SOInter: A Novel Deep Energy Based Interpretation Method for Explaining Structured Output Models

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Abstract—We propose a novel interpretation technique to explain the behavior of structured output models, which learn mappings between an input vector to a set of output variables simultaneously. Because of the complex relationship between the computational path of output variables in structured models, a feature can affect the value of output through other ones. We focus on one of the outputs as the target and try to find the most important features utilized by the structured model to decide on the target in each locality of the input space. In this paper, we assume an arbitrary structured output model is available as a black box and argue how considering the correlations between output variables can improve the explanation performance. The goal is to train a function as an interpreter for the target output variable over the input space. We introduce an energy-based training process for the interpreter function, which effectively considers the structural information incorporated into the model to be explained. The effectiveness of the proposed method is confirmed using a variety of simulated and real data sets.

Index Terms—Interpretation, Structured output, Energy function.

I. INTRODUCTION

The impressive prediction performance of novel machine learning methods has motivated researchers of different fields to apply these models in challenging problems. However, their complex and non-linear inherence limit the ability to explain what they have learned. Interpretation gets more attention when we want to discover the reasons behind the model’s decision and be sure about the trustworthiness and fairness of a trained machine learning model in areas such as medicine, finance, and judgment. Additionally, interpreting a model with a satisfying prediction accuracy in a scientific problem, which results in understanding relationships behind the data, leads to new knowledge about the problem domain.

In many real-world applications, the goal is to map an input variable to a high-dimensional structured output, e.g., image segmentation and sequence labeling. In such problems, the output space includes a set of statistically related random variables. Considering these dependencies can increase the prediction accuracy, many structured output models have been introduced. Many of these methods use graphical models, including random fields, to capture the structural relations between variables. Most define an energy function over these random fields, with a global minimum at the ground truth. Therefore, an inference is needed to find the best configuration of output variables for input by minimizing the energy function in the prediction step. Early efforts to utilize deep neural networks in structured output problems adopt deep networks to extract high-level features from the input vector to incorporate them in calculating the energy function. The computational complexity of the inference step in models that use random fields limits their ability to incorporate complex structures and interactions between output variables. Recent works in [5]–[8] propose to adopt deep networks instead of random fields to model the structure of the output space. Nevertheless, complex interactions between problem variables in such models make their interpretation too challenging, specifically when we focus on the model behavior in predicting a single output variable.

This paper attempts to interpret a structured output model by focusing on each output variable separately. Our approach to model interpretation is based on instance-wise feature selection. Its goal is to find the relative importance of each input feature in predicting a single output variable. The subset of important features can vary across the input space. The complicated interactions between computational paths of output variables in structured output models cause critical challenges for finding a subset of important features associated with each output variable. A feature may not be used directly in the computational path of output but affects its value through relations with other outputs. To compute the importance of a feature for a target output variable, we should aggregate its effect on all output variables correlated to this target.

Existing approaches of model interpretation can be divided into two groups, model-based and post hoc analysis. The model-based interpretation approach encourages machine learning methods that readily provide insight into what the model learned. However, it leads to simple models that are not sufficiently effective for complex structured output problems. Here we follow the post hoc analysis and try to explain the behavior of a trained, structured output model provided as a black box. Many interpretation techniques to find the importance of features as a post hoc analysis have been introduced. Works in [9]–[11] make perturbations to some features and observe their impact on the final prediction. These techniques are computationally inefficient when we search for the most valuable features. Since we should perform a forward propagation for all possible perturbations, in another trend, works in [12], [13] back-propagate an importance signal from the target output through the network to calculate the critical signal of features by calculating the gradient of the target w.r.t the input features. These models are computationally more efficient than perturbation-based techniques because they need
of the network to be known. As this approach may cause a saturation problem, DeepLIFT [14] proposes that instead of propagating a gradient signal, the difference of the output from a reference value in terms of the difference of features from a reference value to be considered. In addition to these approaches, other ideas have also been introduced in model interpretation. Authors in [15] introduce LIME which trains a local interpretable surrogate model to simulate the behavior of a black box model in the vicinity of a sample. It randomly selects a set of instances of the input space around that sample and obtains the black box prediction for them, and trains the surrogate model by this new dataset. Therefore this interpretable model is a good approximation of the black box around the locality of the selected sample. Shapley value, a concept from the game theory, explains how to fairly distribute an obtained payout between coalition players. The work in [16] proposes the kernel SHAP for approximating the shapely value for each feature as its importance for a prediction. As an information-theoretic perspective on interpretation, the work in [17] proposes to find a subset of features with the highest mutual information with the output. This subset is expected to involve the most important features for the output.

