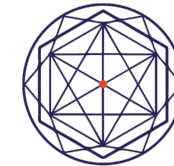


Prospettive future del Calcolo Scientifico nell'ambito del Programma Nazionale per la Ricerca (PNR)

Prof. Salvatore Cuomo



UNIVERSITÀ DEGLI STUDI
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**Think tank
on Scientific Computing
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aula virtuale <https://unicam.webex.com/join/pietruigi.maponi>

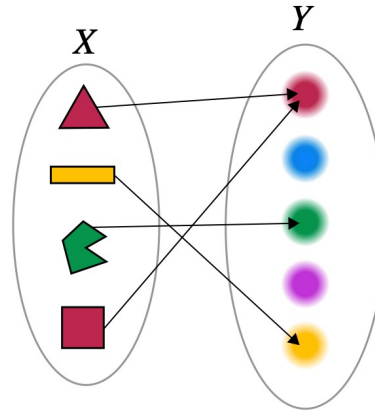
Camerino, 18 Giugno 2021

Considerando che nell'ultimo decennio la crescita delle reti informatiche e delle capacità di memorizzazione dei supporti hanno permesso di avere a **disposizione grandi quantità di dati accessibili** anche in remoto.

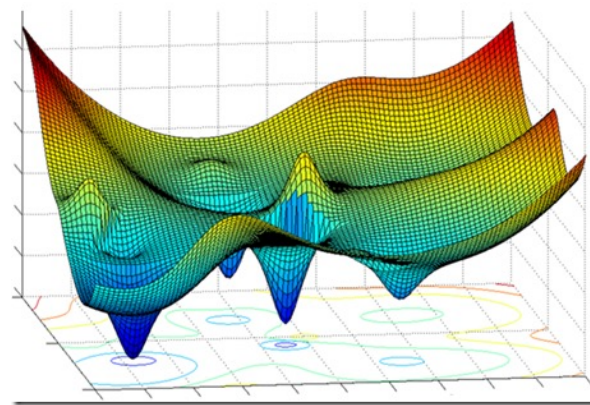
- competenze sull'**apprendimento automatico** e, più in generale, sull'**analisi dati** che necessitano della costruzione di modelli che permettano di **estrarre le informazioni rilevanti** e di **definire algoritmi che possano ricavare le informazioni mancanti**.
- La disponibilità di “**grande quantità di dati**” non è sufficiente a garantire che i modelli generati per lo studio dei fenomeni in esame siano affidabili, per molte ragioni:
 - i dati sono **non strutturati o non completamente affidabili**;
 - i dati sono rappresentati da **un grande numero di variabili**, di cui solo poche possono essere significative per il problema;
 - i dati possono **cambiare rapidamente** nel tempo;
 - la numerosità del campione** può essere **piccola** rispetto alle dimensioni dei dati;
 - il campione può **non essere rappresentativo** dell'intero fenomeno.

Idea «rozza» dati e modelli

✓ In un **corso 0** di Matematica



✓ In un **corso avanzato** di Matematica



Function

$$x \mapsto f(x)$$

Examples by **domain** and **codomain**

$$X \rightarrow B, B \rightarrow X, B^n \rightarrow B$$

$$X \rightarrow Z, Z \rightarrow X$$

$$X \rightarrow R, R \rightarrow X, R^n \rightarrow X$$

$$X \rightarrow C, C \rightarrow X, C^n \rightarrow X$$

Classes/properties

Constant · Identity · Linear · Polynomial ·
Rational · Algebraic · Analytic · Smooth ·
Continuous · Measurable · Injective · Surjective
Bijective

