Handling Missing Data in Daily Activity Sensing

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Background: Activities of Daily Living

Activities of Daily Living (ADL) [1]

- Walking
- Standing
- Walking upstairs/downstairs
- Sitting
- Lying
- Brushing teeth
- …

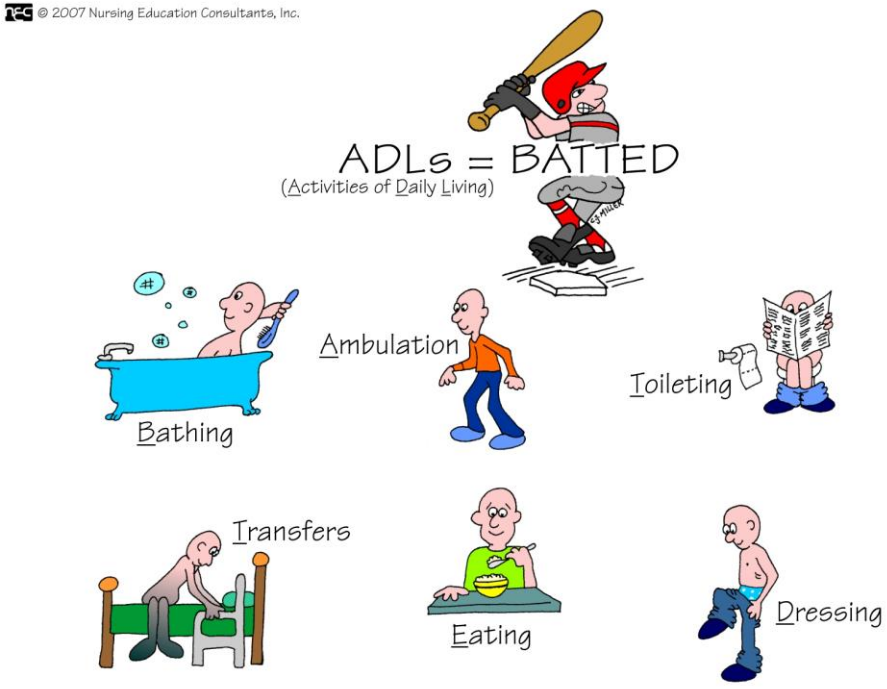

Fig. 1 An example of ADL

[1] Pires, I. M. S., Garcia, N. M., Pombo, N., Flórez-Revuelta, F., Zdravevski, E., & Spinsante, S. (2018). A review on the artificial intelligence algorithms for the recognition of Activities of Daily Living using sensors in mobile devices.
Photo credit: http://www.mwhomecare.com/activities-of-daily-living/

Background: Multimodal Sensing

- Ensembles a set of sensors
- Decisions are made by sensor fusion
- Provides ‘hard’ redundancy
- Increases robustness to faults

- Bulky device
- Likely to lose data[3]

Fig. 2 A hardware implementation of multimodal sensing[2]

[2] Zappi, P., Stiefmeier, T., Farella, E., Roggen, D., Benini, L., & Troster, G. (2007, December). Activity recognition from on-body sensors by classifier fusion: sensor scalability and robustness. In *Intelligent Sensors, Sensor Networks and Information, 2007. ISSNIP 2007. 3rd International Conference on* (pp. 281-286). IEEE.

[3] Jaques, N., Taylor, S., Sano, A., & Picard, R. (2017, October). Multimodal autoencoder: A deep learning approach to filling in missing sensor data and enabling better mood prediction. In *Affective Computing and Intelligent Interaction (ACII), 2017 Seventh International Conference on* (pp. 202-208). IEEE.

Motivation

Case Study #1: Miss sensor tolerant test of Human Activity Recognition Dataset[4]
Test Setup: Trained model w/ all sensors, test with one sensor removed.

