# Integrated Measurement for Pre-Fetching in Mobile Environment

Roziyah Darus, Hamidah Ibrahim, Mohamed Othman and Lilly Suryani Affendey
*Faculty of Computer Science and Information Technology, University Putra Malaysia, 43400 Serdang, Selangor, Malaysia*

Keywords: User Interestingness, Integrated Measurement, Pre-Fetching.

Abstract: Pre-fetching is used to predict next query of data items before any problems occur due to network congestion, delays, and latency problems. Lately, pre-fetching strategies become more complicated in which to support new types of application especially for mobile devices. Sometime the pre-fetched data items are not interested to the users. Due to this complication, an intelligent technique is introduced where an integrated measurement using data mining with Bayesian approach is proposed to improve the query performance. In previous study, the pre-fetched data items were filtered using data driven measurement. The data was generated based on the data frequency metrics whereby the structure of the query pattern is quantified using statistical methods. The measurement is not good enough to solve sequence query in mobile environment. In this paper, a new technique is proposed to generate new and potential pre-fetching set for the users. A subjective measurement is used to determine the pre-fetching set based on user interestingness. The integrated measurement generates strong and weak association rules based on the data and user interestingness criterions. The result shows that the performance is significantly improved whereby the technique managed to quantify the uncertainty of users' expectation in the next possible query.

## 1 INTRODUCTION

In mobile environment, pre-fetching is very tremendous in its functions in terms of providing an effective technique to improve the availability of the required data items or to predict next possible queries for users. Pre-fetching process will pre-fetch the predicted data items from memory into cache before any miss hit problems occur due to network congestion, delays, and latency (Hui and Guohong, 2004; Liqiang and Howard, 2006, Liu et al., 2000). Pre-fetching prevents mobile users from any delay of on-going job or any potential of terminating job due to the disconnection problems. The predicted data items must be useful and really can help users to react on their advantage. Users will feel confident towards the pre-fetched data items that can benefit them in finishing their job successfully especially during disconnection.

In order to pre-fetch the most useful data items, an intelligent technique must consider data driven and user driven criterion (Osmar, 1999). In this research, both criterions of data interestingness and user interestingness are used in determining the predicted data items. User interestingness criterions will be taking into consideration after data interestingness criterions is treated. In previous research (Wang et al., 2002, Hui and Guohong, 2004) the pre-fetched data items were measured based on data interestingness only. The predicted data items are depend on the frequently used items whereby the structure of *($A \rightarrow B$)* is quantified using statistical methods. Another word the quantity and quality of the data items are controlled by data frequency using support and confidence metrics.

The generated rule from data interestingness is more concerned on data driven criterion rather than user driven criterion. The measurement is not good enough to solve rule quality problems that involve users as in answering sequence query problem in mobile environment (Mary et al., 2009). According to (Hyeoncheol and Eun, 2005), frequency based measures can generate uninteresting or incorrect association rules if the dataset includes un-informative instances.

However, according to (Hampton, Moore & Thomas, 1973) a combination of human judgements and Bayes' Theorem will process the information more effectively than either one alone. An intelligent technique is used for data prediction in the pre-fetching process. The association rules in data mining technique are used to generate the candidate sets for the pre-fetching sets. By using the objective measurement, the candidate set is filtered based on

Darus R., Ibrahim H., Othman M. and Suryani Affendey L..
Integrated Measurement for Pre-Fetching in Mobile Environment.
DOI: 10.5220/0004989802050212
In *Proceedings of 3rd International Conference on Data Management Technologies and Applications* (DATA-2014), pages 205-212
ISBN: 978-989-758-035-2

strong association rules using support and confidence metrics. The criterion of the candidate set is towards data driven in which it considers the frequent number of items used only rather than the user involvement in the transaction.

In our approach, the confidence value will be treated as the prior probability to get the posterior probability using Bayesian approach. A prior probability will be assigned as an initial degree of belief to the users as their general knowledge towards the transaction. The pre-fetching set will be generated from an integration of the objective measurement and the subjective measurement of data interestingness and user interestingness. In this research, we will prove that the integrated measurement can give better query performance than the previous work.

