Multi-Modal Multi-Label Classification under Missing Textual/Visual Modalities via Cross-Modal Feature Simulation*

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Abstract. Multi-modal movie genre classification relies heavily on textual modalities, such as plot summaries, which provide rich semantic cues essential for accurate multi-label prediction. However, textual modalities are often incomplete, noisy, or entirely missing in real-world scenarios—a critical challenge for text-oriented applications where textual input plays a central role. We propose a cross-modal feature simulation framework designed to enhance robustness against missing textual modalities (while symmetrically handling missing visual modalities). Lightweight bidirectional simulators are pre-trained to reconstruct textual embeddings from available visual features, and visual embeddings from textual ones—using reconstruction losses on paired samples. During both training and inference, absent textual embeddings are dynamically imputed from visual cues (and vice versa), ensuring complete modality representations. The resulting embeddings—real or imputed—are fused via multi-head self-attention and fed to a multi-label classification head. Evaluated on the MM-IMDb benchmark across various missing-modality configurations, including severe textual absence, our approach demonstrates exceptional resilience, effectively transferring visual information into semantically consistent textual representations at the feature level without requiring raw text generation. This textual-focused, encoder-agnostic strategy achieves near-zero performance degradation even when textual modalities are unavailable, making it particularly suitable for text-scarce multi-modal environments. The source-code is available here: https://github.com/h-ismkhan/Multi-Modal-Multi-Label-Classification-under-Missing-Textual-Visual-Modalities.

Keywords: Textual Data · Missing Modality · Multi-Label Classification.

1 Introduction

Movie genre classification is a fundamental task in multimedia information retrieval and recommendation systems, enabling effective organization, search, and

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personalization of vast film collections. With the proliferation of online platforms hosting user-generated content and official movie databases, automatic genre prediction from multi-modal data—combining visual elements such as posters and textual elements such as plot summaries—has attracted considerable research interest [1][13]. Traditional approaches relied on unimodal features, often focusing on textual metadata like plots or reviews for classification [7][11]. However, these methods overlook the complementary information provided by visual cues, such as movie posters, which convey stylistic, thematic, and atmospheric signals that are particularly useful for genres like horror, action, or comedy [19]. The advent of multi-modal learning has addressed this limitation by jointly modeling visual and textual modalities, leading to significant performance improvements on benchmarks like MM-IMDb [20]. Early multi-modal frameworks employed gated mechanisms or concatenation-based fusion to integrate features from separate encoders [20]. More recently, pre-trained vision-language models have dominated the field, leveraging large-scale contrastive learning to align image and text representations in a shared embedding space, achieving state-of-the-art results in multi-modal movie genre classification [1][17]. Despite these advances, a critical challenge remains: real-world scenarios frequently involve incomplete data, where one modality—most commonly the textual modality (e.g., missing or unavailable plot summaries)—is absent [19][27]. This issue is particularly prevalent in text-oriented applications, such as legacy archives, newly released films without descriptions, or user-uploaded posters lacking accompanying text. Standard multi-modal models suffer substantial degradation under such missing textual modalities, as they typically rely on zero-filling or masking, which disrupts the learned cross-modal alignments [19]. Recent works have explored strategies for handling missing modalities, including knowledge distillation, generative imputation, or modality dropout during training [27]. However, many of these approaches either require expensive generation of raw text or do not fully exploit cross-modal transfer when textual input is severely limited [17]. To bridge this gap, we propose a cross-modal feature simulation framework that specifically targets robustness to missing textual modalities by learning to impute textual embeddings from visual features at the representation level. Our method ensures seamless handling of incomplete textual data during both training and inference, maintaining high performance in text-scarce multi-modal environments. The rest of this paper is organized as follows: Section 2 reviews related work, Section 3 describes the proposed method, Section 4 presents the experimental setup and results, and Section 5 concludes the paper.

2 Related Works

Multi-modal classification has emerged as a key area in computer vision and machine learning, leveraging complementary information from multiple modalities such as images, text, and audio to enhance performance on tasks like sentiment analysis, emotion recognition, and genre classification. Early approaches focused on unimodal representations but evolved to incorporate cross-modal interactions.

