Phonetic Error Analysis
Beyond
Phone Error Rate

Erfan Loweimi

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We will look at ...

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

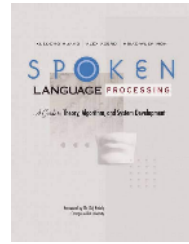
- Analysis beyond PER
  - What / How / Why
- Effect of Various Factors

Analysis beyond PER ...

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

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

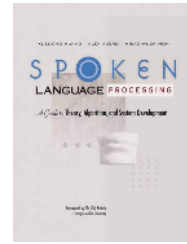
Three BPCs considered ...



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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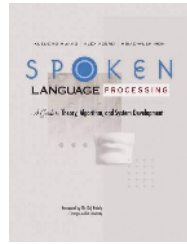
(A) *8-class*

(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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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*

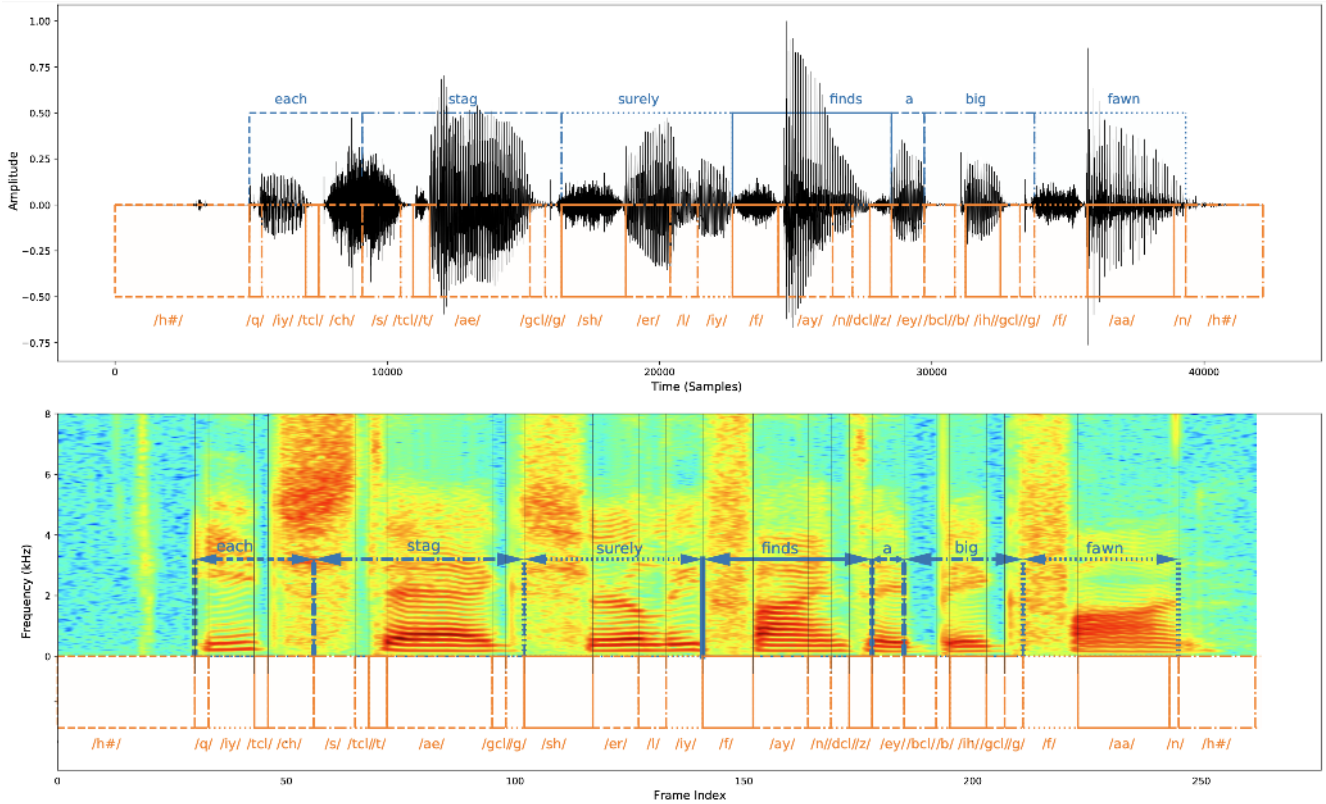
$$\text{Vowel}^+ = \text{Vowel} \cup \text{Diphthong}$$

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

Detail in (A1)

Phonetic Transcription

Data: TIMIT



- Original Transcription: **61** phones

Phonetic Transcription

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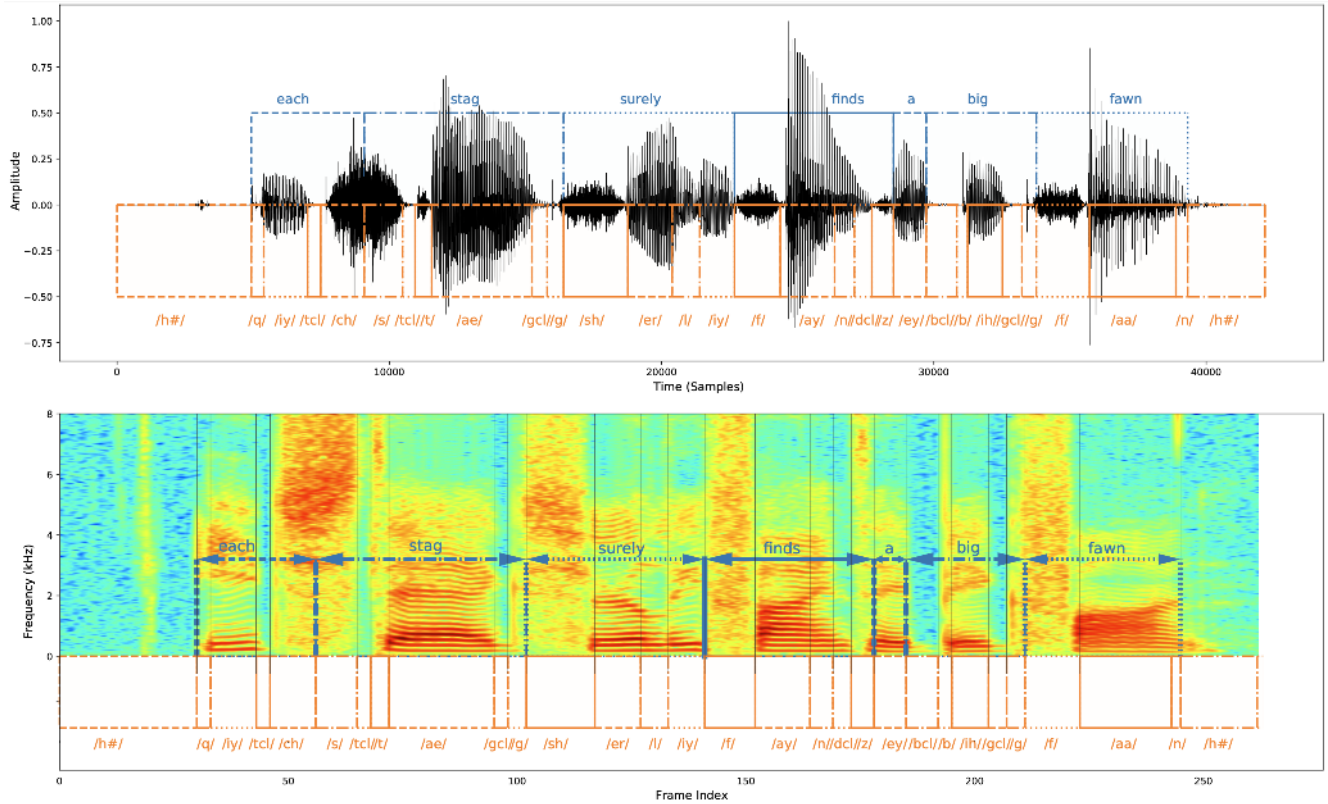


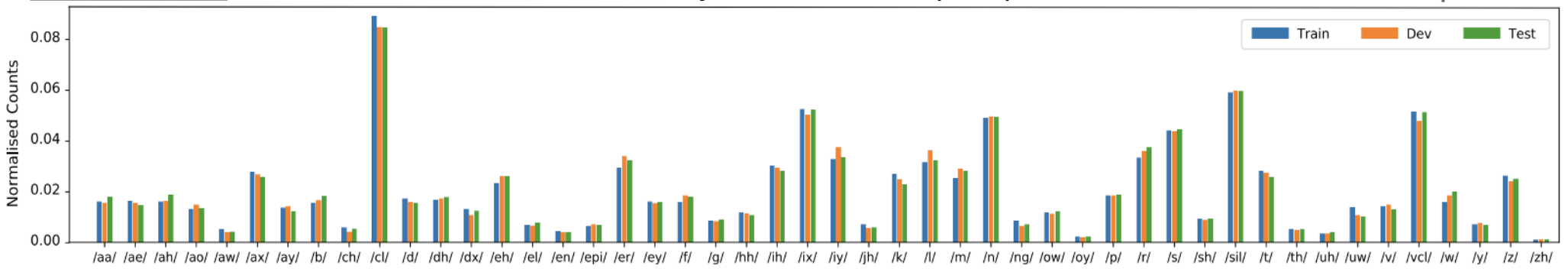
- Original Transcription: **61** phones → Train w/ **48** phones → Decode w/ **39** phones
- Mapping (Kaldi): phones.60-48-39.map

Phonetic Distribution

Data: TIMIT

Probability Mass Function (PMF)

48 phones



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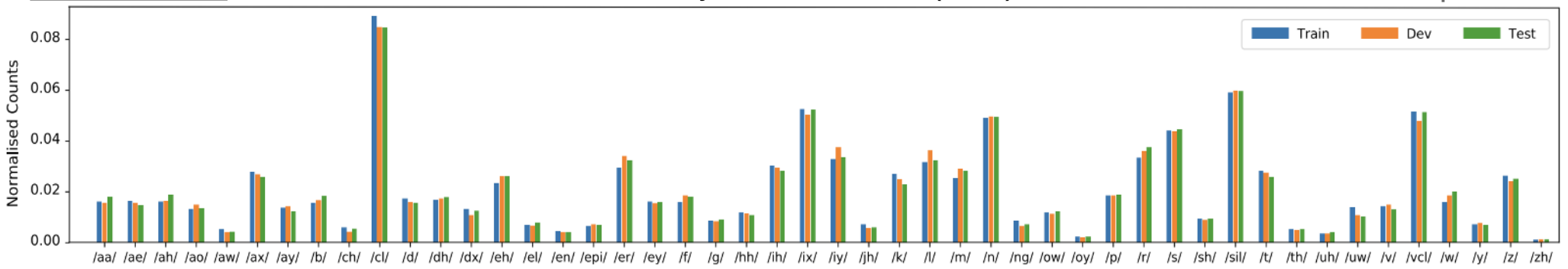

PMF of standard Train/Dev/Test sets is **identical**.

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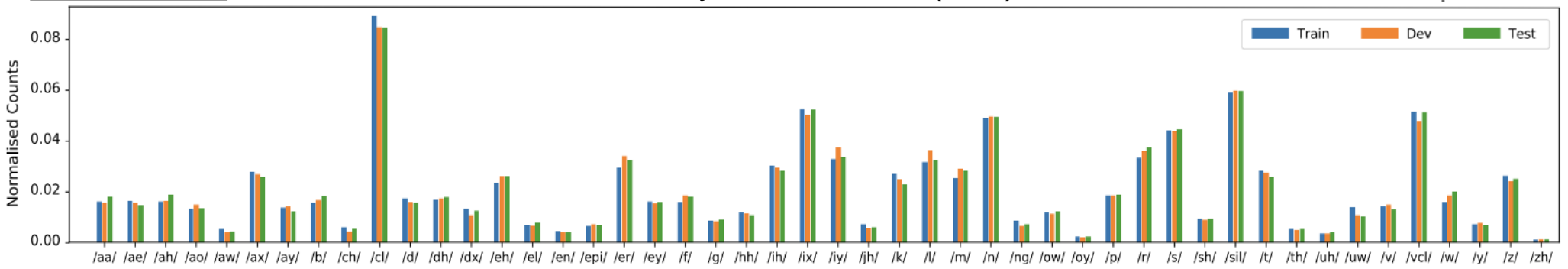

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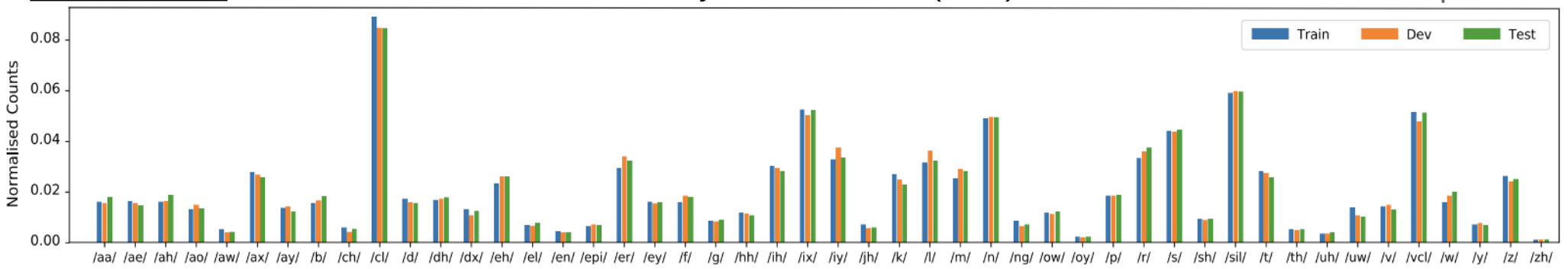


PMF of standard Train/Dev/Test sets is **identical**.

PMF is **not uniform ...**

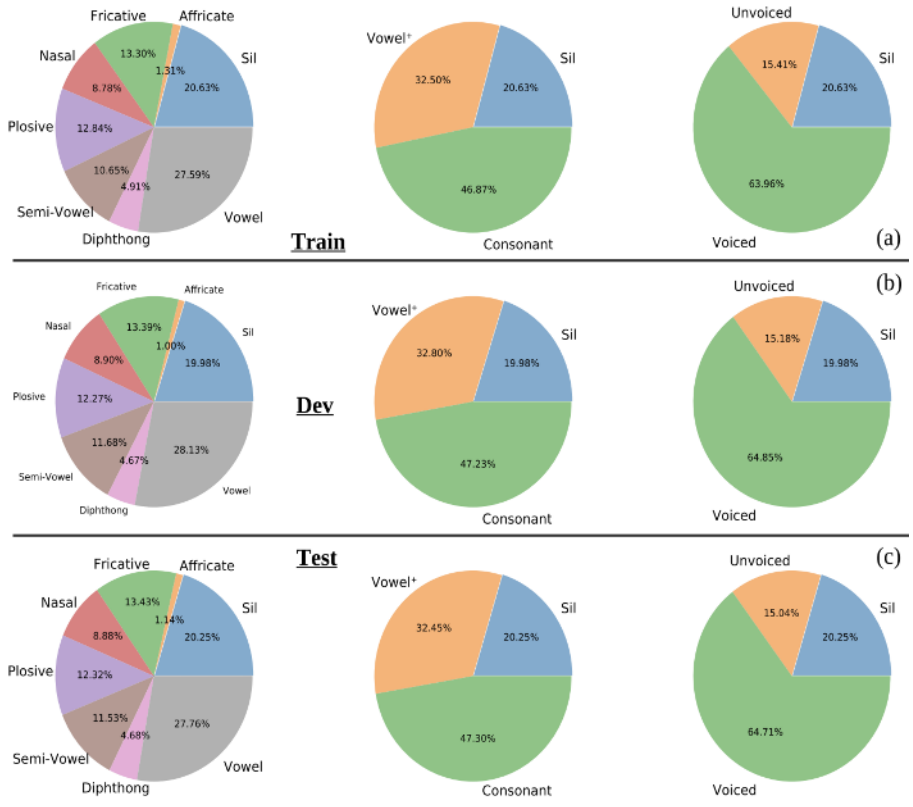
- ✗ Not perfect from *learning* perspective!
- ✔ Not a shortcoming, though → characteristic of natural languages, studied in *Quantal Theory, Adaptive Dispersion, etc*.

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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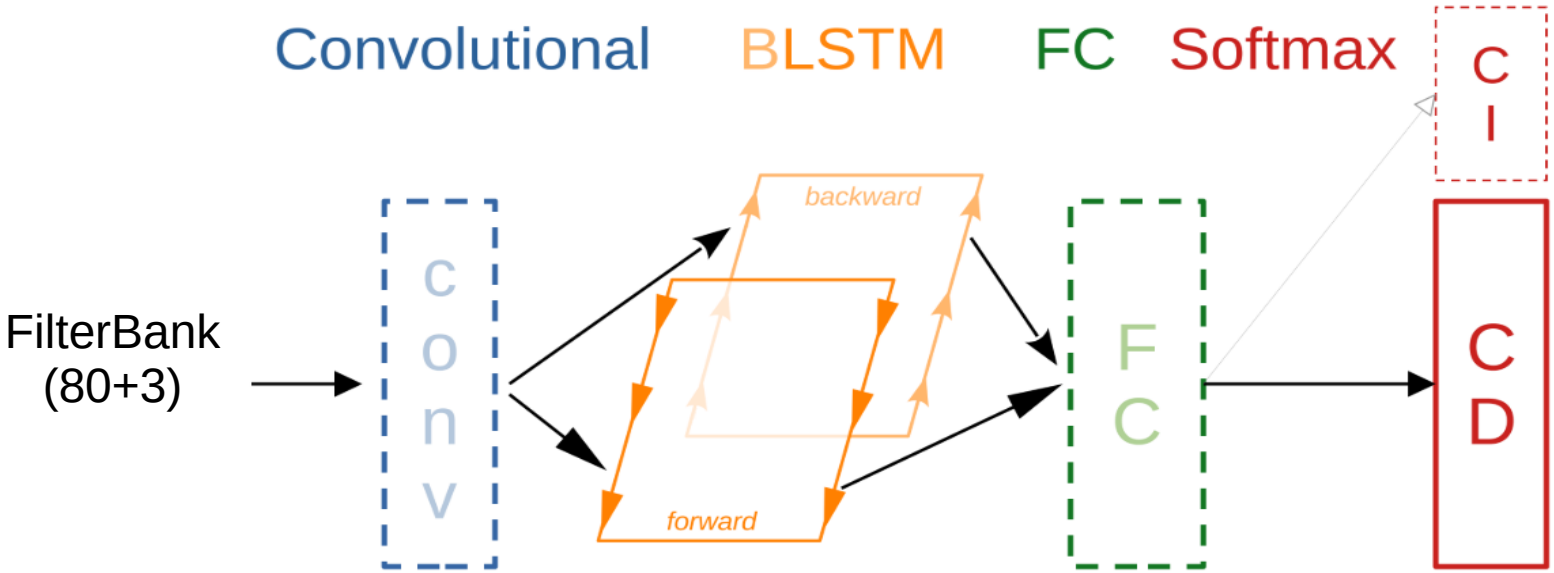
Baseline Arch. $C_iL_jF_k$



$C_iL_jF_k$ → Architecture includes:

