BUT THAT’S NOT WHY: INFECTION ADJUSTMENT BY INTERACTIVE PROTOTYPE DESELECTION

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ABSTRACT

Despite significant advances in machine learning, decision-making of artificial agents is still not perfect and often requires post-hoc human interventions. If the prediction of a model relies on unreasonable factors it is desirable to remove their effect. Deep interactive prototype adjustment enables the user to give hints and correct the model’s reasoning. In this paper, we demonstrate that prototypical-part models are well suited for this task as their prediction is based on prototypical image patches that can be interpreted semantically by the user. It shows that even correct classifications can rely on unreasonable prototypes that result from confounding variables in a dataset. Hence, we propose simple yet effective interaction schemes for inference adjustment: The user is consulted interactively to identify faulty prototypes. Non-object prototypes can be removed by prototype masking or a custom mode of deselection training. Interactive prototype rejection allows machine learning naïve users to adjust the logic of reasoning without compromising the accuracy.

Index Terms— Prototype Learning, Human-AI-Interaction, Interactive ML, Prototype Deselection, Inference Adjustment

1. INTRODUCTION

Human learning typically involves communication between individuals based on shared attributes of symbolic mental representations [1]. However, sub-symbolic processing in artificial neural networks hinders analogous interactions between humans and machines. To overcome this representational divide Interactive Machine Learning (IML) strives to enable novel means of collaborative learning.

The concepts learned by most neural networks can neither be accessed nor interpreted directly. Consequently, it is difficult to incorporate user feedback by a direct modification of the parameters. Instead IML often relies on additional training with modified data [2], [3]. For example, an initial prediction can be refined interactively by re-using manually corrected samples in a segmentation scenario [2]. In an alternative approach an offline-trained neural network is used to propose

a segmentation while a second model is trained online, based on user interaction to refine the initial segmentation [3]. Another way to incorporate feedback is reinforcement learning. It can be used to interactively fuse segmentation hints given by the user with segmentation probabilities [4]. However, none of these approaches allows for symbolic interaction.

While interaction in segmentation tasks has a clear focus on the where aspect, the what aspect underlying the reasoning is equivalently important in classification. However, its compositional and conceptual subtleties are hard to access. In this paper, we build on recent advances in prototype-based learning [5]. It allows to close the gap between cognitive concepts of human users and the representations of the model.

Prototype networks capture certain aspects of mental object representation in the brain. While structural signatures of feed-forward processing can be identified [6], information processing in the brain is also highly associative [7]. Some neurons are known to selectively code for the presence of specific features in their receptive field. Others preferentially link neurons according to the similarity of their response characteristics [7]. In prototypical part networks this strength of reciprocal association is modeled as the latent similarity between a prototype and the patch encodings. Coherently, evidence from cognitive psychology suggests that human cognition relies on conceptual spaces that are organized by prototypes [8], [9]. Similar to latent grids in prototypical part networks, many layers of the visual hierarchy are also organized retinotopically: Receptive fields are arranged in physical space [10]. Both the spatial configuration of receptive fields in physical space and the arrangement of visual features according to similarity, are well preserved by the formalization of prototypical part networks.

Leveraging this similarity of natural and artificial cognitive representation, we propose deep interactive prototype adjustment (DIPA), a novel mode of IML that allows for direct human-AI collaboration and colearning. In Section 2 we revise the basics of prototype-based learning. In Section 3 we explain how DIPA can be used to adjust the inference of the network. Section 4 summarizes how DIPA can be used for inference adjustment without substantially compromising the accuracy of the prediction. Section 5 concludes our paper.
Fig. 1: A prototypical-part network: We use a network of type ProtoPNet with ResNet34 encoder. Prototype convolution computes the euclidean distance between prototypes and feature-vectors. An evidence score is computed for each latent grid position (7x7) and prototype (N=2000) as a function of the inverted distance. The maximum of each heatmap constitutes the input to the classification head. Deselection can be achieved by removing prototypes via masking or by interactively clustering areas in latent space that encode non-object areas in the input images.

