

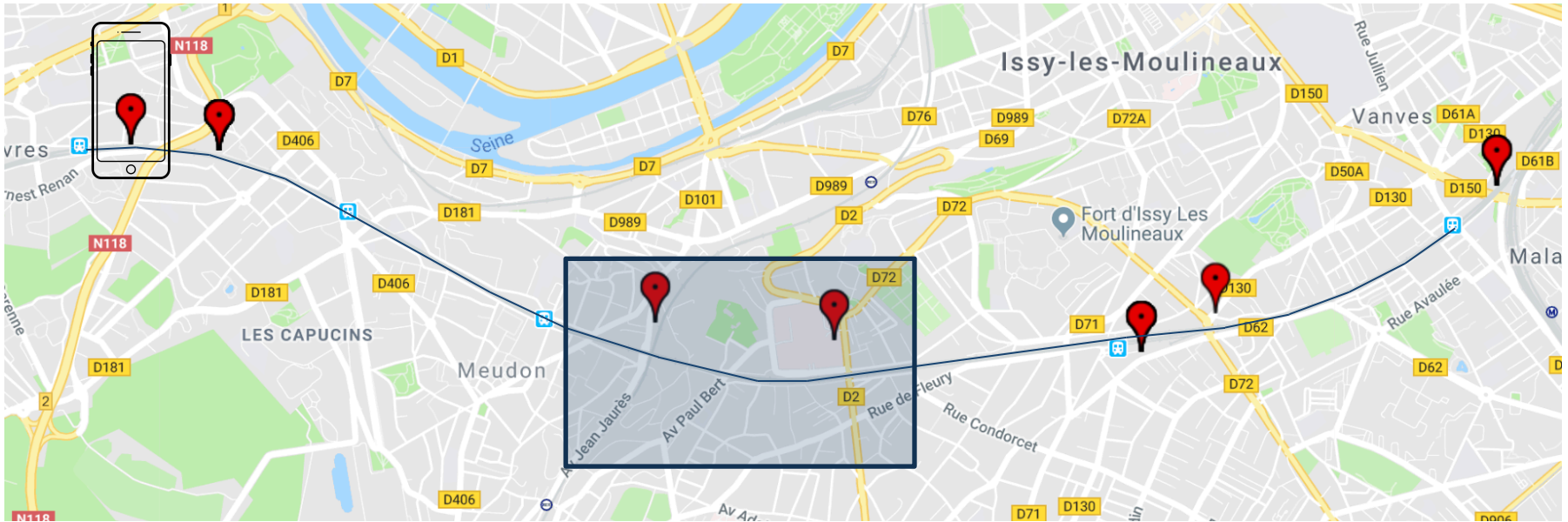


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Detecting Mobile Crowd-sensing Context in the Wild

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Motivation



Motivation

- Identification of context is essential to assess quality of crowd-sensed spatio-temporal datasets collected in the wild and infer human mobility attributes and properties
 - Accelerometer precision can vary when devices are in/out-pocket
 - GPS accuracy can vary in underground places
 - Jump-lengths are shorter and have higher frequency when indoor

Related work

- Most of context identification algorithms rely on rich sensed features
- However, publicly available crowd-sensed datasets lack data from many sensors available on a device

	<i>Features used</i>	<i>SOTA Algorithms use</i>
In/out-Pocket	Light Intensity, Proximity distance, Noise level, Acceleration	Conditional checks, temporal smoothening, GMM, SVM, Variance, FFT
Under/over-ground	Pressure	Moving average
In/out-door	Light intensity, Magnetic strength, WiFi RSSI, Proximity distance, RSSI level, Time, Mobility Activity, Acceleration, Altitude, S/N Ratio, Direction, # turns when moving	HMM, CIMAP, semi-Markov CRF, conditional checks, KNN, modified GPS info. detection, SVM, sliding window

Challenge

- How contexts such as in/out-pocket, under/over-ground, in/out-door can be identified in feature limited datasets that are collected in the wild?

