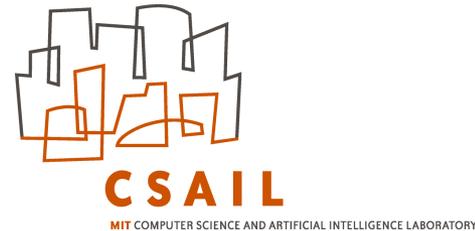

Unsupervised Clustering Approaches for Domain Adaptation in Speaker Recognition Systems

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Unsupervised Clustering Approaches for Domain Adaptation in Speaker Recognition Systems



- **Most current statistical learning techniques assume (incorrectly) that the training and test data come from the same underlying distribution.**
- **Labeled data may exist in one domain, but we want a model that can also perform well on a related, but not identical, domain.**
- **Hand-labeling data in a new domain is difficult and expensive.**
- **What can we do to leverage the original, labeled, “out-of-domain” data when building a model to work on new, unlabeled, “in-domain” data?**

[2] Hal Daume III and Daniel Marcu, “Domain adaptation for statistical classifiers,” Journal of Artificial Intelligence Research, 2006.



Unsupervised Clustering Approaches for Domain Adaptation in Speaker Recognition Systems



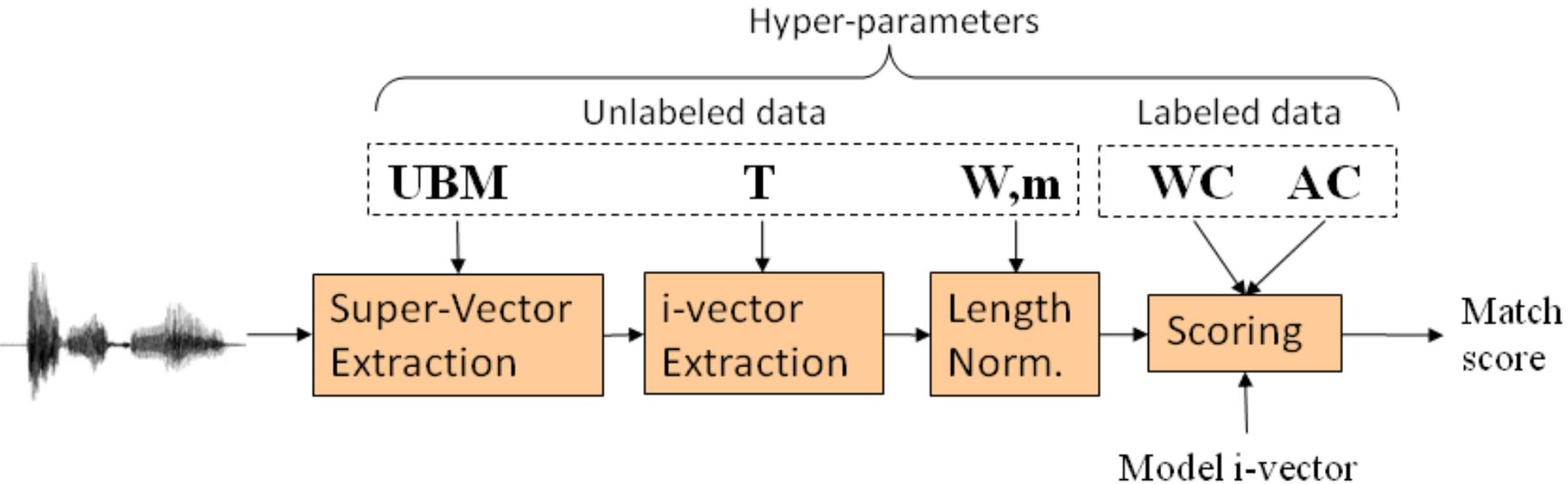
The i-vector approach



- **Segment-length independent, low-dimensional, vector-based summary representation of audio**
- **Allows the use of large amounts of previously collected and labeled audio to characterize and exploit speaker and channel (i.e., all non-speaker) variabilities.**
 - 1000's of speakers making 10's of calls
- **Unrealistic to expect that most applications will have access to such a large set of labeled data from matched conditions.**



Data usage (labeled & unlabeled) in an i-vector system





Demonstrating Mismatch



- **Enroll and score**
 - **SRE10 telephone speech**
- **Matched, “in-domain” SRE data**
 - **All telephone calls from all speakers from SRE 04, 05, 06, and 08 collections**
- **Mismatched “out-of-domain” SWB data**
 - **All calls from all speakers from Switchboard-I and Switchboard-II collections**

