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# Conversational Feedback in Scripted versus Spontaneous Dialogues: A Comparative Analysis

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## Abstract

Scripted dialogues such as movie and TV subtitles constitute a widespread source of training data for conversational NLP models. However, the linguistic characteristics of those dialogues are notably different from those observed in corpora of spontaneous interactions. This difference is particularly marked for communicative feedback and grounding phenomena such as backchannels, acknowledgments, or clarification requests. Such signals are known to constitute a key part of the conversation flow and are used by the dialogue participants to provide feedback to one another on their perception of the ongoing interaction. This paper presents a quantitative analysis of such communicative feedback phenomena in both subtitles and spontaneous conversations. Based on dialogue data in English, French, German, Hungarian, Italian, Japanese, Norwegian and Chinese, we extract both lexical statistics and classification outputs obtained with a neural dialogue act tagger. Two main findings of this empirical study are that (1) conversational feedback is markedly less frequent in subtitles than in spontaneous dialogues and (2) subtitles contain a higher proportion of negative feedback. Furthermore, we show that dialogue responses generated by large language models also follow the same underlying trends and include comparatively few occurrences of communicative feedback, except when those models are explicitly fine-tuned on spontaneous dialogues.

**Keywords:** conversational grounding, conversational feedback, dialogue, spontaneous speech, subtitles

## 1. Introduction

While the amount of text data available online for training NLP models is large and growing steadily, the situation is more contrasted for conversational speech data. Indeed, while corpora of spontaneous spoken interactions have been collected for various languages (Dingemanse and Liesenfeld, 2022),

those are generally of a limited size and often focus on particular topics or tasks. To address this scarcity of available data, a common approach is to instead rely on corpora of authored dialogues extracted from movie scripts (Danescu-Niculescu-Mizil and Lee, 2011) or movie and TV subtitles (Lison et al., 2018; Davies, 2021) when modeling spontaneous conversation.

However, those dialogues have different properties than spontaneous interactions. Most importantly, movie scripts are written for the purpose of narrating a story. Many key conversational phenomena such as disfluencies (Shriberg, 1996), overlapping talk (Schegloff, 2000), and backchannels (Yngve, 1970) are therefore either absent or uncommon, unless they explicitly contribute to the storyline (Berliner, 1999; Chepinchikj and Thompson, 2016). Subtitles, in addition, are also subject to strict length constraints, with a maximum of two lines with at most 40–50 characters per line and an on-screen display time between one and six seconds. As a consequence, subtitles tend to only transcribe the most salient information conveyed in each utterance.

This paper provides a quantitative analysis of how subtitles differ from spontaneous dialogues, focusing more specifically on *conversational feedback* (Allwood et al., 1992) and *grounding* (Clark and Schaefer, 1989) phenomena. Even though feedback cues are often short, non-lexical words, they are essential for moving forward smoothly within a dialogue as they indicate, among others, speakers’ common understanding and agreement (Allwood et al., 1992). To highlight the relevant linguistic properties respectively seen in subtitles and in corpora of spontaneous conversations, we first compile a range of lexical statistics. To go beyond lexical distributions, we subsequently train a neural dialogue act tagger to estimate the relative frequencies of various feedback signals in each corpus. We also apply this tagger on synthetic dialogues generated by different language models and show that only when fine-tuning on unscripted dialogues is the proportion of feedback phenomena comparable to that found in spontaneous conversations. Our experiments are conducted using corpora for eight languages, namely English, Chinese, French, German, Hungarian, Italian, Japanese and Norwegian. Spontaneous dialogue sources for these languages are more readily available and this subset also allows for investigations across different language families. Since there has been a significant increase in the popularity of large language models fine-tuned for conversational interaction, but little is known about the ability of these state-of-the-art systems to handle feedback cues, we also offer a small-scale qualitative analysis of how they deal with such communicative signals.

The paper is structured as follows: Section 2 reviews related work on conversational feedback and the linguistic analysis of subtitles. Section 3 then presents the corpora of both spontaneous and scripted dialogues employed in the experiments. Section 4 describes and discusses the lexical distributions of grounding phenomena observed in these corpora. Building on those results, Section 5 compares them to the frequency of feedback-related linguistic phenomena estimated using a neural dialogue act tagger trained on the Switchboard corpus (Stolcke et al., 1998; Godfrey et al., 1992). We then describe our experiments carried out on synthetic dialogues in Section 6 which is followed by a short analysis of multimodal feedback cues in Section 7. In Section 8, we summarize our observations about how the latest conversational language models deal with feedback signals. Finally, Section 9 concludes the paper and outlines future directions of research.

## 2. Related Work

### 2.1 Conversational Feedback and Grounding

A key aspect of any communicative activity is management of the information flow, a process often called *conversational grounding* (Clark and Schaefer, 1989). The study of grounding and related

phenomena, such as conversational feedback (Allwood et al., 1992), has been instrumental to cognitive approaches to communication (Clark, 1996), and to dialogue system development (Traum, 1994; Paek and Horvitz, 2000; Yaghoubzadeh et al., 2015). Typical feedback signals such as acknowledgments, showing understanding and acceptance were, in fact, also among the criteria suggested for the Empathy Scale for Human-Computer Communication suggested by Concannon and Tomalin (2023).

Conversational feedback may appear at different positions in a dialogue. However, a number of corpus studies found that they have a tendency to occur at specific places, mostly where they cause little interference (Kjellmer, 2009). These places of occurrence have also been referred to as *Feedback Relevant Spaces* (Heldner et al., 2013; Howes and Eshghi, 2021). Even though often considered to be semantically of little relevance, Howes and Eshghi (2021) offer a semantic processing model for conversational feedback phenomena which underlines the crucial role feedback plays in moving forward within a dialogue.

Although, arguably, any utterance relates directly or indirectly to grounding (through implicit and high level pragmatic inference, Clark and Schaefer 1989), *acknowledgments* and other positive feedback signals (see Ex. (1)), along with *repair* (see Ex. (2)), have been identified as the most prominent grounding mechanisms (Jefferson, 1972; Bunt, 1994). Their frequency in human-human dialogue is known to be very high (e.g., Stolcke et al., 2000a) and universal across languages (Liesenfeld and Dingemanse, 2022; Dingemanse et al., 2015). These conversational signals, while they do not cover all grounding phenomena, can therefore be seen as a useful proxy to quantify feedback in a dialogue.

- (1) **A:** and uh it really does irk me to see those guys out there uh you know making that ///much money///  
**B:** ///yeah///<sup>1</sup>

Recent works have emphasized the role of feedback and grounding signals in their study of human-human conversations (Fusaroli et al., 2017; Dideriksen et al., 2022; Dingemanse and Liesenfeld, 2022) as well as human-agent interaction (Visser et al., 2014; Hough and Schlangen, 2016; Buschmeier and Kopp, 2018; Axelsson et al., 2022).

The literature tends to merge the two closely related concepts of *backchannels* and *acknowledgments*. Backchannels (Yngve, 1970), or *continuers* (Schegloff, 1982), are not positioned on the main channel, but uttered by the “listener”, often as low intensity unobtrusive overlapping speech (Heldner et al., 2010) or non-verbally (Allwood et al., 2007; Truong et al., 2011). Acknowledgments, on the other hand, have a slightly broader, functional definition of minimal positive feedback (Jefferson, 1984; Allwood et al., 1992).

There has been a large body of work on lexical markers, also called *cue phrases* or *discourse markers* (Jefferson, 1984; Allwood et al., 1992; Muller and Prévot, 2003), since they present interesting linguistic features and constitute convenient explicit cues for detecting feedback utterances automatically (Jurafsky et al., 1998; Gravano et al., 2012; Prévot et al., 2015). Gravano et al. (2012) developed a list of affirmative cue words made of *alright*, *mm-hm*, *okay*, *right*, *uh-huh*, *yeah*. Form-Function studies of similar lists have been made at least for Swedish (Allwood, 1988), U.S. English (Ward, 2006), and French (Prévot et al., 2015).

There is less emphasis in the literature on direct negative feedback associated with rejection and corrective dialogue acts. Although Allwood et al. (1992) suggests a polarity dimension for

1. Notation: ///text/// produced in overlap with the speech of the other speaker. From Switchboard (Godfrey et al., 1992)

characterizing feedback, most recent studies have focused on positive feedback. Indeed, in collaborative dialogue and everyday conversations, which are the two genres dominating available datasets, positive feedback constitutes the large majority of explicit feedback (e.g., Malisz et al., 2016).

Negative feedback is instead often expressed constructively, using repair mechanisms, specifically *clarification requests* (Purver, 2004). These may rely on simple lexical cues (e.g., for English, *pardon?*, *huh?*), sluices (such as *what?*, *who?*), or on clarification ellipsis, as in the following example (Fernández et al., 2007):

- (2)    **A:** and then we're going to turn east  
           **B:** mmhmm  
           **A:** not straight east slightly sort of northeast  
           **B:** slightly northeast?<sup>2</sup>

Conversational feedback forms a central part of dialogue annotation frameworks (Core and Allen, 1997; Bunt, 2011). In Switchboard-DAMSL (Stolcke et al., 1998; Godfrey et al., 1992), for example, the following acts relate to feedback: *Acknowledge (Backchannel)*, *Agree/Accept*, *Response acknowledgment*, *Repeat-phrase*, *Backchannel in question form*, *Tag-question*, *Signal-non-understanding*. Many acknowledgments and repair-initiators also fit under the concept of *Non Sentential Utterances (NSU)* analyzed for example in Fernández et al. (2007); Ginzburg (2012); Dragone and Lison (2016).

The occurrence of feedback signals in dialogue transcriptions can be detected using various types of sequence labeling models, including classical hidden Markov models (Stolcke et al., 2000b) as well as more recent neural architectures (Liu et al., 2017; Noble and Maraev, 2021).

Conversational feedback can also be delivered in the form of non-verbal signals such as head-gestures, nods and laughter (Schegloff, 1982) which, however, are not necessarily transcribed or thoroughly annotated in the available corpora. Maraev et al. (2021) incorporated information about laughter to improve the performance of a neural dialogue act tagger and found that for 76% of utterances annotated as *non-verbal* in the Switchboard corpus (Godfrey et al., 1992), their system predicted the *Acknowledge (Backchannel)* label.

## 2.2 Analysis of Subtitles

Subtitles are typically short written text snippets and they accompany audiovisual content on the screen. Since they encode spoken language in a written form, they are often subject to condensation and normalization, where non-standard verbal elements (repetitions, signs of hesitation etc.) are omitted or replaced by more standard alternatives (Gottlieb, 2012). This is due to constraints on the length and the readability of the subtitles as well as adherence to writing conventions, especially for professional subtitle writers. As subtitles are meant to be displayed alongside audiovisual content, this is rarely a problem as viewers can typically recover omitted dialogue-relevant cues from the accompanying images and sounds.

We can distinguish between *interlingual subtitling*, where the original language of the audio is different from the subtitling language; and *intra-lingual subtitling*, where the audio and the subtitle language are the same with non-verbal elements also recorded in writing, typically for the benefit of hearing impaired audiences or non-native speakers (Gottlieb, 2012).

Corpora of movie and TV subtitles have been studied in both linguistics and language teaching, where it serves as an easy-to-access approximation of spoken language use (Werner, 2020). Quaglio

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2. From HCRC Map Task (Anderson et al., 1991).

(2008) note that English subtitles of the TV series *Friends* (1994–2004) share some features with natural conversation, while a more detailed analysis reveals a number of differences, notably in terms of expressive language. Pavesi (2020) also found that proximal demonstrative pronouns (e.g., *this*) are more frequent in cinematic discourse than in other spoken corpora. The author argued that this phenomenon is related to these aiding the narrative by directing viewers’ attention towards specific characters or elements in the story.

Rühlemann (2020) compared real conversations and scripted ones and observed that continuers were absent from the latter. Prevot et al. (2019) compared data from the *Open Subtitles* corpus (Lison and Tiedemann, 2016; Lison et al., 2018) in English, French and Mandarin with both written and conversational corpora and found that OpenSubtitles occupied an intermediate position between written and conversational data in terms of lexical and syntactic features.

The present paper differs from previous works in three ways. First, our analysis rests upon a larger number of corpora distributed across eight languages. Second, we rely on both statistics extracted from superficial features (lexical occurrences, utterance lengths) as well as estimates derived from a neural dialogue act tagging model. Finally, we focus specifically on communicative feedback, ignoring other conversational phenomena.

### 3. Corpora

In our experiments, we make use of data from both OpenSubtitles and existing corpora of real conversations in eight different languages. Out of these, five are Indo-European (German, English, French, Italian and Norwegian) and three are from other language families (Hungarian, Japanese and Mandarin Chinese).

#### 3.1 Spontaneous Dialogues

**German (de)** For German, we use the Hamburg MapTask corpus (HZSK, 2010), in which twelve dyads of (L2) speakers of German engage in dyadic task-oriented short dialogues.

**English (en)** Data sources for English dialogues are easily available and cover various genres. We use Switchboard, consisting of dyadic topic oriented phone conversation (Godfrey et al., 1992) as well as Fisher (Cieri et al., 2004) for some experiments; AMI, with multi-party multimodal task-oriented dialogues (Carletta, 2007); HCRC MapTask comprising dyadic task-oriented short dialogues (Anderson et al., 1991); and STAC, a multi-party negotiation chat corpus (Asher et al., 2016).

**French (fr)** The French corpora include CID consisting of dyadic, 1-hour long, loosely topic-oriented face-to-face conversations with 16 participants (Blache et al., 2017); French MapTask with 16 participants (Gorisch et al., 2014); and Aix-DVD, dyadic face-to-face conversations about movie preferences of 16 participants (Prévot et al., 2016).

**Hungarian (hu)** The source for this language is the BUSZI-2 corpus (Budapesti Szociolingvisztikai Interjú, ”Budapest Sociolinguistic Interview”, Váradi, 2003). The data was recorded between 1987–1989, where 50 participants with different educational levels were part of both a 30-minute directed conversation and then performed a set of language tasks. These included, for example, inserting a verb into a sentence in the correct form and grammaticality judgments.

Language	de	en	fr	hu	it	ja	no	zh	total
# conversations	24	2766	48	50	88	120	259	120	<b>3475</b>
# utterances	4K	373K	27K	31K	24K	39K	86K	18K	<b>602K</b>

Table 1: Overview of the spontaneous dialogue data.

