Who is the Most Diligent Employee? A discriminate model for e-Govenment service time analyzing

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Abstract

This paper discuss the human-related factors contributing to the service time for government services. We build a discriminate model to extract the subjective factor, e.g. diligence, and objective factor from the working behaviors in logs. This model can be trained by Maximum Likeness Estimation to get the parameters which denote the factors. To evaluate the accuracy of our model, we conduct an external experiment on a real dataset from the workflow system employed in the government of Hangzhou City in China, which results in 2367598 logs from 400 activities and 732 employees in two years. The experiment result not only proves the correctness of our model but also draws some interesting conclusion about the diligence of different people in different ages and genders.

Keywords: human-related factor, efficiency, e-Government

1. Introduction

The rapid development of Information and Communication Technologies (ICT) [1], brings plenties of chances to solve the classical problems in traditional domains by new perspectives and new approaches. An widely recognized example is e-Government [2][3], which is implemented by various researchers, communities and enterprises in various forms to enhance the efficiency of government service. Most works on e-Government concentrate on the improve the framework and architecture, from Service-oriented Architecture to Cloud based

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Framework. What they ignored is that government service is different with computing program, such as Web Service, because staffs are involved to complete each activity. A well designed e-Government cannot achieve anything without the employees participation. Therefore, efficiency promotion is required, the human-related factors should be considered.

When we talking about the human-related factors, two question should be mentioned, which are frequently considered by the managers.

- Whether the employee is skillful?
- Whether the employee is diligent?

These two questions construct a basic framework to analyze the human-related factor, namely objective factor and subjective factor. A guy is skillful is an objective factor because it is not related to his/her will. This sort of factor is usually easy to study and formalize [4]. Another factor, called subjective factor, is much harder. A skillful guy may be spend more time on a simple task once he/she is too lazy.

Here comes the problem: how to figure out the subjective factor and objective factor from the employees working behaviors? It sounds not an easy task since the behavior is a complicate mixture of these two factors. What helps is the logs, huge number of logs, about when and what activity the employee takes.

In this paper, at first, we build a discriminate model, to determine the service time for an activity and an employee by the subjective factor and objective factors. Then we propose a experiment framework to train and test our model. We predict the service time and compare it with the real service time. The the experiment shows a small difference between the predicted and real service time, which prove the correctness of our model.

The rest of this paper is organized as follows Section 2 studies the motivation scenario. Section 3 introduces the dataset from Hangzhou Government, China. Our model is proposed in Section 4. Section 5 reports the experiment

Employee Name	Activity Name	Accomplishment
Staff A	Acceptance	60 per day
Staff B	Acceptance	34 per day
	Print	34 per day
	Scan	28 per day

Table 1: The comparison on activity and accomplishment for two employees

on our model. Some discussions on the experiment result are shown in section 6. Section 7 discussed the related work. At last section 8 conclude this paper.

2. Motivation Scenario

A detailed motivation scenario is discussed in this section to prove that comparing two employees on diligence is difficult for the manager.

There are two employees in the same government department, in our dataset, which will be studied in next section. For their privacy, we use staff A and staff B to replace their names. Their manager now need to find out who is more diligent. Here is a summary report on their working information.

- Staff A is in charge of activity 'Acceptance'
- Staff B is in charge of activity 'Acceptance', 'Print' and 'Scan'

As illustrated by Tab. 1, the accomplishment of two employees are different on different activity. Though they are both in charge of activity 'Acceptance', staff B takes responsible of another two activities. It enhances the difficulty in comparing these two employees on diligence.

Different activities owns different complexity, the average service time for 'Acceptance' is 353 seconds while the 'Print' is 123 seconds. Therefore we cannot make the conclusion with staff B is more diligent than staff A because B completed more activity instances in total, namely 34+34+28 is larger than 60. In other words the accomplishment on different activities cannot been simply added together. To take the complexity on different activities in to consideration, we extract this factor in comparing employee's diligence.

