Advances in Mechanism Design: Information Management and Information Design

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1 Introduction

The rapid advance of information technologies has changed our access to information and the nature of decision making. Nowadays, a large amount of information is fully and freely available. The gathering of information has become easier, whereas the processing of information has become increasingly challenging. The changes in our information environment are also reflected in some recent developments in economic theory. Questions such as the following currently receive increased attention. When facing a decision, should one use all of the available information? Or could there be benefits from committing to ignore information? Is ignorance bliss? If so, which information should one focus on?

The recent literature on information management and information design addresses these kind of questions, and most of my research falls into this area. In this article, I wish to provide a brief overview on what information design is, and illustrate some questions and findings.

Let me start by explaining how the area developed, what *information design* and *information management* are, and why these topics can be considered as advances or a subfield of mechanism design.

Microeconomic theory is the study of individual behavior, incentives and the allocation of limited resources. A central element in the toolbox of a micro-theorist is game theory. It provides a basis to build mathematical models of economic situations, which are then used to make predictions about outcomes, based on the assumption that the players who interact with each other behave strategically in order to achieve their own goals. Game theoretic models have helped us to better understand the incentives in markets, organizations, and political campaigns, just to name a few.

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Mechanism design takes this idea one step further. Game theory helps us to better understand incentives, whereas mechanism design shifts the focus to influencing incentives. Mechanism design studies how to design a game (or institution) in order to best achieve a desired objective, taking into account the constraints imposed by the private information of agents.[2] Depending on the application, the designer can be a player in the game or a third party. For example, the designer can be a seller aiming to design a mechanism that maximize his revenue from selling an object to privately informed buyers, or a benevolent planner who wishes to maximize welfare and implement the efficient outcome in a market.

Traditionally, in game theory and mechanism design the information structure is given exogenously: There is common knowledge about the structure of the game, a common prior belief about the distribution of players' types, and players may hold private information about their types. A natural step is to endogenize players' private information and include the information generating process into the mechanism design problem. In this case, the designer has to take into account that now the mechanism has a dual purpose. It influences the incentives to acquire or disclose private information, and is then also used to elicit this private information.

The aforementioned changes in our information environment – advancing from a time in which information gathering was costly to today's information age in which enormous amounts of information are freely available – is reflected in the development of the literature. The literature on mechanism design with endogenous information started off by looking at models in which information is costly.[3] Typically information is provided through a specific information technology, and players are able to increase its precision through costly investments. The literature evolved to studying flexible information acquisition and disclosure, and to also consider costless information.[4]

In this article, two concepts that go hand-in-hand and that I consider to bring new, intriguing ideas to mechanism design are discussed: Information management and information design. *Information management* is based on the observation that in various situations of economic interest a designer may not have the authority to change the rules of the game, for example the market structure, or the organizational structure of a company. Still, he may be able to manage the information available to players in the game, that is, he can influence the information environment and hence use information management to influence the incentives for players. *Information design* builds on the same idea, but provides the designer with even more power to design information. First, it aims to understand how in a given game the information environment affects incentives, and to identify the set of outcomes that can be reached by (re-)designing the information environment. The size of the set of achievable outcomes captures how effective information design can be in a specific setting. Second, it analyzes how to design the information environment to influence the

[2] Information asymmetries create incentives for players to strategically misrepresent their types, which imposes restrictions on the outcomes that can be implemented. A mechanism first has to elicit the private information of players, to then use it to determine the outcome.

[3] See for example Persico 2000; Ganuza and Penalva 2010; Shi 2012.

[4] Examples include Kessler 1998 and Bergemann and Pesendorfer 2007.

incentives of self-interested players and to best achieve a given objective. Information design is an addition to the toolbox of a mechanism designer.

2 Illustrations

To illustrate some basic ideas and prospects of information management and information design, I discuss two examples of problems that I have worked on: The role of the information environment – especially the buyer's private information – in an optimal pricing problem, and information management in a promotion contest.

2.1 Buyer's Information and Monopoly Pricing

Consider a standard, simple buyer-seller model, in which a seller (she) wants to sell one object to a buyer (he). Both players are risk-neutral. The buyer's valuation for the object, v is randomly drawn from the uniform distribution on $[0,1]$. The seller's marginal cost is zero. The seller's cost and the distribution of the buyer's valuation are common knowledge.

