MIND READING AT WORK: COOPERATION WITHOUT COMMON GROUND

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ABSTRACT

As Stefan Kopp and Nicole Krämer say in their recent paper [11], despite some very impressive demonstrations over the last decade or so, we still don’t know how to make a computer have a half decent conversation with a human. They argue that the capabilities required to do this include incremental joint co-construction and mentalizing. Although agreeing whole heartedly with their statement of the problem, this paper argues for a different approach to the solution based on the “new” AI of situated action.

1 Introduction

One problem with developing human-computer interfaces is that it involves both engineers and humans. Human behaviour is a tough nut to crack for engineers and those who are expert at human behaviour are rarely able to put things in engineering terms. Kopp and Krämer’s paper gives a succinct introduction to why we need more theory and following Tomasello [18], they say that we need to pay attention to the intentional and cooperative nature of Human-Human Interaction (HHI). However saying that language is intentional and cooperative is simply not as quantitative as scores on a leader board. The aim of this paper is to first translate the problem of human-agent interaction (HAI) and conversational user interfaces into terms engineers will understand, and second, to point out a significant development by engineers and how it applies to this grand challenge. In particular, whereas many readers of the Kopp and Krämer paper will assume “the common ground” must be represented symbolically, engineers are at least sceptical about the notion of symbolic representation and these days have a much better idea of how to make computers reason about action.

2 What we know: the problem

From an engineering perspective, first, we know that communication is always with respect to a model. From Information Theory we know, for instance, that you can communicate the text of “War and Peace” with a single bit of data, if you know that the message is either War and Peace or something else - The Collected Works of Shakespeare perhaps. Compression and encryption techniques rely on having the sender and receiver use exactly the same model. In the early days of NLP it was thought that Russian was simply an encrypted version of English and all that was needed for machine translation was to break the code. The underlying assumption was that all humans share the same model. And as a successful human it seems obvious that, if I order a peperoni pizza with sweet peppers and no olives that, like assembling Lego, the receiver of my order will be able to ground “sweet peppers” to something in the world that will end up on my pizza.

It turns out that HHI does not work that way. The initial assumption in NLP was that humans do indeed share models with enough detail to decode language, but that the language itself was imprecise. The way forward was to map sloppy natural languages into something better that, presumably, looked like predicate calculus. The notion of primitive acts [14] suggested that words like “sell” could be mapped into a longer string of more concise “logical atoms” such as A p-trans B to C; C m-trans D to A; where B is the goods and D is the money. The realisation was that there is an awful lot of this kind of knowledge [11]. There was however plenty of interest in doing the work. Wilks convinced Longmans to provide their Dictionary of Contemporary English in a form that used a limited defining
vocabulary (on magnetic tape!) that might go some way toward identifying a set of semantic primitives \[23\]. It also led to using statistical models of corpora - techniques that today would be marketed as Machine Learning - and to ambitious projects such as the CYC project \[12\] which aimed to hand code the required facts.

Looking back we can say that this programme failed. The failure was however a significant contribution by AI research in that it goes against a long standing tradition that natural languages are some kind of fallen version of something better. An idea that goes back to biblical times and was the motivation for formal logic. More significantly perhaps we now know - or should know - what not to try.

The most recent band of interest in conversational user interfaces puts the focus, not on understanding the problem, but on engineering a solution. Neural Nets and indeed statistical models of dialog avoid the theory by talking of deep learning, hidden layers \[24\] with only speculation to back up any explanation of how it works (when it does work). This is fine as far as it goes, but there is also a tendency, especially under the pressure of conditional funding, to tailor the problem to fit the solution. Looking at the text of the latest “gold standard” dialog system evaluation data \[5\], the tasks are heavily biased toward “understanding” the input text where understanding is defined to be just slot filling. This is in stark contrast to the DARPA Communicator project \[19\] and the Alexa Prize \[2\] which were serious attempts to advance the state of the art – as indeed was the initial Loebner Prize \[16\]. Rather than some made up metric, the Amazon team - with plenty of experience, motivation, and resources - have opted for an evaluation based on human judgement. Human judgement being of course the ultimate, theory free, arbiter of success. While the ML people play with their data, the theory behind language in use does seem to be on hold. And as the limited progress on the Alexa Prize and its predecessors suggests, it would seem theory is what is needed.

