Transfer Learning in Conversational Analysis through Reusing Preprocessing Data as Supervisors

Joshua Yee Kim
University of Sydney
josh.kim@sydney.edu.au

Tongliang Liu
University of Sydney
tongliang.liu@sydney.edu.au

Kalina Yacef
University of Sydney
kalina.yacef@sydney.edu.au

Abstract

Conversational analysis systems are trained using noisy human labels and often require heavy preprocessing during multi-modal feature extraction. Using noisy labels in single-task learning increases the risk of over-fitting. Auxiliary tasks could improve the performance of the primary task learning during the same training – this approach sits in the intersection of transfer learning and multi-task learning (MTL). In this paper, we explore how the preprocessed data used for feature engineering can be re-used as auxiliary tasks, thereby promoting the productive use of data. Our main contributions are: (1) the identification of sixteen beneficially auxiliary tasks, (2) studying the method of distributing learning capacity between the primary and auxiliary tasks, and (3) studying the relative supervision hierarchy between the primary and auxiliary tasks. Extensive experiments on IEMOCAP and SEMAINE data validate the improvements over single-task approaches, and suggest that it may generalize across multiple primary tasks.

1 Introduction

The sharp increase in uses of video-conferencing creates both a need and an opportunity to better understand these conversations (Kim et al., 2019a). In post-event applications, analyzing conversations can give feedback to improve communication skills (Hoque et al., 2013; Naim et al., 2015). In real-time applications, such systems can be useful in legal trials, public speaking, e-health services, and more (Poria et al., 2019; Tanveer et al., 2015).

Analyzing conversations requires both human expertise and a lot of time. However, to build automated analysis systems, analysts often require a training set annotated by humans (Poria et al., 2019). The annotation process is costly, thereby limiting the amount of labeled data. Moreover, third-party annotations on emotions are often noisy. Deep networks coupled with limited noisy labeled data increases the chance of overfitting (James et al., 2013; Zhang et al., 2016). Could data be used more productively?

From the perspective of feature engineering to analyze video-conferences, analysts often employ pre-built libraries (Baltrušaitis et al., 2016; Vokaturi, 2019) to extract multimodal features as inputs to training. This preprocessing phase is often computationally heavy, and the resulting features are only used as inputs. In this paper, we investigate how the preprocessed data can be re-used as auxiliary tasks which provide inductive bias through multiple noisy supervision (Caruana, 1997; Lipton et al., 2015; Ghosn and Bengio, 1997) and consequently, promoting a more productive use of data. Specifically, our main contributions are (1) the identification of beneficially auxiliary tasks, (2) studying the method of distributing learning capacity between the primary and auxiliary tasks, and (3) studying the relative supervision hierarchy between the primary and auxiliary tasks. We demonstrate the value of our approach through predicting emotions on two publicly available datasets, IEMOCAP (Busso et al., 2008) and SEMAINE (McKeown et al., 2011).

2 Related Works and Hypotheses

Multitask learning has a long history in machine learning (Caruana, 1997). In this paper, we focus on transfer learning within MTL, a less commonly discussed subfield within MTL (Mordan et al., 2018). We are concerned with the performance on one (primary) task – the sole motivation of adding auxiliary tasks is to improve the primary task performance.

In recent years, this approach has been gaining attention in computer vision (Yoo et al., 2018; Farhia, 2016; Yang et al., 2018; Mordan et al., 2018; Sadoughi and Busso, 2018), speech recognition (Krishna et al., 2018; Chen and Mak, 2015; Tao and Busso, 2020; Bell et al., 2016; Chen et al.,
The drawback of adding multiple tasks increases the risk of negative transfer (Torrey and Shavlik, 2010; Lee et al., 2016, 2018; Liu et al., 2019; Simm et al., 2014), which leads to many design considerations. Three of such considerations are, identifying (a) what tasks are beneficial, (b) how much of the model parameters to share between the primary and auxiliary tasks, and (c) whether we should prioritize primary supervision by giving it a higher hierarchy than the auxiliary supervision.

In contrast with previous MTL works, our approach (a) identifies sixteen beneficially auxiliary targets, (b) dedicates a primary-specific branch within the network, and (c) investigates the efficacy and generalization of prioritizing primary supervision across eight primary tasks.

Since our input representation is fully text-based, we dive deeper into MTL model architecture designs in NLP. Søgaard and Goldberg (2016) found that lower-level tasks like part-of-speech tagging, are better kept at the lower layers, enabling the higher-level tasks like Combinatory Categorical Grammar tagging to use these lower-level representations. In our approach, our model hierarchy is not based on the difficulty of the tasks, but more simply, we prioritize the primary task. Regarding identifying auxiliary supervisors in NLP, existing works have included tagging the input text (Zalmout and Habash, 2019; Yang et al., 2019; Søgaard and Goldberg, 2016). Text classification with auxiliary supervisors have included research article classification (Du et al., 2017; Yousif et al., 2018), and tweet classification (Arora et al., 2019).

Multimodal analysis of conversations has been gaining attention in deep learning research (Porria et al., 2019). The methods in the recent three years have been intelligently fusing numeric vectors from the text, audio, and video modalities before feeding it to downstream layers. This approach is seen in MFN (Zadeh et al., 2018a), MARN (Zadeh et al., 2018b), CMN (Hazarika et al., 2018b), ICON (Hazarika et al., 2018a), DialogueRNN (Majumder et al., 2019), and M3ER (Mittal et al., 2020). Our approach is different in two ways. (1) Our audio and video information is encoded within text before feeding only the text as input. Having only text as input has the benefits of interpretability, and the ability to present the conversational analysis on paper (Kim et al., 2019b), similar to how the linguistics community performs manual conversational analysis using the Jefferson transcription system (Jefferson, 2004), where the transcripts are marked up with symbols indicating how the speech was articulated. (2) Instead of using the audio and video information as only inputs, we demonstrate how to use multimodal information in both input and as auxiliary supervisors.

**Hypothesis H1:** The introduced set of auxiliary supervision features improves primary task performance. We introduce and motivate the full set of sixteen auxiliary supervisions, all based on existing literature: these are grouped into four families, each with four auxiliary targets. The four families are (1) facial action units, (2) prosody, (3) historical labels, and (4) future labels:

1. Facial action units, from the facial action coding system identifies universal facial expressions of emotions (Ekman, 1997). Particularly, AU 05 (upper lid raiser), 17 (chin raiser), 20 (lip stretcher), 25 (lips part) have been shown to be useful in detecting depression (Yang et al., 2016a; Kim et al., 2019b) and rapport-building (Kim et al., 2021).
2. Prosody, the tone of voice – happiness, sadness, anger, and fear – can project warmth and attitudes (Hall et al., 2009), and has been used as inputs in emotions detection (Garcia-Garcia et al., 2017).

3 and 4 Using features at different historical time-points is a common practice in statistical learning, especially in time-series modelling (Christ et al., 2018). Lastly, predicting future labels as auxiliary tasks can help in learning (Caruana et al., 1996; Cooper et al., 2005; Trinh et al., 2018; Zhu et al., 2020; Shen et al., 2020). We propose using historical and future (up to four talkturns ago or later) target labels as auxiliary targets.

