Incident Ticket Analytics for IT Application Management Services

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Abstract— **An important IT service outsourcing business is to resolve incidents related to IT infrastructures our clients contract our company to support. Incidents are recorded as structured and unstructured data in tickets, which contain various characteristics about the incidents including timestamps, description and resolution Analyzing such incident tickets becomes a critical task in managing the operations of the service in order to keep the operations within the agreed upon service level agreement. Ticket analytics is essential to identify anomalies and trends, as well as detect unusual patterns in the operations; such analysis is hard to do manually especially for large accounts with complex organization and scopes. This paper focuses on ticket analytics and some key statistical techniques applied in the analyses. Finally, we use real-data examples to demonstrate these techniques and discuss major challenges of ticket analyses.**

Keywords-Incident management, IT services management, ticket analytics

I. INTRODUCTION

Application Management Services (AMS) is a type of IT outsourcing service offering that uses well-defined, globally integrated processes, policies, procedures, and standards to manage clients' application portfolios. The offering typically includes services for help desks, application maintenance and support, and application health monitoring. For most enterprises, an application could be a software product such as SAP or Oracle modules, or a solution package such as CRM or client-specific software. An incident ticket is a record of service request for dealing with failures, errors, or any troubles with an application supported by the contracts. It contains a combination of structured and unstructured data. Examples of structured data in a ticket are request type, application area, the organization locus of the problem, who resolves the ticket, timestamps of the request and the resolution and, in some cases, the actual amount of time the ticket resolver spent on resolving the ticket. Examples of unstructured data are textual description of the problem and the documentation of the resolution. The broad goals of ticket analytics include

1. Assessment of ticket volume as indication of operational workload;
2. Assessment of ticket resolution time as indication of operational efficiency;
3. Identification of potential problems that caused the incidents.

We have developed a web-based tool [9] to provision ticket analytics as a standard service to AMS clients. The tool takes operation data of a client and other structured data in the ticket as an input, automatically calculates a number of metrics, assess these metrics, and provide a dashboard summarizing the client's operational performance. While [9] provides details of the tool, this paper will focus on the heart of the analytics and dive deep into the statistical methods used by ticket analytics. We will also provide a case study to demonstrate some of techniques and their business values.

The remainder of this paper is organized as follows. Section 2 provides the context of a real-world business use case for ticket analytics, based on one of our client engagements. Section 3 gives a short description of incident ticket data structure and ticket-related metrics. Section 4 describes in detail the statistical techniques along with their business values. Section 5 shows the architecture of the web-based ticket analytics tool. Section 6 compares this work with related work in the field. Finally Section 7 concludes the paper with a brief description of our future work.

II. WHY TICKETS ANALYTICS? – A BUSINESS CASE

The web-based ticket analytics tool [9] has been used by several dozens of global companies in various sectors and industries over a few years in assisting AMS operations. In this section, we describe a representative usage of this tool by showing typical business questions that the ticket analytics is targeted at addressing, and its business value in helping improve AMS operational performance.

Analytical methods over ticket data were used in client engagements to answer a number of business questions regarding IT incident management operations. Here are some of the key typical questions:

i. *Comparison questions*
  a. Are there any significant differences in the ticket volume across different applications or groups?
  b. How does the actual ticket volume distribution across priorities or severities conform to the original assumptions for the portfolio?
  c. Are there any significant differences in resolution times across different ticket categories or groups?
  d. How do ticket resolutions meet the service level agreement (SLA) requirements?

ii. *Trending questions*

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a. How does the ticket volume change over time? Are there any significant patterns or trends?
b. How does the ticket resolution time change over time?

iii. *Forecasting questions*

a. What are the anticipated ticket volumes for the next time period (month, quarter, etc.)?

iv. *Ticket technique structure and resolution strategy questions*

a. What are the typical problem symptoms or major problematic areas that contribute to most of the tickets?
b. What are the common solutions to tickets of different categories?
c. Is it possible to automate ticket resolution?

