# Multi-Instance Learning for Coarsely Labeled Time-Domain Inference

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## ABSTRACT

In the supervised learning setting, it is essential to have sufficient labeled data; however, in many domains, such as activity recognition, existing labeled data may not be available and the annotation process is often too cumbersome, time-consuming and prone to human error. In this work, we explore the use of Multiple-Instance Learning (MIL) in order to reduce the need for fine-grained labels. We examine the drop in performance on two existing time-domain gesture-annotated datasets and show that MIL given coarse-grain ground-truth annotations can achieve performance metrics comparable with standard supervised Machine Learning approaches given fine-grain labels. We evaluate the performance in a leave-one-participant-out fashion given all combinations of (1) coarse-grain labels, (2) fine-grain labels, and (3) labels from the held-out participant; our analysis shows that coarse-grain labels may suffice for many applications and that even very few labels from the held-out participant improve performance significantly.

### ACM Classification Keywords

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### Author Keywords

Multi-Instance Learning; Data Collection; Time-Domain; Activity Recognition; Eating Detection; Smoking Detection

## INTRODUCTION

The ubiquity of mobile devices has led to a growing body of research in designing and solving gesture recognition tasks. These efforts have enormous implications in the mobile health community, self-tracking fitness industry and the development of state-of-the-art human-computer interfacing. The standard approach to gestural recognition employs an appropriate supervised classifier, which often performs exceptionally well given large amounts of labeled data and a well-chosen feature representation. The bottleneck to this approach is that acquiring sufficient gesture labels may be challenging, time-consuming or costly. While many techniques have been adopted to reduce the data annotation effort, this often comes at the expense of noisy labels due to factors such as human error.

A commonly used lightweight approach to gesture annotation is experience sampling [-1], where human subjects are prompted to label their current activity or recount their previous activity break-down. This is often best suited when the activities span a large enough time interval; otherwise, acquiring fine-grained labels remains difficult and especially prone to human error.

One of the most common solutions to reduce human error in data collection is video annotation. Although video labeling is relatively robust to human error, it is time-consuming, it introduces privacy concerns, and its power consumption is significantly large, making it impractical for collecting large-scale data in the field. Thus, there has been a significant effort to reduce the use of video recordings for annotated data collection while minimizing the label noise. Thomaz et al. [-1] employ an upward-facing camera mounted on a necklace to capture eating gestures in the field; the camera takes a snapshot of the subject every 30 seconds, significantly reducing the power consumption and labeling efforts required. Parate et al. [-1] use a 6-axis inertial sensor equipped on the upper arm in addition to a wrist-worn sensor in order to visualize the arm movements in a virtual 3D environment. This eliminates the need for video recordings while minimally increasing the risk of error. However, the annotation effort remains cumbersome and does not scale well to field data, because the additional armband is obtrusive.

Trabelsi et al. [-1] eliminate the need for training data altogether by using an unsupervised learning approach based on a Hidden Markov Model. While this technique achieves performance comparable to supervised learning approaches, it only provides a partition of the data by class and does not make precise label predictions in the absence of labeled data. When a large number of classes are present or positive labels are sparse, then sufficient annotated data once again becomes essential to realize robust, deployable classification systems.

Recent work by Stikic and Schiele [-1] explores the feasibility of using Multi-Instance Learning (MIL) to reduce the labeling effort of activity recognition tasks while incurring minimal additional classification error.

In this work we further compare the performance of various Multi-Instance Learning techniques on time-domain inertial


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data and evaluate the extent to which session-level and gesture-level labels improve performance. We additionally assess the boost in performance given a small number of fine-grained labels from the test user in a leave-one-participant-out evaluation. The

## MULTI-INSTANCE LEARNING

In the Multi-Instance Learning (MIL) framework, we jointly consider instances, the atomic units over which predictions are made (i.e. gestures), and bags of instances, which may be sessions or longer, manageable time intervals over which an activity is performed. In the binary setting, each bag is assigned a positive label if at least one instance in the bag is positive; bags with no positive instances are assumed to be negative.

