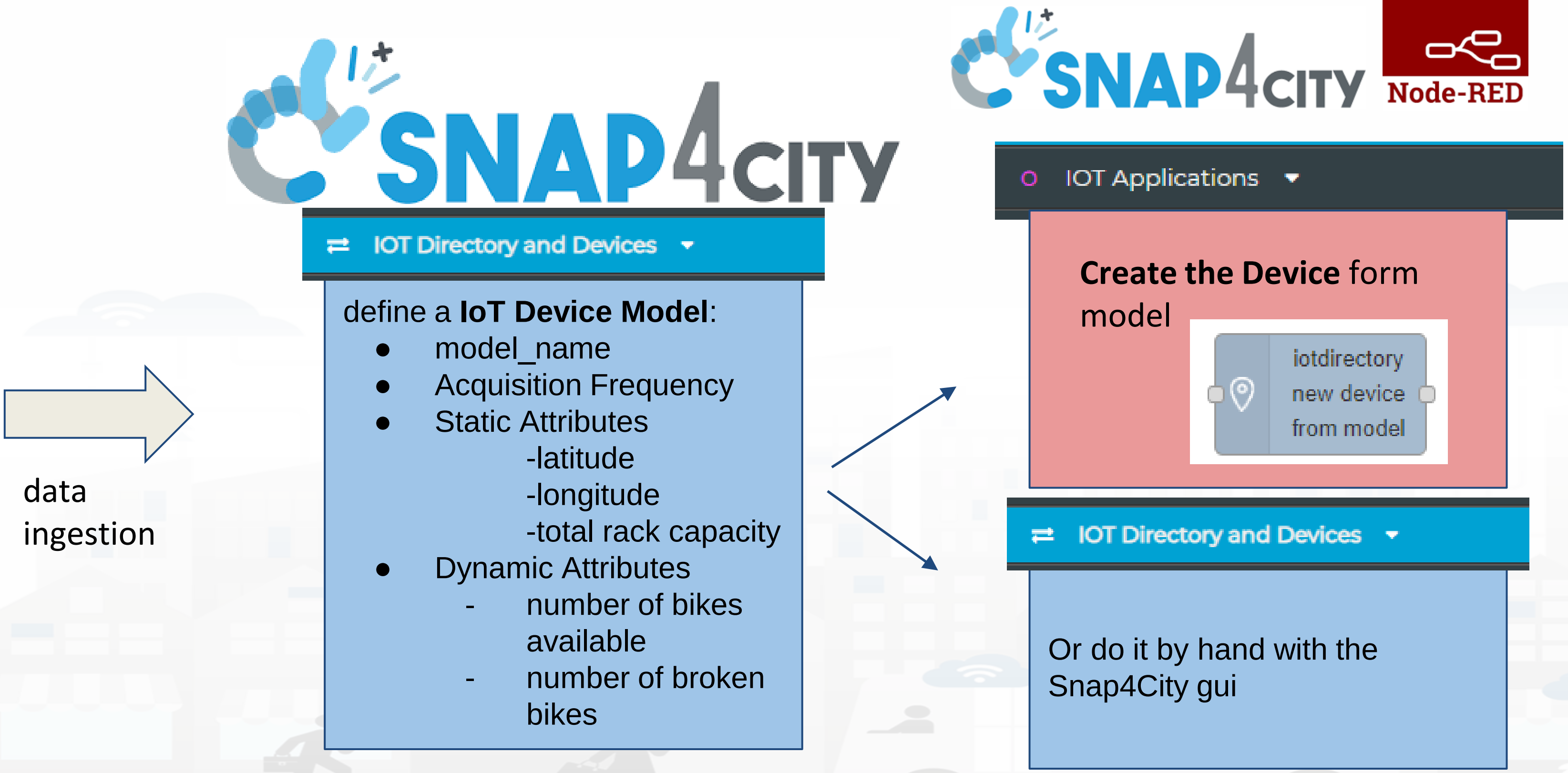
- number of bikes available
- the total capacity of the rack
- the number of broken bikes

data ingestion

define a **IoT Device Model**:

- model_name
- Acquisition Frequency
- Static Attributes
  - -latitude
  - -longitude
  - -total rack capacity
- Dynamic Attributes
  - number of bikes available
  - number of broken bikes

In Depth Scenario



data ingestion

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- model_name
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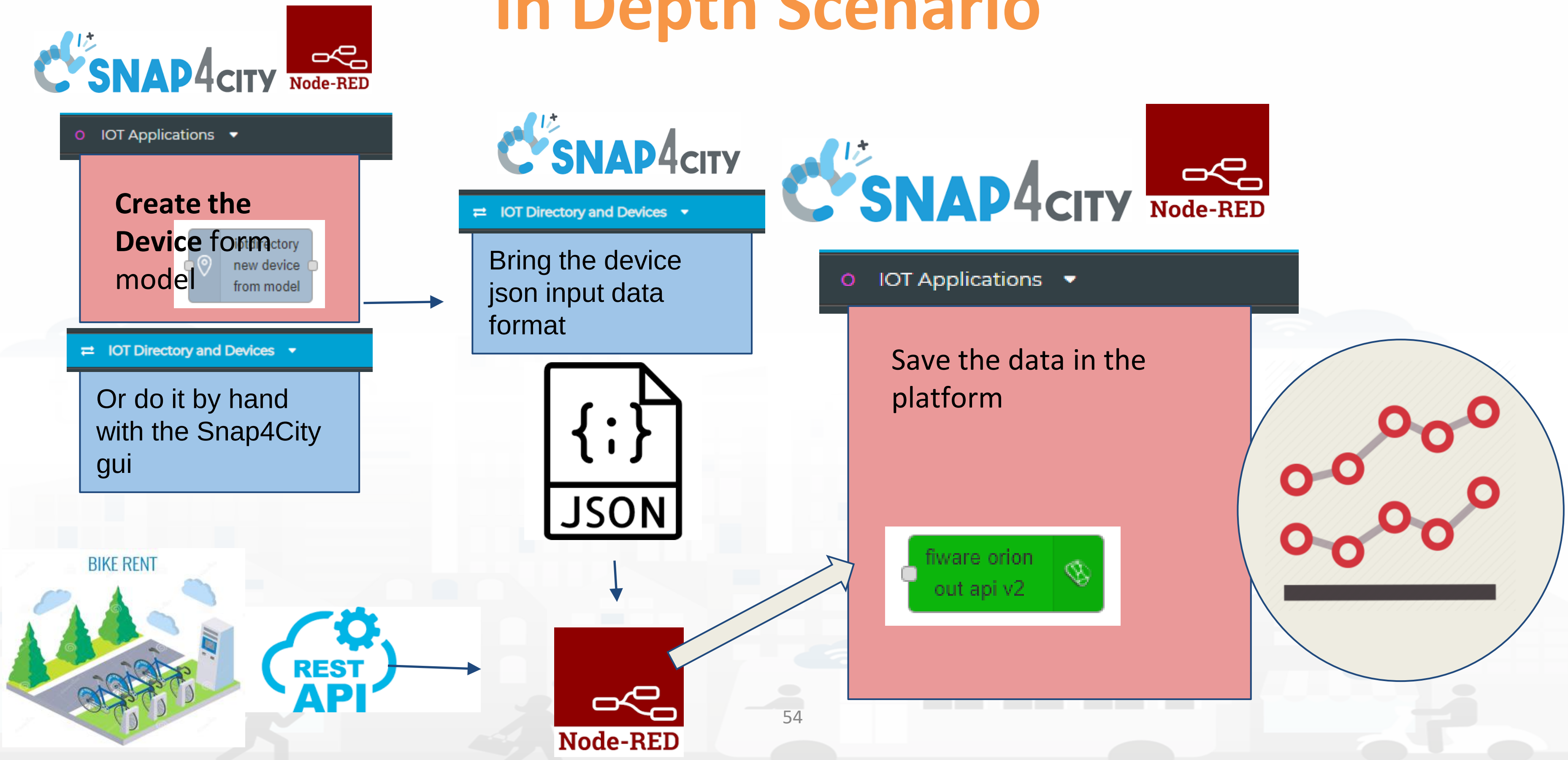
  - -longitude
  - -total rack capacity
- Dynamic Attributes
  - number of bikes available
  - number of broken bikes

Create the Device form model

Or do it by hand with the Snap4City gui

In Depth Scenario



Create the Device form model

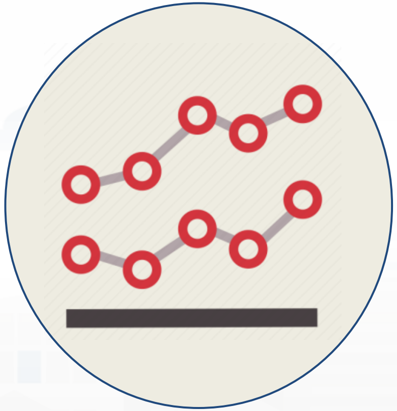
Or do it by hand with the Snap4City gui

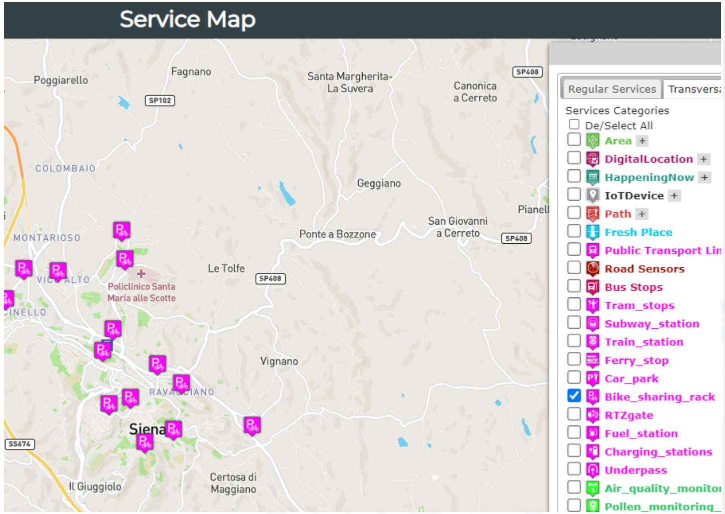
Bring the device json input data format

Save the data in the platform

In Depth Scenario

SNAP4CITY



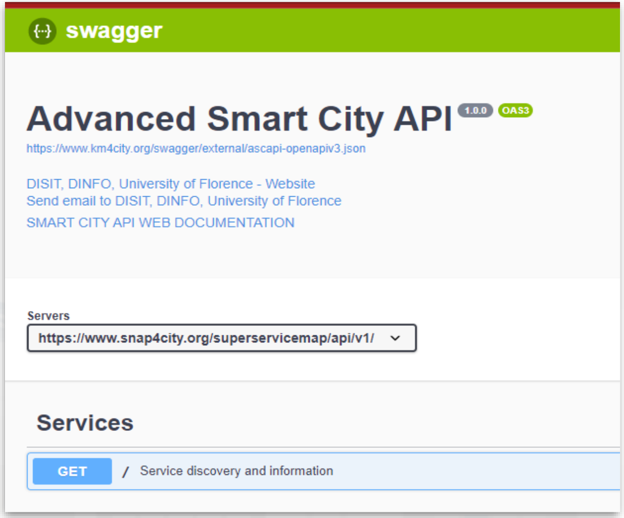


Service Map

Regular Services | Transversa

Services Categories

- □ De/Select All
- □ Area +
- □ DigitalLocation +
- □ HappeningNow +
- □ IoTDevice +
- □ Path +
- □ Fresh Place
- □ Public Transport Lin
- □ Road Sensors
- □ Bus Stops
- □ Tram_stops
- □ Subway_station
- □ Train_station
- □ Ferry_stop
- □ Car_park
- ☑ Bike_sharing_rack
- □ RTZgate
- □ Fuel_station
- □ Charging_stations
- □ Underpass
- □ Air_quality_monitor
- □ Pollen_monitoring_



swagger

Advanced Smart City API 1.0.0 OAS3

https://www.km4city.org/swagger/external/ascapi-openapiv3.json

DISIT, DINFO, University of Florence - Website

Send email to DISIT, DINFO, University of Florence

SMART CITY API WEB DOCUMENTATION

Servers

https://www.snap4city.org/superservicemap/api/v1/

Services

GET / Service discovery and information

CSV
CSV
CSV
CSV
CSV

Data Availability

- The temporal windows of data available for the city of Siena is
  - from June 2019 to January 2020
- The data taken into account for the bike racks of Pisa
  - from December 2019 to March 2020

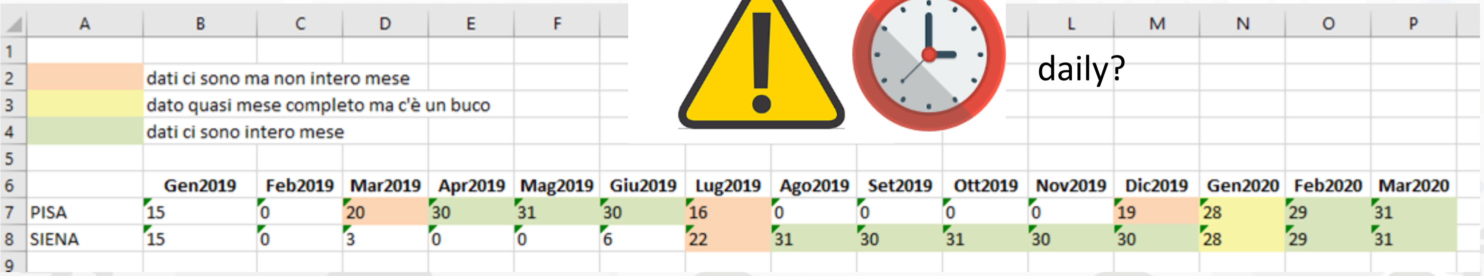
The data acquired by the stations

- the number of bikes available
- the total capacity of the rack
- the number of broken bikes

In Depth Data Availability Analysis

5 PILLARS of Information Quality:

- **Complete** OOPS!
- Accurate ✓
- Consistent ✓
- Validity ✓
- Timely ✓

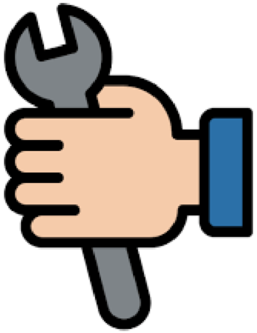


daily?

	A	B	C	D	E	F						L	M	N	O	P
1																
2	🟧	dati ci sono ma non intero mese														
3	🟨	dato quasi mese completo ma c'è un buco														
4	🟩	dati ci sono intero mese														
5																
6		Gen2019	Feb2019	Mar2019	Apr2019	Mag2019	Giu2019	Lug2019	Ago2019	Set2019	Ott2019	Nov2019	Dic2019	Gen2020	Feb2020	Mar2020
7	PISA	15	0	20	30	31	30	16	0	0	0	0	19	28	29	31
8	SIENA	15	0	3	0	0	6	22	31	30	31	30	30	28	29	31
9																

In Depth Data Availability Analysis

- **Data missing is an inevitable problem** when dealing with real world IoT senso networks.
- Sensors may suffer of problems such as detector malfunction and communication failure.
- Or there could be problems in the data acquisition phase.

