Credit rationing with symmetric information

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Résumé

Sans nier l'importance de l'information asymmétrique, cet article soutient que le rationnement du crédit peut surgir aussi par l'impossibilité pour le pretêur à classifier les demandes de prêts dans des categories appropriées. Bien que évident quand des nouvelles technologies ou des nouveaux arrangements institutionnels émergent, la manque de categories appropriées peut affecter chaque demande de prêt, faisant le rationnement du crédit plus commun que retenu avant.

Abstract

Without denying the importance of asymmetric information, this article purports the view that credit rationing may also originate from a lender's inability to classify loan applications into proper risk categories. Although particularly prominent when novel technologies or novel institutional arrangements arise, lack of appropriate categories may affect any request of money lending, making credit rationing much more widespread than previously thought.

Keywords: Credit Rationing, Complexity, Risk Categories, Internal Rating Systems, Deciding not to Decide, Problem Decomposition.

JEL Classification: D81, D89, E51, G21, G24

1 Introduction

It is well known that credit is not conceded to those applicants who would accept the highest interest rate. Rather, it is conceded to those who offer the most reliable prospects that the debt will be repaid. In fact, since applicants may not disclose the true features of their projects, by increasing the interest rate banks would screen for riskier, less profitable projects. Thus, economic theory views credit rationing as an instance of asymmetric information.

Interestingly, practitioners tend to stress another aspect. Giving for granted that loan applicants typically hide some information, they are rather concerned with the content of the information that they provide. Specifically, they are concerned about the soundness of the projects that they should finance and the ability of their proponents to carry them out. In the limit, one may mention a popular guide for venture capitalists listing such things as a deprived childhood, an absent father, a strong mother and a sense of guilt for having not lived up to parents' expectations as the hallmarks of successful entrepreneurs [53].

Be these features relevant or not, the crucial issue is that practitioners want to know whether potential borrowers know what they are doing. After discounting for the fact that loan applicants portray a rosy picture of their enterprise, they want to focus on the details of the projects they are asked to finance.

These details may be quite easy to specify if the project is presented by a well-acquainted firm that is expanding on a stable technology. On the contrary, assessing a project may be a very difficult task when money is demanded for an enterprise of a novel kind, one that has never been undertaken before.

Investments often involve novel technologies, and possibly the creation of novel institutions and consumption habits [38]. Being novel, no objective probability distribution of their success can be measured. Thus, even if information asymmetries would not exist, banks officials would still have a hard time trying to understand whether a potential borrower is a visionary business man or just a mad man.

Distinguishing visionary business men from mad men is a matter of having the right classification criteria, and this problem adds to that of asymmetric information. Even if all information is available to the lender, (s)he may classify a competent business man with a great idea as a mad man. If this happens, credit rationing occurs even if information is perfectly symmetric.

Indeed, credit rationing has been found to be strongest when innovative technologies are involved [32] [3] [4]. Some theorists have objected that the stock market, with its variety of investors, should be able to finance the most innovative enterprises [1]. Yet in practice stock markets are oriented by rating agencies whose classification criteria are so stiff that the most innovative firms are forced to hide their best features in order to be positively valued [60]. The problem is that both banks and financial markets need some form of classification of investment projects, and since classification rests on past experience, innovative projects that do not fit conventional wisdom have a hard time. Simply, bank officials do not lend money for projects that they do not understand, and rating agencies cannot do better.

Several economists have stressed that the inability to classify qualitatively novel projects is at least as important for credit rationing as information asymmetries [19] [20] [50] [58] [10]. It is an issue that has remained quite marginal hitherto, though it may become paramount in a near future. In fact, the *Bank of International Settlements* (BIS) has purported a link between liquidity requirements and the riskiness of loans, and this link is based on internal rating systems [7]. Thus, classification criteria have an impact not only on the decision to concede a loan, but also on the total amount of loans that banks are allowed to concede.

This article attempts to understand classification processes and their possible dynamics. Any lending institution is concerned, including banks, venture capitalists, capital markets and rating agencies with respect to bonds, and others. For simplicity, the word "bank" will be eventually employed as a shorthand for "lending institution" henceforth.

Section (2) reports on qualitative and quantitative empirical evidence on internal classification systems. Section (3) illustrates how credit rationing may occur if lender and borrower classify projects according to different criteria. Section (4) presents a mathematical model. Section (5) explores the processes by which classification systems may be adapted to a changing environment. Finally, section (6) concludes.

2 Empirical Evidence

The process of classifying loan applications into risk categories is at the very core of banking. Traditionally, it has been hidden by strict secrecy. However, since a few years the BIS is searching ways for adapting liquidity requirements to the riskiness of loan portfolios. Consequently, a certain amount of empirical research has been carried out and some results have been published.

According to these investigations, banks make use of categories for the projects which they decide to finance (the so-called "pass-grades") as well as for the projects which they decide not to finance (the so-called "fail-grades"). Categories for projects that are not financed are fewer than the categories for projects that are financed.

Let us focus on categories for projects that are financed. Considering that we are dealing with the most jealously protected information of banking, any piece of even anecdotal evidence should be observed with care, so even scant information will be reported. The available information is presented with respect to three aspects.

First, one may ask how far in the past the judgement is stretched. It is obvious that classification is made depending on past performance, but we may wish to know whether it is a matter of months or decades.

A study carried out by the BIS [6] collected the answer "three years or more", but only from a fraction of the thirty banks that were interviewed. In a public declaration, an official of a large Italian bank also spoke of "three years" [30]. Indeed, a guide for practitioners recommends to focus on the "previous few years" [17]. On the whole, we get an indication in the order of a few years, possibly more than one or two but certainly less than ten.

Secondly, one may want to know the number of risk categories employed by banks. Several studies have shed light on this issue.

In 1995, English and Nelson collected data from 114 U.S. banks. They found that 85% of them had a rating system and that the average number of risk categories ranged from 3.4 for smaller banks to 4.8 for larger banks [12] [24]. In 1997, Treacy and Carey carried out a research among the 50 largest U.S. banks, finding that the number of risk categories ranged from 2 to the low 20s, with an average of 3-4 [55]. In 1998 Weber, Krahnen and Voßman interviewed the four largest German banks and found numbers ranging from 5 to 8 [57]. Similarly, De Laurentis found out that the five largest Italian banks in the years 1996-98 were using 6-7 risk categories [39]. In 1999, the *Bank of International Settlements* examined a sample of over thirty banks, generally large and internationally diversified, finding numbers between 2 and 20 [6]. Finally, by interviewing three specialised German banks in 2001 Norden found that the number of risk categories was 6, 9 and 14, respectively [45].

