HighMMT: Quantifying Modality & Interaction Heterogeneity for High-Modality Representation Learning

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Abstract

Many real-world problems are inherently multimodal, from the communicative modalities humans use to express social and emotional states such as spoken language, gestures, and paralinguistics to the force, proprioception, and visual sensors ubiquitous on robots. While there has been an explosion of interest in multimodal representation learning, these methods are still largely focused on a small set of modalities, primarily in the language, vision, and audio space. In order to accelerate generalization towards diverse and understudied modalities, this paper studies efficient representation learning for high-modality scenarios involving a large set of diverse modalities. Since adding new models for every new modality or task becomes prohibitively expensive, a critical technical challenge is heterogeneity quantification: how can we measure which modalities encode similar information and interactions in order to permit parameter sharing with previous modalities? This paper proposes two new information theoretic metrics for heterogeneity quantification: (1) modality heterogeneity studies how similar 2 modalities \{X_1, X_2\} are by measuring how much information can be transferred from \(X_1\) to \(X_2\), while (2) interaction heterogeneity studies how similarly pairs of modalities \{X_1, X_2\}, \{X_3, X_4\} interact by measuring how much interaction information can be transferred from \{X_1, X_2\} to \{X_3, X_4\}. We show the importance of these 2 proposed metrics in high-modality scenarios as a way to automatically prioritize the fusion of modalities that contain unique information or unique interactions. The result is a single model, HighMMT, that scales up to 10 modalities (text, image, audio, video, sensors, proprioception, speech, time-series, sets, and tables) and 15 tasks from 5 different research areas. Not only does HighMMT outperform prior methods on the tradeoff between performance and efficiency, it also demonstrates a crucial scaling behavior: performance continues to improve with each modality added, and it transfers to entirely new modalities and tasks during fine-tuning.

We release our code and benchmarks, which we hope will present a unified platform for subsequent theoretical and empirical analysis: \url{https://github.com/pliang279/HighMMT}

1 Introduction

Multimodal machine learning brings unique challenges for both computational and theoretical research given the heterogeneity of various data sources \cite{Liang et al. 2022}. While there have been impressive advances in modeling language, vision, and audio \cite{Agrawal et al. 2017, Ramesh et al. 2021}, advances in sensing technologies have resulted in many real-world platforms such as cellphones, smart devices, self-driving cars, healthcare technologies, and robots now integrating a much larger number of sensors such as time-series, proprioception, sets, tables, and high-frequency sensors \cite{Frantzidis et al. 2010, Lee et al. 2019, Leiva et al. 2020, Liang et al. 2021a, Belpaeme et al.}. We release our code and benchmarks, which we hope will present a unified platform for subsequent theoretical and empirical analysis: \url{https://github.com/pliang279/HighMMT}

Figure 1: Heterogeneity quantification: Efficiently learning from many modalities requires measuring (1) modality heterogeneity, which modalities are different and should be separately processed, and (2) interaction heterogeneity, which modality pairs interact differently and should be separately fused. Our proposed HighMMT model uses these new measurements to dynamically group parameters to balance both performance and efficiency.
This new setting of high-modality learning involves learning representations over many diverse modality inputs. As more modalities are introduced, adding new model parameters for every new modality or task becomes prohibitively expensive and not scalable. A critical technical challenge for efficient high-modality learning, therefore, is heterogeneity quantification: how can we measure which modalities encode similar information and similar interactions in order to permit parameter sharing with previous modalities (see Figure 1)? For example, how can one determine whether the same modality encoder can be shared when processing language and speech, or that the same fusion network can be shared when fusing human speech and gestures as well as robot visual and force sensors?

In this paper, we propose a principled approach for heterogeneity quantification via modality information transfer, an information-theoretic approach that measures the amount of transferable usable information from one modality to another. Our first proposed metric, (1) modality heterogeneity studies how similar 2 modalities \{X_1, X_2\} are by measuring how much usable information can be transferred from \(X_1\) to \(X_2\), and our second metric, (2) interaction heterogeneity studies how similarly 2 modality pairs \{\(X_1, X_2\), \(X_3, X_4\)\} interact by measuring how much usable interaction information can be transferred from \{\(X_1, X_2\)\} to \{\(X_3, X_4\)\}. We show the importance of these 2 proposed metrics in high-modality scenarios as a way to automatically prioritize the fusion of modalities that contain unique information or unique interactions, and otherwise sharing parameters across similar modalities displaying similar information or interactions.

Operationalizing these ideas on a suite of 10 modalities, 15 prediction tasks, and 5 research areas, we show how to train a single model, HighMMT, that (1) improves the tradeoff between performance and efficiency over task-specific state-of-the-art models, (2) enables cross-modal transfer by pretraining on source multimodal tasks before transferring to new target modalities and tasks, and (3) is especially beneficial for low-resource scenarios (less training data and partially-observable modalities). Beyond these empirical results, we believe that our insights on quantifying heterogeneity and information sharing in multimodal models are independently useful for future work. Our implementations and benchmarks are publicly available which we hope will present a unified platform for subsequent theoretical and empirical analysis.

## 2 High-Modality Multimodal Transformer

In this section, we describe our overall approach for high-modality representation learning (see Figure 2). In §2.1 we formalize modality and interaction heterogeneity to understand whether modalities should be processed similarly or differently. Using these insights, §2.2 describes our proposed HighMMT model with dynamic parameter sharing based on heterogeneity measurements.

### 2.1 Measuring Heterogeneity via Modality Information Transfer

**Modality heterogeneity** seeks to answer the question: how differently should I encode modality \(X_1\) versus \(X_2\)? **Interaction heterogeneity** aims to answer: how differently should I fuse modalities \{\(X_1, X_2\)\} versus \{\(X_3, X_4\)\}? Together, they help us appropriately design both unimodal and crossmodal components of a multimodal model. We will formalize heterogeneity via modality transfer, an information-theoretic approach that measures the amount of transferable usable information from one modality to another.

**Background: Information theory and usable information.** Information theory is a useful framework to study the utility of data for prediction tasks. Specifically, the mutual information \(I(X; Y)\) measures the amount of uncertainty reduced from \(H(Y)\) to \(H(Y|X)\) when given \(X\) as input, and its estimation has been central to studying representation learning in both unimodal and multimodal settings. Recently, \(V\)-usable information extends traditional Shannon information theory to account for computational constraints: \(I_V(X \rightarrow Y)\) reflects the ease with which a model family \(V\) can predict outcomes \(Y\).
1a. Estimate modality heterogeneity via transfer
1b. Estimate interaction heterogeneity via transfer

2a. Compute modality & interaction heterogeneity matrices
2b. Determine parameter clustering

3. Heterogeneity-aware model across modalities and tasks

Figure 2: **HighMMT workflow:** (1) We estimate modality and interaction heterogeneity via modality transfer to determine which modalities should be processed and fused differently. (2) Using the inferred heterogeneity, we determine the optimal grouping of parameters balancing both total performance and parameter efficiency, which (3) informs our design of a heterogeneity-aware model with dynamic parameter sharing across many modalities and tasks. **HighMMT** enables statistical strength sharing, efficiency, and generalization to new modalities and tasks.

Given inputs $X$:

$$ H_Y(Y) = \inf_{f \in \mathcal{V}} \mathbb{E}[-\log f[\emptyset](Y)], \quad H_Y(Y|X) = \inf_{f \in \mathcal{V}} \mathbb{E}[-\log f[X](Y)], $$

$$ I_Y(X \rightarrow Y) = H_Y(Y) - H_Y(Y|X). $$

where $f[X]$ and $f[\emptyset]$ are both models that produce a probability distribution over the labels, and the goal is to find $f \in \mathcal{V}$ that maximizes the log-likelihood of the data with $(H_Y(Y|X))$ and without $(H_Y(Y))$ the input. Conditioning information on a specific model family $\mathcal{V}$ can help to explain the difficulties of encryption applied to $X$, or the benefits of feature representation learning applied to $X$. For example, processing the input with $\tau$ (e.g., decryption or representation learning) can make prediction easier, allowing $I_Y(\tau(X) \rightarrow Y) \geq I_Y(X \rightarrow Y)$, whereas traditional information theory measures of $I(X;Y)$ would be invariant to these processing steps. Finally, setting $\mathcal{V}$ as the set of all functions (i.e., under unbounded computation) reduces to Shannon information.

**Estimating modality heterogeneity via unimodal information transfer.** We propose to measure heterogeneity between modalities $X_1$ and $X_2$ via unimodal transfer. Given a task $Y$ defined over $X_1$ and $X_2$, how well does an unimodal model trained on $(X_1;Y)$ transfer to $(X_2;Y)$? We choose model transfer as our focus of heterogeneity since it is captured at the level of features extracted via representation learning, rather than at the data-level. Even though the input data may be very different (e.g., images from different cameras or paraphrased sentences), effective feature extractors may be able to learn similar representations from them. Furthermore, it directly models task-relevance: the degree of heterogeneity depends on the end task, which enables using these heterogeneity measures subsequently for end-task optimization.

$\mathcal{V}$-usable information provides a nice formalism to compute unimodal transfer, via the difference in usable information between unimodal models trained on $X_1$ before transfer to $X_2$, versus those trained directly on $X_2$. Specifically, first set the model family $\mathcal{V}$ as the family of unimodal networks on target task $(X_2;Y)$, and the model family $\mathcal{V}(X_1)$ as the family of unimodal networks initialized with pre-trained parameters on task $(X_1;Y)$. Then, the transfer difficulty can be defined as $T(X_1 \rightarrow X_2;Y) = I_Y(X_2 \rightarrow Y) - I_Y(X_1)(X_2 \rightarrow Y)$. Intuitively, $I_Y(X_2 \rightarrow Y)$ measures the (baseline) usable information in $\mathcal{V}$ to predict $Y$ given $X_2$, while $I_Y(X_1)(X_2 \rightarrow Y)$ measures the usable information in $\mathcal{V}(X_1)$ to predict $Y$ given $X_2$. In our experiments, we find that both $\mathcal{V}(X_1)$ and $\mathcal{V}$ are both expressive enough such that $H_Y(X_1)(Y) \approx H_Y(Y)$ reduce to the label entropy, so the simplified form

$$ T(X_1 \rightarrow X_2;Y) = I_Y(X_2 \rightarrow Y) - I_Y(X_1)(X_2 \rightarrow Y) = H_Y(X_1)(Y|X_2) - H_Y(Y|X_2) $$

measures the difficulty of transferring a model trained on the source task $(X_1;Y)$ to a target task $(X_2;Y)$. Note that computing $T(X_1 \rightarrow X_2;Y)$ only requires the training or fine-tuning of 2 models across the source and target modalities, which is efficient.
What are some properties of \(T(X_1 \rightarrow X_2; Y)\)? For very different modalities \(X_1\) and \(X_2\), we typically expect \(\mathcal{V}(X_1)\) to contain less usable information than \(\mathcal{V}\) for a target task \((X_2; Y)\), which would imply that \(T(X_1 \rightarrow X_2; Y) \geq 0\) (i.e., positive difficulty). This is consistent with work demonstrating negative transfer across different modalities [Liang et al. 2021b, Tulving and Watkins 1974, Wang et al. 2019]. Under these scenarios, the larger the positive magnitude of \(T(X_1 \rightarrow X_2; Y)\), the more different modalities \(X_1\) and \(X_2\) are in the context of task \(Y\) (more difficult to transfer). However, there can also be cases of zero or even positive transfer (i.e., \(T(X_1 \rightarrow X_2; Y) \leq 0\)), even in the surprising case of very different modalities [Lu et al. 2021]. These cases reinforce the benefits of feature-based approaches to measure heterogeneity: while the raw modalities themselves seem very different, they can still be processed by similar models resulting in positive transfer, and should be assigned a difference of 0. Our final heterogeneity measure \(d(X_1; X_2)\) aggregates the absolute value (to account for positive transfer) of transfer difficulty statistics across tasks \(Y \in \mathcal{V}\) and across both transfer directions \(X_1 \rightarrow X_2\) and \(X_2 \rightarrow X_1\):

\[
d(X_1; X_2) = \sum_{Y \in \mathcal{V}} |T(X_1 \rightarrow X_2; Y)| + \sum_{Y \in \mathcal{V}} |T(X_2 \rightarrow X_1; Y)|. \tag{4}
\]