Answers to these questions can greatly help account team make decisions in their daily operation. For example, knowing the ticket load variations across applications can help plan staffing with the right skills. This is even more important when resources are not shared across applications due to different skill requirements imposed by applications. The trending questions can help identify underperforming business areas. For example, trending up resolution time without significant changes in ticket volume or applications may indicate a degrading of assignee performance or inefficient staffing.

III. INCIDENT TICKET AND METRICS

Incident tickets are an important vehicle for measuring and achieving AMS quality. Ticket analytics utilizes raw structured ticket data and/or sometimes custom-specific metrics calculated from raw ticket data. For example, operational workload is usually represented as a set of measurable metrics including ticket volume (monthly, weekly, or daily), ticket volume per application or other categories, backlog (i.e., the difference between the number of tickets received and the number of tickets completed by a particular time instant). It is important to model ticket data such that analyses have sufficient information substrate to provide operational insights. In this section we provide some detailed data structure as background for the subsequent analytics section.

Figure 1 shows a sample ticket, which contains the following key attributes:

- Ticket ID: unique identifier of the case;
- Ticket Open Time: a timestamp indicating when the case was submitted;
- Ticket Resolve Time: a timestamp indicating when the case was resolved;
- Ticket Close Time: a timestamp indicating when the case was closed;
- Ticket Status: the current handling status of the ticket;
- Ticket Resolution Time: the elapsed time between ticket close/resolve time and ticket open time, which could be either in calendar days/hours, or business days/hours. Specifically, in the latter case, we need make certain assumption about the ticket resolver's business hours. For instance, he or she works 8 hours a day and 5 days a week. However, such definition could vary with ticket priorities. For more accurate measurement of ticket resolution time, additional metadata describing ticket resolvers' business hours would be required.

Incident ID: INC1
Severity: High
Status: Closed
Open Time: 7/16/2010 6:55:20 AM
Close Time: 7/17/2010 8:31:47 AM
Assignee Name: John Doe
Assignment Group: Account Management
Description: The USER xxx has a successful *login* into the hub after *registration*, but he is *unable to access* SAP. Every time when he clicks on Sap work place, the screen goes blank!
Resolution: Fixed USER xxx permission to access SAP.

Figure 1. A sample incident ticket with a number of typical attributes.

In addition, ticket data contains contextual attributes which enable grouping analysis of tickets. These attributes are as follows:

- Ticket Resolution Code: a classification of the resolution method;
- Ticket Assignee (or Assignment Group): name or ID of the technical staff (or group) assigned to resolve the ticket;
- Application: name of the application that caused the ticket to be created;
- Ticket Severity or Priority: a classification of the severity or priority of the ticket.

In some ticket systems, the time between ticket opening and ticket closing is further divided into some additional segments, such as assigned time (a timestamp indicating when the case was assigned to a technical staff) and resolved time (a timestamp indicating when the case was resolved by the technical staff but was waiting for the client's approval to close the case). In addition, very often Ticket Resolution Code or Applications involved in tickets are not explicitly recorded in tickets due to the lack of explicit classification schemas. In this case, text mining on the ticket text can be an alternative way to group tickets based on ticket symptoms or resolution strategies.

Based on incident tickets, a number of "metrics" can be calculated. For example, ticket volume indicates the number of tickets received within a certain period of time. The volume can be further grouped by attributes such as Severity, Application, Assignment Group, etc. As another example, resolution time can be aggregated and averaged by time period and/or by grouping attributes.

Once the metrics are calculated, we apply a ticket operation assessment process to monitor these metrics, analyze them to understand the normal behaviors, identify anomalous situations, and provide actionable recommendations for improvement. This process not only requires tremendous domain knowledge but also a number of statistical methods, for example, Statistical Process Control (SPC) [11] for anomaly detection, and text mining to identify main problem causes as recorded in ticket text.

In a stable business environment, these metrics usually does not fluctuate dramatically over time. However, unusual movement of these metrics may reflect significant changes in the business environment, for example, new applications release, staff turnover, and application environment issues. Therefore, analysis on these metrics as time series can disclose deep causes and suggest remedies for performance improvement.

