EDUCE: EXPLAINING MODEL DECISIONS THROUGH UNSUPERVISED CONCEPTS EXTRACTION

Anonymous authors
Paper under double-blind review

ABSTRACT

Providing explanations along with predictions is crucial in some text processing tasks. Therefore, we propose a new self-interpretable model that performs output prediction and simultaneously provides an explanation in terms of the presence of particular concepts in the input. To do so, our model's prediction relies solely on a low-dimensional binary representation of the input, where each feature denotes the presence or absence of concepts. The presence of a concept is decided from an excerpt i.e. a small sequence of consecutive words in the text. Relevant concepts for the prediction task at hand are automatically defined by our model, avoiding the need for concept-level annotations. To ease interpretability, we enforce that for each concept, the corresponding excerpts share similar semantics and are differentiable from each others. We experimentally demonstrate the relevance of our approach on text classification and multi-sentiment analysis tasks.

1 INTRODUCTION

While deep learning models are powerful tools to perform a large variety of tasks, their predictive process often remains obscure. Understanding their behavior becomes crucial. This is particularly true with text data, where predicting without justifications has limited applicability. There has been a recent focus on trying to make deep models more interpretable, see for example (Ribeiro et al., 2016; Bach et al., 2015; Shrikumar et al., 2017; Simonyan et al., 2014; Sundararajan et al., 2017). Specifically, methods have been recently proposed to provide such explanations *simultaneously* with the prediction. For example, (Lei et al., 2016; Yu et al., 2019; Bastings et al., 2019) select subsets of words in the input text that can account for the model's prediction (called rationales). In this work, we propose a model that provides an explanation based on the absence or presence "concepts" that are automatically discovered in the texts.

Suppose we ask a user to tell what is the category (or class) of the top text of Figure 1 (text x). She detects that the words *the government said* relate to a specific concept that is present in x, a concept she also detect in the words *made official what* in text x' . Let us call this concept "politics" in the remainder. She also notes that the words *retails sales bounced back* refer to a concept different from the previous one. Let us call this other concept "economy". As the text is concerned with politics and economy she infers that its category is Business. Said otherwise, she detects excerpts that relate to particular concepts and decides on the text category based on the detected concepts.

Similarly, our paradigm assumes that an explanation of a model's prediction is understandable if it relies on a few concepts, where each concept relates to parts of text (referred to as *excerpts*) that are semantically consistent across multiple texts. Our methodology is as follows. First, our model encodes the input text into a binary low-dimensional vector, where each value (0 or 1) is computed from an excerpt and denotes the presence or absence of a specific concept in the input. Then, the prediction is made from this binary vector alone, allowing an easy interpretation of the decision in term of presence/absence of concepts.

While we set a maximal value of the number of concepts (which is the dimensionality of the binary representation), the concepts are **unsupervised and not defined a priori**. The model automatically determines them in a way that eases interpretation: each concept is encouraged to be semantically consistent and not to overlap with other concepts. Therefore, extracted excerpts for a concept must be discriminative of that concept only and share similar semantics. This is enforced through a concept consistency and separability constraint added as an auxiliary loss in the learning optimization problem.

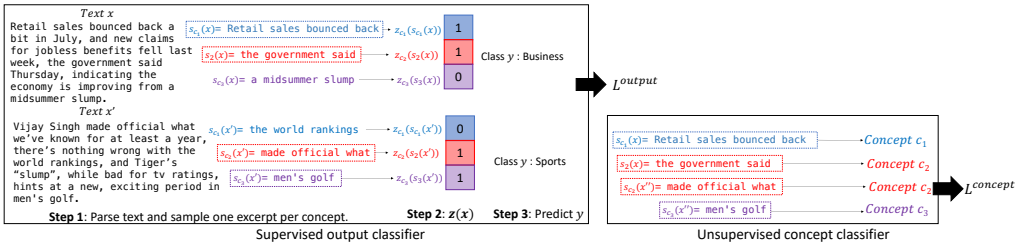


Figure 1: Illustration of EDUCE's prediction process on AGNews topic classification dataset (Zhang & LeCun, 2015) examples. The different steps are explained in the text.

As a result, each discovered concept can be understood from the corresponding excerpts extracted that activate its appearance: in our previous example, the meaning of the first concept the user identifies is inferred from the excerpts she detected for that concept in x and x', i.e. *the government said, made official what*. Looking at these excerpts, we identify that concept as politics.

Our idea relates to Latent Dirichlet Allocation (LDA) (Blei et al., 2003), where text documents are described by a set of topics that are semantically consistent. However, LDA builds a probabilistic model of text generation, whereas our goal is to discover and define latent concepts that are relevant for a prediction task at hand. In comparison to rationale-based text processing models (Lei et al., 2016; Yu et al., 2019; Bastings et al., 2019), we rely on a different paradigm: our model's prediction is based on the absence or presence of discovered concepts, and makes no direct use of the words captured as excerpts. We do so to ease interpretation of the prediction. This makes the interpretation of a different nature than these methods, and simpler to understand for the user.

Our contribution with this work is a new self-interpretable model that predicts solely from the presence/absence of concepts in the input. Concepts are learned unsupervisingly, and described by a semantically consistent set of excerpts. We experiment on three text categorization tasks and a multi-aspect sentiment analysis task, compare our model's performance with state-of-the-art prediction models, and demonstrate its interpretability. Note that an instance of our model for image processing is described in the supplementary Section D with illustrative experiments.

2 THE EDUCE MODEL

We present our model, called EDUCE for Explaining model Decisions through Unsupervised Concepts Extraction, using a multi-class classification task, but our method can be used to perform regression or multi-label classification. We consider a training dataset $\mathcal{D}$ of inputs $(x_1, ..., x_N)$, $x_n \in \mathcal{X}$ and corresponding labels $(y_1, ..., y_N)$, $y_n \in \mathcal{Y}$.

Contrarily to back-box models that use complex computations over low-level input features to predict the output class y, our objective is to enforce the model to map an x input to an easy-to-interpret representation $\boldsymbol{z}(x) \in \{0, 1\}^C$, on which the output prediction relies. EDUCE's inference process consists in the following steps. **Step 1**: For each concept c (i.e. each dimension of $\boldsymbol{z}(x)$), compute $p_\gamma(s|x, c)$: the probability of each excerpt s in x to be selected. Sample a unique excerpt $s_c(x) \sim p_\gamma(s|x, c)$ per concept (per dimension of $\boldsymbol{z}(x)$). Note that the same excerpt can be selected for multiple concepts. **Step 2**: Decide on each value $z_c(x)$ of the representation $\boldsymbol{z}(x)$ by sampling from $p_\alpha(z_c|s_c(x), c)$. Given $s_c(x)$, $z_c(s_c(x)) = 1$ means concept c is detected as present and $z_c(s_c(x)) = 0$ means it is absent. **Step 3**: Predict the output class y from $\boldsymbol{z}(x) = (z_1(s_1(x)), ..., z_C(s_C(x)))$.

We do not have concept-level annotations. To ensure semantic consistency and prevent overlap of the concepts, we jointly train a concept classifier to recognize, for every excerpt $s_c(x)$ such that $z_c(s_c(x)) = 1$, the concept (i.e. the dimension) it was extracted for: the label for each $s_c(x)$ is simply $c \in [1, C]$. Figure 1 illustrates these steps, which we detail below.

2.1 GENERATING PREDICTIONS AND EXPLANATIONS

Step 1: Extract a unique excerpt $s_c(x)$ per concept c. Given an input sentence $x : w_1, ..., w_M$, where each w_i is a word, a excerpt s consists of a span of consecutive words of flexible size between 3 and 10 words: $s = w_k, ..., w_{k+l}, 3 \leq l \leq 10$. For each concept, we extract a unique excerpt,

defined by its first and last word. Our extraction process is very similar to the one proposed in Question-Answering models (e.g Devlin et al. (2019)). An excerpt is sampled by first sampling its *start word* and then its *end word* conditioned on the start word.