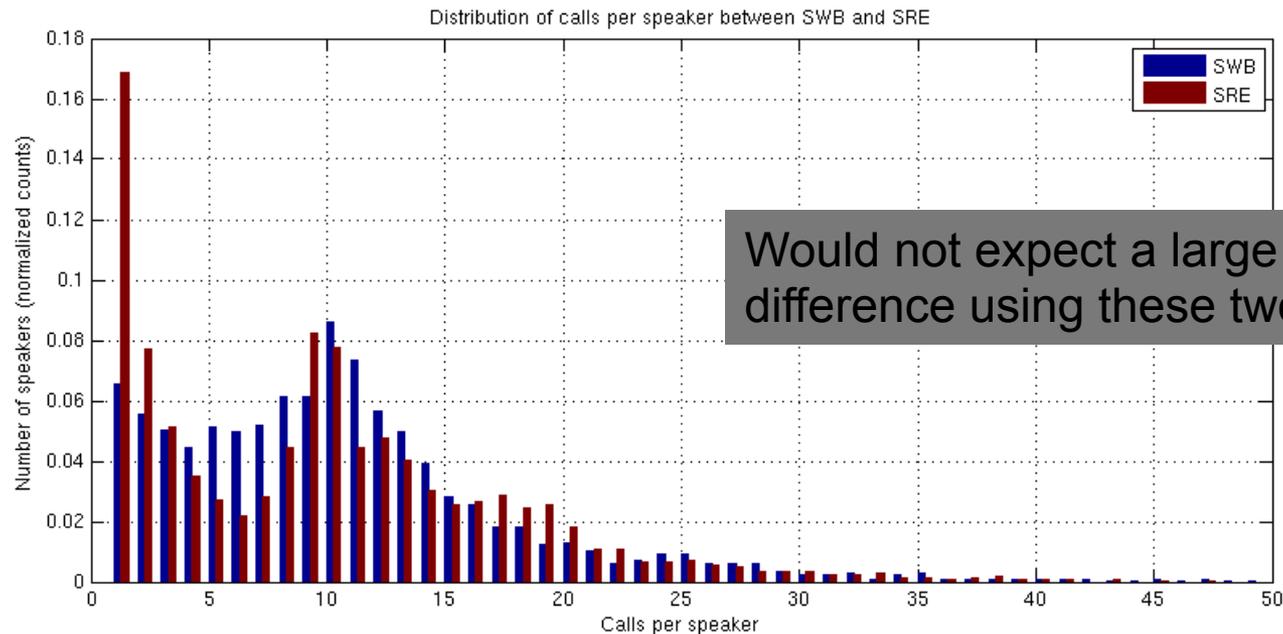


Demonstrating Mismatch



- **Summary statistics for SRE & SWB lists**

Hyper list	# Spkrs	# Males	# Females	# Calls	Avg # calls/spkr	Avg # phone_num/spkr
SWB	3114	1461	1653	33039	10.6	3.8
SRE	3790	1115	2675	36470	9.6	2.8





Demonstrating Mismatch



- **Baseline / Benchmark Results (Equal Error Rate – EER)**

UBM & T	Whitening	WC & AC	JHU	MIT
SWB	SWB	SWB	6.92%	7.57%
SWB	SRE	SWB	5.54%	5.52%
SWB	SRE	SRE	2.30%	2.09%
SRE	SRE	SRE	2.43%	2.48%

- **Focus on the performance gap caused by using SRE instead of SWB labels (SWB/SRE) for WC & AC**
 - Continue using SWB for UBM&T and SRE for Whitening



Challenge Task Rules



- **Allowed to use SWB data *and* their labels**
- **Allowed to use SRE data but not their labels**
- **Evaluate on SRE10.**



Exploring the Domain Mismatch



- ~~Speaker ages?~~
- ~~Languages spoken?~~
 - ~~SWB contains only English~~
 - ~~SRE contains 20+ different languages~~

[11] Carlos Vaquero, “Dataset Shift in PLDA-based Speaker Verification,” in *Proceedings of Odyssey*, 2012.



