Visual Knowledge Negotiation

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***Abstract*—We ask how users interact with 'knowledge' in the context of artificial intelligence systems. Four examples of visual interfaces demonstrate the need for such systems to allow room for negotiation between domain experts, automated statistical models, and the people who are involved in collecting and providing data.**

***Index Terms*—intelligent interfaces, visualisation, knowledge negotiation**

I. Why we Need Knowledge Negotiation

Philip Agre's classic critique of Artificial Intelligence research articulates a key problem in the mechanisation of knowledge, which he formulates as the "discursive practice" of AI research [1]. This is best summarised in his own words:

> AI is a discursive practice. A word such as planning, having been made into a technical term of art, has two very different faces. When a running computer program is described as planning to go shopping, for example, the practitioner's sense of technical accomplishment depends in part upon the vernacular meaning of the word [...] On the other hand, it is only possible to describe a program as "planning" when "planning" is given a formal definition in terms of mathematical entities or computational structures and processes. [...] This dual character of AI terminology — the vernacular and formal faces that each technical term presents — has enormous consequences for the borderlands between AI and its application domains.

Recent critique of machine learning methods, in Cheney-Lippold's "We Are Data" [2], identifies a related issue in machine learning. He proposes that the named categories and labels fundamental to supervised machine learning should always be placed in quotation marks, in order to avoid the implication that these names correspond to the "vernacular face" (in Agre's terms) of concept names outside of the statistical model. For example, Cheney-Lippold notes that his own Google profile identifies him as being "female" (through statistical analysis of his online behaviour) when this is not true. Nevertheless, the statistical observations of Cheney-Lippold as a "female" customer within Google's models may be useful data for their advertisers, and may be a good prediction of Cheney-Lippold's future purchases. But when making use of this fact it is important to remember that this model-label, although potentially useful, is not true.

Building intelligent systems to be useful in some application domain requires constant attention to the necessary dual character of the "knowledge" encoded in the system, and the vernacular language of the user. Where statistical models result in interactive visual languages, we have a critical design problem. Should the visual language correspond to one type of knowledge (which?), or to both?

We claim that visual interaction with intelligent algorithms must be designed in order to allow *negotiation* between the user and the inferred statistical "knowledge". In summary, visual languages support negotiation of knowledge, *because they are not linguistically over-determined.*

II. Visual Design for Knowledge Negotiation

We illustrate this theoretical concern with four practical case studies, supported by visual interfaces as seen in Figures 1, 2, 3 and 4. (Longer descriptions of these case studies are being presented at a satellite workshop of this conference, on Designing Technologies to Support Human Problem Solving [3]).

Each of these four systems is designed for use by a specific class of domain expert — police analysts (Fig 1), business analysts (Fig 2), research translators (Fig 3) and hospital

Fig. 1. In ForensicMesh, computer vision algorithms locate video from a body worn camera in a city location, but emphasising the subjective viewpoint of the person wearing it by rendering that person's body in the foreground, so that the user can interpret this "objective" digital evidence within a subject context.

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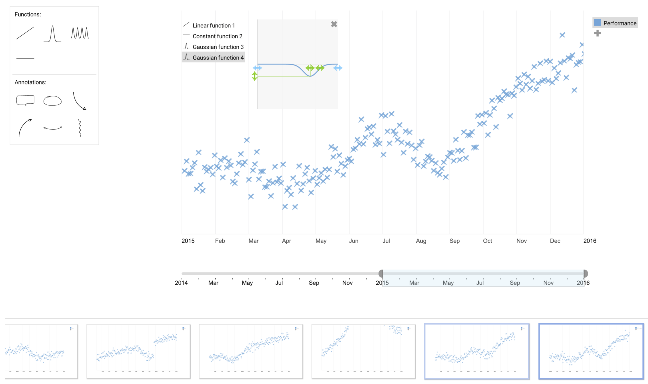

Fig. 2. In SelfRaisingData, a statistical model of unseen data is synthesised by a business analyst as a way of formulating research questions from a user perspective.

