Improving Multimodal Accuracy Through Modality Pre-training and Attention

Aya Abdelsalam Ismail¹, Mahmud Hasan², Faisal Ishtiaq²
asalam@cs.umd.edu, mahmud.ucr@gmail.com, Faisal_Ishtiaq@comcast.com
¹Department of Computer Science, University of Maryland
²Comcast Labs, Washington, DC, USA

Abstract

Training a multimodal network is challenging and it requires complex architectures to achieve reasonable performance. We show that one reason for this phenomena is the difference between the convergence rate of various modalities. We address this by pre-training modality-specific sub-networks in multimodal architectures independently before end-to-end training of the entire network. Furthermore, we show that the addition of an attention mechanism between sub-networks after pre-training helps identify the most important modality during ambiguous scenarios boosting the performance. We demonstrate that by performing these two tricks a simple network can achieve similar performance to a complicated architecture that is significantly more expensive to train on multiple tasks including sentiment analysis, emotion recognition, and speaker trait recognition.

1 Introduction

Multimodal learning [1] means using data from different modalities such as acoustic, visual and language information to perform a certain task. It involves understanding the role each modality plays in the task (intra-modal dynamics) and how modalities interact with each other (inter-modality dynamics). Previous work on multimodal learning focuses on increasing model complexity to boost accuracy. Such sophisticated architectures are needed to overcome the difficulty of training multimodal networks [2,3]. We believe, the main reason behind this training difficulty is that various modalities tend to converge and generalize at different rates (shown in the first column of Figure 2). Training multimodal architecture end-to-end with randomly initialized sub-networks produces a sub-optimal solution.

We address the shortcomings above by taking a two-step approach while training the multimodal network: (1) Each sub-network is pre-trained independently to learn intra-modal dynamics (allowing each modality to convergence at its own rate). (2) Different modalities are then fused by an attention mechanism (that decides which modalities are most important in a particular example at test time) and the entire network is then fine-tuned end-to-end. The entire architecture is shown in Figure [1]

We empirically show that training of multimodal architecture end-to-end from scratch will bias the network towards the modality that has a faster convergence rate. We then show that adding the pre-training step sufficiently improves the performance of multimodal networks. We evaluate our proposed training methods on three publicly available datasets for three multimodal tasks. Our model with simple modality-specific sub-networks shows competitive performance when compared to other models on all three tasks.

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2 Modality Attention Network with Two Step Training

Modality Attention Network (MAN) has two main components: (1) **Sub-networks** - these are independently trained bidirectional LSTM for each modality such as text, audio, and video for emotion recognition task. (2) **Attention Block** - this block estimates a relative salience score for each modality. MAN overview is shown in Figure 1.

Sub-networks: The goal of sub-networks is to learn intra-modal dynamics and produce an embedding for each modality that will be used by the attention block. We use a bidirectional Long-short Term Memory (LSTM) [4] for each sub-network. LSTMs have been widely used in modeling temporal data in many tasks including text classification [5], video classification [6], and voice activity detection [7]. Note that LSTM can be replaced with any neural architecture and the sub-networks are not required to have the same architecture.

Modality-Specific Pre-training: The modality-specific sub-networks are first pre-trained independently on the task of interest. This is done for two reasons: (1) Pre-training allows better learning of intra-modal dynamics since the learning process is not affected by any other modalities at this time. (2) Data from different modalities have different convergence rates, if we train the network end-to-end without the pre-training step, the network tends to focus on the modality that converges faster ignoring others.

The softmax layer at the end of the modality-specific sub-network is removed after pre-training and the last hidden layer is used as a feature representation of that modality and is given as the input to the attention block as shown in Figure 1.

Formally, let the input to the language sub-network be denoted as \( L = [l_0, \ldots, l_t, \ldots, l_n] \) where \( l_t \) is the \( t \)-th word in the sentence and \( l \) is the feature embedding. Similarly, the input to acoustic and visual sub-network is denoted as \( A \) and \( V \) respectively. The output of the sub-networks is the last hidden state of modality-specific network can be written as: \( h_l = \text{Net}_l(L), h_a = \text{Net}_a(A), h_v = \text{Net}_v(V) \).

