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

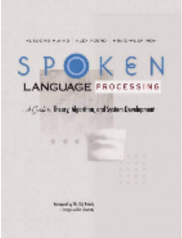
- Effect of Various Factors

Analysis beyond PER ...

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

$$PER = \sum_{c} PER_c$$

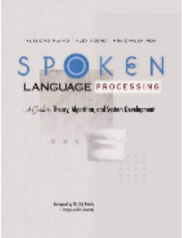
Three BPCs considered ...



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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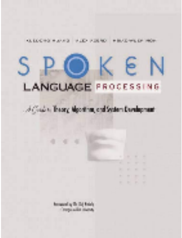
(A) *8-class*

(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 ...



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(B) *3-class*

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Unvoiced	ch f k p s sh t th

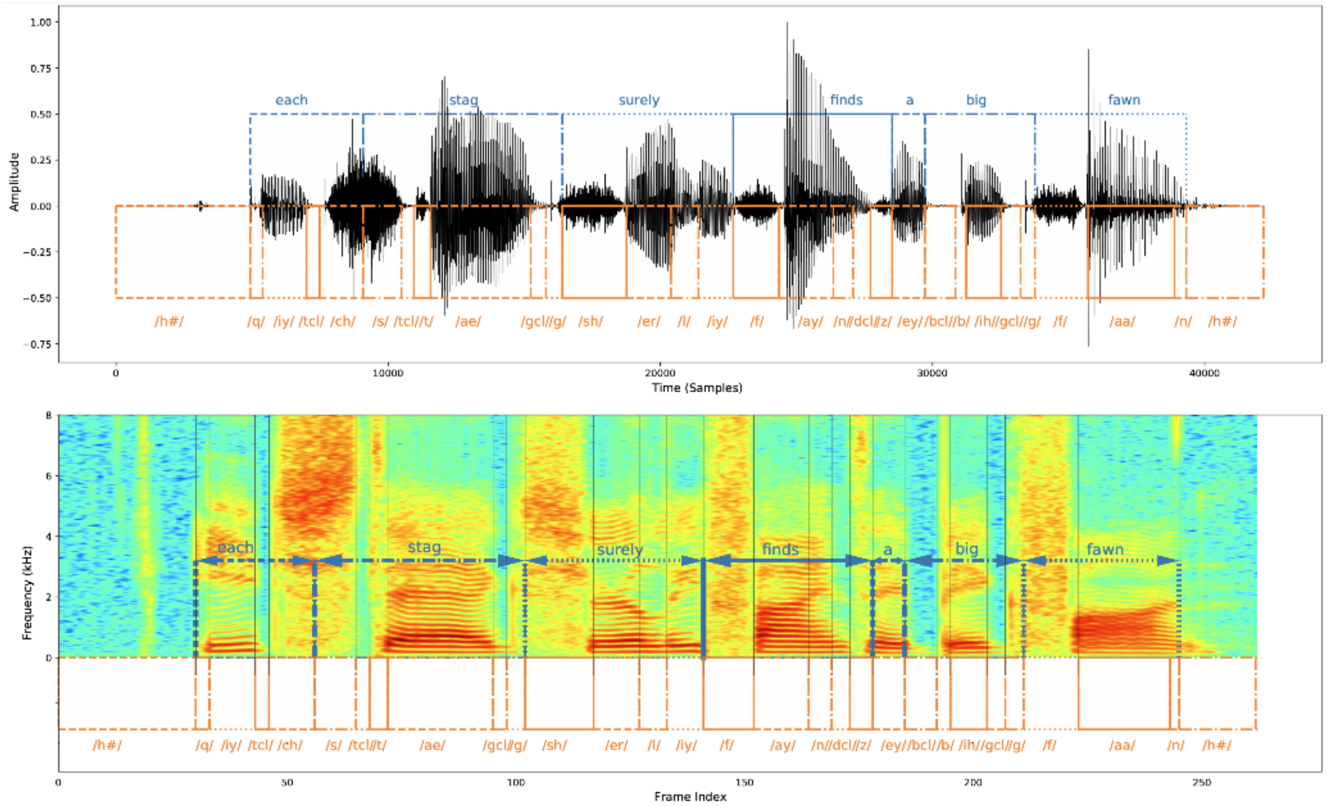
(C) *3-class*

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

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

Phonetic Transcription

Data: TIMIT



- Original Transcription: **61** phones

Phonetic Transcription

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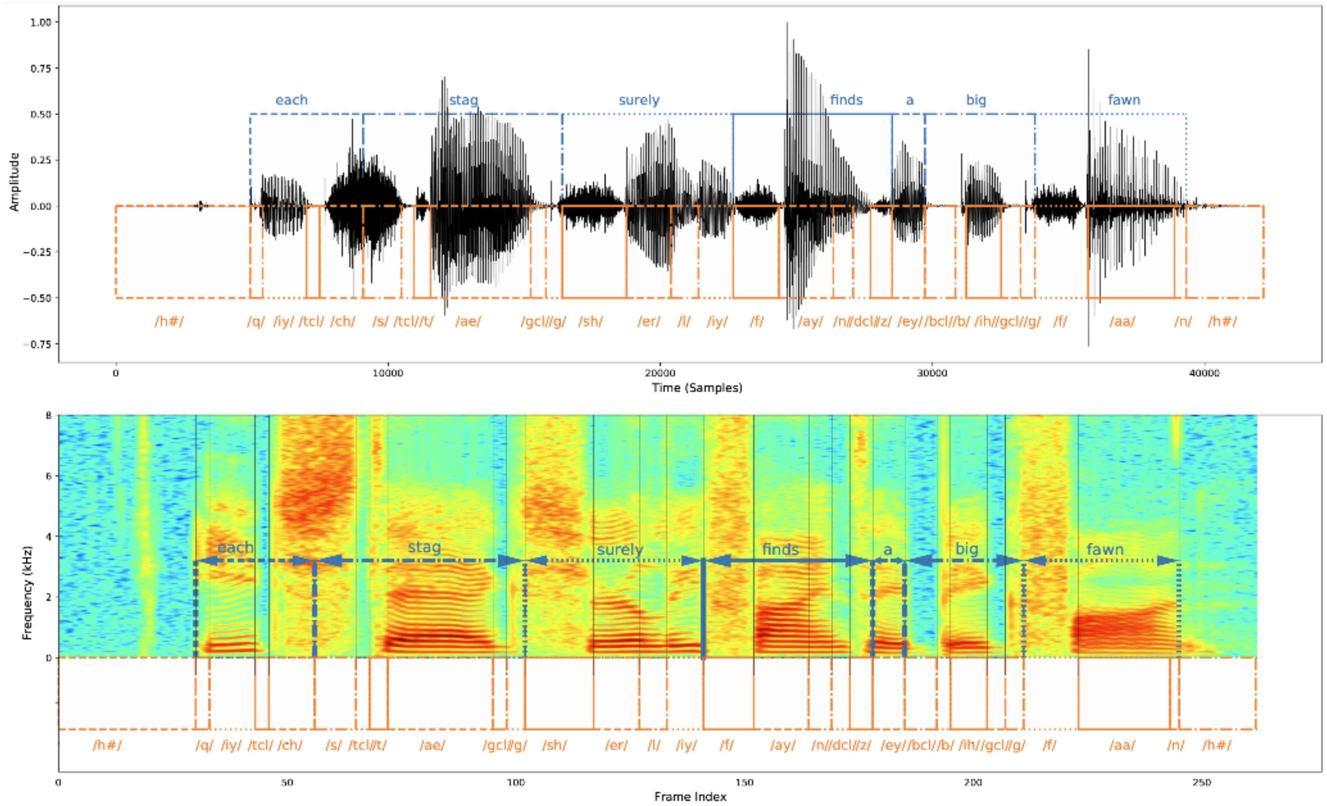


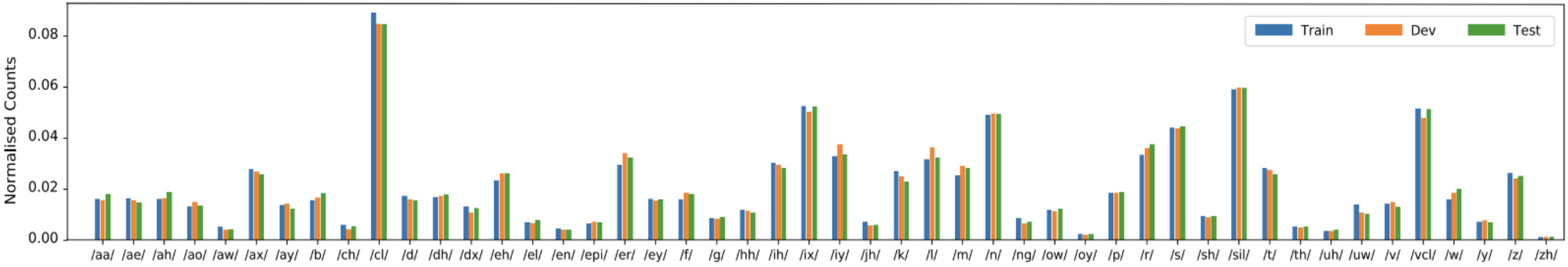
- Original Transcription: **61** phones → Train w/ **48** phones → Decode w/ **39** phones
- Mapping (Kaldi): phones.60-48-39.map

Phonetic Distribution

<u>Data: TIMIT</u>

Probability Mass Function (PMF)

48 phones



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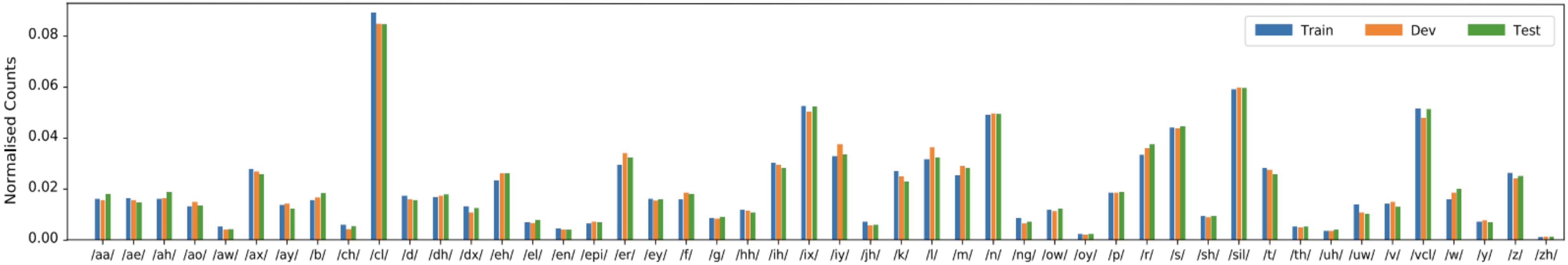


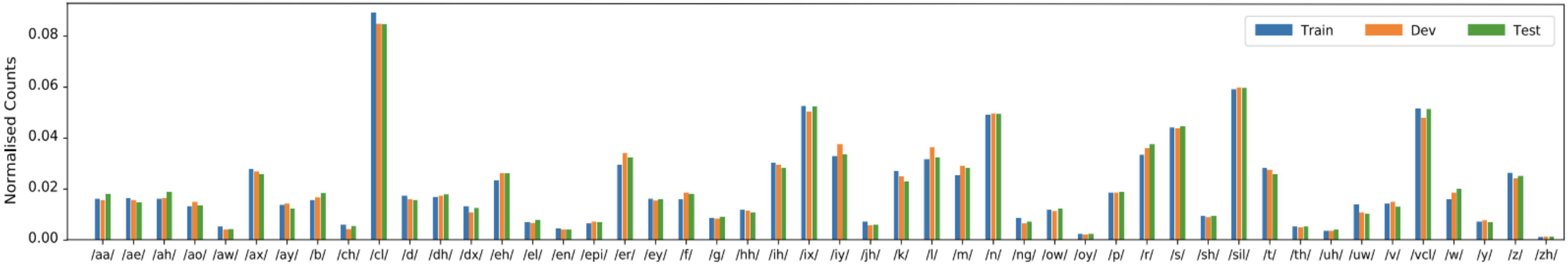
PMF of standard Train/Dev/Test sets is **identical**.

Phonetic Distribution

Data: TIMIT

Probability Mass Function (PMF)

48 phones

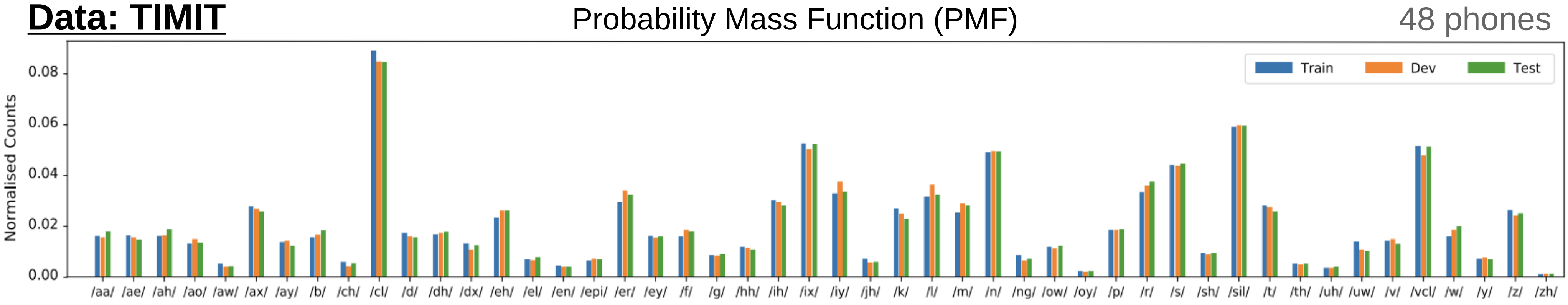


PMF of standard Train/Dev/Test sets is **identical**.

PMF is **not uniform**

Phonetic Distribution

<u>Data: TIMIT</u>



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

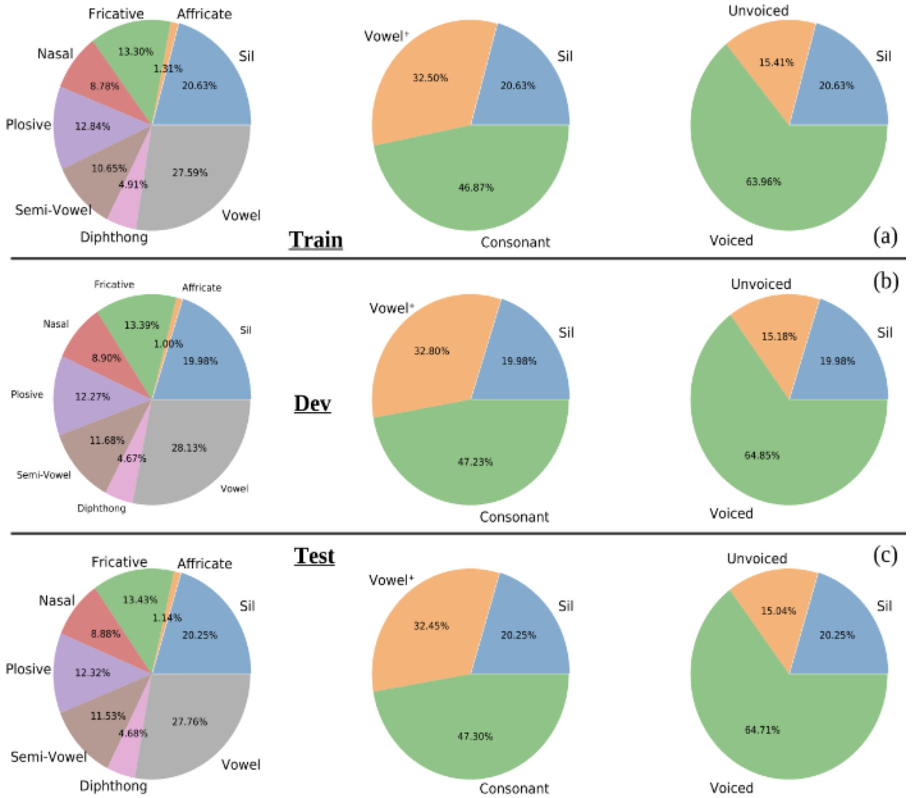
PMF is **not uniform** … not a shortcoming … characteristic of natural languages, studied in *Quantal Theory, Adaptive Dispersion, etc*.

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%



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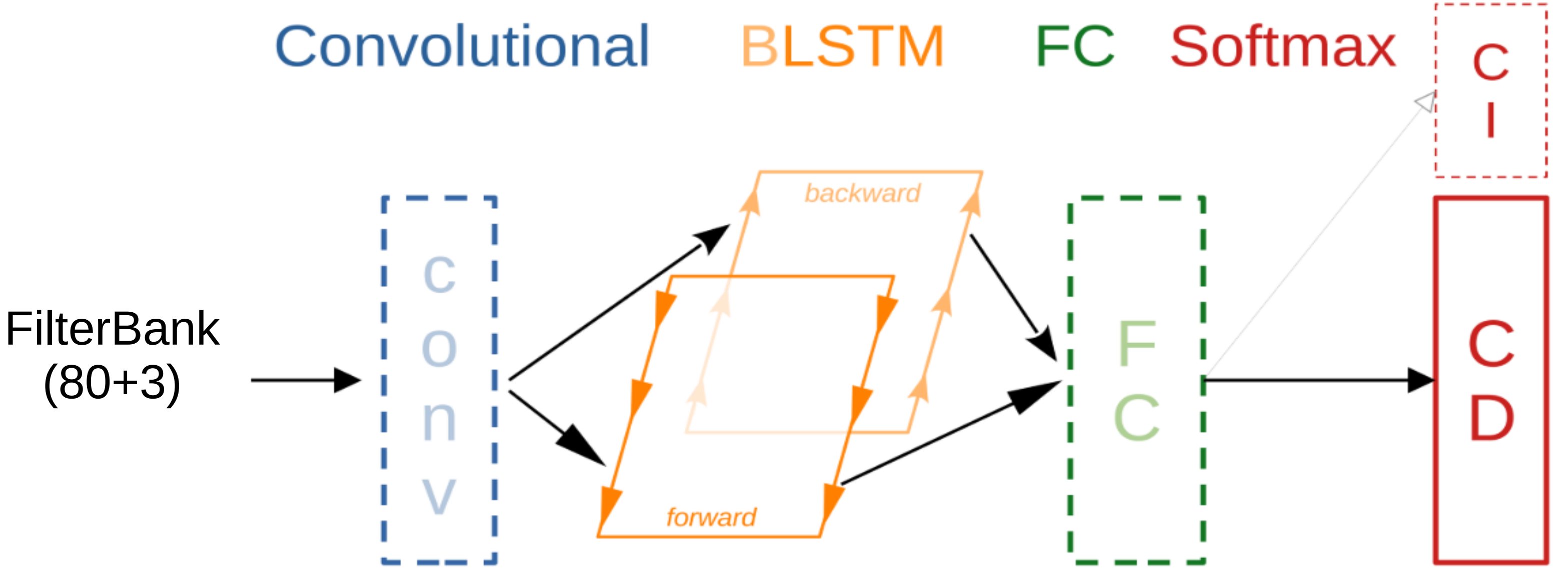
Baseline Arch. $C_iL_jF_k$



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

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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