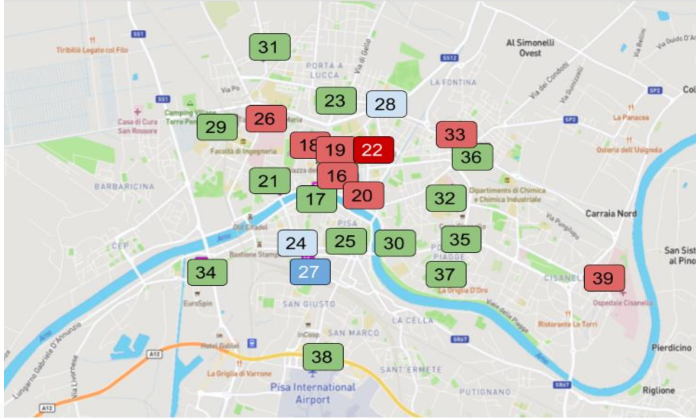


Data Imputation Strategies:

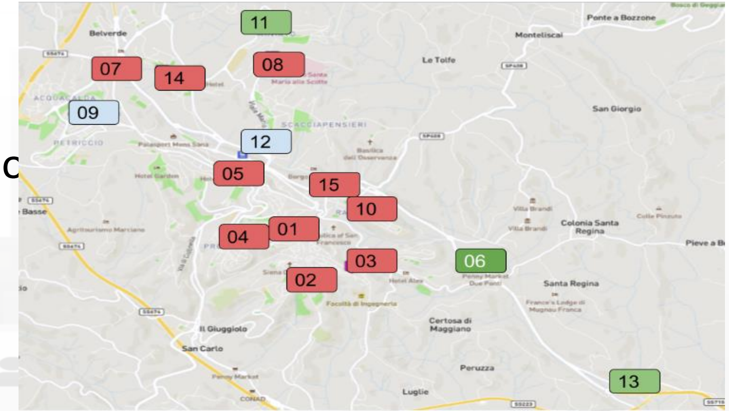
- **Do nothing**
- Imputation using mean/median values
- **Hot Deck Encoding**
- most frequent value
- k nearest neighbours - Mice - Datawig Deep learning based imputation solution

Clustering

- A **clustering** approach has been applied in order to classify Pisa and Siena stations based on their mean trend H24 of bikes availability
  - This is also correlated to the typical services in the neighborhoods



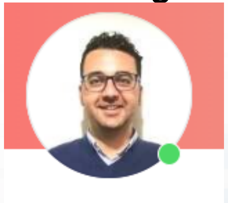
- **K-means** clustering method has been applied to identify clusters
  - The optimal number of clusters resulted to be equal to **3**, and it has been identified by using the **Elbow criteria**

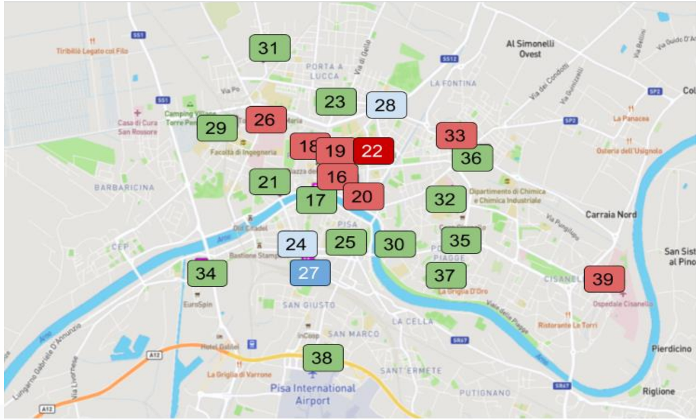


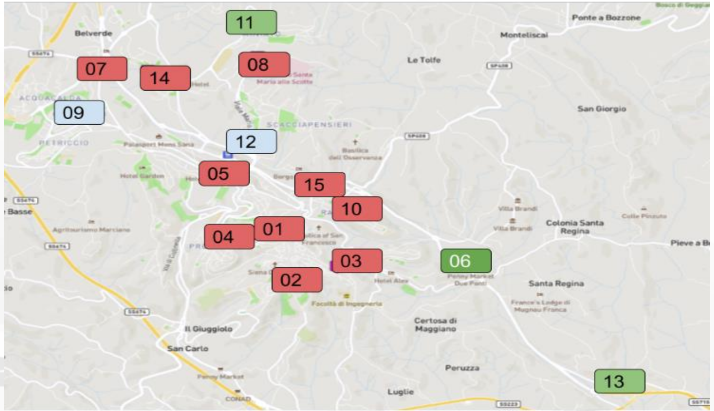
Clustering

Find significant patterns and trends using statistical methods

- Descriptive Statistics
- Trend Plots Analysis
- **Clustering**

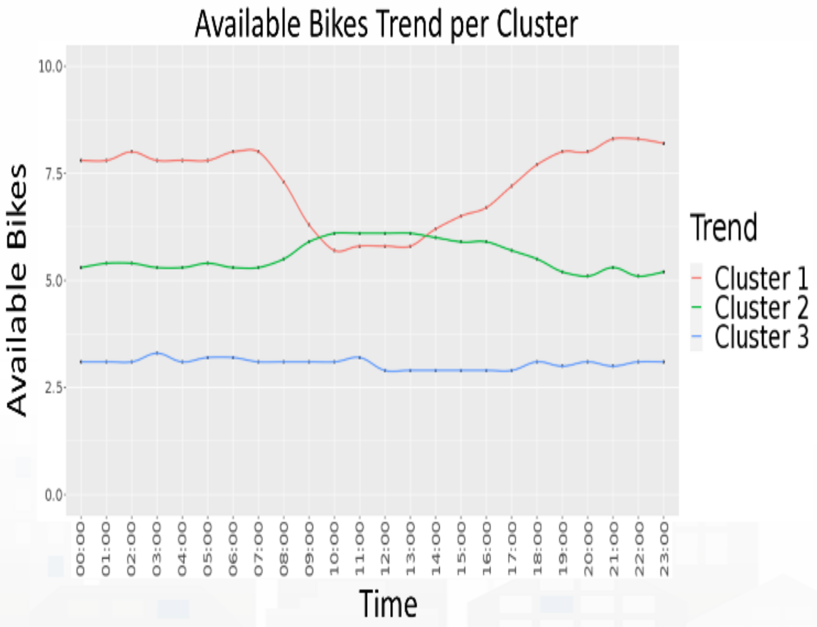






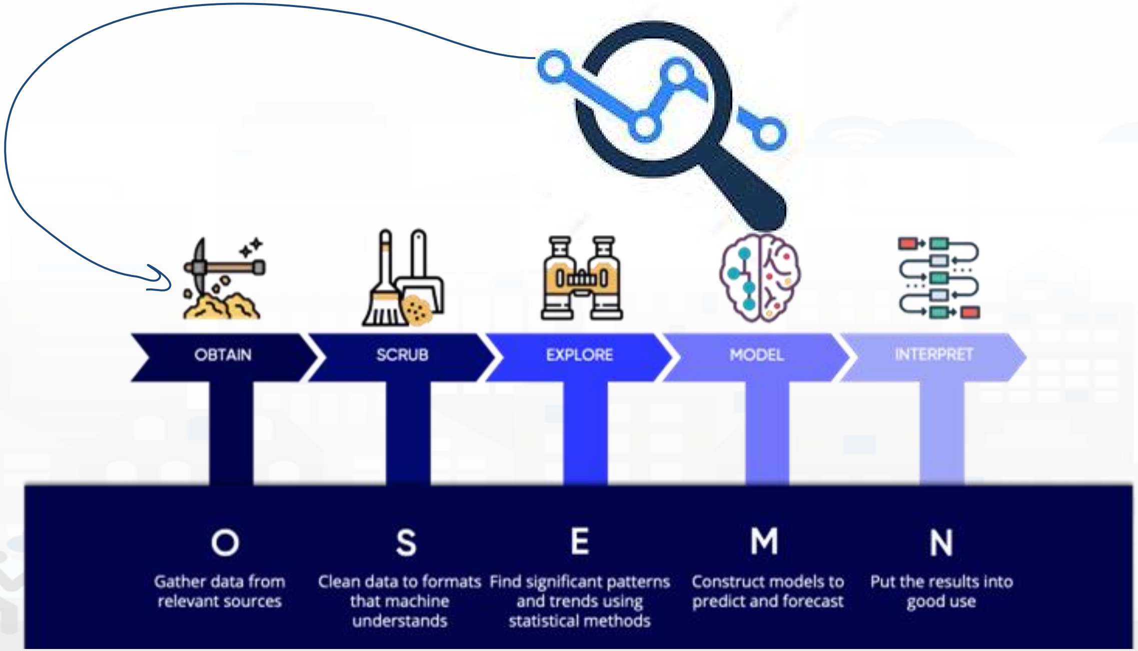
Clustering

- **Cluster 1:**
  - characterized by a decrement of bike availability at lunchtime,
  - Typically located close to the railway stations, airport, etc.
- **Cluster 2:**
  - characterized by an increment of the availability of bikes in the central part of the day (lunch hours, since most of the people are parking their bikes to get lunch).
  - Typically positioned in the central area of the cities,
- **Cluster 3:**
  - almost uniform trend in the bike availability
  - mainly positioned in the peripheral areas of the city



Modelling Phase

State of the Art Analysis of AI architectures & **data sources** used for the prediction


OBTAIN
SCRUB
EXPLORE
MODEL
INTERPRET
O
Gather data from relevant sources
S
Clean data to formats that machine understands
E
Find significant patterns and trends using statistical methods
M
Construct models to predict and forecast
N
Put the results into good use

Modelling Phase

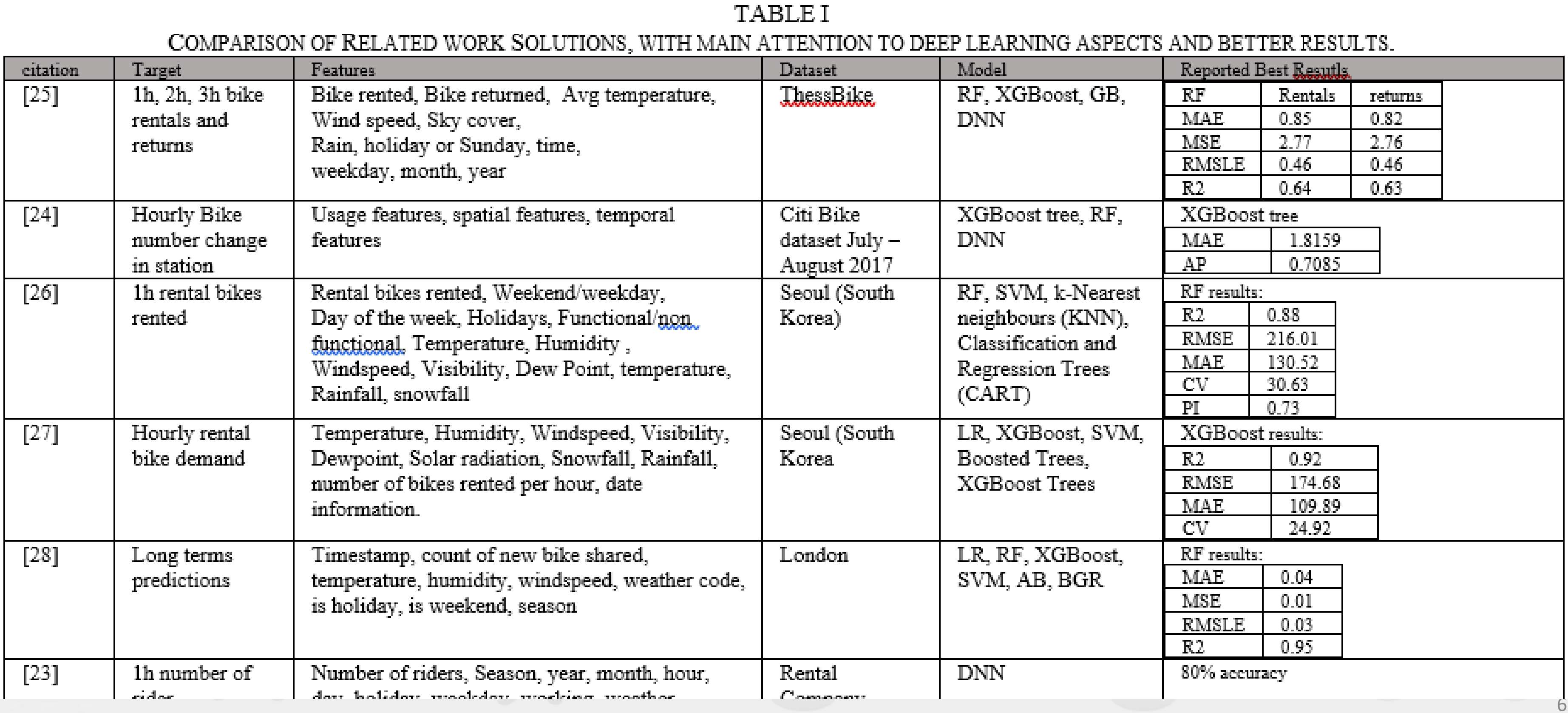


TABLE I

COMPARISON OF RELATED WORK SOLUTIONS, WITH MAIN ATTENTION TO DEEP LEARNING ASPECTS AND BETTER RESULTS.

citation	Target	Features	Dataset	Model	Reported Best Resutls
[25]	1h, 2h, 3h bike rentals and returns	Bike rented, Bike returned, Avg temperature, Wind speed, Sky cover, Rain, holiday or Sunday, time, weekday, month, year	ThessBike	RF, XGBoost, GB, DNN	RF / Rentals / returns MAE / 0.85 / 0.82 MSE / 2.77 / 2.76 RMSLE / 0.46 / 0.46 R2 / 0.64 / 0.63
[24]	Hourly Bike number change in station	Usage features, spatial features, temporal features	Citi Bike dataset July – August 2017	XGBoost tree, RF, DNN	XGBoost tree MAE / 1.8159 AP / 0.7085
[26]	1h rental bikes rented	Rental bikes rented, Weekend/weekday, Day of the week, Holidays, Functional/non functional, Temperature, Humidity , Windspeed, Visibility, Dew Point, temperature, Rainfall, snowfall	Seoul (South Korea)	RF, SVM, k-Nearest neighbours (KNN), Classification and Regression Trees (CART)	RF results: R2 / 0.88 RMSE / 216.01 MAE / 130.52 CV / 30.63 PI / 0.73
[27]	Hourly rental bike demand	Temperature, Humidity, Windspeed, Visibility, Dewpoint, Solar radiation, Snowfall, Rainfall, number of bikes rented per hour, date information.	Seoul (South Korea	LR, XGBoost, SVM, Boosted Trees, XGBoost Trees	XGBoost results: R2 / 0.92 RMSE / 174.68 MAE / 109.89 CV / 24.92
[28]	Long terms predictions	Timestamp, count of new bike shared, temperature, humidity, windspeed, weather code, is holiday, is weekend, season	London	LR, RF, XGBoost, SVM, AB, BGR	RF results: MAE / 0.04 MSE / 0.01 RMSLE / 0.03 R2 / 0.95
[23]	1h number of rider	Number of riders, Season, year, month, hour, day, holiday, weekday, working, weather	Rental Company	DNN	80% accuracy

Features

categories	Metrics	Description of metric variable
BASELINE - HISTORICAL	AvailableBikes	The number of bikes available
	Time, week, month, day	Time of the day of the data, month and week of the year and day of the year
	Day of the week	The day of the week 1,…, 7
	Weekend, holiday	1 if Saturday or Sunday , 0 otherwise 1 if the day is a holiday, 0 otherwise
	Previous week, previous day	The previous week of the year and the previous day of the year

Features

categories	Metrics	Description of metric variable
REAL-TIME WEATHER AND WEATHER FORECAST	Max Temperature, Min Temperature, Temperature	Temperature values
	Humidity	The humidity of the hour prior to the observation measurement in percentage
	Rain	ml of rain registered in the hour prior to the observation measurement
	Pressure	Pressure in mb
	WindSpeed	Average wind speed registered in the hour prior to the observation measurement in km/h
	Cloud Cover Percentage	Cloud Cover expressed in percentage
	Sunrise	Hour of the sunrise

Features

categories	Metrics	Description of metric variable
DIFF FROM ACTUAL VALUES AND PREV. OBSERVATIONS	dPweek	Previous observation’s difference of the previous week
	dSweek	Subsequent observation’s difference of the previous week
	dPDay	Previous observation’s difference of the previous day
	dSDay	Subsequent observation’s difference of the previous day
	dP2weeks	Previous observation’s difference between the previous week and two weeks earlier
	dS2weeks	Subsequent observation’s difference between the previous week and two weeks earlier

Features

categories	Metrics	Description of metric variable
DIFF FROM ACTUAL VALUES AND PREV. OBSERV ATIONS	dPweek	evious week
	dSweek	previous week
	dPDay	evious day
	dSDay	previous day
	dP2weeks	the previous
	dS2weeks	en the previous

the difference between the number of available bikes in the observation day (D) at the time slot t and the number of bikes during the **Previous** time slot (t-1) of the previous day (D-1).

$$dPDay = availableBikes_{D,t} - availableBikes_{D-1,t-1}$$

Predictive AI architecture Analysis

- With a temporal target of 1h, which is the most critical short-term prediction slot ensemble learning techniques such as **Random Forest** (RF) and **Extreme Gradient Boosting Machines** (XGBOOST) are powerful techniques that must be considered for this type of problem.