Constructions

Restriction · Composition · λ · Inverse

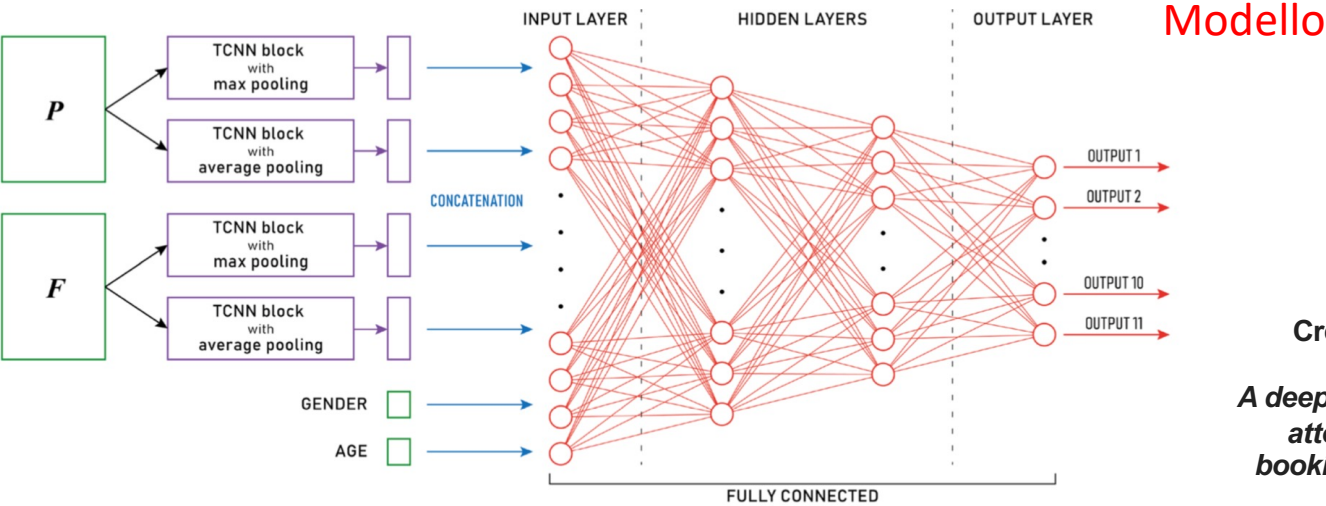
Generalizations

Partial · Multivalued · Implicit

V · T · E

Dati

		Types of data		
		Continuous attributes	Categorical attributes	Mixed attributes
Cardinality of Relationship	Univariate Described by individual attributes (independence)	Type I Extreme value anomaly	Type II Rare class anomaly	Type III Simple mixed data anomaly
	Multivariate Described by multi-dimensionality (dependence)	Type IV Multidimensional numerical anomaly	Type V Multidimensional rare class anomaly	Type VI Multidimensional mixed data anomaly



Credits: Piccialli, F., Cuomo, S., Crisci, D., Prezioso, E., & Mei, G. (2020). *A deep learning approach for facility patient attendance prediction based on medical booking data*. Scientific Reports, 10(1), 1-11.

Machine Learning (ML) e Deep Learning (DL) sono metodologie pervasive in numerosi campi di ricerca. È particolarmente nel calcolo scientifico e nella scienza computazionale.

- Spesso tali metodologie vengono viste come una **magica "scatola nera" non basata su solidi formalismi matematici e principi rigorosamente spiegabili**. Questi approcci di apprendimento rappresentano nuovi paradigmi per risolvere in modo efficiente e accurato i problemi nel Calcolo Scientifico.
- Per quanto riguarda l'efficacia di questa nuova sfida, devono essere affrontate molte questioni cruciali e affascinanti ancora aperte. Per esempio:
 - i) come **le metodologie note della matematica computazionale**, in particolare i kernel numerici, possono essere integrate **e migliorare i modelli di apprendimento automatico**;
 - ii) in che modo gli approcci ML e **DL hanno cambiato** la ricerca nell'analisi numerica, nel calcolo scientifico e più in generale nella scienza computazionale;
 - iii) come ML e DL **influenzeranno la scelta di adottare modelli matematici** complessi e/o approcci data-driven per la risoluzione dei problemi?

L'interesse su tali tematiche sono dimostrate **dai Gruppi UMI TAA e UMI Intelligenza Artificiale**

Settori chiave della ricerca, dell'innovazione, della PA, dell'industria e del benessere della società avanzano una domanda di big data, di piattaforme dati e di sistemi di calcolo a elevate prestazioni.

- Horizon Europe esplicitamente assegna **allo High Performance Computing** (calcolo avanzato e ad alte prestazioni HPC) **e ai big data** (grandi sistemi di dati) un ruolo primario per il perseguimento dei seguenti impatti:
 - **sviluppare un'economia basata sui dati**, dinamica, attrattiva, sicura e fondata su processi agili di gestione e fruizione dei dati (cfr. impatto atteso di Horizon Europe n. 20);
 - **accrescere i livelli di sovranità e indipendenza dell'Unione Europea** nelle esistenti e nelle future tecnologie emergenti ed abilitanti (cfr. impatto atteso di Horizon Europe n. 21);
 - **determinare uno sviluppo umano-centrico ed etico delle tecnologie digitali e industriali** (cfr. impatto atteso di Horizon Europe n. 24).

