Abstract

The human language has heterogeneous sources of information, including tones of voice, facial gestures, and spoken language. Recent advances introduced computational models to combine these multimodal sources and yielded strong performance on human-centric tasks. Nevertheless, most of the models are often black-box, which comes with the price of lacking interpretability. In this paper, we propose Multimodal Routing to separate the contributions to the prediction from each modality and the interactions between modalities. At the heart of our method is a routing mechanism that represents each prediction as a concept, i.e., a vector in a Euclidean space. The concept assumes a linear aggregation from the contributions of multimodal features. Then, the routing procedure iteratively 1) associates a feature and a concept by checking how this concept agrees with this feature and 2) updates the concept based on the associations. In our experiments, we provide both global and local interpretation using Multimodal Routing on sentiment analysis and emotion prediction, without loss of performance compared to state-of-the-art methods. For example, we observe that our model relies mostly on the text modality for neutral sentiment predictions, the acoustic modality for extremely negative predictions, and the text-acoustic bimodal interaction for extremely positive predictions.

1 Introduction

The human multimodal language contains multimodal cues, including textual (e.g., spoken or written words), visual (e.g., body gestures), and acoustic (e.g., voice tones) modalities. It acts as a medium for human communication and has been advanced in areas spanning affect recognition (Busso et al., 2008), media description (Lin et al., 2014), event recognition (Alam et al., 2018), and multimedia information retrieval (Abu-El-Haija et al., 2016). Modeling multimodal sources takes into account the effect of every single modality (defined as unimodal feature) and the interactions between modalities (defined as bimodal or trimodal interactions) (Büchel et al., 1998). For example, the emotion “happy” can be told from a smile (i.e., visual modality solely) or positive texts with excited tones of voice (i.e., the interaction between text and acoustic modality). Recent work (Lazaridou et al., 2015; Fukui et al., 2016) proposed methods to fuse information across modalities and yielded superior performance, but these models are often black-box and lack interpretability.

Interpretability matters. For instance, interpretation allows us to identify important features by elaborating which modality or modality interaction is crucial for model’s prediction, and such insights could be used to improve the model design or debug a dataset. In this paper, we provide an interpretable multimodal language model by addressing the question: How we can distinguish the contributions of unimodal features as well as bimodal and trimodal interactions in multimodal language modeling? We focus on two scopes of interpretability: interpretation of a model’s behavior on the entire dataset (defined as global interpretation), or between a single output and an individual sample (defined as local interpretation). Global interpretation identifies what modality or modality interactions are the most important for the model overall, while local interpretation shows the specific role of modality or interactions given different contexts.

A straightforward interpretable approach is a linear model that takes unimodal, bimodal, and trimodal interaction features as input. The problem of this approach is that there is no local interpretation available. Other interpretation methods (Ribeiro et al., 2016; Lundberg and Lee, 2017; Chen et al.,
We address the problems by presenting Multimodal Routing. Multimodal Routing consists of three stages: encoding, routing, and decoding. The encoding stage encodes raw inputs (speech, text, and visual data) to explanatory features, including unimodal features, bimodal interaction, and trimodal interaction features. This stage also initializes different vectors for different prediction labels, which we call concepts (e.g., a vector for emotion “happy” and another one for “angry”). The routing stage contains a routing procedure (Sabour et al., 2018), which iteratively 1) associates an explanatory feature and a concept vector based on how this concept “agrees” with the contribution from this feature, and 2) updates the concepts based on the associations. This stage will end up with a strong connection between an explanatory feature and a specific concept if this concept explains this feature well enough. As an example, if emotion “happy” can be explained well by text-acoustic interaction during training, our model will route the text-acoustic interaction to the concept of “happiness”. Finally, the decoding stage decodes the model’s prediction from the concepts. Fig. 1 illustrates the proposed approach.

