

# Traffic Sign Recognition

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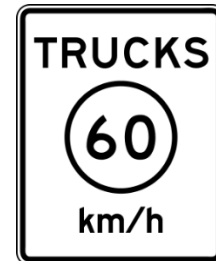
Electrical & Computer Engineering

# Outline

- Introduction
- Traffic sign detection
- Traffic sign classification
- Traffic sign recognition
- Questions

# Introduction

- Traffic signs are signs to give instructions or provide information to road users.
- Color information
- Shape information
- Text information



# Introduction

- The traffic signs in different countries have different representations.
- In China



- In Europe



# Introduction

- Traffic Signs in Germany and Belgium
- Three categories traffic signs are focused in the paper.
- Prohibitory signs, danger signs and mandatory signs.
- Other signs are not considered here.
- Benchmark dataset: GTSD, BTSD, GTSC, BTSC



prohibitory signs

danger signs

mandatory signs

other signs

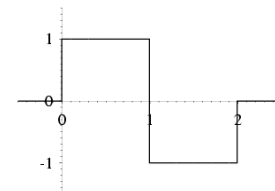
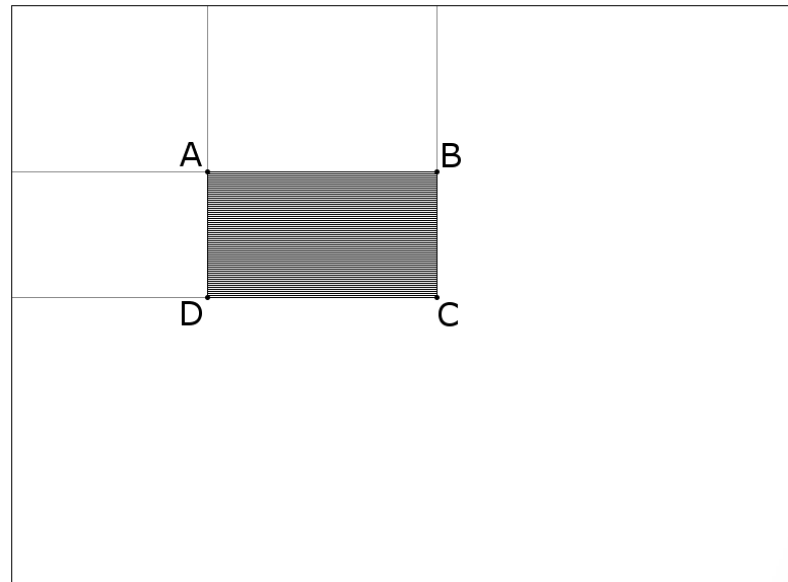
# Detection Methods

- **Viola-Jones detector**
- Brought out by Viola and Jones in 2001.
- Boost the efficiency of the face detection.
- Sliding window are simple Haar-like filters.
- Difference between two windows
- Adaboost classifier



