Biases in Information analysis and Decision Making

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Different types of Biases

Many authors and papers underline the fact that the lack of imagination may be one of the commun point in all types of ignorances.

Effect Dunning and Kruger:
« Ignorance breeds self-confidence more often than knowledge does Charles Darwin). »

The incompetent person tends to overestimate his level of competence;

The incompetent person fails to recognize the competence of those who truly possess it

The incompetent person fails to realize his degree of incompetence;

***If a training of these people leads to a significant improvement of their competence, they will then be able to recognize and accept their previous deficiencies*.**

Different types of Biases

Close Ignorance: Closed ignorance can affect individuals and organizations alike. One form of closed ignorance stems from individuals and groups that are averse to recognizing possible disruptions as they pursue their goals or objectives. This ignorance can be partially countered by opening the system to outside opinion.

Open Ignorance: Open ignorance assumes that key stakeholders of the persistent forecasting system **are willing to admit** to what they don't know.

Personal ignorance,

Communal ignorance,

A technology may not be immediately recognized by a group or community as disruptive for a number of reasons, including an early judgement that it is not likely to be successful, an initially slow rate of adoption, or a lack of imagination

Novelty ignorance, and

Jesus Ramos-Martin suggests that novelty ignorance can stem from the inability to anticipate and prepare for external factors (shocks) or internal factors such as "changes in preferences, technologies, or institutions" eg Weather changes

Complexity ignorance

Surprise may also be caused when information is available **but insufficient tools are available to analyze the data.** Thus, interrelationships, hidden dependencies, feedback loops, and other factors that impact system stability may remain hidden. This special type of challenge is called complexity ignorance.

Different types of Biases

Ages:

One common individual bias is the assumption that future generations' acceptance of new technologies will mirror that of today's users.

A common mistake is to survey opinions of the future only from older and well-established experts in the field.

Cultural bias:

A common mistake is to survey opinions of the future only from older and well-established experts in the field.

They can affect what is seen as disruptive.

Special incentives may be required to motivate individuals to discuss potential disruptive technologies.

Individuals from diverse cultures may feel more or less comfortable about communicating potential disruptions depending on the means of data gathering.

Moreover, cross-cultural conflicts are pervasive throughout the world, and the anger and shame that result from these conflicts can even instigate development of disruptive technologies.

For this reason, it is critical to develop networks of local collaborators around the globe to facilitate the information-gathering process.

Linguistic Bias:

The language in which information is gathered can also bias the responses.

A disruptive technology forecasting system should not be limited to English, and participants should be able to express themselves and respond in their native language.

Epistemological bias:

Avoid to collect data on a fixed period to perform the forecast. This may introduce epistemological bias.

Therefore, it is important to design a data repository that can be initialized with the relevant historical and current data sets and then populated with ongoing, real-time data collections .

Different types of Biases

Biases in academic papers:

Citations introduce important biases if not evaluated correctly. language is overestimated this pleade for an analysis of other languages papers. (Chinise, Russian, English, Japanese, Korean)

Blog and Social Network Biases:

Blogs are as important as other written records like books, magazines, or even graffiti because they allow researchers to access the impressions of others. There are problems with blogs, such as false reporting, but these are biases that can be accounted for. Further, the fact that they are published online allows them to be electronically gathered, searched, and analyzed.

Patent Biases:

Only a few patents are really used (between 2 and 5%). Dilema: apply patents versus issued patents.

Interview Biases:

The background of an interviewer be considered to elicit genuine and unbiased answers from respondents. The background of an interviewer can influence rapport and cause the interviewee to self-disclose more or less, depending upon his or her comfort with the interviewer.

