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TRUST, BELIEF AND DISINFORMATION

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Abstract. The paper deals with one possibility to model human (or social) trust and influence on this. Our approach is based on a derivation of classical information theory. The differences between the probability description (model) and reality is a crucial point of our concept "disinformation".

Key words. Trust, belief, information, disinformation, trust influence

Mathematics Subject Classification: Primary 93A30, 94A17; Secondary 03B42.

1 Introduction

Trust and belief are common phenomena. The people, generally, have a confidence to different information resources. The informational content of received messages changed a specified level of trust to the given resources. The information description of trust is based on Gambetta's idea [1]. Our subjective probability model is one side of information's interaction. The second one is really existing probability. The difference between this can be passive (imperfect observation, knowledge, etc.) or active (to be able to influence neighborhood).

2 Duality of Classic Information and Disinformation

Measures of information suppose real distributions of probabilities. The dual disinformation distribution assumes that heading distribution of probability is not available. In this case we must work with its model that can be different from real situation [1, 3]. Comparative situation in which the model and reality are different is in Table 1. Heading distribution will be denoted as $p(x)$ (respectively $p(x, y)$), its model (the estimation) as $e(x)$ (respectively $e(x, y)$) and the comparative probability as $q(x)$.

[1] Gambetta's definition was derived as a summary of the contributions to the symposium on trust in Cambridge (England, 1988): *Trust (or symmetrically, distrust) is a particular level of the subjective probability with which an agent will perform a particular action, both before we can monitor such an action (or independently of our capacity of ever to be able to monitor it) and in a context in which it affects our own action.*

Table 1 Shannon's classical theory in comparison with the concept of disinformation

MEASURE	SHANNON'S, CLASSICAL	CONCEPT OF DISINFORMATION
Entropy	$H(X) = -\sum_{x} p(x) log\, p(x)$	$H(X;\mathrm{e}) = -\sum_{x} p(x) log\, e(x)$
Mutual information	$I(X:Y) = \sum_{x}\sum_{y} p(x,y) log \frac{p(x,y)}{p(x)p(y)}$	$I(X:Y;e) = \sum_{x}\sum_{y} p(x,y) log \frac{e(x,y)}{e(x)e(y)}$
Divergence of probability models	$D(p\|q) = \sum_{x} p(x) log \frac{p(x)}{q(x)}$	$D(p\|q;e) = \sum_{x} p(x) log \frac{e(x)}{q(x)}$
Symmetrical divergence of probability models	$J(p\|q) = \sum_{x} (p(x) - q(x)) log \frac{p(x)}{q(x)}$ $J(p\|q) = D(p\|q) + D(q\|p)$	$J(p\|q;e) = \sum_{x} (p(x) - q(x)) log \frac{e(x)}{q(x)}$ $J(p\|q;e) = D(p\|q;e) + D(q\|e)$

It is possible to use $p(x)$ as a model of the temporary situation and $e(x)$ as a model of new state after spreading some message, e.g., as a model of trust dissemination.

3 Information Control Model

The model of information control [4] is shown in Figure 1. This model is a transmitting channel that has the same input and the output alphabet. The alphabet X with probability distribution $p(x)$ is on the input. The alphabet X with probability distribution $q(x)$ is on the output which is joined with the noise with the alphabet X with the probability distribution $r(x)$. The alphabet X with the probability distribution $q(x)$ is on the output. The interference of the input signal (X, p) by the control signal (X, r) to the output signal (X, q) is measured as symmetrical divergence J(p||q).