Exploring the Domain Mismatch



- **SWB subsets**
 - **SWPH0 (1992)**
 - **SWPH1 (1996)**
 - **SWPH2 (1997)**
 - **SWPH3 (1997-1998)**
 - **SWCELLP1 (1999)**
 - **SWCELLP2 (2000)**

WC & AC	EER (%)
SWCELLP1/2	4.67%
+ SWPH3	3.51%
+ SWPH1/2	4.85%
+SWPH0	5.54%

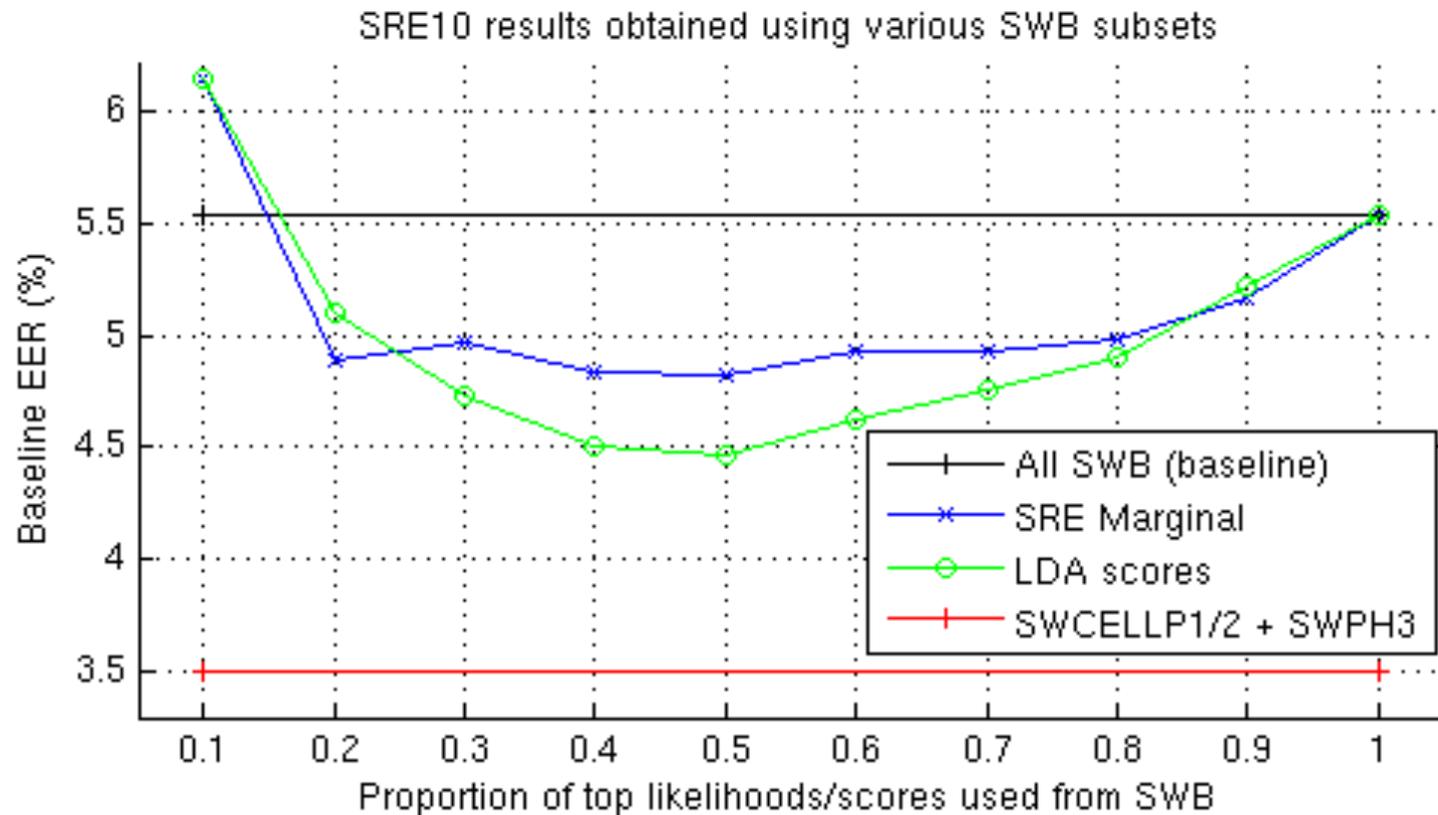
[13] Hagai Aronowitz, “Inter-Dataset Variability Compensation for Speaker Recognition,” in *Proceedings of ICASSP*, 2014.



