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Enhancing Customer Experience through Text Analysis of Survey Comments

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ABSTRACT

Customer feedback is a critical aspect of businesses in today's world as it is invaluable in determining what customers like and dislike about the business' service. This loop of regularly listening to customers' voice through survey comments and improving services based on analytics will lead to better business and more importantly enhancement in customer experience. The challenge here is to classify and analyze these unstructured text comments to gain insights and focus on areas of improvement. The purpose of this paper is to illustrate how Text Mining in SAS Enterprise Miner 14.1 helped one of our clients - a leading financial services company - convert their customer's problems into opportunities.

The customers' feedback pertaining to their experience with Interactive Voice Response (IVR) system is collected by an Enterprise Feedback Management (EFM) Company. The comments are then split into two groups as it helps us differentiate customer opinions. This grouping is based on customers who have given a rating of 0-6 and a rating of 9&10 on a likert scale of 0-10 (10 being extremely satisfied) in the survey questionnaire. Text mining is performed on both of these groups and an algorithm creates clusters that are consequently used to segment customers based on opinions they are interested in voicing about. Furthermore, sentiment scores are calculated for each one of the segments. The scores classify the polarity of their feedback and prioritizes the problems client needs to focus on.

INTRODUCTION

Listening to customers is the one of the key ways for businesses to stay informed on how to improve their services as feedback help businesses measure customer satisfaction, improve customer retention and provide actionable insights to enhance customer experience. And when it comes to getting feedback, surveys are the bread and butter. Surveys can be of three types – surveys with closed questions, open ended questions or a combination of both. Closed question type is one which presents customers with a set of options and their responses are limited to a pre-determined list. Though there are several advantages to this survey type, the major disadvantage is the inability of the customer to freely express their answers. On the other hand, though data from open ended questions such as text feedback can be hard to analyze and quantify, the facility given to the respondent to provide an un-moderated response can result in rich information.

The key part of creating excellent surveys is to make proper use of both open ended and closed questions. Our client - a top financial services company understands the power of such combined surveys. And with the help of an Enterprise Feedback Management (EFM), the company collects responses of customers through a survey questionnaire. Figure 1 shows a simplified overview of the survey process.

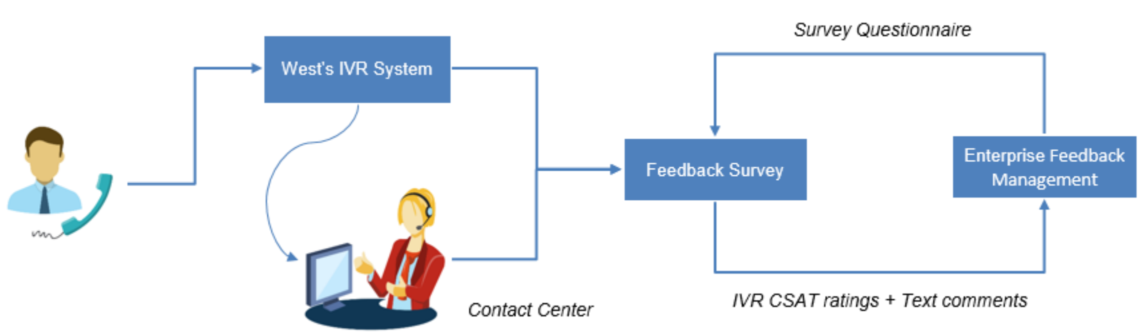

Figure 1. Survey Process Overview

The questionnaire has both likert scale questions and text feedback with respect to their experience with the IVR system as well as the contact center agent who may have helped the caller. The challenge here is to classify and analyze these text comments to gain insights. In order to do such complex analysis on unstructured survey comments and interpret textual data, a powerful tool is needed and text mining available in SAS Enterprise Miner 14.1 has proven to be of great use in performing this.

DATA PREPARATION

The data used in the demonstration is IVR Customer Satisfaction (CSAT) likert ratings and text comments on West's IVR system which are collected by the EFM company in for a specific month. Of the 1,306 customers who were surveyed 730 customers provided textual feedback. These 730 survey comments along with the IVR CSAT ratings are ingested into SAS using SAS/CONNECT to ODBC and the pass-through facility of PROC SQL. Once imported, the comments are split into two groups based on CSAT ratings. Group 1 has the text comments of customers who had given a rating of 0-6 on IVR and group 2 comprises of text comments from customers who had given a rating of 9 or 10.

