Learning Mobile Device Location from Vibration

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Motivation

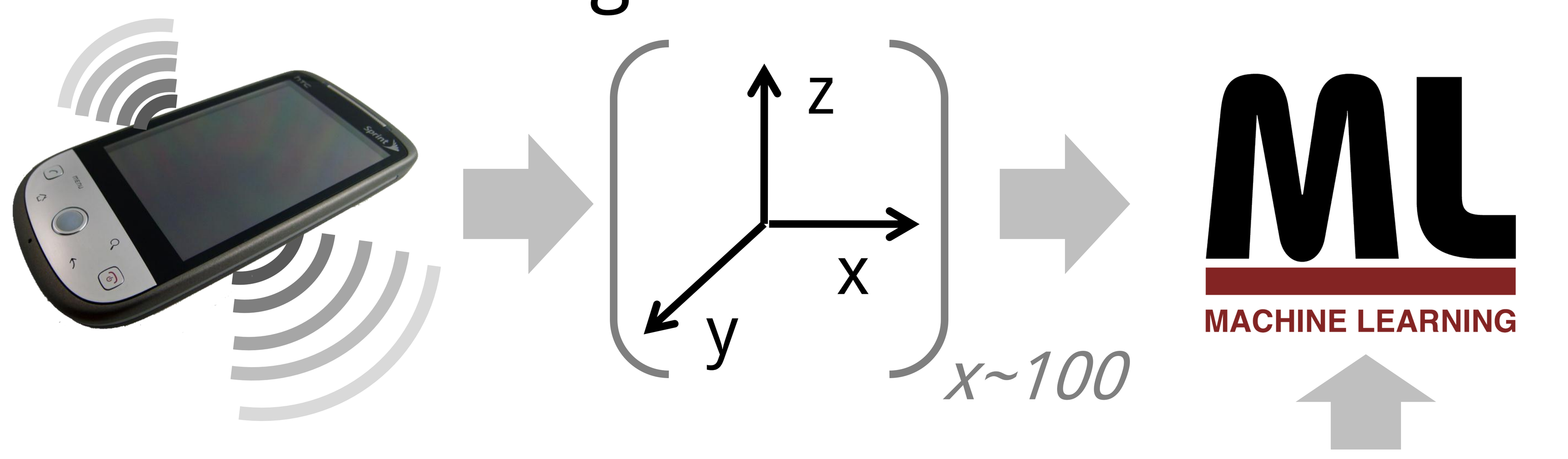
- **Context-Aware Computing**

Semantic Location | "Where is my phone? | What am I doing?"

- **Mobile devices that react based on location**
- *How can we identify the location of a device?*

Approach

- Use active sensing: vibrator + accelerometer



Location Labels

- Obtain coarse system response
- Classify semantic location (table, chair, ...)

Related Work

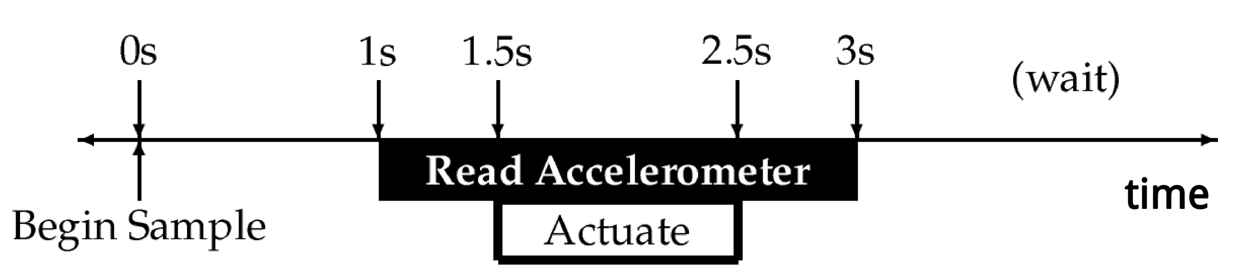
Interest in discriminating time-series data for device context

- Activity recognition: Thresholding, KNN for x/y/z values [aampl]
- Audio classification: Mean, stdev, energy, correlation [cenceme]
- Typically labels from user-trained fingerprints [survey, surroundsense, darwin]

- **Academic:** Mobile Sensing @ Dartmouth, SyNRG @ Duke, ...
- **Industry:** Intel sensor architecture & SENS project, ...

