**Knowledge-Based Learning through Feature Generation**

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**Abstract**

Machine learning algorithms have difficulties to generalize over a small set of examples. Humans can perform such a task by exploiting vast amount of background knowledge they possess. One method for enhancing learning algorithms with external knowledge is through feature generation. In this paper, we introduce a new algorithm for generating features based on a collection of auxiliary datasets. We assume that, in addition to the training set, we have access to additional datasets. Unlike the transfer learning setup, we do not assume that the auxiliary datasets represent learning tasks that are similar to our original one. The algorithm finds features that are common to the training set and the auxiliary datasets. Based on these features and examples from the auxiliary datasets, it induces predictors for new features from the auxiliary datasets. The induced predictors are then added to the original training set as generated features. Our method was tested on a variety of learning tasks, including text classification and medical prediction, and showed a significant improvement over using just the given features.

1 Introduction

Machine learning algorithms attempt to learn a predictor by generalizing over a given set of tagged examples. In recent years, we have seen a significant progress in solving complex learning problems using algorithms based on Artificial Neural Networks (ANN). These algorithms perform well when a large set of tagged examples is available, but their performance rapidly declines when the size of the training set decreases.

While machines find the task of inducing over a small set of examples problematic, humans are usually very good at such tasks. A human is capable, in many cases, to induce over an extremely small set of examples using extensive background knowledge. With the increasing availability of large-scale knowledge bases, machine learning would have significantly benefited if it could have utilized a similar knowledge-based approach.

There are three major approaches for using extra knowledge to overcome the lack of examples. In the 80’s, several research groups had persuaded an approach called Explanation Based Learning [Mitchell et al., 1986; Dejong and Mooney, 1986], where even a single example can be used for induction. The method works by generating and generalizing a proof that explains the example using background knowledge in the form of a set of logical assertions. This approach is still not practical in most cases due to the lack of such logic-based knowledge bases.

A second approach for solving a learning task with a small training set is transfer learning [Pan and Yang, 2010]. This method assumes that, in addition to the original training set, there is another, usually larger, set of examples of a related learning task. The above two approaches are limited in the type of background knowledge they can exploit for enhancing the learning process.

A third approach uses external knowledge to generate new features. Two prominent works in this direction are Explicit Semantic Analysis [Gabrilovich and Markovitch, 2009], where Wikipedia-based conceptual features are generated and added to textual examples, and Word2Vec [Mikolov et al., 2013] where latent concepts, based on a large corpus, are generated and used as features for text classification. These two methods proved to be very effective but they are applicable for text-based learning tasks only.

With the significant growth in the usage of machine learning for various problems domains, the amount of knowledge encoded in datasets has significantly increased. In addition, we are seeing a considerable proliferation in the volume of user-contributed knowledge encoded in relational form. These bodies of external knowledge could have made a great source for enhancing learning algorithms.

In this work we present a general algorithm that enhances machine learning algorithms with features that are automatically generated using such external knowledge sources. Given a learning task with a specific training set, our approach takes a set of external datasets and looks for matching features. For each external dataset, these are its set of features that are in common with the original features of the training set. We use these features to learn a classifier or a regressor that predicts the values of other features in the external dataset. The learned predictors are then applied to the original dataset to get newly generated features.
To understand this process, let us look at the following illustrative example. Assume we are given a small training set for predicting the risk of a patient to have Alzheimer disease. The set of features for this dataset includes, among others, BMI, blood pressure and HDL cholesterol. We also have access to a much larger dataset for evaluating the risk of a patient to have diabetes 2 that also includes these three features. Our method builds a new secondary learning problem, where the examples are those of the diabetes dataset, the features are the three common features, and the target concept is the risk of having diabetes. The resulting classifier predicts the risk of diabetes based on these three features. This classifier will then be applied to the original dataset to yield values for a newly generated feature – the risk of having diabetes. The generated feature is likely to enhance the ability of the learning algorithm to induce a predictor for the original task, predicting the risk of diabetes based on these three features. This classifier will then be applied to the original dataset to yield values for a newly generated feature – the risk of having diabetes.

