Comparing Methods for Segmenting Elementary Discourse Units in a French Conversational Corpus

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Abstract

While discourse parsing has made considerable progress in recent years, discourse segmentation of conversational speech remains a difficult issue. In this paper, we exploit a French data set that has been manually segmented into discourse units to compare two approaches to discourse segmentation: fine-tuning existing systems on manual segmentation vs. using hand-crafted labelling rules to develop a weakly supervised segmenter. Our results show that both approaches yield similar performance in terms of f-score while data programming requires less manual annotation work. In a second experiment we play with the amount of training data used for fine-tuning systems and show that a small amount of hand labelled data is enough to obtain good results (although significantly lower than in the first experiment using all the annotated data available).

1 Introduction

While segmentation of written documents has received a lot of attention from the discourse and NLP community, this is less true for segmentation of conversational speech. Conversational data has mostly been approached from either (i) a dialogue act segmentation and tagging perspective, and usually on rather task-oriented dialogues (Dang et al., 2020) or (ii) punctuation prediction to enrich transcripts obtained with Automatic Speech Recognition (Batista et al., 2012).

We assume that this situation encourages a bias toward written genres that can be very problematic for discourse segmentation, because those genres (newspapers, literature,...) tend to include long complex sentences, while actual conversations are made of rather short contributions. Non-sentential units (Fernández et al., 2007), which often consist of only a single word, are extremely frequent in conversation, and they can convey full communicative acts, such as an answer to a question or a communicative feedback, that are crucial for modelling discourse structure.

In this paper we benefit from a fully segmented corpus, the Corpus of Interactional Data (CID; Blache et al., 2017), for running a set of experiments on discourse segmentation. This data set is challenging in term of discourse segmentation since it is made of 8 long conversations (1 hour each) alternating between interactive narrative sequences like (1) (with a clear dominant speaker holding long turns made of many discourse units) and more dialogical sequences like (2) (made of very short, very often incomplete, turns that sometimes need to be grouped together to form a valid discourse unit). In this work, we use the term *elementary discourse unit* (EDU; Asher and Lascarides, 2003) to designate a minimal speech act or communicative unit whose meaning corresponds to a single fact or event.

(1) [on y va avec des copains]$_{du}$ [on avait pris le ferry en Normandie]$_{du}$ [puisque j'avais un frère qui était en Normandie]$_{du}$ [on traverse]$_{du}$[1]
[we went there with friends]$_{du}$ [we took the ferry in Normandy.]$_{du}$ [since I had a brother who was in Normandy]$_{du}$ [we cross]$_{du}$

(2) A : tu vois à peut près où ///c'est///[2]
you know more or less where ///it is///

[1] Color alternation is used to highlight discourse units.

[2] ///***/// indicates overlapping speech.

B: ///oui///
///yes///
A: ouais
yeah

EDUs have became a central topic for Discourse Parsing (Zeldes et al., 2019a), and in this paper, we present two main experiments designed to (i) compare EDU segmentation approaches on our challenging data set and (ii) evaluate the impact of the amount of hand labelled data used for the training. More precisely we first compare the results of several baselines with (i) *state-of-the-art* level segmentation systems fine-tuned on CID with (ii) a weakly supervised approach bootstrapped by hand crafted labelling functions. Our second experiment consists in varying the amount of hand-labeled data used either for training the base model from scratch or for fine-tuning an existing written text segmenter.

2 Previous and Related work

2.1 Discourse Segmentation

Discourse segmentation had been largely neglected by work in discourse parsing, and mostly applied to English corpora (Wang et al., 2018), until a few years ago when the multilingual, multi-framework `disrpt` campaigns were introduced (Zeldes et al., 2019b, 2021a). The present paper relies heavily on the French model, ToNy (Muller et al., 2019), from those campaigns. Built on the Allen NLP library (Gardner et al., 2018), ToNy is a sequential model over contextual embeddings, namely multilingual BERT (Devlin et al., 2018), that treats segmentation as a token classification problem where each token is either a beginning of a segment or not.

