On the use of Side Information for Mining Text Data

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Abstract—In many text mining applications, side-information is available along with the text documents. Such side-information may be of different kinds, such as document provenance information, the links in the document, user-access behavior from web logs, or other non-textual attributes which are embedded into the text document. Such attributes may contain a tremendous amount of information for clustering purposes. However, the relative importance of this side-information may be difficult to estimate, especially when some of the information is noisy. In such cases, it can be risky to incorporate side-information into the mining process, because it can either improve the quality of the representation for the mining process, or can add noise to the process. Therefore, we need a principled way to perform the mining process, so as to maximize the advantages from using this side information. In this paper, we design an algorithm which combines classical partitioning algorithms with probabilistic models in order to create an effective clustering approach. We then show how to extend the approach to the classification problem. We present experimental results on a number of real data sets in order to illustrate the advantages of using such an approach.

1 Introduction

The problem of text clustering arises in the context of many application domains such as the web, social networks, and other digital collections. The rapidly increasing amounts of text data in the context of these large online collections has led to an interest in creating scalable and effective mining algorithms. A tremendous amount of work has been done in recent years on the problem of clustering in text collections [5], [11], [27], [30], [37] in the database and information retrieval communities. However, this work is primarily designed for the problem of pure text clustering, in the absence of other kinds of attributes. In many application domains, a tremendous amount of side-information is also associated along with the documents. This is because text documents typically occur in the context of a variety of applications in which there may be a large amount of other kinds of database attributes or meta-information which may be useful to the clustering process. Some examples of such side-information are as follows:

- In an application in which we track user access behavior of web documents, the user-access behavior may be captured in the form of web logs. For each document, the meta-information may correspond to the browsing behavior of the different users. Such logs can be used to enhance the quality of the mining process in a way which is more meaningful to the user, and also application-sensitive. This is because the logs can often pick up subtle correlations in content, which cannot be picked up by the raw text alone.
- Many text documents contain links among them, which can also be treated as attributes. Such links contain a lot of useful information for mining purposes. As in the previous case, such attributes may often provide insights about the correlations among documents in a way which may not be easily accessible from raw content.
- Many web documents have meta-data associated with them which correspond to different kinds of attributes such as the provenance or other information about the origin of the document. In other cases, data such as ownership, location, or even temporal information may be informative for mining purposes. In a number of network and user-sharing applications, documents may be associated with user-tags, which may also be quite informative.

While such side-information can sometimes be useful in improving the quality of the clustering process, it can be a risky approach when the side-information is noisy. In such cases, it can actually worsen the quality of the mining process. Therefore, we will use an approach which carefully ascertains the coherence of the clustering characteristics of the side information with that of the text content. This helps

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in magnifying the clustering effects of both kinds of data. The core of the approach is to determine a clustering in which the text attributes and side-information provide similar hints about the nature of the underlying clusters, and at the same time ignore those aspects in which conflicting hints are provided.

In order to achieve this goal, we will combine a partitioning approach with a probabilistic estimation process, which determines the coherence of the side-attributes in the clustering process. A probabilistic model on the side information uses the partitioning information (from text attributes) for the purpose of estimating the coherence of different clusters with side attributes. This helps in abstracting out the noise in the membership behavior of different attributes. The partitioning approach is specifically designed to be very efficient for large data sets. This can be important in scenarios in which the data sets are very large. We will present experimental results on a number of real data sets, and illustrate the effectiveness and efficiency of the approach.

While our primary goal in this paper is to study the clustering problem, we note that such an approach can also be extended in principle to other data mining problems in which auxiliary information is available with text. Such scenarios are very common in a wide variety of data domains. Therefore, we will also propose a method in this paper in order to extend the approach to the problem classification. We will show that the extension of the approach to the classification problem provides superior results because of the incorporation of side information. Our goal is to show that the advantages of using side-information extend beyond a pure clustering task, and can provide competitive advantages for a wider variety of problem scenarios.

This paper is organized as follows. The remainder of this section will present the related work on the topic. In the next section, we will formalize the problem of text clustering with side information. We will also present an algorithm for the clustering process. We will show how to extend these techniques to the classification problem in section 3. In section 4, we will present the experimental results. Section 5 contains the conclusions and summary.

1.1 Related Work

The problem of text-clustering has been studied widely by the database community [18], [25], [34]. The major focus of this work has been on scalable clustering of multi-dimensional data of different types [18], [19], [25], [34]. A general survey of clustering algorithms may be found in [21]. The problem of clustering has also been studied quite extensively in the context of text-data. A survey of text clustering methods may be found in [3]. One of the most well known techniques for text-clustering is the scatter-gather technique [11], which uses a combination of agglomerative and partitional clustering. Other related methods for text-clustering which use similar methods are discussed in [27], [29]. Co-clustering methods for text data are proposed in [12], [13]. An Expectation Maximization (EM) method for text clustering has been proposed in [22]. Matrix-factorization techniques for text clustering are proposed in [32]. This technique selects words from the document based on their relevance to the clustering process, and uses an iterative EM method in order to refine the clusters. A closely related area is that of topic-modeling, event tracking, and text-categorization [6], [9], [15], [16]. In this context, a method for topic-driven clustering for text data has been proposed in [35]. Methods for text clustering in the context of keyword extraction are discussed in [17]. A number of practical tools for text clustering may be found in [23]. A comparative study of different clustering methods may be found in [30].

The problem of text clustering has also been studied in context of scalability in [5], [20], [37]. However, all of these methods are designed for the case of pure text data, and do not work for cases in which the text-data is combined with other forms of data. Some limited work has been done on clustering text in the context of network-based linkage information [1], [2], [8], [10], [24], [31], [36], [33], though this work is not applicable to the case of general side-information attributes. In this paper, we will provide a first approach to using other kinds of attributes in conjunction with text clustering. We will show the advantages of using such an approach over pure text-based clustering. Such an approach is especially useful, when the auxiliary information is highly informative, and provides effective guidance in creating more coherent clusters. We will also extend the method to the problem of text classification, which has been studied extensively in the literature. Detailed surveys on text classification may be found in [4], [28].

2 Clustering with Side Information

In this section, we will discuss an approach for clustering text data with side information. We assume that we have a corpus $\mathcal{S}$ of text documents. The total number of documents is N, and they are denoted by $T_1 \ldots T_N$. It is assumed that the set of distinct words in the entire corpus $\mathcal{S}$ is denoted by $\mathcal{W}$. Associated with each document T_i, we have a set of side attributes $\overline{X_i}$. Each set of side attributes $\overline{X_i}$ has d dimensions, which are denoted by $(x_{i1} \ldots x_{id})$. We refer to such attributes as *auxiliary* attributes. For ease in notation and analysis, we assume that each side-attribute x_{id} is binary, though both numerical and categorical attributes can easily be converted to this format in a fairly straightforward way. This is because the different values of the categorical attribute can be assumed to be separate binary attributes, whereas numerical data can be discretized to binary values with the use of attribute ranges. Some examples of such side-attributes are as follows:

- In a web log analysis application, we assume that x_{ir} corresponds to the 0-1 variable, which indicates whether or not the ith document has been accessed by the rth user. This information can be used in order to cluster the web pages in a site in a more informative way than a techniques which is based purely on the content of the documents. As in the previous case, the number of pages in a site may be large, but the number of documents accessed by a particular user may be relatively small.
- In a network application, we assume that x_{ir} corresponds to the 0-1 variable corresponding to whether or not the ith document T_i has a hyperlink to the rth page T_r. If desired, it can be implicitly assumed that each page links

to itself in order to maximize linkage-based connectivity effects during the clustering process. Since hyperlink graphs are large and sparse, it follows that the number of such auxiliary variables are high, but only a small fraction of them take on the value of 1.
- In a document application with associated GPS or provenance information, the possible attributes may be drawn on a large number of possibilities. Such attributes will naturally satisfy the sparsity property.

As noted in the examples above, such auxiliary attributes are quite sparse in many real applications. This can be a challenge from an efficiency perspective, unless the sparsity is carefully taken into account during the clustering process. Therefore, our techniques will be designed to account for such sparsity. However, it is possible to easily design our approach for non-sparse attributes, by treating the attribute values in a more symmetric way.

