



Phonetic Error Analysis Beyond Phone Error Rate

Erfan Loweimi

CSTR Talk
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Phonetic Error Analysis Beyond Phone Error Rate

Erfan Loweimi , Member, IEEE, Andrea Carmantini , Member, IEEE, Peter Bell , Steve Renals , Fellow, IEEE, and Zoran Cvetkovic , Senior Member, IEEE

E. Loweimi, A. Carmantini, P. Bell, S. Renals and Z. Cvetkovic, “*Phonetic Error Analysis Beyond Phone Error Rate*”, in IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 31, pp. 3346-3361, 2023, doi: 10.1109/TASLP.2023.3313417.

Outline

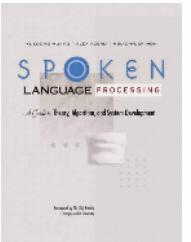
- Analysis beyond PER
 - What / How / Why
- Effect of Various Factors

Analysis beyond PER ...

- What is the contribution of each broad phonetic class (BPC) c in PER?

$$PER = \sum_c PER_c$$

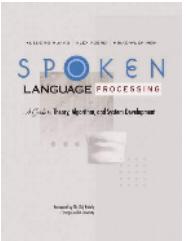
Three BPCs considered ...



classes	phones
Affricates	ch jh
Diphthongs	aw ay ey ow oy
Fricatives	dh f s sh th v z
Nasal	m n ng
Plosive	b d dx g k p t
Semi-vowel	hh l r w y
Vowel	aa ae ah eh er ih iy uh uw
Silence	sil

(A) 8-class

Three BPCs considered ...



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Affricates	ch jh
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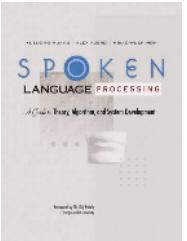
(A) 8-class

(B) 3-class

classes	phones
Vowel ⁺	aw ay ey ow oy aa ae ah eh er ih iy uh uw
Consonant	b ch d dh dx f g hh jh k l m n ng p r s sh t th v w y z
Silence	sil
Voiced	aa ae ah aw ay b d dh dx eh eer ey g hh ih iy jh l m n ng ow oy r uh uw v w y z
Unvoiced	ch f k p s sh t th

(C) 3-class

Three BPCs considered ...



classes	phones
Affricates	ch jh
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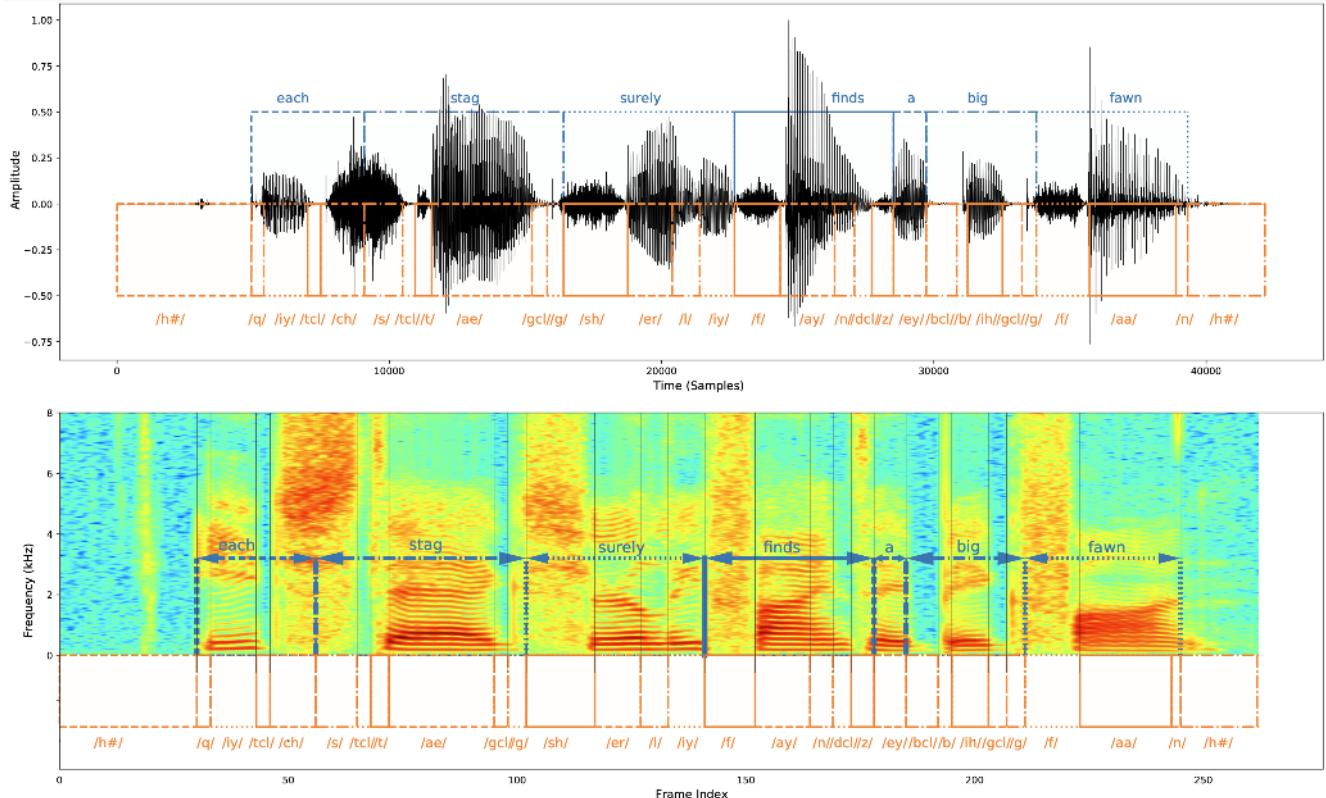
(A) 8-class

$$\text{Vowel}^+ = \text{Vowel} \cup \text{Diphthong}$$

$$\text{Silence} = /h\#/\cup /epi/\cup /pau/\cup \text{Closures}$$

Phonetic Transcription

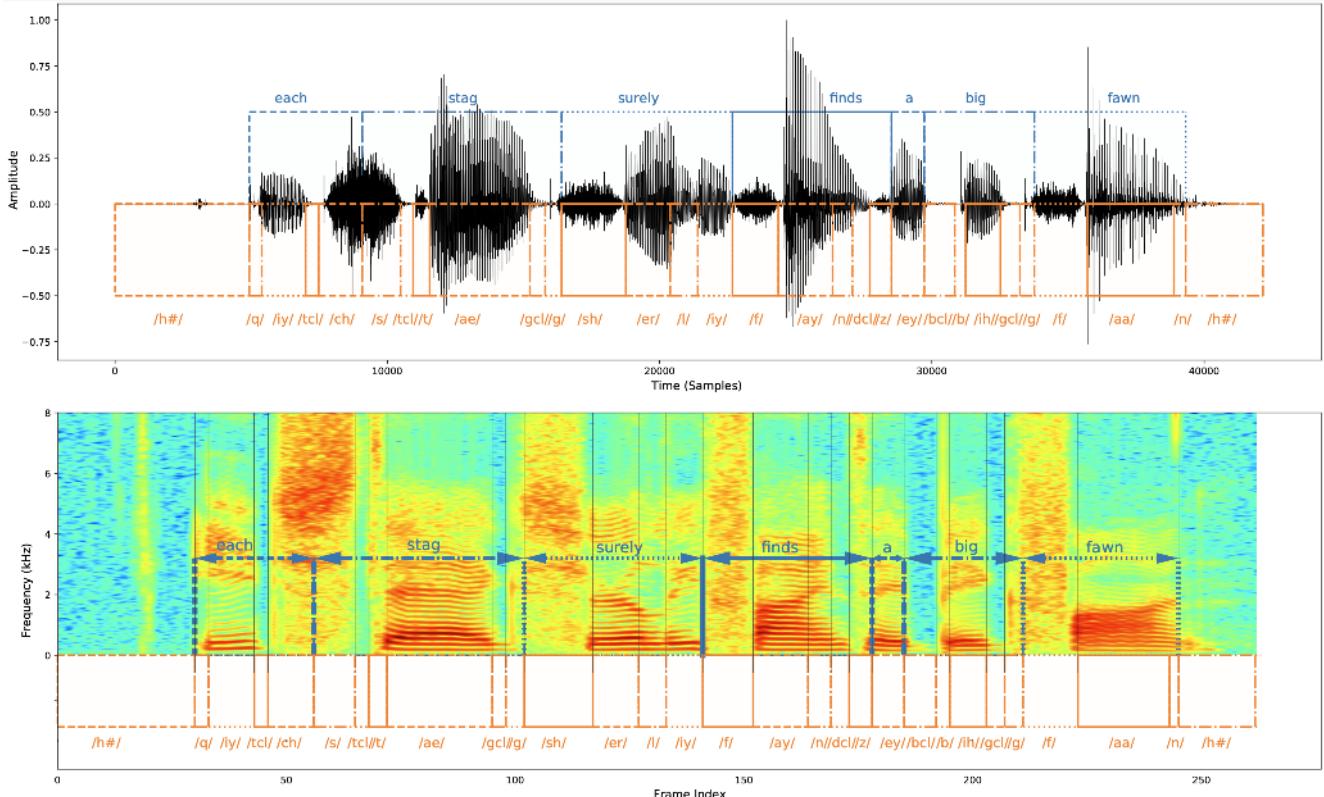
Data: TIMIT



- Original Transcription: **61** phones

Phonetic Transcription

Data: TIMIT



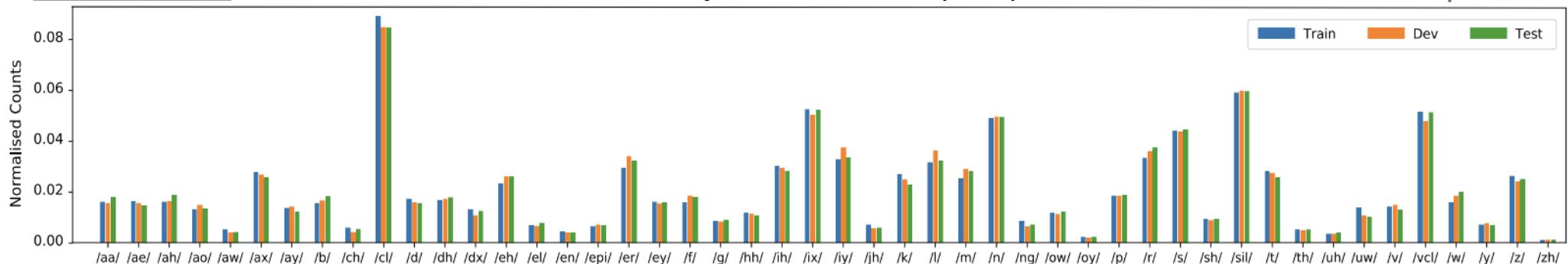
- Original Transcription: **61** phones → Train w/ **48** phones → Decode w/ **39** phones
- Mapping (Kaldi): `phones.60-48-39.map`

Phonetic Distribution

Data: TIMIT

Probability Mass Function (PMF)

48 phones

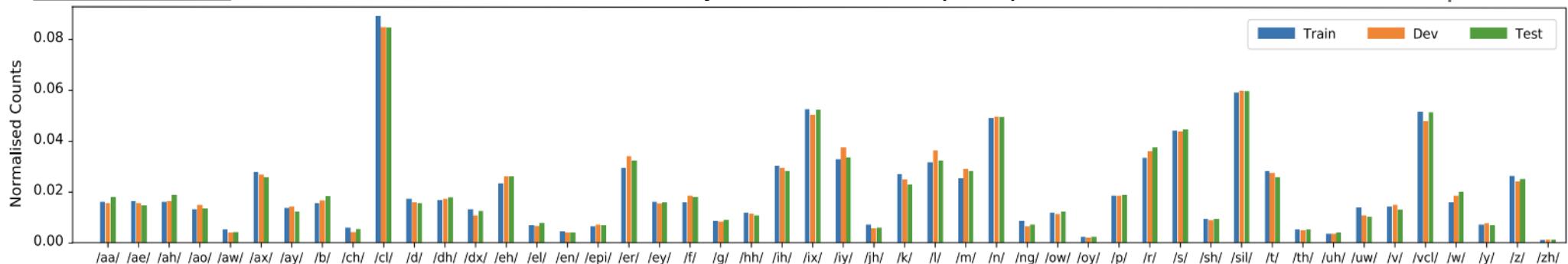


Phonetic Distribution

Data: TIMIT

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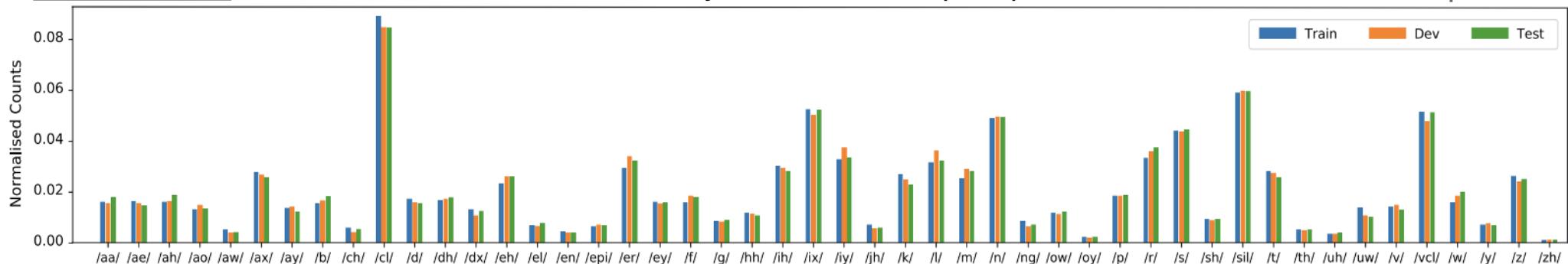
PMF of standard Train/Dev/Test sets is **identical**.

Phonetic Distribution

Data: TIMIT

Probability Mass Function (PMF)

48 phones



PMF of standard Train/Dev/Test sets is **identical**.

PMF is **not uniform**

Phonetic Distribution

Data: TIMIT

Probability Mass Function (PMF)

48 phones



PMF of standard Train/Dev/Test sets is **identical**.

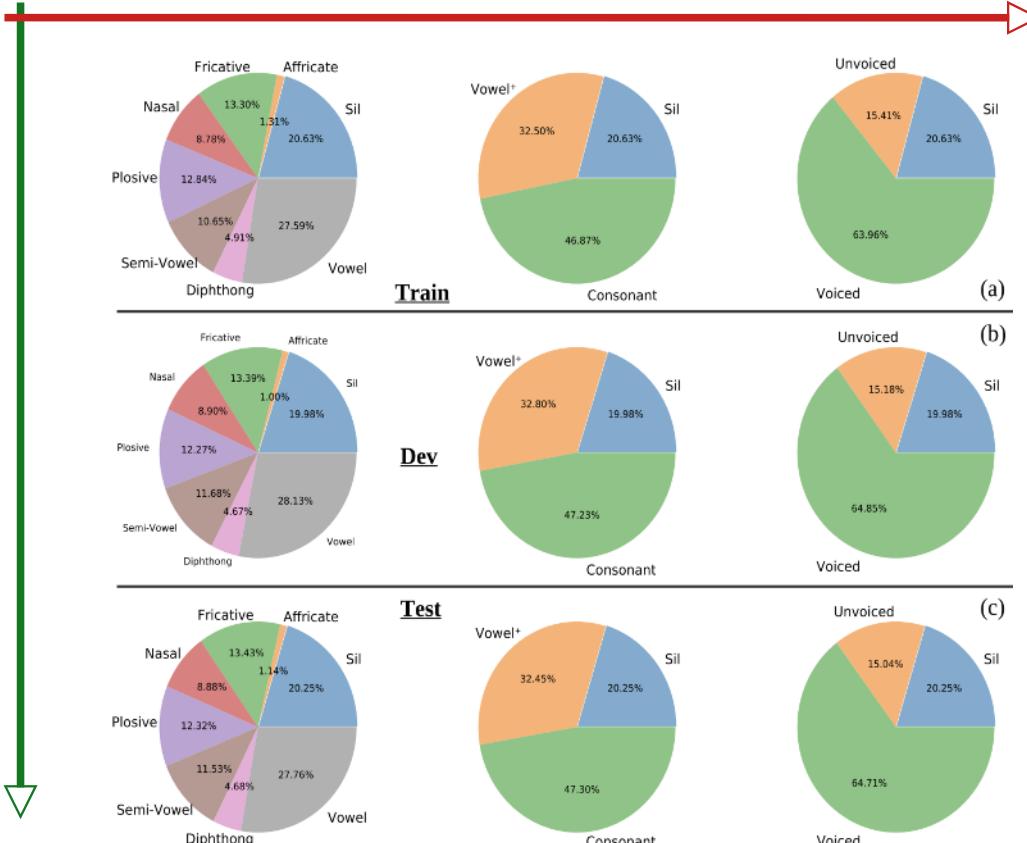
PMF is **not uniform** ... not a shortcoming ... characteristic of natural languages, studied in *Quantal Theory, Adaptive Dispersion, etc.*

PMF over BPCs

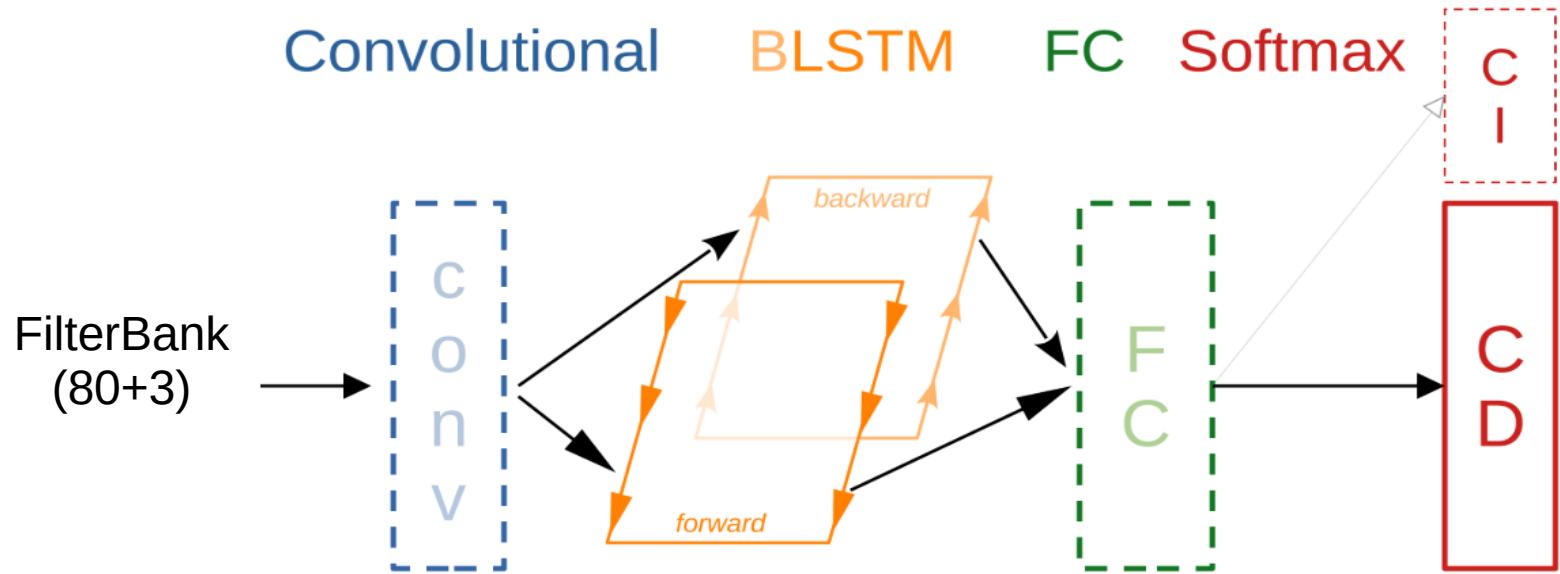
Non-Uniform inside BPC, e.g., Nasal 9%, Vowel 28%, Sil 21%, ...