OSI Open Societal Innovation platform Biases:

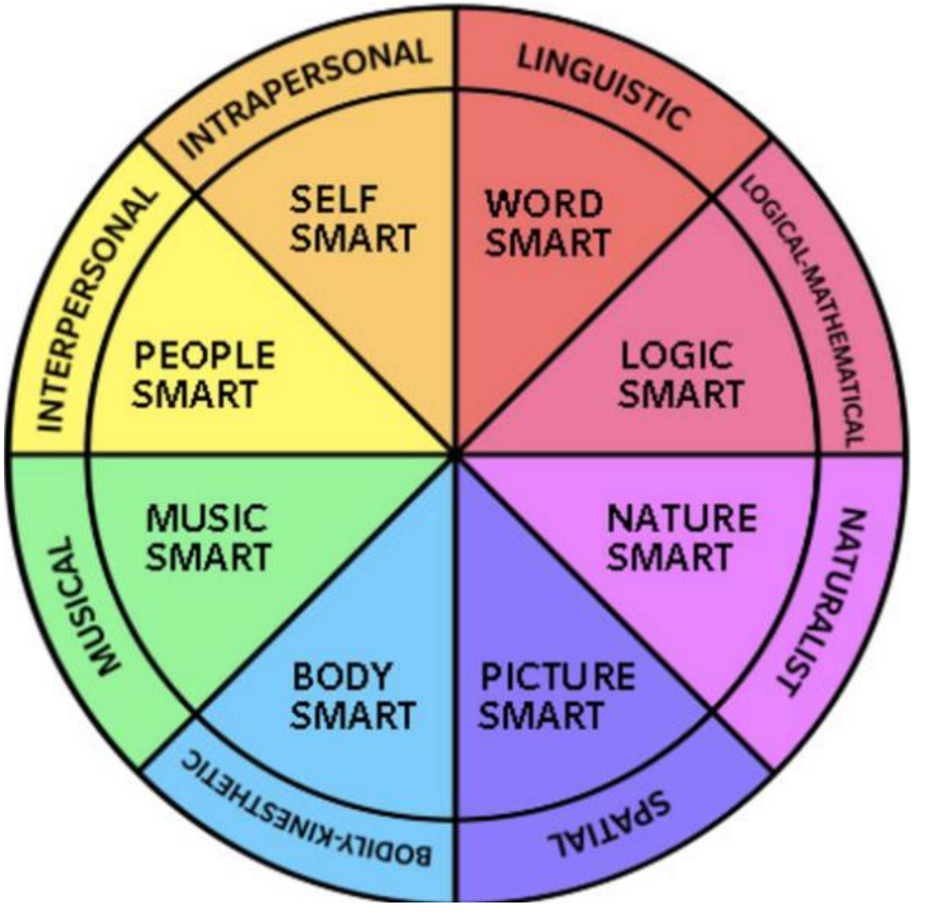
However, because many organizations have polarizing viewpoints, a persistent forecasting system should consider inputs from individuals or groups in all areas of interest to mitigate bias.

Data source Biases:

It is important to reach beyond the Internet and digitized sources to include **offline sources of information** and information from underdeveloped and emerging countries as well as countries that have limited Internet connectivity.

Information integrity can be threatened by bias. **Sourcing and assessing data from multiple perspectives (countries, languages, cultures, and disciplines) can significantly reduce the adverse impact of bias**.

