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Mining the Cause of Delays in Urban Railways based on Association Rules

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Abstract In urban railways, trains are operated densely. Hence, even a small delay easily propagates to other trains and the delay tends to expand. Railway companies are now keen to reduce occurrence and propagation of such small delays which often happen during rush hours. In order to reduce such delays, various kinds of counter measures are taken. However, it is difficult to evaluate if such counter measures worked well or not because situations of train operation vary from day to day, usually a set of different delay reduction measures are introduced at the same time and the timetables are very complicated. In this paper, we propose an algorithm to evaluate if the counter measures already introduced are really effective to reduce delays or not. The algorithm is based on the association rules, which is one of the often used techniques in the world of data mining. The algorithm takes daily train traffic records as an input and produces association rules which mean co-occurrence of delays. By comparing the outputs for the train traffic records before some delay reduction measures were introduced and the train traffic records after the delay reduction measures were introduced, we can know whether each delay reduction measure was effective or not.

Keywords: Robustness · Data Mining · Association Rule · Delay · Railway

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1 Introduction

Trains in Japan are known to be very punctual. But one of the recent problems in Japanese railways in urban area is that small delays often happen during rush hours. Because trains are operated densely, even a small delay easily propagates to other trains and the delay tends to expand.

Delays are categorized into two types: one is a primary delay and the other is a secondary delay (Hansen et al. (2014)). The latter is sometimes called a knock on delay. A delay of a train is called a primary delay if the train itself is responsible for the delay. A secondary delay means that the cause of the delay is not the train itself but the delay was caused by a delay of another train.

Railway companies are now keen to reduce occurrence and propagation of such small delays. In other words, they are trying to reduce both primary delays and secondary delays. In particular, they are interested in introducing delay reduction measures effective to reduce the primary delays which cause secondary delays in wider area. This is because if they succeed to reduce such primary delays, it is more effective to improve the whole situation. Thus, it is more desirable to adopt counter measures which are effective to reduce primary delays influential to many other trains.

In order to decrease primary delays, there exist various kinds of counter measures such as revision of timetables, improvement of signalling systems, deployment of enough number of station staff on a platform and so on and railway companies introduce some of these aiming at reducing primary and (possibly) secondary delays.

The problem which exists now is that it is difficult to evaluate whether such counter measures worked well or not. Nowadays, it is easy to get the data of train traffic which contain actual arrival and departure times of all the trains at every station every day. Railway companies began to use those data to analyse if punctuality is improved or not. As one of the methods, some railway companies introduced a visualization method of these data and try to intuitively grasp if situations has been improved or not.

Such visualization works well to grasp the overall situation. But it is not sufficient to analyse the details, that is, it is difficult to judge if each counter measure was effective or not.

In this paper, we propose an algorithm to evaluate effectiveness of the counter measures which have been already introduced. The algorithm is designed based on the association rules: one of the most popular techniques in the world of the data mining. The algorithm takes daily train traffic records as its input and produces association rules which mean co-occurrence of delays. By comparing the outputs for the train traffic records before some delay reduction measures were introduced and the train traffic records after the delay reduction measures were introduced, we can know which delay reduction measure were effective. For example, if an association rule relating with some station is deduced before and such a rule is not deduced after a delay reduction measure for the station is introduced, we can conclude that the delay reduction measure for the station was effective.

In section 2, we explain why the small delays happen during rush hours and what kinds of counter measures are taken by railway companies to reduce those delays. In section 3, we introduce our algorithm to evaluate if the counter measures are effective together with some explanation about the association rules. In section 4, we show the results which we got by applying our algorithm to actual data.

2 Reduction of small delays

2.1 Small delays

In Japan, there is a big demand for railways in urban areas. As a matter of fact, in Tokyo area (the capital of Japan), the total number of passengers of railways a day in average amount to even 39 million. To transport such a massive amount of passengers, trains are operated very densely. In many railway lines in Tokyo, trains which consist of eight to ten (sometimes even 15) cars are running every two to three minutes on a double track line. This means that 20 to 30 trains are running per hour per direction (Figure 1 shows a typical timetable of a railway line in the Tokyo area. As you can see, trains are running every couple of minutes on this line).

