
Consonant confusions in normal and hearing impaired ears

Acoustic Feature Processing

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- This form of *paradoxical-contradictions* are known as **Yogi-isms**

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- Summary + Conclusions 6 mins $\Sigma 50$

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4. Explain HI ear feature extraction deficiencies, based on *individual-differences* in CV confusions 2012-13
 - Hypothesis: HI Consonant discrimination in noise is due to:
 - \Rightarrow Cochlear Dead regions?
 - \Rightarrow Poor acoustic time/freq edge detection?
 - \Rightarrow Auditory plasticity?

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 - ◆ The history is essential

2. Historical Overview

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- Context:
 - ◆ G.A. Miller 1951 *Language and communication*
 - ◆ G.A. Miller 1962 5-word Grammar \equiv 4 dB of SNR
 - ◆ Boothroyd JASA 1968; Boothroyd & Nittrouer 1988
 - ◆ Bronkhorst et al. JASA 1993

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- Hearing Impaired studies
 - ◆ 2004-2011: Confusion matrices HSR@UIUC

Allen et. al HSR Experiments 2004-2011

Year	Experiment	Student & Allen	Details	Publication
2004	MN04(MN64)	Phatak	16C+4V SWN	JASA (2007)
2005	MN16R HIMCL05	Phatak, Lovitt Yoon, Phatak	MN55R 10 HI ears	JASA (2008) JASA (2009)
2006	HINALR05 Verification CV06-s/w	Yoon <i>et al.</i> Regnier Phatak/Regnier	10 HI ears /ta/ 8C+9V SWN/WN	JSLR (2012) JASA (2008)
2007	CV06 HL07	Pan Li	CV06 Hi/Lo pass	– JASA (2009)
2008	TR08	Li	Furui86	ASSP (2009)
2009	3DDS 3DDS Verification Verification MN64 NZE	Allen, Li Li Abhinauv Cvengros Singh	plosives plosives burst mods burst mods PA07	TASLP (2011) JASA (2010) JASA (2012) Rewrite JASA JASA (2012)
2011	3DDS	Li, Trevino	Fricatives	JASA (2012)
	HINAL11-IV	Han	17 HI ears w NALR	Thesis Ch. 3
2010	HIMCL10-I,II,III	Trevino	17 HI ears @MCL	JASA (2013)

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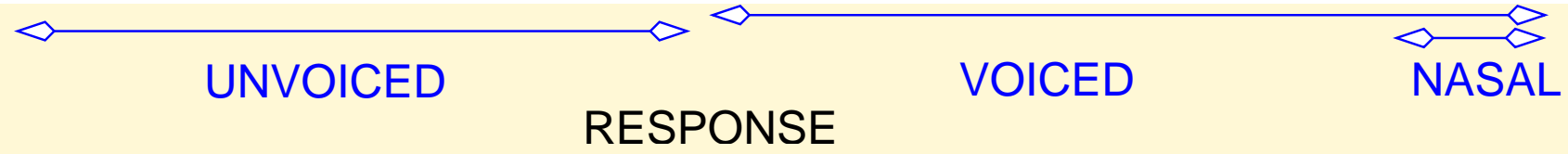
Methods: The count (confusion) matrix

- Miller-Nicely's 1955 articulation matrix $P_{h|s}(SNR)$, measured at [-18, -12, -6 shown, 0, 6, 12] dB SNR

TABLE III. Confusion matrix for $S/N = -6$ db and frequency response of 200–6500 cps.

	<i>p</i>	<i>t</i>	<i>k</i>	<i>f</i>	<i>θ</i>	<i>s</i>	<i>ʃ</i>	<i>b</i>	<i>d</i>	<i>g</i>	<i>v</i>	<i>ð</i>	<i>z</i>	<i>ʒ</i>	<i>m</i>	<i>n</i>
<i>p</i>	80	43	64	17	14	6	2	1	1		1	1			2	
<i>t</i>	71	84	55	5	9	3	8	1				1	2		2	3
<i>k</i>	66	76	107	12	8	9	4					1			1	
<i>f</i>	18	12	9	175	48	11	1	7	2	1	2	2				
<i>θ</i>	19	17	16	104	64	32	7	5	4	5	6	4	5			
<i>s</i>	8	5	4	23	39	107	45	4	2	3	1	1	3	2		1
<i>ʃ</i>	1	6	3	4	6	29	195		3							1
<i>b</i>	1			5	4	4		136	10	9	47	16	6	1	5	4
<i>d</i>							8	5	80	45	11	20	20	26	1	
<i>g</i>					2			3	63	66	3	19	37	56		3
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<i>ʒ</i>								1	26	18	3	8	45	129		2
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STIMULUS

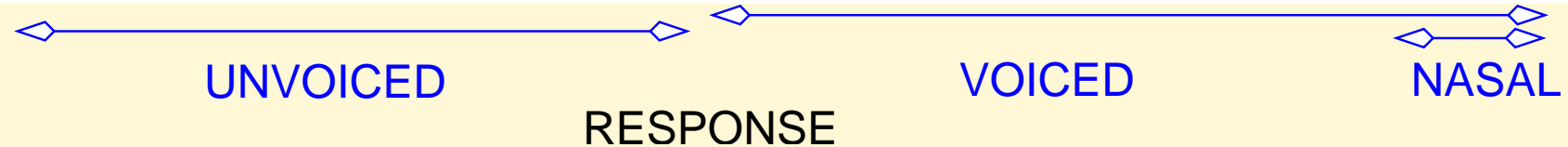


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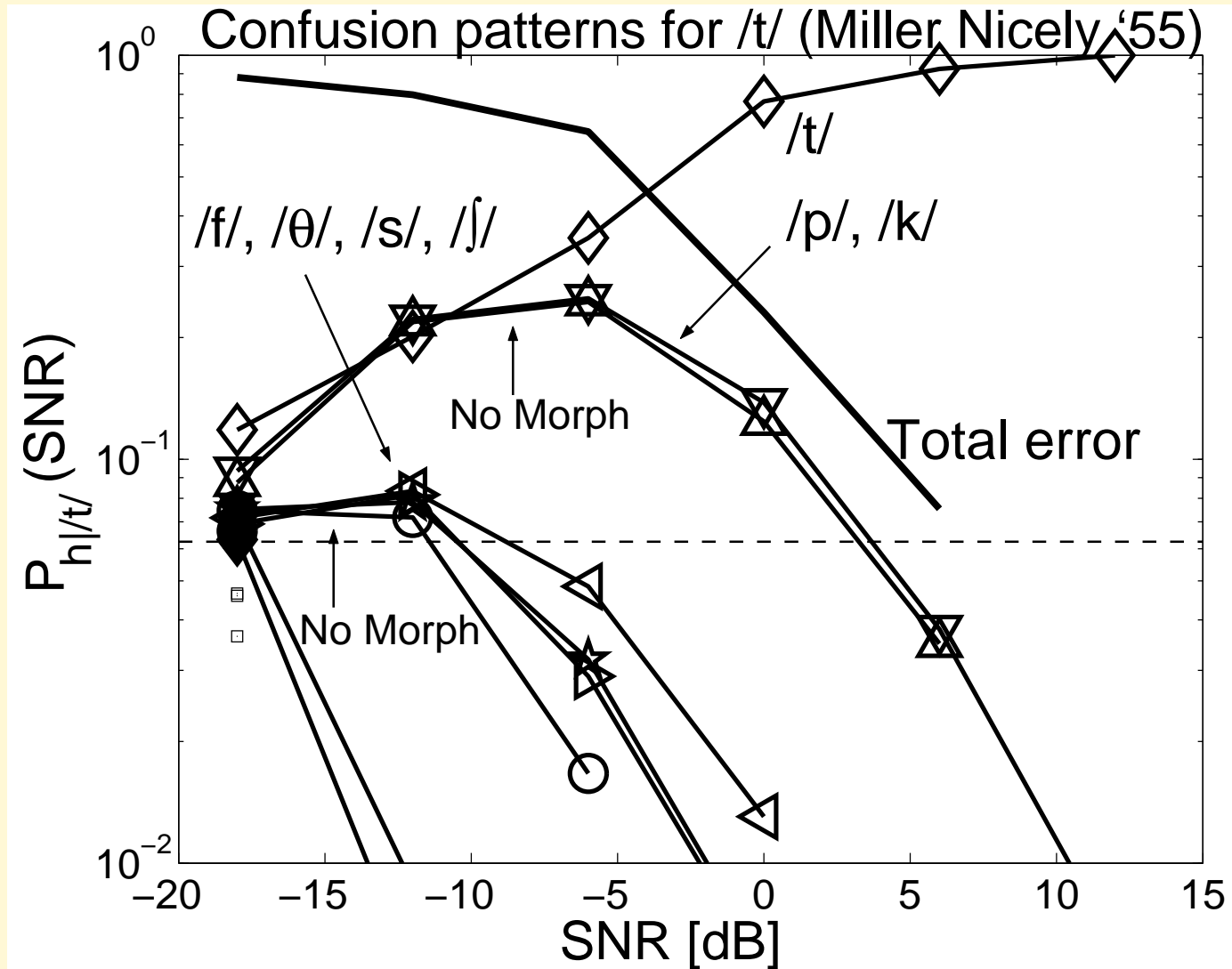
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- Confusion groups \equiv inhomogeneous confusions

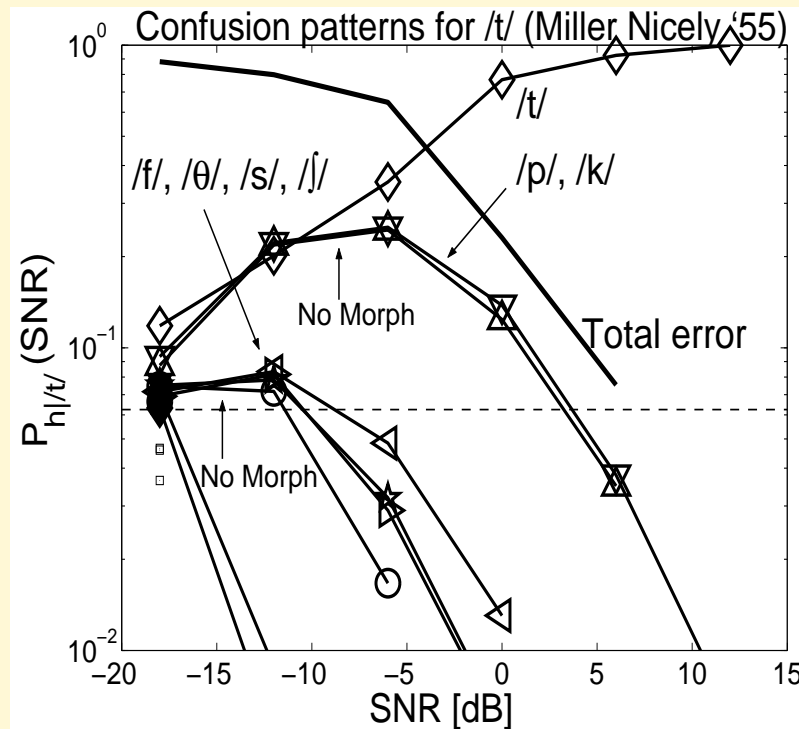
Row of confusion matrix (CM) $P_{h|t/}$

- This *confusion pattern* characterizes the /t/ row vs SNR



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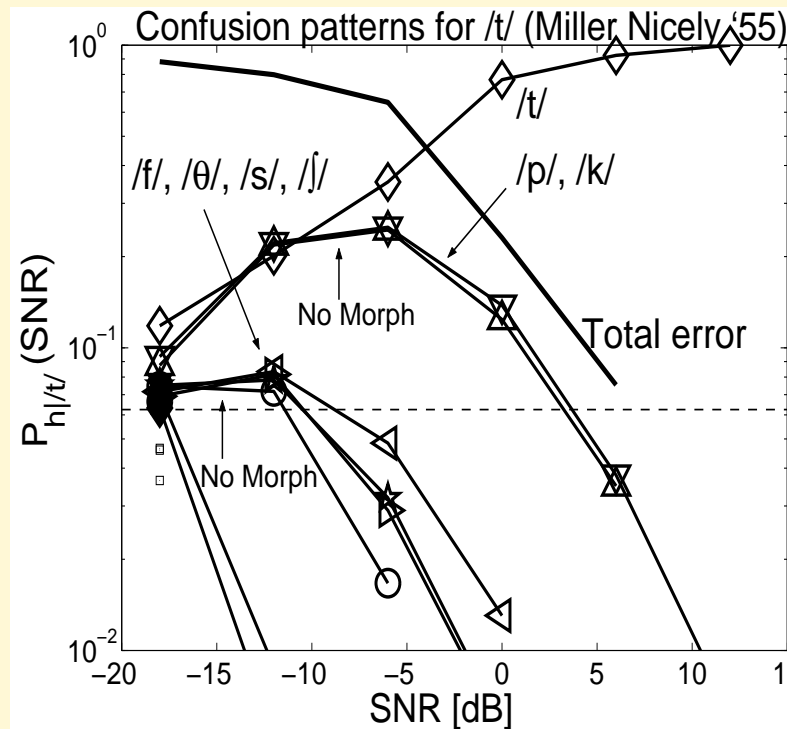
- The SIN_t of averaging across tokens:
 - ◆ Token confusions are strongly **heterogeneous**!
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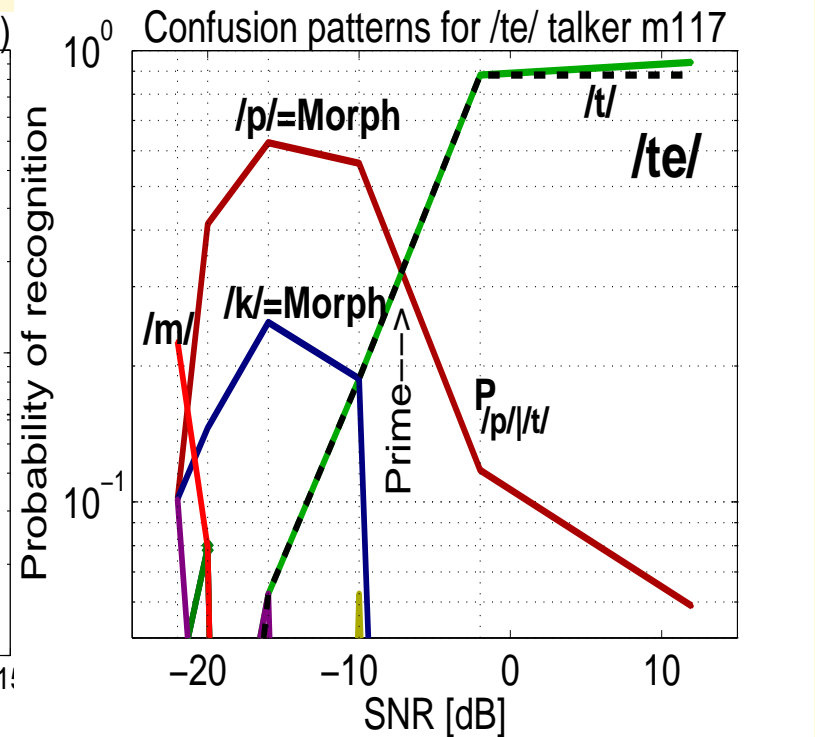
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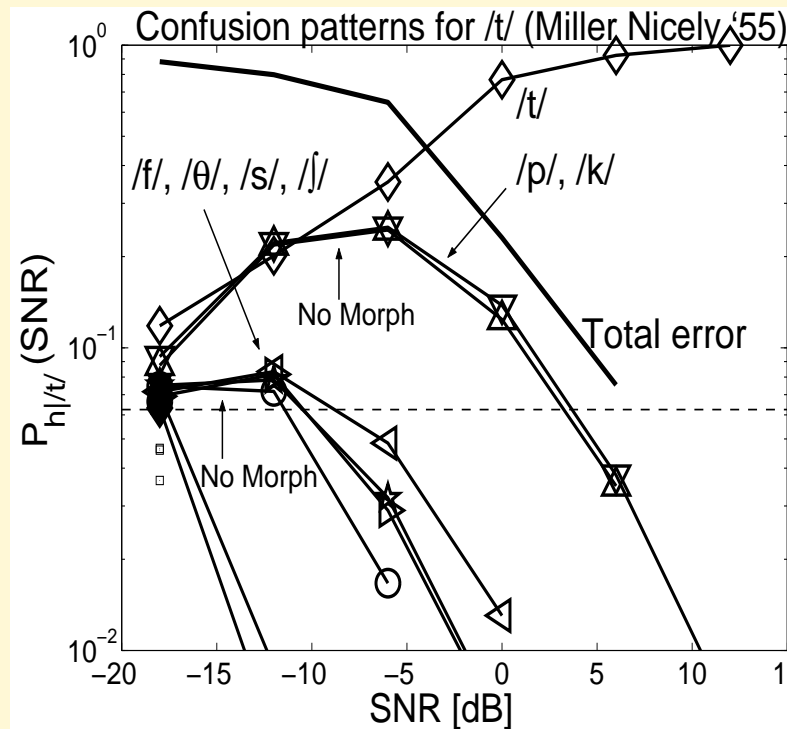
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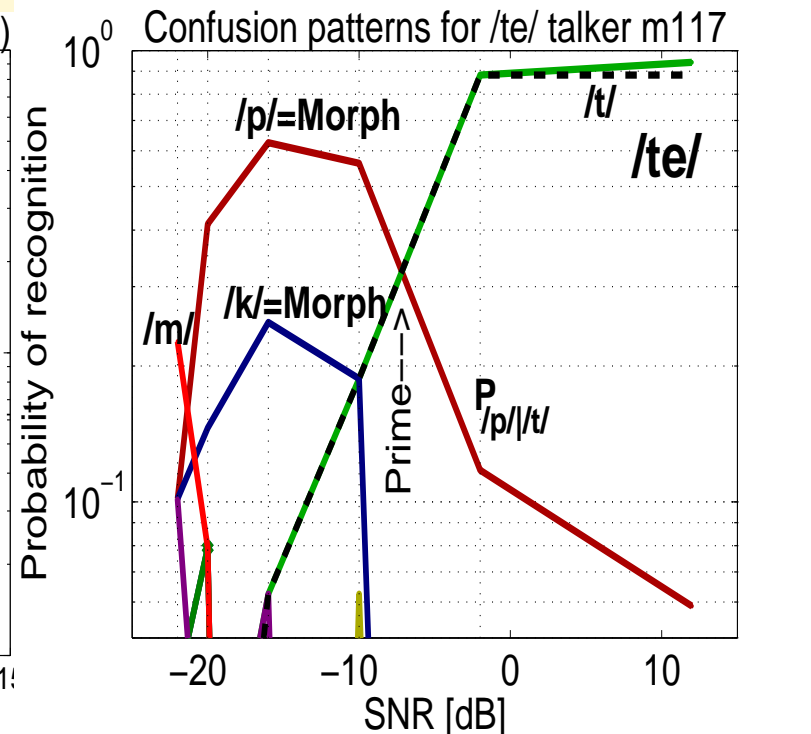
(b) Talker m117 /te/ $P_{h|/ta/}$ (SNR)

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- Methods: Cochlear models & signal processing
 - ◆ Algram **Régnier & Allen 2008; Li & Allen 2009,10,11**

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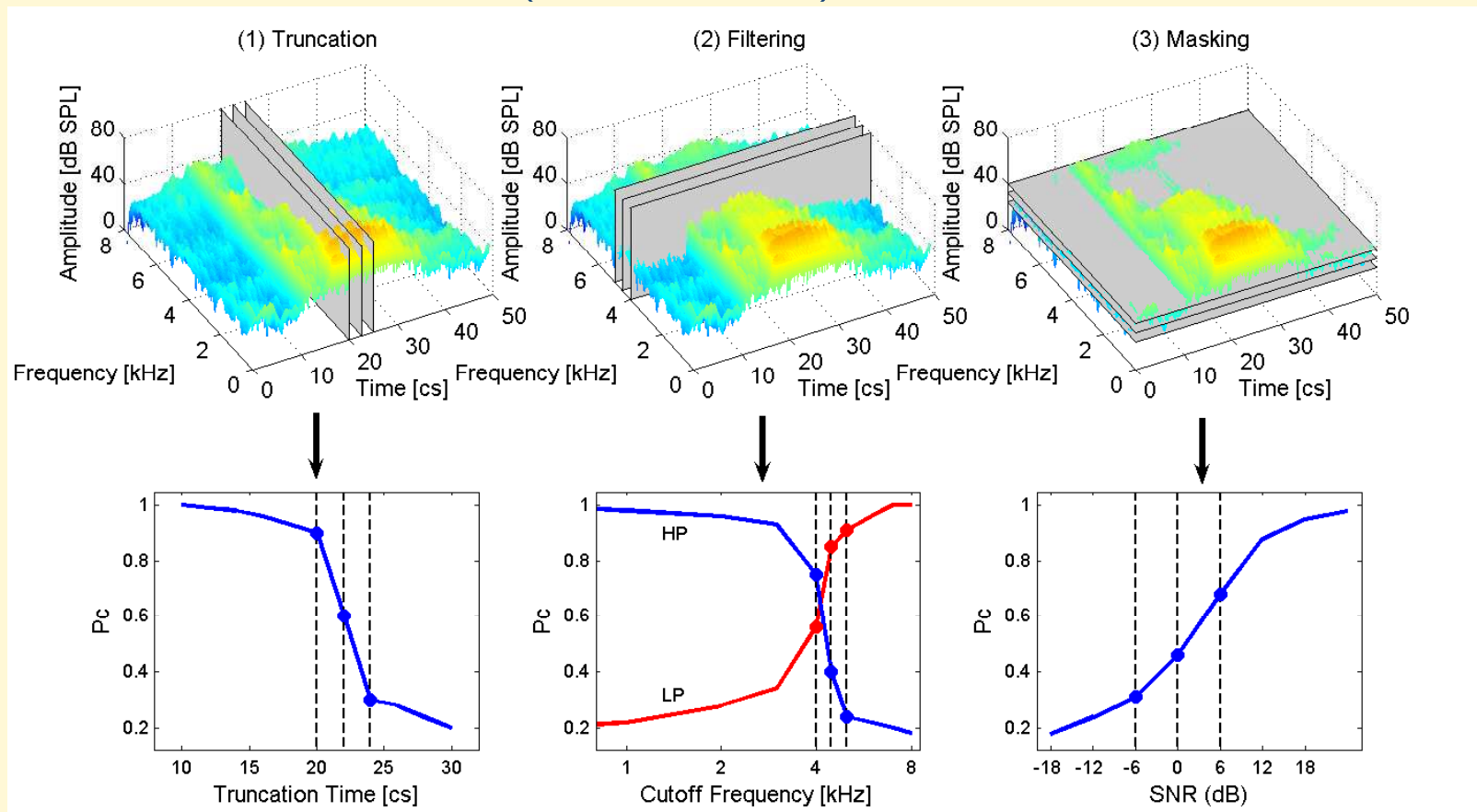
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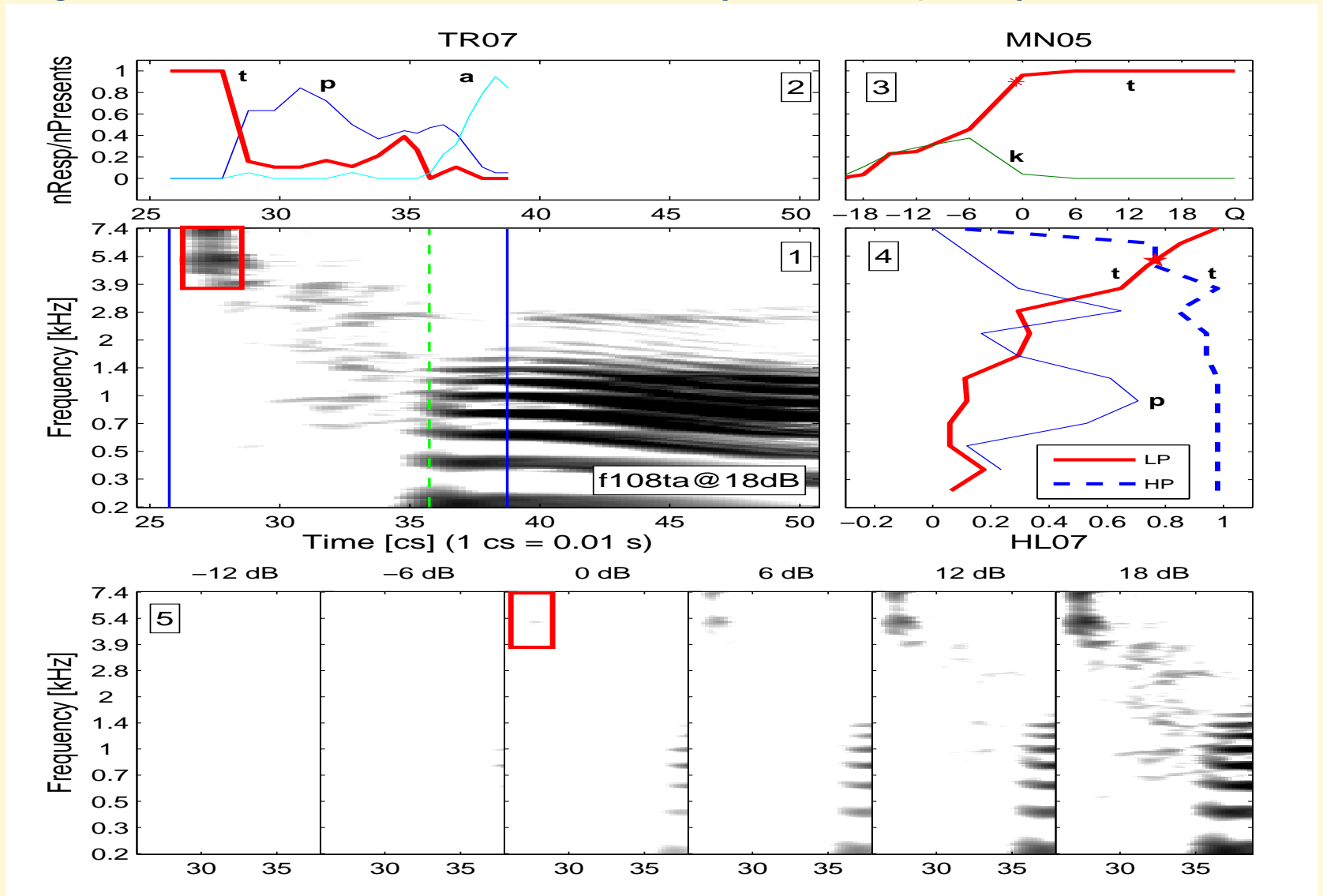
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■ Algram: Truncation in Time, Intensity and Frequency



