Artificial Intelligence as a driver for Innovation in Official Statistics

Francesco Pugliese, Central Directorate for Methodology and Design of Statistical Processes, **Istat**

ARTIFICIAL INTELLIGENCE AND OFFICIAL STATISTICS: THE NEW FRONTIER OF INNOVATION

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QUINDICESIMA GIORNATA ITALIANA DELLA STATISTICA

Società Italiana di Statistica

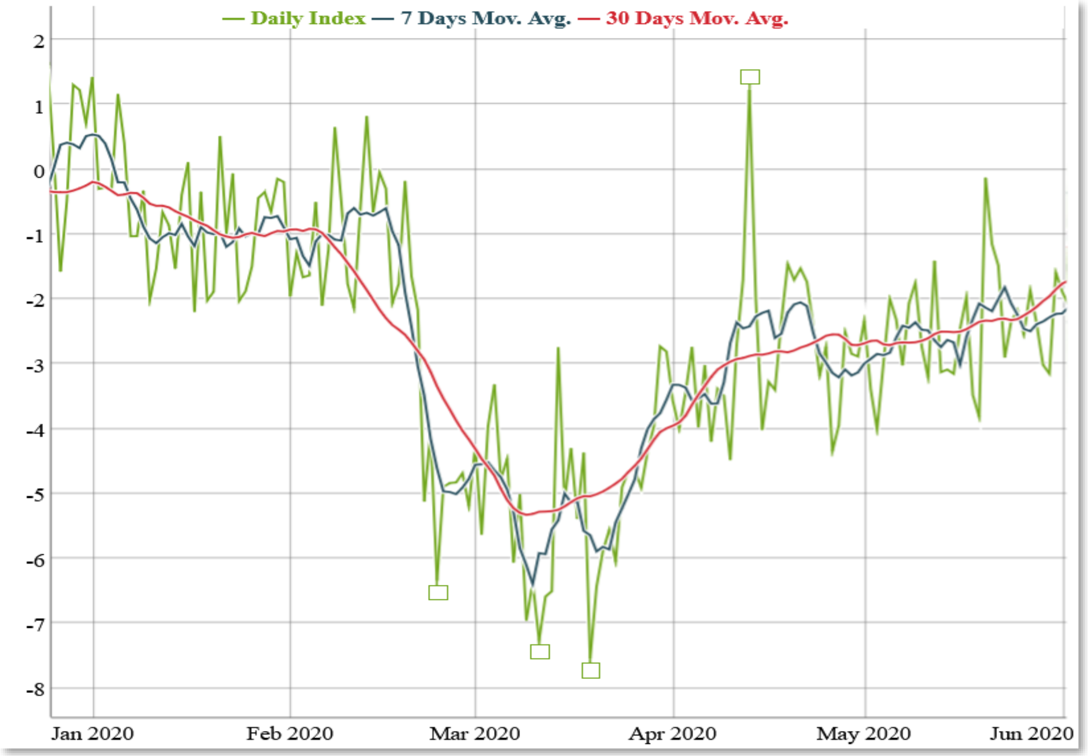
20.10.2025

GIORNATA ITALIANA DELLA STATISTICA

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

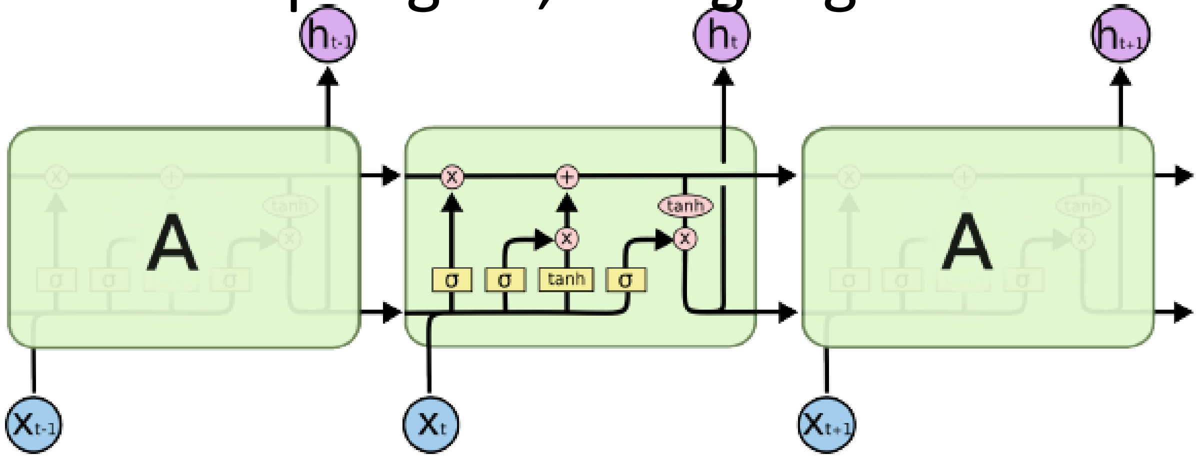
ISTAT's SMEI
January-May 2020:
the Covid outbreak in Italy