We denote the probability over each excerpt s to represent concept c in x as $p_\gamma(s|x,c)$ and we write as the product of (i) $p_{start}(w_k|x,c)$, the probability for s's first word to be the start word of the excerpt to extract and (ii) $p_{stop}(w_{k+l}|x,c,w_k)$ the probability of w_{k+l} to be the stop word given the start word w_k: $p_\gamma(s|x,c) = p_\gamma(w_k,...,w_{k+l}|x,c) = p_{stop}(w_{k+l}|x,c,w_k)p_{start}(w_k|x,c)$. We parametrize $p_{start}(w_k|x,c)$ and $p_{stop}(w_{k+l}|x,c,w_k)$ using recurrent neural networks. First we feed the entire input sentence $x : w_1,...,w_M$ through a bidirectional LSTM, and we represent each word w_i in the sentence as the concatenation of the forward pass and backward pass hidden states for that word: $h_k = [\overrightarrow{h_k}, \overleftarrow{h_k}],\ \forall k \in [1, M]$. Second, each h_k is fed to a linear layer with parameters γ_{start} which outputs a score for w_k, followed by the softmax activation function over all possible words to have the probability distribution over each word to be the *start word*:

$$p_{start}(w_k|x,c) = \frac{\exp(\gamma_{start} \cdot h_k)}{\sum_{k=1}^{M} \exp(\gamma_{start} \cdot h_k)},\ k = 1,...,M. \tag{1}$$

Using this distribution, we can sample a specific start word $w_{start} \sim p_{start}(w_k|x,c)$. Third, we feed again the vectors h_k to another linear layer with parameters γ_{stop} that gives a score for each word to be the *stop word*. We mask out these scores before taking the softmax, such that the probabilities for $w_{start+l}$ with $l < 3$ and $l > 10$ to be the *stop word* are 0.

$$p_{stop}(w_{start+l}|x,c,w_{start}) = \begin{cases} \dfrac{\exp(\gamma_{stop} \cdot h_{start+l})}{\sum_{l=3}^{10} \exp(\gamma_{stop} \cdot h_{start+l})},\ l \geq 3 \text{ or } l \leq 10 \\ 0,\ l < 3 \text{ or } l > 10. \end{cases}$$

We then sample a specific stop word $w_{stop} \sim p_{stop}(w_{start+l}|x,c,w_{start})$[1]. We now have the start word w_{start} and stop word w_{stop}. The corresponding excerpt is $w_{start},...,w_{stop}$ and is represented as a fixed size vector $s_c(x)$ by computing the average of (pre-trained, fixed) words embeddings vectors of $w_{start},...,w_{stop}$. Hence sampled excerpts $s_c(x)$ belong to $\mathbb{R}^d$, where d is the dimension of embedding vectors.

This process is illustrated in Figure 1: For text x, the excerpt *Retails sales bounced back* is selected for concept c_1, *the government said* for concept c_2 and *a midsummer slump* for concept c_3.

Step 2: For each c, from the excerpt $s_c(x)$, decide on the value $z_c(x)$ denoting the presence/absence of concept c. Each extracted excerpt (one per concept) is processed to decide on the absence or presence of each concept in x. Specifically, for each concept c we take the dot product of a weight vector $\alpha_c \in \mathbb{R}^d$ with $s_c(x)$, followed by a sigmoid activation function, in order to obtain the Bernoulli probability

$$p_\alpha(z_c = 1|s_c(x),c) = \sigma(\alpha_c \cdot s_c(x)) \tag{2}$$

This is the probability that $s_c(x)$ extracted from x for concept c triggers the presence of concept c. The binary vector $\boldsymbol{z}(x)$ is obtained by independently sampling each dimension: $\forall c\ z_c \sim p_\alpha(z_c|s_c(x),c)$.

This step can be seen as C independent binary classifiers, each of them deciding on the presence of a particular concept. We illustrate this in Step 2 in Figure 1: For text x, the excerpt *Retails sales bounced back* activates the presence of concept c_1, *the government said* activates the presence of c_2 but *a midsummer slump* does not activate the presence of c_3.

Step 3: Predict y from $\boldsymbol{z}(x)$. As shown in Step 3 of Figure 1, given an input x, the prediction of the output y is made solely from the intermediate binary representation $\boldsymbol{z}(x)$. We use a linear classifier without bias, parametrized by a weight matrix $\delta \in \mathbb{R}^{|\mathcal{Y}| \times \mathcal{C}}$ followed by a softmax activation function, returning $p_\delta(y|\boldsymbol{z}(x)) \forall y \in \mathcal{Y}$.

Output classification training objective. The parameters $\{\gamma, \alpha, \delta\}$ are learned in a end-to-end manner by minimizing cross-entropy, which writes for each x as:

$$\begin{aligned} \mathcal{L}^{output}(x,y,\delta,\alpha,\gamma) &= \mathbb{E}_{\boldsymbol{s}(x) \sim p_\gamma}[\mathbb{E}_{\boldsymbol{z}(x) \sim p_\alpha}[\mathcal{L}^{output}(y, \boldsymbol{z}(x), \delta)]] \\ &= \mathbb{E}_{\forall c\ s_c(x) \sim p_\gamma(s|x,c)}[\mathbb{E}_{\forall c\ z_c \sim p_\alpha(z_c|s_c(x),c)}[-\log p_\delta(y|\boldsymbol{z}(x))]]. \end{aligned} \tag{3}$$

We give details about the optimization in Section 2.3.

[1] We also prevent stop words to be outside of the text length.

2.2 UNSUPERVISED DISCOVERY OF LATENT CONCEPTS

To ease interpretation of the concepts' meaning, we want each dimension $\boldsymbol{z}$ to correspond to semantically consistent concepts. In other words, for a given concept c (i.e. a given dimension z_c), for all inputs where that concept is present (i.e. $\forall x \; s.t. \; z_c(s_c(x)) = 1$), the corresponding excerpts $s_c(x)$ should share common semantics. While the C binary classifiers deciding on the presence of each concept c (Step 2) enforce consistency within the set of extracted excerpts s_c, there is no guarantee that the concepts are not overlapping (i.e. are separable). We want concepts to be separable so that each concept captures a particular notion. Excerpts extracted for concept c must be distinguishable from the excerpts extracted for another concept c'. If we take the example of Figure 1: In Step 2 the excerpt *Retails sales bounced back* is identifiable as relating to economy/finance, contrarily to *the government said, made official what* which trigger the concept politics.

We rephrase our desiderata for consistency and separability as classification of the excerpts, with as many classes as the number of concepts. An external classifier should recognize that elements in the set $\{s_c(x) | \forall x \; z_c(s_c(x)) = 1\}$ belong to concept c, and $\{s_{c'}(x) | \forall x \; z_{c'}(s_{c'}(x)) = 1\}$ belong to concept c' and not c. Recall that **we do not have labels for the concepts**. The ground-truth label of each extracted excerpt $s_c(x)$ is the **index** c of the dimension of $\boldsymbol{z}(x)$ for which it was extracted. We learn a linear *concept classifier* without bias, parametrized by a weight matrix $\theta \in \mathbb{R}^{|\mathcal{C}| \times d}$ followed by a softmax activation function, returning $p_\theta(c' | s_c(x)), \forall c' \in [1, C]$.

The concept classifier is trained by minimizing cross-entropy, where the label of each excerpt $s_c(x)$ the index of the concept for which it was extracted (i.e. c):

$$\begin{aligned} \mathcal{L}^{concept}(x, \theta, \alpha, \gamma) &= \mathbb{E}_{\boldsymbol{s}(x) \sim p_\gamma}[\mathbb{E}_{\boldsymbol{z}(x) \sim p_\alpha}[\mathcal{L}^{concept}(\boldsymbol{z}(x), \boldsymbol{s}(x), \theta)]] \\ &= \mathbb{E}_{\boldsymbol{s}(x) \sim p_\gamma}[\mathbb{E}_{\boldsymbol{z}(x) \sim p_\alpha}[\sum_c -z_c(s_c(x)) \log p_\theta(c | s_c(x))]], \end{aligned} \tag{4}$$

where $\boldsymbol{s}(x)$ refers to the set of excerpts extracted for each concept: $\boldsymbol{s}(x) = \{s_c(x), c = 1, ..., C\}$. The loss considers concepts that are present in x (i.e. $z_c(s_c(x)) = 1$). The role of the concept classifier is to further enforce concepts consistency and to prevent overlap of concepts, and is jointly train with the rest of the model.

Note that adding a sparsity constraint on the number of concepts present in the inputs enforces semantic consistency, as sparse coding has been shown to induce useful, interpretable representations (Bengio et al., 2013a; Mairal et al., 2010). We experimentally demonstrate that a sparsity constraint is not sufficient, and can harm output prediction performance. On the opposite, with our concept classifier, sparsity is encouraged as $\mathcal{L}^{concept}$ depends on the concepts that are present, but if concepts are consistent and separable $\mathcal{L}^{concept}$ can be low without harming task performance.

