An Empirical Study of Topic Transition in Dialogue

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Abstract

Although topic transition has been studied in dialogue for decades, only a handful of corpora based quantitative studies have been conducted to investigate the nature of topic transitions. Towards this end, this study annotates 215 conversations from the switchboard corpus, perform quantitative analysis and finds that 1) longer conversations consist of more topic transitions, 2) topic transition are usually lead by one participant and 3) we found no pattern in time series progression of topic transition. We also model topic transition with a precision of 91%.

1 Introduction

Human conversation consists of multiple natural topic transitions, from introductions, to topics of interest, and on to leave talking, and thus relies on topic change and shading mechanisms to allow participants to maintain and change topics. An example of topic transition can be seen in Figure 1, participants first begin by talking about each other’s age, then move on to the places they want to visit and finally move on to talking about the state of Arizona in the USA. Although topic transition has been studied in linguistics for decades (Gardner, 1984; Lambrecht, 1996; Riou, 2015; Van Dijk, 1977a), there are only a few corpora based studies investigating the nature of topic change. This is because of the labour intensive task of manually annotating datasets. Even though the task of annotation is labour intensive and manual, it is necessary to empirically understand how human participants engage in topic transition in a conversation.

Towards this end, this work annotates 215 conversations from the Switchboard (Godfrey and Holliman, 1993) corpus and studies different aspects of topic transition. To the authors best knowledge, this is the the largest quantitative study conducted on the nature of topic transition in social conversations till date. The dataset curated and code utilized can be found at 2.

2 Background Theory

Definitions of topic in the literature fall into two categories; sentence level (Lambrecht, 1996) and discourse level (Van Dijk, 1977a). Gardner (1984) emphasizes the presence and identification of a topic to be a intuitive phenomenon answering the question of ‘being about’. Multiple Sentence-level topics about the same thing may consist of a discourse-level topic (Van Dijk, 1977b). As this study is concerned with discourse level topic annotation, we adopt the definition of Bonin et al. (2012) which maintains that topic at a discourse level is the "segments of the discourse sharing coherent information (about the same thing)".

Topic transition has been categorized by Gardner (1984), whose model of topic development in
spoken interaction details the multiple means by which humans introduce, maintain, and change topics. Two areas which have received particular attention in the literature are topic change and topic shift. They have been defined as the point between two pieces of discourse which are considered to have different topics. Bublitz (1988) differentiates between topic change and topic shift as having low and high degrees of connectivity respectively to the previous topic. Topic shift includes both topic shading and topic fading (Maynard, 2009; Brown and Yule, 1983; Garcia and Joanette, 1997). Topic change includes reintroduction and full blown change. We annotate all such topic transitions under one common label.

3 Related Work

Related work in the literature is primarily found in the domains of manual topic annotation and automatic topic segmentation.

3.1 Manual Annotation or Segmentation

Early work to manually annotate topic transition was mainly done for the purpose of conversation analysis. Planalp and Tracy (1980) were among the first to annotate topic transition. They showed that information integration by the interlocutors impacts their topic transition strategies. Crow (1983)'s analysis of topic shift in couples’ conversations showed that it occurred fairly frequently; every 48 seconds on average. Later work by Ries (2001) showed that speaker initiative and style can also be indicative of topic transition. Recently, Konigari et al. (2021) annotated a subset of the switchboard corpus (Godfrey and Holliman, 1993) into major, minor and other topics. Sevegnani et al. (2021) introduced a one-turn topic transition corpus by asking annotators to produce bridging sentence connecting two sentences of different topics.

3.2 Automatic Segmentation

There have been many studies to segment text based on topic or detect topic transitions. Unsupervised methods utilize annotated topic transition dataset for testing the algorithms while supervised methods train and test an algorithms on an annotated dataset. Our annotated dataset will be useful in both approaches. A detailed overview of early work is provided by Purver et al. (2011). Among the earliest relevant works is that of Reynar (1994) who proposed a method of identifying topic boundaries based on lexical cohesion and dot plots. Hearst (1997) developed an unsupervised method to separate texts into multiple paragraphs representing subtopics. Passonneau and Litman (1997) developed two algorithms that use utterance features to segment dialogue by topic. Boufaden et al. (2001) used Hidden Markov Models to segment transcriptions of telephone conversations into topics. Galley et al. (2003) tackled the difficult problem of topic segmentation in multiparty speech by focusing on the content of the transcripts and their form, i.e. the linguistic cues in the speech. Hsueh et al. (2006) built on the work of Galley et al. (2003) by combining Automatic Speech Recognition (ASR) with existing text based methods of topic segmentation. Arguello and Rosé (2006) also adopted a hybrid approach by combining linguistic features with local context indicators in the text. Sapru and Bourlard (2014) demonstrated that latent topic features are effective predictors of topic transition in transcripts of multiparty speech from office meetings. Joty et al. (2011) developed a supervised method of segmenting topic in email conversations. More recently, Zhang and Zhou (2019) introduced a method based on BERT and Temporal Convolution Network (TCN). Xing and Carenini (2021) introduced an unsupervised method for topical segmentation of dialog by utterance-pair scoring. There are other relevant techniques and we skip them in the interest of brevity.

