Identification of Real-World Daily Patterns based on Interactions in Online Social Networks

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Introduction - Motivation

Increasing availability of Internet enabled devices and massive use of **OSNs**

Creates a continues stream of information

People tend to publish information from several locations and devices

at different times of the day [2]

> This information contains meta-data (e.g. timestamp or location)

Online Social Networking interactions can be used to address real world challenges [1]

> Analysis of real-world patterns based on users' home or work areas

Real-world incidents/events identification based on anomaly detection Users interaction in Online Social Networks is being influenced by different

factors [3]

We aim in investigating if users' key locations influence their behavior in OSNs

Research Questions

Based on the differences of users' behavior in Online Social Networks during different time-frames, is it possible to identify their key locations by analyzing the meta-data of the information that they publish?

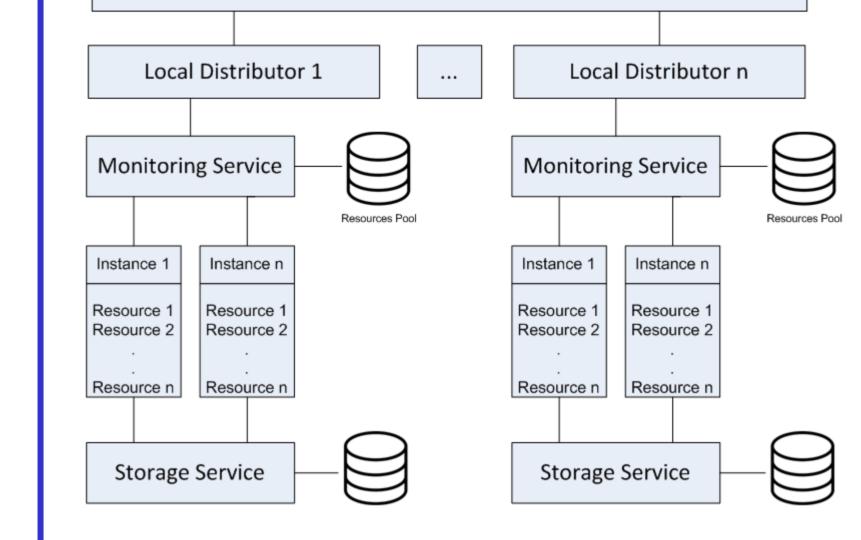
Dataset Collection Framework

Intelligent and efficient Twitter Data Collection

Framework Distributor

Given as input a list of user_ids or screen names:

- Does users' Online Social Networking behavior have a relation 2. with the geographic areas that they live in or visit? Are there differences in social graphs' structure regarding the different characteristics of areas?
- Do users' key geographic areas influence their real-world 3. patterns?



- **Global Workload** is distributed based on the number of Local Distributors
- > Local Workload is distributed in different instances based on availability of local resources
- > Each instance is able to run forever as monitoring service adds or removes resources based on instance needs **Throughput:** 3000 – 3200 users/hour per Local Distributor

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| Online Social Ne | twork Data |
|-------------------------|-------------|
| OSN | Twitter |
| #Users | 99,950 |
| #Tweets | 118,012,958 |
| #Geo-tagged Tweets | 6,161,290 |

| Turnette | D'a tulla sati a sa | |
|----------|---------------------|--|

| Dataset | Descrip | tion - | Anal | ysis |
|---------|---------|--------|------|------|
| | | | | |
| | | | | |

| Ground Truth Data | | | | |
|-------------------|---|--|--|--|
| Source | Twitter | | | |
| escription | Official geographical boundaries of the country of Netherlands. In total 1024 different areas | | | |