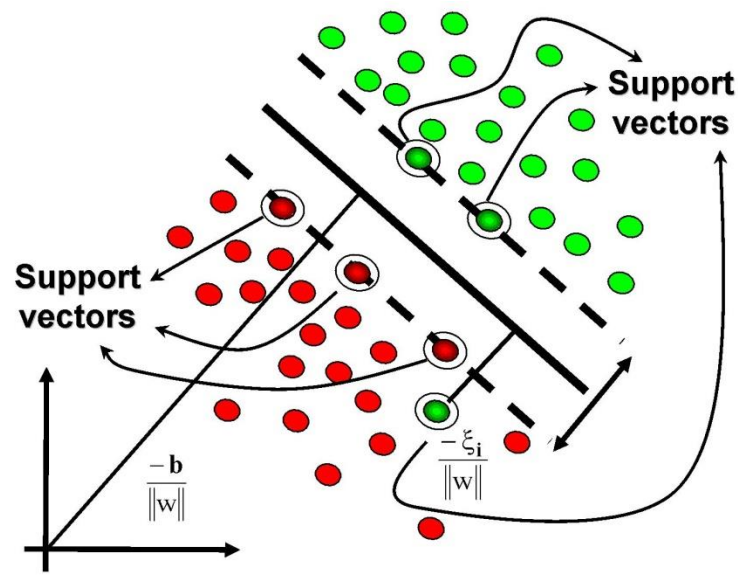
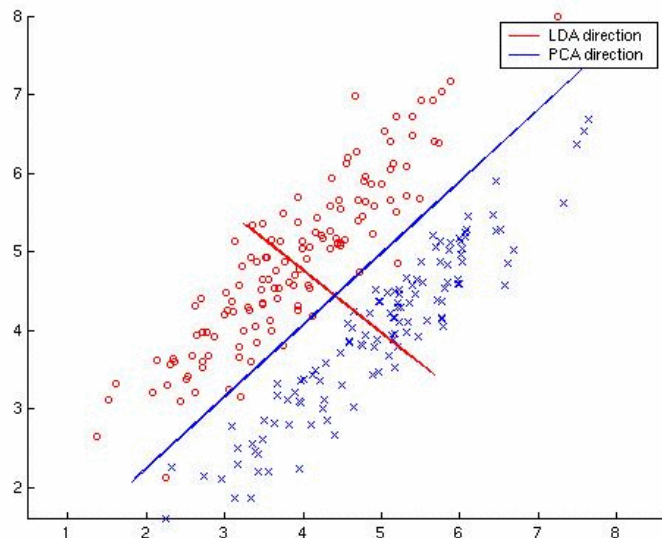
# Detection Methods

- Haar-like feature can be got easily with pre-calculated integral image  $O(mn)$ .
- $\text{sum} = I(C) + I(A) - I(B) - I(D)$
- Some typical Haar features
- $\text{Feature} = \text{sum}(B) - \text{sum}(W)$
- Feature normalization



# Detection Methods

- **Detection based on HOG(Histograms of orientated gradients) features.**
- HOG+SVM(Support Vector Machine)
- HOG+LDA(Linear Discriminant Analysis)
- LDA maximizes the inter-class variance while minimizing the intra-class variance.





# Detection Methods

- **Integral Channel Features Classifier (ChnFtrs)**
- Family of boosted classifiers based on discrete Adaboost.
- Fast with decent quality
- 10 features channels
- 6 orientations, gradient magnitude and LUV channels.



Channels

| / \ - \ |·| L U V

# Detection Methods

- **Model-base method**
- Color is used to find the signs region
- Shape is used for detection
- Canny edge detector
- Hough shape detector is good at recognize the shape of object

# Detection Methods

- “Automatic Traffic Sign Detection” by Jing Zheng

- Modified color segmentation
- Checking candidates axis ratio

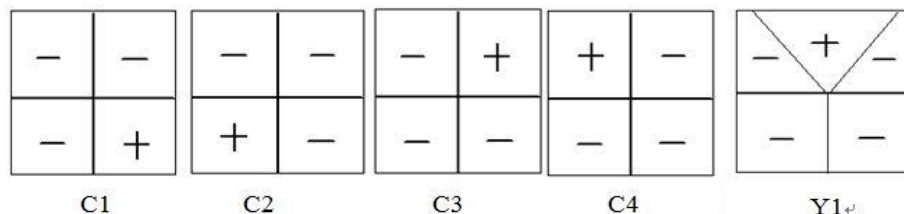
$$g(x, y) = k_1 \begin{cases} R_a \leq f_r(x, y) \leq R_b \\ G_a \leq \frac{f_g(x, y)}{f_r(x, y)} \leq G_b \\ B_a \leq \frac{f_b(x, y)}{f_r(x, y)} \leq B_b \end{cases}$$

