Automatic Detection of Pseudo-codes in Scholarly Documents Using Machine Learning

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***Abstract*—A significant number of scholarly articles in computer science and other disciplines contain algorithms that provide concise descriptions for solving a wide variety of computational problems. For example, Dijkstra's algorithm describes how to find the shortest paths between two nodes in a graph. Automatic identification and extraction of these algorithms from scholarly digital documents would help enable automatic algorithm indexing, searching, analysis and discovery. An algorithm search engine, which identifies pseudo-codes in scholarly documents and makes them searchable, has been implemented as a part of CiteSeer^X suite. Here, we illustrate the limitations of the start-of-the-art rule-based pseudo-code detection approach, and present a novel set of machine learning based techniques that extend the previous method.**

I. Introduction

Algorithms are ubiquitous in the Computer Science and related literature. They offer concise stepwise instructions for solving many computational problems such as searching, sorting, hashing, clustering, decoding, machine learning, etc. Furthermore, in various fields other than Computer Science, efficient solutions to important problems involve transforming the problem into an algorithmic one, often using fairly standard algorithms from other fields. For example, algorithms for stock portfolio optimization are used for diversifying search results in information retrieval systems [1]. Likewise, in Bioinformatics Hirschberg's algorithm [2] is widely used to find maximal global alignments of DNA and protein sequences. A thorough knowledge of state-of-the-art algorithms is also crucial for developing efficient software systems.

Conference	No. of Algorithms
SIGIR	75
SIGMOD	301
STOC	74
VLDB	278
WWW	142

TABLE I. Approximate number of algorithms published in computer science conferences 2005 - 2009.

A. Algorithms in Scholarly Documents

Researchers are constantly developing new algorithms to either solve new problems that have not been solved before, or algorithms that improve upon the existing ones. Often, researchers report their new algorithms in scientific publications. Bhatia et al. [3] provide an estimate of the number of algorithms published in some major computer science conferences during 2005 - 2009 which we reproduce here (Table *I*) for reference. With dozens of new algorithms being reported in these conferences every year, it is crucial to have systems that automatically identify, extract, index and search the ever increasing collection of algorithms, both new and old. Such systems can prove to be useful to researchers and software developers looking for cutting-edge solutions to their problems.

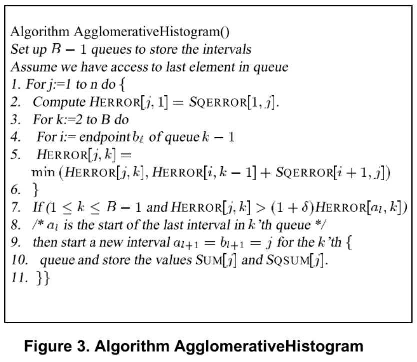
Finding well-known standard algorithms is not difficult, as they are usually already cataloged and made searchable, especially those in online catalogs. We define a standard algorithm as an algorithm that is well known and is usually recognized by its name. Examples of standard algorithms include Dijkstra's shortest-path algorithm, Bellman-Ford algorithm, Quicksort algorithm, and Knuth-Morris-Pratt algorithm. Standard algorithms are usually collected and cataloged manually in algorithm textbooks (e.g. [4]), encyclopedias (especially the ones available online such as Wikipedia[1]), and websites targeted at computer programmers (e.g. Rosettacode.org[2]). As an initial survey, we parsed Wikipedia algorithm pages in 2010, and found that roughly 1,765 standard algorithms are cataloged in Wikipedia.org. The National Institute of Standards and Technology (NIST)[3] also has a dictionary of over 289 standard algorithms. However, unlike these well-known standard algorithms, newly published algorithms are not cataloged by the sources mentioned above, because they are simply too *new* and too *many*. The explosion of newly developed algorithms in scientific and technical documents makes it difficult to manually catalog them.

Manually searching for these newly published algorithms is a nontrivial task. Researchers and others who aim to discover efficient and innovative algorithms would have to actively search and monitor relevant new publications in their fields of study in order to keep abreast of latest algorithmic developments. Having to read entire documents would be tedious. The problem can become even more aggravated if algorithm searchers are novices in document search, especially those who use poor search keyword(s). Thus, we propose automatic identification and extraction of algorithms from digital documents.