Identical over
Train/Dev/Test

e.g., Nasal: 8.8/8.9/8.9%



Baseline Arch. $C_i L_j F_k$



Trained by cross entropy loss

FC: Fully-connected

CI: Context Independent (48D)

CD: Context Dependent (1936D)

Choosing Baseline

Feature	Architecture	Dev	Test	#Param (M)
FBank-83	L2	13.1	15.2	7.2
FBank-83	L3	13.1	14.6	10.9
FBank-83	L4	12.8	14.1	14.5
FBank-83	L5	12.6	14.3	18.2
FBank-83	L6	13.0	15.0	21.8
FBank-83	L4F1	12.9	14.9	15.5
FBank-83	C1L4	12.7	14.4	20.9
FBank-83	C1L4F1	13.0	14.6	21.8
FBank-80	L4	12.8	14.3	14.5
FBank-40	L4	12.7	14.5	14.4
FBank-23	L4	13.2	14.5	14.3
FBank-83*	L4	13.0	14.6	14.4

Choosing Baseline

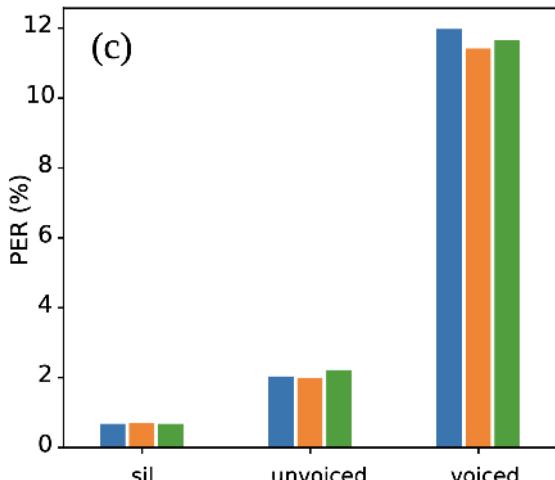
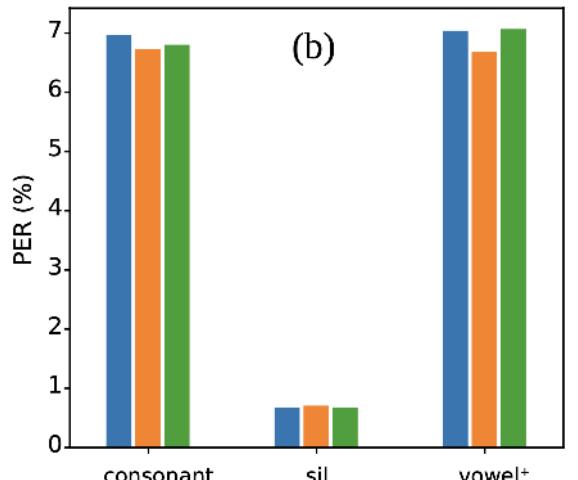
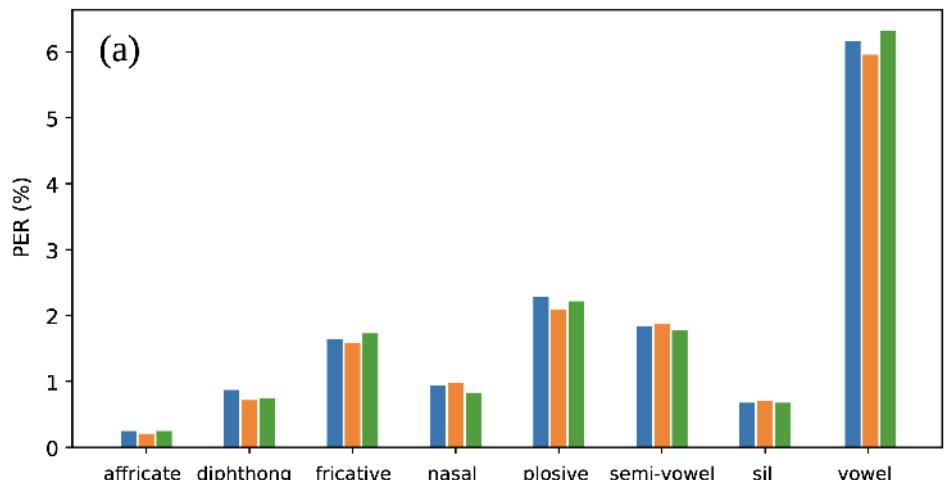
Chosen
Baseline →

w/o F_0 →

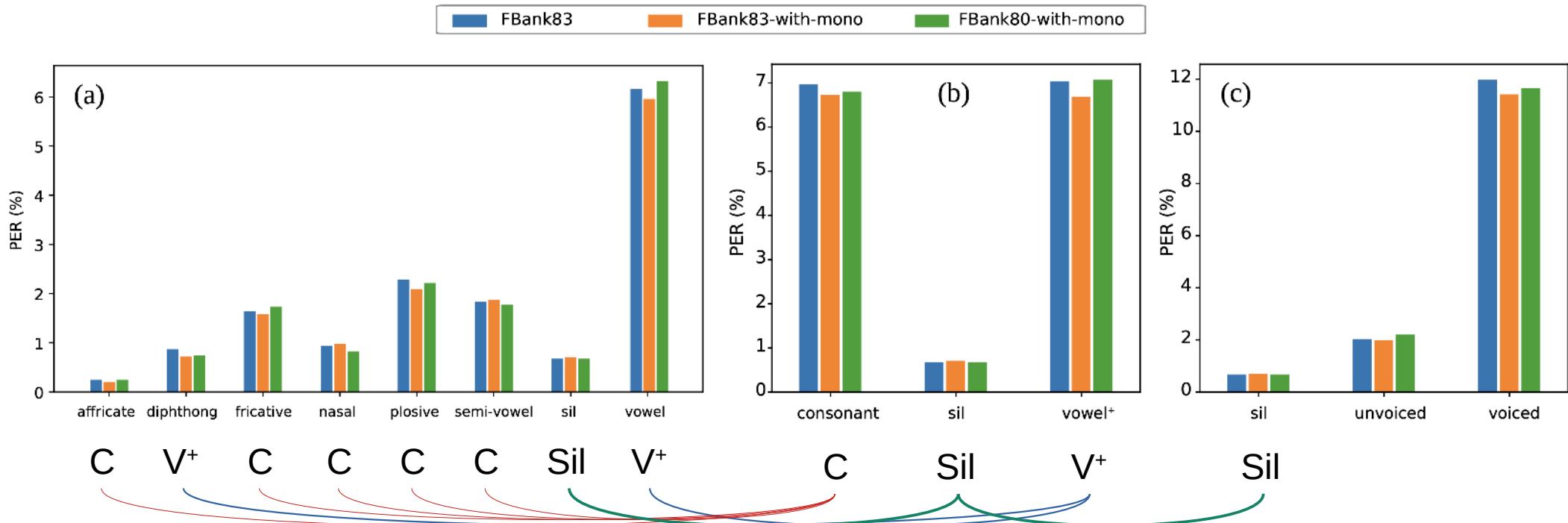
w/o CI →

Feature	Architecture	Dev	Test	#Param (M)
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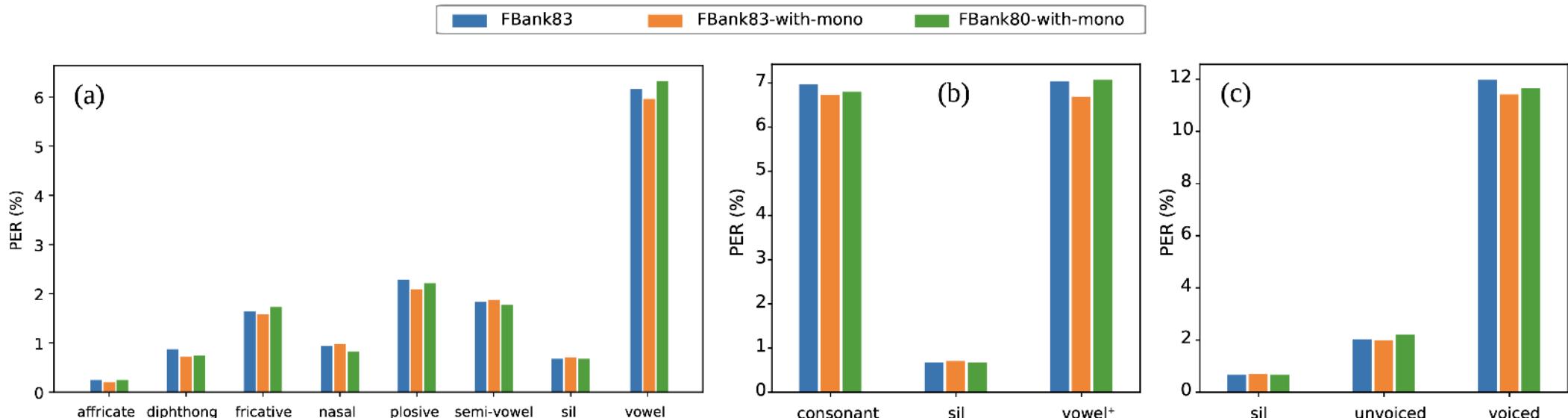
Analysis beyond PER



Analysis beyond PER

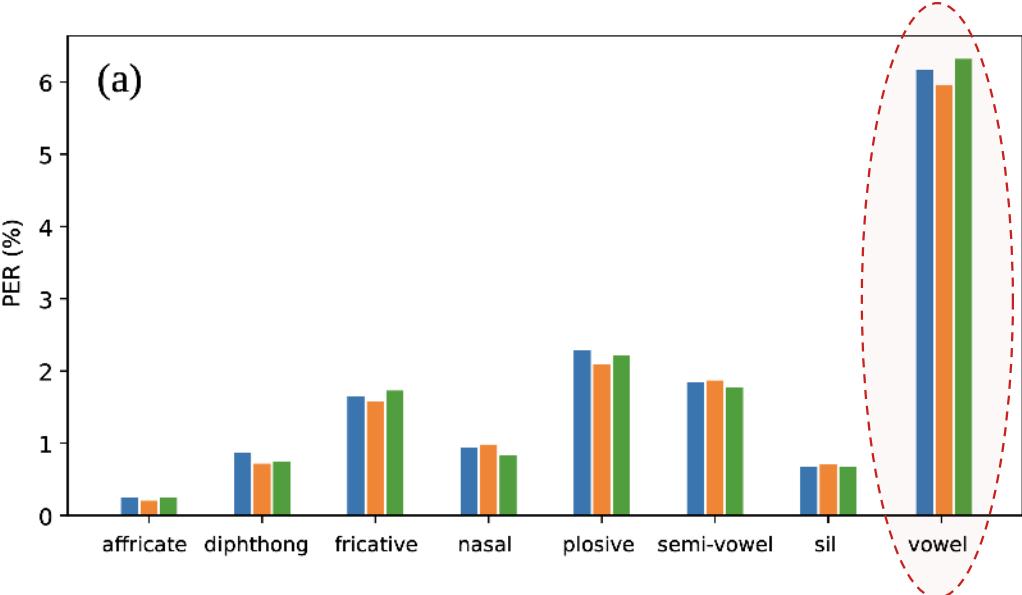


Analysis beyond PER



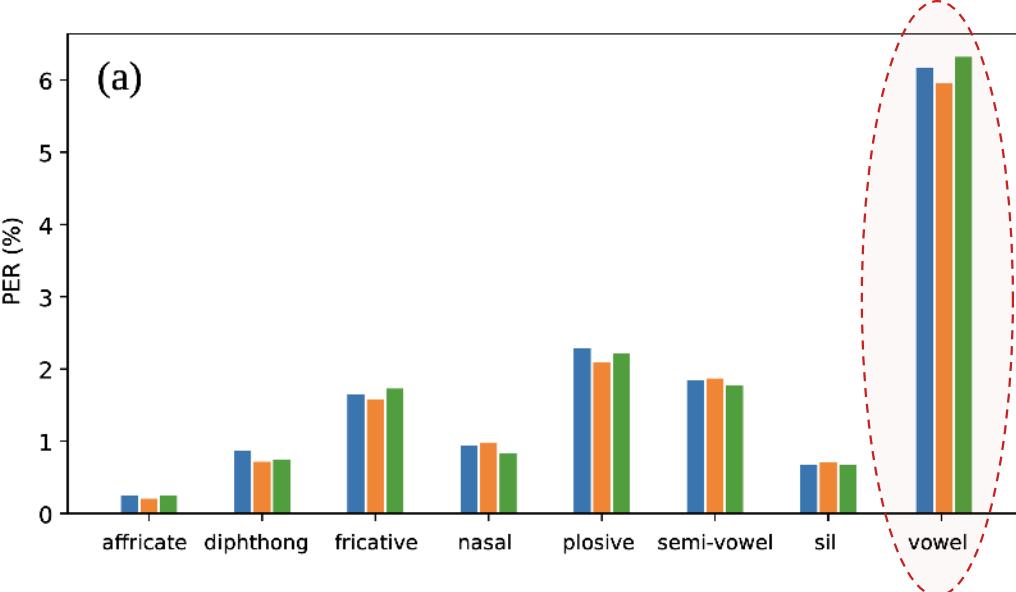
Minor gains after adding F_0 features & regularisation with CI.

Largest PER → Vowels



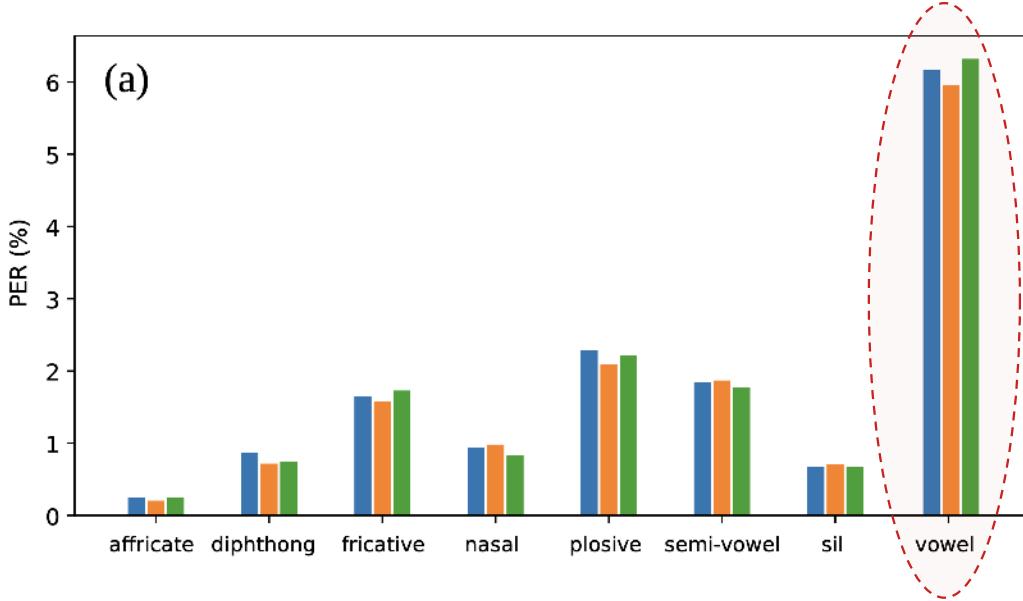
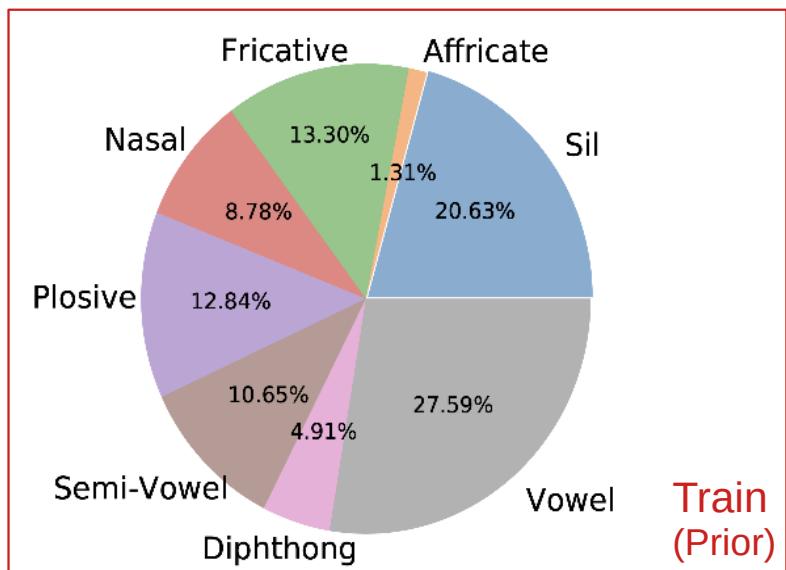
Largest PER → Vowels

- Questions:
 - Training data amount?
 - TIMIT-specific?
 - Why?



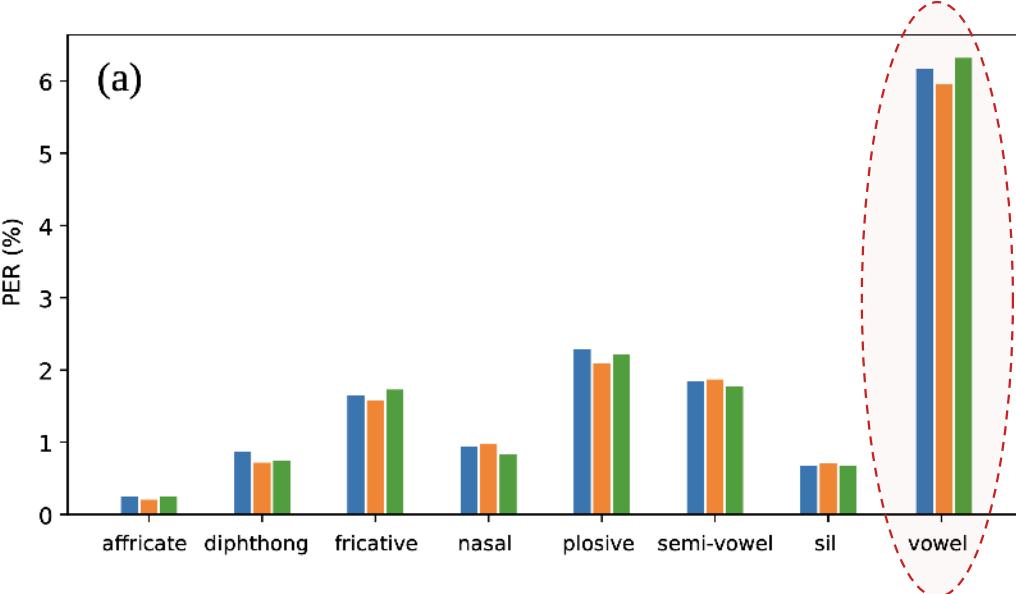
Largest PER → Vowels

- Q1: Training data amount?



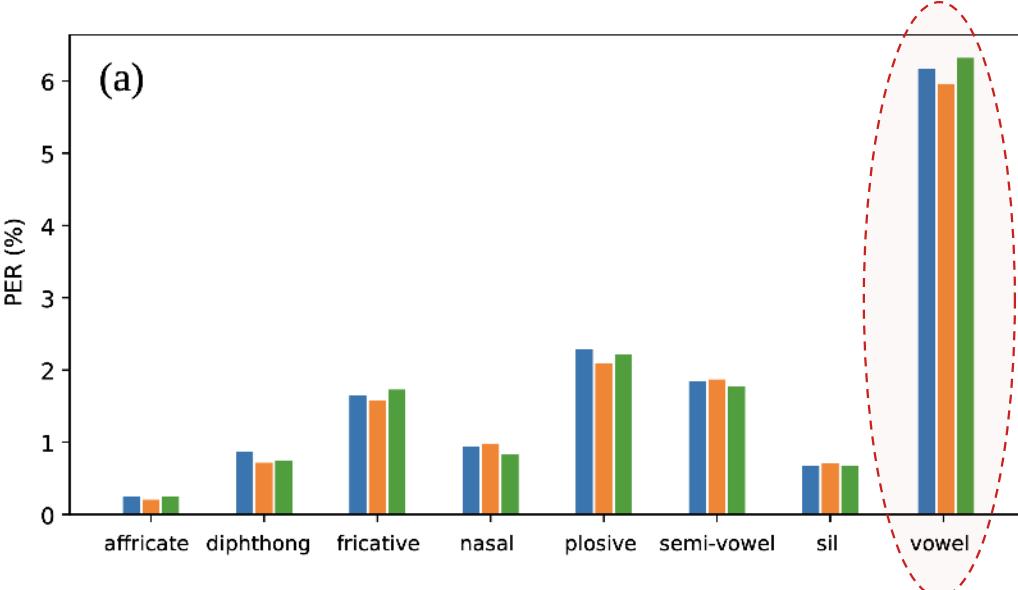
Largest PER → Vowels

- Q2: TIMIT-specific?
 - Similar observation in human phone recognition [69]



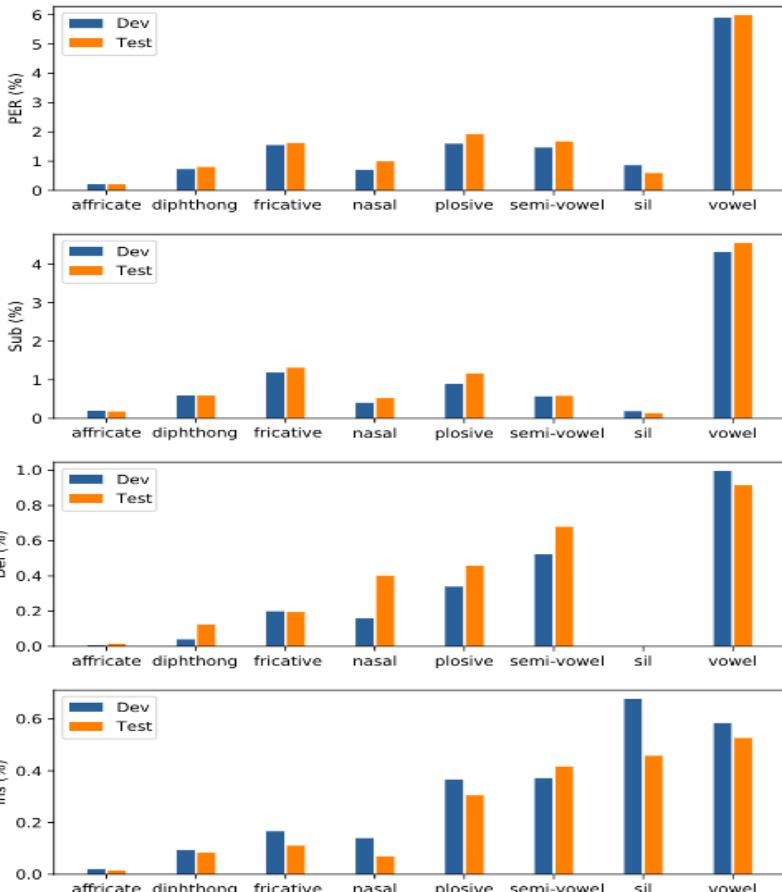
Largest PER → Vowels

- Q2: TIMIT-specific?
 - Similar observation in human phone recognition [69]
- Q3: Why?