Intelligence Biases

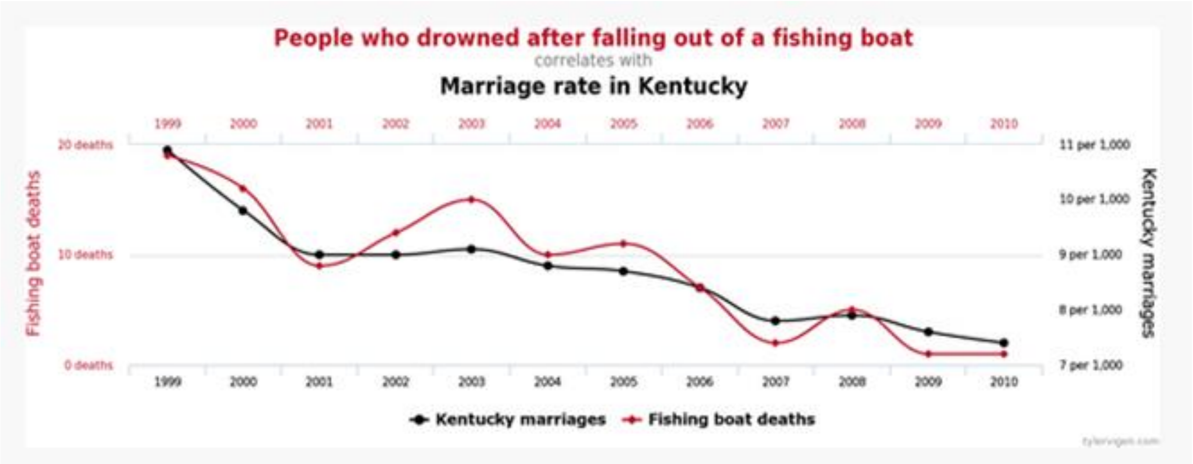


People have different forms of Intelligence. If the composition of an expert group is « unbalanced » this may introduce biases due to the different intelligences and the emotions that information will trigger in their mind.

https://sethperler.com/video-naturalistic-learner-howard-gardners-multiple-intelligences/

Algorythms and big data analysis biases

Spurious correlations



Data homogeneity

Google flu,

https://www.ft.com/content/21a6e7d8-b479-11e3-a09a-00144feabdc0

Gallup

Mr Gallup understood something that The Literary Digest did not. **When it comes to data, size isn't everything.** But if 3,000 interviews were good, why weren't 2.4 million far better? The answer is that sampling error has a far more dangerous friend: **sampling bias**.

Weak signals, predictions and biaises

For the French readers, but easy to translate !
https://signauxfaibles.co/2019/03/23/pourquoi-les-predictions-sont-souvent-fausses-et-quelles-lecons-en-tirer/amp/

Extract

"In her pioneering work on the Japanese Pearl Harbor surprise attack on December 7, 1941, American researcher Roberta Wohlstetter showed that this failure could not be blamed on a lack of attention. weak signals. Indeed, the US Navy had deciphered the codes of the Japanese Navy. It therefore had massive signals in the form of conversations of Japanese admirals. **But it found the hypothesis of a Pearl Harbor attack so absurd that it refused to consider it. An exercise on this theme in the spring of 1941 was even refused. "**
Extract from the book "Welcome to uncertainty!" by Philippe Silberzahn

See also "Fortitude" allies intelligence during world war II.

Algorithm biases – Machine learning Biases

https://searchenterpriseai.techtarget.com/definition/machine-learning-bias-algorithm-bias-or-AI-bias

Organizations should check the data being used to train machine-learning models for comprehensiveness and bias. The data should be representative of different races, genders, backgrounds and cultures who could be adversely affected. Data scientists developing the algorithms should shape data samples in a way that minimizes bias and decision-makers should evaluate when it is appropriate, or inappropriate, to apply machine learning technology.

1. Sample bias

Sample bias is a problem with training data. It occurs when the **data used to train your model does not accurately represent the environment** that the model will operate in.

2. Prejudice bias

Prejudice bias is a result of training data that is influenced by cultural or other stereotypes.

3. Measurement bias

Systematic value distortion happens when there's an issue with the device used to observe or measure

4. Algorithm bias

This final type of bias has nothing to do with data. In fact, this type of bias is a reminder that "bias" is overloaded. **In machine learning, bias is a mathematical property of an algorithm**.

From https://thenextweb.com/contributors/2018/10/27/4-human-caused-biases-machine-learning/

The DELPHI Methodology

The 5 steps of the Delphi

1 A panel of experts is assembled.

2 Forecasting tasks/challenges are set and distributed to the experts.

3 Experts return initial forecasts and justifications. These are compiled and summarised in order to provide feedback.

4 Feedback is provided to the experts, who now review their forecasts in light of the feedback. This step may be iterated until a satisfactory level of consensus is reached.