Learner Setup

Measurements: 7 locations **x** ~230 samples ea.



desk_home
pocket_walk
seat_bus
seat_deskhome
table_dining
table_kitchen
table_placemat

Evaluation Setup: Algorithms + Conditioning

- Classifiers with compact models (avoid storing all data, eg KNN)
- Representative approaches. Implementations: Weka Toolkit

Classifier	Description
NaiveBayes	Strong conditional independence assumption
J48 (tree)	C4.5 algorithm (extends ID3) based on info. gain
LibSVM	SVM with radial basis function as kernel
Logistic	Logistic Regression classifier with max iterations
NBTree	Decision tree with Naïve Bayes at leaves

- Add fill for measurement gaps, ignore mean (from recalibration)

9.8	10.2	9.7	10.4	9.6	10.3	10.2	*10.1*	*10.1*	10.1	9.6	9.8	10.4	9.9	10.7

time

Feature Extraction

Goal: pick a minimal set of summary features (→11)

"Reduced"

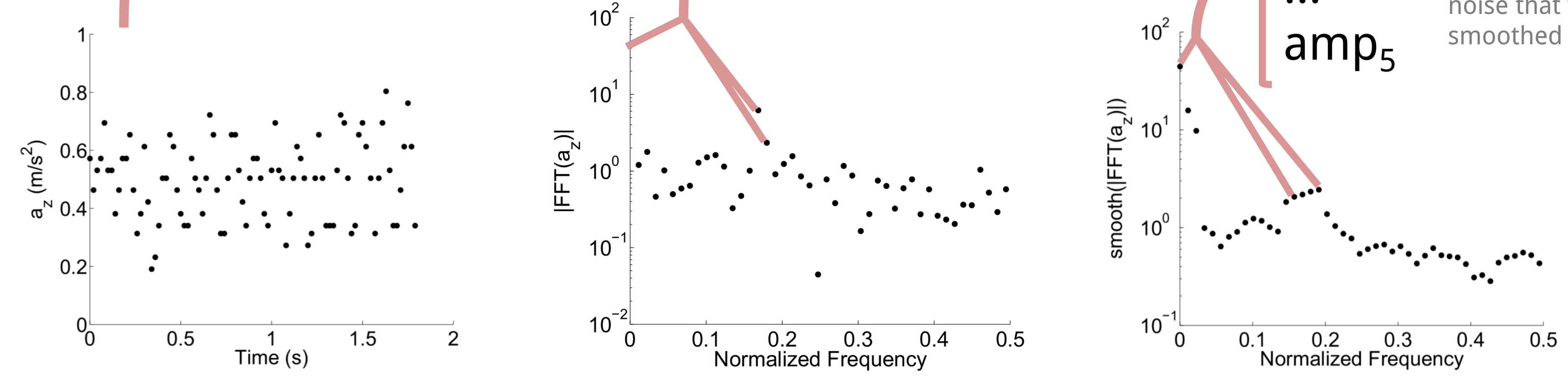
z range
z stdev
x+y range
x+y stdev
x/y range ratio
(*on-line* summary statistics)

$freq_1$
amp_1
...
$freq_n$
amp_n
(too noisy)

Chi-square independence statistic for feature selection: drop peak location (freq), keep amplitudes

$$\text{noise}(x, s) = \sum_{i=1}^{n-w} (s_{i-w} - x_i)^2$$

amp_1
...
amp_5
"noise" term estimates the noise that was smoothed



Time Series Data | **FFT on z-axis** | **Smoothed FFT**

"Raw"

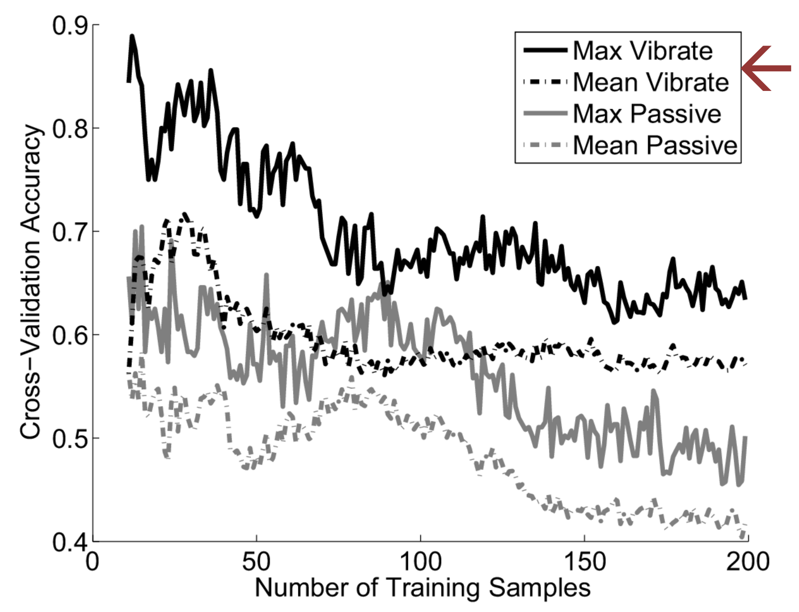
$[x_1 \dots x_n]$
$[y_1 \dots y_n]$
$[z_1 \dots z_n]$