The seller makes a take-it-or-leave-it offer to the buyer. If a buyer with valuation v and the seller trade the object at price p, then the seller's payoff (*revenue*) is $r = p$, and the buyer's net payoff (*surplus*) is $u = v - p$.

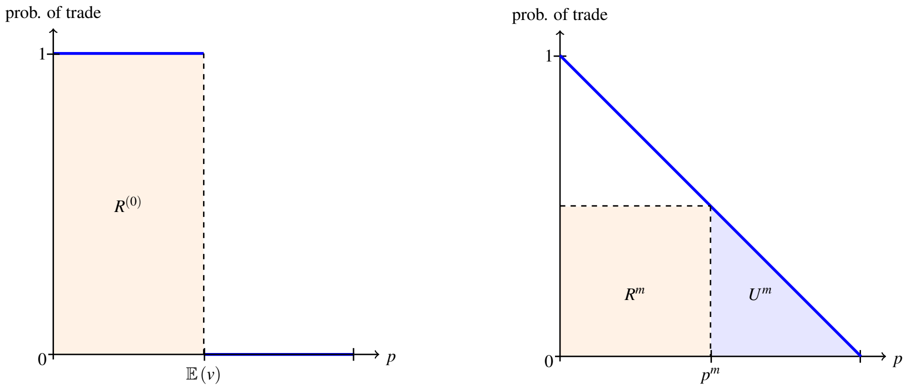
The buyer's private information. In most environments, a buyer has some private information about his valuation for an object. To get an idea of how the private information of the buyer influences the outcome, consider first the two extremes: the case in which the buyer has no additional information about his valuation, and the case in which he is privately informed about his valuation.

In the first case, information is symmetric: both the buyer and the seller only know the distribution of the buyer's valuation. For any price p announced by the seller, the buyer can base his decision whether to buy or not only on the distribution of his valuation. For a risk-neutral buyer it is optimal to trade if and only if his expected value, here $\mathbb{E}(v) = \frac{1}{2}$, is at least as high as the price. It is optimal for the seller to charge a price equal to this expected value, $p = \frac{1}{2}$, and for the buyer to always buy the good. Trade takes place with probability one, and the potential gains from trade are fully realized. The seller extracts all surplus from trade. Her expected revenue is $R^{(0)} = \frac{1}{2}$, the buyer obtains zero surplus.

The second case, in which the buyer is privately informed and knows his true valuation, is the standard monopoly pricing problem. In equilibrium, the seller will charge the revenue-maximizing monopoly price

$$p^m = \arg\max\{p \cdot (1-p)\} = \frac{1}{2},$$

Figure 2.1: Demand function, seller's revenue and buyer's surplus for (a) an uninformed buyer, and (b) a fully informed buyer.



(a) Uninformed buyer.

(b) Fully informed buyer.

and the buyer only buys the good if his true valuation is greater or equal to the price.[5] The seller has to leave information rents to the buyer. Trade is not efficient – there is some deadweight loss.[6] The expected realized gains from trade are $T^m = \frac{3}{8}$, which is split between the buyer and the seller. The seller's expected revenue is $R^m = \frac{1}{4}$, and the buyer's expected surplus is $U^m = \frac{1}{8}$. These two cases with an uninformed and a fully informed buyer, respectively, are illustrated in Figure 2.1.

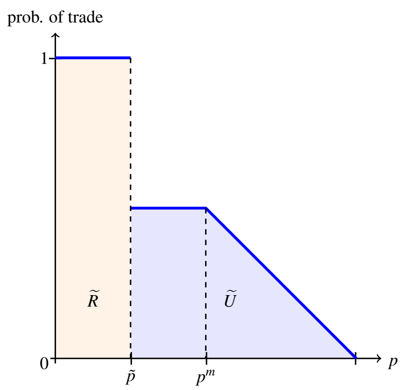
This example already illustrates that the outcome in a pricing model depends on the information held by the players. Here, in the case with symmetric information, trade occurs with probability one, all gains from trade are realized and the seller extracts the full surplus. By contrast, if the buyer is privately informed about his true valuation, he extracts some information rents. Moreover, under the revenue-maximizing price trade is not efficient – not all gains from trade are realized.

