Expressive Explanations of DNNs by Combining Concept Analysis with ILP

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Abstract. Explainable AI has emerged to be a key component for black-box machine learning approaches in domains with a high demand for reliability or transparency. Examples are medical assistant systems, and applications concerned with the General Data Protection Regulation of the European Union, which features transparency as a cornerstone. Such demands require the ability to audit the rationale behind a classifier’s decision. While visualizations are the de facto standard of explanations, they come short in terms of expressiveness in many ways: They cannot distinguish between different attribute manifestations of visual features (e.g. eye open vs. closed), and they cannot accurately describe the influence of absence of, and relations between features. An alternative would be more expressive symbolic surrogate models. However, these require symbolic inputs, which are not readily available in most computer vision tasks. In this paper we investigate how to overcome this: We use inherent features learned by the network to build a global, expressive, verbal explanation of the rationale of a feed-forward convolutional deep neural network (DNN). The semantics of the features are mined by a concept analysis approach trained on a set of human understandable visual concepts. The explanation is found by an Inductive Logic Programming (ILP) method and presented as first-order rules. We show that our explanation is faithful to the original black-box model.

Keywords: Explainable AI · Concept Analysis · Concept Embeddings · Inductive Logic Programming

1 Introduction

Machine learning went through several changes of research perspective since its beginnings more than fifty years ago. Initially, machine learning algorithms were inspired by human learning [13]. Inductive Logic Programming (ILP) [17] and

3 The code for our experiments is available at https://github.com/mc-lovin-mlem/concept-embeddings-and-ilp/tree/ki2020
explanation-based generalization were introduced as integrated approaches which combine reasoning in first-order logic and inductive learning. With the rise of statistical approaches to machine learning, focus shifted from human-like learning to optimizing learning for high predictive accuracy. Deep learning architectures resulted in data-intensive, black-box approaches with impressive performances in domains such as object recognition, machine translation, and game playing. However, since machine learning more and more is moving from the lab to the real world, researchers and practitioners alike realize that interpretable, human-like approaches to machine learning are necessary to allow developers as well as end-users to evaluate and understand classifier decisions or possibly also the learned models themselves.

Consequently there is a growing number of approaches to support explainability of black-box machine learning. Explainable AI (XAI) approaches are proposed to support developers to recognize oversampling and problems with data quality such as number of available data, class imbalance, expensive labeling, and sampling biases. For many application domains, it is a legal as well as an ethical obligation to make classifier decisions transparent and comprehensible to end-users who need to make sense of complex information, for instance in medical diagnosis, automotive safety, or quality control.

A main focus of research on explanations for image classifications is on visual explanations, that is, highlighting of relevant pixels such as LRP or showing relevant areas in the image such as LIME. However, visual explanations can only show which conjunction of information in an image is relevant. In many domains, more sophisticated information needs to be taken into account:

- **Feature values**: highlighting the area of the eye in an image is not helpful to understand that it is important for the class decision that the lids are tightened (indicating pain) in contrast to eyes which are wide open (indicating startle);
- **Quantification**: highlighting all blowholes on the supporting parts of a rim does not make clear that the rim is not a reject because all blowholes are smaller than 0.5 mm;
- **Negation**: highlighting the flower in the hand of a person does not transport the information that this person is not a terrorist because he or she does not hold a weapon;
- **Relations**: highlighting all windows in a building cannot help to discriminate between a tower, where windows are above each other and a bungalow, where windows are beside each other;
- **Recursion**: highlighting all stones within a circle of stones cannot transport the information that there must be a sequence of an arbitrary number of stones with increasing size.

Such information can only be expressed in an expressive language, for instance some subset of first-order logic. In previous work, it has been shown how ILP can be applied to replace the simple linear model agnostic explanations of LIME. Alternatively, it is investigated how knowledge can be incorporated into deep networks. For example, capsule networks are proposed...
to model hierarchical relationships and embeddings of knowledge graphs allow to grasp relationships between entities [3].

