Minimizing Overhead and Improving Energy Level for Android Mobile Devices

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***Abstract*- Reducing the energy consumption of wireless devices is paramount to a wide spread adoption of mobile applications. Cellular communication imposes high energy consumption on the mobile devices due to the radio resource allocation, which differs from other networks such as WiFi. Most applications are unaware of the energy consumption characteristics of third generation cellular communication (3G) and Global Positioning Systems (GPS). This makes the background small data transfers of undisciplined applications an energy burden due to inefficient utilisation of resources.. In order to cover this gap, our work realises an existing energy saving algorithm such as of linear discriminant analysis , k-nearest neighbor, and support vector machines are explored and compared on synthetic and user traces from real-world usage studies within the Android platform, and measures its energy footprint.To maximize the lifetime of an ad hoc network ,it is essential to prolong each individual node(mobile) life through minimizing the total transmission energy consumption for each communication request. This paper proposes novel techniques that exploit types of Spatial locality available in android mobile devices. The experimental results an average improvement of 24% energy savings is achieved compared to state-of-the -art prior work on energy-efficient location sensing.**

***Key Terms* – Spatial, Energy Saving,Machine Learning**

I. INTRODUCTION

Mobile phones and other portable devices (tablets, PDA's) are fundamental everyday tools used in business, communication, and social interactions. As newer technologies (e.g. 4G networking, multicore/GPUs) and applications (e.g. 3D gaming, Apple's FaceTime™) gain popularity, the gap between device usage capabilities and battery lifetime continues to increase, much to the annoyance of users who are now becoming more and more reliant on their mobile devices. The growing disparity between functionality and mobile energy storage has been a strong catalyst in recent years to develop software-centric algorithms and strategies for energy optimization. These software techniques works in tandem with well-known energy optimizations implemented in hardware including CPU DVFS, power/clock gating, and low power mode configurations for device interfaces and chipsets .The notion of smart" mobile devices has recently spawned a number of research efforts on developing "smart" energy optimization strategies. Some of these efforts employ strategies that are context-aware including (location, sensing) of user utilization of device, user spatial application awareness that attempt to dynamically modify or learn optimal device configurations to maximize energy savings with little or negligible impact on user perception and quality of service (QoS) .This general theme of a *smart* and *context-aware* energy optimization strategy is further explored in this paper, in which a select number of machine learning algorithms are proposed and evaluated for their effectiveness in learning a user's mobile device usage pattern pertaining to spatiotemporal and device contexts, to predict data and location interface configurations. These resulting predictions manage the network interface states allowing for dynamic adaptation to optimal energy configurations, while simultaneously maintaining an acceptable level of user satisfaction. This idea is further motivated by considering the power distributions of the Android smartphone illustrated in Figure 1. Even when 3G, WiFi, and GPS interfaces are all enabled and idle, they account for more than 25%of total system energy dissipation.. Furthermore, when only one of the interfaces is active, the other two idle interfaces still consume a non-negligible amount of power. Our work exploits this fact to save energy more aggressively than the default energy management strategy used.

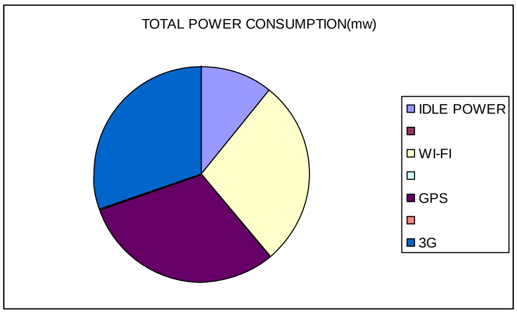


Figure1 Power consumption for Android-Phones

II. RELATED WORK

A large amount of work has been done in the area of energy optimization for mobile devices over the past decade .Much of the recent work focuses on optimizing energy consumed by the device's wireless interfaces by intelligently selecting the most energy-efficient data interface of 3G/EDGE, WiFi. Other work focuses on energy-efficient location sensing schemes aiming to reduce high battery drain caused by location interfaces (e.g. WiFi, GPS) by deciding when to enable/disable location interfaces or modify location acquisition frequency.A substantial amount of research has been dedicated to utilizing machine learning algorithms for the purpose of mobile data user context determination extend a traditional self-organizing map to provide a means of handling missing values and then use it to predict mobile phone settings such as screen lock pattern and WiFi enable/disable. Other works attempt to predict the location of mobile users using machine learning algorithms. We propose a model that predicts spatial context through supervised learning, and the take advantage of signal strength and signal quality history data and model user locations using an extreme learning machine algorithm.

