Application of Machine Learning in Fault Detection Using Control Chart Pattern Recognition

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Outline

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Introduction

Types of Analytical Models:

1. Descriptive Models
   - Shaping the questions and data into a structured problem

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3. Prescriptive Models
   - Seeking optimal decisions to alter the future

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Types of Analytical Models:

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2. **Predictive Models**
   - Understanding the data and predicting the future
3. Prescriptive Models
   - Seeking optimal decisions to alter the future

Introduction

- Predictive models are of interest to statisticians, computer scientists, and us (industrial engineers)!
- They are referred to with terms such as statistical learning, machine learning, and data mining.
- They have been applied to several applications.
  - Image Recognition
  - Manufacturing
  - Health Informatics
  - Cybersecurity

Introduction

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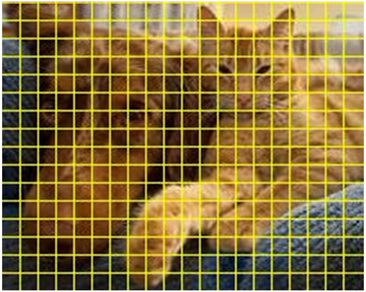
- They are referred to with terms such as statistical learning, machine learning, and data mining.
- They have been applied to several applications.
  - **Image Recognition**

    Why has Image Recognition been at the center of attention for predictive analytics?
  - Manufacturing
  - Health Informatics
  - Cybersecurity

Introduction

Introduction



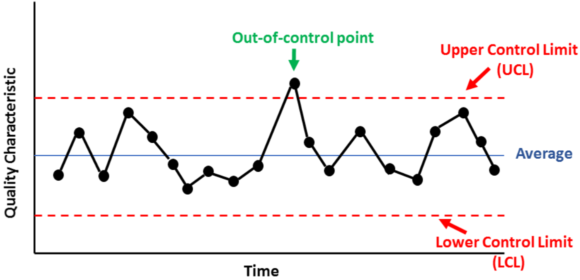
Introduction

The Bad and Good news:

- Not all applications offer a set of clean, perfect, and problem-free data to work.
- It is challenging to recognize and "treat" the issues that appear in real-world datasets.
- Examples of issues: imbalanced-ness, outliers, missing values, and massive size datasets

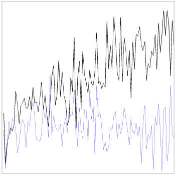
Control Charts

- Control charts are used for monitoring the behavior of a process.
- Control charts, also known as Shewhart charts (Walter A. Shewhart, 1920) or process-behavior charts.
- Control charts are a statistical process control tool used to determine if a manufacturing, chemical or business process is in a state of control.

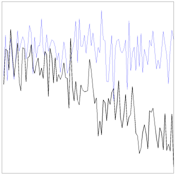


Introduction

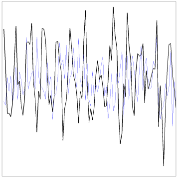
- Control charts are useful to identify not only out-of-control points but also the type of patterns



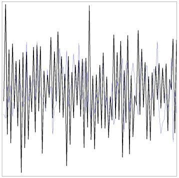
Up trend



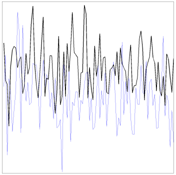
Down trend



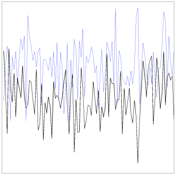
Cyclic



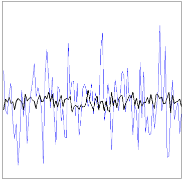
Systematic



Up shift



Down shift

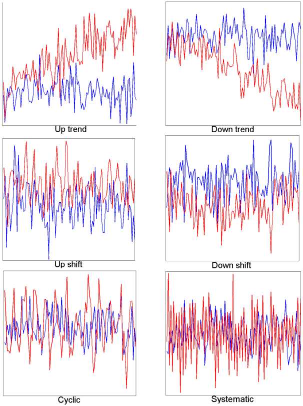


Stratification

Imbalanced Classification

- An application in Quality Control (Control Chart Pattern Recognition) *
  - Trend patterns
    - Stamping tonnage
    - Abnormal signals
  - Shift patterns
    - Variations of machine, material/operator
  - Cyclic Patterns
    - Voltage variability
    - Automotive body assembly
  - Systematic Patterns
    - Automotive body assembly

