

Link-based Text Classification

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Abstract

A key challenge for machine learning is tackling the problem of mining richly structured datasets, where the objects are linked in some way. Links among the objects demonstrate certain patterns, which can be helpful for many machine learning tasks and are usually hard to capture with traditional statistical models. Recently there has been a surge of interest in this area, fueled largely by interest in web and hypertext mining, but also by interest in mining social networks, bibliographic citation data, epidemiological data and other domains best described using a linked or graph structure. In this paper we propose a framework for modeling link distributions, a link-based model that supports discriminative models describing both the link distributions and the attributes of linked objects. We use a structured logistic regression model, capturing both content and links. We systematically evaluate several variants of our link-based model on a range of datasets including both web and citation collections. In all cases, the use of the link distribution improves classification accuracy.

1 Introduction

Traditional data mining tasks such as association rule mining, market basket analysis and cluster analysis commonly attempt to find patterns in a dataset characterized by a collection of independent instances of a single relation. This is consistent with the classical statistical inference problem of trying to identify a model given a random sample from a common underlying distribution.

A key challenge for machine learning is to tackle the problem of mining more richly structured datasets, for example multi-relational datasets in which there are record linkages. In this case, the instances in our dataset are linked in some way, either by an explicit link, such as a URL, or a constructed link, such as join between tables stored in a database. Naively applying traditional statistical inference procedures, which assume that instances are independent, can lead to inappropriate conclusions

[Jensen, 1999]. Care must be taken that potential correlations due to links are handled appropriately. Clearly, this is information that should be exploited to improve the predictive accuracy of the learned models.

Link mining is a newly emerging research area that is at the intersection of the work in link analysis [Jensen & Goldberg, 1998; Feldman, 2002], hypertext and web mining [Chakrabarti, 2002], relational learning and inductive logic programming [Dzeroski & Lavrac, 2001] and graph mining [Cook & Holder, 2000]. Link mining is potentially useful in a wide range of application areas including bio-informatics, bibliographic citations, financial analysis, national security, and the Internet.

In this paper we propose a statistical framework for modeling link distributions. Rather than an ad hoc collection of methods, the proposed framework extends classical statistical approaches to more complex and richly structured domains than commonly studied. It is similar in spirit to the work in conditional random fields [Lafferty et al., 2001], although here we focus on non-sequence data.

The framework we propose stems from our earlier work on link uncertainty in probabilistic relational models [Getoor et al., 2002]. However in this paper, we *do not* construct explicit models for link existence. Instead we model link distributions, which describe the neighborhood of links around an object, and can capture the correlations among links. With these link distributions, we propose algorithms for link-based classification. In order to capture the joint distributions of the links, we use a logistic regression model for both the content and the links.

A second challenge is classification using a learned model. A learned link-based model specifies a joint distribution over link and content attributes and, unlike traditional statistical models, these attributes may be correlated. Intuitively, for linked objects, updating the category of one object can influence our inference about the categories of its linked neighbors. This requires a more complex classification algorithm. Iterative classification algorithms have been proposed for hypertext categorization [Chakrabarti et al., 1998; Oh et al., 2000] and for relational learning [Neville & Jensen, 2000; Taskar et al., 2001; Taskar et al., 2002]. Here, we also use an iter-

ative classification algorithm. One novel aspect is that unlike approaches that make assumptions about the influence of the neighbor's categories (such as that linked objects have similar categories), we explicitly learn how the link distribution affects the category. We also examine a range of ordering strategies for the inference and evaluate their impact on overall classification accuracy.

The main contributions of our work are:

- A statistical framework is proposed for modeling link distributions, the link-based model, which integrates statistical features such as object descriptions with linkage information.
- Experimental results demonstrating that the use of link distributions always improves classification accuracy.
- An evaluation of an iterative categorization algorithm that makes use of a variety of inference strategies.

Related work is discussed in Section 2. Section 3 describes our link-based models. In Section 4, we describe the parameter estimation for the models, and in Section 5 we describe how the link-based model is used for categorization. Experimental results are discussed in Section 6.

