

# Artificial Intelligence as a driver for Innovation in Official Statistics

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## **ARTIFICIAL INTELLIGENCE AND OFFICIAL STATISTICS: THE NEW FRONTIER OF INNOVATION**

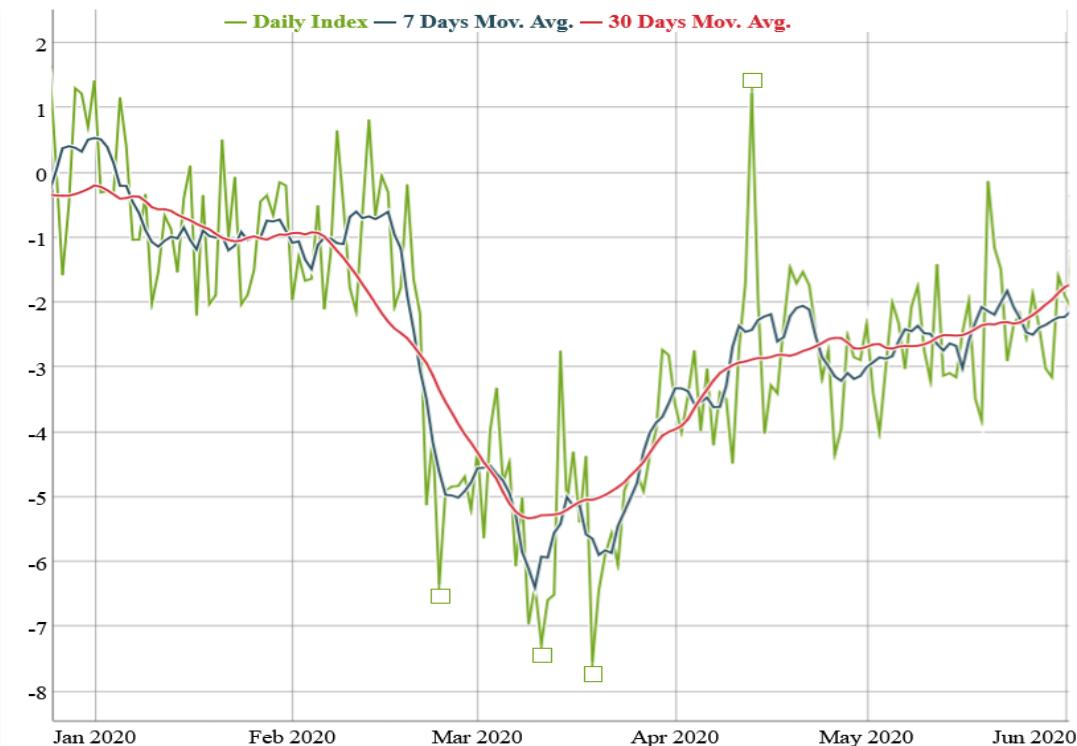
Caserta | 12 November 2025 | University of Campania “Luigi Vanvitelli” | Department of Mathematics and Physics | Abramo Lincoln Street, 5

## **QUINDICESIMA GIORNATA ITALIANA DELLA STATISTICA**

# Use Case 1: AI for Sentiment Analysis

- The Social Mood on Economy Index (SMEI) is developed by ISTAT
- Measures the Italian sentiment on economy
- Extracts the sentiment from Twitter data
- The sentiment analysis is conducted using a lexicon-based, unsupervised, approach

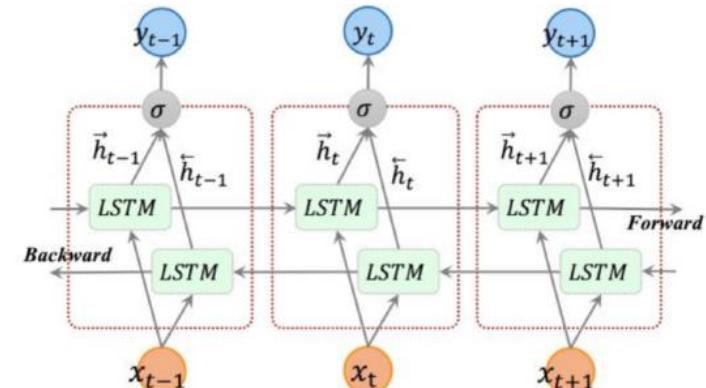
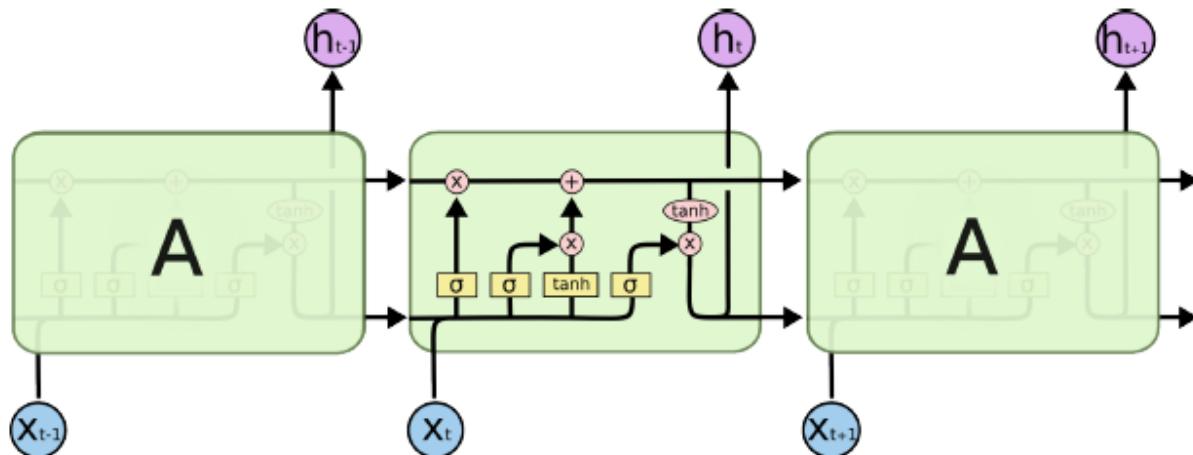
## ISTAT's SMEI January-May 2020: the Covid outbreak in Italy



