Developments in Fuzzy Sets, Intuitionistic Fuzzy Sets, Generalized Nets and Related Topics. Volume I: Foundations

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The use of consistency and confirmation measures in linguistic summaries of time series

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Abstract

We further extend our approach to the linguistic summarization of time series (cf. Kacprzyk, Wilbik and Zadrożny [11, 10, 14, 12, 13, 15]) in which an approach based on a calculus of linguistically quantified propositions is employed, and the essence of the problem is equated with a linguistic quantifier driven aggregation of partial scores (trends). We analyze two quality criteria of linguistic summaries, namely measure of consistency and measure of confirmation show their interesting properties.

Keywords: computing with words, linguistic quantifiers, linguistic summarization, time series summarization.

1 Introduction

Financial data analysis is one of the most important application areas of advanced data mining and knowledge discovery tools and techniques. For instance, in a report presented by Piatetsky-Shapiro (cf. `http://www.kdnug- gets.com`) on top data mining applications in 2008, the first two positions are, in the sense of yearly increase:

• *Investment/Stocks*, up from 3% of respondents in 2007 to 14% of respondents in 2008% (350% increase),

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• *Finance*, up form 7.2% in 2007 to 16.8% in 2008 (108% increase),
and this trend will presumably continue.

This paper is a follow up of our previous works (cf. Kacprzyk, Wilbik, Zadrożny [11, 10, 14, 12, 13, 15] or Kacprzyk, Wilbik [8, 9]) which deal with how to effectively and efficiently support a human decision maker in making decisions concerning investments in mutual funds.

Though decision makers are concerned with possible future gains/losses, and their decisions is related to the future, our aim is not the forecasting of the future daily prices. Instead, we follow a decision support paradigm, that is we try to provide the decision maker with some information that can be useful, not to replace the human decision maker.

For solving the problem, there may be two general approaches: first, to provide means to derive a price forecast for an investment unit so that the decision maker could "automatically" purchase what has been forecast. Unfortunately, the success has been much less than expected. Basically, statistical methods just somehow extrapolate the past and do not use domain knowledge, intuition, inside information, etc. A natural solution may be to try to support the human decision maker by providing him/her with some additional useful information, while not getting involved in the very process of decision making.

From our perspective, the following philosophy will be followed. In all investment decisions the future is what really counts, and the past is irrelevant. But, the past is what we know, and the future is (completely) unknown. Behavior of the human being is to a large extend driven by his/her (already known) past experience. We usually assume that what happened in the past will also happen (to some, maybe large extent) in the future. This is basically, by the way, the very underlying assumption behind the statistical methods too!

This directly implies that the past can be employed to help the human decision maker. We present here a method to subsume the past, the past performance of an investment (mutual) fund, by presenting results in a vary human consistent way, using natural language statements.

To start, in any information leaflet of an investment fund, there is a disclaimer stating that "Past performance is no indication of future returns" which is true. However, on the other hand, in a well known posting "Past Performance Does Not Predict Future Performance" [3], they state something that may look strange in this context, namely: "...according to an Investment Company Institute study, about 75% of all mutual fund investors mistakenly use short-term past performance as their primary reason for buying a specific fund". But, in an equally well known posting "Past performance is not everything" [4], they state: "...disclaimers apart, as a practice investors continue to make investments based on a schemes past performance. To make matters worse, fund houses are only too pleased to toe the line by actively advertising the past performance of their schemes leading investors to conclude that it is the single-most important parameter (if not the most important one) to be considered while investing in a mutual fund scheme".

We can ask a natural question why it is so. Again, in a well known posting "New Year's Eve:Past performance is no indication of future return" [2], they say "...if there is no correlation between past performance and future return, why are we so drawn to looking at charts and looking at past performance? I believe it is because it is in our nature as human beings ...because we don't know what the future holds, we look toward the past ...".

There are a multitude of similar statements in various well known postings, exemplified by Myers [25]: "...Does this mean you should ignore past performance data in selecting a mutual fund? No. But it does mean that you should be wary of how you use that information ...While some research has shown that consistently good performers continue to do well at a better rate than marginal performers, it also has shown a much stronger predictive value for consistently bad performers ...*Lousy performance in the past is indicative of lousy performance in the future...*". And, further (cf. [26]): "While past performance does not necessarily predict future returns, it can tell you how volatile a fund has been". And furthr, in the popular "A 10-step guide to evaluating mutual funds" [1], they say in the last advise: "Evaluate the funds performance. Every fund is benchmarked against an index like the BSE Sensex, Nifty, BSE 200 or the CNX 500 to cite a few names. Investors should compare fund performance over varying time frames vis-a-vis both the benchmark index and peers. Carefully evaluate the funds performance across market cycles particularly the downturns". Therefore we think, that linguistic summaries of the past performers of an investment fund can be here a valuable tool as they may be easily understood by the humans as they are in natural language.

