Data mining is also called knowledge discovery in several databases including mobile databases. In this paper, the consumptive behaviour based on data mining technology will be discussed and analyzed. Mobile search is becoming increasingly important for mobile users as mobile devices are more widely used. Mobile search is quite different from standard PC-based web search in a number of ways: (a) the user interfaces and I/O are limited by screen real estate; (b) keypads are tiny and inconvenient for use, (c) limited bandwidth and (d) costly connection fees. These limitations result in more navigational queries in the mobile search. Furthermore, user location, activities, preferences, and interaction history can also improve accuracy in determining relevance for mobile search. In the past, most personalized search algorithms are studied in the context of PC-based web search. Personalized mobile search should however play a bigger role at improving the user experiences. This paper focuses on the personalization strategies which explicitly and implicitly infer user search context at individual user level. We show that personalized mobile search perform well for ambiguous queries and localized searches. In this paper, a data mining method for generating mobile clients’ location-aware service rules are used and we use a data mining algorithm which involves mining for location-based services.

1. INTRODUCTION
Mobile search is the second most used application only after social networking in wireless internet [1]. Search engine like Google appear in top three of the most visited web sites in terms of wireless internet usage. Most mobile search queries are short due to the hardware limitations such as tiny keypads and small screen. Early studies [2] attempted to provide solutions to mitigate the hardware limitations of the wireless devices. The top 100 mobile queries at AT&T [3] reveal that a great number of search queries are navigational [4] in nature.

The navigational searches, for example “Google”, us usually steer mobile users to specific web sites conveniently. Unlike navigational queries, words like “images” and “free ” which are informational and transactional are ambiguous to search engine. A housewife and an iPhone user interpret “apple” differently in search context. A housewife is likely to know the apple variety and prices at the local grocery stores. While an iPhone user is interested in service or products related to apple. Researchers studied methods and models to determine the query ambiguity. Clarity score [5] was proposed to evaluate the relative entropy between the query language model and the collection language.

2. MOBILE DATA MINING
The goal of mobile data mining is to provide advanced model. Large click entropy indicates that user clicks more web pages to solve the query, thus the query is ambiguous. Small click entropy means mobile users have common understanding for a search query. Song [6] developed classifier to automatically identify three types of queries, ambiguous, broad, or clear query. We believe these methods and algorithms work equally well to identify the query ambiguity in the mobile search. Researchers have explored personalized search to improve topical relevance of result documents in PC-based web search. Shen et al. [7] studied user’s immediate and short-term search context to expand the current query. Qiu and Cho [8] learned user interest from the click history and developed ranking mechanism based on the user interest. Chirita et al. [9] proposed personalized search and summarization algorithms which assist search keywords expansion based on extracted information from local desktop. Duo et al. [10] and Teevan et al. [11] investigated the personalized search strategies and stated that personalization improves the search accuracy on ambiguous queries. So far the personalization is studied only for PC based web search. Most of such personalization strategies are limited to the user search history, returned search results, and documents stored in PC.

Techniques for the analysis and monitoring of critical data from mobile devices. Mobile data mining has to face with the typical issues of a distributed data mining environment, with in addition technological constraints such as low bandwidth networks, reduced storage space, limited battery power, slower processors, and small screens to visualize the results [1]. The mobile data mining field may include several application scenarios in which a mobile device can play the role of data producer, data analyzer, client of remote data miners, or a combination of them. More specifically, we can envision three basic scenarios for mobile data mining:

1. The mobile device is used as terminal for ubiquitous access to a remote server that provides some data mining services. In this scenario, the server analyzes data stored in a local or distributed database, and sends the results of the data mining task to the mobile device for its visualization. The system we describe in this chapter is based on this approach.

2. Data generated in a mobile context are gathered through a mobile device and sent in a stream to a remote server to be stored into a local database. Data can be periodically analyzed by using specific data mining algorithms and the results used for making decisions about a given purpose.

3. Mobile devices are used to perform data mining analysis. Due to the limited computing power and storage space of today’s mobile devices, currently it is not realistic to perform the whole data mining task on a small device. However, some steps of a data mining task (i.e., data selection and pre-processing) could be run on small devices.

MobiMine [2] is an example of data mining environment designed for intelligent monitoring of stock market from mobile devices. MobiMine is based on client-server architecture. The clients, running on mobile devices such as PDAs, monitor a
stream of financial data coming through a server. The server collects the stock market data from different Web sources in a database and processes it on a regular basis using several data mining techniques. The clients query the database for the latest information about quotes and other information. A proxy is used for communication among clients and the database. Thus, when a user has to query the database, she/he sends the query to the proxy which connects to the database, retrieves the results and sends them to the client.