# Use Case 1: AI for Sentiment Analysis

## Bidirectional LSTM

- Our classification model is a Bidirectional Long short-term memory (BiLSTM).  
LSTMs are a type of RNN able to process long sequences of data whereas  
BiLSTM are able to understand the left context and right context of sequences.
- A LSTM memory cell is composed of 4 units exactly: an input gate, an output  
gate, a forget gate and a self-recurrent neuron.



# Use Case 1: AI for Sentiment Analysis

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## FastText

- Our Word Embeddings Model (*Catanese, E., Bruno, M., Stefanelli, L., & Pugliese, F., 2023, September - Winner of the Best Paper Award - 1st Place - CARMA 2023*) is **FastText** which is an evolution of **Word2Vec**.
- **FastText** enables to quickly train models on large corpora
- **FastText** make use of hierarchical soft-max based which is able to noticeably drop computational complexity and can be trained on more than one billion words in less than ten minutes using a standard multicore **CPU**.



# Use Case 1: AI for Sentiment Analysis

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## Why a new Index?

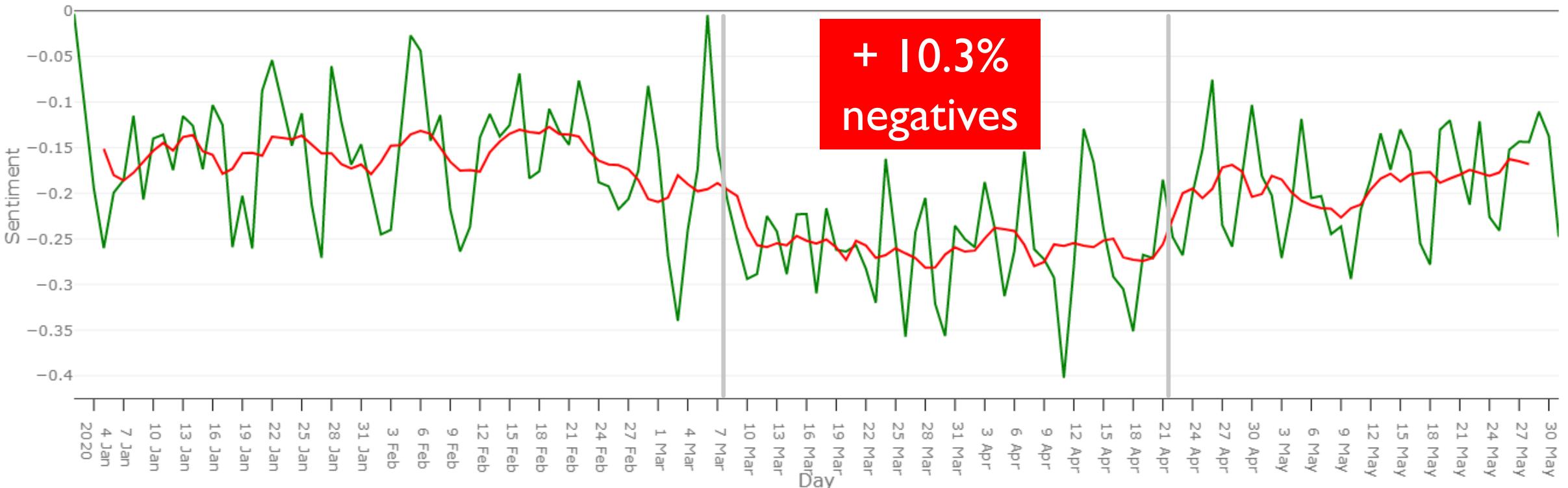
- ISTAT's Index (SMEI) needed a revision to deal with new events (Covid pandemic)
- The proposed model may have a higher adaptability to new information
- The proposed model is a neural network that has been trained on a set of labelled Tweets that do not contain references to the pandemic

- Computed daily using the sentiment predicted by the model on a set of tweets
- The sentiment is predicted using a neural network
- The set of tweets is the same used by ISTAT for the SMEI
- Computed for the first half of 2020

