
Feature/Landmark-based Pronunciation Modeling using Dynamic Bayesian Networks

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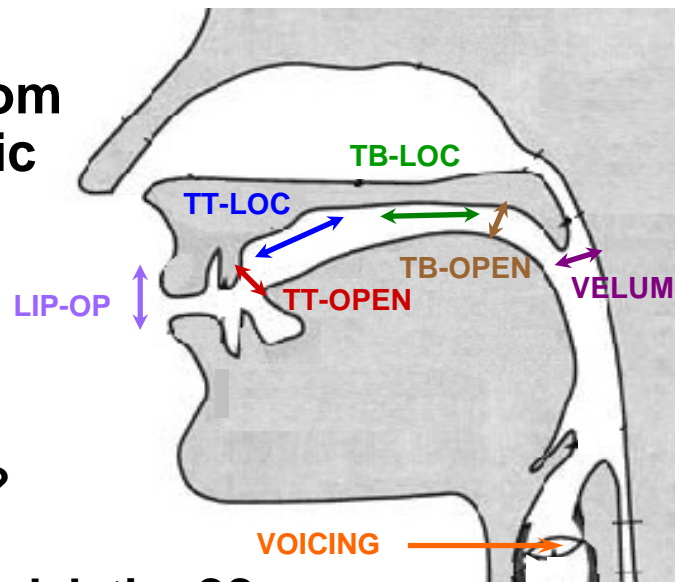
Outline

- **Motivation**
 - **A feature-based pronunciation model**
 - **Using SVM outputs in the pronunciation model**
 - **WS'04 experiments**
 - **Observations and conclusions**
-

Why feature-based pronunciation modeling?

- Many pronunciation phenomena can be parsimoniously described as resulting from *asynchrony* and *reduction* of sub-phonetic features

- One set of features based on articulatory phonology [Browman & Goldstein 1990]:



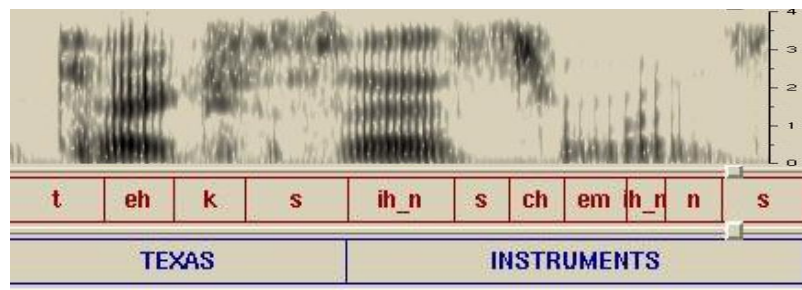
- *warmth* → [w a o r m p th] - Phone insertion?

- *I don't know* → [ah dx uh_n ow_n] - Phone deletion??

- *several* → [s eh r v ax l] - Exchange of two phones???

- *instruments* → [ih_n s ch em ih_n n s]

- *everybody* → [eh r uw ay]



