Rat big, cat eaten!

Ideas for a useful deep-agent protolanguage

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Abstract

Deep-agent communities developing their own language-like communication protocol are a hot (or at least warm) topic in AI. Such agents could be very useful in machine-machine and human-machine interaction scenarios long before they have evolved a protocol as complex as human language. Here, I propose a small set of priorities we should focus on, if we want to get as fast as possible to a stage where deep agents speak a useful protolanguage.

1 Introduction

Deep-agent emergent language research rests on the hypothesis that, if we want deep networks to develop language-like communication skills, we cannot just train them to reproduce statistical regularities in static linguistic corpora (as is done in language modeling, e.g., Radford et al. [2019]), but we should plunge them into interactive scenarios, letting them develop a code to cooperatively solve their tasks (e.g., Foerster et al. [2016], Lazaridou et al. [2017], Cao et al. [2018], Havrylov and Titov [2017], Kottur et al. [2017], Evtimova et al. [2018], Mordatch and Abbeel [2018], Chaabouni et al. [2019], Li and Bowling [2019], Lowe et al. [2019], among many others). I assume here that this is a worthy research program, and that anybody reading this has a minimal degree of interest in it. Lazaridou and Baroni [2020] provide a recent overview of the area.

Both on the phylogenetic and on the ontogenetic scale, human language does not appear all at once in fully-formed garb. Most linguists agree that, as a species, we went through a protolanguage stage involving a small set of simple constructions (Bickerton [2014], Brentari and Goldin-Meadow [2017], Hurford [2014], Jackendoff and Wittenberg [2014]). Children definitely pass through fairly systematic protolanguage phases, such as the “two-word” stage (Bloom
Still, children and, presumably, our ancestors manage(d) to get a lot done with their protolanguages. Similarly, it is productive to ask: how should a useful protolanguage for deep agents look like? And, consequently, what should be our priorities in terms of the linguistic abilities we want the agents to develop?\footnote{Brochhagen [2018].}

Since these are daunting tasks, rather trying to start from abstract, top-down considerations, I will begin by laying out a prototypical scenario in which an emergent language could be deployed, and analyze which environmental and communication needs are important in it.

2 A prototypical scenario and its demands

Here is a concrete scenario that might be only a few years away. A community of differently specialized bots (embodied, virtual, or a mixture of the two) help us in our daily life, going through chores such as checking what we have in the refrigerator, seeing whether the water is boiling, finding our phone for us, etc. The bots will need to communicate with each other, and at least occasionally with us.

Scripting is not an option, because we are stuffing our cupboard with fancy new cereals all the time; we buy new gadgets that then we promptly lose under the sofa; and so on. Not only new things will continuously pop up, but words will have to frequently be combined in novel ways, with subtle semantic shifts that would be extremely difficult to hard-wire: different things in the refrigerator might rot in different ways, a dishwasher and a pot will be considered full under rather different conditions, etc.\footnote{The study of emergent communication has also other worthy goals, such as providing insights into the origins and universal properties of human communication. The priorities I suggest here are strictly from the point of view of my idea of a “useful” protolanguage, but of course other topics might be more important when emergent communication is studied in a different, less applied perspective.}

This is of course just an example of a scenario in which to deploy talking bots, but I think its demands are fully representative of those of many other useful interactive use cases, from purely virtual chatbots to colonies of fully embodied worker robots.

The proposed scenario requires formidable progress in robotics (how do you bend to look for the lost gadget under the sofa?), computer vision (how do you visually recognize a new cereal? how do you transfer rotting cues from chicken to tomatoes?) and other fields. My focus here is exclusively on the language...
side, but many challenges might be best solved jointly (such as learning about the new cereal appearance together with the word to denote it).

2.1 Environmental constraints

Considering the use case above, the protolanguage should be robust to the following environmental characteristics:

1. Agent inputs are continuous and noisy: they might be (representations of) images, actions, sounds, etc. Different instances of the same object (or action, or property) will look at least slightly different, and boundaries between different categories are fuzzy.

2. There is no close set of “things” that agents need to talk about: new objects, actions, properties can always appear.

2.2 Communication needs

At a minimum, an agent might need to inform other agents of the presence of something, as in:

(1) A rat!

