

# Analyzing miscommunications.

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## **Background.**

### **Problem definition.**

Explore and develop various metrics that might possibly help us to detect miscommunication in a task oriented communication session.

### **Working scenario.**

We start with textual corpora transcribed from voice conversations. Therefore, the noise or errors in the textual corpora should be low. Our aim is to run some tests on these corpora and determine which of the metrics (defined here) strongly correlates with miscommunication.

### **Real world observations driving the approach.**

If we put ourselves in the shoes of one of the participants in a meeting or a conversation, one of the first things we can see is that miscommunication do happen. If we think about the detection and repair process adopted by humans, we can see that there are various logical levels at which miscommunication can be detected and later repaired. At the most basic level, we might misunderstand a word immediately as it was spoken, independent of its appearance context. At the next level, we might misunderstand a phrase immediately as it was spoken, again, independent of its appearance context. At the next level, we might misunderstand a sentence immediately as it was spoken. Also, at this level, it might be possible that there might be ambiguities in the meaning of some of the words or phrases in the context of the sentence, i.e., some words or phrases may appear to be out-of-context considering the sentence in which they appear. This would require us to go back to the words or phrases already spoken and interpret in the current context of the sentence to detect any ambiguities. The next logical level is at the dialog level. Usually, miscommunication at this level occurs if we are not able to interpret the logical and coherent meaning of a set of sentences spoken as a part of a dialog. This would ideally require us to request a repeat or more explanation. Also, this would require us to go back to the individual sentences already spoken and interpret it in the context of the current dialog. Continuing this, we could go further and explore characteristics of miscommunication that occur in-between different dialogs, i.e., at the discourse or the story level.

### **A computational approach.**

For automatically detecting miscommunication, we can explore a multi-level approach, analogous to the one used by humans. In general, we need to develop some metrics that could possibly detect miscommunication at each of the word, phrase, sentence, dialog and discourse or story levels in a conversation. In our approach, each of the identified class of miscommunication has two parts – the linguistic part where we define the scope and characteristics of the class and the computational part where we try to develop some metrics and techniques to detect the occurrence of the class. The various

classes and examples of miscommunication explored here are drawn mainly from the paper by Poteet et al and from the book "Fatal words". The classes and techniques explored here are fairly generic and could be applied to any domain specific conversation with minimal amount of tuning or changes. The important fact is that the various techniques and metrics explored here are just hypothesized to be correlated to miscommunication, so we need to carry out experiments to actually verify whether they are indeed correlated.

## **Classes of Miscommunication.**

### **Word level.**

In this section, we will explore the various classes of miscommunication that could occur at the word level and how they could be possibly detected computationally. Here are the various types of miscommunication that could occur at the word level.

#### **Word ambiguity induced by context of use.**

This can happen when a word can have multiple interpretations based on the context in which it is used. The context can be further sub-divided into two other classes.

#### **Sentence context.**

The required context is provided only by the sentence in which the word appears. This happens when a word can have different interpretations that are dependent on only the other words in the sentence. On a general note, this might include polysemes and homonyms. E.g. Financial bank vs. River bank.

#### *Computational approaches for detection.*

Let's say we have a dictionary that contains the list of all possible meanings the given word can have. Now, if we are to disambiguate the given word, we would consider the context provided by the sentence and fix one of the possible meanings for the word. But, for detection purpose, we could just take the count of the number of possible meanings a word can have and flag the word if this number is greater than a threshold. Regarding the dictionary, we can probably use WordNet to retrieve a list of senses the given word can have. Another possible solution, which would require a bit more work, is to use a Word Sense Disambiguation technique which not only outputs the supposedly right sense, but also the confidence score too. This would basically tell us how confidently we can fix a sense for the given word in the given context. If this number is lesser than a threshold, we could flag the word for possible miscommunication. Now, regarding how to do this, we need to explore the available WSD algorithms and evaluate which one can be appropriately modified to return a confidence score. If we use the Lesk algorithm, we could calculate a probability score based on the various statistics used by it.

#### **External context.**

The required context is provided by a combination of some externally defined factor and the sentence in which it appears. More specifically, a word "W" might be interpreted as "WA" by user "A" and "WB" by user B, due to the fact that the external factor might be different for users "A" and "B", even though the sentence context might be the same. An example of the external factor might be different cultures. E.g. "My child is backward". Consider the interpretations for backward - shy vs. retarded.

