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The Approach of Machine Learning to Optimize the Bank-Customer Interaction at Pandemic Epochs

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***Abstract*—Along the pandemic created by the Corona virus 2019 (Covid-19 in shorthand), the global economy was observed to experience various turbulent months that were reflected by the increasing of unemployment and the apparition of a procrastinator behavior in all those customers that received a loan at the months before the beginning of pandemic. Because the apparition of pandemic was totally random, it had effects on the micro-economy that in most cases have turned out on the cuts of salaries. From a basic modeling of loan and Gaussian approach, the criteria of Mitchell are employed. The resulting simulations have yielded that up to a 50% of loaned volume of cash would be recovery. It was found that entropic situations would be in part a cause for the deficient management of loans in epochs of pandemic and crisis.**

***Index Terms*—Pandemic, Crisis, Banks, Economy modeling.**

I. Introduction

With the arrival of Corona virus disease 2019 (Covid-19 in short) [1] the problem of procrastination it was seen not only in developing countries as commonly believed but also has appeared strongly in first-world countries due to social restrictions along 2020 and 2021 fact that has lead to unemployment as well as bankruptcy of a wide spectrum of models of business believed to be robust in mostly scenarios [2][3]. With the apparition of unemployment and the rise of informal economy, the debts and credits have been brought to legal territory in order to define the disputation of released cash at the which, one of them the bank or customer turns out to be the winner based at their arguments [4][5]. In this manner one can wonder: What is the solid mechanism that might to guarantee the success of a credit transaction that Banks provides to potential customers? From the assumption that pandemic has reduced substantially the family economy leading to a implement restricted policies that to some extent would affect the agreed payments from the acquired cash credits. In this manner, the volume of loans might be degraded due to fluctuations stochastic of currency and relevant extraneous factors that might have not any to do withe binomial Bank-customer. In this manner one can wonder about the following:

- It is reasonable to talk about hard deadline at pandemic epochs?
- It is the Bank a loser at pandemic epochs? [6][7].
- It was the Bank prepared for extreme social scenarios?
- Really knows the Bank the human behavior along the months of pandemic?
- There is a need to implement artificial intelligence at the interaction Bank-customer?
- Can artificial intelligence to replace Bank decisions?
- Have Banks anticipated the periods of crisis created by Covid-19?

On the other side one can see that Banks would have to reconfigure their systems of recovery loans might not be same as past but also necessarily would have to combine advanced techniques of prediction that return reliable probabilities about the credit transactions. In fact, being the credits an important role of Banks nowadays, it is deeply desirable that even in emergency scenarios, Banks keeps their ”golden” role as to create an important demand of deposit with implications at the enrollment of potential customers that have had the perception that Banks are strongly supported by a solid finance engineering. In this paper, a theory based at Machine Learning projected onto the binomial Bank-customer is presented [8][9][10]. Basically the problem of procrastination if boarded through the criteria of Tom Mitchell [11][12] that compacts the principles of Machine Learning in three steps. In this manner such criteria target the problem in both sides: In one hand it is expected that Banks can apply their programs of debts payment along the regular ways, and on the other hand customers can preserver the confidence in one end-to-end scheme without to involve iniquitous frictions with creditors. Therefore, Machine Learning emerges as a potential science that might be successfully implemented at the credit dynamics just at the prospectives scenarios that scarcity, unemployment, and recession that can generate turbulences at the country and respectively family economies.
This paper is structured as follows: In second section a simple model of loan is presented. With this in third section, a model of probabilities based at Gaussian profiles is done. In fourth section, the direct application of criteria of Mitchell is done. With this simulations are presented. Finally in fifth section the conclusion of paper is drawn.

