AnnoTainted: Automating Physical Activity Ground Truth Collection Using Smartphones

Rahul Majethia\textsuperscript{1}, Akshit Singhal\textsuperscript{2}, Lakshmi Manasa\textsuperscript{1}, Kunchay Sahiti\textsuperscript{1}, Shubhangi Kishore\textsuperscript{1} and Vijay Nandwani\textsuperscript{1}

\textsuperscript{1}Shiv Nadar University, India
\textsuperscript{2}University of Texas, Arlington

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Summary

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   - Achieving Context
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Motivation 1: Contextual Crowdsensing

- Crowd-working platforms like Amazon Mechanical Turk, CrowdFlower and Others are gaining popularity as supplementary incentive providing systems.
- Problem? - Dependent on manual intervention. Don’t utilize the resource availability of devices or their - both of which help achieve better crowdsourcing results.
- Huge scope to do exploit the exploding sensor-array on Smart devices with very accurate location (indoor/outdoor).
Motivation 2: Ground Truth For Activity Recognition

- Unreliable annotation of data by human collectors - insufficient validation methods.
- Imbalanced Datasets - artificial data generation algorithms seldom suffice\(^1\)
- Inadequate indexing of collected data

\(^1\) C. De Souza. Classification of imbalanced classes.
Motivation

Crowdsourcing Activity Data By Providing Incentives?

- Recent trend of utilizing crowd-working platforms and the Sensing-as-a-Service paradigm\(^2\) to achieve Crowd-sensing.
- Collect sensor data opportunistically, or by manual crowd-worker participation.

Exploiting the Ubiquity of the Accelerometer (and location-mining) in Smartphones!

Classifiers need labeled data, but labeled data is expensive.

- **Method 1: Researcher Annotation.**
  Time consuming, might require activity domain information (hence biased), and most of all non-exhaustive in covering all feature distributions.

- **Method 2: Natural Action + Remote Observance.**
  Constrictive, requires human labour - Difficult to Scale.

- **Method 3: Incentivized Crowdworker Annotation.**
  Unreliable, cannot be used for training data. User Incentivization + Lack of Expertise are the demons.
Key Contributions

- Proposing an indexing scheme based on orthodromic geographical structures called tiles
- Providing probabilistically accurate activity data inventory for custom research applications
- Reducing candidate class labels and classification complexity by using location-specific data
AnnoTainted - Framework

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Area Interpretation - Orthodromic Tiles

Figure: Preliminary stage Tile Definition
Area Interpretation - II

- Maptive was used for plotting the obtained locations of the users, with the pre-defined tile size and structure then superimposed on the map as an initial measure.
- Orthodromic area unit, tile, a 3D structure of variable dimensions.
- The orthodromic character allows for the consideration of the curvature and contours of the earth while determining the dimensions.
The Generic Classifier - Prototype

- Choosing Activity Ensemble
  - Micro-activities - Stationary, Walking, Commuting via motorized transport: can be classified based on accelerometer data. Primary focus on Micro-Activities.

- Sampling Frequency
  - Audit the sampling frequencies of crowd-worker Smartphones.
  - Reject devices below a minimum sampling frequency \( (f_m) \) - set to 32Hz based on findings of prior research\(^3\).

The Generic Classifier - Cont’d.

- Placement and Orientation
  - Placement and orientation of Smartphone during data collection affects accelerometer and gyroscope readings. Consideration of orientation and rotational variations achieves up to 85% accuracy\(^4\).
  - Also, detection of human pose has been possible of late. \(^5\)


Procuring Quality Datasets
Probability-based Quantification of Tiles - Activity Trends

- Real-time recognition of activities in each tile using Generic Classifier
- Modelling the probability of an activity as a function of its past occurrences in the said geographical domain

Recurrence Value ($R$) of an activity $a_i$ in tile $j$ is defined as

$$R_{ij} = \alpha \times P_{n-1}(x_i = 1) + (1 - \alpha) \times P_n(x_i = 1)$$

where $x_i$ is the random discrete variable that describes the occurrence of activity $a_i$ and $n$ is the number of recorded instances until that point of time. $\alpha$ is the EWMA weight indicator.
Optimizing Tile Dimensions - Grave Challenge

- Smaller size implies a better approximation of the periphery of geographical structures - but reduces the number of meaningful data instances that can be collected from it.

\[
\begin{align*}
\text{maximize} \quad & \frac{\text{Area}(s_j)}{\text{Area}(T_j)} \\
\text{subject to} \quad & f_i(x) \leq b_i, \quad i = 1, \ldots, m.
\end{align*}
\]

where \(\text{Area}(T_j)\) represents the area of the Tile \(j\) and \(\text{Area}(s_j)\) is the amount of the structure that lies within tile \(T_j\). The minimum constraint functions \(f_i\) can be one or more of \(P(a_i, T_j), N(a_i, T_j)\).
Activity Validation - Alternative Feature Descriptor

- Utilize data streams from the GPS on the crowd-worker’s Smartphone to mine useful parameters such as velocity, altitude and acceleration.
- Determining thresholds or restrictions which can disqualify certain misclassified instances.
- Thresholds are presently established by examining average walking, jogging and commuting velocities and acceleration from past research. Average pedestrian speeds vary from 3.03ft/s-4.5ft/s.
Activity Validation - Thresholds