The most naive MIL approach is Single-Instance Learning (SIL) [-1], which makes the usually false assumption that every instance in a positive bag is positive. This reduces the problem to a supervised instance-level classification task, which is generally done using a Support Vector Machine (SVM). When positive instances are sparse, the SIL assumption significantly hurts the classification performance.

In the activity recognition setting, Stikic and Schiele use the Maximum Pattern Margin Formulation (miSVM) originally proposed by Andrews et al. [-1] in order to account for the sparsity of positive bags. Due to the non-convexity of the objective function, they use a heuristic to learn the separating hyperplane. They initially train an SIL SVM, whose decision hyperplane is used to relabel the most positive predictions within positive bags. The SVM is then retrained on the relabeled data and the process is repeated until the labels converge. Although this approach accounts for the sparsity of positive gestures, it tends to over-predict the positive class [?] and has no mechanism to adjust the sensitivity based on known density.

Bunescu and Mooney [-1] deal with the challenge of sparse positive bags by using an adaptive SVM constraint (sMIL). In particular, they formulate the MIL constraint that there exists at least one positive instance in every positive bag $X$ as follows

$$w\frac{\phi(X)}{|X|}+b \geq \frac{2-|X|}{|X|}-\xi_X$$
$$\xi_X \geq 0$$

where $w\frac{\phi(X)}{|X|}+b$ is the normalized prediction scores under the feature function $\phi$, weights $w$ and bias $b$, and $\xi_X$ is the non-negative slack parameter that allows some extent of misclassification of instances in $X$ to avoid over-fitting the model to the training data. When the bag size $|X|$ is small, the right-hand side becomes larger, suggesting that smaller positive bags are more informative.

Bunescu and Mooney additionally introduce a balancing parameter $\eta$, indicating the expected class distribution of instances within bags. The sparse balancing MIL (sbMIL) approach initially trains a sMIL classifier, then relabels the $\eta\,|X|$ most positive instances as positive and the remaining instances as negative. The final hyperplane is then learned using SIL given the relabeled data.

## EXPERIMENTAL SETUP

In order to reason in a practical sense about the trade-off between performance and labeling effort under various MIL formulations, we perform several evaluations on two existing datasets: the lab-20 eating detection dataset developed by Edison Thomaz [-1] and the RisQ dataset developed by Parate et al. [-1]. In order to assess how well the model generalizes to unseen users, we perform leave-one-participant-out (LOPO) evaluations; that is, the model is trained on all but one participant and then evaluated on the held out participant.

The lab-20 eating dataset comprises of 25Hz 3-axis accelerometer data collected using a wrist-worn inertial sensor from 20 individuals. Individuals were provided food to eat and were asked to perform other possible confounding actions as they please, including talking on the phone, brushing their teeth and combing their hair. The average duration across participants is 31 minutes 21 seconds and comprises of approximately 48% eating sessions. Note, however, that the proportion of eating gestures is much smaller, since non-eating gestures are frequently present within eating sessions.

We use Thomaz's evaluation as the baseline result for comparison. In his work, he uses a Random Forest classifier over statistical features extracted over windows of about 6 seconds with 50% overlap. He reports a 0.42 average LOPO f1 score. We achieve the same performance using a linear SVM.

The RisQ dataset contains fused 9-axis inertial data in the form of quaternions from ?? subjects. Parate reports a precision of 91% and recall of 81%. The pipeline consists of (1) computing the trajectory from the quaternion stream, (2) identifying candidate windows by locating peak-trough-peak patterns, (3) extracting angle, velocity, displacement and duration features, (4) classifying windows using a Random Forest and (5) smoothing the predictions using a Conditional Random Field.

In our work, we use the same pipeline but replace the Random Forest with a Multi-Instance Learner, allowing labels to be sparse.