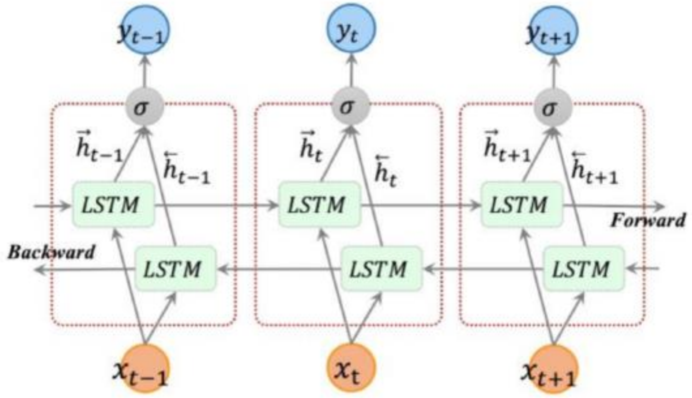


Materials and Methods: BiLSTM

- 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.





Materials and Methods: FastText

- Our Word Embeddings Model 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.

Why a new Index?

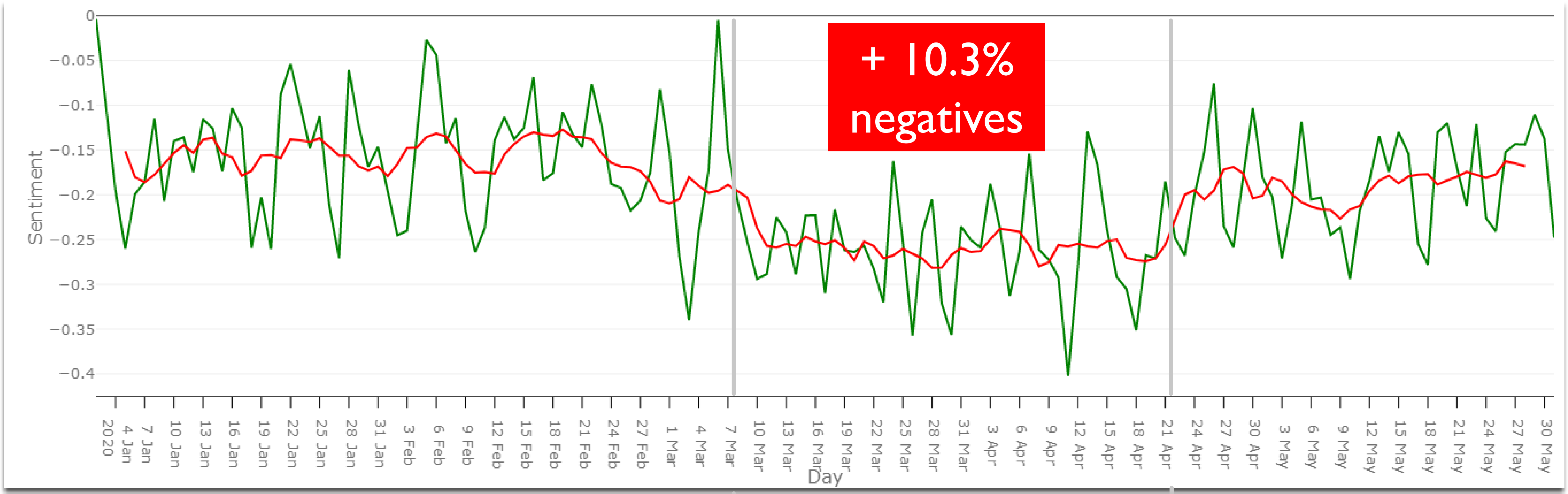
- ISTAT’s Index (SMEI) needed a revision to deal with new events (Covid pandemic)
- The proposed model may have a higher adaptability to new information
- The proposed model is a neural network that has been trained on a set of labelled Tweets that do not contain references to the pandemic