As Kopp and Krämer suggest, the current understanding is that we need a better way for our machines to assemble the common ground in a conversation. Without a shared model to work from, an Information Theoretic perspective suggests HHI builds a shared model as the conversation progresses. The common ground is built on-the-fly.

3 Where we had got to

Those who study HHI have made some observations that may help. First, a human is very good at recognising the intent of his or her CP. That is, we are very good at guessing what our CP wants to do. Note the use of “intent” here is the popular one as in “I intend to pick up some milk on the way home” and not the referential “intent” used in the broader research community as a way of avoiding talk about meaning of words. Note also that recognition of intention is not a skill unique to humans - nor even the great apes. Children develop a ToM - a Theory of Mind in others - from about the age of three, and a sheep dog is very good at guessing where sheep are about to go. Our ability to recognise the intentions of others is not perfect by any means but, second, humans are compelled to work hard to sort out communication failures. That is, they cooperate in the process of understanding, even if they disagree about the content of that communication. Consider this (naturally occurring) example from Eggins and Slade talking about sequential relevance:

A: | What’s that floating in the wine?
B: There aren’t any other solutions.

You will try very hard to find a way of interpreting B’s turn as somehow an answer to A’s question, even though there is no obvious link between them, apart from their appearance in sequence. Perhaps you will have decided that B took a common solution to a resistant wine cork and poked it through into the bottle, and it was floating in the wine. Whatever explanation you came up with, it is unlikely that you looked at the example and simply said ‘it doesn’t make sense’, so strong is the implication that adjacent turns relate to each other \[6\].

Tomasello’s point is that the great apes would look at the utterance, say it didn’t make sense, and move on. Humans on the other hand, are compelled to try and figure it out. This human behaviour is normative. As Tomasello points out \[18\], if an individual in society fails to understand the utterances of others they will be considered simple and lock up. If he or she produces utterances that others cannot understand, then they will be locked up as mad. In order to be treated as human, one must be able to “read minds” and actively cooperate in the communicative processes of the people around you.

The classic approach at this point would be to implement a Good Old Fashioned AI (GOFAI) model of ToM, literally modeling the mind of the system’s conversational partner. This approach was developed in James Allen’s TRAINS programme and turns out to be an extremely costly. There is an alternative approach to ToM that is discussed below but before getting to that however, it is useful to take a step back and look at how HHI works and why something like a ToM is critical.
4 How language works

The above provides an introduction to the problem but engineers tend to want details. In a rare case of an algorithm from the human sciences, Seedhouse [15] summarises the findings of Conversation Analysis as follows. Once a conversation is established between a Speaker and his or her Conversational Partner, at any point:

- the speaker’s utterance will go seen but unnoticed if the utterance is the second part of an adjacency pair - an actual answer to a question or a greeting in response to a greeting. This is the type of interaction we know how to do with a machine. If I walk in to a corner shop and ask for “six first class stamps please”, the person behind a counter in the UK is no doubt going to know exactly what I mean, and so can a machine.

- Often/sometimes however, a speaker’s utterance will not “fit” with what went before. Taking a classic example from the CA literature, consider someone walking into a corner shop and asking “Excuse me. Do you sell stamps?” and the person behind the counter says “first or second class?”. The shop keeper’s response is not an answer to the question. Instead the shop keeper moved on, and the customer automatically noticed and account-for the speaker’s utterance - and account-for it effortlessly. As described above, we humans are compelled to cooperate. The shop keeper is compelled to assume that what was heard made sense to the speaker, and “works hard” to figure it out.

- If the conversational partner cannot account for the speaker’s utterance, then the speaker risks sanction. If, in a breaching experiment, I walk into a shop and ask for “one sixth class stamp please”, the person behind the counter does not say “Sorry I do not have any of those,” but instead might say something like “Sorry?”, meaning please repeat that. What happens next is complex, but not intractable. For instance I might say “Six first class stamps” and the person behind the counter might account for my odd behaviour by deciding I had made an unconscious spoonerism. The process of bringing the conversation back on track is automatic and highly dependent on things like social distance and power relations. Things that we all know how to do even if we don’t notice we’re doing it.

