CLEAVER: CLASSIFICATION OF EVERYDAY ACTIVITIES VIA ENSEMBLE
RECOGNIZERS

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ABSTRACT

CLEAVER: CClassification of Everyday Activities Via Ensemble Recognizers

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Physical activity can have immediate and long-term benefits on health and reduce the risk for chronic diseases. Valid measures of physical activity are needed in order to improve our understanding of the exact relationship between physical activity and health. Activity monitors have become a standard for measuring physical activity; accelerometers in particular are widely used in research and consumer products because they are objective, inexpensive, and practical. Previous studies have experimented with different monitor placements and classification methods. However, the majority of these methods were developed using data collected in controlled, laboratory-based settings, which is not reliably representative of real life data. Therefore, more work is required to validate these methods in free-living settings.

For our work, 25 participants were directly observed by trained observers for two two-hour activity sessions over a seven day timespan. During the sessions, the participants wore accelerometers on the wrist, thigh, and chest. In this thesis, we tested a battery of machine learning techniques, including a hierarchical classification schema and a confusion matrix boosting method to predict activity type, activity intensity, and sedentary time in one-second intervals. To do this, we created a dataset containing almost 100 hours worth of observations from three sets of accelerometer data from an ActiGraph wrist monitor, a BioStampRC thigh monitor, and a BioStampRC chest monitor. Random forest and k -nearest neighbors are shown to consistently perform the best out of our traditional machine learning techniques. In addition, we reduce the severity of error from our traditional random forest classifiers on some monitors using a hierarchical classification approach, and combat the imbalanced nature of our dataset using a multi-class (confusion matrix) boosting method. Out of the

three monitors, our models most accurately predict activity using either or both of the BioStamp accelerometers (with the exception of the chest BioStamp predicting sedentary time). Our results show that we outperform previous methods while still predicting behavior at a more granular level.

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Chapter 1

INTRODUCTION

Physical activity is important for improving health and reducing risk for diseases such as cardiovascular disease, stroke, obesity, diabetes, metabolic syndrome, and some cancers [5, 55, 28]. Accurate measures of physical activity are vital to obtaining a better understanding of the dose-response relationship between physical activity and health [50]. Over recent years, considerable interest has grown in regards to the assessment of physical activity, and human activity monitoring and recognition has been widely studied, using wearable sensors called activity monitors that enable continuous monitoring [55, 36]. Activity monitors are capable of evaluating activity type, duration, and intensity, and specifically accelerometer-based activity monitors have become the ideal measurement tool of choice. They are inexpensive, lightweight, and small enough so that they are unobtrusive to the participants wearing them for long periods of time, making objective activity monitoring practical. Accelerometers are widely used by researchers for assessing physical activity, especially for assessing free-living subjects (i.e., in real-world conditions). [15, 38, 57, 6, 11].

Objective physical activity assessment in a free-living environment is a necessity for a comprehensive understanding of the association between physical activity and health. There have been many successful physical activity classification studies with accelerometers in laboratory-controlled settings which enable the data to be of high quality [19, 21, 38, 6]. However, there is evidence that the laboratory data does not accurately represent human behavior in a free-living, uncontrolled setting [27, 17]. Data collection in a controlled lab setting is also limited to short durations, which is unrealistic for real life applications when an individual would wear the activity monitor for longer periods of time [38].

Earlier work has implemented regression methods to model the relationship between accelerometer data and energy expenditure [8, 13, 24]. More recently, machine learning algorithms have been used in activity classification research, as they can fit a greater variety of activity metrics and provide better prediction accuracy than the regression techniques [6, 15, 57]. However, further exploration of machine learning methods needs to be done in this domain.

Dr. Sarah Kozey Keadle of the Cal Poly Kinesiology and Public Health Department has conducted research validating commercially available monitors for assessing sedentary behavior [33], validating two novel machine learning methods and a laboratory-calibrated neural network in a free-living environment [37], comparing hip and wrist accelerometer estimates of moderate-vigorous physical activity [59], and predicting sedentary behavior from a wrist-worn accelerometer using machine learning [41]. However, these studies had small samples and did not ensure a range of activity types were included in the validation. To address this gap, Dr. Keadle recruited 25 subjects, who participated in two two-hour free-living activity sessions over a period of seven consecutive days. Participants wore accelerometers on the wrist, thigh, and chest, and were directly observed by the trained research assistants during these sessions. The direct observation served as the ground truth for this work; we combined the ground truth observation data with the raw accelerometer data from the three activity monitors to create our dataset.

The objective of this work is to predict an individual’s physical activity/posture based on wrist, thigh, and chest accelerometer data. Dr. Keadle is particularly interested in investigating the following:

1. What monitor placement and machine learning method best determines sedentary vs. non-sedentary behavior?
2. How do our sedentary vs. non-sedentary models compare to previous methods?

3. What monitor placement and machine learning method best estimates activity intensity level?
4. What monitor placement and classifier best predicts posture into 5 general posture classes?
5. What monitor placement and machine learning model best predicts posture/intensity into 14 posture classes?

While we were addressing Dr. Keadle's questions, we came up with a couple additional questions of our own. Specifically, we were interested in investigating new approaches to predict our most granular set of 14 class variables. Our additional questions are:

6. Does a hierarchical random forest ensemble improve classification accuracy for predicting 14 posture classes?
7. Does using a confusion matrix boosting method improve classification accuracy for predicting 14 posture classes?

To address our seven research questions, we used the activity monitor data and the ground truth observation data from the Cal Poly Kinesiology and Public Health Department and created a dataset on which we ran a battery of machine learning methods.

The contributions of this work are as follows:

- Development of the proper ground truth dataset.
- Testing a range of machine learning techniques on three novel sets of monitor data.

- Demonstrating that the predictions of our most granular, 14-class models can be aggregated into 4 class variables and produce similar distributions to new models that have been retrained to learn the less granular coding scheme.
- A hierarchical classification schema that performs competitively with traditional classification models.
- Implementation of a multi-class boosting method that uses the confusion matrix as an error measure to better train classifiers on our imbalanced dataset.
- A collection of studies that address our seven research questions.

This document is organized as follows. Chapter 2 covers background information relevant to physical activity classification and machine learning methods. Then Chapter 3 explores related work in the field of physical activity recognition. Chapter 4 describes our experimental design and implementation. Results are presented in Chapter 5, and Chapter 6 discusses the conclusions of this study. Finally, Chapter 7 concludes with potential directions for future work.

Chapter 2

BACKGROUND

Physical activity is one of the most beneficial things a person can do for their health [32]. Not only does it improve overall physical and mental health, but also reduces the risk of chronic noncommunicable diseases such as cardiovascular disease, obesity, diabetes, metabolic syndrome, and some types of cancer. Cardiovascular disease (CVD) is the leading cause of death in the world, killing 17.3 million per year - this figure is expected to rise to over 23.6 million by 2030 [2]. Obesity and diabetes are key risk factors associated with CVD and are also among the top risks and causes of global deaths. In the United States, 39.8% of adults are considered obese and 9.4% of the entire American population is diabetic [10, 1]. As technology continues to influence modern lifestyle to become more sedentary and relatively inactive compared to previous generations, promoting an active lifestyle is crucial to improving health and reducing preventable deaths in the future. According to the American Heart Association's 2015 Heart Disease and Stroke Statistics Update, 31% of U.S. adults report participating in no leisure time physical activity [2]. Objective and accurate methods of measuring physical activity are required in order to improve our understanding of the exact association between physical activity and specific health outcomes.

Traditionally, physical activity has been measured by self-report questionnaires. Although self-reports are easily administered, low-cost methods that can collect detailed information about an individual's physical activity, people tend to overestimate the amount of time they spend participating in vigorous activity, and underestimate the amount of time they spend participating in unstructured daily physical activity (e.g., walking) [15]. Wearable activity monitors have been developed to objectively capture physical activity with respect to type, duration, and intensity by analyzing

and quantifying human body movements. These activity monitors have advanced from only being able to evaluate the quantity of physical activity (e.g., pedometers), to activity recognition systems that are capable of assessing the quantity and quality of physical activity (e.g., fitness and activity trackers - Fitbit, Apple Watch, Garmin) [27]. Wearable activity sensors provide feedback about the user’s routine with respect to physical activity and thus motivate a more active lifestyle [21]. Wearable accelerometers have been deemed the ideal choice for collecting measurements of physical activity and sedentary behavior. Their small dimensions and light weight allow them to be conveniently worn for extended periods of time while collecting data across multiple aspects of physical activity (i.e., total activity, time in different activity intensity levels, predicted energy expenditure) and remaining relatively inexpensive, making them the most widely studied in the activity recognition field.

Over recent decades, researchers have used classification algorithms with accelerometer data to measure and predict energy expenditure [57, 19], sedentary time[37], activity type and intensity [6], locomotion time [56], and other aspects of human activity. Earlier research focused on classifying activity from data collected in laboratory settings. Although the most common daily activities - sitting, standing, walking, and lying - have been successfully recognized with accelerometers [39, 22, 43, 23, 29, 40], it’s been shown that experiments on laboratory data are not accurate indicators for how the classifiers perform on real-life data [27]. This is due to the fact that laboratory-collected data can potentially fail to represent behavior that happens outside of the laboratory. Studies using laboratory data tend to use data that cover minimal periods of time per activity - sitting, walking on a treadmill, or lying down for a number of seconds, for example. The amount of variability of movement during these couple of minutes in each activity is more likely to be reduced since the activity is only performed for a short period of time. This makes small postural changes, such as typing while sitting, less likely to be recorded because the sitting activity is only

recorded for a few seconds. Because capturing real daily life data is essential to better understand and quantify the relationship between physical activity and specific health outcomes, it is important to evaluate free-living data to achieve valid classification accuracy. Researchers have experimented with a range of data processing methods for activity recognition. Earlier work has used simple regression methods to estimate energy expenditure [8, 13] and classify physical activity [24]. More recently, machine learning approaches have been explored in the physical activity recognition domain, and shown to outperform traditional regression methods [15, 6, 57]. Machine learning methods have the ability to capture more sophisticated dependencies and nonlinearities than simple regression methods; therefore, they can classify specific behaviors that cannot be characterized by simple linear relationships with acceleration data [19]. A variety of machine learning algorithms have been applied to physical activity classification, including support vector machines (SVMs) [53, 27, 38], random forests [18, 19], decision trees [6, 27], and artificial neural networks [15, 57].

2.1 Classification

The main objective of this work is to determine an individual’s activity based on their movements collected from an ActiGraph wrist monitor, a BioStampRC thigh monitor, and a BioStampRC chest monitor. In attempt to do so, this work uses the following models: k -nearest neighbors, support vector machines (SVM), random forests, boosting algorithms, and a hierarchical ensemble.

2.1.1 K -Nearest Neighbors

The K -Nearest Neighbors (KNN) classifier is one of the simplest supervised learning classification algorithms [26]. KNN is a lazy evaluation algorithm; it doesn’t use the training set to build a model, but rather keeps the training set to predict the test

Figure 2.1: KNN example: The star will be classified by the majority vote of its k -nearest neighbors [47]

set. KNN predicts the class of a point d based on its proximity to points with a known class label. The algorithm works by calculating the distance between point d and every other point in the training set D , selecting the k most similar (i.e., closest) points to d , and assigning d 's class to be the majority class from the k closest points. As demonstrated in Figure 2.1, different chosen values of k may result in a different classification of a point d . The distance (or similarity) between two points can be calculated by multiple distance and similarity measures. Some common distance/similarity measures include:

- Euclidean distance:

$$d(d_1, d_2) = \sqrt{\sum_{i=1}^n (d_1[A_i] - d_2[A_i])^2} \quad (2.1)$$

- Manhattan distance:

$$d(d_1, d_2) = \sum_{i=1}^n |d_1[A_i] - d_2[A_i]| \quad (2.2)$$

- Cosine similarity:

$$\cos(d_1, d_2) = \frac{d_1 \cdot d_2}{\|d_1\| \cdot \|d_2\|} = \frac{\sum_{i=1}^n d_1[A_i] \cdot d_2[A_i]}{\sqrt{\sum_{i=1}^n d_1[A_i]^2} \cdot \sqrt{\sum_{i=1}^n d_2[A_i]^2}} \quad (2.3)$$

2.1.2 Support Vector Machine

A Support Vector Machine (SVM) is a supervised machine learning algorithm that essentially builds a hyperplane separating two classes in d -dimensional feature space [12]. Given a training set $(X, Y) = (\bar{x}_i, y_i)$, an SVM attempts to select an optimal hyperplane $h(\bar{x}) = \mathbf{w} \cdot \bar{x} + b$, w.r.t. a specialized criterion. The optimal hyperplane will have maximized the distance between the nearest data point from either class of the training set, called the margin. SVMs use the points in the training set that are closest to the hyperplane, called support vectors, to establish the hyperplane equation. The optimization problem of finding the hyperplane that maximizes the margin is represented as:

$$\min_{\mathbf{w}, b} \left(\frac{\|\mathbf{w}\|^2}{2} \right) \quad (2.4)$$

subject to constraints:

$$y_i(\mathbf{w} \cdot \bar{x}_i + b) \geq 1, \forall \bar{x}_i \in X \quad (2.5)$$

Figure 2.2 shows potential hyperplanes and an optimal hyperplane separating two classes.