We note that our technique is not restricted to binary auxiliary attributes, but can also be applied to attributes of other types. When the auxiliary attributes are of other types (quantitative or categorical), they can be converted to binary attributes with the use of a simple transformation process. For example, numerical data can be discretized into binary attributes. Even in this case, the derived binary attributes are quite sparse especially when the numerical ranges are discretized into a large number of attributes. In the case of categorical data, we can define a binary attribute for each possible categorical value. In many cases, the number of such values may be quite large. Therefore, we will design our techniques under the implicit assumption that such attributes are quite sparse. The formulation for the problem of clustering with side information is as follows:

Text Clustering with Side Information: *Given a corpus $\mathcal{S}$ of documents denoted by $T_1 \ldots T_N$, and a set of auxiliary variables $\overline{X_i}$ associated with document T_i, determine a clustering of the documents into k clusters which are denoted by $\mathcal{C}_1 \ldots \mathcal{C}_k$, based on both the text content and the auxiliary variables.*

We will use the auxiliary information in order to provide additional insights, which can improve the quality of clustering. In many cases, such auxiliary information may be noisy, and may not have useful information for the clustering process. Therefore, we will design our approach in order to magnify the coherence between the text content and the side-information, when this is detected. In cases, in which the text content and side-information do not show coherent behavior for the clustering process, the effects of those portions of the side-information are marginalized.

2.1 The COATES Algorithm

In this section, we will describe our algorithm for text clustering with side-information. We refer to this algorithm as *COATES* throughout the paper, which corresponds to the fact that it is a *COntent and Auxiliary attribute based TExt cluStering* algorithm. We assume that an input to the algorithm is the number of clusters k. As in the case of all text-clustering algorithms, it is assumed that stop-words have been removed, and stemming has been performed in order to improve the discriminatory power of the attributes. The algorithm requires two phases:

- **Initialization:** We use a lightweight initialization phase in which a standard text clustering approach is used without any side-information. For this purpose, we use the algorithm described in [27]. The reason that this algorithm is used, because it is a simple algorithm which can quickly and efficiently provide a reasonable initial starting point. The centroids and the partitioning created by the clusters formed in the first phase provide an initial starting point for the second phase. We note that the first phase is based on text only, and does not use the auxiliary information.
- **Main Phase:** The main phase of the algorithm is executed after the first phase. This phase starts off with these initial groups, and iteratively reconstructs these clusters with the use of *both* the text content and the auxiliary information. This phase performs alternating iterations which use the text content and auxiliary attribute information in order to improve the quality of the clustering. We call these iterations as *content* iterations and *auxiliary iterations* respectively. The combination of the two iterations is referred to as a *major iteration*. Each major iteration thus contains *two minor iterations*, corresponding to the auxiliary and text-based methods respectively.

The focus of the first phase is simply to construct an initialization, which provides a good starting point for the clustering process based on text content. Since the key techniques for content and auxiliary information integration are in the second phase, we will focus most of our subsequent discussion on the second phase of the algorithm. The first phase is simply a direct application of the text clustering algorithm proposed in [27]. The overall approach uses alternating minor iterations of content-based and auxiliary attribute-based clustering. These phases are referred to as *content-based* and *auxiliary attribute-based* iterations respectively. The algorithm maintains a set of seed centroids, which are subsequently refined in the different iterations. In each content-based phase, we assign a document to its closest seed centroid based on a text similarity function. The centroids for the k clusters created during this phase are denoted by $L_1 \ldots L_k$. Specifically, the cosine similarity function is used for assignment purposes. In each auxiliary phase, we create a probabilistic model, which relates the attribute probabilities to the cluster-membership probabilities, based on the clusters which have already been created in the most recent text-based phase. The goal of this modeling is to examine the coherence of the text clustering with the side-information attributes. Before discussing the auxiliary iteration in more detail, we will first introduce some notations and definitions which help in explaining the clustering model for combining auxiliary and text variables.

We assume that the k clusters associated with the data are denoted by $\mathcal{C}_1 \ldots \mathcal{C}_k$. In order to construct a probabilistic model of membership of the data points to clusters, we assume that each auxiliary iteration has a *prior* probability of assignment of documents to clusters (based on the execution of

the algorithm so far), and a *posterior* probability of assignment of documents to clusters with the use of auxiliary variables in that iteration. We denote the prior probability that the document T_i belongs to the cluster $\mathcal{C}_j$ by $P(T_i \in \mathcal{C}_j)$. Once the pure-text clustering phase has been executed, the *a-priori* cluster membership probabilities of the auxiliary attributes are generated with the use of the last content-based iteration from this phase. The *apriori* value of $P(T_i \in \mathcal{C}_j)$ is simply the fraction of documents which have been assigned to the cluster $\mathcal{C}_j$. In order to compute the *posterior* probabilities $P(T_i \in \mathcal{C}_j|\overline{X_i})$ of membership of a record at the end of the auxiliary iteration, we use the auxiliary attributes $\overline{X_i}$ which are associated with T_i. Therefore, we would like to compute the conditional probability $P(T_i \in \mathcal{C}_j|\overline{X_i})$. We will make the approximation of considering only those auxiliary attributes (for a particular document), which take on the value of 1. Since we are focussing on sparse binary data, the value of 1 for an attribute is a much more informative event than the default value of 0. Therefore, it suffices to condition only on the case of attribute values taking on the value of 1. For example, let us consider an application in which the auxiliary information corresponds to users which are browsing specific web pages. In such a case, the clustering behavior is influenced much more significantly by the case when a user *does* browse a particular page, rather than one in which the user *does not* browse a particular page, because most pages will typically not be browsed by a particular user. This is generally the case across many sparse data domains such as attributes corresponding to links, discretized numeric data, or categorical data which is quite often of very high cardinality (such as zip codes).

Furthermore, in order to ensure the robustness of the approach, we need to eliminate the noisy attributes. This is especially important, when the number of auxiliary attributes is quite large. Therefore, at the beginning of each auxiliary iteration, we compute the *gini-index* of each attribute based on the clusters created by the last content-based iteration. This gini-index provides a quantification of the discriminatory power of each attribute with respect to the clustering process. The gini-index is computed as follows. Let f_{rj} be the fraction of the records in the cluster $\mathcal{C}_j$ (created in the last content-based iteration), for which the attribute r takes on the value of 1. Then, we compute the *relative presence* p_{rj} of the attribute r in cluster j as follows:

$$p_{rj} = \frac{f_{rj}}{\sum_{m=1}^{k} f_{rm}} \tag{1}$$

The values of p_{rj} are defined, so that they sum to 1 over a particular attribute r and different clusters j. We note that when all values of p_{rj} take on a similar value of $1/k$, then the attribute values are evenly distributed across the different clusters. Such an attribute is not very discriminative with respect to the clustering process, and it should not be used for clustering. While the auxiliary attributes may have a different clustering behavior than the textual attributes, it is also expected that informative auxiliary attributes are at least somewhat related to the clustering behavior of the textual attributes. This is generally true of many applications such as those in which auxiliary attributes are defined either by linkage-based patterns or by user behavior. On the other hand, completely noisy attributes are unlikely to have any relationship to the text content, and will not be very effective for mining purposes. Therefore, we would like the values of p_{rj} to vary across the different clusters. We refer to this variation as *skew*. The level of skew can be quantified with the use of the gini-index. The gini-index of attribute r is denoted by $\mathcal{G}_r$, and is defined as follows:

$$\mathcal{G}_r = \sum_{j=1}^{k} p_{rj}^2 \tag{2}$$

The value of $\mathcal{G}_r$ lies between $1/k$ and 1. The more discriminative the attribute, the higher the value of $\mathcal{G}_r$. In each iteration, we use only the auxiliary attributes for which the gini-index is above a particular threshold γ. The value of γ is picked to be 1.5 standard deviations below the mean value of the gini-index in that particular iteration. We note that since the clusters may change from one iteration to the next, and the gini-index is defined with respect to the current clusters, the values of the gini-index will also change over the different iterations. Therefore, different auxiliary attributes may be used over different iterations in the clustering process, as the quality of the clusters become more refined, and the corresponding discriminative power of auxiliary attributes can also be computed more effectively.

Let R_i be a set containing the indices of the attributes in $\overline{X_i}$ which are considered discriminative for the clustering process, and for which the value of the corresponding attribute is 1. For example, let us consider an application in which we have 1000 different auxiliary attributes. If the dimension indices of the attributes in the vector $\overline{X_i}$ which take on the value of 1 are 7, 120, 311, and 902 respectively, then we have $R_i = \{7, 120, 311, 902\}$. Therefore, instead of computing $P(T_i \in \mathcal{C}_j|\overline{X_i})$, we will compute the conditional probability of membership based on a particular value of the set R_i. We define this quantity as the *attribute subset based conditional probability of cluster membership*.

Definition 1: The attribute-subset based conditional probability of cluster membership of the document T_i to the cluster $\mathcal{C}_j$ is defined as the conditional probability of membership of document T_i to cluster $\mathcal{C}_j$ based only on the set of attributes R_i from $\overline{X_i}$ which take on the value of 1.

