EmoLASP: Emotion Recognition with Language Models and Answer Set Programming

Anonymous ACL submission

Abstract

Emotion recognition in conversations is increasingly tackled with language models, but these models can be unstable and expensive to fine-tune on long dialogue histories. We propose **EmoLASP**, a framework that combines a language model with declarative reasoning via Answer Set Programming (ASP) to predict VAD scores (Valence-Arousal-Dominance) in conversations. Experiments on a widely used benchmark dataset (IEMOCAP) across six open-source LLMs (3b-120b) and two PLMs (BERT, RoBERTa) show that EmoLASP improves prediction performance compared to using the language model alone, even when the LLMs/PLMs are given no dialogue history in their prompts or input vectors. This demonstrates the potential advantages of using a reasoning approach to ensure emotion prediction consistency and reduce the cost of fine-tuning or prompting language models with long dialogue histories.

1 Introduction

Emotion recognition in conversations (ERC) is the task of identifying the emotional state expressed in each utterance of a dialogue, and it supports various applications including empathetic dialogue systems and mental health support (Chu et al., 2025). Common approaches to ERC include using pretrained language models (PLMs) and fine-tuning them on labelled emotion datasets to predict emotions (Park et al., 2021; Mendes and Martins, 2023). In recent years, large language models (LLMs) have been used to recognise emotions in text (Feng et al., 2024; Liu et al., 2024). However, there are several limitations of previous work that need to be addressed. First, most work on ERC focuses on categorical emotion classification, which is less expressive than dimensional representations such as Valence-Arousal-Dominance (VAD) (Russell and Mehrabian, 1977; Russell, 1980). Additionally, while LLMs/PLMs have shown promising results in emotion recognition, their instability and bias (Wake et al., 2023) mean more research is needed to ensure consistent emotional reasoning in conversations. LLMs are essentially black boxes, which might provide an answer without following logical reasoning such as continuity of an emotional state. Moreover, relying solely on language models can be costly, whether due to fine-tuning on domain-specific datasets or a large number of input tokens required when feeding the entire dialogue history in prompt-based approaches.

In this paper, we present a novel approach combining language models with declarative reasoning for emotion recognition. Declarative reasoning has proven effective in other areas such as logical anomaly detection in Vision-Language Models (Jin et al., 2025). We adopt Answer Set Programming (ASP) as our reasoning framework with the following advantages. First, ASP allows us to express *non-deterministic choice rules* (Eiter et al., 2022), which consider not only the language model's top prediction but also other possible hypotheses with lower confidence. This is particularly useful when outputs are highly uncertain. Second, and on top of this, *weak constraints* in ASP allow us to encode preferences over VAD hypotheses to select the best VAD hypothesis based on the dialogue context. Since *Emotional Contagion Theory* shows that emotions of a person can be influenced by the emotions of others in a conversation (Hatfield et al., 1993), these weak constraints favour hypotheses consistent with prior turns. Moreover, our experiments show that the ASP reasoner can handle historical emotion dynamics and select context-consistent emotional hypotheses even when dialogue history is omitted from the language model's input, which reduces the number of input tokens.

To our knowledge, this is the first work combining language models and declarative reasoning for ERC. Our contributions are: (1) we propose the **EmoLASP** framework, a novel approach integrat-

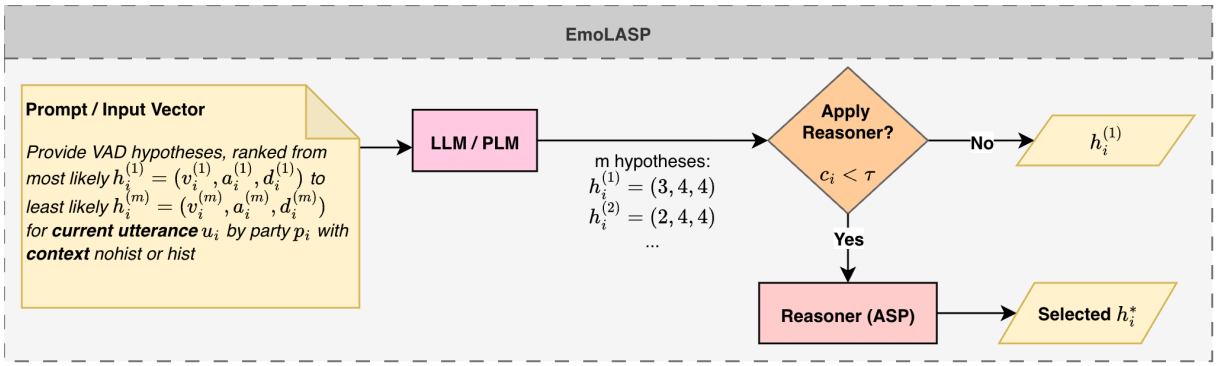

Figure 1: Overview of our EmoLASP framework.

ing a language model with a reasoner for emotion recognition in conversations; (2) we evaluate it against different open-source language models, including LLMs and PLMs on a benchmark dataset; (3) we perform qualitative analysis to identify utterances that are most challenging for LLMs to predict accurate VAD values, even with the help of an ASP reasoner and the presence of dialogue context.

