Smart usage of context information for the analysis, design and generation of power-aware polices for mobile sensing apps

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Introduction

- The popularity of mobile devices is a result of advances in their computation, **sensing**, and communication dimensions [8].
  - The sensing facilities improve interaction with user, turning them into *omni-sensors* able to *know* about its surrounding environment.
  - Smartphones have become *context-aware*, gaining understanding about user's activity and environment.
- However, battery is not evolving at the same pace than the advances in other smartphone's characteristics [11], growing only 5-10% each year [15, 7].
  - The energy constraint becomes more critical when continuous access to sensors is needed, which is the core requirement of **mobile sensing applications**.

Stages of mobile sensing applications

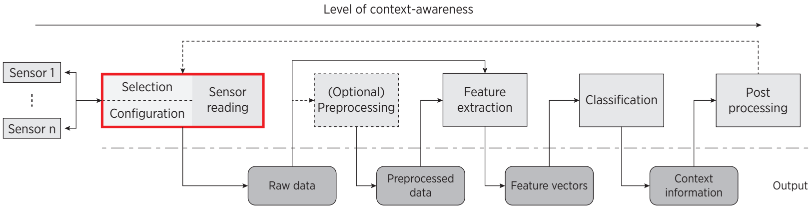

Figure: Stages of mobile sensing applications

There is a tradeoff between the accuracy of context information retrieved and the associated energy consumption [26, 25]. How to face it?

Hypothesis

Hypothesis

Intelligent policies produced through context information built from sensors data can be employed to reduce the energy consumption in a mobile device when performing continuous sensor readings.

- An intelligent policy is a special rule that defines how sensors should be selected and configured to reduce energy consumption and achieve the mobile sensing app's requirements. It is intelligent in terms of self-adaptness to changes detected in context information.
- This research work is aimed at employing GPS and inertial sensors data (accelerometer) for inferring context information in terms of mobility patterns. This context information will then be exploited to adapt sensors' operation and produce power savings.

Problem statement

Problem statement: Mobility pattern identification

Given a set $V = \{v_1, v_2, \ldots, v_n\}$ of data values read from sensor S in the time interval $T \in [t_1, t_2]$, identify the current mobility pattern p_S that represents the activity of user.

$$\text{PatternIdentifier}(V) \longrightarrow p_S \in \textit{Patterns} \tag{1}$$

Where *Patterns* is a set of patterns that represent an interesting state in user mobility, specifically the set $\{no\_movement, walking, running, vehicle\_transportation\}$.

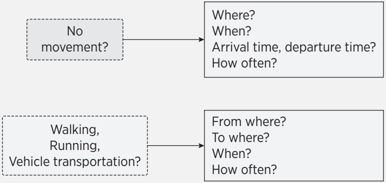

Figure: Context information related to mobility patterns

Problem statement

Problem statement: Policy generation

Given the set of detected mobility patterns $\mathcal{P} = \{p_{S_1}, p_{S_2}, \ldots, p_{S_n}\}$ in data from sensors $\mathcal{S} = \{S_1, S_2, \ldots, S_n\}$, accuracy required a, and physical constraints status c of a mobile device, find a policy that select the proper set of sensors $\mathcal{S}_{new}$ and its associated configuration $\mathcal{S}_{new_{conf}}$ while meeting application requirements.

$$\text{PolicyGeneration}(\mathcal{P}, a, c) \longrightarrow \mathcal{S}_{new}, \mathcal{S}_{new_{conf}} \tag{2}$$

The $\mathcal{S}_{new_{conf}}$ configuration is referred as the *adaptive duty cycle* of associated sensor.

Interaction between problems

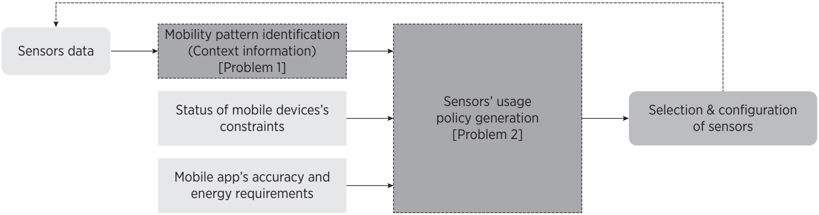

Figure: Interaction between the thesis work's problems

Objectives

Main objective

To reduce energy consumption in the mobile sensing apps, which perform continuous sensor readings, through self-adapting power-aware policies generated from context information obtained from sensors data.

