Learning Interesting Categorical Attributes for Refined Data Exploration

Koninika Pal  
TU Kaiserslautern  
Kaiserslautern, Germany  
pal@cs.uni-kl.de

Sebastian Michel  
TU Kaiserslautern  
Kaiserslautern, Germany  
michel@cs.uni-kl.de

ABSTRACT

This work proposes and evaluates a novel approach to determine interesting categorical attributes for lists of entities. Once identified, such categories are of immense value to allow constraining (filtering) a current view of a user to subsets of entities. We show how a classifier is trained that is able to tell whether or not a categorical attribute can act as a constraint, in the sense of human-perceived interestingness. The training data is harnessed from Web tables, treating the presence or absence of a table as an indication that the attribute used as a filter constraint is reasonable or not. For learning the classification model, we review four well-known statistical measures (features) for categorical attributes—entropy, unalikeability, peculiarity, and coverage. We additionally propose three new statistical measures to capture the distribution of data, tailored to our main objective. The learned model is evaluated by relevance assessments obtained through a user study, reflecting the applicability of the approach as a whole and, further, demonstrates the superiority of the proposed diversity measures over existing statistical measures like information entropy.

1 INTRODUCTION

Rendering large and heterogeneous data accessible to users requires mechanisms that allow querying or exploring it without prior domain knowledge. Consider for instance knowledge bases like YAGO, Freebase, or DBPedia that alone contain hundreds of millions of facts for tens of millions of entities from all kinds of domains and types. One classical approach to make such vast amounts of information accessible to users is to organize data into specific categories according to attributes, e.g., scientists born in Norway, capital cities located in Europe, the tallest buildings in USA, in order to constrain the view of data explorers to such subsets. But, are all possible categories insightful and, if not, who defines meaningful categories?

Consider the case of large businesses with several retail stores across the USA. Clearly, data analysts are likely to investigate properties like the best selling items overall, but in particular also the best selling items per state or city. Likewise, it might also be interesting to investigate the sales of retail stores for specific product categories, or deals accomplished per employee. Analysts frequently use the drill-down operation in OLAP [14, 25] over predefined categories to analyze such cases. For a reasonably small scenarios with well-defined schemata, telling which categories (dimensions) are interesting can be accomplished by domain experts, manually [18]. However, when turning our attention to arbitrary, per se unknown

This work has been supported by the German Research Foundation (DFG) under grant MI 1794/1-1. This is the extended version of the short paper presented at EDBT’16 [22].

Table 1: The World’s Tallest Buildings (Wikipedia)

| Building                  | City      | Country    | Height |
|---------------------------|-----------|------------|--------|
| Burj Khalifa              | Dubai     | UAE        | 828m   |
| Shanghai Tower            | Shanghai  | China      | 632m   |
| Abraj Al-Bait Clock Tower | Mecca     | Saudi Arabia | 601m  |
| Ping An Finance Centre    | Shenzhen  | China      | 599m   |
| Goldin Finance 117        | Tianjin   | China      | 596m   |
| One World Trade Center    | NY City   | United States | 541m  |

scenarios in the age of Big Data, heterogeneity, dynamics, and scale strongly advocate solely automated means.

The overall task we tackle in this work is the following: Given a (Web) table that contains entities and their attributes, we want to determine those categorical attributes (i.e., columns of the table) that can act as filters to constrain the focus of the table, i.e., to categorize the entities, thus, providing more focused and comprehensible information to users.

Let us introduce the problem through an example. Table 1 is showing part of a Wikipedia table reporting on the world’s tallest buildings, sorted by height. This list is quite long, as very many tall buildings from many countries all over the world are captured. A refined view of this large table can be defined by imposing a constraint on the attribute country, such as country=’United States’ or country=’China’. Browsing through such constrained tables fosters exploration/understanding of datasets at hand and can further answer specific information needs of users.

But are all attributes useful in the sense that they define interesting subsets? For humans with domain knowledge, it is a relatively simple task to decide whether a categorical attribute is interesting to be used for further categorizing the entity list, although sometimes subjective. Categorizing skyscrapers by continent, for instance, seems very reasonable, while for organizing them by architect it depends on the number of skyscrapers per architect—boring, if each architect designed only one or two skyscrapers. With large and heterogeneous data available, specifically on the Web, hiring domain experts annotating attributes manually is infeasible. In this work, we propose a fully automated framework in order to learn a classification model that can identify categorical attributes that are suitable for categorizing entities. Suitable in the sense of human-perceived interestingness.

The human perception of ‘interestingness’ is a complex concept that asserts unexpectedness, conciseness, coverage, utility, and diversity [13]. Hence, finding suitable statistical measures that capture interesting or non-interesting characteristics in categorical attributes renders the learning problem difficult. In this paper, we first investigate existing objective measures of interestingness for categorical attributes [13, 19]. As we will see by anecdotal evidence
and later also by experimental results, these empirical probability-based measures fail to capture all aspects of our task to identify interesting categories in many cases, as discussed in Section 3.2. To address the identified shortcomings, we propose three novel statistical measures, P-Diversity, P-Peculiarity, and Max-Info-Gap for categorical attributes. Finally, we learn a robust and accurate classification model using support vector machine (SVM) over combinations of proposed and existing measures. By means of a user study, we show that the trained classifier is able to predict those categorical attributes that are suitable for further categorization of entities—in a human-perceived sense. We will also see later from experimental studies that the proposed statistical measures are more effective in capturing ‘interestingness’ compared to commonly used measures like entropy or coverage. To the best of our knowledge, this is the first full-fledged approach that enables the identification of meaningful categorical attributes, a generic and widely applicable ingredient to data exploration and analytics.

1.1 Problem Statement and Notation
Our objective is to understand which categorical attribute of a specific entity-centric table will be perceived suitable by humans for the task of defining a meaningful subset of the entities. Hence, in this work, a categorical attribute is considered interesting if it is suitable for further categorization of entities.

In order to do so, we investigate a set of tables \( \mathcal{R} \), where a table \( r \in \mathcal{R} \) represents a list of entities of a specific type together with their attributes \( \mathcal{A} \). A set of statistical measures \( \mathcal{F} \) is used to map the categorical attributes (i.e., columns of tables) to the feature space, in order to train a classifier \( C \) that can predict which categorical attributes are interesting for categorizing the entities of the table.

Consider again Table 1 and let us denote with \( \mathcal{V}_{\text{country}} = \{ \text{UAE} (1), \text{China} (3), \text{Saudi Arabia} (1), \text{United States} (1) \} \) the set of values for the attribute country. The numbers in parentheses express the multiplicity. Statistical measures can now be computed based on these numbers, for instance, the Shannon entropy of the according frequency distribution would be 1.792. If we knew that the attribute country is an interesting attribute for categorizing tall buildings, then we could, roughly speaking, learn that an entropy around 1.792 might be an indicator for interesting attributes, in any table we encounter.

To bring this toy example to larger scale, in order to build a reliable classifier, we face the following main tasks:

- First, to the best of our knowledge, there is no dataset available in literature that provides information on which categorical attributes are useful for the categorization of the entities of a specific class. Such training data is, however, crucial for training a classifier, thus, needs to be acquired first—and we want to do so without any manual human intervention.
- Second, we have to identify suitable measures (statistical features) that can capture the characteristics of categorical attributes, tailored to our context of interestingness. Existing features have certain drawbacks that hinder them grasping important characteristics. We will review such weaknesses and explain how the newly proposed measures can reflect them.

1.2 Sketch of our Approach
Our whole approach is divided into two main components as shown in Figure 1. The Information Extraction component first creates the training samples from Wikipedia tables in a completely automated manner. For this purpose, we identify the categorical attributes from a set of Wikipedia tables. Then, we find out whether retrieved categorical attributes will be labeled as ‘interesting’ or ‘non-interesting’ for further categorization of the entities based on a central hypothesis, proposed in Section 2.

After labeling the categorical attributes, the Data Mining component extracts the feature vector \( \mathcal{F} \) for each categorical attribute in the training data. \( \mathcal{F} \) comprises existing and newly proposed statistical measures. Then, a classifier \( C \) is trained over the extracted feature vectors using \( \nu \)-SVM.

1.3 Contribution and Organization
With this work, we make the following contributions:

- We describe a framework to harness training samples of interesting and non-interesting categorical attributes from tables without explicit human intervention.
- We investigate statistical measures that can capture the interestingness of categorical attributes and propose three new statistical measures tailored to our main objective.
- We have conducted a comprehensive evaluation, including a user study, demonstrating the applicability of the general approach and the superiority of the newly proposed features.
The sample training data retrieved from Wikipedia tables, relevance assessments from user, and trained classifiers are made public.