The attribute-subset based conditional probability of document T_i to cluster $\mathcal{C}_j$ is denoted by $P^s(T_i \in \mathcal{C}_j|R_i)$. We note that if R_i contains a modest number of attributes, then it is hard to directly approximate $P^s(T_i \in \mathcal{C}_j|R_i)$ in a data-driven manner. We note that these are the *posterior* probabilities of cluster membership *after* the auxiliary-attribute based iteration, given that particular sets of auxiliary attribute values are presented in the different documents. We will use these posterior probabilities in order to re-adjust the cluster centroids during the auxiliary attribute-based iterations. The *a-priori* probabilities of membership are assigned based on the current *content-based* iteration of the clustering, and are denoted by $P^a(T_i \in \mathcal{C}_j)$. The a-priori and a-posteriori probabilities are

Algorithm *COATES*(NumClusters: k, Corpus: $T_1 \ldots T_N$, Auxiliary Attributes: $\overline{X_1} \ldots \overline{X_N}$);
begin
Use content-based algorithm in [27] to create initial set of k clusters $\mathcal{C}_1 \ldots \mathcal{C}_k$;
Let centroids of $\mathcal{C}_1 \ldots \mathcal{C}_k$ be denoted by $L_1 \ldots L_k$;
$t = 1$;
while not(*termination_criterion*) **do**
begin
{ First minor iteration }
Use cosine-similarity of each document T_i to centroids $L_1 \ldots L_k$ in order to determine the closest cluster to T_i and update the cluster assignments $\mathcal{C}_1 \ldots \mathcal{C}_k$;
Denote assigned cluster index for document T_i by $q_c(i, t)$;
Update cluster centroids $L_1 \ldots L_k$ to the centroids of updated clusters $\mathcal{C}_1 \ldots \mathcal{C}_k$;
{ Second Minor Iteration }
Compute gini-index of $\mathcal{G}_r$ for each auxiliary attribute r with respect to current clusters $\mathcal{C}_1 \ldots \mathcal{C}_k$;
Mark attributes with gini-index which is γ standard-deviations below the mean as non-discriminatory;
{ for document T_i let R_i be the set of attributes which take on the value of 1, and for which gini-index is discriminatory;}
for each document T_i use the method discussed in section 2 to determine the posterior probability $P^n(T_i \in \mathcal{C}_j | R_i)$;
Denote $q_a(i, t)$ as the cluster-index with highest posterior probability of assignment for document T_i;
Update cluster-centroids $L_1 \ldots L_k$ with the use of posterior probabilities as discussed in section 2;
$t = t + 1$;
end
end

Fig. 1. The COATES Algorithm

related as follows:

$$P^s(T_i \in \mathcal{C}_j | R_i) = P^a(R_i | T_i \in C_j) \cdot P^a(T_i \in \mathcal{C}_j) / P^a(R_i) \tag{3}$$

The above equation follows from the simple expansion of the expression for the conditional probabilities. We will also see that each expression on the right-hand side can be estimated in a *data-driven* manner with the use of the conditional estimates from the last iteration. Specifically, the value of $P^a(T_i \in \mathcal{C}_j)$ is simply the fraction of the documents assigned to the cluster $\mathcal{C}_j$ in the last content-based (minor) iteration.

In order to evaluate posterior probabilities from Equation 3, we also need to estimate $P^a(R_i)$ and $P^a(R_i | T_i \in \mathcal{C}_j)$. Since R_i may contain many attributes, this is essentially a joint probability, which is hard to estimate exactly with a limited amount of data. Therefore, we make a *naive Bayes approximation* in order to estimate the values of $P^a(R_i)$ and $P^a(R_i | T_i \in \mathcal{C}_j)$. This approximation has been shown to achieve high quality results in a wide variety of practical scenarios [14]. In order to make this approximation, we assume that the different attributes of R_i are independent of one another. Then, we can approximate $P(R_i)$ as follows:

$$P^a(R_i) = \prod_{r \in R_i} P^a(x_{ir} = 1) \tag{4}$$

This value of $P^a(x_{ir} = 1)$ is simply the fraction of the documents in which the value of the attribute x_{ir} is one. This can be easily estimated from the underlying document collection. Similarly, we use the independence assumption in order to estimate the value of $P^a(R_i | T_i \in \mathcal{C}_j)$.

$$P^a(R_i | T_i \in \mathcal{C}_j) = \prod_{r \in R_i} P^a(x_{ir} = 1 | T_i \in \mathcal{C}_j) \tag{5}$$

The value of $P^a(x_{ir} = 1 | T_i \in \mathcal{C}_j)$ is the fraction of the documents **in cluster** $\mathcal{C}_j$ in which the value of attribute x_{ir} is one. This value can be estimated from the last set of clusters obtained from the content-based clustering phase. For each cluster $\mathcal{C}_j$, we determine the fraction of records for which the value of rth auxiliary attribute is 1. We note that the only difference between the second definition and the first is the fact that in the second case, we are computing the fraction of the documents in the cluster j for which the rth attribute is 1. Then, we can substitute the results of Equations 4 and 5 in Equation 3 in order to obtain the following:

$$P^s(T_i \in \mathcal{C}_j | R_i) = P^a(T_i \in \mathcal{C}_j) \cdot \prod_{r \in R_i} \frac{P^a(x_{ir} = 1 | T_i \in \mathcal{C}_j)}{P^a(x_{ir} = 1)} \tag{6}$$

In order to simplify the expression further in order to make it more intuitive, we compute the interest ratio $I(r, j)$ as the expression $\frac{P^a(x_{ir}=1 | T_i \in \mathcal{C}_j)}{P^a(x_{ir}=1)}$. This is the interest ratio for the rth auxiliary attribute in relation to the jth cluster $\mathcal{C}_j$. We formally define the interest ratio as follows:

Definition 2: The interest ratio $I(r, j)$ defines the importance of attribute r with respect to the jth cluster $\mathcal{C}_j$ This is defined as the ratio of the probability of a document belonging to cluster $\mathcal{C}_j$, when the rth auxiliary attribute of the document is set to 1, to the ratio of the same probability unconditionally. Intuitively, the ratio indicates the proportional increase in likelihood of a document belonging to a particular cluster (from the current set of clusters) because of a particular auxiliary attribute value. In other words, we have:

$$I(r, j) = \frac{P^a(x_{ir} = 1 | T_i \in \mathcal{C}_j)}{P^a(x_{ir} = 1)} \tag{7}$$

A value of $I(r, j)$, which is significantly greater than 1 indicates that the auxiliary attribute r is highly related to the current cluster $\mathcal{C}_j$. The break-even value of $I(r, j)$ is one, and it indicates that the auxiliary attribute r is not specially related to the cluster $\mathcal{C}_j$. We can further simplify the expression for the conditional probability in Equation 6 as follows:

$$P^s(T_i \in \mathcal{C}_j | R_i) = P^a(T_i \in \mathcal{C}_j) \cdot \prod_{r \in R_i} I(r, j) \tag{8}$$

We note that the values of $P^s(T_i \in \mathcal{C}_j|R_i)$ should sum to 1 over the different values of (cluster index) j . However, this may not be the case in practice, because of the use of the independence approximation while computing the probabilities for the different attributes. Therefore, we *normalize* the posteriori probabilities to $P^n(T_i \in \mathcal{C}_j|R_i)$, so that they add up to 1, as follows:

$$P^n(T_i \in \mathcal{C}_j|R_i) = \frac{P^s(T_i \in \mathcal{C}_j|R_i)}{\sum_{m=1}^{k} P^s(T_i \in \mathcal{C}_m|R_i)} \quad (9)$$

These normalized posterior probabilities are then used in order to re-adjust the centroids $L_1 \ldots L_k$. Specifically, each document T_i is assigned to the corresponding centroid L_j with a probability proportional to $P^n(T_i \in \mathcal{C}_j|R_i)$, and the text content of the document T_i is added to the cluster centroid L_j of $\mathcal{C}_j$ with a scaling factor proportional to $P^n(T_i \in \mathcal{C}_j|R_i)$. We note that such an iteration supervises the text content of the centroids on the basis of the auxiliary information, which in turn affects the assignment of documents to centroids in the next content-based iteration. Thus, this approach iteratively tries to build a consensus between the text content-based and auxiliary attribute-based assignments of documents to clusters.

