UNIVERSITY OF TARTU
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COSINE: Collaborator Selector for Cooperative Multi-Device Sensing and Computing

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Importance

- In many everyday situations, there are many devices in each others' communication range

Train station

Source: https://www.railwaypro.com/wp/mernda-rail-extension-opens/

Street

Source: https://www.railwaypro.com/wp/mernda-rail-extension-opens/

Home

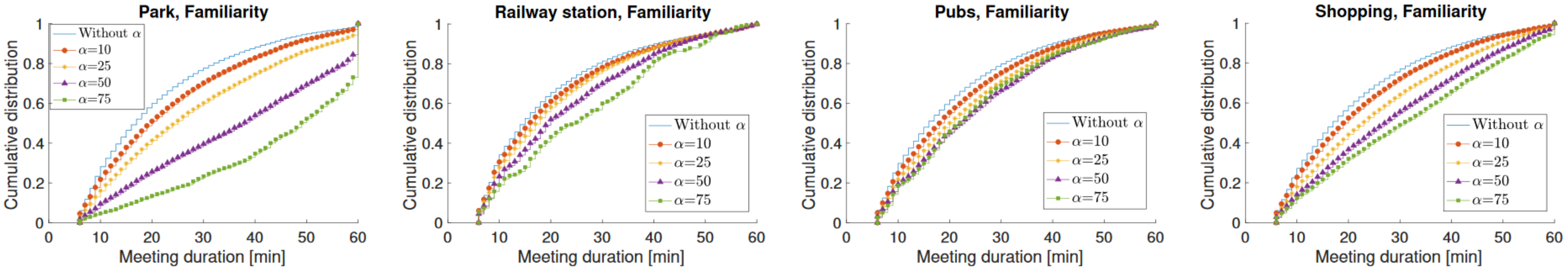
Source: https://www.pinterest.com/pin/484840716132563124/

Massive potential to harness collaboration among devices (e.g., sensing or computing)

Finding collaborators is non-trivial

- Criteria for collaborator selection ***sensitive to type of task***
  - **Collaborative Computing -> need long yet predictable collaboration duration, otherwise task may fail**
  - **Collaborative Sensing -> the longer the duration, the higher the benefits**

- **Randomly** selecting collaborators results in unpredictable collaboration times
- Selecting **familiar** sensitive to human mobility characteristics



(a) Park (b) Railway station (c) Pubs (d) Shopping

1. **How to maximize duration of collaborations?**
2. **How to make variance in time small?**

COSINE: Contributions

- **New method:** We present COSINE, method for selecting optimal collaborators with longer and more consistent duration.

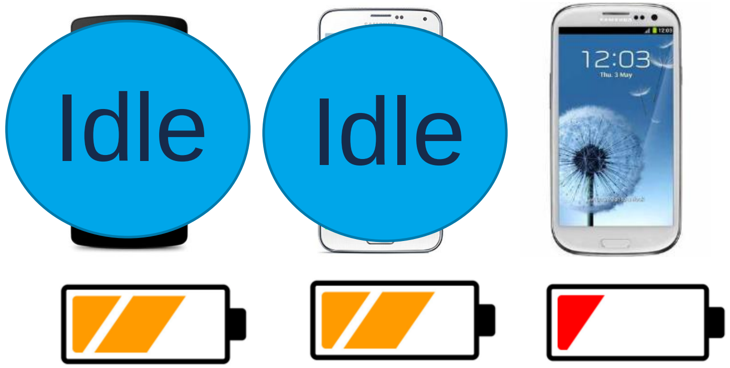
- **New insights:** We demonstrate existing methods are suboptimal and sensitive to characteristics of human mobility.

- **Improved performance:** We demonstrate significant improvements in energy and performance compared to state-of-the-art solutions.

- **New applications:** Our approach enables new types of collaborative applications, e.g., edge intelligence, micro data centres, and federated learning.

Benefits

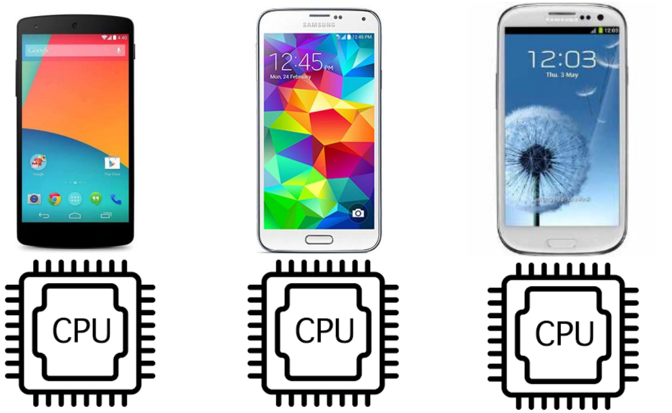
Location estimation task (GPS)