METHODOLOGY

First, to gain insights from the survey data, the text comments are split into two groups. This helps in differentiating the opinions of the customers as they can provide their feedback on automated phone system and on wide variety of other subjects too. Then text mining is performed separately on each one of these groups. Text mining helps us derive quality information from feedback comments and cluster customers into groups such that within each group the customer behavior is similar and between groups the behavior is different. Once text clusters are formed, sentiment scores are calculated using SAS procedures that utilize West proprietary sentiment score algorithms and dictionary. Sentiment scores are used to classify the polarity of the feedback comments – whether the expressed opinion is positive, negative or neutral. These scores help our client to prioritize the problems and show the areas of focus. Recommendations are then drawn from both text clusters and sentiment scores. Figure 2 shows the framework adopted for text analysis.

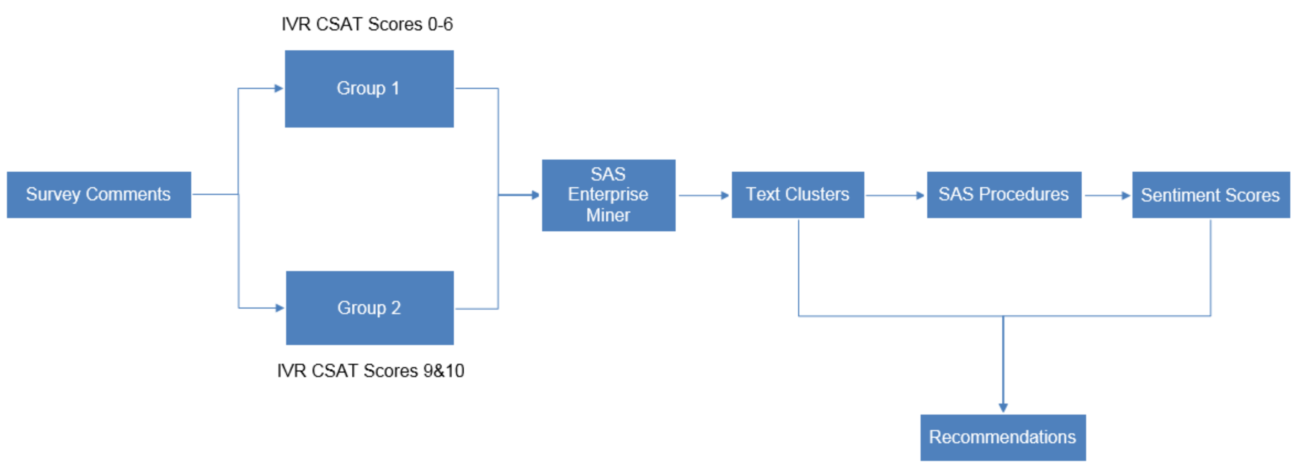

Figure 2. Framework for text analysis

TEXT MINING

Text mining in SAS Enterprise Miner 14.1 is used to derive insights from unstructured customer comments. First, text is parsed to find words of importance, then words are further reduced by text filtering and term by document matrix is created and text clustering is performed on top of that. The process flow of text mining using SAS Enterprise Miner 14.1 is shown in Figure 3.

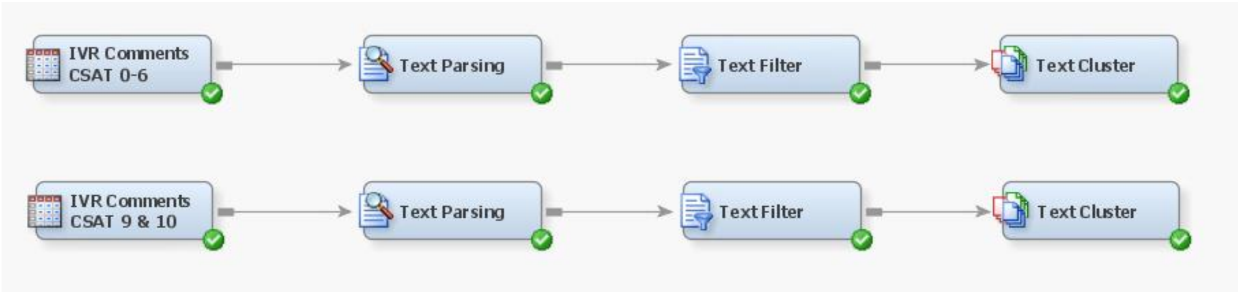

Figure 3. Text mining process flow using SAS Enterprise Miner

Text Parsing

Text parsing is used to analyze comments into logical syntactic components. Text parsing node keeps and drops the words after reviewing the words by their importance. Figure 4 shows the terms table which lists the words that were kept and dropped.