II. Simple Model of Loan

Consider the scenario by which a Bank delivers an amount of money $\mathcal{L}$ as a cash credit, then one can wonder about the percent of recoverability $\mathcal{R}$ of this loan in an agreed time T. Thus one can write down the elementary relationship:

$$\mathcal{R} = \frac{\mathcal{P}}{\mathcal{L}} \tag{1}$$

that is clearly a fraction. The ideal case is when the paid money $\mathcal{P}(T)$ is exactly equal to $\mathcal{L}$. Here $\mathcal{P}(T)$ the paid money at time T. It is feasible to define the procrastination g [13] as the variable the modifies the fraction of Eq.1. Therefore, the recoverability is affected by g as written below:

$$\mathcal{R} = g\frac{\mathcal{P}}{\mathcal{L}}. \tag{2}$$

For $n = 1, N$ loaners with different grade of procrastination g_n then one has below:

$$\mathcal{R}(T) = \sum_{n}^{N} \frac{g_n \mathcal{P}_n(T)}{\mathcal{L}_n} \tag{3}$$

at the agreed time T. Thus one observes procrastination if $\mathcal{R}(T) < \mathcal{R}(T + \Delta T)$ i.e., the recoverability falls down in time. By taking into account that the loaned volume of cash: $V = \sum_n^N \mathcal{L}_n$. In this case:

$$\mathcal{R}(T) = \frac{\sum_n^N g_n \mathcal{P}_n(T)}{V}. \tag{4}$$

In the scenario that only M customers have reached to accomplish the payments due then Eq.3 can be rewritten as:

$$\mathcal{R}(T) = \frac{\sum_{n=1}^{M} g_n \mathcal{P}_n(T)}{V} + \frac{\sum_{q=M+1}^{N} g_q \mathcal{P}_q(T)}{V}. \tag{5}$$

Clearly Bank emphasizes the recoverability to these $N - M$ customers. The prospective success of operation of loan of a volume of cash V it is expected that for a large time:

$$\frac{\sum_{n=1}^{M} g_n \mathcal{P}_n(T)}{V} >> \frac{\sum_{q=M+1}^{N} g_q \mathcal{P}_q(T)}{V}. \tag{6}$$

The inverse case is when that the Bank finds procrastination when it is observed:

$$\frac{\sum_{q=M+1}^{N} g_q \mathcal{P}_q(T)}{V} >> \frac{\sum_{n=1}^{M} g_n \mathcal{P}_n(T)}{V}. \tag{7}$$

Certainly, Bank needs to convince all those inside the territory of procrastination to recover the whole loan. Thus, it is mandatory to push the transition:

$$\frac{\sum_{q=M+1}^{N} g_q \mathcal{P}_q(T)}{V} \Rightarrow \frac{\sum_{q=M+1}^{N} \eta_q \mathcal{P}_q(T)}{V} \tag{8}$$

whose price to pay was the incorporation of a new parameter η_q. It is expected that with this the procrastination would be negligible in large times so that:

$$\frac{\sum_{q=M+1}^{N} \eta_q \mathcal{P}_q(T)}{V} << \frac{\sum_{n=1}^{M} g_n \mathcal{P}_n(T)}{V}. \tag{9}$$

A. The Probabilistic View

Because the apparition of uncertainties in both sides Bank and customers, a valid option to understand this binomial constitutes the theory of probabilities. To derive relationships it is needed to engage the previous equations to a scenario of continue variables. Under this argument the Eq.2 can be written in conjunction to variable $\mathbf{p}(x)$ that emerges from the fact that the paid money can be subject to fluctuations. In this manner one gets below:

$$V(T) = \int_0^T \frac{\eta(t,x)\mathbf{p}(x)\mathcal{P}(t,x)}{\mathcal{R}(t)} dx. \tag{10}$$

This equation can be seen as convolution operation with $\eta(t,x)$ playing the role of kernel and $\mathcal{P}(t,x)$ the input of operation. Actually one can see two inputs because the insertion of $\mathcal{P}(x)$ inside integration. Since $\mathcal{R}(t)$ does not depend on x, then it can be out the integration. Because this various scenarios are analyzed as below:

B. Scenario A: $\mathcal{R}(t) \approx 1$

It is a simple scenario that from Eq.10 it will yield a Wiener series [14] or first order Volterra series under the condition that $\eta(t,x) \times \mathbf{p}(x) \times \mathcal{P}(t) \times \mathbf{P}(x) = \mathbf{G}(t,x)\mathbf{P}(x)$ so that with the approximations $\eta(t,x) \times \mathbf{p}(x) \times \mathcal{P}(t) = \mathbf{G}(t,x)$ one arrives to:

$$V(T) = \int_0^T \mathbf{G}(t,x)\mathbf{P}(x)dx, \tag{11}$$

by which one can see that the kernel $\mathbf{G}(t,x)$ has information about the information of payments and it manages the processing to reach the amount of released cash at the time T.