Approach: Main Ideas

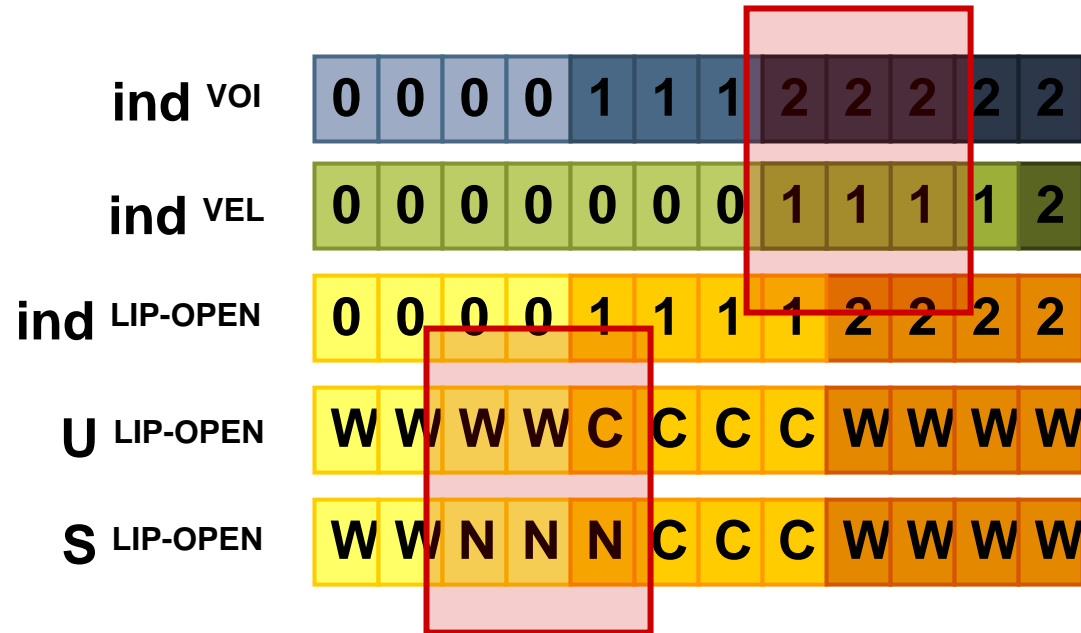
baseform
dictionary

everybody →

<i>index</i>	0	1	2	3	...
<i>phone</i>	eh	v	r	iy	...
<i>voicing</i>	V	V	V	V	...
<i>velum</i>	Off	Off	Off	Off	...
<i>lip opening</i>	Wide	Crit	Wide	Wide	...
...

$$\text{cost}(\text{ind}^{\text{VOI}} - \text{ind}^{\text{VEL}} = 1)$$

+
asynchrony



$$p(s | u)$$

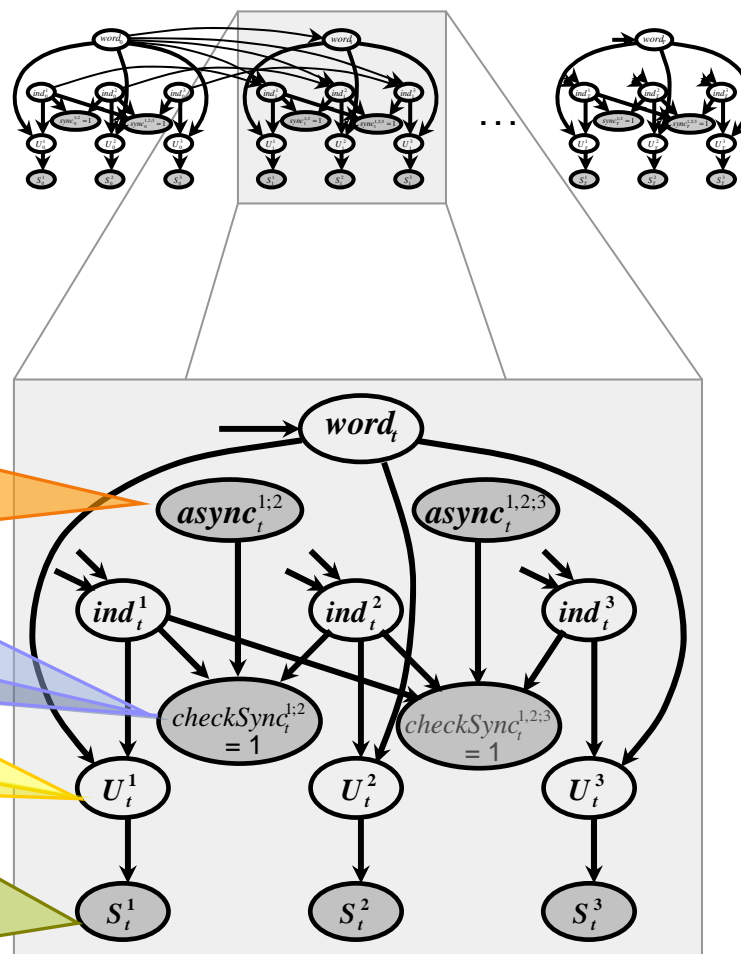
+
feature
substitutions

A feature-based pronunciation model

- The model is implemented as a dynamic Bayesian network (DBN):

