# Careful Use of Machine Learning Methods is needed for Mobile Application A case study on Transportation-mode Detection

By Yu et al (2013)

Presented by

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# Contents

# Introduction

- Machine learning methods are often applied as a black box.
- Example is transportation-mode detection.
- Collect data, use algorithms and compare results.
- Default settings may not be the best one.
- Evaluation criterion (e.g. cross-validation) may not be appropriate.
- Some methods may not be applied due to resource constraints of mobile phones.

This paper focuses on using SVM and how the performance can be optimized.

# Transportation-mode Detection

- The detector can use only up to 16 KB of memory.
- Data consists of log files containing signals from gyroscope, accelerometer and magnetometer.
- Classification was done among

  Still, Walk, Run, Bike, Others

- Five features were extracted by calculating mean or standard deviation of the signals.
- Decision trees, AdaBoost and SVM were employed.

# Transportation-mode Detection

- Results

| Classifiers | CV accuracy (%) | Model size (KB) |
|---|---|---|
| Decision Tree | 89.41 | 76.02 |
| AdaBoost | 91.11 | 1500.54 |
| SVM | 84.72 | 1379.97 |

# Practical use of SVM

- Worse SVM performance may be because of lacking
  - Data scaling
  - Parameter selection
- Given label-instance pairs $(y_1, \boldsymbol{x}_1)\ldots(y_l, \boldsymbol{x}_l)$ with $y_i = \pm 1$, $\boldsymbol{x}_i \in R^n, \forall i$ as the training set. (Primal problem)

$$\min_{\boldsymbol{w},b} \quad \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C\sum_{i=1}^{l}\max(1 - y_i(\boldsymbol{w}^T\phi(\boldsymbol{x}_i) + b), 0).$$

# Practical use of SVM (Cont.)

- Because *w* becomes a huge vector so dual optimization problem is solved. (Dual Problem)

$$\begin{aligned} \min_{\boldsymbol{\alpha}} \quad & \frac{1}{2}\alpha^T Q\alpha - e^T\alpha \\ \text{subject to} \quad & y^T\alpha = 0, \\ & 0 \leq \alpha_i \leq C, i = 1, \ldots, l, \end{aligned}$$

- Where $Q_{ij} = y_i y_j \phi(\boldsymbol{x}_i)^T \phi(\boldsymbol{x}_j) = y_i y_j K(\boldsymbol{x}_i, \boldsymbol{x}_j), \quad \boldsymbol{e} = [1, \ldots, 1]^T$

# Practical use of SVM (Cont.)

- $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ is the kernel function.
- Default kernel function in LIBSVM is RBF (Gaussian) kernel

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = e^{-\gamma \|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2}$$

