

Can Language Models Learn to Listen?

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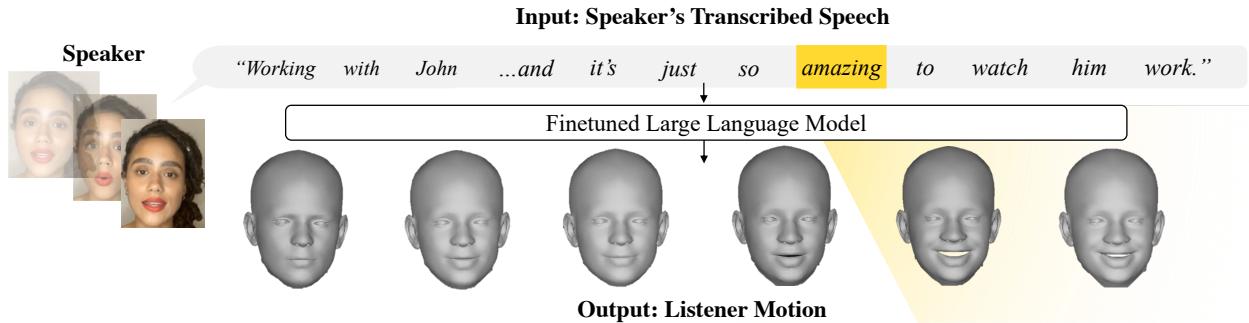


Figure 1: Large language models transfer to listener motion prediction. Given a video of a listener and speaker pair, we extract text corresponding to the spoken words of the speaker. We fine-tune a pretrained large language model to autoregressively generate realistic 3D listener motion in response to the input transcript. Our method generates semantically meaningful gestures (*e.g.* an appropriately timed smile inferred from “amazing”) that synchronously flow with the conversation. We can optionally render the output of our approach as photorealistic video. Video: <https://youtu.be/djpSOhdIU8M>

Abstract

We present a framework for generating appropriate facial responses from a listener in dyadic social interactions based on the speaker’s words. Given an input transcription of the speaker’s words with their timestamps, our approach autoregressively predicts a response of a listener: a sequence of listener facial gestures, quantized using a VQ-VAE. Since gesture is a language component, we propose treating the quantized atomic motion elements as additional language token inputs to a transformer-based large language model. Initializing our transformer with the weights of a language model pre-trained only on text results in significantly higher quality listener responses than training a transformer from scratch. We show that our generated listener motion is fluent and reflective of language semantics through quantitative metrics and a qualitative user study. In our evaluation, we analyze the model’s ability to utilize temporal and semantic aspects of spoken text.

1. Introduction

Human face-to-face communication is multifaceted and multimodal [13, 28]. In particular, the flow and effectiveness of face-to-face dyadic interactions critically depend on non-verbal motions and responses from both participants in the conversation [28, 30, 10]. This paper focuses on the non-verbal facial feedback listeners provide to speakers during a dyadic conversation [34, 49, 18].

When listening to a speaker, we produce gestures in response to several multimodal communication channels, including speech, non-verbal gestures, and lexical semantics (the meaning of words) [28]. Previous studies have shown that speech and gesture are informative of listener responses [34, 49]. Here we ask how far we can get with lexical semantics alone. This question is significant given the abundant availability of textual dialogue data, in contrast to the limited availability of conversational motion datasets. To study the transferability of large language models to the dyadic conversational motion domain, we propose the task depicted in Figure 1 of predicting listener motion from the raw text transcribed from the speaker’s words.