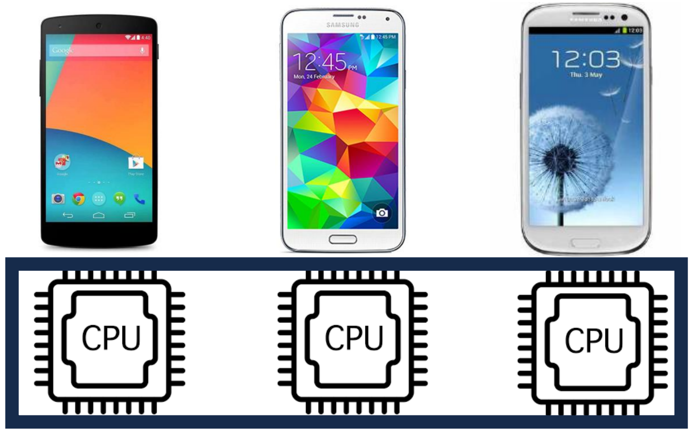


Reduce redundancy

Opportunities

Individual processing power





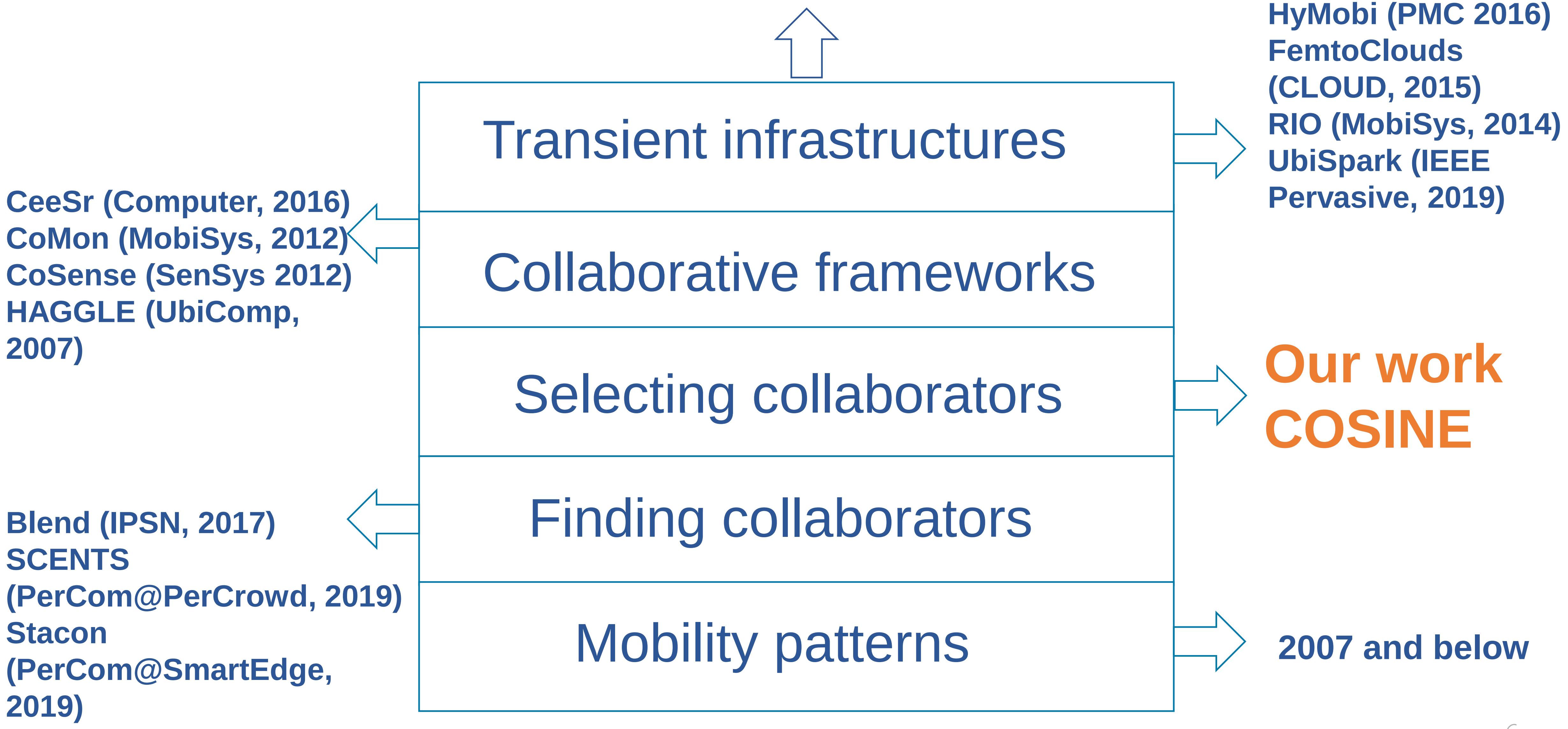
Combined processing power

New applications

Micro data-centres

(e.g., edge intelligence, federated learning)