This mechanism can provide global interpretation using statistical tools (e.g., Central Limit Theorem and confidence interval (Wasserman, 2013)) to reveal which set of features on average significantly contributes to the model’s prediction. It also provides local interpretation by analyzing routing coefficients given a specific sample, since the routing coefficients stand for the agreement between the features of this specific sample and the concepts of the prediction. Moreover, what differs from most of the neural network models is that our method can adjust the coefficients dynamically given a sample during inference, adapting stronger or weaker connections between modality features and the predictive label from the new input. By focusing on sentiment analysis and emotion recognition tasks using two benchmark multimodal language datasets, IEMOCAP (Busso et al., 2008) and CMU-MOSEI (Zadeh et al., 2018), we qualitatively and quantitatively show that our approach leads us to a better understanding of sentiment and emotion prediction, without much losses of predictive power compared to state-of-the-art methods.

2 Related Work

Multimodal language learning are based on the fact that human integrates multiple sources such as acoustic, textual, and visual information to learn language (McGurk and MacDonald, 1976; Ngiam et al., 2011; Baltrušaitis et al., 2018). Recent advances in modeling multimodal language using deep neural networks are not interpretable (Wang et al., 2019; Tsai et al., 2019a). Even though we could use post hoc (interpret predictions given an arbitrary model) methods such as LIME (Ribeiro et al., 2016), SHAP (Lundberg and Lee, 2017), and L2X (Chen et al., 2018) to interpret these black-box models, these interpretation methods are designed to detect the contributions only from unimodal features but not bimodal or trimodal interaction features. It is shown that in human communication, modality interactions are more important than individual modalities (Engle, 1998).
To provide direct interpretability, we could use the straightforward linear method, the Generalized Additive Models (GAMs) (Hastie, 2017). GAMs depend linearly on functions of features and assume the linear coefficients are not covariates of the features. Their major drawbacks have been stated in the introduction section, which include no ability to dynamically adjust coefficients during inference and/or no local interpretability.

Two recent methods, Graph-MFN (Zadeh et al., 2018) and Multimodal Factorized Model (MFM) (Tsai et al., 2019b), attempted to interpret relationships between modality interactions and learning for human language. Nonetheless, Graph-MFN did not separate the contributions among unimodal and multimodal interaction features, and MFM only provided the analysis on trimodal interaction feature. Both of them cannot interpret how both single modality and modality interactions contribute to final prediction at the same time.

Our method is inspired and related to Capsule Networks (Sabour et al., 2017; Hinton et al., 2018), which performs routing between layers of capsules. Each capsule is a group of neurons that encapsulates spatial information as well as the probability of an object being present. On the contrary, our method performs routing between multimodal features (i.e., unimodal, bimodal, and trimodal interaction features) and concepts of the model’s decision.

3 Method

We use v(visual), a(acoustic), and t(ext) to denote the three commonly considered modalities in human multimodal language. Let \( x = \{ x_a, x_v, x_t \} \) represent the multimodal input. \( x_a \in \mathbb{R}^{T_a \times d_a} \) is an audio stream with time length \( T_a \) and feature dimension \( d_a \) (at each time step). Similarly, \( x_v \in \mathbb{R}^{T_v \times d_v} \) is the visual stream and \( x_t \in \mathbb{R}^{T_t \times d_t} \) is the text stream. In the paper, we consider multiclass or multilabel prediction tasks for the multimodal language modeling, in which we use \( y \in \mathbb{R}^J \) to denote the ground truth label with \( J \) being the number of classes or labels, and \( \hat{y} \) to represent the model’s prediction. Our goal is to find the relative importance of the contributions from unimodal (e.g., \( x_a \) itself), bimodal (e.g., the interaction between \( x_a \) and \( x_v \)), and trimodal interactions (e.g., the interaction between \( x_a, x_v, \) and \( x_t \)) to the model prediction \( \hat{y} \).

3.1 Multimodal Routing

The proposed Multimodal Routing contains three stages: encoding, routing, and decoding. (see Fig. 1).