2 Problem definition

We assume that we are given a training set to learn from, and an additional set of auxiliary datasets, either labeled or unlabeled. More formally, we define a dataset \( D \) as a pair \( \langle O, F \rangle \), where \( O \) is a set of objects and \( F \) is a set of features such that \( \forall f \in F : O \subseteq \text{Domain}(f) \). We sometimes denote the set of features of a dataset \( D \) by \( O(D) \).

Given a dataset \( D = \langle O, F \rangle \), a labeled dataset with respect to \( D \) and a target function \( f^* \), is defined as \( \langle E, F \rangle \), where \( E = \{ \langle o, f^*(o) \rangle | o \in O \} \). We sometimes denote the set of objects of a dataset \( D \) by \( O(D) \).

A learning algorithm takes a labeled dataset \( D_l = \langle E_l, F_l \rangle \) and yields a classifier \( f_l : O \rightarrow \text{Range}(f^*) \).

A Feature Generation Task (FGT) is a pair \( \langle D_t, A \rangle \), where \( D_t = \langle E_t, F_t \rangle \) is a labeled training set, and \( A = \{ D_1, ..., D_k \} \), where \( D_i \) is either labeled or unlabeled, is a set of auxiliary datasets.

A knowledge-based feature generation algorithm takes a FGT as an input and generates a set of features \( F_a \) over \( O(D_t) \). We call the dataset \( D_a^k = \langle E_t, F_t \cup F_a \rangle \) the enhanced dataset. We name the main learning algorithm, that will be applied to \( D_a^k \), the primary learning algorithm, and denote it by \( L_p \).

Our goal is to exploit the auxiliary datasets to improve the quality of the induced predictor. We propose to do so via feature generation as described in the next section.

3 The algorithm

In this section we present a feature generation framework that can exploit additional datasets and inject the knowledge embedded in these datasets into the learning process. We start with the basic algorithm and continue with extensions.

3.1 The Basic Algorithm

For each auxiliary dataset \( D_a \), our algorithm first finds the set of common features with the training set \( F^\cap = F(D_a) \cap F(D_t) \), and the set of features \( F^- = F(D_a) - F(D_t) \) that appears only in the auxiliary dataset.

For each feature \( f \in F^- \), the algorithm constructs a new learning problem, called a secondary learning task, where the objects are \( O(D_a) \), the target function is \( f \), and the features are \( F^\cap \). A secondary learning algorithm, denoted by \( L_a \), is then applied to the secondary learning task. Note that \( L_p \) and \( L_a \) are not necessarily related.

The learning process results in a predictor \( f_g \). This is a predictor (a classifier or a regressor) that is based only on the features in \( F^\cap \) and therefore can be added to \( F(D_t) \) as a newly generated feature. Before we add it to the growing set of generated features, we first apply a wrapper selector [Kohavi and John, 1997] and add it only if it has positive utility. The pseudocode for the algorithm is listed below. \( CV \) stands for cross validation estimation.

Algorithm 1 Knowledge-Based Feature Generation Algorithm

| KBFG \( (D_t, D_a) \) |
|---------------------|
| **Input:** \( \langle E_t, F_t \rangle, \langle O_a, F_a \rangle \) |
| 1: \( F_g \leftarrow \{ \} \) |
| 2: \( F_h \leftarrow F_t \cap F_a \) |
| 3: for \( f \in F_h - F^\cap \) do |
| 4: \( E \leftarrow \{ \langle o, f(o) \rangle | o \in O_A \} \) |
| 5: \( f_a \leftarrow L_a(E, F^\cap) \) |
| 6: if \( CV(F_t \cup F_g \cup \{ f_g \}) > CV(F_t \cup F_g) \) then |
| 7: \( F_g \leftarrow F_g \cup \{ f_g \} \) |
| 8: end if |
| 9: end for |
| 10: return \( F_g \) |

3.2 The Secondary Learning Task

The algorithm described in the previous subsection generates new features by creating a new learning problem and solving it. The components of this stage are as follows:

1. The objects of the new problem are the objects of the auxiliary dataset.
2. The target function is a feature in the auxiliary dataset that does not appear in the original dataset. Note that the auxiliary dataset can be either labeled or unlabeled. If it is labeled, we treat its target class as a part of the set of features. Thus, the generated features may include the class.
3. In some datasets, for instance in textual ones, the set of such features is very large. Since each feature requires a full learning process, we may want to prioritize this
set. When there exists a distance function between potential features and the original dataset, it can be used for making prioritization. In the experimental section, we describe an experiment where the auxiliary dataset is a very large text corpus (Wikipedia). The distance function we used there is based on Word2Vec embedding. We compute the similarity of the potential feature to the positive training examples, and the similarity to the negative ones. The maximal similarity taken as its utility.

