Label-Descriptive Patterns and their Application to Characterizing Classification Errors

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Abstract
State-of-the-art deep learning methods achieve human-like performance on many tasks, but make errors nevertheless. Characterizing these errors in easily interpretable terms gives insight into whether a model is prone to making systematic errors, but also gives a way to act and improve the model. In this paper we propose a method that allows us to do so for arbitrary classifiers by mining a small set of patterns that together succinctly describe the input data that is partitioned according to correctness of prediction. We show this is an instance of the more general label description problem, which we formulate in terms of the Minimum Description Length principle. To discover good pattern sets we propose the efficient and hyperparameter-free PREMISE algorithm, which through an extensive set of experiments we show on both synthetic and real-world data performs very well in practice; unlike existing solutions it ably recovers ground truth patterns, even on highly imbalanced data over many unique items, or where patterns are only weakly associated to labels. Through two real-world case studies we confirm that PREMISE gives clear and actionable insight into the systematic errors made by modern NLP classifiers.

1 Introduction

State-of-the-art deep learning methods achieve human-like performance on many tasks. As much as 'to err is human', these models make errors too. Some of these errors are due to noise that is inherent to the process we want to model, and therewith relatively benign. Systematic errors, on the other hand, e.g. those due to bias or misspecification are much more serious as these lead to models that are inherently unreliable. If we know under what conditions a model performs poorly, we can actively intervene, e.g. by augmenting the training data, and so improve overall reliability and performance. Before we can do so, we first need to know whether a model makes systematic errors, and if so, how to characterize them in easily understandable terms.

We propose a method that allows us to do so for arbitrary classification models, simply by partitioning the input data according to correctness of the model's predictions, and then mining those patterns that together describe the partitions most succinctly. As we need to be able to capture subtle yet significant associations, we consider a rich pattern language that allows us to express conjunctions, mutual exclusivity, and nested combinations thereof. This task is an instance of the more general problem of label description, where for given labeled data we are interested in a non-redundant and easily interpretable description of the associations between the data and the given labels. We formulate this problem in terms of the Minimum Description (MDL) length principle, by which we identify the best set of patterns as the one that best compresses the data without loss. As the search space is twice exponential, and does not exhibit any easy-to-exploit structure, we propose the efficient and hyper-parameter-free PREMISE algorithm to heuristically discover the *premises* under which we see the given labels.

The label description problem is obviously related to classification. Here, we however are not so much interested in prediction, but rather description and therewith value interpretability of the results over accuracy. This notion we share with subgroup discovery [1–3], emerging pattern mining [4], and significant pattern mining [5], which aim to discover those conditions under which a target attribute has an exceptional distribution and hence are closely related to finding descriptive rules for the target attribute [6, 7]. The key difference is that we are not interested in discovering *all* patterns that are strongly associated, but rather want a small and non-redundant set of patterns. As such, our approach is an instance of pattern set mining [8–11], but distinct from existing work in the sense that it has to scale to large input domains, discovers noise-robust patterns, considers a richer pattern language, and partitions of the data, all at the same time.

We evaluate PREMISE both on synthetic and real-world data. We show that, unlike the state of the art, PREMISE is robust to noise, scales to large numbers of items, deals well with imbalance, and association to labels. Through two case studies we show that PREMISE discovers patterns that provide clear insight into the systematic errors of NLP classifiers, and, perhaps most

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importantly, are indeed actionable. In particular, we show these patterns elucidate the biases of recent Visual Question Answering (VQA) classifiers, and that we can improve the performance of a neural Named Entity Recognition (NER) model by acting on the patterns PREMISE discovers.

We provide proofs, additional experiments and detail for reproducibility in the Appendix and make our code and data available online.[1]

2 Related Work

Frequent pattern mining was first proposed by Agrawal and Srikant [6], after which research focused on more efficient algorithms [12, 13] and succinct representations [12,14,15],which however yield extremely large and redundant results [8]. Pattern set mining circumvents this by asking for a small *set* of non-redundant patterns that together generalize the data well [16–18]. All of the above are unsupervised in nature, i.e. they do not take label information into account.

Rule mining aims to discover rules of the form $X \to Y$ [6, 7], lending themselves to describe labels, too. Like above, most existing methods evaluate patterns individually, thereby also discovering millions of rules even if the data is pure noise. GRAB [9] instead mines small sets of rules that together summarize the data well, and CLASSY [11] discovers rule lists that characterize a given label. We show that both approaches do not scale well and are sensitive to label imbalancing.

More close to our work is supervised pattern mining, out of which subgroup discovery [1,19,20] and emerging pattern mining [4] are among the most prominent representatives [1]. Whereas emerging pattern mining suffers from similar problems as frequent pattern mining, due to ad-hoc thresholds, subgroup discovery instead follows a top-k approach. This keeps the result sets of manageable size, but does not solve the problem of redundancy [2]. Statistical pattern mining aims to discover patterns that correlate *significantly* to a class label [21–23]. In practice, the multiple hypothesis testing of millions of patterns leads to spurious results, discovering many hundreds of thousands of 'significant' patterns even for small data.

For specific applications, such as characterizing classification errors in NLP models, there exists manual approaches based on challenging test sets [24,25] or testing a hypothetical cause for misclassification [26–28]. Such manual approaches, however, require existing knowledge about the difficulties of the models. In contrast, SliceFinder [29] aims to describe high model loss in terms of data slices, and LIME [30] and ANCHORS [31] analyze and describe the decision boundary of each instance, thus providing only local explanation for individual samples. Furthermore, none of the methods scales well to the data that we consider.

Here, we propose to mine sets of patterns that provide concise, interpretable, and global descriptions of the given label, which we formulate in terms of the MDL principle. We further propose an efficient heuristic to discover such pattern sets in practice, which we test against state-of-the-art across all aforementioned fields on synthethic data with known ground truth, as well as real world case studys. We show that PREMISE is the only approach to be scalable and robust to noise and label imbalancing while retrieving succinct pattern sets, all of which is crucial to solve real world applications.

3 Preliminaries

In this section, we introduce the notation we use throughout the paper and give a brief primer to MDL.

3.1 Notation We consider binary transaction data D over a set of items $\mathcal{I}$, where each transaction $t \in D$ is assigned a binary label $\ell(t) \in \{l_-, l_+\}$. For ease of notation, we define the partition of the database according to this binary label $D^- = \{t \in D \mid \ell(t) = l_-\}$ and $D^+ = \{t \in D \mid \ell(t) = l_+\}$. In general, $X \subseteq \mathcal{I}$ denotes an itemset, the set of transactions that contain X is defined as $T_X = \{t \in D \mid X \subseteq t\}$. The projection of D on an itemset X is $\pi_X(D) = \{t \cap X \mid t \in D\}$.