B. State-of-the-Art in Algorithm Detection

Identifying and extracting various informative entities from scholarly documents is an active area of research. For algorithm detection, Bhatia et al. [5] briefly describe methods

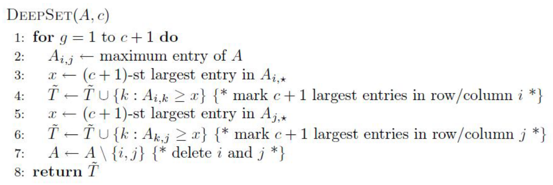
[1]http://www.wikipedia.org/
[2]http://rosettacode.org/wiki/Rosetta_Code/
[3]http://xlinux.nist.gov/dads/



```
Algorithm AgglomerativeHistogram()
Set up $B-1$ queues to store the intervals
Assume we have access to last element in queue
1. For j:=1 to n do {
2.   Compute $\text{HERROR}[j,1] = \text{SQERROR}[1,j]$.
3.   For k:=2 to B do
4.     For i:= endpoint $b_\ell$ of queue $k-1$
5.     $\text{HERROR}[j,k] =$
       $\min(\text{HERROR}[j,k], \text{HERROR}[i,k-1] + \text{SQERROR}[i+1,j])$
6.   }
7.   If $(1 \le k \le B-1$ and $\text{HERROR}[j,k] > (1+\delta)\text{HERROR}[a_l,k])$
8.   /* $a_l$ is the start of the last interval in $k$'th queue */
9.   then start a new interval $a_{l+1} = b_{l+1} = j$ for the $k$'th {
10.    queue and store the values $\text{SUM}[j]$ and $\text{SQSUM}[j]$.
11. }}

Figure 3. Algorithm AgglomerativeHistogram
```

Fig. 1. Example pseudo-code



```
DEEPSET$(A, c)$
1: for $g = 1$ to $c+1$ do
2:     $A_{i,j} \leftarrow$ maximum entry of $A$
3:     $x \leftarrow (c+1)$-st largest entry in $A_{i,\star}$
4:     $\tilde{T} \leftarrow \tilde{T} \cup \{k : A_{i,k} \ge x\}$ {* mark $c+1$ largest entries in row/column $i$ *}
5:     $x \leftarrow (c+1)$-st largest entry in $A_{j,\star}$
6:     $\tilde{T} \leftarrow \tilde{T} \cup \{k : A_{k,j} \ge x\}$ {* mark $c+1$ largest entries in row/column $j$ *}
7:     $A \leftarrow A \setminus \{i,j\}$ {* delete $i$ and $j$ *}
8: return $\tilde{T}$
```

Fig. 2. Example pseudo-code without a caption

for automatic detection of *pseudo-codes* in Computer Science publications. Their method assumes that each pseudo-code is accompanied by a caption. An example of a pseudo-code with a caption is given in Figure 1. Such a pseudo-code can then be identified using a set of regular expressions to detect the presence of the accompanied caption [3], [5]. Such an approach, however, is limited in its coverage due to its reliance on the presence of pseudo-code captions and wide variations in writing styles. From our dataset (DS2) of 258 scholarly documents (see Sect. III), we found 275 pseudo-codes, 25.8% (71 out of 275) of which did not have an accompanied caption. Figure 2 shows an example of a pseudo-code without a caption. Thus, these pseudo-codes will remain undetected by their approach.

Since algorithms represented in documents do not conform to specific styles, and are written in arbitrary formats, this becomes a challenge for effective detection and extraction. Here we improve the performance of pseudo-code detection by capturing both pseudo-code with and without captions.

C. Our Contributions

This work has the following key contributions:

1) We propose three methods for detecting pseudo-codes in scholarly documents, including an extension of the existing rule based method proposed by Bhatia et al. [5], one based on machine learning techniques, and a combination of these two.
2) We use two datasets of scholarly documents selected from Citeseer^X repository: one for identifying rules and features, one for evaluation (the datasets are available for research).
3) We evaluate our proposed methods on a dataset of 258 scholarly PDF documents selected from the Citeseer^X repository.