These works are focused on using user context for device self-configuration and location prediction. context sensors into three categories according to their energy efficiency, using the more energy-efficient sensors to infer the status of high-energy-consuming sensors so that activating them may not be necessary. The major difference between their work and ours is that they use machine learning techniques for learning the inference models to capture relationships between groups of sensors (e.g., between energy-efficient software sensing and high-energy consuming hardware sensing categories), One of the key motivations for applying pattern recognition and classification algorithms to mobile device usage is the observation that user usage patterns are often mutually independent, in that each user generally has a unique device usage pattern. The use of pattern recognition then allows for energy optimization algorithms to be fine-tuned for each user, achieving energy savings without perturbing user satisfaction levels. This idea is further confirmed in mobile usage studies which additionally focused on smartphone usage pattern analysis and its implications on mobile network management and device power management. Although their work had a slightly different focus than our work, the key relevant take-away is that the authors demonstrated from a two month real smartphone usage study that *all users have unique device usage patterns*. Many other works utilize data gathered from groups of real smartphone users to emphasize this same conclusion.

III. ALGORITHMS

Linear Discriminant Analysis

Linear discriminant analysis (LDA) and the related Fisher's linear discriminant are methods used in statistics, pattern recognition and machine learning to find a linear combination of features which characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification. LDA is closely related to ANOVA (analysis of variance) and regression analysis, which also attempt to express one dependent variable as a linear combination of other features or measurements. In the other two methods however, the dependent variable is a numerical quantity, while for LDA it is a categorical variable (*i.e.* the class label). Logistic regression and probit regression are more similar to LDA, as they also explain a categorical variable. These other methods are preferable in applications where it is not reasonable to assume that the independent variables are normally distributed, which is a fundamental assumption of the LDA method.

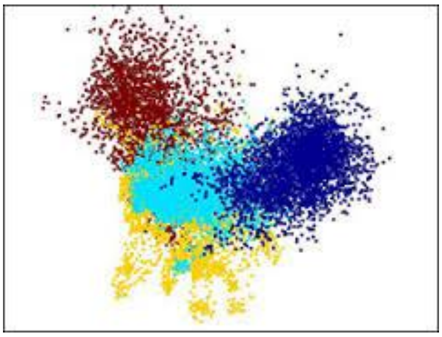


Figure 2 LDA

K-Nearest Neighbor

The k-nearest neighbor (KNN) algorithm is a fairly simple nonparametric unsupervised approach for the data classification problem. A key assumption of non-parametric estimation is that similar inputs have similar outputs. In KNN, new samples are classified by assigning them the class that is the most common among the closest samples in the attribute space. This method requires some form of distance measure for which Euclidean distance is typically used. The Euclidean distance between two points**.**

$$\mathbf{D(a,b) = sqrt(\sum(b_i - a_i)^2)}$$

$$\mathbf{Condition::0<i<n}$$

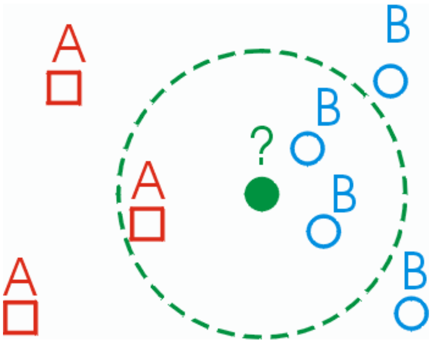


Figure 3 K-Nearest neighbor

Support Vector Machines

In machine learning, support vector machines (SVMs, also support vector networks are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. For this type of SVM, training involves the minimization of the error function:

$$\frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i$$

Subject to the constraints:

$$y_i\left(w^T\phi(x_i)+b\right)\ge 1-\xi_i \text{ and } \xi_i \ge 0,\ i=1,\dots,N$$

Where C is the capacity constant, w is the vector of coefficients, b is a constant, and ξ_i represents parameters for handling nonseparable data (inputs). The index i labels the N training cases. Note that $y \in \pm 1$ represents the class labels and xi represents the independent variables. The kernel ϕ is used to transform data from the input (independent) to the feature space. It should be noted that the larger the C, the more the error is penalized. Thus, C should be chosen with care to avoid over fitting.