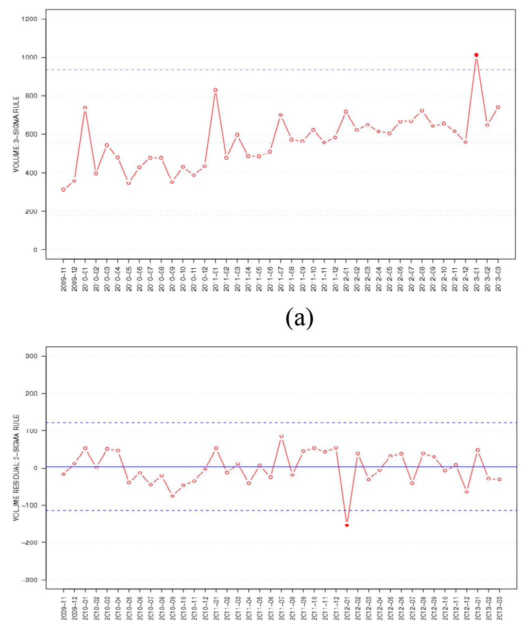
IV. Statistical Methods and Examples of Ticket Analysis

As mentioned previously, statistical methods are used to analyze both structured and unstructured data in incidents tickets. In this section we will detail some key statistical methods applied in our analysis. Section 4.1 to 4.4 will focus on those applied to structured data while Section 4.5 describes data mining on unstructured ticket data.

A. Statistical Process Control for Ticket Volume Analysis

Statistical process control (SPC) is a widely used technique in manufacturing industries for monitoring the quality of parts and for detecting potential defects in the manufacturing process over time. It has also been adopted in services industries as a tool for service quality control. In this work, we have applied the SPC method to monitor the weekly/monthly volume, backlog of tickets, and the weekly/monthly resolution time statistics including standard deviation and quartiles. There are many ways to set up an SPC procedure.

A simple example is a chart which depicts the sequence of the observed values for the variable that we want to monitor together with one or two horizontal lines that depict the 3-sigma rule, i.e., 3 standard deviations (or sigmas) above and below the mean (the latter can be omitted if unusually low values of the variable are of no concern to the user). Any data points that cross the 3-sigma line implies a deviation from the mean by more than 3 times the standard deviation and can be flagged as anomalies (outliers). Unlike manufacturing applications where systematic drift of the mean signifies potential problems with the manufacturing process, trends in ticket volumes are expected as a result of the expansion or contraction of the business. Seasonality in ticket volumes is also expected when serving a business that has cyclical behaviors (retail industry, for example). In situations like these, anomaly detection should be performed by taking the anticipated trend and seasonality into account, and the standard SPC procedure can be applied after the removal of trend and seasonality. The trend and seasonal patterns can be estimated explicitly by least-squares regression techniques. These features are important in their own right for capacity planning purposes. Figure 2 shows an example where the removal of trend and seasonality makes a difference in anomaly detection.



(a)

(b)

Figure 2. Monitoring monthly ticket volumes by a control chart with upper and lower limits defined by the mean plus and minus 3 times the standard deviation. (a) Original time series. (b) Residual time series after the removal of trend and seasonality. Here, solid line indicates the mean while dashed lines indicate the upper and lower limits.

Figure 2(a) depicts the monthly volumes of a certain ticket type from an actual client. The series shows a strong increasing trend with occasional spikes and other more complicated variations. A simple application of a control chart with upper and lower limits defined by the mean plus and minus 3 times the standard deviation finds a mild outlier in January 2013 with an unusually high volume which could be alarming from the business point of view. However, by a closer examination of the volumes in the previous years, we can see that January is often the month when the volume spikes, but these spikes do not exceed the upper limit because they are masked by the increasing trend. To detect anomalies against this background of trend and seasonality, we first assume that the trend is linear and the seasonality is, naturally, 12 month. The resulting model can then be expressed as

$$m(t) = a + bt + \sum_{k=1}^{11} c_k \, I(t = k \bmod 12) \quad (t = 1,2,\ldots).$$

The coefficients in this model are estimated by least squares. By removing the estimated trend and seasonality from the original data $v(t)$, we obtain the residual time series $r(t) = v(t) - m(t)$. Figure 2(b) shows the residual time series together with the control limits defined in the same way as in Figure 2(a). It turns out that January 2013 is no longer an outlier when the trend and seasonality are taken into consideration. Instead, the control chart reveals that January 2012 has an unusually low volume which may not be alarming at all from the business point of view.