- *i* convolutional layers
- *j* BLSTM layers
- *k* FC (fully-connected) layers

Trained by cross entropy loss

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

With F_0 & CI

w/o F_0

w/o CI

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Choosing Baseline

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Chosen Baseline →

w/o F_0 →

w/o CI →

With F_0 & CI

w/o F_0

w/o CI

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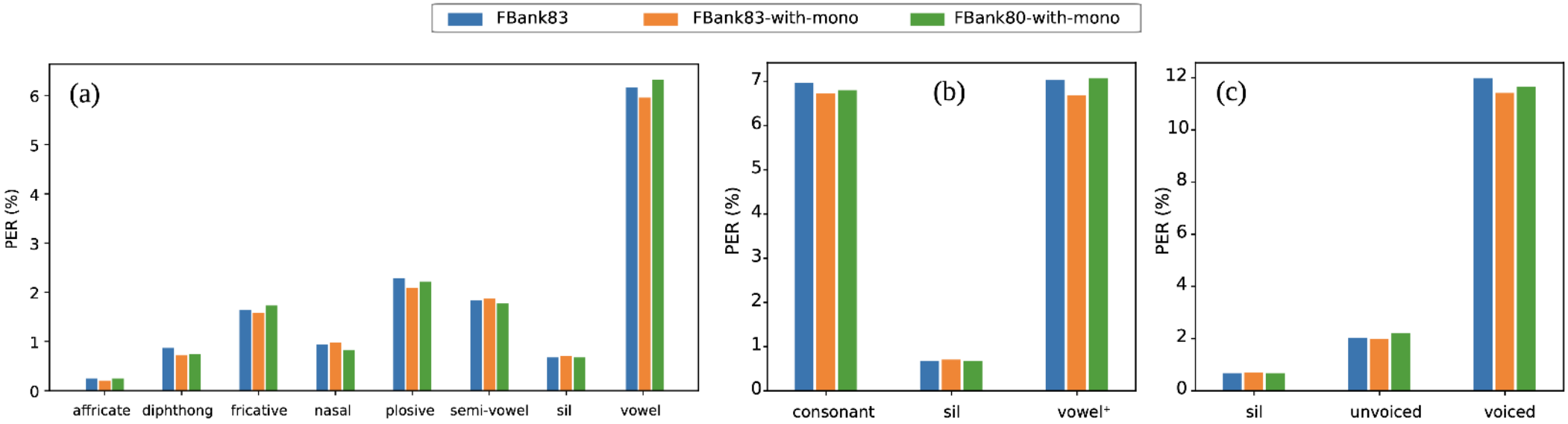
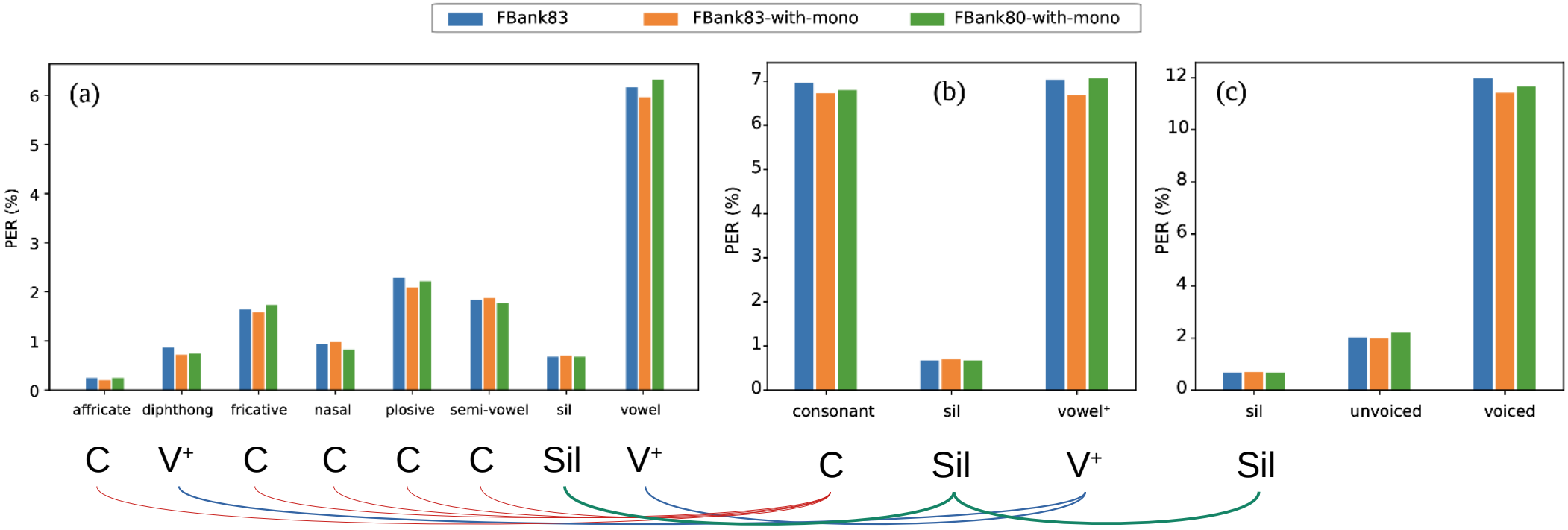
Analysis beyond PER



Analysis beyond PER



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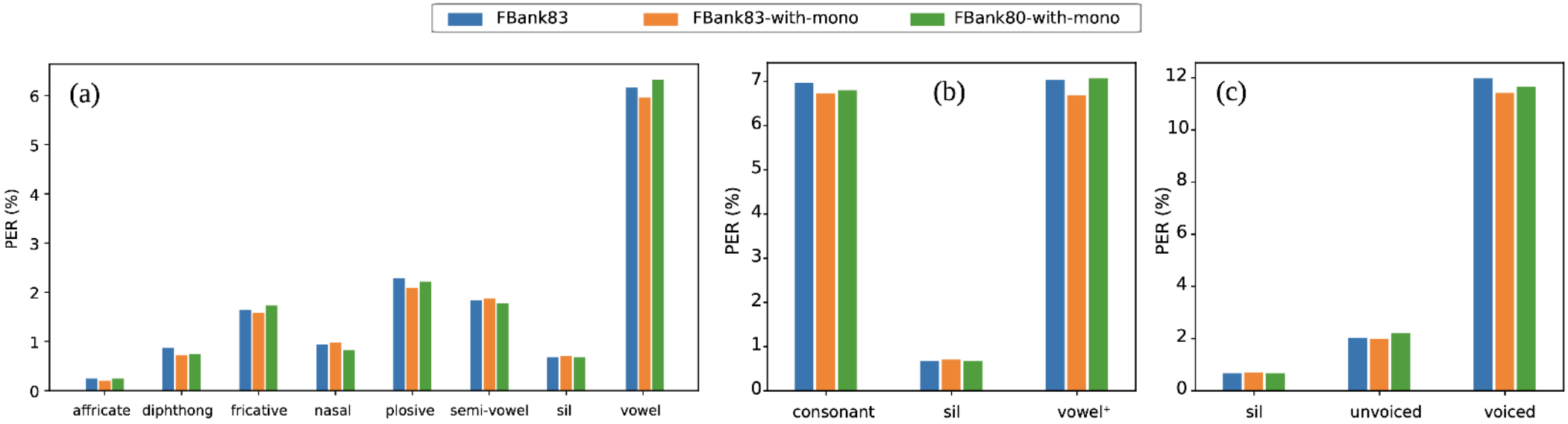
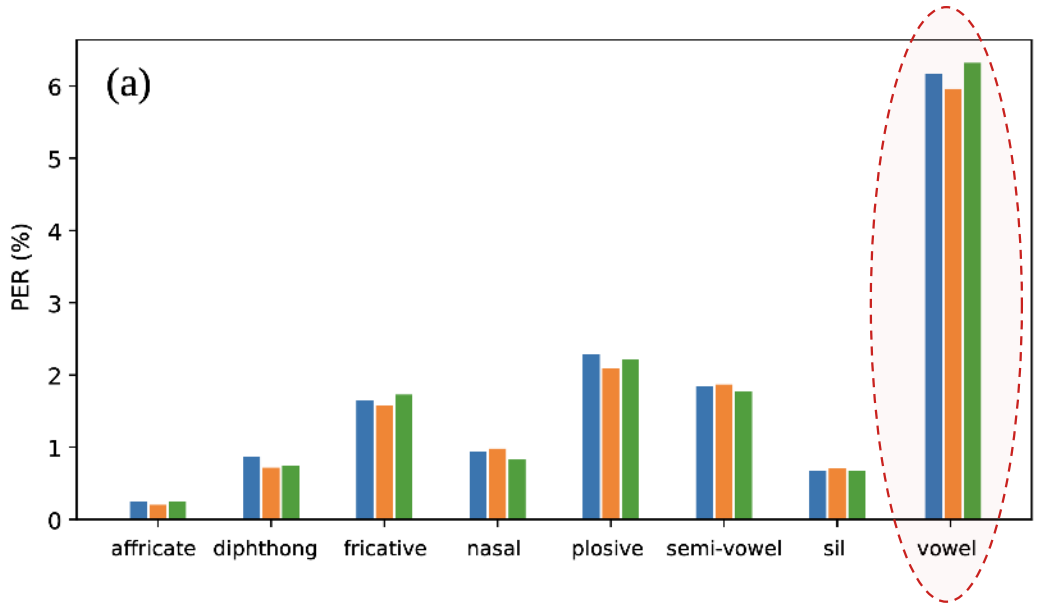


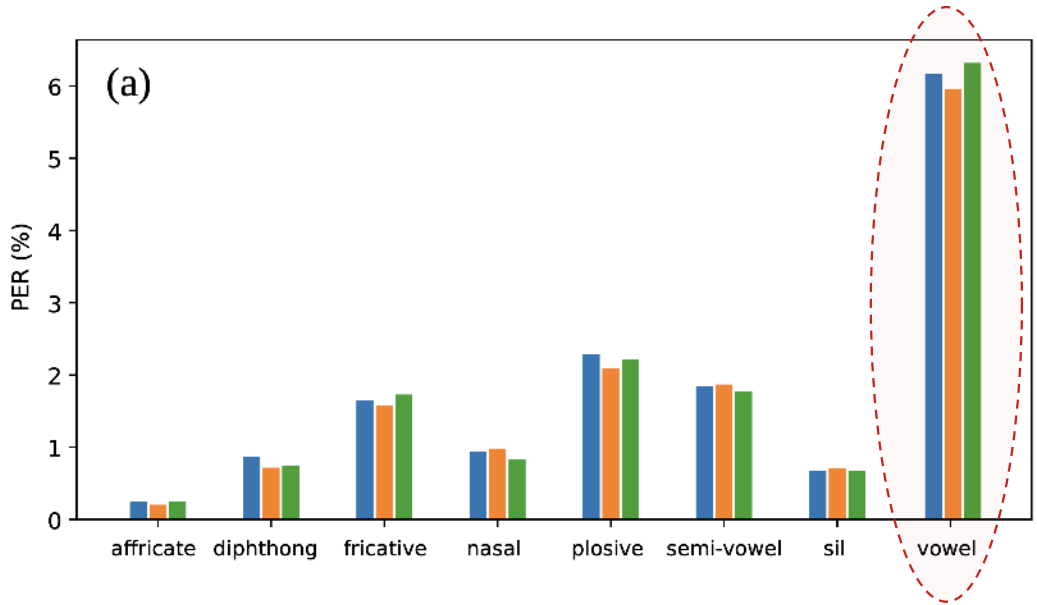
Minor gains after adding F_0 features & regularisation with CI.

Largest PER → Vowels



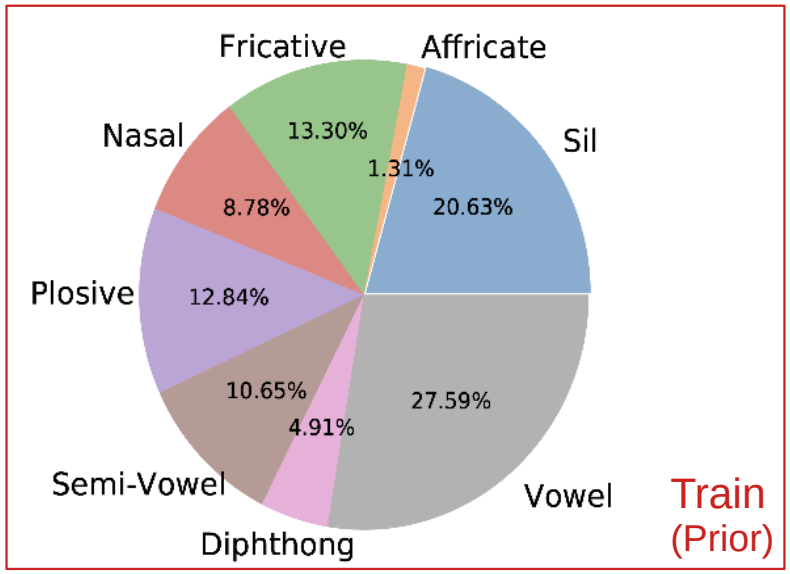
Largest PER → Vowels

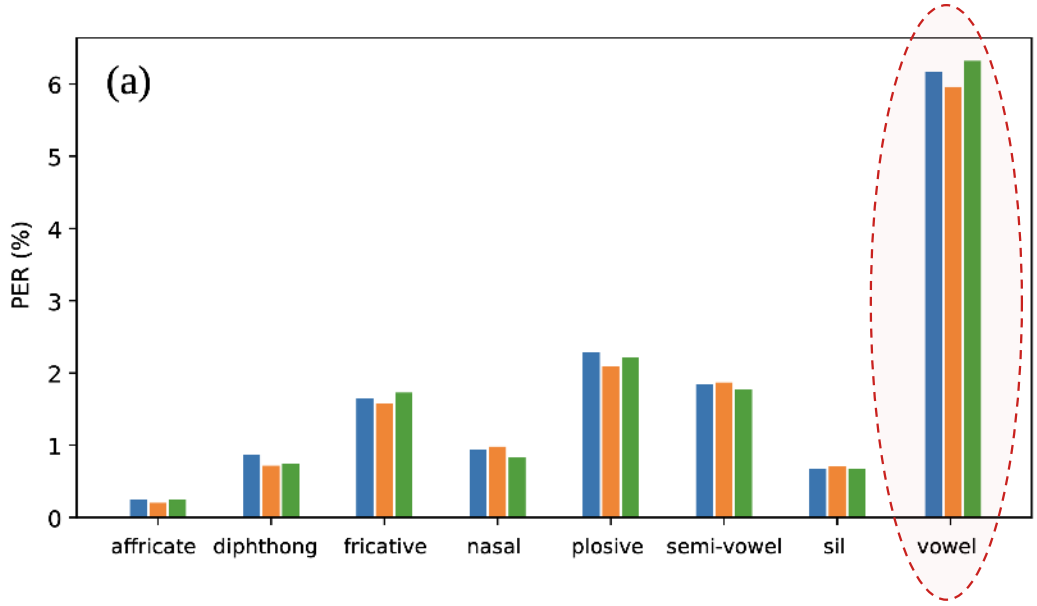
- **Q**uestions:
  - Training data amount?
  - TIMIT-specific?
  - Why?



Largest PER → Vowels

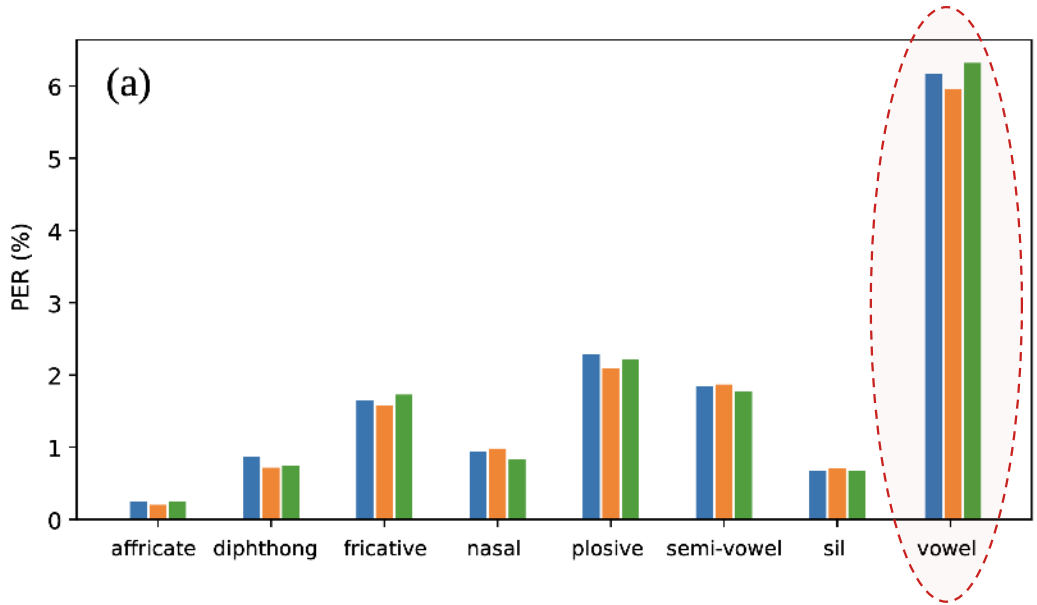
- **Q1**: Training data amount?





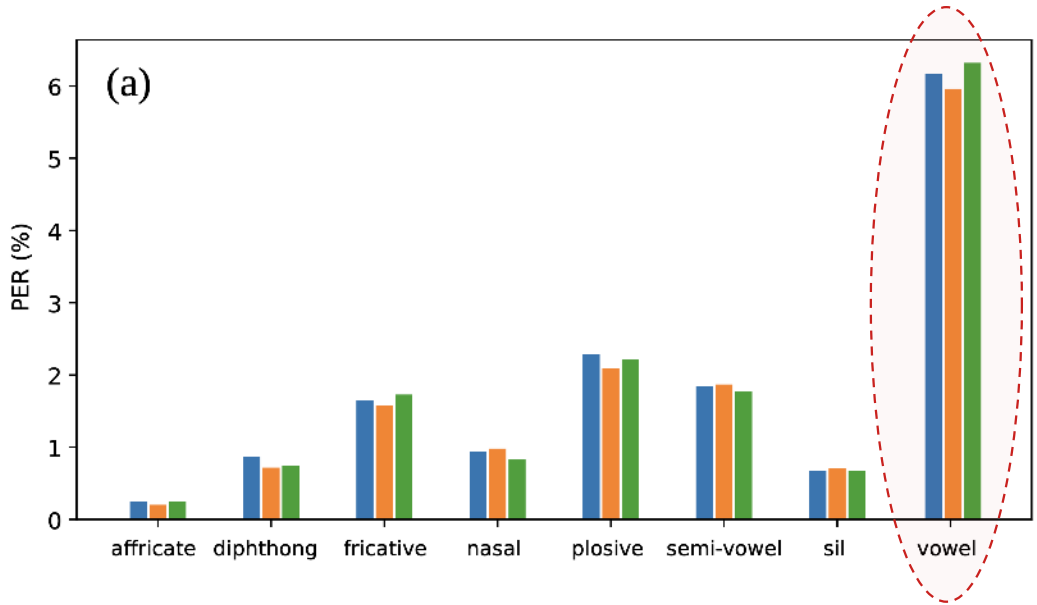
Largest PER → Vowels

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



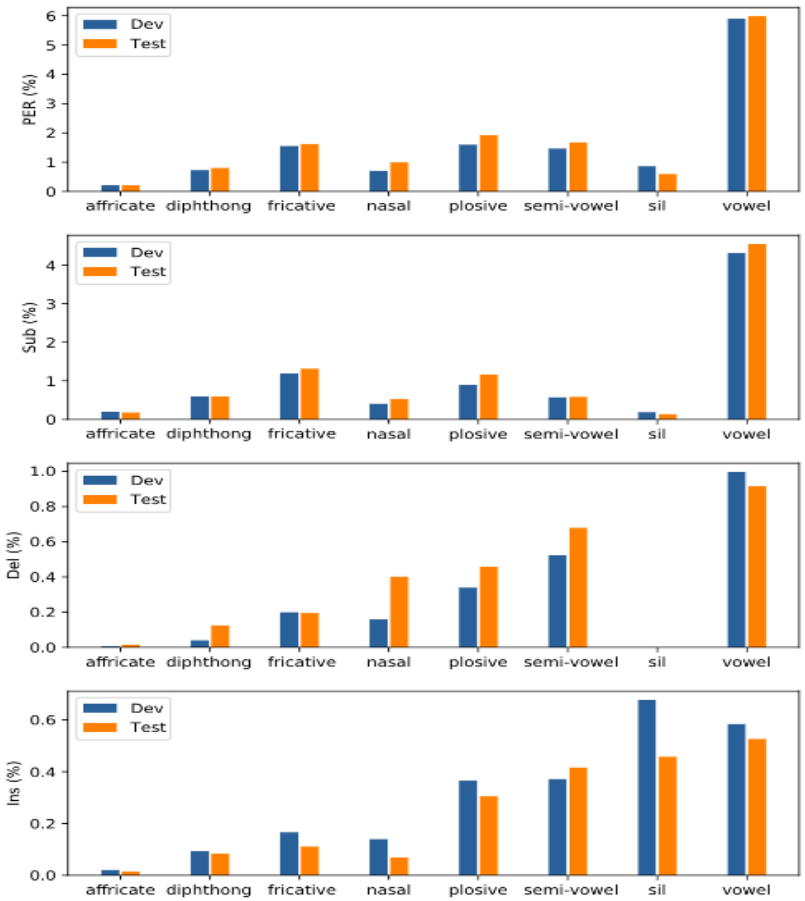
Largest PER → Vowels

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

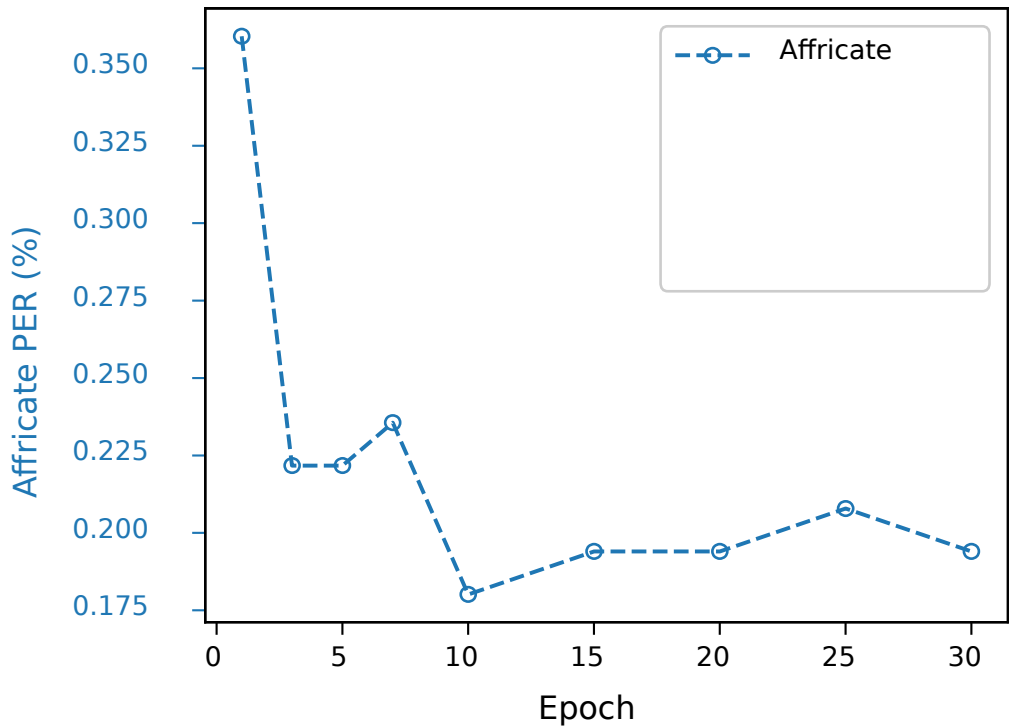


Sub/Del/Ins per BPC

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



Training Dynamics (1)



