



Interspeech2025 Tutorial: *Interpretability Techniques for Speech Models*

# Context-Mixing in Speech Transformers

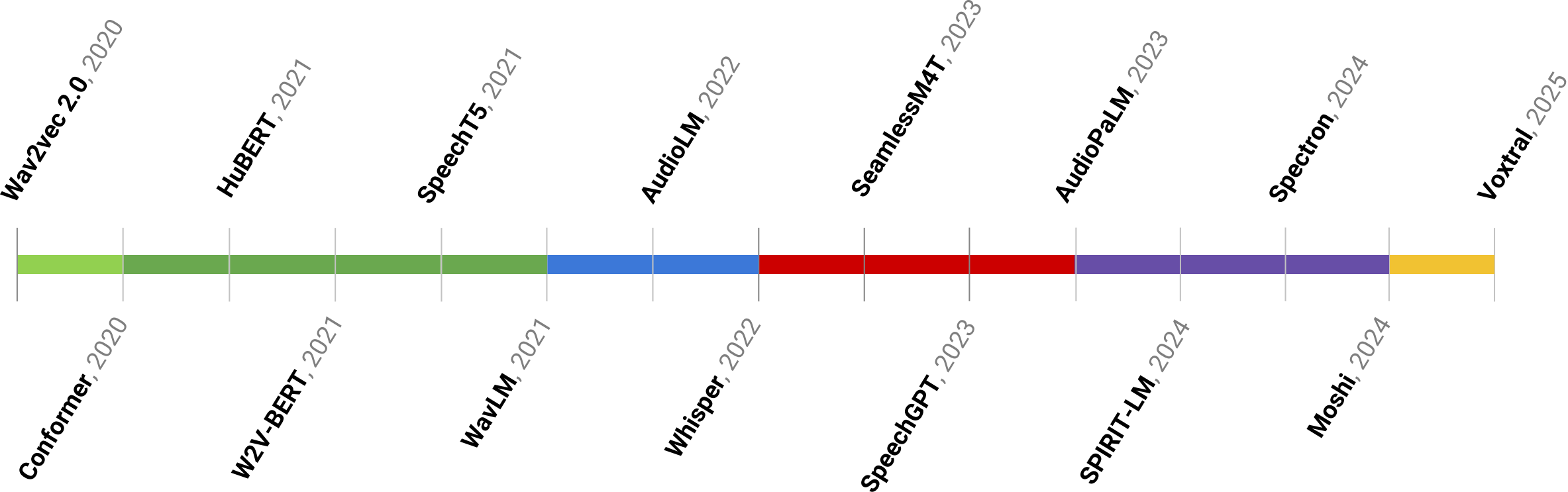
Hosein Mohebbi

August 17, 2025

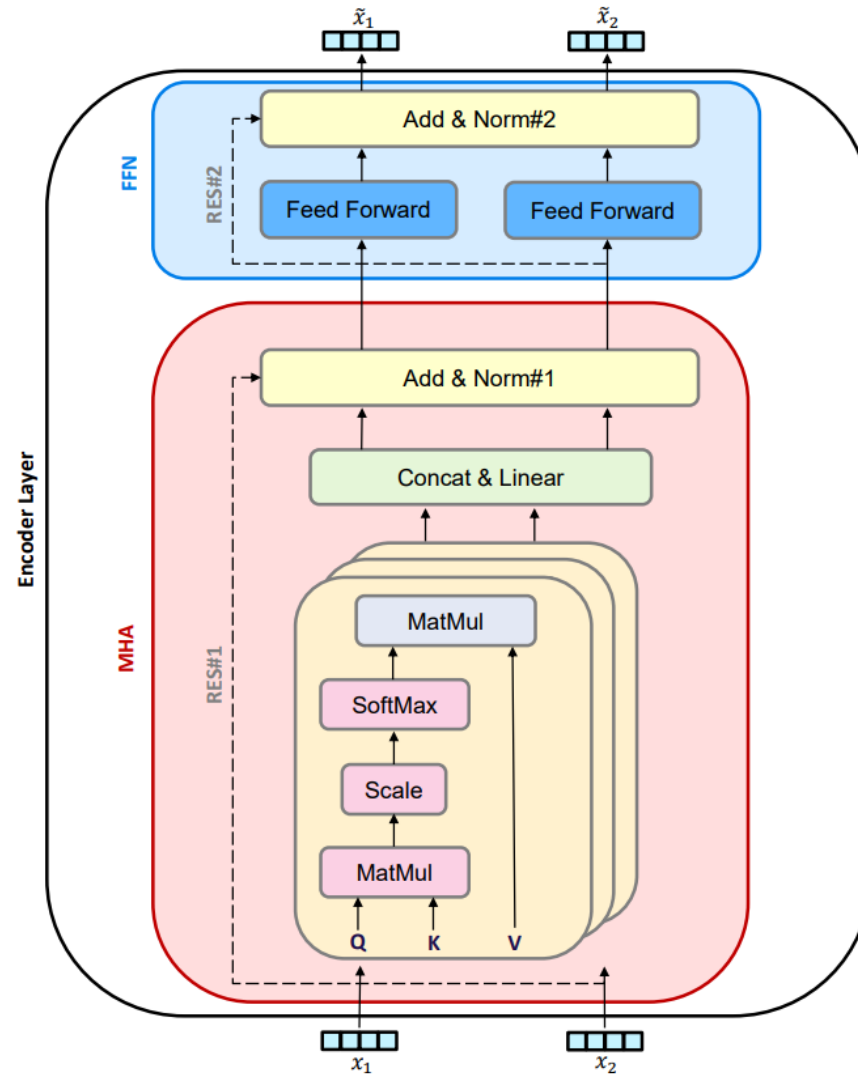
Rotterdam