Chosen Baseline →

w/o F_0 →

w/o CI →

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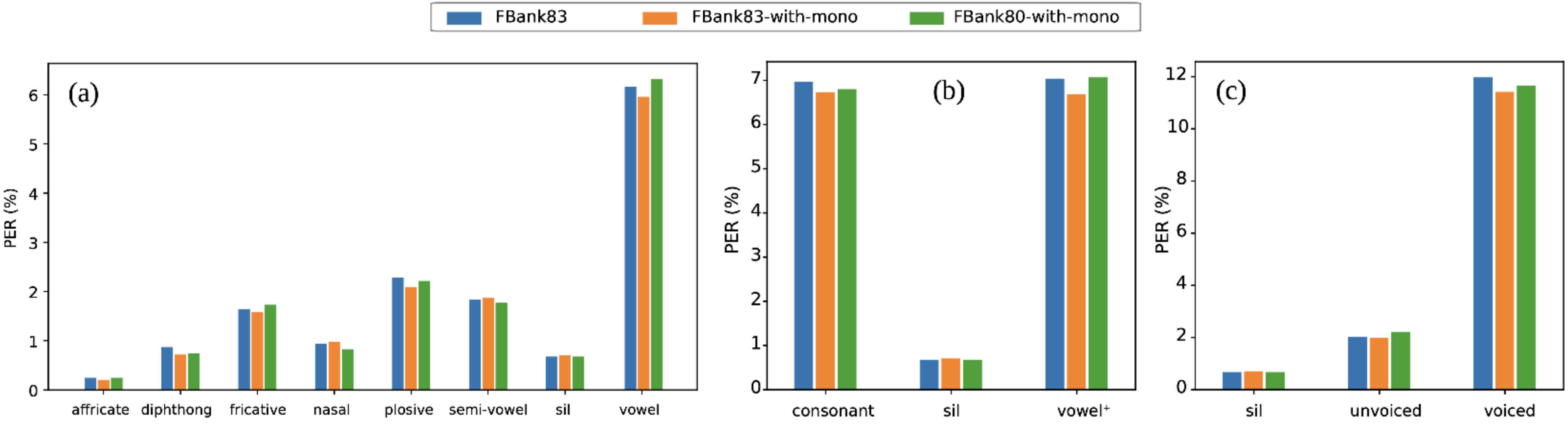
Analysis beyond PER



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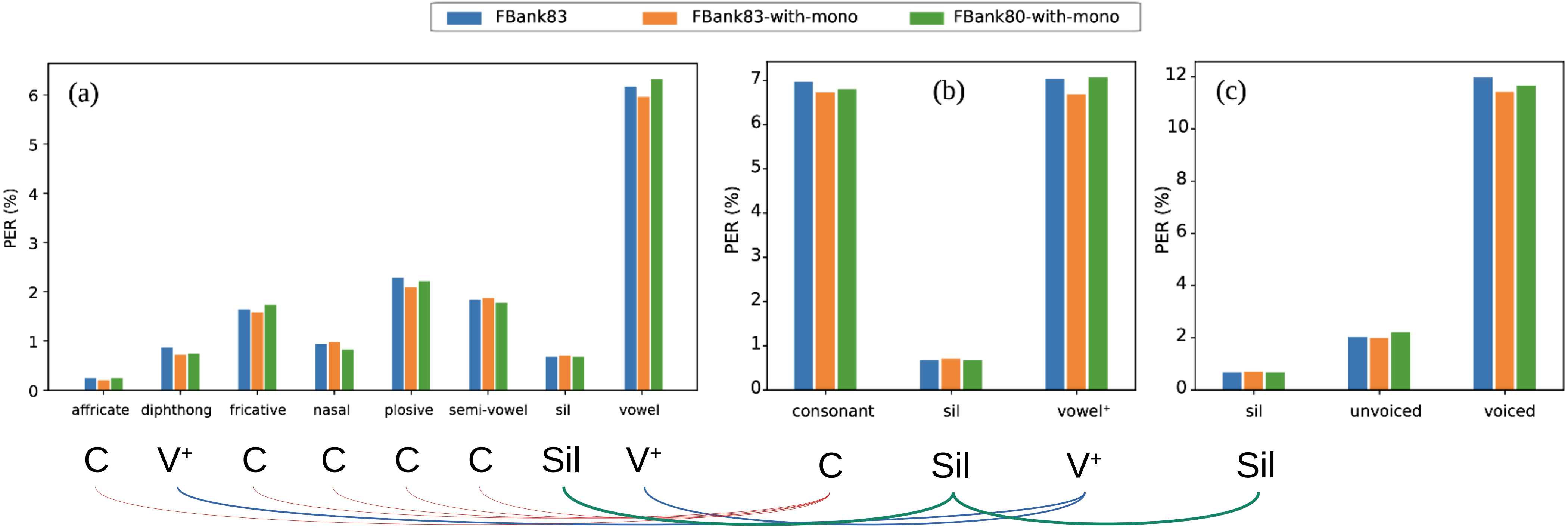

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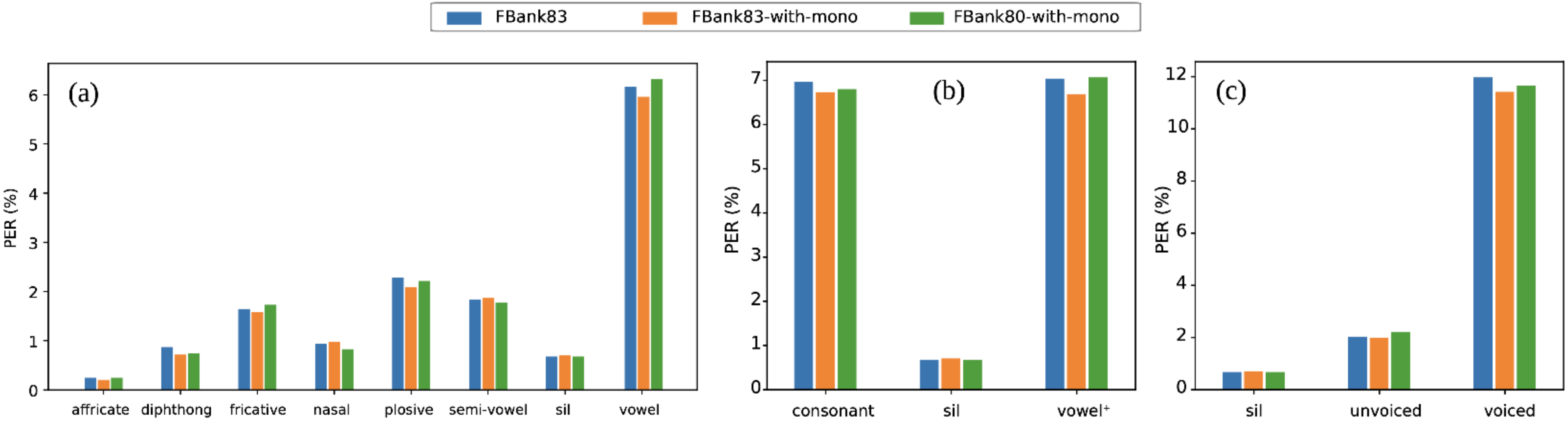
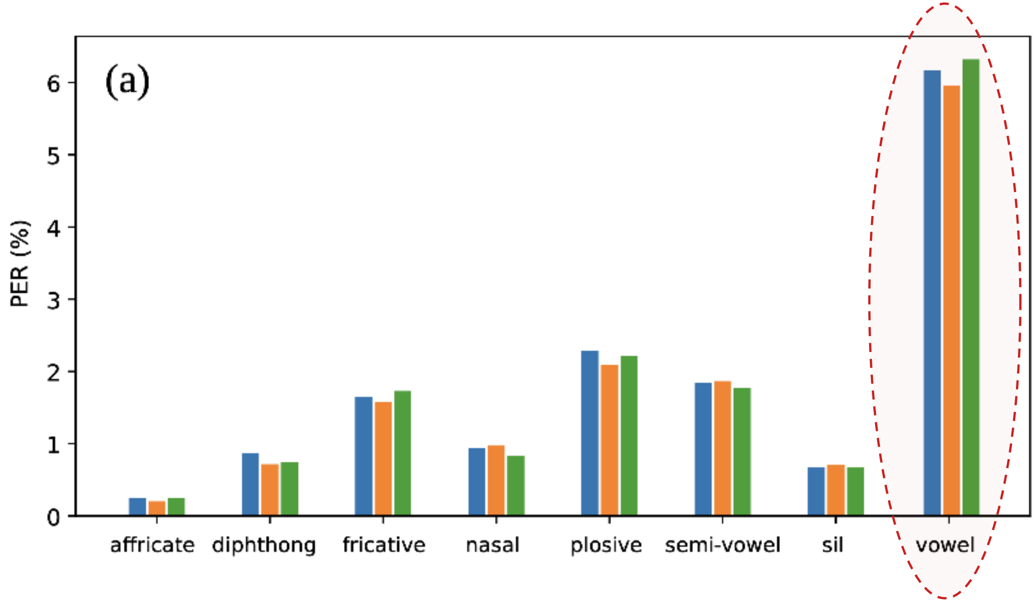


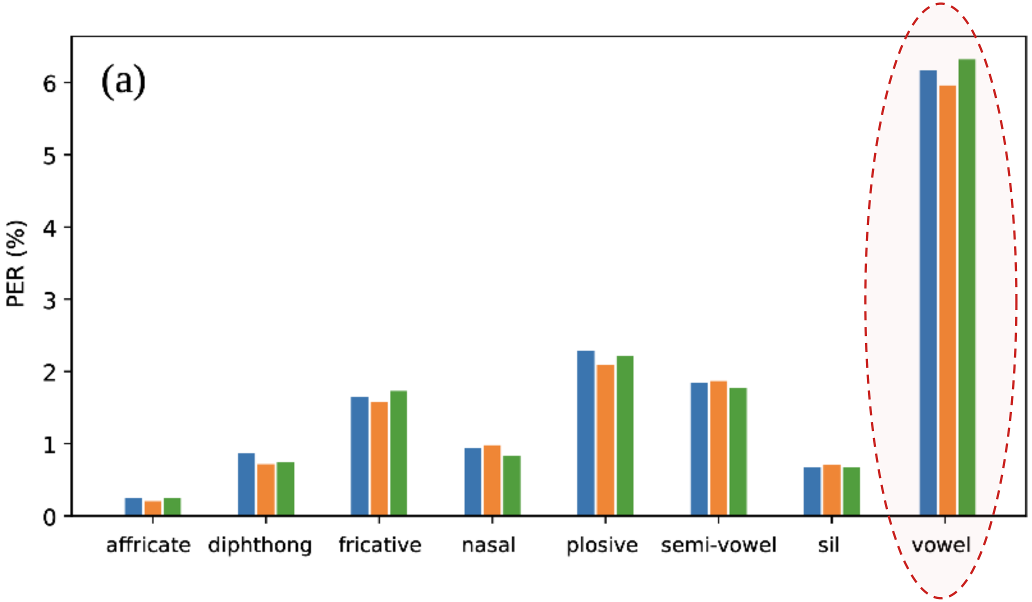
Minor gains after adding F_0 features & regularisation with CI.

Largest PER → Vowels



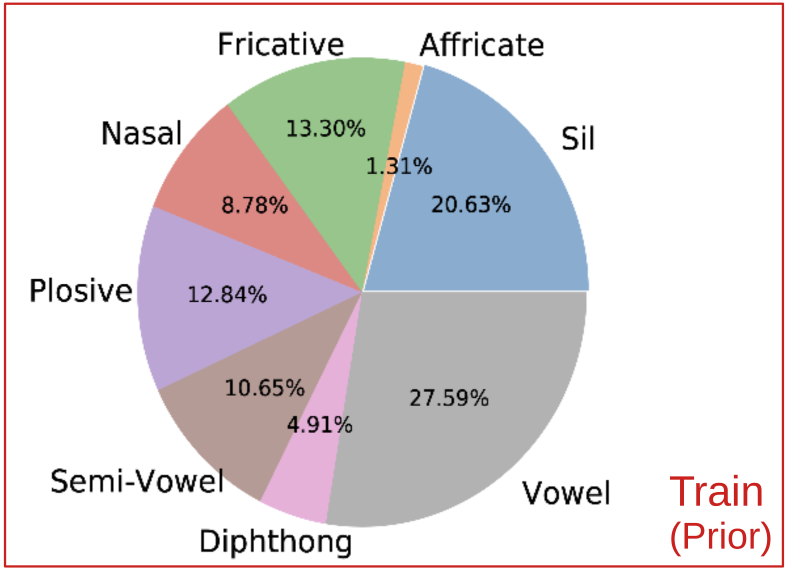
Largest PER → Vowels

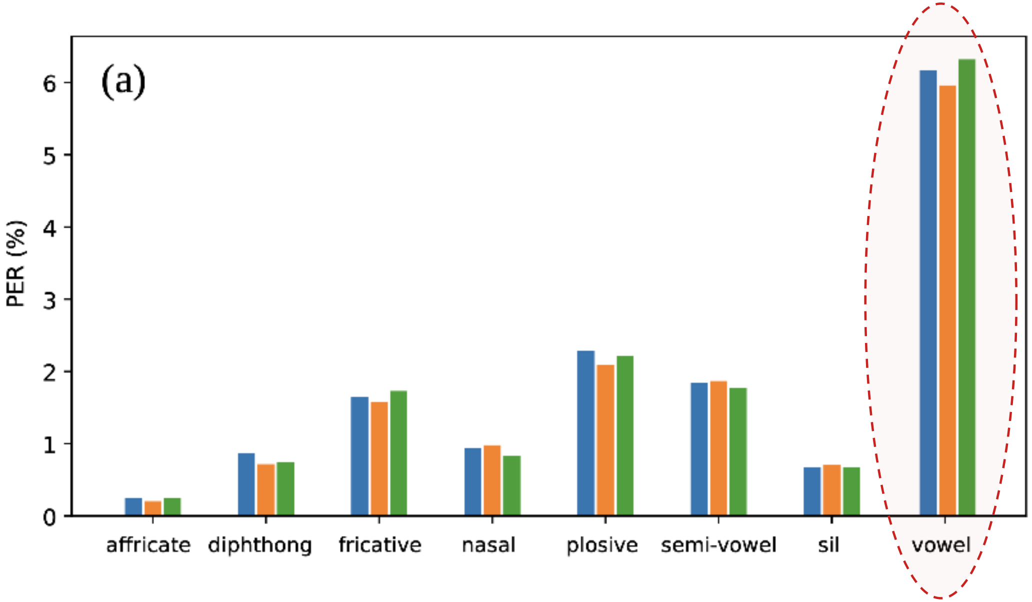
- **Questions:**
  - Training data amount?
  - TIMIT-specific?
  - Why?



Largest PER → Vowels

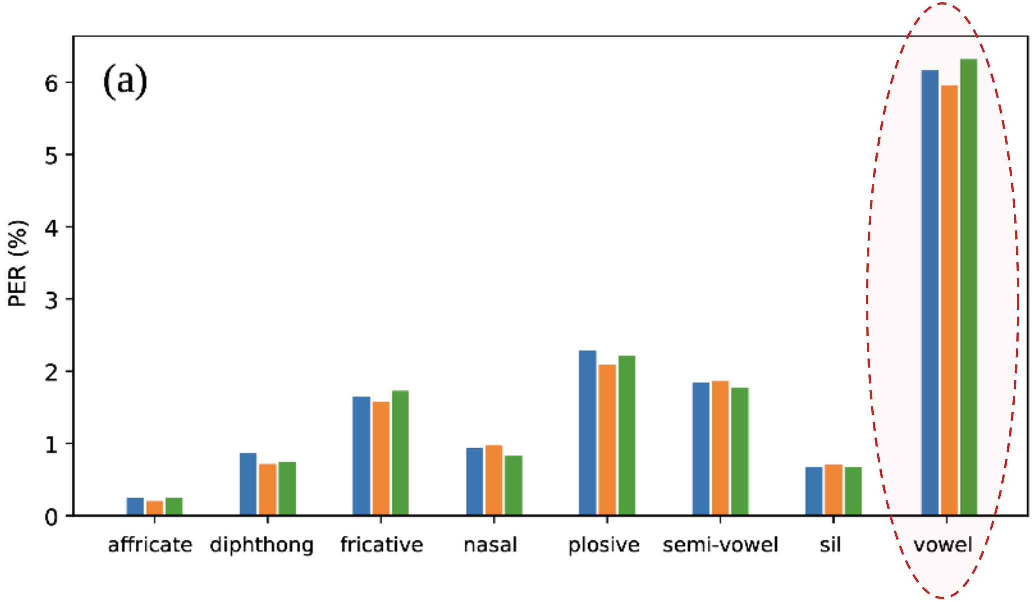
- **Q1**: Training data amount?





Largest PER → Vowels

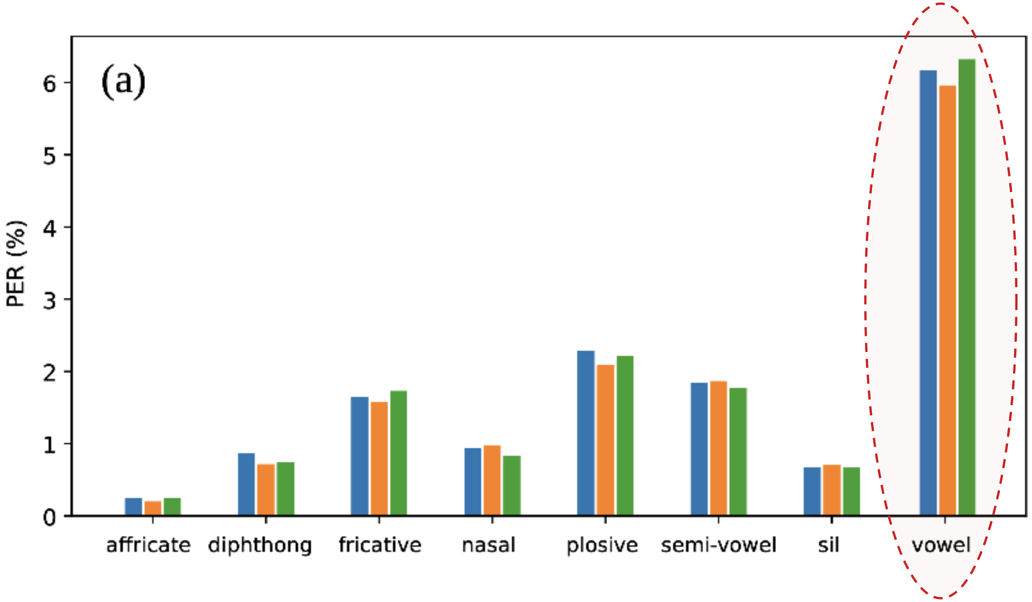
- **Q2:** TIMIT-specific?
  - Similar observation in human phone recognition [69]



Largest PER → Vowels

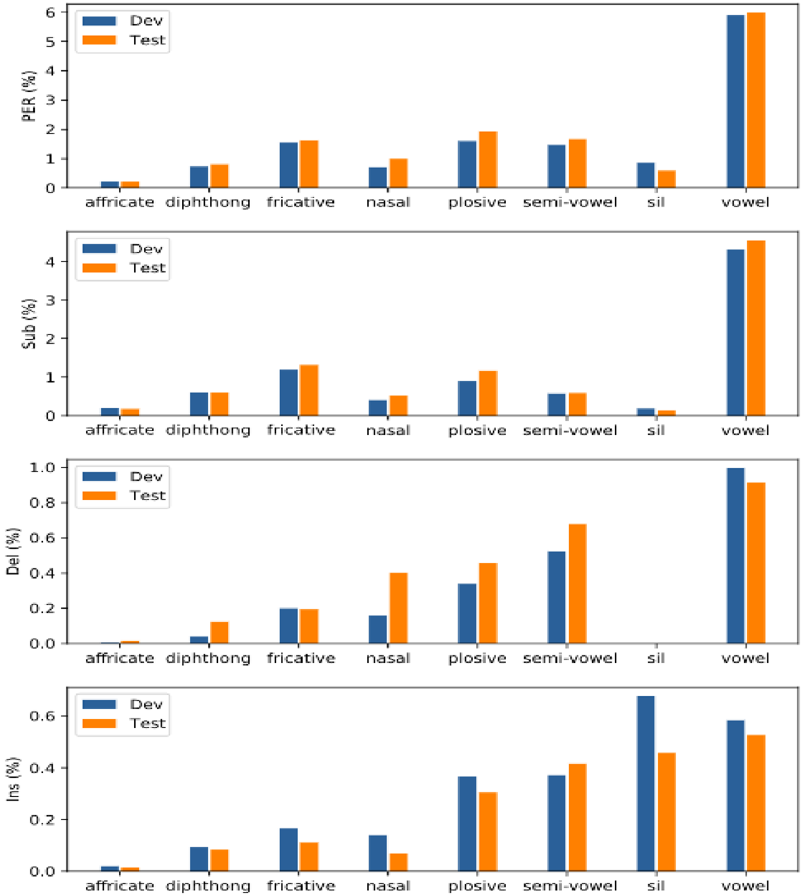
- **Q2:** TIMIT-specific?
  - Similar observation in human phone recognition [69]

- **Q3**: Why?

