Human Activity Prediction on Nonlinear Manifolds

Colin M. Adams[*]
Detection & Estimation
Areté Associates
Northridge, CA 91324
cadams@arete.com

Kai S. Kaneshina
Detection & Estimation
Areté Associates
Northridge, CA 91324
kkaneshina@arete.com

Eli J. Weissler
Detection & Estimation
Areté Associates
Northridge, CA 91324
eweissler@arete.com

Abstract

Hopefully we have some nice results. The abstract must be limited to one paragraph.

1 Progress Report

Instructions from the course website say:
Submit the progress report detailing your progress towards your goal. Typed (LaTeX) summarizing your literature search, specifying what data sets you are using, and what methods you are applying. The write-up should be 3 to 5 pages for a 1 person group, 6 to 8 pages for a 2 person group and 8 to 10 for a 3 person group.

2 Introduction

As of 2019, it was estimated that 5 billion people have mobile devices and over half of these devices are smartphones. The sheer amount of data generated from these devices is enormous; most of them are equipped with accelerometer, gyroscopes, magnetometers, etc. The information from these sensors has enabled the study of Human Activity Recognition (HAR). HAR has a variety of applications including healthcare, sports, continuous user authentication, and biometric key generation. The HAR data is often non-linear, but the approaches used for analysis do not take this into account.

There have been several papers published which utilize machine learning and deep learning techniques for HAR. Previous researchers used labeled accelerometer, gyroscope, magnetometer and electrocardiogram data for HAR [1]. They compared the performance of three different classifiers (Random Forest, Support Vector Machine, Naive Bayes) and three different deep neural network architectures (Multilayer Perceptron, Deep Convolutional Neural Network and Long-Short Term Memory), and found that the deep neural networks performed the best.

Previous researchers compared the performance of traditional machine learning methods (k-NN, SVM) to a residual network (ResNet) [2]. They used a variety of datasets, including motion sense, the dataset that we have used for this paper. They used only the accelerometer data, and compared the classifier performance for using the raw data vs hand-crafted features. For the motion sense dataset, the hand-crafted features gave the best results for the classifier, but the ResNet still performed the best. ResNets allow for skipping between layers; these skips contain non-linearities, which are better able to represent the non-linear accelerometer data [3].

While both papers proved that deep learning architectures are the superior methods for HAR, neither of their traditional approaches accounted for the non-linear aspect of the accelerometer data. We are interested in improving the performance of traditional machine learning methods by accurately accounting for the the non-linearity of the data in a pre-processing step.

[*]All authors contributed equally. The names are ordered alphabetically.

3 The Game Plan

I think this is the story we largely are trying to tell:

1. Can we use cell phone data to accurately and consistently distinguish between the activities people are doing? The answer had better be yes because it seems loads of other folks have done so.
    - What techniques are used to do this? Luckily for us, we have this wonderful set of *labeled* (and somewhat diverse) data. So obviously we are probably interested in looking at how supervised learning techniques perform. The amazing thing is that scikit-learn's syntax is basically identical once the data gets set up so it really becomes a plug and chug type of thing after that. Some techniques includes:
    - Support vector machines (SVM)
    - Some deep/crazy-architectured neural network; since this seems to be all the rage these days and since NN claim to be able to catch non-linearness of problems, it seems like a good thing to compare our results to.
    - Decision trees?
    - SGD classifiers
    - others?
2. But, what I think Prof. Gu is looking for is that we can use manifold learning with linear techniques for an unsupervised set of data. Can we classify accuately with that? Some techniques we may consider
    - k-means
    - PCA
    - Gaussian mixture

4 Our Data

We used the MotionSense data. Blah blah blah.

5 Citations, figures, tables, references

These instructions apply to everyone.

5.1 Citations within the text

The `natbib` package will be loaded for you by default. Citations may be author/year or numeric, as long as you maintain internal consistency. As to the format of the references themselves, any style is acceptable as long as it is used consistently.

The documentation for `natbib` may be found at

```
http://mirrors.ctan.org/macros/latex/contrib/natbib/natnotes.pdf
```

Of note is the command `\citet`, which produces citations appropriate for use in inline text. For example,

```
\citet{hasselmo} investigated\dots
```

produces

> Hasselmo, et al. (1995) investigated...

