Am I Indoor or Outdoor?*

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Motivation

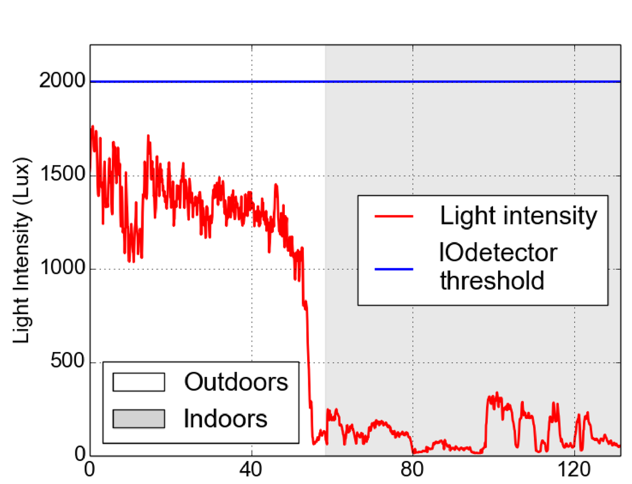
Due to their in-built sensors, smartphones have started being used as context detection tools for different forms of environment. One such case is distinguishing between indoor and outdoor spaces (*IO detection*).

Applications:

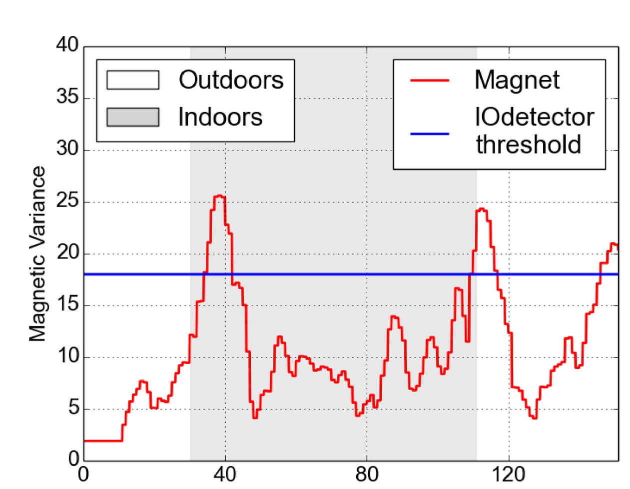
- Adaptation and personal assistants (eg. change volume, screen brightness, application shortcuts),
- power saving (eg. turn off GPS indoors, turn off WiFi outdoors),
- triggering indoor/outdoor localization services.

Current solutions

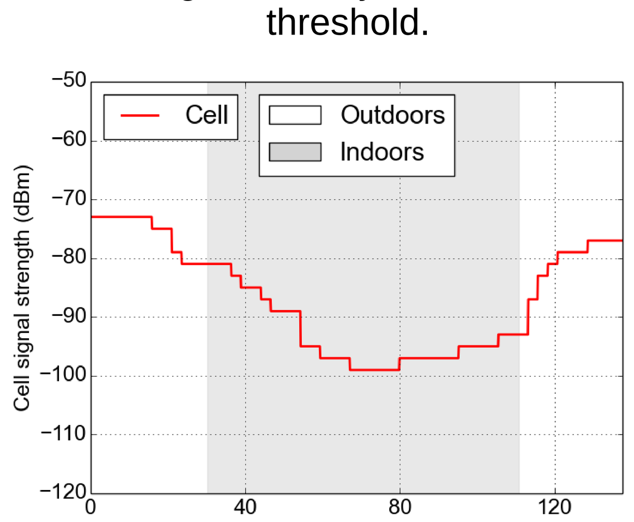
- GPS-based IO detection [1] is energy hungry and inefficient because the estimation inaccuracy is not a reliable separator between the two environments.
- IODetector [2] uses fixed thresholds for sensor features that are not appropriate across different environments.



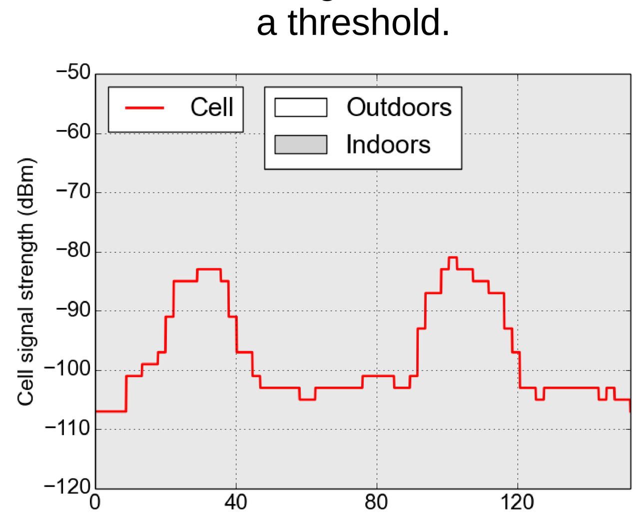
Light intensity below the threshold.



Unreliable magnetic feature with a threshold.