2.3 EDUCE OBJECTIVE FUNCTION AND OPTIMIZATION

We jointly learn the *concept classifier* and *output classifier* and our objective function is the sum Equations 3 and 4:

$$\mathcal{L}(x) = \mathbb{E}_{\boldsymbol{s}(x) \sim p_\gamma}[\mathbb{E}_{\boldsymbol{z}(x) \sim p_\alpha}[\mathcal{L}^{output}(y, \boldsymbol{z}(x), \delta) + \lambda \mathcal{L}^{concept}(\boldsymbol{z}(x), \boldsymbol{s}(x), \theta)]] \tag{5}$$

where λ controls the strength of the concept consistency constraint wrt the output prediction. The loss $\mathcal{L}(x)$ is differentiable, therefore the gradients with respect to the output classifier's weights (δ) and concept classifier's weights (θ) can be computed and back-propagated. However, the gradients with respect to the parameters of the excerpts extraction (γ) and the Bernoulli distribution over presence of concepts (α) pose an issue due to the sampling of these discrete random variables in Steps 1 and 2. As the explicit computation of the expectation involves expensive summations over all possible values of $\boldsymbol{s}(x)$ and $\boldsymbol{z}(x)$, we resort to Monte-Carlo approximations of the gradient (Sutton & Barto, 1998), with the loss $\mathcal{L}(x)$ used as reinforcement signal. The gradient derivation is provided in Supplementary Material. Our code will be released upon acceptance.

3 RELATED WORK

Topic models. Our work relates to topic models, especially to Latent Dirichlet Allocation (LDA) (Blei et al., 2003) where each document is modeled as a mixture of topics and each word in a

document relates to one or more topics. While LDA has been recently combined with recurrent neural networks (Zaheer et al., 2017), the methodology remains different. LDA learns the parameters of a probabilistic graphical model of text generation while we aim at solving a supervised problem in an explanable manner that relies on binary presence/absence of concepts.

A posteriori explanations. Some methods interpret an already trained model, typically using perturbation and gradient-based approach. The most famous method is LIME (Ribeiro et al., 2016), but other exist (Bach et al., 2015; Shrikumar et al., 2017; Simonyan et al., 2014; Sundararajan et al., 2017). Alvarez-Melis & Jaakkola (2017) design a model that detects input-output pairs that are causally related. Kim et al. (2018) learn concept activation vectors. However, the classifier is fixed and concepts are predefined from human annotations, while we learn the concepts unsupervisingly and end-to-end.

Self-interpretable models. Contrarily to the previous line of work, our work falls in the domain of self-interpretable models. Such models produce an explanation simultaneously with their prediction. Related to our work, (Lei et al., 2016; Yu et al., 2019; Bastings et al., 2019) develop interpretable models for NLP tasks by selecting rationales, i.e. parts of text, on which a consequent model bases its prediction. Importantly, a rationale acts as a justification supporting the prediction and is different from our definition of excerpt. In our model, excerpts support the attribution of presence of concepts, and this attribution supports the prediction. Goyal et al. (2019) propose visual explanations of a classifier's decision and Alaniz & Akata (2019) use an architecture composed of an observer and a classifier, whose prediction can be exposed as a binary tree. However, contrarily to ours, their model does not provide a local explanation of the decision based on parts of the input. Alvarez Melis & Jaakkola (2018) learn a self-explaining classifier that takes as input a set of concepts extracted from the original input. While they define a set of desiderata for what is an interpretable concept, they simply represent extracted concepts as an encoding of the input learned with an auto-encoding loss. Quint et al. (2018) extend a classic variational auto-encoder architecture with a differentiable decision tree classifier. However, their methodology is different and they only experiment on image data.

4 TEXT CLASSIFICATION EXPERIMENTS

We experiment on three text classification datasets. The **DBpedia** ontology classification dataset (Zhang et al., 2015) was constructed by picking 14 non-overlapping categories from DBpedia 2014 (Lehmann et al., 2015). There are 14 classes. We use $56,000$ examples of the train dataset for training, and $56,000$ for validation. For testing, we use $7,000$ examples of the test dataset (using stratified sampling). Also in Zhang et al. (2015), the **AGNews** topic classification dataset was constructed from the AG dataset's 4 largest categories. There are 4 classes. We separate the training set into $84,000$ training samples and $24,000$ validation samples and report results on the full test dataset. We also experiment on the Stanford Sentiment Treebank (**SST**) (Socher et al., 2013) that includes 5 sentiment classes. For DBPedia and AGNews we use fixed word vectors trained on Common Crawl (Grave et al., 2018). For SST, we use fixed Glove word vectors (Pennington et al., 2014).

Comparative models. Since we are concerned with building self-interpretable models, we do not compare with the methods presented in Section 3 that explain a model a posteriori. Rather, for comparison, we report the performance of (i) using a Bidirectional LSTM on the full text and predict directly from its hidden state (Baseline) (ii) the No Concept Loss model that uses a binary discrete intermediate representation but no concept classifier, it corresponds to $\lambda = 0$ and its training objective is simply $\mathcal{L}^{output}$ and (iii) adding a L_1-norm sparsity constraint to the No Concept Loss model (referred to as No Concept Loss + L_1), i.e. Equation 5 changes to:

$$\mathcal{L}(x) = \mathbb{E}_{s(x)\sim p_\gamma}[\mathbb{E}_{\boldsymbol{z}(x)\sim p_\alpha}[\mathcal{L}^{output}(y, \boldsymbol{z}(x), \delta) + \lambda_{L_1}|\boldsymbol{z}|]]. \tag{6}$$

Therefore both No Concept Loss and No Concept Loss + L_1 models extract excerpts and use a binary intermediate representation, but are trained without concept loss.

Hyperparameters selection. We tried different values of hyperparameters (details in supplementary Section B.1) and for each set of hyperparameters, we run 5 different random seeds. We choose the best hyperparameters set using its average validation performance over the 5 random seeds.

Metrics. We report the test output accuracy (Output Acc.) over the task. Evaluating interpretability of concepts is challenging. For EDUCE, we can compute the accuracy of the concept classifier on the test data. However, this should be low for models No Concept Loss and No Concept Loss + L_1

Data	Model	Output Acc. (%)	A Posteriori Concept Acc. (%)
DBPedia	EDUCE	97.0 ± 0.1	$\mathbf{82.4 \pm 0.8}$
	No Concept Loss	97.4 ± 0.1	25.9 ± 0.6
	No Concept Loss+L_1	96.5 ± 0.2	44 ± 2.6
	Baseline	$\mathbf{98.75 \pm 0.0}$	n/a
AGNews	EDUCE	87.5 ± 0.2	$\mathbf{78 \pm 6.5}$
	No Concept Loss	88.2 ± 0.1	31.0 ± 0.7
	No Concept Loss+L_1	86.3 ± 0.7	56 ± 3.2
	Baseline	$\mathbf{92.08 \pm 0.1}$	n/a

Table 1: Test performance on DBPedia and AGNews (mean $\pm$ SEM).

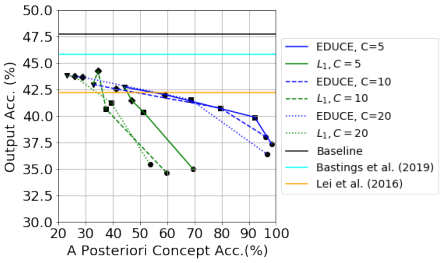


Figure 2: SST test performance, output accuracy vs a posteriori concept accuracy. A posteriori concept accuracy is not applicable for Baseline, Lei et al. (2016) and Bastings et al. (2019).

that do not train with a concept loss. Therefore, to evaluate interpretability, we report an *a posteriori* concept accuracy: after training, for each model (including EDUCE), we gather the excerpts extracted ($z_c = 1$) in the test data. We separate these excerpts into two sets (training and testing, note that these are both generated from the test data). We train a new, separate concept classifier *a posteriori* on the extracted excerpts to evaluate and we report its performance as a posteriori concept accuracy (A Posteriori Concept Acc.).

Quantitative results on DBPedia and AGNews. Table 1 reports test performance on the DBPedia and AGNews datasets for $C = 10$ concepts. We report results with values $\lambda = 0.1$ and $\lambda_{L_1} = 0.1$ that give best trade-off performance between output and concept accuracies. Complete results are available in supplementary Table 4. For all metrics we report the mean and standard error of the mean (SEM) over the training random seeds. Table 1 shows that the Baseline model outperforms the other models that all employ a binary discrete encoding of the input. This is expected, and shows the trade-off between interpretability and output accuracy. In terms of output accuracy, EDUCE is comparable with its counterpart that does not encourage concept consistency (No Concept Loss), loosing only 0.4% on DBPedia and 0.7% on AGNews, and as expected outperforms it in terms of concept accuracy. Adding an L_1 constraint to the No Concept Loss model increases the consistency of the concepts (as per A posteriori Concept Accuracy values) yet is largely outperformed by EDUCE on that metric, and output accuracy is also lower than EDUCE's.