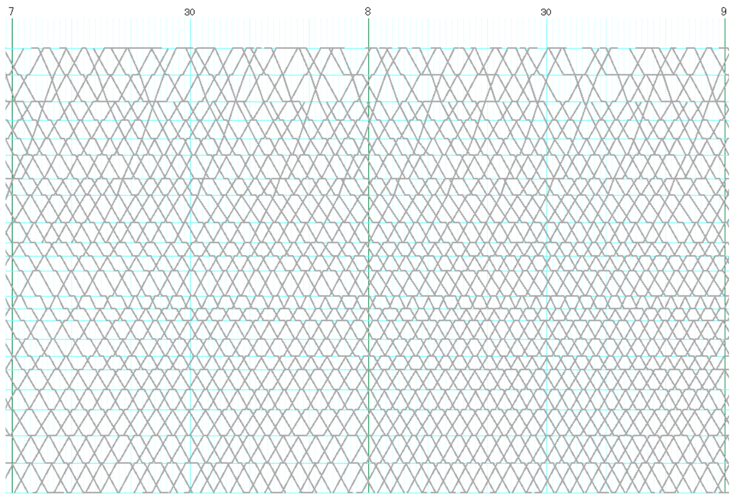

Figure 1: Diagram of an urban railway line (a part – two hours).

Still, trains and stations are very congested as shown in Figure 2. Sometimes, congestion rates of trains during peak hours exceed 150% or much more. The congestion and the density of trains sometimes cause delays.

(1) A passenger becomes sick and in order to rescue him/her, departure of the train is delayed.
(2) Due to congestion, something (a bag, an umbrella etc.) is caught by doors of a train and in order to release that stuff, all the doors of the train are opened again. Thus, departure of the train is delayed.

(3) More passengers than expected get on/off a train and the departure is delayed because of increase of dwell times.

Railway companies are now very keen to reduce the delays and they are making every effort to make their railway system much more robust. Some of their countermeasures are listed below (you can find more in Yamamura et al. 2013).

Figure 2: Trains and platforms are congested.

Figure 3: Deployment of Station Staff on a platform.

1. Modify timetables:
   - Modify timetables so that rapid trains stop at the stations where the number of passengers who use the station has increased. This modification is useful to equalize the congestion rate of trains because otherwise all the passengers have to use a regular train and regular trains become too congested.
   - Adjust intervals of trains. In principle, intervals of trains should be as equal as possible. If there exists a comparatively large interval of trains in the timetable, a lot of passengers arrive there and this causes an increase of the dwell time and the train's departure is delayed.

2. Improve signalling systems
   - Improve the signalling system so that the minimum headway becomes smaller and trains can run with a smaller interval.
3. Improve operation on the platform
   - Deploy a lot of station staff on a platform as shown in Figure 3 in order to prevent the dwell times from becoming too large.
   - Change the location where the trains stop in a station. This is useful for stations where a part of the platform is narrow. Railway companies want to avoid trains stop at the point where the platform is narrow. This makes it possible for passengers move more smoothly and as the result the dwell times do not become too large.
4. Enlarging Platform
   - Some platforms have narrow passages, stairs or ways for transit to and from other lines which will cause uneven congestion. Introduction of cars for the exclusive use of women (in Japan we usually have one car in one train which is dedicated to women) has also caused uneven congestion, leading to extended dwell times. Enlarging platforms would smooth the passenger flow.
5. Introduction of Trains with Wider Doors, Trains with more Doors
   - Improvement of cars would shorten dwell times. Specifically, cars with wider doors or more doors will smooth the passenger flow, leading to shortened dwell times (Figure 4: The train in the left is a normal one and the train in the right is a train with wider doors).

Figure 4: Train with wider doors (right).

2.2 Analysis of Delays

Now, railway companies are analysing the train traffic record data using visualization tools. One such example is the Chromatic diagram as shown in Figures 5 and 6 (Yamamura2013). In the Chromatic diagram, train segments are coloured reflecting the delay of the train. From the visualization of the train traffic record data, they can find the possible cause of delays and figure out how the delay propagates to other trains and they can get a clue to make the timetable more robust.

Such visualization tools are useful to intuitively grasp the situation of the delay propagation. By comparing the visualization before some counter measures were taken and the visualization after the counter measures were taken as shown in Figures 5 and 6, we can intuitively know if the countermeasures were effective on the whole, which is the greatest merit of such visualization.