For a logical condition c, we define a selection operator as $\sigma_c(D) = \{t \in D \mid c(t) \equiv \top\}$. For an item $I \in \mathcal{I}$, it holds that $[c_I(t) \equiv \top \leftrightarrow I \in t]$. The k-ary AND operator $\bigwedge(c_1, \ldots, c_k)$ describes patterns of co-occurrence and holds iff all its conditions hold.Similarly, the k-ary XOR operator $\bigotimes$ describes patterns of mutual exclusivity and holds if exactly one of its condition holds. We denote $it(c)$ for the items in the condition and define the projection on a condition as $\pi_c(D) = \pi_{it(c)}(D)$. Conditions can be nested; specifically we are interested in patterns of AND operator over XOR operations, i.e. $\bigwedge(\bigotimes_{c_1,\ldots,c_k}, \ldots, \bigotimes_{c'_1,\ldots,c'_k})(t)$. An XOR operation is called clause, $\gamma(c)$ lists all clauses in conjunctive condition c. To simplify notation, we drop t where it is clear from context and write I for conditions on a single item $c(I)$. In the text below, we use condition and pattern interchangeably.

3.2 Minimum Description Length The Minimum Description Length (MDL) principle [32] is a practical approximation of Kolmogorov complexity [33] that is both statistically well-founded and computable. It identifies the best model M^* for data D out of a class of models $\mathcal{M}$ as the one that obtains the maximal

[1] https://bit.ly/39TAl7a

lossless compression. For refined, or one-part, MDL, the length of the encoding in bits is obtained using the entire model class $L(D|\mathcal{M})$. While this variant of MDL provides strong optimiality guarantess [34], it is only attainable for certain model classes. In practice, crude two-part MDL is often used, which computes the length of the model encoding $L(M)$ and the length of the description of the data given the model $L(D|M)$ separately. The total length of the encoding is then given as $L(M) + L(D|M)$. We use one-part MDL where possible and two-part MDL otherwise. Here, we are only interested in the codelengths and not the actual codes. Codelengths are measured in bits, hence all log operations are base 2 and we define $0 \log 0 = 0$.

4 Theory

To discover those patterns best describing the given labels, we here introduce the class of models $\mathcal{M}$ and corresponding codelength functions. Before we define these formally, we give the intuition.

4.1 The Problem, informally Given a dataset of binary transaction data and corresponding binary labels, we aim to find a set of patterns that together identify the partitioning of the data according to the labels. As an application, consider the input words of an NLP task as transactions, along with labels that express whether an instance is misclassified by a given model. We are now interested in patterns of words that describe these labels. In essence, we want to find word combinations such as $\bigwedge$(*how, many*), or mutual exclusive patterns, e.g. $\otimes$(*color, colour*), that capture synonyms or different writing styles, all occuring predominantly when a misclassifcation happens. The pattern language we use is a combination of the two, namely conjunctions of mutual exclusive clauses, e.g. $\bigwedge$(*what*, $\otimes$(*color, colour*)). We provide an example in Figure 1.

We thus define a model $M \in \mathcal{M}$ as the set of patterns $\mathcal{P}$ that help to describe given labels. Additionally, to ensure that we can always encode any data, M contains all singleton words $I \in \mathcal{I}$, describing the entire data D label unspecific. The model containing all singletons also acts as a baseline implementing the assumption that there are no associations that describe the label. Whenever there is a structure in the labels that can be explained by a pattern, we transmit data corresponding to a label (D^+, D^-) separately. This allows us to more succinctly transmit where patterns hold.

Let us consider the example in Figure 1, where we would first send $\bigwedge(A, \otimes(B, C))$ occurrences in D^+, and then its occurrences in D^-. Thus, we identify where A, C, and D hold at once, and we leverage the fact that $\bigwedge(A, \otimes(B, C))$ occurs predominantly in D^+, resulting

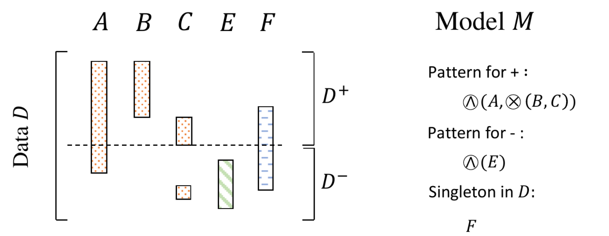


Figure 1: *Example database and model.* A toy database D over a set of items, separated by labels into D^+ and D^-, is given on the left. The corresponding model M containing patterns describing data partitions D^- and D^+ induced by labels l_- and l_+, is given on the right.

in more efficient transmission. Intuitively, a bias of a pattern to occur in one label more than in the other corresponds to a large deviation between the conditional probability – the pattern occurrence conditioned on the label – and the unconditional probability – the pattern occurence in the whole database. In this case, the codes are hence more efficient when sending pattern separately for D^+ and D^-. Coming back to the example, F however occurs similarly often in both labels – there is almost no deviation between conditional and unconditional probability – hence it is unlikely that it identifies a structural error. Here, the baseline encoding transmitting F as singleton in all of D will be most efficient. This approach allows us to identify patterns that occur predominantly for one of the labels as the patterns that yield better compression when conditioned on the labels, and thus characterise labels in easily understandable terms.

We are hence after the model $M^* \in \mathcal{M}$ that minimizes the cost of transmitting the data and model. In the following sections, we will formalize this intuition using an MDL score to identify that pattern set that best describes the data given the labels. We will first detail how to compute the encoding cost for the data given the model and then the cost for the model itself.

4.2 Cost of Data Given Model Let us start by explaining how to encode a database D with singleton items I in the absence of any labels, which will later serve as the baseline encoding corresponding to independence between items and labels. To encode in which transaction an item I holds, optimal data-to-model codes are used, which are indices over canonically ordered enumerations [33]. Hence, the data costs are

$$L\left(\pi_I\left(D\right) \mid I\right) = \log \binom{|D|}{|\sigma_I\left(D\right)|} .$$

Taking into account the partitioning of D along the label, yielding D^+ and D^-, we encode I separately:

$$L\left(\pi_I\left(D\right) \mid I\right) = \log \binom{|D^-|}{|\sigma_I\left(D^-\right)|} + \log \binom{|D^+|}{|\sigma_I\left(D^+\right)|} .$$

As such, we explicitly reward patterns (here, singletons) that have a different distribution between the unconditional probability, i.e. frequency in D of I and the conditional probability of I conditioned on the label – i.e. frequency in D^- respectively D^+. It models the property that we are interested in; a pattern that characterize a certain label. It is straightforward to extend to patterns of co-occurring items $P = \bigwedge(X_1, \ldots, X_k)$ by selecting on transaction where the pattern holds

$$L\left(\pi_P\left(D\right) \mid P\right) = \log \binom{|D^-|}{|\sigma_P\left(D^-\right)|} + \log \binom{|D^+|}{|\sigma_P\left(D^+\right)|} .$$

