NIST SRE 2006 Workshop

STBU

SDV + TNO + BUT + SUN

STBU

SDV (Spescom DataVoice, South Africa)

TNO (Netherlands)

BUT (Brno University of Technology, Czech Republic)

SUN (Stellenbosch University, South Africa)

STBU

Niko Brümmer

David van Leeuwen

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Albert Strasheim, Johan du Preez

Thanks to

- The NIST evaluations that have made our progress possible. The drivers of this progress include:
  - The *challenge* posed by NIST and the *data* they make available.
  - The open *sharing* of knowledge by participants in previous years. I hope that those who have contributed so much to our knowledge (but whos C_{DET}'s didn't make it to the bottom of the pile this year) enjoy seeing their ideas flourish in the work of others.
- My hard-working partners TNO, BUT and SUN.

Good news

- Much of what we did is (after the fact) relatively easy to implement.
  - David will do a *6% EER in 24 hours* slide.
- Most methods allow very fast implementations.

STBU

- Each site developed their own systems, but we worked very closely together, with some common design principles.
- We shared (via wiki, email, sms) papers, advice, ideas, formulas, code, supervectors, scores, EER's etc., over a period of about 10 weeks. Over 600 emails were sent.
- Finally, we fused a selection of all our sub-systems.

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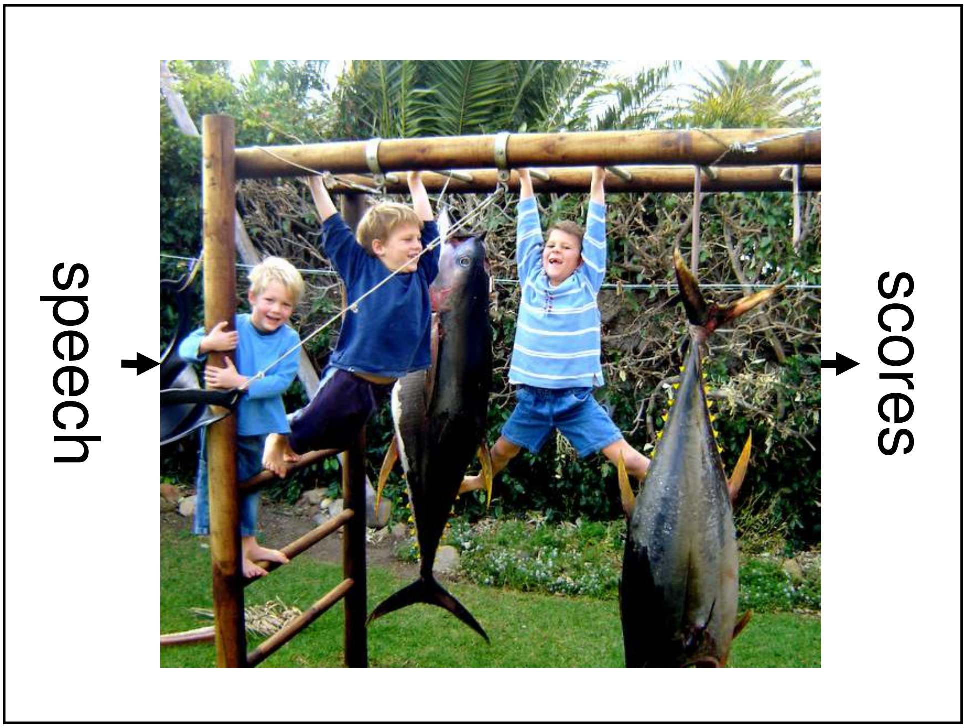
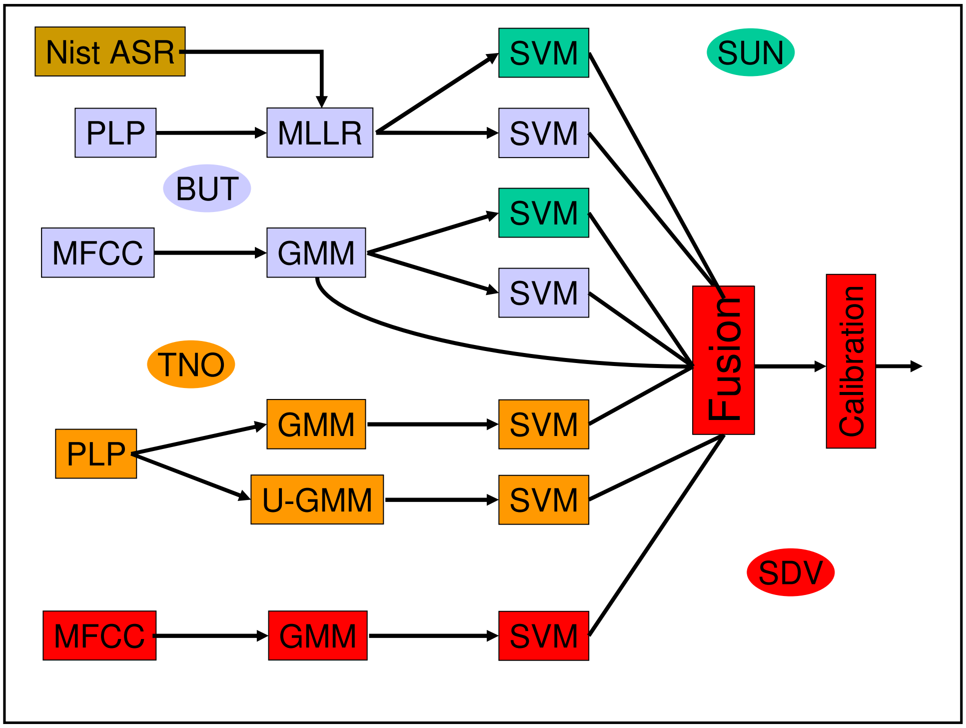
System Skeleton Overview

Unifying design principle

- Express speaker information as a variety of different forms of *supervector*.
- Do *inter-session subspace compensation* in supervector space.

lead to neat system design


speech
scores


Nist ASR
PLP
MLLR
SVM
SVM
SUN
BUT
MFCC
GMM
SVM
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TNO
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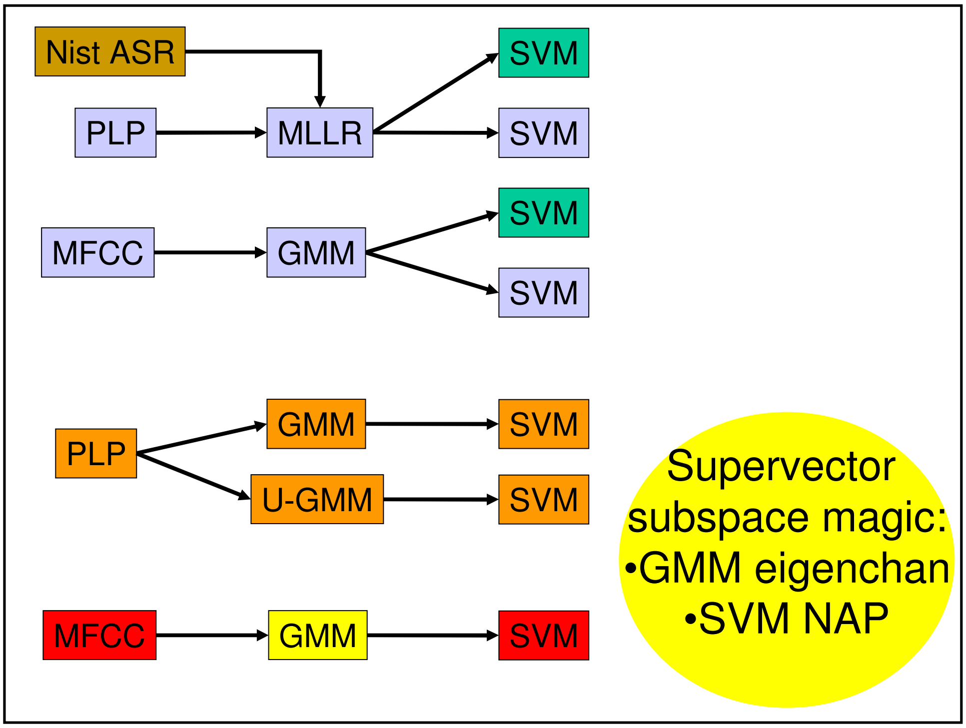
GMM
U-GMM
SVM
SVM
Fusion
Calibration
SDV
MFCC
GMM
SVM