A preliminary version of this work has been published as a short paper at EDBT'16 [22].

The paper is organized as follows. Section 2 proposes the working hypothesis and the algorithm to extract training data. Section 3 discusses the proposed statistical measures and the existing ones, and introduces the learning model. Section 4 presents the experimental results. An overview of related work is presented in Section 5 and Section 6 concludes the paper.

2 AUTOMATED EXTRACTION OF TRAINING DATA

In this section, we describe how training data can be obtained in a fully automated fashion. That means, for categorical attribute $a_c$, (i.e., a column of a table) that appears in a table for entity type $a_s$, we need to determine the label (interesting or not-interesting) that tells whether the attribute allows a suitable categorization of the entities, reflecting a human notion of a meaningful categorization or not. But how can we determine the label without human effort?

We put forward the working assumption that the presence and absence of Web tables is an indicator of general interest or disinterest of humans in such tables. And following this assumption, the presence of a Web table makes a categorical attribute, that is used as a constraint to create that very table, interesting. This observation is cast into our general hypothesis given next. We will see later by experiments on human relevance assessments that this hypothesis is in fact well-grounded, and discuss limitations below.

**Hypothesis 1.** A categorical attribute in a table is considered interesting, thus its statistical features are positive training samples, iff we find at least one table over the same entity class that is created by imposing a constraint over that categorical attribute.

Let us walk through an example to explain the intuition behind this hypothesis. In Table 1, we observe that entities of class 'building' are displayed, together with the categorical attributes 'country' and 'city'. By browsing through Wikipedia, we also find another table, namely the List of Tallest Buildings in the United States, shown in Table 2. As will be described in more detail below, we use in fact the caption of the table, respectively the title of the corresponding Wikipedia table to determine the attribute used as constraint. Clearly, both tables are created on the same entity class, building, and the constraint 'country=United States' is applied in Table 2, we see this in the title/caption of that table. We also find that 'United States' is one of the categorical value for attribute 'country' in Table 1. Consequently, according to our hypothesis, 'country' is considered interesting for entity class 'building', as we found (at least) one table (Table 2) that is created by imposing the constraint 'United States' on the categorical attribute 'country' from Table 1.

Table 2: List of Tallest Buildings in the United States

| Building         | City       | Height |
|------------------|------------|--------|
| One World Trade Center | New York City | 454m   |
| Willis Tower     | Chicago    | 442m   |
| 432 Park Avenue  | New York   | 426m   |

Note that the table "List of Tallest buildings in United States" may not be a subset of the table shown in Table 1, this is irrelevant for our task, however.

Now, once we have found such a pair of tables, we consider Table 1 as parent and Table 2 as child. Then we extract statistical features (for instance, information entropy) from the categorical attribute 'country' of the parent table and consider it as a positive sample in our training data.

Although the final classifier is independent of specific entity types, while generating the training data from tables, an association between subject $a_s$ and categorical attribute $a_c$ is required, as a categorical attribute can be associated with many entity types (e.g., 'length' can be an attribute for highways, bridges, beaches, etc.), thus, the pair $(a_s, a_c)$ provides a unique identification for features retrieved for attribute $a_c$ for entity class $a_s$. It would be misleading, or simply wrong, to search for any table (irrespective of matching entity type) that was generated by using a constraint on categorical attribute $a_c$, to conclude anything useful from the statistics computed from any table that has such an attribute $a_c$. The final classifier is independent of the entity class, as it operates solely on statistical measures retrieved from categorical attribute.

2.1 Algorithm

To find the parent-child relation between two tables, in order to retrieve the label for categorical attributes and its statistics, a brute-force method would visit all pairs of tables. Avoiding the brute-force method, Algorithm 1 scans the tables twice to retrieve the training samples: once to learn from table metadata which constrained tables exist for an entity type and, once to draw the connections between table columns/attributes and existing constrained tables. More precisely, in the first phase, only the table header and metadata for all tables are scanned to retrieve the constraint $r_{cons}$ and subject $a_s$ of the table. The detailed way of retrieving metadata and subject is discussed in Section 2.2. The extracted information is subsequently used to build an index in form of a simple map, called $cons_{map}$. It takes the constraint $r_{cons}$ retrieved from a table as key and corresponding subject $a_s$ of that table as value. For example, considering the two tables "List of Tallest Buildings in the United States" and "List of Universities in the United States", the constraint in both tables is United States, and the corresponding entries in $cons_{map}$ is as follows:

United States → {buildings, universities}.

After creation of $cons_{map}$, a second complete scan over the tables and their columns and headers is done to retrieve all the attributes and their positive or negative label. We remove numeric attributes (cf., Line 7 in Algorithm 1) and only consider the categorical attributes for a specific entity class, i.e., pairs of $(a_s, a_c)$, from each Web table, in order to create the training samples and generate automatically the labels based on Hypothesis 1.

According to this main hypothesis, the label of a categorical attribute is found by identifying the parent-child relation between tables, using that categorical attribute. To determine this, we take $V_{a_s}$, associated with a categorical attribute $a_c$ for a specific entity type $a_s$, and check the $cons_{map}$ for each categorical value in $V_{a_s}$ until we find a match. Once a value from $V_{a_s}$ is contained as key in $cons_{map}$, we scan the subject list associated with the key to see whether the entity class $a_s$ is contained in the list. If it is, we
Algorithm 1: Generating Training Samples

Data: Initialization
\( \text{cons}\_\text{map} : \{\text{key} : \text{constraints}, \text{value} : \text{subjectList}\[\text{[]}\}\} \)

training samples: interesting\[\text{[]}\] // a list of \( \{(a_s, a_c), \mathcal{F}\} \) where \( a_c \) is used to categorize \( a_s \).

Negative training samples: noninteresting\[\text{[]}\] // a list of \( \{(a_s, a_c), \mathcal{F}\} \) where \( a_c \) is not used to categorize \( a_s \).

Procedure generateSamples\( (\text{Web tables } \mathcal{R}) \)

\[
\begin{align*}
&/* \text{ Scan on } \mathcal{R} \text{ to build } \text{cons}\_\text{map} */ \\
&\text{for } r \in \mathcal{R} \text{ do} \\
&\quad r.a_s, \text{rcons} \leftarrow \text{parse metadata}(r) \\
&\quad \text{add } (r.a_s) \text{ to the list of cons}\_\text{map}[\text{rcons}] \\
&/* \text{ Scanning } \mathcal{R} \text{ to build training samples */} \\
&\text{for } r \in \mathcal{R} \text{ do} \\
&\quad \text{List}(r.A) \leftarrow \text{parse}(r) // \text{ Parsing all columns} \\
&\quad \text{List}(r.A_c) \leftarrow \text{List}(r.A) \setminus \{r.a_s \cup \mathcal{N}\} // \text{ Removing numeric attributes} \\
&\quad \text{for } a_c \in \text{List}(r.A_c) \text{ do} \\
&\quad\quad \mathcal{F} \leftarrow \text{calculateFeatures}(V_{a_c}) \\
&\quad\quad /* \text{ Find existence of parent, child table in } \mathcal{R} \text{ based on } V_{a_c} */ \\
&\quad\quad \text{for } x \in V_{a_c} \text{ do} \\
&\quad\quad\quad \text{subjectList} \leftarrow \text{cons}\_\text{map}[x] \\
&\quad\quad\quad \text{if } r.a_s \in \text{subjectList} \text{ then} \\
&\quad\quad\quad\quad \text{add } \{(r.a_s, a_c), \mathcal{F}\} \text{ to interesting[]} \\
&\quad\quad\quad\quad \text{break} \\
&\quad\quad\quad \text{else} \\
&\quad\quad\quad\quad \text{add } \{(r.a_s, a_c), \mathcal{F}\} \text{ to noninteresting[]} \\
&\quad\quad \text{return interesting[]}, \text{noninteresting[]} \\
\end{align*}
\]

know that there exists at least one table that is built over same entity class \( a_s \) and is using one of the categorical value from \( V_{a_c} \), associated with attribute \( a_c \) from the current table we are scanning. Clearly, we identify the current table as a parent table and also find the existence of a child table using \( a_c \). Hence, we label the pair \( (a_s, a_c) \) as “interesting” based on our hypothesis and consider it a positive training samples. If we did not find any match with the key in \( \text{cons}\_\text{map} \) for any of the value from \( V_{a_c} \), we know that no child table is found based on the attribute \( a_c \). Hence, the pair \( (a_s, a_c) \) is labeled as “non-interesting” and is, thus, considered a negative training sample.