There might be transactions where individual items of P are present, but not all of P holds. To ensure a lossless encoding, the singleton code $L(\pi_I\left(D\right) \mid I)$ is modified to cover all item occurrences left unexplained after transmitting $\mathcal{P}$. Hence, we get

$$L_s\left(\pi_I\left(D\right) \mid P\right) = \log \binom{|D|}{|\sigma_I\left(D\right) \setminus \left(\bigcup_{P \in \mathcal{P}, I \in P} \sigma_P\left(D\right)\right)|} .$$

For patterns expressing conjunctions over mutual exclusive items, e.g. $\bigwedge(\bigotimes(A, B), \bigotimes(C, D))$, we first send for both D^- and D^+ for which transactions the pattern holds, after which we specify which of the items is active where. We do that one by one, as we know that when the pattern holds and A is present, B cannot be present too. With each transmitted item of the clause, there are thus fewer transactions where the remaining items could occur, hence the codelength is reduced. More formally, the codelength for a pattern P of conjunctions of clauses is given as

$$L(\pi_P\left(D\right) \mid P) = \sum_{l \in \{-,+\}} \log \binom{|D^l|}{|\sigma_P\left(D^l\right)|} +$$

$$\sum_{\substack{cl \in \\ \gamma(P)}} \sum_{\substack{I \in \\ cl}} \log \binom{|\sigma_P\left(D^l\right)| - \sum_{I' \in cl, I' \leq I} |\sigma_{I'}\left(\sigma_P\left(D^l\right)\right)|}{|\sigma_I\left(\sigma_P\left(D^l\right)\right)|} ,$$

assuming a canonical order on $\mathcal{I}$. With clauses of only length 1 we arrive at a simple conjunctive pattern, and the function resolves to the codelength function for conjunctive patterns discussed above. Note here that the codelength is the same regardless of the order assumed on the $\mathcal{I}$. This statement trivially holds for clauses of length 2, we provide an argument for the case of l items in the Appendix.

This concludes the definition of codelength functions for transmitting the data. The overall cost of transmitting the data D given a model M is hence

$$L(D \mid M) = \Big(\sum_{P \in \mathcal{P}} L(\pi_P\left(D\right) \mid P)\Big) + \Big(\sum_{I \in \mathcal{I}} L_s(\pi_I\left(D\right) \mid P)\Big) .$$

4.3 Cost of the Model Let us now discuss how to transmit the model M for pattern set $\mathcal{P}$. First, we transmit the number of patterns $|\mathcal{P}|$ using the MDL-optimal code for integers $L_{\mathbb{N}}(|\mathcal{P}|)$. It is defined as $L_{\mathbb{N}}(n) = \log^* n + \log c_0$ with $\log^* n = \log n + \log\log n + \ldots$ and c_0 being a constant so that $L_{\mathbb{N}}(n)$ satisfies the Kraft-inequality [35]. Then, for each pattern P, we transmit the number of clauses via $L_{\mathbb{N}}(|\gamma(P)|)$. For each such clause, we transmit the items it contains using a log binomial, requiring $\log \binom{|\mathcal{I}|}{|cl|}$ bits plus a parametric complexity term $L_{pc}(|\mathcal{I}|)$. The log binomial along with the parametric complexity form the normalized maximum likelihood code for multinomials, which is a refined MDL code. The parametric complexity for multinomials is computable in linear time [36]. Lastly, we transmit the parametric complexities of all binomials used in the data encoding.

Combining the above, the overall model cost is

$$L(M) = L_{\mathbb{N}}(|\mathcal{P}|) + \sum_{P \in \mathcal{P}} (L_{\mathbb{N}}(|\gamma(P)|) + L_{pc}(|D^+|) +$$

$$L_{pc}(|D^-|)) + \sum_{cl \in P} \left(\log \binom{|\mathcal{I}|}{|cl|} + L_{pc}(|\mathcal{I}|)\right) + \sum_{I \in \mathcal{I}} L_{pc}(|D|) ,$$

by which we have a lossless MDL score.

4.4 The Problem, formally Based on the above, we can now formally state the problem.

Minimal Label Description Problem *Given data D over $\mathcal{I}$ and partitions D^- and D^+, find model $M \in \mathcal{M}$ that minimizes the codelength $L(M) + L(M \mid D)$.*

Solving this problem through enumeration of all models is computationally infeasible, as the size of the model space is

$$|\mathcal{M}| = 2^{\sum_{i=1}^{|\mathcal{I}|} \binom{|\mathcal{I}|}{i} \times \sum_{j=1}^{i} \left\{ {i \atop j} \right\}} ,$$

where the first term in the summation specifies the number of possible item combinations in a pattern of length i, the second term counts the number of possible ways to separate them into j different clauses via the Stirling number of the second kind and the exponent is introduced as a model M consists of arbitrary combinations of patterns. The MDL score for such complex model classes does not lend itself for easy-to-exploit structure such as monotonicity. Hence, we resort to an efficient bottom-up search heuristic for discovering good models which we introduce in the next section.

5 Premise

To find good pattern sets in practice, we present PREMISE which efficiently explores the search space in a bottom-up heuristic fashion.

5.1 Creating and Merging Patterns PREMISE starts with a model M that contains only singletons. It then iteratively improves the model by adding, extending, and merging patterns until it can not achieve more gain in the MDL score. To ease the explanation, we first introduce the setting with conjunctive patterns only.

- *single items*: $I \in \mathcal{I}$ that improves the MDL score when transmitted separately for D^- and D^+,
- *pairs of items*: a new conjunctive pattern $\varowedge(I_1, I_2) \in \mathcal{I} \times \mathcal{I}$,
- *patterns and items*: a new conjunctive pattern $\varowedge(P, I)$ by merging an existing pattern $P \in M$ with an $I \in \mathcal{I}$,
- *pairs of patterns*: a new conjunctive pattern $\varowedge(P_1, P_2)$ obtained by merging two existing patterns $P_1, P_2 \in M$.

We can speed up the search by pruning infrequent and therewith uninteresting patterns. Pairs of items for which the transaction sets barely overlap are unlikely to compress well as conjunctive patterns. Hence, we introduce a minimum overlap threshold of 0.05 in all experiments. This straightforwardly leads to algorithm `createCandidates` that, based on a current model M, outputs a set of possible candidate patterns that we will consider as additions to the model. We give the corresponding pseudocode in the Appendix.

5.2 Filtering Noise Additionally to the MDL score, [10] proposed to use Fisher's exact test as a filter for spurious patterns. Here, we use it to test our candidate patterns. Fisher's exact test allows to assess statistically whether two items co-occur independently based on contingency tables. We assume the hypothesis of homogeneity; in our case that there is no difference in the pattern's probability between D^- and D^+. Fisher showed that the values of the contingency table follow a hypergeometric distribution [37]. We can then compute the p-value for the one-sided test directly via

$$p = \sum_{i=0}^{\min(a,d)} \frac{\binom{a+b}{a-i}\binom{c+d}{c+i}}{\binom{n}{a+c}}.$$

with $c = |\sigma_P(D)|$, $a = |D| - c$, $d = |\sigma_P(D^+)|$, $b = |D^+| - d$ and $n = |D|$ for a pattern P labeled with l_+. For patterns labeled with l_-, the other tail of the distribution is tested (with a and b as well as c and d switching places). A general problem for statistical pattern mining is the lack of an appropriate multiple test correction. We here however only use the test to *filter* candidates, false positive patterns passing the test are still evaluated in terms of MDL.