Since gesture is a conversational communication chan-

*denotes equal contribution

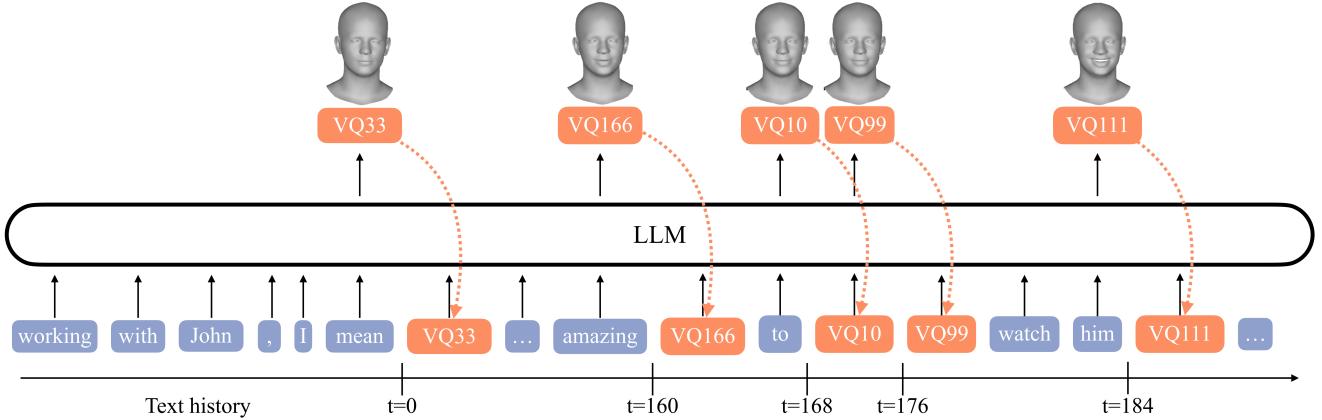


Figure 2: **Listener motion prediction model.** The model takes as input text tokens (blue), along with their timestamps, and predicts tokens representing atomic listener motion elements (orange) that we discretized with a VQ-VAE. We feed in a fixed-size history window of text tokens before the listener response’s onset. Then we generate one discrete gesture token at a time while providing text tokens as the speaker speaks (*i.e.* according to word timestamps). t denotes the number of frames that have elapsed since the start of motion generation. Each discrete motion token represents 8 frames of continuous motion.

nel, our central insight is to transfer knowledge from pre-trained large language models to the gesture generation task. We propose to treat discrete atomic motion elements as novel language tokens. We first learn a data-driven dictionary of discrete atomic gesture elements by training a VQ-VAE [45] to capture the full spectrum of videotaped listener responses [34]. We then fine-tune a pretrained large language model to autoregressively predict these novel motion tokens given temporally-aligned speaker text (see Figure 2). We ensure that each motion token is only generated based on previously spoken words by interleaving the input speaker text tokens with the autoregressively predicted motion tokens. Hence, our causal model can produce listener responses in real-time as it does not rely on future speaker words.

Our text-conditioned model outperforms baselines in both quantitative metrics and human evaluation. Notably, it performs competitively with prior work that uses audio and visual input for listener generation. The generated listener responses are consistently on-par with ground truth listener facial gestures, as our perceptual study demonstrates.

Given these results, we ask why a text-conditioned model performs well on an inherently multimodal task. We focus our analysis of the model on the two main qualities we expect from realistic listener non-verbal feedback: (1) temporally synchronous responses, such as head nods, and (2) semantic, emotionally meaningful responses, such as smiles or looks of puzzlement [9]. We find that a text transcription of a speaker’s utterance carries some temporal signal of when a response is in order. Punctuation, capitalization, and temporal breaks in word delivery are hints about sentence structure that embed this rhythmic information. We further demonstrate that lexical semantics is crucial for producing the correct emotional response, especially when the

speaker’s facial expression does not reflect the emotional affect of their words. Finally, we note that, as expected, our model cannot capture responses for which the facial affect or motion of the speaker is crucial.

2. Related Work

Conversational dynamics Works on animating conversational avatars traditionally involved crafting rule-based designs on lab-captured motion data [8, 20, 24, 3, 42], which often limit the variety of captured gestures, or rely on simplifying assumptions for motion generation that do not hold for in-the-wild data. As a result, several data-driven approaches were proposed for tasks such as predicting the head pose of the speaker and listener [21], turn taking [27, 1], and single-frame facial expressions that summarize the sequence [25, 35]. While these methods focus on a narrow aspect of modeling social dynamics, our approach captures the natural complexity of interactions by considering the full range of facial expressions and head rotations.

More recently, there have been works on modeling a speaker’s fine-grain motion generation conditioned on audio [26, 19], [12] text, or both audio and text [29]. However, all these works focus on modeling monadic conversational settings where the goal is to output speaker motion that directly matches the input signals. In contrast, [15, 26, 34, 49] model cross-person, dyadic interactions by predicting the listener’s 2D [15] or 3D motion [26, 34, 49]. Yet all these prior works condition the listener’s response on the speaker’s motion and audio. In addition, [49] relies on a one-bit semantic affect conditioning that signifies whether the synthesized listener should have a positive, negative, or neutral response. In contrast, we focus on demonstrating that semantically mean-

ingful and temporally realistic responses that correspond to a given speaker are possible from a text-only context.

Most related to our work is [18], which explicitly models the semantics within a conversation. By prompting GPT3 [6] with a predefined goal and text of the speaker, [18] obtains visual details of the listener from which they train a model to retrieve listener clips that most closely match this description within their dataset. Rather than taking the full input text at once, our model ingests time-aligned text and autoregressively outputs corresponding 3D listener motion. Additionally, we *generate* raw 3D motion rather than picking from existing clips, which allows us to derive motion that does not exist in the training set. All these differences allow us to model *both* semantics and temporally realistic responses in dyadic conversations.