2 Method

Our proposed method has two layers: (1) an LLM/-PLM and (2) an answer set program (ASP) implemented in Clingo (Gebser et al., 2019). The overall pipeline is as follows: For each utterance, we first use a language model to provide VAD hypotheses. Then, we feed those hypotheses into an ASP reasoner, which performs *aggregation* and *optimisation* to select the best VAD hypothesis for that turn by reasoning about VAD scores of previous turns. Figure 1 illustrates the overall framework of our method, which we call **EmoLASP** (**Emo**tion recognition with **L**anguage models and **A**nswer **S**et **P**rogramming).

2.1 Preliminaries

Given a conversation C with a sequence of n utterances, $C = \{(u_1, p_1), (u_2, p_2), \ldots, (u_n, p_n)\}$, where utterance u_i is spoken by party p_i, the task of *Emotion Recognition in Conversation* (ERC) is to predict emotional **VAD** scores $y_i = (v_i, a_i, d_i)$ for each utterance u_i, resulting in a sequence $Y = \{y_1, y_2, \ldots, y_n\}$ of VAD scores for C. The scores represent a 3-dimensional model of affect, where **valence** (V) represents the positivity or negativity of an emotion, **arousal** (A) the intensity or activation level, and **dominance** (D) the degree of control conveyed by the emotion. VAD scores can be represented as continuous or ordinal values within a specific range.

2.2 Providing VAD Hypotheses

Large language models (LLMs) or pre-trained language models (PLMs) provide VAD hypotheses for each utterance. Formally, given an utterance u_i, the model produces a set of m VAD hypotheses: $H_i = \{h_i^{(1)}, h_i^{(2)}, \ldots, h_i^{(m)}\}$, where $h_i^{(j)} \in \Re^3$ and each hypothesis $h_i^{(j)}$ consists of three scores: valence $v_i^{(j)}$, arousal $a_i^{(j)}$, and dominance $d_i^{(j)}$.

LLMs We prompt an LLM to output m ranked VAD hypotheses for u_i, ordered from most to least likely according to the model. Depending on the context condition, the prompt includes either only u_i (*nohist*), or u_i together with all previous turns $\{u_1, u_2, \ldots, u_{i-1}\}$ (*hist*). The *nohist* condition reduces the number of input tokens, which benefits smaller LLMs with limited context windows.

PLMs We fine-tune encoder-based PLMs, BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) on the IEMOCAP (Busso et al., 2008) training set with three independent classification heads, one per VAD dimension, each predicting a Likert score in {1, 2, 3, 4, 5}. The *nohist* and *hist* conditions are realised by encoding u_i alone or by prepending the dialogue history with a speaker label before u_i. To produce a ranked set of m hypotheses, we apply a softmax to each dimension's logits. Each candidate triple (v, a, d) is scored by the product of its per-dimension probabilities, and the top m unique triples are returned as H_i, ranked from most to least likely.

2.3 Reasoning with Answer Set Programming

The second layer of our method takes the VAD hypotheses from the language model and applies ASP to optimise emotional dimensions. We first decide whether to invoke ASP using a *confidence threshold* τ; when invoked, ASP performs two steps: (1)

aggregation and (2) *optimisation*.

Confidence Threshold We apply ASP only when the language model is not highly confident about its predictions. A per-turn confidence score is derived from the language model's own probability distribution (from digit-token logprobs for LLMs, and from the per-dimension softmax product for PLMs). Let $p_i^{(j)}$ be the probability that the model assigns to hypothesis $h_i^{(j)}$ for utterance u_i, normalised over the m hypotheses. We define the *confidence score* c_i based on Shannon entropy (Shannon, 1948) as:

$$c_i = 1 - \frac{E(p_i)}{\ln m}, \quad E(p_i) = -\sum_{j=1}^{m} p_i^{(j)} \ln p_i^{(j)}$$

Dividing the Shannon entropy $E(p_i)$ by its maximum value $\ln m$ ensures the score c_i lies in $[0, 1]$ regardless of m. We then apply the ASP reasoner when $c_i < \tau$, where threshold τ is predefined; otherwise, the top-ranked hypothesis $h_i^{(1)}$ is selected.

Aggregation We combine and average the VAD scores from the most recent k turns. Formally, let the conversation history before turn i be $C_{i-1} = \{u_1, u_2, \ldots, u_{i-1}\}$ with corresponding VAD scores $Y_{i-1} = \{y_1, y_2, \ldots, y_{i-1}\}$. We then combine the k most recent VAD scores as $A_i = \frac{1}{k}\sum_{j=i-k}^{i-1} y_j$ so that A_i is the aggregated VAD score for turn i based on the most recent k turns.