While the best segmenter overall on `disrpt` tasks is currently Gessler et al. (2021), this segmenter requires syntactic parsing which is not very reliable for highly spontaneous conversational speech of the kind in CID. Moreover, for the sake of our experiment, simple pipelines (based on plain text for ToNy) are preferable to more sophisticated ones. Finally, if we restrict our focus to French, ToNy is still on par with the best performing model (Bakshi and Sharma, 2021). See (Zeldes et al., 2021b) for details on the performances of existing systems.

Gravellier et al. (2021) adapted ToNy to conversational data by (i) fine-tuning it on a conversational data set and (ii) adopting a data-programming approach similar to what we propose here. However, the transcriptions used in their work were obtained from a recording setting with a unique microphone. In CID, each participant is recorded on a separate channel, and the transcription of the corpus was fully manual and even corrected several times to reach very high transcription accuracy for a conversational corpus. Moreover, only a small portion of the corpus used by Gravellier et al. (2021) contains gold EDU segmentation ($\approx$ 1100 units), as this corpus was segmented to train a weakly supervised labelling model guided by hand-crafted labelling rules. The present work is grounded on a completely different data set, CID (Blache et al., 2009), that has been fully manually segmented. This corpus provides over 17000 discourse units to experiment with. This allows us to evaluate the quantity of supervised data that is needed to equal or improve performance over the weakly supervised model.

2.2 Weak supervision

For the weak supervision part of our experiments, we rely on the so-called "data programming" approach proposed by Ratner et al. (2017). The general principle is to design multiple overlapping heuristic rules for a classification problem, to produce noisy annotations that can be aggregated statistically to automatically label unannotated data that can then be fed to a supervised model. This approach has been implemented in the Snorkel library[3] and also independently adapted in the framework of Lison et al. (2021). The same approach has been used in discourse analysis to enrich a discourse parser (Badene et al., 2019), and is also the basis of the work in Gravellier et al. (2021) mentioned above.

3 Data

The Corpus of Interactional Data (CID) (8 dyadic conversations, 1 hour each) (Blache et al., 2009, 2017) was segmented follow-

[3] `https://www.snorkel.org/`

ing guidelines designed for written documents (Muller et al., 2012) that were modified for spoken conversational data. These guidelines thus combine semantic and discourse criteria (used in particular in monological sequences like (1)) with dialogical and interactional ones (that are more useful in dialogical sequences like (2)). The CID displays highly spontaneous data with colloquial sequences like (3) or strong disfluencies like (4) making discourse segmentation a much more difficult task than on written genres, even for humans. The whole data set is made of 15,463 discourse units resulting from at least two manual annotations (obtained from 4 naive coders and 2 experts). The mean Cohen's κ-score across speaker for naive coders is 0.85 (min: 0.83 ; max :0.87). Annotations were performed with Praat (Boersma, 2002) in order to have access to signal word-alignment when making segmentation decisions. The discourse annotations will be made available from an institutional data repository after reviewing period.

(3) A: [comme ça # ah ouais non c'était]$_{du}$
A: [like that # oh yeah no it was]$_{du}$
B: [ah ouais profitez profitez de vos soirées]$_{du}$
B: [oh yeah enjoy enjoy your evenings]$_{du}$
A: [ouais c'est pour ça]$_{du}$
A: [yeah that's for that]$_{du}$

(4) [ou des euh non pas des f- pas des frustrations]$_{du}$ [des # espèces de euh # mhm # ouais des des vues différentes sur le boulot quoi]$_{du}$
[or some uh no not some f- not some frustrations]$_{du}$ [some kind of uh # mh # yeah some some different views about work what]$_{du}$

4 Method

In this work we use the existing implementation of ToNy (Muller et al., 2019) and of Gravellier et al. (2021), called `tony-w(ritten)` and `tony-s(poken)`, respectively, as baselines. Our first experiment consists in comparing a supervised model (fine-tuning 'ToNy' baselines with our annotated data) against the weakly supervised data-programming approach. In a second experiment, we explore the impact of the amount of data used for fine-tuning the models.