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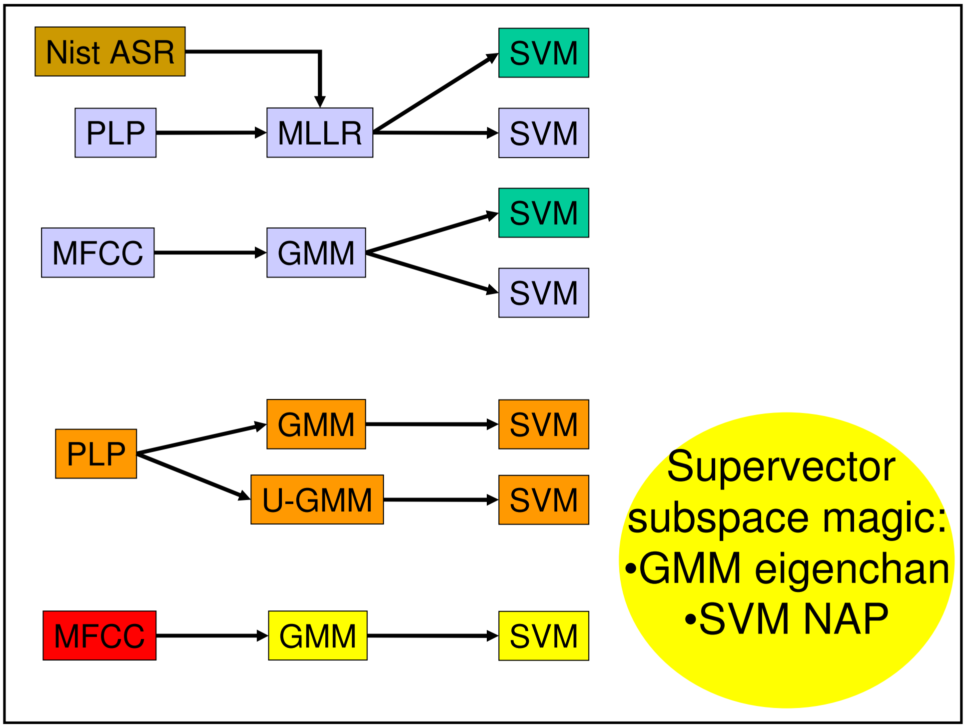
SVM
Supervector
subspace magic:
•GMM eigenchan
•SVM NAP



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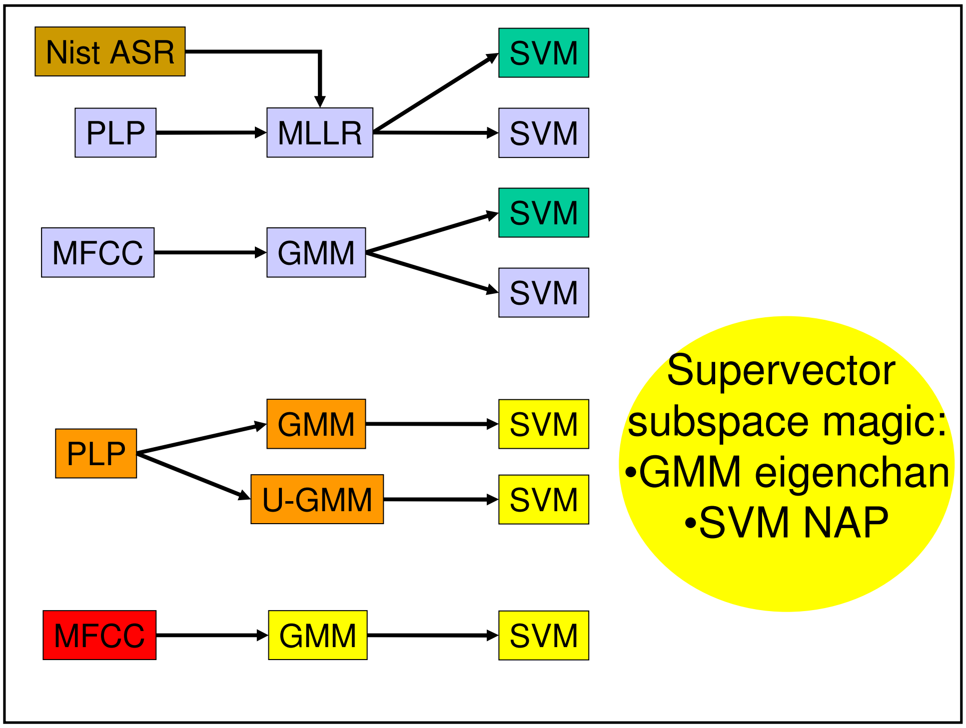
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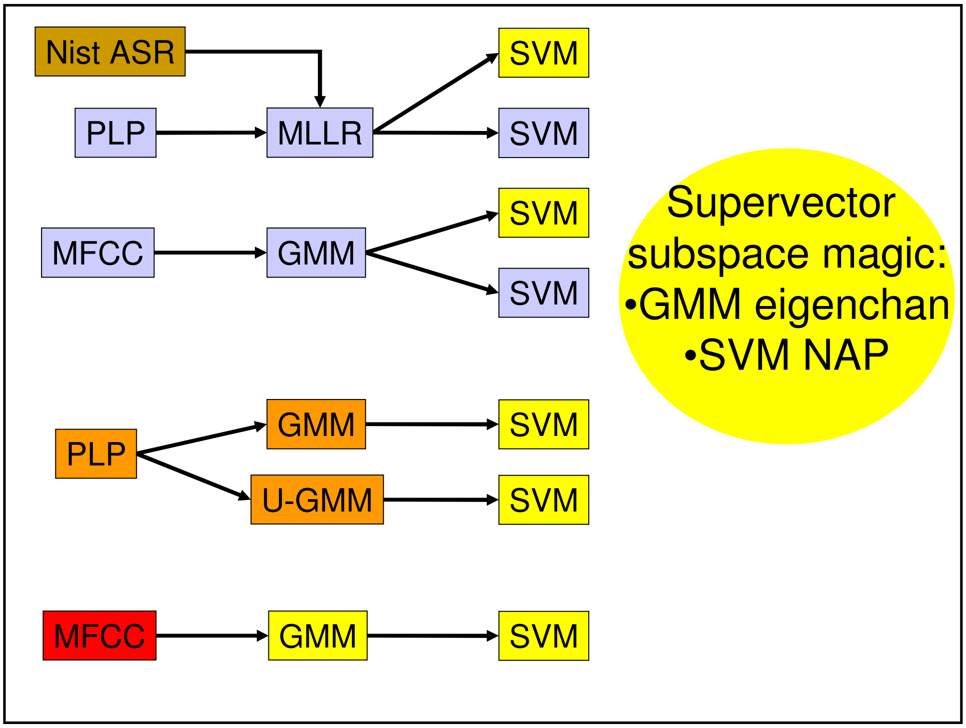
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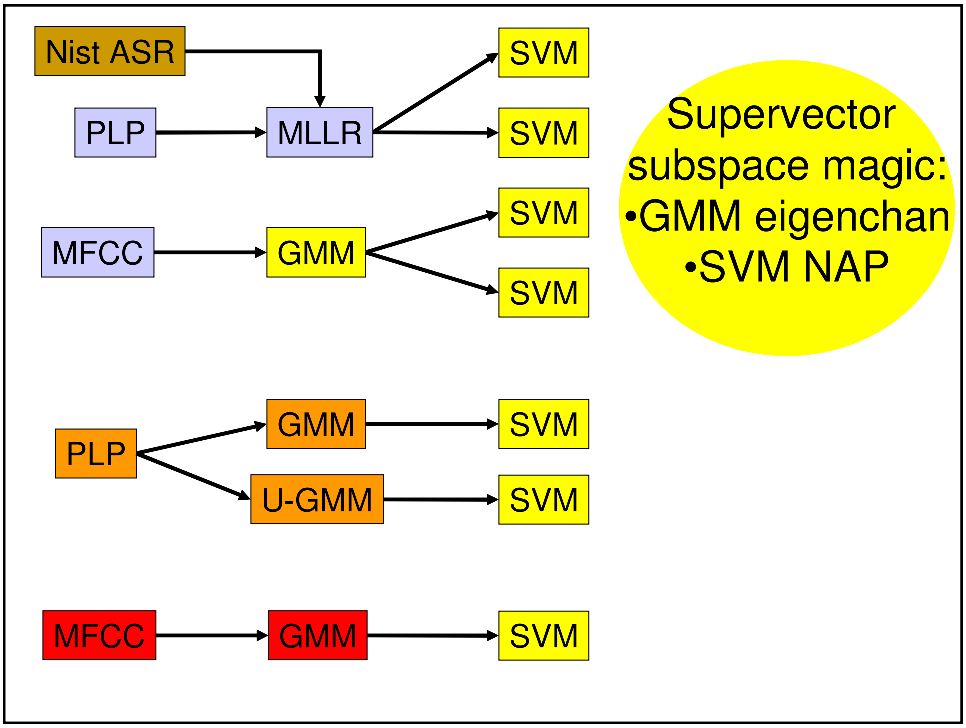

Main strengths

- Diversity (front-ends, data, implementations)
- Development data organization
- Many development experiments (*fast* SVM, and BUT's 100 CPUs)
- Supervector subspace channel compensation (SVM-NAP, GMM-Eigenchannel)
- Fusion
- Calibration

Agenda

- Diversity
- Development data
- *Fast* SVM
- Supervectors
- Sub-system performance
- Fusion
- Calibration

Agenda

- Diversity
- **Development data**
- *Fast* SVM
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Development data