- A representation, via a directed graph, of a distribution over a set of variables that evolve through time

- Example DBN with three features:



$\Pr(async^{1;2} = a) = \Pr(|ind^1 - ind^2| = a)$

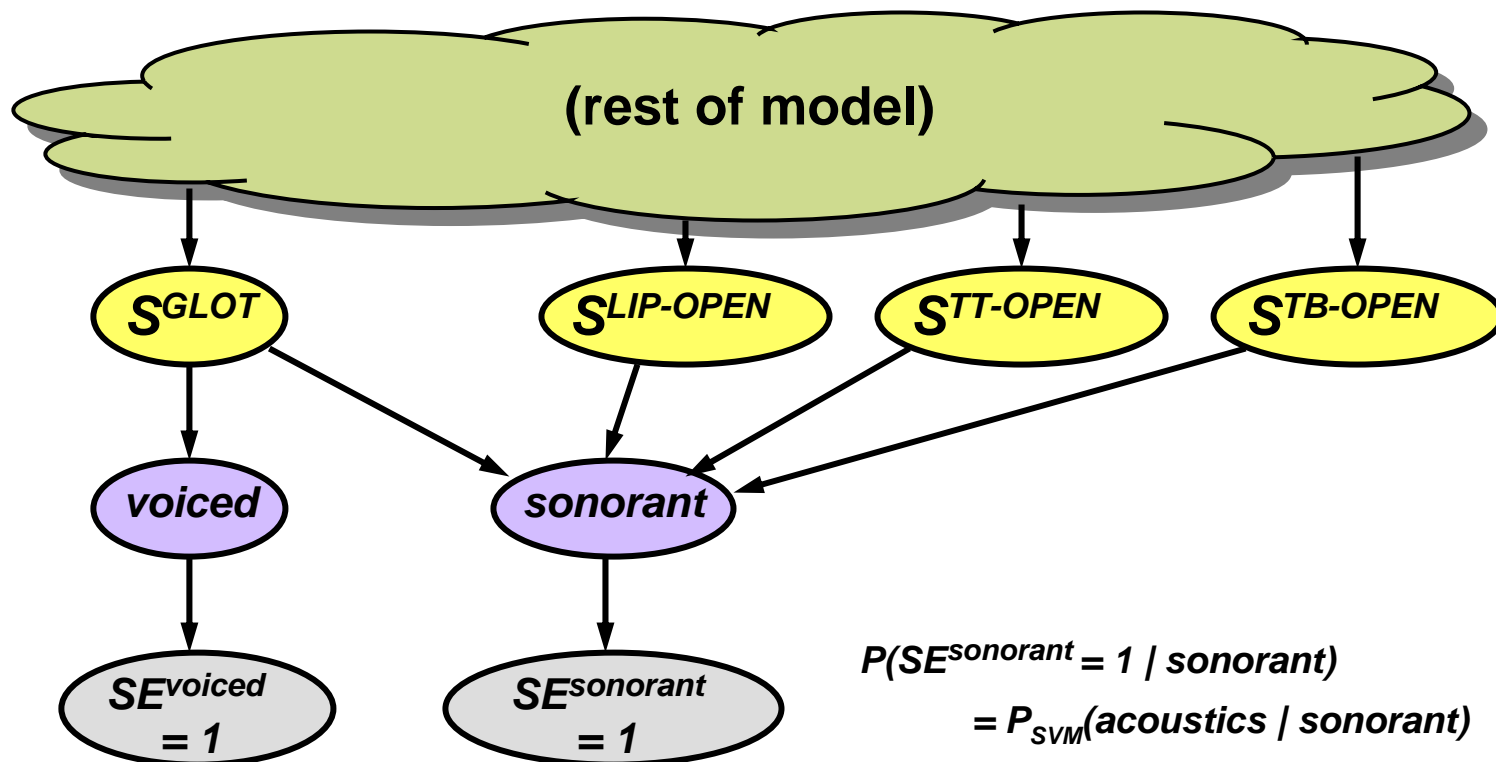
$checkSync^{1;2} = 1$ if $|ind^1 - ind^2| = async^{1;2}$