Encoding Stage. The encoding stage encodes multimodal inputs \( \{ x_a, x_v, x_t \} \) into explanatory factors. We use \( f_i \in \mathbb{R}^{d_i} \) to denote the features with \( i \in \{a, v, t\} \) being unimodal, \( i \in \{av, vt, ta\} \) being bimodal, and \( i \in \{avt\} \) being trimodal interactions. \( d_f \) is the dimension of the feature. These encoding functions take only the inputs from the corresponding modalities to generate the features. That is, \( f_a = F_a(x_a; \theta) \), \( f_{av} = F_{av}(x_a, x_v; \theta) \), and \( f_{avt} = F_{avt}(x_a, x_v, x_t; \theta) \) with \( \theta \) as the parameters of the encoding functions and \( F \) as the encoding functions. Multimodal Transformer (MulT) (Tsai et al., 2019a) is adopted as the design of the encoding functions \( F_i \). To be precise, the trimodal function \( F_{avt} \) encodes sequences from three modalities into a unified representation, \( F_{av} \) encodes acoustic and visual modalities, and \( F_a \) encodes acoustic input.

This stage also constructs concepts to represent each decision from the model. The concepts are individual one-dimensional vectors denoted by \( \{c_j\}_{j=1}^J \) with \( c_j \in \mathbb{R}^{d_c} \) representing the concept of the \( j \)th class or label. \( d_c \) is the dimension of the concept. \( \{c_j\}_{j=1}^J \) will be updated dynamically in the routing stage. Hence, the concepts are not fixed through the entire dataset but dependent on an input sample. For instance, if \( c_j \) refers to the concept “happy”, this concept represents the input’s belief (not a general belief) of happiness.

Routing Stage. The routing stage performs routing between each explanatory feature \( f_i \) and each concept \( c_j \). Following prior work (Sabour et al., 2017; Hinton et al., 2018), a feature \( f_i \) is routed to a concept \( c_j \) if this feature is likely to present and this concept agrees with this feature. Then, we update the concepts based on the agreements.

\[ p_i \in [0, 1] \] is a scalar representing how each feature \( f_i \) is activated in the model. Similar to \( f_i \), we also use MulT to encode \( p_i \) from the input \( x_i \). That is, \( p_a = P_a(x_a; \theta') \), \( p_{av} = P_{av}(x_a, x_v, \theta') \), and \( p_{avt} = P_{avt}(x_a, x_v, x_t, \theta') \) with \( \theta' \) as the parameters of MulT.1 And \( p_i \) as corresponding encoding

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functions. After \( p_i \) is obtained, we perform the core of routing stage by executing agreement and update steps iteratively, as explained below.

**Agreement.** To seek an agreement between a feature \( f_i \) and a concept \( c_j \), we use a bilinear model, \( f_i W_{ij} \), to make it more flexible to represent the relationship between each feature-concept pair, where \( W_{ij} \in \mathbb{R}^{d_f \times d_c} \) are learnable parameters. Then, we define the routing coefficient \( r_{ij} \in [0, 1] \) by measuring the similarity \(^2\) between \( f_i W_{ij} \) and \( c_j \):

\[
    r_{ij} = \frac{\exp(\langle f_i W_{ij}, c_j \rangle)}{\sum_{j'} \exp(\langle f_i W_{ij'}, c_{j'} \rangle)}.
\]

We note that \( r_{ij} \) is normalized over all concepts \( c_j \). Hence, it is an agreement coefficient, and \( r_{ij} \) takes high value only when \( f_i \) is in agreement with \( c_j \) but not with \( c_{j'} \), where \( j' \neq j \).

**Update.** After obtaining \( p_i \) and agreements \( r_{ij} \), we update concepts \( c_j \) using weighted average as follows:

\[
    c_j = \sum_i p_i r_{ij} (f_i W_{ij}).
\]

Note that \( c_j \) is a linear aggregation from \( (f_i W_{ij}) \) with weights \( p_i r_{ij} \).

We summarize the routing procedure in Procedure 1, which returns concepts \( (c_j) \) given explanatory features \( (f_i) \), weights \( (W_{ij}) \) and \( p_i \). First, we randomly initialize the concepts. Then, we iteratively perform an adjustment on routing coefficients \( r_{ij} \) and update concepts. Finally, we return the updated concepts.