5.3 The Premise Algorithm Combining the candidate generation and the MDL score from Section 4, we obtain PREMISE. We give the pseudo-code in Algorithm 1. Starting with the empty model, we generate candidates, for which pseudocode is given in the Appendix, and for each of those, we compute the gain in terms of MDL (line 7) as well as the pattern's p-value (line 8). We select the candidate below a significance threshold α that reaches the highest gain (line 9-11) and add it to the model. If we created the pattern through a merge, we remove its parent patterns from M. We repeat the process until no candidate provides further gain in codelength.

Algorithm 1 PREMISE

1: **Input:** D, significance threshold α
2: **Output:** approximation M of M^*
3: **repeat**
4: $\quad \Delta' \leftarrow 0$
5: $\quad M' \leftarrow M$
6: $\quad C \leftarrow$`createCandidates`(M)
7: $\quad$ **for** $P \in C$ **do**
8: $\quad\quad \Delta \leftarrow L(D, M \oplus P) - L(D, M)$ ▷ gain
9: $\quad\quad p \leftarrow$`FisherExactTest`(P) ▷ p-value
10: $\quad\quad$ **if** $p < \alpha$ and $\Delta > \Delta'$ **then**
11: $\quad\quad\quad \Delta' \leftarrow \Delta$
12: $\quad\quad\quad M' \leftarrow M \oplus P$
13: $\quad\quad$ **end if**
14: $\quad$ **end for**
15: $\quad M \leftarrow M'$
16: **until** $\Delta' > 0$
17: **return** M

5.4 Mutual Exclusivity In our practical applications from NLP, we are interested in finding clauses expressing words that are synonyms, that reflect similar concepts, or language variations, such as $\owedge$(*which,*$\otimes$(*color, colour*)) or $\otimes$(*could, can*). Such statements, however, require a richer pattern language than given by the purely conjunctive patterns discovered by the state-of-the-art. We discussed above how to identify the best model over such a richer pattern language of clauses in terms of MDL. Instead of enumerating all possible clauses exhaustively or searching for an XOR structure like in [10], for NLP applications, we follow a more informed approach, taking into account information from pre-trained, classifier-independent word embeddings. We provide all details in the Appendix.

5.5 Complexity While it is common to consider the complexity in terms of the size of the input, the bound it would give – which is exponential in the number of items as discussed in the theory section – is neither helpful nor tight considering the discovery of small models. we thus analyze the complexity of PREMISE in terms of the size of the model. We get a worst case time complexity of $O(k\,l\,(k\,l + m^2))$ for k conjunctive patterns of maximum length l for a dataset with m items. Including clauses containing mutual exclusivity, this extends to $O(k\,l\,(k\,l+(m\,c)^2))$ for c closest words in a given embedding. See Appendix for a full derivation.

6 Experiments

We evaluate our approach on synthetic data with known ground truth, as well as on real world NLP tasks to characterise misclassifications. We compare against the state-of-the-art from subgroup discovery [38], significant pattern mining (SPuManTe [5]), rule sets mining (Grab [9]), and rule lists (Classy [11]). As representatives of interpretable machine learning models we consider the rule-learner Ripper [39] and patterns derived from classification trees. Due to runtime issues, we compare to Anchors [31] only in the NER experiment. For similar reason, we exclude SliceFinder [29], and disjunctive emerging patterns [40]; neither completed a single run within 12 hours. Further details are given in the Appendix with datasets and code available online.

6.1 Synthetic Data Unless specified differently, for each of the experiments we generate a data matrix with 10 000 samples, half of which get label l_-. The set of items $\mathcal{I}$ has size 1000. We draw patterns of length $2-5$ from $\mathcal{I}$ with replacement until 50% of items are covered. For each pattern we then draw $k \sim \mathcal{N}(150, 20)$ and set the items of the pattern in $.9k$ random transactions from D^+, and $.1k$ transaction from D^- to 1. This corresponds to a typical sparsity level for pattern mining problems. Additionally, for each item that is part in a pattern, we let it occur in $k \sim \mathcal{N}(50, 20)$ random transactions from D. For all items not part of a pattern, we let them occur in $k \sim \mathcal{N}(150, 20)$ transactions from D. Lastly, we introduce background noise by flipping .1% of the matrix values.

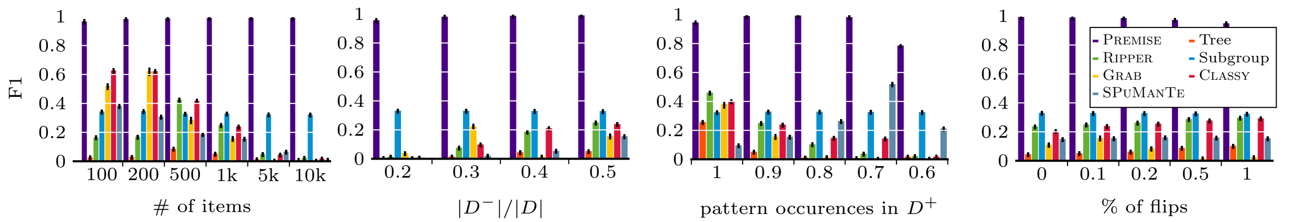
We evaluate all methods with respect to *scalability* (size of item sets $\mathcal{I}$), *label imbalance* (proportion of transactions having label l_-), *label shift* (patterns occurring not exclusively in one of the labels) and *robustness to background noise* (flipping a fraction of entries of the data matrix). The results are shown in Fig. 2.

The performance of most existing methods deteriorates already for data with several hundred items. We observe similar effects for increasing label imbalance which is e.g. encountered in misclassified samples that make up only a small fraction of overall samples. For label shift, we adapt the occurrence of patterns between 1, meaning the pattern occurs exclusively in one partition of the database, to .6, meaning that 60% of the transaction where a pattern occurs have one label, the others have the other label. Again, most baselines struggle with this setting. Subgroup discovery and PREMISE are robust against the four different factors. Subgroup discovery, however, yields (soft) F1 scores up to .4 while PREMISE performs close to 1 in most settings.

Synthetic text data. For an evaluation with known ground truth more similar to the NLP application domain, we evaluate how well all methods cope with item – or token – distributions similar to real text. We report these experiments in the Appendix. For most most baselines performance quickly deteriorates for longer patterns. Grab is able to retrieve longer patterns and is resistant to shift and noise in the form of non-systematic label errors. PREMISE outperforms all competitors, achieving consistently high F1 scores beyond .92. For complex patterns consisting of conjunctive clauses of disjunctions, we verify that PREMISE is able to retrieve them even in the presence of noise.