C. Scenario B: $\mathcal{R}(t) < 1$

From Eq.2 and Eq.10 one can argue that

$$\frac{\eta(t,x)\mathcal{P}(t,x)}{\mathcal{R}(t)} = v(t,x) \tag{12}$$

is actually a kind of returned volume of cash. So that the corresponding integral of convolution can be written as:

$$V(T) = \int_0^T v(t,x)\mathbf{p}(x)dx, \tag{13}$$

that is actually the case that is close to a one where economy is plagued of random fluctuations: cuts of jobs, and the degradation of incomes, facts that would sustain the argument that the programmed recover of cash is subject to perturbations. In Fig.1 (Up) an illustration of Eq.13 is plotted . Here the model of convolution given by $5.5\int_0^t dx \mathrm{Exp}[-(x+nt)^2]\,(1+x^q)$ with a kernel of type Gaussian and an input fully polynomial, has resulted in the predominance of Gaussian profile. It actually would be denoting various scenarios (as seen in the colors) the possible up at the recovering of cash but the the time namely $t = 0.3$ the maximum gets falling fast indicating that the recovering also does it. Th variable t is expressing period $\times$ year. A similar scenario is seen at the Down panel when it is plotted $1.5\int_0^t dx \mathrm{Exp}[-(n \times tx)^2]\,(1 + x^q)$.

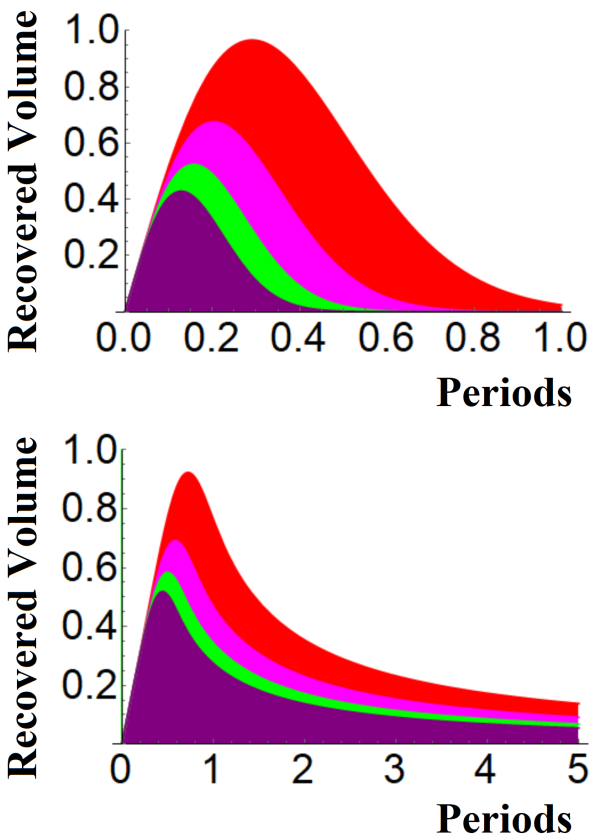

Fig. 1. Distributions of cash recovering derived from Eq.13. Up: the case of $5.5\int_0^t dx\mathrm{Exp}[-(x+nt)^2]\ (1+x^q)$ and (Down): $1.5\int_0^t dx\mathrm{Exp}[-(n\times tx)^2]$ $(1+x^q)$ with q an integer number.

