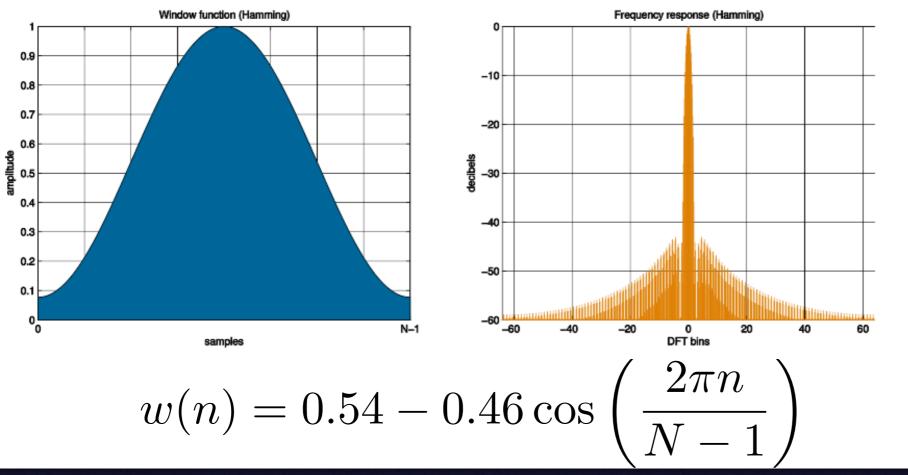
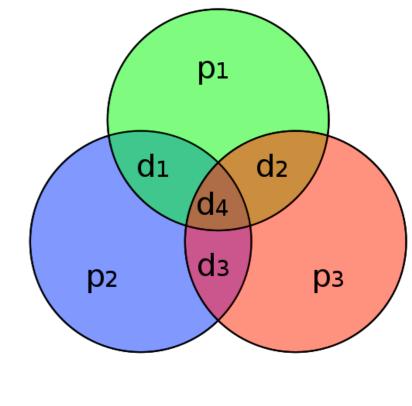
Natural Speech Technology