We know how to make computers do the seen but unnoticed, and we are all socialized humans who know how to ramp up toward sanction when needed. The hard part is making machines that can account-for a speaker’s utterance that succeeds and fails as humans expect it to. It is here that mind reading becomes critical.

The purpose of this paper is to present an alternative to the idea that we need to implement some model of Theory-of-Mind in order to do the accounting-for. Key to this alternative is that “mind reading” happens within this seen-but-unnoticed / noticed-and-accounted-for / works-toward-sanction framework. For want of a better acronym, let us call this the sbu/naaf/wts loop.

5 Mental Models and Accounting for

In the late 1980’s through the 1990’s Brooks’ robots [4] caused a revolution in AI when he abandoned planning in favour of a reactive architecture that became Behaviour-Based Robotics [3]. Rather than sensing the world, modeling it, then planning and acting, a software unit here called a “behaviour” connects sensing to action in a continuous process. Any reasoning - often also quite reactive - then inhibits, stimulates, or in other ways modifies, the parameters of the behaviour. This, it turns out, is how real situated agents work, anything from the bug spotting neurons in frogs, to humans using a photocopier [17], through to trans national corporations managing their supply chain [9]. The proposal is that rather than reasoning about other minds, we should figure out a situated approach to mind reading.

The enactivists have indeed been doing this and talk about “interpersonal primary subjectivity,” writing books to explain what this is and how it addresses various problems [7]. The gist, as I see it, is that when I see a helicopter hover over head, I actually see at most half a helicopter, but if you ask me I would say I perceive a helicopter. Perception comes with assumptions and hence may be wrong, but the process is automatic. A hovering metal orb may turn out to be a soup ladle [13], but I have already perceived a hovering orb in the same way as I directly perceive the helicopter. The enactivist argument is that we humans directly perceive the intent of others. What we see is things like where their attention is focused, their prior actions that led to their current potential for action, and so on, but the process of turning that into a perception is, like walking on two legs, hardwired.. or at least in the firmware.

This is all well and good, but like Brooks’ robots, the philosophy and psychology tend to support the idea that evolution works on the engineers’ KISS principle[1]

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[1] KISS – keep it simple stupid.
### 6 An engineering approach

Our epiphany was to realise that for task based dialogs there is no point recognising the intent of the system’s conversational partner if the system does not have a means of dealing with it. This is especially true given intention recognition happens within the sbu/naaf/wts loop, giving our agent a (socially proscribed) means of signaling if the mechanism fails. Rather than planning from first principles as the TRAINS system did, we proposed a dialog management system that works from a library of behaviours, each of which addresses a use-case. The sleight-of-hand here is that use-cases are normally associated with some goal, and by tagging the behaviour with the relevant goal, we can fake mind reading.

Consider a system that enables me to ring up and order a pizza. If I order a peperoni pizza with sweet peppers and no olives, and the system knows how to create such a pizza, then the process is straightforward (the seen but unnoticed). If I ring the service and order a taxi - something for which our pizza ordering system cannot, quite reasonably, account for - the system can work toward sanction. It might, for instance say “you have called Papa Gino’s Pizzeria. How can I help?” which as a speech act is, among other things, a refusal to talk about taxis (see for a detailed discussion). Recognising what the caller wants when it is reasonable, but not explicit, is the hard part.

So imagine the situation where the caller’s opening statement is “Peperoni, peppers, no olives”. We humans expect the caller wants to order a pizza even though he has not said that. The standard HCI approach would be to design in the assumption and have the system present itself as all and only a pizza ordering system. This way it is the user’s fault if he tries to do something else with it. An alternative is to acknowledge that the user is more than a user – users are also humans, embedded in a soup of social relations that need to be negotiated. The system is thus expected to negotiate a shared intent, which requires some level of mind reading.