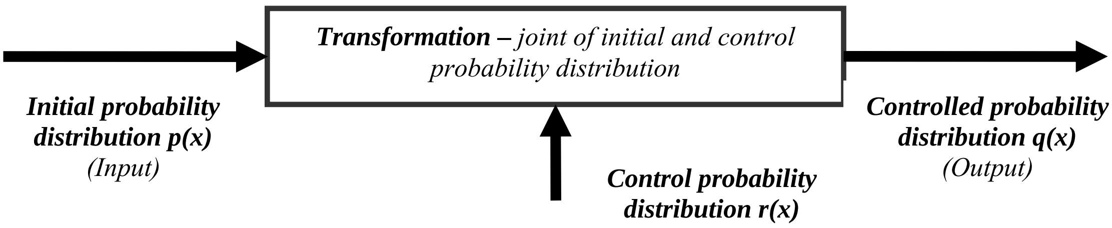

Figure 1 The model of information control

We can adjust to finish this measure by the following:

$$J(p\|q) = \sum_{x \in X} (p(x) - q(x)) log \frac{p(x)}{q(x)} = \sum_{x \in X} (p(x) - r(x) + r(x) - q(x)) log \frac{p(x)}{q(x)} \frac{r(x)}{r(x)} =$$

$$= \sum_{x \in X} ((p(x) - r(x)) - (q(x) - r(x))) \left(log \frac{p(x)}{r(x)} - log \frac{q(x)}{r(x)} \right) =$$

$$= \sum_{x\in X} \big(p(x)-r(x)\big)log\frac{p(x)}{r(x)} - \sum_{x\in X} \big(p(x)-r(x)\big)log\frac{q(x)}{r(x)} -$$

$$- \sum_{x\in X} \big(q(x)-r(x)\big)log\frac{p(x)}{r(x)} - \sum_{x\in X} \big(q(x)-r(x)\big)log\frac{q(x)}{r(x)} =$$

$$= J(p\| r) + J(q\| r) - \sum_{x\in X} \big(p(x)-r(x)\big)log\frac{q(x)}{r(x)} - \sum_{x\in X} \big(q(x)-r(x)\big)log\frac{p(x)}{r(x)} =$$

$$= J(p\| r) + J(q\| r) - J(p\| r;q) - J(q\| r;p) \qquad (3.1)$$

The final form is

$$J(p \,\|\, q) = \big[J(p \,\|\, r) - J(p \,\|\, r,q)\big] + \big[J(q \,\|\, r) - J(q \,\|\, r,p)\big], \text{ where} \qquad (3.2)$$

$$J(p\| r;q) = \sum_{x\in X} \big(p(x)-r(x)\big)log\frac{q(x)}{r(x)} \qquad J(q\| r;p) = \sum_{x\in X} \big(q(x)-r(x)\big)log\frac{p(x)}{r(x)}. \qquad (3.3)$$

The decomposition of "distance = difference" $J(p\| q)$ to both of terms is divided into two parts (the first term $\big[J(p\| r) - J(p\| r;q)\big]$ and the second one $\big[J(q\| r) - J(q\| r;p)\big]$). The first of both that is interference of input reality by the control impulses, i.e. "creation of the information bubble" and the second one this information bubble is compared with the reality. It can act positively (strengthening) or negatively (correction, i.e. complete or partial reduction). Each of the terms has two components. First one is a symmetrical divergence between input (output) and active incidence. The second one is a disinformation (information) correction. The former term in both of differences is an idealized "distance" between the input (output) and the incidence, the later term is actually a model of second side reaction, i.e. output on control and input or input on control and output.

We cannot help remarking what the apparatus of information theory (in classical Shannon's version) is able to do. It is convenient for measuring, quantifying and evaluation. Classical theory does not involve the orientation. Mutual information is symmetrical, it does not discern between the input (cause) side and the output (consequence) side. Nevertheless, the classical information theory is able to represent such systems. But the results demonstrate some relationships (binding rate, interconnect), no flux, i.e. running from anywhere to anywhere. More information about this topic can be found in [2].

4 Demonstration Examples

Two examples present the technique introduced above. They are the examples of recognition the result of fictive aggressive advertisement (puffery). The first one, relatively neutral, where it did not come about the essential interference, i.e. no trust turn, and the second one, successful, where it came about behaviour change, i.e. the trust interference.