Given that we are extracting actions and prosody families as inputs, we propose to explore whether they can be reused as supervisors (see Fig. 1). Our hypothesis H1 is that re-using them as auxiliary supervision improves primary task performance. This is related to using hints in the existing MTL literature, where the auxiliary tasks promote the learning of the feature (Cheng et al., 2015; Yu and Jiang, 2016).

**Hypothesis H2:** When the primary branch is given maximum learning capacity, it would not be outperformed by models with primary branch having less than the maximum learning capacity. Deeper models with higher learning ca-
Figure 1: Reusing components (dotted lines) of the feature engineering process as auxiliary targets (in blue). The MONAH framework (Kim et al., 2021) is introduced in section 4.2.

Pacility produce better results (Huang et al., 2019; Nakkiran et al., 2019; Menegola et al., 2017; Blumberg et al., 2018; Romero et al., 2014). Also, since the auxiliary branch is shared with the primary supervision, the auxiliary capacity should be limited to improve primary task performance (Wu et al., 2020) because limiting the auxiliary capacity will force the branch to learn common knowledge (instead of auxiliary specific knowledge) across the auxiliary tasks (Arpit et al., 2017). Therefore, given a fixed learning capacity budget, our hypothesis H2 implies that we should allocate the maximum learning capacity to the primary branch because we care only about the primary task performance.

Hypothesis H3: Auxiliary supervision at the lower hierarchy yields better primary task performance as compared to flat-MTL. Having the auxiliary tasks at the same supervisory level as the primary task is inherently sub-optimal because we care only about the performance of the primary task (Mordan et al., 2018). Information at the lower hierarchy learns basic structures that are easy to transfer, whilst upper hierarchy learns more semantic information that is less transferable (Zeiler and Fergus, 2014). Therefore, we propose that the auxiliary supervision to be at the lower hierarchy than the primary supervision.

3 Model Architecture

3.1 Flat-MTL Hierarchical Attention Model

We start with an introduction of the Hierarchical Attention Model (HAN) (Yang et al., 2016b). We chose HAN because of its easy interpretability as it only uses single-head attention layers. There are four parts to the HAN model, (1) text input, (2) word encoder, (3) talkturn encoder, and (4) the predictor. In our application, we perform our predictions at the talkturn-level for both IEMOCAP and SEMAINE. For notation, let $s_t$ represent the $i$-th talkturn and $w_{it}$ represent the $t$-th word in the $i$-th talkturn. Each single talkturn can contain up to $T$ words, and each input talkturn can contain up to $L$ past talkturns to give content context (see section 4.2).

Given a talkturn of words, we first convert the words into vectors through an embedding matrix $W_e$, and the word selection one-hot vector, $w_{it}$. The word encoder comprises of bidirectional GRUs (Bahdanau et al., 2014) and a single head attention to aggregate word embeddings into talkturn embeddings. Given the vectors $x_{it}$, the bidirectional GRU reads the words from left to right as well as from right to left (as indicated by the direction of the GRU arrows) and concatenates the two hidden states together to form $h_{it}$. We then aggregate the hidden states into one talkturn embedding through the attention mechanism. $u_{it}$ is the hidden state from feeding $h_{it}$ into a one-layer perceptron (with weights $W_u$ and biases $b_u$). The attention weight $(a_{it})$ given to $u_{it}$ is the softmax normalized weight of the similarity between itself ($u_{it}$) and $u_{aw}$, which are all randomly initialized and learnt jointly.

$$x_{it} = W_e w_{it}, t \in [1, T].$$
$$\overrightarrow{h}_{it} = \overrightarrow{GRU}(x_{it}), t \in [1, T].$$
$$\overleftarrow{h}_{it} = \overleftarrow{GRU}(x_{it}), t \in [T, 1].$$
$$h_{it} = (\overrightarrow{h}_{it}, \overleftarrow{h}_{it}).$$
$$u_{it} = \text{relu}(W_u h_{it} + b_u).$$
\[ s_i = \sum_t \alpha_{it} u_{it}, \]
\[ \alpha_{it} = \frac{\exp(u_{it}^\top u_w)}{\sum_t \exp(u_{it}^\top u_w)}. \]

With the current and past talkturn embeddings (content context, to discuss in section 4.2), the talkturn encoder aggregates them into a single talkturn representation \( v \) in a similar fashion, as shown below.

\[ \vec{h}_i = \overrightarrow{\text{GRU}}(s_i), i \in [1, L]. \]
\[ \overrightarrow{h}_i = \overleftarrow{\text{GRU}}(s_i), i \in [L, 1]. \]
\[ h_i = (\vec{h}_i, \overrightarrow{h}_i). \]
\[ u_i = \text{relu}(W_a h_i + b_a). \]
\[ \alpha_i = \frac{\exp(u_{it}^\top u_{aw})}{\sum_t \exp(u_{it}^\top u_{aw})}. \]
\[ v = \sum_i \alpha_i u_i. \]

The simplest way of adding the sixteen auxiliary task predictors would be to append them to where the primary task predictor is, as illustrated in Fig. 2. That way, all predictors use the same representation \( v \). We refer to this architecture as flat-MTL, but we are unable to test \( \textbf{H2} \) and \( \textbf{H3} \) using this architecture. Therefore, we introduce HAN-ROCK next.

3.2 HAN-ROCK

We adapted\(^1\) the ROCK architecture (Mordan et al., 2018) which was built for Convolutional Neural Networks (LeCun et al., 1995) found in ResNet-SSD (He et al., 2016; Liu et al., 2016) to suit GRUs (Bahdanau et al., 2014) found in HAN (Yang et al., 2016b) (see Fig. 3). To study \( \textbf{H3} \), we bring the auxiliary task predictors forward (see Fig. 3), so that the back-propagation from the primary supervision is able to temper the back-propagation from the auxiliary supervision but not vice-versa. This also sets us up to study \( \textbf{H2} \). Each of the auxiliary tasks has its own talkturn encoder but shares one word encoder in the auxiliary branch (to keep the network small). Subscript \( a \) indicates whether the word encoder is for the primary or auxiliary branch:

\[ x_{it} = W_c w_{it}, t \in [1, T] \]
\[ \vec{h}_{ait} = \overrightarrow{\text{GRU}}_a(x_{it}), t \in [1, T], a \in \{ \text{pri, aux} \} \]
\[ \overrightarrow{h}_{ait} = \overleftarrow{\text{GRU}}_a(x_{it}), t \in [T, 1], a \in \{ \text{pri, aux} \} \]
\[ h_{ait} = (\vec{h}_{ait}, \overrightarrow{h}_{ait}) \]
\[ u_{ait} = \text{relu}(W_{aw} h_{ait} + b_{aw}) \]
\[ \alpha_{ait} = \frac{\exp(u_{ait}^\top u_{aw})}{\sum_t \exp(u_{ait}^\top u_{aw})} \]
\[ s_{ait} = \sum_t \alpha_{ait} u_{ait} \]

