

# Intel Research : User Activity based Adaptive Power Management (APM)

- **Intel Research**
  - Nilesh Shah- Principal Investigator.
  - Georgios Theodorou
  - Prashant Gandhi
- **McGill U**
  - Shie Mannor
- **MIT**
  - Leslie Kaelbling
- **U of Pittsburgh**
  - Branislav Kveton
- **CMU**
  - Sajid Siddiqi
- **Harvard**
  - Chih-Han Yu
- **Santa Clara U**
  - Ogi Petrovic
- **Kentucky State U**
  - Vamsi Gudivada

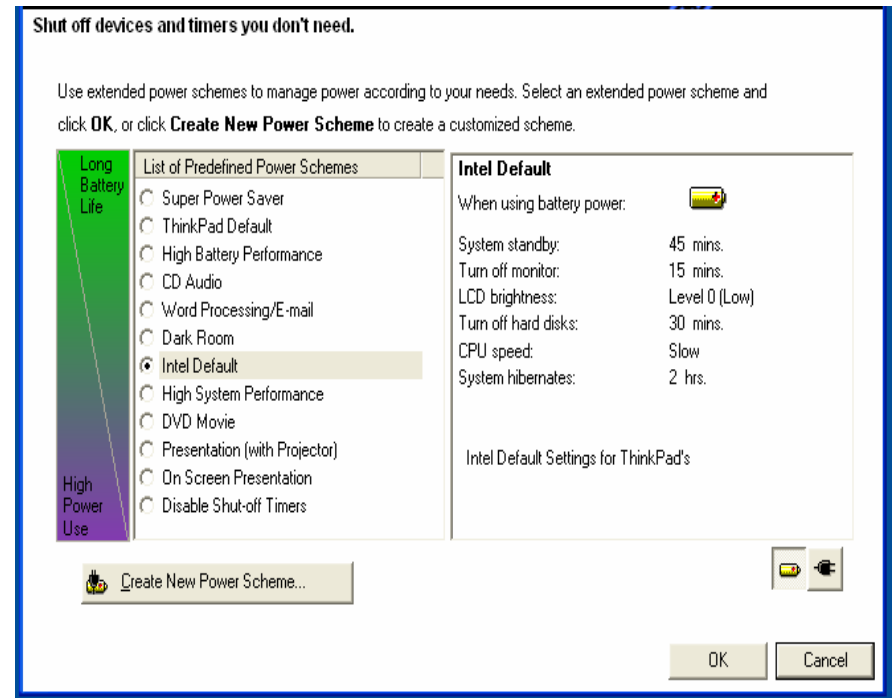
# Intel Research : User Activity based Adaptive Power Management (APM)

- Agenda
  - What we want to enable.
  - Challenges.
  - Details.
  - Ideas/Feedback/Q and A.



# What we want to enable

- Commercial products implement simple timeout based Power Management Policies.
  - Require manual interruption, waste power and annoy the user .
- We want to enable automated dynamic power management based on user-activity to maximize battery lifetime while maximizing **\*perceived\*** performance.
  - focus on mobile devices



Commercial timeout based Power Management Policies on mobile devices.