- It has also been taken into consideration deep learning solutions such as **DNN** architecture with **LSTM** and based on the results of the related works also with a **Deep Bidirectional-LSTM (Bi-LSTM)** Neural Network

Evaluation Metrics

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(obs_i - pred_i)^2}{n}}$$

R-Squared(R2)

- $\overline{y} = \frac{1}{n}\sum_{i=1}^{\mathrm{n}} \mathrm{obs_i}$
- $R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(obs_i - pred_i)^2}{\sum_{i=1}^{\mathrm{n}}(obs_i - \overline{y})^2}\right)$

Mean Absolute Scaled Error (MASE)

$$q_t = \frac{obs_t - pred_t}{\frac{1}{n-1}\sum_{i=2}^{n}|\,obs_i - \ obs_{i-1}|}$$

$$MASE = mean\,(|q_t|), \qquad t = 1, \dots, n$$

Mean Absolute Error (MAE)

$$MAE = \frac{\sum_{i=1}^{n}|obs_i - pred_i|^2}{n}$$

Deep Learning Models Configuration

The architecture of the Deep Learning neural networks is made up of **4 layers** with specific units of the selected architecture (e.g.: LSTM units for LSTM networks) and optimized hyperparameters via random search.

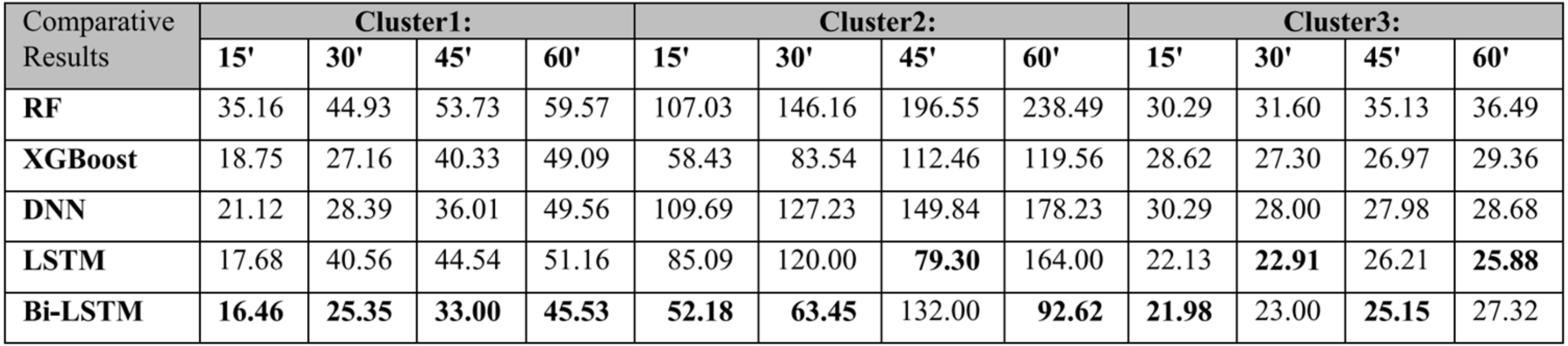
- The number of neurons for the input layer is equal to 64 or 128;
- for the 2nd layer 64, 32;
- for the 3rd layer 16, 32.
- The last layer has only one neuron with a sigmoid activation function, in order to obtain a value in the range 0, 1 (the input data for the models were normalized using a Min Max scaler).

Deep Learning Models Configuration

- The **batch size** was set to 32 and 64 samples.
- The **dropout rate** for each layer was optimized with the values 0.1, 0.25, 0.5.
- For each model, the **Adam Optimizer** has been chosen with learning rate optimized among 0.05, 0.005, 0.0005 and 0.00005.
- **MSE** was selected as loss function to be monitored during the optimization.
- The number of epochs was set to a maximum value of 1000, because the training strategy used the **Early Stopping** method for determining the optimum epoch number minimizing the RMSE of the validation set, restoring the weights of the best model at the end of the learning process.
- As to LSTMs and Bi-LSTMs inputs were organized through a sliding window with **4 timesteps**, which is equivalent to the values of the previous hour with respect to the prediction time.

Experimental Results

- The data used for this training range from the 16th of December 2019 to the 9th of February 2020. The successive two weeks (10/02/2020 – 23/02/2020) have been used for the validation and the test set includes data from the 24th of February 2020 to the 8th of March 2020
- The machine learning solutions were compared based on the **MAPE** for the prediction targets of 15, 30, 45 and 60 minutes.



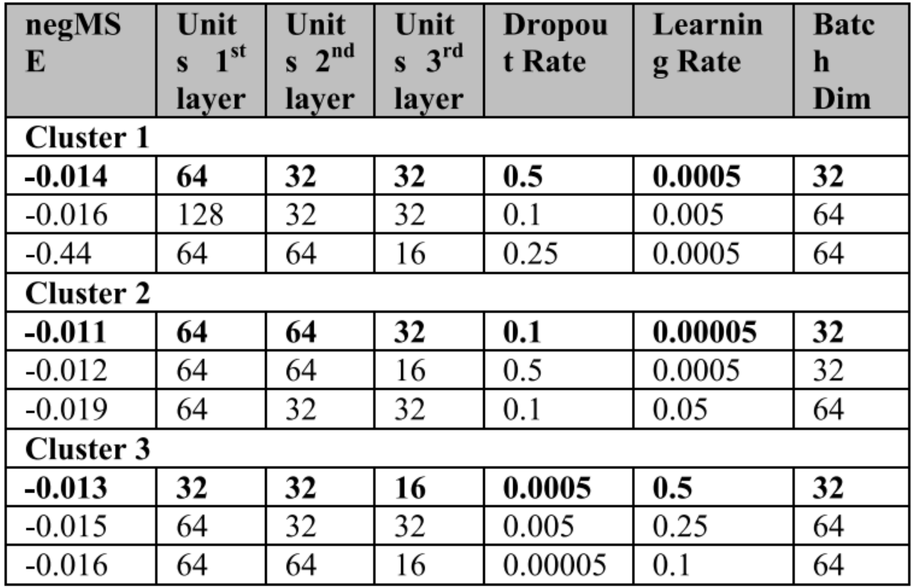
Comparative Results	**Cluster1:**				**Cluster2:**				**Cluster3:**			
	15'	**30'**	**45'**	**60'**	**15'**	**30'**	**45'**	**60'**	**15'**	**30'**	**45'**	**60'**
RF	35.16	44.93	53.73	59.57	107.03	146.16	196.55	238.49	30.29	31.60	35.13	36.49
XGBoost	18.75	27.16	40.33	49.09	58.43	83.54	112.46	119.56	28.62	27.30	26.97	29.36
DNN	21.12	28.39	36.01	49.56	109.69	127.23	149.84	178.23	30.29	28.00	27.98	28.68
LSTM	17.68	40.56	44.54	51.16	85.09	120.00	**79.30**	164.00	22.13	**22.91**	26.21	**25.88**
Bi-LSTM	**16.46**	**25.35**	**33.00**	**45.53**	**52.18**	**63.45**	132.00	**92.62**	**21.98**	23.00	**25.15**	27.32

Hyperparameter Details

In general, Deep Recurrent Neural Networks architectures outperformed the ensemble learning techniques.

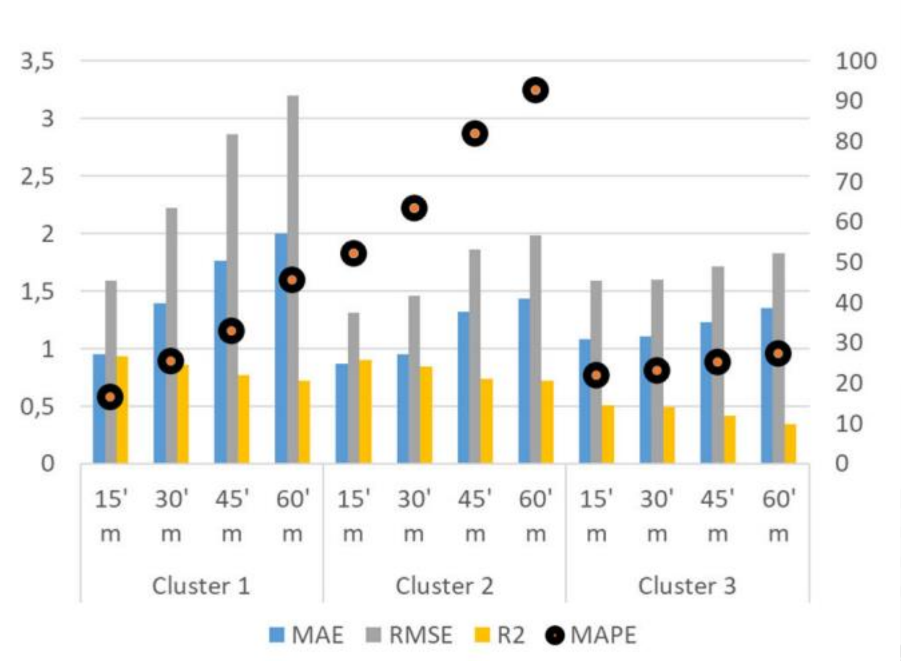
Overall, the best machine learning technique for the prediction of the number of available bikes turned out to be the Bi-LSTM.

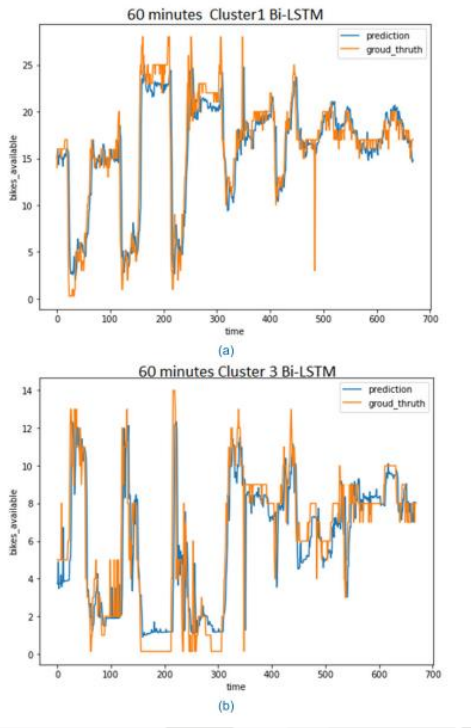
The details on the hyperparameters resulting from Random Search Optimization of Bi-LSTM for the temporal target of 60 minutes are reported



negMSE	Units 1st layer	Units 2nd layer	Units 3rd layer	Dropout Rate	Learning Rate	Batch Dim
Cluster 1						
-0.014	**64**	**32**	**32**	**0.5**	**0.0005**	**32**
-0.016	128	32	32	0.1	0.005	64
-0.44	64	64	16	0.25	0.0005	64
Cluster 2						
-0.011	**64**	**64**	**32**	**0.1**	**0.00005**	**32**
-0.012	64	64	16	0.5	0.0005	32
-0.019	64	32	32	0.1	0.05	64
Cluster 3						
-0.013	**32**	**32**	**16**	**0.0005**	**0.5**	**32**
-0.015	64	32	32	0.005	0.25	64
-0.016	64	64	16	0.00005	0.1	64

Predictions On Representative Sensors



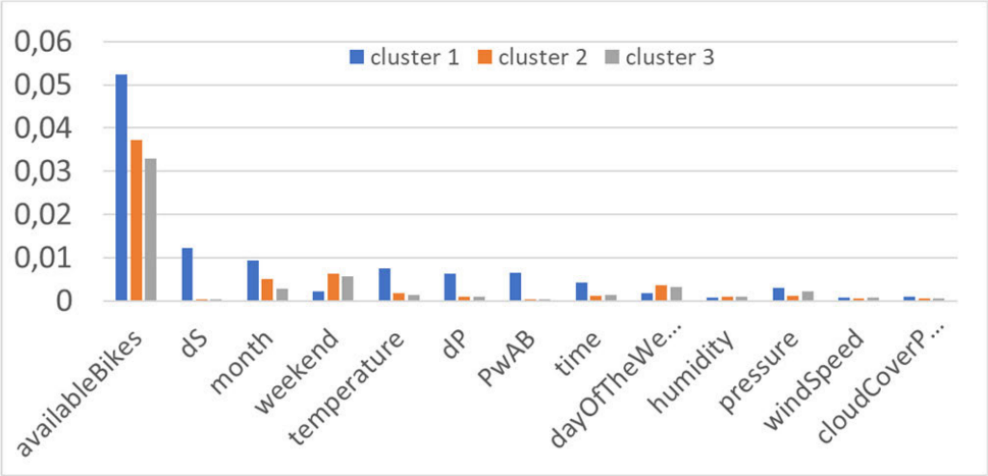


(a)

(b)

Feature Importance Analysis

To evaluate the relevance of features used by Bi-LSTMs for short-term bike availability prediction on the representative bike racks of Pisa and Siena, a SHapley Additive exPlanations (**SHAP**) feature importance analysis was performed



Conclusions

- This work studied machine learning methods to predict **bike availability in bike-sharing systems with smart stations**.
- The proposed method takes high dimensional time-series data from each station and uses real-time and forecast weather information as input to perform long term **predictions 15-30-45-60 minutes**
- The **clustering** process classified bike racks into 3 clusters, where the representative sensors were identified.
- The proposed solution demonstrated that when it comes to short-term prediction the **Bi-LSTM** neural network architecture is the most suitable machine learning technique for this problem.
- The results in terms of **Mean Absolute Error** in the worst-case have achieved an error of **2 bikes** for the 60 minutes prediction on the bike rack.
- The most important feature which has been identified by using **SHAP** analysis **is the number of available bikes in all the clusters**.

