There is no Artificial General Intelligence

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December 2, 2019

The goal of creating Artificial General Intelligence (AGI) – or in other words of creating Turing machines (modern computers) that can behave in a way that mimics human intelligence – has occupied AI researchers ever since the idea of AI was first proposed. One common theme in these discussions is the thesis that the ability of a machine to conduct convincing dialogues with human beings can serve as at least a sufficient criterion of AGI. We argue that this very ability should be accepted also as a necessary condition of AGI, and we provide a description of the nature of human dialogue in particular and of human language in general against this background. We then argue that it is for mathematical reasons impossible to program a machine in such a way that it could master human dialogue behaviour in its full generality. This is (1) because there are no traditional explicitly designed mathematical models that could be used as a starting point for creating such programs; and (2) because even the sorts of automated models generated by using machine learning, which have been used successfully in areas such as machine translation, cannot be extended to cope with human dialogue. If this is so,

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then we can conclude that a Turing machine also cannot possess AGI, because it fails to fulfil a necessary condition thereof. At the same time, however, we acknowledge the potential of Turing machines to master dialogue behaviour in highly restricted contexts, where what is called "narrow" AI can still be of considerable utility.

1. Introduction

Since the research field of AI was first conceived in the late 1940s, the ability of machines to conduct convincing dialogues with human beings has been seen as a necessary criterion for achieving artificial intelligence (Turing, 1950). There are important proponents of the attempt to realize what is called artificial general intelligence (AGI) who hold that the ability to engage in dialogue is "only a sufficient, but not a necessary criterion for achieving AGI" (Pennachin and Goertzel, 2007). Thus they argue that "general intelligence does not necessarily require the accurate simulation of human intelligence" (Pennachin and Goertzel, 2007, p. 21). There are good reasons, however, to take human intelligence as our starting point for understanding what AGI is. This is because, as the just quoted paper by Pennachin and Goertzel makes clear, when we engage in speculation as to the nature of 'intelligence' independently of what we know about human intelligence, then we descend very quickly into a modern form of speculative metaphysics. Thus for example the authors define intelligence as the "ability to perform complex goals in complex environments." According to this definition, the 1 mm-long nematode *Caenorhabditis elegans* with 302 neurons would be intelligent, because it can achieve sexual reproduction (a complex goal) in its natural habitat (such as a pile of compost, which is undoubtedly a complex environment).

We will assume further that the ability to use language is not only a very good proxy for general *human* intelligence but also that it should be seen as a necessary condition for the existence of general *artificial* intelligence. Communication using language is an activity that differentiates *homo sapiens* from all other species. It is through language that we express our consciousness of reality and our ability to think and act freely. Conversation is the foundation of human society and of human culture. We believe that it is for this reason that Turing selected language as the core of his proposed method, later to be called the "Turing Test", to determine whether machines can emulate the human ability to think. Though for many reasons (not analysed here), the ability to pass the test as it was described by Turing himself in 1950 is not a useful criterion for AGI, Turing's core idea – namely that we can gauge intelligence by gauging the ability

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of a machine to mimic human dialogue – remains central to our argument. For it will follow from the assumption that the ability to engage in fluent dialogue with human beings is a necessary condition for the existence of AGI, that if we can show that this ability is not realizable in a machine then we can infer that AGI, too, is impossible.

1.1. Why dialogue matters

Why, then, the central role of dialogue? This is because dialogue ability is critical for any practical use that we might want to make of AGI, for example in a business enterprise or in government. *How could we primarily use AGI, if we had it?* What type of work could AGI machines perform that could not be performed either by human beings or by machines possessing one or other of the sorts of narrow AI that we already have at our disposal? We consider the possible answers to this question under three headings: (a) mobile physical work; (b) intellectual work that does not involve engaging in dialogue; and (c) work primarily involving communication.

(a) Machines (robots) possessing AGI could use their intelligence to move freely and interact with dynamically changing, highly complex environments. Even if the work they were doing was entirely physical, for example transporting goods or disposing of waste, they would still have to be able to react to many kinds of environmental signals, among which human utterances are the most important. The utility of such machines would thus greatly increase were they able to understand and follow instructions issued by humans, even if they could only respond with stereotypical utterances such as "Yes, master" or "I am sorry, master." Also, they should be able to react to human warnings, or understand suggestions from humans concerning better ways to do things. In other words, the ability to correctly interpret complex human utterances would still be required

(b) Machines performing intellectual work of the sort that does not involve spoken dialogue with humans – for example loan application or insurance claim processing – would still need to understand text, because the material they have to process is often provided in this form. Such work does not, in the normal case, require dialogue. But to process such documents with an error rate no worse than that of human beings, machines would need to exactly understand the meanings of the texts they process.

(c) Machines performing activities involving communication with human beings – for example IM-chat or phone dialogues – would need to be able to conduct such dialogues in a way that, at a minimum, allows the human user of the system to achieve her goals in an effective and efficient manner. And in order to justify a claim that a machine engaged in such activities possessed AGI, we would need to show that the machine has the ability to engage in dialogue with a human about an open-ended variety of topics

in a way that does not require the human being to make specific sorts of extra efforts because they are dealing with a machine.

We note that in all three sorts of cases the AGI involved would need to demonstrate in its use of language to communicate with humans the ability to take account of highly complex contextual dependencies.

1.2. AI conversation emulation and its failures

Many in the AI community are convinced that it is possible to create a machine with dialogue ability because they share Turing's view that building such a machine is just a matter of storage and computation (Turing, 1950; Goertzel and Pennachin, 2007). This in turn reflects a common assumption that human cognition and consciousness are themselves just a matter of storage and computation.

Here, however, we are not interested in the question whether machines can achieve consciousness, but rather only whether they can interpret complex texts and engage in dialogue with humans. Such conversation machines have been under construction since the 1960s. Efforts are directed mainly towards what are called *dialogue systems*, or in other words systems able to engage in two-party conversations, which are optimistically projected to be widely used in commercial agent-based applications in areas such as travel booking or service scheduling. However, despite major efforts – from ELIZA (Weizenbaum, 1966) to the computer-driven dialogue systems of the present day (including Siri and Alexa) – nothing close to dialogue emulation has thus far been achieved.[1]

The tenacious optimism in the field is, we hold, based on the one hand on an unrealistically simplified view of what human dialogue behaviour involves, and on the other hand on a series of impressive successes in other areas of AI research – above all in reinforcement learning, where solving the game of Go (Silver, Hassabis, et al., 2016) and achieving mastery in first-person shooter games such as Doom and Counter-Strike (Jaderberg and Czarnecki, 2018) have significantly raised expectations as to what might be possible in other areas.

Counting against this optimism, however, is the repeated failure of attempts to build machines able to perform in a satisfactory way when engaging in dialogue with humans. This rests, we believe, on the complexity of the systems for generating and interpreting language that have evolved in humans and on the huge landscape of variance in natural language usage ensuing therefrom, some features of which were recognized by philoso-

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[1]See 3.4.3.2 below.

phers starting as early as Thomas Reid[2], later by Schopenhauer[3], and then by Adolf Reinach[4].

Arnold Gehlen explored the field from the biological and anthropological perspective in his main work *Man*, first published in 1940 (Gehlen, 1988). A decade later Wittgenstein's *Philosophical Investigations* gave rise to a significant enhancement in our understanding of how (especially spoken) language works, which was refined by the contributions of philosophers such as Austin and Grice and has since been consolidated in the huge body of research in the philosophy of language, linguistics, semantics and pragmatics, upon which we draw extensively in what follows.

1.3. Main arguments of this paper

To see why human dialogue eludes mathematical modelling we must first describe how humans generate and interpret language when engaged in dialogue and why the capacity for such generation and interpretation is part of an essential survival strategy for *homo sapiens*. We shall see that language is a sensory-motor human capability, which arose in the evolution of our species as a genus-specific way to interact with our environment in an abstract, controlled fashion that replaces the instinctive behaviour of our non-human ancestors (Gehlen, 1988). Briefly, language enables us to shape and realize our intentions (for example through deliberation and planning), and we will show that this implies a potentially infinite variance in the ways we use it. We contrast this to the capabilities of Turing machines, first expressed more than 175 years ago by Ada Lovelace in her

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[2]Schuhmann and Smith (1990) provide a list of the variety of uses of language discussed by Reid, incorporating questioning (asking for information, for advice asking for a favour). providing testimony, commanding, promising, accepting / refusing (advice, a favour, testimony, a promise), contracting, threatening, supplicating, bargaining, declaring, and not last plighting (one's faith, one's veracity, one's fidelity.

[3]"It is by the help of language alone that reason accomplishes its most important achievements, – the united action of several individuals, the planned cooperation of many thousands, civilisation, the state; also science, the storing up of experience, the uniting of common properties in one concept, the communication of truth, the spread of error, thoughts and poems, dogmas and superstitions." *The World as Will and Representation*, §8.

[4]As Mulligan (1987, pp. 1-2) makes clear, the primary objective of both Reinach and his Anglo-Saxon successor J. L. Austin (Austin, 1962), "is to bring into focus, and fully describe, a phenomenon of which promising is their favourite example. Other social acts dealt with in some detail by Reinach are requesting, questioning, ordering, imparting information, accepting a promise and legal enactment, which – except for the last two – are all at least touched on by Austin. In all these social acts we have 'acts of the mind' which do not have in words and the like their accidental additional expression. Rather, they 'are performed in the very act of speaking'. These cases of doing something by saying something are, and give rise to, changes in the world. They are associated with a variety of different effects. Examples of the effectivity (Wirksamkeit) of social acts are both the obligations and claims to which promises and orders give rise and the behaviour, whether a social act or a non-linguistic action, which some social acts are intended to bring about."

statement to the effect that the Analytical Engine[5] "has no pretensions to originate anything. It can do whatever we know how to order it to perform" (Lovelace and Menabrea, 1843). We interpret Lovelace here as asserting that the machine will never develop a counterpart of (for example) human intentions[6], and thus also not learn in the way that humans do, *until we know how to tell it to do so.* But to achieve this, we would have to create mathematical models of these human characteristics, since – as was often pointed out by Turing himself – *we can only model what we can describe mathematically,* and we shall see that this is beyond the bounds of what is possible given our current mathematics. We thus go one step further than Searle's Chinese room (John Searle, 1980), which states that machines cannot emulate consciousness: For we reject the very idea that a Turing machine could be built that would emulate human conversational behaviour.

1.3.1. Mathematical models of human dialogue

What, then, of the mathematical representation of human dialogue? A dialogue is a complex stochastic temporal process of a certain sort – as we shall see, it is a process that lacks the Markov property (according to which state transition probability depends only on the immediately preceding state). Processes in the human brain quite generally are of this sort, as are (for example) the processes generated by the global climate system. All such systems, as we shall see, elude mathematical modelling.

Certainly, some stochastic processes can be modelled mathematically using what are called stochastic models (Parzen, 2015). But for this to be possible, we need input-output data tuples where the inputs are connected to the outputs probabilistically, which means that there is a certain (measurable) likelihood that a given input will be associated with a given output (Landgrebe and Smith, 2019).

This is the basis of so-called "machine learning", which applies in the most straightforward case in situations in which (1) human beings repeatedly process data in a certain way, (2) we are able to collect large quantities of the input data that are used for this purpose and (3) associate these data with the output data humans have created therefrom. An example is the behaviour of humans in identifying spam in their email. Here the sender, subject and text of an email serve as input, while the human decision to put this email into the spam folder provides the output. The process of training the machine

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[5]This is the machine built by Charles Babbage which, as Turing points out (*op.cit.*), is mathematically equivalent to a Turing machine.

[6]This is true even though dNN can now be built that develop new automated models which have not been designed explicitly by humans, see section 3.4.2.4.

with these data yields a gigantically large equation that models the relationship between the input and output data that have been used for training. This model is then narrowly tied to the training data that generated it, so that if the equation (the trained model) is applied to new data that is not drawn from the same distribution as the original training data, it will compute undesired outputs.[7]

Only if we have a sufficiently large collection of input-output tuples in which the outputs have been appropriately tagged can we use the data to train a machine that, given new inputs sufficiently similar to those in the training data, is able to predict corresponding outputs with a certain (useful) degree of accuracy.

What 'sufficiently large' and 'sufficiently similar' mean, here, are questions of mathematics. We shall see that, when these questions are raised in relation to those sorts of stochastic temporal processes which are human dialogues, then it becomes clear that there are in fact *three* insurmountable hurdles to realizing the scenario in which a machine could be trained to engage convincingly in human conversation, namely

1. that human dialogue processes do not meet the conditions needed for the application of any known type of mathematical model,

2. that, due to the inexhaustible variance which human dialogues exhibit – which is as huge as the variance in human culture and behaviour in its entirety – we could never have sufficiently large amounts of data to train a machine, and

3. that to learn the correct interpretations of the dialogue utterances, interpretations which are indispensable to adequate dialogue production, the utterances themselves are insufficient; what is implicit in the dialogue cannot be fully derived from what is given explicitly.