- The optimal solution satisfies

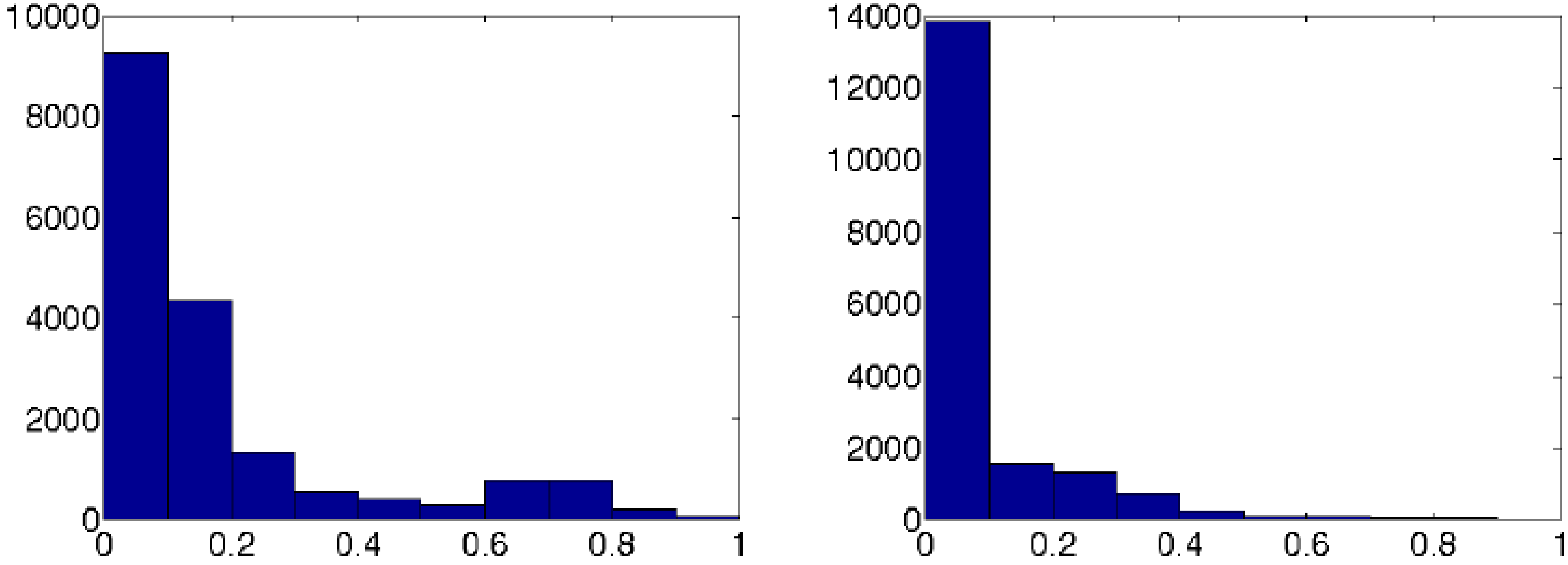
$$w = \sum_{i=1}^{l} \alpha_i y_i \phi(\boldsymbol{x}_i).$$

# Practical use of SVM (Cont.)

- Linear scaling of features is done

