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Big data based fraud risk management at Alibaba

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Abstract

With development of mobile internet and finance, fraud risk comes in all shapes and sizes. This paper is to introduce the Fraud Risk Management at Alibaba under big data. Alibaba has built a fraud risk monitoring and management system based on real-time big data processing and intelligent risk models. It captures fraud signals directly from huge amount data of user behaviors and network, analyzes them in real-time using machine learning, and accurately predicts the bad users and transactions. To extend the fraud risk prevention ability to external customers, Alibaba also built up a big data based fraud prevention product called AntBuckler. AntBuckler aims to identify and prevent all flavors of malicious behaviors with flexibility and intelligence for online merchants and banks. By combining large amount data of Alibaba and customers', AntBuckler uses the RAIN score engine to quantify risk levels of users or transactions for fraud prevention. It also has a user-friendly visualization UI with risk scores, top reasons and fraud connections.

Keywords: Fraud detection and prevention; Risk model; Malicious behavior; Risk score; Big data analysis

1. Introduction

Big data is an all-encompassing term for any collection of data sets which are large, complex and unstructured, so that it becomes difficult to process using traditional data processing applications. Big data “size” is dynamic and constantly growing, as of 2012 ranging from a few dozen terabytes to many petabytes of data by the time when the article is written. It is also a set of techniques and technologies that to analyze, capture, curate, manage and process data within a tolerable elapsed time (Wikipedia).

Big data has many different purposes − fraud risk management, web display advertising, call center optimization, social media analysis, intelligent traffic management and among other things. Most of these analytical solutions were not possible previously because data technology were unable to store such huge size of data or processing technologies were not capable of handling large volume of workload or it was too costly to implement the solution in a timely manner.

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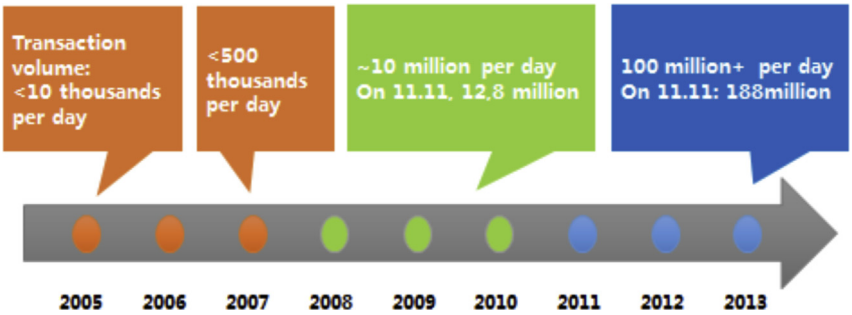


Graph 1. Transaction volume increases at Alibaba.

With business needs arose, Alibaba employed optimized system and platform and developed advanced methodology and approach to handle 10 billion level daily volume. It started from data platform of RAC in 2009, via GP (Green Plum, an EMC product, see EMC[2]) and Hadoop (see White[7]), and is using ODPS now. Data processing and analyzing is also improved from T + 1 mode[1] to near real-time mode.

By adapting big data techniques, Alibaba highlights advances made in the area of fraud risk management. It invents a real-time payment fraud prevention monitoring system, called CTU (Counter Terrorist Unit). And CTU becomes one of the most advanced online payment fraud management system in China, which can track and analyze accounts' or users' behavior, identify suspicious activities and can apply different levels of treatments based on intelligent arbitration.

Fraud risk models are one of the supportive layers of CTU[2] (Counter Terrorist Centre). They use statistical and engineering techniques to analyze the aggregated risk of an intermediary (an account, a user or a device etc). Detailed attributes are generated as inputs. Different algorithms are to assess the correlations of these attributes and fraud activities, and to separate good ones from bad ones. Validating and tuning are to make sure models apply to different scenarios. Big data at Alibaba produces thousands and thousands of attributes, and fraud risk models are built to deal with various of fraud activities.

Those big data based fraud models are widely used in almost every procedure within Alibaba to monitor fraud, such as account opening, identity verification, order placement, before and after transaction, withdrawal of money, etc. To build up a safe and clean payment environment, Alibaba decides to expand this ability to external users. A user-friendly product is built, called AntBuckler. AntBuckler is a product to help merchants and banks to identify cyber-crime risks and fraud activities. And a risk score (RAIN Score) is generated based on big data analysis and given to merchants and banks to tell the risk level.