On the other hand, for monitoring backlogs whose volume is usually low as compared to regular ticket volume, the so-called c-chart seems more appropriate. Figure 3 shows a real-data example. This chart is similar to the one shown in Figure 2 except that the upper limit is defined as the mean plus 3 times the square root of the mean instead of 3 times the standard deviation. The c-chart is more suitable for monitoring time series of small counts for which the underlying normality assumption in Figure 2 becomes less warranted. The c-chart is based on the Poisson assumption which is bounded below by zero and has a longer upper tail than a normal distribution.

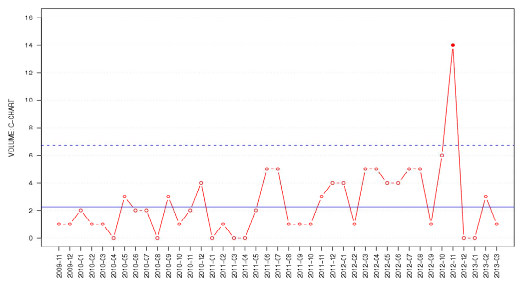


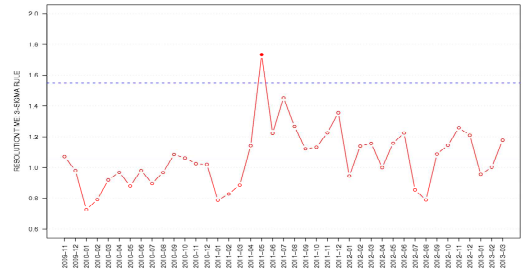
Figure 3. Monitoring monthly backlogs by a c-chart with the upper limit defined as the mean plus 3 times the square root of the mean.

B. Statistical Process Control Methods for Ticket Resolution Time Analysis

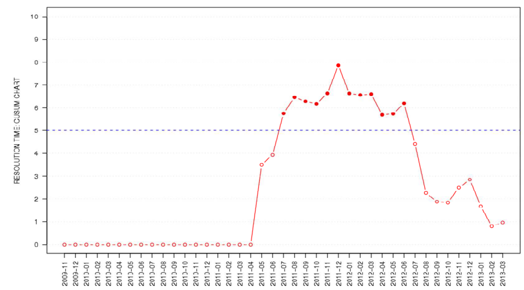
The resolution time can vary dramatically from ticket to ticket. The variability depends on the nature of the ticket as well as the skill and performance of the technical staff who resolves the ticket. To monitor the behavior of ticket resolution time, one has to focus on certain meaningful statistics. The mean resolution time is one of such statistics. Figure 4 shows an example of monitoring the monthly mean resolution time of tickets for a real application. While the control chart in Figure 4(a) detects an outlier in May 2011, a closer look shows that the mean resolution time experiences an upward shift which lasts for several months. To detect such moderate but persistent shifts, one can use the so-called cusum chart, which shown in Figure 4(b). The (standardized) cusums of a series $X(t)$ are defined as

$$S(0) = 0,$$
$$S(t) = \max\{0, S(t-1) + [X(t) - \mu - \delta/2]/\sigma\} \quad (t = 1,2,\ldots),$$

where μ is the reference value for the mean ($\mu = 1$), δ is the target shift in mean for detection ($\delta = 0.3$), and σ is the standard deviation ($\sigma = 0.17$). An upward shift is declared once $S(t)$ exceeds an upper limit h which is typically set at 4 or 5. Figure 4(b) shows the cusum chart with $h = 4$. As we can see, it detects an upward shift during the period of July 2011 to July 2012. The mean resolution time falls back below the detection limit after June 2012, indicating an improvement in the handling of the tickets.