4. The features used for the secondary learning problem are those that are common to the original dataset and the auxiliary dataset. When this set is very large we perform a feature selection.

5. The learning algorithm produces a classifier when the target feature is nominal, and a regressor if it is continuous. In the experiments reported here, we have used a random forest classifier (or regressor) but any other algorithm can be used.

The architecture of our framework is illustrated in Figure 1.

3.3 Feature Matching

Our algorithm assumes that \( F \cap F_a \) is computable. One way to achieve this is to manually specify a feature matching table by the user. Otherwise, we need an automatic way to do the matching. If the names of the features are given explicitly, such as in the UCI collection [Dua and Karra Taniskidou, 2017], and the same names are used in the training dataset and the auxiliary dataset (or the same keys such in SQL databases), the matching is straightforward.

Otherwise, we define some similarity measure between features, and match them only if their similarity is above some threshold. If the names are only slightly different, we can use stemming and Levenshtein distance to find matching. If the names differ, we can use embedding such as Word2Vec to estimate the similarity between pairs of feature names. When descriptions for features are given, such as in many UCI datasets, we embed their description as well.

If feature names are not given, we can estimate the similarity of two categorical or numerical features by measuring the distance between the distributions of their values, using common distribution distance measures.

3.4 Recurrent Feature Generation

Once algorithm 1 generates a feature \( f_g \) and add it to the training set, the intersection set \( F \) now includes a new member. By the way we defined the process, we now have a state where \( f_g \) is in the enhanced training features, and the feature it approximates, \( f \), exists in the auxiliary set of features. Therefore, we are able to match these two features and expand the intersection set, which may lead to an improvement in the induction of additional generated features. The recurrent version of our algorithm includes one additional line. After the last step of the \( f \) loop, we add the following statement: \( F \leftarrow F \cup \{ f_g \} \).

3.5 Using Multiple Auxiliary Datasets

When we get a set of auxiliary datasets, we can call our basic feature-generation algorithm, \( KBFG \), for each auxiliary dataset sequentially. One drawback of this approach, is that the wrapper feature selector evaluates each generated feature only with respect to the local set of features generated for the particular dataset, and not with respect to the global generated set of features. Therefore, we propose to add an extra feature selection stage that will be performed on the accumulated set of generated features after processing all the auxiliary datasets.

We considered the wrapper approach, which iteratively evaluates the contribution of each feature with respect to the current set and adds the one with the best utility. This, however, has quadratic complexity (with respect to \( n = |F| \), the number of generated features). With thousands of generated features, it may require millions of cross-validation experiments.

An alternative cheap method for selection is the filtering approach, where we compute some statistical measure for each feature, such as information gain, and select only the top features. This method, however, evaluates each feature independently of the others.

We have therefore designed a hybrid feature selection approach that performs an order of \( n \) cross validation operations. We first sort the features \( F \) by their information gain, starting with the highest. Then we start to add them to \( F \) one by one, evaluating their relative utility using cross validation. The pseudo-code for the \( KBFG^* \) feature generation with multiple-auxiliary datasets is listed in Algorithm 2.

There are several other considerations when using multiple datasets:

1. Obviously, there is no point in using an auxiliary dataset if the intersection set is empty.

2. It is possible that a feature \( f \) belongs to multiple datasets and therefore multiple approximations of it, \( F = \{ f_1, \ldots, f_k \} \), will be induced. One option to deal with this case is choosing

\[
\hat{f} = \arg \max_{f \in F} U(f, D_1)
\]

where \( U \) is any feature evaluation method such as wrapper or information gain. Alternatively, we can form a committee \( \{ f_1^*, \ldots, f_k^* \} \) that will serve as the new generated feature \( f_g^* \).
3. We can use the recurrent version of the algorithm with multiple auxiliary datasets. Assume that \( f_g \) was generated using an auxiliary dataset \( D_a \). We can add this feature to other auxiliary datasets, thus enhancing their expressiveness. This can be done only if the features used to learn it are included there.