Language	de	en	fr	hu	it	ja	no	zh	total
# movies	98	100	100	68	95	74	87	93	<b>715</b>
# utterances	131K	140K	126K	93K	138K	106K	98K	114K	<b>946K</b>

Table 2: Overview of the subtitle data.

**Italian (it)** We use the spontaneous dialogues from the CLIPS corpus (Savy and Cutugno, 2009), consisting of two subsets: one based on a map task, and another elicited via spotting differences between two slightly different images. Dialogues with a high proportion ( $> 10\%$ ) of utterances with dialectal words were excluded. All markups indicating comments, unfilled pauses etc. were removed, but markups containing filled pauses (e.g.,  $\langle mh \rangle$ ) were kept and reduced to plain text in the utterances since many were connected to feedback.

**Japanese (ja)** We employ the transcripts of the CallHome Japanese corpus (Den and Fry, 2000) consisting of 120 unscripted telephone conversations between native speakers, mostly family members or close friends.

**Norwegian (no)** The Norwegian data consists of the NoTa-Oslo corpus (Johannessen et al., 2007), containing interviews and conversations from 2004–2006 with 166 informants from the Oslo area. The informants were selected to be representative in terms of age, gender and education. The dialogues consist of 10-minute semi-formal interviews and 30-min informal dialogues with other informants.

**Mandarin Chinese (zh)** The source of our Mandarin Chinese data was CALLHOME (Wheatley, 1996) consisting of unscripted telephone conversations between native speakers.

### 3.2 Subtitles

The scripted dialogues are extracted from OpenSubtitles 2018 (Lison et al., 2018), a large collection of subtitles of over 3.7 million subtitles (amounting to  $\approx 22.1$  billion words) extracted from the OpenSubtitles.org database and covering 60 languages. We include both (1) subtitles for the hearing impaired, where the subtitle language and the language employed in the movie/episode are identical and (2) subtitles for foreign audiences as two separate subtitle subsets. The subtitles are then filtered according to the following criteria:

1. We only consider recent movies (year  $\geq 1990$ ) to reflect contemporary language use, in line with the corpora of spontaneous conversations.
2. We ignore subtitles with less than 100 utterances and exclude genres that are less relevant for the present study (Documentary, Reality-TV, Biography, Sport, Musical, Music, Adult, Animation, Short and Game-Show).

We select ten movies per audience type (hearing impaired vs. foreign viewers) from the five genres with the largest number of subtitles available in our English data, which were, in decreasing order of frequency: drama, comedy, crime, action, and romance.<sup>3</sup> A movie could involve more than one genres thus we also check for this. Table 2 shows the amount of movies and utterances per language for the selected subtitles.<sup>4</sup>

## 4. Lexical Statistics

We start by computing lexical distributions to compare the datasets presented in the previous section with regard to communicative feedback patterns.

### 4.1 Lexical Overview of Short Utterances

The lexical statistics of acknowledgment cues can give a first picture of the feedback content in subtitles. In spoken dialogue, acknowledgments tend to be produced by the addressee (not the speaker) and therefore they are short productions uttered in overlap and potentially with a lower voice. Out of those three properties (brevity, overlap, lower volume), only the first one is accessible in our dataset, as the subtitles (and the STAC corpus for English) are purely text-based. Given the correlation between acknowledgments and utterance length, we start by analyzing “very short utterances” (Edlund et al., 2009), defined here as three tokens or less.

We rely on the *scatter text* visualization (Kessler, 2017, see Dingemanse and Liesenfeld 2022 for a similar use) to get a first overview of lexical differences between subtitles and spontaneous dialogues. Figure 1 compares English-language *romance* subtitles with Switchboard corpus by plotting the scaled *f*-score for each term against both corpora. This scaled *f*-score is computed as the harmonic mean of *term precision*, that is, the number of times a word occurs in a category divided by the number of times the word occurs in all categories; and *term frequency*, i.e., the number of times a word occurs in a category divided by the number of words in that category. In this figure, the more a token is located in the bottom right corner (marked with dark red dots), the more it is over-represented in spontaneous dialogues; while items in the upper-left corner (dark blue dots) are frequent words in subtitles. Tokens close to the diagonal, represented with yellow and orange dots, are associated with both datasets.

In Figure 1, besides some preprocessing differences (e.g., *that’s*, *bye-bye*, *@*, (*laughter*)), we can observe a number of acknowledgment cues that occur more often in spontaneous speech, such as *gosh*, *yep*, *etc.* and to a lesser extent *wow*, *hum*, *uh*, *etc.*, which also occur in subtitles but relatively less frequently. On the other hand, the tokens over-represented in subtitles often relate to action verbs (*come*, *listen*), vocative expressions (*dad*, *mom*), politeness forms (*thanks*, *please*), although some tokens can also be related to feedback (e.g., *hey*, *alright*, *damn*). See Appendix A for the other languages and genres.

3. The number of available movies for the hearing impaired subset is  $< 10$  for the following languages and genres: de-action (8), it-action (5), no-action (3), no-romance (4). This is mostly due to missing information about the original language of the movie in OpenSubtitles. To increase the number of available subtitles to work with for Japanese, we also included Animation among the listed genres for this language.

4. In subtitles, and for several other corpora, we did not have a segmentation into properly defined utterances. OpenSubtitles “utterances” included subtitling constraints. As a consequence, for simplicity reasons, we use the term “utterance” in the paper, but it should be understood broadly.



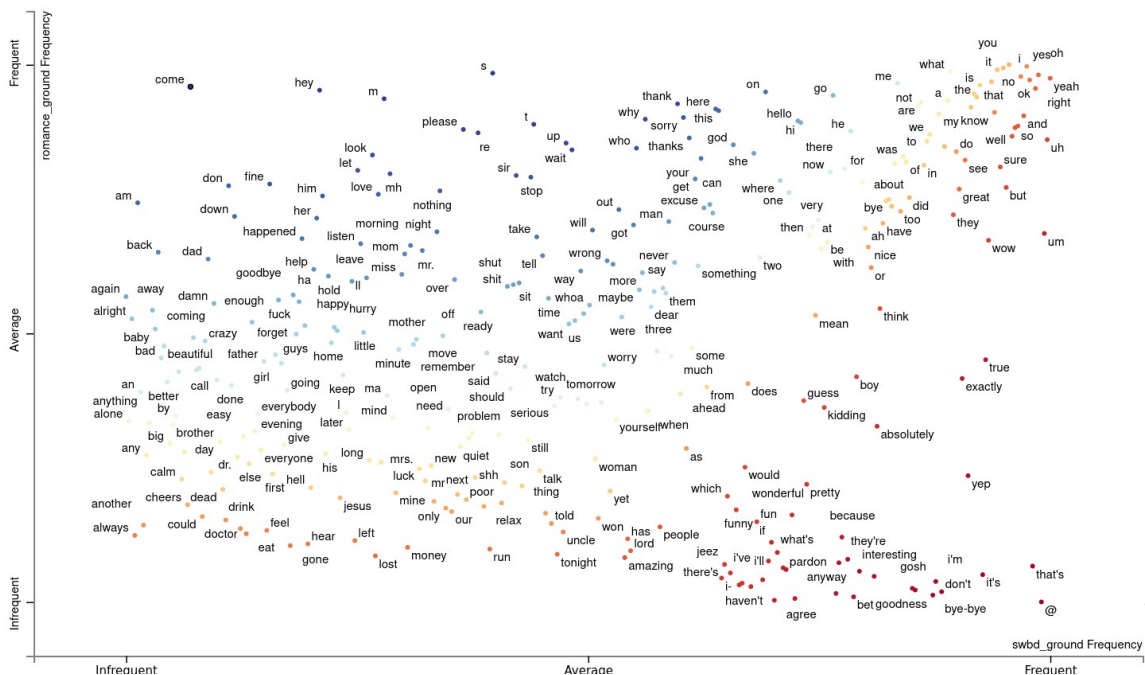


Figure 1: Scatter text visualization for short utterances (comprising three tokens or less) in English-language subtitles (*romance* genre) vs. spontaneous dialogues from Switchboard.

## 4.2 Feedback Utterances

To target more precisely lexical items related to communicative feedback, we extract the uni-, bi- and trigrams of very short utterances from both subtitles and spontaneous dialogues. Moreover, feedback can also be added in initial position of longer turns/contributions. When extracting feedback-related lexical material, we therefore extract two locations: ‘very short utterances’ (less than three tokens) and initial positions (one token) of all other utterances. Comparing term frequencies between these locations and the overall corpus allowed us to design language-specific cue word lists. Those lists, provided in Table 9 in Appendix A, distinguish between four core classes of feedback:

- positive feedback/acknowledgment (+)
- neutral/continuer (=)
- negative feedback (-)
- clarification request (?).

We plot the proportion of utterances corresponding to these definitions in each corpus. In Figures 2, 3 and 4, plots (a) illustrate the proportion of utterances mapped to the above labels across all utterances in the corpus and plots (b) focus on the utterances that have received a label other than OTH. Figure 5 shows the lexical distribution of the most frequent lexical items observed in the utterances of plots (b) for English and French.

As can be seen in the figures, the cue-based statistics differ radically between subtitle datasets and spontaneous dialogue. This difference is observed across all languages and sub-genres, (see

CONVERSATIONAL FEEDBACK IN SCRIPTED VERSUS SPONTANEOUS DIALOGUES

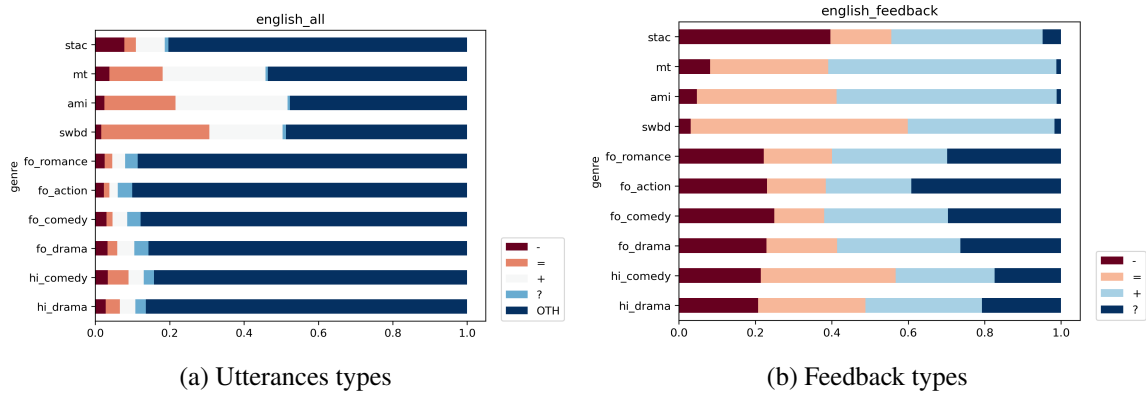


Figure 2: English across genres (rule-based, based on cue word lists).

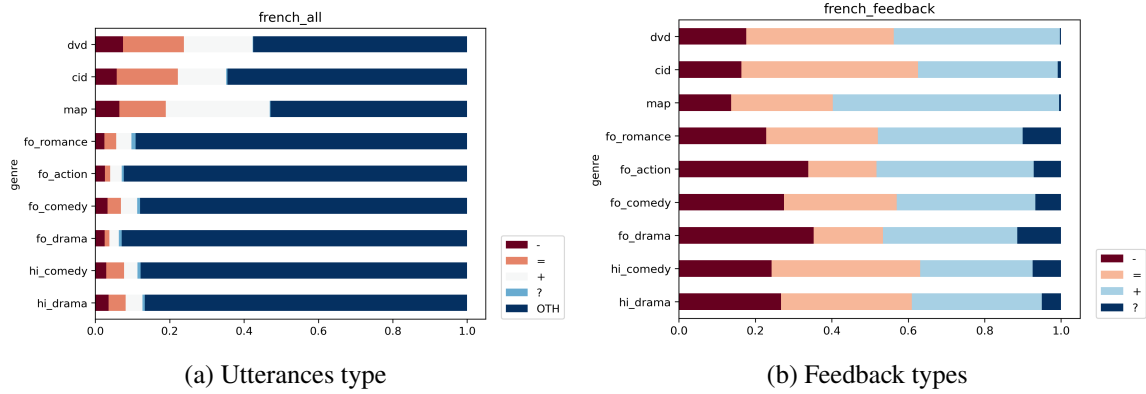


Figure 3: French across genres (rule-based, based on cue word lists).

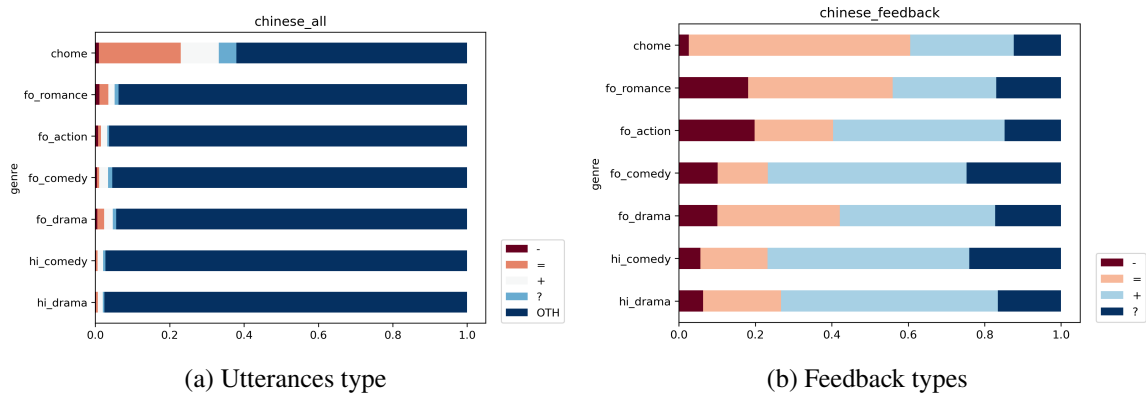


Figure 4: Mandarin Chinese across genres (rule-based, based on cue word lists).