given by baseform pronunciations

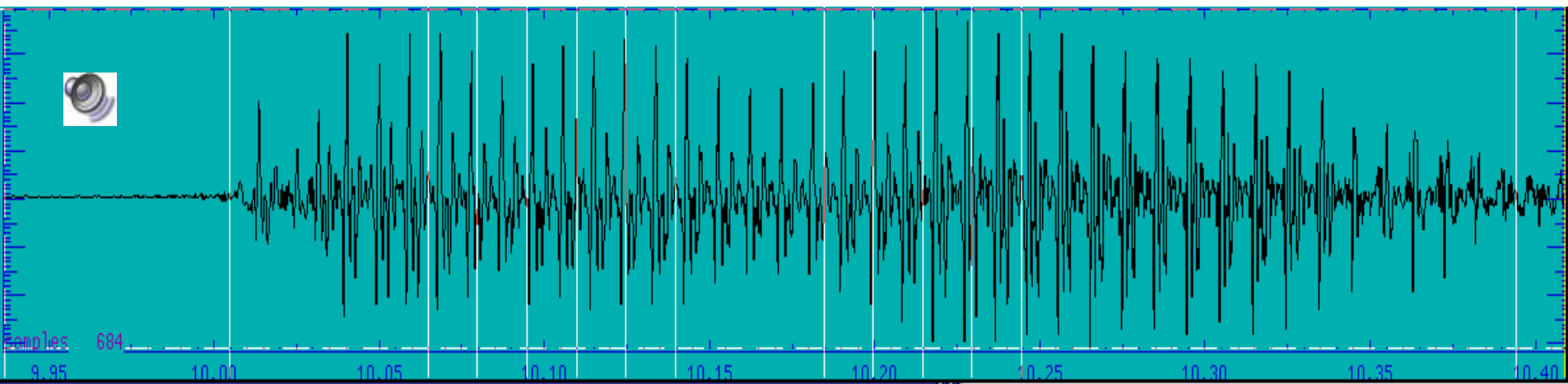
	0	1	2	3	4	...
0	.7	.2	.1	0	0	...
1	0	.7	.2	.1	0	...
2	0	0	.7	.2	.1	...
...

Combining SVM outputs with the DBN

- Task 1: Converting between articulatory features and SVM distinctive features (DFs)
 - Method: Add DBN variables corresponding to DFs, and add deterministic mappings from surface articulatory variables to DFs
- Task 2: Incorporating SVM output probabilities
 - Method: Soft evidence – similar in spirit to HMM/ANNs