Existing interpretation techniques can be applied to explain the behavior of a structured model, w.r.t. a single output, by ignoring other output variables. However, none of these approaches consider possible correlations between output variables and only analyze the marginal behavior of the black box on the target. In this paper, we attempt to incorporate the structural information between output variables during training the interpreter. As our goal is to present a local interpreter, which is trained globally as [17], we train a function over the input space which returns the index of most important features for decision making about the target output. Since the value of other output variables affects the value of the target, incorporating them into the training procedure of an interpreter function may lead to higher performance and decrease our uncertainty about the black box behavior. To the best of our knowledge, this is the first time an interpreter is designed mainly for structured output models, and dependencies between output variables are considered during training the interpreter.

II. PRELIMINARIES AND MOTIVATION

Structured output prediction models map an arbitrary n-dimensional feature vector \( x \in \mathcal{X} \) to the output \( y \in \mathcal{Y} \) where \( y = \{y_1, y_2, \ldots, y_d\} \) includes a set of correlated variables with known and unknown complex relationships and \( \mathcal{Y} \) shows a set of valid configurations.

Now we explain our intuition about an interpreter, which explains the behavior of a structured output model in predicting a single output variable. We assume a structured model is available as a black box we do not know about. Our goal is to find indices of \( k \) important features of \( x \) which affect the black box prediction about the target output \( y_t \). As for different localities of the input space these indices may vary, the proposed interpreter is a function \( \mathcal{I}\mathcal{N}_t(x; \alpha) : \mathcal{X} \rightarrow \{0, 1\}^n \) over the input space with a set of parameters \( \alpha \) which returns an n-dimensional \( k \)-hot vector. In this vector, the value of 1 shows the indices of selected \( k \) important features for target output \( y_t \).

We define \( \Theta_{sb} \) as the set of all parameters and hidden variables inside the structured black box. The probabilistic graphical model of Fig. 1 describes dependencies between problem variables. In this figure, \( x \) shows the input variable, \( y_t^{sb} \) and \( y_t^{sb} \) show black box predictions and \( \alpha_{\mathcal{I}\mathcal{N}_t} \) is the set of parameters of \( \mathcal{I}\mathcal{N}_t \). The bidirectional edge between \( y_t^{sb} \) and \( y_{\bar{t}}^{sb} \) emphasizes the correlation between the outputs of a structured model. In fact \( \alpha_{\mathcal{I}\mathcal{N}_t} \) is determined based on \( \Theta_{sb} \) and the black box architecture, and the final prediction of the \( y_t^{sb} \) does not directly affect its value. However, here, \( \Theta_{sb} \) is a latent variable which makes active paths between \( \alpha_{\mathcal{I}\mathcal{N}_t} \) and output values \( y_t^{sb} \) and \( y_{\bar{t}}^{sb} \). Therefore \( \alpha_{\mathcal{I}\mathcal{N}_t} \) and \( y_t^{sb} \) are dependent random variables and we have:

\[
H(\alpha_{\mathcal{I}\mathcal{N}_t} | x, y_t^{sb}) > H(\alpha_{\mathcal{I}\mathcal{N}_t} | x, y_{\bar{t}}^{sb}, y_{\bar{t}}^{sb})
\]  