5 Final forecasts are constructed by aggregating the experts' forecasts.

Biases in the Delphi method

Bias	Source(s)	Description
Collective unconscious	Durkheim (1982)	The theory of collective unconscious (i.e., the bandwagon effect), states that decision makers tend to join a popular trend. In other words, individuals are likely to unconsciously feel pressure to conform to the common or standard beliefs within a particular group.
Contrast effect	Bjarnason and Jonsson (2005)	The contrast effect occurs when the perception of a given subject is enhanced or diminished by the value of the immediately preceding subject. In theory, the contrast effect can cause significant bias, especially when individuals are asked to rate back-to-back factors .
Neglect of probability	Martin (2006); Rottenstreich and Hsee (2001)	There are many cases where individuals underestimate the role of probability in the subjective quantification of risk. This bias involves the disregard of likelihood when making a decision under uncertainty. Any study that involves risk quantification or ratings of likelihood may be susceptible to the neglect of probability bias.
Von Restorff effect	Restorff (1933); Krimsky and Golding (1992)	The Von Restorff Effect was first introduced to the field of psychology when subjects were found to recognize and remember relatively extreme events more often and more accurately than less extreme events. In theory, individuals are more likely to remember events associated with severe outcomes thereby distorting the perception of probability. This effectively creates an artificially inflated risk score for potential events associated with a higher level of severity.
Myside bias	Perkins (1989); Baron (2003)	Myside bias occurs when an individual generates arguments only on one side of an issue. Participants can be easily prompted for additional arguments on the other side, although prompting for further arguments on their favored side is less effective. The persistence of irrational belief is generally a result of one's personal opinion with little basis in pure fact.
Recency effect		The recency effect occurs when subjects are more likely to artificially inflate risk ratings because similar incidents have recently occurred in their personal lives (i.e., recent events are given inappropriate levels of salience in relation to others). The effect of recency is relatively common.

Primacy Effect		The primacy effect results from the unconscious assignment of importance to initial questions, observations, or other stimuli. The theory states that individuals are inherently more concerned with initial stimuli.
Dominance	Linstone and Turoff (1975)	Dominance occurs when one, usually very vocal group member, exhibits great control over the ratings of the other members. This common source of bias is typical in studies that attempt to gather group opinion such as the Nominal Group Technique or focus groups.

See also:
Winkler, J. and Moser, R., 2016. Biases in future-oriented Delphi studies: A cognitive perspective. *Technological forecasting and social change*, *105*, pp.63-76.

The Delphi method being widely used, it is interesting to look to the various biases encountered during its use.

Biases in the Delphi method

Improving panellist recruitment and retention over Delphi rounds, through:
Using a person-to-person cascade approach (i.e., “snowballing”) to secure easy agreement to panellist invitations (which will also strengthen subsequent panellist retention)
Making use of publically-available bibliographic information to identify potential expert panellists
Noting that self-rated experts tend to exhibit less drop-out over Delphi rounds than those who rate themselves as less-expert
Stressing the practical policy application of the Delphi yield to expert panellists to aid their retention
If panellists are widely scattered across the world, being aware of the de-motivating effect of poor internet speeds with complex graphical content in communications
Using social rewards for recognition of participation — such as subsequently publishing panel membership listings.

Creating useful heterogeneity in panel membership through:
Including experts and laypeople to increase the variety of viewpoints amongst first round opinions — even though the lay opinions will be less stable and tend to reduce to expert viewpoints over rounds
Creating artificial heterogeneity in opinions at the first Delphi round – using role-playing, devil's advocacy, and dialectical inquiry – and in this way, facilitating alternative framings

Enhancing information exchange between panellists, through:
Removing any indicators of the prevalence of majority or minority opinions
Removing any indication of panellists' confidence levels
Using rich qualitative feedback of panellists' rationales and reasoning behind their judgments
Being alert to stability in dissensus over Delphi rounds — which could indicate the need to explore panellists' underpinning assumptions and logics in subsequent face-to-face meetings

Biases in the Delphi method

Improving question formulation through:
Using an exploratory workshop to refine first-round Delphi questions
Using easy-to-answer questioning, preferably involving closed questions, for use in Delphi rounds
Using simple English expression in questions when panellists do not have English as a first language — but noting that exchange of rationales and reasons between panellists will likely also be similarly restricted
Using Delphi questions with unambiguous wording such that subsequent evaluation of event outcomes is clear-cut

Considering combining Delphi with other techniques: •
Being aware of the benefits of technique combination to enhance panellist creativity and commitment
Being aware of the usefulness of Delphi as a means of eliciting group-based judgments for integration with other futures methodologies (as well as, for example, for establishing exogenous variables for econometric models, or in forming the coefficients for an input-output table)
Measuring forecast desirability expressions of individual panel members and thus identifying potential optimism and pessimism bias
Being aware that real-time Delphi and conventional Delphi produce similar results and that choice of the former approach has potential benefits

From
Rowe, G. and Wright, G., 2011. The Delphi technique: Past, present, and future prospects—Introduction to the special issue. *Technological forecasting and social change*, *78*(9), pp.1487-1490.