II. Background and Related Work

Identifying and extracting informative entities such as mathematical expressions [6]–[10], tables [11]–[14], and figures [15], [16] from documents has long been extensively studied. Kataria et al. [16] employ image processing and Optical Character Recognition (OCR) approaches for automatic extraction of data points and text blocks from 2-D plots. They also propose a way to index the extracted information and make it available through a search interface to the end user. Liu et al. [14] present *TableSeer*, a method which automatically identifies and extracts tables in digital documents. BioText[4] search engine, a specialized search engine for biology documents, also offers the capability to extract figures and tables [17]. Bhatia et al. [3], [5] propose a set of methods used for detecting document-elements, e.g. tables, figures, and algorithms. Their methods rely on the assumption that the document-elements are presented along with captions. They detect the presence of a document-element by detecting the corresponding caption using a set of regular expressions. Bhatia et al. [3] propose an algorithm search engine for software developers. Their system collects pseudo-codes available in scholarly documents and make them searchable via full text search powered by Solr/Lucene[5]. Our work here extends their pseudo-code detection approach.

III. Datasets

Two datasets are used in this paper. The first dataset (DS1) contains 100 scholarly documents selected from Citeseer^X repository, consisting of diverse types of pseudo-codes. This dataset is used to construct rules and regular expressions for our rule based methods, and determine feature sets for our machine learning based methods. The other dataset (DS2) consists of 258 scholarly PDF documents randomly selected from Citeseer^X repository. This dataset consists of 275 pseudo-codes, and is used for validating our methods.

A. Preprocessing

Textual information is extracted from each PDF document using PDFBox[6]. We experiment across text extraction tools (i.e. PDFTextStream[7], Xpdf[8], TET[9], and PDFBox), and find PDFBox to be the most suitable since it best preserves line sequences. We modify the source code in PDFBox to also extract font size information from each text line.

B. Data Labeling

A document is treated as a sequence of text lines, each identified with a line number. We manually label each line as following:

0	Not part of pseudo-code content
1	Part of pseudo-code content

Note that a pseudo-code caption is treated as pseudo-code content. A line labeled with *1* is said to be a positive line,

[4]http://biosearch.berkeley.edu
[5]http://lucene.apache.org/solr/
[6]http://pdfbox.apache.org/
[7]http://snowtide.com/PDFTextStream
[8]http://www.foolabs.com/xpdf
[9]http://www.pdflib.com/products/tet/

otherwise it is negative. A pseudo-code is defined as a set of consecutive positive lines.

IV. Our Approaches

```
<CAPTION> ::= <DOC_EL_TYPE> <Integer> <DELIMITER> <TEXT>
<DOC_EL_TYPE> ::= <FIG_TYPE> | <TABLE_TYPE> | <ALGO_TYPE>
<FIG_TYPE> ::= FIGURE|Figure|FIG.|Fig.
<TABLE_TYPE> ::= TABLE|Table
<ALGO_TYPE> ::= Algorithm|algorithm|Algo.|algo.
<DELIMITER> ::= : | .
<TEXT> ::= <A String of Characters>
```

TABLE II. A GRAMMAR FOR DOCUMENT-ELEMENT CAPTIONS

Most scientific documents use pseudo-codes for compact and concise illustrations of algorithms. Pseudo-codes are normally treated as document elements separate from the running text, and usually are accompanied with identifiers such as captions, function names, and/or algorithm names. Since pseudo-codes can appear anywhere in a document, these identifiers usually serve the purpose of being anchors which can be referred to by context in the running text. Here we present three algorithms for detecting pseudo-codes in scholarly documents: a rule based method (PC-RB), a machine learning based method (PC-ML), and a combined method (PC-CB).

A. *Rule Based Method (PC-RB)*

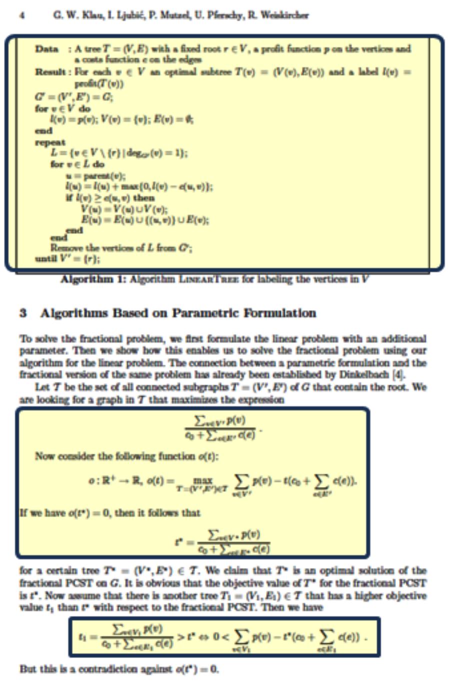
We earlier proposed a rule based pseudo-code detection algorithm in [3], which utilizes a grammar for document-element captions to detect the presence of pseudo-code captions (See Table II). Here, we extend the previous approach by adding the following rules to improve the coverage and reduce the false positives:

- A pseudo-code caption must contain at least one algorithm keyword, namely *pseudo-code*, *algorithm*, and *procedure*.
- Captions in which the algorithm keywords appear after prepositions (e.g. *'Figure 15: The robust envelope obtained* ***by*** *the proposed* ***algorithm****'*) are excluded, as these are not likely captions of pseudo-codes.

Hence, given a document, the PC-RB method outputs a set of line numbers, each of which represents a pseudo-code caption.

B. *Machine Learning Based Method (PC-ML)*

The PC-RB method yields high precision, however it still suffers from low coverage resulting in poor recall. We found that 25.8% of pseudo-codes in our dataset DS2 do not have accompanied captions. These pseudo-codes would remain undetected by the PC-RB method. To correct this, we propose a machine learning based (PC-ML) method to directly detect the presence of pseudo-code content (instead of their captions). This originates from the observation that most pseudo-codes are written in a sparse manner, resulting in sparse regions in documents. We call such sparse regions *sparse boxes*. The PC-ML method first detects and extracts these sparse boxes, then classifies each box whether it is a pseudo-code or not. The following subsections explain the sparse box identification, the feature sets, and the classification algorithms used. Given a


4 G. W. Klau, I. Ljubić, P. Mutzel, U. Pferschy, R. Weiskircher

```
Data   : A tree $T = (V, E)$ with a fixed root $r \in V$, a profit function $p$ on the vertices and
         a costs function $c$ on the edges
Result : For each $v \in V$ an optimal subtree $T(v) = (V(v), E(v))$ and a label $l(v) =$
         profit$(T(v))$
$G' = (V', E') = G$;
for $v \in V$ do
    $l(v) = p(v)$; $V(v) = \{v\}$; $E(v) = \emptyset$;
end
repeat
    $L = \{v \in V \setminus \{r\} \mid \deg_{G'}(v) = 1\}$;
    for $v \in L$ do
        $u = \text{parent}(v)$;
        $l(u) = l(u) + \max\{0, l(v) - c(u, v)\}$;
        if $l(v) \geq c(u, v)$ then
            $V(u) = V(u) \cup V(v)$;
            $E(u) = E(u) \cup \{(u, v)\} \cup E(v)$;
        end
    end
    Remove the vertices of $L$ from $G'$;
until $V' = \{r\}$;
```

Algorithm 1: Algorithm LinearTree for labeling the vertices in V

3 Algorithms Based on Parametric Formulation

To solve the fractional problem, we first formulate the linear problem with an additional parameter. Then we show how this enables us to solve the fractional problem using our algorithm for the linear problem. The connection between a parametric formulation and the fractional version of the same problem has already been established by Dinkelbach [4].

Let $\mathcal{T}$ be the set of all connected subgraphs $T = (V', E')$ of G that contain the root. We are looking for a graph in $\mathcal{T}$ that maximizes the expression

$$\frac{\sum_{v \in V'} p(v)}{c_0 + \sum_{e \in E'} c(e)} .$$

Now consider the following function $o(t)$:

$$o : \mathbb{R}^+ \to \mathbb{R},\ o(t) = \max_{T=(V',E') \in \mathcal{T}} \sum_{v \in V'} p(v) - t(c_0 + \sum_{e \in E'} c(e)).$$

If we have $o(t^*) = 0$, then it follows that

$$t^* = \frac{\sum_{v \in V^*} p(v)}{c_0 + \sum_{e \in E^*} c(e)}$$

for a certain tree $T^* = (V^*, E^*) \in \mathcal{T}$. We claim that T^* is an optimal solution of the fractional PCST on G. It is obvious that the objective value of T^* for the fractional PCST is t^*. Now assume that there is another tree $T_1 = (V_1, E_1) \in \mathcal{T}$ that has a higher objective value t_1 than t^* with respect to the fractional PCST. Then we have

$$t_1 = \frac{\sum_{v \in V_1} p(v)}{c_0 + \sum_{e \in E_1} c(e)} > t^* \Leftrightarrow 0 < \sum_{v \in V_1} p(v) - t^*(c_0 + \sum_{e \in E_1} c(e)) .$$

But this is a contradiction against $o(t^*) = 0$.

