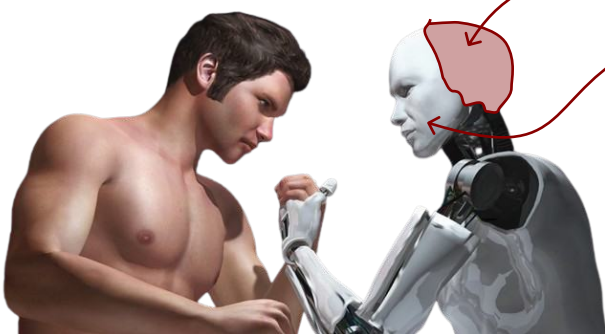


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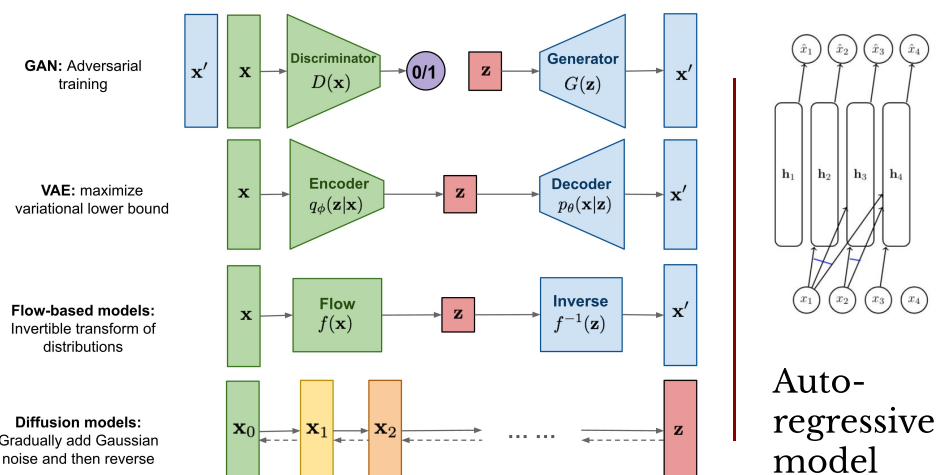
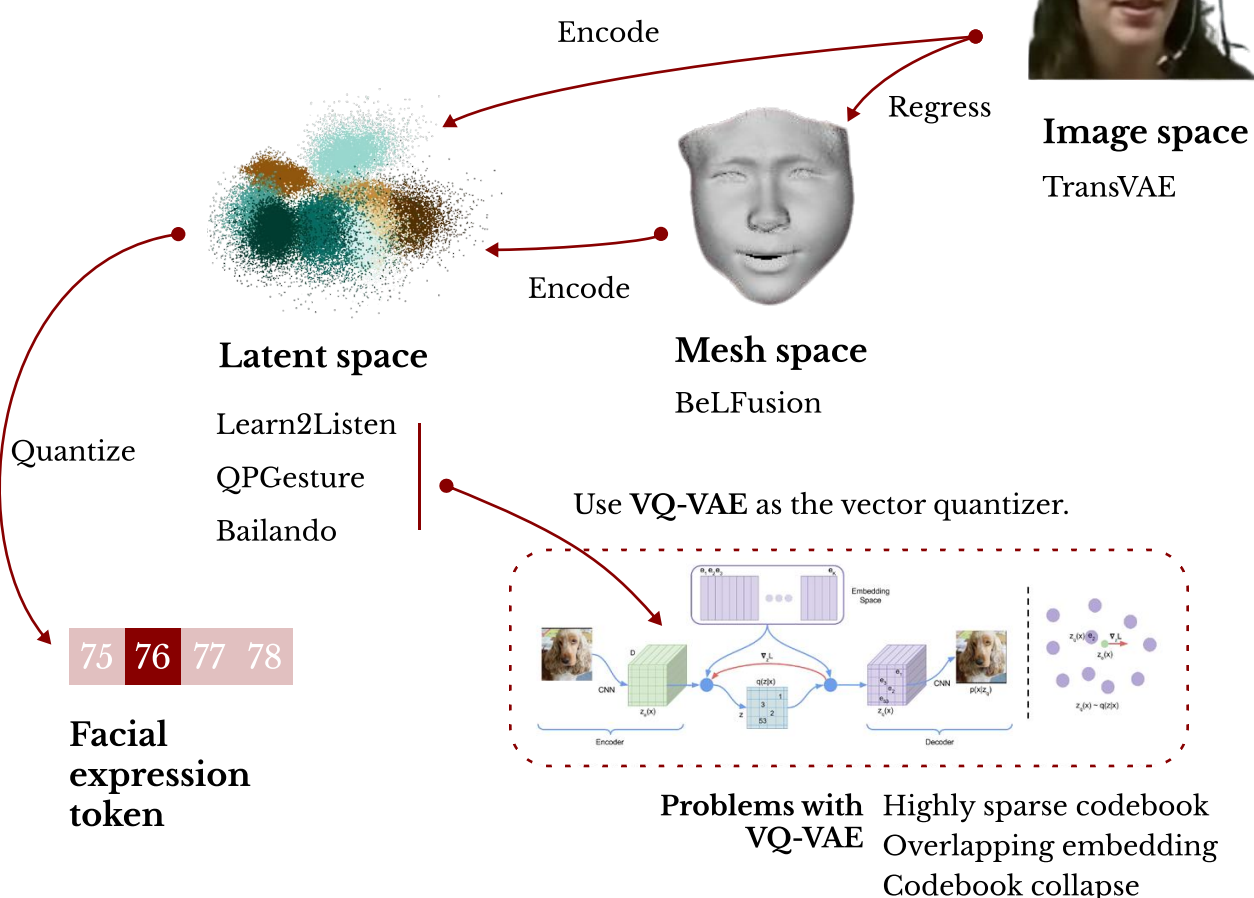
Research background & problem definition