Interpreting EDUCE on AGNews. We turn to show how EDUCE's output prediction is easily interpretable. The following results were generated with $\lambda = 0.1$ and $C = 10$ concepts. Figure 3a shows examples of the AGNews test set that were correctly classified by EDUCE. The underlined words correspond to the excerpts extracted for different concepts. Separately, in Figure 3b we show, for each concept detected in the examples of Figure 3a, examplar excerpts extracted from others test documents (excerpts are separated by "/"). We interpret the concepts' meaning as follows: concept 0 maps to informatics notions, concept 2 to corporations/petrol, concept 4 to the notions of investments and finance, concept 6 to sports events and concept 8 to governmental/state affaires. Concept 1 is less clearly defined. Note that in Figure 3b excerpts are consistent yet are extracted in texts from multiple output classes. The excerpts extracted in the examples of Figure 3a are consistent with these interpretations. These results show how easily the classification of any text can be explained by the detection of multiple, relevant, and intelligible concepts. More qualitative examples are in supplementary Section C.

SST dataset Figure 2 shows output accuracy versus a posteriori concept accuracy on the SST dataset, for different different number of concepts C and different values of λ: Each marker is a different value of λ, and values are (from left to right markers) $\{0, 0.01, 0.1, 0.5\}$. We do the same for the No Concept Loss + L_1 model. Note that the left most markers in all curves correspond to $\lambda = 0$ and $\lambda_{L_1} = 0$, therefore to the model referred to as No Concept Loss. While our goal and model is very different than Lei et al. (2016); Bastings et al. (2019), we report their test scores (obtained using 40% of the text on the SST dataset, we report directly from Bastings et al. (2019)). The a posteriori concept accuracy for Baseline, Lei et al. (2016) and Bastings et al. (2019) is not applicable. Figure 2 confirms our results: EDUCE (in blue) overperforms the model No Concept Loss + L_1 (in green) on both output and a posteriori concept accuracies, and achieve output accuracy comparable to Lei et al. (2016) (orange line) while having 60% a posteriori concept accuracy.

Class Business:	*sports retailer jjb yesterday reported a near 25 drop in profits and continuing poor sales , and ended shareholders #39 hopes of a takeover by announcing that a potential bidder had walked away .*
Class World:	*bangkok , thailand sept . 30 , 2004 - millions of volunteers led by emergency teams fanned out across thailand on thursday in a new drive to fight bird flu after the prime minister gave officials 30 days to eradicate the epidemic .*
Class Sports:	*the spanish government responded to diplomatic pressure from britain yesterday by starting a search for fans who racially abused england players during a quot friendly quot football match with spain .*
Class Sci/Tech:	*los angeles (reuters) - a group of technology companies including texas instruments inc . <lt txn . n>gt , stmicroelectronics <lt stm . pa>gt and broadcom corp . <lt brcm . o>gt , on thursday said they will propose a new wireless networking standard up to 10 times the speed of the current generation .*

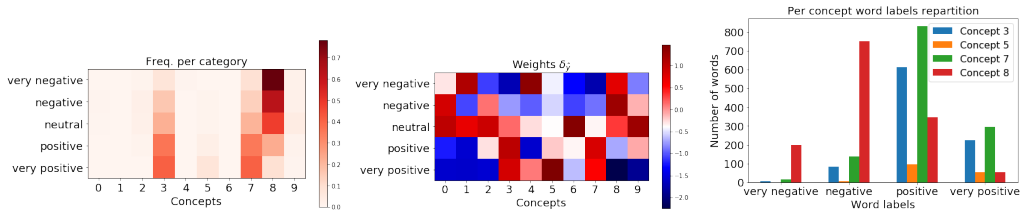
(a) AGNews test examples correctly classified by EDUCE. Underlined set of words are excerpts extracted, one color per concept.

Concept 0	software services giant / moonwalk to home / video display chip / downloading music .
Concept 1	upcoming my prerogative video / his ever-growing swimming / launch of a video display chip / illegality of downloading
Concept 2	oil market . / oil giant sibneft / oil prices and / corp . <lt brcm
Concept 4	cash settlement of up to #36 50 million / six-year deal worth about $40 million / the dollar dipped to a four-week low against the euro / five shares ,
Concept 6	olympic 100-meter freestyle / sox ' family / olympics should help / athletes were already
Concept 8	frail pope john paul / indian army major shot / unions representing workers / goverment representatives .

(b) Examples of excerpts that are extracted **accross the test set**, corresponding to the concepts detected in Figure 3a. Colors match the colors used in Figure 3a.

Figure 3: Interpretation of EDUCE prediction through concept analysis.

Figure 4a shows the empirical frequency of presence of each concept, per output class in the SST dataset, using $\lambda = 0.1$ and $C = 10$ concepts. We see that concepts 3, 5 and 7 are often triggered when a sample is positive or very positive, and on the opposite concept 8 is present in negative/very negative texts. The values of weight matrix δ of the output classifier in Figure 4b proves that the presence of these concepts is responsible for the output classifier's prediction. We can further analyze the concepts: Each word in SST sentences is annotated with a label for the sentiment it expresses, referred to as *word label*. We do not use them during training or validation, but at test-time this allows us to analyze the repartition of words labels in the set of excerpts extracted for each concept. Figure 4c shows that indeed the excerpts selected for concepts 3, 5 and 7 are mostly composed of positive or very positive words, and the excerpts extracted when concept 8 is triggered are mostly composed of negative or very negative words[2].



(a) Per class concept frequency. (b) Output classifier weight matrix δ. (c) Repartition of words labels for concepts 3, 5, 7 and 8.

Figure 4: Analysis of concepts on SST.

5 Multi aspect Sentiment Analysis experiment

BeerAdvocate dataset While our paradigm is different than Lei et al. (2016); Bastings et al. (2019), we also perform a multi-aspect sentiment regression experiment on the pre-processed subset of the BeerAdvocate[3] dataset (McAuley et al., 2012). It consists of $260,000$ beer reviews where ratings

[2]We do not show the amount of neutral words selected as it squeezes the histograms.

[3]https://www.beeradvocate.com/

for four aspects (look, smell, palate and taste) are given, as well as an overall rating. The reviews are separated into training/validation sets specific to each aspect, and ratings are mapped to scalars in $[0, 1]$. This is a regression task, so we modify the Baseline model and EDUCE in the last layer of the prediction with a sigmoid activation function, and use Mean Squared Error (MSE) instead of cross-entropy for $\mathcal{L}^{output}(y, \boldsymbol{z}(x), \delta)$. McAuley et al. (2012) provided a test set (994 reviews) with sentence-level rationale annotations: different parts of each review are annotated with one (or multiple) aspect label, indicating what aspect it covers (referred to as gold rationales). Importantly, we do not use these gold rationales during training or validation, but use to evaluate our model. Hyperparameters selection is similar to our classification experiments.

We train EDUCE on the prediction of the 5-values vector at once (4 aspects and the overall score, there are therefore 5 scalar ratings to predict) using the $260,000$ reviews. We compare EDUCE's performance with the Baseline that accesses the full text. The test MSE is 0.0089 ± 0.0 (mean and SEM accross training seeds) for the Baseline model and 0.0119 ± 0.0 for EDUCE using $\lambda = 0.01$ and $C = 10$ concepts, with a corresponding concept accuracy of 92.8 ± 0.7. Of specific interest to us is the per-concept precision of gold rationales and the total percentage of selected words. Indeed, Table 3 shows that when predicting the 4 aspects and the overall score, some concepts are capturing a specific aspect: for example, the precision of Concept 7 on the Appearance aspect is 97.09%. This is confirmed by Table 2 that shows that excerpts extracted for Concept 7 are mostly related to the color and head (the frothy foam on top of beer) of the beer[4]. Supplementary Table 5 reports examplar excerpts for all concepts.

Concept 0	fruity esters , and/ fruits , caramelized pecans , and/ toffee and caramel accents ,/ coffee and chocolate flavors/ earthy hop resin .
Concept 2	creamy and a/ chewy and rich and drinkability/ creamy mouthfeel that/ smooth and just velvety on the/ thick , and
Concept 3	rich malt scents/ aroma is quite hoppy with big citrus/ tons of different sweet malts , toffe/ smells extremely roasty/ boom of grapefruity
Concept 7	good head and lacing/ beautiful golden-amber color/ creamy tan head/ nice deep brown color/ proud head has settled . nothing
Concept 9	carbonation is graceful/ drinkability is excellent/ mouthfeel is wonderful/ mouthfeel is exemplary/ drinkability : excellent

Table 2: Examples of excerpts extracted on the Beer test set.

