Support Vector Machine in the Task of Voice Activity Detection

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Prerequisities – Voice Activity Detector (VAD)

- Basic idea: Classifies a given sound frame as a speech or as a non-speech.
- Needed in most speech technology applications. E.g. in
  - speech recognition/enhancement, and
  - voice biometric.
- No “one-solution-fits-all” exists.

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Prerequisities – Support Vector Machine (SVM)

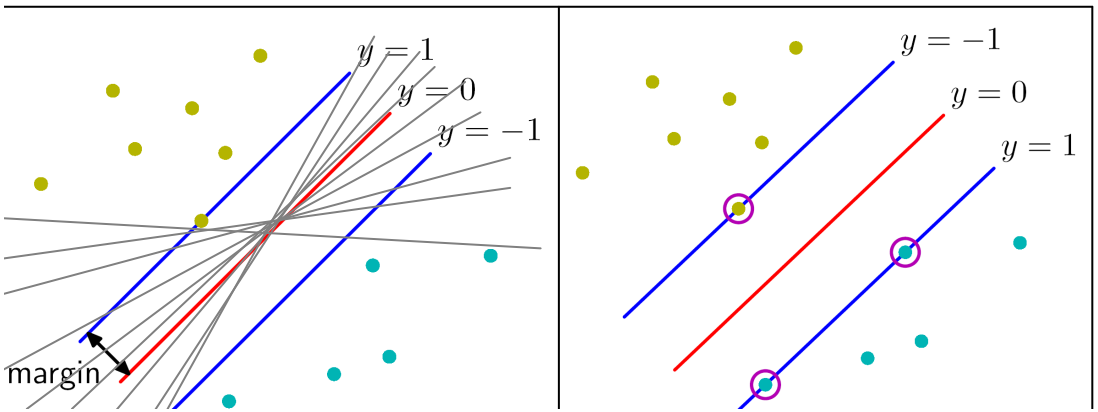
- Binary classifier, classes separated by a hyperplane.
- Goal is to design such a classifier, which both
  - maximizes width of the margin between classes, and
  - minimizes the margin errors.
- Finding optimal hyperplane (or support vectors) is a NP-complete problem => we use (non-optimal) SVMlight tool for calculations.
- SVM decision function:

support vectors

unclassified test vector

$$f(\mathbf{y}) = \sum_{i=1}^{N} \alpha_i K(\mathbf{x}_i, \mathbf{y}) + b$$

parameters for the decision hyperplane



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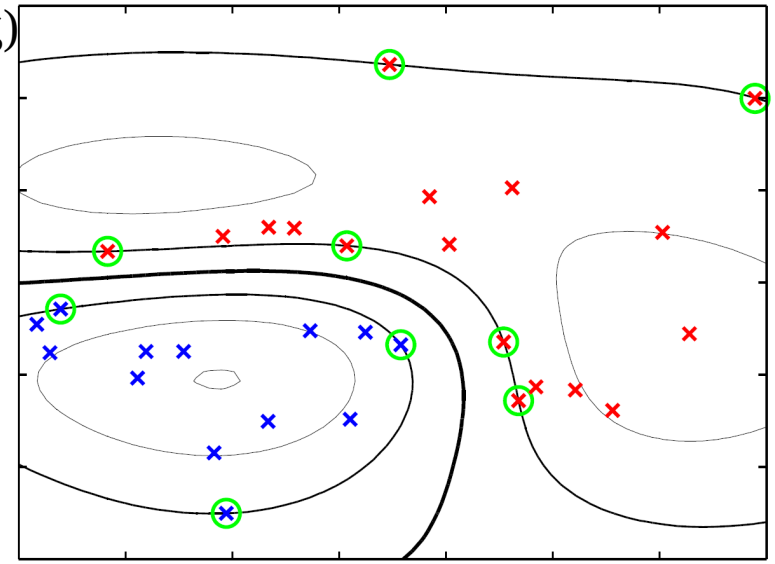
Prerequisities – Kernel function

- Implicit mapping into a high-dimensional feature space.
- We consider linear and Radial Basis Function (RBF) kernel functions.

$$K_{\text{lin}}(\mathbf{x},\mathbf{y}) = <\mathbf{x},\mathbf{y}> \text{(identity mapping)}$$
$$K_{\text{RBF}}(\mathbf{x},\mathbf{y}) = \exp\left(-\gamma \| \mathbf{x}-\mathbf{y} \|^2\right)$$

Potentially we can obtain better results by using RBF kernel compared with linear kernel, because then we can separate non-linear classes.