### *Computational approaches for detection.*

We could probably think on similar lines as we did for the previous class. The only difference here is that the context is provided by some external factor like culture, domain etc. So, let's consider the same dictionary approach. Here, we would probably need a set of dictionaries, one for each external context. In order to compare between dictionaries, we need a standard representation for all of these. So, each word in a dictionary should be mapped to an interpretation selected from a standard set of interpretations. Therefore, the set of interpretations remain the same across all the dictionaries, but the assigned interpretation for the given word changes depending on the external context. Once we have this set of dictionaries, we can determine whether the given word can lead to miscommunication. Let's say we have a dictionary "DA" for user "A" and "DB" for user "B". If the word "W" does not map back to the same standard representation in both "DA" and "DB", we know "W" means different things for "A" and "B" and hence might cause miscommunication. The fact to note here is that the required context is provided by the individual dictionaries and the overall framework for detecting miscommunication of this class remains the same for different contexts. So, we can just swap in the required dictionaries depending on the external context required, as long as the words map back to a standard representation. Now, the next problem is about how we can build such dictionaries and what standard representation should we choose. For building the dictionaries, we have a couple of options. The first one is to have a person, who is an expert in the required domain, to provide us with a set of words and their mappings. The second approach, which is better suited, is to use information extraction techniques on large corpora of annotated domain specific conversations to collect a set of words and their mappings. If we choose the second option, we might have to manually go through each possibly ambiguous word for a specific domain and tag it with its domain-specific standard interpretation. Once we have the annotated corpora ready, we can run information extraction algorithms to build a dictionary. An example might be having two different dictionaries for each of U.S. military personnel and U.K. military personnel. Now, let's consider what the standard representation can be. Here, we can keep talking about the various characteristics that this standard representation should satisfy and all. But leaving that alone, one possible choice, which might turn out to be really effective, is the WordNet's "synset" representation. A "synset" is basically a collection of synonyms. If we consider the previous example related to the use of "backward" and map it to "synset", we would have "diffident, shy, timid, unsure" for user "A" and "idiot, imbecile, cretin, moron, changeling, half-wit, retard" for user "B". Another advantage of using "synset" is that we can exploit the full power of WordNet ontology later when required, even though the domain considered might be very different. One such possible extension might be comparing the two standard representations based on their "semantic distance" instead of trying to match them exactly.

### **Acronyms and Jargons.**

By definition, acronyms and jargons are defined specific to a group.

The use of acronyms and jargons within the group might not give rise to miscommunication. But, when it is used while communicating with people outside of the group, there are chances of miscommunication. E.g. Usage of the term "VOIP" while speaking with a doctor, Usage of U.S. military specific commands and acronyms when communicating with U.K. military personnel.

### *Computational approaches for detection.*

In the previous class, we considered words that were common for a set of externally defined contexts, but having different interpretations based on the context. Here, we consider words that appear only in a certain external context, but not in others. For simplicity, we can assume that the groups with which the specific jargon or acronyms are associated are functions of external context, i.e. group is just a type of externally determined context. Now, let's explore a method using which we can detect the appearance

of these. Let's say we have a set of dictionaries containing list of acronyms and jargons, optionally mapped to a standard representation, for each of the externally defined context under consideration. Let's say a user "A" belonging to group "GA" is communicating with a user "B" belonging to group "GB". If "A" uses a word that's present only in the dictionary for "GA" and not in the dictionary for "GB", it might lead to miscommunication. Now, the next question is how to construct these domain-specific dictionaries. Again, we have a couple of methods. For the first method, we can get the required words from a domain expert. For the second method, which is more flexible, we need large amounts of annotated corpora containing dialogs of users of different domains. We can run various algorithms to automatically extract acronyms and jargons from the corpora. One such algorithm can be based on the fact that the domain specific words usually occur frequently in the dialogs of a particular domain and do not occur in others. E.g. we might see the word "VOIP" frequently in dialogs related to "Internet Telephony" but infrequently in dialogs related to "Study of rabbits". There are various other algorithms published that can automatically extract acronyms and jargons from corpora. Another interesting solution can be to determine the topic referred to by the different users based on their dialogs and checking to see if they are talking about the same topic. Again, we need to explore more into this area to see if we could come up with algorithms to do this or if there is some existing work that we could implement.