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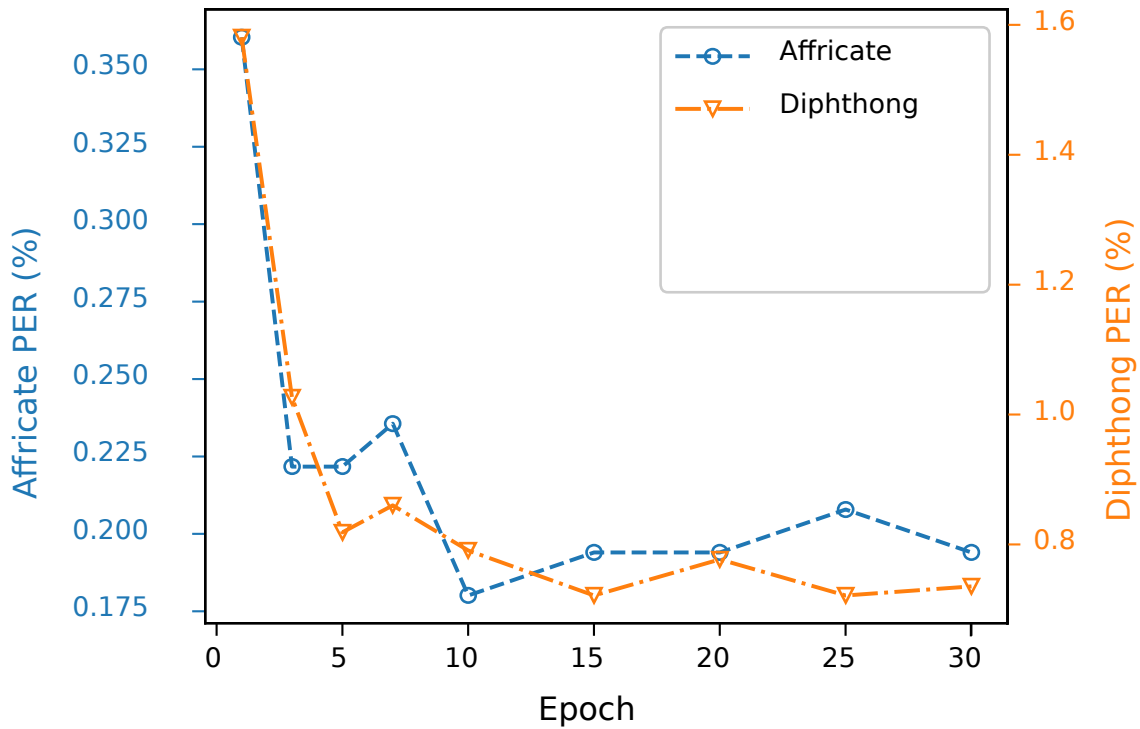

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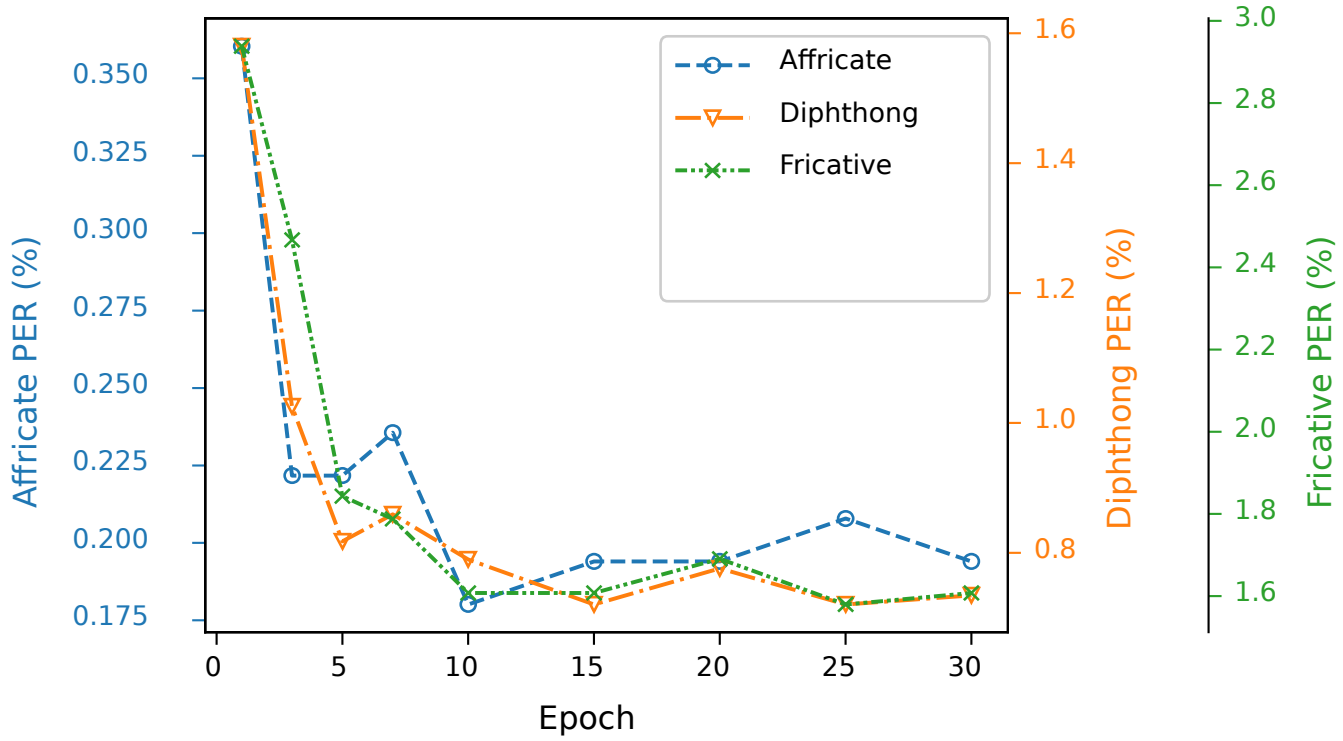

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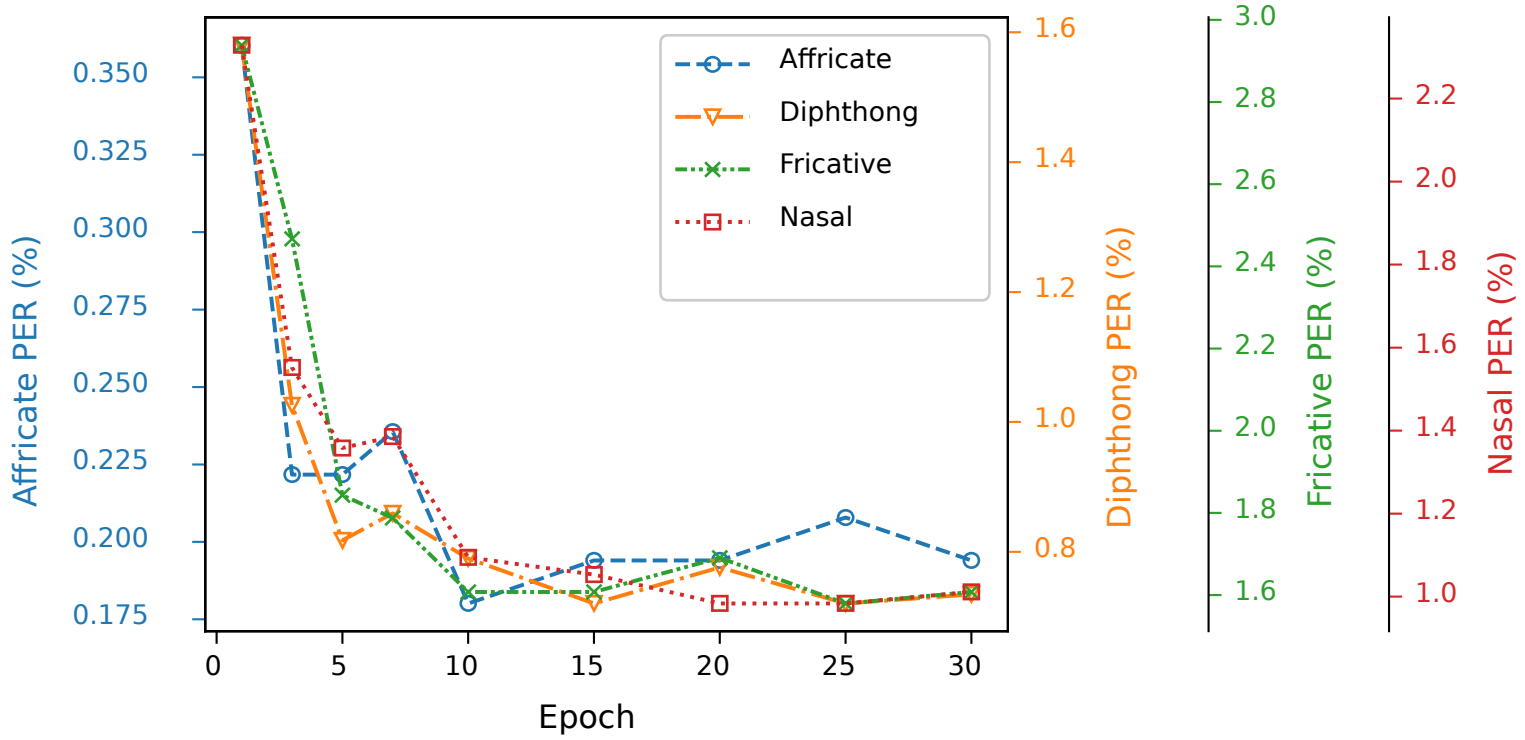

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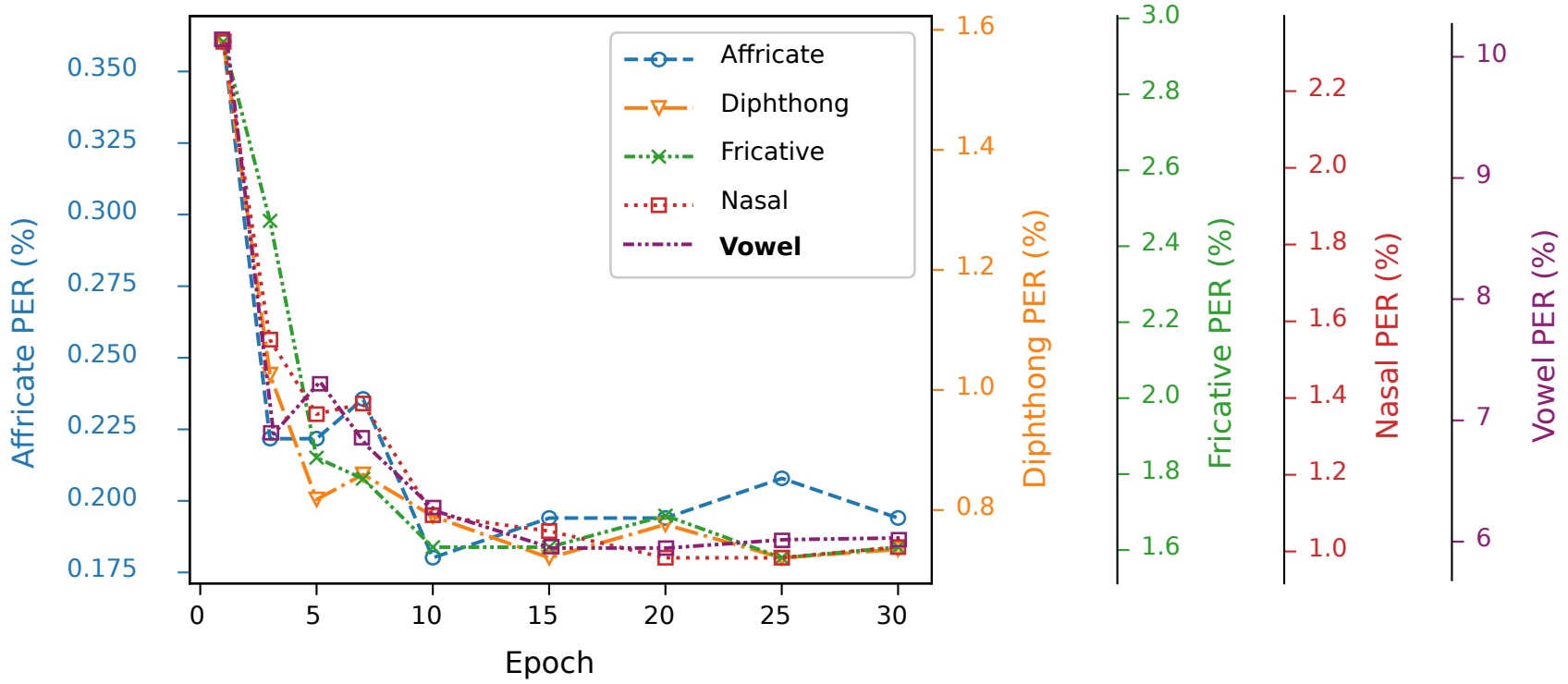
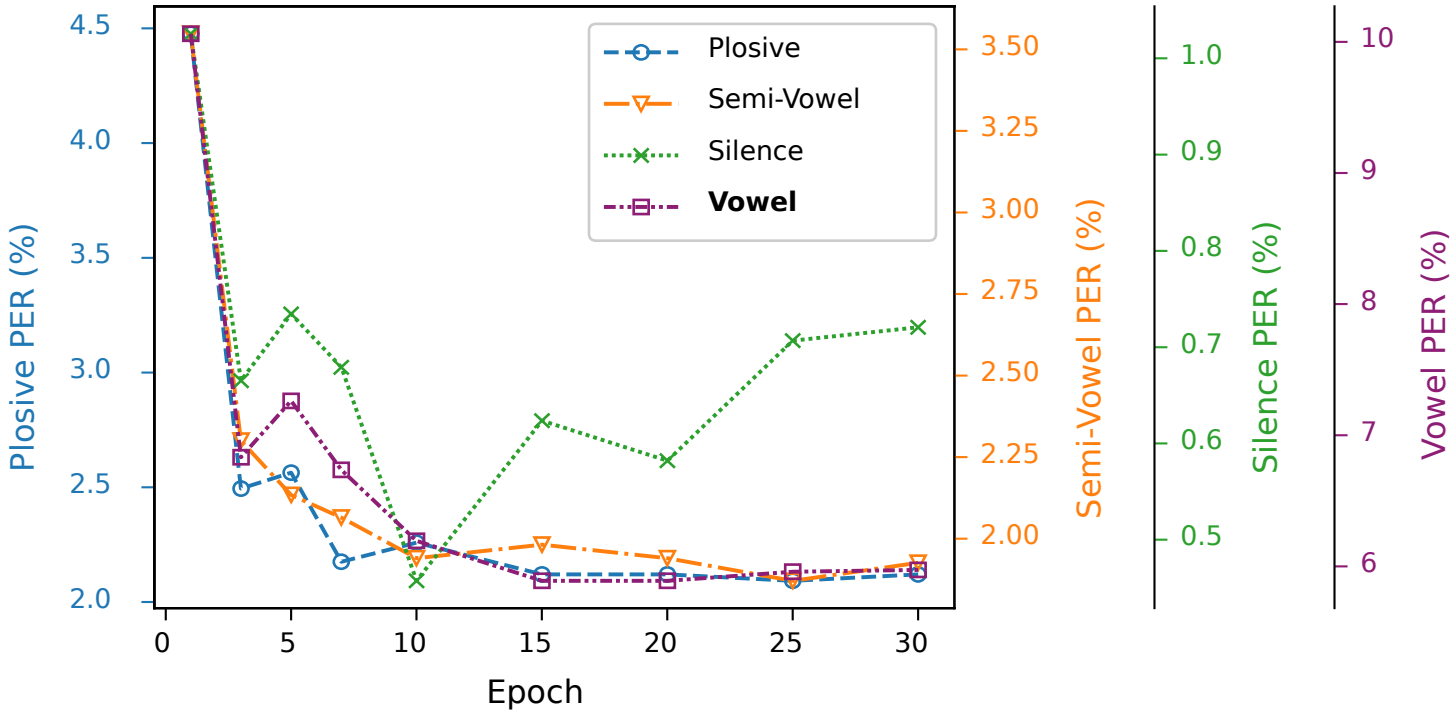
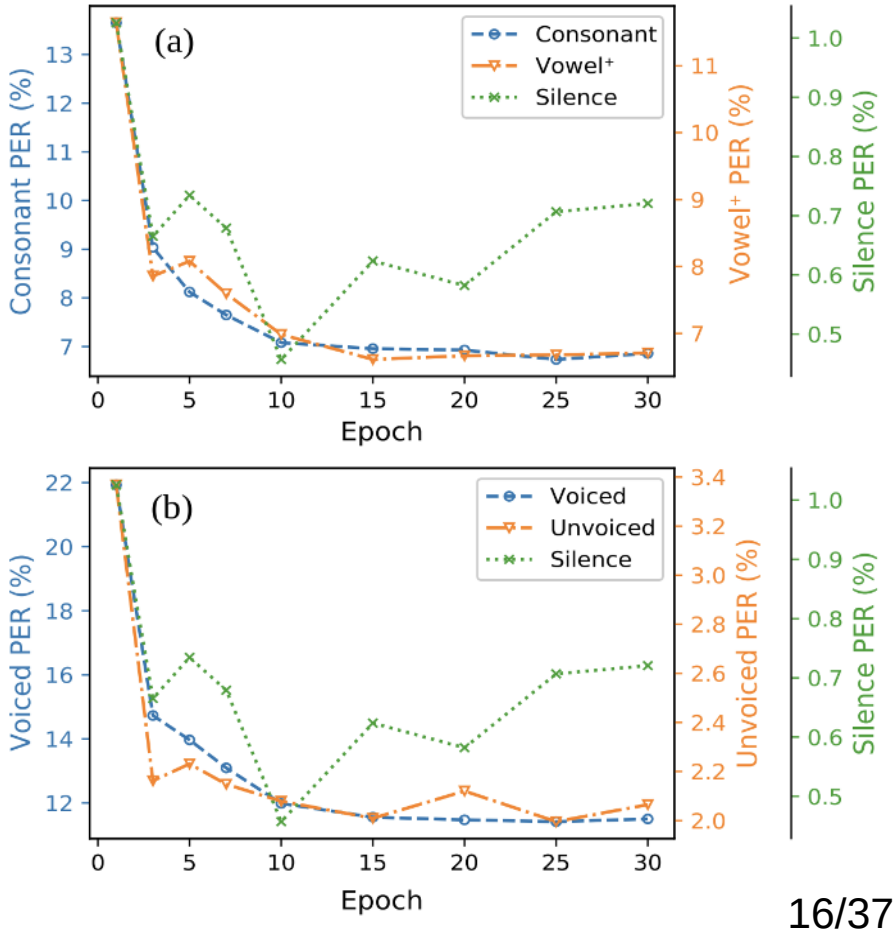


Training Dynamics (2)



Training Dynamics (3)