We note that our modality heterogeneity measure \(d(X_1; X_2)\) is not a strict metric space: while it satisfies non-negativity: \(d(X_1; X_2) \geq 0\), with \(d(X_1; X_2) = 0\) when \(X_1 = X_2\), symmetry: \(d(X_1; X_2) = d(X_2; X_1)\), and triangle inequality: \(d(X_1; X_3) \leq d(X_1; X_2) + d(X_2; X_3)\), it does not satisfy positivity: there are a few cases of \(X_1 \neq X_2\) but \(d(X_1; X_2) = 0\) due to positive transfer.

**Estimating interaction heterogeneity via crossmodal information transfer.** We are also interested in interaction heterogeneity: specifically, how differently should I fuse modalities \(\{X_1, X_2\}\) versus \(\{X_3, X_4\}\)? We therefore extend to crossmodal transfer by comparing the difference in usable information between a pretrained multimodal model on \((X_1, X_2; Y)\) before transfer to \((X_3, X_4; Y)\), versus those trained directly on the target task \((X_3, X_4; Y)\). In other words, we measure the quantity

\[
T(X_1, X_2 \rightarrow X_3, X_4; Y) = I_Y(X_3, X_4 \rightarrow Y) - I_{Y(X_1, X_2)}(X_3, X_4 \rightarrow Y) \tag{5}
\]

\[
= H_Y(X_3, X_4 | X_1, X_2) - H_Y(Y | X_3, X_4). \tag{6}
\]

The resulting set of distances \(d(X_1, X_2; X_3, X_4)\) after aggregation over tasks and transfer directions estimates the interaction heterogeneity between \(\{X_1, X_2\}\) and \(\{X_3, X_4\}\).

**Modality and interaction heterogeneity matrix.** Finally, we construct a modality heterogeneity matrix \(M_U(i, j) = d(X_i; X_j)\) and an interaction heterogeneity matrix (technically 4D-tensor) \(M_C(i, j, k, l) = d(X_i, X_j; X_k, X_l)\). As a side note, observe that these matrices are highly structured due to distances satisfying the triangle inequality, which implies that we do not need to compute all entries and instead rely on low-rank reconstruction from partial entries in practice [Drineas et al. 2006, Lisissa and Lai 2018] (see Appendix A for details, and see an example in §3.1).

**Determining parameter groupings** to balance both total performance and parameter efficiency can be solved via agglomerative hierarchical clustering where modalities are nodes and heterogeneity measurements are edges. The number of clusters \(k\) is treated as a hyperparameter dependent on the parameter budget (see Appendix A for details, and see clustering examples in §3.1). Clustering on the modality heterogeneity matrix \(M_U\) results in a grouping of modalities based on similarity (e.g., \(U_1 = \{X_1, X_2, X_4\}, U_2 = \{X_3\}, U_3 = \{X_5\}\)), and likewise for the crossmodal heterogeneity matrix \(M_C\) (e.g., \(C_1 = \{\{X_1, X_2\}, \{X_1, X_3\}, \{X_4, X_5\}\}, C_2 = \{\{X_2, X_3\}, C_3 = \{\{X_4, X_6\}, \{X_5, X_6\}\}, and so on.

### 2.2 Capturing Heterogeneity and Homogeneity in HighMMT

Using these insights, we now describe our approach for a general model HighMMT suitable for high-modality representation across many modalities and tasks. Our approach takes 2 main steps (see Figure 3): (1) **homogeneous pre-training** of a fully shared model across all modalities, before (2) **heterogeneity-aware fine-tuning** to respect modality and interaction heterogeneity.

**Homogeneous pre-training.** We first design a homogeneous multimodal model fully shared across all modalities and tasks with the following key components (see more details in Appendix B).

1. **Standardized input sequence:** We first standardize modalities as a sequence of embeddings, as is already done for sequential data such as text, audio, and time series, and recently adapted for image patches...
1. Homogeneous Pre-training

2. Heterogeneity-aware Fine-tuning

Finally, on top of concatenated and multimodal representations \( z_m \), we use a separate linear classification layer per task for task-specific prediction. To enable information sharing across modalities and tasks, homogeneous pre-training is performed across a diverse set of datasets in a multitask manner by optimizing a weighted sum of losses over tasks. The result is a single set of shared unimodal parameters \( U^* \) that encodes all modalities, and a single set of shared crossmodal parameters \( C^* \) that captures all pairwise interactions between modality pairs, along with all modality-specific embeddings \( \mathbb{E}^* \) and task-specific classifiers \( \mathbb{T}^* \).

Heterogeneity-aware fine-tuning. Finally, we account for heterogeneity by grouping unimodal parameters based on modalities that we know to be similar from \([2, 1]\) (e.g., setting \( U_1 = \{U_1, U_2\}, U_3 = \{U_3, U_4\} \)), and likewise for the crossmodal parameters (e.g., \( C_1 = \{C_{12}, C_{13}, C_{14}\}, C_2 = \{C_{23}, C_{15}\}, C_3 = \{C_{24}, ...\} \)). These groups of parameters are first initialized with the homogeneous model \( U^* \) and \( C^* \) before separate fine-tuning, which results in final parameters \( U^* \rightarrow \{U^*_1, U^*_2, ...\} \) and \( C^* \rightarrow \{C^*_1, C^*_2, ...\} \). The modality too (Dosovitskiy et al., 2021). For tables, sets, and graphs we treat each element in the table/set/graph as an element in the sequence. The end result is a standardized input data format of dimension \( x_{m} \in \mathbb{R}^{n \times t_{m} \times d_{m}} \), where \( n \) is the common batch-size, \( t_{m} \) is a modality and task-specific input sequence length, and \( d_{m} \) is a modality and task-specific input dimension.

2. Modality-specific embedding and positional encoding. For each distinct modality \( m \in M \) (which may appear across multiple tasks), we define a one-hot modality embedding \( \mathbf{e}_m \in \mathbb{R}^{|M|} \), where \( |M| \) is the total number of distinct modalities, to identify common modalities across different tasks for information sharing. We also introduce Fourier feature positional encodings \( \mathbf{p}_m \in \mathbb{R}^{t_{m} \times d_{pm}} \), where \( d_{pm} \) is the positional encoding dimension, to capture temporal and positional information across each modality. For multimodal tasks where a common dimension is shared across time (e.g., videos/time series), we apply a common positional encoding to capture the common time dimension.

3. Shared unimodal networks. Given modality-specific embeddings and positional encodings, the final input representation can now be processed by a general unimodal encoder with parameters \( U \) via a Transformer-based Perceiver block (Jaegle et al., 2021b). The input layer query is first set with a latent \( d_{LN} \) to attend to \( x_1 \) and keys and values \( K, V = z_2 \) to learn attention from \( X_1 \) to \( X_2 \), and a separate block to capture the attention in the opposite direction. A Crossmodal Transformer block using \( z_1 \) to attend to \( z_2 \) (and vice-versa) results in a final multimodal representation \( z_{mm} = [z_{1 \rightarrow 2}, z_{2 \rightarrow 1}] = [\text{CT}(z_1, z_2), \text{CT}(z_2, z_1)] \). For tasks with more than 2 modalities, a Crossmodal block is applied for each pair of modalities before concatenating.

4. Shared crossmodal networks. To learn multimodal representations, we use a shared Crossmodal Transformer block with parameters \( C \) (Tsai et al., 2019; Lu et al., 2019). Given 2 unimodal representations \( z_1 \) and \( z_2 \), a Crossmodal Transformer (CT) block uses crossmodal self-attention by setting the input layer query \( Q = z_1 \) and keys and values \( K, V = z_2 \) to learn attention from \( X_1 \) to \( X_2 \), and a separate block to capture the attention in the opposite direction. A Crossmodal Transformer block using \( z_1 \) to attend to \( z_2 \) (and vice-versa) results in a final multimodal representation \( z_{mm} = [z_{1 \rightarrow 2}, z_{2 \rightarrow 1}] = [\text{CT}(z_1, z_2), \text{CT}(z_2, z_1)] \). For tasks with more than 2 modalities, a Crossmodal block is applied for each pair of modalities before concatenating.

5. Task-specific classifier and multitask pre-training. Finally, on top of concatenated and multimodal representations \( z_{mm} \), we use a separate linear classification layer per task for task-specific prediction. To enable information sharing across modalities and tasks, homogeneous pre-training is performed across a diverse set of datasets in a multitask manner by optimizing a weighted sum of losses over tasks. The result is a single set of shared unimodal parameters \( U^* \) that encodes all modalities, and a single set of shared crossmodal parameters \( C^* \) that captures all pairwise interactions between modality pairs, along with all modality-specific embeddings \( \mathbb{E}^* \) and task-specific classifiers \( \mathbb{T}^* \).

Figure 3: **HighMMT Training** involves 2 steps: (1) homogeneous pre-training of a fully shared model across all modalities, before (2) heterogeneity-aware fine-tuning of parameters in different groups to respect modality and interaction heterogeneity respectively.
We begin with a study of the heterogeneity measurements (see modality and interaction heterogeneity matrices in Figure 4) and the resulting parameter groups.

**Modality heterogeneity:** We first notice that the modalities from AV-MNIST only transfer well to each other and has high difficulty transferring to other modalities from the other datasets. The same modality across different tasks is generally similar to each other (e.g., text between AV-MNIST and MOSEI, audio between AV-MNIST and MOSEI). There is generally more interaction heterogeneity than unimodal, implying that while the modality features are similar, the crossmodal interactions between modality pairs are more unique. We also find that the same modality pairs (video+text) and (video+audio) shows crossmodal similarity across both datasets they appear in: MOSEI and UR-FUNNY.

