Solving Customer Problems using Intention Analysis

Cohan Sujay Carlos
Aiaioo Labs
Bangalore, India
http://www.aiaioo.com
cohan@aiaioo.com

Abstract

It might be possible to use the insights derived from analyzing call center traffic to improve customer satisfaction, reduce wait times in call centers (improve throughputs) and reduce call volumes by analysing the causes of customer interactions. An understanding of the causes might emerge from a study of the intentions of callers, and intentions might themselves be discoverable in call transcripts. Once the intentions and the causes are understood, the problems that need to be resolved might be easier to identify, and the means of solving these problems might prove easier to find.

1 Call Center Analytics

There are many ways in which call center logs may be analysed, and the method of analysis is mostly determined by the use-cases driving the analysis. Call center analysis normally focuses on improving customer satisfaction and on monitoring Quality of Service parameters, so most call-center data mining tasks focus on customer satisfaction ratings, call pickup times, call throughput, and other such structured parameters.

However, there are problems for which an analysis of structured data might not suffice. One such problem *might* be identifying the main causes that resulted in a call to a call center. The reason for this is that the cause of a call is not a quantity that can be easily measured. The causes of a customer call might however be possible to discover in the unstructured data that is available in Customer Relationship Management (CRM) systems used in call centers.

In the next section, we shall see how such unstructured data might be made to reveal the reasons that drive people to approach a customer service center.

2 Causes of Calls to Call Centers

Whenever a user calls in, there is an intention driving the user's actions. The user might be driven by the:

- Intent to seek information (inquire intention)
- Intent to complain about a product or service (complain intention)
- Intent to issue an operational instruction (direct intention)
- Intent to purchase a product (purchase intention)

2.1 Inquire Intention

If a large portion of calls come from users seeking information (intention to inquire), the cause could be a poor online help system and the remedy might just be a better online knowledge management solution.

2.2 Complain Intention

If the intention to complain is the main reason for a segment of call-center traffic, there might be processes and products that need improvement. In service and process settings, these might point to processes that need streamlining and simplification.

2.3 Direct Intention

If the primary intention of a set of callers is to issue operational instructions (perhaps to request that a change of some sort be made), there might be limitations or usability issues with the online tools that have been provided to users.

2.4 Purchase Intention

If the intention to purchase a product predominates, then if the item being requested is a high ticket item, there is no problem at all. If the item

Category	Parent	Interest
Purchase		Sales
Sell		Procurement
Inquire		Sales
Direct		Operations
Compare		Analytics
Suggest		Analytics
Praise	Opine	Analytics
Criticise	Opine	Analytics
Complain		Operations
Accuse		Operations
Quit		Operations
Thank	Express	Training
Apologize	Express	Training
Empathise	Express	Training
Wish		Sales
Meet		User
Advocate		Analytics

Table 1: List of Intention Types.

that is mainly sought after in calls with intent to purchase is a low-ticket item, then perhaps the item is not available to customers through the right channels.

So, it can be seen that an analysis of intentions can point to problems (if any) that might be facing customers.

In the next section, we shall study what intention analysis is and how many types of intentions it is possible to detect.

3 Intention Analysis

Intention Analysis is the identification of intentions from text, be it the intention to *purchase* or the intention to *sell* or to *complain*, *accuse*, *inquire*, *opine*, *advocate* or to *quit*, in incoming customer messages or in call center transcripts.

A comprehensive list of intentions can be found in Table 1.

The work that intention analysis is based on goes as far back as 1962 when J. L. Austin noted that not all utterances are statements whose truth and falsity are at stake, and that there was a class of utterances like "I pronounce you husband and wife" that are actions (Terry Winograd, 1987).

In 1975, Searle identified the following broad categories of illocutionary (causing an action to happen) speech acts (Terry Winograd, 1987):

- Assertive – Committing the speaker to the truth of a proposition
- Directive – Attempting to get the listener to do something
- Commissive – Committing the speaker to a course of action
- Declaration – Bringing about something (eg., pronouncing someone married)
- Expressive – Expressing a psychological state

It is these speech acts that we believe we can analyse to discover intent, and the set of intentions that we can discover is a set of commercially valuable intentions (from an infinite space of intentions) that we have, through trial and error, found it possible to train machine learning algorithms to identify.

4 Remedies for Customer Problems

Once the customer problems have been identified, remedies may be obtained, sometimes through the use of text analytics. Some text analytics solutions that can act as remedies include the following:

- Social CRM Solutions
- Knowledge Management Solutions
- Call Center Automation Solutions

4.1 Social CRM Solutions

Social CRM solutions (or add-ons and plugins) can be a handy remedy where call-center quality is low or call center volumes too high for quality improvements to be made at the call-center level.

Social CRM tools can deliver customer support over social media, bypassing call-centers and other traditional service channels. A good example is "Airtel Presence", which is a service that tracks mentions of the Airtel brand name on the internet. Whenever negative mentions are detected on social media, customer service representatives are alerted to the mention and someone responds to the aggrieved customer.

This kind of interaction is particularly effective on forums where it serves to ease the build-up of negative sentiment and reduces the chances of call centers having to deal with irate customers.