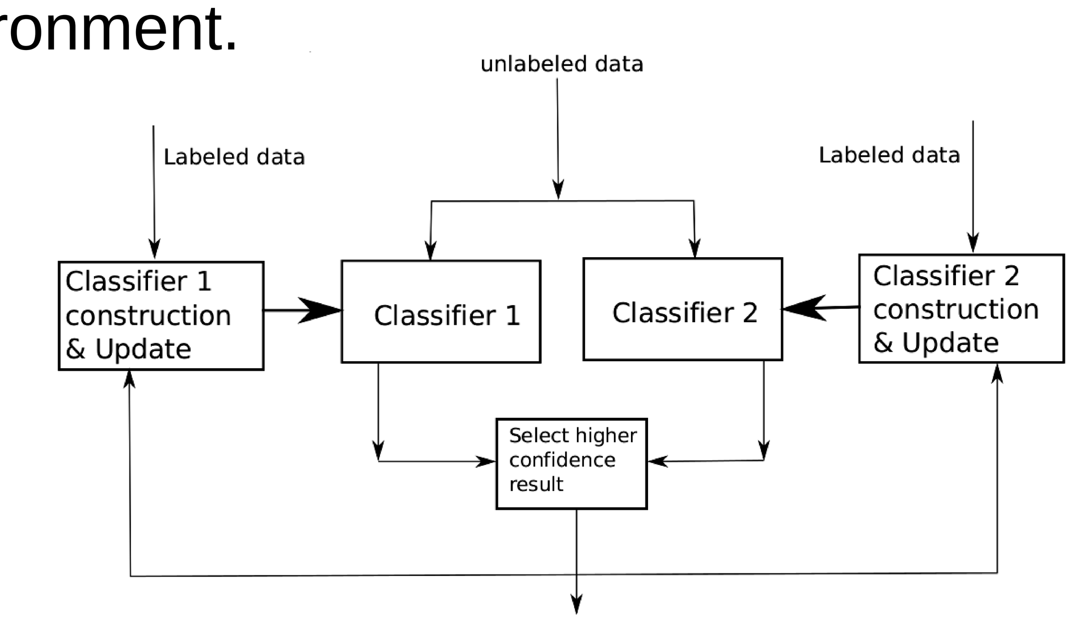
Different cellular signal strength slopes for IO transitions.



Abrupt increases and decreases of the cellular signal strength indoors.

Robust IO detection with semi-supervised learning

- Adaptive model for IO detection to learn changes in the characteristics of the ambient environment (weather, geography, seasons).
- **Co-training** uses two independent classifiers to assist each other to continuously learn the environment.



- We balanced the sensor features into two sets based on their reliability using two techniques:
  - Naive Bayes analysis of feature importance:
    - Set1 {light intensity, time of the day, proximity value and battery temperature}
    - Set2 {sound amplitude, cell signal strength, magnetic variance}
  - SVM Attribute ranking:
    - Set1 {cell signal strength, light intensity, time of day and proximity value }
    - Set2 {battery temperature, sound amplitude and magnetic variance}

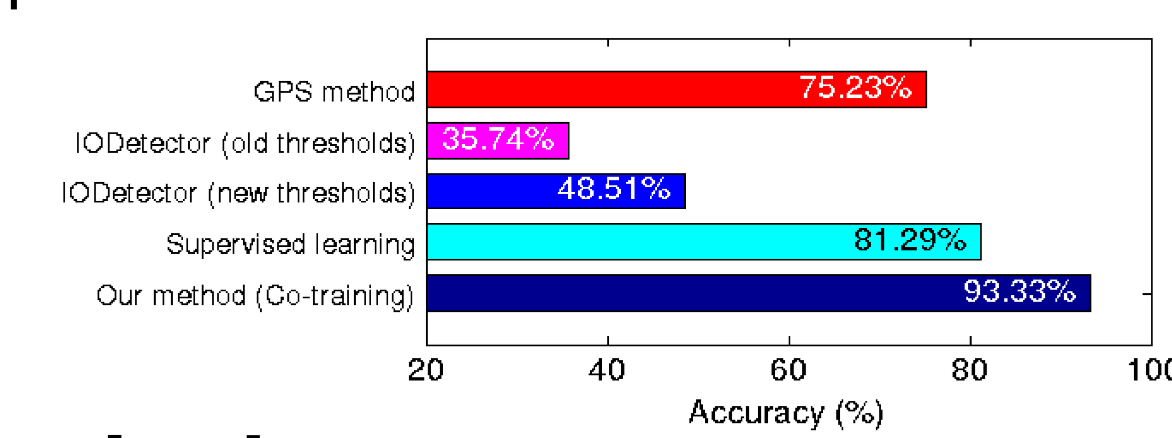
Evaluation

We collected more than 3800 samples of sensor data from three environments: university campus, city center and residential area. Volunteers participating in the data collection provided the ground-truth, to use for evaluation.

The best performance is achieved by co-training using the SVM features distribution and Naive Bayes classifiers.

Features Distribution	Classifier 1	Classifier 2	Accuracy Co-training (%)
Naive Bayes based	J48	J48	83.0
	LWL	LWL	78.17
	Naive Bayes	Naive Bayes	91.66
SVM Attribute ranking based	J48	J48	86.67
	LWL	LWL	78.16
	Naive Bayes	**Naive Bayes**	**93.33**

Comparison with the other IO detection solutions:



Conclusions

- Current solutions for IO detection are too energy hungry (GPS) or fail to provide accurate results across a range of environments.
- Our novel approach performs IO detection using an adaptive model, transparent to the smartphone user.

References

[1] L. Ravindranath, et al. Improving Wireless Network Performance Using Sensor Hints. In Proc. USENIX NSDI, 2011.

[2] P. Zhou, et al. IODetector: A Generic Service for Indoor Outdoor Detection. In Proc. SenSys, 2012.

* Full version of this work will appear in Proc. ACM SenSys Conference, Nov. 2014.