A survey on Self Supervised learning approaches for improving Multimodal representation learning

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Abstract
Recently self supervised learning has seen explosive growth and use in variety of machine learning tasks because of its ability to avoid the cost of annotating large-scale datasets. This paper gives an overview for best self supervised learning approaches for multimodal learning. The presented approaches have been aggregated by extensive study of the literature and tackle the application of self supervised learning in different ways. The approaches discussed are cross modal generation, cross modal pretraining, cyclic translation, and generating unimodal labels in self supervised fashion.

1 Introduction
Multimodal machine learning is a vibrant multi-disciplinary research field that aims to design intelligent systems for understanding, reasoning, and learning through integrating multiple communicative modalities, including linguistic, acoustic, visual, tactile, and physiological messages. Multimodal learning attracts intensive research interest because of broad applications such as intelligent tutoring [Petrovica et al., 2017], robotics [Noda et al., 2014], and healthcare [Frantzidis et al., 2010]. Generally speaking, existing research efforts mainly focus on how to fuse multimodal data effectively and how to learn a good representation for each modality. Further the extensive survey by Liang et al. [2022] gives a taxonomy of the challenges in multimodal learning as showing in Figure 1.
Self-supervised learning [Jaiswal et al., 2020] obtains supervisory signals from the data itself, often leveraging the underlying structure in the data. The general technique of self-supervised learning is to predict any unobserved or hidden part (or property) of the input from any observed or unhidden part of the input. For example, as is common in NLP, we can hide part of a sentence and predict the hidden words from the remaining words.

The aim of this paper is to provide an overview of best self supervised learning approaches which tackle the representation challenge in multimodal learning. We present 4 approaches after extensive survey of literature in the domain.

1. We look at cross modal generation which basically for a given image-text pair, generates image-to-text and text-to-image. We then compare the generated text and image samples with the input pair.

2. We then look at cross modal transformer which uses cues from different modality namely audio and video to do predict the masked token in masked language modelling.

3. We then look at the approach of cyclic translation between modalities using a Seq2Seq network. A given modality is translated to another modality and then back translated. The learned hidden encoding is used for final prediction.
4. Finally we look at approach of generating unimodal labels from multimodal datasets in self supervised fashion. Multitask learning is used to jointly train on both multimodal and unimodal labels.

For brevity purpose we give a high level detail of each method while omit the superficial details and refer the reader to the original work for further reference.

2 Methodology

2.1 Cross-modal generation

The main idea proposed by Gu et al. [2018] is addition to conventional cross-modal feature embedding at the global semantic level, to introduce an additional cross-modal feature embedding at the local level, which is grounded by two generative models: image-to-text and text-to-image. Figure 2 illustrates the concept of the proposed cross-modal feature embedding with generative models at high level, which includes three learning steps: look, imagine, and match. Given a query in image or text, first look at the query to extract an abstract representation. Then, imagine what the target item (text or image) in the other modality should look like, and get a more concrete grounded representation. This is accomplish by using the representation of one modality (to be estimated) to generate the item in the other modality, and comparing the generated items with gold standards. After that, in match step the right image-text pairs using the relevance score which is calculated based on a combination of grounded and abstract representations.

Architecture Figure 3 shows the overall architecture for the proposed generative cross-modal feature learning framework. The entire system consists of three training paths: multi-modal feature embedding (the entire upper part), image-to-text generative feature learning (the blue path), and text-to-image generative adversarial feature learning (the green path). The first path is similar to the existing cross-modal feature embedding that maps different modality features into a common space. However, the difference here is that they use two branches of feature embedding, i.e., making the embedded visual feature $v_h$ (resp. $v_l$) and the textual feature $t_h$ (resp. $t_l$) closer. They consider $(v_h, t_h)$ as high-level abstract features and $(v_l, t_l)$ as detailed grounded features. The grounded features
Figure 2: Conceptual illustration of the crossmodal feature embedding with generative models. The cross-modal retrievals (Image-to-Text and Text-to-Image) are shown in different color. The two blue boxes are crossmodal data, and the generated data are shown in two dashed yellow clouds.

will be used and regularized in the other two generative feature learning paths. The entire first training path mainly includes one image encode CNN Enc and two sentence encoders RNNl Enc and RNNr Enc. The second training path (the blue path) is to generate a sentence from the embedded generative visual feature vl. It consists of the image encoder CNN Enc and a sentence detector RNNDec. With a proper loss against ground-truth sentences, the grounded feature vl will be adjusted via back propagation. The third training path (the green path) is to generate an image from the textual feature tl. Here we adopt the generative adversarial model, which comprises a generator / decoder CNNDec and a discriminator Dl.