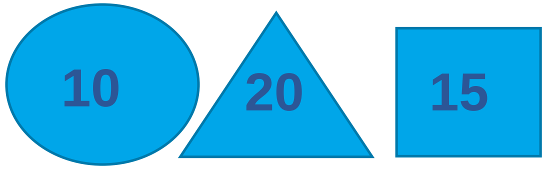
State-of-the-art solutions



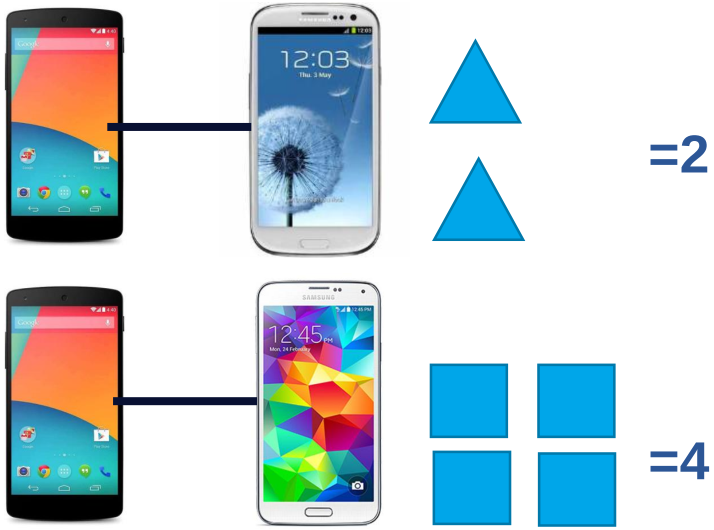
COSINE: Overview

- ***Quantifies regularity of encounters*** between devices,
- Selects collaborators based on ***duration*** and ***regularity***
  - Regularity = (Markov trajectory) entropy values

Device to device encounter



Each encounter is associated to a duration [in min]