Another challenge comes from the delay of switching from one kind of activity to another. For staff B, he may use 1 min on walking from his computer seat to the printer if he needs to carry out a 'Print' activity after accomplish an instance of 'Acceptance'. 34*1 min is near half an hour which means 1/16 of the total working time, 8 hours a day. It means that although staff B is really diligent, he still wastes lots of time in switching his working context from one kind of activity to another.

As we discussed above, comparing the pure diligence between two employees are really difficult in practice. Therefore in this paper, we concentrate on the problem of comparing two employee's diligence by their working logs. In our model, we extract all the external factors, from the performance of employees to estimate the pure diligence, a quantitative value, which guarantees the comparison between any two employees.

3. Dataset

To support our research, we collect the working logs data from the workflow system of Hangzhou Government, China. The dataset contains more than 2,367,598 event logs which spans from May. 2013 to Apr. 2015. It consists of 400 activities, 2,367,598 activities instances and 732 employees.

A data fragment is presented in Fig. 1. An event log, recording the life cycle of an activity instance, contains following attributes:

- *InstActivityId*: the identity number of this activity instance,
- *DefActivityId*: the identity number of the activity,
- *InstProcessId*: the identity number of the process instance that it belongs to,
- *DefProcessId*: the identity number of the process that it belongs to,

InstActivityId	DefActivityId	InstProcessId	DefProcessId	StaffId	Signin	Complete
2c90e4db43672ba901436f9075025983	actif1e7b7c88770	2c90e4db43672ba901436b8a77792f31	defpfa0a22cc8670	2c918a053463e2e7013463eeb53902ef	2014/9/10 15:10:03	2014/9/10 15:30:01
2c90e4da451670a40145205a7a466b24	actif1e7b7c88770	2c90e4da451670a40145205a79db6b23	defpfa0a22cc8670	20130511025034usrKFS100184	2014/9/10 15:12:35	2014/9/10 16:10:03
2c90e4dc45166f5b01451c30f67363cf	actif3bd1374877e	2c90e4dc45166f5b01451c30f61963cc	defpfa0a22cc8670	2c90e4da3e4b39fc013e4e097e24026f	2014/9/10 15:13:40	2014/9/10 15:19:12
2c90e4dc45183d7001451c01412f29f7	actif1e7b7c88770	2c90e4dc44f254d30144f2d9be520975	defpfa0a22cc8670	2c90e4db3b3fba44013b40a964d0127b	2014/9/10 15:13:42	2014/9/10 15:32:23

Figure 1: The dataset fragment consists of 4 activity instances from 2 activities in RetAP.

- *StaffId*: the identity number of the staff who take responsibility of this activity,
- *Signin*: the timestamp that this activity instance created and
- *Complete*: the timestamp that this activity instance completed.

4. Solution Framework

As we have mentioned, our work is to build a math model, extracting the employee's diligence, separating the external factors, e.g. the activity complexity, from the employee's performance in the working logs. In this section, we fully study our solution framework including our model and some necessary pre-operations.

4.1. Notations

To simplify our description, we summarize the notations used in table 2.

4.2. Factors

A working log records a five tuple $< a, e, c, la, y >$ where

- a is the id of this activity,
- e is the id of employee,
- c is the instance number of activity a that employee e accomplished before,

Notation	Explanation
a,e	activity id and employee id
c	the instance number of activity a that employee e accomplished before
la	the last activity id that employee e did
y	the service time
$T(a)$	complexity of activity a
$D(e)$	diligence of employee e
$F(a, e, c)$	familiarity of employee e on activity a with c instance done
$W(a, la)$	switching delay between a and la.

Table 2: The notation summarization

- la is the last activity id that employee e did before this record
- and y is the time interval of this record, namely the service time of employee e used in activity a in this record.

There are four major factors contributes in the value of y.

4.2.1. Activity Complexity

The complexity of activity a is the first major factor, denoted by $T(a)$. This factor is easy to understand because some activities are naturally more complex than others. Intuitively, $T(a_1) > T(a_2)$ if a_1 is more complex than a_2. Since $T(a)$ is a random variable related to a, we can use an appropriate prior distribution, e.g. the normal distribution, helps to estimate the parameters. In other words, $T \sim Normal(\lambda, \sigma^2)$ where both λ and σ are hyper-parameters in prior distribution.