Particular objectives

- To identify mobility patterns from context information obtained from an inertial sensor (accelerometer) and location providers (GPS, WPS).
- To generate policies for a self-adapting sensors' usage from identified mobility patterns, accuracy and energy requirements of mobile application, and status of mobile device's constraints.
- To ease the development of mobile sensing applications that require user location tracking, i.e., LBS, isolating the complexity of sensors' access and the associated efficient energy management.

Problem’s scenario

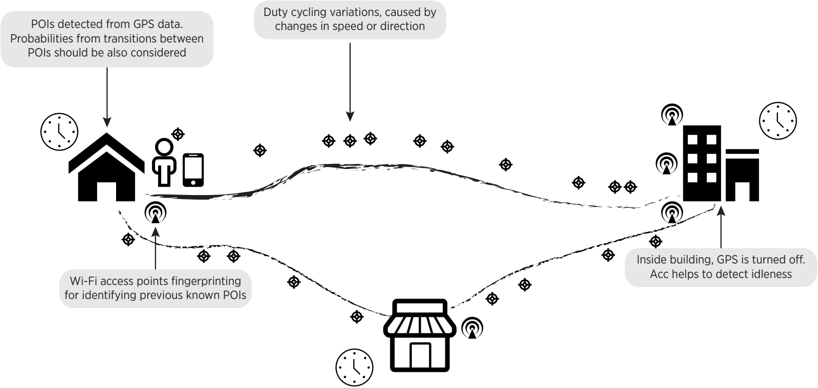

Figure: Basic problem’s scenario

Methodology

1. **Familiarization with state-of-art power-aware sensing related techniques**
2. **Formal definition and selection of mobility patterns to be identified**
3. **Research on pattern recognition algorithms focused on mobility patterns identification**
4. **Design of the Pattern Identification Element (PIE)**
5. Research on and proposition of adaptive policies for energy efficient usage of sensors
6. Design of the Policy Generation Element (PGE)
7. Development of a middleware involving the PIE and PGE for the Android platform
8. Experimentation in terms of accuracy and energy efficiency

Taxonomy of state of art solutions

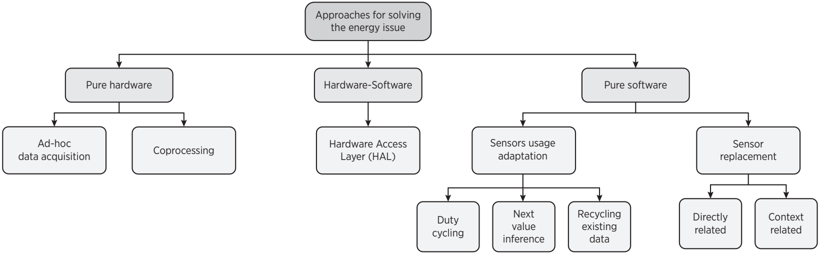

Figure: Taxonomy of solutions, seen from the sensors adaptation's perspective

Distribution of approaches

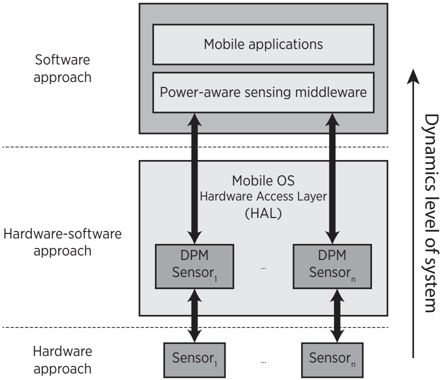

Figure: Distribution of approaches across mobile platform's layers

Characteristics of pure software approach solutions

Distinctive characteristics of pure software solutions

- **Optimization oriented (OO)**: Optimization orientation focused on minimizing energy consumption and/or the error in activity tracking.
- **Online learning (OL)**: Online learning from context information, enabling predictive features thanks to observance over long-time windows of sensory data.
- **User state oriented (US)**: Modeling of an enriched version of the context information, user state (US), for achieving full activity-awareness and ease the adaptation over the sensing dimension.