To efficiently communicate data mining models over wireless links with limited bandwidth, MobiMine uses a Fourier-based approach to represent the decision trees, which saves both memory on mobile device and network bandwidth. Another example of mobile data mining system is proposed in [3]. Such system creates a single logical database that is split into a number of fragments. Each fragment is stored on one or more computers connected by a communication network, either wiredly or wirelessly. Each site is capable of processing user requests that require access to local or remote data. Users can access corporate data from their mobile devices. Depending on the particular requirements of mobile applications, in some cases the user of a mobile device may log on to a corporate database server and work with data there. In other cases the user may download data and work with it on a mobile device or upload data captured at the remote site to the corporate database. The system defines a distributed algorithm for global association rule mining, which does not need to ship all of local data to one site, thereby not causing excessive network communication cost. Another promising application of mobile data mining is the analysis of streams of data generated from mobile devices. Some possible scenarios are patient health monitoring, environment surveillance, and sensor networks. The Vehicle Data Stream mining (VEDAS) system [4] is an example of mobile environment for monitoring and mining vehicle data streams in real time. The system is designed to monitor vehicles using onboard PDA based systems connected through wireless networks. VEDAS continuously analyzes the data generated by the sensors located on most modern vehicles, identifies the emerging patterns, and reports them to a remote control center over a lowband width wireless network connection. The overall objective of VEDAS is supporting drivers by characterizing their status, and helping the fleet managers by quickly detecting security threats and vehicle problems.

**Location-aware service mining**

To understand the behaviour of the clients, mining data log will play an important role. The issue of multilevel association mining was first proposed by Han (Han, & Fu, 1999). It is incorporated the taxonomy to demonstration the data hierarchy relations. Different minimum supports may be assigned for each level. Tseng (Tseng, & Tsui, 2004) exploited the multilevel association rule mining to discover the location-aware service rules. The service and location concept hierarchy trees were constructed to mining frequent patterns. Let HL and HS be two different hierarchy trees and representing the location and the service hierarchical concept respectively. Let \( P = \{P_1, P_2, PK\} \) be a set of items from mobile device. Some possible scenarios are patient health monitoring, environment surveillance, and sensor networks. The Vehicle Data Stream mining (VEDAS) system [4] is an example of mobile environment for monitoring and mining vehicle data streams in real time. The system is designed to monitor vehicles using onboard PDA based systems connected through wireless networks. VEDAS continuously analyzes the data generated by the sensors located on most modern vehicles, identifies the emerging patterns, and reports them to a remote control center over a lowband width wireless network connection. The overall objective of VEDAS is supporting drivers by characterizing their status, and helping the fleet managers by quickly detecting security threats and vehicle problems.

**Location-aware service mining**

To understand the behaviour of the clients, mining data log will play an important role. The issue of multilevel association mining was first proposed by Han (Han, & Fu, 1999). It is incorporated the taxonomy to demonstration the data hierarchy relations. Different minimum supports may be assigned for each level. Tseng (Tseng, & Tsui, 2004) exploited the multilevel association rule mining to discover the location-aware service rules. The service and location concept hierarchy trees were constructed to mining frequent patterns. Let HL and HS be two different hierarchy trees and representing the location and the service hierarchical concept respectively. Let \( P = \{P_1, P_2, PK\} \) be a set of items from mobile device. Some possible scenarios are patient health monitoring, environment surveillance, and sensor networks. The Vehicle Data Stream mining (VEDAS) system [4] is an example of mobile environment for monitoring and mining vehicle data streams in real time. The system is designed to monitor vehicles using onboard PDA based systems connected through wireless networks. VEDAS continuously analyzes the data generated by the sensors located on most modern vehicles, identifies the emerging patterns, and reports them to a remote control center over a lowband width wireless network connection. The overall objective of VEDAS is supporting drivers by characterizing their status, and helping the fleet managers by quickly detecting security threats and vehicle problems.