- “Real-time Traffic Sign Detection” by Hassan Shojanian

- Corner Detector Design
- Optimal corner detector

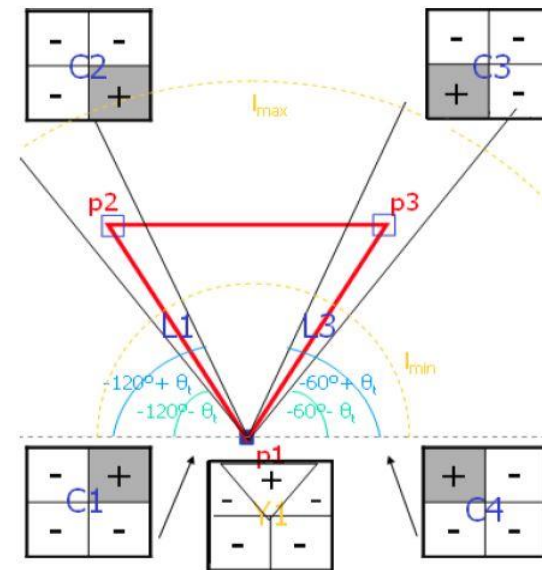
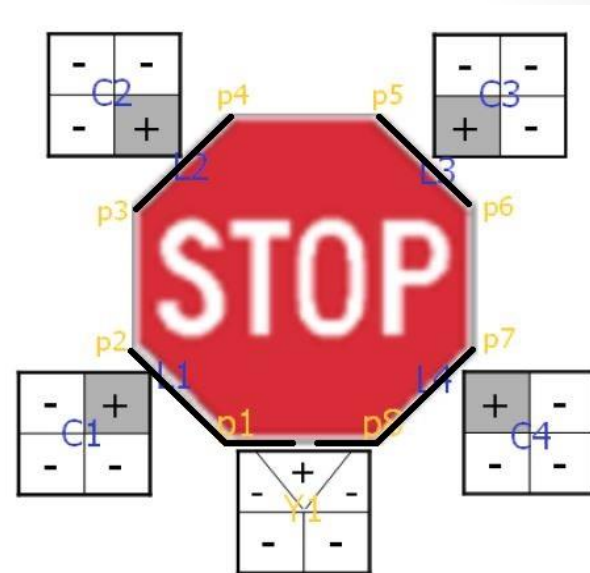
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-11	-18	-18	-11	0	-11	-18	-18	-11
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-6	-11	-11	-6	0	-6	-11	-11	-6
0	0	0	0	0	12	20	20	12
-6	-11	-11	-6	0	12	19	19	12
-11	-18	-18	-11	0	10	17	17	10
-11	-18	-18	-11	0	8	13	13	8
-6	-11	-11	-6	0	4	7	7	4

0	12	20	20	12	20	20	12	0
-6	-11	10	12	12	12	10	-11	-6
-11	-18	17	19	20	19	17	-18	-11
-11	-18	-18	19	20	19	-18	-18	-11
-6	-11	-11	12	12	12	-11	-11	-6
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-11	-18	-18	-11	0	-11	-18	-18	-11
-11	-18	-18	-11	0	-11	-18	-18	-11
-6	-11	-11	-6	0	-6	-11	-11	-6



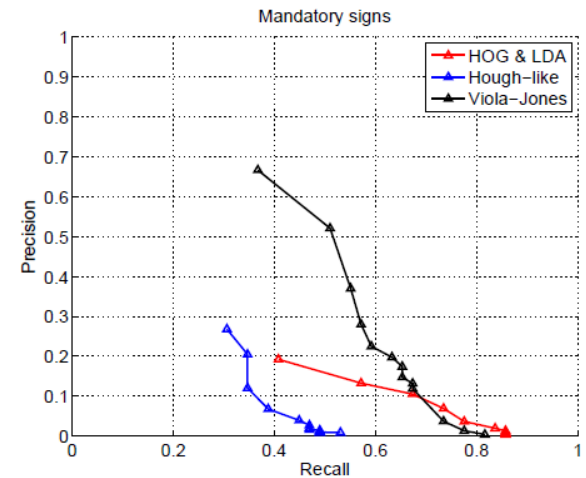
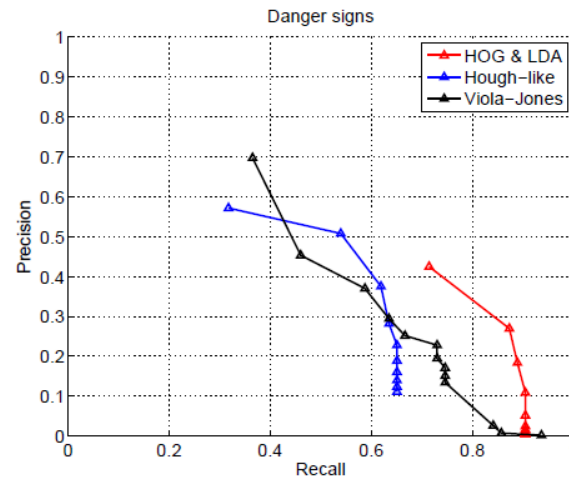
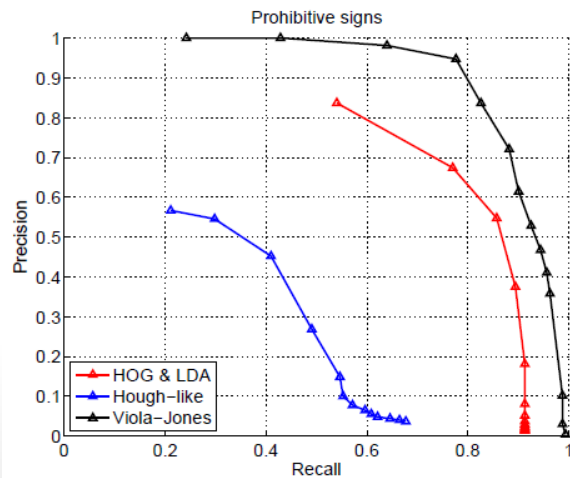
# Detection Methods