- Gli impatti attesi n. 21 e 24 di Horizon Europe includono lo sviluppo di tecnologie a sostegno delle grandi sfide sociali e sistemiche, come quelle **per la prevenzione e la sostenibilità di epidemie e pandemie**.
- Finanzieranno un progetto ad alto impatto dedicato allo “**sviluppo di spazi comuni europei di dati e interconnessione delle infrastrutture cloud**”.

Il progetto si fonda sulla promozione di **investimenti combinati di 4-6.000 milioni di euro**, con una prima fase di attuazione prevista per il 2022.

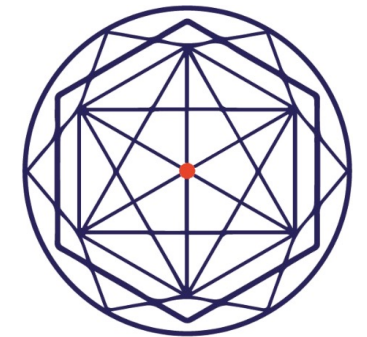


The Turin's High-Performance Centre for Artificial Intelligence

The University of Turin and Polytechnic University of Turin have joined forces to create a federated competence centre on High-Performance Computing (HPC), Artificial Intelligence (AI) and Big Data Analytics (BDA). HPC4AI is designed as a centre capable of collaborating with entrepreneurs to boost their ability to innovate on data-driven technologies and applications. HPC4AI started in 2017 with the construction of four new federated computing laboratories completed at the end of 2020. HPC4AI is organized in two poles: one at the University of Turin (UNITO), which coordinated the design and implementation phase of HPC4AI, and another at the Polytechnic of Turin (POLITO).

All laboratories are now fully operative. More details on offered services can be found at Università di Torino HPC4AI@UNITO Politecnico di Torino

- In questo ambito presso l'Università degli Napoli Federico II, abbiamo condotti studi con il Laboratorio Mathematical Modelling and Data Analysis Laboratory (MODAL) ricerche su Intelligenza Artificiale e Machine Learning in vari ambiti
- L'attività di MODAL è condotta direttamente da
 - Salvatore Cuomo**, Prof. Associato Analisi Numerica, Dipartimento di Matematica e Applicazioni;
 - Francesco Piccialli**, Rtd-B Informatica, Dipartimento di Matematica e Applicazioni;
 - Fabio Giampaolo**, Dottorando;
 - Eduardo Prezioso**, Dottorando Industriale;
 - Vincenzo Schiano di Cola**, Dottorando Industriale;
 - Federico Izzo**, Borsista di Ricerca;
 - Federico Gatta**, Borsista di Ricerca;



Mathematical mOdeling and
Data AnaLysis research group
<http://www.labdma.unina.it>

Collegi di Università straniere ed italiane tra cui.

Università Politecnica di Madrid, Università delle Geoscience di Pechino, Università di Stanford, Università di Padova, Università di Firenze.

A Deep Learning approach for facility patient attendance prediction based on medical booking data



Francesco Piccialli^{1*}, Salvatore Cuomo¹, Danilo Crisci¹, Edoardo Prezioso¹ and Gang Mei²

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²School of Engineering and Technology, China University of Geosciences, 100083 Beijing, China



Abstract

Nowadays, data-driven methodologies based on the clinical history of patients represent a promising research field in which personalized and intelligent healthcare systems can be opportunely designed and developed. In this perspective, Machine Learning (ML) algorithms can be efficiently adopted to deploy smart services to enhance the overall quality of healthcare systems. In this work, starting from an in-depth analysis of a data set composed of millions of medical booking records collected from the public healthcare organization in the region of Campania, Italy, we have developed a predictive model to extract useful knowledge on patients, medical staff, and related healthcare structures. In more detail, the main contribution is to suggest a Deep Learning (DL) methodology able to predict the access of a patient in one or more medical facilities of a fixed set in the immediate future, the subsequent two months. A structured Temporal Convolutional Neural Network (TCNN) is designed to extract temporal patterns from the administrative medical history of a patient. The experiment shows the goodness of the designed methodology. Finally, this work represents a novel application of a TCNN model to a multi-label classification problem not linked to text categorization or image recognition.