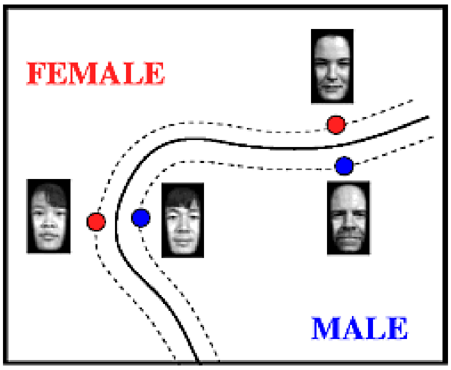
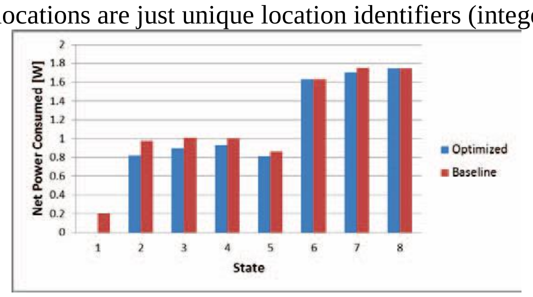
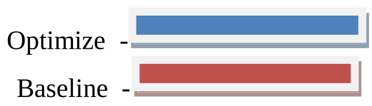


Figure 4 Support Machine Vector

IV. EXPERIMENTAL RESULTS

In addition to testing our energy saving techniques on Three real user profiles, a set of synthetic user profiles were also created for three different idealized and generalized models of average user (i) a College Student (ii) a Business man (iii) Traveller.if a user was at an outdoor location, larger GPS satellite values and weak WiFi RSSI values were used as opposed to when the user was indoors. We created the synthetic profiles ourselves by modeling what we considered typical behavior of each stereotype. For instance, we envisioned the 8-5 Business Worker waking up at 6:30 a.m., driving to work at 7:30 a.m., arriving at his/her desk at 8:30 a.m., working until noon then taking a lunch break, etc. The interface configuration states and locations in the charts attempt to capture this behavior. Recall that the locations are just unique location identifiers (integers).





Energy Saving

Mobile and broadband traffic continue to grow at an exponential rate resulting in further capacity investment and the requirement for new spectrum and advanced air interfaces which provide greater spectral efficiency. Installing new capacity and providing improved coverage will yield environmental savings through better use and adoption of Mobile and Wireless ICT services. Energy use and costs continue to rise, creating the need for future network energy efficiency to be significantly improved to ensure energy usage does not increase at the same growth rate as traffic running over the networks. The introduction of new spectrally efficient air interfaces, presents new challenges in terms of energy efficiency and a key objective in developing new networks will be to drive down the energy consumption per bit transmitted, manage equipment more efficiently and leverage natural energy sources. The amount of potential energy savings is still highly dependent on the user's device usage pattern and if the algorithms are positively or negatively predicting states where energy can be conserved. More complicated user patterns are more difficult for the algorithms to predict correctly. In addition, false predictions can cause either more or less energy to be consumed. Wireless networks usually consist of mobile battery operated computing devices that communicate over the wireless medium. While the processing capacity and the memory space of computing devices increase at a very fast speed, the battery technique lags far behind. Therefore, it is critical to derive energy conservation schemes to increase the device and network operation time.

V. CONCLUSION AND FUTURE WORK

In this paper, we surveyed and classified a number of energy aware schemes. In many cases, it is difficult to compare them directly method has a different goal with different assumptions and employs different means to achieve the goal. For example, when the transmission power is controllable, the optimal adjustment of the power level is essential not only for energy conservation but also for the interference control. we demonstrated the effectiveness of using various machine learning algorithms on user spatial techniques We demonstrated up to a 90% successful prediction using support vector machines, LDA and k-nearest neighbor algorithms**.**

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