## 2 RELATED WORK

There are many pre-fetching strategies that have been introduced in previous works. The trend in pre-fetching strategy started with semi-automated hoarding set where they rely on user intervention to some extent (Geoffrey et al., 1997, James and Mahadev, 1992). Their works were based on observing past accessed patterns of users and involved in maintaining the user's profiles. Another pre-fetching approach was designed and operated in specific environment and focused was on semi-structured data such as for location dependent web pages and location dependent data services (Ho and Hwan, 2004; Mariano and Ana, 2006; Shi et al., 2005).

Lately, with the advancement of mobile computing technology the pre-fetching techniques in mobile systems become more complicated in which to support new types of applications such as in mobile environments (Shi et al., 2005, Darus and Ibrahim, 2010, Darus and Ibrahim, 2011). Due to this complication, researchers started to introduce new intelligent technique which requires data mining process (Yucel et al., 2000). Existing automated pre-fetching techniques did not focus on the granularity of mobile databases. They focused on the files such as web pages (Wang et al., 2002, Hui and Guohong, 2004). The pre-fetching set was measured by data driven measurement in which the data generated were based on the frequent data items in structure of query patterns. The quantity and the quality of generated data items are controlled by the support and confidence metric only.

Other researchers concentrated on mining tuples in a mobile relational DBMS environment, however their approach can still be further improved to get optimal solutions (Abhinav, 2005, Li and Lv, 2007). They also used data driven measurement where the pre-fetched data items (*A→B)* were computed based on support and confidence in which the items are un-logically related and sometime meaningless for certain mobile users.

There are many pre-fetching strategies that have been introduced but from our knowledge, none of them are concerned on including user interestingness by using Bayesian approach to contribute additional criterion for the pre-fetching set.

## 3 INTEGRATED MEASUREMENT

By using a-priori algorithm (Agrawal et al., 1993), an association rule is used to produce an initial pattern (*X→Y*) for data interestingness. A list of strong rules is generated in which to satisfy certain threshold for minimum support (min_sup) and minimum confidence (min_conf) values. The strong rules in the objective measurement become the candidate set in determining the potential of pre-fetching set.

The candidate sets then are treated in the subjective measurement. According to (Avi & Alexander, 1996), they represented α, ξ and E as degree of belief, previous evidence and new evidence of knowledge in a belief system, B, respectively. P (α | ξ) is defined as a conditional probability that α holds, with some previous evidence ξ supporting that belief. Then we compute the subjective probability of the users.

Equation (3.1) refers to the confidence values, $\alpha_i$, with previous evidence and will be treated as the prior probability in the measurement. The confidence value is assigned as the initial degree of belief in a belief system concept (Liqiang & Howard, 2006).

- *Confidence* ($\alpha_i$)*: Initial degree of Belief* = $d(\alpha_i \mid \xi) = P(\alpha \mid \xi)$ (3.1)

Equation (3.2) is introduced as a normalized weighted support values, $w_i$, in which to reduce any bias occur, as in (Hampton, Moore & Thomas, 1973).

- *Weight:* $w_i = Support(\alpha_i)/\Sigma\, Support(\alpha_i)$ (3.2)

According to (Liqiang and Howard, 2006), an equation (3.3) is used in which the weight, $w_i$, and the confidence values are used to find the value of user interestingness, $I(\alpha_i, B, \xi)$.

- *User Interestingness:* $I(\alpha_i, B, \xi) = d(\alpha_i \mid \alpha_i', \xi) - d(\alpha_i \mid \xi) = \mid Confidence(\alpha_i') - Confidence(\alpha_i) \mid = \mid P(E \mid \alpha, \xi) - P(\alpha \mid \xi) \mid$ (3.3)

A new degree of belief denoted as $P(\alpha \mid E, \xi)$ in which the belief, α is based on the new evidence $E$ in the context of the old evidence ξ. It can be computed using Bayes' rule, as given in equation (3.4).

- *New degree of Belief:* $P(\alpha \mid E, \xi) = P(E \mid \alpha, \xi)\, P(\alpha \mid \xi) / \{P(E \mid \alpha, \xi)\, P(\alpha \mid \xi) + P(E \mid \neg\alpha, \xi)\, P((\neg\alpha \mid \xi)$ (3.4)

An interestingness of pattern p, relative to previous evidence ξ can be determined by P (α | p, ξ) whereby it represents the confidence of rule p, given belief α as in equation (3.5). It also can be defined as the user interestingness relative to the difference between the prior and posterior probabilities in the belief system.