<table>
<thead>
<tr>
<th>Activity</th>
<th>Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walking&lt;sup&gt;6,7&lt;/sup&gt;</td>
<td>$3.03 \text{ft/s} &lt; V_{GPS} &lt; 4.5 \text{ft/s}$</td>
</tr>
<tr>
<td>Stationary</td>
<td>$V_{GPS} \approx 0 \text{ km/h} &amp; A_{GPS} \approx 0 \text{ m/s}^2$</td>
</tr>
<tr>
<td>Commuting (Motorized)</td>
<td>$A_{GPS} &gt; 4 \text{ m/s}^2$</td>
</tr>
<tr>
<td>Ascending Stairs&lt;sup&gt;8&lt;/sup&gt;</td>
<td>$0.44 \text{m/s} &lt; V_{GPS} &lt; 0.91 \text{m/s}$</td>
</tr>
<tr>
<td>Descending Stairs</td>
<td>$0.47 \text{m/s} &lt; V_{GPS} &lt; 0.87 \text{m/s}$</td>
</tr>
</tbody>
</table>

Table: Activity Validation - Thresholds

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<sup>7</sup> Fruin, J.J. and Benz, G.P., 1984. Pedestrian time-space concept for analyzing corners and crosswalks (No. HS-038 227).

Figure: After Activity Validation
Data Procuring Algorithm

Algorithm 1: AnnoTainted - Data Fetching

Data: $\tilde{A}$, activity subset wanted
Data: $N(\tilde{a}_i)$, # of instances wanted for activity $\tilde{a}_i$
Data: $P(\tilde{a}_i, T_j)$, Probability of $\tilde{a}_i$ at tile $T_j$
Data: $I(\tilde{a}_i, T_j)$, Instance Set of $\tilde{a}_i$ at tile $T_j$
Result: $I_F$, Final Quality Data-set

Function knapsackActivityData($\tilde{A}, N$)

$\begin{align*}
I_F & = \emptyset \\
/* \text{ For all Required Activities } & */ \\
\text{ for } i & = 1, 2, \ldots, |\tilde{A}| \text{ do} \\
/* \text{ Pick Data from high } P(\tilde{a}_i) & */ \\
& \text{ sortIndescending}(P(\tilde{a}_i, T)) \\
& \text{ for } j = 1, 2, \ldots, |T| \text{ do} \\
& \quad \text{ if } \tilde{I} + I(\tilde{a}_i, t_j) \leq N(\tilde{a}_i) \text{ then} \\
& \quad & \tilde{I} = \tilde{I} \cup I(\tilde{a}_i, t_j) \\
& \quad \text{ else} \\
& \quad & /* n = |N(\tilde{a}_i)| - |\tilde{I}| & */ \\
& \quad & \tilde{I} = \tilde{I} \cup (I_n \subseteq I(\tilde{a}_i, t_j)) \\
& \quad & \text{break} \\
& \quad I_F = I_F \cup \tilde{I} \\
& \text{ return } I_F
\end{align*}$

Figure: Data Procuring Algorithm

Figure: Location Based Activity Preference
Generic Classifier Evolution

- Retrain the classifier with only informative examples that are furthest from the decision hyper-plane of the Classifier.

- Exploring Co-Training to correct mis-classified instances using an alternative and independent feature set (e.g. Classification from Activity Validation Only)
Location-Specific Data
Applications of Location-Specific Data Streams

- Data stream of the form \( \{(\text{data}_1, \text{label}_1), (\text{data}_2, \text{label}_2)\} \) is obtained from every tile \( T_j \) and made available for location-specific classification purposes.

- Location sensitive data can also help in representing subsets of the original class labels in a particular tile, thereby building location-specific classifiers with \((l - k)\) labels.
Location-Specific Classifier

- Trained using accelerometer feature vectors collected from a particular tile $T_j$ that have been labelled by the GC - supervised learning.

- As more instances emerge from $T_j$, we apply an incremental learning approach to include these in the training set.

- We define an *epoch* - a set $I_E$ of instances with an adaptive cardinality $c$. After every epoch of feature vectors collected and labeled from $T_j$, the LC is updated taking into account this labeled data.
Accuracy Trade-off

- The LC is trained only on the basis of instances that have been labelled by the GC until the end of the last epoch. Any instance of a new activity is therefore absent from the training set and is hence treated as an anomaly.

- The size of the epoch is application adaptive. Depending on the purpose of usage, classifier confidence correction mechanisms need to be applied.
Confidence Correction

- LC is to be used in conjunction or alternation with the GC, in a sequence determined by weighted random scheduling algorithms.
- For a required confidence threshold $\epsilon \in \mathbb{R}[0, 1]$ (set by the application developer), we use the LC with probability $\epsilon$ and both LC and GC with probability $(1 - \epsilon)$.
- Every time both the classifiers are used, a match (or mismatch) of the classified label updates the confidence value of the LC.
- An epoch ends when the confidence of the classifier has fallen beyond a particular threshold and cannot be sustained any longer without updating.
Applications of Location-Specific Classifiers

- **One-v-All Classification.** Location-specific classifiers can be deployed in the tile or group of tiles corresponding to a city park to identify evolving gathering points. (focus on stationary-v-others classification).

- **Exploit Binary-Class Existence.** Wearable bands at amusement parks can provide insights about which rides peoples tend to stop at, i.e., are interested in, and which ones they usually pass by (Only Stationary and Walking Classes Applicable).
Ongoing and Future Work
Ongoing and Future Work

- Designing multiple classifiers to identify activities from data streams sourced from Smartphones with different sampling frequencies.

- Introducing evolving tile sizes to ensure each tile has maximum probability of occurrence of a predominant activity that can be sourced from it.

- Devising payment models for crowd-workers based on their degree of mobility and the hardware capabilities of their devices.
Additional References


Questions?

"Always ask the questions you want to, life is too short to know if you’ll get a second chance to ask .."  
- Kaitlin Hollon