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Quality/Quantitative Financial Analysis

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ABSTRACT

Using as much information as possible, we provide a strategy for doing financial analysis. We are tasked with evaluating potential investment opportunities in order to decide whether or not they will turn a profit. If there's a lot of data, we may accomplish the work at the qualitative, semi quantitative, or quantitative levels. Using this strategy, you may get some results even if you have very little knowledge regarding amounts. Order of Magnitude Relations (omrs) between model variables are the bare minimum of information that the system can operate with. These omrs can inform us whether an investment idea is good or not by disambiguating the outcomes of our model. If we just have a few omrs to work with, the conclusion of our investment project analysis may or may not be determined. We will be able to fine-tune the findings in the future by providing the algorithm with more information (perhaps imprecise). The more exact the findings are, the more precise the information presented is. Traditional analysis will provide the same answers if all of the variables presented are accurate at the conclusion of the process.

Keywords: reasoning in terms of size, approximation, quality, calculation across intervals, and financial analysis

INTRODUCTION

The Benefit-Cost technique is often used in financial analysis to analyse whether or not an investment project will be successful (see [González99]). Using this metric, you may see how much money you'll make on a specific project compared to how much it will cost you. The analysis is carried out within a certain timeframe. Equation shows the

$$\frac{B}{C} = \frac{\sum_{t=0}^{n} FF_t^{+} \Big/ (1+i)^t}{\sum_{t=0}^{n} FF_t^{-} \Big/ (1+i)^t}$$

benefit-cost rate formula (1).

There are two types of cash flow: positive cash flow and negative cash flow. I is the investment cost, and t is the

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length of time considered in the planning process (0, 1, 2,..., n). This is how decisions are made:

$$B/C \begin{cases} > 1 & OK \\ = 1 & Equilibrium \\ < 1 & Loses \end{cases}$$

González ([González85]) defined the criterion for computing FFt. González demonstrates this in his paper:

I (3) FF = NUL - D + A + RV NULt is an acronym for "net unutility" or "net loss." Dt is the abbreviation for "depreciation." Amortization is referred to as "At." RVt = Recovery Value It is the same as making an investment.

Discrimination criteria in Eq. 2 may be evaluated using fuzzy numbers or intervals, as shown in the literature [Gotz83, Kosko96 and Pedrycz98]. This does not pose a difficulty under an approximate representation of quantities. However, dealing with omrs propagation methods does find it difficult.

$$B - C \begin{cases} > 0 & OK \\ = 0 & Equilibrium \\ < 0 & Loses \end{cases}$$

It is possible to undertake Financial Analysis at different granularities using the method we propose in this study. The number of layers of granularity is unlimited since its fundamental representation technique is intervals. If you want usable findings at the simplest level possible, you need to execute OMR (Order of Magnitude Reasoning). The remainder of the paper is laid out in this way. Using an approximation of values may assist us solve an issue when we don't know the exact answer. We employ intervals and contrast solutions in an alternate representation. OMRS, the propagation algorithms, and a new representation are all introduced in Section 3, along with comparisons of the results obtained using these methods with prior ones. OMRs are proposed in Section 4 as a method for evaluating discriminating criteria. As more data becomes available, the quality of the answers produced by this method may be improved upon, according to Section 5. Section 6 sums up the essay, stressing the advantages and disadvantages, and suggesting new research avenues for further investigation.

APPROXIMATE SOLUTIONS

In order to demonstrate the many ideas and difficulties raised in each section, we offer part of an example throughout the article. Consider a group of people who wish to form a new business. To determine whether this is possible, a feasibility study is carried out. For many months to come, we forecasted the company's cash flow using financial analysis, market research, and more. The B/C indication is what we're looking for. Fuzzy numbers are used to represent the data in Table 1. (each triplet represents a Triangular Fuzzy Number). An interest rate of interest and the Cash Flow are given for each monthly period. Using a fuzzy representation of quantities, [González99] has performed all operations in the fuzzy domain with respect to the prior case. Instead, we recommend making use of intervals. Because intervals may be used to express many kinds of information in a consistent way, this is why. omrs may be expressed as intervals, as can sign values and ambiguous information; real numbers can be represented as point intervals. The three integers indicate the extremes and the midpoints of a triangle fuzzy number, according to the fuzzy method. When calculating intervals, the intermediate number is ignored and the interval is defined using the extremes. When dealing with real numbers, we take the centre point of the fuzzy number to represent the genuine magnitude of the concerned quantity. B/C ratio was calculated using the formalisms presented. Table 2 displays the findings. It's possible to achieve results that contain zero if you make the fuzzy numbers and intervals as large as possible. The goal question could not be answered in some circumstances (i.e. the evaluation of B-C). Taking things to their logical conclusion, it's possible that we have no idea what any of those numbers mean at all. Even if we can't get to the bottom of the uncertainty, we may still be able to come up with a solution using other knowledge. omrs are the key to solving our issue. After omrs is introduced and OMR (Order of Magnitude Reasoning) is explained, the technique for determining B-C is proposed in section 4.