Exploring the Domain Mismatch



- Naïve “adaptation” via automatic subset selection





Unsupervised Clustering

Approaches for Domain Adaptation in Speaker Recognition Systems



Proposed (Bootstrap) Framework



- **Begin with Σ_{SWB} (WC) and Φ_{SWB} (AC).**
- **Use PLDA and Σ_{SWB} , Φ_{SWB} to compute pairwise affinity matrix, Λ , on SRE data.**
- **Cluster Λ to obtain hypothesized speaker labels.**
- **Use labels to obtain Σ_{SRE} and Φ_{SRE}**
- **Linearly interpolate (via α_{WC} and α_{AC}) between prior (SWB) and new (SRE) covariance matrices to obtain final hyper-parameters:**

$$\Sigma_{\text{F}} = \alpha_{\text{WC}} \cdot \Sigma_{\text{SRE}} + (1 - \alpha_{\text{WC}}) \cdot \Sigma_{\text{SWB}}$$

$$\Phi_{\text{F}} = \alpha_{\text{AC}} \cdot \Phi_{\text{SRE}} + (1 - \alpha_{\text{AC}}) \cdot \Phi_{\text{SWB}}$$

- **Iterate?**



(Unsupervised) Clustering



- **Agglomerative hierarchical clustering (AHC)**
 - Requires as input the number of clusters at which to stop
- **Graph-based random walk algorithms**
 - Infomap [24]
 - Markov Clustering (MCL) [25]

[24] Martin Rosvall and Carl T. Bergstrom, “Maps of Random Walks on Complex Networks Reveal Community Structure”, in *Proceedings of the National Academy of Sciences*, 2008.

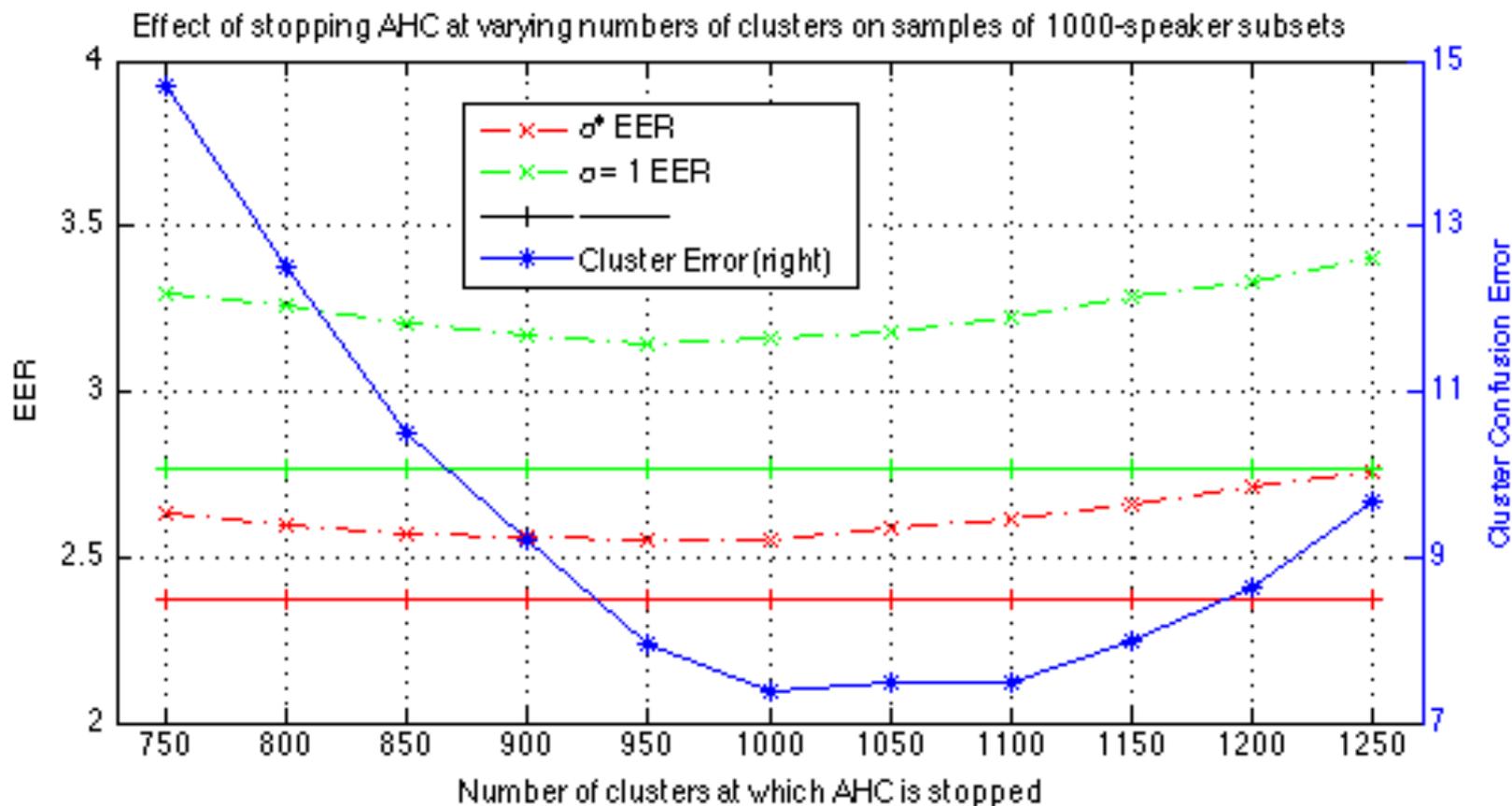
[25] Stijn van Dongen, [Graph Clustering by Flow Simulation](#), Ph.D. Thesis, University of Utrecht, May 2000.



