RANK MINER
PREDICTIVE ANALYTICS

Monitoring and Measuring Agent Performance

Executive Summary

In this paper we discuss what it means to gauge agent performance and how Artificial Intelligence can automate this process to provide multiple benefits to call center operations. RankMiner customer tests describe the tremendous impact that optimizing the monitoring and measurement approach have on their business.

Monitoring and measuring employee performance has always been a large factor in improving business performance. It is especially critical in the telecommunications space, as a negative review on an agent can have immediate, widespread, and harmful effects on a business' reputation. Today, most call center-focused companies employ a Quality Assurance department where QA representatives sample phone calls across call agents and score them on knowledge and "soft skills"—for example, enthusiasm of the employee, helpfulness, empathy, etc. These soft skills are often crucial to garnering a sale or payment of debt, especially in today's environment where call scripts are very detailed and adherence to those scripts is monitored closely.

RankMiner's patented software gives clients the ability to automate the decision making process across their entire base of phone agent employees thereby systematically improving phone agent performance.

Introduction

It's no surprise that labor costs are the number one expense in call center operations. Research shows that frontline phone agents and supervisor costs are about 70% of total call center expenses. Hiring the best, training them well and giving them the right tools as they start their jobs are naturally the best things you can do with new employees. Monitoring and measuring employees' performance and progression within your business are equally critical since the agents in your call center are dynamic and in need of regular "tune-ups" to maintain peak performance.

Ever notice how a small portion of phone agents are consistently more successful than the rest even though they have the same scripts and work the same hours?

How many times have you experienced that "It's not what you say, but how you say it that really matters…"

Unlike businesses that operate in a face-to-face capacity, call-center based businesses can't pick up on body language or facial expressions, so understanding the meaning behind the words is critical. Unfortunately, this is not an easy task even for the best phone agents and difficult for most.

Defining Agent Performance

RankMiner's predictive technology differentiates itself by providing structure to a call's unstructured data (i.e. raw audio signal) and defining patterns for "good" versus "poor" agent performance in a specific context. Once established, these patterns can be fit to profiles based on what is considered a good call versus what is considered a poor call in terms of agent performance. Providing many examples helps to solidify these profiles, a process often known as training a prediction policy.

$$X_k = \sum_{n=0}^{N-1} X_n e^{-i2\pi k \frac{n}{N}} \qquad k = 0, \ldots, N-1$$

Discretizing the audio signal into the frequency domain

$$w_{(k)} = \arg\max_{\|w\|=1} \left\{ \left\| \hat{X}_k \right\|^2 \right\}$$

Commonly effective way of isolating principal features of discrete data

Once trained, the policy can quantitatively evaluate new unidentified calls' structures to either stochastically determine the profile of the unidentified call or deterministically calculate a score by which to gauge an agent's performance relative to the scores of other calls—whether the same agent or another agent makes the evaluated calls. The latter method is often preferred, as it provides a guideline rather than an instruction for how to proceed. It is the approach RankMiner uses since it *augments the existing policies and practices companies already have in place.*

$$\Sigma^{-1}(\vec{\mu}_1 - \vec{\mu}_0) \cdot \vec{x} > \frac{1}{2}(T - \vec{\mu}_0^T \Sigma_0^{-1} \vec{\mu}_0 + \vec{\mu}_1^T \Sigma_1^{-1} \vec{\mu}_1)$$

Scoring method based on exceeding a likelihood threshold

One obvious and immediate benefit is that once policies are trained, this supplemental information is provided company-wide, not just on the limited call volume which QA representatives can actually listen to and evaluate. Providing even greater benefit, the next step is to correlate relevant soft skills to actual receipt of sales and payments.