**Decoding Stage.** The decoding stage determines the prediction \( \hat{y} \) from the concept \( c_j \). Here, we apply linear transformations to concept \( c_j \) to obtain the logits. Specifically, the \( j \)th logit is formulated as

\[
    \logit_j = o_j^\top c_j,
\]

\[
    = \sum_i p_i r_{ij} o_j^\top (f_i W_{ij}),
\]

where \( o_j \in \mathbb{R}^{d_c} \) and is the weight of the linear transformation for the \( j \)th concept. Then, the Softmax (for multi-class task) or Sigmoid (for multi-label task) function is applied on the logits to obtain the prediction \( \hat{y} \).

### 3.2 Interpretability

In this section, we provide the framework of interpreting relative importance of unimodal, bimodal, and trimodal interaction features to model prediction, both across the whole datasets (global interpretation), and on individual samples (local interpretation), and show how to interpret the routing coefficients \( r_{ij} \), which represents the agreement between feature \( f_i \) and concept \( c_j \).

#### 3.2.1 Global Interpretation

To globally interpret Multimodal Routing, we analyze \( \overline{r_{ij}} \), the average values of routing coefficients \( r_{ij} \)’s over the entire dataset. Since eq. (1) considers a linear effect from \( f_i p_i r_{ij} \) to logit \( j \), \( \overline{r_{ij}} \) represents the average assignment from feature \( f_i \) to the \( j \)th logit. Instead of reporting the values for \( \overline{r_{ij}} \), we provide a statistical interpretation on \( \overline{r_{ij}} \) with statistical tools such as confidence interval which provides a range of possible plausible coefficients with probability guarantees. Similar tests on \( p_i \) and \( p_i r_{ij} \) are provided in Supplementary Materials. Here we choose confidence intervals over \( p \)-values because they provide much richer information (Ranstam, 2012; Du Prel et al., 2009).

Suppose we have \( n \) data with the corresponding \( r_{ij} = \{r_{ij,1}, r_{ij,2}, \ldots, r_{ij,n}\} \). If \( n \) is large enough and \( r_{ij} \) has finite mean and finite variance (it suffices since \( r_{ij} \in [0, 1] \) is bounded), according to Central Limit Theorem, \( \overline{r_{ij}} \) (i.e., mean of \( r_{ij} \)) follows a Normal distribution:

\[
    \overline{r_{ij}} \sim \mathcal{N}\left( \mu, \frac{s_n^2}{n} \right),
\]

where \( \mu \) is the true mean of \( r_{ij} \) and \( s_n^2 \) is the sample variance in \( r_{ij} \). Using eq. (2), we can provide a confidence interval for \( \overline{r_{ij}} \). We follow 95% confidence in our analysis.

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\(^2\)We use dot-product as the similarity measurement as in prior work (Sabour et al., 2017). Another choice can be the probability of a fit under a Gaussian distribution (Hinton et al., 2018).
3.2.2 Local Interpretation

In eq. (1), a decision logit considers an addition of the contributions from the unimodal \( \{f_a, f_v, f_l\} \), bimodal \( \{f_{av}, f_{vt}, f_{ta}\} \), and trimodal \( f_{avt} \) interaction features. The particular contribution from the feature \( f_i \) to the \( j \)th concept is represented by \( p_ir_{ij}o_{ij}(f_iW_{ij}) \). It takes large value when 1) \( p_i \) of the feature \( f_i \) is large; 2) the agreement \( r_{ij} \) is high (the feature \( f_i \) is in agreement with concept \( c_j \) and is not in agreement with \( c_{j'} \), where \( j' \neq j \); and 3) the dot product \( o_{ij}f_iW_{ij} \) is large. Note that \( p_i/r_{ij}/f_i \) are the covariates and \( o_{ij}/W_{ij} \) are the parameters in the model. Since different input samples yield distinct \( p_i \) and \( r_{ij} \), we can locally interpret \( p_i \) and \( r_{ij} \) as the effects of the feature \( f_i \) contributing to the \( j \)th logit of the model. We will show examples of local interpretations in later sections.