(a)



(b)

Figure 4. Monitoring monthly mean resolution time. (a) Control chart with the upper limit defined as the mean plus 3 times the standard deviation. (b) Cusum chart with the upper limit set at 5. Here, the solid line in (a) indicates the mean while the dashed lines in (a) and (b) indicate the upper limits.

C. Statistical Process Control for Service Quality Assurance

For service quality assurance, benchmarking, and many other reasons, it is necessary to compare resolution time for different ticket categories. Figure 5 shows the cumulative probability distribution of resolution time for tickets of five different categories within a month.

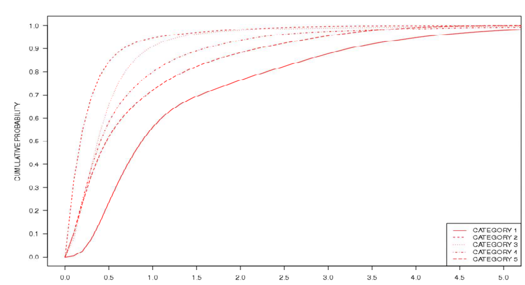


Figure 5. Probability distribution of resolution time for tickets from five categories.

A simple parametric model for ticket resolution time is the log-normal distribution, where the logarithmic transform of the resolution time is assumed to be a random variable with a Gaussian distribution which is indexed by two parameters, the mean and the variance. Under this assumption, one can perform a pairwise *t*-test to compare the resolution time from all pairs of applications (Holm 1976).

Let y_i, s_i, and n_i denote the mean, the standard deviation, and the sample size of the log resolution time for tickets from category i. Given a pair of categories, i and j, the t-test employs the standardized difference in mean defined by

$$t_{ij} = \frac{y_i - y_j}{\sqrt{s_i^2 / n_i + s_j^2 / n_j}}.$$

If the absolute value of this quantity is greater than a predetermined threshold, then categories i and j are considered as having significantly different means in their resolution time. A p-value is calculated for each pair of comparison as an indication of statistical significance. It is the likelihood of false positive.

Table I contains the t-statistics and their p-values for testing the equality of the means for every pair of the five categories. It shows that eight out of ten pairs have significantly different means, only the 3-4 pair and the 4-5 pair do not have significantly different means.

TABLE I. THE TEST STATISTICS AND THEIR P-VALUES FOR PAIRWISE COMPARISON OF TICKET RESOLUTION TIME FOR FIVE CATEGORIES. THE OVERALL FALSE POSITIVE RATE IS SET AT 0.05.

Category Pair	Pairwise *t*-Test		Pairwise Rank Test	
	Test Statistic	***p-Value***	***Test Statistic***	***p-Value***
2-1	–30.1	0.00	–0.43	0.00
3-1	–19.8	0.00	–0.34	0.00
4-1	–9.0	0.00	–0.27	0.00
5-1	–8.2	0.00	–0.20	0.00
3-2	20.5	0.00	0.27	0.00
4-2	9.9	0.00	0.26	0.00
5-2	12.9	0.00	0.27	0.00
4-3	1.6	0.21	0.02	0.99
5-3	3.9	0.00	0.06	0.14
5-4	1.4	0.21	0.04	0.75

In addition to the pairwise t-test, which requires the Gaussian assumption for the log resolution time, one can also perform a pairwise comparison based on the ranks of the data without any assumption about the distributions (Konietschke et al. 2012). Unlike the pairwise t-test, the rank-based test measures the difference between a pair of distributions i and j by the so-called relative effect score defined as

$$d_{ij} = \frac{1}{n_j}\left\{ r_i^{(ij)} - \frac{n_i + 1}{2} \right\} - \frac{1}{2},$$

where $r_i^{(ij)}$ denotes the average rank of the resolution times x_{ik} ($k = 1,\ldots,n_i$) from category i in the combined sample $\{x_{ik}, x_{jl}$: $k = 1,\ldots,n_i$; $l = 1,\ldots,n_j\}$ with category j. The statistic d_{ij} is positive if the resolution time of tickets from category i tends to be longer than that from category j; it is negative if the resolution time of tickets from application j tends to be longer than that from category i. If the statistic is sufficiently small in absolute value, then the two distributions are considered statistically indistinguishable.