- Detection Candidates sets
- Candidates sets shape depends on signs shape
- Shape recognition
- Length and angle of lines between corner detected candidates have important information



# Detection Result

- Precision Recall plot of all chosen categories.
- Precision: result retrieved by a search is relevant
- Recall: relevant documents were retrieved by the search
- AUC: Area Under Curve



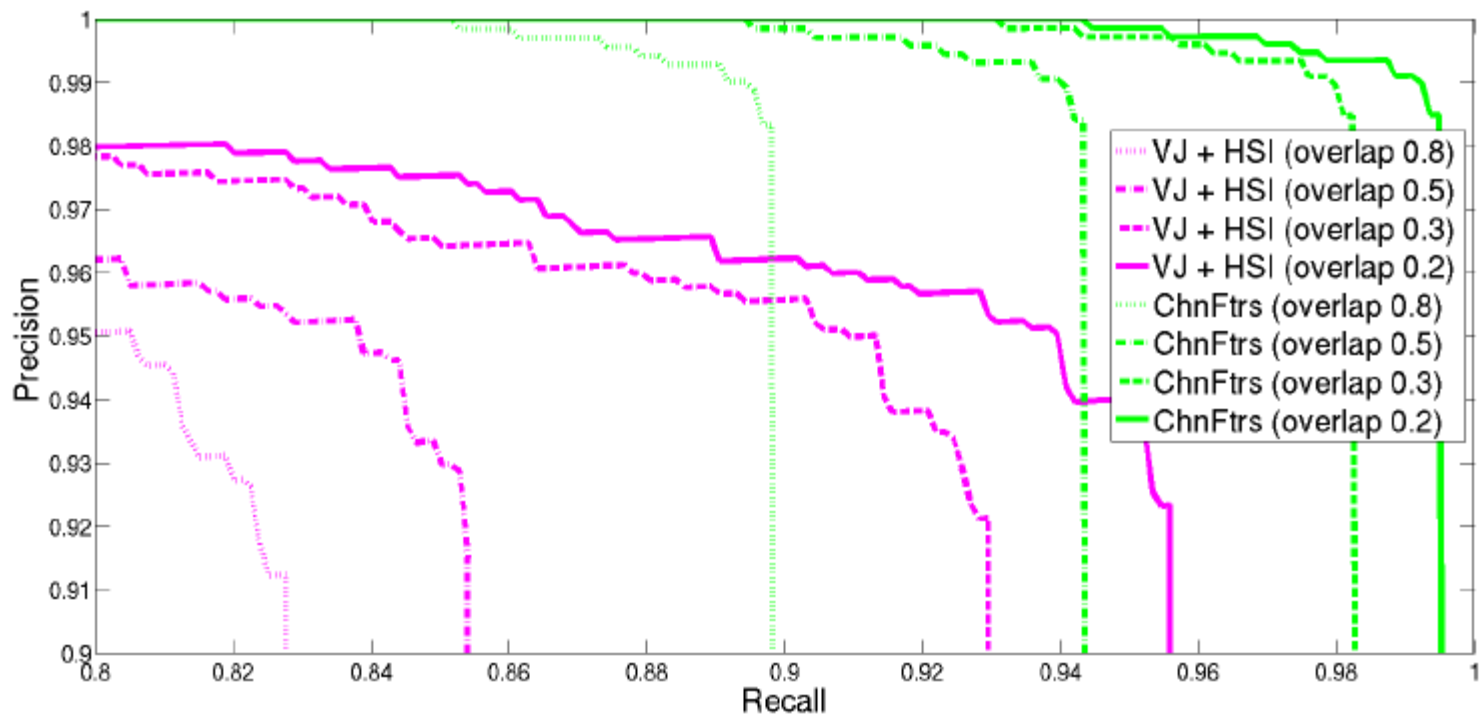
# Detection Result

- GTSDB competition result
- Area under curve(%)
- Just baseline methods

Team	Prohibitive	Danger	Mandatory
wgy@HIT501	100% (91%)	99.91% (86%)	100% (79%)
visics	100% (88%)	100% (87%)	96.98% (90%)
LITS1	100% (87%)	98.85% (86%)	92% (89%)
BolognaCVLab	99.98% (85%)	98.72% (87%)	95.76% (86%)
NII-UIT	98.11% (82%)	—	86.97% (82%)
wff	—	99.78% (86%)	97.62% (85%)
milan	—	96.55% (86%)	96% (89%)
Viola-Jones	90.81% (88%)	46.26% (84%)	44.87% (88%)
HOG + LDA	70.33% (78%)	35.94% (79%)	12.01% (77%)
Hough-like	26.09% (76%)	30.41% (68%)	12.86% (78%)

