COMPARABILITY AND MENTAL ACCOUNTS

Praveen Paritosh
Department of Computer Science
Northwestern University, Evanston IL 60201
paritosh@cs.northwestern.edu
Wednesday, March 13, 2002

1 Introduction

Money is money, but the phenomenon of mental accounting shows us violations of this basic fungibility of money. One aspect of mental accounting is the fact that the single dimension of money is differentiated into more finer dimensions, e.g., gift money, hard-earned money, etc. And this differentiation might be one of the reasons why certain transactions are maintained *within* certain accounts. Money is an example of many dimensions that we see around us – length, mass, time, color, etc. So, lets look around and see if we find similar differentiation of otherwise very similar dimension for other dimensions beside money. Physics has given us seven dimensions[1] that are sufficient to describe the world around us – clearly, most of us perceive more than that. Some of these dimensions are continuous, or conceptualized as such (e.g. length, temperature, price, etc.) and some are discrete (e.g. color, sex, etc.)[2]. A quantitative representation serves to be a very fine grained and powerful representation for the continuous dimensions. We carve up the world into these dimensions so that we can usefully interact with the world. The aim of this paper is to get to a better account of mental accounting, and the key argument is that a better understanding of dimensions – "our sense of quantity" is needed to

[1] Mass, Length, Time, Current, Temperature, Amount (moles), and Luminosity.
[2] Note that continuous doesn't mean strict mathematical continuity, for example money is quantized, and so might be most dimensions. Strictly speaking, we have four types of quantity spaces – (1) *Nominal*: permits only qualitative classification, e.g., race, gender, city, color, etc. (2) *Ordinal*: permits a rank order, but we cant talk about differences, e.g., upper class, middle class and lower class section of society. (3) *Interval*: permits a rank order as well as allows us to talk about differences as well, e.g., Temperature on Celsius or Fahrenheit scale. (4) *Ratio*: in addition to all the qualities of an interval scale, defines an absolute zero, thus permitting division on the scale, e.g., Temperature on Kelvin scale.

reach there. I talk about some of the principles that I think underlie mental accounting, then present a brief review of research related to people's perception of qualitative dimensions, and then present a model that could learn that from exposure to multiple examples.

2 Mental accounting

Mental accounting is the set of cognitive operation used by people to organize, evaluate, and make decisions about financial activities. There have been a bunch of very interesting results, notably deviations from the general utility theory predictions about such accounting, many of them violating the underlying notion of fungibility of money. Money, designed to be a currency for exchange, allows us to compare apples and oranges, but yet, mental accounting research shows that people still think of money-for-apples and money-for-oranges, and don't always think of money as money. There has been a large body of data of different effects of this phenomenon, starting from Tversky and Kahneman's (1981) lost-money-theater-ticket[3] example and calculator-jacket example[4]. Surprisingly, there are not many attempts to come up with a processing account of mental accounting. There have been surmises that it is like categorization (Henderson and Peterson, 1992), and that it is like goal-derived categories (*Goals-representativeness* model, Brendl, Markman and Higgins, 1998). These accounts have not been very clear of the representation of mental accounts, categories and goals; and though they have definitely shown some of the intuitions underlying mental accounts, they are far from being process models that can be used for simulation experiments to make predictions. This paper

[3] In the lost money condition, subjects are told "Imagine that you have decided to see a play where admission is $10 per ticket. As you enter the theater you discover that you have lost a $10 bill. Would you still pay $10 for a ticket for the play?", 88% of subjects say Yes. In the lost ticket condition, subjects are told "Imagine that you have decided to see a play and paid the admission price of $10 per ticket. As you enter the theater you discover that you have lost the ticket. The seat was not marked and the ticket cannot be recovered. Would you pay $10 for another ticket?", 46% of subjects say Yes.

[4] In the $15 conditon, subjects are told "Imagine that you are about to purchase a jacket for $125, and a calculator for $15. The calculator salesman informs you that the calculator you wish to buy is on sale for $10 at the other branch of the store, located 20 minutes drive away. Would you make a trip to the other store?", 68% of subjects say Yes. In the $125 condition, subjects are told "Imagine that you are about to purchase a jacket for $15, and a calculator for $125. The calculator salesman informs you that the calculator you wish to buy is on sale for $120 at the other branch of the store, located 20 minutes drive away. Would you make a trip to the other store?, 29% of the subjects say yes. Surprisingly, Brendl et al (1998) paper misquotes the study – 1. in the $125 condition, they mention that people are saving money on the jacket, and 2. the numbers are quite different. But of course, the qualitative idea remains the same.

makes an attempt to come up with such a process model. Surely this is far from being a complete account, but my hope is that this will set the ground for some predictions and modeling ideas.