Algorithm 2 The \( KBFG^* \) For Feature Generation with Multiple Auxiliary Datasets

\[
KBFG^*(D_t, A)
\]

Input: \( \langle E_t, F_t \rangle, A \)

1: \( F_g \leftarrow \{ \} \)
2: for \( (O_a, F_a) \in A \) do
3: \( F_g = KBFG^*(\langle E_t, F_t \rangle, \langle O_a, F_a \rangle) \)
4: \( F_g \leftarrow F_g \cup F_g \)
5: end for
6: Sort \( F_g \) by information gain in descending order
7: \( G \leftarrow \{ \} \)
8: for \( f_g \in F_g \) do
9: if \( CV(L_p, F_t \cup G \cup \{ f_g \}) > CV(L_p, F_t \cup G) \) then
10: \( G \leftarrow G \cup \{ f_g \} \)
11: end if
12: end for
13: return \( G \)

4 Empirical evaluation

We have tested our framework using an extensive collection of training sets with associated auxiliary datasets.

4.1 Experimental Methodology

We have used 12 original datasets that served as the basis for our feature generation experiments\(^1\). The first three are textual datasets of reviews tagged with their sentiment. The rest are datasets taken from the UCI [Dua and Karra Taniskidou, 2017] and Kaggle repositories.

Creating Feature Generation Tasks

A feature generation task (FGT) is a pair of a training set and a set of auxiliary datasets. In all experiments except those described in 4.4, we always use one auxiliary dataset. One major step in implementing our framework is finding matching between the features of the training set and those of the auxiliary dataset. For the text classification tasks, we have just matched the stemmed words. Thus, we created 6 feature generation tasks out of the 3 sentiment analysis datasets. \( Pima \) and \( Breast Cancer \) datasets are medical records containing common features such as Glucose and BMI, and therefore could be paired for feature generation. So are the \( Indian Liver \) and \( Hepatitis \) datasets, with common features such as Bilirubin and Age.

Since we needed more FGTs, we have designed a method of creating an FGT out of one dataset. The examples of the datasets are randomly partitioned to create two disjoint sets of examples, one used for the training and one for the auxiliary dataset. The feature set is also carefully partitioned so that we can control the size of the intersection.

Let \( D = \langle E, F \rangle \) be a labeled dataset:

1. Randomly partition \( E \) into two nearly equal sized sets \( E_1 \) and \( E_2 \).
2. Randomly select a subset from \( F \) of size \( \mu_1 |F| \) (\( \mu_1 = \frac{1}{3} \) in our experiments) and mark it as the intersection set, denoted by \( F^\cap \).
3. Randomly partition \( F - F^\cap \) into two sets: \( F_1 \) of size \( \mu_2 |F - F^\cap| \) and \( F_2 \) (\( \mu_2 = \frac{2}{3} \) in our experiments).
4. The training set will be \( \langle E_1, F_1 \cup F^\cap \rangle \) and the auxiliary dataset \( \langle E_2, F_2 \cup F^\cap \rangle \).

Testing Protocol

One prominent motivation for our work is to overcome the problem of lack of examples by using external knowledge. Therefore we have followed a special testing protocol that simulates such scenarios by reducing the number of examples in the training set.