In the next *content-based* iteration, we assign the documents to the modified cluster-centroids based on the cosine similarity of the documents to the cluster centroids [26]. Each document is assigned to its closest cluster centroid based on the cosine similarity. The assigned documents are then aggregated in order to create a new centroid meta-document which aggregates the frequency of the words in the documents for that cluster. The least frequent words in this cluster are then pruned away, so as to use a vector of only the most frequent words in the cluster centroid with their corresponding frequencies. This new assignment of documents to clusters is again used for defining the a-priori probabilities for the auxiliary attributes in the next iteration. A key issue for the algorithm is the convergence of the algorithm towards a uniform solution. In order to compute convergence, we assume that we have an identifier associated with each cluster in the data. This identifier does not change from one iteration to the next for a particular centroid. Within the tth major iteration, we compute the following quantities for each document for the two different minor iterations:

- We compute the cluster identifier to which the document T_i was assigned in the content-based step of the tth major iteration. This is denoted by $qc(i, t)$.
- We compute the cluster identifier to which the document T_i had the highest *probability of assignment* in the auxiliary-attribute set of the tth major iteration. This is denoted by $qa(i, t)$.

In order to determine when the iterative process should terminate, we would like the documents to have assignments to similar clusters in the $(t-1)$th and tth steps at the end of both the auxiliary-attribute and content-based steps. In other words, we would like $qc(i, t-1)$, $qa(i, t-1)$ $qc(i, t)$ and $qa(i, t)$ to be as similar as possible. Therefore, we compute the number of documents for which all four of these quantities are the same. As the algorithm progresses, the number of such records will initially increase rapidly, and then slowly level off. The algorithm is assumed to have terminated, when the number of such records does not increase by more than 1% from one iteration to the next. At this point, the algorithm is assumed to have reached a certain level of stability in terms of its assignment behavior, and it can therefore be terminated. An important point to be remembered is that the output to the algorithm are both the vectors $qc(\cdot, t)$ and $qa(\cdot, t)$. While the clustering process is inherently designed to converge to clusters which use both content and auxiliary information, some of the documents cannot be made to agree in the clustering behavior with the use of different criteria. The common assignments in $qc(\cdot, t)$ and $qa(\cdot, t)$ correspond to the cases in which the content-based and auxiliary-assignments can be made to agree with a well-designed clustering process, and the differences in the two vectors correspond to those documents which show different clustering behavior for the auxiliary and content-based information. Such documents are interesting, because they provide *intensional understanding* of how some of the content-based information may be different from the auxiliary information in the clustering process. The overall clustering algorithm is illustrated in Figure 1.

2.2 Smoothing Issues

An important smoothing issue arises in process of evaluating the right hand side of Equation 6. Specifically, the expression denoted by $\prod_{r \in R_i} \frac{P^a(x_{ir}=1|T_i \in \mathcal{C}_j)}{P^a(x_{ir}=1)}$ may contain zero values for $P^a(x_{ir} = 1|T_i \in \mathcal{C}_j)$. Even a single such zero value could set the whole expression to zero. This will result in an ineffective clustering process. In order to avoid this problem, we use a smoothing parameter ϵ_r for the rth auxiliary attribute. Specifically, the expression in Equation 6. Therefore, the corresponding expression is evaluated by $\prod_{r \in R_i} \frac{P^a(x_{ir}=1|T_i \in \mathcal{C}_j)+\epsilon_r}{P^a(x_{ir}=1)+\epsilon_r}$. The value of ϵ_r is fixed to within a small fraction of $P^a(x_{ir} = 1)$.

2.3 Time Complexity

The time complexity of the approach is dominated by the time required for the content-based and auxiliary minor iterations. We will determine this running time in terms of the number of clusters k, the number of words in the text lexicon d_t, the number of auxiliary attributes d, and the total number of documents N. In each iteration of the approach, $O(k)$ cosine distance computations are performed. For N documents, we require $O(N \cdot k)$ cosine computations. Since each cosine computation may require $O(d_t)$ time, this running time is given by $O(N \cdot k \cdot d_t)$. In addition, each iteration requires us to compute the similarity with the auxiliary attributes. The major difference from the content-based computation is that this requires $O(d)$ time. Therefore, the total running time required *for each iteration* is $O(N \cdot k \cdot (d + d_t))$. Therefore, the overall running time may be obtained by multiplying this value with the total number of iterations. In practice, a small number of iterations (between 3 to 8) are sufficient to reach convergence in most scenarios. Therefore, in practice, the total running time is given by $O(N \cdot k \cdot (d + d_t))$.

3 Extension to Classification

In this section, we will discuss how to extend the approach to classification. We will extend our earlier clustering approach in order to incorporate supervision, and create a model which summarizes the class distribution in the data in terms of the clusters. Then, we will show how to use the summarized model for effective classification.

First, we will introduce some notations and definitions which are specific to the classification problem. As before, we assume that we have a text corpus $\mathcal{S}$ of documents. The total number of documents in the training data is N, and they are denoted by $T_1 \ldots T_N$. Associated with each text document T_i, we also have a training label l_i', which is drawn from $\{1 \ldots k\}$. As before, we assume that the side information associated with the ith training document is denoted by $\overline{X_i}$. It is assumed that a total of N' test documents are available, which are denoted by $T_1' \ldots T_{N'}'$. It is assumed that the side information associated with the ith document is denoted by $\overline{X_i'}$.

We refer to our algorithm as the *COLT* algorithm throughout the paper, which refers to the fact that it is a *COntent and auxiLiary attribute-based Text classification algorithm*. The algorithm uses a supervised clustering approach in order to partition the data into k different clusters. This partitioning is then used for the purposes of classification. The steps used in the training algorithm are as follows:

- **Feature Selection:** In the first step, we use feature selection to remove those attributes, which are not related to the class label. This is performed both for the text attributes and the auxiliary attributes.
- **Initialization:** In this step, we use a *supervised* k-means approach in order to perform the initialization, with the use of purely text content. The main difference between a supervised k-means initialization, and an unsupervised initialization is that the class memberships of the records in each cluster are pure for the case of supervised initialization. Thus, the k-means clustering algorithm is modified, so that each cluster only contains records of a particular class.
- **Cluster-Training Model Construction:** In this phase, a combination of the text and side-information is used for the purposes of creating a cluster-based model. As in the case of initialization, the purity of the clusters in maintained during this phase.

Once the set of supervised clusters are constructed, these are used for the purposes of classification. We will discuss each of these steps in some detail below.

Next, we will describe the training process for the *COLT* algorithm. The first step in the training process is to create a set of supervised clusters, which are then leveraged for the classification.

The first step in the supervised clustering process is to perform the feature selection, in which only the discriminative attributes are retained. In this feature selection process, we compute the gini-index for each attribute in the data with respect to the class label. If the gini index is γ standard deviations (or more) below the average gini index of all attributes, then these attributes are pruned globally, and are

Algorithm *COLT*(NumClusters: k, Corpus: $T_1 \ldots T_N$,
Auxiliary Attributes: $\overline{X_1} \ldots \overline{X_N}$
Labels $l_1 \ldots l_N$);
begin
Perform feature selection on text and auxiliary attributes with the use of class labels and gini index as explained in section 3;
Use supervised version of algorithm in [27] to create initial set of k clusters denoted by $\mathcal{C}_1 \ldots \mathcal{C}_k$, so that each cluster $\mathcal{C}_i$ contains only records of a particular class;
Let centroids of $\mathcal{C}_1 \ldots \mathcal{C}_k$ be denoted by $L_1 \ldots L_k$;
$t = 1$;
while not(*termination_criterion*) **do**
begin
{ First minor iteration }
Use cosine-similarity of each document T_i to centroids $L_1 \ldots L_k$ in order to determine the closest cluster to T_i (which belongs to same class) and update the cluster assignments $\mathcal{C}_1 \ldots \mathcal{C}_k$;
Denote assigned cluster index for document T_i by $q_c(i, t)$;
Update cluster centroids $L_1 \ldots L_k$ to the centroids of updated clusters $\mathcal{C}_1 \ldots \mathcal{C}_k$;
{ Second Minor Iteration }
Compute gini-index of $\mathcal{G}_r$ for each auxiliary attribute r with respect to current clusters $\mathcal{C}_1 \ldots \mathcal{C}_k$;
Mark attributes with gini-index which is γ standard-deviations below the mean as non-discriminatory;
{ for document T_i let R_i be the set of attributes which take on the value of 1, and for which gini-index is discriminatory;}
for each document T_i use the method discussed in section 2 to determine the posterior probability $P^n(T_i \in \mathcal{C}_j | R_i)$;
Denote $q_a(i, t)$ as the cluster-index with highest posterior probability of assignment for document T_i which also belongs to the same class;
Update cluster-centroids $L_1 \ldots L_k$ with the use of posterior probabilities as discussed in section 2;
$t = t + 1$;
end
end

Fig. 2. The *COLT* Training Process

Algorithm *COLTClassify*(Clusters: $\mathcal{C}_1 \ldots \mathcal{C}_k$, Test Instance: T_i', Auxiliary Attributes of Test Instance: $\overline{X_i'}$)
begin
Determine top r closest clusters in $\mathcal{C}_1 \ldots \mathcal{C}_k$ to T_i' based on cosine similarity with the text attributes;
Derive the set R_i' from X_i', which is the set of non-zero attributes in X_i';
Compute $P^s(T_i' \in \mathcal{C}_j | R_i')$ with the use of Equation 8;
Determine top r clusters in $\mathcal{C}_1 \ldots \mathcal{C}_k$ to X_i' based on the largest value of $P^s(T_i' \in \mathcal{C}_j | R_i')$;
Determine the majority class label from the $2 \cdot r$ labeled clusters thus determined;
return majority label;
end

Fig. 3. The *COLT* Classification Process with the use of the Supervised Clusters

never used further in the clustering process. With some abuse of notation, we can assume that the documents T_i and auxiliary attributes $\overline{X_i}$ refer to these pruned representations. We note that this gini index computation is different from the gini-index computation with respect to the auxiliary attributes. The latter is performed during the main phase of the algorithm.