$$\frac{(x_i)_s - \min\,(x_t)_s}{\max\,(x_t)_s - \min\,(x_t)_s}, \forall s = 1, \ldots, n.$$

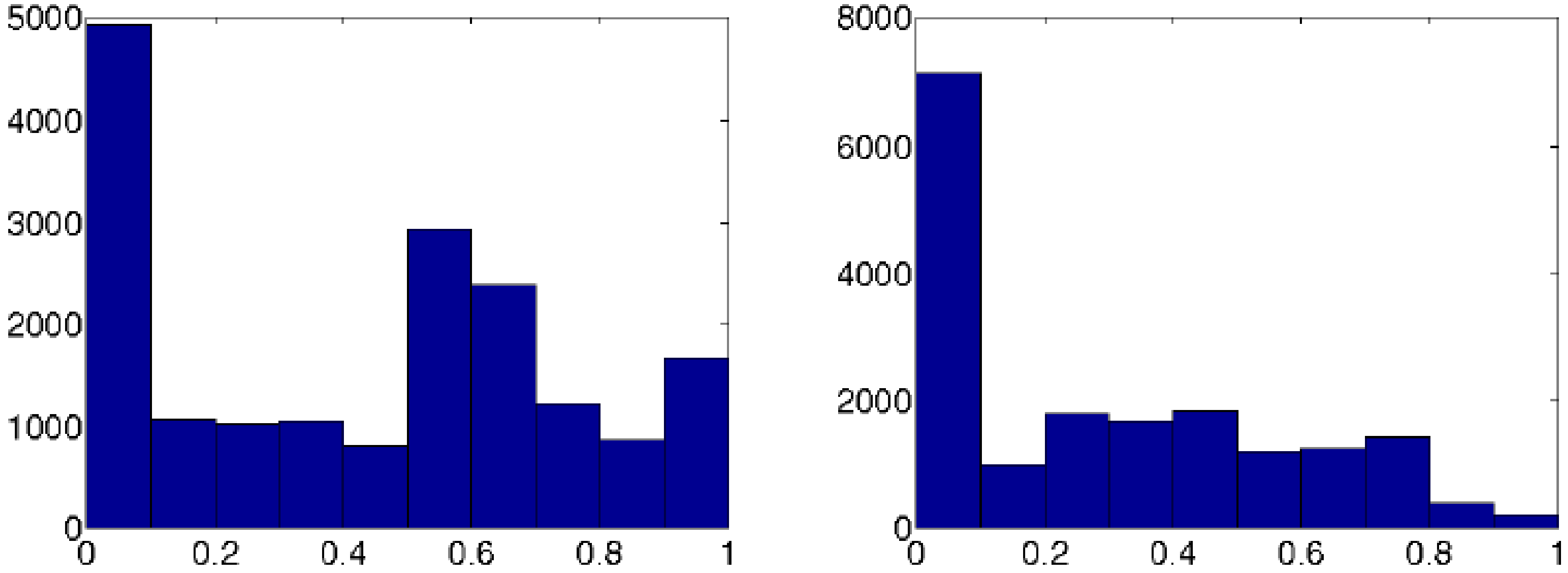
# Practical use of SVM (Cont.)




