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USE OF SOCIAL NETWORK ANALYSIS TO IMPROVE WIRELESS DATA DISTRIBUTION

This paper describes an approach for using social network analysis techniques to enhance the delivery of content to mobile users while improving the quality of service as perceived by the users. The essence of the approach is to employ aggressive prefetching and caching of data. The proposed approach for prefetching is based on a user's social network and on a user's historical content access patterns. The paper illustrates the dramatic potential for improvement in the delivery of content that using knowledge of the user's social network facilitates by a simplified analysis of performance. An example scenario using realistic numbers demonstrated that significant improvements in overall quality of service can be achieved when wireless network service providers exploit knowledge of social networks to guide on-device caching on such networks. Analyses based on realistic scenarios indicate that the proposed approach has the potential to decrease the probability of data service failure on wireless networks due to congestion by a factor ranging from 1.5X up to 5X.

Keywords: *wireless networks, multi-mode radio terminals, social networks, social network aware prefetching.*

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ИСПОЛЬЗОВАНИЕ АНАЛИЗА СОЦИАЛЬНЫХ СЕТЕЙ ДЛЯ УЛУЧШЕНИЯ БЕСПРОВОДНОГО РАСПРОСТРАНЕНИЯ ДАННЫХ

В статье описывается подход, позволяющий улучшить доставку контента пользователям мобильной связи и повысить качество сервиса за счет анализа социальных сетей. Суть нашего подхода заключается в том, чтобы использовать агрессивный префетчинг и кэширование данных. Предлагаемый подход базируется на использовании социальной сети пользователя и анализе пользовательской истории доступа к данным. Статья демонстрирует значительный потенциал улучшения доставки контента за счет упрощенного анализа производительности, основанно-

го на знании социальной сети пользователя. Экспериментальный сценарий, использующий реалистичные цифры, продемонстрировал, что использование знания о социальных сетях для организации кэширования мобильными устройствами беспроводной сети позволит провайдерам существенно повысить общее качество услуг. Анализ, базирующийся на реалистичных сценариях, показывает, что предлагаемый подход может обеспечить снижение вероятности сбоя информационного сервиса беспроводных сетей от перегрузки от 1,5 до 5 раз.

Ключевые слова: *беспроводные сети, мульти-модальные радиотерминалы, социальные сети, префетчинг с учетом социальной сети.*

1. Inroduction

The use of wireless mobile devices by human beings for accessing data has increased steadily over the last decade. The introduction of touch-screen media-centric "smart" phones has spurred a rapid evolution in the role of wireless mobile devices as primary content downloading and delivery devices. Wireless Service Providers (WSPs) have been on a steady march to increase the data delivery capability of their wireless wide area networks (WWANs) in order to handle this increasing data demand. For example, in the USA, just as the roll out of third generation (3G) wireless data networks was reaching maturity, WSPs began a race to deploy fourth generation (4G) wireless data networks; whereas, traditional business strategy would have been to delay the rollout of 4G networks until the profits from the 3G network had repaid the investment cost of the 3G network. Due to the efforts of the WSPs, the data rate available to the average cell phone user has increased dramatically enabling the wireless delivery of a whole new range of content and services; e.g., television programs can now be delivered on cellular handsets. AT&T projects (against a baseline of 2G data traffic in 2007) that by 2018 3G+4G wireless data traffic will expand by a factor of 250X (conservative estimate) to 600X (aggressive estimate) (Keathley 2008). Unfortunately, the available radio frequency spectrum simply cannot support this 250X to 600X increase in wireless data traffic. Other approaches to decreasing the fraction of this data demand that travel over the WWAN must be developed.

This paper suggests an innovation in how content is delivered to mobile users around the world that is based on analyzing and understanding the social network in which the human user of a wireless mobile device is embedded.

2. Background

The obvious approaches to increasing the data delivery capacity of WWANs are already relatively mature. For example, the radios in 3G cell phones employ bandwidth-efficient modulation codes; e.g., code division multiple access (CDMA) is approximately 0.75 bits/s/Hz. 4G standards are moving to even more efficient modulation codes such as orthogonal frequency-division multiplexing (OFDM) reaching approximately 1.5 bits/s/Hz. Unfortunately, only limited increases in data rate / Hz are likely to be achieved with future improvements in hardware.