Steve Renals

Hamming Seminar

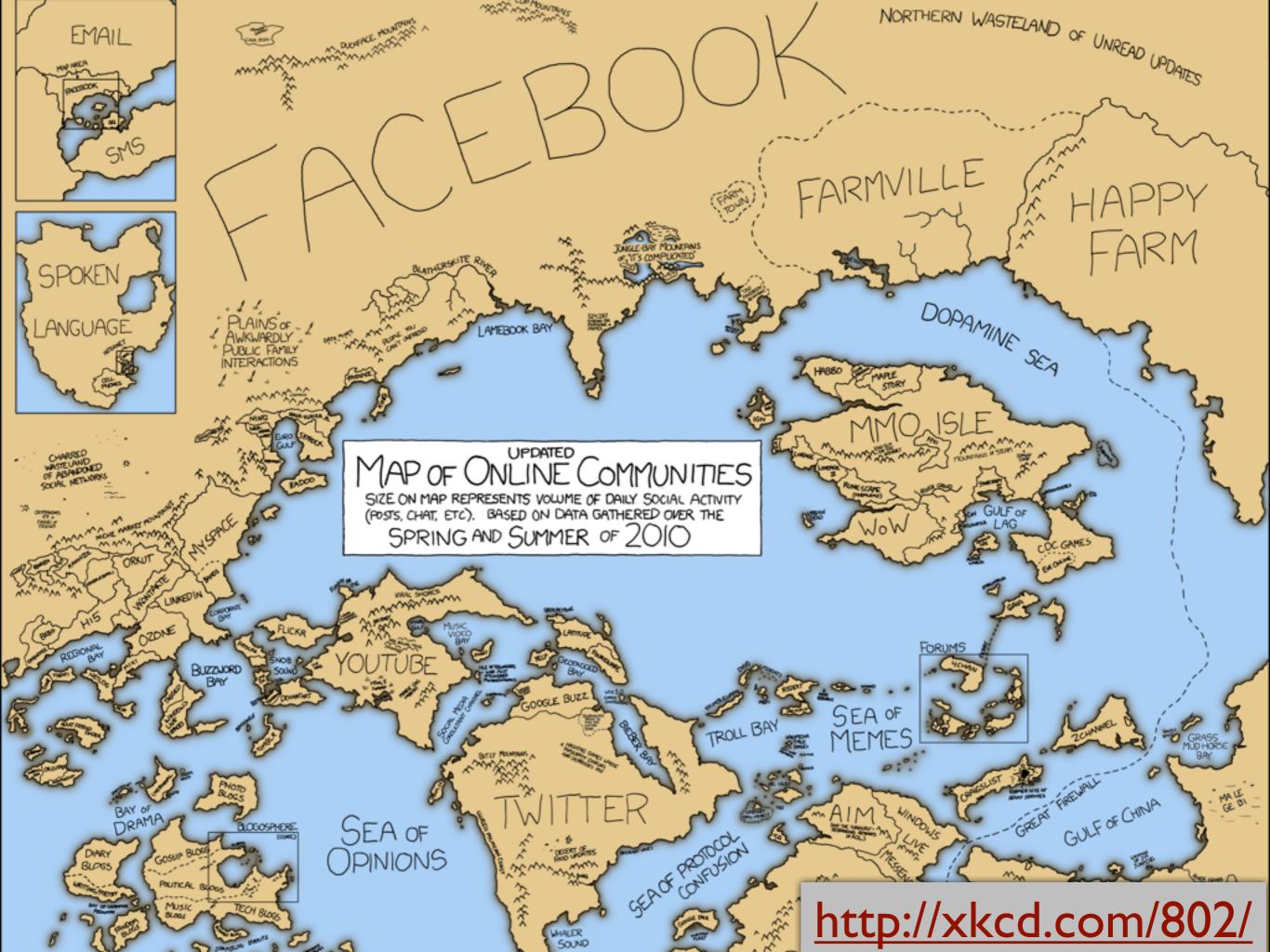


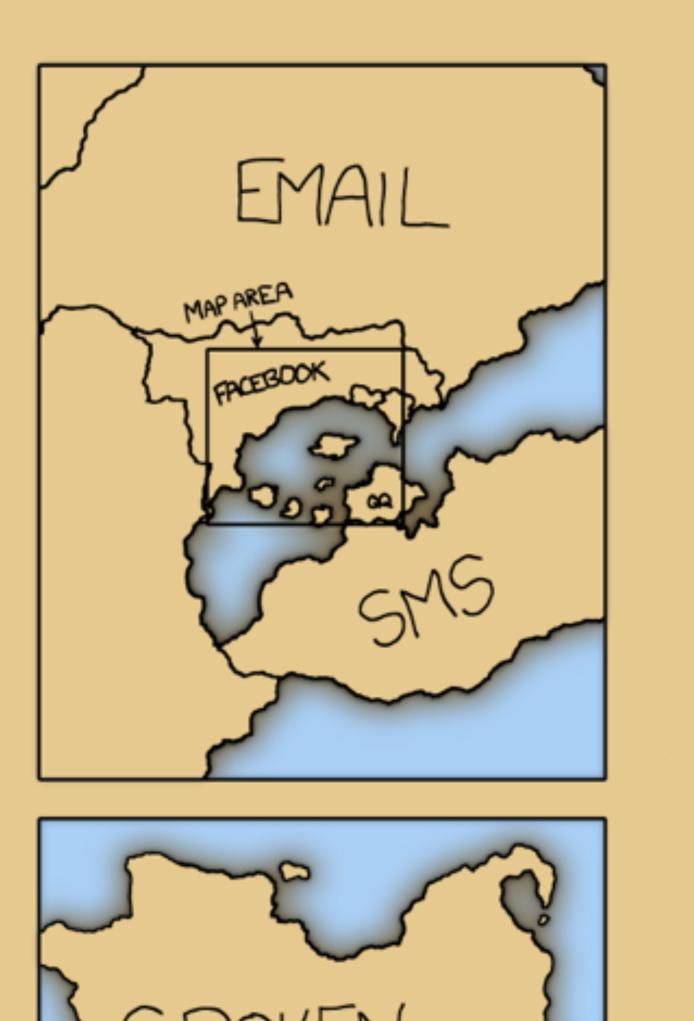




- I. Drop modesty
- 2. Prepare your mind
- 3. Brains and courage
- 4. Age is important
- 5. Make the best of your working conditions

- 6. Work hard & effectively
- 7. Believe and doubt your hypotheses
- 8. Work on the important problems
- 9. Be committed
- 10. Leave your door open

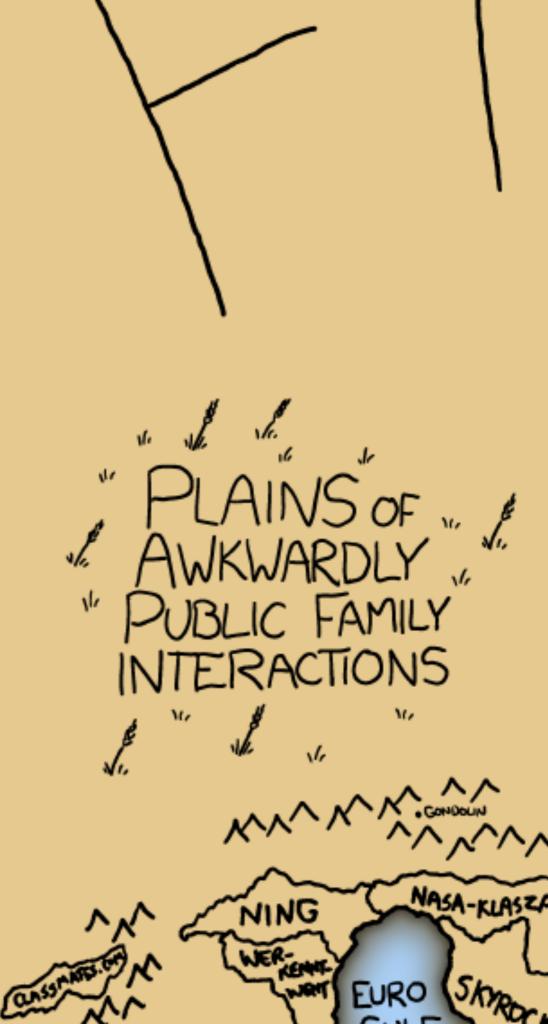








http://xkcd.com/802/



Speech technology seems to evoke two types of response

I. It's a solved problem

2. It's hopeless

A natural speech technology

Speech recognition

 systems that can detect "who spoke what, when and how" for any acoustic environment and task domain