Term	Role	Attribute	Freq	# Docs	Keep	Parent/Child Status	Parent ID	Rank for Variable numdocs
not ...		Alpha	151	107	N		1319	1
+ be ...		Alpha	153	98	N	+	1312	2
+ have ...		Alpha	104	83	N	+	1309	3
+ do ...		Alpha	73	57	N	+	1317	4
+ person ...		Alpha	62	53	Y	+	913	5
+ get ...		Alpha	62	52	N	+	1318	6
+ live ...		Alpha	50	48	Y	+	809	7
money ...		Alpha	56	47	Y		915	8
+ system ...		Alpha	50	45	Y	+	645	9
+ service ...		Alpha	48	42	Y	+	488	10

Figure 4. List of terms parsed

Text Filtering

The text filter node is used for further reduction of the parsed terms, thus retaining only relevant information. This node assigns weight to the words based on their relative frequencies. Term by document matrix is created with terms and their respective weights. Figure 5 shows the term by document matrix.

Term	Role	Attribute	Status	Weight ▼	Imported Frequency	Freq	Number of Imported Documents	# Docs	Rank	Parent/Child Status	Parent ID
+ agent ...		Alpha	Keep	0.752	4	4	4	4	69	+	19
speed ...		Alpha	Keep	0.752	4	4	4	4	69		74
long ...		Alpha	Keep	0.752	4	4	4	4	69		75
clear ...		Alpha	Keep	0.752	4	4	4	4	69		89
+ solve ...		Alpha	Keep	0.752	4	4	4	4	69	+	93
+ transfer ...		Alpha	Keep	0.752	4	4	4	4	69	+	127
knowledge...		Alpha	Keep	0.752	4	4	4	4	69		187
helpful ...		Alpha	Keep	0.752	4	4	4	4	69		204
+ line ...		Alpha	Keep	0.752	4	4	4	4	69	+	246
ease ...		Alpha	Keep	0.752	4	4	4	4	69		270
+ hassle ...		Alpha	Keep	0.752	3	4	3	4	69	+	437

Figure 5. Term by document matrix

Text Clustering

Clustering is used to naturally group text comments into clusters. This implies that text comments in a cluster will be similar to other comments in the same cluster. However, comments in different clusters are dissimilar to each other. Two variants of clustering algorithms – Hierarchical and Expectation-

Maximization (EM) are available for analyzing data in Enterprise Miner. However EM algorithm assumes that variables are normally distributed in each cluster and then it applies an iterative optimization to estimate the probabilities for each observation to belong to each cluster and thus this variant is adopted.

SENTIMENT ANALYSIS

Once the text clusters are formed, sentiment analysis is performed on the clustered comments. West uses a proprietary, industry specific sentiment dictionary with thousands of words. The sentiment values of these range from **-5** to **+5.** The words in the survey comments are checked against the dictionary and a net sentiment score is calculated for each text comment. This is followed by calculating adjusted sentiment score (by dividing the number of words in each text comment). Then the sentiment scores are averaged for each of the text clusters and the final sentiment score is calculated. Sentiment scores for this study range from **-0.75** to **3.25.**

RESULTS DISCUSSION

TEXT CLUSTERS OF IVR CSAT SCORES 9&10

Text Cluster 1 - Delighted Customers

This is the cluster that has about **30%** of all customers who had provided a score of 9 or 10 for the IVR system. This cluster represents customers who are delighted with their IVR experience as it exceeded their expectations. It created a positive emotional reaction. The average IVR CSAT score of this cluster is **9.75** and the sentiment score of this cluster is found to be **2.04.** Some of the example customer comments from this segment are shown below and the descriptive terms of this cluster are shown in Figure 6.

- *“I was surprised how easy, pleasant, and quick Company X’s phone service is. Thank you!’*
- *“It was my first time using Company X’s financial services and the automated phone system made me feel confident in using again”*
- *“Very quick and easy to understand options”*

