

# Laughter and Topic Changes: Temporal Distribution and Information Flow

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**Abstract**—Laughter is an important component of social interaction that has attracted interest within conversational analysis. However, it is not universally accepted that laughs have a function in discourse structure. In this study we explore laughter in conversation in relation to topic changes trying to understand whether laughter can be considered as a signal of discourse structure, whether there is a recurrent pattern in laughter distribution with respect to topic changes, and whether laughter has a function in predicting topic changes. In order to answer these general questions, we investigate the laughter-topic change relation from two different points of view (timing and information flow), finding interesting regularities in laughter distributions. Thus, laughter has a function in discourse structure and, although not sufficient to predict a topic change in isolation, it can be an important indicator together with other sources of information.

## I. INTRODUCTION

Laughter, as component of social interaction, has attracted interest within conversational analysis [6], [8]. While laughter can be expressed in different contexts, voluntary or involuntary [12], and diverse in function and degree of functionality [6], its timing is not random.<sup>1</sup> Understanding laughter as a reaction to dialog content (when not in response to situations or events outside the dialog context in which it occurs), laughter has been studied in relation to preceding utterances [16]; however, it can also be understood in relation to utterances that follow, inasmuch as it provides a signal of topic completion.<sup>2</sup> It is not universally accepted that laughter is signal of discourse structure; others have made the argument that filled-pauses do have a “symbolic function in discourse structure”, in contrast to laughing [15, p494]. However, if it is possible to find a relation between laughter and topic boundaries, it would be possible to interpret laughter as a signal in discourse structure.

As a suggestive indication, we show in Fig. 1 approximately eight minutes of talk from conversations the rest of which are analyzed more deeply in the remainder of the paper.<sup>3</sup>

<sup>1</sup>The internal structure of laugh-constituting noise may well be random [1].

<sup>2</sup>We accept distinctions made by others, for example [3], about the need to separate spontaneous laughter from its more conscious counterparts and think it is possibly the spontaneous laughter that is more linked to what has come immediately before than what follows in the very near future.

<sup>3</sup>The corpus records conversation in English, including non-native speakers of English, among five individuals over three sessions of approximately 1.5 hours each [2]. This corpus has been studied independently [9].

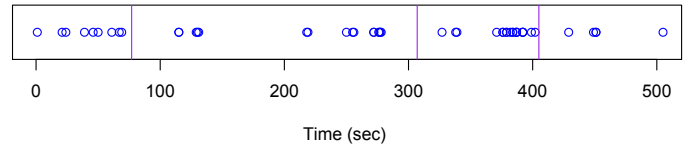


Fig. 1. Laughter distribution over time. Circles represent laughter, vertical lines represent topic boundaries. (No other vocalization is plotted.)

Two observations are available: firstly, bundles of laughter can anticipate a topic change, but are not a reliable signal of topic change; conversely, when a topic has changed, laughs do not follow immediately. This segment of conversation is representative of the entire dataset.

We study the laughter-topic change relation from two different points of view: with respect to timing (whether recurrent patterns in the relation laughter distribution-topic changes exist, whether laughter is a reliable topic termination cue) and with respect to information content (whether laughter can be considered milestone of changes in the information flow).

From the timing point of view, others also approached this problem. In [4], [5] regularities have been analyzed in the occurrence of shared and not-shared laughter and their different conversational functions [4]. From a large collection of instances two persistent patterns are noted: shared laughter is often associated with topic termination and solo laughter with topic continuation. It has been observed that laughter invites reciprocal laughter [8]; however, Holt qualifies this with analysis of cases in which the listener seemingly refuses the laugh-invitation by continuing the topic with further information, instead. Keeping in mind Holt’s analysis [4], [5], we explore a corpus of multiparty spontaneous chat (see §III) approaching the problem in two steps: analyzing the general distribution of laughter and then at a finer level distinguishing between shared laughter and solo laughter.

