A survey of neural models for the automatic analysis of conversation: Towards a better integration of the social sciences.

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Abstract

Some exciting new approaches to neural architectures for the analysis of conversation have been introduced over the past couple of years. These include neural architectures for detecting emotion, dialogue acts, and sentiment polarity. They take advantage of some of the key attributes of contemporary machine learning, such as recurrent neural networks with attention mechanisms and transformer-based approaches. However, while the architectures themselves are extremely promising, the phenomena they have been applied to to date are but a small part of what makes conversation engaging. In this paper we survey these neural architectures and what they have been applied to. On the basis of the social science literature, we then describe what we believe to be the most fundamental and definitional feature of conversation, which is its co-construction over time by two or more interlocutors. We discuss how neural architectures of the sort surveyed could profitably be applied to these more fundamental aspects of conversation, and what this buys us in terms of a better analysis of conversation and even, in the longer term, a better way of generating conversation for a conversational system.

1 Introduction

With the rise of call centers, chat applications and social media sites it has become essential to be able to automatically analyze human conversation. Automatic analysis can flag problematic conversations for customer relationship management, or identify the nature of the collaboration within a student group for e-learning. Automatically analyzing conversations is also paramount for conversational systems by enabling them to provide the right answers at the right time in the right way. With this in mind, a new generation of neural architectures such as recurrent neural networks has arisen to detect conversational phenomena. These architectures have good potential for modeling the context of a speaker-turn and the conversation dynamics between speakers. They have shown good performance for turn-level prediction of dialog acts, and basic emotion/sentiment categories.

More fundamentally, however, we argue that these neural architectures can be extended to other essential conversational phenomena, inspired by the social science literature. In particular, when studying conversations, the social sciences have shown the importance of collaborative and dyadic processes in interactions and their joint and evolving mechanisms. But deep learning research has yet to be mobilized in this direction, despite calls to action such as [Kopp and Krämer, 2021; Eskenazi and Zhao, 2020]. In this paper, we take up the challenge by investigating how the recent neural architectures that we survey in Section 2 can be leveraged to mirror the collaborative and dyadic conversational processes highlighted by the social sciences, and that we survey in Section 3, along with some attempts to integrate those processes into computational systems. In Section 4 we then outline future directions for the deployment of neural architectures that take the social science perspective into account. In Section 5, we end the paper by opening the discussion on how these conversational features could also be integrated into current neural architectures for conversational systems in order for them to evolve into true partners to their human users.

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While there exist survey papers on neural architectures for the analysis of conversation, such as [Poria et al., 2019; Deng and Ren, 2021], they need to be supplemented with the latest advances (e.g., transformer-based and graph-based) and discussed from a social science perspective. The current paper thus constitutes the first survey in this area that comprehensively presents existing neural architectures and introduces related problems from a social science perspective, to provide research insights for the future. Given the short format of a survey paper, our coverage of current work is not exhaustive. For each type of neural architectures or each approach to dyadic processes, we give one representative example, knowing that other studies could also have been cited.

2 Modeling Context in Conversations

To date, the NLP community has concentrated on research gathered under the title of dialogue understanding. This: primarily emotion recognition, sentiment analysis, dialogue intent classification, and dialogue state tracking. These tasks necessitate a transcript of conversational data, usually separated into utterances from different speakers, and mainly aim to classify the utterances using different possible sets of labels. In the following section, we focus on these tasks and how neural models are used to solve them, as a way of describing the current state of affairs, and we clarify what bridges can be built to the perspective we describe in Section 3. Conversation has a particular structure, with dependencies mirroring a number of interactions, as depicted in Figure 2: between speakers, but also among a speaker’s own utterances [Poria et al., 2019]. The relevant information may be close or distant, and may also be hidden behind a chain of co-references. Next, the labels associated with the aforementioned tasks are also interdependent. Finally, there exist dependencies among the different modalities involved in conversations, usually including natural language, nonverbal and acoustic features. Context, as in most of NLP, is thus key for dialogue: utterances are not considered independently, and neural models usually include neighboring utterances to make predictions. In order to extract contextual information, which is essential to understand conversational behavior, the current literature mainly leverages neural architectures.