For instance, in medical image modality classification, combining visual descriptors (e.g., local binary patterns, scale-invariant feature transform) with textual annotations significantly improves accuracy, as visual features capture structural variations while text provides semantic context [10]. Similarly, in crisis management, attention-based models fuse textual tweets and visual images to classify disaster-related content as informative or non-informative, highlighting the role of cross-modal attention in handling noisy social media data [1] [13]. Hateful meme classification further demonstrates the need for multi-modal reasoning, where prompt-based methods using pre-trained language models like RoBERTa exploit implicit knowledge from visual-textual pairs, achieving high AUC scores without altering network structures [7]. In depression detection, additive cross-modal attention networks integrate audio and textual features, outperforming unimodal baselines by capturing inter-modal relationships [11]. Hierarchical fusion techniques, such as cross-modal complementary networks, model intra- and inter-modal interactions for sentiment classification, outperforming state-of-the-art methods on public datasets [20]. Expanding large pre-trained unimodal models like DenseNet or BERT with multi-modal information injection plug-ins enables fine-tuning for image-text recognition, balancing intra-modal processing and inter-modal interactions [17]. Scene-text-based fine-grained classification employs graph convolutional networks to reason over visual and textual cues, enriching features for tasks like storefront or bottle categorization [19]. Emotion classification refines this by multi-level semantic reasoning networks, exploring object-word and regional-global relations for fine-grained predictions [27]. Multi-modal sarcasm and humor detection in code-mixed conversations uses hierarchical attention to fuse textual and contextual modalities, improving performance on benchmarks [6]. Missing-modality-aware healthcare models, such as knowledge distillation frameworks, adapt to incomplete data in segmentation and classification tasks [24]. Document understanding benefits from vision-language contrastive pre-training, aligning modalities for classification despite heterogeneity [4]. Protein sequence learning with textual descriptions via contrastive objectives enables zero-shot function prediction [23]. A critical challenge in multi-modal learning is handling missing modalities, which can occur due to privacy, device failures, or data incompleteness, leading to performance degradation in real-world applications. Synthesis-based methods reconstruct missing modalities from available ones, such as using generative adversarial networks for MRI sequences [3]. Knowledge distillation approaches transfer robust representations from complete-modality teachers to modality-agnostic students, improving segmentation in brain tumor datasets [22]. Common latent space models map modalities to shared subspaces, enabling imputation and alignment under missing conditions [25]. Prompt-based adaptations mitigate missing modalities in transformers by learning modality-agnostic prompts, reducing fine-tuning costs while maintaining robustness [15]. Transformer robustness studies reveal sensitivity to missing data, with optimal fusion strategies varying by dataset; principle-based searches for fusion improve performance across benchmarks like MM-IMDb [18]. Modality-agnostic person re-identification unifies text and sketch queries via dual-encoders and task-aware training, enhancing generalization to uncertain inputs [8]. Rethinking missing modality from a decoding perspective proposes generative strategies to hallucinate absent features [12]. Fake news detection integrates multi-grained textual and visual features, using attention to fuse modalities robustly [26]. Structured text understanding employs multi-modal transformers for entity recognition, handling layout and visual cues [16]. Cross-modal distillation with audio-text fusion via transformers like Wav2Vec and BERT enables fine-grained emotion classification, addressing data scarcity [14]. Multi-modal prompting explores visual-textual baselines for attribute recognition, leveraging textual annotations to mine correlations [9][21]. While these works advance multi-modal handling of missing data, they often focus on specific tasks (e.g., medical segmentation [10][3] or sentiment analysis [20][27]) or assume modality completeness during training [7][11]. In contrast, our cross-modal feature simulation framework targets movie genre classification, emphasizing robustness to missing textual modalities through bidirectional embedding reconstruction and attention fusion, extending prior imputation strategies [25][22] to vision-language settings without raw generation or heavy retraining.