While retrieving \( V_{a_c} \) for a categorical attribute \( a_c \), the frequency count of the entities appearing in the table associated with each categorical value in \( V_{a_c} \) is also captured (e.g., in Table 2, \( V_{city} = \{\text{New York City} (2), \text{Chicago} (2)\}\)). This information is then used to map a pair \( (a_s, a_c) \) to feature space \( \mathcal{F} \), capturing the empirical characteristics, such as information entropy, of the pair \( (a_s, a_c) \); discussed in detail in Section 3.

Note that Web tables are not always fully consistent in data representation and column descriptions \([17, 26]\). As ambiguous representations of numeric types can generate wrong classification labels to categorical attributes, Algorithm 1 excludes all attributes of numeric type, which results in removing categorical attributes such as years etc., when generating the training data.

### 2.2 Harnessing Wikipedia

In this work, we specifically use the English Wikipedia corpus to generate training samples. The major difficulties in extracting and understanding information from Web tables arise due to inherent heterogeneity in schema and data representation \([9, 33]\). Here, we discuss in more detail why Wikipedia is an excellent source for our endeavor.

First of all, by enforcing collaborative editing policies and controlling duplicated information across multiple pages, Wikipedia maintains high information quality and thus generally considered credible for knowledge exploration \([2, 8, 21]\). We also excluded user pages to avoid biased data.

Second, Wikipedia contains tables that provide surprisingly many categorical attributes. Such information is not available in Web portals like rankopedia.com or ranker.com where tables are created based on crowdsourcing, with only numeric attributes (mainly number of upvotes) being available for the entities. More precisely, 3/4 of all Wikipedia tables investigated for this work contain categorical attributes. The distribution of the number of categorical attributes per table can be well described by a Poisson distribution with mean \( \lambda = 1.9 \) (with relative sum square error of \(< 0.00001\))

Third, the structure of the tables in Wikipedia is quite consistent and the metadata of tables, required by Algorithm 1, can be extracted. However, we noticed that often enough not all pages have sufficient information associated via html tags, not even the title of the table. Hence, retrieving metadata from arbitrary tables would require sophisticated NLP techniques and perhaps further demand user interaction for checking the correctness of the results. Thus, in this work, we consider only those tables that are created with a page title beginning with the phrase “List of…” and have the property of being sortable. This greatly helps to accurately collect metadata, such as subject, constraint, etc., of the tables by parsing the title/caption of the table or the title of the Wikipepge. These page titles have a very simple sentence structures that can be easily parsed by using propositions from the English dictionary, in order to retrieve the subject and the constraints of a table. For example, from the page title “List of Tallest Buildings in the Unites States”, we retrieve subject of the table as ‘Tallest Buildings’ and ‘Unites States’ as constraint, based on prepositions ‘of’ and ‘in’. Although sometimes page titles are more complex than the example given, they are still easily parseable as usually much less complicated than full-fledged sentences in regular text paragraphs.

Now, we will discuss briefly how to extract the subject and the applied categorical attributes/constraints from a table. As mentioned before, we get a hint about the subject and the constraint of a table by parsing the title of the page from where the table is retrieved. Using this hint, we identify the subject column in the table. To do so, we check whether any of the table’s column headers matches with the subject retrieved from the page title. The match is considered true if any of the stemmed words (nouns) retrieved as subject from the page title matches with the stemmed column headers. Then, the matched keyword is considered the subject for the training sample and the corresponding column is identifies as subject column for that table.
There are few cases where no match was found with the table header, as the subject obtained from the page title and the header of the subject column in the table do not use the same common noun for the subject. For example, in many cases, we found the table header of the subject column given simply as ‘name’. In such cases, we use the retrieved subject from the page title as the subject for the training sample and the adjacent column to the sortable column (ranking column) of the table is considered the subject column. We filter the numeric attributes during our sample generation as presented in Line 7 of Algorithm 1. To do so, we employ a dictionary of unites to recognize numeric attributes, i.e., if the table header or cells contain ‘lbs’ or ‘kg’. The presence of only numeric content in a cell of a table column is considered as numeric attribute. Although the structure of tables are well defined in Wikipedia, the data is not free from ambiguity. For instance, in some tables, numerical data (e.g., age) are spelled-out, thus, are retrieved as non-numeric categorical values which leads to a false identification of numeric attribute as categorical attribute in our training data. Here, more sophisticated extraction methods [3, 20] could be used in Algorithm 1 for metadata extraction, but this is orthogonal to our hypothesis. It should be emphasized, however, that despite this restriction in obtaining training data, the learned model can in fact predict interesting categorical attributes of numeric type.

Potential Limitations: Not surprisingly, in various cases, the absence of a table in Wikipedia might be due to the limited manpower and not due to general disinterest in that table. In fact, we found cases of tables missing in Wikipedia where human evaluators in our user study unanimously state that they are interesting and, following our hypothesis, should exist. For instance, the list of the gold medalists in Olympic history, grouped by the type of sport, was not present in Wikipedia at the time of harnessing training data, but marked interesting by the majority of voters in our user study. In fact, at the time of writing this paper, several such lists of gold medalists were added to Wikipedia. Due to this characteristics, the accuracy of the samples extracted by Algorithm 1 suffers from false positive data and reaches only 68.9% overall accuracy according to user assessments. However, even though few training samples were apparently misleading, our classifier was able to correctly classify the task according to the evaluators’ judgments. Supported by such exemplary evidence, and the overall performance shown in the experimental evaluation, we believe the hypothesis is reasonable to generate labeled training data for our learning task, as important tables are created supposedly before people spend effort in creating less important ones.

### Table 3: Sample Data and Corresponding Measures

| Example 1 | Example 2 | Example 3 |
|-----------|-----------|-----------|
| USA(12)   | USA(2)    | USA(12)   |
| Spain(8)  | Germany(2)| Germany(2)|
| Germany(2)| China(2)  | China(2)  |
| Australia(2)| Australia(2)|
| France(2) | Switzerland(1) | France(2) |
| Switzerland(1) | Russia(1) | Switzerland(1) |
| Russia(1) |                     | Russia(1) |

|   | Example 1 | Example 2 | Example 3 |
|---|-----------|-----------|-----------|
| $H$ | 0.44      | 0.77      | 0.48      |
| $mCov$ | 0.43      | 0.17      | 0.55      |
| $MIq$ | 0.75      | 0.28      | 0.8       |
| $U$ | 0.71      | 0.85      | 0.67      |
| $D$ | 0.74      | 0.92      | 0.7       |
| $pPec$ | 0.58      | 0.33      | 0.69      |
| $pVar$ | 0.36      | 0.66      | 0.49      |

Before we dive into the concrete definitions of the individual measures, let us have a look at Table 3 in order to understand better on which data these measures are actually executed. In the heading of the table, we see values and their frequencies (i.e., the set $V_{ac}$) for three made-up exemplary tables for a categorical attribute ‘country’. We see that the different measures vary quite strongly, relative to each other, but also compared to the same measure for different table characteristics. For instance, for the first table on the left side, Entropy ($\hat{H}$) is quite low compared to the almost uniform (random) distribution of frequencies in the table in the middle which has, thus, a high Entropy. This is the key point—individual measures highlight different aspects of the data, for instance the degree of randomness or the degree of dominance of categorical values.

### 3.1 Existing Features for Categorical Attributes

There are several probability-based objective measures proposed in literature, specifically for mining association or classification rules, capturing the generality or reliability of such rules. One of the most prevalent measures is Entropy, mainly used for mining attribute-value pairs. Statistical measures that are capturing diversity of categorical attributes are, on the other hand, less prominently investigated [11]. Below, we briefly review four traditional measures and how to employ them as features to learn the classifier.