Concept	Appearance	Smell	Palate	Taste
Concept 0	0.85	**55.75**	1.79	40.60
Concept 1	0.54	5.48	11.70	30.58
Concept 2	1.22	0.90	**78.18**	15.03
Concept 3	1.46	**92.39**	0.30	5.34
Concept 4	45.33	0.23	0.26	0.16
Concept 5	7.27	22.50	2.27	28.86
Concept 6	0.36	5.86	6.40	28.73
Concept 7	**97.09**	0.98	0.45	0.53
Concept 8	0.18	0.09	18.07	5.93
Concept 9	0.00	0.00	**68.42**	10.53

Table 3: Per-concept precision of gold rationales (in % for each aspect), trained to predict all 4 aspects and the overall score. In bold we emphasize the concepts which precision is above 50% for an aspect's gold rationales.

As in Lei et al. (2016); Bastings et al. (2019) we also train EDUCE on the prediction of each of the first three aspects separately. Supplementary Table 6 reports the precision of gold rationales for each aspect. While the results are less convincing than the models specifically designed for this task, extracted excerpts match gold rationales to a certain extent.

6 Discussion and perspectives

We propose a new self-interpretable model, EDUCE, that maps inputs to an easy-to-interpret representation on which the output prediction relies. We experimentally demonstrate its ability (i) to extract semantically meaningful concepts described by consistent excerpts, and (ii) to ground its output prediction on the presence/absence of these concepts in each input. EDUCE generates relevant explanations while retaining high predictive performance. As future direction for research, we contemplate using hierarchical representations, as human notions can often be represented with hierarchical structures, for example as in WordNet (Miller, 1995). Furthemore, our principles can be applied on different types of inputs like images, and we provide initial experiment in Supplementary Section D.

[4]Tables 3 and 2 reports results of the best seed for the cross-validated hyperparameters.

REFERENCES

Stephan Alaniz and Zeynep Akata. XOC: explainable observer-classifier for explainable binary decisions. *CoRR*, abs/1902.01780, 2019. URL http://arxiv.org/abs/1902.01780.

David Alvarez Melis and Tommi Jaakkola. Towards robust interpretability with self-explaining neural networks. In S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett (eds.), *Advances in Neural Information Processing Systems 31*, pp. 7775–7784. 2018.

David Alvarez-Melis and Tommi S. Jaakkola. A causal framework for explaining the predictions of black-box sequence-to-sequence models. In *EMNLP*, pp. 412–421. Association for Computational Linguistics, 2017.

Sebastian Bach, Alexander Binder, Grégoire Montavon, Frederick Klauschen, Klaus-Robert Müller, and Wojciech Samek. On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. *PLoS ONE*, 10(7):e0130140, 07 2015. doi: 10.1371/journal.pone.0130140.

Joost Bastings, Wilker Aziz, and Ivan Titov. Interpretable neural predictions with differentiable binary variables, 2019.

Yoshua Bengio, Aaron Courville, and Pascal Vincent. Representation learning: A review and new perspectives. *IEEE Trans. Pattern Anal. Mach. Intell.*, 35(8), August 2013a.

Yoshua Bengio, Nicholas Léonard, and Aaron C. Courville. Estimating or propagating gradients through stochastic neurons for conditional computation. abs/1308.3432, 2013b. URL http://arxiv.org/abs/1308.3432.

David M. Blei, Andrew Y. Ng, Michael I. Jordan, and John Lafferty. Latent dirichlet allocation. *Journal of Machine Learning Research*, 3:2003, 2003.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 2019.

Yash Goyal, Ziyan Wu, Jan Ernst, Dhruv Batra, Devi Parikh, and Stefan Lee. Counterfactual visual explanations, 2019.

Edouard Grave, Piotr Bojanowski, Prakhar Gupta, Armand Joulin, and Tomas Mikolov. Learning word vectors for 157 languages. In *Proceedings of the International Conference on Language Resources and Evaluation (LREC 2018)*, 2018.

Kaggle. Kaggle dogs vs cats dataset, 2013.

Been Kim, Martin Wattenberg, Justin Gilmer, Carrie J. Cai, James Wexler, Fernanda B. Viégas, and Rory Sayres. Interpretability beyond feature attribution: Quantitative testing with concept activation vectors (TCAV). In *Proceedings of the 35th International Conference on Machine Learning,ICML*, pp. 2673–2682, 2018.

Diederik Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *International Conference on Learning Representations*, 12 2014.

Jens Lehmann, Robert Isele, Max Jakob, Anja Jentzsch, Dimitris Kontokostas, Pablo N. Mendes, Sebastian Hellmann, Mohamed Morsey, Patrick van Kleef, Sören Auer, and Christian Bizer. DBpedia - a large-scale, multilingual knowledge base extracted from wikipedia. *Semantic Web Journal*, 6(2):167–195, 2015.

Tao Lei, Regina Barzilay, and Tommi Jaakkola. Rationalizing neural predictions. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pp. 107–117, Austin, Texas, November 2016. Association for Computational Linguistics. doi: 10.18653/v1/D16-1011.

Julien Mairal, Francis Bach, Jean Ponce, and Guillermo Sapiro. Online learning for matrix factorization and sparse coding. *JMLR*, 11, March 2010.

Julian McAuley, Jure Leskovec, and Dan Jurafsky. Learning attitudes and attributes from multi-aspect reviews. In *Proceedings of the 2012 IEEE 12th International Conference on Data Mining*, ICDM '12, pp. 1020–1025, Washington, DC, USA, 2012. IEEE Computer Society. ISBN 978-0-7695-4905-7. doi: 10.1109/ICDM.2012.110.

George A. Miller. Wordnet: A lexical database for english. *Commun. ACM*, 38(11):39–41, 1995. ISSN 0001-0782.

Jeffrey Pennington, Richard Socher, and Christopher D. Manning. Glove: Global vectors for word representation. 2014.

Eleanor Quint, Garrett Wirka, Jacob Williams, Stephen Scott, and N.V. Vinodchandran. Interpretable classification via supervised variational autoencoders and differentiable decision trees, 2018.

Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. "Why Should I Trust You?": Explaining the predictions of any classifier. In *Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '16. ACM, 2016.

Avanti Shrikumar, Peyton Greenside, and Anshul Kundaje. Learning important features through propagating activation differences. *CoRR*, abs/1704.02685, 2017.

K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014.

Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. Deep inside convolutional networks: Visualising image classification models and saliency maps. *ICLR Workshop Track*, 2014.

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pp. 1631–1642, Seattle, Washington, USA, October 2013. Association for Computational Linguistics.

Mukund Sundararajan, Ankur Taly, and Qiqi Yan. Axiomatic attribution for deep networks. In *Proceedings of the 34th International Conference on Machine Learning*, ICML, 2017.

Richard S. Sutton and Andrew G. Barto. *Introduction to Reinforcement Learning*. MIT Press, Cambridge, MA, USA, 1st edition, 1998. ISBN 0262193981.

C. Wah, S. Branson, P. Welinder, P. Perona, and S. Belongie. The Caltech-UCSD Birds-200-2011 Dataset. Technical Report CNS-TR-2011-001, California Institute of Technology, 2011.

Mo Yu, Shiyu Chang, and Tommi S Jaakkola. Learning corresponded rationales for text matching, 2019. URL `https://openreview.net/forum?id=rklQas09tm`.

Manzil Zaheer, Amr Ahmed, and Alexander Smola. Latent lstm allocation: Joint clustering and non-linear dynamic modeling of sequence data. 2017.

Xiang Zhang and Yann LeCun. Text understanding from scratch. *CoRR*, abs/1502.01710, 2015. URL `http://arxiv.org/abs/1502.01710`.

Xiang Zhang, Junbo Zhao, and Yann LeCun. Character-level convolutional networks for text classification. In *Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 1*, NIPS'15, pp. 649–657, Cambridge, MA, USA, 2015. MIT Press.

A Details on the learning algorithm

As mentioned in our main paper, when computing Equation 5 the cross-entropy losses of the output classifier and concept classifier are differentiable, therefore the gradients with respect to the weights δ and θ can be computed. However, the gradients with respect to the parameters of the LSTM (γ) and the Bernouilli distribution over presence of concepts (α) pose a difficulty because we sample $\forall c\ s_c(x) \sim p_\gamma(s|x, c)$ and $\forall c\ z_c \sim p_\alpha(z_c|s_c(x), c)$.