On the other hand, however, from visualization it is not possible to know if each counter measure was effective or not. Even if we can know the overall situation was improved, it is difficult to judge which counter measures were effective and which ones were not. This is because situations of train operation vary from day to day, usually a set of different delay reduction counter measures are taken at the same time, timetables are very complicated and so on. Thus, railway companies are longing for a method to evaluate effectiveness of each counter measure.

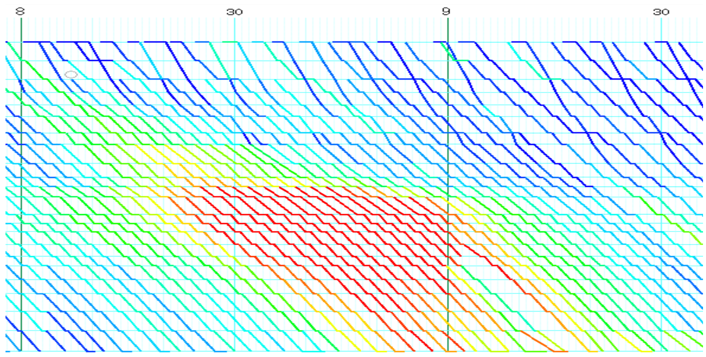

Figure 5: Chromatic diagram for “before.”

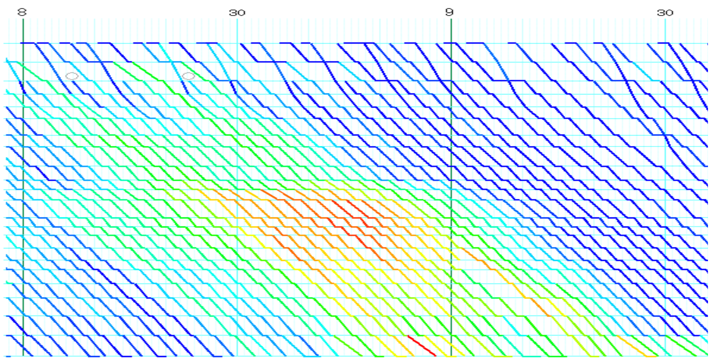

Figure 6: Chromatic diagram for “after.”

2.3 Related works

There are many papers which deal with an algorithm to make timetables more robust.

Yamamura et al. (2012) introduced an idea to apply an algorithm to find the longest path (see Sedgewick and Wayne 2011) which is an often used technique in PERT/CPM (Program Evaluation and Review Technique/Critical Path Method).

They express the train traffic records by a directed graph and introduced an idea to trace back the critical path on the graph from the delay in focus to its origin, which is regarded to be the cause of the delay, namely the primary delay. The algorithm works well if you can properly identify the critical path. But the problem is because the trains do not always run ideally (for example, trains' running times are not always exactly the same as the technically minimum running times), it is not an easy job to identify the critical path.

Conte and Schöbel (2007) introduced an idea "a tri-graph" to analyse the delay propagation. Arrival and departure delays of trains are associated with random variables. But they assume that they know the delay distribution in advance.

Flier et al. (2009) introduced an algorithm to detect the two types of dependencies among delays, namely dependencies due to resource conflicts and due to maintained connections. But they only examine the delay dependency in a station and they are not dealing with the network-wide dependency of delays.

Büker and Seybold (2012) introduced an algorithm to estimate delay propagation using an analytical approach. Their approach is completely analytical and they do not resort to the Monte Carlo simulation. But on the other side, this means that they have to prepare the probabilistic distribution function of delays which properly reflect the real world.

Cule et al. (2011) introduced an algorithm based on a technique which is often used in the data mining: that is "mining of frequent episodes." An episode is considered to be a set of events that reoccurs in the sequence within a window of specified length and one example they showed is "Trains A, B, and C, with C departing before A and B, are often delayed at a specific location, approximately at the same time." But they are more interested in the episode of each train (their algorithm identifies the train numbers) and do not deal with the group of trains, which is necessary in urban railways.

As far as the authors know, there have been no papers which explicitly deal with evaluation of the counter measures for delay reduction.

3 Evaluation of delay reduction measures based on association rules

3.1 Association rules

Let $I = \{i_1, i_2, \ldots, i_n\}$ be a set of n binary attributes called items. Let $T = \{t_1, t_2, \ldots, t_m\}$ be a set of transactions. Each transaction in T contains a subset of the items in I. An association rule is defined as an implication of the form $X \Rightarrow Y$ where $X, Y \subseteq I$ and $X \cap Y = \emptyset$. The set of items X and Y are called the left hand side (LHS) and the right hand side (RHS) of the association rule respectively.