Fig. 3. Example of sparse regions (sparse boxes)

document, the PC-ML method outputs are a set of tuples of $\langle start, end \rangle$ line numbers, each of which represents the start and end lines of a pseudo-code.

1) Sparse Box Extraction: We define a sparse box as a set of at least N consecutive sparse lines. Figure 3 shows an example of sparse boxes. A sparse line is a line whose ratio of the number of non-space characters to the average number of characters per line is less than threshold M. We found that $N = 4$ and $M = 0.8$ work best for our dataset. We evaluate our sparse box extraction method in two perspectives: *coverage* and *accuracy*. Given a set of sparse boxes B extracted from a document d, the *coverage* is defined as following:

$$Coverage = \frac{|\{l|l \in b, b \in B, l\ is\ positive\}|}{|\{l|l \in b, b \in B\}|}$$

The coverage utilizes line-wise recall to quantifiy how much pseudo-code content can be captured within the extracted sparse boxes. Our sparse box extraction method yields a coverage of 92.99%. Among all the sparse boxes detected in our dataset, we found 237 (out of 275 (86.18%) actual pseudo codes) pseudo-code boxes.

The *accuracy* is measured using the delta evaluation for the pseudo-code boxes. For each pseudo-code box, we measure both the upper boundary delta (the start line number of the actual pseudo-code minus the start line number of the sparse box) and lower boundary delta (the end line number of the actual pseudo-code minus the end line number of the sparse box). Figure 4 and 5 show the upper and lower boundary delta distributions of the 237 pseudo-code boxes.

2) Feature Sets: We extract 47 features from each of the sparse boxes, listed in Figure 6. These features are classified into 4 groups: font-style based (FS), context based (CX), content based (CN), and structure based (ST). The *FS* features