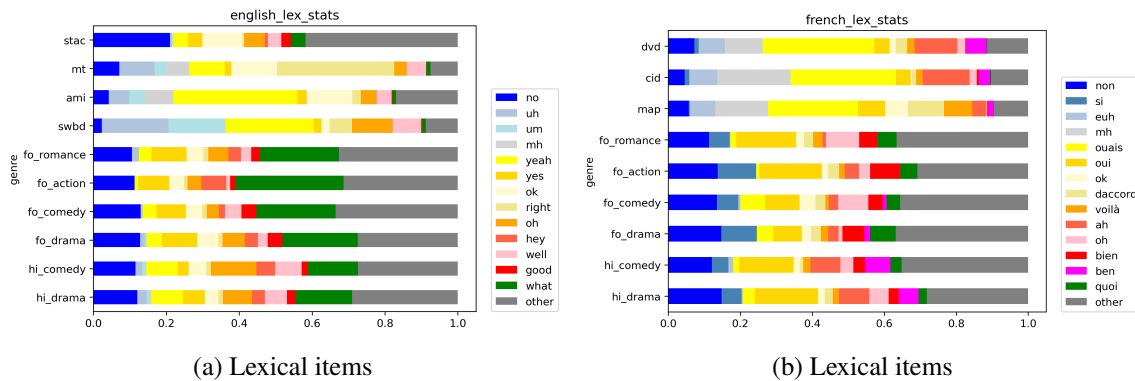


Figure 5: Most common lexical items found in feedback utterances in English and French.

Appendix A for other languages). Given the noisy nature of our data, we worked to identify and reduce other sources of divergence between our sub-corpora. STAC, as a chat corpus, present a different picture than other dialogue corpora, notably due to the extensive use of emojis. Similarly, for English and French, we explored the impact of expressions of politeness (highly frequent in OpenSubtitles) on the provided statistics. In both cases those particularities contribute significantly to the distributions but did not change the overall picture of our analysis (see Figure 13 in Appendix A).

One key difference between the corpora relates to the overall frequency of feedback cues (labeled as positive, neutral, negative, or expressing a clarification request), which is much higher in spontaneous dialogues (40–50%) than in subtitles (10–20%), as observed in the plots (a). Furthermore, as shown in the plots (b), feedback in spontaneous dialogues consists mostly of positive or neutral (continuers) feedback, while subtitles have very few neutral signals but exhibit a much higher proportion of negative feedback and clarification request. This may be explained by the prevalence of “confrontational” dialogues in movie and TV subtitles, which are more useful from a narrative perspective.

Feedback utterances are not only expressed through a restricted set of lexical items. Repeated material is another important clue to spot such utterances. In the case of continuers and assessments, lexical items are dominating the phenomena. Clarification requests are more difficult to assess, as those are often formulated as repeated material requiring clarification. We tried to extract those as well, but faced the problem of turn alternations. Most of our spontaneous dialogue corpora are well segmented in speaker turns, a new turn indicating a change of speakers. Speaker information is unfortunately absent from subtitles (Lison and Meena, 2016), where segments merely indicate a continuous sequence displayed on screen, without indication of turn boundaries. We also observed that compared to spontaneous dialogues, subtitles host a large number of verbatim repeats produced by the movie situations (e.g someone not answering being called) and emphasis for more lively discussion (e.g question repeated several time because lack of answers). As a consequence, heuristics to detect clarification request by repetitions are difficult to establish for Open Subtitles.

### 4.3 Length Distributions

The differences in lexical statistics between OpenSubtitles and corpora of spontaneous dialogues are substantial. To shed light on those differences, Figure 6 shows the length (in tokens) of utterances for three English datasets. We compared the lengths distribution for utterances classified as feedback/grounding (gr, in blue) or not (oth, in red) based on our cue-word extraction. While in

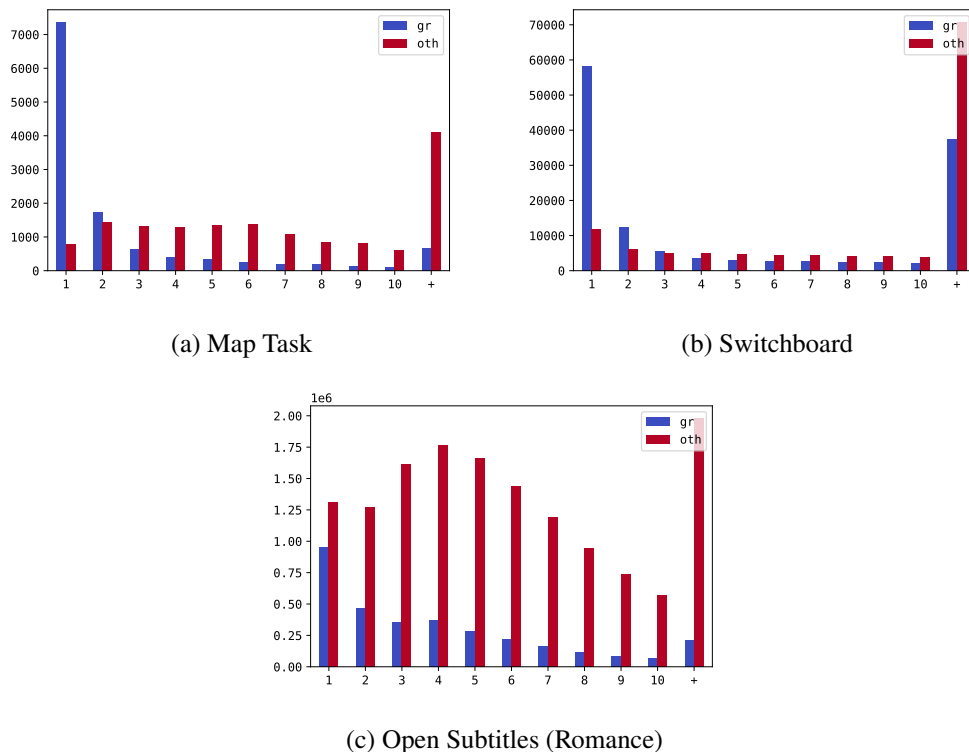


Figure 6: Utterance lengths distribution (in tokens) across different English datasets.

spontaneous dialogue, utterances of 1 or 2 tokens are overwhelmingly feedback-related signals, this is not the case for subtitles, where many very short utterances relate to verbs, vocative expressions or politeness forms (see Section 4.1). Subtitles are indeed designed to be displayed under strict time constraints, thereby favoring short, action-oriented utterances.

#### 4.4 Evaluation of the Cue Word Lists

To gain insights into the reliability of the above estimates, we evaluate the quality of our English cue word lists on a dataset annotated with dialogue acts, namely the Switchboard corpus (Stolcke et al., 1998). We make a binary distinction and group, on the one hand, all feedback-related labels into a *Feedback* category, where we included the same subset of Switchboard (SWBD) tags as for the *Backchannel* and the *Assessment* classes used for our neural tagger (see Table 4 for details). On the other hand, all labels that are not connected to communicative feedback are merged into a single *Other* category. We find that the cue word lists have an accuracy of 85%, an F1 of 0.76 and a recall of 0.89 for feedback cues with respect to the annotated SWBD labels (Table 3). They can thus serve as a useful basis for frequency estimates for comparing spontaneous and scripted dialogues.<sup>5</sup>

5. It is worth noting again in connection to these performance scores that the cue word lists were compiled, in part, by inspecting token frequencies in our corpora (see Section 4.2), including Switchboard, a higher recall is therefore expected, but not necessarily a high precision.

Utterance type	P	R	$F_1$	# instances
<b>Feedback</b>	0.67	0.89	0.76	56,744
<b>Other</b>	0.95	0.84	0.89	153,835
<b>Macro avg</b>	0.81	0.86	0.83	210,579
<b>Weighted avg</b>	0.88	0.85	0.86	210,579

Table 3: Results for the English cue word lists applied on the Switchboard corpus.

The cue word lists overestimate somewhat the proportion of feedback (26.9% vs. the annotated 35.5%). False positive feedback include a few cases with answers to yes-no questions and *well* in utterance initial position. We find that the DAMSL Switchboard label *Abandoned or Turn-Exit* includes some feedback-related phenomena e.g., *Uh d* together with other types of utterances unrelated to feedback (e.g., *but she was*). Given its miscellaneous nature, we have excluded this label from our feedback category and thus, when cue words identify these as feedback, they count towards incorrect matches even if they indeed contain feedback cues. Sources of false negatives include demonstratives (*That*) and other words and phrases with multiple communicative functions (*Do you?*, *Pardon me?*) which are not covered by our lists.

## 5. Neural Dialogue Act Tagging

Although the above statistics allowed us to uncover substantial differences in subtitles and spontaneous dialogues, they remain somewhat noisy estimates, as many feedback-related lexical items tend to be ambiguous. In this section, we refine our analysis by employing a neural dialogue act tagging model to quantify more precisely the frequency of a more varied set of feedback signals in subtitles and spontaneous dialogues.

### 5.1 Data

As training data for our dialogue act model, we use the DAMSL-Switchboard corpus (Stolcke et al., 1998; Godfrey et al., 1992), where we map the original (finer-grained) set of Switchboard (SWBD) tags, and their clustered DAMSL-SWBD equivalents, into five coarse dialogue act (DA) classes: *Forward looking*, *Yes/no answers*, *Assessment*, *Backchannel* and *Other*. The two classes most directly relevant for feedback, namely *Backchannel* and *Assessment*, are inspired, in part, by Mezza et al. (2018). Distinguishing between these two feedback-related classes is also motivated by Goodwin (1986), who outline a number of positional and functional differences between these. The *Backchannel* category consists of the SWBD-DAMSL labels *Acknowledge (Backchannel)*, (SWBD tag b), *Backchannel in question form* (bh), *Response Acknowledgment* (bk), *Summarize/reformulate* (bf) and *Signal-non-understanding* (br). As this latter tag shows, negative feedback signals are also part of the *Backchannel* category, which is motivated by the small amount of relevant instances that would likely not be sufficient for reliably learning a separate class for these. The *Assessment* category comprises not only the labels *Agree/Accept* (aa), but also *Appreciation* (ba) and *Exclamation* (fe). The forward looking category contains utterances expressing explanations, instructions and suggestions

Mapped DA group	# instances	SWBD labels
<b>Forward looking</b>	109,382	sd, fx/sv, bf, na, ny <sup>e</sup> , arp, nd, no, cc, co, oo, ad, qr/qy, qw, qw <sup>d</sup> , qh, qo
<b>Backchannel</b>	41,017	b, bk, bh, bf, br
<b>Assessment</b>	15,727	aa, fe/ba
<b>Yes/no answer</b>	4,324	ny, nn
<b>Other</b>	40,124	<i>all other categories</i>
<b>Total</b>	<b>210,574</b>	

Table 4: SWBD labels mapped to coarse-grained dialogue act groups.

as well as questions. Table 4 shows the distribution of instances per label and their corresponding SWBD tag.<sup>6</sup>

## 5.2 Model Training

We opt for BERT as our neural architecture (Devlin et al., 2019) for the sequence labelling. We fine-tune the monolingual bert-base-cased pre-trained model using 80% of the (cased) Switchboard data as training data. The remaining 20% is divided equally between a development and a test set. We set up the task as a sequence classification problem, where the preceding utterance is included as context. Since the dataset is highly unbalanced, with some of the classes of interest having considerably fewer instances than the majority classes, we apply class-weighted training.<sup>7</sup> We train the model for five epochs with default early stopping parameters, except for patience, which we set to 5. The batch size is set to 8 and the learning rate to  $4e - 5$ . We run and compare three different random seeds, which achieve comparable performance.<sup>8</sup> We adopt the best performing model out of the three tested seeds, which is trained for three epochs before exiting with early stopping.

To further improve the recall for feedback phenomena, we also adjust the probability threshold for assigning an output label, and raise the threshold to 0.8 and 0.6 for the *Forward looking* and *Other* categories respectively and we lower the threshold to 0.25 for the *Yes/no answer* and *Assessment* classes. In case none of the predicted labels are above these thresholds, we pick the label with the highest probability excluding *Forward looking* to account for a potential majority class bias.

Table 5 provides details on the tagging performance of the neural dialogue act tagger on the test set of the Switchboard corpus. The model performs relatively well overall, with an accuracy of 0.81. The detection of the feedback-related classes varies, with *Backchannel* being detected rather well (0.84 precision, 0.83 recall) while *Assessment* achieving somewhat lower scores (0.53 precision, 0.67 recall). See Appendix B for more detailed results reported for each individual corpus.

6. [web.stanford.edu/~jurafsky/ws97/manual.august1.html](http://web.stanford.edu/~jurafsky/ws97/manual.august1.html)

7. The class weights are set to 0.7 for forward-looking utterances and to 0.9 for the other classes.

8. The average performance for the three runs is 0.73( $\pm 0.03$ ) macro F1 and 0.83( $\pm 0.01$ ) weighted F1 before modifying the standard probability thresholds for predictions.

Dialogue act group	P	R	$F_1$	# instances
<b>Forward looking</b>	0.93	0.83	0.88	10,938
<b>Other</b>	0.66	0.78	0.71	4,012
<b>Assessment</b>	0.53	0.67	0.59	1,573
<b>Backchannel</b>	0.84	0.83	0.83	4,102
<b>Yes/no answer</b>	0.67	0.76	0.71	432
<b>Macro avg</b>	0.73	0.77	0.75	21,057
<b>Weighted avg</b>	0.83	0.81	0.81	21,057

Table 5: Results for the best performing neural tagger on the Switchboard test set.

### 5.3 Detection Results for Dialogue Act Groups

We then apply the trained dialogue act tagger on all spontaneous dialogue corpora (except Switchboard) and the subtitle data described in Section 3.2 to automatically detect linguistic signals of conversational feedback.

Before applying the tagger on non-English corpora, we machine translate the data using the Google Translate API.<sup>9</sup> This choice was preferable to training dialogue act tagging models for each of the languages separately as the quality of current machine translation systems is generally considered high enough for being a viable alternative (Isbister et al., 2021) and publicly available conversational corpora with dialogue act annotations is often scarce or nonexistent for languages other than English. Furthermore, preliminary results with `bert-base-multilingual-cased` have also indicated poorer performance compared to the English model applied on translated data.

To make our data sources more consistent and less noisy, we filter out utterances containing a single character as well as markers representing meta-linguistic information in some spontaneous dialogue corpora (e.g., double brackets in Fischer and smiley faces in STAC). Those markers are also removed from the Switchboard data before both training and testing.