Appendix

Ensemble Learning Techniques Details

The number of trees parameter for the RF was set to 300, with a minimum sample split set equal to 2, minimum number of samples allowed for a leaf equal to 1, without limits on the maximum number of features considered to split a node as well as on the number of leaves, with the construction of bootstrapped datasets to create the related trees.

The XGBoost regressor uses the least-squares loss function with learning rate optimized with values 0.1, 0.01, and 0.001 with max depth equal to 3 and minimum sample split, minimum sample leaf, maximum number of features equal to the ones chosen for the RF.

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Long Term Predictions of NO2 Average Values via Deep Learning

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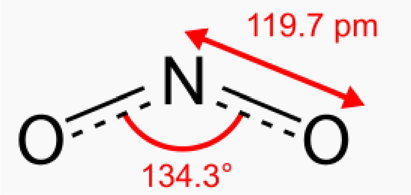
NO2



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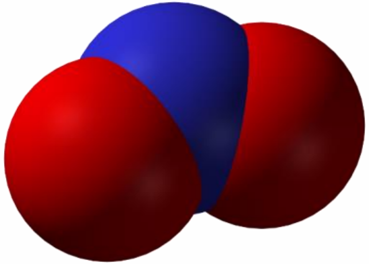


The *European Union* has created a legislative program in which are defined limits on the hourly and yearly concentration of the pollutants (**40 µg/m3 for the yearly mean value of NO2**)

THE CHALLENGES

- The majority of works at the **state-of-the-art** in the Air Quality Prediction are **short-term** based hourly or a few days of the concentrations of the air pollutants.
- In order to make long-term predictions we developed six **Deep Long Short-Term Memory Neural Network** to make the predictions for the temporal taget of **30, 60, 90, 120, 150, 180** days.

The Target

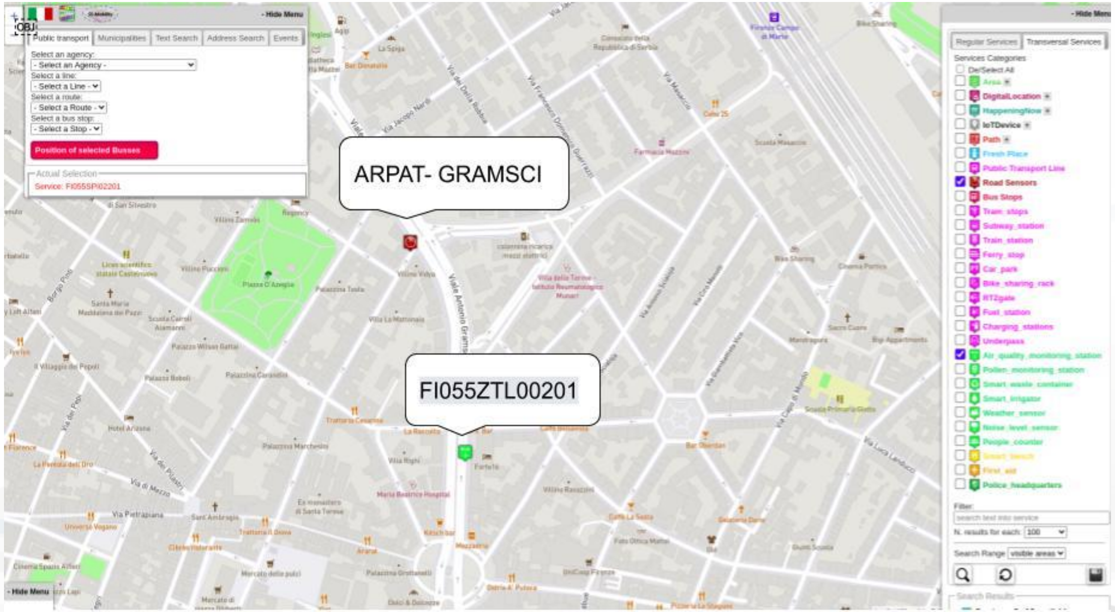
To estimate the **yearly mean value of NO2** it has been used the **progressive mean value** of this pollutant. This value is calculated day after day cumulating the mean daily value and divide this by the number of cumulated days

$$\mathrm{NO_2Cumulated_i} = \sum_{\mathrm{k=1}}^{\mathrm{i}} \mathrm{NO_2}_{\mathrm{k}}$$

$$\mathrm{NO_2progressiveMean_i} = \frac{\mathrm{NO_2Cumulated_i}}{\mathrm{i}}$$

i-th day
i={1,365}

Iot Sensors used



Select an agency: - Select an Agency -
Select a line: - Select a Line -
Select a route: - Select a Route -
Select a bus stop: - Select a Stop -

Actual Selection
Service: FI055SPI02201

Services Categories
- □ De/Select All
- □ Area
- □ DigitalLocation
- □ HappeningNow
- □ IoTDevice
- □ Path
- □ Fresh Place
- □ Public Transport Line
- ☑ Road Sensors
- □ Bus Stops
- □ Tram_stops
- □ Subway_station
- □ Train_station
- □ Ferry_stop
- □ Car_park
- □ Bike_sharing_rack
- □ RTZgate
- □ Fuel_station
- □ Charging_stations
- □ Underpass
- ☑ Air_quality_monitoring_station
- □ Pollen_monitoring_station
- □ Smart_waste_container
- □ Smart_irrigator
- □ Weather_sensor
- □ Noise_level_sensor
- □ People_counter
- □ Smart_bench
- □ First_aid
- □ Police_headquarters

Filter: search text into service
N. results for each: 100
Search Range: visible areas
Search Results

Service Map

METEOROLOGICAL FEATURES

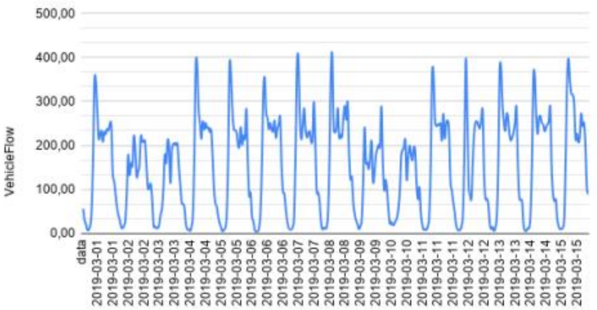
More Data

TEMPORAL INFORMATIONS

iL Meteo

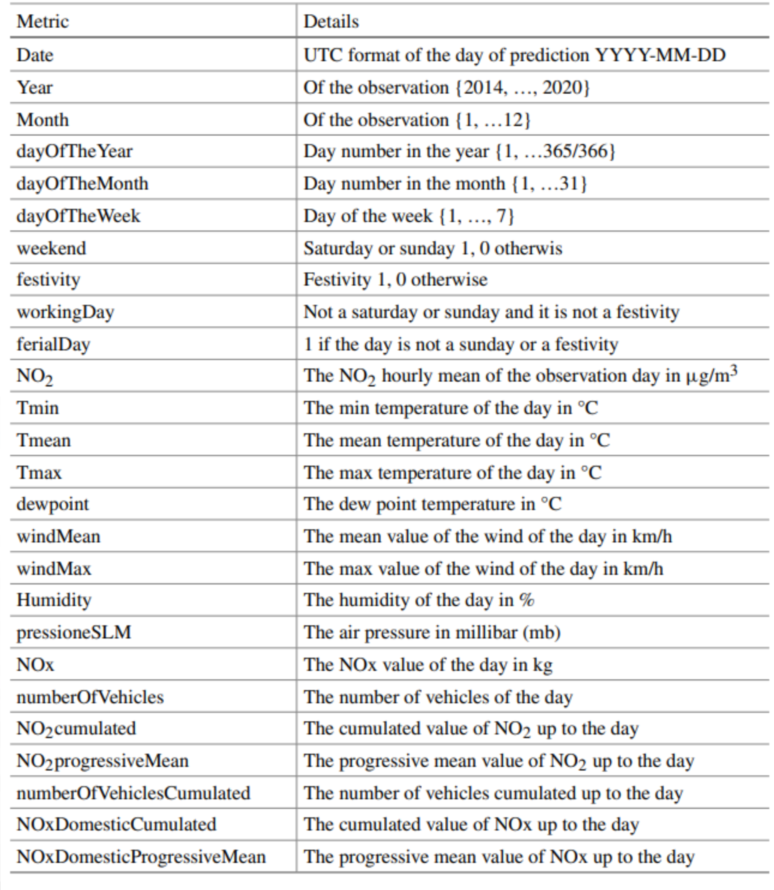
NOX

VehicleFlow first 15 days of March 2019



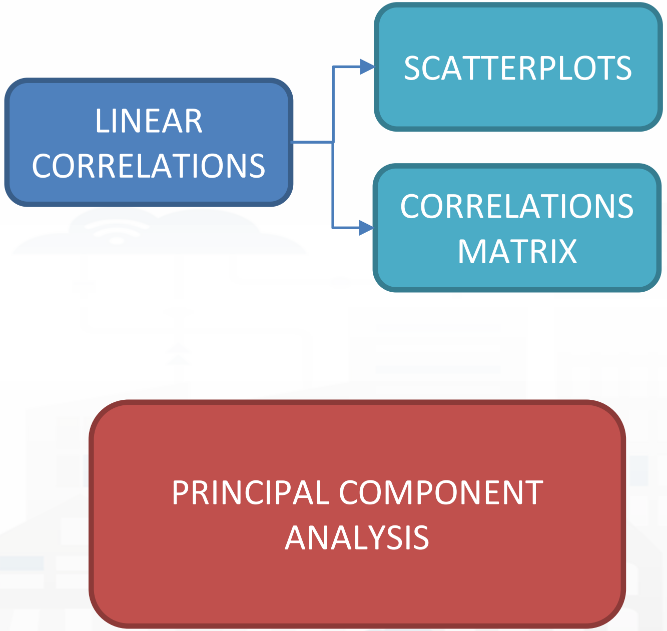
$$NO_x Domestic_i = (K + A * Tmedia_i + B * Tmedia_i^2) * 1000$$

where: $K = 2.224884427$, $A = -0.148281912$, $B = 0.00276720916887206$



Metric	Details
Date	UTC format of the day of prediction YYYY-MM-DD
Year	Of the observation {2014, …, 2020}
Month	Of the observation {1, …12}
dayOfTheYear	Day number in the year {1, …365/366}
dayOfTheMonth	Day number in the month {1, …31}
dayOfTheWeek	Day of the week {1, …, 7}
weekend	Saturday or sunday 1, 0 otherwis
festivity	Festivity 1, 0 otherwise
workingDay	Not a saturday or sunday and it is not a festivity
ferialDay	1 if the day is not a sunday or a festivity
NO_2	The NO_2 hourly mean of the observation day in $\mu g/m^3$
Tmin	The min temperature of the day in °C
Tmean	The mean temperature of the day in °C
Tmax	The max temperature of the day in °C
dewpoint	The dew point temperature in °C
windMean	The mean value of the wind of the day in km/h
windMax	The max value of the wind of the day in km/h
Humidity	The humidity of the day in %
pressioneSLM	The air pressure in millibar (mb)
NOx	The NOx value of the day in kg
numberOfVehicles	The number of vehicles of the day
NO_2cumulated	The cumulated value of NO_2 up to the day
NO_2progressiveMean	The progressive mean value of NO_2 up to the day
numberOfVehiclesCumulated	The number of vehicles cumulated up to the day
NOxDomesticCumulated	The cumulated value of NOx up to the day
NOxDomesticProgressiveMean	The progressive mean value of NOx up to the day

Feature Identification



- The features used as input for the predictive models are:

- **Month**
- **dayOfTheYear**
- **NO2**
- **Tmean**
- **Humidity**
- **windMean**
- **NoxDomestic**
- **numberOfVehicles**
- **NO2cumulated**
- **NO2progresseveMean**
- **numberOfVehiclesCumulated**

In Depth Feature Selection

Why don’t we give all the features to the ML algorithm and let it decide which feature is important?

- **Curse of dimensionality**: as the number of features or dimensions grows, the amount of data we need to generalize accurately grows exponentially.
- **Occam’s Razor**: We want our models to be simple and explainable. We lose explainability when we have a lot of features.
- **Garbage In Garbage out**: Most of the times, we will have many non-informative features. For Example, Name or ID variables. Poor-quality input will produce Poor-Quality output.

There are plenty of possibilities to conduct a feature selection analysis

- Linear Correlation Analysis
- Principal Component Analysis

In Depth Feature Selection

Linear Correlation Analysis

- Through correlation, we can predict one variable from the other.
- The logic behind using correlation for feature selection is that the good variables are highly correlated with the target.
- Otherwise If two variables are correlated, we can predict one from the other. Therefore, if two features are correlated, the model only really needs one of them, as the second one does not add additional information

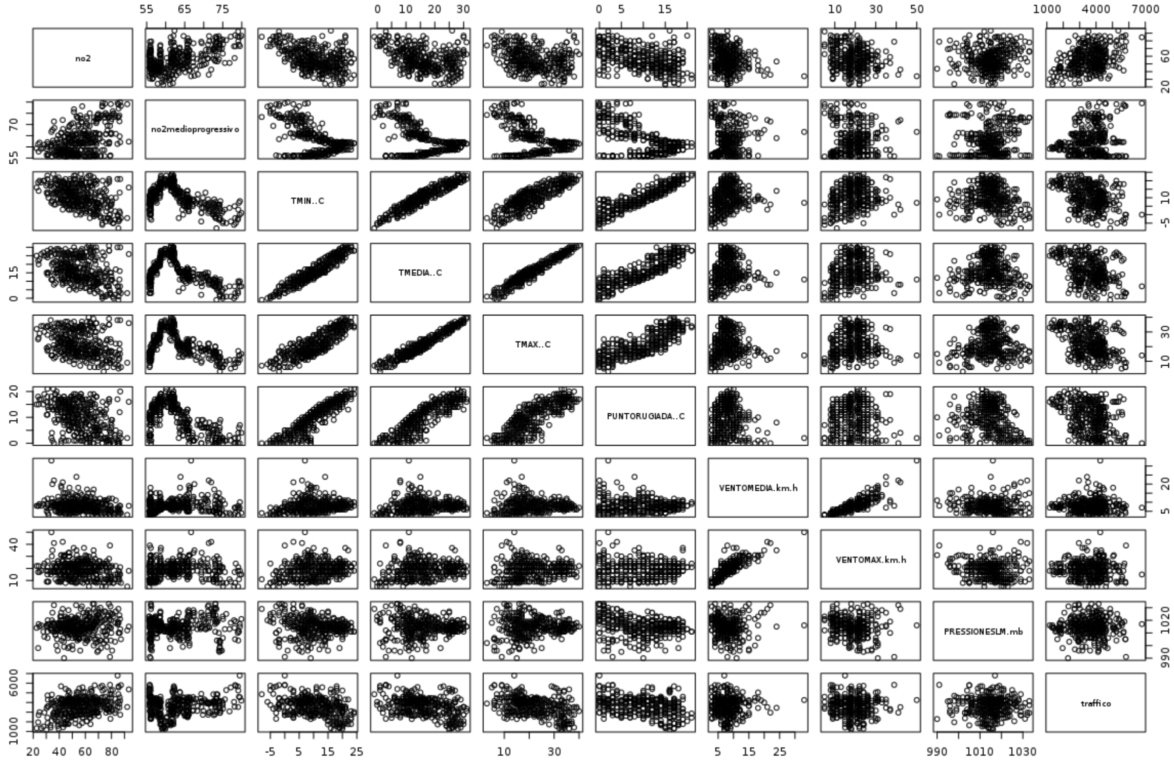
Qualitative evaluation with **scatterplots**

Quantitative evaluation using the Pearson **Correlation** coefficient.