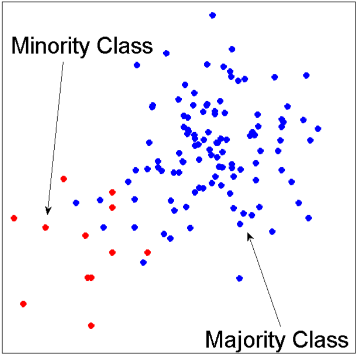
Western Electric Company (1958)



Control Chart Pattern Recognition(CCPR)

- Hachicha, W., & Ghorbel, A. (2012). A survey of control-chart pattern-recognition literature (1991-2010) based on a new conceptual classification scheme. *Computers & Industrial Engineering*, 36(1), 204-222
- However, one important parameter has been ***neglected***!!
  - Abnormal patterns are ***rare*** but important to detect
  - Normal patterns are ***common***
- CCPR belongs to the category of **imbalanced classification**

Imbalanced Data



Applications:

- Breast cancer detection (Verma et al., 2010)
- Credit card fraud detection (Wei et al., 2012)
- Oil spills detection in satellite radar images (Kubat et al., 1998)
- Network intrusion detection (Xu et al., 2011)
- **Control chart pattern recognition** (Xanthopolous & Razzaghi, 2014)

* *T. Razzaghi, P. Xanthopoulos, and A. Otero. Imbalanced Classification: Methods and Applications in Business Analytics. In Encyclopedia of Business Analytics and Optimization. IGI Global, 2014.*

Binary Classification Problem Definition

Preliminaries:

- Data represented by $(x_i, y_i) \in \mathbb{R}^m \times \{-1, 1\}$
  - x_i: actual *data*
  - y_i: corresponding *label* (binary case)

Classification Problem:

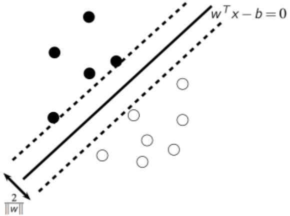
- Find a *classifier* function $f : \mathbb{R}^m \mapsto \{-1, 1\}$
- It can be used to predict the labels y_i^{test} of a group of data samples x_i^{test}
- Classification performance is evaluated through performance measures such as *Accuracy*, *Sensitivity*, *Specificity* and *G-mean*

Support Vector Machines (Vapnik, 2000):

- Classifier is obtained from solution of a *Quadratic Optimization* problem (Computationally tractable)
- Less over fitting in practice (unlike Artificial Neural Networks)
- Nice optimization problem structure

Proposed Methodology

- **Hard Margin Support Vector Machines**



- **Maximize** (*objective*) the separation margin ($2/\|w\|$) subject to **correct classification** (*constraints*)

$$\min_{w,b} \quad \frac{1}{2}\|w\|^2 \tag{1a}$$

$$\text{s.t.} \quad y_i(w^T x_i - b) \geq 1, \qquad i = 1, \ldots, n \tag{1b}$$

Dual Formulation

- An arbitrary data sample x_u is assigned to a class y_u based on the following rule:

$$y_u = sgn(w^T x_u - b) \tag{2}$$

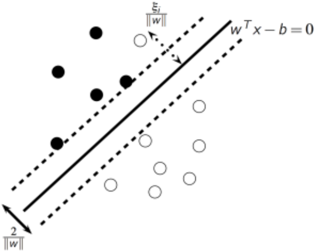
where $sgn(\cdot)$ is the sign function

- The separation hyperplane can be computed as follows:

$$w^* = \sum_{i=1}^{n} y_i \alpha_i^* x_i, \quad b^* = -\frac{\max_{y_i=-1}\langle w^* x_i\rangle + \min_{y_i=1}\langle w^* x_i\rangle}{2} \tag{3}$$

where a_i are the dual variables (or Lagrange multipliers associated with the the i^{th} constraint of the primal)

Inseparable Case: Soft Margin SVM



$$\min_{w,b,\xi} \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \tag{4a}$$

$$\text{s.t.} \quad y_i(w^T x_i - b) \geq 1 - \xi_i, \qquad i = 1, \ldots, n \tag{4b}$$

- Parameter C controls misclassification penalty

Inseparable Case: Soft Margin SVM

- The dual is calculated by the *Karush-Kuhn-Tucker (KKT)* conditions.