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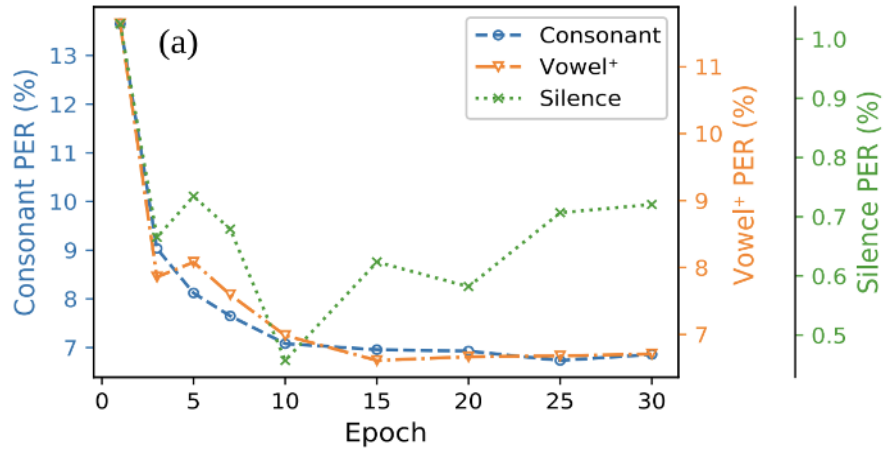
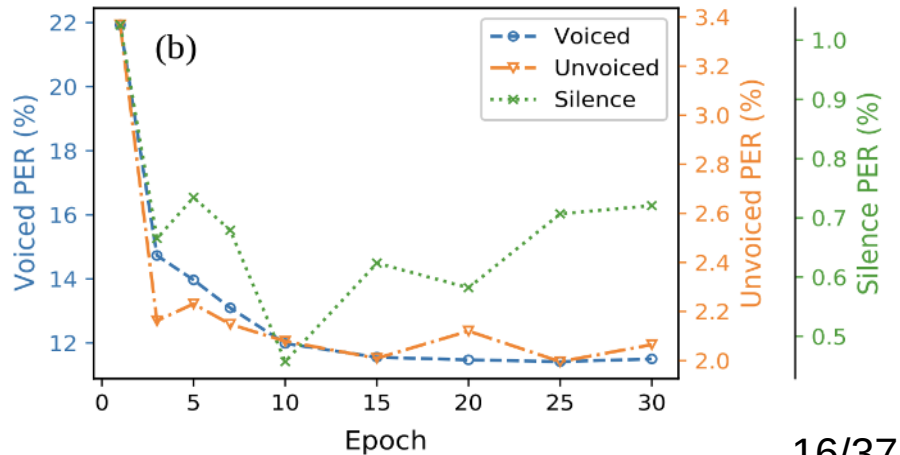
Training Dynamics (3)

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

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





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Confusion Matrices

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

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

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

(a)

(b)

True Label \ Predicted Label	sil	con	vow+
sil	0	**13**	1
con	12	**403**	88
vow+	3	78	**660**

(c)

True Label \ Predicted Label	sil	unv	voi
sil	0	2	**12**
unv	5	55	**84**
voi	10	125	**965**

Confusion Matrices

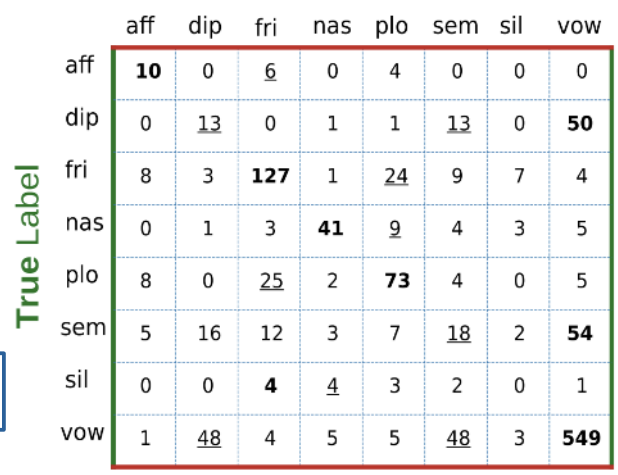
Fricatives are MCW **Fricatives** & Plosives.

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

Silence is MCW **Fricatives** & Nasals.

⋮

MCW: mostly confused with



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nas: nasal
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sem: semi-vowel
sil: silence
vow: vowel

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

sil: silence
unv: unvoiced
voi: voiced

(a)

(b)

	sil	con	vow⁺
sil	0	**13**	1
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(c)

	sil	unv	voi
sil	0	2	**12**
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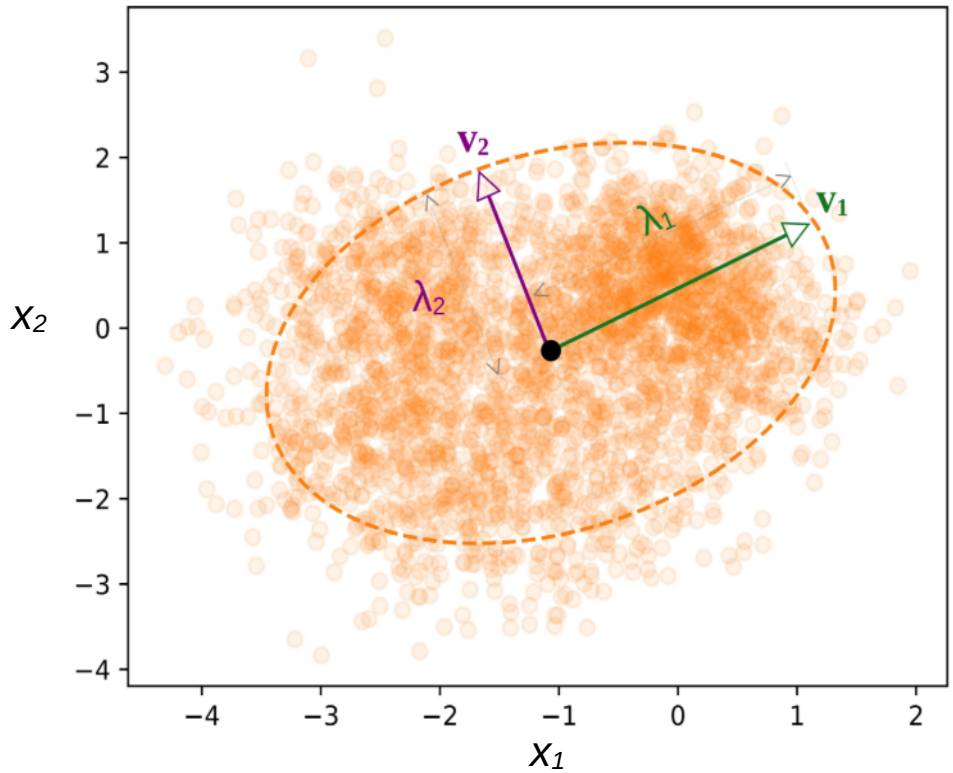
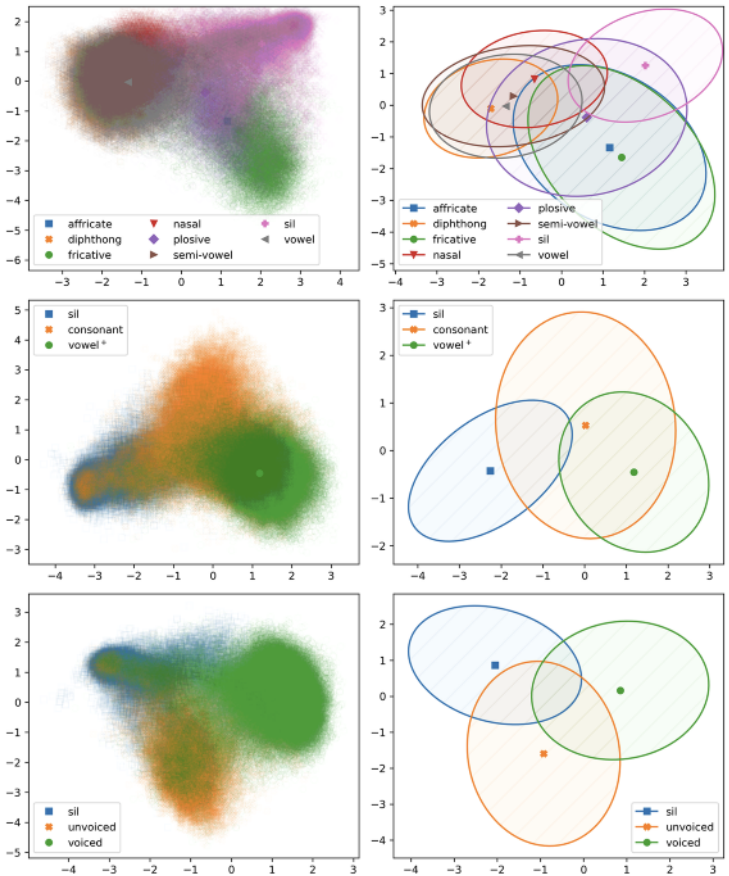
Scatter Plot in 2D

- How:
  - LDA (t-SNE later)
  - Fit an ellipse



* LDA: Linear Discriminant Analysis

Scatter Plots



Acoustic Model

Acoustic Feature

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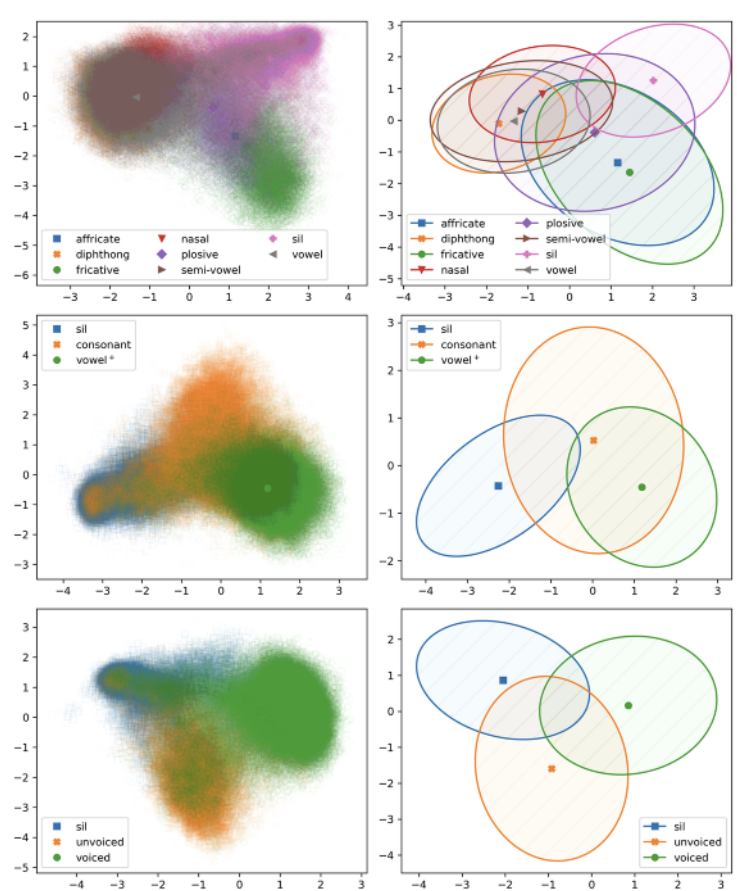
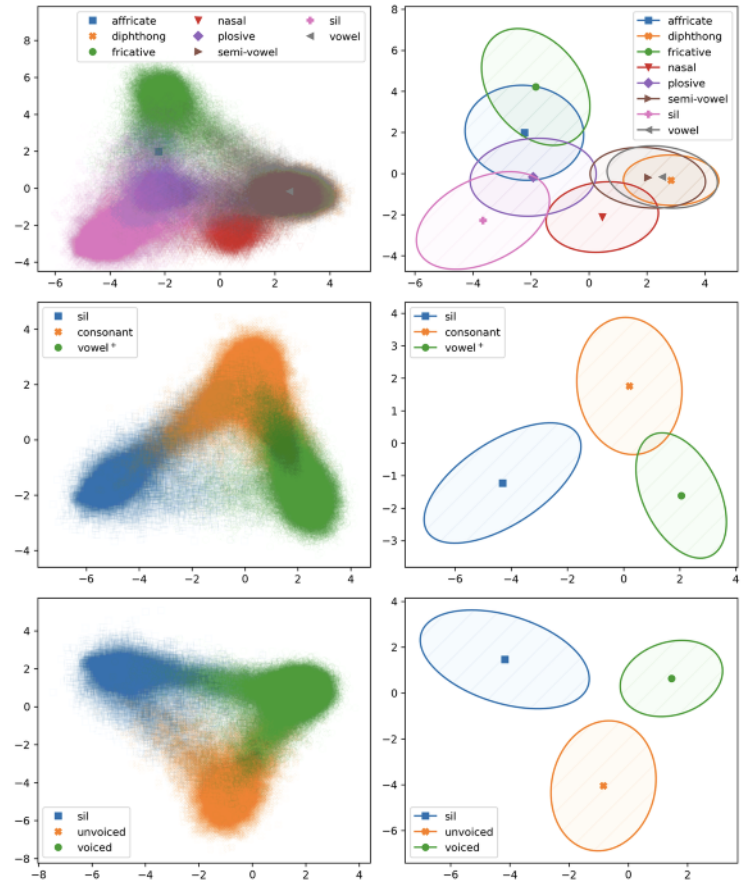
Scatter Plots



Acoustic Feature

Acoustic Model



Logit (Baseline)

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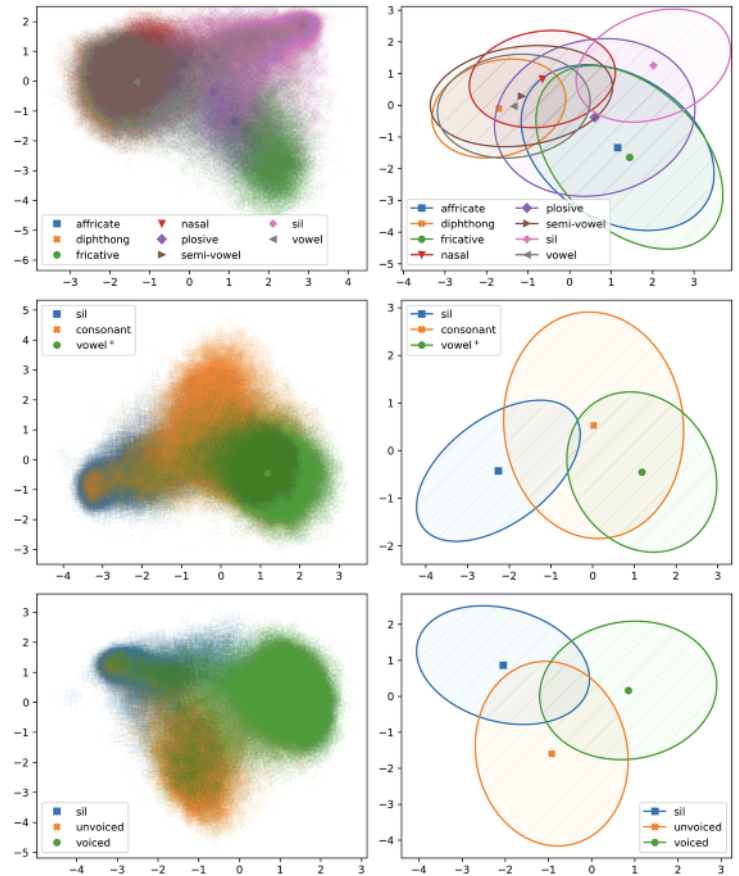
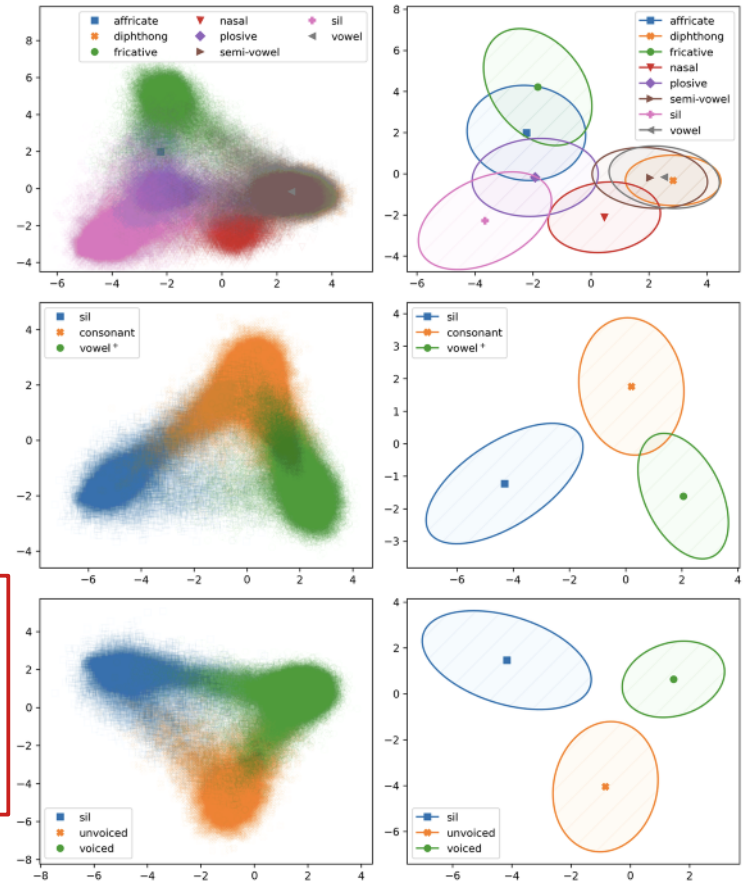
Scatter Plots



Acoustic Model



✔ →More distinct clusters→

✗ Scatter plots justify confusions (but not perfectly!)

Acoustic Feature

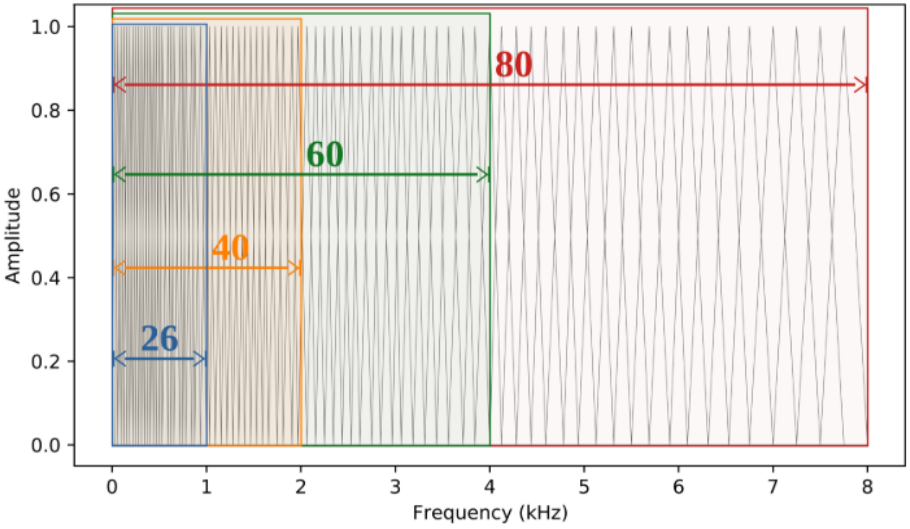
Loweimi et al

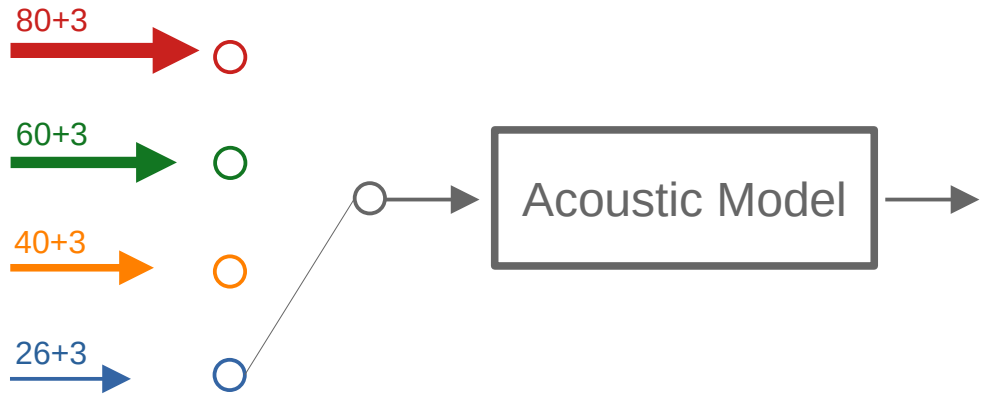
Logit (Baseline)