**Location-aware service mining**

To understand the behaviour of the clients, mining data log will play an important role. The issue of multilevel association mining was first proposed by Han (Han, & Fu, 1999). It is incorporated the taxonomy to demonstration the data hierarchy relations. Different minimum supports may be assigned for each level. Tseng (Tseng, & Tsui, 2004) exploited the multilevel association rule mining to discover the location-aware service rules. The service and location concept hierarchy trees were constructed to mining frequent patterns. Let HL and HS be two different hierarchy trees and representing the location and the service hierarchical concept respectively. Let \( P = \{P_1, P_2, PK\} \) be a set of items from mobile device. Some possible scenarios are patient health monitoring, environment surveillance, and sensor networks. The Vehicle Data Stream mining (VEDAS) system [4] is an example of mobile environment for monitoring and mining vehicle data streams in real time. The system is designed to monitor vehicles using onboard PDA based systems connected through wireless networks. VEDAS continuously analyzes the data generated by the sensors located on most modern vehicles, identifies the emerging patterns, and reports them to a remote control center over a lowband width wireless network connection. The overall objective of VEDAS is supporting drivers by characterizing their status, and helping the fleet managers by quickly detecting security threats and vehicle problems.

**Location-aware service mining**

To understand the behaviour of the clients, mining data log will play an important role. The issue of multilevel association mining was first proposed by Han (Han, & Fu, 1999). It is incorporated the taxonomy to demonstration the data hierarchy relations. Different minimum supports may be assigned for each level. Tseng (Tseng, & Tsui, 2004) exploited the multilevel association rule mining to discover the location-aware service rules. The service and location concept hierarchy trees were constructed to mining frequent patterns. Let HL and HS be two different hierarchy trees and representing the location and the service hierarchical concept respectively. Let \( P = \{P_1, P_2, PK\} \) be a set of items from mobile device. Some possible scenarios are patient health monitoring, environment surveillance, and sensor networks. The Vehicle Data Stream mining (VEDAS) system [4] is an example of mobile environment for monitoring and mining vehicle data streams in real time. The system is designed to monitor vehicles using onboard PDA based systems connected through wireless networks. VEDAS continuously analyzes the data generated by the sensors located on most modern vehicles, identifies the emerging patterns, and reports them to a remote control center over a lowband width wireless network connection. The overall objective of VEDAS is supporting drivers by characterizing their status, and helping the fleet managers by quickly detecting security threats and vehicle problems.

**Location-aware service mining**

To understand the behaviour of the clients, mining data log will play an important role. The issue of multilevel association mining was first proposed by Han (Han, & Fu, 1999). It is incorporated the taxonomy to demonstration the data hierarchy relations. Different minimum supports may be assigned for each level. Tseng (Tseng, & Tsui, 2004) exploited the multilevel association rule mining to discover the location-aware service rules. The service and location concept hierarchy trees were constructed to mining frequent patterns. Let HL and HS be two different hierarchy trees and representing the location and the service hierarchical concept respectively. Let \( P = \{P_1, P_2, PK\} \) be a set of items from mobile device. Some possible scenarios are patient health monitoring, environment surveillance, and sensor networks. The Vehicle Data Stream mining (VEDAS) system [4] is an example of mobile environment for monitoring and mining vehicle data streams in real time. The system is designed to monitor vehicles using onboard PDA based systems connected through wireless networks. VEDAS continuously analyzes the data generated by the sensors located on most modern vehicles, identifies the emerging patterns, and reports them to a remote control center over a lowband width wireless network connection. The overall objective of VEDAS is supporting drivers by characterizing their status, and helping the fleet managers by quickly detecting security threats and vehicle problems.

**Location-aware service mining**

To understand the behaviour of the clients, mining data log will play an important role. The issue of multilevel association mining was first proposed by Han (Han, & Fu, 1999). It is incorporated the taxonomy to demonstration the data hierarchy relations. Different minimum supports may be assigned for each level. Tseng (Tseng, & Tsui, 2004) exploited the multilevel association rule mining to discover the location-aware service rules. The service and location concept hierarchy trees were constructed to mining frequent patterns. Let HL and HS be two different hierarchy trees and representing the location and the service hierarchical concept respectively. Let \( P = \{P_1, P_2, PK\} \) be a set of items from mobile device. Some possible scenarios are patient health monitoring, environment surveillance, and sensor networks. The Vehicle Data Stream mining (VEDAS) system [4] is an example of mobile environment for monitoring and mining vehicle data streams in real time. The system is designed to monitor vehicles using onboard PDA based systems connected through wireless networks. VEDAS continuously analyzes the data generated by the sensors located on most modern vehicles, identifies the emerging patterns, and reports them to a remote control center over a lowband width wireless network connection. The overall objective of VEDAS is supporting drivers by characterizing their status, and helping the fleet managers by quickly detecting security threats and vehicle problems.