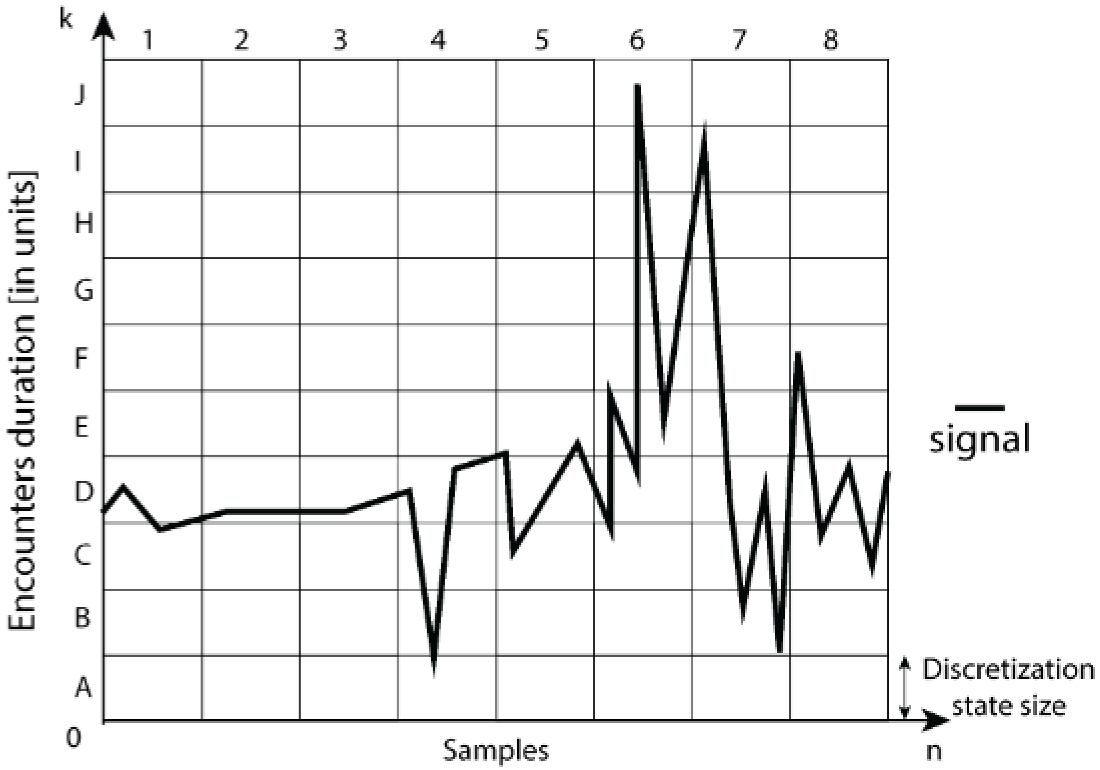


Quantify regularity of encounters

Ranked candidates based on regularity

COSINE: Quantization of measurements

Phase 1

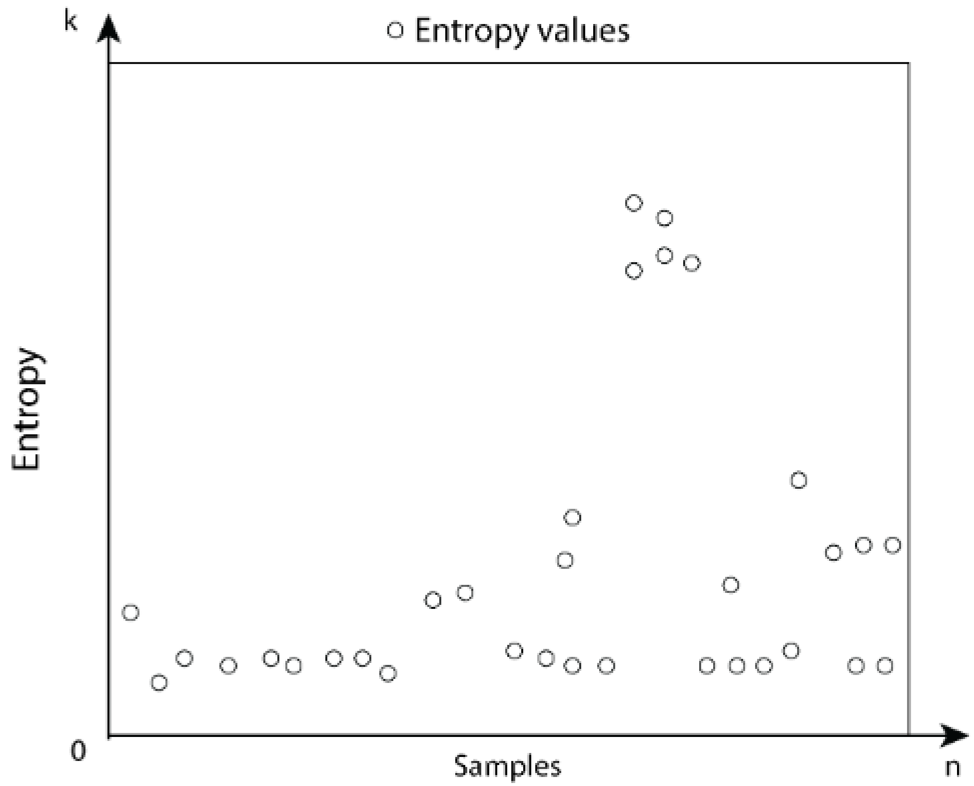


(a) Quantization of measurements

- Aggregate samples into a signal
  - Data-intensive analysis
- Quantize the signal
  - Reduce details while preserving relative patterns
  - Prepare for regularity extraction

COSINE: Extraction of regularity

Phase 2

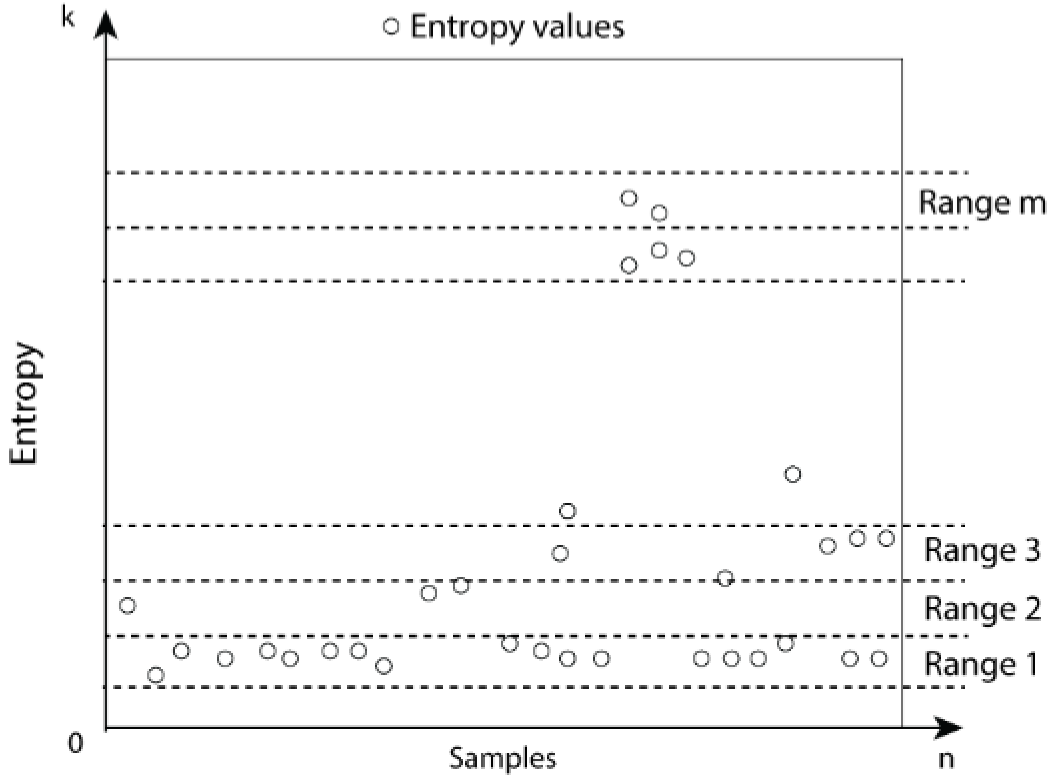


(b) Extraction of regularity

- Build a Markov trajectory entropy matrix
  - Quantized signal is taken as input
- Estimate the predictability of consistent encounters
  - The higher the entropy, the more consistent (longer duration) and vice versa