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

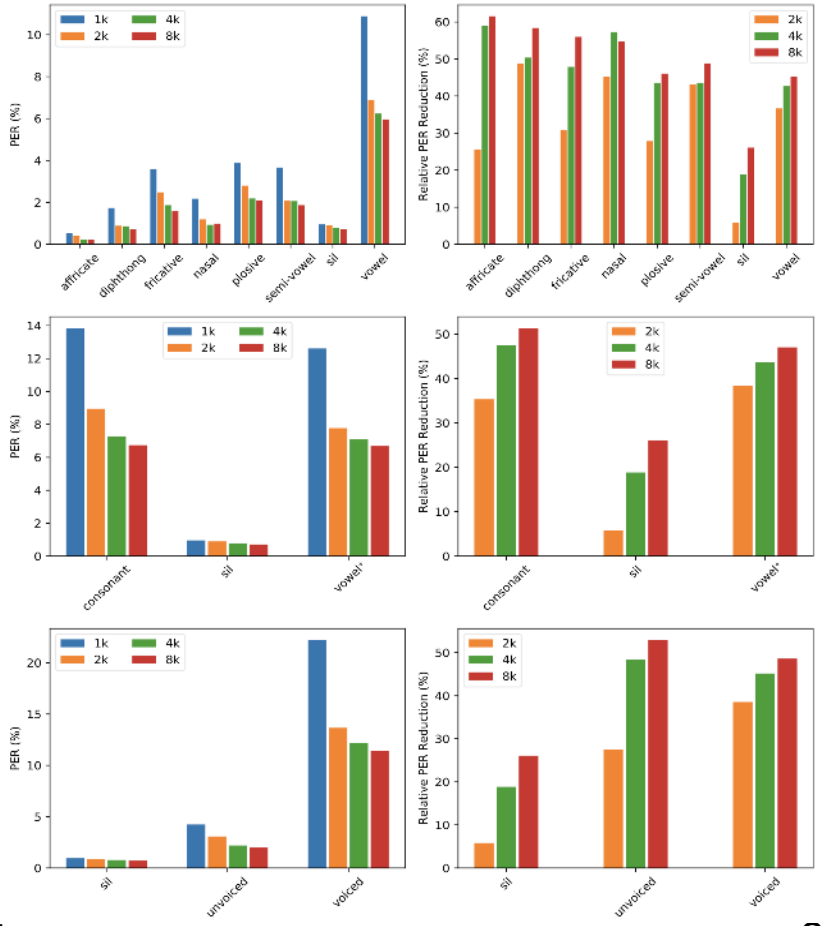
Effect of Sub-bands





Effect of Sub-bands

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

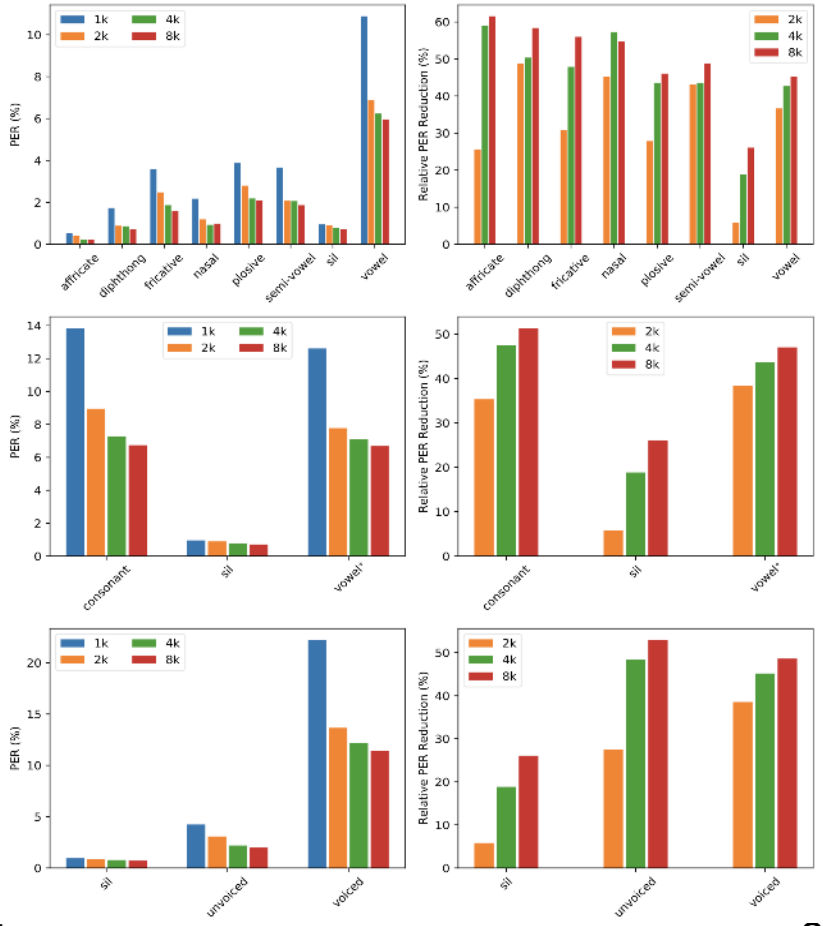


Effect of Sub-bands

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

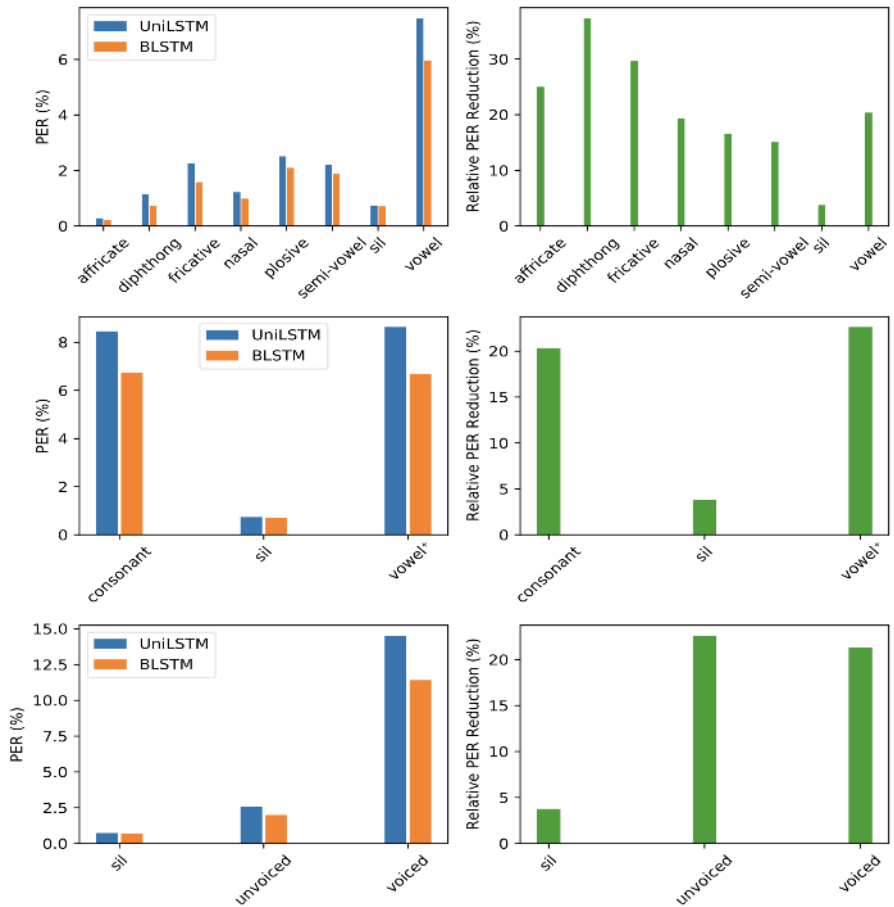
Including freq > 2kHz ...

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



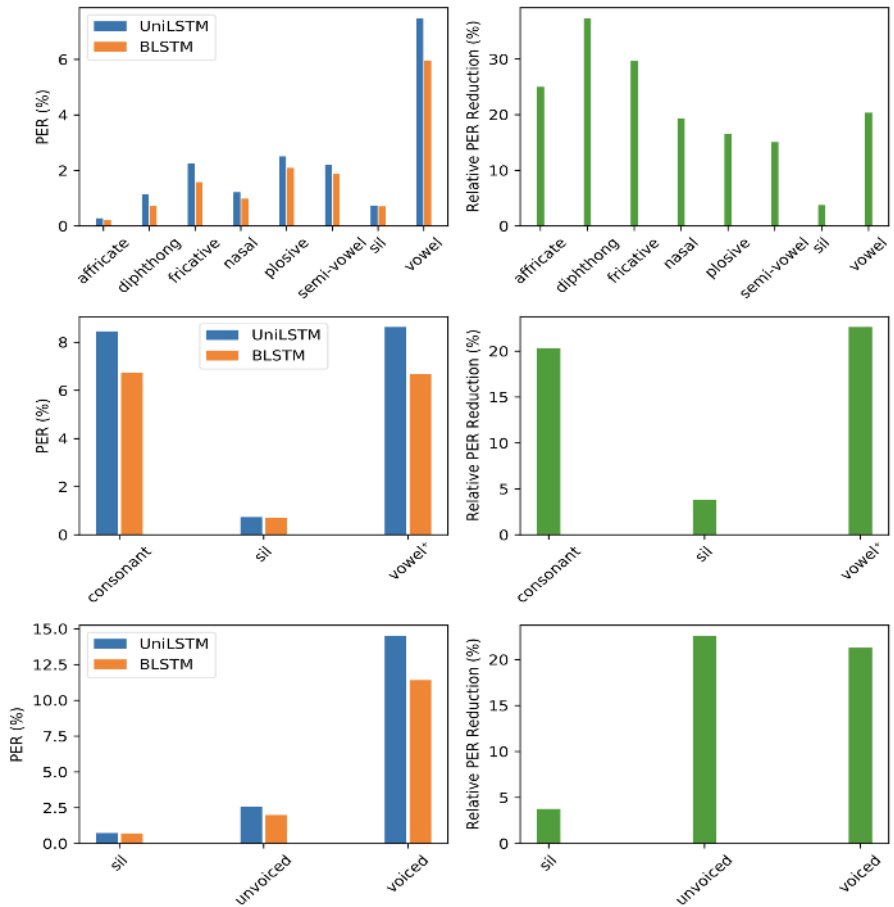
Uni- vs Bi-Directional

- Relative Gain:
  - Typically 15% to 40%



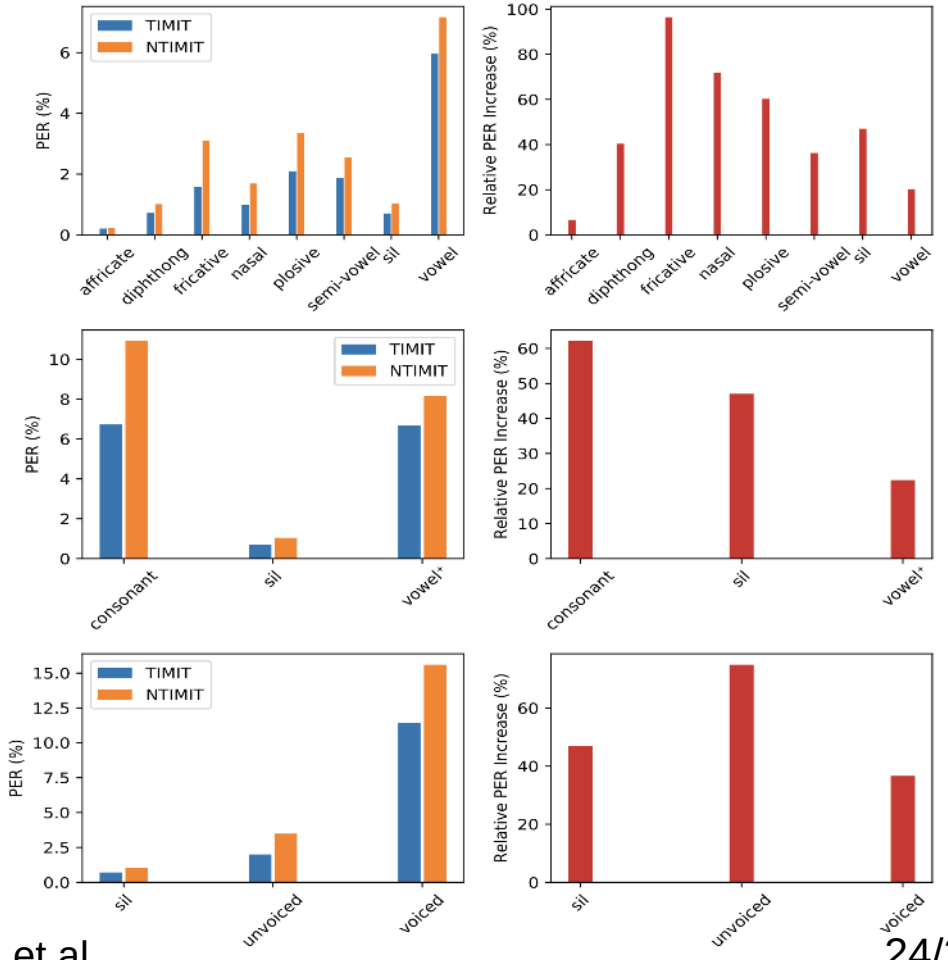
Uni- vs Bi-Directional

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



NTIMIT

- Relative gain: -21% to -95%



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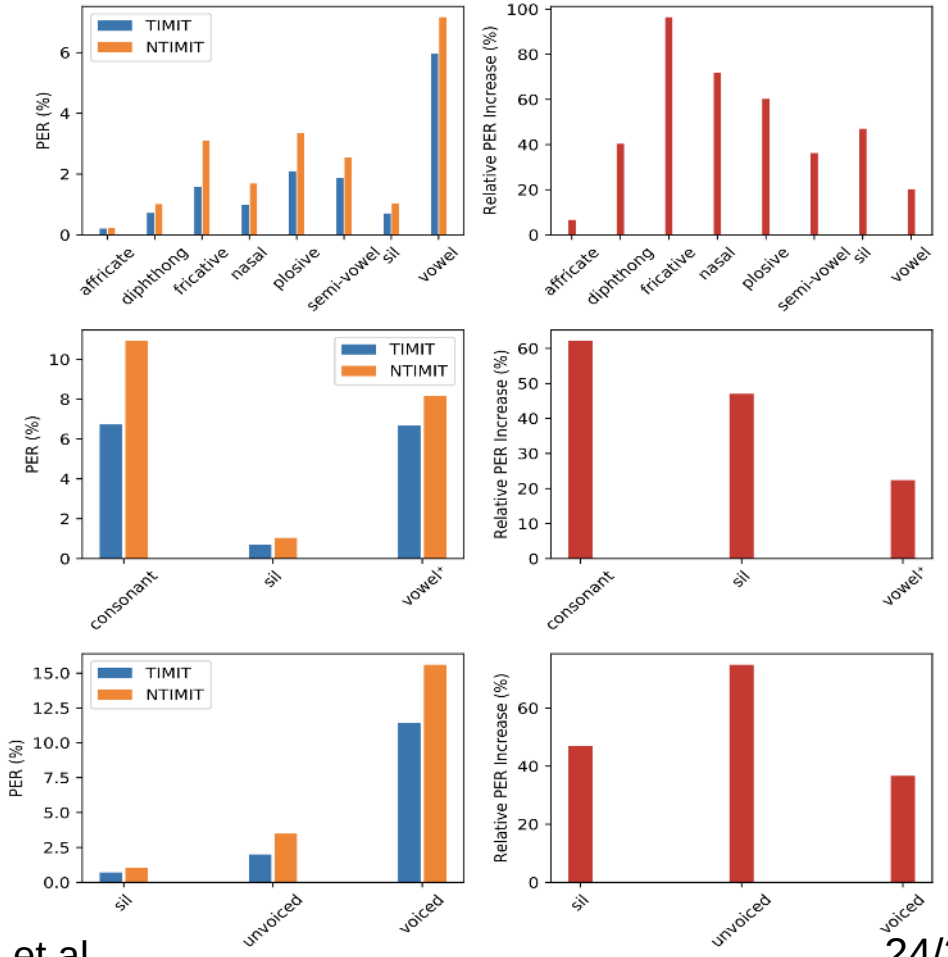
NTIMIT

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



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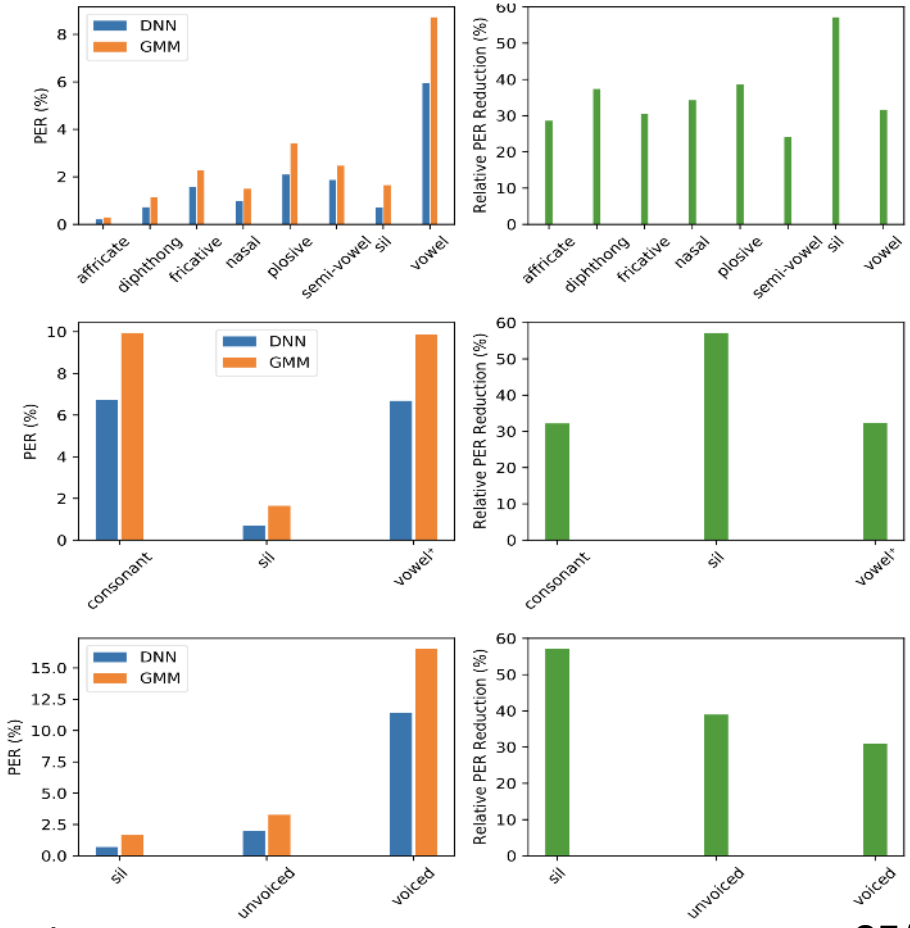
GMM-HMM vs DNN-HMM

- Relative Gain: 25% to 55%



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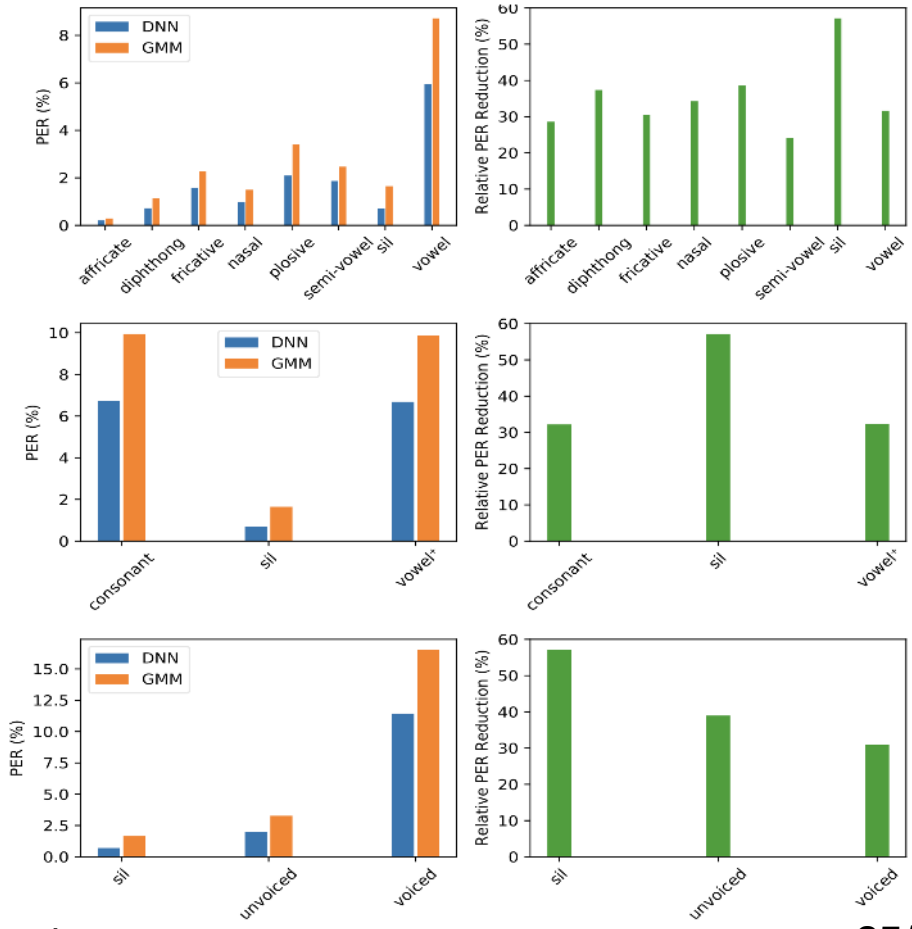
GMM-HMM vs DNN-HMM