where \( H(\cdot | \cdot) \) shows the conditional entropy. We use the strict inequality because \( \alpha_{\mathcal{I}\mathcal{N}_t} \) and \( y_t^{sb} \) are dependent random variables. The left term measures our uncertainty when we train the interpreter only by observing the target output \( y_t^{sb} \). This inequality confirms that the uncertainty is decreased when we consider observed \( y_{\bar{t}}^{sb} \) during estimating \( \alpha_{\mathcal{I}\mathcal{N}_t} \). Motivated by this fact we propose a training procedure for an interpreter \( \mathcal{I}\mathcal{N}_t \) which incorporates the structural information of the output space by observing the black box prediction on all output variables.

We call our method SOInter as we propose it to train an Interpreter specifically for Structured Output models.

III. PROPOSED METHOD

We consider \( p_{sb}(y|x) \) as the distribution by which the structured black box predicts the output as follows,

\[
y^{sb} = \arg\max_y p_{sb}(y|x).
\]  

Our goal is to train the interpreter \( \mathcal{I}\mathcal{N}_t(x; \alpha) \) which explores a subset of most important features that affects the value of black-box prediction on the target output \( y_t \) in each locality of the input space. The interpreter \( \mathcal{I}\mathcal{N}_t(x; \alpha) \) returns a \( k \)-hot vector in which the value of 1 shows the index of a selected feature. As the desired interpreter detects the subset of most important features, we expect perturbing other ones does not change the black box prediction of the target \( y_t \). Motivated by this statement, we are encouraged to compare...
the black box prediction for the target output when a sample and its perturbated version are passed through the black box. We expect the value of the $h$th element of predictions to be the same, and we can define a penalty over the value of the target in these two situations. However, since the structure of the black box is unknown, a loss function that directly compares these two output values cannot be used to find the optimal interpreter. Therefore, in the following subsection, we try to achieve a penalty according to the difference between these values for the target, which can transfer the gradient to the interpreter block.

A. Obtaining a tractable loss function

We consider $\tilde{y}$ as the black box prediction when the masked input $\tilde{x}$ is given to the black box i.e.,

$$\tilde{y} = \arg\max_y p_{\tilde{x}}(y|x \odot \mathcal{N}_I(x; \alpha)). \quad (3)$$

We define a random field over the input space $x$ and output space $y$ with the energy function $E_{sb}$. We assume this random field describes inputs and their corresponding outputs of the structured black block. Therefore we have

$$y^{sb} = \arg\min_y E_{sb}(x, y) \quad (4)$$

and according to the eq. $\text{(3)}$ we have,

$$\tilde{y} = \arg\min_y E_{sb}(x \odot \mathcal{N}_I(x; \alpha), y) \quad (5)$$

As the ideal interpreter selects a subset of most effective features on the value of the $h$th element, it is expected that the $h$th element of $\tilde{y}$ and $y^{sb}$ to be the same. Otherwise, by substituting the $h$th element of $\tilde{y}$ with the $h$th element of $y^{sb}$, the energy value $E_{sb}$ is increased. We propose to consider this increase as a penalty for the interpreter,

$$E_{sb}(x \odot \mathcal{N}_I(x; \alpha), [y^{sb}_h, \tilde{y} - 1]) - \quad (6)$$

$$E_{sb}(x \odot \mathcal{N}_I(x; \alpha), \tilde{y})$$

which is the zero function when $y^{sb}_h = \tilde{y}_h$.