# Transformers for speech processing

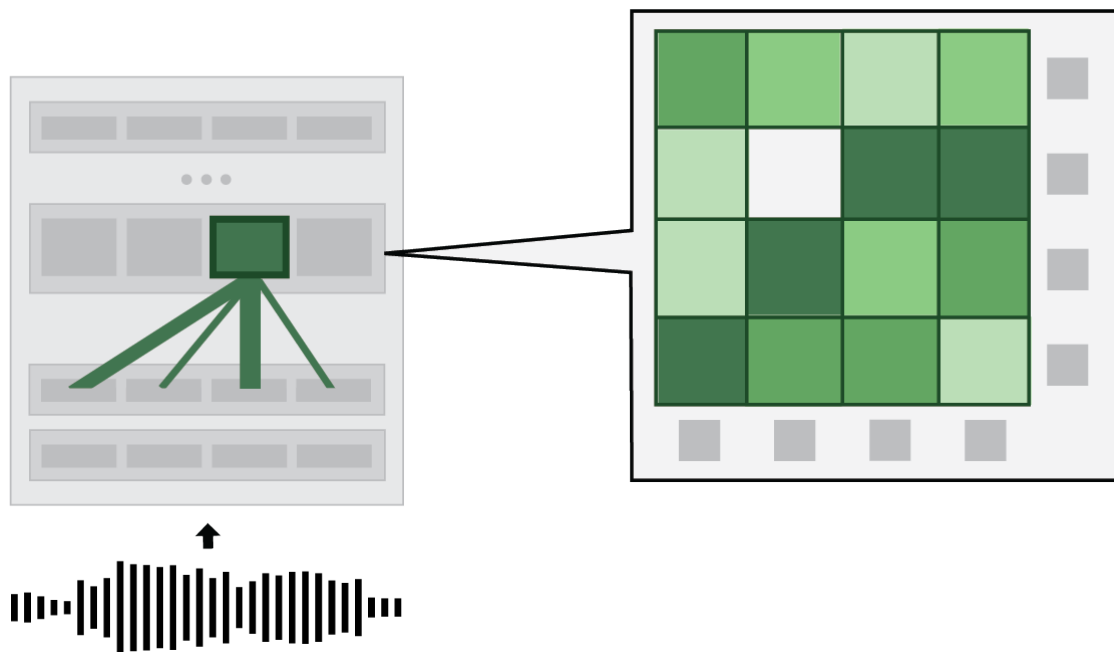


# Transformer

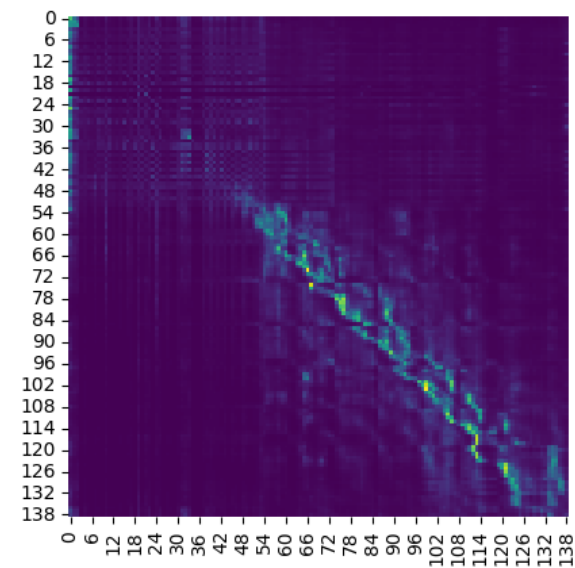


([Vaswani et al., 2017](#))

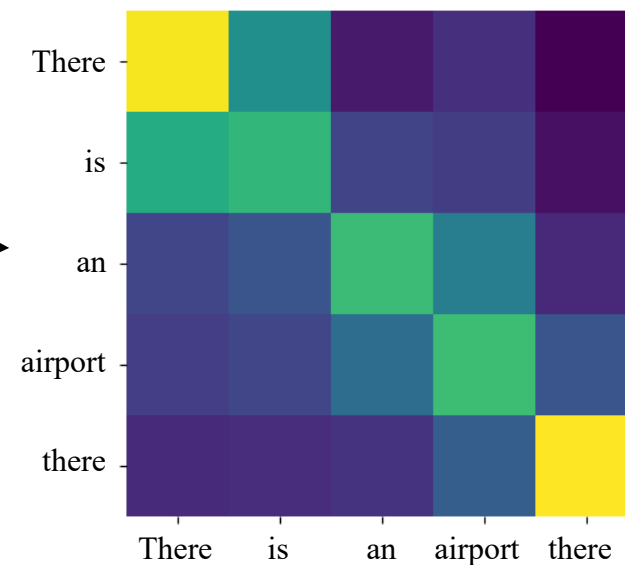
# What is Context Mixing?