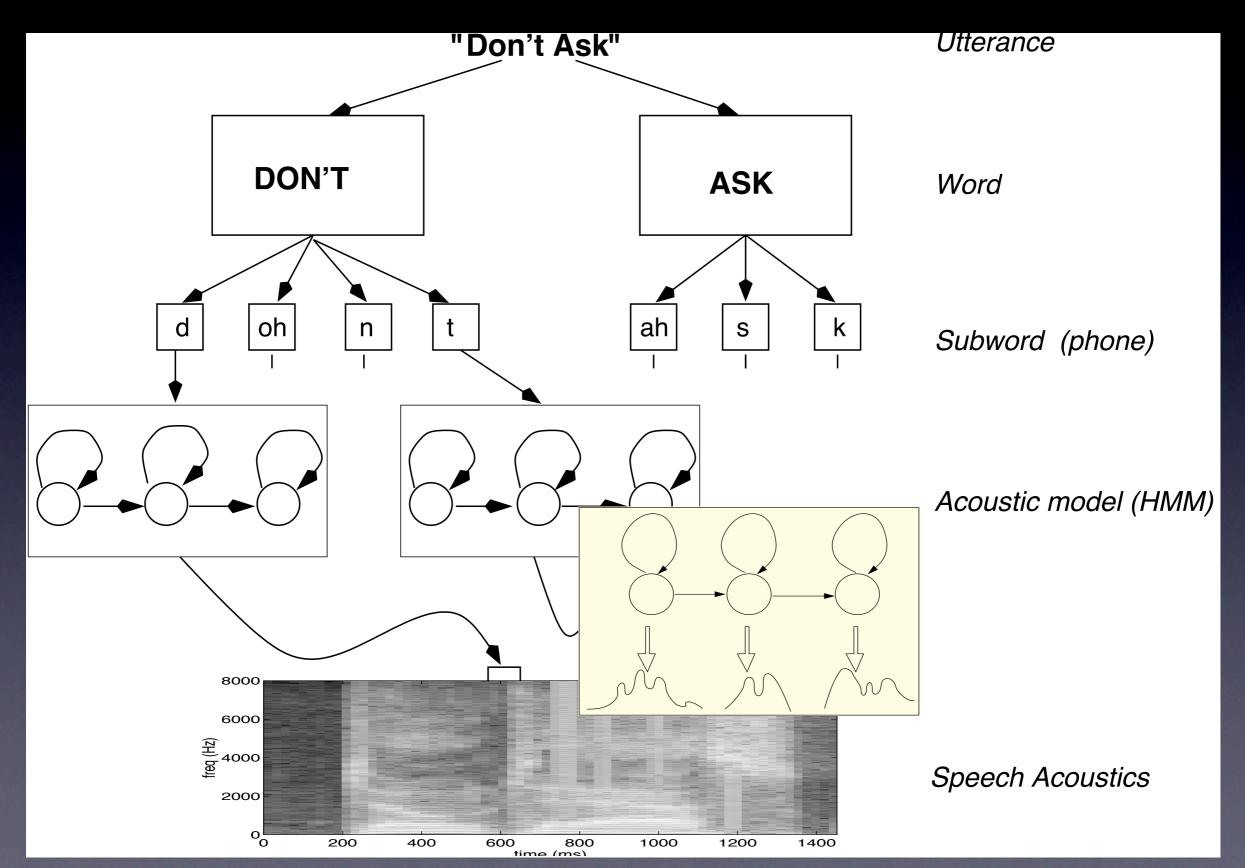
Speech synthesis

- controllable systems capable of generating natural and expressive speech in a given voice
- Adaptation, Personalisation, Expression

Speech recognition

- Dictated newspaper text ("Wall Street Journal")
- Conversational telephone speech ("Switchboard")
- Multiparty conversations ("AMI Meetings")