6.2 Real Data: VQA Visual Question Answering (VQA) is the popular and challenging task of answering textual questions about a given image. We analyze the misclassification of Visual7W [41] and the state-of-the-art LXMERT [42], both specific architectures for different VQA tasks. Visual7W reaches 54% accuracy in 4-option multiple choice, LXMERT a validation score of 70%. Both classifiers perform far from optimal and thus serve as interesting applications for describing (misclassification) labels. We derive misclassification data sets from applying the classifiers to the development sets.

In Tab. 2 in the Appendix, we provide statistics about the data and retrieved patterns. Both the tree based method and SPuManTe discover several hundred or thousand patterns making it difficult to



(a) Varying number of items (b) Varying label ratio (c) Varying label shift (d) Varying background noise

Figure 2: *Synthetic data results.* As competitors only recover fragments of patterns, the results are in terms of a soft F1 score, which also rewards the discovery of fragments, as defined in the Appendix (Section 9.5).

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interpret the results. Furthermore, we know from the previous experiments that these methods find thousands of patterns even when there exist only few ground truth patterns. The subgroup discovery approach requires the user to specify the number of patterns a-priori, which is not known. The discovered patterns are highly redundant with often ten or more patterns expressing the same cause for misclassification. It is thus hard to get a full description of what goes wrong, it lacks the power of set mining approaches that evaluate patterns *together*. The majority of patterns found by Classy consist of only one token. Grab and Ripper fail to retrieve meaningful results.

In Tab. 3 in the Appendix, we list patterns found by Premise. We can clearly see the advantage of the richer pattern language, allowing to find patterns with related concepts such as $\owedge$(*what,* $\otimes$(*color, colors, colour*)). Generally, the patterns found by Premise highlight different types of wrongly answered questions, including counting questions, identification of objects and their colors, spatial reasoning, and higher reasoning tasks like reading signs. Furthermore, Premise retrieves both frequent patterns, such as $\owedge$(*how, many*) and rare patterns such as $\owedge$(*on, wall, hanging*).

Premise also discovers patterns that are biased towards correct classification. These can indicate issues with the dataset. For instance, $\owedge$(*who, took,* $\otimes$(*photo, picture, pic, photos, photograph*)), although a difficult question, is nearly always answered by "photographer" and thus easy to learn. Another problematic question is indicated by the pattern $\owedge$(*clock, time*), where usually the answer is "UNK", the actual time being replaced with the unknown word token by the limited vocabulary of Visual7W. The pattern hence indicates a setting where the VQA classifier undeservedly gets a good score.

By adding additional information as items to each instance, it is possible to gain further insights. Appending the correct output to each instance, we observe for the question when the picture was taken two different trends. On the one hand, the discovered pattern $\owedge$(*when,* $\otimes$(*daytime, nighttime*)) is associated with correct classification, the pattern $\owedge$(*when,* $\otimes$(*evening, morning, afternoon, lunchtime*)), on the other hand, points towards misclassification. This is intuitively consistent as the answers "daytime" and "nighttime" are easier to choose based on a picture.

We observe in the discovered patterns that the Visual7W and LXMERT classifiers share certain issues, like the counting questions. However, no patterns regarding color or spatial position are retrieved. This seems to indicate that the more recent LXMERT classifier can handle these better.

6.3 Real Data: NER A machine learning classifier might perform well during development, its performance when deployed "in the wild" however is often much worse. Understanding the difference is important for being able to improve the classifier. Here, we investigate the popular LSTM+CNN+CRF architecture [43] for Named Entity Recognition (NER). The classifier is trained on the standard NER dataset CoNLL03, where it achieves a good performance (F1-score of 0.93). On OntoNotes, a dataset covering a wider range of topics, the performance drops to 0.61 F1 on the development set. We evaluate on this split of the data consisting of 16k sentences and 23k unique items.

Anchor [31] allows to obtain conjunctive patterns to explain NLP instances locally. It took, however, several days to analyze all misclassifications on modern GPU hardware due to the necessary, repeated queries to the NER classifier. Anchorfinds 4.1k patterns with many redundant and overly long and specific patterns. As expected from a local method, the patterns are highly specific and thus identify problems of the model for particular instances rather than identifying the general issues that the model has. Premise retrieves a concise set of 190 patterns. An example is $\owedge$(*-LRB-, -RRB-*) that indicates different preprocessing of the text. Patterns also indicate problems with differing labeling conventions. For example, we find the patterns $\owedge$(*'s*) and $\owedge$(*Wall, Street*), which are handled differently for entities in OntoNotes. We can also isolate issues with OntoNotes alone, which contains bible excerpts that are not labeled at all. We discover this through patterns that describe this domain (*God*, *Jesus*, *Samuel*).

As there is no ground truth available and to empirically validate that the found patterns affect the classifier's performance, we select the top 50 patterns according to gain in MDL and for each pattern sample 5 sentences containing it uniformly at random from the OntoNotes training data. The CoNLL03 classifier is then fine-tuned on this data. Sampling and fine-tuning is repeated 20 times with different seeds. Using the pattern-guided data, the performance is improved to 0.67 mean F1 score (SE 0.003) compared to sampling fully at random where only a small improvement to 0.62 (SE 0.005) is achieved. This shows that the patterns discovered by Premise provide actionable insights into how a classifier can be improved.

7 Discussion

On synthetic data, we find that the state-of-the-art methods across different fields have severe difficulties finding the ground truth pattern set. Premise is the only approach that is at the same time robust to noise, label imbalance, and easily scaling to thousands of items. For task like characterising misclassifications of NLP models, the labels are inherently imbalanced and the sets of items – in this case tokens – is large. Besides, to capture the structures of word associations, we need a richer pattern language capturing mutual exclusiveness, which only Premise is able to express.

On two models for VQA, we set for characterising their misclassifications. While some of the competing methods retrieve reasonable explanations, these are highly redundant with several hundred or thousand patterns. Premise, on the other hand, discovers succinct sets of patterns that provide interesting characterizations, revealing that models struggle with counting, spatial orientation, reading, and identifies shortcomings in training data. For a popular NER classifier, we consider a model applied to text of a different source and characterize the resulting classification errors. Compared to the local explanation method Anchors, Premise retrieves a more succinct set of patterns in less time and we also show that the obtained insights are actionable.

8 Conclusion

We considered the problem of finding interpretable and succinct descriptions of a given label, and proposed to discover succinct pattern sets to describe the labels based on the Minimum Description Length Principle. To solve this formulation in practice, we formulated an efficient bottom-up heuristic Premise. Our method showed to be the only approach that scales well to data typical in real world problem settings, while at the same time being robust to noise, and label imbalance. With these abilities, combined with a more expressive pattern language compared to the state-of-the-art capturing also mutual exclusive relationship, Premise discovered succinct, informative, and actionable pattern sets that characterize misclassifications of NLP models in two challenging settings, which capture general problems of the model rather than instance specific (local) issues. It hence fills the gap of a robust approach to describe labels in terms of human-interpretable patterns, suited to take on problems such as characterizing misclassifications of deep NLP models.