COSINE: Selection of collaborators

Phase 3



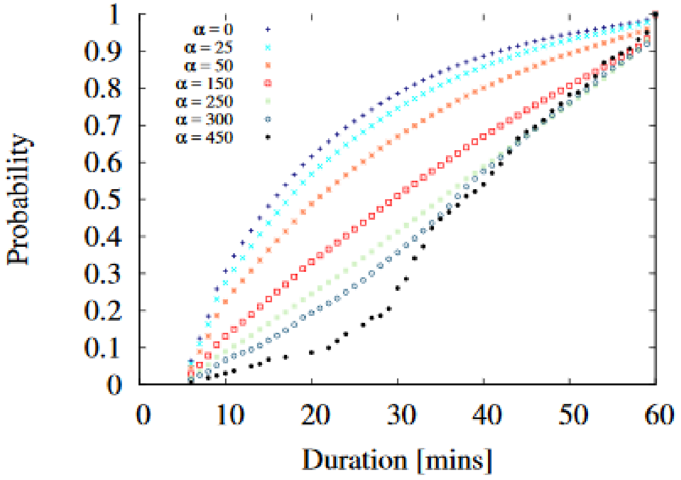
(c) Selection of collaborators

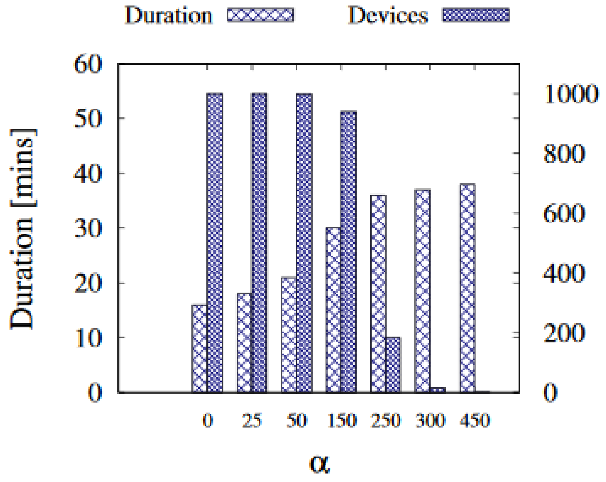
- Derive entropy ranges with upper and lower bounds that depict grouping of entropy values
- Entropy ranges are ranked based on cardinality
  - Candidates are selected according to the frequency of their entropy range