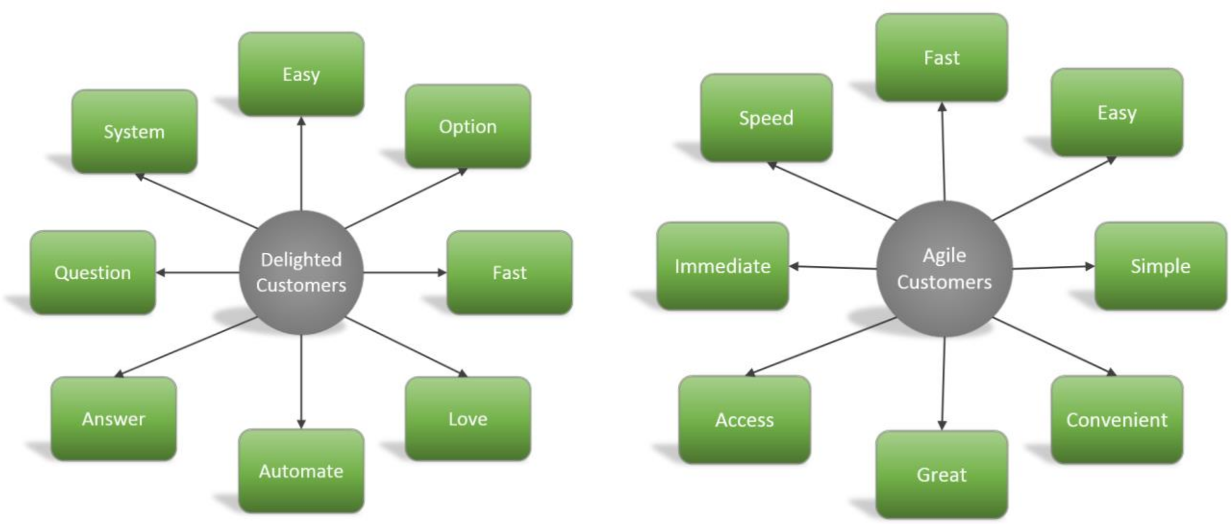

Figure 6. Descriptive terms of text clusters 1 and 2

Text Cluster 2 - Agile Customers

Cluster 2 comprises about **9%** of all customers who had given a score of 9 or 10 for the IVR system. The cluster represents customers who find IVR an easy and quick way to carry out transactions. The average IVR CSAT score of this cluster is **9.80** and the sentiment score of this cluster is found to be **1.93.** Some of

the example customer comments from this segment are shown below and the descriptive terms of this cluster are shown in Figure 6.

- *"It's awesome and fast."*
- *"It was easy and simple"*
- *"Fast &efficient"*
- *"It was easy and direct to the point"*

Text Cluster 3 - Self-Served Customers

This cluster consists of about **19%** of all customers who had given a score of 9 or 10 for the IVR system. It represents customers who were able to self-serve within IVR without having to talk to a live agent. The average IVR CSAT score of this cluster is **9.73** and the sentiment score of this cluster is **3.25.** Examples of customer comments of this cluster are shown below and the descriptive terms of this cluster are shown in Figure 7.

- *"Clear what the choices were on the phone system so I could get the information I wanted"*
- *"My problem was solved with the system without having to talk to a representative."*
- *"I didn't have to talk to a live person."*
- *"The system was easy to navigate and I had to go through minimal number of steps."*