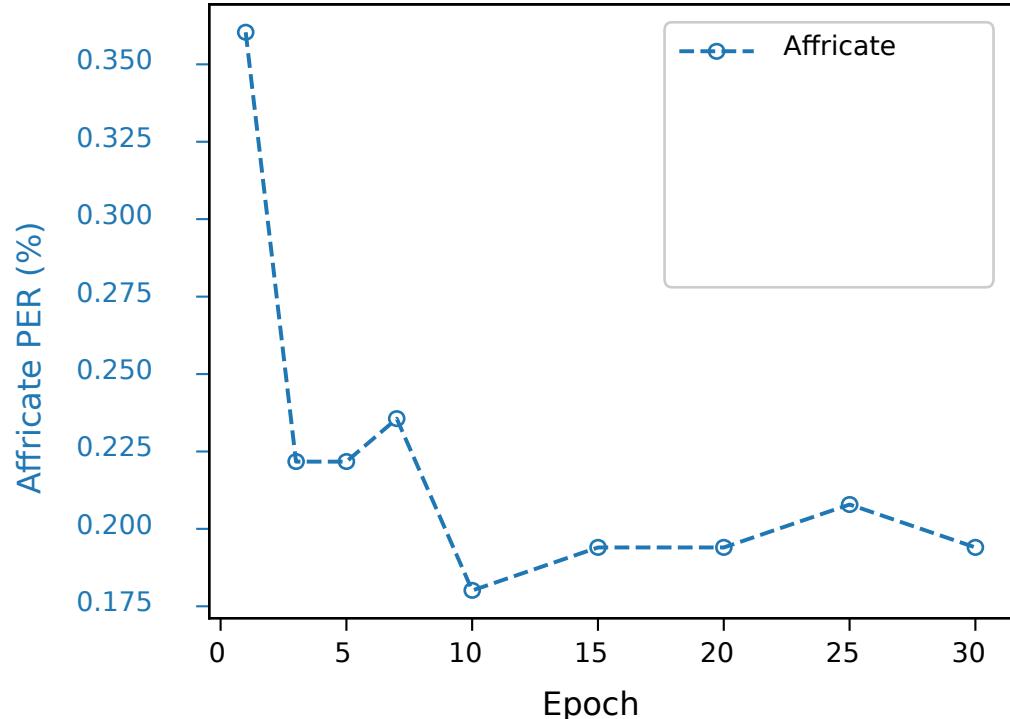


Sub/Del/Ins per BPC

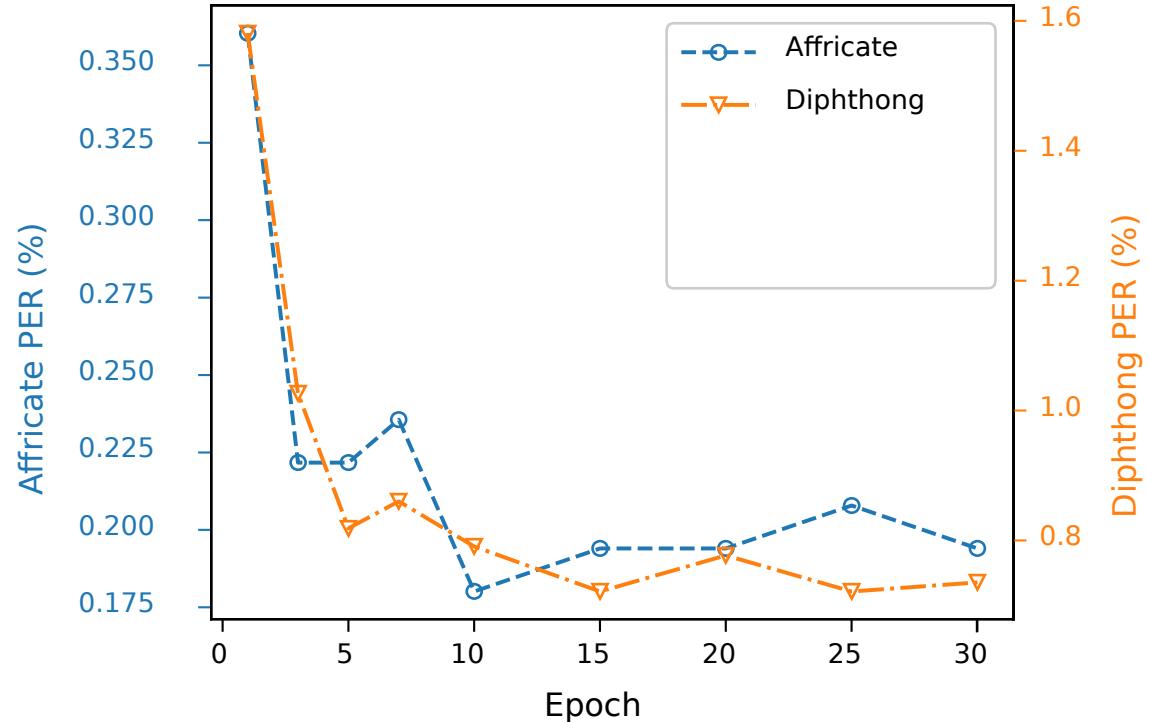
- Vowels
 - largest Sub/Del/Ins
- Silence
 - Small(est) Del
 - large(st) Ins



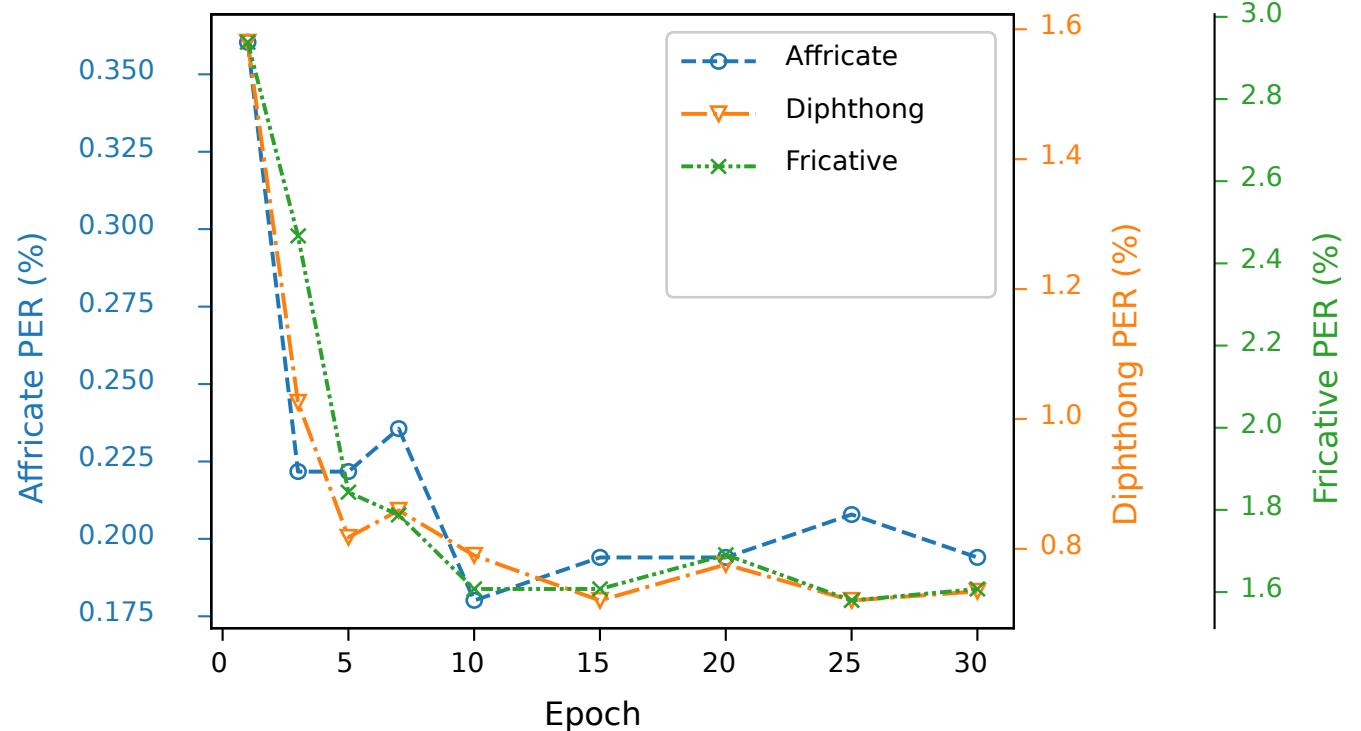
Training Dynamics (1)



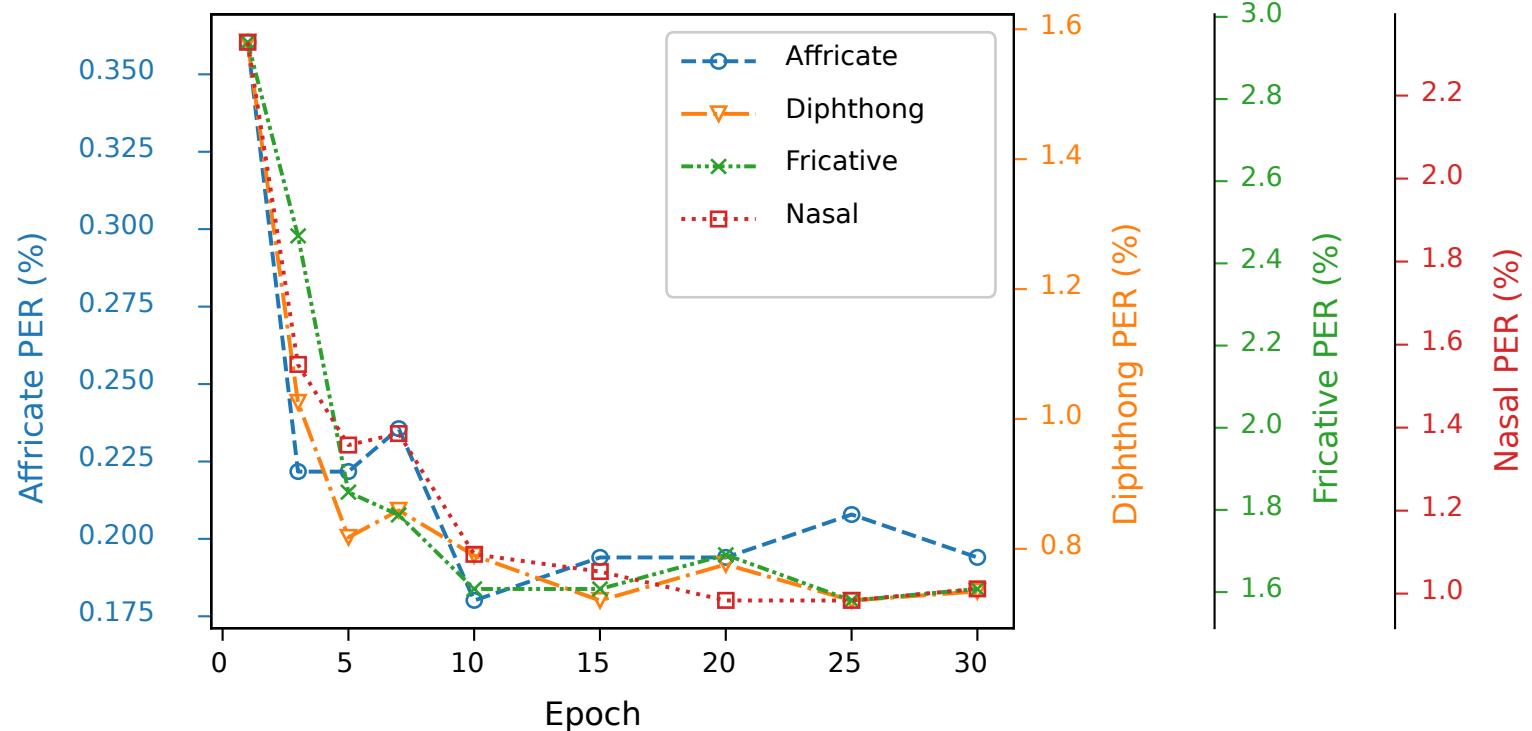
Training Dynamics (1)



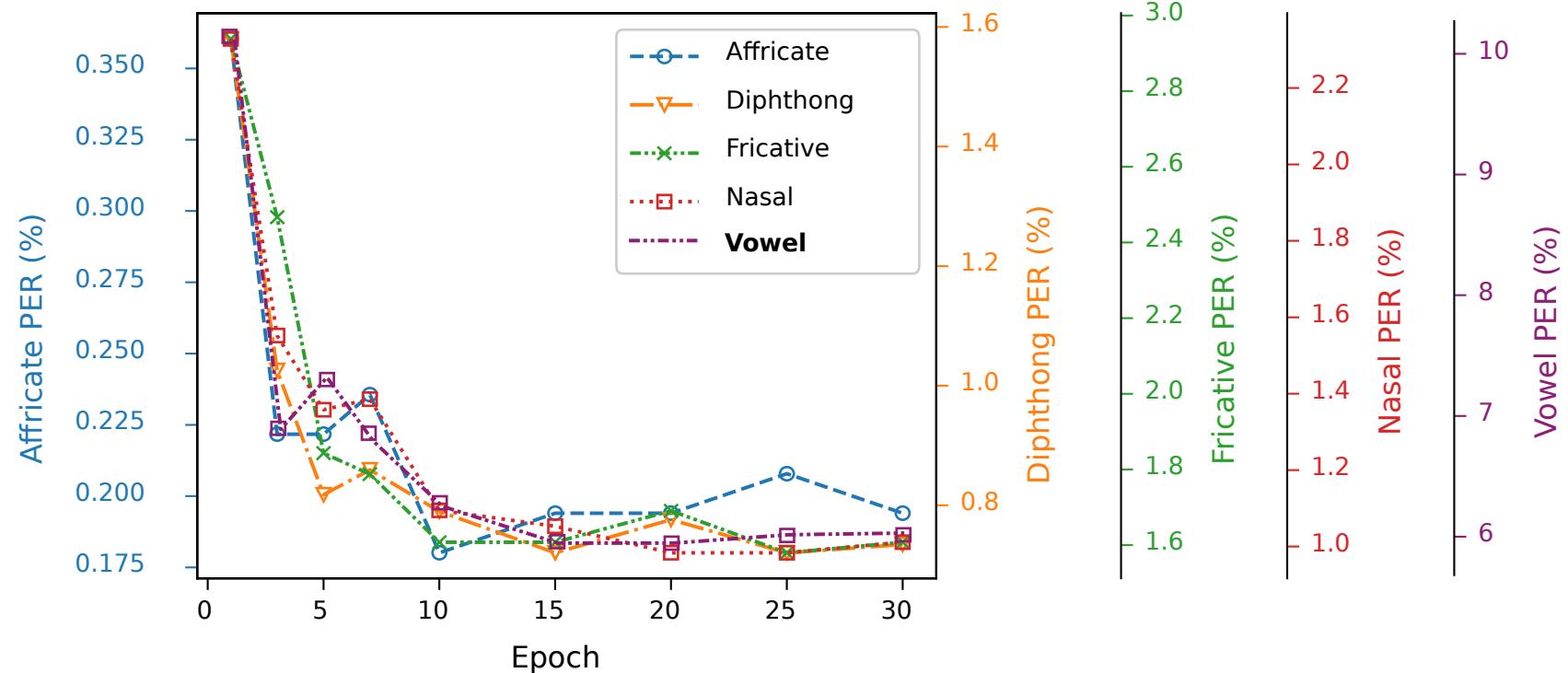
Training Dynamics (1)



Training Dynamics (1)



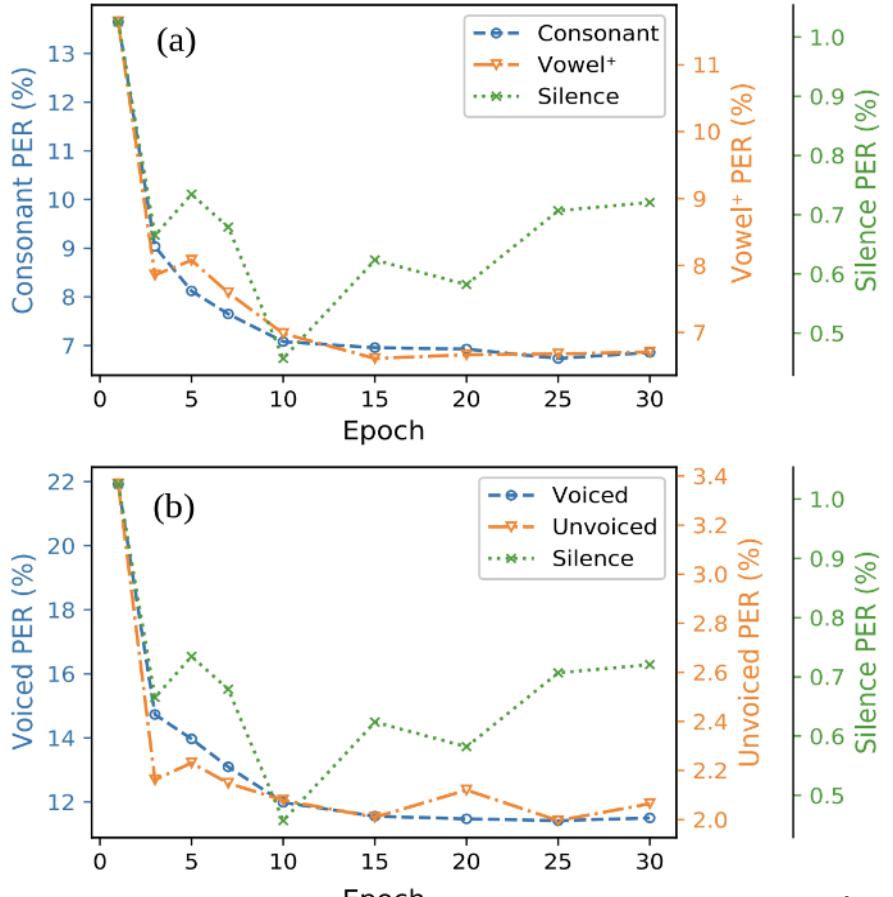
Training Dynamics (1)



Training Dynamics (2)



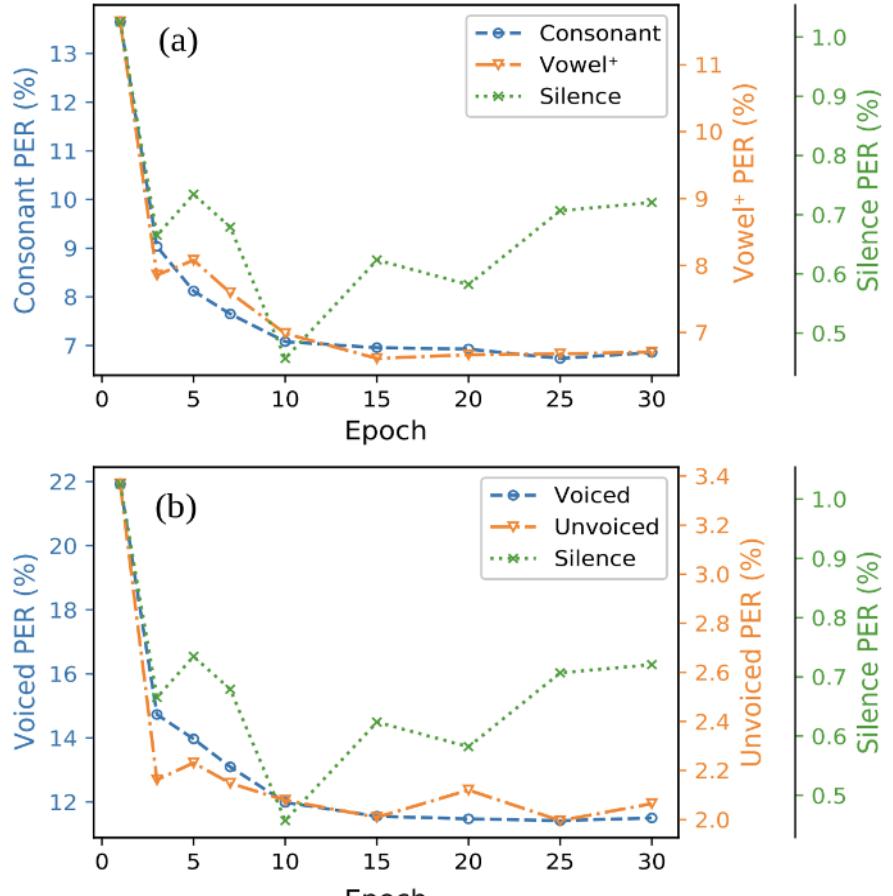
Training Dynamics (3)



Training Dynamics (3)

Similar dynamics for all classes;
despite different PER (except Silence).