- *User Interestingness measurement pattern p:* $I(p, B, \xi) = \sum_{\alpha i \in B} \{\mid P(\alpha \mid p, \xi) - P(\alpha \mid \xi) \mid\} / P(\alpha \mid \xi)$ (3.5)

By taking the confidence values as the initial degree of belief in a belief system, a new pattern using user interestingness values, $I(\alpha_i, B, \xi)$ will be generated and the patterns for pre-fetching set and candidate set will be compared and analysed.

Let us consider Table 1 as a sample of online customer order information. In this example, we want to show that the pre-fetched items or products using the integrated measurement really meaningful for the user.

First, we generate the list of products from Table 1 for the candidate set using a-priori algorithm. We specify the minimum support value (min_sup) = 4 and the minimum confidence value (min_conf) = 0.5, to produce the list of strong association rules as in Table 2. A list consists of the most frequently ordered products which has been filtered using support and confidence metrics. In this case, the objective measurement in which the data interestingness of the products has been considered.

From Table 2, the highest confidence value is for products B#3→B#4, i.e. B#3 and B#4. Then it followed by B#4 and B#5 and so on. It means that these are the products which are the most frequently ordered products by the customer. Based on data interestingness, these are the products that will be pre-fetched as the pre- fetching set. This approach has been used in the previous work

Then we extend the previous work by introducing our approach called integrated measurement.

After the objective measurement process has been carried out, a subjective measurement is introduced to filter according to the user interestingness products. After the products from the strong rules are treated for the candidate set, we then treat the highest confidence value as the initial belief of user in a belief system for the transaction. This belief is important in determining the future products to be ordered by the user. The initial belief represents general knowledge of ordering behaviour of the user.

By using equation (3.1) to (3.5), we compute the results to determine the pre-fetching set from strong rules as in Table 3. It consists of nine beliefs, in which support is used to calculate weights for non-bias values and confidence value is treated as the initial confidence for each belief.

Table 1: Sample of a Customer Order information.

| Cust _ID | Order_Date | Product_Query | Cust _ID | Order_Date | Product_Query |
|---|---|---|---|---|---|
| CO1 | 2-May-07 | B#6,B#8,B#16 | CO1 | 3-October-08 | B#12 |
| | 26-May-07 | B#4,B#10,B#15,B#20,B#5,B#8 | | 10-November-08 | B#2 |
| | 2-Jun -07 | B#2,B#5,B#3 | | 29-Disember-08 | B#8,B#6,B#5,B#4 |
| | 6-Jul-07 | B#6,B#9,B#5,B#4,B#25,B#10 | | 27-Jan-09 | B#4,B#12,B#6 |
| | 3-Jan-08 | B#2,B#20,B#6 | | 5-Feb-09 | B#3 |
| | 12-Apr-08 | B#5,B#4,B#6,B#3,B#15,B#16 | | 12-Apr-09 | B#20,B#2,B#8 |
| | 9-May-08 | B#8,B#2,B#15 | | 15-May-09 | B#2,B#1 |
| | 7-Jun-08 | B#4,B#25,B#6,B#5 | | 15-Jun-09 | B#8,B#3,B#4,B#5,B#2,B#16,B#5 |
| | 19-July-08 | B#16,B#12,B#4,B#20,B#10 | | 11-July-09 | B#9 |
| | 1-August-08 | B#8,B#4,B#15,B#3,B#12,B#2 | | 14-August-09 | B#9,B#20,B#4,B#3,B#15,B#1 |
| | 15-Sept-08 | B#8,B#25,B#3,B#4,B#5,B#20 | | 15-September-09 | B#9,B#8,B#3,B#5,B#4,B#15 |

Table 2: Strong Association Rules as the candidate sets.