\(^1\)Implementation will be available at GitHub; Please see attached supplementary material during the review phase.
Each task has its own talkturn encoder. Subscript $b$ indicates which of the seventeen tasks – the primary talkturn task or one of the sixteen auxiliary tasks – is the talkturn encoder is dedicated to:

\[
\overrightarrow{h}_{abi} = \text{GRU}_{ab}(s_{ai}), i \in [1, L], a \in \{\text{pri}, \text{aux}\}, b \in \{\text{pri}, \text{aux1}, \text{aux2}, \ldots, \text{aux16}\}
\]

\[
\overleftarrow{h}_{abi} = \text{GRU}_{ab}(s_{ai}), i \in [L, 1], a \in \{\text{pri}, \text{aux}\}, b \in \{\text{pri}, \text{aux1}, \text{aux2}, \ldots, \text{aux16}\}
\]

\[
h_{abi} = (\overrightarrow{h}_{abi}, \overleftarrow{h}_{abi})
\]

\[
u_{abi} = \text{relu}(W_b h_{abi} + b_b)
\]

\[
\alpha_{abi} = \frac{\exp(v_{abi}^\top u_{b})}{\sum_i \exp(v_{abi}^\top u_{b})}
\]

\[
v_{ab} = \sum_i \alpha_{abi} v_{abi}
\]

The seventeen talkturn embeddings ($v_{ab}$) goes through a concatenation, then the single head attention, aggregating talkturn embeddings across seventeen tasks into one talkturn embedding for the primary task predictor. Subscript $c$ pertains to the fusion module.

\[
\text{concatenation: } v_c = (v_{ab}), a \in \{\text{pri}, \text{aux}\}, b \in \{\text{pri}, \text{aux1}, \text{aux2}, \ldots, \text{aux16}\}
\]

\[
\text{attention: } \alpha_c = \frac{\exp(v_c^\top u_c)}{\sum_i \exp(v_c^\top u_i)}
\]

\[
\text{overall primary talkturn vector: } v = \sum_c \alpha_c v_c
\]

4 Experiments

4.1 Data and Primary Tasks

We validate our approach using two datasets with a total of eight primary tasks: the IEMOCAP (Busso et al., 2008) and the SEMAINE (McKeown et al., 2011) datasets. Both datasets are used in multimodal emotions detection research (Poria et al., 2011) datasets. Both datasets are used in multimodal emotions detection research (Poria et al., 2011). We divided the datasets into train, development, and test sets in an approximate 60/20/20 ratio such that the sets do not share any speaker (Appendix A.1 details the splits).

The target labels of the eight primary tasks are all at the talkturn-level. The four primary tasks of IEMOCAP consists of the four-class emotions classification (angry, happy, neutral, sad), and three regression problems – valence (1-negative, 5-positive), activation (1-calm, 5-excited), and dominance (1-weak, 5-strong). The four-class emotions classification target is common for IEMOCAP (Latif et al., 2020; Xia and Liu, 2015; Li et al., 2019; Hazarika et al., 2018b; Mittal et al., 2020). For SEMAINE, there are four regression problems – activation, intensity, power, valence. We use two standard evaluation metrics, mean absolute error (MAE), and 4-class weighted mean classification accuracy, MA(4).

4.2 Input

Multimodal feature extraction is computed using the MONAH framework (Kim et al., 2021). This framework uses a variety of pre-trained models to extract nine multimodal features, associated with the prosody of the speech and the actions of the speaker, and weaves them into a multimodal text narrative. We refer the reader to Kim et al. (2021) for the details and efficacy of the MONAH framework. The benefit of the created narrative is that it describes what is said together with how it is said for each talkturn, giving richer nonverbal context to the talkturn (see Fig. 4 for an example). Being fully text-based means that the analysis product can be printed out on paper, without the need for speakers nor monitors to replay the conversation on a computer.

In addition to nonverbal context, we concatenated a variable number of preceding talkturns to the current talkturn as content context. Content context has been proven to be useful in CMN (Hazarika et al., 2018b) and ICON (Hazarika et al., 2018a), DialogueRNN (Majumder et al., 2019). The content-context size is tuned as a hyperparameter. The resulting multimodal text narrative, consisting of both nonverbal and context context, is used as the sole input to the model.

4.3 Auxiliary Targets

We first clarify the method of extraction for the auxiliary families. The OpenFace algorithm (Baltrušaitis et al., 2016) is used to extract the four continuous facial action units (AU) – AU 05, 17, 20, 25. The Vokaturi algorithm (Vokaturi, 2019) is used to extract the four continuous dimensions in the tone of voice – happiness, sadness, anger, and fear. As for historical and future features, we simply look up the target label for the past four talkturns and future four talkturns. Any label that is not available (for example, the label four talkturns ago is not available for the third talkturn) is substituted with the next nearest non-missing label.

All auxiliary targets that reused the input features (actions and prosody) are converted into a percentile rank that has the range [0,1] using the
values from the train partition. This is a subtle but note-worthy transformation. When reusing an input as an auxiliary target, it would be trivial if the input can easily predict the target. For example, given the following MONAH transcript as input, "The woman sadly and slowly said no." It would be trivial to use a binary (quantized) auxiliary target of "was the tone sad?" because we would only be training the model to look for the word "sadly". However, if the auxiliary target is a percentile rank (less quantized) of the sadness in tone, then the presence of the word "sadly" increases the predicted rank, but the model could still use the rest of the nonverbal cues ("slowly") and what is being said ("no") to predict the degree of sadness. That way, representations learnt for the auxiliary tasks uses more of the input.

Percentile rank also has the convenient property of having the range [0,1]. We scaled the percentile ranks so that they all have the same range as the primary task (see appendix A.2 for transformation details). This ensures that if we assigned equal loss weights to all tasks, the contribution of every task is of the same order of magnitude (Gong et al., 2019; Hassani and Haley, 2019; Sener and Koltun, 2018).

4.4 Models, training, and hyperparameters tuning

The overall loss is calculated as the weighted average across all seventeen tasks: (1) we picked a random weight for the primary task from the range [0.50, 0.99]; this ensures that the primary task has the majority weight. (2) For the remaining weights (1 - primary weight), we allocated them to the sixteen auxiliary tasks by: (a) random, (b) linearly-normalized mutual information, or (c) softmax-normalized mutual information. (a) is self-explanatory. As for (b) and (c), mutual information has been shown to be the best predictor - compared to entropy and conditional entropy - of whether the auxiliary task would be helpful (Bjerva, 2017). We computed the mutual information (vector $m$) of each auxiliary variable with the primary target variable (Kraskov et al., 2004; Ross, 2014) using scikit-learn (Pedregosa et al., 2011). Then, we linearly-normalized or softmax-normalized $m$ to sum up to 1. Finally, we multiplied the normalized $m$ with the remaining weights from (2); this ensures that the primary weight and the sixteen auxiliary weight sum up to one. (a), (b), and (c) have ten trials each during hyper-parameters tuning.

Two variants of the HAN architectures are used (Fig 2 and 3). For hypotheses testing, we bootstrapped confidence intervals (appendix A.4).

5 Results and Discussion

The key takeaways are: (H1) The introduced set of auxiliary supervision improves primary task performance significantly in six of the eight primary tasks. (H2) Maximum learning capacity should be given to the primary branch as a default. (H3) HAN-ROCK is unlikely (in one of the eight tasks) to degrade primary task performance significantly, and sometimes significantly improves it (in four of the eight tasks).