However, most useful messages will highlight a property of an object that is important for current purposes, as in:

(2) a. rat big
    b. cat dead
    c. sister running
    d. child hungry
    e. apple eaten

I will call the structure exemplified in (2), in which a property is asserted of an object, a predication. I am using “property” in a very broad sense. In particular, it can be a feature that natural languages would likely denote through an adjective, but it could also be an action or state typically denoted by a verb. Indeed, even example (1) above could be seen as a concise way to express a predication akin to (3):

(3) rat near

Agents can go a long way with basic predication. In the next few sections I will discuss more complicated things that natural language can also do, which I think we can either i) ignore for the time being (Sec. 2.2.1), or ii) expect to be handled by context in the situated, goal-driven communication settings we envisage (Sec. 2.2.2), or iii) capture through simple predication and massive parataxis (Sec. 2.2.3).

\[4\text{In linguistics, parataxis defines the tendency to juxtapose simple clauses, instead of subordinating them to construct complex sentences. Cf. “I came, I saw, I conquered” vs. “After coming, having seen, I decided to conquer”}\].

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2.2.1 Language feats we can ignore for the time being

Being able to refer to abstract concepts is a huge part of what makes language so powerful. Yet, I conjecture that agents can be very useful without the need to think in abstract terms. Moreover, being able to talk about concrete things is probably a necessary stepping stone towards abstract language (Lakoff and Johnson [1999]).

We can moreover let the language be quite rough in its ways of reference, akin to the children’s two-word stage. Let’s forget for now about the nuances afforded by adverbial and clausal modification.

Finally, the protolanguage need not support the further expressive power complex verbal morphology and sentential scaffoldings would provide: for example, the ability to express counterfactuals, hypotheticals, belief degrees, etc.

2.2.2 Context can provide a lot of side information

Primitive talking agents will have to deal with a relatively small number of environments and tasks, where a relatively stable extra-linguistic context can provide a lot of information. If our home-bound agents are speaking of chicken, it’s definitely the food and not the animal. Consequently, for the time being, we probably do not need to worry about (inter alia):

Genericity. Does “rat big” mean that rats are big in general, or that there is a big rat in the kitchen? Does “apple eaten” mean that apples are edible, or that someone is eating an apple? At least in a relatively restricted domain, there might be only one natural reading for each expression, or the intended meaning might be clear from context. Similarly, issues of definiteness (do we want that specific apple, or any apple will do?) can be left to extra-linguistic means of disambiguation.

Speech acts. In (2a), are you asking me if the rat is big, or informing me that it is? When uttering (2c), are you stating that your sister is running, or are you ordering her to? Again, context (who is the addressee, what are the current information needs, etc.) can take care of that.

2.2.3 Pushing simple predication to the limit

Expressing more complex concepts through massive parataxis. The agents can concatenate multiple predications to articulate more complex concepts, leaving the appropriate binding to context. Consider for example two-argument predicates, such as transitive verbs. As a primitive surrogate, our protolanguage could have separate predicates for the agent and theme roles, and closely juxtapose two predications to express the composite concept. So, “a rat is eating the cat” could be expressed by something like:

(4) rat eating... cat eaten
Similarly, temporal or causal links could be expressed by parataxis aided by iconicity (that is, ordering predications in the way in which the corresponding events occurred, placing the cause before the effect, etc.):

(5)  a. rat running... cheese reached... rat stopping  
    b. rat hungry... rat eating

Coreference can be left implicit or provided by sheer repetition of the same nouns, as in the examples in (5). Similar strategies will break down when a certain level of complexity is reached, but we can probably go a long way before we get there.

**Personal pronouns, proper nouns, quantification.** A lot of things that formal semanticists have very rightly argued cannot be treated as standard nouns or adjectives could be treated as standard nouns or adjectives in our protolanguage (when the relevant meaning facets cannot directly be left to context). The list includes i) personal pronouns, treated just like any other noun, except that their reference will be context-dependent (“me hungry”); ii) proper nouns, that, to the horror of philosophers of language, could be treated nouns that happen to denote one entity only (“Marco hungry”); and iii) quantities, such as “many” and “three”, that would be treated just like other property-denoting predicates (“rat many”).