(a) Linearly scaled to [0,1].

# Practical use of SVM (Cont.)

linear scaling $\rightarrow$ log(feature value + 0.01) $\rightarrow$ linear scaling.




(b) A log-scaling procedure by (7).

# Practical use of SVM (Cont.)

- Parameter selection
  - Regularization parameter (C)
  - Kernel parameter ($\gamma$ in case of RBF kernel)

$$C \in \{2^{-1}, 2^{0}, \ldots, 2^{9}\} \text{ and } \gamma \in \{2^{0}, 2^{1}, \ldots, 2^{8}\}$$

  - Select the one achieving the best five-fold CV accuracy

# Practical use of SVM (Cont.)

- Results

| SVM procedures | CV accuracy (%) |
|---|---|
| Linear scaling + parameter selection | 89.20 |
| Log scaling + parameter selection | 90.48 |

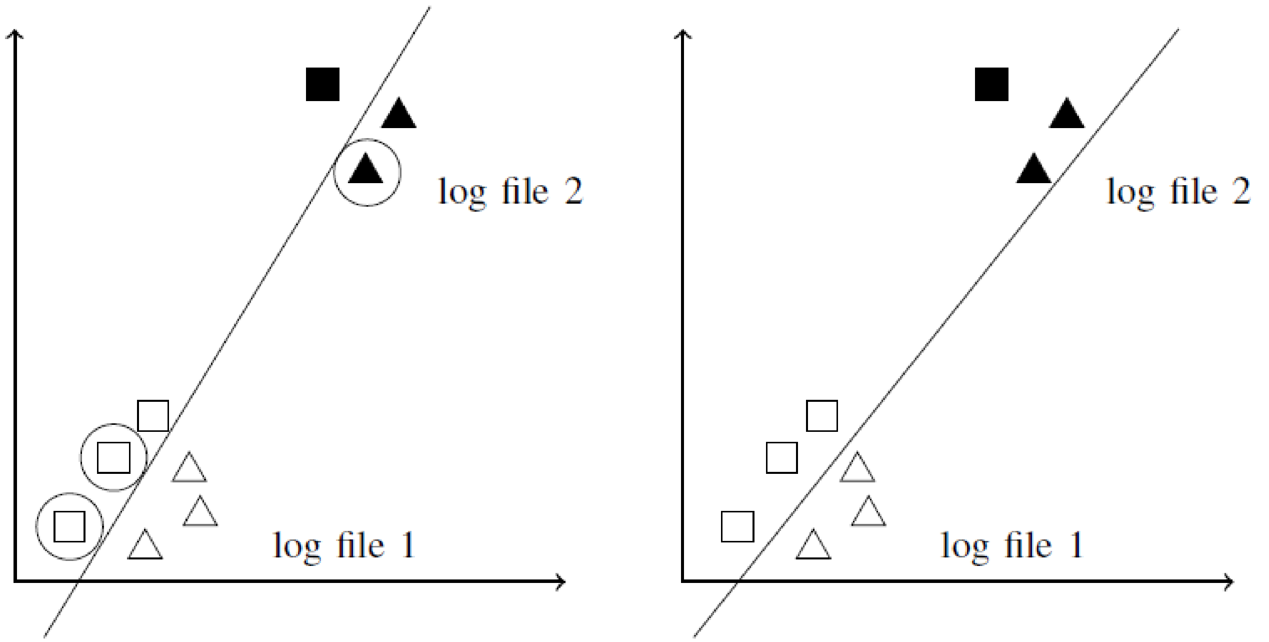
# Pitfall of CV accuracy

- Although CV accuracy is most widely used evaluation measure but it can over-estimate the real performance.
- Assume each user records 10 log files and each log file generates 100 feature vectors.

| | | |
|---|---|---|
| user 1 | log file 1 | $x_1, \ldots, x_{100}$ |
| | log file 2 | $x_{101}, \ldots, x_{200}$ |
| | $\vdots$ | |
| | log file 10 | $x_{901}, \ldots, x_{1000}$ |
| user 2 | log file 11 | $x_{1001}, \ldots, x_{1100}$ |
| | $\vdots$ | |

# Pitfall of CV accuracy (Cont.)

- Feature vector in the same log file shares some information.
- In CV procedure if data from one log file appear in both training and validation sets, then the prediction becomes easy.



# Pitfall of CV accuracy (Cont.)

- Therefore the standard instance-wise split of data may easily over-estimate the real performance.
- To eliminate the sharing of meta-information, data split should be made at higher level such as logs or users.

| CV strategy | SVM CV accuracy (%) |
|---|---|
| Instance-wise CV | 90.48 |
| Log-wise CV | 83.37 |

# Pitfall of CV accuracy (Cont.)

- Although log-wise CV is more reasonable but its better to have an independent test set collected by a completely different group of users.

| Classifiers | CV accuracy (%) | Test accuracy (%) | Model size (KB) |
|---|---|---|---|
| Decision Tree | 89.41 | 77.77 | 76.02 |
| AdaBoost | 91.11 | 78.84 | 1500.54 |
| SVM | 90.48 | 85.14 | 1379.97 |

- The result confirms that instance-wise CV may severely over-estimate.

# Pitfall of CV accuracy (Cont.)

- Similarly in "Towards physical activity diary: motion recognition using simple acceleration features with mobile phones" by J. Yang (2009)

| | |
|---|---|
| Reported CV accuracy | 80 – 90 % |
| Reported Test accuracy | < 70 % |

| | 2 folds | 5 folds | 8 folds |
|---|---|---|---|
| CV accuracy | 85.05 | 83.37 | 82.21 |
| Test accuracy | 85.33 | 85.14 | 84.66 |

# Model size reduction

- Although good accuracy achieved but the model size is much larger than 16 KB.
- Large size due to storage of optimal solution $\alpha$ and support vectors.
- Because it is a multi-class problem and LIBSVM uses one-against-one method so for k-class problem the model size is

$$\binom{k}{2} \times \#\ \text{support vectors} \times (k+n) \times 4\text{bytes}$$

- Where $n$ is the number of features.

# Model size reduction (Cont.)

- To reduce size use polynomial kernel.