3 Cross-modal feature simulation under missing textual and visual modalities

Consider a task for a bi-modal dataset with modalities $\mathcal{M} = \{\mathbf{M}_1, \mathbf{M}_2\}$. Each sample consists of observations $(\mathbf{m}_1, \mathbf{m}_2, \mathbf{t})$, where $\mathbf{m}_k \in \mathcal{X}_k$ for $k \in \{1, 2\}$ may be observed or missing, and $\mathbf{t} \in \mathcal{T}$ is the target label set. Let $\mathcal{A} \subseteq \{1, 2\}$ denote the set of available modalities for a given sample. The goal is to learn a predictor $f : \mathcal{X}_1 \times \mathcal{X}_2 \to \mathcal{T}$ that performs robustly regardless of which modalities are available at training or inference time.

3.1 Model Architecture

Feature Extraction. For each modality $k \in \{1, 2\}$, a pretrained encoder $E_k : \mathcal{X}_k \to R^{d_k}$ with frozen parameters extracts embeddings:

$$\mathbf{M}'_k = E_k(\mathbf{m}_k), \quad \mathbf{M}'_k \in R^{d_k}.$$

Frozen encoders leverage transfer learning while keeping computational overhead low. When a modality is unavailable, its corresponding feature must be simulated.

Cross-Modal Simulation. To handle missing modalities, we employ trainable bidirectional simulators that map features from one modality space to another:

$$\hat{\mathbf{M}}'_1 = S_{2\to1}(\mathbf{M}'_2), \quad \hat{\mathbf{M}}'_2 = S_{1\to2}(\mathbf{M}'_1),$$

where $S_{2\to1} : R^{d_2} \to R^{d_1}$ and $S_{1\to2} : R^{d_1} \to R^{d_2}$ are multi-layer perceptrons. These simulators enable the model to reconstruct missing modality features and learn shared cross-modal representations.

Multi-Modal Fusion and Classification. After obtaining both modality features (either true or simulated), we apply a fusion module $f_{\text{fusion}} : R^{d_1} \times R^{d_2} \to R^{d_f}$ to integrate information from both modalities. The fused representation is then passed to a classification head $g : R^{d_f} \to R^C$, which is a multi-layer perceptron that produces multi-label predictions.

3.2 Training Procedure

The training procedure combines simulation and task objectives to learn representations that are robust to missing modalities. For each sample with available modalities $\mathcal{A}$, we extract the corresponding true features $\{\mathbf{M}'_k\}_{k\in\mathcal{A}}$ and simulate any missing features to form a complete bi-modal representation $\{\tilde{\mathbf{M}}'_1, \tilde{\mathbf{M}}'_2\}$, where:

$$\tilde{\mathbf{M}}'_k = \begin{cases} \mathbf{M}'_k & \text{if } k \in \mathcal{A} \\ \hat{\mathbf{M}}'_k & \text{if } k \notin \mathcal{A} \end{cases}$$

These features are then fused via f_{fusion} to produce the fused representation $\mathbf{H}$, and the final prediction is obtained as $\hat{\mathbf{t}} = g(\mathbf{H})$.

The total loss balances reconstruction fidelity and task accuracy:

$$\mathcal{L} = \alpha\mathcal{L}_{\text{sim}} + \beta\mathcal{L}_{\text{task}},$$

where $\alpha, \beta > 0$ are hyperparameters. Only the simulators, fusion module, and classification head are updated during training; the encoders remain frozen.

Simulation Loss. The simulation loss $\mathcal{L}_{\text{sim}}$ enforces cross-modal consistency and depends on the availability pattern. When only one modality is observed ($|\mathcal{A}| = 1$), we simulate the missing one but cannot compute reconstruction loss due to the absence of ground truth, thus $\mathcal{L}_{\text{sim}} = 0$. The simulators are refined indirectly through the task loss in this case. When both modalities are present ($|\mathcal{A}| = 2$), we perform bidirectional simulation and compute the reconstruction loss:

$$\mathcal{L}_{\text{sim}} = \|\mathbf{M}'_1 - S_{2\to1}(\mathbf{M}'_2)\|^2 + \|\mathbf{M}'_2 - S_{1\to2}(\mathbf{M}'_1)\|^2.$$

This encourages the simulators to learn accurate cross-modal mappings that preserve semantic information.