Dynamics is not class-specific;
depends on architecture, loss and data.



Confusion Matrices

Confusion matrices are computed using **Sub** errors.

The **bold** & underlined indicate the 1st & 2nd mostly confused classes.

True Label	aff	dip	fri	nas	plo	sem	sil	vow
aff	10	0	6	0	4	0	0	0
dip	0	<u>13</u>	0	1	1	<u>13</u>	0	50
fri	8	3	127	1	<u>24</u>	9	7	4
nas	0	1	3	41	<u>9</u>	4	3	5
plo	8	0	<u>25</u>	2	73	4	0	5
sem	5	16	12	3	7	<u>18</u>	2	54
sil	0	0	4	<u>4</u>	3	2	0	1
vow	1	<u>48</u>	4	5	5	48	3	549

(a)	Predicted Label								
(b)	sil con vow ⁺			sil unv voi					
sil	0	13	<u>1</u>	sil	0	2	12		
con	12	403	<u>88</u>	unv	5	<u>55</u>	84		
vow ⁺	3	<u>78</u>	660	voi	10	<u>125</u>	965		

Confusion Matrices

Fricatives are MCW Fricatives & Plosives.

Semi-vowels are MCW Vowels & Semi-vowels.

Silence is MCW Fricatives & Nasals.

⋮

MCW: mostly confused with

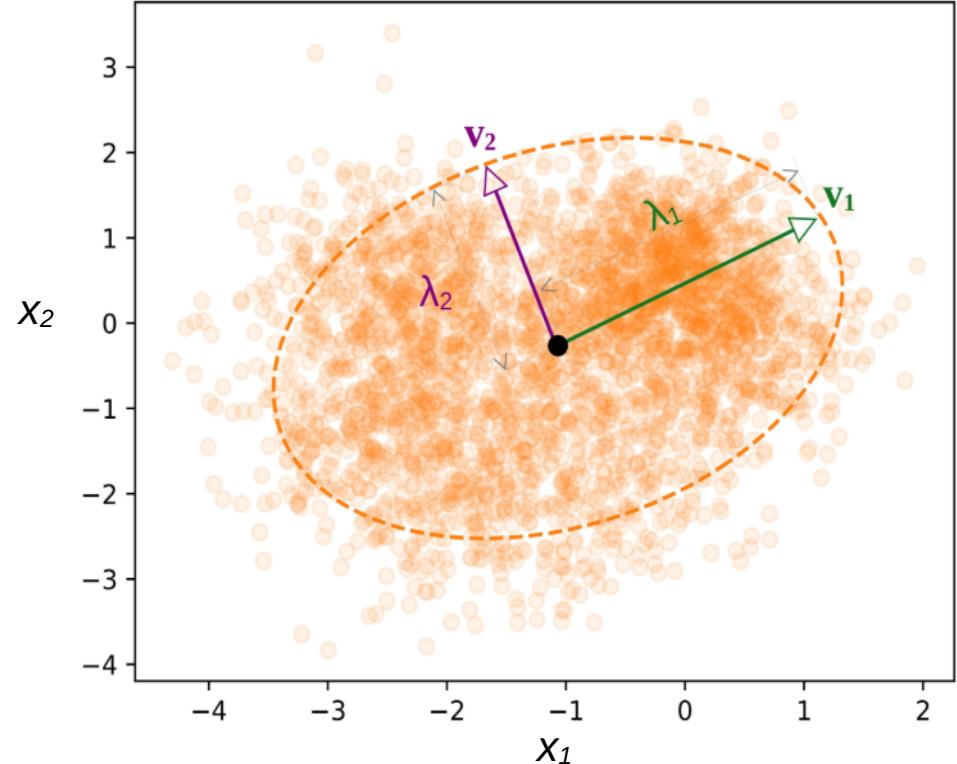
	aff	dip	fri	nas	plo	sem	sil	vow
aff	10	0	6	0	4	0	0	0
dip	0	13	0	1	1	13	0	50
fri	8	3	127	1	24	9	7	4
nas	0	1	3	41	9	4	3	5
plo	8	0	25	2	73	4	0	5
sem	5	16	12	3	7	18	2	54
sil	0	0	4	4	3	2	0	1
vow	1	48	4	5	5	48	3	549

	Predicted Label		
(a)			
(b)	sil	con	vow ⁺
sil	0	13	1
con	12	403	88
vow ⁺	3	78	660

	sil	unv	voi
(c)			
sil	0	2	12
unv	5	55	84
voi	10	125	965

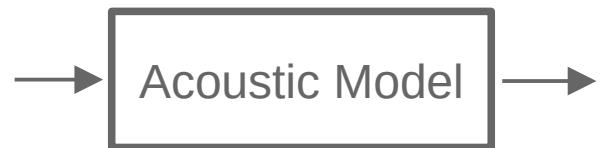
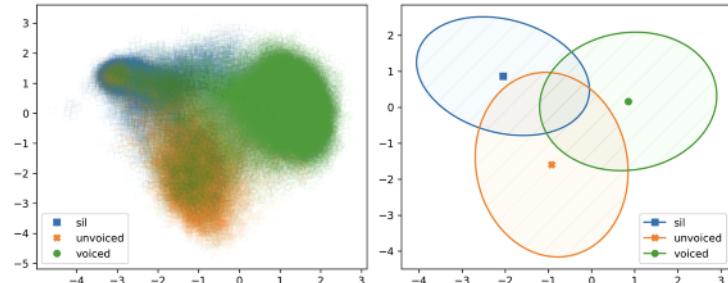
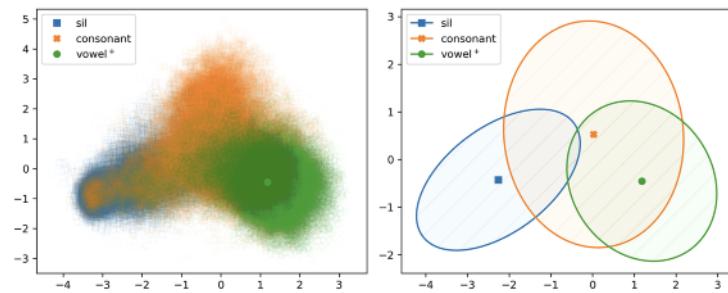
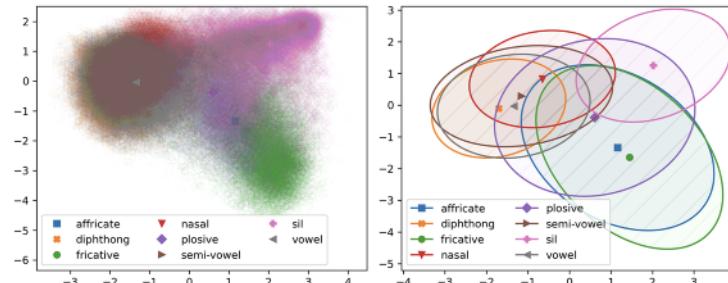
Scatter Plot in 2D

- How:
 - LDA (t-SNE in A4)
 - Fit an ellipse

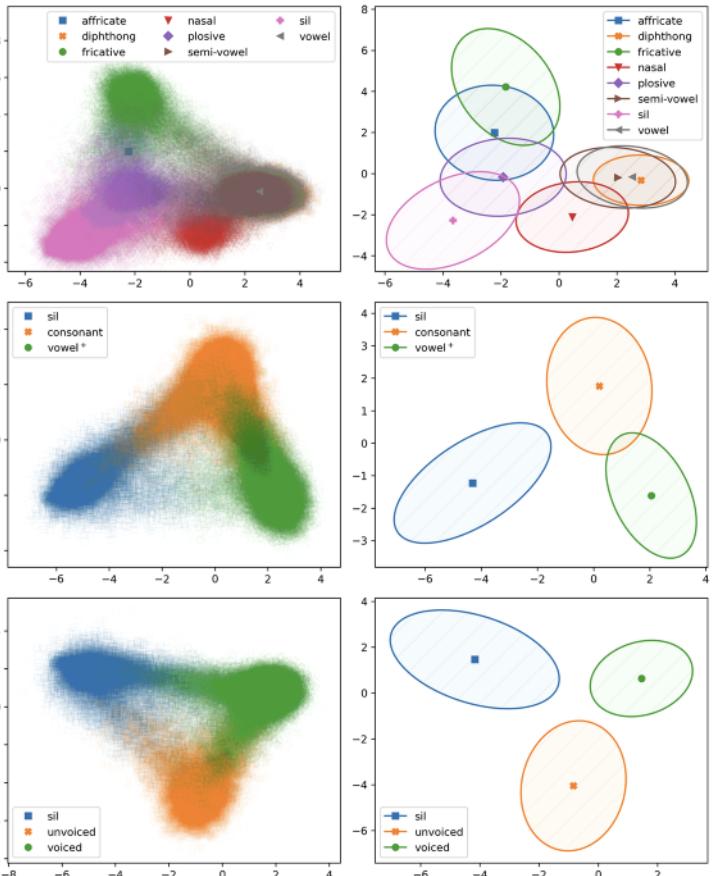
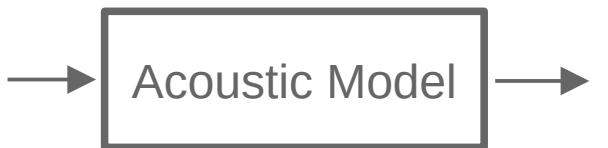
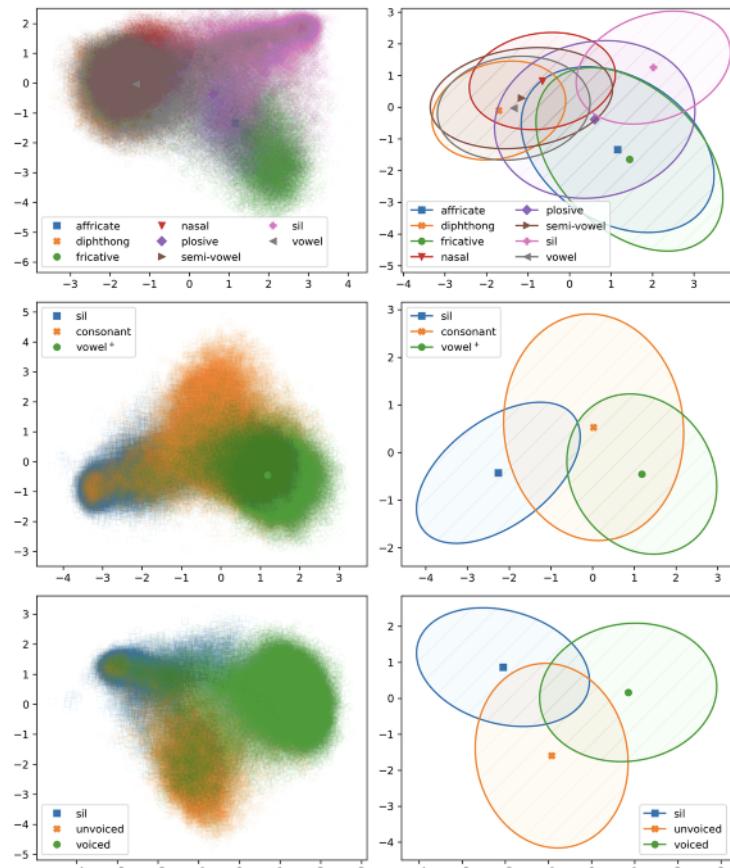


* LDA: Linear Discriminant Analysis

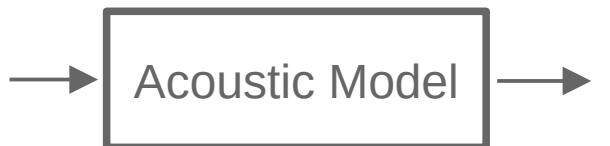
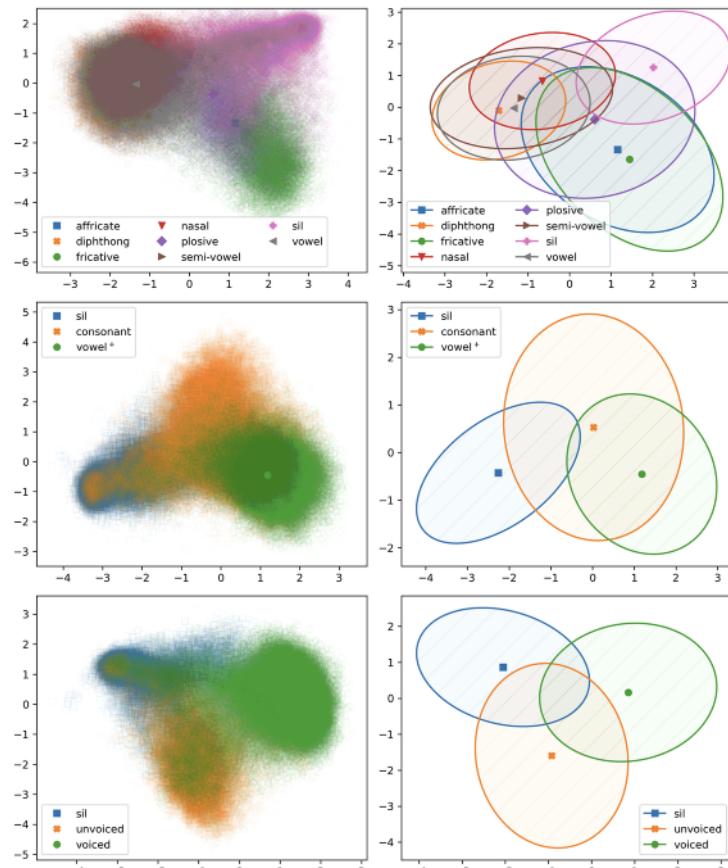
Scatter Plots



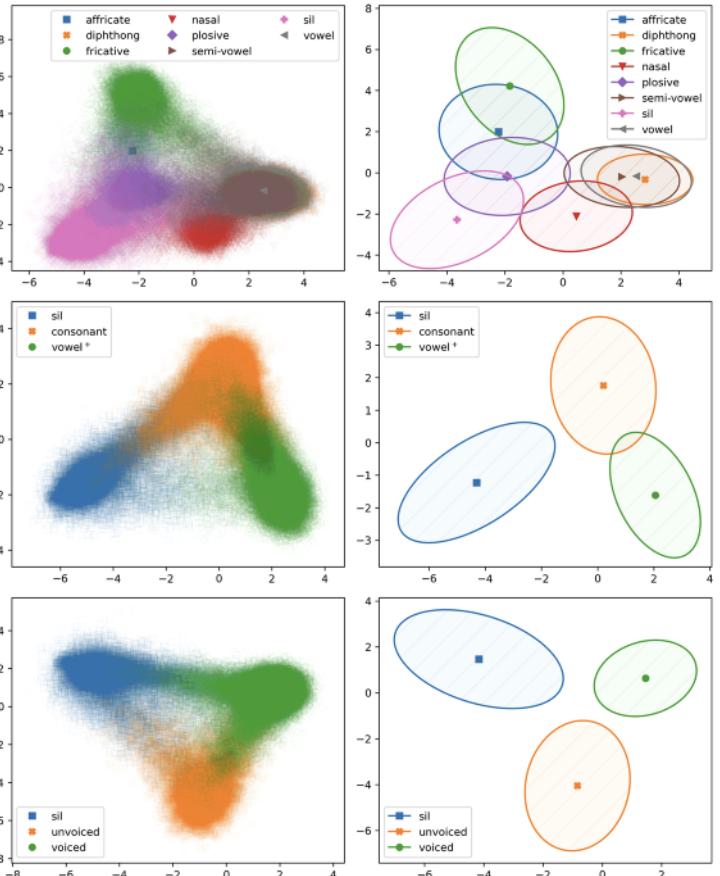
Scatter Plots



Scatter Plots



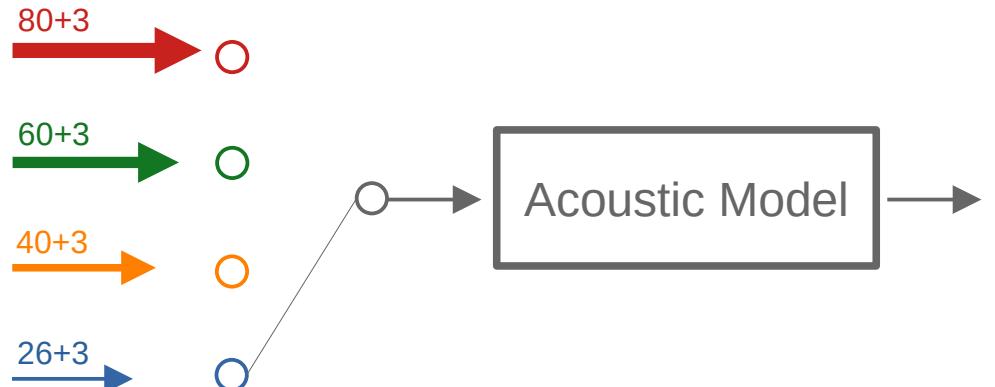
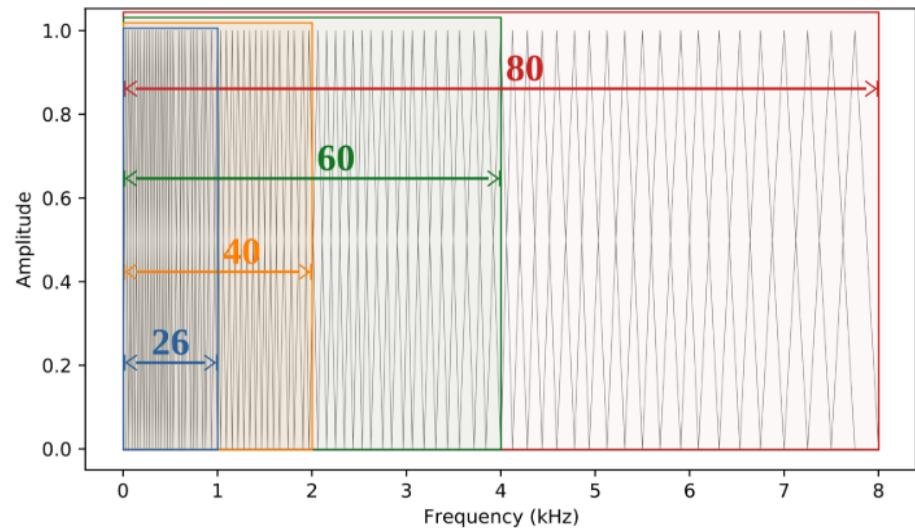
- ✓ → More distinct clusters →
- ✗ Scatter plots do not perfectly justify confusions



Various Systems

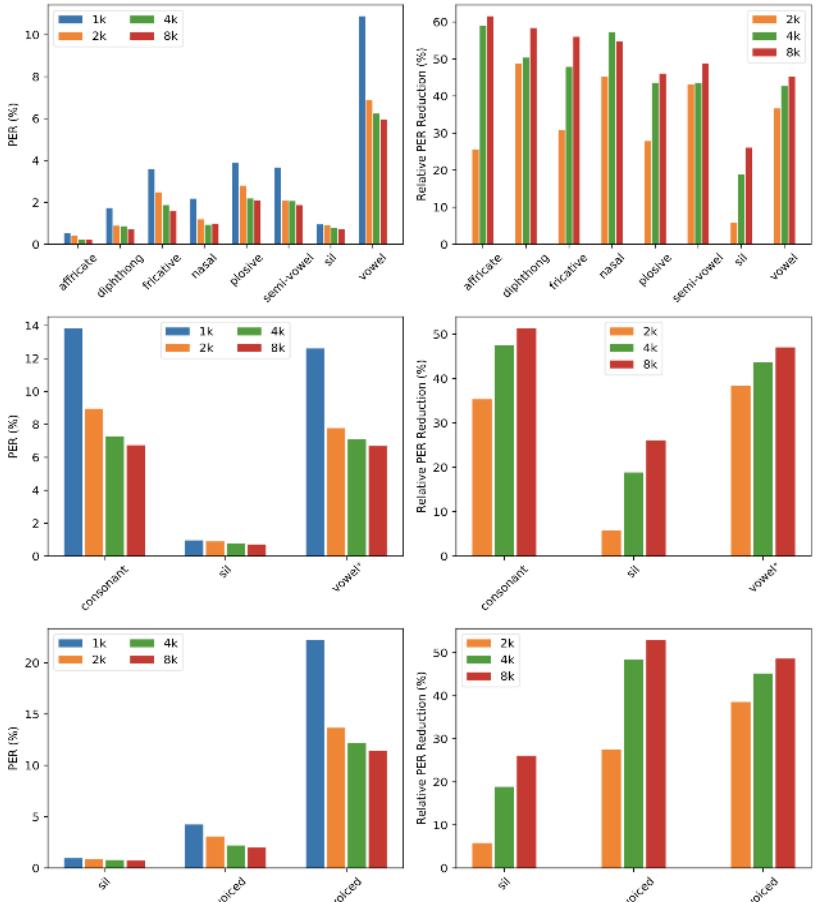
Model	Task	Architecture	Dev	Test
Baseline	TIMIT	L4-Hybrid	12.8	14.1
Subband-1k	TIMIT	L4-Hybrid	25.1	27.3
Subband-2k	TIMIT	L4-Hybrid	16.8	17.6
Subband-4k	TIMIT	L4-Hybrid	13.4	15.0
UniLSTM	TIMIT	L4-Hybrid	15.9	17.8
Baseline	NTIMIT	L4-Hybrid	19.2	20.1
GMM-HMM	TIMIT	SAT-MLLT-LDA	20.5	21.5
Baseline (WSJ*)	TIMIT	L4-Hybrid	11.5	13.1
Conformer	TIMIT	E2E	18.2	20.0
wav2vec 2.0	TIMIT	E2E (pre-trained)	7.1	8.3

Effect of Sub-bands



Effect of Sub-bands

Relative gain computed w.r.t. 1 kHz system.

