# Digested Information, a Non-Semantic Motivation for Agent-Agent Interaction

Christoph Salge
Adaptive Systems Research Group, University of Hertfordshire
Address for correspondence: Science and Technology Research Institute (STRI), University of Hertfordshire, College Lane, Hatfield, Hertfordshire AL10 9AB, UK; c.salge@herts.ac.uk

## Summary

Digested Information is a theory that aims to explain, at the non-semantic level of Information Theory, why it makes sense for one agent to observe another. Based on the formalism of Relevant Information, defined as the minimum amount of information an agent needs in order to determine its optimal strategy, I argue that, following its own motivation, an agent (1) obtains relevant information from the environment (2) displays it in the environment through its own actions, and (3) is likely to display information in a higher density in regard to its bandwidth than other parts of the environment. Furthermore, I argue that this information is also relevant to other, similar, agents and that this could be used to motivate agent-agent interaction (such as observing other agents) in a framework where agent behaviour is determined by information maximisation.

## Abstract

Modelling agent-world interaction in terms of Information Theory (Shannon 1948) has advanced our understanding of simple AI mechanisms. For example, Klyubin (2005) and Der (1999) have demonstrated that simple "intelligent" behaviour can be created by agent centric maximisation of channel capacity and information parsimony (Tishby 1999); all while staying purely "syntactical" (Nehaniv 1999), that is, while there is no actual meaning assigned to input or output states, as in symbolic AI. Also, work in biology (Vergassola 2007, Dauchin 2004) suggests that similar Shannon information based mechanism could explain basic animal behaviour. I argue that those principles can be used to motivate both agent-agent interaction and the development of the simple abilities needed for it, such as attention towards other agents, or the ability to even identify another agent.

The argument presented uses the term information, associated with Shannon's Information Theory, as the mutual information (Shannon 1948) between two random variables X and Y. Consequently, the world is described as a set of random variables, which can be modelled as a Causal Bayesian Network as described by Pearl (2000). To define an agent in this world one first divides all the random variables into either belonging or not belonging to the agent. The non-agent variables are used to form a compound random variable, called the environment R. Furthermore, the agent is organised into three sets of random variables, the sensors S, the actuators A and the memory M.

It is assumed that the agent's actions are connected to some unspecified form of utility function (for example survival probability, or fitness), which determines the different payoffs, depending on the agent's action and the state of the environment. For every state of the environment, there exists a set of actions which result in the highest expected utility; a collection of such actions for each state of the world is called an *optimal strategy*.

*Relevant Information* is defined (Polani 2001) as the (minimal) average amount of information the agent needs to acquire from the environment to act according to one optimal strategy. Mathematically, this is defined as the minimal amount of mutual information between R and A for all optimal strategies.

However, since the mutual information is symmetric, the relevant information is not only the amount the agent has to obtain through its sensors, it is also the amount of information its actions contain about the environment. If the agent uses one of the optimal strategies, it has to act accordingly, and displays (automatically) in its actions at least the amount of relevant information, simply in virtue of acting optimally.

By extension, the relevant information of a sub-optimal payoff level is defined as the minimum mutual information of all strategies that reach that payoff level (Polani 2006). Thereby, any sub-optimal strategy requires less, or the same amount of relevant information. Conversely, an agent that increases its payoff level by choosing a better strategy increases the amount of relevant information, both obtained and displayed, or at least keeps it the same. This gives agents an incentive to increase the relevant information displayed in their actions, since it is a by-product of increasing their performance.

Furthermore, the agent's actions typically have a much smaller state space than the rest of the environment, and hence a much smaller bandwidth, but still need to contain the same amount of relevant information. This creates an "Information Bottleneck" (Tishby 1999), and it indicates that the agent's actions could contain a much higher "concentration" of relevant information per bit than other parts of the environment.