Initial Findings



- In the presence of interpolation ($0 < \alpha < 1$), an imperfect clustering is forgivable.

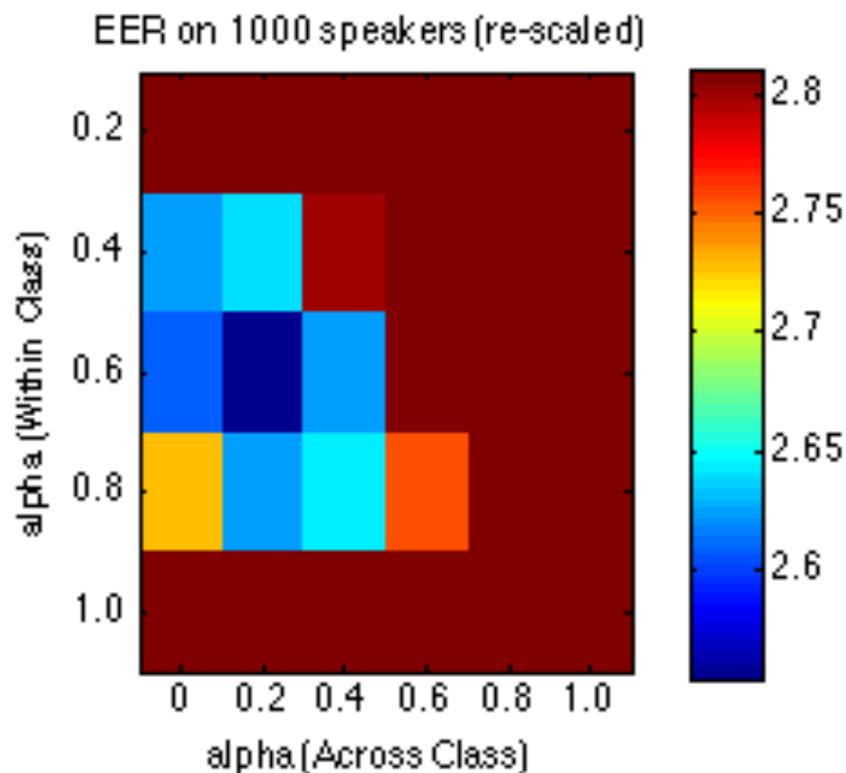
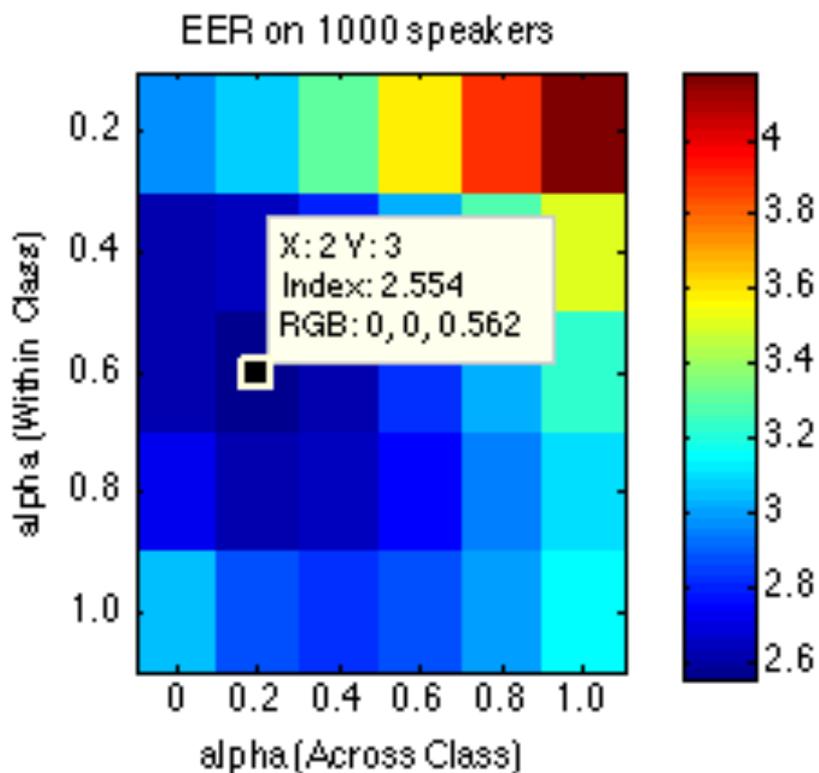