While our approach scales already to tens of thousands of features, it makes for engaging future work to scale it even further towards hundreds of thousands of features or to extend the work on characterizing misclassifications incorporating elements of the classifier itself, such as neuron activations.

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9 Appendix

Algorithm 2 createCandidates

Input: D, patterns $\mathcal{P}$ in current M, max neighbour distance K
Output: Set of candidate patterns $\mathcal{P}$
▷ Define $nb(I, 0) = I$ for simplicity
$C \leftarrow \{\}$
▷ Single item and its neighbours
for $I \in \mathcal{I}$ **do**
  $A \leftarrow \{\}$
  for $k \in \{0, \ldots, K\}$ **do**
    $A \leftarrow A \cup \{nb(I, k)\}$
    $C \leftarrow C \cup \{\bigotimes(A)\}$
  end for
end for
▷ Pairs of items and their neighbours
for $(I_1, I_2) \in \mathcal{I} \times \mathcal{I}$ **do**
  $A_1 \leftarrow \{\}$
  for $k_1 \in \{0, \ldots, K\}$ **do**
    $A_1 \leftarrow A_1 \cup \{nb(I_1, k_1)\}$
    $A_2 \leftarrow \{\}$
    for $k_2 \in \{0, \ldots, K\}$ **do**
      $A_2 \leftarrow A_2 \cup \{nb(I_2, k_2)\}$
      $C \leftarrow C \cup \{\bigotimes(\bigotimes(A_1), \bigotimes(A_2))\}$
    end for
  end for
end for
▷ Pattern + item and its neighbours
for P in $\mathcal{P}$ **do**
  for $I \in \mathcal{I}$ **do**
    $A \leftarrow \{\}$
    for $k \in \{0, \ldots, K\}$ **do**
      $A \leftarrow A \cup \{nb(I, k)\}$
      $C \leftarrow C \cup \{\bigotimes(\gamma(P) \cup \{A\})\}$
    end for
  end for
end for
▷ Pattern + Pattern
for $(P_1, P_2) \in \mathcal{P} \times \mathcal{P}$ **do**
  $C \leftarrow C \cup \{\bigotimes(\gamma(P_1) \cup \gamma(P_2))\}$
end for
▷ see Sections 4 and 5 for filter criteria
$C \leftarrow$ `Filter`(C)
return C

9.1 Proof: Order of Items Here, we provide a proof that the codelength is independent on the order of items in mutual exclusive clauses. The proof closely follows that of Fischer & Vreeken [10].

Given a clause $cl = \bigotimes(i, j, k)$ with corresponding margins n_i, n_j, n_k, it does not matter in which order we transmit where the items hold. We show that we can flip the item order without changing the cost. Assume a new order $P = \bigotimes(k, i, j)$, then we show

$$\log \binom{n}{n_i} + \log \binom{n - n_i}{n_j} + \log \binom{n - n_i - n_j}{n_k} \stackrel{!}{=} \log \binom{n}{n_k} + \log \binom{n - n_k}{n_i} + \log \binom{n - n_i - n_k}{n_j} .$$

With the definition of the binomial using factorials and standard math, adding new terms that add up to 0, we show that the above equation hold.

$$\begin{aligned}
&\log \frac{n!}{(n - n_i)!n_i!} + \log \frac{(n - n_i)!}{(n - n_i - n_j)!n_j!} \\
&+ \log \frac{(n - n_i - n_j)!}{(n - n_i - n_j - n_k)!n_k!} \\
=& \log(n!) - \cancel{\log((n - n_i)!)} - \log(n_i!) + \cancel{\log((n - n_i)!)} \\
&- \cancel{\log((n - n_i - n_j)!)} - \log(n_j!) + \cancel{\log((n - n_i - n_j)!)} \\
&- \log((n - n_i - n_j - n_k)!) - \log(n_k!) \\
&\underbrace{+ \log((n - n_k)!) - \log((n - n_k)!)}_{=0} \\
&\underbrace{+ \log((n - n_i - n_k)!) - \log((n - n_i - n_k)!)}_{=0} \\
=& \log \frac{n!}{(n - n_k)!n_k!} + \log \frac{(n - n_k)!}{(n - n_i - n_k)!n_i!} \\
&+ \log \frac{(n - n_i - n_k)!}{(n - n_i - n_j - n_k)!n_j!} .
\end{aligned}$$

Other permutations and larger clauses follow the same reasoning.

9.2 Mutual Exclusivity and Word Neighbors For the clauses of mutually exclusive items, we are interested in finding words that are synonyms or that reflect similar concepts, such as $\bigotimes$(*color, colour*) or $\bigotimes$(*could, can*). Research in NLP has proposed various techniques for identifying such pairs including manually created ontologies such as WordNet [44] or word embeddings that are learned through co-occurrences in text and map words to vector representations. This information about related words can be used to guide the search for mutually exclusive patterns. Using such pretrained embeddings rather than deriving them from the given input data has the advantage that we are independent of the size of the input data set, and receive reliable embeddings, which were trained on very large, domain independent text corpora.

While our approach is independent of the specific method, we have chosen FastText word embeddings trained on CommonCrawl and Wikipedia [45]. In

Word	5-nearest neighborhood
photo	photograph, photos, picture, pic, pictures
color	colour, colors, purple, colored, gray
can	could, will, may, might, able
say	know, think, tell, mean, want

Table 1: Words and their nearest neighbors on *Visual7W*.

contrast to word ontologies, word embeddings have a broader vocabulary coverage. They also do not impose strict restrictions such as a particular definition of synonyms and instead reflect relatedness concepts learned from the text. FastText embeddings have the additional benefit that they use subword information, removing the issue of out-of-vocabulary words. The word embeddings are independent of the machine learning classifier we study. As measure of relatedness m between two items I_1, I_2, we use cosine similarity, i.e. $m = cos(emb(I_1), emb(I_2))$ where emb is the mapping between an item/word and its vector representation. We define $nb(I, k)$ as the $I' \in \mathcal{I}$ for which $m(I, I')$ is the k-highest. Examples for words and their neighbours in FastText embeddings are given in Table 1.

Based on the information of the embedding, we derive $\bigotimes$-clauses. For each item I, we explore mutual exclusivity in its $1 \ldots K$ closest neighbors, i.e. from $\bigotimes(I, nb(I, 1))$ until $\bigotimes(I, nb(I, 1), \ldots, nb(I, K))$ where K is the maximum neighborhood size. For that, we adapt the `createCandidates` algorithm from Section 5.1 so that whenever we consider merging with an item I, we also consider merging with the $\bigotimes$-clauses containing additionally the $1, 2, \ldots K$ closest neighbours (see Alg. 2).