HMM/GMM



Basic Framework



Acoustic Features



HMM



Objective function



HMM



Feature Normalisation

CMN VTLN MLE CVN HMM

PLP

Adaptation

CMN VTLN MLE CVN HMM MLLR PLP

CMLLR

Adaptive Training

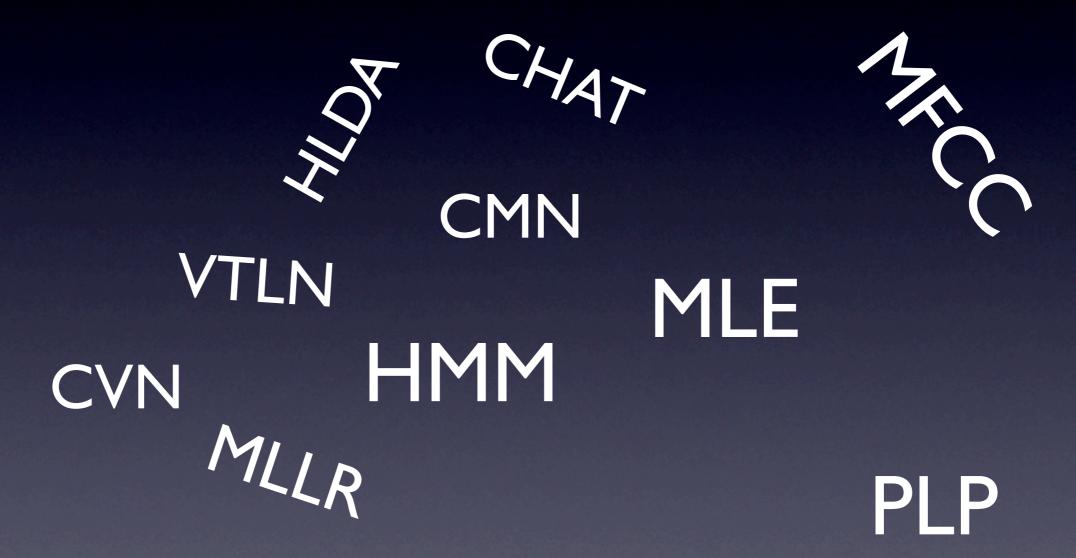
GHAT

CMN VTLN MLE HMM CVN MLLR PLP

CMLLR

SAT

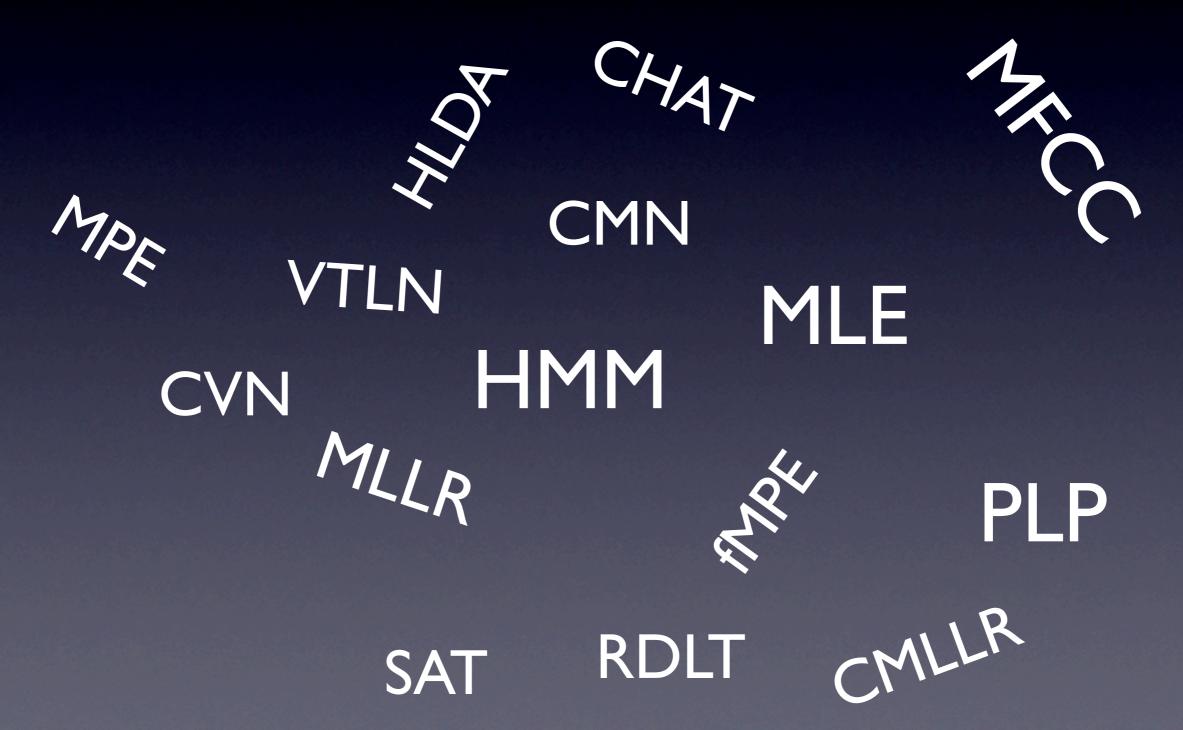
Feature Transformation



CMLLR

SAT

Discriminative Training



Task adaptation