Money is a quantitative, (for most practical purposes) continuous dimension. Besides being able to compare two different instances of money, and make judgments about which is more or less; money has another interesting property which not all dimensions have – it can be accumulated. So, we can add/subtract instances of money, define a notion of total asset (which is the sum of all the money that I have). Consider other dimensions like height of people, horsepower of cars, size of buildings – usually, its difficult to imagine having a notion of total asset for these. Other examples of dimensions that allow definition of total asset are – time, goals scored by a soccer player, space in your living room, etc. This cumulative property of having an asset allows us to maintain accounts for these dimensions. Lets call these dimensions *accountable dimensions.* The total asset is an ecologically valuable notion, which helps us make decisions about individual instances, so it makes sense that people will maintain accounts for such dimensions. However, in contradiction to general utility theory, people don't maintain just one account, but many, leading to sometimes myopic, and sometimes very limited and "irrational" ("rationality" being what utility theory tells us) decisions.

2.1 Principles of Mental Accounting

Very similar to general accounting principles, our mental accounts have the following (reasonable and obvious) properties –

1. Similar things (e.g., (expenses associated with) two different textbooks) tend to go into one mental account, or, different things (e.g., textbooks and rent) tend to go into different accounts. By similarity, here I mean top-down, structural similarity between the two items, and that the expense/money/cost comes out as an aligned dimension (Markman and Gentner, 1993) in the similarity comparison.
2. Related things (e.g., gift and gift-wrap, pen and ink) tend to go into one mental account, or, unrelated things (e.g. shoes and blanket) tend to go to different accounts.
    a. Corollary: Relatedness is context-sensitive, therefore, providing an external goal that makes things related (Barsalou, 1991), will tend to push them into one mental

account (like going on a camping trip as the goal for buying the shoes and blanket in example above).

   b. This point is similar to that made in the *goals-representativeness* model of Brendl et al (1998). Mental accounts do seem to bear similarities to goal-derived categories, however with one important difference. In a goal-derived category, all members contribute positively to achieving the goal; but a mental account can have entries that contribute negatively as well (entries corresponding to losses).

3. Externally enforced budgets will tend to push things into one mental account (e.g., the last week of a usual month I have about $50 to spend – so haircut, beer, food, all are considered in one account).
4. Bottom-up effects: The above three are variations of *top-down* effect in mental accounting. Similarity, Relatedness, and External Budgets affect our processing of different instances for consideration into different mental accounts. There are *bottom-up* effects as well, which are not guided by such high-level constraints, but just low level similarity of the dimensions (instances of money). Some examples could be –
   a. Temporal locality and/or spatial locality (like Thaler's (1999) example of how he could justify the astronomical expenses in Switzerland, as he had received a hefty fee for his talk, but if he was paid the same fee a week earlier in New York, that wouldn't have created the same effect (a case of both spatial and temporal locality of expenses and earning led them to be considered in the same account)). As expected, temporal and spatial remoteness will push things into different mental accounts.
   b. Perceptual salience/closeness – Sometimes, we make comparisons of pure dimensional values as if they were independent of any larger schema they participated in, e.g., one can compare the color of the Sun and an orange.
   c. Conventions – Having similar units for describing things that could be conceptualized differently (length and perimeter are both measured in similar units), as well as words in language – bright, intense, high, etc, which can be used to make cross-dimensional comparisons.

The above three (4a, 4b and 4c) might give rise to a dimensional hierarchy, as shown in Figure 1, which reflects the ease of comparison of values along the dimensions, when they are considered all by themselves, in a bottom-up fashion. One might speculate that this dimensional hierarchy arises out of top-down comparisons. Bottom-up effects of comparability can clearly influence mental accounting, as the ease of comparison makes two different instances better candidates for being considered in a mental account.

However, the current paper is most concerned with the effect of top-down processing (1, 2, and 3) and most importantly the affect of top-down structural comparability and alignability on mental accounts. Besides accounting for money, we do a lot of dimensional processing that's very similar to processing any other continuous dimension. In the next sections, I will focus on our representations and processes of/with quantitative, continuous dimensions.