(H1): To test H1 (whether the introduced set of auxiliary supervision improves primary task performance), we first train the model with all sixteen auxiliary targets (from families: actions, prosody, historical, and future). Then, to differentiate the effect from the historical and future supervision, we set the loss weights from historical and future targets to be zero; effectively, there is only supervision from eight auxiliary targets (actions and prosody). Lastly, for the baseline model (no auxiliary supervision), we set the loss weights from all sixteen auxiliary targets to zero.

Given auxiliary supervision, the model significantly outperforms the baseline of not having auxiliary supervision in six out of the eight primary tasks (Table 1). Comparing the baseline model with the model with two auxiliary target families, they significantly outperformed the baseline model in five out of eight primary tasks. The addition of two auxiliary target families (historical and future labels) sometimes significantly improved primary task performance (valence in IEMOCAP), but it also sometimes significantly made it worse (activation and intensity in SEMAINE). This shows that the value of auxiliary tasks, and the associated risk of negative transfer, depends on the auxiliary task.

(H2): To test H2 (whether maximum learning
Table 1: H1 Results. *: the model performance has a statistically significant difference with the baseline model. a: action, p: prosody, h: historical labels, f: future labels.

| Aux. Target | IEMOCAP | SEMAINE |
|-------------|---------|---------|
|             | Classif. MA(4) | Val. MAE | Act. MAE | Dom. MAE | Act. MAE | Int. MAE | Pow. MAE | Val. MAE |
| None (Baseline) | 0.625 | 0.527 | 0.518 | 0.667 | 0.194 | 0.238 | 0.170 | 0.177 |
| ap | 0.715* | 0.538 | 0.507 | 0.600* | 0.184* | 0.218* | 0.167* | 0.178 |
| aphf | 0.706* | 0.497* | 0.504 | 0.587* | 0.187 | 0.231 | 0.165* | 0.169 |

Table 2: H2 Results. *: the model performance has a statistically significant difference with the baseline model (P = 256). ^: Assigning 1 GRU to the auxiliary task talkturn encoder yields a statistically significant difference with assigning 0 GRU.

| Pri. GRU | IEMOCAP | SEMAINE |
|----------|---------|---------|
|          | Classif. MA(4) | Val. MAE | Act. MAE | Dom. MAE | Act. MAE | Int. MAE | Pow. MAE | Val. MAE |
| 256 (Baseline) | 0.715^ | 0.538 | 0.507 | 0.587^ | 0.187 | 0.231 | 0.165^ | 0.169^ |
| 192 | 0.736 | 0.509 | 0.518 | 0.604 | 0.187 | 0.228 | 0.165 | 0.184^ |
| 128 | 0.711 | 0.537 | 0.512 | 0.597 | 0.189 | 0.216 | 0.176* | 0.196* |
| 64 | 0.687 | 0.540 | 0.507 | 0.593 | 0.191 | 0.234 | 0.167 | 0.192* |
| 1 | 0.656 | 0.554 | 0.509 | 0.599 | 0.190 | 0.229 | 0.168* | 0.191* |

capacity should be given to the primary branch), we let P represent the number of GRU assigned to the primary talkturn encoder, and A represent the number of GRU assigned to each of the sixteen auxiliary talkturn encoder. We constrained P + A to be equal to 257. During our experiments, we set P to 1, 64, 128, 192, and 256. We set 256 as the baseline model because it is the maximum learning capacity we can give to the primary branch while giving 1 GRU (= 257 – 256) to each of the sixteen auxiliary talkturn encoders.

In all primary tasks, the baseline model of assigning 256 GRUs to the primary branch is not significantly outperformed by models that assigned 1, 64, 128, 192 GRUs (Table 2). Generally, the performance decreased as the number of GRUs assigned to the primary talkturn encoder decreased from 256 to 1. We observed significantly worse performance in two out of eight tasks – in power and valence in SEMAINE. Also, assigning 256 GRU to the primary talkturn encoders and 1 to each of the sixteen auxiliary talkturn encoders yields the smallest model, and thus trains the fastest. Therefore, we recommend that the maximum capacity be given to the primary branch as a default.

That said, the presence of an auxiliary branch is still important. The baseline of H1 (no auxiliary supervision, Table 1) can be approximated as P=256 + 16 × 1, A=0 . We compared the former to the baseline in Table 2, and found that four out of eight primary tasks have significant improvements by changing the number of talkturn encoders assigned to each auxiliary task from zero to one.

(H3): To test H3 (whether auxiliary supervision should be given a lower hierarchy), we compare the results from the flat-MTL HAN architecture (baseline) against the HAN-ROCK architecture (Table 3). Placing auxiliary supervision at the lower hierarchy significantly improves primary task performance in four out of eight tasks. In only one out of eight tasks (power in SEMAINE), auxiliary supervision significantly degrades primary task performance. Further improvements are possible through the fusion module with future research.

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2As opposed to assigning 1 GRU to the primary talkturn encoder and 256 GRU to each of the sixteen auxiliary encoder.

3Same model architecture except that the loss weights of all auxiliary tasks are zero.
Table 3: H3 Results. *: the model performance has a significant difference with the baseline.

| Hierarchy      | IEMOCAP |         | SEMAINE |         |
|----------------|---------|---------|---------|---------|
|                | Classif. | Val. | Act. | Dom. | Act. | Int. | Pow. | Val. |
| Flat (Baseline)| MA(4)   | MAE   | MAE  | MAE  | MAE  | MAE  | MAE  | MAE  |
|                | 0.699   | 0.520 | 0.526| 0.606| 0.183| 0.164| 0.185|      |
| HAN-ROCK       |         |       |      |      |      |      |      |      |
|                | 0.715   | 0.538 | 0.507*| 0.600*| 0.184| 0.218*| 0.167*| 0.178*|

Table 4: Class-wise classification F1 score on IEMOCAP. Baseline (challenger) refers to HAN-Rock architecture under the three hypotheses. *: the challenger performance has a statistically significant difference with the baseline model.

| Distribution | H1 | H2 | H3 | SoTA |
|--------------|----|----|----|------|
|              | Baseline | Challenger | Baseline | Challenger |
|              | Aux | Auxiliary target: | Pri | Auxiliary target: | Pri |
|              | GRU: | aphpf | GRU: | HAN ROCK |
| Label        |     | None | 256 | Flat |
| Sad          | 1,084 | 0.573 | 0.689* | 0.699 | 0.591* | 0.674 | 0.704* | 0.775 |
| Anger        | 1,103 | 0.531 | 0.683 | 0.752 | 0.672* | 0.657 | 0.720* | 0.862 |
| Happy        | 1,636 | 0.772 | 0.784 | 0.776 | 0.754* | 0.804 | 0.806 | 0.862 |
| Neutral      | 1,708 | 0.664 | 0.636 | 0.688 | 0.627* | 0.645 | 0.631 | 0.745 |

5.1 Class-wise Performance and SoTA

Generally, we found that all hypotheses effects are stronger in lower resource labels (sad and anger, Table 4). We also present the performance of M3ER (Mittal et al., 2020), a previous state-of-the-art (SoTA) approach. We do not expect the performance of our text-only input to match the SoTA approach, which is confirmed in Table 4. By fusing numerical vectors from the three modalities prevalent in SoTA approaches (Zadeh et al., 2018a,b; Hazarika et al., 2018b,a; Majumder et al., 2019; Mittal et al., 2020), the inputs are of a much higher granularity as compared to our approach of describing the multimodal cues using discrete words. Although the text-based input is likely to constrain model performance, the multimodal transcription could be helpful for a human to analyze the conversation, we could also overlay the model perspective on the multimodal transcription to augment human analysis (see Appendix A.5).