- Switchboard (UBM, feature mapping)
- Fisher (SVM background, t-norm, UBM, feature mapping)
- SRE-04 (NAP + Eigenchannel subspace training, t-norm, feature mapping, UBM)
- SRE-05 (development test set, fusion/calibration training)

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Agenda

- Diversity
- Development data
- ***Fast* SVM**
- Supervectors
- Sub-system performance
- Fusion
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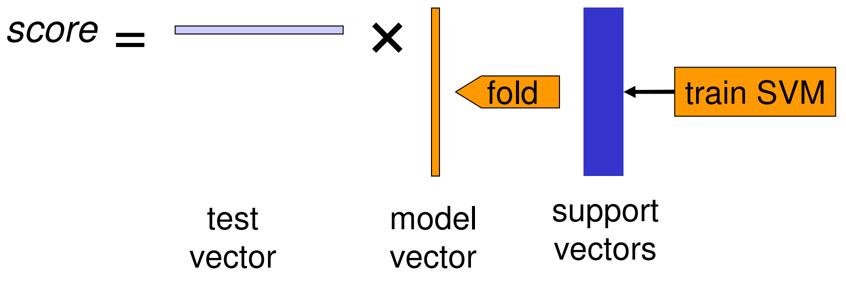
Fast SVM

- It is known that linear SVMs can *score* test segments really fast when all support vectors are folded into a single model supervector.
- But *training* can also be done really fast.
  - To train an SVM it needs to form *all* of the dot-products between all (thousands of) training vectors. This product matrix is called the *Gram* or *kernel* matrix.
  - When the same background set is used for every speaker model, *almost the whole* Gram matrix stays constant. We implemented our SVM training code to make use of this fact.

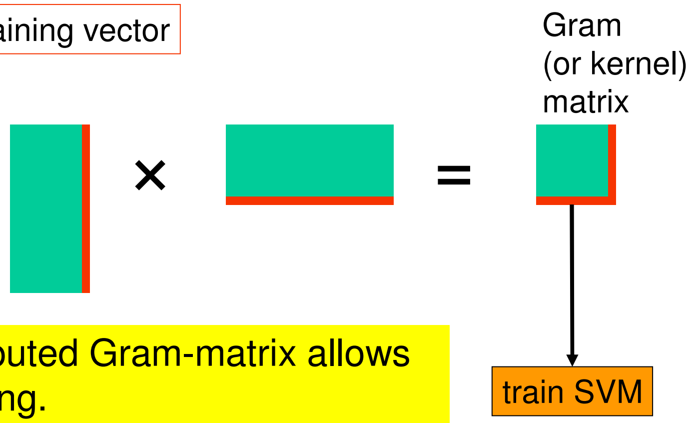
Fast SVM

Linear SVM allows *fast* single dot-product scoring:



thousands of background vectors
(this is constant and can be done *once only*)

single training vector



Pre-computed Gram-matrix allows fast training.

(0.75s per model)

Fast SVM

- With fast SVM train/test, we were able to run whole development test cycles in a few minutes.
- This allowed us to:
  - re-do and re-do and re-do our NAP transforms
  - experiment with the selection of background and T-norm sets

  until we eventually got our various SVMs working well.

Fast SVM

- See [1] for Albert's (Google sponsored) Python code which builds a fast SVM implementation on top of LibSVM [2].

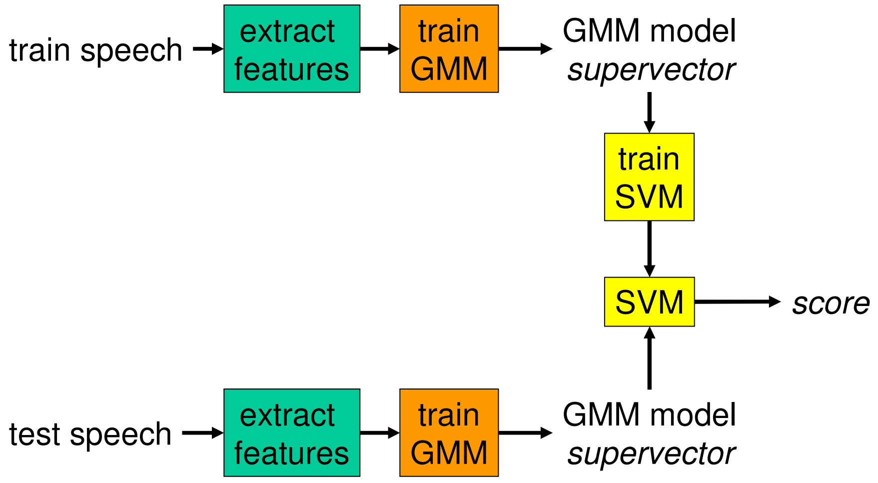
Agenda

- Diversity
- Development data
- *Fast* SVM
- **Supervectors**
- Sub-system performance
- Fusion
- Calibration

Supervectors

- We used 2 kinds of supervector:
  - **MLLR-transform** supervectors (due to SRI [3][4]).
  - **GMM-mean** supervectors (has origins in speech recognition, see e.g. [5]. You will see a lot more of this idea at NIST'06 and Odyssey'06.)

GMM-SVM



Supervector Subspace Magic

- Two types of inter-session sub-space compensation:
  - **GMM**: ***eigen-channel*** MAP-adaptation
  - **SVM**: nuisance attribute projection *(**NAP**),* applied to both GMM and MLLR supervectors.

GMM eigen-channel

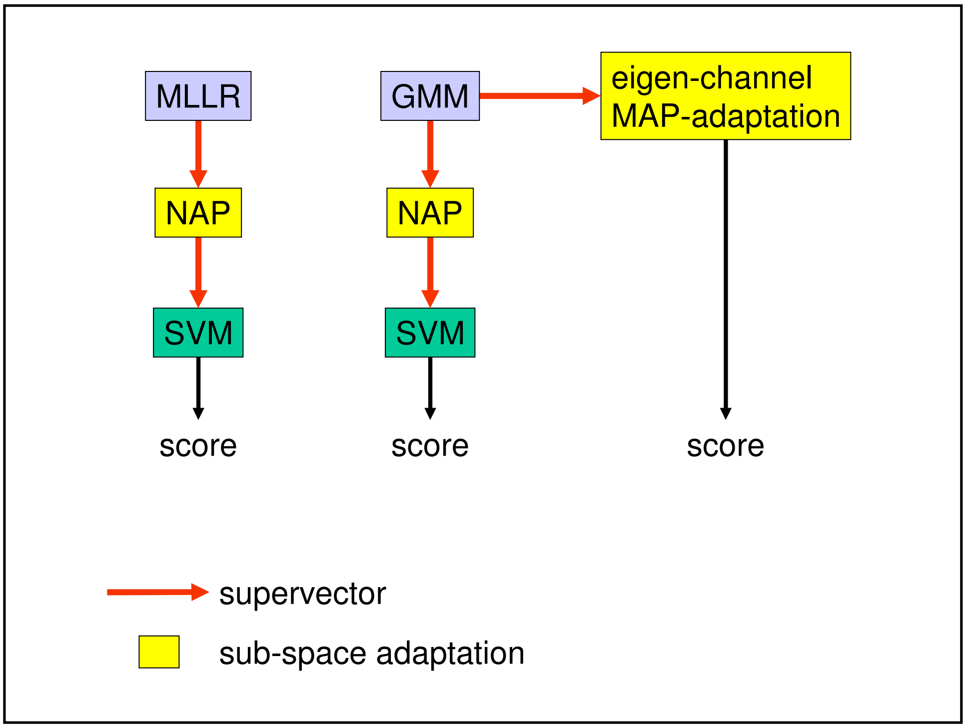
- There are a few different variants and as many different names.
- Was brought to Odyssey’04 by CRIM [5] and NIST SRE ’04 by SDV [6].
- CRIM, SDV and QUT [7][8] again fielded eigen-channel systems for NIST SRE’05.

GMM eigen-channel

- I’m going to leave detailed explanations of GMM subspace compensation to other presenters today: BUT, QUT, LPT, CRIM and MIT.
- Variants include:
  - Model MAP-adaptation during test (BUT,MIT), or train and test (QUT).
  - Feature adaptation, prior to test and train (LPT).
  - Integration over all possible adaptations (CRIM).

SVM NAP

- Due to MIT in 2004 [9][10]
- Variants, based on:
  - Supervised discrete channels
  - Unsupervised continuous inter-session
- We used the latter variant, which is very similar to eigen-channel.



Our SVM-NAP recipe

- SRE-04 works really well as training data!
- Get multiple recording sessions of all speakers (about 310 speakers in 2004).
- Create a supervector per session.
- Calculate speaker mean supervectors.
- Subtract each speaker mean from all sessions of that speaker. This leaves a data matrix with most speaker info removed, but inter-session variability still present.
- Simply do a principal component analysis (PCA) on this 'channel' data. MATLAB's `eigs()` works well for this.