Frame-level

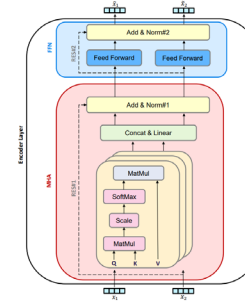
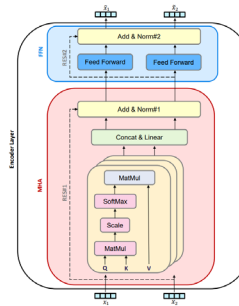
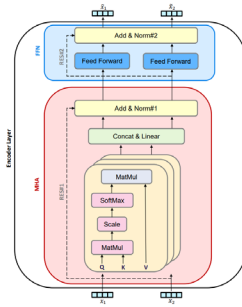


Word-level

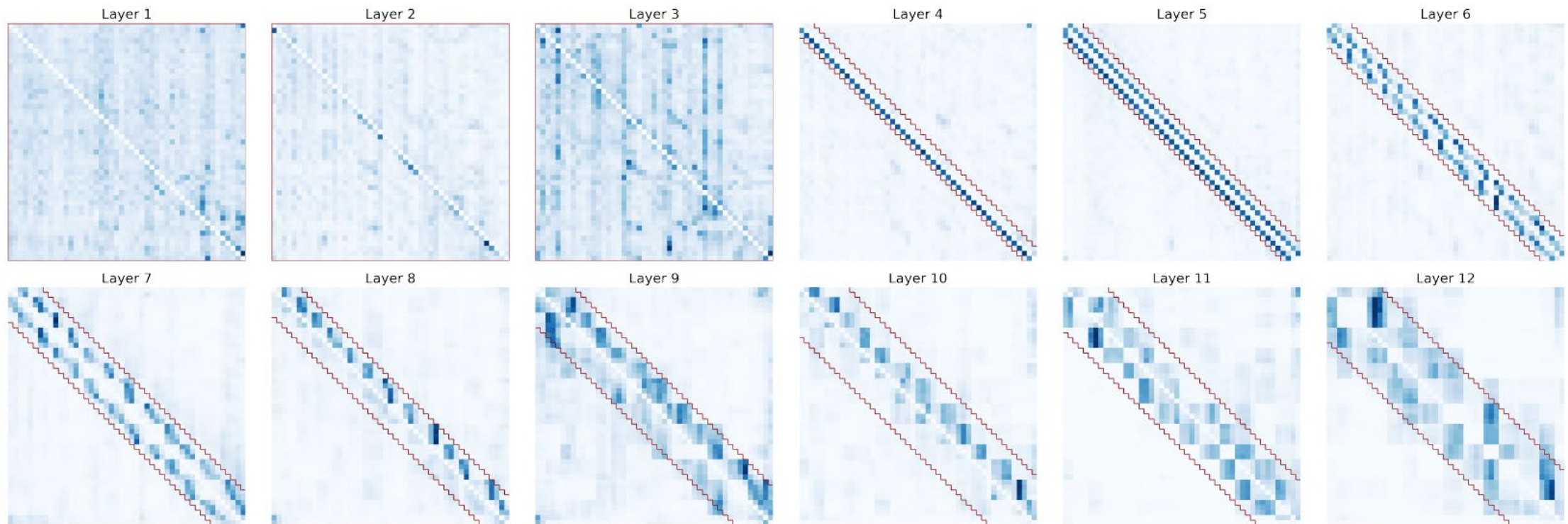


# Measures of *Context-mixing*

- Attention
- Attention-Norm
- Value Zeroing



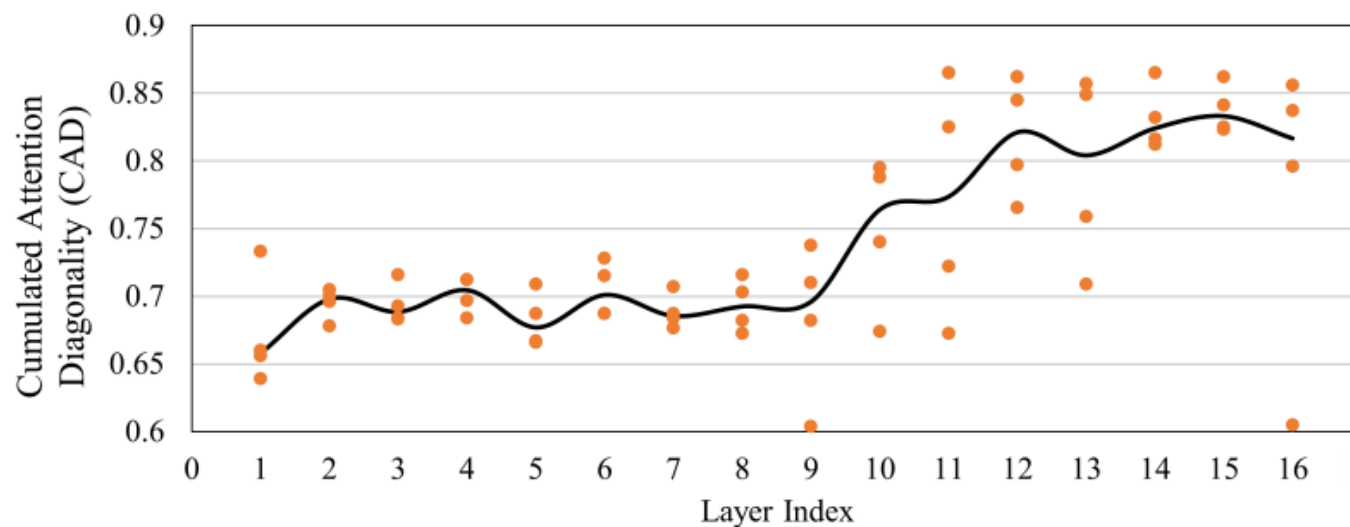
# Diagonality



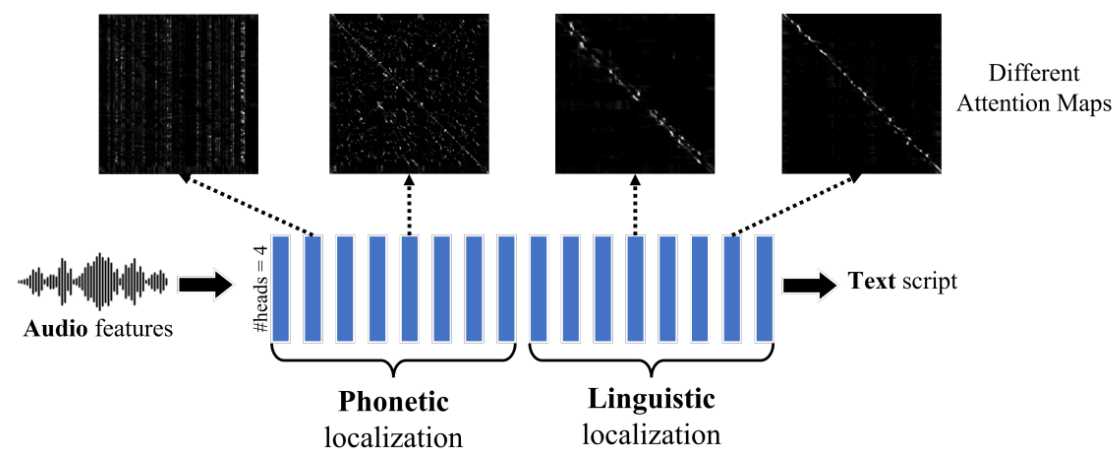