The last two columns in Table I contain the d-statistics and their p-values of this test. The seven pairs of categories tested positive are identical with those found by the pairwise t-test. However, the pair consisting of categories 3 and 5 is now considered having indistinguishable distributions. Therefore, based on the rank test, one can regard applications 3, 4, and 5 as a cluster in which the resolution times have similar distributions, whereas categories 1 and 2 have distinct distributions from each other as well as from the cluster consisting of categories 3, 4, and 5.

D. Statistical Process Control for Ticket Volume Forecasting

Finally, let us consider the problem of ticket volume forecasting. There is a wide range of time series models that can be used to forecast ticket volumes, depending on the behavior of the volumes to be forecasted. As an example, consider monthly ticket volumes shown in Figure 2(a). This series has an increasing trend as well as a strong 12-month periodicity. A suitable model for such time series is the seasonal autoregressive integrated moving average (ARIMA) model (Box et al. 2008), denoted as ARIMA(p,d,q)×(P,D,Q), where p, d, and q represent the orders of ordinary autoregression, differencing, and moving average, respectively, and P, D, and Q represent the orders of seasonal autoregression, differencing, and moving average.

Figure 6 depicts the time series and the 12-month ahead forecasts for the monthly ticket volumes shown in Figure 2(a), using the celebrated (0,1,1)×(0,1,1) model with the 12-month periodicity. The trend and seasonality are well reflected in the forecasts which extend the increasing trend as well as the seasonality with a strong peak in December and a mild peak in July.

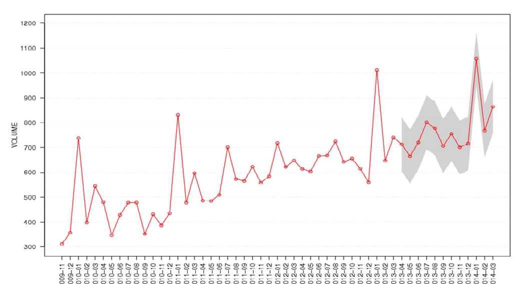


Figure 6. Forecasting monthly ticket volumes. The last twelve values from April 2013 through March 2014 are the forecasted volumes, and the shaded area around these values represents the 90% confidence band.

E. Text Mining for Clustering Tickets by Symptoms Positioning

Clustering tickets based on their text description can often provide insights on the technical mixture of tickets. There are a number of effective clustering techniques to process documents and cluster documents, for example, K-nearest Neighbor (KNN), hierarchical clustering, Latent Semantic Analysis (LSA), Latent Dirichlet Allocation (LDA), etc. [1]. As an example, Table II shows the clustering result of tickets related to a transaction processing application. Specifically, we first processed the text of 1445 tickets related to this application by extracting keywords and phrases that have classification power. Then, each ticket is represented as a vector of extracted keywords/phrases following the vector space model [12]. The similarity between a pair of tickets is measured as the similarity between these two vectors. Finally, we apply hierarchical clustering algorithm to group tickets based on ticket similarity.

TABLE II. CLUSTERING INCIDENT TICKETS FOR A TRANSACTION PROCESSING APPLICATION BASED ON TICKET TEXT. THE RESULT SHOWS THAT THE MAJORITY OF TICKETS ARE CAUSED BY MESSAGE QUEUE OVERFLOW.

Cluster	Number of Tickets	Percentage
Message queue overflow	864	59.79%
Communication channel errors	190	13.15%
Disk space issues	94	6.51%
Data format mismatch	76	5.26%
Security & user access	58	4.01%
Database issues	22	1.52%
Others	141	9.76%
Total	**1445**	**100.00%**

This ticket clustering can provide further insight on improving AMS operation. As indicated in Table 2, any effort to significantly reduce the volume of tickets or automate the resolution to tickets in the "Message queue overflow" cluster can effectively improve AMS performance. In addition, this clustering creates an additional grouping attribute for tickets. We can also analyze ticket volume or resolution for each cluster along time dimension as described before.