Optimisation We use *weak constraints* in ASP to encode objectives for selecting the best VAD hypothesis based on the dialogue context:

```
:~ pick(N,H), hist_penalty(N,H,P). [P@2, N, H]
:~ pick(N,H). [H@1, N, H]
```

Intuitively, priority `@2` (first preference) picks the hypothesis H for turn N with the smallest distance P to the history aggregate A_i. Given a set of hypotheses H_i provided by the language model, let the best hypothesis be h_i^*, then the distance is measured using the L_1 norm: $h_i^* = \arg\min_{h_i^{(j)} \in H_i} \|h_i^{(j)} - A_i\|_1$. The idea is that the selected VAD hypothesis should be close to the aggregated VAD score, which captures the emotional context from previous turns. When several hypotheses share the minimal distance, priority `@1` (second preference) picks the hypothesis with the smallest index H, corresponding to the higher-ranked hypothesis from the language model.

3 Experiment

Dataset We use the IEMOCAP dataset (Busso et al., 2008), which is annotated with VAD scores that serve as labels for evaluation. This dataset contains a total of 115 dialogues across 5 dyadic conversational sessions. Each utterance in the dialogue is annotated with 5-point ordinal ratings (1 to 5) for VAD. The final VAD labels are obtained by averaging the ratings from multiple human annotators: Across 10,039 utterances, annotator counts range from 1 to 4: 8,666 have two, 1,297 have three, 58 have four, and only 36 have one annotated score.

Metrics There are two metrics used to evaluate the performance. The first is Mean Absolute Error (MAE), which quantifies the average absolute difference between model predictions and the average of human ratings (treated as continuous values). The second is Krippendorff's α, which measures how well the model agrees with the human annotators on the original ordinal ratings. To compute α, we add the model's prediction as one extra rater alongside the per-utterance human annotators. We also report Krippendorff's α among only the human annotators as a reference point for human-level agreement.

Baselines Open-source LLMs publicly available on Ollama [1] and two PLMs (BERT, RoBERTa) are used as baselines for comparison. For each language model, there are two context settings: (1) *nohist*: prompt/input vector has only the current utterance; (2) *hist*: prompt/input vector includes all previous conversation turns and the current utterance. Since there are five different sessions of the IEMOCAP dataset, for PLMs we test on each session and use the remaining four sessions for training. For LLMs, we evaluate on each session separately. Results are reported as the mean and standard deviation across five sessions. Prompts and hyperparameters are detailed in Appendix C.

4 Results

RQ1: Can EmoLASP improve ERC performance compared to LM alone? The results in Table 1 show that adding a reasoner (ASP) improves ERC performance in terms of MAE for most models. Full paired t-test results are shown in Appendix D.1. Across nearly all LLMs/PLMs, EmoLASP gives lower MAE than the No Reasoner

[1] https://ollama.com/

		MAE (lower is better)				Krippendorff's α (higher is better)			
		No Reasoner		(Ours) EmoLASP		No Reasoner		(Ours) EmoLASP	
Category	**Model**	nohist	hist	nohist	hist	nohist	hist	nohist	hist
Humans alone		—				$\bar{\alpha} = 0.39 \pm 0.03$			
< 10b	llama3.2:3b	0.88 ± 0.03	1.01 ± 0.02	$\mathbf{0.83 \pm 0.02}$	0.95 ± 0.01	$\mathbf{0.21 \pm 0.02}$	0.18 ± 0.02	$\mathbf{0.21 \pm 0.02}$	0.19 ± 0.02
	gemma3:4b	$0.76 \pm 0.03^{\dagger}$	0.84 ± 0.03	$\mathbf{0.74 \pm 0.03}^{\dagger}$	0.76 ± 0.04	$\mathbf{0.26 \pm 0.02}$	0.25 ± 0.02	0.23 ± 0.02	0.24 ± 0.02
20-30b	gpt-oss:20b	0.84 ± 0.02	0.82 ± 0.03	0.76 ± 0.02	$\mathbf{0.73 \pm 0.02}$	0.28 ± 0.02	$\mathbf{0.32 \pm 0.02}^{\dagger}$	0.28 ± 0.02	$\mathbf{0.32 \pm 0.02}^{\dagger}$
	gemma3:27b	0.77 ± 0.01	$\mathbf{0.75 \pm 0.02}$	0.77 ± 0.01	$\mathbf{0.75 \pm 0.01}$	0.28 ± 0.02	$\mathbf{0.30 \pm 0.02}$	0.22 ± 0.02	0.26 ± 0.03
> 60b	llama3.3:70b	0.96 ± 0.02	0.91 ± 0.04	$\mathbf{0.81 \pm 0.02}$	$\mathbf{0.81 \pm 0.03}$	$0.29 \pm 0.02^{\dagger}$	$\mathbf{0.32 \pm 0.02}^{\dagger}$	$0.29 \pm 0.02^{\dagger}$	$\mathbf{0.32 \pm 0.02}^{\dagger}$
	gpt-oss:120b	0.91 ± 0.02	0.85 ± 0.03	0.75 ± 0.01	$\mathbf{0.71 \pm 0.02}^{\dagger}$	0.27 ± 0.02	$\mathbf{0.31 \pm 0.02}$	0.27 ± 0.02	0.30 ± 0.02
PLM	bert	0.78 ± 0.03	0.74 ± 0.03	0.77 ± 0.03	$\mathbf{0.73 \pm 0.03}$	$0.29 \pm 0.03^{\dagger}$	$\mathbf{0.30 \pm 0.02}$	$0.29 \pm 0.03^{\dagger}$	$\mathbf{0.30 \pm 0.02}$
	roberta-large	0.78 ± 0.02	$0.72 \pm 0.04^{\dagger}$	0.77 ± 0.02	$\mathbf{0.71 \pm 0.05}^{\dagger}$	0.28 ± 0.02	$\mathbf{0.32 \pm 0.03}^{\dagger}$	$0.29 \pm 0.02^{\dagger}$	$\mathbf{0.32 \pm 0.03}^{\dagger}$