4.2.2. Employee Diligence

The diligence of employee is the most interesting factor, which is what we want to estimate from the logs, denoted by $D(e)$. Intuitively, if e_1 is more diligent than e_2, $D(e_1) > D(e_2)$. in following discussion, we replace $D(e_i)$ by d_i for simplicity.

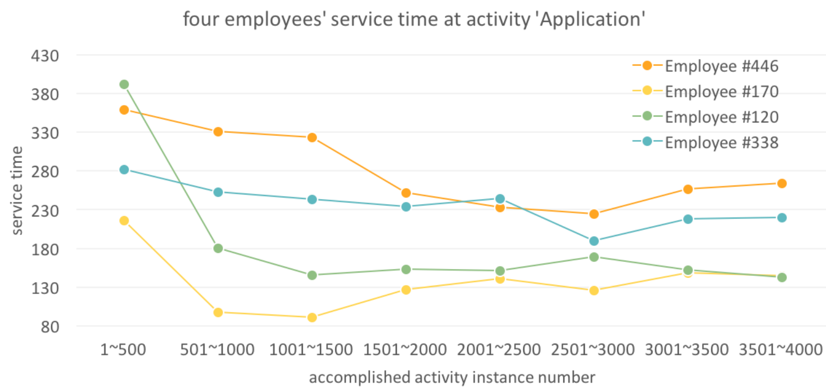

Figure 2: The service time decrease for each employee when they have accomplished more instances of the same activity.

4.2.3. Familiarity

We introduce a familiarity factor, denoted by $F(a, e, c)$, standing for whether employee e is familiar with activity a. The smaller factor value means the employee e is more familiar with the activity a. Figure 2 illustrates the relation between service time and the accomplished instances number. We can come to the conclusion that employees get trained by accumulate the instances number and carry out a smaller service time. Therefore, we assume an exponential relation between instance number c and the familiarity factor F.

$$F(a, e, c) = 1 + \exp(f(a) - c) \tag{1}$$

4.2.4. Switching Delay

Comparing the employees who are taking responsible of only one kind of activity, e.g. staff A in above discussion, those in charge of multi-activities, e.g. staff B, the later spend more time on switching the working environment. In our model, we introduce a factor called switching delay, denoted by $W(a, la)$. The switching delay is the time used in switching the context from activity la to activity a.

4.3. Discriminate Model

With the factors we introduced before, the service time y can be estimated by the discriminate model as follows.

$$
\begin{aligned}
y &= \frac{T(a) * F(a,e,c)}{D(e)} + W(a,la) + \varepsilon \\
&= \frac{T(a) * (1 + \exp(f(a) - c))}{D(e)} + W(a,la) + \varepsilon
\end{aligned}
\tag{2}
$$

In formula 2, ε is the noise term in the norm distribution. Considering the dataset with N activities and M employees, both T and f are in the size of $N \times 1$, D in the size of $M \times 1$ and W is the matrix in $W \in \mathcal{R}^{N*N}$.

4.4. Training

To train this discriminate model, we employ Maximum Likeness Estimation (MLE) on following object function:

$$
\begin{aligned}
\arg_{T,D,f,W} \min \quad & \sum (y - \frac{T(a) * (1 + \exp(f(a) - c))}{D(e)} - W(a,la)) \\
s.t. \quad & T(i) > 0 \text{ for any i} \\
& D(i) > 0 \text{ for any i} \\
& W(i,j) > 0 \text{ for any i, j}
\end{aligned}
\tag{3}
$$

To handle the non-equal conditions on T, D, W, we introduce the Lagrangian factors λ, σ, ν.

$$
\begin{aligned}
\arg_{T,D,f,W} \min \quad & \sum (y - \frac{T(a) * (1 + \exp(f(a) - c))}{D(e)} - W(a,la)) \\
& - \lambda * \sum_{i}^{N} (T_i) - \sigma * \sum_{i}^{N} (D_i) - \nu * \sum_{i}^{N} \sum_{j}^{N} (W_{ij})
\end{aligned}
\tag{4}
$$