Table 6 presents the results obtained after applying the dialogue act tagger on our spontaneous dialogues and subtitle corpora for all eight languages included in this study. From this we can observe that *Backchannel* instances are considerably more frequent (by a factor three) in spontaneous dialogues than in subtitles for half of the languages – which is in line with the results of our lexical analysis in Section 4. For Hungarian, Italian and Chinese, the difference between the two types of corpora in instances categorized as *Backchannel* is somewhat smaller than for the other languages, but subtitles still contain fewer backchannels. Moreover, *Backchannel* instances are slightly more frequent in subtitles than in spontaneous conversations for Norwegian based on the tagger output. The number of utterances labeled as *Assessment* differs less, but subtitles still seem to contain fewer utterances of this feedback type for almost all genres and languages, except French (see Appendix B for detailed results).

### 5.4 Error Analysis

To have a better understanding of tagger performance and the frequency estimates of feedback cues relying on it, we conduct a more in-depth examination of the tagger’s output.

<sup>9</sup> <https://cloud.google.com/translate>

Language	Data	de	en	fr	hu	it	ja	no	zh
<b>Forward look.</b>	<b>SPCONV</b>	16.60	41.71	43.18	58.37	33.55	42.34	52.26	53.95
	<b>SUBS</b>	59.11	63.06	61.87	58.81	59.94	51.15	64.83	62.50
<b>Other</b>	<b>SPCONV</b>	53.12	37.24	39.01	17.86	41.52	20.11	22.93	32.44
	<b>SUBS</b>	26.35	24.78	25.74	26.95	26.89	37.49	22.85	28.74
<b>Assessment</b>	<b>SPCONV</b>	16.50	9.11	4.62	15.49	12.64	15.74	17.05	6.96
	<b>SUBS</b>	9.08	7.07	7.72	9.29	8.34	6.48	6.53	5.00
<b>Backchannel</b>	<b>SPCONV</b>	11.57	10.79	11.96	4.28	5.73	18.96	2.67	5.65
	<b>SUBS</b>	3.49	3.72	3.44	3.48	3.45	3.74	3.47	3.00
<b>Yes/no answer</b>	<b>SPCONV</b>	2.22	1.15	1.24	4.00	6.55	2.84	5.09	1.00
	<b>SUBS</b>	1.97	1.37	1.68	1.47	1.38	1.15	2.32	0.76

Table 6: Proportions (%) of dialogue act groups detected by our neural tagger in the spontaneous conversation (SPCONV) and in the subtitle (SUBS) corpora.

In general, the proportion of the *Backchannel* category for SPCONV is considerably lower for Hungarian, Italian, Norwegian and Mandarin than for the other languages. The reason behind this is the taggers inability to generalize to spelling variants of backchannel signals such as *hmm*, *mh*, which are missing from or are underrepresented in its training data and are hence often misclassified.

As we have seen in Table 6, our tagger labels slightly more utterances as *Backchannel* in subtitles than in spontaneous conversations for Norwegian. At a closer inspection, however, Norwegian subtitles seem to contain more false positives in the *Backchannel* category compared to other languages. These include, for example, questions, e.g., (context: *Det er så tragisk*. “It’s so tragic.”) *Hva er tragisk?* “What is tragic?” and (context: *Dette er ikke ditt oppgjør*. “This is not your settlement.”) *Overrasket?* “Surprised?”.

Moreover, fewer assessments are automatically detected in the spontaneous dialogues than in the subtitle corpora for French. We found that the tagger had difficulty detecting feedback clues when they are part of longer utterances, independent of whether they appear in an utterance-initial position or not. Assessments occurring in longer utterances are more common in the CID corpus, where, for example, *on a été voir euh Rois et Reine* “we went to see uh kings and queen” was followed by the utterance *ah oui je voulais le voir ce film* “oh yes I wanted to see this film”, which was labeled as forward looking.

We also inspect the most frequent utterances tagged as *Backchannel* and as *Assessment* to gain additional insight into the types of feedback occurring in these data sources. While results for English are mostly correct, results for other languages contain some misclassifications, partly due to actual or apparent translation issues since, as mentioned before, those labels are obtained via translations into English. A translation challenge for short utterances that we can notice is related to polysemy, e.g., *Cosa?* “Thing?”, also translatable as “What?”, in Italian. Furthermore, the most frequent utterances classified as one of the two feedback categories end considerably less often in a punctuation in spontaneous dialogues than in subtitles (see Tables 13-15 and Tables 16-18 in Appendix B for a list of the top ten predicted backchannel utterances in spontaneous conversations and dialogues respectively). This might be, in part, due to transcription conventions for speech data where such



marks are sometimes omitted. In general, the tagger seemed to display some tendency to associate sentence final question marks to feedback cues when applied to subtitles.

## 6. Conversational Feedback in Synthetic Dialogues

The previous sections have investigated the differences between scripted and spontaneous dialogues when it comes to the presence of feedback phenomena, on the basis of available corpora. This analysis was to a large extent motivated by the fact that scripted dialogues, given their much broader availability as a source of training material, may have a substantial influence on the ability of large language models to process and generate communicative feedback.

In this section, we investigate this question more thoroughly. More precisely, we further train existing language models on the various conversational corpora presented in Section 3 and use those to generate synthetic dialogues. The goal of such experiments is to assess whether language models trained on scripted vs. spontaneous dialogues do indeed exhibit the same differences in communicative feedback as the ones observed in the previous section.

We start the training process with a pretrained GPT-2 model (Radford et al., 2019) for the language in question<sup>10</sup>, and further train this model using a language modeling objective separately on each corpora. To account for the corpus size differences, the number of epochs is adjusted to ensure that the total number of gradient updates is similar across all corpora.

The GPT-2 models trained on each corpora are then employed to produce a set of synthetic dialogues (100 dialogues of about 50 turns per model<sup>11</sup>). For the fine-tuned models, all turns are automatically generated, while for the base models, the following dialogue beginning is used as context: *Hi! – Hi, how are you? – Fine, and you?* to improve the quality of the output. Finally, the neural dialogue tagger from Section 5 is applied on those dialogues (translated into English) to assess the relative frequency of various dialogue act groups, as shown in Table 7. Here, we include results for the base models without further fine-tuning ( $\text{BASE}_{syn}$ ) as well as scores for these base models separately fine-tuned on subtitles ( $\text{SUBS}_{syn}$ ) and spontaneous conversations ( $\text{SPCONV}_{syn}$ ). We also repeat the results from Table 6 for our original, non-synthetic subtitle ( $\text{SUBS}$ ) and spontaneous dialogue ( $\text{SPCONV}$ ) data for an easier comparison.

We can observe from Table 7 that the difference in proportion of communicative feedback (*Assessment* and *Backchannel* classes) in the synthetic data is similar to that in the original datasets used for training. The synthetic data produced by the models fine-tuned on subtitles contain a slightly higher proportion of feedback than what can be found in the data generated with the  $\text{BASE}$  models for most languages. The difference is much more striking, however, between the dialogues generated when training on spontaneous vs. the scripted conversations. Exceptions to these trends are: (1) the *Assessment* class in French, due to the particular nature of the CID and STAC corpora discussed in the previous sections; and (2) the *Backchannel* class for Hungarian. Although 11% of all Hungarian  $\text{SPCONV}_{syn}$  utterances contained (or consisted of) *hmm*, most of these have been classified by the tagger as *Other* or *Forward looking*. A qualitative analysis of the dialogues also shows that the initial turns of the synthetic dialogues has a large influence on the rest of the dialogue. In particular,

10. The following pretrained models available from the HuggingFace repository (<https://huggingface.co/models>) are employed: `gpt2-base` (English), `gpt-fr-cased-small` (French), `german-gpt2` (German), `gpt2-small-italian` (Italian), `PULI-GPT-2` (Hungarian), `norwegian-gpt2` (Norwegian), `gpt2-chinese-cluecorpussmall` (Mandarin Chinese), and `japanese-gpt2-medium` (Japanese).

11. We exclude 8 synthetic Japanese dialogues from the results, as they contain a large amount of noise (utterances consisting of almost only non-alphabetical characters).

Language	Data	de	en	fr	hu	it	ja	no	zh
<b>Forward I.</b>	<b>BASE<sub>syn</sub></b>	67.88	48.52	74.55	63.57	71.81	60.62	87.02	90.92
	<b>SUBS<sub>syn</sub></b>	54.0	42.0	55.6	33.0	52.1	50.76	51.7	43.33
	<b>SPCONV<sub>syn</sub></b>	18.5	36.5	44.6	48.3	36.2	53.11	53.0	46.14
	<b>SUBS</b>	59.11	63.06	61.87	58.81	59.94	51.15	64.83	62.50
	<b>SPCONV</b>	16.60	41.71	43.18	58.37	33.55	42.34	52.26	53.95
<b>Other</b>	<b>BASE<sub>syn</sub></b>	23.84	40.96	16.96	28.16	22.59	33.59	10.48	7.38
	<b>SUBS<sub>syn</sub></b>	36.1	47.9	36.2	52.3	38.0	36.09	40.6	44.29
	<b>SPCONV<sub>syn</sub></b>	51.2	39.7	36.1	31.4	34.0	14.27	20.9	32.62
	<b>SUBS</b>	26.35	24.78	25.74	26.95	26.89	37.49	22.85	28.74
	<b>SPCONV</b>	53.12	37.24	39.01	17.86	41.52	20.11	22.93	32.44
<b>Assessment</b>	<b>BASE<sub>syn</sub></b>	5.06	5.55	5.36	5.31	2.47	3.39	1.86	1.08
	<b>SUBS<sub>syn</sub></b>	5.5	4.4	3.9	9.3	3.6	7.52	3.3	7.42
	<b>SPCONV<sub>syn</sub></b>	16.8	7.5	4.3	13.8	15.5	19.78	18.7	9.62
	<b>SUBS</b>	9.08	7.07	7.72	9.29	8.34	6.48	6.53	5.00
	<b>SPCONV</b>	16.50	9.11	4.62	15.49	12.64	15.74	17.05	6.96
<b>Backchannel</b>	<b>BASE<sub>syn</sub></b>	2.05	3.05	1.69	2.17	1.11	2.04	0.52	0.44
	<b>SUBS<sub>syn</sub></b>	2.5	2.8	1.9	2.8	2.8	4.18	1.6	3.80
	<b>SPCONV<sub>syn</sub></b>	16.8	13.0	13.5	2.4	6.8	9.89	2.2	9.69
	<b>SUBS</b>	3.49	3.72	3.44	3.48	3.45	3.74	3.47	3.00
	<b>SPCONV</b>	11.57	10.79	11.96	4.28	5.73	18.96	2.67	5.65
<b>Yes/no ans.</b>	<b>BASE<sub>syn</sub></b>	1.16	1.93	1.44	0.80	2.01	0.36	0.11	0.18
	<b>SUBS<sub>syn</sub></b>	2.0	2.9	2.4	2.6	3.5	1.45	2.9	1.16
	<b>SPCONV<sub>syn</sub></b>	1.4	3.2	1.5	4.1	7.5	2.94	5.2	1.92
	<b>SUBS</b>	1.97	1.37	1.68	1.47	1.38	1.15	2.32	0.76
	<b>SPCONV</b>	2.22	1.15	1.24	4.00	6.55	2.84	5.09	1.00

Table 7: Proportion (%) of dialogue act groups detected by our neural tagger in the synthetic dialogues with no fine-tuning (**BASE<sub>syn</sub>**), as well as fine-tuned on spontaneous conversations (**SPCONV<sub>syn</sub>**) and subtitles (**SUBS<sub>syn</sub>**). For easier reference, we also include in this table the results on the original subtitle and spontaneous dialogue data (**SUBS** and **SPCONV**), initially shown in Table 6.

dialogues in which the first turns included fewer feedback phenomena tended to reproduce this pattern in the subsequent turns.

## 7. Multimodal Feedback Cues in Movies

Conversational feedback in human face-to-face interaction makes extensive use of nonverbal multi-modal behaviors such as head gestures (nods, tilts, shakes; e.g., Allwood et al. 2007; Malisz et al. 2016), facial expressions (smiles, frowns; e.g., Bavelas and Chovil 2018), and gaze (Bavelas et al., 2002). Because film is an inherently visual medium, it could be argued that conversational feedback

Title	Length (min)	Nonverbal			Vocal	Subtitles
		Smile	Nod	Shake		
<b>Enola Holmes</b>	122	20	8	3	8	8
<b>White Collar</b>	55	23	37	15	8	7

Table 8: Amount and type of multimodal feedback in manually annotated video content.

in film dialogues takes place in the visual realm as well and therefore may not be fully captured in movie subtitles.

To investigate whether this is the case, we analyze the subtitles of a randomly selected movie (Enola Holmes, 122 min) and one episode of a series (White Collar, S1E1, 55 min). We annotate the conversational nonverbal feedback behavior of the characters, transcribed their verbal/vocal feedback (i.e., backchannels and the like) and compare these to the subtitles from the MovieSubtitles corpus.

As Table 8 shows, both movies differ with respect to the frequency of use of nonverbal feedback behaviors. While we find 20 instances of smile, 8 instances of head nod and 3 shakes in Enola Holmes, the White Collar episode we analyze (which is less than half in length) contains 23 instances of smiles, 37 instances of head nods and 15 shakes. Only few instances (8) of verbal/vocal feedback (*mhm*, *hm*, *mm*, *huh*, etc.) are present in each movie and all but one of them are part of the subtitles. As also these numbers indicate, only a small fraction of all feedback phenomena are verbalized and mentioned in subtitles. Therefore, for a more complete modeling of conversational feedback, incorporating information from multimodal sources is essential.

## 8. Looking Ahead: The Latest Chatbots and Conversational Feedback

There has been a recent surge in the availability of large language models fine-tuned to interact with human users through conversation. Details about the training data behind many of these chat models are often not (or only partly) disclosed, but they most likely include some dialogue-related sources such as subtitles, discussion forums and possibly also transcriptions of spontaneous speech, although in much smaller quantities given their limited availability. Despite the emphasis on the conversational aspect, it is unclear to date how well these systems can actually handle communicative feedback signals.