In this paper, we show that Alibaba applies the big data techniques and utilizes those techniques in fraud risk management models and systems. We also present the methodology and application of the big data based fraud prevention product AntBuckler used by Alibaba.

The remainder of the paper is organized as follows. Section 2 introduces big data applications and basic computing process at Alibaba. Section 3 explains fraud risk management at Alibaba in details and fraud risk modeling. Section 4 provides an explanation of AntBuckler. We conclude in Section 5.

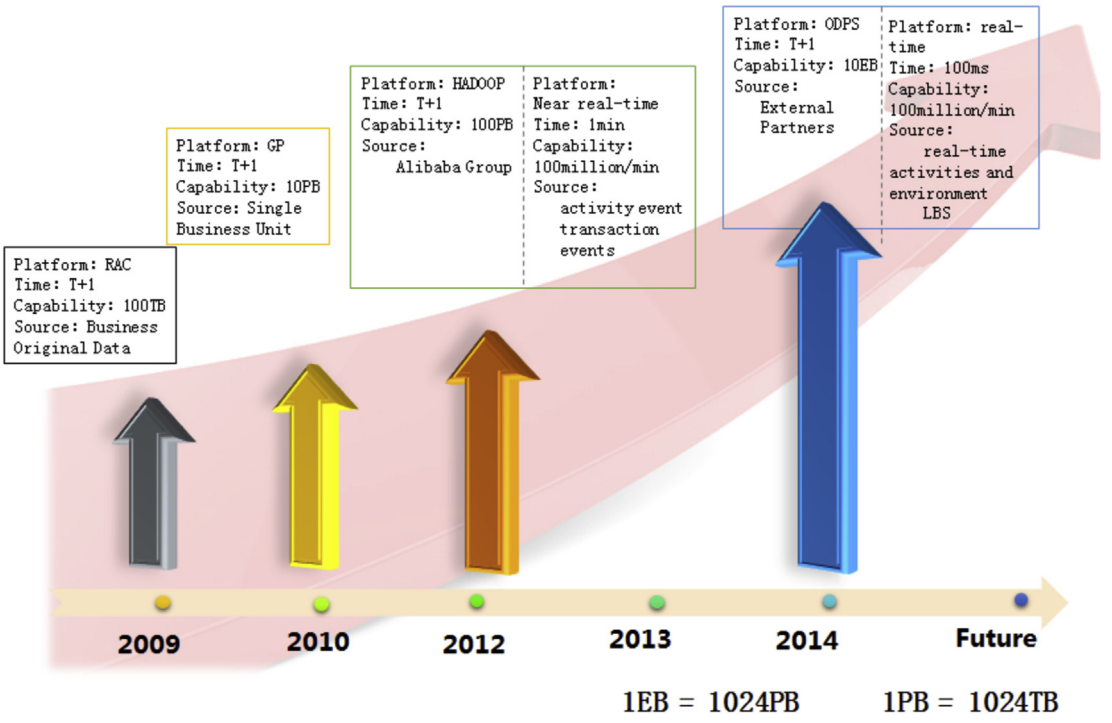
2. Big data applications at Alibaba

Alibaba grows fast in past 10 years. In 2005, daily transaction volume was less than 10 thousands per day. It reached to 188 million on Nov 11th, 2013 one day. Graph 1 illustrates that the transaction volume at Alibaba changes from 2005 to 2013 on daily basis.

With business growing exponentially, data computing, processing system and data storage are bound to change as well. It started from data computing platform of RAC (Oracle Real Application Clusters (see Oracle white paper[1])) in 2009, via GP and Hadoop, and is using ODPS now. Data processing and analyzing is also improved from T + 1 mode

[1] T + N mode: T is time, when system runs. N is time interval. T + 1 means the system runs on the second day.

[2] CTU: Alipay's internal risk control system, which is fully developed and designed by Alibaba. This name is inspired by American TV series <<24>>.



Graph 2. Big data computing progress at Alibaba.

to real-time mode, especially in risk prevention at Alibaba, fraud check on each transaction can be controlled within 100 ms (millisecond). Moreover, data sources are extended from single unit data to a combination of internal group data and external bureau data. Graph 2 illustrates that the big data computing process at Alibaba progress extensively since 2009. Alibaba has data not only from Taobao, Tmall and Alipay, but also from partners like Gaode Maps and others. Data from various sources builds up an integrated data platform, the platform from business scenarios extends largely as well. Marketing uses data analysis to target users accurately and to provide customers service personally. Merchants and financial companies need professional data classification to filter out valuable customers. Intelligent customer service can effectively and efficiently solve users' requests and complaints using comprehensive data platform. And the online payment services and systems, Alibaba, among leaders of online payment service providers, builds up a fraud risk management platform to ensure both buyers and sellers with fast and safe transactions. Alibaba deals with big data extensively on credit score and insurance prices as well as other types of business.