4 Experiments

In this section, we first provide details of experiments we perform and comparison between our proposed model and state-of-the-art (SOTA) method, as well as baseline models. We include interpretability analysis in the next section.

4.1 Datasets

We provide experimental setups of two publicly available benchmarks for human multimodal affect recognition: CMU-MOSEI (Zadeh et al., 2018) and IEMOCAP (Busso et al., 2008). CMU-MOSEI (Zadeh et al., 2018) contains 23,454 movie review video clips taken from YouTube. For each clip, there are two tasks: sentiment prediction (multiclass classification) and emotion recognition (multilabel classification). For the sentiment prediction task, each sample is labeled by an integer score in the range \([-3, 3]\), indicating highly negative sentiment(-3) to highly positive sentiment(3). We choose the metrics in prior work (Zadeh et al., 2018): seven class accuracy (\( Acc_7 \): seven class classification in \( \mathbb{Z} \in [-3, 3] \)), binary accuracy (\( Acc_2 \): two-class classification in \( \{-1, +1\} \)), and F1 score of predictions. For the emotion recognition task, each sample is labeled by one or more emotions from \{Happy, Sad, Angry, Fear, Disgust, Surprise\}. We report the metrics (Zadeh et al., 2018): six-class accuracy (multilabel accuracy of predicting six emotion labels) and F1 score.

IEMOCAP consists of 10K video clips for human emotion analysis. Each clip is evaluated and then assigned (possibly more than one) labels of emotions, making it a multilabel learning task. Following prior work and insight (Tsai et al., 2019a; Tripathi et al., 2018; Jack et al., 2014), we report on four emotions (happy, sad, angry, and neutral), with metrics four-class accuracy and F1 score.

For both datasets, multimodal features are extracted from textual (GloVe word embedding (Pennington et al., 2014)), visual (Facet (iMotions, 2019)), and acoustic (COVAREP (Degottex et al., 2014)) modalities. They can be downloaded at the publicly available link: https://github.com/A2Zadeh/CMU-MultimodalSDK. The acoustic and vision features are processed to be aligned with the words (i.e., text features). We present results using this word-aligned setting in this paper. Still, ours can work on unaligned multimodal language sequences, which comprises features with different time steps because of different sampling rates, an advantage over some other models (Wang et al., 2019).

4.2 Baseline Models

We provide two interpretable methods as baselines: Generalized Additive Model (GAM) (Hastie, 2017), which is a generalized version of the linear model, and our proposed Multimodal Routing without iterative routings (denoted as Multimodal Routing*). GAM directly sums over unimodal, bimodal, and trimodal interaction features and then applies a linear transformation to obtain a prediction. Multimodal Routing* performs only one routing iteration (by setting \( t = 1 \) in Procedure 1), which does not iteratively adjust the routing and update the concepts. We also choose other non-interpretable methods that achieved SOTA, or common human multimodal language models: Early Fusion LSTM (EF-LSTM), Late Fusion LSTM (LF-LSTM) (Hochreiter and Schmidhuber, 1997), Recurrent Attended Variation Embedding Network (RAVEN) (Wang et al., 2019), and Multimodal Transformer (Tsai et al., 2019a).

4.3 Results and Comparisons

CMU-MOSEI sentiment. As shown in Table 1. We first compare all the interpretable methods. We see that Multimodal Routing enjoys performance improvement over both GAM (Hastie, 2017) and Multimodal Routing*. The improvement suggests the proposed iterative routing can obtain a more robust prediction by dynamically associating the features and the concepts of the model’s predictions. Next, when comparing to the non-interpretable
### Table 1: Left: CMU-MOSEI sentiment prediction. Right: IEMOCAP emotion recognition. Multimodal Routing* denotes our method without iterative routing. Our results are better or close to the state-of-the-art (Tsai et al., 2019a). We make our results bold if it is SOTA or close to SOTA (<1%).