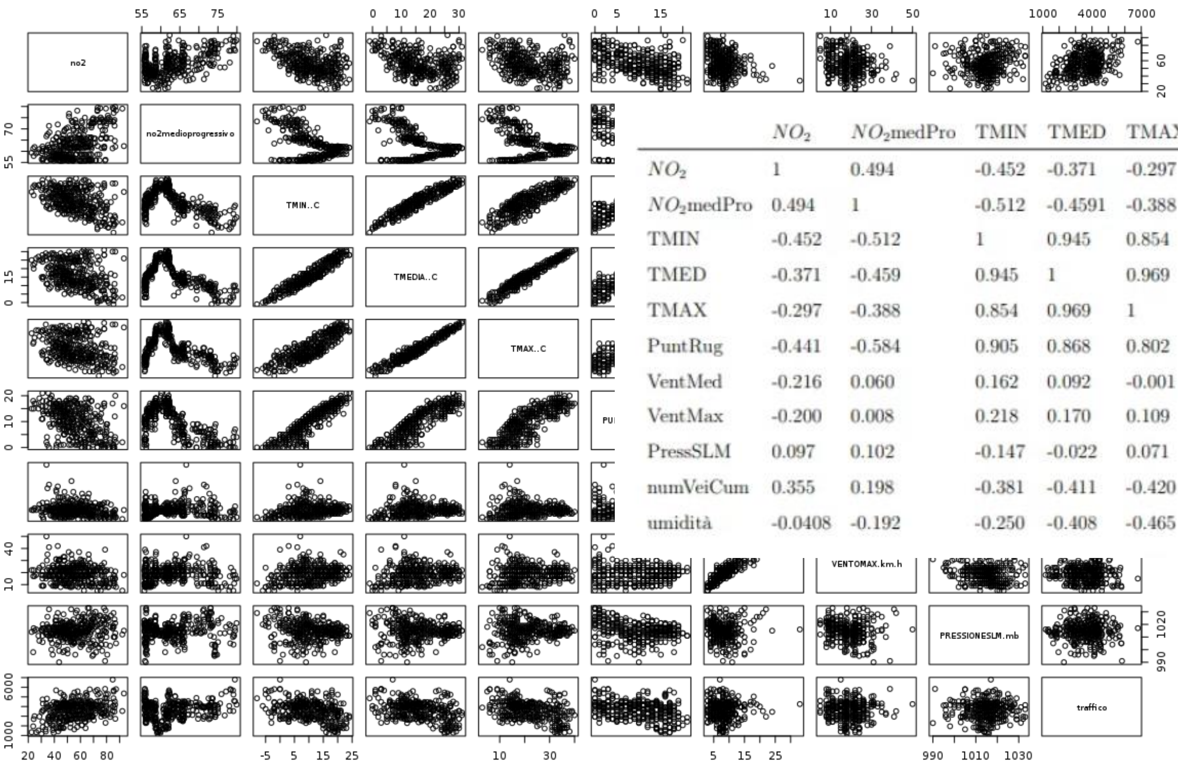
-> We need to set an absolute value, say 0.5 as the threshold for selecting the variables. If we find that the predictor variables are correlated among themselves, we can drop the variable which has a lower correlation coefficient value with the target variable.

$$\rho_{X,Y} = \frac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{\mathbb{E}[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y}$$

Scatterplots



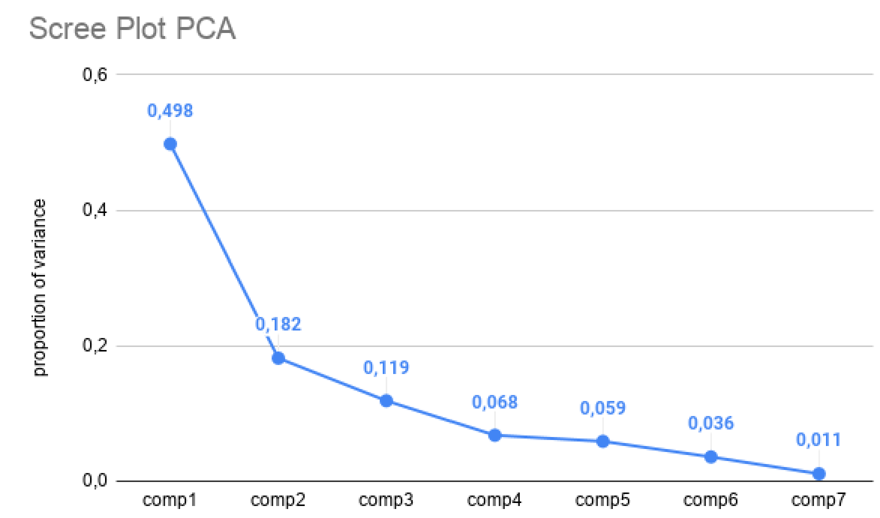
Correlation Matrix

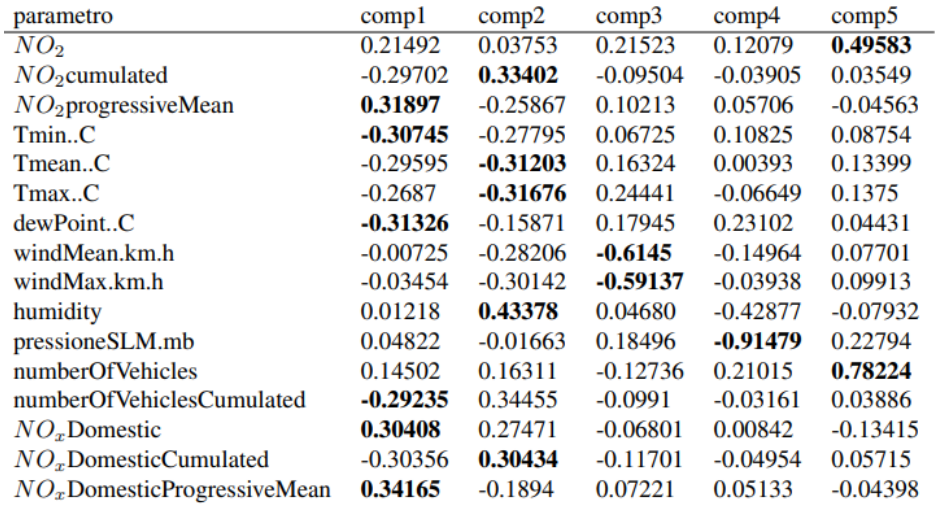


	NO_2	NO_2medPro	TMIN	TMED	TMAX	PuntRug	VentMed	VentMax	PressSLM	numVeiCum	umidità
NO_2	1	0.494	-0.452	-0.371	-0.297	-0.441	-0.216	-0.200	0.097	0.355	-0.408
NO_2medPro	0.494	1	-0.512	-0.4591	-0.388	-0.584	0.060	0.008	0.102	0.198	-0.192
TMIN	-0.452	-0.512	1	0.945	0.854	0.905	0.162	0.218	-0.147	-0.381	-0.250
TMED	-0.371	-0.459	0.945	1	0.969	0.868	0.092	0.170	-0.022	-0.411	-0.408
TMAX	-0.297	-0.388	0.854	0.969	1	0.802	-0.001	0.109	0.071	-0.420	-0.465
PuntRug	-0.441	-0.584	0.905	0.868	0.802	1	-0.096	0.022	-0.225	-0.344	0.061
VentMed	-0.216	0.060	0.162	0.092	-0.001	-0.0969	1	0.833	-0.046	0.001,	-0.442
VentMax	-0.200	0.008	0.218	0.170	0.109	0.022	0.833	1	-0.138	-0.029	-0.379
PressSLM	0.097	0.102	-0.147	-0.022	0.071	-0.225	-0.046	-0.138	1	-0.010	0.395
numVeiCum	0.355	0.198	-0.381	-0.411	-0.420	-0.344	0.001	-0.029	-0.010	1	0.171
umidità	-0.0408	-0.192	-0.250	-0.408	-0.465	0.061	-0.442	-0.379	0.395	0.171	1

Principal Component Analysis

- PCA is a multivariate data analysis based on projection methods that results in a matrix that summarizes how our variables all relate to one another in different **principal components**.
- data reduction technique that transform the dataset into a compressed form that capture maximum information (**proportion of variance** top principal components)





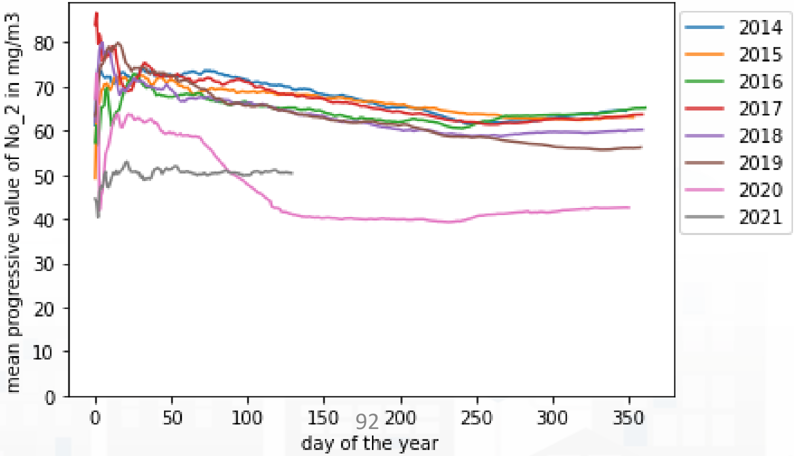
parametro	comp1	comp2	comp3	comp4	comp5
NO_2	0.21492	0.03753	0.21523	0.12079	**0.49583**
NO_2cumulated	-0.29702	**0.33402**	-0.09504	-0.03905	0.03549
NO_2progressiveMean	**0.31897**	-0.25867	0.10213	0.05706	-0.04563
Tmin..C	**-0.30745**	-0.27795	0.06725	0.10825	0.08754
Tmean..C	-0.29595	**-0.31203**	0.16324	0.00393	0.13399
Tmax..C	-0.2687	**-0.31676**	0.24441	-0.06649	0.1375
dewPoint..C	**-0.31326**	-0.15871	0.17945	0.23102	0.04431
windMean.km.h	-0.00725	-0.28206	**-0.6145**	-0.14964	0.07701
windMax.km.h	-0.03454	-0.30142	**-0.59137**	-0.03938	0.09913
humidity	0.01218	**0.43378**	0.04680	-0.42877	-0.07932
pressioneSLM.mb	0.04822	-0.01663	0.18496	**-0.91479**	0.22794
numberOfVehicles	0.14502	0.16311	-0.12736	0.21015	**0.78224**
numberOfVehiclesCumulated	**-0.29235**	0.34455	-0.0991	-0.03161	0.03886
NO_xDomestic	**0.30408**	0.27471	-0.06801	0.00842	-0.13415
NO_xDomesticCumulated	-0.30356	**0.30434**	-0.11701	-0.04954	0.05715
NO_xDomesticProgressiveMean	**0.34165**	-0.1894	0.07221	0.05133	-0.04398

Table 2. Principal Components analysis (a part).

Actual Time Trends

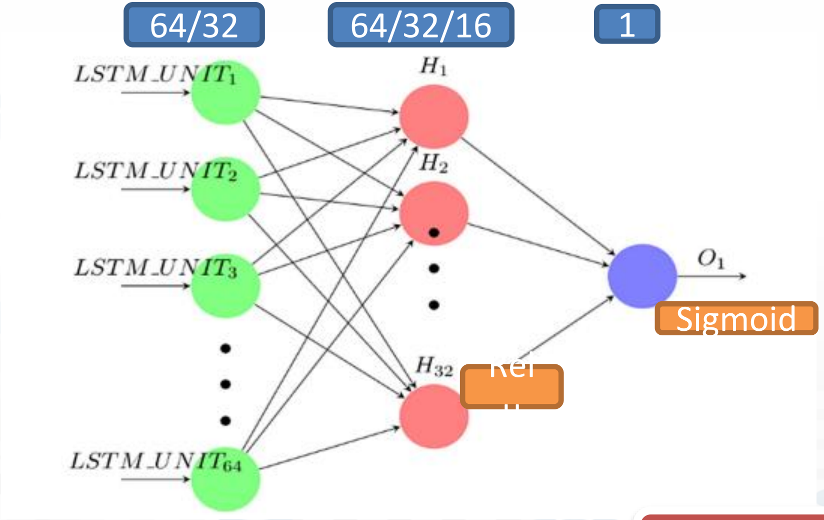
- The data used refers to the years from 2014 to 2020.