Initial Findings



- **Automatic estimation of α^***
 - Open and unsolved, but not a huge problem





Results So Far



- Via clustering and optimal adaptation

	\hat{K}	Perfect	Hypothesized	Gap (%)
AHC	3790*	2.23	2.58	16%
Infomap+AHC	3196	—	2.53	13%
MCL+AHC	3971	—	2.61	17%

- Initial baseline and benchmark

UBM & T	Whitening	WC & AC	JHU
SWB	SRE	SWB	5.54%
SWB	SRE	SRE	2.30%



Take-home Ideas



- **In the presence of interpolation, α , an imprecise estimate of the number of clusters is forgivable.**
- **Range of adaptation parameters yield decent results.**
 - **The selection of optimal values is still an open question.**
- **Best automatic system so far obtains SRE10 performance that is within 15% of a system that has access to all speaker labels.**



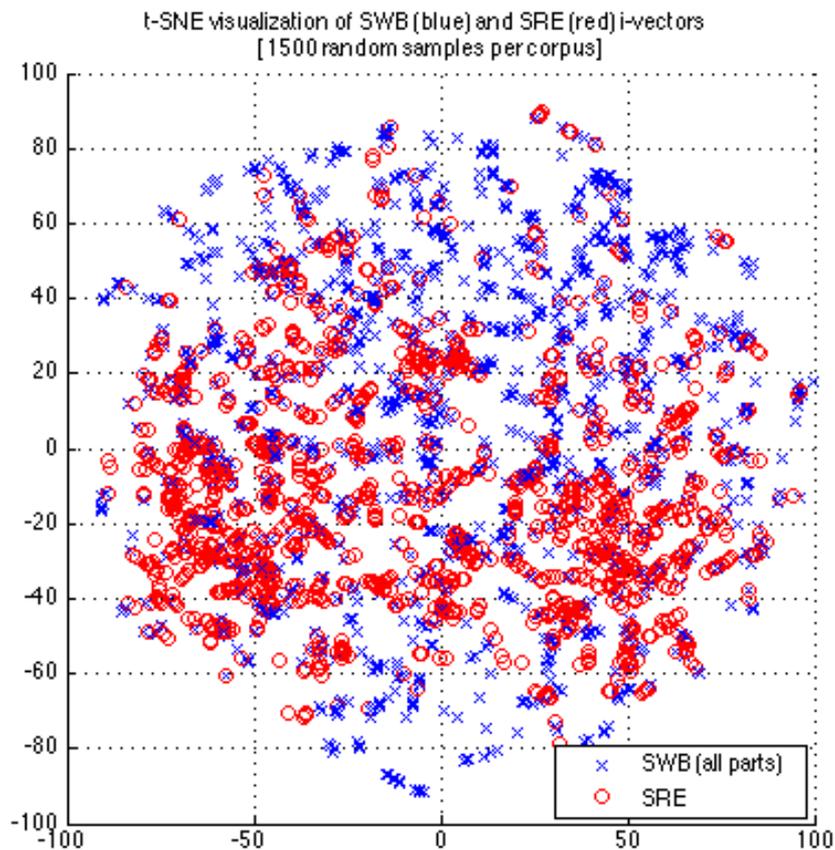
What's Next?



- **Telephone – Telephone domain mismatch**
 - Simple solutions work well already.
 - Explicitly identifying the source of the performance degradation via metadata analysis, etc.
- **Telephone – Microphone domain mismatch**
 - Expected to be a more difficult problem
- **Out-of-domain detection**
 - Not unlike outlier/novelty detection