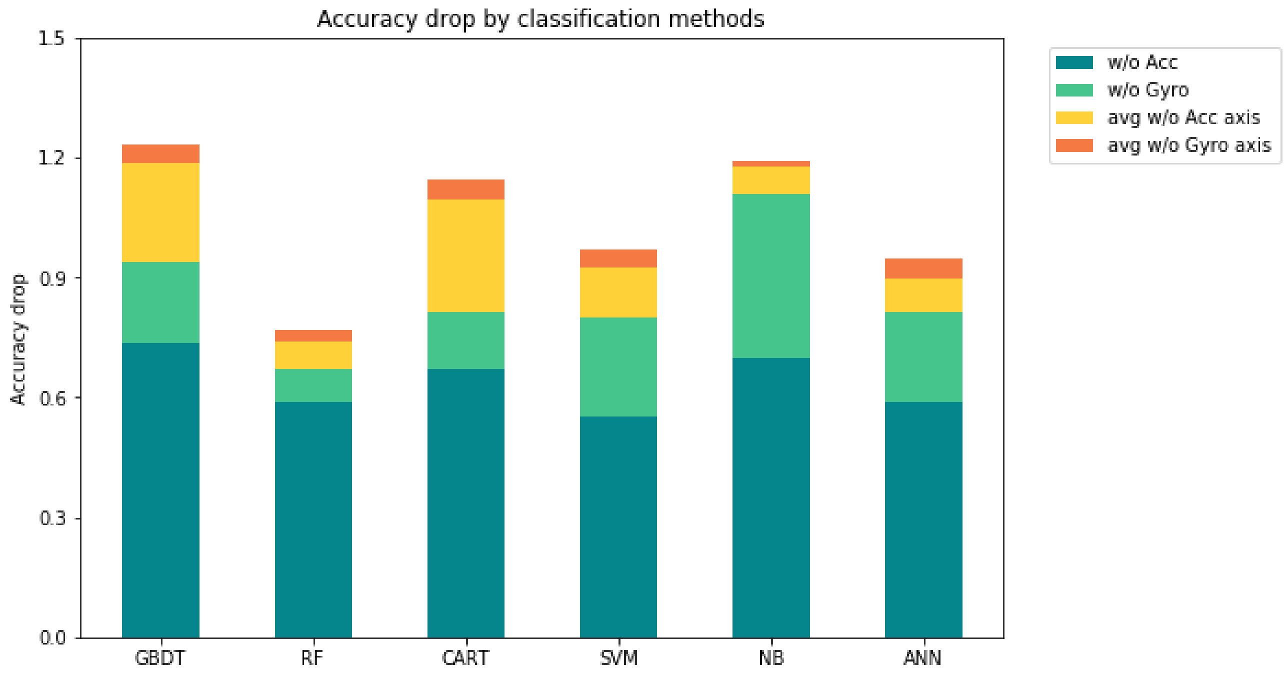

Fig. 4 Accuracy drop with lost sensors by various classification models

Result:

- All recognition models cannot do well if accelerometer is removed. (216/561 features left)
- w/o Accelerometer: 92% -> 33%
- w/o Gyro: 92% -> 84%

[4] Anguita, D., Ghio, A., Oneto, L., Parra, X., & Reyes-Ortiz, J. L. (2013, April). A public domain dataset for human activity recognition using smartphones. In *ESANN*.

Motivation

- Develop an algorithm to provide a ‘soft’ redundancy to multimodal sensing
- The algorithm can recover missing data/features
- Help reduce number of sensors used
- Find a balance: minimum set of sensors, maximum identification accuracy

Methodology

Identification(Full dataset) = High accuracy (~90%)

Identification(Full dataset – missing sensors) = Low accuracy (~30%)

Hypothesis:

Partial features **+** ***Background knowledge*** = *Reconstructed dataset?*

Identification(Reconstructed dataset) = *High accuracy?*

Methodology

Partial features + *Background knowledge* = Full dataset

Use *Autoencoder* to reconstruct missing features:

- Unsupervised learning technique
- Symmetric neural network
- Consists of an *encoder* and a *decoder*
- Robust to noise

