Abstract—In this paper, we present a method aimed at integrating domain knowledge abstracted as logic rules into the predictive behavior of a neural network using feature extracting functions for visual sentiment analysis. We combine the declarative first-order logic rules which represent the human knowledge in a logically-structured format making use of feature-extracting functions. These functions are embodied as programming functions which can represent, in a straightforward manner, the applicable domain knowledge as a set of logical instructions and provide a cumulative set of probability distributions of the input data. These distributions can then be used during the training process in a mini-batch strategy. In contrast with other neural logic approaches, the programmatic nature in practice of these functions do not require any kind of special mathematical encoding, which makes our method very general in nature. We also illustrate the utility of our method for sentiment analysis and compare our results to those obtained using a number of alternatives elsewhere in the literature.

Index Terms—Neural logic, feature extracting functions, rule learning

I. INTRODUCTION

Deep Neural Networks have made a significant impact in the field of machine learning. They are able to provide high levels of performance in terms of both accuracy and efficiency on all kinds of supervised and unsupervised problems. One of these is sentiment analysis, where neural networks have been applied to Twitter images [1], [2] and to generating image descriptions with sentiments [3].

Despite their success, these methods often require large amounts of labelled data for training. This is mainly due to the notion that neural network training is often purely data-driven, with no direct or indirect human intervention or domain knowledge involved. As a result, the interpretation of the transformation between input and output is often challenging if not almost intractable, whereby deep networks do not have an inherent representation of causality or logical rule application. Previous work has shown that supervision purely in the form of data can lead a model to learn some unwanted patterns and provide wrong predictions [4] [5]. It is worth noting in passing that this is not exclusive to sentiment analysis, but rather is a drawback that has hindered the application of deep learning in a wide variety of areas such as safety critical systems, medical applications, food security, fault detection, power generation and transmission and critical environmental management which require a level of trust or confidence associated with the predictions of the network [6].

One of the ways to make network predictions interpretable is to encode the intended rules or patterns derived from human domain knowledge in their trainable parameters. That is, to provide some sort of direct or indirect supervision in their training process to make them capture categorical or logic rules together with the target discriminative patterns. This can be viewed as the process of combining structured knowledge representing high-level cognition with neural systems [7]. This is quite relevant to sentiment analysis since sentiment analysis in images is naturally based upon ontologies [8]. Here, we note that logic rules provide a means to represent the human knowledge in a structured format but suffer from limited expressiveness and flexibility issues as they need to be translated from natural language to logical representations. Moreover, they also require a proper encoding format which is not a straightforward task since, in most cases, this encoding is task specific.

In sentiment analysis, probably the closest approach to the one presented here is that applied to text and presented in [9]. Along these lines, Hu et al. [9] present a method for encoding human knowledge into the parameters of the model via an indirect supervision training method called Iterative-knowledge Distillation. Iterative-knowledge Distillation represents logical, structured knowledge in the form of a set of declarative first-order logic rules which are encoded using soft-logic [10]. In [9], a parametric base neural network is used as a “student” which needs to be provided with logical knowledge by a non-parametric “teacher” network. The teacher network is a projection of the base network over a regularized subspace whereby the training data is constrained by logical rules. This is achieved via adapting posterior-regularization [11] making use of constraints defined by logic-rules. The authors demonstrate their framework by performing sentiment analysis on a variety of text data sets. A basic overview of their method is shown in Figure 1.

In contrast, and in order to apply neural logic rule to visual sentiment analysis, we use logic rules for representing human knowledge as applied to feature extraction on the network. This tackles the main drawback in the work presented in [9], where the teacher network represents soft-predictions calculated using text-based rules, which are transferred into the weights of the student network via an appropriate loss function. Thus, we propose the use of feature-extracting functions instead of constructing a teacher network with logic rules. These functions are directly applied on the imagery so as to transfer the human knowledge into a distribution of the input data. This approach also eliminates the need of assuming, a priori, the initial posterior distributions of features in train,
valent and test data. This, in turn, avoids the conversion of human knowledge from natural language to logical rules and the subsequent requirement of any special encoding for these rules which is specific to the task in hand.

In our approach, we derive a feature-extracting function from each logic rule. We do this by viewing this function as a mini-batch processing step during each iteration. Since this function is applied directly to the data, we do not compute probability distributions nor construct a teacher network. This effectively reduces the complexity of the method. Also, these feature-extracting functions can be modified at any time during the training process, thus providing a lot of flexibility in adapting to qualitative and quantitative characteristics of data. This is consistent with the well known properties of feature-extracting functions to represent expressive capabilities in natural language [12], exploiting these traits for the training of deep networks to provide a more direct nature of supervision based upon the input data.