3 Experiments

**Setup:** In this section, we design experiments to analyze the multitask, transfer, and generalization capabilities of HighMMMT. We use a large collection of multimodal datasets provided in MultiBench (Liang et al., 2021b) spanning 10 modalities, 15 prediction tasks, and 5 research areas. We trained 3 multitask models across combinations of these datasets (see Table C in Appendix C for details). Overall, the total size of datasets involved in our experiments exceeds 370,000 and covers diverse modalities such as images, video, audio, text, time-series, various robotics sensors, sets, and tables, prediction tasks spanning the prediction of matching images and captions, robot pose, object pose, robot contact, design interfaces, digits, humor, sentiment, emotions, mortality rate, and ICD-9 codes, as well as multiple research areas of affective computing, healthcare, multimedia, robotics, and HCI.

3.1 Heterogeneity Measurements and Parameter Groups

We begin with a study of the heterogeneity measurements (see modality and interaction heterogeneity matrices in Figure 4) and the resulting parameter groups.

Embeddings $E^*$ and task classifiers $T^*$ are jointly fine-tuned as well. Fine-tuning is also performed in a multitask manner by optimizing a weighted sum of supervised losses across all modalities and tasks.
audio}, \mathcal{U}_3 = \{ \text{MIMIC timeseries}, \text{MOSEI text}, \text{UR-FUNNY text} \}, \text{and } \mathcal{U}_4 = \{ \text{MOSEI audio}, \text{UR-FUNNY audio} \}.

**Interaction heterogeneity:** At a high level, there is generally more interaction heterogeneity than unimodal, implying that while the modality features are similar, the crossmodal interactions between modality pairs are more unique. Again, we notice the general poor transfer from the modality pair (image+audio) in AV-MNIST to all other pairs, and the general strong transfer from (audio+text) in UR-FUNNY to the rest, which shows a higher-order relationship between modality and interaction heterogeneity. We also find that the same modality pairs (video+text) and (video+audio) show crossmodal similarity across both datasets they appear in: MOSEI and UR-FUNNY. Finally, while the triplet of crossmodal pairs in MOSEI are quite different from each other, those in UR-FUNNY are more similar. Using these measurements, the final groups of crossmodal pairs (and therefore crossmodal parameters) we obtain after clustering are: \(C_1 = \{ \text{MIMIC table+timeseries, MOSEI video+text, UR-FUNNY video+text} \}, \mathcal{C}_2 = \{ \text{AV-MNIST image+audio} \}, \mathcal{C}_3 = \{ \text{MOSEI video+audio} \}, \text{and } \mathcal{C}_4 = \{ \text{MOSEI audio+text, UR-FUNNY video+audio, UR-FUNNY audio+text} \}.

### 3.2 Qualitative Results

We now present our results on the multitask, transfer, and generalization capabilities of HighMMT using performance and efficiency metrics. Henceforth, we will refer to the following models:

1. **HighMMT share none** refers to individual copies of HighMMT models, one for each task.

2. **HighMMT share all** refers to one single HighMMT model fully shared across all modalities and tasks.

3. **HighMMT** refers to the full heterogeneity-aware HighMMT model across all modalities and tasks with learned parameter groupings based on heterogeneity measurements.

**Multitask performance and efficiency.** In Figure 5, we summarize the overall tradeoff between performance and efficiency using existing task-specific models and variants of HighMMT. The blue dots represent all possible combinations of task-specific models across multiple datasets (summarized in MultiBench \cite{Liang2021b}). \( > 10^5 \) total combinations) with their overall performance (scaled to a 0 – 1 range before averaging across datasets) and overall efficiency (inverted total number of parameters). The red dots represent the state-of-the-art Pareto front: points that are not strictly dominated in both performance and efficiency. In light green, separate single-task HighMMT models (share none) already improve parameter efficiency as compared to standard Multimodal Transformers \cite{Lu2019, Tsai2019}. In dark green is HighMMT (share all) trained in a homogeneous multitask manner (i.e., with full parameter sharing across unimodal and multimodal layers within and across tasks), which further pushes forward the Pareto front by improving both performance and efficiency. Finally, in orange, HighMMT with heterogeneity-aware fine-tuning achieves significantly better tradeoffs between performance and efficiency, with a controlled increase in parameters but much higher increases in performance across multiple modalities and tasks. The suite of HighMMT models is obtained by tuning \( k \), the number of parameter groups (i.e., number of clusters when clustering heterogeneity matrices).

**Positive transfer to new modalities and tasks.** HighMMT also offers opportunities to study whether we can transfer knowledge between completely different modalities and tasks. We pre-trained a fully-shared HighMMT model on 1/2/3 of the 4 tasks before fine-tuning on the fourth task only (e.g., train on

![Figure 5: Overall tradeoff.](image-url)
Table 1: Cross-modal transfer to new modalities and tasks. We train a fully-shared multitask HiGHMMT on 1/2/3 datasets and find that it generalizes to new modalities and tasks on the 4th dataset, with improved performance over single-task training on the 4th dataset. Cross-modal transfer improves with more pretraining tasks and works best on the smallest target tasks (UR-FUNNY).

| # Source tasks | Target task              |
|----------------|--------------------------|
| 0 (no transfer)| UR-FUNNY  | MOSEI  | MIMIC | AV-MNIST |
| 1              | 63.3      | 79.4   | 67.7  | 70.4     |
| 2              | 64.1      | 79.4   | 68.3  | 70.4     |
| 3              | 65.5      | 80.0   | 68.5  | 70.5     |

Table 2: HiGHMMT achieves strong performance on overall performance and efficiency, sometimes even beating (shown in bold) the task-specific state-of-the-art, especially on the relatively understudied modalities (time-series, robotics sensors, and sets) from the robotics (Push, V&T HCI (ENRICO), and healthcare (MIMIC) research areas, while using 10× fewer parameters due to parameter sharing and multitask learning. SOTA captures the max performance and parameters of more than 20 recent multimodal models implemented in MultiBench (Liang et al., 2021b).

| Model  | ENRICO ↑ | Push ↓ | V&T ↑ | UR-FUNNY ↑ | MOSEI ↑ | MIMIC ↑ | AV-MNIST ↑ | Params (M) ↓ |
|--------|----------|--------|-------|------------|---------|---------|------------|--------------|
| SOTA   | 51.0 ± 1.4 | 0.290 ± 0.1 | 93.6 ± 0.1 | 66.7 ± 0.3 | 82.1 ± 0.5 | 68.9 ± 0.5 | 72.5 ± 0.2 | 32.3         |
| HiGHMMT| 52.7 ± 0.6 | 0.277 ± 0.1 | 96.3 ± 0.2 | 66.2 ± 0.4 | 80.2 ± 0.2 | 68.2 ± 0.3 | 71.1 ± 0.2 | 3.01         |

UR-FUNNY, MOSEI, MIMIC and transfer to AV-MNIST). From Table 1, we found that on all four combinations of multitask pretraining and fine-tuning, weights learned from other multimodal tasks generalize well to new modalities and tasks, improving performance over single target-task training. When we increase the number of pretraining datasets, we observe a consistent improvement in fine-tuned target task performance. There is an inverse correlation between target task size and performance improvement: the smallest dataset, UR-FUNNY, benefited the most (+2.4%) from transfer learning from 0 to 3 multitask datasets. This implies that our multimodal pretrained-fine-tuning paradigm is useful for low-resource target modalities and tasks. Finally, we compare transfer learning performance across different levels of partial observability. While one would expect the transfer to MIMIC to be the hardest due to its modality set {time-series, table} being completely disjoint from the remaining 3 datasets, we still observe a +0.8% gain as compared to single-task training. Therefore, HiGHMMT can generalize to new modalities and tasks. Unsurprisingly, for datasets with more overlap (e.g., UR-FUNNY with complete overlap in {text, video, audio} with respect to pretraining), we find larger improvements using transfer learning over single-task models (+2.4%).

Comparison with task-specific state-of-the-art. In Table 2, we compare multitask performance and efficiency with task-specific state-of-the-art models. We achieve performance within the range of published models (and usually close to the individual task-specific state-of-the-art) in MultiBench, which tallies more than 20 recent multimodal models in each task’s literature (Liang et al., 2021b). In fact, HiGHMMT even sets new state-of-the-art results on several datasets, especially on the relatively understudied modalities (time-series, force and proprioception sensors, and sets) from the robotics (Push, V&T) and HCI (ENRICO) research areas. On top of strong performance, the main benefit lies in using fewer total parameters as compared to separate task-specific models - more than 10× reduction. Since this reduction grows with the number of tasks, our approach is scalable to high-modality scenarios.

Partial-observability. Observe HiGHMMT performance on partially-observable modality subsets (i.e., target task involving modalities not present in the other tasks): from Table 2, we find that the model performs well on the MIMIC dataset despite its modality set {time-series, table} being completely disjoint from the remaining 3 datasets - we obtain similar performance across both multitask and single-task models (68.2 ± 0.3% vs 68.9 ± 0.5%). We find that HiGHMMT multitask also works on ENRICO dataset in the HCI domain (52.7 ± 0.6% multitask vs 51.0 ± 1.4% single-task) despite it having completely disjoint modality inputs.

Multitask fusion and retrieval. We perform multitask training over multimodal fusion in AV-MNIST and retrieval in CIFAR-ESC. While fusion emphasizes information integration from complementary data sources, retrieval focuses on aligning corresponding elements expressed through different views of the data (Liang et al., 2022). Even across these vastly different prediction tasks, we find that multitask training (60.5% retrieval
3.3 Ablation Studies

In this subsection, we carefully ablate each part of the model, between the model architectures, various ways of performing parameter sharing, and training decisions.

Architectural ablations. We first analyze each architectural component of HighMMT: (1) \textit{w/o embeddings} removes the only modality-specific component in the model - the modality embeddings. We set embeddings for all modalities to be the same to test whether a modality-specific component is necessary to capture heterogeneity across input data sources, (2) \textit{w/o unimodal} removes the unimodal encoder and directly applies the cross-attention layer, and \textit{w/o crossmodal} replaces the crossmodal layer with a concatenation of unimodal features and a linear classification layer. The latter resembles the most direct multimodal extension of existing work in shared unimodal encoders like Perceiver [Jaegle et al., 2021b], MultiModel [Kaiser et al., 2017], ViT-BERT [Li et al., 2021] or PolyViT [Likhosherstov et al., 2022]. From Table 3, removing any of the 3 components in HighMMT results in worse performance. The unimodal encoder is particularly important for best performance.