V. TICKET ANALYTICS SYSTEM ARCHITECTURE

Figure 7 shows the architecture of the Web-based Ticket Analytics System at a high level, showing different layers including the data, tools, operations and presentation, and different types of users of the system who bring in different analysis use scenarios for the system. The design objective of the system architecture is to provide a standardized, integrated analytics platform supporting AMS delivery that is built by using the standard open stack software on a Web platform, enhanced with advanced analytics, to improve productivity and quality of delivery of the AMS practice. Incident ticket data is usually proprietary to the system that records, and is often stored in different formats from one ticket system to another.

While detailed description of each layer in the system can be found in another paper [9], we briefly discuss the Tools layer. The Ticket Analytics tool is for reporting the analysis described in this paper. The current implementation is on the IBM Cognos Business Intelligence Server. It lets experienced analyst users to configure the analytics reports with valid and meaningful options for the report parameters and filters. Less sophisticated users and account executives can take advantage of predefined reports and dashboards by merely selecting predefined parameters and filters.

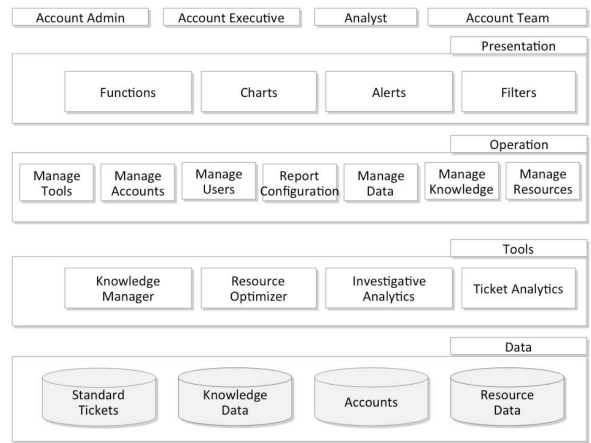


Figure 7. Ticket Analytics System Architecture.

The Investigative Analytics tool can help an account manage and track IT problems for root causes. The process often involves several phases of investigation. The tool provides various diagnosis algorithms to narrow down to a problematic subset of incident data. Also, it ensures a continuous and seamless experience in the incident diagnosis process.

The Knowledge Management tool can be used by the incident resolution practitioners. By capturing and authoring resolution knowledge for frequently reoccurring incidents and facilitating the reuse of the knowledge by the practitioners in a time-constrained environment, the tool helps improve the AMS delivery practice. The Resource Management tool helps the delivery executives understand the utilization of the delivery resources and plan the resource needs within and across customer accounts.

VI. RELATED WORK

IT Service Management (ITSM) is a new area that concerns contribution of IT to the customer's business. ITSM is different from the traditional technology-centered approaches to IT management and business interaction [6, 13, 14]. Incident Management is an IT service management process area [7]. The objective of Incident Management is to restore a normal service operation as quickly as possible and to minimize the impact on business operations, thus ensuring that the best possible levels of service quality and availability are maintained. Information Technology Infrastructure Library (ITIL) is a set of practices for ITSM that focuses on aligning IT services with the needs of business [4]. The main processes of incident management include incident detection and recording, classification and initial support, investigation and diagnosis, resolution and recovery, incident closure, and incident ownership, monitoring, tracking and communication. The AMS Analytics System presented in this paper concerns mostly about the operational analysis, investigation and diagnosis of incidents in ITSM.

In addition, the AMS Analytics System provides advanced analysis capabilities in knowledge management, resource management and operational forecast analysis model. Forecast analysis or predictive analysis is an area of statistical analysis that deals with extracting information from data and using it to predict future trends and behavior patterns [2, 10]. The core of predictive analytics relies on capturing relationships between explanatory variables and the predicted variables from past occurrences, and exploiting it to predict future outcomes. Due to its significant importance in business, incident diagnosis and the application of predictive analytics has been discussed among practitioners through forums and other media [6]. However, the problem is tackled only recently with a rigorous academic method.