- Training set 2014 – 2017
- Test set 2019



Deep LSTM Networks Details

Random Search Hyperparameters Optimization



Mean Squared Error Loss

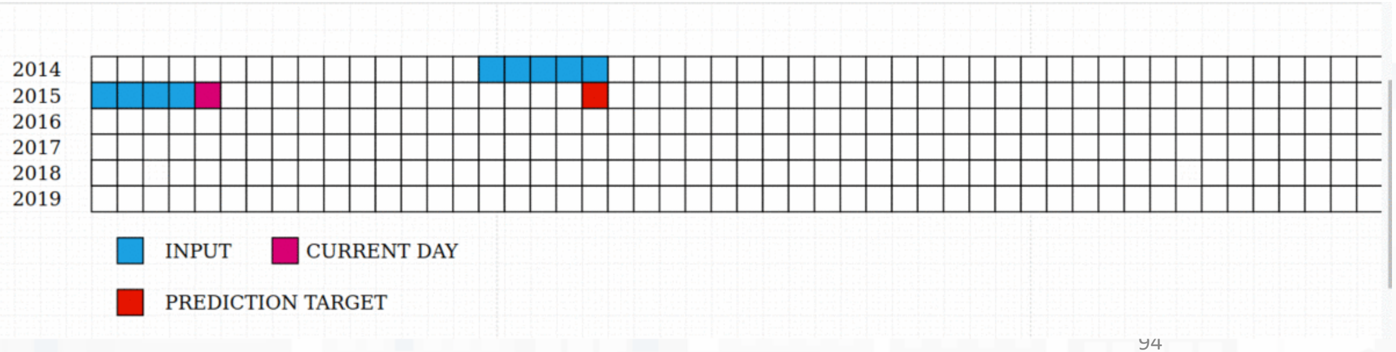
$$L(y,\hat{y}) = \frac{1}{N}\sum_{i=0}^{N}(y-\hat{y}_i)^2$$

Adam Optimizer
Lr between 0,05 0,005 0,0005

Batch size 32 or 64

Early Stopping

- The data have been organized using a sliding window approach made of:
  - The data of 20 days preceding the prediction day
  - The data of 20 days preceding the day of the prediction target of the previous year



(batch_size, timesteps, features)

Evaluation Metrics

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(obs_i - pred_i)^2}{n}}$$

R-Squared(R2)

- $\overline{y} = \frac{1}{n}\sum_{i=1}^{\mathrm{n}} \mathrm{obs_i}$
- $R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(obs_i - pred_i)^2}{\sum_{i=1}^{\mathrm{n}}(obs_i - \overline{y})^2}\right)$

Mean Absolute Scaled Error (MASE)

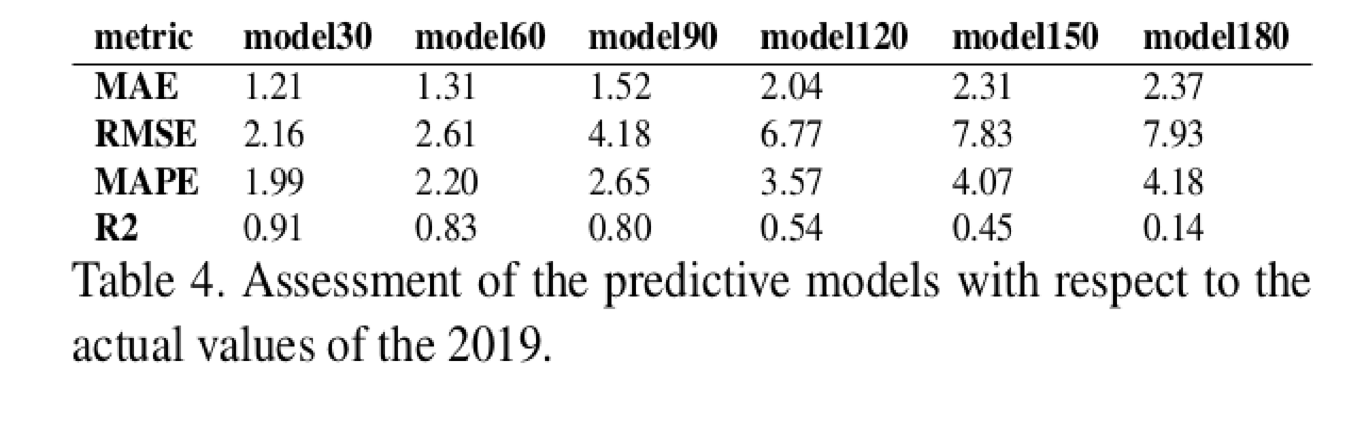
$$q_t = \frac{obs_t - pred_t}{\frac{1}{n-1}\sum_{i=2}^{n}|obs_i - \ obs_{i-1}|}$$

$$MASE = mean\,(|q_t|), \qquad t = 1, \dots, n$$

Mean Absolute Error (MAE)

$$MAE = \frac{\sum_{i=1}^{n}|obs_i - pred_i|^2}{n}$$

Results

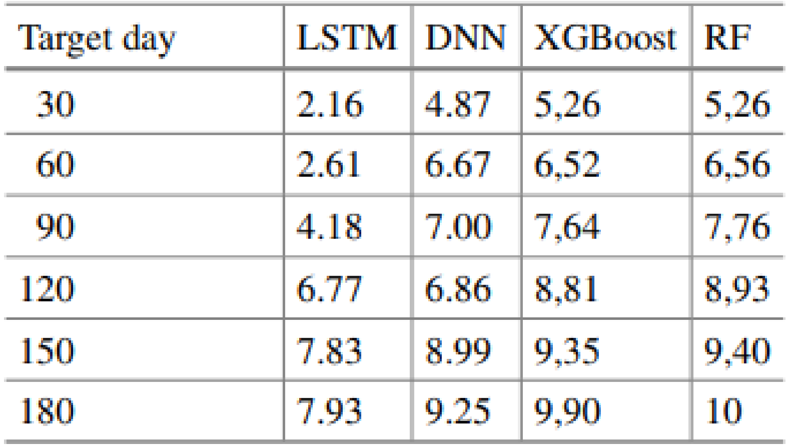


metric	model30	model60	model90	model120	model150	model180
MAE	1.21	1.31	1.52	2.04	2.31	2.37
RMSE	2.16	2.61	4.18	6.77	7.83	7.93
MAPE	1.99	2.20	2.65	3.57	4.07	4.18
R2	0.91	0.83	0.80	0.54	0.45	0.14

Table 4. Assessment of the predictive models with respect to the actual values of the 2019.

Model Comparison

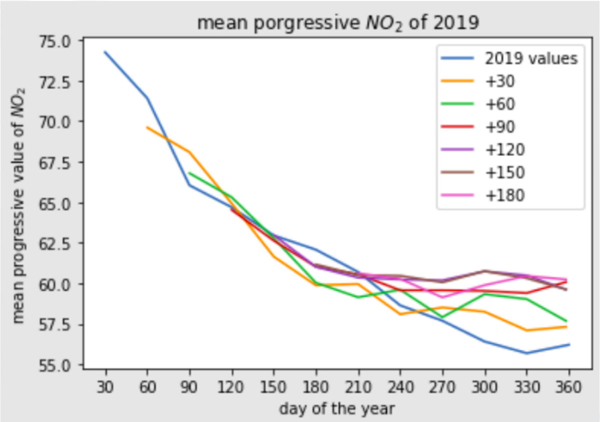
The results of the Deep LSTM Neural Networks have been compared in terms of MAPE, Mean Absolute Percentage Error results for the prediction targets of 30, 60, 90, 120, 150, and 180 days with a DNN, with the same number of layers as the LSTM architecture described in the previous section, an XGBoost and RF.

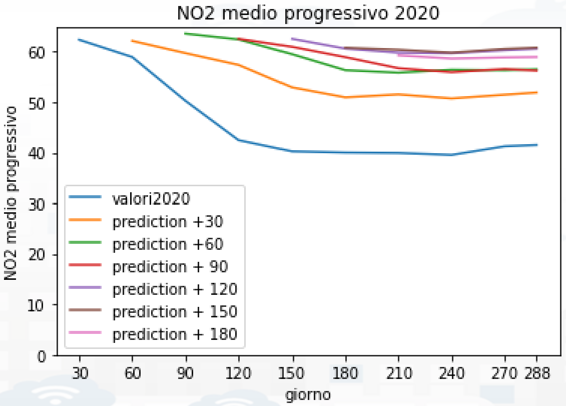


Target day	LSTM	DNN	XGBoost	RF
30	2.16	4.87	5,26	5,26
60	2.61	6.67	6,52	6,56
90	4.18	7.00	7,64	7,76
120	6.77	6.86	8,81	8,93
150	7.83	8.99	9,35	9,40
180	7.93	9.25	9,90	10

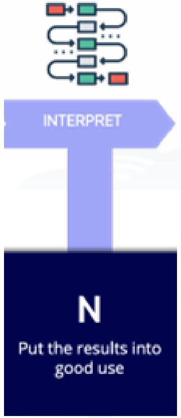
Predictions Visualization

- The results of the models for the years 2019 and 2020 are reported in the figures:





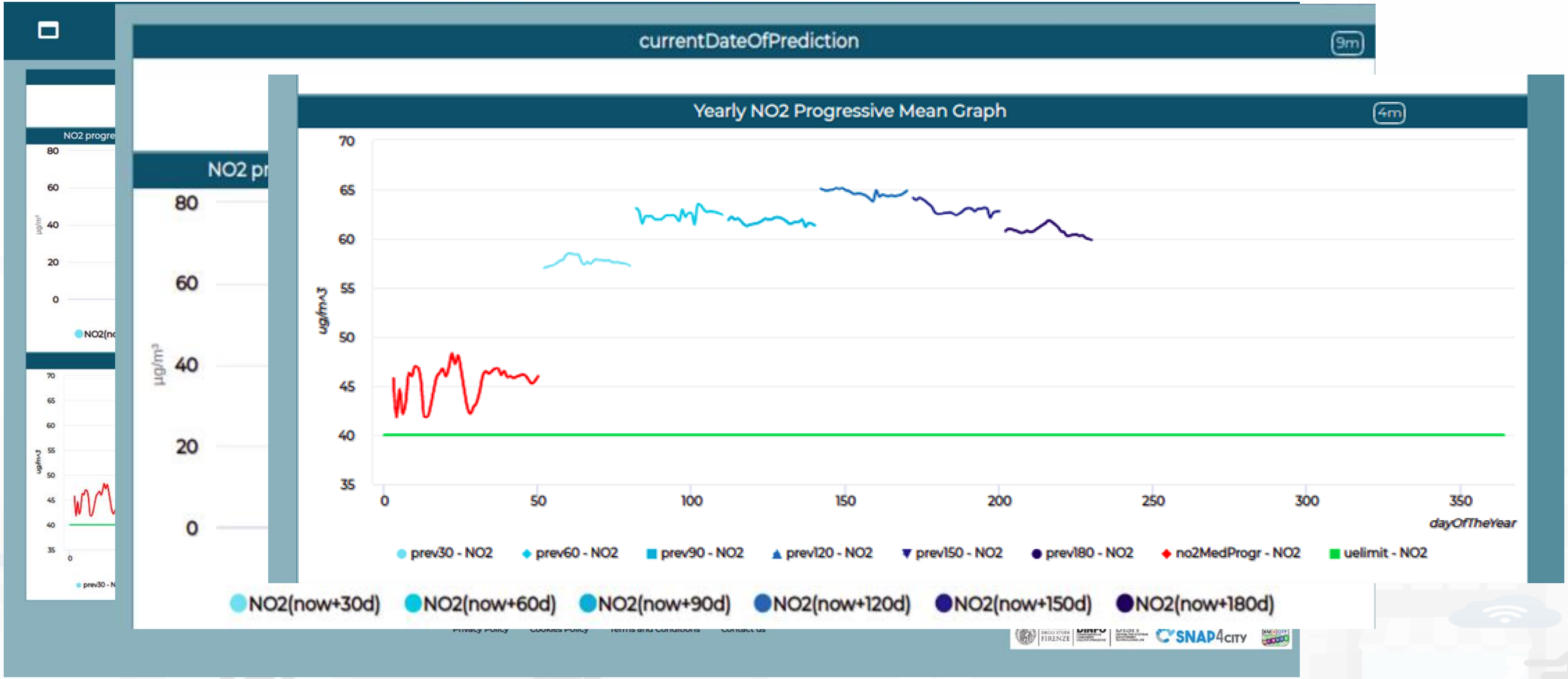
In Depth: Time Series in good use: Monitoring Dashboard



- The models developed have been inserted in **an automated process** that every day generates the input for the models and makes the predictions using a service of the SNAP4City platform, the IoTApp.
- The results are saved in the infrastructure and used to generate a **dashboard** <u>to monitor the trend of the progressive mean of the NO2.</u>

Node-RED

Dashboard for Real-Time Monitoring And Prediction



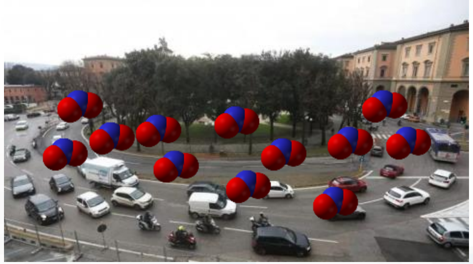
Conclusions And Future Developments

- The **dashboard** developed allows to **monitor the trend** of the progressive mean of the NO2 for the city of **Florence**, Italy.
- The results are generated by 6 **Deep LSTM Neural Networks** for the temporal targets of 30, 60, 90, 120, 150, 180 days in advance to the prediction time. These models on the test set (2019) reached results starting from a **MAPE of 1.99%** for the 30-days prediction up to a **4.18%** for the 180-days prediction.

- The presented **approach** can be applied to other air pollutants as the **PM10, CO, PM2.5** for which the UE has set limits on the yearly mean concentrations and can be **applied** to others **Smart City scenarios** assuming that the available data covers a sufficient temporal window.

What's Next

Study the state-of-the-art AI solutions to model smart mobility **traffic flow forecasting** system from 10 to 60 minutes per 10-minute time interval on the traffic network of the **Metropolitan City of Florence**.



- Deepening into data missing robustness

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SNAP4CITY

Short-Term Prediction of City Vehicle Flow via Convolutional Deep Learning

City Vehicle Flow

– Traffic Flow data can be used for a number of applications:
  - Traffic Flow Analysis and reconstruction
  - What-if-analysis
  - forecasting of pollutants

– The main problem is the need of consistent data:
  - Traffic Flow sensor are not 100% reliable
  - There could be some problem in data acquisition process

⍰ providing **PREDICTIONS** can be useful to improve quality of service

GOALS & Research Questions

- This research project has the goal to exploit a solution to compute short-term traffic flow sensors predictions up to 1 hour in advance, with a resolution of 10 minutes. The research questions at the base of this project are:

RS1) Which are the representative sensors based on a **clustering** process on the sets of traffic IoT sensor of the Metropolitan City of Florence?
RS2) Is there an **AI architecture** that achieves **best** results for the short-term prediction problem on the **case study of the Metropolitan City of Florence** compared to those used at the state of the art?
RS3) Which are the **features** actually **relevant** (historical, seasonality, weather, pollutant, etc.) in prediction computation?
RS4) How much the final architecture is **robust** for the problem of **data missing**?

Metropolitan City of Florence

- The solution and its validation have been performed by using data collected from the sensors in the Metropolitan City of Florence
- Traffic flow in cities are tendentially **very noisy** with respect to the ones measured in high speed roads, the latter being the validation context for the majority of state of the art solutions.
- The temporal windows of data used for this research project has been from September 2019 to February 2020

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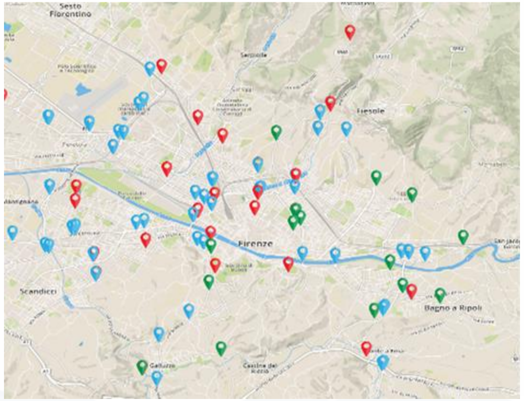
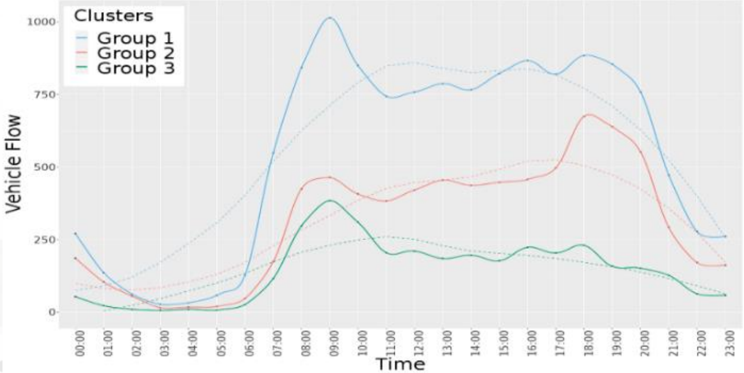
Data Clustering

- Trends of traffic flow data are strongly dependent on a number of road features:
  - road relevance (primary, secondary, etc.)
  - number of lanes, speed limits
  - presence of speed meters
  - distance from road crossing, etc
- In order to characterize the typical time trend H24 of the whole traffic flow sensors located in the city, a clustering was carried out. This approach allowed us to aggregate device sensors with the same behaviour over time.