We shall see that nothing has changed in this respect even with all the advances made in machine learning in recent years (including reinforcement learning (see 3.4.2.6), adversarial learning and unsupervised sequence learning (see 3.4.3.4)). For again: the limitations on what machine learning can do are of a mathematical nature.

Nothing has changed, either, as a result of the impressive accumulation of data pertaining to human language use, including large amounts of dialogue content in the form of Youtube interviews or of data deriving from use of Siri, Alexa and similar services. Interview data are typically highly stylized and thus represent only a small fraction of

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[7]We deal with this matter at greater length in our discussion of the spam filter and other examples in (Landgrebe and Smith, 2019).

the variance needed to be useful to support machine learning of the sort needed to implement a machine counterpart of general human dialogue. Siri/Alexa data, on the other hand, are merely recordings of human- machine interactions, and so are of zero utility for our purposes here. Both sorts of data are also severely limited by the restriction to what is explicit, and thus recordable.

1.3.2. There can be no AGI

In this communication, we will give evidence for the soundness and validity of the following syllogism concerning the creation of AGI:

- There can be no mathematical models for the type of behaviour occurring in human dialogues.

- Therefore, there can be no computer programs implementing such models.

- The ability to emulate human dialogue behaviour is a necessary condition for implementing AGI.

- Therefore, there can be no AGI.

This does not of course mean that all is lost for AI in the realm of human dialogue. For we also review the current state of the art in dialogue system building and conclude by identifying what we see as the potential for dialogue systems that would still be *useful* even though they fall far short of AGI. This essay thus complements our previous paper Landgrebe and Smith (2019), where we defended a sceptical attitude to the current euphoria surrounding "deep neural networks", while at the same time pointing to AI applications which provide significant utility in addressing specific sets of real-world problems.

2. Language and dialogues

2.1. The nature of human language

Our use of language is the expression of our will to interact with the physical world around us and with other humans in pursuit of our goals (Schopenhauer, 1986). We shall refer to these goals as they impact our day-to-day behaviour as *intentions* (Bratman, 2009).

We concentrate in what follows on the use of spoken language, which is a sensory-motor activity closely related to, for example, hand movements involved in grasping

an object.[8] When we perform motor activities, we simultaneously obtain propriosensory feedback from the performance itself. In the case of the arm-hand movement for grasping, proprioception is augmented by a second sort of feedback deriving from the object as we touch it, feedback which confirms that we have achieved our grasping intentions. These two sorts of feedback – from our own body and from our environment via our sensory system – allow us to continuously adjust our intentions.

Language is however a much more powerful type of motor activity than all the others. The sensory-motor feedback occurs as we hear our own words as we are speaking; but now the proprioception is augmented through the feedback we receive from our interlocutor – for example in the form of facial expressions, gestures, as well as further speech. We continuously use this feedback to adjust not just what we say and the way we speak but also the intentions we are seeking to realize by engaging in dialogue (Gehlen, 1988, chapter 33).

2.1.1. Language functions

Animals act on the basis of instinct, and they therefore ignore those sensory inputs that do not stimulate their pre-defined response spectrum. A passive, static filter blocks non-relevant stimuli and lets through only those stimuli that trigger instinctive behaviours (Gehlen (1988, chapter 15), Milton (2000)).

Humans, in contrast, have no such passive filter governing what they experience, but are able to deal freely with the full breadth of sensory inputs. In contrast to animals, humans live in this sense in an open world (Scheler, 1976). This is, on the one hand, a defect. For it means that humans do not have at their disposal the sorts of instinctive routines that would make them well adapted to their natural environments. But on the other hand it is a benefit, since it means that humans are adaptable to ever new environments through use not only of their mental capacities but also of tools (including language). This adaptability is seemingly without limits. Hence *general intelligence.*

At any given moment, humans can choose from a broad and ever-changing repertoire of environmental inputs, and already from early infancy humans manifest strategies to avoid being overwhelmed by sensory inputs. These include apprehending their environment not as a meaningless mosaic of sensations, but rather as a world of enduring objects (including persons) divided into different kinds (for example animate and inanimate), linked by causal relations, and manifesting characteristic functions and rule-governed behaviours (Gibson, 1979; Keil, 1989).

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[8]These similarities were first comprehensively described by Gehlen (1988, chapters 19ff.); for a contemporary treatment, see Gómez-Vilda et al. (2013).

Over time, infants apprehend a subset of the behaviours of their fellow human beings as of special significance, namely those which involve the production of linguistic utterances, which they themselves imitate. With increasing sophistication, they themselves begin to use language in ways which enhance inborn tendencies to recognize classificatory hierarchy and causal and functional patterns in the world. For example, they learn to identify a wooden stick as a pencil, and thus as a tool for writing. By using general terms to describe both the things in the world to which our intentionality is directed and the associated sensations and emotions, language enables us to distance ourselves from our immediate experience of what is particular in external reality and from our spontaneous emotional reactions (Gehlen, 1988, chapter 28).

In his paper about illocutionary acts, J.R. Searle (1975) introduces the distinction between two 'directions of fit' between words and world. On the one hand is world-to-word direction of fit, for example when I make a list of items I need to pack for the holidays and then act in such a way as to make the world match my list. On the other hand is the word-to-world direction of fit, when I make a list of items actually packed. Lists of this sort illustrate how language creates a new plane of activity through which we can shape and view the world. I can use my list as a tool to help me realize my intention *to pack my bag*, or as a basis for reflecting on what items I will really need.

The list illustrates more generally how by using language (including silent soliloquy) we are able to distance ourselves from the stream of our present experiences, both inner and outer. The example list shows us how we use language to engage in *planning behaviour*, which involves engaging in a sort of abstract simulation of different courses of action. The example also illustrates the way in which language serves as the foundation of progressively more ambitious social interactions: from using a simple list as the means to have someone else pack your bag to enabling the sorts of collective agency needed to build cathedrals and space ships or maintain a legal system or an industrial enterprise.

Language allows us to deal with increasing sophistication with patterns in the ways causal (including intentional) processes unfold and to shape these patterns by providing a powerful vehicle for the forming and realization of our individual and collective intentions. It allows us to react in ever more flexible and useful ways to what would otherwise be an overwhelming flood of stimuli, and to do this at successively more general and abstract levels as concerns not only our interactions with the external world but also the ways we cope with our own inner sensations and emotional reactions.[9]

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[9]As when someone reasons in their mind as follows: "I have been feeling angry in situations like this before, but my previous overreaction only aggravated my situation, so this time I will attempt to control my responses."

2.1.2. Foundations of the language background

Language is a complex of capabilities that are applied by humans to enhance their processing of both external and internal reality. Although the ability to use language is genetically encoded, the specific languages that people use are parts of culture and must be learned. Each individual uses language in a specific way, which depends on their specific experiences in interacting with the world (including their fellow human beings) from infancy onwards.

In particular, the general terms we use in describing reality have a foundation in our physical experience. We learn to use 'bitter' by registering that contexts in which we experience tastes of a certain sort go hand in hand with contexts in which people use this word. Such abstractions can also arise from associations at higher levels, as when the positive feeling we experience when eating something sweet gives us an understanding of the adjective 'delicious'.

2.2. Dialogues

We engage in dialogues in order to interact with other people to achieve certain ends (berating, guiding, learning, persuading, socializing, and many more). As our interlocutor responds, we take what we hear and view it, typically spontaneously and unconsciously, in light of our current intentions and what we have experienced in previous encounters. We thereby once again condense the sensory input down to the abstract linguistic plane encompassing just what is needed to understand what has been said.

Utterances and interpretations take place in time and (more or less) in sequence. Both involve the making of conscious and unconscious choices, which are *implicit* in the sense that they are accessible to the dialogue partner – and to any external human or machine observer – at best indirectly, for example via facial expressions or via the utterances to which they lead.

Our intentions thereby interact with the intentions of our interlocutor as the dialogue proceeds through successive cycles of turn-taking,[10] a phenomenon which seems to be found in all human cultures (Schegloff, 2017; Stivers et al., 2009). In each cycle the drivers of the conversation for both participants are their respective intentions – the goals they each want to achieve by means of their utterances (Grice, 1957; Austin, 1962; John Searle, 1983).[11] When it is Mary's turn to speak in a dialogue with Jack,

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[10]Turn taking is guided by rules and also by what (Sacks*op. cit.*) calls turn-constructional units, an important subtype of which are "possible completion points", which are signals in the dialogue that indicate the opportunity for a role switch.

[11]If the dialogue arises spontaneously, only the first utterer may have an intention; but the interpreter

she tries to fulfil her intentions by conveying content meaningful to Jack and in a way that Jack will find persuasive. As Mary tries to influence Jack, so she in turn may be influenced by the ways in which Jack responds. In this way, a conversation will typically bring about changes in the intentions of its participants. A speaker may foresee the reactions of his interlocutor to his utterances and consciously or unconsciously plan out the conversation flow in advance. Creating such a plan is sometimes even the explicit intent of the conversation, as when people sit down together to reach decisions about how to synchronize their intentions.

2.3. Habits, capabilities and intentions

In every case, dialogue interaction take place against an enduring, and typically slowly changing, background, consisting of the evolving intentions of the interlocutors and of their respective personalities, habits, capabilities and other elements drawn from their personal biographies.

These form what we shall call the 'identity' of a human being, by which we mean that highly complex individual pattern of dispositions, among which the most important are (in ascending order) the visceral, motor, affective and cognitive dispositions that determine a person's possibilities of reaction to internal or external stimuli.[12]

Your identity, in this sense, results from the combination of genotypic and environmental influences which affect your neural (or more generally your physical[13]) substrate as it develops through time.[14] A the huge variance involved in the different sorts and

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will very quickly form intentions of her own as soon as she is addressed, including the intention to refuse engagement in a dialogue.

[12]The underlying account of dispositions is sketched in Hastings et al. (2011). This draws in turn on the ontology framework described in Arp et al. (2015)

[13]In language production the physical substrate consists not only of your brain but also of your diaphragm, lungs, and the entire vocal apparatus.

[14]Our 'identity' thus comes close to what Searle calls 'The Background' (John Searle, 1978), of which Searle himself says that it is at one and the same time (i) "derived from the entire congeries of relations which each biological-social being has to the world around itself" and (ii) purely a matter of that being's neurophysiology (John Searle, 1983, p. 154).

We can distinguish three main families of dispositions through the realization of which our identity is manifested:

1. habits, tendencies, personality traits (for example tendencies to stutter, to fret, to avoid commitment, to behave politely, to behave honestly, ...)

2. capabilities (to speak a language, to play the piano, to manage complex activities, to do long division, to play championship tennis, to practice law, ...)

3. intentions, goals, objectives (to pass this or that exam, to marry Jack, to impress Jack's mother, to lose weight, to heal the rift with your bother, ...)

Our intentions are the drivers of our behaviour and are typically short-lived; intentions may be adjusted, for example, with each successive utterance in a dialogue. Our habits and capabilities are

features of utterance structures that can be produced in the course of a dialogue.

Matters are made still more complicated by the fact that a decisive role in the formation of both utterances and interpretations is played by the contexts in which communicative acts take place (Fetzer, 2017). We show in the Appendix A.2 that there is a vast range of multiple types and levels of such contexts. And, to make matters worse, the range of possible choices is not static or stable (Verschueren, 1999, p. 59).

The result is that there are so many different sources and dimensions of variance involved in a communicative act that the possibilities of forming an utterance are practically infinite. Humans can cope with this degree of variance because they can actively form and interpret utterances based on their own intentions. Even a total lack of understanding of a sentence spoken in a foreign language can be brought into congruence with one's own intentions, for example by actively giving up the attempt at communication or by communicating using gestures.

3. Why machines cannot conduct real dialogues

For a machine to possess dialogue ability, it would have to display the same "general experiential understanding of its environments that humans possess" (Muehlhauser, 2013) and also the same spectrum of abilities to react to these environments that humans possess (including human reactions that fall short because they involve mistaken uses of language, or errors resting on misunderstandings, or slurring of words resting on intoxication, and many other departures from the norm).

How a dialogue participant reacts at each moment of a dialogue is determined

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longer lasting. They rest on enduring patterns in the underlying physical substrate and shape which intentions we develop and how (and whether) they are realized.