Text driven motion synthesis Several prior works considered text-conditioned 3D motion generation [37, 43, 44, 22, 47]. [43, 44] leverage existing pretrained large language models to produce semantically meaningful embeddings as input to their system. In contrast to these methods, we consider text-conditioned motion in conversational settings. We explore the potential for using pretrained large language models to discover semantic and temporal information from a speaker’s transcript. We demonstrate that from text alone, we can generate temporally aligned motion indicative of synchronous responses in conversational settings.

Recent work showed that knowledge from large language models can transfer to other tasks by finetuning pretrained models [33, 40, 32]. We leverage this insight and demonstrate that finetuning on a pretrained large language model transfers well to conversational motion generation.

3. Listener Motion Generation with LLMs

Given the speaker’s transcribed speech in a dyadic conversation, we aim to generate corresponding listener facial motions. Our system consists of two components: (1) a model that converts listener motion into a sequence of discrete tokens and (2) an autoregressive model that predicts future motion tokens conditioned on previously generated motion tokens and previously spoken words.

3.1. Problem Definition

Let $\mathbf{F} = \{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_T\}$ represent the listener’s face across T frames during one of the speaker’s turns in the conversation. Let $W = (w_1, w_2, \dots, w_N)$ be a sequence of text tokens corresponding to the words spoken during the time spanned by frames 1 to T . Let $M = (m_1, m_2, \dots, m_N)$ be the corresponding timestamps, where $m_i \in \{1, 2, \dots, T\}$ denotes the timestamp of the frame corresponding to the end of the interval in which token w_i was spoken. For each pair of frames $t_1 < t_2$, we denote by $W_{t_1:t_2}$ the sequence of words spoken between frames t_1 and t_2 .

Additionally, we consider some historical text context corresponding to words the speaker said earlier in their turn, before frame 1. Let $W^{history} = (w_1^{history}, w_2^{history}, \dots, w_{N'}^{history})$ be the sequence of text tokens spoken during the H seconds of the speaker’s turn before frame 1.

Our generator \mathcal{G} takes as input W , $W^{history}$, and M and predicts \mathbf{F} . Specifically, the t -th predicted face in the sequence is given by

$$\hat{\mathbf{f}}_t = \mathcal{G}(W^{history}, W_{1:t}, M_{1:t}, \mathbf{F}_{1:t-1}).$$

To estimate 3D facial expressions and orientations from video frames of human conversations, we represent the face of the listener in every frame using a 3D Morphable Face Model (3DMM) [2, 36, 7, 31]. 3DMMs are parametric facial models that allow us to directly regress disentangled coefficients corresponding to facial expression, head orientation, and identity-specific shape from a single image [50]. We obtain facial expression coefficients $\beta_t \in \mathbb{R}^{d_m}$, where d_m is the dimension of the expression coefficient, a normalized 3D head pose $R_t \in SO(3)$, and shape coefficients that we discard to obtain an identity-agnostic representation. Our facial representation at time t , $\mathbf{f}_t \in \mathbb{R}^{d_m+3}$, is a concatenation of expression and orientation (in Euler angles):

$$\mathbf{f}_t = [\beta_t, R_t]. \quad (1)$$

3.2. Discretizing Listener Motion

Predicting the sequence of facial expressions \mathbf{F} is challenging because the coefficients of \mathbf{f}_t are real-valued and require regression-based methods. Following recent work in motion generation [34, 47], we use a VQ-VAE [45] to encode a sequence of facial expressions into a sequence of discrete tokens. We can then predict these discrete tokens via straightforward classification-based methods.

The VQ-VAE consists of an *encoder* neural network, a *decoder* neural network, and a set of *codebook* embeddings $\mathbf{C} \in \mathbb{R}^{V_{vq} \times d_c}$, where V_{vq} is the size of the codebook and d_c is the dimension of the embeddings. Each codebook embedding corresponds to a unique discrete token in the codebook. The encoder takes as input the sequence of facial expressions $F^L = (\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_T)$, normalized by the mean and standard deviation across all training examples, and produces as output a sequence of latent features $\mathbf{Z} = (\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_{T/r})$, where r is the downsampling rate of the encoder and each $\mathbf{z}_i \in \mathbb{R}^{d_c}$. The *quantizer* Q is a deterministic, parameter-free function that converts each vector of this sequence to a codebook token:

$$Q(\mathbf{z}_i) = \arg \min_{1 \leq j \leq V} \|\mathbf{z}_i - \mathbf{C}_j\|^2$$

We denote by $q_i = Q(\mathbf{z}_i)$ the i th VQ token. The decoder takes as input a sequence of codebook embeddings

$(\mathbf{C}_1, \mathbf{C}_2, \dots, \mathbf{C}_{T/r})$ and, after reverse normalization by mean and standard deviation, produces as output a continuous sequence of facial expressions $\hat{\mathbf{F}}^L = (\hat{\mathbf{f}}_1, \hat{\mathbf{f}}_2, \dots, \hat{\mathbf{f}}_3)$.