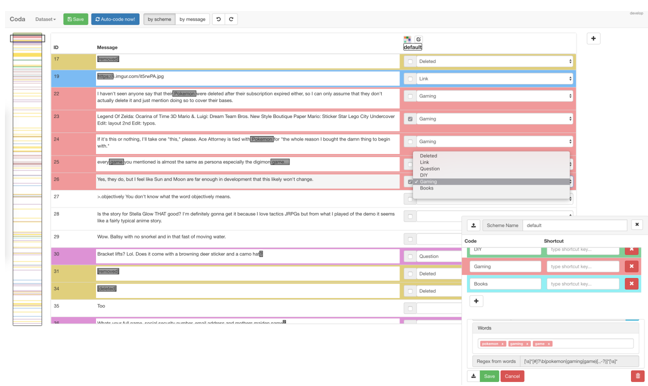

Fig. 3. In Coda, Somali translators classify SMS messages relating to public health, with semi-automated labels negotiated through varying shades of the category colours. [1]

clinicians (Fig 4). In each case, a model has been constructed on the basis of data originally acquired from human sources. A statistical model, more or less complete and more or less accurate, has been created on the basis of that data. And in each case, the domain expert who interacts with the system has a richer, more sophisticated and more complete understanding of the context than has been embedded in the model.

That expert understanding extends beyond critical evaluation of the predictive power of the statistical models — it also extends to critical understanding of the data from which the model has been created, and of the human agency through which the data was captured. We therefore try to avoid system designs in which models are trained with a pre-defined set of labels that might be liable to simple acceptance as the full and complete truth — so in Coda (Fig 3), the set of labels can always be expanded, redefined, or replaced with other sets.

We also try to highlight the human origins of apparently mechanical data acquisition, for example in ForensicMesh (Fig 1) we render a human figure into the scene, representing the police officer who was wearing a body-worn camera from which video was collected.

In the extreme case of SelfRaisingData (Fig 2), we proceed with no data at all, giving expert analysts the opportunity to negotiate far further down the 'supply chain' of statistical inference by *creating* a data set. This has no objective status at all, in that no data exists, but provides a basis for negotiating the model that might be created.

ICUMAP (Fig 4) also subverts the conventional visual language of statistics by creating a clustering algorithm that is not a simple dimension reduction of a multivariate space, but modifies the t-SNE distance metric to allow the narrative of a journey (through placing successive time-point samples nearby), and explicitly reflecting the clinicians' prior expectation (by weighting clusters to represent the most salient clinical category of surgical procedure). These allow clinicians to reason 'outward' from their own knowledge to explore statistical similarities beyond the 'obvious' (to clinicians) prior expectations.

To conclude, these design case studies demonstrate how visual languages can support negotiation of knowledge, where statistical terminology fails to distinguish between model and application.

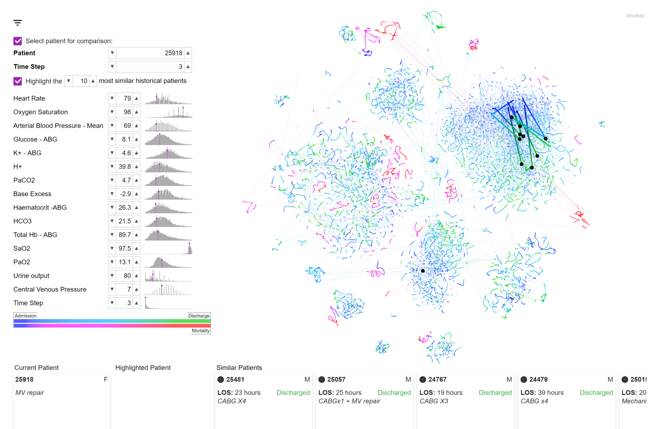

Fig. 4. In ICUMAP, the outcomes of post-surgery intensive care are visualised as trajectories toward discharge (green) or mortality (red), so that clinicians can assess typicality or risk of new cases in relation to precedent, but without relinquishing judgment.

References

[1] P. E. Agre, "Toward a Critical Technical Practice: Lessons Learned in Trying to Reform AI," in *Bridging the Great Divide: Social Science, Technical Systems, and Cooperative Work*, L. S. Les Gasser and G. B. Bill Turner, Eds. Erlbaum, 1997.

[2] J. Cheney-Lippold, *We are data: Algorithms and the making of our digital selves*. NYU Press, 2017.

[3] A. Blackwell, L. Church, M. Jones, R. Jones, M. Mahmoudi, M. Marasoiu, S. Makins, D. Nauck, K. Prince, A. Semrov, A. Simpson, M. Spott, A. Vuylsteke, and X. Wang, "Computer says 'don't know' - interacting visually with incomplete AI models," in *Designing Technologies to Support Human Problem Solving Workshop - A Workshop in Conjunction with VL/HCC 2018*, 2018.

[1]Since the data Coda is used with is usually sensitive, the data in this screenshot is a sample from the Reddit comment data available on Google BigQuery (https://bigquery.cloud.google.com/table/fh-bigquery:reddit_comments)