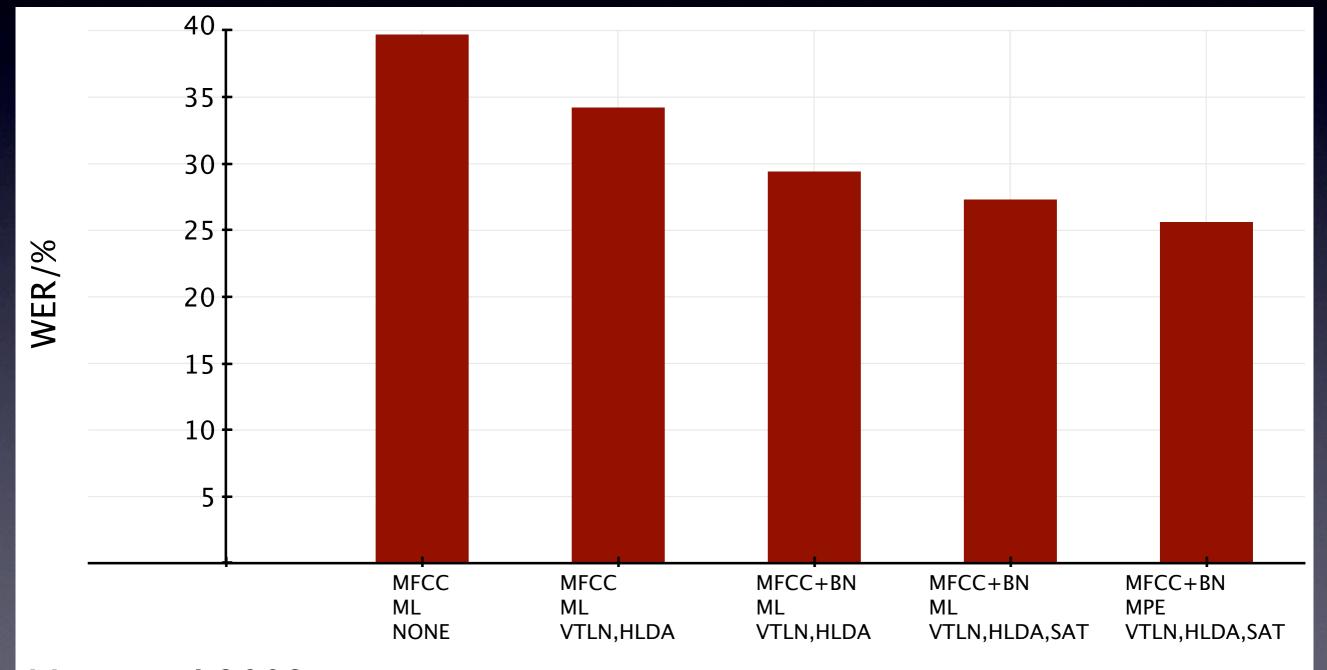
Posterior features



Model Combination



Additive gains on meeting recognition



Hain et al 2009

Features / Training / Adapt

Speech synthesis

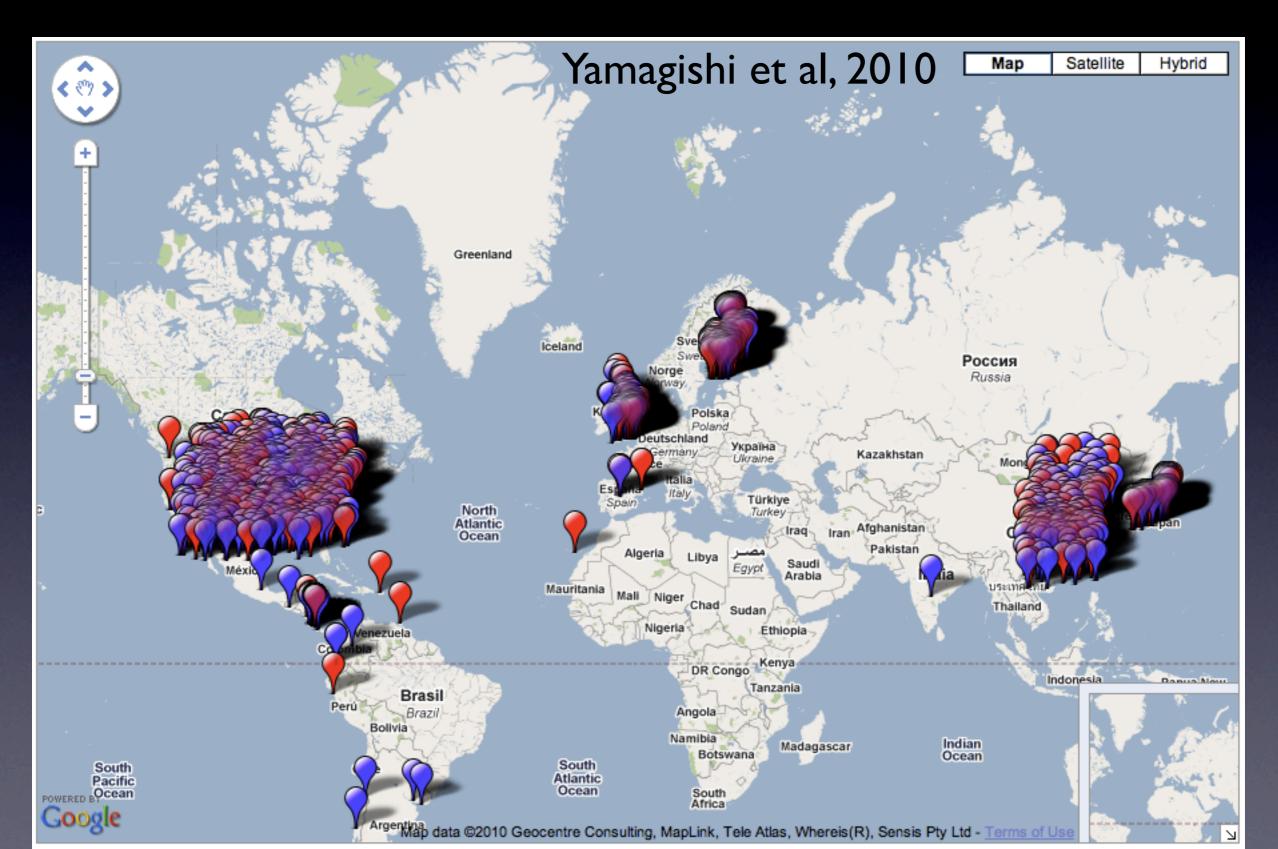
- 1970-80s: parametric, rule-based
- 1980-90s: data-driven, concatenate diphones
- 1990-2000s: data-driven, concatenative, unit selection
- 2000-2010s: statistical parametric (HMM) synthesis