Given an FGT \( \langle \langle E_t, F_t \rangle, \langle O_a, F_a \rangle \rangle \):

1. Partition \( E_t \) into \( k \) partitions (10 in our experiments) with testing sets \( T_1, \ldots, T_k \) and corresponding training sets \( \langle E_t - T_i, F_t \rangle \).
2. For each test set \( T_i \) and a set of examples \( B_i = E_t - T_i \):
   (a) Reduce the number of examples in \( B_i \) by randomly selecting a subset \( B_i^\alpha \) of size \( \alpha \cdot |B_i| \) (\( \alpha = 0.25 \) in our experiments).
   (b) Generate a set \( G_i \) of new features based on the auxiliary dataset.
   (c) Sort \( G_i \) by information gain with respect to \( E_t \). For the textual datasets, in which the size of \( F^\cap \) is large, we select the best 50.
   (d) For each \( f \) in the sorted \( G_i \), test if it has a positive utility value by the wrapper method, and add it to \( F_t \) if it does. We denote the enhanced feature set by \( \hat{F}_t \).
   (e) Learn from \( \langle B_i^\alpha, \hat{F}_t \rangle \).
   (f) Test on \( T_i \).
3. Repeat step 2 for each \( L_p \) used in the experiments.

The list of FGTs used for our experiments is shown in Table 1. The superscript next to each dataset stands for the parameter used to reduce the number of examples.

4.2 Performance With the Generated Features

We performed a set of experiments to test the utility of our feature generation algorithm. Each experiment involved generating a set of features with a given FGT, and testing the enhanced feature set with various learning algorithms, including Decision Tree, Linear SVM, KNN (N=3) and Multilayer perceptron. We used the implementation in \( sklearn \) with the default parameters.

Tables 2 and 3 show the results achieved. For each learning algorithm the tables present the performance on the testing set without and with the generated features. The third column

\(^1\)Each dataset was used after preprocessing and normalization.
shows the added accuracy. We mark by bold differences that are statistically significant by paired t-test with $p < 0.05$.

We can see that the generated features significantly enhance the performance in almost all cases. Note that the improvements are orthogonal to potential other improvements that may be achieved by feature-combination algorithms or by feature generation algorithms that use other external resources.

4.3 Experimenting with a Very Large Auxiliary Dataset

We have performed another experiment with textual learning task, where the auxiliary dataset is the whole Wikipedia corpus. We consider each Wikipedia article as one object. Using such a large dataset is problematic. The Bag-O-Words matrix is, after filtering, of size $850,000 \times 700,000$ approximately. As the training dataset contains only a few thousands of words (the size of $F_1$), the size of $F^{-} = F_a - F_1$ is also of size of almost $850,000$.

As we cannot afford initiating $850,000$ learning processes, we applied the similarity-based prioritization as described in subsection 3.2. Specifically, we have used Word2Vec distance to select the 5,000 features closest to the centroid of the positive examples of the training set, and another 5,000 features closest to the negative one.

The results are shown in Table 4. We can see that the new features added about 5% in accuracy (statistically significant with $p < 0.05$) with both datasets tested.

4.4 Experimenting with multiple datasets

We have designed a feature generation task that involve multiple auxiliary datasets.

1. Training set: YELP.
2. Auxiliary datasets: IMDB and AMAZON.

We have applied our $KBFG^*$ Algorithm (see Algorithm 2) to the task described. For comparison, we have also tested the basic $KBFG$ algorithm with each of the auxiliary

| Training Set | #Examples | Auxiliary dataset | #Examples | SVM | SVM + FG | Diff SVM |
|--------------|-----------|-------------------|-----------|-----|---------|---------|
| IMDB$^{0.25}$ | 225 | AMAZON | 1000 | 0.611 | 0.705 |
| AMAZON$^{0.25}$ | 225 | IMDB | 1000 | 0.611 | 0.705 |
| IMDB$^{0.25}$ | 225 | YELP | 1000 | 0.642 | 873 |
| YELP$^{0.25}$ | 225 | IMDB | 1000 | 0.642 | 873 |
| AMAZON$^{0.25}$ | 225 | YELP | 1000 | 0.494 | 822 |
| YELP$^{0.25}$ | 225 | AMAZON | 1000 | 0.494 | 822 |
| Pima$^{0.25}$ | 172 | Breast Cancer | 116 | 4 | 5 |
| Breast Cancer$^{0.25}$ | 26 | Pima | 768 | 4 | 4 |
| ILPD$^{0.25}$ | 130 | Hepatitis | 80 | 5 | 14 |
| Hepatitis$^{0.25}$ | 18 | ILPD | 579 | 5 | 5 |
| Cylinder$^{0.25}$ | 61 | Cylinder | 265 | 16 | 21 |
| SPECTF$^{0.25}$ | 40 | SPECTF | 137 | 18 | 24 |
| QSAR$^{0.25}$ | 117 | QSAR | 531 | 17 | 22 |
| Z-Alizadeh$^{0.25}$ | 32 | Z-Alizadeh | 159 | 24 | 32 |
| Cardio$^{0.25}$ | 235 | Cardio | 1077 | 9 | 11 |

