Location Prediction

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Learning Objectives

- Know why location prediction is important
- Understand basics of human movement
- Creation of data set as basis for prediction
- Understand techniques for location prediction
- Realize simple prediction-based application

Context-Aware Applications

- Applications that adapt to *context*
- Context includes:
  - User behavior
    - Where the user goes
    - What the user does
  - Environment
    - Available connectivity
    - Charging opportunities
    - Location

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- Context includes:
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    - Where the user goes
    - What the user does
  - Environment
    - Available connectivity
    - Charging opportunities
    - Location
- Observations:
  - *Location* links facts
  - Predicting location $\implies$ predicting future context

Example Use of Context Prediction

- Automatically turn heater on when user heads home
- Predict presence of friends nearby
- Vary QoS according to future energy availability
- Prefetching messages or alerts / delaying uploads

Prefetching

- Potential benefits:
  - Saves energy
  - Conserves data allowance
  - Reduces network congestion
  - Reduces latency
  - Hides spotty network coverage
  - Reduces dependency on centralized infrastructure

[1] O'Donnell and Draper. *How Machine Delays Change User Strategies.* SIGCHI Bull., 1996.

[2] Trestian, et al., *Connecting People, Locations And Interests In A Mobile 3g Network.* ACM SIGCOMM, 2009.

Prefetching

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  - Saves energy
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  - Hides spotty network coverage
  - Reduces dependency on centralized infrastructure
- More than nice to have: potential *emergent behavior*
  - Reducing latency changes how people interact with programs[1]
  - Users conservative about energy and bandwidth use[2]

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Location for Context-aware Applications

- Requirements
  - Current *place* (home, work, etc.)
  - Geographic coordinates not always required

    $\Longrightarrow$ potential for increased privacy / energy savings

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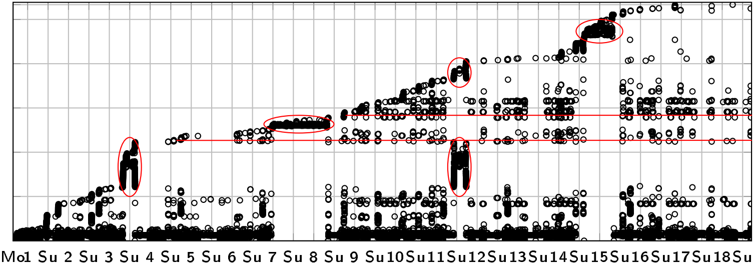
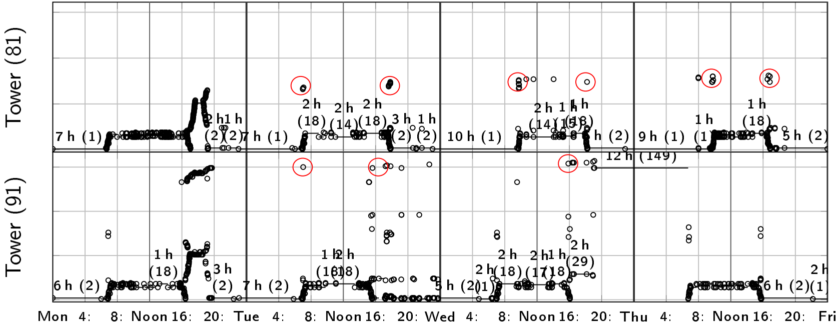
- GPS
  - Energy intense
  - No indoor coverage
  - Urban canyons
- Cell towers as landmarks
  - Available for "free"
  - Requires *cleaning*
    - Tower transitions when stationary

Overview



- Main location ("home") appears as a black line (bottom)
- Regular activities appear as dotted lines
- 4 trips - minor *regime changes*
  - Week 3 & week 11 to same location
  - Similar route, but note newly discovered towers
  - Week 7/8 & Week 15 trips probably with plane