# Detection Result

- Performance of on BTSD
- Integral Channel Features Classifier vs. VJ+HSI



# Detection Result

- AUC in %
- Stunning benchmark result

Team	Method	GTSD			BTSD		
		M	D	P	M	D	P
Ours Baseline	ChnFtrs, trained on GTSD	91.91	100	99.34	92.55	95.76	84.60
Ours Baseline	ChnFtrs, trained on BTSD	76.38	78.5	91.06	97.96	97.40	94.44
Ours Competition	ChnFtrs, trained on GTSD	<i>96.98</i>	<i>100.00</i>	<i>100.00</i>	94.79	96.40	86.51
[3]	VJ+HSI, trained on BTSD	61.12	79.43	72.60	92.32	95.91	84.27
wgy@HIT501[9]	HOG+LDA+SVM	100.00	99.91	100.00	—	—	—
BolognaCVLab[9]	MSER+HOG+SVM	95.76	98.72	99.98	—	—	—
LITS1[9]	HOG+SVM	92.00	98.85	100.00	—	—	—
wff[9]	HOG+CNN	97.62	99.73	—	—	—	—



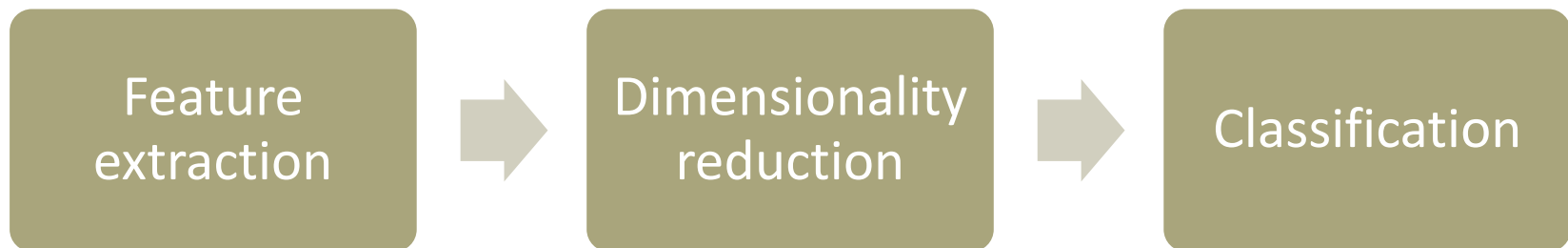
# Detection Failure Cases

- Difficult conditions
- Unexpected annotations
- Unclear class



# Classification

- A classic case of supervised object classification
- The pipeline of traffic sign classification