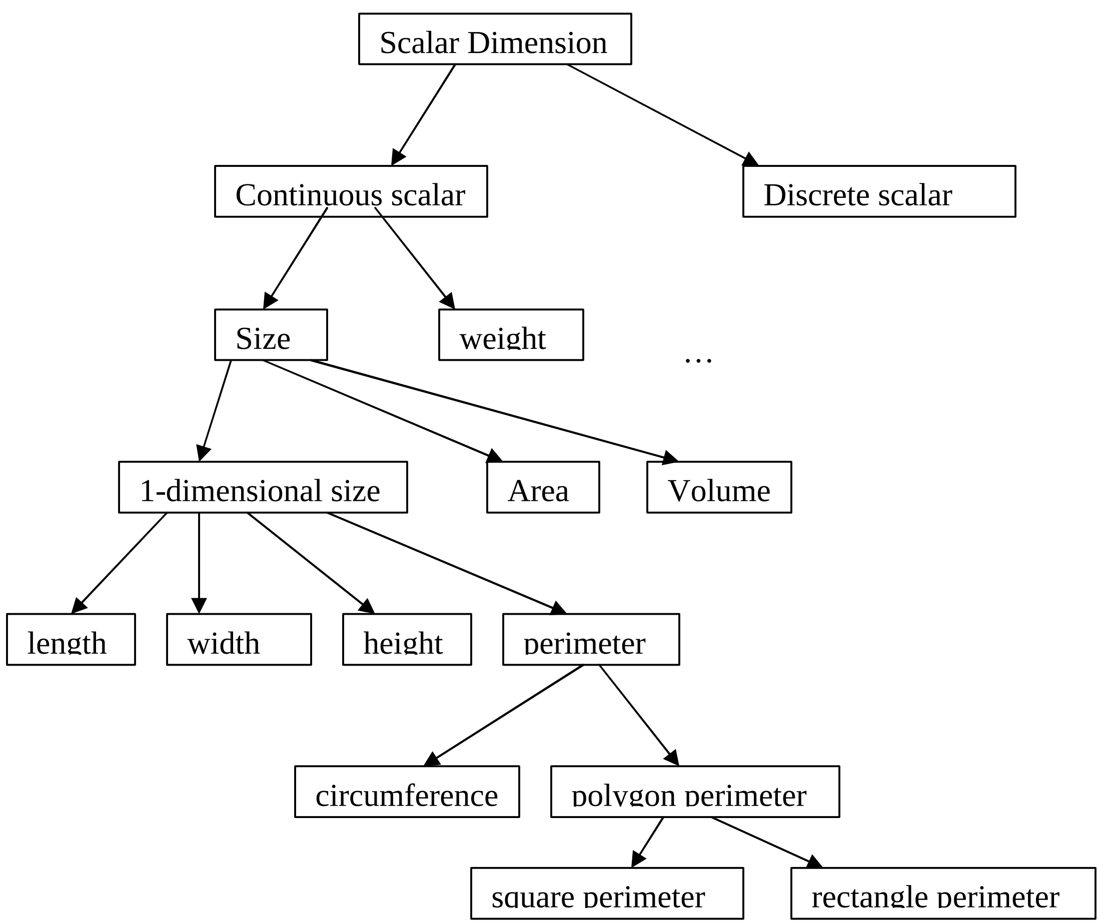

Fig 1. An example dimensional hierarchy for sizes of things. Two nodes closer in this hierarchy stand for more comparable dimensions than two farther, in a bottom-up, dimensional comparison.

3 Dimensions

Many of the physical dimensions (size, distance, duration) are perceptually continuous; and many conceptual dimensions (pleasantness, number) are also subjectively continuous. Although our sensory abilities to perceive these dimensions seem to be quite rich and continuous, our memory of them seems discrete[5]. We live in a world of quantitative dimensions, and ability to reasonably accurately compare, estimate, and comprehend quantitative values is necessary for understanding and interacting with the world. Our life is full of evaluations and rough estimates of all sorts. How long will it take to get there? Do I have enough money with me? How much of the load can I carry at once? These everyday, common sense estimates utilize our ability to draw a quantitative sense of world from our experiences. One might not know anything about power, RAM or disk-speed of computers, but by being exposed to the domain, we soon learn to makes sense of these numbers. This kind of information seems to be an integral part of our knowledge of categories in the world.