The probability distribution $p(x)$ is the model of the market shares before the advertisement; the distribution $r(x)$ is the model of the market shares which is expected by the advertisement. The distribution $q(x)$ is the model of the model of the market shares after advertisement release.

Figure 2 shows the first example, when the neutral advertisement took effect. The probabilities of product A, i.e. the probability of purchase ahead of advertisement *p(i)* changed from the value 0,25 to the probability of purchase after advertisement *q(i)* = 0,35 only. The probabilities of other products stood the same or decreased (especially product *D*). The market did not accept the incidence of advertisement.

Product	Probability of purchase ahead of advertisement	Probability of purchase pretended by advertisement	Probability purchase after advertisement	Terms J(p||r) and J(p||r)	Terms J(p||r;q) and J(p||r;q)	Difference J(p||r)-J(p||r;q)	Terms J(q||r) and J(q||r)	Terms J(q||r;p) and J(q||r;p)	Difference J(q||r)-J(q||r;p)	Terms J(p||q) and J(p||q)
	p(i)	*r(i)*	*q(i)*							
A	0,2500	0,9000	**0,3500**	1,2012	0,8857		0,7494	1,0164		0,0485
B	0,1667	0,0250	*0,1500*	0,3877	0,3662		0,3231	0,3421		0,0025
C	0,1250	0,0250	*0,1200*	0,2322	0,2263		0,2150	0,2206		0,0003
D	0,4000	0,0250	*0,3000*	1,5000	1,3444		0,9859	1,1000		0,0415
E	0,0583	0,0250	*0,0800*	0,0407	0,0559		0,0923	0,0672		0,0099
				3,3619	2,8785	**0,4834**	2,3657	2,7463	**-0,3807**	**0,1027**