#### Shannon Entropy:

Entropy reflects the degree of uncertainty in the information, described by a discrete random variable. In this work, a categorical attribute $a_c$ is treated as a random variable where $V_{ac}$ is the set of possible values that $a_c$ can hold. Shannon entropy for $a_c$ is calculated by $H(a_c) = -\sum_{x \in V_{ac}} P(x) \log_2 P(x)$, with $P(x) = \text{count}(x)/|T|$, where $|T|$ is the size of the table and $\text{count}(x)$ is the frequency of value $x \in V_{ac}$. We use the normalized entropy, given by

$$\hat{H}(a_c) = \frac{\sum_{x \in V_{ac}} P(x) \log_2 P(x)}{\log_2 |T|}$$

How can we relate entropy to the interestingness of categorical attributes? Intuitively, a piece of information is considered interesting when the randomness of the information content is neither extremely high (i.e., $\hat{H}(a_c) = 1$) nor extremely low (i.e., $\hat{H}(a_c) = 0$). This interpretation of entropy in our context is reflected in Figure 2(a) and 2(b). It shows that 69% of the seemingly interesting
categories have an entropy value in $[0.2, 0.8]$ and 71% of the non-interesting categories have an entropy value in $[0, 0.2]$ or $[0.8, 1]$.

**Max-Coverage.** Coverage is a commonly used measure in itemset mining. It captures the comprehensiveness of a pattern. In this paper, we use maximum coverage of a categorical value as one of the features. It is denoted as $m\text{Cover}(a_c)$, and is calculated as

$$m\text{Cover}(a_c) = \max_{x \in V_{a_c}} (P(x))$$

$m\text{Cover}$ captures dominance of a categorical value. If all the entities in the table have the same value for $a_c$, then $m\text{Cover}(a_c) = 1$. Such an extreme case is definitely not an interesting one. On the other hand, $m\text{Cover}(a_c) \to 0$ when too many categorical values are associated with $a_c$ and each entity holds a different categorical value. This scenario is also not an interesting one. Intuitively, a mid range in $[0,1]$ might represent $m\text{Cover}$-value for a interesting category. According to the distribution of the measure $m\text{Cover}(a_c)$ in our training samples, presented in Figure 2(a) and 2(b), 66% of interesting categories have a Max-Coverage in $[0.2, 0.8]$ and 47% of the non-interesting categories have a $m\text{Cover}$-value in $[0, 0.2]$.

It should be mentioned here that for large entity list, both cases, a skewed distribution with high $m\text{Cover}$-value and a uniform distribution with lower $m\text{Cover}$-value are suitable for further categorization of entities. But these ranges of $m\text{Cover}$-value identify the categorical attributes as not interesting for categorization.

**Unalikeability.** Variance is a common measure for describing the degree of diversity present in the data. For categorical data, Kader and Perry [19] discuss a variation coefficient, called Unalikeability, denoted as $U(X)$ for a random variable $X$. Instead of measuring how much a observation of random variable differs, it essentially captures how often observations of a random variable differ from one another.

For a categorical attribute $a_c$, it is calculated as

$$U(a_c) = 1 - \sum_{x \in V_{a_c}} P(x)^2$$

$U(a_c) = 0$ shows that all the entities have the same value for $a_c$ and, thus, categorical attribute $a_c$ for that entity class becomes less interesting. Similarly, $a_c$ becomes non-interesting while $U(a_c) \to 1$. It signifies that $a_c$ is too diverse to choose an attribute value pair for further refinement of entity list. Figure 2(d) reflects this characteristic, 83% of non-interesting categories hold Unalikeability values in $[0, 0.2]$ or $[0.8, 1]$.

**Peculiarity.** Simpson’s index is the most commonly used diversity measure for categorical attributes and it is also referred as peculiarity measure in the context of mathematical ecology as discussed in Kader and Pielou [23]. It is defined by the probability that a randomly chosen categorical value has not been seen previously, denoted as $D(X)$ for random variable $X$. For a categorical attribute $a_c$, it is calculated as

$$D(a_c) = 1 - \sum_{x \in V_{a_c}} \frac{\text{count}(x)(\text{count}(x) - 1)}{|T|(|T| - 1)}$$

$D(a_c)$ also shows the same characteristic as $U(a_c)$ with respect to understanding the interestingness of categorical attributes. Figure 2(d) reflects this characteristic of Peculiarity. Around 74% of non-interesting categories hold feature values within the range of $[0, 0.2]$ or $[0.8, 1]$. Both diversity measures show that an ideal interesting category is more prone to have a diversity-value in mid-range of $[0.1]$, near to 0.5.

### 3.2 Novel Features for Categorical Attributes

The existing measures discussed above are commonly used as impurity measure in classification methods, such as decision trees, and are able to capture the distribution of categorical values. But capturing the distribution or uncertainty in information content of categorical values for an entity class is not enough to understand whether that distribution would be interesting enough for further categorization of the entities, or not. The problem we are addressing in this paper calls for a more fine-tuned understanding of the data distribution. In the following, we propose three probability-based statistical measures: (i) Max-Info-Gap, (ii) P-Diversity, and (iii) P-Peculiarity. We also discuss how these measures provide more distinctive information to understand which distribution of categorical values would be interesting in our context, compared to the above existing statistical measures.

**Max-Info-Gap.** Consider a specific value $x$, say ‘China’, of a categorical attribute $a_c$ in a table. If $x$ is very frequent, the information contained in that column of the categorical value is low, with the extreme case of one unique value for all entities with respect to $a_c$. This extreme case could in fact indicate that the table was explicitly created for entities that hold this one specific value. Following information theory, the maximum amount of information that a specific categorical value can hold is $-\log_2 \frac{1}{|T|}$ for a table $T$ with $|T|$ rows; basically when it is describing only one entity in the table. Now, the idea behind Max-Info-Gap is to quantify the maximum difference between the information expressed by one specific categorical value within $V_{a_c}$ and the maximum information content a categorical value can hold hypothetically for that table, given by

$$\max_{x \in V_{a_c}} \left\{ (-\log_2 |T|^{-1}) - (\log_2 P(x)) \right\}$$
The maximum difference occurs due to the categorical value having maximum coverage. Compared to Max-Coverage, that is concerned with solely maximizing \( P(x) \), Max-Info-Gap specifically incorporates the size of the table. It signifies the dominance of a categorical value compared to others. With the existing notion of Max-Coverage, we can define Max-Info-Gap as follows.

**Definition 3.1.** Max-Info-Gap is the maximum information gap between the maximum information that a categorical value can hold for the categorical attribute and the actual information it is holding. It is denoted as \( mIg(a_c) \) for categorical attribute \( a_c \), and is calculated as follows:

\[
mIg(a_c) = 1 - \frac{\log_2 mCov(a_c)}{\log_2 |T|}^{-1}
\]

The values of \( mIg(a_c) \) fall by definition into \([0, 1]\). Full diversity in the values of \( a_c \) renders \( mIg(a_c) = 0 \), clearly not an interesting scenario for further categorizing entities. For a fixed table size, as the dominance of one specific value increases, \( mIg(a_c) \) also increases. In general, we can say that a skewed distribution of categorical values hold higher \( mIg \) measure than the uniform distribution for fixed table size. In extreme case, when all entities hold the same categorical value then \( mIg(a_c) = 1 \) as \( mCov(a_c) = 1 \). For example, if we compare the values of \( mIg \) in Table 3, we find that the \( mIg \)-value of the Example 1 and Example 3 are higher than for Example 2 as the distribution of categorical values in Example 1 and Example 3 are skewed. We can also see that \( mIg \)-value of Example 3 is slightly higher than for Example 1, as the dominance of ‘USA’ is higher in Example 3, considering that the table length of both examples is comparable.

It is important to discuss here how significantly \( mIg \) differs from \( mCov \), as both of these measures quantify the dominance of categorical value in a table. Both measures, \( mIg \) and \( mCov \) hold a value towards 1 if one categorical value is very dominant. But \( mIg \) considers the table length to reward the coverage value as table length increases. In Figure 3, we present how the measure \( mIg \) rewards coverage value with varying table length. We can see from the Figure 3 that for higher \( mCov = 0.9 \), \( mIg \)-value does not differ much which clearly signifies existence of one very dominating categorical value. On the other hand, with low coverage value, representing a non-skewed distribution of categorical values, significantly differs from \( mCov \)-value as table length increases. In Figure 3, we can see that with a fixed low \( mCov = 0.2 \), a small table of length 10 holds \( mIg = 0.3 \) where a larger table with 100 entities reach \( mIg = 0.63 \), significantly higher to indicate a further categorization of entity based on that categorical value. The \( mCov \) measures cannot capture this insight from data.

| Example 4 | USA | Spain | Germany | China | Australia | France |
|-----------|-----|-------|---------|-------|-----------|--------|
|           | (60)| (50)  | (45)    | (60)  | (40)      | (60)   |

From Example 2 and Example 4, we can see that Example 4 is more suitable for further categorization compared to Example 2. Both examples have \( mCov = 0.16 \) but \( mIg \)-value for Example 4 is 0.74, emphasizing a possible interesting further categorization; whereas the \( mIg \) value of Example 2 is very low (cf., Table 3). In line with the discussion, Figure 2(a) and 2(b) shows that 19% interesting and 24% non-interesting samples have \( mCov \leq 0.1 \) in our training data whereas 3% of the interesting and 39% of the non-interesting samples have \( mIg \leq 0.1 \). This means, Max-Info-Gap \( (mIg) \) can better distinguish interesting categorical attributes from non-interesting ones.