Some Details on the TCNN

In detail, the Temporal CNN (TCNN) block takes as input:

- a $t \times d$ matrix ($t = 52$ and $d = 8, 19$ in our application);
- a set S of n_s sizes as parameters ($S = \{6, 9, \dots, 51\}$ in experimental tests).

For each $s \in S$, 64 filters with a $s \times d$ kernel operate on the input matrix to discover different patterns, obtaining $64 \times t \times 1$ arrays to which a 2×1 pooling is applied.

At this point the $\frac{1}{2} \times 1$ are added to produce a single vector.

The n_s vectors obtained by varying $s \in S$ are then concatenated.

Hence, the output of the TCNN block is an $n_s \times \frac{t}{2}$ column vector.

The convolutional layer of the proposed method is composed of four TCNN blocks, to apply a maximum or an average pooling to each temporal matrix.

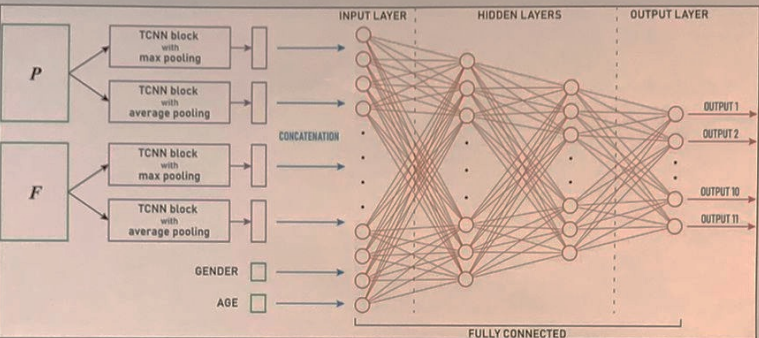
Next, by concatenating the output column vectors also with the gender and age features, the vector of $4 \times n_s \times \frac{t}{2} + 2$ components becomes the input of a feedforward fully connected neural network with two hidden layers (respectively of 128 and 32 perceptrons) and an output layer composed of 11 units, which generates the final output of the method.

References

Cheng, Y., Wang, F., Zhang, P. & Hu, J. Risk Prediction with Electronic Health Records: A Deep Learning Approach, 432–440 (Society for Industrial and Applied Mathematics, 2016).

Min, X., Yu, B. & Wang, F. Predictive modeling of the hospital readmission risk from patients' claims data using machine learning: A case study on covid. Sci. Rep. 9, 2362.

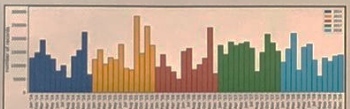
Artificial Intelligence for Healthcare management



The design of our proposed method has been done to explore and extrapolate information from the temporal evolution of the medical booking history of the patients. A previous work, done by Cheng et al., proposed a Temporal Fusion Convolutional Neural Networks (TFCNN) study the clinical history as a matrix.

The Data

The main table of the database has more than 13 million unique rows, referring to booking appointments and medical prescriptions covering the period 2014–2018.



The histogram shows the number of records relating to each month of the examined period, 2014–2018.

Medical facility	Number of appointments
1 PSI Napoli Est	399448
2 PSP C.so Vittorio Emanuele	354489
3 PSP Santa Maria di Loreto Crispi	349398
4 Poliambulatorio Scampia	311289
5 Poliambulatorio Palazzo Ex INAM	301247
6 Presidio San Gennaro	298928
7 Poliambulatorio Winspeare	289084
8 Poliambulatorio Cesare Battisti	274538
9 Ambulatorio San Gennaro ad Antignano	261734
10 PO Dei Pellegrini	248924

The top 10 medical facilities in Naples, Campania, sorted by the number of appointments in the extracted windows during the preprocessing phase, from 2014 to 2018.

Experimental Results

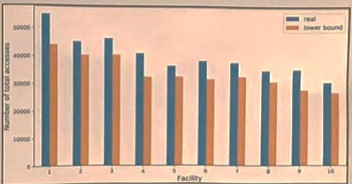
The following tables show that the proposed method outperforms the traditional method according to any of the considered metrics.