Peterson and Beach (1967) review a set of psychological studies to test people's abilities to derive statistical measures of populations and samples such as proportions, means, variances, correlations, etc. Although some of the studies have conflicting results, the key result that people are quite good at abstracting measures of central tendency, and there are systematic differences in intuitive judgments and objective statistical values. For example, people don't weigh all deviations equally in computing variance. Instead, they are quick to believe in a distribution even from a few samples, and tend to be conservative in revising their measures on the basis of new data points. Tversky and Kahneman (1974) reported people's assessment of probabilities of uncertain events. In a very important set of results, they show that people make systematic errors because of a set of heuristics that they employ.

---

[5] Qualitative Process Theory (Forbus, 1984) has a very relevant representational choice for such. It assumes that there are a small and finite set of qualitative distinctions that one needs to make on any infinite continuous range of a parameter; which is sufficient to talk about the qualitatively interesting properties of the system. So, one should make only the necessary and relevant distinctions, e.g. 0 and 100 degree Celsius partition the scale of temperature of water into regions in which qualitatively different behaviors happen (state changes). Further, ordinal relations between the various points in the quantity space provide (at least) a partial ordering of these parameters. From just these, one can do very interesting and rich reasoning.

Brown and Siegler (1993) proposed a framework for real-world quantitative estimation called the *metrics and mappings* framework. They make a distinction between the quantitative, or metric knowledge (which includes distributional properties of parameters), and ordinal information (mapping knowledge). Through a set of experiments they showed that the ways people revise and assimilate quantitative and ordinal information are quite different. Their experiments involved subjects making quantitative estimates of populations of ninety-nine countries. Afterwards participants were told the correct value for populations of 24 of the countries, and then they went through and re-estimated the full set of 99 populations (the 24 seed countries and 75 transfer countries). Metric properties (as measured by sum of absolute value of errors for all of the estimates) improved, but ordinal knowledge (the order of different population, as measured by the rank-order correlation) remained unchanged. On the other hand, telling them laws like “Population of European countries are generally overestimated”, and “Population of Asian countries are generally underestimated”, improved their ordinal knowledge.

There are some interesting results, which are very telling about how our low-level processing of these dimensions might be happening. Symbolic distance effect is the phenomenon that it is easier to discriminate two items on a single dimension when they are far apart than when they are close together. The most intriguing version of this is when subjects are presented adjacent pairs like A>B, B>C, and C>D (from which they can infer A>C, for example, but they aren’t told that). Even though they are only shown adjacent pairs, subjects are faster and more accurate with remote pairs (A-C, A-D, B-D) (Potts, 1972). Then there is the congruity effect that says that it is easier to discriminate two objects when the form of the question matches the magnitude of the objects, e.g., it is easier to choose the larger, rather than the smaller of elephant and rhino; but it is easier to choose the smaller, rather than the larger, of mouse and cat. The last of these is the bowed serial position effect, which says that it is easier to discriminate items at the end of the scale than items at the middle of a scale (Shoben et al, 1989).

In the next section, I present how one could acquire/learn this sense of the quantitative.

4 Learning the sense of the quantitative

A large part of the sense of quantitative comes from exposure to multiple exemplars (cars, computers, etc). I will assume that we have structured representations for the exemplars, and we are gradually building up our categories by structural clustering. SEQL is a structural account for generalizations based on experiential knowledge (Skorstad, Gentner and Medin, 1988; Kuehne *et al*, 2000). With a large number of examples, such generalizations will serve to ease the organization of information, and also help in defining typicality and representativeness with respect to parameter values, e.g., the number of cylinders in a sports car, the weight of a truck, etc. Given a sequence of exemplars, SEQL tries to compute the structural overlap between them using SME (Structure Matching Engine, Falkenhainer, Forbus and Gentner, 1989), and if there is sufficient overlap, that is abstracted away as a generalization, if not, the exemplar is kept as such in the working memory. Each incoming exemplar is matched to all the generalizations and exemplars in the working memory. After going through all the exemplars, SEQL then provides us with a bunch of generalizations, and a bunch of exemplars that didn't go into any of the generalizations. In the Skorstad et al (1988) paper, SEQL had been used to model sequence effects, namely the effect of order of presentation of the exemplars on the generalizations abstracted. I think that there are many more interesting things one could do and explain using the underlying notion of structural alignment to build our category structure, trying to learn the sense of the quantity being one of them that highlights a lot of interesting voids in the model.