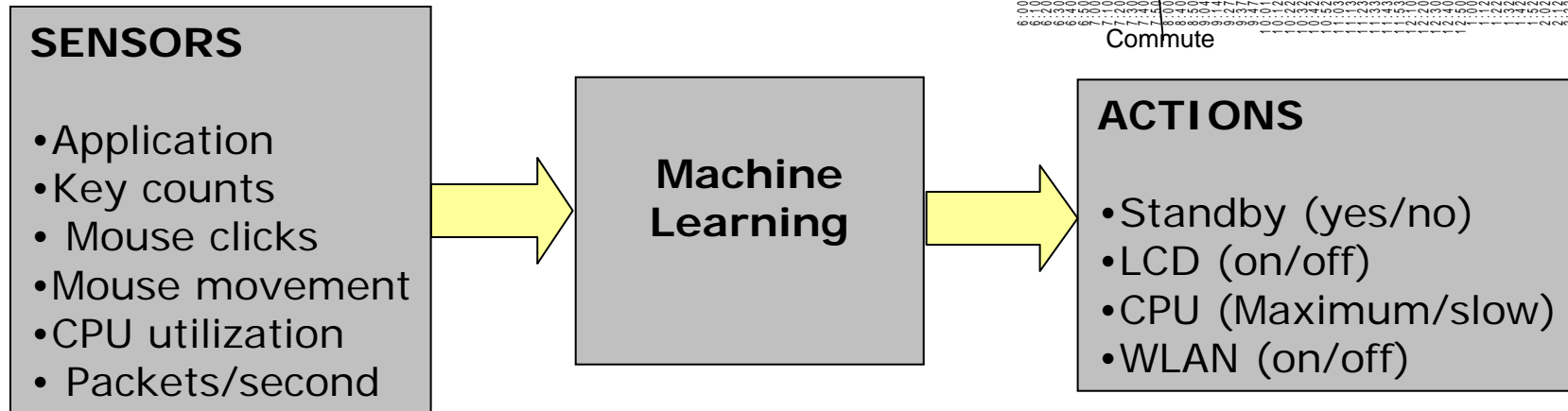
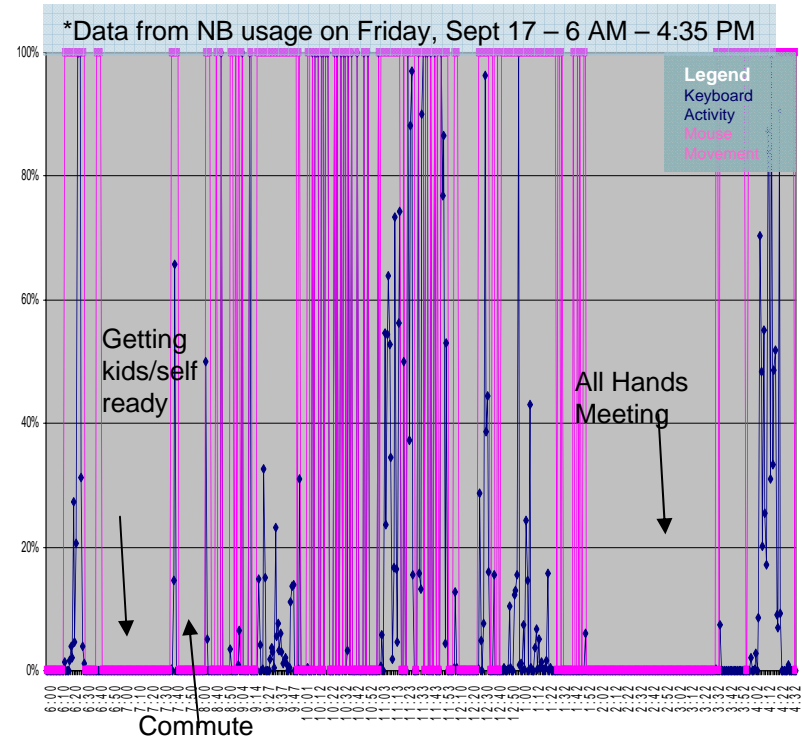
- Recent research focused on modeling system dynamics using relatively small data corpus, rather than usage patterns, user not considered.

# Challenges

- Labeling input data given a partially observable user.
  - Multi-objective optimization.
  - Local and Global Learning (varying time scales, varying users).
  - Data driven validation. – Non trivial problem, actions affect user behavior.
- Develop machine learning algorithms that take up less resource than they save.**

# Experimental setup

- **System Inputs:** Activity sensors on laptops (Software, User, Network, CPU, etc)
- **System Outputs :** 4 Binary Actions LCD, CPU, WLAN, Standby.