From the information point of view, we analyze the content flow with respect to laughter and topic boundaries. The content of conversation that is not composed of laughter or silence, where that content is linguistic, contains either informational

flow or mutual affirmation of known information (such as comment on the weather at a bus stop). Others have shown deictic gesture to relate to known referents more than new entities in discourse [10], while at the same time, coinciding with the onset of conversational contributions [9]. Further, laughter has been analyzed as a sort of gesture [13]. Given that we are also analyzing laughter as a kind of milestone in conversation, it is relevant to compare measures of information content on either side of laughter, in relation to topic boundaries.

The focus of the present work can be summarized in two main lines of research: a temporal analysis of laughter distribution over the conversation with respect to topic boundaries, and a kind of quantitative analysis of the information content with respect to laughter and topic boundaries. In analyzing the timing of laughter we seek answers to these questions:

- (1) how is laughter distributed around topic boundaries?
- (2) is there evidence of the “shared laughter-topic termination” relation or of the “solo laughter-topic continuation” relation, as articulated by [4]?

In content analysis we seek answer to this question:

- (3) is there a well-motivated measure of information content which is different when measured between two sorts of periods: (a) the last laugh and the subsequent topic boundary (topic termination), and (b) the topic boundary (topic beginning) and the first subsequent laugh?

The paper is structured as follow: Section II describes a set operational definitions that will be used in the following sections. In Section III, we describe a particular corpus of informal chat upon which we base the empirical analysis. Section IV addresses the temporal distribution analysis, tackling questions (1), in IV-A, and (2), in IV-B and IV-C. Finally, Section V refers to the content analysis, tackling question (3), analyzing the information flow with respect to laughter and topic boundaries. Conclusions are drawn in Section VI.

## II. OPERATIONAL DEFINITIONS

### A. Definition of Topic

In order to approach the problem of topic change, we need to introduce one of the main issues of the topic segmentation literature: what a topic is. Many diverse definitions have been given while addressing the problem from different points of view and in different contexts. In linguistic literature topic has been addressed at two different levels: at sentence level [28], and at discourse level [29]. In the context of topic segmentation algorithms, topic has been mostly referred to at a discourse level, as segments of the discourse sharing coherent information (*about the same thing* [33]). However this definition is not the only one. Passonneau et al., [23], notice how topic can be interpreted also in terms of speakers’ *intentions*, and topic changes in conversations as changes in the participants’ activities (information-giving, decision-making). In topic segmentation applications, topics have been seen as lexically coherent segments of the discourse, and topic changes as drops in such coherence, [26]. Arguello et al., [27], use a functional definition of topic, based on the satisfaction of

three criteria: it should be reproducible by manual annotators,<sup>4</sup> it should not rely on domain-specific knowledge and, third, shifts in topic should be evident from surface characteristics of the language. For the present work, topic has been considered at a discourse level, and from the content point of view, as a section of conversation characterized by a coherent content (i.e. *japanese restaurants*, *word meanings*, *tv shows*, etc).

Many different topic segmentation algorithms have been developed; some are based on lexical cohesion as TextTiling [26] or in [30], some on clustering (with a binary approach on whether sentence boundary is or not a topic boundary) [31], others exploit discourse markers that provides clues about the discourse structure [32]. Understanding whether laughter has a function in the discourse structure plays a crucial role in the framework of those algorithm, as laughs could constitute an informative feature to boost topic segmentation efficacy.

### B. Temporal analysis definitions

For temporal analysis, we idealize T-events as an instantaneous points of conversational topic shift and identify them with the first contribution of the onset of the new topic. Further, we consider the laugh events in relation to T-events. Laughter and topic boundaries constitute milestones in conversation. At first we are interested in any sort of laugh. Therefore, we discriminate the time spans between the last laugh in topic A and T-event (namely LT) and the T-event and the first laugh in topic B (namely TL) (Fig. 2).