Framework for analyzing pure software solutions

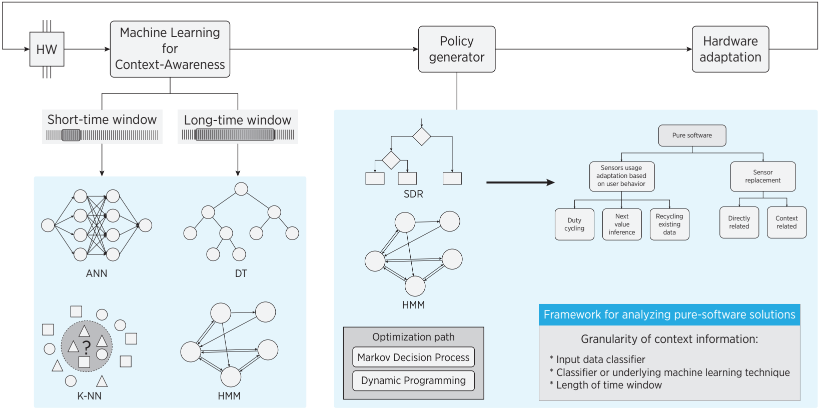

Figure: Decomposition of solutions

Proposed solution

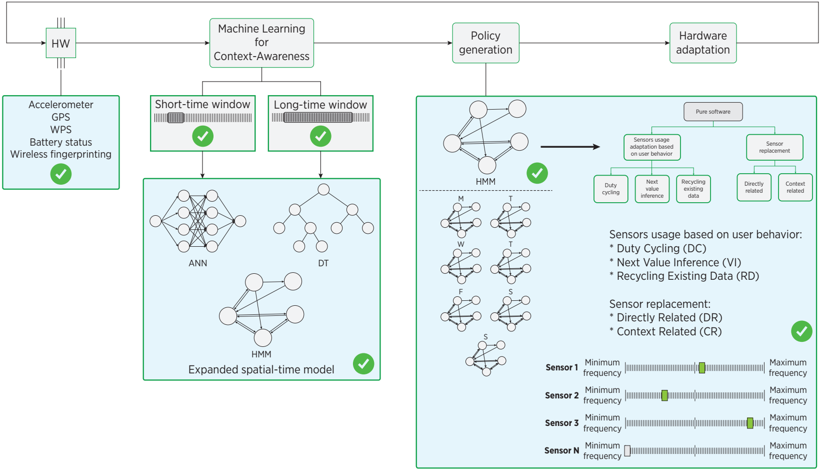

Figure: Decomposition of our solution

Proposed solution

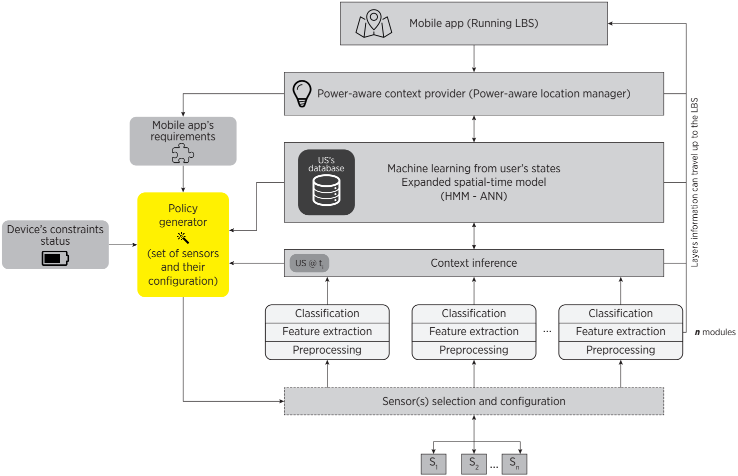

Figure: Overview of current solution

The model of information learned in proposed solution

- The overall problem can be divided into learning and detection of stay points, and the trajectory tracking.
- The information can be represented through an expanded-spatial time model.