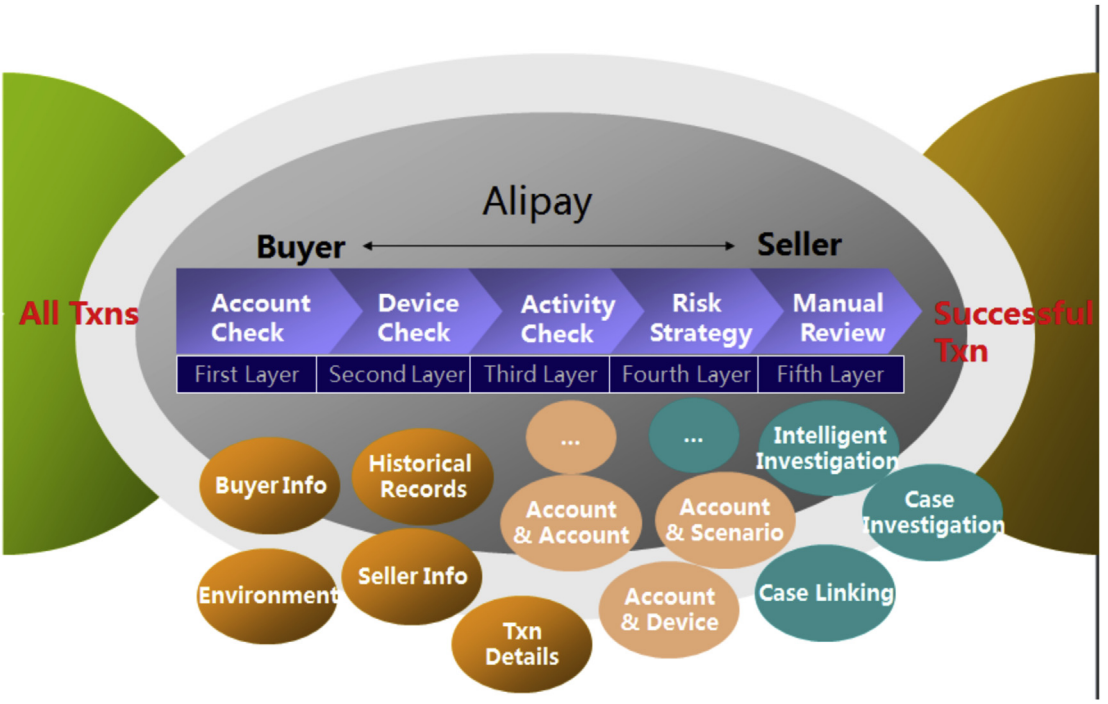
3. Fraud risk management at Alibaba

3.1. Framework for fraud risks

Fraud risk management at Alibaba is totally different from that of traditional financial and banking system now due to big data. To deal with real-time frauds, new engineering approaches are gradually developed to handle such quantity of data. On top of hardware system, risk prevention framework is also built up to support new methodology and algorithm. There are a few different kinds of risk prevention frameworks.

One fundamental framework of fraud risk that Alibaba uses is called multi-layer risk prevention framework. Graph 3 illustrates the multi-layer risk prevention framework Alibaba uses in Alipay System. There are total five layers in this system.

At Alibaba, there are 5 layers to prevent fraud for a transaction. The five layers are (1) Account Check, (2) Device Check, (3) Activity Check, (4) Risk Strategy and (5) Manual Review. One fraudster can pass first layer on account check, and then there are still four layers ahead to block the fraudster. When a transaction is initiated, the first layer is



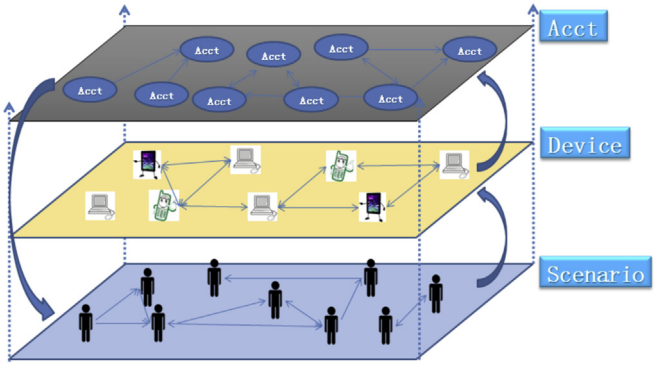
Graph 3. Multi-layer risk prevention framework.