Period t	FF_t	i_t
0	-25000	0
1	(12000, 15419, 16500)	(0.20, 0.25, 0.2
2	(15000, 14891, 20000)	(0.25 0.26, 0.2
3	(16000, 18335, 19500)	(0.29, 0.30, 0.3
4	(16000, 18820, 19000)	(0.31, 0.32, 0.3
5	(16000, 17389, 18000)	(0.36, 0.37, 0.3
6	(16000, 18761, 19000)	(0.38, 0.39, 0.4
7	(15500, 18759, 19500)	(0.38, 0.39, 0.4
8	(18000, 18666, 20000)	(0.38, 0.39, 0.4
9	(16000, 18640, 19000)	(0.40, 0.41, 0.4
10	(16000, 18555, 19000)	(0.40, 0.41, 0.4
11	(6000, 9980, 10000)	(0.42, 0.42, 0.4

Table 1. Expected Cash Flows and Interest Rates for Example

	Real	Fuzzy	Intervals
B/C	2.0191	(1.707, 2.0191, 2.0327)	(1.6, 2.16)

Table 2. Results of Financial Analysis applied to Example of Table 1

ORDER OF MAGNITUDE REASONING

Partial order is imposed on the quantity space via ordering restrictions. Constraints of this kind include A = B, A B, and A > B, where A and B are model variables. It should be possible for the system to infer A C based on the restrictions A B and B C (all valid inferences need to be sanctioned, of course). Ordering limitations are the only ones mentioned in the previous paragraph. People and engineers who work with numerical expressions often employ order-of-magnitude relationships to make things easier to understand. Assuming that the deleted term is insignificant in relation to the rest of the equation, physics textbooks often remove a term from an expression to make it easier for readers to understand a model. Table 3 shows the om operators and their semantics, which help us deal with these scenarios.

Operator	Meaning
<<	Much smaller
-<	Moderately smaller
~<	Slightly smaller
=	Equal
>~	Slightly greater
>-	Moderately greater
>>	Much greater

Table 3. Order of Magnitude Operators

For the purpose of inferring omr properties, many definitions have been made in the literature [Raiman86, Mavrovouniotis87, and Flores96]. Aggressiveness is the defining characteristic of these two individuals. This means that some sanction inferences such as A B and A C, which are error-prone yet right enough to satisfy an individual, are sanctioned by these institutions.

INTERVAL REPRESENTATION

We have opted to allow the operators listed in Table 1 for executing OMR. There must be some tiny e in order for the ratio A/B to be less than 1, which means that A/B must be smaller than 1. For the relation A B, A/B [0, e], which means that the ratio A/B must be in an interval [0, e] for any small real integer e. In Figure 1, we can see how we may define the collection of operators.

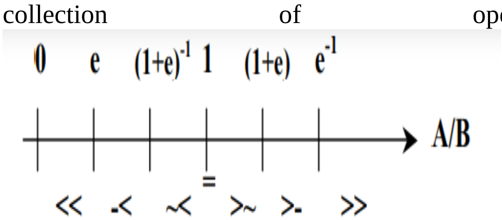

Figure 1. Intervals in the Order of Magnitude Operators

The intuitive semantics stated in [Mavrovouniotis87] apply to all operators in Figure 1. The traditional meaning of A = B is that A is equal to B; A B implies that A is somewhat less than B; A -B means that A is much less than B; and A B means that A is inconsequential in comparison to B. All of these expressions suggest that A is significantly less than B. We may create composite OM relations using the interval representation. Intervals are defined as the sum of the three intervals between operators and a and b.