In this paper, we investigate how symbolic knowledge can be extracted from the inner layers of a deep convolutional neural network to uncover and extract relational information to build an expressive global explanation for the network. In the following, we first introduce concept embedding analysis (to extract visual concepts) and ILP (to build the explanation). In section 3, the proposed approach to model-inherent generation of symbolic relational explanations is presented. We present a variety of experiments on a new “Picasso” data set of faces with permuted positions of sub-parts such as eyes, mouth, and nose. We conclude with an outlook to extend this first, preliminary investigation in the future.

2 Theoretical Background

2.1 Concept Embedding Analysis

To understand the process flow of an algorithm, it is of great value to have access to interpretable intermediate outputs. The goal of concept embedding analysis is to answer whether, how well, how, and with what contribution to the reasoning information about semantic concepts is embedded into the latent spaces (intermediate outputs) of DNNs, and to provide the result in an explainable way. Focus currently lies on finding embeddings in either the complete output of a layer (image-level concepts), or single pixels of an activation map of a convolutional DNN (concept segmentation). To answer the whether, one can try to find a decoder for the information about the concept of interest, the concept embedding. This means, one is looking for a classifier on the latent space that can predict the presence of the concept. The performance of the classifier provides a measure of how well the concept is embedded. For an explainable answer of how a concept is embedded, the decoder should be easily interpretable. One constraint to this is introduced by the rich vector space structure of the space of semantic concepts respectively word vector spaces [15]: The decoder map from latent to semantic space should preserve at least a similarity measure. For example, the encodings of “cat” and “dog” should be quite similar, whereas that of a “car” should be relatively distant from the two. The methods in literature can essentially be grouped by their choice of distance measure $\langle -,-\rangle$ used on the latent vector space. A concept embedding classifier $E_c$ predicting the presence of concept $c$ in the latent space $L$ then is of the form $E_c(v) = \langle v_c, v \rangle > t_c$ for $v \in L$, where $v_c \in L$ is the concept vector of the embedding, and $t_c \in \mathbb{R}$.

Automated concept explanations [6] uses $L_2$ distance as similarity measure. They discover concepts in an unsupervised fashion by k-means clustering of the latent space representations of input samples. The concept vectors of the discovered concepts are the cluster centers. In TCAV [11] it is claimed that the mapping from semantic to latent space should be linear for best interpretability. To achieve this, they suggest to use linear classifiers as concept embeddings. This means they try to find a separation hyperplane between the latent space representations of positive and negative samples of the concept. A normal vector of
the hyperplane then is their concept vector, and the distance to the hyperplane is used as distance measure. As method to obtain the embedding they use support vector machines (SVMs). TCAV further investigated the contribution of concepts to given output classes by sensitivity analysis. A very similar approach to TCAV, only instead relying on logistic regression, is followed by Net2Vec [5]. As a regularization, they add a filter-specific cut-off before the concept embedding analysis to remove noisy small activations. The advantage of Net2Vec over the SVMs in TCAV is that they can more easily be used in a convolutional setting: They used a 1×1-convolution to do a prediction of the concept for each activation map pixel, providing a segmentation of the concept. This was extended by [26], who suggested to allow larger convolution windows to ensure that the receptive field of the window can cover the complete concept. This avoids a focus on local patterns. A measure that can be applied to concept vectors of the same layer regardless of the analysis method, is that of completeness suggested in [31]. They try to measure, how much of the information relevant to the final output of the DNN is covered by a chosen set of concepts vectors. They also suggested a metric to compare the attribution of each concept to the completeness score of a set of concepts.

2.2 Inductive Logic Programming

Inductive Logic Programming (ILP) [17] is a machine learning technique that builds a logic theory over positive and negative examples \((E^+, E^-)\). The examples consist of symbolic background knowledge (BK) in the form of first-order logic predicates, e.g. \(\text{contains}(\text{Example}, \text{Part}), \text{isa}(\text{Part}, \text{nose})\). Here the upper case symbols are variables and the lower case symbol is a constant. The given BK describes that example \(\text{Example}\) contains a part \(\text{Part}\) which is a nose. Based on the examples, a logic theory can be learned. The hypothesis language of this theory consists of logic Horn clauses that contain predicates from the BK. We write the Horn clauses as implication rules, e.g.

\[
\text{face}(\text{Example}) :- \text{contains}(\text{Example}, \text{Part}), \text{isa}(\text{Part}, \text{nose}).
\]

For this work we obey the syntactic rules of the Prolog programming language. The \(:-\) denotes the logic implication \((\leftarrow)\). We call the part before the implication the head of a rule and the part after it the body or preconditions of a rule.

