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Department of Distributed and Multimedia Systems

On Movement Activities Estimation for Mobile Opportunistic Networking

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Overview

- Movement **feature extraction** from every-day trips
- Method for estimating type of **movement activity** based on features
- Final objectives
  - Investigate use of activity information in opportunistic networks
  - Estimate preferable forwarding nodes in delay-tolerant routing
- First results described in:
  - Karin A. Hummel, Andrea Hess: **Movement Activity Estimation for Opportunistic Networking Based on Urban Mobility Traces**. 3rd IFIP Wireless Days (WD'10). Venice, Italy, October 20-22, 2010.
  - Karin A. Hummel, Andrea Hess: **Estimating Human Movement Activities for Opportunistic Networking: A Study of Movement Features**. IEEE WoWMoM 2011, Lucca, Italy, June 20-24, 2011.

Outline of the Talk

- Motivation
  - Mobility-assisted forwarding in opportunistic networks
- Deriving features from mobility traces
- Use mobility features to estimate activities
- Experimental results
  - Empirical CDF of mobility features
  - Movement activity classification based on Naïve Bayes
- Conclusion and future work

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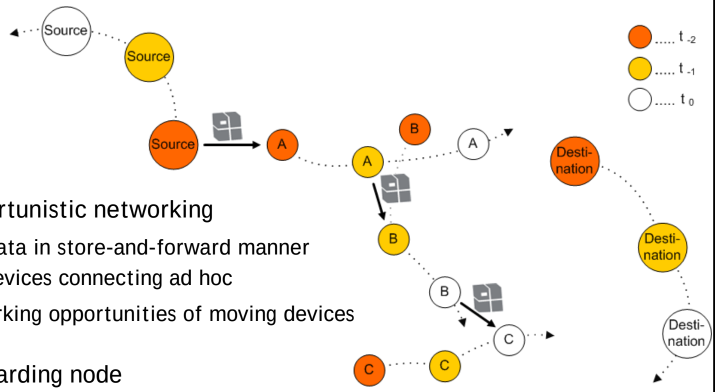
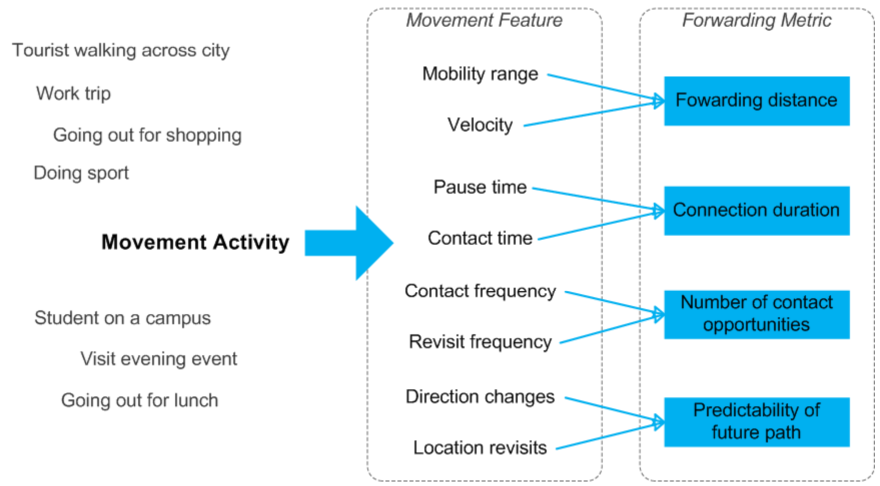
Mobility-Assisted Forwarding in Opportunistic Networks



- Concept of opportunistic networking
  - Disseminate data in store-and-forward manner by mobile devices connecting ad hoc
  - Exploit networking opportunities of moving devices
- Select best forwarding node
  - predict forwarding capabilities of each device
  - e.g., expected traveling distance and likelihood of revisiting locations
- How are **forwarding metrics** affected by **movement patterns**?

Effects of Activities on Networking



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Model to Estimate Movement Activities

- Movement Activity
  = composition of movements, name corresponds to trip purpose
- Bayes classification approach
  - detect activity given a specific mobility feature vector

$$P(A_j|V_i) = \frac{P(V_i|A_j)P(A_j)}{P(V_i)}$$

  - A_j … movement activity
  - V_i … feature vector observed
- GPS-based positioning method
  - offers finer granular movement information than cellular or WLAN data
- Define feature set based on literature survey

Typical Features Extracted – Summary of Literature Survey

- Spatial characteristics
  - **Prevalence** - fraction of time user spends at an AP
    spatial distribution -> 'location visiting preferences', 'hotspot regions'
  - **Activity range** - area covering all locations that have been visited
- Temporal characteristics
  - **Pause time**
  - **Persistence** - time a user stays continuously connected to one AP
- Spatio-temporal characteristics
  - **Revisit metrics**, e.g., 'periodical re-appearances', 'return time'
  - **Meeting metrics**, e.g., 'inter-contact time', 'contact time', 'inter-meeting time', 'time distance'