Human-robot conversation

Language and sound model is advancing very fast  OpenAI  Gemini

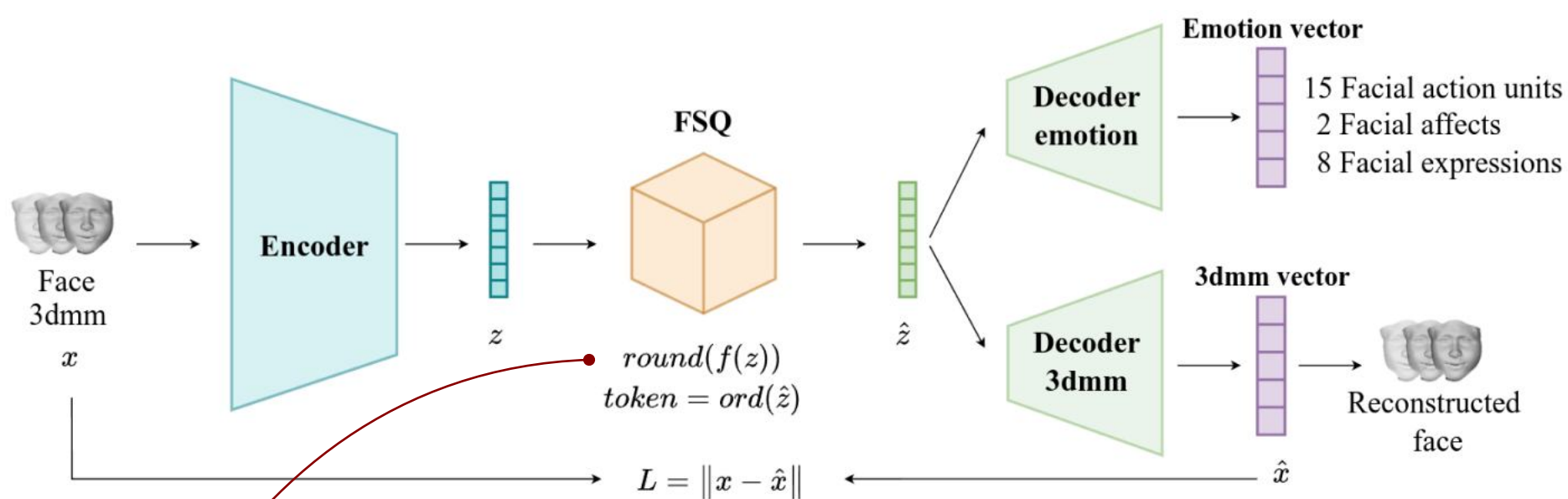
Facial expression make interaction more natural

Generative model taxonomy

Image source: <https://lilianweng.github.io/posts/2021-07-11-diffusion-models/>

Methodology

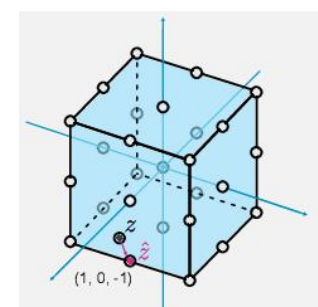
A face state is a token.