Example of the RBF kernel function.

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Motivation

- Model-based VAD can be rather easily adapted into new conditions.
- SVM has shown excellent performance in many other classification tasks, e.g. in speaker verification (Campbell et al., 2006).
- MFCC features are standard features used in speech processing and thus easily available.

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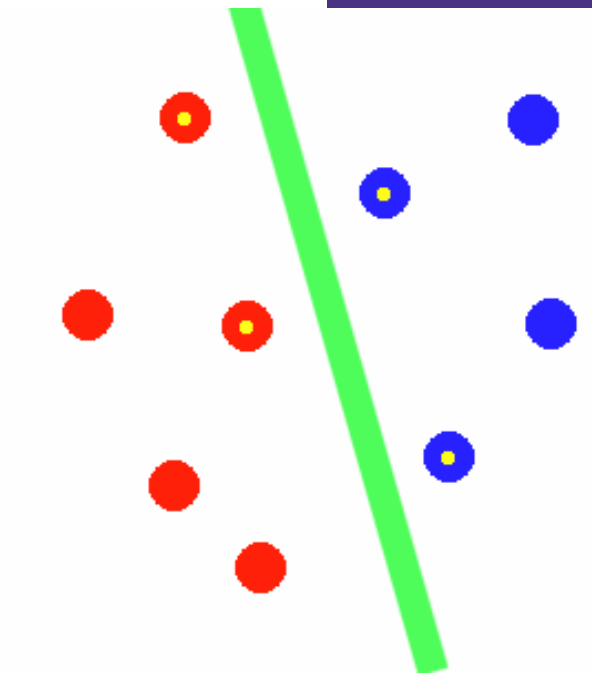
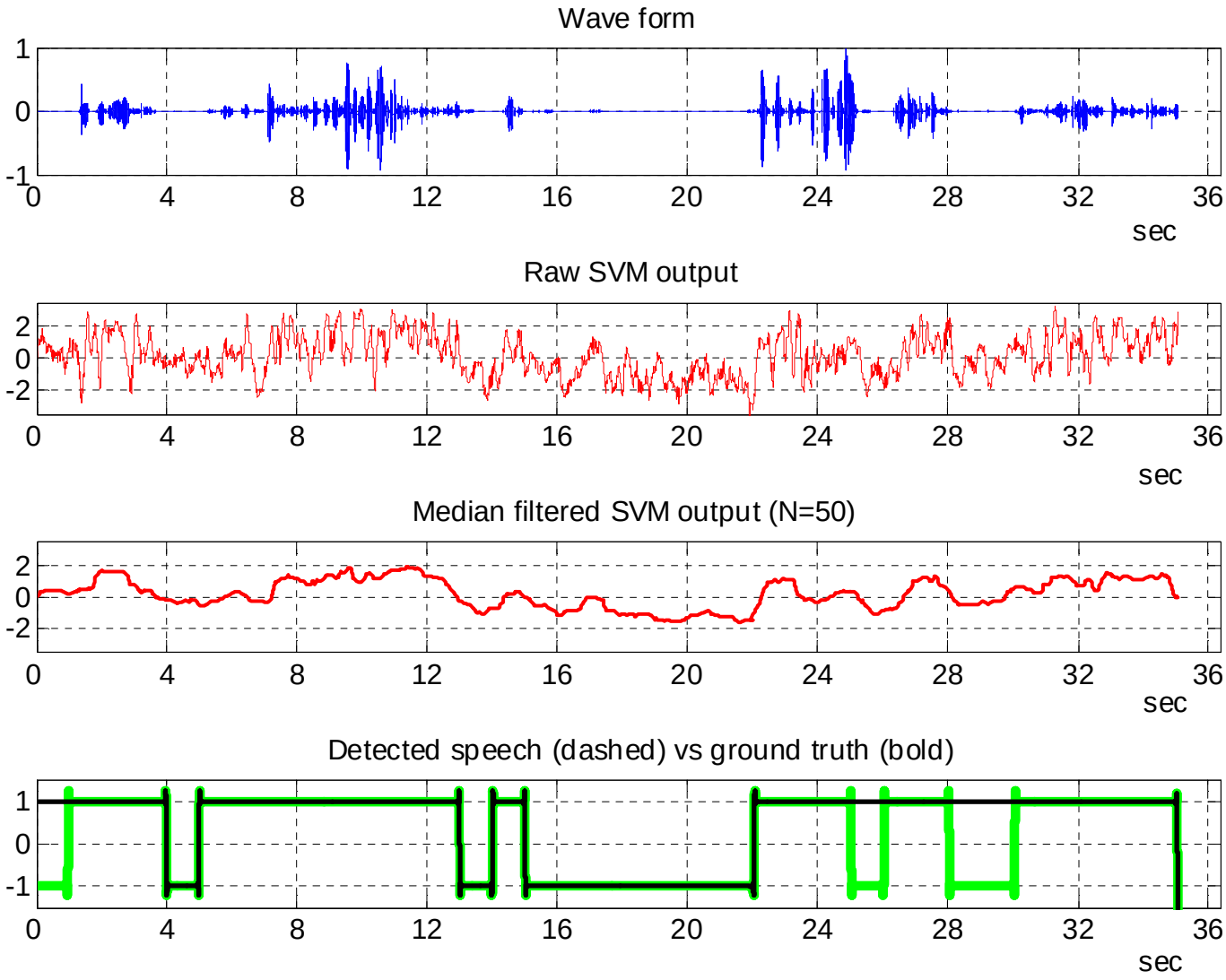
SVM VAD (proposed)