Account Check, which includes buyer account information and seller account information. Several checks on the first layer Account Check are designed as questions: does the buyer or seller account have bad/suspicious activity before? Is there any possibility the buyer account stolen etc? Extremely suspicious transactions may be declined to protect genuine buyers, or extra authentic methods may be trigged to double confirmation in this situation. The second layer is Device Check, which includes the IP address check and operation check on the same device. Similarly, checks on the second layer Device Check are designed from passing several questions: whether there are huge quantify of transactions from the same device? Any transaction is from bad devices? The third layer is Activity Check, called as Behavior Check as well, which checks historical records, buyer and seller behavior pattern, linking among accounts, devices and scenarios. Checks on the third layer Activity Check are designed as questions as well: whether the buyer or seller account link to an identified bad account? The fourth layer is Risk Strategy, which makes final judgment and takes appropriate action. Checks on the fourth layer Risk Strategy are designed to aggregate all results from previous checks according to severity levels. Some transactions are sent to auto-decision due to obvious fraud activities. Some grey cases are sent to Manual Review. On one hand, Alipay would like to provide better services and experiences for both parties. On the other hand, Alipay does not want to misjudge any case. Without strong evidence, suspicious cases will be manually reviewed in the last layer Manual Review, where more evidences are revealed and some phone calls may be made to verify or remind or check with buyers or sellers.

Another key difference between fraud risk management at Alibaba and “that” of traditional financial and banking system is the risky party. Customers are evaluated to be the main risky party in banking system. At Alibaba, there are 3 layers of risky party. The three layers are (1) Customer level, (2) Account level and (3) Scenario level. See Graph 4. Risk fraud prevention at Alibaba is for both customers whether they are buyers or sellers or not, for both accounts whether those accounts are prestigious for big company or a single individual or not, for both scenarios whether those activities happen during account opening or money withdrawal.

3.2. *CTU − fraud prevention monitoring system*

CTU is a real-time payment fraud prevention monitoring system, which can track and analyze accounts' or users' behavior, identify suspicious activities and apply different level of treatments based on intelligent arbitration. The first



Graph 4. Multi-layer risk prevention framework.

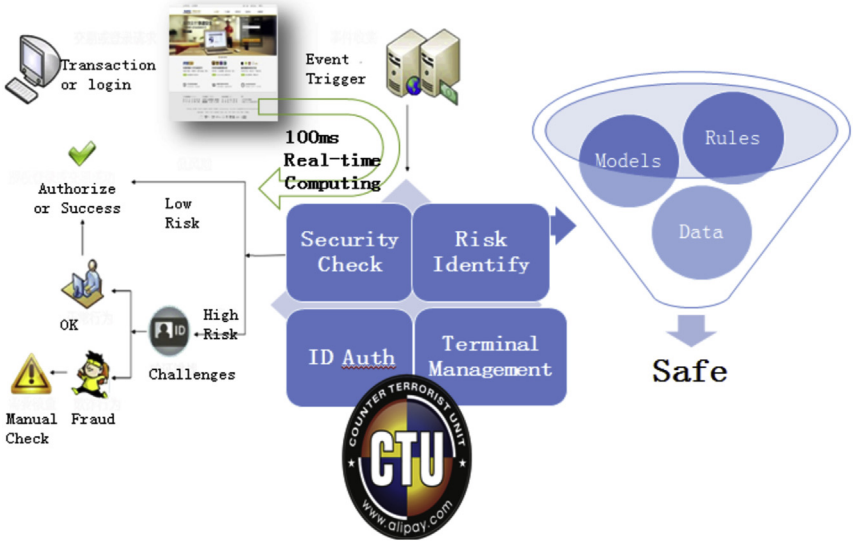
version launched on 1st Aug, 2005. This system is independently developed by Alipay's risk control team. At that time, it focused more on large transaction investigation, suspicious refund, etc. Now it extends to money laundry, marketing fraud, accounts, and card stolen/loss as well as cash monetization. Additionally, it is a 24 h monitoring system, which provides throughout protection at any time.