In all our experiments, pauses over 200 ms were used to generate commas in the transcript transmitted to baseline models in order to help these systems trained on textual data and written genres. The idea behind such a short pause duration is that pauses signal places in which a discourse segmentation is likely to happen. The systems then try to distinguish the pauses corresponding to discourse breaks from the other ones.

4.1 Fine Tuning

Fine tuning both `tony-w` and `tony-s` was done in the same way: we continued to train the original model with the same configuration but with CID labelled data. We conducted a cross-validation experiment in which 7 conversations – 7 hours– are used for fine-tuning both models and tested on the remaining eighth conversation, and performed a permutation to obtain a cross-validation.

4.2 Data-Programming

Snorkel, a data programming paradigm, provides a weakly supervised learning framework based on heuristics rules. The general idea is to leverage expert knowledge by writing a set of labeling functions (*LF*) that can be developed and tested over a very small amount of annotated development data. The system builds a profile for each (*LF*) and a model is trained by combining all *LFs* (LFs being weighted by their accuracies). This model is then used for labeling a training set and finally a supervised model is trained on the dataset that had been annotated by the label model.

Writing hand-crafted rules (i.e the labelling functions) for the data programming approach was based on our linguistic knowledge of conversational French. Compared to (Gravellier et al., 2021), the data sets and the preprocessing not being the same, different options were offered while writing the rules. For example, (Gravellier et al., 2021) attempted to use rules exploiting more prosodic and acoustic information while our approach is based solely on time-aligned (at token level) transcription, NLP

annotations (POS-tagging) and durations (in particular pause durations). Moreover we used a different POS-tagger in this experiment. While (Gravellier et al., 2021) relied on Spacy (Honnibal and Montani, 2017) we used Stanza (Qi et al., 2020) since it offers a 'spoken' model for French which proved to be more reliable than Spacy for tagging crucial tokens specific to conversational speech. Tony base models (not fine-tuned on conversations) are used as LF among others in order to build a hybrid label model.

Table 1 presents the most important labeling functions (LF) retained after various experiments on the development set. The columns of this table are the ones produced by the *Labeling Function Analysis* function provided by snorkel: *Polarity* states whether the LF labels a break or an absence of a break; *Coverage* corresponds to the percentage of instances for which the LF was triggered; *Overlaps* quantifies the proportion of times other LFs are firing at same time as a given LF; *Conflict* quantifies whether any other LFs predict a different label; *Correct/Incorrect* is the amount of correct/incorrect labels based on the reference data set and this also defines Accuracy. Unsurprisingly `tony` is a crucial part of information for segmenting. Other important rules were based on pause durations (e.g. `long_pause` in Figure 1), POS and token lists (being identified as either cues for starting/ending –or not starting/ending– discourse units. For example, NON ENDING TOKENS included various pronouns, determiners, prepositions, negations and initiating discourse markers (See full list in **Appendix**). Most of the selected rules that involved tokens and POS use pauses as additional criteria `pause_ending_pos`). The rules `repeat`, `filled_pause` and `truncated_word` target disfluencies since the annotating guidelines specifically say that they do not constitute EDU boundaries. Finally `feedback_cluster` target sequence of acknowledgement tokens that generally constitute a single EDU *(e.g ah ouais d'accord/ oh yeah right)*.

4.3 Amount of labeled data

We experimented on varying the amount of labeled data used to train the supervised model (10, 20, 30, 50 or 80%). This was done either as fine-tuning of `tony-w (ft)` or as direct training from the base model (`no-model`) which is a simple BERT model in our case.