III. The Gaussian Approach

In virtue of Fig.1 one can see that the simulation of toy model yields interesting shapes for the distribution of recovered of loaned volume. As seen at experience, the pandemic has brought to scenarios of recession since curfew and social distancing has forced to people to be apart of each other, in some cases it was canceled all events where people come be together (education, work in plants, etc) [14][15]. This was seen at mostly places from April 2020 until September 2020 when it was seen that infections as well as fatalities could fall down to a low fraction of the total seen at the beginning in February, March, April in some countries. While loans is a primary activity of banks then one can wonder: How did banks to keep their stability against the peaks of pandemic? In some countries banks received support from country government to make more dynamics the macro-economy. In terms of Machine Learning then the role of bank is as follows: (i) Once a volume of loans is approved to be loaned, (ii) the bank performs a tracking of those, (iii) if the volume begins to be positively recovered then it is feasible to repeat the action of loan. Finally once the volume of loans has been recovered at a high percent, the bank back again to loan same volume but in this time to a different group of customers. It is noteworthy that the return of loans might to be dictated by aspects stochastic entirely related to human behavior. Thus one can argue that the mechanism of return the loans is a chain of conditional probability as follows: The probability to get the month payment in pandemic times is equal to the probability of having the money at a time $P_M = T \in [0,t]$ times the probability of decision to realize the payment at the time $P_D = T \in [0,t]$ times the probability of expense that money at same time $P_E = T \in [0,t]$. Mathematically speaking the one has below:

$$P_M(T) = \int_0^T \mathrm{Exp}\left[-\left(\frac{t-t_0}{\Delta_M}\right)^2\right] \tag{14}$$

$$P_D(T) = \int_0^T \mathrm{Exp}\left[-\left(\frac{t-t_0}{\Delta_D}\right)^2\right] \tag{15}$$

$$P_E(T) = \int_0^T \mathrm{Exp}\left[-\left(\frac{t-t_0}{\Delta_E}\right)^2\right]. \tag{16}$$

So that one gets that the full probability can be written as:

$$P = P_M(T)\otimes P_D(T)\otimes P_E(T) = \int_0^T \mathrm{Exp}\left[-\left(\frac{t-t_0}{\Delta_M}\right)^2\right]dt \times \mathrm{Exp}\left[-\left(\frac{t-t_0}{\Delta_D}\right)^2\right]dt \times \mathrm{Exp}\left[-\left(\frac{t-t_0}{\Delta_E}\right)^2\right]dt. \tag{17}$$

While t_0 denotes the peak of Gaussian distribution, it is possible to argue that the widths for all three cases are similar, supported by the fact that the customer have same time to make actions that can be positive or negative respect to the payment of cash. It is actually what have could happened at the first periods of Covid-19 pandemic: While the customer have could or also not could to gather the money to accomplish the monthly payment, then it is expected that because of "many" reasons it is not necessarily that there is a firm approval to employ that cash to pay to Bank. It is actually encompassing the fact that in just critic time emerge random situations: clinic, pharmacology against the Covid-19, etc. Therefore, the cash is expended in different things. Then, since all Gaussian have same width then Eq.17 can be written as:

$$P = \int_0^T \mathrm{Exp}\left[-\ell\left(\frac{t-t_0}{\Delta_M}\right)^2\right]dt \tag{18}$$

with the integer ℓ denoting the number of situations against

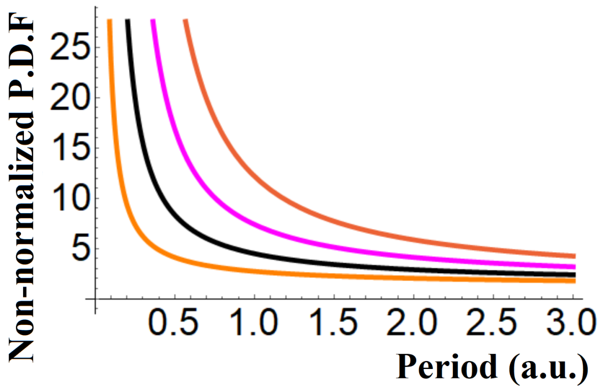

Fig. 2. Distributions of Eq.21 when Δ_M is varying for 4 scenarios of ℓ indicating that the more bigger is the width the probability of recovering becomes smaller.