The proposed Index: DL-SMEI

- 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

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

The proposed Index (DL-SMEI)



-0.157 | -0.260 | -0.190

1st January – 7th March

8th March – 21st April

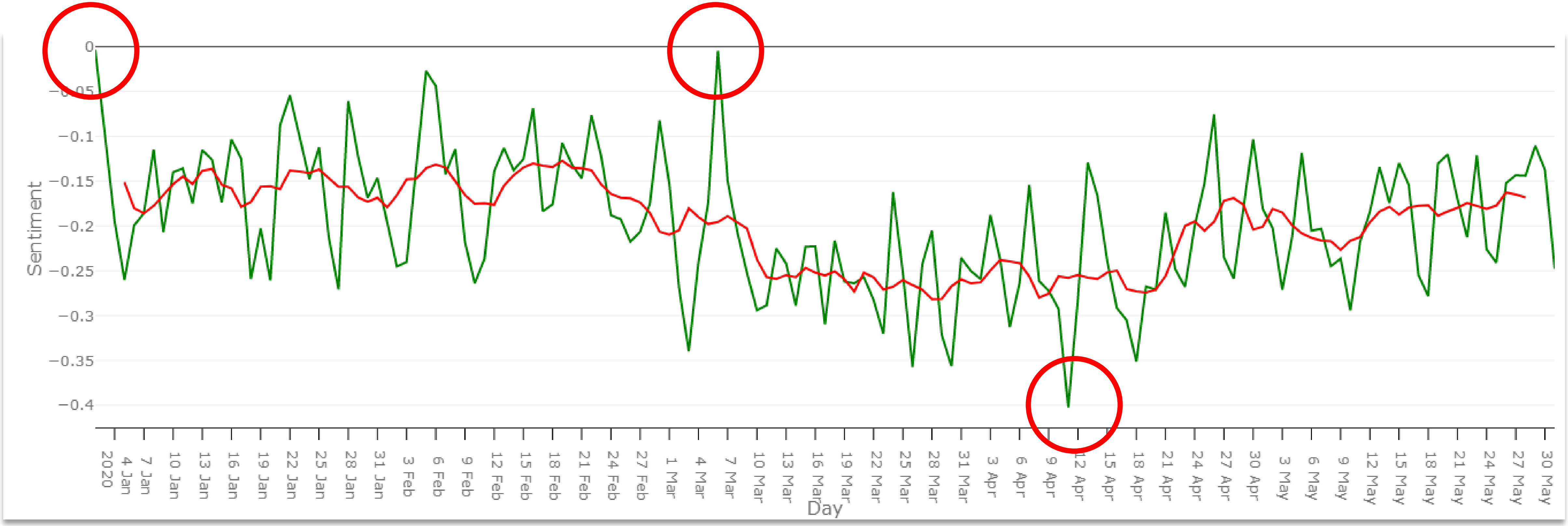
22nd April – 31st May

Focus on second period (8th March – 21st April)

Positive words

Negative words

Maximum and Minimum points



Second Maximum on the 6th March

Positive words

Negative words

Limitations

Misclassification of Covid: updated training set may increase accuracy

Unrepresentativeness of Social Media data

Difficult to evaluate the accuracy of the Index: need of a reference measure

Future Directions

- Label a more accurate Istat's training set
- Adopt more powerful and "state-of-art" models in Sentimen Analysis such as Bert and its derivations.