Here we extend our previous works on linguistic summarization of time series (cf. Kacprzyk, Wilbik, Zadrożny [11, 10, 14, 12, 13, 15] or Kacprzyk, Wilbik [8, 9]), mainly towards a more complex evaluation of results. The basic criterion for evaluation linguistic summaries is a degree of truth (cf. our papers [11, 13, 16]). However, later Kacprzyk and Yager [17] and Kacprzyk, Yager and Zadrożny [18, 19] and Kacprzyk and Zadrożny [21, 20] introduced additional quality criteria, e.g. degree of specificity, covering and appropriateness. Cerny Cerny1978 proposed two additional measures: measure of consistency and measure of confirmation. We will analyze those measures and show some interesting properties.

2 Linguistic data summaries

As a *linguistic summary of data (base)* we understand a (usually short) sentence (or a few sentences) that captures the very essence of the set of data, that is numeric, large, and because of its size is not comprehensible for human being.

We use Yager's basic approach [27]. , and later papers on this topic, as well as here the following notation is used:

- $Y = \{y_1, y_2, \ldots, y_n\}$ is the set of objects (records) in the database D, e.g., a set of employees;
- $A = \{A_1, A_2, \ldots, A_m\}$ is the set of attributes (features) characterizing objects from Y, e.g., a salary, age in the set of employees.

A linguistic summary includes:

- a summarizer P (e.g. *low* for attribute *salary*);
- a quantity in agreement Q, i.e. a linguistic quantifier (e.g. *most*);
- truth (validity) $\mathcal{T}$ of the summary;
- optionally, a qualifier R (e.g. *young* for attribute *age*).

Thus, a linguistic summary may be exemplified by

$$\mathcal{T}(most \text{ of employees earn } low \text{ salary}) = 0.7 \quad (1)$$

or in richer (extended) form, including a qualifier (e.g. *young*), by

$$\mathcal{T}(most \text{ of } young \text{ employees earn } low \text{ salary}) = 0.82 \quad (2)$$

Thus, basically the core of a linguistic summary is a linguistically quantified proposition in the sense of Zadeh [29] which for (1) and (2) may be written, respectively as

$$Qy's \text{ are } P \quad (3)$$

$$QRy's \text{ are } P \quad (4)$$

Then the truth (validity), $\mathcal{T}$, of a linguistic summary directly corresponds to the truth value of (3) and (4). This may be calculated using either original Zadeh's calculus of quantified propositions (cf. [29]) or other interpretations of linguistic quantifiers. In the former case the truth values of (3) and (4) are calculated, respectively, as

$$\mathcal{T}(Qy's \text{ are } P) = \mu_Q\left(\frac{1}{n}\sum_{i=1}^{n}\mu_P(y_i)\right) \tag{5}$$

$$\mathcal{T}(QRy's \text{ are } P) = \mu_Q\left(\frac{\sum_{i=1}^{n}\mu_P(y_i)\wedge\mu_R(y_i)}{\sum_{i=1}^{n}\mu_R(y_i)}\right) \tag{6}$$

where $\wedge$ is the minimum operation (more generally it can be another appropriate operator, notably a t-norm), and Q is a fuzzy set representing the linguistic quantifier in the sense of Zadeh [29], i.e. regular, nondecreasing and monotone:

(a) $\mu_Q(0) = 0$,

(b) $\mu_Q(1) = 1$, and

(c) if $x > y$, then $\mu_Q(x) \geq \mu_Q(y)$;

It may be exemplified by *most* given by

$$\mu_Q(x) = \begin{cases} 1 & \text{for } x \geq 0.8 \\ 2x - 0.6 & \text{for } 0.3 < x < 0.8 \\ 0 & \text{for } x \leq 0.3 \end{cases} \tag{7}$$

3 Linguistic summaries of trends

In our first approach we summarize the trends (segments) extracted from time series. Therefore as the first step we need to extract the segments. We assume that segment is represented by a fragment of straight line, because such segments are easy for interpretation.

There are many algorithms for the piecewise linear segmentation of time series data, including e.g. on-line (sliding window) algorithms, bottom-up or top-down strategies (cf. Keogh [22, 23]).