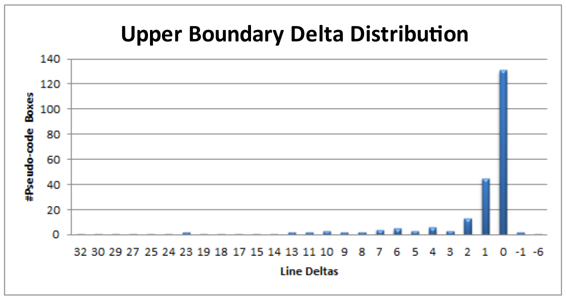


Fig. 4. Distribution of upper boundary deltas of pseudo-code boxes

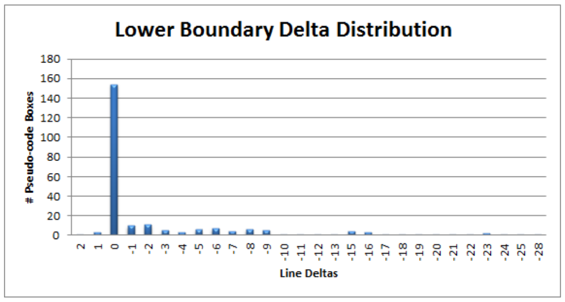


Fig. 5. Distribution of lower boundary deltas of pseudo-code boxes

Grp	Feature	Description
FS	INDENTATION VARIANCE	Variance of the positions of the first character in each line
	FIRST 4CHARS INDENTATION VARIANCE	Variance of the average of the positions of the first 4
	NUM DIFF FONTSTYLES	# of different font styles. Ex. 'X***X***X***X***' has 2 font styles.
	NUM FONTSTYLE CHANGES	# of character pairs whose font styles are different. Ex. 'XXXX' has 3 font style changes.
	FRACTION NUM FONTSTYLE CHANGES	Fraction of number of font style changes to number of lines.
CX	HAS CAPTION NEARBY	Whether there is a caption near (within 3 upper/lower lines)
	HAS PC CAPTION NEARBY	Whether there is a pseudo-code caption near the sparse box.
	HAS PC NAME NEARBY	Whether there is an algorithm name (e.g. `*Algorithm ABC*') near the sparse box.
CN	NUM PC WORDS	Number of pseudo-code keywords (e.g. *forall* , *for, if, else, iffalse, iftrue, endif,* etc.)
	FRACTION PC WORDS TO NUMWORDS	Fraction of pseudo-code keywords to number of words.
	FRACTION PC WORDS TO NUMLINES	Fraction of pseudo-code keywords to number of lines.
	NUM ALGO WORDS	# of algorithm keywords (e.g. algorithm, pseudo-code,etc.)
	FRAC ALGO WORDS TO NUMWORDS	Fraction of # of algorithm keywords to # of words
	FRAC NUM ALGO WORDS TO NUMLINES	Fraction of # of algorithm keywords to # of lines
	NUM LINES BEGIN WITH PC WORDS	# of lines beginning with a pseudo-code keyword
	FRAC NLINES BEG. W/ PCWORDS TO NLINES	Fraction of # of lines beginning with a pseudo-code word to #
	NUM FUNCTIONS	# of functions. Ex. *Scan(f, x)*
	FRACTION NUM FUNCTIONS TO NUMLINES	Fraction of # of functions to # of lines
ST	NUM CHARS	# of characters
	FRACTION NUM CHARS TO NUMLINES	Fraction of # of characters to # of lines
	NUM SYMBOLS	# of symbols
	FRACTION NUM SYMBOLS TO NUMCHARS	Fraction of # of symbols to # of characters
	NUM ALPHABETS	# of alphabets
	FRACTION NUM ALPHABETS TO NUMCHARS	Fraction of # of alphabets to # of characters
	NUM DIGITS	# of digits
	FRACTION NUM DIGITS TO NUMCHARS	Fraction of # of digits to # of characters
	NUM ALPHANUMERS	# of alphanumeric characters
	FRAC NUM ALPHANUMBERS TO NUMCHARS	Fraction of # of alphanumeric characters to # of characters
	NUM NON-ALPHANUMBERS	# of non-alphanumeric characters
	FRAC NON-ALPHANUMBERS TO NUMCHARS	Fraction of # of non-alphanumeric characters to # of characters
	NUM GREEKCHARS	# of Greek characters
	FRAC NUM GREEKCHARS TO NUMCHARS	Fraction of # of Greek characters to # of characters
	NUM ARROWS	# of arrow symbols
	FRACTION NUM ARROWS TO NUMCHARS	Fraction of # of arrow characters to # of all characters
	NUM MATHOPS	# of math operators (e.g. +,-,$\sum$,$\cdot$,$\prod$, etc.)
	FRACTION NUM MATHOPS TO NUMCHARS	Fraction of # of math operators to # of characters
	NUM 1-CHAR WORDS	# of 1-character words (e.g. `x xx x' has 2 1-character words)
	FRAC NUM 1-CHAR WORDS TO NUMLINES	Fraction of # of single-char words to # of lines
	FRAC NUM 1-CHAR LINES TO NUMLINES	Fraction of # of 1-character lines to # of all lines
	NUM IJK	# of characters `i', 'j', and `k'
	FRACTION NUM IJK TO NUMLINES	Fraction of # of `i', 'j', `k' characters to # of lines
	NUM CODING SYMBOLS	# of coding symbols (e.g. \{,\},[,],@,/)
	FRAC NUM CODING SYMBOLS TO NUMLINES	Fraction of # of coding symbols to # of lines
	NUM LINES END WITH DOT	Number of lines ending with `.'
	FRAC NUMLINES END W/ DOT TO NUMLINES	Fraction of # of lines ending with `.' to # of lines
	NUM LINES BEGIN WITH NUMBER	# of lines beginning with a number
	FRAC LINES BEG. W/ NUMBER TO NUMLINES	Fraction of # of lines beginning with anumber to # of lines

Fig. 6. Features set for pseudo-code box classification can be divided into 4 groups-font style based (FS), context based (CX), content based (CN), and structure based (ST)

capture the various font styles used in pseudo-codes. The *CX* features detect the presence of pseudo-code captions. The *CN* features capture the pseudo-code specific keywords and coding styles. The *ST* features characterize the sparsity of pseudo-codes and the symbols used.

3) Classification Models: Each detected sparse box is classified whether it is a pseudo-code box or not. We try 12 base classification algorithms using the features described in Figure 6, namely, Logistic Model Trees (LMT), Multinomial Logistic Regression (MLR), Repeated Incremental Pruning to Produce Error Reduction (RIPPER), Linear Logistic Regression (LLR), Support Vector Machine (SVM), Random Forest (RF), C4.5 decision tree, REPTree, Decision Table (DT), Random Tree (RT), Naive Bayes (NB), and Decision Stump (DS).