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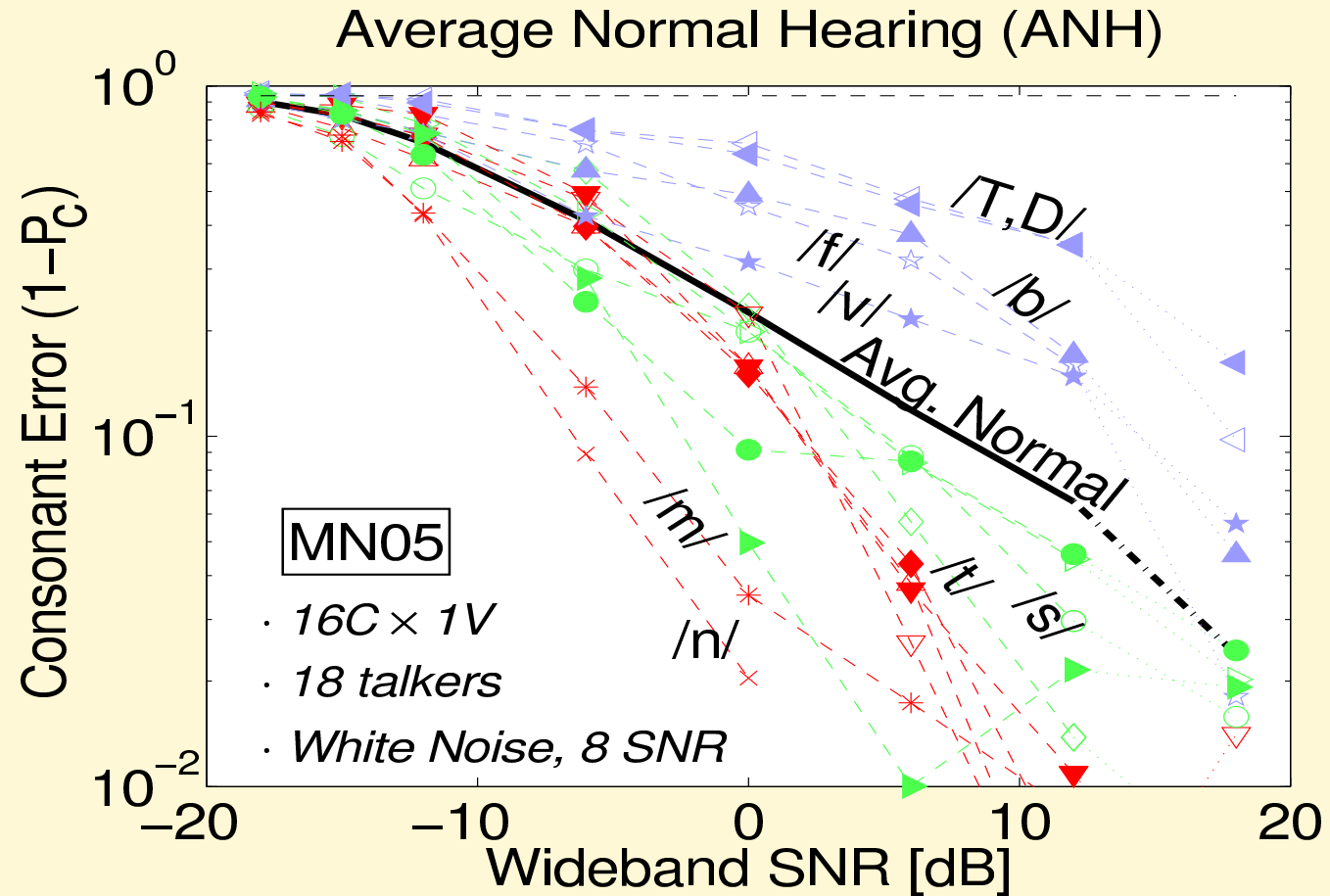
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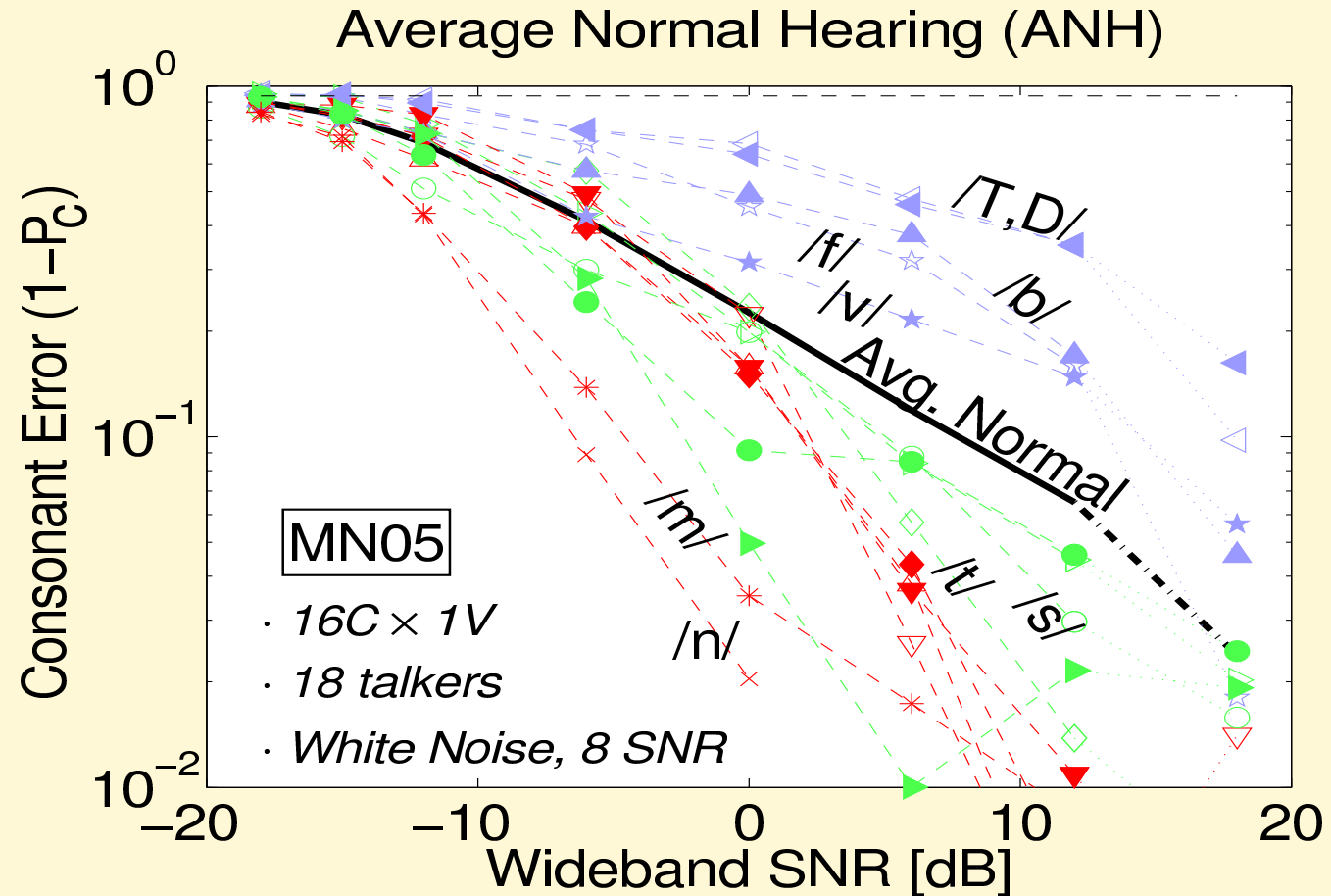
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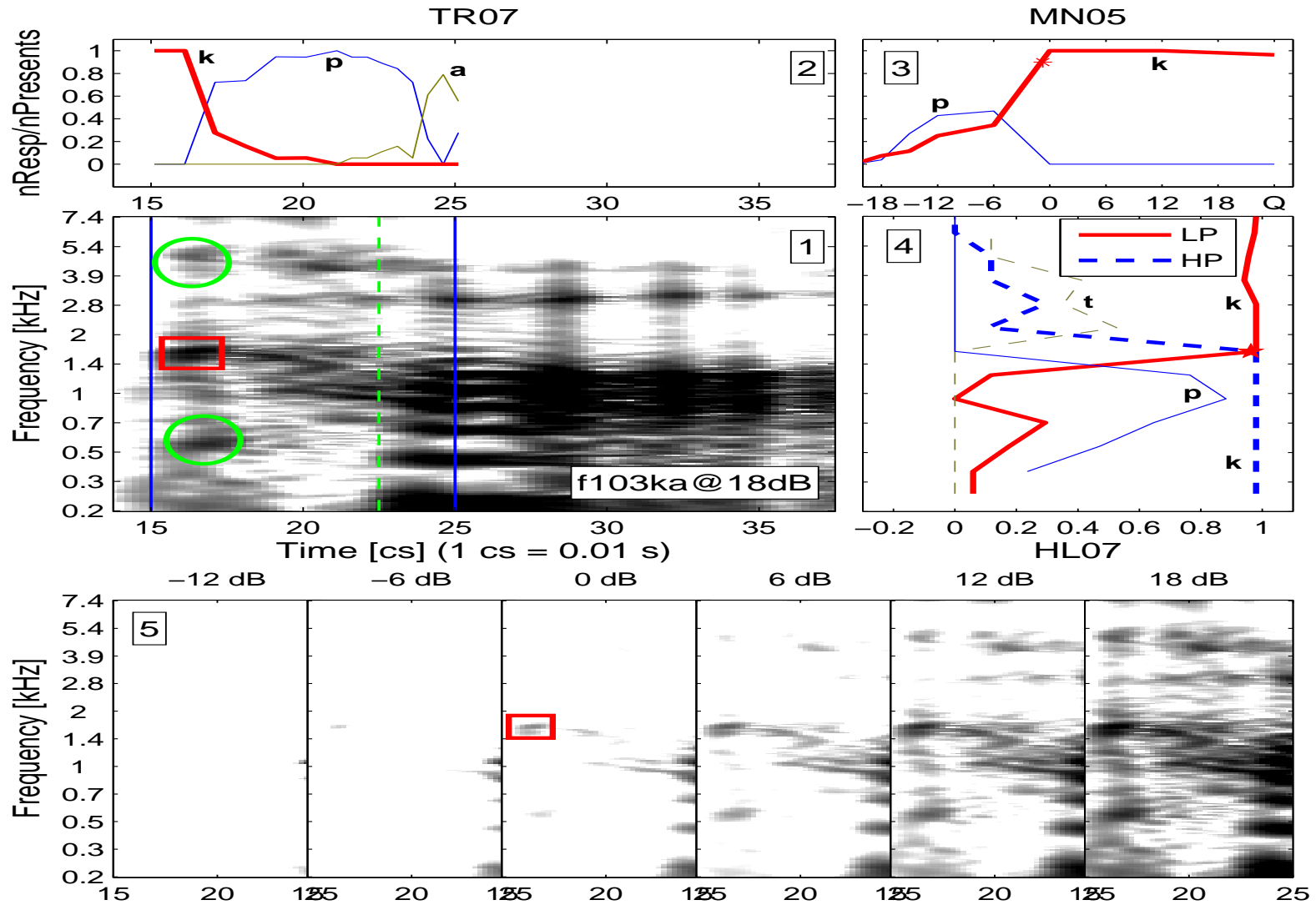
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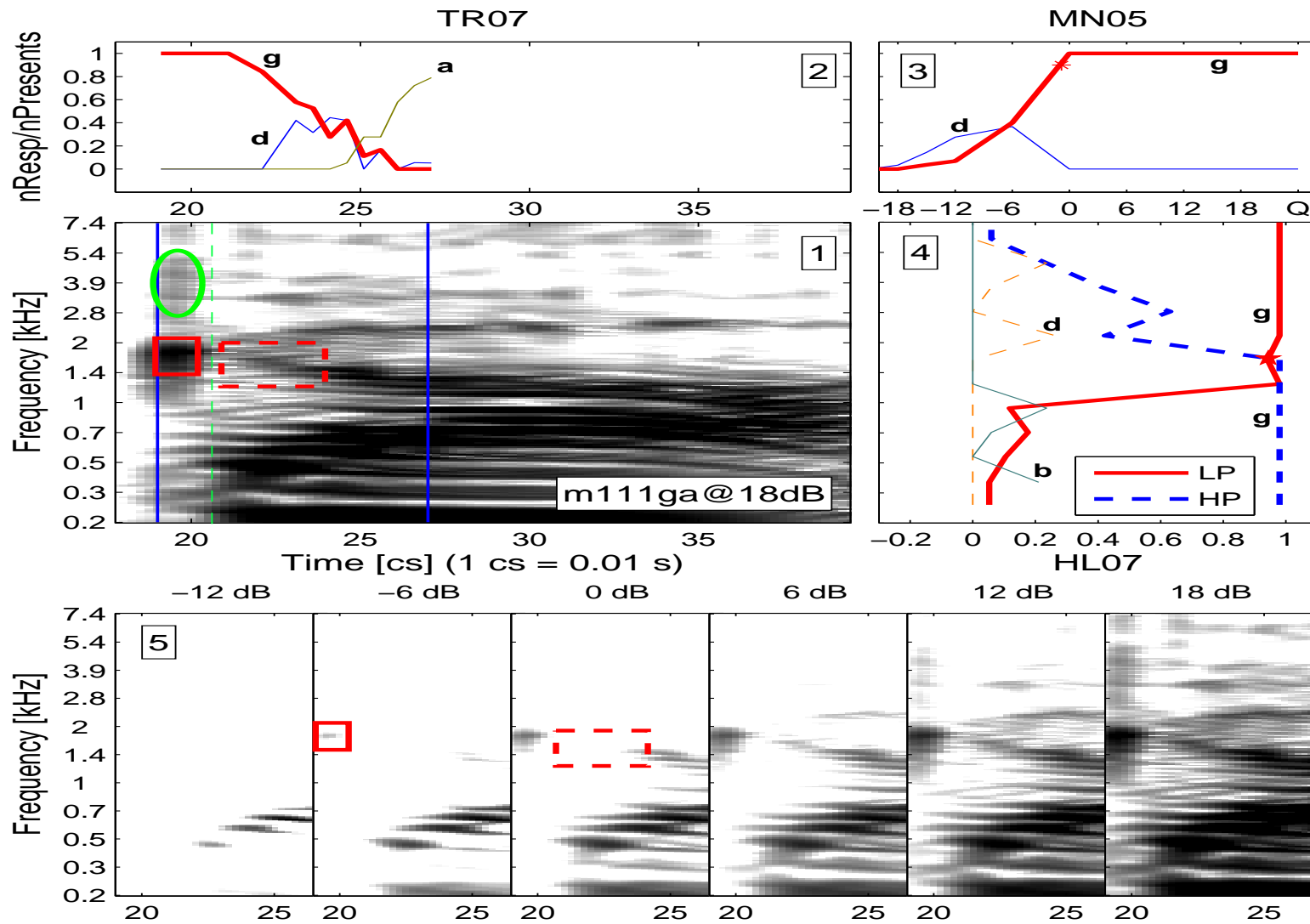


- Averaging obscures the multimodal consonant error distribution

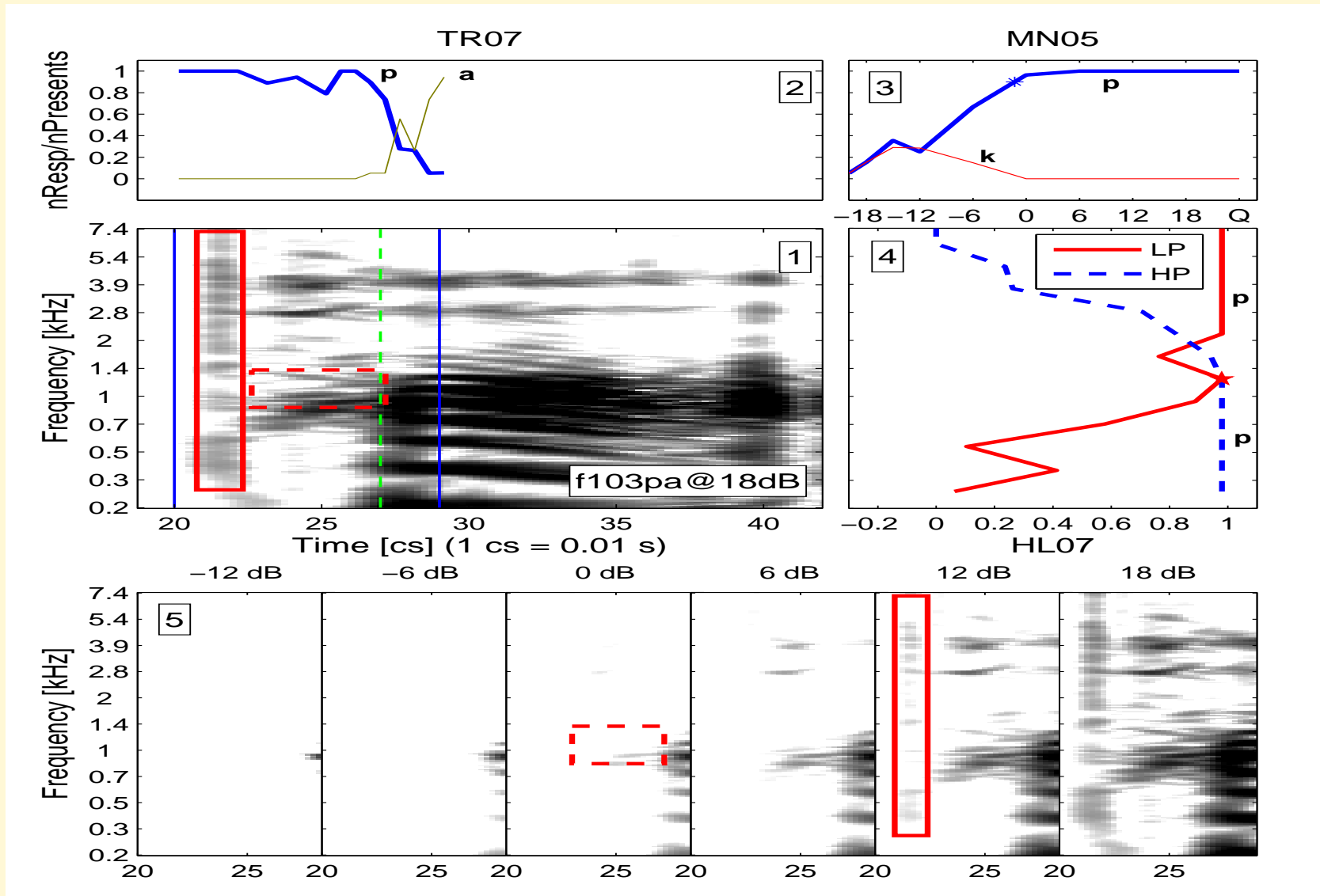
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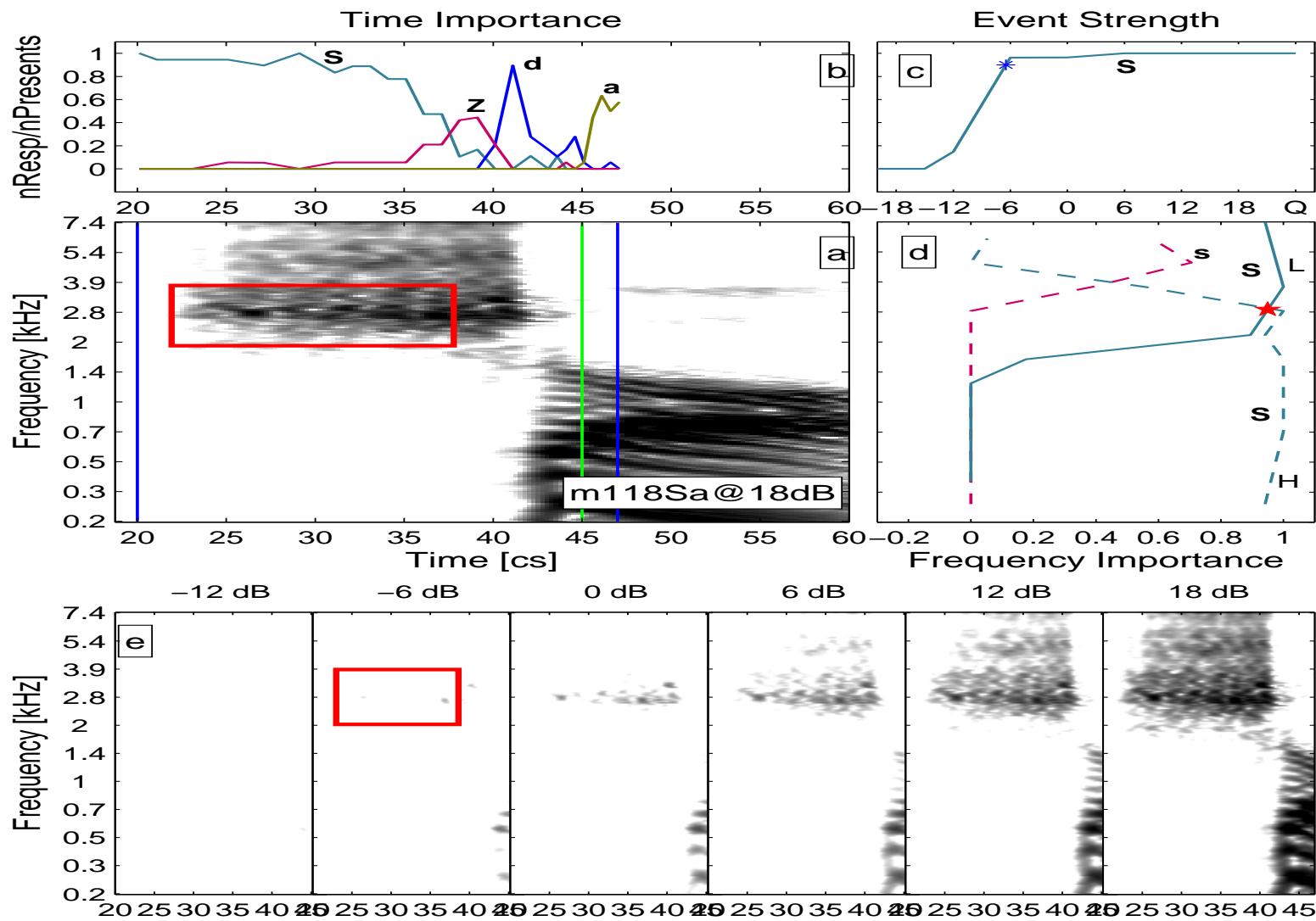
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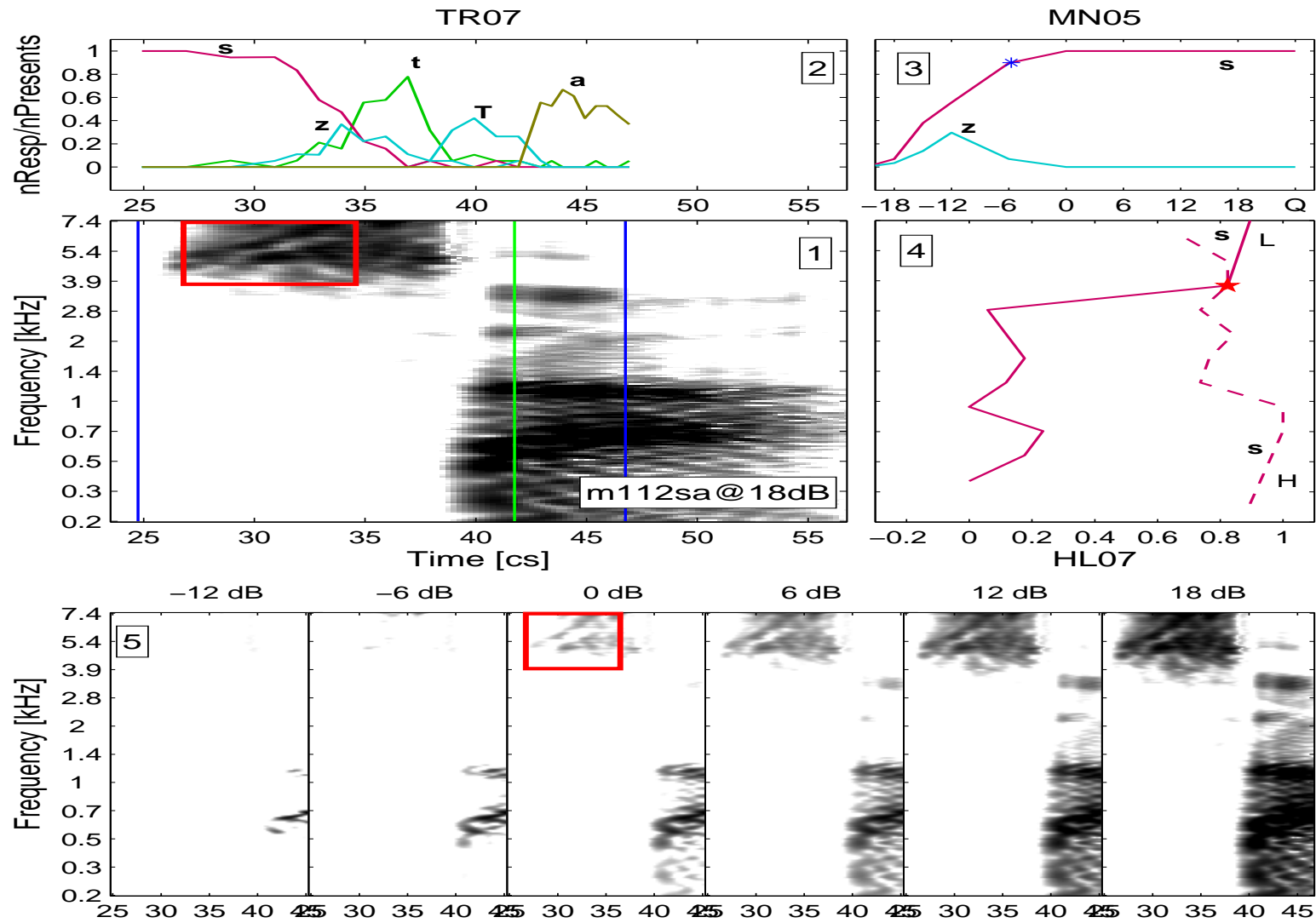
3DDS Method /pa/