Figure (1) reports the distribution of the number of risk categories found by the BIS. The number of risk categories ranges between 2 and 20. Thus, this range includes the numbers found by other studies.

In their empirical study of 1997, Treacy and Carey revisited older investigations. They came to the conclusion that a decade earlier the number of risk categories might have been smaller, in the order of three if they were in place at

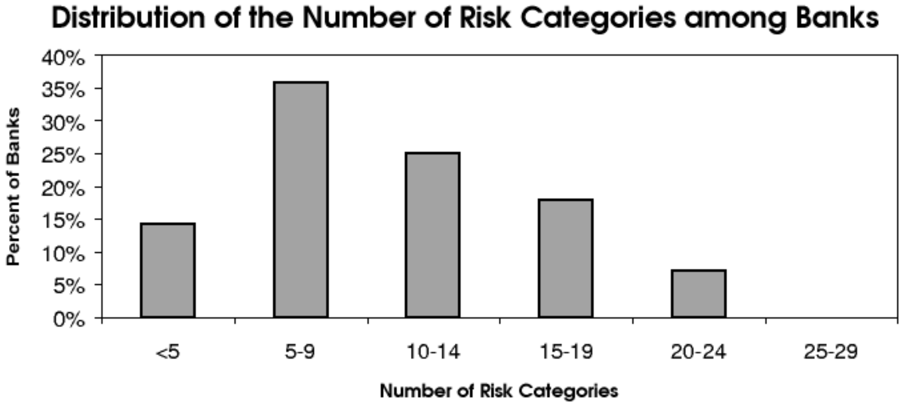

Figure 1: The distribution of the number of risk categories among thirty large international banks. By courtesy of the ©*Bank of International Settlements* [6]

all [55]. They remarked that the number of risk categories increased both with time and with the size of banks, but not indefinitely. According to their suggested interpretation, a ceiling may exist due to a trade-off between the advantages of having a large number of categories in order to run automatized systems that detect problem loans on the one hand, and the difficulties posed by large number of categories to boundedly rational decision-makers on the other hand.

Notably, banks that use a very large number of categories generally derive them by adding a "+" or a "-" to a smaller set of categories. For instance, a system with 6 categories can be easily turned into a system of 12 categories by requiring bank officials to specify whether the loan is in the upper end of the category (with a "+") or in the lower end (with a "-"). By doing so, human operators can approach the classification problem in two steps [55].

Finally, it is most important to know the criteria by which loan applications are classified. In particular, this is important in order to formulate guidelines along which the classification criteria may be changed with time.

According to several empirical studies, it appears that both "hard" and "soft" aspects are considered by banks, though this distinction is blurred by the fact that even "soft" aspects are translated into numerical values [13] [6] [31]. A possible list of the aspects involved may be the following:

1. Loan specification in terms of collaterals and terms of payment [11] [39] [6] [46]. In particular, securities are often a condition for evaluating other aspects [17].

2. Financial indicators [57] [39] [6], eventually used by automatized procedures such as the *Z-score* [2] or neural networks [36]. For very small businesses, the consumer credit score of the business owner is employed [9]. For venture capitalists, the liquidity of assets is also important [43].

3. The technology employed by the project, to be evaluated with respect to the industries on which it is expected to impact [41] [57]. In particular, marginal firms in mature sectors are often regarded as sources of financial distress [17]. By contrast, proprietary or otherwise protected technologies and products are positively valued [43].

4. Psychological features of the applying executive/entrepreneur and quality of the management team, to be considered in conjunction with the structure of the industry where the applicant operates [8] [51] [41] [57] [6]. Management quality may be inferred by the absence of litigations, suppliers satisfaction and managers succession plans [17]. In high-tech start-ups, the willingness of scientists to give up managing positions to professional managers is highly valued [5].

5. Reliability of the information provided by the applicant. Reliability is increased by a lasting acquaintance [23] [39] but may eventually be disrupted by signals of increasing information asymmetries such as changes of accounting procedures or a growing reluctance to provide information [18]. Long-term relations have been found to integrate, not to substitute collaterals [46].

6. Information provided by the stock market and its rating agencies, or by customers and suppliers of the applicant [11] [39] [6]. For firms with over 25% of operations abroad, the country risk as evaluated by rating agencies may be included as well [17].

It has been observed that several banks are shifting from rating systems based on one single set of categories to rating systems based on several sets of categories, each for a different aspect of a loan application. The most common distinction is between aspects that pertain to the applicant (issues 2, 4 and 5 above) and aspects that pertain to the particular project for which a loan is requested (issues 1, 3 and 6 above) [55] [6] [39]. However, it appears that some banks are moving even further, evaluating several or all of the above aspects separately or, in some cases, even subdividing them according to their components [57]. By having different bank officials specialised in one or a few aspects of rating, a bank is better able to detect warning signs that involve only one aspect. Eventually, a thorough examination of all the aspects may be undertaken at a later stage [39].

This suggests that the number of aspects that are considered separately has a huge impact on lending decisions. The more aspects are considered separately, the easier it is for a bank to detect problem loans. However, too subtle categories may impair the evaluation of innovative projects that cut across the borders of existing categories.

In § (5) we shall examine the consequences of having multiple aspects to be considered in separate sets of categories. In the ensuing § (3), credit rationing is examined in the simple case of one single set of risk categories, ordered from "low risk" to "high risk". In this simple setting, which is still a realistic description of the functioning of many lending institutions, each category refers to a different class of risk though each category encompasses all of the above aspects.

3 Classification Failure

This section illustrates a procedure for modelling credit rationing due to a bank's inability to classify the qualitative features of loan applications in proper categories. Since credit rationing due to classification failure is complementary to credit rationing due to asymmetric information, they should be described by one single model. Thus, this section begins with recalling the basic model of credit rationing due to asymmetric information.

Formalisations of credit rationing make use of the expressions "classes of risk" and "classes of return". The empirical litterature mentioned in § (2) employed the expression "risk categories", which is often more appropriate to our discourse. Henceforth, the expressions "classes of risk" and "risk categories" will be used as synonyms.