In spite of all the advances in neurology in recent years, the human neural substrate is still little understood. Indeed, it is not understood at all if we define 'understanding' as the ability to model and predict the phenomenon we claim to understand. Thus, it cannot be captured in a formal, let alone machine-processable, way. The same applies also to the array of dispositions – which we share to a greater or lesser extent with our fellow human beings – of which it serves as the material basis. It is this array of dispositions that makes conversation (and indeed all use of language, indeed all human activity) possible. It shapes and determines the repertoire of the types of speech acts that we have at our disposal while at the same time ensuring that the deployment of this repertoire is to a large extent a matter of ingrained reflex – or at least a matter over which we have only very fragmentary conscious control (Billig, 1997).

Realizations of our linguistic dispositions are triggered in various ways, including by the utterances of our dialogue partners. Sometimes, such realizations may involve conscious choices, for instance the choice of whether to adopt a retaliatory or conciliatory tone in response to a threatening utterance, or the choice of which answer to give to a difficult (perhaps a trick) question. More often, however, selection takes place spontaneously and unconsciously. It occurs, moreover, on a number of different levels, affecting both verbal and non-verbal aspects of communication, and we document in the Appendix

- by his intentions of the moment,

- by his language abilities,

- by what he perceives in the course of the dialogue itself,

- by what he (most of the time unconsciously or implicitly) remembers (both emotionally and intellectually) from his life experiences and

- by how all of these factors are related together.

3.1. Language as a necessary condition for AGI: Criteria

We think that mastering of language and dialogue is a necessary condition for AGI because it is the primary medium of expression of the human intellect and because many conceivable AGI applications would need to interact with humans via language. If, therefore, the following criteria could be satisfied by a machine engaging in spoken dialogue, then we believe that this would provide strong evidence for its being a realisation of AGI[15]:

1. the machine has the capability to engage in a convincing manner with a human interlocutor in dialogues of arbitrary length in such a way that the human interlocutor does not feel constrained in the realisation of his dialogue-triggering intentions by the machine-dialogue partner. This means that when the human interlocutor engages in the dialogue, he must be able to realise his intentions without making the sort of special effort he would need to make when dealing with a machine.

2. the cycles in such a dialogue are not restricted to cases where the machine merely reacts to a human trigger, as in a succession of question-answer-pairs; rather, the interlocutors behave exactly as they would in a normal dialogue;

3. that the dialogue would be in spoken form[16] and

4. that the machine would *see* the human interlocutor, since the machine has to demonstrate that it can react appropriately to the whole habitus of its human dialogue partner and not just to her speech: Many utterances cannot be adequately

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[15]These criteria form the basis for a more realistic version of the Turing test that is described in FORTHCOMING, Grazer Philosophische Studien.

[16]A spoken dialogue of this sort would require a solution to the (hard) problem of engineering a machine with a voice production capability that does not impede the dialogue flow to avoid a violation of the first criterion.

interpreted without taking into account gestures and facial expressions. A machine without vision would thus not be able to perform the utterance interpretations expected in many types of human dialogue[17].

3.2. Human and machine identity

When a normal human being engages in conversation, she is able to draw on her entire personal history and on her repertoire of capabilities, not just of a linguistic nature, but also capabilities she has acquired in the course of her life in navigating many other aspects of reality. She is able to manifest, in other words, what we have called her "identity" (see section 2.3). The vividness and emotional adequacy of a dialogue requires an identity as dialogue foundation. Machines do not have personalities or identities. Therefore, a dialogue with a machine will always have a static character and lack the vivacity conveyed by the richness of a real life. Therefore, the first of the criteria we list above, namely that the human interlocutor is able to realise his intentions in the course of the dialogue without making the sort of special effort applied when dealing with a machine, will not be satisfied.

3.3. Initial utterance production

In providing an account of the powers that would be required of a machine purporting to emulate human dialogue behaviour, we distinguish between two sorts of task: (1) the production of the initial utterance of a dialogue, and (2) the maintenance of subsequent dialogue flow.

The act of producing an initial utterance requires only the ability to understand the context in which the dialogue partners find themselves, while dynamic dialogue maintenance requires taking into account the switching of roles over time. We will begin with the initial utterance, and show that the machine struggles even here.

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[17]Note that this would require that the machine learns to integrate visual sensory input into the interpretation of language. The problem of visual sensory input interpretation is harder than language interpretation because visual input is non-processed raw input devoid of any semantics. Animals interpret it based on instincts, but humans interpret it based on the meaning for their survival. Currently, machines do not interpret visual input at all: contrarywise, when they classify images, they use image elements that are unrelated to the elements used by humans (Moosavi-Dezfooli et al., 2016; Jo and Bengio, 2017). Not only do we not know how to change this in dNN, but we have no way of modelling how our mind integrates sound and vision, when, for example, interpreting a slapstick-scene in a movie and laughing about it.

3.3.1. Initial utterance production by machines

Contexts of the sort in which an AGI might need to produce an initial utterance are, for example, a traffic accident, where the AGI acts as robot policeman or paramedic. The AGI would need to understand the situation in order to make an appropriate initial utterance. This is not by any means a trivial task, given the massive variation in real traffic situations we are faced with in everyday life.[18] The AGI would need not only to understand the overall situation, but also to find the appropriate words to use when speaking to just these human beings in just this psychologically fraught situation. Pre-programmed initiating sequences, such as "Hello, I am your automated police officer Hal. I have registered your participation in an accident. Please show your driver's license" typically will not do[19].

3.3.2. Initial utterance interpretation by humans

What now as regards the *interpretation* of a single utterance of the sort we are called upon to perform in relation to the first utterance in a dialogue? For humans, according to current understanding, this task has two steps: first is a syntactic step, which is realized through a dynamic process of syntactical sentence parsing and construction using the structural elements constituting the uttered sentence.[20]

This syntactical analysis yields the basis for the second, semantic step, which is the context-dependent assigning of meaning to the uttered sentence (Loebner, 2013). Even for one sentence this process has a dynamic aspect. This is because, beginning with the very first word, the syntactic construction and semantic interpretation interact. This can require several successive cycles of revision, as an initial syntactic construction is revised as earlier parts of the sentence are re-interpreted in light of the ways they interact with parts coming later. Auer (2009) has coined the term "on-line syntax" to describe this phenomenon.

For a single utterance in a face-to-face dialogue, the core context required for its interpretation by a human is what Barker (1968) refers to as the ecological setting. This is the salient part of the environmental (physical) context in which the dialogue takes place and which will typically be centred on the person by whom the initiating utterance is made. When a dialogue is initiated on the phone, the absence of such

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[18]The huge degree of variance can be understood by examining court rulings arising from random traffic disputes.

[19]Matters of suitable tone, prosody and intonation would also have to be taken into account, see Appendix A.4.5

[20]There are several grammatical theories about how this happens, ranging from generative to constraint-based theories. Müller (2016) gives an overview.

a context explains why many humans find it hard to speak with someone they have never met or spoken to: the absence of a shared physical environment severely reduces the amount of context usable by the interlocutors and thereby creates a barrier to the transmission of meaning.

When interpreting the single utterance, the human has to apply contexts available to her from her own biography together with any clues she can draw from her interlocutor's tone, dialect, physical appearance, behaviour and so forth. Discourse economy[21] forces her to make assumptions on this basis in her attempt to understand those aspects of meaning left implicit by a speaker, for example in order to disambiguate ambiguous aspects of his utterance, or gauge the force of turns of phrase that might in some contexts be threatening or indicative of deceit. In face-to-face conversations, humans can use contextual cues to achieve this. For example, when negotiating the purchase of a used car, the buyer will look for non-verbal cues indicating the reliability and honesty of the seller to make up for the information asymmetry inherent to the situation (Akerlof, 1970).

In addition, humans interpret static utterances by using knowledge they have derived through processing their own experiences over time, above all knowledge acquired through practical experience of the way the world around them is structured causally. From these experiences (combined with innate capabilities) they acquire an ability to reason about the relationships which link together entities in their environment into different families of predictable patterns.[22] The latter are then extended also to the entities referred to in dialogue utterances, and this enables these utterances to be interpreted, for example in terms of their practical relevance to the interpreter.

3.3.2.1. Human interpretation of multi-sentence initial utterances   Initial utterances consisting of more than one sentence are still more challenging for humans to interpret than single-sentence utterances. This is because the sentences now contextualise each other: there are syntactic and semantic as well as explicit and implicit interdependencies which link them together.[23] For example, sentences may be connected explicitly, via anaphora, or as chains of steps in an argument or chronological narrative, or implicitly, through analogies or historical resonances attached to certain words or phrases.

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[21]Cf. Appendix A.3

[22]This ability is sometimes called 'common sense' (Smith, 1995). Compare also section 2.2 of Landgrebe and Smith (2019).

[23]We deal in Appendix A.3.1.4 with the phenomenon whereby a part of a dialogue can itself serve as context for another part of the dialogue.

3.3.3. Initial utterance interpretation by machines

How, then, does the *machine* interpret the initial utterance? Here again two steps are involved: of syntactic construction and semantic interpretation. We deal with these in turn.

The syntactic construction using structural elements that humans perform according to the grammatical theories referred to in 3.3.2 can be mimicked by the machine quite effectively for written text, when no non-lexematic structural language material has to be taken into account.[24] Machines fail, however, as soon as non-lexematic structural material such as facial expression, gestures, posture, or sound structures come into play (see Appendix A.4.5). This is because the world knowledge enabling the interpretation of this material – which can be combined in arbitrary forms to create many different sorts of contexts – cannot be learned without life experience and it cannot be mathematically formalised (see Appendix 2.1 and sub-section 3.3.5 later in this section).

For the interpretation of a single sentence – ignoring for now gestures and other non-lexematic material – the machine would need to reproduce the syntactic construction achieved by humans if the static interpretation pattern used by the human brain (syntactical analysis followed by semantic step) is to be reproduced.[25]

This requires use of computational phrase structure grammar, dependency grammar or compositional grammar parsers.[26]

All of these create trees which represent the syntactic structure of the sentence. The parsers work well if the input sentences are syntactically valid. However, if a sentence is syntactically valid but semantically ambiguous, as in:

(4) He saw old men and women,

an ideal computational parser will create two syntactic trees representing each sense.[27]

It is with the *interpretation* of the syntactic structure – in other words with the move from syntax to semantics – that machines struggle, and this holds even in the static single sentence utterance case. *For what is the context which the machine could use to assign meaning to a single sentence?*

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[24]By 'lexematic material', here, we mean those structural elements that can be directly reduced to lexemes – essentially wordforms and all their variants and composites. Lexematic material is subset of verbal material, while non-verbal material is the part of communication that is not produced via sound: facial expression, gesture, posture, movement patterns.

[25]The core of the machine-learning-NLP community currently thinks this is no longer necessary. All is supposed to be computed implicitly using "end-to-end deep neural networks". See Hirschberg and Manning (2015).

[26]An overview is given in Manning and Schütze (1999).

[27]This feature is only available with compositional grammar parsers (Moortgat, 1997). With a sufficiently sophisticated computational setup, a context-dependent disambiguation may be possible.

The machine cannot decide this on its own. The multitude of combinations of language elements described in Appendix A allows allow for a huge number of interpretation possibilities even at the single sentence level. The machine cannot decide, for instance, how to fill in implicit meaning generated as a result of language economy, or of the use of incomplete utterances or ellipses.

To achieve this, the machine would need an appropriate context and dialogue horizon. Background information would thus need once more to be *given* to the machine, analogous to the sort of information given to an undercover agent to provide him with a cover story – information needed to enable the machine to mimic a human dialogue partner when discussions turn to matters biographical.

If the scope of the anticipated subsequent sentences is very narrow, one can create a library of contexts and use a classifier to determine an appropriate context choice for a given input sentence. This context can be loaded and used to assign a meaning to the sentence with the help of logical inference. To achieve this, the logical language to be used needs to have the properties of completeness and compactness (Boolos et al., 2007). This means, however, that the expressiveness of both the sentence to be interpreted and the specification of contexts must be severely restricted – thus they cannot include, for example, intensionality[28], verb modality[29] or second-order- logic predicates[30] – thus marking one more dimension along which the machine will fall short of AGI[31].

What can be achieved in this fashion is illustrated in the field of customer correspondence management, where there are repetitive customer concerns that can be classified and for which pre-fabricated narrow background contexts can be stored in the machine using first-order logic. Customer texts can then be understood by relating them to this knowledge base.[32] However, it can be applied only in those special sorts of situation where the relevant contexts can be foreseen and documented in advance.

When, in contrast, a machine has the task of engaging in dialogue with a human being, the range of language production possibilities and of contexts and context combinations is as vast as the human imagination. The human interlocutor can speak about anything he has experienced, read about or can imagine, depending on his biography, his current mood and intentions and their interaction with the situation he is in. It is impossible to build a library of contexts that would prepare a Turing machine for this kind of

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[28]Predicates predicating over potentially non-existing entities.