Metric	Training distance	Test distance	No. of misclassification
AP	0.4000 ± 0.0000	0.4000 ± 0.0000	0.4000 ± 0.0000
RF	0.4000 ± 0.0000	0.4000 ± 0.0000	0.4000 ± 0.0000
LR	0.4000 ± 0.0000	0.4000 ± 0.0000	0.4000 ± 0.0000

Metric	Overall accuracy	Overall precision	Overall recall
AP	0.7700 ± 0.0000	0.7700 ± 0.0000	0.7700 ± 0.0000
RF	0.7700 ± 0.0000	0.7700 ± 0.0000	0.7700 ± 0.0000
LR	0.7700 ± 0.0000	0.7700 ± 0.0000	0.7700 ± 0.0000

Starting from the previous year's clinical history, the proposed method attempts to predict if and in which facility a patient will have at least one appointment.

By this feature, this method may be useful to the health authority management, since it can provide a non-trivial lower bound on the facility patient attendance in terms of patients' accesses.



Conclusion

Healthcare technologies are not necessarily confined to patient management and care but can also have a great significance concerning prevention. The greater is the emphasis placed on preventive medicine rather than the mere treatment of the symptoms, the more effective will the healthcare system be for everyone, both for the healthcare management and the wider community. In this paper we have presented a Temporal Fusion CNN adapted for the multi-label problem described. Starting from only administrative information about the previous year's clinical history of a patient, the goal of the model has been to predict if and in which facility the patient will book an appointment. Even though the administrative data do not store information about medical examination outcomes or reports, the experimental results prove the quality of the model constructed. As future research, with additional information about patients and HS provisions, it would be interesting to evaluate the model predictions for patient health, not only from that of administration, in the latter part of the work, we have proposed a patient attendance lower bound for each facility as a service to the health authority. As a further future research project, supported by supplementary financial information, it may also be possible to provide statistical data to optimize the funding distribution of the regional health system.



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Esempi di Ricerche supportate da progetti di ricerca

Artificial Intelligence and Healthcare: Forecasting of medical bookings through multi-source time-series fusion



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²Universidad Politécnica de Madrid, AIDA - Applied Intelligence and Data Analysis Research Group, Madrid, Spain

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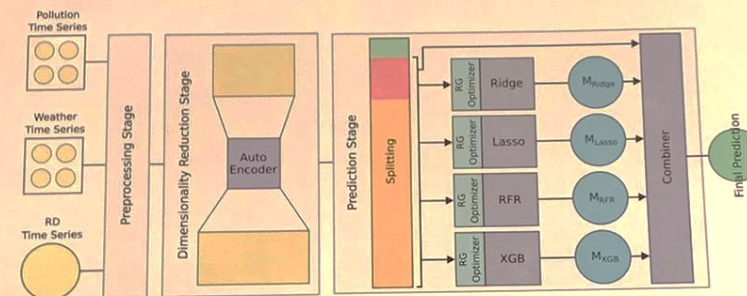


POLITÉCNICA

Abstract

Nowadays, Artificial intelligence (AI) combined with the digitalization of healthcare can lead to substantial improvements in Patient Care, Disease Management, Hospital Administration, and supply chain effectiveness. Among predictive analytics tools, time series forecasting represents a central task to support healthcare management in terms of bookings and medical services predictions. In this context, the development of flexible frameworks to provide robust and reliable predictions became a central point in this healthcare innovation process. This paper presents and discusses a multi-source time series fusion and forecasting framework relying on Deep Learning. By combining weather, air-quality and medical bookings time series through a feature compression stage which preserves temporal patterns, the prediction is provided through a flexible ensemble technique based on machine learning models and a hybrid neural network. The proposed system is able to predict the number of bookings related to a specific medical examination for a 7-days horizon period. To assess the proposed approach's effectiveness, we rely on time series extracted from a real dataset of administrative e-health records provided by the Campania Region health department, in Italy.

The proposed AI framework



Temporal sequences of respiratory diseases bookings, weather and air-quality variables are preprocessed, then the dimensionality reduction strategy is applied on the subset composed by lagged variables extracted from exogenous time series. Finally, the obtained dataset is split in train/validation/test sets, used to train, optimize and validate the whole procedure: the machine learning predictors are trained over the train set (in yellow), their hyperparameters are optimized through a random grid search, and their forecast on the validation set (in red) fed the Combiner, with lagged and periodicity features, which is trained in recognizing patterns between Time Series attributes and forecasts produced by predictive models.