### 8.1 Understanding Feedback Signals

To get a first impression of how well latest models understand feedback cues, we test the reaction of CHATGPT (OpenAI, 2023) to some short feedback cue words within two short conversations, one focusing on positive, the other on negative feedback. Example (3) shows part of the interaction with positive feedback signals.<sup>12</sup>

- (3) **Prompt:** Uhm  
**Response:** It seems like you might have something on your mind. If you have a question or if there’s a topic you’d like to discuss, please feel free to share, and I’ll be happy to assist you!  
**Prompt:** ok

12. For all examples involving CHATGPT, we used the CHATGPT August 3, 2023 Version (relying on GPT-3.5).

**Response:** If you're ready to continue the conversation or if you have a specific question or topic in mind, just let me know. I'm here to help with any information or guidance you need.

**Prompt:** well

**Response:** If you're feeling uncertain or if there's something you'd like to discuss, don't hesitate to let me know. Whether you have a question, need advice, or just want to chat, I'm here to assist you. Just provide me with some context or a topic you're interested in, and we can continue the conversation from there.

As we can see in Example (3), the system responses to the cue words often contain a spelled-out interpretation of what it supposes its interlocutor's communicative intention is. It understands most of them correctly, however, in a few cases, the evaluative sentence or an appropriate reaction is missing and the system resorts to repeating whether it could help answering any questions as illustrated in Example (4).

(4) **Prompt:** oh my

**Response:** Is there anything specific you'd like to discuss or ask about? I'm here to engage in conversation and help with any questions or topics you have in mind. Whether it's something light-hearted, informative, or just a friendly chat, feel free to let me know! <sup>13</sup>

Inspired by the regular occurrence of a communicative intent “summary” in the system outputs, we conduct a small qualitative evaluation in a zero-shot setting, where we prompt CHATGPT with the following instruction: *In the conversation below, can you explain in square brackets after each line what the speaker is trying to communicate?* As input text, we provide a conversation from the Switchboard corpus (file *sw\_0001\_4325*), as one utterance per line, delimited by double quotation marks and separated with a new line from the instruction. Punctuation, transcription symbols (e.g., indicating pause or simultaneity in speech) and speaker information are not included in the utterances. For the utterances annotated as feedback, the system quite consistently adds plausible explanations such as *Acknowledging*, *Agreeing*, *Affirming*. Interestingly, however, for ca. 14% (21 out of 152) of utterances, CHATGPT does not provide a tag even after a follow-up prompt asking it to add one for the lines that it has skipped at the first attempt (with *some lines are missing an explanation in square brackets, could you add those?*). Half of these “ignored” utterances were annotated in Switchboard as abandoned turns (e.g., *So, but we don't, Um*), where the utterance type could not be clearly determined by annotators, and about a third of them were labeled as *Backchannel*. (One utterance of this type is even removed from the conversation by CHATGPT, possibly already during the preprocessing stage of the system.)

For comparison, we also test the same task with another language model, namely the smaller, but open source LLAMA 2-CHAT 7B (Touvron et al., 2023). Since LLAMA 2-CHAT outputs are rather verbose, we use an additional sentence (*Use maximum 3 words as explanation.*) in the prompt to obtain explanations that would be easier to analyze and more comparable to the CHATGPT output. We observe a similar trend, namely that a number of utterances (13%) are disregarded (completely removed, not only not tagged) in the output.<sup>14</sup> About half of skipped utterances (6 out of 13) are annotated in Switchboard either as *Acknowledgment* or as *Agree/accept*. Moreover, multi-line utterance

13. For additional context, see the complete dialogue in Example (6) in the Appendix C.

14. The system only tagged 101 lines from the original dialogue before a time out error, possible connected to its token limit.

removals occur both times after backchannels. For example explanations provided by the two tested systems see Table 19 in Appendix C.

When repeating the same prompt, or a slightly modified version of it, we find that the output of both systems varies to some degree both in terms of the output format (e.g., more verbose tags, guessing also the speaker for each utterance, line numbering) and in terms of the type of skipped utterances, if any. Typically, prompting for shorter labels seems to reduce the utterance-skipping behavior.

## 8.2 Production of Feedback Cues

We also briefly test CHATGPT’s ability to generate short feedback cues and find that despite follow-up prompts specifically requesting basic conversational feedback, the system seems unable to produce these, regardless of the use of context conversations or example cues provided (e.g., *mh* vs. *yeah*). Example prompts exhibiting this behavior are shown in Example (5). Short feedback cues are not only not produced, but they are even discarded as the last *mh* in the example (and the system response following it) demonstrate.

- (5) **Prompt:** Hi, I would like you to help me with simple dialogues in English since I am not a native speaker. Can you propose me follow-up utterances to the short conversations I give you below?

A : It was when i was in college

B: mh

A : We travelled to UK with friends..

B : mh

A: during summer holidays

**Response:** B: Oh, that sounds like a fun trip! What did you do there?

**Prompt:** Thanks, can you now suggest follow-up that are minimal and simply display that you are following the conversation?

A : I remember one time we were invited for dinner

B: mh

A : but not at our friends place

B : mh

A : at friends of our parents

B : mh

A : and the food was horrible

B : mh

**Response:** B: Oh no, that doesn’t sound pleasant. How was the dinner experience at your parents’ friends’ place?

The limited evidence summarized here thus indicates that recent conversational models might have some difficulties producing and handling certain short communicative feedback signs, but the reason behind this and its systematicity remains unclear. Nevertheless, recent studies (Zhan et al., 2023; Labruna et al., 2023) have already started exploring these language models also for generating datasets of synthetic dialogues to alleviate the cost and time required for collecting data from human-human interactions. A more in-depth evaluation of the conversational ability of these models would therefore be timely.

## 9. Conclusion and Future Work

As described in this paper, movie and TV subtitles exhibit notable linguistic differences to actual spontaneous dialogues in the amount and type of conversational feedback they include. Based on a collection of corpora of both spontaneous dialogues and subtitles across eight languages, we provide both lexical statistics and dialogue act estimates derived with a fine-tuned neural language model. The results of those quantitative analyses show that the proportion of conversational feedback is considerably lower in subtitles than in spontaneous dialogues across the corpora and languages included. Furthermore, the type of conversational feedback also differs, as negative feedback is proportionally more frequent in subtitles. The difference in the proportion of feedback phenomena is also evidently propagated to synthetic dialogues generated by models trained on subtitles and unscripted dialogues.

Beyond their linguistic interest, these results can also provide useful insights into the development of data-driven neural conversational models, as those are often trained on scripted dialogues such as movie scripts and subtitles, and might therefore struggle to (1) understand communicative feedback from the user and (2) produce such feedback themselves. Our small-scale evaluation of conversational language models revealed, in fact, that while the latest systems have a rather good understanding of the communicative intent behind feedback cues, there are indications that they do not interpret and build on some of these while progressing within the dialogue. Integrating a larger amount of spontaneous dialogues in the training process when available could, therefore, prove valuable to mitigate these potential limitations. Currently there is a substantial lack of transparency about the training data used for fine-tuning most chat models. Consequently, investigating their ability to handle and reproduce phenomena typical of spontaneous dialogues more in depth constitutes a promising direction for further research. This could help prevent the propagation of any potential incorrect use or under-representation of conversational cues when fine-tuning language models with quasi-spontaneous dialogues such as subtitles or synthetic dialogues.

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## Appendix A. Conversational Feedback Lexical Statistics

In Table 9, we present the list of cue words used for computing the lexical statistics in Section 4.

**Content warning:** the lists contain potentially offensive language.

Language	Feedback	Lexical cues
de	+	ja, jaa, jaha, jap, jep, jo, joa, aha, hey, ach, achso, okay, ok, richtig, sicher, verstehe, cool, wow, klar, gut, definitiv, absolut, genau, natürlich, ja ja, jaja, ja okay, okay ja, ja genau, ja klar, ja gut, gut okay, ah ja, ja richtig, aber sicher, aber klar, na klar, ich weiß, weiß ich, das stimmt, du hast recht, sie haben recht, ja genau richtig, vermutlich, ja vermutlich, aber wirklich
	-	nein, nee, nö, niemals, stimmt nicht, das glaube ich nicht, glaube nicht, das glaub ich nicht, glaub nicht, vermutlich nicht
	?	wirklich, bitte, entschuldige, häh, was, wo, warum welchen, welcher, welche, welches, echt, bist du sicher, sind sie sicher
	=	mhm, m, mm, hm, ähm, mh, oh, äh
en	+	yes, yeah, yep, okay, oh, right, alright, good, ok, sure, ah, nice, cool, exactly, absolutely, true, great, oh wow, right right, oh okay, oh yeah, yeah right, um-hum yeah, that's great, yes yes, yeah yeah, uh-huh yeah, that's right, right yeah, oh yes, i see, i know, that right, that's true, that's good, all right, of course, got it, is he, oh that's nice, oh that's good, well that's nice, oh i see, oh that's great, yeah that's true, well that's good, well that's great, right that's right, oh yeah yeah, that sounds good, yeah that's right, yeah yeah yeah, yeah oh yeah, oh yeah oh, well that's true, i guess so, yeah i agree, yeah it is, i think so, oh i know, yeah i know, it really is, it is, i agree, definitely, i do too, you bet, you're right, it does, i think so too, that's it, i think you're right, i know it, i agree with you, it was, i agree with that, they are, deal, indeed, obviously, clearly, precisely, certainly, no doubt, so do I, I guess so, they really are, it did, they were, they did, me too, to me too, for me too
	-	no, wait, gosh, nope, my goodness, oh no, but um, but uh, stop it, oh my goodness, oh my gosh, wait a minute, oh my god, not really, not much, no way, shit, fuck, oh no
	?	what, really, oh really, why not, you sure, is that right
	=	um-hum, uh-huh, huh-uh, uh, hum, hm, hey, well, wow, um, huh, mh, mmhmm, m, um-hum um-hum, oh uh-huh, uh-huh uh-huh, um-hum um-hum um-hum, oh, ooh, hmm, mm, mmm
fr	+	oui, ouais, ok, ah, voilà, bien, d'accord, super, parfait, exactement, ah ouais, ouais ouais, et ouais, d'accord, ah oui, oui oui, c'est ça, eh ouais, ah ouais, je sais, très bien, je comprends, bien sûr, ouais ouais ouais, ah ouais ouais, c'est vrai, ah ouais d'accord, ah d'accord, ah ouais OK, ah ouais ok, ah oui oui, ah ben oui, tu m'étonnes, c'est bien, sans doute, tout à fait, absolument, vachement, je suis d'accord, moi aussi, c'est vrai, c'est juste, c'est exactement ça

	-	non, putain, pff, si, merde, oh putain, non non, mon dieu, oh mon dieu, je sais pas, non non non, pas trop, pas vraiment, pas possible
	?	hein, quoi, vraiment, comment ça
	=	ah, mh, euh, oh, han, ben, bon, hm, hum, peut-être, m, mh mh, mh ouais, ah bon, mh mh mh, eh, hé, hey
no	+	ja, jo, å ja, ok, oi, greit, presis, wow, riktig, sant, nettopp, absolutt, jepp, definitivt, åpenbart, deal, selvfølgelig, sikkert, akkurat, god, bra, helt sikkert, jeg vet, jeg skjønner, helt riktig, det stemmer, klart det, uten tvil, det er riktig, det er greit, det er sant, det er det, jeg er enig, du har rett, det gjør det, jeg tror det, jeg vet det, det var det, det gjør jeg, jeg antar det, det gjorde det, det gjør jeg også, det tror jeg også, jeg tror du har rett, jeg er enig med deg, jeg er enig i det, de er det, de var, det gjorde de, meg også, til meg også, for meg også
	-	nei, faen, javel, herregud, ikke helt, ikke mulig, ikke i det hele tatt
	?	virkelig, hva, hæ
	=	m, mhm, mh, hmm, mm, mmm, mmhmm, hm, uh-huh, ikke sant
hu	+	igen, tényleg, úgy van, helyes, jogos, igaz, valóban, pontosan, tudom, rendben, ok, oké, okés, okszi, igen az, de az, bizony, természetesen, határozottan, feltétlenül, mindenképp, egyetértek, szerintem is, ó igen, hogyan, tényleg az, én is, nekem is, engem is, tőlem is, bennem is, igazad van, naná, mi az hogy, meghiszem azt, biztosra veheted, biztos lehetsz benne, jó, ja, szerintem igen, szerintem is, én is így gondolom, én is úgy gondolom, ennyi, ez az, így van, úgy van, szerintem igazad van, szerintem igazatok van, tudom, jól tudom, egyetértek, az volt, ez volt, de, azok, igen, azok, megegyeztünk, egyértelműen, azt hiszem, kétségtelenül, biztosan, persze, értem, tudod, stimmel, valóban, hát igen, hát dehogynem
	-	nem, nem igazán, nem létezik, a francba, a fenét, ne, a csodát, hogy a csodába, hát nem
	?	ó tényleg, micsoda, tényleg, miért ne, biztos
	=	aha, hú, ú, ó, óh, hű, ja, mhm, mm, mmm, hmm, hmmm, wow, azta, ejha, nahát, ühüm
it	+	ehi, okay, okay, ok, sì, si, vabbè, ecco, perfetto, wow, esatto, certamente, esattamente, assolutamente, sicuramente, decisamente, ovviamente, precisamente, di sicuro, sono d'accordo, concordo, eccellente, grandioso, ottimo, certo, infatti, fantastico, magnifico, naturalmente, giusto, bene, già, lo ben so, ah ah, ah ha, vero, é vero, lo so, lo è, davvero, vero, oh sì, lo è veramente, anch'io, anche io, hai ragione, d'accordo, va bene, benissimo, bello, buono, penso di sì, credo di sì, mi sa di sì, mi pare di sì, anche secondo me, lo penso anch'io, è così, penso che tu abbia ragione, penso tu abbia ragione, credo che tu abbia ragione, credo tu abbia ragione, mi sa che hai ragione, sono d'accordo con te, sono d'accordo con voi, lo era, lo è stato, lo è stata, sono d'accordo con ciò, lo sono, senza dubbio, a posto, ci sto, lo sono stati, lo erano, anche a me
	-	oddio, merda, no, non proprio, non molto, non è possibile, cazzo, oh no, macché
	?	come, davvero, cosa



	=	eh, Mm-hmm, hmm, mmm, mh, eh, mhmh, eh, m, hm, ah, oh, beh, uh-huh, mmh, eeh
ja	+ = - ?	そう, はい, ええ, そうか, はあ, どうぞ, 本当, は, あっ, ああ, あ, ね うん, ふーん, えっ, へえ, うーん, ふん, え, う ううん, いいえ, いや, いえ, ない, 全くない, ちょっと 何
zh	+  - ? =	okay, yeah, yes, ok, 对, 哦, 好, 是, 有, 真的, 还行, 然, , 太好了, 耶, 行, 一定, 没错, 那好, 对了, 真好, 好啊, 好吧, 可以, 太棒了, 太棒了, 好极了, 说得对, 没问题, 我同意, 懂了, 一样, 我也是, 不错, 是啊, 就是这样, 当然可以 不, 没有, 不起, 不是 啊, 是吗, 什麼, 什么, 为什么 hey, oh, 嘿, 嗯, 呃, 哼, 哈, 嘘, 喔, 呵呵, 噢, 哇, 哦, 哟, 咦

Table 9: Lists of cue phrases employed in the lexical overview of Section 4.1. We distinguish between four core categories of feedback, namely positive feedback/acknowledgment (+), neutral/continuer (=), negative (-), and clarification request (?).