[29]For example, deontic assertions or wishful propositions

[30]For example: 'Mars is red. Red is a color.' (example from Gamut (1991)). In the second sentence 'is a color' predicates over the predicate 'is red' from the first asentence.

[31]Deterministic workarounds are possible for the mentioned phenomena but they have nothing to do with AGI

[32]This is the approach described in section 3.2 of Landgrebe and Smith (2019).

variation. In nearly all situations, therefore, the machine will not have any context to load in order to assign a meaning to the sentence, let alone to carry out routine tasks such as disambiguating *personal pronoun anaphora* of the sort illustrated in a sentence such as:

(5) They caught a lot of fish in the stream, but one of *them* died.

3.3.4. Machine interpretation of suprasentential utterances

The space of possible contexts is all the more immense when we consider multi-sentence (suprasentential) utterances. Here interpretation requires the ability to identify and interpret complicated relationships between sentences, including all the syntactic and semantic as well as explicit and implicit sentence interdependencies of the sorts identified in 3.3.2.1. In open text-understanding tasks[33] it is impossible to foresee the possible sentence relationships and to provide in advance knowledge of the sort that would enable the machine to interpret them adequately.

Consider, to take a toy example, the tasks the machine would face in interpreting the following sentences:

(6) The salmon caught the smelt because it was quick.

(7) But the otter caught it because it was slow.

First, to understand that the explicit anaphora 'it' refers to 'salmon' in both (6) and (7) – even though two contradictory properties ('slow' and 'quick') are attributed to it – and thus to understand the reason for the adversative 'but' in (7), the machine needs biological knowledge about the species involved and about their respective hunting behaviours[34]. Given such knowledge it can contextualise the two adjectives by tying them to different parts of the total situation described in the sentence pair. Already this is difficult – but infinitely many such combinations with much higher levels of difficulty are possible (for instance, consider this very text which you, the reader, now have before you).

3.3.4.1. Machine non-interpretation
Another aspect that is difficult to model in a machine-compatible fashion is human conscious or unconscious non-interpretation of

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[33]Closed tasks are those in which a large proportion of the texts to be understood contain repetitive patterns, such as customer or creditor correspondence or notices of tax assessment.

[34]The interpretation of the second 'it' as referring to the smelt is perhaps still possible. Ambiguity is often simply not fully resolvable

lexemes or phrases in dialogue, the phenomenon which Putnam calls 'linguistic division of labour' (see Appendix A.3.3). How should a machine know whether it can afford to *not* interpret a lexeme?

3.3.5. Machine interpretation of static non-lexematic material

As described above (see section 3.1), in a real conversation with a human, the machine has to interpret the entire structural material of an utterance, including the non-lexematic parts, which means: facial expressions, gestures, body language, as well as sound structures emanating from the interlocutor. Any of these can transform the interpretation of the utterance conceived on the level of purely lexematic structures.

We will see that it is impossible for machines to detect such clues and to combine them with lexematic material in a way that would make it possible for them to achieve the sort of adequacy of interpretation that would be required to lead an adequate conversation with a human – for the reason that the variance resulting from such combinations is effectively infinite, and each combination is a rare event for which the needed training material could never be assembled in sufficient quantities. Furthermore, each combination of structural utterance material allows different interpretations. To make a selection from them and to create a reply based thereon that seems natural (non-stereotypical) to a human interlocutor requires an array of capabilities and intentions rooted in experiences of manifold different sorts of contexts which the machine lacks.

3.4. Modelling dialogue dynamics mathematically

In the previous section we have seen that it is very hard to make machines utter and interpret single utterances. What happens in an entire, extended dialogue? As described in Appendix A.5, the evolution of a dialogue can be highly dynamic. The interlocutors switch roles as utterers and interpreters as they take turns based on cues from their interlocutor in ordered or unordered form (cutting each other short, interrupting, speaking at the same time). While this is happening, their respective dialogue horizons are in constant movement, and so are the intentions and speech acts based thereon. New utterances interact with older ones, the dialogue creates its own context, see Appendix A.3.1.4.

From a mathematical perspective, a dialogue is a temporal process in which each utterance produced is drawn from an extremely high dimensional, multivariate distribution.[35] Each produced utterance can relate to the utterances that preceded it in an

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[35]A multivariate distribution is a distribution that can be modelled using the vector spaces employed

erratic manner. In other words: there is no way to formalise the relationship between the utterance and what preceded it.[36] Each utterance interpretation is drawn from a distribution of similar complexity, and it too can relate also to the utterance that preceded it in an erratic manner.

To see the sorts of problems that can arise, consider a dialogue between Mary and Jack spanning several rounds of role-switching. Mary makes an utterance at round 7, which requires Jack to take into account an utterance from round 3. Based on this, Jack associates with Mary's utterance an experience from his own past, of which Mary knew nothing, and he provides an answer relating to this experience. This utterance from Jack is for Mary quite unexcepted (erratic) given her utterance in round 7. But, given his inner experience, it is perfectly coherent from the perspective of Jack. Phenomena such as this imply that there is no way to formalize the relationship between an interpretation of an utterance and this utterance itself. Such phenomena break the Markov assumption employed by the relevant temporal process models.

3.4.1. Modelling dialogues as temporal processes

To understand the dialogue as a temporal process, four types of events need to be distinguished:

1. initial utterance production, followed by

2. initial utterance interpretation, followed by

3. dialogue-dependent responding utterance production, followed by

4. dialogue-dependent utterance interpretation.

These are linked via relations of dependence. In the prototypical case, pairs of events of types 3. and 4. are repeated until the dialogue concludes.

The distribution from which each of these events is drawn varies massively with the passage of time, as ever new utterances are generated and interpreted.

Both utterer and interpreter have a huge number of choices to make when generating and interpreting meaning, and because these choices depend on the diverse dialogue contexts (including the dialogue itself) and on their respective horizons, as well as on the biographies, personalities, capabilities, intentions, (and so forth), of the participants themselves, it follows that each utterance and each interpretation thereof is *erratic*. Such

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in stochastics. (Klenke, 2013)

[36]Falling in love at first sight is a classic example of an event relating in an erratic manner to the events that precede it.

an event, like the nuclear fission event occurring in radioactive decay, is unrelated to the events that precede it, it is purely random, which means: it cannot be modelled as depending on what occurs in the immediately preceding dialogue step.

To make matters worse, we still have not taken into account the fact that most human dialogues deviate from the turn-taking prototype, and it is not conceivable that we could create a mathematical model that would enable the computation of the appropriate interpretation of interrupted statements, or of statements made by people who are talking over each other, see Appendix A.4.3.1.

Or consider the problem of computing the appropriate length of a pause in a conversation (or, equivalently, of inferring from context the reason why your dialogue partner is not responding in a timely manner to what you have just said). Appropriate pause length may depend on context (remembrance dinner, cocktail party), on emotional loading of the situation, on knowledge of the other person's social standing or dialogue history, or on what the other person is doing (perhaps looking at his phone) when the conversation pauses. Pauses are context modifiers which influence or are important ingredients of the overall dialogue interpretation. They often contain subtle non- verbal cues, for example, the fiddling of the interlocutor with a small object indicating irritation or nervousness. The machine must somehow assess all of these factors to determine how it should react to the pause – which might signify that for the interlocutor the dialogue is at an end, or that he is inviting a break in the expended role-change cycle, or that he is engaging in a battle of wills. To be done properly this assessment requires both (1) a human background of life-long experience, and (2) an intention to achieve something by reacting to the pause in a certain manner, for example: to heal the breach, to win the battle of wills, and so forth. Machines lack both.

3.4.2. Mathematical models of temporal processes

On the other side of the ledger, the range of options for mathematical treatment of dialogue is strictly limited. In fact there are only two types of explicit mathematical methods available to model temporal processes: *differential equations* and *stochastic process models*. Given that there are no other methods available,[37] any Turing machine able to model such processes would have to draw from these alternatives or from some combination thereof.

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[37]That is, nothing else exists in the currently available body of knowledge of mathematics and theoretical physics.

3.4.2.1. Differential equation models Such models can be used to provide adequate representations of the changes in related variables when their relationships follow deterministic patterns of the sort that can be observed in the physical realm (for example radioactive decay over time). By "adequate model", we mean a scientific model that is able (in ascending order of scientific utility) to 1. describe, 2. explain or 3. predict phenomena and their relationships (Weber, 1988), the latter with different degrees of accuracy.

Description is the minimum requirement for any scientific model, but the other two properties are also needed to make the model useful. Differential equations can be used, for example, to make predications regarding changes such as are involved in the distribution of heat from a source in space, something that is modelled using the so-called heat equation, which is a partial differential equation first developed by Fourier in 1822. But such models can only deal with a small number of variables and their interrelations, and they are of the sort that can be verified using physical experiments.

To conduct an adequate conversation, plausible utterances have to be produced by the machine. Mathematically speaking, an utterance produced by the machine – no matter what algorithm is used – is a model-based prediction conditioned on the previous utterances in the dialogue and on the context. The machine predicts what the next move in the dialogue should be, just as a Go-playing machine predicts its own next move conditioned on the opponent's last move and the overall situation on the board).

We note that the situation is different in the case of a human dialogue partner, where humans do not necessarily need to predict what their own next move in the dialogue will be because they themselves are deciding that next move on the basis of their intentions - however, their response to a given utterance corresponds to a prediction computed by a machine based on a given utterance. But because the machine has no intentions and life-experience, it will not be able to compute an adequate response, and even less to predict the reactions of the interlocutor in the way that humans (in many cases) can. The machine will therefore have a massively shallower basis for selecting an appropriate utterance.

At the same time, however, the machine-predictions would need to be highly accurate (where accuracy, for stochastic models is measured by the percentage of predictions that match human expectations). In the case at issue here, this would mean a high degree of utterance salience. Further, their accuracy in this sense has to be maintained over the entire course of the dialogue, otherwise the first criterion of the test will fail because the human will have to make a conscious effort of the sort that is associated with the need to interact with a machine.

It is a problem therefore, that differential equations cannot even provide descriptions, much less explanations or predictions, of the changes involved as concerns social processes in particular and biological phenomena in general. This follows already from the fact that the number of variables involved in such phenomena is too large, and their interdependences too complex, to make such modelling possible. Evidence that proposed models do not work in these sorts of contexts is provided by the fact that they are repeatedly falsified by empirical observations. Where differential equations are used successfully in biology this is because the number of variables has been limited artificially, for example when organism population growth is modelled under simplified laboratory conditions.

The application of differential equation-based models to the problem of dialogue production and interpretation is for the same reason impossible. There are far too many variables, and we cannot even begin to formulate equations that would describe their relationships. The reason for this is that, although all the parts of the brain function in accordance with the laws of nature, the system behaviour is hypercomplex (Thurner et al., 2018) in each of its behavioural patterns, [38] which include all the phenomena of language production addressed in the in Appendix An erratic event, on the other hand, cannot be modelled using differential equations (Schuster and Just, 2005). We cannot even describe it in these terms, much less obtain predictions.

3.4.2.2. Stochastic process models   Stochastic process models can represent the behaviour of a one- or multi-dimensional *random* stochastic process X, but only if

1. the random event, and thus the associated random variable (in what follows: r.v.) X_t, has a distribution over time belonging to the exponential family,[39]

2. the process has additional properties that allow mathematical modelling (specifically, it must have independent and stationary increments, as further specified below).

The most expressive family of stochastic models, and thus the models that have had the widest usage in describing phenomena based on human interactions, are the Wiener process models (also referred to under the heading "Brownian motion"), which have been used extensively (indeed, too extensively, as we shall see) to model financial market processes such as movements in stock or derivative prices (Jeamblanc et al., 2009). Such

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[38]A hypercomplex system obeys deterministic laws but cannot be mathematically modelled due to overcomplexity.
[39]Often this is the Gaussian distribution, i.e. $X_t \sim \mathcal{N}(\mu, \sigma^2)$.

prices are an expression of the aggregated intentions of very many market participants. The models make strong mathematical assumptions, for example that a price change process X is a case of Brownian motion, or in other words that it satisfies the following conditions:

1. it has independent r.v. increments: for any pair of time points (s, t), $X_{t+s} - X_s \perp\!\!\!\perp \mathcal{F}_s^X$, where $\mathcal{F}_s^X$ models the time before t,

2. it is stationary: $\forall s > 0 : (X_{t+s}) = (X_t), t \geq 0$, and

3. for any time point $t > 0$, $X_t \sim \mathcal{N}(0, t)$.

Condition 1. expresses the fact that each increment of the r.v. is independent of what happened in the past; condition 2. that the unconditional joint probability distribution[40] of the process does not change when shifted in time; condition 3. expresses the fact that the r.v. is distributed according to the Gaussian distribution.