Secondarily we analyze, at finer level, the distinction between shared and solo laughter and their relation with topic changes. In this case, the last solo (SO) and shared (SH) laughs prior to a T-event (named last-laugh or LL: SoLL or ShLL, respectively) and the first solo and shared laughs subsequent to a T-event (FL: SoFL, ShFL) are of particular interest among laughs.<sup>5</sup> See Fig. 3. We denote the measure of this distance between T-events and boundary laughs as  $\mu$ .

In what follows we consider the differences between  $\mu(LT)$  and  $\mu(TL)$  as well as between  $\mu(SoLT)$  and  $\mu(ShLT)$ , and between  $\mu(SoTL)$  and  $\mu(ShTL)$ .

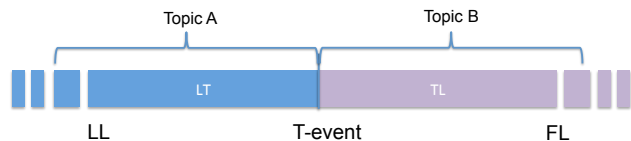


Fig. 2. Topic boundary neighborhood. LL and FL represent last and first laugh. LT and TL represent respectively a topic termination segment and a topic beginning segment.

Finally, since a conversation is characterized also by a dichotomous distinction between moments of topic continuation and moments of topic transition, we analyze the distribution of laughter among those segments. We construct operational models of topic continuation segments, calling

<sup>4</sup> [24] describes the difficulties of this task also for manual annotators.

<sup>5</sup>Note that for some T-event, FL might not occur before a T-event follows. The same FL may serve both T-events, but with distinct TLs, accordingly.

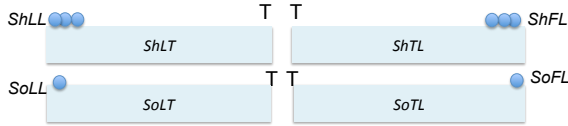


Fig. 3. Topic boundary neighborhoods with shared and solo last laughs (ShLL and SoLL) and shared and solo first laughs (ShFL and SoFL). ShLT, ShTL, SoLT, SoTL represent topic termination and topic beginning segments.

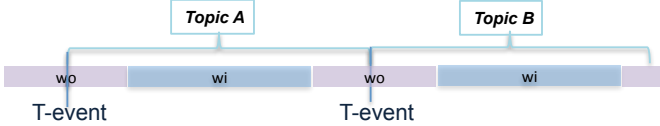


Fig. 4. Topic continuum vs topic transition segmentation

them *wi* segments, and topic transition segments, calling them *wo* segments. We define these as follows (see Fig. 4):

- *wi* segments: the central half of each topic (blue in Fig. 4);
- *wo* segments: the final quarter of one topic and first quarter of the next topic (pink areas in Fig. 4).

The core of discussion of a topic may be expected to be found *within* a *wi* segment, but outside (ie. *without*) a *wo* segment. By construction, *wi* segments do not include a topic transition *within* them, while *wo* segments do (and thus can be expected to include the talk that winds down one topic and commences another, including core content of both). Because they are in each case defined in relation to the duration of a sequential pair of topics, the construction is a rational decomposition of conversational flow into segments containing topic-core talk and segments containing topic transitions.

### C. Linguistic content analysis definitions

Conversation is also constituted by much linguistic content which drives the information flow throughout the conversation.<sup>6</sup> Hence, we can analyze the before mentioned LT and TL segments of the conversation with respect to their lexical richness. We refer to the lexical richness of LT and TL as  $\Lambda$ , respectively  $\Lambda(LT_t)$  and  $\Lambda(TL_t)$ . For each T-event,  $t$ , we define  $\Lambda(LT_t)$  with (4) and  $\Lambda(TL_t)$  with (5).