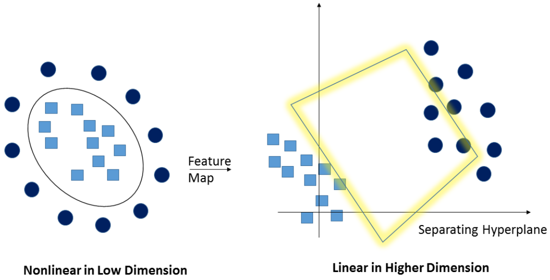
$$\max \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle \tag{5a}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} \alpha_i y_i = 0 \tag{5b}$$

$$0 \leq \alpha_i \leq C \qquad i = 1, \ldots, n \tag{5c}$$

Extension to Nonlinear Classification (Kernels)

- Often the data sets are not linearly separable and the soft margin SVM, while feasible, yields poor performance (Cristianini and Shawe-Taylor, 2000)



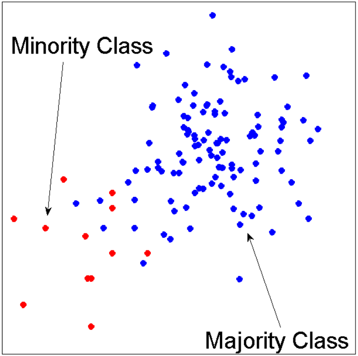
Extension to Non Linear Classification (Kernels)

- Embed data from **input space** to a higher dimension **feature space**
- This is done through an embedding function $\phi(x)$
- We denote $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$
- Popular kernel functions include:

Name	**Function**
Polynomial*	$\left(a x_i^T x_j + c\right)^d$
RBF	$\exp\left(-\gamma \|x_i - x_j\|^2\right)$
Cauchy	$\left(1 + \frac{1}{\alpha}\|x_i - x_j\|^2\right)^{-1}$
Inverse multi quadratic	$\left(\|x_i - x_j\|^2 + \alpha^2\right)^{-1/2}$

* For $a = 1, c = 0$ and $d = 1$ it is a *linear* kernel

Imbalanced Classification



Methods:

- Resampling (Chawla et al., 2002)
- Ensemble Learning (Boosting, bagging, etc.) (Freund and Schapire., 1997)
- **Cost-sensitive Learning** (Veropoulos et al., 1999)

Cost-Sensitive SVM

- Penalize misclassification of each class with different coefficient (Veropoulos, 1999)

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C^+ \sum_{\{i|y_i=+1\}}^{n^+} \xi_i + C^- \sum_{\{i|y_i=-1\}}^{n^-} \xi_i \tag{6a}$$

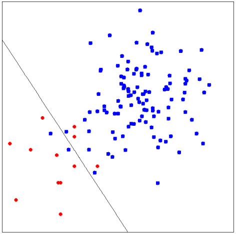
$$\text{s.t.} \quad y_i(w^T\phi(x_i) - b) \geq 1 - \xi_i, \qquad i = 1, \ldots, n \tag{6b}$$

$$\xi_i \geq 0, \qquad i = 1, \ldots, n \tag{6c}$$

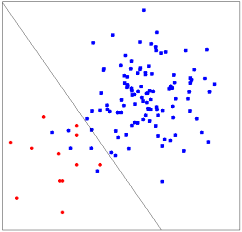
- The weights are usually chosen to be inversely proportional to the size of each class (n^+ and n^-):

$$C^+ = \frac{C}{n^+}, \quad C^- = \frac{C}{n^-} \tag{7}$$

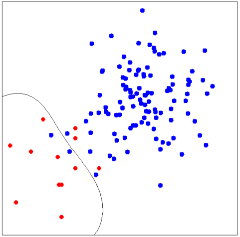
Proposed Methodology



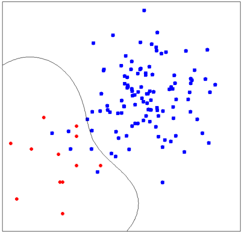
(a) Linear SVM



(b) Linear WSVM



(c) SVM with RBF kernel



(d) WSVM with RBF kernel

Performance Measures

- **Accuracy**: the percent of the correctly classified examples over the total number of examples
- **Sensitivity**
- **Specificity**

$$Sensitivity = \frac{TP}{TP + FN}, \quad Specificity = \frac{TN}{TN + FP} \tag{8}$$

- **G-mean**

$$G - Mean = \sqrt{Sensitivity * Specificity} \tag{9}$$

Table: Confusion Matrix

	Positive class	Negative class
Positive class	TP	FP
Negative class	FN	TN

Other Performance Measures for CCPR

- **Average Target Pattern Run Length (ATPRL)** (Hwarng & Hubele, 1991): the the average number of samples needed for discovering an abnormal pattern.
- **Average Run Length Index (ARLIDX)** (Hwarng & Hubele, 1991): which equals to the fraction of ATPRL divided by the discovery rate of abnormal patterns.