However, if the $E_{sb}$ does not describe the black box behavior perfectly, it may be possible that the energy value to be decreased when $y^{sb}_h \neq \tilde{y}_h$. In this situation, the penalty in eq. $\text{(6)}$ should not be considered to avoid the propagation of the energy block fault. Therefore the following form of eq. $\text{(6)}$ is more preferable,

$$\max \{0, E_{sb}(x \odot \mathcal{N}_I(x; \alpha), [y^{sb}_h, \tilde{y} - 1]) - E_{sb}(x \odot \mathcal{N}_I(x; \alpha), \tilde{y})\} \quad (7)$$

Meanwhile, the energy may not change after substituting the $h$th element of $\tilde{y}$ even with a perfect energy function $E_{sb}$. When both pairs of $(x \odot \mathcal{N}_I(x; \alpha), [y^{sb}_h, \tilde{y} - 1])$ and $(x \odot \mathcal{N}_I(x; \alpha), \tilde{y})$ have a same chance to be the input and outputs of the black box and we have,

$$p(y = y^{sb}_h|x, \tilde{y}, \mathcal{N}_I(x; \alpha)) = p(y = \tilde{y}_h|x, \tilde{y}, \mathcal{N}_I(x; \alpha)) \quad \text{for some} \quad y^{sb}_h \neq \tilde{y}_h \quad (8)$$

the energy value does not change. In this situation least important features are selected by the interpreter and important ones are padded with zero and decreasing the value of penalty in $\text{(6)}$ can guide to a better interpreter. Therefore, we add a margin $m$ to the penalty in $\text{(7)}$ as follows,

$$\max \{0, E_{sb}(x \odot \mathcal{N}_I(x; \alpha), [y^{sb}_h, \tilde{y} - 1]) - E_{sb}(x \odot \mathcal{N}_I(x; \alpha), \tilde{y}) + y^{fr}_h, \tilde{y}_u\} \quad (9)$$

which leads the gradient to be back propagated in the described situation. The obtained form of loss function in $\text{(9)}$ is analogous to the structured hinge loss, however has a different motivation. As $E_{sb}$ is a deep neural network and a function of element-wise multiplication of $x$ and $\mathcal{N}_I(x; \alpha)$, the gradient over the penalty of $\text{(9)}$ can be back-propagated through the interpreter block. The variable $\tilde{y}$ is a function of the interpreter and is obtained by passing the perturbated version of the input.
vector \( x \) to the black box. So we should iteratively calculate the \( \tilde{y} \) and then calculate the loss function \( [9] \) to update the interpreter. It is worth mentioning that we consider a constraint only over the \( y_{sb}^{th} \) as we intend to find the best interpreter for the target.

We will explain the final optimization problem for training the interpreter block after presenting some details about the energy block \( E_{sb} \) and interpreter block \( \mathcal{I} \mathcal{N}_t(x; \alpha) \) in the following subsections.

**B. The energy block**

The energy block \( E_{sb} \) is a deep network that evaluates the consistency of a pair \( (x, y) \) with the structural information incorporated into the black box. Therefore, for an input feature \( x \), the minimum value of the energy function \( E_{sb}(x, y) \) should occur when \( y \) is equal to the black box prediction for \( x \). We train this network in two steps. First, in a pre-training phase, we generate a set of training samples by sampling from the input space and obtaining their associated outputs predicted by the black box. Different techniques to train an energy network have been introduced recently [5]–[7] which can be used to train \( E_{sb} \) in a pre-training phase. Here we use the work in [6].

As shown in [2] to calculate the penalty function we should obtain the energy value \( E_{sb} \), for perturbated versions of samples from the input space. For different interpreters these samples come from different regions of the space. Therefore we consider a fine tuning step for the energy network in which it is adjusted to the interpreter. As mentioned the interpreter block is iteratively optimized and updated, so in each iteration the energy block should be adjusted to the new interpreter. For an arbitrary input vector \( x \), the minimum of the \( E_{sb}(x, y) \) should be occurred for \( y = \tilde{y} \) according to the definition of the energy function. However if the energy network does not simulate the behavior of the black box perfectly, this minimum may occur for a different value of \( y \). As a common loss function in the structured learning literature, we propose to update the energy network based on the structured hinge loss which is obtained as follows,