We use the framework Aleph [28] for this work since it is a flexible and adaptive general purpose ILP toolbox. Aleph’s built in algorithm attempts to induce a logic theory from the given BK to cover as many positive examples \(E^+\) as possible while avoiding covering the negative examples \(E^-\). The general algorithm of Aleph can be summarized as follows [28]:

1. As long as positive examples exist, select one. Otherwise halt.
2. Construct the most-specific clause that entails the selected example and is within the language constraints.
3. Find a more general clause which is a subset of the current literals in the clause.
4. Remove examples covered by the current clause.
5. Repeat from step 1.
3 Explaining a DNN with Concept Localization and ILP

When building explanations for a DNN via approximate rule sets, the underlying logic and predicates of the rules should reflect the capabilities of the model. For example, spatial relations like top_of or right_of should be covered, as e.g. dense layers of a DNN are capable of encoding these. Spatial relations cannot be represented by current visualization methods for explainable AI, which only feature predicates of the form contains(Example, Part) and at_position(Part, xy). Rule-based methods like ILP are able to incorporate richer predicates into the output. However, their input must be symbolic background knowledge about the training and inference samples which is formulated using these predicates explicitly. For computer vision tasks with pixel-level input, this encoding of the background knowledge about samples is not available. To remedy this, we propose to use existing concept mining techniques for extraction of the required background knowledge:

1. Associate pre-defined visual semantic concepts with intermediate output of the DNN. Concepts can be local, like parts and textures, or image-level.
2. Automatically infer the background knowledge about a sample Ex given the additional concept output, which defines predicates isa(C, concept), and isa(Ex, C) (image-level) or contains(Ex, C) with at_position(C, xy). From this, spatial relations and negations can be extracted.
3. Given background knowledge for a set of training samples, apply an inductive logic programming approach to learn an expressive set of rules for the DNN.

The approach presented in this paper differs from the previous work outlined in [19] by the following main aspects:

- We will find a global verbal explanation for a black-box decision in contrast to a local explanation.
- We directly make use of information stored in the building blocks of the DNN instead of relying on the linear surrogate model generated by LIME.

3.1 Enrich DNN Output via Concept Embedding Analysis

We directly built upon the concept detection approach from [5,26], suggesting some further improvements. Net2Vec bilinearly upscalled the predicted masks before applying the sigmoid for logistic regression. This overrates the contribution to the loss by pixels at the edges from positive to negative predicted pixels. We instead apply upscaling after applying the sigmoid. Instead of the suggested IoU penalty from [26], we propose a more stable Dice loss to fit the overlap objective, supported by a small summand of the balanced binary cross-entropy (bBCE) suggested in Net2Vec to ensure pixel-wise accuracy.

One major disadvantage of the linear model approaches over the clustering ones is their instability, i.e. several runs for the same concept yield different concept vectors. Reasons may be dependence on the outliers of the concept cluster (SVM); non-unique solutions due to a margin between the clusters; and
inherent variance of the used optimization methods. To decrease dependence on
the training set selection and ordering, and the initialization values, we for now
simply use ensembling. For this we define a hyperplane \( H \) as the zero set of the
distance function \( d_H(v) = (v - b_H \cdot v_H) \circ v_H \) for the normal vector \( v_H \)
and the support vector \( b_H \), \( b_H \in \mathbb{R} \). Then, the zero set of the mean \( \frac{1}{N} \sum_{i=1}^{N} d_{H_i} \), of
the distance functions of hyperplanes \( H_i \) again defines a hyperplane with
\[
\begin{align*}
v_H &= \frac{1}{N} \sum_{i=1}^{N} v_{H_i} \\
b_H &= \frac{1}{\|v_H\|_2} \frac{1}{N} \sum_{i=1}^{N} (b_{H_i} \|v_{H_i}\|^2).
\end{align*}
\]
Note, that hyperplanes with longer normal vectors (i.e. higher confidence values)
are overrated in this calculation. To remedy this, concept vectors are normalized
before ensembling, using the property \( (w - b \cdot v) \circ v = \|v\| \cdot (w - (b\|v\|) \cdot \frac{v}{\|v\|}) \cdot \frac{v}{\|v\|} \)
of the distance function for scalar \( b \) and vectors \( v, w \).