3 Priorities for emergent language research

To get us to the stage outlined in the previous section, we need the emergent language to have the following characteristics:

- use words to categorize inputs lying on a continuous space into distinct classes (different objects, such as rats, actions, such as running, and properties, such as being yellow);
- seamlessly create new words when new concepts are encountered;
- express combinations of arguments and predicates.

I will next discuss each of these priorities in turn, and conclude the section with some remarks about the issue of making the protolanguage human-understandable.

3.1 Categorization

You never step into the same river twice, but you still conceptualize it as a single river; the way a kangaroo jumps is very different from the way a grasshopper

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*Formal semanticists with a heart condition might want to stop reading at this point.

*Morphemes is probably a more accurate term here, but let’s not get too technical.
jumps; we call a broad range of animals “dogs”, but it is useful to think of wolves and hyenas as categorically different. Languages strike a good balance between splitting the world into classes that are so detailed as to be of no use (my keyboard at 3.30pm on February 14th 2020) and classes that are so broad as to be again useless (“entity”). There is however little ongoing language emergence research on how agents categorize their perceptual input through language. The focus in the area has recently shifted to toy environments where the input is either already conveniently split into symbolically represented categories, or in any case rather artificial, e.g., synthetic images of geometric shapes (Lazaridou et al., 2018 showed that already using synthetic images instead of purely symbolic inputs has a big impact on the emerging language).

3.2 Word coinage

Agents should be able to refer to new things that might appear on their horizon, such as a new type of cereal (or new ways to categorize existing things, like when you learned that a subset of the grains you already knew were cereals).

One way to do this is to provide the agents with a very large vocabulary of primitive symbols (say, 20k symbols, a conservative estimate of the lexical knowledge of an average English speaker), so that they can recruit hitherto unused symbols to refer to new concepts on demand.

A more human-like (and probably more promising) approach is to lead agents to exploit duality of patterning (Martinet [1965]), that is, treating primitive symbols as meaningless units to be combined into meaningful words. Agents are provided with a small set of symbols, more akin to a phoneme inventory or alphabet, so that, from the very start, they must make up words by concatenating symbols from this alphabet. Even limiting alphabet size and maximum utterance length, this immediately provides the potential to coin a very large number of words.

New word coinage is not systematically studied in the current language emergence literature. What is extensively studied instead is the case where new referents are composite, and the question is whether the emergent language can harness this composite structure to quickly generalize (aka compositionality, see, e.g., [Kottur et al. 2017], Lazaridou et al. [2018], Mordatch and Abbeel 2018, Andreas 2019, Guo et al. 2019, Resnick et al. 2020). This is of course an important question, but simple-word coinage should come first. From an evolutionary perspective, it only makes sense for a language to start composing words in order to denote complex meanings after the language has coined enough primitive words to justify combinatorial strategies. From a methodological perspective, if we do not understand the means a language uses to refer to new primitive concepts, we will be doomed when trying to analyze how it refers to composite ones. Without an understanding of basic word coinage, it will be hard to tell whether, when an agent utters “baama” in response to a red triangle, it is using “baa” to refer to redness and “maa” to refer to triangles, or whether it is treating

[https://bit.ly/2T7CV0P]
the whole as new primitive concept that it is labeling with the string “baama”.

3.3 Argument-predicate combinations

Agents able to communicate about an open set of primitive categories by adding new words to their repertoire would already be quite a feat. The expressiveness of the language would however enormously increase if object-denoting and action-state-or-property-denoting words could be combined in simple predication structures. This is close to what is currently studied under the rubric of compositionality in emergent language (see above). However, there are some aspects of compositionality that I would like to prioritize, based on the desiderata for the protolanguage I have outlined.

Most importantly, if we want to develop a language that can eventually be deployed in the real world, the agents should be able to detect the properties to be denoted by predicates in perceptually realistic inputs, rather than in abstract symbolic representations. It is one thing to learn a red predicate from input objects represented by attribute-value sets such as \{color:RED, shape:SQUARE\}, and another to discover that red hair and red tomatoes, as depicted in natural images, have something in common that can be captured by a shared red predicate. Decomposing a dynamic scene into an agent or patient and the action or event they are involved in is even more challenging (and could perhaps be left to a later stage of research).