- The ARL-based measures are important especially for applications where **the production of each sample is cost and labor intensive.**
- Ultimately one wants to detect an anomaly with the **lower** ATPRL possible.

Experimental Setup

- SVM and WSVM models were solved using LIBSVM-3.12 and LIBSVM-weights-3.12.
- Data processing and further scripting were done in MATLAB.
- Experiments were conducted for highly imbalanced problems where 97.5% of the data belong to the normal class and only 2.5% belong to the abnormal.
- For each classification problem, we generate a total of 1000 data points and for cross validation purposes, 90% of the data was used for training and the rest 10% was used for testing.
- All data are normalized prior to classification, so that they have zero mean and unitary standard deviation.
- Radial basis function (RBF) kernel was used.

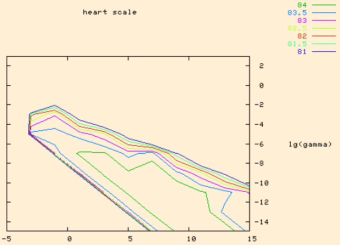
LIBSVM – A Library for Support Vector Machines

https://www.csie.ntu.edu.tw/~cjlin/libsvm/

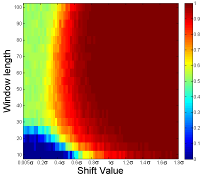
LIBSVM -- A Library for Support Vector Machines

Chih-Chung Chang and Chih-Jen Lin

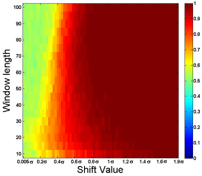
NEW Version 3.23 released on July 15, 2018. It conducts some minor fixes.
NEW LIBSVM tools provides **many extensions** of LIBSVM. Please check it if you need some functions not supported in LIBSVM.
NEW We now have a nice page LIBSVM data sets providing problems in LIBSVM format.
NEW A practical guide to SVM classification is available now! (mainly written for beginners)
We now have an easy script (easy.py) for users who know NOTHING about SVM. It makes everything automatic--from data scaling to parameter selection.
The parameter selection tool grid.py generates the following contour of cross-validation accuracy. To use this tool, you also need to install python and gnuplot.



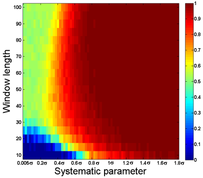
Computational Results



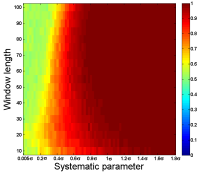
(c) Up shift/ Down shift (SVM)



(d) Up shift/ Down shift (WSVM)



(e) Systematic (SVM)



(f) Systematic (WSVM)

- SVM results in **poor classification performance** for inseparable and partially separable cases
- Our proposed WSVM is **effective** for CCPR in **a highly imbalanced environment**!

SVMs: more than 2 classes?

- The SVM as defined works for $K = 2$ classes. What do we do if we have $K > 2$ classes?
  - **One versus All (OVA)**: Fit K different 2-class SVM classifiers $\hat{f}_k(x)$, $k = 1, \ldots, K$; each class versus the rest. Classify x^* to the class for which $\hat{f}_k(x^*)$ is largest.
  - **One versus One (OVO)**: Fit all $\binom{k}{2}$ pairwise classifiers $\hat{f}_{kl}(x)$. Classify x^* to the class that wins the most pairwise competitions.
- Which to choose? If K is not too large, use OVO.

Multi-class classification

- The weighting Strategy for **multi-class WSVM** for CCPR

$$C_i = \frac{C}{n_i} \qquad i = 1, 2, \ldots, m \tag{10}$$

Table: Classification results for multi-class SVM and WSVM for CCPR with window length=10 and highly imbalanced data. Rows are related to predicted class labels and the columns are related to real labels.