2 Related Work

There has been a growing interest in learning from structured data. By structured data, we simply mean data best described by a graph where the nodes in the graph are objects and the edges/hyper-edges in the graph are links or relations between objects. Tasks include hypertext classification, segmentation, information extraction, searching and information retrieval, discovery of authorities and link discovery. Domains include the worldwide web, bibliographic citations, criminology and bioinformatics to name just a few. Learning tasks range from predictive tasks, such as classification, to descriptive tasks, such as the discovery of frequently occurring sub-patterns.

Here, we describe some of the most closely related work to ours, however because of the surge in recent interest, and the wide range of venues where research is reported (including WWW, NIPS, ICML, SIGIR, SIGMOD, VLDB), our list is sure to be incomplete.

Probably the most famous example of exploiting link structure is the use of links to improve information retrieval results. Both the well-known page rank [Page et al., 1998] and hubs and authority scores [Kleinberg, 1999] are based on the link-structure of the web. Dean and Henzinger (1999) propose an algorithm based on co-citation to find related web pages. Kubica et al. (2002) have proposed a probabilistic model for link detection and modeling groups.

One line of work closely related to link-based classification is hypertext and web page classification. This work has its roots in the information retrieval community. A hypertext collection has a richer structure than a collection of text documents. In addition to words,

hypertext has both incoming and outgoing links. Traditional bag-of-words model discard this rich structures of hypertext and do not make full use of link structure of hypertext. In the web page classification problem, the web is viewed as a large directed graph, and our objective is to label the category of a web page, based on features of the current page and features of linked neighbors. With the use of linkage information, anchor text and neighboring text around each incoming link, better categorization results can be achieved.

Chakrabarti et al. (1998) propose a probabilistic model to utilize both text and linkage information to classify a database of patents and a small web collection. They showed that naively incorporating words from neighboring pages reduces performance, while incorporating category information, such as hierarchical category prefixes, improves performance. Oh et al. (2000) reported similar results on a collection of encyclopedia articles: simply incorporating words from neighboring documents was not helpful, while making use of the predicted class of neighboring documents was helpful.

These results indicate that simply assuming that link documents are on the same topic, and incorporating the features of linked neighbors is not generally effective. Another line of works tries to construct features from related documents. The first example is the work of Slatery and Craven (1998). They propose a model which beyond using words in a hypertext document, makes use of anchor text, neighboring text, capitalized words and alphanumeric words. Using these statistical features and a relational rule learner based on FOIL [Quinlan & Cameron-Jones, 1993], they propose a combined model for text classification. Popescul et al. (2002) also combine a relational learner with a logistic regression model to improve accuracy for document mining.

Another approach is to identify certain types of hypertext regularities such as encyclopedic regularity (linked objects typically have the same class) and co-citation regularity (linked objects do not share the same class, but objects that are cited by the same object tend to have the same class). Yang et al. (2002) gives an in-depth investigation of the validity of these regularities across several datasets and using a range of classifiers. They found that the usefulness of the regularities varied, depending on both the dataset and the classifier being used.

Others have proposed generative probabilistic models for linked data. Cohn and Hofmann (2001) propose a probabilistic model for hypertext content and links. In earlier work [Getoor et al., 2002], we also proposed a generative model for relational data, both content and links.

Here, we propose a method that can learn a variety of different regularities among the categories of linked objects. However, unlike Joachims et al. (2001) in which the citation matrix is explicitly modeled, here we use a much simpler model that captures the topic distribution, rather than the identities of the particular documents.

In contrast to work which constructs relational features, we use a simpler model that tries to capture the link

distribution. Other approaches such as relational Markov networks [Taskar et al., 2002] support arbitrary dependency. Here we assume a fixed model that combines two sub-models built over both content and link information. Because we are combining predictions from two distinct models, there is some similarity with co-training [Blum & Mitchell, 1998], although the way in which we make use of unlabeled data is rather different.

Like Joachims et al. (2001); Taskar et al. (2002); Popescul et al. (2002), our approach is based on a logistic regression model. The Naive Bayes model has been used more extensively for text categorization, but for the data sets examined here, we found the logistic regression model consistently improved our accuracy. Ng and Jordan (2002) give a more thorough comparison of the two models.

3 Link-based models

In our original work on link uncertainty [Getoor et al., 2002], we proposed two simple models for link uncertainty. We showed that these models improved predictive accuracy in a variety of domains, including a web page classification problem [Craven et al., 1998] and a scientific paper classification problem [McCallum et al., 2000]. While the models we proposed improved performance, they were rather simplistic. Similar to a Naive Bayes model, the existence of a link is independent of the other links—it does depend on attributes of related objects; however one cannot reason directly about groups of links.