The basic model of credit rationing with asymmetric information begins with the observation that, by increasing the interest rate, the least risky loans drop out of a bank's portfolio. Thus, it is not convenient for banks to select loan applications by means of the interest rate. Rather, banks should segment the market classifying loan applications in a discrete number of classes of risk. To each class of risk, a different interest rate applies.

For interest rates $r < r_1$, all projects are proposed to the bank. Thus, by increasing $r \in (0, r_1)$ the bank makes higher profits. However, for $r \geq r_1$ the least risky projects are no longer proposed. Thus, at $r = r_1$ the expected return to the bank drops. It increases again with r for $r_1 \leq r < r_2$, to drop again at $r = r_2$ and so on up to r_n. Thus, it is convenient for the bank to segment the market by classifying loan applicants into n classes of risk applying a different interest rate to each class.

The highest interest rate, r_n, does not necessarily coincide with the interest rate that would obtain by equating demand and supply. In fact, if the bank suspects that the equilibrium interest rate would only attract swindlers, it may not concede any loan at that rate. Thus in general it is $r_n \leq r^*$, where r^* is the interest rate that obtains at market equilibrium.

Since $r_1 < r_2 < \ldots < r_n$, for $\forall i < n$ it is $r_i < r^*$. Thus, at least to the applicants borrowing at $r_i < r_n$, credit is rationed. The ultimate reason is that loan applicants typically hide information to banks, and that banks are aware of this information asymmetry.

Note that credit is allocated by classifying the projects waiting for a loan into n categories ordered by increasing risk and characterized by increasing interest rates $r_1 < r_2 < \ldots < r_n$. Thus, a decision about the interest rates is made at the same time a loan applicant is classified in a risk category. Henceforth, risk categories will be identified with their interest rate.

Let us now consider credit rationing due to classification failure. From projects classified in risk category r_i, a return R_i is expected. In general, the higher the risk (and the interest rate), the higher the expected return. [1]

Let $R_1 < R_2 < \ldots < R_n$ denote the returns expected from financed projects. The bank financed these projects expecting a one-to-one correspondence between classes of risk and classes of returns, as in figure (2).

Suppose that the bank did not correctly classify some projects, for instance because the projects entailed some technological innovation that the bank officials were not able to understand, or because institutional or political changes occurred, that bank officials were not able to foresee. Then, some projects may yield a much lower (or higher) return than expected. Thus, the one-to-one connections of figure (2) may turn into one-to-many connections, as in figure (3).

A bank that is facing a map as in figure (3) understands that it should revise its classification criteria until a one-to-one map as in figure (2) is established again. Returns that turn out to be higher than expected do not pose big problems, but returns that turn out to be lower than expected do.

[1] By "expected return" we do not mean an expected value where several possible returns are weighted by their probability. Simply, a project is supposed to yield a return in the future. This is what is here called "expected return".

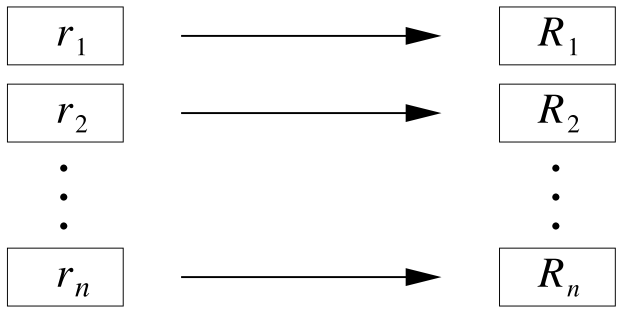

Figure 2: When risk categories work properly, to each risk category corresponds a different return.

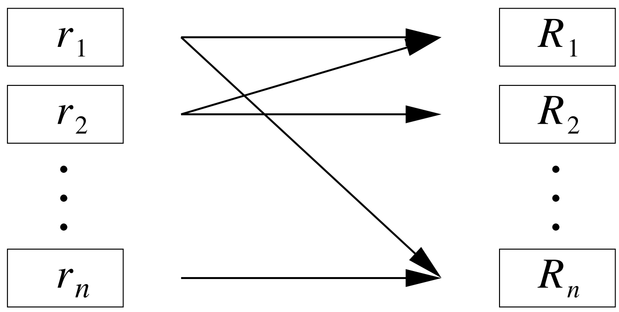

Figure 3: If some projects obtain very different returns from those that were expected, then the causal relationships from classes of risk to classes of returns may become one-to-many.

During all the time where there are one-to-many connections between classes of risk and classes of return, a bank is unable to assign a project to a proper class of risk. Therefore, it may not concede credit altogether.

Let us assume that the applicant receives the same information as the bank, but that he classifies it differently. For instance, the loan applicant may have a detailed knowledge of a novel technology that enables her to create a new market, or that she has so detailed a knowledge of an economy in turmoil that she is able to identify a profitable business opportunity. The bank, with its rough classifications, has a one-to-many map as in figure (3). The loan applicant, with her unique knowledge of the details, is able to draw the lines that distinguish good business from bad business, so her map is one-to-one as in figure (2). If the loan applicant has a one-to-one mapping while the bank has a one-to-many mapping, then credit is rationed. Appendix (A) tells a real story where this kind of differential mapping occurred.

Note that this mechanism did not require asymmetric information. Asymmetric information may be there to make things worse, but credit rationing is inherent in the fact that banks generally have coarser classification criteria than applicants. This difference may be small in quiet times, where banks may learn how to infer the relevant features from certain indicators, but it may be large at times where technological or institutional novelties emerge.

The above account assumed rationality of both the bank and the applicant, in the sense that both employ their expertise rationally to make sense of available information. The issue is that, having different expertise, they may come out with different maps of the same information.

The above account does not hold if the applicant is not rational. If the applicant did not develop a one-to-one map because he is a smart businessman, but just because he is a mad man, then the bank has good reasons to refuse a loan. This is still credit rationing, but not of a kind to be avoided.

Finally, the case has to be mentioned where the would-be applicant, just as the bank, is unable to develop a one-to-one map. The would-be applicant, just as the bank, has a one-to many map. In this case no credit rationing takes place, simply because this person does not apply for a loan.