Param sharing ablations. We further ablate with respect to possible parameter sharing settings in HighMMT. Beyond fully single-task and multitask variants, (1) \textit{share none} uses separate unimodal and multimodal layers reminiscent of typical single-task multimodal transformers [Tsai et al., 2019; Lu et al., 2019; Hendricks et al., 2021], (2-3) \textit{share unimodal (crossmodal)} only shares the unimodal (crossmodal) layer during multitask training, (4) \textit{share all} shares all parameters without accounting for possible heterogeneity [Reed et al., 2022], (5) \textit{random difference} determines \( k \) parameter groups randomly rather than via heterogeneity measurements, (6) \textit{feature difference} is a simple baseline using feature-level divergences on jointly trained unimodal encoders (i.e., \( \|U(X_1) - U(X_2)\|_2^2 \)) rather than transfer performance to measure heterogeneity as is commonly done in transfer learning and domain adaptation [Daumé III, 2007; Sun et al., 2016]. From Table 3, using separate parameters for unimodal or multimodal layers also decreases performance, which implies that parameter sharing learns improved generalizable representations. Furthermore, our proposed heterogeneity-aware parameter grouping results in the best overall performance as compared to fully shared, fully separate, or parameter grouping informed by other heterogeneity measures such as random or feature distance.

Training ablations. Finally, we explore \textit{direct training} of the learned parameter groups as opposed to performing homogeneous pre-training before fine-tuning them into parameter groups. From Table 3 we find that this ablation underperforms - training multiple parameter groups from scratch overfits quickly to smaller datasets which hurts overall generalization performance.
3.4 Understanding homogeneity and heterogeneity in HighMMT

The above subsections have demonstrated the strong abilities of HIGHMMT in multitask, transfer, and few-shot learning settings across diverse modalities and tasks. We now take a deeper empirical analysis to better understand the extent of homogeneity and heterogeneity captured by HIGHMMT. To do so, we design two experiments investigating parameter overlap and parameter interference in a fully trained HIGHMMT model. We also investigate several other model properties and visualizations in Appendix D.4.

Parameter overlap. We first investigate the extent of parameter overlap in a fully shared HIGHMMT model across modalities and tasks. Starting with a trained multitask HIGHMMT model, we use a gradient-based analysis method (in the same vein of studying gradients to look at prediction influence (Han et al., 2020)) to determine how much each parameter is involved in a specific task. For each task $T$ and parameter $\theta \in \Theta$ in multitask model $M_\Theta$, we compute the involvement $I_T(\theta) = E_{(x,y)\in T}[\nabla_\theta M_\Theta(y|x)]$ where $M_\Theta(y|x)$ is the predicted probability of correct target $y$ by $M_\Theta$ given $x$ as input. In other words, this measures the absolute gradient with respect to $\theta$ when predicting $y$ given $x$ in task $T$. A higher absolute gradient implies “activated” neurons and vice-versa for gradients closer to 0. This enables us to compute the extent a parameter $\theta$ is involved for each task. The number of tasks a given parameter $\theta$ is involved in can then be approximated by thresholding and summing up $n(\theta) = \sum_T \mathbb{1}(I_T(\theta) > \epsilon \max(I_1(\theta), I_2(\theta), I_3(\theta), I_4(\theta)))$ which returns an integer from 1 to 4. We chose a threshold $\epsilon$ such that parameters are classified as active about half the time on average, which occurs at $\epsilon = 0.2$.

Since we are interested in the level of parameter overlap in the shared unimodal encoder and multimodal layer, we set $\theta$ as these 2 modules and report results in Table 4. There is evidence of significant parameter overlap across unimodal encoders: more than 92% of neurons are involved in at least 3 of the 4 tasks. On the other hand, there is not nearly as much parameter overlap in the multimodal layer: only 10% of neurons are involved in 3 or 4 tasks. Hence, it seems like the shared unimodal encoders learn task-agnostic representations, but the subsequent multimodal layers (closer to task-specific classifiers) capture more task-specific information. This also reinforces our observation in §3.1 that there is generally more interaction heterogeneity than modality heterogeneity, which suggests using fewer unimodal parameter groups and more crossmodal parameter groups.

| Component          | Number of involved tasks |
|--------------------|--------------------------|
| Unimodal layers    | 2.8% 5.1% 61.1% 31.1%    |
| Crossmodal layers  | 48.8% 39.7% 9.9% 1.6%     |

Table 4: We find evidence of significant parameter overlap across unimodal encoders: >92% of neurons are involved in at least 3 of the 4 tasks. On the other hand, the multimodal layers are more task-specific: only 10% of neurons are involved in 3 or 4 tasks.

Parameter interference. Another empirical proof for parameter sharing in multitask models is the phenomenon of parameter interference: to what extent do parameters across tasks interfere with each other? Parameter interference is inspired by catastrophic forgetting (French, 1999; Toneva et al., 2018) - where pre-trained models fine-tuned on a new dataset tend to ‘forget’ how to perform on their pre-trained datasets due to the same group of parameters interfering with each other as the task changes. We perform a similar experiment to investigate parameter interference: we pick one task and flip the labels in its training set, train the multitask model on the modified training set, and see how the incorrectly labeled task affects performance on other tasks. This experiment provides evidence of information sharing: if the multitask model does not share information (i.e., the model learns independent subspaces for each task), then one would not observe a negative interference phenomenon from one noisy dataset. We study negative interference under 3 configurations of training (a) the whole model; (b) only the unimodal encoder, and (c) only the multimodal layer on the flipped training set.

From Table 5, we observe that certain tasks are more affected by negative interference (e.g., AV-MNIST), while some tasks are not influenced as much (e.g., UR-FUNNY). Again, this exactly reflects our heterogeneity measurements in §3.1 where we find that AV-MNIST displays high heterogeneity to other modalities and tasks from the other datasets. Furthermore, we observe that performance drops due to training the shared unimodal encoders are the most significant, which corroborates with our parameter overlap and heterogeneity analysis that general unimodal encoders contain more entangled parameters which are more sensitive to task changes. On the other hand, multimodal layers contain more disentangled parameters that share less information across tasks, which results in higher heterogeneity measurements and suitability for more separate parameter groups.
Table 5: **Parameter interference**: we observe different degrees of performance drops on each task (columns) after training on one task with flipped labels (rows). Training the shared unimodal encoders causes the most harm, which implies that unimodal encoders contain more shared neurons sensitive to task changes. Red for drops greater than 20%, yellow for drops between 10 and 20%, and green for drops below 10%.

| Flipped task | UR-FUNNY | MOSEI | MIMIC | AV-MNIST |
|--------------|----------|-------|-------|----------|
| (a) Training entire model | | | | |
| UR-FUNNY     | -24.6    | -8.33 | -10.6 | -57.7    |
| MOSEI        | -4.07    | -59.7 | -20.3 | -53.2    |
| MIMIC        | -3.59    | -5.83 | -33.1 | -37.5    |
| AV-MNIST     | -3.50    | -1.23 | -4.87 | -68.9    |
| (b) Only training unimodal encoder | | | | |
| UR-FUNNY     | -29.8    | -10.1 | -12.8 | -56.3    |
| MOSEI        | -5.77    | -5.63 | -21.1 | -52.7    |
| MIMIC        | -3.03    | -3.54 | -35.0 | -56.3    |
| AV-MNIST     | -2.94    | -7.82 | -53.6 | -69.3    |
| (c) Only training multimodal layer | | | | |
| UR-FUNNY     | -25.2    | -8.34 | -2.67 | -8.16    |
| MOSEI        | 0.47     | -59.6 | -19.8 | -8.19    |
| MIMIC        | 0.19     | -0.76 | -35.2 | -4.87    |
| AV-MNIST     | -1.61    | -1.48 | -2.23 | -69.1    |

4 Related Work

**Multimodal Transformers** have emerged as strong general-purpose models for representation learning. Building upon the initial text-based Transformer model (Vaswani et al., 2017), these multimodal extensions typically use either full self-attention over modalities concatenated across the sequence dimension (Li et al., 2019; Sun et al., 2019; Su et al., 2020; Chen et al., 2020) or a cross-modal attention layer (Lu et al., 2019; Tsai et al., 2019; Tan and Bansal, 2019), and are useful for sequential data by automatically aligning and capturing complementary features at different time-steps (Tsai et al., 2019; Yao and Wan, 2020; Lee et al., 2020c). Self-supervised multimodal pretraining has emerged as an effective way to train these powerful architectures, with the aim of learning general-purpose representations from larger-scale unlabeled multimodal data before transferring to specific downstream tasks via supervised fine-tuning (Lu et al., 2019; Li et al., 2019; Su et al., 2020). These pretraining objectives typically consist of unimodal masked prediction, cross-modal masked prediction, and multimodal alignment prediction (Hendricks et al., 2021).

**Unified encoder for unimodal learning.** Several works such as Perceiver (Jaegle et al., 2021a,b), MultiModel (Kaiser et al., 2017), ViT-BERT (Li et al., 2021), and PolyViT (Likhosherstov et al., 2022) have explored the possibility of using the same unimodal encoder architecture for different inputs on unimodal tasks (i.e., language, image, video, or audio-only). The Transformer architecture has emerged as a popular choice due to its suitability for serialized inputs such as text (Devlin et al., 2019), images (Dosovitskiy et al., 2021), video (Sun et al., 2019), and time-series data (Lim et al., 2021), a phenomenon further observed by Lu et al. (2021) where a single Transformer pretrained on text transfers to other unimodal tasks including sequence modeling and image classification. While these serve as building blocks in our model, our focus is on a general-purpose multimodal model for multitask and transfer learning across different subsets of modalities rather than unimodal tasks. We summarize some of these differences in Figure 6.

**Multimodal multitask and transfer learning.** There have also been several attempts to build a single model that works well on a suite of multimodal tasks (Li et al., 2019; Su et al., 2020; Cho et al., 2021; Reed et al., 2022). For example, UniT (Hu and Singh, 2021), VLBERT (Su et al., 2020), ViLBERT (Lu et al., 2019), and VL-T5 (Cho et al., 2021) are all unifying models for vision-and-language tasks, with some models also possessing generalization to vision-only and language-only tasks. VATT (Akbari et al., 2021) jointly trains a shared model on video, audio, and text data to perform audio-only, video-only,
### 5 Conclusion

In conclusion, this paper proposes an information transfer approach for estimating modality and interaction heterogeneity, a key component towards automatically determining which modalities should be processed and fused jointly for efficient representation learning in high-modality scenarios. Our resulting model, HighMMT dynamically determines the optimal parameter groupings balancing total performance and parameter efficiency, simultaneously achieves strong results on 10 modalities (text, image, video, audio, time-series, sensors, tables, and sets) and 15 tasks from 5 different research areas, and transfers to entirely new modalities and tasks during fine-tuning. We release our code and benchmarks which we hope will present a unified platform for subsequent theoretical and empirical analysis.
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Figure 7: General architecture of HighMMT: Given arbitrary modalities, (1) the inputs are standardized into a sequence and padded, (2) modality embeddings and positional encodings are added to the serialized raw input, (3) a single shared unimodal Perceiver encoder is applied to all modalities to learn general-purpose representations regardless of the specific input modality, (4) each pair of unimodal representations is fed through a shared multimodal cross-attention layer twice (the first time with one modality as query and the other as context, and the second time vice versa) to learn general multimodal representations regardless of the input modalities and task, and finally (5) all outputs from cross-attention layers are concatenated, batch-normalized, and fed through a task-specific classification head to make a prediction. The unimodal encoders and multimodal layers are shared across tasks during multitask learning to enable statistical strength sharing, parameter efficiency, and quick generalization across diverse modalities and tasks.

