LA VEJEZ: CONOCIMIENTO, VIVENCIA Y EXPERIENCIA

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TELEMEDICINE, ARTIFICIAL INTELLIGENCE, BIG DATA AND FORECASTING MODELS

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Introduction

Health monitoring, crisis prevention and support for everyday activities represents an emerging field of application at a national level, with particular reference to fragile individuals, the elderly and people with chronic diseases. An important aspect that should be explored by the end of this decade is how the technologies of artificial intelligence, as applied in the health context, might ultimately improve the quality of the current system and whether the work done as part of the efforts now being made is optimised and sufficient to achieve new objectives. In particular, the ability to process large quantities of data will act as a catalyst, triggering an extremely high number of benefits in the health and wellness sector in terms of prevention, diagnosis and individual treatment.

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The pandemic Covid 19 emergency has put in crisis the health system and also the Italian economy. It is, however, clear to everyone that the road to return to normal will still be long and difficult and it is clear to everyone that the lock down is a one-shot strategy that is impossible to re-propose without destroying the economy. It is therefore necessary to enrich the toolbox for combating the epidemic with new tools. In this perspective, the prevention of outbreaks and clusters that will inevitably emerge on the territory with technological tools and technological management of the patients is of particular importance.

In this study we want to show a model that helps to understand the epidemic trend in relation to the variations of contagion and therefore to the different containment maneuvers of the pandemic itself.

Towards a predictive medicine

Starting with Hippocrates, basing medicine on the observation of events has long been the guiding epistemological criterion of the healthcare profession.

This criterion evolved as medicine progressed, resulting in the formula of *Evidence-Based Medicine (EMB),* which can be defined as "the process of systematic search, assessment and use of the results of contemporary research as a basis for clinical decisions" or also as "the use of mathematical estimates of risks, benefits and damage derived from high-quality studies conducted on population samples to support the clinical decision-making process in diagnosis or in the management of individual patients". The possibility of using big data and artificial intelligence (1, 2) has had a strong impact on this epistemological assumption of present-day clinical practice. The use of big data and artificial intelligence is ushering in a type of medicine based on elements that are not apparent to human doctors but can be extracted by using big data and deep learning techniques, due to the ability of computers to cover and process a far larger amount of information than a human being.

Today, by using big data and deep learning techniques we can deliver effective preventive medicine long before the onset of symptoms. For chronic and degenerative diseases, this provides a significant advantage. Instant access to the entire set of data makes it possible to plan evolution of the clinical presentation by means of algorithms supporting decision-making, improving the overall efficiency of the process. The overall process is constructivist and is aimed at delivering significant benefits in terms of patients' treatment and care.

The diagnostic and care model also based on the patient's personalised electronic medical record will respond to the demand for increasingly effective, efficient and high-quality diagnosis, prognosis and treatment services. A good trade-off between quality of service and implementation costs can be achieved via the application of innovative technologies, systems and procedures for management of the clinical process, based on an e-Health Service Management logic. Creation of the electronic medical record, constantly updated with data from remote monitoring will favour very early diagnosis of many diseases, the identification of risks and the remote delivery of treatment and care. Health status monitoring, prevention of acute episodes and support in daily life are all emerging areas for e-health services, in particular for fragile and elderly individuals and people with chronic diseases.

This revolution can help to cut significantly the costs of healthcare, by reducing sharply the number of acute cases, preventing the development of many chronic diseases and delivering tele assistance and telemedicine (1,2).

Predictive medicine and Covid 19

The pandemic Covid 19 emergency has put in crisis the health system and also the Italian economy.. It is, however, clear to everyone that the road to return to normal will still be long and difficult and it is clear to everyone that the lock down is a one-shot strategy that is impossible to re-propose without destroying the economy. It is therefore necessary to enrich the toolbox for combating the epidemic with new tools. In this perspective, the prevention of outbreaks and clusters that will inevitably emerge on the territory with technological tools and technological management of the patients is of particular importance. Therefore, statistical-mathematical tools are used to study the phenomena and to try to build predictive models that help the decision-maker to face the problem.