Task Loss. For multi-label classification with C classes, the classification head produces logits $\hat{\mathbf{t}} \in R^C$, and we use binary cross-entropy loss:

$$\mathcal{L}_{\text{task}} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C}\left[t_{i,c}\log(\sigma(\hat{\mathbf{t}}_{i,c})) + (1 - t_{i,c})\log(1 - \sigma(\hat{\mathbf{t}}_{i,c}))\right],$$

where $\sigma(\cdot)$ is the sigmoid function, $t_{i,c} \in \{0, 1\}$ indicates whether sample i belongs to class c, and $\hat{\mathbf{t}}_{i,c}$ is the predicted logit for class c.

The training procedure processes batches with mixed availability patterns. For each batch, we extract features from available modalities, simulate missing ones, compute both $\mathcal{L}_{\text{sim}}$ (when both modalities are present) and $\mathcal{L}_{\text{task}}$ (for all samples), and update the simulators, fusion module, and classification head using standard gradient-based optimization.

3.3 Inference

During inference, the procedure adapts seamlessly to any availability pattern $\mathcal{A}$. We extract available features $\{\mathbf{M}'_k\}_{k \in \mathcal{A}}$ using the frozen encoders, simulate any missing features using the trained simulators, form the complete representation $\{\tilde{\mathbf{M}}'_1, \tilde{\mathbf{M}}'_2\}$, apply the fusion module to obtain $\mathbf{H} = f_{\text{fusion}}(\tilde{\mathbf{M}}'_1, \tilde{\mathbf{M}}'_2)$, and produce predictions $\hat{\mathbf{t}} = g(\mathbf{H})$. This unified inference procedure handles uni-modal and bi-modal inputs identically, ensuring consistent predictions regardless of which modalities are present.

4 Experimental setup, dataset, and results

As the proposed multi-label multi-modal classification method in this paper simulates features embedding of missing modalities, it is referred by SIM-C. Training optimizes all trainable components (simulators, fusion module, and classification head) jointly using the combined loss $\mathcal{L} = \alpha\mathcal{L}_{\text{sim}} + \beta\mathcal{L}_{\text{task}}$ with batch size 8.

Model Architecture. We use frozen CLIP ViT-B/32 encoders for both visual and textual modalities, producing 512-dimensional embeddings. Each bidirectional simulator $S_{1\to2}$ and $S_{2\to1}$ is implemented as a 3-layer MLP with hidden dimension 256 and ReLU activations. The fusion module f_{fusion} employs multi-head self-attention with 4 attention heads and 2 layers. Input features are first projected to a common dimension of 256, processed through attention layers with residual connections and layer normalization, then mean-pooled across modalities. The classification head consists of a 3-layer MLP (256→128→64→27) with ReLU activations and dropout (0.1). We set hyperparameters $\alpha = 0.5$ and $\beta = 1.0$ for the combined loss. Training uses the Adam optimizer with learning rate 5×10^{-5} for 20 epochs.

MM-IMDb. The MM-IMDb dataset [2] is a large-scale multi-modal benchmark comprising thousands of movie entries, each featuring a poster image as the visual modality, a plot summary as the textual modality, and multi-label annotations across multiple genres. This dataset is characterized by significant class imbalance and multi-label complexity, making it an ideal testbed for evaluating multi-modal learning approaches, especially those handling incomplete data. It is for movie genre classification across 27 distinct genres including Drama, Comedy, Thriller, and Romance. Each sample can be associated with multiple genres simultaneously, making this a challenging multi-label classification task. To simulate missing modalities, we configure datasets with various availability patterns:

- *100_image_20_text*: 100% image with 20% text,
- *20_image_100_text*: 20% image with 100% text,
- *complex_20_40_40*: 20% both-modalities-presence, 40% image only and 40% text only,
- *complex_30_35_35*: 30% both-modalities-presence, 35% image only and 35% text only,

Table 1: F-micro obtained by the algorithms on MM-IMDB

Method	100_image_100_text	100_image_20_text	20_image_100_text	complex_10_45_45	complex_20_40_40	complex_30_35_35
ShaSpec	0.49	0.39	0.45	0.39	0.38	0.43
M3Care	0.46	0.39	0.43	0.43	0.37	0.45
PmcmFL	0.66	0.51	0.48	0.50	0.51	0.54
SIM-C	**0.94**	**0.93**	**0.93**	**0.93**	**0.93**	**0.93**

- *complex_10_45_45*: 10% both-modalities-presence, 45% image only and 45% text only.