(Alastruey et al., 2022)

# Two distinct roles

$$\text{CAD}_h = \int_{r=0}^1 \frac{1}{T} \sum_{i=1}^T \left( \sum_{j=\max(1, i-r(T-1))}^{\min(T, i+r(T-1))} A_h[i, j] \right) dr = \int_{r=0}^1 D(r) dr$$



([Shim et al., 2022](#))



# Diversity Loss

Attention → Highest

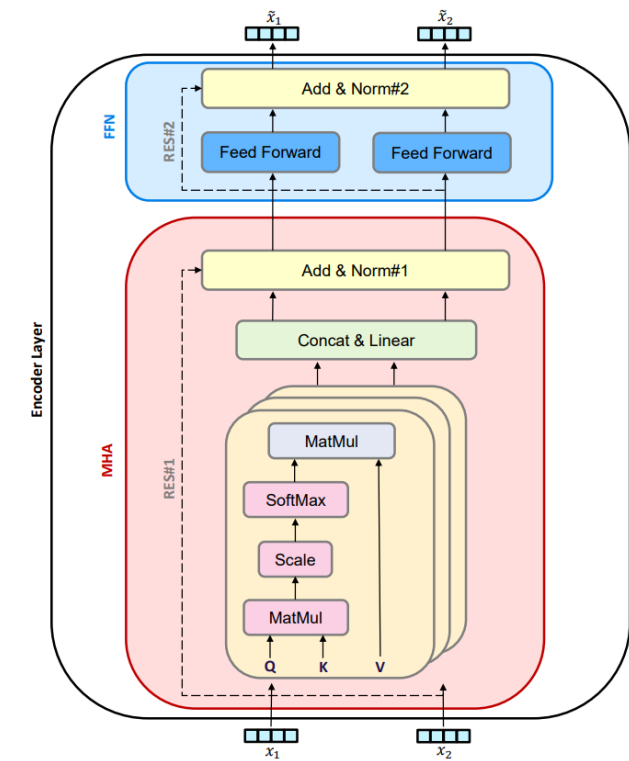
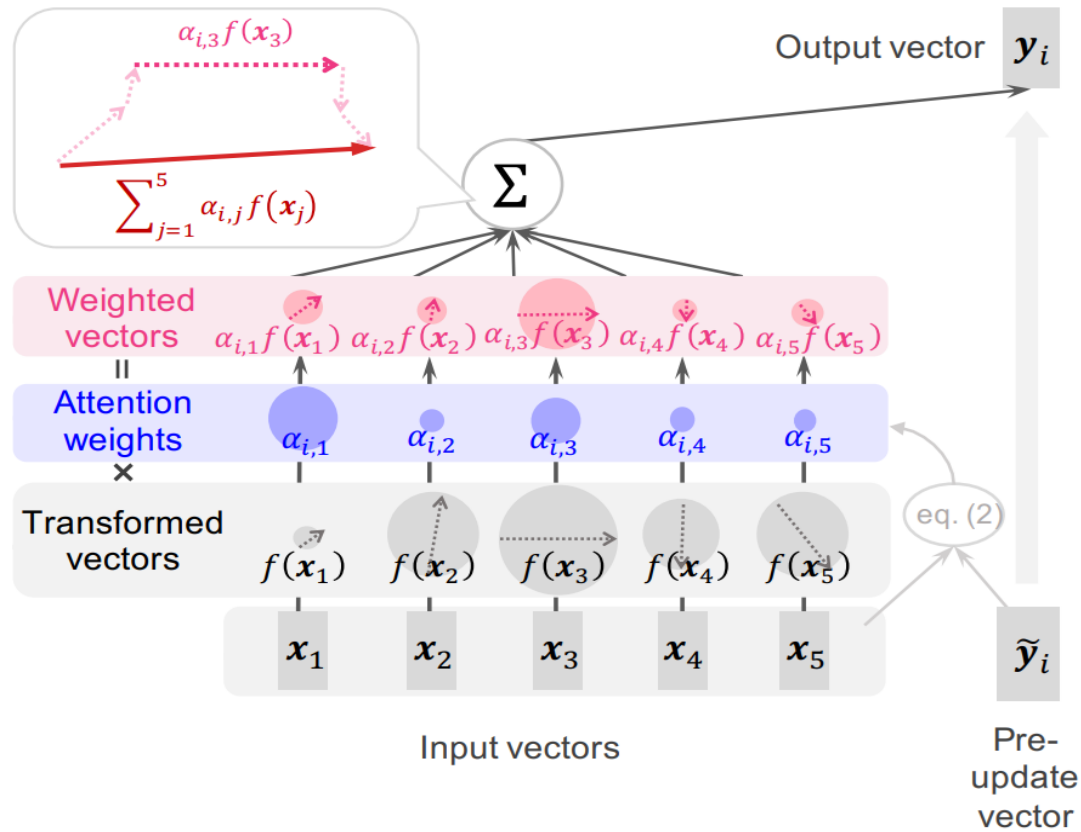
Value vectors → Lowest