$$DL - SMEI = \frac{N_P - N_N}{N_P + N_N}$$

# Use Case 1: AI for Sentiment Analysis

## The proposed Index (DL-SMEI)



-0.157

-0.260

-0.190

# Use Case 1: AI for Sentiment Analysis

1<sup>st</sup> January – 7<sup>th</sup> March

8<sup>th</sup> March – 21<sup>st</sup> April

22<sup>nd</sup> April – 31<sup>st</sup> May



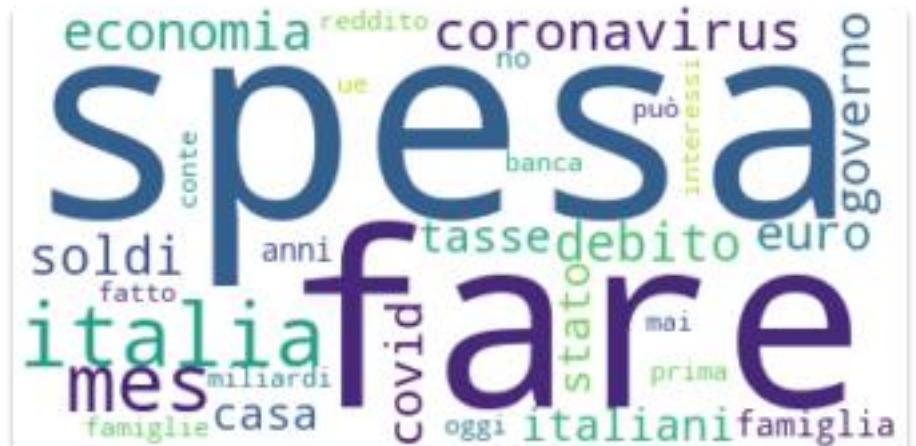
# Use Case 1: AI for Sentiment Analysis

Focus on second period (8<sup>th</sup> March – 21<sup>st</sup> April)

○ Positive words

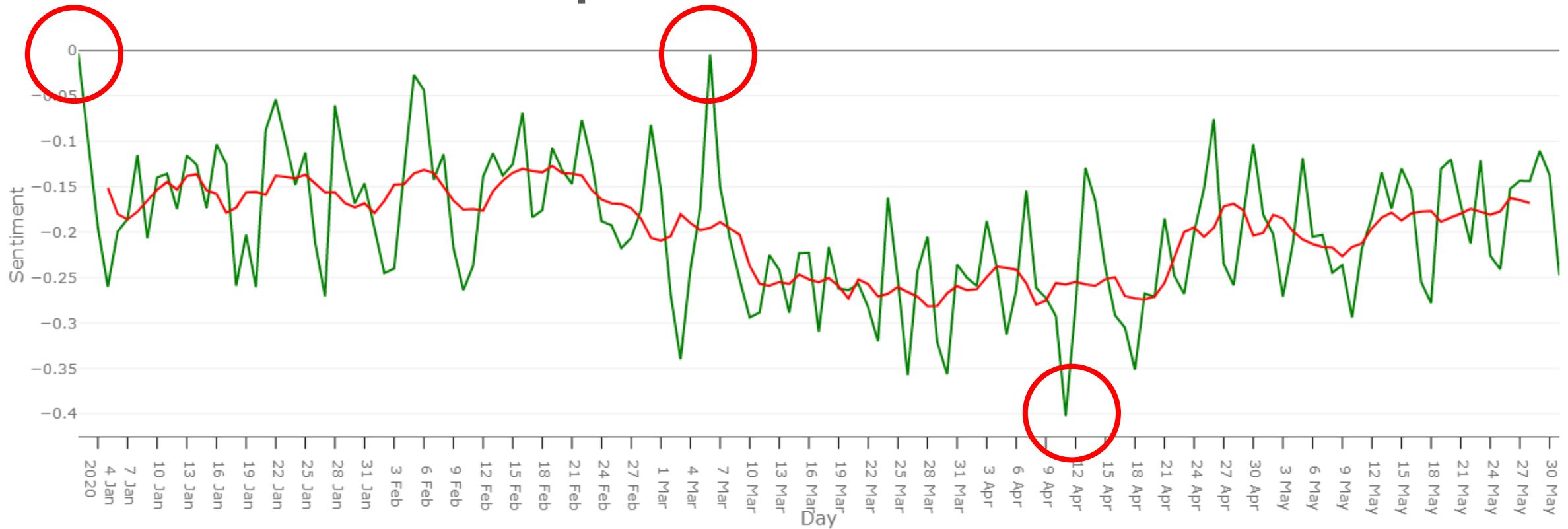


Negative words



# Use Case 1: AI for Sentiment Analysis

## Maximum and Minimum points



# Use Case 1: AI for Sentiment Analysis

## Second Maximum on the 6<sup>th</sup> March

o Positive words



Negative words



# Use Case 2: AI for Land Cover

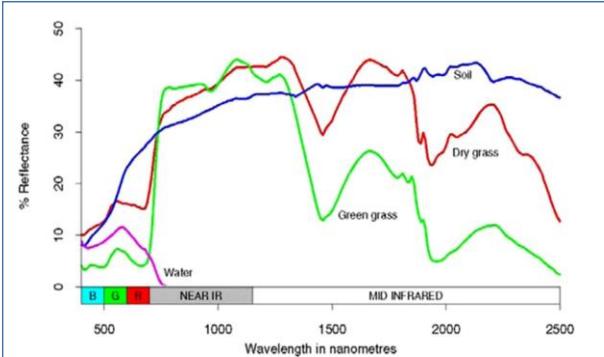
## GOALS

**Land Cover (LC) statistics** (*Bernasconi, E., De Fausti, F., Pugliese, F., Scannapieco, M., & Zardetto, D., 2022*) and maps are a very important statistical product. As they require a big effort to be created, the idea is to build an automatic system that processes satellite imagery.