Since not all words have K neighbors that represent similar words, we additionally filter neighbourhoods such that $\frac{\bigcap_I \sigma_I(D)}{\bigcup_I \sigma_I(D)} < a$ and $m(I, nb(I, k)) > b_k$ for all items I in the clause, i.e. we require that their transactions barely overlap (mutual exclusivity), and that their embeddings are reasonably close. In all experiments we set $K = 5$, $a = 0.05$ and b_k to the 3rd quartile of $\{m(I, nb(I, k)) \mid I \in \mathcal{I}\}$.

In the general case for arbitrary labeled data, we could follow the proposal of [10] to search for potential XOR structure, which however would lead to a much increased search space and hence computational costs, without any benefits for the specific applications.

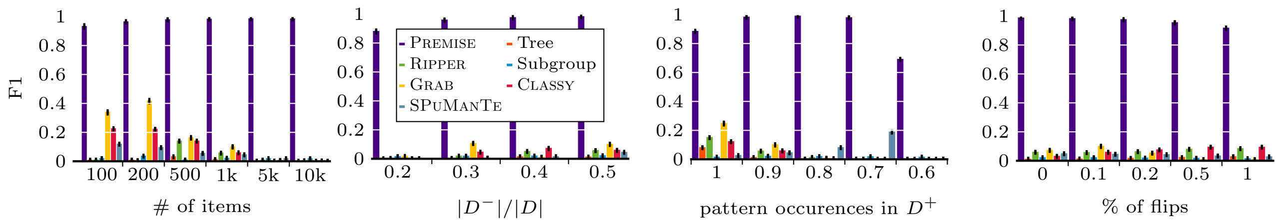
9.3 Complexity Consider Premise finds k conjunctive patterns of maximum length l for a dataset with m items. Since in every round either a new singleton or pair is generated that belongs to one of the k final patterns, or two existing patterns are merged, the algorithm runs $O(k\,l)$ rounds. In each round, the dominating factor is the candidate generation, out of which there are $O(m)$ potential singletons, $O(m^2)$ pairs, and at maximum $O(k\,l)$ pattern merges, corresponding to the case that all parts of the final patterns exist as singleton patterns in the current round. Hence, we get a worst case time complexity of $O(k\,l\,(k\,l + m^2))$.

For clauses containing mutual exclusivity, for all practical applications we consider XOR statements of the c closest words in a given embedding, where c is a small constant. We hence consider $O(m\,c)$ single XOR clauses, $O((m\,c)^2)$ pairs, and at maximum $O(k\,l)$ pattern merges, where again this corresponds to the case that all parts of the final patterns exist as singleton patterns in the current round. Hence we get a worst case time complexity of $O(k\,l\,(k\,l + (m\,c)^2))$. For the general case, when searching for arbitrary AND and XOR combinations, we refer to Fischer & Vreeken [10].

9.4 Experimental Details Experiments were performed on an Intel i7-7700 machine with 31GB RAM running Linux. For the single-threaded C++ implementation of Premise, all synthetic data experiments finished within minutes for the moderately sized data sets, and within hours for the larger datasets with 5k and 10k items. On the VQA datasets Premise finished within 20 minutes and on the NER data within 4 hours.

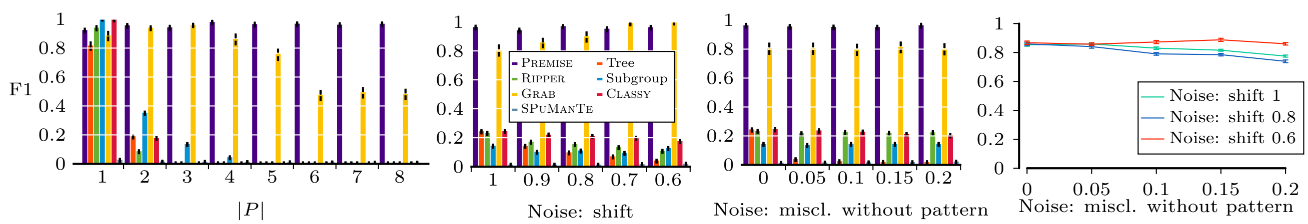
For the decision tree, patterns are exracted from a tree trained on the misclassification data. Each of the tree's inner nodes is a binary decision regarding the presence of an item and a pattern is the conjunctive path from the tree's root to one of its leafs. The model is trained with Gini impurity as decision criterion in the implementation from scikit-learn.

For subgroup discovery, the implementation by Lemmerich and Becker [46] is used with depth-first search and weighted relative accuracy as quality function. The size of the result set and the maximum depth are set to the ground truth for the synthetic data and to 100. On the synthetic data, it hence has an advantage over all other approaches which would not hold in a real-world scenario. Maximum depth is set to 5 for the VQA datasets. SPuManTe is used with the authors' default parameters, setting its sample size to the dataset size. For Grab we use the publicly available implementation by the authors, which we tailored for the task at hand by restricting the possible rule-heads to the labels only, but allowing tails over all other items. For Classy we used the publicly available implementation by the authors as used in the original publication. Minimum support is set to 1 and maximum rule length to the ground truth for the synthetic data and 5 for the VQA datasets.



(a) Varying number of items (b) Varying label ratio (c) Varying label shift (d) Varying background noise

Figure 3: *Synthetic data results (F1 score).* We visualize results on synthetic data with varying number of items (a), label ratio (b), label shift (c) and amount of background noise (d). The results are in terms of F1 score with respect to the ground truth.



(a) Varying pattern length (b) Varying shift noise (c) Varying label noise (d) Complex clauses

Figure 4: *Synthetic text data results.* On synthetic text data, varying the number of items per pattern (a), the amount of *shift noise* (b), and the amount of *label noise* (c), we visualize the results in terms of F1 score with respect to the ground truth for existing methods and PREMISE. We additionally provide the results of PREMISE on data containing patterns of mutual exclusive clauses for varying amounts of *shift noise* (d).

For Visual7W and LXMERT, we use the published, pretrained models by the corresponding authors. For LXMERT, the minival version of the development set is used. For the LSTM+CNN+CRF classifier for NER, we follow the specific set-up from Hedderich et al. [47] with English FastText embeddings. OntoNotes was split and preprocessed using the script from `https://github.com/yuchenlin/OntoNotes-5.0-NER-BIO`. The fine-tuning data consists of 240 instances/sentences as two patterns did not match any training data. Fine-tuning on the additional data is performed for 30 epochs. As labels, the intersection between CoNLL03 and OntoNotes is used (PER, LOC, ORG) in the BIO2 format.