SVM NAP recipe

- (For *eigenchannel* you need principal *eigenvectors* and *eigenvalues*.)
- For NAP, you need only the principal eigenvectors. You need to optimize for the number of eigenvectors. We used more for large GMM supervectors and fewer for smaller MLLR vectors.
- Make sure your eigenvectors are nicely ortho-normal. If they are not, they don't project completely away. Singular-value-decomposition (SVD) is good for ensuring ortho-normality.

SVM NAP recipe

- Project NAP subspace (principal eigenvectors) away from all supervectors involved in SVM training. You *have* to do it prior to training.
- You don't need to project NAP subspace away during test. (But it does no harm).

SVM NAP recipe

- NAP projection, where
  - *v* is original supervector,
  - *w* is projected supervector
  - *S* is matrix of principal (ortho-normal) inter-session covariance eigenvectors
  - ^{T} is transpose

$$w = v - S(S^T v)$$

Eigenchannel vs NAP?

- Is it better to do
  - eigenchannel GMM, or
  - to do straight GMM and then SVM-NAP?
- SDV did both and found the latter to work better.
- BUT did both and found the former to work better.
- TNO and SUN did the latter and found it to work well.
- Who cares. They fuse!

Warning

- Methods that use database-wide training such as NAP and eigen-channel can wreck your calibration, because performance becomes overoptimistic.
- Make sure you train fusions and calibrations on fresh data which has not been exposed to such training.

Subspace methods vs Feature mapping

- Both BUT and TNO used traditional discrete-channel-and-gender-based *feature mapping,* in combination with their subspace methods.
- However, BUT's post-eval experiments show that simpler (2-class) male-female mapping is sufficient, letting subspace methods alone deal with channel mismatch.

Agenda

- Diversity
- Development data
- *Fast* SVM
- Supervectors
- **Sub-system performance**
- Fusion
- Calibration

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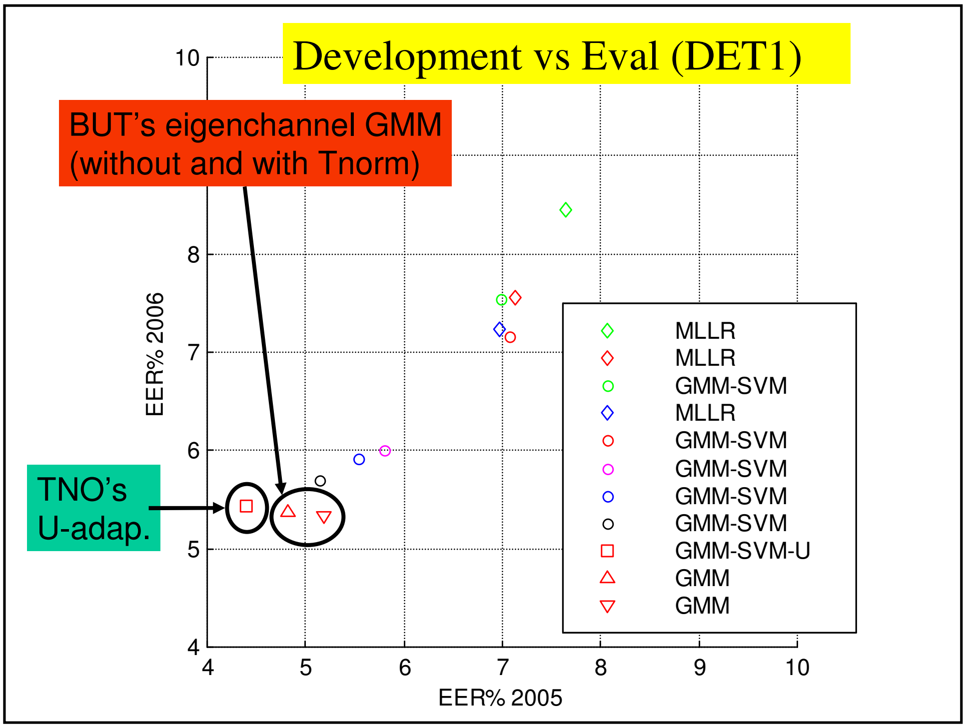
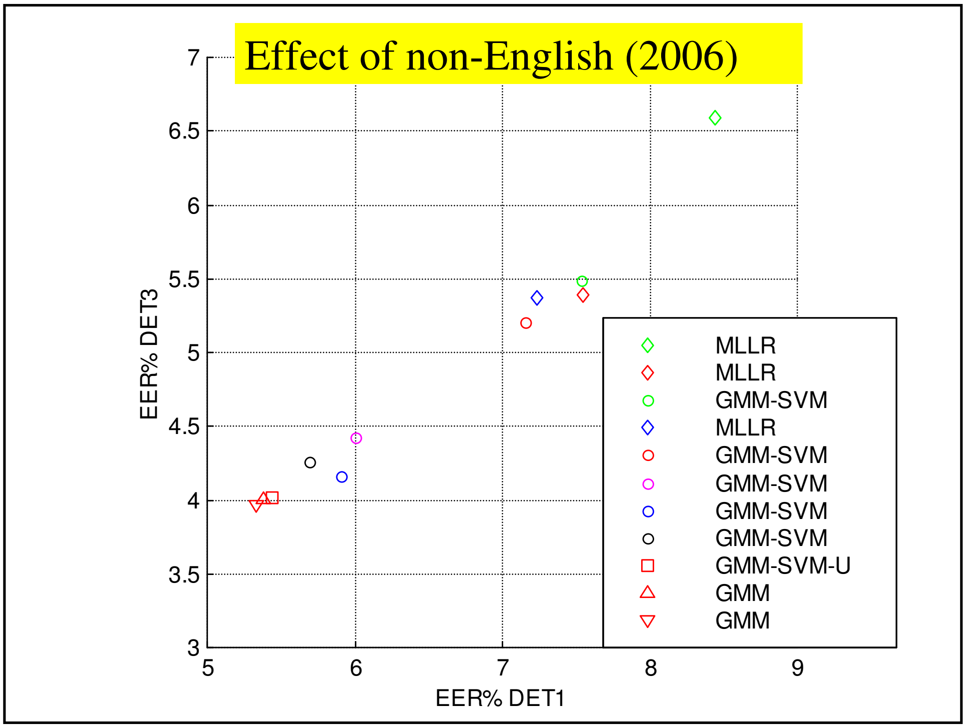
Sub-system result analysis

- 11 sub-systems:
  - 2 GMM systems (± Tnorm)
  - 5 GMM-SVM systems
  - 3 MLLR-SVM systems
  - 1 unsupervised adaptation GMM-SVM


Development vs Eval (DET1)
BUT's eigenchannel GMM
(without and with Tnorm)
TNO's
U-adap.
EER% 2006
EER% 2005
10
8
7
6
5
4
4
5
6
7
8
9
10
MLLR
MLLR
GMM-SVM
MLLR
GMM-SVM
GMM-SVM
GMM-SVM
GMM-SVM
GMM-SVM-U
GMM
GMM


Effect of non-English (2006)
EER% DET3
EER% DET1
7
6.5
6
5.5
5
4.5
4
3.5
3
5
6
7
8
9
MLLR
MLLR
GMM-SVM
MLLR
GMM-SVM
GMM-SVM
GMM-SVM
GMM-SVM
GMM-SVM-U
GMM
GMM

Observations

- There is a mild increase in error-rate from development (2005) to evaluation (2006).
  - Worst affected was unsupervised adaptation.
- On 2006 data, all systems do somewhat better on DET3 than on DET1.

Observations

- MLLR, which is partly dependent on English ASR input, seems not to be affected by the DET3 / DET1 difference any more than the short-time cepstral systems.

Agenda

- Diversity
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- **Fusion**
- Calibration

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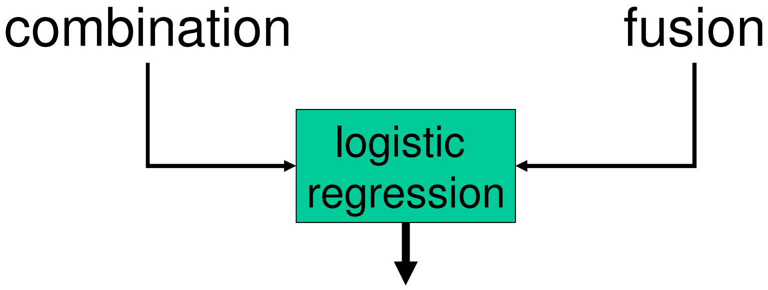
Terminology

- *Combination* in Western USA
- *Fusion* elsewhere.