COSINE: Evaluation and Results

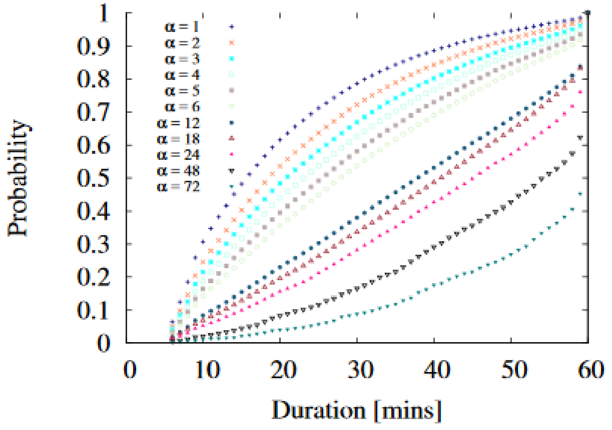
Baselines

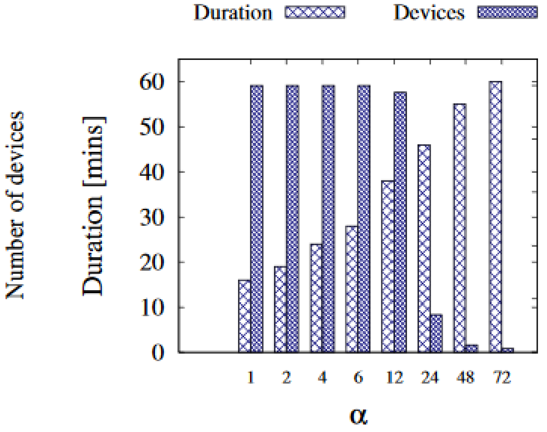
- Familiarity



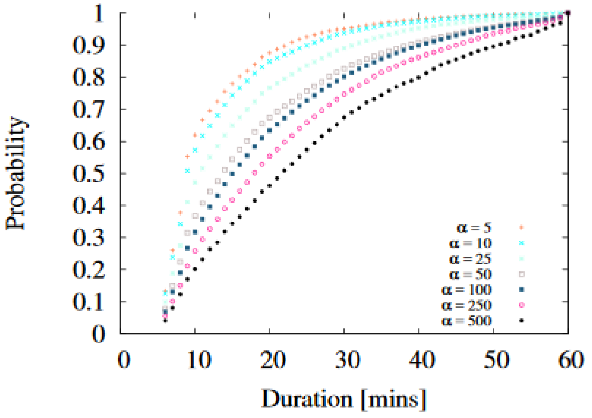


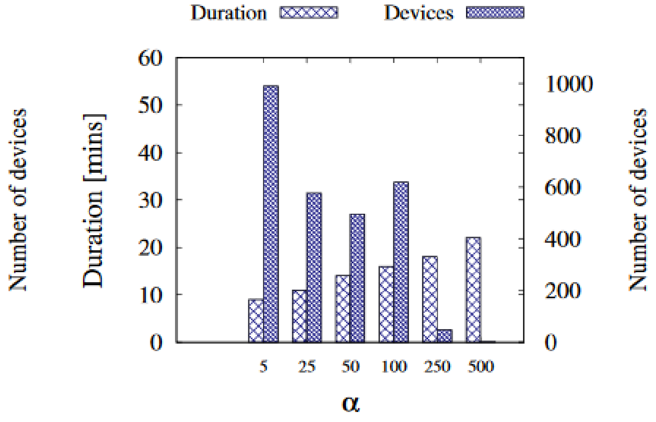
- Permanency





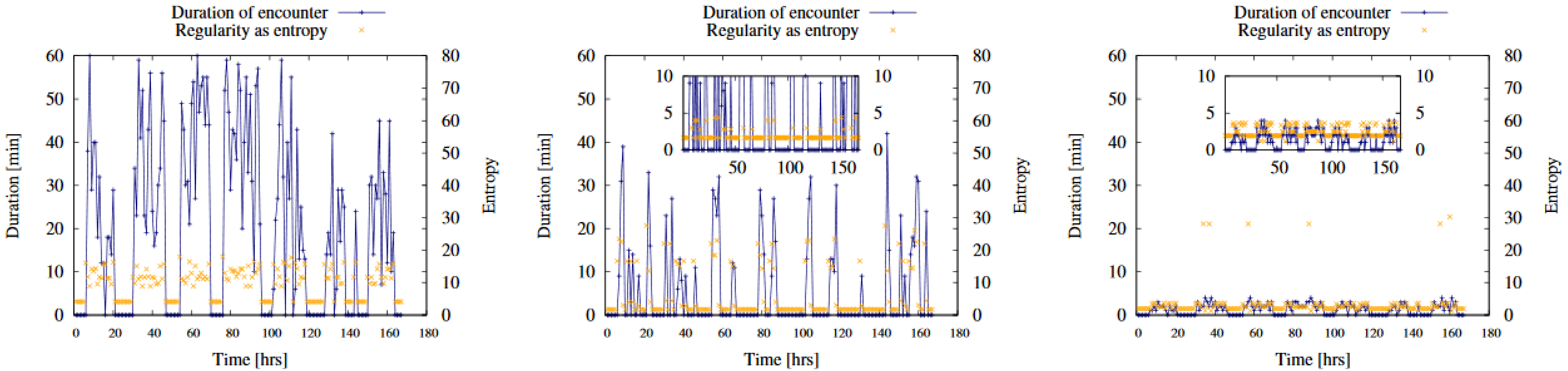
- Magnitude





COSINE: Evaluation

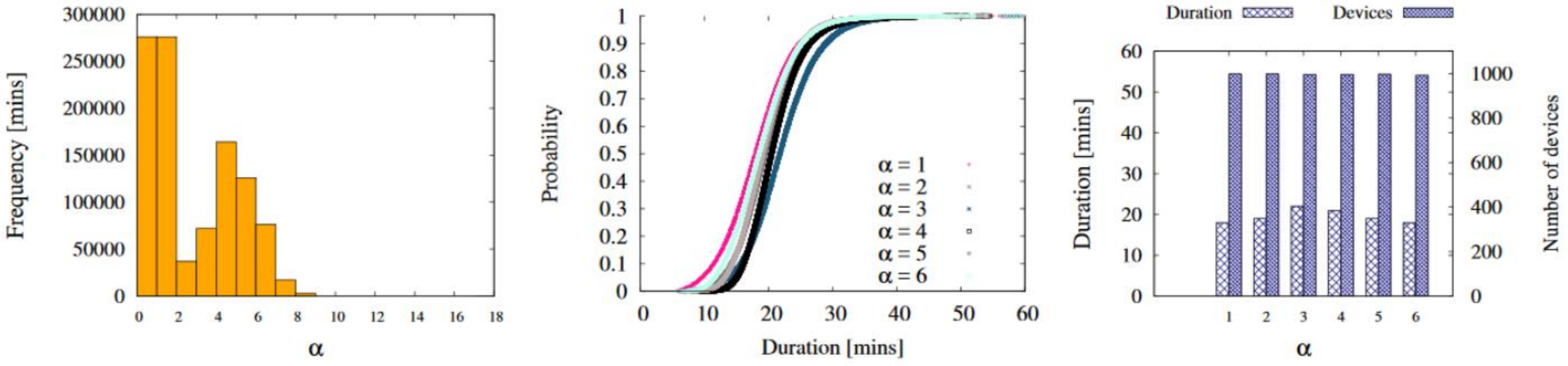
Result: Enough regularity to model different types of encounters