5 Results and Discussion

5.1 Fine-tuning vs. Data programming

The results of the baselines, fine-tuning and the data-programming approach constitute a global coherent picture. Tony baselines show a high recall (Figure 2) but with a relatively low precision (Figure 3). `tony-spoken` starts out significantly worse than `tony-written`. This is probably due to (i) the relative low quality of the transcriptions used for training `tony-spoken` and perhaps the nature of our data which is conversational but hosts a significant amount of narrative sequences.

The baselines based on pause durations only (we show here pause baselines at 200ms and 500ms) exhibits a surprisingly high precision, showing the relevance of using this cue as a signal for discourse units. They do miss quite a few cases but overall perform well (specially with a threshold set-up at 200ms). The missing boundaries are discourse units not separated by any pauses, like in (1) for example.

Fine-tuning really helps `tony` models: recall remains high and precision increases significantly (Figure 4). Fine-tuning allows the model to distinguish which commas (pauses) do not introduce discourse segments.

The comparison of f-scores (Figure 4) of fine-tuning and data-programming approaches does not yield significant differences. It seems to validate the interest of the weakly supervised data programming approach since writing the labeling rules represents much less effort than manually segmenting a large amount of corpus.

5.2 Amount of hand labeled data

In the previous experiment, data programming appears to be more efficient that fine-tuning on manually annotated data due to the prohibitive annotation cost. We continued our experiments by trying to use

name	Polarity	Coverage	Overlaps	Conflict	Correct	Incorrect	Accuracy
tony_written	0,1	1.000	0.976	0.0632	102446	8994	0.919
no_pause	0	0.898	0.898	0.0474	94706	5415	0.946
long_pause	1	0.054	0.054	0.0094	5353	683	0.887
very_long_pause	1	0.032	0.032	0.0051	3399	162	0.955
extreme_pause	1	0.022	0.022	0.0037	2357	48	0.980
pause_begin_pos	1	0.042	0.042	0.0101	4362	328	0.930
pause_ending_pos	1	0.036	0.036	0.0097	3338	652	0.837
non_ending_tok	0	0.323	0.323	0.0009	35579	365	0.990
pause_begin_tok	1	0.055	0.055	0.0111	5533	617	0.900
pause_ending_tok	1	0.005	0.005	0.0005	550	22	0.962
dm_bi_ini	1	0.012	0.012	0.0059	1146	222	0.838
non_begin_tok	0	0.005	0.005	0.0001	530	9	0.983
feedback_cluster	0	0.026	0.026	0.0012	2763	87	0.969
repeat	0	0.088	0.088	0.0124	8678	1141	0.884
filled_pause	0	0.071	0.071	0.0055	7428	570	0.929
truncated_word	0	0.016	0.016	0.0013	1629	169	0.906

Table 1: Labelling Function Description

less annotated data for training the models in order to check whether performance will decrease strongly if only a small amount of annotated data is provided.

The results presented in figure 5 suggest that even if more data is better, a small amount of training data (here 10% corresponds to about 1500 discourse units which is still a significant annotation effort) is enough to really improve the base model. This result mitigates the previous finding: since efficiently fine-tuning existing models does not seem to require annotating a lot of data, the difference in terms of efficiency between hand-labeling and developing a set of labeling functions is not huge, suggesting that both approaches are worth exploring depending on the use case.

5.3 Error Analysis

Error analysis of both data programming and the fine-tuned models yields interesting observations. As expected, phenomena that are really specific to conversational speech are the main sources of errors. For example *'quoi'* / *'what'* is a very common French function word that is heavily used in final position in conversational speech (with a rather unclear function) (Delafontaine, 2020). This item was a major source of errors.

Another source of errors were the relative clauses anchored on extremely light hosts and having a restrictive function like in (5). The data-programming version tended to segment on relative pronouns whether they introduced restrictive or non-restrictive clauses, which generated some over-segmentation.

(5) [genre des gens || qui étaient au même niveau que moi]$_{du}$
[like people || that were at the same level as me]$_{du}$[4]

Another important source of errors are complex disfluencies that involved discourse markers like (6).