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



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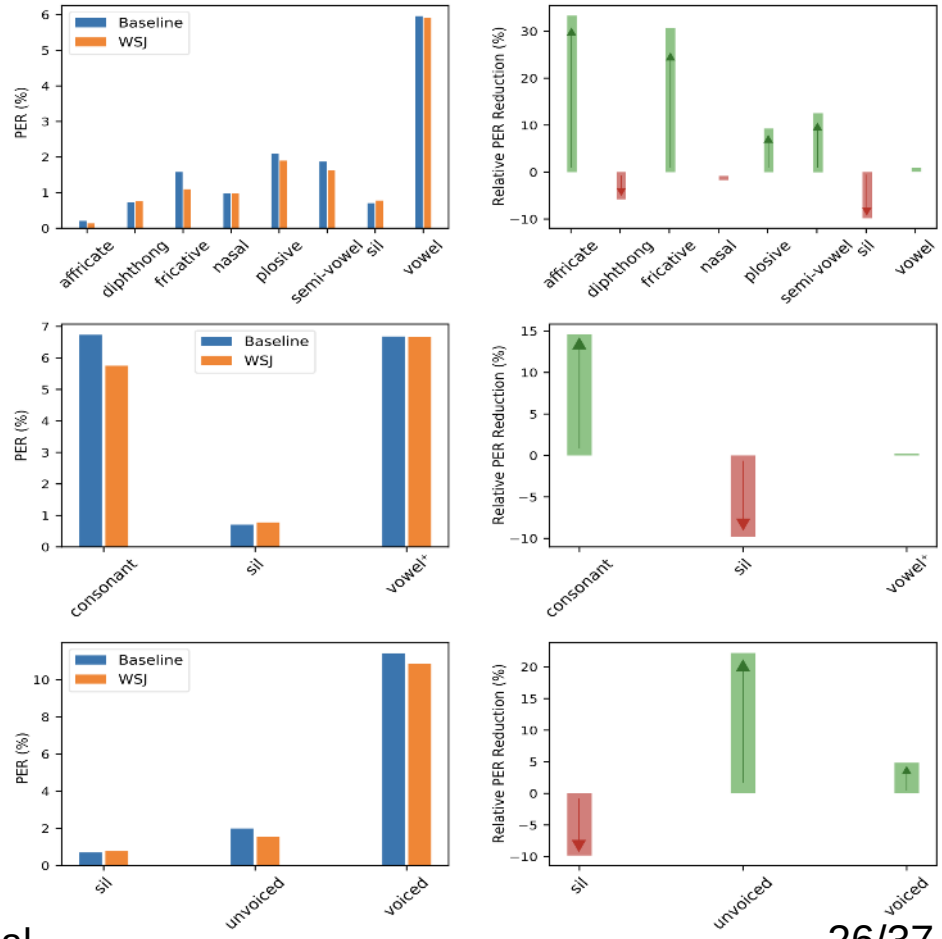
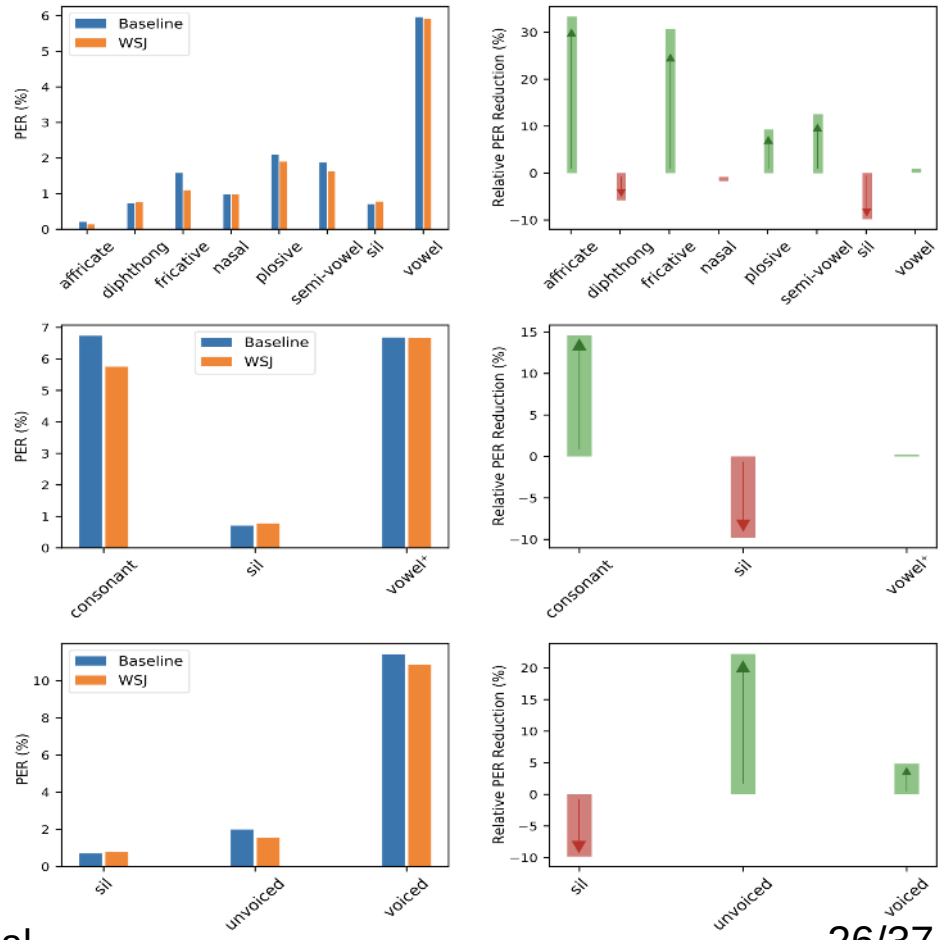
Transfer Learning from WSJ

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



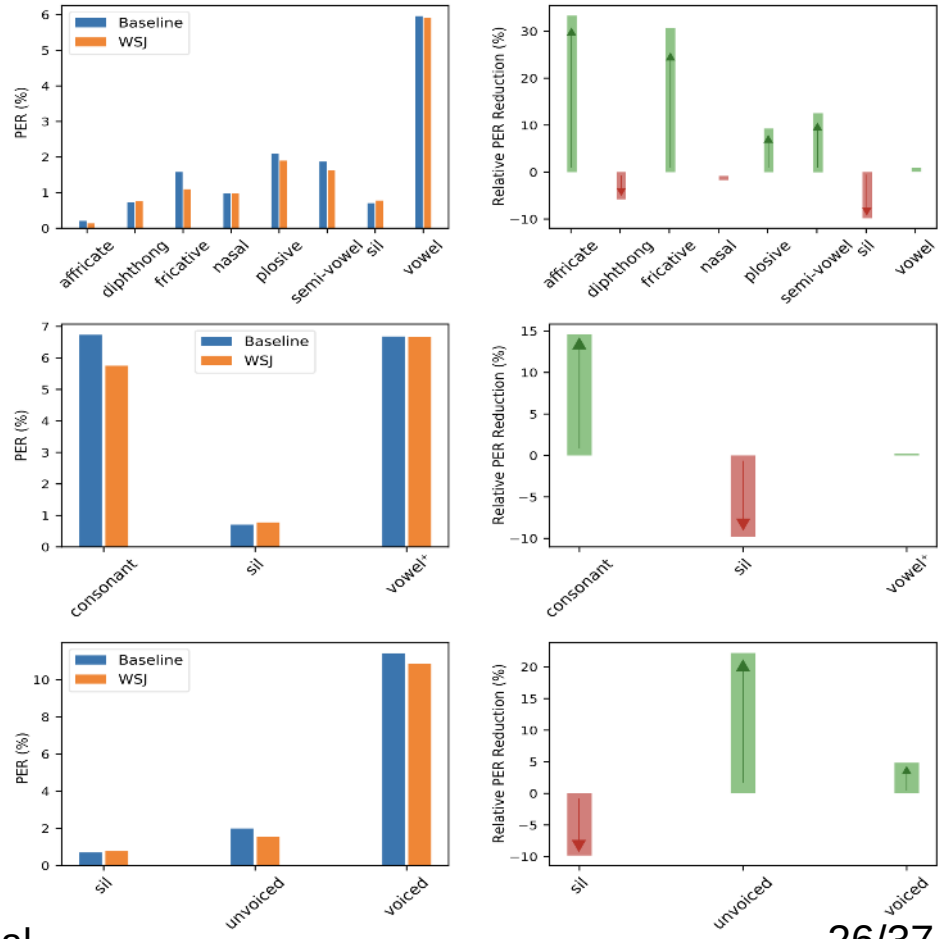
Transfer Learning from WSJ

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



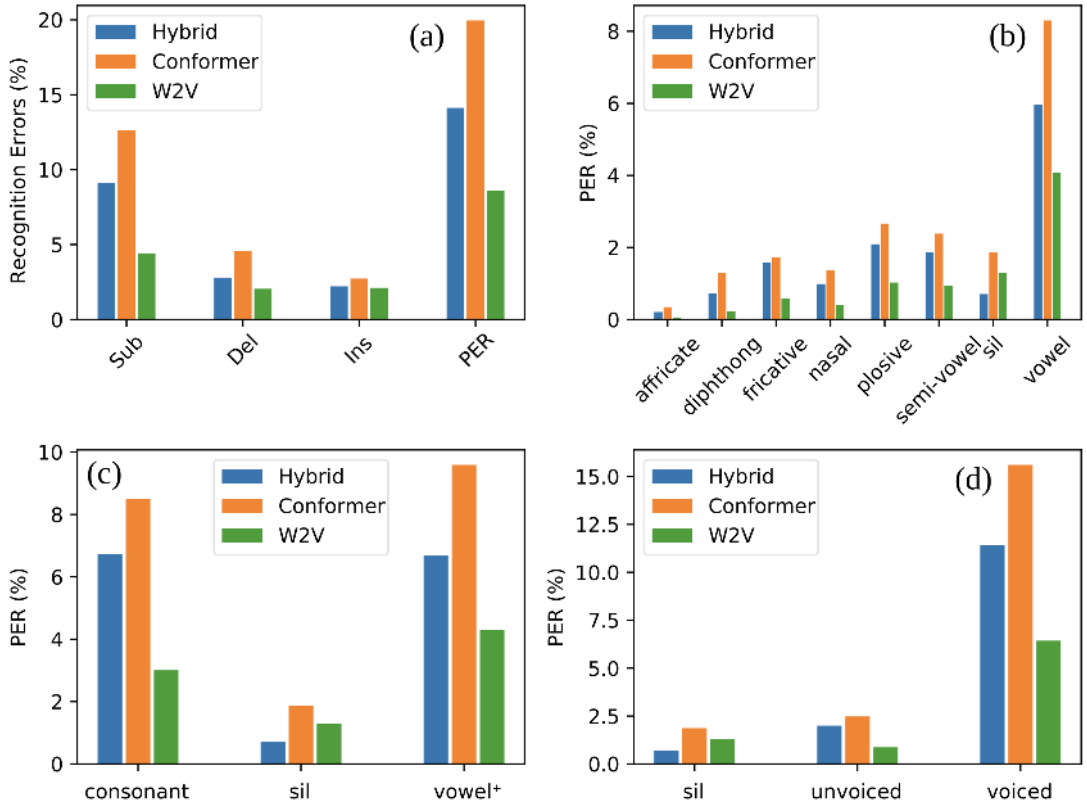
Transfer Learning from WSJ

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

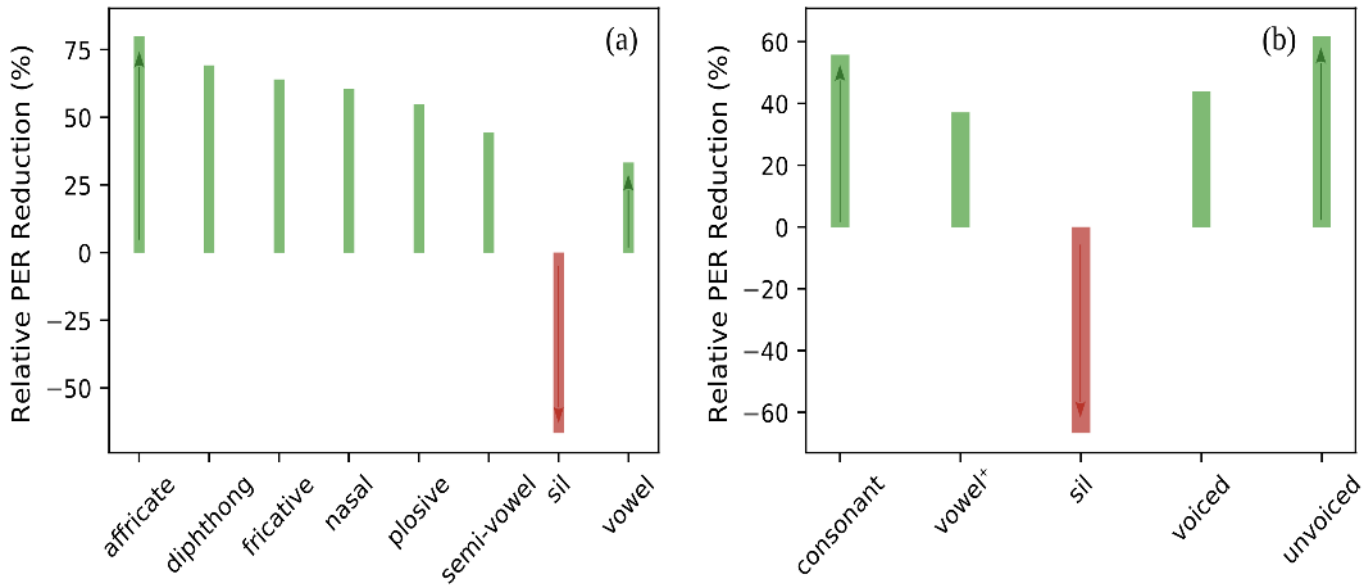


End-to-end (E2E) vs Hybrid

- 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+

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Confusion Matrices

Baseline (DNN-HMM)

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

(a)

(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

True Label \ Predicted 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**

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

(a)

(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**

Confusion Matrices

Baseline (DNN-HMM)

True \ Predicted	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

Wav2vec 2.0

True \ Predicted	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**

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

Sparser but Similar Patterns

(a)

(b)

True \ Predicted	sil	con	vow$^+$
sil	0	**13**	1
con	12	**403**	88
vow$^+$	3	78	**660**

(c)

True \ Predicted	sil	unv	voi
sil	0	2	**12**
unv	5	55	**84**
voi	10	125	**965**

(b)

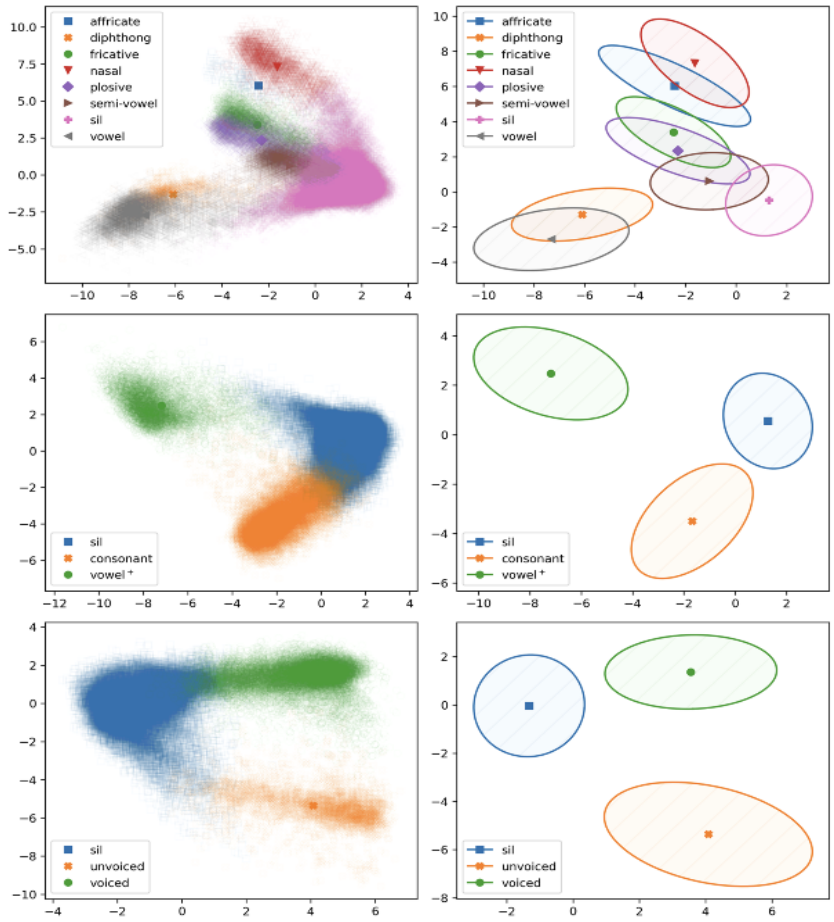
True \ Predicted	sil	con	vow$^+$
sil	0	**10**	0
con	5	**83**	28
vow$^+$	2	21	**400**

(c)

True \ Predicted	sil	unv	voi
sil	0	1	**9**
unv	1	4	**27**
voi	6	24	**477**

Scatter Plots

Logit (wav2vec 2.0)



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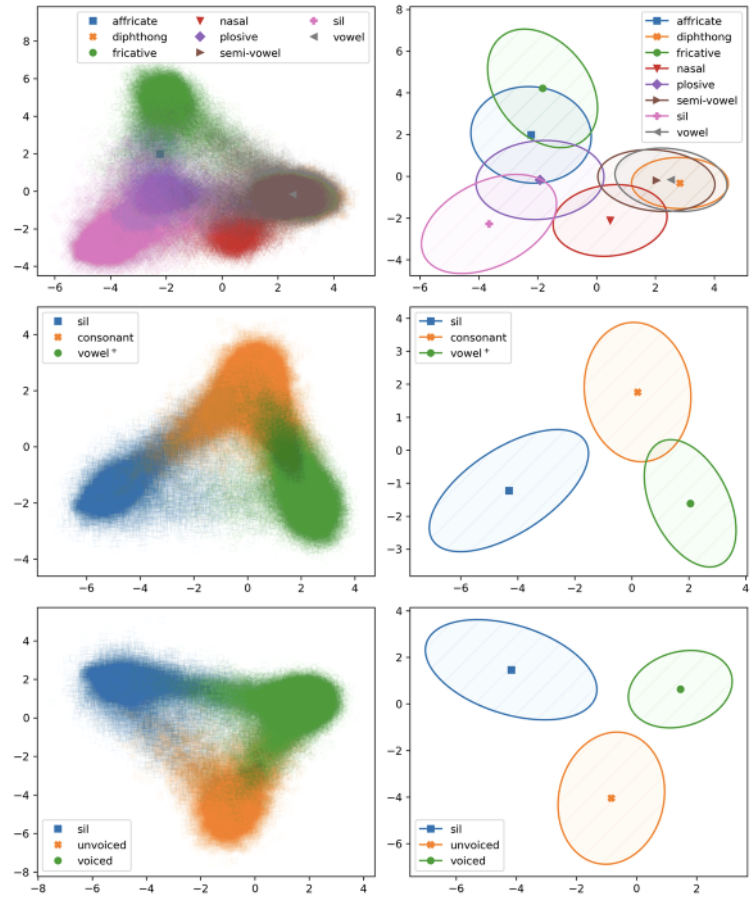
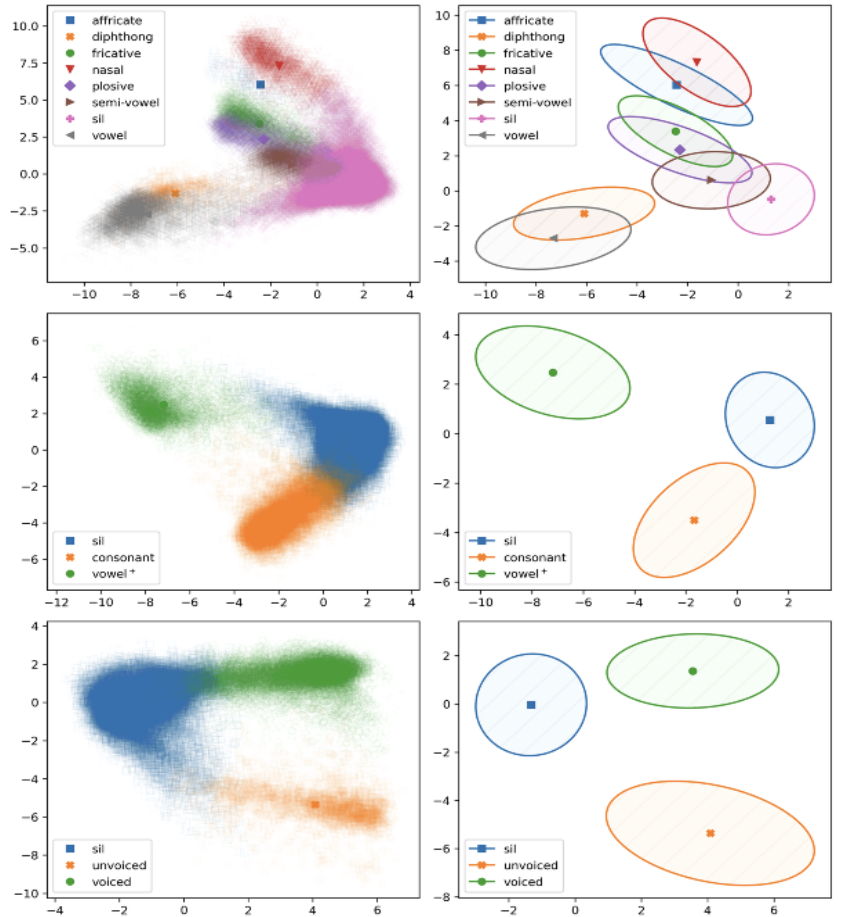
Scatter Plots