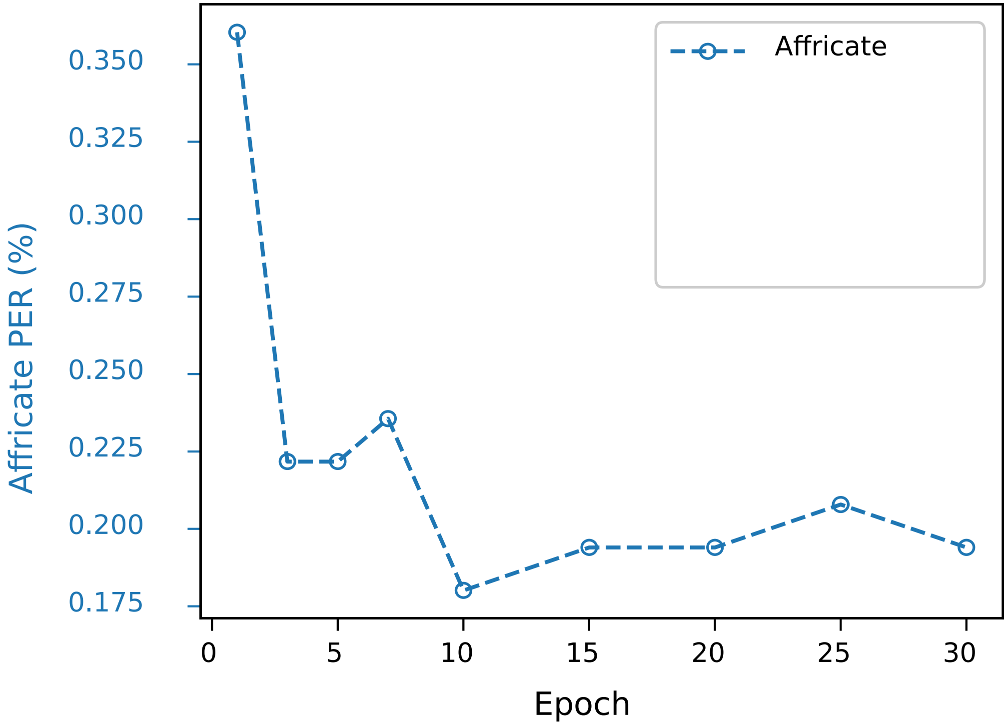


Sub/Del/Ins per BPC

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



Training Dynamics (1)



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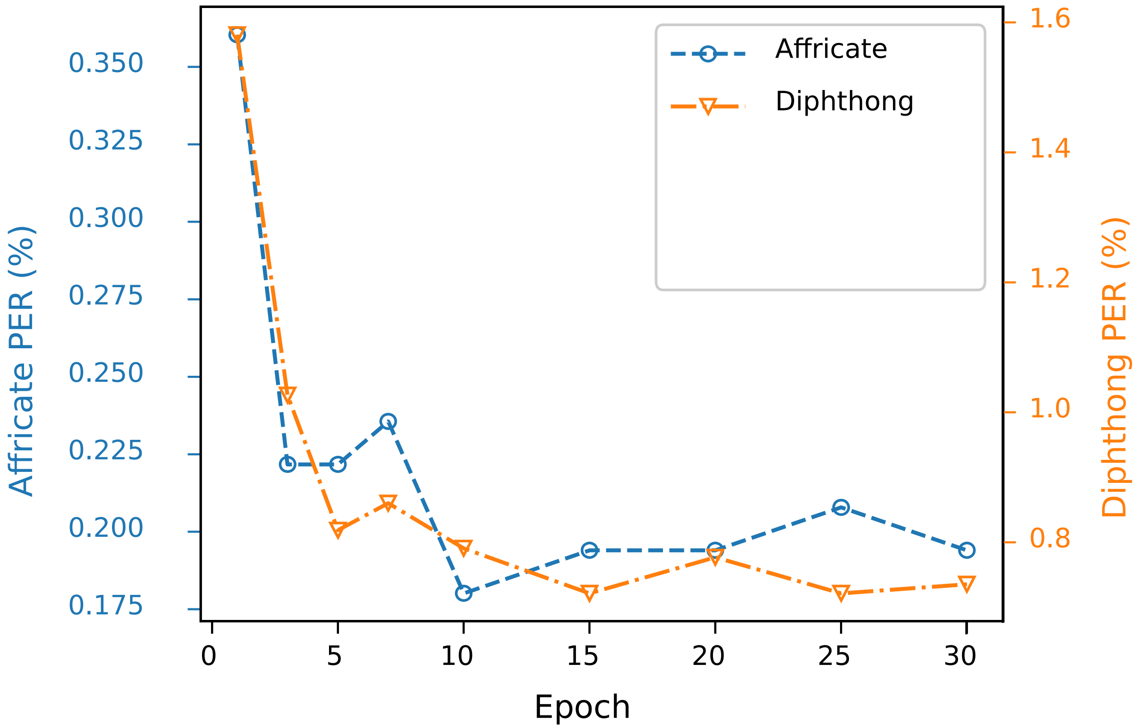

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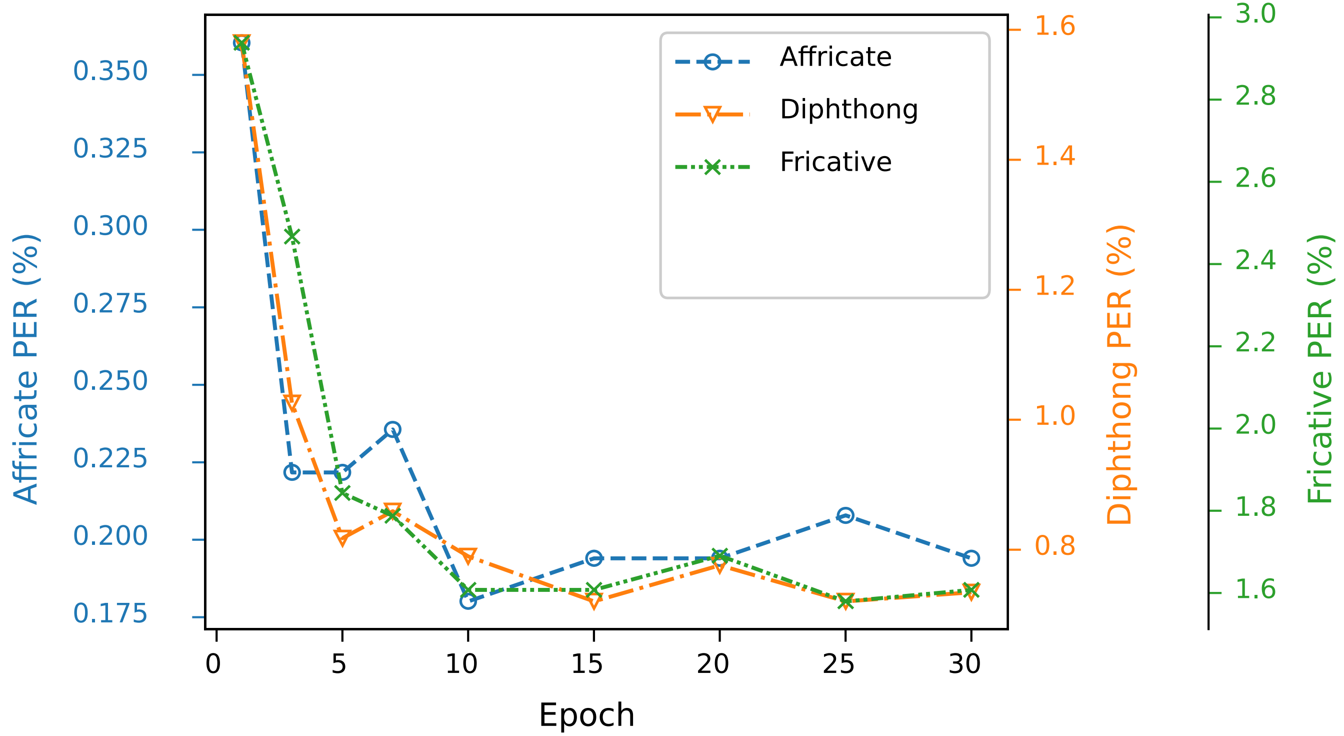

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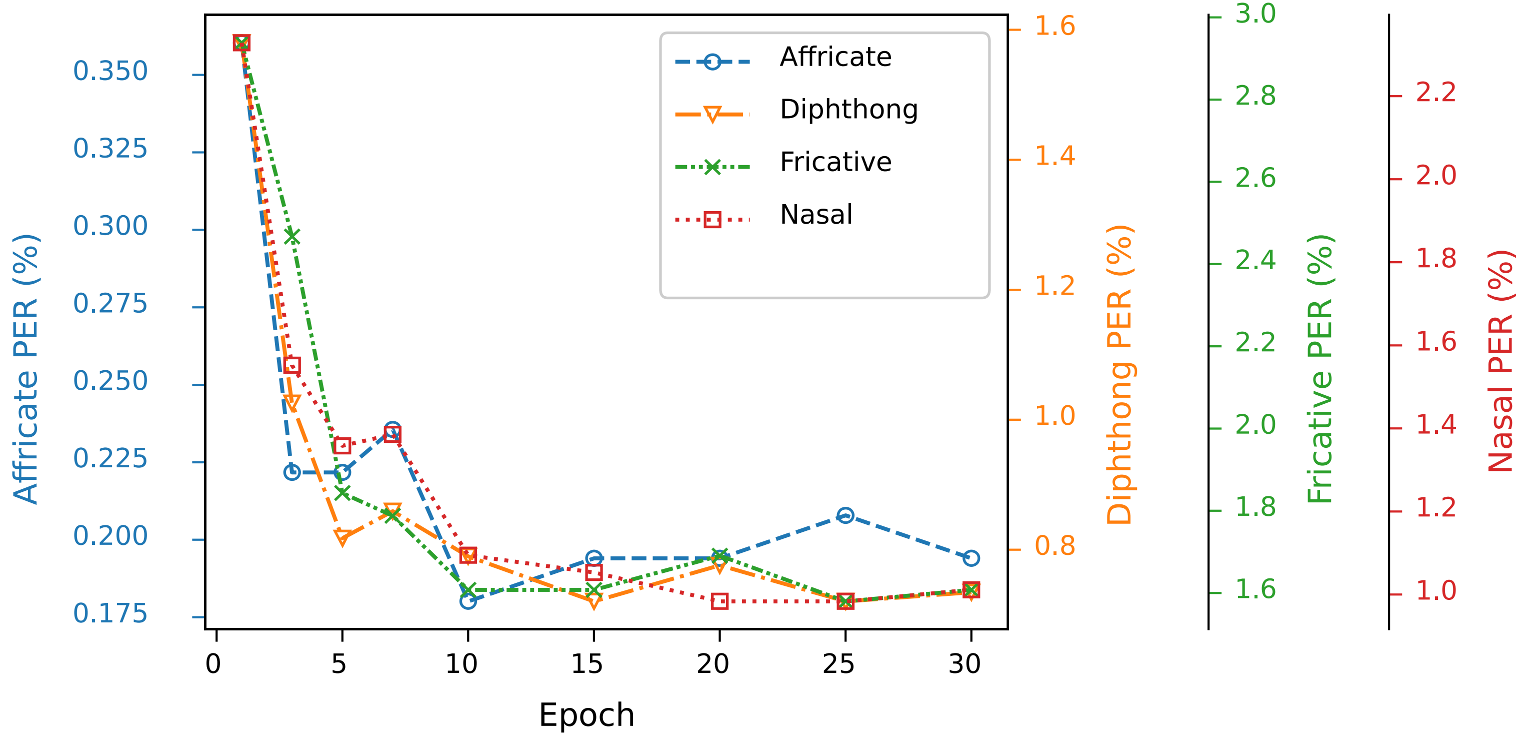

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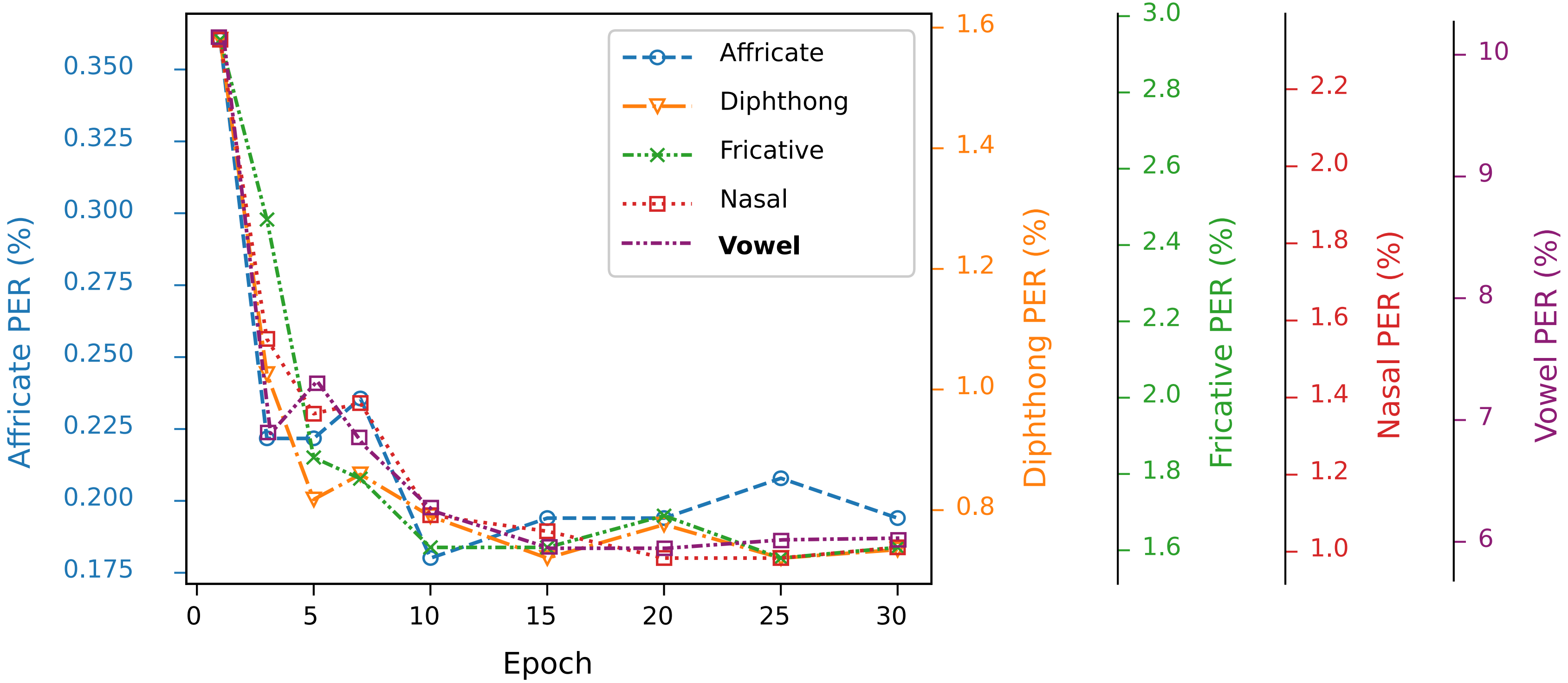
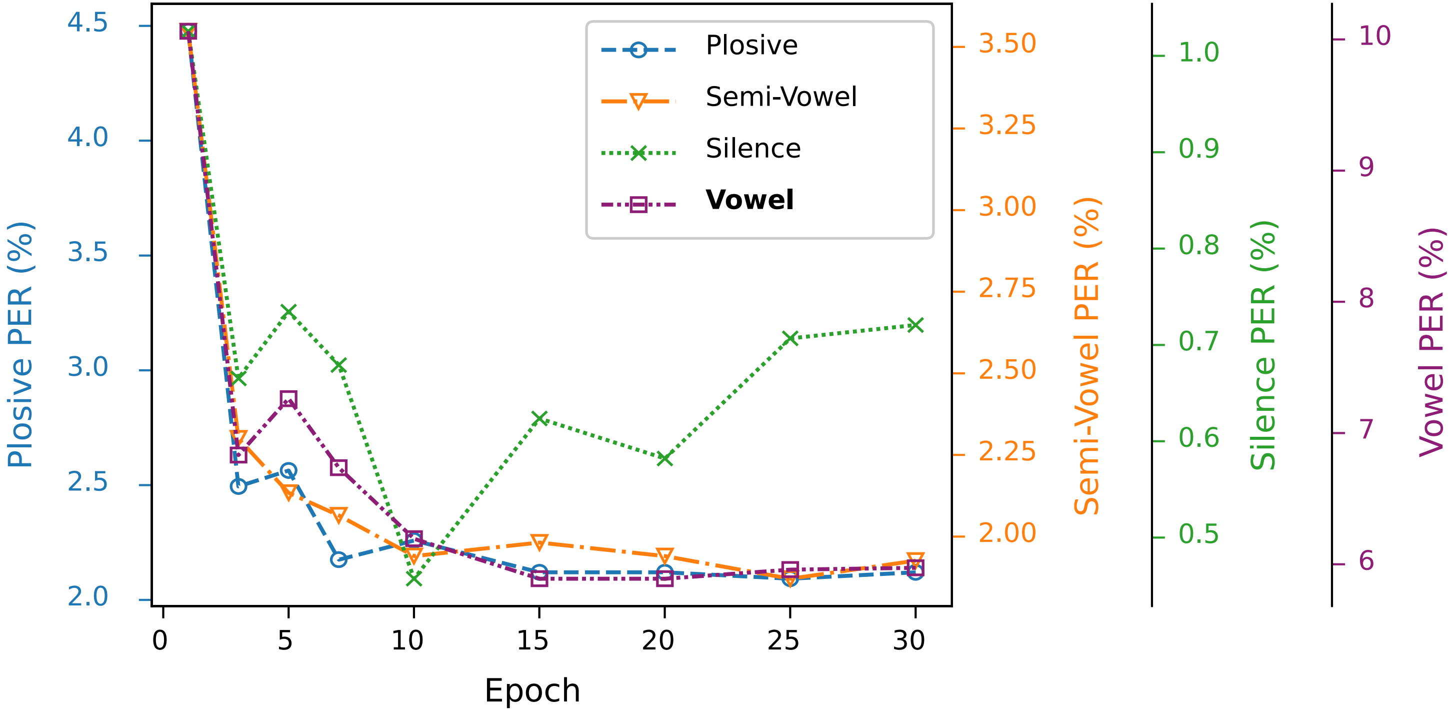
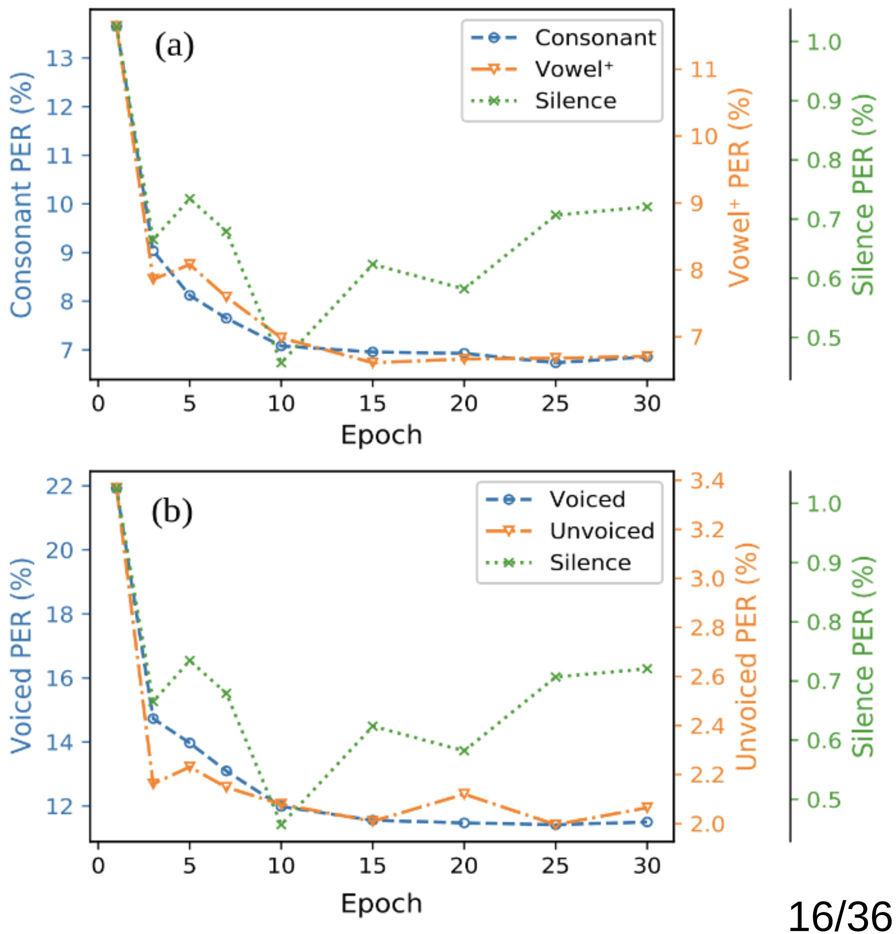