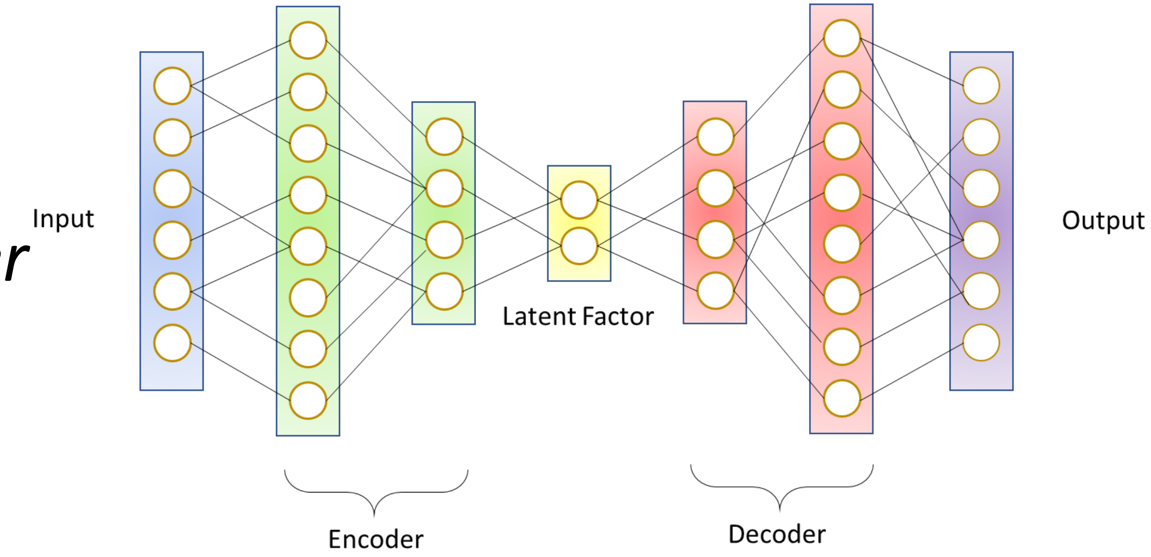

Fig. 5 Illustration of Autoencoder

Recover missing features with deep learning

Case Study #2: Feature reconstruction test of Human Activity Recognition Dataset

Network Structure:

Input: 561 dim
Output: 561 dim
Latent Factors: 6

Result:

Training MSE: 5.24E-3
Validation MSE: 5.65E-3

Depth	Input Type	Activation	Neurons
1	Input	relu	561
2	Encoder		128
3			16
4	Latent		6
5	Decoder		16
6			128
7	Output		561