Once the features have been selected, the initialization of the training procedure is performed only with the content attributes. This is achieved by applying a k-means type algorithm as discussed in [27] to the approach, except that class label constraints are used in the process of assigning data points to clusters. Each cluster is associated with a particular class and all the records in the cluster belong to that class. This goal is achieved by first creating unsupervised cluster centroids, and then adding supervision to the process. In order to achieve this goal, the *first two iterations* of the k-means type algorithm are run in exactly the same way as in [27], where the clusters are allowed to have different class labels. After the second iteration, each cluster centroid is strictly associated with a class label, which is identified as the majority class in that cluster at that point. In subsequent iterations, the records are *constrained* to only be assigned to the cluster with the associated class label. Therefore, in each iteration, for a given document, its distance is computed only to clusters which have the same label as the document. The document is then assigned to that cluster. This approach is continued to convergence.

Once the initialization has been performed, the main process of creating supervised clusters with the use of a combination of content and auxiliary attributes is started. As in the previous case, we use two minor iterations within a major iteration. One minor iteration corresponds to content-based assignment, whereas another minor iteration corresponds to an auxiliary attribute-based assignment. The main difference is that class-based supervision is used in the assignment process. For the case of content-based assignment, we only assign a document to the closest cluster centroid, which belongs to the same label. For the case of the auxiliary minor iteration, we compute the prior probability $P^a(T_i \in \mathcal{C}_j)$ and the posterior probability $P^s(T_i \in \mathcal{C}_j | R_i)$, as in the previous case, except that this is done only for cluster indices which belong to the same class label. The document is assigned to one of the cluster indices with the largest posterior probability. Thus, the assignment is always performed to a cluster with the same label, and each cluster maintain homogeneity of class distribution. As in the previous case, this approach is applied to convergence. The overall training algorithm is illustrated in Figure 2.

Once the supervised clusters have been created, they can be used for the purpose of classification. The supervised clusters provide an effective summary of the data which can be used for classification purposes. Both the content- and auxiliary-information is used in this classification process. In order to perform the classification, we separately compute the r closest clusters to the test instance T_i' with the use of both content and auxiliary attributes. Specifically, for the case of content attributes, we use the similarity based on the content attributes, whereas, for the case of the auxiliary attributes, we determine the probability $P^s(T_i' \in \mathcal{C}_j | R_i')$ for the test instance. In the former case, the r clusters with largest similarity are determined, whereas in the latter case, the r clusters with the largest posterior probability are determined. We note that each of these $2 \cdot r$ clusters is associated with a class label. The number of labels for the different classes are computed from these $2 \cdot r$ possibilities. The label with the largest presence from these $2 \cdot r$ clusters is reported as the relevant class label for the test instance T_i'. The overall procedure for classification is illustrated in Figure 3.

3.1 Time Complexity

The time complexity of the *COLT* algorithm is very similar to the *COATES* algorithm, because the *COLT* algorithm is essentially implemented as a supervised version of the *COATES* algorithm. One major advantage of the *COLT* algorithm over the *COATES* algorithm is that the clusters are class-specific, and therefore the a training document only needs to be compared to clusters of the same class. However, from a *worst-case perspective*, this could still require a comparison to $O(k)$ clusters. Therefore, the worst-case time-complexity of the *COLT* algorithm is still the same, which is given by $O(N \cdot k \cdot (d + d_t))$.

4 Experimental Results

In this section, we compare our clustering and classification methods against a number of baseline techniques on real and synthetic data sets. We refer to our clustering approach as *COntent and Auxiliary attribute based TExt cluStering (COATES)*. As the baseline, we used two different methods: **(1)** An efficient projection based clustering approach [27] which adapts the k-means approach to text. This approach is widely known to provide excellent clustering results in a very efficient way. We refer to this algorithms as *SchutzeSilverstein [text only]* in all figure legends in the experimental section. **(2)** We adapt the k-means approach with the use of both text and

side information directly. We refer to this baseline as *K-Means [text+side]* in all figure legends.

For the case of the classification problem, we tested the *COLT* methods against the following baseline methods: **(1)** We tested against a *Naive Bayes Classifier* which uses only text. **(2)** We tested against an *SVM classifier* which uses only text. **(3)** We tested against a supervised clustering method which uses bboth text and side information.

Thus, we compare our algorithms with baselines which are chosen in such a way that we can evaluate the advantage of our approach over both a pure text-mining method and a natural alternative which uses both text and side-information. In order to adapt the k-means approach to the case where both text and side-information is used, the auxiliary attributes were simply used as text-content in the form of "pseudo-words" in the collection. This makes it relatively simple to modify the k-means algorithm to that case. We will show that our approach has significant advantages for both the clustering and classification problems.

4.1 Data Sets

We used three real data sets in order to test our approach. The data sets used were as follows:

(1) Cora Data Set: The Cora data set[1] contains 19,396 scientific publications in the computer science domain. Each research paper in the Cora data set is classified into a topic hierarchy. On the leaf level, there are 73 classes in total. We used the second level labels in the topic hierarchy, and there are 10 class labels, which are *Information Retrieval, Databases, Artificial Intelligence, Encryption and Compression, Operating Systems, Networking, Hardware and Architecture, Data Structures Algorithms and Theory, Programming* and *Human Computer Interaction*. We further obtained two types of side information from the data set: citation and authorship. These were used as separate attributes in order to assist in the clustering process. There are 75,021 citations and 24,961 authors. One paper has 2.58 authors in average, and there are 50,080 paper-author pairs in total.

(2) DBLP-Four-Area Data Set: The *DBLP-Four-Area data set* [31] is a subset extracted from DBLP that contains four data mining related research areas, which are database, data mining, information retrieval and machine learning. This data set contains 28,702 authors, and the texts are the important terms associated with the papers that were published by these authors. In addition, the data set contained information about the conferences in which each author published. There are 20 conferences in these four areas and 44,748 author-conference pairs. Besides the author-conference attribute, we also used co-authorship as another type of side information, and there were 66,832 coauthor pairs in total.

(3) IMDB Data Set: The **I**nternet **M**ovie **D**ata**B**ase (**IMDB**) is an online collection[2] of movie information. We obtained ten-year movie data from 1996 to 2005 from IMDB in order to perform text clustering. We used the plots of each movie as text to perform pure text clustering. The genre of each movie is regarded as its class label. We extracted movies from the top four genres in *IMDB* which were labeled by *Short*, *Drama*, *Comedy*, and *Documentary*. We removed the movies which contain more than two above genres. There were 9,793 movies in total, which contain 1,718 movies from the *Short* genre, 3,359 movies from the *Drama* genre, 2,324 movies from the *Comedy* genre and 2,392 movies from the *Documentary* genre. The names of the directors, actors, actresses, and producers were used as categorical attributed corresponding to side information. The *IMDB* data set contained 14,374 movie-director pairs, 154,340 movie-actor pairs, 86,465 movie-actress pairs and 36,925 movie-producer pairs.