(a) Some potential hyperplanes separating two classes.

(b) The optimal hyperplane maximizes the margin between two classes.

Figure 2.2: Support Vector Machine hyperplane example [44]

2.1.3 Random Forests

Random Forest is a bagging extension of the Decision Tree classifier [7]. Decision trees are simple and efficient supervised learning classifiers that represent a tree-like model of decisions. The C4.5 recursive decision tree induction algorithm, proposed by Quinlan in [52], divides the data into smaller and smaller subsets based on chosen attributes until either the subset contains only points with the same class label or there are no more attributes to split the data on, and constructs the tree. The splitting attribute can be selected based on the information gain measure or the information gain ratio, so that the data is split into the purest subsets.

Shown in Algorithm 1, Random Forest builds an ensemble of decision trees, where each decision tree is built from a subset of the training data and a subset of the attributes. The subsets of training data are built from resampling the training set with replacement, while the subsets of attributes are randomly sampled without replacement. By creating decision trees from different subsets of the training data, Random Forests can help prevent the overfitting problem that decision trees sometimes exhibit. In addition, combining the decision trees allows variance to decrease without increasing the bias, which allows for Random Forest to achieve a higher accuracy than decision trees.

2.1.4 Boosting

Boosting is an ensemble technique for reducing misclassification error of any given classifier. The main idea of boosting is to sequentially train a set of weak classifiers into a strong one, and in doing so generating an ensemble of classifiers. Each new classifier is built to correct its predecessor's errors by giving higher weights to the misclassified data points in the training set. This way, the new classifier knows which points to focus on. The final classifier is built through weighting the full ensemble's

Algorithm 1 Random Forest

Data: Training set D , attribute set A

Result: Random forest classifier

select m = number of attributes to select for each decision tree

select N = number of decision trees to build

while $j \leq N$ **do**

 | build set $D_j \subseteq D$

 | select m random attributes $A_1^j, \dots, A_m^j$

 | build decision tree T_j

end

for each data point $d \in D$ **do**

 | get classification decisions $c^1, \dots, c^N$ from trees $T_1, \dots, T_N$

 | $\text{class}(d_i) = \text{mode}(c^1, \dots, c^N)$

end

votes by their weighted classification error rate. The classic example of a boosting classifier is AdaBoost, or the Adaptive Boosting algorithm [25]. In our work, we use an extension of the original AdaBoost algorithm, AdaBoost-SAMME [62], which we describe in further detail in Chapter 4.

Similar to AdaBoost, gradient boosting also sequentially trains an ensemble of classifiers, with each new classifier attempting to correct the previous one. The difference between gradient boosting and AdaBoost is that, rather than updating the weights of every misclassified point at every iteration, gradient boosting attempts to train the new classifier with the residual errors made by its predecessor. It gradually minimizes the loss function using gradient descent to find the mistakes in the previous classifier's attempt.

2.1.5 Hierarchical Classification

Traditional classification problems involving no inherent class hierarchy are sometimes referred to as flat classification problems. In hierarchical classification problems, the classes are structured in a hierarchy with parent-child relationships between classes. This hierarchical structure can either be a tree or a directly acyclic graph (DAG). In

this work, we use a tree-based class hierarchy, as each child posture can only belong to one parent posture.

Figure 2.3: Four types of hierarchical classification approaches [46]

Figure 2.3 shows four types of hierarchical classification approaches, where the dashed squares illustrate classifiers predicting child classes. A simple example of a hierarchical classification problem - classifying fruit - is shown in Figure 2.4. The flat classification approach (Figure 2.3(a)) is the simplest as it predicts only leaf classes and works like a traditional classification algorithm. For instance, in the example illustrated in Figure 2.4, a flat classifier would be predicting the following class labels: “red apple”, “cherry”, “strawberry”, “banana”, “lemon”, “green apple”, “pear”, and “green grape”. Hierarchical classification algorithms can be categorized into two approaches: local or global. The global approach trains a single model for all of the hierarchical classes. In contrast, local approaches train a hierarchy of models, where one model is associated with each class node and predicts the subclasses of this node. Depending on how the classifiers explore the local hierarchy, local approaches

fall into three categories: local per node, local per parent node, and local per level [54]. Figure 2.3(b) illustrates the local classifier per node approach, where a single binary classifier is trained on each node of the hierarchy, excluding the root node. This results in a hierarchy of flat classifiers. For the example in Figure 2.4, binary classifiers are trained on all nodes except for the root “Fruit” node. In the local classifier per parent node approach, each parent node has a classifier that is trained to classify its child classes, shown in Figure 2.3(c). Per the example, separate classifiers are trained on “fruit”, “red fruit”, “medium-sized red fruit”, “small red fruit”, “yellow fruit”, “thin-shaped yellow fruit”, “round yellow fruit”, “green fruit”, “medium-sized green fruit”, “small green fruit”, “round green fruit”, and “non-round green fruit”. Finally, the local classifier per level approach trains one flat classifier on each hierarchical

Figure 2.4: Example of a hierarchical classification problem

level. Figure 2.3(d) illustrates this classifier.

In this work, we use the local classifier per parent node approach on two different hierarchical class structures.

Chapter 3

RELATED WORK

Previous studies have validated various monitor types and monitor placements using different data processing methods in controlled laboratory settings. Zhang et al. [61] successfully classified 32 physical activity types using an Intelligent Device for Energy Expenditure and Activity (IDEEA), a new microcomputer-based portable physical activity measurement system consisting of several accelerometers positioned on the chest, thighs, and feet. Bonomi et al.[6] used decision tree models to identify seven activity classes from accelerometers placed on participants' lower backs. Although they were able to obtain a classification accuracy of 93% using intervals of 6.4 or 12.8 seconds, future work needs to be done in order to validate their models in a free-living setting. Gyllensten et al. [27] trained support vector machine, feed-forward neural network, decision tree, and majority voting models on a waist-mounted accelerometer, and evaluated the reproducibility of the accuracy of laboratory-trained classifiers on real life data. They found that the performance of all four laboratory-trained classification algorithms significantly decreased when using free-living data, with the largest decrease in F -score being from 99% to 55%.

Staudenmayer et al. [56] developed a method using neural networks, SVMs, and random forest to predict energy expenditure, activity intensity, sedentary time, and locomotion time on laboratory data from a wrist-worn ActiGraph monitor. Using 15-second windows, their random forest performed the best out of all of their machine learning models, predicting activity intensity with 75% accuracy, locomotion time with 99% accuracy, and sedentary time with 96% accuracy. Although the Staudenmayer method provides evidence that wrist acceleration data can be used to estimate energy expenditure and detect sedentary and locomotion time relatively accurately

on laboratory data, it doesn't go without its limitations. For instance, they placed the ActiGraph on the dominant wrist rather than non-dominant wrist, which is what is used in the National Health and Nutrition Examination Survey's (NHANES) ActiGraph data analysis, the largest nationally representative database for objectively monitored human physical activity. The data in their study was also collected from a small number of participants in a laboratory setting, which is considered a limitation as there have been studies that show models trained on laboratory collected data do not necessarily perform as well on free-living data [27, 20]. Staudenmayer et al. obtained some promising preliminary results by applying their methods to two participants' free-living wrist accelerometer data, but additional investigation is needed to further validate that their methods work with free-living data. Our work builds on the work in [56] by collecting a larger sample of free-living data from an ActiGraph placed on the non-dominant wrist, and making use of the same seven variables to summarize acceleration signals of 1 second intervals. We also used this series of features to summarize thigh and chest-mounted accelerometer signals.

Ellis et al. [20] classified hip and wrist accelerometer data into four activity classes using a two-layer machine learning method consisting of a random forest and hidden Markov model. In their study, 40 participants were recruited and free-living data was collected over seven consecutive days as a SenseCam wearable camera captured ground truth behavior data. Their hip classifier achieved an average of 89.4% balanced accuracy over the four activities, and their wrist classifier obtained 84.6% using one-minute interval windows. Ellis et al. captured their ground truth using a SenseCam which took still images every 20 seconds. In our work, we collect video using a GoPro Hero 5 camera, which allows us to perform more detailed analysis and therefore classify more detailed activity classes than when using the still images from the SenseCam. We set up a similar experiment to [20] to observe how our models perform when trying to predict the same activity classes.

Dr. Sarah Kozey Keadle of the Cal Poly Kinesiology and Public Health Department collaborated with Cal Poly Data Science Capstone students to develop machine learning models to predict sedentary versus non-sedentary behavior using free-living data from a wrist-worn accelerometer [41]. Their study uses a subset of the same Actigraph wrist monitor data that is used in this thesis, and therefore lays some of the groundwork for our work. The Data Science Capstone work considers 25 people who wore an Actigraph wrist monitor for seven consecutive days and participated in two two-hour direct observation sessions belonging to one out of five activity domains (active leisure, sedentary leisure, household, errands, and work). Cal Poly Kinesiology and Public Health Department research assistants manually coded the ground truth criterion into seven activity classes: active, sitting still, sitting and typing, sitting with upper body movement, lying, kneeling, and private / not coded. Because the ground truth criterion is manually coded via a frame-by-frame analysis of the observation video, only 20 observation sessions amongst 12 participants were coded completely by the time of their investigation. Their most successful model was their random forest classifier, which predicted sedentary vs. non-sedentary behavior with an overall accuracy of 73.98% using k -fold cross validation ($k = 5$) [41]. The Data Science Capstone work demonstrated that models trained on free-living data more accurately predict sedentary behavior at the second level than previous lab-trained models, specifically [56]. The work documented in this thesis uses the completely coded dataset of 25 participants wearing the Actigraph on their wrist, in addition to two BioStamp monitors on their thigh and chest. Using the Data Science Capstone team’s project as baseline, we continue and expand on their work by exploring more models and increasing the granularity of the activity types we are predicting.

Chapter 4

DESIGN AND IMPLEMENTATION

This work utilizes data collected by the Cal Poly Kinesiology and Public Health Department. We used the raw accelerometer data they collected from three different monitors to create features that describe participants' acceleration per second, and merged these features with the ground truth observation data they provided to construct our training set. We used flat classification algorithms as well as a top-down hierarchical classification approach to predict sedentary versus non-sedentary behavior and type of physical activity to different levels of granularity.

4.1 Kinesiology Experimental Design

The data collection took place at the Cal Poly Department of Kinesiology and Public Health. In total, 25 participants between 18-59 years old were recruited and signed informed consent documents. Each participant completed two two-hour sessions over a period of seven days. While they were observed, they wore two BioStamp accelerometers - one on their chest and another on their thigh, and one ActiGraph monitor on their non-dominant wrist. During these direct observation sessions, the research assistants recorded participants with a GoPro Hero 5 camera, which served as the ground truth, as they completed two out of five activity domains that are representative of activities done in daily life with distinct movement patterns: active, household, errands, leisure, and work.

Once data was collected, research assistants performed a frame-by-frame analysis of the observation session video recordings using an event recorder program, Observer XT. Each video was manually coded to identify type of behavior and posture

Activity Domain	Description
Household	Household activities or self-care activities for a minimum of 30 minutes observed time (e.g., meal prep, clean up)
Work	Typical work-related activities; getting up from the chair at least twice during observation
Errands and Transportation	Behaviors in community (e.g., errands, shopping, attending an event) Some forms of transportation (car, bus, train, walk, or bike)
Sedentary Leisure	Typical leisure time behaviors; out of work/school or on the weekend. At some point watching TV/video or playing video games
Active Leisure	Spending at least 30-45 minutes in exercise or sport

Table 4.1: Activity domains and participant directions

according to a multi-pass coding scheme. The behavior coding identifies what the participant is doing, specifically taking into consideration the location and purpose of the activity. Behaviors are coded in accordance with the American Time Use Survey Activity Lexicon [9]. Inter-rater agreement between coders was high (intraclass correlation coefficient > 0.9). Table 4.2 lists the behavior coding options.