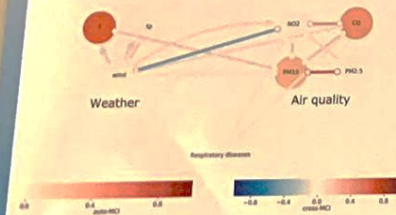
Discussion

The proposed data fusion strategy provides a low-dimensional feature space which avoids the 'curse of dimensionality' issue and reduces the noise without a feature selection procedure. Simultaneously, it preserves the weak relations, identified through a preliminary statistical analysis, between the sequence under investigation and the candidate causal ones. On the other side, the proposed ensemble strategy, exploiting the machine learning forecasts and information extracted from the time sequences, can reliably recover and model temporal patterns, providing a final prediction with enhanced accuracy. As can be observed from the obtained results, all the workflow is proven to outperform widely used forecasting models and combination strategies, attaining significant improvements in short-term predictions of the analysed respiratory diseases bookings time series.

Finally, even though the pipeline has been designed to face the specific problem presented in this work, the characteristics of robustness and accuracy exhibited by the framework, together with the flexibility provided by the modular architecture, pave the way to further studies on the proposed approach.

Correlation and causality analysis

Since the time series present large weekly variations, the question which arises is whether or not the forecasting can be boosted with external knowledge, as the air-quality and the weather condition information: validating the hypothesis that relations exist between the respiratory diseases sequence and the external time series considered is necessary to design a fusion strategy that preserves such relations, in order to exploit them in the forecasting phase.

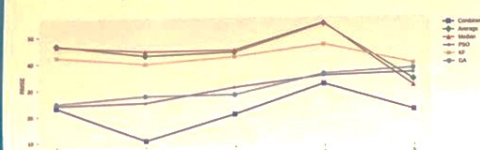


Graph of causality relations obtained with PCMCi+. The links with an arrow indicate direct causality towards the pointed variable, while the non-arrowed links indicate unclear direction of causality. The more the link is blue, the more adverse is the effect, while the more the link is red, the causality is proactive. According to this graph, weak relations from the air quality measurements to the respiratory diseases bookings are present. At the same time, the weather influences only the air quality (negatively for the wind speed [wind], while positive for temperature).

Results – part I

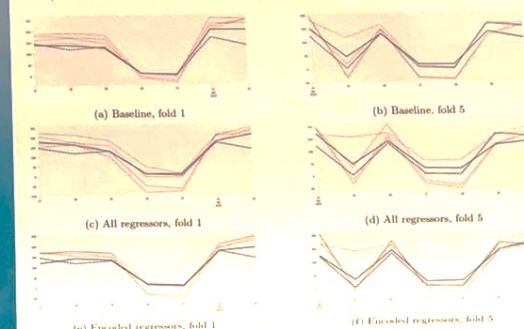
Model	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Baseline	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Baseline	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Lasso	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Ridge	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
RFR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
XGB	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Combiner	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Comparison of 5-Fold Cross Validation results for 7-days ahead forecasts between single predictors (Lasso and Ridge, Boosted Trees and Random Forest predictors), models and combination strategies, and the proposed framework according to error measures presented in this Section. The measures are expressed as mean $\pm$ standard deviation of the k-fold results. Best values are highlighted in bold, while second best ones are underlined.

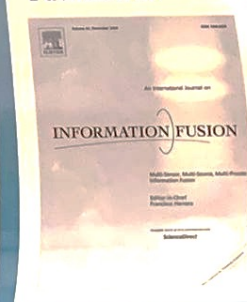


Results – part II

A visual comparison between forecasts obtained through the machine learning regressors, then exploited for the combining stage, and the prediction provided by the Combiner. Also, the ground truth is shown as a dotted black line. As can be observed the Hybrid Network presented in this work always produce a reliable 7-days-ahead prediction, as evidenced by the coherent reproduction of temporal fluctuations (as confirmed by the high R^2 score) of the real data.