VII. Concluding Remarks

In this paper, we have demonstrated some statistical techniques for ticket analysis. As any advanced analytics, a successful application of these techniques requires certain understanding of the underlying assumptions and their pitfalls, especially when these techniques are automated in a ticket analysis system.

For example, ticket volumes may exhibit very complicated patterns that cannot be adequately modeled as a linear function plus seasonal adjustments. Although more sophisticated techniques are available to deal with such patterns for anomaly detection, it remains a challenging task to automate the selection of these methods to suite the wide range of ticket volume volatilities. Without a proper account for these patterns, the SPC techniques could yield excessive false positives or miss important real anomalies.

Ticket backlogs are typically calculated as the cumulative sum over time for the number of tickets opened in a period of time minus the number of tickets closed in that period of time. In this case, they should be interpreted as the accumulation over time of tickets to be closed rather than the accumulation of tickets waiting to be resolved. As such, they are affected by the business practice of closing a resolved ticket. Therefore, ticket backlogs should be monitored at a frequency which is compatible with the business practice. For example, if tickets are closed immediately after resolution, the time elapsed between opening and closing tends to be short (e.g., in hours). In this case, backlog calculation should be done in a short time interval (e.g., daily). On the other hand, if it takes days or weeks to close a ticket for certain type of requests, then a weekly or monthly frequency should be sufficient.

Ticket resolution times often contain outliers that can easily obscure the calculated mean resolution time. Therefore, more robust metrics, such as the median, should be considered as a possible alternative to the mean for monitoring the resolution time.

The variability of ticket resolution time can vary dramatically across different ticket categories. This complicates the cross-category comparison, because the mean resolution time is no longer as meaningful as it is when the variability remains the same for all categories. In such cases, other metrics, such as the relative effect score, may be considered as possible alternatives.

References

[1] Berkhin, Pavel. A survey of clustering data mining techniques. Grouping Multidimen-sional data. Springer Berlin Heidelberg, 2006. 25-71.

[2] Bishop, C. (2006). Pattern Recognition and Machine Learning, Springer ISBN 0-387-31073-8.

[3] Box, G. E. P., Jenkins, G. M., and Reinsel, G. C. (2008), Time Series Analysis: Forecast-ing and Control, 4th Edition, New York: Wiley.

[4] Clifford, David; van Bon, J. (2008). Implementing ISO/IEC 20000 Certification: The Roadmap. ITSM Library. Van Haren Publishing. ISBN 908753082X.

[5] Holm, S. (1979), A simple sequentially rejective multiple test procedure. Scandinavian Journal of Statistics, vol. 6, pages 65-70.

[6] IT Service Management Forum – USA. http://www.itsmfusa.org/.

[7] ITIL Incident Management - The ITIL Open Guide, http://www.itlibrary.org/index.php?page=Incident_Management.

[8] Konietschke, F., Hothorn, L. A., and Brunner, E. (2012), Rank-based multiple test proce-dures and simultaneous confidence intervals. Electronic Journal of Statistics, vol. 6, pp. 738-759.

[9] Li, Y., Li, T-H., Liu, R., Yang, J., and Lee, J. (2103), Application Management Services Analytics. 2013 IEEE International Conference on Service Operations and Logistics, and Informatics, July 28-30, 2013, Dongguan, Guangdong, China.

[10] Mitchell, T. (1997). Machine Learning, McGraw Hill. ISBN 0-07-042807-7.

[11] Oakland, J. (2002) Statistical Process Control ISBN 0-7506-5766-9.

[12] Salton, G., A. Wong, and C. S. Yang (1975), A Vector Space Model for Automatic Index-ing. Communications of the ACM, vol. 18, nr. 11, pages 613–620

[13] Van Bon, J. ed. (2002). IT Service Management: An Introduction. Van Haren Publishing. ISBN 9080671347.

[14] Van Bon, J. (Editor) (2002). The guide to IT service management. Addison Wesley. ISBN 0201737922.