| Models            | CMU-MOSEI Sentiment | IEMOCAP Emotion |
|-------------------|---------------------|-----------------|
|                   | Acc7   | Acc2 | F1 | Happy Acc | Sad F1 | Angry F1 | Neutral F1 |
| Non-Interpretable Methods |         |      |    |           |       |          |             |
| EF-LSTM           | 47.4   | 78.2 | 77.9 | 86.0 | 84.2 | 80.2 | 85.2 | 84.5 | 67.8 | 67.1 |
| LF-LSTM           | 48.8   | 80.6 | 80.6 | 85.1 | 86.3 | 78.9 | 81.7 | 84.7 | 83.0 | 67.1 | 67.6 |
| RAVEN (Wang et al., 2019) | 50.0 | 79.1 | 79.5 | 87.3 | 85.8 | 83.4 | 83.1 | 87.3 | 86.7 | 69.7 | 69.3 |
| MulT (Tsai et al., 2019a) | 51.8 | 82.5 | 82.3 | 90.7 | 88.6 | 86.7 | 86.0 | 87.4 | 87.0 | 72.4 | 70.7 |

| Interpretable Methods | CMU-MOSEI Emotion | IEMOCAP Emotion |
|-----------------------|-------------------|-----------------|
|                       | Happy Acc | Sad F1 | Angry Acc | Disgust Acc | Fear F1 | Surprise F1 |
| Non-Interpretable Methods |         |      |      |           |       |          |
| GAM (Hastie, 2017)    | 48.6     | 79.5  | 79.4  | 87.0     | 84.3  | 83.2     | 82.4     | 85.2     | 84.8  | 67.4  | 66.6 |
| Multimodal Routing*   | 50.6     | 81.2  | 81.3  | 85.4     | 81.7  | 84.2     | 83.2     | 83.5     | 83.6  | 86.7  | 67.1  | 66.3 |
| Multimodal Routing     | 51.6     | 81.7  | 81.8  | 87.3     | 84.7  | 85.7     | 85.2     | 87.9     | 87.7  | 70.4  | 70.0  |

| Models            | IEMOCAP Emotion |
|-------------------|-----------------|
|                   | Happy Acc | Sad F1 | Angry Acc | Disgust Acc | Fear F1 | Surprise F1 |
| Non-Interpretable Methods |         |      |      |           |       |          |
| GAM (Hastie, 2017) | 69.6     | 69.6  | 76.2  | 67.8     | 77.5  | 69.7     | 90.5     | 86.0     | 84.2  | 80.8  | 91.7  | 87.8 |
| Multimodal Routing* | 69.4     | 69.3  | 76.2  | 68.8     | 77.5  | 69.1     | 90.5     | 86.0     | 84.1  | 81.6  | 91.7  | 87.8 |
| Multimodal Routing | 69.7     | 69.4  | 76.0  | 72.1     | 77.6  | 72.8     | 90.5     | 86.0     | 83.1  | 82.3  | 91.7  | 87.8 |

### Table 2: CMU-MOSEI emotion recognition. Multimodal Routing* denotes our method without iterative routing. We make our results bold if it is the best or close to the best (<1%).

methods, Multimodal Routing outperforms all the other models and performs either closely with or better than SOTA method MulT (Tsai et al., 2019a). Therefore, the proposed method can provide better interpretability while not sacrificing performance.

**CMU-MOSEI emotion.** We report the results in Table 2. We do not report RAVEN (Wang et al., 2019) and MulT (Tsai et al., 2019a) since they did not report CMU-MOSEI results. Compared with all the baselines, Multimodal Routing performs the best on most of the results metrics. We note that the distribution of labels is skewed (e.g., there are disproportionately very few samples labeled as “surprise”). Hence, this skewness somehow results in the fact that the model always predicts not having emotion “surprise”, thus the same accuracy for “surprise” across different approaches.