| ***Strong Rule Expression*** | ***Support*** | ***Confidence*** |
|---|---|---|
| B#2→B#8 | 4 | 4/8 = 0.5 |
| B#3→B#5 | 5 | 5/8 = 0.6 |
| B#3→B#4 - Based on data interestingness this is the most interesting products | 6 | 6/8 = 0.8 - Highest confidence value so it becomes the initial degree of belief of the user |
| B#3→B#8 | 4 | 4/8 = 0.5 |
| B#4→B#5 | 8 | 8/12 = 0.7 |
| B#4→B#8 | 6 | 6/12 = 0.5 |
| B#4→B#15 | 6 | 6/12 = 0.5 |
| B#5→B#6 | 5 | 5/9 = 0.6 |
| B#5→B#8 | 5 | 5/9 = 0.6 |
| ∑ Support ($\alpha_i$) | 48 | |

Table 3: Computing User Interestingness for Strong Association Rules.

| ***Belief*** | ***Expression*** | ***Weight, $w_i$ = Support($\alpha_i$) / Σ Support($\alpha_i$)*** | ***Initial confidence for each belief $d(\alpha_i \mid \xi) = P(\alpha_0 \mid \xi)$*** | ***Local confidence, $d(\alpha_i \mid \alpha_{i'}, \xi) = P(E_0 \mid \alpha_0, \xi)$*** | ***$I(\alpha_i', Y, \xi) = d(\alpha_i \mid \alpha_{i'}, \xi) - d(\alpha_i \mid \xi)$ = \| Confidence ($\alpha_i$') –Confidence ($\alpha_i$) \|*** | ***Interestingness for each belief = $w_i I(\alpha_i', Y, \xi)$*** |
|---|---|---|---|---|---|---|
| $\alpha_1$ | B#2→B#8 | 4/48 = 0.083 | 4/8 = 0.5 | 1/3=0.3 | (\|0.33 – 0.5\|) = 0.17 | 0.01411 |
| $\alpha_2$ | B#3→B#5 | 5/48 = 0.104 | 5/8 = 0.6 | 3/4=0.8 | (\|0.75 – 0.625\|) = 0.125 | 0.013 |
| $\alpha_3$ | B#3→B#4 | 6/48 = 0.125 | 6/8 = 0.8 | 2/4=0.5 | (\|0.5– 0.75\|) = 0.25 | 0.03125 |
| $\alpha_4$ | B#3→B#8 | 4/48 = 0.083 | 4/8 = 0.5 | 2/4=0.5 | (\|0.5– 0.5\|) = 0 | 0 |
| $\alpha_5$ | B#4→B#5 | 8/48 = 0.167 | 8/12 = 0.7 | 4/5=0.8 | (\|0.8-0.67\|) = 0.13 | 0.02171 |
| $\alpha_6$ | B#4→B#8 Based on user interestingness, i.e. the most interesting products | 6/48 = 0.125 | 6/12 = 0.5 | 4/5 = 0.8 | (\|0.8-0.5\|) = 0.3 | 0.0375 - The highest Interestingness value |
| $\alpha_7$ | B#4→B#15 | 6/48 = 0.125 | 6/12 = 0.5 | 3/5 = 0.6 | (\|0.6-0.5\|) = 0.1 | 0.0125 |
| $\alpha_8$ | B#5→B#6 | 5/48 = 0.104 | 5/9 = 0.6 | 1/5 = 0.2 | (\|0.2-0.56\|) = 0.3 | 0.0312 |
| $\alpha_9$ | B#5→B#8 | 5/48 = 0.104 | 5/9 = 0.6 | 4/5=0.8 | (\|0.8– 0.556\|) = 0.244 | 0.025376 |
| *New Degree of Belief : P (α \| E, ξ)* = (0.8x0.8) / (0.8x0.8) + (0.2x(1-0.8)) = 0.9412 | | | | | | |
| *Relative Interestingness Measurement: I (p, B, ξ)* = \|0.9412 – 0.8 \|/ 0.8 = 0.1765 | | | | | | |

By referring to the results from Table 3, the new degree of belief towards the new pre-fetching set B#4→B#8 with the initial belief for the new evidence is 94.12%. Products B#4 and B#8 have the highest interestingness value then followed by B#3 and B#4 and so on.

It means that these are the products which are the most interesting products to be ordered by the user based on user interestingness.