Architecture and Training The architectures of the VQ-VAE encoder and decoder mainly consist of convolutional and residual layers and are shown in supplemental. We train the VQ-VAE with a combination of four losses:

$$\begin{aligned} L_{embed} &= \sum_{t=1}^{T/r} \|\mathbf{z}_t - sg[C_{q_t}]\|^2 \\ L_{reconstruct} &= \sum_{t=1}^T \mathcal{L}_1^{smooth}(\hat{\mathbf{f}}_t, \mathbf{f}_t) \\ L_{velocity} &= \sum_{t=1}^{T-1} \mathcal{L}_1^{smooth}(\hat{\mathbf{f}}_{t+1} - \hat{\mathbf{f}}_t, \mathbf{f}_{t+1} - \mathbf{f}_t) \end{aligned}$$

Here sg denotes the stop-gradient operator, and \mathcal{L}_1^{smooth} denotes the L1 smooth loss function. The total training loss is a weighted sum of these four losses. We also use exponential moving average and codebook reset when training.

3.3. Text-conditioned Motion Generation

Our autoregressive motion generation model \mathcal{G} outputs listener facial responses in two steps. First, we predict a series of discrete codebook tokens. Second, we decode these discrete tokens via the VQ-VAE decoder to a sequence of 3DMM coefficient vectors representing continuous motion. Figure 2 illustrates our architecture.

We instantiate \mathcal{G} with a language model (LM) based on a transformer architecture [46]. Specifically, we use GPT2 [39]. A LM takes as input a sequence of text tokens $\{w_1, w_2, \dots, w_H\}$ and outputs a distribution over the vocabulary for the next token. The first layer in the LM is an embedding $E_{word} \in \mathbb{R}^{V_{word} \times d_w}$, where V_w is the vocabulary size and d_w is the embedding dimension, that converts the token indices to embeddings $\{\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_H\}$. We use a positional embedding matrix $P \times \mathbb{R}^{H \times d_w}$ to add positional information to each token’s embedding: $\mathbf{e}'_i = \mathbf{e}_i + P_i$.

Each of the remaining layers in the model takes a sequence of vectors $\{\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_H\}$ which can be represented as a matrix $A \in \mathbb{R}^{H \times d_w}$ and uses linear projections on A to produce *query*, *key*, and *value* matrices $Q, K, V \in \mathbb{R}^{H \times d_w}$. Let L_T be a $H \times H$ matrix in which elements on and below the diagonal are 1, and all other elements are $-\infty$. Then for each position in the sequence, self-attention is computed between Q and K to compute a distribution over the sequence, and the output representation A' is a weighted sum of the value vectors according to this distribution:

$$\alpha = \text{softmax} \left(L_T \odot \frac{QK^T}{\sqrt{d_w}} \right)$$

$$A' = \alpha V$$

Here \odot denotes the element-wise product. In contrast to a bidirectional transformer where each position attends to all others, this *causal* attention mechanism ensures that each position attends only to itself and previous ones. Finally, we apply LayerNorm and a feedforward network to A' to produce the input to the following layer. The final layer of the LM is an affine projection that predicts the next token in the sequence.

To enable the LM to generate motion VQ tokens, we instantiate randomly initialized word embeddings $E_{VQ} \in \mathbb{R}^{V_{vq} \times d_w}$ for each of the VQ tokens, and we replace the output layer with a randomly initialized affine projection that outputs logits for each of the VQ tokens. We determine the order of the text and VQ tokens by ensuring that for each VQ token, the previous text tokens are those whose timestamp is less than the timestamp of the current VQ token.

Often a listener’s reaction is not only determined by what is immediately being said but also by what has already been said. To model this additional context in the conversation, we also include history tokens for the text that has occurred before the first frame at $t = 1$. The first N' tokens in the input are the text history tokens $W^{history}$. The listener motion tokens $q_1, q_2, \dots, q_{T/r}$ are placed in order after the history tokens. The text tokens spoken during the segment are placed as follows: for each $t \in \{1, 2, \dots, T/r - 1\}$, the set of text tokens that are placed between q_t and q_{t+1} is $W_{rt,r(t+1)}$. We also place a space token (*i.e.*, the textual space token from the GPT2 tokenizer) just before each listener motion token.

