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 (1) coarsely labeled field data, (2) finely labeled lab data and (3) coarsely labeled data from the held-out participant. Our analysis shows that we can achieve competitive performance given a small number of fine-grained labels in addition to many coarse-grained labels and that even very few labeled sessions from the held-out participant improve performance significantly. We use this to design a system that gives recommendations to developers on the granularity of the field data, based on an initial lab dataset.

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous; See http://acm.org/about/class/1998/ for the full list of ACM classifiers. This section is required.

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.

Every submission will be assigned their own unique DOI string to be included here.

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. Although they show that comparable performance can be achieved with coarse-grained labels, they do not consider the case when the developers provide a small number of fine-grained labels in addition to field data.

In this work we demonstrate the on time-domain inertial 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 correspond to 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

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

where $w\frac{\phi(X)}{|X|} + b$ is the normalized prediction scores under the feature function ϕ, weights w and bias b, and ξ_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 η, 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.

In this work we employ the sbMIL due to the sparsity of positive labels.

DATA

In order to reason in a practical sense about the trade-off between performance and labeling effort under the MIL formulation, we perform several evaluations on two existing datasets: the lab-20 eating dataset developed by Edison Thomaz [-1] and the RisQ smoking 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.

Lab-20 Eating

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 15 statistical features (mean, variance, skew, kurtosis and root mean square over each axis) extracted over windows of 6 seconds with 50% overlap. He reports a 0.42 average LOPO f1 score. We achieve similar performance using a linear SVM.

RisQ Dataset

The RisQ smoking dataset contains 50Hz fused 9-axis inertial data in the form of quaternions from 15 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 37 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 classifier with a sbMIL classifier to allow for sparse labels.

(a) M = 150 (b) M = 300 (c) M = 450

Figure 2: Average LOPO performance of sbMIL on Lab-20 dataset as a function of the bag size given 150, 300 and 450 additional labeled training instances respectively

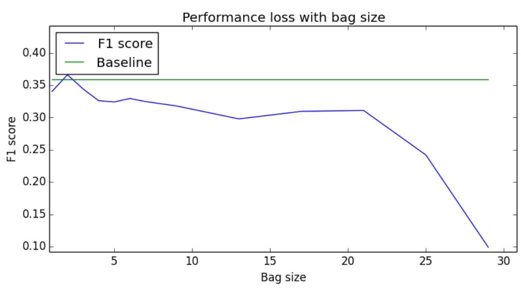

Figure 1: Average LOPO f1 score of sbMIL on Lab-20 dataset as a function of the bag size

EXPERIMENTAL SETUP

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 for the Lab-20 eating dataset 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 are provided by the remaining 14 participants. The coarse-grained labels may either be labeled sessions, which may vary in duration, or partitions of the data with a fixed duration. As a personalization step for enhancing performance, 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.

In each of the experiments, a subset of the training data is used and is therefore selected uniformly from the entire training data; to smooth out noise introduced by the randomness, the performance is averaged over 10 trials. The performance reported is in each case the best performance achieved using cross-validation over the model hyperparameters. These parameters include the expected class weights, the sparse balancing parameter η and the SVM regularization constant C.

EVALUATION

Lab-20 Eating

From figure 1 it is clear that the performance drops very quickly as the granularity of the labels decreases. However, figure 2 demonstrates that this drop in performance is minimal even for large bag sizes, if in additional to coarse labels, fine grained labels are provided. This is shown when 150, 300 or 450 labeled training instances are provided from the lab data. When $M = 450$, the performance remains roughly the same, meaning it may be acceptable to use field data with bag sizes of up to 300.

Figure 3 shows the average LOPO performance on the Lab-20 eating dataset as the number of bags increases for bag sizes of 15, 150 and 300 instances. These correspond roughly to 1.5, 15 and 30 minute bags respectively. As the amount of training data increases, the f1 score increases, as expected. Interestingly, the performance is greater given larger bags, even when fewer labels are available. This suggests that many unlabeled instances are preferable to few labeled instances. This is the essential advantage of using MIL techniques.

RisQ Dataset

In the RisQ dataset

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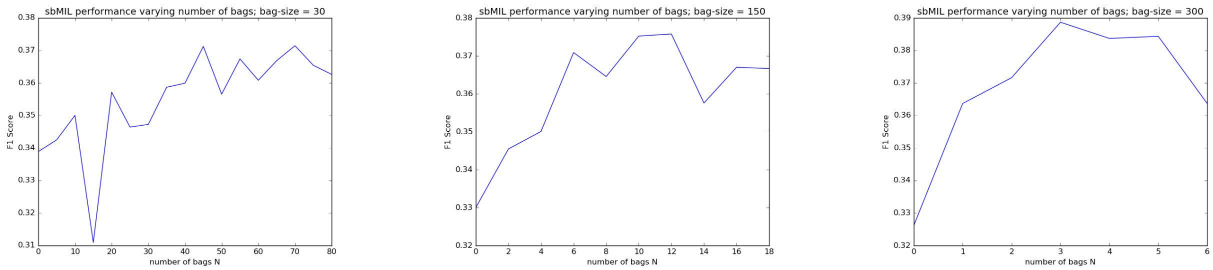

(a) bag size : 15 (1 min 30 s)　(b) bag size : 150 (15 min)　(c) bag size : 300 (30 min)

Figure 3: Average LOPO performance of sbMIL on Lab-20 dataset as a function of the number of bags given bag sizes of 15, 150 and 300 respectively

	Test Conditions		
Name	*First*	*Second*	*Final*
Marsden	223.0	44	432,321
Nass	22.2	16	234,333
Borriello	22.9	11	93,123
Karat	34.9	2200	103,322

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