Specifically, the existing studies usually consider a conversation C as a sequence of utterances \( (u_i)_{i=1}^{l} \). In order to map the sequence of utterances to a sequence of labels \( (y_i)_{i=1}^{l} \), the trend is to use neural end-to-end models. In particular, the models usually follow the encoder-decoder paradigm, consisting of a feature extractor on which an auto-regressive language model is conditioned, and they use traditional architectures, such as recurrent, attention, transformers. In the present section, we focus on how and where context is integrated in addition to the representation of the current utterance. Our goal is to understand how current NLP tools – mainly from the deep learning toolbox – have shaped how context is used in dialogue, and what limits are associated to this use, which will allow us to better address them in the next sections. Hence, we will subsequently summarize recent progress in exploiting context for dialogue understanding tasks with sequential modeling; including recent transformer-based models making use of pre-training; then, with hierarchical modeling, followed by modeling dependencies between labels and, when available, between modalities.

2.1 Recurrent-based Sequence Modeling

Since sequential architectures have become ubiquitous in NLP, it has become straightforward to encode an utterance into a representation of its words. In this context, capturing contextual dependencies between utterances has been done by carrying over the most recent utterance representation via memory [Chen et al., 2016]; then, past utterances without distinction [Bapna et al., 2017]. [Hazarka et al., 2018] were first to model self-speaker dynamics, using a recurrent architecture for each speaker. The extracted states are then fed to a recurrent module that models inter-speaker dynamics and maintains a global context of the conversation. [Majumder et al., 2019] improve on this by separating the speaker and listener into different roles, adding a recurrent architecture to track the global state of the conversation. [Xing et al., 2020] propose a memory module to model interpersonal dependencies. Inversely, as a way to focus solely on emotion representations, [Lian et al., 2019] use adversarial training to obtain a common representation between speakers, building a speaker-independent model.

Recently, [Ghosal et al., 2020] studied the role of context for dialogue understanding tasks, presenting a series of exhaustive experiments with contextual baselines based on recurrent networks, among which the model of [Majumder et al., 2019], and a non-contextual one. Their first conclusion is that the contextual models perform largely better than the non-contextual in most cases; they also find out that the speaker-specific tracking of [Majumder et al., 2019] is also useful in a large part of the experiments.

2.2 Self-supervised Conversation Modeling

The recent trend of using large transformer-based models like BERT [Devlin et al., 2019], pre-trained on huge amounts of textual data, marks a milestone in context modeling: with specific self-supervised and non-autoregressive learning objectives, they accumulate considerable knowledge about language. The most common of these objectives, Masked Language Modeling (MLM) and Next Sentence Prediction (NSP), have been adapted to the structure of dialogue,
first with recurrent models [Mehri et al., 2019], then with transformer-based models [Chapuis et al., 2020]; notably, by acting at both the word and utterance level (for example, by masking and retrieving complete utterances), these objectives encourage representations to integrate both local and global context. Such architectures are also used to build contextual representations for response selection [Whang et al., 2020] and generation [Zhang et al., 2019] in dialogue and question answering systems: in Section 5, we will come back to how these models are considered in conversational AI.

Several studies investigate the representations they learn, whether based on recurrent or transformer networks: [Sankar et al., 2019] show that they are not significantly affected by perturbations to the dialogue history. Similarly, [Saleh et al., 2020] probe internal representations of dialogue models with several tasks, among which are dialogue understanding tasks, and find that shuffling the training data does not significantly decrease performance on probing tasks, even for model pre-trained with self-supervised objectives: hence, these architectures fail to leverage the turn-taking structure of dialogue.

2.3 Hierarchical and Graph-based Conversation Modeling

Most of the works mentioned until now model dialogue structure in some way, usually through encoding the difference between speakers - but we are interested here in how to model a conversation in structures more complex than flat sequences of utterances, which is often done with hierarchical neural architectures, or graphs. The hierarchical recurrent neural network in [Li et al., 2019] models the natural hierarchical structure of a conversation (character, word, utterance, and conversation levels), while [Chapuis et al., 2020] propose to pre-train hierarchical transformers on two levels (word and utterances). Very recently, [Hazarika et al., 2021] presented an hybrid approach with a transformer at the word level and RNN at the utterance level, while [Hu et al., 2021] propose a model that uses attention to iteratively extract emotional information from two global context representations modeling inter and intra-speaker dynamics.

