Word-Level Error Analysis in Decoding Systems: From Speech Recognition to Brain-Computer Interfaces

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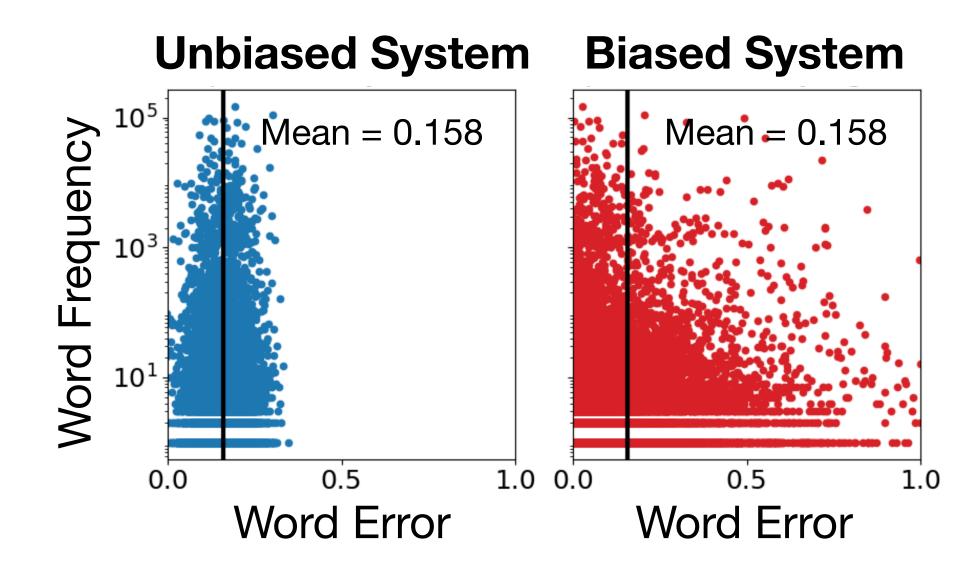
Low Word Error Rate (WER) ≠ Low Error for Every Word

- BCIs restore movement or communication (via Brain-to-Text) for individuals with motor and speech impairments
- SOTA Brain-to-Text achieves 4.2% WER and 32 words per minute, supporting daily conversation use (Willet et al. 2023, Card et al. 2024)
- Brain to text (BTT) and Automatic Speech Recognition (ASR)
 - Shared goal: transcribe intended speech to text
 - Different inputs: data statistics, quality, abundance
 - Shared challenge: learning classification + temporal alignment
- Method: refined word-level metrics for correctness and semantic cost
- **Finding:** SOTA models (1 BTT, 3 ASR) show frequency–driven error gaps
- Impact: closing the word generalization gap improves ASR & BTT usability

Same WER, Different Error Patterns

"We have covered all the chapters for the exam." "The car was covered in snow."

Decoded as "The car was come over in snow." "The car as covered in snow."



Word-Level Error Metrics

Different Alignment Strategies Shift How Error are Attributed

Reference: They worked to straighten out the misunderstanding They worked street Decoded: out the misunderstanding [D] Naïve Word Edit: [S] They worked to straighten out the misunderstanding Reference: Decoded: stree t out the misunderstanding They worked Refined Char Edit:

Word metrics on edit pairs

(e.g., "straighten" \rightarrow "street")

- Word-CER: degree of textual variation
- Word-Recall: rate of correct recall
- Word-EMBdist: semantic distance of the edit
- Word-BERTrecall: recoverability with context

[S]

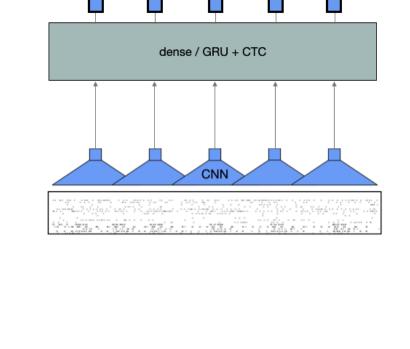
Word-Level Generalization Gap in SOTA BTT and ASR Systems