4 A Mathematical Model

Since in our case the decision not to grant a loan depends on detecting unexpected novelties, the recognition of a one-to-many map must be based on a restricted number of recent observations. Let $m \in \mathcal{N}$ denote the number of past time intervals upon which bank officers evaluate the appropriateness of their causal map. Henceforth, m will be called the *memory* of bank officers. It is obviously $m \geq 0$, with $m = 0$ in the special case when bank officers look only at current occurrences.

Let us define the *complexity* of the decision-making problem as a measure of the extent to which the connections that occurred in the last m time intervals are intertwined [27]. The ensuing account is an excerpt of more technical publications [15], [25], [26]. For technical background and an example of the concepts and methods employed henceforth, see Appendix (B).

The structure of connections between classes of risk and classes of return can be usefully subsumed by means of a *simplicial complex*. This is composed by connected simplices, one for each class of risk. The vertices of each simplex are the classes of return to which a particular class of risk is connected.

If the connections between classes of risk and classes of return are one-to-one as in figure (2), simplices are isolated points so no simplicial complex exists. In this case, complexity is zero.

On the contrary, if at least two simplices have at least one vertex in common, a simplicial complex exists and complexity is greater than zero. For instance, the connections of figure (3) corresponds to a simplicial complex made of n simplices $r_1, r_2, \ldots r_n$. The simplex r_1 is a segment whose vertices are R_1 and R_n. The simplex r_2 is a segment whose vertices are R_1 and R_2. More intertwined connections may be represented by simplicial complexes composed by many more simplices, possibly of higher dimension.

Two simplices are connected if they have at least one common vertex. Two simplices that have no common vertex may nonetheless be connected by a chain of simplices having common vertices with one another. Let us say that simplices $r_{i'}$ and $r_{i''}$ are $q-connected$ if there exists a chain of simplices $\{r_u, r_v, \ldots r_w\}$ such that $q = \min\{l_{i'u}, l_{uv}, \ldots l_{wi''}\} \geq 0$, where l_{xy} is the dimension of the common face between r_x and r_y. In particular, two contiguous simplices are connected at level q if they have a common face of dimension q.

Let us consider the common faces between simplices and let us focus on the face of largest dimension. Let Q denote the dimension of this face. It is $Q \leq n-1$, where $Q = n-1$ means that there are at least two overlapping simplices that include all possible vertices.

Let us partition the set of simplices that compose the simplicial complex according to their connection level q. In general, for $\forall\, q$ there exist several classes of simplices such that the simplices belonging to a class are connected at q. Let us introduce a *structure vector* $\mathbf{s}$ whose q-th component s_q denotes the number of disjoint classes of simplices that are connected at level q. Since $q = 0, 1, \ldots Q$, vector $\mathbf{s}$ has $Q+1$ rows.

In order to avoid repetitions in the calculus of complexity, a class of simplices connected at level q is not considered to be connected at levels $q-1$, $q-2$, ... 0 as well. For instance, let simplices r_1 and r_2 be connected at level $q = 2$, and let simplex r_3 be connected with r_2 at level $q = 1$. Then, $\{r_1, r_2\}$ is a class of simplices connected at $q = 2$ and $\{r_1, r_2, r_3\}$ is a class of simplices connected at $q = 1$. However, $\{r_1, r_2\}$ is *not* a class of simplices connected at level $q = 0$.

The following measure for the complexity of a simplicial complex has been proposed by Casti [15] and improved by Fioretti [25], [26]:

$$C(\mathcal{F}; m, n) = \begin{cases} 0 & \text{if all connections are one-to-one} \\ \sum_{q=0}^{Q} \frac{q+1}{s_q} & \text{otherwise} \end{cases} \tag{1}$$

where the sum extends only to the terms such that $s_q \neq 0$. Finally, it is stipulated that the complexity of two or more disconnected simplicial complexes is the sum of their complexities.

The complexity seen by a bank official who is evaluating the reliability of an attribution of classes of risk depends on the observed connections between classes of risk and classes of return, which realise out of an unknown stochastic distribution $\mathcal{F}$. It also depends on m, the memory length, as well as on n, the number of classes of risk. While $\mathcal{F}$ is unknown by the bank official, m and n are parameters under her control.

Expression (1) takes account of two opposite effects. On the one hand, the numerator increases with the number of connections between classes of risk and classes of return. Thus, it simply measures the extent to which novel connections confuse the causal map. On the other hand, the denominator of (1) makes complexity decrease if cross-connections are separated in distinct groups.

Complexity (1) increases monotonically with both m and n. On the contrary, its dependence on $\mathcal{F}$ is more interesting.

Let us consider the simple case where cross connections occur stochastically as a fraction f of all connections. Thus, $C(\mathcal{F}; m, n)$ becomes $C(f; m, n)$. Considering the empirical evidence of § (2), $m = 3$ and $n = 10$ appears an appropriate choice. Figure (4) illustrates the ensuing values of complexity with f increasing from 0 to 100% of total connections.

Figure (4) makes clear that complexity is different from "randomness", "disorder" or any other property of the environment. Rather, it is a subjective evaluation. Up to a fraction of cross-connections of about 35-40%, a bank official may judge

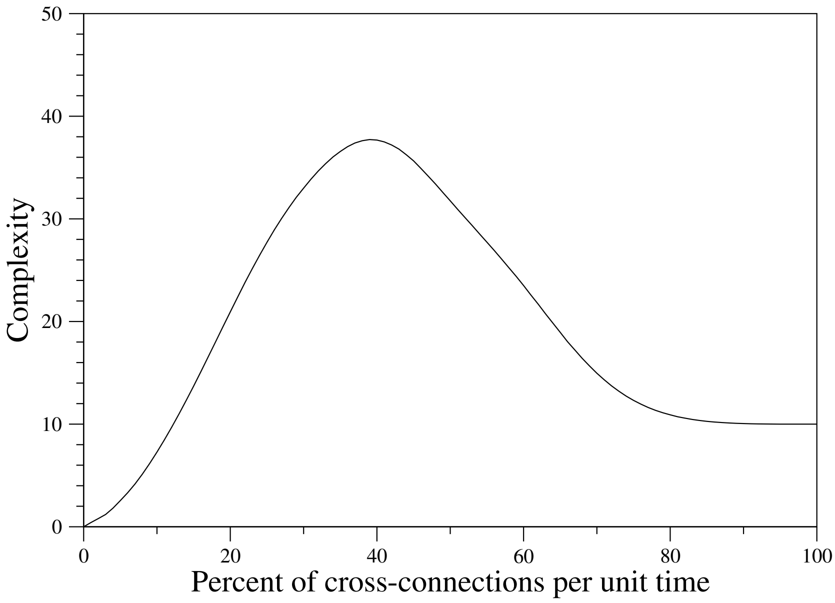

Figure 4: Complexity as a function of f, with $m = 3$, $n = 10$. All values have been averaged over 1,000,000 steps.

that the more disordered the connections, the more "complex" the environment. Beyond this threshold, cross-connections are so many that the bank official may judge that it is not worth to distinguish among projects whose returns are totally unpredictable. Consequently, the business environment is less "complex" for her. More precisely, complexity approaches n for very high values of f.