Based on the preceding discussion, it may at first seem like the relation between a buyer's private information and his expected payoff is monotone. If the buyer has more information, he can extract more information rents and hence is better off. However, this conjecture turns out to be wrong. The buyer only benefits from information if he can extract information rents. Hence, he does not benefit from information that separates values below the price that the seller charges – which is $\frac{1}{2}$ in the above example. If instead of becoming fully informed, the buyer only obtains a perfectly informative signal for valuations above $\frac{1}{2}$, and otherwise just learns that his valuation is lower, this does not affect his payoff as long as the price remains the same. Upon observing the low signal, the buyer's expected valuation is $\frac{1}{4}$ and he does not buy at price $\frac{1}{2}$; for higher valuations he buys the good. Notice moreover, that the seller now faces an effective demand function with a mass point at $\frac{1}{4}$ and a linear demand for prices of $\frac{1}{2}$ and above. This is illustrated in Figure 2.2. The seller is indifferent between charging a price of $\frac{1}{2}$ and trade half of the time, and charging a

[5] It is irrelevant whether the buyer buys the good or not if he is indifferent, since the event that the buyer's valuation is equal to the price is a zero-probability event.

[6] Not all gains from trade are realized since buyers with valuation below $\frac{1}{2}$ do not participate in trade.

Figure 2.2: Demand function, seller's revenue and buyer's surplus for a partially informed buyer.

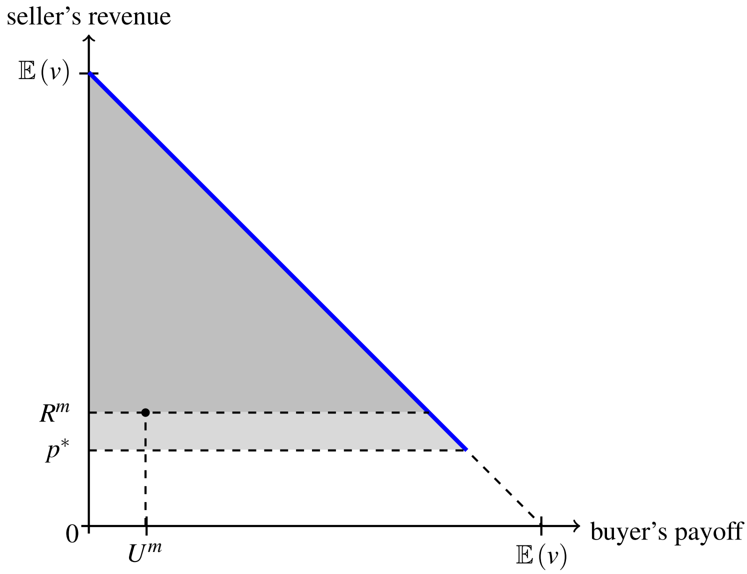


price of $\frac{1}{4}$ and sell for sure. In both cases, her revenue is $\widetilde{R} = \frac{1}{4}$. Hence, there exists an equilibrium in which trade occurs with probability one, all gains from trade are realized, and seller and buyer both obtain a surplus of $\frac{1}{4}$. Under this information structure, the buyer's expected surplus doubles compared to the case in which he knows his true valuation. Here, the buyer is better off by knowing less.

What is the economic intuition behind this result? If the buyer is oblivious to information that would separate low values, he effectively commits to sometimes buy at a price that is higher than his true valuation. As a result additional gains from trade are realized. This induces the seller to offer better terms of trade, that is, a lower price, in return for the increase probability of trade. The positive effect of the additionally realized gains from trade reverberates back to the buyer.

The discussion illustrates how information design may be used to achieve a desired outcome. The outcome of the pricing model depends on the information environment, here, the buyer's private information. The example shows that the buyer may be better off by knowing less. But is this the end of the story? Which outcomes can be achieved for different information structures of the buyer? And what is the optimal information environment for the buyer? These questions are studied in Roesler and Szentes 2016. It is shown that the buyer can do even better. Roesler and Szentes 2016 identify the posterior distribution and the price induced by a buyer-optimal signal. The buyer-optimal signal induces a unit-elastic demand function for the seller, who charges a price equal to the lower bound of the support of the posterior distribution. Trade occurs with probability one. Given the distribution of her value estimate, the buyer always buys the good at the equilibrium price, even though the price may exceed her true valuation. This offers the seller a higher probability of trade at intermediate prices. The intuition from the above example still applies: Under the buyer-optimal signal, the seller offers better terms of trade in return for the increased probability of trade. The buyer's optimal learning is driven by the goal of generating a demand function which induces the lowest possible price p^* subject to all gains from trade being realized. To understand the unit-elastic demand property, notice that if all gains from trade are realized, then the buyer's surplus just depends on how the total surplus is shared. The seller has to choose a price.