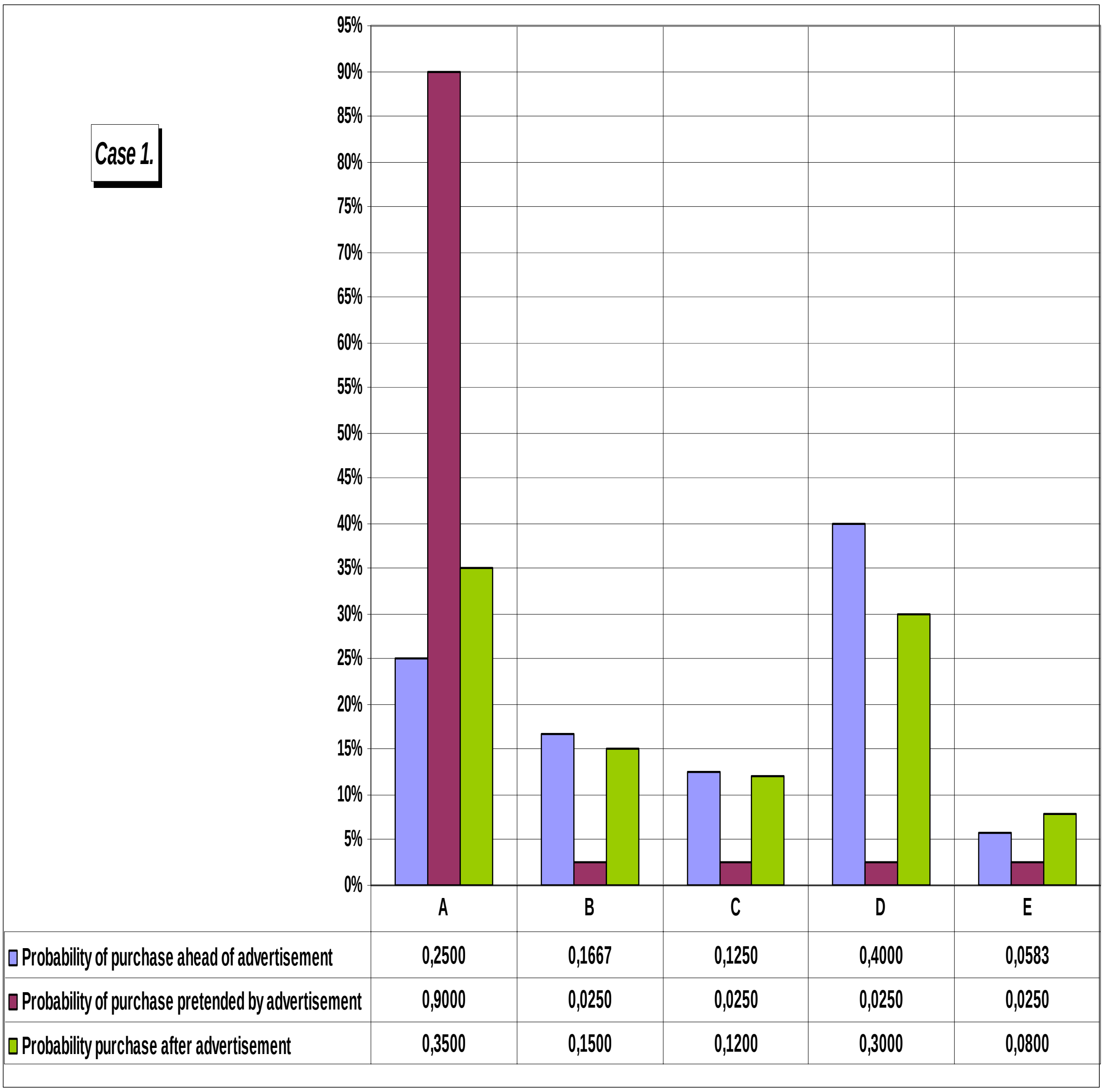

Figure 2 The case of neutral advertisement

Figure 3 illustrates the second example, when the aggressive advertisement took effect. The probability of purchase ahead of advertisement *p(i)* of the product *A* increased from the value 0,25 to the probability of purchase after advertisement $q(i) = 0{,}55$. The probabilities of other products decreased (especially product *D* over again). The market accepted the incidence of advertisement.

Product	*Probability of purchase ahead of advertisement*	*Probability of purchase pretended by advertisement*	*Probability purchase after advertisement*	*Terms $J(p \Vert r)$ and $J(p \Vert r)$*	*Terms $J(p \Vert r;q)$ and $J(p \Vert r;q)$*	*Difference $J(p \Vert r)$-$J(p \Vert r;q)$*	*Terms $J(q \Vert r)$ and $J(q \Vert r)$*	*Terms $J(q \Vert r;p)$ and $J(q \Vert r;p)$*	*Difference $J(q \Vert r)$-$J(q \Vert r;p)$*	*Terms $J(p \Vert q)$ and $J(p \Vert q)$*
	p(i)	*r(i)*	*q(i)*							
A	0,2500	0,9000	**0,5500**	1,2012	0,4618		0,2487	0,6468		0,3413
B	0,1667	0,0250	*0,1000*	0,3877	0,2833		0,1500	0,2053		0,0491
C	0,1250	0,0250	*0,1200*	0,2322	0,2263		0,2150	0,2206		0,0003
D	0,4000	0,0250	*0,1800*	1,5000	1,0680		0,4414	0,6200		0,2534
E	0,0583	0,0250	*0,0500*	0,0407	0,0333		0,0250	0,0306		0,0019
				3,3619	2,0728	**1,2891**	1,0801	1,7232	**-0,6431**	**0,6460**