1. http://www.cs.umass.edu/~mccallum/code-data.html
2. http://www.imdb.com

4.2 Evaluation Metrics

The aim is to show that our approach is superior to natural clustering alternatives with the use of either pure text or with the use of both text and side information. In each data set, the class labels were given, but they were not used in the clustering process. For each class, we computed the cluster purity, which is defined as the fraction of documents in the clusters which correspond to its dominant class. The average cluster purity over all clusters (weighted by cluster size) was reported as a surrogate for the quality of the clustering process. Let the number of data points in the k clusters be denoted by $n_1 \ldots n_k$. We denote the dominant input cluster label in the k clusters by $l_1 \ldots l_k$. Let the number of data points with input cluster label l_i be denoted by c_i. Then, the overall cluster purity P is defined by the fraction of data points in the clustering which occur as a dominant input cluster label. Therefore, we have:

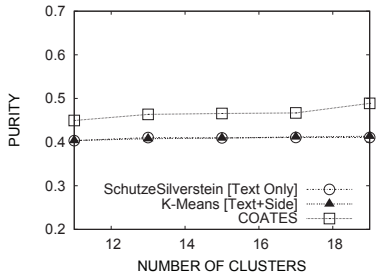
$$P = \frac{\sum_{i=1}^{k} c_i}{\sum_{i=1}^{k} n_i} \tag{10}$$

The cluster purity always lies between 0 and 1. Clearly, a perfect clustering will provide a cluster purity of almost 1, whereas a poor clustering will provide very low values of the cluster purity. For efficiency, we tested the execution time of our method with respect to the baseline over three real data sets.

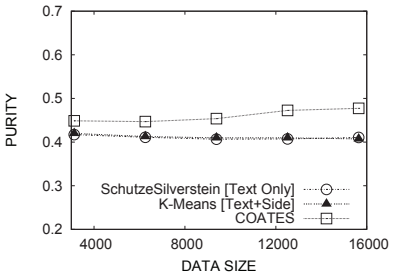
Since the quality of content-based clustering varies based on random initialization, we repeated each test ten times with different random seeds and reported the average as the final score. Unless otherwise mentioned, the default value of the number of input clusters used for the *Cora*, *DBLP-Four-Area* and *IMDB* data sets were 16, 8 and 6 respectively. These default sizes were chosen based on the size of the underlying data set. All results were tested on a Debian GNU/Linux server. The system used double dual-core 2.4 GHz Opteron processors with 4GB RAM.

4.3 Effectiveness Results

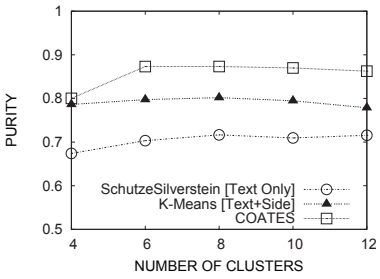
In this section, we will present the effectiveness results for all three data sets. The effectiveness results for the two baseline algorithms and *COATES* algorithms with increasing number of clusters for the *CORA*, *DBLP* and *IMDB* data sets are illustrated in Figures 4(a), (c) and (e) respectively. The number of clusters is illustrated on the X-axis, whereas the cluster



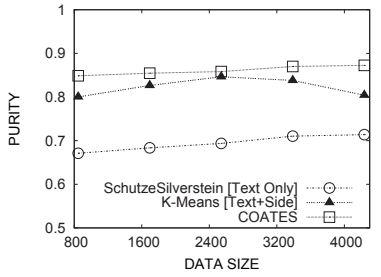
(a) CORA (Effectiveness vs. number of clusters)



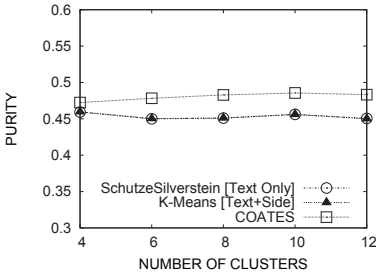
(b) CORA (Effectiveness vs. data size)



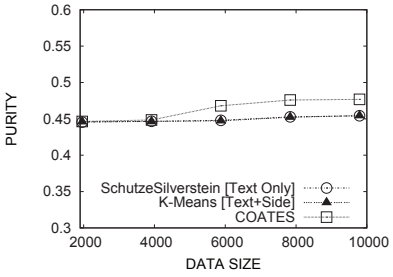
(c) DBLP (Effectiveness vs. number of clusters)



(d) DBLP (Effectiveness vs. data size)

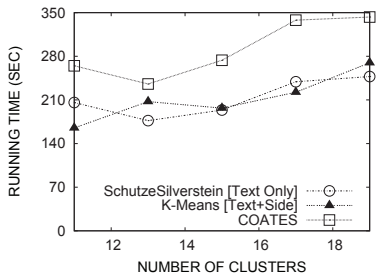


(e) IMDB (Effectiveness vs. number of clusters)

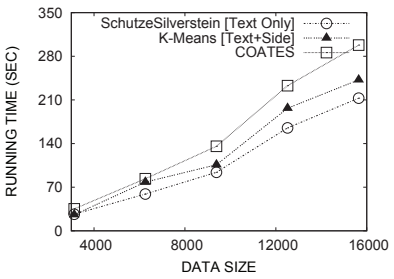


(f) IMDB (Effectiveness vs. data size)

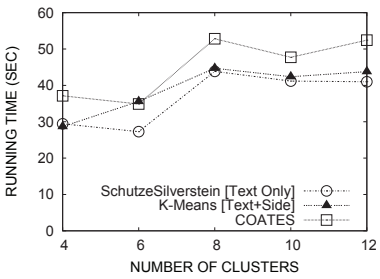
Fig. 4. Effectiveness Results on all Data Sets



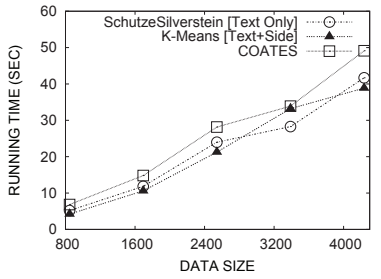
(a) CORA (Efficiency vs. number of clusters)



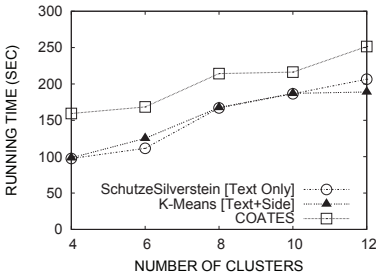
(b) CORA (Efficiency vs. data size)



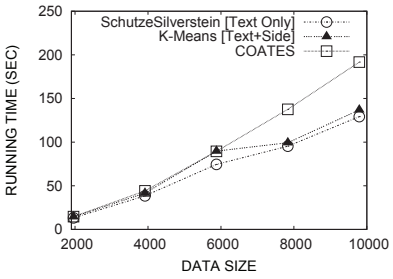
(c) DBLP (Efficiency vs. number of clusters)



(d) DBLP (Efficiency vs. data size)



(e) IMDB (Efficiency vs. number of clusters)



(f) IMDB (Efficiency vs. data size)

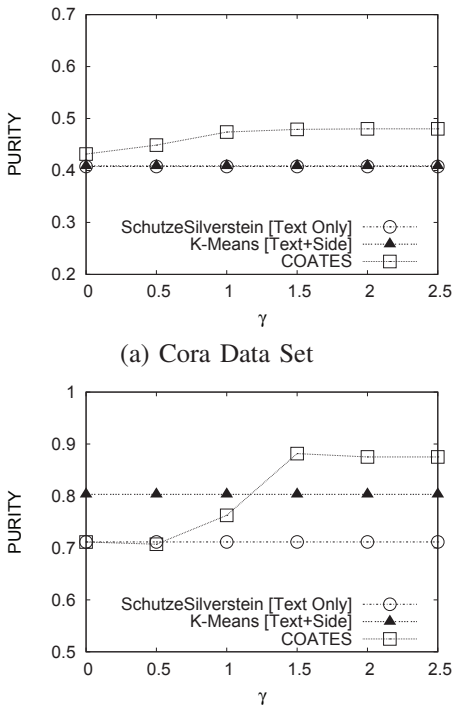
Fig. 5. Efficiency Results on all Data Sets

purity with respect to the ground truth is illustrated on the Y-axis. Since the data sets are quite noisy, the purity numbers are somewhat low both for the *COATES* algorithm and the baselines. We notice that the purity will slightly increase when the number of clusters increases on all three data sets. This is quite natural, since larger number of clusters results in a finer granularity of partitioning. We further notice that *COATES* outperforms the baselines on all three data sets by a wide margin in terms of purity. In the *Cora* and *IMDB* data sets, there was not much difference between the two baselines (which differ in terms of their use of side information or not), because the k-means baseline was unable to leverage the low frequency side information effectively, and the effects of the text content dominated the clustering results. This shows that the side-information is not only important in the clustering process, but it is also important to leverage it properly in order to obtain the maximum gains during the clustering. The improvement in quality over both baselines remains competitive throughout different settings on the number of clusters. This suggests that the *COATES* algorithm is consistently superior to the different baselines, irrespective of the value of this parameter. This suggests that the *COATES* scheme is able to use the side information in a robust and consistent way over different numbers of clusters.