In [Ghosal et al., 2019], a conversation is modeled as a graph whose nodes and edges respectively represent utterances and temporal dependencies between them, and emotion recognition is modeled as a node classification task using graph convolutional networks (GCNs). These architectures allow addressing context propagation issues usually associated with RNNs on long sequences. [Ishiwatari et al., 2020] propose to add positional information to the graph to take in account the classical sequential structure. Similarly, [Shen et al., 2021] use directed acyclic graphs to model the structure within the conversation, as an attempt to combine the strength of graph-based and recurrent-based approaches. But another issue is that conversational topics are not necessarily organized in a sequence during an interaction, which is why learning to refer to the relevant part of the context is important. For dialogue act classification, [Wang et al., 2020] groups previous contexts by labels and integrate them to the representation through an heterogeneous graph, before using a GCN to model the interaction. Besides integrating the context through an interaction graph, [Li et al., 2021] adds outside knowledge from a pre-trained common sense model to more accurately model relations between speakers.

However, to the best of our knowledge, no experimental study looks further than performance on dialogue understanding tasks to confirm that hierarchical and graph-based conversational models are effectively leveraging the particular structure of dialogue, such as done for recurrent architectures.

2.4 Modeling at the Decoder Level

For a sequence labeling task, it is natural to try to model dependencies between neighboring labels: for example, with Conditional Random Fields (CRFs) on top of a neural recurrent model [Kumar et al., 2018]. In [Colombo et al., 2020], the authors go further and compare the task of sequence labelling as Neural Machine Translation (NMT) which maps a sequence of words in a given language to a sequence of words in another language leveraging progress made in NMT as most models generating text based on a separate textual input. In particular, with the popularization of the sequence-to-sequence architecture, sequence labeling tasks have begun to be treated as text generation, with the sequential decoder integrating the conversational aspects and contextual dependencies between the labels. Then, decoding can be guided by attention, while still enhanced with a supplementary CRF [Colombo et al., 2020]. [Lu et al., 2020] use an iterative emotion interaction network to model the interaction among emotion labels and deal with the lack of gold labels at inference time. Another way to leverage dependencies between labels is to train a model simultaneously on two different tasks, as [Li et al., 2019], who use attention and CRFs on two separate but linked decoders to predict both dialogue acts and topics. Similarly, [Qin et al., 2020] propose ‘relation layers’ between encoder and decoder to model the interactions between emotions and dialogue states to be predicted by two separates decoders.

2.5 Aligning multiple modalities

The shift to data-driven neural end-to-end systems allows one to automatically obtain a data representation, avoiding feature engineering. This means that these systems allow information coming from different modalities to be represented in the same space. A wide array of work has investigated how best to fuse these modalities for dialogue understanding tasks, going from simply concatenating features to proposing recurrent neural models capable of modeling both inter and intra-modality dynamics [Zadeh et al., 2017]. However, modalities are heterogeneous, and often unaligned. Additionally, sequence-based networks have difficulty modeling long-range dependencies between modalities. The attention mechanism is a first step to address the issue [Ghosal et al., 2018], improved upon by using transformer models [Tsai et al., 2019]. Going further, [Tang et al., 2021] propose a translation-inspired fusion network, establishing pairwise translation modules between modalities with the purpose of dealing with missing modalities at prediction time.

3 A Perspective from the Social Sciences

While the architectures presented in the previous section are extremely promising, the phenomena they have been applied
to date represent but a small part of what makes conversation engaging - in fact, they don’t take into account to the extent possible what defines conversation as studied by the social science literature. Before introducing the future directions, we look back at the main studies in social sciences defining what we believe to be the most fundamental and definitional feature of conversation, which is its co-construction over time by two or more interlocutors, and at the computational studies that aim to integrate such a feature for the automatic analysis of conversations.