Diversity loss	dev	dev-other	test	test-other
$d^A(m, n)$	6.37	6.02	6.31	6.10
$d^Q(m, n)$	0.53	0.59	0.54	0.55
$d^K(m, n)$	0.57	0.61	0.61	0.58
$d^V(m, n)$	0.13	0.14	0.13	0.14

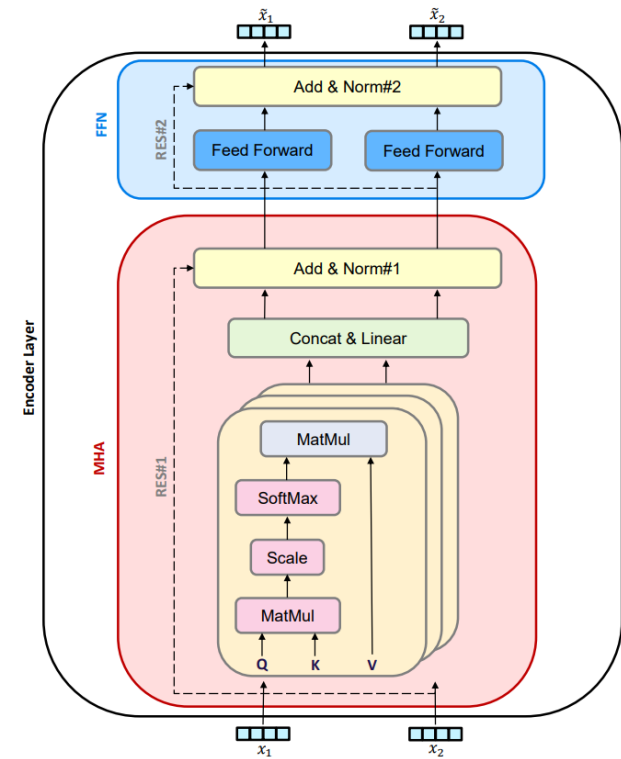
Table 3: Attention diversity losses summed over all layers of the Conformer acoustic encoder for the baseline full-context Librispeech model.



# Attention-Norm



# Value Zeroing



# Value Zeroing

$$C_{i,j} = ?$$


# Value Zeroing

$$(\mathbf{x}_1, \dots, \mathbf{x}_n)$$

$$\left. \begin{aligned} \mathbf{q}_i^h &= \mathbf{x}_i \mathbf{W}_Q^h + \mathbf{b}_Q^h \\ \mathbf{k}_i^h &= \mathbf{x}_i \mathbf{W}_K^h + \mathbf{b}_K^h \\ \mathbf{v}_i^h &= \mathbf{x}_i \mathbf{W}_V^h + \mathbf{b}_V^h \end{aligned} \right\} \alpha_{i,j} = \operatorname{softmax}_{\mathbf{x}_j \in \mathcal{X}} \left( \frac{\mathbf{q}_i \mathbf{k}_j^\top}{\sqrt{d}} \right) \in \mathbb{R}$$

$$\mathbf{z}_i^h = \sum_{j=1}^n \alpha_{i,j}^h \mathbf{v}_j^h$$

$$\mathbf{z}_i = \operatorname{CONCAT}(\mathbf{z}_i^1, \dots, \mathbf{z}_i^H) \mathbf{W}_O$$

$$\mathbf{z}_i = \operatorname{LN}_{\text{MHA}}(\mathbf{z}_i + \mathbf{x}_i)$$

$$\tilde{\mathbf{x}}_i = \max(0, \mathbf{z}_i \mathbf{W}_1 + \mathbf{b}_1) \mathbf{W}_2 + \mathbf{b}_2$$

$$\tilde{\mathbf{x}}_i = \operatorname{LN}_{\text{FFN}}(\tilde{\mathbf{x}}_i + \mathbf{z}_i)$$

$$\mathcal{C}_{i,j} = ?$$

$$\mathbf{v}_j^h \leftarrow \mathbf{0}, \forall h \in H$$

$$\mathcal{C}_{i,j} = \tilde{\mathbf{x}}_i^{\neg j} * \tilde{\mathbf{x}}_i$$

Let's Evaluate!

# Evaluation

Controlled task: homophony in French

**Target**

**livre** (singular)

/livʁ/

**livres** (plural)



Elle a perdu les **livres**

(She lost the books)

# Evaluation

Controlled task: homophony in French

**Target**

**livre** (singular)

/livʁ/

**livres** (plural)



Elle a perdu les **livres**

**le** (singular) /lə/

**les** (plural) /le/

**Cue**

# Defined Templates

Pattern	Examples of transcription	#
Det_Noun	C'est <u>le</u> septième <b>titre</b> de champion de Syrie de l'histoire du club Il y mène <u>une</u> <b>vie</b> d'études et de recherches	720
Pronoun_Verb	Chaque jour, leurs concurrents les voient sortir de pistes dont <u>ils</u> <b>ignorent</b> l'existence <u>On</u> y <b>trouve</b> une plage naturiste	257
Det_Noun_Verb	Peu après cette élimination, <u>le</u> <b>club</b> et Alexander se <b>séparent</b> à l'amiable À la fin, <u>les</u> <b>enfants</b> se <b>révoltent</b> et détruisent l'école.	23

Table 1: Examples of the extracted audios from the Common Voice corpus based on defined patterns. Last column shows the number of examples obtained. Cue and Target words are underlined and **bolded**, respectively.