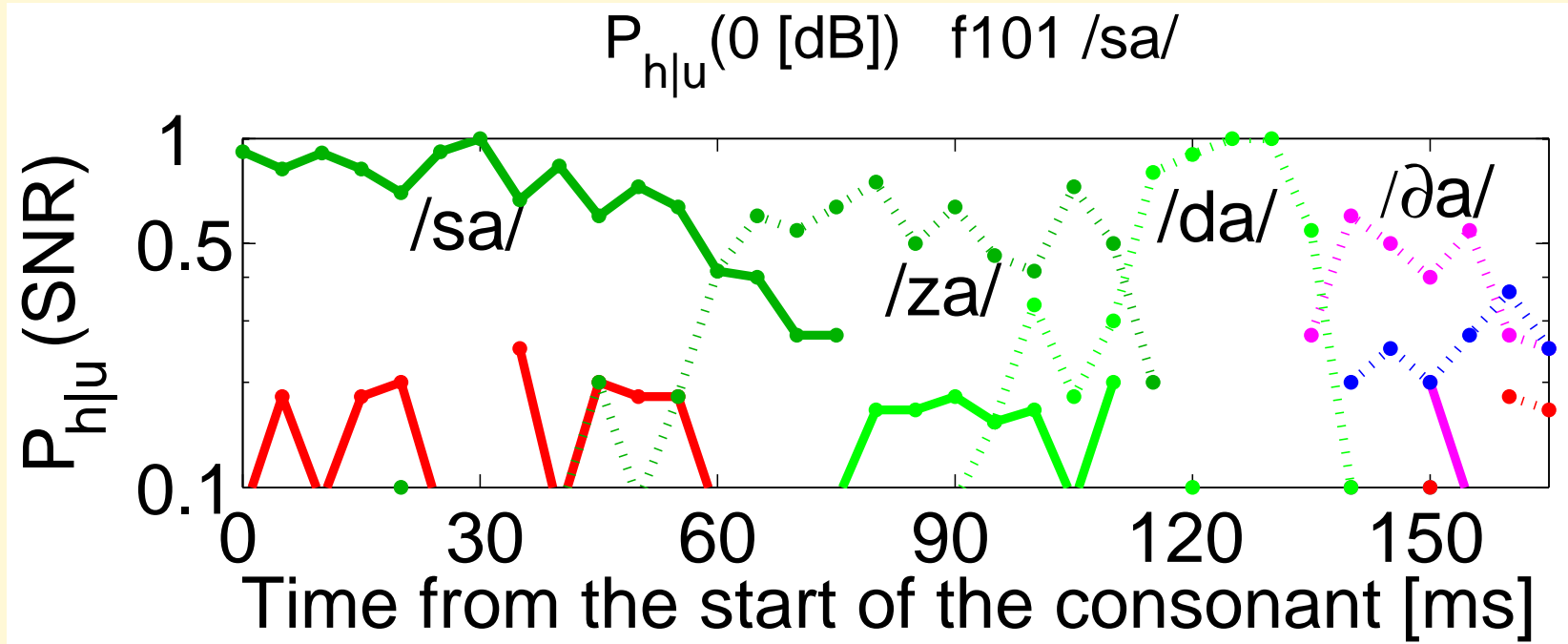
3^d-DS Method /ʃa/



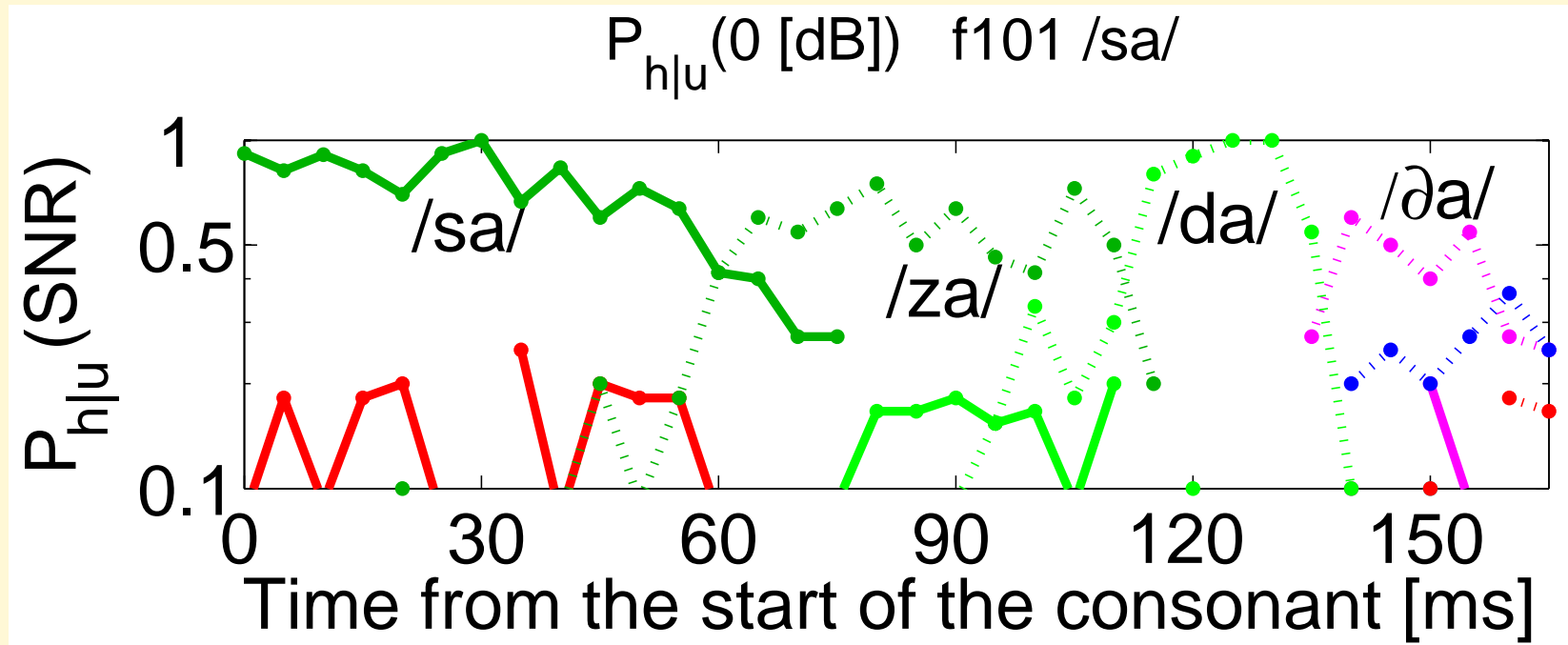
3DDS Method /sa/



Truncation of f101 /sa/

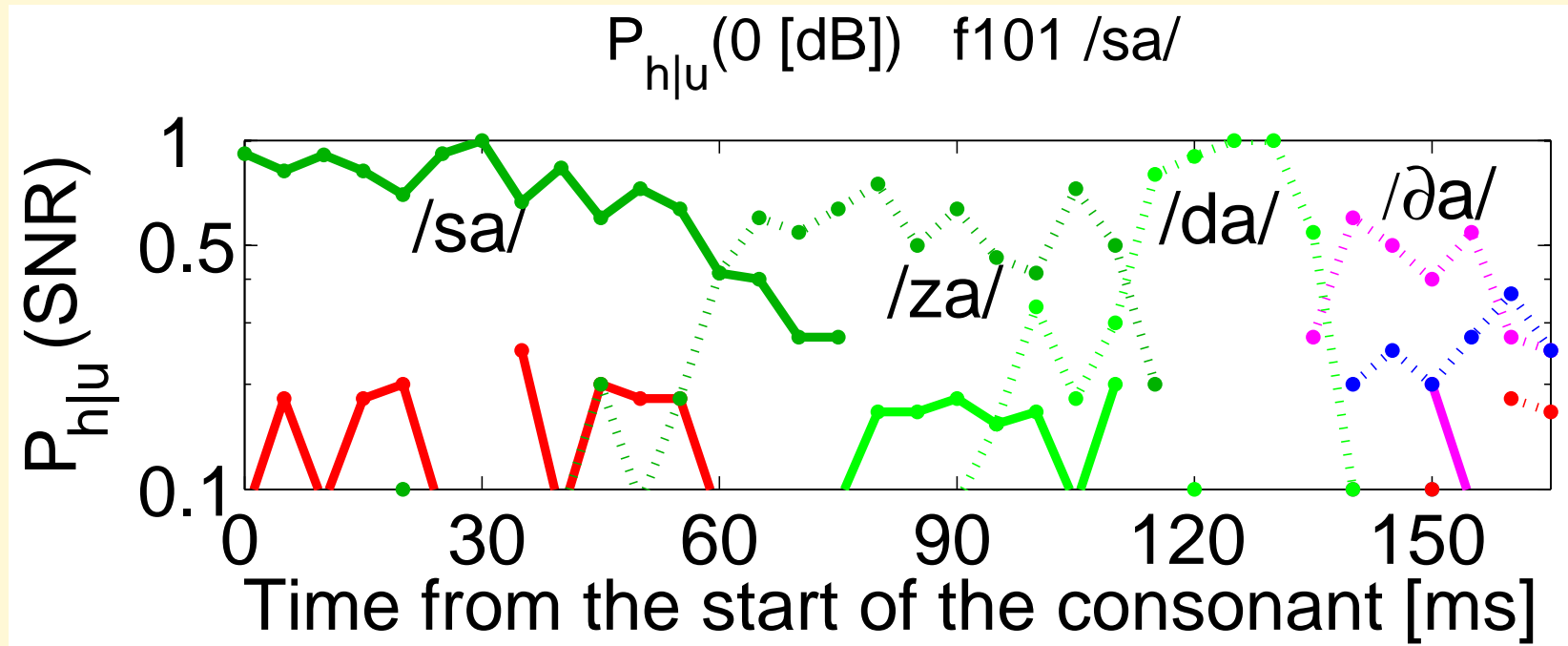


Truncation of f101 /sa/



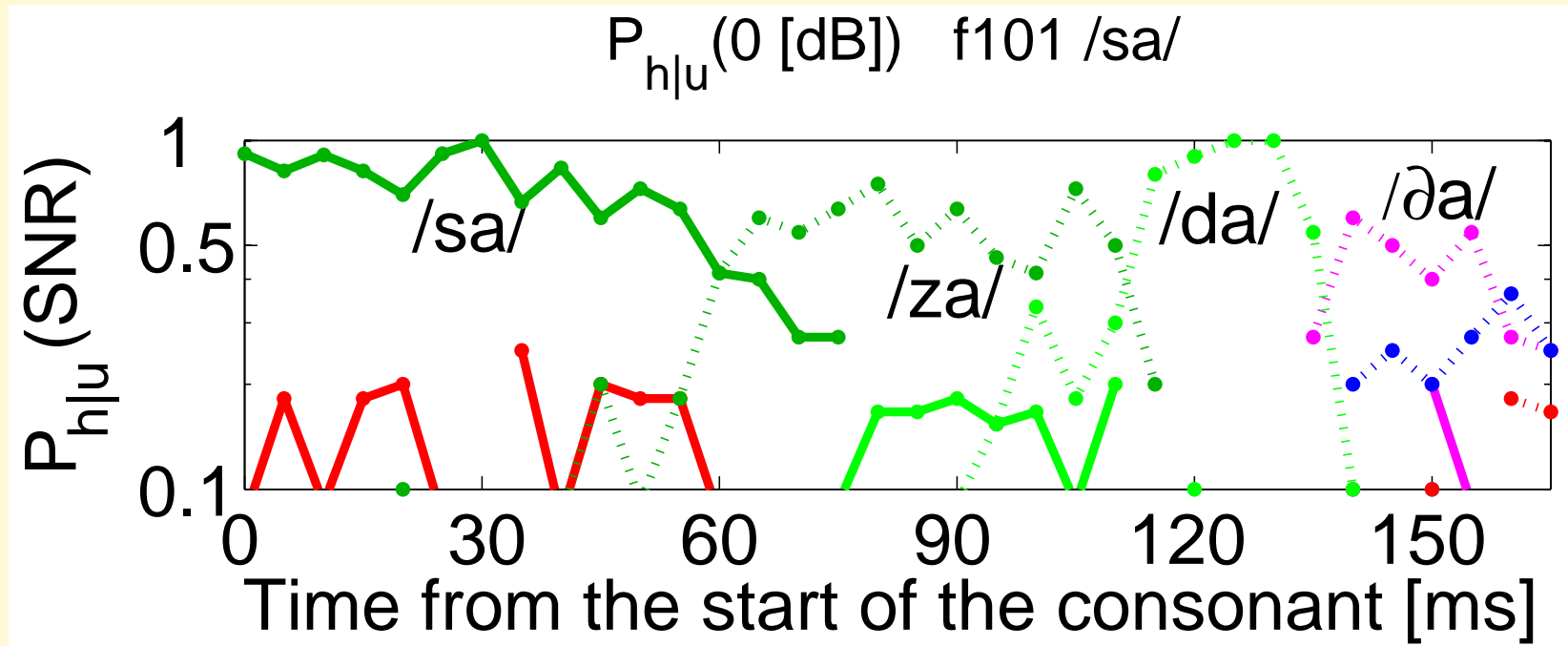
- NH responses to onset truncation /sa/

Truncation of f101 /sa/



- NH responses to onset truncation /sa/
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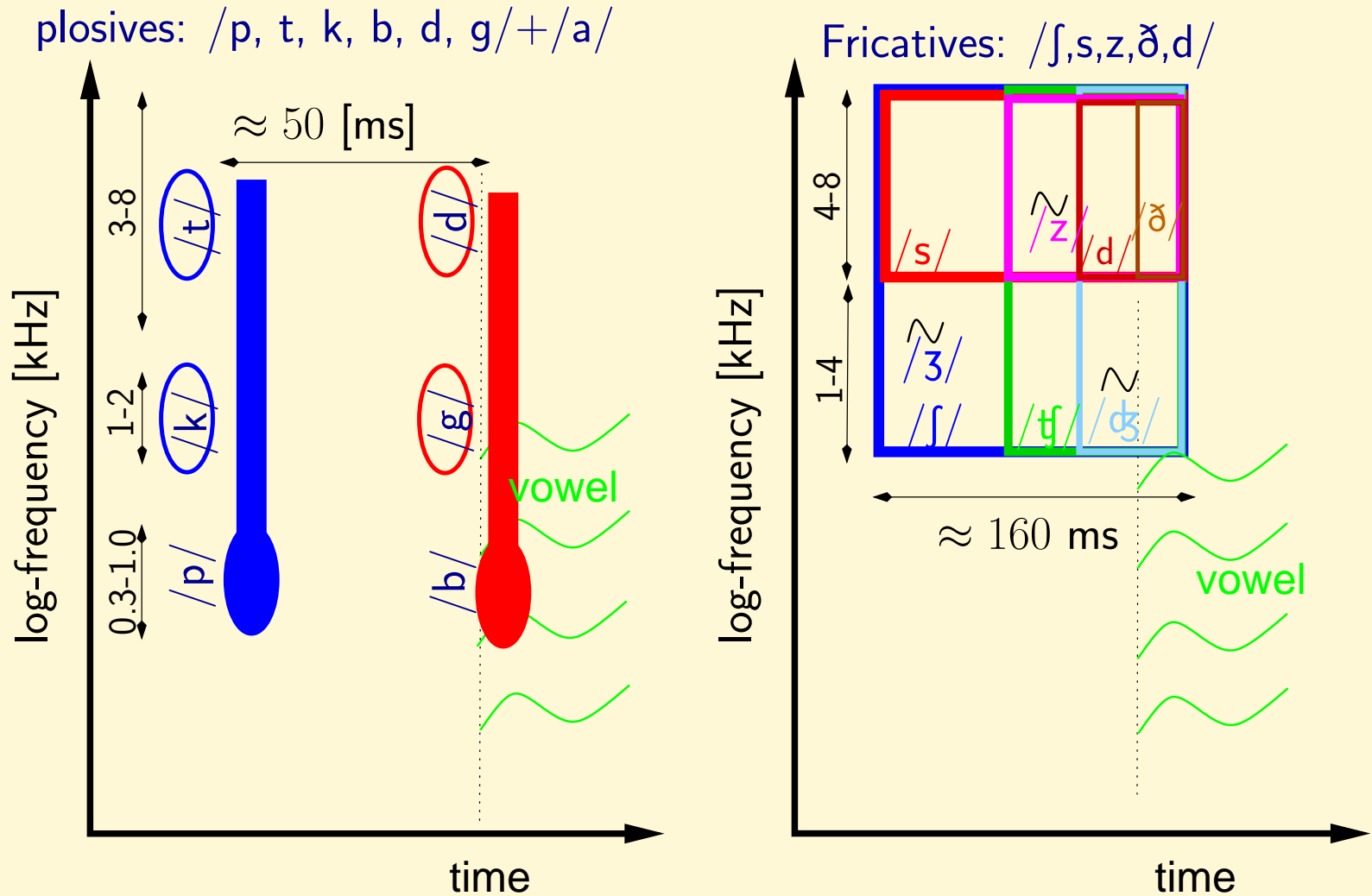
Truncation of f101 /sa/



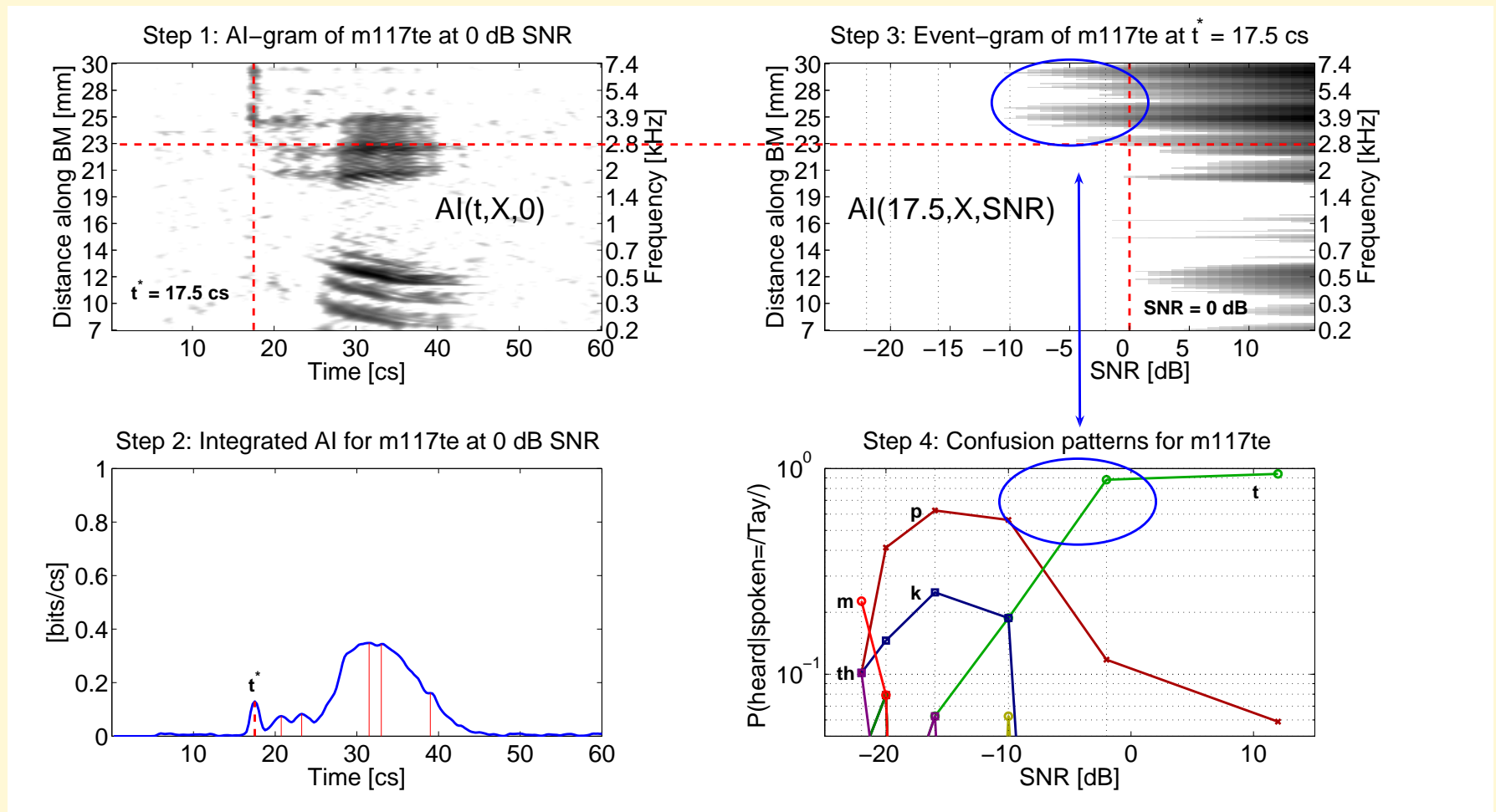
- NH responses to onset truncation /sa/
- Morphing from /sa/ \rightarrow /za/ \rightarrow /da/ \rightarrow /ɖa/
- Duration, low-frequency edge and F_0 modulations define a fricative cue