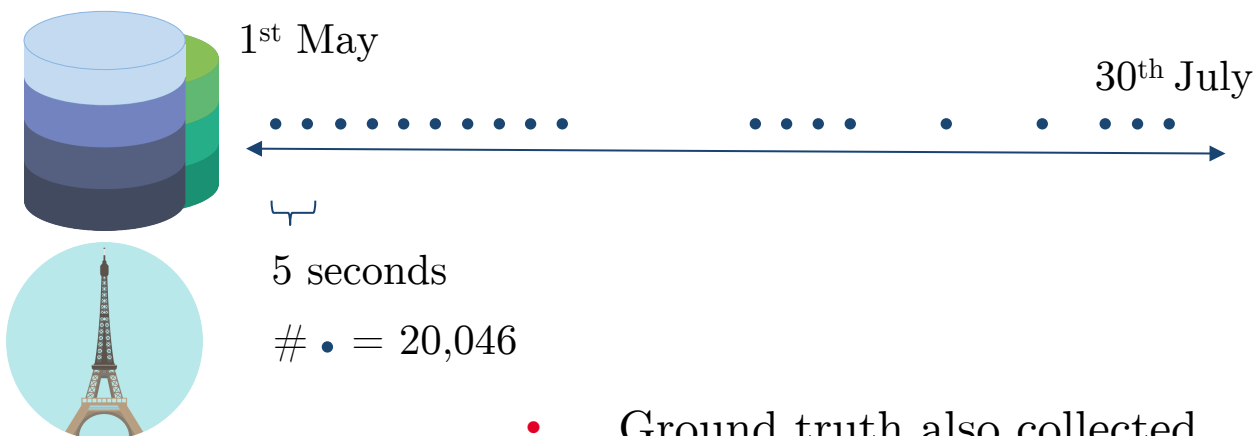
Our Proposal: Context Identification

- Based on available features in a dataset
- Rule based
- Unsupervised binary classifiers
- Heuristics
- Simple and effective

```
underground = False
if altitude >= 0 then
    underground = False
else if altitude < 0 then
    underground = True
else
    # also valid in case when altitude is
    # not given;
    if distance(point, underground station) <  $\tau^{uo}$  then
        underground = True
    end
end
```

Evaluation: Dataset

- Sparse dataset with features: GPS information, Activity Mode, Network connection type, Proximity, Collection mode

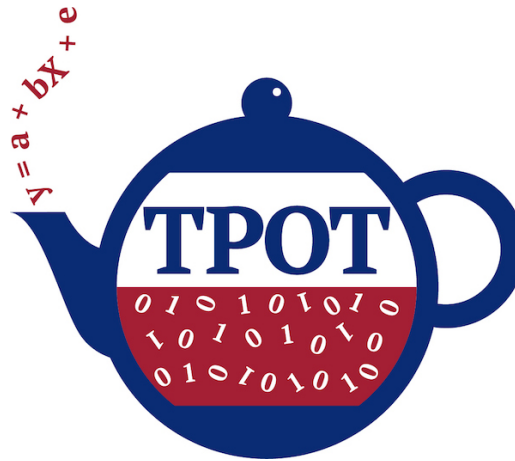


- Ground truth also collected
- 4838 in-pocket, 3310 underground, and 5672 indoor points.
- Use Paris metro³ dataset to identify underground points