## EVALUATION

### Lab-20 Eating

In order to reason about the effectiveness of MIL techniques in gesture recognition, we evaluate the average LOPO performance for various bag sizes. Figure 1 shows that as the bag size decreases, the performance of each MIL technique drops, and it is upper bounded by the baseline SVM performance.

Evidently, the performance is greater given more finely-grained labels. However, given that these labels may be difficult to acquire, we must ask: How many such labels do we need?

In order to address this, we evaluate several experiments in which $M$ fine-grained labels are provided by 5 participants and $N$ coarse-grained labels for a fixed bag size ?? are provided

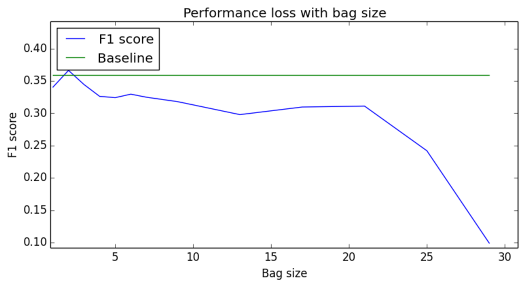


**Figure 1. Average F1 Score across LOPO evaluations of sbMIL**

by the remaining 14 participants. In order to enhance the model's generalization capabilities, we additionally include *K* instances from the held-out participant in the training data, which are then excluded from the test set. Our experiments involve varying the values of *N*, *M* and *K*.

Figure ?? shows the best cross-validated F1 Score for SIL, miSVM, sMIL and sbMIL averaged over each held-out participant. The bag size is ??, the value of N is fixed to be maximal for each training set, K is set to 10 and the value of M is varied. Figure ?? shows the same evaluation when N is fixed to 0, i.e. the training set consists of only single instances from 5 participants.

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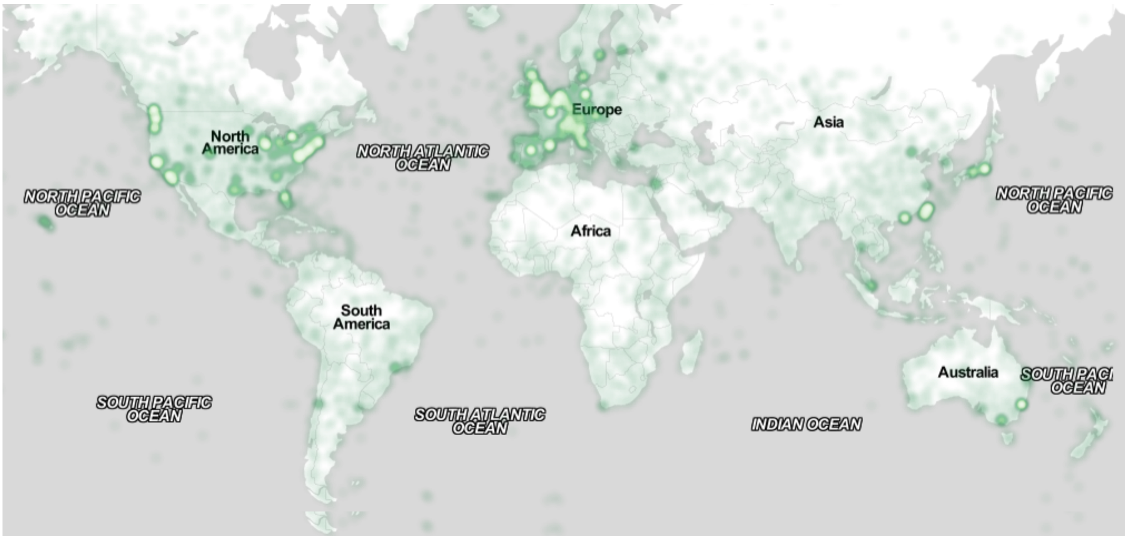


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