An important topic to explore is therefore how artificial intelligence technologies can be applied to the health context in relation to the pandemic Covid 19. In particular, the ability to process large amounts of data will catalyze a very high number of health benefits in the prevention, diagnosis, care of Covid 19.

The use of health big data and Artificial Intelligence to better exploit the potential of health big data represents a further weapon against Covid 19.

The use of artificial intelligence techniques to produce predictive models capable of highlighting on one hand the probable evolution of the epidemic by identifying in advance the territorial contexts or sectors that are most likely to develop clusters and outbreaks. This prediction will be made by processing not only the epidemiological data and the characteristics of the spread of the virus, but also inserting data on mobility, transport, weather conditions and air pollution, on the organizational methods work in the various sectors and finally on the urban characteristics of the different contexts.

These results will be able to provide a support tool in the identification of risk areas, but they will be of great use for contrasting, as the interventions can be calibrated in close relationship with the specific contexts. Finally, through artificial intelligence, we will also be able to identify the patients most in need of treatment and the contexts in which the risk of an excess of serious cases is greater.

The development of a diagnostic and care model that will be capable of meeting the demand for ever more effective, efficient and quality diagnosis, prognosis and treatment services for Covid 19 patients.

The development of a prototype for a personalized electronic health record for Covid 19 positive linked to decision-making support systems, will lead to an improvement in the effectiveness, efficiency and quality of healthcare processes and of the services provided insofar as:

- it favours the diffusion of punctual and precise prevention models;
- it permits an association to be made between individual clinical data and clinical knowledge;
- it serves as an information base for the development of software specializing in the management of Covid 19 patients;
- it guarantees greater healthcare continuity.

The paper will lead to the development of predictive model, based on innovative statistical and computational algorithms, capable of providing clinicians with a support tool (accessible through IT applications) in identifying the pandemic evolution at local level. The purpose of this work is to understand what are the variables in question and how the decision maker can act to adapt the model in relation to the variation of certain conditions.

The traditional Exponential Model

The exponential models come from an intuition of Malthus the first to observe that any organism can potentially increase in number following a geometric series and that each subject S reproduces according to a given R index every period t:

$$\eta_1 = \eta_0 \cdot R, \qquad \eta_1 = \eta_0 \cdot R^1, \qquad \eta_2 = \eta_0 \cdot r^2$$

Then

$$\eta_t = \eta_0 \cdot r^t$$

As t increases we can therefore approximate this relationship with an exponential function:

$$\eta_t = \eta_0 \cdot \exp (r \cdot t) \qquad (1)$$

Now we have three possible cases:

1. Population exponentially declines (r < 0);

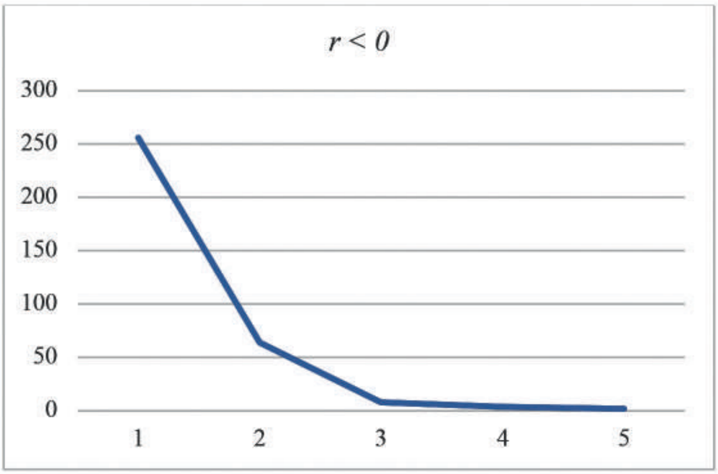

Fig. 1 (Source: Own processing)