3.2 Automatic Generation of Symbolic Background Knowledge

The output of the concept analysis step (binary masks indicating the spatial lo-
cation of semantic concepts) can be used to build a symbolic global explanation
for the behavior of the original black-box model. We obtain the explanation by
finding a first-order logic theory with the ILP approach Aleph (see Section 2.2).
Since Aleph needs a set of positive and negative examples \( (E^+, E^-) \), the first
step is to obtain these examples along with their corresponding symbolic back-
ground knowledge (BK). In order to obtain a good approximation of the behavior
of the model, we sample \( N^+ \) binary masks from positively predicted images and
\( N^- \) binary masks from negatively predicted images that lie close to the decision
boundary of the original black-box model using the concept analysis model de-
scribed above. Let \( M^+, M^- \) be the set of positive and negative binary masks.
Let \( m^+ \in M^+ \), \( m^- \in M^- \) be single masks. Each mask (e.g. \( m^+ \)) consists of mul-
tiple mask layers (e.g. \( l_c \in m^+, c \in C \)) for the different human understandable
concepts from the pool of concepts \( C \). These mask layers are sparse matrices up-
sampled to the same size as the original images they are masking. The matrices
have the value 1 at all the positions where the concept analysis model detected
the respective concept and 0 at all other positions.

The symbolic explanation of the original model should consist of logic rules
that establish the prototypical constellation of visual parts of an image that
resembles the positive class as seen by the DNN. We therefore need not only the
information about occurrence of certain visual parts in the sampled examples
but also the different relations that hold between the parts. In the next sections
we adhere to the following general workflow:

1. Find positions of visual parts in the examples and name them.
2. Find relations between parts.
3. Build BK with the information from step 1 and 2.
4. Induce a logic theory with Aleph.
Find Visual Parts

One mask layer \( I_c \) contains possibly multiple contiguous clusters of concept propositions. Therefore, as a denoising step, we only take the cluster with the largest area into account. As a proposition for the position of the concept \( c \) in the picture, in this cluster we take the mean point of the area \( A_{\text{max}} \) of 1's in \( I_c \). We therefore find the position \( p_c = (x, y) \) with
\[
x = \frac{\min_x(A_{\text{max}}) + \max_x(A_{\text{max}})}{2}
\]
\[
y = \frac{\min_y(A_{\text{max}}) + \max_y(A_{\text{max}})}{2}.
\]
This procedure can be followed for all masks \( I_c \) that are contained in all \( m^+ \in M^+ \) and \( m^- \in M^- \).

Find Relations Between Parts

By taking relationships between the parts into account, we strive for more expressive explanations. For this work we limit ourselves to spatial relationships that hold between the parts that were found in the previous steps. We assume that pairs of two parts can be in the following four relationships to each other: left_of, right_of, top_of, bottom_of. We declare part \( A \) to be top_of part \( B \) if the vertical component \( y_A \) of the position \( p_A \) is above \( y_B \) and the value for the horizontal offset \( \Delta x = x_A - x_B \) does not diverge from the value for the vertical offset \( \Delta y = y_A - y_B \) by more than double. The other spatial relations can be formalized in an analogous manner. Thus, the relations that can hold between two parts \( A \) and \( B \) can be visualized as in Fig. 1.