**P-Diversity:** To understand the deviation of the distribution of categorical values from a predefined reference distribution, we propose the P-Diversity measure. In contrast to the concept of Unlikeability \( U(a_c) \), it aims at describing how often the observation of a random variable varies with respect to an established reference frequency. This reference frequency is defined based on how we define the interesting categorical attribute. For a categorical attribute \( a_c \), if all entities have the identical value then there is no diversity among the observations (in such case, \( U(a_c) = 0 \)). In this scenario, imposing a constraint on \( a_c \) cannot create a new, refined table. Hence, \( a_c \) is not interesting. So, the categorical attribute needs to have at least two values, introducing the possibility of having refined tables that are created by putting a constraint over values of \( a_c \). In an ideal case, these two categorical values will be equally distributed over the entity list which defines the reference frequency 0.5. It represents the minimum diversity for a categorical attribute to become interesting. Relative to this reference frequency, we define the measure P-Diversity of a categorical attribute as follows.

**Definition 3.2.** P-Diversity is the square root of the sum of squares of the differences between the actual coverage of a categorical value to the reference coverage value 0.5. It is denoted as \( pVar(a_c) \) for \( a_c \), and is calculated as

\[
pVar(a_c) = \sqrt{\sum_{x \in V_{a_c}} (P(x) - 0.5)^2}
\]

Note that the maximum \( pVar(a_c) \) is equal to \((1 - 0.5|T|)/\sqrt{n}\), which occurs whenever the categorical attribute holds different values for each entity in the table. The normalized P-Diversity is, thus, given by

\[
p\hat{v}ar(a_c) = \sqrt{\frac{\sum_{x \in V_{a_c}} (P(x) - 0.5)^2}{(1 - 0.5|T|)/\sqrt{n}}}
\]
Here, \( pVar(a_c) = 1 \) if the categorical attribute holds different values for each of the entity. Therefore, \( pVar \rightarrow 1 \) signifies the cases where further categorizations are not suitable. On the other hand, \( pVar \rightarrow 0 \) while the coverage of categorical values near 0.5, indicates the possibility of further categorization. The normalizing factor for P-Diversity also considers the size of the table and reward \( pVar \) value as size increases. Hence, a uniform distribution with coverage value far from 0.5 might hold \( pVar \) value close to 0 if table size is large. Rewarding the table with larger size even for small coverage value is perfectly in line with the consideration for further categorization, in our context. For example, let us consider Example 2 and Example 4 where both lists have almost similar distribution of categorical values where coverage of each categorical value is less than 0.2, significantly smaller than the reference coverage of 0.5. But due to large table size, Example 4 holds \( pVar = 0.09 \), close to 0, indicating further categorization of the table while Example 2 holds \( pVar = 0.66 \), indicating less importance of a further categorization of the entities. The measure Unalikeability cannot capture this characteristic and holds almost similar \( U \) value 0.85 and 0.83 respectively for Example 2 and Example 4, respectively, indicating both are not suitable for further categorization of entity list. We can observe from the distribution of \( pVar \)-value, shown in Figure 2 (d) that 50% of retrieved non-interesting training samples holds \( pVar \) value in range of \([0.9, 1]\) and 72% non-interesting training samples \( pVar \) value \( \geq 0.5 \). According to the definition of \( pVar \), a uniform distribution of categorical values is considered to be more useful for further categorization compared to a highly skewed distribution where \( pVar \rightarrow 1 \). We can see in Table 3 that Example 1 has lower \( pVar \) value compared to Example 3 because Example 1 is less skewed than Example 3.

What exactly is the difference between P-Diversity and existing diversity measures? Let us consider the example in Table 4. In the first row, we represent two lists where list1 is more skewed than the list2. The second row holds list3 and list4 with an identical distribution of values as list1 and list2, respectively, but both lists are of smaller size. As Unalikeability does not consider the list size, it cannot distinguish between list1 and list3 as distribution of both lists are same. In contrast, \( pVar(list1) \) is very close to 0, indicating the potential for further categorization of list1 whereas \( pVar(list3) = 0.63 \), which tells that list3 is not interesting for any further categorization of its entities. On the other hand, the Peculiarity measure increases as the table size decreases. Hence, for a skewed distribution of values, a small table is considered more interesting than the larger one. For example, Table 4 shows that \( D(list3) = 0.4 \) is closer to 0.5 than \( D(list1) = 0.32 \). As mentioned earlier, \( D \) value close to 0.5 characterize interesting attributes, and thus list3 is more suitable for categorization than list1, according to Peculiarity, which is clearly not the case. In this table, we can also see that as list size grows the difference between \( pVar \)-value for skewed and uniform distribution decrease as expected.

In the experimental study in Section 4, we will see that the learning model created by using P-Diversity performs better than the model that is considering existing diversity measures.

Next, P-Peculiarity is proposed to capture the unexpectedness of categorical values that are distributed over the table. There is no peculiarity in a categorical attribute if the categorical values are equally distributed over the entities. Thus, this measure quantifies the skewness of data by finding the difference of its distribution from uniform distribution. Unlike the \( mlg \) measure, where the skewness of the most skewed categorical value is used to quantify the skewness, here, all categorical values is considered i.e., the actual probability distribution of the categorical attribute is considered.

Definition 3.3. P-peculiarity is the absolute difference between the actual probability distribution of the categorical values and the uniform probability distribution. P-peculiarity is denoted as \( pPec(a_c) \) for categorical attribute \( a_c \), and is given by

\[
pPec(a_c) = \sum_{x \in V_{a_c}} |P(x) - \frac{1}{|V_{a_c}|}|
\]

Again, we now investigate how this measure can be normalized. We observe that the maximum deviation from the uniform distribution occurs when all categorical values, except one, occur exactly once. The remaining one occurs for all other entities in the table. Hence, P-Peculiarity normalized to \([0, 1]\) by factor \( \max(pPec(a_c)) \) is given by:

\[
\hat{pPec}(a_c) = \frac{\sum_{x \in V_{a_c}} |P(x) - \frac{1}{|V_{a_c}|}|}{\max(pPec(a_c))}
\]

According to the formulation of \( \max(pPec(a_c)) \), it is clear that \( pPec(a_c) = 1 \) indicates that one specific categorical value has almost full coverage over the entities. On the other hand, \( pPec(a_c) = 0 \) only when each categorical value has exactly same coverage. Both cases are considered to be not-interesting for further categorization of entity list. Our intuition is that \( pPec(a_c) \)-value in mid range of \([0,1]\) is considered to be interesting for further categorization of entity list. From Figure 2(c) and Figure 2(d), we can observe this characteristic of distribution of \( pPec(a_c) \)-value; 78% of the interesting categories hold \( pPec \)-values in \([0.2, 0.8]\) and 67% non-interesting categories hold \( pPec \)-values within \([0.2 \text{ and } 0.8]\).

| Table 4: Comparing \( pVar \)-value with Unalikeability |
|----------------|----------------|------|------|
| Table size | list | \( pVar \) | U | D |
| 100 | list1: { USA(80), Spain(20)} | 0.09 | 0.32 | 0.32 |
| | list2: {USA(60), Spain(40)} | 0.03 | 0.48 | 0.48 |
| 5 | list3: {USA(4), Spain(1)} | 0.63 | 0.32 | 0.4 |
| | list4: {USA(3), Spain(2)} | 0.21 | 0.48 | 0.6 |

| Table 5: Comparing \( pVar \)-value with \( mlg \) |
|----------------|----------------|------|
| Table size | list | \( pVar \) | \( mlg \) |
| 100 | list1: { USA(90), Spain(10)} | 0.82 | 0.98 |
| 10 | list2: {USA(9), Spain(1)} | 1.0 | 0.95 |

Similar to the \( mlg \) measure, the normalizing factor used in P-Peculiarity also rewards the \( \hat{pPec} \) value as table size increases. But
Unlike $mlg$, this measure incorporates the influence of the table size in skewed distributions. For example, consider Table 5, we can see for list2, $pFec = 1$, clearly indicating not an interesting case for further categorization of entity list whereas $mlg = 0.95$ expressing an interesting case for further categorization (recall that $mlg \rightarrow 1$ indicates interesting scenarios). On the other hand, we can see, as the table size increases for the same skewed distribution, the $pFec$ value comes close to the mid range for list1, signifying an increasing interestingness of a further categorization.