Blendshape loss optimizes with more addressing to face features.

$$L_{\text{Blendshape}}(E, D_{3\text{dmm}}) = \|x_{\text{eyebrow}} - \hat{x}_{\text{eyebrow}}\| + \|x_{\text{eyemovement}} - \hat{x}_{\text{eyemovement}}\| + \dots + \|x_{\text{rotation}} - \hat{x}_{\text{rotation}}\| + \|x_{\text{translation}} - \hat{x}_{\text{translation}}\|.$$

$$L(D_{\text{emotion}}) = \|x_{\text{emotion}} - \hat{x}_{\text{emotion}}\|.$$



$$\hat{z}_i = f(z_i) := \text{round}\left(\left\lfloor \frac{L}{2} \right\rfloor \tanh(z_i)\right) \in \{-1, 0, 1\}.$$

FSQ enforce stronger regularization creating a more meaningful and compressed latent space.

Patch-based output to optimize inference



- Speaker feature encoder to process sound and facial expression of the human.
- Listener decoder to align next feature to its past facial expression.

TABLE I

BASELINES. COMPARISON OF OUR APPROACH WITH BASELINE MODELS [14] ON THE TEST SET.

	Appropriateness		Diversity			Realism	Synchrony
	FRCorr (\uparrow)	FRDist (\downarrow)	FRDiv (\uparrow)	FRVar (\uparrow)	FRDvs (\uparrow)	FRRea (\downarrow)	FRSyn (\cdot)
Ground truth	8.73	0.00	0.0000	0.0724	0.2483	-	47.69
Random	0.05	237.23	0.1667	0.0833	0.1667	-	44.10
Mime	0.38	92.94	0.0000	0.0724	0.2483	-	38.54
MeanSeq	0.01	97.13	0.0000	0.0000	0.0000	-	45.28
MeanFr	0.00	97.86	0.0000	0.0000	0.0000	-	49.00
Trans-VAE	0.07	90.31	0.0064	0.0012	0.0009	69.19	44.65
BeLFusion(k=10)+BinarizedAUs	0.12	94.09	0.0379	0.0248	0.0397	-	49.00
Ours	0.31	84.93	0.1164	0.0348	0.1166	34.66	47.42

(\cdot) means the closer to the ground truth, the better.

indicates the best average performance among the heuristic baselines for the groups of metrics.

Use NoXi and RECOLA internet conference dataset, we evaluated our method using metrics and baselines proposed in the REACT Competition 2024.

References:


[NoXI database] A. Cafaro, et al. The noxi database: multimodal recordings of mediated novice-expert interactions. ICMI '17.

[RECOLA database] F. Ringeval, et al. Introducing the recola multimodal corpus of remote collaborative and affective inter actions. FG '13.

[REACT Competition 2024] Song, et al. “REACT 2024: The Second Multiple Appropriate Facial Reaction Generation Challenge.” arXiv, January 10, 2024.

priority when designing the model

	Appropriateness		Diversity			Realism	Synchrony
	FRC	FRD	FRDvs	FRVar	FRDiv	FRRea	FRSyn
FSQ-val	0.2737	86.6145	0.1162	0.0345	0.1163	81.2801	45.7206
LFQ-val	0.2625	99.8672	0.1213	0.0434	0.1213	73.2092	45.8896
VQ-val	0.2693	91.5249	0.0943	0.0370	0.0943	96.1280	46.2099

Please check qualitative results in our presentation laptop. 

Key takeaway

1. We turn **facial expressions into a finite meaningful vocabulary** using Finite Scalar Quantization.
2. Then, we use an **autoregressive cross-modality transformer-based** model to generate multiple appropriate facial responses in dyadic conversation context.
3. The method achieves the best performance in the REACT2024 challenge.