Attention Block: Hidden layers from sub-networks \( h_l, h_a, \) and \( h_v \) each have a same dimension of \( N \). Matrix \( H \) is the input to attention block where \( H = [h_l, h_a, h_v] \); \( H \) has a dimension of \( m \times N \), where \( m \) is the number of modalities. The output of the attention block is a weight matrix \( A \).

Attention matrix \( A \) is given as: \( \text{softmax} (W_2 \text{tanh}(W_1 H^T + b_1)) + b_2 \). Weight matrix \( W_1 \) and \( W_2 \) have dimensions of \( k \times N \) and \( 1 \times k \) respectively, where \( k \) is a hyper-parameter; \( b_1 \) and \( b_2 \) are bias parameter and the \( \text{softmax}() \) ensures that all the computed weights are sum to 1. In the attention matrix \( A = [w_l, w_a, w_v] \), weights \( w_l, w_a, \) and \( w_v \) represent importance of different modalities.

Output of MAN: The hidden layer of each sub-network is multiplied by its weights, which is then concatenated together and passed to a fully connected layer and a \( \text{softmax} \) layer for the final classification. The entire architecture is then trained end-to-end together, which fine-tunes the sub-networks in the process. This helps to capture both intra-modal and inter-modal dynamics.

3 Experiments

We evaluated the proposed framework on three real-world applications: sentiment analysis, emotion recognition, and speaker trait recognition. The experiments have been designed to investigate the
following: (a) The performance of MAN in terms of accuracy, complexity, and training time when compared to other networks. (b) The effect of pre-training the sub-networks versus end-to-end training of the entire network for multimodal networks. (c) The importance of attention module in differentiating between important and ambiguous modalities. Detailed description of datasets, baselines and experiments is available in the supplementary material.

Datasets: We selected three publicly available multimodal datasets that contain spoken language, acoustic and visual information. Multimodal Sentiment Analysis CMU MOSI dataset [9], Multimodal Emotion Recognition CMU MOSEI dataset [9] and Multimodal Speaker Trait Recognition Persuasion Opinion Multimodal POM dataset [10].

Computational Descriptors: Language Features: GloVe [11] word embeddings are used to convert the transcripts into word embeddings. Acoustic Features: COVAREP [12] acoustic analysis framework is used to extract low level acoustic features. Visual Features: Facial expression analysis toolkit FACET [13] is used as visual feature extractor.

Baseline Models We compare the performance of MAN to a variety of models for multimodal language analysis; all models are trained using the same feature embeddings: LF-LSTM Late Fusion LSTM, MAF Modality Attention Fusion [14], TFN Tensor Fusion Network [15], LMF Low-rank Multimodal Fusion [16]. MFM Multimodal Factorization Model [18] and RAVEN Recurrent Attended Variation Embedding Network [19].

Evaluation Metrics For regression, we report Mean Absolute Error. For classification accuracy, we report $A^C$ where $C$ is the number of classes. In addition, we report the mean epoch training time in seconds and inference time in milliseconds.

4 Results and Discussion

Performance of MAN We show the results in Table 1. There is no single model that always outperform others in all metrics across different tasks, in terms of accuracy and MAE. MAN shows competitive performance when compared against the other models. Generally best performing models are RAVEN and MAN; while MAN requires less training time.

| Method       | CMU-MOSI | CMU-MOSEI | POM       |
|--------------|----------|-----------|-----------|
|              | $A^2$    | MAE ep. In. | $A^4$    | MAE ep. In. | $A^7$    | MAE ep. In. |
| LF-LSTM      | 0.747    | 1.025, 1.92 | 0.36      | 0.645    | 0.155 | 19.02 | 0.04 | 0.366    | 0.832 | 8.25 | 0.25 |
| MAF          | 0.762    | 1.002, 1.19 | 0.17      | 0.673    | 0.159 | 13.96 | 0.02 | 0.381    | 0.823 | 4.27 | 0.13 |
| TFN          | 0.753    | 1.011, 1.07 | 0.23      | 0.701    | 0.176 | 9.72  | 0.04 | 0.367    | 0.826 | 2.75 | 0.06 |
| LMF          | 0.766    | 1.002, 0.96 | 0.24      | 0.761    | 0.160 | 9.53  | 0.04 | 0.362    | 0.844 | 4.03 | 0.07 |
| MFM          | 0.750    | 1.027, 6.75 | 1.16      | 0.723    | 0.163 | 79.28 | 0.16 | 0.360    | 0.838 | 8.28 | 1.40 |
| RAVEN        | 0.761    | 1.010, 9.52 | 1.52      | 0.632    | 0.163 | 114.42 | 0.19 | 0.366    | 0.854 | 131.79 | 1.94 |