		N	Dt	Ut	S	Ds	Us	C	Str
SVM	N	**1.00**	0.00	0.00	0.05	1.00	1.00	1.00	1.00
	Dt	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	Ut	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	S	0.00	0.00	0.00	0.95	0.00	0.00	0.00	0.00
	Ds	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Us	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Str	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WSVM	N	0.65	0.00	0.00	0.00	0.15	0.19	0.13	0.31
	Dt	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00
	Ut	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00
	S	0.00	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00
	Ds	0.06	0.00	0.00	0.00	**0.75**	0.00	0.00	0.08
	Us	0.10	0.00	0.00	0.00	0.00	**0.77**	0.00	0.00
	C	0.07	0.00	0.00	0.00	0.00	0.04	**0.70**	0.00
	Str	0.11	0.00	0.00	0.00	0.10	0.00	0.17	**0.61**

Multi-class classification

Table: Classification results for multi-class SVM and WSVM for CCPR with window length=50 and highly imbalanced data. Rows are related to predicted class labels and the columns are related to real labels.

		N	Dt	Ut	S	Ds	Us	C	Str
SVM	N	**1.00**	0.00	0.00	0.00	**0.40**	**1.00**	**0.47**	**1.00**
	Dt	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00
	Ut	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00
	S	0.00	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00
	Ds	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00
	Us	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	C	0.00	0.00	0.00	0.00	0.00	0.00	0.53	0.00
	Str	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WSVM	N	0.98	0.00	0.00	0.00	0.20	0.37	0.27	0.37
	Dt	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00
	Ut	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00
	S	0.00	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00
	Ds	0.00	0.50	0.00	0.00	**0.80**	0.00	0.00	0.00
	Us	0.00	0.00	0.00	0.00	0.00	**0.63**	0.00	0.00
	C	0.00	0.00	0.00	0.00	0.00	0.00	**0.73**	0.00
	Str	0.01	0.00	0.00	0.00	0.00	0.00	0.00	**0.63**

Wafer dataset (Adopted from UCR Time Series Classification Archive)

- Electronics manufacturing usually involves a large number of steps (> 250) which can induce defects to the final product.
- Quality control is performed by recording the different frequencies that are emitted by the plasma during the process.
- The data set composed of 1000 training samples (of length152 each) and 6174 testing samples of the same length (Olszewski, 2001; Keogh et al., 2011). The training samples are imbalanced (903 are majority and 97 minority).

Table: Performance for the wafer manufacturing industry dataset

		Sensitivity	Specificity	Gmean	Accuracy
Training	SVM	**0.9996**	0.9160	0.9156	**0.9913**
	WSVM	0.9967	**0.9350**	**0.9319**	0.9905
Testing	SVM	**0.9971**	0.9654	0.9811	**0.9937**
	WSVM	0.9895	**0.9895**	**0.9895**	0.9895

Results (cont'd)

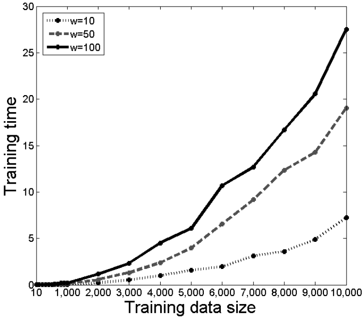


Figure: WSVM training and testing time vs. training size for cyclic pattern

Results (cont'd)

- For all patterns and most problem instances, **WSVM** has **lower ARLIDX**
- **Lower ARLIDX** are obtained compared to the ARLIDXin