² <http://www.ambiciti.io>

³ <https://github.com/ragarwa2/metroStations/tree/master/IledeFrance>

Evaluation: Comparison



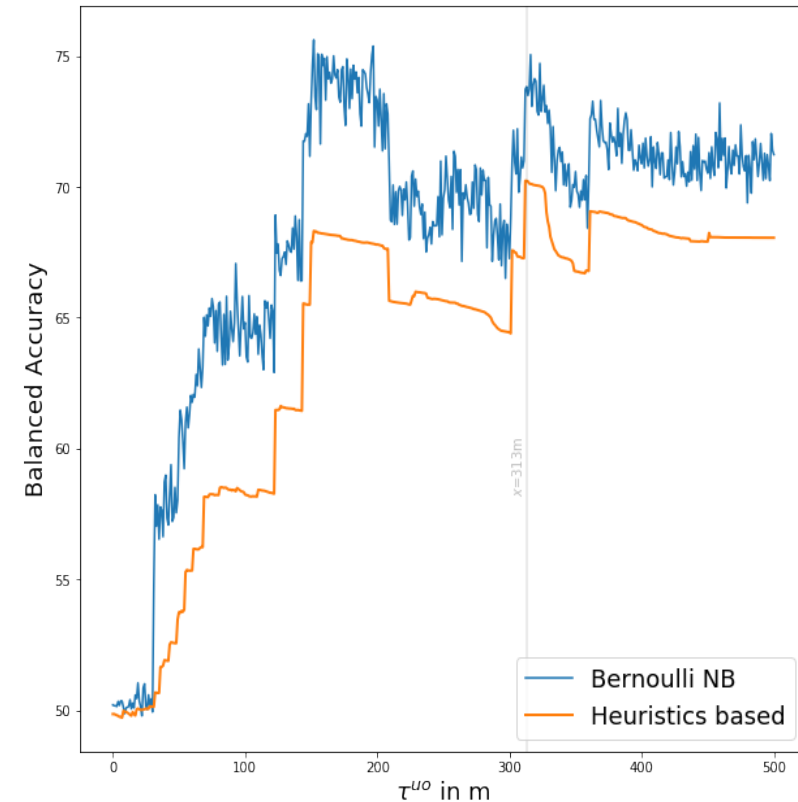
- Trained on 80% dataset
- Identify Balanced Accuracy, Precision, Recall and F1 score

¹ R. S. Olson, N. Bartley, R. J. Urbanowicz, and J. H. Moore, “Evaluation of a tree-based pipeline optimization tool for automating data science,” in Proceedings of the Genetic and Evolutionary Computation Conference 2016, ser. GECCO '16. New York, NY, USA: ACM, 2016, pp. 485–492

Results

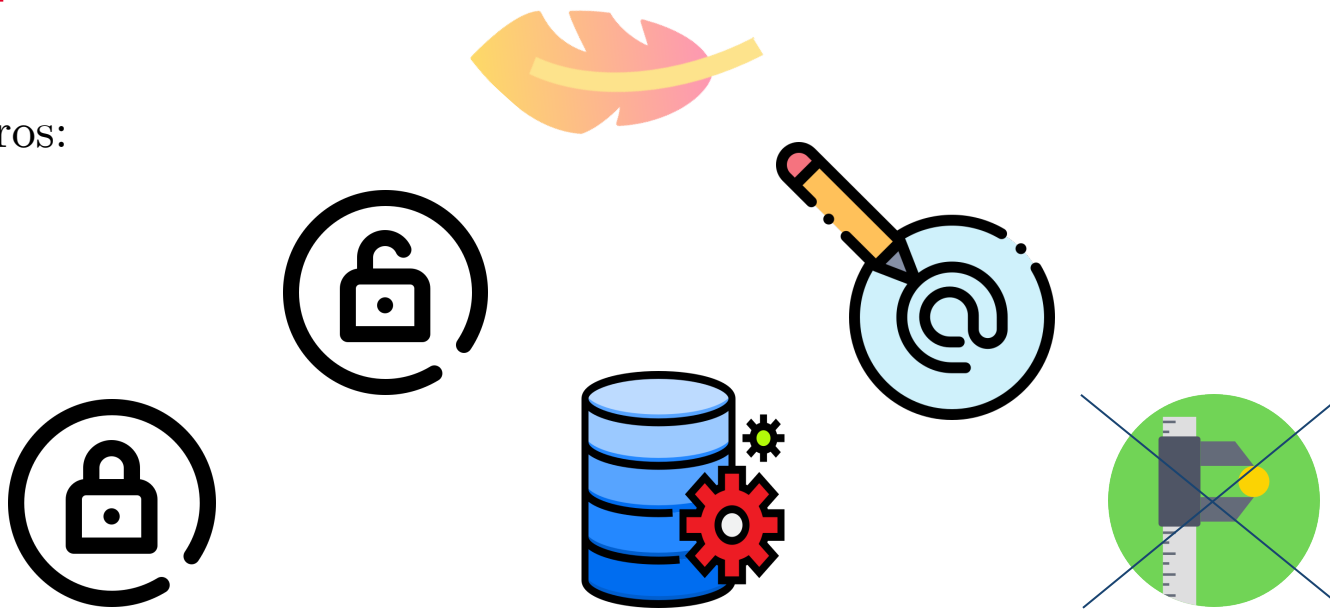
- Best balanced accuracy for underground context is achieved when $\tau^{uo} = 313$ m.
- In/out-pocket achieves equivalent performance, under/over-ground and in/out-door achieve balanced accuracy 4.3% and 1%, respectively, lower