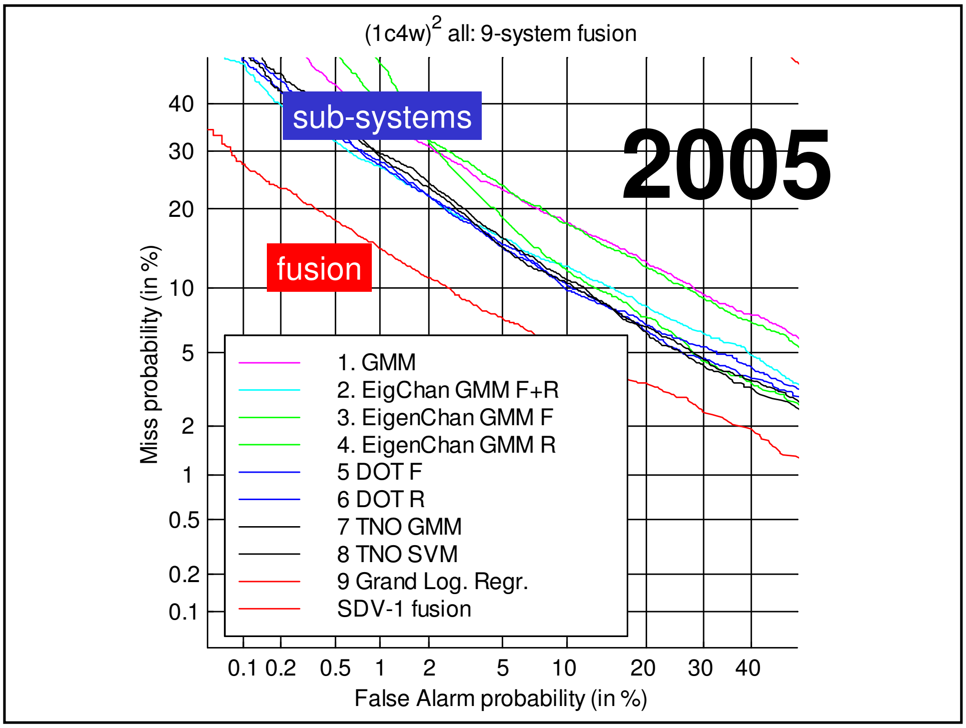
Proposal for a unified terminology:



comfusion?

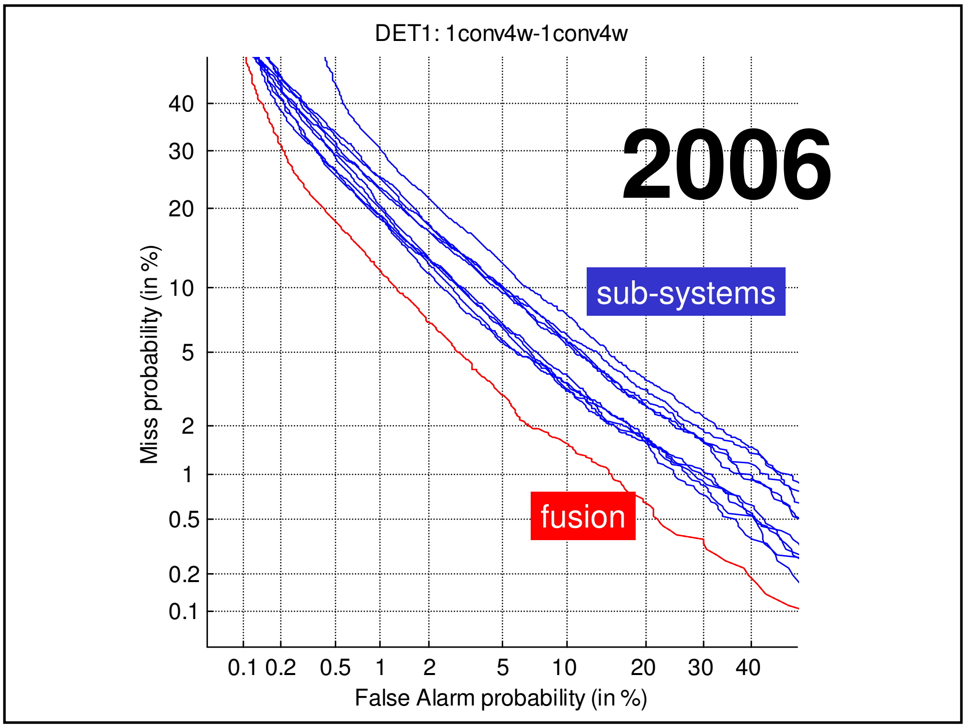
Fusion

- In SRE'05, the SDV+TNO fusion proved that multiple *mediocre* (EER 10%) systems can produce *good* (EER 6%) results.



Fusion

- This year we wanted to repeat that exercise over four sites, but then my partners started cheating! Suddenly they were contributing *good* (5%, 6% EER) systems to the fusion.
- This makes the fusion more difficult. Does fusion still work when development error-rates are low?



Fusion

- There are many ways to fuse, including both *generative* and *discriminative* methods.
- (In language recognition generative methods like LDA seem to be more popular.)
- In speaker detection discriminative methods like Logistic Regression, MLP and SVM are popular.
- Simple equal-weight summation of T-normed scores is also not a bad idea at all. (Requires no training.)

Fusion

- I chose to use logistic regression again this year.
- But I did a 10-fold cross-validation as a sanity check to see if the fusion would remain stable on unseen data, which it did.
- Finally, I used the same procedure as last year, which indeed:
  - Gave a nice gain over the whole DET-curve (EER 2.3% for English; 3.3% all)
  - Gave reasonable calibration

Logistic Regression Fusion

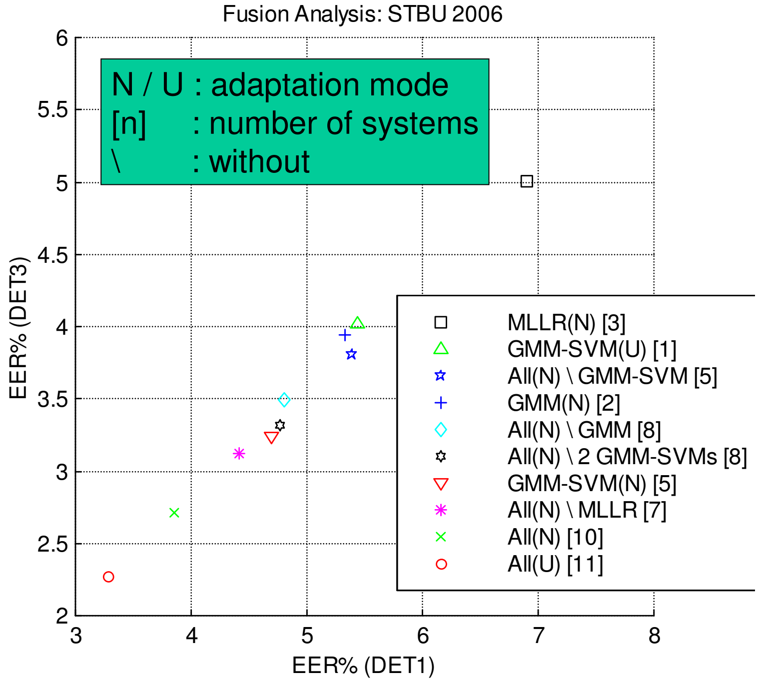
- Logistic regression fusion is an affine transform from multi-score space to log-likelihood-ratio.
- It is easy to implement: see Focal toolkit [11].
- In addition to fusion, it also *calibrates*. We had no need to choose an empirical decision threshold.
- It is robust

Why Robust?

- Training is a convex optimization problem: there is a unique global optimum.
- It has a low number of parameters, *N+1*, for *N* scores.
- It optimizes the fusion over the *whole* DET-curve, not specifically at the CDET operating point.
- Logistic regression also helped QNI, BUT, CRIM and TNO to perform successful fusion and/or calibration this year.

Fusion analysis

- We analyze DET1 and DET3 EER's for a few different fusions of **subsets** of our original 11-system fusion.
- All fusions are trained on 2005 and tested on 2006.