**IEMOCAP emotion.** From Table 1, we could tell that the trends of the results are similar to both CMU-MOSEI sentiment and CMU-MOSEI emotion, that we can achieve performance close to the SOTA method. We see a performance drop in the emotion “happy”, but our model outperforms the SOTA method for the emotion “angry”.

To conclude, in terms of model performance, we show that Multimodal Routing does not sacrifice too much from the non-interpretable methods, with 74% of the metrics reported in the tables close to (less than 1% absolute performance difference) or better than SOTA. Compared to other interpretable methods, our model with iterative routing mechanism has a better discriminative power.

### 5 Interpretation Analysis

In this section, we mainly address the question in the introduction: how to identify the importance or contribution of unimodal features and the bimodal or trimodal interactions by providing global and local interpretation analysis.

#### 5.1 Global Interpretation Analysis

Here we analyze the global interpretation of Multimodal Routing. Given the averaged routing coefficients $\overline{r}_{ij}$ generated and aggregated locally from samples, we want to know the overall connection between each modality or modality interaction and each concept across the whole dataset. Without any learning, a trivial assumption sets all the routing coefficients to be uniform, because a uniform routing gives no preference for any feature-concept pairs.
We could tell from the table that our model relies on...
Figure 2: Local interpretation (qualitative results) for Multimodal Routing. The upper row contains three examples from CMU-MOSEI sentiment prediction task; the bottom row contains three examples from CMU-MOSEI emotion recognition task. $p_{ij}$ represents the contribution from the explanatory features $i$ (unimodal/bimodal/trimodal interaction features) to the prediction $\logit_j$ (see eq. 1). In these examples, $j$ is chosen to be the ground truth label.

In the upper-left example in Fig. 2, a speaker is introducing the movie, Sweeny Todd. He says the movie is musical and suggests those who dislike musicals not to see the movie. Since he has no personal judgment on whether he personally likes or dislikes the movie, his sentiment is classified as neutral (0), although the text modality (i.e., transcript) contains a “don’t”. In the vision modality (i.e., videos), he frowns when he mentions this movie is musical, but we cannot conclude his sentiment to be neutral by only looking at the visual modality. When we look at both vision and text together (their interaction), we can be more confirmed that his sentiment is neutral, therefore the text-vision interaction feature is highly contributed to the prediction.

Similarly, for the bottom-left example, the speaker is sharing her experience on how to audition for a Broadway show. She talks about a very detailed and successful experience of herself and describes “love” in her audition monologue, which is present in the text. Also, she has a dramatic smile and a happy tone. As a result, the trinodal interaction feature contributes significantly to the prediction of happiness.

6 Conclusion

In human multimodal language, we present Multimodal Routing to identify the relative importance of the contributions from unimodal features as well as bimodal and trimodal interaction features to predictions. Our method dynamically associates an interaction feature with a prediction if the feature explains the prediction well. Then, we interpret our approach by analyzing the routing coefficients globally (i.e., on the entire dataset) and locally (i.e., given specific input). From our analysis, the acoustic features are crucial for predicting negative sentiments or emotions, and the acoustic-visual interactions are crucial for predicting emotion angry. Both statements are confirmed by psychological research. All of these are achieved without much loss of performance compared to the SOTA methods. We believe that this work sheds light on the advantages of understanding human behaviors from a multimodal perspective, and makes a step towards introducing more interpretable multimodal language models.
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For the encoding stage, we use MuLT (Tsai et al., 2019a) as feature extractor. After the encoder producing unimodal, bimodal, and trimodal features, we performs linear transformation for each feature, and output feature vectors with dimension $d_f = 64$.

We perform two iterations of routing between features and concepts with dimension $d_c = 64$ where $d_c$ is the dimension of concepts. All experiments use the same hyper-parameter configuration in this paper.

### .2 Remarks on CMU-MOSEI Sentiment

Our model poses the problem as classification and predicts only integer labels, so we don’t provide mean average error and correlation metrics.