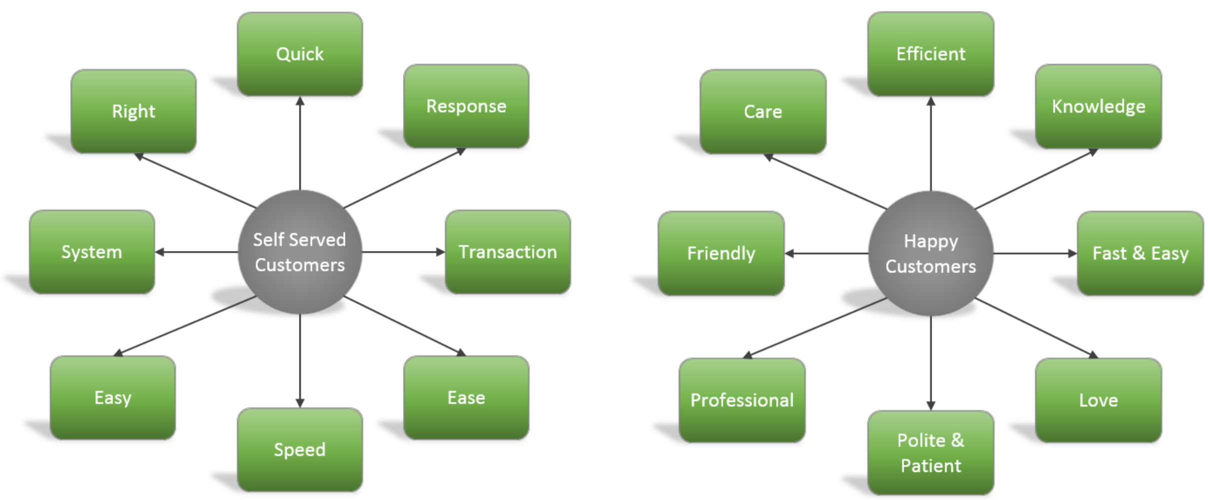

Figure 7. Descriptive terms of text clusters 3 and 4

Text Cluster 4 - Happy Customers

Cluster 4 has **16%** of all customers who had given a score of 9 or 10 for the IVR system. It represents customers who liked their interaction with representative and are happy with their customer experience. The average IVR CSAT score of this cluster is **9.76** and the sentiment score of this cluster is **2.77.** Examples of customer comments of this cluster are shown below and the descriptive terms of this cluster are shown in Figure 7.

- *"The rep was knowledgeable"*
- *"Friendly representative. Prompt and very knowledgeable"*
- *"The courtesy and professionalism of the agent."*
- *"Great, great customer service, thank you!"*

TEXT CLUSTERS OF IVR CSAT SCORES 0-6

Text Cluster 5 - Resolving Customer Issues

Cluster 5 comprises about **10%** of all customers who had given a score between 0 and 6 for the IVR system. The cluster represents customers who were disappointed as their issues were not resolved. The average IVR CSAT score of this cluster **1.71** and the sentiment score of this cluster is found to be **-0.38.** Some of the example customer comments from this segment are shown below and the descriptive terms of this cluster are shown in Figure 8.

- *"Your whole process to resolve issues needs some serious updating..."*
- *"Train your personnel to resolve the issue."*
- *""Resolve my issue"*
- *"I was told 3 different answers from 3 different people each time I called in. I was always given incorrect information. My issue is still not resolved."*

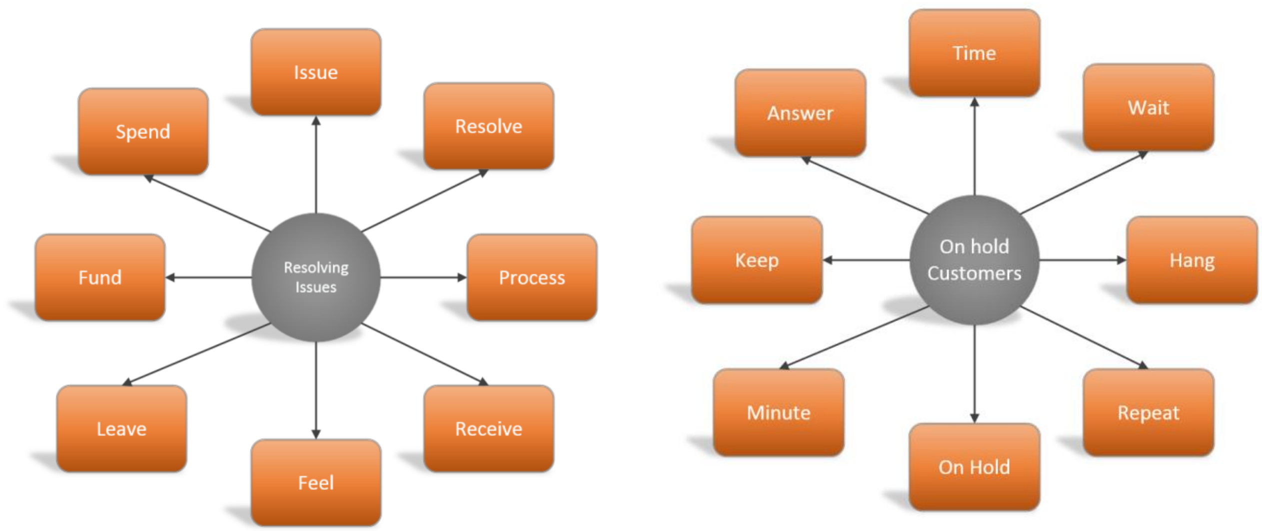

Figure 8. Descriptive terms of text clusters 5 and 6

Text Cluster 6 - On Hold Customers

This cluster consists of **15%** of all customers who had given a score between 0 and 6 for the IVR system. It represents customers who were unhappy as they were put on hold for a long time. The average IVR CSAT score of this cluster is **2.07** and the sentiment score of this cluster is **-0.21.** Examples of customer comments of this cluster are shown below and the descriptive terms of this cluster are shown in Figure 8.