As in text-only LMs, we train the model using cross-entropy loss on the task of next-token prediction with teacher-forcing:

$$\mathcal{L} = - \sum_{t=1}^{T/r} \log \Pr [\mathcal{G}(W^{history}, W_{1:rt}, q_{1:t-1}) = q_t]$$

At test time, we use greedy decoding to predict the sequence of motion tokens.

4. Experimental Setup

We conduct quantitative experiments to validate the effectiveness of our method in comparison with baselines (section 5.1). We then demonstrate, via an A/B test on Mechanical Turk, that our results are comparable to ground truth and preferable to those produced by baselines (section 5.2).

We then analyze why the text-conditioned model performs well on this multimodal task. We examine the two qualities expected from listener non-verbal feedback: (1) temporally synchronous (sec. 6.1) and (2) semantically-meaningful (sec. 6.2) responses. We demonstrate that text carries some temporal information that informs when a response is appropriate. We further find that lexical semantics is crucial for producing the correct emotional response. Finally, we show that more historical text context improves performance, but

	L2 ↓	FD ↓	variation	diversity	P-FD ↓	L2 Affect (10^2) ↓
<i>GT</i>			0.11	2.59		
Random Train	0.63 ± 0.02	30.35 ± 1.0	0.088 ± 0.005	2.26 ± 0.06	31.47 ± 1.0	11.91 ± 0.73
Random VQ	0.71 ± 0.01	29.31 ± 0.6	0.269 ± 0.004	4.83 ± 0.05	31.44 ± 0.6	10.14 ± 0.53
NN	0.52 ± 0.02	23.68 ± 1.1	0.087 ± 0.004	2.25 ± 0.05	24.78 ± 1.1	7.88 ± 0.56
Uncond	0.39 ± 0.02	21.28 ± 0.9	0.002 ± 0.000	0.42 ± 0.00	21.65 ± 0.9	7.63 ± 0.56
Full	0.43 ± 0.02	18.22 ± 0.7	0.116 ± 0.005	2.81 ± 0.06	19.63 ± 0.8	6.36 ± 0.47

Table 1: **Results.** Comparison against ground truth annotations (GT). ↓ indicates lower is better; closer to GT is better for no arrow. We average each metric over the test set instances. Standard error is computed via bootstrap (using 10,000 samples).

too much context leads to degradation 6.3. For implementation details, see supplemental.

4.1. Dataset

As in prior work on listener motion generation [34], we focus on the person-specific modeling setting, in which all videos share the same listener. We evaluate on one of the listeners (Trevor Noah) in the dataset introduced by [34]. We improve this dataset in three ways. First, we segment the raw videos into longer segments. The original dataset included 2-second segments, but more context is needed here since text is a sparse signal. We train and evaluate on segments of up to 8 seconds (not including the length of the text history provided to the model). To identify the listener segments, we use PyAnnote to perform speech diarization [5, 4]. Second, to extract 3DMMs from the videos, we use EMOCA [14, 17], a more expressive model than DECA [16], used for the original dataset. Finally, we extract time-aligned speech transcriptions using Whisper [38]. During training and testing, we only include motion that starts at least 3 seconds after the start of the speaker’s turn, and only consider segments that are at least 24 frames. This procedure results in 2366 training, 222 validation, and 543 test segments.

4.2. Evaluation Metrics

Due to the difficulty of quantitatively evaluating realism in multimodal motion generation, we use an extensive suite of metrics that evaluate our predictions along multiple axes. Inspired by prior work [34], we focus on assessing our predicted listeners’ realism, diversity, and synchrony with speaker motion.

- *L2*: on ground truth expression coefficients and pose
- *Frechet distance (FD) for realism*: Motion realism measured by distribution distance between generated and ground-truth motion. We calculate FD [23] in the expression $\mathbb{R}^{T \times d_m}$ and head pose $\mathbb{R}^{T \times 3}$ space of the full motion sequence.
- *Variation for diversity*: Variance calculated across the sequence of expression coefficients or 3D rotations.

- *Diversity*: Following [48], we randomly sample 30 pairs of listener pose and expression parameters within a sequence of motion and compute the average Euclidean distances between the pairs to measure motion diversity in the set.
- *Paired FD for synchrony*: Quality of listener-speaker dynamics measured by distribution distances on listener-speaker pairs (P-FD). FD [23] on concatenated listener-speaker motion $\mathbb{R}^{T \times (d_m + d_m)}$ / pose $\mathbb{R}^{T \times (3+3)}$.
- *L2 Affect for synchrony*: Measures the accuracy of the produced listener facial affect across the sequence. We average listener facial affect over a 1-second window and compute the L2 against ground truth in a sliding window manner.