Summary of Consonant structure

- Time-frequency structure of plosives and fricatives

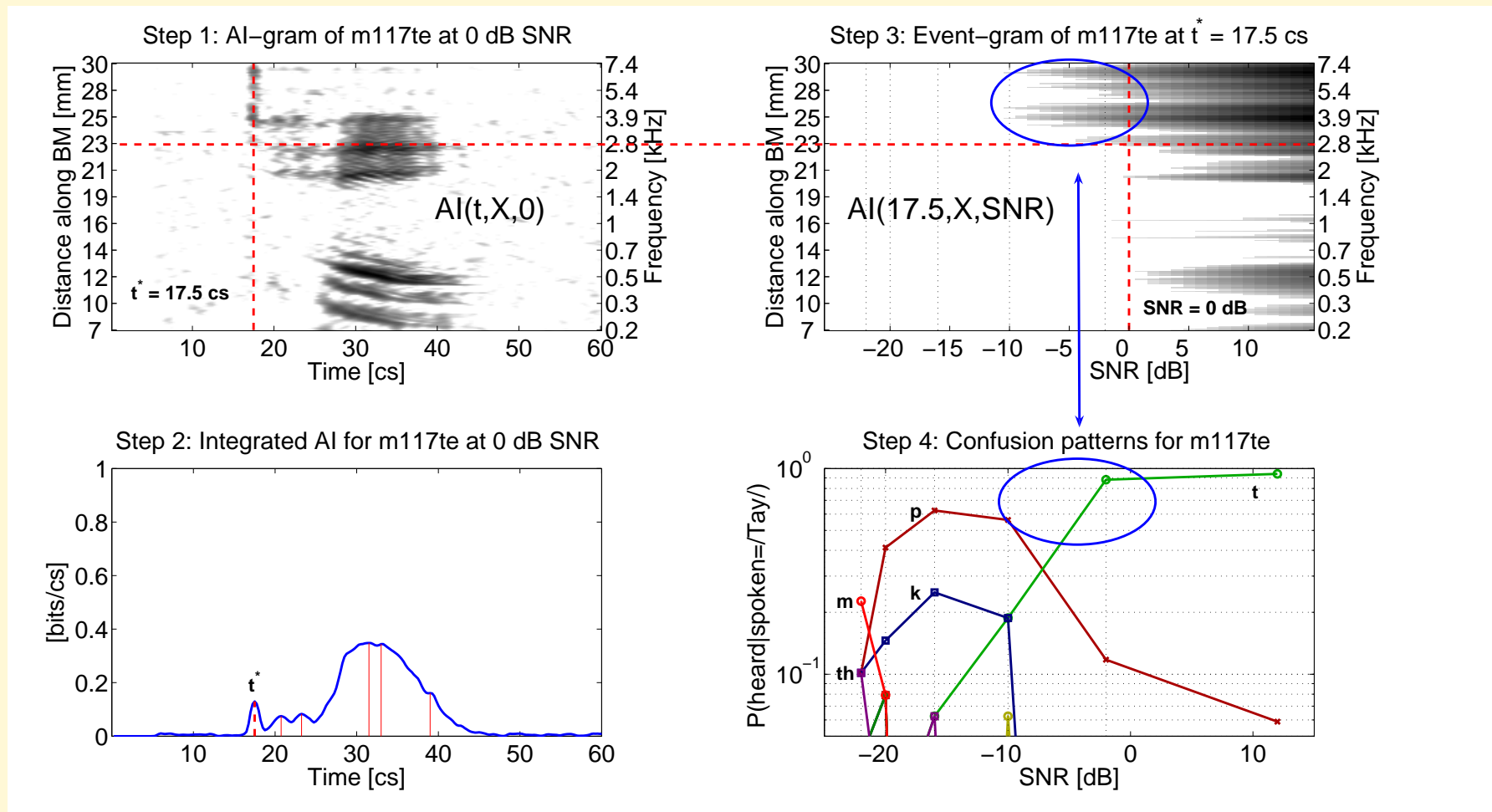


m117/te/ in speech-weighted noise



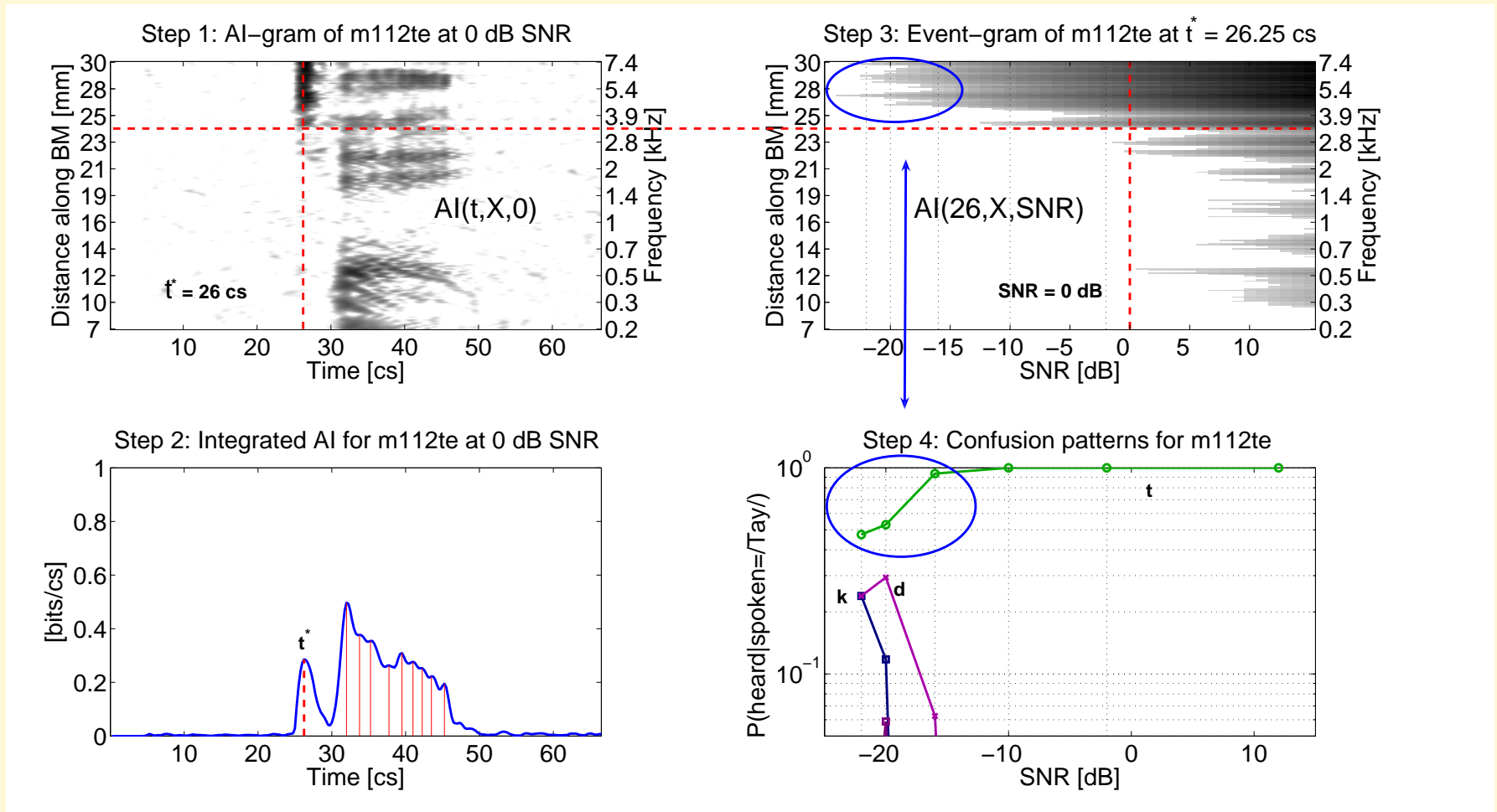
- /t/ confusion threshold at $P_c(SNR_{90}^* = -2)$ dB at 90% correct

m117/te/ in speech-weighted noise



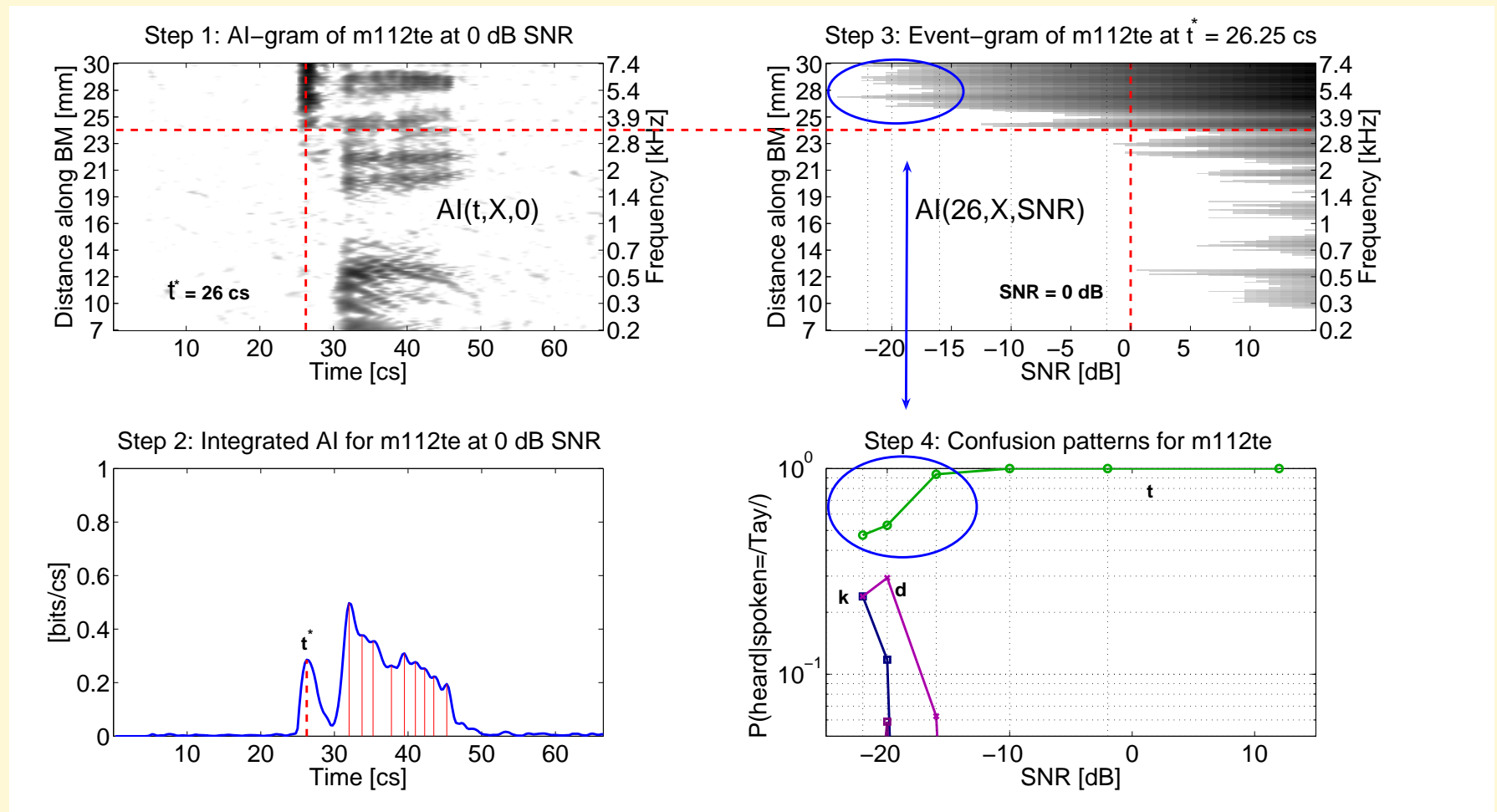
- /t/ confusion threshold at $P_c(SNR_{90}^* = -2)$ dB at 90% correct
- This is an example of a **high-error /te/**

m112/te/ in speech-weighted noise



- /t/ confusion threshold at $P_c(SNR_{90}^* = -16)$ dB at 90% correct

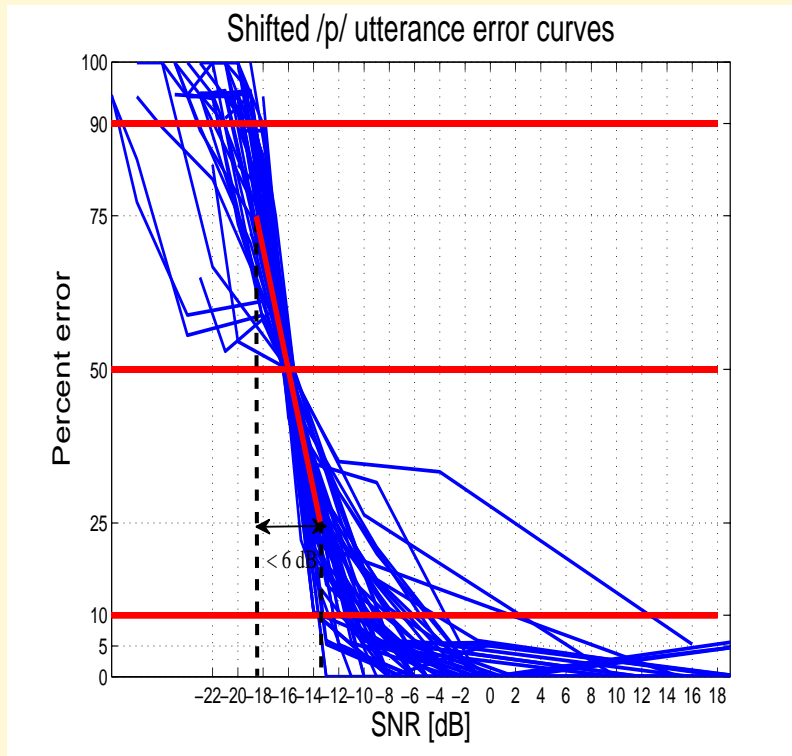
m112/te/ in speech-weighted noise



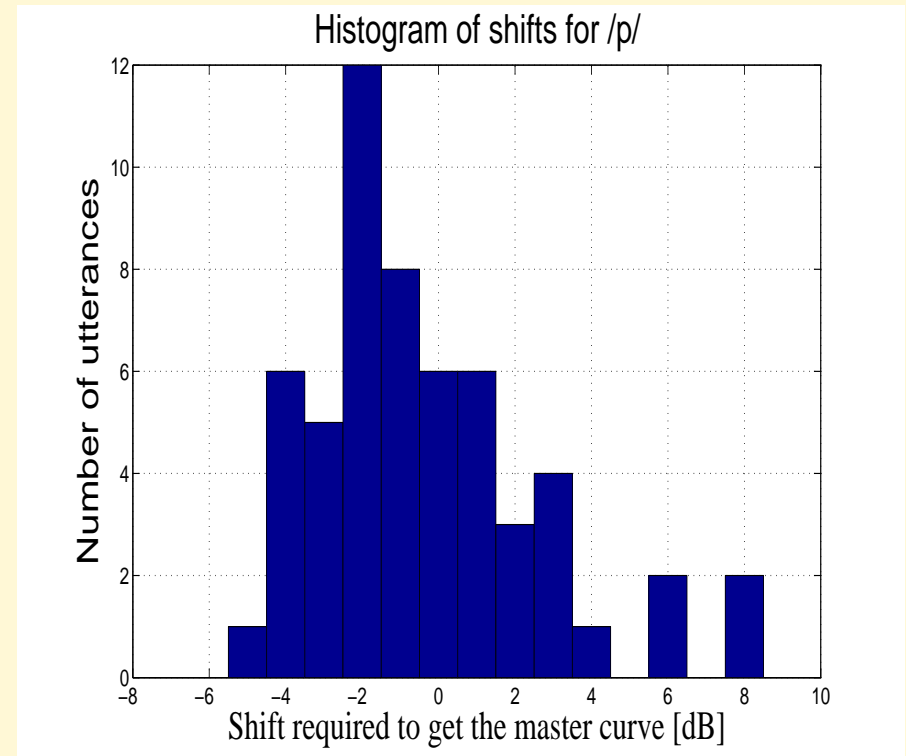
- /t/ confusion threshold at $P_c(SNR_{90}^* = -16)$ dB at 90% correct
- This is an example of a **low-error /te/**

Properties of $P_e(SNR)$ for /p/

- Error vs. SNR shifted to 50% threshold SNR_{50}^* (LEFT)
- Histogram of 50% error thresholds (RIGHT)
- ◆ Sharp transition \Rightarrow Binary Plosive identification!



(a) $P_e(SNR - SNR_{50}^*)$



(b) Distribution of SNR_{50}^*

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 - ◆ We have identified specific consonant cues
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 - 2 Across talker dependent thresholds (SNR_{50} 20 dB)
- I have not yet discussed the HI token dependence

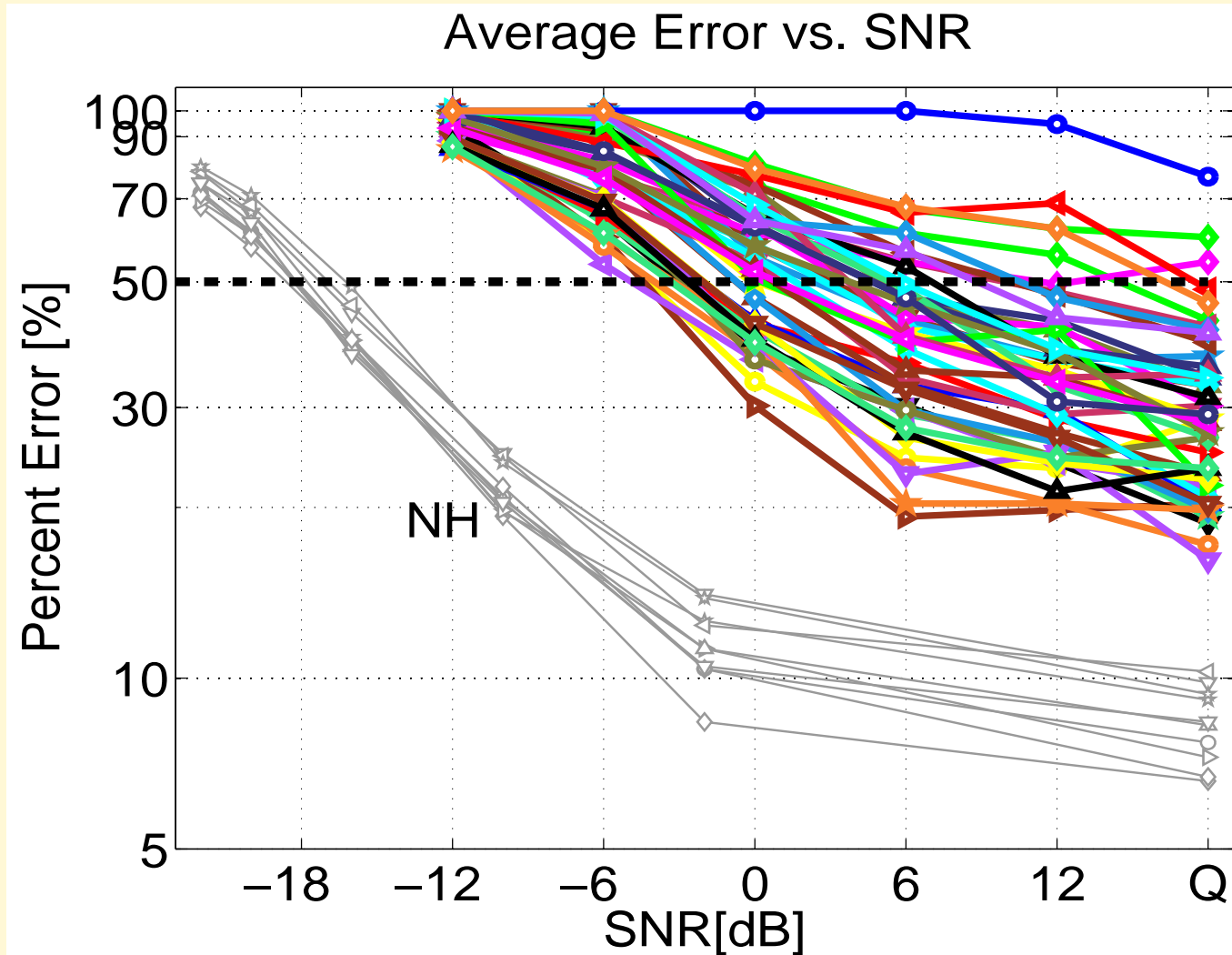
1. Intro + Objectives 2 mins
 - Research objectives
2. Historical overview 4 mins $\Sigma 6$
 - AG Bell (1860), Rayleigh (1910) to Shannon (1948)
 - Speech-feature studies (>1950)
3. Methods 8 mins $\Sigma 14$
 - Channel capacity and the Articulation Index
 - Psychophysics of speech/Algram/3DDS
4. Results with NH ears 10 mins $\Sigma 24$
 - Binary features; Confusions; Primes and Morphs;
5. Results with HI ears 20 mins $\Sigma 44$
 - Individual differences of consonant confusions
6. Summary + Conclusions 6 mins $\Sigma 50$

Yogi Berra Quote:

- "You can observe a lot by watching."

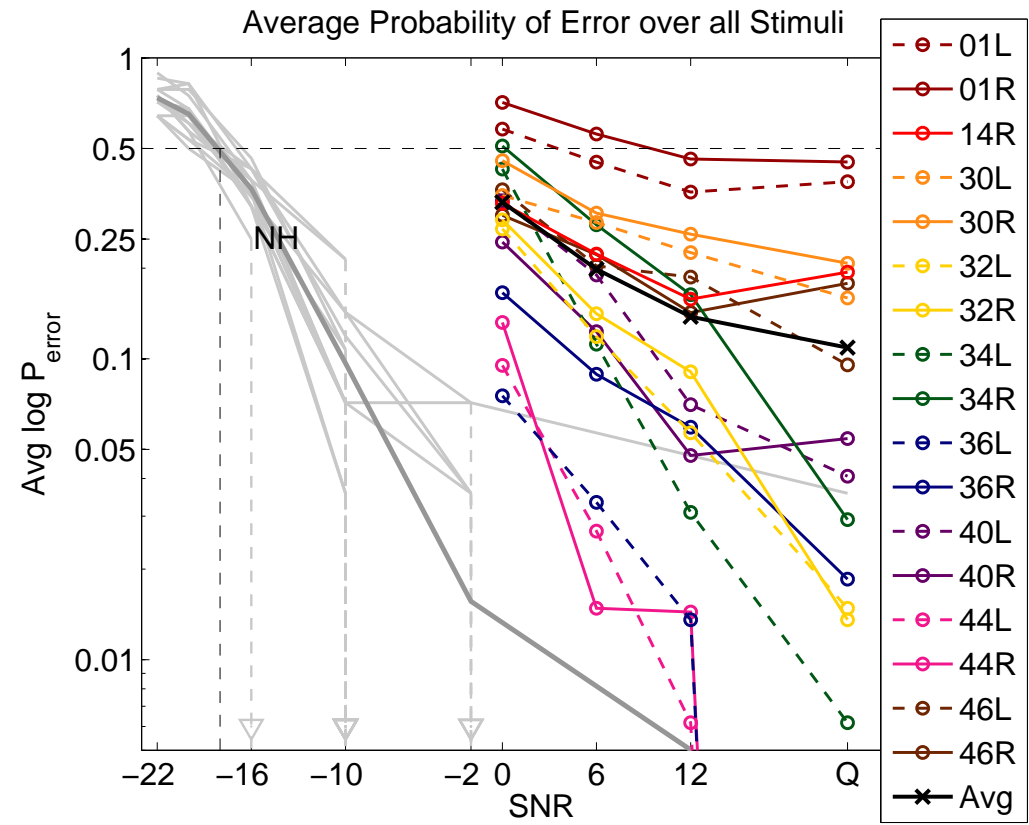
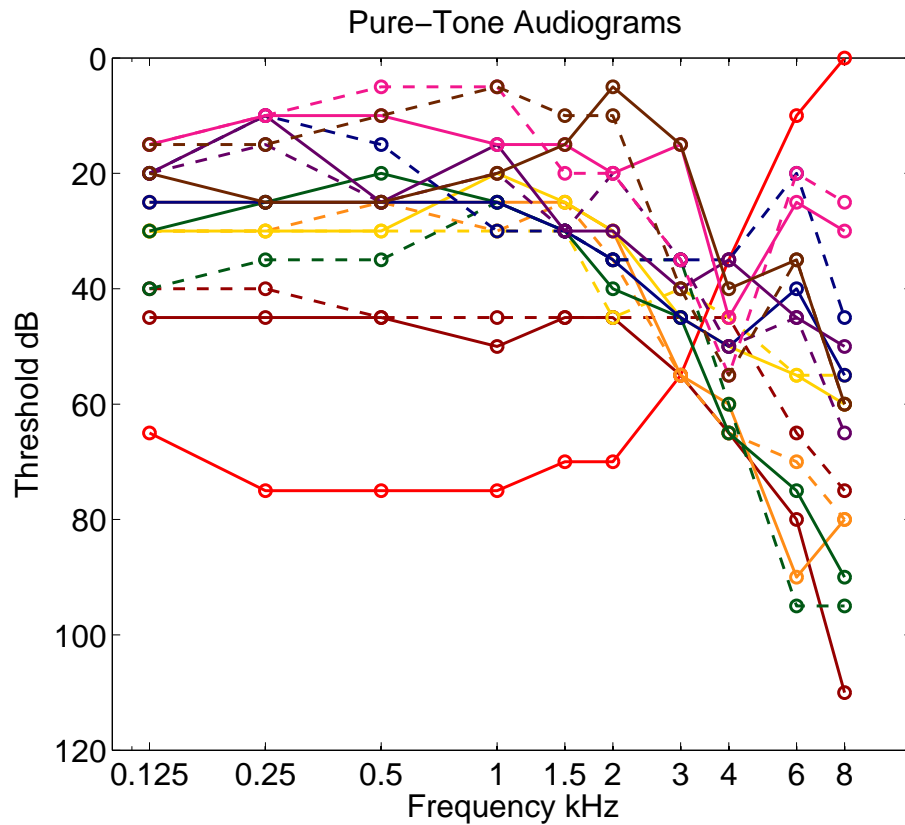
Exp I: 46 HI ears: $P_e(SNR)$