Training Dynamics (2)



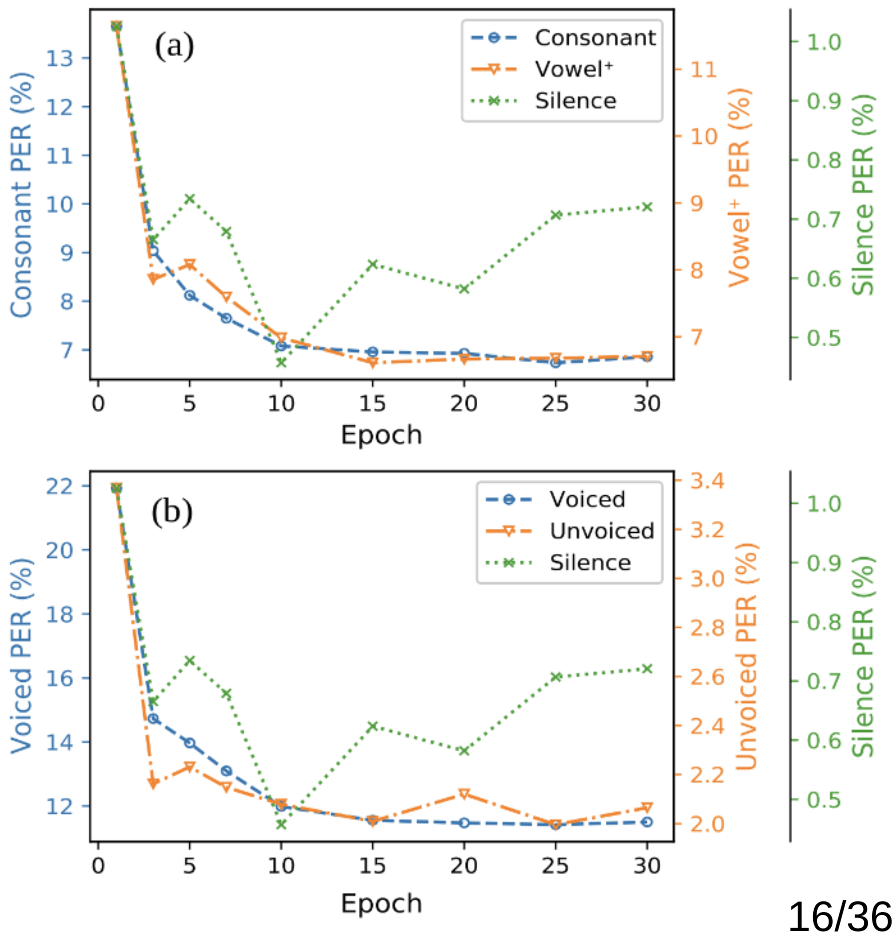
Training Dynamics (3)



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.

(a)

True Label \ Predicted 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

(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**

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Confusion Matrices

Fricatives are MCW **Fricatives** & Plosives.

Semi-vowels are MCW **Vowels** & Semi-vowels.

Silence is MCW **Fricatives** & Nasals.

⋮

MCW: mostly confused with

True Label / Predicted Label

	aff	dip	fri	nas	plo	sem	sil	vow
aff	**10**	0	6	0	4	0	0	0
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Predicted Label

(a)

(b)

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

(c)

	sil	unv	voi
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vow^{+}: vow+dip

sil: silence
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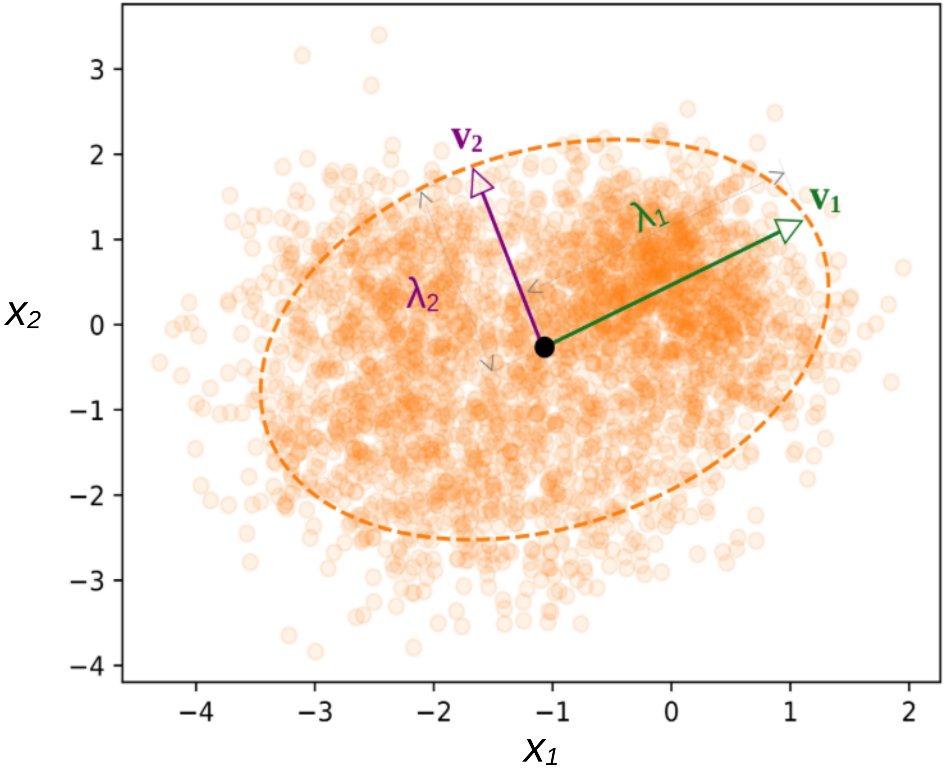
voi: voiced

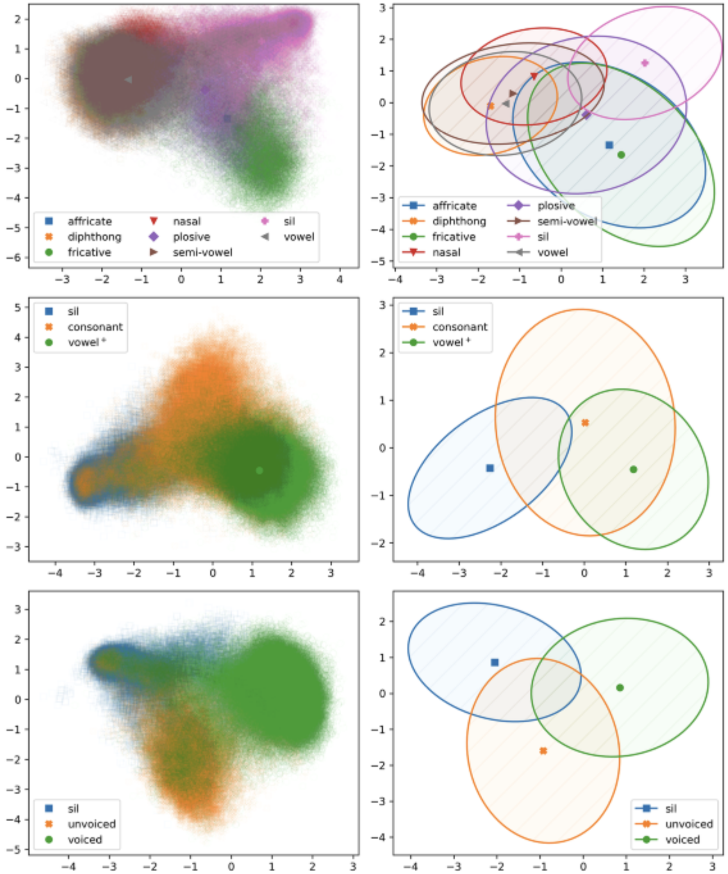
Scatter Plot in 2D

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



* LDA: Linear Discriminant Analysis

Scatter Plots



Acoustic Feature

→ Acoustic Model →

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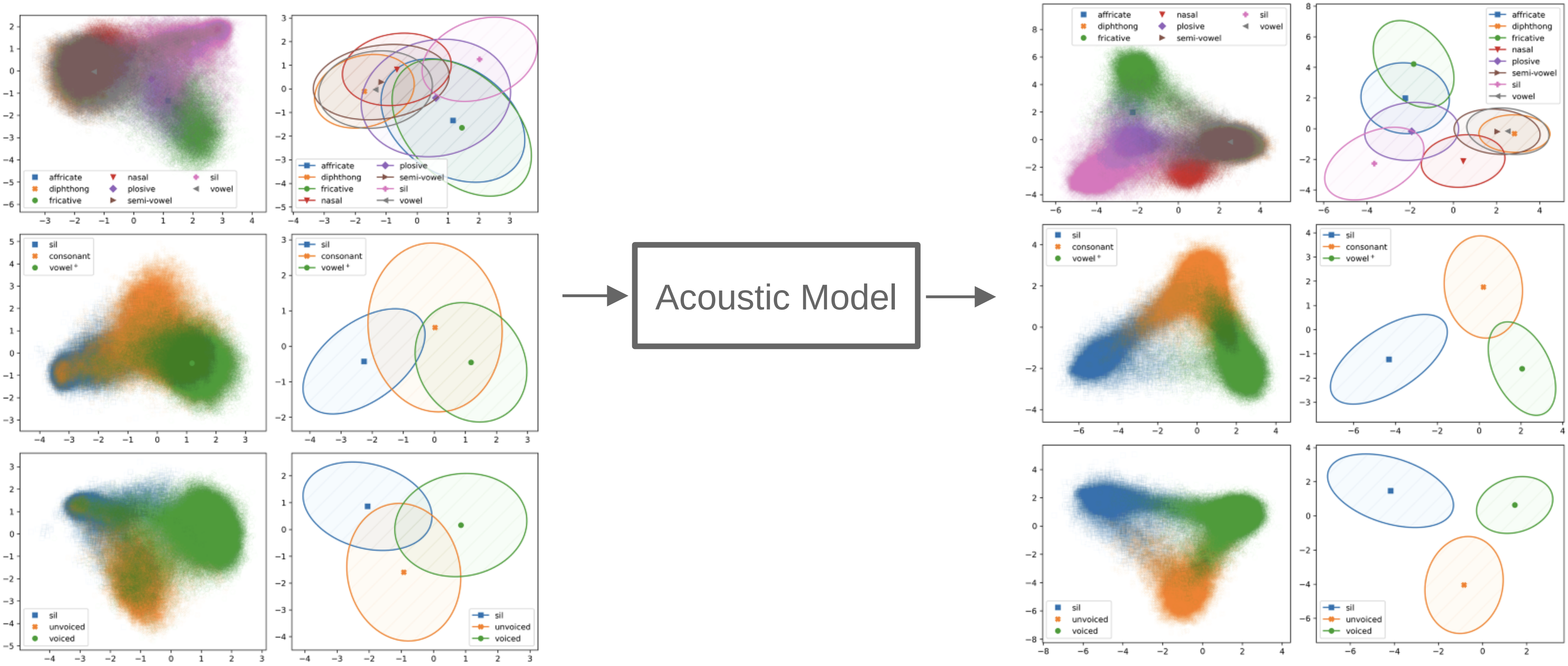
Scatter Plots



Acoustic Feature

Logit (Baseline)

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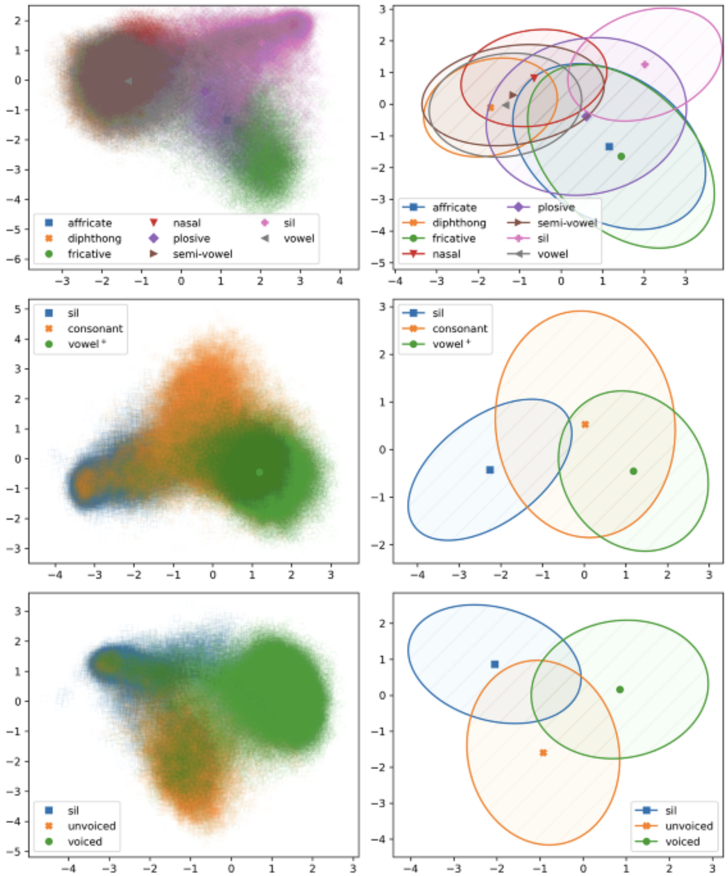
Scatter Plots



Acoustic Feature

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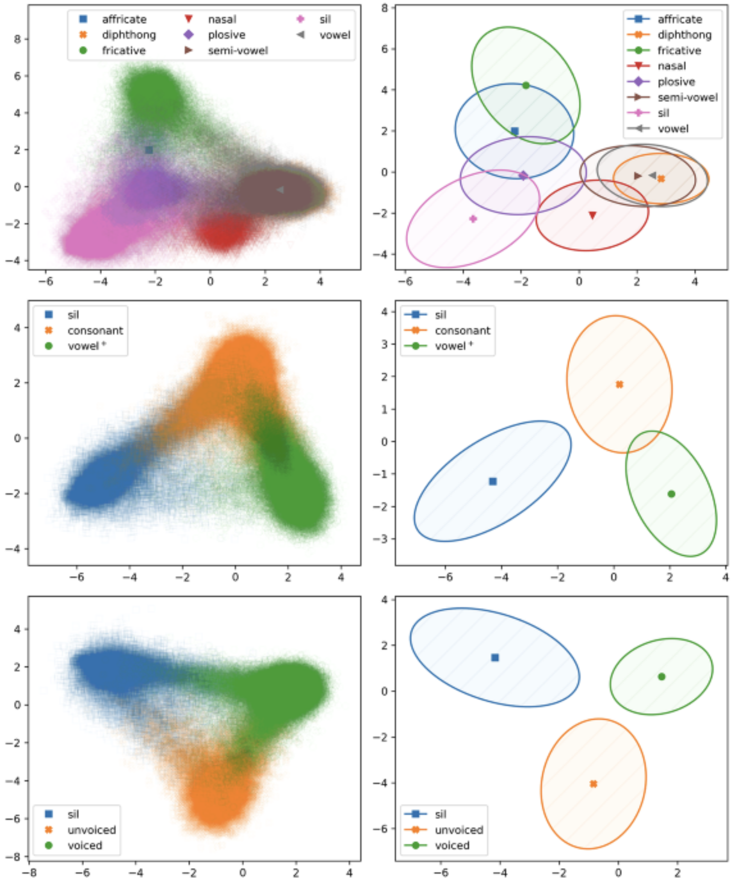


Logit (Baseline)

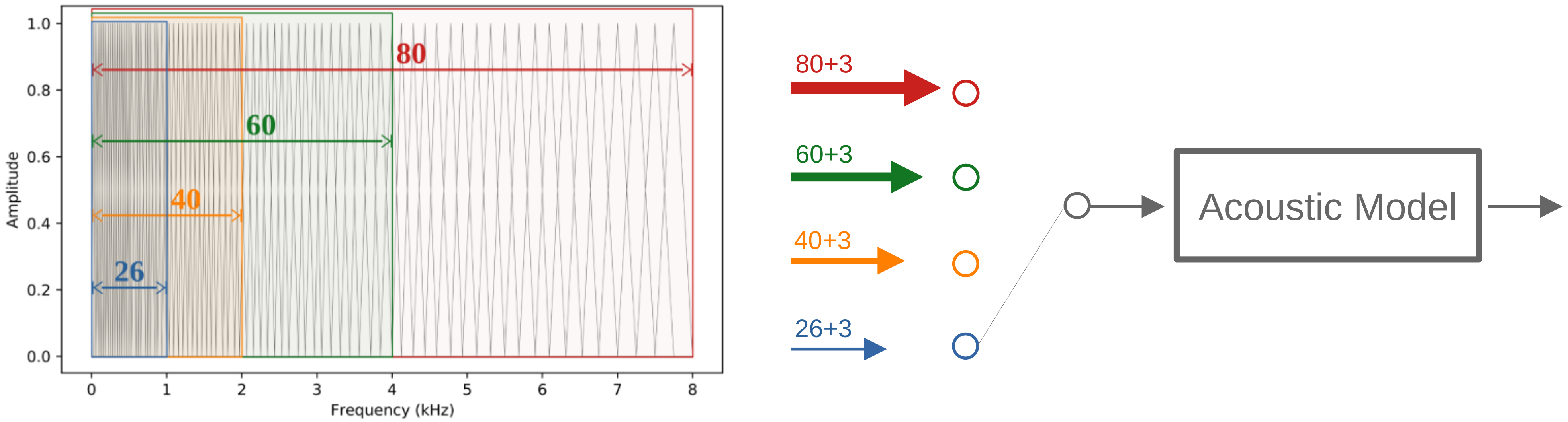
✔ → More distinct clusters →

✗ Scatter plots do not perfectly justify confusions

Various Systems

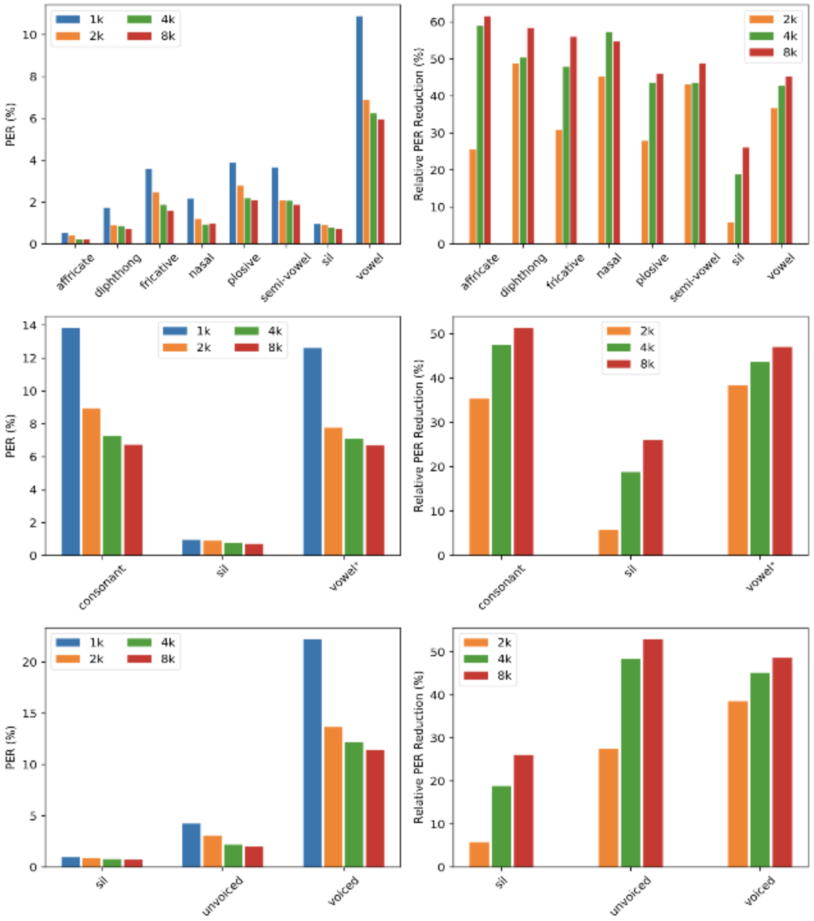
Model	Task	Architecture	Dev	Test
Baseline	TIMIT	L4-Hybrid	12.8	14.1
Subband-1k	TIMIT	L4-Hybrid	25.1	27.3
Subband-2k	TIMIT	L4-Hybrid	16.8	17.6
Subband-4k	TIMIT	L4-Hybrid	13.4	15.0
UniLSTM	TIMIT	L4-Hybrid	15.9	17.8
Baseline	NTIMIT	L4-Hybrid	19.2	20.1
GMM-HMM	TIMIT	SAT-MLLT-LDA	20.5	21.5
Baseline (WSJ*)	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