(6) [mais là # || mais euh || mais là c' est normal]$_{du}$
[but in that case ||# but uh || but in that case it is normal]$_{du}$

The fine-tuned model also introduced different errors. It did not segment on some discourse marker cues like *'mais'* / *'but'* and *'si'*. It does not seem to trust them enough as initiators of discourse units.

A second source or error for this model is the repetition of presentative constructions *'c'est* / *it is'* of which an extreme example is given in (7).

(7) [non c' est plus de la recherche]$_{du}$ $$ [c' est de la c' est de la # c' est # a-]$_{du}$ # [ouais voilà]$_{du}$ # [c' est de la t- c- c' est]$_{du}$ $$ # [co- comment ça

[4] In the error analysis examples, || stands for a false positive (added a boundary in a wrong place) and $$ for false negative (missed a boundary).

```
@labelling_function()
def long_pause(x):
    return BEG if (x["prev-tok"]=='#' and x['prev_dur'] > LONG_PAUSE) else ABSTAIN

@labelling_function()
def non_ending_tok(x):
    return NOBEG if x["prev-tok"] in NON_ENDING else ABSTAIN

@labelling_function()
def pause_and_ending_pos(x):
    if ((x["prev-tok"]=='#') and (x["prev_dur"] > PAUSE)
            and (x["pprev-pos"] in ENDING_POS)):
        return BEG
    else:
        return ABSTAIN

@labelling_function()
def repeat(x):
    return NOBEG if x["tok"] in [x["prev-tok"],x["pprev-tok"],x['ppprev-tok']]
                                                  else ABSTAIN

@labelling_function()
def filled_pause(x):
    return NOBEG if ((x["prev-tok"] in FP) or (x["tok"] in FP))  else ABSTAIN

@labelling_function()
def truncated_word(x):
    if (str(x["prev-tok"])[-1]=='-'):
        return NOBEG
    elif ((str(x["pprev-tok"])[-1]=='-') and (x["prev-tok"] in [',','*','euh'])):
        return NOBEG
    else:
        return ABSTAIN
```

Figure 1: Labeling Function examples

s' appelle]$_{du}$ $$ [c' est de la # || de la capitalisation]$_{du}$
[no it is not research anymore]$_{du}$ $$ [it is some is is some # it is # a-]$_{du}$ # [yeah that's right]$_{du}$ [# it is some t- c- it is h-]$_{du}$ # [how do you call it]$_{du}$ $$ [it is some # some capitalisation]$_{du}$

There are a wide range of other errors represented, even though they are less frequent. They included (i) long pauses (>1s) that did not split a discourse unit (we had a preprocessing step that did not allow for considering EDU split by very long pauses); (ii) dialogical structures (involving both speakers) that are currently not handled; (iii) reported speech (that was systemically segmented in the manual annotation even if sometimes the reported speech introduction was extremely light in content).

In the corpus we are working with, there are two kinds of sequences: (i) narrative sequences in which one of the participants tells a story (with an interactive flavor involving feedback and production from the other participant but in which there is a clear main speaker and a narrative flow), and (ii) transition se-

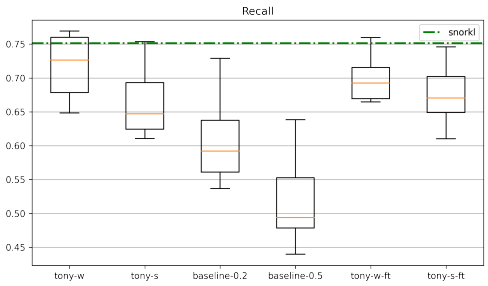

Figure 2: Boundary recall for various configurations; green dashed line = Data-programming

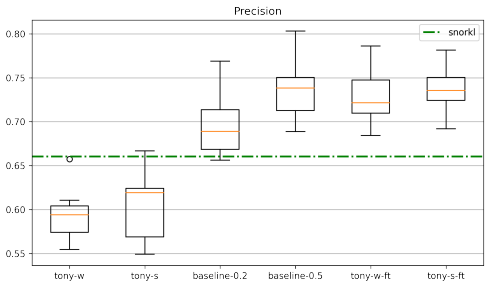

Figure 3: Boundary Precision for various configurations, green dashed line = Data-programming

quences where the participants comment and chat about these stories, as well as negotiate who will tell the next story and what it will be about. As expected, narrative sequences are better handled by our models, even when produced at a relatively fast pace that did not allow for pauses between discourse units like (8) which is the continuation of our example (1) and in which there is not any pause (longer than 200 ms) but several discourse units.