A Measuring Heterogeneity via Modality Information Transfer

A.1 Modality and interaction heterogeneity matrix

We construct a modality heterogeneity matrix $M_U(i, j) = d(X_i; X_j)$ and an interaction heterogeneity matrix (technically 4D-tensor) $M_C(i, j, k, \ell) = d(X_i, X_j; X_k, X_\ell)$. As a side note, observe that these matrices are highly structured due to distances satisfying the triangle inequality, which implies that we do not need to compute all entries and instead rely on low-rank reconstruction from partial entries in practice (Drineas et al., 2006; Tasissa and Lai, 2018). For example, we can approximate the modality heterogeneity matrix $M_U = \sum_{i=1}^{h} u_i v_i^T$ as an outer product of $k$ individual basis vectors $u_i$ and $v_i$, where $h$ is a smaller number than the actual dimension of $M_U$.

A.2 Determining parameter groupings

We balance both total performance and parameter efficiency via agglomerative hierarchical clustering where modalities are nodes and heterogeneity measurements are edges. The number of clusters $k$ is treated as a hyperparameter dependent on the parameter budget. Clustering on the modality heterogeneity matrix $M_U$ results in a grouping of modalities based on similarity (e.g., $U_1 = \{X_1, X_2, X_4\}, U_2 = \{X_3\}, U_3 = \{X_5\}$), and likewise for the interaction matrix $M_C$ (e.g., $C_1 = \{\{X_1, X_2\}, \{X_1, X_3\}, \{X_4, X_5\}\}, C_2 = \{\{X_2, X_3\}, C_3 = \{\{X_4, X_6\}, \{X_5, X_6\}\}$, and so on. How can we choose the number of clusters $k$? Note that if $k$ is equal to the total number of modalities (or modality pairs) then it reduces to having separate models for each modality (and interaction), while $k = 1$ implies using a single model for all modalities and interactions. $k$ is therefore most suitably seen as a ‘parameter budget’ that one would like to control for efficiency. In our experiments, we explored a range of $k$ giving rise to a suite of models across controlled trade-offs between performance and efficiency (see Figure 5).
B HighMMT Details

At a high level, HighMMT includes the following components: (1) the inputs are standardized into a sequence and padded, (2) the perceiver input processing adds modality-specific modality embeddings and positional encodings to the serialized raw input; (3) the processed input from each modality is fed into a shared unimodal perceiver encoder; (4) each pair of unimodal perceiver output (unimodal representations) is fed through a shared crossmodal transformer layer twice (the first time with one modality as query and the other as context, and the second time vice versa); (5) finally, all outputs from multimodal layers are concatenated, batch-normalized to form a multimodal representation, and fed through a task-specific classification head to make a prediction. Figure 7 is an illustration of the high-level architecture.

B.1 Perceiver Input Processing

We follow the data processing pipeline in the GitHub implementation for multimodal perceivers: https://github.com/fac2003/perceiver-multi-modality-pytorch. For each modality, we must specify in advance the channel size (i.e., embedding size) and how many extra dimensions there are other than the channel/embedding dimension.

The modality embedding is just a one-hot vector denoting the index of the current modality, and the size of the vector is equal to the total number of modalities involved. This embedding layer identifies common modalities across different tasks to enable sharing of information. For example, the modality embedding of the image sequence for a video classification task will be shared with that of an input (static) image for an image and text question-answering task.

We also specify a few hyperparameters (such as num_freq_bands and max_freq) for the Fourier transformation used in the positional encoding. The positional encoding represents where this embedding is at through Fourier transformations (so if there is 1 extra dimension, then the positional encoding will encode the 1D position of each embedding; if there are 2 extra dimensions, then the positional encoding will encode the 2D position of each embedding). The positional encoding length can vary for each modality depending on the number of extra dimensions and the Fourier transformation hyperparameters.

The total embedding size of the processed output will be equal to \( d_{all} = \max_{m \in M}(d_m + d_{pm} + |M|) \), where \( M \) is the set of all modalities involved, \( d_m \) is the channel size of modality \( m \), \( d_{pm} \) is the positional encoding size of modality \( m \), and \( |M| \) is the modality encoding size (i.e., the total number of involved modalities). When processing each modality, we concatenate the input channels, the positional encoding, and the modality encoding along the channel/embedding axis before adding zero-padding along this axis to match a desired total embedding size \( d_{all} \). As a result, all modalities will be processed to have the same embedding size \( d_{all} \).

We also flatten all non-embedding dimensions so the processed input will always have shape \( n \times t_m \times d_{all} \) where \( n \) is a common batchsize, \( t_m \) is a modality-specific sequence length, and \( d_{all} \) is the common embedding dimension.

For example, during multitask learning in the large setting (4 datasets involved: UR-FUNNY, MOSEI, MIMIC, and AV-MNIST), \( d_{all} = 387 \) (because the image modality from UR-FUNNY has a channel size of 371, positional encoding size of 7, and modality encoding size of 9). When processing the colorless image modality from AVMNIST (7 × 7 × 16), we have a channel size of 16, positional encoding size of 26, and modality encoding size of 9, so the processed output will be 49 × 387 where the first 16 dimensions along the last dimension represent 16 raw input dimensions, the next 336 dimensions are padded zeroes, the next 26 dimensions are positional encodings, and the final 9 dimensions are modality encodings.

Note that during this entire processing step all procedures are programmatic and there are no trainable parameters involved.

B.2 Unimodal Perceiver Encoder

Now that we have standardized all modality inputs into a common representation, we follow the Perceiver architecture [Jaegle et al., 2021b] to perform modality and task-agnostic representation learning from each input modality. Starting with a latent array of shape \( d_{LN} \times d_{LS} \) (array size configurable as a hyperparameter,
where $d_{LN}$ is the number of latent vectors and $d_{LS}$ is the latent dimension) with trainable initialization, for each layer, we first perform cross-attention on the latent array using the processed input array (of shape $t_m \times d_{all}$) as context. Cross-attention between the latent vector and the input modality sequence learns relationships between elements in each modality, resulting in unimodal contextualized representations. The resulting latent array then goes through a latent transformer (with self-attention and feed-forward layers). We repeat this architecture for each layer within the encoder. The main advantage of this Perceiver encoder is that it can encode the input into a common $d_{LN} \times d_{LS}$ latent array regardless of the input shape $t_m \times d_{all}$, and the total runtime is linear with respect to the size of $t_m$ which scales to high-modality scenarios. Note that only one copy of a unimodal Transformer (Perceiver) block is used to encode all modalities simultaneously, which enables statistical strength sharing and general-purpose representation learning regardless of the specific input modality.

### B.3 Crossmodal Transformer layer

To learn modality and task-agnostic multimodal representations, we use multiple layers of a general-purpose Crossmodal Transformer block (Tsai et al., 2019; Lu et al., 2019). Given 2 unimodal representations $z_1$ and $z_2$ of common shape $d_{LN} \times d_{LS}$ learned from unimodal Perceiver encoders, a Crossmodal Transformer (CT) block uses crossmodal self-attention by setting the input layer query $Q = z_1$ and keys and values $K, V = z_2$ to learn attention from modality 1 to modality 2, and a separate block to capture the attention in the opposite direction. This step enables one modality’s sequence elements to discover correspondences in another. A Crossmodal Transformer block using $z_1$ to attend to $z_2$ (and vice-versa) results in a multimodal representation $z_{mm} = [z_{1\rightarrow2}, z_{2\rightarrow1}] = [CT(z_1, z_2), CT(z_2, z_1)]$. For each layer, we first perform cross-attention followed by self-attention and feed-forward functions. In the end, we only take the last $d_{LS}$-dimensional vector out of the $d_{LN} \times d_{LS}$ final latent array as the output of this module. For tasks with more than 2 modalities, a Crossmodal Transformer block is applied for each pair of modalities before concatenating all multimodal representations. Again, only one copy of a multimodal layer is used on all tasks to learn general representations regardless of the input modalities and task.

### B.4 Task-specific classifiers

Since each task may have a different number of modalities and output classes, we create a separate classification head for each task. For each classification head, it concatenates all outputs of the Crossmodal Transformer layer (so 2-modality tasks have concatenated size of $2d_{LS}$, 3-modality tasks have concatenated size of $6d_{LS}$, etc), performs batch-normalization, and feeds the normalized multimodal representation $z_{mm}$ into a linear layer that maps to the logits for this task. This classification layer composes individual correspondences learned within and across modalities to form a final prediction.

### B.5 Homogeneous multitask pre-training

Since each task has a different number of training batches, not all tasks will be involved in each training step. We arrange the tasks to be included in each training step such that more tasks will be trained simultaneously towards the end of an epoch. For example, if task $A$ has 300 training batches, task $B$ has 200 training batches, and task $C$ has 100 training batches, then for the first 100 training steps in an epoch, only task $A$ will be used; then for the next 100 steps both $A$ and $B$ will be used; and for the last 100 steps, all three tasks will be used. This approach tends to work better than including all tasks in all steps via uniform batch sampling because the task with fewer training batches tends to overfit in the latter approach.

Within each training step, we compute the losses of the batch from each task used and compute the gradient using a weighted sum of the losses. The weights are part of the hyperparameters that we can tune to ensure balanced training. Then we update the model using the computed gradients.

We compute validation performance after each epoch for each task, and aggregate validation performances across all tasks (this is necessary because different tasks are measured differently, sometimes bigger is better, sometimes smaller is better). When all tasks are accuracy-based (such as the large setting), we just weigh
them equally. Then we report test performance on the checkpoint with the highest aggregated validation performance.

The result from homogeneous multitask pre-training is a set of modality embeddings, common unimodal and crossmodal parameters $U^*$ and $C^*$, and individual task classifiers.

### B.6 Heterogeneity-aware fine-tuning

We account for heterogeneity by grouping unimodal parameters based on modalities that we know to be similar from §2.1 (e.g., setting $U_1 = \{U_1, U_2\}, U_2 = \{U_3\}, U_3 = \{U_4, U_5, U_6\}$), and likewise for the crossmodal parameters (e.g., $C_1 = \{C_{12}, C_{13}, C_{14}\}, C_2 = \{C_{23}, C_{15}\}, C_3 = \{C_{24}, \ldots\}$). These groups of parameters are first initialized with the homogeneous model $U^*$ and $C^*$ before separate fine-tuning, which results in final parameters $U^* \rightarrow \{U^*_1, U^*_2, \ldots\}$ and $C^* \rightarrow \{C^*_1, C^*_2, \ldots\}$. The modality embeddings and task classifiers are jointly fine-tuned as well.

