ECE 5424: Introduction to Machine Learning

Comparative Study of Machine Learning Techniques for Human Activity Recognition

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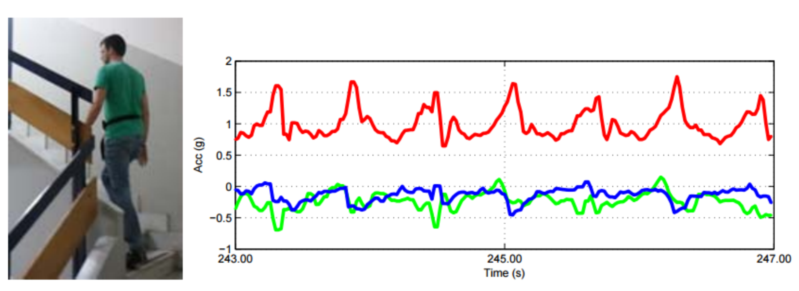
Introduction

- Human Activity Recognition (HAR) – detect activity of user using sensors embedded on smartphones/smartwatches.
- Essentially a multi-class classification problem.
- High accuracies of ML algorithms on different datasets
  - Need for a unified comparison on single dataset

Reference [1]

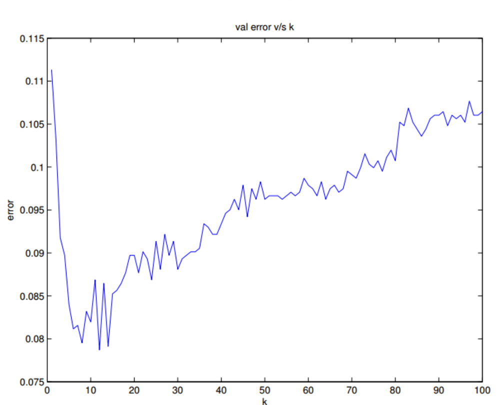
Dataset & Techniques Used

- **Dataset**
  - UCI Machine Learning Repository
  - 6 activities – Walking, Walking Upstairs, Walking Downstairs, Sitting, Standing, Laying Down
  - Accelerometer and gyroscope data collected
  - 10299 (7352 training + 2947 test) data points, each with 561 features
- **Techniques implemented**
  - K-Nearest Neighbors
  - Gaussian Naïve Bayes
  - Logistic Regression
  - Multi-class SVM
  - Artificial Neural Networks
- **In-built packages used**
  - Random Forests


"Walking Upstairs" [1]

K-NN & Gaussian NB

- **K-Nearest Neighbors**



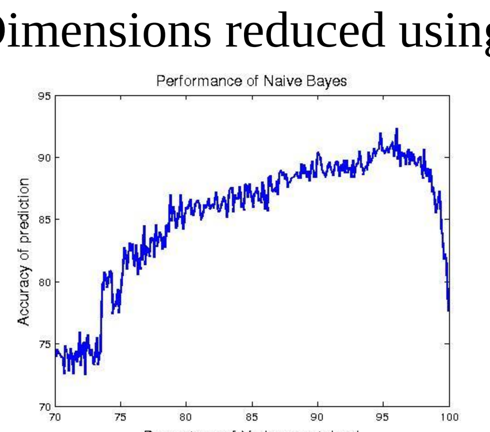
	Walking	Upstairs	Downstairs	Sitting	Standing	Laying	Precision
Walking	486	0	10	0	0	0	0.9798
Upstairs	37	427	7	0	0	0	0.9066
Downstairs	43	43	334	0	0	0	0.7952
Sitting	0	4	0	371	116	0	0.7556
Standing	0	0	0	26	506	0	0.9511
Laying	0	0	0	1	1	535	0.9963
Recall	0.8587	0.9008	0.9516	0.9322	0.8122	1	

Confusion Matrix for 14-NN, Euclidian distance

- **Gaussian Naïve Bayes**
  - Assumption: Each feature has an underlying Gaussian distribution

$$\mathrm{p}(\mathrm{X}_i = x|Y = y) = \frac{1}{\sqrt{2\pi\sigma_{ik}^2}} e^{-\frac{1}{2}\left(\frac{x-\mu_{ik}}{\sigma_{ik}}\right)^2}$$

  - Mean and Variance of each feature and class estimated
  - Direct Implementation gives poor results, 78% accuracy.
  - Dimensions reduced using PCA, significant improvement, 90.4% acc.