Clustering

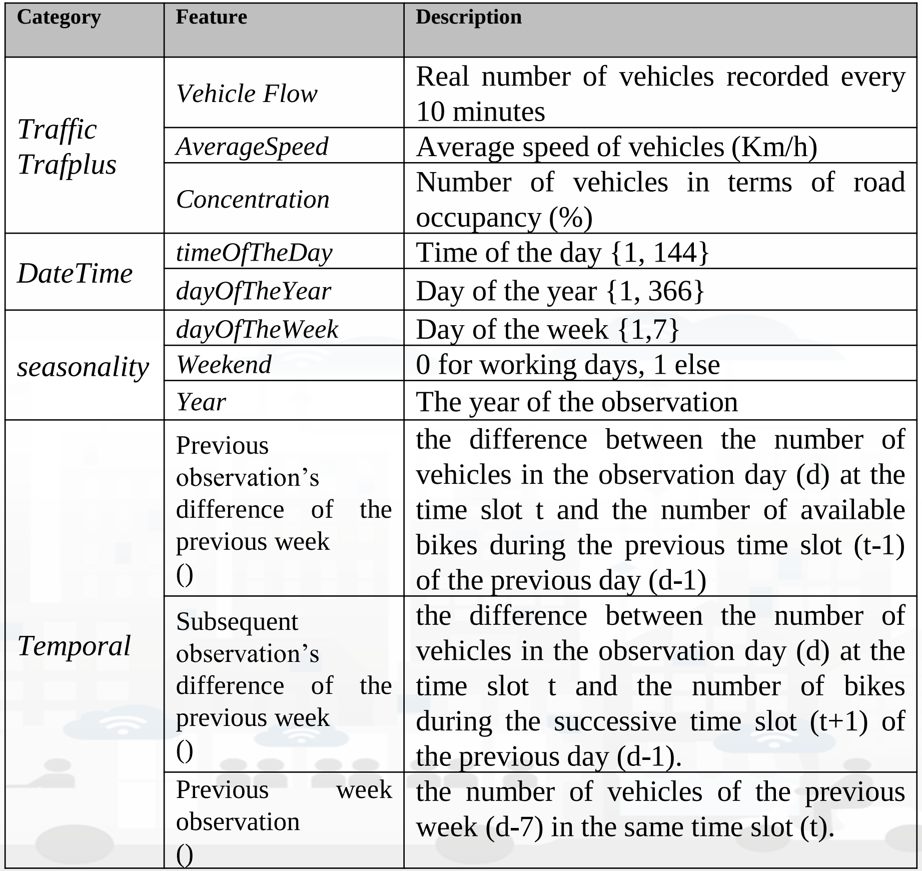
- The clustering has been performed on the basis of the time trend H24, considering the normalized vehicle flow measures.
- The optimal number of clusters turned out to be 3 and it has been identified by using **elbow** criteria
- **K-means** clustering method has been applied to identify clusters
  - The optimal number of clusters resulted to be equal to **3**, and it has been identified by using the **Elbow criteria**





Features

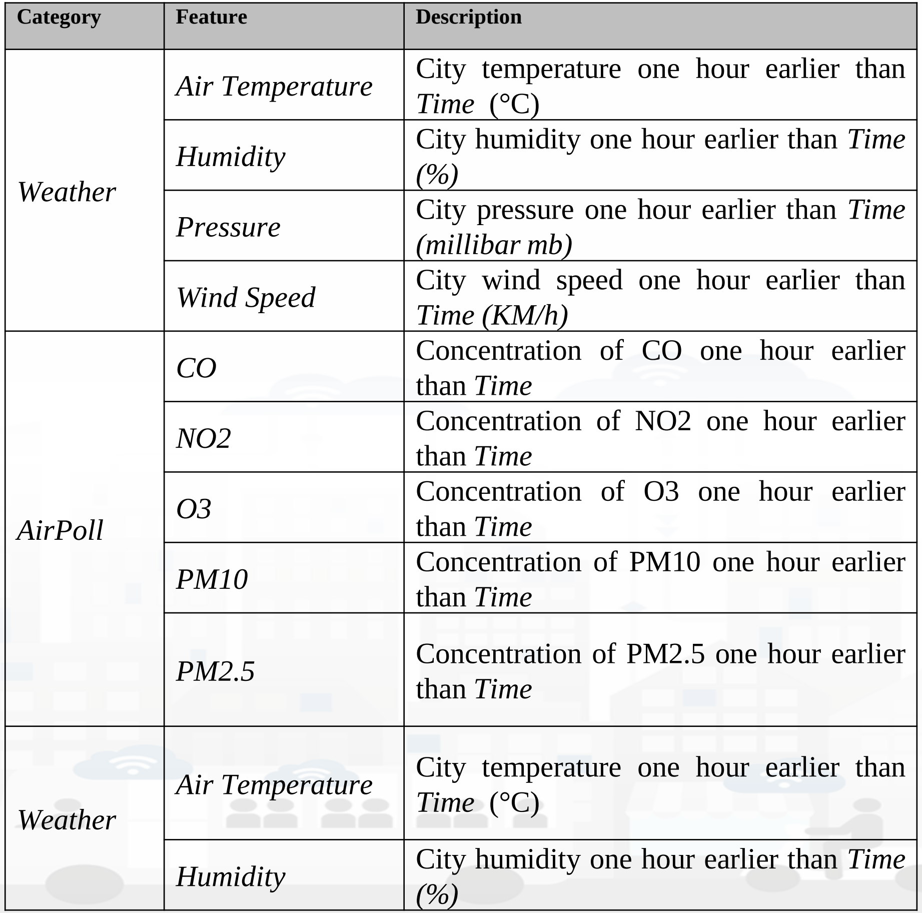
- One of the goals of this work has been conquer a general understanding above the factors that are more relevant for predicting traffic conditions in the city. Based on the related works, a set of data composed of **temporal variables, traffic-related features, weather** information, and **air pollution** has been considered.



Category	Feature	Description
Traffic Trafplus	*Vehicle Flow*	Real number of vehicles recorded every 10 minutes
	AverageSpeed	Average speed of vehicles (Km/h)
	Concentration	Number of vehicles in terms of road occupancy (%)
DateTime	*timeOfTheDay*	Time of the day {1, 144}
	dayOfTheYear	Day of the year {1, 366}
seasonality	*dayOfTheWeek*	Day of the week {1,7}
	Weekend	0 for working days, 1 else
	Year	The year of the observation
Temporal	Previous observation's difference of the previous week ()	the difference between the number of vehicles in the observation day (d) at the time slot t and the number of available bikes during the previous time slot (t-1) of the previous day (d-1)
	Subsequent observation's difference of the previous week ()	the difference between the number of vehicles in the observation day (d) at the time slot t and the number of bikes during the successive time slot (t+1) of the previous day (d-1).
	Previous week observation ()	the number of vehicles of the previous week (d-7) in the same time slot (t).

Features

- One of the goals of this work has been conquer a general understanding above the factors that are more relevant for predicting traffic conditions in the city. Based on the related works, a set of data composed of **temporal variables, traffic-related features**, **weather** information, and **air pollution** has been considered.



Category	Feature	Description
Weather	*Air Temperature*	City temperature one hour earlier than *Time* (°C)
	Humidity	City humidity one hour earlier than *Time (%)*
	Pressure	City pressure one hour earlier than *Time (millibar mb)*
	Wind Speed	City wind speed one hour earlier than *Time (KM/h)*
AirPoll	*CO*	Concentration of CO one hour earlier than *Time*
	NO2	Concentration of NO2 one hour earlier than *Time*
	O3	Concentration of O3 one hour earlier than *Time*
	PM10	Concentration of PM10 one hour earlier than *Time*
	PM2.5	Concentration of PM2.5 one hour earlier than *Time*
Weather	*Air Temperature*	City temperature one hour earlier than *Time* (°C)
	Humidity	City humidity one hour earlier than *Time (%)*

Work plan

- With a temporal target of 1h, which is the most critical short-term prediction slot ensemble learning techniques such as **Random Forest** (RF) and **Extreme Gradient Boosting Machines** (XGBOOST) are powerful techniques that must be considered for this type of problem.
- Regarding the deep learning techniques for this research project it has been proposed a new architecture **CONV-BI-LSTM** that will be compared to other solutions as **Deep Neural Network** (DNN), Deep **LSTM**, Deep **BI-LSTM** Neural Network , **Autoencoder BI-LSTM**, and an **attention-based CONV-LSTM** to assess the research question of which will be the best AI architecture for the problem of short-term prediction of vehicle flow based on this case study.

Evaluation Metrics

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(obs_i - pred_i)^2}{n}}$$

R-Squared(R2)

- $\overline{y} = \frac{1}{n} \sum_{i=1}^{\mathrm{n}} \mathrm{obs_i}$
- $R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(obs_i - pred_i)^2}{\sum_{i=1}^{\mathrm{n}}(obs_i - \overline{y})^2}\right)$

Mean Absolute Scaled Error (MASE)

$$q_t = \frac{obs_t - pred_t}{\frac{1}{n-1}\sum_{i=2}^{n} | \, obs_i - \ obs_{i-1} |}$$

$$MASE = mean\,(|q_t|), \qquad t = 1, \dots, n$$

Mean Absolute Error (MAE)

$$MAE = \frac{\sum_{i=1}^{n} |obs_i - pred_i|^2}{n}$$

CONV-BI-LSTM Architecture Proposed

The defined **CONV-BI-LSTM** network is made up of 3 components:

- The first component is made up of a **Convolutional 1-dimensional layer** with 48 filters and a kernel size of 16, and a Max Pooling layer of 2x2 and stride equal to 1.
- The second component is the **BI-LSTMs** layers, in particular **6 layers** with **32 units** per layer and **dropout of 0,25**.
- The last one is made of **3 fully connected layers with number of neurons of 32-16-1**. The last one has a sigmoid activation to produce the prediction.

The used optimizer is **Adam Optimizer** with learning rate between **0.005 and 0.008**. **MSE** was selected as the loss function to be monitored during **optimization**. The **batch size** has been set to **512** and the number of epochs was set to a maximum value of 1000, because the training strategy used the **Early Stopping** method with patience parameter set to 100 to determine the optimum epoch number minimizing the MSE of the validation set, restoring the weights of the best model at the end of the learning process.

Results

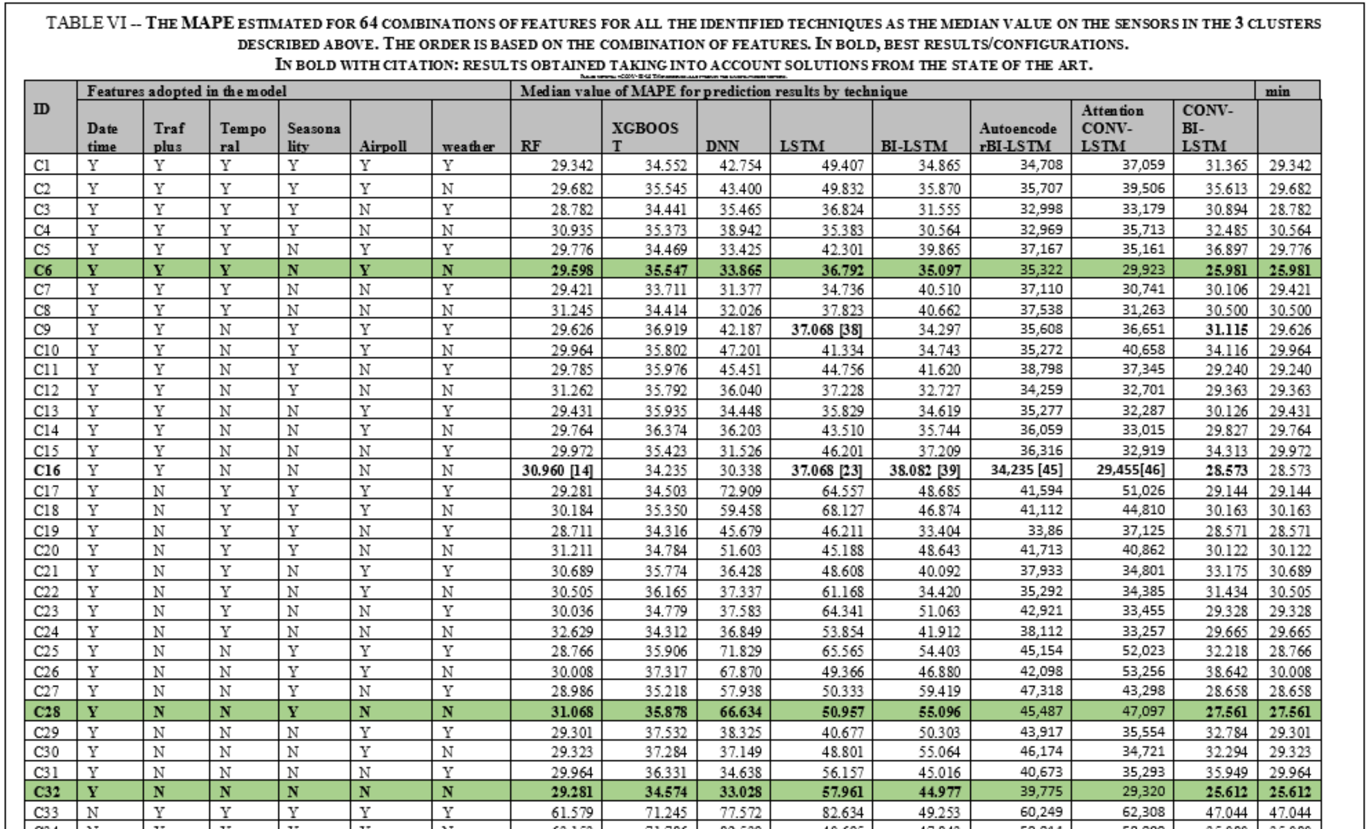


TABLE VI -- THE MAPE ESTIMATED FOR 64 COMBINATIONS OF FEATURES FOR ALL THE IDENTIFIED TECHNIQUES AS THE MEDIAN VALUE ON THE SENSORS IN THE 3 CLUSTERS DESCRIBED ABOVE. THE ORDER IS BASED ON THE COMBINATION OF FEATURES. IN BOLD, BEST RESULTS/CONFIGURATIONS.
IN BOLD WITH CITATION: RESULTS OBTAINED TAKING INTO ACCOUNT SOLUTIONS FROM THE STATE OF THE ART.