When an event happens, it passes through CTU for judgment. An event is defined to be that a user logins, changes profiles, initiates transactions, withdraws money from Alibaba to other bank accounts and others. There are hundreds of kinds of events. A suspicious event triggers models and rules behind the CTU for real-time computing, and within 100 ms, CTU returns the result with risk decision. If this is a low risk from CTU return, the event is passed to continue its operation. If this is a high risk, the CTU will direct a stop or a further challenge step to continue the process. Graph 5 illustrates the CTU operating process.

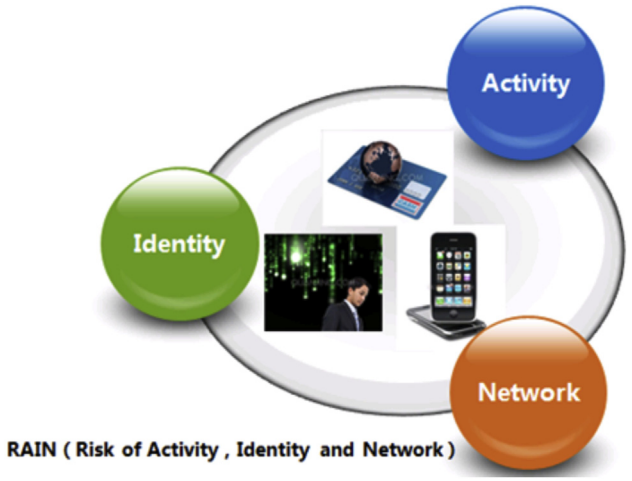
3.3. Fraud risk modeling

The data that supports CTU judgment is from historical cases, user behaviors, linking relationship and so on. Risk models are built to analyze fraudsters' cheating patterns, relations among fraudsters, different behaviors between a group of good users and a group of bad ones.

There are a few factors to consider during building risk models. Bias and Variance are usually concerned together to balance the effectiveness and impact of a risk model. Bias is a factor to measure how a model fits for the risk, how to



Graph 5. CTU-risk prevention system at Alibaba.



Graph 6. Three dimension of RAIN score.

find the risk of account or transaction accurately. Variance is to measure whether a model is stable or not, whether it can sustain a relative longer lifecycle in business. Negative positive rate, also called wrong cover rate, is to measure how the accuracy a model is. High negative positive rate will bring company huge business pressure and bad user experience. Moreover, interpretability is necessary to explain to users the reason that a model gives such risk level to his account or transaction. In big data age, except for factors mentioned above, data scientists keep fighting for data deficiency, data sparsity and data skewness.

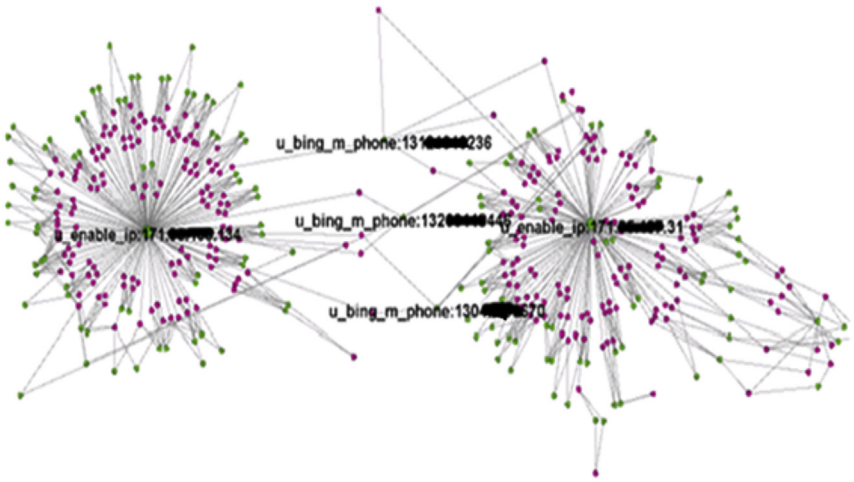
Model building process is also relatively mature at Alibaba after repeated deliberation. White and black samples are chosen first. White samples are good risk parties. Black samples are usually risky parties judged as bad. A good model can differentiate white and black samples to the most degree. Behavior data and activity data are collected for both samples to generate original variables from abstracting aggregated variables. Through testing, some variables are validated effectively. They can be finally used in model building. From our modeling experience by using Alibaba big data, decision tree C5.0 and Random Forest have better performance to balance between Bias and Variance. One obvious reason is that they do not assume data distribution since they are algorithmic models rather than data models. When a model is able to better separate good and bad ones among samples, the model is basically adapted to process. However, to make sure it applicable to different scenario, validation is also important. A model can be launched if it works effectively and efficiently on testing and validating data. Then, the fraud risk prevention models are needed to be deployed in the production environment, and are used in CTU combining with other strategies and rules.