### **Connotations of word.**

A word might have a positive or a negative connotation. It might also have multiple connotations based on the context in which it is used. Miscommunication might occur if a word with a negative connotation is lying around in a sentence with many words having positive connotations. E.g. the backward child was praised highly by the teachers. Here, we can figure out that backward has a negative connotation whereas highly and praised both have positive connotations and hence something might be wrong. If we consider the sentence "The backward area is neglected by politicians", we can see that backward, neglected both have negative connotation and there are no words with positive connotation. Hence, the intended meaning might be conveyed in this case. This class and the class of contextually ambiguous words share a common subset. On a general note, techniques addressing this class can be used as a fallback to detect those words missed by the techniques addressing the class of contextually ambiguous words.

### **Computational approaches for detection.**

Detecting the connotation of words, phrases, sentences and dialogs can be taken up as a significant project by itself. This technique is referred to as "Sentiment Analysis" in the computational linguistics literature. We need to explore the various work published for this topic and also need to evaluate which one to adopt for this task.

### **Phrase level.**

In this section, we will explore the various classes of miscommunication that could occur at the phrase level and how they could be possibly detected computationally.

### **Slangs and colloquialism.**

These are by definition limited to small groups of people, like jargon. But the difference being that they span across words, that is, they are used as phrases. Again, usage between people of different groups might lead to miscommunication. E.g. "Idiot's guide" in UK vs. "Dummies guide" in US.

### *Computational approaches for detection.*

This can be similar to the approach we took while discussing about Acronyms and Jargons. The main difference here would be that there is more than a word in a unit. We can explore some work done in the field of detecting multiword expressions and also make use of ngram (n=2 and 3) analysis techniques to automatically detect multiword phrases. We can then determine which of the phrases are relevant to the current domain using the same techniques (phrase frequency and inverse document frequency) discussed while addressing Acronyms and Jargons.

### **Connotations.**

Similar to the one defined at word level, but extended to include phrases too. This means that if a phrase with negative connotation is lying between words with positive connotation, we can say it might lead to miscommunication. E.g. "Thank you for the idiot's guide as it was extremely helpful". Here we can know something is wrong with Idiot's guide as its sitting among words having positive connotation. Also, if a positive phrase for a user "A" means something negative for a user "B", there might be possibility for miscommunication. Again, this can be used as a fallback mechanism for the class addressing slangs.

### *Computational approaches for detection.*

The techniques described for the word level can be applied here too. In addition to that, we have to evaluate whether it's possible to fix the connotation for a phrase depending on an external context like culture, domain etc. i.e. can we detect whether a phrase means positive for user "A", but negative for user "B"? Again, we have lots of literature to explore before we get any definite answers.

### **Sentence level.**

In this section, we will explore the various classes of miscommunication that could occur at the sentence level and how they could be possibly detected computationally.

### **Garden path sentences.**

There might be some sentence which has more than one meaning depending on how we interpret the grammatical parts of the sentence. E.g. "She said that he snored loudly". Here is it the saying that's loud or the snoring that's loud? These types of sentences might possibly lead to miscommunication. A fact to be noted here is that no external or domain-dependent factors are affecting this and it's solely the structure of the sentence that's causing the problem.

### *Computational approaches for detection.*

To parse a sentence, we need a grammar and a parsing algorithm. For the grammar, we can use the set of CFG's used by the Stanford parser. For parsing, we can use any parsing algorithm, like the Earley parser, which can be modified to return a set of all the possible parse trees.

### **Grammatical correctness.**

A grammatically incorrect sentence might lead to miscommunication.

### *Computational approaches for detection.*

We can use any of the available parsers, along with some basic language-specific rules to verify grammatical correctness.

### **Sentence connotation.**

The presence of a negative connotation sentence in the midst of a set of sentences having positive connotation might represent miscommunication.

### ***Computational approaches for detection.***

Similar to the sentiment analysis approach described before.

### **Dialog level.**

In this section, we will explore the various classes of miscommunication that could occur at the sentence level and how they could be possibly detected computationally.

### **Frequent occurrence of some dialog classes.**

We can try to observe the frequent dialog classes like request for repeat, positive and negative acknowledgement etc. and try to find patterns leading to miscommunication.

### ***Computational approaches for detection.***

We need to review the work done in dialog and discourse analysis literature. More specifically, we need to look into work related to “dialog classification”. One of the influential works was by Daniel Jurafsky et al.