# Cue Contribution score

Target word


Cue word

# Cue Contribution

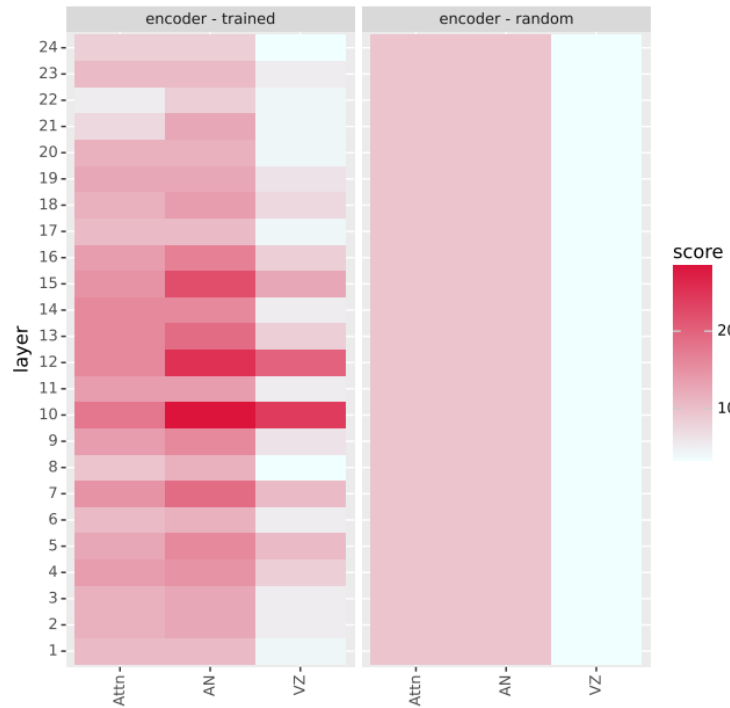


Figure 1: Layer-wise cue contribution according to different analysis methods averaged over all examples for XLSR-53, trained (left) vs. randomly initialized (right).

([Mohebbi et al., 2023](#))

# Cue Contribution

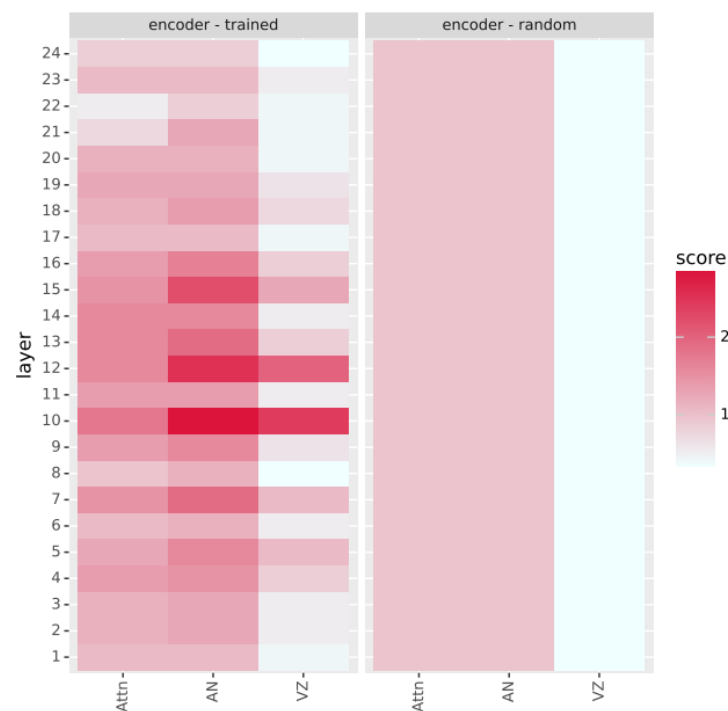


Figure 1: Layer-wise cue contribution according to different analysis methods averaged over all examples for XLSR-53, trained (left) vs. randomly initialized (right).

([Mohebbi et al., 2023](#))

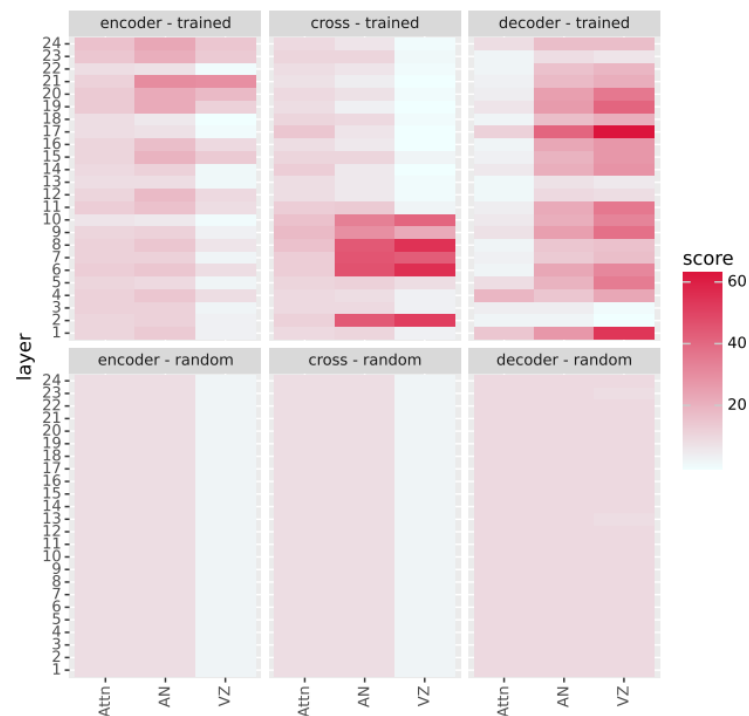


Figure 2: Layer-wise cue contribution according to different analysis methods averaged over all examples for Whisper-medium, trained (top) vs. randomly initialized (bottom).