Posture was coded to identify body postures, and extra detail was provided classifying upper body movement and intensity. Intensity is coded in terms of metabolic equivalents (METs). METs are the most common unit for measuring activity intensity, and are used to describe the four intensity categories: less than 1.5 METs is categorized as sedentary, between 1.5-2.99 METs is categorized as light intensity, moderate intensity is described as between 3.0-5.99 METs, and activity greater than 6.0 METs is categorized as vigorous intensity [37]. Figure A.3 in Appendix A provides the posture coding options and their associated upper body and intensity options. The frame-by-frame analysis generated the ground truth criterion data that was used to develop the training set.

Major Behavior Category	2nd-Tier Behavior Category
Personal Care	Sleeping Grooming, Health-related Other personal care
Household Activities	Housework Food prep and cleanup Interior maintenance, repair, and decoration Exterior maintenance, repair, and decoration Lawn, garden, and houseplants Animals and pets Household management/other household activities
Caring For and Helping Household Members	Caring for and helping children Caring for and helping adults
Work and Work-Related Activities	General Screen-based
Education	Taking class, research, homework Extracurricular (not sports)
Organizational, Civic, and Religious Activities	Organizational civic, volunteer, and religious activities
Purchases	Purchasing goods and services
Eating and Drinking	Eating and drinking, waiting
Socializing, Relaxing, and Leisure	Socializing, communicating, non-screen based Screen-based (TV, video games, computer, phone)
Sports, Exercise, and Recreation	Participating in sport, exercise or recreation Attending sport, exercise or recreation event, performance
Traveling	Driver (car/truck/motorcycle) Passenger (car/truck/motorcycle) Passenger (bus/train/airplane) Biking Walking General

Table 4.2: Behavior coding options.

4.2 Dataset Construction

The research team provided two datasets: ground truth data and raw accelerometer data for all three monitors that were used to create the training dataset. Developing the proper training set was a non-trivial process. The provided ground truth data described each two-hour direct observation session by the amount of time relative to

Posture	Upper body Modifier	Intensity Modifier
Lying down	No movement, Unidentifiable, typing, yes movement	Sedentary
Sitting/reclining	No movement, Unidentifiable, typing, yes movement	Sedentary
Kneeling/squatting	No movement, Unidentifiable, typing, yes movement	Sedentary
Stretching	Unknown	Sedentary, light, moderate, vigorous
Standing	No movement, Unidentifiable, typing, yes movement	Light
Stand and move	No movement	Light, moderate, vigorous
Stand and move with upper body movement	Yes	Light, moderate, vigorous
Stand and move with unidentifiable upper body movement	Unknown	Light, moderate, vigorous
Walk	Unknown	Light, moderate, vigorous
Walk with load	Unknown	Light, moderate, vigorous
Running	Unknown	Moderate, vigorous
Bike	No	Moderate, vigorous
Ascending stairs	Unknown	Moderate, vigorous
Descending stairs	Unknown	Moderate, vigorous
Sports	Unknown	Light, moderate, vigorous

Table 4.3: Posture coding options with their upper body and intensity modifier options.

the start of the observation, the duration of each behavior/posture, the actual behavior/posture of the observed participant, optional upper body movement, sporting activity, posture intensity, and type of work modifiers, and the state of the behavior/posture. Table 4.4 further details the columns provided in the ground truth criterion log; a sample of the ground truth data is provided in Appendix A.

4.2.1 Ground Truth.

We reformatted and expanded the ground truth criterion log into the proper format to be merged with the monitor data using R. Each row now serves as one second of

Column Name	Description
Date_Time_Absolute_dmy_hmsf	Date and time the observation was coded
Date_dmy	Date, month, and year the observation was coded
Time_Absolute_hms	Time in hours, minutes, and seconds the observation was coded
Time_Absolute_f	Fraction of a second of the time the observation was coded
Time_Relative_hmsf	Time relative to the start of the observation in hours, minutes, seconds, and fraction of a second
Time_Relative_hms	Time relative to the start of the observation in hours, minutes, and seconds
Time_Relative_sf	Time in seconds and fraction thereof relative to the start of the observation
Duration_sf	Duration in seconds and fraction thereof the behavior was performed for
Observation	Name of the observation session
Event_log	Event log
Behavior	Behavior or posture coding
Modifier_1	Upper body modifier (Yes movement, no movement, unidentifiable, typing)
Modifier_2	Sport modifier (Type of sport being played)
Modifier_3	Intensity modifier (Sedentary, light, moderate, vigorous)
Modifier_4	Work modifier (Type of work)
Event_Type	State of the behavior/posture being observed (i.e., state start, state stop, state point)
Comment	Additional comments

Table 4.4: Columns in the provided ground truth criterion log.

observation that is labelled with a particular behavior/posture. The actual date and time of the observation session is acquired from the direct observation timestamp log provided by the research team, presented in Appendix A. Because postures change within and across behaviors, and behaviors can also change during the same and across different postures, we split the original *Behavior* column into two columns to separate behaviors and postures. The original *Modifier_1* and *Modifier_3* columns are specific to posture, representing upper body movement and intensity level and we relabelled them as such. We populated any blank cells in these columns with the appropriate default value for the associated posture (i.e., “unknown” for upper body,

Column	Description
Observation	Name of the observation session
Date	Date of the observation session
Coding	Sedentary/non-sedentary behavior coding
Primary_behavior	Behavior observed for at least half of the current second
Primary_posture	Posture observed for at least half of the current second
Primary_upper body	Upper body modifier for the primary_posture
Primary_intensity	Intensity level of the primary_posture
Secondary_behavior	Behavior observed for less than half of the current second
Secondary_posture	Posture observed for less than half of the current second
Secondary_upper body	Upper body modifier for the secondary_posture
Secondary_intensity	Intensity level of the secondary_posture
Num_postures	Number of total postures observed within the current second
Transition	1 if the second contains a transition between postures, otherwise 0
Actual_time	Time of the observation session
Time	Time relative to the start of the observation session, in seconds

Table 4.5: Columns in the second-by-second ground truth files.

the posture’s lowest intensity level as shown in Appendix A, Figure A.3). The original *Modifier_2* column represents the type of sporting activity, and is only associated with the “EX-participating in sport, exercise or recreation” behavior. For the final ground truth data we absorbed the type of sporting activity into the name of the behavior. For example, if the original provided ground truth criterion had a “EX-participating in sport, exercise or recreation” as the *Behavior* and “jogging” as its *Modifier_2*, the final ground truth data represents this as “EX-jogging”. *Modifier_4* represents work type (i.e., “Education and Health Services” or “Office (business, professional services, finance, info)”). It is only associated with the two working behaviors (“WRK- general”, “WRK- screen based”) and is handled similarly to the sport modifier.

In the provided ground truth data, behavior and posture changes were coded up to the hundred-thousandths of a second; therefore, one second could be split by more than one behavior and/or more than one posture. In order to properly

demonstrate this, the final ground truth data contains two sets of behavior/posture codings: primary and secondary. The primary coding represents the behavior and/or posture that is maintained for more than 50% of the second, and the secondary coding represents the behavior and/or posture for the remainder of the second. However, if a behavior and/or posture is maintained for at least 80% of the second, it is considered as the majority coding. In this case, the primary coding is this majority coding, and there is no secondary coding. We created a transition column, where seconds are labelled 1 if they contain a transition between more than one posture, and 0 otherwise. The number of postures contained in each second is also recorded. Finally, in order to directly compare model performance with the methods in [56], we added an extra coding column to label the posture as either a “sedentary” or “non-sedentary” behavior. The outputs of this data transformation are second-by-second ground truth files for each individual participant’s direct observation sessions. Table 4.5 lists the columns of the second-by-second ground truth files.

4.2.2 Raw Accelerometer Data.

We ran the provided raw accelerometer data through another R script based on code from [56] to produce aggregated data for each participant. We generalized the R code to account for the different sampling frequencies of the different monitors, as the ActiGraph has a sampling rate of 80 Hertz (Hz), while the BioStamps have a 31.25 Hz sampling rate. The raw accelerometer data from the Actigraph contained seven days’ worth of data for each participant, totalling over 48 million acceleration samples per data file. An example of a participant’s raw data file is shown in Figure 4.1.

We modified the R code from from [56] to generate aggregated features for every 80 acceleration samples. One second time intervals were chosen because they are a small enough epoch length to observe transitions between behaviors, and further

granularity is not physiologically meaningful and difficult to code. We identified seven features to describe the movement the monitor experienced each second. To be directly comparable to the work documented in [56], the same series of features were used: mean vector magnitude, standard deviation vector magnitude, mean acceleration angle, standard deviation acceleration angle, percentage of power between 0.6 and 2.5 Hz, dominant frequency (from the Fourier transform), and the fraction of the dominant frequency over all others. We also created 16 additional features as an attempt to provide more information about the acceleration signal. These additional features are listed in Table 4.6. In total, we aggregated 23 total features for each second, generating second-by-second files that span the seven consecutive days the participant wore the ActiGraph monitor.

Because the ground truth only spans two two-hour segments of these seven days, only the aggregated features from the seconds that took place during the direct observation sessions were needed. Using Python, we merged the ground truth for each participant’s two hour direct observation session with the aggregated data.

The raw data from the BioStamp accelerometers was provided in a slightly dif-

----- Data File Created By ActiGraph GT3X+ ActiLife v6.12.1 Firmware v1.9.2 date format M/d/yyyy at 80 Hz Filter Normal -----											
Serial Number: MOS2C23151271											
Start Time 10:15:00											
Start Date 10/2/2017											
Epoch Period (hh:mm:ss) 00:00:00											
Download Time 11:02:52											
Download Date 10/9/2017											
Current Memory Address: 0											
Current Battery Voltage: 4.01 Mode = 12											

Accelerometer X	Accelerometer Y	Accelerometer Z									
0.254	0.953	-0.32									
0.25	0.926	-0.324									
0.25	0.926	-0.332									
0.25	0.926	-0.324									
0.254	0.922	-0.32									
0.246	0.922	-0.324									
0.246	0.922	-0.328									
0.25	0.918	-0.324									

Figure 4.1: An example of the raw data from the Actigraph wrist monitor.

ferent format, illustrated in Figure 4.2. As previously mentioned, the BioStamps have a 31.25 Hz sampling rate, meaning each second had *about* 31 samples in the raw data file. Because the monitors did not necessarily start collecting data at the exact start of a second, the number of samples per second range between 29 and 32 samples. In order to create second-by-second features, we looped through each data file and labelled each sample with the second it belonged to, using the Unix Epoch timestamp provided in the first column. The BioStamp data files were also stored in nested directories, so we modified the R code to traverse the directory structure.

Unlike the Actigraph, the BioStamps were only worn for a duration of two hours per observation. However, the data for the thigh and chest monitors would start and end at different times for the same observation, therefore the raw thigh and chest data were not exactly synchronized in time. In order to make these monitors comparable to one another and to the Actigraph, we sliced the raw data so that only the seconds that were directly observed according to the timestamp log (Appendix A) were used

Statistical feature	Definition
$\text{Min}(x)$	Minimum x acceleration in interval
$\text{Min}(y)$	Minimum y acceleration in interval
$\text{Min}(z)$	Minimum z acceleration in interval
$\text{Max}(x)$	Maximum x acceleration in interval
$\text{Max}(y)$	Maximum y acceleration in interval
$\text{Max}(z)$	Maximum z acceleration in interval
$\text{Mean}(x)$	Mean x acceleration in interval
$\text{Mean}(y)$	Mean y acceleration in interval
$\text{Mean}(z)$	Mean z acceleration in interval
$\text{SD}(x)$	Standard deviation of x acceleration in interval
$\text{SD}(y)$	Standard deviation of y acceleration in interval
$\text{SD}(z)$	Standard deviation of z acceleration in interval
$\text{Mean}(x * y)$	Mean $x * y$ acceleration in interval
$\text{Mean}(y * z)$	Mean $y * z$ acceleration in interval
$\text{Mean}(x * z)$	Mean $x * z$ acceleration in interval
$\text{Mean}(x * y * z)$	Mean $x * y * z$ acceleration in interval

Table 4.6: Additional statistical features used to summarize the accelerometer signals.

to create features. Once the appropriate data samples were obtained, we identified features to describe the acceleration in each second - the same 23 features used for the Actigraph. The thigh and chest features were merged by the second using Python, thus creating second-by-second files describing thigh and chest movement for each participant's observation session.