4 The Annotation Framework

We annotate 215 conversations from the Switchboard-1 Release 2 corpus (Godfrey and Holliman, 1993). Annotations are based on previous studies demonstrating that naive annotators are capable of annotating topic transition with success. (Mann et al., 1977; Passonneau and Litman, 1997; Planalp and Tracy, 1980).

Switchboard Corpus The Switchboard-1 Release 2 Corpus consists of recordings of about 2400 telephone conversations between 543 distinct speakers who did not know each other (Calhoun et al., 2010). All interlocutors spoke American English. They choose a topic from a list of about 70 topics and were connected to another interlocutor by a switchboard robot. About 50 of the 70 topics were chosen regularly. The conversation is not limited to the initial topic and participants could transition topics at any time. The individual conversation transcripts have been transcribed and
annotated to the utterance level and include conversation IDs, time stamps, and label for speakers identity.

**Annotation Framework** 215 conversations were drawn at random from the switchboard corpus are annotated at sentence-level. The annotation were performed for start (S) and end (E) of the conversation, greeting and leave taking (GIL), topic, topic transition (C), and failed topic transition (X). Detailed annotation guidelines can be seen in appendix D. This manually annotated corpus consists of 20,566 turns from 215 conversation.

The average number of turns per conversation is 96 with the shortest conversation lasting 33 turns and the longest conversation lasting 242 turns. Mean turns per conversation were found to be 8 and mean turns per topic were observed to be 12. The conversations were annotated by two annotators. The inter-annotator agreement (Cohen’s Kappa) obtained on a sample of five conversations is 0.64, signifying substantial agreement.

## 5 Empirical Studies of Topic Transitions

Having obtained an annotated corpus of 215 corpus, we conducted quantitative analysis on some aspects nature of topic change. The empirical findings are discussed in the subsections below.

![Figure 2: Scatter plot of number of topic transitions and length of conversations](image)

### Length of A Conversation and Number of Topic Transitions

Longer conversation are a sign of successful and engaging conversation. We wanted to examine if longer conversation consist of more topic transitions than shorter conversation or the number of topic transitions remains similar and some topics are conversed for more turns than others. Towards investigating this relationship, we calculate number of topic transitions per conversation and plot it in Figure 2. The value of Pearson correlation coefficient is found to be 0.74, indicating a positive correlation between length of a conversation and number of topic transitions. We also plot a linear regression line and observe a $R^2$ value of 0.55 ($p << 0.001$). Figure 2 further highlights that number of topic transitions increase as length of a conversation increases. Most conversations consist of five to thirteen topic transitions. Thus, it is observed that longer conversations have more topic transitions.

### Share of Topic Transition by Participants

We wanted to explore further if the topic transitions are carried out evenly by both participant or if, one participant carries out more topic transitions. To investigate this, we first calculate the difference in number of topic transitions carried out by each participant for each conversation. We observe that only about 38% of conversations had an equal or only one more topic transition than the other per participant. In about 62% of conversations, one participant initiated at least two more topic transition than the other. It is thus observed that topic transitions are unequally carried out between participants ($\chi^2 = 403.41, p << 0.005$).

### Time Series Analysis of Topic transition

Next, the study investigate the distribution of utterances per topic as the conversation progresses. Mean and standard deviation of turns/topic is computed for all conversations. It is observed that standard deviation from mean of number of utterances is significant for all topics within a conversation. Hence, we use median to construct a line chart as median is a better measure of central tendency when there are outliers. The correlation between topic time series and number of utterances is observed to be 0.21 signifying only a weak correlation. Figure 3 shows a line plot of the number of turns per topic across the manually annotated dataset. Thus, this study did not find any pattern topic transition time series and number of utterances ($\chi^2 = 11.27, p = 0.98$).

## 6 Modelling Topic Transition

In addition to the empirical studies performed, we also modelled topic transition on the manually annotated switchboard corpus, described in section 4. Before describing the modelling in detail, we briefly describe the approaches to model topic transition in literature.
Approaches to topical segmentation in dialogue include unsupervised and supervised methods. Unsupervised algorithm work on finding similarity or dissimilarity between segments of text. TextTiling (Hearst, 1997) is a seminal work in unsupervised topic segmentation. Supervised approaches work with hand-crafted features or deep learning-based methods such as used (Arguello and Rosé, 2006; Xing and Carenini, 2021; Konigari et al., 2021).