SME and SEQL have to be extended so that they can make sense of quantitative information. That is, they already can handle representations with numerical parameters, but similarity in aligned numerical parameter values does not affect the perceived similarity of the descriptions compared. How do we generalize along quantitative dimensions? For domains like the price of a computer, for example, there is no formal way to carve the parameter space into qualitatively distinct regions (in the QP Theory style). Yet, with exposure to multiple examples, we sharpen our notions of what it means for a personal computer to be cheap, medium-range, or expensive. For most of dimensions like the sizes of objects, price of particular consumer goods, etc., we typically encounter multiple different values for a particular parameter whose statistical distribution is unknown to us. By exposure to quantitative dimensions like length, price, weight, we build a sense of the quantity. The sense of quantity in a dimension (like “power of computers”) has two distinct components –

1. *Symbolic discretization* – The landmarks in the dimension (possibly corresponding to (the power of) handhelds, laptops, desktops, servers, supercomputers). These are arrived at by looking at the value of the alignable dimensions along structurally different generalizations.
2. *Distributional information* – Distributions within each of the generalizations – This ties the above symbolic values like power of desktops to a distribution, so we know about ranges, representative values, variability (power of laptops (because of size constraints) is relatively less variable than desktops which is way lesser than those of supercomputers (extremely wide range of performance)). These distributions might also be providing a finer sense of quantity, useful in coming-up and fine-tuning with categorical estimates. Also, if within a generalization we find that a lot of quantitative attributes have multi-modal distributions, that might trigger considering breaking up that category into sub-categories.

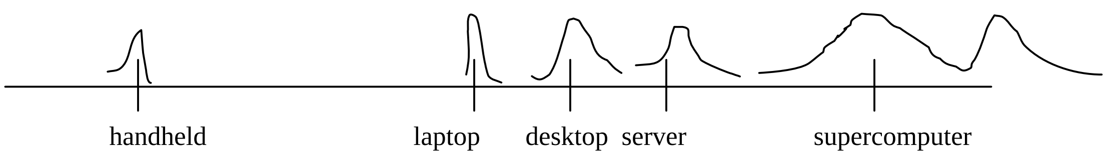

Fig 2. The two parts to the knowledge of a dimension. For the power of computer, the first is knowing that {handheld, laptop, desktop, server, supercomputer} serves as a neat discretization of the space. And the second part is the distributional information tied to each of these.

So, the idea is that one takes many (say, a hundred) structured representations of computers, and finds the structurally similar clusters – lets say that’s successful and we find clusters corresponding to handhelds, laptops, desktops, servers, and supercomputers. For dimension that’s aligned across all of these, like power, now one can find a symbolic discretization, and it corresponds to the (partial) order produced by the values of that dimension in different clusters. Within each of the clusters, one can either incrementally, or at the end of producing the clusters, can build the distribution of that parameter. There are two serious problems with this model –

1. Maintaining feature correlations – the simplest mechanism might be having strict thresholds to be considered in the same generalization. It seems reasonable to assume that feature correlations are maintained at the level of subordinates, and not so much for basic and higher level. Since subordinates are very similar, a high threshold there makes sense.
2. Structural clusters might not always partition the space in neat nice orders. What if two different dimensions partition the space in different orders?

These extensions and the model for learning these quantity scales is not fully fleshed out. Currently I am building a case library of many examples rich in both qualitative and structural information, which will be used to experiment with some of these ideas.

Money is very much similar to other dimensions (and more so to *accountable* dimensions). The real claim of this paper is that any of these dimensions are not independent, all by themselves, but have a role in the larger, relational structure of the event or the object that the dimension describes. And when we think of an object, or an event, the structured representation of it comes to mind, and it is difficult to tear out the dimension from that and look at it independently[6]. And so in the Tversky's calculator-jacket example, people are thinking $5-saved-on-a-$15-calculator, and not $5 saved. In fact, in the process of learning dimensions, we have built symbolic discretizations and distributional information about/of the space, and this quantity information is very tied to the structural clusters which it represents. So, we don't have global, over-arching notions of quantity like "price of all things which can be bought" or "length" in our head, but "price of computers" and "length of people". These specialized dimensions like "length of people" and "price of computers" are interesting and sensible because not only can these dimensions be compared, by themselves, but, the overall structures of which they are a part are also structurally comparable. So, when we see something that has a particular dimension, what comes to mind is not other values on that dimension, but other structurally similar things to it (examples or categories/generalizations) that also have that dimension and they are alignable. If a category is retrieved, we have also a quantity scale for that dimension tied to the category