Feature Extraction I

- Direct metrics derived from traces
  - **1. Velocity**
    speed between two positions measured consecutively (position sampling interval is 1 s)
  - **2. Direction changes**
    difference between current direction and direction measured 20 m earlier
- Spatial metrics
  - **3. Flight length**
    length of path (in meters) traveled between two consecutive pauses
  - **4. Mobility range**
    distance of GPS position to the center of rectangle covering trip

Feature Extraction II

- Temporal metrics
  - **5. Pause time**
    duration between two consecutive movement phases (v<0.5 m/s for t≥5 s)
  - **6. Start time**
    hour of day trip started
- Combined metrics
  - **7. Number of revisits of a position**
    position is assumed to be the same if within position radius of 20 m
  - **8. Time between revisits**

Study of Movement Features for Activity Estimation

- Can activities be recognized based on **mobility feature set**?
- 4 types of movement activities considered
  - **Way to work**
  - **Evening activity**
  - **Shopping activity**
  - **Tourist activity**
- Data set of 252 trips
  - GPS traces of daily trips of 13 test persons
  - semantic information about trips noted by test persons
- Empirical CDF for 8 features
  - determine suitability for activity estimation
- Naïve Bayes classifier
  - categorize trips into 4 activities

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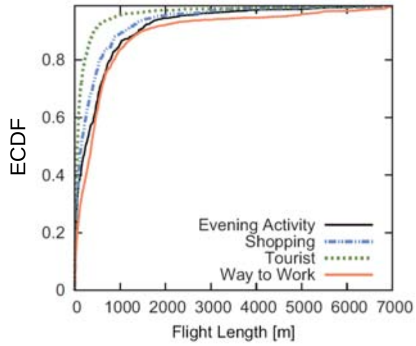
Features Observed – Ex 1: **Flight Length**

- *Tourist*: 80% below 230 m
  corresponds to the behavior of tourists walking between sights
- *Way to Work* and *Evening*: longer flight lengths due to public means of transport and cars



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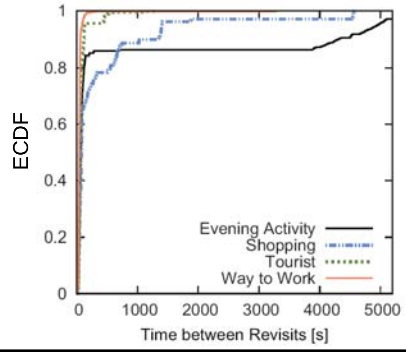
Features Observed – Ex 2: **Time betw. Revisits**

- *Way to Work*: 99% of return times < 160 s
  (e.g., walking back a street after getting off a bus)
- *Evening*: highest values due to longer pauses and similar return paths
- *Shopping*: 90% of positions revisited after 20 min,
  small number up to 75 min



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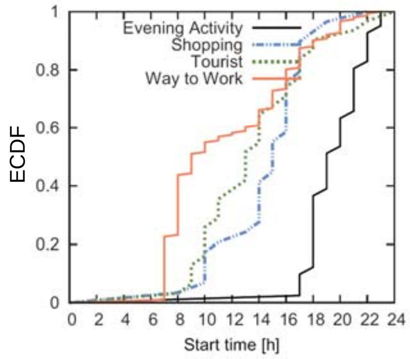
Features Observed – Ex 3: **Start Time**

- *Way to Work*: 55% from 6:00 to 10:00, wider range for second bunch of trips
- *Evening*: 17:00-23:00 as one would expect
- *Shopping* and *Tourist*: *Tourist* curve shows steeper ascent in the afternoon, *Shopping* trips start earlier in the morning



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Movement Activity Recognition – Classification Results

- Training of Naïve Bayes classifier
  - 50% of trips in each activity category
- Overall success rate of 80.65%
  - Classification matrix:

	Assigned label A	B	C	D
Evening (A)	16	0	1	3
Shopping (B)	0	8	2	4
Tourist (C)	0	6	8	1
Way to Work (D)	4	0	3	68

- Trips classified wrongly expose similarities
  - e.g., some *Tourist* trips show similarities with *Shopping* trips
  - *Way to Work* trips classified as *Evening* trip if taking place with pauses at a later hour

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Fitting Set of Movement Features

- Test all feature combinations
  - classify test set by using reduced feature set (1 to 7 features out of 8)
  - Mean success rate [%] and standard deviation:

	Number of features (n)						
	7	6	5	4	3	2	1
Mean	79.74	77.71	76.40	73.76	71.39	67.68	62.30
Stdv	1.32	1.95	2.63	2.93	4.07	4.71	3.65

- Combination of six features
  - best combination of **six features** achieves 80.65% as well
  - omitting important features - **num. of revisits**, **start time** - yields lowest rate
- Combination of two features
  - **num. of revisits** and **start time** achieved best result

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Conclusion and Future Work

- Activity estimation based on mobility features
  - 4 typical movement activities, 8 features
  - 80.65% success rate for Naïve Bayes approach
- Potential use of activity estimation
  - forwarding in mobility-assisted networks
  - estimate user-caused network traffic
  - applications: situation-aware services
- Current and Future Work
  - extend data set of daily trips
  - correlation betw. activities and forwarding behaviour
  - propose best forwarding node estimation for routing mechanism