Figure 2.3: Surplus triangle. The darker shaded triangle is the set of outcomes attainable by changing the seller's information. The larger, lighter-shaded triangle is the set of outcomes attainable for all possible information environments in the pricing problem.



The unit-elastic demand property of the buyer-optimal signal, pins the seller to a revenue level. It leaves her with just enough surplus to guarantee that she does not want to deviate to a higher price.

Naturally, one can ask the complementary question, how the seller's information affects the outcome in a pricing problem. This problem is studied in Bergemann, Brooks, and Morris 2015. They consider a privately informed buyer and analyze how the information of the seller influences the outcome. More information on the side of the seller means that he can price discriminate. Bergemann, Brooks, and Morris 2015 identify the set of outcomes that is achievable by changing the information held by the seller. It is the set of the surplus triangle for which the seller's revenue is bounded below by the monopoly revenue, the buyer's surplus is non-negative, and total surplus is weakly less than the maximally realizable gains of trade. This is the smaller, darker-shaded triangle in Figure 2.3.

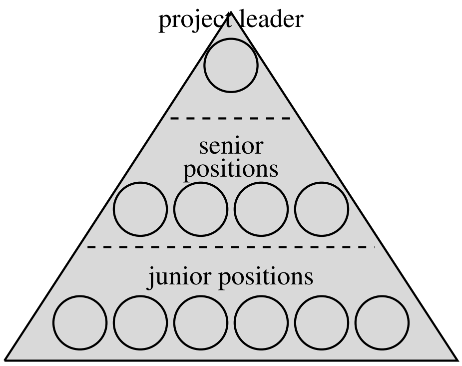
Combining the insights about how the buyer's and seller's information influence the outcome of the pricing problem, yields the set outcomes that are attainable for all possible information environments, for a given underlying prior distribution of the buyer's valuations. This result is formally established in Roesler and Szentes 2016, and illustrated as the larger, lighter-shaded triangle in Figure 2.3.

2.2 Information Management and Feedback in Promotion Tournaments

Information management plays an important role in situation in which the designer cannot change certain features of the environment, that is, if from a theoretical perspective the game is fixed.

In order to illustrate this consider the following example. A designer wishes to create an incentive scheme to maximize total efforts within a specific division of a company. He faces the problem that the organizational structure of the division, as well as the compensation-scheme for the positions is fixed (wages, benefits, etc.) and cannot be changed. For concreteness, suppose that the division has 11 position, a project leader, four senior consultants, and six junior consultants. This organizational structure is illustrated in Figure 2.4.

Figure 2.4: Organizational structure.



Suppose, that the company employs an up-or-out policy: every five years, employees at the same level are ranked according to their efforts. Based on this ranking it is decided whether an employee is promoted to a higher position, otherwise he has to leave the company.[7] Employees find themselves in a promotion contest in which they exert costly effort in order to be promoted to a higher position.

Let us set up a simple, stylized model for this situation. It is common to model contests as an all-pay auction with multiple prizes.[8] Bids correspond to exerted effort, and winning a prize in the contest corresponds to being promoted. Consider the situation for the junior consultants. There are six contestants $i \in \{1,\dots,6\}$, described by their *types* x_i, which are drawn independently from the uniform distribution on $[0,1]$. Players' types reflect their skill levels or abilities. The positions for which they compete are modeled as *prizes* of value $(y_1,\dots,y_6) = (4,3,2,1,0,0)$, where a prize of value 0 represents no promotion.[9] A player with type x_i obtains payoff $x_i y_j$ from winning prize y_j. This payoff structure implies that employees with higher types can generate higher payoff from

[7]For simplicity, we abstract away from the situation of the project leader, and simply assume that this position becomes available after five years. The project leader leaves the division and moves on e.g. to a different company, or to another position within the company.

[8]See for example Moldovanu and Sela 2001 and Olszewski and Siegel 2016b.