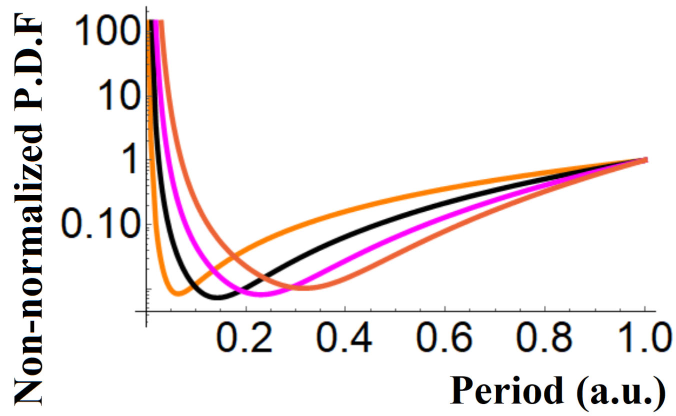

Fig. 3. Distributions of Eq.23 when has been aggregated the $\eta\Delta^\ell$ for 4 scenarios of ℓ. All P.D.F. have reached a common point at t=1.

the payment to Bank. When T is big with respect to time of individual situation then one arrives to:

$$P = \int_0^\infty \mathrm{Exp}\left[-\left(\frac{t-t_0}{\Delta_M/\sqrt{\ell}}\right)^2\right] dt = \sqrt{\frac{\pi\sqrt{\ell}}{\Delta_M}}. \quad (19)$$

Under an entropic perception, one can write down Eq.19 as the product of two factors:

$$P = \sqrt{\pi\sqrt{\ell}}(\sqrt{\Delta_M})^{-1/2} \quad (20)$$

where the probability is recovered if it is assumed that there is a kind of entropy or probably a certain disorder created by the customer. Then one gets below a probability distribution function (P.D.F.) given by:

$$p = \left[\mathrm{Exp}(\sqrt{\pi\sqrt{\ell}})\right]^{(\Delta_M)^{-1/2}} \quad (21)$$

that convert the probability Eq.19 in a kind of entropy of Shannon S [16] given by:

$$S = \mathrm{Log}(p) = \mathrm{Log}\left[\left(\mathrm{Exp}(\sqrt{\pi\sqrt{\ell}})\right)^{(\Delta_M)^{-1/2}}\right] \quad (22)$$

IV. Machine Learning Through the Mitchell Criteria

From Fig.2 one can see that the growth of Δ_M makes that the probability of recovery becomes smaller. It is noteworthy the a fluid communication between customer and bank might be fruitful in the sense that the Bank can see a space by which it is rather probable a continue recovery of loan. In this manner, it can be applied algorithms coming the artificial intelligence such as Machine Learning [17]. In particular this study shall be focused on the criteria of Tom Mitchell. Therefore one can project the central problem seen so far: To increase the probability of recovery at the established periods i according to the previous agreements between customer and Bank. Then it is feasible to design a strategy to minimize any collision agains each one of involved parties:

1) Task: The Bank has as central target to achieve that the customer do the payments at the agreed periods. Thus from Eq.21 one can write down an alternative P.D.F. as:

$$p(\Delta) = \left[\mathrm{Exp}(\sqrt{\pi\sqrt{\ell}})\right]^{(\Delta)^{-1/2}} + \eta(\Delta)^\ell \quad (23)$$

with η a random parameter between 0 and 1.0. An example of Eq.23 is seen at Fig.3 where all curves have reached their minimum and then pass to acquire high values, fact that is translated as the flip of decision or have taken the best decision.

2) Performance: In this stage, it is desired that exists a tangible consistency of that high probabilities. With the definition of $h(\Delta) = \left[\mathrm{Exp}(\sqrt{\pi\sqrt{\ell}})\right]^{(\Delta)^{-1/2}}$, then Eq.23 can also be written as:

$$p(\Delta) = \eta(\Delta)^\ell + h(\Delta) = \eta(\Delta)^\ell\left(1 + \frac{h(\Delta)}{\eta(\Delta)^\ell}\right). \quad (24)$$

Here it should be noted that for large values of $\eta(\Delta)^\ell$ the one can apply the approximation:

$$1 + \frac{h(\Delta)}{\eta(\Delta)^\ell} = 1 + \frac{h(\Delta)}{\eta(\Delta)^\ell} + \sum_{n\geq 2}^{\infty}\frac{1}{n!}\left(\frac{h(\Delta)}{\eta(\Delta)^\ell}\right)^n \quad (25)$$

if only if satisfies:

$$\sum_{n\geq 2}^{\infty}\frac{1}{n!}\left(\frac{h(\Delta)}{\eta(\Delta)^\ell}\right)^n \approx 0. \quad (26)$$