Overall, through these two paths of cross-modal generative feature learning, authors hope to learn powerful cross-modal feature representations. During the testing stage, vh, vl and th, tl will be used as the final feature representations for cross-modal retrieval.

Figure 3: The generative cross-modal learning framework. The entire framework consists of three training paths: cross-modal feature embedding (the entire upper part), image-to-text generative feature learning (the blue path), and text-to-image generative adversarial feature learning (the green path). It includes six networks: two sentence encoders RNNl Enc (dark green) and RNNr Enc (light green), one image encoder CNN Enc (blue), one sentence decoder RNNDec, one image decoder CNNDec and one discriminator Dl.
2.2 Cross-modal pretraining for transformers

The main idea proposed by Khare et al. [2021] is to pretrain a cross-modal transformer in self-supervised fashion and then finetune the transformer for emotion recognition. This allows for attending to specific input features (visual frames, words, speech segments) that are relevant to the task.

The first part of the model architecture achieves this by using self-attention based transformer encoder for individual modalities. After encoding from unimodal encoder, authors obtain the self-attended outputs $S_A$, $S_V$ and $S_T$ from the audio, visual and text modalities respectively.

Next, the authors combine the uni-modal transformer encoder outputs, $S_A$, $S_V$ and $S_T$, to learn the final multi-modal representation for emotion recognition. This is done by the cross-modal transformer, which computes the attention map between features from two different modalities $M_1$ and $M_2$. The cross-modal attention allows for increasing attention weights on features that are deemed important for emotion recognition by more than one modality.

Pretraining For pretraining the model in self-supervised fashion, the authors use a variation of masked LM task to train the model. They propose to predict words by looking at audio and visual context in addition to the context words around the masked input. Intuitively, the auxiliary information present in visual expressions and audio features like intonation would provide relevant input for predicting the masked words. For example, consider the phrase “This movie is [MASK]” as an input to the model. The [MASK] word could be predicted as “amazing” if the audio and visual features show that speaker is happy. Alternatively, the prediction could be “terrible” if the speaker seems discontent while talking. This information cannot be derived from text only input. They posit that the latent representations learned using the masked LM task with multi-modal input will not just encode context, but also the relevant emotional information which could be used to predict those words.

2.3 Self-supervised cyclic translation

With the recent success of sequence to sequence (Seq2Seq) models in machine translation, there is an opportunity to explore new ways of learning joint representations that may not require all input modalities at test time. Pham et al. [2019] propose a method to learn robust joint representations by translating between modalities. Our method is based on the key insight that translation from a source to a target modality provides a method of learning joint representations using only the source
modality as input. They augment modality translations with a cycle consistency loss to ensure that the joint representations retain maximal information from all modalities. Once the translation model is trained with paired multimodal data, one only needs data from the source modality at test time for final sentiment prediction.

Figure 5: Learning robust joint representations via multimodal cyclic translations. Top: cyclic translations from a source modality (language) to a target modality (visual). Bottom: the representation learned between language and vision are further translated into the acoustic modality, forming the final joint representation. In both cases, the joint representation is then used for sentiment prediction.

The proposed model learns robust joint multimodal representations by translating between modalities. Figure 5 illustrates these translations between two or three modalities. The method is based on the key insight that translation from a source modality \( S \) to a target modality \( T \) results in an intermediate representation that captures joint information between modalities \( S \) and \( T \). Author then extend this insight using a cyclic translation loss involving both forward translations from source to target modalities, and backward translations from the predicted target back to the source modality. Together, these multimodal cyclic translations ensure that the learned joint representations capture maximal information from both modalities. They also propose a hierarchical setting to learn joint representations between a source modality and multiple target modalities. The proposed approach is trainable end-to-end with a coupled translation-prediction loss which consists of (1) the cyclic translation loss, and (2) a prediction loss to ensure that the learned joint representations are task-specific (i.e. multimodal sentiment analysis).