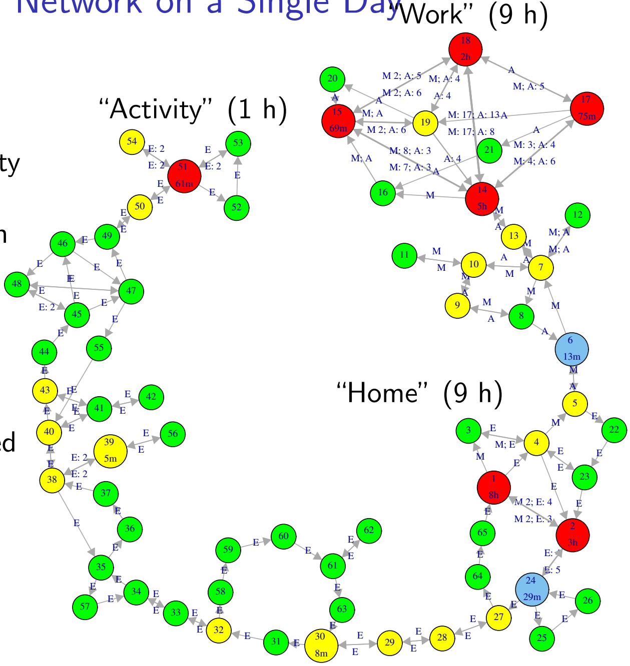
Week-by-Week View



- “home” at night (except second Wed. night)
- At “work” during the day
- Path to and from “work” is similar, but see new towers
- “activity” Monday evenings

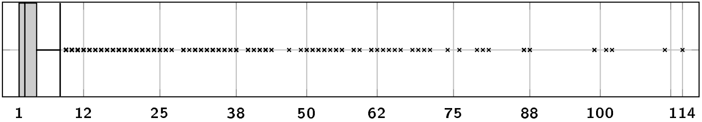
Induced Cell Tower Network on a Single Day

- 3 major areas of activity
- Device connects to multiple towers in each area; many transitions
  - Device samples nearby cells
  - Core & periphery towers
- Effect more pronounced with more data



Tower Sampling Experiment

- Is the device really stationary during some transitions?



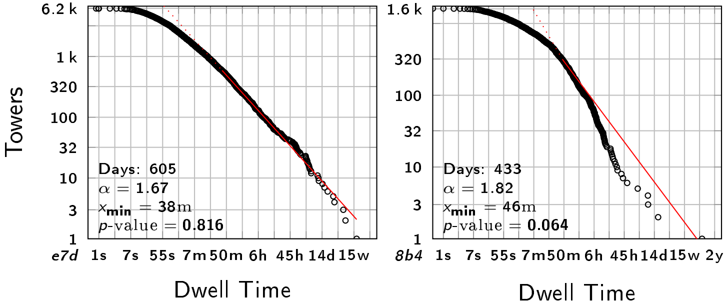
- $\#$ Towers seen during each **wall charge** ($>$ 30 min.)
  - 6289 wall charges across all traces
  - Median: 2 (MAD: 1.48)
  - Upper quartile: 4

Tower Sampling is Real

- Locations not covered by a single tower
- Phone appears to sample towers in its vicinity

- Conclusions
  - Cell tower data higher resolution than places
  - Tower transitions do not correspond to user movement
  - Need to aggregate towers to identify:
    - Landmarks
    - User movement

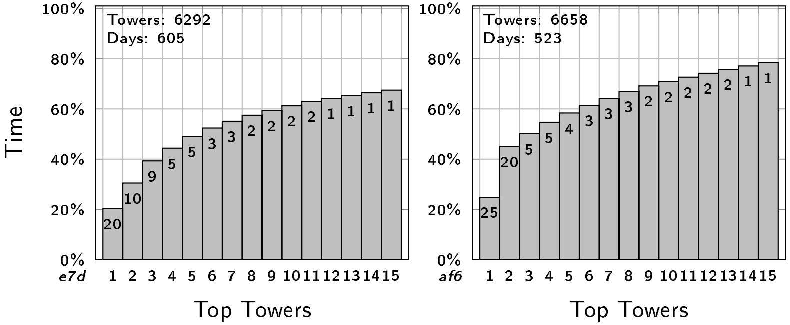
Time Spent at Each Tower (1/2)



- CCDF plots of the total time spent at a tower (by user)
- 44 of the fits (75%) are significant fits to a power law