Parameter	Uptrend		Upshift		Systematic		Cyclic		Stratification	
	SVM	WSVM	SVM	WSVM	SVM	WSVM	SVM	WSVM	SVM	WSVM
0	155.54	155.19	155.65	155.06	155.21	155.19	155.92	155.83	155.28	155.22
0.005	16.33	**14.60**	138.41	**111.11**	110.83	**90.91**	78.51	**66.85**	7.90	**7.36**
0.03	13.04	**9.83**	129.87	**96.67**	106.90	**70.87**	**56.12**	56.64	8.00	**7.49**
0.055	11.34	**6.64**	**81.49**	81.75	94.95	**67.39**	75.76	**67.50**	8.03	**7.46**
0.08	9.46	**6.61**	103.12	**66.67**	80.73	**53.62**	**51.37**	63.33	8.05	**7.47**
0.105	8.37	**7.28**	106.51	**59.09**	80.36	**44.00**	67.11	**62.50**	7.96	**7.47**
0.13	8.09	**7.84**	90.50	**51.73**	62.92	**53.36**	67.40	**54.04**	7.99	**7.53**
0.155	7.50	**6.96**	70.50	**53.83**	74.21	**26.98**	69.64	**66.67**	8.05	**7.43**
0.18	7.10	**6.96**	73.83	**33.55**	59.54	**25.72**	67.94	**42.83**	8.10	**7.37**
0.205	6.81	**6.24**	62.91	**24.07**	67.33	**22.34**	53.69	**44.60**	7.91	**7.50**
0.23	7.47	**7.12**	76.66	**20.64**	77.87	**10.29**	69.44	**38.27**	8.20	**7.44**
0.255	7.01	**6.89**	37.44	**19.59**	62.76	**10.34**	59.36	**26.54**	8.11	**7.57**
0.28	7.66	**6.97**	40.74	**6.99**	79.42	**9.38**	69.61	**21.10**	8.08	**7.54**
0.305	7.01	**6.75**	49.65	**7.62**	52.66	**4.89**	75.76	**12.86**	8.16	**7.46**
0.33	7.27	**6.94**	60.99	**6.82**	36.13	**5.16**	59.33	**11.31**	8.24	**7.68**
0.355	6.49	**6.27**	37.28	**8.05**	49.41	**6.12**	54.31	**7.20**	8.47	**7.56**
0.38	7.50	**7.37**	25.59	**6.52**	48.56	**5.39**	56.96	**5.67**	8.50	**7.77**
0.405	**6.67**	6.69	24.99	**6.57**	27.87	**4.64**	66.00	**5.69**	9.06	**7.85**
0.43	6.75	**6.69**	18.74	**6.04**	22.04	**4.96**	46.91	**6.11**	9.56	**8.60**
0.455	6.76	6.76	19.08	**6.13**	23.24	**5.39**	45.03	**7.40**	10.76	**9.52**
0.48	6.50	**6.48**	15.13	**5.59**	25.15	**5.11**	42.57	**6.45**	37.64	**24.38**
0.505	**6.50**	6.52	14.86	**5.86**	16.26	**5.20**	38.86	**7.29**	**16.39**	16.44
0.53	6.85	**6.84**	13.81	**6.34**	13.82	**5.94**	45.88	**7.08**	40.81	**34.74**
0.555	6.69	6.69	13.33	**6.40**	15.65	**5.84**	44.54	**6.39**	47.17	**32.24**
0.58	6.51	6.51	12.59	**5.44**	22.55	**4.75**	40.28	**5.57**	72.46	**32.87**
0.605	**6.61**	6.65	16.58	**6.20**	20.11	**6.02**	37.30	**6.43**		
0.63	6.44	**6.43**	11.40	**5.85**	13.22	**5.61**	39.77	**6.83**		
0.655	**6.45**	6.50	13.81	**5.75**	12.36	**5.16**	31.47	**6.24**		
0.68	**6.21**	6.23	10.61	**5.71**	10.90	**5.48**	21.48	**6.56**		
0.705	**6.29**	6.30	12.46	**6.32**	16.04	**5.14**	18.27	**5.51**		
0.73	6.38	**6.34**	8.33	**5.89**	10.78	**5.97**	25.24	**6.21**		
0.755	6.26	**6.23**	10.09	**5.91**	10.19	**5.95**	17.92	**5.59**		
0.78	**6.18**	6.21	8.07	**5.93**	11.58	**5.71**	15.82	**7.25**		

Conclusion

- The proposed WSVM is **more effective** for imbalanced learning in CCPR problem.
- Current study results are **encouraging enough** in terms of average run length, computational time, and G-mean.
- **WSVM multi-class classification** helps to detect the abnormal points based on their types which **outperforms** SVM multi-class classification under **a highly imbalanced environment**.
- **Accuracy** might not be a proper performance indicator for imbalanced classification problems.
- SVMs do not directly provide **probability estimates**, these are calculated using an expensive five-fold cross-validation (Plat, 1999).
- For **nonlinear boundaries**, kernel SVMs are popular. Can use kernels with LR and LDA as well, but computations are more expensive.

Thank you!