Table 1: MAE (left) and Krippendorff's α (right). *Humans alone* is α over only the human annotators. † = best in the same column; **bold** = best in the same row within its metric block; *gray highlight* = handicap comparison.

baseline under both the *nohist* and *hist* settings ($p < 0.001$). As highlighted in Table 1, a key comparison (*handicap*) is between the No Reasoner baseline with full dialogue history in the prompt (*hist*) and the EmoLASP without any history in the prompt (*nohist*). For most LLMs, EmoLASP (*nohist*) reaches a lower MAE than the No Reasoner baseline (*hist*), even though the LLM in EmoLASP sees only the current utterance. For example, MAE drops from 0.91 to 0.81 for `llama3.3:70b` ($p < 0.001$). This is an important finding because EmoLASP (*nohist*) uses fewer input tokens than the No Reasoner baseline (*hist*). However, for PLMs and `gemma3:27b`, the No Reasoner (*hist*) still gives slightly lower MAE than EmoLASP (*nohist*), but the difference is only statistically significant for `roberta-large` ($0.72 \rightarrow 0.77$, $p < 0.05$) and not for `gemma3:27b` or `bert` ($p > 0.05$). This suggests that fine-tuned PLMs are better at making use of the dialogue history in their input, with the obvious caveat that fine-tuning is expensive and not always possible for LLMs.

The results for Krippendorff's α tell a slightly different story. The human inter-annotator agreement is 0.39, while the best model α is 0.32 (e.g., `gpt-oss:20b`, `roberta-large` with *hist*). This means that no model reaches human-level agreement yet, but larger LLMs and PLMs come closer than the smaller ones. Paired t-tests show that EmoLASP significantly decreases α in some cases, most notably for `gemma3:27b` under both *nohist* and *hist* contexts and for some larger LLMs (e.g., `llama3.3:70b`) under the *handicap* comparison ($p < 0.01$). For the remaining models, the changes in α are not statistically significant.

RQ2: Which utterances have high VAD prediction errors across all LLMs? In this section, we identify some examples of utterances that are challenging to predict. A longer list of examples can be found in the Appendix D.2. A clear pattern appearing across these cases is that while the ground-truth annotations reflect extreme emotions in the VAD space (1 or 5), every model predicts values close to the middle (around 2 to 4). The issues share two main causes. The first is very short utterances or surface-neutral utterances. One example utterance is *"Hmm"* with human-annotated scores (5, 4, 0.5), meaning the speaker feels very positive, yet every model predicts mid-range valence values from 2 to 3. In another example (*"Are you cold, huh? Do you want to go home?"*), the utterance looks like a caring question, but the label (4.50, 4.50, 1.00) reflects strong feeling with very low dominance, which all models miss.

The second cause is figurative or metaphorical language. In one case (*"...I'd like a family. I'd like some kids."*), the label is (1, 4.5, 5), expressing deep frustration, but models read the words "family" and "kids" as positive and predict high valence (around 4 to 5). Another example (*"God I feel as though my entire life is going to be spent standing on the beach...waiting for the fish to show up"*) uses the fish as a metaphor for life-long disappointment, with label (1, 5, 5). Some models (e.g., `gpt-oss:120b`, `gpt-oss:20b`) correctly pick up the low valence and high arousal, but they underestimate the dominance by predicting 1 instead of 5. ASP does not change this much because LLMs are responsible for generating the VAD hypotheses.

Conclusions EmoLASP reduces MAE without significantly hurting agreement with human annotators in most cases. However, qualitative analysis reveals a key limitation of current LLM-based approaches: they struggle to capture extreme emotions in brief utterances or those relying on metaphorical language.

Limitations

Our study has several limitations. First, we evaluate EmoLASP on a single dataset (IEMOCAP). To the best of our knowledge, this is the only publicly available dataset with human VAD annotations at the dialogue level. While there are other datasets with VAD annotations, such as EmoBank (Buechel and Hahn, 2017) or NRC VAD (Mohammad, 2025), they are sentence-level or word-level datasets. In the IEMOCAP dataset, human annotators annotate the video data, which includes both audio and visual cues, but our models only have access to the text data. This mismatch may contribute to the disagreement between model predictions and human annotations, and it also means that our models are not fully leveraging the multimodal nature of the data. Also, the number of annotators per utterance varies across utterances, with the majority (8,666 out of 10,039) having only two annotators.