[9]Notice that this payoff structure implies that positions on the senior level are ranked, i.e., there are more and less attractive positions on that level.

being promoted than lower types.[10] Employees compete for positions by exerting costly effort. If a player of type x_i exerts effort $b \in [0,1]$ and wins prize y_j, his payoff is $x_i y_j - b$. Employees are promoted according to their effort, the employee with the highest effort wins y_1, the second highest y_2, and so on. The described setting is an all-pay auction, a standard model in auction theory. For the case in which players' types are private information to the players, following Vickrey 1961, Clarke 1971, and Groves 1973 there exists an equilibrium in which players are matched to prizes assortatively according to their types, and effort levels are given by VCG-payments: The expected payment of each player is equal to the externality that he imposes on the other players. In a contest with n players, for the player with the i^{th}-highest type – which we denote by $x_{i:n}$ – his expected payment is

$$t_{(i)} = \sum_{j=i}^{n} \mathbb{E}\left(x_{i+1:n}\right) \cdot \left(y_j - y_{j+1}\right), \tag{1}$$

where $\mathbb{E}\left(x_{i+1:n}\right)$ is the expected value of the $(i+1)^{th}$ highest type among n players.[11] The designer wishes to maximizes total efforts which is given by the sum of individual efforts

$$\begin{aligned} T &= \sum_{i=1}^{n} t_{(i)} = \sum_{i=1}^{n}\sum_{j=i}^{n} \mathbb{E}\left(x_{i+1:n}\right) \cdot \left(y_j - y_{j+1}\right) \\ &= \sum_{i=1}^{n} i \cdot \mathbb{E}\left(x_{i+1:n}\right) \cdot \left(y_i - y_{i+1}\right). \end{aligned} \tag{2}$$

This problem has been analyzed as a mechanism design problem. As shown in Moldovanu and Sela 2001 the optimal contest which maximizes total effort would only provide one prize and have contestants compete for it.[12] However, in the current example we assume that the organizational structure of the division is fixed and cannot be altered by the designer. This is where information management comes into play. A way to influence the incentives of employees to exert effort is to design the feedback system of the division. Feedback is given to employees to provide them with information about their "type" in the company, which allows them to form a better estimate of how they rank compared to their peers and hence their prospects to be promoted. This may encourage or discourage employees to exert more effort.

Consider the following simple information technology to model feedback. Each employee obtains a private signal $s \in [0,1]$, which with probability $\alpha \in [0,1]$ is his true type, and with probability $1-\alpha$ is pure noise. The employee cannot identify whether he observed his true type or noise. The employee updates his belief based on his private signal. Upon observing s, his posterior type is

$$\mathbb{E}\left(x|s\right) = \alpha s + (1-\alpha)\mathbb{E}(x). \tag{3}$$

[10] This is true for many position, think for example about bonus payments, or the option to engage in side-projects.

[11] Technically, $x_{i:n}$ denotes the i^{th} order statistics, that is, is distributed according to the i^{th}-highest among n random draws from the distribution F – here the uniform distribution on $[0,1]$.

[12] Olszewski and Siegel 2016a confirm and generalize this result. They show that a contest with a single prizes is optimal whenever prize valuations are linear or convex and effort costs are linear, or when prize valuations are linear and effort costs are linear or concave.

Here, the parameter α captures the precision of the information technology; for higher α, the signal is more precise.

Consider the following extension of the contest model. A priori contestants have no private information about their type but learn about it through the feedback provided to them before entering the contest.[13] Formally, they receive a private (partially) informative signal s_i through an information technology of precision α. With this private information players then enter the promotion contest. In the contest, the same considerations as presented above apply. Equilibrium efforts still satisfy (1) and (2), but now the (distribution of) true types $x_1,\dots,x_6$ has to be replaced by the player's (distribution of) posterior types, $\mathbb{E}(x|s_1),\dots,\mathbb{E}(x|s_6)$.