4.2.3 Merging Ground Truth with Features.

The final portion of our data construction pipeline combines the aggregated features with the ground truth. Using Python, we extracted the two-hour observation sessions from the aggregated Actigraph features and matched the features with the ground truth observation data for that session. During the merge, we also added a column that contained the activity domain type and participant ID number, so that we could perform leave-one-out cross validation as well as evaluate model performance by activity domain. We created the complete Actigraph dataset by appending all of the observation sessions together.

Merging the aggregated BioStamp features with the ground truth was slightly

Timestamp (ms)	Accel X (g)	Accel Y (g)	Accel Z (g)
1.50708E+12	0.22437	0.7234	0.63551
1.50708E+12	0.21509	0.73219	0.64039
1.50708E+12	0.21314	0.76246	0.60865
1.50708E+12	0.20288	0.78248	0.62281
1.50708E+12	0.21704	0.78541	0.61891
1.50708E+12	0.22681	0.77418	0.62037
1.50708E+12	0.19507	0.75319	0.62184
1.50708E+12	0.198	0.74879	0.62574
1.50708E+12	0.19898	0.74879	0.62281
1.50708E+12	0.1897	0.75758	0.62184
1.50708E+12	0.18238	0.78639	0.63014
1.50708E+12	0.17847	0.76979	0.62428
1.50708E+12	0.16187	0.77711	0.63111
1.50708E+12	0.16529	0.77565	0.6277

Figure 4.2: An example of the raw data from the BioStamp chest monitor.

New Posture Coding	Description/Original Postures
Lying down	Lying down
Sitting	Sitting, sedentary kneeling/squatting, sedentary stretching
Standing	Standing
Stand and move light	Stand and move, stand and move with upper body movement, stand and move with unidentifiable upper body movement at light intensity
Stand and move moderate	Stand and move, stand and move with upper body movement, stand and move with unidentifiable upper body movement at moderate intensity
Stand and move vigorous	Stand and move, stand and move with upper body movement, stand and move with unidentifiable upper body movement at vigorous intensity
Walk light	Walk, walk with load at light intensity
Walk moderate	Walk, walk with load at moderate intensity
Walk vigorous	Walk, walk with load at vigorous intensity
Running	Running
Bike	Bike
Ascending stairs	Ascending stairs
Descending stairs	Descending stairs
Sports	Sports

Table 4.7: The new posture coding scheme.

simpler than the Actigraph. Since the aggregated data only spanned the duration of the observation session, we simply had to add a column with the activity domain type and participant ID number, and then merge the aggregated features with the ground truth to create the complete BioStamp dataset.

4.2.4 Final Dataset.

We deemed the granularity level of the provided ground truth data logs posture codings too specific for the purpose of this work. Using Python, we constructed a new posture coding column that represents the types of postures we are interested in predicting. This new posture coding scheme is presented in Table 4.7, and is referred to as the full coding scheme in this work.

4.3 Questions

This thesis aims to predict an individual’s physical activity/posture based on data from a wrist, thigh, and chest-worn monitor, specifically answering the following questions:

Question 1. *What monitor placement and machine learning method best determines sedentary vs. non-sedentary behavior?* Prolonged periods of sedentary behavior has been shown to negatively influence metabolic health[45]. Dr. Keadle is interested in understanding the effect of sedentary time on health.

Question 2. *How do our sedentary vs. non-sedentary models compare to previous methods?* Staudenmayer et. al [56] used laboratory-collected data from a wrist monitor to predict energy expenditure, activity intensity level, sedentary behavior, and locomotion time. We compare the classification accuracies of our models with the random forest model from [56] predicting sedentary vs. non-sedentary behavior.

Question 3. *What monitor placement and machine learning method best estimates activity intensity level?* Previous investigations [37, 56] have developed methods to estimate minutes in different activity intensities. We build predictive models to determine activity intensity from the three monitors.

Question 4. *What monitor placement and classifier best predicts posture into 5 general posture classes?* Ellis et. al [20] developed a method to classify free-living behaviors into four behavior labels. While the ground truth coded in our work codes postures into 14 labels, we generalized these labels to five categories in order to observe how our models perform in comparison to the results in [20].

Question 5. *What monitor placement and machine learning model best predicts posture/intensity into 14 posture classes?* Dr. Keadle is interested in developing models to predict activity type at a more granular level. In this work, we generated training models to classify 14 activity labels.

Question 6. *Does a hierarchical random forest ensemble improve classification accuracy for predicting 14 posture classes?* The 14 class labels of our ground truth can be hierarchically structured. As an attempt to gain lift from our random forest classifiers, we built an ensemble of random forest classifiers to hierarchically classify 14 posture labels.

Question 7. *Does using a confusion matrix boosting method improve classification accuracy for predicting 14 posture classes?* Given the imbalanced nature of our dataset with respect to the 14 posture classes, we implemented Koço and Capponi’s confusion matrix boosting algorithm [34] using Python to overcome the class-imbalance problem.

4.4 Experiments

In order to answer our questions, we tested a battery of machine learning models on our monitor data using different coding schemes as class variables. The purpose of the different coding schemes, listed in Table 4.8, are to have different levels of granularity in terms of the number of class labels. This allows us to observe model performance as we increase the number of classes we are trying to predict, compare against previous work, and answer our research questions. For our non-binary classifiers, we omitted transition seconds - seconds of which more than one posture was observed - from our dataset. This provides us with “purer” data that happens to be consistent with the experimental circumstances in previous work [20]. Because there are less transitions

between sedentary to non-sedentary behaviors than there are for our other coding schemes, we did not feel the need to omit transition seconds for our binary classifiers.

Coding Scheme	# Classes	Description/Postures
Sedentary/Non-sedentary	2	Sedentary, non-sedentary
METs	4	Sedentary, light, moderate, vigorous
General postures	5	Sit, stand, walk/run, riding in vehicle, other
Full coding scheme	14	See Table 4.7

Table 4.8: Different coding schemes.

4.4.1 *K*-Nearest Neighbors.

We tested multiple values of k for our k -nearest neighbors model. In [41], $K = 15$ was shown to maximize testing accuracy, so we built a set of models with this value. We then continuously increased k and found that $k = 100$ was the best value for all monitors on all coding schemes except for the wrist monitor on the sedentary vs. non-sedentary coding scheme, which performed best when $k = 5$. Uniform weights were used (all points in the neighborhood are given equal weights) in both cases.

4.4.2 Support Vector Machine.

We used scikit-learn’s Linear Support Vector Classifier (LinearSVC) with the maximum number of iterations set to 100 for our SVM model. We chose LinearSVC over SVC because SVC would terminate early without converging to a solution; LinearSVC tends to converge faster than SVC as the number of samples increases. It’s important to note that although we limited the maximum number of iterations being 100 for the sake of time, our SVMs still failed to converge. Therefore, the accuracies achieved by these models do not necessarily reflect the true performance of SVMs on this data.

4.4.3 Random Forest.

We tested different sets hyperparameters when building our random forest classifier, varying the maximum depth of the tree, the number of trees in the forest, and the minimum number of samples required to be at a leaf node. While we found that increasing all of these parameters resulted in better performance, we observed the largest improvement when varying the maximum tree depth. All other parameters fell to their default values. We observed that the best value for maximum tree depth was dependent on the monitor and test case. A maximum tree depth of 5 was used in [41] on a subset of our data. We found that this value maximizes testing accuracy for our sedentary vs. non-sedentary coding scheme. However, for our more granular coding schemes, our random forests achieved better performance using a maximum depth of 15.

4.4.4 AdaBoost.

We ran scikit-learn’s AdaBoost classifier on our monitor data using 100 random forests. Scikit-learn’s AdaBoost classifier implements the *SAMME* (Stagewise Additive Modeling using a Multi-class Exponential loss function) algorithm, which is an extension of the original AdaBoost algorithm [25] to the multi-class setting without reducing the problem into multiple two-class problems [62].

4.4.5 Gradient Boosting.

Since gradient boosting tends to be resilient to over-fitting, we chose to perform 200 boosting iterations. The number of nodes in the tree were limited to 7. Our gradient boosting model has these properties for our results comparison.

4.4.6 Hierarchical Classifier.

We observed that our single-classifier models were only predicting 6 out of 14 classes out of the full coding scheme: sitting, standing, stand and move light, walk moderate, running, and biking. The other intensities of the stand and move and walking postures were not learned and therefore not distinguished from each other. We considered two explanations for this phenomenon. One explanation is that in presence of other data, the differences between certain postures become harder for our models to learn. Therefore, we attempted to improve classification accuracy by structuring our posture classes in a hierarchy and training classifiers to distinguish between more specific postures. A second reason would be that our models are not able to confidently learn the difference between intensities in addition to types of postures because they are learning from an imbalanced dataset.

As an attempt to improve the performance of our single-classifier models, we built an ensemble of classifiers using the local classifier per parent node approach for hierarchical classification to predict the full coding scheme. For this classifier, we structured the postures into a 3-level class hierarchy, shown in Figure 4.3.

Our ensemble consists of five random forest classifiers, one per parent node. The root classifier predicts six postures - lying down, sitting, standing, locomotion, biking, and other sport. A standing classifier which is trained on only standing and stand and move data, predicts stand or stand and move from the points the root classifier labelled as standing. Another classifier is trained on locomotion data, which includes observations that were coded as walking, ascending stairs, descending stairs, and running. This locomotion classifier predicts these child classes from the data points the root classifier labelled as locomotion. We use the last two classifiers to predict the final level of the hierarchy. The stand and move points labelled by the standing classifier are used by one classifier, which was trained on stand and move data. This

Figure 4.3: Our 3-tier class hierarchy.

stand and move intensity classifier is used to distinguish between the three stand and move intensity levels and predicts stand and move light, stand and move moderate, and stand and move vigorous. Finally the last classifier, trained on purely walking data (i.e., observations that were only coded as walking), predicts the level of walking intensity from the walking points labelled by the walking classifier.

4.4.7 Confusion Matrix Boosting (CoMBo).

Our dataset has an imbalance ratio of 0.000017, from having only 3 *other sport movement* observations versus 171,985 *sitting* observation seconds. We implemented the Confusion Matrix BOosting algorithm (CoMBo) [34], an algorithm proposed by Koço and Capponi which extends the multi-class boosting method AdaBoost.MM [42] to

the imbalanced class problem via greedily minimizing the empirical norm of the confusion matrix. The confusion matrix is one of the most informative performance measures for machine learning classification. It contains the different combinations of predicted versus actual values, and demonstrates the classifier’s “confusion” among classes by showing how accurate the classifier is at predicting a certain class, as well as how the classifier tends to misclassify (“confuse”) a certain class for another. In order to learn classifiers for the imbalanced class problem, Koço and Capponi [34] propose a framework that makes use of the confusion matrix as an error measure.

In [34], the probabilistic confusion matrix is used overcome the class-imbalance problem. The probabilistic confusion matrix is computed from the raw confusion matrix (i.e., what we know as the standard confusion matrix, where the values of each row sum up to the number of samples of the class of the respective row). In the probabilistic confusion matrix, the values of a row add up to 1. With this property, Koço and Capponi [34] propose that directly minimizing the confusion matrix norm aids in smoothing the accuracy among imbalanced classes. They introduce an algorithm that minimizes the norm of the confusion matrix, CoMBo, which is shown in Algorithm 2. Let S be a training sample, T be the total number of iterations, and W be a weak learner. The score functions f are initialized to zero and the cost matrix $\mathbf{D}$ is initialized so that classes with a larger number of samples are assigned a smaller misclassification cost than classes with less samples. For each training iteration, the weak learner W is used to build the weak classifier h_t using the cost matrix $\mathbf{D}_t$, which is also used to compute the weight α_t for h_t . Also referred to as the importance of h_t , α_t depends on the edge δ_t which measures the difference between the performance of classifier h_t versus random guessing. The cost matrix $\mathbf{D}_t$ is updated so that misclassified points are given a higher cost than correctly classified points - similarly to how in regular AdaBoost, the misclassified points are given a higher weight. In addition to the ability to correctly predict more difficult samples, the misclassification

costs are also dependent on the number of samples having the same class y_i , which is represented by the term $1/m_{y_i}$. Finally, the output prediction is the simple weighted majority vote of all T weak classifiers.