5. Experiment

We randomly pick out 2367598 records from the original dataset and divide them into a training set, which contains 2130838 records, and a testing set, which contains 236760 records. The rate between training set and testing set

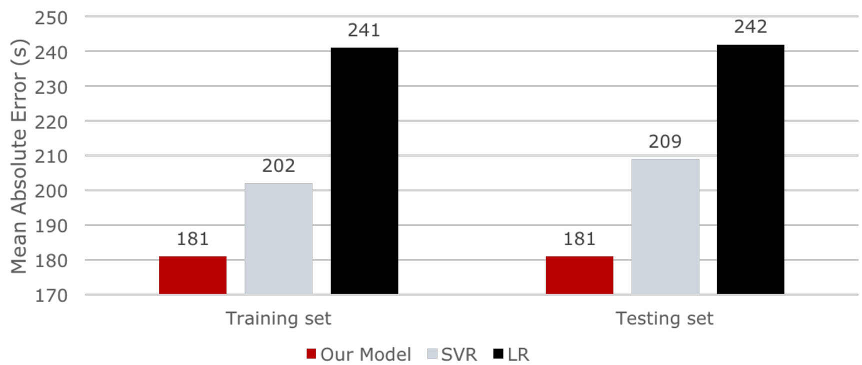

Figure 3: The experiment reports on different methods on training set and testing set.

is 9:1. And the dataset involves 400 activities and 732 employees. A record is formatted as $< a, e, c, la, y >$ where a is the activity index, e is the employee index, c is the instance number of activity a that e completed before, la is the last activity before this record, and y is the service time. Our experiment plan contains two steps

- training model by training set
- predicting service time $\hat{y}$ in testing set
- evaluating the error with predicted $\hat{y}$ and real y.

We employ Mean Absolute Error as the error measurement

$$MAE = \frac{\sum_i^H \|\hat{y} - y\|}{H} \tag{5}$$

where H in 5 is the number of records in testing set.

In this experiment, we use SVM and Logistic Regression as the base line.

- Supported Vector Machine (SVM) is a widely used classification method [5]. In our experiment, we use LibSVM [6], a famous SVM tool.
- Logistic Regression (LR) is another basic and regression method [7].

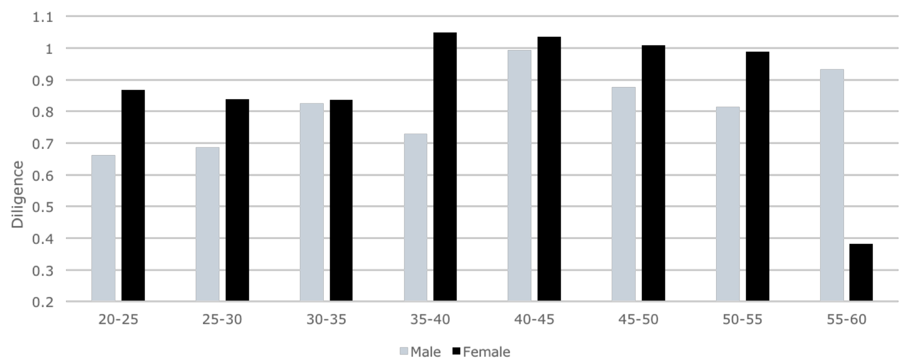

Figure 4: The diligence of different age and gender group.

Figure 3 illustrates the reports of experiments on different methods. As showed by the left bar chart, our model outperforms both SVM and LR in MAE on training set. The right bar chart depicts the results on testing set. Another interesting fact is that both SVM and LR performs worse on testing set than training set. Our model, however, gets a small MAE on testing set as good on training set.

6. Discussion

This section discusses some discovery from our experiment.

6.1. Diligence on ages and genders

Once trained on the dataset, our model depicts the employees' diligence by parameter D. For any two employee e_1 and e_2, the non-equal relation $D(e_1) > D(e_2)$ denotes that e_1 is more diligent than e_2.