### 3.1 Some Definitions

Much of computer science, including some computational linguistics, has maintained a certain loyalty to Shannon and Weaver’s 1948 Mathematical Theory of Communication [Shannon, 1948] whereby a message is passed from sender to receiver via a channel. While this model was extremely influential in its time, it has since been replaced in much of the social sciences by models that take into account the collaborative nature of conversation. For example, [Clark, 1996] highlights the joint responsibility of the participants to ensure that contributions to the conversation are mutually understood, what he calls “grounding.” In the ethnomethodology or conversational analysis literature, [Schegloff, 2007] highlights the contributions of the participants to the temporal sequentiality of talk, and how it can be moved forward via units such as response pairs where one interlocutor’s contribution is not complete until the second interlocutor responds to it. That conversation evolves over time implies that, rather than looking at context as a function of one single utterance or turn, the analysis of these phenomena must include looking at time as continuous, and longer than a single turn or two turns - indeed, even stretching over multiple interactions.

Similarly, sociolinguists such as Spencer-Oatey [Spencer-Oatey, 2005] highlight the joint contribution of interlocutors to the evolving social relationship, where one cannot even distinguish the contribution of each interlocutor, because the very concept of a social phenomenon such as rapport is dyadic or mutual and jointly evolves across the interaction [Cassell and Bickmore, 2003]. In addition to rapport, other examples of dyadic phenomena joint between two or more speakers include alignment, affiliation [Stivers, 2008], and interpersonal trust [Bickmore and Cassell, 2001]. From both a social science and a computational perspective, the analysis of these phenomena implies a unit of analysis that is not an interlocutor or a message but a dyad or a group. Novel coding schemes, statistical analyses [Kenny et al., 2020], and computational models all must be adapted to take into account the dyadic nature of these phenomena. We can contrast these phenomena with engagement, for example, that has a fairly long history in systems that analyze user behavior, but that does not need to be dyadic - one interactant can be engaged while the other is not. Likewise one participant in a conversation can be hostile towards the other without that second person being hostile - or even aware of hostility.

### 3.2 Existing Coding Schemes

Work integrating dyadic processes is still rare in deep learning for NLP, although there does exist research that develops coding schemes to provide ground truth for dyadic phenomena. One example comes from the annotation of how rapport evolves dyadically in conversation [Zhao et al., 2014], [Cerekovic et al., 2016]; another comes from annotation of group cohesion in [Kantharaju et al., 2020]. The units used for the annotation reflect the different temporalities of dyadic processes. Both rely on fixed-size segments (annotation of rapport on windows from 30 seconds to 1-minute and, for cohesion, on 2-minute windows). [Ambady and Rosenthal, 1992] have shown that the annotation of these very short windows demonstrates good test-retest reliability for a number of psychological processes, including rapport, and has high inter-rater reliability among 3 or more annotators.

In [Langlet and Clavel, 2015], on the other hand, the coding scheme relies on a smaller and turn-based unit, the adjacency pair, for annotation of shared likes and dislikes of the interaction partners. An additional way to obtain ground truth for dyadic processes, but at the level of the interaction, is to use self-reported measures obtained through questionnaires in order to evaluate models of an agent’s overall nonverbal behavior (e.g., the rapport questionnaire in [Gratch et al., 2007], [Cerekovic et al., 2016]). It is not entirely clear, however, how reliable self-report is, nor whether the processes are truly dyadic, since only the human participants annotate their rapport.

### 3.3 Existing Prediction Models

Research also exists that provides automatic measures of dyadic processes. [Langlet and Clavel, 2015] use reasoning models that take the form of hand-crafted linguistic rules for analyzing shared likes and dislikes of the interaction partners. Temporal association rules built from data mining are used in [Madaio et al., 2017] for rapport estimation. Classical machine learning models such as Support Vector Machines in [Müller et al., 2018; Hagad et al., 2011] or regression models in [Cercoivic et al., 2016] are used for rapport estimation. Recurrent neural architectures such as bi-directional LSTM with temporal selective attention in [Yu et al., 2017] are used to integrate multimodal context. For the last two, the model relies strongly on the design of knowledge-driven multimodal features that allow social science knowledge about dyadic processes to be integrated. In [Müller et al., 2018], the non-verbal rapport features are speech, facial expressions, hand motions, and cross-modal synchronization features. Postural cues are studied in [Hagad et al., 2011]. In [Cerekovic et al., 2016], multimodal features are mixed with information on human personality traits. The time window for the extraction of features is linked to that used for the supervision. The specificity of dyadic processes is to require the design of both intermodal and interspeaker synchronization features (e.g., the number of synchronous smiles in a given window).