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Classical means of determining how two variables correlate

Optimizing the Approach

Whether agent performance is gauged upon soft skill acumen or raw sales figures or some combination, there is a clear-cut way to label good versus poor agent performance. This fact allows RankMiner software to automatically correlate acumen and profit, thereby training an optimal policy based on a dynamic combination of profiles determined through both methods. All that remains is to train each policy. In the former case, QA representatives can provide feedback with a subjective assessment of an agent's performance based on soft skills. In the latter, call metadata which is recorded in an automated fashion can be mined for call disposition and associated with the agent that took the call. Training a policy using the combination of soft skill acumen with raw performance data from call metadata provides a clear advantage—specifically by providing a way to automate individual subjective assessments and thereby transforming subjectivity into objectivity.

RankMiner transforms subjectivity into objectivity by producing an Artificial Intelligence ("AI") learning model that represents the aggregate view across the assessments that a company has conducted for its phone agents. With this approach, QA assessments will be seen as the supplement to the AI model's prediction mostly for the purposes of ensuring that the learning model remains calibrated to potential environmental and cultural shifts.

$$\hat{y} = \arg \max_{k \in \{1,\ldots,K\}} p(C_k) \prod_{i=1}^{n} p(x_i | C_k)$$

Stochastic model for assigning predictions or scores

The Results

Early indications when applying RankMiner's predictive models to improve Agent Success are impressive:

"RankMiner's Agent Performance models have allowed us to automatically evaluate 100% of our call volume *and* increased our QA productivity by over 50%" according to Mike Anna Sr., DCI's Chief Quality Officer.

"Moreover, it used to take us 4–5 weeks to establish a particular trend for a given phone agent. With RankMiner's Agent Performance solution, we're able to spot meaningful trends with certain agents within a couple of days."

Identifying those trends early translates into big dollars for DCI. "We conducted a test of phone agents who were identified as in need of 'Speech Therapy' training—*the month over month improvement that the agents showed in gross collections was dramatic.* Within the test group, our agents were able to increase their gross collections by over 21.6% on average, which translated into approximately $6,000 more in gross collections for each of those agents in a single month!" states Gordon Beck, DCI's Chief Operating Officer.

While preliminary results show very positive indications, RankMiner continues to test and evaluate new ways to improve business performance. No matter which industry your business operates in or what business function you'd like to improve, RankMiner is poised to provide call-center focused companies solutions to revolutionize the way they do business by helping them work smarter and close faster.

APPENDIX A

Technical Reference

The agent scoring process follows a general algorithm such that each step can be broken down into constituent parts comprised mostly of popular methods in practice today, but also of RankMiner's proprietary formulations and heuristics. The first step is to define an equation or set of equations, either constrained or unconstrained, that describes the input (in this case raw audio signals) and the goals of the company (typically maximizing profit or minimizing cost) accurately and completely, being careful not to introduce redundancies in the definitions. RankMiner currently derives its models from the fundamental concepts of statistical regression and popular stochastic classifiers. Next, audio signals are associated with the defined outcomes of the model; in the simplest case, they are given values that correspond to "good" (e.g. 1) and "poor" (0). The unstructured data of the raw audio signal is then put through various calculations defined by the model to give it its mathematical representation. Audio signals are almost always converted into a mathematical form by taking the time-based signal and translating it to the frequency domain via Fourier sampling and transformation methods, and this is the case with RankMiner. Once each audio signal is given its mathematical structure and associated numeric label, both quantities are fed into the model's equations. These equations are parameterized, so that what is usually considered variable (the signal input) is treated as a fixed value in order to find the optimal set of parameters. Once calculated from the labeled data, the calibrated parameters allow subsequent audio signals to be treated as variable. Indeed they are, for anything to be predicted or scored by definition cannot have a label associated with it. These parameters are not fixed, as a typical constant in an equation would be however. Every time new audio data can be given a label, either through automated means or by human evaluation, the parameters can be made "variable" again to fine-tune the model with the newly discovered information. In this respect, the dynamic learning model becomes more and more effective as time goes on. This is the fundamental concept behind RankMiner's predictive analytics engines.