Example alignment using SVM/DBN



fsh_60386_1_0119400_0131440

LIPPosition	0	1	2	3	4	5	6	7	8	9	10	11
TTPosition	0	1	2	3	4	5	6	7	8	9	10	11
VELPosition	0	1	2	3	4	5	6	7	8	9	10	11
LIPPhone	ay1	ay2	dcl	d	ow1	ow2	ntcln	tn	n	ow1	ow2	
TTPhone	ay1	ay2	dcl	d	ow1	ow2	ntcln	tn	n	ow1	ow2	
VELPhone	ay1	ay2	dcl	d	ow1	ow2	ntcln	tn	n	ow1	ow2	
actualLIP-OPEN					WI	NA				WI	NA	
actualTT-LOC				ALV	RET	P-A			ALV		P-A	
TT-OPEN	WI	M-N	CL	CR	WI		CL	CR	CL		WI	
actualTT-OPEN	WI	M-N		NA	WI	NA	CL	M-N	NA		WI	
actualTB-LOC	PHA			VEL	UV	VEL	UV	VEL		UV	VEL	
actualTB-OPEN		M-N		MID	M-N	NA		MID		M-N	NA	
actualVEL					CL		OP	CL		OP	CL	
actualGLOT							CR	WI			CR	
LightSilence							-	+			-	
LightSonor							+	-			+	
LightSC			-		+	-	+	-		+	-	
LightStops							-	+			-	
LightVowelRound					-	+				-	+	
owNasalization									-	+		

Design decisions

- **What kind of SVM outputs should be used in the DBN?**
 - **Method 1 (EBS/DBN):** Generate landmark segmentation with EBS using manner SVMs, then apply place SVMs at appropriate points in the segmentation
 - * Force DBN to use EBS segmentation
 - * Allow DBN to stray from EBS segmentation, using place/voicing SVM outputs whenever available
 - **Method 2 (SVM/DBN):** Apply all SVMs in all frames, allow DBN to consider all possible segmentations
 - * In a single pass
 - * In two passes: (1) manner-based segmentation; (2) place+manner scoring
 - **How should we take into account the distinctive feature hierarchy?**
 - **How do we avoid “over-counting” evidence?**
 - **How do we train the DBN (feature transcriptions vs. SVM outputs)?**
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A chronology of DBN/SVM rescoring experiments

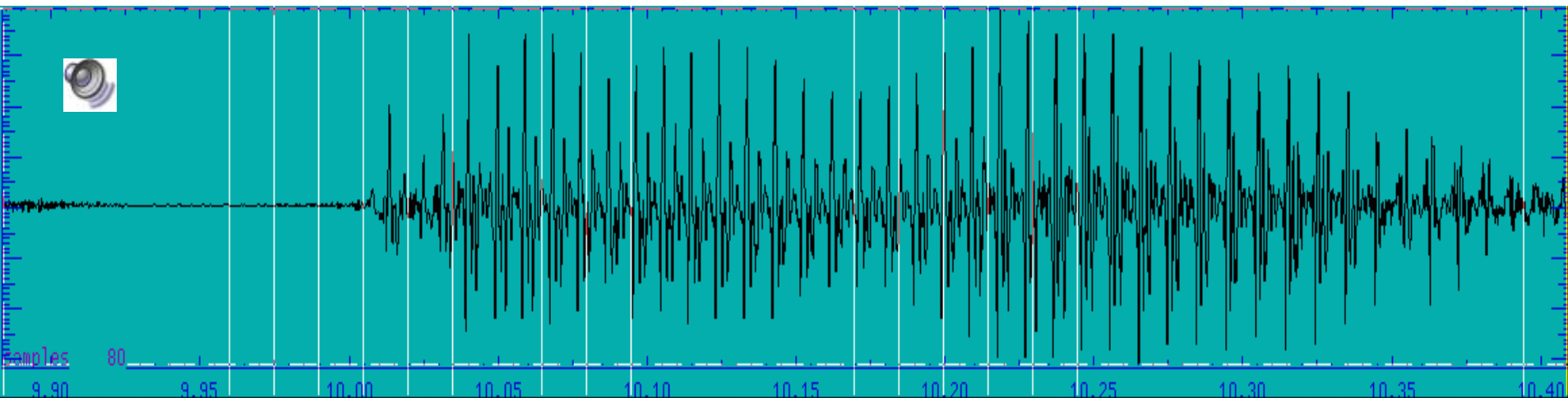
- For each lattice edge:
 - SVM probabilities computed over edge duration and used as soft evidence in DBN
 - DBN computes a score $S \propto P(\text{word} \mid \text{evidence})$
 - Final edge score is a weighted interpolation of baseline scores and EBS/DBN or SVM/DBN score