$$(4) \quad \Lambda(LT_t) = TTR(LT_t) / Length(LT_t)$$

$$(5) \quad \Lambda(TL_t) = TTR(TL_t) / Length(TL_t)$$

In these equations, TTR is the Type-Token Ratio.<sup>7</sup>

## III. CORPUS DESCRIPTION

The corpus, Table-Talk,<sup>8</sup> was recorded at ATR in Japan. As indicated above (note 3), the multi-modal corpus records conversation in English, including non-native speakers of

<sup>6</sup>Seemingly inevitably, linguistic content will also include digressions, and the total information flow in a conversation will include non-linguistic content about the empathetic and sympathetic states of the participants with respect to each other.

<sup>7</sup>For any segment, the total number of unique words divided by total number of words – the value for this footnote is  $\frac{21}{29}$  for all words,  $\frac{12}{16}$  on only content.

<sup>8</sup><http://sspnnet.eu/2010/02/freetalk/> – last verified November 2012.

English, among five individuals over three sessions [2]. In order to collect as natural data as possible, neither topics of discussion nor activities were restricted in advance. The recordings were made in an informal setting over coffee. A more complete description of the corpus can be found in [19].

Speaker	Shared	Solo	Total Laughs	Total # turns
d	7	30	37	1581
g	13	17	30	420
k	67	127	194	1172
n	78	157	235	1580
y	76	141	217	1226

TABLE I  
DISTRIBUTION OF LAUGHTER AMONG SPEAKERS

For this research, all three days have been used, for a total length of about 3h 30', 31523 tokens and 5980 turns. Transcripts present a specific tag for laugh (@w), and report the start and end time of the laugh (unless inserted in a longer context). The total number of laughter is 713, counting shared and solo laughter. In this study, we defined shared laughter situations in which at least two speakers overlap laughing. Table I reports the amount of laughter, both solo and shared, per speaker. For the lexical analysis, the transcripts have been processed using the Stanford PoS Tagger [18]. This corpus has been studied independently [9] and its transcripts have also provided data for analysis of repetition in dialog [17].

## IV. DISTRIBUTION OF LAUGHTER: TEMPORAL ANALYSIS

### A. Temporal distribution of Laughter

The first analysis is meant to answer (1), and characterize how laughter is distributed over topic boundaries. We examine the left (LTs) and right sides (TLs) of topic boundaries considering  $\mu(LT)$  and  $\mu(TL)$  (Fig. 2). As shown by Shapiro-Wilk test (p-value = 2.443e-15 and p-value = 1.624e-10),  $\mu(LT)$  and  $\mu(TL)$  are not normally distributed, hence the non-parametric wilcox test has been used for significance testing.

We notice that LLs tend to occur at a shorter temporal distance from the T-event, than FLs:  $\mu(LT) < \mu(TL)$ .<sup>9</sup> The temporal distance between the last laugh of a topic and topic boundary, is significantly shorter than the temporal distance between the topic boundary and the first laugh, and Fig. 5 shows this difference in distributions. The boxplot of the left shows the distribution of  $\mu(LT)$ , while the boxplot on the right shows the distribution of  $\mu(TL)$ . Although limited to this corpus, an interesting finding emerges: laughter is more likely as the temporal distance from the topic boundary increases. This does not mean that laughter can be considered a topic termination cue, however, knowing that laughter is more likely to appear immediately before than immediately after a topic boundary suggests that laughter do have some function in the discourse structure and this could be a useful information when trying to automatically detect topic boundaries (cf. [11]).

<sup>9</sup>One tail wilcox.test, mu=0, alternative less: p-value = 2.418e-11.