We also tested the effectiveness of the method with increasing data size. This is done by sampling a portion of the data, and reporting the results for different sample sizes. The effectiveness results with increasing data size for the *Cora*, *DBLP*, and *IMDB* data sets are illustrated in Figures 4(b), (d) and (f) respectively. In all figures, the X-axis illustrates the size of data and the Y-axis represents the cluster purity. We find that the improvement in quality with the use of side information is more pronounced for the case of larger data sets. In particular, we can see that at the lower end of the X-axis (corresponding to data samples which are only about 20% of the full size), the effectiveness of adding side information is insignificant in terms of improvement. That is because of the fact that the sparse side information associated with data sets becomes less effective when the data set itself is very small. In such cases, most side information attributes appear very infrequently and thus, it is difficult to leverage them in order to obtain better clustering assignments. When the data size increases to around 40% of the whole data, it has enough side information to improve the quality of clustering. As the size of the data set increases, the improvement in quality becomes even more significant. We can also infer that *COATES* works especially well when the data set is fairly large, because in such cases there are lots of repetitions of the same attribute value of a particular kind of side information, especially when it is sparse. The repetition of the same attribute value of the side information is critical in being able to leverage it for improving clustering quality. In addition the *COATES* algorithm was consistently superior to both the baselines in terms of clustering quality.

4.4 Efficiency Results

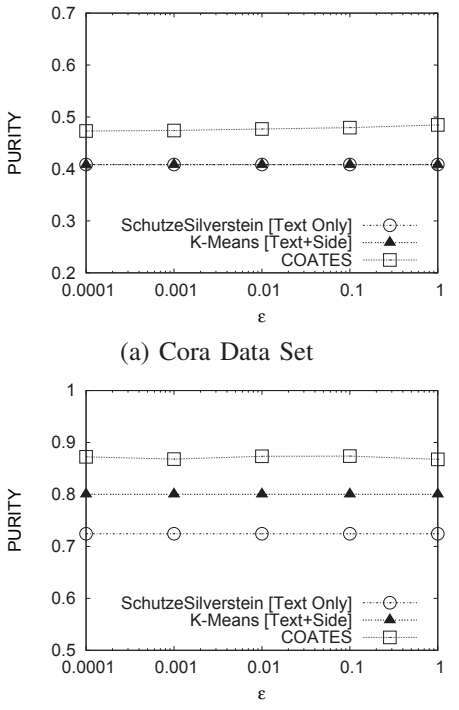
In this section, we present the running times for *COATES* and the two different baselines. We note that all approaches



(a) Cora Data Set

(b) DBLP-Four-Area Data Set

Fig. 6. Sensitivity Analysis with Threshold γ



(a) Cora Data Set

(b) DBLP-Four-Area Data Set

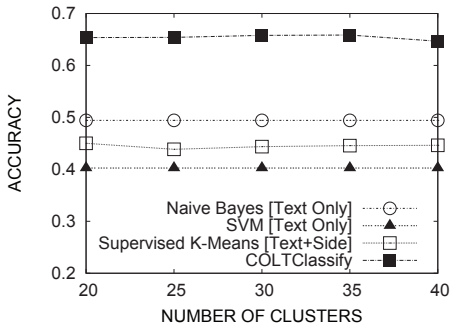
Fig. 7. Sensitivity Analysis with Smoothing Parameter ϵ

use the same text preprocessing methods, such as stops words removal, stemming and term frequency computation, and the time required for side-information pre-processing is negligible. Therefore, the pre-processing time for both methods is virtually the same for all methods, and we present the running times only for the clustering portions in order to sharpen the comparisons and make them more meaningful. We further note that since the *COATES* algorithm is expected to incorporate side-information into the clustering process in a much more significant way than both the baselines, its running times are correspondingly expected to be somewhat higher. The goal is to show that the overheads associated with the better qualitative results of the *COATES* algorithm are somewhat low. We first tested the efficiency of the different methods with respect to the number of clusters, and the results of the *CORA*, *DBLP* and *IMDB* data sets are reported in Figures 5(a), (c) and (e) respectively. The number of clusters are illustrated on the X-axis, and the running time is illustrated on the Y-axis. From the figures, it is evident that the *COATES* algorithm consumes more running time compared with the baselines, though it is only slightly slower than both baselines. The reason is that *COATES* method focusses on the side information in a much more focussed way, which slightly increases its running time. For example, in the *Cora* data set, the side information comprises 50,080 paper-author pairs and 75,021 citing paper-cited paper pairs. It is important to understand that the *COATES* clustering process needs to create a separate iteration in order to effectively process the side information. Therefore, the slight overhead of 10%- to 30% on the running time of the *COATES* algorithm is quite acceptable. From the figures, it is evident that the *COATES* algorithm scales linearly with increasing number of clusters for all data sets. This is because the distance function computations and posterior probability computations scale linearly with increasing number of clusters.

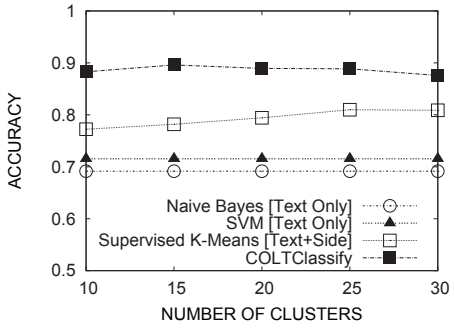
It is also valuable to test the scalability of the proposed approach with increasing data size. The results for the *Cora*, *DBLP*, and *IMDB* data sets are illustrated in Figures 5(b), (d) and (f) respectively. In all figures, the X-axis illustrates the size of data, and the Y-axis illustrates the running time. As in the previous case, the *COATES* algorithm consumes a little more time than the baseline algorithms. These results also show that the running time scales linearly with increasing data size. This is because the number of distance function computations and posterior probability computations scale linearly with the number of documents in each iteration. The linear scalability implies that the technique can be used very effectively for large text data sets.

4.5 Sensitivity Analysis

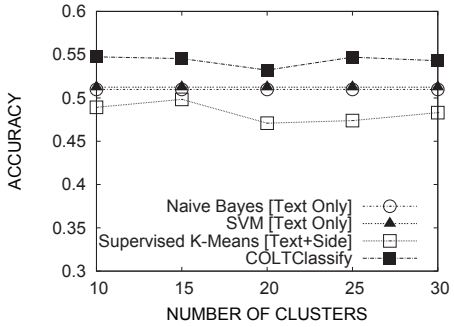
We also tested the sensitivity of the *COATES* algorithm with respect to two important parameters. We will present the sensitivity results on the *Cora* and *DBLP-Four-Area data sets*. As mentioned in the algorithm in Figure 1, we used threshold γ to select discriminative auxiliary attributes. While the default value of the parameter was chosen to be 1.5, we also present the effects of varying this parameter. Figures 6 (a) and (b) show the effects on cluster purity by varying the value of



(a) Cora Data Set



(b) DBLP-Four-Area Data Set

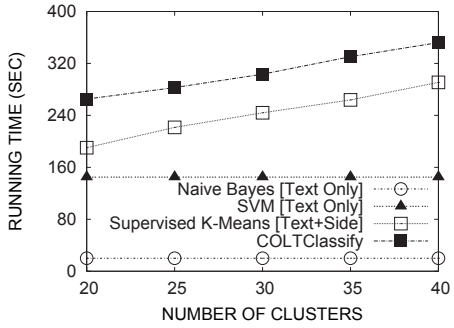


(c) IMDB Data Set

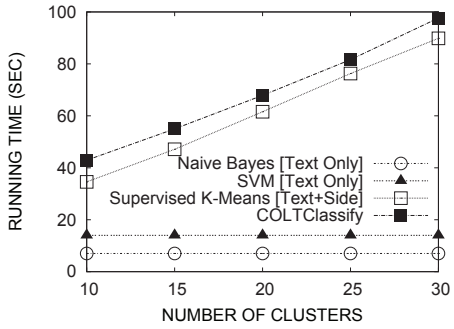
Fig. 8. Classification Accuracy with the Number of Clusters

threshold γ from 0 to 2.5 on the *Cora* and *DBLP-Four-Area data sets*. In both figures, the X-axis illustrates the value of threshold γ, and the Y-axis presents the purity. The results are constant for both baseline methods because they do not use this parameter. It is evident from both figures that setting the threshold γ too low results in purity degradation, since the algorithm will prune the auxiliary attributes too aggressively in this case. On both data sets, the *COATES* algorithm achieves good purity results when γ is set to be 1.5. Further increasing the value of γ will reduce the purity slightly because setting γ too high will result in also including noisy attributes. Typically by picking γ in the range of $(1.5, 2.5)$, the best results were observed. Therefore, the algorithm shows good performance for a fairly large range of values of γ. This suggests that the approach is quite robust.