Here we propose a general notion of a link-based model that supports much richer probabilistic models based on the distribution of links and based on attributes of linked objects.

3.1 Definitions

The generic link-based model presented in this section is essentially a directed graph, in which the nodes are objects and edges are links between objects. Our model will support classification of objects based both on features of the object *and* on properties of the link distribution. We capture the link distribution of incoming, outgoing and co-citation links.

\mathcal{O} - The collection of objects, $\mathcal{O} = \{X_1, \dots, X_N\}$ where X_i is an object, or node in the graph. \mathcal{O} is the set of nodes in the graph.

\mathcal{L} - The collections of links between objects. $L_{i \rightarrow j}$ is a link between object X_i and object X_j . \mathcal{L} is the set of edges in the graph.

$\mathcal{G}(\mathcal{O}, \mathcal{L})$ - The directed graph defined over \mathcal{O} by \mathcal{L} .

\mathcal{C} - a finite set of categories, $\mathcal{C} = \{c_1, \dots, c_k\}$; $c(X)$ is the category c of object X .

$I(X_i)$ - the set of incoming neighbors of object X_i , $\{X_j \mid L_{j \rightarrow i} \in \mathcal{L}\}$.

$O(X_i)$ - the set of outgoing neighbors of object X_i , $\{X_j \mid L_{i \rightarrow j} \in \mathcal{L}\}$.

$Co(X)$ - The set of objects co-cited with object X :

$$Co(X) = \{X_i \mid X_i \neq X \text{ and there is a third object } X_j \text{ links to both } X \text{ and } X_i\}.$$

3.2 Object features

The attributes of an object provide a basic description of the object. Traditional classification algorithms are based on these types of object features. In a linked-based approach, it may also make sense to use attributes of *linked* objects. Further, if the links themselves have attributes, these may also be used. Essentially, this is a proposition-alization [Flach & Lavrac, 2000; Kramer et al., 2001] of the aspects of the neighborhood of an object in the graph. This is a technique that has been proposed in the inductive logic programming community and is applicable here.

Here we simply use object attributes, and we use the notation $OA(X)$. As an example, in the scientific literature domain, the object features might consist of a variety of text information such as title, abstract, authorship and content. Here we can use features of the document text such as word occurrence as object features.

3.3 Link features

To capture the link patterns, we introduce the notion of link features as a way of capturing the salient features of the objects' links. We examine a variety of simple mechanisms for doing this. All are based on the *categories* of the linked objects rather than the *identity* of the linked objects. Describing only the categories of links is significantly more compact than the link incidence matrix.

Definition 1: (Category Distribution) Given a set of objects S , and the set of categories $\{c_1, \dots, c_k\}$, the category distribution CD is a k element vector, where entry $i = \sum_{Y \in S} \mathcal{I}(c(Y), c_i)$ and \mathcal{I} is an indicator function that is 1 if the category of object Y , $c(Y)$, is c_i .

Definition 2: (Link Distribution) The link distribution for an object X consists of the category distributions of incoming, outgoing and co-citations, $CD(I(X))$, $CD(O(X))$ and $CD(Co(X))$.

The link distribution for an object is just the histogram or counts of the occurrences of different categories of incoming, outgoing and co-citations links for that object. From this, we would like to construct a model that captures useful features of the link category distribution, which we will call the link statistics $LS(X)$.

We examine several ways of doing this. In this section we discuss the general the features or statistics used by the models, in the next section we will describe the model built over these features.

We can use the link distribution directly; we refer to this as the **count-link** model. In this case, while we have lost the information about the individual entity to which the object is connected, we maintain the frequencies of the different categories.

The simplest statistic to compute is a single feature, the mode, for each set of inlinks, outlinks and co-citation links. We call this **mode-link** model.

A middle ground between these two is a simple binary vector; for each category, if it occurs at least once, the corresponding entry is 1; the entry is 0 if there are no links to this category. In this case, we use the term **binary-link** model.

The distinction between the binary-link and count-link models is akin to the distinction between binary and multinomial Naive Bayes models [McCallum & Nigam, 1998]. However here we use a discriminative model (logistic regression) rather than a generative model (Naive Bayes).