3.4. RAIN score, a risk model

RAIN is one kind of risk models. RAIN stands for Risk of Activity, Identity and Network. Basically, the risk of an object (a user, an account or even a card) is composited of three dimensions of variables, activity, identity and network. Graph 6 illustrates the three dimensions of RAIN score. Hundreds of variables are first selected to interpret status and behavior of an object. Based on testing, verifying and validating from fraud risk models, variables are selected and kept. A RAIN score is generated based on different weight of variables within these three dimensions. Variables and weight of variables may differ according to different risk scenarios. For example, for a card stolen scenario, more Identity variables may be selected and with higher weight. While for a credit speculation scenario, more Network variables may be selected and are given higher rate. Weights of variables are trained by different machine learning algorithms, such as logistic regression.

3.5. An example of network-based analysis in fraud risk detection

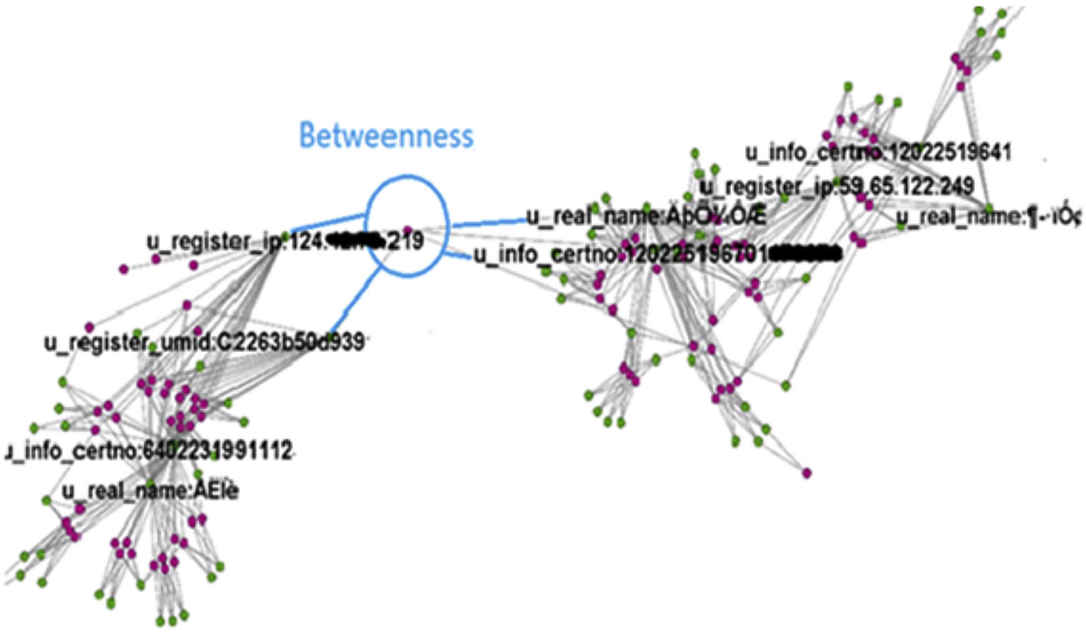
Graph theory (Network-based Analysis), an applied mathematical subject is commonly applied on social network analysis (see Wasserman[6]). Facebook, Twitter apply the Graph theory on their social network analysis. Network-based



Graph 7. Network of accounts and information.

analysis plays a new role in the risk control. Fraudsters nowadays are mischievous. They know that online risk models are constantly checking whether fraud accounts are from same name, address, phone and credit card, etc. Hence, they try new ways to hide the connections. Therefore, network based analysis is introduced to reveal the connection in this area. For example, if each account is considered as a node, network-based analysis is to locate edges among different nodes if they are owned by a physical person. If there are reasonable ways to define the edges among different nodes, some interesting groups can be disclosed.

In Graph 7, the red nodes represent accounts and green nodes are detailed profile information for those accounts, such as enabled IPs, phone numbers, name, address, etc. If an account (red node) has detailed profile information (green node), network analysis draws a line between this red and green node to show the relationship and the line is an edge. Graph 7 illustrates the network analysis that both groups have their own enabled IPs. However some accounts in two groups shared same bind phone numbers. This exposes the connections between two groups. Another example as below.



Graph 8. Betweenness detection.

Graph 8 tells us another story. One account shares the same register IP and register device footprint with the left group. It also shares the same name and info number with the right group. This is a strong evidence to prove the connections between two groups of accounts.