# Classification

- **Feature extraction**

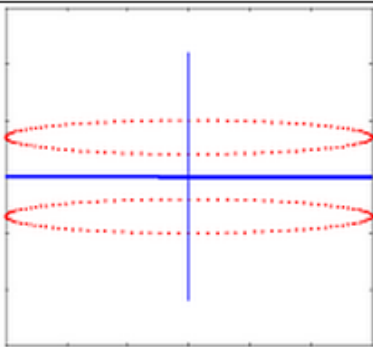
- I: grayscale value of image cropped to 28\*28 pixels.
- PI: the pyramid of HOG features with optimal parameter settings
- HOG1, HOG2, HOG3: different number of HOG cells and extraction grid.

- **Dimensionality reduction**

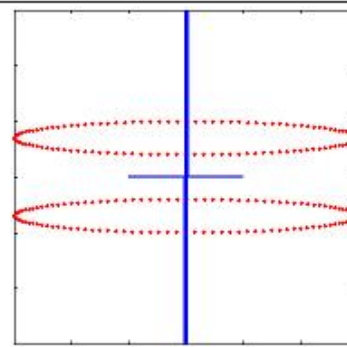
- Linear Discriminant Analysis (LDA)
- Sparse Representation based Linear Projection (SRLP)
- Iterative Nearest Neighbors based Linear Project (INNLP)

# Classification

- SRLP and INNLP are both based on Locality preserving projections(LPP).
- LPP is linear approximation of nonlinear Laplacian Eigenmap
- LPP preserves the local affinities from the original space



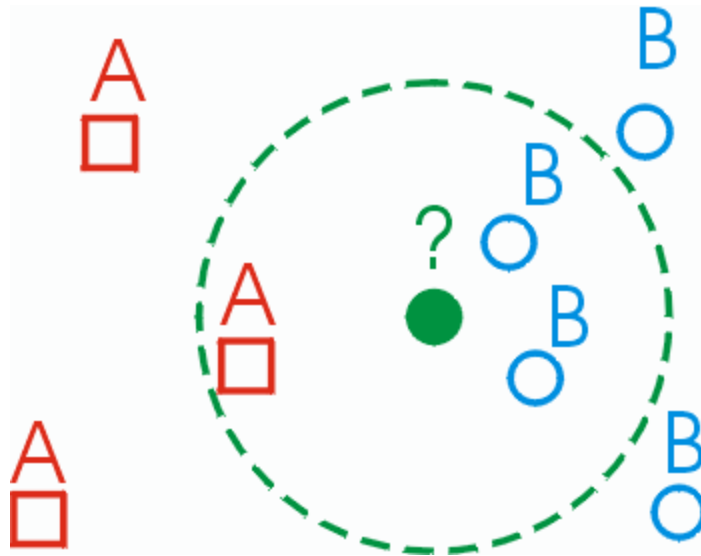
PCA



LPP

# Classification Method

- **Nearest Neighbor Classifier (NN)**
- Pick the label of the training sample which provides the minimum least squares



# Classification Method

- **Sparse Representation-based Classifier (SRC)**
- **Iterative Nearest Neighbors Classifier (INNC)**
- Both use the least squares
- Not constrained to one training sample
- Linearly combine all the training samples

# Classification Method

- **Support Vector Machine (SVM)**
- Kernel trick: Only depends on the data through inner product  $k(x,y)$
- Different kernels: linear, intersection, polynomial and radial basis function
- LSVM, IKSVM, POLYSVM and RBFSVM