- *"The lady should not have left me on hold for so long -- perhaps saying: you might have to wait 5-10 mins or so - at least I would know she hadn't forgotten about me and have to hang up."*
- *"Do not have customers on hold for extended period of time"*
- *"After twenty minutes on hold I went to Company Y (Competitor) who answered in three minutes"*

Text Cluster 7 - Need for Customer Service Representative (CSR) Interaction

Cluster 7 has **24%** of all customers who had given a score between 0 and 6 for the IVR system. It talks about customers who felt that it took long time for them to get connected to a live agent. The average IVR CSAT score of this cluster **2.13** and the sentiment score of this cluster is **-0.02.** Examples of customer comments of this cluster are shown below and the descriptive terms of this cluster are shown in Figure 9.

- *“Took excessive time to get to a customer rep”*
- *“It took too long to get in contact with a representative.”*
- *“The 18 minutes I was on hold.”*

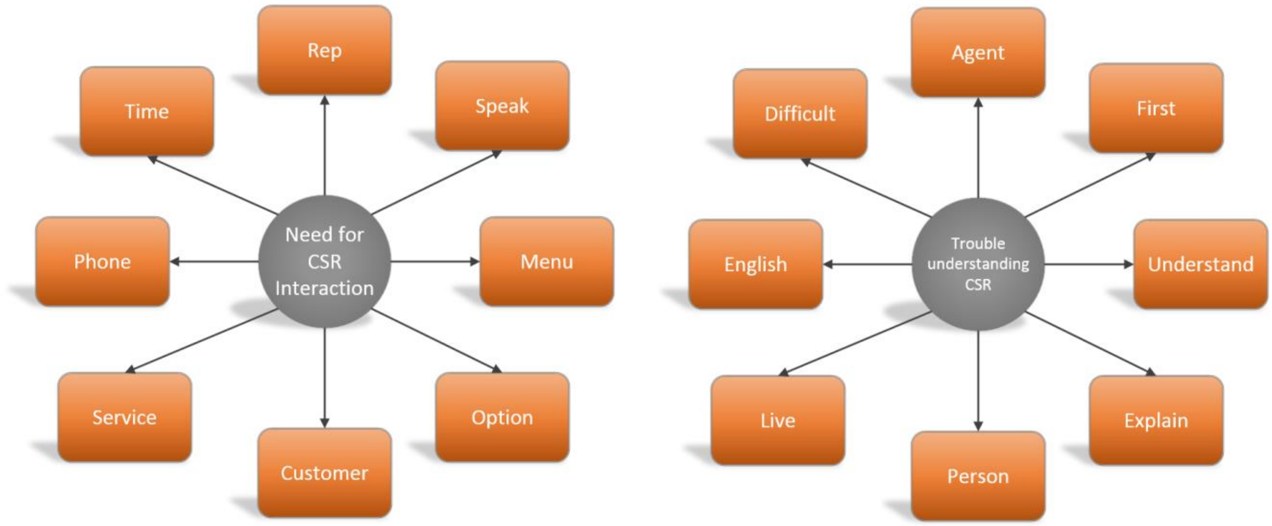

Figure 9. Descriptive terms of text clusters 7 and 8

Text Cluster 8 – Trouble Understanding Customer Service Representative (CSR)

This is the cluster that has about **23%** of all customers who had given a score between 0 and 6 for the IVR system. This cluster represents the customers who had hard time understanding customer service representative. The average IVR CSAT score of this cluster is **2.46** and the sentiment score of this is -**0.03.** Some of the example customer comments from this segment are shown below and the descriptive terms of this cluster are shown in Figure 9.

- *“Unfortunately, there is/was a language barrier”*
- *“Your representative was extremely difficult to understand because of a very thick accent”*
- *“Be more understanding.”*

CONCLUSION AND NEXT STEPS

Text mining and sentiment analysis of survey comments helped us identify two major challenges faced by customers – long hold time and trouble understanding live agents. Further research shows that customers who had compliance issues with money transactions were the ones who had long hold time. Steps are being taken to track the call back to the contact center to narrow down which centers contribute to the language barrier. Resolving these issues will lead to enhancement in customer experience.

The use of text mining is growing rapidly as organizations are realizing the value of unstructured data. Center for Data Science at West is helping operational teams and clients uncover useful information from unstructured data using SAS. The team has realized the potential of non-words like emoticons in conveying customer’s sentiment in feedback. As a next step our approach would be to convert emoticons into text and use that information as part of Text mining process.

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