Suppose now that the designer can choose the precision of the information technology. Notice that for a more precise information technology the support of posterior types gets larger. To see this consider the two extremes: no feedback and perfect feedback. For no feedback – corresponding to an information technology that is pure noise, $\alpha = 0$ – the posterior type $\mathbb{E}(x|s)$ given by (3) always equals the prior mean $\mathbb{E}(x)$. The support of posterior types is a singleton. A signal contains no information for a player and hence, in the contest all players act as if their type were $\mathbb{E}(x)$. The resulting allocation is random and players' total exerted efforts given by (2) are $T^{(0)} = 5$. For perfect feedback, corresponding to an information technology with $\alpha = 1$, the signal realizations correspond to the players' true types and so do the posterior types, $\mathbb{E}(x|s_i) = s_i$ for all $s_i \in [0,1]$. The posterior types are distributed uniformly on $[0,1]$, and players total efforts are $T(1) = 4\frac{2}{7}$. In this case, the optimal, effort-maximizing feedback policy is to provide no feedback to contestants.

Consider the contest that the senior consultants face. At this level, four contestants compete for one prize, say of value $y = 1$. In this case, with feedback of precision α, total effort of contestants as given by (2) is $\frac{5+\alpha}{10}$. It is easy to see that this is increasing in α and hence providing perfect feedback is optimal at this stage.

What is the economic intuition behind this observation? Increasing the precision of feedback and hence the private information held by contestants has two important effects: an *allocation effect* and a *competition effect*. On the one hand, if contestants receive more precise feedback, this increases the probability that the contestant with the highest type receives the best feedback, hence exerts the highest effort and is promoted to the best position. More precise information allows for a better allocation. On the other hand, the information precision affects the competition among employees. More precise information will increase the effort levels of high (posterior) types since they now know that they are competing against their peers – other high types. However, feedback will discourage low types to exert effort. For more precise information the posterior types are more in line (correlated) with the underlying true types, which results in a better allocation of prizes to contestants. Hence, for a low-type contestant the probability that he is lucky and receives a prize decreases, which results in reduced effort.

This intuition suggests that the optimal feedback policy depends on the ratio of contestants to

[13] For example, this could be a performance report given to employees after being hired or promoted.

prizes. If there are only a few prizes then only the contestants with a high posterior type will be matched. Hence, for a more precise signal, the increased competition among high-type contestants is the driving force and will result in higher total efforts. By contrast, if a high proportion of contestants expects to receive a prize, the effort-reducing effect of more precise information for low-type contestants becomes more relevant. Total efforts may decrease in the precision of feedback.

In Roesler 2015 it is shown that the insights from this example generalize.[14] The optimal precision of information or feedback in a contest depends on the ratio of prizes to contestants. For any given set of prizes, there exists a number $\hat{n}$ such that the effort-maximizing feedback policy is to provide perfect information if the number of competitors is sufficiently large (i.e. $n \geq \hat{n}$) and no information otherwise.

Notice that we only consider a very simple, stylized example here. We do not consider coarse, more flexible, or dynamic feedback or information technologies, and do not take into account that implementing more precise feedback may be costly. It is possible to incorporate these and other features in the model which is the subject of ongoing research. However, the simple example presented here already shows that information management and design are important additions to the toolbox of a (mechanism) designer.

The observations presented here and the results in Roesler 2015 suggest that we should observe different feedback systems in companies, depending on their organizational structure. In organizations with steeper hierarchies in which employees face fierce competition for job promotions, well-established, precise feedback systems are optimal. By contrast, for organizations with flat hierarchies or promotion by seniority practices, less sophisticated feedback structures are optimal. These predictions seem to be in line with common practices. For example, highly competitive environments like large consulting firms are known to have very rigorous feedback systems.

3 Conclusion

This article provided a brief introduction to information design and presented two examples to illustrate some of the questions that are studied on this topic. There is plenty of exciting research in this area that could not be covered in this short article. Bayesian persuasion is one of these topics. A seminal paper is Kamenica and Gentzkow 2011, in which the authors analyze how a sender can design the information environment of the receiver in order to persuade the receiver to take the sender's preferred action. For the interested reader the note by Bergemann and Morris 2016 provides and excellent introduction and overview on related topics.

One of the intriguing aspects of information design for me is that similar questions and topics

[14]To more general information technologies and prior distributions of types.

have been around and studied by micro-theorists for a while. However, the developments in our information environment have shifted the focus of research in information economics and brought forward new questions. Being involved in research in an area that is motivated by and has partially evolved from changes in our environment is very exciting, and allows to be inspired by experiences and occurrences in everyday situations. Without a doubt there are plenty of open questions related to the topic of information design. I am curious to see how this research area will develop and grow.

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