Table 1 presents the F-micro scores achieved by the compared methods across different modality configurations on the MM-IMDb dataset. The baseline methods—ShaSpec [22], M3Care [24], and PmcmFL [5]—exhibit varying performance under full and missing modality settings. ShaSpec achieves an F-micro of 0.49 on the complete dataset (100_image_100_text) but drops to 0.39–0.45 in missing scenarios, indicating moderate robustness. M3Care performs slightly lower at 0.46 on full data, with scores ranging from 0.37 to 0.45 in missing cases, showing similar sensitivity to modality absence. PmcmFL starts stronger at 0.66 on complete data but degrades to 0.48–0.54 when modalities are missing, suggesting it benefits more from full availability but struggles with imputation. In contrast, our SIM-C method consistently achieves the highest scores, with 0.94 on full data and 0.93 across all missing configurations. This near-perfect stability highlights SIM-C's superior ability to simulate and compensate for absent modalities, outperforming baselines by a wide margin (e.g., 42.42% improvement over PmcmFL on full data). On average, across missing configurations, SIM-C attains an F-micro of 0.93, compared to 0.41 for ShaSpec, 0.41 for M3Care, and 0.51 for PmcmFL. This represents average improvements of 127.94% over ShaSpec, 124.64% over M3Care, and 83.07% over PmcmFL, underscoring SIM-C's effectiveness in handling diverse missing patterns, particularly in complex mixed settings where modality presence varies unpredictably.

Table 2 quantifies the relative error (%) of each method on missing configurations compared to their performance on the complete dataset (100_image_100_text). The relative error (%) for a given missing-modality configuration is computed as

$$\text{Error (\%)} = \frac{F_{\text{full}} - F_{\text{missing}}}{F_{\text{missing}}} \times 100,$$

Table 2: Error(%) of each algorithm in comparison to result on complete MM-IMDB

Method	100_image_20_text	20_image_100_text	complex_10_45_45	complex_20_40_40	complex_30_35_35
ShaSpec	25.64	8.89	25.64	28.95	13.95
M3Care	17.95	6.98	6.98	24.32	2.22
PmcmFL	29.41	37.5	32	29.41	22.22
SIM-C	**0.97**	**0.54**	**1.08**	**0.97**	**0.75**

where F_{full} denotes the performance (e.g., F-micro or F-samples) achieved on the complete dataset (100% image + 100% text), and F_{missing} is the performance on the respective missing-modality setting (provided that $F_{\text{missing}} < F_{\text{full}}$). To the best of our knowledge, this normalized error metric is introduced for the first time in this paper. It quantifies the percentage degradation relative to the performance observed under the missing-modality condition itself, rather than relative to the full-modality baseline in absolute terms. This formulation provides a robust, scale-invariant measure of degradation that enables fair comparison across methods with differing absolute performance levels, while emphasizing how much a method loses proportionally when modalities are absent. ShaSpec shows errors ranging from 8.89% to 28.95%, with an average of 20.61%, reflecting inconsistent handling of missing text or images. M3Care has lower variability (2.22% to 24.32%, avg. 11.69%), but still degrades notably in complex_20_40_40. PmcmFL exhibits the highest errors (22.22% to 37.5%, avg. 30.11%), particularly in text-heavy missing cases like 20_image_100_text, indicating reliance on visual completeness. SIM-C, however, maintains minimal errors (0.54% to 1.08%, avg. 0.86%), demonstrating exceptional robustness. This translates to average error reductions of 95.82% over ShaSpec, 92.63% over M3Care, and 97.14% over PmcmFL, validating SIM-C's bidirectional simulation as highly effective for mitigating performance drops across all tested missing patterns.