(8) [on y va avec des copains]$_{du}$ [on avait pris le ferry en Normandie]$_{du}$ [puisque j' avais un frère qui était en Normandie]$_{du}$ [on traverse]$_{du}$ [on avait passé une nuit épouvantable sur le ferry]$_{du}$

–

[we went there with friends]$_{du}$ [we took the ferry in Normandy.]$_{du}$ [since I had a brother who was in Normandy]$_{du}$ [we cross]$_{du}$ [we spent a terrible night on the ferry]$_{du}$

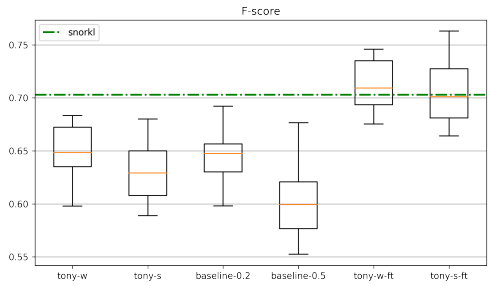

Figure 4: Boundary F-score; green dashed line = Data-programming

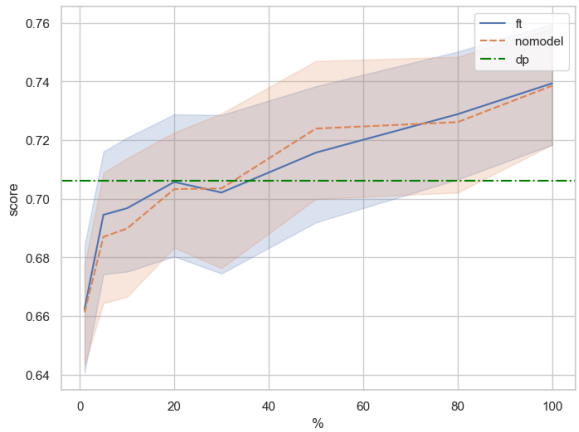

Figure 5: F-score for the supervised models trained on 1,5,10,20,30,50,80% of the original training data set (nomodel: just BERT, ft: fine-tuned). We also indicate the score of the data programming model (dp). Bands are 95% confidence interval based on the cross-validation.

However, even in narrative sequences some common spoken constructions seem to cause problem to the models like presentatives *y a / y avait* (Lambrecht, 1988) in (9).

(9) [on est rentré dans un bar # qui faisait boîte]$_{du}$ $$ [y avait # que nous]$_{du}$ # $$ [y avait la musique # à fond les ballons]$_{du}$

–

[we entered in a bar # that was also a nightclub]$_{du}$ $$ [there were # only us]$_{du}$ # $$ [there was music # extremely loud]$_{du}$