This contrasts with the method in [9], which transfers logic rules to the parameters of the network using posterior-regularization [11]. Despite effective for weakly supervised learning tasks, this approach is mainly aimed at language-related tasks. Moreover, our method does not employ transfer learning such as the approach in [1] or requires image de-

A. Distillation vs Feature Extraction

Recall that, in iterative distillation [9], the student network is made to learn from both, labeled instances and structured logical knowledge, so as to represent a set of declarative first-order logic rules. These logic rules are encoded using soft-logic [10] for the sake of constructing soft-boundaries and for calculating rule-regularized distributions. Thus, the training data comprises both, a set $D = \{(x_n, y_n)\}_{n=1}^N$ of $N$ tuples $(x, y)$ where $x$ is an input instance, i.e. an independent variable or a set of independent variables, and $y$ is the corresponding target. The set of logic rules are expressed as $R = \{R_l\}_{l=1}^L$ where $R_l$ is the $l^{th}$ rule constructed from human knowledge and corresponding $\lambda_l$ is the confidence value. A logic-rule can be made up of several conditions or logic expressions. These logic expressions in [9] are called groundings and represent a rule as a set of $D$ and $R$ is called learning resources.

For example, consider a set of movie reviews in which $x$ comprises a set of tokens or words and the target $y$ represents the sentiment value which is 0 for negative and 1 for positive reviews. From the use of the language and propositional logic, we know that, if a sentence is stated in the form of “A-but-B”, then the sentiment of the review should be consistent with that of “B”. Therefore, we can express this, in a straightforward manner, the “A-but-B” statement as a logic rule stated as $R_1$ with $\lambda_1 = 1$ since it will be applied fully given the presence of “A-but-B” structure in input sentence $x$. To encode this formally, we can define a Boolean random variable $r_{1_l}(x, y)$ “If the sentence $x$ has an “A-but-B” structure”, then apply a expectation operator on it to calculate sets of valid distributions in $D$ such that $\lambda = 1$ which will be further used to construct a “teacher network”. This process is a complex and time consuming one which is not applicable, in a straightforward manner, to visual data.

To tackle this drawback, our method combines the input and human knowledge to provide a pre-processed data set which can be used for training the neural network. For the sake of consistency, here we denote the input data be $D = \{(x_n, y_n)\}_{n=1}^N$ a set of $N$ tuples $(x, y)$ where $x$ is a set of input independent variables and the corresponding target is given by $y$. And the human knowledge $F = \{F_l(D)\}_{l=1}^L$ as a set of $L$ feature extracting functions which are applied on $D$. With these ingredients, in the previous example, instead of using soft-logic using auxiliary random variables, for the “A-but-B” rule, we write a function $F_l = A - but - B(x, y)$ which outputs $(x, y)$ where $x$ has only ‘B’ features, which is consistent with $\lambda_l = 1$ as presented above.

In our case, we have a set of images in which $x$ comprises a set of pixel-values or a feature-map of pixels and the target $y$ represents the sentiment value which is 0 for negative and 1 for positive images. As explained by Truong and Lau in [4], we can frame the problem of visual sentiment analysis as a function of image features or properties like aesthetic score, color properties etc. and contexts which can be well captured by captions, tags, categories etc. Also, the identification of presence of adult and gore like contents which defines the theme can play a crucial role in understanding the sentiment of an image. Thus, we can construct a logic
Fig. 1. Iterative rule-knowledge distillation overview [9]. At each iteration, a teacher network \( q(y|x) \) is constructed as a rule-regularized projection of student network \( p_\theta(y|x) \). The student network is trained to imitate both, the ground truth labels from the training data and the teacher network output.

rule as “The sentiment of an image can be determined by a combination of its contextual features and properties”. From this rule, we can define a feature-extracting function \( F_1 = \text{Image} - \text{features}(x,y) \) on set \( D \) which takes the input image-label pair and outputs the corresponding image features.

B. Feature-Extracting Functions

Consider the conditional probability distribution \( p_\theta(y_i|x_i) \) with parameter set \( \theta \) and let the distribution for every rule-based feature be governed by a set of random variables \( \{r_{l,g}(D)\}_{g=1}^{G_l} \) calculated from the data set \( D \). In order to find a posterior probability distribution \( q(y_i|x_i) \) which captures the rule-set we can adapt the posterior regularization technique in [11] to find a set of valid or “allowed” distributions \( Q \). This opens-up the possibility of applying an Expectation operator to recover \( Q \).