- Very large spread of error vs. SNR



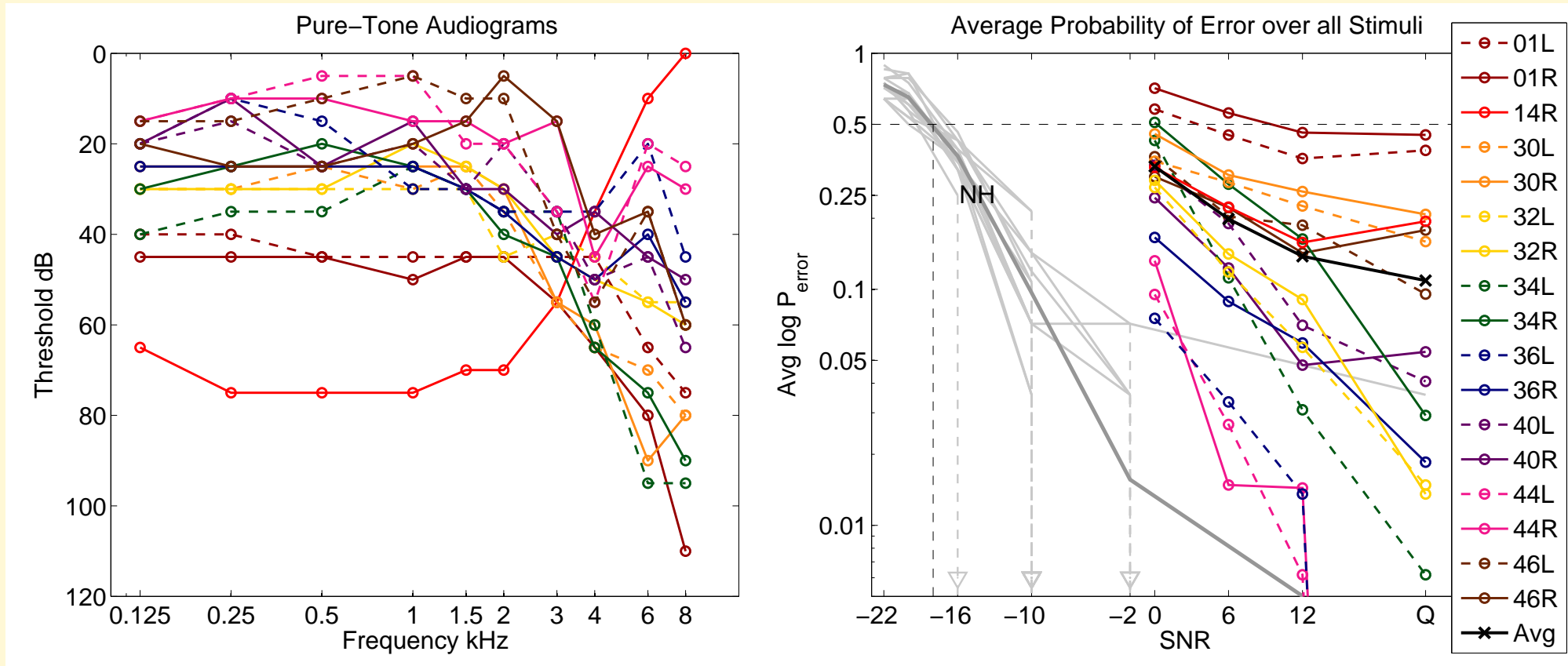
PTA & Average CV error over 17 HI ears

- 14 Miller-Nicely zero-error CV tokens:
/p,t,k, b,d,g, f,s,ʃ, v,z,ʒ, m,n/+/a/



PTA & Average CV error over 17 HI ears

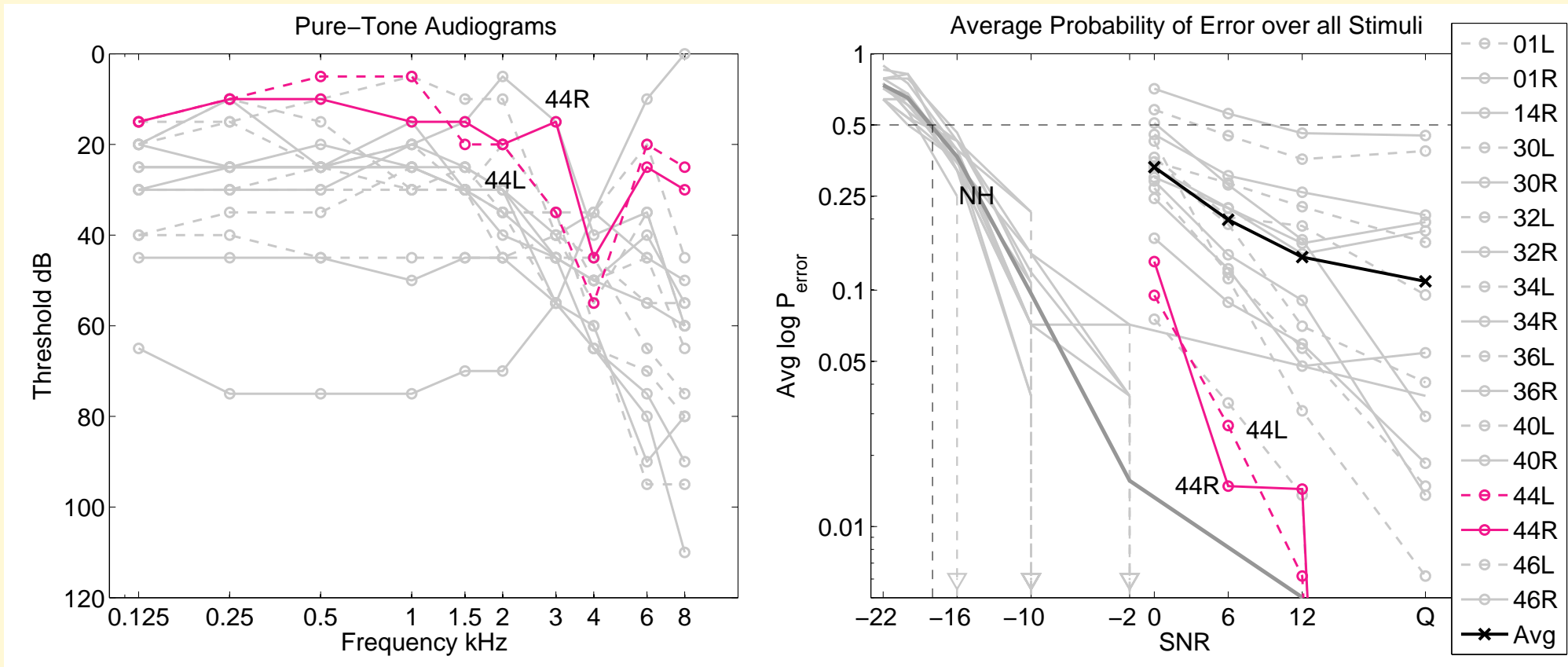
- 14 Miller-Nicely zero-error CV tokens:
/p,t,k, b,d,g, f,s,ʃ, v,z,ʒ, m,n/+/a/



- 2 tokens for each CV (1-male & 1-female)

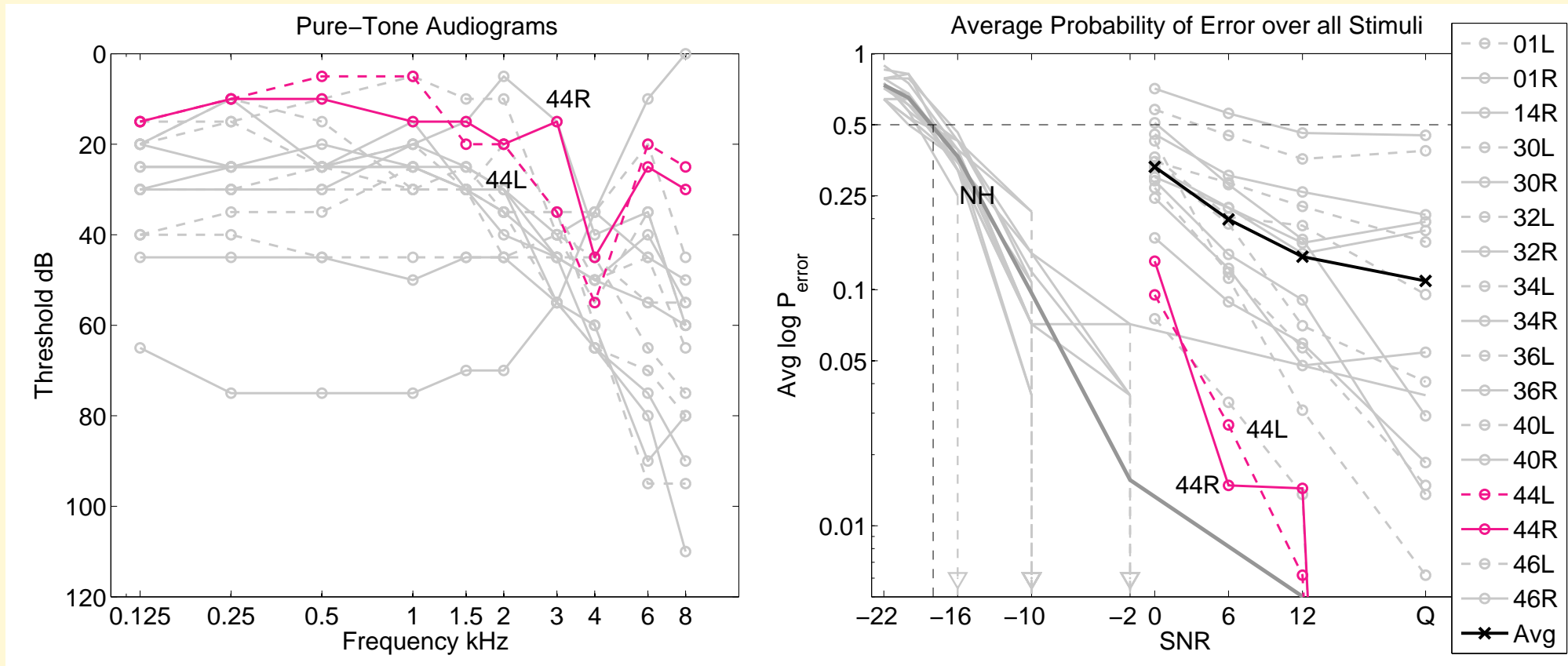
PTA & Average CV error – 44-L/R

- Subject 44-L/R (Left/Right) is our “best” listener!



PTA & Average CV error – 44-L/R

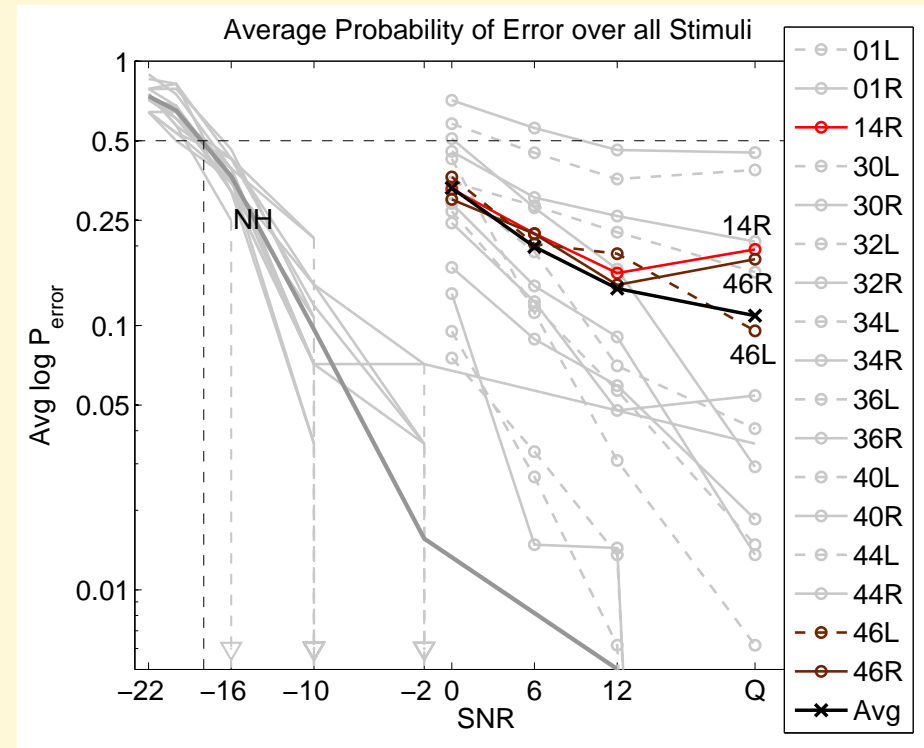
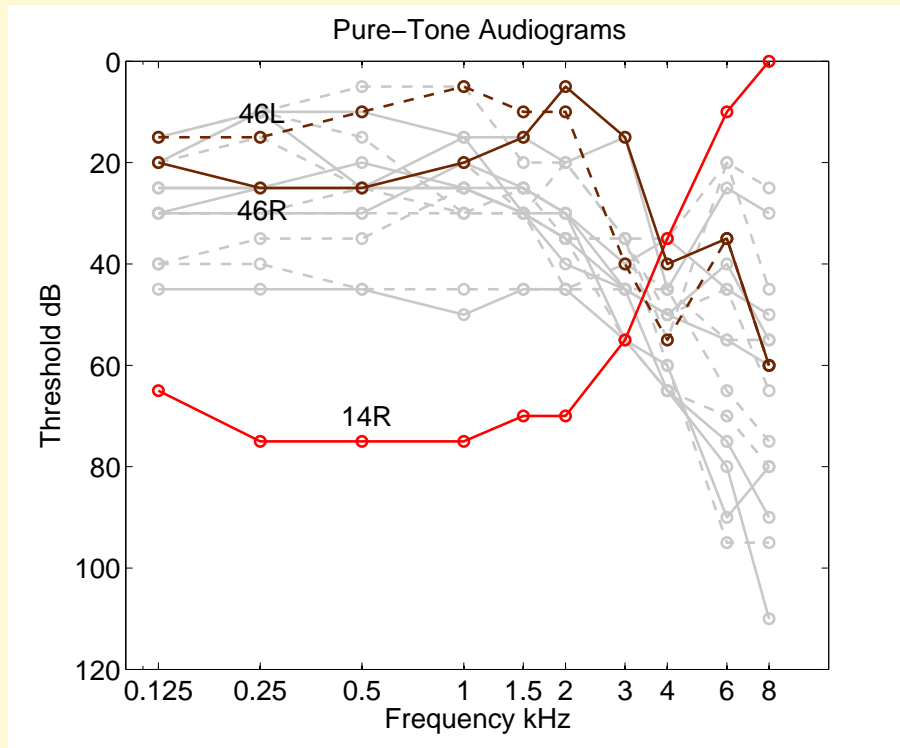
- Subject 44-L/R (Left/Right) is our “best” listener!



If only life were always this simple!

PTA & Average CV error: 14R, 46L/R

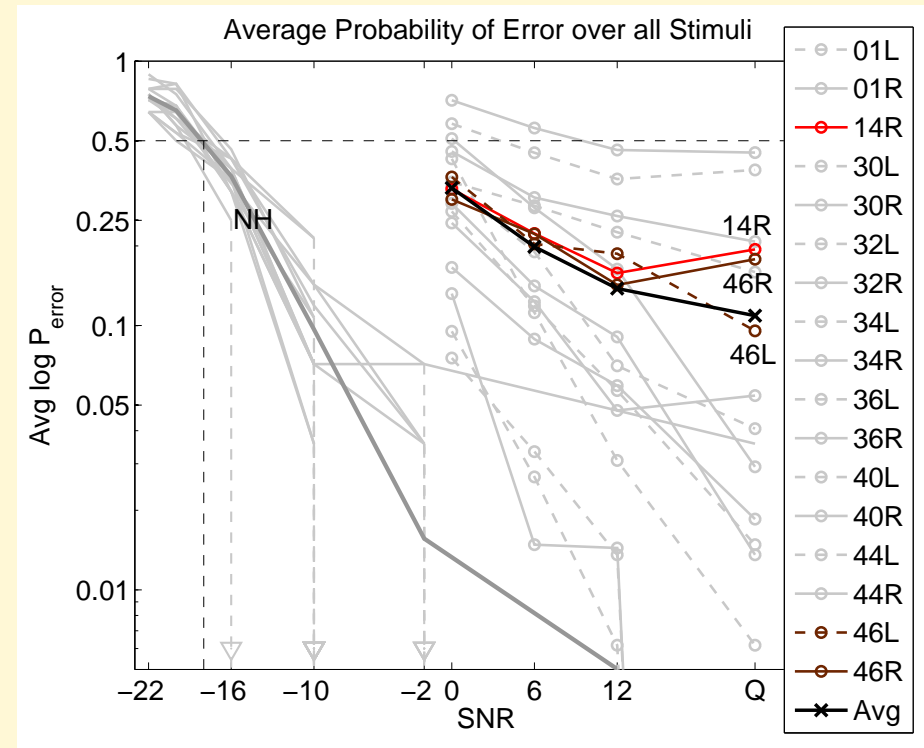
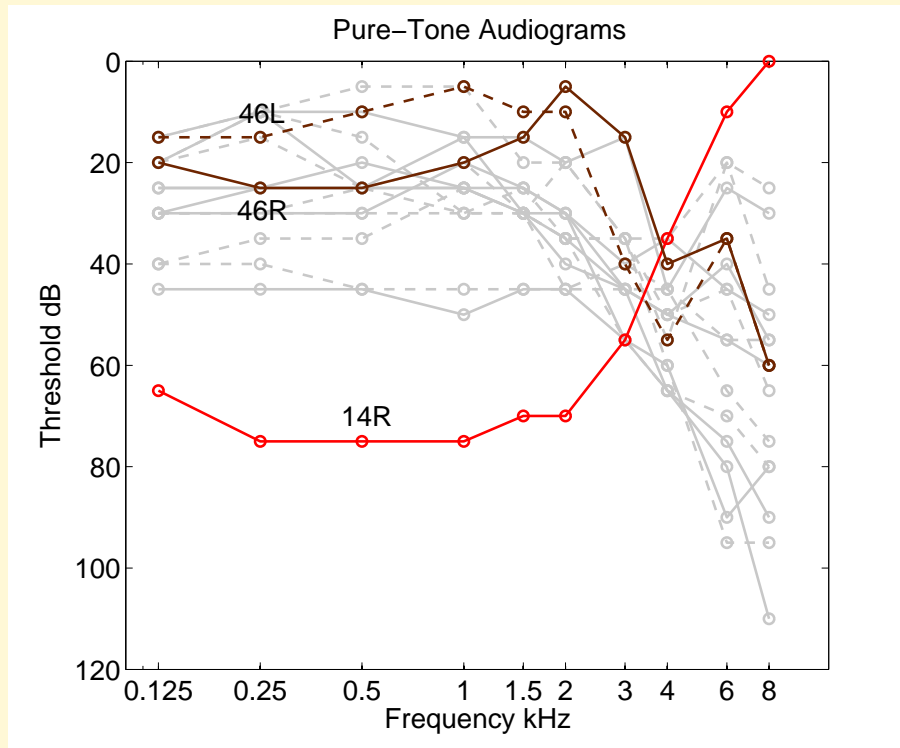
- Very different HL with nearly identical average speech scores



- Average speech scores show no correlation with hearing-level,

PTA & Average CV error: 14R, 46L/R

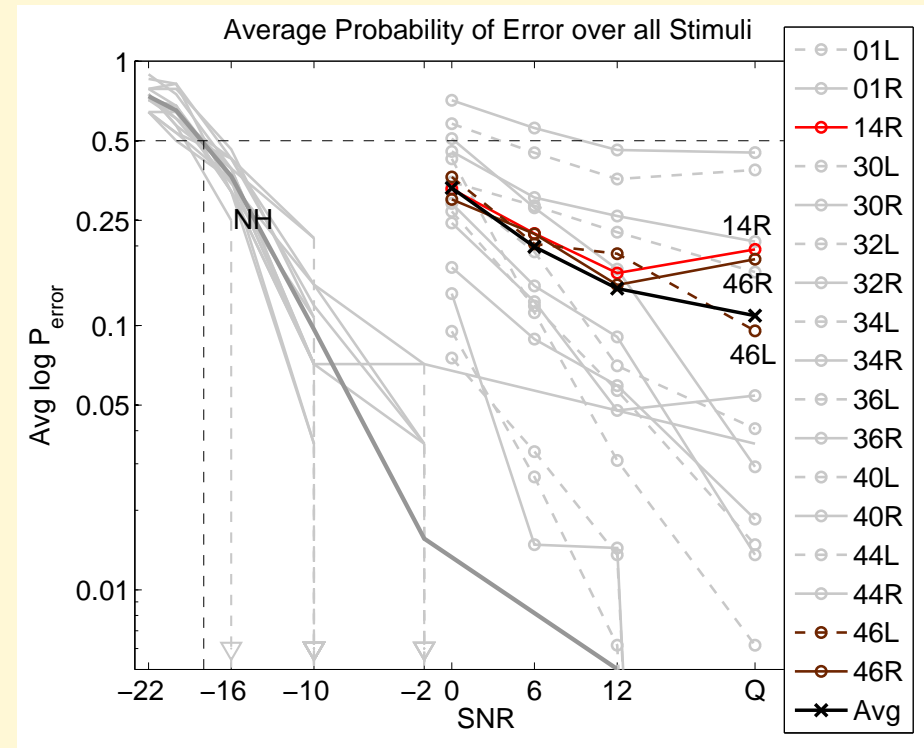
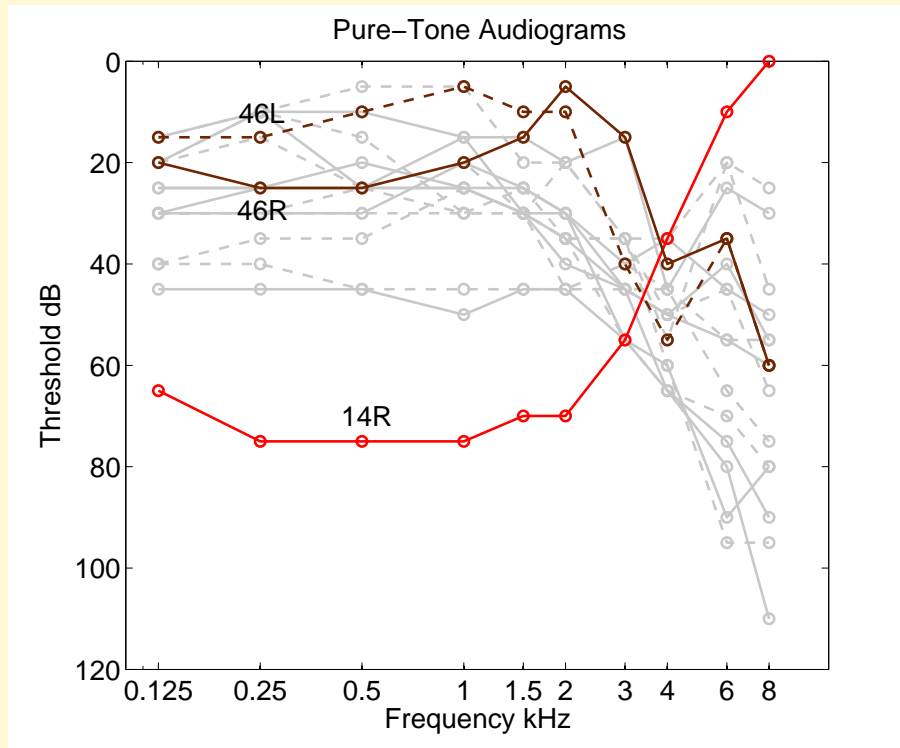
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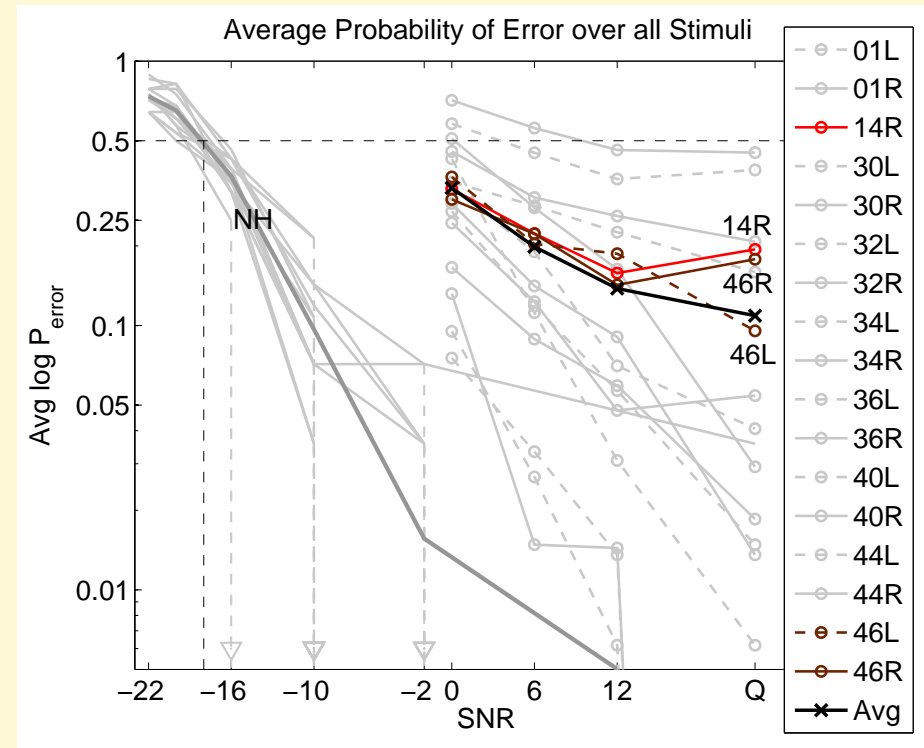
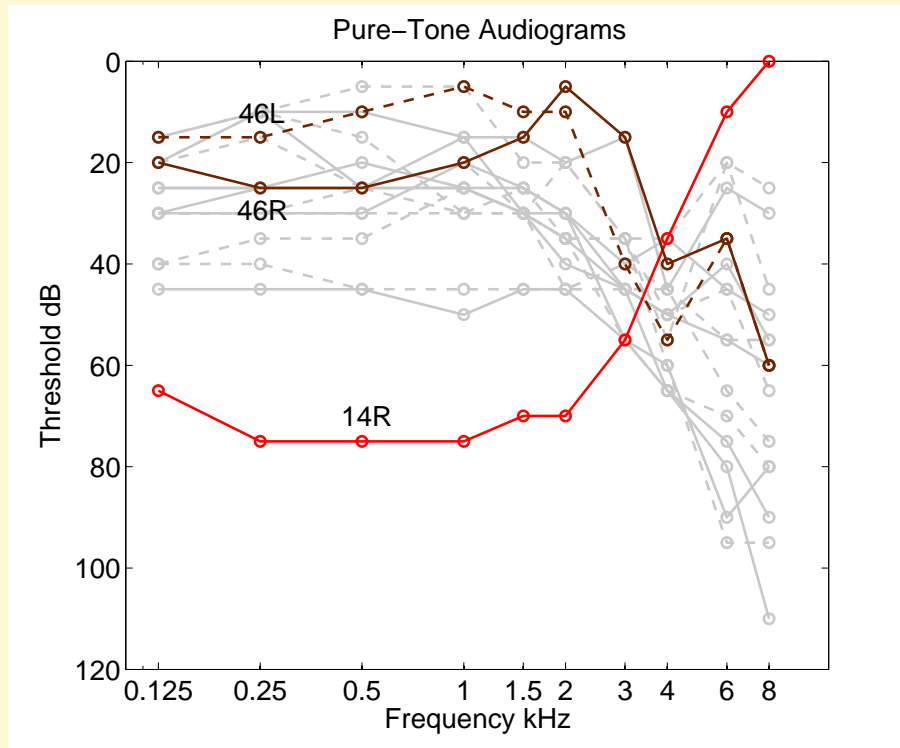


- Average speech scores show no correlation with hearing-level, with massively different audiograms!