However, things change if cross-connections do not extend very far. Let us assume that projects in a class of risk r_i may turn out to yield a return in the interval $R_{i-\delta} \leq R_i \leq R_{i+\delta}$ ($R_1 \leq R_i \leq R_{i+\delta}$ if $i < \delta$, $R_{i-\delta} \leq R_i \leq R_n$ if $i > n-\delta$). The previous case obtains if $\delta = n-1$. If $\delta = 0$ no cross-connections occur, so complexity is zero. In all intermediate cases some cross-connections do occur, but they are localised in a spot of radius δ around each r_i.

Figure (5) illustrates simulations with $\delta = 1, 2, \ldots 9$, all other parameters as in figure (4). Cross-connections occur with increasing probability, but only within an interval specified by the parameter δ.

In figure (5) we see that if cross-connections are sufficiently localised, confusion between causal attributions of returns to classes of risk never grows so large that a decision-maker may give up the hope to improve classification criteria — i.e. complexity never decreases. It reaches plateaus, however. These may sug-

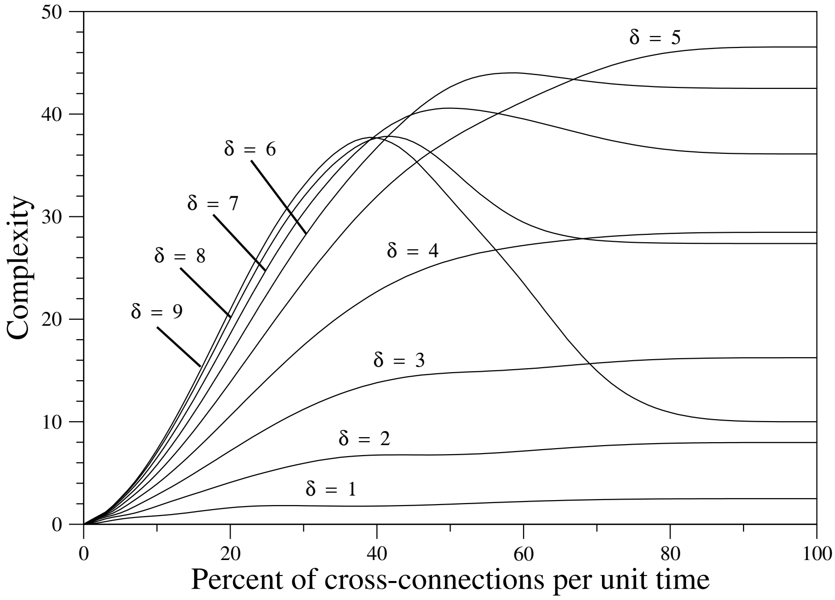

Figure 5: Complexity as a function of f, with $m = 3$, $n = 10$, for $\delta = 1, 2, \ldots 9$. With $\delta = 9$, the case of figure (4) obtains. All results have been averaged over 1,000,000 steps.

gest bank officials to accept as unavoidable a certain level of imperfection of their classification criteria.

Let us assume bounded rationality and let us think of bank officials as satisfycing decision-makers who make a decision if a relevant variable exceeds a threshold. Since complexity measures the unreliability of classification criteria as it is subjectively evaluated by bank officials, it is sensible to assume that they may decide to revise these criteria whenever $C > \overline{C}$, where $\overline{C}$ is a proper threshold. So long C remains greater than $\overline{C}$, loans are not conceded, no matter which interest rate the applicant is willing to pay.

The threshold $\overline{C}$ may depend on past experiences, market specificities and institutional arrangements. It may change with time, though at a lower time scale than C.

Eventually, the above description may be duplicated across markets or geographical area. For instance, a bank may carry out separate classifications of loan applications in different industries or regions.

5 Revising the Classification Criteria

If complexity is greater than zero, bank officials set out to revise the criteria by which they classify loan applications. If bank officials employ one single set of risk categories $r_1, r_2, \ldots r_n$, the process of revising the classification criteria is largely carried out informally in their minds. Little can be said about it, either because it is tacit knowledge or because explicit rules are eventually covered by secrecy.

However, the empirical investigations reported in § (2) revealed that banks are moving towards an arrangement of the classification process where different aspects are considered separately (financial indicators, management quality etc.). Allegedly, the reason is that if one single aspect becomes problematic, a thorough evaluation of all aspects of a loan is carried out.

Suppose that N aspects are considered, denoted by an index $i = 1, 2, \ldots N$. The model expounded in § (4) can be applied to each separate aspect yielding N complexity values $C^1, C^2, \ldots C^N$.

So long all C^is are zero (or below a pre-defined threshold), the classification criteria are not doubted. A loan application may be classified in different classes of risk for each different aspect, and the overall class of risk may result out of a weighted average of the classes of risk in each aspect.

As we learned in § (2), several banks have shifted from rating systems based on one single set of categories to rating systems based on several sets of categories, each for a different aspect of a loan application. By having different bank officials specialised in one or a few aspects of rating, a bank is better able to detect warning signs that involve only one aspect. Thus, if $\exists\, i$ such that $C^i > 0$ (or above a pre-defined threshold) the classification criteria are doubted. Bank officials must engage in a re-definition of classification criteria in such a way that all mappings between classes of risk and interest rates are one-to-one so all C^is are zero.

The collection of empirical testimonies reported in § (2) identified a maximum of six broad aspects, depending in their turn on finer sub-aspects. For instance, the aspect "financial indicators" may be broken down in a number of accounting variables, and the same holds for technologies, management features and so on. If complexity is greater than zero (or above a pre-defined threshold), bank officials may need to re-distribute sub-aspects in order to change the content of the aspects that generated too high a complexity. By doing so, the classification criteria of the categories defined on the aspects involved may change.