Inferring Global Symbolic Explanations

After the inference of visual parts and the relationships that hold between them, we can build the BK needed for Aleph. Part affiliation to an example can be declared by the contains predicate. We give all parts a unique name over all examples. Suppose part \( A \) is part of a particular example \( E \) and describes the human understandable concept \( c \in C \). Then the example affiliation can be stated by the predicates contains(\( E, A \)), isa(\( A, c \)). Likewise for the relations we can use 2-ary predicates that state the constellation that holds between the parts. When part \( A \) is left of part \( B \) we incorporate the predicate left_of(\( A, B \)) in the BK and likewise for the other relations. When the BK for the positive and negative examples \( E^+ \) and \( E^- \) is found, we can use Aleph’s induction mechanism to find the set of rules that best fit the examples. The complete algorithm for the process is stated in Algorithm 1.
Algorithm 1 Verbal Explanation Generation for DNNs

1: Require: Positive and negative binary masks $M^+$, $M^-$
2: Require: Pool of human understandable concepts $C$
3: $E^+ \leftarrow \{\}$
4: $E^- \leftarrow \{\}$
5: for each $\odot \in \{+,-\}$ do
6:   for each $m^\odot \in M^\odot$ do
7:     $P \leftarrow \{\}$
8:     for each $l_c \in m^\odot$ where $c \in C$ do
9:       $p_c \leftarrow calculatePartPosition(l_c)$
10:      $P \leftarrow P \cup \{(c, p_c)\}$
11:     $R \leftarrow calculateRelations(P)$
12:     $E^\odot \leftarrow E^\odot \cup (P, R)$
13:     $T \leftarrow Aleph(E^+, E^-)$
14: return $T$

4 Experiments and Results

We conducted a variety of experiments to audit our previously described approach. As a running example we used a DNN which we trained on images from a generated dataset we dubbed Picasso Dataset. The foundation are images of human faces we took from the FASSEG dataset [9,10]. The Picasso Dataset contains collage images of faces with the facial features (eyes, mouth, nose) either in the correct constellation (positive class) or in a mixed-up constellation (negative class). See Fig. 2 for examples. No distinction is made between originally left and right eyes.

Fig. 2. Examples from the Picasso Dataset (left: positive class, right: negative).

In order to not establish a divergence in the image space of the two classes, the positive and negative classes contain facial features that were cut out of a set of images from the original FASSEG dataset. As a canvas to include the features, we took a set of original faces and got rid of the facial features by giving the complete facial area a similar skin-like texture. Then we included the cut out facial features onto the original positions of the original features in the faces.

The face images in Fig. 2 show that the resulting dataset is rather constructed. This however will suffice for a proof of concept to show that our ap-
proach in fact exploits object parts and their relations. In the future we plan on moving towards more natural datasets.

4.1 Analyzed DNNs

We evaluated our method on three different architectures from the pytorch model-zoo[^1]: AlexNet [12], VGG16 [27], and ResNeXt-50 [30]. The convolutional parts of the networks were initialized with weights pre-trained on the ImageNet dataset. For fine-tuning the DNNs for the Picasso Dataset task, the output dimension was reduced to one and the in- and output dimension of the second to last hidden dense layer was reduced to 512 for AlexNet and VGG16. Then the dense layers and the last two convolutional layers (AlexNet, VGG16) respectively bottleneck blocks (ResNeXt) were fine-tuned. The fine-tuning was conducted in one epoch on a training set of 18,002 generated, 224 × 224-sized picasso samples with equal distribution of positive and negative class. All models achieved accuracy greater than 99% on a test set of 999 positive and 999 negative samples.