Biases coming from individual, group or company archetypes

Substance →	Macro Transformations →	Micro Transformations →	Value
Food	Chewing, Biting	Cell Chemistry	Energy, Tissue
Information	Analysis	Communication	Knowledge, Actions Decisions

Starting from the **metabolism of Information**, we can move to organizations and people. The people archetypes can be analyzed according Jung and Simondon (**individuation process**). The understanding of the « outside world », will lead to the **information function**, exogeneous and **endogeneous**. The endogeneous information function will modify through the **epigenetic** the behavior of the individual creating a mutation which will change the individual archetypes. This can be applied to organizations, because organizations are made from people of various kinds and functions. Thus « **critical memes** » can be develop. This will make a **mutation partialy transmissible** and help the organization and its people to better understand their environment (« **outside world according Simondon** »).

The meme, or cultural equivalent of the gene, is described as "an element of a culture (taken here in the sense of civilization) that can be considered as transmitted by non-genetic means, in particular by imitation"

From :

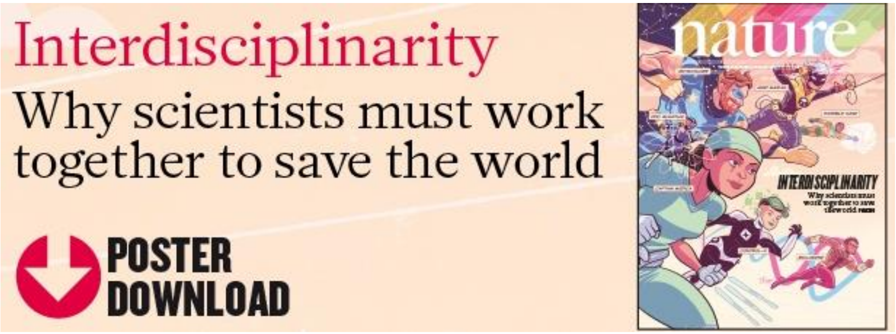
Dou H., Du métabolisme de l'information à l'Intelligence Economique, R2IE Revue Internationale d'Intelligence Economique, 10/1,pp.7-11,2018

Translation in English is available at: http://s244543015.onlinehome.fr/ciworldwide/?p=2283

Interdiscipnarity a must to avoid Biases

In a recent issue of nature (NATURE 2015), a group of authors pin pointed the fact that to solve the world facing problems (pollution, weather change, population, health, starvation, water supply …) one unique scientific discipline cannot solve or gives some solutions to those problems which are associated in nature. Then came to the scene the necessity to organize and justify the development of interdisciplinary work……..

(*extract from International Symposium « Pluridisciplinarity » University of Corte, France – 5-6-7 July 2017, Dou Henri, A catalyst for interdisciplinarity in Science : the patent information, available from http://s244543015.onlinehome.fr/ciworldwide/?p=2051)*



https://www.nature.com/news/why-interdisciplinary-research-matters-1.18370

Nature (2015), Interdisciplinarity, vol 525, Macmillan publisher, nature.com.inter

Conclusion

Even if various tentatives are done to use software and artificial intelligence to prevent biases, all the studies show that most of the biases are due to human factors.

Most of the human environment will interact with the fealing and the **emotions** tant information trigger in an individual or even a group.

Variety, pluridisciplinarity, different backgrouds, languages, origins, ages, may help to struggle againts biases.

Imagination is one of the best frame of mind to develop from information various hypothesis.

But before thinking to BIASES, it is necessary to have in hand the best qualified information available, and this is a challenge because information according to it source contains de facto biases!

Thank you for your attention