### .3 Remarks on CMU-MOSEI Emotion

Due to the introduction of concepts in our model, we transform the CMU-MOSEI emotion recognition task from a regression problem (every emotion has a score in $[0, 3]$ indicating how strong the evidence of that emotion is) to a classification problem. For each sample with six emotion scores, we label all emotions with scores greater than zero to be present in the sample. Then a data sample would have a multiclass label.

### .4 Global Interpretation Result

We analyze global interpretation of both CMU-MOSEI sentiment and emotion task.

**CMU-MOSEI Sentiment** The analysis of the routing coefficients $r_{ij}$ is included in the main paper. We then analyze $p_i$ (table 6) and the products $p_i r_{ij}$ (table 4). Same as analysis in the main paper, our model relies on acoustic modality for extremely negative predictions (row $r_{i1}$ column -3) and text-acoustic bimodal interaction for extremely positive predictions (row $r_{i6}$ column 3). The sentiments that are neutral or less extreme are predicted by contributions from many different modalities / interactions. The activation table shows high activation value (> 0.8) for most modality / interactions except $r_{ci}$.

**CMU-MOSEI Emotion** Same as above, we analyze $p_i$ (Table 7) and the product $p_i r_{ij}$ (Table 5). The result is very similar to that of $r_{ij}$. The activation table shows high activation value (> 0.8) for most modality / interactions except $p_{ci}$, same as CMU-MOSEI sentiment. We see strong connections between audio-visual interactions and angry,

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**.1 Training Details and Hyper-parameters**

Our model is trained using the Adam (Kingma and Ba, 2014) optimizer with a batch size of 32. The learning rate is 1e-4 for CMU-MOSEI Sentiment and IEMOCAP, and 1e-5 for CMU-MOSEI emotion. We apply a dropout (Srivastava et al., 2014) of 0.5 during training.
Table 4: Global interpretation (quantitative results) for Multimodal Routing. Confidence Interval of $p_{ij}$, sampled from CMU-MOSEI sentiment task.

|                 | Happy | Sad    | Angry | Fear  | Disgust | Surprise |
|-----------------|-------|--------|-------|-------|---------|----------|
| $p_{i \tau}$    | (0.137, 0.183) | (0.071, 0.099) | (0.107, 0.174) | **(0.280, 0.481)** | (0.106, 0.138) | (0.068, 0.123) |
| $p_{\alpha \tau}$ | (0.105, 0.156) | (0.094, 0.113) | (0.104, 0.149) | (0.129, 0.160) | **(0.310, 0.442)** | (0.078, 0.099) |
| $p_{\nu \tau}$  | (0.123, 0.141) | (0.099, 0.129) | (0.189, 0.221) | (0.141, 0.162) | (0.119, 0.128) | (0.103, 0.114) |
| $p_{\alpha \nu \tau}$ | (0.070, 0.101) | (0.045, 0.065) | (0.127, 0.165) | (0.052, 0.078) | (0.044, 0.065) | **(0.504, 0.648)** |
| $p_{\nu \alpha \nu \tau}$ | (0.104, 0.138) | (0.059, 0.076) | **(0.286, 0.395)** | (0.200, 0.252) | (0.062, 0.100) | (0.089, 0.102) |
| $p_{\nu \alpha \tau \nu \tau}$ | (0.131, 0.173) | (0.050, 0.068) | (0.152, 0.199) | (0.122, 0.149) | (0.096, 0.118) | (0.093, 0.115) |
| $p_{\nu \alpha \tau \tau \nu \tau}$ | (0.160, 0.187) | (0.132, 0.197) | (0.132, 0.174) | (0.151, 0.183) | (0.151, 0.173) | (0.096, 0.111) |

Table 5: Global interpretation (quantitative results) for Multimodal Routing. Confidence Interval of $p_{i \tau}$, sampled from CMU-MOSEI emotion task.

Table 6: Global interpretation (quantitative results) for Multimodal Routing. Confidence interval of $p_{i \tau}$, sampled from CMU-MOSEI sentiment task.

Table 7: Global interpretation (quantitative results) for Multimodal Routing. Confidence interval of $p_{i \tau}$, sampled from CMU-MOSEI emotion task.