Table 1: The FGTs in our experiments. $\alpha = 0.25$, $F_a = f^+ \cup f^-$

| Training Set | Auxiliary dataset | DT | DT + FG | Diff DT | SVM | SVM + FG | Diff SVM |
|--------------|-------------------|----|---------|---------|-----|---------|---------|
| IMDB$^{0.25}$ | AMAZON | 0.566 | 0.621 | +0.055 | 0.695 | 0.709 | +0.014 |
| AMAZON$^{0.25}$ | IMDB | 0.542 | 0.615 | +0.073 | 0.732 | 0.735 | +0.003 |
| IMDB$^{0.25}$ | YELP | 0.539 | 0.610 | +0.071 | 0.691 | 0.711 | +0.020 |
| YELP$^{0.25}$ | IMDB | 0.554 | 0.612 | +0.058 | 0.695 | 0.710 | +0.015 |
| AMAZON$^{0.25}$ | YELP | 0.593 | 0.672 | +0.079 | 0.720 | 0.749 | +0.029 |
| YELP$^{0.25}$ | AMAZON | 0.553 | 0.666 | +0.113 | 0.696 | 0.717 | +0.021 |
| Pima$^{0.25}$ | Breast Cancer | 0.751 | 0.828 | +0.077 | 0.576 | 0.703 | +0.127 |
| Breast Cancer$^{0.25}$ | Pima | 0.721 | 0.738 | +0.017 | 0.602 | 0.688 | +0.086 |
| ILPD$^{0.25}$ | Hepatitis | 0.660 | 0.694 | +0.034 | 0.550 | 0.706 | +0.156 |
| Hepatitis$^{0.25}$ | ILPD | 0.700 | 0.774 | +0.074 | 0.790 | 0.840 | +0.050 |
| Cylinder$^{0.25}$ | Cylinder | 0.633 | 0.692 | +0.059 | 0.578 | 0.610 | +0.032 |
| SPECTF$^{0.25}$ | SPECTF | 0.615 | 0.721 | +0.106 | 0.677 | 0.812 | +0.135 |
| QSAR$^{0.25}$ | QSAR | 0.686 | 0.732 | +0.046 | 0.726 | 0.791 | +0.065 |
| Z-Alizadeh$^{0.25}$ | Z-Alizadeh | 0.621 | 0.718 | +0.097 | 0.619 | 0.706 | +0.087 |
| Cardio$^{0.25}$ | Cardio | 0.790 | 0.816 | +0.026 | 0.757 | 0.804 | +0.047 |

Table 2: The effect of feature generation on the performance of two learning algorithms: Decision Tree With pruning and linear SVM.
datasets separately. We ran each of the 3 scenarios until 50 generated features passed the wrapper filter.

The experiment was stopped after each 5 features were accepted and the accuracy of the classifier induced with the added features was measured as described in the testing protocol. That is, the pool of 50 ordered features, was split into 10 groups of 5 items per each. Each point in the graphs, is an addition of the next ranked group of 5 features, where the zero point represent the original set of features (i.e., without any additional features).

It is important to mention that the accuracy was measured using the same folds. That is, the only different is the features added using the single or multiple auxiliary. The number of the features and training set examples, are preserved.