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = (\gamma \boldsymbol{x}_i^T \boldsymbol{x}_j + 1)^d$$

- Where $\gamma$ is the kernel parameter and *d* is the degree.
- The kernel is the inner product of two vectors $\phi(x\downarrow i)$ and $\phi(x\downarrow j)$
- If d = 3

$$\begin{aligned}\phi(\boldsymbol{x}) = &[1, \sqrt{3\gamma}x_1, \ldots, \sqrt{3\gamma}x_n, \sqrt{3}\gamma x_1^2, \ldots, \sqrt{3}\gamma x_n^2, \\ &\sqrt{6}\gamma x_1 x_2, \ldots, \sqrt{6}\gamma x_{n-1}x_n, \gamma^{3/2}x_1^3, \ldots, \gamma^{3/2}x_n^3, \\ &\sqrt{3}\gamma^{3/2}x_1^2 x_2, \ldots, \sqrt{3}\gamma^{3/2}x_n^2 x_{n-1}, \sqrt{6}\gamma^{3/2}x_1 x_2 x_3, \ldots, \sqrt{6}\gamma^{3/2}x_{n-2}x_{n-1}x_n]^T.\end{aligned}$$

# Model size reduction (Cont.)

- Only $w$ and $b$ need to be stored.

$$
\begin{aligned}
&\binom{k}{2} \times (\text{length of } w + 1) \times 4\text{bytes} \\
=&\binom{k}{2} \times \left(\binom{n+d}{d} + 1\right) \times 4\text{bytes.}
\end{aligned}
$$

- For d = 3, the model size turns out to be 2.28 KB

# Model size reduction (Cont.)

- Comparison among kernels

| SVM method | Test accuracy (%) | Model size (KB) |
|---|---|---|
| RBF kernel | 85.33 | 1287.15 |
| Polynomial kernel | 84.79 | 2.28 |
| Linear kernel | 78.51 | 0.24 |

# Fast training by optimization

1. The training of kernel SVM is known to be slow.
2. Because of using $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ rather than $\phi(x_i)$ or $\phi(x_j)$, the setting is very restricted.

- For linear SVM the optimization problem becomes

$$\min_{\boldsymbol{w}} \quad \frac{1}{2} \boldsymbol{w}^T \boldsymbol{w} + C \sum_{i=1}^{l} \xi(\boldsymbol{w}; \boldsymbol{x}_i, y_i)$$

- Where $\xi(w; x_i, y_i)$ is the loss function

# Fast training by optimization (Cont.)

- Commonly used loss functions

| | |
|---|---|
| $e^{-y_i \boldsymbol{w}^T \boldsymbol{x}_i}$ | logistic regression |
| $\max(1 - y_i \boldsymbol{w}^T \boldsymbol{x}_i, 0)$ | hinge-loss (l1-loss) SVM |
| $\max(1 - y_i \boldsymbol{w}^T \boldsymbol{x}_i, 0)^2$ | squared hinge-loss (l2-loss) SVM |

- The three loss functions are related so they give similar test result.

# Fast training by optimization (Cont.)

- Comparison scenarios

I. LIBSVM: polynomial kernel with hinge loss.
II. LIBLINEAR (primal): Linear SVM with squared hinge loss.
III. LIBLINEAR (dual): Linear SVM with squared hinge loss.

# Fast training by optimization (Cont.)

| | LIBSVM | LIBLINEAR | |
|---|---|---|---|
| | | Primal | Dual |
| Test accuracy | 84.79 | 84.52 | 84.31 |
| Training time | 30519.10 | 1368.25 | 4039.20 |

- LIBSVM and LIBLINEAR (primal) give similar accuracy.
- Training time of LIBSVM is significantly high.
- In theory, both primal and dual solvers give exactly same accuracy.

# Multi-class SVM

- SVM is designed for two-class classification.
- For multi-class two methods are used

- One-against-one (Stores $k(k-1)/2$ weight vectors)
- One-against-rest (Stores $k$ weight vectors)

