Research Statement – Guangyi Chen

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Over the last decade, the great progress has been achieved in the field of computer vision by the success of deep learning. Despite the powerful representation ability of deep neural network, it is still challenging to imagine and reason like human. Therefore, my research aims at developing robust and explainable visual understanding models by imitating the cognitive process of human brain. There are two principal directions I have explored: 1) attention learning, and 2) causal learning.

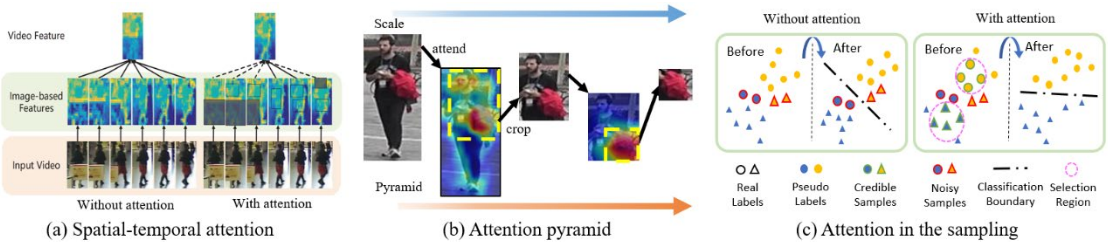


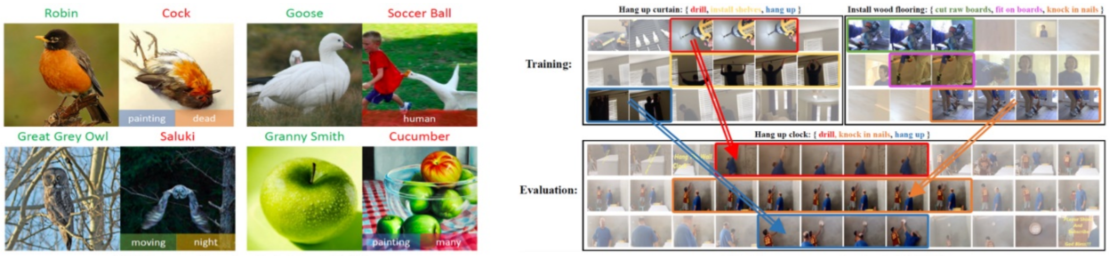
Figure 1: The proposed attention learning methods: (a) Learning spatial-temporal attention for video understanding; (b) Learning attention pyramid for multi-scale saliences; (c) introducing the attention in the sampling process.

1 Attention Learning

Attention mechanism plays an important role in the human conscious processing to abstract out the irrelevant information. I have been working on exploring the attention mechanism in the computer vision system, which aim to facilitate high-performance recognition by discovering discriminative regions and mitigating the negative effects brought by diverse visual appearance, cluttered backgrounds, occlusions, pose variations, etc. In the past years, my research about attention learning mainly focused on three problems: designing effective attention models [3,4,5,7,8] (especially for videos containing complex spatial-temporal clues [3,4,5]), learning attentions in the weakly-supervised manner [1,10], and introducing the attention model in the sampling process of metric learning [2,6].

Designing effective attention models. The videos contain complex spatial-temporal clues and heavy negative misalignments. As shown in Figure 1 (a), I have explored to develop the spatial-temporal attention model [3] to learn the robust representations by jointly mining the salient clues of videos in both spatial and temporal domain. Moving ahead, motivated by the inherent consistencies between spatial and temporal clues, I have proposed to attend the 3D regions by treating the video as a unified 3D bin [4]. Besides, as shown in Figure 1 (b), in order to mine the salient clues in different scales, I have developed an attention pyramid network with the designed "split-attend-merge-stack" principle. Results show the robust representation ability brought by these attention models.

Learning attentions in the weakly-supervised manner. Despite the widespread use, the problem of how to learn effective attention is still barely studied. Most existing methods learn the visual attention in a weakly-supervised manner, i.e., the attention modules are simply supervised by the final loss function, without a powerful supervisory signal to guide the training process. Hence, I proposed a self-critical attention learning method [1] which learns a critic to measure the attention quality and provide supervisory signals. Furthermore, I explored the attention learning in a causal perspective and proposed a counterfactual attention learning [10] to analyze the effects of learned visual attention with counterfactual causality. These methods improve the learning process of attention and achieve better performance on fine-grained recognition.