	In/out-pocket	Under/over-ground	In/out-door
Memory	0 kB	4 kB	0 kB
Time	0.08 sec	0.17 sec	0.003 sec



+/-

- Pros:



- Con:
 - Heuristics based on assumptions
 - Feature limited

Conclusion and Future work

- Conclusion
 - Heuristics based unsupervised binary classifiers that performs with satisfactory accuracy when compared with ML algorithm obtained by TPOT
- Future perspectives
 - Integrate our algorithms into mobile applications that target human mobility
 - Exploit additional sensor data such as, e.g., light, which can be used to improve the accuracy

Thank you



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Icon made by [Freepik](#) from www.flaticon.com

Related study

Related study	Uses	Data collection			Reported accuracy in %	Power, energy, Battery duration, CPU consumption
		# of devices/users	Duration	Other details		
[14]	Conditional checks	no training needed			>98	6mW, CPU≈0
[20]	Variance FFT Angle	4	10m	-	>96	-
[6]	Temporal smoothening GMM, SVM	2	14m	‡	≈80	-
[7]	moving avg.	2	3d	20+19 ⁺	>55.6 [†]	-
[12]	HMM	3	30d	19 ⁺	>82	>7.2hr
[19]	HMM, SVM, sliding window	-	1d	-	≈75	5.7mAh
[21]	SVM	19	169m	-	>86* >96	-
[17]	KNN	1	-	-	97.27	-
[18]	modified GPS info. detection	1	-	79 ⁺ , 2595 ^p	85.6	143.1mW
[15]	semi-Markov CRF	3	env. dependent		96	>13.7hr
[13]	CIMAP	1	-	-	>98	4mW
[16]	conditional checks	no training needed			>92	-

d: days, m: minutes, s: seconds, *: baseline, +: trajectories, *p*: points in diverse environment, ‡: 116k samples (50% used in training), †: for different cities and cases different accuracies are reported.

In/out-pocket Context

- Assumptions
 - Features such as proximity and how the measurement is made are available

```
inPocket = False
if measurement is made “manually” then
    inPocket = False
else
    if proximity == True then
        inPocket = True
    end
end
```

Under/over-ground Context

- Assumption
 - Flat terrain at sea-level for simplification
 - Places within τ^{uo} meters of underground metro stations are underground
 - Features such as altitude is available

```
underground = False
if altitude >= 0 then
    underground = False
else if altitude < 0 then
    underground = True
else
    # also valid in case when altitude is
    # not given;
    if distance(point, underground station) <
 $\tau^{uo}$  then
        underground = True
    end
end
```

In/out-door Context

- Assumption
 - Features such as connected via is available
 - If underground, the data point is deemed indoor
 - If stationary, we assume the data point is collected in indoor setting

```
indoor = False
if underground == True then
    indoor = True
else
    if activity is still or stationary then
        indoor = True
    else
        if connected via WiFi then
            indoor = True
        end
    end
end
```


Results

	<i>Method</i>		<i>Balanced Accuracy (%)</i>	<i>Precision</i>		<i>recall</i>		<i>F1 score</i>	
		τ^{uo} in m	<i>80-20 split</i>	<i>in</i>	<i>out</i>	<i>in</i>	<i>out</i>	<i>in</i>	<i>out</i>
In/out-Pocket	Gaussian NB ^{+,#}	-	54	0.33	0.78	0.19	0.89	0.24	0.83
	Our	-	54	0.19	0.89	0.19	0.89	0.19	0.89
Under/over-ground	Bernauli NB ^{+,*}	313	74.5	0.33	0.97	0.81	0.68	0.46	0.79
	Our	313	70.2	0.62	0.78	0.62	0.78	0.62	0.78
In/out-door	Bernauli NB ^{+, -}	313	66	0.42	0.84	0.7	0.62	0.53	0.71
	Our	313	65	0.62	0.68	0.62	0.68	0.62	0.68

+: Best algorithm identified by TPOT, #: priors = None, var_smoothing = 10^{-9} , *: $\alpha = 1$, binarize = 0.0, fit_prior = False, class_prior = None, -: $\alpha = 0.001$, binarize = 0.0, class_prior = None, fit_prior = False