An interpretable latent variable model for attribute applicability in the Amazon catalogue

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Abstract

Learning attribute applicability of products in the Amazon catalog (e.g., predicting that a shoe should have a value for size, but not for battery-type) at scale is a challenge. The need for an interpretable model is contingent on (1) the lack of ground truth training data, (2) the need to utilise prior information about the underlying latent space and (3) the ability to understand the quality of predictions on new, unseen data. To this end, we develop the MaxMachine, a probabilistic latent variable model that learns distributed binary representations, associated to sets of features that are likely to co-occur in the data. Layers of MaxMachines can be stacked such that higher layers encode more abstract information. Any set of variables can be clamped to encode prior information. We develop fast sampling based posterior inference. Preliminary results show that the model improves over the baseline in 17 out of 19 product groups and provides qualitatively reasonable predictions.

1 Attribute Applicability

Many real-world datasets can be viewed as object-by-attribute matrices. A prominent example is the Amazon catalogue which contains over 100 million products (objects) and hundreds of attributes, of which only a small subset is assigned to each product. Thus, product-attribute-assignment can be viewed as a sparse binary matrix, shown for a small subsample of the German Amazon marketplace in Fig. 1. Being able to distinguish between attributes that are truly non-applicable (e.g., battery-type for a shoe), attributes that could reasonably be applied (e.g., weight for a book), and attributes that are clearly applicable (e.g., size for a T-shirt) is crucial for applications such as attribute imputation models, data quality management, template generation, product comparison and virtually all customer-facing downstream applications.

We can cast the task of predicting attribute applicability as a multi-label classification problem, where each attribute constitutes a label and an arbitrary number of labels is assigned to each product. While there is recent progress in such extreme multi-label classification problems [1, 2], we face a particular challenge: The absence of reliable training labels makes it difficult to define a training metric. Therefore, we approach attribute applicability as an unsupervised problem and develop a probabilistic latent variable model that describes the generative process by which the binary product/applicability matrix is generated from a set of latent features. We aim to retain a simple, interpretable model, resembling the process of a marketplace seller who is filling in attributes for their product. The rationale behind the model is that each latent feature corresponds to a set of attributes that are likely to appear together such as (title, pages, language, release date) or (width, height, length). Each of these sets is represented by a latent dimension and the generative process for any product-attribute-pair is a noisy disjunction of these feature sets. The model design is further

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motivated by keeping sampling-based posterior inference scalable. We also assume that additional product or attribute specific prior information is available. Here, this is exemplified by the product type, a string attribute that is assigned to a majority of products. Product types are curated such that there exist only around 500 distinct values. They provide useful information that we need to leverage for optimal performance. Moreover, attribute assignments have a strong product type specific pattern which lets us use the product type specific attribute frequency as a baseline probability estimate.

2 MaxMachine Model

A first candidate model is Boolean Matrix Factorisation [3], where, both, the features and their allocations are binary. The data generating process is a noisy matrix product between these binary matrices whose result is thresholded at 1. With $N$ products and $D$ attributes $x_{nd} \in \{0, 1\}$ denotes the application status for a product-attribute-pair. We have $L$ latent dimensions and the factor matrices are denoted as $U \in \{0, 1\}^{L \times D}$ and $Z \in \{0, 1\}^{N \times L}$, such that $u_{l,d}=1 \ldots D$ encodes a set of co-occurring attributes and $z_{n,l}=1 \ldots L$ denotes the compressed representation of observation $x_n$. The likelihood for Boolean Matrix Factorisation then takes the form $p(x_{nd}|.) = \sigma[\lambda \tilde{x}_{nd}(1 - 2 \prod_l (1 - z_{nl} u_{ld}))]$, where $\sigma$ is the logistics sigmoid and $\tilde{x} = 2x-1$. Note that the product over $l$ is the Boolean disjunction. This model has a global noise parameter, $\lambda \in \mathbb{R}^+$, that governs the random flipping of bits. However, due to the heterogeneity in the data, we require a more expressive model that can capture heteroscedastic noise. To this end, we propose the MaxMachine. Here, the noise for each latent dimension is governed by a separate parameter and each data point is generated from the least noisy associated latent dimension. Hence the model retains composability and is easily interpretable. The likelihood takes the form $p(x_{nd}|.) = \sigma[\tilde{x}_{nd} \max_l (\lambda_l z_{nl} u_{ld})]$, where $\lambda_l \in \mathbb{R}$. Using the max-operation, the latent dimensions compete for explaining the observations. The winner is the most accurate predictor and gets to fully explain the observation. In order for the model to be well defined we have an additional, clamped latent dimension with $u_{l,d}=z_{nl}=1 \forall (n, d)$. We propose a beta prior on each $\sigma(\lambda_l)$ and binomial priors on the cardinality of the rows of $U$. The latter can encode our prior belief that the number of co-occurring attributes in each set is much smaller than the total number of attributes.