As the implementation of this algorithm isn't publicly available, we implemented the CoMBo algorithm according to the pseudo-code in Algorithm 2. Because our dataset is significantly larger compared to those run in [34] (the largest dataset they tested on was not even 20% the size of our monitor data), we split our dataset by activity domain and trained on each activity domain separately.

Algorithm 2 CoMBo: Confusion Matrix BOosting

Given

- $S = \{(x_1, y_1), \dots, (x_m, y_m)\}$ where $x_i \in X, y_i \in 1, \dots, K$
- T : number of iterations, W : weak learner
- $\forall i \in \{1, \dots, m\}, \forall l \in \{1, \dots, K\}, f_1(i, l) = 0$
- $\mathbf{D}_1(i, l) = \begin{cases} \frac{1}{m_{y_i}} & \text{if } y_i \neq l \\ \frac{-(K-1)}{m_{y_i}} & \text{if } y_i = l \end{cases}$

for $t = 1$ **to** T **do**

Use W to learn h_t with edge δ_t on $\mathbf{D}_t$, and $\alpha_t = \frac{1}{2} \ln \frac{1+\delta_t}{1-\delta_t}$
where:

$$\delta_t = \frac{-\sum_{i=1}^m (\mathbf{D}_t(i, h_t(x_i)))}{\sum_{i=1}^m \sum_{l \neq y_i} (\mathbf{D}_t(i, l))} \quad (4.1)$$

Update $\mathbf{D}$:

$$\mathbf{D}_{t+1}(i, l) = \begin{cases} \frac{1}{m_{y_i}} \exp(f_{t+1}(i, l) - f_{t+1}(i, y_i)) & \text{if } l \neq y_i \\ -\frac{1}{m_{y_i}} \sum_{j \neq y_i}^k \exp(f_{t+1}(i, j) - f_{t+1}(i, y_i)) & \text{if } l = y_i \end{cases} \quad (4.2)$$

where $f_{t+1}(i, l) = \sum_{z=1}^t \Pi[h_z(i) = l] \alpha_z$

end for

Output final hypothesis:

$$H(x) = \operatorname{argmax}_{l \in 1, \dots, k} f_T(x, l), \text{ where } f_T(x, l) = \sum_{t=1}^T \Pi[h_t(x) = l] \alpha_t \quad (4.3)$$

Chapter 5

RESULTS

Model performance was compared and evaluated using leave-one-out cross validation. Leave-one-out validation consists of dividing the data into subsets by observation, and then training the models on data from all observations except for the one that is used for testing. Since each participant had two observation sessions, we also used leave-one-participant-out validation to verify that no bias exists towards participants.

5.1 Evaluation Methods

The objective of our work is to determine an individual’s behavior on a second-by-second basis. Because we are trying to make predictions at such a granular level, we measure our results in two ways.

5.1.1 Micro-level Evaluation

First, we measure our results on a micro-level. This is in terms of how well our models can predict a person’s behavior on a second-by-second level. We evaluate this using classification accuracy, precision, and recall. Classification accuracy for this work is simply: $\frac{\text{the number of correctly predicted seconds}}{\text{the total number of observation seconds}}$. Precision is the percentage of true positives in the set of all positively classified samples, and recall is defined as the percentage of true positive in the set of all actual positive samples.

5.1.2 Macro-level Evaluation

We also measure our results on a macro-level. That is, we are interested in looking at the amount of time spent in each activity domain, or posture. We evaluate this

by comparing the true proportions of the observed activities to our models’ predicted proportions using a measure called Kullback-Leibler divergence [35]. Kullback-Leibler divergence, or simply called KL divergence, is a measure of the difference between two probability distributions $p(x)$ and $q(x)$. Let $p(x)$ be the actual distribution of classes and $q(x)$ be the predicted distribution. The KL divergence of $p(x)$ and $q(x)$ is defined as:

$$D_{KL}(p(x)||q(x)) = \sum_{x \in X} p(x) \ln \frac{p(x)}{q(x)} \quad (5.1)$$

5.2 Model Results

We test a range of models on each coding scheme and observe model performance as we increase the granularity of our class variables.

5.2.1 Sedentary vs. Non-Sedentary Coding Results

For our binary classification, we ran *KNN*, *SVM*, random forest, and gradient boosting on our monitors. Table 5.1 reports the performance of our models on the Actigraph and BioStamp monitor data using the seven Staudenmayer features.

Model	Accuracy (%)			
	Actigraph Wrist	BioStamp Thigh and Chest	BioStamp Thigh	BioStamp Chest
<i>K</i> -Nearest Neighbors	63.72	98.61	98.62	76.38
SVM	47.14	89.44	94.58	50.97
Random Forest	76.42	98.54	98.51	77.17
Gradient Boosting	75.59	98.13	98.07	76.04

Table 5.1: Model performance predicting sedentary time using the 7 features from [56].

In terms of what monitor and classifier best predicts sedentary versus non-sedentary time - the best performance was demonstrated by the BioStamp thigh monitor and combined thigh and chest monitors across all classifiers, while the Actigraph wrist

	Predicted			
Actual		Sedentary	Non-sedentary	Recall
	Sedentary	135491	40857	0.768
	Non-sedentary	41898	132742	0.76
	Precision	0.764	0.765	0.764

Table 5.2: Overall confusion matrix for RF predicting sedentary time from wrist Actigraph.

	Predicted			
Actual		Sedentary	Non-sedentary	Recall
	Sedentary	178654	2082	0.988
	Non-sedentary	3098	171078	0.982
	Precision	0.983	0.988	0.985

Table 5.3: Overall confusion matrix for RF predicting sedentary time from thigh and chest BioStamps.

monitor gave us the worst performance. Tables 5.2 and 5.3 show the confusion matrices for the wrist Actigraph and the thigh and chest BioStamps. The wrist’s lower accuracy can be due to the amount of noise the wrist monitor records, as wrist movement does not necessarily directly correspond to an individual’s behavior. In addition, the chest BioStamp on its own performed similarly to the wrist on most classifiers, with the exception of *KNN* as the chest performed better. The lower accuracy of the chest monitor can be attributed to the fact that some sedentary behaviors look very similar to non-sedentary behaviors with respect to the individual’s chest (i.e., sitting versus standing).

We also evaluated model accuracy on a larger scale with respect to activity domains. Figure 5.1 shows a comparison of our random forest classifier’s predictions of sedentary time on the Actigraph wrist monitor and the combined thigh and chest BioStamp monitors. Color-coded by activity domain, each point represents one two-hour observation session. The random forest using the thigh and chest monitors has an almost perfect direct relationship, with a regression coefficient of 0.9992. The wrist-fitted random forest performs reasonably well, with a regression coefficient of

(a) Actigraph wrist

(b) BioStamp thigh and chest

Figure 5.1: Actual by predicted sedentary time by activity domain.

0.8421.

To see how our models compare, we ran the random forest model from Staudenmayer et. al [56] on our wrist Actigraph data. The Staudenmayer method predicted sedentary time with 70.86% accuracy. Our random forest and gradient boosting models achieve higher accuracies than the Staudenmayer method on our wrist Actigraph data, which further supports the claim that models trained on free-living data outperform lab-trained models.

Remember that we created 16 additional features to attempt to provide more information about the accelerometer signals to our models. We found that adding more features improved sedentary/non-sedentary classification accuracy by up to 6.3%, in the case of the combined thigh and chest BioStamps’ SVM (shown in Appendix C). To make sure our models were achieving the best possible accuracy scores, the total 23 features were used for the reported accuracies of all other coding schemes.

5.2.2 Activity Intensity (METs) Results

Seeing as prior work [61, 56] has predicted energy expenditure from accelerometer data and metabolic equivalents (METs) are known to be the most common unit for measuring activity intensity, we aggregated the predictions of our most granular, 14-class coding scheme in accordance with Table 5.4. The aggregated results of our models for the activity intensity coding scheme are shown in Table 5.5. We observe that the models we trained to learn 14 posture classes, can accurately recognize ac-

Intensity Level	# Postures
Sedentary	Lying down, sitting, kneeling/squatting
Light	Stand, stand and move
Moderate	Walk, ascending stairs, descending stairs
Vigorous	Sports, running, biking

Table 5.4: Postures that fall under each intensity label.

Model	Accuracy (%)			
	Actigraph Wrist	BioStamp Thigh and Chest	BioStamp Thigh	BioStamp Chest
<i>K</i> -Nearest Neighbors	53.43	94.07	93.93	93.61
SVM	39.33	89.8	90.91	84.96
Random Forest	68.08	94.67	94.48	94.33

Table 5.5: Model performance predicting activity intensity (METs) from aggregating our 14-class models.

tivity intensity. In terms of what monitor and ML method best predicts activity intensity, all BioStamp monitors performed comparably to one another on all classifiers, while the wrist Actigraph still gave us a significantly lower accuracy. We also observe that the chest BioStamp was able to more accurately estimate activity intensity than sedentary time, which demonstrates that more vigorous activities can be distinguished from more sedentary activities from chest movement.

We also trained some new models to learn activity intensity. Although the research team had already coded intensity with respect to each posture in the full coding scheme, we defined intensities by posture type for these models consistently with our aggregated results (Table 5.4). As shown in Table 5.6, re-training new models provides similar classification accuracies to the aggregated results of our full coding scheme models.

We used KL divergence to evaluate our models with respect to the true proportion

Model	Accuracy (%)			
	Actigraph Wrist	BioStamp Thigh and Chest	BioStamp Thigh	BioStamp Chest
<i>KNN</i> aggregated	53.43	94.07	93.93	93.61
<i>KNN</i> retrained	53.19	94.07	93.99	93.63
RF aggregated	68.08	94.67	94.48	94.33
RF retrained	69.08	94.47	94.55	94.18

Table 5.6: Classification accuracies predicting activity intensities (METs) from aggregating our 14-class models vs. our retrained models.

of activity intensity levels versus our predicted proportion. Figure 5.2 shows the actual and predicted probability distributions for our activity intensity coding scheme, and Table 5.7 compares our aggregated 14-class models with our retrained models in terms of KL divergence. Recall the KL divergence is 0 if our predicted class distribution is the exact same as the actual class distribution of data. The KL divergence between our aggregated vs. retrained models show similar distributions. This is a significant discovery; the aggregation method lets us train one model to learn a more granular set of class variables and can still achieve competitive results on less granular coding schemes to models that have been retrained on the less granular coding scheme. Sometimes the aggregation method even provides better results than the retrained models.

Figure 5.2: Actual vs. predicted probability distributions of random forests predicting activity intensity.

Model	Accuracy (%)			
	Actigraph Wrist	BioStamp Thigh and Chest	BioStamp Thigh	BioStamp Chest
KNN aggregated	0.0761	0.0002	0.00008	0.0002
KNN retrained	0.0029	0.0002	0.0001	0.0002
RF aggregated	0.0191	0.001	0.0014	0.0016
RF retrained	0.018	0.0013	0.001	0.0019

Table 5.7: KL divergence of our aggregated 14-class models vs. our re-trained models.

5.2.3 General Postures Results

Since our full coding scheme is significantly more detailed than those used in previous work, we generalized postures down to a total of five posture labels in order to more directly compare our results with other work. Ellis et. al [20] classified free-living wrist accelerometer data into four activity classes: *sit*, *stand*, *walk/run*, and *riding in a vehicle*; we used these activity classes as four out of five of our postures in this general coding scheme. Our dataset included observations that did not fall into any of these classes, so we added an *other* class. The postures from the full coding scheme are absorbed into these five activity classes as described in Table 5.8. The classification accuracies of our retrained models on this general postures coding scheme is reported in Table 5.9. Aggregating results from our 14-posture class models proved to be unfeasible, simply because *riding in a vehicle* in our original ground truth is coded as a *traveling* behavior, not a posture. This information was dropped while training

General Posture Coding	Description/Postures from Full Coding Scheme
Sit	Lying down, sitting, kneeling/squatting
Stand	Stand, stand and move
Walk/Run	Walk, ascending stairs, descending stairs, running
Riding in Vehicle	Traveling behaviors - driving or riding in a car/truck/motorcycle
Other	Sports, biking

Table 5.8: Postures/behaviors that are considered for each general posture.