AI for Land Cover

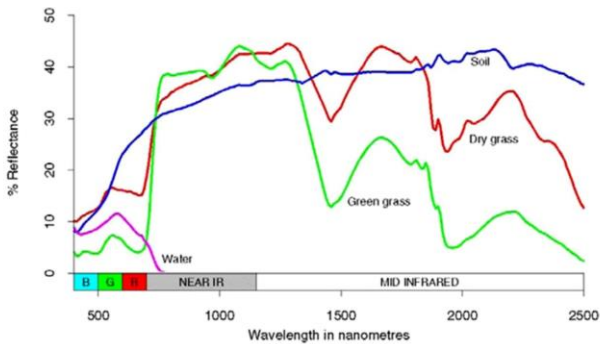
GOALS

Land Cover (LC) statistics 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 images in order to generate:

- Automatic Land Cover Estimates
- Automatic Land Cover Maps

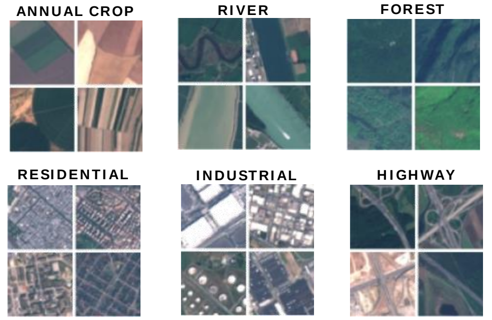
ML Approaches to LC from Images

Standard approach: Spectral Signature



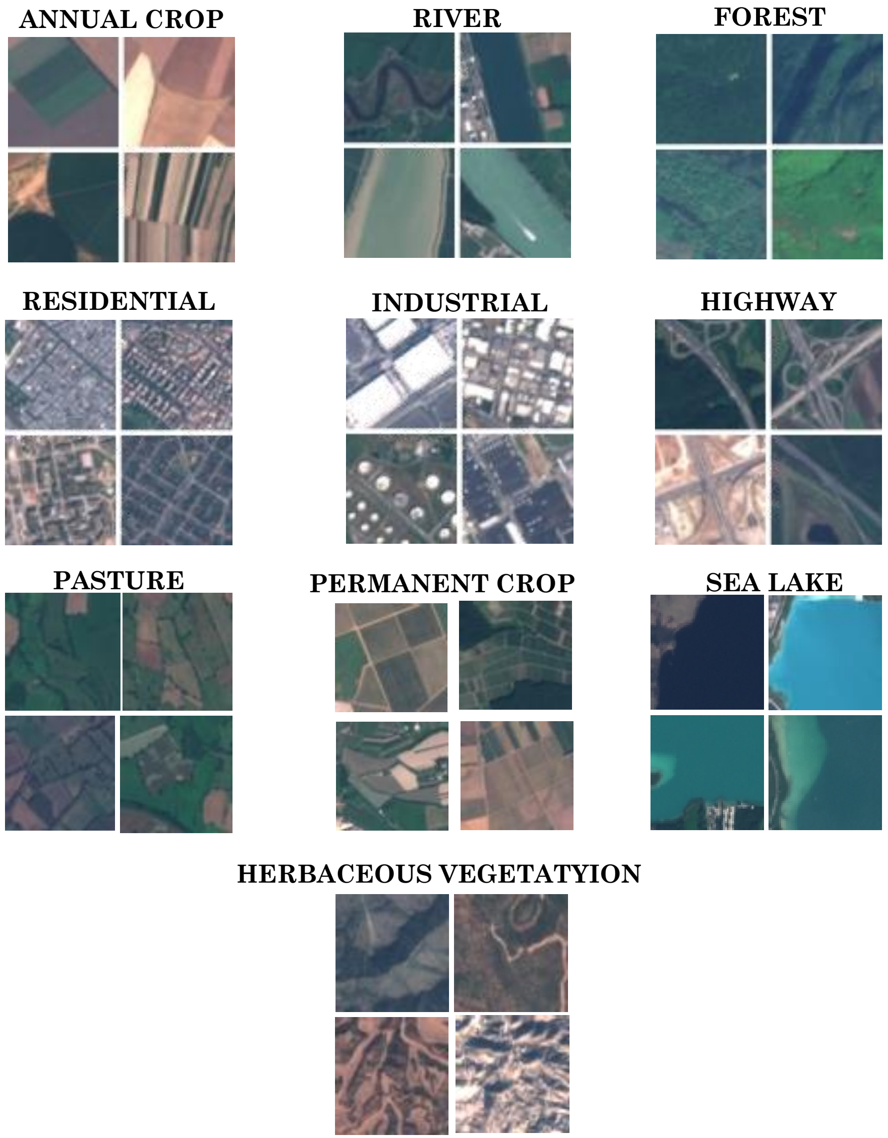
- Different LC classes have different reflectance spectra
  - ✓ Variation of reflectance with EM frequency can be used to predict LC class
  - ✓ Trained ML algo predicts the LC class of image pixels independently
  - ✓ Decision on each pixel does not depend on neighboring pixels