Two examples above are just a simple case. In the real world, connections are extremely complicated. We have to use paralleled graph algorithms and special graph storage to handle the huge network connection graph. The betweenness nodes (concepts from network-based analysis, see Freeman[5]) play important roles in finding connections of different accounts, where betweenness nodes are the betweenness centralities used in the network analysis. Connections now is widely used to judge relationship of accounts, this effectively prevent fraudsters building up their own networks.

4. AntBuckler − a big data based fraud prevention product

To build up a safe and clean pay0ment environment, Alibaba decides to expand its risk prevention ability to external users. A big data based fraud management product is built and called AntBuckler. This product is fully developed by Alipay.

AntBuckler is a product to help merchants and banks to identify cyber-crime risks and fraud activities. We find that merchants generally deal with similar fraud patterns. One example is marketing program fraud. Merchants often give cash reward or voucher certificate to new users to expand their user base. Fraudsters often take this opportunity to create hundreds of different accounts. To merchants, the marketing resource is not given to correct user base. To good users, they cannot benefit the cash reward or voucher certificate. Fraudsters may also sell their accounts with coupon in higher price. This not only damages the merchant's brand image and reputation, but also confuses the market and potential customers.

Antbuckler uses the RAIN model engine and generates a risk score (RAIN Score) to quantify the risk level. The score ranges from 0 to 100. The higher, the riskier. It also has user-friendly visualization. Top reasons are shown on top with a higher weight and brighter colors. Connection, through account, email, phone, card and so on, are presented using network based view. See Fig. 1. Fig. 1 is the main interface of one risky account. The interface gives detailed

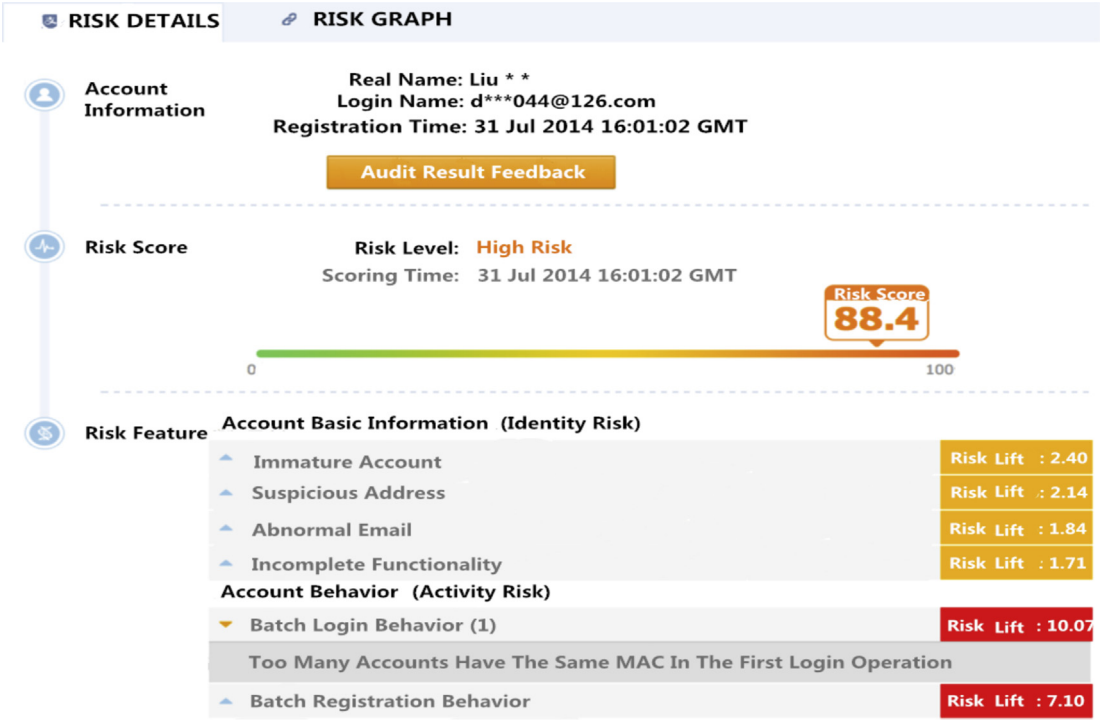


Fig. 1. User-friendly visualization of AntBuckler.