- Automatic Land Cover Estimates
- Automatic Land Cover Maps

## ML Approaches to LC from Images

Standard approach: Spectral Signature



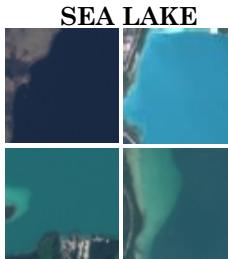
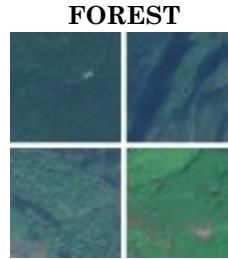
- Different LC classes have different reflectance spectra
  - ✓ Variation of reflectance with EM frequency can be used to predict LC class
  - ✓ Trained ML algo predicts the LC class of image pixels independently
  - ✓ Decision on each pixel does not depend on neighboring pixels

New approach: Computer Vision (Deep Learning)



- Different LC classes have different visual/spatial patterns
  - ✓ Variation of visual/spatial patterns can be used to predict LC class
  - ✓ Trained ML algo (CNN/U-net) predicts LC class of image pixels based on information from neighboring pixels
  - ✓ Decision on each pixel depends on the whole sub-image (tile) the pixel belongs to

# Use Case 2: AI for Land Cover (



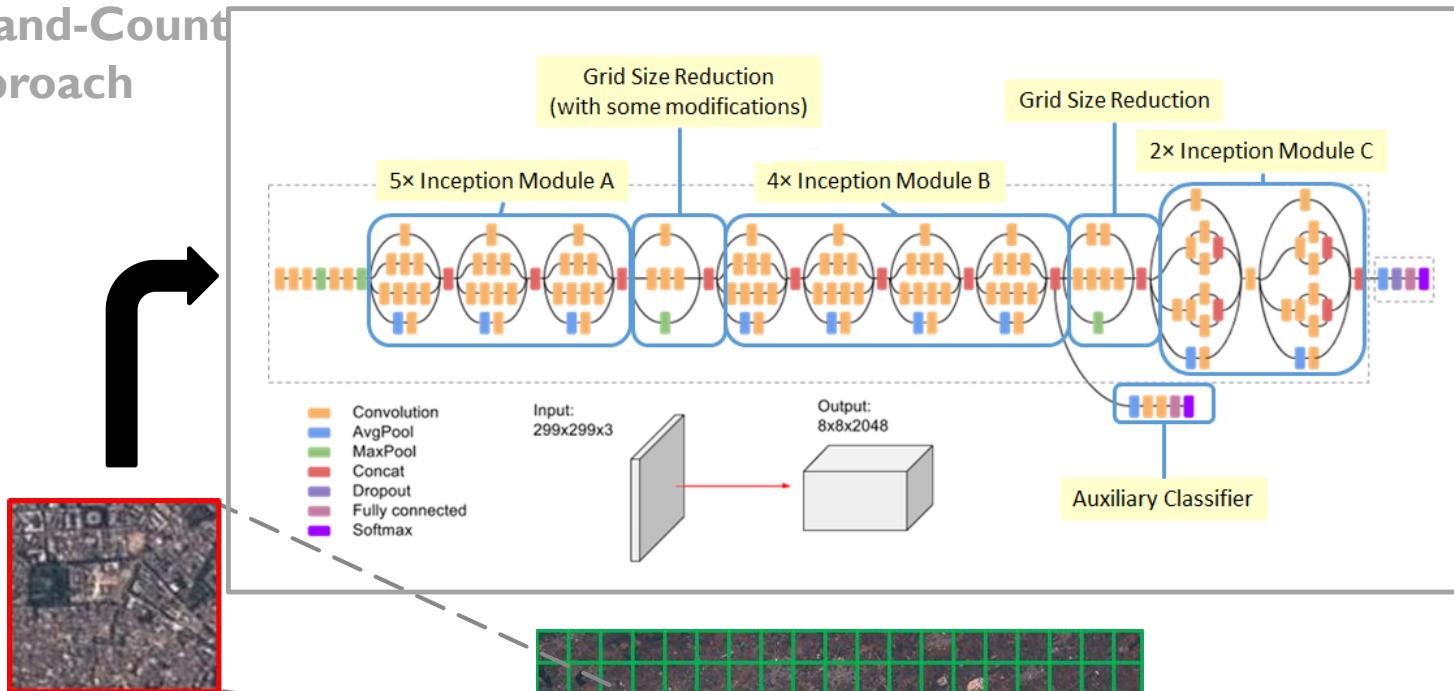
## EuroSAT dataset

(<https://github.com/phelber/eurosat>):

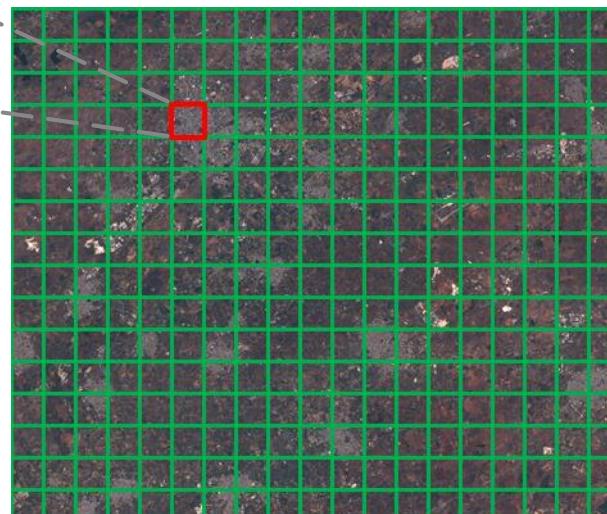
- Based on Sentinel-2 satellite images
- 27000 geo-referenced and labeled image patches (each one of 64x64 pixels)
- 10 different Land Use and Land Cover classes, with 2000-3000 images per class
- RGB (8-bit) and Multi-Spectral (13 spectral bands, 16-bit) versions available

# Use Case 2: AI for Land Cover

Classify-and-Count Approach



Input Satellite Image



CNN: Inception-V3 Archite

RESIDENTIAL



LAND COVER CLASS	AREA SHARE
...	...
RESIDENTIAL	$\frac{45}{16 * 19} \cong 15\%$
...	...