2. Population exponentially increases (r > 0);

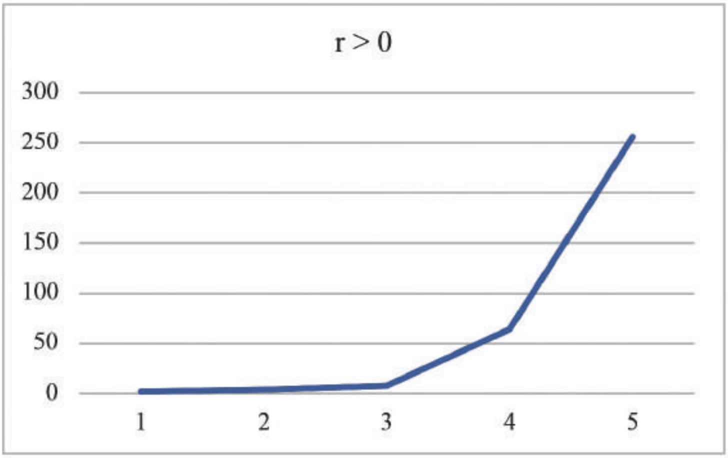

Fig. 2 (Source: Own processing)

3. Population does not change (r = 0);

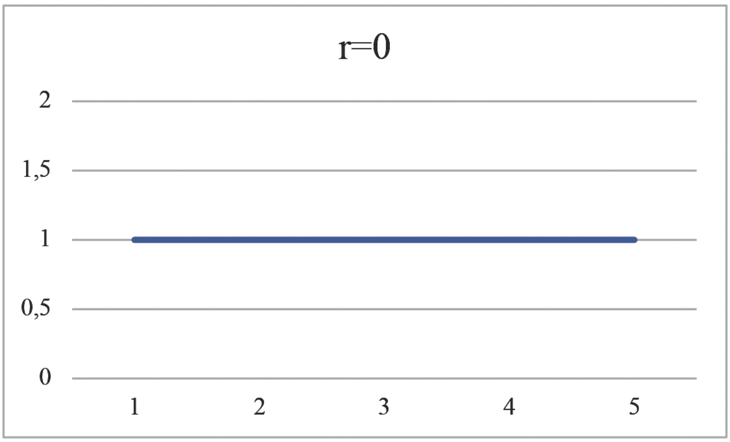

Fig. 3 (Source: Own processing)

The r parameter (also called Malthusian paramenter) therefore represents the rate of increase or decrease of contagion, so it shows how many people can be infected by a sick person.

From this it is inferred that if this index is less than 0 the disease will tend to extinguish itself.

However, it should be noted that this index in the case of containment measures adopted, and that these measures are modified alter this parameter.

We could assume simplifying:

$$r_{t_n} = \frac{infected_{t_n}}{infected_{t_{n-1}}} \qquad (2)$$

For what said above the prerequisites for this model to work are:

- the continuity (and therefore no influence from the outside)
- All possible hosts of the virus are identical (immune systems in the same conditions).
- All viral loads are similar and that the virus does not undergo mutation or loss of aggression.
- Infectious individuals are unlimited.

It is therefore easy to guess that this model is not appropriate in the case of a pandemic involving people with different immune systems due to age or previous diseases, legal systems that apply different containment actions, and countries that do not offer the same health conditions, nor as quality (think of the third world) or insurance is required to get treatment.

An approach with several variables

Here we will take into account several variables for the calculation of the maximum number of people exposed to infection in a country.

The number of people exposed is essential to verify the course of the infection curve.

Therefore, some corrections will be applied to the growth models.

We will not deal with the following variables for which we will propose an approach in the next section:

- Use Containment measures
- Healthcare system efficiency
- State health system

Let *k* be an index that represents the probability of being infected again, and calculated indicatively from the number of healed people who have been infected again:

$$\Omega_{t_1} = \eta_{t_1} - [\tau_{t_0} + (\beta_{t_1} \cdot \kappa)] \qquad (3)$$

where Ω_{t_1} represents the number of infected people in the country at time t_1, η the number of inhabitants at time t_n, τ the number of infected people, β the number of healed people.