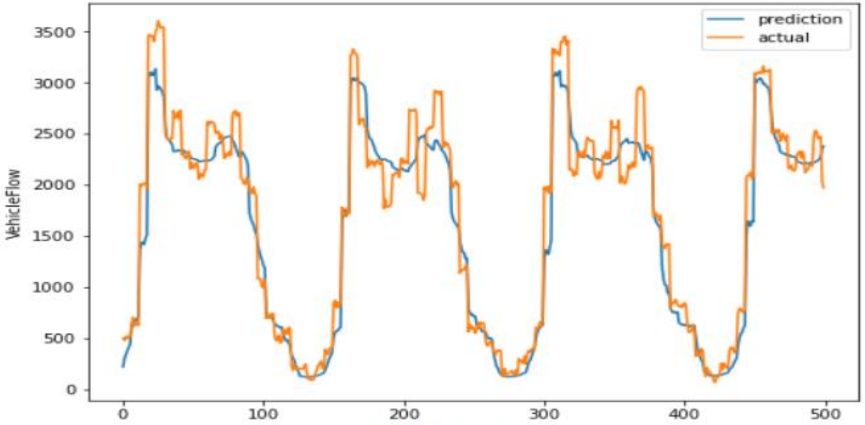
ID	Features adopted in the model						Median value of MAPE for prediction results by technique								min
	Date time	Traf plus	Tempo ral	Seasonality	Airpoll	weather	RF	XGBOOST	DNN	LSTM	BI-LSTM	Autoencoder BI-LSTM	Attention CONV-LSTM	CONV-BI-LSTM	
C1	Y	Y	Y	Y	Y	Y	29.342	34.552	42.754	49.407	34.865	34,708	37,059	31.365	29.342
C2	Y	Y	Y	Y	Y	N	29.682	35.545	43.400	49.832	35.870	35,707	39,506	35.613	29.682
C3	Y	Y	Y	Y	N	Y	28.782	34.441	35.465	36.824	31.555	32,998	33,179	30.894	28.782
C4	Y	Y	Y	Y	N	N	30.935	35.373	38.942	35.383	30.564	32,969	35,713	32.485	30.564
C5	Y	Y	Y	N	Y	Y	29.776	34.469	33.425	42.301	39.865	37,167	35,161	36.897	29.776
C6	**Y**	**Y**	**Y**	**N**	**Y**	**N**	**29.598**	**35.547**	**33.865**	**36.792**	**35.097**	35,322	29,923	**25.981**	**25.981**
C7	Y	Y	Y	N	N	Y	29.421	33.711	31.377	34.736	40.510	37,110	30,741	30.106	29.421
C8	Y	Y	Y	N	N	N	31.245	34.414	32.026	37.823	40.662	37,538	31,263	30.500	30.500
C9	Y	Y	N	Y	Y	Y	29.626	36.919	42.187	**37.068 [38]**	34.297	35,608	36,651	**31.115**	29.626
C10	Y	Y	N	Y	Y	N	29.964	35.802	47.201	41.334	34.743	35,272	40,658	34.116	29.964
C11	Y	Y	N	Y	N	Y	29.785	35.976	45.451	44.756	41.620	38,798	37,345	29.240	29.240
C12	Y	Y	N	Y	N	N	31.262	35.792	36.040	37.228	32.727	34,259	32,701	29.363	29.363
C13	Y	Y	N	N	Y	Y	29.431	35.935	34.448	35.829	34.619	35,277	32,287	30.126	29.431
C14	Y	Y	N	N	Y	N	29.764	36.374	36.203	43.510	35.744	36,059	33,015	29.827	29.764
C15	Y	Y	N	N	N	Y	29.972	35.423	31.526	46.201	37.209	36,316	32,919	34.313	29.972
C16	Y	Y	N	N	N	N	**30.960 [14]**	34.235	30.338	**37.068 [23]**	**38.082 [39]**	**34,235 [45]**	**29,455[46]**	**28.573**	28.573
C17	Y	N	Y	Y	Y	Y	29.281	34.503	72.909	64.557	48.685	41,594	51,026	29.144	29.144
C18	Y	N	Y	Y	Y	N	30.184	35.350	59.458	68.127	46.874	41,112	44,810	30.163	30.163
C19	Y	N	Y	Y	N	Y	28.711	34.316	45.679	46.211	33.404	33,86	37,125	28.571	28.571
C20	Y	N	Y	Y	N	N	31.211	34.784	51.603	45.188	48.643	41,713	40,862	30.122	30.122
C21	Y	N	Y	N	Y	Y	30.689	35.774	36.428	48.608	40.092	37,933	34,801	33.175	30.689
C22	Y	N	Y	N	Y	N	30.505	36.165	37.337	61.168	34.420	35,292	34,385	31.434	30.505
C23	Y	N	Y	N	N	Y	30.036	34.779	37.583	64.341	51.063	42,921	33,455	29.328	29.328
C24	Y	N	Y	N	N	N	32.629	34.312	36.849	53.854	41.912	38,112	33,257	29.665	29.665
C25	Y	N	N	Y	Y	Y	28.766	35.906	71.829	65.565	54.403	45,154	52,023	32.218	28.766
C26	Y	N	N	Y	Y	N	30.008	37.317	67.870	49.366	46.880	42,098	53,256	38.642	30.008
C27	Y	N	N	Y	N	Y	28.986	35.218	57.938	50.333	59.419	47,318	43,298	28.658	28.658
C28	**Y**	**N**	**N**	**Y**	**N**	**N**	**31.068**	**35.878**	**66.634**	**50.957**	**55.096**	45,487	47,097	**27.561**	**27.561**
C29	Y	N	N	N	Y	Y	29.301	37.532	38.325	40.677	50.303	43,917	35,554	32.784	29.301
C30	Y	N	N	N	Y	N	29.323	37.284	37.149	48.801	55.064	46,174	34,721	32.294	29.323
C31	Y	N	N	N	N	Y	29.964	36.331	34.638	56.157	45.016	40,673	35,293	35.949	29.964
C32	**Y**	**N**	**N**	**N**	**N**	**N**	**29.281**	**34.574**	**33.028**	**57.961**	**44.977**	39,775	29,320	**25.612**	**25.612**
C33	N	Y	Y	Y	Y	Y	61.579	71.245	77.572	82.634	49.253	60,249	62,308	47.044	47.044

Results

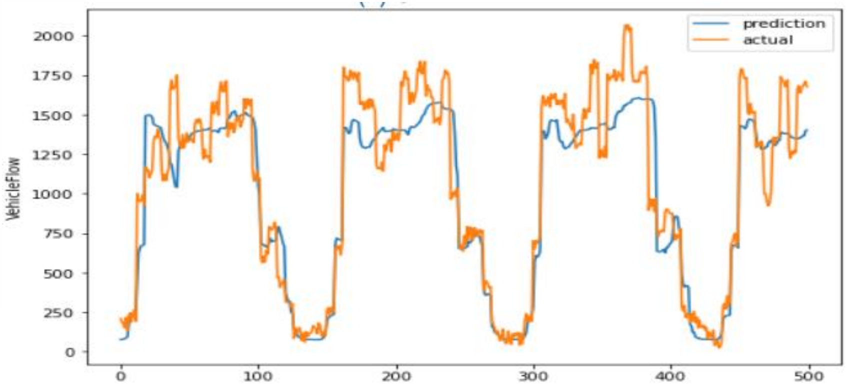
- The proposed architecture achieved promising results based on the evaluation metrics introduced.

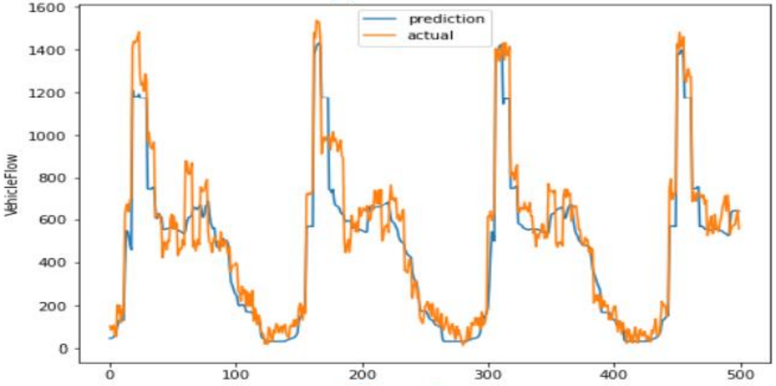
Representative sensor	MAE	RMSE	R2	MASE
Cluster-1	161,42	221,84	0.95	0.51
Cluster-2	138,98	182,48	0.90	0.60
Cluster-3	81,86	124,82	0.89	0.57

Predictions On Representative Sensors



(a) Cluster 1





l Cluster 3

FEATURE CATEGORY IMPORTANCE ANALYSIS

- It has been performed a feature importance analysis using the CONV-BI-LSTM model on the representative sensor of Cluster-1.
- The analysis calculated the MAPEs using all the features except the specific considered category excluding recursively each single feature category
- The DMAPE is defined as the difference of MAPE with respect to the minimum MAPE registered for the CONV-BI-LSTM such as:

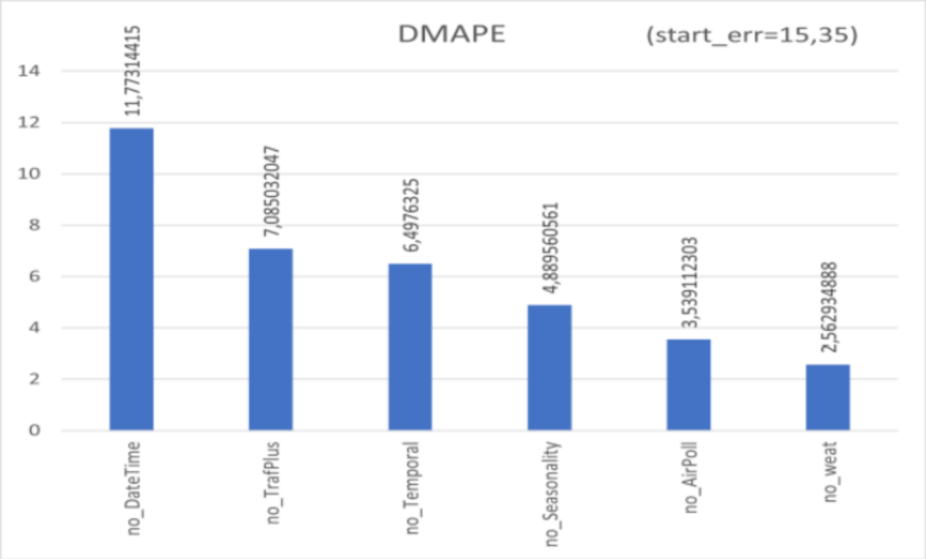
$$DMAPE_i = MAPE_{all-cat_i} - minMAPE$$

Where: i = 1, …, number of categories-1 (all, except the traffic, for a total of 6).

Categories with a higher DMAPE are the most relevant ones, since they do not cause larger differences / errors.

FEATURE CATEGORY IMPORTANCE ANALYSIS

- The feature category with the highest DMAPE is the **DateTime** followed by the **Trafplus**, and the **Temporal feature** category. Additional information on data seasonality for short-term prediction has been ranked 4th , ahead of Air Pollution feature category which in turn beats also Weather features



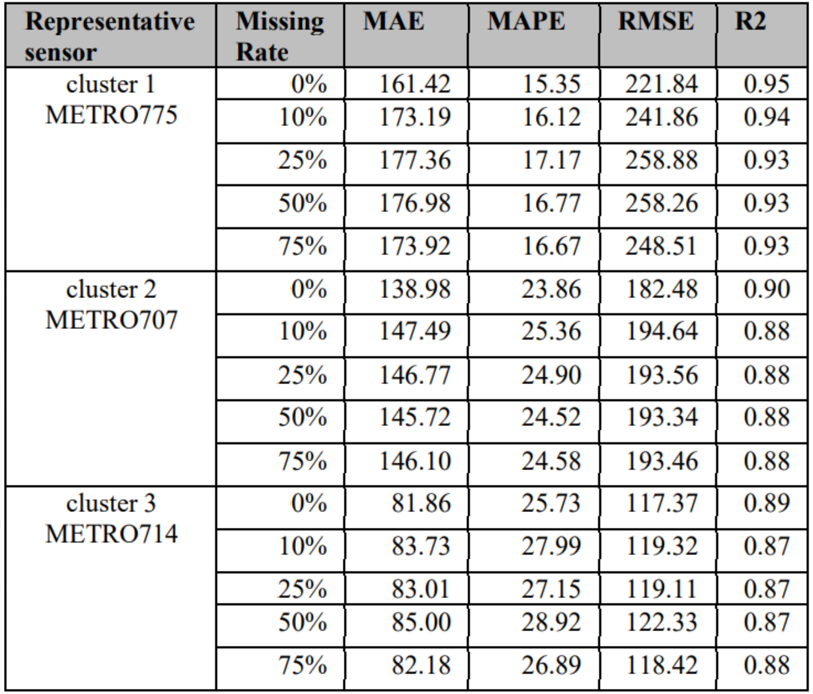
IMPACT OF DATA MISSING ON PRECISION

- **Data missing is an inevitable problem** when dealing with real world IoT sensor networks. Traffic sensors may suffer of problems such as detector malfunction and communication failure.
- The presence of missing data samples in making predictions (execution of the predictive model)may impact on the precision, up to make **impossible to produce the prediction**
- The approach of data imputation can be a valid option to produce surrogate data.
- In this case it has been used an **Hot-Deck** imputation.

Deepening into data missing robustness

- The robustness has been assessed on the test dataset from 10/02/2020 to 16/02/2020 randomly setting to missing the Vehicle Flow of a percentage of the total dataset based on the missing rates chosen (10%, 25%, 50%, 75%) and then imputing the missing data.
- The imputation strategy proposed to handle missing data reports valid results for the missing rates of 10%, 25%, 50%, 75% on all the representative sensors of the three clusters.

TABLE VIII - DATA MISSING ANALYSIS BASED ON DIFFERENT MISSING RATES ON THE CLUSTERS REPRESENTATIVE SENSORS OF TABLE VII.



Representative sensor	Missing Rate	MAE	MAPE	RMSE	R2
cluster 1 METRO775	0%	161.42	15.35	221.84	0.95
	10%	173.19	16.12	241.86	0.94
	25%	177.36	17.17	258.88	0.93
	50%	176.98	16.77	258.26	0.93
	75%	173.92	16.67	248.51	0.93
cluster 2 METRO707	0%	138.98	23.86	182.48	0.90
	10%	147.49	25.36	194.64	0.88
	25%	146.77	24.90	193.56	0.88
	50%	145.72	24.52	193.34	0.88
	75%	146.10	24.58	193.46	0.88
cluster 3 METRO714	0%	81.86	25.73	117.37	0.89
	10%	83.73	27.99	119.32	0.87
	25%	83.01	27.15	119.11	0.87
	50%	85.00	28.92	122.33	0.87
	75%	82.18	26.89	118.42	0.88

Conclusions

- Accessing precise traffic flow data is mandatory to guarantee **high level of services** such as: traffic flow reconstruction, which in turn is used to perform what-if analysis, conditioned routing, etc. They have to be **reliable and precise for possible rescue teams** and fire brigades.
- It has been conducted a **clustering** process to determine the 3 main representative sensors of the road network of the Metropolitan City of Florence
- The **proposed architecture** achieved promising results for the short-term 1h prediction of city vehicle flow on all the representative sensors
- The most important feature categories are the **DateTime** followed by the **Trafplus**, and the **Temporal** feature category. The weather data are not so relevant despite what is reported in the state-of-the-art.
- The solution using a **Hot Deck data imputation strategy is robust on eventual data missing** events.