## CONVERSATIONAL FEEDBACK IN SCRIPTED VERSUS SPONTANEOUS DIALOGUES

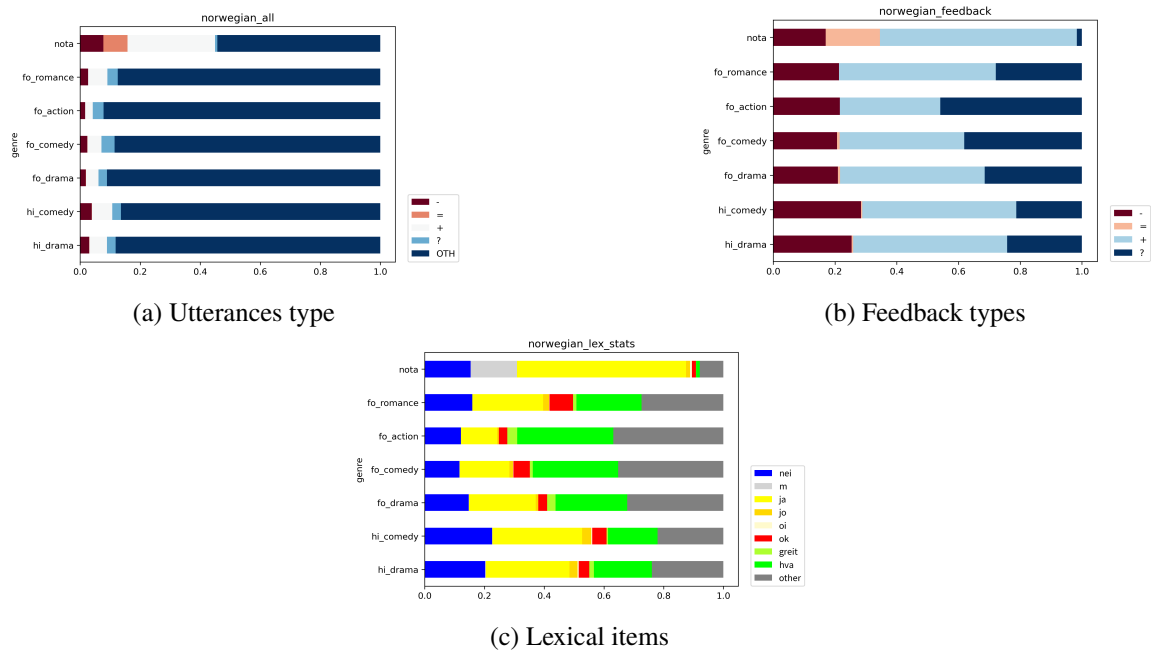


Figure 7: Norwegian across genres (rule-based, based on cue word lists).

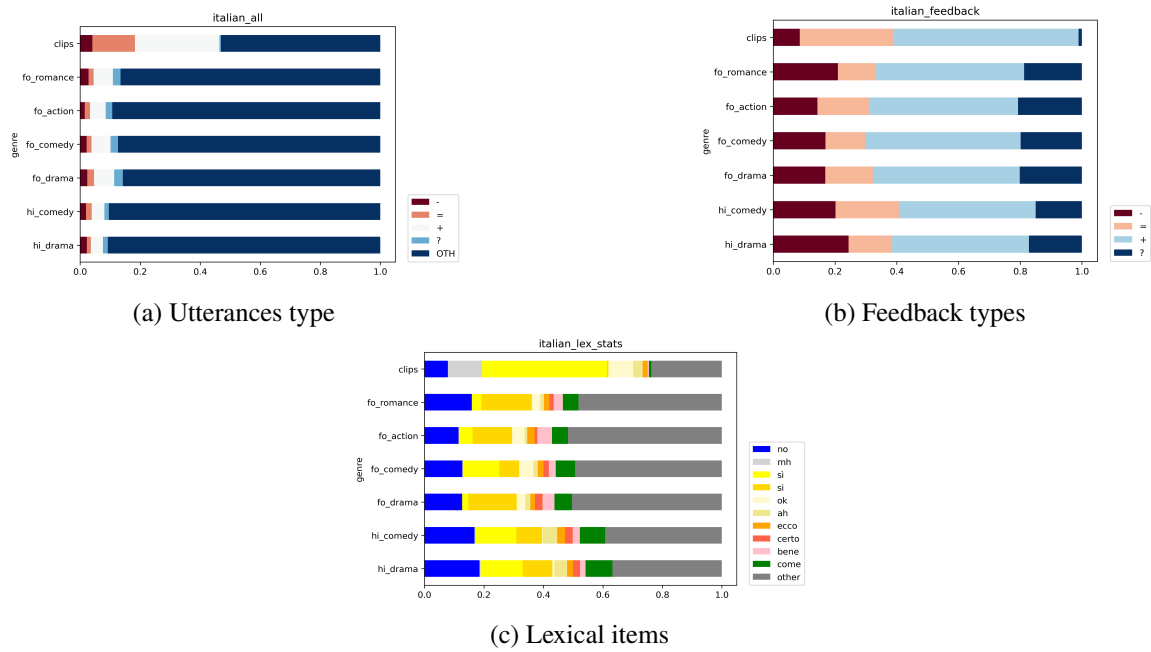


Figure 8: Italian across genres (rule-based, based on cue word lists).

Figures 7 – 12 present statistics for utterance and feedback type as well as common feedback-related lexical items for different languages.

Figure 13 shows politeness keywords and emojis in our English and French corpora.

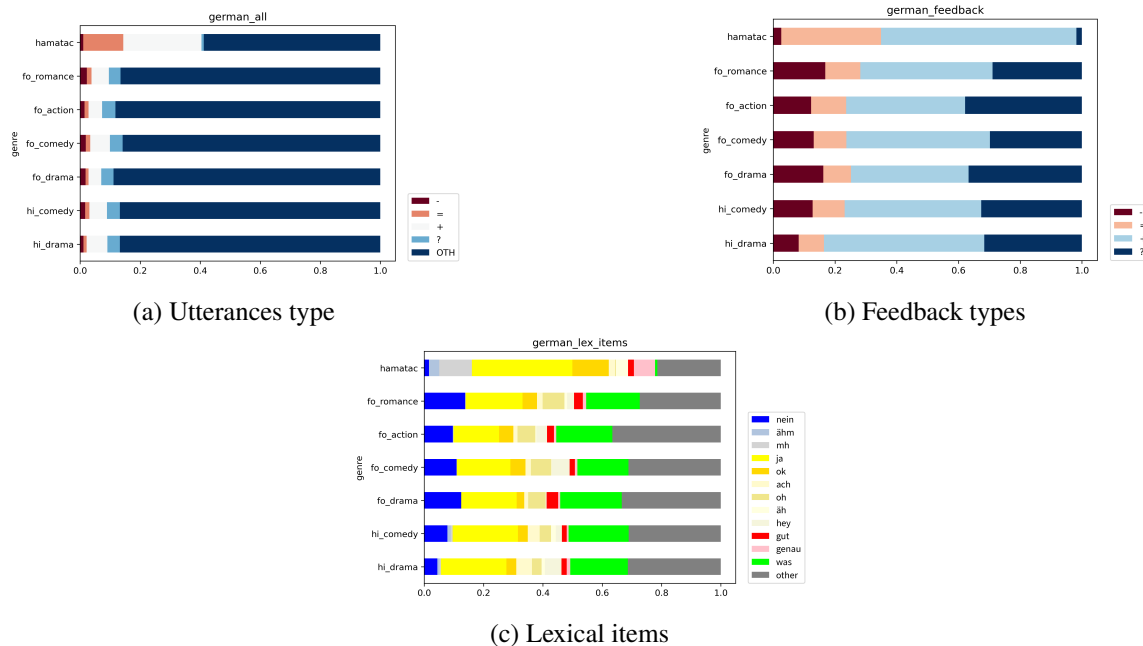


Figure 9: German across genres (rule-based, based on cue word lists).

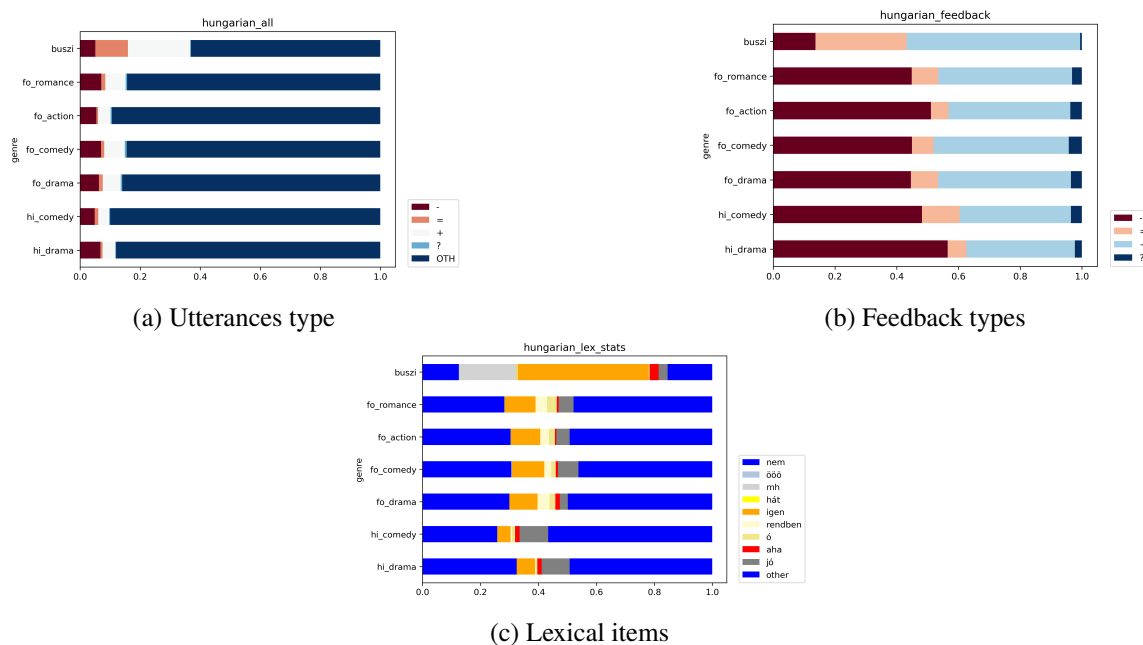


Figure 10: Hungarian across genres (rule-based, based on cue word lists).

CONVERSATIONAL FEEDBACK IN SCRIPTED VERSUS SPONTANEOUS DIALOGUES

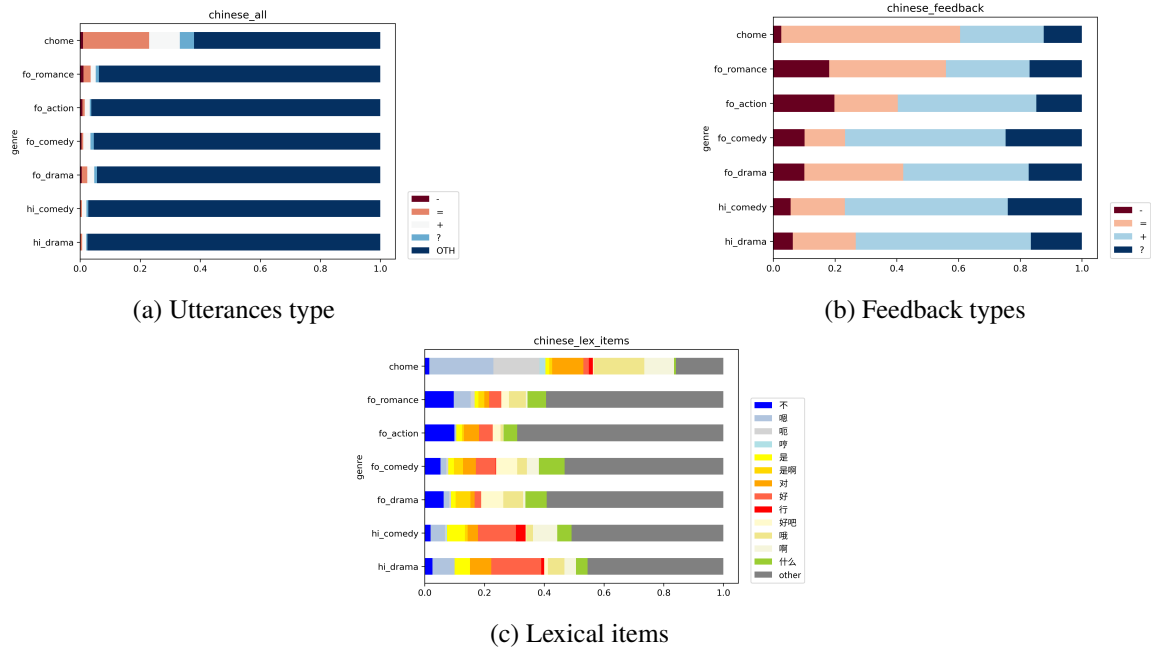


Figure 11: Mandarin Chinese across genres (rule-based, based on cue word lists).