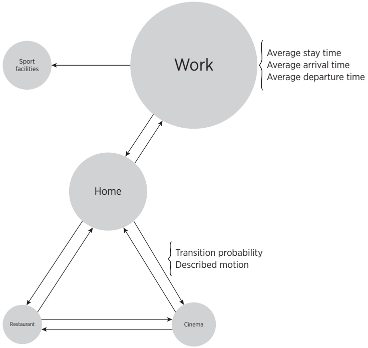

Figure: Basic unit of information learned in the expanded spatial-time model (User state)

The model of information learned in proposed solution

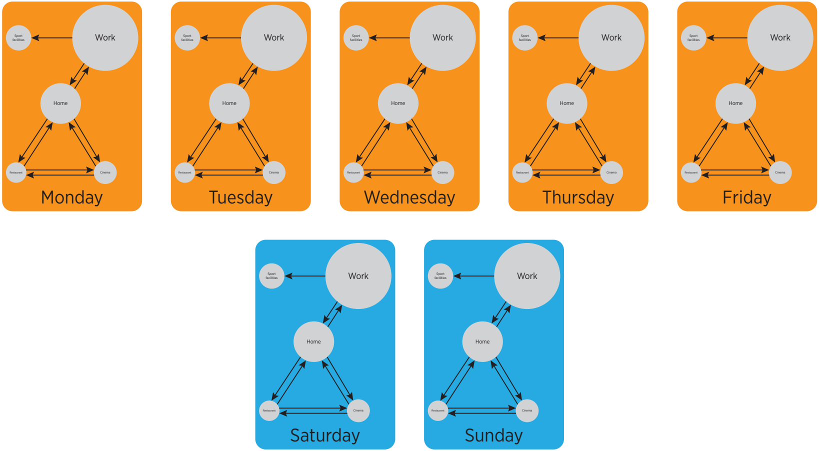

Figure: The spatial-time models can be built and learned over longer time windows

First steps towards expanded spatial-time model: a proof of concept

- A proof-of-concept experimentation for studying the feasibility of on-device learning the spatial-time model has been conducted.
- An **event-oriented** methodology was followed.
- The methodology involved the adaptation of classic stay points algorithms [19, 31] for *online* operation, while reducing memory footprint.

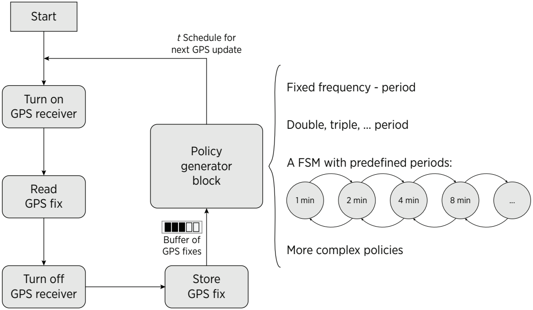

Figure: Logical workflow of the platform for on-device stay points detection

Results of early experimentation

- The first experiment is aimed at ensuring the calculation of stay points locally at the smartphone [1].
- *Spending power to save power* (process GPS data for learning mobility patterns and use this information for sensory adaptation) can be possible.

GPS reading period	Algorithm	Stay points detected	Average fixes	Maximum fixes	GPS accesses	Running time (hours)
1 minute	Sigma Montoliou	27	70	652	2251	43.68
1 minute	Buffered Montoliou	26	79	685	2334	43.92
3 minutes	Sigma Montoliou	47	27	248	1361	71.84
3 minutes	Buffered Montoliou	28	41	248	1241	64.96
5 minutes	Sigma Montoliou	43	25	154	1119	95.88
5 minutes	Buffered Montoliou	45	21	154	1021	87.78
Doubling 1-2-4-8-16	Sigma Montoliou	59	17	80	1223	189.69
Linear 1-3-5-9-12-15	Sigma Montoliou	35	21	84	888	144.85

Table: Results of the first experiment

[1] Samsung Galaxy Note II, quadcore 1.6 GHz processor, 16 GB RAM, 3,100 mAh battery

Scientific products

- As a product of the analysis of related solutions, we have prepared a survey[2] covering:
  - Smartphone-based sensing's characteristics.
  - The power-awareness challenge in smartphone-based sensing.
  - A taxonomy of the solutions for energy efficiency in smartphone-based sensing.
  - The tendencies and open challenges of the field.
- The aforementioned experimentation is work in progress for preparing an article focused on:
  - On-device learning of mobility information with an event-oriented perspective.
  - The usage of this information for a power efficient adaptation of the sensing dimension.
  - Setting the base for further modules and strategies for boosting the learning of mobility patterns.