- MFCC features with deltas, 36-d.
- SVM is used as a binary classifier for VAD.
- Things to consider:
  - Selection of the kernel: linear vs. RBF kernel.
  - Effect of the training material.
- Model-based!



SVM VAD – illustration



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GMM VAD (Reynolds et al, 2000)

- MFCC features with deltas, 36-d.
- Speech and non-speech models adapted from UBM (Maximum A Posteriori adaptation).
- Log likelihood ratio computed using the fast N-top scoring.
- Model-based!

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Energy-based VAD

- Simple energy-based approach that was used in NIST-06 eval (Tong et al., 2006).
- Measures intra-frame energy by calculating standard deviation of the frame.
- Not model-based.

$$S_i = 20 \log_{10} \sqrt{\frac{1}{N-1} \sum_{j=1}^{W} (x_j^{(i)} - \bar{x}^{(i)})^2},$$

Then frame i is detected as speech
if $S_i > (\max_j S_j - T)$ and $S_i > -55$.

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Long Term Spectral Divergence VAD

- Compares the long-term spectral envelope to the average noise spectrum (Ramirèz et al., 2004).
- Not model-based!

$$\mathrm{LTSE}_M(k,l) = \max_{j=-M}^{M} X(k,l+j),$$

$$\mathrm{LTSD}_M(l) = 10\log_{10}\left(\frac{1}{NS}\sum_{k=0}^{NS-1}\frac{\mathrm{LTSE}^2(k,l)}{N^2(k)}\right)$$

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Speech segmentation experiments
test setup

- Segment the audio signal in time to alternating speech and non-speech blocks.
- For evaluating segmentations, we have formed correct segmentation manually using one second resolution.
- Two types of errors: false accept (FA), and false reject (FR).
- Equal Error Rate (EER) is the point, where FA = FR.

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Speech segmentation experiments
data sets

	NIST 2005	**Bus stop**	**Lab**
Recording equipment	Telephone	Telephone	Labtec PC microphone
Training section	25 min (5 spk x 5min)	61 min	85 min
Test section	50 min (10 spk x 5min)	105 min	170 min
Speech-to-non-speech ratio	53%:47%	75%:25%	12%:88%