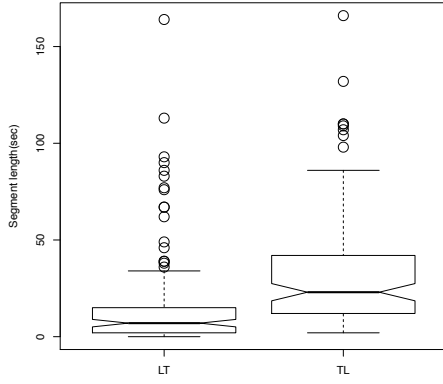


Fig. 5.  $\mu(LT)$  vs  $\mu(TL)$  comparison

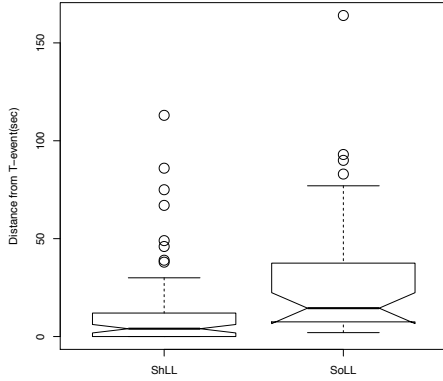


Fig. 6.  $\mu(ShLT)$  vs  $\mu(SoLT)$  comparison: SH laughs tend to occur in proximity of topic boundaries

### B. Shared Laughter and Topic Termination

Next we investigate whether shared laughter is related to topic termination in a stronger way than solo laughter, as in [4], and whether shared laughs contribute to development of topic termination sequences. Holt in [4] notes a clear distinction between shared laughter and solo laughter. According to her analysis, shared laughter is linked with topic termination: it cannot be considered as an independent topic-closing cue, but it may be a supplemental indicator of a topic closing when it occurs in a sequence that is already potentially termination relevant. In order to explore this statement in our corpus, we repeat the previous analysis of  $\mu(LT)$  vs  $\mu(TL)$ , distinguishing shared (SH) vs solo (SO) laugh. Since we are interested only in the topic termination section we focus on the topic boundary left neighborhood ( $\mu(LT)$ ). In Fig. 6 we can see the comparison between the  $\mu(SoLT)$  and  $\mu(ShLT)$ : while in the median distance between SH laughter and T-event is about 4 sec, the median distance between SO and T-event is about 13 sec. One tail Wilcox test confirms a statistically significance difference among the means ( $p$ -value =  $1.278e-06$ ).

SH laughter, rather than SO, tends to occur near a topic termination, and seems to fall in the time-frame that Schegloff defines *topic closing sequence* [14]. Thus, we can argue

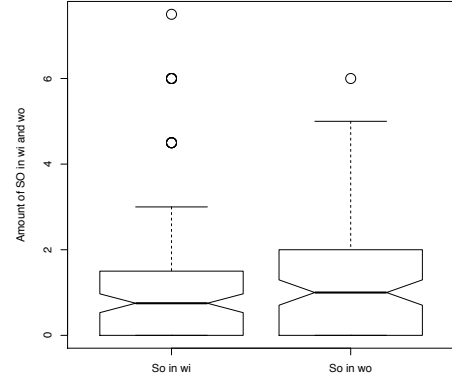


Fig. 7. SO Laughter distribution in *wi* and *wo* segments

(supporting Holt) that: given a topic termination, it is more likely to find a SH rather than a SO laughter in the topic closing sequence. Again, this does not mean that SH are sufficient to cue topic termination, but their presence can be a further indicator of a topic termination sequence.

### C. Solo Laughter and topic continuation

The second statement in Holt's analysis is the relation between solo laughter and topic continuation. Recalling the observation in [8], that laughter can invite reciprocal laughter, Holt interprets solo laughter as rejected invitations. She notices that those invitations are refused, when recipients want to add information and develop the topic. In order to investigate this, we analyze the distribution of solo laughter, exploring whether it is more likely to find a SO rather than a SH in relation with a topic continuation segment of the conversation. As mentioned in section II, we define *wi* and *wo* segments respectively topic continuation and topic transition segments. If solo laughs are related to topic continuation, we would expect more SO in topic continuation segments (*wi*) than in topic transition segments (*wo*); on the contrary, as shown in Fig. 7, we do not find a significant difference in the distribution of SO laughter among *wi* and *wo* sections (two tailed wilcox test  $p$ -value = 0.2805), where the left boxplot (distribution of SO in *wi*) and right boxplot (distribution of SO in *wo*) strongly overlap.