Model	Accuracy (%)			
	Actigraph Wrist	BioStamp Thigh and Chest	BioStamp Thigh	BioStamp Chest
<i>K</i> -Nearest Neighbors	53.57	93.6	93.49	93.18
SVM	49.55	80.66	79.59	76.22
Random Forest	68.92	93.81	94.08	93.55

Table 5.9: Model performance predicting the general coding scheme with 5 posture labels.

our most granular 14-class models, and therefore is no longer available to aggregate by.

Similar to our results for the activity intensity coding scheme, all of the BioStamp models outperform the Actigraph models. Given the classification accuracies that our models achieved predicting our five activity classes, we conclude that our methods outperform Ellis et al., as they obtained a balanced accuracies of 89.4% and 84.6% from their hip and wrist accelerometers for predicting four activity classes. Recall that Ellis et al. used one-minute interval windows, while our models use intervals of one second. One minute intervals would most likely further increase our model performance. It is also worth noting that our ground truth was constructed through a very thorough and detailed coding process using a GoPro Hero 5 video camera; a SenseCam that captured still images approximately every 20 seconds served as the ground truth for [20]. Therefore it is likely that the ground truth labels in [20] are not entirely accurate in a handful of cases. For instance, a participant could easily transition from sitting in a chair, to walking across a room, back to sitting in a chair within a 20-second time span. The SenseCam would have, and likely did, miss capturing these behaviors.

Tables 5.10 and 5.11 report the confusion matrices of our best and worst models. We observe that the thigh and chest BioStamps’ random forest classifier is able to recognize the *other* postures much better than the wrist’s *KNN* classifier. We also

	Predicted						
Actual		sit	standing	walk/run	riding in vehicle	other	Recall
	sit	167836	2286	293	87	25	0.9842
	standing	1489	106434	4302	0	50	0.948
	walk/run	326	9156	46176	0	36	0.829
	riding in vehicle	1460	15	45	0	0	0
	other	354	891	608	0	4191	0.6934
	Precision	0.9788	0.896	0.8979	0	0.9742	

Table 5.10: Confusion matrix for RF predicting 5 general activity classes using the thigh and chest BioStamps.

	Predicted						
Actual		sit	standing	walk/run	riding in vehicle	other	0.7872
	sit	113564	46066	9744	594	1019	0.6068
	standing	52031	42042	12711	171	1056	
	walk/run	14390	15992	23107	24	2099	0.6413
	riding in vehicle	1073	401	41	0	5	0
	other	1736	1908	2397	3	0	0
	Precision	0.756	0.5331	0.5331	0	0	

Table 5.11: Confusion matrix for KNN classifier predicting 5 general activity classes using wrist Actigraph.

find that neither of these models capture *riding in a vehicle* at all. However, both models predicted *sit* the most for these observations. Given that a person is typically sitting while riding in a vehicle, we consider this misclassification acceptable.

5.2.4 Full Coding Scheme Results

Dr. Keadle was also interested in increasing the granularity of our class variables and seeing whether our models could accurately recognize 14 posture classes. The accuracy of our models on the full coding scheme of fourteen class labels is presented in Table 5.12. We see a significant drop in performance as we increase the granularity of our class variables. However, our models continue to perform consistently with respect

Model	Accuracy (%)			
	Actigraph Wrist	BioStamp Thigh and Chest	BioStamp Thigh	BioStamp Chest
<i>K</i> -Nearest Neighbors	50.49	85.37	85.38	85.02
SVM	43.94	78.87	79.87	80.37
Random Forest	61.61	85.98	85.73	85.47

Table 5.12: Model performance on the full coding scheme.

how they compare with one another. Our wrist models are again outperformed by all of the BioStamps. In this specific case, the best predictor of posture is the random forest using the combined thigh and chest data.

The confusion matrix for our combined thigh and chest random forest is in Table 5.13. Here we can closely observe the class imbalance problem within our dataset. Firstly, our models have almost no chance of learning *lying* or *other sport* postures, given that *lying* only has 25 observation seconds and *other sport* only has 2. On the other end of the spectrum, *sitting* has the largest observation sample size with 171985 seconds. Our random forest also seemed to favor predicting *stand and move light* more than the other intensities *stand and move moderate* and *stand and move vigorous*. This can be attributed to the larger sample size of the *stand and move light* class. The class imbalance problem is also exhibited through the different intensities of *walking*; *walk moderate* got the majority of our model’s predictions as it has a larger sample size than the other intensities. Table 5.14 presents the precision, recall, and F-measures (harmonic mean of precision and recall) for each posture class along with the number of samples and their percentage of our dataset; the classes are plotted according to their percentage of the dataset and their F-measures on a log scale in Figure 5.3. We observe that the more samples a class has in the dataset, the better the F-measure.

Reviewing our results at a macro-level, we calculated the KL divergence of our random forest models on each posture class and present them in Figure 5.4. KL

	Predicted												
	lying	sitting	standing	stand & move light	stand & move mod	stand & move vig	walk light	walk mod	walk vig	ascend stairs	descend stairs	running	other sport
Actual	lying	0	25	0	0	0	0	0	0	0	0	0	0
	sitting	41	169247	1884	455	9	73	229	0	5	4	0	0
	standing	0	1062	79481	4445	50	413	874	3	13	12	6	0
	stand & move light	0	436	13118	6620	58	848	1296	2	27	11	74	0
	stand & move mod	0	7	1538	1229	21	58	292	1	39	7	80	0
	stand & move vig	0	2	20	41	6	1	3	0	2	0	1	0
	walk light	0	241	1675	2735	9	1488	3511	1	17	9	4	0
	walk mod	0	104	906	1730	21	2377	27305	153	87	22	19	0
	walk vig	0	5	62	62	1	37	1789	0	17	0	1	0
	ascend stairs	0	8	33	89	22	79	542	4	264	2	74	0
	descend stairs	0	21	7	38	7	49	734	0	13	81	57	0
	running	0	0	15	249	358	1	27	1	5	3	8529	0
	other sport	0	0	2	0	0	0	0	0	0	0	0	0
	bike	0	446	180	428	56	23	85	1	223	36	39	0
													4520

Table 5.13: Confusion matrix for our random forest model predicting the full coding scheme using the combined thigh and chest monitor data

Posture class	Precision	Recall	F-measure	# samples	% of dataset
Sitting	0.9862	0.9841	0.9852	171985	0.49698
Standing	0.8035	0.9201	0.8579	86381	0.249613
Walk moderate	0.7443	0.8342	0.7867	32731	0.094582
Stand and move light	0.3653	0.2939	0.3257	22524	0.065087
Walk light	0.2732	0.1535	0.1966	9694	0.028012
Running	0.96	0.9279	0.9437	9192	0.026562
Bike	0.9685	0.7481	0.8441	6042	0.017459
Stand and move moderate	0.034	0.0064	0.0107	3295	0.009521
Walk vigorous	0	0	0	1974	0.005704
Ascending stairs	0.3708	0.2357	0.2882	1120	0.003236
Descending stairs	0.433	0.0796	0.1346	1017	0.002939
Stand and move vigorous	0	0	0	78	0.000225
Lying	0	0	0	25	0.000072
Sports	0	0	0	2	0.000006

Table 5.14: Precision, recall, and f-measures of our thigh and chest BioStamps random forest, sorted by class proportion to the dataset.

Figure 5.3: Posture proportions to our dataset by their F-measures.

Figure 5.4: KL divergence of our random forest models.

divergence is a measure of how different two probability distributions are - the closer to 0, the more similar our models are to our ground truth. This graph also allows us to notice the differences in our model predictions using different monitors, specifically the difference between our wrist method and the BioStamps.

Another one of our research questions asked whether using a hierarchical classification schema would improve performance. We were specifically interested in finding out whether the presence of other data made the differences between certain postures less recognizable. Therefore, we attempted to improve classification accuracy by structuring our posture classes in a hierarchy and training classifiers to distinguish between more specific postures. Table 5.15 shows a comparison of the differences in classification accuracy from our flat random forest classifiers to our hierarchical

approach using random forests. As shown, the hierarchy did not provide any lift in classification accuracy.

Model	Accuracy (%)			
	Actigraph Wrist	BioStamp Thigh and Chest	BioStamp Thigh	BioStamp Chest
Random Forest	61.61	85.98	85.73	85.47
Random Forest Hierarchy	61.21	85.11	85.15	84.88

Table 5.15: Flat random forest classifier versus random forest ensemble hierarchy performance.

One main disadvantage of our hierarchical classification approach is that misclassifications made at higher levels of the hierarchy are inherited by the classifiers at the lower levels. For instance, the *sitting* observation samples that the root classifier classified as *stand*, will not be corrected by the standing classifier since it only predicts between *stand* and *stand and move*. Table 5.16 shows the confusion matrix for our random forest classifier predicting the postures in the first class level of the posture hierarchy using the combination of the thigh and chest BioStamps; the final confusion matrix of our hierarchical random forest ensemble predicting all 14 postures is in Table 5.17.

In addition to the standard accuracy measure of the percentage of correctly predicted observations, we also evaluated model performance using the mean absolute error metric (MAE) and the macro-averaged mean absolute error metric (MA-MAE). MAE is a commonly used loss function that equals the sum of the absolute differences between our ground truth and predicted variables. Given a vector $\mathbf{v} = (v_1, \dots, v_n)$ of ground truth values and a vector of predictions $\mathbf{p} = (p_1, \dots, p_n)$, the prediction’s MAE is calculated as

$$MAE(p, v) = \frac{1}{n} \sum_{i=1}^n |p_i - v_i| \quad (5.2)$$

In other words, the MAE of a prediction represents the average magnitude of errors

	Predicted					
	lying	sitting	standing	walk	other sport	bike
Actual	lying	0	25	0	0	0
	sitting	85	168762	331	0	25
	standing	0	1413	106601	4227	37
	walk	0	350	9157	46190	31
	other sport	0	0	2	0	0
	bike	0	315	1157	640	3930

Table 5.16: Confusion matrix for the random forest classifier predicting the first class level of the hierarchy from the combination of the thigh and chest monitor data.

	Predicted													
	lying	sitting	standing	stand & move light	stand & move mod	stand & move vig	walk light	walk mod	walk vig	ascend stairs	descend stairs	running	other sport	bike
Actual	lying	0	25	0	0	0	0	0	0	0	0	0	0	0
	sitting	85	168762	2104	654	23	1	110	205	0	10	6	0	25
	standing	0	1012	77815	6065	134	3	485	818	1	12	15	7	14
	stand & move light	0	394	12247	7394	149	0	978	1230	6	21	10	83	0
	stand & move mod	0	7	1342	1300	84	0	92	315	6	33	6	101	0
	stand & move vig	0	0	13	36	19	0	1	6	0	0	0	1	0
	walk light	0	228	1504	2812	27	0	2017	3075	4	16	6	4	0
	walk mod	0	91	814	1741	24	1	2873	26865	160	78	59	21	0
	walk vig	0	6	57	55	3	0	73	1747	11	16	2	3	0
	ascend stairs	0	3	35	71	22	0	108	524	4	280	9	60	0
	descend stairs	0	22	4	31	6	0	89	601	3	17	179	56	0
	running	0	0	168	542	1238	2	1	30	4	6	3	7186	0
	other sport	0	0	2	0	0	0	0	0	0	0	0	0	0
	bike	0	315	254	801	93	9	41	346	13	174	44	22	3930

Table 5.17: Confusion matrix for our hierarchical random forest ensemble predicting the full coding scheme using the combined thigh and chest monitor data

from a set of predictions, regardless of the direction of error. MAE can range from 0 to ∞ , with the best value being 0. Because MAE has no maximum bound, we also use a variant of the MAE metric that scores between $[0, 1]$, called the macro-averaged mean absolute error (MA-MAE). This metric is used on ordinal classes and aims to punish certain errors more based on the severity of the error. For instance, in terms of our classification problem, misclassifying *lying* as running would be considered a severe error and would be penalized more by MA-MAE, while misclassifying *stand and move light* for *stand and move moderate* would be a less severe error and penalized less. The MA-MAE for this experiment is computed by separating the test set into 14 subsets - one per posture class - then independently calculating each class category’s MAE, and finally combining the normalized MAEs into a weighted sum, which is subtracted from 1 to be consistent with the “higher is better” intuition. The MAEs of each subset are normalized by the highest possible error for a data point with the given posture. Since MA-MAE is a metric used on ordinal classes, we made our ground truth labels ordinal as defined in Table 5.18.