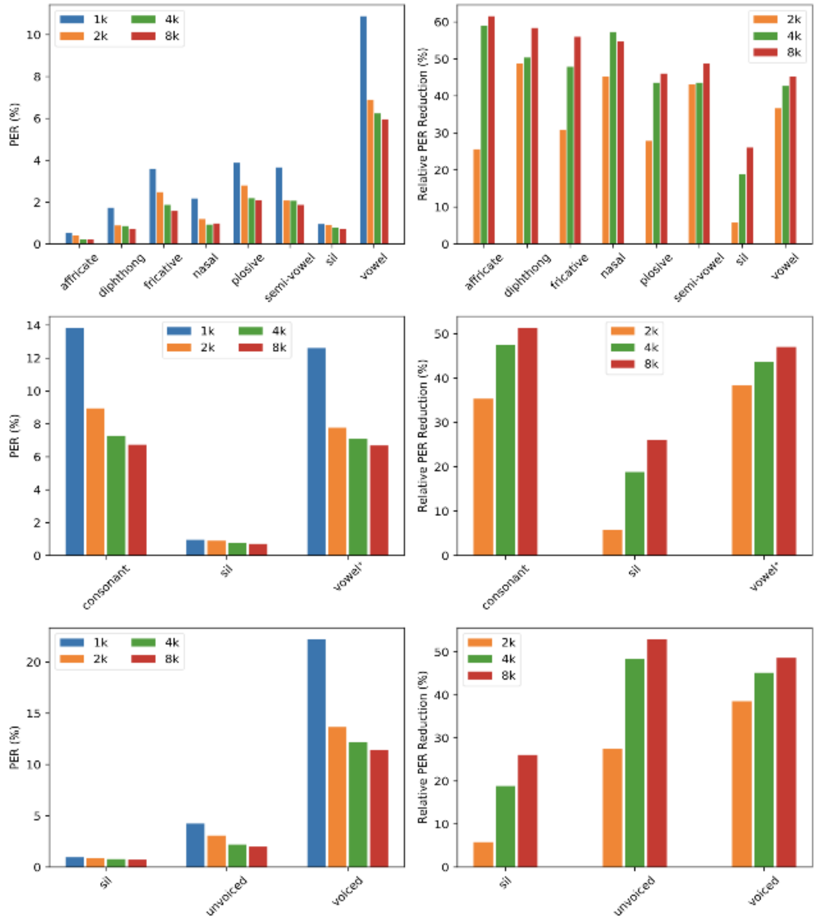
Relative gain computed w.r.t. 1 kHz system.



Effect of Sub-bands

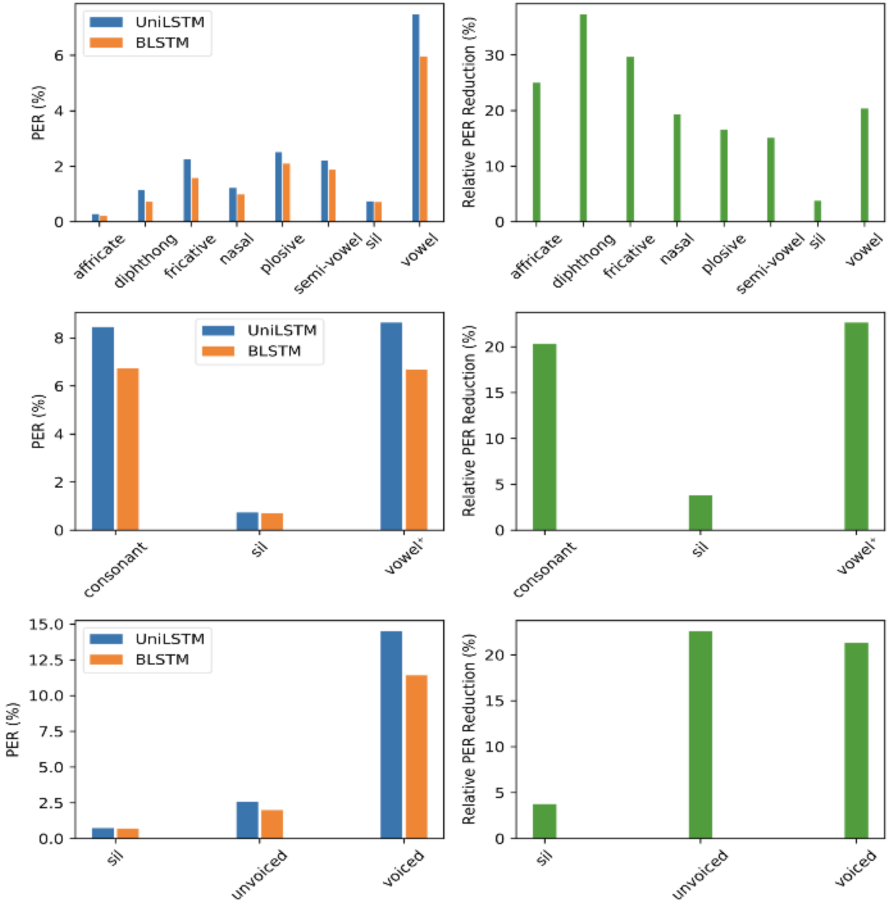
Relative gain computed w.r.t. 1 kHz system.

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%



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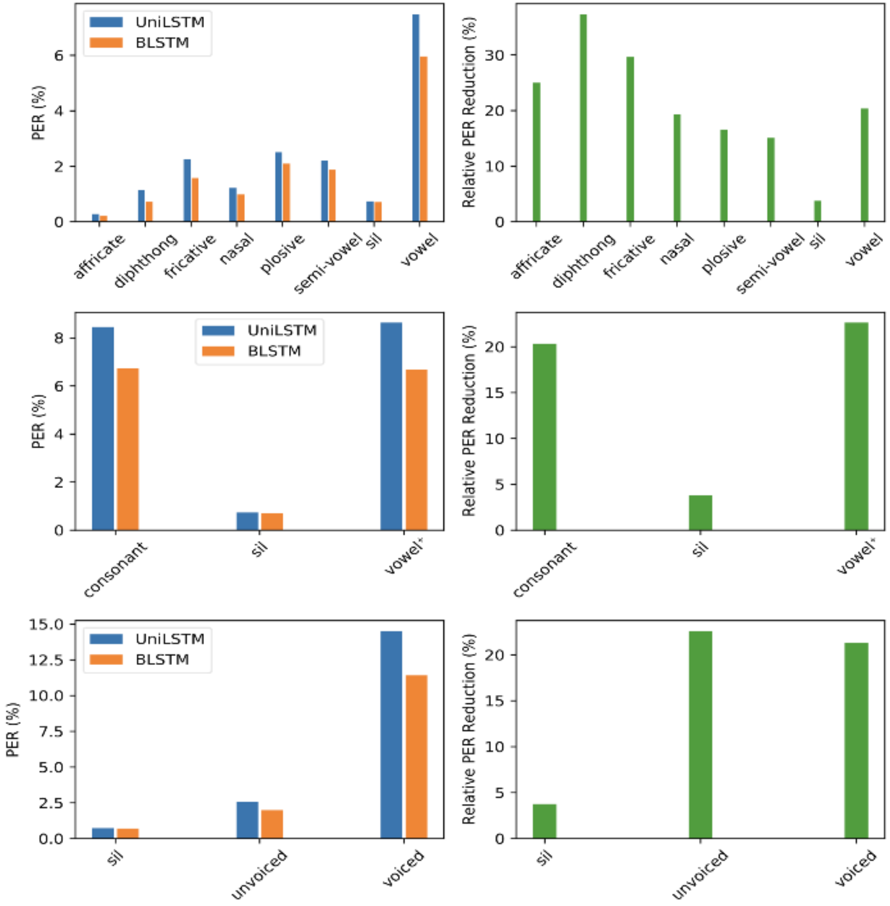
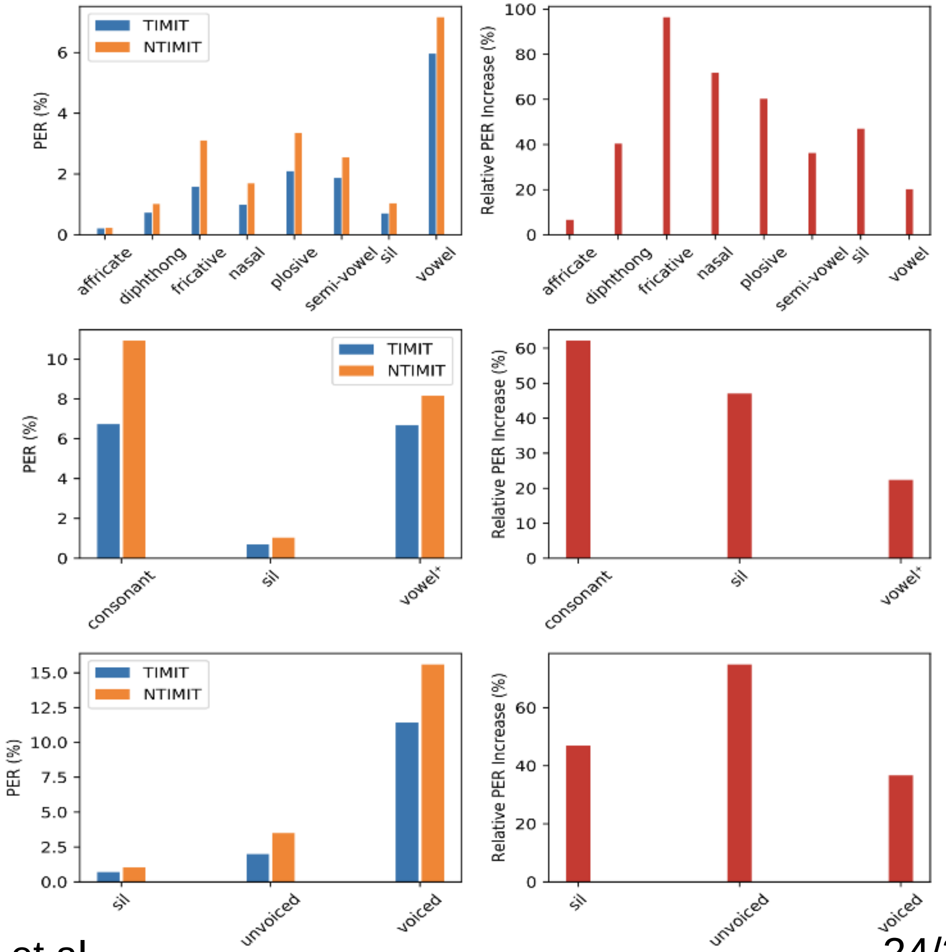
Uni- vs Bi-Directional

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



NTIMIT

- Relative gain: -21% to -95%



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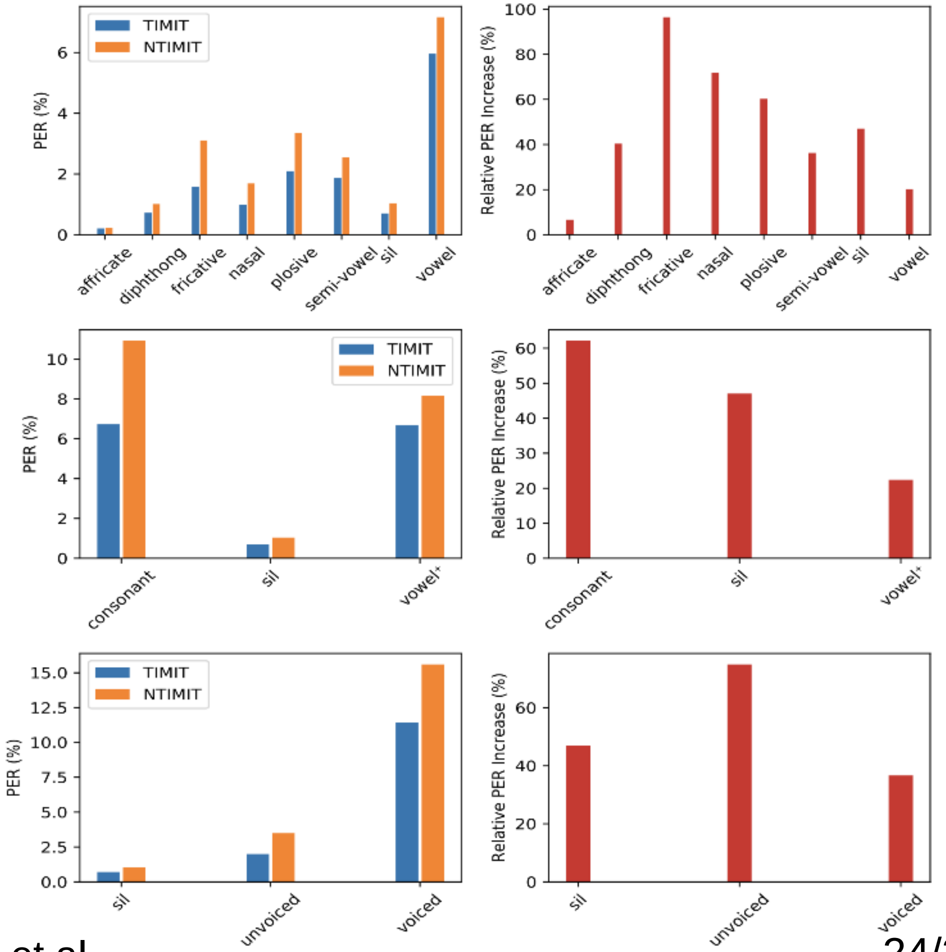
NTIMIT

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



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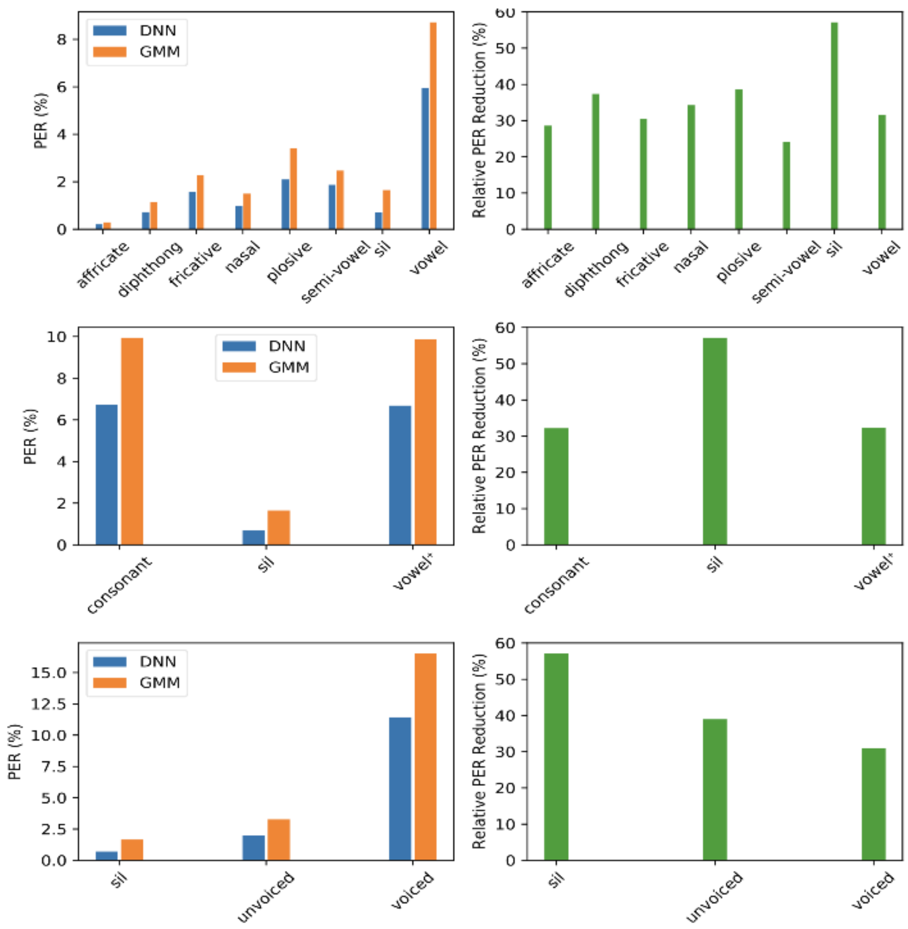
GMM-HMM vs DNN-HMM

- Relative Gain: 25% to 55%



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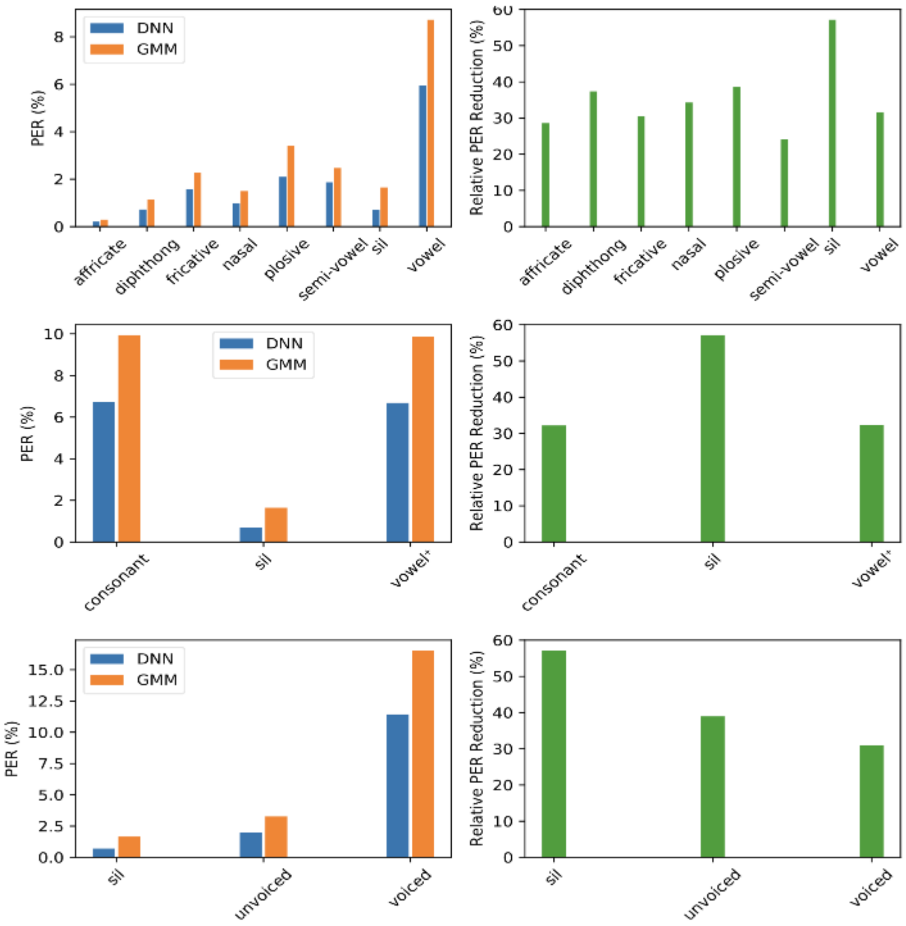
GMM-HMM vs DNN-HMM

- Relative Gain: 25% to <u>55%</u>
- Silence benefits the <u>most</u>
  - Why?