$\Longrightarrow$ Users may visits thousands of towers, but spend nearly all of their time at a few locations

Time Spent at Each Tower (2/2)



- CDF of time at top towers
- Top few towers *dominate*

Approaches for mapping Tower $\rightarrow$ Place

- Collapse oscillation sequences
  - Relatively simple heuristic
- Place detection

Place Detection

- Observation:
  - Places automatically carved out via user movement
  - Places are islands of high dwell time

Related Work (1/2): Geography

- Scellato et al., Kim et al.
  - Place a 2-D Gaussian at each GPS sample & normalize
  - Islands above a threshold (15% of max) $\Longrightarrow$ place
  - Recall:
    - Tower dwell time consistent with a power law

  $\Longrightarrow$ 15% will only identify 1–3 places!

Related Work (2/2): Network Theory

- Eagle et al.
  - Community detection
    - Partition graph such that the number of edges between subgraphs is lower than expected
  - Makes places too large (include routes)
  - Computationally expensive and thus can only be run offline

A Good Strategy

- Identify graph structures that are typical of places:
  - Primary characteristic: High density subgraphs
  - Look for cliques, size ≥ 4

When to Run

Look for new subgraphs *whenever* there is a new edge

- Only need to look near the edge

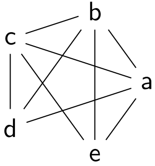
$\Longrightarrow$ fast

$\Longrightarrow$ appropriate for online use

Naming

- When merging, use longest used name
  - Example: a: 3 h, b: 4 h $\implies$ b
  - But, if tower b called b for 0.5 h and x for 3.5 h, then use x

  - Overlapping clusters usually share a name
  - Example: 5-clique missing 1 edge $\implies$ two 4-cliques



Exercise

You implemented an (background) App that:

- Frequently records user's location[3]
- Location method is up to you (Cell tower, WLAN, GPS, multiple)
- Possibly record auxiliary data (power status, usage, etc.)
- Export data in CSV format

You should have 2-3 week mobility data by now!

Now implement tools to (if applicable):

- Convert CSV to (graphviz/dot) transition graph
- Cluster cell towers into locations
- Import GPS locations into GIS database
- Compute location dwell time statistics

[3] Ideally, batch write to disk to safe battery!

Location Prediction: Related Work Overview

- Most work focused on predicting *next* tower
  - Relevant to network management
  - Approaches:
    - Markov chain (François et al., Song et al.)
    - Graphical models (Eagle et al.)
    - LZ-based predictor (Song et al.)
- Location in x hours:
  - Non-linear time series (NextPlace, Scellato et al.)
  - Recognize routes (Laasonen)
  - $P(\mathrm{place}|\mathrm{tod})$ (Burbey and Martin)
    - Simple scheme
    - Extensions by Walfield et al. work best

    $\Rightarrow$ We will focus on this scheme

Simple Idea

- Solve: $argmax_{t \in T} \, P(t|\mathbf{c})$
  - t: tower aggregate
  - $\mathbf{c}$: a set of conditions

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- Solve: $argmax_{t \in T} P(t|\mathbf{c})$
  - t: tower aggregate
  - $\mathbf{c}$: a set of conditions
- Why argmax?
  - Simplicity of evaluation
  - NextPlace does it
  - Easily modified to return rank or whole CPT, if appropriate

Evaluation

- Every half hour, make a series of predictions
- Predictions for 0.5 h, 1.5 h, ..., 23.5 hours in the future
- Prediction correct if predicted aggregate visited within ± 15 min of prediction time