One of the most popular applications of the association rule is the market basket analysis. A record of a purchase at a supermarket of a person is regarded as one transaction which contains a set of purchased items. By the analysis of the records, we can for example get a result "On Thursdays, grocery store consumers often purchase diapers and beer together." (Berry and Linoff 1997)

The support **supp(X)** of an item (or a set of items) X is defined as the proportion of transactions which contain X in the whole transactions.

The confidence of an association rule is defined as **conf ($X \Rightarrow Y$) = supp ($X \cup Y$)/supp(X).**

3.2 Algorithm

(1) Basic ideas

We propose to consider the following as an item:

- a delay of a train at a station.
- an increase of a dwell time of a train at a station.
- an increase of a running times of a train from a station to the next station.
- an increase of an interval between two trains at a station.

A set of items above mentioned for one train is regarded as a transaction. Then, we try to obtain association rules from these data. We expect to find an association rule such as "if a delay of a train at Station A is larger than α seconds, then the train's delay becomes larger than β seconds at Station B." (We assume that Station B is a big and an important station in this railway line).

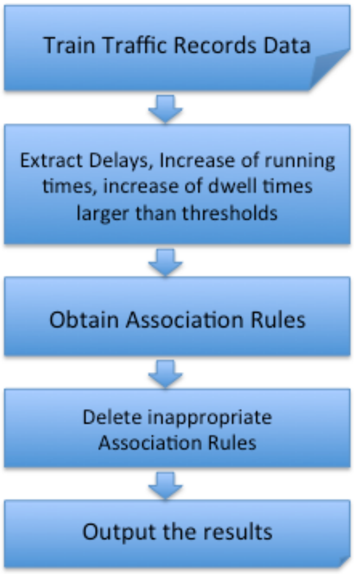

Figure 7: Overall structure of the algorithm.

(2) Overall structure of the algorithm

We show the overall structure of our algorithm in Figure 7. The input of the algorithms is train traffic record data which contain actual and planed arrival / departure times of all the trains for a certain period of time.

Then, from these data, we construct a matrix as a preparation to induce association rules. An example of this process is expressed in Table 1. Let us assume that there exist seven trains (Train 1 to Train 7) and six stations (Station A to Station F) as shown in Figure 8. Let us also assume that problems are happening at the point where a circle is depicted in Figure 8. For simplicity, in this example, we deal with only delays.

From these data, we make a matrix as shown in Table 1 and try to deduce useful association rules. In this case, the total number of transactions is seven (the number of trains). We may be able to deduce a lot of association rules. Some of them might be:

(1) $B \Rightarrow A$ with confidence =1.0 and support = 0.85

(2) $A \Rightarrow D$ with confidence =0.83 and support = 0.71

The confidence of Rule (1) is calculated by (number of cases when both Train A and Train B were delayed)/(number of cases when Train B was delayed) = 6/6=1.0. The support of Rule (1) is calculated by (number of cases when both Train A and Train B were delayed) / total number of transactions = 6/7= 0.85

Likewise, we can calculate the confidence and the support of Rule 2.

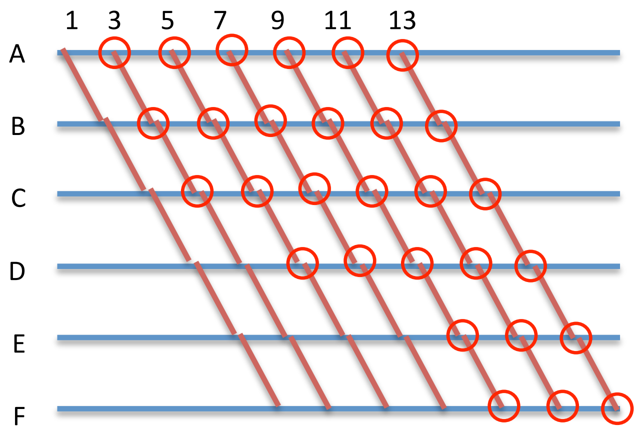

Figure 8: Delays.

Table 1: Matrix for preparation

Train \ Station	A	B	C	D	E	F
1	0	0	0	0	0	0
3	1	1	1	0	0	0
5	1	1	1	1	0	0
7	1	1	1	1	0	0
9	1	1	1	1	1	1
11	1	1	1	1	1	1
13	1	1	1	1	1	1

Usually, there exist a lot of association rules and we should select meaningful ones focusing on the confidence and the support.