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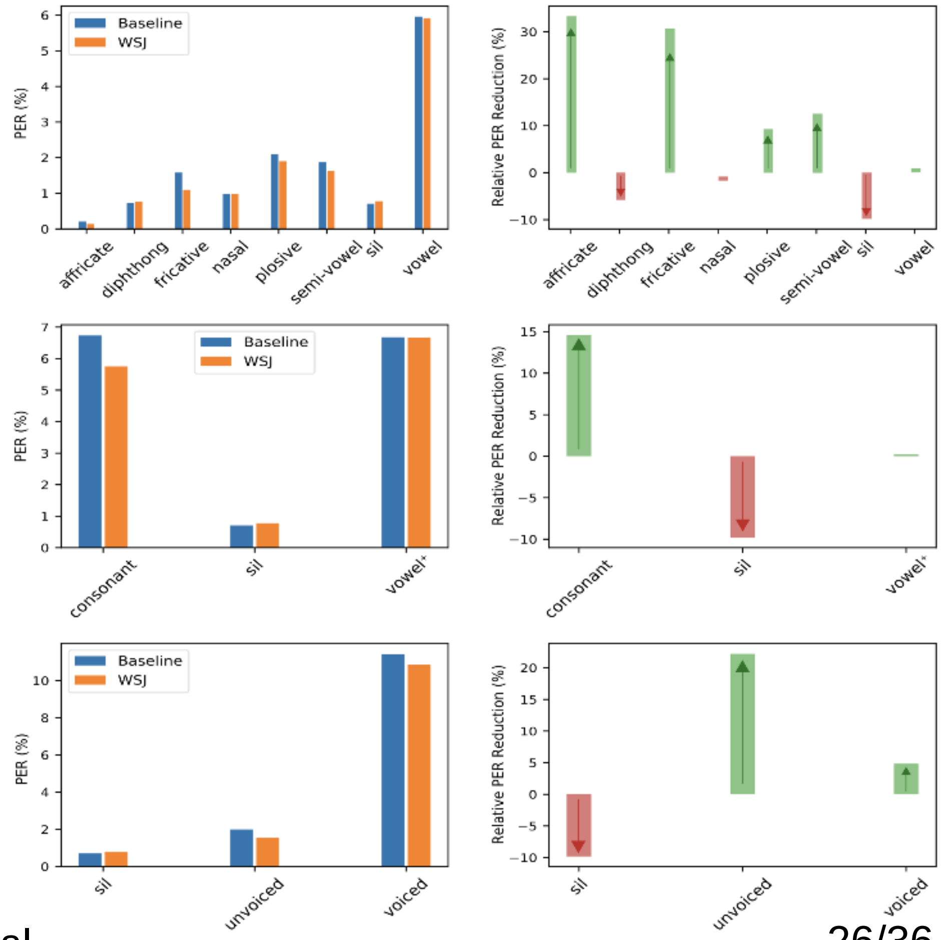
Transfer Learning from WSJ

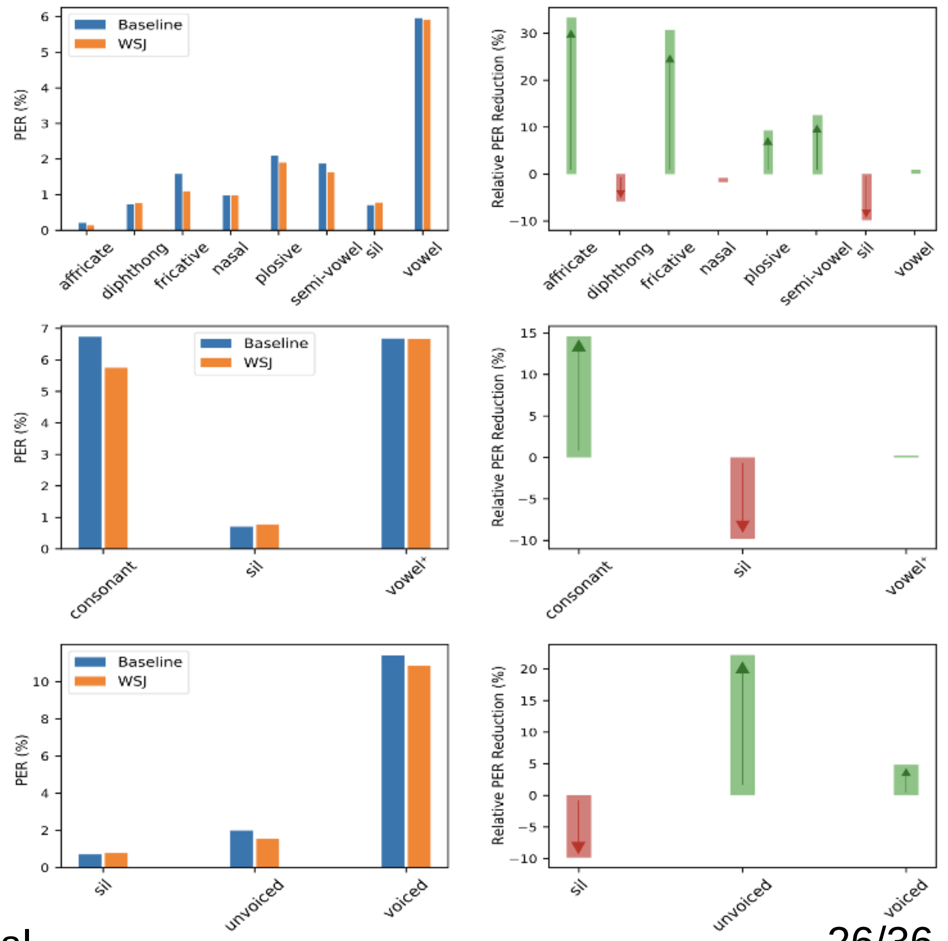
- Average relative gain:
  - Dev: 10%, Test: 7%



Transfer Learning from WSJ

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

- Negative gain (-10%) for Silence!
  - Why?



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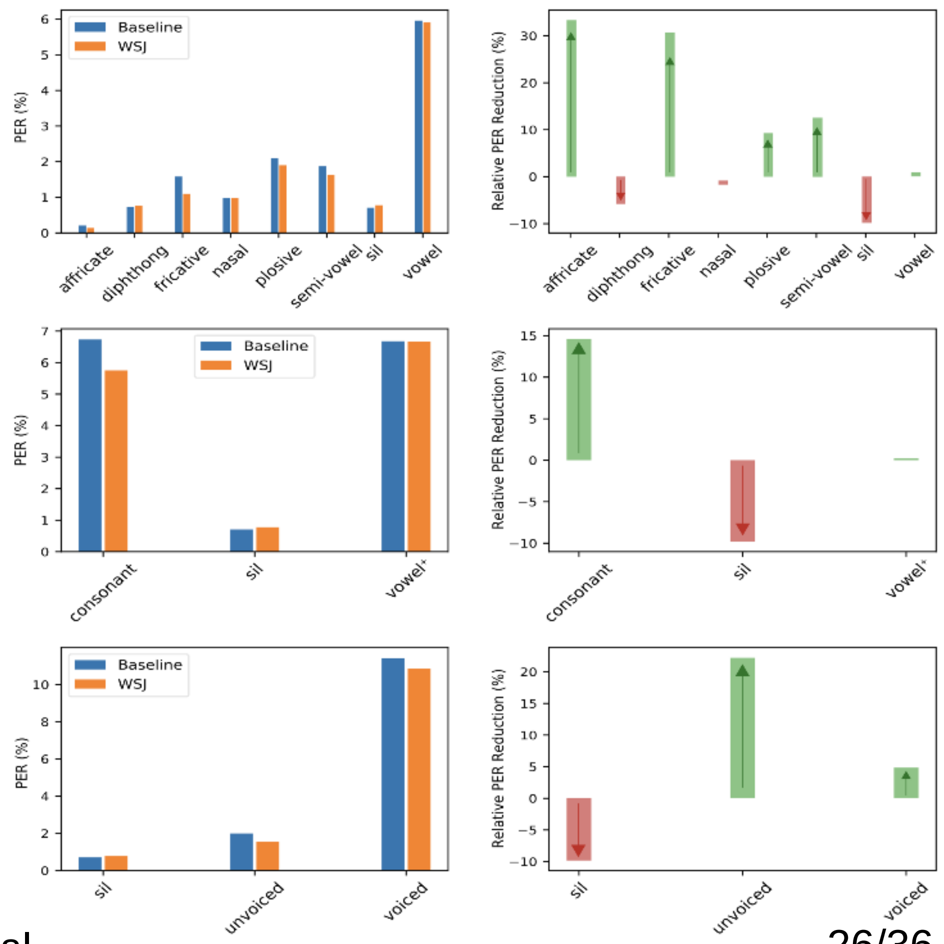
Transfer Learning from WSJ

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



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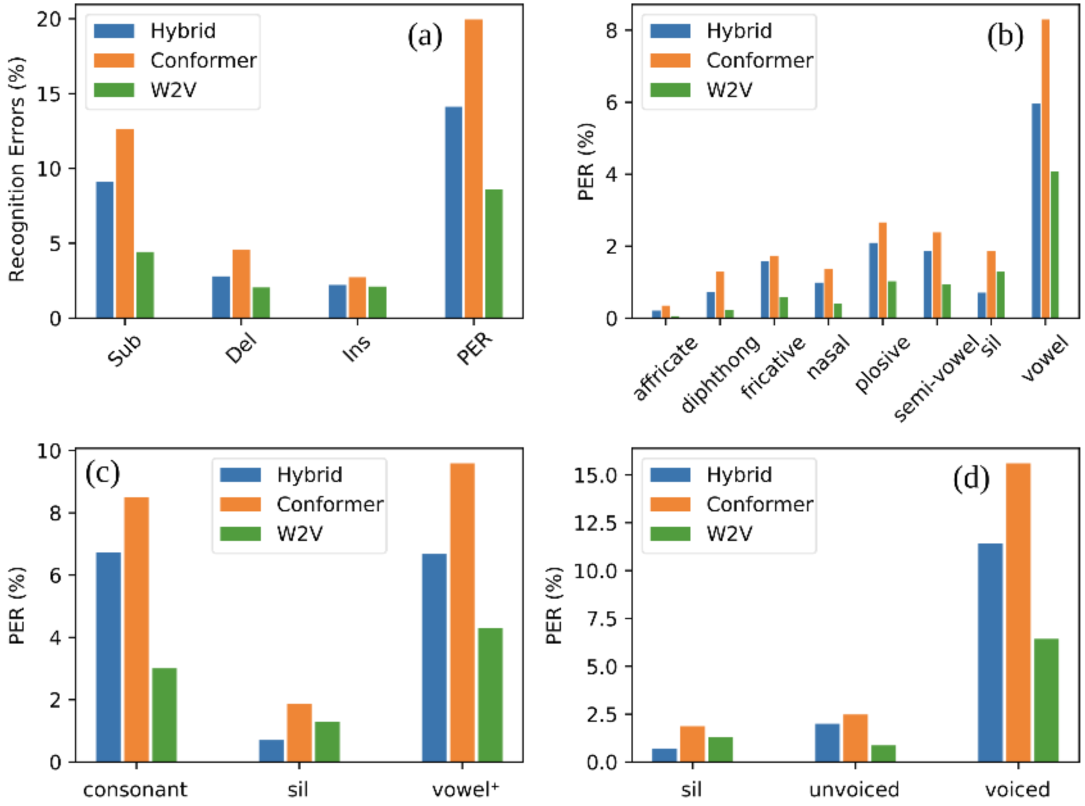
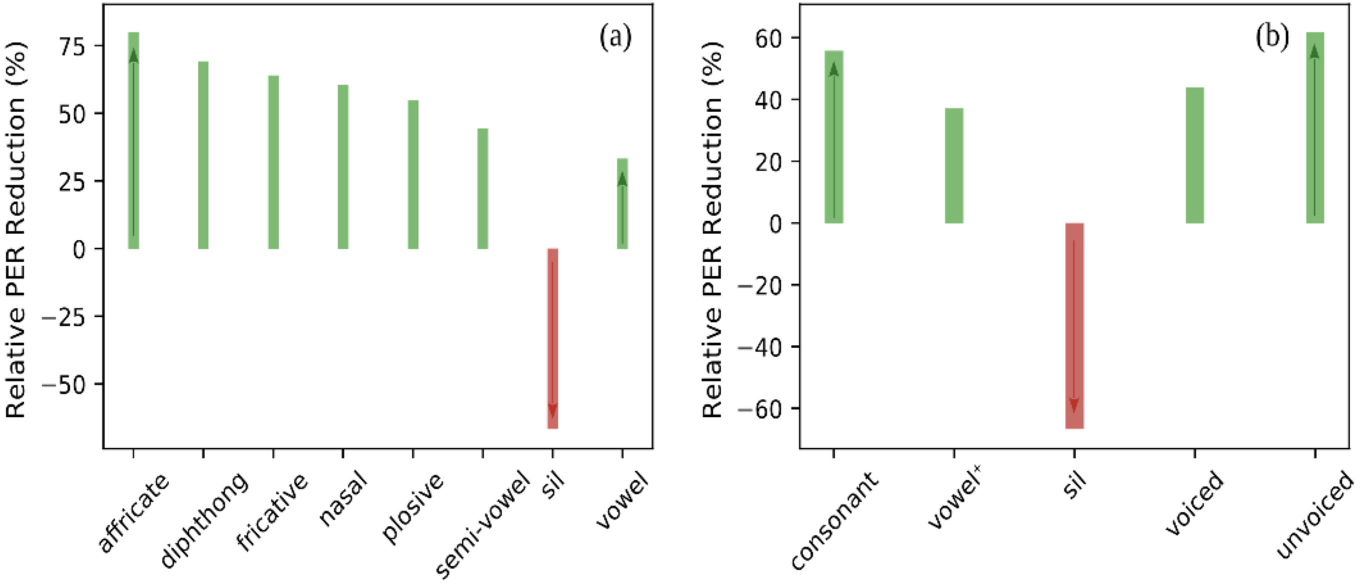
End-to-end (E2E) vs Hybrid

- 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^+

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Confusion Matrices

Baseline (DNN-HMM)

(a) True Label (rows) × Predicted Label (columns)

	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

(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**

Wav2vec 2.0

(a) True Label (rows) × Predicted Label (columns)

	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**

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voi: voiced

(b)

	sil	con	vow^{+}
sil	0	**10**	0
con	5	**83**	28
vow^{+}	2	21	**400**

(c)

	sil	unv	voi
sil	0	1	**9**
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sil: silence
unv: unvoiced
voi: voiced

Sparser but Similar Patterns

(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**

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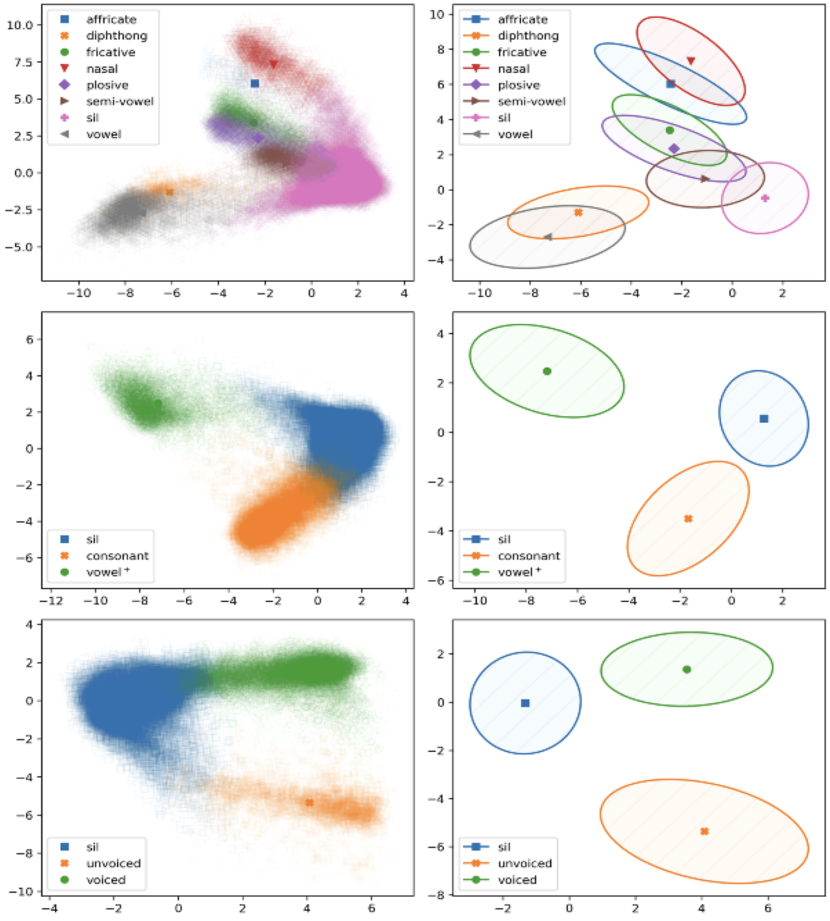
Scatter Plots

Logit (wav2vec 2.0)



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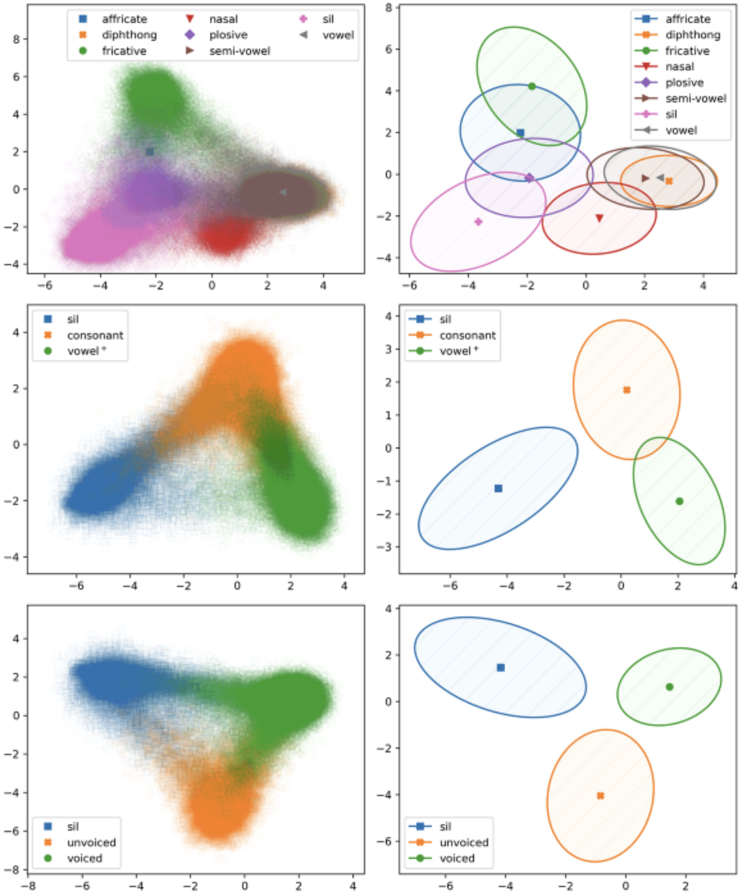
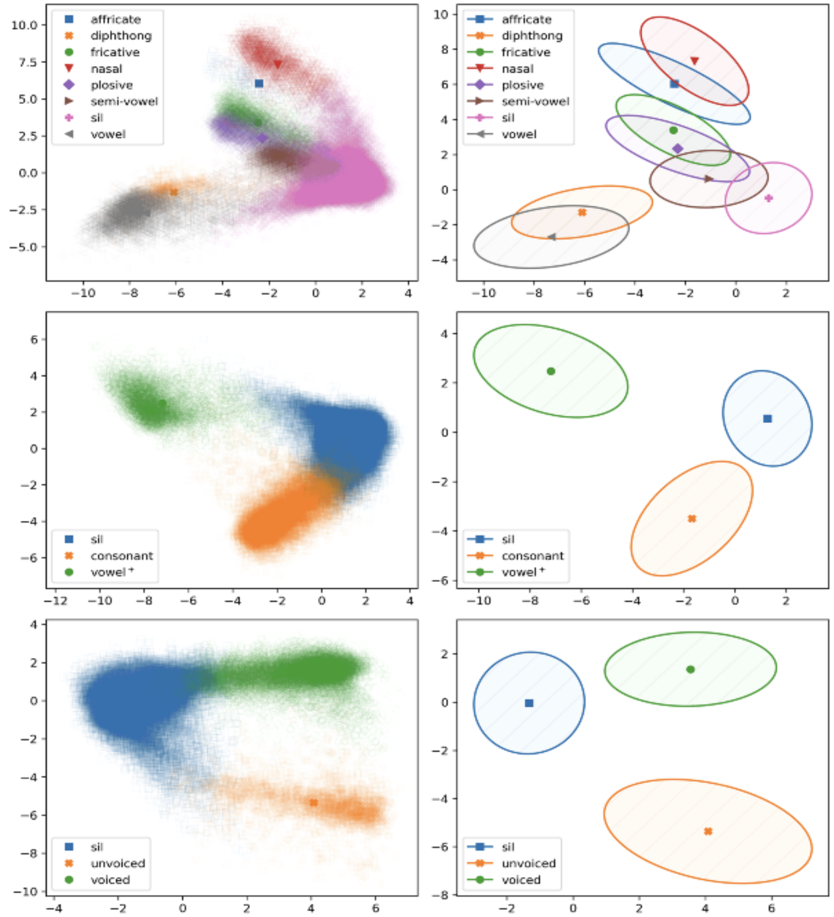
Scatter Plots