4 Predictive model for object classification

Logistic regression [Hosmer & Lemeshow, 1989] has been used in statistical analysis for many years. Support Vector Machines (SVMs), which can be regarded as an approximation and limiting case of a generalized logistic regression family, has been successfully applied for text categorization [Joachims, 1998]. Now logistic regression is gaining considerable interest in application for categorization. Here we present an approach to compute the conditional probability distribution $P(c \mid OA(X), LD(X))$ based on the logistic regression method.

A binary or dichotomous classification problem is to determine a label (dependent variable) $c \in \{-1, +1\}$ given an input vector (explanatory variable) x . Logistic regression is a discriminative method for solving this problem, which models the conditional probability $P(c = 1 \mid w, x)$ with a logit transformation:

$$g(P(c = 1 \mid w, x)) = w^T x$$

where $g(t) = \ln[\frac{t}{1-t}]$ is called a logit function.

So we have $P(c \mid w, x) = \frac{1}{\exp(-w^T x c) + 1}$, where $c \in \{-1, +1\}$. Given a training set of labeled data (x_i, c_i) , where $i = 1, 2, \dots, n$ and $c_i \in \{-1, +1\}$, to compute the conditional probability $P(c \mid w, x)$ is to find the optimal w for the discriminative function, which is equivalent to the following regularized logistic regression formulation [Zhang & OLES, 2001]:

$$\hat{w} = \operatorname{arginf}_w \frac{1}{n} \sum_{i=1}^n \ln(1 + \exp(-w^T x_i c_i)) + \lambda w^2$$

where we use a zero-mean independent Gaussian prior for the parameter w : $P(w) = \exp(-\lambda w^2)$. A penalized likelihood method [Zhang & OLES, 2001], which can be interpreted as a MAP estimator with prior $P(w) \exp(\lambda w * w)$, is used to optimize the parameters for our regularized logistic regression model.

For our predictive model, we compare a variety of regularized logistic regression models. We explore the use of a structured logistic regression model. Regularized logistic regression is used to compute the posterior probability $P(c \mid OA(X))$ and $P(c \mid LD(X))$ separately.

We tuned the regularization parameter λ separately on a held-out validation set.

$$P(c \mid w_o, OA(X)) = \frac{1}{\exp(-w_o^T OA(X)c) + 1}$$

$$P(c \mid w_l, LM(X)) = \frac{1}{\exp(-w_l^T LM(X)c) + 1}$$

where w_o and w_l are the parameters for $P(c \mid OA(X))$ and $P(c \mid LM(X))$ respectively.

Now the MAP estimation for categorization becomes

$$\hat{C}(X) = \operatorname{argmax}_{c \in C} P(c \mid OA(X)) P(c \mid LD(X))$$

For multi-class categorization, we trained one-against-others logistic regression model for each category and during testing, picked the category with the largest margin.

5 Link-based classification

Our proposed model is learned from a fully labeled training data set. In order to make use of it for prediction, we are in a more challenging situation than classical prediction. Here, we have an unlabeled graph of over a collection of objects. The object attributes and the links are observed, only the categories are unobserved. We need to be able to predict the categories of all of the objects at once—clearly each of these predictions depends on neighboring predictions. In our model, to predict the category for one object, we need the categories of object's neighbors, which will also be unlabeled.

In the spirit of Chakrabarti et al. (1998) and Neville and Jensen (2000), we propose an iterative classification algorithm (ICA). The general approach has been studied in numerous fields, including relaxation-labeling in computer vision [Hummel & Zucker, 1983], inference in Markov random fields [Chellappa & Jain, 1993] and loopy belief propagation in Bayesian networks [Murphy & Weiss, 1999]. Here, the challenging aspect is the non-regular structure of the inference, and the novelty of our approach is our attempt to make use of this in the inference.

Our ICA has two stages: bootstrap and iteration. From the start, all the objects are unlabeled, and thus the link statistics are unknown. A bootstrap stage is used to assign an initial category to each object, based solely on the object attributes (which are observed). This simplified model is used to give an initial classification for each object. During the iteration phase, the full version of our model is used to update the classifications of the objects. The algorithm terminates when it converges (there are no longer any updates to the categories) or a maximum number of steps has been reached.

Step 1: (Bootstrap) Using only the object attributes, assign an initial category for each object in the test set.