The above mentioned work is representative of the majority of the studies carried out on automatically measured dyadic processes in interactions, i.e. they make very little use of the verbal modality and, methodologically, prefer knowledge-driven methods to deep learning methods. Thus, neural models integrating dyadic processes are still rare in NLP research.
4 Future Directions

As described in Section 2, current neural architectures are able to model intra-speaker, inter-speaker and inter-modal dynamics. But what is still missing is the integration of the dyadic processes as a joint action of participants to understand each other, to maintain the flow of the interaction and to create a social relationship.

Reframing the Supervision The various neural architectures seen in Section 2 can be leveraged with a different kind of supervision than currently (e.g., using the speaker turn as a unit and basic emotion categories as a label). It implies using units of analysis and labels of the kind proposed by the coding schemes presented in Section 3.2. (e.g., a rapport level for each 30-second frame), and working on the last layers of the neural architectures in order to integrate the slowly evolving nature of co-construction processes.

Use Intermediate Predictions In dyadic processes, the response pair (that is, the unit of analysis that includes one speaker’s contribution and the other’s reply) can be taken as an intermediate level of analysis. One example comes from the automatic prediction of conversational strategies across speakers with the aim to improve the prediction of rapport [Zhao et al., 2016]. Another example comes from the automatic prediction of shared likes and dislikes in two speakers [Langlet and Clavel, 2015]. An interesting direction is the training of the models to predict dyadic processes at these two levels (the response pair and the longer window) using joint learning objectives inspired by the recent advances in multi-task learning in NLP [Garcia et al., 2019].

Developing New Datasets Using such neural models is based on the assumption that there is enough annotated data in dyadic processes to build deep architectures. If large datasets of interactions are already available, only a small part of them are annotated for dyadic processes. Researchers in deep learning must mobilize to develop new datasets annotated for dyadic processes in collaboration with researchers from the social sciences.

Pre-training Objectives on Unlabelled Data As seen in Section 2, the integration of the conversational aspects by capturing contextual dependencies between utterances can be done through unsupervised pretraining objectives (e.g., next utterance retrieval) for learning dialogue context representation using sequential encoders or transformer-based approaches. But the self-supervised objectives developed to date are still rare and they do not exploit the full structural richness of dyadic processes. We need thus to develop new methods able to train representations on unlabelled data with pre-training objectives and architectures dedicated to the modelling of the definitional features of dyadic processes.

The evaluation of what is exactly learned by these representations need to be done via dedicated methods such as probing (see Section 2.2). We need also to work on a grounding of these evaluation methods in social sciences.

Tractable Models In order to handle the lack of labelled data, deep learning research offers method such as meta-learning, few-shot learning and multi-task learning in order to foster the tractability of the models [Deng et al., 2020]. Such methods investigate how we can train models with few annotated data by relying on models trained on different data source with different labels. The application of such methods for the analysis of conversations is emerging and not trivial [Guibon et al., 2021]. We should leverage this research progress in order to take advantage of all the already existing corpora where similar but different phenomena (e.g., engagement, sentiment) are annotated.

Hybrid Models One promising approach, beginning to be found in the literature, is to integrate social science-based rules as features in the encoding stage of neural architectures. Similarly pre-trained representations using a knowledge base from the social science literature can be integrated into graph neural architectures [Li et al., 2021]. In addition to being particularly applicable to dyadic features, this approach has the benefit of allowing greater explainability of the output. It has, however, been little attempted to date.

5 The Case of Conversational AI

As described in the introduction, the analysis of dyadic processes in conversation is essential to making conversational AI into a true partner to its human users. The goal here is different from that of the automatic analysis of conversation, as the system must generate the utterances of one of the partners (the agent) [Clavel and Callejas, 2015]. The question, then, lies in how to select or generate the agent’s utterances as a function of different criteria of relevance to the user’s previous utterances. In this section, we point towards the future by examining how the extent to which existing work on neural conversational AI is conducive to the integration of dyadic processes.