We use straight-through estimator (Bengio et al., 2013b) in the backward pass for the parameters α, and resort to Monte-Carlo approximations of the gradient employed in Reinforcement Learning (Sutton & Barto, 1998) for the parameters γ. The loss $\mathcal{L}(x)$ serves as reinforcement signal. We weight the two terms of the gradient using a parameter r as follows:

$$\nabla_{\delta,\theta,\gamma,\alpha}\mathcal{L}(x) \widehat{=} (1-r)\nabla_{\delta,\theta,\alpha}\mathcal{L}(x) + r\mathbb{E}_{s(x)\sim p_\gamma}[(\mathcal{L}(x)-b)\nabla_\gamma \log p_\gamma(s(x)|x)] \tag{7}$$

where r controls the strength of the Reinforcement Learning term and b is the average of the loss, used as control variate.

B EXPERIMENTAL DETAILS AND DETAILED RESULTS.

We monitor validation performance and use early stopping. For the comparative models we monitor the output prediction accuracy. For EDUCE we monitor the sum of the output prediction accuracy and the concept classifier accuracy (weighted by the parameter λ).

B.1 HYPERPARAMETERS CONSIDERED

In all experiment, we increase the value of λ by 10% every epoch. In order to choose the best set of hyperparameters, we take the average value on the 5 random seeds.

DBPedia and AGNews We try the following ranges of hyperparameters $\lambda \in \{0.0, 0.001, 0.01, 0.1\}$, $\lambda_{L1} = \{0.0, 0.001, 0.01, 0.1, 1\}$, $r \in \{0.01, 0.1\}$, learning rate $lr = \{0.0005, 0.001\}$. The hidden state of the LSTM is of size 200. We use Adam optimizer (Kingma & Ba, 2014), batches of size 64. For the Baseline model, we try adding weight decay in $\{0.0, 1e-6\}$ and dropout in $\{0.0, 0.1, 0.2\}$.

SST We try the following ranges of hyperparameters $\lambda \in \{0.0, 0.001, 0.01, 0.1\}$, $\lambda_{L1} = \{0.0, 0.001, 0.01, 0.1, 1\}$, $r \in \{0.01, 0.1\}$, learning rate $lr = \{0.0002, 0.001\}$ and weight decay in $\{0.0, 1e-6\}$. The hidden state of the LSTM is of size 150. We use Adam optimizer (Kingma & Ba, 2014), batches of size 25. For the Baseline model, we follow Bastings et al. (2019) and use weight decay $1e-6$ and dropout $\{0.5\}$.

BEER We try the following ranges of hyperparameters $\lambda \in \{0.001, 0.01, 0.1\}$, $r \in \{0.001, 0.01, 0.1\}$, learning rate $lr = \{0.0005, 0.001\}$. The hidden state of the LSTM is of size 200. We use Adam optimizer (Kingma & Ba, 2014), batches of size 256. We also clip the gradient to the value of 1 and employ an entropy maximization regularization on mean of the Bernoulli distributions $\forall c, p_\alpha(z_c|s_c(x), c)$, weighted by 0.001. We train all models for 250 epochs and use early stopping on the validation set. For the Baseline model on the BEER dataset, we use the same hyperparameters as in Bastings et al. (2019) ($lr = 0.0004$, hidden dimension 200, dropout in $\{0.1, 0.2\}$ and weight decay $1e-6$) and train for 100 epochs.

B.1.1 DETAILED RESULTS ON AGNEWS AND DBPEDIA

Table 4 details output accuracy, a posteriori concept accuracy, and sparsity (number of concepts presents per input) for different values of λ and λ_{L_1} considered.

B.2 ADDITIONAL RESULTS ON BEER

As in Lei et al. (2016); Bastings et al. (2019), we also train EDUCE on the prediction of each of the first three aspects (the 4th aspect they do not experiment on)[5]. Table 6 reports the precision of gold rationales for that aspect and the total percentage of selected words, values for Lei et al. (2016); Bastings et al. (2019) are taken from Bastings et al. (2019). We use $C = 10$ and $\lambda = 0.1$. We consider a word as selected if any of the concept selects it, and count it as one selected even if it is selected by multiple concepts. While the results are less convincing than the aforementioned rationales models that are specifically designed for this task, we see that extracted excerpts match gold rationales to a certain extent, especially for the aspects Appearance and Smell. For the Palate aspect, manual inspection shows us that for some seeds, the model defines a concept dedicated to the notion of numbers (e.g. corresponding to excerpts "12 ounce bottle") that is consistent, yet not part of the gold rationale.

[5]Bastings et al. (2019) call the third aspect Taste but they actually refer to Palate.

Dataset	Model	Output Acc. (%)	A Posteriori Concept Acc. (%)	Sparsity
DBPEDIA	Baseline	98.75 ± 0.0	n/a	n/a
	No Concept Loss	97.4 ± 0.1	25.9 ± 0.6	5.51 ± 0.1
	EDUCE $\lambda = 0.001$	97.3 ± 0.1	28 ± 1.7	5.60 ± 0.1
	EDUCE $\lambda = 0.01$	97.3 ± 0.1	39 ± 3.5	5.39 ± 0.1
	EDUCE $\lambda = 0.1$	97.0 ± 0.1	82.4 ± 0.8	3.5 ± 0.2
	No Concept Loss + L_1, $\lambda_{L_1} = 0.001$	97.4 ± 0.1	27 ± 1.9	5.5 ± 0.1
	No Concept Loss + L_1, $\lambda_{L_1} = 0.01$	97.46 ± 0.1	28 ± 2.1	5.12 ± 0.0
	No Concept Loss + L_1, $\lambda_{L_1} = 0.1$	96.5 ± 0.2	44 ± 2.6	3.1 ± 0.1
	No Concept Loss + L_1, $\lambda_{L_1} = 1.00$	84 ± 2.0	77 ± 2.4	1.31 ± 0.0
AGNews	Baseline	92.08 ± 0.1	n/a	n/a
	No Concept Loss	88.2 ± 0.1	31.0 ± 0.7	5.2 ± 0.2
	EDUCE $\lambda = 0.001$	88.4 ± 0.1	33 ± 1.6	5.2 ± 0.2
	EDUCE $\lambda = 0.01$	88.6 ± 0.1	40 ± 2.1	4.6 ± 0.2
	EDUCE $\lambda = 0.1$	87.5 ± 0.2	78 ± 6.5	2.4 ± 0.2
	No Concept Loss + L_1, $\lambda_{L_1} = 0.001$	88.3 ± 0.2	31.6 ± 0.7	5.1 ± 0.2
	No Concept Loss + L_1, $\lambda_{L_1} = 0.01$	88.7 ± 0.2	34 ± 1.4	4.6 ± 0.2
	No Concept Loss + L_1, $\lambda_{L_1} = 0.1$	86.3 ± 0.7	56 ± 3.2	2.2 ± 0.1
	No Concept Loss + L_1, $\lambda_{L_1} = 1.00$	53 ± 3.2	89 ± 2.8	0.50 ± 0.0

Table 4: Test performance on DBPedia and AGNews (mean $\pm$ SEM) for all values of λ and λ_{L_1}.

Concept 0	fruity esters , and/ fruits , caramelized pecans , and/ toffee and caramel accents ,/ coffee and chocolate flavors/ earthy hop resin .
Concept 1	delicious and with/ enjoyed this beer/ damn good beer/ nice stout that/ good beer to
Concept 2	creamy and a/ chewy and rich and drinkability/ creamy mouthfeel that/ smooth and just velvety on the/ thick , and
Concept 3	rich malt scents/ aroma is quite hoppy with big citrus/ tons of different sweet malts , toffe/ smells extremely roasty/ boom of grapefruity
Concept 4	octoberfest : say the word and you probably/ 2004 vintage : pours/ 12 ounce bottle acquired in a trade/ i hate to be the guy/ 12oz bottle , best before 9/09 , sampled 5/16/09
Concept 5	which is fantastic/ it is delicious/ is intensely packed/ and a lovely/ builds a wonderful
Concept 6	'm really digging/ a damn good/ a super fresh growler/ the better abitas/ a great traditional
Concept 7	good head and lacing/ beautiful golden-amber color/ creamy tan head/ nice deep brown color/ proud head has settled . nothing
Concept 8	easy to drink/ hot summer day/ drinkability easy/ easy to down/ can easily turn this 'strong ale ' into a session
Concept 9	carbonation is graceful/ drinkability is excellent/ mouthfeel is wonderful/ mouthfeel is exemplary/ drinkability : excellent

Table 5: Examples of excerpts extracted on the Beer test set.