Logit (Hybrid)

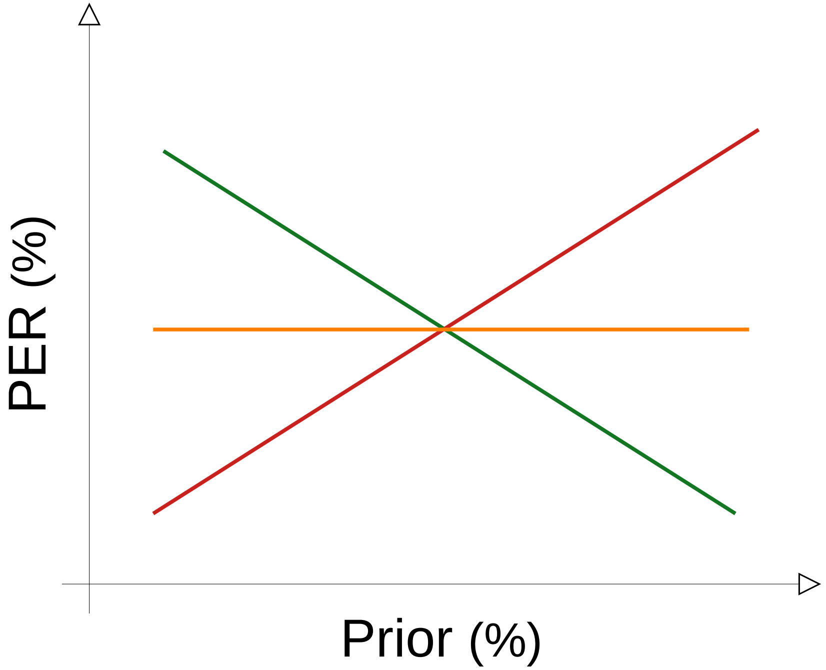


More distinct clusters

Logit (wav2vec 2.0)

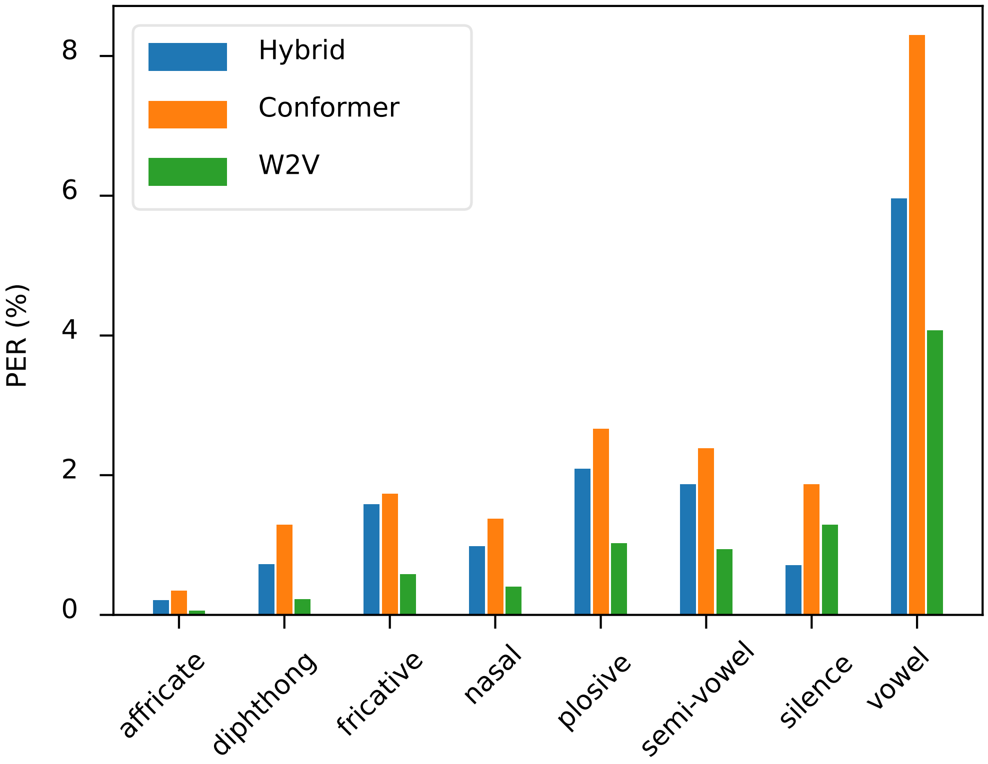


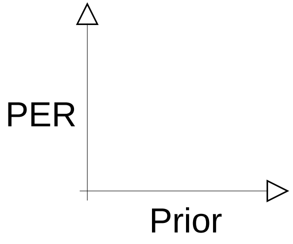
PER vs Prior (1)

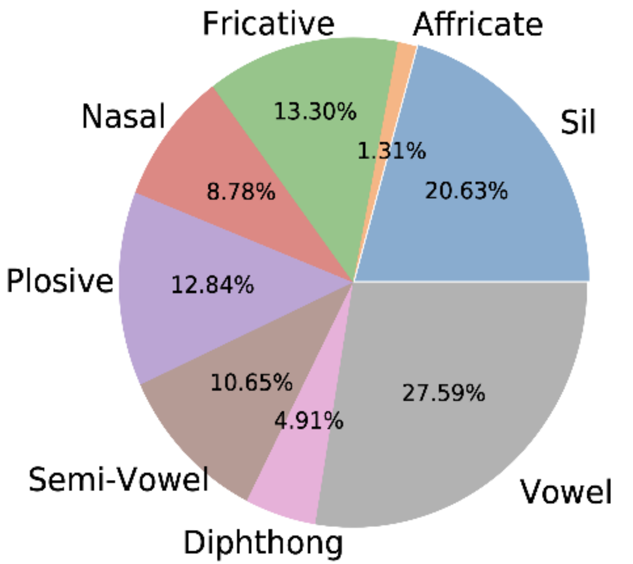


Trend ???

PER vs Prior (1)

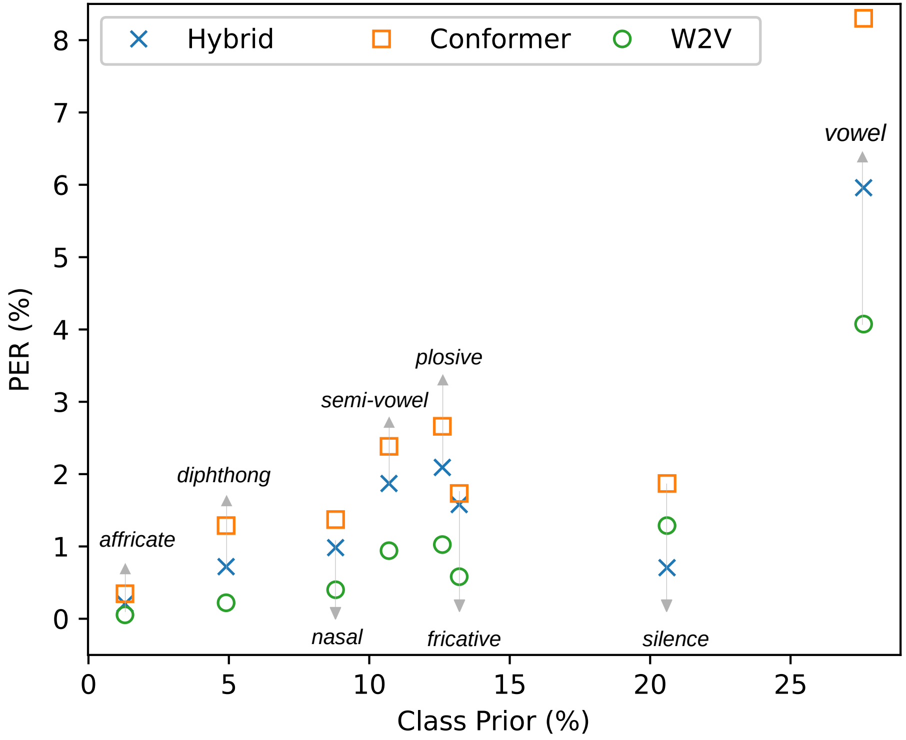




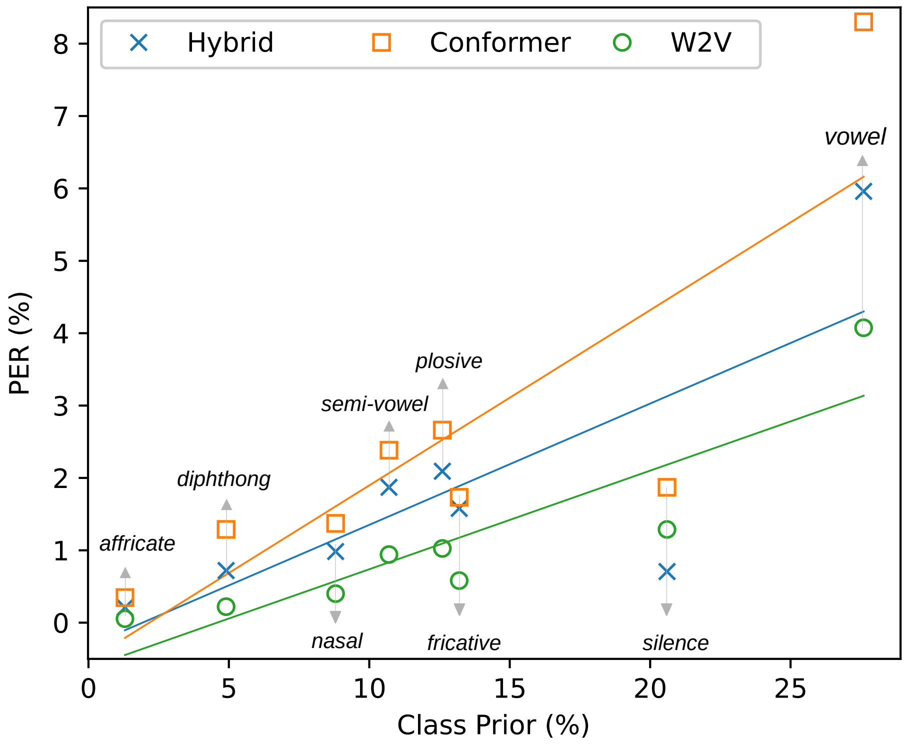


BPC’s Prior

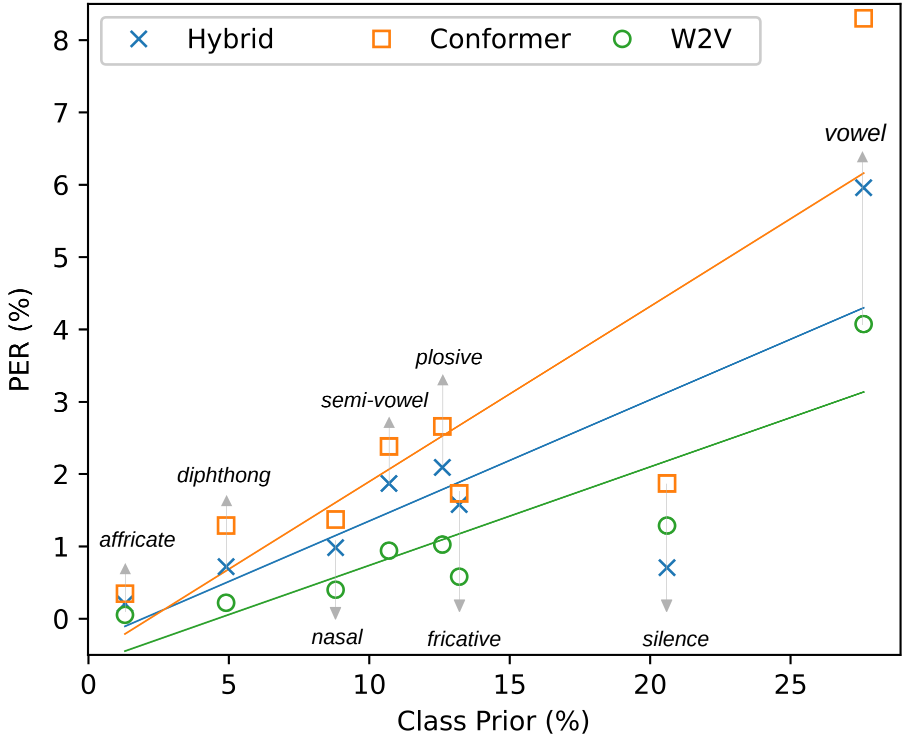
PER vs Prior (2)



PER vs Prior (2)



PER vs Prior (2)



The higher the training data, the higher the PER!

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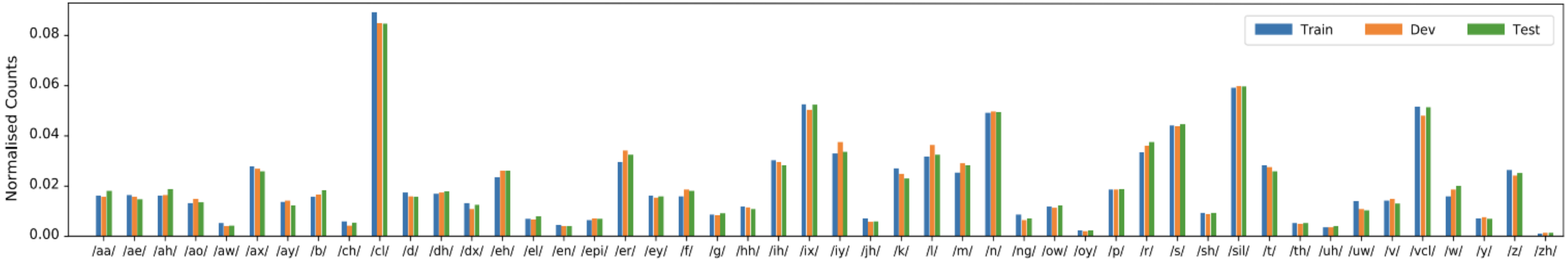
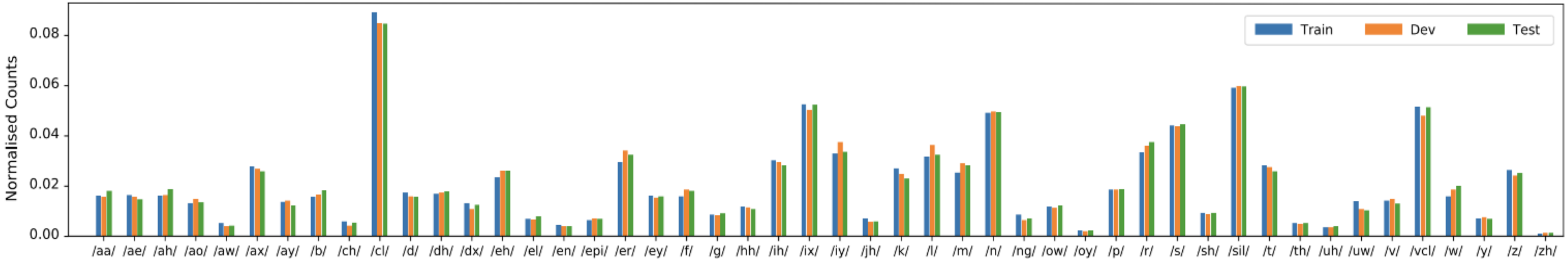
TIMIT's Special Case ...



TIMIT's Special Case ...



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

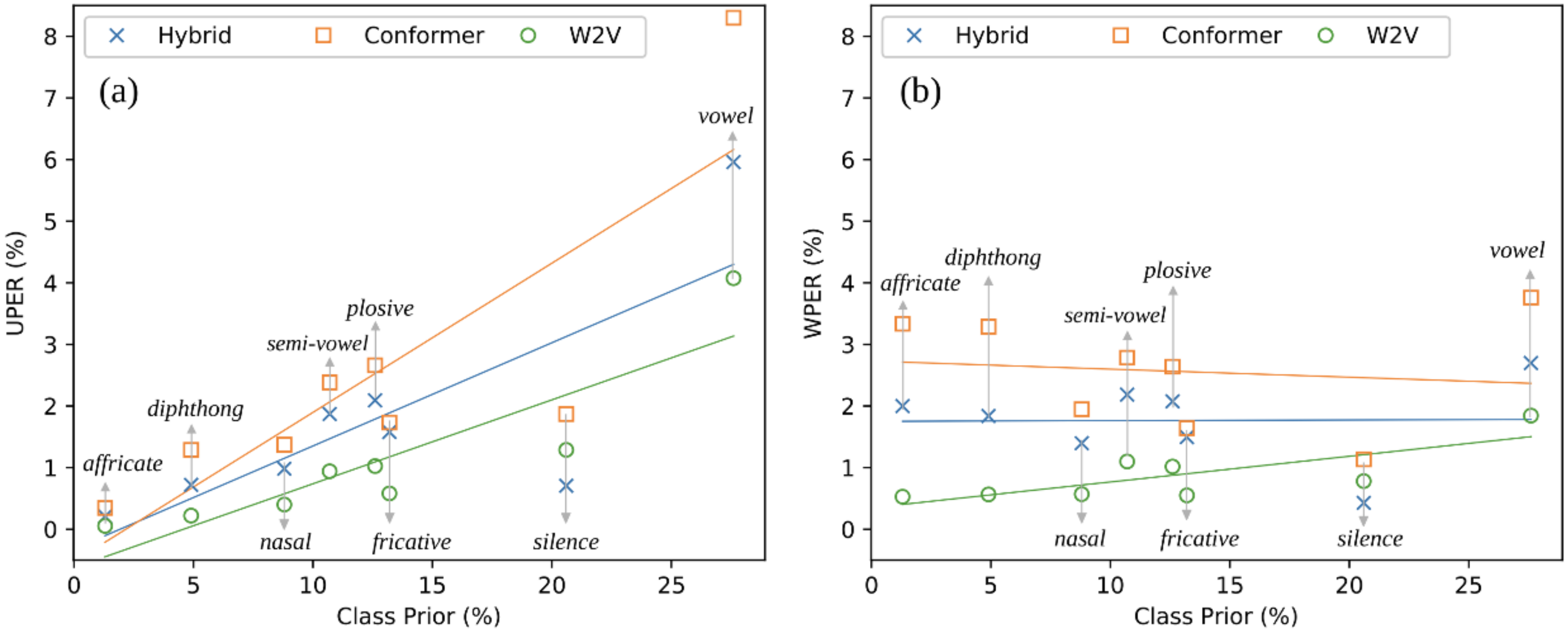
Unweighted vs Weighted PER

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

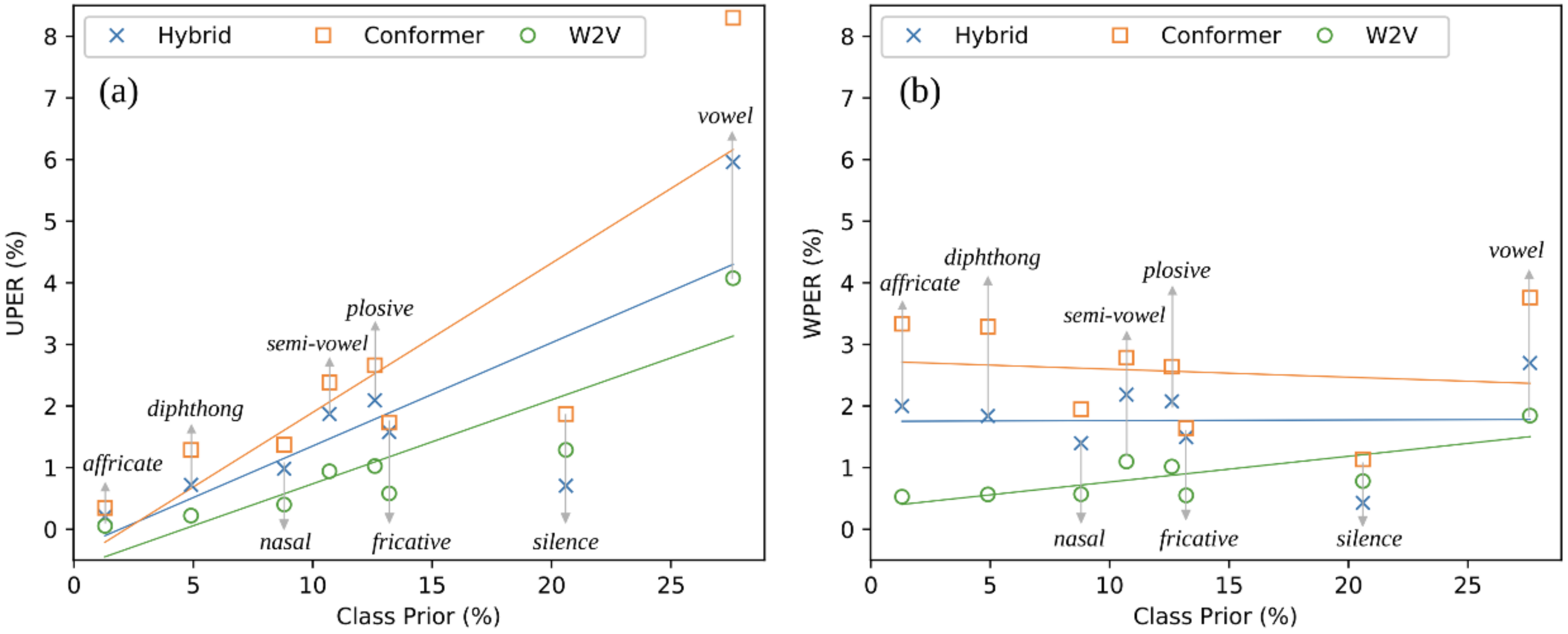
$$WPER = \frac{1}{C}\sum_{c=1}^{C}\frac{Sub_c + Del_c + Ins_c}{N\ \ P_c}$$