- Why? ...

PTA & Average CV error: 14R, 46L/R

- Very different HL with nearly identical average speech scores

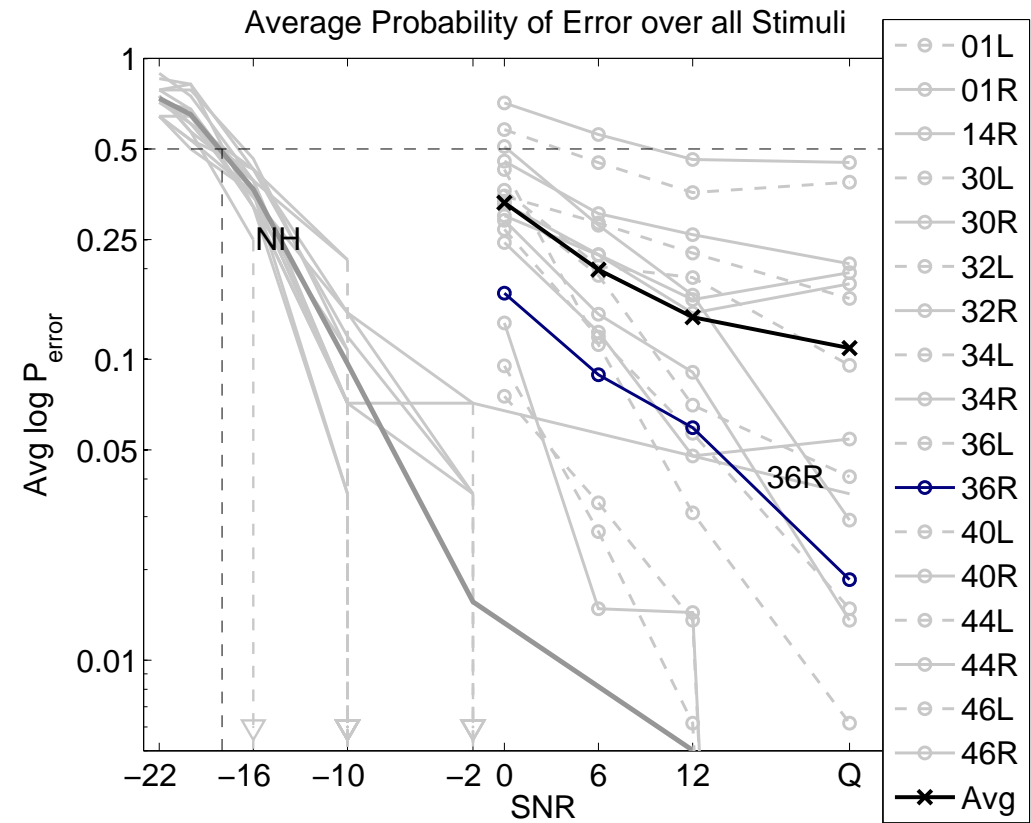
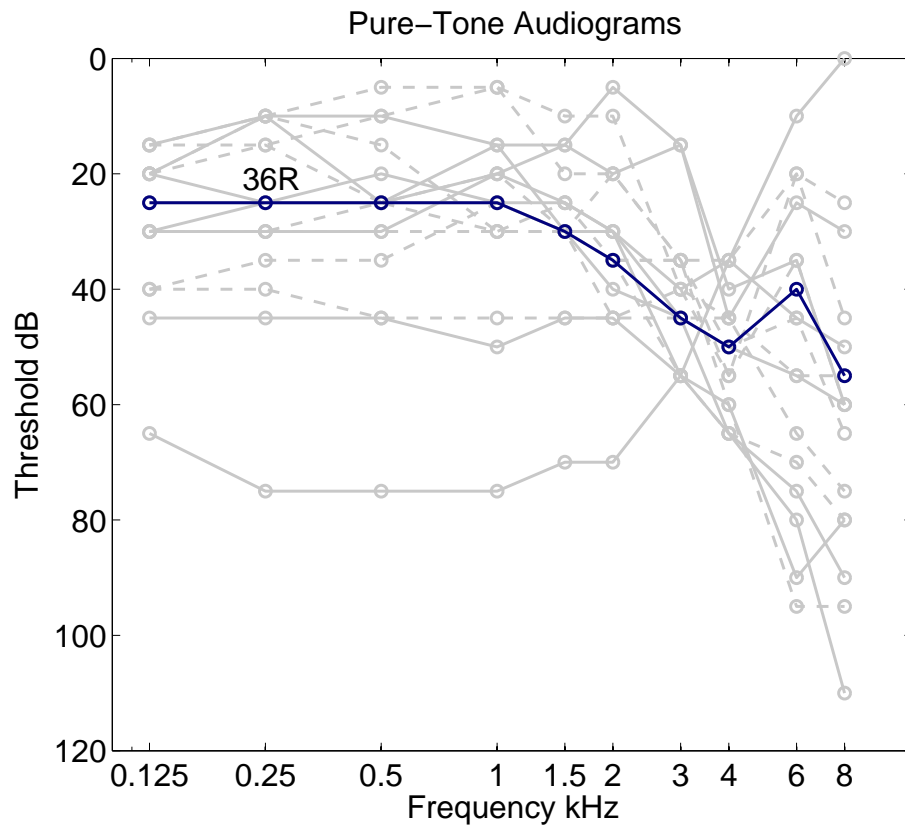


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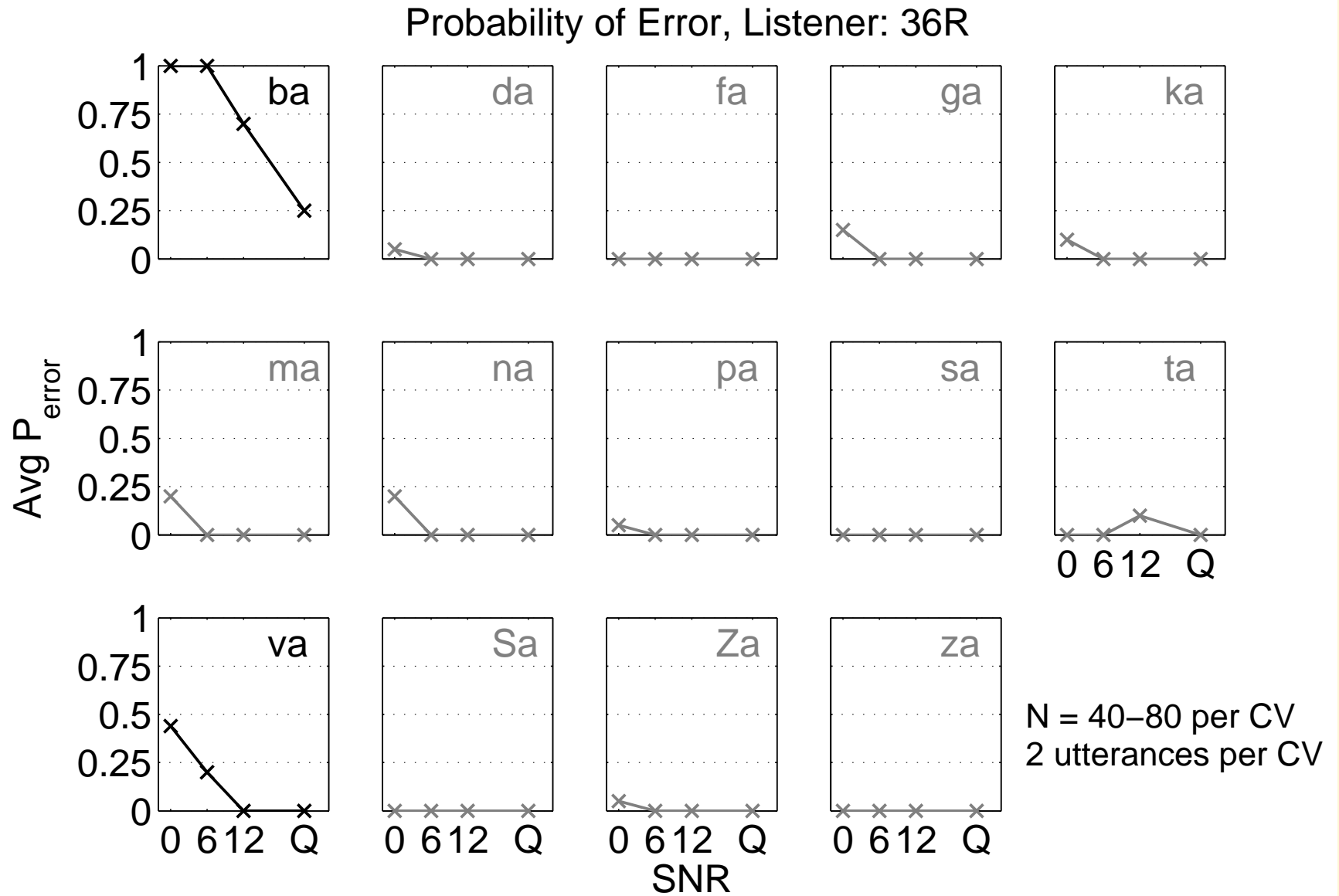
- Why? ... Too much averaging!

PTA & Average CV error: 36R

■ Case study for 36-R

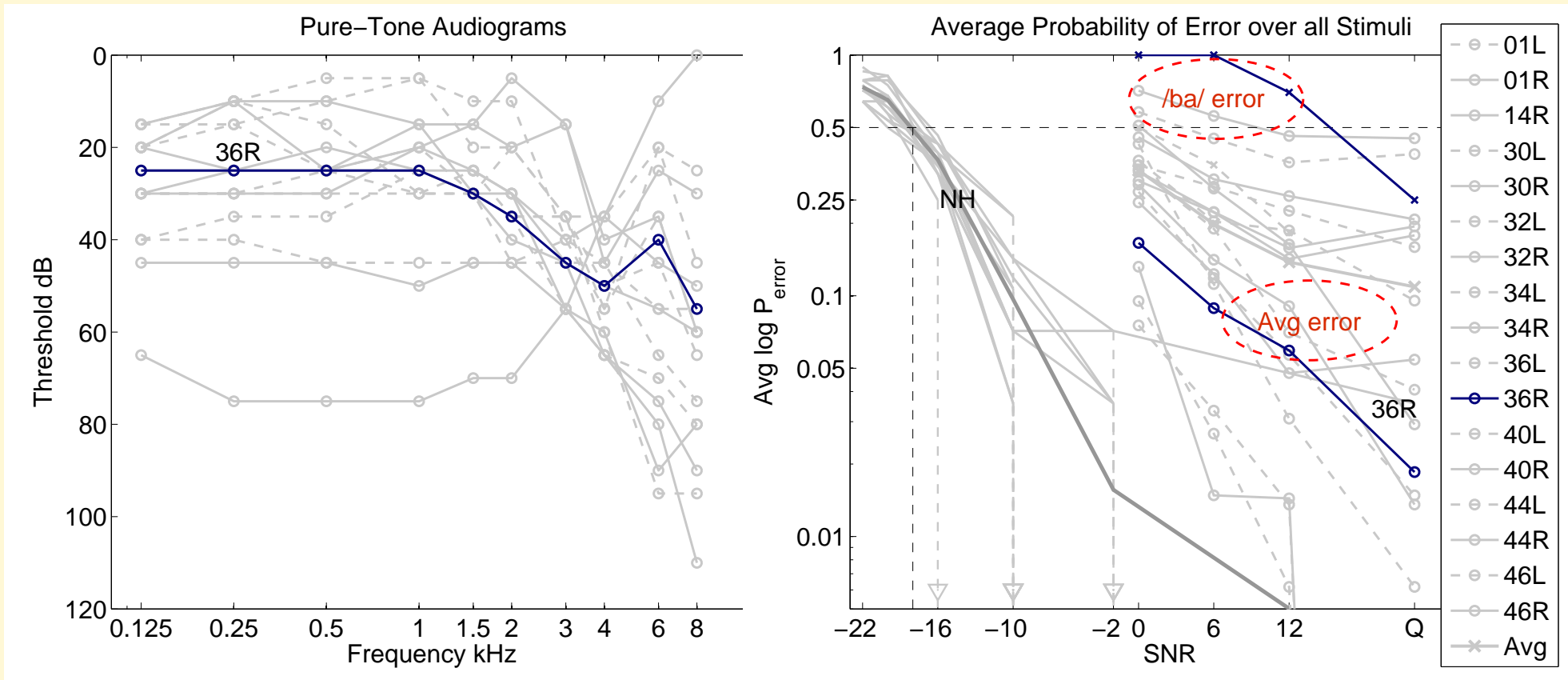


For Subj 36R: only /ba, va/ have errors!