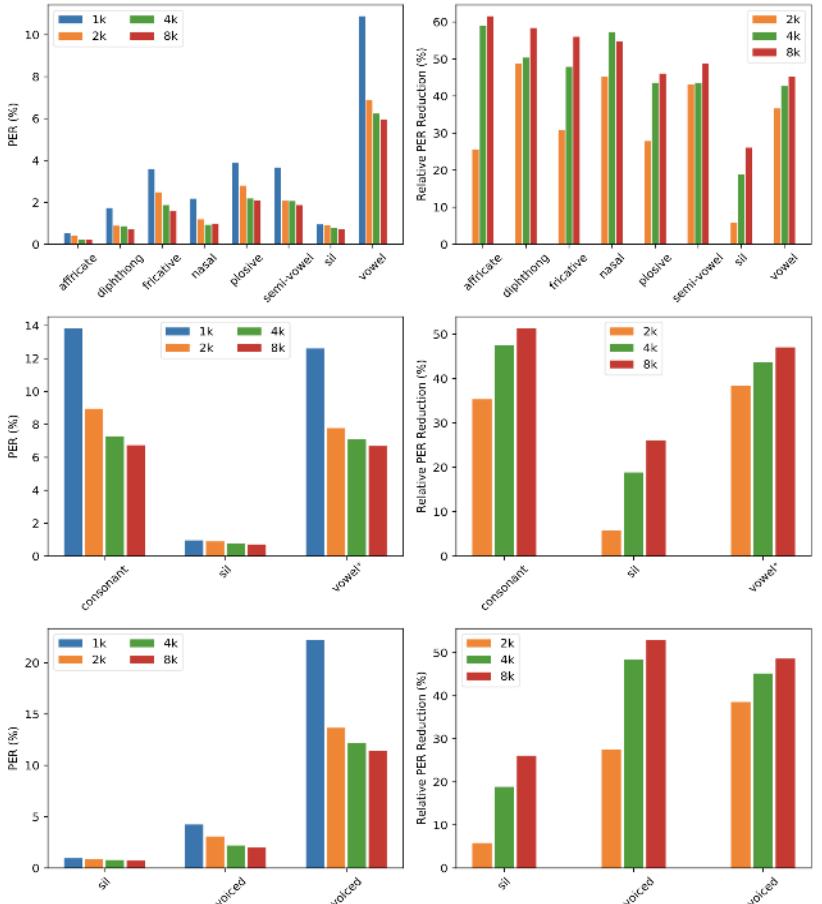


Effect of Sub-bands

Relative gain computed w.r.t. 1 kHz system.

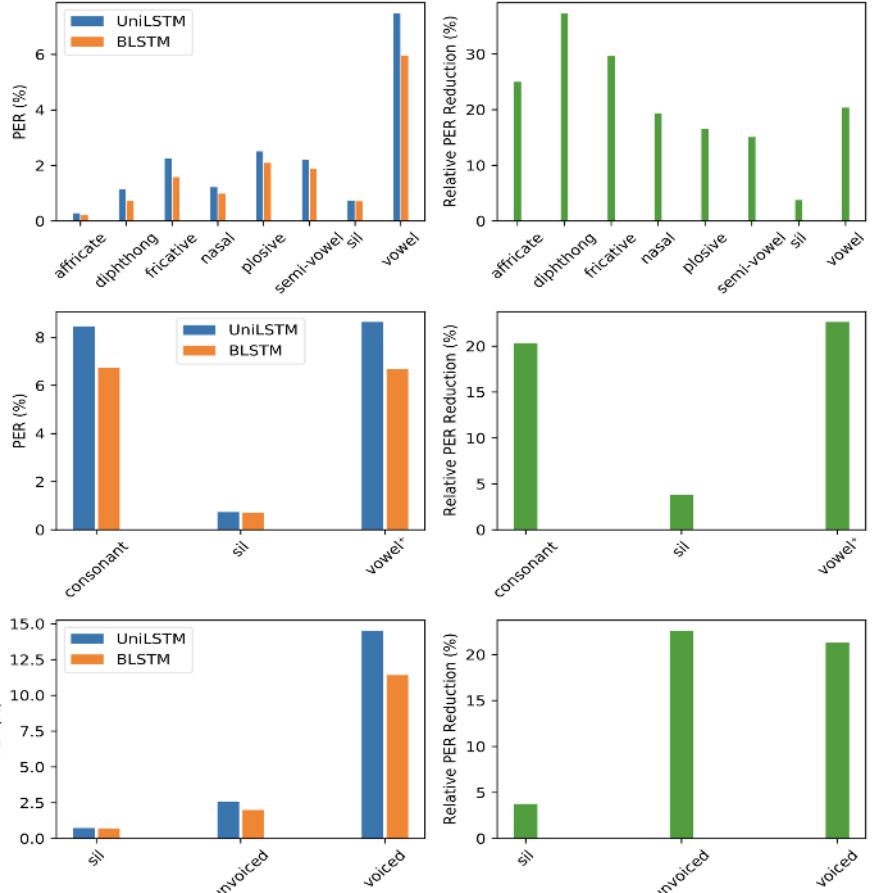
Including freq > 2kHz ...

- Small yet consistent gain for Voiced, Semi/V⁺.
- Notable gain for Unvoiced, Aff/Fri/Nas/Plo/Sil



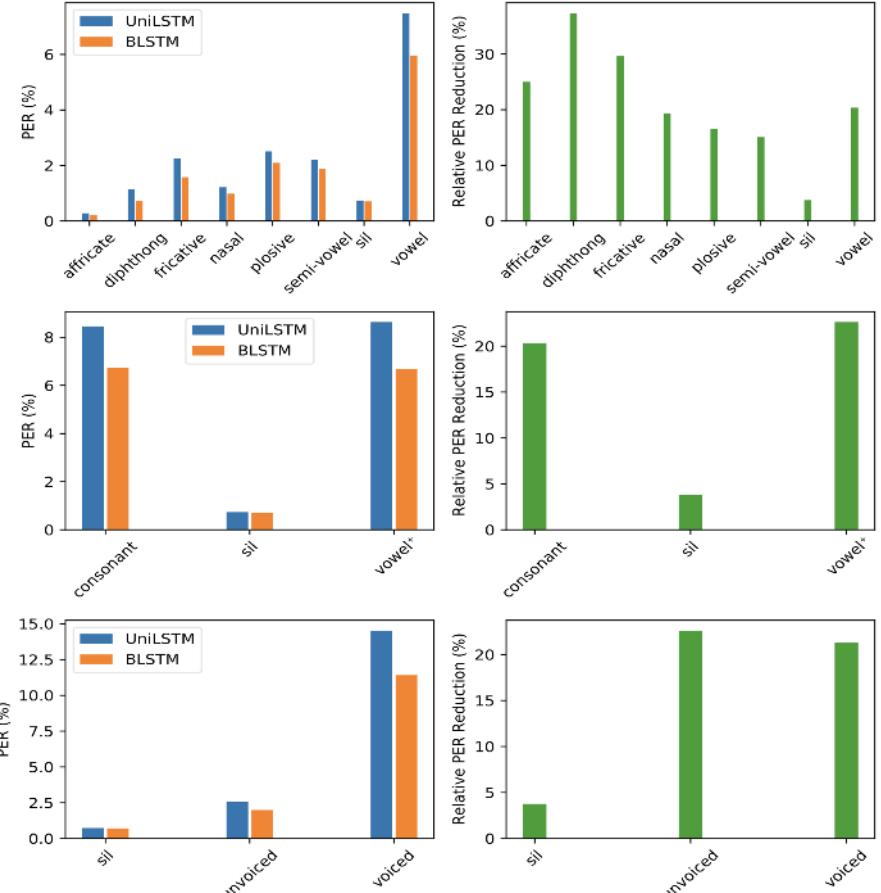
Uni- vs Bi-Directional

- Relative Gain:
 - Typically 15% to 40%



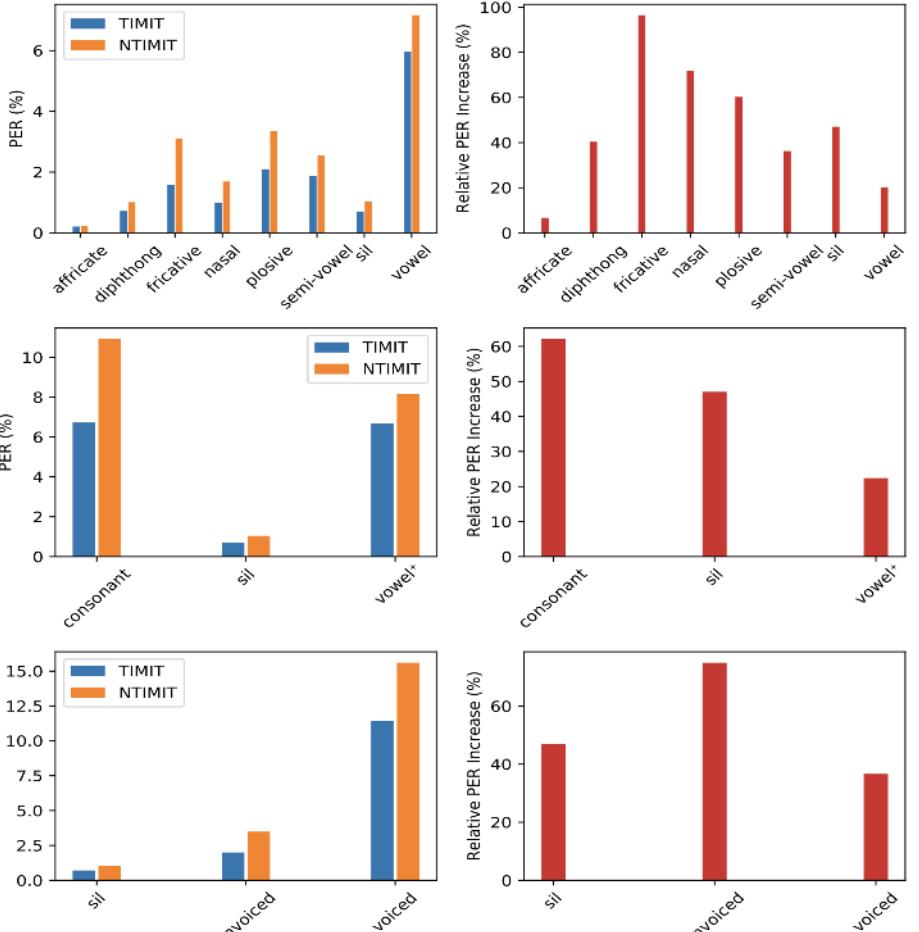
Uni- vs Bi-Directional

- Relative Gain:
 - Typically 15% to 40%
- Silence benefits the least (4%)
 - Why?



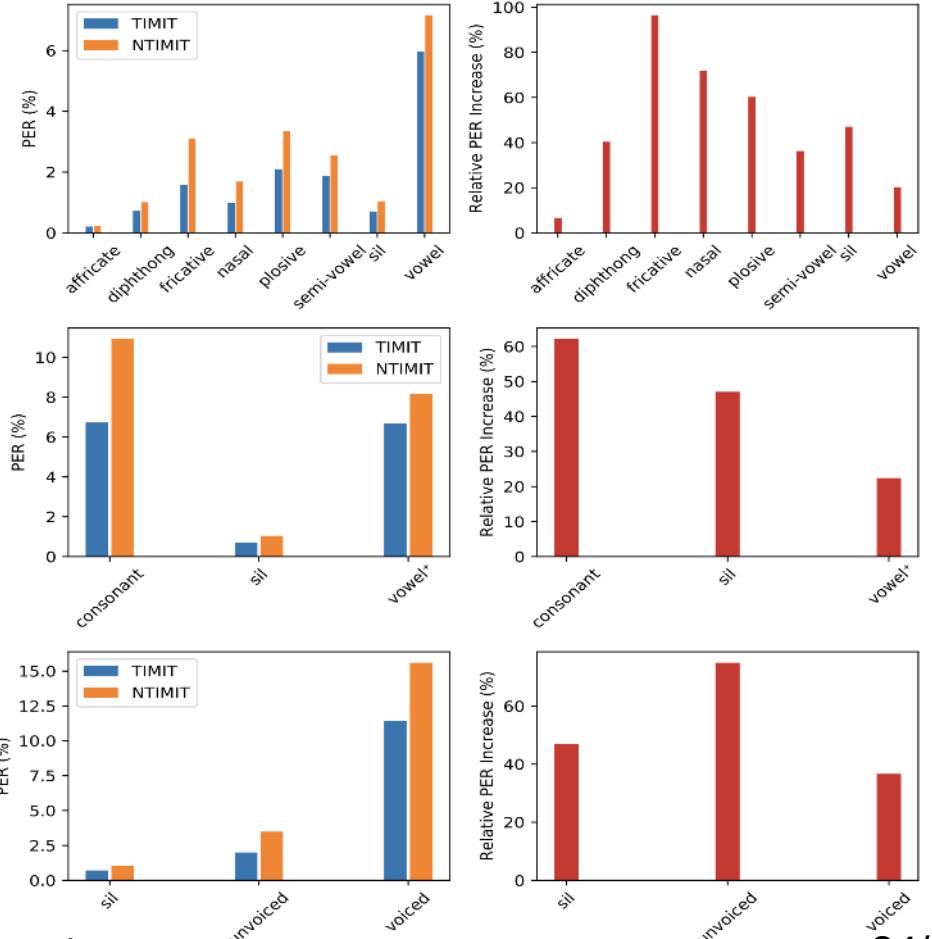
NTIMIT

- Relative gain: -21% to -95%



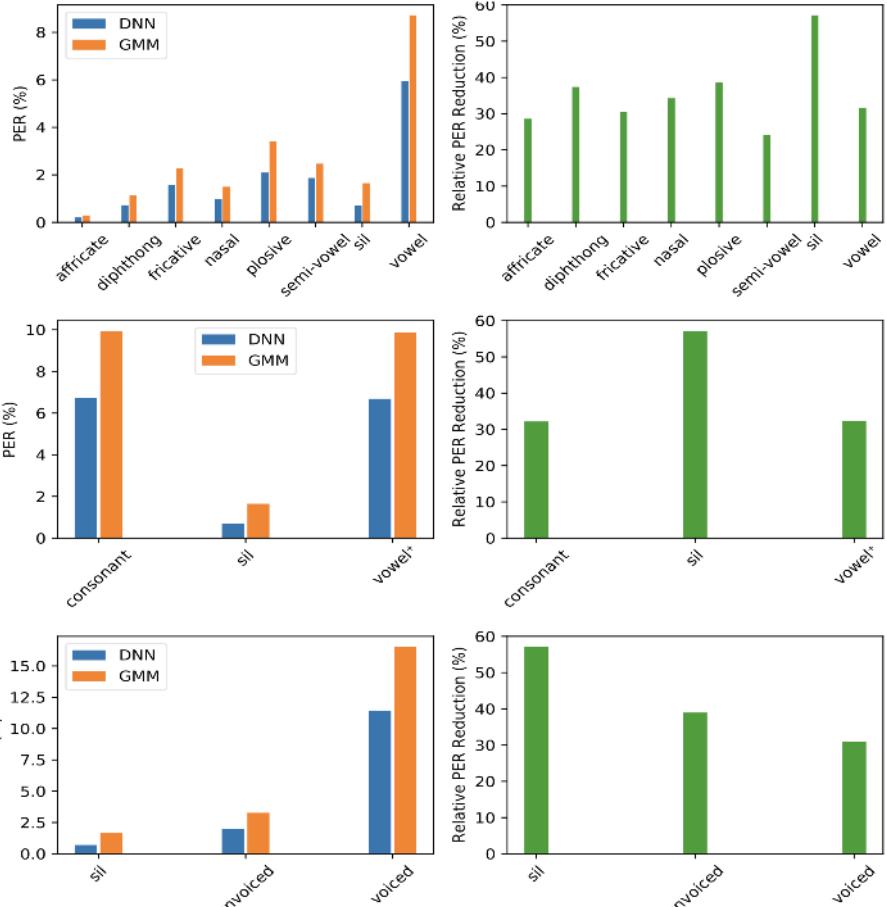
NTIMIT

- Relative gain: -21% to -95%
- Robustness
 - Most: Vowels
 - Least: Fricatives
- Why?



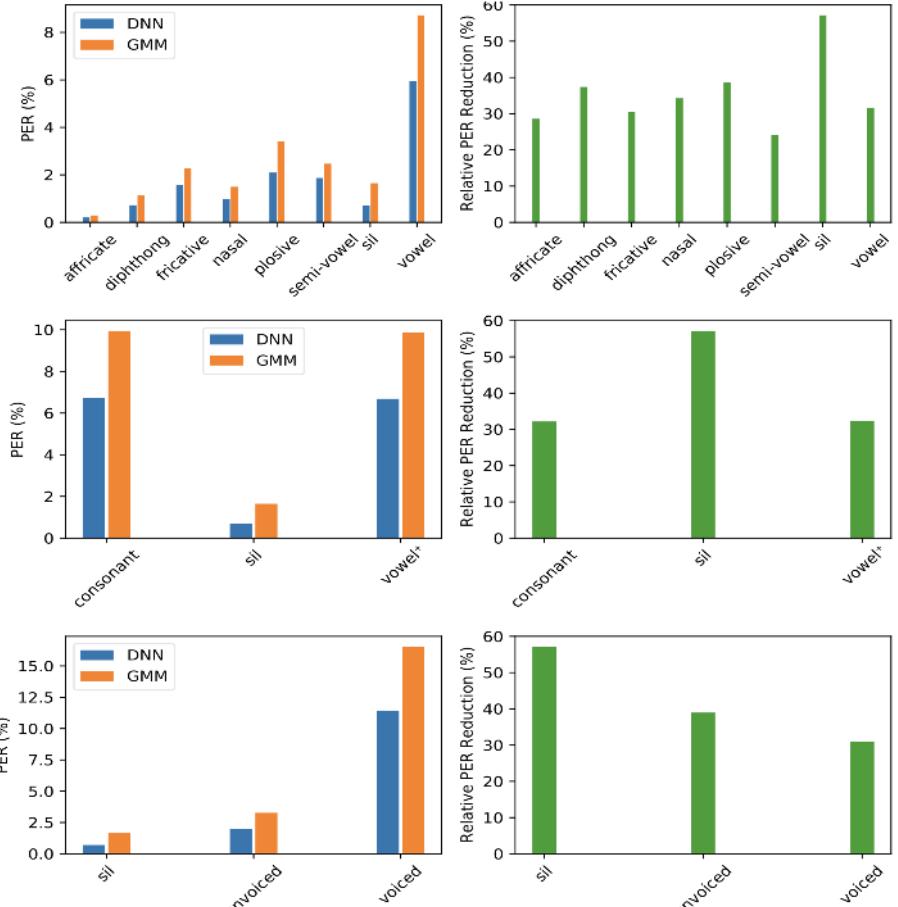
GMM-HMM vs DNN-HMM

- Relative Gain: 25% to 55%



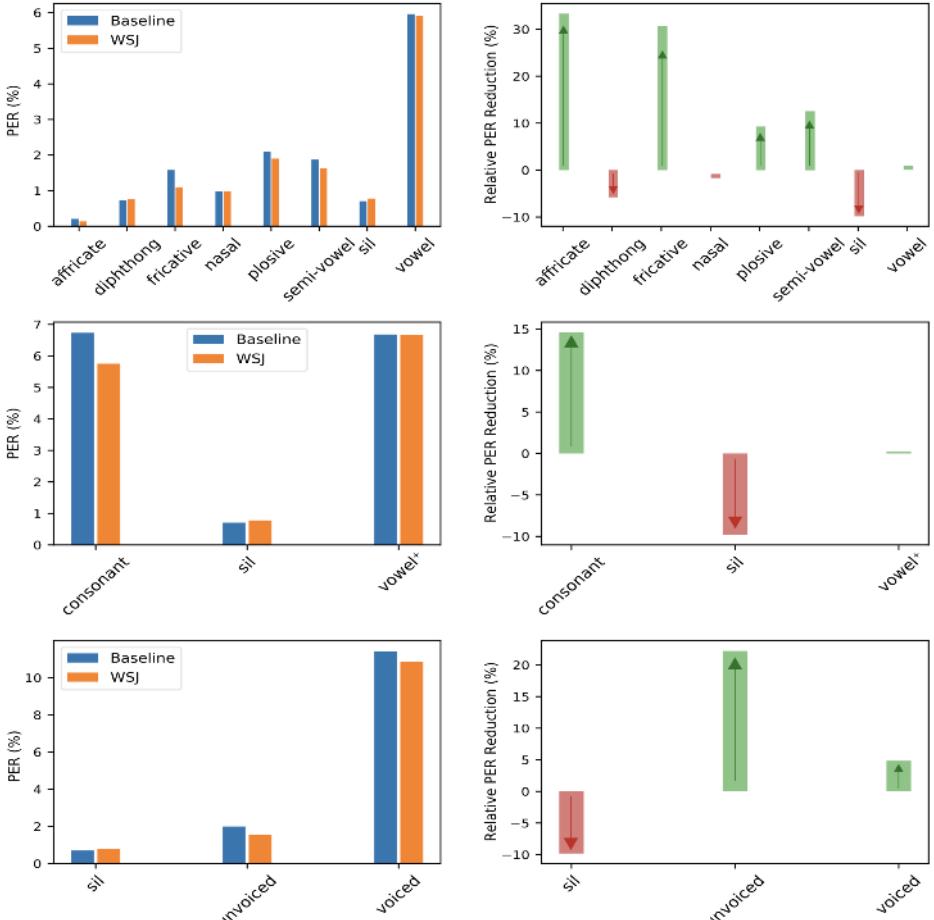
GMM-HMM vs DNN-HMM

- Relative Gain: 25% to 55%
- Silence benefits the most
 - Why?