Figure 6: The architecture for two modalities: the source modality \( X^S \) and the target modality \( X^T \). The joint representation \( E_{S\leftarrow T} \) is obtained via a cyclic translation between \( X^S \) and \( X^T \). Next, the joint representation \( E_{S\leftarrow T} \) is used for sentiment prediction. The model is trained end-to-end with a coupled translation-prediction objective. At test time, only the source modality \( X^S \) is required.
2.4 Self supervised unimodal label prediction and Multi-task for better representation

The main idea proposed by Yu et al. [2021] is that representation learning only using multimodal labels is only targeted at learning differential information. But usually unimodal labels for a multimodal dataset are not available. Hence, the authors propose a strategy to generate unimodal labels in self-supervised fashion. These unimodal labels are joined with multimodal labels to train the model. Further, during the training stage, authors design a weight-adjustment strategy to balance the learning progress among different subtasks.

![Figure 7: The overall architecture of Self-Supervised Multi-task Multimodal model. The \( \hat{y}_m, \hat{y}_t, \hat{y}_a, \) and \( \hat{y}_v \) are the predictive outputs of the multimodal task and the three unimodal tasks, respectively. The \( y_m \) is the multimodal annotation by human. The \( y_t, y_a, \) and \( y_v \) are the unimodal supervision generated by the self-supervised strategy. Finally, \( \hat{y}_m \) is used as the sentiment output.](image)

**Unimodal Label Generation Module** The ULGM aims to generate uni-modal supervision values based on multimodal annotations and modality representations. In order to avoid unnecessary interference with the update of network parameters, the ULGM is designed as a non-parameter module. Generally, unimodal supervision values are highly correlated with multimodal labels. Therefore, the ULGM calculates the offset according to the relative distance from modality representations to class centers. It basically estimates the unimodal label from the multimodal label using the relative distance from the modality specific class center for the specific modality as shown in figure 8.

![Figure 8: Unimodal label generation. Multimodal representation \( F_m^* \) is closer to the positive center (m-pos) while unimodal representation is closer to the negative center (s-neg). Therefore, unimodal supervision \( y_s \) is added a negative offset \( \delta_{sm} \) to the multimodal label \( y_m \Rightarrow y_s = y_m + \alpha_s - \alpha_m \).](image)
3 Conclusion

This paper presents the best approaches to improve the learned representation in multimodal learning in a self supervised fashion. The various presented approaches are generic and work by different principles - cross modal generation, cross modal pretraining, cyclic translation, and generating unimodal learning. The field of self supervised learning is ever evolving and its application to other areas in machine learning are yet to fully realized.

References

Christos A Frantzidis, Charalampos Bratsas, Manousos A Klados, Evdokimos Konstantinidis, Chrysa D Lithari, Ana B Vivas, Christos L Papadelis, Eleni Kaldoudi, Costas Pappas, and Panagiotis D Bamidis. On the classification of emotional biosignals evoked while viewing affective pictures: an integrated data-mining-based approach for healthcare applications. *IEEE Transactions on Information Technology in Biomedicine*, 14(2):309–318, 2010.

Jiuxiang Gu, Jianfei Cai, Shafiq R Joty, Li Niu, and Gang Wang. Look, imagine and match: Improving textual-visual cross-modal retrieval with generative models. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7181–7189, 2018.

Ashish Jaiswal, Ashwin Ramesh Babu, Mohammad Zaki Zadeh, Deapriya Banerjee, and Fillia Makedon. A survey on contrastive self-supervised learning. *Technologies*, 9(1):2, 2020.

Aparna Khare, Srinivas Parthasarathy, and Shiva Sundaram. Self-supervised learning with cross-modal transformers for emotion recognition. In *2021 IEEE Spoken Language Technology Workshop (SLT)*, pages 381–388. IEEE, 2021.

Paul Pu Liang, Amir Zadeh, and Louis-Philippe Morency. Foundations and recent trends in multimodal machine learning: Principles, challenges, and open questions. *arXiv preprint arXiv:2209.03430*, 2022.

Kuniaki Noda, Hiroaki Arie, Yuki Suga, and Tetsuya Ogata. Multimodal integration learning of robot behavior using deep neural networks. *Robotics and Autonomous Systems*, 62(6):721–736, 2014.

Sintija Petrovica, Alla Anohina-Naumeca, and Hazım Kemal Ekenel. Emotion recognition in affective tutoring systems: Collection of ground-truth data. *Procedia Computer Science*, 104:437–444, 2017.

Hai Pham, Paul Pu Liang, Thomas Manzini, Louis-Philippe Morency, and Barnabás Póczos. Found in translation: Learning robust joint representations by cyclic translations between modalities. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 6892–6899, 2019.

Wenheng Yu, Hua Xu, Ziqi Yuan, and Jiele Wu. Learning modality-specific representations with self-supervised multi-task learning for multimodal sentiment analysis. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 10790–10797, 2021.