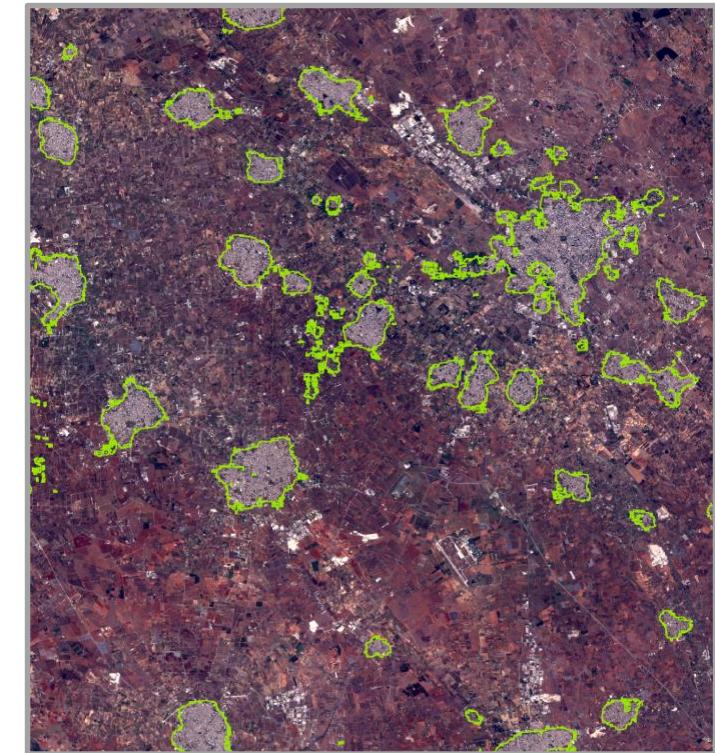
## Use Case 2: AI for Land Cover



[A]  
The ‘Lecce image’  
(751 km<sup>2</sup>)



[B]  
Automated LC map derived  
from the ‘Lecce image’



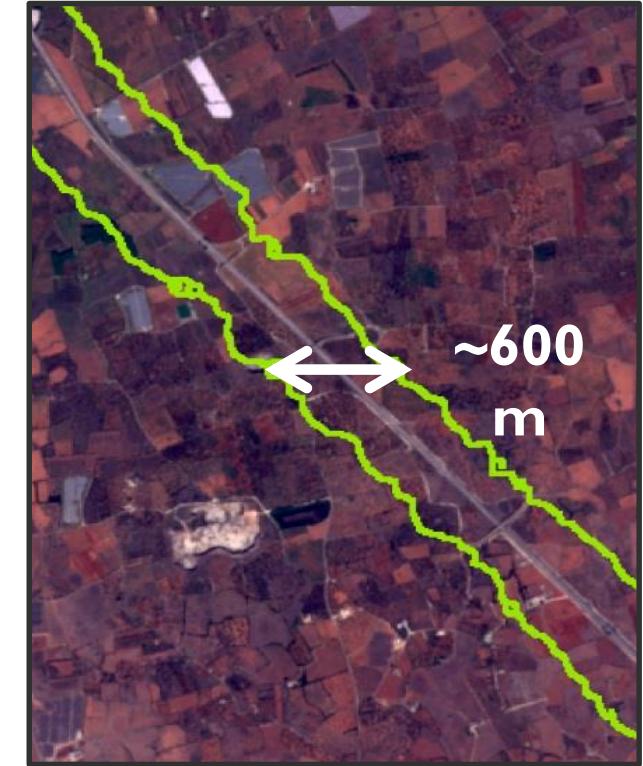
[C]  
Edge line of the ‘Residential’  
class derived from [B] overlaid  
on [A]

## Use Case 2: AI for Land Cover



[D]

A detailed view of the course of the Arno River (cropped from the '[Pisa image](#)', 443 km<sup>2</sup>) overlaid with a semitransparent version of the corresponding automated LC map

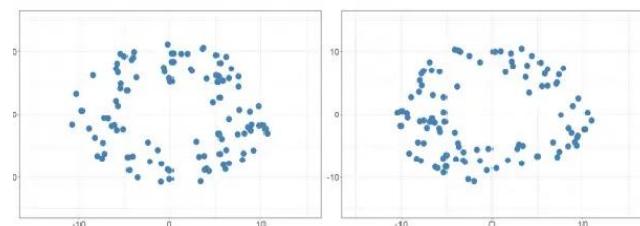


[E]

A highway fragment from the '[Lecce image](#)' overlaid with the edge line of the 'Highway' class

# Use Case 3: AI for the generation of Synthetic Data

- ✓ With the **digitalization of information** and the increasing accessibility of **administrative** data, the amount of data to be handled has grown substantially in recent years. This raises significant concerns about **data protection** and **privacy** since the disclosure of sensitive information can pose serious risks to individuals, institutions, and public administrations.
- ✓ **Synthetic data (Pugliese, F., Pappagallo, A., & De Cubellis, M., 2024, June)** are artificially created datasets intended to **replicate** the statistical characteristics and structure of real data, while preventing the exposure of **sensitive or personally identifiable** information.