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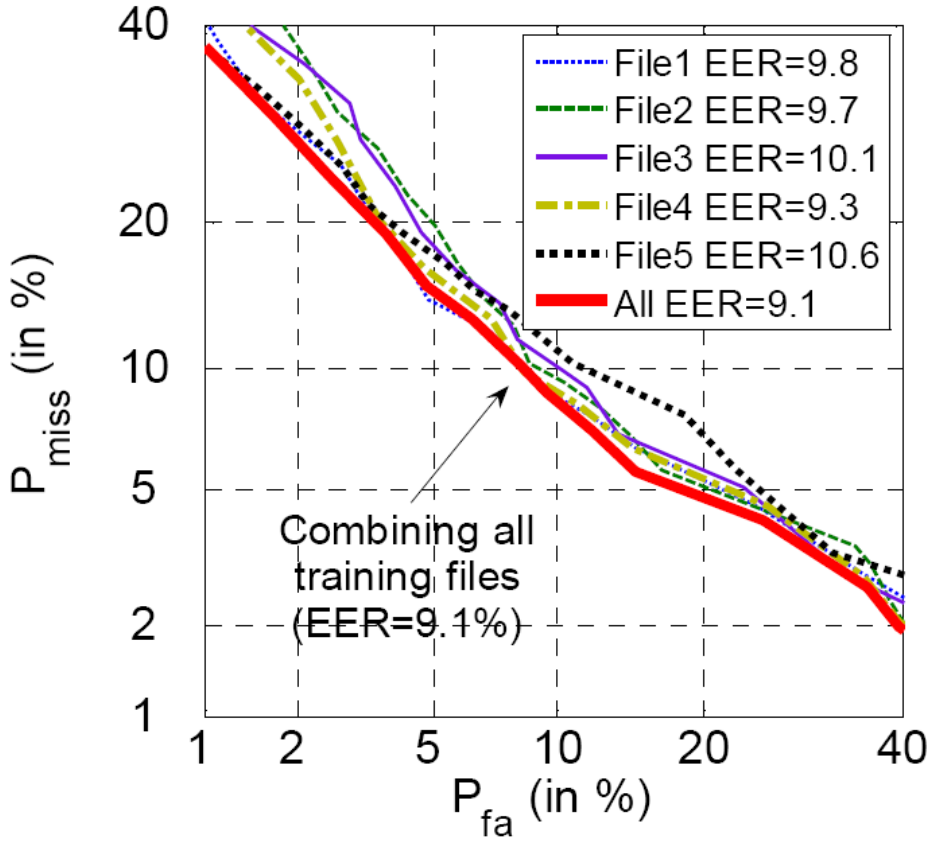
Speech segmentation experiments
SVM VAD tuning: single- vs. multispkr

- Combining training files improves accuracy => pooled data sets.



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Speech segmentation experiments
SVM VAD tuning: training data length

- Rather independent to the training data length.
- Even 10 seconds is sufficient!

Training length	10 sec	30 sec	1min	3 min	5 min	10 min
EER (%)	9.3	8.8	9.1	9.3	9.4	9.4

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Speech segmentation experiments
SVM VAD tuning: selection of kernel

- The RBF kernel slightly outperforms the linear one.
- However, running times with RBF are much higher => we use linear kernel.

SVM kernel	Accuracy (EER %)	Training time (s)	Test time(s)
Linear	9.1	429	107
RBF (γ=0.3)	8.1	1776	924
RBF (γ=0.6)	8.0	2010	1062

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Speech segmentation experiments **results (1)**

Table 4: Comparison of different VAD methods on the three datasets using three different operating points.

		Adaptive		Trained	
		Energy [10]	LTSD [3]	SVM	GMM [11]
NIST 2005	EER	1.5	40.0	8.0	12.8
	$P_{miss}@P_{fa}= 2\%$	1.4	40.0	26.7	43.3
	$P_{fa}@P_{miss}= 2\%$	1.2	62.5	21.5	32.6
Bus stop	EER	14.6	19.2	13.1	34.0
	$P_{miss}@P_{fa}= 2\%$	62.3	100.0	40.9	99.1
	$P_{fa}@P_{miss}= 2\%$	27.2	36.0	53.4	68.4
Lab	EER	16.8	14.4	19.0	15.3
	$P_{miss}@P_{fa}= 2\%$	80.6	76.8	54.7	59.8
	$P_{fa}@P_{miss}= 2\%$	65.3	19.3	89.1	67.8