### 3.3 Tailoring Support Vector Machines

After having discussed possible features, we now describe how a classifier is created based on combinations of them. We opted for applying the support vector machine (SVM) approach, a widely known and well understood concept. In the easiest case, training data is balanced (roughly the same number of positive and negative samples) and linearly separable, which renders the application of simple Linear-SVMs possible. However, as we extracted the training data from Wikipedia it contains noise for the various reasons discussed earlier. Hence, we need to employ a soft-margin classifier, specifically, $\nu$-SVM [30] which can detect outliers while learning the classification model from the training data. In $\nu$-SVM, the parameter $\nu$ is tunable within $[0, 1]$ and controls the lower and upper bound on the number of misclassified samples that are allowed in the training phase of the classifier, i.e., the training error. As $\nu$ increases the model becomes more biased and it is under-fitting the data. Moreover, we also notice that the statistical measures that we are going to use as feature space are not linearly separable. Because for a statistical measure, multiple non-contiguous ranges of values can be associated with a particular class of samples. Hence, we use the popular radial basis function (RBF) as kernel function [29] that transforms our training data to higher dimensional space using a non-linear mapping. This ‘kernel’ method allows classifying the training data linearly in higher dimensional space. In the RBF kernel, a parameter $\gamma$ is used to control the radius of influence of the support vectors. For example, a high value of $\gamma$ discards the influence of $\nu$, and cannot prevent overfitting. In Section 4, we will discuss how the optimal values for $\nu$ and $\gamma$ are calculated to train the classifier.

In this work, we extracted 16 times more negative samples than positive ones from Wikipedia tables using Algorithm 1 (see details in Section 4). For such unbalance training data, the one-class SVM [28] approach can be employed, where the classifier is trained based on the samples from a single class (either positive or negative training samples). Another option could be the use of sampling to train balanced samples. In the RBF kernel, a parameter $\gamma$ is used to control the radius of influence of the support vectors. For example, a high value of $\gamma$ discards the influence of $\nu$, and cannot prevent overfitting. In Section 4, we will discuss how the optimal values for $\nu$ and $\gamma$ are calculated to train the classifier.

In this work, we extracted 16 times more negative samples than positive ones from Wikipedia tables using Algorithm 1 (see details in Section 4). For such unbalance training data, the one-class SVM [28] approach can be employed, where the classifier is trained based on the samples from a single class (either positive or negative training samples). Another option could be the use of sampling to train balanced samples. In the RBF kernel, a parameter $\gamma$ is used to control the radius of influence of the support vectors. For example, a high value of $\gamma$ discards the influence of $\nu$, and cannot prevent overfitting. In Section 4, we will discuss how the optimal values for $\nu$ and $\gamma$ are calculated to train the classifier.

### 3.4 Evaluation Methodology

The learning model is validated in two different ways: (i) based on held-out test data and (ii) by means of a user study.

For held-out test data, the samples extracted from Wikipedia tables using Algorithm 1 are considered as ground truth to evaluate the performance of learned classification model. We use accuracy as the performance metric. Class-specific accuracy is the fraction of correctly predicted samples over all the test samples predicted to be that specific class according the classifier, which is also called precision for that specific class.

Our objective is to learn a classifier that can classify which categories are interesting to a user to categorize the entity list. Therefore, we also validate the classification model by means of a user study. As human-perceived interestingness is not a fixed concept, choices/preferences of users can differ. The human assessors are asked to classify each samples into one of three possible categories: interesting, non-interesting, and not sure.

Subsequently, we define ground truth depending on the agreement level of the human responses. The higher the agreement level (e.g., all agree on a label), the more “obvious” the task appears, and thus, it is presumably also easier for the classifier to correctly classify it. We see later that this is indeed the fact.

Consider a total of $y$ users that provide assessments of the test samples. Different agreement levels are considered based on majority voting: For the $x/y$ agreement level, where $x > y/2$, one of the three possible choices is considered as ground truth for a sample if at least $x$ users agree on that choice. The samples which are marked as not sure are excluded from the ground truth. For different agreement levels, class-specific accuracy/precision, recall, and $F_1$ measures are used to validate the prediction of learning model against the ground truth, generated from the user study [34]. In order to quantify the reliability of user agreements, Fleiss’ kappa [12] is calculated.

### 4 EXPERIMENTAL EVALUATION

To obtained the training samples, we have used the English version of Wikipedia dump file of 2016. We have implemented Algorithm 1 in Java 1.8. Experiments are executed on an Intel Core i7 CPU@3GHz machine, with 16GB main memory. For the SVM classifier, the LIBSVM [5] library is used to create the learning models. The entire process of extracting the training samples from the 50.49GB (uncompressed) Wikipedia dump took around 30 minutes, where most of the time was spent on actually cleaning-up the raw dump file before Algorithm 1 was applied. A total of 2045 ranking tables from Wikipedia pages entitled “List of . . .” are extracted. From these tables, based on Algorithm 1, 2519 categorical attributes are labeled as “non-interesting”, are considered negative samples and 158 categorical attributes are labeled as “interesting”, are considered as positive samples.

For the training data, 75% of positive and negative samples are randomly selected. The remaining 25% of samples from each class are considered as held out test data, denoted as TestPos and TestNeg, respectively positive and negative samples. These two test datasets are merged into a set denoted as Test, containing 669 samples. We retrieved significantly fewer positive samples than negative samples. In order to create balanced training samples, we equally divided the negative samples into ten smaller chunks and then merged each of these chunks with the positive training samples, resulting in 10 sub-training files, each containing 306 training samples. The ratio of positive and negative samples in these sub-training files are 1:1.5.

The labeled training data according to Algorithm 1, the 10 sub-training files, and the results of the user study are publicly available.
online on http://dbis.informatik.uni-kl.de/catmining/ for repeatability and adoption.

4.1 User-Study Setup

As mentioned earlier in Section 3.4, we set up a user study to validate the trained classifier. To do so, 110 randomly selected samples from Wikipedia are presented to users. The samples are displayed to the users in form of “A(a): B”. In this format, ‘A’ represents the title of the Wikipedia table, ‘a’ represent the subject of the table, and ‘B’ represent a categorical attribute associated with the entity lists in the table. Users are asked to label the samples in three categories: (i) If a user is interested to categorize the entities in table ‘A’ by using categorical attribute ‘B’, then the sample is labeled as interesting. (ii) If a user thinks it is not interesting to categorize the entities in the table ‘A’ by using categorical attribute ‘B’, then the sample should be annotated with non-interesting. (iii) a user can also label a sample not sure in case the user cannot decide any of the two options before.

Overall, each question is evaluated by nine human evaluators. Four evaluators are in fact enough to achieve a significance level1 of α = 0.05. On average, an evaluator has marked 35.5% questions with interesting, 53.5% questions with non-interesting, and 20% with not sure. As the user choices differ, we use Fleiss’ kappa to understand the reliability of agreement. For each testing sample, nine user choices are taken for assessment. For the nine evaluators, the calculated kappa value is 0.45 and the 95% confidence interval for Kappa has a range between 0.42 and 0.48 for the collected user data. Moreover, this range of values significantly differs from zero and with p-value = 0 (i.e., < 0.05), we can reject the null hypothesis that the agreement among users is achieved randomly.

4.2 Parameter Selection and Evaluation

Due to the imbalanced size of the available training samples, discussed earlier, it seems feasible to use a one-class SVM to learn a model separately for each class. Alternatively, we also have created the 10 balanced sub-training files from the original training sample, as mentioned above. Here, we evaluate the performance of classification models created by all feature combinations from F, in total 2|F| − 1 combinations. The classification models are created for all possible feature combinations from each sub-training file. Modifying the parameter tuning in LIBSVM library, we implemented a grid search for ν-SVM with 5-fold cross-validation method to find the optimal parameter pair (ν, γ) for each sub-training file. Then, the classification model is learned with optimal ν and γ value. According to the theoretical discussion in [7], for our training set, the solution of ν-SVM is only feasible with 0 ≤ ν ≤ 0.77. In fact, in line with the theoretical study, we found that the optimal ν-value lies in [0.41, 0.61] for different sub-training files with optimal γ = 0.0003. For each feature combination, the average training time of 10 sub-training files is 13.813s.