CONSTRAINT PROPAGATION

An analogous challenge to inferring new constraints is to compute the transitive closure of a labelled graph, in which the vertices are variables and edges denote interactions between any two vertices. This issue can be solved in O(n3) 1 time by using the Floyd-Warshall method, where n is the total number of variables in the model. An index-by-variable matrix M makes coding this procedure more simpler. The constraint set may be represented as a matrix M with A and B as rows and columns. There are n variables in the matrix, where T and Told are temporal ones, as shown in Figure 2.

```
Transitive_closure(M)
  T ← M
  For k = 1 to n
    T[k, k] ← =
  For k = 1 to n
    T_old ← T
    For i = 1 to n
      For j = 1 to n
        if i ≠ j then
          T[i,j] ← OR(T_old [i,j],
                      AND(T_old [i,k], T_old [k,j]))
  Return T
```

Based on an additional variable k, the method computes the relationship between two variables I and j). A comparison is made between the newly discovered relationship and what we already knew about I and j. The operator Whereas is used for inference, and the operator OR is used for comparison with previously known information. Let i=A, j=B, k=C, T[i,j]= (i.e. A B), and T[j,k]= (i.e. B C) return to the previous example. Intuitive knowledge is represented by AND(). A = B, B = C, A = A, and so on. This implies that if we had no prior knowledge of the relationship between A and C (represented by?), and we find that A C, we may accept the new relationship as legitimate. Relations are used to explain the semantics of the AND and OR functions in certain other implementations (e.g. Flores97, Flores96, Mavrovouniotis87) (i.e. triplets). Using AND(C, we can deduce A C. Since A C is a more constrained interpretation of OR(C, we may revise our understanding of the link between A and C to A C. OR(knew that A C, and learn that A C, our discovery contradicts our earlier knowledge. In section 1.1, omrs are represented as intervals. Interval operations, rather than qualitative (symbolic) inference rules, may be used to code inferences under this representation (less intuitive, though). Assuming X = (A/B) (B/C) = A/C and that Y = B/C > [x1, x2], then XY = (A/B) (B/C) = A/C yields the correct relationship. As long as X falls inside the interval [x1, x2], then Y falls within the interval [y1, y2]. In this way, the Floyd-Warshallalgorithm's AND function may be implemented using interval product, as stated in the standard literature. In other words, Z = X AND Y = [x1, x2] [y1, y2].. This is a good example of how we may use our knowledge of A/B to find A/B [x3, x4]. For A/B, we've found a new lower left limit for x1=x3. To maintain the former limit, we need to know that at least as good (tighter) x1>= x3 For the correct amount of time, we continue in the same way. As a result, interval intersection may be used to build the OR update function. An example of omrs is a restriction on the ratios of quantities. It is possible to interpret the OR function as an update to those restrictions, where the intersection of the left and right bounds of those intervals is updated. We may state that we have generated contradicting constraints when we derive two intervals that do not overlap. It is possible to state that these constraints are contradictory because their respective interval representations do not cross if we know, for example, that the interval representations of these constraints are not equal to the interval representations of the other. In other words, the equation is [0, 0.2] [0.833, 1] = As an illustration of inference, consider the following scenario:

$$A << B \rightarrow A/B \in [0, e] = [0, 0.2]$$
$$B -< C \rightarrow B/C \in [e, (1+e)^{-1}] = [0.2, 0.833]$$
$$(A/B)\ (B/C) = A/C \in [0, e/(1+e)] = [0, 0.166]$$

Using this formula, we may conclude that A C. The intersection of the two intervals, supposing we already knew that A/C = [0, 1] (i.e. A C), would provide us with fresh information.

$$[0, 1] \cap [0, 0.166] = [0, 0.166]$$

More aggressive conclusions may be drawn while still being safe when utilising interval inference, as opposed to previous methods such as [Flores96, Mavrovouniotis87, Raiman86]. 1 is a good example. We assume that e=0.2 throughout the article. Based on [Mavrovouniotis87], the application domain determines the value of e. Quantities that are less than 1 to 5 (e=0.2) may be considered unimportant in certain areas, whereas those that are less than 1 to 20 (e=0.05) may be considered significant in other domains.

$$A \ll B \rightarrow A/B \in [0, 0.2]$$
$$B >\sim C \rightarrow B/C \in [1, 1+e]=[1, 1.2]$$
$$A/C \in [0, 0.24] \rightarrow A \ll \ldots -< C$$
$$C \sim< D \rightarrow C/D \in [0.833, 1]$$
$$A/D \in [0, 0.24] \rightarrow A \ll \ldots -< D$$