	Walking	Upstairs	Downstairs	Sitting	Standing	Laying	Precision
Walking	464	0	32	0	0	0	0.9355
Upstairs	31	401	39	0	0	0	0.8514
Downstairs	50	40	330	0	0	0	0.7857
Sitting	0	1	1	353	119	17	0.7189
Standing	4	1	3	43	478	3	0.8985
Laying	0	0	0	0	0	537	1
Recall	0.8425	0.9052	0.8148	0.8914	0.8007	0.9641	

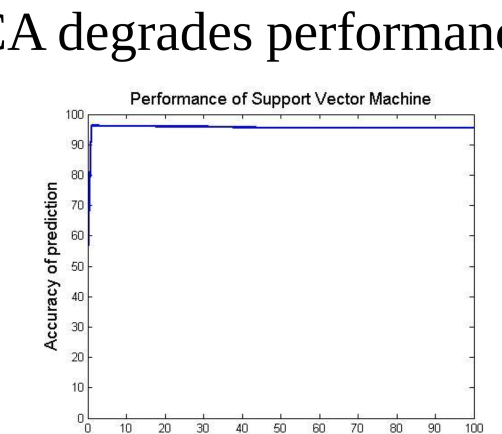
Confusion Matrix for GNB, Variance retained = 95%

Multi-class SVM

- Problem of finding K support vectors equivalent to solving

$$\min_{w_m,\xi_i} \quad \frac{1}{2}\sum_{m=1}^{k} w_m^T w_m + C\sum_{i=1}^{l}\xi_i$$
$$w_{y_i}^T\phi(x_i) - w_m^T\phi(x_i) \geq e_i^m - \xi_i, i = 1,\ldots,l.$$

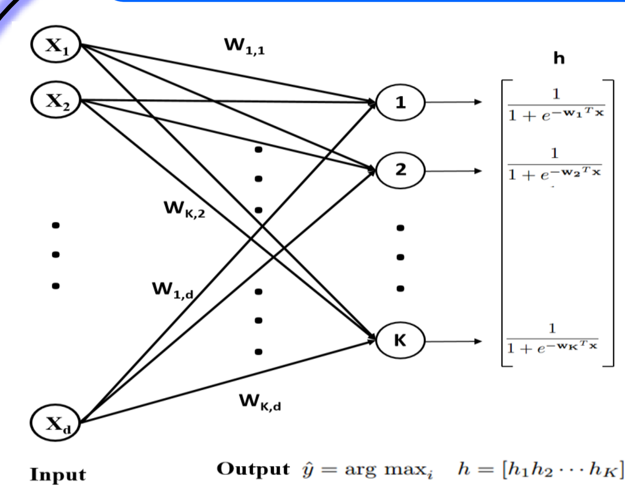
- Highest Accuracy among all techniques, accuracy = 96.34%, C=1 (tested for C = 0, 1, 5, 10, 25, 50, 100)
- PCA degrades performance



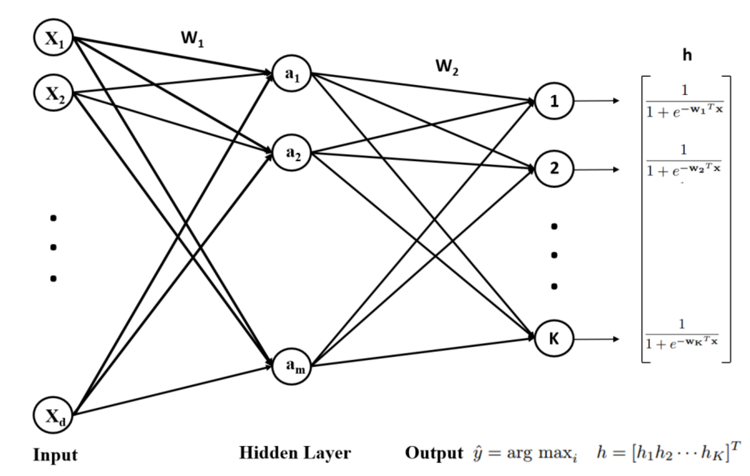
	Walking	Upstairs	Downstairs	Sitting	Standing	Laying	Precision
Walking	494	1	1	0	0	0	0.9960
Upstairs	21	450	0	0	0	0	0.9554
Downstairs	3	6	411	0	0	0	0.9786
Sitting	0	3	0	429	55	4	0.8737
Standing	2	0	0	12	518	0	0.9737
Laying	0	0	0	0	0	537	1
Recall	0.9500	0.9783	0.9976	0.9728	0.9040	0.9926	