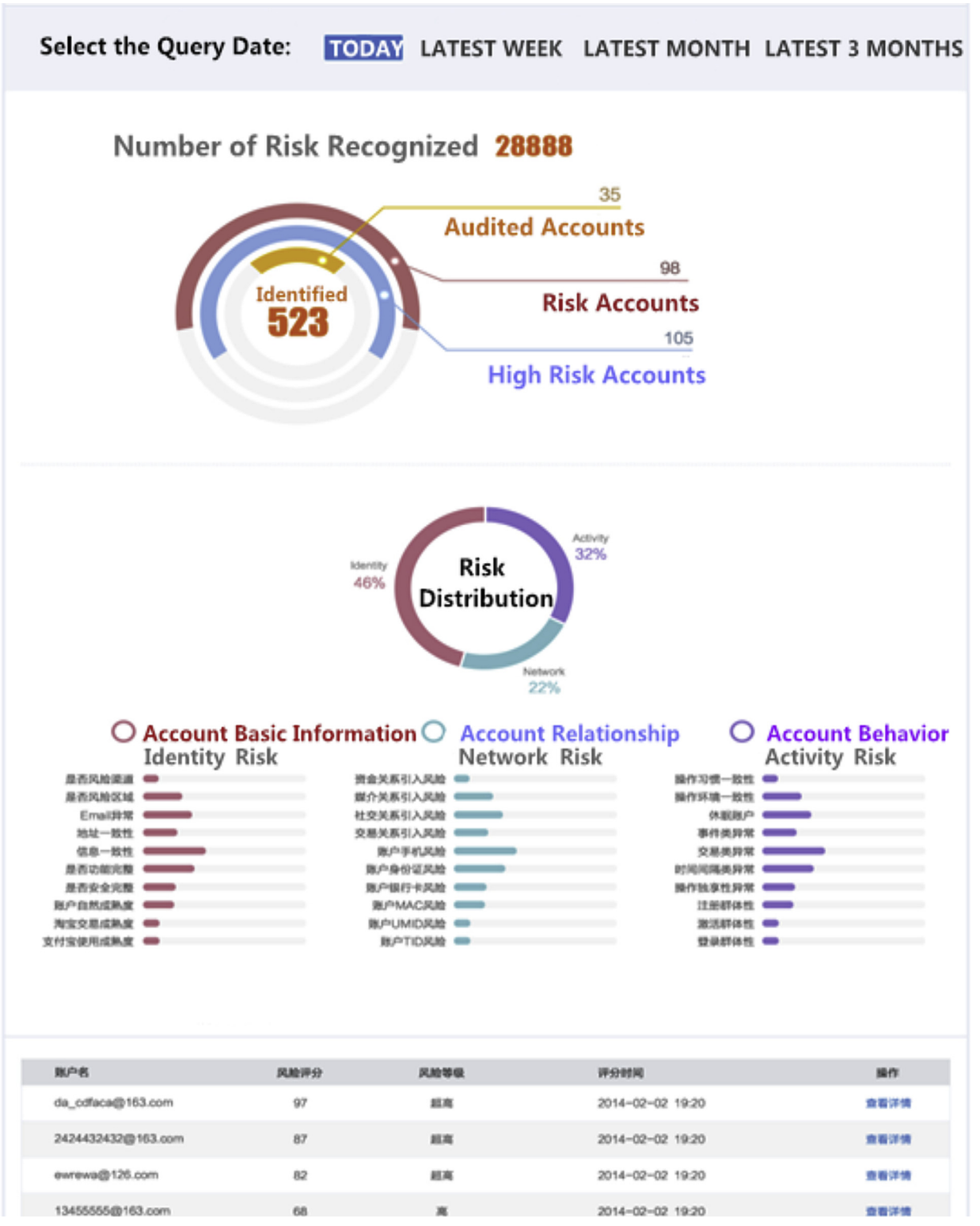


Fig. 2. Operation dashboard of AntBuckler.

account information, such as name, login email and registered time. RAIN score is shown together with a colorful bar. Green means safer and red means riskier. The operation dashboard tells how many accounts are judged by AntBuckler, how many accounts are identified with risk, where risky accounts are distributed, etc. See Fig. 2. Fig. 2 is an example of operation dashboard.

5. Conclusion

Big data based fraud risk management is a new trend in payment service business. It leads to a new generation of fraud monitoring and fraud risk management, which is based on big data processing and computing technology, real-time fraud prevention system and risk models. Alibaba has successfully used big data based fraud risk management to deal with daily fraud events. In this paper, we outline the fraud risk management at Alibaba and a big data based fraud prevention product. We would like to extend the analysis to build a safer and cleaner payment environment.

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