Furthermore, our analysis in Section 4 shows that the framework still struggles with very short utterances (e.g., *"Hmm"*) and figurative language. Addressing this issue likely requires changes to how hypotheses are generated, which depends on the language models, not just how they are selected by the ASP reasoner. In addition, the aggregation window k and number of hypotheses m are fixed to $k = 2$ and $m = 3$ in our experiment, which may not be optimal for all cases. Moreover, our PLMs use three independent classification heads over a 5-point Likert scale, which assumes independence across V, A, and D. Finally, all evaluated LLMs are open-source models available through Ollama, and we do not test closed-source models such as GPT-5, so the conclusions may not generalise to all LLMs.

Ethics Considerations

We use the IEMOCAP dataset (Busso et al., 2008) for research purposes only, consistent with the terms of its license. Our experiments use only the text transcriptions of utterances and do not process the audio or video recordings. The transcriptions provided by the dataset have been de-identified. In terms of demographics, the corpus consists of acted dyadic dialogues in English, recorded in a single cultural and institutional setting (a US university drama department). The speakers are ten actors (five male, five female) whose demographic characteristics beyond gender are not documented in the original release.

Potential Risks Emotion recognition systems carry some risks. First, dimensional VAD predictors can be repurposed for affect-based advertising or surveillance without user consent, even though our motivating applications are empathetic dialogue and mental health support. Second, our qualitative analysis (Section 4) shows that most evaluated LLMs systematically compress predictions toward the middle of the VAD scale and miss extreme states conveyed through short or figurative utterances. In safety-critical settings such as mental health support, this could cause systems to underestimate distress in exactly the moments when accurate recognition matters most, and EmoLASP does not resolve this compression. Third, IEMOCAP consists of acted English dyadic dialogues from a single cultural setting, which limits generalisation to other populations and languages.

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A AI Assistants In Research Or Writing

We use AI assistants, including Claude and ChatGPT, for coding assistance, grammar checks and stylistic improvements.

B Extended Background

In this section, we provide more details about other related work on applying answer set programming (ASP) to affective computing. Galindo et al. (2020) introduced an E-friend chatbot for mental well-being that maintains a model of the user's emotion and mental state using logic rules. In their system, psychological theories such as the Ortony, Clore, and Collins (OCC) model (Ortony et al., 2022) are represented as ASP rules. The ASP reasoning module helps the chatbot decide on strategies such as asking questions or suggesting activities to improve the user's emotional state. Another example is the work by Brännström and Nieves (2022) on emotion-aware agent planning, where they formalise emotional dynamics as an action language and translate it to ASP for reasoning about how an agent's actions influence human emotions. Moreover, Eiter et al. (2023) also took advantage of weak constraints in ASP, similar to our approach, but in the context of generating counterfactual explanations in the visual question answering domain. This approach uses ASP to provide explanations given an image and a user query; in contrast, we use ASP to select among emotion hypotheses produced by a language model. They nevertheless highlight that ASP can be powerful for ensuring logical consistency and integrating human knowledge about emotions.

Moreover, LM-ASP pipelines have been explored in Natural Language Understanding (NLU) tasks, but to our knowledge, not yet for emotion recognition. For example, a common approach is to use LLMs to translate the problem description and user query into ASP syntax, then apply an ASP solver to perform reasoning tasks (Yang et al., 2023; Alviano et al., 2025). Another line of work uses LLMs to generate candidate continuations of a story, and ASP for filtering out illogical continuations (Nye et al., 2021). In handling dialogues, the LM-ASP combination has been used in the task-oriented chatbot domain (Rajasekharan et al., 2023; Zeng et al., 2024), where LLMs are used to extract knowledge from the dialogue, and ASP is executed to decide on the next action of the chatbot, such as recommending a restaurant or answering a question. However, that work is restricted to movie and restaurant recommendation domains and has not been applied to emotion understanding. Unlike pipelines that translate the full problem into ASP and let the solver do the heavy reasoning, EmoLASP uses ASP specifically for its choice rules and weak constraints with priorities, which let us encode preferences over LM-produced VAD hypotheses while still leveraging the language model for semantic interpretation.

In the ERC domain, several related works have used purely neural or neuro-symbolic approaches. Majumder et al. (2019) applied an RNN to track individual speaker states for emotion classification. Ghosal et al. (2019) presented a graph convolutional network (GCN) to model the inter-speaker dependency. Additionally, Yu et al. (2025) developed a graph neural network to simulate the emotional contagion process (Hatfield et al., 1993). Furthermore, to integrate knowledge beyond the conversation context, Li et al. (2023) utilised an external commonsense knowledge base to understand relations between two different concepts and hence infer the emotion class of an utterance from its context. Unlike these neural approaches that predict categorical emotion labels, EmoLASP targets VAD dimensions and uses ASP to enforce contextual consistency over LM-produced hypotheses, without requiring the extensive neural-network training that these methods rely on; such training is outside

the scope of our paper.

C Experiment Details

C.1 Licenses

Our code will be publicly released upon publication under the MIT License to allow reproducibility and future research. The dataset used in this paper, IEMOCAP (Busso et al., 2008), is shared for research purposes only.