Model	Appearance		Smell		Palate	
	Prec.	Extr.	Prec.	Extr.	Prec.	Extr.
EDUCE	81 ± 6.9	4.9 ± 0.5	79 ± 3.1	4.8 ± 0.4	50 ± 6.6	4.1 ± 0.6
Lei et al. (2016)	96.3	14	95.1	7	80.2	7
Bastings et al. (2019)	98.1	13	96.8	7	89.8	7

Table 6: Precision (Prec., in %) of gold rationales and percentage of extracted text (Extr. in %) when trained separately on each aspect.

C Additional qualitative examples on DBPedia and AGNews

Class Sports:	*just imagine what david ortiz could do on a good night ' s rest . ortiz spent the night before last with his baby boy , d ' angelo , who is barely 1 month old . he had planned on attending the red sox ' family day at fenway park yesterday morning , but he had to sleep in . after all , ortiz had a son at home , and he . . .*
Class Sports:	*foxborough – looking at his ridiculously developed upper body , with huge biceps and hardly an ounce of fat , it ' s easy to see why ty law , arguably the best cornerback in football , chooses physical play over finesse . that ' s not to imply that he ' s lacking a finesse component , because he can shut down his side of the field much as deion sanders . . .*
Class Sports:	*ap - american natalie coughlin won olympic gold in the 100-meter backstroke monday night . coughlin , the only woman ever to swim under 1 minute in the event , finished first in 1 minute , 0 . 37 seconds . kirsty coventry of zimbabwe , who swims at auburn university in alabama , earned the silver in 1 00 . 50 . laure manaudou of france took bronze in 1 00 . 88 .*
Class World:	*lourdes , france - a frail pope john paul ii , breathing heavily and gasping at times , celebrated an open-air mass on sunday for several hundred thousand pilgrims , many in wheelchairs , at a shrine to the virgin mary that is associated with miraculous cures . at one point he said help me in polish while struggling through his homily in french . . .*
Class World:	*najaf , iraq - explosions and gunfire rattled through the city of najaf as u . s . troops in armored vehicles and tanks rolled back into the streets here sunday , a day after the collapse of talks - and with them a temporary cease-fire - intended to end the fighting in this holy city . . .*
Class World:	*kabul , afghanistan - government troops intervened in afghanistan ' s latest outbreak of deadly fighting between warlords , flying from the capital to the far west on u . s . and nato airplanes to retake an air base contested in the violence , officials said sunday . . .*
Class Business:	*london (reuters) - the dollar dipped to a four-week low against the euro on monday before rising slightly on profit-taking , but steep oil prices and weak u . s . data continued to fan worries about the health of the world ' s largest economy .*
Class Business:	*new york (reuters) - the dollar extended gains against the euro on monday after a report on flows into u . s . assets showed enough of a rise in foreign investments to offset the current account gap for the month .*
Class Business:	*reuters - apparel retailers are hoping theirback-to-school fashions will make the grade amongstyle-conscious teens and young adults this fall , but it couldbe a tough sell , with students and parents keeping a tighterhold on their wallets .*

Table 7: AGNews test examples correctly classified by EDUCE. Underlined set of words are excerpts extracted, one color per concept.

Concept 0	software services giant / moonwalk to home / video display chip / downloading music .
Concept 1	upcoming my prerogative video / his ever-growing swimming / launch of a video display chip / illegality of downloading
Concept 2	oil market . / oil giant sibneft / oil prices and / ipos . public
Concept 3	100-meter freestyle preliminaries tuesday , a stunning blow for a / the red sox ' family day at / the winner . / entire era .
Concept 4	cash settlement of up to #36 50 million / six-year deal worth about $40 million / the dollar dipped to a four-week low against the euro / five shares ,
Concept 5	york , light / boston and texas / london (reuters / newsday #146 s
Concept 6	olympic 100-meter freestyle / sox ' family / olympics should help / athletes were already
Concept 7	gunfire rattled through the / election . on / democratic coordination or cd as the / wiretapping internet phones to monitor criminals and terrorists is
Concept 8	frail pope john paul / indian army major shot / unions representing workers / goverment representatives .
Concept 9	lourdes , france / ap - american natalie / new york - / ap - it

Table 8: Examples of excerpts that are extracted on AGNews for all 10 concepts. Colors match the colors used in Table 7.

Class Company:	*transurban manages and develops urban toll road networks in australia and north america . it is a top 50 company on the australian securities exchange (asx) and has been in business since 1996 . in australia transurban has a stake in five of sydney ' s nine motorways and in melbourne it is the full owner of citylink which connects three of the city ' s major freeways . in the usa transurban has ownership interests in the 495 express lanes on a section of the capital beltway around washington dc .*
Class Animal:	*the red-necked falcon or red-headed merlin (falco chicquera) is a bird of prey in the falcon family . this bird is a widespread resident in india and adjacent regions as well as sub-saharan africa . it is sometimes called turumti locally . the red-necked falcon is a medium-sized long-winged species with a bright rufous crown and nape . it is on average 30–36 cm in length with a wingspan of 85 cm . the sexes are similar except in size males are smaller than females as is usual in falcons .*
Class Plant:	*astroloma is an endemic australian genus of around 20 species of flowering plants in the family ericaceae . the majority of the species are endemic in western australia but a few species occur in new south wales victoria tasmania and south australia . species include astroloma baxteri a . cunn . ex dc . astroloma cataphractum a . j . g . wilson ms astroloma ciliatum (lindl .) druce astroloma compactum r . br . astroloma conostephioides (sond .) f . muell . ex benth .*
Class Album:	*stars and hank forever was the second (and last) release in the american composers series by the avant garde band the residents . the album was released in 1986 . this particular release featured a side of hank williams songs and a medley of john philip sousa marches . this was also the last studio album to feature snakefinger . kaw-liga samples the rhythm to michael jackson ' s billie jean and did well in europe it is as close as the residents ever got to a bona fide commercial hit .*
Class Written Work:	*fire ice is the third book in the numa files series of books co-written by best-selling author clive cussler and paul kemprecos and was published in 2002 . the main character of this series is kurt austin . in this novel a russian businessman with tsarist ambitions masterminds a plot against america which involves triggering a set of earthquakes on the ocean floor creating a number of tsunami to hit the usa coastline . it is up to kurt and his team and some new allies to stop his plans .*
Class Educational Inst.:	*avon high school is a secondary school for grades 9-12 located in avon ohio . its enrollment neared 1000 as of the 2008-2009 school year with a 2008 graduating class of 215 . the school colors are purple and gold . the school mascot is an eagle . the avon eagles are part of the west shore conference . they will be moving to the southwestern conference beginning in the 2015-2016 school year .*
Class Artist:	*vicky hamilton (born april 1 1958) is an american record executive personal manager promoter and club booker writer (journalist playwright and screenwriter) documentary film maker and artist . hamilton is noted for managing the early careers of guns n ' roses poison and faster pussycat for being a management consultant for mötley crüe and stryper a 1980s concert promoter on the sunset strip and a club booker at bar sinister from 2001 to 2010 . [...]*
Class Athlete:	*james jim arthur bacon (birth registered october–december 1896 in newport district — death unknown) was a welsh rugby union and professional rugby league footballer of the 1910s and ' 20s and coach of the 1920s playing club level rugby union (ru) for cross keys rfc and representative level rugby league (rl) for great britain and wales and at club level for leeds as a wing or centre i . e . number 2 or 5 or 3 or 4 and coaching club level rugby league (rl) for castleford .*
Class Office Holder:	*jonathan david morris (october 8 1804 - may 16 1875) was a u . s . representative from ohio son of thomas morris and brother of isaac n . morris . born in columbia hamilton county ohio morris attended the public schools . he studied law . he was admitted to the bar and commenced practice in batavia ohio . he served as clerk of the courts of clermont county . morris was elected as a democrat to the thirtieth congress to fill the vacancy caused by the death of thomas l .*
Class Mean Of Transp.:	*german submarine u-32 was a type viia u-boat of nazi germany ' s kriegsmarine during world war ii . her keel was laid down on 15 march 1936 by ag weser of bremen as werk 913 . she was launched on 25 february 1937 and commissioned on 15 april with kapitänleutnant (kptlt .) werner lott in command . on 15 august 1937 lott was relieved by korvettenkapitän (krv . kpt .) paul büchel and on 12 february 1940 oberleutnant zur see (oblt . z . s .) hans jenisch took over he was in charge of the boat until her loss .*
Class Building:	*the tootell house (also called king ' s row or hedgerow) is a house at 1747 mooresfield road in kingston rhode island that is listed on the national register of historic places . the two-story wood-shingled colonial revival house on a 3-acre (12000 m2) tract was designed by gunther and beamis associates of boston for mr . & mrs . f . delmont tootell and was built in 1932-1933 . house design was by john j . g . gunther and elizabeth clark gunther was the landscape architect for the grounds .*
Class Village:	*angamoozhi is a village in pathanamthitta district located in kerala state india . angamoozhi is near seethathodu town . geographically angamoozhi is a high-range area . it is mainly a plantation township . both state run ksrtc and private operated buses connect angamoozhi to pathanamthitta city . tourist can avail the travelling facility by ksrtc service (morning 5 30 from kumili and 11 30 from pathanamthitta) in between kumili and pathanamthitta via vallakkadavu angamoozhi kakki dam and vadaserikkara and can enjoy the beauty of the forest . [citation needed]*

Table 9: DBPedia test examples correctly classified by EDUCE. Underlined set of words are excerpts extracted, one color per concept.