We indicate with γ the probability related to the viral load. To calculate this probability we can simply give it before:

$$\gamma_{t_1} = \frac{\max \gamma_{t_1}}{\max \gamma_0} \qquad (4)$$

we obtain a representative index, which multiplied by the quantity Ω_{t_1} will make us understand if the probability of contagion increases or decreases according to γ_{t_x}.

Let's now see how to simplify the calculation of an approximate index for the probability of being infected by previous age/pathologies:

- we indicate with *Max*(ε) the maximum average life expectancy;
- with $\bar{\varepsilon}$ the average age of the citizens of the country.

Then

$$\xi_{\varepsilon} = \left(\frac{Max(\varepsilon) \cdot \bar{\varepsilon}}{100}\right) \qquad (5)$$

Which represents the normalised value that takes into account the average age and therefore the potential danger of infection as this value increases.

Let us now see how to approximate ξ_ρ, which represents the average vulnerability of the population in relation to past pathologies.

Given the number η of inhabitants of the country and the number of inhabitants with chronic pathologies registered at the Health Authorities, (considering that the establishment of a statistical observatory is fundamental) η_ρ:

$$\xi_{\rho} = \frac{\eta_{\rho}}{\eta} \qquad (6)$$

So we define an index ξ that will provide us with a normalisation parameter on the vulnerability of individuals based on age and past pathologies:

$$\xi = \xi_{\varepsilon}{}^{(1+\xi_{\rho})} \qquad (7)$$

Now, let's define the maximum number of contactable people for each t_n time.

From (3), we multiply the virally charged probability:

$$\Omega_{t_n} = \{\eta_{t_n} - [\tau_{t_{n-1}} + (\beta_{t_n} \cdot \kappa)]\} \cdot \frac{\max \gamma_{t_n}}{\max \gamma_{t_{n-1}}} \qquad (8)$$

Then we consider on the relation (8) the index ξ (7):

$$\Omega_{t_n} = \left\{\{\eta_{t_n} - [\tau_{t_{n-1}} + (\beta_{t_n} \cdot \kappa)]\} \cdot \frac{\max \gamma_{t_n}}{\max \gamma_{t_{n-1}}}\right\} \cdot \left(\frac{Max(\varepsilon_{t_n}) \cdot \bar{\varepsilon}_{t_n}}{100}\right)^{1+\frac{\eta_{\rho_{t_n}}}{\eta_{t_n}}} \qquad (9)$$

The (9) therefore represents the maximum number of infected persons, and represents the Max of the exponential function to which the r index is applied.

Taking into account that the probability of infection is given:

$$P_{in} = \frac{infected_{t_n}}{\Omega_{t_n}}$$

Let's see how reached a given moment t_x the spread of the pandemic will anyway be in remission (flock immunity), just as the trend of the contagion curve is not exactly exponential but rather more flattened (fig.4).

If we add to this the measures taken by governments, through a hypothesis proposed later, the curve will follow an even flatter trend.

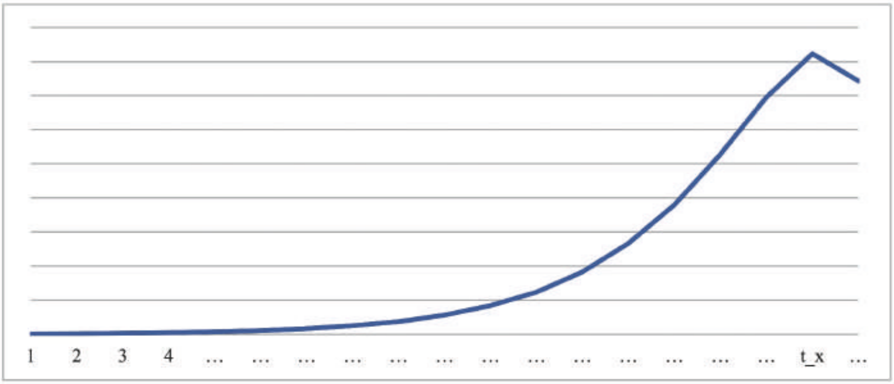

Fig. 4 (Source: Own processing)

In this way, the exponential trend undergoes a variation, tending to flatten as the number of infected subjects decreases with the passage of time, both because many have already had the infection and because those who are not infected have an immune system in which antibodies are present or are more strong.