C.2 Hyperparameters

Our experiments were conducted on a shared computing infrastructure equipped with NVIDIA V100, A100, and H200 GPUs. We used a single GPU per job. A total of 8 (models) $\times$ 2 (contexts: nohist, hist) $\times$ 5 (dialogue sessions) = 80 jobs were run.

When training PLMs, we set the learning rate to 2e-5, batch size to 16, max context length of 512, and train for 20 epochs. There are two PLMs: BERT has ~ 110 million parameters, and RoBERTa-large has ~ 355 million parameters. For each model, we ran 10 jobs (2 contexts $\times$ 5 dialogue sessions). We estimate the total running time to be approximately 10 hours for the two models.

For LLMs, we set the temperature to 0, and the number of VAD hypotheses m to 3. For ASP, we set the confidence threshold τ to 0.25 and the aggregation window size k to 2. We use six LLMs with sizes ranging from 3 billion to 120 billion parameters. For each model, we ran 10 jobs (2 contexts $\times$ 5 dialogue sessions). The total running time is estimated to be approximately 170 hours for all six LLMs.

Why $\tau = 0.25$? Specifically, with $m = 3$, let the highest probability for utterance u_i be $p_i^* = 0.7$ and assume the two other hypotheses have the same probability of 0.15 (highest uncertainty); the corresponding Shannon entropy is $E(p_i) = -0.7 \ln 0.7 - 0.15 \ln 0.15 - 0.15 \ln 0.15 \approx 0.82$. The confidence score is then $c_i = 1 - \frac{E(p_i)}{\ln m} = 1 - \frac{0.82}{\ln 3} \approx 0.25$. Therefore, setting $\tau = 0.25$ means that we apply ASP when the language model's best hypothesis has a probability lower than 0.7.

C.3 Prompt Templates

We provide the full prompt templates for LLM hypothesis generation in Figures 2 and 3. The only difference between the two prompts is that the `hist` prompt includes the dialogue context, while the `nohist` prompt does not. The 5-point Likert scale for VAD is based on the Self-Assessment Manikin (SAM) (Bradley and Lang, 1994, 1999).

```
Analyze the emotion expressed in the following
     text and provide 3 plausible Valence,
    Arousal, and Dominance (VAD) hypotheses,
    ranked from most likely (H1) to least
    likely (H3).

Each score must be an integer from 1 to 5 (
    inclusive). Use only whole numbers 1, 2,
    3, 4, or 5.

**Valence (V)** - happiness vs unhappiness:
- 1 = Complete unhappiness, annoyance,
    unsatisfaction, melancholia, or boredom.
- 2 = Mostly negative, low pleasure.
- 3 = Neutral; neither clear happiness nor
    sadness.
- 4 = Mostly positive, moderate pleasure.
- 5 = Complete happiness, pleasure,
    satisfaction, contentment, or hope.

**Arousal (A)** - calm vs excited:
- 1 = Complete relaxation, calmness,
    sluggishness, dullness, sleepiness, or
    lack of excitement.
- 2 = Mostly calm, low energy.
- 3 = Neutral; neither calm nor excited.
- 4 = Mostly stimulated, moderate energy.
- 5 = Complete stimulation, excitement, frenzy,
     nervousness, or high arousal.

**Dominance (D)** - controlled vs in-control:
- 1 = Complete feeling of being controlled,
    influenced, cared-for, awed, submissive,
    or guided.
- 2 = Mostly submissive, low control.
- 3 = Neutral; neither controlling nor
    controlled.
- 4 = Mostly in-control, moderate dominance.
- 5 = Complete feeling in-control, influential,
     important, dominant, autonomous, or
    controlling.

Text: "<UTTERANCE>"

Return exactly 3 ranked hypotheses, one per
    line, with H1 the most likely and H3 the
    least likely:
H1: V=X, A=X, D=X
H2: V=X, A=X, D=X
H3: V=X, A=X, D=X
(X must be one of 1, 2, 3, 4, or 5)
Your output:
```

Figure 2: LLM hypothesis-generation prompt without dialogue context (`nohist`).

```
Analyze the emotion expressed in the current
    text based on the dialogue context and
    provide 3 plausible Valence, Arousal, and
    Dominance (VAD) hypotheses,
ranked from most likely (H1) to least likely (
    H3).

Each score must be an integer from 1 to 5 (
    inclusive). Use only whole numbers 1, 2,
    3, 4, or 5.

**Valence (V)** - happiness vs unhappiness:
- 1 = Complete unhappiness, annoyance,
    unsatisfaction, melancholia, or boredom.
- 2 = Mostly negative, low pleasure.
- 3 = Neutral; neither clear happiness nor
    sadness.
- 4 = Mostly positive, moderate pleasure.
- 5 = Complete happiness, pleasure,
    satisfaction, contentment, or hope.

**Arousal (A)** - calm vs excited:
- 1 = Complete relaxation, calmness,
    sluggishness, dullness, sleepiness, or
    lack of excitement.
- 2 = Mostly calm, low energy.
- 3 = Neutral; neither calm nor excited.
- 4 = Mostly stimulated, moderate energy.
- 5 = Complete stimulation, excitement, frenzy,
     nervousness, or high arousal.

**Dominance (D)** - controlled vs in-control:
- 1 = Complete feeling of being controlled,
    influenced, cared-for, awed, submissive,
    or guided.
- 2 = Mostly submissive, low control.
- 3 = Neutral; neither controlling nor
    controlled.
- 4 = Mostly in-control, moderate dominance.
- 5 = Complete feeling in-control, influential,
     important, dominant, autonomous, or
    controlling.

Dialogue Context:
Person A: <PRIOR UTTERANCE 1>
Person B: <PRIOR UTTERANCE 2>
...

Current Text: "<SPEAKER LABEL>: <UTTERANCE>"

Return exactly 3 ranked hypotheses, one per
    line, with H1 the most likely and H3 the
    least likely:
H1: V=X, A=X, D=X
H2: V=X, A=X, D=X
H3: V=X, A=X, D=X
(X must be one of 1, 2, 3, 4, or 5)
Your output:
```