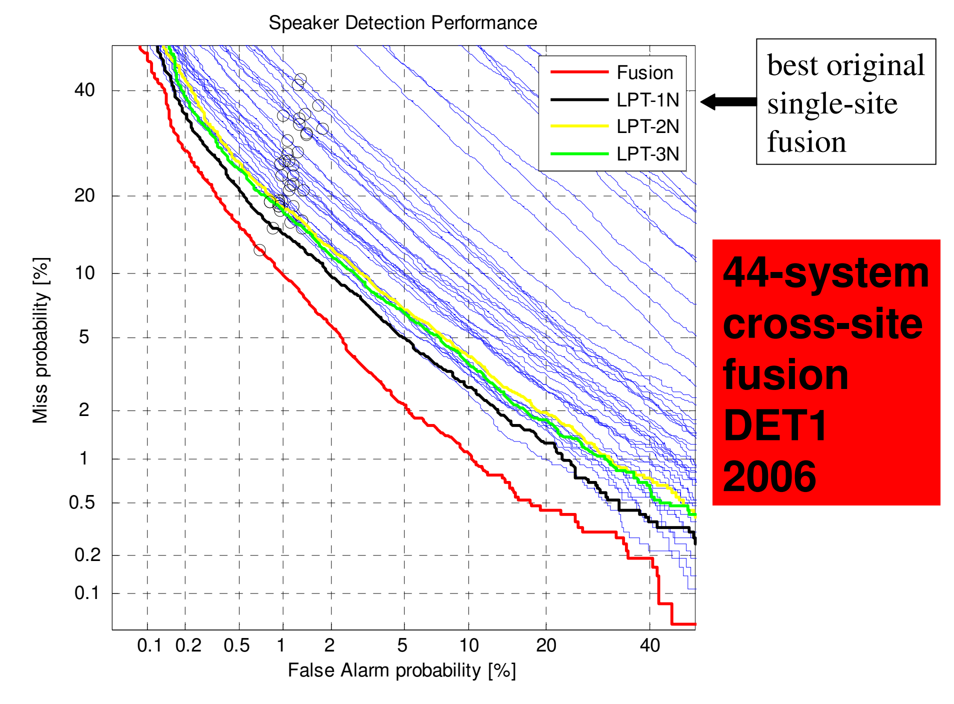


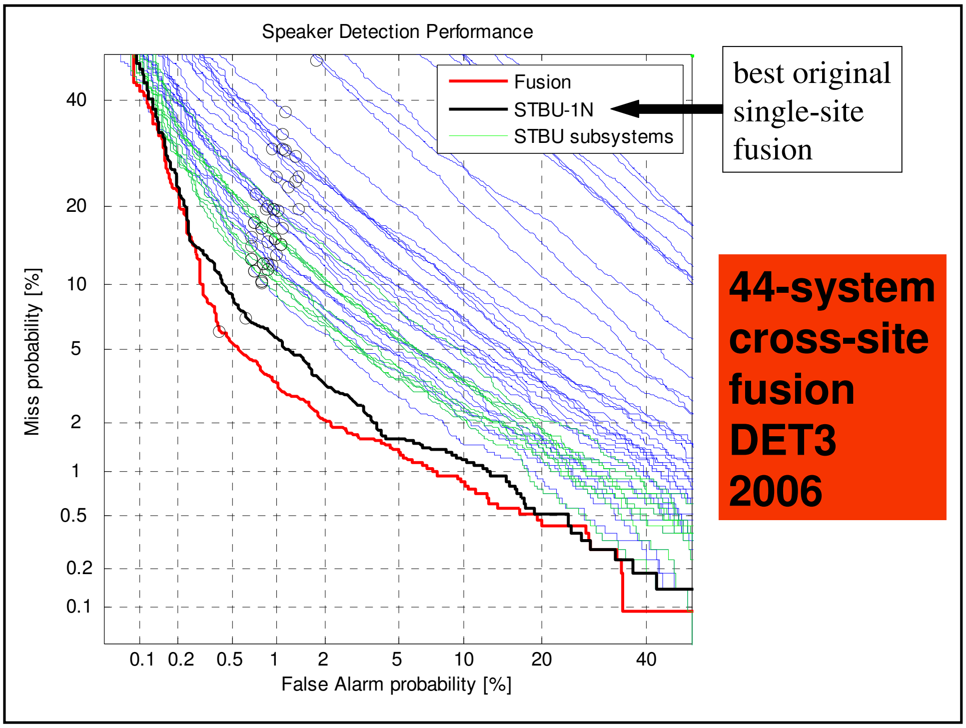
Observations (for DET1, N-mode)

- All systems: EER = 3.9%
- All fast systems (no MLLR): EER = 4.4%
- Different *methods* fuse, but different *implementations* of same methods also fuse:
  - Effect of removing 2 weakest of the 5 GMM-SVM systems increases EER from 3.9% to 4.8%

Cross-site fusion result

- As a post-eval experiment, we collected 1conv4w-1conv4w scores from multiple sites.
- In the end we fused a whole 44 sub-system scores from 12 different sites.
- (No unsupervised adaptation was used.)
- Logistic regression fusion was trained on 2005 scores.
- Results are for 2006: DET1 and DET3





Cross-site fusion

- Fusion still works when using very many systems and when error-rates are low!
- DET1 EER = 3.3%
- DET3 EER = 2.0%

Agenda

- Diversity
- Development data
- *Fast* SVM
- Supervectors
- Sub-system performance
- Fusion
- **Calibration**

Calibration

- If your speaker recognition ambitions end at doing well in the NIST SRE, then calibration means empirically choosing a decision threshold that optimizes for the *single operating point* represented by *actual* C_{DET}.
- Yes, you can go and re-optimize for other single operating points. But there are richer types of applications that require simultaneous operation over a wide range of operating points.

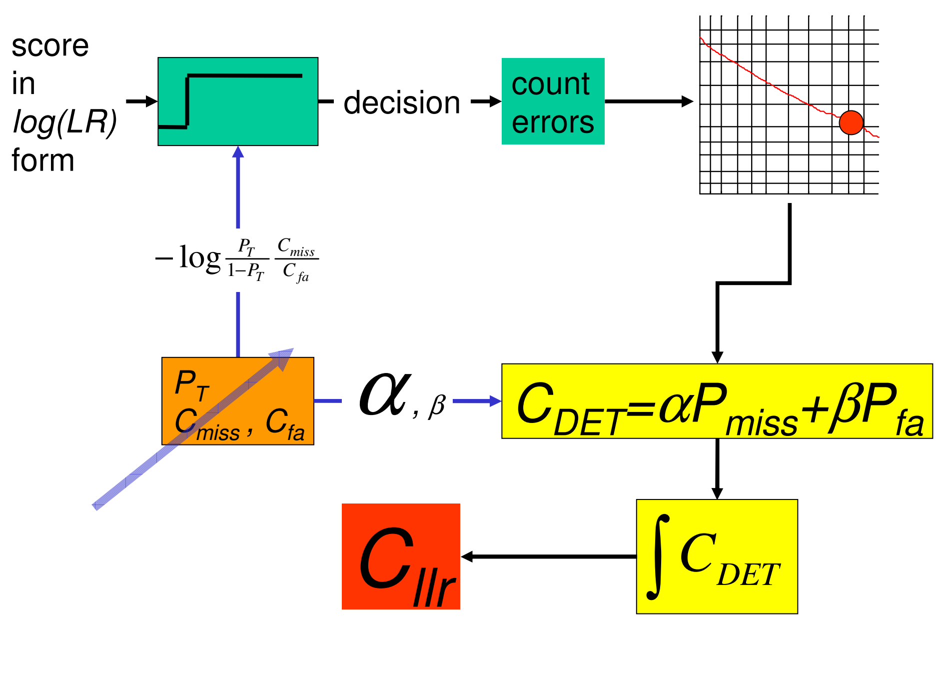
Examples

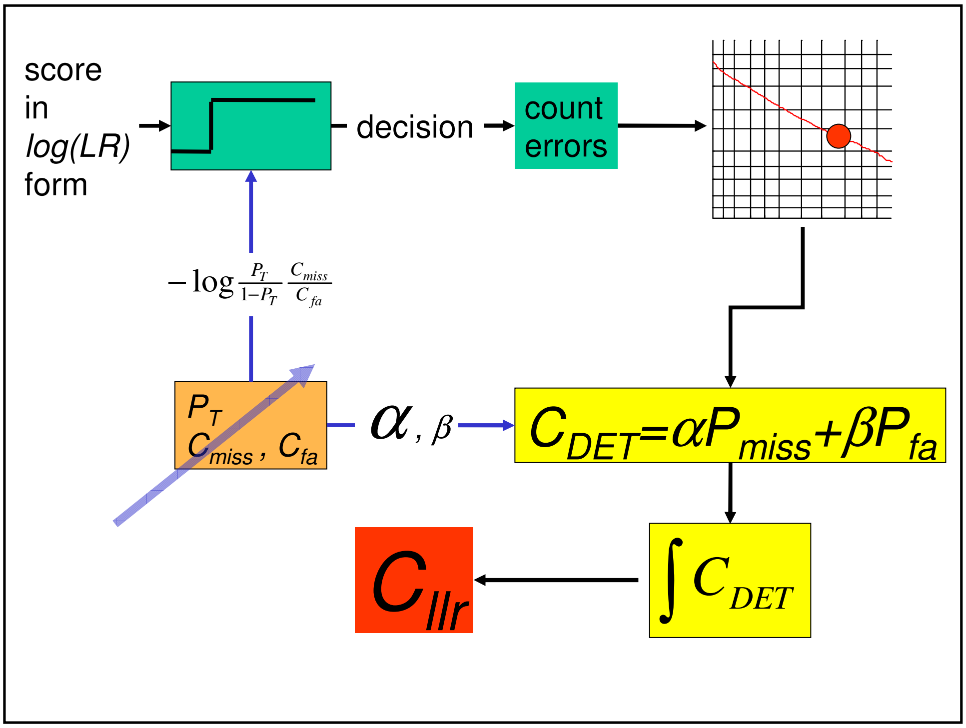
- A speaker recognizer that can advise the user of things like:
  - The *probability* of finding a target speaker in a given set of recordings which it has processed.
  - The *expected time* required of the user to find this speaker amongst those recordings, when sorted in order of likelihood.
- A forensic speaker recognition system that delivers not hard decisions, but detection *confidence* (weight-of-evidence) to the user.