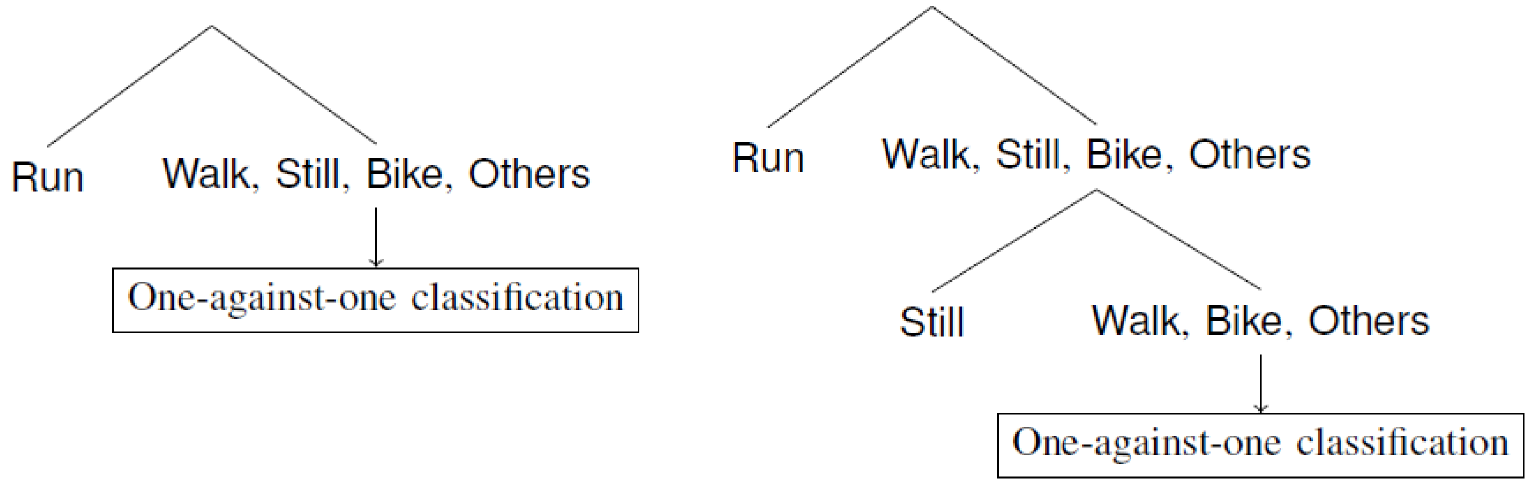
- For 5 transport modes, we need 10 and 5 vectors respectively.

# Multi-class SVM (Cont.)

- Results

| SVM method | Test accuracy (%) | Model size (KB) |
|---|---|---|
| One-against-one | 84.52 | 2.24 |
| One-against-rest | 83.95 | 1.12 |

# Multi-class SVM (Cont.)




(a) A hierarchical setting to identify the mode Run first.

(b) A hierarchical setting to identify the modes Run and Still first.

a. 1 + 4(4 – 1)/2 = 7 weight vectors
b. 1 + 1 + 3(3 – 1)/2 = 5 weight vectors

# Multi-class SVM (Cont.)

- Results

| SVM method | Test accuracy (%) | Model size (KB) |
|---|---|---|
| One-against-one | 84.52 | 2.24 |
| One-against-rest | 83.95 | 1.12 |
| Hierarchy 1 | 84.46 | 1.57 |
| Hierarchy 2 | 84.53 | 1.12 |

# Non-machine learning issues

- <u>Feature engineering</u>

- Extracting important features is one of the most crucial steps.
- Added two frequency-domain features.

a. Peak magnitude: index of the highest FFT value.
b. Ratio: ratio between largest and second largest FFT values.

# Non-machine learning issues (Cont.)

- Results

| CV strategy | 5 features | Adding 2 FFT features |
| --- | --- | --- |
| Instance-wise CV | 89.90 | 92.98 |
| Log-wise CV | 85.05 | 89.26 |
| Test accuracy | 85.33 | 91.53 |

# Non-machine learning issues (Cont.)

- <u>Use of Domain knowledge</u>

- Using information from past predictions.
- Power saving by not enabling the classifier in some situations.

# Conclusion

- Direct use of a machine learning method may not give satisfactory results.
- Careful evaluation criterion must be chosen as this study showed that standard CV accuracy can slightly over-estimate.
- Practitioner should take care while employing classifiers and should have deeper understanding of the methodology.