• Population and number of Employees for each area

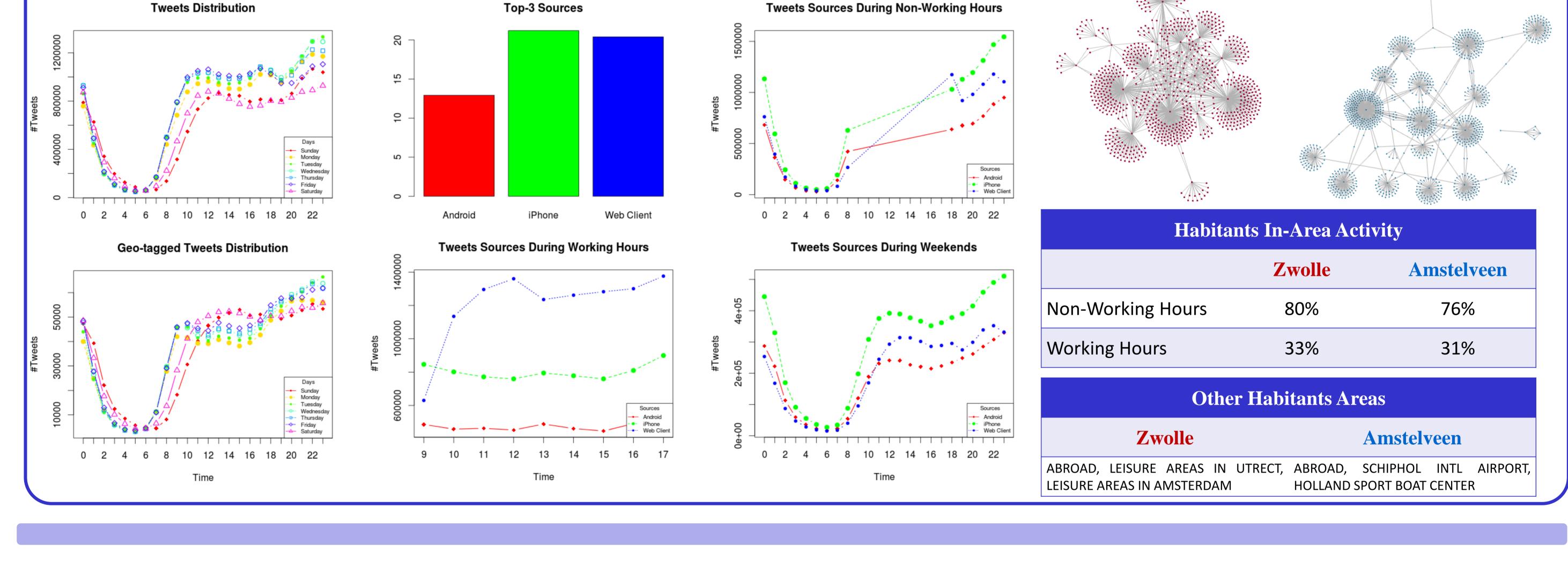
Zwolle is a municipality and the capital city of the province of Overijssel, Netherlands [Wikipedia]

- Population: about 125,000
- Its habitants are mostly locals

Amstelveen is a municipality in the province of

North Holland, Netherlands [Wikipedia]

- Population: about 85,000
- A large percentage of its habitants are students, as VU Amsterdam is located in this area



Future Plan

References

[1] Abel Fabian, Claudia Hauff, Geert-Jan Houben, Richard Stronkman, Ke Tao.

> Model and Simulate social graph's evolution based on users' key locations

> Model and Simulate Online Social Networking behavior based on users' key locations

"Semantics+ filtering+ search= twitcident. exploring information in social web streams." Proceedings of the 23rd ACM conference on Hypertext and social media. ACM, 2012.

[2] Katragadda Satya, Miao Jin, Vijay Raghavan. "An Unsupervised Approach to Identify Location Based on the Content of User's Tweet History." Active Media Technology. Springer International Publishing, 2014. 311-323.

[3] Sadilek Adam, Henry Kautz, Jeffrey P. Bigham. "Finding your friends and following them to where you are." *Proceedings of the fifth ACM international conference on* Web search and data mining. ACM, 2012.