### B.7 Transfer learning details

If we are trying to transfer from tasks $\{A, B, C\}$ to $D$, initially we start with a randomly initialized HighMMT model that defines modality embeddings for all modalities in $\{A, B, C, D\}$ as well as a classification head for each. Then, we pretrain the model using multitask learning on $\{A, B, C\}$ using the same procedure as before. After saving a good checkpoint as measured by aggregated validation performance on pretraining tasks $\{A, B, C\}$, we finetune the trained model on target task $D$. The modality and tasks in $\{A, B, C\}$ present during multitask pretraining can be very different from those encountered in $D$ during fine-tuning.

### B.8 Few-shot multitask learning details

We also investigated few-shot learning using limited labeled data in a target task. When we perform few-shot learning on task $D$ with the help of tasks $\{A, B, C\}$, we jointly train $\{A, B, C, D\}$ together in the same multitask manner as before, but since we don’t care about the performance of our model on auxiliary tasks $\{A, B, C\}$, we assign a higher weight to the losses on task $D$ and keep track of the best validation performance on $D$ when selecting checkpoints.

### C Experimental Setup

In this section, we provide additional details on the experimental setup to analyze the multitask, transfer, and generalization capabilities of HighMMT.

#### C.1 Setup

We use a large collection of multimodal datasets provided in the standardized and public MultiBench benchmark [Liang et al. 2021b]. This benchmark spans 15 real-world datasets, 10 modalities, 20 prediction tasks, and 6 research areas. Each of these datasets requires a model to learn basic representations of features in each modality and aggregate complementary information across multiple modalities to make a prediction.

**Affective computing** involves understanding our natural display of multimodal signals spanning language (spoken words), visual (facial expressions, gestures), and acoustic (prosody, speech tone) in order to predict human affective states (emotions, sentiment, and personalities) [Picard 2000]. We test on 2 datasets involving fusing *language, video, and audio* time-series data to predict sentiment and emotions (MOSEI [Zadeh et al. 2018]) as well as humor (UR-FUNNY [Hasan et al. 2019]).

**Healthcare**: Medical decision-making often involves integrating multiple sensory readings from instruments such as lab tests, imaging reports, and patient-doctor conversations [Amisha et al. 2019]. We experiment with the large-scale MIMIC dataset [Johnson et al. 2016] which records ICU patient data including time-series data measured every hour and other demographic variables in the form of *tabular numerical* data. These are used to predict the disease ICD-9 code and mortality rate.
Robotics: Modern robot systems are equipped with multiple sensors in order to capture complementary signals useful for holistic decision-making. We test on the large-scale MuJoCo PUSH [Lee et al. 2020a] and V&T (Vision&Touch) [Lee et al. 2020b] datasets which record the manipulation of simulated and real robotic arms equipped with visual (RGB and depth), force, and proprioception sensors. In PUSH, the goal is to predict the pose of the object being pushed by the robot end-effector. In V&T, the goal is to predict action-conditional learning objectives that capture forward dynamics (contact prediction and robot end-effector pose).

Human Computer Interaction (HCI) studies the design of computer technology and interactive interfaces between humans and computers [Dix et al. 2000]. We use the Enrico dataset [Deka et al. 2017; Leiva et al. 2020] of Android app screens (consisting of an image as well as a set of apps and their locations) categorized by their design motifs and collected for data-driven design applications such as design search, user interface (UI) layout generation, UI code generation, and user interaction modeling.

Multimedia: A significant body of research in multimodal learning has been fueled by the large availability of multimedia data (language, image, video, and audio) on the internet. We experiment on 2 large-scale multimedia datasets with varying sizes and levels of difficulty: (1) AV-MNIST [Vielzeuf et al. 2018] is assembled from images of handwritten digits [LeCun et al. 1998] and audio samples of spoken digits [Leonard and Doddington 1993], and (2) CIFAR-ESC [Liang et al. 2021c] is an image-audio retrieval dataset. To construct CIFAR-ESC, we follow [Liang et al. 2021c] and combine 100 classes from CIFAR-10 and 10 classes from ESC-50 [Piczak 2015]. To bridge these two modalities with partially related label spaces, we define 17 shared classes across the 2 datasets for weak concept alignment. These clusters are obtained by mapping similar classes between the datasets using similarities from WordNet [Miller 1995] and text cooccurrence, and we show the resulting 17 clustered concepts we used for weak alignment in Figure 8. For the retrieval task, we first split all images and audio into a 3/1/1 train/valid/test split. Within each split, we paired each image with one randomly selected audio clip from the same shared class and label that pair as positive, and with one randomly selected audio clip from a different shared class and label that pair as negative. We evaluate retrieval performance via binary classification accuracy of an image and audio clip classified into either positive or negative pairs. The final retrieval dataset consists of 38K training pairs, 13K validation pairs and 13K test pairs.

Multitask setup: We trained 3 multitask models across combinations of the aforementioned datasets. Each multitask setup is designed to include tasks with different modality inputs and prediction objectives.

1. **Small:** PUSH, V&T: 2 tasks in the same research area (robotics) but with different modality inputs: \{image, force, proprioception, control\} and \{image, force, proprioception, depth\} respectively. Furthermore, each robot’s sensor readings come from different robot-dependent sensors.

2. **Medium:** ENRICO, PUSH, AV-MNIST across 3 domains (multimedia, HCI, and robotics) with different modalities: \{image, set\}, \{image, force, proprioception, control\}, and \{image, audio\}. 

Figure 8: The 17 concepts shared across image and audio datasets that were used to define positive retrieval groups in CIFAR-ESC. Note that we only show the images - the audio spectrograms make up the second modality in each concept.
Table 6: We investigate 3 multitask training setups to evaluate the performance of HighMMT. Each multitask setup is designed to include tasks with different modality inputs and prediction objectives. The total size of datasets involved in our experiments exceeds 370,000 and covers diverse modalities such as images, video, audio, text, time-series, various robotics sensors, sets, and tables, as well as multiple research areas and prediction tasks from affective computing, healthcare, multimedia, robotics, and HCI.

| Setting | Datasets | Modalities | Size     | Prediction task | Research Area |
|---------|----------|------------|----------|-----------------|---------------|
| Small   | Push     | {image, force, proprioception, control} | 37,990   | object pose    | Robotics      |
|         | V&T      | {image, force, proprioception, depth}   | 147,000  | contact, robot pose | Robotics     |
| Medium  | ENRICO   | {image, set}                                 | 1,460    | design interface | HCI           |
|         | Push     | {image, force, proprioception, control} | 37,990   | object pose    | Robotics      |
|         | AV-MNIST | {image, audio}                               | 70,000   | digit          | Multimedia    |
| Large   | UR-FUNNY | {text, video, audio}                         | 16,314   | humor          | Affective Computing |
|         | MOSEI    | {text, video, audio}                         | 22,777   | sentiment, emotions | Affective Computing |
|         | MIMIC    | {time-series, table}                         | 36,212   | mortality, ICD-9 codes | Healthcare |
|         | AV-MNIST | {image, audio}                               | 70,000   | digit          | Multimedia    |

3. **Large**: UR-FUNNY, MOSEI, MIMIC, and AV-MNIST, across 3 domains (affective computing, healthcare, and multimedia), again with different modalities: {text, video, audio} for the first 2 tasks with different format of preprocessed embeddings of video and audio, {time-series, table}, and {image, audio}.

We summarize these experimental settings in Table 6. Overall, the total size of datasets involved in our experiments exceeds 370,000 and covers diverse modalities such as time-series, various robotics sensors, sets, and tables, as well as multiple research areas and prediction tasks from affective computing, healthcare, multimedia, robotics, and HCI.

### C.2 Hyperparameters and training details

We list hyperparameters used throughout our models in Table 7, Table 8, and Table 9 for small, medium, and large multitask settings respectively. Code is also included in the supplementary material for reproducibility.
Table 7: Table of hyperparameters for multitask prediction on the small setting involving Push, V&T: 2 tasks in the same research area (robotics) but with different modality inputs: \{image, force, proprioception, control\} and \{image, force, proprioception, depth\} respectively, and readings come from different robot-dependent sensors.

| Part of Model                          | Hyperparameter            | Values                  |
|----------------------------------------|---------------------------|-------------------------|
|                                        | PUSH                      | V&T                     |
| **Unimodal Perceiver Encoder**         | Depth                     | 1                       |
|                                        | Num Latents               | 20                      |
|                                        | Latent Dim                | 64                      |
|                                        | Cross Attention Heads     | 1                       |
|                                        | Latent Self-Attention Heads| 8                      |
|                                        | Cross Head Dim            | 64                      |
|                                        | Latent Head Dim           | 64                      |
|                                        | Num Latent Blocks Per Layer| 1                      |
| **Multimodal Cross-Attention Layer**   | Depth                     | 1                       |
|                                        | Num Latents               | 20                      |
|                                        | Latent Dim                | 64                      |
|                                        | Cross Attention Heads     | 1                       |
|                                        | Latent Self-Attention Heads| 8                      |
|                                        | Cross Head Dim            | 64                      |
|                                        | Latent Head Dim           | 64                      |
|                                        | Num Latent Blocks Per Layer| 1                      |
| **Classification Heads**               | Input/output dimensions   | 756/32                  | 1280/1                   |
| (BatchNorm+Linear)                     | Optimizer                 | Adam                    |
|                                        | Learning rate             | 0.0005                  |
|                                        | Weight decay              | 0.0                     |
|                                        | Training loss weights     | 100.0                   | 1.0                      |
|                                        | Batchsize                 | 18                      | 64                       |
|                                        | Evaluation weights        | 100.0                   | 1.0                      |
|                                        | Original MultiBench       |                          |
| **Input Dimensions**                   | Gripper Pos: 16x3         | Image: 128x128x3         |
|                                        | Gripper Sensors: 16x7     | Force: 6x32              |
|                                        | Image: 16x32x32           | Proprio: 8               |
|                                        | Control: 16x7             | Depth: 128x128           |
|                                        | Grippe: 3                 | Action: 4                |
|                                        | Gripper Sensors: 7        |                          |
|                                        | Image: 1                  |                          |
|                                        | Control: 7                |                          |
|                                        |                          |                          |
| **Perceiver Input**                    |                          |                          |
| **Channel Size**                       |                          |                          |
|                                        |                          |                          |
| **Extra Axis**                         |                          |                          |
|                                        |                          |                          |
| **Num_freq_bands**                     |                          |                          |
|                                        |                          |                          |
| **Max_freq**                           |                          |                          |
|                                        |                          |                          |
| **Shared Modality Encoding**           | N/A                       |                          |
Table 8: Table of hyperparameters for multitask prediction on the medium setting involving AV-MNIST, ENRICO and PUSH: 3 tasks across 3 domains (multimedia, HCI, and affective computing), again with vastly different modality sets: \{image, audio\}, \{image, set\}, and \{image, force, proprioception, control\} for each task.