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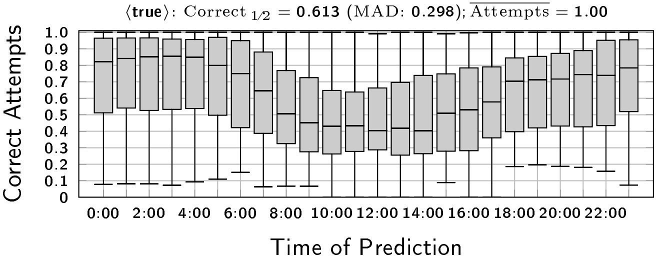
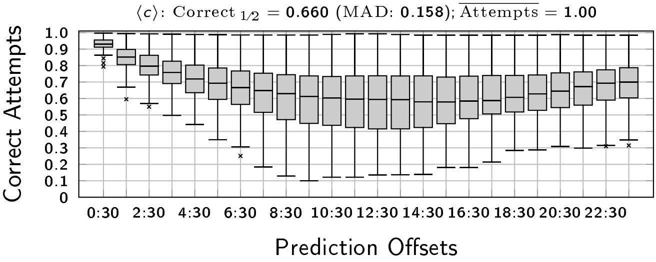
- Only attempt a prediction if $\mathbf{c}$ has $\geq 2h$ of data
    - Larger reduces attempts
    - Too large ($\geq 8h$) also reduces precision
        - Rarely visited locations apparently highly predictive
        - e.g., after shopping, user goes home

Baseline 1/2



- Unconditional predictor
  - Current dominant aggregate
  - Probably where user usually sleeps
- Results consistent with power law behavior

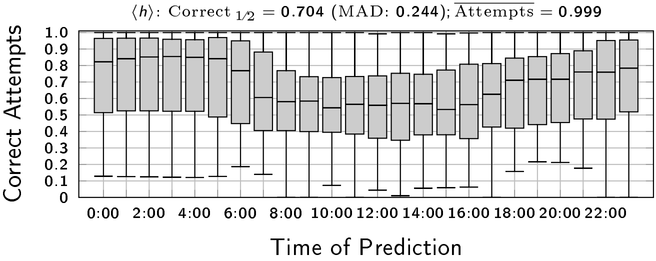
Baseline 2/2



- Note: x axis is prediction offset, not time of day

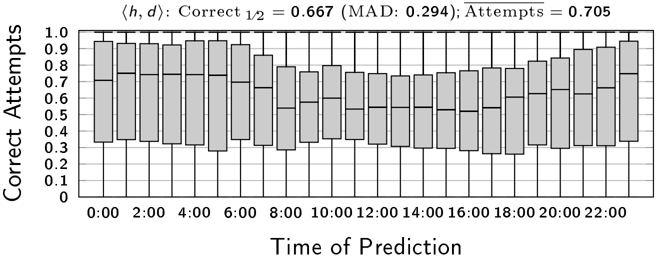
- Current tower predictor
- Strong tendency to stay at a location for at least half an hour
- Increase for $\Delta > 17h \implies$ diurnal behavior

Time of Day



- Idea: daily routines
- Condition on current hour or half hour
  - Both perform similarly
  - We prefer hour due to smaller CPT

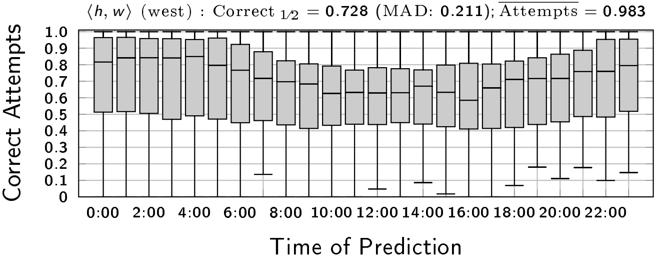
Time of Day and Day of Week



- Reduction in performance! (66.7% vs. 70.4% for $\langle h\rangle$)
- Low number of attempts (70.5%)
- Just considering long traces (¿ 16 weeks):
  - Score: 74.1%
  - Attempts: 95.8%

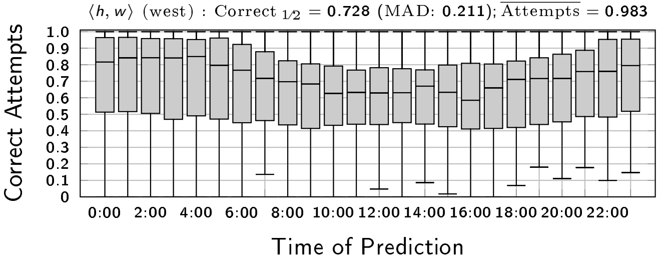
$\Longrightarrow$ data too spread out!