4.2 Training the Concept Models

In our example we determined the best ensembled detection concept vectors for the concepts EYES, MOUTH and NOSE amongst the considered layers. We excluded layers with low receptive field, as they are assumed to hold only very local features (for the layers used see Fig. 3). Convolutional output was only considered after the activation. For each concept, 452 training/validation, and 48 test picasso samples with segmentation masks were used. The training objective was: Predict at each activation map pixel whether the kernel window centered there lies “over” an instance of the concept. Over meant that the fuzzy intersection of the concept segmentation and the kernel window area exceeds a threshold (intersection encoding). This fuzzy definition of a box center tackles the problem of sub-optimal intersections in later layers due to low resolution. Too high values may lead to elimination of an instance, and thresholds were

![Fig. 3. The layer-wise mean set IoU results of the concept analysis runs.](https://pytorch.org/docs/stable/torchvision/models.html)
chosen to avoid such issues with values 0.5/0.8/0.7 for nose/mouth/eye. We implemented the encoding via a convolution. As evaluation metric we use set IoU (sIoU) between the detection masks and the intersection encoded masks as in Net2Vec. On each dataset and each layer, 15 concept models were trained in three 5-fold-cross-validation runs with the following settings: Adam optimization with mean best learning rate of 0.001, a weighting of 5:1 of Dice to bBCE loss, batch size of 8, and two epochs (all layers showed quick convergence).

**Results** Our normalized ensembling approach proved valuable as it yielded mean or slightly better performance compared to the single runs. For the considered models, meaningful embeddings of all concepts could be found (see Tab. 1). The layers all reached sIoU values greater than 0.22 despite of the still seemingly high influence of sub-optimal resolutions of the activation maps. Fig. 4 shows some exemplary outputs. The concepts were best embedded in earlier layers, while different concepts did not necessarily share the same layer.

|                | L  | sIoU | Cos.d. |
|----------------|----|------|--------|
|                |    |      |        |
| AlexNet        |    |      |        |
| NOSE           | 2  | 0.228| 0.040  |
| MOUTH          | 2  | 0.239| 0.040  |
| EYES           | 2  | 0.272| 0.058  |
| VGG16          |    |      |        |
| NOSE           | 7  | 0.332| 0.104  |
| MOUTH          | 6  | 0.296| 0.154  |
| EYES           | 6  | 0.350| 0.197  |
| ResNeXt        |    |      |        |
| NOSE           | 6  | 0.264| 0.017  |
| MOUTH          | 5  | 0.237| 0.020  |
| EYES           | 7  | 0.302| 0.020  |

**Fig. 4.** Ensemble embedding outputs of **nose** (green), **mouth** (blue), **eyes** (red).

### 4.3 Example Selection for ILP Training

The goal of the ILP model is to approximate the behavior of the main DNN, i.e. its decision boundary. For this, few but meaningful training samples and their
DNN output are needed: class-prototypes as well as ones that tightly frame the 
DNN decision boundary. From the 1,998 samples in the picasso test set, in total 
100 samples were chosen from the DNN test set to train the ILP model. The 
DNN confidence score here was used to estimate the proximity of a data point 
to the decision boundary. For each class, we selected the 50 samples predicted 
to be in this class and with confidence closest to the class boundary of 0.5. In 
our setup this provided a wide range of confidence values (including 0 and 1).

4.4 Finding the Symbolic Explanation

In order to find the background knowledge needed for Aleph to generate the 
explanation, we need to extract the information about the facial features and 
their constellations from the masks of the samples drawn in the previous step. 
Abiding the procedure described in Sec. 3.2, we first find contiguous clusters 
in the mask layers to then infer the positional information for them. This is 
straight-forward for the nose and the mouth but imposes a problem for the eyes, 
since we do not want to have a single position proposal for them in the eye that 
produces the biggest cluster in the mask layer. Thus, we allow for the top two 
biggest clusters to infer a position. Although we give them unique constants in 
the BK, we both give them the type $\text{eye} \in \mathcal{C}$.

The next step consists of the extraction of the spatial features between 
the found parts. Since the relation pair $\text{left_of} / \text{right_of}$ as well as $\text{top_of} / \text{bottom_of}$ 
can be seen as the inverses of the respective other relation, we omit the 
relations $\text{right_of}$ and $\text{bottom_of}$ in the BK. This is possible, because the Closed 
World Assumption holds (Everything that is not stated explicitly is false).