9.5 F1 Metric A standard metric to evaluate success of a model is the F1 score – the harmonic mean between precision and recall – which for discovered pattern set P_d and ground truth pattern set P_g is defined as $\mathrm{F1}(P_d, P_g) = |P_d \cap P_g| / \left(|P_d \cap P_g| + \frac{1}{2}|P_d \Delta P_g|\right)$, where Δ is the symmetric difference between two sets. As competitors only recover fragments of patterns and hence they obtain very low F1 scores, we instead report a soft F1 score that rewards also fragments. We define it as harmonic mean between a soft precision and a soft recall:

$$\mathrm{SoftPrec}(P_d, P_g) = \sum_{p_d \in P_d} \operatorname*{argmax}_{p_g \in P_g} \frac{|p_d \cap p_g|}{|p_g|} ,$$

$$\mathrm{SoftRec}(P_d, P_g) = \sum_{p_g \in P_g} \operatorname*{argmax}_{p_d \in P_d} \frac{|p_d \cap p_g|}{|p_g|} ,$$

$$\mathrm{F1}(P_d, P_g) = \frac{2 * \mathrm{SoftPrec} * \mathrm{SoftRec}}{\mathrm{SoftPrec} + \mathrm{SoftRec}} .$$

Results with the original F1 score are given in Fig. 3.

9.6 Synthetic Text Data Experiments To obtain a synthetic data set with similar item/token distributions as natural language text, we derive transactions/instances from the around 3.4k sentences in the development set of the PennTreebank Corpus. In particular, we draw 12 distinct patterns, for each pattern choosing items from the vocabulary tokens at random. To ensure that we introduce only new patterns into the data, we verify that none of the items in the patterns co-occur in the original data. We then insert each pattern into a random subset of the PennTreebank instances, where the number of instances to be covered is drawn from a normal $\mathcal{N}(150, 20)$. The data contains 6k unique items. To evaluate settings typical for classification, we then vary two types of noise. *Shift noise* indicates the

Dataset	$\lvert\mathcal{I}\rvert$	$\lvert D\rvert$	Premise k^-	Premise k^+	Premise $\overline{\lvert p\rvert}$	Tree k	Tree $\overline{\lvert p\rvert}$	Ripper k	Ripper $\overline{\lvert p\rvert}$	Subgroup k	Subgroup $\overline{\lvert p\rvert}$	SPuManTe k	SPuManTe $\overline{\lvert p\rvert}$	Classy k	Classy $\overline{\lvert p\rvert}$	Grab k	Grab $\overline{\lvert p\rvert}$
Visual7W	2429	28032	29	26	3.38	4309	3.55	0	0.00	100	2.32	575	2.92	19	1.26	1	1
LXMERT	5351	25994	41	34	2.69	3371	2.71	3	3.00	100	2.52	951	3.90	36	1.28	1	1

Table 2: *VQA data statistics.* For the two VQA classifiers, we provide general statistics about data dimensions, and for each method the number of discovered patterns ($k = |P|$) or if applicable number of patterns explaining misclassification ($k^- = |P^-|$), respectively correct classification ($k^+ = |P^+|$) and the average pattern length $\overline{|p|}$.

percentage of instances with a pattern that are actually labeled as misclassifications, lower values mean that the model is still able to predict correctly in some of the instances – e.g. because a network leverages additional information in the data. The second type of noise is labeling instances as misclassification although there is no pattern occurrence – i.e. non-systematic errors – which we refer to as *label noise*. For all samples with pattern occurences, we label a fraction of those as misclassification according to the *shift noise*, and then introduce *label noise*.

Experimental setups We generate four different sets of experiments. In the first set, we introduce conjunctive patterns varying pattern length of the introduced patterns between 1 and 8 without noise. In the second set of experiments we vary the amount of *shift noise*, introducing shifts of $\{0.6, 0.7, 0.8, 0.9, 1\}$, and choosing pattern length uniformly in 1 to 5. In the third set we instead change the amount *label noise*, varying in $\{0, 0.05, 0.1, 0.15, 0.2\}$. In the fourth set of experiments, we introduce patterns consisting of conjunctions of mutual exclusive itemsets. The number of clauses per pattern and the number of items for each clause is chosen uniformly at random between 1 and 5. A pattern is only added to an instance if this would not break the mutual exclusivity assumptions of all patterns. For the word neighborhoods, items in the same clause obtain embeddings located around a randomly chosen centroid. All other items obtain random embeddings. We repeat all experiments 10 times and report the F1 score – the harmonic mean between precision and recall – as average across repetitions.

Results For the first experiment set (Fig. 4a) of varying pattern length, we observe that subgroup discovery is able to retrieve short patterns well, failing however to discover any larger patterns, instead retrieving large sets of redundant patterns. Decision trees perform similarly due to overfitting, finding a plethora of highly redundant patterns. SPuManTe, which although based on statistical testing, consistently finds thousands of redundant patterns, performing worst of all in this regard. The rule set miner Grab recovers small patterns well, it performs however much poorer in retrieving patterns of larger size. Premise is the only approach to consistently recover the ground truth in all data sets.

For both noise experiments, visualized in Fig. 4b and 4c, the tree based method completely breaks down already for moderate amounts of noise. Subgroup Discovery and SPuManTe both perform consistently bad with F1 scores below .2. Out of the existing approaches, only Grab is able to recover the ground truth well. Premise outperforms all existing methods in each of our noise experiments, achieving consistently high F1 scores beyond .92.

Since most baselines do not support discovering mutual exclusivity or proved to fail in the more simple setup of conjunctions, we only evaluate our proposed method on the fourth set of experiments. We observe that Premise is still able to retrieve patterns even in this challenging setup of complex clauses, with F1 scores close to .9, and is able to discover clauses in the presence of noise (Fig. 4d).

pattern	example
UNK	how are the UNK covered
$\owedge$(*how, many*)	how many elephants are there
$\owedge$(*what,* $\otimes$(*color, colors, colour*))	what color is the bench
$\owedge$(*on, top, of*)	what is on the top of the cake
$\owedge$(*left, to*)	what can be seen to the left
$\owedge$(*on, wall, hanging*)	what is hanging on the wall
$\owedge$(*how, does, look*)	how does the woman look
$\owedge$(*what, does,* $\otimes$(*say, like, think, know, want*))	what does the sign say

(a) Visual7W

pattern	example
$\owedge$(*How, many*)	How many kites are flying?
$\owedge$(*hanging, from*)	What is hanging from a hook?
$\owedge$($\otimes$(*kind, sort*), of)	What kind of birds are these?
$\owedge$($\otimes$(*would, could, might, can*), *you*)	How would you describe the decor?
$\owedge$(*name, of*)	What is the name of this restaurant?
number	What is the pitchers number?
$\otimes$(*letter, letters*)	What letter appears on the box?
$\owedge$(*How, much,* $\otimes$(*cost,costs*))	How much does the fruit cost?

(b) LXMERT

Table 3: *VQA example patterns.* Our method discovers meaningful and easily interpretable patterns. For Visual7W (left) and LXMERT (right), we show a subset of the patterns highlighting different reasons for misclassification along with examples from the corresponding datasets. The full list of retrieved patterns for all methods is given in the additional material.