Figure 3: LLM hypothesis-generation prompt with dialogue context (`hist`). All prior same-dialogue turns are included, each prefixed with its `Person A` or `Person B` speaker label.

Category	Model	MAE			Krippendorff's α		
		nohist	hist	handicap	nohist	hist	handicap
< 10b	llama3.2:3b	$\mathbf{-0.049}^{***}$	$\mathbf{-0.062}^{***}$	$\mathbf{-0.174}^{***}$	-0.002	$+0.007$	$\mathbf{+0.024}^{**}$
	gemma3:4b	-0.014	$\mathbf{-0.075}^{**}$	$\mathbf{-0.093}^{***}$	-0.029^{**}	-0.010	-0.016
20-30b	gpt-oss:20b	$\mathbf{-0.078}^{***}$	$\mathbf{-0.091}^{***}$	$\mathbf{-0.062}^{**}$	$+0.002$	-0.002	-0.036^{***}
	gemma3:27b	$+0.002$	$+0.001$	$+0.022$	-0.061^{***}	-0.047^{***}	-0.079^{***}
> 60b	llama3.3:70b	$\mathbf{-0.153}^{***}$	$\mathbf{-0.094}^{***}$	$\mathbf{-0.097}^{***}$	$+0.000$	$+0.000$	-0.025^{**}
	gpt-oss:120b	$\mathbf{-0.158}^{***}$	$\mathbf{-0.133}^{***}$	$\mathbf{-0.096}^{***}$	-0.004	-0.004	-0.039^{***}
PLM	bert	$\mathbf{-0.015}^{***}$	-0.009	$+0.030$	$\mathbf{+0.006}^{*}$	-0.002	-0.012
	roberta-large	$\mathbf{-0.014}^{**}$	-0.005	$+0.051^{*}$	$\mathbf{+0.004}^{*}$	-0.003	-0.029^{*}

Table 2: Paired t-test of **No Reasoner** vs. **(Ours) EmoLASP** on the IEMOCAP dataset. Each cell reports $\Delta = \overline{\text{EmoLASP}} - \overline{\text{No Reasoner}}$, the mean score difference over the paired units. For MAE a negative Δ favours EmoLASP; for α a positive Δ favours EmoLASP. Significance is from a two-sided paired t-test: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. **Bold** marks a statistically significant improvement by EmoLASP. Columns `nohist`/`hist` compare the two approaches (No Reasoner vs. EmoLASP) under the same context; `handicap` pits the strongest no-reasoner setting (No Reasoner+hist) against EmoLASP stripped of its history (EmoLASP+nohist), so any win there cannot be attributed to dialogue context. Config: num previous turns k=2, num hypotheses m=3, confidence threshold ≥ 0.25 .

D Results

D.1 Paired t-tests

Table 2 shows the full results of paired t-tests for Table 1. For MAE, out of 24 comparisons, 16 show a significant improvement of EmoLASP over the baseline, 7 show no significant difference, and only 1 shows a significant decrease. For Krippendorff's α, out of 24 comparisons, 3 show a significant improvement of EmoLASP over the baseline, 13 show no significant difference, and 8 show a significant decrease.

D.2 Qualitative Analysis

Table 3 shows the five highest-error cases by MAE where all LLMs fail to predict accurate VAD scores even after applying ASP. In this analysis, we focus on LLMs rather than PLMs, because it is unfair to compare LLMs directly with PLMs that have been fine-tuned on the dataset.