According to [Raiman86], the notation A ... - C represents an OMR with a range of to -B and the relation A ... -C is produced by B>C. As a result of this, our intuition tells us that C – A, which is paradoxical, is now B > A and B is now C > D, which is also counterintuitive. Let's have a look at how the inference process worked in this case without having to describe the semantics for each potential combination of omrs. The formalism of [Mavrovouniotis87] provides 28 legal omrs; in our representation, we preserve the omrs as intervals all the time, allowing for an endless number of potential omrs. As illustrated in Figure 2, the omrs output is transformed into qualitative values using the interval definition.

DISAMBIGUATION ALGORITHM

Sign algebra is a frequent data type in Qualitative Reasoning [DeKleer84]. B-C is unclear in most circumstances if we utilize sign algebra to address this issue. Omrs can help us resolve this conundrum. However, it is difficult or very expensive to deduce an omr between B and C even if omrs are included in the model. Additionally, we may only have a few omrs linking a portion of the model variables in certain instances. Still, we may utilize that information to see whether there are any sets of variables in B or C that are more dominant than others. Variables are represented as nodes in a network by omrs, and omrs connect those nodes. It is possible to ascertain whether the interval B-C is less than, contains to, or is greater than zero by referring to the first variable (it might be any one). We have islands of connected variables if the data we have does not propagate to a complete network. If we don't consider omrs connected to each other, all islands have two variables in common. An island will arise if any variable does not participate in any omr. Assuming the graph comprises islands, we group the variables Vi and assign each island to the first positive one. It's impossible to verify whether all groups have the same sign, but if that sign does, we can utilize a data structure called as Union-Find to identify the islands. Each variable is first kept in a heap. We combine the piles of Vi and Vj for every omr. The islands in the graph are represented by the piles created by the omrs. Using an omr graph, the islands can be found in Figure 3 and the discriminant B-C can be found in Figure 4.

```
Find-Islands(omrs, V)
   For I=1 to |V|
      Make-heap(Vi)
   For each (Vi r Vj) ∈ omrs
      Union(Find(Vi), Find(Vj))
```

Figure 3. Algorithm for the Determination of Islands in the omr graph

```
Qualitative-BC(omrs, V)
   Find-islands(omrs)
   Outcome = 0
   For each island in the graph
   Refer all variables to the first one in the island
   Determine result (sign) for that island
         outcome += result
   Return outcome
```

Figure 4. Algorithm for Qualitative Financial Analysis

In deciding the outcome of each island, we are utilisingomrs to find out if the positive or the negative factors outweight the other ones, providing a positive or negative result. That can be done because, all variables in an islad are related by omrs. After the determination of the result of all islands, we add those results to determine the discriminant B-C. We cannot link all outcomes to a variable since variables on separate islands are not related by omrs, thus we need to go to a coarser scale, sign algebra. The results of all islands, expressed as sign values have to be added using sign algebra to determine the B-C discriminant. All operators in sign algebra can be implemented as tables. For instance ADD(+,+,+) says that the addition of two positive values results in a positive value, ADD(+,-,?) says that the addition of one positive value plus one negative value results in an unknown value. Subtraction is defined analogously. Consider an example with eight variables, where V1, V3, V4, V5, and V7 are positive (i.e. they contribute to B), whereas V2, V6, V5, V7, and V8 are negative. The initial omrs are shown in Figure 5 (dark nodes are negative variables) (dark nodes are negative variables). After propagation, the final matrix still maintains the two islands. The resultant matrix is displayed in Table 4. All operators have been written in their smallest form, some of them match a qualitative connection, hence they are printed in their symbolic form. ? stands for an unknown value.

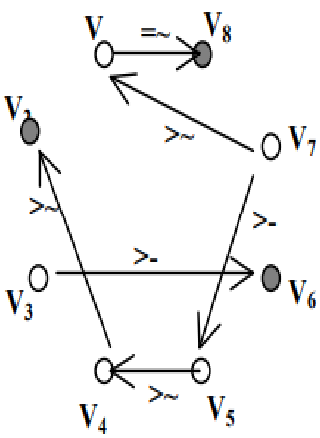

Figure 5. Constraint Graph for Example

After propagation, the matrix includes the best information we have about the relationship between every pair of variables.. The relationship between variables (provided in the matrix) may be used to refer to the first positive variable on an island. A favourable outcome will lead to the group's inclusion. Using V1 (1, 22.22) V2 as an example, we may say that V1/V2 = (1, 22.22), or that V2 = V1/V1 (1, 22.22). For our first island, which is made up of V3 and V6, we have the following:To calculate V3, use the formula: (0.048, 0.95) + (0.048, 0.95).

