Supplements: Distilling Knowledge in Causal Inference for Unbiased Visual Question Answering

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1 DETAILS OF CAUSAL GRAPH

1.1 An Example for Building A Causal Graph

The causal graph is used to model causal assumption [3]. In this section, an example is given to well explain the process of building a causal graph. Let U be a set of exogenous variables, V be the set of endogenous variables, and F be a set of functions. The formal expressions of variables and functions are as follows.

$$U = \{X, Y\}, V = \{Z\}, F = \{f_Z\} \quad (1)$$

$$f_Z : Z = 2X + 3Y \quad (2)$$

The causal graph associated with Eq. (1) and Eq. (2) is illustrated in Figure 1.

Figure 1: The example of the causal graph associated

Link $X \rightarrow Z$ and $Y \rightarrow Z$ are caused by the function f_Z . This is because the function f_Z obtains Z through X and Y .

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1.2 Causal Graph of The VQA Model

As introduced in 1.1, the causal graph of the VQA model is built by the calculation process of the UpDn model [1]. The meanings of the causal relations and nodes are as follows.

Node Q (Question). The embeddings of words in questions are initialized by GloVe [4]. GRU [2] is utilized as the question encoder to encode the question q_i to a vector f_i^q .

Node V (Object feature). The exogenous variable of Node V is the visual features of detected object regions $\mathbf{o}_i = \{f_{i,m}^v\}_{m \in [1:M]}$. The object feature $\mathbf{o}_i$ is extracted by a pre-trained and frozen Faster R-CNN [5], where $\mathbf{o}_i$ indicates the object features of the i -th sample, M indicates the number of region, $f_{i,m}^v$ indicates the object feature extracted from the m -th region of the i -th sample. The variable of node V denotes the visual feature obtained by the question-guided attention mechanism.

Node B (Bias learned from data). The conventional VQA model learn the data bias between questions and answers. The bias in the conventional VQA model is a mediation between Q and A (i.e., $Q \rightarrow B \rightarrow A$). It is worth noting that it is hard to confirm which features in the question leads to the model bias since unbiased VQA data is difficult to be obtained.

Link $Q \rightarrow V$ (Attention mechanism). Question-guided attention $\alpha_i \in \mathbb{R}^M$ is formulated as $\alpha_i = att(repeat(f_i^q) \odot \mathbf{o}_i)$, where α_i indicates the attention of the i -th sample, $\odot$ denotes the element-wise product, att is the fully connected layer, $repeat(f_i^q)$ is used to repeat f_i^q M times and stack the repeated vector to a matrix. And the m -th region visual feature $f_{i,m}^v$ is calculated by $f_{i,m}^v = \alpha_{i,m} * f_{i,m}^v$, $\alpha_{i,m}$ is the m -th element of α_i .

Link $Q \rightarrow B$ (Bias caused by question). The Q-only model has good performance on the standard VQA datasets since the question encoder learns the statistical correlation between questions and answers. Therefore, the question encoder in VQA models may cause the bias in model.

Link $\{Q, V, B\} \rightarrow A$ (Answer classification). We introduce *sumpooling* to fuse visual features $\{f_{i,m}^v\}_{m \in M}$. The answer classifier is formulated as $\hat{p}_i = softmax(f_i^q \odot \sum_m f_{i,m}^v)$, where $\hat{p}_i \in \mathbb{R}^K$ is the confidence of candidate answers. Due to f_i^q and $f_{i,m}^v$ come from the encoding feature of the observed values of Q and V respectively, causality relation $\{Q, V\} \rightarrow A$ is defined. Since the biases come from the question feature f_i^q , causality relation $B \rightarrow A$ is defined.

Node A (Predicted answer). The final predicted answer is generated by the answer classifier based on the inputs from three branches.

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