The graphs in figure 2 show the average accuracy of a classifier induced by decision tree with pruning with the added generated features, on the YELP dataset, for the 3 scenarios. We can see that the $KBFG^*$ algorithm had significant advantage over $KBFG$ with each of the single auxiliary dataset (about 10% difference in accuracy).

| Training Set | Auxiliary dataset | 3NN | 3NN + FG | Diff 3NN | MLP | MLP + FG | Diff MLP |
|--------------|-------------------|-----|----------|----------|-----|----------|----------|
| IMDB$^{0.25}$ | AMAZON            | 0.573 | 0.610   | +0.037   | 0.709 | 0.741   | +0.032   |
| AMAZON$^{0.25}$ | IMDB              | 0.609 | 0.655   | +0.046   | 0.752 | 0.771   | +0.019   |
| IMDB$^{0.25}$ | YELP              | 0.552 | 0.587   | +0.035   | 0.715 | 0.738   | +0.023   |
| YELP$^{0.25}$ | IMDB              | 0.567 | 0.607   | +0.040   | 0.733 | 0.747   | +0.014   |
| AMAZON$^{0.25}$ | YELP              | 0.609 | 0.659   | +0.050   | 0.739 | 0.773   | +0.034   |
| YELP$^{0.25}$ | AMAZON            | 0.593 | 0.659   | +0.066   | 0.724 | 0.794   | +0.025   |
| Pima$^{0.25}$ | Breast Cancer     | 0.673 | 0.729   | +0.056   | 0.658 | 0.664   | +0.096   |
| Breast Cancer$^{0.25}$ | Pima | 0.531 | 0.548   | +0.017   | 0.547 | 0.608   | +0.061   |
| ILPD$^{0.25}$ | Hepatitis         | 0.646 | 0.675   | +0.029   | 0.658 | 0.727   | +0.069   |
| Hepatitis$^{0.25}$ | ILPD               | 0.814 | 0.840   | +0.026   | 0.795 | 0.837   | +0.042   |
| Cylinder$^{0.25}$ | Cylinder       | 0.547 | 0.570   | +0.023   | 0.563 | 0.582   | +0.019   |
| SPECTF$^{0.25}$ | SPECTF           | 0.635 | 0.729   | +0.094   | 0.576 | 0.710   | +0.134   |
| QSAR$^{0.25}$ | QSAR             | 0.706 | 0.762   | +0.056   | 0.714 | 0.703   | -0.011   |
| Z-Alizadeh$^{0.25}$ | Z-Alizadeh     | 0.575 | 0.711   | +0.136   | 0.590 | 0.728   | +0.138   |
| Cardio$^{0.25}$ | Cardio          | 0.708 | 0.799   | +0.091   | 0.710 | 0.773   | +0.063   |

Table 3: The effect of feature generation on the performance of two learning algorithms: KNN with K=3 and Multi-layer perceptron

| Training Set | Auxiliary dataset | DT | DT + FG | Diff DT |
|--------------|-------------------|----|--------|--------|
| IMDB$^{0.25}$ | Wikipedia         | 0.593 | 0.640 | +0.047 |
| AMAZON$^{0.25}$ | Wikipedia         | 0.690 | 0.742 | +0.052 |

Table 4: The results of generating word-based features using the Wikipedia corpus. The improvement (almost 5%) is statistically significant with $p < 0.05$.

5 Related work

Many feature generation methods have been developed in an attempt to construct new features that better represent the target concept. The most common approach for feature generation (feature engineering) is by constructing new features that are combinations of the given ones. The early GALA algorithm [Hu and Kibler, 1996] utilizes a set of logical operators to combine Boolean attributes. Another example is the LFC [Ragavan et al., 1993] algorithm that combines binary features through the use of logical operators such as $\lor$, $\neg$. 

Figure 2: The effect of the addition of features generated in our algorithm, on the accuracy achieved by decision tree with pruning, on the YELP dataset.
The CITRE algorithm [Matheus and Rendell, 1989] constructs new features by combining basic features using decision trees. The FICUS algorithm [Markovitch and Rosenstein, 2002] presents a general framework that, given a set of constructing functions, applies them over existing features, included generated ones. The more recent ExploreKit algorithm [Katz et al., 2016] uses a similar technique. The FEADIS [Dor and Reich, 2012] algorithm and the Deep Feature Synthesis algorithm [Kanter and Veeramachaneni, 2015] form new features using mathematical functions. The work of [Tran et al., 2016] uses genetic programming (GP) with an embedded approach to construct and select new features for binary classification problems.