** Dyadic processes in modular approaches Traditionally the generation phase of conversational systems is carried out in a modular way. The agent’s utterance is selected or generated according to a dialogue policy which is, in turn, selected according to the current user’s state and intents. The three modules (tracking user’s state, selecting agent’s policy, and conditional generation of agent’s utterance) rely on separate neural architectures. In order to better take into account the dyadic processes of conversation using modular approaches, the user’s state analysis module must be replaced by a module capable of analyzing the behaviors of the dyad formed by the agent and the user, considering them as interaction partners in the joint construction of the conversation. The selection of the agent’s policy and the generation of the agent’s utterance has to be chosen with this aim of fostering dyadic processes. Perhaps the most promising approach is to use reinforcement learning with a reward based on the relevant social science literature. This is in line with what has been proposed recently by [Pecune and Marsella, 2020].

** Dyadic processes in end-to-end systems Recent work in the field of natural language generation for dialogue systems has moved to a reliance on end-to-end systems [Gao et al., 2019]. By dispensing with the steps of classifying the user’s utterance and identifying the relevant dialogue policy, end-to-end systems make it possible to directly generate (such as by using DialoGPT [Zhang et al., 2019]) or select responses
imitate the racist and sexist content its users served up. The issue of how to control the nature of the input, an issue of considerable importance, is raised. Additionally, fully data-driven neural dialogue models raise the question of how to control the dyadic processes, but they can be a way to free the process from the turn-based analysis of a user’s state implied by modular approaches. However, very recently, [Benotti and Blackburn, 2021] calls into question the ability of these models that are simply trained on large amounts of successful dialogues to reproduce human-analogous collaborative grounding. Enabling end-to-end neural models of this sort to integrate dyadic processes without any strong supervision does not appear to be trivial. One approach is to leverage DialogGPT [Liu et al., 2021] or BlenderBot [Smith et al., 2020] but to introduce supervision into the generation process. For example, in [Liu et al., 2021], DialogGPT is used with supervision to generate the agent’s response as a condition of conversational strategies oriented towards the user’s emotional support. [Zhong et al., 2020] rely on retrieval-based conversational models (e.g., selecting the most relevant utterance for the agent from a set of utterances) and learn a neural model (Bert model named CoBERT) on the basis of empathetic conversations for response selection. The supervision stage here is relatively simple and relies on the selection of empathetic conversations to train the empathy model which is then compared to a non-empathetic model trained on non-empathetic conversations. In that approach, however, there is no option to explicitly control the level or the kind of empathy at the utterance level, and it is difficult to explain the rationale for the system’s answer.

Open Discussion We argue that a smarter and multi-level coupling of analysis and generation is required in order to better integrate the dyadic processes of conversation. We have given examples of how modular approaches can control the generation process in such a way as to handle dyadic phenomena. It is less obvious how to integrate these dyadic processes without adding supervision in end-to-end generation models. Additionally, fully data-driven neural dialogue models raise the issue of how to control the nature of the input, an issue highlighted by systems such as Tay, that quickly learned to imitate the racist and sexist content its users served up [Eskenazi and Zhao, 2020]. Generating utterances for dialogue systems that distribute information across modalities, and where this information responds to the multimodal context of the dyad, also remains an open problem for unsupervised neural models for conversational AI.

6 Conclusions Research in neural architectures for the analysis of conversation is booming, and has led to high-performing and innovative models. In parallel, although with a longer history, the social science study of conversation has provided an increasingly rich and relevant literature on the fundamental aspects of conversation. The two research areas, however, are still quite disconnected, which deprives the computational analysis of conversation of some important insights and tools. After an inter-disciplinary literature review, the current paper identifies future directions that arise from cross-fertilization between the two research approaches.

In order for the cross-fertilization to take root, a common formalism will be required to make a bridge between structural aspects of conversation as defined by the social sciences and the architectures underlying the different neural models. As an example, we must progress beyond the prediction of a sequence of emotion categories by considering interaction between two or more participants (whether they are agents, people or a combination of the two) as a co-construction process evolving over time. We showed here some ways in which interpersonal dynamics are already integrated into existing neural architectures. Now the architectures must be adapted in order to go beyond interpersonal modeling to considering the dyad formed by the participants as a single analytic unit.

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