2. PROTOTYPE-BASED LEARNING

Prototype-based deep learning builds on the insight that similar features form compact clusters in latent space. Hence, certain sub-volumes represent specific classes. The surface between areas that are assigned to different labels represents the decision boundary: Prototypes are understood as concepts that are more central for a class as compared to instances which reside close to the decision boundary [11]. Typically, prototypes are modeled as vectors in embedding space. Latent features can be represented by a single vector or a latent grid [5], [12]. Fig. 1 shows the structure of the model used here. If a latent grid is used, prototypical patches can be detected spatially. Prototypes cluster feature space analogously to centroids in K-means. They can also be pushed to the closest feature vectors such that the latent encoding of an image patch coincides with the prototype-vector [5]. Hence, they can be conceptually equated with image patches of the training set. Training can be end-to-end using a suitable loss function [5], [12], [13]. Alternatively, iterative training algorithms or alternating schemes have been developed [14], [15]. Recent work addressed hierarchical prototypes that follow predefined taxonomies and shows that prototype based decision trees can be constructed [16], [17]. Besides classification, prototype-based deep learning is used for segmentation or tracking of objects in videos. Special prototypes can be retrieved from previous frames and used as sparse memory-encodings for spatial attention [18]. Some approaches address data scarcity and have particularly been developed for few-shot problems making predictions for a new class with few labels (n < 20). They can be used for classification or semantic segmentation [15], [19]. The benefits of deep prototype learning are the high accuracy and robustness [12], its potentials for outlier detection [12], the ability to yield good predictions in few shot problems [15], [19], and an increased interpretability that allows for intuitive interaction with the represented concepts [5], [16].

3. INTERACTIVE PROTOTYPE ADJUSTMENT

Fig. 2: Interactive prototype rejection: The prediction of a class is based on the detection of its previously learned prototypes. User feedback can be used to reject invalid prototypes such that inference is based on object-prototypes only.

We present two modes of prototype rejection for DIPA. Inference can be adjusted (1) by masking the evidence from undesired prototypes or (2) by iterative prototype rejection via repetitive user feedback and a custom loss-function: Prototypes are removed from areas of latent space that encode non-object patches as the user inserts antitypes at the location of undesired vectors.

Here, the network acts as the student that consults the teacher to retrieve information about the learned prototypes. The user takes on the role of the teacher and either accepts or rejects the prototypes presented by the student (Fig. 2). Feedback can take different forms. We provide user interfaces that allow to iterate over the prototypes of different classes. Latent space can also be explored by the selection of images with highlighted prototypes that are arranged in an interactive cloud. The position of each image is defined by the projection of the prototypes to their first three principal components (Fig. 3). For deselection without replacement, a mask is assembled to exclude prototypes from inference. To adjust for a decrease in accuracy the final layer of the network is trained afterwards. Prototype rejection with replacement can be achieved with a
special loss term \( \text{Reject} \) which represents a function of the \( L_2 \) norm of the prototypes \( p_j \) and the antitypes \( q_s \). The term represents a logarithmically decaying cost which is maximal if antitype and a prototype coincide and encourages the prototypes to diverge from latent encodings of non-object patches.

\[
\text{Reject} = \max_i \log \left( \frac{d_i + 1}{d_i + \epsilon} \right), \quad \text{where } d_i = \|p_j - q_s\|_2^2
\]

The antitype vectors are initialized with the prototypes that the user identifies as non-object patch encodings. A second term \( \text{Con} \) imposes a soft-constraint and ensures that prototypes stay in the hyper-cube that contains the latent vectors by penalizing any value \( i \) of each prototype-vector \( j \) outside the desired range.

\[
\text{Con} = \sum_j \sum_i v_{i,j} \text{where } v_{i,j} = \begin{cases} 1, & \text{if } (p_{i,j} > 1) \lor (p_{i,j} < 0) \\ 0, & \text{otherwise} \end{cases}
\]

These terms are used to assemble a modified loss function. It additionally contains the cross-entropy \( \text{CrsEnt} \), the clustering cost \( \text{Clst} \) and the separation cost \( \text{Sep} \) as well as the \( L_1 \) term from the original loss of ProtoPNet.

\[
L = \text{CrsEnt} + \lambda_1 \text{Clst} + \lambda_2 \text{Sep} + \lambda_3 \text{L1} + \lambda_4 \text{Reject} + \lambda_4 \text{Con}
\]

Although prototypes diverge from the deselected feature vectors, it shows that some move towards areas in latent space that encode other non-object patches. Hence, deselection training is repeated for several iterations to remove these prototypes. Multiple user consultations are necessary.

The user repeatedly interacts with the model and successively explores areas in latent space that are covered by non-object patch encodings. At the beginning of each repetition the prototypes are pushed to the closest feature vector to identify the prototypical image patches. In the next step the user is consulted to reject unreasonable prototypes.

The set of antitypes \( Q \) is united with the subset of the prototypes \( P \) that are identified as non-object and the network is trained using our deselection loss. Hence, the areas of latent space that encode undesired features are successively clustered by the interplay of user and model (Alg. 1).