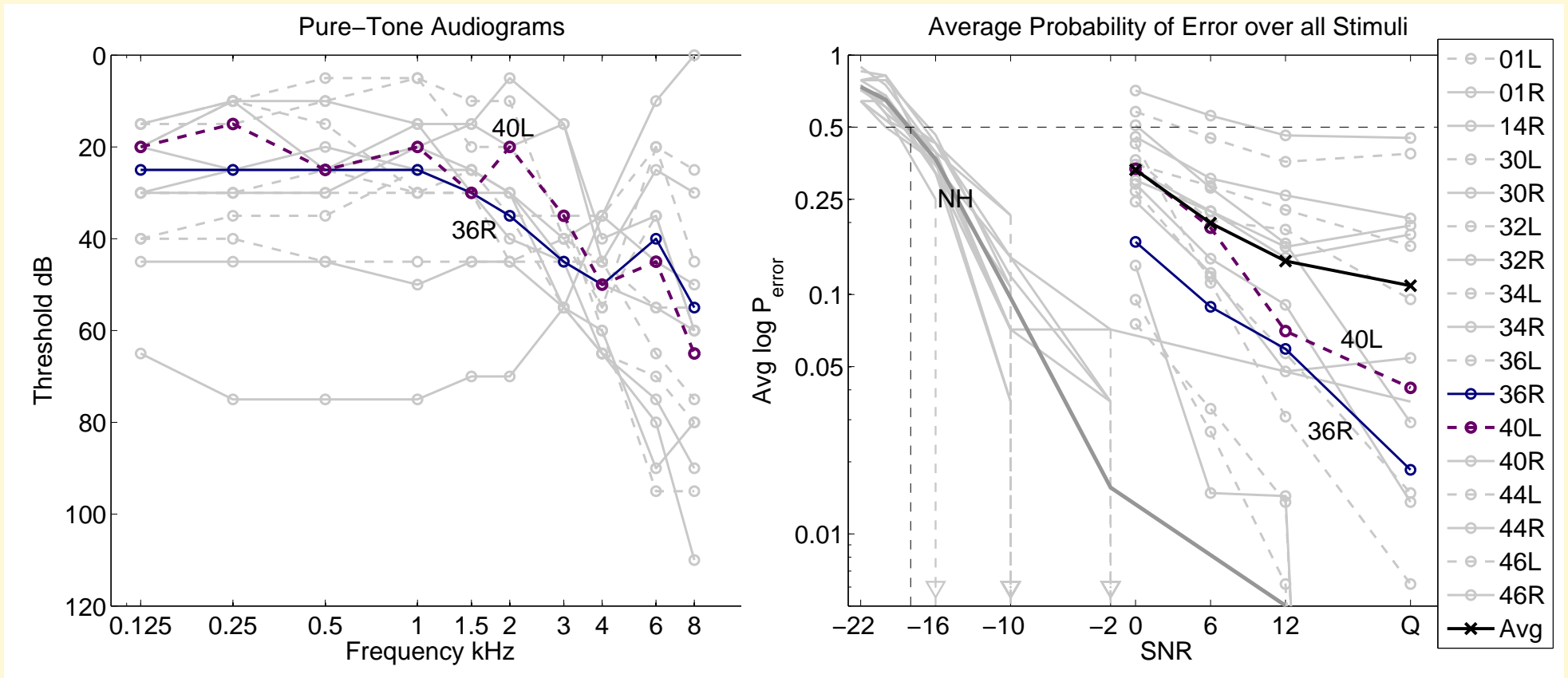
The token SIN_t of Averaging

■ Case study for 36R



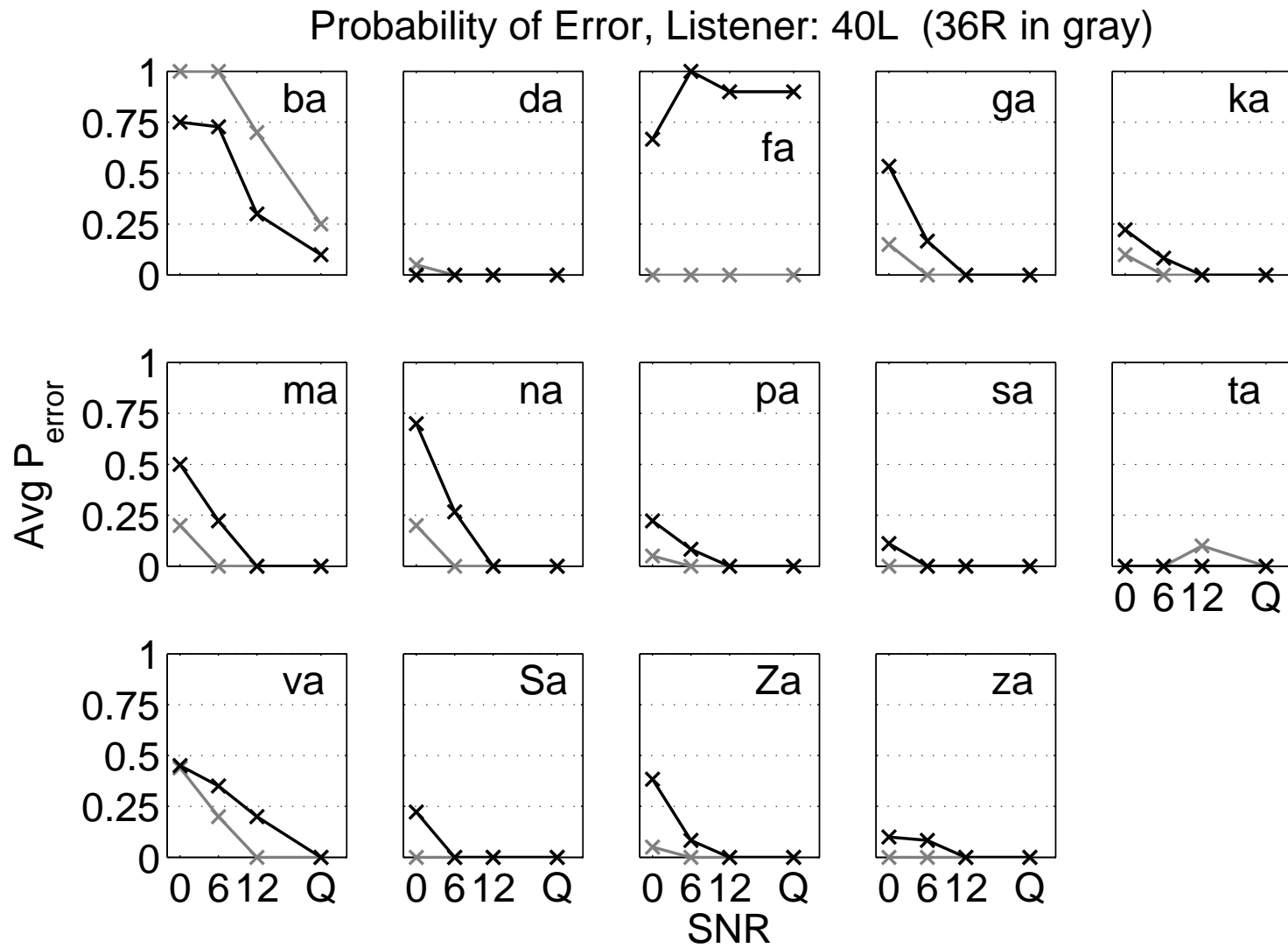
PTA & Average CV error: 40L vs 36R

■ Case study for 40L



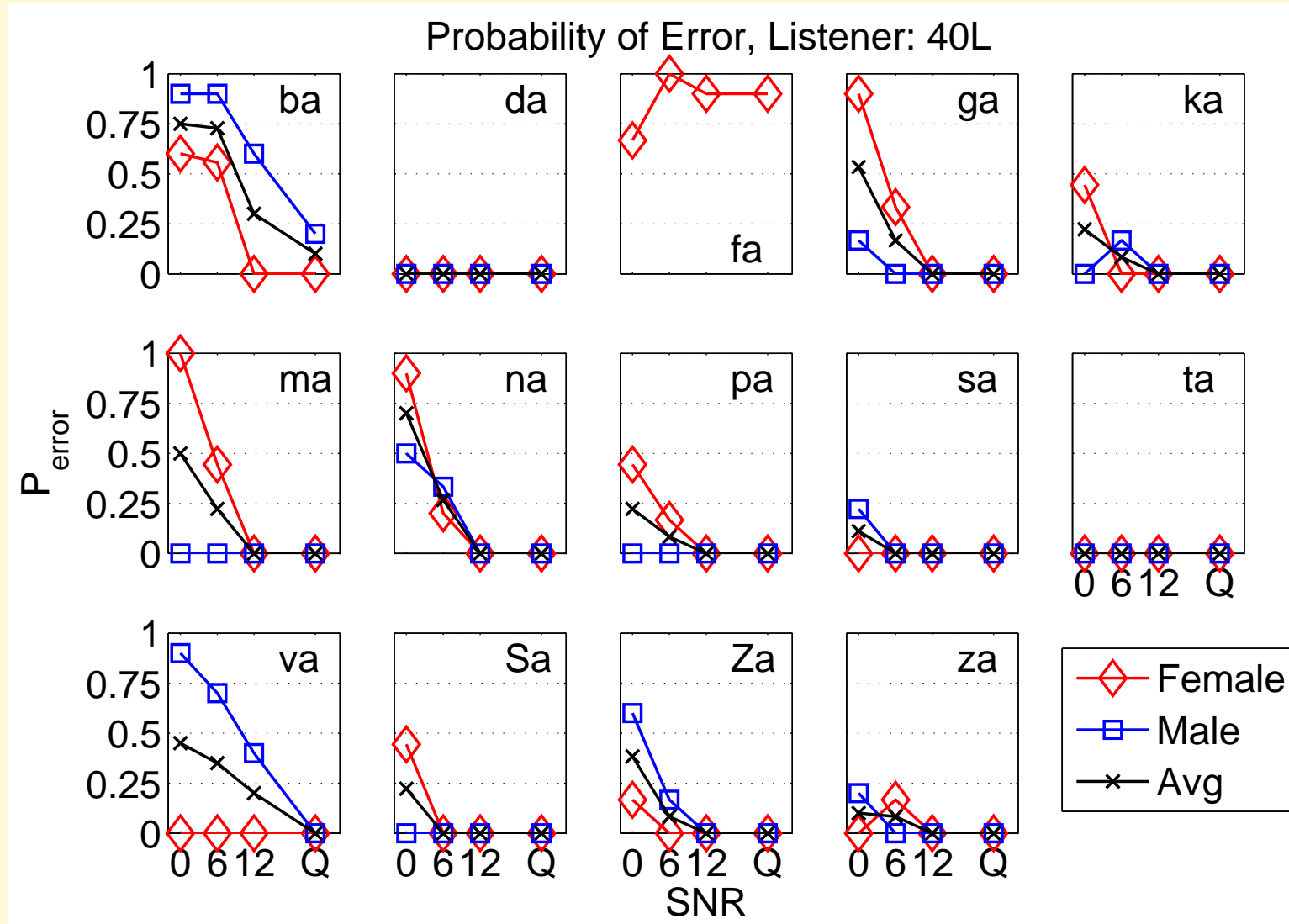
Subject 40L error > 36R

- Errors for 40L re 36R: /ba, fa, ga, ka, ma, na, pa, va, za/



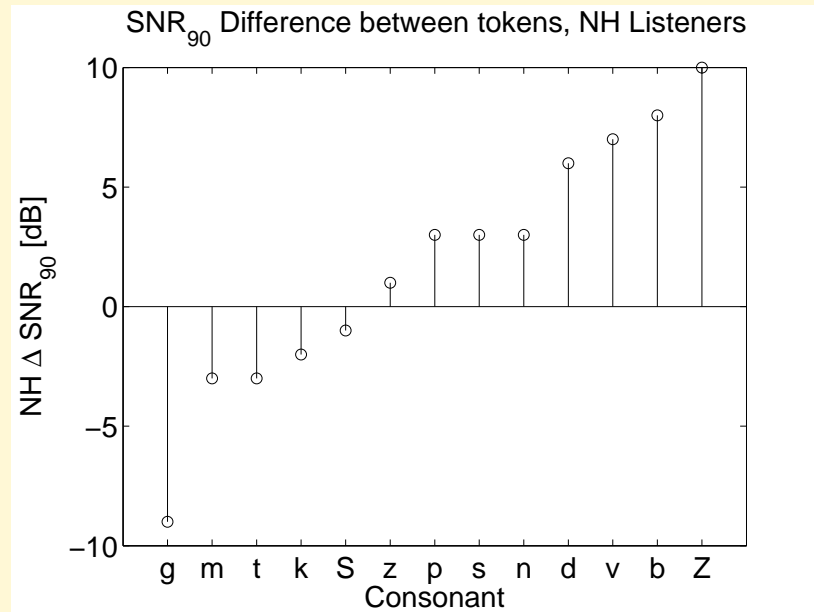
Token error SIN_t #3

- The token (i.e., talker) errors across CVs are asymmetric



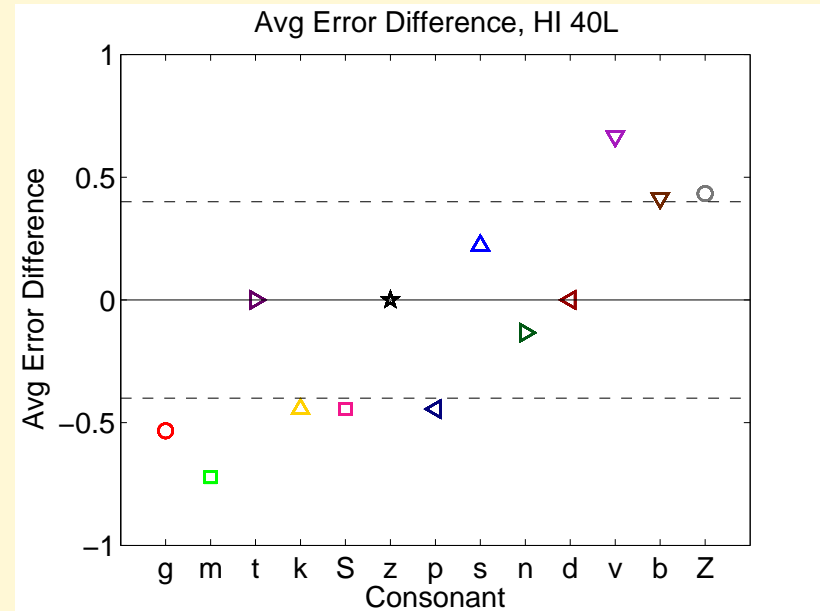
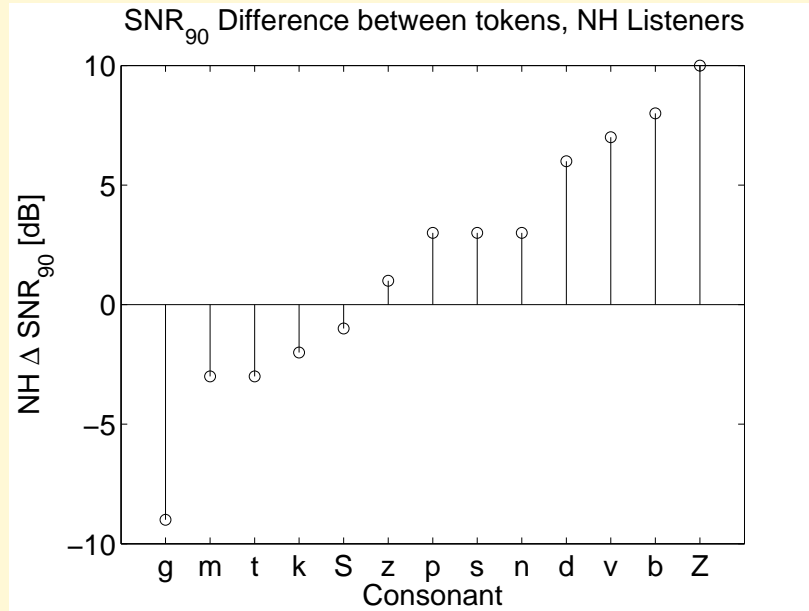
NH vs. HI Utterance differences

Rank order of consonants by SNR_{90}



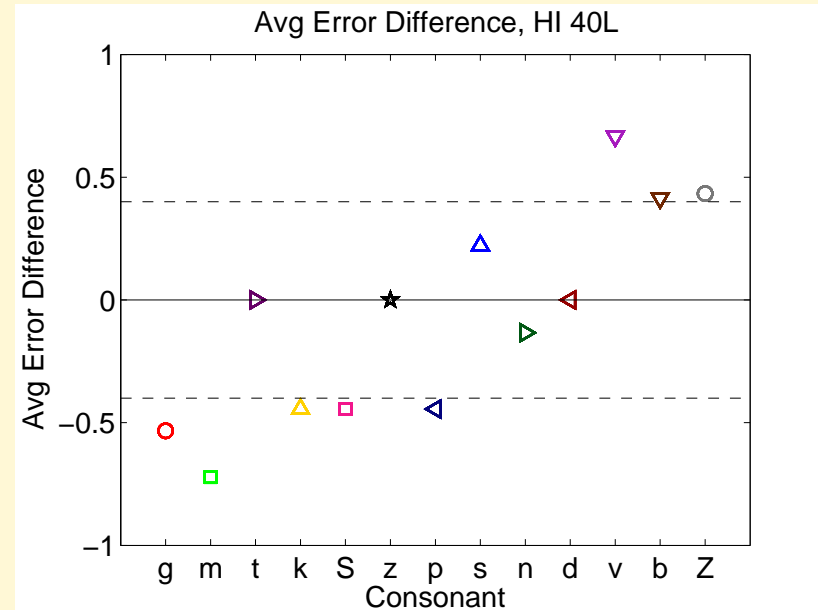
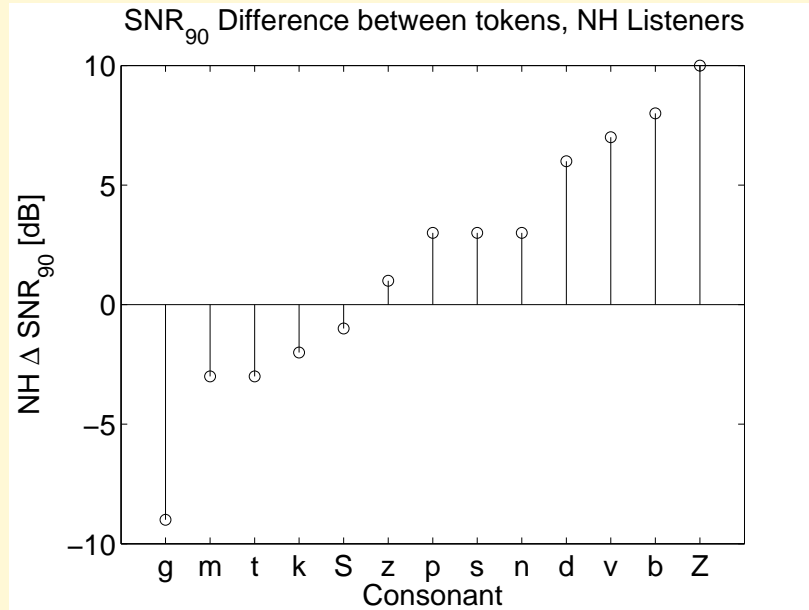
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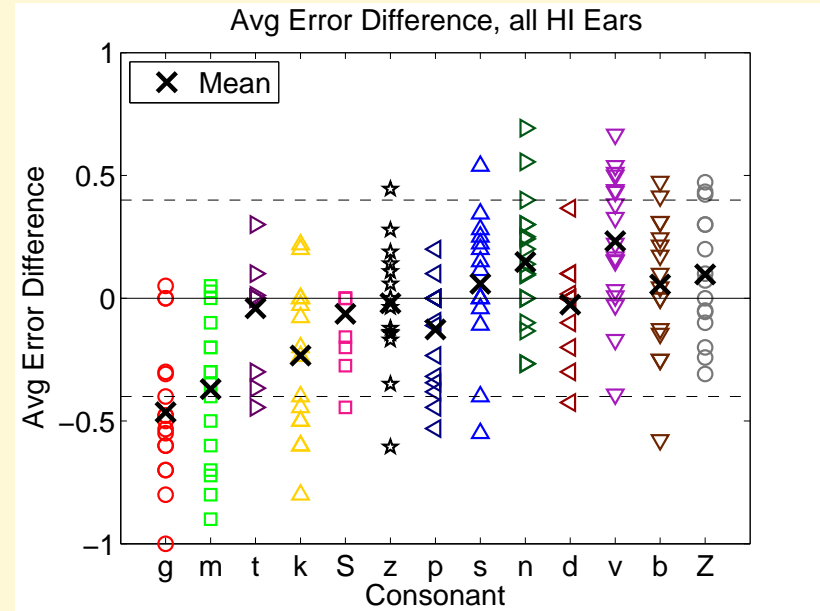
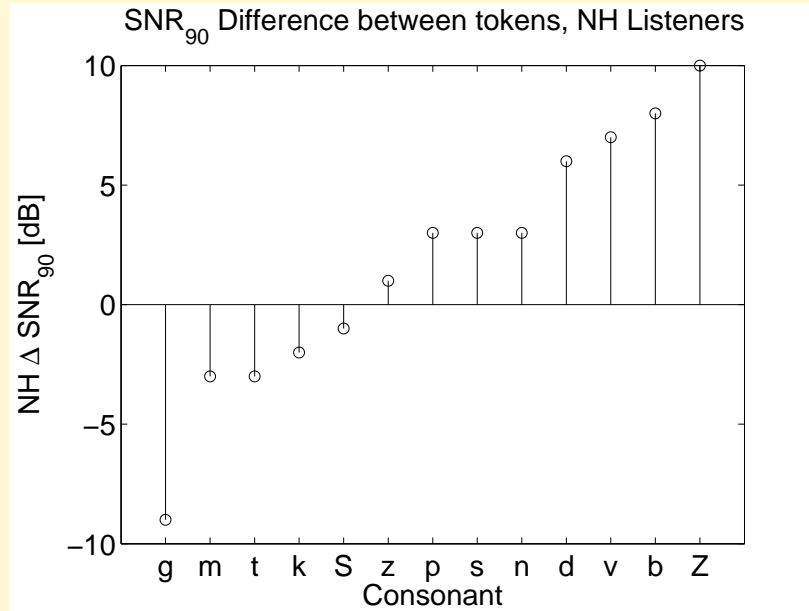
Rank order of consonants by SNR_{90}



- Note tight relationship in the error difference for NH ears (left) and subject 40L (right)

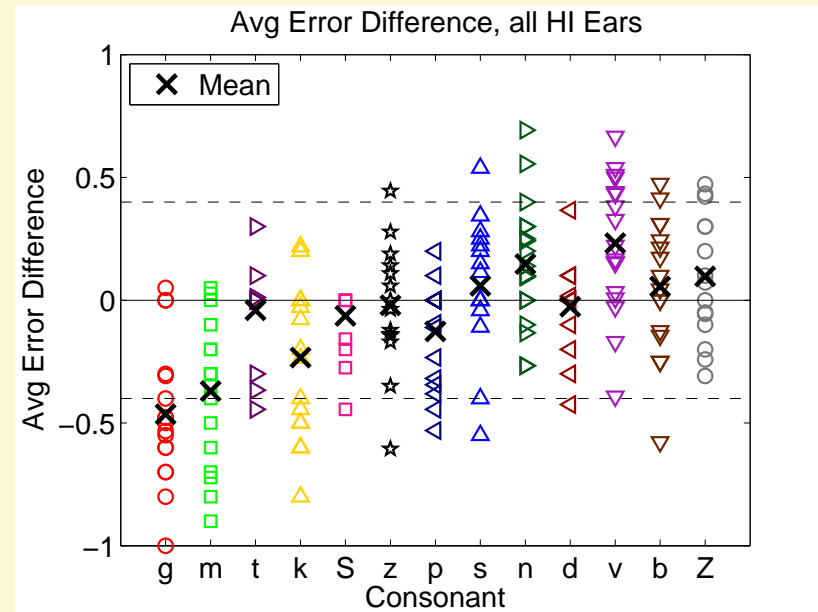
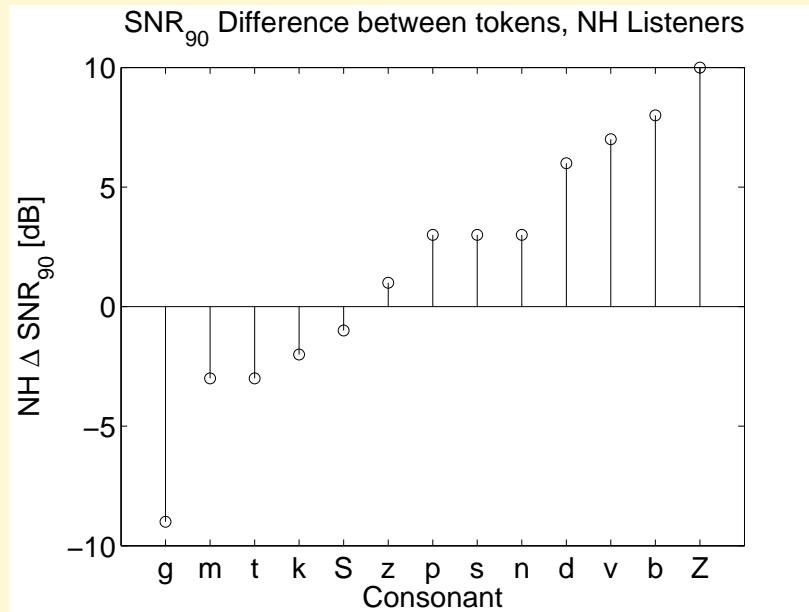
NH vs. HI Utterance differences

Rank order of consonants by SNR_{90}



NH vs. HI Utterance differences

Rank order of consonants by SNR₉₀



- Note the order correlation between NH and HI listeners ($\rho = 0.81, p < 0.001$)

Yogi Berra Quote:

- We made too many wrong mistakes.

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- The **Audiogram** and **Average Consonant errors** have low correlation

Conclusion on HI errors

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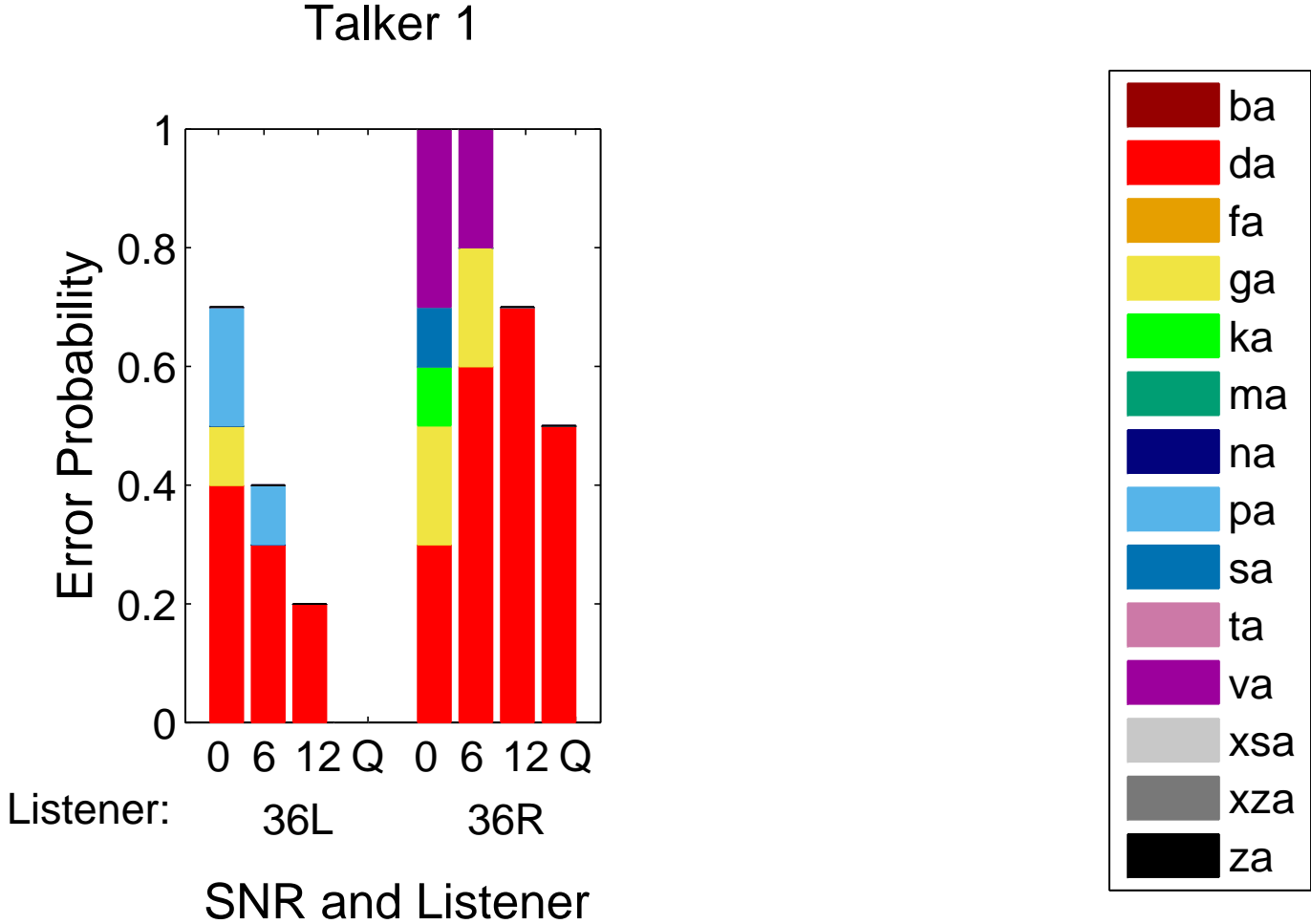
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Conclusion on HI errors

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 - ◆ Making the HI subject *appear* as inconsistent
- The 3 deadly SINS of averaging:
 - 1 Across *HI subjects*: SIN_s
 - 2 Across *consonants*: SIN_c
 - 3 Across *tokens*: SIN_t