To support this claim we have implemented a grid world scenario where artificial agents search for the location of food (Salge 2009), controlled by a biologically inspired Infotaxis search (Vergassola 2007). Our simulation showed that agents' actions contained:

a. relevant information (measured as mutual information between actions A and a random variable F denoting the location of the food)
b. more relevant information per bit than any other part of the environment
c. more relevant information if the agents performance increased

Now consider a scenario with several agents that have a similar embodiment and utility, and therefore need to obtain similar relevant information. In this case, the actions of one agent are part of the environment of another agent, which can obtain its relevant information also by observing the other agent. Given the prior results, this seems a sensible thing to do, especially if an agent can only use a specified amount of sensor bandwidth to observe the environment.

An extension of the experiment in (Salge 2009) demonstrates that agents that perform a Bayesian update with other agents' actions are not only able to outperform those which do not, but also outperform the mathematically optimal strategy for any single agent. The limitation of the optimal performance is determined limited amount of information about the environment the agent can gain per time step, if the agent is only observing the non-agent environment. Therefore, to perform better, the agent has to obtain (relevant) information from the actions of other agents which is unobtainable from the rest of the environment. The presence of this additional information, which is not present in the current local environment of the two agents, can be explained via the agent's memory. By retaining information about the environment the agent creates a channel from an information source, which is spatially or temporally removed, to its current, local actions.

Concluding, the "Digested Information", the relevant information present in an agent's action, has several qualities that make it beneficial for other, similar agent to observe those actions. Especially interesting is the likely higher per bit density of relevant information if an agent has only a limited amount of sensor bandwidth to obtain information from the environment. Also, the possibility of gaining information in a place and time removed from the original source is very helpful for an agent aiming to maximize its information about the environment.

## References


AY N and Polani D (2008b) Information Flows in Causal Networks, *Advances in Complex Systems*, 11(1):pp. 17-41,2008.

DANCHIN E, Giraldeau L-A, Valone T J, and Wagner R H (2004) Public information: From nosy neighbors to cultural evolution, *Science,* 305 (5683), July 2004, pp. 487 - 491.

DER R, Steinmetz U and Pasemann F (1999) Homeokinesis--a new principle to back up evolution with learning, M. Mohammadian (editors), *Computational intelligence for modeling, control, and automation,* Amsterdam, IOS Press, (pp. 43-47), 1999.

KLYUBIN A S, Polani D and Nehaniv C L (2005) All Else Being Equal Be Empowered. In M. S. Capcarrère, A. A. Freitas, P. J. Bentley, C. G. Johnson, and J. Timmis, (editors), *Advances in Artificial Life: Proceedings of the 8th European Conference on Artificial Life*, volume 3630 of *Lecture Notes in Artificial Intelligence*, pages 744-753. Springer, Sep 2005.

NEHANIV C L (1999) Meaning for observers and agents. *IEEE International Symposium on Intelligent Control / Intelligent Systems and Semiotics (ISIC/ISAS'99)*, IEEE Press, 1999, pp. 435 - 440.

PEARL J (2000) *Causality*, Cambridge University Press, 2000

POLANI D, Martinetz T and Kim J T (2001) An information-theoretic approach for the quantification of relevance, *Proceedings of the 6th European Conference on Advances in Artificial Life,* Springer-Verlag, London, 2001, pp. 704 – 713.

POLANI D, Nehaniv C, Martinetz T, and Kim J T (2006) Relevant Information in Optimized Persistence vs. Progeny Strategies, in M.Rocha, L., Bedau, M., Floreano, D., Goldstone, R., Vespignani, A., and Yaeger, L., editors, *Proc. Artificial Life X*, August 2006, pp. 337 – 343.

SALGE C and Polani D (2009) *Information Theoretic Incentives for Social Interaction*, *Technical Report 495*, University of Hertfordshire, Hatfield, 2009.

SHANNON C E (1948) A mathematical theory of communication, *Bell System, Technical Journal*, 27, July 1948, pp. 379 – 423.

TISHBY N, Pereira F C and Bialek W (1999) The information bottleneck method, *Proc. of the 37-th Annual Allerton Conference on Communication, Control and Computing*, 1999, pp. 368 – 377.

VERGASSOLA M, Villermaux E and Shraiman B I (2007) "info-taxis" as a strategy for searching without gradients, *Nature*, 445(7126), 2007, pp. 406 – 409.