| MAN          | 0.784    | 0.970, 1.76 | 0.37      | 0.7604*  | 0.147 | 19.47 | 0.04 | 0.378*   | 0.807 | 11.39 | 0.28 |

Table 1: Results on different datasets. $A^C$ is accuracy, MAE is Mean absolute error, ep. denotes the mean epoch training time in seconds, and In. is mean inference time in milliseconds. Best results are bolded and the 2nd best is noted with *.

Why do we need modality-specific pre-training? Different modalities converge and generalize at different rates. Consider Figure 2(a), the 1st column shows how language modality converges faster than the acoustic and the visual modality for MOSI dataset. In this case, end-to-end training leads to favoring language modality as shown in the 2nd column, where the attention module assigns higher weights to the language. As the network continues to learn, the effect of acoustic and visual modalities tend to diminish over time. If we pre-train the sub-networks and then fine-tune the entire architecture, we eliminate the bias introduced by the difference in convergence rate of different modalities, as shown in the 3rd column; where network learns that both language and visual modalities are equally important in this task. For MOSEI and POM (the 1st column of Figures 2(b) and 2(c) respectively), the differences in convergence rate among the modalities are not as significant as the MOSI dataset. However, training without pre-training the sub-networks leads to a biased distribution of the weights among the modalities as shown in the 2nd column. This is fixed when we pre-train the sub-networks as shown in the 3rd column, which eventually leads to better performance.
The effect of pre-training on different multimodal architectures: We repeated MOSI experiment with pre-training for LF-LSTM and MAF since they allow separation of sub-networks. Table 2 shows that pre-training sub-networks before end-to-end training improves the accuracy on both.

|                | GloVe | BERT |
|----------------|-------|------|
| Text Only      | 0.756 | 0.793|
| MAN - Atten.   | 0.762 | 0.808|
| MAN - pre-training | 0.765 | 0.802|
| MAN            | **0.784** | **0.812** |

Table 2: $A^2$ with & without Pre-training.

Why is Attention needed? The attention module produces a single weight for each modality pointing out which modality is important in a particular example allowing the network to focus on the feature representation of that modality which results in a boost in accuracy as shown in Table 3. In addition, attention weights can also be used as a method of model interpretation [20–24]. This is not the case in many methods such as tensor factorization, features from different modalities are multiplied together so it becomes unclear which modality is the most important. In Figure 3, shows an example from MOSI dataset on sentiment analysis task, where the speaker appears smiling and laughing; however, the text is negative and model was able to attend on the correct modality. More examples are available in the supplementary material.

Better word embeddings better accuracy Table 3 show the difference in accuracy on MOSI when replacing the text sub-network with BERT [25]. Since BERT produces better word embeddings than GloVe replacing text sub-network with BERT improves accuracy. Similar, to GloVe, the addition of pre-training step along with the attention module before end-to-end training improves the accuracy.

5 Conclusion

In this paper, we identify the difference in the convergence rate of various modalities as one of the reasons behind the difficulty of training multimodal networks. We find that this can be overcome by pre-training individual modality-specific sub-networks followed by end-to-end fine-tuning of the entire network. Finally, we can improve the accuracy further through an attention module that attends to different modalities after pre-training.
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Related Work

Previous work on multimodal reasoning focuses on audio-visual data \cite{26, 29}. Human communication uses both verbal and nonverbal modalities. Ignoring the contribution of text can cause misinterpretation as shown in example (b) in Figure 4. Recent work recognizes the importance of adding text as a modality, leading to a blossom of language-audio-visual datasets in tasks such as emotion recognition and sentiment analysis \cite{31-34, 8, 9, 35}. Models in previous work can be divided into three major categories: (1) early fusion, (2) late fusion, and (3) multi-view learning.