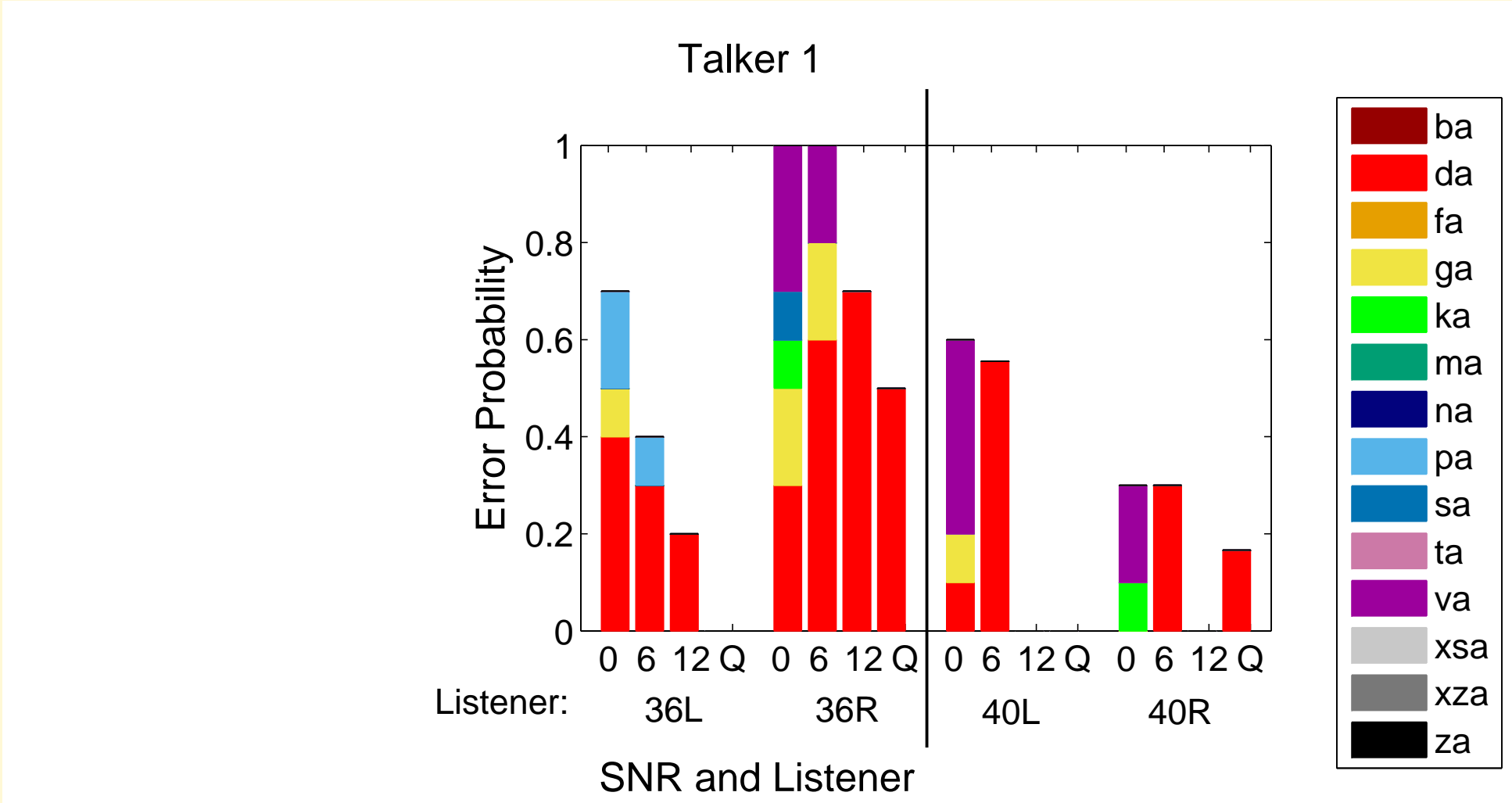
Confusions for Talker 1 of /ba/

- Colors label the confusions



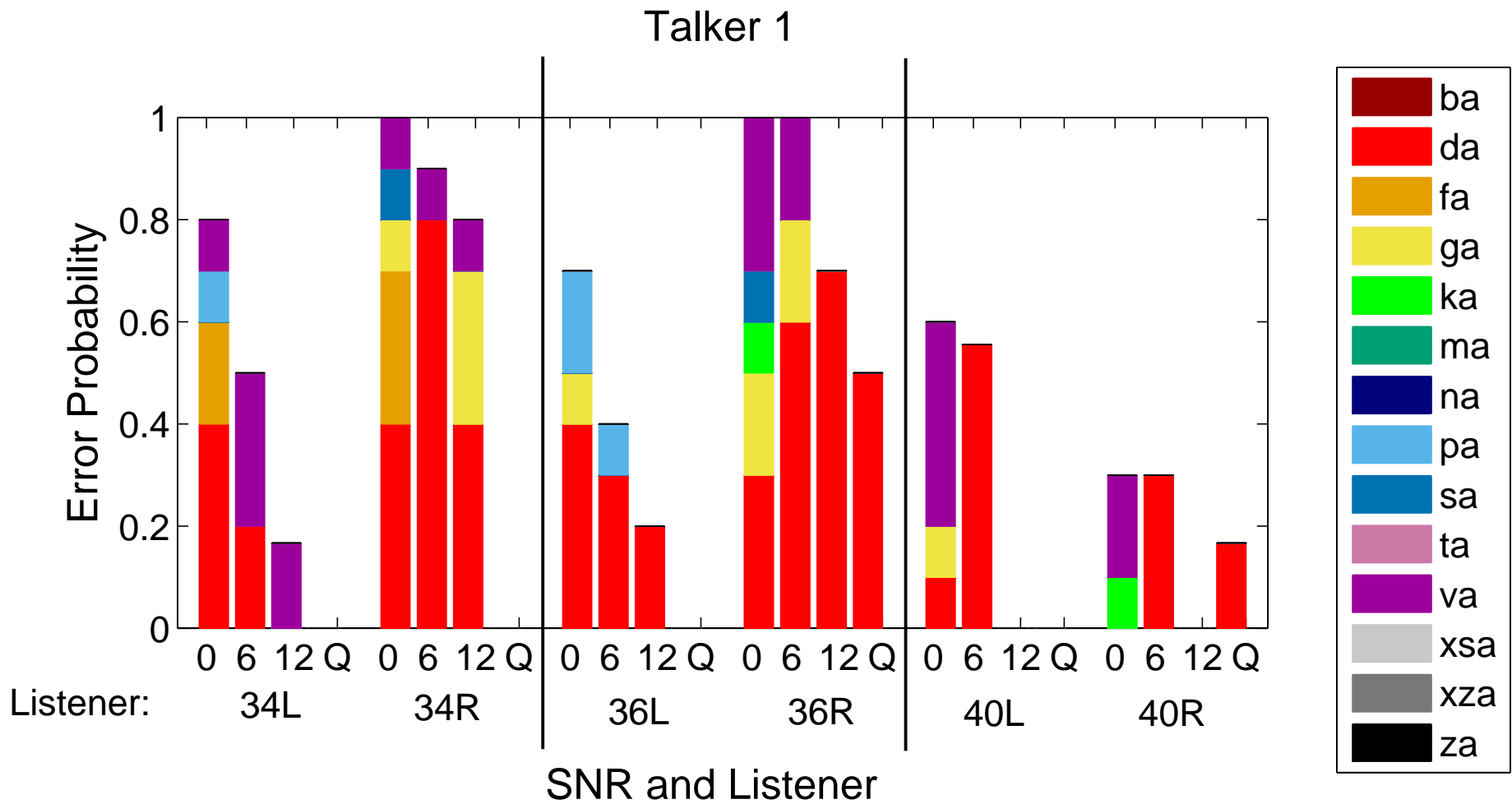
Confusions for Talker 1 of /ba/

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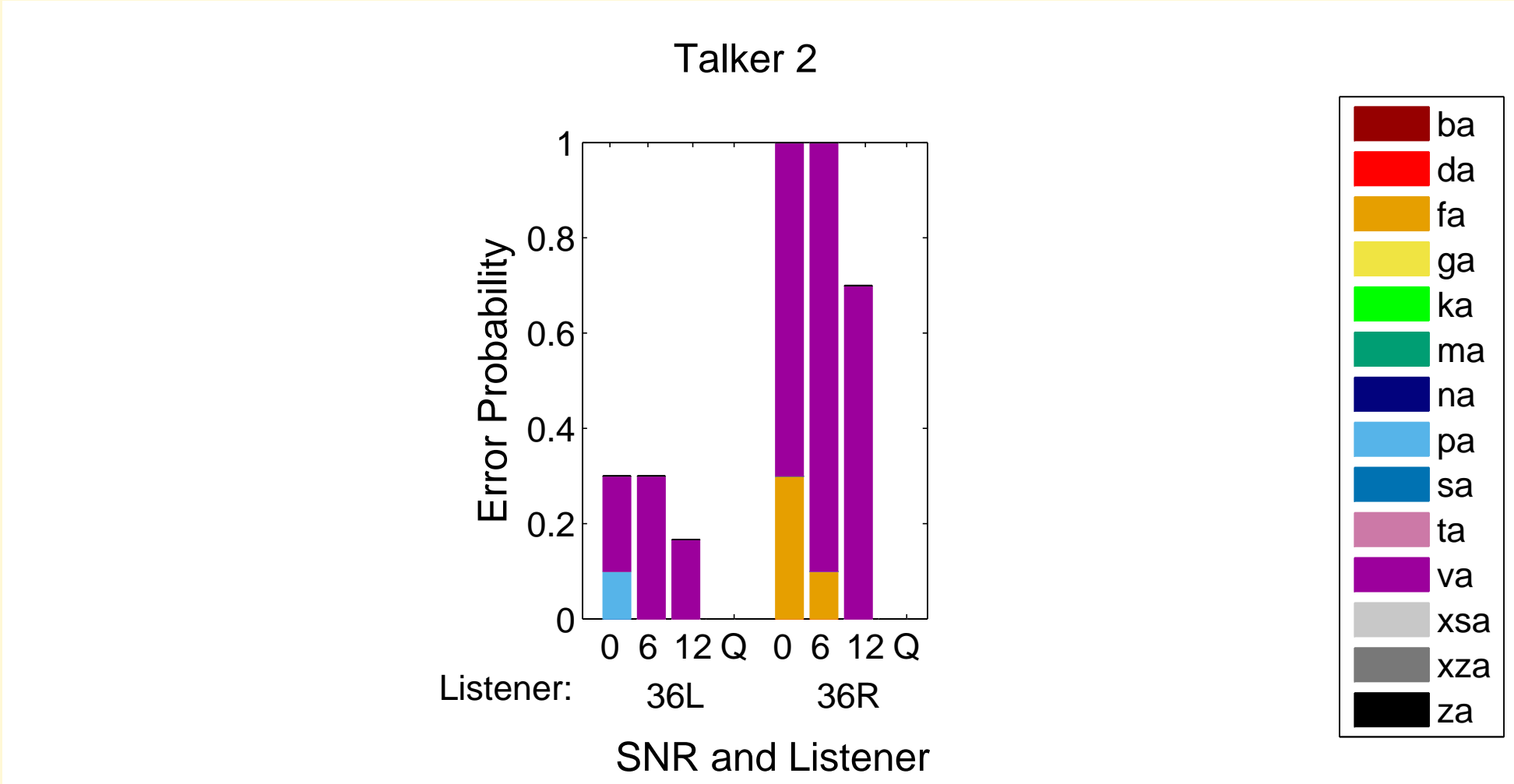
Confusions for Talker 1 of /ba/

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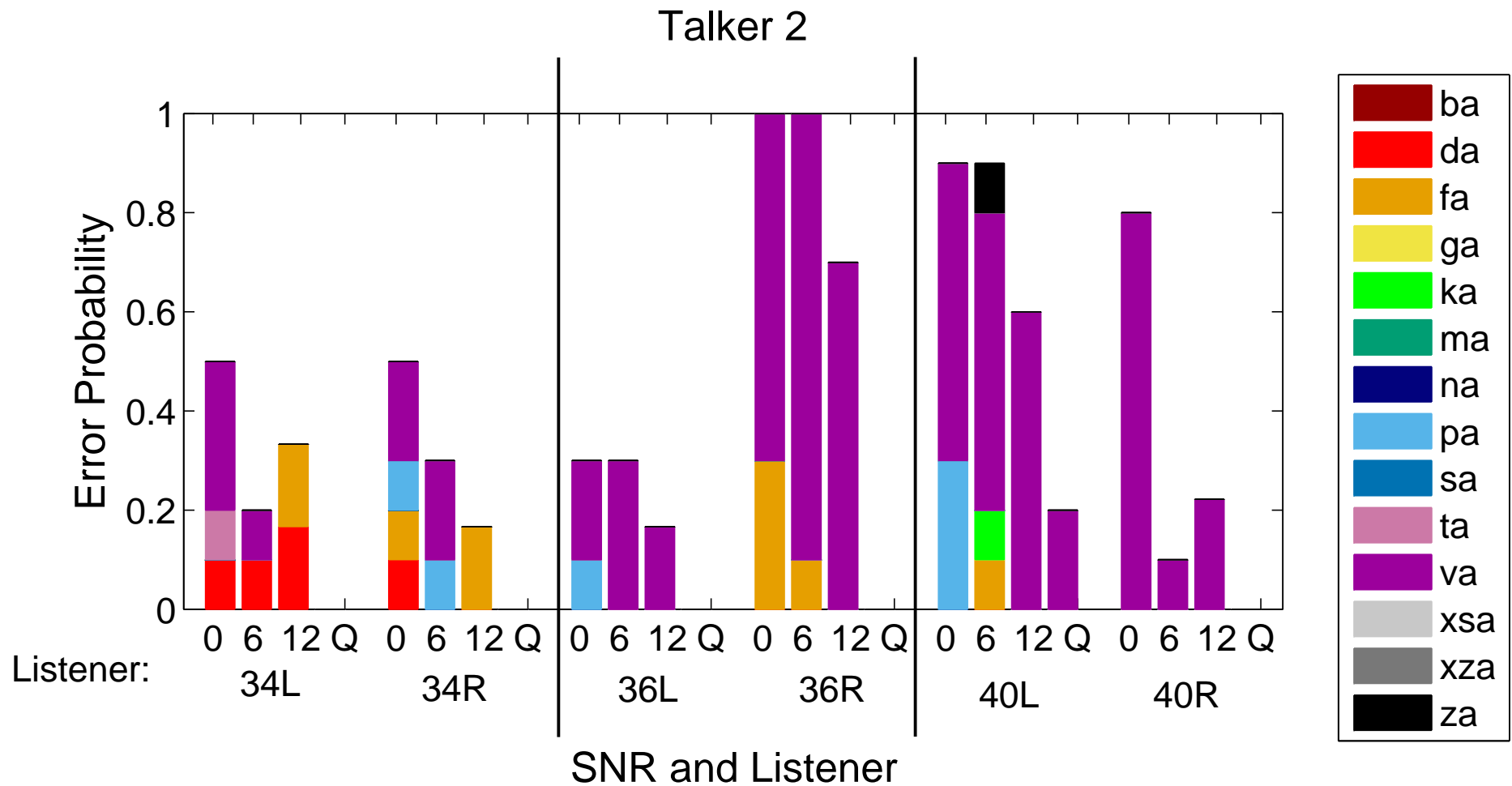
Confusions for Talker 2 of /ba/

- Colors label the confusions



Confusions for Talker 2 of /ba/

- Colors label the confusions

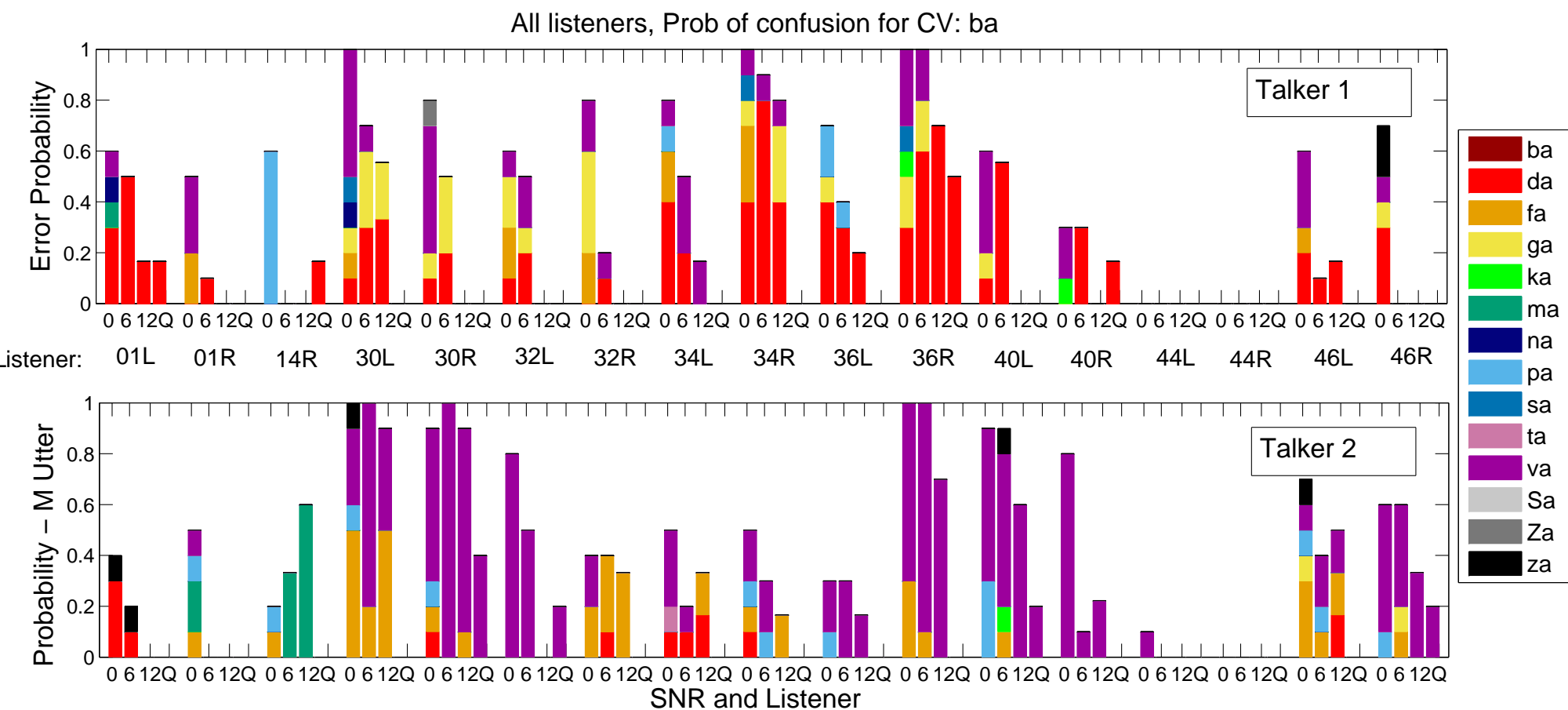


Confusions for two tokens of /ba/

■ Colors label the confusions

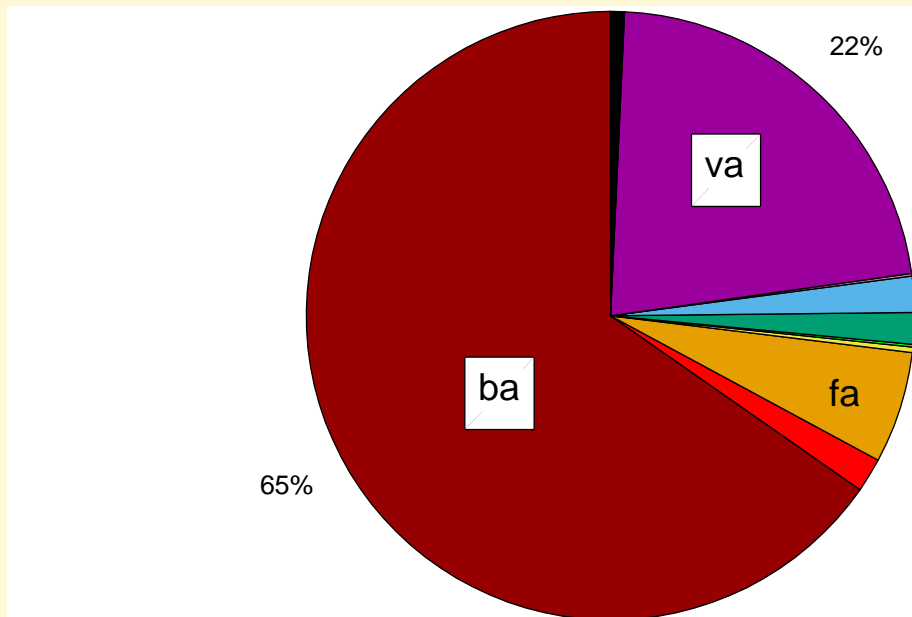
◆ Talker 1 /ba/ → /da/

◆ Talker 2 /ba/ → /va/

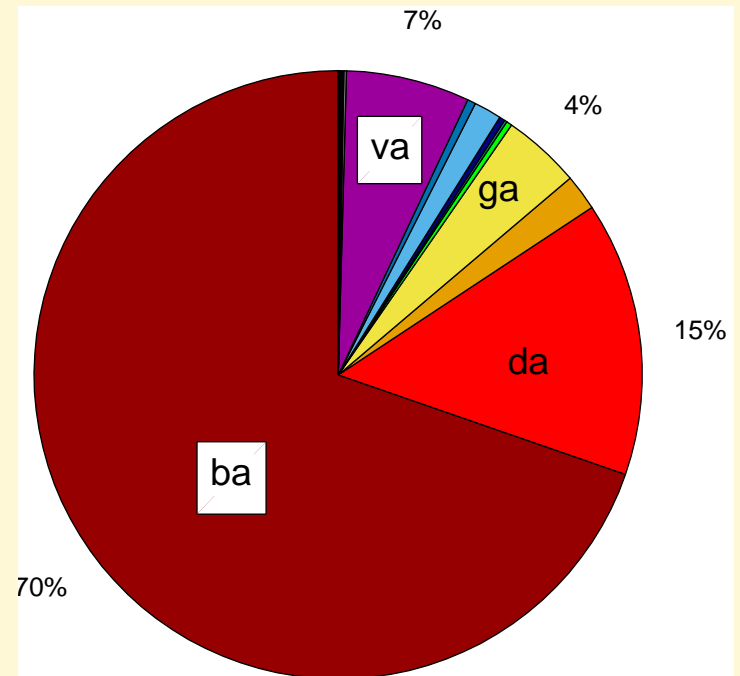


Confusions for two tokens of /ba/

- Average confusions for /ba/
- ◆ Do NOT average across tokens: $SIN_t \#3$!



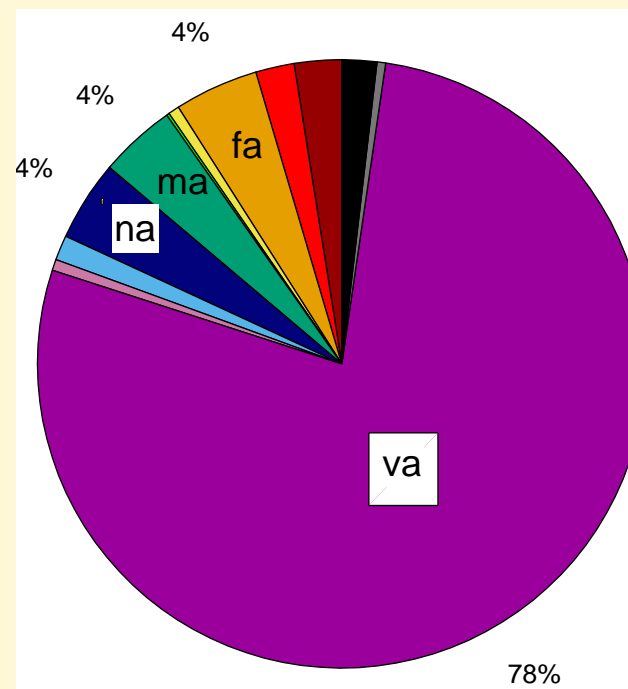
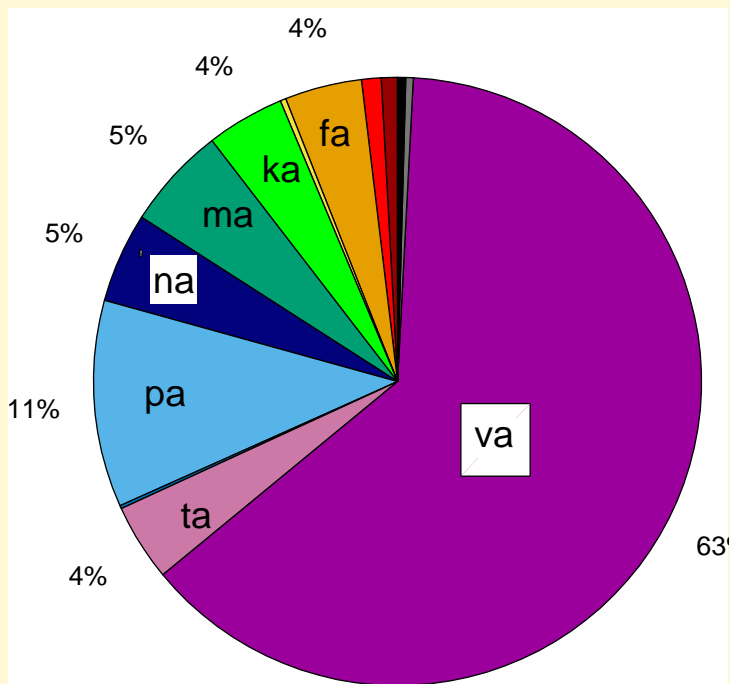
(a) Talker 1



(b) Talker 2

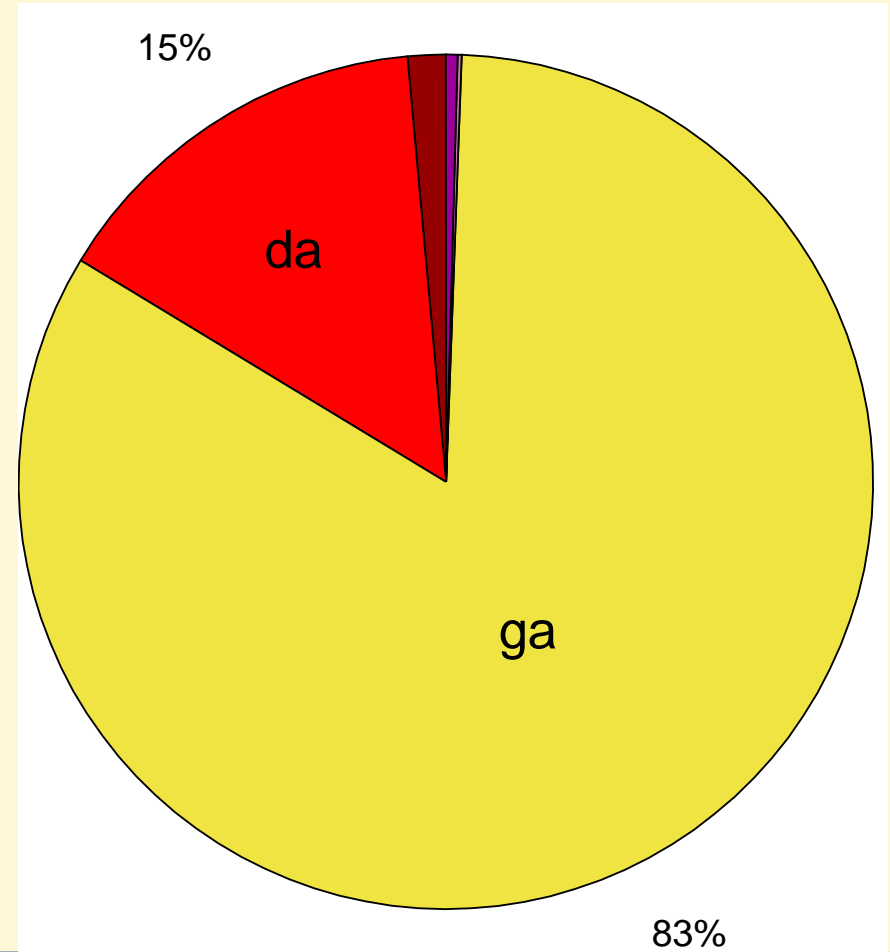
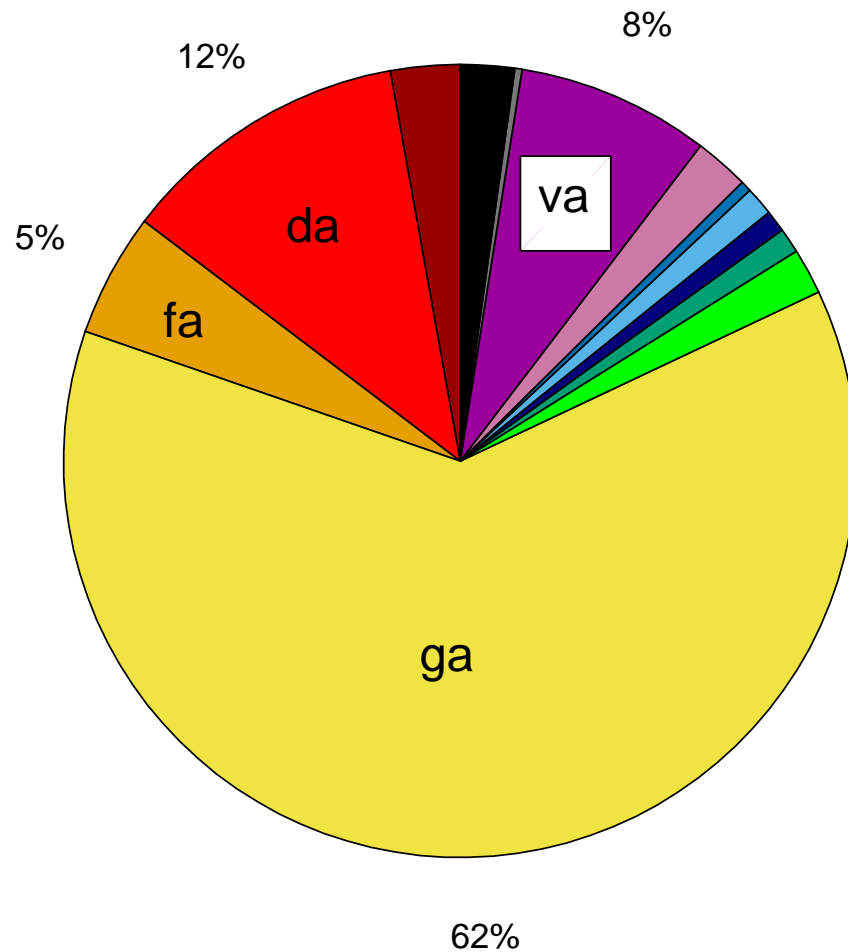
Confusions for two tokens of /va/

- Average confusions for /va/
- ◆ Do NOT average across tokens: $SIN_t \#3$!



Confusions for two tokens of /ga/

- Average confusions for /ga/
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1. Intro + Objectives 2 mins
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6. **Summary + Conclusions** **6 mins $\Sigma 50$**

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 1. *Al-gram* to visualize speech features

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2. **3DDS** (truncate: time, freq, intensity) to isolated cues: **Plosives** /p, t, k/, /b, d, g/ + **Fricatives** /θ, ʃ, tʃ, s, h, f/, /z, ʒ, v, ð/) + vowels /o, e, ɪ/

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 3. Data on discriminating consonants in noise, NH listeners use
 - Plosives: *Burst + timing to Voicing*
 - Fricatives: *Low-frequency edge + duration + F_0 modulation*

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 2. How the AI works:
 - ◆ Burst, frequency-edge, timing & SNR₅₀ distributions
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 2. Each ear has a different consonant recognition strategy
 3. A better understanding of HI acoustic cue detection will lead to:
 - ◆ Improved understanding of HSR for NH & HI ears
 - ◆ Better signal processing methods
 - ◆ Speech-aware hearing aids in 5 years >c2016
 - Fittings based on confusions

**Question your basic
assumptions**

Thank you for your attention

`http://hear.ai.uiuc.edu/`

`http://hear.ai.uiuc.edu/wiki/Main/Publications`