Moreover, we do not find any significant difference between the distribution of SH laughter and SO laughter with respect to this segmentation; our interpretation of this is that, wrt to our corpus, SH and SO can equally occur in the context of a topic continuation. Thus, there is no evidence of a particular relation SO laughter-topic continuation.

## V. LINGUISTIC CONTENT AND LAUGHTER DISTRIBUTION

In this section we address the second main focus of our study: quantitative analysis of the information content with respect to laughter and topic boundaries. We take LL and FL as milestones to determine our topic termination segments and topic beginning segments (LT and TL of Fig. 2). Since we are interested in investigating differences in information content at topic termination and topic beginning (when new information is added to conversation vs. when no information is added),

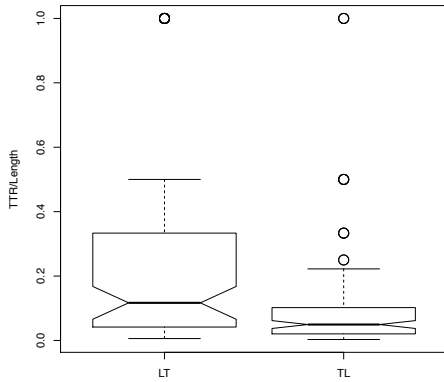


Fig. 8.  $\Lambda(LT)$  vs  $\Lambda(TL)$

we take into account the lexical variation index, using the type token ratio (TTR) measure, normalized over the length of the segment, as in (4) and (5). We calculate  $\Lambda()$  over LT and TL. This index yields a measure of the lexical variety of those conversation segments. Closed-class categories (function words) have not been taken into consideration; lexical variation has been calculated over nouns, verbs and adjectives.

Analyses result in two distributions: one showing the tendency of the lexical variety of all LT segments ( $\Lambda(LT)$ ) in the conversation (lexical variety at topic termination) and one showing the tendency of the lexical variety of all TL segments ( $\Lambda(TL)$ ), lexical variety at topic beginning. Comparing those distributions, we can notice a significant difference between  $\Lambda(LT)$  and  $\Lambda(TL)$ :  $\Lambda(LT)$  tends to be higher than  $\Lambda(TL)$ , with statistical significance.<sup>10</sup> Results are plotted in Fig. 8.

Surprisingly, segments of conversation representing topic termination sequences seem to have greater lexical variety than topic beginning segments. It seems counterintuitive for topic termination exchange segments to show higher lexical variety than topic beginning segments, although the latter introduce new topics (and accompanying terminology) into conversation.

Results are consistent with a finer analysis in which we investigated the lexical variety of ShLT, ShTL, SoLT and SoTL ( $\Lambda(ShLT), \Lambda(ShTL), \Lambda(SoLT), \Lambda(SoTL)$ ). In fact, it appears that all the topic termination segments (either introduced by a SH or by a SO) present more lexical variety than segments at topic beginning. Table II shows the alternative hypotheses (H1) accepted in one-tailed Wilcoxon tests, with corresponding  $p$ -values (ie.,  $H_0: \Lambda(LT) \leq \Lambda(TL)$ ). We propose two possible hypotheses that could illuminate this counterintuitive result.