[2] *Power management techniques in smartphone-based mobile sensing: a survey*, first review round, Pervasive and mobile computing (Elsevier)

Future work

		2014	2015			2016		
		3rd	1st	2nd	3rd	1st	2nd	3rd
	Step I							
1	State-of-art reading							
2	State-of-art works categorization							
3	Documentation of information found (committee request)							
	Step II							
4	Development of a mobile app for the Android platform that collects accelerometer and location data							
5	Analysis of data delivered by the mobile app							
6	Creation of the formal definition of mobility pattern							
7	Selection of the mobility patterns to be recognizable by the system							
	Step III							
8	Research on classification algorithms adequate to work with mobility patterns							
9	Definition of metrics for evaluating algorithms when executing on a mobile platform							
10	Implementation of algorithms (including proper adaptations towards running on a mobile platform) for evaluation							
11	Selection of best algorithms according to metrics							
	Step IV							
12	Definition and modeling of parameters needed by the PIE							
13	Building of the PIE							

Table: Schedule of activities (each column represents a four months period)

Schedule

		2016 1st	2016 2nd	2016 3rd	2017 1st	2017 2nd	2017 3rd
	Step V						
14	Creation of the formal definition of policy			■			
15	Research and evaluation of techniques for generation and adaption of policies			■	■		
16	Design and execution of experiments with techniques applied to use cases			■	■		
17	Selection of best techniques				■		
	Step VI						
18	Definition and modeling of parameters needed by the PGE					■	
19	Building of the PGE					■	
	Step VII						
20	Analysis of elements involved into software abstractions					■	
21	Research on Android API for specialized components					■	
22	Development of the middleware					■	

Table: Schedule of activities (each column represents a four months period)

Schedule

	Step VIII	2017 1st	2017 2nd	2017 3rd	2018 1st	2018 2nd
23	Definition of experiments targeting accuracy and energy consumption axes					
24	Development of needed sample mobile apps for running experimentation					
25	Execution of experimentation					
26	Results analysis					

Table: Schedule of activities (each column represents a four months period)

Schedule

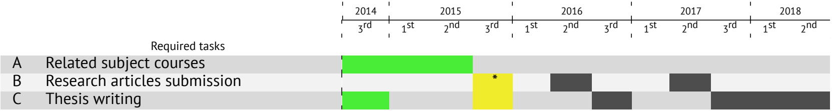

Table: Schedule of required activities

* Survey was out of original schedule, however, it brings added value to our work and also acts as a scientific booster for improving and achieving our solution.

Conclusions

- A brief analysis of the problem addressed by this thesis work has been presented.
- A summary of related state of art solutions, as suggested by committee, has been covered:
  - A taxonomy for categorizing of the solutions.
  - A new framework for decomposing and studying them.
- The general approach of our solution, which is based on an expanded spatial-time model for identifying and learning user mobility, has been introduced.
- An experimental step that shows the feasibility of performing the on-device building of such expanded models has been also presented.

Thank You
for your attention!

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Montoliou's algorithm for stay points detection [19]

Require: A GPS trajectory $T = \{p_1, p_2, \ldots, p_N\}$, a distance threshold θ_d, a minimum time threshold θ_{tmin}, and a maximum time threshold θ_{tmax}.
Ensure: A set of points of interest Π

$i \leftarrow 1$
$\Pi \leftarrow \emptyset$
while $i < N$ **do**
    $j = i + 1$
    while $j < N$ **do**
        $t \leftarrow$ **timeDifference**(p_j, p_{j-1})
        if $t > \theta_{tmax}$ **then**
            $i \leftarrow j$
            break
        end if
        $d \leftarrow distance(p_i, p_j)$
        if $d > \theta_d$ **then**
            $t \leftarrow$ **timeDifference**(p_i, p_{j-1})
            if $t > \theta_{tmin}$ **then**
                $\pi.\text{lat} = \sum_{k=i}^{j-1} \frac{p_k.\text{lat}}{|j-1-i|}$
                $\pi.\text{lon} = \sum_{k=i}^{j-1} \frac{p_k.\text{lon}}{|j-1-i|}$
                $\pi.\text{at} = p_i.\text{ts}$
                $\pi.\text{dt} = p_{j-1}.\text{ts}$
                $\Pi \leftarrow \Pi \cup \pi$
            end if
            $i \leftarrow j$
            break
        end if
        $j \leftarrow j + 1;$
    end while
end while