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

AI for Land Cover



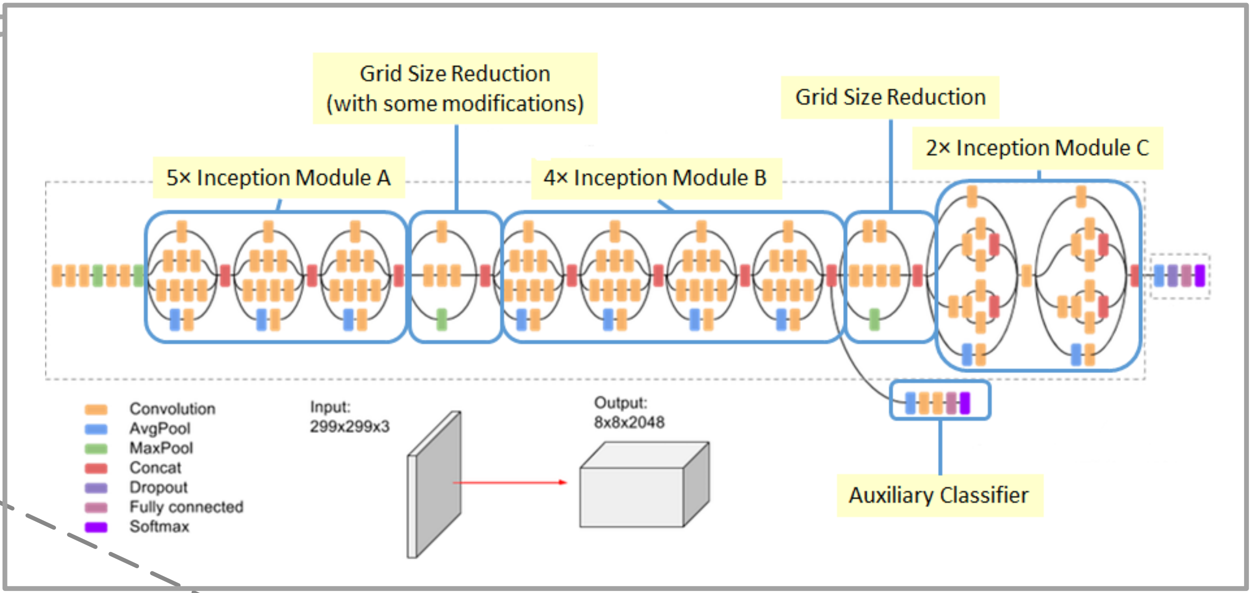
EuroSAT dataset
(https://github.com/phelber/eurosat):