HMM Speech Synthesis

• Use the HMM generative model to generate speech

- automatic estimation of parameters
- different objective functions possible
- HMM/GMM adaptation algorithms possible to develop new synthetic voices with a few mins of data
- uses highly context dependent models
- need to model duration, F0, multiband energy amplitude

A world of synthetic voices



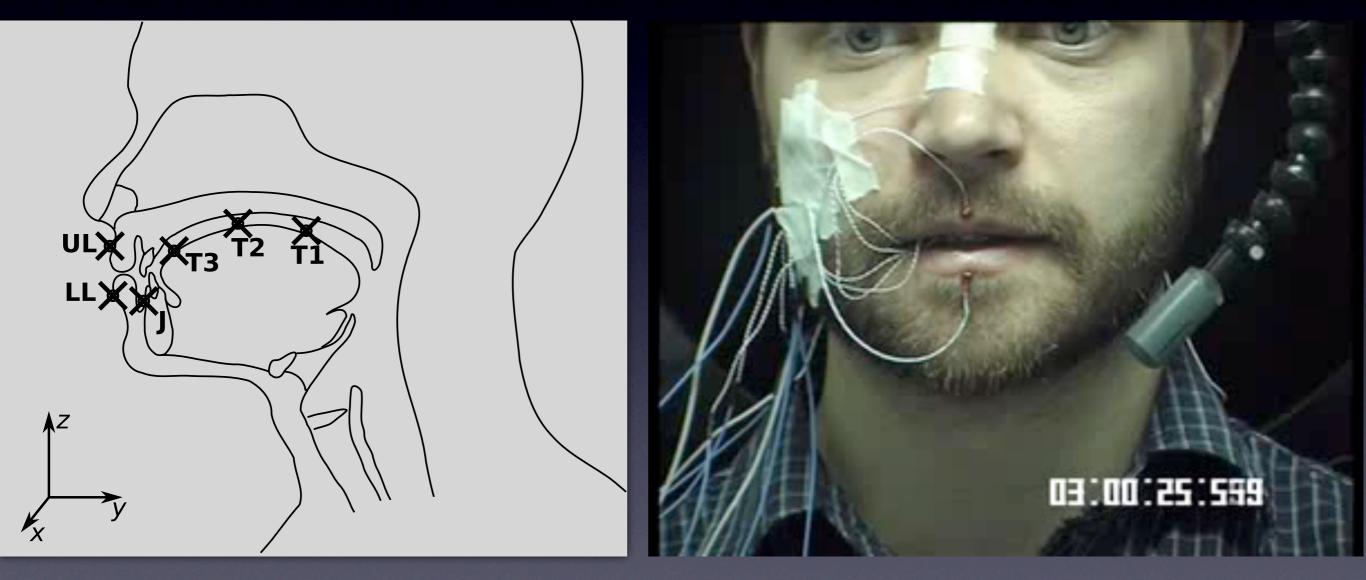
Key advances

- Speaker adaptation: MLLR and MAP families
- Context-dependent modelling: divide and conquer using phonetic decision trees
- Different training criteria: maximum likelihood, minimum phone error, minimum generation error
- Discriminative long-term features "posteriograms"

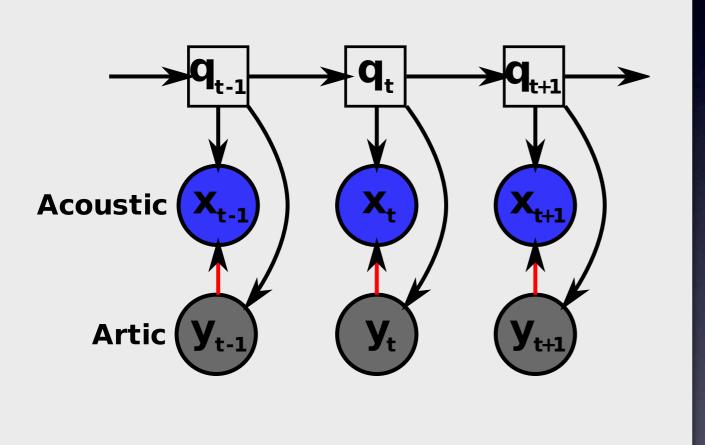
What's lacking?

- I. Speech knowledge
- 2. Factorisation in speech recognition, control in speech synthesis
- 3. Multilinguality
- 4. Rich transcription
- 5. Operating in complex acoustic environments
- 6. Unsupervised learning