![Fig. 3: User Interfaces: Custom interfaces target at interactive modes for the exploration of prototype space.](image)

**4. RESULTS**

We perform three experiments with ten repetitions each. The experiments begin after the first two stages of the original training schedule of ProtoPNet are completed [5]. For that purpose we use the CUB200-2011 dataset while the initial encoder weights stem from pre-training on ImageNet. The model is trained for five epochs with the encoder weights fixed, then all layers and the prototype-vectors are trained jointly with decaying weights for the convolutional blocks. Afterwards, we push the prototypes to the closest patch encoding of any training image of the prototype’s class. Finally the classification head is trained to adjust for the changes and allow for the \( L_1 \) term to converge [5].

To enable reproducibility we simulate the user interaction computationally for named experiments. To this end we rely on pixelwise annotations included in the dataset [20]. Prototypes are considered non-object if no ground-truth pixel indicates differently in the image patch that corresponds to the upscaled grid-cell of the prototype.

After initial training between 157 and 251 of the 2000 prototypes were identified as non-object prototypes \((n_{bg} = 206, \bar{n}_{fg} = 1794)\). Fig. 4b shows a random selection of non-object prototypes for a sample run. Here, an overlap of at least 75% exists only for 1077 prototypes. Analogously, Fig. 4c shows all prototypes for the class “Eastern Towhee”.

The final layer uses the maximal evidence for each prototype to predict the image class [5]. Hence, the weights of a prototype in the classification head reflect the impact it has on the final prediction. Fig. 4d shows the distribution for object and non-object prototypes in a representative run with a Gaussian fit for the PDF. Larger weights are more frequent for object prototypes with a peak in the PDF at \( w = 1.2 \). However, substantial weights exist also for non-object prototypes indicating their relevance for the prediction.

1: \( Q \leftarrow \emptyset \)
2: for repetition = 1, 2, ..., N do
3: \( p_j \leftarrow \arg \min_{z \in Z_j} \|z - p_j\| \) \( \triangleright \) Push prototypes
4: \( Q \leftarrow Q \cup \text{non-object}(P) \) \( \triangleright \) Consult user
5: for epoch = 1, 2, ..., M do
6: for batch of Dataset do
7: loss \( \leftarrow L(y, \text{net(batch)}, P, Q) \)
8: net \( \leftarrow \text{SGD(net, loss)} \) \( \triangleright \) Move prototypes
9: end for
10: end for
11: end for

**Alg. 1: Iterative prototype rejection**
In the first experiment we employ prototype masking after the first push. Evidence from prototypes with no object-overlap is cancelled out. An adjustment of the weights of the final layer is necessary to compensate for the deselection. The average accuracy for the ten repetitions is .778 before deselection and drops to .77 upon deselection masking. After training of the last layer it mostly recovers. With an average of .776 it is marginally lower than before. The T-statistic indicates that the difference is insignificant (p = .29).

In the second experiment we achieve inference adjustment by training the network with fixed encoder weights and the presented deselection loss. After the subsequent push to the closest patches between 38 and 77 prototypes revealed themselves as non-object prototypes. None of these prototypes covers the same image patch as before. These prototypes are removed and the accuracy drops to an average of .732 and recovers to a level of .745 when the last layer is trained to compensate for the changes due to shifting the prototypes.

The third experiment employs our iterative scheme. Instead of removing new non-object prototypes the user is consulted multiple times. The average accuracy is slightly higher than in the previous experiment at .739 before and .749 after fine-tuning of the last layer. The procedure yields the highest number of prototypes with near complete object-overlap (Fig. 5). After iterative rejection 1583 of the 2000 prototypes show an overlap of at least 75% with the object they represent.

5. CONCLUSION

This paper shows that the inference of prototypical part networks cannot only be understood but also adjusted. Prototypes can be reassigned such that the prediction is restricted to meaningful features. Removing the effect of antitypes leads to a marginal loss in accuracy (1.4%). A slightly larger drop occurs for our deselection loss (2.9%). This is arguably due to the greater loss of information from non-object prototypes as larger areas of feature space are excluded.

DIPA has further potentials. It could be used to model configurations of prototypes, for example in conjunction with interactive learning of deformable parts [21]. Potentials of prototypes for the prediction of bounding boxes that cluster the combined conceptual and physical space should be investigated. They could potentially help to model whole-part relationships in neural networks [22]. Refining the sensitivity and specificity of prototypes would increase interpretability. DIPA with active learning schemes could leverage potentials for increased labeling efficiency [23]. Future research should also address prototype learning for interactive labeling and collaborative procedures to address the cold start problem that occurs in the first stage of the interactive collection of labels.
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