Once the BK is found for all examples, we can let Aleph induce a theory of 
logic rules. Consider the induced theory for the trained VGG16 network:

$$\text{face}(F) \leftarrow \text{contains}(F, A), \text{isa}(A, \text{nose}), \text{contains}(F, B), \text{isa}(B, \text{mouth}),$$
$$\text{top_of}(A, B), \text{contains}(F, C), \text{top_of}(C, A).$$

The rule explicitly names the required facial concepts $\text{nose}$ and $\text{mouth}$ and the 
fact that the nose has to be above the mouth in order for an image to be a face. 
Further there is another unnamed component $\mathcal{C}$ required which has to be placed 
above the nose. By construction this has to be one of the eyes. The rule makes 
sense intuitively as it describes a subset of correct constellations of the features 
of a human face.

To further test the fidelity of the generated explanations to the original black-
box network, we calculated several performance metrics for a test set of 1998 
test images (999 positive and 999 negative examples). We handled the learned 
explanation rules as binary classification model for the test images in BK rep-
resentation. If an image representation is covered by the explanation rules, it 
is predicted to be positive, otherwise negative. We now can handle the binary 
output of the black-box model as ground truth to our explanation predictions. 
The performance metrics together with the induced explanation rules for several 
DNN architectures are listed in Tab. 2. It can be seen that the explanations stay 
true to the original black-box model.
Table 2. Learned rules for different architectures and their fidelity scores (accuracy and F1 score wrt. to the original model predictions). Learned rules are of common form

\[ \text{face}(F) :- \text{contains}(F, A), \text{isa}(A, \text{nose}), \text{contains}(F, B), \text{isa}(B, \text{mouth}), \text{distinctPart} \]

| Arch.   | Accuracy | F1   | Distinct rule part                                      |
|---------|----------|------|--------------------------------------------------------|
| VGG16   | 99.60%   | 99.60%| top_of(A, B), contains(F, C), top_of(C, A)             |
| AlexNet | 99.05%   | 99.04%| contains(F, C), left_of(C, A), top_of(C, B), top_of(C, A) |
| ResNext | 99.75%   | 99.75%| top_of(A, B), contains(F, C), top_of(C, A)             |

5 Conclusion and Future Work

Within the described simple experiment we showed that expressive, verbal surrogate models with high fidelity can be found for DNNs using the developed methodology. We suggest that the approach is promising and worth future research and optimization.

The proposed concept detection approach requires a concept to have little variance in its size. It should easily extend to a concept with several size categories (e.g. close by and far away faces) by merging the result for each category. A next step for the background knowledge extraction would be to extend it to an arbitrary number of concept occurrences per image, where currently the algorithm assumes a fixed amount (exactly one \text{mouth}, one \text{nose}, two \text{eyes}). This could e.g. be achieved by allowing a maximum number per sliding window rather than an exact amount per image. In cases, where the predicates cannot be pre-defined, one can learn the relations as functions on the DNN output from examples as demonstrated in [4].

We further did not consider completeness (cf. Sec. 2.1) of the chosen concepts: They may not be well aligned with the decision relevant features used by the DNN, infringing fidelity of the surrogate model. We suggest two ways to remedy this: One could rely on (possibly less interpretable) concepts found via concept mining [6]. Or, since ILP is good at rejecting irrelevant information, one can start with a much larger set of pre-defined, domain related concepts. We further assume that best fidelity can only be achieved with the minimal complete sub-set of most decision-relevant concepts, which fosters uniqueness of the solution. For a decision relevance measure see e.g. [6].

It may be noted that the presented concept analysis approach is not tied to image classification: As long as the ground truth for concepts in the form of masks or classification values is available, the method can be applied to any DNN latent space (imagine e.g. audio, text, or video classification). However, spatial or temporal positions and relations are currently inferred using the receptive field information of convolutional DNNs. This restriction may again be resolved by learning of relations.

Lastly, in order to examine the understandability of the induced explanation in a real world scenario, we need to let explanations be evaluated in a human user study. For this matter, subjective evaluation measures have to be specifically designed for verbal explanations.
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