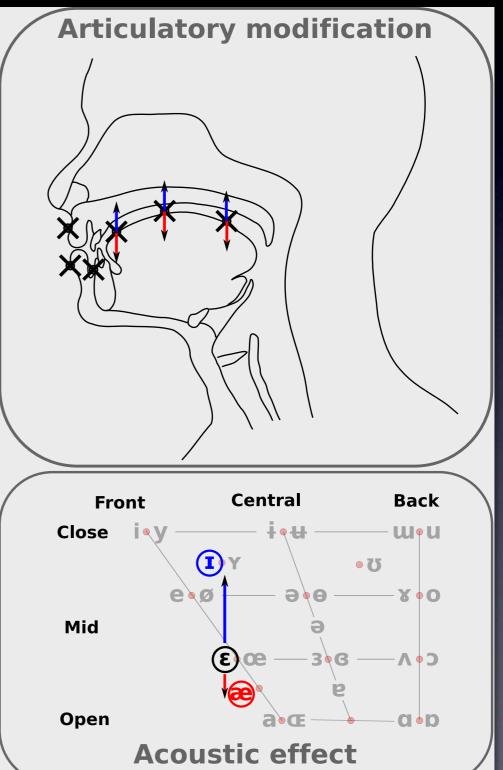
I. Speech knowledge



Acoustic-Articulatory HMM Synthesis



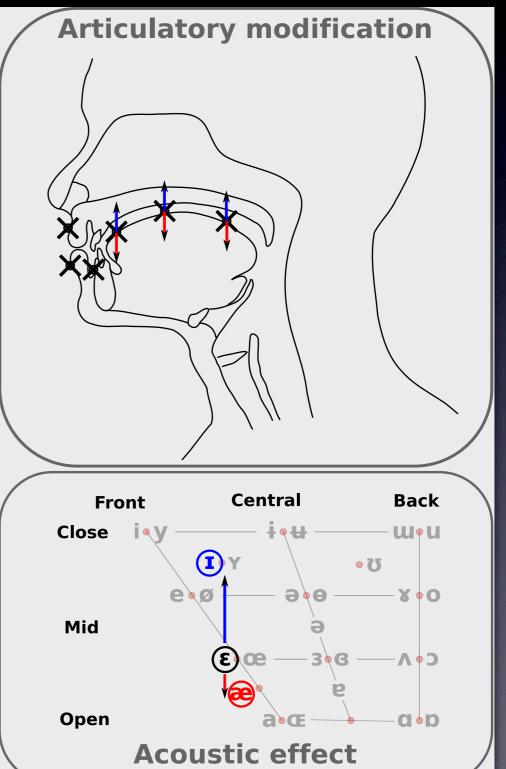
Ling, Richmond, Yamagishi & Wang, 2009



Acoustic-Articulatory HMM Synthesis

Tongue height (cm)	+1.5	
	+1.0	
	+0.5	
	default	peck
	-0.5	
	-1.0	
-	-1.5	

Ling, Richmond, Yamagishi & Wang, 2009



2. Factorisation

- Adaptation algorithms successfully operate by transform model parameters (or features) based on small amount of data
- But they are a blunt instrument, adapting for whatever changes are in the data
 - channel
 - speaker
 - task

• Can we treat different factors separately?

JFA and Subspace Models

- Factorisation in speaker identification: verify the talker not the telephone channel!
 - Joint factor analysis factor out the speaker and channel aspects of the model (Kenny et al, 2007)
- Factorisation in speech recognition
 - Subspace models low dimensional global subspace, combined with state-specific parameters (Povey, Burget et al, 2010)

3. Multilinguality

- The power of the statistical framework:
 - we can use the same software to train systems in any language!
- But this assumes
 - transcribed acoustic training data
 - pronunciation dictionary
 - text data for language modeling
- Not all language are well resourced

Multilingual challenges

- Share common acoustic model information across languages
 - subspace models
- Cross-lingual adaptation (e.g. speak Japanese in your own voice)
 - EMIME
- Inference of pronunciations for new languages
- Automatic data collection

3 (a). Accents

- Accents implicitly modelled by the acoustic model treat accent as separately modelled factor?
- Structured accent models for synthesis and for recognition
- Can we make use of accent-specific pronunciations?