Concept 0	a top 50 company / the regular seasonal movement / the production of port wine / the american composers / a bollywood film / the third book / a secondary school / an american record executive personal manager promoter / a well-known v8 supercars presenter and commentator / a merchant and public official / a type viia u-boat / a house at / the main fort / a major poet
Concept 1	born in philadelphia / tranquil star (foaled / instructional documentary produced / bollywood film released in / nineteenth instalment in / secondary school for / born april 1 1958 / birth registered october–december 1896 / october 8 1804 - may 16 1875 / academy is the volleyball academy of / village in pathanamthitta
Concept 2	(1800–1870) probably born in / (12 april /) release in / is a bollywood film released in / an omnibus release from / a studio school located in / (born april / gunji 8 july / (october 8 1804 - may 16 / an iron collier in / of historic places . / fort (also called
Concept 3	top 50 company / medium-sized long-winged species with a bright rufous crown / endemic australian genus / album was released / bollywood film released / paul kemprecos and was published / inns of court exclusively entitled / debut album explores / lagarto (lizard / hong kong cross-media creator / bird park in / wild blackwater river
Concept 4	beltway around washington dc . / democratic republic of / plants in the / party live in / my texas . / asheville north carolina . / ohio . its / executive . he / democrat to the / south africa . / mooresfield road in kingston rhode island that / north to south . / kerala state india .
Concept 5	is a top 50 company / is a genus of crane fly / is a red portuguese wine grape / is the debut studio record / is an abc family original movie / was a regional fashion entertainment and lifestyle publication / interactive technologies institute / is a beirut-based lebanese haute couture fashion designer / was a montenegrin serb boxer / is the chief technology officer / was a type viia u-boat / of historic places . the two-story wood-shingled / fort (also / is a village
Concept 6	company on the / bird of prey in / apple . in / documentary produced by / film released in / sequel to the / school for grades / animator . he / catcher . he / cross-media creator who / aircraft corporation to / museum was made in
Concept 7	the brands club mahindra holidays club mahindra travel club / a bird of prey in / an endemic australian genus of around / snooker world rankings 1978/1979 the professional world rankings for / a black and white chinese animation short made in / a british rugby league periodical that / a russian youth football academy based in / a turkish cypriot singer and athlete . / a welsh rugby union and professional rugby league footballer of / a planter a confederate cavalry general in / a type viia u-boat of / a volleyball academy . / an uninhabited steep rocky island west of
Concept 8	street sounds was / medium-sized long-winged species with a bright rufous / rataj places it / ep by linkin park / white chinese animation / british schools (/ secondary school for grades / argentine painter of the concretist and cubist schools / eminent anglican priest / hospital ships was built / national register of historic places / uninhabited steep rocky island west / village in pathanamthitta district
Concept 9	translation pension fund for / adaptation which enables / mopeds produced by / instructional documentary produced by / bollywood film released in / book in the / river in kwazulu-natal / memoir of her / boxer in the / presidency of dmitry medvedev began / u-boat of nazi / harbour of helsingør dedicated to / uninhabited steep rocky island west of

Table 10: Examples of excerpts that are extracted on DBPedia for all 10 concepts. Colors match the colors used in Table 9.

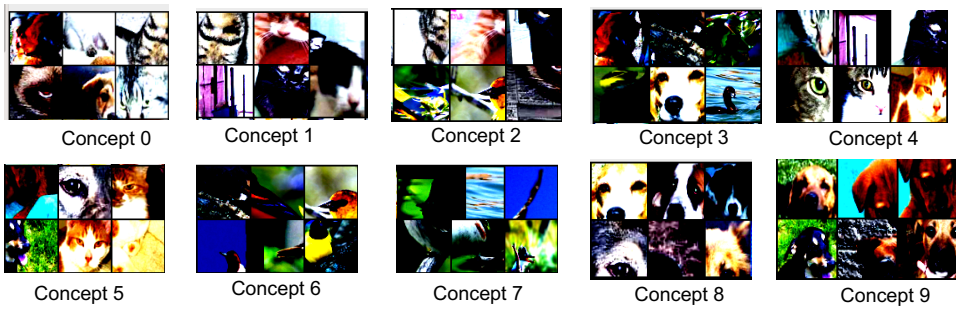


Figure 5: Samples of patterns extracted for each concept in the birds-cats-dogs dataset.

D APPLYING EDUCE PRINCIPLES FOR IMAGE CLASSIFICATION

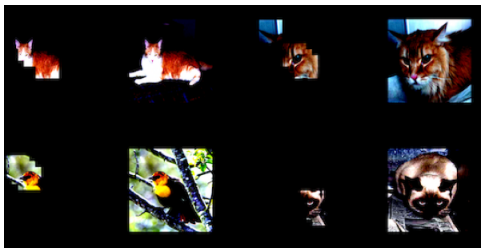
Having assessed the relevance of our model on text data, we now turn to image data and explore if EDUCE is also able to extract meaningful concepts. In that case, the excerpts extracted in textual data are replaced by regions (or patches) in an image, and the recurrent neural architecture processing text is replaced by a classical convolutional neural network.

Principles: Each image x is first encoded through a convolutional neural network that output a representation in $h(x) = \mathbb{R}^{W \times H \times D}$ where D is the number of output filters. Each vector $h_{i,j,.}(x) \in \mathbb{R}^D$ corresponds to a particular region s of the input image (i.e the receptive field of the convolutional neural network). Then each $h_{i,j,.}$ is used to compute $p_\gamma(s|x, c)$ through a linear model and a softmax activation as in Section 2.1 (step 1), and to compute $p_\alpha(z_c = 1|s_c(x), c)$ (Section 2.1, step 2) here again with a linear model and a Bernoulli distribution. The semantics homogeneity is ensured by using an image classification network over the region captured by the receptive field in the previous convolutional neural networks that ensure that all regions captured from a particular concept "look the same" and look differently from the regions captured for other concepts.

Experiments: To ensure the validity of our adaptation of EDUCE to images, we conduct very simple experiments on a dataset composed of 224×224 RGB images split in 3 categories: dogs, cats, and birds[6] in equal proportion. We train on $3,000$ images and test on $3,000$ images. We build our model on top of a pretrained VGG-11 model Simonyan & Zisserman (2014) which is used for computing the intermediate representations $h(x)$. Said otherwise, the output of the VGG-11 model is used for both detecting relevant regions and thus building the binary representation z, but also to ensure the homogeneity of extracted regions during training. Figure 5 shows extracted patterns and associated categories. Final classification performance is 91.6% with 10 concepts. In Figure 5 we plot extracted patterns for the 10 concepts and report in Figure 6a the weights of the final classifier. From these two figures, we can interpret the model's behavior: concept 8 and concept 9 show what differentiates a *dog* from a *cat* or a *bird*, and support the classifier's prediction of the dog category. Moreover, by looking at which regions are extracted by our model (Figure 6b), we can see that EDUCE can focus its attention to discriminative regions of the images.

[6]We construct this dataset by combining random images from the Caltech Bird 200-2011 dataset (Wah et al., 2011) with images of the cats-and-dogs Kaggle dataset (Kaggle, 2013)

(a) Final Classifier weights, each column is a concept (0 to 9, from left to right) each row a final category. The lighter, the higher the weight is. Concepts 6 and 7 are associated to category 'Bird', Concept 1 and 4 to 'Cat' and concepts 8 and 9 to 'Dog'.



(b) Examples of classified images (column 2 and 4) and corresponding extracted patterns (column 1 and 3) for concept detected as present.

Figure 6: Interpretation of EDUCE on images.