**Early Fusion** concatenates input-level feature from different modalities. The fused features are then passed to a generic model. Intra-modal dynamics are not modeled explicitly when using this method of fusion \cite{36, 37, 30}. Early fusion methods can preserve the temporal nature of data by using recurrent neural networks, or totally ignores the time factor when using classical machine learning methods such as Support Vector Machines \cite{8, 32}. Due to the lack of specific intra-modal models, this fusion method tends to overfit on small datasets \cite{38}.

**Late Fusion** models each modality separately, then the outputs are combined in the decision phase. This can be done by majority voting, weighted averaging \cite{39}, or the output of modality networks are combined with a joint neural network that is trained to make final decision \cite{40}.

**Multi-view learning** is a broader class of methods that aim to learn both intra-modal dynamics and inter-modality dynamics jointly. To place our work in the context of prior research we divide multi-view learning into the following subcategories:  
(a) **Non-attention based fusion methods:** this includes tensor-based multimodal representations created from expensive tensor product \cite{15} or low-rank tensors approximation \cite{16}, generative representation learning \cite{41, 1}, word-level factorized multimodal representation \cite{18} and variations to word representations by word-level fusion with nonverbal features \cite{19}. Such methods (excluding \cite{16}) are rather slow and suffer from exponentially increasing computational complexity as the number of modalities increase.  
(b) **Attention based fusion methods:** The work in \cite{17, 42} used attention to discover interactions between modalities through time. Method proposed in \cite{43} decomposes the fusion problem into multiple stages and
focuses on a subset of multimodal signals at each stage. In [14], authors apply both feature attention and modality attention to classify utterance-level speech data.

MAN belongs to the attention based fusion subcategory; however, we differ from current methods by our ability to view modalities independently and quantize how each modality influences the final decision of the network. Additionally, the pre-training step allows our model to produce competitive results when compared to more complex architectures.

Detailed description of the experiments

Datasets

Details of each dataset is described in the section below and data split is shown in Table 4. Each datasets that contain spoken language, acoustic and visual information.

| Dataset       | CMU-MOSI | CMU-MOSEI | POM |
|---------------|----------|-----------|-----|
| # Training    | 1281     | 16265     | 560 |
| # Validation  | 229      | 1869      | 92  |
| # Testing     | 685      | 4643      | 188 |

Table 4: Number of training, validation and testing samples in each dataset.

Multimodal Sentiment Analysis: CMU-MOSI dataset [8] is a collection of 93 review videos in English with 2199 utterance segments. Each utterance is annotated with sentiment by five individual annotators in the range [-3,3], where -3 indicates highly negative and 3 indicates highly positive.

Multimodal Emotion Recognition: CMU-MOSEI dataset [9] is a collection of 3,229 videos spanning over 23,000 utterances from more than 1,000 online YouTube speakers. Each utterance is annotated with sentiment in the range [-3, 3] similar to CMU-MOSI dataset. In addition, utterances are annotated for Ekman emotions [44] of happiness, sadness, anger, fear, disgust, and surprise with values in range [0, 3].

Multimodal Speaker Trait Recognition: POM Persuasion Opinion Multimodal dataset [10] contains 1,000 movie review videos annotated for 16 different speaker traits: confidence, passion, voice pleasant, dominance, credibility, vividness, expertise, entertaining, reserved, trusting, relaxed, outgoing, thorough, nervous, humorous, and persuasive.

Feature Embedding

Following prior practice [16, 43, 45, 19], we use features provided by CMU-Multimodal SDK[1].

- **Language Features:** Pre-trained word embeddings GloVe [11] are used to convert the transcripts of videos into sequence of 300-dimensional word embeddings.
- **Acoustic Features:** COVAREP [12] acoustic analysis framework is used to extract low level acoustic features. The features include pitch tracking, polarity estimation, glottal closure instants, spectral envelope, glottal flow estimation and 12 Mel-frequency cepstral coefficients along with other features.
- **Visual Features:** Facial expression analysis toolkit FACET[2] is used as visual feature extractor. Features include facial action units, facial landmarks, head pose, gaze tracking and HOG features.