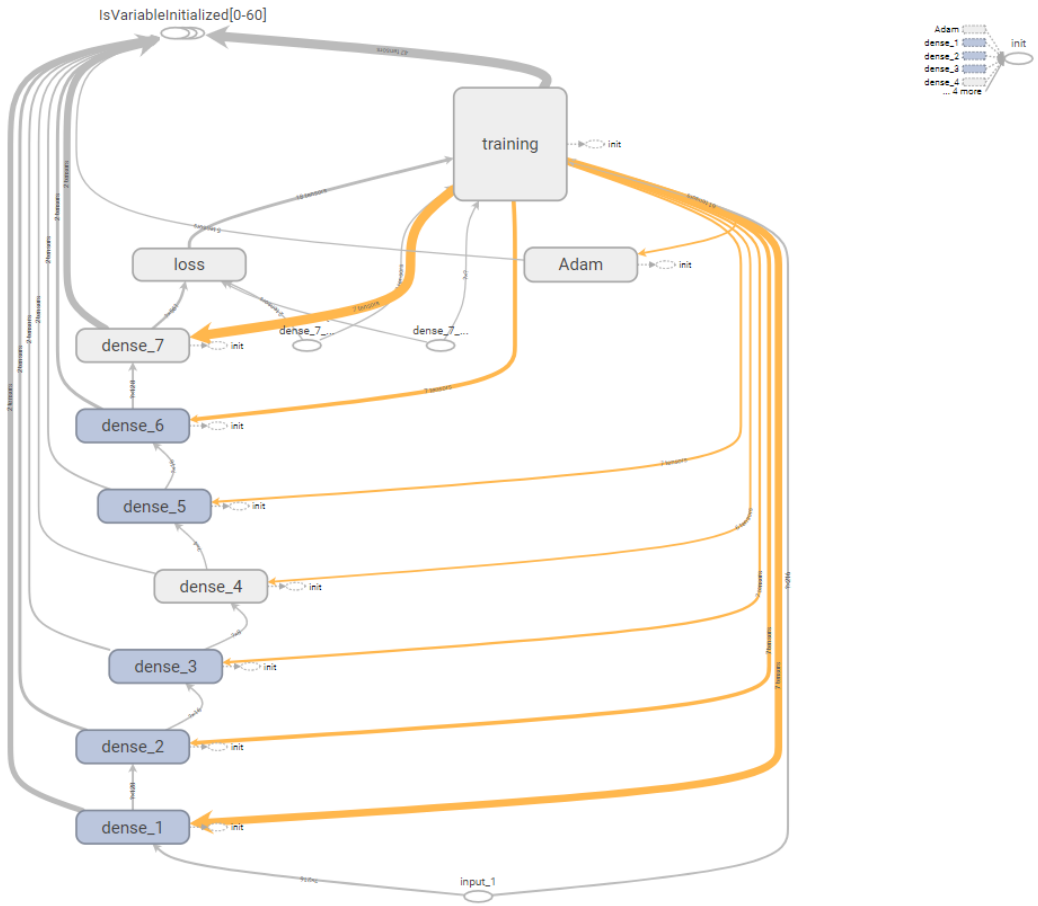

Fig. 6 Real Structure of Autoencoder Network

Refill missing features with deep learning

Case Study #2: Feature reconstruction test of Human Activity Recognition Dataset

Identification(Reconstructed dataset) = High accuracy

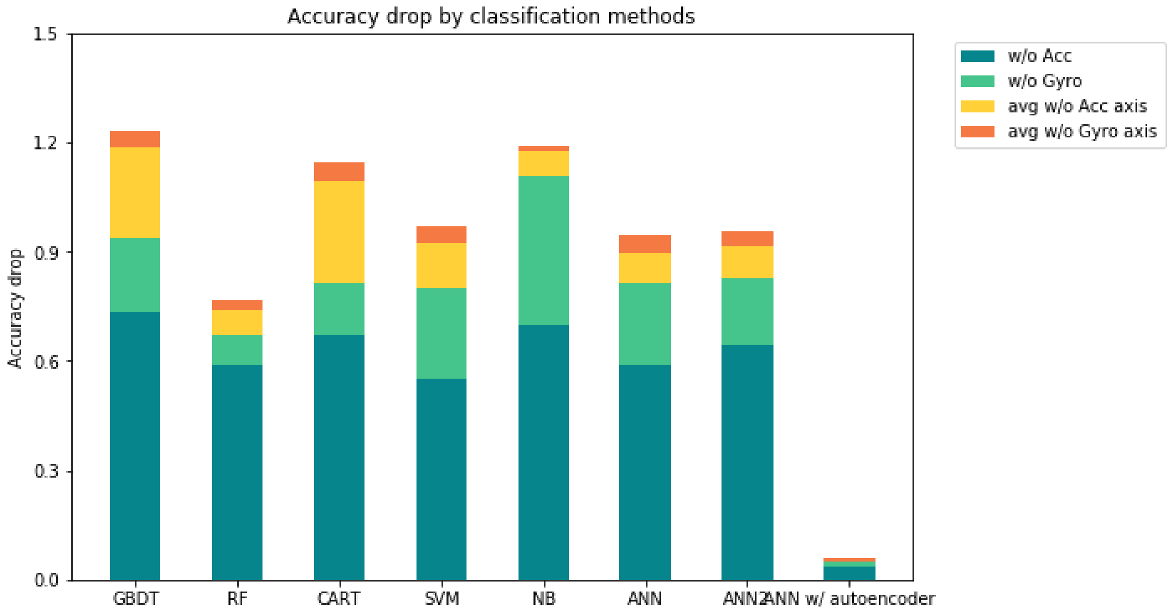

Fig. 7 Accuracy drop with lost sensors by various classification models

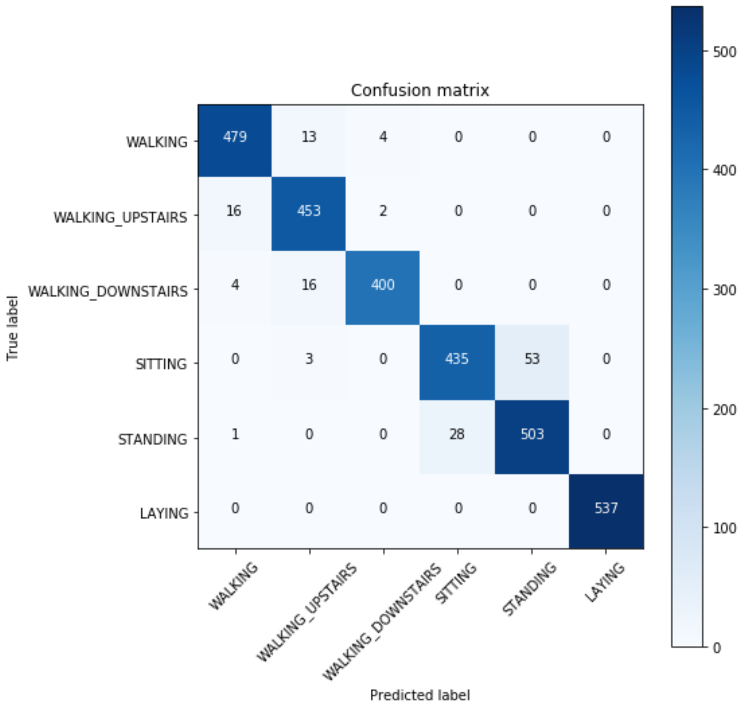

Fig. 8 Confusion matrix from reconstructed data (w/ accelerometer masked)

Accuracy = 84%

Refill missing features with deep learning

Case Study #2: Feature reconstruction test of Human Activity Recognition Dataset

	Random Forest	Artificial Neural Network	ANN w/ autoencoder	Better
w/o Acc	0.33	0.25	**0.84**	ANN w/ autoencoder
w/o Acc X	0.76	0.82	**0.89**	ANN w/ autoencoder
w/o Acc Y	**0.88**	0.85	0.87	RF
w/o Acc Z	0.89	**0.92**	0.88	ANN
w/o Gyro	0.84	0.80	**0.86**	ANN w/ autoencoder
w/o Gyro X	**0.87**	0.85	0.86	RF
w/o Gyro Y	0.90	**0.95**	0.86	ANN
w/o Gyro Z	0.91	**0.94**	0.86	ANN
Full Sensors	0.92	**0.95**	0.87	ANN

A Brief Summary: What can we get from result?

- Multimodal sensing provides a ‘hard’ redundancy for ADL recognition
- A generalized model trained with all features is not likely tolerate feature/sensor loss