Table 3 reports F-samples scores, which provide a balanced measure of precision and recall across samples. On complete data, PmcmFL leads with 0.66, followed by SIM-C at 0.64, ShaSpec at 0.5, and M3Care at 0.45. In missing scenarios, SIM-C consistently outperforms with scores of 0.57–0.60, while baselines range from 0.36–0.54. Averaging over missing configs, SIM-C achieves 0.58, compared to 0.40 (ShaSpec), 0.41 (M3Care), and 0.49 (PmcmFL), yielding improvements of 43.07% over ShaSpec, 42.36% over M3Care, and 17.96% over PmcmFL. This suggests SIM-C not only maintains high aggregate performance (F-micro) but also ensures balanced classification across individual samples, particularly beneficial

Table 3: F-samples obtained by the algorithms on MM-IMDB

Method	100_image_100_text	100_image_20_text	20_image_100_text	complex_10_45_45	complex_20_40_40	complex_30_35_35
ShaSpec	0.5	0.38	0.44	0.39	0.38	0.43
M3Care	0.45	0.38	0.43	0.42	0.36	0.44
PmcmFL	**0.66**	0.49	0.45	0.48	0.49	0.54
SIM-C	0.64	**0.57**	**0.60**	**0.57**	**0.57**	**0.58**

in multi-label tasks with class imbalance like genre prediction. Overall Analysis: Across all metrics, SIM-C demonstrates superior robustness to missing modalities, with near-zero degradation from full-data performance. Baselines suffer 11–30% average errors, while SIM-C's is under 1%, indicating effective cross-modal simulation. In complex mixed settings, where modality presence mimics real-world variability, SIM-C's consistency (0.93 F-micro) contrasts baselines' fluctuations (0.36–0.54), highlighting its practical utility. Compared to knowledge distillation-focused methods like M3Care and ShaSpec, SIM-C's bidirectional reconstruction better preserves semantic alignments. While PmcmFL excels on complete data due to strong classification, its modality sensitivity limits it; SIM-C balances strong full-data performance (42.42% improvement over PmcmFL) with minimal missing-data loss. These results affirm SIM-C as a state-of-the-art solution for multi-modal genre classification under uncertainty.

Figure 1 provides a qualitative analysis of the quality of imputed embeddings produced by each method under the complex_20_40_40 missing-modality setting, where only 20% of samples have both modalities available, 40% have image only, and 40% have text only. We apply t-SNE dimensionality reduction to project the high-dimensional feature embeddings into 2D space. Yellow points correspond to ground-truth embeddings (from samples where the modality is actually present), while red and blue points represent the imputed image and text embeddings, respectively.

For the baseline methods (ShaSpec, M3Care, and PmcmFL), the imputed embeddings (both image and text) form distinct clusters that are noticeably separated from the ground-truth distribution (yellow). This separation indicates that the simulated features deviate substantially from the true manifold, potentially introducing distributional shift and degrading downstream classification performance.

In stark contrast, our SIM-C method produces imputed embeddings (red for image, blue for text) that closely overlap and intermix with the ground-truth yellow points in both modalities. The imputed points are well-distributed within the real embedding manifold, demonstrating that SIM-C's bidirectional simulation modules successfully generate semantically consistent and faithful representations even when the corresponding modality is absent. This superior alignment qualitatively explains the minimal performance degradation observed for SIM-C in quantitative results (Tables 1–3) and confirms the effectiveness of the proposed cross-modal reconstruction objective in preserving the joint embedding space.

5 Conclusion

In this paper, we addressed the challenge of multi-modal movie genre classification under missing textual/visual modalities, a prevalent issue in real-world applications where plot summaries may be incomplete or absent. We proposed SIM-C, a cross-modal feature simulation framework that reconstructs missing embeddings in CLIP's joint space using lightweight bidirectional simulators trained on reconstruction losses. By dynamically imputing absent features during both training and inference, and fusing them via multi-head self-attention, SIM-C ensures robust multi-label classification without requiring raw text generation or heavy model retraining.

Extensive experiments on the MM-IMDb dataset demonstrated SIM-C's superiority, achieving F-micro scores of 0.93–0.94 across various missing-modality configurations, with minimal relative errors (<1%) compared to baselines (11–30%). t-SNE visualizations further confirmed the fidelity of imputed embeddings, closely aligned with ground-truth distributions. These results highlight SIM-C's effectiveness in preserving semantic alignments and handling modality incompleteness, outperforming state-of-the-art methods like ShaSpec, M3Care, and PmcmFL by substantial margins.