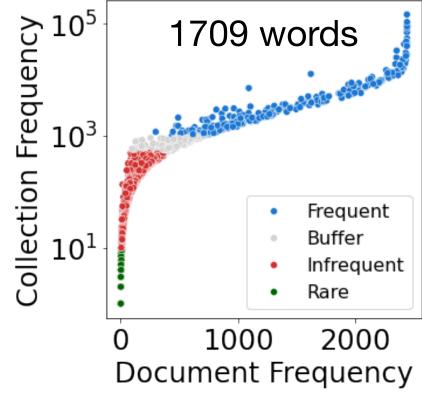
- Subword decoding still yields uneven word accuracy, with bias likely from imbalanced word occurrence in sentences
- Context variability and alignment ambiguity may amplify bias, mitigable through better representation learning
- Closing the generalization gap for infrequent words can enhance the semantic relevance of decoded output

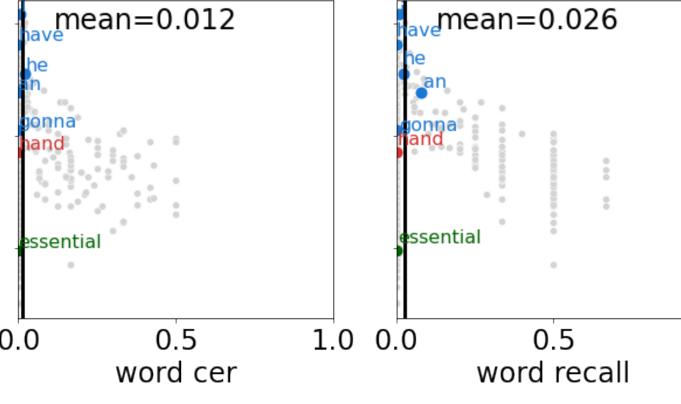
	Infrequent - Frequent				Rare - Frequent			
ASR-CRDNN	37.6%	69.7%	93.9%	32.7%	199.3%	263.0%	383.5%	126.2%
LMrnn	***	***	***	***	***	***	***	***
ASR-Transformer LMtransformer	38.8%	61.9%	84.8%	32.1%	182.0%	248.9%	343.5%	134.4%
	***	***	***	***	***	***	***	***
ASR-Wav2Vec2	33.4% ***	65.2% ***	102.0% ***	31.1%	192.2% ***	321.9% ***	486.5% ***	155.7% ***
BTT-RNN	286.6%	326.3%	418.9%	137.0%	664.5%	811.2%	1074.7%	369.5%
LMngram+GPT	***	***	***	***	***	***	***	***
	Word	Word	Word	Word	Word	Word	Word	Word
	CER	Recall	EMBdist	BERTrecall	CER	Recall	EMBdist	BERTrecal

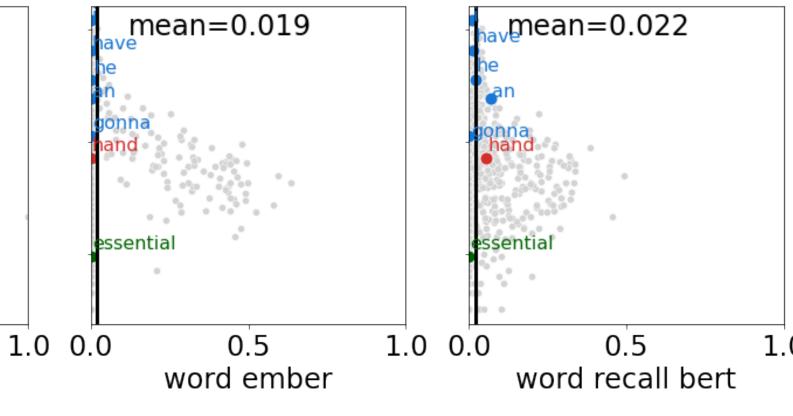
SOTA BTT and ASR Both Show the Word-Level Generalization Gap

BTT-RNN WER=0.042 Single speaker Neural spike train 19k Train Sen.