# Cue Contribution v.s. ‘Number encoding’ probe

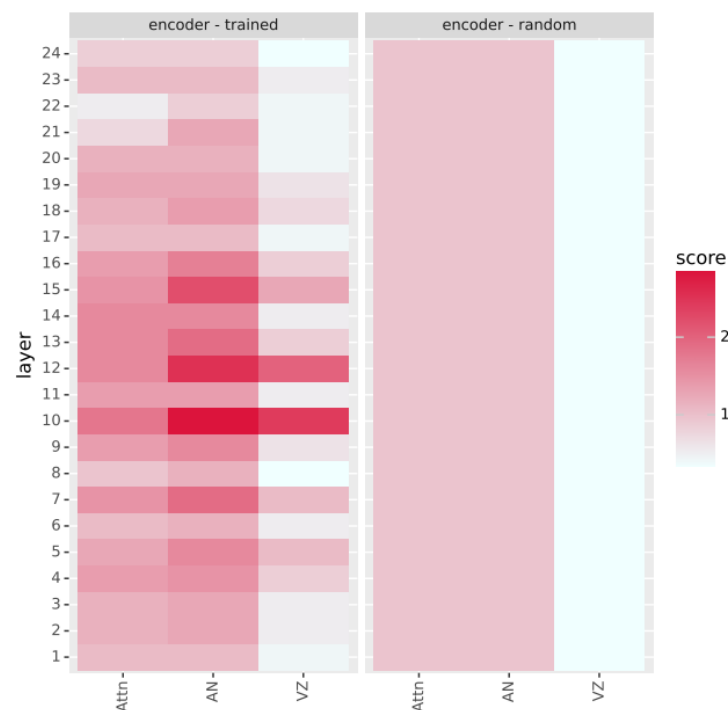


Figure 1: Layer-wise cue contribution according to different analysis methods averaged over all examples for XLSR-53, trained (left) vs. randomly initialized (right).

([Mohebbi et al., 2023](#))

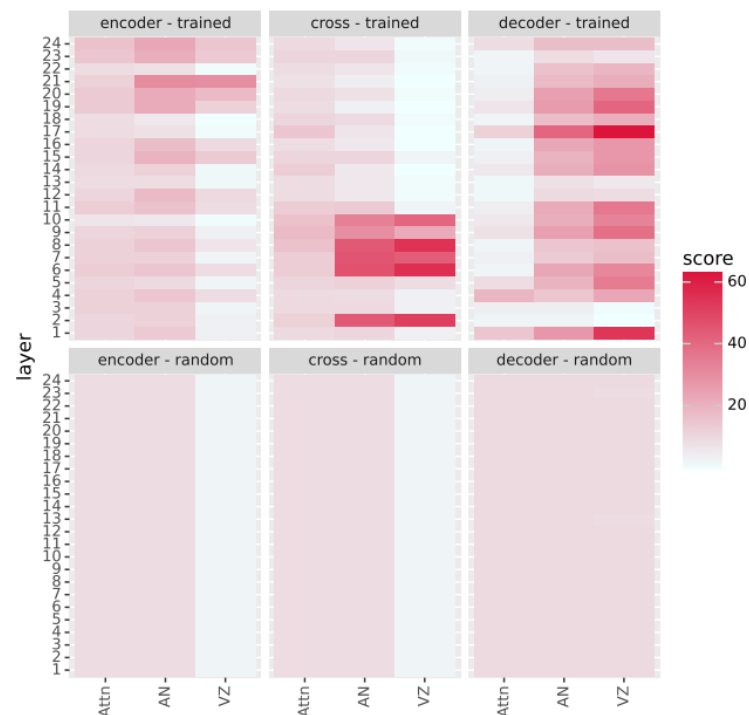


Figure 2: Layer-wise cue contribution according to different analysis methods averaged over all examples for Whisper-medium, trained (top) vs. randomly initialized (bottom).