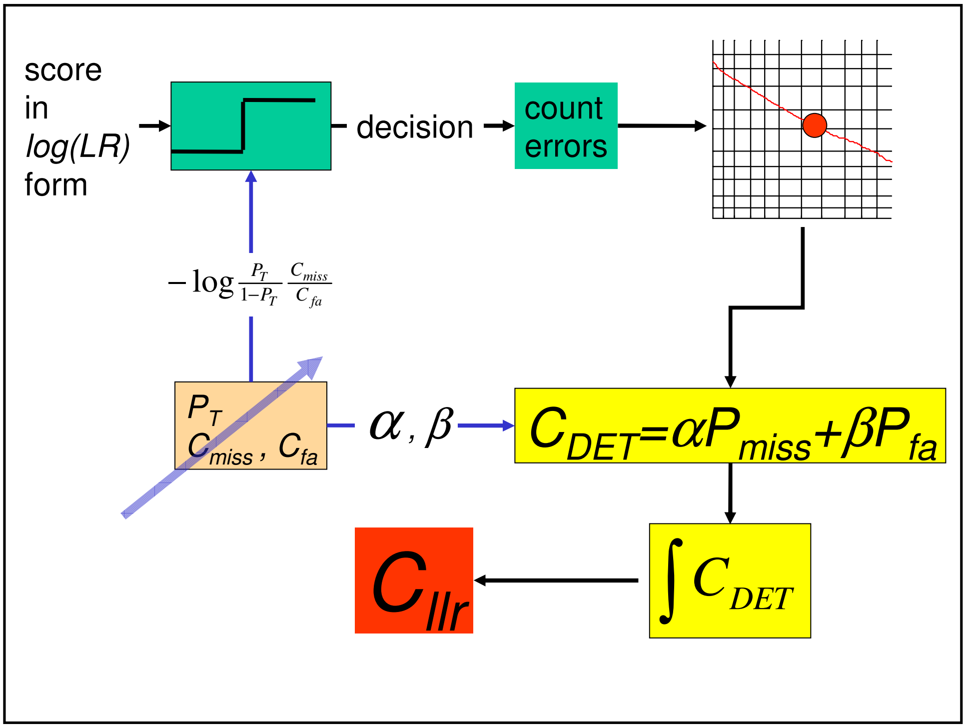
Calibration

- If your application needs are more general, there are many good reasons (see my paper [12]) to use C_{llr} as evaluation objective rather than C_{DET}.
- C_{llr} represents performance over a wide range of operating points.
- *Calibration* is now the act of designing a mapping which outputs scores in log-likelihood-ratio format, such that C_{llr} (rather than C_{DET}) is optimized.

C_{llr} is simply C_{DET} integrated over a wide range of operating points.




score
in
log(LR)
form
decision
count
errors
$-\log \frac{P_T}{1-P_T}\frac{C_{miss}}{C_{fa}}$
P_T
C_{miss}, C_{fa}
α, β
$C_{DET}=\alpha P_{miss}+\beta P_{fa}$
C_{llr}
$\int C_{DET}$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P_T
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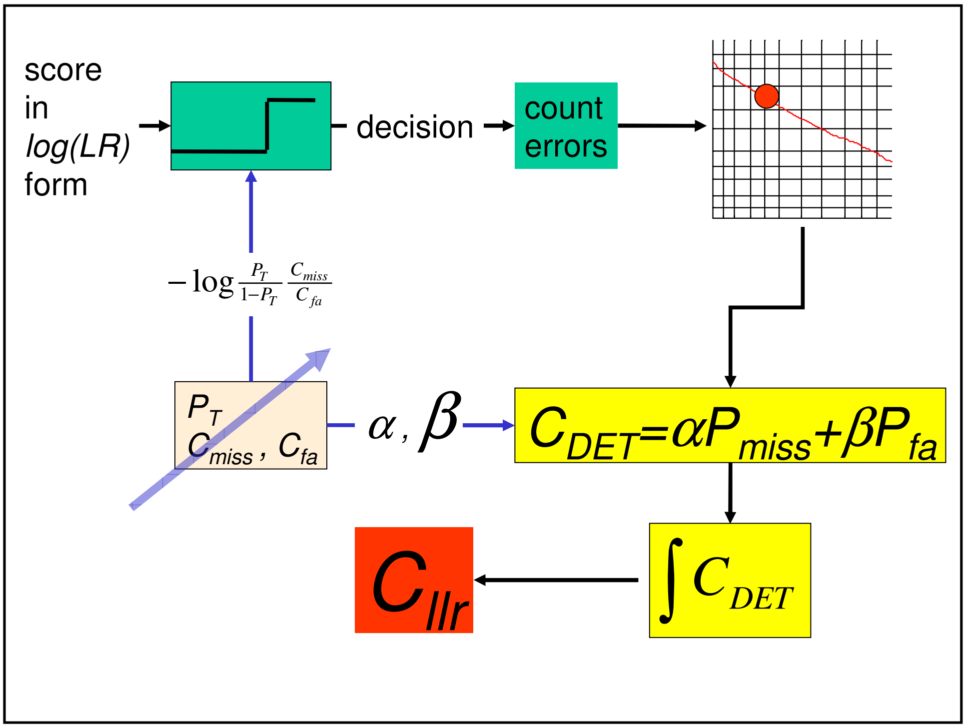
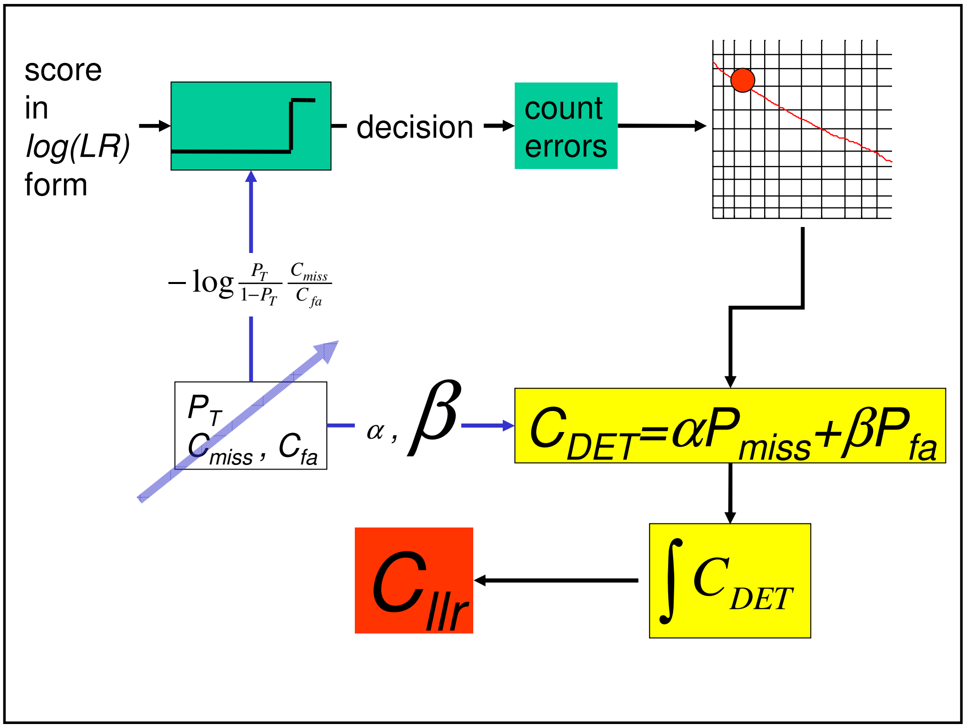
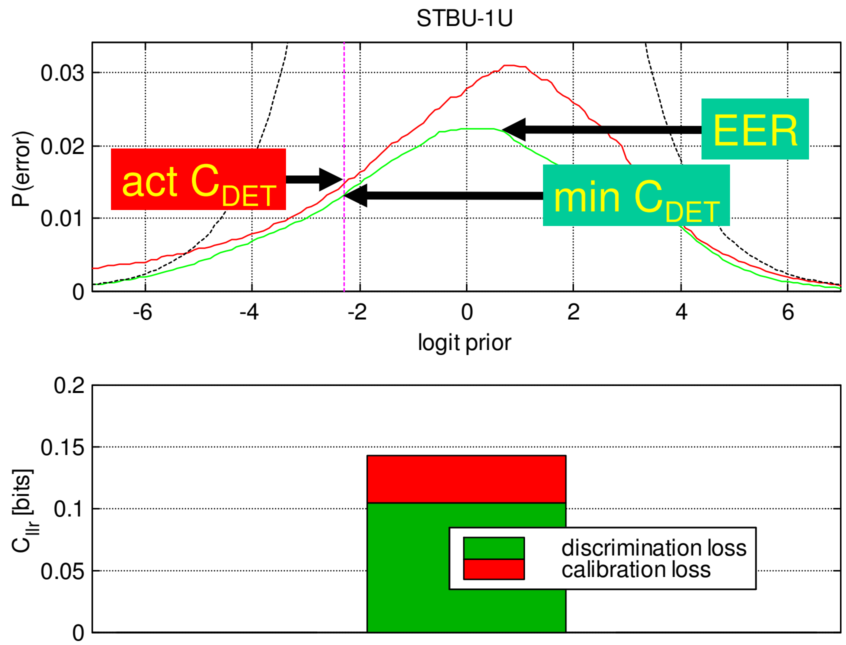
C_{llr}
$\int C_{DET}$