**Location-aware service mining**

To understand the behaviour of the clients, mining data log will play an important role. The issue of multilevel association mining was first proposed by Han (Han, & Fu, 1999). It is incorporated the taxonomy to demonstration the data hierarchy relations. Different minimum supports may be assigned for each level. Tseng (Tseng, & Tsui, 2004) exploited the multilevel association rule mining to discover the location-aware service rules. The service and location concept hierarchy trees were constructed to mining frequent patterns. Let HL and HS be two different hierarchy trees and representing the location and the service hierarchical concept respectively. Let \( P = \{P_1, P_2, PK\} \) be a set of items from mobile device. Some possible scenarios are patient health monitoring, environment surveillance, and sensor networks. The Vehicle Data Stream mining (VEDAS) system [4] is an example of mobile environment for monitoring and mining vehicle data streams in real time. The system is designed to monitor vehicles using onboard PDA based systems connected through wireless networks. VEDAS continuously analyzes the data generated by the sensors located on most modern vehicles, identifies the emerging patterns, and reports them to a remote control center over a lowband width wireless network connection. The overall objective of VEDAS is supporting drivers by characterizing their status, and helping the fleet managers by quickly detecting security threats and vehicle problems.
implement data mining techniques on small devices such as mobile phone, PDA so that only required data will be getting due to filtration. User can access web services in short period of time and with good performance. Mobile users retrieve information and services efficiently i.e. speed increases and saves memory.

**REFERENCE**

[1]. S. Pittie, H. Kargupta, B. Park. Dependency detection in MobiMine: a systems perspective. Information Sciences, 155(34): 227243 (2003).
[2]. H. Kargupta, B. Park, S. Pitties, L. Liu, D. Kushraj, K. Sarkar. Mobimine: monitoring the stock marked from a PDA. ACM SIGKDD Explorations, 3(2): 3746 (2002).
[3]. F. Wang, N. Helian, Y. Guo, H. Jin. A Distributed and Mobile Data Mining System. Proc. Int. Conf. on Parallel and Distributed Computing, Applications and Technologies (2003).
[4]. H. Kargupta, R. Bhargava, K. Liu, M. Powers, P. Blair, S. Bushra, J. Dull. VEDAS: A Mobile and Distributed Data Stream Mining System for RealTime Vehicle Monitoring. Proc. SIAM Data Mining Conference (2003).
[5]. Domenico Talia and Paolo Trunfio, “Mobile Dat a Mining on Small Devices Through Web Sevices” (2010).
[6]. Pittie, H. Kargupta, B. Park, “Dependency detection in MobiMine: a systems perspective” Information Sciences, 155(34):227243 (2003).
[7]. H. Kargupta, B. Park, S. Pitties, L. Liu, D. Kushraj, K. Sarkar, “Mobimine: monitoring the stock marked from a PDA” ACM SIGKDD Explorations, 3(2):3746 (2002).
[8]. M. Ađaçal, A.B. Bener, “Mobile Web Services: A new Agent B asked Framework” IEEE Internet Computing, 10(3): 5865 (2006).
[9]. M. Tian, Voigt, T. Naumowicz, H. Ritter, J. Schiller, “Performance Considerations for Mobile Web Services” Computer Communications, 27(11): 10971105 (2004).
[10]. H. Chu, C. You, C. Teng, “Challenges: WirelessWeb Services” Proc. Int. Conf. Parallel and Distributed Systems (ICPADS 04), IEEE CS Press (2004).
[11]. W. Zahreddine, Q. H. Mahmoud, “An Agent-based Approach to Composite Mobile Web Services”, Proc. Int. Conf. Advanced Information Networking and Applications (AINA'05), IEEE CS Press (2005).
[12]. Khaled M. Hammouda and Mohamed S. Kamel, “Hierarchically Distributed Peer-to-Peer Document Clustering and Cluster Summarization”, IEEE Transactions on knowledge and data engineering, Vol. 21(5), pp. 681-698 (2009).
[13]. Hyun-suk, Hwang, Seon-hyunShin, Ki-ukKim, Sook- CheolLee, Chang-sokkim, “A Context-aware System Architecture using Personal Information based on Ontology”, 5th IEEE Int’l (2007).
[14]. Chih-Hao Liu Jason Jen-Yen Chen, Jhong-Li, Taiwan, “Mobile User Agent with User Ontology for Personalized Web Service Access” IEEE (2010).