Figure 4 illustrates the diligence statistical result on different age and gender group. The grey bar represents the male and black bar the female. From this diagram we can get some conclusions.

- In the young age, 20-30, female is more diligent than male. It is really fact-based, because in this ages, young men are more likely to be distracted by various factors, e.g. video games. The deeper reason is that women is more mature psychologically than young men.

- The middle aged employees, 35-50, are most diligent. Under the economic pressure of family and especially the education of children, the middle aged adults pay most attention on their works.

- There is a huge gap between female and male in 55-60. At this age, the diligence of female decreases a lot. This is because according to the policy in China, most women are retired at 55. Therefore in this age group, 55-60, female employees almost do not participate in the work.

6.2. Activity Difficulty to handle

In our model, parameter $f(a)$ denotes the degree of difficulty to handle activity a. The greater $f(a)$ means that activity a is more tough to get familiar. In Tab. 3, the left part lists 10 activities with least f, which means the easiest activities to get familiar. As we can see that both 1, 2, 3 and 4 are different kind of scanning, which is an easy task in practice. Both 5, 6, 7, 8, 9 and 10 are different sort of application, which is also an easy task. The right part of Tab. 3 lists 10 activities with largest f, which means the hardest activities to get familiar. Activity 2, 3, 4, 5, 6 and 9 are both certification and review, which are hard to handle in practice. This result, from another perspective, prove the correctness of our model.

7. Related Works

In this section, we make a simple review of researches on employee's efficiency from (a) management science and (b) information science.

Lots of researchers and communities have completed several works on finding out the factors to human efficiency. In the early researches, Hockey studied the noise, which produces a narrowing of attention [8]. Literature [9] emphasize the importance of delegation in enhancing the work efficiency. Paarlberg introduced the impact of customer orientation on government employee performance [10].

10 activities with least f	**10 activities with largest f**
1. Combine Scan	1. Review on Housing-reformation
2. Pre Scan	2. Certification(1)
3. Post Scan	3. Preliminary Review in City Level
4. Scan Activity	4. Preliminary Review
5. Deposite Application	5. Certification(1)
6. Application	6. Certification of Manager
7. Real Estate Project Application	7. Conclusion Scan
8. Online Application	8. Charge
9. Agreement Template Application	9. Certification in City Level
10. Preliminary Application	10. Approval

Table 3: 10 activities with least f and 10 activities with largest f

Elena et. al. developed the schematic scientifically grounded criteria to evaluate the effectiveness of the employees [11]. Employee Participation in Profit and Ownership is discussed in [12]. This approaches, however, are both lacking of either quantitatively analyzing or experimental proof. On one hand, our model, built on the concrete work logs, has a solid math foundation and divides the factors qualitatively. On the other hand, the results of our model is provable on practical dataset.

From the perspective of information science, the information and communication technology in public administrations with organizational changes and new skills in order to improve public services and democratic processes, and to strengthen support to public policies, is called e-Government [2][3]. As discussed in [13] , efficiency improvement is one of the major challenges for e-Government. Virile [14] studied the e-Government plan in Italy and emphasized the attention on efficiency. Liang [15] proposed the models, service models and selection strategies to promote the efficiency of e-Government by Cloud techniques. These works, though both emphasize the importance of efficiency in e-Government. They, However, focus only on the efficiency of computing instead of employees.

These techniques both ignore the delays brought by the human factors. And It brings a huge gap between ideal working efficiency and practical efficiency. Therefore, our model concentrates on the real efficiency, namely the service time, in practice. As reported in above section, our model really predicts the service time and even divides the activity-related factors and human-related factors.

8. Conclusion

This paper focus the problem of extracting the subjective factor and objective factor in employees working behaviors in the government services. We introduce a discriminate model involving the employees diligence, familiarity, switching delay and activity complexity. By train our model on the dataset, we can inferring the employees diligence from the parameter and even draw some interesting statistical conclusions. Furthermore, the experiment results reports the effectiveness of our model. The future work is about how to involving more factors and archiving a more accurate service time prediction approach.

Acknowledgments

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