Using the formula (V1+V4+V5+V7-V2-V3) (9) for the second island, we get (V1(0.047, 3.053) + (0.045, 1)) – ((0.045, 1) + (0.952, 1.05)).

As a result, we may be certain that B-C will be positive. Investing in this venture is feasible..

MIXED PROPAGATION

For the sake of mixed propagation, Flores [Flores97, Flores96] created a framework in the course of his dissertation. HRCP (Hybrid Representation Constraint Propagation) is an inference engine that receives a collection of heterogeneous constraints and computes and refines as many derived constraints as possible. Constraints may be in the form of omrs, algebraic restrictions, value restrictions, and so on. We may utilise that system and think of it as a black box that does precisely what we want it to do for us. The Floyd-Warshall method may be used to perform Omr propagation derivations. An algorithm for doing mixed propagation has been created by Flores for his dissertation [Flores97, Flores96]. Those constraints are accepted by an inference engine known as HRCP (Hybrid Representation Constraint Propagation), which computes many derived constraints from the original set, as well as fine-tuning others. Constraints may be in the form of omrs, algebraic restrictions, value restrictions, and so on. To put it another way, we may think of this system as a black box that does precisely what we ask of it. The Floyd-Warshall method may be used to perform Omr propagation derivations.

With this inference engine, we can design a system that receives incremental data, executes propagation as new facts arrive, and improves the solutions it delivers based on the latest data as it comes to hand. With the information we have at hand, we may not be able to say much about a particular investment project. However, further knowledge will allow us to make more informed decisions in the future. The answer gets more precise as we continue to improve our data (i.e., reduce the intervals). Consider the case when V3 >- V6, which is stated in Eq. 4, is unknown. Qualitative-conclusion BC's would be unknowable in this situation. V3 = (2.1, 20) and V6 = (2.1, 20) are the user's assertions (1, 2). V3 (0.05, 0.952) and V6 (0.05, 0.952) are the points at which the system may identify a good investment project outcome.

	1	2	3	4	5	6	7	8
1	=	(1, 22.222)	?	(1, 21)	(1, 20)	?	<~	=~
2	(0.045, 1)	=	?	<~	(0.9063, 1)	?	(0.045, 0.952)	(0.42, 1.049)
3	?	?	=	?	?	>-	?	?
4	(0.047, 1)	>~	?	=	<~	?	(0.0476, 0..952)	(0.44, 1.05)
5	(0.05, 1)	(1, 1.103)	?	>~	=	?	<-	(0.0476, 1.05)
6	?	?	<-	?	?	=	?	?
7	>~	(1.05, 22.05)	?	(1.05, 21)	>-	?	=	(0.952, 1.1025)
8	=~	(0.0952, 23.809)	?	(0.952, 22.349)	(0.952, 21.008)	?	(0.907, 1.050)	=

Table 4. omr Matrix after Propagation

CONCLUSIONS

It is now possible to undertake financial analysis at a variety of scales, based on the uncertainty of the supplied data. Variations in the degree of uncertainty may include anything from omrs and sign values to more exact (actual) numbers. In circumstances when previous techniques have failed, this representation scheme is the best option. In other words, alternative systems would fail to provide a judgement given the level of uncertainty in the information we require. Our system also has the advantage of working in small steps. That is, at some point, the user's input may not be sufficient to provide a result that is clear and unambiguous. Information that comes in later might help clear up any confusion. In addition, there is also. A genuine number is generated if all variables are defined accurately. A single run of the programme may do all of this; it is not essential to rerun the programme in order to add fresh data. Since the average planning horizon is one year, the number of periods is usually 12 or a multiple of 12, which is what we use for Financial Analysis. Because of the scale of the issue, the propagation methods are able to be implemented quickly. As additional data is included into the value propagation process (such as when calculating B-value), C's the final result becomes better. A reduction in the number of interpolation intervals results in a reduction in interpolation gaps.

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