- 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

Istat

AI for Land Cover

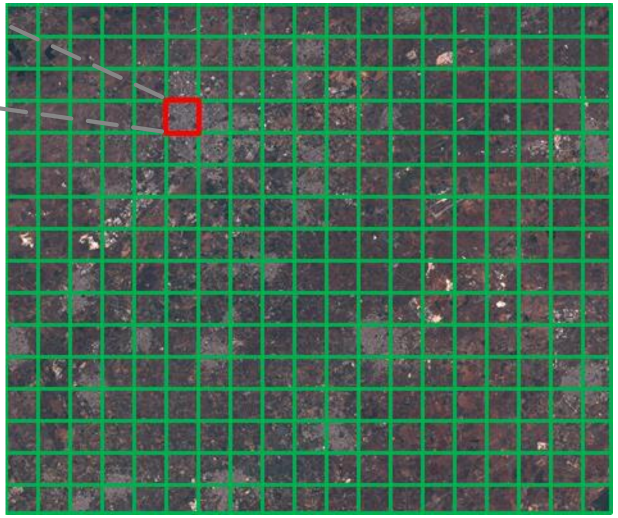
Classify-and-Count Approach



CNN: Inception-V3 Archite

RESIDENTIAL

Input Satellite Image



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

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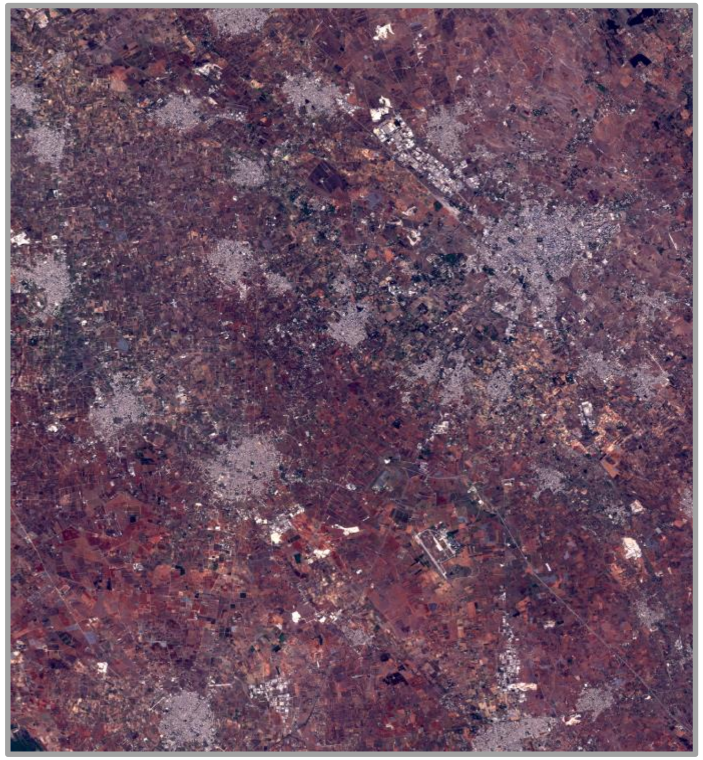
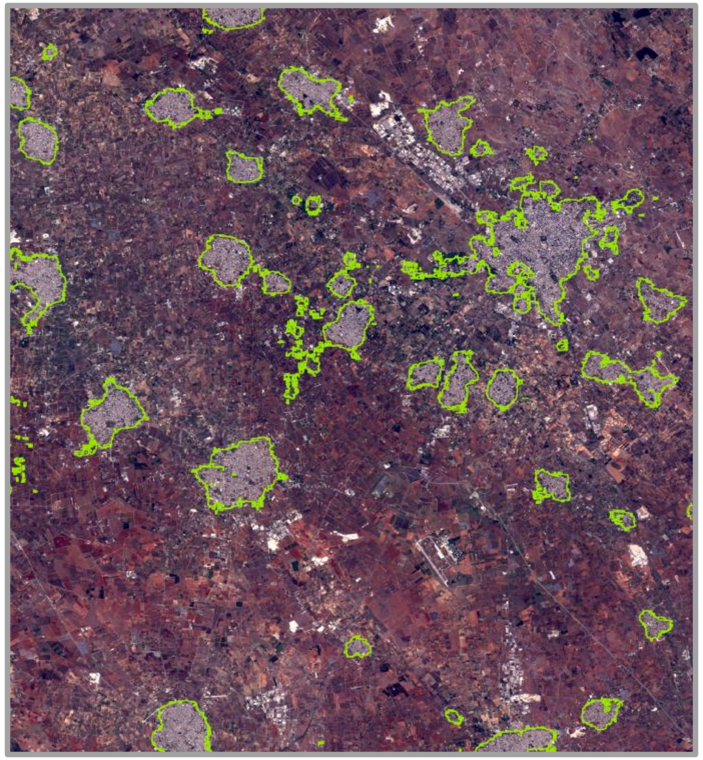
AI for Land Cover