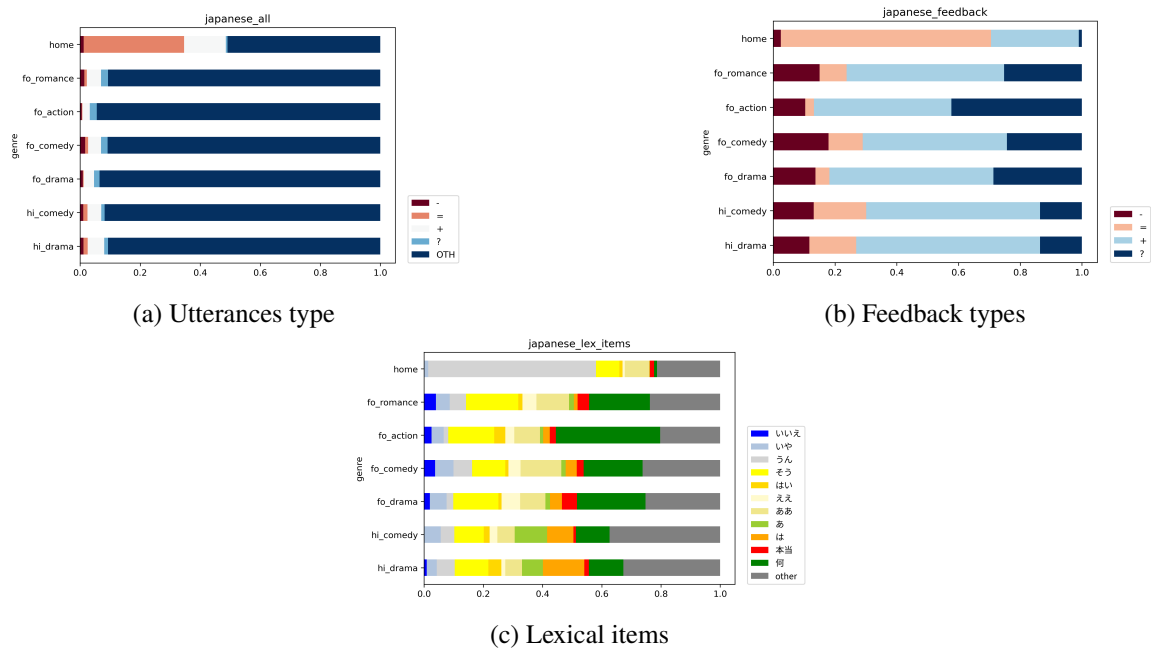


Figure 12: Japanese across genres (rule-based, based on cue word lists).

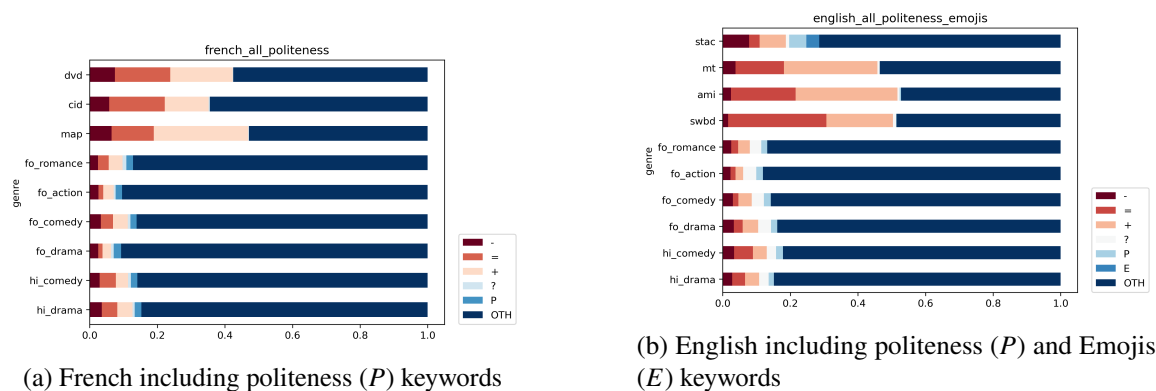


Figure 13: Short utterance distribution including politeness and emojis.

Lang	Corpus	# utt	# feedback	%
<b>de</b>	hamatac	4,012	1,126	28.07
<b>en</b>	ami	83,085	20,044	24.12
	fisher	2,117,748	421,069	19.88
	maptask	26,949	8,366	31.04
	stac	5,841	514	8.8
<b>fr</b>	cid	12,326	1,754	14.23
	dvd	7,578	1,323	17.46
	maptask	6,046	1,226	20.28
<b>hu</b>	buszi	30,979	6,125	19.77
<b>it</b>	clips	24,289	4,461	18.37
<b>ja</b>	chome	38,701	13,432	34.71
<b>no</b>	nota	85,506	16,861	19.72
<b>zh</b>	cn-chome	17,853	2,251	12.61

Table 10: Amount of feedback phenomena using the neural tagger DA-tagger on spontaneous dialogue corpora. Non-English datasets were automatically translated into English with Google Translate API before inference.

## Appendix B. Detailed Dialogue Act Tagging Results

### B.1 Results per Corpus

Tables 10 and 11 present the results of our dialogue act tagger per (sub)corpus used. Here, we only make a binary distinction by grouping the feedback-relevant classes *Backchannel* and *Assessment* into a single *Feedback* category. The number of utterances refers to the final version of the data after pre-processing with meta-linguistic information removed.

<b>Lang</b>	<b>Corpus</b>	<b># utt</b>	<b># feedback</b>	<b>% feedback</b>
<b>de</b>	action_foreign	12,760	1,703	13.35
	action	12,134	1,637	13.49
	comedy_foreign	12,627	1,849	14.64
	comedy	16,152	2,369	14.67
	crime_foreign	12,589	1,245	9.89
	crime	11,817	1,581	13.38
	drama_foreign	14,669	1,350	9.2
	drama	11,460	1,452	12.67
	romance_foreign	13,499	1,500	11.11
	romance	11,809	1,596	13.52
<b>en</b>	action	11,094	1,437	12.95
	action_foreign	12,908	1,448	11.22
	comedy	13,948	1,665	11.94
	comedy_foreign	13,533	1,677	12.39
	crime	14,990	1,700	11.34
	crime_foreign	13,911	1,267	9.11
	drama	14,944	1,729	11.57
	drama_foreign	10,243	1,041	10.16
	romance	16,132	2,166	13.43
	romance_foreign	15,521	1,698	10.94
<b>fr</b>	action_foreign	11,236	1,119	9.96
	action	12,406	1,453	11.71
	comedy_foreign	17,239	1,788	10.37
	comedy	13,932	1,913	13.73
	crime_foreign	12,159	1,017	8.36
	crime	10,821	1,003	9.27
	drama_foreign	10,002	804	8.04
	drama	11,094	1,313	11.84
	romance_foreign	12,043	1,360	11.29
	romance	13,959	1,604	11.49
<b>hu</b>	action_foreign	12,781	1,377	10.77
	comedy_foreign	15,031	1,998	13.29
	comedy	14,692	2,462	16.76
	crime_foreign	13,620	1,655	12.15
	drama_foreign	13,138	1,400	10.66
	drama	7,872	1,103	14.01
	romance_foreign	13,771	1,611	11.7
<b>it</b>	action_foreign	12,010	1,585	13.2
	action	7,703	826	10.72
	comedy_foreign	15,055	2,058	13.67
	comedy	15,363	1,777	11.57

	crime_foreign	12,454	1,320	10.6
	crime	13,885	1,479	10.65
	drama_foreign	17,444	2,289	13.12
	drama	12,838	1,467	11.43
	romance_foreign	14,702	1,696	11.54
	romance	14,573	1,549	10.63
<b>ja</b>	action_foreign	11,245	967	8.6
	action	3,007	443	14.73
	comedy_foreign	16,173	1,777	10.99
	comedy	15,675	2,555	16.3
	crime_foreign	16,296	1,311	8.04
	drama_foreign	14,201	997	7.02
	drama	11,410	1,204	10.55
	romance_foreign	14,042	1,210	8.62
	romance	1,780	145	8.15
<b>no</b>	action_foreign	10,480	892	8.51
	action	1,855	290	15.63
	comedy_foreign	14,406	1,834	12.73
	comedy	11,957	1,199	10.03
	crime_foreign	12,788	1,137	8.89
	crime	9,863	853	8.65
	drama_foreign	12,031	1,202	9.99
	drama	6,688	589	8.81
	romance_foreign	12,830	1,313	10.23
	romance	4,197	399	9.51
<b>zh</b>	action_foreign	11,570	967	8.36
	action	2,722	159	5.84
	comedy_foreign	14,692	1,564	10.65
	comedy	13,587	1,034	7.61
	crime_foreign	10,778	795	7.38
	crime	11,182	697	6.23
	drama_foreign	14,527	1,330	9.16
	drama	9,567	743	7.77
	romance_foreign	13,362	1,079	8.08
	romance	11,440	700	6.12

Table 11: Proportion of feedback phenomena using a neural tagger on our subtitle corpora. Non-English datasets were automatically translated into English before inference.

Dialogue act group	Conversations		Subtitles	
	#	%	#	%
<b>Forward looking</b>	1,070,090	42.26	517,458	60.04
<b>Other</b>	919,323	36.31	237,453	27.55
<b>Assessment</b>	241,669	9.54	64,041	7.43
<b>Backchannel</b>	265,580	10.49	29,783	3.46
<b>Yes/no answer</b>	35,359	1.40	13,071	1.52

Table 12: Amount and proportion of dialogue act groups detected with our neural tagger aggregated per corpus type (English, German, French, Italian, Japanese, Chinese, Hungarian and Norwegian).

de	en	no
okay	yeah	ja “yes”
hm	uh-huh	ok
ja “yes”	oh	mm
mhm	okay	oi “hey”
links “left”	right	hæ ? “huh?”
ach “oh”	oh okay	å “oh”
nach rechts “to the right”	oh really	ja ikke sant “yeah right?”
rechts “right”	oh yeah	jo “yes”
ach so “oh, I see”	yeah yeah	ja ja “yes, yes”
nach oben “upward”	right right	å ja “oh yes”

Table 13: Most frequent *Backchannel* instances in the spontaneous dialogues for Germanic languages.

## B.2 Amount and Proportion of Detected Dialogue Acts

Table 12 includes both the percentage and the exact number of instances classified as a certain class by the DA tagger in both the spontaneous dialogues and the subtitle data.

## B.3 Most Frequent Backchannel Instances

The most frequent utterances in the translated data classified as *Backchannel* per language for real conversations and subtitles separately are presented in Tables 13 – 18.



fr	it
ouais “yeah”	okay
d’accord “alright”	eh “uh”
ah ouais “ah yeah”	mhmh
ok	sì “yes”
ouais ouais “yeah yeah”	va bene “alright”
mh mh “uh uh”	mh okay
oui “yes”	ah okay
d’ accord “alright”	sì okay “yes okay”
mh “uh”	okay sì “okay yes”
ouais ouais ouais “yeah yeah yeah”	eh sì “uh yes”

Table 14: Most frequent *Backchannel* instances in the spontaneous dialogues for Romance languages.

hu	ja	zh
Igen. “Yes.”	うん “Yeah”	啊 ? “Ah?”
Igen? “Yes?”	うん うん “Yeah yeah”	哦, “Oh,”
Mhm. “Mhm.”	ああ “Ah”	嗯哼. “Hmm, hmm.”
Nem? “No?”	へえ “Huh?”	嗯? “Hmm?”
Igen, igen. “Yes, yes.”	うん うん うん “Yeah yeah yeah”	是吗? “Is it?”
Tényleg? “Really?”	ふーん “Huh”	嗯, 嗯. “Hmm, hmm.”
Micsoda? “What?”	ああ そう “Ah, I see”	对. “Right.”
Na? “Well?”	あっ “Ah”	okay
Igen, mhm. “Yes, mhm.”	うん うん うん うん “Yeah yeah yeah yeah”	对对对. “Right, right, right.”
Hát? “Well?”	ああああ “Ah ah”	嗯, 嗯, “Hmm, hmm.”

Table 15: Most frequent *Backchannel* instances in the spontaneous dialogues for Hungarian, Japanese and Chinese.

de	en	no
Was? “What?”	What?	Hva? “What?”
Ja? “Yes?”	Yeah.	Unnskyld. “Pardon.”
Hallo? “Hello?”	Really?	Ja? “Yes?”
Wieso? “Why?”	Okay.	Hallo? “Hello?”
Hm? “Hm?”	Yeah?	Hva da? “So what?”
Was ist das? “What is that?”	Huh?	Ok.
Wirklich? “Really?”	Hello?	Greit. “Alright.”
Was ist? “What is it?”	Who?	Hæ? “What?”
Wer? “Who?”	Okay?	Hvem? “Who?”
Echt? “Real?”	Yes?	Ja “Yes”

Table 16: Most frequent *Backchannel* instances in the subtitle data for Germanic languages.

fr	it
Quoi ? “What?”	Cosa? “What?”
Hein ? “Huh?”	Davvero? “Really?”
Oui ? “Yes?”	Eh? “Huh?”
Vraiment ? “Really?”	Chi? “What?”
Comment ça ? “How?”	Sí? “Yes?”
Ouais. “Yeah.”	Perchè? “Why?”
Pardon ? “Sorry?”	No? “No?”
Et alors ? “So?”	Che cosa? “What?”
Qui ? “Who?”	Scusa. “Sorry.”
h oui ? “Oh yeah?”	Si ’? “Yes?”

 Table 17: Most frequent *Backchannel* instances in the subtitle data for Romance languages.

hu	ja	zh
Mi van? “What’s up?”	何 ? “What?”	什么? “What?”
Mi? “What?”	何だ ? “What is it?”	是吗? “Is it?”
Tényleg? “Really?”	そうか “Is that so?”	什么? “What?”
Igen? “Yes?”	なに ? “What?”	好吧 “Okay”
Mit? “What?”	何だって ? “What?”	好的 “Okay”
Mi az? “What is it?”	何か ? “What?”	喂? “Hello?”
Micsoda? “What?”	大丈夫か ? “Are you ok?”	谁? “Who?”
Jól vagy? “Are you alright?”	すみません “Excuse me”	啊? “Ah?”
Nem? “No?”	本当に ? “Really?”	真的吗? “Really?”
Oké. “Okay.”	退 “Retreat”	哦 “Oh”

 Table 18: Most frequent *Backchannel* instances in the subtitle data for Hungarian, Japanese and Chinese.