<i>Date</i>	<i>Experimental setup</i>	<i>3-speaker WER (# errors)</i>	<i>RT03 dev WER</i>
<i>- ∞</i>	Baseline	27.7 (550)	26.8
<i>Jul31_0</i>	EBS/DBN, “hierarchically-normalized” SVM output probabilities, DBN trained on subset of ICSI transcriptions	27.6 (549)	26.8
<i>Aug1_19</i>	+ improved silence modeling	27.6 (549)	
<i>Aug2_19</i>	EBS/DBN, unnormalized SVM probs + fricative lip feature	27.3 (543)	26.8
<i>Aug4_2</i>	+ DBN trained using SVM outputs	27.3 (543)	
<i>Aug6_20</i>	+ full feature hierarchy in DBN	27.4 (545)	
<i>Aug7_3</i>	+ reduction probabilities depend on word frequency	27.4 (544)	
<i>Aug8_19</i>	+ retrained SVMs + nasal classifier + DBN bug fixes	27.4 (544)	
<i>Aug11_19</i>	SVM/DBN, 1 pass	<i>Miserable failure!</i>	
<i>Aug14_0</i>	SVM/DBN, 2 pass	27.3 (542)	
<i>Aug14_20</i>	SVM/DBN, 2 pass, using only high-accuracy SVMs	27.2 (541)	

Some complicating factors...

- **Practicalities:**
 - Inaccurate word boundaries in lattices
 - Very short words
 - Pauses, laughter, non-words
- **More general issues:**
 - Relative weighting of soft evidence vs. articulatory variables
 - Over-counting of evidence largely not addressed
 - SVM/DBN rescoring complicated by context-dependent SVM training

The word boundary problem



fsh_60386_1_0119400_0131440

LIPPosition	0	1	2	3	4		5		6	7	8	9		10		
TTPosition	0	1	2	3			4	5		6	7	8		9	10	
VELPosition	0	1	2	3			4	5		6	7	8		9	10	
LIPPhone	ay1	ay2	dc1	d	ow1			ow2		rtcln		n	ow1		ow2	
TTPhone	ay1	ay2	dc1	d				ow1	ow2	rtcln		n			ow1	ow2
VELPhone	ay1	ay2	dc1	d				ow1	ow2	rtcln		n			ow1	ow2
actualLIP-OPEN					WI			NA				WI			NA	
actualTT-LOC		ALV	DEN	ALV			P-A	RET	P-A			ALV			P-A	
TT-OPEN	WI	M-N	CL	CR								CL			WI	
actualTT-OPEN	WI	M-N	CL	CR				WI				CL	NA		WI	
actualTB-LOC	PHA			VEL				UV	VEL			UV	VEL		UV	VEL
actualTB-OPEN		M-N		MID				M-N	NA			MID			M-N	NA
actualVEL									CL		OP	CL		OP		CL
actualGLOT										CR	WI					CR
LightSilence		-	+							-	+					-
LightSonor		+		-						+	-					+
LightSC										+	-		+			-
LightStops		-	+							-	+					-

Some conclusions

- **No major error rate improvements yet... BUT:**
 - **The SVM/DBN system produces reasonable analyses of reduction and coarticulation in spontaneous speech**
 - **EM parameter learning produces reasonable distributions**
 - **Many ideas for future work, e.g.:**
 - **Further analysis of the current system**
 - * Error analysis
 - * Computational complexity analysis
 - **More context-dependent modeling (based on syllable structure, stress accent, position in word, speaker clustering)**
 - **Investigation of the usefulness of different features**
 - **Better understanding of the mathematical issues of feature hierarchies in landmark-based recognition**
 - **Exploration of soft evidence in DBNs for ASR in general**
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