6 Conclusion

We proposed to re-use feature engineering preprocessing data as auxiliary tasks to improve performance and transfer learning. Three hypotheses were tested. The experimental results confirm H1 – Introducing our set of sixteen auxiliary supervisors resulted in better performance in most primary tasks. For H2, maximum learning capacity should be given to the primary branch. Lastly, for H3, placing the auxiliary supervision in a lower hierarchy is unlikely to hurt performance significantly, and it sometimes significantly improves performance. This is encouraging news for multi-modal conversational analysis systems as we have demonstrated how pre-processed data can be used twice to improve performance, once as inputs, and again as auxiliary tasks.

The first limitation of our paper is that the solutions are evaluated on eight tasks in the conversational analysis domain, and it is not clear if these would generalize outside of this domain. The second limitation is that we have evaluated on HAN, but not on other network architectures.

A challenge to be addressed is the apriori selection of the auxiliary targets. Future research could investigate targets selection, including how to use a much larger range of auxiliary targets, how to decide the optimum number of auxiliary targets, and whether it is possible to perform these automatically.
References

Udit Arora, William Scott Paka, and Tanmoy Chakraborty. 2019. Multitask learning for blacklist market tweet detection. In Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, pages 127–130.

Devansh Arpit, Stanislaw Jastrzȩbski, Nicolas Ballas, David Krueger, Emmanuel Bengio, Maxinder S Kanwal, Tegan Maharaj, Asja Fischer, Aaron Courville, Yoshua Bengio, et al. 2017. A closer look at memorization in deep networks. In International Conference on Machine Learning, pages 233–242. PMLR.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2014. Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473.

Tadas Baltrušaitis, Peter Robinson, and Louis-Philippe Morency. 2016. Openface: an open source facial behavior analysis toolkit. In Applications of Computer Vision (WACV), 2016 IEEE Winter Conference on, pages 1–10. IEEE.

Peter Bell, Pawel Swietojanski, and Steve Renals. 2016. Multitask learning of context-dependent targets in deep neural network acoustic models. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 25(2):238–247.

James Bergstra and Yoshua Bengio. 2012. Random search for hyper-parameter optimization. The Journal of Machine Learning Research, 13(1):281–305.

Johannes Bjerva. 2017. Will my auxiliary tagging task help? estimating auxiliary tasks effectivity in multi-task learning. In Proceedings of the 21st Nordic Conference on Computational Linguistics, pages 216–220.

Stefano B Blumberg, Ryutaro Tanno, Iasonas Kokkinos, and Daniel C Alexander. 2018. Deeper image quality transfer: Training low-memory neural networks for 3d images. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pages 118–125. Springer.

Carlos Busso, Murtaza Bulut, Chi-Chun Lee, Abe Kazemzadeh, Emily Mower, Samuel Kim, Jeanette N Chang, Sungbok Lee, and Shrikanth S Narayanan. 2008. IEMOCAP: Interactive emotional dyadic motion capture database. Language resources and evaluation, 42(4):355.

Rich Caruana. 1997. Multitask learning. Machine learning, 28(1):41–75.

Rich Caruana, Shumeet Baluja, and Tom Mitchell. 1996. Using the future to "sort out" the present: Rankprop and multitask learning for medical risk evaluation. In Advances in neural information processing systems, pages 959–965.

Dongpeng Chen, Brian Mak, Cheung-Chi Leung, and Sunil Sivadas. 2014. Joint acoustic modeling of triphones and trigraphemes by multi-task learning deep neural networks for low-resource speech recognition. In 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 5592–5596. IEEE.

Dongpeng Chen and Brian Kan-Wing Mak. 2015. Multitask learning of deep neural networks for low-resource speech recognition. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 23(7):1172–1183.

Hao Cheng, Hao Fang, and Mari Ostendorf. 2015. Open-domain name error detection using a multitask ran. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 737–746.

Maximilian Christ, Nils Braun, Julius Neuffer, and Andreas W Kempa-Liehr. 2018. Time series feature extraction on basis of scalable hypothesis tests (tsfresh–a python package). Neurocomputing, 307:72–77.

Gregory F Cooper, Vijoy Abraham, Constantin F Aliferis, John M Aronis, Bruce G Buchanan, Richard Caruana, Michael J Fine, Janine E Janosky, Gary Livingston, Tom Mitchell, et al. 2005. Predicting dire outcomes of patients with community-acquired pneumonia. Journal of biomedical informatics, 38(5):347–366.

Yongping Du, Yunpeng Pan, and Junzhong Ji. 2017. A novel serial deep multi-task learning model for large scale biomedical semantic indexing. In 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pages 533–537. IEEE.

Rosenberg Ekman. 1997. What the face reveals: Basic and applied studies of spontaneous expression using the Facial Action Coding System (FACS). Oxford University Press, USA.

Anna Fariha. 2016. Automatic image captioning using multitask learning. In The Proceedings of Neural Information Processing Systems, volume 20, pages 11–20.

Jose Maria Garcia-Garcia, Victor MR Penichet, and Maria D Lozano. 2017. Emotion detection: a technology review. In Proceedings of the XVIII international conference on human computer interaction, pages 1–8.

Joumana Ghosn and Yoshua Bengio. 1997. Multi-task learning for black-box optimization. In Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining, pages 1487–1495.
Ting Gong, Tyler Lee, Cory Stephenson, Venkata Renduchintala, Suchismita Padhy, Anthony Ndirango, Goke Keskin, and Oguz H Elibol. 2019. A comparison of loss weighting strategies for multi-task learning in deep neural networks. *IEEE Access*, 7:141627–141632.

Judith A Hall, Debra L Roter, Danielle C Blanch, and Richard M Frankel. 2009. Observer-rated rapport in interactions between medical students and standardized patients. *Patient Education and Counseling*, 76(3):323–327.

Kaveh Hassani and Mike Haley. 2019. Unsupervised multi-task feature learning on point clouds. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 8160–8171.

Devamanyu Hazarika, Soujanya Poria, Rada Mihalcea, Erik Cambria, and Roger Zimmermann. 2018a. Icon: Interactive conversational memory network for multimodal emotion detection. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2594–2604.

Devamanyu Hazarika, Soujanya Poria, Amir Zadeh, Erik Cambria, Louis-Philippe Morency, and Roger Zimmermann. 2018b. Conversational memory network for emotion recognition in dyadic dialogue videos. In *Proceedings of the conference. Association for Computational Linguistics. North American Chapter. Meeting*, volume 2018, page 2122. NIH Public Access.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778.

Mohammed Hoque, Matthieu Courgeon, Jean-Claude Martin, Bilge Mutlu, and Rosalind W Picard. 2013. Mach: My automated conversation coach. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing*, pages 697–706.

Yanping Huang, Youlong Cheng, Ankur Bapna, Orhan Firat, Dehao Chen, Mia Chen, HyoukJoong Lee, Ji-quan Ngiam, Quoc V Le, Yonghui Wu, et al. 2019. Gpipe: Efficient training of giant neural networks using pipeline parallelism. In *Advances in neural information processing systems*, pages 103–112.

Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani. 2013. *An introduction to statistical learning*, volume 112. Springer.

Gail Jefferson. 2004. Glossary of transcript symbols with an introduction. *Pragmatics and Beyond New Series*, 125:13–34.

Joshua Y Kim, Rafael A Calvo, Kalina Yacef, and NJ Enfield. 2019a. A review on dyadic conversation visualizations-purposes, data, lens of analysis. *arXiv preprint arXiv:1905.00653*.

Joshua Y Kim, Greyson Y Kim, and Kalina Yacef. 2019b. Detecting depression in dyadic conversations with multimodal narratives and visualizations. In *Australasian Joint Conference on Artificial Intelligence*, pages 303–314. Springer.

Joshua Y Kim, Kalina Yacef, Greyson Y Kim, Chunfeng Liu, Rafael Calvo, and Silas CR Taylor. 2021. Monah: Multi-modal narratives for humans to analyze conversations. *arXiv preprint arXiv:2101.07339*.

Alexander Kraskov, Harald Stögbauer, and Peter Grassberger. 2004. Estimating mutual information. *Physical review E*, 69(6):066138.

Kalpesh Krishna, Shubham Toshniwal, and Karen Livescu. 2018. Hierarchical multitask learning for ctc-based speech recognition. *arXiv preprint arXiv:1807.06234*.

Siddique Latif, Rajib Rana, Sara Khalifa, Raja Jurdak, Julien Epps, and Björn Wolfgang Schuller. 2020. Multi-task semi-supervised adversarial autoencoding for speech emotion recognition. *IEEE Transactions on Affective Computing*.

Yann LeCun, Yoshua Bengio, et al. 1995. Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks*, 3361(10):1995.

Giwoong Lee, Eunho Yang, and Sung Hwang. 2016. Asymmetric multi-task learning based on task relatedness and loss. In *International Conference on Machine Learning*, pages 230–238.

Hae Beom Lee, Eunho Yang, and Sung Ju Hwang. 2018. Deep asymmetric multi-task feature learning. In *International Conference on Machine Learning*, pages 2956–2964. PMLR.

Yuanchao Li, Tianyu Zhao, and Tatsuya Kawahara. 2019. Improved end-to-end speech emotion recognition using self attention mechanism and multitask learning. In *Interspeech*, pages 2803–2807.

Zachary C Lipton, David C Kale, Charles Elkan, and Randall Wetzel. 2015. Learning to diagnose with lstm recurrent neural networks. *arXiv preprint arXiv:1511.03677*.

Shengchao Liu, Yingyu Liang, and Anthony Gitter. 2019. Loss-balanced task weighting to reduce negative transfer in multi-task learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 9977–9978.

Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, and Alexander C Berg. 2016. Ssd: Single shot multibox detector. In *European conference on computer vision*, pages 21–37. Springer.
Navonil Majumder, Soujanya Poria, Devamanyu Hazarika, Rada Mihalcea, Alexander Gelbukh, and Erik Cambria. 2019. Dialoguermn: An attentive rnn for emotion detection in conversations. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 6818–6825.

Gary McKeown, Michel Valstar, Roddy Cowie, Maja Pantic, and Marc Schroder. 2011. The semaine database: Annotated multimodal records of emotionally colored conversations between a person and a limited agent. *IEEE transactions on affective computing*, 3(1):5–17.

Afonso Menegola, Michel Formaniali, Ramon Pires, Flávia Vasques Bittencourt, Sandra Avila, and Eduardo Valle. 2017. Knowledge transfer for melanoma screening with deep learning. In 2017 *IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017)*, pages 297–300. IEEE.

Trisha Mittal, Uttaran Bhattacharya, Rohan Chandra, Aniket Bera, and Dinesh Manocha. 2020. M3er: Multiplicative multimodal emotion recognition using facial, textual, and speech cues. In *AAAI*, pages 1359–1367.

Taylor Mordan, Nicolas Thome, Gilles Henaff, and Matthieu Cord. 2018. Revisiting multi-task learning with rock: a deep residual auxiliary block for visual detection. In *Advances in Neural Information Processing Systems*, pages 1310–1322.

Iftekhar Naim, M Iftekhar Tanveer, Daniel Gildea, and Mohammed Ehsan Hoque. 2015. Automated prediction and analysis of job interview performance: The role of what you say and how you say it. In 2015 *11th IEEE international conference and workshops on automatic face and gesture recognition (FG)*, volume 1, pages 1–6. IEEE.

Preetum Nakkiran, Gal Kaplun, Yamini Bansal, Tristan Yang, Boaz Barak, and Ilya Sutskever. 2019. Deep double descent: Where bigger models and more data hurt. *arXiv preprint arXiv:1912.02292*.

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine learning in *Python*. *Journal of Machine Learning Research*, 12:2825–2830.

Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 1532–1543.

Soujanya Poria, Navonil Majumder, Rada Mihalcea, and Eduard Hovy. 2019. Emotion recognition in conversation: Research challenges, datasets, and recent advances. *IEEE Access*, 7:100943–100953.

Adriana Romero, Nicolas Ballas, Samira Ebrahimi Kazemi, Antoine Chassang, Carlo Gatta, and Yoshua Bengio. 2014. Fitnets: Hints for thin deep nets. *arXiv preprint arXiv:1412.6550*.

Brian C Ross. 2014. Mutual information between discrete and continuous data sets. *PloS one*, 9(2):e87357.

Najmeh Sadoughi and Carlos Busso. 2018. Expressive speech-driven lip movements with multitask learning. In *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018)*, pages 409–415. IEEE.

Ozan Sener and Vladlen Koltun. 2018. Multi-task learning as multi-objective optimization. In *Advances in Neural Information Processing Systems*, pages 527–538.

Wei Shen, Xiaohan He, Chuheng Zhang, Qiang Ni, Wanchun Dou, and Yan Wang. 2020. Auxiliary-task based deep reinforcement learning for participant selection problem in mobile crowdsourcing. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, pages 1355–1364.

Jaak Simm, Ildefons Magrans de Abril, and Masashi Sugiyama. 2014. Tree-based ensemble multi-task learning method for classification and regression. *IEICE TRANSACTIONS on Information and Systems*, 97(6):1677–1681.

Anders Sogaard and Yoav Goldberg. 2016. Deep multitask learning with low level tasks supervised at lower layers. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 231–235.

M Iftekhar Tanveer, Emy Lin, and Mohammed Hoque. 2015. Rhema: A real-time in-situ intelligent interface to help people with public speaking. In *Proceedings of the 20th International Conference on Intelligent User Interfaces*, pages 286–295.

Fei Tao and Carlos Busso. 2020. End-to-end audio-visual speech recognition system with multitask learning. *IEEE Transactions on Multimedia*.

Lisa Torrey and Jude Shavlik. 2010. Transfer learning. In *Handbook of research on machine learning applications and trends: algorithms, methods, and techniques*, pages 242–264. IGI global.

Trieu H Trinh, Andrew M Dai, Minh-Thang Luong, and Quoc V Le. 2018. Learning longer-term dependencies in rnns with auxiliary losses. *arXiv preprint arXiv:1803.00144*.