The system we proposed has a library of behaviours, each tagged with the goal it achieves. Let’s say that of those behaviours, B17 has, among other things, slots for required and disrequired toppings, and that match pepperoni and peppers, and olives. In addition B17 (see Figure) is tagged with the goal “order a pizza”. If B17 is identified as the behaviour with the best match with the user’s utterance above, the system can respond with: “You want to order a pizza. Great! pepperoni ...”. The system, with no more than classic slot filling techniques and a use-case, has performed what looks like mind reading.

This is no doubt completely underwhelming to many and that is exactly the point. For us humans the process is automatic, but consider how the same result would have to be achieved with a GOFAI approach. There is no description of a pizza in the opening statement and only a bunch of ingredients in the common ground. With the GOFAI approach, the user and the system co-construct a shared model of a pizza, and then the system has a separate planning system to decide how to make the thing represented. Here there is no shared model, but rather two models of what is being talked about. The caller’s head might contain a model of a pizza, but for the system the pizza is represented by specifications for a process.

#### 6.1 A minor extension

The argument is that this model of mind reading is not very robust but that is not critical because the whole process operates within the sbu/naaf/wts loop. If the system gets it wrong, the human will let the machine know by working

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**Figure 1:** A behaviour, task, plan, or activity, for ordering a pizza. Note the conversational opening and closing are handled by the separate sbu/naaf/wts loop.

| Behaviour: B17 |
|---------------|
| achieves: "order a pizza" |
| Slot: toppings = new Slot(TOPPINGS, {"What would you like on your pizza?" ..}); |
| Slot: size = new Slot(SIZE, {"What size pizza would you like?" ..}); |
| Slot: disrequired = new Slot(TOPPINGS); |
| Slot: summary = new Slot(String); |
| Slot: address = new Slot(ADDRESS, {"What address should we give the delivery guy?"); |
| Slot: paid = new Slot(Boolean); |

- toppings.get(); size.get(); confirmation.get(); address.get(); paid.get()
towards sanction. The challenge is to recognise this. The important point is that the human is compelled to do this in HHI, and will reliably continue to do this as long as he or she is treating the agent as a human in the interaction.

Consider the case where I ring up and say I would like to order a peperoni pizza with sweet peppers and absolutely no olives. In this case the “absolutely” may seem rather redundant. The perfect system - the theory about how HAI ought to work - would actively account-for everything in the user’s utterance that does not go seen-but-unnoticed. In the terminology of Conversation Analysis, the system would actively seek out an answer the question “why this, in this way, right here, right now?” The appearance of “absolutely” is anomalous and so why is it there? Like the wine bottle example above, the system may simply decide it doesn’t make sense and move on, but if our pizza ordering system has a behaviour for checking for allergies, this might be a good time for the system to use it. The mechanism for triggering this could be simply key-word spotting, but a post-hoc explanation would be based on the goal associated with the allergy checking behaviour. A follow-up question by the system might be “No olives. Olive oil is okay?” and the caller might say “sure” in a way that suggests that is an odd question. The system might then help the caller account-for its utterance by saying ”I just wanted to <goal>check for allergies</goal>.” Although the evidence for an allergy is weak, the interactive nature of dialog means that getting it wrong here does not matter. As long as the caller can account-for the system’s utterances, the system does not bring on sanction.

In combination with the sbu/naaf/wts loop, our engineer’s solution to mind reading is more than a cheap trick and indeed provides an enactivist model of HHI.

7 Summary

Making a machine capable of intention recognition is difficult using the techniques of classic AI, but we now know that classic AI was wrong about how minds work. Rather than conversational partners constructing a shared model of a pizza on common ground, a conversation is the negotiation of independent models of what the relevant CP wants. Rather than grounding language in apparently objective things, the above pizza making agent grounds language in the doing, as represented by use cases. The way people think about doing, is in terms of goals, and goals are thus inherent in the way we use language to communicate. Recognising the intentions of others is not a reliable process, but the normative structure of human communication as represented here by the sbu/naaf/wts framework provides a robust repair mechanism. This approach is not only practical for HAI but also based on current trends in HHI.

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