Unfortunately, processes satisfying these conditions are nowhere to be found in actual markets. This is, again, because the preferences and intentions of human beings are erratic (in part because they depend on real world events, for example geopolitical events, which are also erratic). This is why, whenever collective decisions are off-trend, financial stochastic process models fail (McCauley, 2009).

Dialogues, too, as we have seen, are multivariate processes, with the r.v. – utterances and interpretations – drawn from immense, typically unknown, and in any case not modellable, multivariate distributions. Neither utterances nor interpretations are distributed according to a multivariate Gaussian distribution, since they are non-stationary and non-independent. And, to make matters even worse, interpretations are not directly observable (see Appendix A.3).

The Brownian motion model is therefore not applicable, as none of its three conditions is satisfied.

3.4.2.2.1. Hidden Markov Models A hidden Markov model (HMM) is a stochastic model which models a process as a Markov chain where successive observable events are generated by transitions between unobservable states.

If a dialogue would meet (1) the cardinal assumption of an HMM, namely satisfaction of the Markov property, together with (2) the assumption that transition probabilities remain constant over time, then it could in theory be used to model dialogue utterances as emanations from those unobservable mental events that lead to the utterance generation

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[40]'Unconditional' means that the distribution involves no dependence on any particular starting value.

and interpretation. Unfortunately, HMMs cannot be used to model dialogues, since dialogues violate both assumptions.

3.4.2.3. Stochastic differential equation models Differential equations can be extended to model temporal processes subjected to stochastic effects (noise), for example to model molecular dynamics. Again, however, even stochastically modified differential equations would still not be applicable to the problem of dialogue process modelling, since this would require that the assumptions needed for the applicability of *both* differential equations *and* stochastic process models would need to hold simultaneously for processes of language use. In fact, however, both of these sets of assumptions fail.

3.4.2.4. Deep Neural Network (dNN) models These are a subclass of stochastic models that in recent years have sparked considerable enthusiasm, triggered above all by:

1. the successes achieved since 2014 in improving automated translation through use of dNNs,

2. the popularisation by Goodfellow, Bengio, et al. (2014) of generative adversarial networks (GANs),[41] and

3. the invention of reinforcement learning, which brought the capability to outperform human beings, for example in the game of Go (Silver, Hassabis, et al., 2016).

dNNs were accordingly tested early on in the domain of process modelling. They differ from classical mathematical models, which are explicitly designed in a conscious mathematical effort, for example when observing process data and figuring out an equation to desribe them. In contrast to this, dNN-models are created automatically by an optimisation algorithm which is merely *constrained* by humans. As is also the case with traditional multivariate regression models, which have been used routinely since the 1970s (Hastie et al., 2008), the optimisation algorithms can create new models that humans would not be able to construct when modelling explicitly. These dNN-generated-models are *automated*. The equations they consist of are not created by human effort, but rather by the optimisation algorithm working under constraints (for example the loss function and the hyperparamters of the dNN). How the resulting equations (which can be inspected) solve the machine learning problem at hand often cannot be understood by humans – hence the explainability problem of AI (Goebel et al., 2018). However, this ability to auto-compute models does not mean that machines develop intentions – the

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[41]Invented and first described by Schmidhuber (1990).

equations are just functionals or operators relating an input vector to a certain output – in other words, they are nothing but a special case of regression models.

We review the potential capability of three seemingly promising dNN-methods to model human dialogues, before looking at the empirical evidence yielded by experiments in dialogue emulation.

3.4.2.5. Deep recurrent neural network (rNN) models   Deep recurrent neural networks are dNNs in which the connections between the nodes of the dNN graph allow the modelling of temporal sequences. They are often called sequence-to-sequence-dNNs, because they can be used to create one sequence from another (for example, a translation from an input sentence). Often long-term-short-term-memory (LSTM) (Hochreiter and Schmidhuber, 1997) and its numerous extensions are used in practical AI-applications of this sort, including Google Translate. Because classical stochastic process models are not able to model multivariate processes, the ability of rNNs to model temporal processes of this sort has been investigated in recent years as a potential saving alternative (Dasgupta and Osogami, 2017; Neil et al., 2016; Lai et al., 2017). The results have performed well for certain sorts of tasks, for example modelling road traffic occupancy, solar power production, or electricity consumption over time (Lai et al., 2017). As the latter reports, they have outperformed classical stochastic process models in certain tasks, especially when two processes with different patterns are overlaid in a series of observations.

We can infer from these examples several reasons why rNNs work well on such numerical time-series data:

1. data of these sorts approximately fulfil the assumptions needed for stochastic process modelling in general (of which dNNs, and thus rNNs, are a special case),

2. the data are *repetitive* and huge historical datasets are available for training purposes,

3. the dimensionality and the variance of the data is low,[42]

4. dNN architectures can be used to model temporal pattern overlays of the sort observed for example in traffic occupancy, which has both a circadian and a workday vs. weekend rhythm.

Human dialogues, however,

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[42]Exchange rates, another example modelled using dNNs, form a special case. This is because outcome dimensionality and variance are here relatively low in the short term. Unfortunately, mid-term outcomes are erratic, and thus the models work less successfully. (Lai et al., 2017).

i. are not repetitive, but erratic;

ii. do not fulfil the central assumptions presupposed by temporal process models which must also be satisfied for rNN to succeed in this modelling task;

iii. are of extremely high dimensionality; and

iv. manifest variance that is as large as the sum of the results of all human activities since the emergence of our species.

Moreover, because the interpretations involved at each stage of the dialogue are implicit (see A.3), we can never use the interpretation step in human dialogue as a source of training data.

This will mean that there can never be training data to cover the dependencies that hold between successive utterances occurring over time, since interpretations are an essential link in the dependency chain that binds one utterance to its predecessor.

Note again, however, that all of this holds only for dialogues *in general*, the mastery of which is a criterion of AGI. As we shall see, for very stereotypical dialogues, for example the telephone scheduling of a haircut or the reservation of a hotel room, there could eventually be sufficient training data for a dNN-based approach to be of value.

3.4.2.5.1. Generative adversarial network (GAN) models work using two networks, one discriminative, the other generative (Goodfellow, Bengio, et al., 2014). The former is trained to discriminate classes of input data using annotated training material, often pictures tagged by human beings (for example pictures in which humans can be distinguished from other items represented). The generative network is then tasked to create new samples of one desired class (for example pictures of humans, (Karras et al., 2018), which it can indeed do). The two networks are then chained together by having the samples yielded by the generative network passed on to the discriminative network for classification. Finally, the system is optimised to minimise the rate at which samples are generated that are not classified by the discriminative network as belonging to the desired class. This approach works very well with pictures, because the discriminative net can be pretrained with adequate training material (data tagged by humans).

Again, however, GANs are not applicable to language in the form that we encounter it in general spoken dialogue. For to build an utterance-generating GAN that creates meaningful output one would need to pretrain a discriminative net that can distinguish meaningful from non-meaningful utterances. The problem is that, because the meaningfulness of an utterance depends on its context and interpretation, there is again no

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conceivable way in which a sufficient body of training material could be assembled to cover the practically infinite variance of human utterances. It is therefore not possible to create a discriminative net that can be used to build a meaningful-utterance-producing GAN.

3.4.2.6. Models based on reinforcement learning In reinforcement learning (Sutton and Barto, 2018), a reward (score) is assigned when a certain step in a repeatable type of finite process is realized by the machine. 'Finite', here means that the process ends after a series of steps that is not too long, such as a game of Go or a first-person shooter game in which killing sequences are repeated. In Go, for example, a trained algorithm is used to assign a score after each action the machine performs in each game. The machine obtains one point for each of the opponent's stones it captures and one point for each grid intersection of territory it occupies. The trained algorithm is optimised to maximise the total score obtained over the entire game. This is done by having the computer play the game millions to billions of times in different situations, so that optimal paths for these situations can be found and stored in the model.

Crucial, for such optimization to be possible, is that the scores for every move can be assigned automatically by the machine. Machine learning of this sort can thus be used only in those situations in which the results of machine decisions *can be scored through further machine decisions*. This is primarily in games, but the method can be extended, for example, to debris cleaning, where what is scored is the number of units of debris removed. In such narrowly defined situations, machines can find strategies that outperform human behaviour (Jaderberg and Czarnecki, 2018). Lastly, reverse reinforcement learning (Arora and Doshi, 2018), a technique to automatically learn an adequate reward score from observed situations, does not help in the dialogue case, because there is here no adequate set of observed situations since, again, too few patterns are repeated sufficiently many times.

Reinforcement learning cannot, therefore, be applied to the engineering of convincing dialogue systems. There is here nothing to which the needed sorts of scores can be assigned. (There is no *winning*, as we might say; or at least no winning of the sort that can be generally, and repeatedly, and consistently, and automatically scored.) We note also that the truly impressive successes of reinforcement learning do not provide evidence that AGI is about to be achieved. This is because the scope of applicability of such algorithms is narrowly limited to situations in which automatic scoring *is* possible. It is also because the meta-parameter for the algorithms which compute the optimisation, including how its scores (and many other parameters) are to be defined, needs to be set

in each case by engineers.

3.4.3. Current state-of-the-art in dialogue systems: A review of what has been achieved thus far

Even given all of the above, dialogue emulation is an area of considerable activity in AI circles. The resultant dialogue systems – also called 'agents' (or in some circles 'chatbots') – are designed and built to fulfil three tasks (citing (Gao et al., 2018, p. 6)):

1. Question Answering – "the agent needs to provide concise, direct answers to user queries based on rich knowledge drawn from various data sources"

2. Task Completion – "the agent needs to accomplish user tasks ranging from restaurant reservation to meeting scheduling ... and business trip planning"

3. Social Chat – "the agent needs to converse seamlessly and appropriately with users – it is performance along this dimension that defines the quality of being human – and provide useful recommendations"[43].

In our view at least, the third task could only be performed by a machine with AGI. Indeed, it would precisely be one of the purposes of AGI to perform tasks of this sort.

3.4.3.1. Question Answering and Task Completion   Question Answering and Task Completion are areas in which dialogue systems are already of considerable commercial value, mainly because customers with relatively homogeneous cultural backgrounds can be motivated to reduce their utterance variance – for example by articulating clearly and using sentences from a pre-determined repertoire – if by interacting with a bot they can quickly obtain answers to questions or resolution of boring tasks. In the medium term, technologies of these sorts will enable systems which can satisfy a double-digit percentage of customer requests.

However, Question Answering and Task Completion clearly have nothing to do with conducting conversations in a way that would be indicative of AGI. Fulfilment of each is (thus far) something that is achieved simply by using appropriately configured software tools, which every user identifies as such immediately on first engagement.

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[43]To this belongs the ability to adjust the dialogue horizon to the dialogue partner, for example to adjust their respective intentions.

3.4.3.2. Social Chat What, then, about social chat (also called 'neural chitchat') applications? Here, research is currently focused on two approaches:

- supervised learning with core technology end-to-end sequence-to-sequence deep networks using LSTM (section 3.4.2.5) with several extensions and variations, including use of GANs,[44] and

- reinforcement learning used to train conversational choice-patterns over time (the optimal path of machine utterances during a dialogue).[45]

Strong claims are made on behalf of such approaches, for example in Zhou et al. (2018), which describes Microsoft's XiaoIce system – "XiaoIce" is Chinese for "little Bing" – said to be "the most popular social chatbot in the world". XiaoIce was "designed as an AI companion with an emotional connection to satisfy the human need for communication, affection, and social belonging." The paper claims that XiaoIce "dynamically recognizes human feelings and states, understands user intents, and responds to user needs throughout long conversations." Since its release in 2014, XiaoIce has, we are told, "communicated with over 660 million users and succeeded in establishing long-term relationships with many of them."

Like other "neural" chitchat applications, however, XiaoIce displays two major flaws, either of which will cause any interlocutor to realise immediately that they are not dealing with a human being and which will prevent any sane user from "establishing a long-term relationship" with the algorithm.

First, such applications create repetitive, generic, deflective and bland responses, such as "I don't know" or "I'm OK". This is because the training corpora they are parametrised from contain many such answers, and so the likelihood that such an answer might somehow fit is rated by the system as high. Several attempts have been made to improve answer quality in this respect, but the utterances produced by the algorithms are still very poor. The reason is that the algorithms merely *mimic* existing input-utterance-to-output-utterance sequences without *interpreting* the specific (context-dependent) input utterance the system is reacting to.