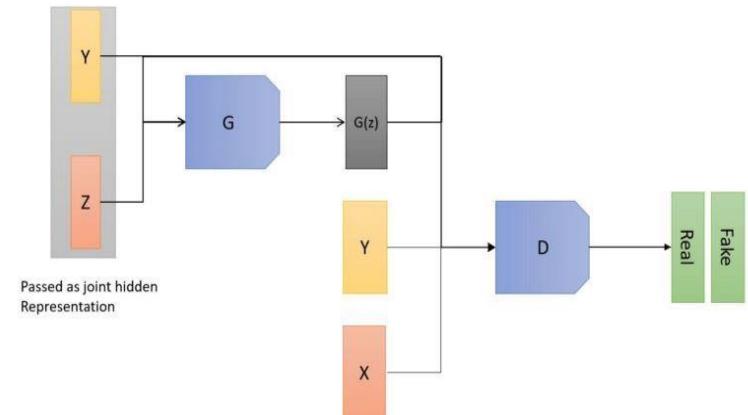


Original data

Synthetic data

# Use Case 3: AI for the generation of Synthetic Data

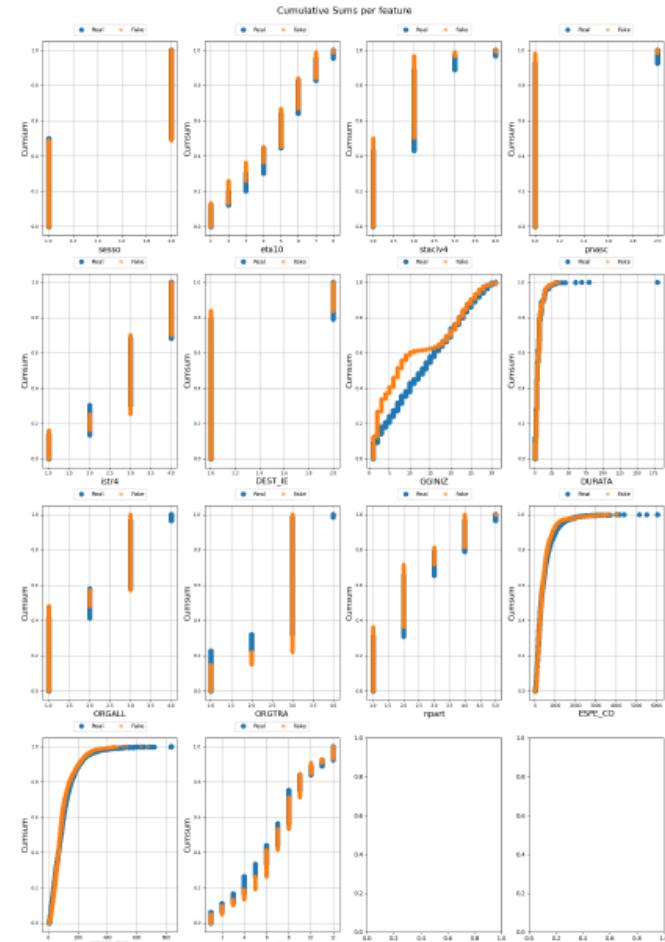
- ✓ **Keep in mind!** Synthetic data do not necessarily reproduce the atomic data (categorical, numerical, etc) from the original source. **Synthesis** capability might rely rather on the **relationships** between different kind of **entities**, such as people and objects, school and neighborhoods, or users and cellular antennas.
- ✓ In this study, the **analyzed data** relate to the frequency and attributes of trips and vacations undertaken by residents of Italy. They originate from **the Istat Trips and Holidays survey**, as a module of the **Household Budget Survey (HBS)** which collects information on the tourism flows of residents. This information includes journeys made for leisure or work, both domestically and internationally.
- ✓ In the WP13's Istat PoC of AI/ML Essnet project, we compared different AI methods: **CT-GAN, VAEs, DP-CTGAN, SMOTENC, Random Forest, XGBoost**



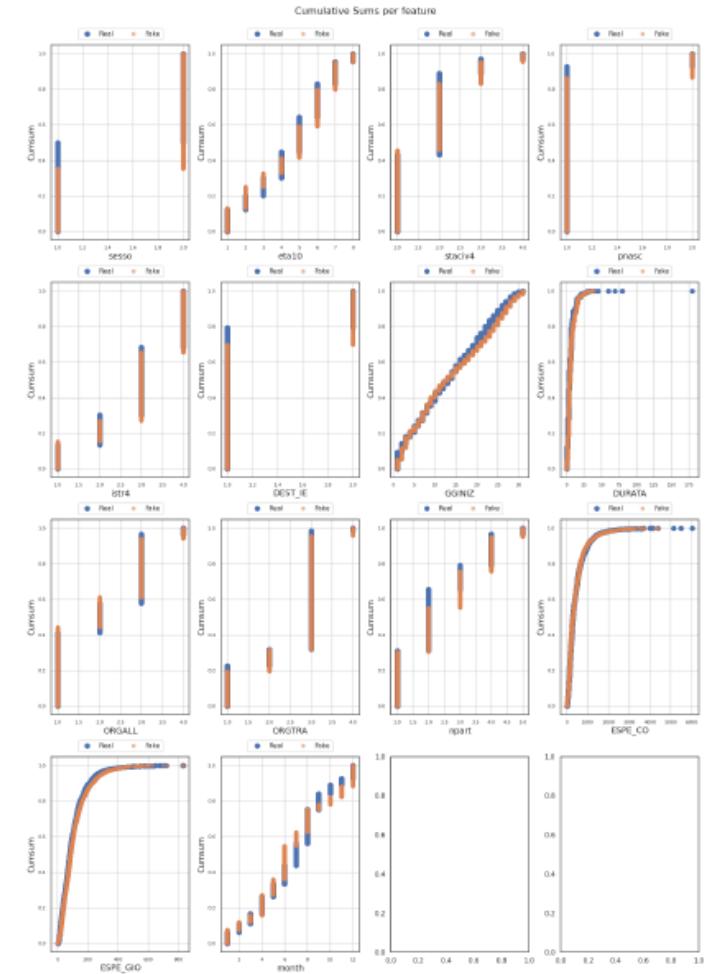
# Use Case 3: AI for the generation of Synthetic Data

- ✓ Note: In the **original distribution itself**, the values are *not* sums of previous values. Only in the **cumulative sum version** do the values accumulate.
- ✓ It is **evident** from the **cumulative distributions** that the less effective methods, such as **Random Forest** or **XGBoost**, are **less** efficient on categorical variables, where they often **fail** to reproduce the categories, i.e. the domain values of these variables.