As an algorithm to deduce meaningful association rules based on the values of the confidence and the support, an efficient algorithm called "a priori algorithm" is proposed by Agrawal and Srikant (1994).

We have implemented our algorithm using R (R 2015) which is a free software environment for statistical computing and graphics.

In the example of Table 1 and Figure 8, two association rules whose LHS and RHS are just opposite, such as $A \Rightarrow D$ and $D \Rightarrow A$ could be deduced. What we have to note is that an association rule does not always imply causality. An association rule originally means that two items occurred at the same time. Hence, if two association rules whose LHS and RHS are just opposite appear, we select one of them whose confidence is larger. In this example, the confidence of $D \Rightarrow A$ is 1.00 whereas the confidence of $A \Rightarrow D$ is 0.83. So, $A \Rightarrow D$ is deleted.

4. Numerical Experiments

4.1 Hanzomon Line

We have applied our algorithm to actual data in order to confirm if it works well. The data we used are the train traffic records of Hanzomon Line of Tokyo Metro subway company in Tokyo.

Hanzomon line is located in the centre of Tokyo connecting Shibuya (hereafter Station Shi) and Oshiage (Station Oshi). The length of the track is 16.8 km and there exist 14 stations as shown in Figure 9. During the busiest hours, 28 trains are running per direction on a double track. Trains directly come from and go to suburban railway lines of other railway companies at both ends (namely, at Station Shi and Station Oshi). In Hanzomon line, only regular trains are operated and they stop at every station. In our numerical experiments, we analyzed the trains from Station Shi to Station Oshi.

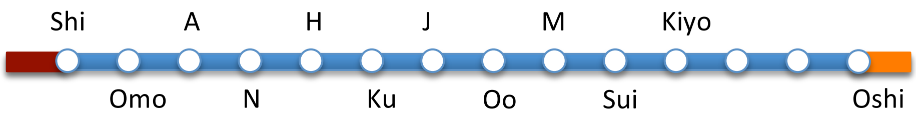

Figure 9: Hanzomon Line (only the names of relevant stations are shown).

4.2 Counter measures to reduce delays in Hanzomon line

Once, trains in Hanzomon line were not so punctual. Delays of several minutes quite often happened. Hence, Tokyo metro gradually took several counter measures to regain punctuality as shown in Table 2. On February 3rd 2014, they began to deploy more number of station staff on the platform of Station N. In this station, a lot of passengers get on and off to transfer between another railway line and the front part of the trains tend to be congested because the stairs for transfer exist there. Thus, dwell times tend to increase at this station. Those staff on the platform helps passengers get on and off smoothly and sometimes prevent them from rushing into the train because otherwise they might be caught by doors and the doors have to be reopened. This means the dwell time increases and a delay occurs. So, after February 3rd 2014, we can expect dwell times at this station do not tend to increase.

On March 29th 2014, the signaling facilities of Station Ku were improved so that the minimum headway becomes smaller and trains can run with a shorter interval. Before, because the distance between Station Ku and the next station is rather short and the signaling facilities are not so smart, intervals between trains at Station Ku tend to increase and delays were occurring there.

Table 2: Counter measures introduced in Hanzomon Line

Period	Date	Counter measure introduced
A		
B	Feb. 3 2014	deployed more number of station staff on the platform of Staion N.
C	March 29 2014	improved signalling facilities at Station K so that the minimum headway becomes smaller.

By an intensive analysis conducted by Tokyo Metro, we now know both of these counter measures were very effective to reduce delays. We show some of the evidence in Figures 10 and 11. Figures 10 (a), 10 (b) and 10 (c) show the average delay during rush hours at each station from Station Shi (left) to Station Oshi (right) of one day from Period A, B and C respectively. Figure 10 shows the comparison of the dwell times of trains during rush hours at Station N on one day in Period A (yellow) and one day in Period B (blue).

From Figure 10 (a), we can know that in Period A, delays tended to increase around Station N (the red circle on this graph) and around Station Ku (the blue circle). In Period B, however, increase of delays at Station N was avoided (Figure 10(b)). In Period C, the increase of delays around Station Ku was also avoided. From Figure 11, we can now know that dwell times at Station N was reduced in Period B compared with Period A.