Telephone vs. Telephone



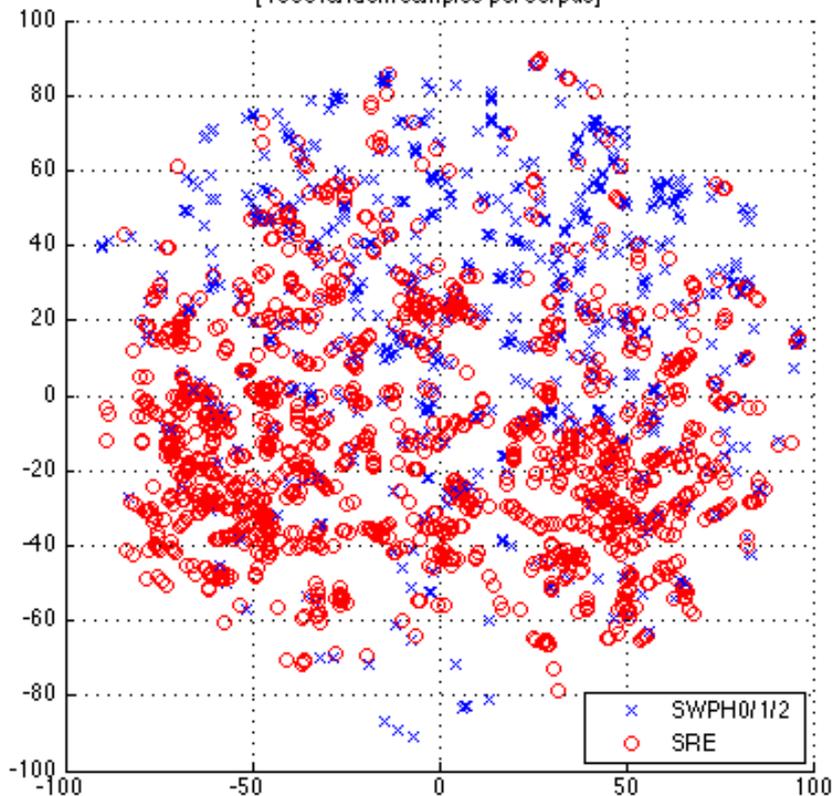
[--] Laurens van der Maaten and Geoffrey Hinton, "Visualizing data using t-SNE," [Journal of Machine Learning Research](#), 2008.



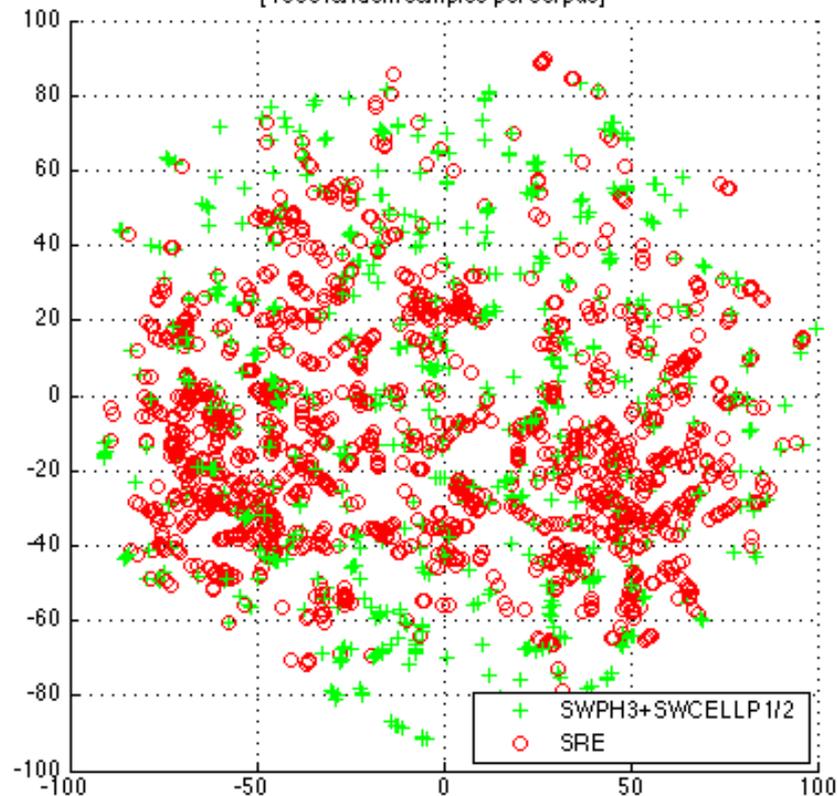
Telephone vs. Telephone



t-SNE visualization of SWB (blue) and SRE (red) i-vectors
[1500 random samples per corpus]