# Classification Result

Feature	Projection	Classifier	Accuracy	Training time	Testing time
I,PI,HOGs	INNLP	INNC ( $K = 62$ )	<b>98.53%</b>	none	$\sim 10\text{m}$
		INNC ( $K = 14$ )	98.27%	none	$\sim 3\text{m}$
	SRLP	SRC	98.50%	none	$\sim 9\text{h}$
PI,HOGs	LDA	INNC	98.33%	none	$\sim 3\text{m}$
		SRC	98.30%	none	$\sim 3\text{h}$
	SRLP	RBFSVM	98.32%	$\sim 5\text{h}$	$\sim 4\text{m}$
PI	none	IKSVM	97.14%	$\sim 1\text{day}$	$\sim 4\text{m}$
	SRLP	POLYSVM	96.84%	$\sim 0.3\text{h}$	$\sim 0.5\text{m}$
HOG2	INNLP	LSVM	96.51%	$\sim 1\text{m}$	$\sim 1\text{s}$
		RBFSVM	97.08%	$\sim 0.5\text{h}$	$\sim 3\text{m}$
	SRLP	IKSVM	96.81%	$\sim 0.5\text{h}$	$\sim 0.5\text{m}$
		INNC ( $K = 14$ )	97.57%	none	$\sim 1\text{m}$
		INNC ( $K = 62$ )	97.65%	none	$\sim 3.5\text{m}$
		SRC	97.53%	none	$\sim 1.5\text{h}$
	LDA	NN	96.97%	none	$\sim 5\text{s}$



# Classification Result

- BTSC

	I	PI	LDA I	LDA PI	SRLP I	SRLP PI	INNLP I	INNLP PI	Avg.
NN	77.15	88.52	92.46	97.47	93.06	97.20	93.61	97.08	92.07
SRC	91.00	95.42	94.67	97.34	95.15	<b>97.55</b>	94.80	<b>97.83</b>	<b>95.60</b>
INNC	86.15	94.79	94.71	<b>97.67</b>	95.15	97.47	94.83	97.55	94.79
LSVM	90.69	96.68	91.48	96.73	91.83	97.32	91.87	97.24	94.23
IKSVM	91.36	<b>97.79</b>	92.22	96.80	91.83	97.08	92.86	97.08	94.63
POLYSVM	89.94	96.61	91.79	96.45	92.85	97.00	93.13	96.96	94.34
RBFSVM	90.41	96.57	91.79	97.08	92.90	97.43	93.37	97.26	94.60
Avg.	88.10	95.20	92.87	96.64	93.25	<b>97.29</b>	93.50	<b>97.29</b>	

- GTSC

	LDA PI	LDA HOG2	SRLP PI	SRLP HOG2	INNLP PI	INNLP HOG2	Avg.
NN	95.83	96.97	95.26	96.56	93.28	96.47	94.05
SRC	96.33	97.20	96.69	<b>97.51</b>	96.70	<b>97.53</b>	<b>95.87</b>
INNC	96.52	97.47	96.54	<b>97.57</b>	95.15	<b>97.65</b>	95.86
LSVM	95.16	96.42	96.03	96.37	96.15	96.51	93.31
IKSVM	95.08	96.22	96.40	96.81	96.43	96.73	93.91
POLYSVM	95.36	96.58	96.84	96.93	96.68	96.84	95.22
RBFSVM	95.34	96.65	96.82	96.95	96.85	97.08	95.30
Avg.	95.66	96.79	96.37	<b>96.96</b>	95.89	<b>96.97</b>	

# Classification Result

- Merging features on GTSC

Classifier	LDA	SRLP	INNLP
NN	97.65	97.57	97.60
SRC	<b>98.28</b>	<b>98.50</b>	98.31
INNC	98.20	98.25	<b>98.53</b>
LSVM	97.82	97.47	97.25
IKSVM	97.78	98.15	98.13
POLYSVM	97.91	98.16	98.02
RBFSVM	97.94	98.16	98.05

# Recognition

- Run the detection and classification jointly
- Fed the detected signs into classifier
- The whole system can reach the detection rate around 90%-93%

# Questions

- 1. What are three categories of traffic signs used in the GTSD?
- 2. List three detection algorithms.
- 3. What is the advantage of LDA compared to the SVM?
- 4. When does it mean when recall equals to “1”?
- 5. For multiple kind of classification features, what should we do to increase the classification accuracy effectively?
- 6. What are the differences of LPP compared to PCA?