The result also shows that, a relative difference in terms of interestingness measurement of pattern towards the new pre-fetching set is 17.65%. Then we also work on the weak association rules. In this case we want to show that even though there are products which are not chosen as the candidate set, but still the products are useful to users.

In this example, we want to identify, what are the other possible products that can be chosen as the potential to be the pre-fetching set for the user in case of insufficient of pre-fetching set. In this case, we specify lower minimum values for minimum support and minimum confidence where min_sup = 2 and min_conf = 0.4 from Table 1 to produce a list of weak association rules as in Table 4. Again, by using the equation of (3.1) to (3.5), we compute the results to determine the other possible to be pre-fetching set from weak rules as in Table 4

Table 4: The Weak Association Rules - Parameters and their values in a belief system.

| ***Belief* ($\alpha_i$)** | ***Rule Expression*** | ***Support*** | ***Confidence value for each belief,* $d(\alpha_i \mid \xi) = P(\alpha_0 \mid \xi)$** | ***Weight,* $w_i = Support(\alpha_i) / \sum Support(\alpha_i)$** | ***Local Confidence for each belief,* $d(\alpha_i \mid \alpha_{i'}, \xi) = P(E_0 \mid \alpha_0, \xi)$** | **$I(\alpha_i, Y, \xi) = d(\alpha_i \mid \alpha_{i'}, \xi) - d(\alpha_i \mid \xi) =$ $\mid Confidence(\alpha_i') - Confidence(\alpha_i) \mid$** | ***Interestingness for each belief =* $w_i I(\alpha_i', Y, \xi)$** |
|---|---|---|---|---|---|---|---|
| $\alpha_1$ | B#4→B#6 | 5 | 5/12=0.421 | 0.05 | 4/6 = 0.67 | \|0.67 – 0.421\| = 0.249 | 0.01245 (The highest interestingness value |
| $\alpha_2$ | B#9→B#15 | 2 | 2/4=0.5 | 0.02 | 2/2 = 1 | \|1 – 0.5\| = 0.5 | 0.01 |
| $\alpha_3$ | B#9→B#20 | 2 | 2/4=0.5 | 0.02 | 1/2 = 0.5 | \|0.5 – 0.5\| = 0 | 0 |
| $\alpha_4$ | B#10→B#20 | 2 | 2/3=0.67 (The highest confidence value) | 0.02 | 1/1 = 1 | \|1 – 0.67\| = 0.333 | 0.00666 |
| *New Degree of Belief: P (α \| E, ξ)* = (1x0.67) / (1x0.67) + (0.5x(1-0.67)) = 0.8024 | | | | | | | |
| *Relative Interestingness Measurement: I (p, B, ξ)* = \|0.8024 – 0.67 \|/ 0.67 = 0. 1976 | | | | | | | |



Based on the results from Table 4, the new degree of belief towards the new potential to be pre-fetching set with an initial degree of belief as the new evidence is 80.2 %. Products B#4 and B#6 have the highest interestingness value then followed by B#9 and B#15 and so on. It means that these are among the products that can be considered as part of the pre-fetching sets for the user. The relative difference in terms of Interestingness measurement pattern towards the new potential to be pre-fetching set is 19.76%.

In Table 5, we summarize all the pre-fetching set based on data interestingness and user interestingness values. First we refer to products B#4 and B#8 in which these products are very meaningful from user perspective but not as meaningful as from data interestingness point of view. In fact some of the products can be discarded from the pre-fetching set as in this case we refer to products B#3 and B#8. These products are meaningful after the products were treated in objective measurement but then the products are meaningless after being treated in subjective measurement. Lastly, there are many other products that are not considered as the candidate set, or in weak association rules, can also be part of the interesting products and potential to be the pre-fetching set as for products B#4 and B#6.

# 4 EXPERIMENTS

We carried out an experiment to identify whether the pre-fetching set and also the potential to be the pre-fetching set from strong and weak association rules can contribute for better query performances. The integrated measurement is performed by applying the objective measurement and then the subjective measurement process. The data set used in the experiment is taken from TPC-D data schema as in (Shi et al., 2005). The data set was generated using random generator given by Transaction Processing Council, for Decision Making as in the TPC-D database schema. The data set consists of four main entities, i.e. regions, nations, customers and products/items. For analysis purposes we choose a sample of customers and products from Vietnam. We treated data region=Asia as global data set and data nation=Vietnam as local data set.