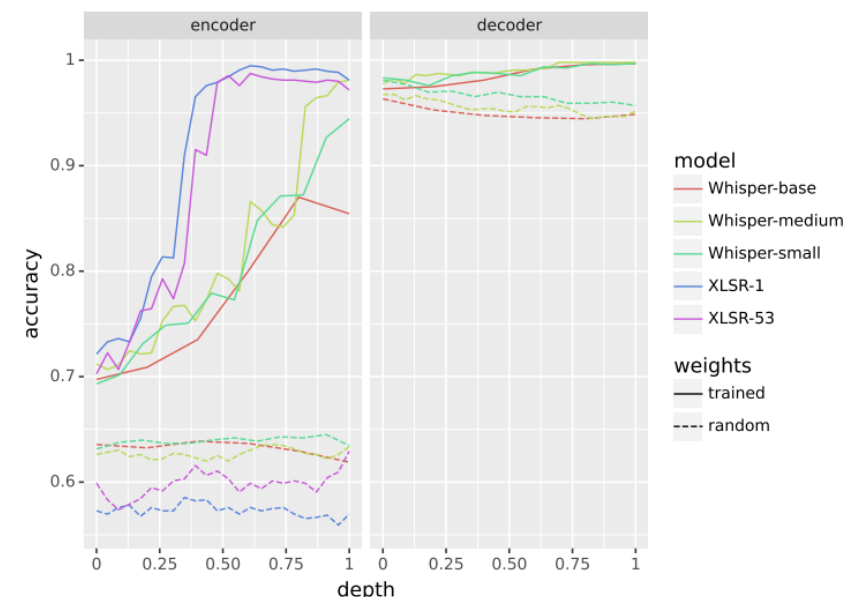
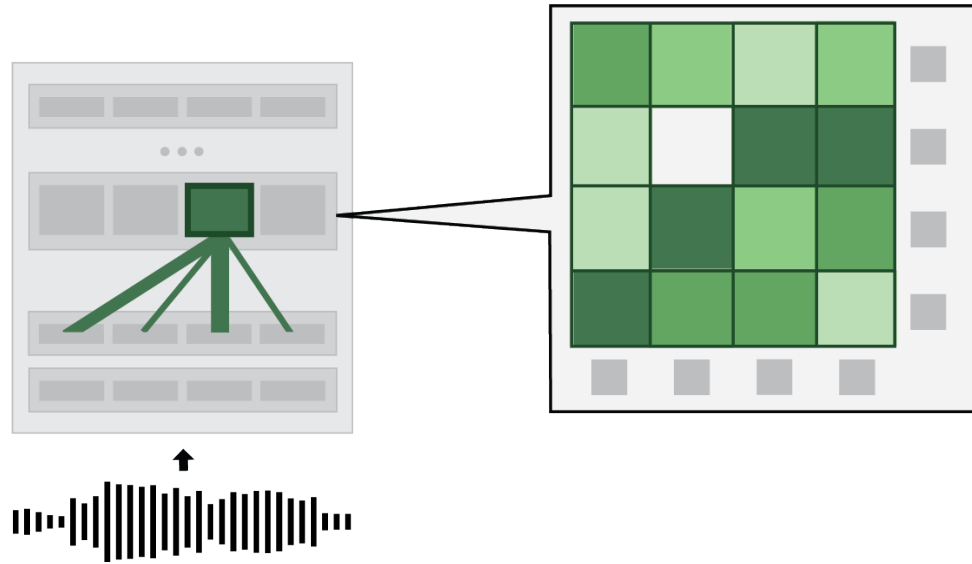


Figure 4: Accuracy of probing classifiers trained on frozen target representations obtained from various ASR models. The depth of Whisper-base (6) and Whisper-small (12), has been normalized to 1 to facilitate comparisons.

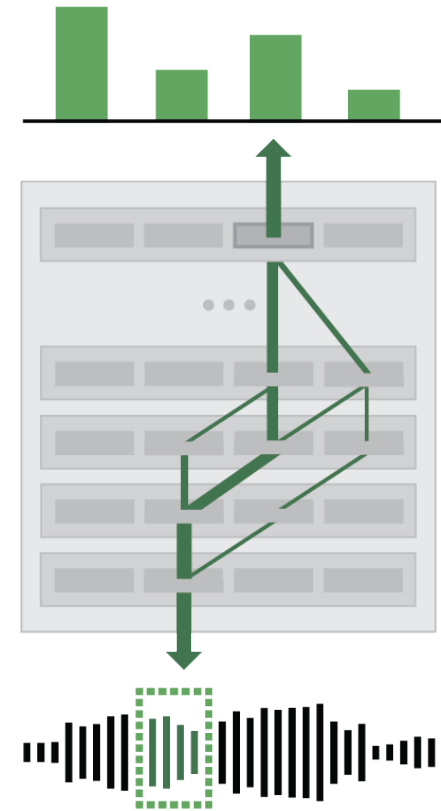
# Wrapping up

- Analyzed the pattern of attentions in speech Transformers (e.g., diagonality, diversity)
- Pointed out the limitations of attention as a measure of context-mixing
- Analyzed context-mixing beyond attention (using e.g., Attention-Norm, Value Zeroing)
- Context-mixing vs. Feature attribution

# Context-Mixing vs. Feature Attribution



(illustration by Marianne)



Thanks!  
Question?

**Feel free to reach out for any questions:**

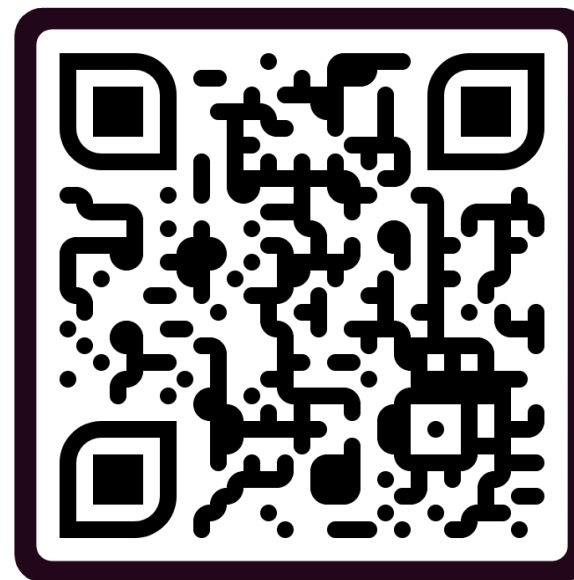
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Thank you!



Website



Notebook