An example is in order. No empirical evidence is available concerning the sub-aspects employed by banks, but a good deal of information is available regarding the classification criteria employed by venture capitalists. Although this is a very particular case of money lending institution, its logic is not different from that of the other ones.

Let us consider aspect (3) in § (2), labelled "The technology employed by the project, to be evaluated with respect to the industries on which it is expected to impact". From the main studies of the classification criteria employed by venture capitalists [56] [40] [41] [37] [33] [29] [48] [44] [47] [16] [43], one can excerpt that venture capitalists declare that the above aspect is composed by the following sub-aspects:

1. The product is protected from imitation by the law or by its technical features;

2. Uniqueness of product (the product has very imperfect substitutes);

3. The product has been developed up to the stage of a functioning prototype;

4. The product has a demonstrated market acceptance;

5. Availability of raw materials and stability of their price;

6. Easiness of procurement of specialised labour;

7. Availability of specialised equipment;
8. The venture will stimulate an existing market or create a new market;
9. This market has a high expected growth rate;
10. There is a well-developed distribution system;
11. Favourable geographical location and good export potential.

There is quite a clear distinction between aspects 1 to 7, which pertain to the product, and the aspects 8 to 11, which pertain to its market. Thus, venture capitalists generally decompose the aspect "The technology employed by the project, to be evaluated with respect to the industries on which it is expected to impact" into two aspects: "characteristics of product", entailing sub-aspects 1 to 7, and "characteristics of market", entailing sub-aspects 8 to 11. So venture capitalists distinguish two aspects where banks distinguish only one.

This means that venture capitalists have remarked that, in their fields of activity, technological considerations can be safely decoupled from market considerations. In the terms of our model this means that, in this case, by subdividing this aspect in two, the correspondence between risk categories and interest rates in closer to be one-to-one in at least one of the two derived aspects. Other money-lending institutions, in other contexts, may find it useful to group aspects together; others still, may find it useful to re-distribute sub-aspects among existing aspects.

The issue is that of arranging sub-aspects into aspects in such a way that while sub-aspects are strongly related to one another within the aspect in which they are included, aspects are largely independent of one another. Only if this can be done, aspects can be considered independently of one another when deciding whether a loan can be conceded. It is an instance of problem decomposition [54] [21] [22], where the problem of classifying loan applicants into proper classes of risk can be eased if the features of the applicant can be considered separately along nearly-independent aspects.

The properties of problem decomposition have been investigated by means of computer simulations where a "problem", consisting of guessing a string of numbers created with some rule, could be "solved" by mutating blocks of variables of different lengths. This problem is akin to the Rubik cube, where the goal of having all squares on each face of a uniform colour must be reached by moving blocks of squares. However, the Rubik cube forces players to decompose the problem by means of sub-problems entailing as many squares as there are on a face of the cube. In these simulations the problem could be decomposed into blocks of different size [28] [42] [14]. Clearly, a solution to the problem of guessing numbers exists, and the computer eventually finds it after a sufficiently large number of trials. The issue is whether it finds it within a reasonable time, and how fast it finds it depending on the size of the blocks into which the problem has been decomposed.

These simulations are relevant, because they admit a simple mapping into our context. In fact, decomposing a problem by means of blocks of different size corresponds to having sub-aspects that can be grouped into a certain number of aspects. The issue is finding the optimal number of aspects and, most importantly, what sub-aspects they should entail in order to arrive at a set of risk categories that enables a bank to draw a set of (nearly) one-to-one correspondences with classes of return. We may want to know whether a bank can arrive at such a set of correspondences, and how fast.

The results of these simulations can be summarised as follows:

- If the decomposition is coarser than the optimal one, then the solution is found, but it is found later. In our context, this means that too few sub-aspects may slow down the process of arranging aspects into categories that allow one-to-one correspondences between risks and returns.

- If the decomposition is finer than the optimal one, a partial solution is found (only some numbers are guessed correctly). However, during the initial trials the partial solution may perform better than the complete solution. Thus, the solution may be crowded out by partial solutions that perform better in the short run. In our context, this means that too many sub-aspects may impair the bank from finding the optimal arrangement of aspects, precisely because they enable it to reach an acceptable arrangement quickly.

These results suggest that much of the quest that banks have undertaken for distinguishing aspects and sub-aspects may have been motivated by the need of having a classification system in place before their rivals had one, rather than by the goal of optimizing lending procedures. Speed in decision-making on loan applications may have been attained, but at the cost of worsening the quality of decision-making.

Other simulations on problem-solving were made, where the solution was allowed to change with time [28] [14] [42]. In this setting, the problem-solver must chase a solution that escapes any attempt to be reached. In these simulations coarse decompositions performed best, since by allowing longer jumps in the space of solutions they enabled the problem-solver to approach the solution from time to time, albeit she may remain far from it most of the times.

This result may suggest that those credit institutions that are most often concerned with financing innovative projects should not subdivide their judgement into a large number of "aspects" and "sub-aspects". However, we have seen in this section that venture capitalists seem to do the opposite, i.e., they consider several aspects, subdivide them into a large number of sub-aspects and are keen of explaining their classification criteria to researchers.

A possible explanation might be that what venture capitalists actually do, is not what they claim or think that they do. Indeed, a stream of literature questions the results obtained by simply asking venture capitalists what their classification criteria are. In fact, although the main aspects considered by venture capitalists are really those that best indicate the future evolution of a business venture [49], too many aspects may decrease the judgement efficiency of venture capitalists [59]. In reality, venture capitalists may employ just a few of the many aspects that they mention [52]. Indeed, theoretical considerations suggest that it may be rational for a decision-maker to ignore some information if this increases her likelihood to make mistakes [34].

Further insights could be gained by a better understanding of the processes of problem decomposition. For the moment, it is clear that the processes actually used in order to change classification criteria are much more difficult to understand than the mere decision not to grant a loan.

6 Conclusion

Credit rationing is one of those issues where the neoclassical model of competitive markets does not apply. Similarly to other market failures, asymmetric information has been suggested as an explanation.

Since asymmetric information is sufficient to justify the existence of credit rationing, little effort has been devoted to alternative, or additional explanations. Though a few economists voiced that uncertainty does play a role in credit rationing, this argument has not been pursued in either empirical or analytical terms.