Vokaturi. 2019. *Vokaturi Overview*.

Sen Wu, Hongyang R Zhang, and Christopher Ré. 2020. Understanding and improving information transfer in multi-task learning. *arXiv preprint arXiv:2005.00944*. 


Rui Xia and Yang Liu. 2015. A multi-task learning framework for emotion recognition using 2d continuous space. *IEEE Transactions on affective computing*, 8(1):3–14.

Jianliang Yang, Yuenan Liu, Minghui Qian, Chenghua Guan, and Xiangfei Yuan. 2019. Information extraction from electronic medical records using multitask recurrent neural network with contextual word embedding. *Applied Sciences*, 9(18):3658.

Le Yang, Dongmei Jiang, Lang He, Ercheng Pei, Meshia Cédric Oveneke, and Hichem Sahli. 2016a. Decision tree based depression classification from audio video and language information. In *Proceedings of the 6th international workshop on audio/visual emotion challenge*, pages 89–96.

Min Yang, Wei Zhao, Wei Xu, Yabing Feng, Zhou Zhao, Xiaojun Chen, and Kai Lei. 2018. Multitask learning for cross-domain image captioning. *IEEE Transactions on Multimedia*, 21(4):1047–1061.

Zichao Yang, Diyi Yang, Chris Dyer, Xiaodong He, Alex Smola, and Eduard Hovy. 2016b. Hierarchical attention networks for document classification. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1480–1489.

ByungIn Yoo, Youngjun Kwak, Youngsung Kim, Changkyu Choi, and Junno Kim. 2018. Deep facial age estimation using conditional multitask learning with weak label expansion. *IEEE Signal Processing Letters*, 25(6):808–812.

Abdallah Yousif, Zhendong Niu, and Ally S Nyamawe. 2018. Citation classification using multitask convolutional neural network model. In *International Conference on Knowledge Science, Engineering and Management*, pages 232–243. Springer.

Jianfei Yu and Jing Jiang. 2016. Learning sentence embeddings with auxiliary tasks for cross-domain sentiment classification. In *Association for Computational Linguistics*.

Amir Zadeh, Paul Pu Liang, Navonil Mazumder, Soujanya Poria, Erik Cambria, and Louis-Philippe Morency. 2018a. Memory fusion network for multi-view sequential learning. *arXiv preprint arXiv:1802.00927*.

Amir Zadeh, Paul Pu Liang, Soujanya Poria, Prateek Vij, Erik Cambria, and Louis-Philippe Morency. 2018b. Multi-attention recurrent network for human communication comprehension. In *Proceedings of the... AAAI Conference on Artificial Intelligence. AAAI Conference on Artificial Intelligence*, volume 2018, page 5642. NIH Public Access.

Nasser Zalmout and Nizar Habash. 2019. Adversarial multitask learning for joint multi-feature and multidialect morphological modeling. *arXiv preprint arXiv:1910.12702*.

Matthew D Zeiler and Rob Fergus. 2014. Visualizing and understanding convolutional networks. In *European conference on computer vision*, pages 818–833. Springer.

Chiyuan Zhang, Samy Bengio, Moritz Hardt, Benjamin Recht, and Oriol Vinyals. 2016. Understanding deep learning requires rethinking generalization. *arXiv preprint arXiv:1611.03530*.

Fengda Zhu, Yi Zhu, Xiaojun Chang, and Xiaodan Liang. 2020. Vision-language navigation with self-supervised auxiliary reasoning tasks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10012–10022.
A Appendix

A.1 Dataset partitions
We detail the dataset partition in Table 5 for aid reproducibility.

A.2 Scaling the auxiliary targets
We detail the operations in scaling the percentile scores that range [0,1] to various primary tasks. For IEMOCAP Primary Tasks that are regression problems, we multiply the percentile score by 4 and add 1 to obtain the range [1,5]. For IEMOCAP classification task, we leave the auxiliary targets in the range of [0,1]. As for SEMAINE tasks, which are all regression problems, we multiply the percentile score by 2 and minus 1 to obtain the range [-1,1].

A.3 Hyperparameters tuning process
Glove word embeddings (300-dimensions) are used to represent the words (Pennington et al., 2014). Hyper-parameters tuning is crucial because different combinations of primary and auxiliary tasks require different sets of hyperparameters. For hyperparameters tuning, we used random search (Bergstra and Bengio, 2012) with thirty trials. We tuned the learning rate, batch size, L2 regularization, the number of GRUs assigned to the primary and auxiliary branches, the auxiliary weights assignment, the content-context size, and lastly the GRU dropout and recurrent dropout (as detailed in Table 6).

Training is done on a RTX2070 or a V100 GPU, for up to 350 epochs. Early stopping is possible via the median-stopping rule (Golovin et al., 2017) after the fifth epoch and after every two epochs (i.e., at epoch number 5, 7, 9, ..., 349). Table 7 details the hyperparameters of models that performed the best on the development set.

A.4 Details of computing the bootstrap confidence interval
Baseline models for each hypothesis are detailed in section 2. All non-baseline models are referred to as challenger models. We created 1000 bootstrap samples of the test set performance by (1) resampling the development set performance, then (2) selecting the set of hyperparameters that resulted in the best development set performance, and (3) looking up the test set performance given the set of best-performing hyperparameters for the development set. To judge whether the challenger outperforms the baseline, we computed the 95 percent confidence interval by (1) performing element-wise subtraction between the resampled test set performance of the baseline against the challenger, (2) removing the top and bottom 2.5 percent from the differences, and (3) observing whether the remaining 95 percent confidence interval includes zero. If it does not include zero, then the difference is statistically significant.

A.5 Visualization from HAN-ROCK
We demonstrate how the HAN-ROCK model could be used to support humans analyze conversations using only text-based inputs. We visualized the attention weights from two models, (1) MTL refers to the classification model with auxiliary supervisors, whilst (2) STL refers to the same model architecture, but its auxiliary supervisors’ loss weights are set to zero. In principle, the MTL model should exhibit attention weights that are less likely to overfit because the weights are tempered by auxiliary supervisors. We observe that across the two models, both use the historical talkturns more so than the current talkturn; secondly, both assign high attention to the second word of the talkturns, which is interesting because the second word is where the multimodal annotations are inserted.