Posture Coding	Ordinal Coding
Lying down	0
Sitting	1
Standing	2
Stand and move light	3
Stand and move moderate	4
Stand and move vigorous	5
Walk light	6
Walk moderate	7
Walk vigorous	8
Ascending stairs	9
Descending stairs	10
Running	11
Sports	12
Bike	13

Table 5.18: The ordinal coding of the posture classes.

With this ordinal coding of postures, the highest possible error would be from

misclassifying *lying down* as *sports*, or vice versa. The normalization factor in these misclassification cases is $|0 - 13| = 13$, or $|13 - 0| = 13$. As another example, the highest possible error for *walk moderate* is $|7 - 0| = 7$. Our MA-MAE formula is therefore:

$$MA_MAE(p, v) = 1 - \frac{\left(\frac{MAE(p_0, v_0)}{13} + \dots + \frac{MAE(p_6, v_6)}{7} + \frac{MAE(p_7, v_7)}{7} + \dots + \frac{MAE(p_{13}, v_{13})}{13}\right)}{14} \quad (5.3)$$

We compare the MA-MAEs for our random forest and hierarchical random forest classifiers. In this case, our hierarchical approach achieved a better MA-MAE score for the wrist and the thigh models, and fell slightly short with the chest and the thigh and chest models. By changing the nature of error, we see that although our hierarchical classifier predicted more errors in all cases, it predicts less severe errors in some cases.

Model	MA-MAE			
	Actigraph Wrist	BioStamp Thigh and Chest	BioStamp Thigh	BioStamp Chest
Random Forest	0.6697	0.8051	0.8013	0.7943
Random Forest Hierarchy	0.6854	0.8007	0.8033	0.7934

Table 5.19: MA-MAE comparison of models.

Using AdaBoost also failed to provide us with the lift we hoped for. It is possible that because of the imbalanced nature of our dataset, even Adaboost struggled to learn certain classes that had a significantly smaller sample size. The confusion matrix for AdaBoost with the thigh and chest BioStamp is shown in Table B.15, and can be found in Appendix B.

When working with imbalanced classes, the classification accuracy may not be the ideal metric for us to optimize. As the confusion matrices demonstrate, models tend to favor the majority classes, while failing to recognize the minority classes.

Our final investigation was to implement a multi-class boosting method that uses the confusion matrix as the optimizing measure and to observe whether classification accuracy increases. Our implementation of CoMBo combats the class imbalance problem by considering the number of samples for each class while updating the misclassification costs for each class, in addition to the level of difficulty associated with classifying a sample. Due to the time complexity that came with updating the score functions and cost matrices in this algorithm, we trained five CoMBo models - one per activity domain - which allowed us to subset our data. A smaller training set made the cost matrices significantly smaller and therefore decreased training time. Although training time was decreased substantially, our models have not predicted every observation session by the end of this work. These preliminary results present accuracies missing about ten total observation sessions. Regardless of these several missing predictions, we believe our results are still informative. Table 5.20 shows the preliminary accuracies for each of the activity domains using leave-one-out cross validation.

Activity Domain	Accuracy (%)
Active	80.74
Errands	74.12
Leisure	94.7
Household	89.88
Work	93.49

Table 5.20: Preliminary CoMBo accuracies by activity domain for combined thigh and chest BioStamps.

Chapter 6

DISCUSSION AND CONCLUSION

In this work, we developed models to predict a person’s physical activity/posture based on three sets of monitor data. We ran experiments to answer questions posed by Dr. Keadle from Cal Poly’s Department of Kinesiology and Public Health.

Question 1. Our first round of experiments was dedicated to finding out the best monitor placement and machine learning method for estimating sedentary versus non-sedentary behavior. In these experiments, we were able to achieve nearly perfect performance in predicting sedentary time within a given second, with the thigh *KNN* model achieving the highest accuracy (98.62%) amongst our models in this particular case. In addition, we demonstrate that our models can almost perfectly recognize sedentary vs. non-sedentary behavior, no matter the activity domain.

Question 2. Another contribution of this thesis was to compare our methods to previously developed methods. We tested our dataset on Staudenmayer et al’s random forest method, and found that our wrist model outperforms theirs. With this result, we are able to provide further support to the claim that laboratory-trained models are not the best predictors of free-living data.

Question 3. Dr. Keadle’s third question required us to validate different monitors and monitor placements using different classifiers to estimate activity intensity. We observed two sets of results for this question. Our first set of results is referred to as our aggregated results. We took our most granular, 14-posture models and aggregated the predicted results from the 14-posture coding scheme into activity intensities. The

other set of results is obtained from retraining new models for this activity intensity coding scheme. From observing two sets of results, we found that our most granular models estimate activity intensity equally as well as our models retrained the predict intensity levels. This is a significant contribution of our work as the aggregation method is more cost-effective, allowing us to only train one model that predicts a much granular coding scheme, while still accurately predicting a less granular coding scheme via aggregation. Taking both sets of results into consideration, the best predictor of activity intensity is our random forest classifier using the combined thigh and chest monitors.

Question 4. We were also interested in building predictive models to learn behaviors that were more specific than simply sedentary vs. non-sedentary. We created a new coding scheme to train on from our 14 class variables generalizing down to five activity classes, and obtained promising results in comparison to previous work [20]. In terms of what monitor and method best predicts the five general posture classes, our thigh and chest random forest model was the top contender for our experiments. However, all of our models failed to capture *riding in a vehicle*. This is due to the non-uniformity of our dataset, which is result of the nature of free-living data - humans tend to perform some activities more than others. Another reason *riding in a vehicle* was so difficult for our models to learn is because *riding in a vehicle* is essentially sitting.

Question 5. Dr. Keadle wanted to develop methods to predict activity type at an even more granular level than five postures. We developed models which correctly classified a participant's posture into 14 classes with up to 85.98% accuracy. In our particular set of experiments, we found that the combination of thigh and chest acceleration is the best indicator of physical posture and that random forest performs

the best out of our traditional classifiers.

Question 6. Given that our 14 activity classes could be structured into a 3-level hierarchy, we used the local classifier per parent node approach and built a hierarchical ensemble of random forest classifiers. Although our attempt to use a hierarchical ensemble did not prove to be as successful as we had hoped - we found that changing our error measure to evaluate the severity of our misclassifications revealed that using a hierarchical classification approach could result in less severe errors than some of our traditional classifiers.

Question 7. Our traditional and hierarchical classification approaches both struggled with recognizing underrepresented postures. The final question this thesis addresses is whether a multi-class boosting method, specifically a confusion matrix boosting algorithm, successfully combats the class-imbalance problem within our dataset. Our experiments show great promise with confusion matrix boosting as it proves to be successful when trained by activity domain.

Overall, we developed a dataset containing almost 100 hours of direct observation from three novel sets of accelerometer data collected by the Cal Poly Kinesiology and Public Health Department. This dataset is structured in a way that lays out multiple directions for future work. We were successful in detecting the amount of time an individual spends performing an activity. Across the board on all coding schemes, we found the BioStamp monitors were much better indicators of physical activity on a second-by-second basis than the wrist-worn Actigraph. This is most likely due to the amount of noise the wrist accelerometer experiences while it is worn. One exception to this conclusion would be in our sedentary versus non-sedentary experiments, where the chest BioStamp performed similarly to the wrist. Out of all of the machine learn-

ing techniques we tested on our accelerometer data, random forests and k -nearest neighbors both performed comparably and were the best estimators of behavior for each activity monitor. Furthermore, our hierarchical classification schema was able to reduce the severity of error from our traditional random forest classifiers on some monitors. Finally, we made an effort to better predict classes that are underrepresented in our dataset using the confusion matrix boosting algorithm proposed by [34], which achieved promising preliminary results in our experiments.

Chapter 7

FUTURE WORK

This work trains models on a novel free-living accelerometer dataset and compares performance to that of a laboratory-trained model. There are many other publicly-available activity recognition methods that would be interesting to include in a side-by-side performance comparison. Future work should test previously developed models on our data so that the performance of our models can be evaluated alongside others. Our work also estimates physical activity on a second-by-second level. Prior work has used larger time intervals, ranging from 15 seconds to one minute. In order to more directly compare performance with other methods, future work should evaluate our models using larger time windows.

We used sci-kit learn’s AdaBoost and gradient boosting classifiers as an attempt to improve classification accuracy. Given the imbalanced nature of our dataset, we also implemented the CoMBo algorithm [34] in an effort to combat the class-imbalance problem. Future work should evaluate our models on a more balanced dataset. Another direction for future work would be to investigate developing a boosting method that uses domain knowledge about the activity classes to reweigh the dataset after each classification attempt rather than the standard reweighing technique AdaBoost uses. This boosting method could reweigh the misclassified data points by using prior domain knowledge about the importance of detecting certain misclassification situations. For example, according to Dr. Keadle, misclassifying *sitting* as *running* is absolutely unacceptable, but the misclassification of *sitting* for *standing* is less of an issue, because the activities are more closely related. In this scenario, the weights for the *sitting* data points that were misclassified as *running* would be greater than the weights of the *sitting* points that were misclassified as *standing* due to a hard-coded

rule that *sitting* being misclassified as *running* is a more important problem than *sitting* being misclassified as *standing*.

In addition, when creating our ground truth dataset, we added a column that labels seconds that contain more than one posture, which we refer to as transition seconds. For most of our experiments, we excluded these seconds in order to provide our models with “purer” training data. Future work should investigate training models to learn seconds in which multiple postures are observed.

Finally, future work should build models to learn *riding in a vehicle*. This may potentially require studies to try to “control” the nature of free-living data by collecting more samples of *riding in a vehicle*.

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APPENDICES

Appendix A

DATASET SAMPLES

ID	session	type	start_month	start_day	start_year	Actual Start	Actual Stop	Duration
AM01	DO1	L	10	3	2017	18:44:45	20:47:00	2:02:15
AM01	DO2	H	10	6	2017	16:43:57	18:45:00	2:01:03
AM02	DO1	H	7	24	2017	13:17:10	15:17:32	2:00:22
AM02	DO2_a	A	7	25	2017	8:00:27	8:52:32	0:52:05
AM02	DO2_b	A	7	25	2017	8:56:13	10:12:29	1:16:16
AM03	DO1	L	7	25	2017	14:00:10	16:00:23	2:00:13
AM03	DO2	H	7	27	2017	13:01:29	15:00:39	1:59:10
AM04	DO1	W	9	12	2017	12:02:56	14:04:00	2:01:04
AM04	DO2	A	9	17	2017	14:15:58	16:16:00	2:00:02
AM05	DO2	L	9	19	2017	19:38:53	21:40:00	2:01:07
AM06	DO1	E	7	31	2017	8:35:23	10:36:03	2:00:40
AM06	DO2	A	8	1	2017	8:09:22	10:10:03	2:00:41
AM07	DO1	H	8	2	2017	9:01:18	11:01:27	2:00:09
AM07	DO2	E	8	2	2017	11:30:08	13:30:19	2:00:11
AM08	DO1_a	E	8	3	2017	9:08:47	10:24:09	1:15:22
AM08	DO1_b	E	8	3	2017	10:26:00	11:10:52	0:44:52
AM08	DO2	A	8	7	2017	9:30:17	11:30:47	2:00:30
AM09	DO1	W	8	10	2017	13:26:00	15:08:44	1:42:44
AM09	DO2	A	8	10	2017	16:18:04	18:18:36	2:00:32

Figure A.1: A snapshot of the direct observation timestamp log as provided by the Cal Poly Kinesiology and Public Health Department.