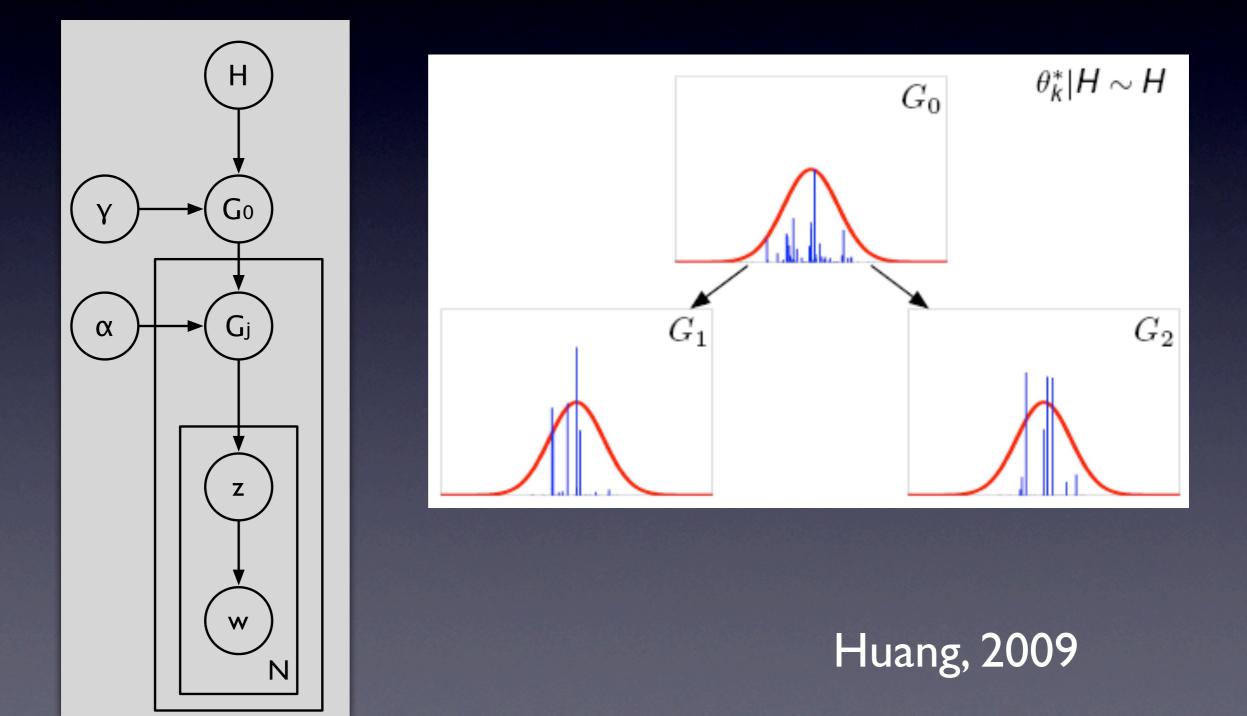
4. Rich transcription

- Speech contains more than just the words recognise (and synthesise) metadata
- Analyse and synthesise social content
 - expression
 - subjectivity
 - social role

Towards speech understanding

- summarisation
- topic extraction

Incorporate topics, social role, etc.



5. Complex acoustic environments

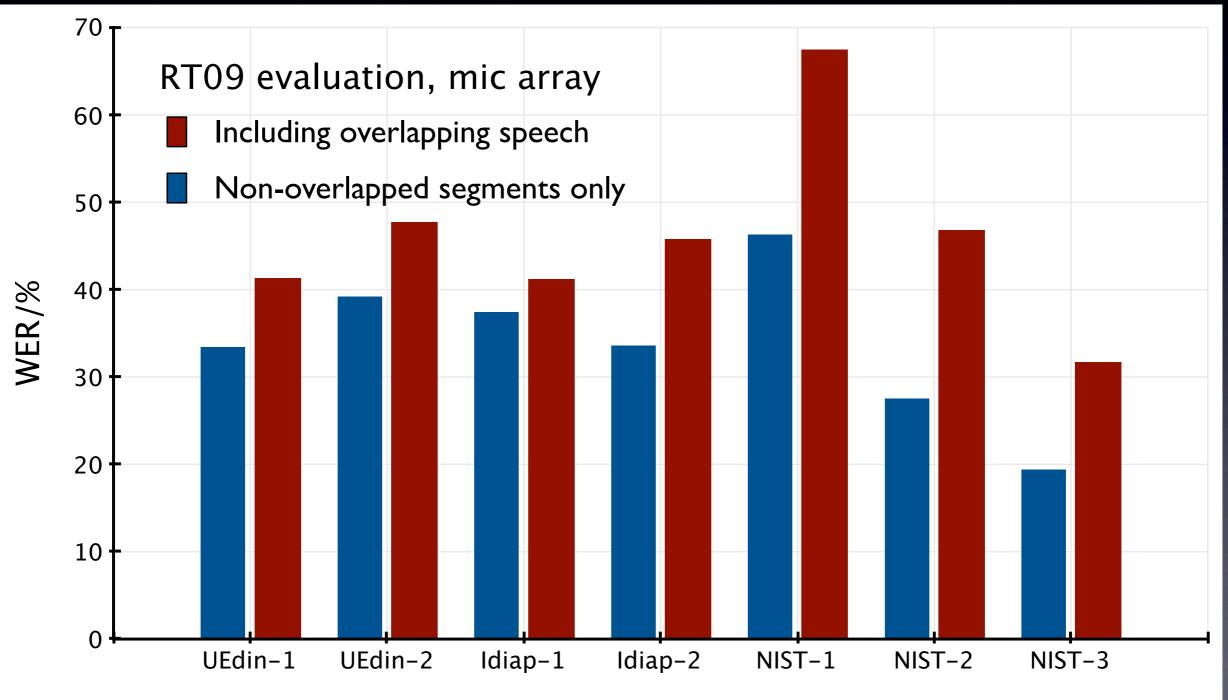
- Natural environments have many acoustic sources
- Capture and analyse the sounds in an environment

microcone/

Distant speech recognition

- Using recognition models rather than enhancement models for (uncalibrated) microphone arrays
- Combining separation with recognition overlapped speech
- Large arrays of inexpensive silicon microphones
- Uncalibrated arrays (no common clock, no position information)
- Analyse all the acoustic sources in a scene

Overlapped speech NIST RT-2009 evaluation



Meeting Recording

6. Unsupervised learning

- It's not really economic to manually annotate the diversity of human speech
- Unsupervised / lightly supervised learning
 - web resources
 - combined generative/discriminative models
- One million hours of speech? OK!
- Twenty-five million hour of annotation? hmmm...
- Move from fixed corpora to never-ending streams?

Summary

- Adaptation, Personalisation, Expression
 - Incorporate speech knowledge
 - Factorisation and control
 - Multilinguality
 - Accents
 - Rich transcription
 - Complex acoustic environments
 - Unsupervised learning