More formally, this is expressed by \( Q = \{q(y_i|x_i) : E_{q}[r_{l,g}(D)] = 1, \forall q \in Q \} \), where every \( q(y|x) \) in \( Q \) defines a valid distribution which can be viewed as a rule-regularized subspace in \( D \). Since we aim at finding a \( q(y_i|x_i) \) in \( Q \) which is “close” to \( p_\theta(y_i|x_i) \), we can opt to minimise the KL-Divergence so as to obtain the rule-to-knowledge conditional probability distribution. This yields the following optimisation problem

\[
\min_{q,\xi \geq 0} KL(q(y_i|x_i)||p_\theta(y_i|x_i)) + C \sum_{l,g} \xi_{l,g}
\]

where \( \lambda_l(1 - E_{q}[r_{l,g}(D)]) \leq \xi_{l,g} \) and \( g_l = 1,\ldots,G_l, l = 1,\ldots,L \). Note that, at each iteration, solving Equation 1 in which \( \xi_{l,g} \geq 0 \) represents introducing a slack variable for each of the rules under consideration.

Here, inspired by the labeling functions used by Ratner et al. in [15], we use the input instance \( x_i \) to compute an post-processed instance \( x_i^* \). We can view the post-processed instance \( x_i^* \) as an explicit representation of the domain knowledge, expressed in the rule under consideration and mapped onto the input instance \( x_i \). This is an important observation since it hints at a minimisation problem on the cumulative output on the feature extracting functions so as to obtain the parameter set \( \theta \) which can be expressed formally as follows

\[
\theta = \arg \min_{\theta \in \Theta} \frac{1}{N} \sum_{n=1}^{N} L(y_n, p_\theta(Y|X^*))
\]
where \( L(\cdot) \) is the loss function of choice and \( p_\theta(Y|X) \) is the conditional probability distribution of the target set \( Y \) given the set \( X^* \) of all the post-processed instances \( x^*_i \). Since the information is purely present in the modified feature-set, the feature extracting functions become an post-processed input data for the network.

The treatment above also has the advantage of ease of implementation. We summarise the training and testing process of our method in Algorithms 1 and 2, respectively. Note that, at each training iteration, we calculate the post-processed data set \( D^* = \{(x^*_i, y_n)\}_{n=1}^N \) using the feature extracting functions \( F_1 \in F \) as applied on the input batch \( D = \{(x_n, y_n)\}_{n=1}^N \). These are passed on to the neural network so as to calculate the conditional probability \( p_\theta(y_i|x^*_i) \) for each \( (x^*_i, y_i) \in D^* \).

**Algorithm 1: Training**

**Input:** The training batch \( D = \{(x_n, y_n)\}_{n=1}^N \).
The functions set \( F = \{F_1(D)\}_{l=1}^L \).
Initialize the neural network parameters \( \theta \).

**while** Iteration **do**

1. Calculate \( D^* = \{(x^*_i, y_n)\}_{n=1}^N \).
2. Calculate the probability distribution \( p_\theta(Y|X^*) \).
3. Update the parameters \( \theta \) using objective function in Eq.(2)

**end**

**Output:** Trained neural network

**Algorithm 2: Testing**

**Input:** The testing batch \( D = \{(x_n, y_n)\}_{n=1}^N \).
The functions set \( F = \{F_1(D)\}_{l=1}^L \).
1. Calculate \( D^* = \{(x^*_i, y_n)\}_{n=1}^N \).
2. Calculate probability distribution \( p_\theta(Y|X^*) \).
3. Predict the class-label using \( \arg \max p_\theta(y_i|x^*_i) \)

**Output:** Neural network prediction

### III. Experiments

We now turn our attention to the application of our method for visual sentiment classification. In our experiments, we define a logic rule motivated from the findings in [14] which states that “The sentiment of an image can be determined by a combination of its contextual features and properties”. This is consistent with the developments presented previously and, accordingly, we define the feature extracting function as presented in Section [13].

To this end, we extract a rich set of visual features based on the image content which comprise image properties, category classification, a flag for adult content, the dominant colors, object tags and simplified captions which provide a factual description. These features are then combined to form a sentence-level string which can be used to perform sentiment analysis and classify each image into positive or negative categories.