$$n = \frac{t_{end} - t_{start}}{\text{SamplePeriod} \cdot \text{BinWidth}}$$

(binned into fewer samples; value of bin is the mean of its samples)

Selected Results

Analyses: 10-fold cross-validation on 70% of data



Active > Passive

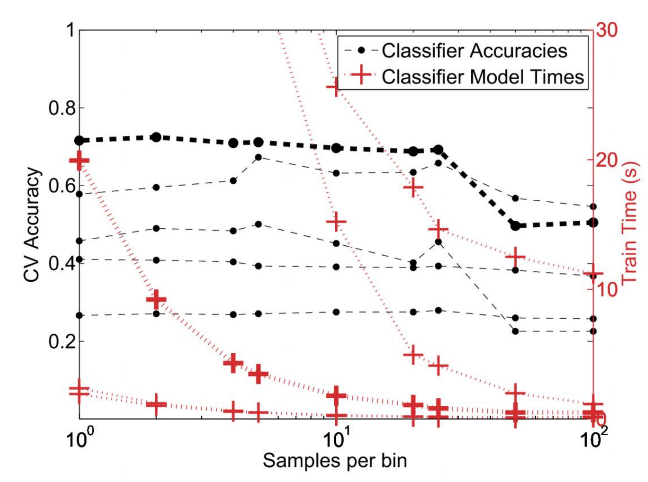
For comparison with existing approaches: gather samples from four locations *without* vibration.

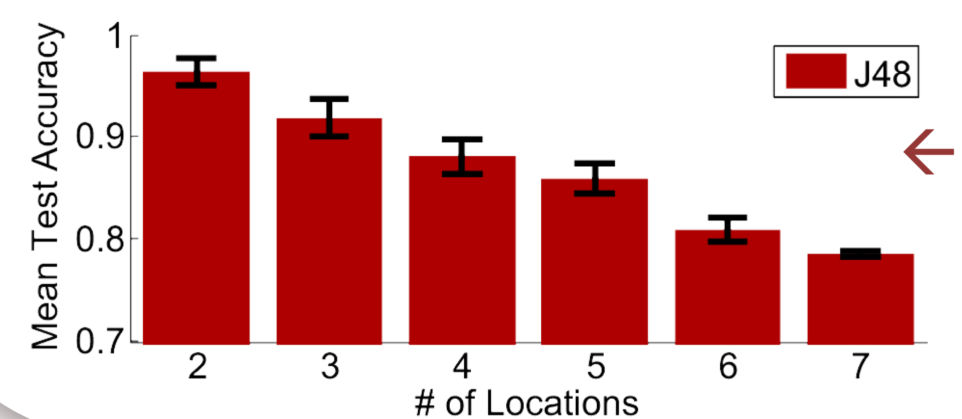
- Best (solid) classifier performs **significantly better** with active data
- On full location set, J48 achieves consistent >78% CV accuracy, 0.5s t_{build}

Raw: Promise, but expensive →

Best classifier (SVM) shown in bold – robust to many irrelevant features

- Achieves ~71% CV accuracy on full set
- Training time becomes large for BinWidth=1 (one feature per datapoint)





← Test Accuracy

Plot: result of applying best classifier from model selection on test data, 95% CI for mean.

Conclusions

- Exploit **active sensing** to distinguish "hard" locations
- Reduce need for user training through **device** specificity
- Features beyond summary stats → better classification

- *Tradeoffs:* feature space size, training time, on-lining
- *Future work:* test across multiple devices & with users

Acknowledgements + References

Tzu-Kuo Huang, Aarti Singh, 10-781 F2010, others...

For paper and full list of references, please visit
www.mrcaps.com/#proj/sel/LocationVibration