Another approach that has been pursued aggressively in the 802.11 area is the use of antenna diversity to increase data throughput by relying on the multipath nature of typical RF channels. Unfortunately, because antennas need to be orthogonal, they must typically be place at least half a wavelength apart (e.g., at 2GHz this is 15cm). In a typical mobile handset, at most two antennas can be included at this separation offering limited increase in overall data rate.

Overall wireless data delivery capacity can be dramatically increased by adding more RF bandwidth; however, adding RF frequency bands is a one-time increase and requires significant complication of base station and mobile radio design to handle a multiplicity of different RF frequency bands. Although making additional spectrum available for wireless communications will provide significant expansion in the data delivery capacity in the next five years, other approaches will be necessary in the longer term if user demand for data continues to grow as per the projection made by Keathley (ibid.).

Another standard approach for increasing wireless data capacity is to add more base stations enabling a higher degree of spectrum reuse. Many wireless network service providers already take this approach. However, the cost of rolling out more base stations across an entire network is extremely high. The end result will be a significant increase in the cost/bit delivered using such networks. However, even adopting all of the above strategies will not keep up with the demand for wireless data access predicted for the year 2018 in (ibid,).

An additional strategy for increasing data capacity takes advantage of the fact that there already exist other parallel data networks which can be leveraged to supplement the WWAN network. For example, there are many WiFi hot spots using 802.11 radios and many mobile devices today have 802.11 radios. When in range of an accessible 802.11 wireless access point, a mobile device can download data at higher data rates than are possible over the WWAN and at lower cost per bit (or even free). In addition, future wireless mobile devices could have very-high-data-rate (> 1Gb/s) very-short-range radios that could be used to connect to nearby fixed portals and to other nearby wireless mobile devices. We refer to the very short range (less than 5m) networks formed between such ultra-high-data-rate radios as wireless high speed personal area networks (WHSPAN). Such short range radios would be similar to the Bluetooth radios included in a majority of cell phones today, except that they would be capable of transferring data at Gb/s data rates. Both ultra-wide-band (UWB) and 60GHz approaches are being developed for WHSPAN radios. Most proposed approaches for implementing WHSPAN radios would operate at higher frequencies than WWAN radios to avoid the already congested spectrum in the 0.8GHz — 2.5GHz frequency range. Since they are intended only for very short range communications, the poor signal propagation characteristics of higher frequency RF bands is not a significant limitation. Note, the 60GHz radio band is extremely attractive for this application because there is a great deal of spectrum available in unlicensed bands (bandwidths of 2GHz are easily supported) in a majority of Countries around the world. An IEEE Standard, 802.15.3c, has already been defined for Gb/s communication in the 60GHz bands. Such radios could easily appear in cellular handsets by the year 2018 or even before then (Dawn et al. 2007; Guo et al. 2007).

Given the above strategy for a hierarchical system of radios that can all deliver data to a wireless mobile device, the operating protocol of such devices is an open research topic. In particular, the wireless mobile devices of Year 2018 might well have (1) WWAN radios capable of peak rates of 5-20Mb/s, but suffering from RF spectrum congestion, RF interference, and high cost per bit; (2) WLAN (802.11a/b/g/n) radios capable of peak rates of 54-200Mb/s but only available when near to an accessible 802.11 base station able to deliver data that would be very low in cost compared to WWAN delivered data or free; and (3) WHSPAN radios capable of >1Gb/s but only available between nearby WHSPAN portals and between WHSPAN equipped mobile devices and data would also be either very low in cost or free. Note, we anticipate that the cost of WHSPAN portals will also be extremely low. If the cost is low enough, it is likely every PC manufactured after 2018 could include a WHSPAN radio and if connected to the wired internet could act as a WHSPAN portal. Therefore, an extremely dense network of WHSPAN portals could be created with very little expense.

Another observation about wireless mobile devices in 2018 is that they could economically employ large amounts of nonvolatile memory. In 2009, a typical nonvolatile (Flash) Memory IC could hold about 8Gb — 16Gb of data (Roadmap... 2009). The average "smartphone" in the year 2010 was purchased with 8-16GB of memory (Meredith 2010) and 32GB became common in 2011. Based on the scaling of lithography feature sizes, the capacity of nonvolatile memory ICs is expected to increase by about 2X every 2 years for the next ten years. Therefore, is it reasonable to expect that wireless mobile devices in the year 2018 will have roughly 16X the capacity of such devices in 2010; therefore, wireless mobile devices of the year 2018 could have on the order of 128GB-256GB of nonvolatile memory capacity.