6 Conclusion and Discussion

In this work we have compared different approaches for building a discourse unit segmenter adapted to French conversations. We had access to a manually segmented corpus of significant size which allowed us to perform a wide range of experiments. First we compared the option of (i) fine-tuning on our conversational data set an existing discourse segmenter developed and trained for written data, (ii) a data-programming approach that makes use of the same "text-based" discourse segmenter but enriched with manual rules (Labeling Functions). We found that both approaches yielded similar results. This suggests that both approaches are worth considering depending on the exact use case. While data-programming requires some heuristic rules engineering, fine-tuning requires annotated data that is costly to obtain, especially for relatively expert tasks such as discourse segmentation. We then ran a second experiment to investigate (i) how much manually annotated data is required before reaching the same performance as the data-programming approach; (ii) whether starting from a written base segmentation model was useful at all (compared to training the segmenter directly over the BERT pretrained language model). To the first question, it is striking to observe that, given the important variability between folds, only a small amount of annotated data ($\sim 20\%$) is sufficient to get close to the best results we obtained. Moreover, starting from a written discourse segmenter model or directly from BERT did not change significantly the results. To conclude about the strategy to select: our findings suggest that annotating (segmenting) large amount of conversation might not be necessary since both the data-programming approach (that makes use of existing discourse segmenter developed on written data) and training a model with not so much data (here about 2700 discourse units to reach very results) yielded comparable results as our model fined-tuned on our whole training set (13500 discourse units).

We recap now on which aspects these different models are good and where they fail. Comparing to the pause baselines, the fine-tuned model and the weakly supervised one, we can see that the pause baselines are missing boundaries. While pauses are strong predictors (rather high precision for a baseline), many discourse units are not preceded by a pause. Both models seem to easily learn how to segment within "fluent monologues" (even without pauses). Probably, the existing discourse segmenter and the relevant language model helps a lot. However, when speech becomes strongly disfluent,[5] in particular when disfluency gets tangled up with discourse markers that typically signal discourse segment starts, both approaches are struggling. Finally, some constructions like presentatives, frequent in conversational language but absent from written data are also an issue. Overall while the models are definitely useful as discourse segmenters, their scores are way below the state-of-the-art obtained on written text. Beside the fact that the task might be more difficult, the underlying "written-biased" language model could be a reason why all our models remain relatively confused when facing token sequences found only in conversational data sets, despite the fine-tuning or our attempt at adding heuristic specific rules.

As future work, we plan to refine our experiments by separating discourse units into two categories: easy and difficult to segment. Indeed, in conversation, a sizeable amount of discourse units are trivial to segment (e.g a lexical feedback item preceded and followed by very long pauses) while some other as we have seen in error analysis are really complex to delineate. Our opinion is that separating these two cases at all stages (including inter-coder agreement measures) will allow us to learn more about discourse segmentation of conversation and ultimately help in developing better performing models.

Ethics Statement

This paper does not process any sensitive material and does not generate any content. It does not raise any ethical issues.

[5] Both approaches seem to overcome simple disfluency like the presence a filled pause and / or a content word repetition, relatively well.

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A Useful token list for Labelling Functions

- BEGIN_TOK = DM_INI + PRO_SUJ + FEEDBACK
- ENDING_TOK = quoi,hein
- NON_ENDING_TOK = PRO_SUB + PRO_OTH + PRO_REL + DEM + DET + PREP + OTHER + NEG + DM_INI

with the following lists:

- PRO_SUB = je, tu, il, vous, on, nous, elle, ils, elles, j',c',t',y
- PRO_OTH = me, te, se, mes, tes, ses, mon, ton, son, ma, ta, sa, nos, vos , leur ,ceux
- PRO_REL = qu', que, qui, quel
- DEM = ce, cette, ces, cet
- DET = le, la, les, un, une, des , l', d'
- PREP = à, de, par, pour, en, dans, chez, sur, sous, pendant, avec
- OTHER = soit, juste, pendant, surtout, chaque, quelque, quelques, sauf
- NEG = n', ne
- DM_INI = mais, donc, parce, ah, alors, c'est-à-dire, puisque, bah
- FEEDBACK = mh, ouais, ah, oui, bon, voilà, putain,oh, okay,ok,euh,ben,et,d'accord, non

B Part-of-Speech list for Labelling Functions

- NON_ENDING_POS = DET, CCONJ, SCONJ, ADP
- ENDING_POS = INTJ
- BEGINNING_POS = INTJ, CCONJ, SCONJ
- NON_BEGINNING_POS = VERB, AUX
- NO_RULES = ADJ, NOUN, ADV, NUM, PROPN, X