(a) High encounter (b) Medium encounter (c) Low encounter

COSINE: Evaluation

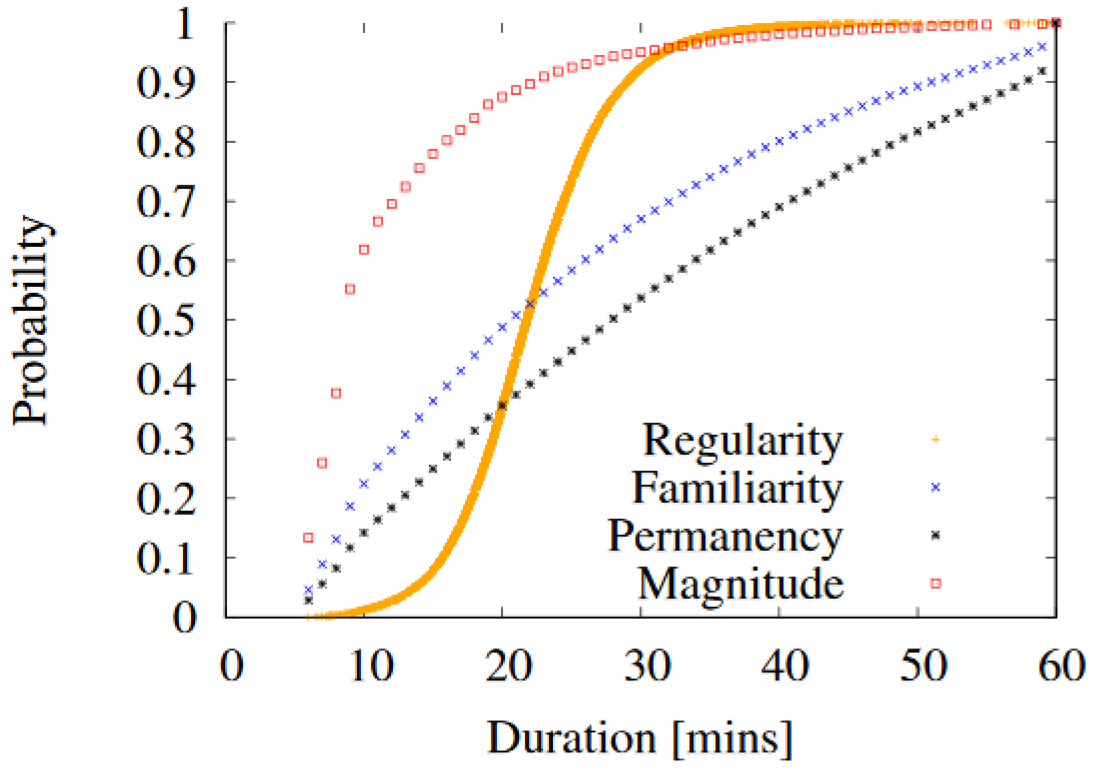
Result: Regularity can be used to characterize different types of encounters in a more consistent manner



(a) Characterization of candidates (b) Candidates assessment (c) Available devices

COSINE: Performance

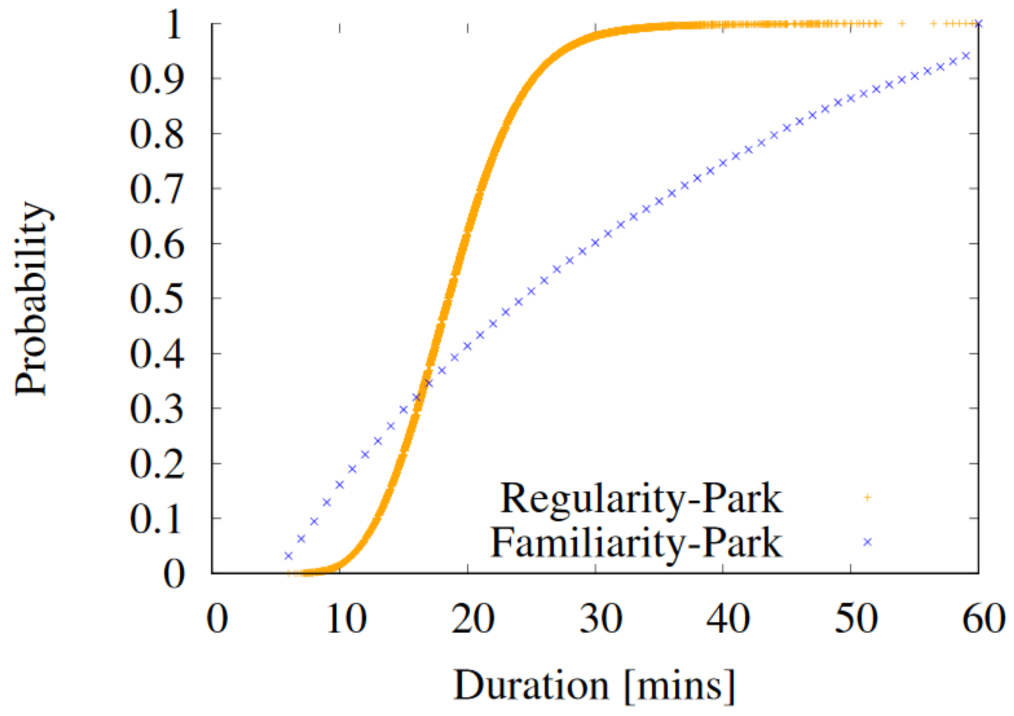
Result: Selection of collaborators has longer duration and is more consistent