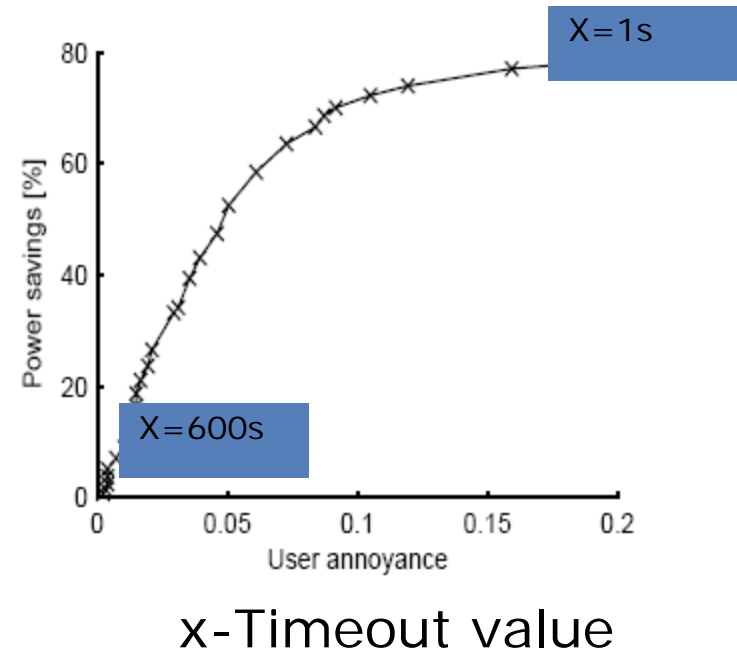


- Ad hoc rules used to label data to provide a target policy.



# Optimization Objective

- Every action is assigned a cost.
- Incorrect actions incur cost, increase user annoyance.



- Optimal operating point may be different for every user.

# Learning setup : Naïve approach

- Reduce problem to 4 separate binary classification problems corresponding to each of the 4 actions.
- “Oracle” policy used for labeling, benchmark.
- Current sensor space restricted to 6 dimensions.
- Predict idleness over fixed look ahead window.
- Input dimension is unrestricted.

• **Future work : Predict exact duration of idleness.**



# Context-based classification

- **Context = Time from last activity of component (LCD, WLAN, CPU, Standby).**
  - F = mixture of expert classifiers.
  - $1\{.\}$  = Indicator function.
  - $C(x)$  = map input space to set of contexts.
  - $h_\ell$  = classifier corresponding to  $\ell$ -th context. (logistic regression model)
  - $b_\ell$  = bias corresponding to  $\ell$ -th context.
- **Optimization – difficult problem.**
  - $y_t$  = Label of training data.
  - $A_0$  = Annoyance constraint.
  - Maximize total power savings subject to annoyance constraint. (set  $b_\ell$  to perform well on whole data set)

K=29

$$f(\mathbf{x}) = \sum_{\ell=1}^k 1\{c(\mathbf{x}) = \ell\} \text{sgn}(h_\ell(\mathbf{x}) + b_\ell),$$

Greater the Threshold, less aggressive is the timeout.

**Non-linear optimization: Threshold impacts Power and Annoyance.**

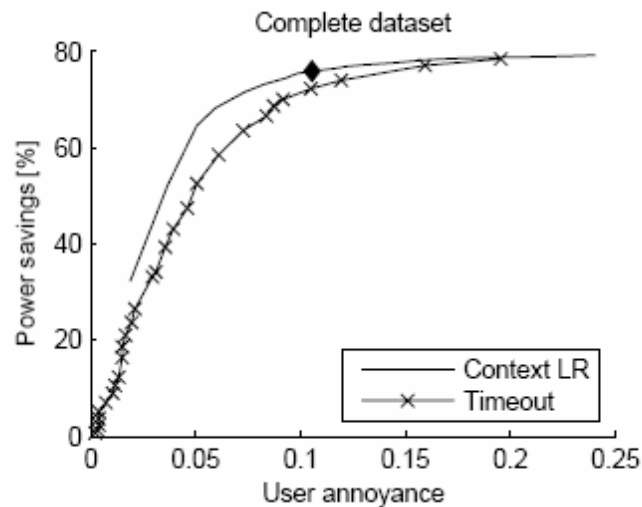
$$\begin{aligned} \max_{b_1, \dots, b_k} \quad & \text{PowerSavings} \left( \{y_t, f(\mathbf{x}_t)\}_{t=1}^T \right) \\ \text{s.t. :} \quad & \frac{1}{T} \sum_{t=1}^T \text{Annoyance}(y_t, f(\mathbf{x}_t)) \leq A_0 \end{aligned}$$

- **Interesting fact : The particular algorithm does not matter as much as problem setup. We tried KNN, C45, SVM, naive Bayes, etc with minimal difference.**