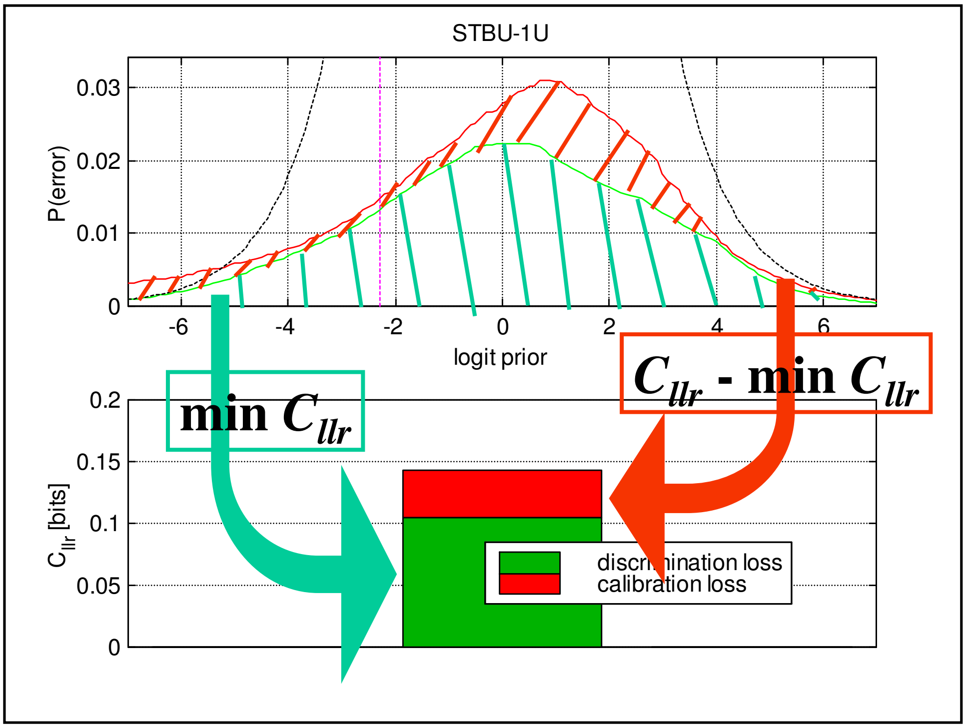

score in log(LR) form
decision
count errors
$-\log \frac{P_T}{1-P_T} \frac{C_{miss}}{C_{fa}}$
P_T
C_{miss}, C_{fa}
α, β
$C_{DET}=\alpha P_{miss}+\beta P_{fa}$
$\int C_{DET}$
C_{llr}


score in log(LR) form
decision
count errors
$-\log \frac{P_T}{1-P_T} \frac{C_{miss}}{C_{fa}}$
P_T
C_{miss}, C_{fa}
α, β
$C_{DET}=\alpha P_{miss}+\beta P_{fa}$
$\int C_{DET}$
C_{llr}

Measuring calibration

- **Point calibration** can be measured via the discrepancy between *actual* C_{DET} and *minimum* C_{DET} ,
- **General calibration** can be:
  - measured via discrepancy between *actual* C_{llr} and *minimum* C_{llr} .
  - analyzed with applied probability of error (APE) curves.





STBU-1 Calibration

11 sub-system scores

↓

logistic regression fusion ← prior = 0.0917 (to optimize wide operating range around C_{DET} operating point)

↓

log(LR) score

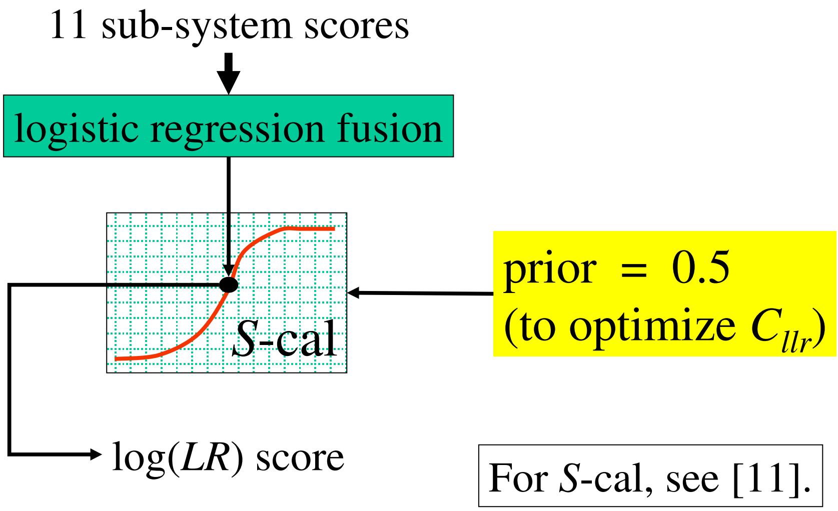
↓

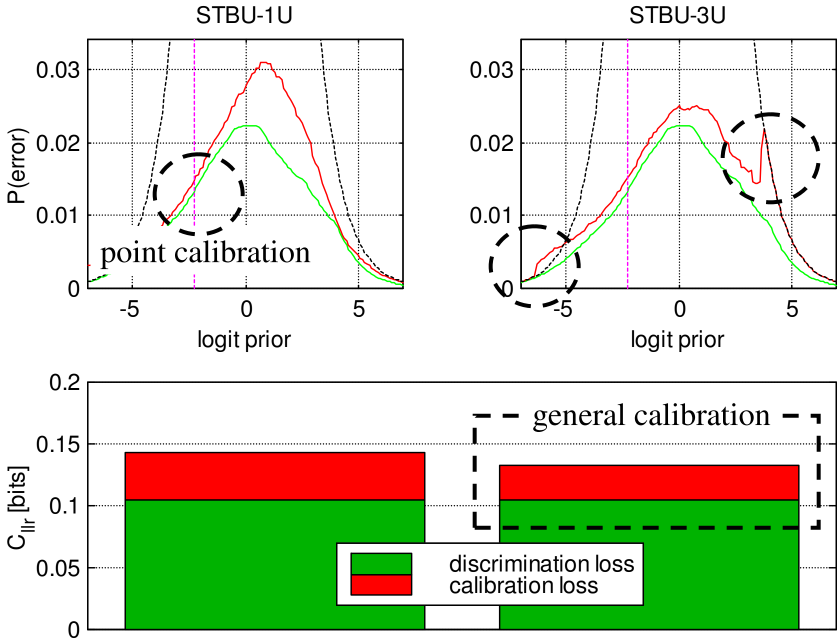
threshold @ 2.29

↓

decision

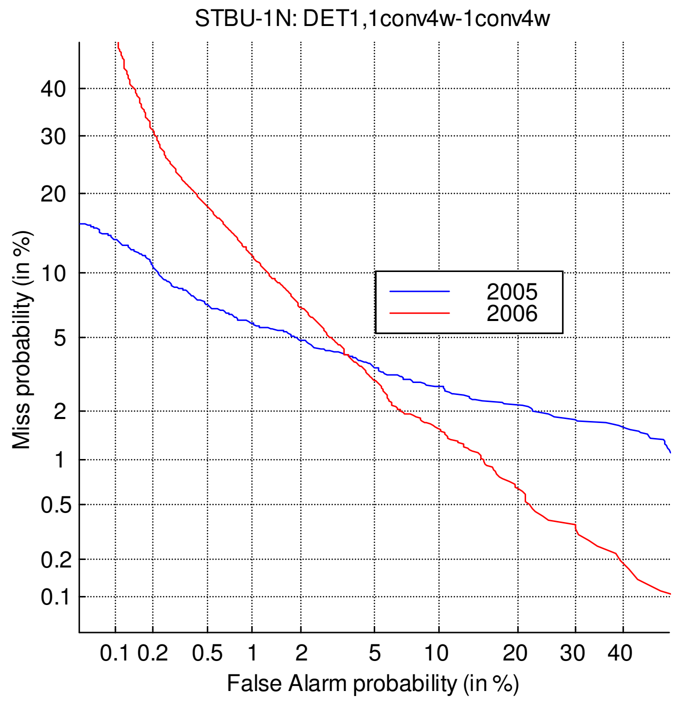
STBU-3 Calibration





Calibration complication

- For STBU-1, our development (2005) EER and eval (2006) EER are almost identical.
- But DET-curves are very different ….



Calibration complication

- The ratio of target and non-target score variances changed a lot between 2005 and 2006!
- This is part of the reason why our calibration is not quite as neat as last year.
- The challenge is therefore to get calibration more stable across different environments.

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Conclusion

- Fast short-time cepstrum systems are very effective when supervector subspace compensations are applied.
- No single system gets it quite right --- fusion between different systems usually helps.
- Slower ASR-based systems can add further value.

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