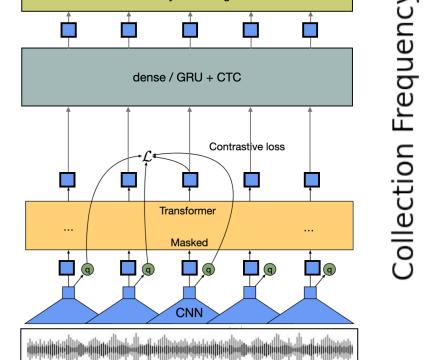


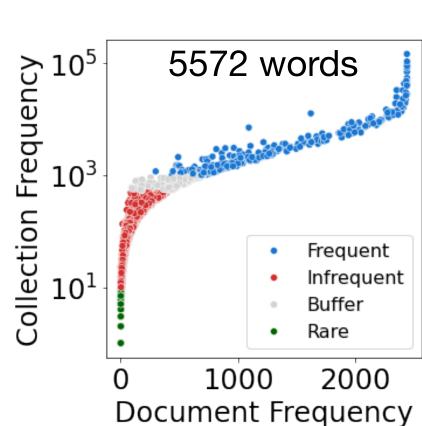


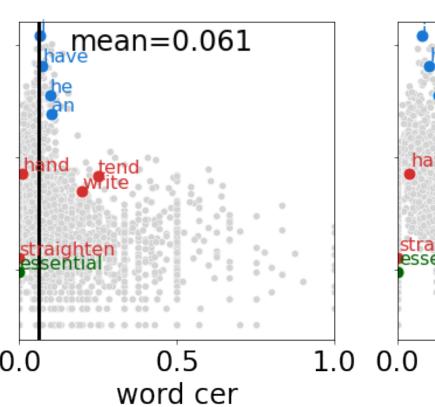
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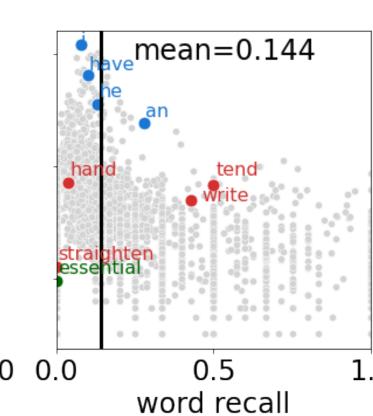
% Increase in Error

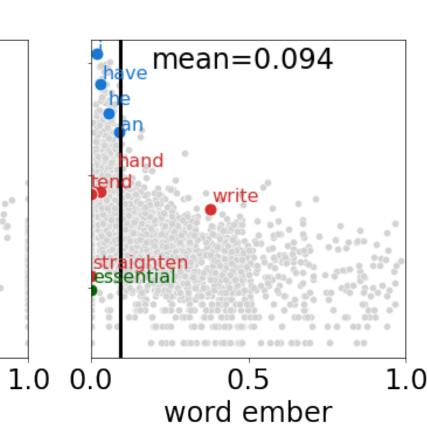
ASR-Wav2Vec2 WER=0.1585 Multiple speaker Acoustic waveform 500k Train Sen.

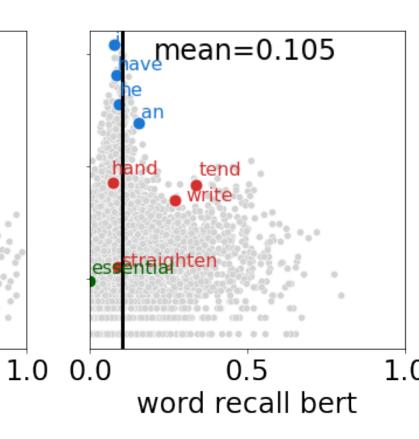












Infrequent word edits cause greater semantic distortion

Model	Decoded Sentence	Infrequent Word Edit Only	Frequent Word Edit Only
ASR-	but you will still have to have a north ndon	but you will still have to have an north-ndon	but you will still have to have a orthodontist
Wav2Vec2	straight now your teeth	to straight out your teeth	straighten now your teeth
ASR-	but you will still have to have an orthodontist	but you will still have to have an orthodontist	but you will still have to have an orthodontist
Transformer	the street now you are cheap	to street out your cheap	the straighten now you are teeth
ASR-	but you will still have to have a north that do	but you will still have to have an north to	but you will still have a orthodontist that do
CRDNN	not it is the street now you keep	street out your keep	not it is the straighten now you keep



Code Available

^{*}Additionally, account for compound and split word variations (e.g., "rain-bow" ↔ "rainbow")