## Variational Autoencoder (VAE)



## CT-GAN



# Use Case 3: AI for the generation of Synthetic Data

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- ✓ As we can observe, apart from **SMOTENC** which tends to reproduce the data exactly, the best methods seem to be the deep learning-based ones such as CTGAN and VAE, as they achieve high accuracy but not identical to the original dataset, as expected. In fact, during the synthetic data generation process something is always **lost** in terms of the **properties** of the data being reproduced.

Model	Accuracy	F1-Score	Recall
<b>Original Data</b>	<b>0.964516848</b>	<b>0.964516848</b>	<b>0.964516848</b>
<b>RF</b>	<b>0.660685592</b>	<b>0.660685592</b>	<b>0.660685592</b>
<b>XGB</b>	<b>4.46349e-05</b>	<b>4.46349e-05</b>	<b>4.46349e-05</b>
<b>SMOTENC</b>	<b>0.992813783</b>	<b>0.992813783</b>	<b>0.992813783</b>
<b>DPCTGAN</b>	<b>4.46349e-05</b>	<b>4.46349e-05</b>	<b>4.46349e-05</b>
<b>VAE</b>	<b>0.892385288</b>	<b>0.892385288</b>	<b>0.892385288</b>
<b>CTGAN</b>	<b>0.896134619</b>	<b>0.896134619</b>	<b>0.896134619</b>

## **Use Case 4: AI for the automatic classification of Causes of Death**

# Detection Model

**For each individual death occurring within the national territory, the certifying physician records the information on the causes of death in this part of the paper certificate**

# Use Case 4: AI for the automatic classification of Causes of Death

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## **The project aims to:**

- identify the most suitable AI methods for coding causes of death;
- create an algorithm for coding causes of death by applying these methods;
- evaluate the performance of automatic coding and the quality of the data by applying this algorithm.

## **The main expected results are:**

- a reduction in coding variability among coders and in errors, resulting in improved quality;
- in view of the imminent replacement of the paper form with an electronic model, AI methods will be useful to maintain high performance in recognizing medical text, even in the absence of the preprocessing currently applied during the registration of paper forms.
- an increase in the number of death certificates coded completely automatically, without human intervention;

## Use Case 4: AI for the automatic classification of Causes of Death

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The information on the causes is recorded by physicians on a paper death certificate, digitized, and coded according to the **tenth revision of the International Classification of Diseases (ICD-10)** of the **World Health Organization (WHO)**.

The application of the ICD is a complex process that involves:

- first, assigning a code to all the causes certified by physicians on the forms (multiple causes).
- then, selecting only one code for each death: the **underlying cause**.

Both phases are carried out according to the rules described in the ICD, and both the multiple causes and the underlying cause are used for mortality statistics.

# Use Case 4: AI for the automatic classification of Causes of Death

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**Training set 22\_23:** about 4 million texts.

53,876 classes after class cleaning and drops with cutoff.

Too much data for training: we sample progressively (starting from 300,000 texts).

**DS\_Gold\_standard (external):** 951 texts assigned a code whose correctness has been verified.

**TEST\_08\_09 (test\_set\_blind):** 11,909 texts to be labeled.

## Valid ICD codes

**Flag** (A, C, CON, P, etc). Example:

**Separators** (‘;’, ‘/’, etc). Example: **CACHESSIA TERMINALE CON IRA IN GRANDE ANZIANO** coded as **N179 / R54**.

(Note: “*Cachessia terminale con IRA in grande anziano*” = “Terminal cachexia with acute renal failure in a very elderly patient.”)

# Use Case 4: AI for the automatic classification of Causes of Death

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**TF-IDF** on the dataset to obtain the normalized term-document matrix; **Random Forest** is used for classification (which works on SL).

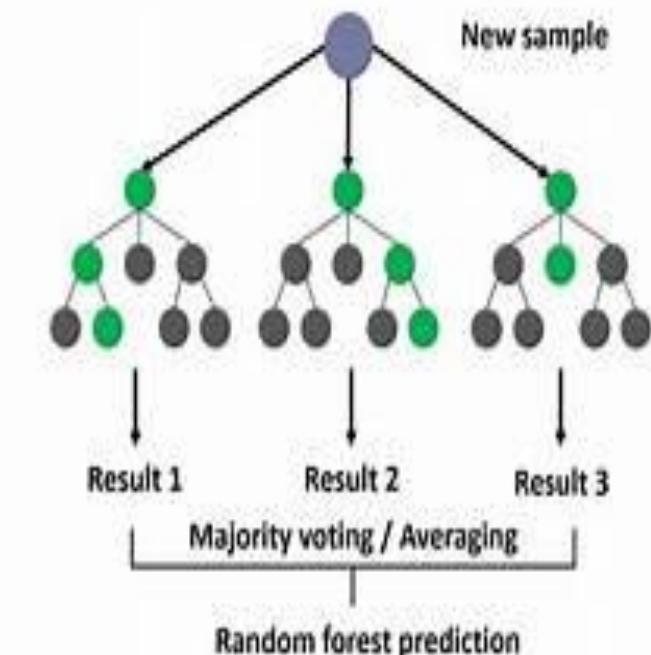
We take a sample of **300,000 texts** for training.