Given the above vision of a future wireless mobile device with very large capacity nonvolatile memory and in which access to higher data download rates and lower cost data is intermittent, the obvious research question is how to develop a prefetching strategy for data that maximizes user satisfaction with the overall service. That is, how can the wireless mobile device anticipate the data requests of its user, and prefetch likely to be requested data when low-cost high-speed data network access is available. If this is done successfully, it could result in a dramatic reduction in the load the user places on the WWAN.

The idea of caching content based on locality and popularity has been used to achieve dramatic improvements in performance for content distribution networks and wireless data providers. For example, one study on wired internet users reports that for search engine queries, 16-22% of all queries were repeats of a query made earlier by the same user (Xie and O'Hallaron, 2002). There is no reason to expect that the same statistics would not apply to wireless mobile users as well. Clearly, caching the results of past queries on the mobile device has a high potential payoff. And, for web sites with dynamic content, caching updated versions of previously accessed web pages when high-speed low-cost data access is available is also an effective strategy — one that we term "history-based prefetching." In this paper we adopt the concept of history-based prefetching as a minimal starting point. We augment it with a strategy we call "social-network-based prefetching" to further improving the cache hit rate.

We note that the idea of using data caches in mobile devices for which the cost of data access and the speed of data access can vary with time has a long tradition. For example, Ebling, Mummert and Steere (1994) proposed prescient prefetching as a strategy for managing data traffic on wireless mobile devices that had different data access costs at different times in 1994. Drew and Liang (2004) proposed a mobility-aware prefetching strategy to minimize data access cost for dual-mode (in their case WLAN and WWAN) wireless devices in which the low cost mode (WLAN) was only intermittently available (see also Liang and Drew 2006). However, the only work to date on making use of knowledge of the users social network as the basis for a prefetching strategy is in Carley and Carley (2010).

In this work, we take advantage of such tenets of social network theory as homophily. Homophily is the principle that a contact between similar people occurs at a higher rate than among dissimilar people. This correlation also means that individuals who are proximal, either physically, socially, or affectively are likely to have a higher than average degree of similarity. From which, we infer that such individuals will also have a higher than average degree of similarity in their wireless data requests. Simply put, we assume that users are likely to make the similar data requests on a wireless device as do those users who are near to them (in physical space or cyber space), as do those who are like them, and as do those with whom they are friends (Dekker et al. 2002; Panzarasa et al. 2009; Wang et al. 2005). These increased correlations for future wireless data requests are presumed to be more strongly correlated for users in a social network who are strongly connected. Opportunistically prefetching data files that others who are strongly connected to one in the social network, either proximally, socially, or affectively, is the strategy proposed in this paper. Fortunately, extensive literature exists for finding such pairs of similar individuals in social network data; e.g., ORA (Carley et al. 2012).

Social networks have been considered for use in communications networks to supplement and guide data packet routing. In Mobile Ad-Hoc Networks (MANETs), researchers have developed mechanisms for measuring important social network statistics at wireless communications nodes in order to guide routing (e.g., Daly and Haahr 2007; Dinh et al. 2009). In Bigrigg et al. (2009), the social network was even employed as an added communications link in the overall communications network to improve robustness. However, when the data set of interest is all subscribers of a single Wireless Service Provider (WSP), finding the social network among all users can be a challenging endeavor. Fortunately, the WSPs have available to them both demographic data on users and behavioral data concerning communications that the users have made over the provider's network. We assume that the WSP has a record of all communications carried out by all of the wireless mobile devices on their network. This data set would include text message data, voice call data (including duration of call) and data download requests. Since the efficiency improvement achievable by prefetching small data downloads is minimal, the WSP would need only focus on analyzing large data download requests (e.g., TV shows, Movies, YouTube Videos, etc.) when extracting the social network between users. Further, by analyzing the correlation of large data download requests between all possible pairs of users of a given wireless service provider, the wireless service provider can build a social network graph based on similarity. Interestingly, two users who have never met might still share similar tastes in terms of what movies they want to download to the wireless mobile devices; hence, each would be a good indicator of potential content to be prefetched to the other.

Note, we argue that in calculating the degree to which large data access by one user will correlate with large data access by another user, the WSPs must make use of all possible information they have about the similarity of those two users. This is because the patterns of homophily tend to grow stronger as more types of relationships exist between two people, indicating that homophily on each type of relation cumulates to generate greater homophily for multiplex than simplex ties (Fischer 1982). Therefore, it is important for the wireless network service providers to look at similarity on all of the demographic information they have on their users in addition to similarity in large data requests.