We consider the following three features of (global) trends in time series: (1) dynamics of change, (2) duration, and (3) variability. By *dynamics of change* we understand the speed of change of the consecutive values of time series. It may be described by the slope of a line representing the trend, represented by a linguistic variable. *Duration* is the length of a single trend, and is also represented by a linguistic variable. *Variability* describes how "spread out" a group of data is. We compute it as a weighted average of values taken by some measures used in statistics: (1) the range, (2) the interquartile range (IQR), (3) the variance, (4) the standard deviation, and (5) the mean absolute deviation (MAD). This is also treated as a linguistic variable.

For practical reasons for all we use a fuzzy granulation (cf. Bathyrshin at al. [5, 6]) to represent the values by a small set of linguistic labels as, e.g.: increasing, slowly increasing, constant, slowly decreasing, decreasing. These values are equated with fuzzy sets.

For clarity and convenience we employ Zadeh's [30] protoforms for dealing with linguistic summaries [21]. A protoform is defined as a more or less abstract prototype (template) of a linguistically quantified proposition. We have two types of protoforms of linguistic summaries of trends:

- a short form:

$$\text{Among all segments, } Q \text{ are } P \tag{8}$$

  e.g.: "Among all segments, *most* are *slowly increasing*".

- an extended form:

$$\text{Among all } R \text{ segments, } Q \text{ are } P \tag{9}$$

  e.g.: "Among all *short* segments, *most* are *slowly increasing*".

The quality of linguistic summaries can be evaluated in many different ways, eg. using the degree of truth, covering or others.

Here we will focus our attention on two measures that are used for evaluation of rules and see if we may find their equivalents in the field of linguistic summaries. First we describe shortly two measures of linguistic summaries, degree of truth and the degree of covering, as they will be useful in our further discussion.

3.1 Truth value

The truth value (a degree of truth or validity), introduced by Yager in [27], is the basic criterion describing the degree of truth (from $[0, 1]$) to which a linguistically quantified proposition equated with a linguistic summary is true.

Using Zadeh's calculus of linguistically quantified propositions [29] it is calculated in dynamic context using the same formulas as in the static case. Thus, the truth value is calculated for the simple and extended form as, respectively:

$$\mathcal{T}(\text{Among all } y\text{'s, } Q \text{ are } P) = \mu_Q\left(\frac{1}{n}\sum_{i=1}^{n}\mu_P(y_i)\right) \tag{10}$$

$$\mathcal{T}(\text{Among all } Ry\text{'s, } Q \text{ are } P) = \mu_Q\left(\frac{\sum_{i=1}^{n}\mu_R(y_i)\wedge\mu_P(y_i)}{\sum_{i=1}^{n}\mu_R(y_i)}\right) \tag{11}$$

where $\wedge$ is the minimum operation (more generally it can be another appropriate operator, notably a t-norm). In Kacprzyk, Wilbik and Zadrozny [14] results obtained by using different t-norms were compared. Various t-norms can be in principle used in Zadeh's calculus but clearly their use may result in different results of the linguistic quantifier driven aggregation. It seems that the minimum operation is a good choice since it can be easily interpreted and the numerical values correspond to the intuition.

3.2 Degree of covering (suport)

The degree of covering says how many objects in the data set corresponding to the query are "covered" by the particular summary, i.e. to the particular description P [17]. It yields the proportion of elements exhibiting both P and R to the number of elements in the set. This measure is somehow similar to the measure of support of association rules. Also Lietard [24] proposed a measure evaluating summaries similar in spirit.

Basically, if the degree of covering is low, such a summary describes a (local) pattern seldom occurring. This is the main motivation for using this measure in our context since we wish to avoid summaries that seldom happen. Hence, the degree of covering for the simple and extended protoforms, is calculated, respectively, as:

$$d_c(\text{Among all } Y,\ Q \text{ are } P) = \frac{1}{n}\sum_{i=1}^{n} \mu_P(y_i) \tag{12}$$

$$d_c(\text{Among all } RY,\ Q \text{ are } P) = \frac{1}{n}\sum_{i=1}^{n} \mu_R(y_i) \wedge \mu_P(y_i) \tag{13}$$

$\wedge$ is minimum, but we could also use a different t-norm.

4 Measure of confirmation

In [7] proposes the measure of confirmation. They consider implication:

$$\text{If X is LARGE then Y is SMALL} \tag{14}$$

with the definitions of LARGE and SMALL given by some appropriate sets. For the data with n subjects, where X and Y are attributes of each subject, we can rewrite two phrases as

$$X_i \text{ is LARGE is } T_i = \mu_1(u_i) \tag{15}$$

$$Y_i \text{ is SMALL is } S_i = \mu_2(v_i) \tag{16}$$

where T_i and S_i are truth values.

$$CF_1 = \frac{\sum_{i=1}^{n} \mu_1(u_i)\mu_1(v_i)}{\sum_{i=1}^{n} \mu_1(u_i)} \tag{17}$$

or alternatively in a stronger form

$$CF_2 = \frac{\sum_{i=1}^{n} \mu_1(u_i)\mu_1(v_i)}{n} \tag{18}$$

Let us first consider the measure of confirmation given by equation (17). This equation computes the proportion of subjects fulfilling both properties to number of subject fulfilling the one in the condition.