If you wish to load the `natbib` package with options, you may add the following before loading the `nips_2016` package:

```
\PassOptionsToPackage{options}{natbib}
```

If `natbib` clashes with another package you load, you can add the optional argument `nonatbib` when loading the style file:

```
\usepackage[nonatbib]{nips_2016}
```

As submission is double blind, refer to your own published work in the third person. That is, use "In the previous work of Jones et al. [4]," not "In our previous work [4]." If you cite your other papers that are not widely available (e.g., a journal paper under review), use anonymous author names in the citation, e.g., an author of the form "A. Anonymous."

5.2 Footnotes

Footnotes should be used sparingly. If you do require a footnote, indicate footnotes with a number[2] in the text. Place the footnotes at the bottom of the page on which they appear. Precede the footnote with a horizontal rule of 2 inches (12 picas).

Note that footnotes are properly typeset *after* punctuation marks.[3]

5.3 Figures

All artwork must be neat, clean, and legible. Lines should be dark enough for purposes of reproduction. The figure number and caption always appear after the figure. Place one line space before the figure caption and one line space after the figure. The figure caption should be lower case (except for first word and proper nouns); figures are numbered consecutively.

You may use color figures. However, it is best for the figure captions and the paper body to be legible if the paper is printed in either black/white or in color.

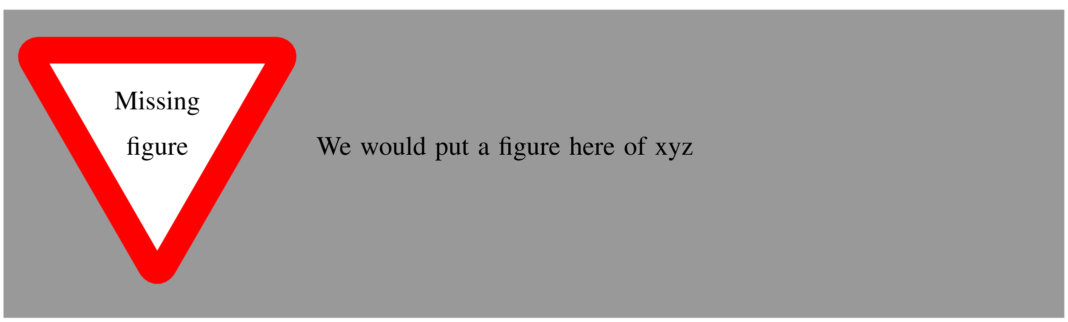

Figure 1: Sample figure caption.

5.4 Tables

All tables must be centered, neat, clean and legible. The table number and title always appear before the table. See Table 1.

Place one line space before the table title, one line space after the table title, and one line space after the table. The table title must be lower case (except for first word and proper nouns); tables are numbered consecutively.

Note that publication-quality tables *do not contain vertical rules.* We strongly suggest the use of the `booktabs` package, which allows for typesetting high-quality, professional tables:

`https://www.ctan.org/pkg/booktabs`

This package was used to typeset Table 1.

[2]Sample of the first footnote.
[3]As in this example.

Table 1: **Table 1:** Sample table title

Part		
Name	**Description**	**Size** (μm)
Dendrite	Input terminal	$\sim$100
Axon	Output terminal	$\sim$10
Soma	Cell body	up to 10^6

Acknowledgments

We would like to thank people. Probably our lord and savior Prof. Gu for teaching us everything we know about nonlinear data analysis.[4]

References

[1] Abdul Kadar Muhammad Masum, Erfanul Hoque Bahadur, Ahmed Shan-A-Alahi, Md Akib Uz Zaman Chowdhury, Mir Reaz Uddin, and Abdullah Al Noman. Human activity recognition using accelerometer, gyroscope and magnetometer sensors: Deep neural network approaches. pages 1–6, 2019.

[2] Anna Ferrari, Daniela Micucci, Marco Mobilio, and Paolo Napoletano. Hand-crafted features vs residual networks for human activities recognition using accelerometer. pages 153–156, 2019.

[3] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[4] Freeman J Dyson. Correlations between eigenvalues of a random matrix. *Communications in Mathematical Physics*, 19(3):235–250, 1970.