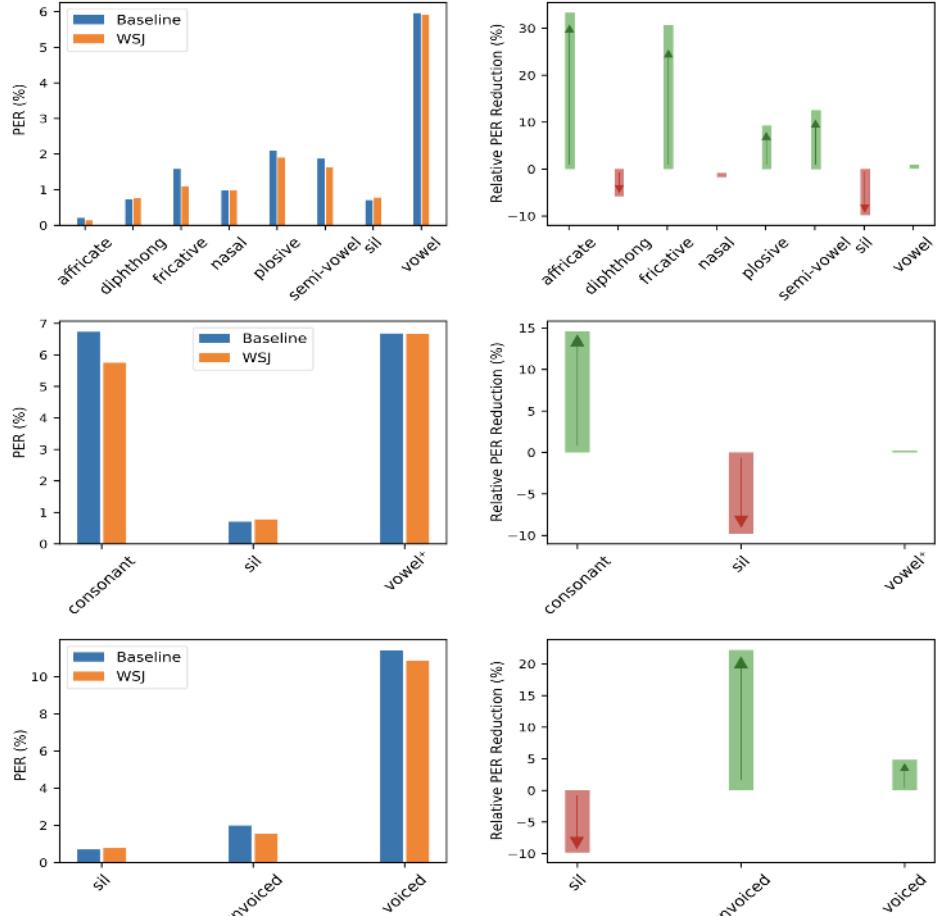
Transfer Learning from WSJ

- Average relative gain:
 - Dev: 10%, Test: 7%



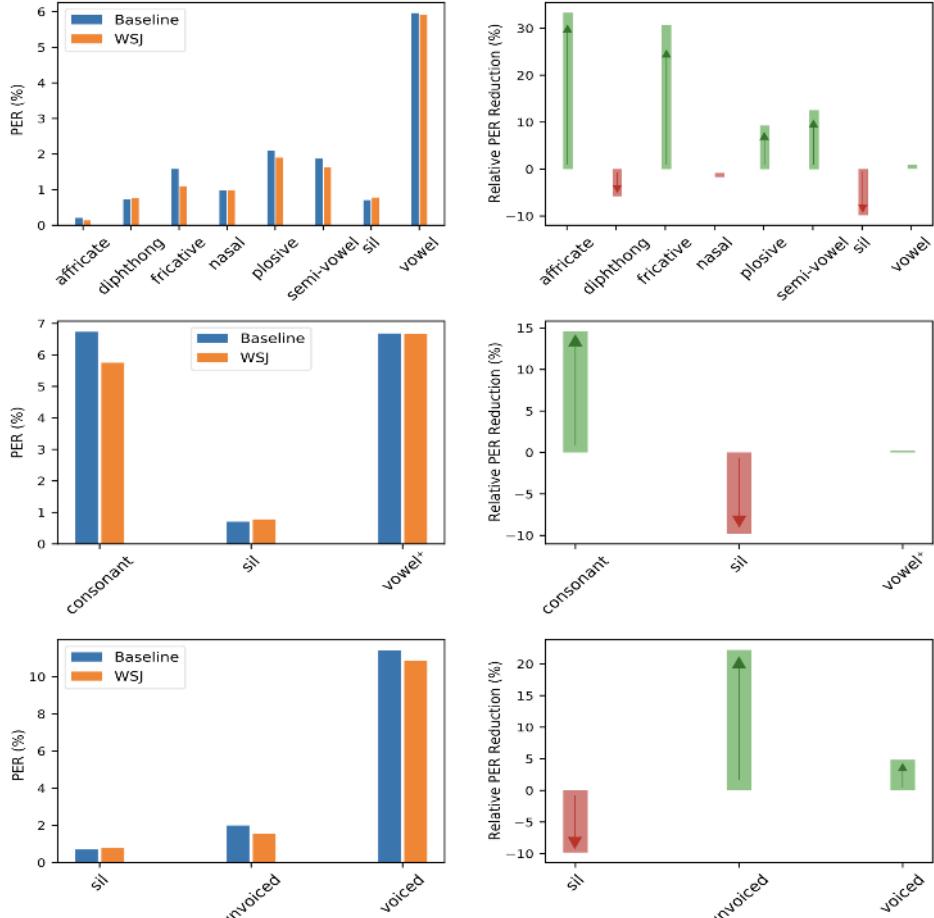
Transfer Learning from WSJ

- Average relative gain:
 - Dev: 10%, Test: 7%
- Negative gain (**-10%**) for Silence!
 - Why?



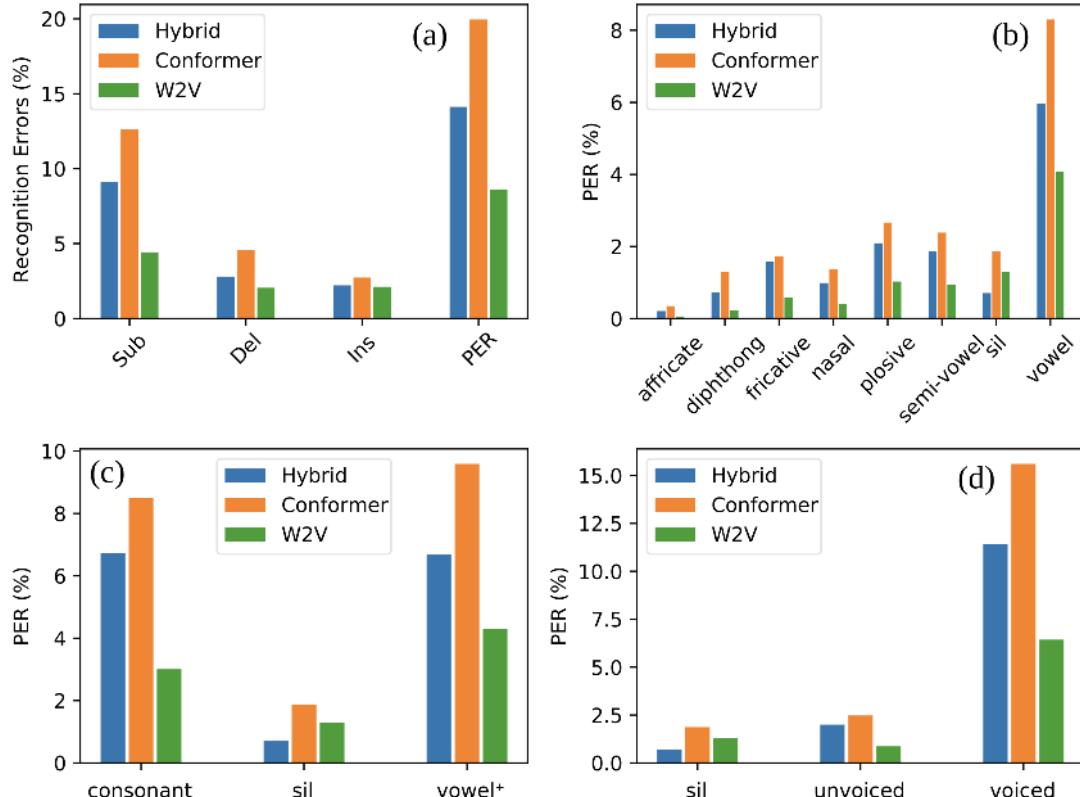
Transfer Learning from WSJ

- Average relative gain:
 - Dev: 10%, Test: 7%
- Negative gain (-10%) for Silence!
 - Why?
- Average gain for $C > V^+$
 - Why?

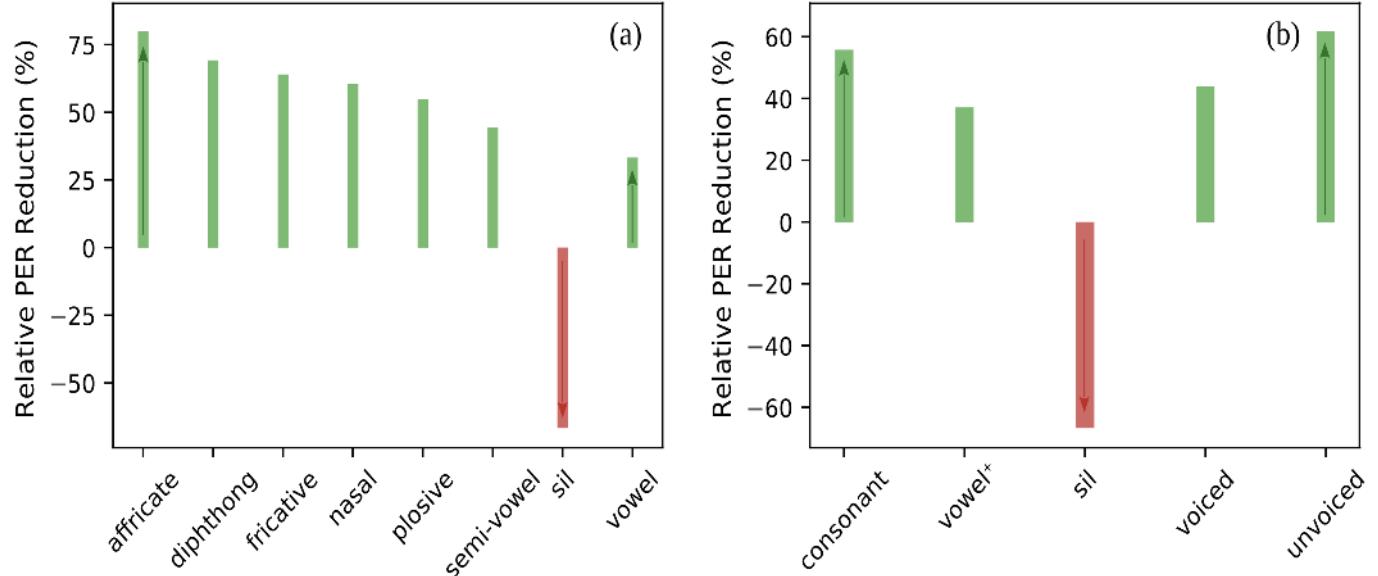


End-to-end (E2E) vs Hybrid

- E2E systems
 - Conformer
 - Wav2vec 2.0
- Details in the paper ...



HMM-DNN → Wav2Vec 2.0



- Relative Gain: +25% to 75%
- Negative gain (-60%) for Silence!
- Average gain C > V⁺

Confusion Matrices

Baseline (DNN-HMM)

True Label

	aff	dip	fri	nas	plo	sem	sil	vow
aff	10	0	6	0	4	0	0	0
dip	0	13	0	1	1	13	0	50
fri	8	3	127	1	24	9	7	4
nas	0	1	3	41	9	4	3	5
plo	8	0	25	2	73	4	0	5
sem	5	16	12	3	7	18	2	54
sil	0	0	4	4	3	2	0	1
vow	1	48	4	5	5	48	3	549

Legend

aff: affricate
dip: diphthong
fri: fricative
nas: nasal
plo: plosive
sem: semi-vowel
sil: silence
vow: vowel

con: consonant
sil: silence
vow⁺: vow+dip

sil: silence
unv: unvoiced
voi: voiced

Predicted Label

(a)

	sil	con	vow ⁺
sil	0	13	1
con	12	403	88
vow ⁺	3	78	660

(b)

	sil	unv	voi
sil	0	2	12
unv	5	55	84
voi	10	125	965

Wav2vec 2.0

True Label

	aff	dip	fri	nas	plo	sem	sil	vow
aff	0	0	0	0	2	1	0	0
dip	0	0	0	0	0	1	1	8
fri	1	0	37	0	2	1	2	0
nas	0	0	0	12	0	0	2	0
plo	2	0	2	0	19	0	1	0
sem	1	0	1	0	1	1	0	28
sil	0	0	1	0	8	1	0	0
vow	0	19	2	2	0	16	1	373

Predicted Label

(a)

	sil	con	vow ⁺
sil	0	10	0
con	5	83	28
vow ⁺	2	21	400

(b)

	sil	unv	voi
sil	0	1	9
unv	1	4	27
voi	6	24	477

Confusion Matrices

Baseline (DNN-HMM)

True Label

	aff	dip	fri	nas	plo	sem	sil	vow
aff	10	0	6	0	4	0	0	0
dip	0	13	0	1	1	13	0	50
fri	8	3	127	1	24	9	7	4
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plo	8	0	25	2	73	4	0	5
sem	5	16	12	3	7	18	2	54
sil	0	0	4	4	3	2	0	1
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sil: silence
vow⁺: vow+dip

sil: silence
unv: unvoiced
voi: voiced

(a)

Predicted Label

Sparser but Similar Patterns

Wav2vec 2.0

True Label

	aff	dip	fri	nas	plo	sem	sil	vow
aff	0	0	0	0	2	1	0	0
dip	0	0	0	0	0	1	1	8
fri	1	0	37	0	2	1	2	0
nas	0	0	0	12	0	0	2	0
plo	2	0	2	0	19	0	1	0
sem	1	0	1	0	1	1	0	28
sil	0	0	1	0	8	1	0	0
vow	0	19	2	2	0	16	1	373

Predicted Label

Legend

aff: affricate
dip: diphthong
fri: fricative
nas: nasal
plo: plosive
sem: semi-vowel
sil: silence
vow: vowel

con: consonant
sil: silence
vow⁺: vow+dip

sil: silence
unv: unvoiced
voi: voiced

(b)

	sil	con	vow ⁺
sil	0	13	1
con	12	403	88
vow ⁺	3	78	660

(c)

	sil	unv	voi
sil	0	2	12
unv	5	55	84
voi	10	125	965

(b)

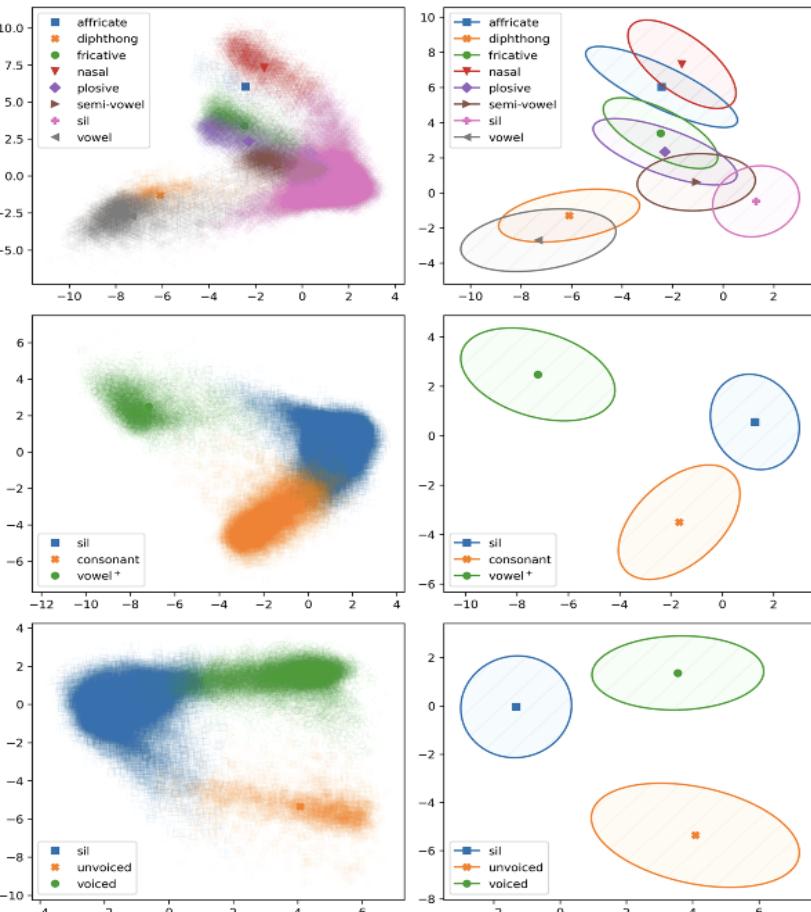
	sil	con	vow ⁺
sil	0	10	0
con	5	83	28
vow ⁺	2	21	400

(c)

	sil	unv	voi
sil	0	1	9
unv	1	4	27
voi	6	24	477

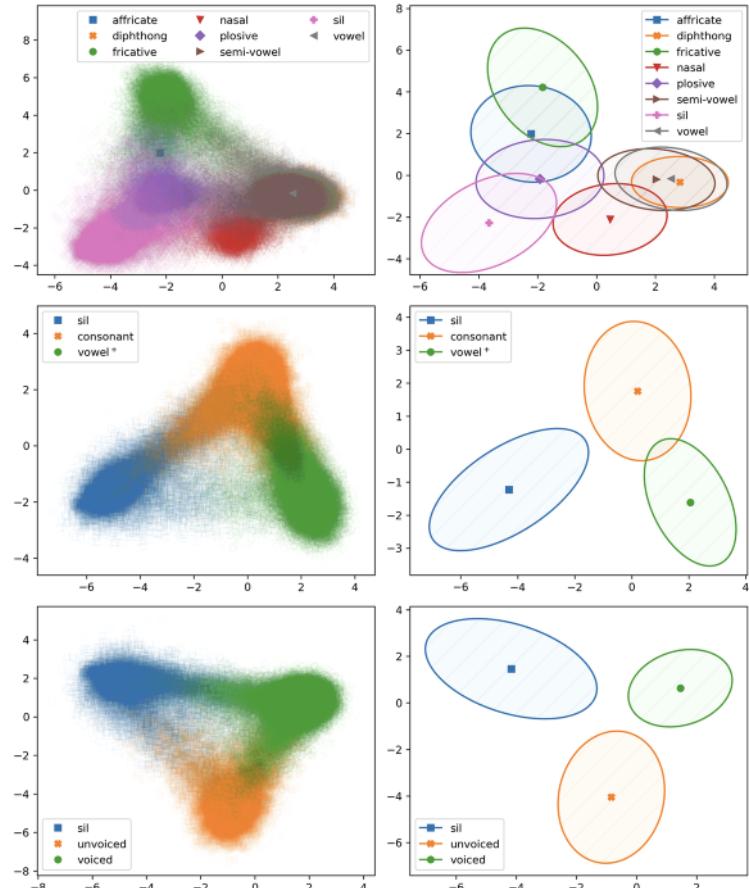
Scatter Plots

Logit (wav2vec 2.0)