(a) Examples in FairBench1K (b) An example in GAIN

Figure 2: The examples of benchmarks for fairness and generalizability: (a) The examples with out-of-distribution attributes; (b) An example of how to generate out-of-distribution instructional task.

Introducing the attention model in the sampling process. In the training, the effects of samples have a large variance, where easy samples hardly produce effective gradient while hard samples caused by noise labels may mislead the model. To mine valuable samples, I have introduced the attention model in the sampling process. I have proposed a deep meta metric learning method, which formulates the metric learning process in a meta learning perspective and apples attention to mine representative samples in the set to learn the set-based distance. Besides, as shown Figure 1 (c), I have also proposed to mine credible samples for unsupervised domain adaptation to avoid the misleading from noise labels.

2 Causal Learning

Existing computer vision systems are good at learning what the object is (i.e., visual recognition) or where it is (i.e. object detection and segmentation), yet bad at explaining why it is that. These systems learn to predict based on likelihood, instead of the underlying causation. Recently, I have been working on applying the tools of causal inference for computer vision systems to alleviate the negative effects brought by confounding data bias and enhance the model's generalizability, fairness, and explainability. My research focuses on benchmarking the fairness and generalizability by causal inference [11,13] and mitigating the data bias by counterfactual comparison [9,10,12].

Benchmarking the fairness and generalizability. Despite the remarkable progress on computer vision thanks to the deep learning techniques, computer vision models still perform unfavorably for out-of-distribution samples due to the dataset bias. This fact reveals that traditional metrics like classification accuracy may overestimate the capacity and reliability of the models. Towards a more comprehensive evaluation, I have introduced a large real-world dataset to benchmark fairness of image recognition models [11]. As shown in Figure 2 (a), the examples with out-of-distribution attributes require the fairness of models with regard to different protected attributes. Besides, I have also introduced a dataset to benchmark the generalizability of instructional video analysis models [13]. Figure 2 (b) illustrates an example that an out-of-distribution task are generated with in-distribution training samples. I furthermore proposed a method to enhance the generalizability by cutting off excessive contextual dependency with sampling intervention.

Mitigating the data bias by counterfactual intervention. Limited by the dataset scale and annotation level, the models are always inevitably misled by the data bias to focus on the spurious correlations in training data. To mitigate the influence of confounding data bias, I have proposed to learn the model by counterfactual intervention. Counterfactual intervention is of critical importance in causal inference, which encourages the model to involve consideration of an alternate version of a past event. I have proposed to conduct counterfactual attention by imagining non-existent attention maps, and maximize the effect of attention model by comparison [10]. Besides, I proposed a retrieval-based counterfactual intervention method which retrieves videos from an off-line video pool as counterfactual example to optimize the unintentional action localization model [12].

3 Future Research Plans

My goal for research is teaching computer vision systems to understand the causal effect and acquire commonsense knowledge in the world. Towards this goal, my future research plans are organized around two themes: 1) general causal learning and 2) commonsense knowledge.

General causal learning. Beyond the conventional statistical learning, I believe the causal learning has a great potential to allow the models to support intervention, planning, and reasoning. Many efforts have been made to develop causal learning to improve machine learning methods. However, most existing causal learning methods analyze causations only in high-level semantic information and specific task. A possible goal is towards general causal learning, which adaptively discovers causal relations from low-level observations and learn the causations without the prior of causal structure.

Commonsense knowledge. I believe the commonsense is key for computer vision systems to understand the real world. It is desired to build the commonsense knowledge graph in the field of computer vision. It is still challenging when climbing this ladder. In [12], I built an offline video pool as the commonsense to analyze the intention of human action. I also explored the attribute disentangling of visual objects in [8] and [11]. Motivated by these experiences, I plan to build commonsense knowledge graph with the intrinsic relations among attributes.

There is still a long way to go towards these goals. I am excited about and ready for these new challenges.

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