There is a significant difference between a rule described by an implication and linguistic summary, notably the presence of quantifier in the latter one. However if we look closer to the degree of truth (eq. (11)), we may notice that first we compute the proportion of subjects fulfilling both properties to number of subject fulfilling the one in the qualifier. Than we compute the degree to which this proportion may be expressed by the quantifier. Therefore we think that there is the same philosophy behind the degree of confirmation described by the formula (17) and the truth value described in the section 3.1.

Now let us consider the second formula, shown in equation (18). According to this formula we compute the proportion of subjects fulfilling both properties in the data set. The degree of covering (support) (eq. (13)) computes the same proportion.

Therefore we may look at the measure of conformation in the field of fuzzy rules as the equivalent of the truth value or degree of covering in the field of linguistic summaries.

4.1 Consistency

In [7] the authors propose also a measure of consistency.

They consider again implication (14). Fuzzy logic evaluates this implication for each subject as $LARGE' \oplus SMALL$. For each subject $\mu(u_i, v_i) = \min(1, 1 - \mu_1(u)i) + \mu_2(v_i))$.

The measure of consistency is defined as the grade of membership over the entire population in $(U \times V) \times U$, or the possibility that the data base fits the hipothesis.

$$CS = \frac{\sum_{i=1}^{n} \mu(u_i, v_i) \wedge \mu_1(u_i)}{\sum_{i=1}^{n} \mu_1(u_i)} \tag{19}$$

CS represents the degree to which the data set does not disagree with, or contradict, the reference proportion.

Inspired by this measure we may try to compute similar quantity in the field of linguistic summaries. Yager [28] proposed a rule of equivalence, according to which the following summaries are equivalent to each other:

- "Among all y's, Q are P" with the truth value $\mathcal{T}$
- "Among all y's, $\hat{Q}$ are $\bar{P}$" with the truth value $\mathcal{T}$
- "Among all y's, $\bar{Q}$ are P" with the truth value $1 - \mathcal{T}$

where $\hat{A}$ is the antonym of A (i.e. $\hat{A}(x) = A(\bar{x})$) and $\bar{A}$ is the negation of A (i.e. $\bar{A}(x) = 1 - A(x)$).

Generally we are interested in the summaries which are true, i.e their truth value is high. Then from the rule of equivalence we know that $\hat{Q}$ elements contradict the summary. Therefore the degree of consistency may be described by a linguistic label $\hat{Q}$. Of course we could calculate the accurate crisp value, as it was done before. However we believe this is not necessary and it is enough to express the value of consistency as $\hat{Q}$.

5 Conclusions

We have analyzed two quality measures taken from the filed of fuzzy rules, namely confirmation and consistency. We have shown that the measure of confirmation has its counterparts (depending on the interpretation) in the field of linguistic summaries. They are the truth value and degree of covering. Regarding the measure of consistency we have shown that the value expressed by this measure is hidden in the form of the summary, and therefore an explicit measure is not needed.

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The papers presented in this Volume 2 constitute a collection of contributions, both of a foundational and applied type, by both well-known experts and young researchers in various fields of broadly perceived intelligent systems.
It may be viewed as a result of fruitful discussions held during the Eighth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2009) organized in Warsaw on October 16, 2009 by the Systems Research Institute, Polish Academy of Sciences, in Warsaw, Poland, Centre for Biomedical Engineering, Bulgarian Academy of Sciences in Sofia, Bulgaria, and WIT – Warsaw School of Information Technology in Warsaw, Poland, and co-organized by: the Matej Bel University, Banska Bistrica, Slovakia, Universidad Publica de Navarra, Pamplona, Spain, Universidade de Tras-Os-Montes e Alto Douro, Vila Real, Portugal, and the University of Westminster, Harrow, UK:

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The Eighth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2009) has been meant to commence a new series of scientific events primarily focused on new developments in foundations and applications of intuitionistic fuzzy sets and generalized nets pioneered by Professor Krassimir T. Atanassov. Moreover, other topics related to broadly perceived representation and processing of uncertain and imprecise information and intelligent systems are discussed.

We hope that a collection of main contributions presented at the Workshop, completed with many papers by leading experts who have not been able to participate, will provide a source of much needed information on recent trends in the topics considered.

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