The empirical evidence on credit rationing to high-tech firms is questioning this approach, since there is no reason why information asymmetries should be higher if sophisticated technologies are involved. Furthermore, the new accord on capital requirements (Basel II) is emphasising the importance of bank internal rating systems, a circumstance that triggered many interesting empirical investigations. Both streams of enquiry point to the difficulties posed by difficult classification problems, and this issue needs to be faced.

Credit rationing due to classification failure does not have the same dynamical properties as credit rationing due to information asymmetries. In fact, credit rationing due to information asymmetries is likely to be constant with time, for information asymmetries exist all the time. On the contrary, credit rationing due to classification failures is stronger when uncertainty is high because important novelties are emerging. Often, this happens at crisis times, just when it would be most important that firms can access credit. Thus, credit rationing due to classification failure has important consequences for economic dynamics.

Credit rationing due to classification failures suggests that economic policy is not just a matter of managing money, but also a matter of providing economic actors with visions, confidence, and directions for the future. The mappings between classes of risk and classes of return that we used to explain credit rationing are a representation of cognitive states, and as such, they are subject to persuasion.

A Cognitive Maps in the Biotech Industry

Mappings from classes of risk to classes of return exist in the minds of the bank officials who make decisions regarding loans. Essentially, they are instances of cognitive maps.

A cognitive map provides orientation by telling a decision-maker what it is 'normal' for him to expect. It is a set of causal relationships that link a set of possible causes with a set of possible effects.

It is important to realize that mental categories do not evolve independently of the cognitive map in which they are embedded. Rather, mental categories are constructed in order to fit into a particular cognitive map. In its turn, a cognitive map is arranged with the purpose of making the causal links between mental categories as simple as possible.

As an illustrative example, the following figures (6) and (7) tell the story of a change of the cognitive map of U.S. biotech companies as has been recorded by their industry association [35].

Since its products take years to reach the market, and since commercialization requires a sales and marketing organization that is beyond the reach of small high-tech firms, biotech companies cannot draw their revenues from consumers. Thus, they establish strategic alliances with large pharmaceutical companies that advance the capital for R&D in exchange of patents. As can be seen from figure (6),

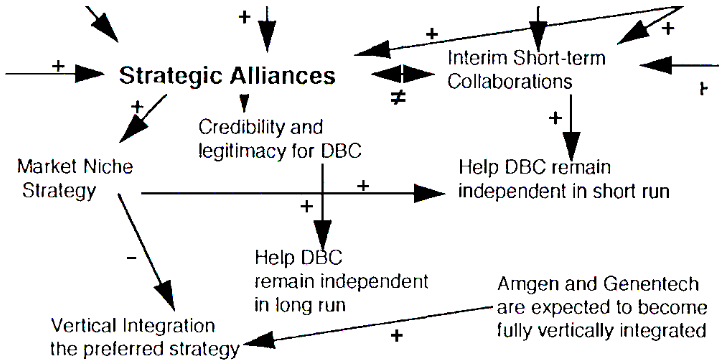

Figure 6: A part of the cognitive map of American dedicated biotech companies in 1989 (Amgen and Genentech are the two most successful companies). Incoming arrows stem from parts of the map not shown in this figure. By courtesy of Gail James ©, expounded from [35].

in 1989 biotech companies saw this process as sustaining their independence albeit at the cost of hindering expansion through vertical integration.

One year later, 1990, biotech companies suddenly realized that pharmaceutical companies were acquiring sensible knowledge that would enable them to develop in-house biotechnologies and, most importantly, that contracts were so tightly written that biotech companies could not transfer the expertise that they developed through a collaboration with a pharmaceutical company onto other fields. Biotech companies defined strategic alliances with pharmaceutical companies as "poison pills". Figure (7) shows that their cognitive map changed dramatically.

The cognitive map of 1989 provided a positive orientation to the future that suggested biotech companies to invest and banks to concede loans. Suddenly, in 1990, the certainties of the 1989 map disappeared. There was no longer a clear direction of what to do, no long-term strategy embedded in causal relations connecting what can be done to what can be obtained. The figures (2) and (3) of § (3) are sketchy representations of a cognitive map that provides certainties and a cognitive map that offers none, respectively.

The rest of the story is that biotech companies realized that by writing proper contracts their independence could be safeguarded; at the same time, pharmaceutical companies realized that independent biotech companies guarantee edge research. Thus, in the end the cognitive maps of biotech companies since 1991 returned to pretty much what they used to be prior to 1990, except that a concept was included, specifying that strategic alliances should be flexible and contemplate an

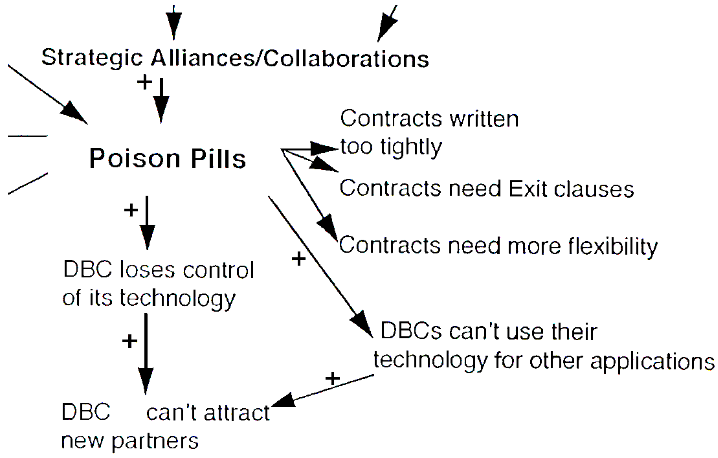

Figure 7: A part of the cognitive map of American dedicated biotech companies in 1990. Incoming arrows stem from parts of the map not shown in this figure. By courtesy of Gail James ©, expounded from [35].

exit clause.

As explained above, the maps shown in figures (6) and (7) were expunged from official communications of the industrial association of biotech companies. Thus, they reflect the prevailing opinion in this industrial sector at that time. We can safely assume that banks generally conformed to this opinion.

Now suppose that a biotech company re-gained, or never lost its confidence in the future while banks were still confused. For instance, a particular biotech company and its pharmaceutical partner may have recognized their mutual interdependence earlier than the rest of the industry, while banks were still reluctant to conceive the possibility of a long-term accord between these subjects. This firm would have probably suffered credit rationing, even if both the firm and its bank had the same information. It all depends on how this information was arranged in their cognitive maps.