Baseline Models

**Late Fusion:** A sub-network is learned for each modality such as language, acoustic, and visual. As a baseline, we use a bidirectional LSTM for each sub-network. The last hidden layer from sub-networks are concatenated together and passed to a dense layer. This is referred to as LF-LSTM.
Hybrid Attention based Multimodal Network (MAF)\cite{14} a deep multimodal network with both feature attention and modality attention. The hybrid attention architecture helps the system focus on learning informative representations for both modality-specific feature extraction and model fusion.

Tensor Fusion Network (TFN)\cite{15} learns intra-modality and inter-modality dynamics by creating a multi-dimensional tensor that captures unimodal, bimodal and trimodal interactions across modalities.

Low-rank Multimodal Fusion (LMF)\cite{16} performs multimodal fusion using low-rank tensors to improve efficiency.

Memory Fusion Network (MFN)\cite{17} a multi-view sequential learning neural network that accounts for both view-specific and cross-view interactions through time. View-specific interactions are learned through assigning an LSTM function to each view. The cross-view interactions are identified using a special attention mechanism and summarized through time with a multi-view gated Memory.

Multimodal Factorization Model (MFM)\cite{18} a model that factorizes representations into two sets of independent factors: multimodal discriminative and modality-specific generative factors then optimizes for a joint generative-discriminative objective across multimodal data and labels.

Recurrent Attended Variation Embedding Network (RAVEN)\cite{19} a model for human multimodal language that considers the fine-grained structure of nonverbal subword sequences and dynamically shifts the word representations based on these nonverbal cues.

Training Models

All models are trained on NVIDIA Tesla K80 GPU. For each dataset, we use the hyper-parameters reported by the baseline methods for that particular dataset. If the hyper-parameters were not reported in the paper, we perform an extensive grid search to find the best performing hyper-parameters. We use the same grid search method to find the best hyper-parameters for our method as well.

Understanding the Importance of Different Modalities through Attention

Human’s ability to communicate effectively comes from their understanding of different modalities\cite{46}. The context in which a modality occurs changes its underlying meaning; a laugh can be both happy or sarcastic. In such cases, not all modalities are equally important for revealing the meaning of human interaction. Consider examples in Figure 4 for an emotion classification task: In example (a), we can easily perceive that the emotion is fear as the visual signal is very prominent. In example (b), visual signals are ambiguous and not useful; however, by looking at the sentence, the word "Wow" allows us to conclude that the emotion is surprise. In example (c), visual and language signals are misleading and acoustic features help make correct perception. Humans can identify the important modality in cases where some modalities are ambiguous or may lead to wrong judgment.

![Figure 4](image)

Figure 4: Video examples for an emotion classification task. (a) Visual images are enough to make correct classification. (b) Language is most informative modality. (c) Visual and language modalities are misleading and acoustic features are most important.
The goal of the attention block in MAN is to mimic human’s ability to understand the context of multimodal data by identifying the importance of modality. In Figure 3, we showed an example from MOSI where MAN can successfully detect the essence of different modalities. Figure 5 shows examples from MOSEI and POM. Figure 5(a) An example from MOSEI dataset on emotion classification task, all modalities point to happy emotion; MAN also produces similar weights for all modalities. Figure 5(b) An example from POM dataset on personality trait recognition. Here the speaker is confident; it is difficult to recognize this from text but the calmness in the speaker’s voice helped the model to make a correct prediction. MAN’s ability to differentiate between modalities makes it in some sense more explainable.

(a) For this emotion recognition task in MOSEI, looking at any modality separately one can deduce that the speaker is happy; MAN gave modalities similar weights.

(b) In a personality trait recognition task from POM dataset, the calmness in the speakers voice manifests how confident the speaker is, MAN assigns the highest weights to the acoustic modality.

Figure 5: Video examples from three datasets on different classification tasks; in each example we show the attention weight MAN produced for each modality.