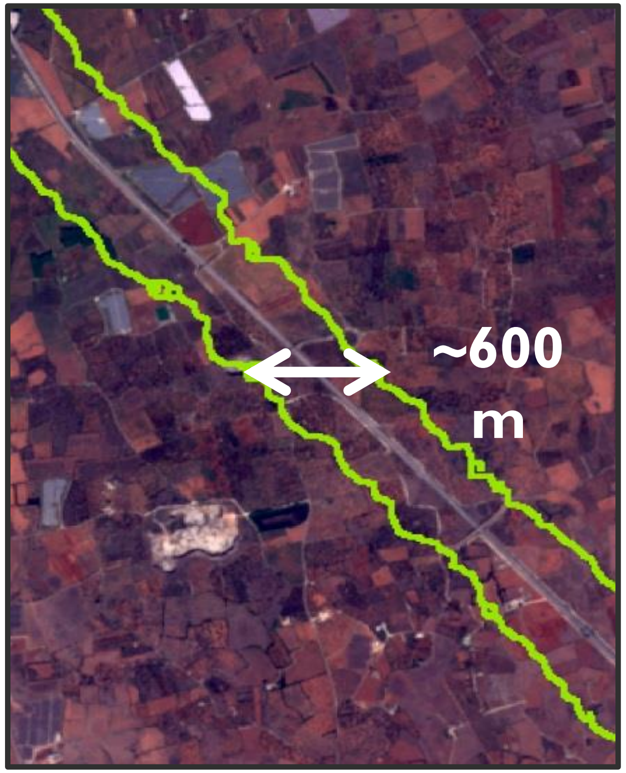
[A]
The **'Lecce image'**
(751 km^2)

[B]
Automated LC map derived from the 'Lecce image'



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

AI for Land Cover



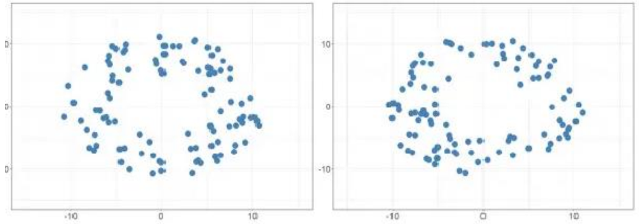
[D]
A detailed view of the course of the Arno River (cropped from the **'Pisa image'**, 443 km^2) overlaid with a semitransparent version of the corresponding automated LC map

[E]
A highway fragment from the **'Lecce image'** overlaid with the edge line of the 'Highway' class

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** 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.