Together, these metrics measure both the semantic appropriateness and the temporal synchrony of gestures between a speaker and listener in conversation.

Baselines We compare to the following baselines:

- **NN text**: A segment-search method commonly used for synthesis. Given input speaker text, we find its nearest neighbor from the training set and use its corresponding listener segment as the prediction. We use the `all-mpnet-base-v2` model from Sentence-Transformers [41] to encode text, commonly used for text retrieval.¹ On the validation set, this model performs slightly better than GPT2-medium on L2/FD and slightly worse on L2 Affect.
- **Random**: Return a randomly-chosen sequence of a listener from the training set.
- **Mean**: Simple yet strong baseline exploiting prior that listener is often still. We compute mean expression and pose from the training set.
- **Uncond**: Unconditional model that learns to produce motion sequences without text conditioning. Note that

¹<https://www.sbert.net/index.html>

	PT	GPT	align	ordered	text type	L2 ↓	FD ↓	variation	diversity	P-FD ↓	L2 Affect (10^2) ↓
<i>GT</i>											
NoPT		\times	✓	✓	given	0.53 ± 0.02	22.81 ± 0.9	0.14 ± 0.005	3.21 ± 0.06	24.38 ± 0.9	8.41 ± 0.53
Unaligned		✓	\times	✓	given	0.45 ± 0.02	19.03 ± 0.8	0.11 ± 0.005	2.71 ± 0.06	20.40 ± 0.8	6.66 ± 0.51
Scrambled		✓	✓	\times	given	0.49 ± 0.02	19.96 ± 0.7	0.12 ± 0.004	2.86 ± 0.06	21.59 ± 0.8	7.37 ± 0.50
FixTok		✓	✓	✓	fixed	0.73 ± 0.02	37.31 ± 1.2	0.05 ± 0.003	1.58 ± 0.04	38.36 ± 1.2	13.45 ± 0.86
FixTok-Punc		✓	✓	✓	punc. +fixed	0.60 ± 0.02	29.07 ± 1.1	0.09 ± 0.005	2.31 ± 0.06	30.41 ± 1.1	10.18 ± 0.65
Full		✓	✓	✓	given	0.43 ± 0.02	18.22 ± 0.7	0.12 ± 0.005	2.81 ± 0.06	19.63 ± 0.8	6.36 ± 0.47

Table 2: **Ablations.** Each metric is averaged over the test set instances. Standard error is computed via bootstrap (using 10,000 samples).

since we use greedy decoding, this method produces the same motion sequence for a given sequence length.

- **NoPT:** Our method without GPT pretrained weights.

5. Results

Through quantitative experiments, we demonstrate that our proposed method outperforms all baselines. In a Mechanical Turk A/B test, we further show that our predictions realistically correspond to the speaker and are competitive with an existing approach for listener motion synthesis conditioned on the speaker’s speech and gesture.

5.1. Quantitative Results

Table 1 shows our proposed method outperforms all other baselines and that finetuning on GPT2 is crucial. Overall, **Full** achieves the best balance of performance across all the various metrics. According to the FD, our method produces motion that matches the distribution of the ground truth dataset. Furthermore, the motion produced is similar in variation and diversity to real motion. Most notably, we generate synchronous motion, as shown by our method’s strong performance in P-FD and L2 Affect over all baselines. As a result, this suggests our model generates accurate facial expressions that match the dynamics of the conversation.

Furthermore, we calculate the Shannon Index [34] on facial gestures to measure the overall entropy of generated expressions. Ours (2.52) is similar to the ground truth (2.68), which shows a fair amount of diversity and demonstrates that our predictions do not simply collapse into two modes (smile/not smile).

While **Uncond** has a lower L2, it performs significantly worse in all other metrics. This confirms that our model successfully leverages the text input. Similarly, **NoPT** performs poorly across the board, suggesting that GPT2 finetuning is advantageous for our task.

5.2. Human Evaluation

To corroborate our quantitative results and gain insight into how our synthesized listeners perceptually compare to

real motion , we conducted an A/B test on Amazon Mechanical Turk. We visualized listener motion using videos of grayscale 3D facial meshes.

Participants watched a series of video pairs. In each pair, our model generated one video; an ablation or a baseline produced the other. Participants were then asked to identify the video containing the listener that looks like they are listening and paying *more* attention to the speaker. Videos of at least 8 seconds each of resolution 849×450 (downsampled from 1132×600 in order to fit two videos vertically stacked on different screen sizes) were shown, and after each pair, participants were given unlimited time to respond. Since the most tell-tale moments for when a listener is truly listening are during defining moments (speaker tells a joke, shares a sad story, *etc.*) that illicit strong responses, we manually curated 47 such notable moment sequences from our held-out test data. We then predicted a corresponding listener 3D facial motion sequence using each method. For every test sequence, each A/B comparison was made by 3 evaluators.