\[
\max \{0, E_{sb}(x \odot \mathcal{I} \mathcal{N}_t(x; \alpha), y) - E_{sb}(x \odot \mathcal{I} \mathcal{N}_t(x; \alpha), \tilde{y}) + m/\tau \} \tag{10}
\]

where

\[
y_t = \arg \min_y E_{sb}(x \odot \mathcal{I} \mathcal{N}_t(x; \alpha), y) \tag{11}
\]

\[
\tilde{y} = \arg \max_y p_{sb}(y|x \odot \mathcal{I} \mathcal{N}_t(x; \alpha)) \tag{12}
\]

and \( m/\tau \) is a constant margin. The minimum value of the energy function \( E_{sb}(x, y) \) is occurred for \( y = y_t \) which should be equal to \( \tilde{y} \). Otherwise, the loss function of \( [10] \) considers a penalty for the energy network. In the proposed procedure, we update the energy network according to \( [10] \) in each iteration of training the interpreter to adjust it to updated versions of the interpreter.

**C. The interpreter block**

The interpreter \( \mathcal{I} \mathcal{N}_t \) includes a deep neural network, with a set of parameters \( \alpha \), followed by a Gumbel-Softmax [18] unit. The detailed architecture of the deep network depends on the inherence of \( x \). The dimension of the interpreter output is the same as the feature vector \( x \). Fig. [2] describes the architecture used for training the interpreter \( \mathcal{I} \mathcal{N}_t(x, \alpha) \). The output of the deep network \( \mathcal{W}_t \) shows the importance of the elements of the feature vector \( x \). To encourage the interpreter to find top \( k \) important features associated with the target output \( y_t \), we use the Gumbel-Softmax trick as proposed in [17]. To obtain top \( k \) important features, we consider the output of \( \mathcal{W}_t(x) \) as parameters of the categorical distribution. Then we can independently draw a sample for \( k \) times. Each sample is a one-hot vector in which the element with the value of 1 shows the selected feature. To have a \( k \)-hot vector, we can simply get the element-wise maximum of these one-hot vectors. However this sampling process is not differentiable and we use its continuous approximation introduced by the Gumbel-Softmax trick. Considering following random variables,

\[
g_i = -\log(-\log(u_i)) \tag{12}
\]

where \( u_i \sim \text{Uniform}(0, 1) \), we can use the reparameterization trick instead of direct sampling from \( \mathcal{W}_t(x) \) as follows:

\[
c_i = \frac{\exp\{\log(\mathcal{W}_t(x)_i) + g_i)/\tau\}}{\sum_j \exp\{\log(\mathcal{W}_t(x)_j) + g_j)/\tau\}} \tag{13}
\]

The vector \( c \) is the continuous approximation of the sampled one-hot vector. To have \( k \) selected features, we draw \( k \) vectors \( c_j, j = 1 \ldots k \) and obtain their element-wise maximum as follows [17].

\[
\mathcal{I} \mathcal{N}_t(x, \alpha)_i = \max_j \{c_i, j = 1 \ldots k\} \tag{14}
\]

**D. The proposed optimization problem**

Finally, parameters of the ideal interpreter can be described as follows,

\[
\alpha_{opt} = \arg \min_{\alpha} \mathbb{E}_{p(x)} [\max\{0, E_{sb}(x \odot \mathcal{I} \mathcal{N}_t(x; \alpha), [y_{sb}^t, \tilde{y}_{t-1}]) - E_{sb}(x \odot \mathcal{I} \mathcal{N}_t(x; \alpha), \tilde{y}) + \mathcal{L}(y_{sb}^t, \tilde{y}_{t-1})\}] \tag{15}
\]

subject to:

\[
\tilde{y} = \arg \max_y p_{sb}(y|x \odot \mathcal{I} \mathcal{N}_t(x; \alpha)) \tag{16}
\]