Now, we include the product-type information by adding another layer of matrix factorisation in the spirit of a Bayesian hierarchical model. This means that the prior on the matrix of latent representation is factorised according to another MaxMachine model. Here, the higher-order object specific factor matrix is fixed to an encoding of the product type in a one-hot fashion.
2.1 Inference

The inference task amounts to estimating, both, the attribute sets and their assignments and is combinatorially challenging. We develop sampling based posterior inference, an approach that has been shown to outperform competing methods in Boolean Matrix Factorisation [3]. Computation of the full conditional probabilities of each variable $u_{it}$ or $z_{it}$ generally depends on the variables full Markov blanket. We make use of several algorithmic tricks and leverage the purely binary states of all variables as well as the lack of interaction between dimensions that is induced by the max operation. This enables efficient updates, such that the algorithm converges for hundreds of thousands of data points within few minutes on a laptop. After every sweep through all entries of $U$ and $Z$, we set all $\lambda$ to their MAP estimate which is analytically available. Following posterior inference, we can compute Monte Carlo estimates of the posterior predictive and thus predict applicability.

3 Experiments and Results

We consider a snapshot of the Amazon German marketplace that have been found to be particularly important to customers. In order to simplify analysis and evaluation we stratify the data into 19 different clusters corresponding to related types of products, such as clothing, computers or jewellery. Each cluster consists of products from a variety of product types (1-50). In particular products from different clusters share only very few attributes and therefore share no co-occurrence patterns of mutual relevance. We train on only 500 randomly sampled products from each product type, since a further increase in training data has no effect on the quality of the results. This is due to the redundancy in the binary data.

We measure test-set performance by treating randomly selected product-attribute pairs as unobserved during training and evaluate the area under the ROC curve for the posterior predictive on these test data points. For the following, experiments we choose binomial(0.1) priors on the cardinality of each latent set of attributes, reflecting our prior belief that the number of attributes in each co-occurring set is relatively small. For the noise parameters (mapped to $[0, 1]$), we use a beta(10,1) prior, encoding our belief that attribute sets that are applied to a product are relatively likely to be actually present in the data. Based on random search, we choose the remaining hyperparameters.

Figure 2: Patterns of attribute co-occurrence. Shown are posterior means of the inferred codes $U$ (black: 1, white: 0). Each row denotes a set of frequently co-occurring attributes, each column denote an attribute; $\nu$ denotes the expected percentage of ones in the data that are explained by the corresponding dimension, $\hat{\lambda}$ is the average posterior MAP of the noise parameter.

We show the inferred sets of co-occurring attributes for clothing products in Fig. 2. They indicate reasonable co-occurrences such as (waist-style, waist-size, inseam-length, ...). The corresponding posterior predictive achieves a ROC-AUC of 94% on held out data, while the product type mean reaches close to 93%. The moderate improvements in ROC-AUC can partly be attributed to...
the fact that the product-type mean predictor has a higher certainty for attributes that are present in almost all products. Qualitative evaluation shows that the model makes reasonable predictions, as for instance to add the attribute material to most products of type bra or the attribute manufacturer to products of type shirt, more anecdotal evidence is provided in Table[1] We find a non-zero, but rather low probability of adding the attribute cup-size to products of type bra. This can be understood by noting that cup-size occurs for no other product type and, therefore, cannot be inferred from correlation. While the probability is low, it is notable evidence if considered in relative terms: compared to any other product types, products of the type bra have by far the highest probability of the attribute cup-size being applicable. This suggests the exploration of attribute-specific thresholds for practical applications.

We repeat this experiment across all product types in the catalogues and find that the MaxMachine outperforms the baseline by margins between 1% and 15% in 17 out of 19 clusters. The slightly weaker performance in the remaining cluster can largely be explained by extremely homogeneous attribute distributions for each of the contained product types.

Table 1: Anecdotal evidence – for three attributes we list the product types that they are most likely applied to by the model. The percentage is the mean probability of being applied for all products in the product type. In brackets we give the mean probability only for those products that do not have corresponding attribute assigned.

| Attribute | cup-size | closure-type | leather-type |
|-----------|----------|--------------|--------------|
| Product types with largest p(apply) | | | |
| Bra | 22%(10)% | Shoes 48(18)% | Shoes 48(15)% |
| Swimwear | 3(2)% | Pants 24(10)% | Outerwear 3(3)% |
| Underwear | 3(2)% | Shorts 6(3)% | Shorts 2(2)% |
| Shoes | 2(2)% | Outerwear 4(2)% | (< 1%) |
| Suit | 2(2)% | Bra 2(2)% | |