In this experiment, sequence query pattern is used as in (Shi, Binshan and Qun, 2005) to identify the query performance. Comparisons of results by using pre-fetching set and potential to be the pre-fetching set from four different cache sizes have been carried out. We apply the a-priori algorithm and the equation of (3.1) to equation (3.5) to generate the pre-fetching set. A sequence query pattern is used to identify the query performance. Results are shown in Figure 1 and Figure 2.

Table 5: Results of Pre-fetching Set using Objective Measurement (OM) and Integrated Measurement (IM) for Strong Association Rules and Weak Association Rules.

| **Pre-fetching Set from Strong Association Rules using Objective Measurement for Data Interestingness** | | **Pre-fetching Set from Strong Association Rules using Subjective Measurement for User Interestingness** | | **Pre-fetching Set from Weak Association Rules using Subjective Measurement for User Interestingness** | |
|---|---|---|---|---|---|
| Pre-fetching Set | Confidence Values, C | Pre-fetching Set | User Interestingness Values, I | Pre-fetching Set | User Interestingness Values, I |
| 1. B#3→B#4 | 0.8 | **1. B#4→B#8** | **0.038** | **1. B#4→B#6** | **0.012** |
| 2. B#4→B#5 | 0.7 | 2. B#3→B#4 | 0.031 | 2. B#9→B#15 | 0.010 |
| 3. B#5→B#6 | 0.63 | 3. B#5→B#6 | 0.031 | 3. B#2→B#3 | 0.008 |
| 4. B#3→B#5 | 0.6 | 4. B#5→B#8 | 0.025 | 4. B#10→B#15 | 0.007 |
| 5. B#5→B#8 | 0.6 | 5. B#4→B#5 | 0.022 | 5. B#10→B#20 | 0.007 |
| **6. B#4→B#8** | **0.5** | 6. B#2→B#8 | 0.014 | 6. B#4→B#25 | 0.007 |
| 7. B#4→B#15 | 0.5 | 7. B#3→B#5 | 0.013 | 7. B#3→B#9 | 0.005 |
| 8. B#2→B#8 | 0.5 | 8. B#4→B#5 | 0.013 | 8. B#4→B#9 | 0.003 |
| 9. **B#3→B#8** | 0.5 | **9. B#3→B#8** | 0 | 9. B#4→B#10 | 0.003 |

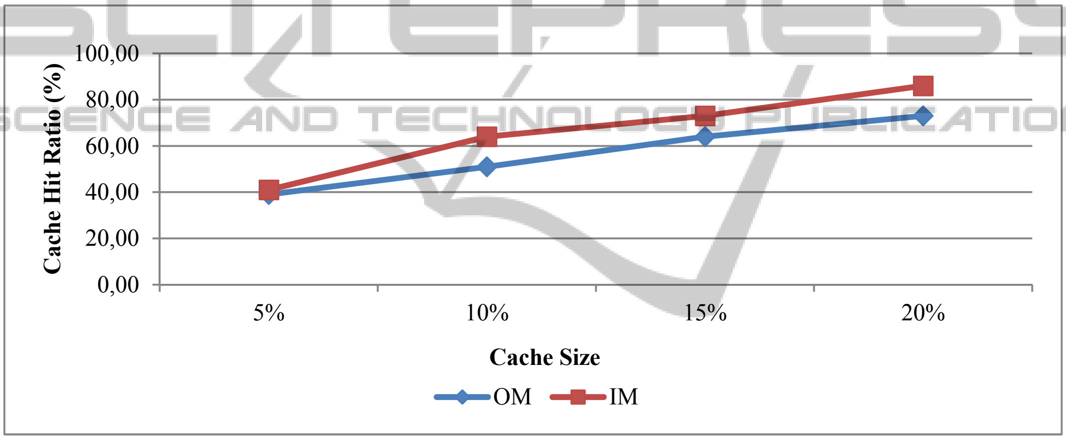


Figure 1: Comparison of Average for Query Performance in Pre-fetching Set from Strong Association Rules between Objective Measurement (OM) and Integrated Measurement (IM).