Each input is treated, in fact, as if it were the input to a machine translation engine of the sort which merely reproduces sentence pairs from existing training sets. The difference is that here the training sets consist of pairs of sentences succeeding each other in one or other of the dialogues stored in a large dialogue corpus. The result is that,

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[44]Discussed in 3.4.2.5.1 above, and in (Gao et al., 2018, pp. 53-56)
[45]Discussed in 3.4.2.6 above, and (Gao et al., 2018, pp. 59-61).

with the exception of a small subset of the structural elements, none of the sources of human discourse variance listed in section A are taken into account in generating output utterances. Again, no attempt is made to *interpret* utterance inputs. Rather, the machine in responding simply tries to copy those utterances in the training set which immediately follow syntactically and morphologically similar input symbol sequences. This means that utterances are decoupled from context, and so responses appear ungrounded. Attempts to improve matters using what are called "Grounded Conversation Models" (Gao et al., 2018, section 5.3)– which try to include background- or context-specific knowledge – have not solved the problem. The failure to model the variance of the utterance sources persists.

Second, these sorts of applications create ever more incoherent utterances over time. This is first of all because they cannot keep track of the dialogue as its own context (Appendix A.2.4), and secondly because the datasets they are trained from are actually *models of inconsistency* due to the fact that they are created as mere collections of fragments drawn from large numbers of different dialogues. Attempts to alleviate the problem using "speaker" embeddings or "persona"-based response-generation models have improved the situation slightly (Ghazvininejad et al., 2017), but they do not come close to ensuring realistic, convincing conversations.

Given that machines of the mentioned sorts can neither *interpret* utterances by taking into account the sources of variance, nor *produce* utterances on the basis of such interpretations together with associated (for example biographical) knowledge, the approach cannot be seen as promising when it comes to conducting convincing conversations.

3.4.3.3. Reinforcement learning in neural chitchat The basic problem of reinforcement learning (RL) for social dialogue is that it is impossible to define a meaningful reward. XiaoIce itself uses CPS (conversation turns per session, (Zhou et al., 2018)), a measure that maximises the duration of a conversation. We doubt, however, that a human would be impressed by dialogue behaviour generated to optimise a measure of this sort.

Li et al. (2016) used a more sophisticated reward system by training an RL-algorithm using dNN-generated synthetic utterances (because using real human utterances would be prohibitively expensive) together with a tripartite reward function rewarding

1. non-dull responses (using as benchmark a static list of dull phrases such as "I don't know")

2. non-identical machine utterances, and

3. Markov-like short-term consistency.

The results are appalling, and one wonders why this type of research is being conducted at all, given that – as a result of its use of synthetic data – it violates the basic principles of experimental design as concerns adequacy of measurement setup for observation of interest.

3.4.3.4. Multi-purpose dNN language models Recently, Radford et al. (nodate) created multitask dNN-language models from large corpora by formulating the learning task as the ability to predict a language symbol – for example a single word – based on the symbols preceding it. These models were trained using an unsupervised approach, but with the possibility to condition the model on certain task types (McCann et al., 2017).[46] The model that results (dubbed "GTP-2") is then conditioned with problem-specific input data to produce model-based predictions to solve NLP benchmarks ("zero shot predictions"). For some basic tasks amenable to sequence-modelling (including translation and text gap filling) the performance is good. For question answering, however, which is the only dialogue-related task that was tested, only 4.1% of questions[47] were answered correctly.

3.4.4. Problem-specific AI: Turing machines enriched by prior knowledge

Looking at the main problem of social chatbots, namely their inability to interpret utterances and to react to them with context-adequate, biography- and knowledge-grounded responses, one could indeed imagine endowing an algorithm with systematic prior knowledge of the sort required for conversations. The system presented in the Appendix to Landgrebe and Smith (2019) incorporates prior knowledge in this way, focusing on knowledge of the sort needed to complete tasks such as simple letter and email answering or repair bill validation. It uses this prior knowledge and logical inference in combination with machine learning to explicitly interpret texts on the basis of their business context and to create adequate interpretation-based responses. However, it works only because it has strong, in-built restrictions.

- The range of linguistic inputs it has to deal with is very narrow (for example car glass damage repair bills or customer change of address requests), thereby avoiding the problem of complex and nested or self-referential contexts (section A.2).

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[46]In the type of unsupervised learning described there, the algorithm learns models of probability distributions for symbol sequences from unlabelled input data. These models reflect symbol sequence distributions. Once created, they can be used to predict symbol sequences given conditioned input.

[47]Typical example: "Largest state in the US by land mass?"

- It is not a conversation system and does not have to model a stochastic process, because it reacts always to just one language input, thereby avoiding the problem of temporal dynamics (see Appendix A.5) – a problem that is not amenable to mathematical modelling (see section 3.4).

Such a system would fail in dialogues, and this would be so even if it was stuffed to the gills with (for example) biographical knowledge of the dialogue participants. This is because it could not cope with either the complex dialogue contexts or the dialogue dynamics. These phenomena aggravate the difficulties in dealing with language economy, dialogue structure and modality, because the contexts and the dynamics create a huge range of interpretation possibilities on all such levels. The resultant infinite variance makes it impossible to provide the machine with sufficient knowledge to derive meaningful responses.

4. Conclusions

How, then, do *humans* conduct convincing conversations? Answer: by using language, as humans do. Language is a unique human ability that evolved over millions of years of evolutionary selection pressure. Using language gives us the ability to realize our intentions, for instance by generating initial utterances (engaging in dialogue as a means of expressing ideas or desires) and by dynamically interpreting an interlocutor's utterances. This then allows us to react adequately, either with further utterances or with corresponding actions. Subconsciously or consciously, a human interlocutor is thereby able to sense the purposes of a fellow human being with whom he interacts because this is a survival-critical ability. As Gehlen points out, using language effectively in a given situation requires the dynamic exploitation of our past experiences, both inner and outer, as these have become engrained within our neural substrate.

Using language in the way that humans use language cannot be conceived without a body of the sort that has grown up in a world of sensory experiences and practical agency. Machines lack this type of experience and they lack any framework of intentions that could shape the way in which they interpret or generate utterances.

Ultimately, most human interlocutors will notice that a machine has no intentions because of its inability to react properly to a dynamic conversation. An analogous lack of intentions and purpose can be experienced when speaking to long-term schizophrenics with acquired autistic syndrome. Their reaction patterns are immediately perceived as non-normal because their ability to interpret and create utterances has deteriorated

(Bleuler, 1983). Machines perform much worse than do such patients, and therefore most interlocutors will rapidly sense their "non-normality".

The AI community has so far failed to come to grips with the physical, bodily side of human language production and interpretation and the infinite landscape of variance in dialogue utterances which it brings in its wake. Could they take these factors into account with new system designs? We have argued that there is no way to mathematically model the human use of language. Certainly novel approaches such as adversarial dNN and reinforcement learning paradigms have enabled the creation by the machine of novel algorithms, which are notable exceptions to Ada Lovelace's proposition that a Turing machine cannot learn anything new. But as we have seen, they will not learn to speak as humans do, because what they can generate is by far too restricted to emulate human language ability. This would still be so even if we could make available the huge quantities of data – orders of magnitude greater than the datasets used to train Google Translate – that such a model would need if a machine was to be trained to implement it.

Until the time is reached where a type of mathematical model is proposed that would be in a position to represent the dynamic properties of human dialogue, we believe that the idea that the ability to use language properly will somehow emerge spontaneously in the machine when storage and computing power reach a certain threshold will remain a product of magical thinking. Our understanding of the human brain, and of the evolution of the human physical substrate, and of how this physical substrate is shaped by what the individual learns from its surrounding culture, will, to be sure, increase tremendously over the decades and centuries to come. But this physical substrate will remain a complex system in the sense of (Thurner et al., 2018), and so it will remain subject to the same fundamental obstacles to mathematical modelling that we have already described.

We do not, however, wish to imply that only something with our kind of DNA, neurons, and so forth, could conduct convincing conversations. We think that any entity with real intentions and the ability to undergo auto-modifications analogous to those inherited changes of genotype which have affected modern human beings and their ancestors over some 3 million years could evolve to conduct convincing conversations given enough time and environmental pressure.

A. Appendix: Variance and context in human dialogue

A.1. Levels of language production and interpretation

To document the enormous potential for variation in human dialogue interactions, we describe in detail the different levels on which the context and structure of a dialogue and the form of its dynamic interaction processes are determined.

Loosely following Verschueren (1999), we distinguish five levels of *language production and interpretation*, namely:

1. context,

2. language economics (deixis and implicit meaning),

3. dialogue structure (words, sentences, gestures, ...)[48],

4. force/modality,

5. dialogue dynamics.

When humans engage in conversation all of these levels interact. Their separate treatment here is necessary merely in order to enable systematic description; in reality they can never be properly spliced apart.

A.2. Types of dialogue context

The *dialogue context* is a "setting", where this term is to be understood in a broad sense to embrace, for instance: one's place at the dinner table, one's place in society, a geographical place, the time of day at which a dialogue occurs, and many more (Barker, 1968). In each case the context is determined by an interplay between the wider environment and the identities of the parties involved, including their mental attitudes, capabilities, and intentions.

A.2.1. The dialogue horizon

Dialogue contexts are marked not by sharp boundaries but by what is called a "horizon" of possibilities, for example the possibility that our dialogue partner might be lying, or intending to report our conversation to his superiors. The horizon of a spatial context might include the possibility of leaving through the back door; the horizon of a temporal

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[48]We follow Verschueren (*op. cit.*) in using the term "structure" to designate what might otherwise be referred to as "content" or "material". Utterance structure can be both verbal and non-verbal (for example when it involves use of gestures).

context that one's husband may return at any moment. For each interlocutor, the dialogue context is thus in some ways analogous to the visual field of an individual subject: now more things, now fewer things fall within its compass. And the things which do fall within its compass do so in a way that encompasses a penumbra of possibilities.[49] Consider for example how facial expressions become apparent as we move closer to persons in our visual field, and how these facial expressions themselves bring to light new potentialities for greeting and embracing.

In each dialogue, each dialogue participant will have at any given stage a *dialogue horizon*, which results from the combined effects of all his salient dialogue contexts at that stage.

This dialogue horizon encompasses all possibilities that fall within the scope of what is relevant to the interlocutor, as determined not only by his identity, and by his intentions of the moment, but also by the social and cultural setting of the dialogue and by other contextual factors. The way each interlocutor shifts his intentions alters his dialogue horizon, which in turn determines how he perceives new utterance material. This then has a dynamic effect on new intentions, which further shape his interpretation and the way new speech acts are formed and new contexts for interpretation are created.

A.2.2. Social, cultural and environmental contexts

A.2.2.1. Social context is the social setting of the conversation (W. Hanks, 1996), for example the context of a family outing, of two strangers bumping into each other on a railway platform, of a teacher berating a failing student, of a session in parliament. As the latter cases make clear, a social context may include institutional elements, and in such cases we can refer also to an institutional context. The social context exists in virtue of the fact that the participants in the conversation have formally or informally defined *roles* in virtue of which they are subject to certain norms. The social and institutional rewards and sanctions associated with these norms then form part of the dialogue horizon. They influence not only what the dialogue partners say (and what they do not say), but also the ways they speak and act.

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[49]Compare Husserl: "The world is pregiven to us, the waking, always somehow practically interested subjects, not occasionally but always and necessarily as universal field of all actual and possible practice, as horizon." In our natural, normal life "we move in a current of ever new experiences, judgments, valuations, decisions", in each of which consciousness "is directed towards objects in its surrounding world" surrounded by a horizon of fluently moving potentialities (Husserl, 1989, pp. 142,149).

A.2.2.2. Cultural context is a special sub-type of social context. It is the setting created by those socialisation patterns which come into play where the participants in a dialogue draw on a common cultural background passed on from one generation to the next. The cultural context is thus determined by those habits, norms and values which result from similar types of upbringing, education, and so forth.

The social context of a conversation constrains in each case the space of permissible utterances. A relatively open space is obtained where social peers speak in private; a much narrow space arises when institutional or social inferiors and superiors speak in an institutional setting, for example judge and defendant in a criminal case. (We note that even here both parties will sometimes step outside the institutionally accepted norms. As in every other type of dialogue, the possibility that a participant forms the desire, for example, to shock or bamboozle his interlocutor can never be ruled out.) On the other hand, if dialogue partners do not share any cultural context or tradition, and do not know about each other's social roles, then they will likely choose a very general communication context that is appropriate simply for an encounter between fellow humans. Even here, however, there is no simple recipe to determine what communication context will arise. This may turn on the fact that the interlocutors belong to the same age cohort, or that they are waiting on the same railway platform for the same train. Ad hoc features of this sort can affect all context selection in a way that cannot be predicted in advance, for example by some algorithm.

A.2.2.3. Contextual constraints on language use   There is a variety of social contexts which constrain our dispositions and choices when producing language, and conversation participants may engage one or more of these within a single conversation. Each determines a particular variety (a "code" or "register") of the language used in the conversation. A *sociolect* is an expression of the constrained dispositions and choices of those language users who share a social background resulting from a shared pattern of socialisation. Age cohorts also have sociolects, as do members of specific criminal gangs.