[6] Although we are capable of that, and do that, sometimes purposefully, sometimes unwittingly, and that is what I call the bottom-up effect.

representation where we can map it[7]. Dimensions are differentiated when the overall structures are not comparable. Differentiated dimensions (gift money, hard-earned money, etc.) tend to go into different mental accounts. So, the higher the structural comparability of the overall structures, the more chances of two (or more) different instances being considered in the same mental account. Some of the other important factors that might mediate the creation of mental accounts, and the entries in our mental accounts are –

1. Irreplacability
2. Uniqueness
3. Personal/Historical significance
4. Protected values

None of these will be explained by a top-down structural comparability account.

7 Conclusion

In this paper, I have tried to argue that to understand mental accounting properly, it might be instructive to have a better understanding of dimensions in general. Money is very similar to most dimensions, but also has the interesting property of accountability. The emphasis on understanding dimensions seems to be to abstract it away from concrete instances. So we have units and scales and measures of comparison, so one might get carried away with that idea and start thinking that the dimensions are all by themselves – “length is length” or “money is money”. But if one looks closely at how are notions associated with dimensions develop, it seems plausible that they are very tied to the overall representation of the instance they represent. I talked about how we can get SEQL to learn this sense of quantity by exposure to multiple examples. I also presented the principles that I think are underlying mental accounting. To me, this looks quite exciting, and along the way of building simulation models of mental accounting phenomenon.

[7] This can also help explain Hsee’s (1998, 1999) results on attribute evaluability, where people’s rank order of evaluations of multiple objects differed where the objects were evaluated separately or jointly.

8 References

Barsalou, L.W. (1991). Deriving categories to achieve goals. In G. H. Bower (Ed.), The psychology of learning and motivation: Advances in research and theory, 1-64, San Diego, CA: Academic Press.

Brendl, C.M., Markman, A. and Higgins, T.E., (1998) , Mentale Kontoführung als Selbst-Regulation. Representativität für zielgeleitete Kategorien [Mental accounting as self-regulation. Representativeness to goal-derived categories], *Zeitschrift für Sozialpsychologie. Sonderheft Konsumentenpsychologie*, **29**, 89-104.

Brown, N. R., & Siegler, R. S. (1993). Metrics and mappings: A framework for understanding real-world quantitative estimation. *Psychological Review,* **100**(3), 511-534.

Cech, C.G., and Shoben, E.J., (2001), Categorization Processes in Mental Accounting, JEP: Learning, Memory and Cognition, 27(3), 800-816.

Falkenhainer, B., Forbus, K. D., & Gentner, D. (1989). The structure-mapping engine: Algorithm and examples. *Artificial Intelligence, 41,* 1-63.

Forbus, K. D. (1984). Qualitative process theory. *Journal of Artificial Intelligence, 24,* 85-168.

Henderson, P.W. and Peterson, R.A., 1992, Mental Accounting and Categorization, Organizational Behavior and Human Decision Processes, **51**, 92-117.

Markman, A. B., & Gentner, D. (1993). Structural alignment during similarity comparisons. *Cognitive Psychology*, ***25****,* 431-467.

Peterson, C.R., and Beach, L.R. (1967). Man as an intuitive statistician, *Psychological Bulletin*, **68**(1), pp 29-46.

Potts, G.R., Information processing strategies used in encodings of linear orderings, Journal of verbal learning and verbal behavior, 72, 11, 727-740.

Skorstad, J., Gentner, D., & Medin, D. (1988). Abstraction processes during concept learning: A structural view. *Proceedings of the Tenth Annual Conference of the Cognitive Science Society*, 419-425.

Tversky, A., and Kahneman, D. (1981). The framing of decisions and psychology of choice. Science, **211**, 453-458.

Thaler, R.H., (1999). Mental accounting matters, *J. Behav. Dec. Making,* **12,** 183-206.