3. Prefetching

Although future wireless mobile devices are expected to have large nonvolatile memory, it is not infinite. That is to say, prefetching must be done in an intelligent manner in order to avoid filling the device's available data cache with information that will never be requested by the user. For this reason, we propose to carry out multi-dimensional social network analysis to identify the set of most highly correlated individuals (those with the highest degree of homophily) as the basis for deciding which data to prefetch and which to discard from the cache. In this paper, we consider three different approaches to prefetching.

No Prefetching. This is the case today. The user stores personal files and programs on the wireless mobile device, but downloaded data files are discarded as soon as they have been viewed. This is the baseline case for this study.

Personal Historical Archive. As large data files are downloaded from the WWAN, they are kept in a historical queue in the cache memory. The oldest data files are removed in order to make space for the newest data files. Mobile users of the internet often request the same content multiple times on wireless mobile devices, and the frequency of such repeated requests would determine the value of this approach (Church et al. 2007; Xie and O'Hallaron, 2002).

Automated Prefetching based on social networks. It is possible to identify and prefetch files that a user will want to download before the user even knows of the existence of the large data file (Chwe 2000). Such "prescient" prefetching is based on the idea that pairs of users with strong similarity in the social network sense will have a much higher than random probability of wanting to download the same data files. If a WSP knows which users are highly similar, it can expect that the large data files requested by one user will be highly correlated with the large data files that will be requested by strongly similar users and vice versa. Let us consider an example. Joe and his fellow employee, John, work for the same company in the same location. They are often in close proximity to each other. The WSP can make use of information about when the wireless mobile device of one user is in proximity to the wireless mobile device of another user using the WHSPAN capability. This proximity data, in addition to other demographic and data download history that the WSP has about these two users, may cause them to be strongly similar in the social network sense. Therefore, the WSP can anticipate that Joe will want to see a download that was requested by John and can instruct Joe's wireless mobile device to prefetch that data file onto Joe's wireless terminal whenever high speed low cost data access is available. In fact, if both Joe and John's wireless devices were equipped with WHSPAN radios the data file could be transferred between them any time they are in proximity. In fact, the video could be being prefetched in a mobile-to-mobile ad-hoc connection while John is telling Joe how funny the video was.

Implementing the proposed Social Network Aware prefetching algorithm, requires efficiently finding the social network. There are numerous data sets that the wireless network service provider can use to learn about the social network. These include, e.g., the history of data downloads requested by all users, the time-stamped location of wireless terminals in a given region (from GPS data), text and voice contacts between users, proximity of users to each other (from WHSPAN contact data) and so on. Further, open-source demographic databases such as census and organizational memberships could also be used to further help identify likely work and community groups to which a user might belong. For example, a multi-modal analysis across all of these data sets can be carried out using software tools such as the ORA tool set developed at Carnegie Mellon University (Carley et al. 2012) to determine a social network and the group structure.

4. Analysis

In this section we provide a simplified analysis that estimates the impact of using social network analysis to guide prefetching.

4.1. The Simplified Model

In order to gain insight into the applicability of the proposed technique for social network aware prefetching we use an extremely simplified model. The model is built under the following assumptions:

- The WWAN network suffers from congestions; hence, and a fixed fraction of the time, F, access to large data files is not available.
- For a fraction of the time, W, the user is not in range of either an accessible WHSLAN or accessible WLAN. We assume that wheneve the user is within range of either of these services that large data files will be accessed from the internet with 100% success.
- Time is broken up into periods of equal length. These units could be hours, days, weeks, etc.
- Every user requests M large data files during a time period.
- The number of requests by a user that are repeats of large file data requests from the current or immediately prior time period is R. We assume that the number of large data files downloaded by the users in a time period is small enough that the history cache can store all of them. This assumption is reasonable for short time periods but may be unrealistic for long time periods and very active users.
- There is a Social Network Analysis Cache memory within the wireless terminal that has a capacity of X large data files.

- The number of all possible large data files that could be downloaded by all users is *TD*. As will be seen, the results are nearly independent of the value of *TD*, so the fact that it is hard to estimate is not a big concern.
- The probability that a large data file selected by a user matches any of the data files in the Top X most likely to be selected large data files for that user based on social network analysis by the wireless service provider is *P(SNA)*.
- Prefetching is assumed to be perfect and instant. That is, whatever the Top X most likely to be requested files, based on social network analysis of the user, will be kept in the user's wireless mobile device cache using some combination of the WHSPAN, WLAN, and WWAN. Note, when using the WWAN, the requests can be timed so that they do not load down the wireless data network by only downloading large data files when there is spare WWAN capacity. We assume that the cache can be updated without interfering with other data requests of the user.