Confusion Matrix for SVM, C = 1

Logistic Regression & ANN



Model for Logistic Regression



Model for Artificial Neural Networks, 1 hidden layer, m neurons

- **Logistic Regression**
  - Maximum accuracy: 94.16%
  - Dimensionality reduction degrades performance
  - 95% variance achieves near-maximum performance

	Walking	Upstairs	Downstairs	Sitting	Standing	Laying	Precision
Walking	489	0	7	0	0	0	0.9859
Upstairs	22	440	9	0	0	0	0.9342
Downstairs	10	20	390	0	0	0	0.9286
Sitting	0	3	0	421	67	0	0.8574
Standing	2	0	0	32	498	0	0.9361
Laying	0	0	0	0	0	537	1
Recall	0.9350	0.9503	0.9606	0.9294	0.8814	1	

Confusion Matrix for Logistic Regression

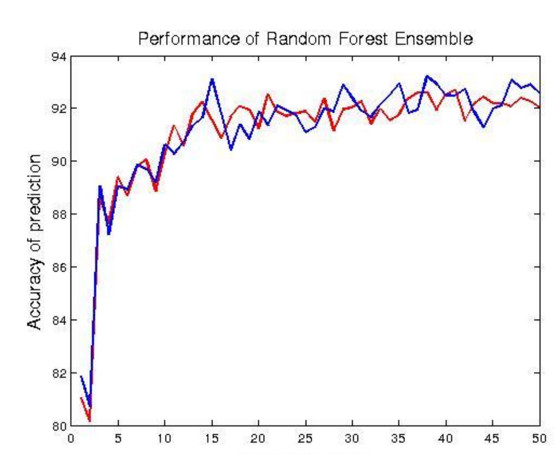
- **Artificial Neural Networks**
  - High number of neurons does not improve accuracy
  - Maximum accuracy: 95.87% for m =10 neurons (tested for m = 10, 25, 50, 100, 200, 250)
  - PCA yields no improvement

	Walking	Upstairs	Downstairs	Sitting	Standing	Laying	Precision
Walking	482	1	13	0	0	0	0.9718
Upstairs	27	444	0	0	0	0	0.9427
Downstairs	13	17	390	0	0	0	09286
Sitting	0	2	0	435	54	0	0.8859
Standing	0	0	0	19	513	0	0.9643
Laying	0	0	0	0	0	537	1
Recall	0.9234	0.9569	0.9677	0.9581	0.9048	1	

Confusion Matrix for Artificial Neural Networks, 10 Neurons

Random Forests

- Implemented with and without out-of-bag classification
- Number of trees varied from 1 to 50
- As the number of trees increases, out-of-bag classification performs better for the same number of decision trees
- PCA yields no improvement



	Walking	Upstairs	Downstairs	Sitting	Standing	Laying	Precision
Walking	480	8	8	0	0	0	0.9677
Upstairs	35	429	7	0	0	0	0.9108
Downstairs	18	44	358	0	0	0	0.8524
Sitting	0	0	0	438	53	0	0.8921
Standing	0	0	0	46	486	0	0.9135
Laying	0	0	0	0	0	537	1
Recall	0.9006	0.8919	0.9598	0.9050	0.9017	1	

Confusion Matrix for Random Forest. Xx trees

Discussions & Conclusions

- Poor Naïve Bayes performance when used on original dataset, but improvement on dimension reduction ⇨ high feature correlation
- SVM achieves the best performance (without using kernels) ⇨ data is linearly separable in the subspace which data occupies
- Performance degradation on using PCA for all methods except Naïve Bayes ⇨ data projected on lower dimension subspace is not linearly separable.
  - Potential fix: use Gaussian kernel.
- Class "Laying" has highest precision and recall for all techniques
- Most techniques make errors in classifying "Sitting" and "Standing"
- Achieved accuracy on par with those in literature.

Reference	Technique	Accuracy
[2]	Linear Multi-class SVM	96.40%
[3]	Kernel variant of learning vector quantization	96.23%
[4]	Ada-boost	94.33%

References

[1] D Anguita, et. al. "Human Activity Recognition on Smartphones using a Multiclass Hardware-Friendly Support Vector Machine," IWAAL 2012.
[2] B. Paredes, et. al. "A one-vs-one classifier ensemble with majority voting for activity recognition," ESANN 2013.
[3] M. Kastner, et. al. "A sparse kernelized matrix learning vector quantization model for human activity recognition," ESANN 2013.
[4] Attila Reiss, et.al. "A competitive approach for human activity recognition on smartphones," ESANN 2013.