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The role of Artificial Intelligence in fighting the COVID-19 pandemic



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²University of Naples Federico II, Department of Electrical Engineering and Information Technology, Naples, Italy



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Abstract

The first few months of 2020 have profoundly changed the way we live our lives and carry out our daily activities. Although the widespread use of futuristic robotaxis and self-driving commercial vehicles has not yet become a reality, the COVID-19 pandemic has dramatically accelerated the adoption of Artificial Intelligence (AI) in different fields. We have witnessed the equivalent of two years of digital transformation compressed into just a few months. Whether it is in tracing epidemiological peaks or in transacting contactless payments, the impact of these developments has been almost immediate, and a window has opened up on what is to come. Here we analyze and discuss how AI can support us in facing the ongoing pandemic. Despite the numerous and undeniable contributions of AI, clinical trials and human skills are still required. Even if different strategies have been developed in different states worldwide, the fight against the pandemic seems to have found everywhere a valuable ally in AI, a global and open-source tool capable of providing assistance in this health emergency. A careful AI application would enable us to operate within this complex scenario involving healthcare, society and research.

The Worldwide map of scientific production related to AI and COVID-19



Thanks to the Bibliometrix¹ tool, developed by M. Aria and C. Cuccurullo, and the Scopus database, it has been possible to show that more than 1000 peer-reviewed papers containing the keywords "COVID-19" and "Artificial Intelligence" have been published from the outbreak of the epidemic to 1st March 2021.

As reported in Figure, even though, not surprisingly, most of this scientific production come from "first-world" nations, these topics have also aroused considerable interest in countries from mid-east Asia and North Africa. For instance, in states such as Iran, the COVID-19 pandemic has struck with particular strength due to a deficiency in monitoring actions and a weaker healthcare system. AI technologies, expecting to offer efficient and low-cost models to address medical and social issues, have naturally attracted many of the more seriously affected regions. Countries such as Iran, Turkey and Egypt, alongside the USA, China, India, Italy and the UK, are among the top ten states where more peer-reviewed papers related to the application of AI technologies to COVID-19 issues have been written.

¹ <https://www.bibliometrix.org/>

The Pandemic Dynamics: a Conceptual Overview

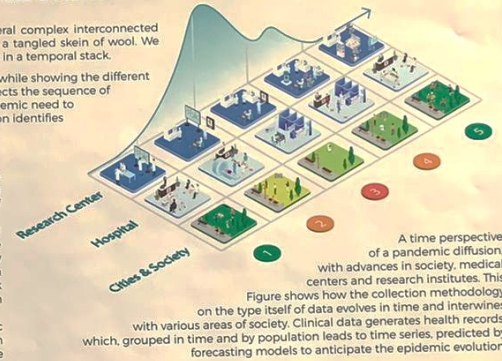
The pandemic dynamics landscape is composed of several complex interconnected relations among data, models, and applications, just like a tangled skein of wool. We aim to untangle such dynamics by freezing the pandemic in a temporal stack.

The Figure illustrates the evolution in time of a pandemic while showing the different contexts and the related AI applications. The timeline reflects the sequence of decisions relating to how the different phases of the pandemic need to be addressed, according to the WHO (2009). This institution identifies six pandemic phases plus two other periods (a post-peak and a post-pandemic).

These can be grouped into five periods, according to the actions needed to be taken into account. The Figure shows data generated in different phases and areas of society.

As the clinical data is generated from patients and analyzed in laboratories, patient health records and time series are deduced from the pan-demic data and X-Ray and CT are generated in hospitals; all this data results in a range of applications that AI can enhance outbreak prediction, spread tracking, diagnosis, drug production and drug repurposing.

Technically speaking, at different stages of the pandemic spreading timeline, scientific papers report information about the data collected and cases tested to investigate the disease's characteristics.

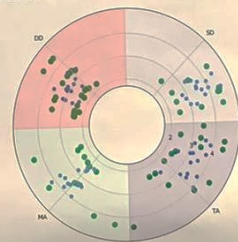


A time perspective of a pandemic diffusion, with advances in society, medical centers and research institutes. This Figure shows how the collection methodology on the type itself of data evolves in time and intertwines with various areas of society. Clinical data generates health records, which, grouped in time and by population leads to time series, predicted by forecasting models to anticipate the epidemic evolution.

Fields of Application



AI can be defined in terms of stages of observation and action. In the context of a pandemic, AI is applied in two main areas, namely medical research and the social context. Therefore, in order to study AI applied during a pandemic, we need to focus on four areas: disease detection (diagnosis), social dynamics observation (predictions), medical actions (treatments) and social management (tracking). Points plotted on the polar graph represent the papers in the literature. The positions depend on how much each paper we analyzed we considered belonging to each of area, within the 3 central stages of the pandemic.