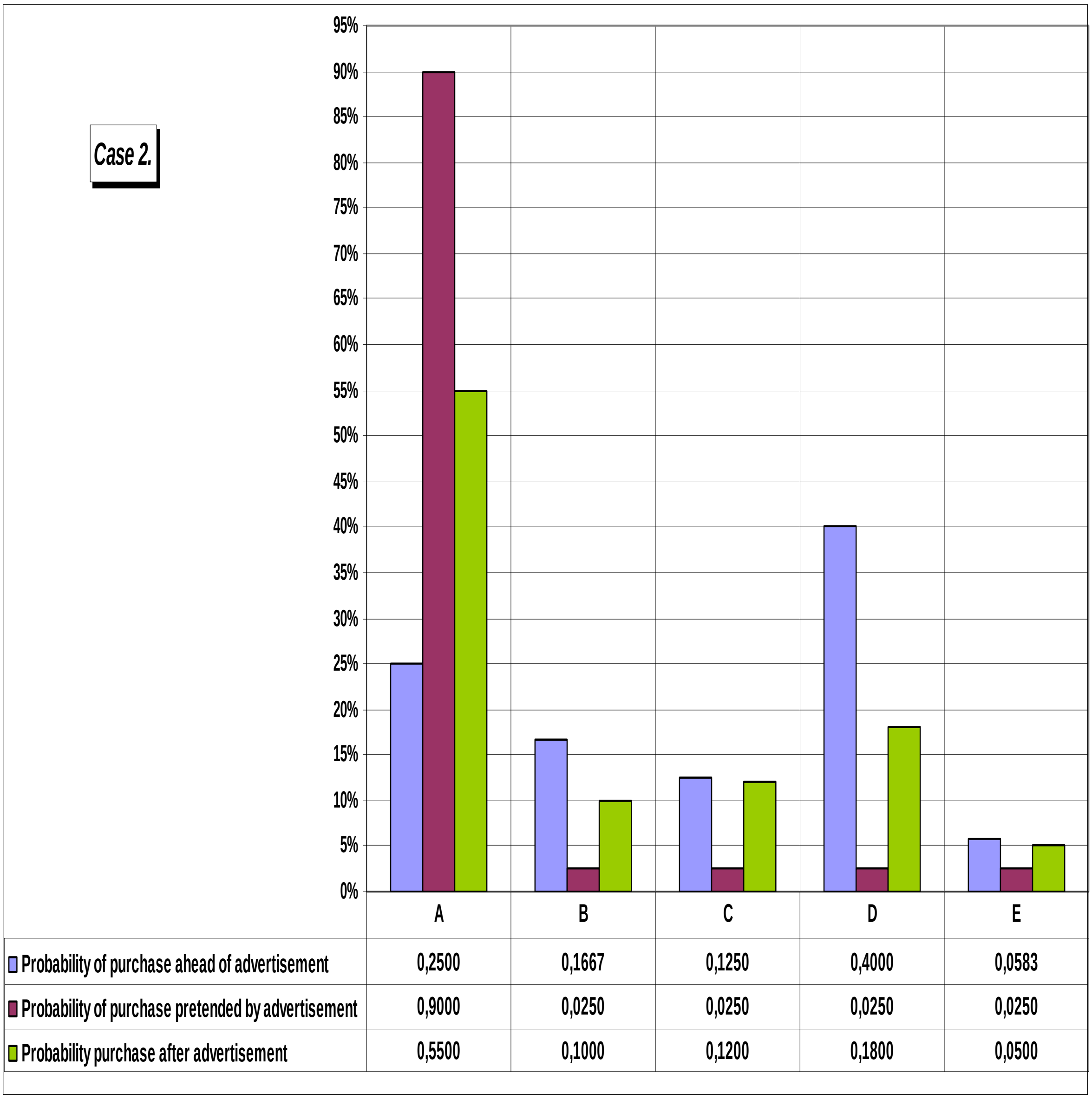

Figure 3 The case of aggressive advertisement

Both examples represent the following situation. The bubble is injected by a control action. It is consecutively corrected by interaction with the environment, in which it took effect. Analogous mechanisms perceptibly operate also on the stock market.

5 Conclusions

We have described the approach to the measurement of the trust by means of disinformation. The information control model was introduced and two examples have presented this technique. The trust representation will be one of the components for the modeling of the trust in the community, e.g. using agent technology.

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