Our work advances multi-modal robustness in vision-language tasks, with implications for text-scarce environments like legacy media archives or emerging content platforms. Future directions include extending SIM-C to additional modalities (e.g., audio) and exploring zero-shot adaptation for unseen genres or datasets.

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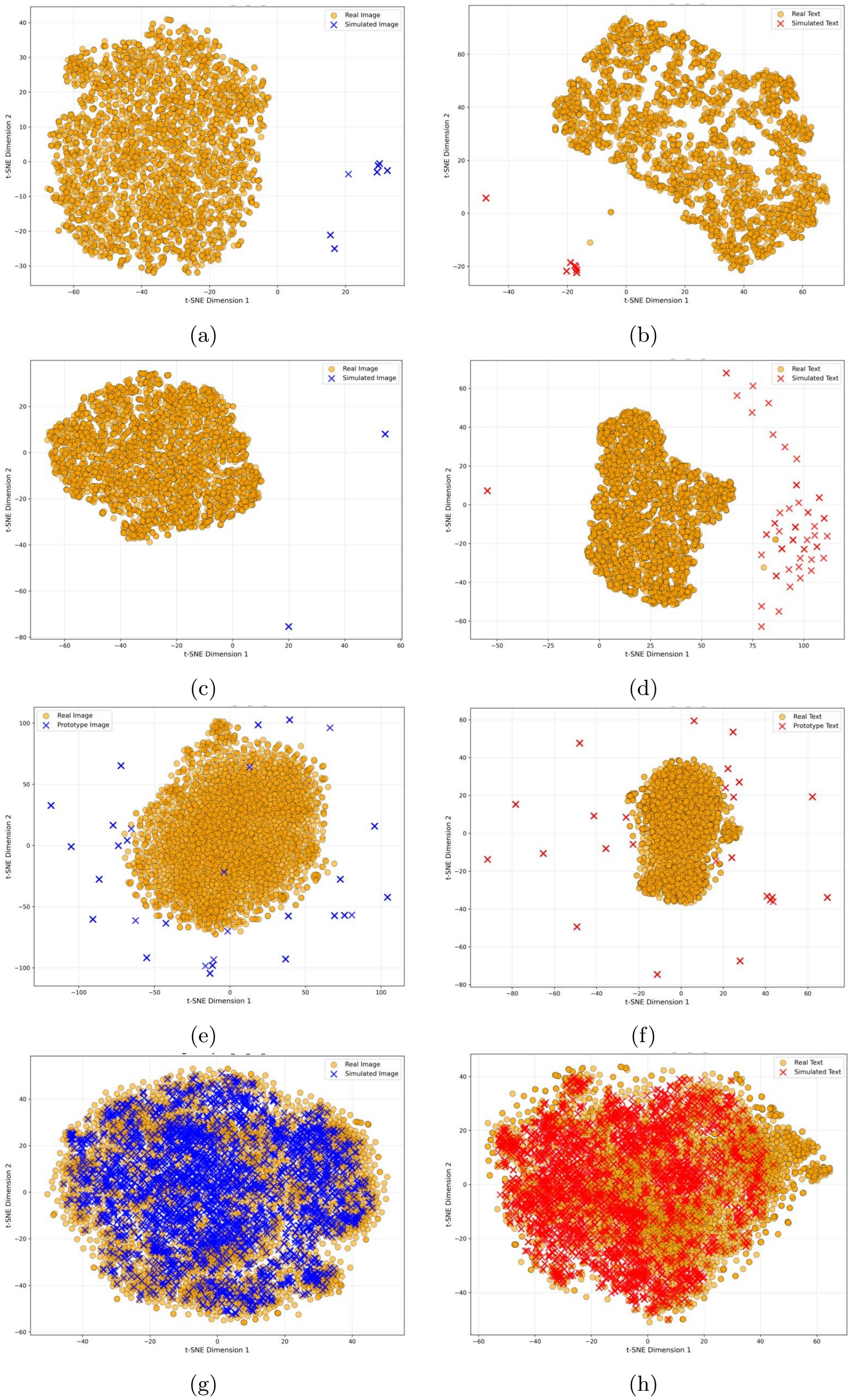

(a) (b)

(c) (d)

(e) (f)

(g) (h)

Fig. 1: Visualisation of the feature embedding of the missing modalities.