4.3 Results Based on Held-Out Data

The performance of the classification models created on sub-training files is first evaluated on held-out test data. The held-out test data is created by random selecting of 25% samples from complete samples. As complete samples retrieved from Wikipedia using Algorithm 1 is unbalanced, reflecting the same characteristic of original data, the held-out test data also contains 16 times more non-interesting samples than interesting ones. Therefore, a high overall accuracy on Test data does not imply that the class-specific accuracy is also high, i.e., the model performs well for both TestPos and TestNeg data separately. Hence, rather considering the overall accuracy of the classification models on Test, we consider class-specific accuracy i.e., precision of TestPos and TestNeg separately to evaluate the classification model. For each feature combination f ∈ 2F, we train 10 classifiers based on the 10 sub-training files and choose the ones, called bestf, that have minimum classification error on both the TestPos and TestNeg. Finally, the classification model which performs best among all bestf for feature combinations f ∈ 2F, is chosen as the final model, coined final-M in this paper. By doing so, we found out that the final-M is trained using all features except entropy and unlikeliness, reaching a accuracy of 80% and 82.005% for TestPos and TestNeg datasets, respectively.

For TestPos and TestNeg datasets separately, Figure 4 compares the performance among a one-class SVM model built on positive and negative samples separately, final-M, and the average performance of all bestf created on feature combinations f ∈ 2F. From the figure, we can observe that the performance of the classification model created from interesting training samples using one-class SVM reaches 77.46% accuracy for TestNeg. But its performance is very poor (only 7.5%) for TestPos. This model is clearly unable to detect outliers and is under-fitting the data, which is unacceptable for a reasonable classifier. Though, the classification model built on non-interesting samples using one-class SVM has consistent performance on both TestPos and TestNeg, the performance is inferior to the average performance of bestf created by using ν-SVM method. Finally, we see that final-M is clearly outperforming all other models.

4.4 Evaluation Based on User Study

Let us now evaluate the classification model based on user study to validate our whole approach. As mentioned earlier in Section 3.4, we consider different levels of user agreement based on majority voting. For each x/y agreement level, we divide the ground truth into two test files. The samples which are marked ‘interesting’ in the ground truth of user study with x/y agreement level, is denoted

![Figure 4: Comparison among different type of classification models](image-url)
as $x/y$-userPos. On the other hand, the samples which are marked ‘non-interesting’ in the ground truth of $x/y$ agreement level are denoted as $x/y$-userNeg. Further, we exclude the samples which are marked as ‘not sure’ from the ground truth. As the agreement level decreases, the user-evaluated test dataset contains more non-interesting samples than interesting ones. For the lowest agreement label, the 5/9-userNeg dataset contains almost two times more samples than dataset 5/9-userPos.

### 4.4.1 Performance of Individual Features
To understand how well each of the features, i.e., the statistical measures, can classify the data, Figure 5 compares the performance across the best classification models created with one single feature $f \in \mathcal{F}$. The ground truth is considered 6/9 agreement level of user assessment for this figure. We can see from the figure that the model created based on P-Diversity is outperforming the other models (72.41% overall accuracy), for complete user study. Another model which is also performing well (70.69% overall accuracy) is based on Max-Info-gap. The strong performance of these models is consistent throughout all agreement level, except 8/9 agreement level where the model based on entropy reaches slightly higher accuracy—not shown here for space limitations. Figure 5 also shows that all these models have an inferior precision value for 6/9-userPos than 6/9-userNeg. The precision improves as the agreement level increases and reaches 100% and 83.33% for 9/9-userPos and 9/9-userNeg respectively. Comparing the $F_1$ measure, i.e., the harmonic mean of precision and recall, we observe that the model created using P-Diversity is outperforming the other models created on single features. It supports our claim that the proposed measures can capture the perception of human interests better than the existing ones. Also, the performance of the classification model trained on Max-Info-gap shows superiority over the model trained on Max-Coverage, as discussed in Section 3.2.

### 4.4.2 Performance of Feature Combinations
Now we investigate the performance of the \texttt{final-M} which is trained using the features Peculiarity, P-Diversity, Max-Coverage, Max-Info-Gap, and P-Peculiarity with the model created based on the existing measures only, i.e., Entropy, Unalikability, Peculiarity, and Max-Coverage, denoted as \texttt{M-Ex}. \texttt{final-M} achieves 79.31% overall accuracy, which is much higher compared to \texttt{M-Ex} that achieves only 67.24% for the 6/9 agreement level. Figure 6 shows that \texttt{final-M} is more robust and achieves higher $F_1$-measure than \texttt{M-Ex} based on 6/9 agreement level of user study.

![Figure 5: Comparison among classification models using single feature considering 6/9 agreement level as ground truth](image)

![Figure 6: Performance of \texttt{M} vs. \texttt{M-Ex}](image)

| Agreement level | userNeg Samples | userPos samples | Acc. |
|-----------------|-----------------|-----------------|------|
| 9/9             | Rec. | Prec. | $F_1$ | Rec. | Prec. | $F_1$ | 69.31 |
| 9/9             | 100.0 | 83.33 | 90.9 | 83.33 | 100.0 | 90.9 | 90.9 |
| 8/9             | 91.67 | 78.57 | 84.61 | 70.0 | 87.5 | 77.78 | 81.81 |
| 7/9             | 86.36 | 82.61 | 84.44 | 75.0 | 80.0 | 77.41 | 81.58 |
| 6/9             | 86.48 | 82.05 | 84.21 | 66.67 | 73.68 | 70.0 | 79.31 |
| 5/9             | 84.21 | 78.69 | 81.36 | 53.57 | 62.5 | 57.69 | 74.12 |

Table 6 reports on the performance of \texttt{final-M} for different agreement levels. The table includes evaluations from all possible feature combinations into 7 groups based on the number of features are used to train the model, i.e., $1 \leq |f| \leq |\mathcal{F}|$. Then, the best performing model from the each group is taken and their performances is reported in Figure 7 based on 6/9 agreement level. In this figure we also mention which features are used to create the best one among the group. For instance, the model using the features Entropy, P-Diversity, and Max-Info-Gap is performing best among all the models created by combining any 3 features from $\mathcal{F}$.

### 4.4.3 Assessment of Main Hypothesis
Figure 8 presents an evaluation of Algorithm 1, respectively our main hypothesis, directly.
We can summarize the main findings of the experimental studies in the following four lessons learned.

1. Our working hypothesis, which is the main idea behind Algorithm 1, is well-grounded: The positive and negative training samples in the obtained training data are generally confirmed by human evaluators.

2. Our study shows that P-Diversity outperforms existing measures for the task to capture diversity in our context. Max-Info-Gap performs better than Max-Coverage and Entropy.

3. Final-M is able to achieve 79.31% overall accuracy, with ground truth given by the 6/9 user-agreement level. It uses all the features discussed in this paper, except entropy and unlikability, to learn the model.

4. Final-M can accurately classify the data even when disagreement among the users increases (i.e., the classification task gets more difficult).

5 RELATED WORK

Understanding data is a primary necessity for scientific discovery. Data analysts often use OLAP-cubes [14, 25] or mining algorithms [35] to explore data. Different approaches to drill-down operations are proposed in literature to make OLAP smarter and more efficient for large data. Joglekar et al. [18] propose an interaction operator to extend the scope of drill-down operations. It allows online user interaction and enables browsing the top-k most interesting explorative facts about the data, based on the dimensions preferred by the data analyst. Our approach can be used orthogonally, as an enabling step, to such approaches by providing recommendations of meaningful dimensions. Algorithms for clustering and classification [35] commonly define the interestingness of discovered patterns in statistical ways, without considering the users’ utility. Bie [4] proposed a mathematical framework to formulate interestingness of mining patterns, considering user utility as an important parameter. Tuzhilin [32] proposes an approach to measure interestingness w.r.t. the belief system of users. All these works need user intervention to capture the utility function.