A *dialect* is a sociolect of those language users who share a social background that is regionally determined. A *grapholect* is a written language as standardized for example in a dictionary. A *cognolect* reflects the constraints imposed on an utterer by her intellectual abilities and education level, which may include a common professional or disciplinary socialization in, for example, architecture or rap music.

A.2.3. Spatial and temporal context

Spatial context is the *site* of the dialogue, formed by the physical place (the park bench, spaceship, bus, hospital, pub, bed, and so on) in which it takes place. Temporal context is the time (dusk, Christmas, tea break) in which the dialogue takes place. Both temporal and spatial context can include (at several levels) other spaces and times nested within them, for instance when a dialogue relating to the food on the dinner table suddenly switches its context as the diners become aware that someone is banging hard on the front door, or when a dialogue happens at one time but the interlocutors speak about other times and about their temporal order. Consider a conversation between a police officer and the various parties, including witnesses, involved in a car accident. Consider such a conversation where, among the various parties, there are some who speak different languages.

Both spatial and temporal context are determined in part by the *communication channel* used in the dialogue. This can be local, in case of face-to-face communication, or remote. It can be spoken versus written, and direct versus asynchronous, with different degrees of delay (such as chat – text message – email – letter). Skype combines verbal, visual and textual (chat) elements, and both of the latter can be enhanced in turn with emojis. Again, there are different sorts of rules and norms associated with different sorts of channel, and different channels are more or less adequate or appropriate to different sorts of communication. A text message channel may be adequate for announcing one's arrival time; not however for expressing condolence on the occasion of someone's death (Westmyer et al., 1998).

A.2.3.1. Environmental context is the setting formed by that part of the world in which the conversation takes place. It is a combination of spatial and social context, and thus includes both physical and social constraints. It is made up of what Barker calls "ecological units" (Barker, 1968), for example the kitchen while Raymond is having breakfast, the interior of the school bus while he is travelling to school, his classroom while a lesson is taking place, the school yard during break.[50]

The environmental contexts of participants in a dialogue may differ, as for example when Mary is driving and Jack, sitting next to her, is navigating. Here the environmental contexts of the dialogue share in common the car interior, the road, the route ahead, and the share the same destination as part of their dialogue horizon. Jack's environmental context includes in addition the map he is using to navigate. Mary's environmental

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[50]Wright and Barker (1951) record a sequence of some 1000s of settings through which one boy progresses in a single day.

context includes the set of driver affordances making up the car cockpit. That dialogues of this sort so often go wrong rests in part on the fact that there are different ways in which space itself is demarcated in different registers (Matthiessen and Kashyap, 2014).

Relations between environmental contexts may involve also elements of territoriality, for example when Jack seeks to engage Mary in dialogue by inserting himself into her personal space through displays of dominance or enticement. Environmental context also comprises those environments where political or military power is projected (Popitz, 2017), such as the layout of a prison in which an overseer can interact via intercom with the prison inmates. Here the environmental context of the overseer comprehends multiple prison security, video surveillance and communication systems extending across the entire prison and its surroundings; the environmental context of the inmate extends hardly beyond the walls of her cell.

A.2.4. Discourse context and interpretation

The dialogue *is its own context* at all levels of language production and interpretation. What this means is that, just as the constituents of a sentence contextualise each other, so do the successive sentences themselves. Each utterance is contextualised by its preceding utterances, and its potential future utterances form part of the context horizon of each present utterance. The degree by which preceding statements influence the interpretation of the current statement is called the *contextual weight* of these statements. In prototypical conversations this weight decreases over time, so that the immediately preceding utterance has the strongest weight and more remote utterances have less as they fall away into the background. There are however cases where interlocutors can suddenly reach back to utterances made much earlier in the dialogue and bring them once more into the foreground. From a mathematical point of view, such discontinuities in the dialogue are erratic (non-Markov).

One important family of cases of this sort results from misunderstandings. We pointed out already that acts of choosing how to respond to a dialogue utterance are implicit. The same applies also to the interpretations of an utterance on the part of the receiver. The latter are observable only indirectly, for example by inference from the utterances the interpreter produces after a role switch between the interlocutors has occurred. This means that the continuous feedback which we rely on to adjust our intentions during dialogue gives us only a partial picture of how our interlocutor is responding to our utterances. This in turn leads to misunderstandings, which may remain undetected through the entire length of the dialogue. Where they are detected, this will often force an utterer to revise a statement from further back in the conversation when she realises,

on the basis of how her interlocutor is now responding, that she has been misunderstood.

Discourse context is also present at a level above that of a single dialogue, for example when one dialogue is embedded inside another, or when succeeding dialogues are entangled with each other, as in a court case, where earlier dialogues may be inserted into the present dialogue context in the form of written documentation.

A.3. Discourse economy: implicit meaning

Discourse economy occurs where the intended meaning remains partially implicit, so that the interpreter is required to take account of context for interpretation. Such implicit meaning is generated almost always unconsciously, because parties to a dialogue automatically assume that they share sufficient general as well as context-specific knowledge to allow each of them to contextualise successfully the utterances of the other. Thus, they can still effectuate an adequate interpretation, even though not everything is said explicitly. This is of importance not least because it reflects the way in which the structure of the dialogue is influenced by interactions between the respective identities of its participants, above all by which intentions and background (linguistic and other) capabilities they share.[51]

The need for economy in use of language turns on the fact that each speaker will in normal circumstances want to obtain from her speech acts maximal effect in a limited time, and implicitness at the right level allows her to pass over details that would otherwise disturb the conversational flow or be boring to her interlocutor. Avoiding explicitness can also be used as a conversational tactic, for example to maintain politeness or mask deception.

To achieve a dialogue that is productive on both sides, the preponderance of implicit meaning on the side of what is communicated by the utterer must still allow its understanding by the interpreter in a way that is close to the utterer's intention. In his *Studies in the Way of Words*, Grice (1989) formulates in this connection what he calls the "Cooperative Principle", in which he recognises not only the need for dialogue economy but also its two-sided nature. For cooperativeness, as Grice understands it, incorporates both a maxim of *quantity* – be as informative as you possibly can, and give as much information as is needed – and a maxim of *manner* – be as clear, as brief, and as orderly as you can in what you say, and avoid ambiguity. These requirements are clearly in competition with each other. If brevity is taken too far, for example, then the

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[51]Verschueren (1999, p. 26) gives an example of our almost universal reliance on dialogue economy by describing his attempt to make fully explicit the colloquial statement: "Go anywhere today?" This resulted in a text of 15 lines that still does not achieve full.

interlocutors will typically later require more explicitness in order to resolve potential misunderstandings.

A.3.1. Deixis

The most important form of implicit meaning is deixis, which is the use of language elements whose reference is determined by some feature of the context of utterance that is in the scope of awareness of the dialogue partners. Deictic expressions – such as "him", "next week", "there" – need to be interpreted by the receiver adverting to features of this sort.[52] Four important forms of deixis are: person deixis, temporal deixis, spatial deixis and discourse deixis.

A.3.1.1. Person deixis means: references to a person, where who the person is can be inferred only if contextual information is available (Meibauer, 2001; Sidnell and Enfield, 2017). The utterer knows who he himself is, and in the setting of a face-to-face communication the interpreter knows who the utterer is, and is thus able to resolve the deictic pronouns "I" and "you".

A.3.1.2. Spatial deixis is a phenomenon arising when reference to space requires for disambiguation spatial features that are themselves parts of or are anchored to the context (Lyons, 1977). It can be seen at work in the use of prepositions such as "in", "out", "below"; also of verbs such as "enter", "go to", "leave"; of adverbs such as "here", "there"; and of demonstrative pronouns such as "these" and "those". For example, the utterance "Let's go downtown" when uttered in Berlin needs context to be disambiguated, since "downtown" can mean (at least) Berlin Zoologischer Garten and Berlin Mitte. Between 1961 and 1990 the term "Berlin" itself needed context for disambiguation.

A.3.1.3. Temporal deixis is the analogous phenomenon involving reference to time (Lyons, 1977). To resolve the meaning of utterances like "Yesterday Trump met Kim" or "Next February I will travel to Rome" *event time point*, *time point of utterance* and *reference time scale* need to be applied in disambiguation (Thomsen and Smith, 2018).

The need to keep track of temporal order inside a dialogue is illustrated by a statement such as

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[52]Talmy (2018) provides a survey of such cues as part of an account of how the utterer in a dialogue draws the attention of the interpreter to the particular entity that she wants to communicate about by using both speech-external and speech-internal context. He describes the vast array of strategies humans use to bring this about, given that the utterer cannot somehow reach into the hearer's mind and directly place his focus of attention on that target.

(1) After Paris we need to get to Abbeville before nightfall.

This involves four temporal references, one (implicit) present and three (explicit) in successive futures, as well as three spatial references: present location at time of utterance (implicit), Paris and Abbeville (explicit). We can use this example to illustrate how the context and horizon of a conversation influence each other mutually. On the one hand, if the sentence is used in a conversation between two British tourists planning a trip from Paris to Normandy, the horizon might include potential closing times on Somme battlefield memorial sites. If, on the other hand, it is used in a conversation between two Oklahoma truck drivers, then the dialogue horizon might include potential traffic holdups on Interstate 49 on the way from Paris, Texas to Abbeville, Louisiana.

A.3.1.4. Discourse deixis is the use of an utterance in a conversation to refer to this utterance itself or to previous or future parts of the conversation (Levinson, 1983). Examples are: "What you just said contradicts your previous statements", or "So what does it feel like, getting caught up in a conversation like this one?"; or again: "This conversation must stop immediately!" or "I contest the legitimacy of these entire proceedings!" While change in dialogue horizon normally takes place gradually and without being noticed, the employment of discourse deixis brings the ongoing dynamics of horizon change into the foreground. Discourse deixis is often an element of a meta-discourse, for example when three persons leave the room and then one of the remaining interlocutors says: "That was a strange conversation."

A.3.2. Other forms of implicit meaning

A.3.2.1. Non-deictic reference is a way of expressing the relation to an entity using a fixed reference, as in proper names or definite descriptions (Abbott, 2017). Proper names and other fixed references, too, require background (world) knowledge to be interpreted correctly.

A.3.2.2. Presupposition is the usage of an implicit unit of meaning in a way that implies that the interpreter will have to draw on contextual knowledge to understand the intended meaning, as in the sentence "Let us meet the chancellor", which carries the presupposition that the interlocutor knows who the chancellor is. A variant type of presupposition (as in: "Have you stopped beating your wife?") is sometimes used as a way of tricking a dialogue partner in unfriendly interactions.

A.3.2.3. Implicature occurs where there is a unit of meaning which the speaker does not make explicit in his utterance, but which the interpreter can deduce from this utterance. Huang (2017) gives the following example: "The soup is warm" implies that the soup is neither hot nor cold. This differs from presupposition, because the implication can be resolved without background knowledge; only minimal language competence at the lexeme level is required.

A.3.3. Non-interpretation: Linguistic division of labour

Not all implicit or ambiguous lexemes or phrases have to be interpreted or disambiguated by every utterer or recipient of an utterance because this is not always required to realise their intentions. Hillary Putnam gives an important example of the interaction of utterance and intention in his paper on what he calls the 'linguistic division of labour' (Putnam, 1975, p. 144). As he points out, there are many lexemes which are used by speakers without their full understanding. This phenomenon allows speakers and recipients to both tacitly use a lexeme while leaving its full understanding and definition to experts on which they rely, as when two politicians talk about nuclear power generation on TV. Both tacitly agree that they do not understand how nuclear power works, but they use the term nonetheless in order to sharpen their political profiles. When such tacit understanding is undermined by someone with genuine expertise, this leads to confusion and anger, because it adds a new, and undesired layer of interpretation to the dialogue in a way that disturbs their initial political intentions.

A.4. Structural elements of dialogue

When a human subject initiates a dialogue, she can draw, first, on multiple sets of options at many levels of *language production*, starting with: which language to use (for example when travelling in a foreign country); the topic to be addressed; intonation, pitch, syntax, vocabulary, volume, as well as code and style of language (brazen, cautious, elegant, pious, rough, wistful . . .); and so on.

Second, she can draw on a wide repertoire of *non-verbal utterance accompaniments*, such as gesture, mimicry, gaze, posture. These elements (documented in detail below) evince (or mask) underlying intentions of the speaker, which can be argumentative, jocular, overbearing, serious, submissive, supplicative, teasing, threatening, and so forth (Smith (2001), section 4).

According to her intentions of the moment, the utterer can use different combinations of the above as she adjusts to the responses of the recipient in accordance with the

physical (temporal, spatial), and social and conversational context within which the dialogue takes place.