Logit (Hybrid)



More distinct clusters

Logit (wav2vec 2.0)



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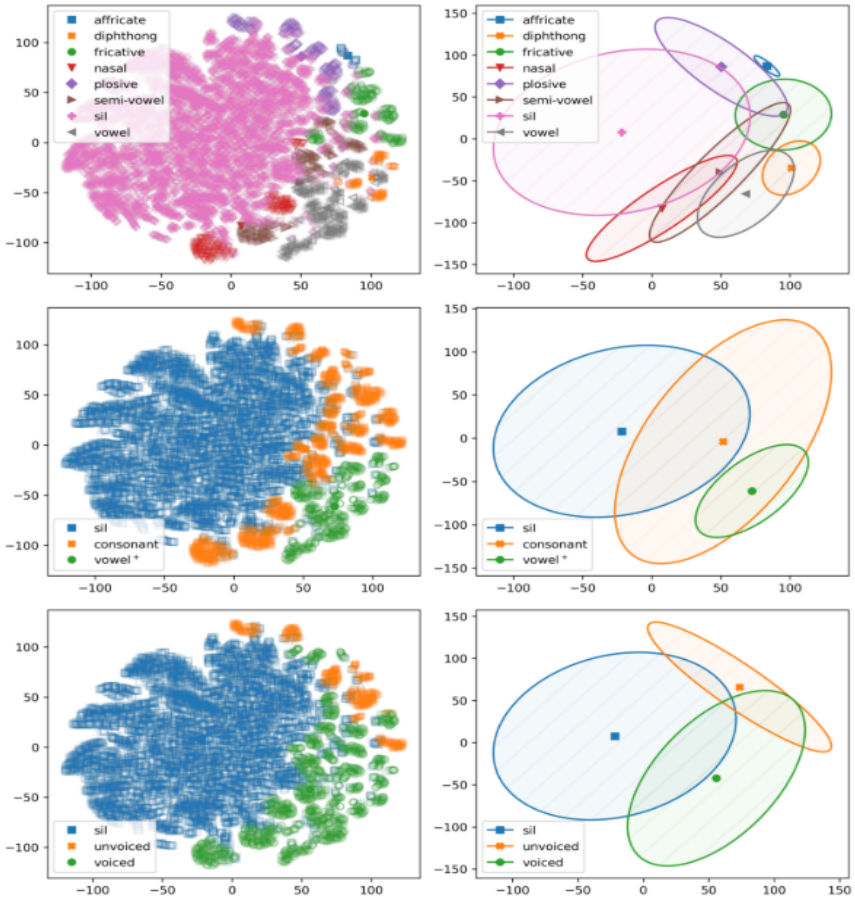
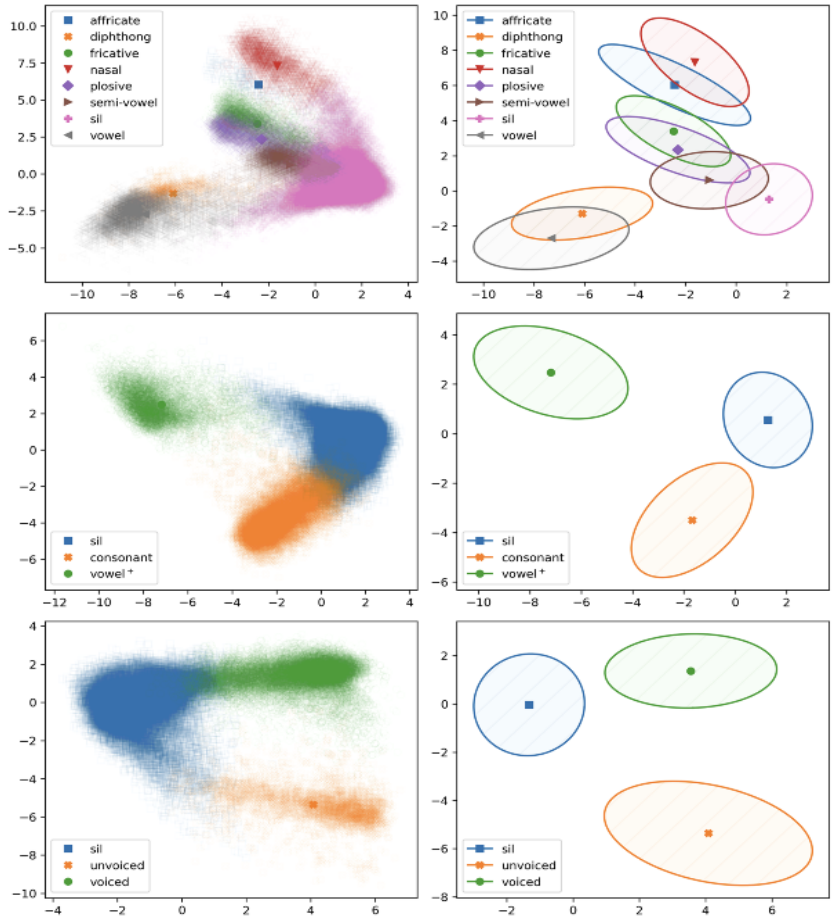
t-SNE vs LDA

t-SNE



LDA



Logits (Wav2vec 2.0)

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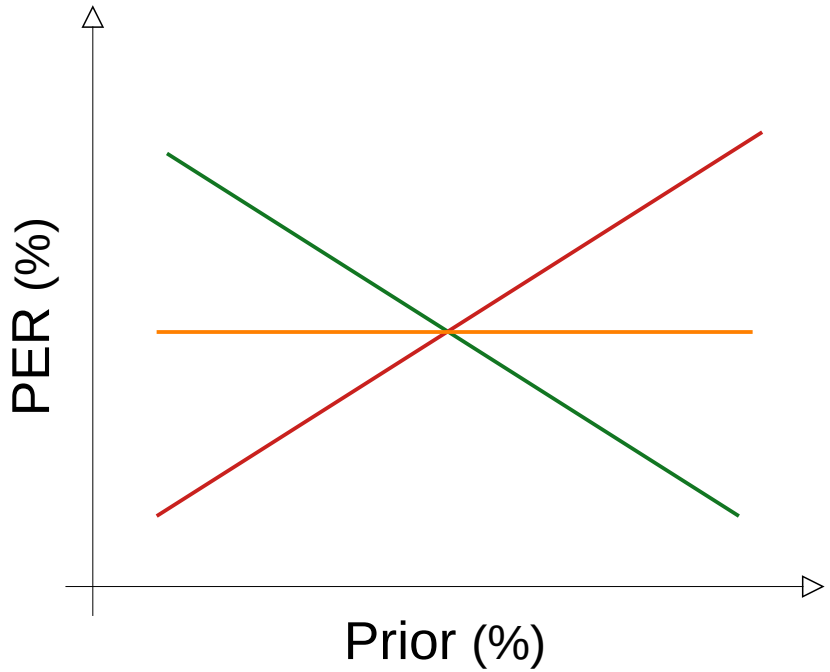
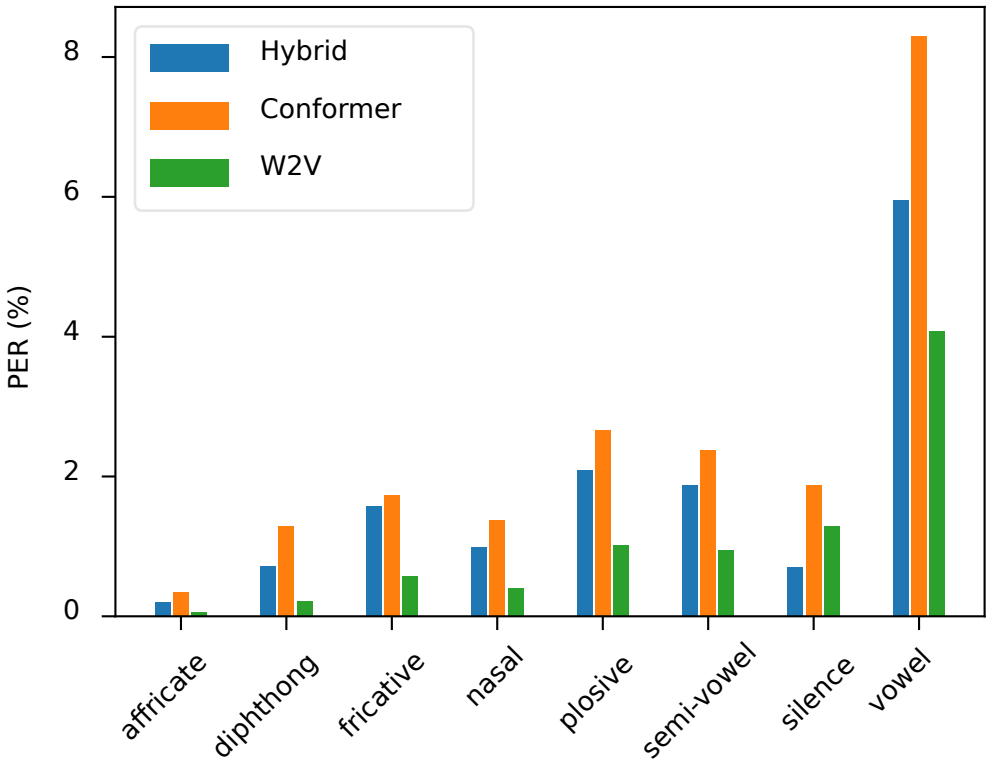
Logits (Wav2vec 2.0)

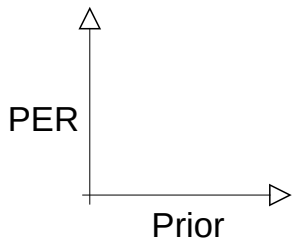
PER vs Prior (1)

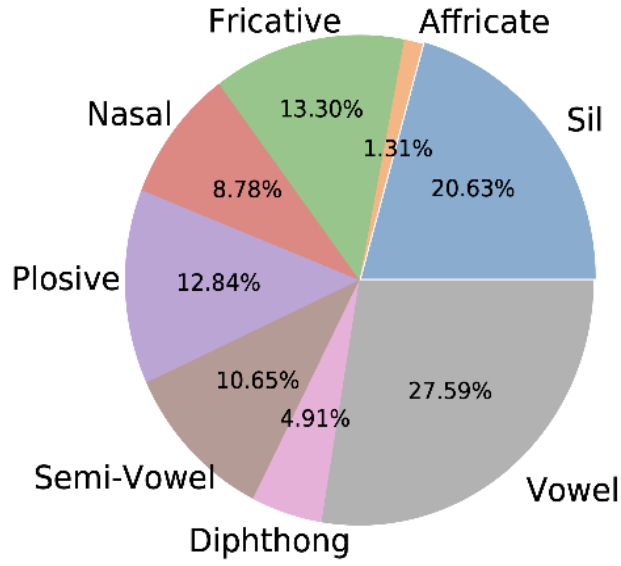


Trend ???

PER vs Prior (1)







BPC's Prior

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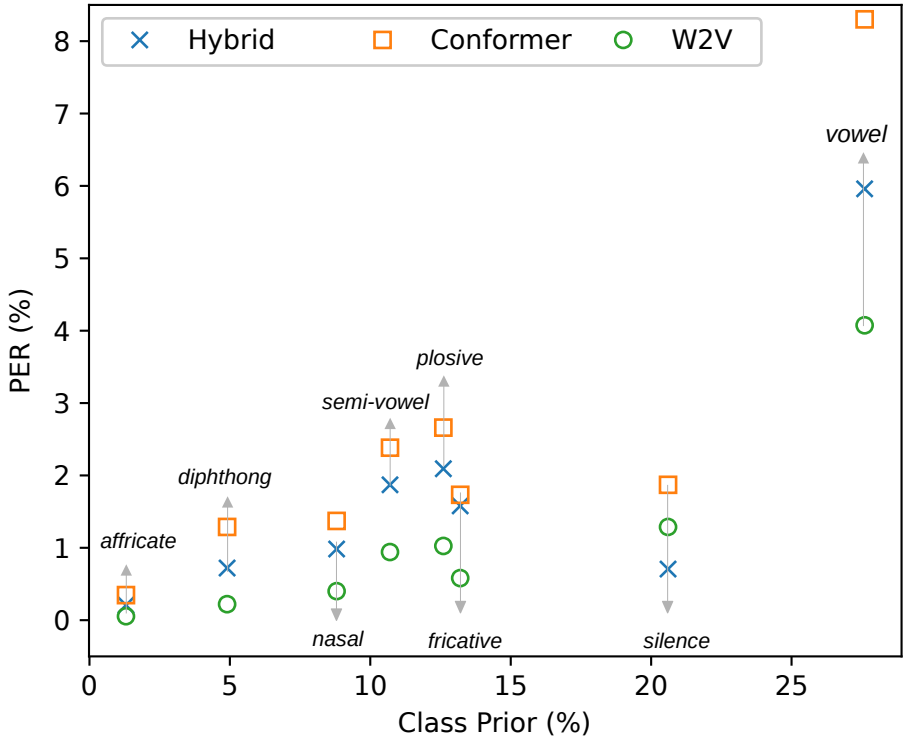
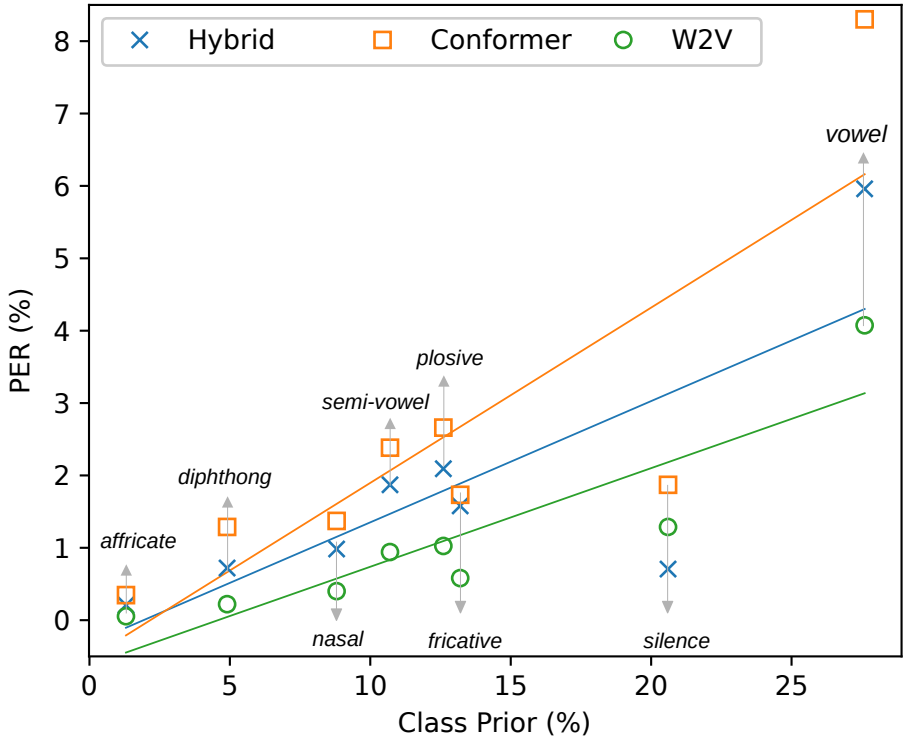
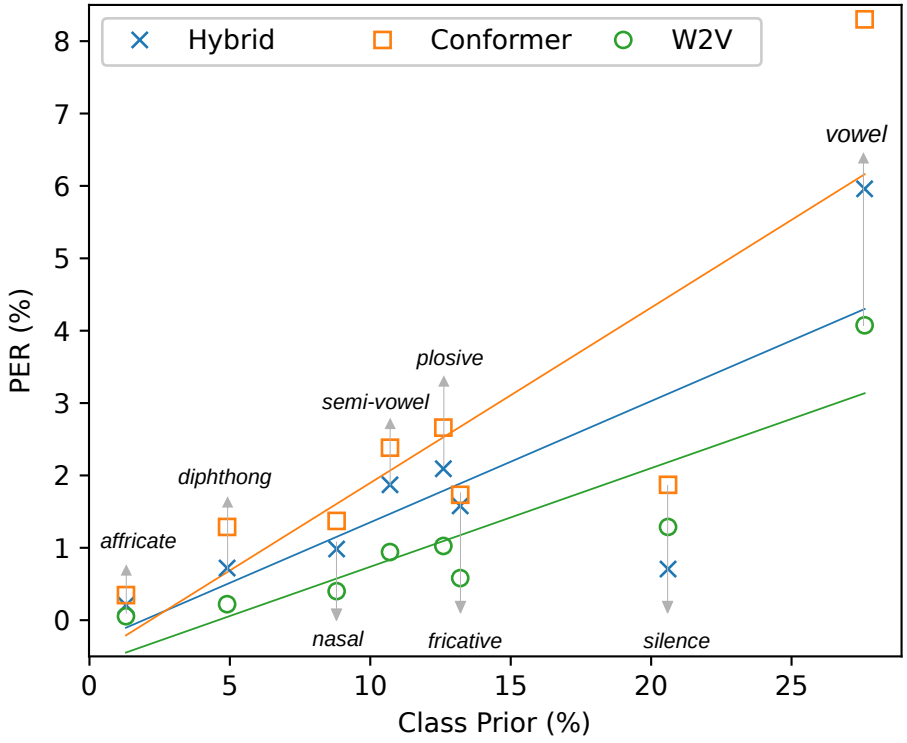
PER vs Prior (2)



PER vs Prior (2)



PER vs Prior (2)



The higher the training data, the higher the PER!

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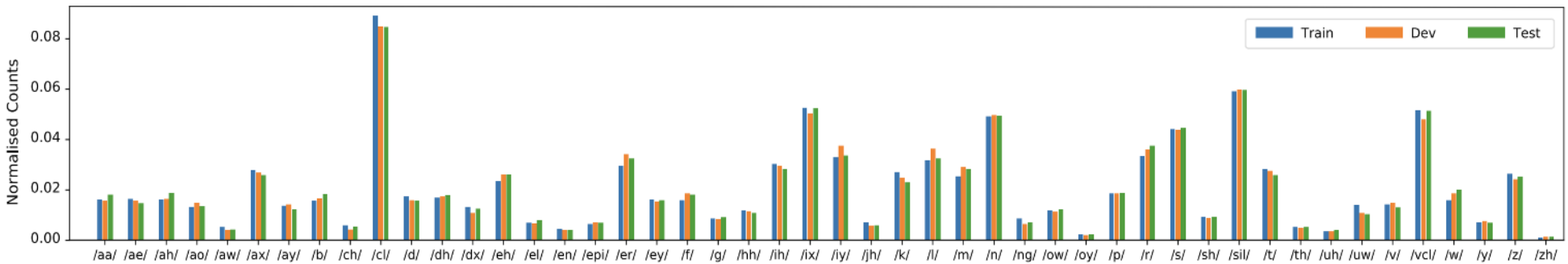
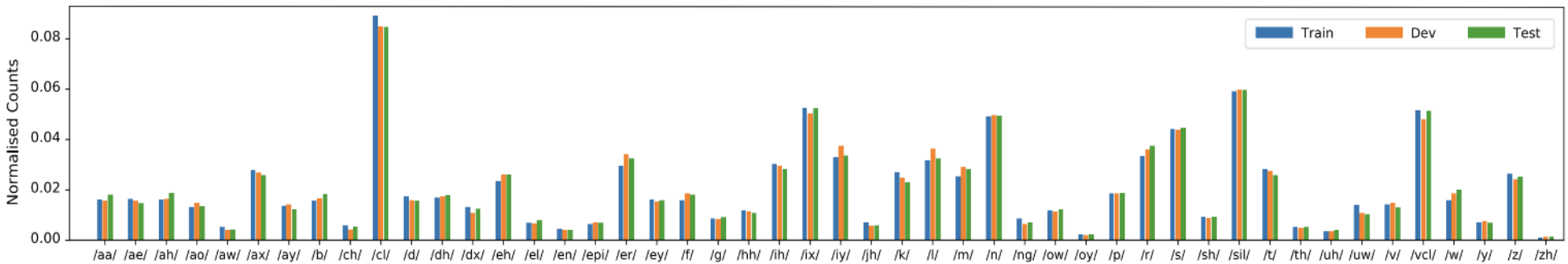
TIMIT's Special Case ...



TIMIT's Special Case ...