The survey by Geng and Hamilton [13] provides a detailed discussion on subjective and objective measures used to capture ‘interestingness’ of data for association or classification rule mining. Henzgen and Hüllemeyer [15] present an analogy of the itemset-mining measures support and interest applied to mining subrankings. Different context-specific diversity measures are proposed in the area of Web search [1, 10, 24], entity summarization [31], and recommender systems [27]. These diversity measures are not applicable to our work and not all of them are based on empirical probabilities. Hilderman and Hamilton [16] present a comparative evaluation of diversity measures that are available to capture interestingness of patterns. They show that a small subset of these measures are in...
fact useful and can capture the characteristics of interestingness. In this work, we have used the diversity measures, Peculiaritiy and Unlikeliness, based on empirical probabilities, discussed by Kader and Perry [19].

Web tables are considered a rich source of information and mining Web tables is very popular nowadays for extracting accurate and robust information [9, 26, 33]. In particular, tables in Wikipedia are considered a rich and credible source for information, leading to knowledge bases like YAGO and DBpedia that are created based on Wikipedia pages. Availability of such high quality information in Wikipedia facilitate mining of Wikipedia tables to explore knowledge about entities [2, 8, 17].

The concept of SVMs is a well-known supervised learning algorithm and generally considered robust and accurate. Different variations of SVM are developed in order to cope with different characteristics of the available training data. Schölkopf et al. [28] present the one-class SVM which is able to learn a classification model that is presenting only a single class. This SVM variant is shown to perform well in cases where the training data is unbalanced. Another variant, coined ν-SVM, is discussed in [7, 30] for learning classification model from noisy data. SVM is also capable to classify non-linear data by using various kernel methods, discussed in [29]. One of the widely used kernel methods is the Gaussian kernel [6].

6 CONCLUSION

Categorical attributes allow grouping items in meaningful ways and, thus, are key to render data accessible. We presented a new approach to capture human interest in categorical attributes. We started with providing the hypothesis that training data can be derived from Wikipedia based on the presence or absence of specific tables. We motivated and defined three new statistical measures to capture subjective interestingness measures for our context. The results of the experimental study, involving a user study, show that using features combination, a classification model can well reflect human interests on categorical attributes. It also shows that the proposed statistical measures are more suitable to capture the characteristics of the interesting categorical attributes compared to the traditional measures like information entropy. Applications are manifold, ranging from mining interesting patterns in data or understanding dependencies between table columns, to clustering or filtering entities and finding dimensions of interest in data warehouses.

REFERENCES

[1] Rakesh Agrawal, Sreenivas Gollapudi, Alan Halverson, and Samuel Leong. 2009. Diversifying search results. WSDM.
[2] Chandra Sekhar Bhagavatula, Thanaon Noraset, and Doug Downey. 2013. Measuring attributes for exploring and mining tables on Wikipedia. IDEAS@KDD.
[3] Chandra Sekhar Bhagavatula, Thanaon Noraset, and Doug Downey. 2015. TabEL: Entity Linking in Web Tables. ISWC.
[4] Tijl De Bie. 2013. Subjective Interestingness in Exploratory Data Mining. IDBA.
[5] Chih-Chung Chang and Chih-Jen Lin. 2011. LIBSVM: A library for support vector machines. ACM Transactions on Intelligent Systems and Technology 2, 3.
[6] Yin-Wen Chang, Cho-Jui Hsieh, Kai-Wei Chang, Michael Ringgaard, and Chih-Jen Lin. 2010. Training and Testing Low-degree Polynomial Data Mappings via Linear SVM. Journal of Machine Learning Research 11
[7] Pai-H. Chen, Chih-J. Lin, and Bernhard Schölkopf. 2005. A Tutorial on ν-support vector machines.
[8] Fernando Chirigati, Junlu Liu, Flip Kom, You Wu, Cong Yu, and Hao Zhang. 2016. Knowledge Exploration using Tables on the Web. PVLDB 10, 3
[9] Eric Crestan and Patrick Pantel. 2011. Web-scale table census and classification. In WSDM.
[10] Van Dang and W. Bruce Croft. 2012. Diversity by proportionality: an election-based approach to search result diversification. In SIGIR.
[11] Josep Domingo-Ferrer and Agusti Solanas. 2008. A measure of variance for hierarchical nominal attributes. Inf. Sci. 178, 24.
[12] J.L. Fleiss et al. 1971. Measuring nominal scale agreement among many raters.
[13] Liqiang Geng and Howard J. Hamilton. 2006. Interestingness measures for data mining: A survey. ACM Comput. Surv. 38, 3.
[14] Jim Gray, Saurajit Chaudhuri, Adam Bosworth, Andrew Layman, Don Reichart, Muruki Venkatraj, Frank Fellow, and Hamid Pirahesh. 1997. Data Cube: A Relational Aggregation Operator Generalizing Group-by, Cross-Tab, and Sub Totals. Data Min. Knowl. Discov. 1, 1.
[15] Sascha Henzgen and Eyke Hüllermeier. 2014. Mining Rank Data. In DS.
[16] Robert J. Hilderman and Howard J. Hamilton. 2001. Evaluation of Interestingness Measures for Ranking Discovered Knowledge. In PAKDD.
[17] Yaarou Braham, Mirek Riedewald, and Gerhard Weikum. 2016. Making Sense of Entities and Quantities in Web Tables. In CIKM.
[18] Manas Joglekar, Hector Garcia-Molina, and Aditya G. Parameswaran. 2016. Interactive data exploration with smart drill-down. In ICDE.
[19] Gary D. Kader and Mike Perry. 2007. Utility for Variational Categorical Variables. Journal of Statistics Education 15, 2.
[20] Girija Limaye, Sunita Sarawagi, and Soumen Chakrabarti. 2010. Annotating and Searching Web Tables Using Entities, Types and Relationships. PVLDB 3, 1.
[21] David N. Milne and Ian H. Witten. 2008. Learning to link with wikipedia. CIKM.
[22] Konnica Pal and Sebastian Michel. 2016. A Data Mining Approach to Choosing Categorical Attributes for Ranked List. EDBT.
[23] E. C. Pieiou. 1969. An introduction to mathematical ecology. Wiley InterScience.
[24] John Wiley & Sons, New York, USA.
[25] Davood Rafiei, Krishna Bharat, and Anand Shukla. 2010. Diversifying web search results. WWW.
[26] Sunita Sarawagi, Rakesh Agrawal, and Nimrod Megiddo. 1998. Discovery-Driven Exploration of OLAP Data Cubes. EDBT.
[27] Sunita Sarawagi and Soumen Chakrabarti. 2014. Open-domain quantity queries on web tables: annotation, response, and consensus models. SIGKDD.
[28] Markus Schell and David Haugser. 2015. Tailoring Music Recommendations to Users by Considering Diversity, Mainstreamness, and Novelty. SIGIR.
[29] Bernhard Schölkopf, John C. Platt, John Shawe-Taylor, Alexander J. Smola, and Robert C. Williamson. 2001. Estimating the Support of a High-Dimensional Distribution. Neural Computation 13, 7.
[30] Bernhard Schölkopf and Alexander J. Smola. 2002. Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond. MIT Press, Cambridge, MA, USA.
[31] Bernhard Schölkopf, Alexander J. Smola, Robert C. Williamson, and Peter L. Bartlett. 2000. New Support Vector Algorithms. Neural Computation 12, 5.
[32] Marcin Sydow, Mariusz Pikoł, and Ralf Schenkel. 2013. The notion of diversity in graphical entity summarisation on semantic knowledge graphs. J. Intell. Inf. Syst. 41, 2.
[33] Alexander Tuzhilin. 1995. On subjective measures of interestingness in knowledge discovery. SIGKDD.
[34] Jingjing Wang, Haixun Wang, Zhongyuan Wang, and Kenny Qili Zhu. 2012. Understanding Tables on the Web. ER.
[35] Shuo Wang and Xin Yao. 2009. Theoretical Study of the Relationship between Diversity and Single-Class Measures for Class Imbalance Learning. ICDM.
[36] Xindong Wu, Vipin Kumar, J. Ross Quinlan, Joydeep Ghosh, Qiang Yang, Hiroshi Motoda, Geoffrey J. McLachlan, Angus F. M. Ng, Bing Liu, Philip S. Yu, Zhijian Zhou, Michael Steinbach, David J. Hand, and Dan Steinberg. 2008. Top 10 algorithms in data mining. Knolw. Inf. Syst. 14, 1.