## 5 RESULTS AND DISCUSSION

By using the integrated measurement process, Figure 1 shows that the pre-fetching set from strong rules contributes a significant difference in query performance, i.e. by an average of 35%. Even though the pre-fetched data items are limited in terms of availability at lower cache size but the pre-fetched data items are increased tremendously at higher cache size for the two measurements process. From the result, it shows that by using IM, the sequence query pattern performed better than OM approach.

In Figure 2, the result shows that the pre-fetching set from weak association rules contributes slightly difference in query performance, i.e. by an average of 9.2 % for the two types of measurements. The pre-fetched data items are limited in terms of availability at lower cache size compared to higher cache size in the two measurements process. Again the results show that by using IM approach, the sequence pattern query can still performed better than OM even though from the potential to be pre-fetching set of weak association rules.

## 6 CONCLUSIONS

The integrated measurement technique manages to generate many interesting data items for pre-fetching set based on user interestingness values. By taking into consideration the confidence value from data interestingness as the initial belief of users, we managed to generate an un-expected pattern for

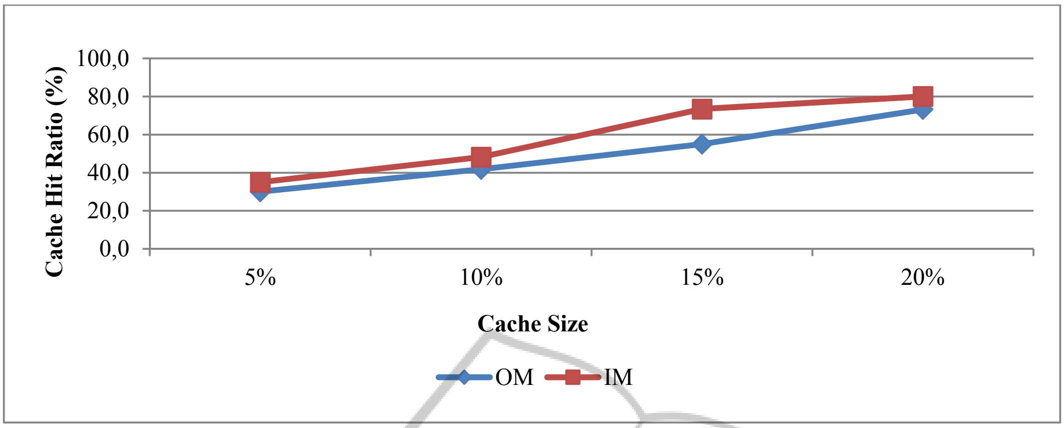


Figure 2: Comparison of Average for Query Performance in Pre-fetching Set from Weak Association Rules between Objective Measurement (OM) and Integrated Measurement (IM).

## REFERENCES


Abhinav, A. V. 2005. Data Stashing Strategies for Disconnected and Partially Connected Mobile Environments. In Doctoral Thesis, RMIT University. Doi=10.1.1.112.308

Agrawal R., T. Imielinski & A. N. Swami 1993. Mining Association Rules between Sets of Items in Large Databases, In *Proceedings of the 1993 ACM SIGMOD Conference*, pp. 207–216.Doi>10.1145/170036. 170072

Avi, S. & Alexander,T. (1996). What Makes Patterns Interesting in Knowledge Discovery Systems. *IEEE Transactions on Knowledge and Data Engineering*, Vol.8, No. 6, pp. 970-974. Doi:10.1109/69.553165

Darus R. & Ibrahim H. 2010. New Prediction Model for Pre-fetching in Mobile Database. In *Proceedings of the 12th International Conference on Information Integration and Web-based Applications & Services (iiWAS)*, pp. 938-942. Doi>10.1145/1967486.1967653

Darus R. & Ibrahim H. 2011. User Interestingness for Pre-fetching in Mobile Environment. In *Proceedings of the International Conference on Information Technology and Multimedia (ICIM)*, pp. 1-6. Doi:10.1109/ ICIMU.2011.6122738

Geoffrey, H., Kuenning & Gerald, J. P. 1997. Automated Hoarding for Mobile Computers, *SOSP-16 10197 ACM*, pp. 264-275. Doi:10.1.1.15.9270