Date_Time_Absolute_dmy_hmsf	Date_dmy	Time_Absolute_hm_Abs	Time_Relative_hmsf	Time_Relative_active_hm	Time_Relative_relative_f	Time_Relative_relative_sf	Duration_n_sf	Observation	Event_Log	Behavior	Modifier_1	Modifier_2_r_2	Modifier_3_r_3	Modifier_4_r_4	Event_Type	Comment
07-03-2018 13:30:26.511	07-03-2018	13:30:26	511	00:00:00.000	00:00:00	0	0	43.415 AM01DO1_J_FINAL	Event log	LES- socializing, communicating, leisure time not screen	No movement				State start	
07-03-2018 13:30:26.511	07-03-2018	13:30:26	511	00:00:00.000	00:00:00	0	0	35.849 AM01DO1_J_FINAL	Event log	LA- stand	No movement				State start	
07-03-2018 13:31:02.359	07-03-2018	13:31:02	359	00:00:35.849	00:00:35	849	35.849	0 AM01DO1_J_FINAL	Event log	LA- stand	No movement				State stop	
07-03-2018 13:31:02.359	07-03-2018	13:31:02	359	00:00:35.849	00:00:35	849	35.849	9.483 AM01DO1_J_FINAL	Event log	LA- stand and move			light		State start	
07-03-2018 13:31:09.926	07-03-2018	13:31:09	926	00:00:43.415	00:00:43	415	43.415	0 AM01DO1_J_FINAL	Event log	LES- socializing, communicating, leisure time not screen					State stop	
07-03-2018 13:31:09.926	07-03-2018	13:31:09	926	00:00:43.415	00:00:43	415	43.415	118.5 AM01DO1_J_FINAL	Event log	HA- food prep and cleanup					State start	
07-03-2018 13:31:11.842	07-03-2018	13:31:11	842	00:00:45.332	00:00:45	332	45.332	0 AM01DO1_J_FINAL	Event log	LA- stand and move			light		State stop	
07-03-2018 13:31:11.842	07-03-2018	13:31:11	842	00:00:45.332	00:00:45	332	45.332	5.5664 AM01DO1_J_FINAL	Event log	LA- stand	No movement				State start	
07-03-2018 13:31:17.409	07-03-2018	13:31:17	409	00:00:50.898	00:00:50	898	50.898	0 AM01DO1_J_FINAL	Event log	LA- stand	No movement				State stop	
07-03-2018 13:31:17.409	07-03-2018	13:31:17	409	00:00:50.898	00:00:50	898	50.898	10.483 AM01DO1_J_FINAL	Event log	LA- stand	Yes movement				State start	
07-03-2018 13:31:27.892	07-03-2018	13:31:27	892	00:01:01.381	00:01:01	381	61.381	0 AM01DO1_J_FINAL	Event log	LA- stand	Yes movement				State stop	
07-03-2018 13:31:27.892	07-03-2018	13:31:27	892	00:01:01.381	00:01:01	381	61.381	9.9829 AM01DO1_J_FINAL	Event log	LA- stand	Unidentifiable				State start	
07-03-2018 13:31:37.875	07-03-2018	13:31:37	875	00:01:11.364	00:01:11	364	71.364	0 AM01DO1_J_FINAL	Event log	LA- stand	Unidentifiable				State stop	
07-03-2018 13:31:37.875	07-03-2018	13:31:37	875	00:01:11.364	00:01:11	364	71.364	47.765 AM01DO1_J_FINAL	Event log	LA- stand	Yes movement				State start	
07-03-2018 13:32:25.639	07-03-2018	13:32:25	639	00:01:59.129	00:01:59	129	119.13	0 AM01DO1_J_FINAL	Event log	LA- stand	Yes movement				State stop	
07-03-2018 13:32:25.639	07-03-2018	13:32:25	639	00:01:59.129	00:01:59	129	119.13	3.3999 AM01DO1_J_FINAL	Event log	LA- stand and move		light			State start	

Figure A.2: A snapshot of the ground truth criterion log as provided by the Cal Poly Kinesiology and Public Health Department.

Specific Posture/movement	Modifier options	Modifier_1 (upper_body)	Modifier_3 (intensity)	Point event
Lying Down	Upper body	no movement, Unidentifiable, typing, yes movement	sedentary	kick, jump, throw, swing
Sitting/reclining	Upper body	no movement, Unidentifiable, typing, yes movement	sedentary	kick, jump, throw, swing
Kneeling/squatting	Upper body	no movement, Unidentifiable, typing, yes movement	sedentary	kick, jump, throw, swing
Stretching	Intensity	unknown	sedentary, light, moderate, vigorous	kick, jump, throw, swing
Standing	Upper body	no movement, Unidentifiable, typing, yes movement	light	kick, jump, throw, swing
Stand and move	Intensity	no	light, moderate, vigorous	kick, jump, throw, swing
Stand and move upper	Intensity	yes	light, moderate, vigorous	kick, jump, throw, swing
Walk	Intensity	NA	light, moderate, vigorous	kick, jump, throw, swing
Walking with a Load	Intensity	NA	light, moderate, vigorous	kick, jump, throw, swing
Running	Intensity	NA	moderate, vigorous	kick, jump, throw, swing
Bike	Intensity	no	moderate, vigorous	kick, jump, throw, swing
Ascend	Intensity	NA	moderate, vigorous	kick, jump, throw, swing
Descend	Intensity	NA	moderate, vigorous	kick, jump, throw, swing
Muscle strengthening activities	Intensity	NA	light, moderate, vigorous	kick, jump, throw, swing
sports	Intensity	NA	light, moderate, vigorous	kick, jump, throw, swing
Private/not coded	NA	Private/not coded	Private/not coded	NA

Figure A.3: Posture coding options and their respective modifier options.

Appendix B

CONFUSION MATRICES

	Predicted				
Actual		sedentary	light	moderate	vigorous
	sedentary	112313	48393	10172	958
	light	49610	44405	12609	1316
	moderate	13365	15739	15019	2325
	vigorous	1693	3316	3339	6876

Table B.1: Confusion matrix for retrained random forest model predicting METs from wrist Actigraph.

	Predicted				
Actual		sedentary	light	moderate	vigorous
	sedentary	169021	2626	342	21
	light	1406	106482	4171	219
	moderate	361	7174	38814	187
	vigorous	410	1345	610	12871

Table B.2: Confusion matrix for retrained random forest model predicting METs from thigh BioStamp.

	Predicted				
Actual		sedentary	light	moderate	vigorous
	sedentary	169040	2621	319	30
	light	1373	106587	4082	236
	moderate	342	7291	38724	179
	vigorous	876	2492	310	11558

Table B.3: Confusion matrix for retrained random forest predicting METs from chest BioStamp.

	Predicted				
Actual		sedentary	light	moderate	vigorous
	sedentary	168887	2752	332	39
	light	1441	106605	3997	235
	moderate	353	7137	38876	170
	vigorous	348	2059	266	12563

Table B.4: Confusion matrix for retrained random forest predicting METs from thigh and chest BioStamps.

	Predicted			
Actual		Sedentary	Non-sedentary	Recall
	Sedentary	46977	3342	0.934
	Non-sedentary	5867	17895	0.753
	Precision	0.889	0.843	0.876

Table B.5: Confusion matrix for RF predicting sedentary time from wrist Actigraph on *active* observation sessions.

	Predicted			
Actual		Sedentary	Non-sedentary	Recall
	Sedentary	33716	17231	0.662
	Non-sedentary	7538	9958	0.569
	Precision	0.817	0.366	0.638

Table B.6: Confusion matrix for RF predicting sedentary time from wrist Actigraph on *errands* observation sessions.

	Predicted			
Actual		Sedentary	Non-sedentary	Recall
	Sedentary	11118	8210	0.575
	Non-sedentary	11999	37937	0.76
	Precision	0.481	0.822	0.708

Table B.7: Confusion matrix for RF predicting sedentary time from wrist Actigraph on *work* observation sessions.

	Predicted			
Actual		Sedentary	Non-sedentary	Recall
	Sedentary	4617	954	0.829
	Non-sedentary	10125	52079	0.837
	Precision	0.313	0.982	0.837

Table B.8: Confusion matrix for RF predicting sedentary time from wrist Actigraph on *leisure* observation sessions.

	Predicted			
Actual		Sedentary	Non-sedentary	Recall
	Sedentary	39063	11120	0.778
	Non-sedentary	6369	14873	0.7
	Precision	0.86	0.572	0.755

Table B.9: Confusion matrix for RF predicting sedentary time from wrist Actigraph on *household* observation sessions.

	Predicted			
Actual		Sedentary	Non-sedentary	Recall
	Sedentary	50035	284	0.994
	Non-sedentary	575	23187	0.976
	Precision	0.989	0.988	0.989

Table B.10: Confusion matrix for RF predicting sedentary time from thigh and chest BioStamps on *active* observation sessions.

	Predicted			
Actual		Sedentary	Non-sedentary	Recall
	Sedentary	55048	287	0.995
	Non-sedentary	581	16915	0.967
	Precision	0.99	0.983	0.988

Table B.11: Confusion matrix for RF predicting sedentary time from thigh and chest BioStamps on *errands* observation sessions.

	Predicted			
Actual		Sedentary	Non-sedentary	Recall
	Sedentary	18942	386	0.98
	Non-sedentary	548	49053	0.989
	Precision	0.972	0.992	0.986

Table B.12: Confusion matrix for RF predicting sedentary time from thigh and chest BioStamps on *work* observation sessions.

	Predicted			
Actual		Sedentary	Non-sedentary	Recall
	Sedentary	5427	144	0.974
	Non-sedentary	189	62015	0.997
	Precision	0.966	0.998	0.995

Table B.13: Confusion matrix for RF predicting sedentary time from thigh and chest BioStamps on *leisure* observation sessions.

	Predicted			
Actual		Sedentary	Non-sedentary	Recall
	Sedentary	49202	981	0.98
	Non-sedentary	1205	19908	0.943
	Precision	0.976	0.953	0.969

Table B.14: Confusion matrix for RF predicting sedentary time from thigh and chest BioStamps on *household* observation sessions.

Predicted														
	lying	sitting	standing	stand & move light	stand & move mod	stand & move vig	walk light	walk mod	walk vig	ascend stairs	descend stairs	running	other sport	bike
Actual	lying	0	25	0	0	0	0	0	0	0	0	0	0	0
	sitting	85	169364	1528	0	0	78	290	0	4	1	0	0	10
	standing	0	992	75838	8167	5	0	459	910	0	2	0	3	0
	stand & move light	0	420	11454	8253	7	0	811	1516	0	2	1	55	0
	stand & move mod	0	8	1222	1470	2	0	63	467	0	0	0	63	0
	stand & move vig	0	2	14	53	0	0	0	6	0	0	0	1	0
	walk light	0	228	1276	3627	1	0	1491	3064	0	3	0	3	0
	walk mod	0	90	699	2515	1	0	1905	27486	0	21	0	12	0
	walk vig	0	5	48	64	0	0	28	1825	0	3	0	1	0
	ascend stairs	0	1	26	82	9	0	58	733	0	151	0	58	0
	descend stairs	0	21	3	45	0	0	41	853	0	1	2	44	0
	running	0	0	11	185	90	0	2	89	0	0	0	8815	0
	other sport	0	0	2	0	0	0	0	0	0	0	0	0	0
	bike	0	426	202	821	5	0	11	1233	0	392	0	9	0

Table B.15: Confusion matrix for AdaBoost predicting the full coding scheme on combined BioStamp thigh and chest monitor data.

Appendix C

MODEL ACCURACIES

Model	Accuracy (%)			
	Actigraph Wrist	BioStamp Thigh and Chest	BioStamp Thigh	BioStamp Chest
Random Forest with transitions	61.41	84.13	84.03	84.12
Random Forest without transitions Hierarchy	61.61	85.98	85.73	85.47

Table C.1: Test accuracy comparison of random forests with transition seconds in the dataset vs. excluding transition seconds from the dataset on the full coding scheme across all monitors.

Model	Accuracy (%)			
	Actigraph Wrist	BioStamp Thigh and Chest	BioStamp Thigh	BioStamp Chest
Random Forest <i>maxdepth</i> = 5	76.42	95.54	98.51	77.17
Random Forest <i>maxdepth</i> = 15	76.12	98.5	98.45	76.34

Table C.2: Test accuracy comparison of random forests using different maximum tree depths on the sedentary coding scheme.

Model	Accuracy (%)			
	Actigraph Wrist <i>KNN</i>	Actigraph Wrist <i>RF</i>	BioStamp Thigh and Chest <i>SVM</i>	BioStamp Thigh and Chest <i>RF</i>
7 Features	62.55	76.42	89.44	98.54
23 Features	63.72	77.17	95.77	98.6

Table C.3: Test accuracy comparison of models with different number of total features on the sedentary coding scheme.