## Appendix C. Conversational Large Language Model Outputs

Example (6) shows one of the conversations with CHATGPT, where the understanding and management of feedback signals was investigated. This dialogue contains also a number of negative feedback signals, to some of which the system simply repeated that it is at the user's disposal as a reaction (e.g., *but um, oh my, yeah...*) without offering a more specific follow-up or other explicit signals of noticing and interpreting the user's intention (unlike in other cases). The output formatting below aims at reflecting the original system outputs as closely as possible (e.g. use of bold face and numbered lists).

- (6) **Prompt:** Hi there!  
**Response:** Hello! How can I assist you today?  
**Prompt:** Just feeling like having a chat  
**Response:** Of course, I'm here for a chat! Is there a particular topic on your mind, or should we just dive into a random conversation? Whether it's about hobbies, interests, life experiences, or something else entirely, I'm here to engage with you. So, what's on your mind?  
**Prompt:** Are you alone?  
**Response:** Yes, I'm here to chat with you, and there's no one else involved in our conversation. It's just you and me! How can I make our conversation enjoyable or helpful for you today? Is there something specific you'd like to discuss?  
**Prompt** but um  
**Response:** I'm here to help and have a conversation with you. If you have any questions, thoughts, or topics you'd like to discuss, feel free to let me know. There's no rush, so take your time. What's on your mind?  
**Prompt:** well, um, aren't there developers around you?  
**Response:** I'm a program developed by OpenAI called GPT-3. While there are developers and researchers at OpenAI who work on creating, training, and improving models like me, I don't have direct interactions with them during our conversation. Our conversation is between you and the AI, and the responses you receive are generated based on patterns and information learned from a diverse range of sources up until my last knowledge update in September 2021. How can I assist you further? Is there something specific you'd like to talk about?  
**Prompt:** oh my  
**Response:** Is there anything specific you'd like to discuss or ask about? I'm here to engage in conversation and help with any questions or topics you have in mind. Whether it's something light-hearted, informative, or just a friendly chat, feel free to let me know!  
**Prompt:** so, mhm, any tips on what I can do on a rainy day?  
**Response:** Certainly! Rainy days can provide a cozy and relaxing atmosphere for various activities. Here are some ideas for things you can do on a rainy day:
1. Read a Book: There's nothing quite like curling up with a good book and a cup of hot beverage when it's raining outside.
  2. Watch Movies or TV Shows: Have a movie marathon or catch up on your favorite TV shows.
- [...]  
Remember, rainy days can be an opportunity to enjoy indoor activities and create a cozy atmosphere. Choose something that resonates with your interests and enjoy the day!  
**Prompt:** no way

**Response:** I apologize if my previous response didn't align with what you were looking for. If you have something else in mind or if there's a specific topic or activity you'd like to discuss, please let me know, and I'll be more than happy to help or provide information on that. Just let me know how I can assist you!

**Prompt:** Something more social, in person?

**Response:** Certainly! If you're looking for social activities to do in person on a rainy day, here are some ideas:

1. **Board Game or Card Game Night:** Invite friends or family over for a cozy board game or card game night. It's a great way to have fun and bond indoors.
2. **Cooking or Potluck Party:** Organize a cooking or potluck party where everyone prepares and shares their favorite dishes.
3. **Movie Marathon:** Invite friends over for a movie marathon, complete with popcorn and comfy blankets.
4. **Indoor Picnic:** Set up an indoor picnic with blankets and cushions. Enjoy finger foods, sandwiches, and treats while chatting and playing games.

[...]

Remember to consider the preferences and comfort of your guests when planning any in-person gathering. These ideas can help you create enjoyable and memorable moments even when the weather is gloomy outside.

**Prompt:** wait a minute, indoor picnic?

**Response:** Absolutely! An indoor picnic is a creative and cozy way to enjoy the comforts of a picnic without having to worry about the weather. Here's how you can set up a delightful indoor picnic:

1. **Choose a Spot:** Pick a comfortable area in your living room, dining room, or even a spacious hallway where you can lay down blankets and cushions

[...]

An indoor picnic is not only a fun and unique activity but also a way to create a special atmosphere and spend quality time with others. It's perfect for rainy days when going outside isn't ideal.

**Prompt:** yeah...

**Response:** If you have any more questions or if there's anything else you'd like to discuss, whether it's related to indoor activities, different topics, or just a friendly chat, feel free to let me know. I'm here to help and engage in conversation with you!

**Prompt:** nope

**Response:** Alright, if you ever have more questions or just want to chat in the future, feel free to reach out. Have a great day!

Table 19 shows the responses of two large language models fine-tuned for conversation (CHATGPT and LLAMA 2-CHAT 7B) for the following prompt: *In the conversation below, can you explain in square brackets after each line what the speaker is trying to communicate?.* We include here the 101 utterances for which we have an output from both systems (as LLAMA 2-CHAT produced a timeout error for the remainder of the conversation). The SWBD column contains the dialogue act

annotations from the Switchboard corpus (with minor simplifications) <sup>15</sup>. The analyzed conversation from Switchboard was the first file, *sw\_0001\_4325*. The tag *REMOVED* shows utterances missing from the system output, while *NO LABEL* indicates utterances preserved in the output, but without an explanation provided. Utterances in bold face are communicative feedback cues. (Square brackets, double quotation marks and other purely formatting elements have been removed from system outputs for improved readability.)

Input utterance	CHATGPT	LLAMA 2-CHAT 7B	SWBD
So	Starting the conversation	Expressing confusion or uncertainty	qw
I guess	Expressing uncertainty	(merged with previous)	qy
What kind of experience do you do you have then with child care?	Asking about the listener's experience with child care	REMOVED	+
I think uh I wonder if that worked	Reflecting on a previous action	Thinking aloud or expressing a question	+
Does it say something?	Asking for clarification	Asking for clarification or information	qy
I think it usually does	Stating a general observation	Expressing a belief or opinion	sd
You might try uh	Suggesting a course of action	Suggesting a course of action	ad
I don't know	Expressing uncertainty	Expressing a lack of knowledge or information	h
hold it down a little longer	Giving advice	Unclear or nonsensical	ad
and see if it uh	Suggesting an experiment	Unclear or nonsensical	ad
<b>Okay</b>	Acknowledging	Expressing agreement or confirmation	aa
Well	Pause	Expressing surprise or confirmation	qy
<b>Okay</b>	Agreeing	REMOVED	b
I	Pause	Expressing uncertainty or lack of knowledge	sd
Does it usually make a recording or s	Seeking information	Unclear or nonsensical	+
Well I don't remember	Expressing uncertainty	Expressing a lack of memory or information	+
It seemed like it did	Sharing an observation	Expressing uncertainty or lack of knowledge	sd

15. See <https://web.stanford.edu/~jurafsky/ws97/manual.august1.html> for the list of tags names.

Input utterance	CHATGPT	LLAMA 2-CHAT 7B	SWBD
but it might not	Qualifying the previous statement	(merged with previous)	sd
I guess	Expressing uncertainty	Expressing uncertainty or lack of knowledge	sv
<b>Okay</b>	Agreeing	Expressing agreement or confirmation	bk
I guess we can start Uh	Considering the next action	REMOVED	+
<b>Okay</b>	Agreeing	REMOVED	aa
No	NO LABEL	REMOVED	nn
I don't have any kids	Stating absence of children	Expressing a lack of personal experience or information	sd
I uh my sister has a she just had a baby	Explaining the situation	Expressing personal information or experience	sd
he's about five months old	Specifying the baby's age	Expressing a personal experience or information	sd
and she was worrying about going back to work and what she was going to do with him and	Describing the sister's concern	Expressing a personal concern or issue	sd
<b>Uhhuh</b>	Affirming	Expressing agreement or confirmation	b
the different	NO LABEL	Unclear or nonsensical	+
do you have kids?	Asking about the listener's family	Asking a personal question	qy
I have three	Stating the number of children	Expressing personal information or experience	na
<b>Oh really?</b>	Expressing surprise	Expressing surprise or confirmation	bh
Uhhuh	Affirming	Expressing agreement or confirmation	ny
<b>Yeah</b>	NO LABEL	Expressing agreement or confirmation	b
I do	NO LABEL	Expressing personal information or experience	sd
Yes uh	NO LABEL	Expressing agreement or confirmation	%
I don't work though	Explaining current situation	Expressing a personal lack of work experience	sd

Input utterance	CHATGPT	LLAMA 2-CHAT 7B	SWBD
but I used to work and when I had two children	Explaining past work experience	Expressing personal information or experience	sd
<b>Uhhuh</b>	Affirming	Expressing agreement or confirmation	b
I work off and on just temporarily and usually find friends to babysit	Explaining current work situation	Expressing personal information or experience	sd
but I don't envy anybody who's in that situation to find day care	Expressing empathy	Expressing a personal perspective or opinion	sd
<b>Yeah</b>	Agreeing	Expressing agreement or confirmation	b
But does your sister live in a big community?	Asking about the listener's sister	Asking a personal question	qy
Uh yeah	Affirming	Expressing agreement or confirmation	ny
she lives	NO LABEL	Expressing personal information or experience	sd
it's a it's a fairly large community	Describing the sister's living situation	Expressing personal information or experience	sd
She uh got real lucky though	Explaining the sister's fortunate situation	Expressing a personal perspective or opinion	sd
He had a boss who uh moved into a larger office	Explaining how the sister's situation improved	Expressing personal information or experience	sd
<b>Uhhuh</b>	Affirming	Expressing agreement or confirmation	b
and she's able to take her baby to work with her	Explaining the sister's childcare arrangement	REMOVED	sd
<b>Oh really?</b>	Expressing surprise	REMOVED	bh
And it's a small office that she works in	Describing the sister's workplace	REMOVED	sd
<b>Uhhuh</b>	Affirming	REMOVED	b
and uh it's a it's a legal firm office	Describing the nature of the workplace	Expressing personal information or experience	sd
and it's just one lawyer	Explaining the office's setup	Expressing personal information or experience	sd
Um	NO LABEL	Expressing uncertainty or lack of knowledge	%

Input utterance	CHATGPT	LLAMA 2-CHAT 7B	SWBD
and so she's the only one really that takes care of the office	Describing the office dynamics	Expressing a personal perspective or opinion	sd
There's no one else that works there	Clarifying the situation	Unclear or nonsensical	sd
<b>Uhhuh</b>	Affirming	Expressing agreement or confirmation	b
And so they have an extra room and everything for the baby	Explaining the childcare setup	Expressing personal information or experience	sd
so it works out pretty good for her	Describing the positive outcome	Expressing a personal perspective or opinion	sd
<b>Wow</b>	Expressing amazement	Expressing surprise or confirmation	ba
<b>How lucky</b>	Expressing admiration	REMOVED	ba
I I know a lot of people around here sometimes have like mothers or grandmothers	Sharing common knowledge	Expressing personal information or experience	sd
<b>Yeah</b>	NO LABEL	Expressing agreement or confirmation	b
that take care of their kids	Explaining common childcare arrangement	Expressing personal information or experience	+
and but the community I'm in is not a real large one	Describing the speaker's community	Expressing personal information or experience	sd
so there are a lot of people who babysit in their homes that you know	Explaining common childcare arrangement	Expressing personal information or experience	sd
you either know them or know somebody who knows them to get to	Explaining how childcare is facilitated	Expressing a personal perspective or opinion	sd
<b>Yeah</b>	REMOVED	Expressing agreement or confirmation	b
<b>so it's fairly safe</b>	Assessing the safety of the community	Expressing a personal perspective or opinion	bf
<b>Yeah</b>	Agreeing	Expressing agreement or confirmation	aa
to get references and that	Explaining the process	REMOVED	sd
so but uh	NO LABEL	REMOVED	%



Input utterance	CHATGPT	LLAMA 2-CHAT 7B	SWBD
I I d don't feel comfortable about leaving my kids in a big day care center but simply because there's so many kids and so many	Expressing discomfort with large daycare centers	Expressing a personal perspective or opinion	sd
Worried that they're not going to get enough attention?	Asking about the listener's concern	Expressing a personal concern or issue	qy
Yeah	Affirming	Expressing agreement or confirmation	ny
and uh you know colds and things like that get	Explaining health concerns	Expressing personal information or experience	sd
<b>Yeah</b>	NO LABEL	Expressing agreement or confirmation	b
spread real easy and things	Elaborating on health concerns	Expressing personal information or experience	+
but and they're expensive	Pointing out the cost factor	Expressing a personal perspective or opinion	sv
and course there's a lot of different types of day care available too you know where they teach them academic things	Explaining the diversity of daycare options	Expressing personal information or experience	sd
<b>Yes</b>	NO LABEL	REMOVED	aa
Or they just watch them and let them play and things like that	Describing different approaches to daycare	Expressing personal information or experience	sd
but	NO LABEL	Expressing a personal perspective or opinion	%
take a long time to find the right place	Explaining the challenge of finding suitable daycare	(merged with previous)	sv
<b>Yeah</b>	Agreeing	Expressing agreement or confirmation	aa
and you and you don't always even know if it's going to be the right place or not	Expressing uncertainty	Expressing a personal perspective or opinion	sv
<b>Uhhuh</b>	Affirming	Expressing agreement or confirmation	b

Input utterance	CHATGPT	LLAMA 2-CHAT 7B	SWBD
Anything I guess could happen <b>Uhhuh</b>	Acknowledging the un- predictability Affirming	Expressing a personal per- spective or opinion Expressing agreement or confirmation	sv b
Because after I guess after he you know gets to a certain age she’s going to have to take him to a day care <b>Uhhuh</b>	Explaining future plans Affirming	Expressing a personal per- spective or opinion Expressing agreement or confirmation	qy ny
when he starts tod- dling around and stuff <b>Yeah</b>	Explaining the need for daycare as the child grows NO LABEL	Expressing personal infor- mation or experience Expressing agreement or confirmation	sd b
<b>Yeah</b>	NO LABEL	Expressing agreement or confirmation	b
When when he’s not when she can’t keep control of him and he starts crawling	Explaining the need for daycare as the child be- comes more active Describing child’s devel- opmental stage	Expressing personal infor- mation or experience (merged with previous)	sd sd
that’s <b>Uhhuh</b>	Clarifying Affirming	Expressing a personal per- spective or opinion Expressing agreement or confirmation	% aa
It would be hard	Expressing empathy	Expressing a personal per- spective or opinion	sv

Table 19: Comparison of explanations of speaker intention generated by two conversational language models for utterances from the Switchboard corpus. The dialogue act tag annotations are reported in the SWBD column.