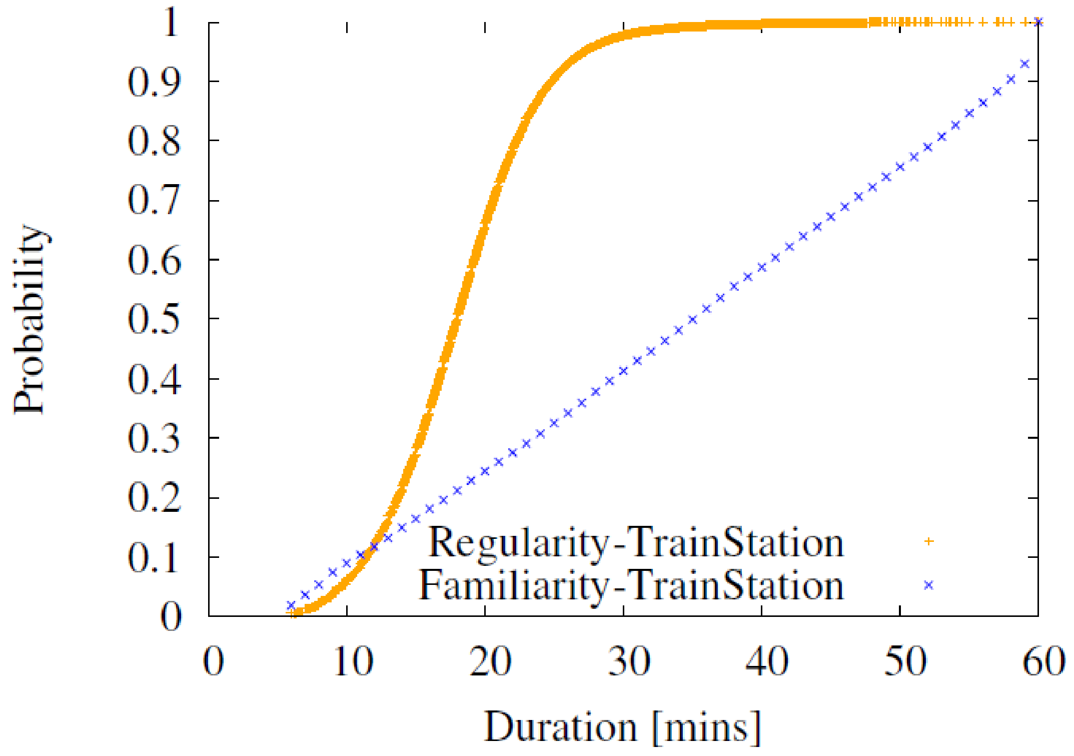
Selector mechanism	Average duration (min)	MAD
Regularity	22	5.66
Familiarity	20	13.74
Permanency	28	13.74
Magnitude	9	13.34

COSINE: Different contexts

Result: Our approach adapts to different characteristics of human mobility



Park



Train station

COSINE: Energy saving

Google Nexus Samsung S5

Collaboration	Familiarity (mW)	Regularity (mW)	+Benefit (mW)
S5 executes Nexus saves			
Augment	12421.52	13663.68	1242.16
Chess	8158.19	8974.01	815.82
Face recognition	10121.57	11133.73	1021.16
Nexus executes S5 saves			
Augment	10094.80	11104.28	1009.48
Chess	9881.48	10869.63	988.15
Face recognition	9850.64	10835.71	985.07

10% additional energy saving in a single collaboration

Summary and conclusions

- **New method:** We present COSINE, method for selecting optimal collaborators with longer and more consistent duration.
- **New insights:** We demonstrate existing methods are suboptimal and sensitive to characteristics of human mobility.
- **Improved performance:** We demonstrate significant improvements in energy and performance compared to state-of-the-art solutions.
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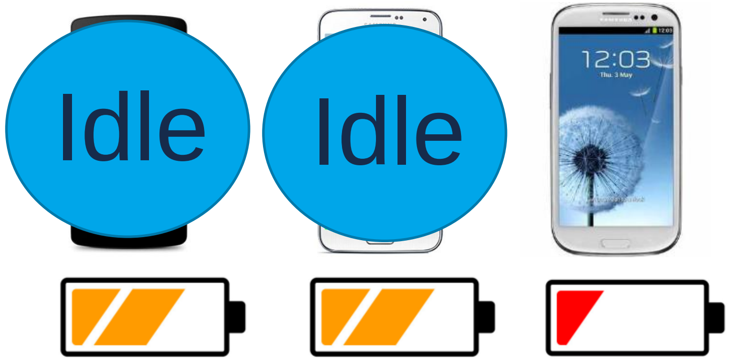
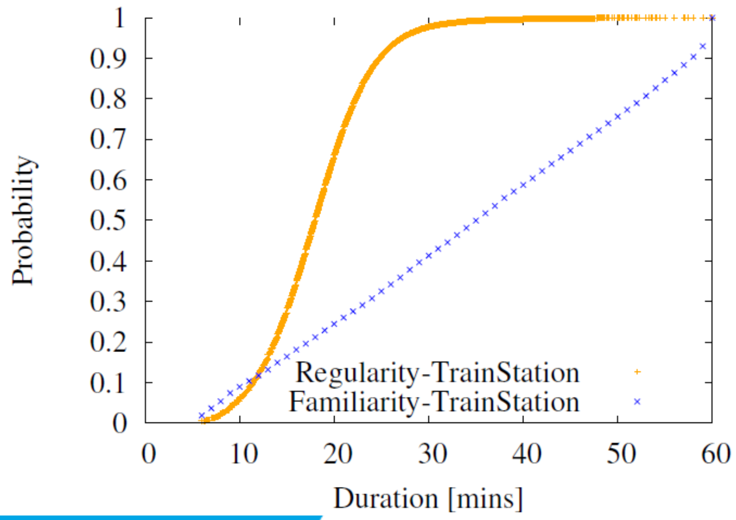
Questions?



Reduce redundancy



Thank you! (Do not hesitate to reach us via e-mail)

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