How to Make Decisions: Consider Multiple Scenarios, Consult Experts, Play Down Emotions – Quantitative Explanation of Commonsense Ideas

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Abstract

There are a lot of commonsense advices in decision making: e.g., we should consider multiple scenarios, we should consult experts, we should play down emotions. Many of these advices come supported by a surprisingly consistent quantitative evidence. In this paper, on the example of the above advices, we provide a theoretical explanations for these quantitative facts.

1 Need to Consider Multiple Scenarios: Theoretical Explanation of an Empirical Observation

Empirical observation that needs explaining. How do companies make big decision and how often do they make right decisions? Analyzing dozens of cases, P. C. Nutt [4, 9] concluded that in the vast majority of cases, companies considered only one alternative.

It turns out that in such cases, the correct decision was made in half of the times (actually, slightly less than half); in other 50% of the cases, the decision led to a failure.

In several cases, companies considered two different alternatives before making a decision. In such cases, the companies were successful $\frac{2}{3}$ of the time.

How can we explain this empirical data?

Our explanation. Usually, a big company has one major competitor. Thus, a company's project leads to a success if this project is better than a project implemented by a competing company.

Let us first consider the case when a company considers only one alternative. Since the vast majority of companies only consider one alternative, it is reasonable to assume that the competitor also considers only one alternatives. One of the two considered alternatives is better. In our analysis, we consider both companies; so, the situation is symmetric: the probability that the first company's project is better is the same as the probability that the second company's project is better. These two probabilities should add up to 1, so each company prevails with probability 50%. Thus, the 50% observation is explained.

On the other hand, if a company consider two alternatives, then, since a competitor usually considers only one, now we have three possible projects to consider. The probability for each of these projects to be the best is the same – i.e., $\frac{1}{3}$. The first company wins if one of its two projects is the best – i.e.,

- either its first project is the best
- or its second project is the best.

The probability of this happening is equal to

$$\frac{1}{3} + \frac{1}{3} = \frac{2}{3}.$$

This explains the second empirical observation.

Comment. In the one-alternative case, we can also take into account that sometimes, the competitor considers two alternatives. In such cases, the probability for the first company to succeed is $\frac{1}{3}$. So:

- in most cases, the company succeeds with probability $\frac{1}{2}$, but
- in some cases, it succeeds with a lower probability $\frac{1}{3}$.

Thus, overall, the probability of success is slightly lower than $\frac{1}{2}$ – which is exactly what was observed.

Comment. These explanations were previously announced in [1].

2 Using Experts: Theoretical Explanation of an Empirical Observation

Empirical observation that needs explaining. It is known that the use of expert knowledge makes predictions more accurate. This makes perfect sense.

From the commonsense viewpoint, we can expect all kinds of improvements. Interestingly, it turns out that there is not much of variability: a typical improvement – as cited, e.g., in [12] on the example of meteorological temperature forecasts – is that the accuracy consistently improves by 10%.

How can we explain quantitative phenomenon?

Towards an explanation. Use of expert knowledge means, in effect, that we combine an estimate produced by a computer model with an expert estimate.

Let σ_m and σ_e denote the standard deviations, correspondingly, of the model and of the expert estimate.

In effect, the only information that we have about comparing the two accuracies is that expert estimates are usually less accurate than model results: $\sigma_m < \sigma_e$. So, if we fix σ_e, then the only information that we have about the value σ_m is that it is somewhere between 0 and σ_e.

We have no reason to assume that some values from the interval $[0, \sigma_e]$ are more probable than others. Thus, it makes sense to assume that all these values are equally probable, i.e., that we have a uniform distribution on this interval; see, e.g., [3]. For this uniform distribution, the average value of σ_m is equal to $0.5 \cdot \sigma_e$. Thus, we have

$$\sigma_e = 2 \cdot \sigma_m.$$

In general, if we combine two estimates x_m and x_e with accuracies σ_m and σ_e, then the combined estimate x_c – obtained by minimizing the sum

$$\frac{(x_m - x_c)^2}{\sigma_m^2} + \frac{(x_e - x_c)^2}{\sigma_e^2}$$

is

$$x_c = \frac{x_m \cdot \sigma_m^{-2} + x_e \cdot \sigma_e^{-2}}{\sigma_m^{-2} + \sigma_e^{-2}},$$

with accuracy

$$\sigma_c^2 = \frac{1}{\sigma_m^{-2} + \sigma_e^{-2}};$$

see, e.g., [11].

For $\sigma_e = 2\sigma_m$, we have $\sigma_e^{-2} = 0.25 \cdot \sigma_m^{-2}$, thus

$$\sigma_c^2 = \sigma_m^2 \cdot \frac{1}{1 + 0.25} = \sigma_m^2 \cdot \frac{1}{1.25} = 0.8 \cdot \sigma_m^2,$$

hence

$$\sigma_c \approx 0.9 \cdot \sigma_m.$$

So we indeed get a 10% increase in the resulting prediction.

Comment. This explanation was previously announced in [13].

3 Why Should We Play Down Emotions: A Theoretical Explanation

Formulation of the problem. There are very good people in this world, people who empathize with others, people who actively help others. Based on all the nice and helpful things that these good people do, one would expect that other people would appreciate them, cherish them, and that, in general, their attitude towards these good people would be positive. However, in real life, the attitude is often neutral or even negative. The resulting emotions hurt our ability to listen to their advice and thus, improve our decisions.

Why? Is there a rational explanation for these emotions?

Towards explanation. Each person's happiness is determined not only by this person's satisfaction with life, but also by other people's happiness: it is difficult to enjoy good life if many people around you suffer. Let us denote the Person i's satisfaction with life by s_i, and this person's level of happiness by h_i. Then, h_i depends on s_i and on h_j for all other j.

In the first approximation, we can assume that this dependence is linear:

$$h_i = s_i + \sum_{j \neq i} a_{ij} \cdot h_j.$$

A very good person v is very happy when others are happy and suffers when others suffer, i.e., $a_{vj} \approx 1$ for all j.

Let us consider a simplified model in which everyone's satisfaction is the same $s_i = s > 0$, everyone's attitude to v is the same: $a_{jv} = a$, and we ignore attitude towards everyone else. Then, $h_v = s + n \cdot h_j$, where n is the number of people except for v, and $h_j = s + a \cdot h_v$. Substituting the above expression for h_v into this formula, we get

$$h_j = s + a \cdot s + a \cdot n \cdot h_j,$$

so

$$h_j = \frac{a + a \cdot s}{1 - a \cdot n}.$$

If a is reasonably positive, i.e., if $a > \frac{1}{n}$, then $h_j < 0$ – i.e., everyone will be unhappy. Thus, the desire to be happy implies that $a < \frac{1}{n}$.

With n in billions, this explains why on average, the attitude should be either neutral or negative.

Commonsense explanation. From the common sense viewpoint, the above mathematics makes perfect sense: A very good person is unhappy if other people are unhappy. If we empathize with this person, we become unhappy too, and since people do not want to be unhappy, they prefer (at best) to ignore others' unhappiness – or even blame them for their own unhappiness.

Comment. The above theoretical explanation was previously announced in [5].

This explanation is somewhat similar to the explanation of other similar phenomena which was presented in [8] based on formal decision theory (see, e.g., [2, 6, 7, 8, 10]).

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