Under the proposed strategy, the wireless terminal downloads data files from its prefetch queue whenever (a) there are files in the WSP's list of Top X files that are not in the wireless mobile device's cache and (b) the wireless mobile device is within range of a WHSPAN portal, or a WLAN portal to the high bandwidth wired network, or within range of another wireless terminal that has the desired data file already stored in its cache, or the WWAN has sufficient data deliver capacity to deliver this file without interrupting any other user's services. Note, the list of Top X files will be continuously changing as other users who are highly similar to the user in question download new large data files.

In all of the scenarios below, we will compute a Service Quality Metric that is the % of requests that the user makes for large data files that fail to deliver that file in a timely manner. Note, the delivery would be successful if the large data file requested is already in the History Cache, in the Social Network Analysis Cache, or is downloaded in a timely manner from the WWAN.

4.2. Network Performance with No Cache

With no History Cache and no Social Network Analysis Cache, the probability of a Service Failure is just the probability that the wireless mobile device is not currently able to access large data files from any of (a) the WWAN, (b) the WLAN, or (c) the WHSPAN. Therefore:

$$P(Service\ Failure) = W\,F$$

where W is the Probability that neither WHSPAN nor WLAN data file access is available and F is the Probability that data file access via the WWAN is not available due to congestion.

4.3. Network Performance with History Cache

Next we analyze the case where the History Cache is enabled and records all past large data file accesses. We simplify this analysis, by assuming that the history cache is sufficiently large to be able to hold all repeat requests for large data files for the current and previous time period. At some point, new requests will cause old requests in the History Cache to be deleted; therefore, this assumes that the repeat requests are within the time window covered by the History Cache. Note, we adjust for this factor in part by choosing a typical hit rate for History Cache at the low end of the 16–22% range suggested by (Xie and O'Hallaron 2002) in the example scenario below.

$$P(Service\ Failure) = W\ F\ (M - R)\ /\ M$$

where W is the Probability that neither WHSPAN nor WLAN data file access is available, F is the Probability that data file access via the WWAN is not available due to congestion, M is the number of large data file requests and R is the number of large data file requests that are repeats.

4.4. Social Network Aware Prefetching Scenario

In this case we assume that both a History Cache and a Social Network Analysis Cache are used in the wireless mobile device. For comparison purposes, we first consider the improvement offered by randomly selecting files to add to the wireless mobile device cache with equal probability from all possible large data files. Note, in reality, this should be a weighted sum where the probability of selecting a large data file is weighted by the overall popularity of that large data file. However, we have chosen to ignore data on large data file popularity in this analysis. Note, taking popularity scores into account should only further increase the impact achieved by the proposed technique.

For the Random Cache filling case, we choose files to fill the Cache with randomly from the total population of TD large data files. We can then adjust the probability for the historical cache case with a new factor based on the probability of correctly having anticipated a file the user requests. Therefore:

$$P(Service\ Failure) = W\ F\ [(M - R)\ /\ M]\ [(TD - X)\ /\ TD]$$

where X is the number of large data files that can be kept in the Social Network Analysis Cache and TD is the total number of large data files available for download.

From this equation, it is obvious that except for artificial situations with extremely small number of total files available for download that this approach is only infinitesimally better than a simple Historical Cache scenario. In the limit of large TD, this expression approaches the previous expression for Probability of Service Failure using History Cache.

Now consider that case where the Social Network Analysis Cache is filled based on a list maintained by the WSP of the Top X files most likely to be downloaded by each user. Note, this list explicitly excludes any files that have been recently downloaded because those would be covered by the Historical Cache. We assume that for any large data file selected for download by the user and that is not in the Historical Cache, there is a Probability $P(SNA)$ that it is contained in the Top X list for that user. Given our additional assumption that the Social Network Analysis Cache in the wireless device has been synchronized with the Top X list maintained by the wireless service provider, we can calculate the Probability of a Service Failure as:

$$P(Service\ Failure) = W\ F\ [(M - R)\ /\ M]\ [1 - P(SNA]$$

where $[1\text{-}P(SNA)]$ is the Probability that the users large data file request does not match any of the files in the Top X list.