Step 2: (Iteration) Iteratively apply the full model to classify each object until the termination criterion have been satisfied. For each object,

1. Compute the link statistics, based on the current assignments to linked objects
2. Compute the posterior probability for the category of this object.
3. The category with the largest posterior probability is chosen as a new category for current object.

In the iterative step there are many possible orderings for objects. One approach is based simply on the number of links; Oh et al. (2000) report no significant improvement using this method. Neville and Jensen (2000) propose an iterative classification algorithm where the ordering is based on the inference posterior probability of the categories. They report an improvement in classification accuracy. We explore several alternate orderings based on the estimated link statistics. We propose a range of link-based adaptive strategies which we call *Link Diversity*. Link diversity measures the number of different categories to which an object is linked. The idea is that, in some domains at least, we may be more confident of categorizations of objects with low link-diversity, in essence, the object's neighbors are all in agreement. So we may wish to make these assignments first, and then move on to the rest of the pages. In our experiments, we evaluate the effectiveness of different ordering schemes based on link diversity.

6 Experimental Results

We evaluated our link-based classification algorithm on two standard datasets Cora [McCallum et al., 2000] and WebKB [Craven et al., 1998] and a dataset that we constructed from citeseer entries [Giles et al., 1998], which we call CiteSeer.

The Cora dataset contains 4000 machine learning papers, each categorized into one of seven possible topics. After stemming and removing stop words and rare words, the dictionary contains 1400 words. We split the dataset into three separate approximately equally sized parts, and any citations across different parts are not included.

The WebKB dataset contains web pages from four computer science departments, categorized into topics such as faculty, student, project, and course, where all pages not classified are put into category other. In our experiments we discard pages in other category, which generates a dataset with 700 pages. After stemming and removing stop words, the dictionary contains 2338 words. For WebKB, we use the standard split along different schools.

The CiteSeer dataset has approximately 7000 papers from six categories: Agents, Artificial Intelligence, Database, Human Computer Interaction, Machine Learning and Information Retrieval. The dictionary contains 3000 words. Similar to the Cora dataset, we split the dataset into three roughly equal size splits.

On Cora and CiteSeer, for each experiment, we take one split as a test set, and the remaining two splits are used to train our model: one for training and the other

split is used as a validation which works with the training set to find the appropriate regularization parameter λ which is used for test. On WebKB, we learned models for a variety of λ ; here we show the best result.

In our experiments, we compare several baseline models with models which use the link descriptions. We compare the models:

- **Content-Only:** Uses only object attributes.
- **Mode-Link:** Combines a logistic regression model over the object attributes with a separate logistic regression model over the mode of the inlinks, outlinks and co-citations
- **Binary-Link:** Combines a logistic regression model over the object attributes with a separate logistic regression model over the binary link statistics for the inlinks, outlinks and co-citations
- **Count-Link:** Combines a logistic regression model over the object attributes with a separate logistic regression model over the counts link statistics for the inlinks, outlinks and co-citations

We also compared a variety of ordering schemes for the iterative categorization algorithm. For each of the link models, we compare the following link diversity orderings:

- **In:** uses the inlink diversity.
- **Out:** uses the outlink diversity.
- **Co:** uses the colink diversity.

We compared both orderings in terms of increasing diversity and decreasing diversity. We also compared with a random ordering and an ordering based on the posterior probability of the categories as done in Neville and Jensen (2000).

6.1 Results

Table 1, Table 2 and Table 3 show summaries of our results on the different datasets. In all three data sets, we compute the average test error, precision, recall and F1 Measure. To compare the performance of different models, we did paired t-test with F1 Measure. In all cases, the link-based models outperformed the content-only models. In all cases, these results are statistically significant at the 95% confidence level or above, based on a paired t-test.

In all cases, the count-link models achieved the highest overall F1 measure, while for Cora data set there is no significant difference between the performance of count-link model and binary-link model. For WebKB, the count-link model outperforms the binary-link model at a 90% significance level. For CiteSeer, the count-link model outperformed the binary-link model at only an 80% significance level. In all cases, our count-link model outperforms the baseline models: content and mode-link.