Hampton, J. M., Moore & P. G, Thomas, H. 1973. Subjective Probability and Its Measurement. In *Journal of the Royal Statistical Society*. Series A, Vol. 136, No. 1, pp.21-42. http://links.jstor.org/sici?sici=0035-238%281973%29136%3AI%3C2I%3ASPAIM%3E2.0.CO%3B2-P

Ho, S. K. & Hwan, S. Y. 2004. Association Based Pre-fetching Algorithm in Mobile Environments. In *Proceedings of the International Conference on Embedded Software and Systems, (ICESS), Springer-Verlag Berlin Heidelberg, 2005*, pp. 243–250. Doi:10.1007/11535409_34

Hui, S. & Guohong, C. 2004. Cache-Miss-Initiated Pre-fetch in Mobile Environments. In *Proceedings of the International Conference on Mobile Data Management, IEEE*. Vol. 28, Issue 7, pp. 741-753. Doi:ieeecomputersociety.org/10.1109/MDM.2004.1263086

Hyeoncheol, K. & Eun, Y. K. 2005. Information-Based Pruning for Interesting Association Rule Mining in the Item Response Dataset. In *Proceedings of the International Conferences in Knowledge-Based and Intelligent Engineering & Information Systems* (*KES 2005*), © Springer-Verlag Berlin Heidelberg, pp. 372-378. Doi:10.1007/11552413_54

James J. K. & Mahadev, S. 1992. Disconnected Operation in the Coda File System. *ACM Transactions on Computer Systems*, Vol. 10, Issue 1, pp. 3-25. Doi=10. 1.1.12.448

Liqiang Geng & Howard J. Hamilton. 2006. Interestingness Measures for Data Mining: A Survey, *Journal ACM Computing Surveys (CSUR)*, Vol. 38, Issue 3, pp.1-32. Doi:1145/1132960.1132963

Li Yi-jun & Lv Ying-jie. 2007. Research on Different Customer Purchase Pattern Based on Subjective Interestingness. *In Proceedings of the International Conference on Management Science & Engineering* (*ICMSE 2007*), pp. 3-8. Doi:10.1109/ICMSE.2007. 4421816

Liu B., Hsu W., Chen S. & Ma Y. 2000. Analyzing the Subjective Interestingness of Association Rules. In *Journal Intelligent Systems and their Applications, IEEE*, Sep/Oct 2000, pp. 47-55. Doi:10. 1109/5254.889106

Mariano, C. T. N. & Ana, C. S. 2006. Hoarding and Pre-fetching for Mobile Databases. *In Proceedings of the 5th IEEE/ACIS International Conference on Computer and Information Science and 1st IEEE/ACIS International Workshop on Component-Based Software Engineering, Software Architecture and Reuse, IEEE*, pp. 219-224. Doi:10.1109/ICIS-COMSAR.2006.44

Mary, M. J. F., Ilayaraja N. & Nadarajan R. 2009. Cache Pre-fetch and Replacement with Dual Valid Scopes for Location Dependent Data in Mobile Environments. *In Proceedings of the 11th International Conference on Information Integration and web-based Applications and Services.* pp. 364-371. Doi:10.1145/1806338. 1806404

Osmar R. Zaiane, 1999. CMPUT690 Principles of Knowledge Discovery in Databases.

Shi, M. H., Binshan, L. & Qun, S. D. 2005. Intelligent Cache Management for Mobile Data Warehouse Systems. *Journal of Database Management*, Vol. 16, No. 2, pp. 46-65. Doi:10.4018/jdm.2005040103

Wang, K., Zhou, S. & Han, J. 2002. Profit Mining: From Patterns to Actions. In *Proceedings of the 8th Conference on Extending Database Technology,* pp. 70–87. Doi=10.1.1.12.7328

Yucel, S., Ozgur. U. & Ahmed, K. E. 2000. Association Rules for Supporting Hoarding in Mobile Computing Environments. In *Proceedings of the 10th International Workshop on Research Issues in Data Engineering, IEEE Computing Society Press*, pp. 389-401. Doi:ieee computersociety.org/10.1109/RIDE.2000.836502