State-of-art solutions

Name	Variants	Machine learning technique	Sensors involved	Complex-ity	OL	OO	US
G-Sense [23]	User behavior learning (DC)	SDR	GPS	low			
Perez-Torres [24]	User behavior learning (DC)	SDR	GPS	low			
SenseLess [1]	User behavior learning (DC), Sensor replacement (CR, DR)	SDR	WPS, GPS, ACC	low			
SensTrack [30]	User behavior learning (DC), Sensor replacement (CR, DR)	SDR	ACC, orientation sensor, GPS, WPS	low			
Man and Ngai [17]	User behavior learning (DC, VI), Sensor replacement (CR)	SDR	ACC, magnetic field sensor, GPS	low			
EnLoc [5]	User behavior learning (DC, VI), Sensor replacement (DR)	SDR, Mobility Tree	WPS, GPS, cellular ID	medium		✓	
EnTracked [12]	User behavior learning (DC), Sensor replacement (CR)	SDR	ACC, GPS	medium		✓	

Table: Pure software solutions. (OL: Online Learning from user data, OO: Optimization Oriented solution, US: User State context insight)

State-of-art solutions

Name	Variants	Machine learning technique	Sensors involved	Complex-ity	OL	OO	US
Alvarez, Morillo [2, 20]	–	Ameva algorithm	ACC	medium			
Mazilu [18]	Sensor replacement (CR)	DT	Temperature, humidity, pressure	medium			
Srinivasan [27]	User behavior learning (DC)	DT	ACC	medium			
Khalifa [9]	Sensor replacement (CR)	KNN	Model of ACC-based harvesting device	medium			

Table: Pure software solutions. (OL: Online Learning from user data, OO: Optimization Oriented solution, US: User State context insight)

State-of-art solutions

Name	Variants	Machine learning technique	Sensors involved	Complex-ity	OL	OO	US
SensLoc [10]	User behavior learning (DC, RD), Sensor replacement (CR)	SDR	Wi-Fi fingerprinting, GPS, ACC	medium	✓		
CAPS [22]	User behavior learning (DC, RD), Sensor replacement (CR)	SDR	GPS, cellular ID	medium	✓		
RAPS [21]	User behavior learning (DC, RD), Sensor replacement (CR, DR)	SDR	WPS, GPS, ACC, Bluetooth, cellular ID	medium	✓		
A-Loc [13]	User behavior learning (DC, RD), Sensor replacement (CR, DR)	HMM, Bayesian estimation framework	GPS, WPS, Bluetooth, cellular ID	medium	✓	✓	
SmartDC [4]	User behavior learning (DC, RD), Sensor replacement (CR, DR)	HMM and LZ predictor	GPS, WPS, Wi-Fi and cellular ID fingerprinting	medium	✓	✓	

Table: Pure software solutions. (OL: Online Learning from user data, OO: Optimization Oriented solution, US: User State context insight)

State-of-art solutions

Name	Variants	Machine learning technique	Sensors involved	Complex-ity	OL	OO	US
Jigsaw [14]	User behavior learning (DC), Sensor replacement (CR)	Microphone: NB with Gaussian Mixture Model (GMM). ACC: DT. GPS: MDP.	ACC, Microphone, GPS	high		✓	✓
Donohoo [6]	User behavior learning (DC)	Several. KNN and NN selected as best.	ACC, GPS, WPS, cellular ID, light, device data, mobile app requirements	high			✓
EEMSS [28]	User behavior learning (DC), Sensor replacement (CR, DR)	GPS and ACC: SDR. Microphone: SSCH algorithm.	ACC, microphone, GPS	high			✓
iLoc [16]	User behavior learning (RD), Sensor replacement (CR)	HMM	Wi-Fi & GSM fingerprinting	high	✓		✓
Yurur [29]	User behavior learning (DC, RD)	HMM	ACC	high	✓		✓
FreeTrack [3]	User behavior learning (DC, RD), Sensor replacement (CR, DR)	HMM	GPS, Wi-Fi, cellular ID, battery status	high	✓		✓

Table: Pure software solutions. (OL: Online Learning from user data, OO: Optimization Oriented solution, US: User State context insight)