Thus, Eq.24 is proportional to an negative exponential as written below:

$$p(\Delta) = \eta(\Delta)^\ell + h(\Delta) = \eta(\Delta)^\ell \mathrm{Exp}\left[-\frac{h(\Delta)}{\eta(\Delta)^\ell}\right]. \quad (27)$$

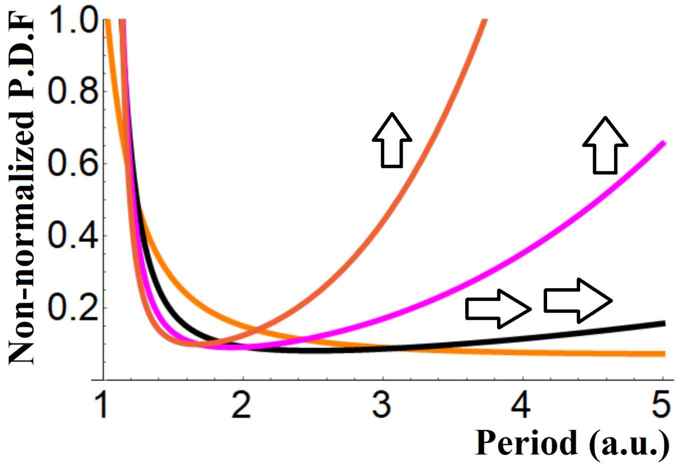

Fig. 4. Distributions of Eq.28 when for 4 scenarios of ℓ. The arrows are indicating up to types of experiences after the procedure applied. Arrws go up and two of them keep their value.

3) Experience: In Fig.4 the resulting P.D.F. are exhibiting the experience denoted by Eq.27

$$p(\Delta) = \eta(\Delta)^{\ell}\text{Exp}\left[-\frac{h(\Delta)}{\eta(\Delta)^{\ell}}\right], \tag{28}$$

with η=0.5. Here the performance has achieved an efficient probability for recover the cash in a 50% since at least two curves (Grey and Magenta color) are pointing up fact that is interpreted as the chances of Bank for recover the loan cash. On the other hand, two curves (black and orange colors) seems to be that are not affected by the performance and continue to have low P.D.F. In other words, one might expect that a 50% of loaners could not be doing the payments due to a certain period that enabled two scenarios (arrows pointing up) but in the inverse case, stopped some fraction of loaners to make payments. A possible cure to this situation is again to incorporate an extra terms that contains a polynomial in ℓ such as:

$$p(\Delta) = \eta(\Delta)^{\ell}\text{Exp}\left[-\frac{h(\Delta)}{\eta(\Delta)^{\ell}}\right] + \beta\Delta^{k}\delta_{\ell,k} \tag{29}$$

with $\delta_{\ell,k}$ the Delta of Kronecker $\delta_{\ell,k}$=1 if $\ell = k$ otherwise is 0. The constant β is also a number between 0 and 1. Finally one can argue that the fact that exists a partial recovery of loaned cash, make us to suppose that crisis like the ongoing Covid-19 would have to find solutions in the sense that loaners would seek novel opportunities that allow them to reach the completion of incomes previous to the arrival of pandemic. In the side of Bank, official would suggest to them new avenues that would guarantee an alternative income to keep a optimal quality of life. Of course more detailed study is required.

V. Conclusion

In this paper, the problem of interaction Bank-customer has been studied from the angle of Machine Learning based at the Mitchell's criteria. From a simple model of loan, it is seen that Gaussian functions can model well the probabilities at the process of payments the cash. Because of this, has emerged an integer number ℓ that has direct implications at the formulation of Shannon's entropy. This entropy can be understood as a kind of disorder driven by the width of Gaussian profiles. Thus, the Mitchell's criteria have been applied. As seen at Fig.4, the probability for recovery the loan cash has turned out to be partial in a 50% due to the apparition of entropic events that is totally consistent with the random apparition of pandemic. Although one might expect a recovery of cash more than 50% a deeply treatment the projection of the main macro-economical variables to the dynamics created by the binomial Bank-customer, is needed.

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