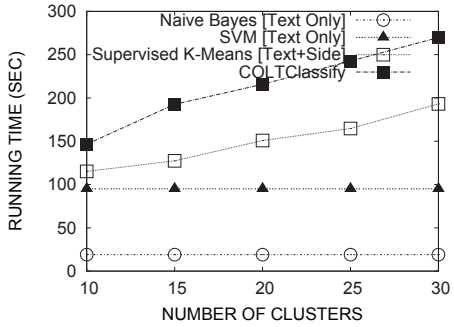
Figures 7 (a) and (b) illustrate the impact of the smoothing parameter ϵ on the effectiveness of the clustering process. The value of the smoothing parameter ϵ is illustrated on a loga-



(a) Cora Data Set



(b) DBLP-Four-Area Data Set



(c) IMDB Data Set

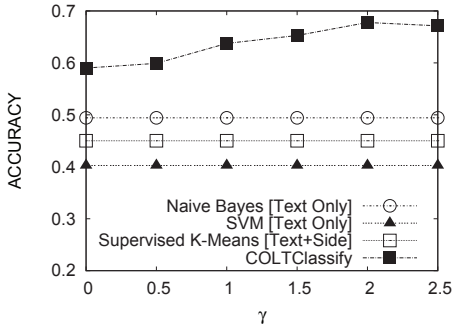
Fig. 9. Classification Efficiency with the Number of Clusters

rithmic scale on the X-axis, whereas the purity is illustrated on the Y-axis. Although the X-axis is on a logarithmic scale, the purity is quite stable across all ranges. But we have to note that ϵ should not be set to too large a value, because this will reduce the positive effects of the additional knowledge added by the auxiliary variables. However, the robustness of the approach over large ranges of values of ϵ shows that the method can be used quite safely for different values of the parameter ϵ.

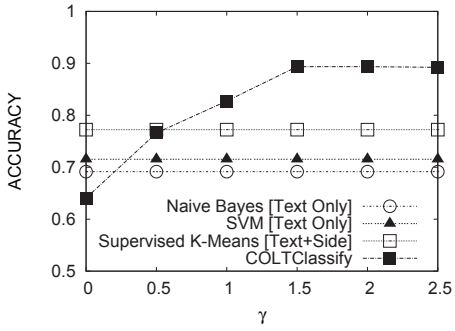
4.6 Extension to Classification

We also tested the classification accuracy of the *COLTClassify* method, which uses both text and side-information. As baselines, the following algorithms were tested (a) A Naive Bayes Classifier[3], (b) An SVM Classifier[4], and (c) A supervised k-means method which is based on both text and side

3. http://www.cs.waikato.ac.nz/ml/weka/
4. http://www.csie.ntu.edu.tw/~cjlin/libsvm/

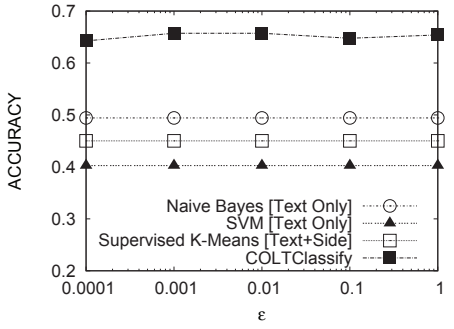


(a) Cora Data Set

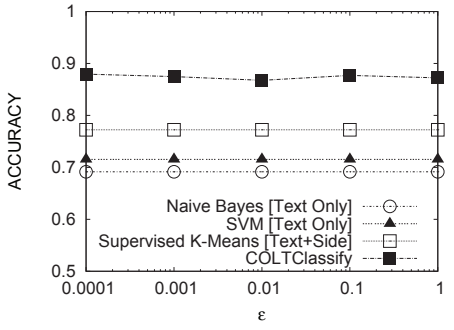


(b) DBLP-Four-Area Data Set

Fig. 10. Variation of classification accuracy with the threshold γ



(a) Cora Data Set



(b) DBLP-Four-Area Data Set

Fig. 11. Variation of classification accuracy with the smoothing factor

information. In the last case, the classification is performed by using the nearest cluster based on text+side.

For each of the data sets, we used 10-fold cross-validation to evaluate the classification model. Clearly, the accuracy of such a model would depend upon the underlying model parameters. For example, the number of clusters in the model may affect the accuracy of the clustering process. In Figure 8, we have illustrated the variation in accuracy with the number of clusters for each of the three data sets. The results for the *CORA*, *DBLP* and *IMDB* data sets are illustrated in Figures 8(a), (b) and (c) respectively. The values of r, γ and ϵ were set to 2, 1.5 and 0.001 respectively. The number of clusters are illustrated on the X-axis, and the classification accuracy is illustrated on the Y-axis. We note that the SVM and Bayes classifiers are not dependent on clustering, and therefore the classification accuracy is a horizontal line. In each case, it can be clearly seen that the accuracy of the *COLTClassify* method was significantly higher than all the other methods. There were some variations in the classification accuracy across the different methods for different data sets. However, the *COLTClassify* method retained the largest accuracy over all data sets, and was quite robust to the number of clusters. This suggests that the method is quite robust both to the choice of the data set and the model parameters.

Next, we test the efficiency of our classification scheme. Since our scheme uses both text and side information, and therefore has a much more complex model, it is reasonable to assume that it would require more time than (the simpler) text-only models. However, we will show that our scheme continues to retain practical running times, in light of their substantial effectiveness. We present the running time of the classification scheme and baselines in Figures 9 (a)-(c). The number of clusters is illustrated on the X-axis, and the running time in seconds is shown on the Y-axis. Similar to the results on classification accuracy, the SVM and Bayes classifiers are horizontal lines in the figures because they are not dependent on the number of clusters. The running time of clustering based methods (supervised k-means and *COLTClassify*) increases with a larger number of clusters. It is clear that the Bayes classifier achieves the best efficiency due to the simplicity of its model, and followed by the SVM classifier. We note that both the supervised k-means method and *COLTClassify* consume longer time. The reasons are both methods process more data including text as well as side information, and they are iterative approaches extended from clustering methods. In addition, *COLTClassify* is a more complex model than the supervised k-means algorithm, and therefore consumes more time. However, considering the effectiveness gained by *COLTClassify*, the overhead in running time is quite acceptable.

We also tested the sensitivity of the classification scheme to the parameters γ and ϵ. The sensitivity of the scheme with respect to the parameter γ for the *Cora* and *DBLP* data sets is presented in Figures 10(a) and (b) respectively. The threshold γ is illustrated on the X-axis, and the classification accuracy is illustrated on the Y-axis. The baselines are also illustrated in the same Figure. It is evident that for most of the ranges of the parameter γ, the scheme continues to perform much better than the baseline. The only case where it does not do as well is the case where the feature selection threshold is chosen to be too small. This is because the feature selection tends to be too aggressive for those cases, and this leads to a loss of accuracy. Further increasing the value of γ beyond 1.5 will reduce the accuracy slightly because setting γ too high will result in also including noisy attributes. However, for most of the range, the *COLTClassify* technique tends to retain its effectiveness with respect to the other methods. In general, since the value of γ is expressed in terms of normalized standard deviations, it is expected to not vary too much with data set. In our experience, the approach worked quite well for γ in the range $(1.5, 2.5)$. This tends to suggest the high level of robustness of the scheme to a wide range of the choice of threshold parameter γ.

The sensitivity of the scheme with respect to the smoothing parameter ϵ for the *Cora* and *DBLP* data sets is presented in Figures 11(a) and (b) respectively. The smoothing parameter ϵ is illustrated on the X-axis, and the accuracy is illustrated on the Y-axis. We note that the smoothing parameter was not required for the other schemes, and therefore the accuracy is presented as a horizontal line in those cases. For the entire range of values for the smoothing parameter ϵ, the *COLTClassify* method performs much more effectively with respect to the other schemes. In fact, the classification accuracy did not change very much across the entire range of the smoothing parameter. Therefore, our technique is very robust to the choice of the smoothing parameter ϵ as well.

5 Conclusions and Summary

In this paper, we presented methods for mining text data with the use of side-information. Many forms of text-databases contain a large amount of side-information or meta-information, which may be used in order to improve the clustering process. In order to design the clustering method, we combined an iterative partitioning technique with a probability estimation process which computes the importance of different kinds of side-information. This general approach is used in order to design both clustering and classification algorithms. We present results on real data sets illustrating the effectiveness of our approach. The results show that the use of side-information can greatly enhance the quality of text clustering and classification, while maintaining a high level of efficiency.

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