B The Measurement of Complexity

This appendix provides an example of complexity measurement. Figures (8) and (9) illustrate a possible map between classes of risk and returns and the corresponding simplicial complex, respectively.

A *simplex* is the convex hull of a set of $(n+1)$ independent points in some

Euclidean space of dimension n or higher, that are its *vertices*. In plain language, a simplex is the n-dimensional analogue of a triangle. For example, a 0-simplex is a point, a 1-simplex is a line segment, a 2-simplex is a triangle, a 3-simplex is a tetrahedron, a 4-simplex is a pentachoron, etc.

Let us represent classes of risk as simplices whose vertices are the classes of return to which they are connected. So a class of risk is represented by a point if it is connected to one single class of return, a segment if it is connected to two classes of return, a triangle if it is connected to three classes of return, and so on.

In the case of figure (8) simplices are either points, or segments, or triangles, and a tetrahedron. In fact, the simplex r_1 is made by its only vertex R_1, the simplex r_7 is made by its only vertex R_7, and the simplex r_9 is made by its only vertex R_9. On the contrary, the simplex r_4 is the segment connecting vertices R_4 and R_5, and the simplex r_8 is the segment connecting vertices R_8 and R_9. The simplex r_2 is a triangle of vertices R_1, R_2, R_3, the simplex r_3 is a triangle of vertices R_2, R_3, R_4, and the simplex r_5 is a triangle of vertices R_5, R_6, R_7. Finally, the simplex r_6 is a tetrahedron of vertices R_6, R_7, R_8 and R_9.

We do not care about the size of simplices. Rather, we focus on the structure of their connections.

The convex hull of any non-empty subset of the $(n+1)$ points that define a simplex is called a *face* of the simplex. In particular, 0-faces are the vertices of a simplex, 1-faces are segments, and the n-face is the simplex itself. Two simplices are connected if they have a common face. A set of (at least) pairwise connected simplices is a *simplicial complex*.

In our example, simplices r_1 and r_2 have vertex R_1 as their common face, simplices r_2 and r_3 have the segment $R_2 - R_3$ as their common face, simplices r_3 and r_4 have common vertex R_4, simplices r_4 and r_5 have common vertex R_5, simplices r_5 and r_6 have the segment $R_6 - R_7$ in common, simplices r_5, r_6 and r_7 share the vertex R_7, simplices r_6 and r_8 have the vertex R_8 in common and simplices r_8 and r_9 have vertex R_9 in common. Each simplex is connected to at least one other simplex, so they form one single simplicial complex as illustrated in figure (9). Note that some simplices are included in others (r_1 is included in r_2; r_7 is included in both r_5 and r_6; r_8 and r_9 are included in r_6).

In the simplicial complex of figure (9) there is one class of simplices connected at $q = 0$ (the class $\{r_1, r_2, r_3, r_4, r_5, r_6, r_7, r_8, r_9\}$, because each of these simplices have at least one vertex in common with another simplex in the class). Furthermore, there are two classes of simplices connected at $q = 1$ (the class $\{r_2, r_3\}$, because r_2 and r_3 have the segment $R_2 - R_3$ in common, and the class $\{r_5, r_6\}$, because r_5 and r_6 have the segment $R_6 - R_7$ in common).

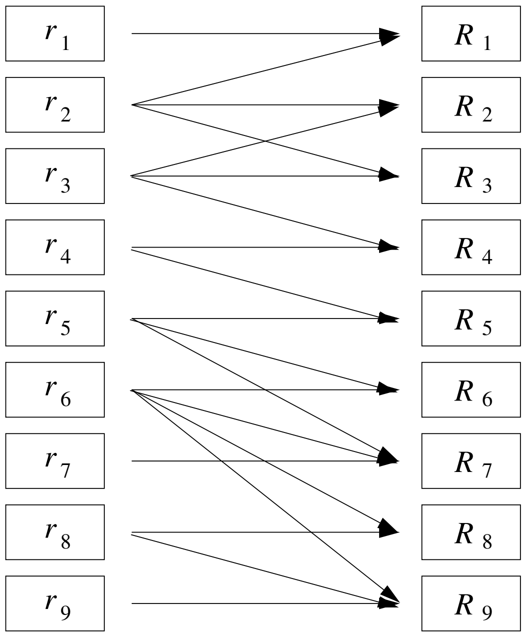

Figure 8: A map between classes of risk and classes of return. Each class of risk corresponds to a simplex whose vertices are the classes of return to which it is connected.

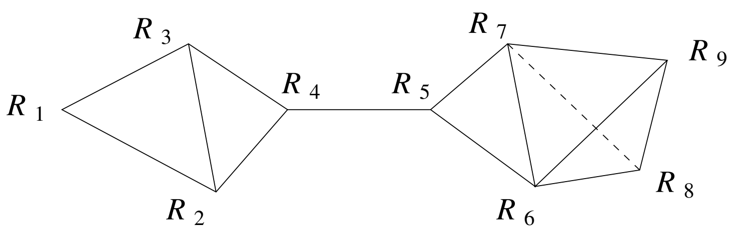

Figure 9: The simplicial complex corresponding to the map of figure (8). The dotted line represents the hidden edge of tetrahedron r_6, whose vertices are R_6, R_7, R_8 and R_9.

Thus, it is $s_0 = 1$ and $s_1 = 2$. With these numbers, eq. (1) yields $\mathcal{C}(\mathcal{F}; m, n) = 1.5$.

In the above example it was $n = 9$. The choice of the correct memory length m did not appear in the example because it determines the map which, in figure (8), was assumed to be given. However, the rationales for its choice are worth mentioning.

Complexity is due to qualitative features and causal relationships that surprise the observer as absolutely novel. It follows that only recent information is relevant, and only qualitatively, not quantitatively. This is one general reason for a small m.

Furthermore, there exists a criterion to determine how small m must be with respect to the information on which complexity is computed. When calculating complexity, one does not care whether a causal connection occurred one, two, three times or more, but only if it ever occurred, or not. Thus, it does not make sense to have more than one or two repetitions of a particular connection. If this occurs, this means that m is too large. And too large an m produces too high complexity values.

Further details on the computation of complexity can be found in [25], [26] and [27].

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