Time of Day and Work Day



- Just distinguish between workdays and days of rest
- Increase in performance (72.8% vs. 70.4% for $\langle h \rangle$)
- High portion of attempts

Time of Day and Work Day



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- Also tried country-specific days of rest, same performance
- Perhaps bias?
- Ideally learn workdays from data

Regimes

- Weak location-dependent predictor
- Regime classification
  0 Dominant tower over past 24 hours
  1 Current tower's primary regime ($argmax\, P(r|t)$)

Regime-based Predictor

Predictor	Correct Attempts	Attempts
$\langle h, w \rangle$	72.8%	98.3%
$\langle r, h \rangle$	77.6%	91.7%
$\langle r, h, d \rangle$	76.7%	55.8%
$\langle r, h, w \rangle$	81.1%	86.9%

- Significant improvement in correct attempts
- Trade-off: Fewer attempts

Current Tower Aggregate-based Predictor

- Strong location-dependent predictor
- Note:
  - $\langle c \rangle$ is the current tower predictor (our baseline)
  - Need a temporal reference, e.g., the prediction offset (Δ)

Evaluation

Predictor	Correct Attempts	Attempts
$\langle r, h, w \rangle$	81.1%	86.9%
$\langle h, \Delta, c \rangle$	81.3%	73.8%
$\langle h, d, \Delta, c \rangle$	81.4%	38.2%
$\langle h, w, \Delta, c \rangle$	83.0%	66.1%

- Slight improvement in correct attempts
- Tradeoff: significant decrease in portion of attempts

Aging

- Idea: Adapt to changes in behavior
- Approaches:
  1. Keep last x days of data
  2. Keep last x days per *primary* condition
     - Idea: behavior at secondary regimes likely stable
     - Example: parents' or remote office visited every few months

Aging Evaluation

- Used approach 2
- Tried different amounts of aging
  - 1, 2, 3, 4, 6 weeks

Aging Evaluation

- Used approach 2
- Tried different amounts of aging
  - 1, 2, 3, 4, 6 weeks
- Results:
  - Aging $\langle h \rangle$: 1 week improved precision from 70.4% to 75%
  - Aging r-based predictors: status quo for 3–4 weeks
  - Aging c-based predictors: status quo for 3–4 weeks
- Conclusion:
  - Conditioning on r or c already captures dynamic behavior
- Recommendation:
  - 3–4 weeks of aging to reduce amount of data stored

Combining Predictors

- If a predictor doesn't have enough data, fallback to another
- Prefer high precision predictors
- Results:
  - $> 99\%$ attempts
  - $\langle r, h, w \rangle$,$\langle r, h \rangle$,$\langle r \rangle$: 80% correct
  - $\langle h, w, c, \Delta \rangle$,$\langle h, c, \Delta \rangle$,$\langle r, h, w \rangle$,$\langle r, h \rangle$,$\langle r \rangle$: 79% correct

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- Per prediction offset-based predictors:
  - $0.5h$: Current tower aggregate baseline (93%)
  - $1.5h - 2.5h$: Current tower-aggregate based ($80\% - 85\%$)
  - $> 2.5h$: Regime-based ($78\% - 80\%$)
  - Result ($24h$): 82%

Exercise

1. Design high-level location prediction API
2. Implement baseline predictor
3. Implement current tower-aggregate predictor $(1 - 2.5h)$
4. Use prediction to:
   - Enable/disable home heating (project!)
   - Prefetch weather data (going to Bern or skiing?)
   - Disable GSM/WLAN ("user rarely uses it on the train")
   - Make suggestions for when to schedule appointments
   - ...

API Design Hints

- Start by defining “Location” abstraction
- Input for location prediction is time in future
- Plan for “no prediction” as possible answer!
- Output may include level of uncertanity or multi-set with probabilities

Your final design will likely depend on your method to record locations and your application!

Exam reminder

1. You may be asked questions about the project
2. You may be asked questions about QR/GPS/GIS/LOC that exercises would help you answer

Acknowlegements

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