which is an optimization problem with an equality constraint. The final proposed greedy iterative optimization procedure for training the interpreter block can be expressed as follows,

\[
\alpha^{(k)} \leftarrow \beta \nabla_{\alpha} \mathbb{E}_{p(x)} [\max\{0, E_{sb}^{(k-1)}(x \odot \mathcal{I} \mathcal{N}_t(x; \alpha), [y_{t}^{(k-1)}, \tilde{y}_{t-1}^{(k-1)})] - E_{sb}^{(k-1)}(x \odot \mathcal{I} \mathcal{N}_t(x; \alpha), \tilde{y})^{(k-1)} + m/\tau\} \tag{17}
\]

\[
\tilde{y}^{(k)} = \arg \max_y p_{sb}(y|x \odot \mathcal{I} \mathcal{N}_t(x; \alpha^{(k)})) \tag{18}
\]

\[
y_{t}^{(k)} = \arg \min_y E_{sb}^{(k-1)}(x \odot \mathcal{I} \mathcal{N}_t(x; \alpha^{(k)}), y) \tag{19}
\]

\[
E_{sb}^{(k)} \leftarrow \beta \nabla_{E_{sb}} \mathbb{E}_{p(x)} [\max\{0, E_{sb}(x \odot \mathcal{I} \mathcal{N}_t(x; \alpha^{(k)}), y_{t}^{(k)})) - E_{sb}(x \odot \mathcal{I} \mathcal{N}_t(x; \alpha^{(k)}), \tilde{y})^{(k)} + m/\tau\} \tag{20}
\]

where \( y_{sb}^{th} = \arg \max_y p_{sb}(y|x) \). At the first step of each iteration, parameters of the interpreter block is updated according to the loss function introduced in [9]. Then the solution of the black box for perturbated versions of the input vectors are
calculated in the second step. In the third and fourth steps the energy block $E_{sb}$ is fine tuned.

The initial value $\alpha(0)$ is randomly selected and its associated $\hat{y}(0)$ is obtained using the second step of (16). The energy network is also initialized by the pre-trained network. The algorithm is continued until the value of the penalty does not considerably change which is usually obtained in less than 100 iterations.

IV. EXPERIMENTS

We evaluate the performance of our proposed interpreter on both synthetic and real datasets. In section IV-A we define two arbitrary energy functions to synthesize structured data. We compare the performance of SOInter with two well-known interpretation techniques, Lime and Kernel-Shap, which are frequently used to evaluate the performance of interpretation methods, and L2X [17] which proposes an information-Theoretic method for interpretation. None of these techniques are specifically designed for structured models. Indeed, they only consider the target output and ignore other ones. In section IV-B and IV-C the efficiency of SOInter is shown with two real text and image datasets.

A. Synthetic Data

Here we define two arbitrary energy functions on input vector $x$ and output variables $y$, $E_1$ and $E_2$ in (17), which are linear and non-linear functions respectively according to the input features.

$$E_1 = (x_1y_1 + x_4)(1 - y_2) + (x_2(1 - y_1) + x_3)y_2$$

(17)

$$E_2 = (\sin(x_1)y_1y_3 + |x_4|)(1 - y_2)y_4 + \left(\exp\left(\frac{x_2}{10} - 1\right)(1 - y_1)(1 - y_3) + x_3\right)y_2(1 - y_4)$$

(18)

Input features are randomly generated using the standard normal distribution. Output variables are considered as binary discrete variables. For each input vector $x$, we found the corresponding output by the following optimization,

$$y^* = \arg\min_y E(x, y)$$

(19)
where \( E \) shows the energy function from which we attempt to generate data. \( E_1 \) describes the energy value over a structured output of size 2 and \( E_2 \) describes an output of size 4. For each scenario, we simulate input vectors with the dimension of 5, 10, 15 and 20.