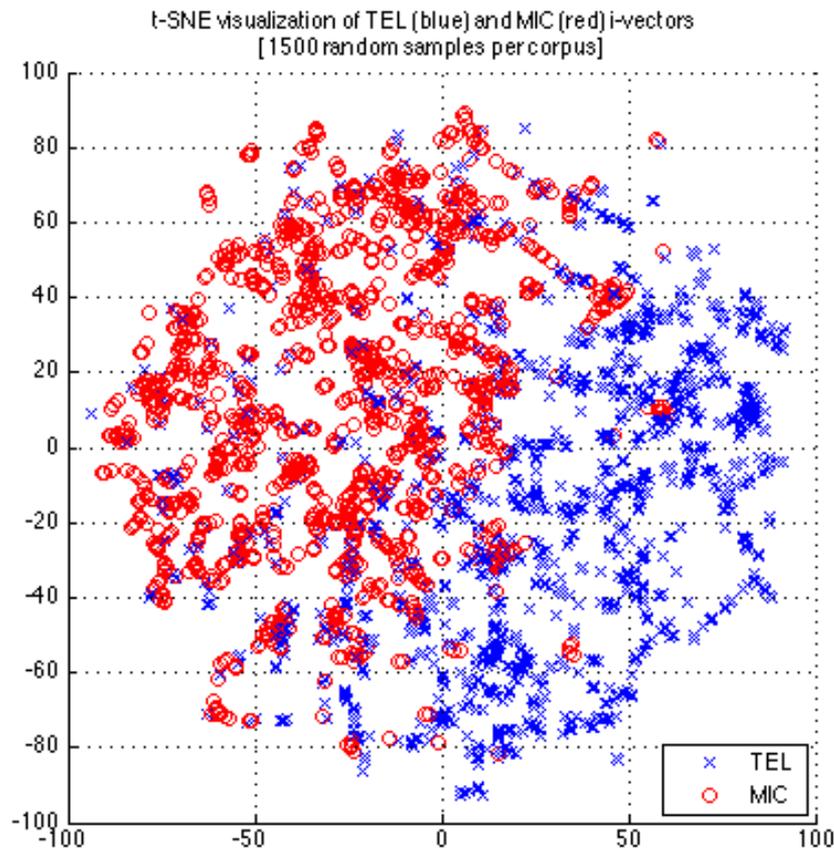
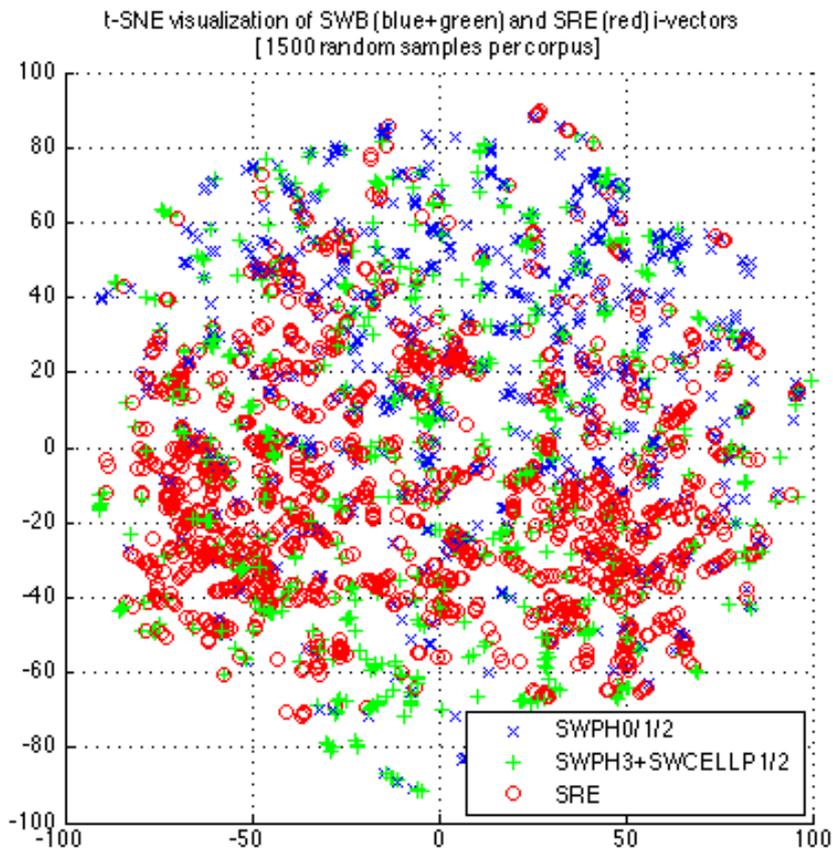


t-SNE visualization of SWB (green) and SRE (red) i-vectors
[1500 random samples per corpus]





Telephone vs. Microphone



TEL = {SWB, SRE};
MIC = {SRE 05, 06, 08 microphone}



Microphone vs. Microphone



t-SNE visualization of SRE-mic (blue), interview-mic (red), and room-mic (green) i-vectors
[440 random samples per corpus]