In our experiments, we have used the Azure vision API [1] to obtain the image properties, category classification, a flag for adult content, the dominant colors and the object tags. For the captions, we have used the deep generative LSTM model in Vinyals et al. [16], which is a state-of-the-art method for generating image captions that won the 2015 MS-COCO image captioning challenge [18]. For our base network in Figure 2 and Section [1], we have used the Convolutional Neural Network architecture proposed in [17]. Our motivation for choosing this network resides in the fact that it has achieved compelling performance on various sentiment classification benchmarks. We use it’s “non-static” version with the exact same configuration as that presented by the authors. We have initialised word vectors using word2vec [19] and used fine tuning, training the neural network using stochastic gradient descent (SGD) with the AdaDelta updates [20].

To illustrate the utility of our method for purposes of visual sentiment classification, we have used two publicly available data-sets. The first one of these is Image Polarity Dataset [1] which is publicly available at Data-World and consists of 15,613 images. The imagery in the data set is divided into 5 classes - highly negative, negative, neutral, positive and highly positive. The second one is the Twitter data set presented in [1] which consists of 1269 images categorized into positive and negative classes. For our method, we have pre-processed the Image Polarity data set to convert all the highly positive classes to just positive and highly negative classes to just negative classes. We have also removed all the neutral class images. This leaves 10,680 images, which we use as our training dataset. We use the Twitter data set for testing.

For purposes of evaluating our results and comparing against alternatives elsewhere in the literature, we use the CNN and PCNN models in [13] as published by the authors. Here, we provide results for two instances of our method, CNN-C and CNN-F, which were trained using our feature-extracting function defined in Section [1]. For CNN-C, we analyse only captions of images generated by the deep generative LSTM model [16] that is, given an input image, our feature-extracting function will pass only it’s simplified caption to the base Convolutional neural network in [17]. For the second model, CNN-F, we combine caption features with the categories, adult content flag, dominant colors and object tags features extracted by the Azure vision API and pass them as a single set of features to the neural network. In Figure 5 we illustrate our approach for both cases, when only the captions are used (CNN-C) and when these are combined with the output of the Azure vision API (CNN-F).

In our experiments, we have compared our results against those yielded by the trained from scratch CNN and PCNN models in [1] that is, those models which were trained using

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1. More information on the API can be found at https://azure.microsoft.com/en-us/services/cognitive-services/computer-vision/
2. The dataset is accessible at https://data.world/crowdflower/image-sentiment-polarity
3. The dataset is widely available at https://www.cs.rochester.edu/u/qyou/DeepSent/deepsentiment.html
Fig. 3. Overview of our framework. At each iteration, an image $x$ is passed on to a feature-extracting function $F$, which extracts image features such as captions and properties using the generative model in [16] and the Azure vision API respectively. These features are then passed to the neural network in [17].

The full half-a-million Flickr image set from SentiBank[^1] and tested on the Twitter dataset containing 1269 images. We do not compare with the results from their transfer-learning models as they are fine-tuned using a subset of Twitter dataset which we use only for testing. Note the Flickr images are weakly labelled since each of these belongs to one adjective noun pair. Moreover, the alternatives in [1] employ approximately half-a-million images for training. This contrasts with our training scheme, whereby, instead of using a query-based, weakly labelled data set, with a large number of images, we have used a much smaller set for training.

Both, our method and the alternatives, have been tested on the Twitter data set. In our results, we use the same “$x$ agree” scheme where $x = \{3, 4, 5\}$. This is since the Twitter data set was labelled using Amazon Mechanical Turk (AMT) in order to generate sentiment labels. These labels were assigned by 5 workers on AMT. This implies that, as the number of workers in agreement reduces, the sentiment of the image is more ambiguous in nature. In our experiments, and for all our methods, including ours, we have used the same batch size as those used in [1], i.e. 882 for “3 agree”, 1116 for “4 agree” and 1269 for “5 agree”.

In Table I we show the accuracy yielded by our methods (CNN-C and CNN-F), which were trained on 10,680 Image Polarity dataset images. The CNN-C results were obtained when training was effected using only captions whereas CNN-F results are those yielded by making use of all image features. The table also shows the Precision, Recall and F1 scores for the each of the “$x$ agree” cases of the Twitter data set. From the experimental results, we can appreciate that our methods performs better on all three cases of the Twitter data set. Moreover, even for the more ambiguous case where at least 3

[^1]: For more information, we remit the interested reader to [http://visual-sentiment-ontology.appspot.com/](http://visual-sentiment-ontology.appspot.com/)
agree, the CNN-F provides a clear margin of advantage against all the alternatives.

To supplement our results on visual sentiment analysis and, in order to show a comparison with the method in [9], we have also performed sentence-level sentiment analysis and classified each sentence into the positive or negative categories. As in our visual sentiment analysis experiments, we have used the Convolutional Neural Network architecture proposed in [17] employing it’s “non-static” version with the exact same configuration as that presented by the authors. Again, we have initialised word vectors using word2vec [19] and used fine tuning, training the neural network using stochastic gradient descent (SGD) with the AdaDelta updates [20].