The recipient of an utterance will similarly face many options on the basis of which to attribute meaning to the utterances he hears. He can be suspicious, trusting, fully or only partially attentive, and so on. Which options are engaged on either side may of course change as the conversation unfolds, either for reasons internal to the content of the conversation itself, or because the interlocutors are influenced by external factors such as effects of alcohol, or inclement weather, or indeed for no reason at all. Conversations often involve random changes of subject matter, of tone, of loudness, and so forth.

All the units that allow speakers to express their intentions are defined as structural language elements (Verschueren, 1999). They are, from the coarse to the fine-grained:[53]

1. non-verbal level: including facial expression, gestures and body language,

2. whole language level: including language choice, language code and language style,

3. level of single dialogue contributions: sentential and suprasentential utterance units,

4. level of morphemes and words,

5. level of sound structures.

A.4.1. Non-verbal structural elements of dialogue

Facial expression, glances, gestures and body language are important ways in which uses of language are supported by non-verbal structures (Verschueren, 1999, 100ff.). All of them can potentially transform the sense of a verbal utterance, so that even a statement of condolence can be accompanied by facial expressions that make it appear cynical to the interpreter. In negotiations (and negotiation-based games such as poker) body language and facial impression may be indispensable to obtaining the desired results. It has been shown that their effect on the interpretation of contexts, situations and even the personality of the interlocutor is quite strong (Ambady and Rosenthali, 1992), and they form part of the deep-rooted cheater-detection mechanisms that have

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[53]Ingarden (1973, 29f.) identifies a similar pattern of layers in his analysis of the ontology of the literary work of art, and points out how each can contribute to the aesthetic quality of the work as a whole. He emphasises that, despite the heterogeneous character of these layers, the work nonetheless constitutes an organic unity, since the layers are unified unproblematically by the reader in virtue of the dimension of meaning which runs through them all. Something similar applies in the dialogue case, though here there are two – potentially conflicting – chains of meaning which unify the layers, one for each of the two dialogue partners.

evolved in human beings to deal especially with social interactions involving exchange (Cosmides and Tooby, 2005). Communicating via gestures is also an important non-verbal component of dialogue, and is used very often to disambiguate spatial from person deixis, including by means of simple pointing (Sidnell and Enfield, 2017).

A.4.2. Language code and style

Code – also called "register" – is a matter of the language choices systematically made by a social group, such as the inhabitants of an area or the members of a social class or profession. Dialogue participants can switch codes, for example, to convey special meaning or emphasis, or to communicate mockery or disdain.

Style concerns the level of *formality* of language use (Verschueren, 1999); a speaker may switch, for example, to a more aggressive style, in order to intimidate or punish his dialogue partner. Both code and style are important dimensions of variance in utterance formation and interpretation.

A.4.3. Sentential and suprasentential utterances

A sentential utterance expresses a relatively closed unit of meaning encompassing the basic functions of reference and predication. Subkinds are: statement, question, command, request and exclamation (Dürscheid, 2012). Statements are characterised by features such as reference (subject in noun phrase) and predication (verb phrase). Typically, they are expressed as complete sentences, but ellipses are also used, as in "Guilty, your honour". Such expressions are also a form of dialogue economy.

A suprasentential utterance is a sequence of sentential utterances which the utterer uses to optimise the fulfilment of her intentions by conveying her meaning in corresponding detail. The way this is done, too, depends on context.

A.4.3.1. Incompleteness and ellipses Sentential and suprasentential utterances are often incomplete or elliptical. This may result from interruption or from the inability of the speaker to finish his thought. But often, such utterances can be completed by elements of the situation and are not pragmatically incomplete (Mulligan, 1997). In such cases humans can interpret even incomplete utterances in a sense that is close to the meaning intended by the utterer.

A.4.3.2. Force and modality Force describes utterance styles characteristic of assertion, command, request, question, and so forth. In addition, there are varying degrees of

force, so that, depending on the emotional involvement and inclinations of the speaker, a request to obtain something might be phrased either as a question or as an imperative.

With Frege (1879) and John Searle (1978) one might take the view that an expressed proposition can be evaluated independently of the force with which it is communicated. P. Hanks (2007), however, gives strong evidence to the effect that propositional content and force interact. Thus, while logicians and computer scientists have sometimes held that the linguistic subdiscipline of semantics can hold itself separate from concerns with matters of pragmatics, a view of this sort cannot be maintained even for the language used in silent monologue (Clark, 1996). Such a view will certainly be inadequate when it comes to that sort of language whose mastery is needed to conduct a convincing conversation.

The philosopher's understanding of force is closely related to the linguistic notion of *modality*, which describes aspects of attitude – of how the utterer relates to his utterance, signalling properties such as: degree of certainty, optionality, urgency, hesitancy, vagueness, possibility, necessity, and so forth (Verschueren, 1999).

But modality as understood by linguists comprehends also other aspects of the utterer's attitude, for example that he is joking, lying, flattering, ordering, arguing, interrogating, pleading. The verbal expression of modality is often combined with non-verbal language-supporting elements (see A.4.1), for example when the utterer is holding a gun to the head of the interpreter, or is kneeling before the interpreter in the middle of the street while holding a ring in his hand.

A.4.3.3. Lying and deception   Lying and deception are frequent phenomena in language use; Nietzsche (1980) even sees them as an essential part of language usage. Their source is the desire to achieve one's goals and intentions without the knowledge of the interlocutor or against her will. Lying changes the entire meaning of a dialogue both for the deceiver and, in the case that she becomes aware of the deception, for the deceived person. Sometimes the deception may be made explicit by the deceived person ("You must be lying to me because at that time you could not have been at home!"), but otherwise it remains implicit because the deceiver will have no motive to reveal it. It is generally therefore not possible to model lying and deception using what is observable in a dialogue.

A.4.4. Lexemes

Lexemes are the carriers of the minimal units of linguistic meaning – for example RUN or HAT. The building blocks of sentences are lexemes in their inflected forms, which are

called wordforms – for example *runs*, *ran*, *running* or *hats*, *hat's*, *behatted*. For any given language there is a relatively small set of lexemes that has to cover a very wide range of possible topics. This is because it is not possible to have an exact word for each and every aspect of reality if the size of the lexicon is to be kept small enough that it can be managed by a single human being. Lexemes are therefore prototypes (Rosch, 1975). They obtain part of their meaning from the context created by the other lexemes they are used with in a sentence, as well as by all the other contextual dimensions identified above. For example, the lexeme FREEDOM has a very different meaning in (2) and (3):

(2) Do not clutter my desk with stuff, I need freedom to move.

(3) We want freedom of speech!

Depending on intention and context, lexemes at varying levels of abstractness and generality may be chosen in the course of a single dialogue. In everyday usage it is the mid-level that dominates. For instance, when talking about pets, the participants in a dialogue will typically use mid-level terms such as "dog" or "cat" rather than the low-level "dachshund" or the high-level "animal". Something similar holds when we describe an ailment (where we refer in a dialogue to a fracture of the *foot*, rather than of the *fifth metatarsal bone*). When we introduce ourselves in a dialogue, we (prototypically) talk about our place of origin by referring to city or region rather than to neighbourhood or street. Utterers, normally unconsciously, select the level of abstractness or generality that is salient to the dialogue context (compare A.2.4).

A.4.5. Sound structure

In its sound structure, speech is built out of elementary phonetic segments (vowels and consonants), which are combined into composite sounds beginning with syllables and words and proceeding to entire sentential and supersentential utterances. We can compare the former to single notes in music, and the latter to melodic structures formed by notes in sequential combination.[54] Each entire utterance is made with a specific *prosody*, by which is meant that aspect of speech sound that inheres in composite sound units. Among the various dimensions of prosody, intonation and pace are the most important.

Variations in *intonation* – for example suddenly switching to a high-pitched voice – are used to express emotions or attitudes of the speaker, or to distinguish sentential units of

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[54]The elementary phonetic segments of vocal utterances have features comparable to the pitch, overtone composition, and amplitude of single notes in music.

different modalities (for example statements from questions), or for purposes of emphasizing or highlighting certain aspects of the dialogue, or to regulate the conversational flow.

Sounds and the meanings they convey are tightly associated with our physical experience, as is evident from visceral reactions such as nausea or sexual excitement that certain speech sound types can evoke.[55] Another aspect of sound structure that can influence interpretation is *voice quality*, such as the use of a soft or hard voice, or the use of mere vocal cues such as throat-clearing, grunts, sniffs, unintelligibly muttering under one's breath.[56]

Pace comprises rhythm, speed – for example speeding up or pausing, hesitating in mid-sentence – all of which can be selected, consciously or unconsciously, to shape the ways an utterance or sequence of utterances is interpreted. Pausing can also be used as a device to signal to one's interlocutor that a conversation is reaching its end. Different types and layers of sound can be used together, for example when a dialogue partner responds to an utterance with a slow hand clap, or when Romeo serenades his sweetheart with musical accompaniment.

A.5. Dialogue dynamics

The production of meaning in the course of a dialogue is a highly dynamic process, which may unfold on all of the levels distinguished above: the intentions of the interlocutors, the dialogue horizon generated by the interaction of relevant dialogue contexts (see A.2), deixis and other forms of implicit meaning, and all the dialogue's structural elements. As we have seen above, the ways dialogue participants interpret each other's utterances depends on their past experiences, and may have a strong emotional component (Drace, 2013). In their utterance production, each can draw on a huge variety of interacting combinations of the structural elements. Moreover, while this is happening, the dialogue horizon itself is evolving: some things and processes move into the field of what is relevant to the dialogue, others fall away. Where the dialogue itself becomes its own context, this leads to a refocussing and potentially to a reinterpretation of all earlier contexts, which then influences how subsequent (unconscious and conscious) choices will be made in

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[55]Note that the pitch variation in intonation is different from *tone*, another type of pitch modulation, that is used to distinguish grammatical or lexical meaning. In Mandarin, for example, lexemes are differentiated via differences in what is called syllable pitch.

[56]We focus here on sound structure as it appears in the flow of a spoken dialogue. But sound structure can play a role, too, in written dialogue, for example when our minds associate the words in an email message with a certain intonation. This is an example of the subtlety and massive complexity of language interpretation as it occurs in the dynamic flow of inner mental experience.

utterance formation and interpretation as the conversation proceeds. For example, an interlocutor might say: "The facts that you bring up now contradict the conclusions you drew just half an hour ago."

A.5.1. Dialogue flow interruptions

While in a prototypical dialogue the interlocutors take turns, clean and regular turn taking is rather exception than rule, because most dialogues contain interruptions, and sometimes, as in the conversational style favoured among Parisian intellectuals, consists entirely of interruptions. Conversational turn-taking is displayed in its ideal form in the strings of characters printed by a teleprinter on a moving paper tape, where only one person can have control over the input mechanism at any one time. This ideal form is illustrated also by a published interview after an editor has worked to create a polished textual flow.

In actually occurring spoken dialogues, however, there are frequent deviations from this ideal. The utterer may pause or hesitate or stutter, create false starts, make mistakes, interrupt herself or try to add retrospective corrections to what she has said earlier, suddenly change the subject of the dialogue entirely. The interpreter may seize the speaker role by forcing a role switch before the utterer has finished her statement. If the utterer does not yield to the interruption, this leads to utterances occurring simultaneously, so that the flow of meaning transmission breaks. Sometimes, the interpreter anticipates the next statement of the utterer and takes a turn before the latter has finished. All these deviations increase the complexity of the role context and add to the pressures on the dialogue participants both in forming and in interpreting dialogue utterances. They often go hand in hand with emotional layers to the dialogue flow, which support specific sorts of interpretation of dialogue utterances, for example where one dialogue partner seeks to influence the other by (as we say) playing on his emotions.

A.6. Summary remarks on dialogue variance

We invite the reader to note not merely the many *levels of dialogue variance* distinguished in the above but also the degree to which these variations depend on multiple factors (indeed multiple levels of multiple factors), both inside and outside the dialogue itself, factors which can extend to include almost any matter within the biographies and within the scope of the knowledge and interests of the dialogue partners.

We note further the degree to which many of these factors are a matter of continuous variation in the sense that the range of options forms a continuum, as for example

between speaking with a soft and a loud voice, or with a calm and an angry voice.

Movements along multiple such continua may take place within a single dialogue, and when such movements are effected by one dialogue partner they will typically call forth some concordant movement on the side of her interlocutor.

In all respects, indeed, preserving the flow of a dialogue rests on the capacity of humans to adjust their contributions to fit those of the dialogue partner, for example to adjust their respective intentions.

This capacity is applied even in the most heated of disputes between friends or lovers, where even the most acrimonious of dialogue partners are able to maintain a conversation flow for considerable periods of time. This is achieved through a type of homeostatic process, whereby, when the conversation seems to be going completely off the rails, one or other partner succeeds in pulling it back from the brink and initiating another phase of what is once more recognizable as coherent verbal exchange.

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