For each generated dataset, we train a structured prediction energy network introduced in [6]. As it has the sufficient ability to learn energy functions in (17), we can assume it has successfully captured the important features with a negligible error rate. We adopt each interpretation techniques to explain trained energy networks. According to (17) first four features affect the value of outputs. Fig. 3 compares the accuracy of results obtained by each method during the interpretation. Diagrams of Fig. 3 show results for target outputs \( y_1 \) and \( y_2 \) in \( E_1 \) and two arbitrary outputs \( y_3 \) and \( y_4 \) in \( E_2 \). There may be randomness in interpretation methods, and we run each interpreter five times for each dataset. Each line in the diagrams shows the average value, and the highlighted area shows the standard deviation. SOInter has an overall better performance compared to others.

As the accuracy measures the exact match of the subset of important features with ground truths, we consider an order for features and report the median rank of important ones in Fig. 4 as proposed in [17]. As the first four features are the solution, the desired median rank is 2.5 in all situations. As shown, SOInter has the nearest median rank to 2.5 nearly in all cases.

As the number of input features is increased, the performance of methods is generally degraded. This is because the ratio of important features compared to the size of the input vector is decreased, which can lead to confusion of the interpreter.

However, the obtained results confirm the robustness of SOInter for the more significant number of input features. Thus the proposed method is more reliable when the size of the input vector is large.

**B. Multi-label Classification on Bibtex Dataset**

Bibtex is a standard dataset for the multi-label classification of texts. Each sample in Bibtex involves an input feature vector corresponding to 1836 words mapped to a 159-dimensional
output vector. Elements of the output vector are associated with a set of tags that describes the sample subject. We train a structured prediction energy network (SPEN) as a multi-label classifier on Bibtex with a desirable accuracy as shown in [5]. A SPEN as a structured black box is a challenging benchmark for an interpreter because of its ability to capture more complicated relations between output variables. During interpreting this classifier with SOInter, we select an output variable, i.e., a tag, as a target of explanation and find the top 30 features related to this tag for each sample. According to SPEN decisions, we aggregate those top features over all samples for each tag and find the top 30 features expected to be correlated to this tag. Table I shows the general top 30 features for different 3 tags. More results are provided in Table ?? of Appendix ??.

C. Image Segmentation on Weizmann-Horse Dataset

Image segmentation is another structured output learning task in which the image is partitioned into semantic regions. Here we again train a SPEN for segmentation of 24 × 24 Weizmann-horse dataset. Each image of this dataset is partitioned into two regions that determine the horse’s borders. During the interpretation, we consider a pixel as the target and find pixels of the image that affect the target’s output.

In Fig. 5 the pixel in [10, 10] is considered as target and the interpretation results for arbitrary images are shown. We do experiments for different numbers of important features of 5, 10, 50, and 100. The red pixel shows the target, and green ones are obtained important input features as expected green pixels are placed in the locality of the target.

V. Conclusion

We have presented SOInter, an interpreter for explaining structured output models. We focused on a single output variable of a structured model, available as a black box, as the target. Then we train a function over the input space, which returns a subset of important features for the black box to decide on the target. This is the first time an interpreter has been designed explicitly for structured output models to the best of our knowledge. These models learn complex relations between output variables which ignoring them while interpreting a single output can decline the explanation performance. We used an energy model to learn the structural information of the black box and utilize it during the interpreter’s training. The effectiveness of SO-Inter is confirmed using synthetic and real structured datasets.

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Fig. 5. Results on Weizmann-horse images.

| Number of selected features | 150 | 100 | 50 | 20 |
|-----------------------------|-----|-----|----|----|
| **F1**-Selected by SOInter  | 0/261 | 0/228 | 0/224 | 0/275 |
| **F1**-Randomly selected    | 0/057 | 0/036 | 0/024 | 0/022 |

**TABLE II**

*F1 measure obtained by selected features*

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