As explained in Section 3.2, there are three levels of attention over the internal representations, word ($\alpha_{it}$), talkturn ($\alpha_{abi}$), and task ($\alpha_c$). To compute the overall word and talkturn attention, we compute the weighted average of $\alpha_{it}$ and $\alpha_{abi}$ using the $\alpha_c$ (task attention) as weights. Once we have the overall word and talkturn attention, we standardize the weights by computing the z-score. Depending on the z-score, we bucket the attention in none ($z < 0$), low (0 < $z < 1$), medium (1 < $z < 2$), or high (2 < $z$). We plan to validate the efficacy of the attention weights with human users in future research.
Table 5: Dataset partitions

| IEMOCAP | SEMAINE |
|---------|---------|
| Partition | Session | Count | Partition | Session | Count |
| Train | Ses01F | 861 | Train | 2008.12.05.16.03.15 | 424 |
| Train | Ses01M | 958 | Train | 2009.01.30.12.00.35 | 404 |
| Train | Ses02F | 889 | Train | 2009.02.12.10.49.45 | 686 |
| Train | Ses02M | 922 | Train | 2009.05.15.15.04.29 | 436 |
| Train | Ses03F | 958 | Train | 2009.05.29.14.30.05 | 760 |
| Train | Ses03M | 1178 | Train | 2009.05.22.15.17.45 | 668 |
| Dev | Ses04F | 1105 | Train | 2009.05.25.11.23.09 | 928 |
| Dev | Ses04M | 998 | Train | 2009.05.26.10.19.53 | 790 |
| Test | Ses05F | 1128 | Train | 2009.06.05.10.14.28 | 732 |
| Test | Ses05M | 1042 | Train | 2009.06.15.12.13.06 | 958 |
| Test | | | Train | 2009.06.19.14.01.24 | 586 |
| Test | | | Train | 2009.10.27.16.17.38 | 440 |
| Test | | | Dev | 2008.12.19.11.03.11 | 188 |
| Test | | | Dev | 2009.01.06.14.53.49 | 472 |
| Test | | | Dev | 2009.05.12.15.02.01 | 448 |
| Test | | | Dev | 2009.05.08.11.28.48 | 752 |
| Test | | | Dev | 2009.06.26.14.38.17 | 404 |
| Test | | | Test | 2008.12.14.14.47.07 | 372 |
| Test | | | Test | 2009.01.06.12.41.42 | 264 |
| Test | | | Test | 2009.01.28.15.35.20 | 364 |
| Test | | | Test | 2009.06.26.14.38.17 | 440 |
| Test | | | Test | 2009.06.26.14.09.45 | 448 |

Table 6: Range of Hyperparameters tuned. U: Uniform sampling, LU: Uniform sampling on the logarithmic scale.

| Name | Min. | Max | Sampling |
|------|------|-----|----------|
| Learning rate | $2^{-10}$ | $2^{-5}$ | LU |
| Batch-Size | 32 | 256 | U |
| Pri GRU | 1, 64, 128, 192, 256 | U |
| Aux GRU | 257 - (minus) Pri GRU | U |
| Loss-weights Assignment | Random, Linear-Normalized, Softmax-Normalized | U |
| L2 Regularization | 0.0 | 0.50 | LU |
| Content-Size | 1 | 30 | U |
| GRU dropout | 0.01 | 0.50 | U |
| Recurrent dropout | 0.01 | 0.50 | U |
Table 7: Best Hyperparameters settings for development set. R: Random, L: Linear-Normalized, S: Softmax-Normalized.

|                  | IEMOCAP | SEMAINE |
|------------------|---------|---------|
|                  | Classif. MA(4) | Val. MAE | Act. MAE | Dom. MAE | Act. MAE | Int. MAE | Pow. MAE | Val. MAE |
| Dev. set         | 0.714   | 0.482   | 0.492    | 0.570    | 0.118    | 0.164    | 0.135    | 0.138    |
| Test set         | 0.747   | 0.497   | 0.499    | 0.587    | 0.184    | 0.215    | 0.164    | 0.169    |
| Learning rate    | 6.21e-03 | 2.21e-02 | 1.44e-02 | 3.13e-02 | 2.43e-02 | 1.58e-02 | 3.04e-03 | 2.94e-02 |
| Batch size       | 43      | 43      | 62       | 77       | 41       | 43       | 33       | 62       |
| Pri GRU          | 256     | 256     | 256      | 256      | 256      | 256      | 192      | 256      |
| Aux GRU          | 1       | 1       | 1        | 1        | 1        | 65       | 1        |          |
| L2 regularization| 2.25e-05 | 0       | 1.43e-05 | 2.41e-04 | 0        | 0        | 0        | 0        |
| Content-Size     | 18      | 4       | 3        | 3        | 17       | 21       | 19       | 14       |
| GRU dropout      | 0.27    | 0.49    | 0.33     | 0.30     | 0.06     | 0.17     | 0.05     | 0.07     |
| Recurrent dropout| 0.04    | 0.03    | 0.02     | 0.32     | 0.25     | 0.28     | 0.08     | 0.26     |
| Epoch No.        | 232     | 161     | 74       | 14       | 48       | 116      | 110      | 110      |
| Aux. weights assignment | S | R | L | L | R | S | R |
| Main loss        | 0.840   | 0.560   | 0.810    | 0.610    | 0.870    | 0.940    | 0.950    | 0.920    |
| AU05 loss        | 0.009   | 0.013   | 0.014    | 0.000    | 0.000    | 0.002    | 0.002    | 0.008    |
| AU17 loss        | 0.009   | 0.027   | 0.009    | 0.003    | 0.002    | 0.004    | 0.002    | 0.003    |
| AU20 loss        | 0.009   | 0.028   | 0.0      | 0.001    | 0.000    | 0.007    | 0.002    | 0.006    |
| AU25 loss        | 0.009   | 0.031   | 0.006    | 0.002    | 0.015    | 0.008    | 0.002    | 0.009    |
| Happy tone loss  | 0.010   | 0.023   | 0.038    | 0.006    | 0.021    | 0.013    | 0.002    | 0.003    |
| Sad tone loss    | 0.010   | 0.028   | 0.053    | 0.008    | 0.037    | 0.010    | 0.002    | 0.003    |
| Angry tone loss  | 0.010   | 0.016   | 0.034    | 0.006    | 0.055    | 0.011    | 0.002    | 0.000    |
| Fear tone loss   | 0.010   | 0.043   | 0.036    | 0.004    | 0.000    | 0.004    | 0.002    | 0.003    |
| $Y_{t-1}$ loss   | 0.010   | 0.030   | 0.0      | 0.040    | 0.000    | 0.000    | 0.005    | 0.006    |
| $Y_{t-2}$ loss   | 0.011   | 0.022   | 0.0      | 0.049    | 0.000    | 0.000    | 0.004    | 0.004    |
| $Y_{t-3}$ loss   | 0.010   | 0.006   | 0.0      | 0.046    | 0.000    | 0.000    | 0.003    | 0.006    |
| $Y_{t-4}$ loss   | 0.010   | 0.040   | 0.0      | 0.044    | 0.000    | 0.000    | 0.003    | 0.007    |
| $Y_{t+1}$ loss   | 0.010   | 0.042   | 0.0      | 0.042    | 0.000    | 0.000    | 0.005    | 0.005    |
| $Y_{t+2}$ loss   | 0.011   | 0.0      | 0.0      | 0.052    | 0.000    | 0.000    | 0.004    | 0.006    |
| $Y_{t+3}$ loss   | 0.010   | 0.050   | 0.0      | 0.043    | 0.000    | 0.000    | 0.003    | 0.008    |
| $Y_{t+4}$ loss   | 0.010   | 0.038   | 0.0      | 0.044    | 0.000    | 0.000    | 0.003    | 0.003    |
Figure 5: Conversation analysis example. Both models predicted the class label (anger) correctly. The left-most column denotes the talkturn context – i refers to the current talkturn where the target emotion class is predicted. The square boxes indicate the level of attention (N: None, L: Low, M: Medium, H: High) assigned to the talkturn. Within the talkturn, we also enlarge and darken the font color to visualize higher attention weights.