We also investigated the use of a Naive Bayes model for content and links, but the logistic regression model outperformed these models in all cases. Future work includes exploring the use of richer models of dependence

dataset	Content-Only	Mode-Link	Binary-Link	Count-Link
Avg. Test Error	32.2	30.4	27.6	27.5
Avg. Precision	64.9	68.3	73.1	72.5
Avg. Recall	63.1	67.5	68.3	68
Avg. F1 Measure	64.6	67.8	70.2	70.2

Table 1: Summary of average results on Cora. The random iteration ordering strategy is used.

dataset	Content-Only	Mode-Link	Binary-Link	Count-Link
Avg. Test Error	38.8	35.4	35.9	34.1
Avg. Precision	55.4	56.9	58.2	58.7
Avg. Recall	55.8	57.2	57.7	58.3
Avg. F1 Measure	55.8	57	58	58.4

Table 2: Summary of average results on CiteSeer. The random iteration ordering strategy is used.

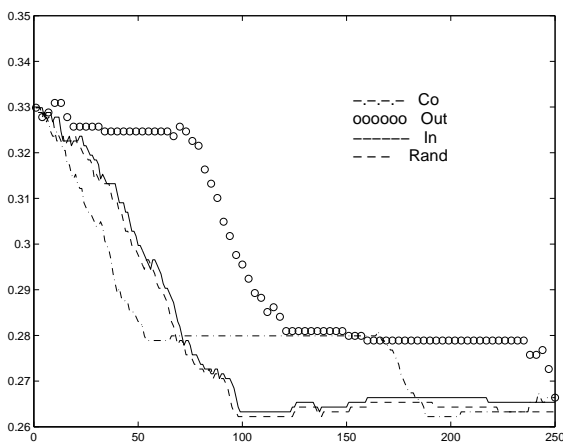


Figure 1: The accuracy of different iteration methods

between the link attributes. However our preliminary results have not been promising.

Next we examined a number of ICA ordering strategies. As Table 4 shows, our experiments indicate that the test errors with various link diversity have a standard deviation around 0.001. There is no significant difference with various link diversity to order the predictions. We also compared with an ordering based on the posterior probability of the categories as done in Neville and Jensen (2000), denoted PP. For the domains we examined, the PP ordering performs slightly worse than the other ordering schemes.

To understand the effect of the ordering scheme at a bit finer level of detail, Figure 1 shows an example of the accuracy of the different iteration schemes for the Cora data set. As we see, while the different iteration schemes converge to about the same accuracy, their convergence rate varies. Using the order by co-citation link diversity, our model converges more quickly at the start. Rand and order by incoming link diversity converge moderately quickly, eventually overtaking co-citation. The graph shows that the outgoing link diversity has the slowest

convergence rate. These results are representative, although preliminary. We hope to investigate the convergence behavior further.

7 Conclusions

Many real-world datasets have rich structures, where the objects are linked in some way. Link mining targets data mining tasks on this richly-structured data. One major task of link mining is to model and exploit the link distributions among objects. Here we focus on using the link structure to help improve classification accuracy.

In this paper we have proposed a simple framework for modeling link distributions, based on link statistics. We have seen that for the domains we examined, a combined logistic classifier built over the object attributes and link statistics outperforms a simple content-only classifier. More surprisingly, the mode of the link statistics is not enough to capture the dependence. Actually modeling the distribution of the link categories at a finer grain is useful.

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dataset	Content-Only	Mode-Link	Binary-Link	Count-Link
Avg. Test Error	15.9	18.1	15	14.7
Avg. Precision	87.6	87.3	87	86.3
Avg. Recall	75.2	70.9	76.9	80.2
Avg. F1 Measure	80.8	78.2	81.6	83.2

Table 3: Summary of average results on WebKB. The random iteration ordering strategy is used.

dataset	Binary-Link							Count-Link						
	In		Out		Co		PP	In		Out		Co		PP
	INC	DEC	INC	DEC	INC	DEC		INC	DEC	INC	DEC	INC	DEC	
Cora	27.7	27.6	27.8	27.7	27.9	27.8	27.7	28	28	28.2	28	28.1	28	30.6
Citeseer	36	36	35.8	36.2	36.2	36	41.5	34.9	35	34.9	35.2	35.3	35	39.5
WebKB	15.6	15.3	15.6	15.7	15.7	15.3	19.2	16.3	16.2	16.3	16.2	16.5	16.4	20

Table 4: Results using different iteration strategies on Cora, Citeseer and WebKB.

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