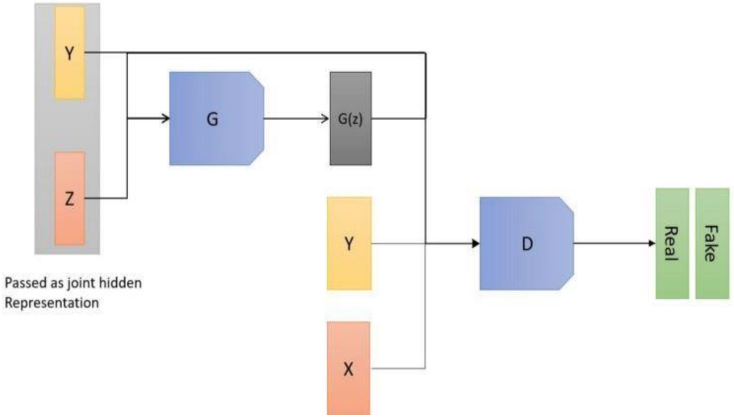
Original data   Synthetic data

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**



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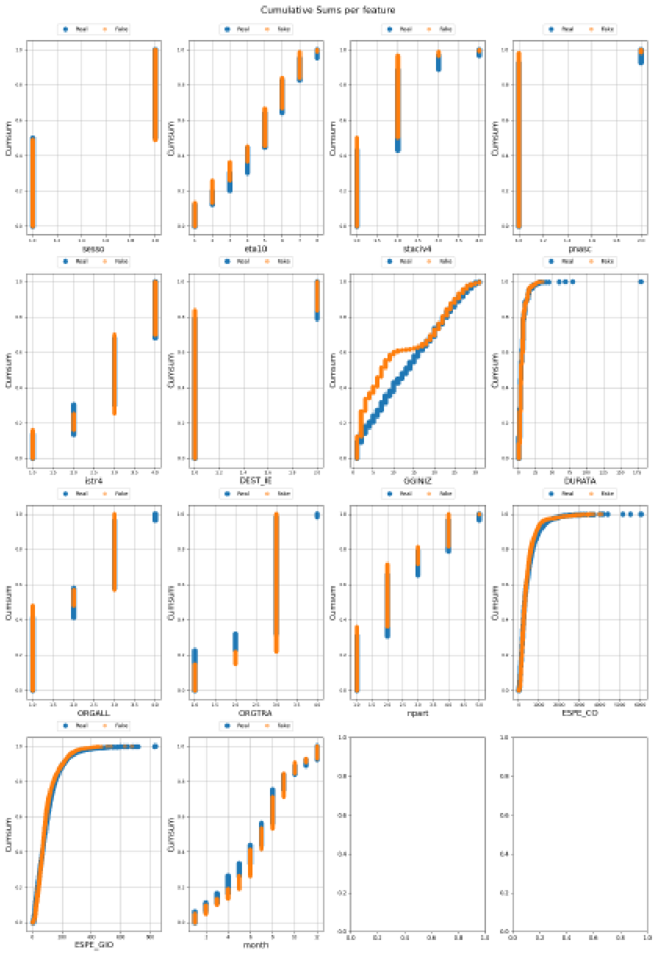
AI for the generation of Synthetic Data

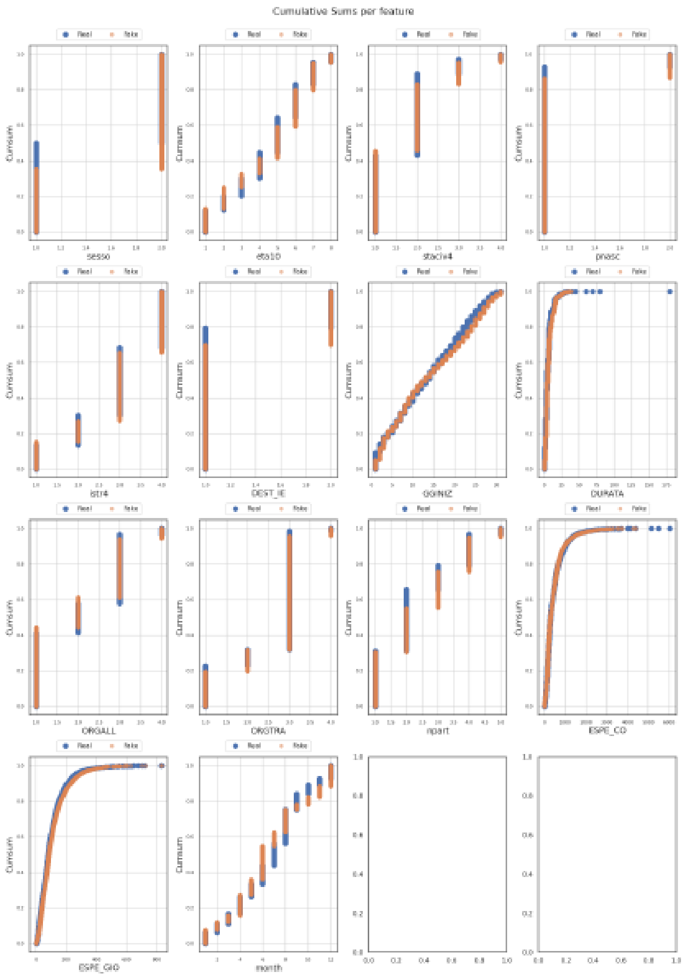
- ✓ Note: In the **original distribution itself**, the values are *not* sums of previous values. Only in the **cumulative sum version** do the values accumulate.

- ✓ 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



AI for the generation of Synthetic Data

- ✓ 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
Original Data	0.964516848	0.964516848	0.964516848
RF	0.660685592	0.660685592	0.660685592
XGB	4.46349e-05	4.46349e-05	4.46349e-05
SMOTENC	0.992813783	0.992813783	0.992813783
DPCTGAN	4.46349e-05	4.46349e-05	4.46349e-05
VAE	0.892385288	0.892385288	0.892385288
CTGAN	0.896134619	0.896134619	0.896134619

Conclusions and Next Steps

Conclusions

References

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. *Advances in neural information processing systems*, *27*.

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Thanks

FRANCESCO PUGLIESE | francesco.pugliese@istat.it