We compared our strongest baselines **NN** and **Uncond** to our proposed model and recorded the percentage of times participants preferred our method over the baseline models or vice versa. **Ours** significantly outperformed. 70.1% of the total 150 evaluators preferred **Ours** over **NN**, and 92.8% preferred **Ours** over **Uncond**. These statistics reflect the quantitative trends in Table 1. Furthermore, in a comparison against avatars rendered from ground truth listeners, evaluators preferred **Ours** 49.7% of the time. This *highlights the perceptual realism of our predicted listener motion*.

Additionally, we compare against prior SOTA Learning to Listen(L2L) [34] that models the temporal synchrony of a speaker-listener dyad from speech audio and motion. AMT evaluators preferred ours over L2L 55.7% of the time. This suggests that our text-only approach models synchronous motion comparable to that of an approach that explicitly models temporal synchrony through prosody, which is known to encode the beats and pacing of a conversation through inflections, tones, and rhythm of speech. That said, we note that for this comparison we used the original L2L implementation, which relied on DECA [16], an older and less



Figure 3: Where we win and where we lose. Our model responds in an emotionally-appropriate manner when lexical semantics is crucial. For example, when it is not appropriate to smile despite a speaker’s uneasy laughter (Left). We fail to capture cases that can only rely on the speaker’s facial motion, such as sarcastic jokes (Middle). In many cases, both the textual sentence structure and the speaker’s gesture contain hints of *when* a response, such as a nod, is appropriate, allowing us to model speaker-listener synchrony despite no access to motion (Right). See <https://youtu.be/djpSOhdIU8M> for a video version of these examples.

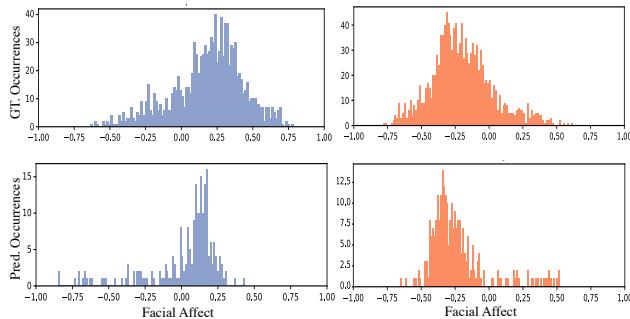


Figure 4: Positive phrases elicit positive affect, and vice versa. Given the top 100 most positive (left) and negative (right) phrases, we plot a histogram of the facial affect of a listener during and 2 seconds after the stated phrase. -1 corresponds to very upset. The ground truth distribution (top), computed over all the data, and our predicted distribution (bottom), computed over the test data, exhibit a robust correlation.

expressive 3DMM than EMOCA [14].

6. Analysis of the Text-based Method

Responding to a speaker nonverbally is inherently a multimodal task [28]. And yet, we demonstrated that we could design a competitive method for this task that relies on text input alone. We now analyze our proposed approach to unearth some reasons for its success. We discuss the two qualities of non-verbal listening feedback corresponding to successful listening feedback [8]: temporal synchrony with the speaker and semantically-appropriate responses. We then consider the effect of varying lengths of historical temporal context in the input text. We conclude this section by discussing the limitations of taking only text as input.

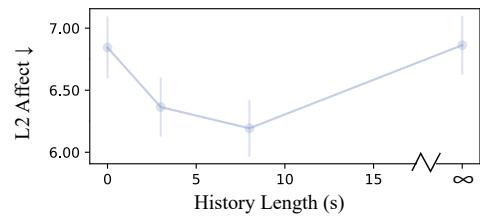


Figure 5: Effect of text history. Providing text history helps, but too much history hurts the model in terms of affect.

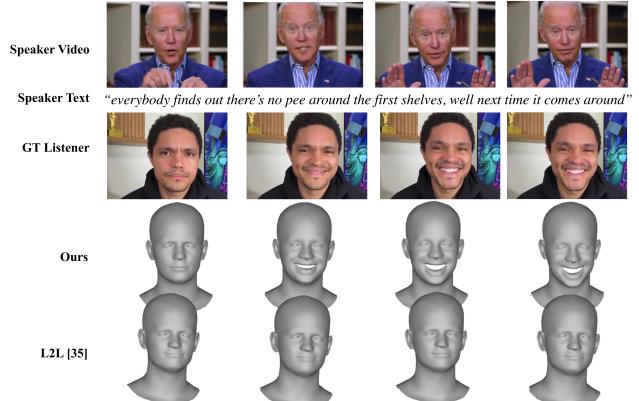


Figure 6: Success in modeling humor. In contrast to L2L [34], conditioned on speaker motion and speech, our text-based model correctly generates laughter in response to humorous language.