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

UPER & WPER vs Prior



UPER & WPER vs Prior



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

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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

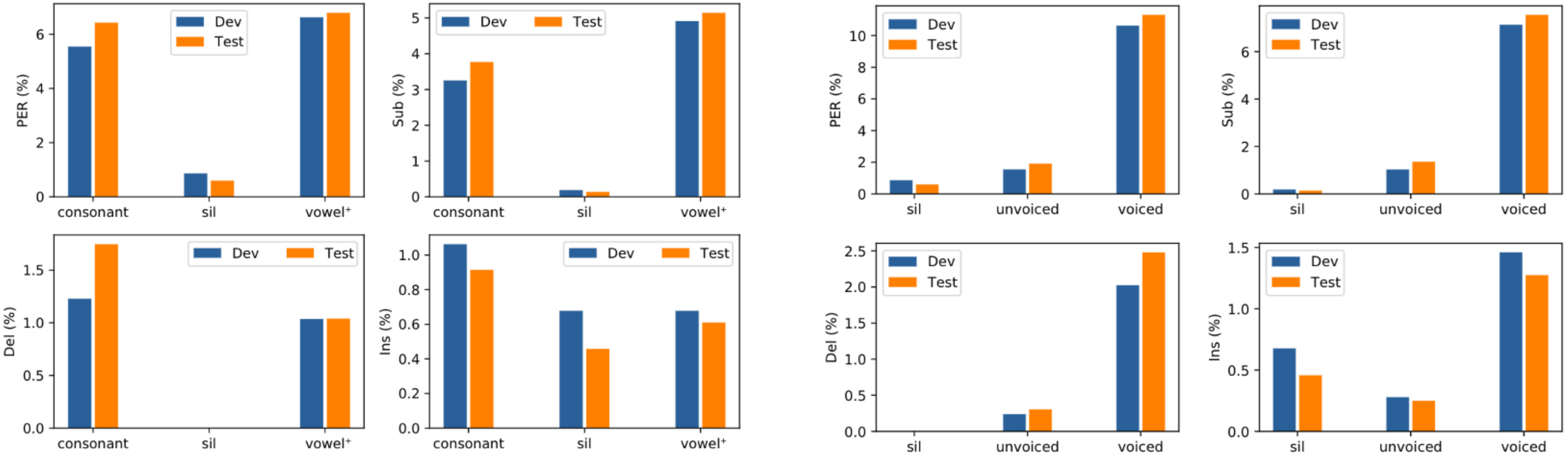
    A1) Sub/Del/Ins of C/V^{+} & V/U

    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



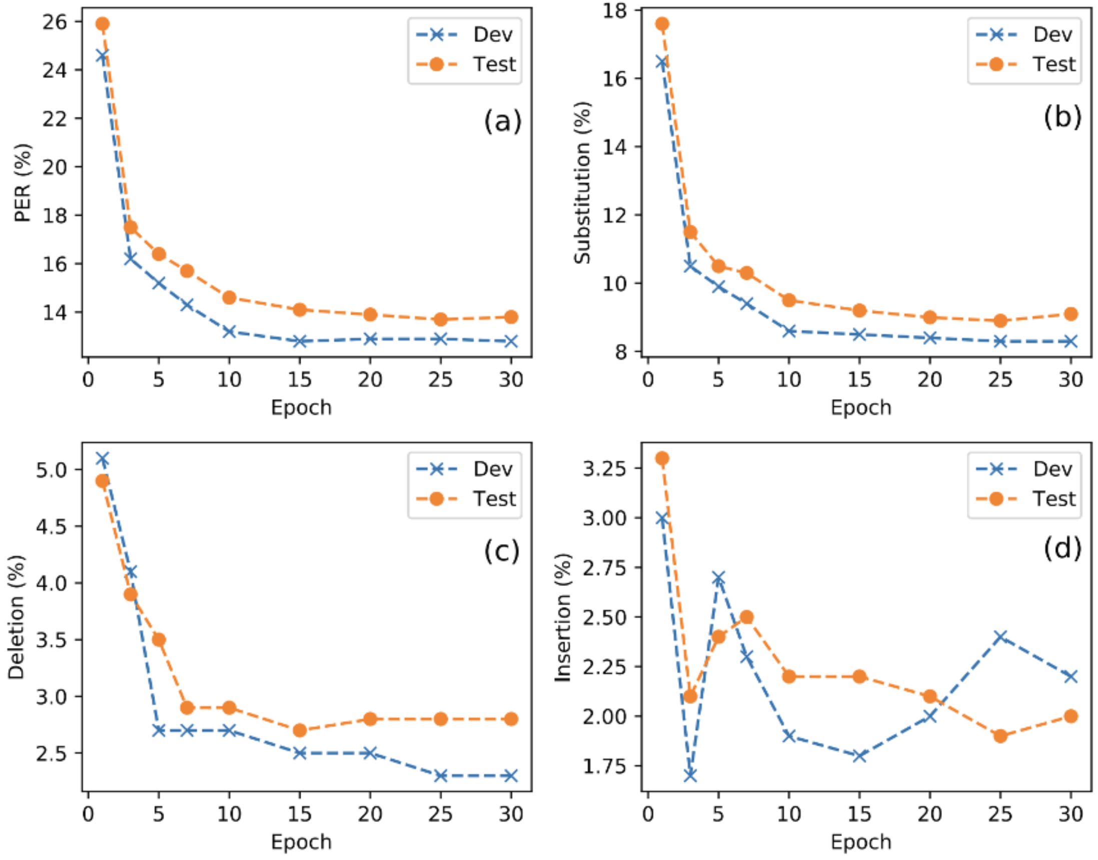
- Vowels have larger Sub.
- Consonants have a larger Del & Ins.

Errors' Largest share belongs to Voiced.

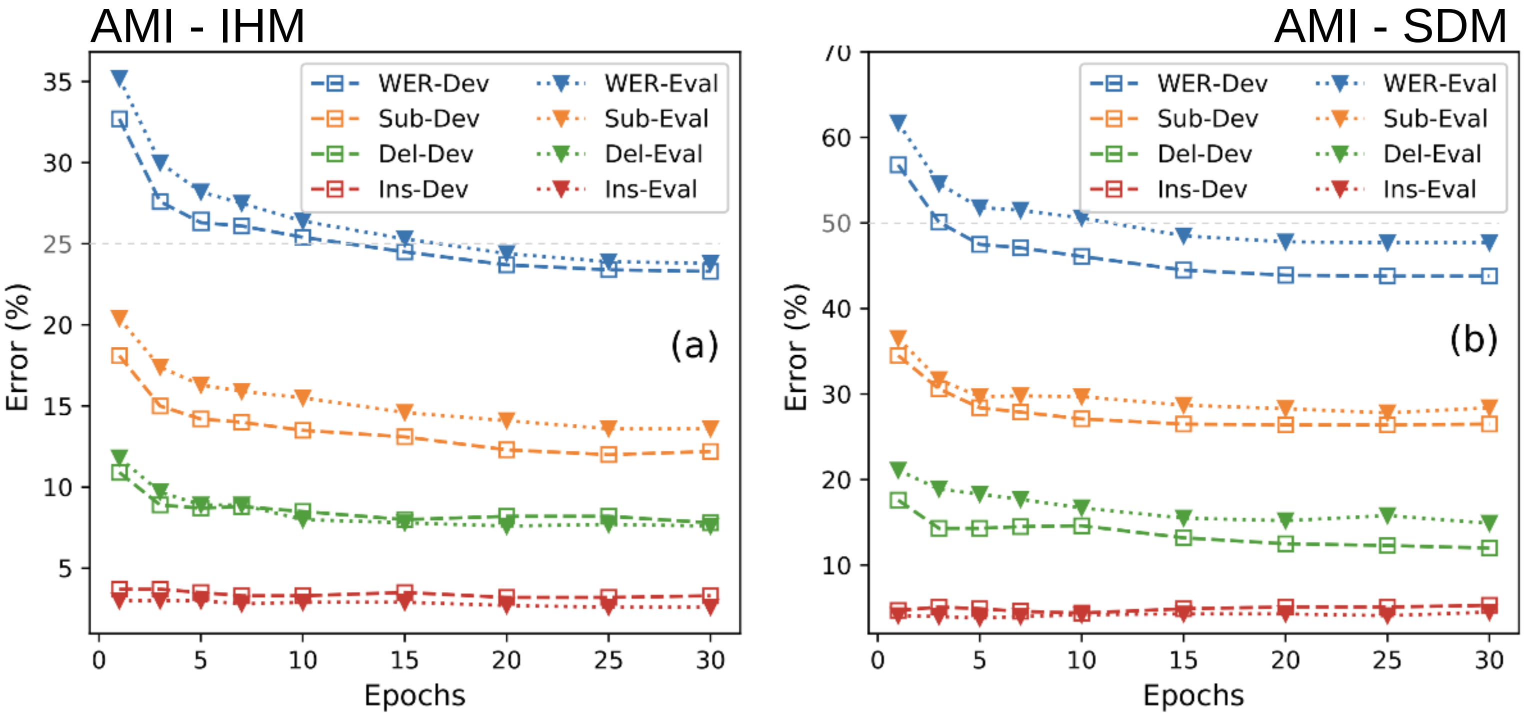
(A2) Sub/Del/Ins Dynamics

Strongest Correlation: PER & Sub

- Sub convergences slowly
- Del converges fast
- Ins oscillates



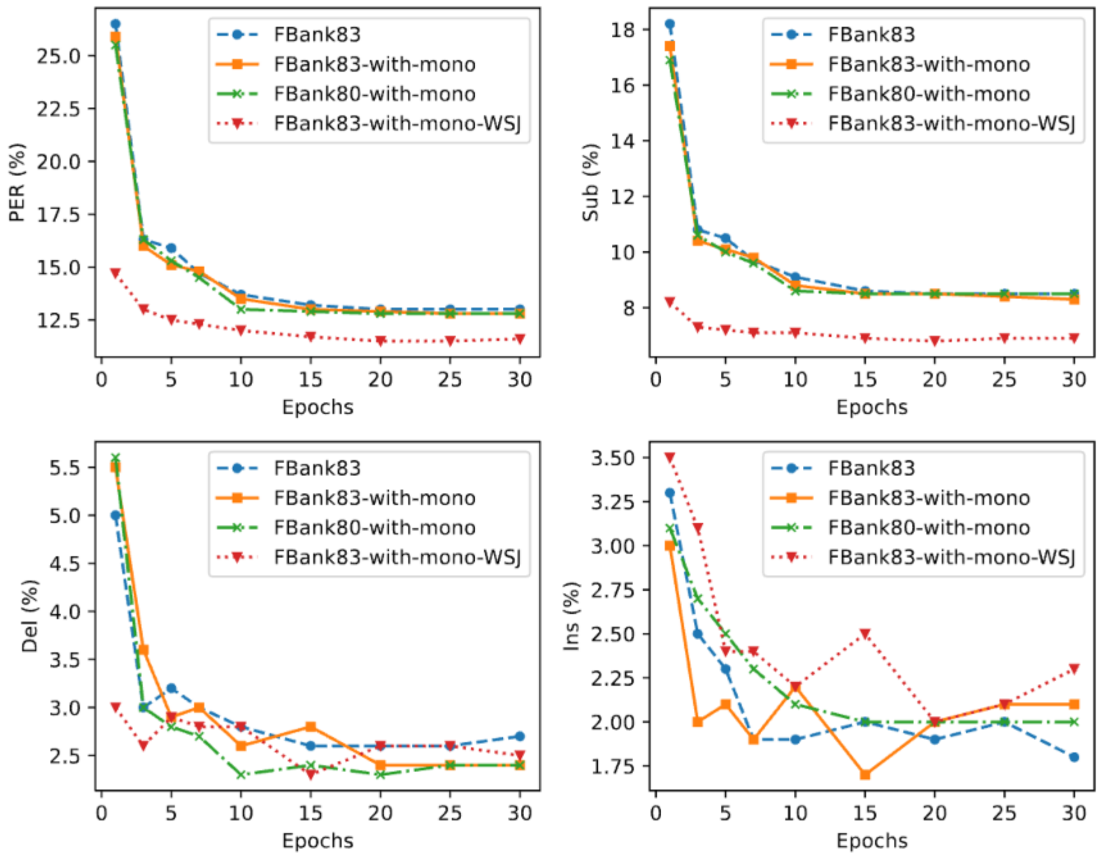
(A2) Similar observations in [67]



(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

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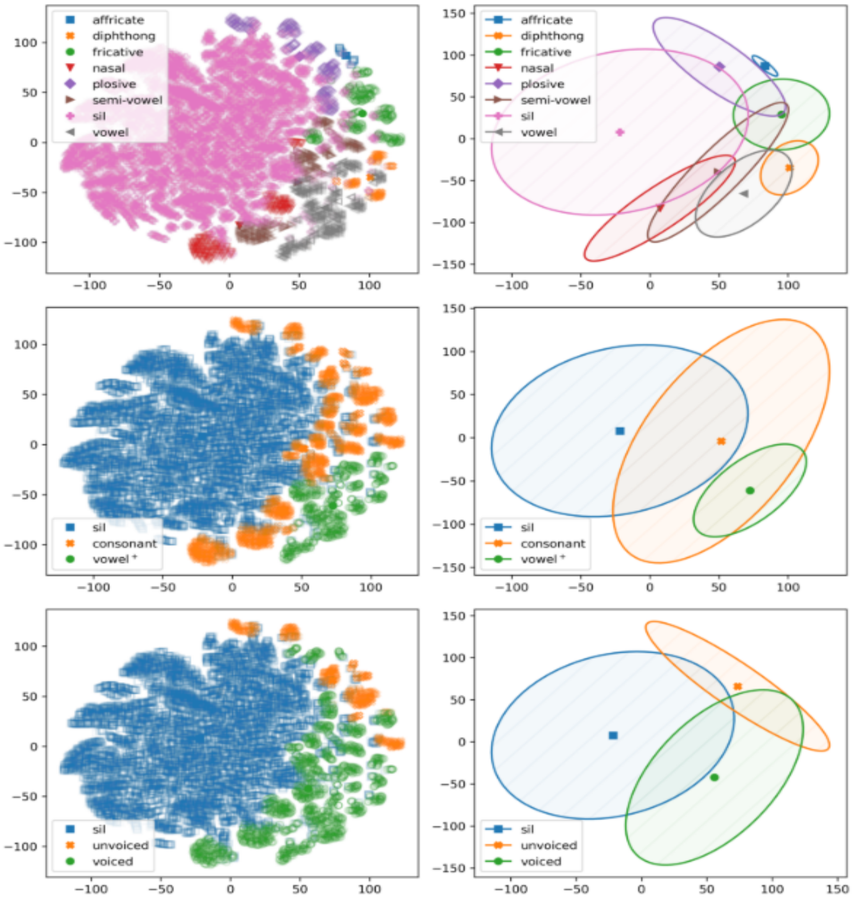
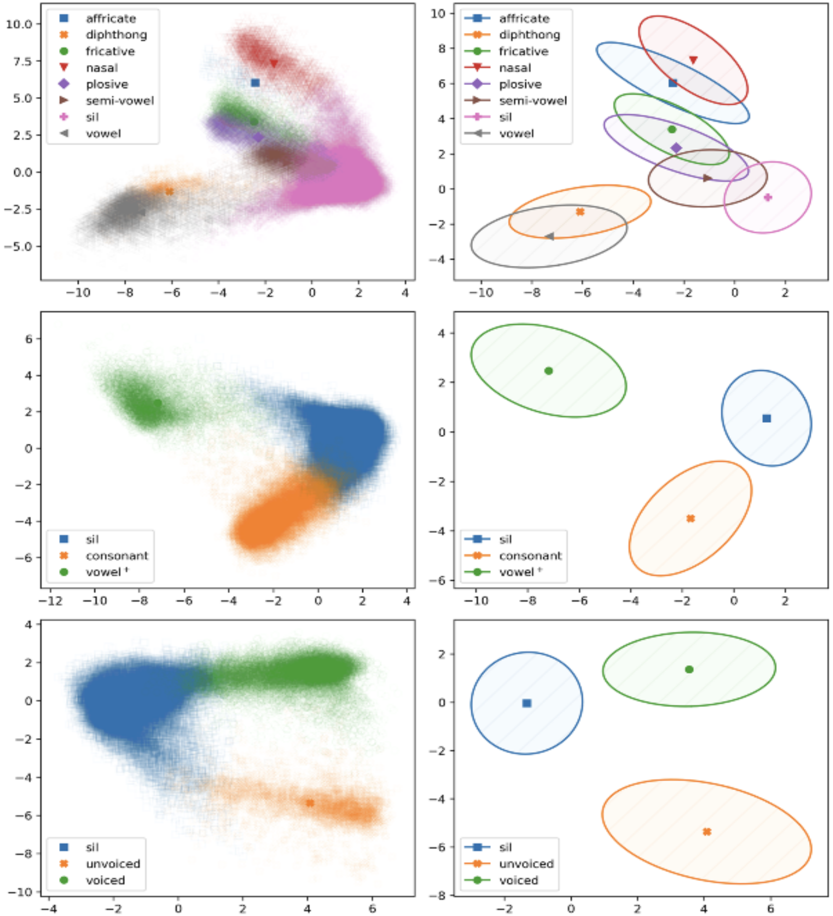
(A4) t-SNE vs LDA

t-SNE



Logits (Wav2vec 2.0)

LDA



Logits (Wav2vec 2.0)

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