Scaling up, I described above a way to refer to more complex situations by paratactic concatenation of unary predications (“rat eating . . . cat eaten”). I think however that we already have enough on our plate dealing with the single predication case. Needless to say, more ambitious forms of composition, such as clausal subordination and recursion, are best left to future work.

3.4 Humans in the protolanguage loop

In the framework of emergent communication, we do not directly control the actual form agent language will take. Consequently, the linguistic examples I presented above are just human-friendly illustrations of the structures I’d like to see in the emergent protolanguage. The way the same communicative needs are satisfied by the protolanguage could be very different.

Since one of our goals is human-machine interaction, if the protolanguage drifts too far from anything human-like (consider a language that achieves composition by symbol inter-leaving: “readr” denoting a red car), we’ll need to bring it back to Terran grounds somehow. We can take here inspiration from current research on limiting emergent language drift, either by forcing the agents to directly mimic natural language (Havrylov and Titov 2017, Lazaridou et al. 2017, Lee et al. 2018), or by imposing human-like bottlenecks, for example, on agent memory and channel capacity (Kottur et al. 2017, Resnick et al. 2020). More generally, we can find inspiration in the growing area of model interpretability and explainability (e.g., Ribeiro et al. 2016).
Still, just as we have no big trouble interacting with children, or to quickly pick up fundamental words and constructions in a foreign language, once machines are endowed with a minimally sensible protolanguage, I expect humans would be willing and able to make an effort to understand what they mean.

4 How do we get there?

Let’s recall, again, that we are considering the emergent language setup, where agents develop a communication protocol in order to solve a task together, without any supervision on the protocol itself. I am not proposing to force the properties I outlined above into the emergent language by manual coding or ad-hoc training. Decades of failed attempts in ML/AI suggest that manual language coding is invariably a bad idea, as shown by the current dominance of end-to-end deep networks over systems relying on explicit linguistic structures in virtually all domains of natural language processing (see, e.g., the state of the art in tasks such as machine translation, and machine comprehension; Cui et al. [2017], Edunov et al. [2018]). At the same time, coming up with “protolanguage” data to train agents is a contrived and difficult enterprise (the whole idea of language emergence arose in the deep NLP community because it is not clear how to train an interactive talking agent in a supervised way!). The focus should be instead on designing environments and tasks/games in which the agents are naturally encouraged to develop the properties of interest.

Coming back to my application scenario above, a simplified laboratory setup could involve multiple agents that have to jointly maintain a set of household goods in stock. Minimally, there are two agents. A pantry agent keeps track of the current supply level, that is constantly in flux as some items are consumed, others go bad, etc.. A shopping agent would have to provide missing goods, possibly with budgetary restrictions.

In a first iteration, the game could mix realistic components and opportunistic choices dictated by practical considerations. For example, the distribution of natural images of household goods could be taken from a database such as LVIS where objects have a realistic long-tail distribution. To encourage predication, attribute classifiers could automatically tag the images with properties such as color (Farhadi et al. [2009]), and the stock could be built to contain many objects only differing in some attribute value (e.g., candies of different colors). On the other hand, changes in stock would be guided by random processes; change of state (e.g., rotting) could be simulated by techniques to deform shapes in pictures, and so on. This scenario should meet my desiderata: realistic perceptual input, new objects steadily popping up, at least some degree of predication needed (“tomatoes green”, “potatoes out”, “mozzarella rotten”).

\footnote{Coming up with proper evaluation methods is equally important. The latter should not only quantify task success, but also the properties of the emergent language we find desirable, which is a huge challenge in and by itself (Bouchacourt and Baroni [2018], Lazaridou et al. [2018], Lowe et al. [2018]).}

\footnote{\url{https://www.lvisdataset.org/}}
However, I recognize that my sketch is rather hand-wavy. I hope these notes will inspire other researchers to brainstorm together about better ideas on how to get started.

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