6.1. Temporal Synchrony with the Speaker

To understand which parts of our model contribute to its temporal performance, we evaluate variants of our model in Table 2. First, we consider the possibility that the temporal alignment and interleaving of language tokens (past listener

and speaker text tokens) with listener motion tokens result in more temporally-synchronous motion. **Unaligned** is a variant we train with all text tokens prepended together *in order*, followed by the autoregressively generated motion tokens. For **Unaligned**, we also remove the space before each VQ token. While **Full** performs slightly better than **Unaligned** in all metrics, the improvements are not significant. This indicates that the network can reason about the temporal interleaving of motion and language tokens without relying on their proximity in the input. Yet, we get notably poorer performance when we test the importance of word order by randomizing the input text tokens **Scrambled**. This suggests that our model leverages text *ordering* as an important signal.

We find evidence in the ground truth data that temporal information, essential for the synchrony of a dyad, can be learned from a text-only model. Analysis of the ground truth listener in the dataset demonstrates that punctuation is essential in regulating when to nod. For instance, around 51% of the statements immediately before nods include some punctuation, while in the non-nodding case, only 15% of utterances do. Similarly, smiles correlate more with “!!” punctuation than plain faces (see supplemental for analysis). Therefore, we test the importance of punctuation in our model via two variations that introduce a new, fixed text token. We then replace all the input text with this new text token **FixTok** or replace all but punctuation **FixTok-Punc**. Note that in both these setups, we still preserve space tokens since we place spaces before each VQ token. We use a new text token instead of an existing one to avoid potential biases induced by pre-existing words or spaces. Comparing the two in Table 1, we see that punctuation significantly improves speaker-listener synchrony via P-FD.

We conclude that through the formalization of sentence structure, speaker text transcriptions contain some temporal signal reflecting the nodding beat-like motions of the speaker, thus providing a hint for when it is appropriate for a listener to respond. This is also evident from cases where the appropriate response could rely on *either* speaker motion or sentence structure as shown in Figure 3 (right).

6.2. Semantically-appropriate Responses

In the ground truth dataset, we analytically demonstrate common patterns from a listener’s reaction to the speaker’s words. Figure 4 plots the listener’s facial affect (1.0 corresponds to very happy, -1.0 corresponds to very upset) associated with the top 100 most positive or negative phrases within the dataset. We calculate the average facial affect for each phrase during the utterance and in the 2 seconds that follow. The graphs exhibit a strong correlation between positive phrases and positive listener facial reactions and vice versa. Furthermore, Figure 4 demonstrates that our finetuned model can capture the distribution of these associations well. Figure 6 shows an example where our model generates laughter

in response to humor—a joke that goes over the head of a motion-and-audio conditioned baseline. In Figure 3 (left), we show a case where our predicted listener is appropriately serious, despite the nervous laughter of the speaker.

Most notably, the fixed token experiment confirms our approach can properly model conversations’ semantic alignment. Note that the fixed token models are the only ones with no semantic information since we replace all words with the same token. As a result, both models perform significantly worse than even **NoPT**. We further analyze semantic knowledge captured via word clouds in supplemental.

6.3. The Effect of Historical Context

We consider the importance of historical lexical semantic context in conversation. A listener’s response often depends on things said in the recent past. Figure 5 demonstrates having no context at all results in worse performance. As we increase the amount of history we feed into the network, the predicted affect becomes more aligned with the ground truth, with a sweet spot of 8 seconds of history. However, adding too much context again results in poor performance.

6.4. Limitations

Given that listening is an inherently multimodal task involving visual and auditory signals from the speaker, our method is limited in that it does not take visual or audio input. For instance, Figure 3 (middle) shows an example where the speaker laughs, but the text does not contain an explicit joke. In other cases, the speaker may prompt the listener to nod through their motion or prosody rather than through words. More powerful language models may also improve our results. For instance, when prompted with humorous text, our model does not always generate laughter. Larger language models have demonstrated an improved capacity to model jokes [11], so integrating them into our framework may improve responses to such examples.

7. Discussion

We presented a transfer-based approach from pretrained large language models to human conversational gestures in dyadic interactions. This approach relies on the insight that gesture can be discretized into its atomic elements and treated as novel language tokens. We can, therefore, seamlessly integrate language and motion to extend state-of-the-art methods in language modeling to this setting. Integrating text input with other modalities for this task is a compelling direction for future work.

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