4.3 Application of the algorithm

We apply our algorithm to these data to confirm if the algorithm produces similar results. If we succeed to obtain similar results, we can conclude that we can evaluate the counter measures to reduce delays more efficiently, namely much more quickly with less workload.

We applied our algorithm for three typical days in Period A (before February 3rd 2014), Period B (between February 3rd and March 29th 2014) and Period C (after March 29th 2014). More exactly speaking, we selected November 11 2013 from Period A, February 26th from Period B and May 1st from Period C respectively.

We set the threshold as follows: Delay = 60 seconds, increase of dwell times = 10 seconds, increase of intervals of trains = 180 seconds, increase of running times between stations = 30 seconds.

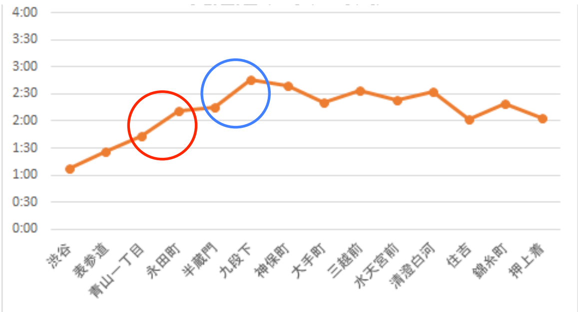

Figure 10 (a) Average Delay – Period A

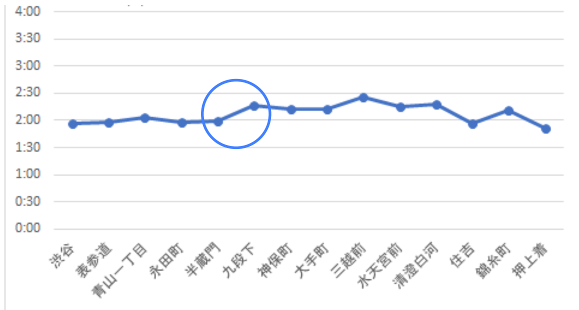

Figure 10 (b) Average Delay – Period B

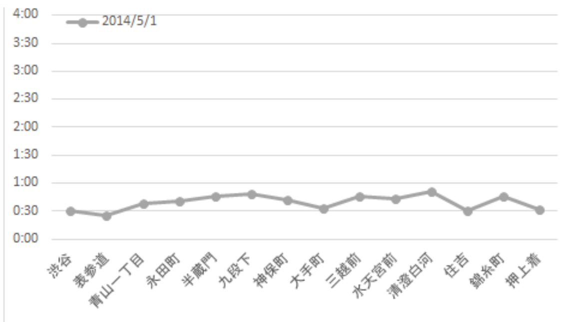

Figure 10 (c) Average Delay – Period C

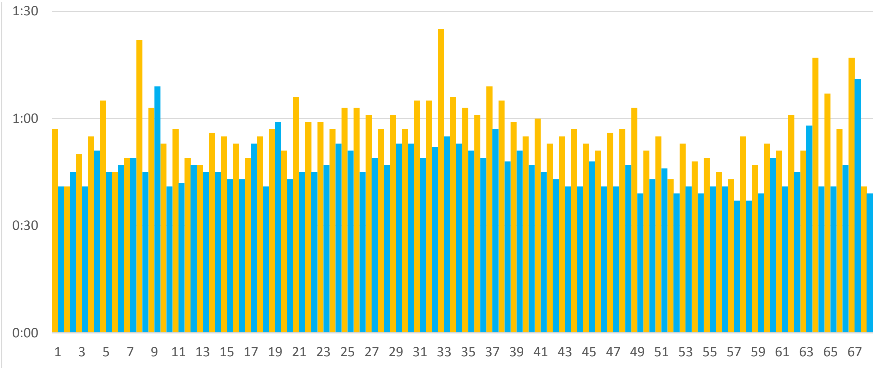

Figure 11: Comparison of dwell times of trains at Station N – Period A and B.

If our algorithm works properly, it is expected that the outputs must be as follows:

Period A:

(1) Association rules relating with the increase of dwell times at Station N will be obtained.

(2) Association rules relating with the increase of running times around Station Ku will be obtained.

Period B:

(1) Association rules relating with the increase of dwell times at Station N will **not** be obtained.

(2) Association rules relating with the increase of running times around Station Ku will **still** be obtained.