| Part of Model               | Hyperparameter                  | Values                          |
|-----------------------------|---------------------------------|---------------------------------|
|                             |                                 | AV-MNIST | ENRICO | PUSH  |
| Unimodal Perceiver Encoder  | Depth                           | 1        |        |       |
|                             | Num Latents                     | 12       |        |        |
|                             | Latent Dim                      | 64       |        |        |
|                             | Cross Attention Heads           | 1        |        |        |
|                             | Latent Self-Attention Heads     | 8        |        |        |
|                             | Cross Head Dim                  | 64       |        |        |
|                             | Latent Head Dim                 | 64       |        |        |
|                             | Num Latent Blocks Per Layer     | 1        |        |        |
| Multimodal Cross-Attention Layer | Depth                           | 1        |        |        |
|                             | Num Latents                     | 12       |        |        |
|                             | Latent Dim                      | 64       |        |        |
|                             | Cross Attention Heads           | 1        |        |        |
|                             | Latent Self-Attention Heads     | 8        |        |        |
|                             | Cross Head Dim                  | 64       |        |        |
|                             | Latent Head Dim                 | 64       |        |        |
|                             | Num Latent Blocks Per Layer     | 1        |        |        |
| Classification Heads        | Input/output dimensions         | 128/10   | 128/20 | 768/2 |
| (BatchNorm+Linear)          | Optimizer                       | Adam     |        |        |
|                             | Learning rate                   | 0.001    |        |        |
|                             | Weight decay                    | 0.0      |        |        |
|                             | Training loss weights           | 0.8      | 1.0    | 1.1    |
|                             | Batchsize                       | 32       | 32     | 32     |
|                             | Evaluation weights              | 1        | 1      | 1      |
| Training                    | Original MultiBench Input       | Colorless Image: 28x28          | Grippe |            |
|                             | Dimensions                      | Audio Spectogram: 112x112       | Pos: 16x3 |
|                             | Perceiver Input Channel Size    | Image: 256x128x3                 | Gripper Sensors: 16x7 |
|                             |                                 | Set: 256x128x3                  | Image: 16x32x32 |
|                             |                                 | Control: 16x7                   |                  |
|                             | Perceiver Input Extra Axis      | Colorless Image: 2              | Grippe |            |
|                             | Num_freq_bands                  | Audio Spectogram: 2             | Pos: 3 |
|                             |                                 | Set: 2                           | Gripper Sensors: 7 |
|                             |                                 | Control: 3                       | Image: 1 |
|                             |                                 |                                 | Control: 7 |
|                             | Perceiver Input                 | Colorless Image: 6              | Grippe |            |
|                             | Max_freq                        | Audio Spectogram: 6              | Pos: 6 |
|                             |                                 | Set: 6                           | Gripper Sensors: 6 |
|                             |                                 |                                 | Image: 6 |
|                             |                                 |                                 | Control: 6 |
|                             | Shared Modality Encoding        | N/A                               |        |        |
Table 9: Table of hyperparameters for multitask prediction on the large setting involving MIMIC, AV-MNIST, MOSEI and UR-FUNNY: 4 tasks across 3 domains (healthcare, multimedia, and affective computing), again with vastly different modality sets: {time-series, table}, {image, audio}, and {text, video, audio} for the final 2 tasks with different format of preprocessed embeddings of video and audio.

| Part of Model                      | Hyperparameter       | MIMIC | AV-MNIST | MOSEI | UR-FUNNY |
|------------------------------------|----------------------|-------|----------|-------|----------|
| Unimodal Perceiver Encoder        | Depth                | 1     |          |       |          |
|                                   | Num Latents          | 20    |          |       |          |
|                                   | Latent Dim           | 64    |          |       |          |
|                                   | Cross Attention Heads| 1     |          |       |          |
|                                   | Latent Self-Attention Heads | 6    |          |       |          |
|                                   | Cross Head Dim       | 64    |          |       |          |
|                                   | Latent Head Dim      | 64    |          |       |          |
|                                   | Num Latent Blocks Per Layer | 1  |          |       |          |
| Multimodal Cross-Attention Layer  | Depth                | 1     |          |       |          |
|                                   | Num Latents          | 20    |          |       |          |
|                                   | Latent Dim           | 64    |          |       |          |
|                                   | Cross Attention Heads| 4     |          |       |          |
|                                   | Latent Self-Attention Heads | 6    |          |       |          |
|                                   | Cross Head Dim       | 64    |          |       |          |
|                                   | Latent Head Dim      | 64    |          |       |          |
|                                   | Num Latent Blocks Per Layer | 1  |          |       |          |
| Classification Heads (BatchNorm+Linear) | Input/output dimensions | 128/2 | 128/10  | 384/2 | 384/2    |
| Training                          | Optimizer            | Adam  |          |       |          |
|                                   | Learning rate        | 0.0008|          |       |          |
|                                   | Weight decay         | 0.001 |          |       |          |
|                                   | Training loss weights| 1.2   | 0.9      | 1.1   | 1.5      |
|                                   | Batchsize            | 20    | 40       | 32    | 32       |
|                                   | Evaluation weights   | 1     | 1        | 1     | 1        |
| Original MultiBench Input Dimension | Static: 5            | Colorless Image: 28x28 | Image: 50x35 |          |
|                                   | Timeseries: 24x12    | Audio Spectrogram: 112x112 | Audio: 50x74 |          |
| Perceiver Input Channel Size      | Static: 1            | Colorless Image: 16 (cut into 4x4 squares) | Image: 35 |          |
|                                   | Timeseries: 1        | Audio Spectrogram: 256 (cut into 16x16 squares) | Audio: 74 |          |
|                                   |                      | Image: 3 |          |       |          |
| Perceiver Input Extra Axis        | Static: 1            | Colorless Image: 2 | Image: 1 |          |
|                                   | Timeseries: 2        | Audio Spectrogram: 2 | Audio: 1 |          |
|                                   |                      | Image: 1 |          |       |          |
| Perceiver Input Num_freq_bands    | Static: 6            | Colorless Image: 6 | Image: 3 |          |
|                                   | Timeseries: 6        | Audio Spectrogram: 6 | Audio: 3 |          |
|                                   |                      | Image: 3 |          |       |          |
| Perceiver Input Max_freq          | Static: 1            | Colorless Image: 1 | Image: 1 |          |
|                                   | Timeseries: 1        | Audio Spectrogram: 1 | Audio: 1 |          |
|                                   |                      | Image: 1 |          |       |          |
| Shared Modality Encoding          | The text modality from MOSEI and UR-FUNNY are shared. |       |          |       |          |
Table 10: We train multitask HighMMT on 1/2/3 datasets and find that it generalizes to new modalities and tasks on the 4th dataset, with improved performance over single-task training on the 4th dataset. 0 source tasks implies transferring randomly initialized parameters, which is equivalent to single-task training on the target task. Cross-modal transfer improves with the number of pretraining tasks and works best on the smallest target tasks (UR-FUNNY).

| Source tasks | Target task  |
|--------------|--------------|
| 0 (no transfer) | UR-FUNNY 63.3 |
| MOSEI | 64.1 |
| MOSEI + AV-MNIST | 65.5 |
| MOSEI + MIMIC + AV-MNIST | 65.7 |

| Source tasks | Target task  |
|--------------|--------------|
| 0 (no transfer) | MOSEI 79.4 |
| AV-MNIST | 79.4 |
| AV-MNIST + MIMIC | 80.0 |
| UR-FUNNY + MIMIC + AV-MNIST | 80.5 |

| Source tasks | Target task  |
|--------------|--------------|
| 0 (no transfer) | MIMIC 67.7 |
| MOSEI | 68.3 |
| AV-MNIST + MOSEI | 68.5 |
| UR-FUNNY + MOSEI + AV-MNIST | 68.5 |

| Source tasks | Target task  |
|--------------|--------------|
| 0 (no transfer) | AV-MNIST 70.4 |
| MOSEI | 70.4 |
| MIMIC + MOSEI | 70.5 |
| UR-FUNNY + MOSEI + MIMIC | 70.5 |

D Additional Results

In this section, we detail additional experimental results that support the multitask, transfer, and generalization capabilities of HighMMT.

D.1 Generalization to new modalities and tasks

HighMMT also offers opportunities to study whether we can transfer knowledge between completely different tasks and modalities. On the large setting, we first pretrained a model on 0/1/2/3 of the four tasks before fine-tuning on the fourth task only. We show these full results in Table 10. On all four target tasks, our proposed multitask pretraining and fine-tuning paradigm improves performance over single target-task training. Therefore, weights learned from other multimodal tasks indeed generalize well to new modalities and tasks. We further analyze this transfer learning phenomenon by studying the following research questions:

Effect of pretraining datasets. When we vary the number of pretraining datasets, we observe a consistent improvement on fine-tuned target task performance across all datasets. This effect is particularly pronounced on the UR-FUNNY target task, which shows the biggest improvement using pretrained parameters from 0 to 3 multitask datasets. This implies that HighMMT learns more generalizable multimodal features as more tasks are involved in multitask training.

Effect of target dataset size. We observed an inverse correlation between target task size and performance improvement: the smallest dataset, UR-FUNNY, benefited the most (+2.4%) from transfer learning. This implies that this multimodal pretraining-fine-tuning paradigm is useful for improving performance for low-resource target modalities and tasks.

Effect of transfer modalities. We compare transfer learning performance across different levels of partial observability. While one would expect transfer to the MIMIC dataset to be the hardest due to its modality
Figure 9: **Few-shot results** on new modalities and tasks. Multimodal multitask training using HighMMT learns more generalizable representations which improves performance across all ranges of data. The x-axis shows the percentage of labeled data used during training.

set \{time-series, table\} being completely disjoint from the remaining 3 datasets, we still observe a +0.8% gain as compared to single-task training. Therefore, HighMMT can generalize to new modalities and tasks.

Unsurprisingly, for datasets with more overlap in modality sets (e.g., UR-FUNNY with complete overlap in \{text, video, audio\} as compared to the other 3 datasets used for pretraining, we find larger improvements using transfer learning over single-task models (+2.4%).

**Comparisons to unimodal transfer.** Recent work has explored the possibility of transferring Transformer representations trained in one modality to another. Lu et al. (2021) found that a frozen pretrained Transformer on text surprisingly transfers to a variety of sequence classification tasks of different modalities spanning numerical computation, vision, and protein fold prediction. This observation had been previously observed in transfer learning from language to vision (Kiela et al., 2019), referential communication games to real-world NLP tasks (Li et al., 2020), computational primitives to transfer to mathematics tasks (Wu et al., 2021), and between code, different languages, and music (Papadimitriou and Jurafsky, 2020). Our transfer experiments also corroborate these findings in a multimodal setting with promising results on new modalities and tasks, especially involving real-world, smaller, and noisier datasets such as those involving human videos (MOSEI and UR-FUNNY), medical data (MIMIC), or real and simulated robots (PUSH and V&T).