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

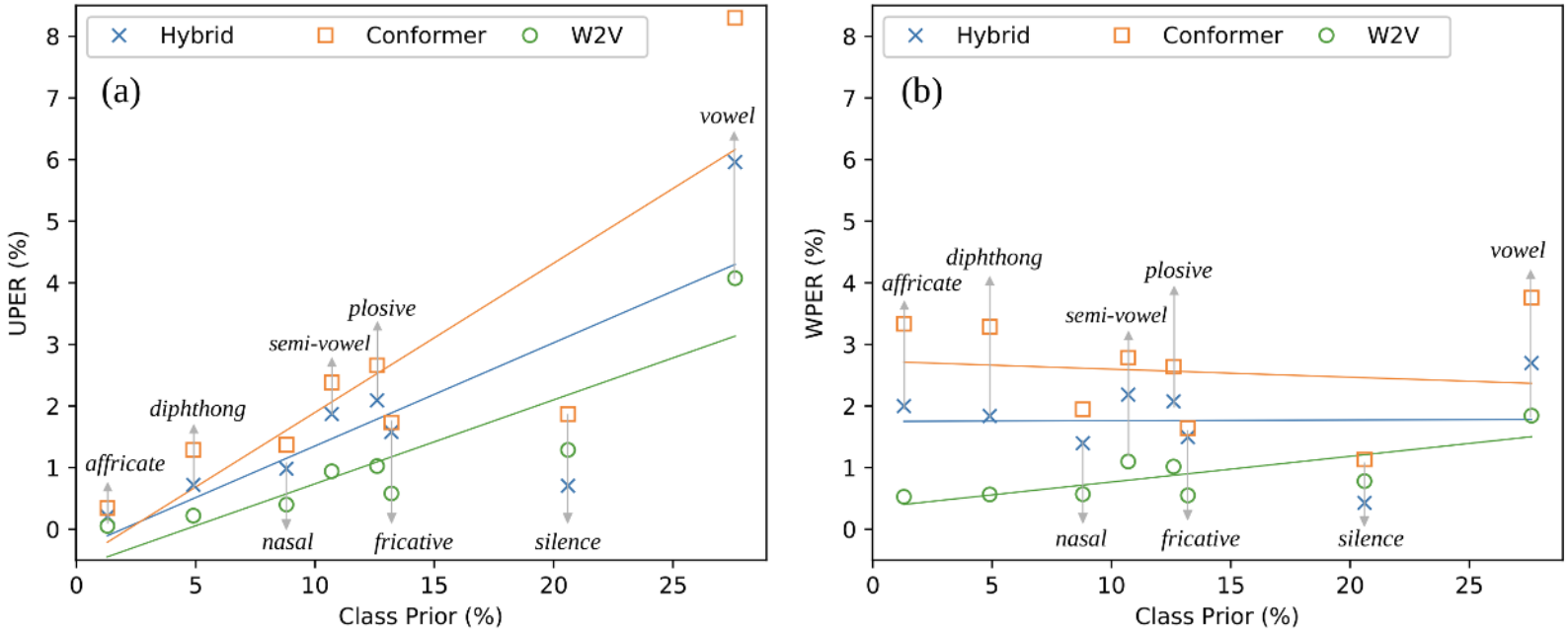
Unweighted vs Weighted PER

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

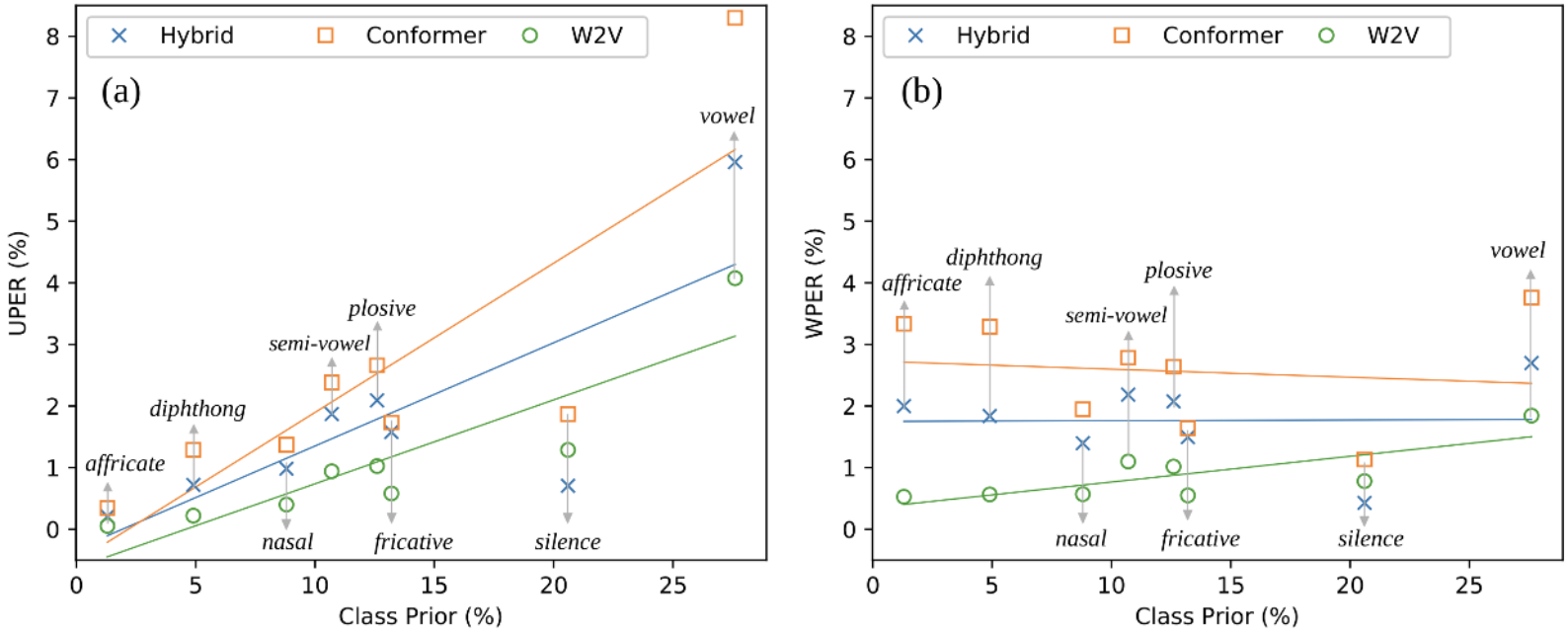
$$WPER = \frac{1}{C} \sum_{c=1}^{C} \frac{Sub_c + Del_c + Ins_c}{N P_c}$$

- To compensate for non-uniform prior ($P \not\equiv 1/C$), we use WPER.
- Analogous to *weighted accuracy*, weight $\propto$ 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!

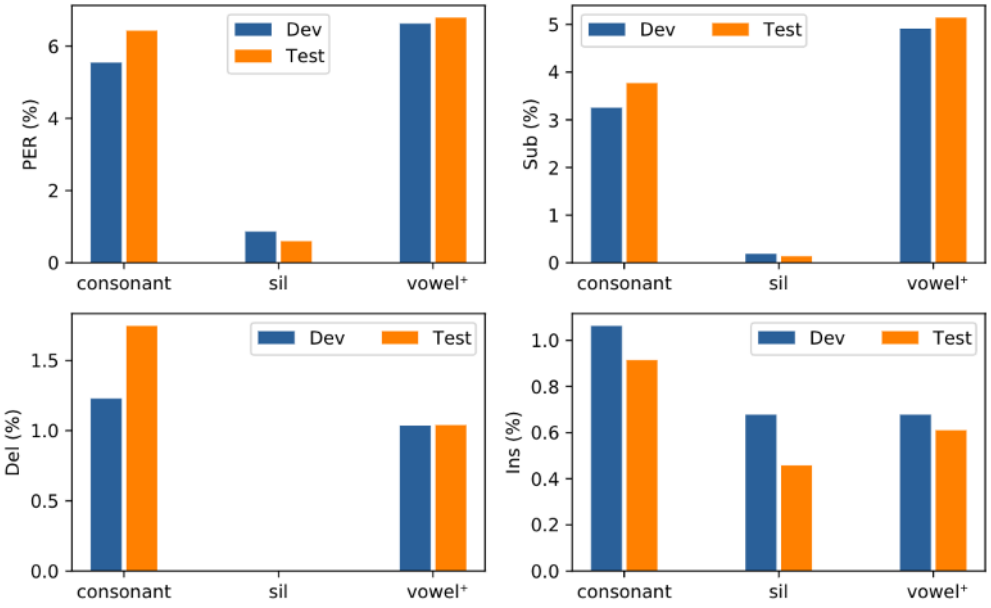
- Thank you!
- Q&A

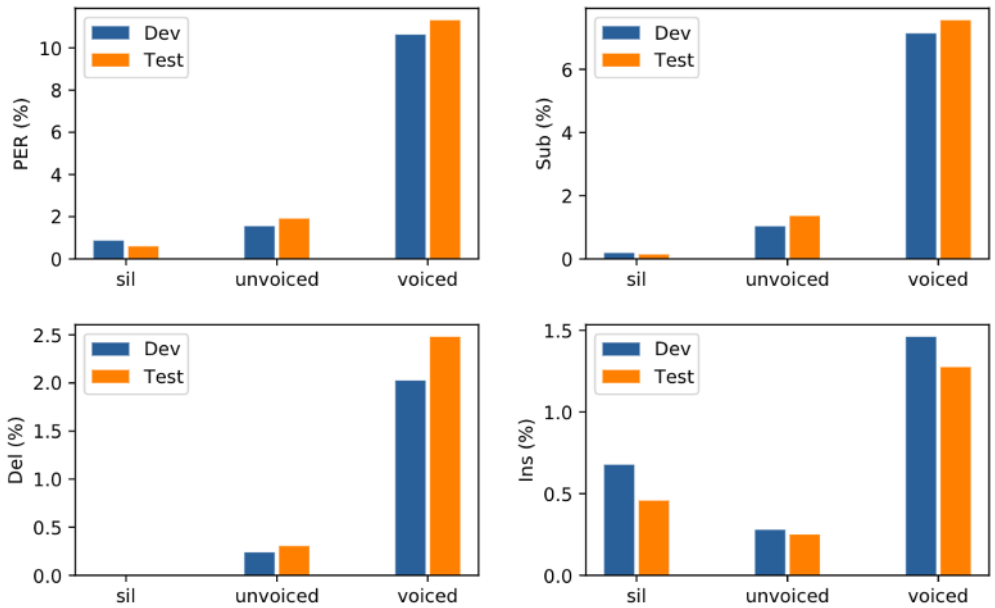
- Appendices
  - (A1) Silence Class
  - (A2) Sub/Del/Ins of C/V^+ & V/U
  - (A3) Sub/Del/Ins Dynamics
  - (A4) Transfer Learning's Effect on Errors & Dynamics

(A1) Silence Class is Union of ...

- ***/h#/***: Silence (≡ non-speech) at **B**eginning & **E**nd
- ***/epi/***: epenthetic silence between a fricative & a nasal or semi-vowel
  - Within a word: small, prince
  - between words: "*... lines must ...*" (*sx352.phn*)
- ***/pau/***: short pause within a sentence
- ***/closures/***: closures before stops (plosives)
  - Union of /bcl/, /dcl/, /gcl/, /kcl/, /pcl/ and /tcl/

(A2) Sub/Del/Ins Errors for C/V+ & V/U





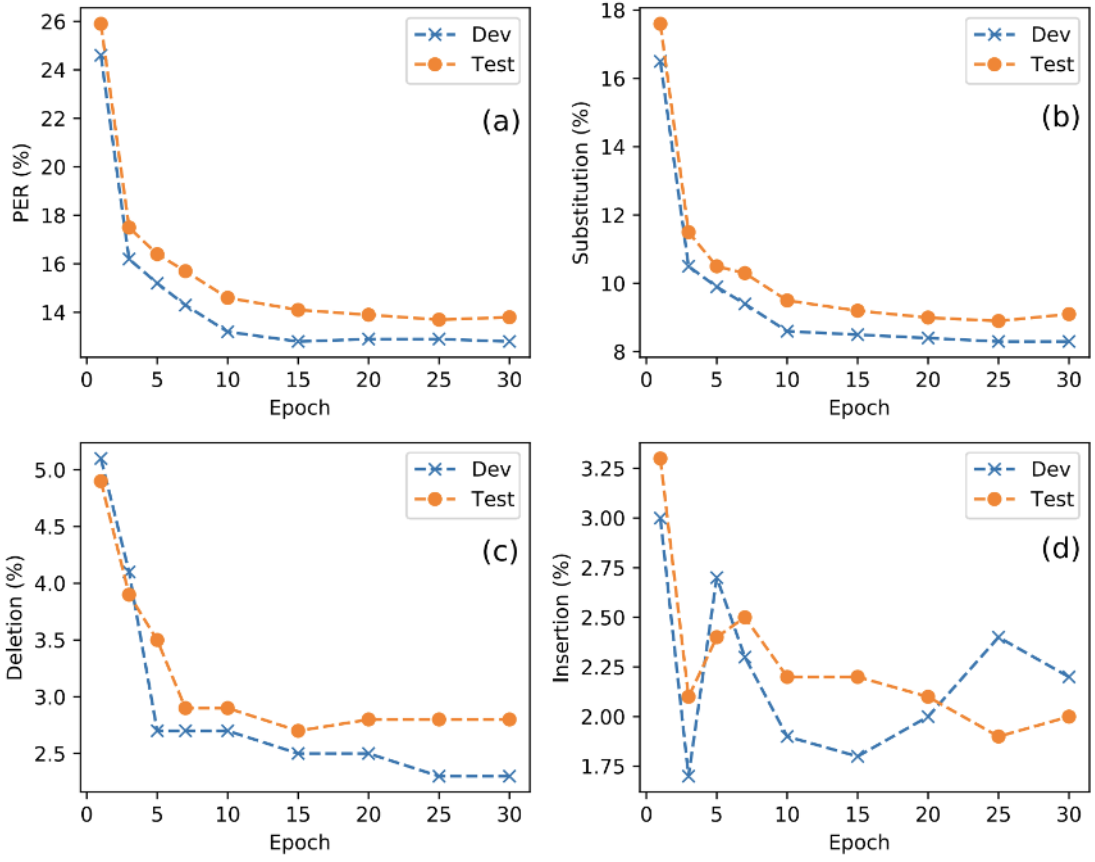
- Vowels have larger Sub.
- Consonants have a larger Del & Ins.

Errors' Largest share belongs to Voiced.

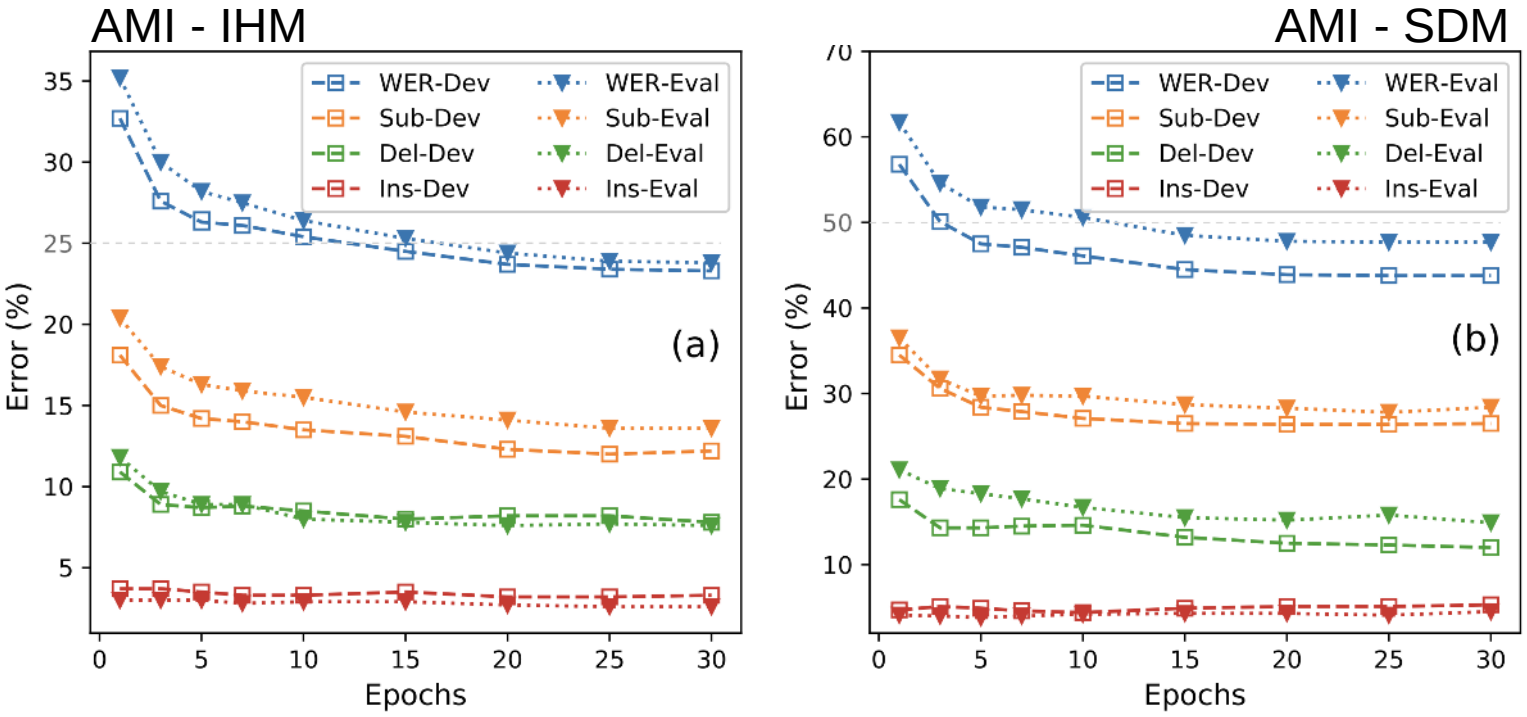
(A3) Sub/Del/Ins Dynamics

Strongest Correlation: PER & Sub

- Sub convergences slowly
- Del converges fast
- Ins oscillates



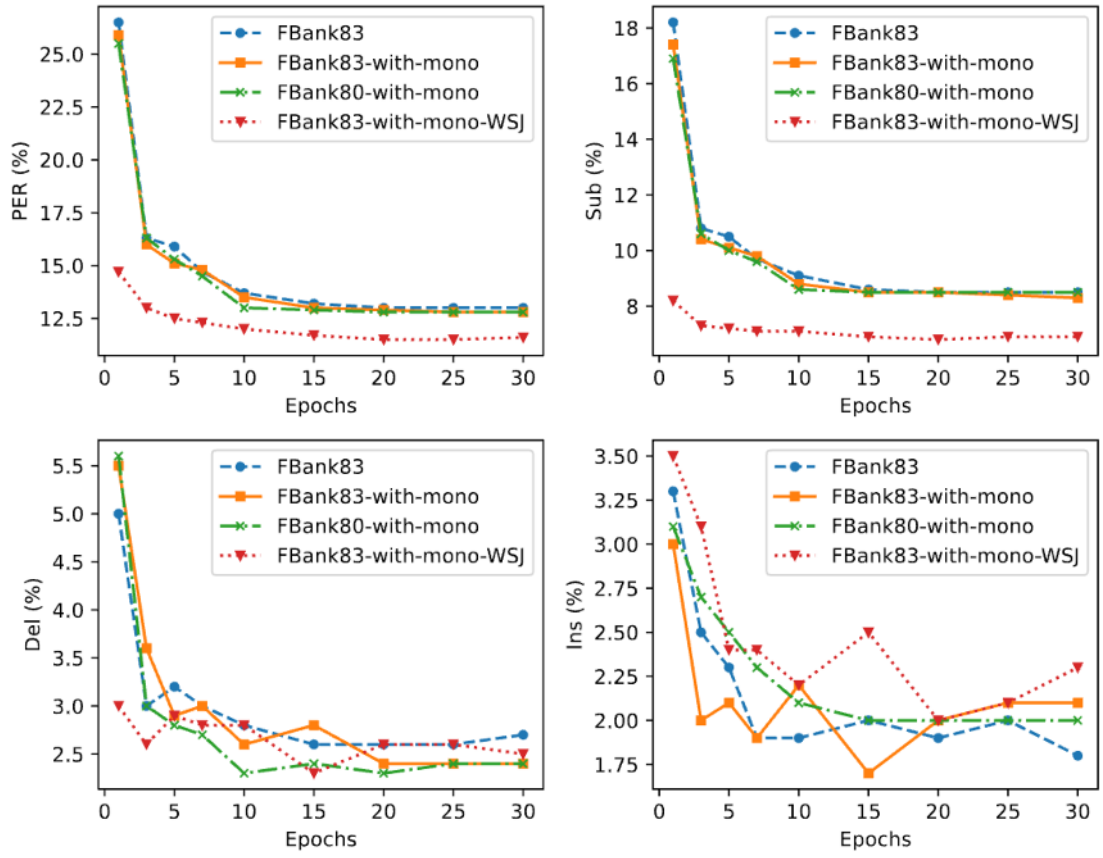
(A3) Similar observations in [67]



(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.

(A4) 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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