A new approach through chaos theory

The possible forecast of pandemic infections still lacks the probability that citizens will be alert to the prevention measures recommended or imposed by governments.

This approach can be considered through chaos theory.

This theory introduced by Edward Norton Lorenz reminds us that most of us are subject to a worldview where everything seems predictable at first glance. However, at a given moment, the unexpected, the unpredictable, the chaotic arises.

An unpredictable event that we are obliged to accept and rationalize.

Now let us introduce some basic concepts related to dynamic systems that introduce the Chaos Theory.

A dynamic system is formally defined by:

a) a space of the phases W, consisting of the possible states of the system;

b) a law of deterministic temporal evolution which, given the state of the system at time t=0, specified by the vector $x(0) \in W$, determines the state x(t) at time t in an univocal way, that is to say:

c) $x\,(0) \rightarrow x\,(\mathrm{t})\ Utx\,(0)$

d) a measure of probability *dm(x),* invariant under temporal evolution*:*

$$\text{i.} \qquad m(A)m(U^{-t}A),$$

where A is a set in W and $U^{-t}A$ is the set of points found in A after a t time.

The most common laws of deterministic evolution are maps and differential equations; in the first case time takes on discrete values:

$$x\,(t+1) = g[x(t)] \qquad (10)$$

in the second case the law of evolution is:

$$\frac{dx}{dt} = f(x) \qquad (11)$$

For maps determinism is very evident: given x(0), the (10) allows to calculate x(1) and, iterating the procedure, x(2), x(3),..., until obtaining x(t).

For differential equations, determinism is a consequence of the theorem, valid under very general hypotheses, of existence and uniqueness of solutions.

The simplest dynamic systems are the linear ones, that is:

$$x(t\ +1) = \hat{G}[x(t)]$$
$$\frac{dx}{dt} = \hat{F}(x)$$

where $\hat{G}$ e F are matrices whose elements are constant over time. In cases like these, it is immediate to determine the solution at any time t, of the type:

$$x(t\ ) = \hat{G}^{I}x(0) \text{ e } x(t) = \left[exp\left\{t\hat{F}\right\}\right]x(0) \qquad (12)$$

although only fairly simple solutions can be obtained: relaxation towards stationary solutions, or (almost) periodic movements.

From here it is possible to start a study on the problems in question, considering that the approach is absolutely new and original and there is no study in the field.

Conclusion

From what has been said, one can see how impossible it is to establish a self-sufficient model when faced with any pandemic. In fact, many of the variables taken into consideration are the work of a decision maker, both taken during the pandemic and related to public works and investments in public health. Obviously, the creation of international statistical observatories, linked to the health authorities, becomes indispensable, which through a BigData collect and manage data on world health. A Deep learning algorithm linked to BigData that examines what happens when the variables change can help the decision maker to prevent states of saturation of health services, transport and public management. The creation of a telemedicine and remote monitoring system, will offer support for the long-term care of/ provision for diseases by: (i) guaranteeing continuity of care at a hospital and regional level, (ii) integrating social and healthcare activities, (iii) favouring the continuation of such activities within the patient's own living environment for as long as possible and (iv) improving the patient's quality of life, in addition to providing improved support for diagnosis and treatment.

This approach is consistent with both international and national strategies for innovation, above all since it is developing new decision-making paradigms. As the result of the instantaneous access to the entire data set, provision can be made for the development of the health record through decision-making support algorithms, which make the entire process more efficient.

This revolution can help to cut significantly the costs of healthcare, by reducing sharply the number of acute cases, preventing the development of many chronic diseases and delivering tele assistance and telemedicine.

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