Cognito [Khurana et al., 2016] performs automatic feature engineering by exploring various feature construction choices in a hierarchical and non-exhaustive approach using a greedy strategy. Khurana et al. [2017] used reinforcement learning to explore the feature transformation graph. The AutoLearn algorithm [Kaul et al., 2017] identifies associations between feature pairs and uses a regularized regression model to construct a new feature from each pair. The LFE algorithm [Nargesian et al., 2017] learns patterns between feature characteristics, class distributions, and useful transformations, in order to construct a more effective generated feature.

All these methods are based on the assumption that merely combining existing features is sufficient to allow a learner that uses the combined features to yield better classifiers than by using only the original ones.

Another group of feature-generation methods use external knowledge to generate new features. Our algorithm belongs to this class of approaches. Explicit Semantic Analysis (ESA) [Gabrilovich and Markovitch, 2009] uses semantic concepts extracted from knowledge sources such as Wikipedia as features for text classification tasks. Word2Vec [Mikolov et al., 2013] generates latent concepts based on a large corpus that can also be used for text classification.

Other Algorithms for specific problem domains use domain background knowledge to construct special features. The bootstrapping algorithm was applied in the domain of molecular biology [Hirsh and Japkowicz, 1994] to generate new features by using an initial set of feature sequences produced by human experts and by using a special set of operators. The features are represented as nucleotides sequences whose structure is modified by biology-based operators determined by existing background knowledge.

Propositionalization approaches [Kramer and Frank, 2000] rely on relational data to serve as external knowledge. They take advantage of several operators to create first-order logic predicates connecting existing data and relational knowledge. Cheng et al. [2011] devised a generic propositionalization framework using linked data via relation-based queries. FeGeLOD [Paulheim and Fümkranz, 2012] also utilizes linked data to automatically enrich existing datasets. FeGeLOD uses feature values as entities and adds related knowledge to the example, thus creating additional features. OneBM [Lam et al., 2017] works with multiple raw tables in a database. It joins the tables and applies corresponding pre-defined transformation functions on the given features types.

Some learning algorithms employ an internal process that can be viewed as feature generation. One example is the family of multilayer Neural Network (NN) algorithms which includes Deep learning algorithms [LeCun et al., 1998], where the activation functions of nodes in the hidden layers together with the weights of their inputs can be considered as features that had been built during the training process. Other ensemble models, such as Random Forest (RF), use randomization to create data subsets where the new generated features are the output of decision trees applies on these data subsets.

6 Conclusion

One of the advantages of human learners over machine learning algorithms is their ability to exploit excessive background knowledge during the induction process. This ability allows them to generalize even when a small set of labeled examples is given. In this paper, we presented a novel algorithm that allows machine learning procedures to similarly exploit external knowledge via feature generation.

The core of our method is the realization that many datasets deal with similar types of objects, such as people and texts. Thus, many datasets are using common features. Given a dataset to learn from, our method utilizes its common features with other available datasets to learn to predict additional features from these external datasets. The predictors are then added as generated features to the original dataset. We have shown that our method significantly enhances the performance of existing learning algorithms.

One potential difficulty for our method is an auxiliary dataset where all features are orthogonal. In such a case the secondary learning process may not be able to learn good predictors. Note, however, that in most real datasets, the features are not fully orthogonal. Even the Naive Bayes assumption, that the features are independent given the class, does not hold in most realistic learning tasks. In addition, for labeled auxiliary datasets, we always have at least one non-orthogonal feature: the class itself. In any case, low-quality predictors will be filtered out by our wrapper-based feature selection. Our experiments show that in all the datasets used in our experiments, the generated features improved the performance on the held-out test set.

The features generated using our method are not replacing the original features but added to them. Therefore, other methods that use external knowledge can still be applied, potentially even better as they now have access to an enhanced feature set. Similarly, feature-combination algorithms, such as Cognito [Khurana et al., 2016], LFE [Nargesian et al., 2017] and ExploreKit [Katz et al., 2016], can now use the generated features, in addition to the original set of features, in the combination functions.

We are currently in the process of utilizing MIMIC [Johnson et al., 2016], a very large medical dataset, as our auxiliary source for generating features for medical learning tasks. The main challenge we are tackling is developing a good feature matching strategy. We believe that using our method with this extensive knowledge base may significantly enhance the performance of the learned classifiers in this important domain.
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