#	Context Summary	Current Utterance	No Reasoner (hist)	EmoLASP (hist)	Label (V, A, D)
1	**Summary:** Person B tells Person A that Person C (the father) is still obsessed with missing Larry. Person B insists it's dishonest to pretend Larry is alive and reveals he wants to marry Annie, who is Larry's former girlfriend, but Person A fears this will devastate Person C and disrupt the family and business. **Two prior turns:** Person B: The business? The business doesn't inspire me. Person A: Must you be inspired?	Person B: Yeah, I'd like one hour a day. If I have to grub for money all day long, I'd like to go home to something beautiful. I'd like a family. I'd like some kids.	gemma3:4b: (4.00, 4.00, 4.00) gemma3:27b: (4.00, 2.00, 3.00) gpt-oss:20b: (5.00, 3.00, 3.00) gpt-oss:120b: (4.00, 2.00, 2.00) llama3.2:3b: (4.00, 3.00, 4.00) llama3.3:70b: (4.00, 3.00, 4.00)	gemma3:4b: (4.00, 4.00, 4.00) gemma3:27b: (4.00, 2.00, 3.00) gpt-oss:20b: (5.00, 3.00, 3.00) gpt-oss:120b: (3.00, 3.00, 2.00) llama3.2:3b: (4.00, 3.00, 3.00) llama3.3:70b: (4.00, 3.00, 4.00)	(1.00, 4.50, 5.00)
2	**Summary:** Person A and Person B, a married couple on a beach at night waiting for grunion, argue about unmet expectations in their marriage and past disappointments but then reassure each other of their commitment. They share a quiet, intimate moment, and decide to stay together in that spot, hoping the fish might come. **Two prior turns:** Person A: Or not. Person B: Or not.	Person A: Hmm.	gemma3:4b: (2.00, 4.00, 3.00) gemma3:27b: (2.00, 2.00, 2.00) gpt-oss:20b: (2.00, 2.00, 2.00) gpt-oss:120b: (2.00, 2.00, 2.00) llama3.2:3b: (3.00, 3.00, 4.00) llama3.3:70b: (3.00, 2.00, 3.00)	gemma3:4b: (2.00, 4.00, 3.00) gemma3:27b: (3.00, 2.00, 3.00) gpt-oss:20b: (2.00, 2.00, 2.00) gpt-oss:120b: (3.00, 2.00, 3.00) llama3.2:3b: (3.00, 2.00, 3.00) llama3.3:70b: (3.00, 2.00, 3.00)	(5.00, 4.00, 0.50)
3	**Summary:** Person A and Person B, a married couple on a beach waiting to see fish that never seem to appear, argue about disappointment and unmet expectations in their lives and relationship, then gradually reassure each other that despite feeling let down by how things have turned out, they still want to be together. **Two prior turns:** Person B: It's not champagne. Person A: I guess we don't need glasses.	Person B: Are you cold, huh? Do you want to go home?	gemma3:4b: (2.00, 4.00, 3.00) gemma3:27b: (3.00, 2.00, 4.00) gpt-oss:20b: (4.00, 2.00, 3.00) gpt-oss:120b: (4.00, 2.00, 3.00) llama3.2:3b: (2.00, 2.00, 2.00) llama3.3:70b: (3.00, 2.00, 4.00)	gemma3:4b: (2.00, 4.00, 3.00) gemma3:27b: (3.00, 2.00, 4.00) gpt-oss:20b: (4.00, 2.00, 3.00) gpt-oss:120b: (3.00, 3.00, 3.00) llama3.2:3b: (2.00, 2.00, 2.00) llama3.3:70b: (3.00, 2.00, 4.00)	(4.50, 4.50, 1.00)
4	**Summary:** Person A and Person B are arguing on a beach because Person B is excited about seeing grunion fish while Person A is frustrated, dismisses it as PR hype, insists the outing isn't really about the fish, and complains that they never actually see them. **Two prior turns:** Person B: We'll see them this year. Person A: No, we won't. It's pointless. It's like waiting up to see Santa Clause.	Person A: God I feel as though my entire life is going to be spent standing on the beach with my eyes wide open and my hands clasped expectantly waiting for the fish to show up.	gemma3:4b: (2.00, 4.00, 3.00) gemma3:27b: (2.00, 3.00, 2.00) gpt-oss:20b: (2.00, 4.00, 1.00) gpt-oss:120b: (1.00, 3.00, 1.00) llama3.2:3b: (4.00, 5.00, 2.00) llama3.3:70b: (2.00, 4.00, 1.00)	gemma3:4b: (2.00, 4.00, 3.00) gemma3:27b: (2.00, 3.00, 2.00) gpt-oss:20b: (1.00, 3.00, 2.00) gpt-oss:120b: (2.00, 4.00, 2.00) llama3.2:3b: (4.00, 5.00, 2.00) llama3.3:70b: (2.00, 4.00, 1.00)	(1.00, 5.00, 5.00)
5	This is the first turn in the conversation; there are no previous turns.	Person A: Look at this, goose bumps .	gemma3:4b: (4.00, 3.00, 4.00) gemma3:27b: (4.00, 4.00, 3.00) gpt-oss:20b: (4.00, 5.00, 3.00) gpt-oss:120b: (4.00, 5.00, 3.00) llama3.2:3b: (5.00, 5.00, 5.00) llama3.3:70b: (5.00, 5.00, 4.00)	gemma3:4b: (4.00, 3.00, 4.00) gemma3:27b: (4.00, 4.00, 3.00) gpt-oss:20b: (4.00, 5.00, 3.00) gpt-oss:120b: (4.00, 5.00, 3.00) llama3.2:3b: (5.00, 5.00, 5.00) llama3.3:70b: (5.00, 5.00, 4.00)	(3.00, 1.50, 2.50)

Table 3: Turns where **No reasoner** (hist) and **EmoLASP** (hist) predictions both have high error.