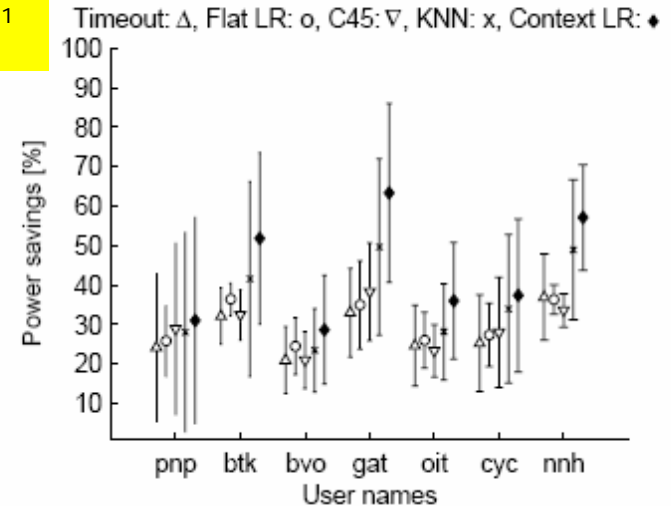


# Current results

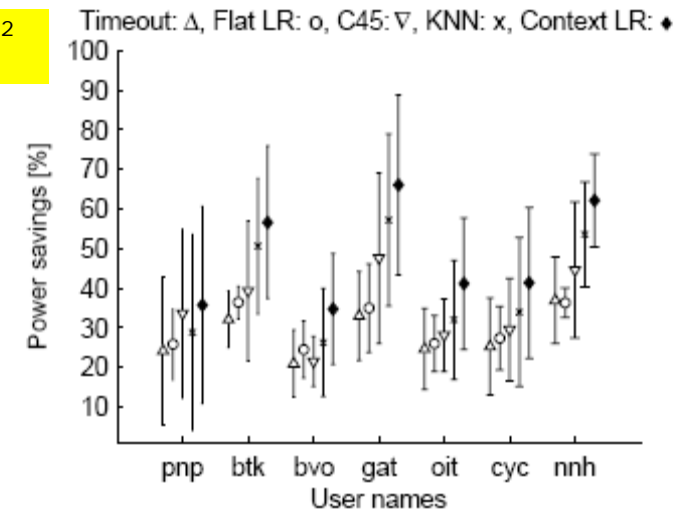
- Initial data set
  - 42 traces from 7 users, 210 usage hours collected on laptops.
  - Variance of power savings indicates need for Adaptive algorithms.



Annoyance=0.1



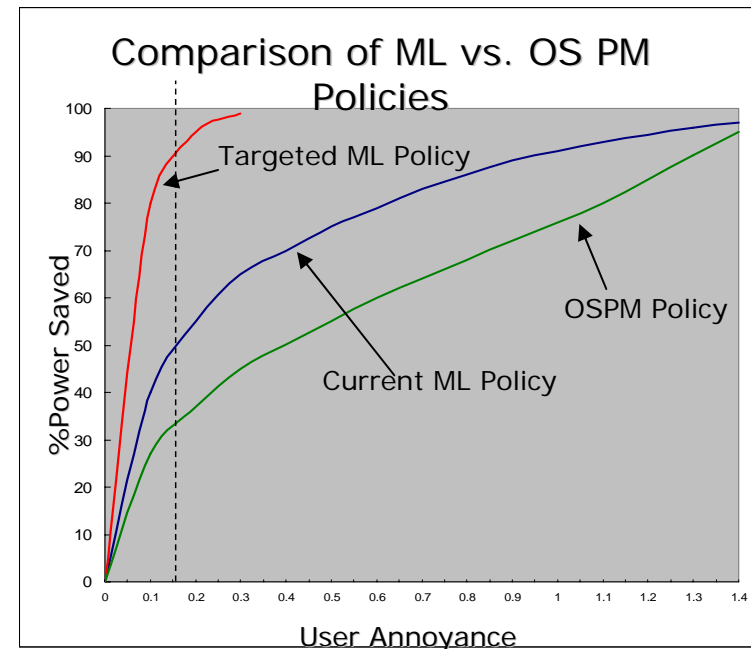
Annoyance=0.2



- Context in classification of future idleness crucial, more so than choice of classifier. Mixture of classifiers utilized, each classifier suited for a particular context.

# Further Research Goals

- Discover modes of user behavior (contexts)
  - Segmentation and clustering techniques such as Hidden Markov Models.
- Estimate system idle durations from user activities
  - Semi-Markov Dynamic Bayesian Net models for activity-idleness relations.
- Maximize power savings with minimum annoyance level of current timeout policies
  - Algorithms to switch between timeout policies based on past user behavior
- Learn when to turn components ON before needed (pre-empt).
- Accurate and *\*individual\** measures of annoyance.



- Ensure results are valid real time "online" on laptops across variety of usage models and users.

**Ideas, Feedback, Q/A  
Thank You !**