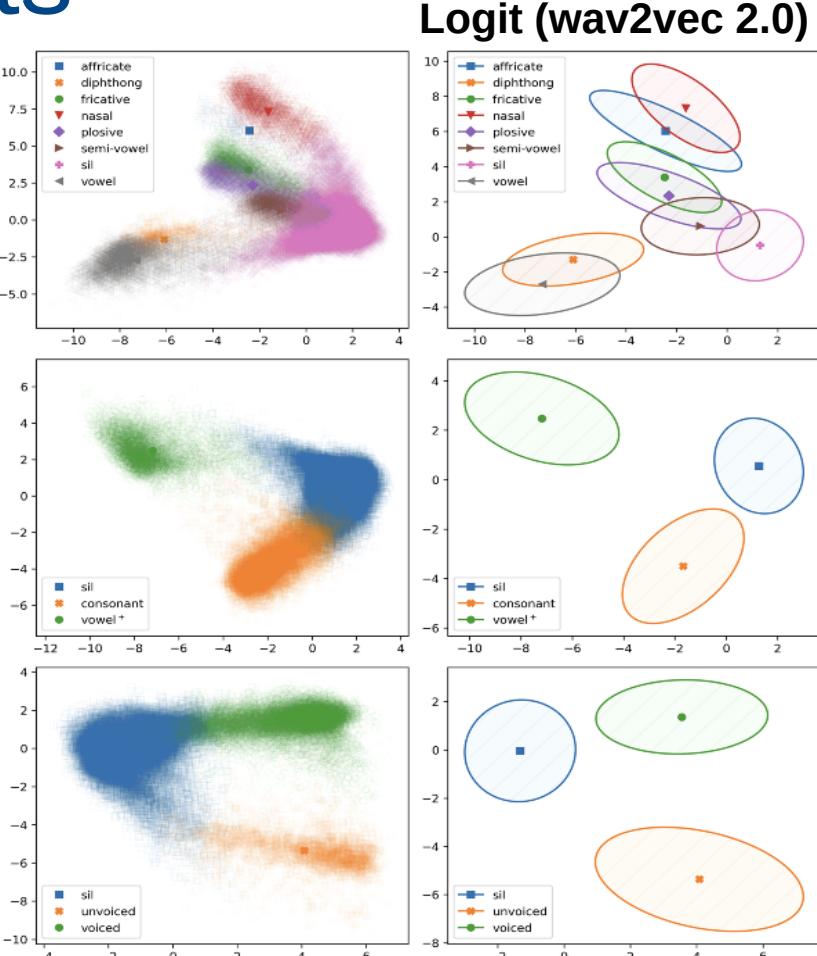


Scatter Plots

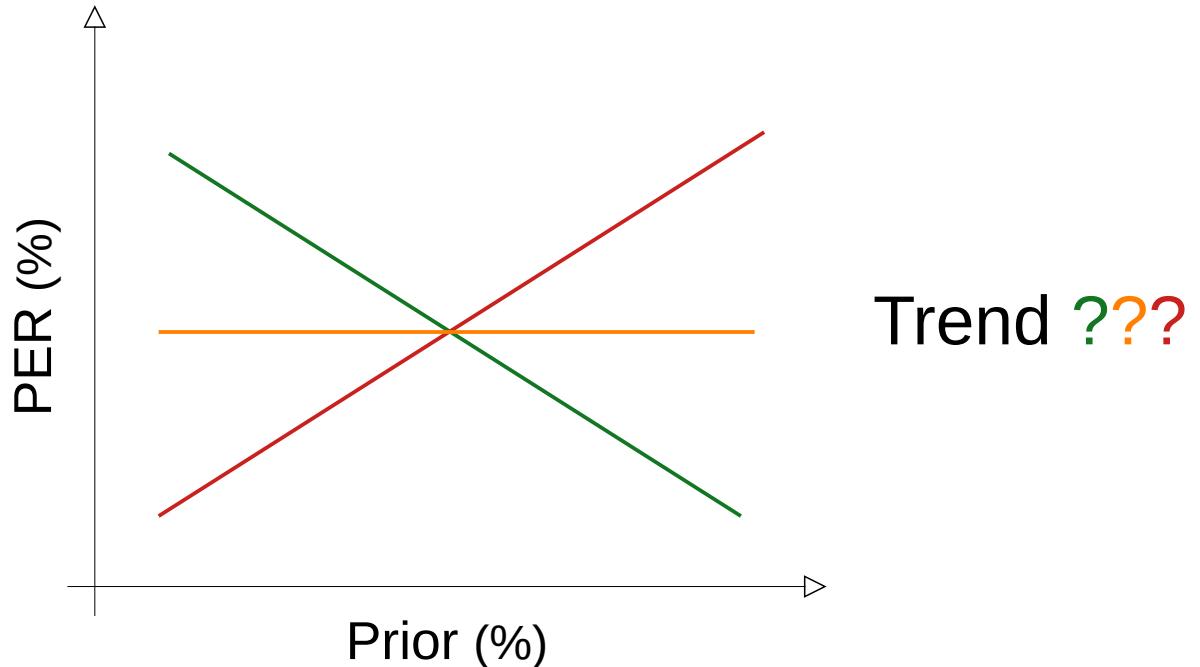
Logit (Hybrid)



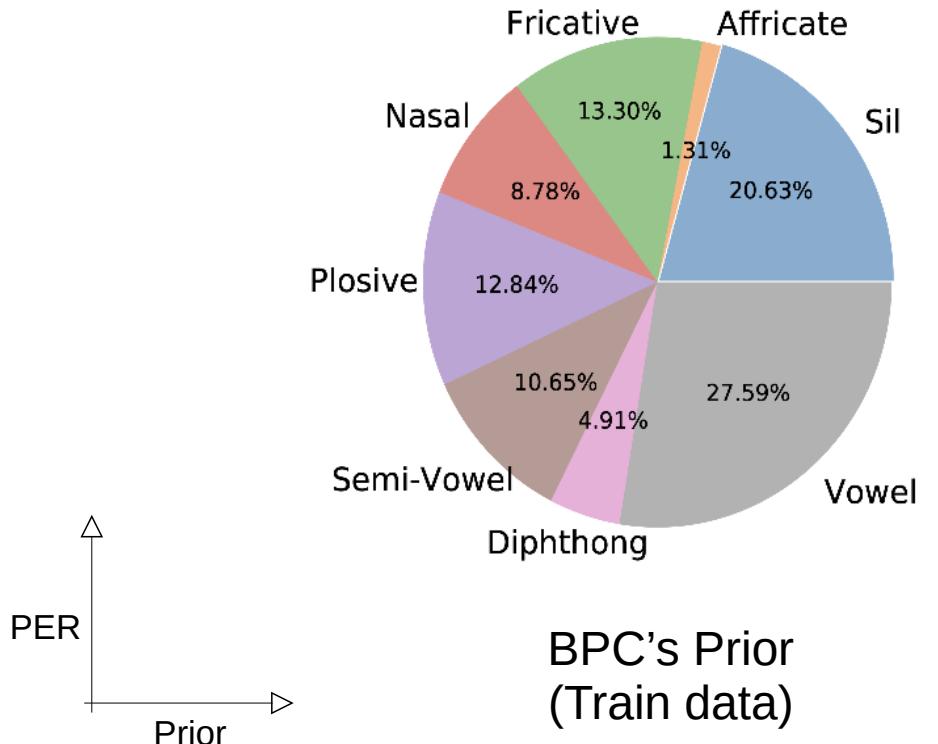
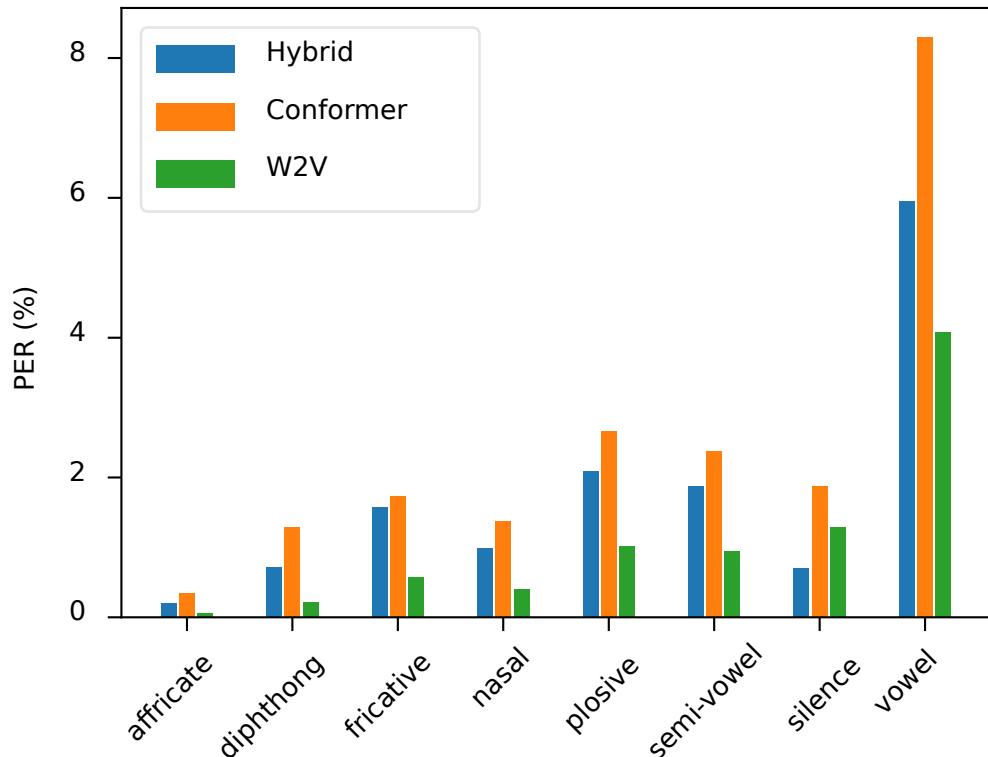
More distinct clusters



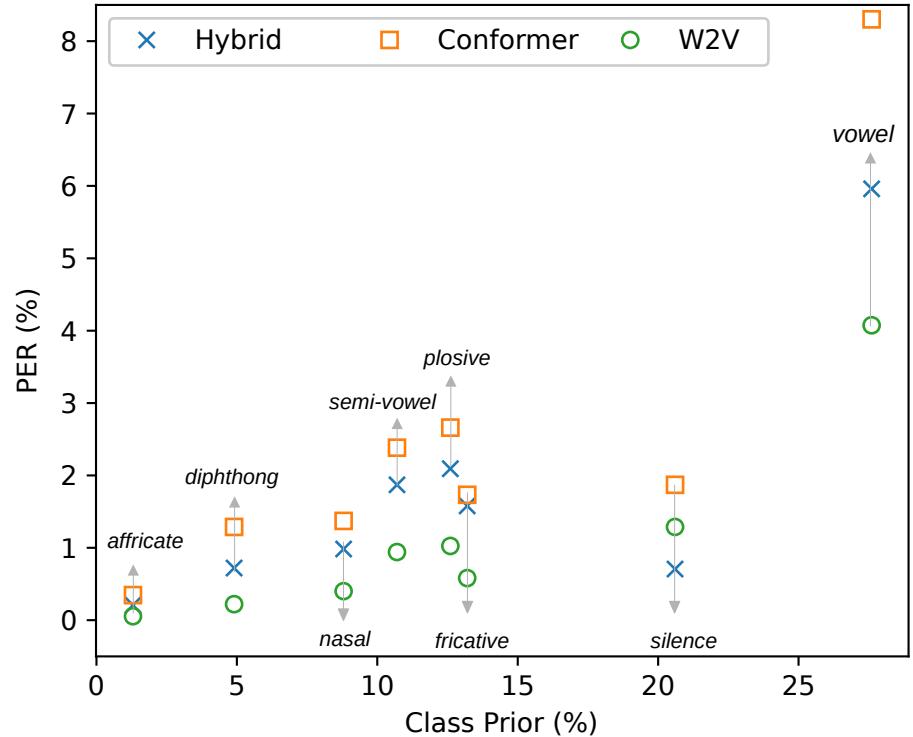
PER vs Prior (1)



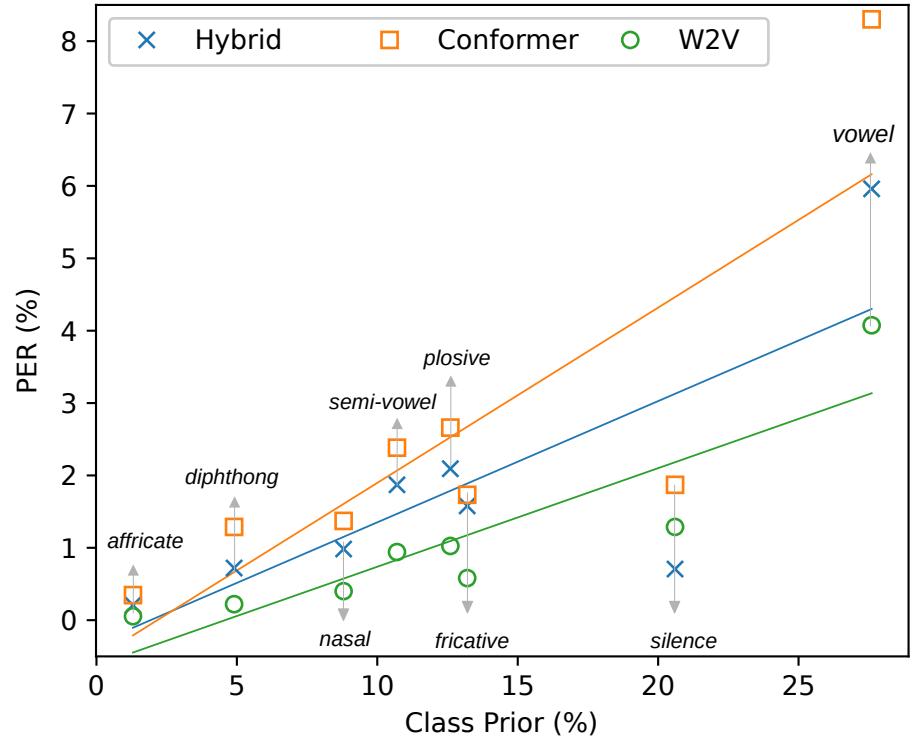
PER vs Prior (1)



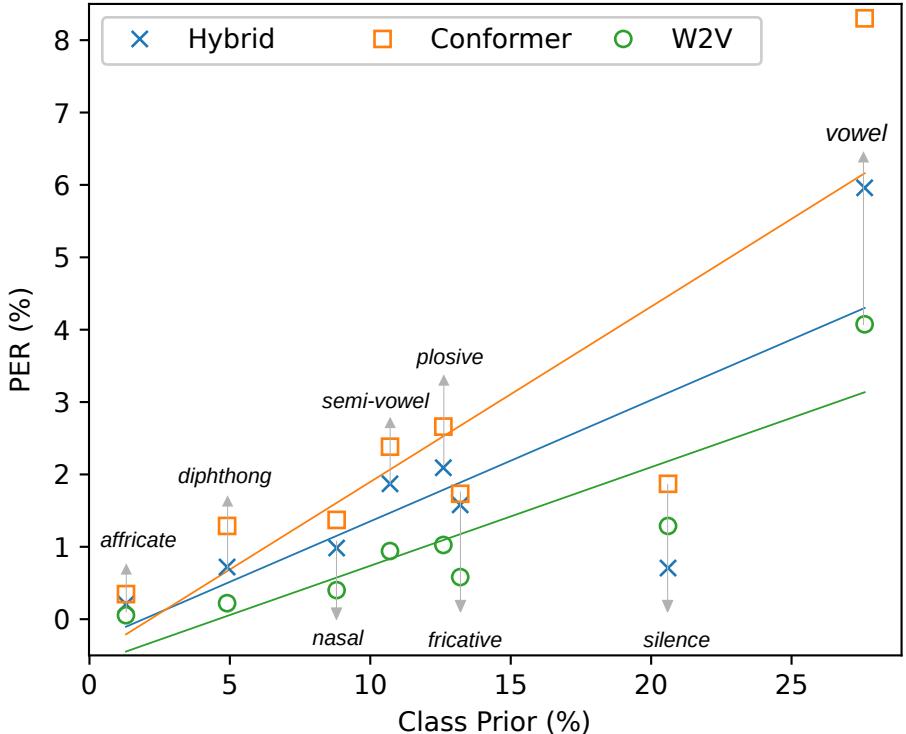
PER vs Prior (2)



PER vs Prior (2)

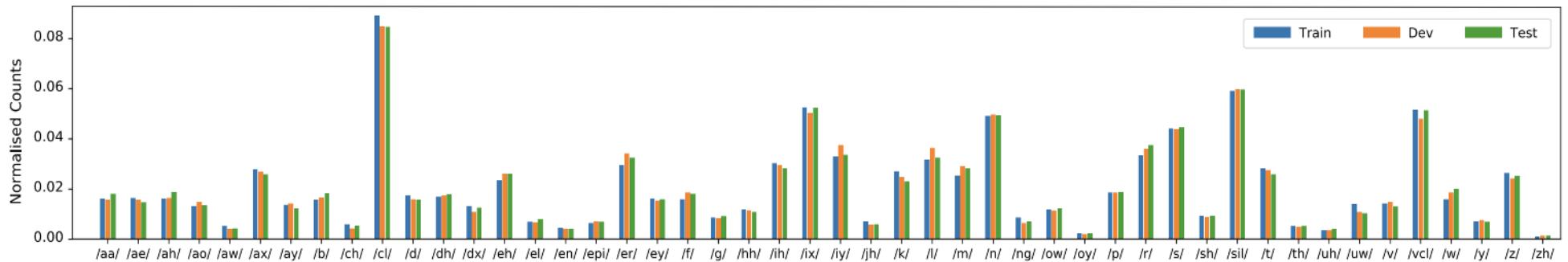


PER vs Prior (2)

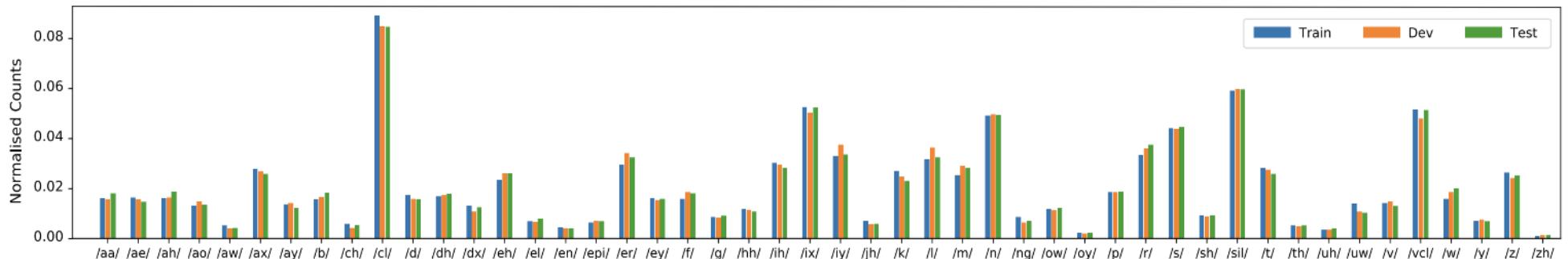


The higher the training data, the higher the PER!

TIMIT's Special Case ...



TIMIT's Special Case ...



The higher the training data, the larger/richer the test set, the higher the PER!