To better organize and explain all the possible applications during a pandemic of AI methodologies, we divided them into four main application areas. The areas shown in Figure encompass two pillars of AI - action and detection - related to two context namely society and health. In each temporal stage, different pandemic dynamics act on the environment, determining consequences on social behavior and healthcare status.

Where we are and What is next

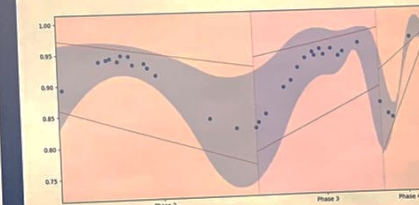
The proposed overview of scientific works published during the ongoing COVID-19 pandemic highlights some achievements and limitations of AI in tackling the 2020 pandemic.

By considering the four domains (health and society applications able to detect and act), there are still requirements that AI cannot quite attempt. Indeed, AI still holds three well-known features which can result in potential failure: the absence of strong AI, its inability to work without knowledge of the domain, and the need for good quality and flow of data. Furthermore, ML and DL techniques must be scrutinized in order to determine what are the best current solutions, as well as future developments and research perspectives, without ignoring ethical concerns (such as trust and privacy) that currently hinder AI usage in our society.

The new society's nature, intertwined with AI after the pandemic, is fraught with problems, especially about ethical issues, such as trust, accountability and privacy. When an algorithm fails to diagnose a health issue, what needs to be taken into account? Governments play a critical role in enabling AI to reveal its capacity to assist in tackling a pandemic. It is a lesson we have learned already, from the SARS epidemic in 2002.

Machine Learning aspects

To better observe how proposed research works have improved performance in classification tasks, we plotted the Receiver Operating Characteristics Area Under the Curve (ROC-AUC). The AUC trend shown in the Figure depicts how qualitative behaviour of published models improved during the pandemic, in terms of classification performances with respect to AUC. In Phase 2, papers mainly analyze known models on the first bench of data. The AUC decreases due to the exploration of new techniques that require a tuning step. In Phase 3, based on explorations conducted during Phase 2, models become more robust, and min a max AUC values come closer, and optimal AUC values emerge. In Phase 4, challenging models are implemented, and accuracy can easily increase since a wide spectrum of data is coming, while fine-tuning procedures have become more feasible.



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M.O.D.A.L.
Mathematical modelling and
Data Analysis Laboratory

Dispositivi medicali, organi artificiali e tecnologie neuromorfiche per la medicina bionica e rigenerativa

- *Priorità di ricerca:* sviluppo di **nuove tecnologie per la progettazione di soluzioni biomedicali specifiche per il paziente e la produzione di dispositivi impiantabili e non**, in particolare di quelli endovascolari e intravascolari; sistemi innovativi per la sostituzione della funzione d'organo (nuovi sistemi dialitici per l'adozione dell'emodialisi domiciliare e ridurre i costi dei trattamenti dialitici, strategie per ridurre le complicanze dei dispositivi VAD, strategie per aumentare efficienza e automazione dei sistemi ECMO, sistemi di preservazione della funzione degli organi in vista del trapianto, endoprotesi);
- tecnologie neuromorfiche per applicazioni **in medicina e tecnologie a bassa invasività** per il sistema nervoso centrale e/o quello periferico; tecnologie per la rigenerazione di tessuti complessi *in vitro* e *in vivo* anche attraverso l'utilizzo di tecnologie di stampa 3D ottenute da informazioni anatomiche derivanti da immagini cliniche;
- integrazione in clinica di sistemi per produzione di modelli fisici 3D anche per la pianificazione chirurgica e il training chirurgico; **sviluppo di modelli fisici e computazionali.**

Bioinformatica e biologia sintetica

- *Priorità di ricerca*: nuovi algoritmi, metodologie e tecnologie per l'analisi di dati biologici e la modellazione dei sistemi biologici (*high-throughput screening, High Performance Computing, data bioscience*);
- analisi e modellazione dei sistemi biologici con riferimento alla fisiopatologia umana mediante metodi e **strumenti bio-informatici e matematici innovativi.**



*VI ASPETTIAMO A NAPOLI
(...POST COVID-19)*