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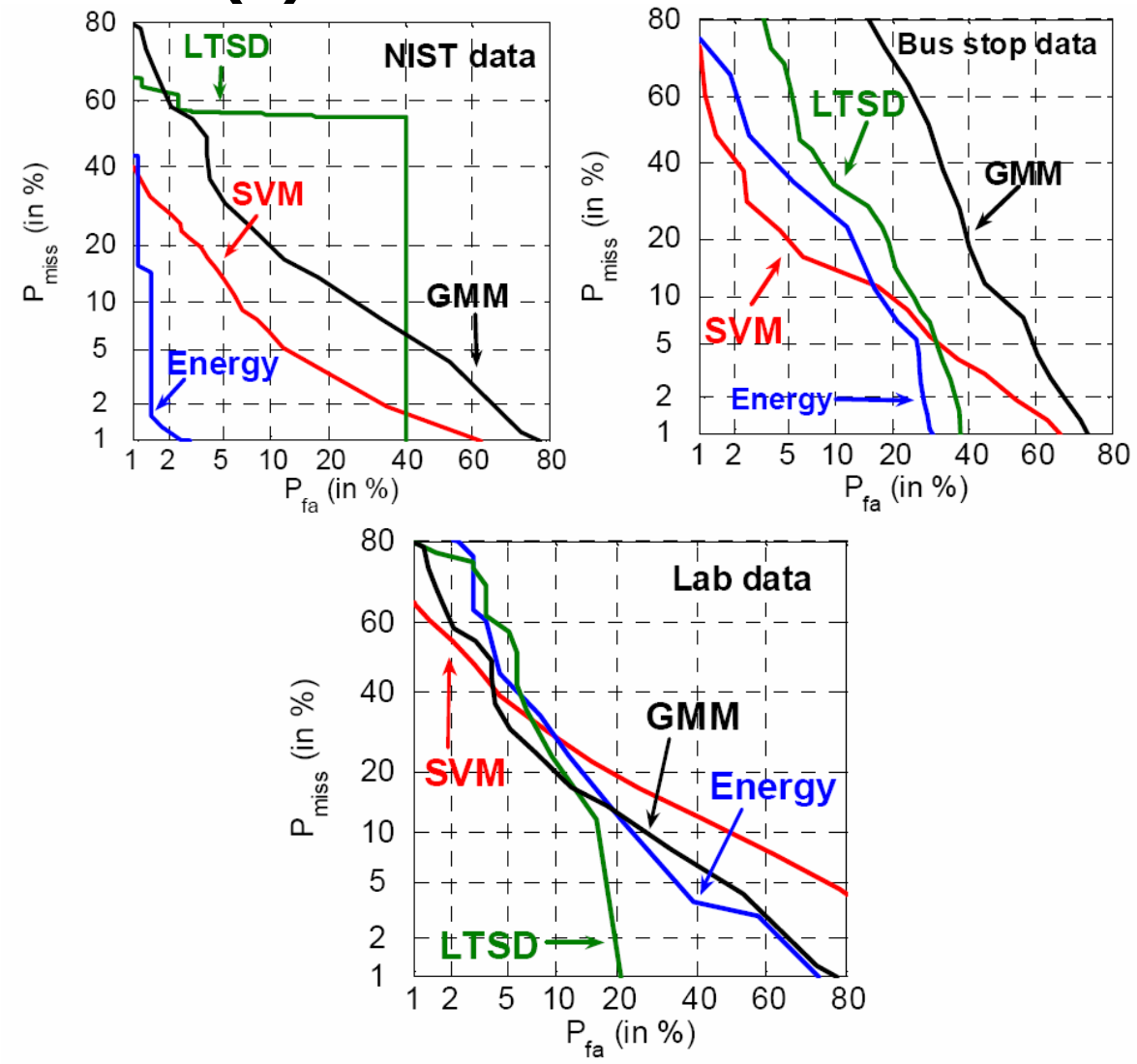
Speech segmentation experiments **results (2)**



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Summary

- Voice activity detection is defined as a binary classification problem and solved using SVM.
- Model-based VAD can be rather easily adapted into new conditions.
- Works consistently with different corpora; good when small FA is desired.

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- Questions?

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