Following the related research work, we formulate topic transition turn detection as a binary classification problem. We implement TextTiling (Hearst, 1997) as a baseline and then proceed to implement classical machine learning as well as deep learning-based classification algorithms.

Since, dialogue is inherently context-based *i.e.* the next utterance is influenced by previous utterances and a topic can span across multiple turns, consecutive utterances are grouped by speaker and termed *turn*.

TextTiling (Hearst, 1997) is implemented (employing the code from NLTK (Bird et al., 2009)).

| Model          | Precision | Recall | F1  |
|----------------|-----------|--------|-----|
| Naive Bayes    | 0.55      | 0.57   | 0.40|
| LightGBM       | 0.91      | 0.50   | 0.46|
| TextTiling     | 0.58      | 0.59   | 0.58|
| XLNet-base     | 0.68      | 0.61   | 0.62|

Table 1: Evaluation scores for various algorithms on test set

Results and Error Analysis

Results in Table 1 show that turns where topic transitions occur can be differentiated from turns where topics are continued. Evaluation is performed on a test set which is a subset of annotated switchboard corpus (described in section 4.2). It is observed from this study that TextTiling (Hearst, 1997) is more suitable for expository text since it works with lexical cohesion and requires input text to be in paragraphs, which is a property of expository text and not necessarily of a text conversation. Previous studies Konigari et al. (2021) have also demonstrated that TextTiling (Hearst, 1997) is more suitable for text with clearly defined topics. In terms of precision, LightGBM performs better than other algorithms with a precision of 0.91. In terms of recall and f1 score, XLNet-base performs better than other algorithms. XLNet is state-of-the-art in text classification tasks (Minaee et al., 2020). XLNet-base is fine-tuned with 4 epochs using AdamW (Adam with weight decay) optimizer with Learning Rate of $1e^{-5}$. More than 4 epochs reduce the train error rate but the difference in validation and train error rate increases. The fine-tuning was done on a single GPU. One epoch took about 28 minutes to complete. The performance of algorithms is evaluated against macro-averaged precision, recall and f1 score. Precision is a metric indicating how accurately topic transition turn is detected and the values obtained can be seen in Table 2.

7 Limitations and Future Work

Future work will include the application of insights derived from empirical studies to apply them in open-domain dialogue systems such as using the topic transition trained to re-rank responses on topicality. A limitation of this work is the inter-annotator agreement could only be obtained on a small sample of conversation. Future work will include obtaining inter-annotator agreement for all 215 Switchboard.

8 Conclusion

Empirical study on how participants engage in topic transitions in a dyad is presented. It is observed that longer conversations have more topic transitions, topic transition is generally carried out...
more by one participant and there is no particular pattern observed in time series of topic transition. This study was also able to detect topic transition in dialogue with 91% precision.

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A  Utterance Count Per Topic

In addition to plotting median utterances per topic, we also plot mean, minimum and maximum number of utterances as topic order progresses.

Figure 4: Line plot of mean utterances per topic

Figure 5: Line plot of minimum utterances per topic

Figure 6: Line plot of maximum utterances per topic

B  Share of topics by participants

Below we plot difference of topic transitions per participants across conversations. Figure below shows a bar plot of topic transition difference and percentage of conversations with such difference.

Figure 7: Share of topics per participants across conversations.

C  t-SNE Visualizations

To empirically understand the separation of topic transition turns and topic continuation turns, we visualize the two classes using a t-SNE plot.

Figure 8: t-SNE visualization of utterances

D  Annotation Guidelines

For a conversation, first, a topic is identified and then the topic transition is marked. For some conversation, it could be more difficult to mark the topic transition and may require reading the whole conversation.

start of topic:  The first utterance, pertinent to a conversation, is marked as ‘s’. Here the first utterance is “[noise]” and therefore not pertinent. But the next line, a topic is introduced and therefore pertinent. This will be the starting a point for the conversation so will be marked with an “s”. Non-pertinent utterances include greetings/introductions and leave-taking (GIL) as this is not the focus of this part of the project.

topic transition:  This is the point when a new topic is introduced. For example, if Speaker B
introduces a new topic and then speaker A complies with the change in topic by either contributing or acknowledging the change in topic. This point of topic shift/change is marked with a “c”. Here is an annotated example.

This example shows the point of topic transition. This can be seen when the point of the conversation changes from being about “recycling” to being about “recycling programs”. This is then marked with a “c”.

**end of a topic:** We also denote the end of a topic. This is like beginning the topic where utterances may not be pertinent. When marking the end of the topic, it is marked with an “e” on the last utterance pertinent to the current topic. Here is an example.