Initially **54,767 classes**, later reduced to **27,364**, after non-semantic splitting (in cases where the number of classes equals the number of texts).

We use a **cutoff of 2**, meaning we consider only classes with at least two instances.

There are about **17,666 classes** that appear only once, and these are removed.

In the end, we are left with **9,698 classes**.



# Use Case 4: AI for the automatic classification of Causes of Death

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**On training set of 300,000:**

Accuracy: 0.9761%

F1-score (macro-weighted): 0.9745%

**On test set (20%):**

Accuracy: 0.9467%

F1-score (macro-weighted): 0.9422%

**Accuracy on test set of about 65,161 texts:**

- #codes = #texts (size = 63,636, 97.66% of the test dataset): Accuracy: 0.9528% – F1-score (macro-weighted): 0.9505%
- #codes > #texts (size = 1,525, 2.34% of the test dataset): Accuracy: 0.69% – F1-score (macro-weighted): 0.71% → 1,060 correct, 465 incorrect (outputs exported to Excel and CSV for sharing)
- #texts > #codes (size = 0)

*(Note: The “%” signs seem to be used instead of decimals — e.g., accuracy 0.9761 likely means 97.61%.)*

## Use Case 4: AI for the automatic classification of Causes of Death

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**Accuracy on test set of about 65,161 texts:**

#codes > #texts (size = 1,525, 2.34% of the test dataset): Accuracy: 0.69% – F1-score (macro-weighted): 0.71% → 1,060 correct, 465 incorrect.

The correct cases are mostly those in which one text corresponds to two codes.

We check what percentage of the texts corresponding to the correct cases are present in the training set: **915 out of 1,050 (86%)**.

We check what percentage of the texts corresponding to the incorrect cases are present in the training set: **76 out of 475 (16%)**.

**Theory:** Random Forest performs well when it finds the same words combined in the same way in the training set.

# Use Case 4: AI for the automatic classification of Causes of Death

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## Accuracy on test set (sample of 950 “gold\_standard” texts):

For this dataset, the initial number of classes is **876**. After non-semantic splitting (in cases where the number of classes equals the number of texts — i.e., for 197 cases), we obtain **847 classes**, and the number of texts to be classified becomes **1,154**.

The classes are reduced to **716** after removing the time period.

**Accuracy on “gold\_standard” test set:** overall **0.41% F1-score** → problem: only **24% of the gold standard texts** are present in the training set, while **62% of the classes** are present in the training set.

- #codes = #texts (size = 948, 82.15% of the gold standard dataset): Accuracy: 0.55% – F1-score (macro-weighted): 0.52%
- #codes > #texts (size = 206, 17.85% of the gold standard dataset): Accuracy: 0.033% – F1-score (macro-weighted): 0.033% → 7 correct, 199 incorrect (outputs exported to Excel and CSV for sharing)
- #texts > #codes (size = 0)

**OBSERVATION:** for the label encoding of the classes, we include both the classes present in the training set and those in the gold standard, to prevent cases where classes in the gold standard are missing from the training data.

In the previous case, this issue did not arise because we had obtained it using a **stratified train-test split**, which ensures that each class has a sample in both the training and test sets.

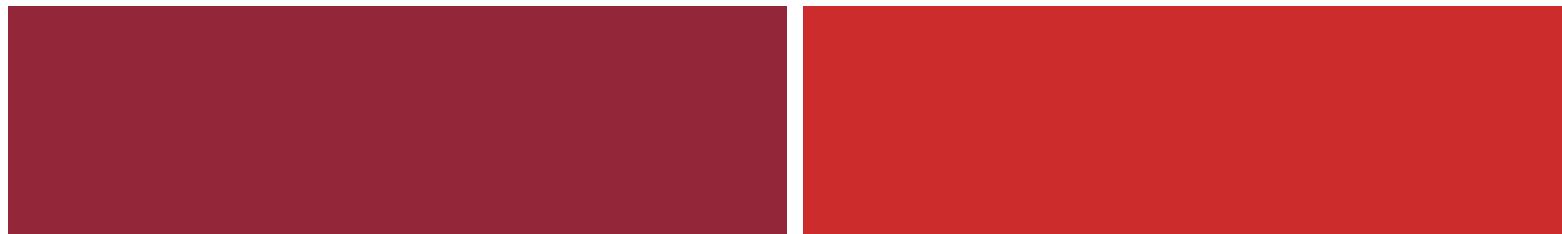
# References

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- [1] Catanese, E., Bruno, M., Stefanelli, L., & Pugliese, F. (2023, September). Measuring Social Mood on Economy during Covid times: effects of retraining Supervised Deep Neural Networks. In *5th International Conference on Advanced Research Methods and Analytics (CARMA 2023)* (pp. 139-147). Editorial Universitat Politècnica de València.
- [2] Bernasconi, E., De Fausti, F., Pugliese, F., Scannapieco, M., & Zardetto, D. (2022). Automatic extraction of land cover statistics from satellite imagery by deep learning. *Statistical Journal of the IAOS*, 38(1), 183-199.
- [3] Pugliese, F., Pappagallo, A., & De Cubellis, M. (2024, June). Generation of Synthetic Data from Mobile Network Operators (MNO) Data Through Generative Adversarial Networks (GANs). In *Scientific Meeting of the Italian Statistical Society* (pp. 69-74). Cham: Springer Nature Switzerland.

# Thanks

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