5. Example results

In this section we plug realistic numbers into the above analysis in order to gain some insight into when the proposed approach will offer significant advantages to the overall data delivery system.

First, we compare Probability of Service Failure for the schemes analyzed above. We assumed that the Probability of a Repeat request was 16% and that the ratio of the Social Network Analysis Cache size to the total population of large data files was 1/100,000. While this may seem small, it was selected to represent the fact that by using overall popularity ratings, rarely downloaded files can be excluded from competition for placement in the Social Network Analysis Data Cache. And, as already noted, none of the results depend significantly on this value. Fig. 1 shows a comparison of the Probability of Service Failure as the P(SNA) is varied from 4.8% up to 80%. As can be seen in Fig. 1, a noticeable decrease in the Probability of Service Failure can be achieved by modest (10-20%) probabilities of correctly predicting the future requests of the user. Note, in Fig. 1, the curve for Historical Cache only and the curve for Historical Cache plus Random file selection are on top of each other; that is, adding files to the Top X list randomly accomplished nothing.

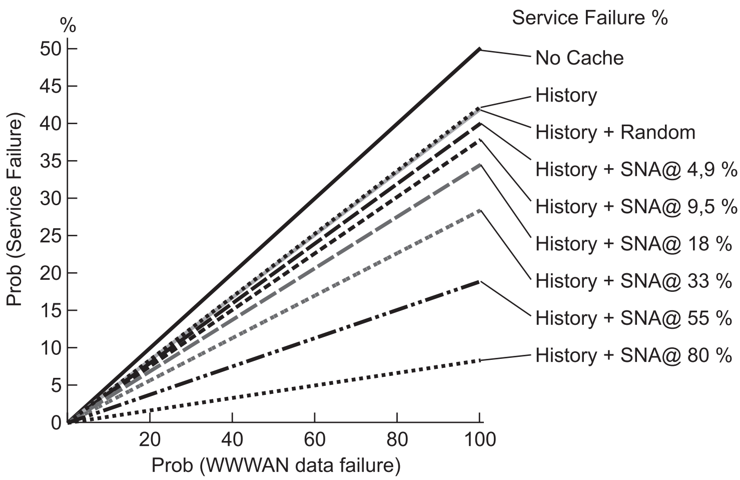

Figure 1. Probability(Service Failure) versus Probability(WWAN data access failure) for all of the scenarios analyzed

In Fig. 2, we take the same scenario as was used above, but now vary the size of the Social Network Analysis Cache. As the latter grows, the probability of correctly predicting the user's future large file data requests increases and the Probability of Service Failure drops. However, there appears to be a diminishing return trend starting at roughly 200 data items.

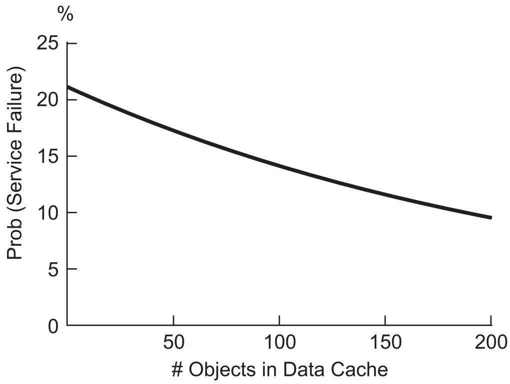

Figure 2. Probability(Service Failure) versus the size of the Social Network Analysis Data Cache

6. Conclusions

In this paper, an approach for selecting large data files to be migrated to a data cache in wireless mobile devices has been presented. We developed analytical formulas for the Probability of Service Failure that suggest that with realistic data cache sizes, user experience of data service failure could be reduced by 50-400%, depending on the accuracy of the Top X list derived from social network analysis.

There remain a number of key issues that need to be managed for the proposed system to be effective. First, large data files need to be identified with a unique identifier so that when a data file is distributed across a number of servers to increase accessibility, it does not appear to be a number of different files. Second, many data files require a subscription or a fee for access. To improve performance for these files, the large data files could be distributed as described, but the key that unlocks the content could be provided to the user only if they are a user or if they pay the required fee. This sort of key enabled content has already been developed, but would have to be standardized to allow such content files to be supported by the proposed Social Network Analysis Caching approach.

In conclusion, this paper suggests that social network aware prefetching has the potential to dramatically improve quality of wireless service. Compared with using just information on the user's personal download history, prefetching based on social network analysis can significantly increase cache hit performance and decrease the Probability of Data Service Failure.

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