Another use of social CRM tools is to decrease the time taken to identify and respond to genuine and serious customer complaints. When Netflix tweaked its product pricing in 2011, the new pricing was perceived as unfair, and a large number of customers quit. Had Netflix been aware of the quit intentions spiking, it might have been able to respond faster.

4.2 Knowledge Management Solutions

If a sizeable portion of call-center traffic involves inquiries (requests for information), then there may be a need for knowledge management solutions including consumer/partner forums and question search tools. Xurmo is a firm that develops such tools.

4.3 Call Center Automation Solutions

Intention analysis can be used to improve the customer experience by automating task prioritization and task routing. Customers who are likely to churn can get priority service. Routing of inquiries can take a different form from the routing of purchase intentions. Incoming tickets can also be automatically automatically raised to the most appropriate level. This can speed up resolution of issues and reduce the workload of Level 1 support.

The following section deals with a side benefit of call center text analysis which might include improved customer satisfaction and decreased customer churn.

5 Predictive Models

Intention and event analysis yield structured output from unstructured data and these can be used in conjunction with standard BI tools to develop predictive models.

Two predictive models that might be enhanced by intention analysis are described below:

5.1 Customer Churn Models

One of the problems facing telecom service providers is high rates of customer churn (reportedly in some cases $30-35\%$ year on year).

Three intentions that might be useful in detecting churn are: *complain intent* (reporting a problem), *accuse intent* (blaming the firm), *quit intent* (leaving the firm).

The detection of these three intentions in customer communications might help a firm reduce its customer churn rate.

5.2 Product Acceptance Models

With modern text analytics tools, it is possible to analyze product launches.

We tracked the Google+ launch as a competitor to Facebook between 30th June 2011 and 10th July 2011.

The number of tweets expressing intent to quit rose rapidly from 30th June to 4th July. On the 4th of July, Google+ became open to all users (anyone could join it henceforth without invitation).

The next day, the number of tweets expressing an intention to quit dropped sharply. Once users had been able to try out Google+, they had realized that they couldn't bring all their friends along from Facebook to Google+ and that Google+ wasn't going to be fun without them.

So, we could tell that Google+ wasn't going to be a Facebook killer like many tweets before July 4th had suggested, or atleast not yet. And we could tell that in just 4 days.

6 Brand Metrics

Intention analysis also helps brand owners gauge customer perception of their brand.

One of the metrics in common use is customer satisfaction (*CSAT*).

$$CSAT = \frac{positive}{positive\ +\ negative}$$

With a richer set of intentions, one can even estimate customer loyalty.

$$CLOY(loyalty) = 1 - \frac{quit\ intention}{complain\ intention}$$

In one of our experiments, it was found that the CLOY for Starbucks was 41.8% whereas for laptops, it was 51.9%.

It would be intuitively expected that high-ticket items like laptops would have a higher hesitation factor before a purchase action than low-ticket items like coffee.

$$CHES(hesitation) = \frac{compare\ intention}{purchase\ intention}$$

In a study on Starbucks and on laptops, it was found that $CHES$ for Starbucks was 37.9% while for laptops, it was 59.5%.

Market commoditization is the fraction of utterances containing the intention to purchase, that have as the object a branded product:

$$commoditization = \frac{brand\ name\ mentions}{generic\ mentions}$$

All the metrics proposed in this section are measurement proxies. They need to be tested and validated by correlation with real-world figures.

7 Related Work

Lampert et al (2010) studied message-level identification of requests in the context of email communication. They also distinguished between message-level identification (the task of determining whether a message contains a request) and utterance-level identification (which they described as 'the task of determining precisely where and how the request is expressed').

The intention to purchase and the intention to make a suggestion have been studied by Ramanand et al (2010). Ramanand et al (2010) proposed rule-based methods to identify two kinds of 'wishes' or intentions - one, the wish to make a suggestion (with the goal of suggesting an improvement in a product or service), and the other, the wish to purchase a product or service.

7.1 Related Whitepapers

There are a couple of related articles from Aiaioo Labs dealing with a) The use of intention analysis in converting utterances into structured data (we propose a strategy for converting various kinds of unstructured text into a structured form that is compatible with OLTP systems) and b) A game theory model of customer support strategy (a preliminary study).

8 Conclusion

In this concept paper, we have proposed possible applications of intention analysis to the task of solving customer problems. In Section 2 we have studied the reasons for which customers might call a support team and how these causes might be identified through a study of intentions in call center transcripts or CRM messages. In Section 4 we have studied remedies that might improve the customer experience. In Sections 5 and 6 we have attempted to show how call center text analytics might provide insights into brand health as well as assist in the creation of predictive models.

References

Andrew Lampert, Robert Dale and Cecile Paris. 2010. *Detecting Emails Containing Requests for Action*. HLT '10 Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics, Stroudsburg, PA, USA.

J. Ramanand, Krishna Bhavsar and Niranjan Pedanekar. 2010. *Wishful thinking: finding suggestions and 'buy' wishes from product reviews*. CAAGET '10 Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text, Stroudsburg, PA, USA.

Terry Winograd. 1987. *A Language/Action Perspective on the Design of Cooperative Work*. Human-Computer Interaction 3:1 (1987-88), 3-30.