Period C:

(1) Association rules relating with the increase of dwell times at Station N will **not** be obtained.

(2) Association rules relating with the increase of running times around Station Ku will **not** be obtained.

4.4 Application of our algorithm

We show the results of our algorithm in Table 3. The column “Number of rules” means how many association rules which have the items in “Station” column in LHS were obtained. The bigger this figure is, the more influential the items in LHS are. The column “Confidence (Max)” means the highest value of the confidence among the obtained rules. “DT” means an increase of dwell times and “X – Y” means an increase of the running time between Station X and Station Y.

Table 3 : Results of the numerical experiments.

Period A

	Station	Confidence(Max)	Number of rules
1	Omo - A	1.000	16
2	Sui - Kiyo	1.000	13
3	H - Ku	1.000	4
4	N DT	0.886	6
5	A DT	0.882	7
6	Omo DT	0.842	2

Period B

	Station	Confidence(Max)	Number of rules
1	J - Oo	1.000	5
2	Shi - Omo	1.000	12
3	H - Ku	1.000	11
4	Oshi	1.00	14
5	Sui - Kiyo	0.875	4
6	M DT	0.875	1
7	Omo DT	0.846	8

Period C

	Station	Confidence(Max)	Number of rules
1	Omo - A	1.000	6
2	Sumi	1.000	9
3	Omo	0.889	4

4.5 Discussions

From Table 3, we may well conclude that we obtained the results as we expected. For Period A, association rules which have a delay at Station N as an item in LHS were found (underlined in red). Whereas such rules were not found for Periods B and C. Association rules which have an increase of running times between Station H and Station Ku were found for Periods A and B (also underlined in red) but such rules were not found for Period C.

On the other hand, we learned that we sometimes need to "interpret" the deduced rules. For example, as stated above, association rules which have an increase of running times between Station H and Station Ku are found for Periods A and B and they disappeared for Period C. But the counter measure taken was an improvement of the signaling facilities at Station Ku and the purpose of this was to decrease the minimum headway at Station Ku. Our guess is that in Period A, intervals between trains are likely to expand at Station Ku because of the poor signaling facilities and trains are more likely to be compelled to stay longer at

Station Ku, which means that the track in Station Ku is occupied longer than expected. Thus, the succeeding train cannot arrive at Station Ku and has to stop between stations before it arrives at Station Ku and the running time from Station H to Station Ku becomes longer. We believe this estimation is quite reasonable and we can conclude that our algorithm proved that the improvement of the signaling facilities of Station Ku was successful. It is more desirable, however, if we could get a result which more directly explains the situation, namely, it is more desirable if we could get an association rule relating with the interval of trains at Station Ku.

The reason which lies in the background is that an increase of the dwell time, a delay, an increase of the running time and an increase of the headway are not independent but closely interrelated. So, in our future work, we would like to give "interpretation" for the obtained association rules considering the interrelationship between delays, increases of dwell times, running times and headways.

Other future works of us should be:

- How to decide the thresholds. At the moment, we decide the threshold based on our experience but we need a more reasonable approach. At the same time, we should conduct a sensitivity analysis for thresholds.
- Improvement of models. Our model does not directly deal with the propagation of delays to other trains. We think we should improve our model so that propagation of delays is more explicitly expressed.
- Analysis of average situation. In this paper, we showed cases in which we applied our algorithm for one day each. But railway companies in principle are more interested in the punctuality in a long term. It is desirable to evaluate delay reduction measures from the data of longer terms.
- Consideration of causality. As we have already mentioned, association rules do not always imply an existence of causality. We need to continue more profound consideration on this matter.
- Application to detect influential primary delays. In this paper, we introduced an idea to apply our algorithm to evaluate effectiveness of already introduced delay reduction measures. Our algorithm, however, could be easily applied to detect influential primary delays without giving significant changes.

5. Conclusions

We have introduced an algorithm to evaluate if each of delay reduction measures already introduced is really effective to reduce delays or not. The algorithm is based on the association rules, which is one of the often used techniques in the world of data mining. The algorithm takes daily train traffic records as an input and produces association rules which mean co-occurrence of delays. By comparing the outputs for the train traffic records before some delay reduction measures were introduced and ones for the train traffic records after the delay reduction measures were introduced, we can know whether each delay reduction measure was effective or not.

We have applied our algorithm to actual data and confirmed our algorithm is promising although there remain several issues to be clarified in the future.

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