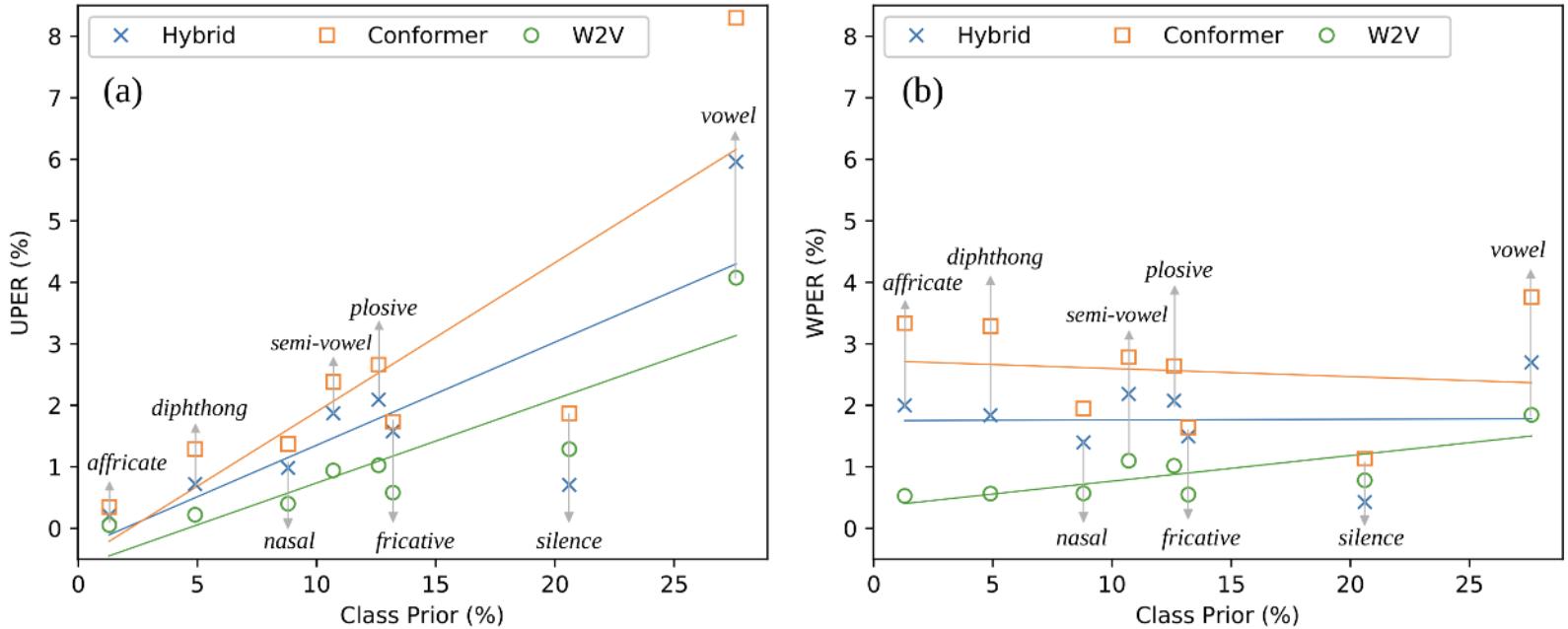
Unweighted vs Weighted PER

$$PER = UPER = \frac{1}{N} \sum_{c=1}^C (Sub_c + Del_c + Ins_c)$$

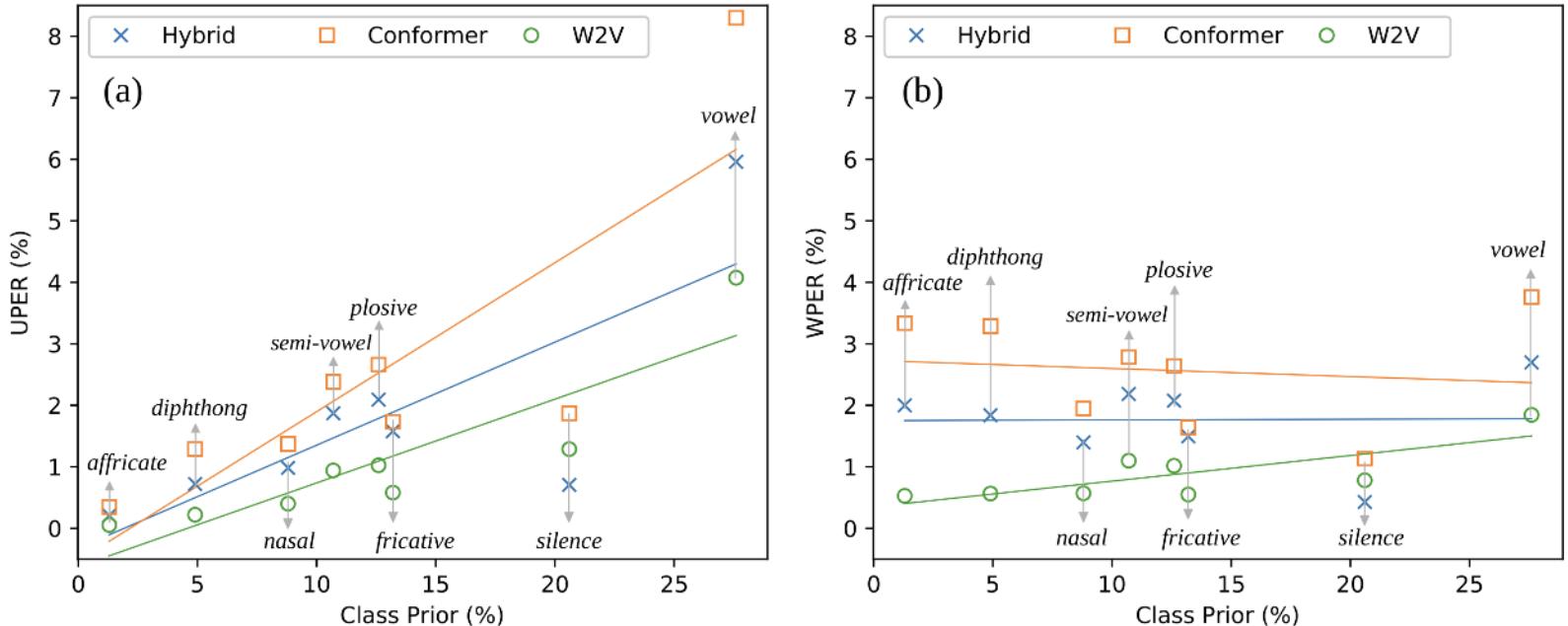
$$WPER = \frac{1}{C} \sum_{c=1}^C \frac{Sub_c + Del_c + Ins_c}{N P_c}$$

- To compensate for non-uniform prior (P), we can use WPER.
- Analogous to *weighted accuracy*, $w \propto 1/P$.

UPER & WPER vs Prior



UPER & WPER vs Prior



- Weighting flattens PER vs Prior
- Vowels still have the largest PER

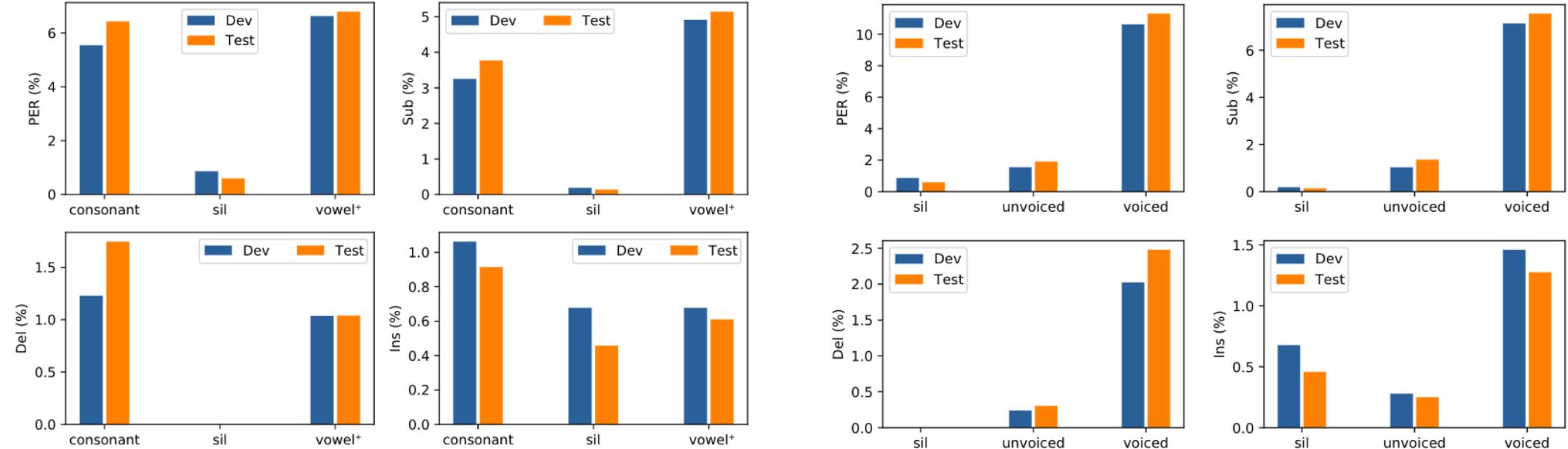
Wrap-up

- **Goal:** Break down PER, using broad phonetic classes
- **Findings:**
 - Largest PER share belongs to Vowels
 - Training dynamics is similar for all, except Silence
 - Uni → bi-directional seq. modelling is least useful for Silence
 - GMM → DNN is most useful for Silence
 - **Most/Least** robust classes to noise (NTIMIT) → **Vowels/Fricatives**
 - Transfer learning or pre-training are useful for all, except Silence
 - Consonants benefit more than Vowels from more data

That's It!

- Thank you!
- Q&A
- Appendices
 - A1) Sub/Del/Ins of C/V⁺ & V/U
 - A2) Sub/Del/Ins Dynamics
 - A3) Transfer Learning's Effect on Errors & Dynamics
 - A4) t-SNE vs LDA (wav2vec)

(A1) Sub/Del/Ins Errors for C/V⁺ & V/U



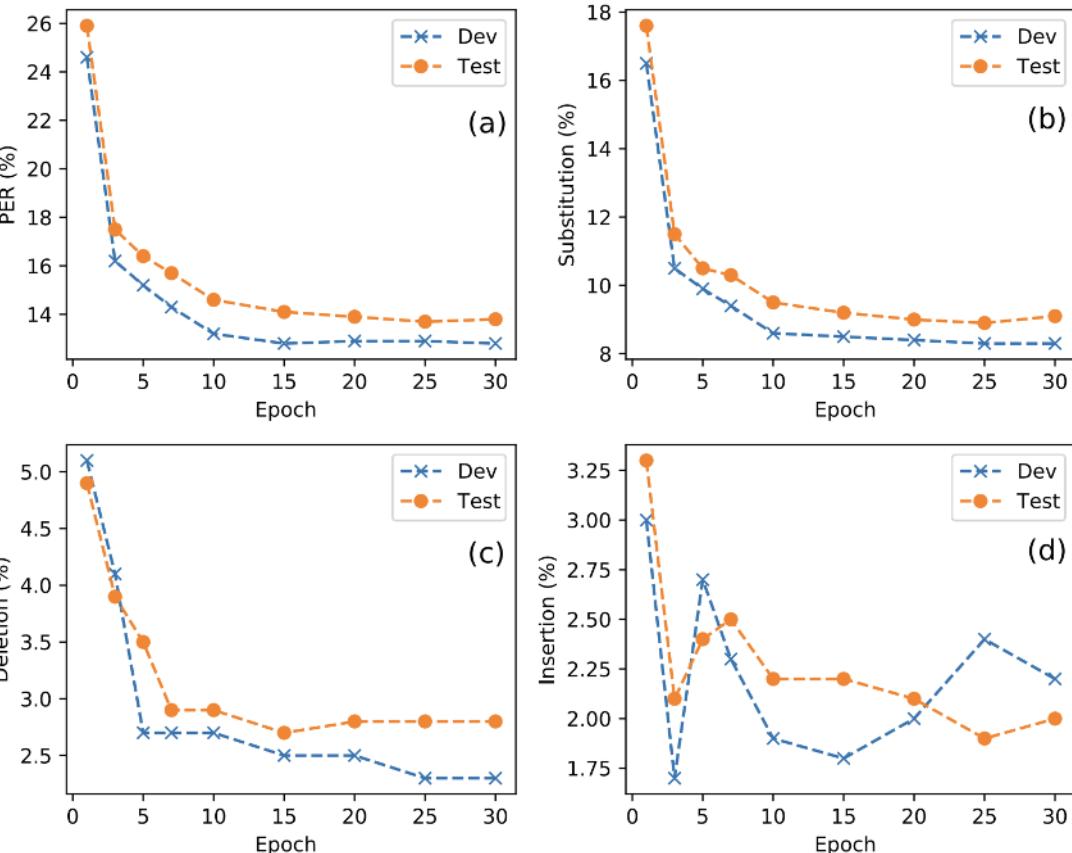
- Vowels have larger Sub.
- Consonants have a larger Del & Ins.

Errors' Largest share belongs to Voiced.

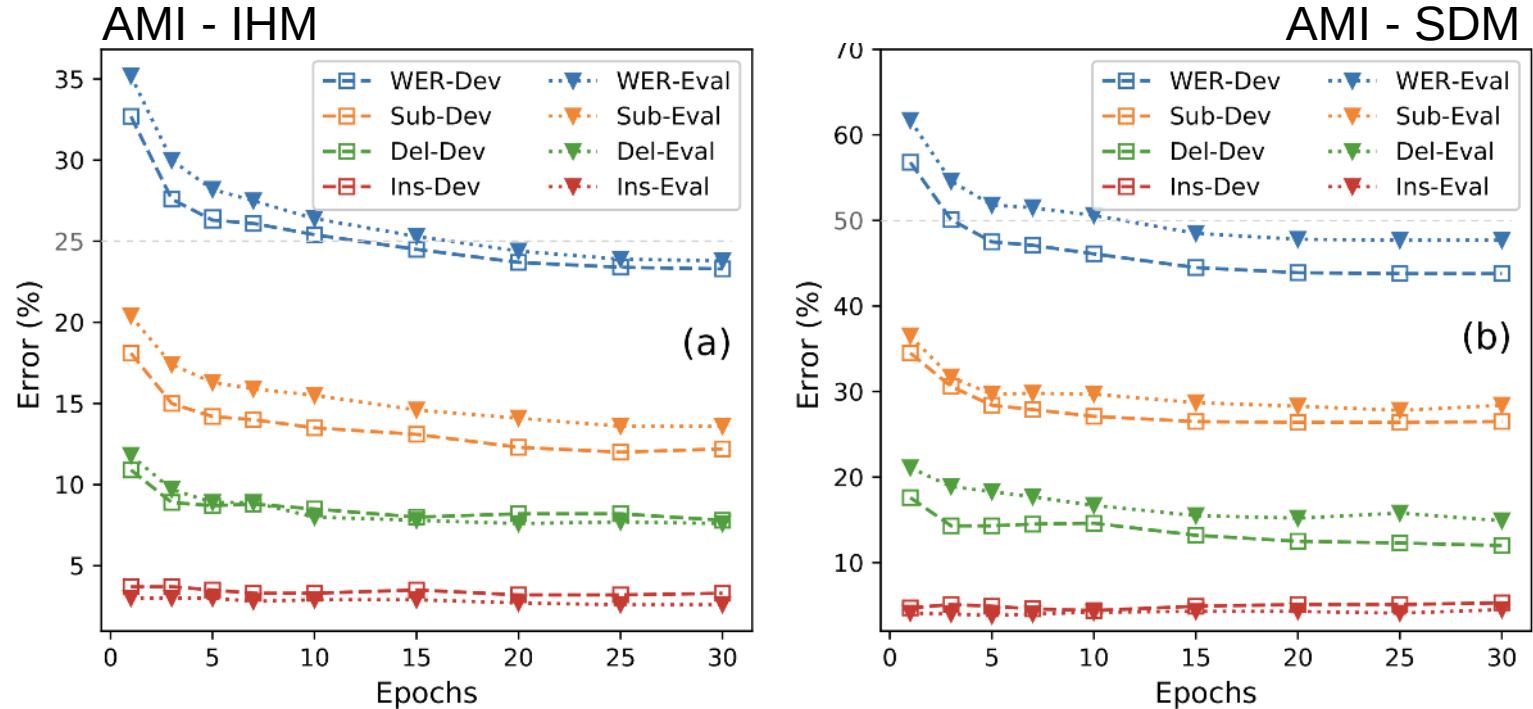
(A2) Sub/Del/Ins Dynamics

Strongest Correlation: PER & Sub

- Sub converges slowly
- Del converges fast
- Ins oscillates



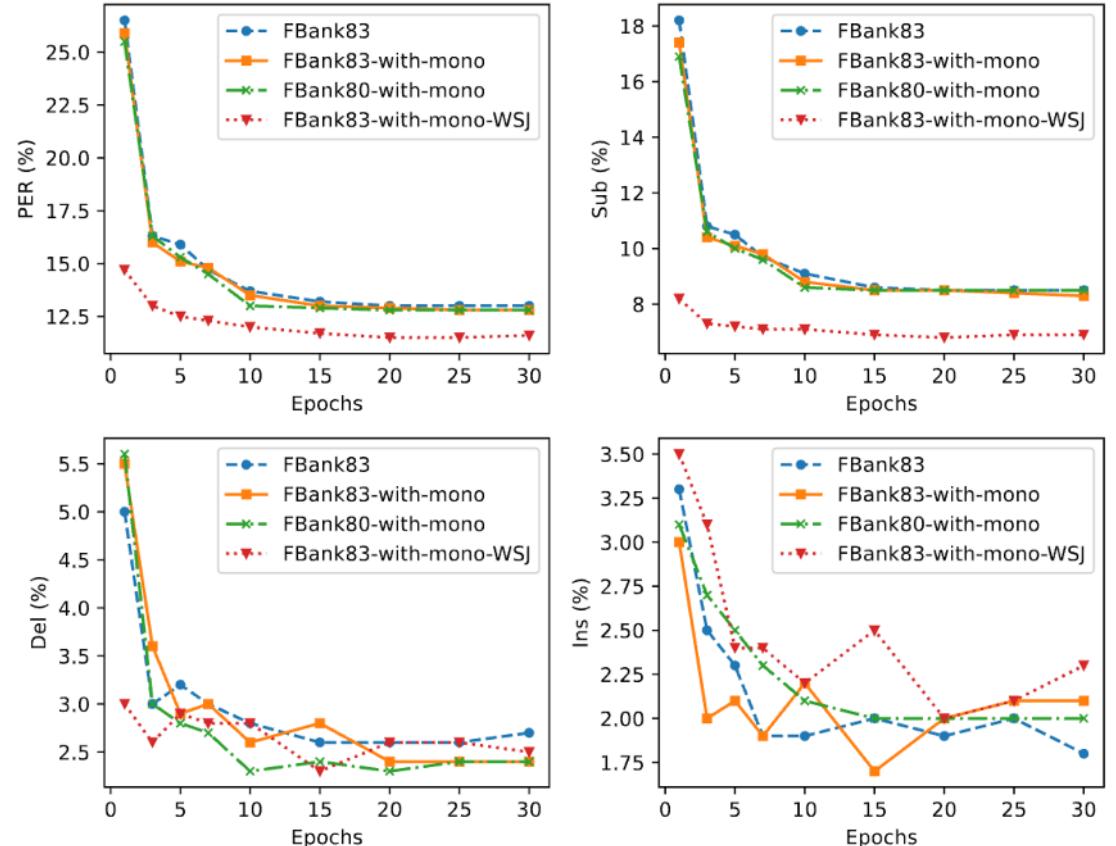
(A2) Similar observations in [67]



(Fig. 15 in) E. Loweimi, Z. Yue, P. Bell, S. Renals, and Z. Cvetkovic, "Multi-stream Acoustic Modelling using Raw Real and Imaginary Parts of the Fourier Transform", in IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 31, pp. 876-890, 2023, doi: 10.1109/TASLP.2023.3237167.

(A3) TF's Effect on Errors & Dynamics

- Dynamic range becomes smaller.
- Mostly improves Sub error.
- Slightly makes Ins worse.



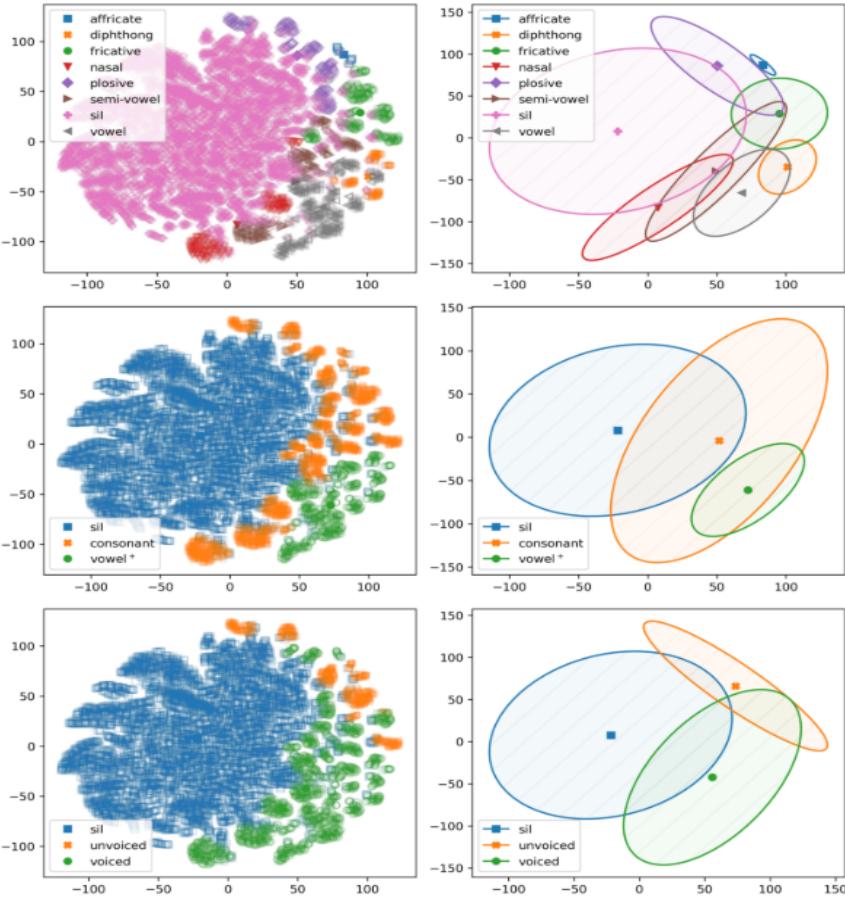
* TF: Transfer Learning

Loweimi et al

A3/4

(A4) t-SNE vs LDA

t-SNE



LDA