Since contrastive senses are hard to capture, we define a linguistically motivated rule called “A-but-B” rule akin to that in [9] which states that if a sentence has an “A-but-B” structure, the sentiment of the whole sentence will be consistent with the sentiment of it’s “B” statement. From this rule, we can define a feature-extracting function \( f_1 = A \rightarrow but \rightarrow B(x, y) \) on set \( D \) which takes the input pair of sentence-label \( (x, y) \) and outputs \( (x, y) \) where \( x^* \) is corresponding features of “B”.

We evaluate our method on three public data-sets. The first of these is the Stanford sentiment treebank (SST2) [21] which contains 2 classes (negative and positive), and 6920/872/1821 sentences in the train/dev/test sets, respectively. Following [17] we train the models on both, sentences and phrases. The second data set used here is the movie review one (MR) introduced in [22]. This data set consists of 10,662 one-sentence movie reviews with negative or positive sentiments. Finally, we also employ the customer reviews of various products data set (CR) presented in [23], which contains 2 classes and 3,775 instances. For the MR and CR, we use 10-fold cross validation so as to be consistent with previous works in [9] and [17].

Here, we have compared our results with the non-static version of the network in [17] as published by the authors and the Iterative-distillation method in [9] on the three data sets under consideration. To this end, in Table II we show the accuracy yielded by our method (CNN-F), the method in [9] (CNN-rule) and that in [17] (CNN). Table III shows the Precision, Recall and F1-scores for the three data sets. In both tables, where applicable, i.e. the MR and CR data sets, we also show the corresponding variance over the ten trails corresponding to the 10-fold cross validation. From the experimental results, we can appreciate that our method performs better on both, the SST2 and MR data sets by all measures. It is quite competitive on the CR data set too, just barely behind the method in [9].

### IV. Conclusions

In this paper, we have shown how feature extracting functions can be employed to learn logic rules for visual sentiment

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**TABLE I**

| Approach | Accuracy | Precision | Recall | F1-score |
|----------|----------|-----------|--------|----------|
| CNN-C    | 74.7     | 0.74      | 0.92   | 0.82     |
| CNN-F    | 77.1     | 0.79      | 0.93   | 0.85     |
| CNN      | 72.2     | 0.749     | 0.869  | 0.805    |
| PCNN     | 74.7     | 0.77      | 0.878  | 0.821    |

**TABLE II**

| Approach | SST2     | MR        | CR        |
|----------|----------|-----------|-----------|
| CNN      | 87.2     | 81.3±0.1  | 84.3±0.2  |
| CNN-rule | 88.8     | 81.6±0.1  | 85.0±0.3  |
| CNN-F    | 89.1     | 81.8±0.4  | 84.8±0.1  |

**TABLE III**

| Approach | SST2     | MR        | CR        |
|----------|----------|-----------|-----------|
| CNN      | 0.89     | 0.85      | 0.87      |
| CNN-rule | 0.90     | 0.87      | 0.88      |
| CNN-F    | 0.91     | 0.87      | 0.89      |

| Approach | MR       | Recall | F1-score |
|----------|----------|--------|----------|
| CNN      | 0.80±0.004 | 0.82±0.005 | 0.81±0.003 |
| CNN-rule | 0.81±0.005 | 0.82±0.007 | 0.81±0.003 |
| CNN-F    | 0.81±0.005 | 0.83±0.004 | 0.82±0.002 |

| Approach | CR       | Recall | F1-score |
|----------|----------|--------|----------|
| CNN      | 0.78±0.012 | 0.78±0.017 | 0.78±0.009 |
| CNN-rule | 0.77±0.014 | 0.79±0.014 | 0.78±0.008 |
| CNN-F    | 0.76±0.014 | 0.78±0.015 | 0.77±0.008 |
analysis. This provides a means to representing human knowledge in neural networks via programmable feature extracting functions. Moreover, we have shown that, using these feature extracting functions, we can obtain a model whose posterior output can be influenced by domain knowledge expressed in terms of logic rules without the need of transferring these into the network parameters. The approach presented here is quite general in nature, being applicable to a wide variety of logic rules that can be expressed using rule-to-knowledge conditional probability distributions. We have illustrated the utility of our method for visual sentiment analysis and compared our results with those yielded by a number of alternatives. In our experiments, our method was quite competitive, outperforming the alternatives despite using a much smaller data set for training.

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