The first hypothesis is related to the repetition phenomenon that occurs while the new topic is developing. As a new topic begins, the lexical alignment effect increases [22], since speakers tend to find, from the very beginning of a topic, a common lexicon; e.g, the excerpt in Fig. 9 represents the beginning of a topic in Table-Talk and, we can notice that each speaker is repeating the words *Kura* and *sushi*, establishing a common ground, before developing the topic. This alignment phenomenon influences the lexical variety results.

```

y after that we went to Kura sushi
y hum
n Kura sushi, yeah
d Kura sushi
y just to have fun with, for foreigners
  they know sushi train
n Kura sushi is a kind of tourist, yeah
y I know, I know yeah
n yeah
d hum
y but
d maa maa
y the Sushi train?
n Kame sushi in Osaka is lovely!

```

Fig. 9. Example of topic onset (*Kura Sushi*)

The second hypothesis focuses on the topic termination segment. According to Schegloff [14, p186], topic-closing sequences are complex sequences composed of three turns that shift the conversation to the new topic. We have already noticed, in line with [4], that shared laughter can have a discourse function in these topic-closing sequences; however, there may be also other functional elements of the conversation that play a role in those sequences and that increase lexical variety. In other words, it could be possible that in closing a topic, participants add to the content, linguistic and non-linguistic elements which drive the conversation to the new topic. Future investigation will explore those phenomena.

	Laugh-type	$\Lambda()$	P-Value
H1	Shared	$\Lambda(ShLT) > \Lambda(ShTL)$	p-value = 1.116e-08
H1	Solo	$\Lambda(SoLT) > \Lambda(SoTL)$	p-value = 0.04584

TABLE II  
ONE-TAILED WILCOX TESTS BETWEEN DIFFERENT  $\Lambda()$  DISTRIBUTIONS

## VI. CONCLUSIONS

In this study, we explored laughter and its functions in discourse with respect to topic changes from two points of view: temporal distribution and information content. In the former (questions (1) and (2) of §I), we were interested in understanding whether there is some sort of temporal relation between laughter and topic changes. In the latter (question (3) of §I), we were interested in understanding whether there was some sort of relation between laughter, topic changes and information flow: if there is a well-motivated measure of information content which is different when assessed between two sort of periods (topic termination and topic beginning).

With respect to (1), we show that there is a higher probability of finding laughter as the distance from the topic boundary increases. With respect to (2), shared laughter tends to occur as topic terminations approach, more than solo laughter. Therefore, although neither shared nor solo laughter are reliable indicators of topic termination in isolation, shared laughter, more than solo, can contribute (with other features) to what Schegloff defines a *topic-closing sequence*. We can

<sup>10</sup>One tail wilcoxon test, mu=0, alternative=g: p-value = 7.108e-06

conclude that laughter has, in this respect, a function in the discourse structure, a function that we believe, it is worth further investigation. In addition, we notice that solo laughter is equally distributed between topic continuation moments and topic transition moments; we do not find, in our corpus, a strong relation between solo laughter and topic continuation, contrary to the suggestion of [4].

With respect to (3), we found that lexical variety seems to differ consistently between the topic termination and topic beginning segments. However, it does not differ as expected: topic termination segments seems to have higher lexical variety than topic beginning segments. Two suggestions have been suggested in §V in order to explain this interesting phenomenon, and further investigation will explore those hypotheses. Further developments will also tackle the content distribution analysis using different lexical measures, and will develop the temporal distribution analysis with a survival analysis approach. We must also analyze other corpora, investigating how different sorts of laughter may have different discourse functions, merging linguistic and prosodic approaches.

Our work is at the intersection of the theories of communication and informatics, approaching social interactions as the integration of different dimensions (linguistic content and social interaction). Understanding the functional role of laughter in discourse structure requires such integration. Laughter is a communicative social signal in human to human communication behaviors. We have argued that our analysis of the role and timing of laughter, sensitive to speech science and linguistic content analysis, may have interdisciplinary application in, for example, enhancing automatic topic segmentation for dialog (thereby enhancing augmented social intelligence within dialog systems) by providing additional filters on candidate topic change points on the basis of behavioral effects identified. Interdisciplinary applications provide additional impetus to pursue this interdisciplinary theoretical exploration.

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