- Our autoencoder implementation provides a ‘soft’ redundancy to multimodal sensing
- The autoencoder can help reconstruct missing features in HAR dataset and can help achieve a high accuracy, even if an important sensor is missing.

Future Works and Timeline

- Explore various structures of Autoencoders and try to reduce reconstruction error (~1 week)
- Implement GAN to feature reconstruction and compare the performance between GAN and autoencoder (~2 weeks)
- Case study 3 & 4: Applying autoencoder to OPPORTUNITY dataset[5] (~3 weeks)
- Case study 5 & 6: Applying autoencoder to CMU MMAC dataset[6] (~3 weeks)
- Develop a demonstration app with iOS device and perform real-time ADL detection on smart devices (~3 weeks)

[5] Chavarriaga, R., Sagha, H., Calatroni, A., Digumarti, S. T., Tröster, G., Millán, J. D. R., & Roggen, D. (2013). The Opportunity challenge: A benchmark database for on-body sensor-based activity recognition. *Pattern Recognition Letters*, *34*(15), 2033-2042.
[6] De la Torre, F., Hodgins, J., Bargteil, A., Martin, X., Macey, J., Collado, A., & Beltran, P. (2008). Guide to the carnegie mellon university multimodal activity (cmu-mmac) database. *Robotics Institute*, 135.

Q & A

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