### D.2 Few-shot learning

HighMMT offers opportunities for statistical strength sharing across tasks. We test this hypothesis in the few-shot learning scenario, by evaluating whether multitask information sharing can improve performance on low-resource target tasks. We compare a single-task HighMMT trained only on a percentage $p$ of labeled training data in the target task with multitask HighMMT trained on the same percentage $p$ (during multitask training we prioritize performance of the target task over others). By varying $p \in [0.1, 1.0]$, we plot the performance under few-shot settings in Figure 9. We find that multitask training is consistently better across all ranges of data, which supports the fact that more generalizable representations across modalities and tasks are learned in HighMMT. The main takeaway is that if it is too difficult to collect data in a target domain, collecting data from a different domain and using a shared multimodal model is an alternative approach for improving performance.

### D.3 Multitask fusion and retrieval

To assess task generalization, we train multitask models over fusion in AV-MNIST and retrieval in CIFAR-ESC. While fusion emphasizes information integration from complementary data sources, retrieval focuses on aligning corresponding elements expressed through different views of the data (Baltrušaitis et al., 2018). Table 11 shows the full results of this experiment: even across vastly different multimodal prediction tasks, we find that multitask training (60.5% retrieval accuracy) improves upon single-task training (58.8% accuracy), while performance on the AV-MNIST fusion tasks is similar for both single-task and multitask learning. Not only have the unimodal encoders simultaneously processed different modalities, the multimodal attention layer has also learned to capture correspondences useful for both fusion and retrieval, while halving the total number of parameters required as compared to task-specific modeling.
Table 11: Multitask HighMMT also enables training a single model for both multimodal fusion and retrieval tasks.

| Model               | AV-MNIST ↑ | CIFAR-ESC ↑ | Params (M) ↓ |
|---------------------|------------|-------------|--------------|
| HighMMT             | 70.4       | 68.8        | 1.04         |
| HighMMT multitask   | 70.4       | 60.5        | 0.52         |

Table 12: We conduct in-depth ablation studies on the architecture design, parameter sharing settings, and fine-tuning strategies in HighMMT, and find strong evidence for (1) having separate unimodal and interaction architecture layers, (2) determining parameter sharing via feature transfer rather than having parameters fully separate, fully shared, or computed via feature difference across modalities and tasks, and (3) homogeneous pre-training before heterogeneity-aware fine-tuning into parameter groups rather than directly training for heterogeneity.

| Model               | UR-FUNNY ↑ | MOSEI ↑ | MIMIC ↑ | AV-MNIST ↑ | Ave ↑ |
|---------------------|------------|---------|---------|------------|-------|
| HighMMT             | 66.3       | 80.2    | 68.5    | 71.3       | 71.6  |
| Architecture ablations |
| - w/o embeddings    | 62.5       | 78.4    | 67.9    | 69.5       | 69.6  |
| - w/o unimodal      | 57.6       | 61.8    | 63.0    | 59.1       | 60.4  |
| - w/o crossmodal    | 61.3       | 80.3    | 67.7    | 69.4       | 69.7  |
| Param sharing ablations |
| - share none        | 63.4       | 79.7    | 68.5    | 69.0       | 70.2  |
| - share unimodal    | 63.5       | 79.5    | 65.3    | 70.0       | 69.6  |
| - share crossmodal  | 64.6       | 79.9    | 65.4    | 69.3       | 69.9  |
| - share all         | 63.0       | 79.9    | 67.8    | 70.4       | 70.3  |
| - random difference | 62.4       | 79.5    | 67.6    | 70.4       | 70.4  |
| - feature difference| 63.0       | 79.7    | 68.1    | 70.5       | 70.3  |
| Training ablations  |
| - direct training   | 61.2       | 78.5    | 64.8    | 71.1       | 69.9  |

D.4 Understanding HighMMT

In this subsection, we analyze why this general model achieves strong results in multitask, transfer, and few-shot settings. Based on prior work in multitask learning (Caruana, 1997; Ruder, 2017; Zhang and Yang, 2021), we set up two possible hypotheses: (1) improved generalization and (2) improved regularization. We supplement the results in the main paper with additional visualizations and comparisons in this subsection.

D.4.1 Hypothesis 1: Improved generalization

Investigating parameter sharing. In which components of the HighMMT model is parameter sharing important?

We further study the importance of parameter sharing in HighMMT. From the ablation studies in Table 12 using separate parameters for either unimodal or multimodal layers results in worse performance. The full model with completely separate unimodal and multimodal layers is reminiscent of typical single-task multimodal transformers (Tsai et al., 2019; Lu et al., 2019; Hendricks et al., 2021) trained separately for each task. We show that HighMMT maintains competitive performance (with slightly better performance on several datasets) due to statistical strength sharing, while also reducing parameters by 6× due to sharing of unimodal encoders and multimodal layers across tasks.

Furthermore, we surprisingly find that removing the modality-specific embedding layer results in only slightly worse performance (70.3 to 69.6 average score). This implies that the shared unimodal encoder has learned generalizable feature extractors that can encode heterogeneous modalities even without a modality identifier.

Visualization of attention patterns. How do the shared unimodal encoders attend to modality-specific tokens?

Given that parameter sharing seems to be useful for performance and efficiency, we aim to better visualize the nature of information sharing in the attention layers of unimodal encoders. We perform inference on a trained multitask HighMMT model on the test data of the large multitask setting, and average the attention patterns across test datapoints for each dataset. Following Lu et al. (2021), the average attention pattern provides information on general inductive biases captured by the unimodal encoders and enables us to make holistic conclusions rather than comparing attention maps on individual datapoints.
From Figure 10, we actually find that a common attention pattern emerges across modalities and tasks. First looking across modalities in the same dataset, we find that the model captures common temporal patterns at the same time steps, which makes sense since the 3 modalities are time-aligned in a video. The attention patterns are quite similar which implies that the same attention strategy can often work well across different modalities and tasks. This could be an explanation of why our model is able to perform multiple tasks simultaneously using shared parameters in attention layers.

It is also interesting to see how the model automatically learns to “divide up work” amongst its 20 latent tokens (numbered 0-19): the latent tokens 10 – 13 typically all focus on the region about two-thirds after the start of the input sequence, while latent tokens 1 and 3 always focuses on the region about one-third from the start. Certain tokens (3 and 18) seem to learn oscillating attention patterns, and certain pairs of tokens learn complementary attention patterns (e.g., 4, 5, and 6 attend one after the other). There are also some latent tokens that more evenly attend to the whole input sequence, such as latent tokens 9 and 17, which can be seen as “summary” tokens. This shows that the perceiver-based encoder is able to divide up its limited latent space well to capture important information both in specific time-steps and contextual information across all the time-steps, thus creating a holistic representation of the input using a much smaller set of latent variables.

D.4.2 Hypothesis 2: Improved regularization

In parallel to improved generalization, another line of research has focused on the regularization effects of multitask learning. Baxter (1997) showed that multitask parameter sharing reduces the risk of overfitting on the original task by forcing the model to learn across multiple tasks. We study the following regularization effects:

Training dynamics. In Figure 11, we traced the train and valid accuracies across 60 training epochs (with multitask training in the large setting). The training process of HighMMMT converges at about the same rate between single-task and multitask learning, but the multitask model overfits less (a smaller gap between
Figure 11: Multitask models converge as fast but overfit less (a smaller gap between train and valid accuracies) vs single-task models, which implies that multitask training helps to regularize the joint parameters and reduces overfitting on the target task.

Figure 12: Multitask performance can sometimes be sensitive to task weights especially when prediction objectives are of different scales (i.e., MSE for Push vs accuracy for V&T), in a manner similar to how carefully-tuned regularization terms help in training models.

Training and valid accuracies). This implies that multitask training helps to regularize the joint parameters and alleviates their overfitting on the target task.

Task weights. We found that optimizing a simple weighted sum of loss functions over all tasks was sufficient to obtain strong multitask performance. Instead of assigning uniform weights to each task, sometimes we found it helpful to set the weight higher for more challenging datasets during HighMMT multitask training. We show some examples of this phenomenon in Figure 12 where multitask performance can sometimes be sensitive to weights especially when prediction objectives are of different scales (i.e., MSE vs accuracy). This supports the regularization argument where carefully tuned weighted auxiliary objectives encouraging the model to also fit other auxiliary tasks can help improve performance on a target task. However, doing so would not achieve the best performance on auxiliary tasks.

D.5 Summary of main take-away messages

In conclusion, we designed a general multimodal multitask model for high-modality (a large set of diverse modalities) and partially-observable (each task only defined on a small subset of modalities) scenarios. Our approach relies on training for multitask and transfer learning: multitask learning with shared unimodal and multimodal layers enables stable parameter counts (addressing scalability) and cross-modal transfer learning enables information sharing across modalities and tasks (addressing partial observability). Through an extensive set of experiments and analysis, we summarize our main take-away messages as follows:

1. Standardized multitask modeling. We train a single multitask HighMMT model for numerous high-modality and partially-observable multimodal tasks (across 10 modalities, 15 prediction tasks, and 5 research areas), achieving strong performance while reducing total parameter counts. We believe that standardized modeling leads to a smaller set of architectural decisions, enables transfer to understudied modalities and tasks, and present a unified platform for subsequent theoretical and empirical analysis.
2. **Cross-modal transfer to new modalities and tasks.** Multitask H\text{ighMMT} enables cross-modal information transfer by pretraining on source multimodal tasks before transferring to completely new target modalities and tasks. Involving more tasks during pretraining improves performance, and gains are more apparent when fine-tuning on low-resource target tasks. This finding can supplement current pretrain-finetune paradigms typically performed on the same modality (e.g., text-only or image-only), and encourage research in more general multimodal pretraining over high-modality settings before fine-tuning on only a partial subset of all observed modalities.

3. **Tradeoff between performance and efficiency.** Multitask H\text{ighMMT} improves the tradeoff between performance and efficiency over task-specific state-of-the-art models especially in low-resource scenarios (less training data and partially-observable modalities). Coupled with the relatively fewer architectural decisions and generalization to understudied modalities and tasks, we believe that multitask H\text{ighMMT} and similar architectures should be a starting point for future research.

4. **Few-shot multitask learning.** Multitask information sharing can improve performance on low-resource target tasks with limited labeled training data. Therefore, if it is too difficult to collect data in a target domain, collecting data from a different domain and using a shared multimodal model is an alternative approach for improving performance.

5. **Information sharing.** Finally, our analysis reveals surprising insights regarding the nature of information sharing in multimodal and multitask models, which may be of independent interest. Specifically, there are both generalization and regularization effects at play in our implementation of multimodal multitask learning:
   - On the generalization side, information sharing is present across modalities and tasks, but at different levels across shared unimodal and multimodal layers. Information sharing enables strong multitask performance even under partial-observability and generalization to new modalities and tasks via transfer learning.
   - While using modality-specific embeddings achieves the best performance, there is only a minor drop when removing them, which implies that shared unimodal encoders can learn generalizable feature extractors even without a modality identifier.
   - On the regularization side, well-tuned regularization weights yield training dynamics that display less overfitting on target tasks as compared to single-task learning.