In addition to the base classifiers listed above, we also try ensemble methods such as uniform weighted majority voting and probability averaging methods among these base classifiers. First, the 12 base classifiers are tested and ranked by their precision, recall, and F1 scores. Then, the first 2, 3, ..., 12 ranked classifiers in each ranked list are used for majority voting and probability averaging methods. Note that we also try other ensemble methods such as Adaboost, Bagging, and Rotation Forest but overall the majority voting and probability averaging methods perform much better.

C. Combine Method (PC-CB)

Though the PC-ML method can capture the pseudo-codes which do not have accompanied captions, some pseudo-codes which are not first captured in one of the sparse boxes would still remain undetected. Mostly, such pseudo-codes are either written in a descriptive manner (hence do not result in sparse regions in the document), or figures (the text extractor cannot extract images). In our dataset DS2, 35 pseudo-codes (out of 275 actual pseudo-codes) cannot be captured using the sparse box extraction. However, these undetected pseudo-codes may have accompanied captions and hence might still be detected using the PC-RB method. We propose a combine method (PC-CB) of the PC-RB and the PC-ML using a simple heuristic as follows:

STEP1 For a given document, run both PC-RB and PC-ML.
STEP2 For each pseudo-code box detected by PC-ML, check whether there is a pseudo-code caption detected by PC-RB nearby. If there is, the pseudo-code box and the caption are combined.

V. Evaluation and Discussions

We evaluate the three pseudo-code detection algorithms on dataset DS2, using 10-fold document-wise cross validation. This way we can make sure that both the test and train sets do not contain instances from the same documents.

A. Evaluation Metrics

Standard precision, recall, and F1 are used for evaluating the performance. Let T_g be the set of all pseudo-codes, T_r be the set of detected pseudo-codes, so that the correctly detected pseudo-codes are $T_g \bigcap T_r$. These metrics are defined as follows:

$$precision = \frac{|T_g \bigcap T_r|}{|T_r|}, recall = \frac{|T_g \bigcap T_r|}{|T_g|}, F1 = \frac{2 \cdot precision \cdot recall}{precision + recall}$$

Method	Model	Pr%	Re%	F1%
PC-RB	RuleBased	87.12	44.57	58.97
PC-ML	MLR†	80.35	56.78	66.54
PC-ML	!LMT-RF-RIPPER-MLR	85.31	57.04	68.37
PC-ML	+NB-RIPPER-LMT-MLR	79.61	59.37	68.02
PC-ML	!NB-RIPPER-LMT-MLR	78.26	60.05	67.96
PC-ML	!LMT-RF-RIPPER	**88.84**	53.74	66.97
PC-CB	LMT‡	79.64	67.89	73.30
PC-CB	!LMT-RF-RIPPER§	87.37	67.17	**75.95**
PC-CB	+LMT-RF-RIPPER	83.49	67.92	74.90
PC-CB	!NB-RIPPER-LMT-MLR	78.28	70.72	74.31
PC-CB	NB	37.86	**75.89**	50.52

TABLE III. PRECISION, RECALL, AND F1 OF THE PSEUDO-CODE DETECTION METHODS USING DIFFERENT CLASSIFICATION MODELS. ('**!**' DENOTES MAJORITY VOTING, '**+**' DENOTES PROBABILITY AVERAGING)

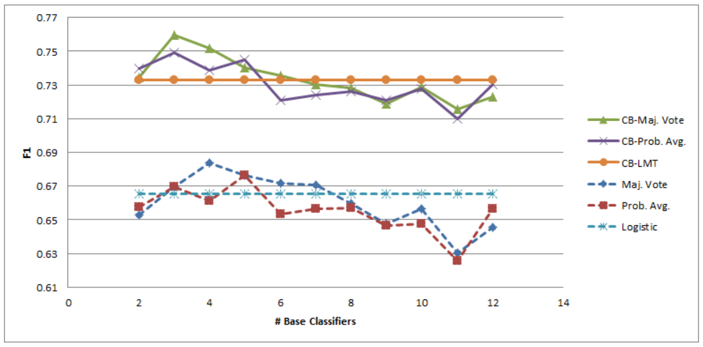


Fig. 7. Comparison of the ensemble methods against the best base classifiers in PC-ML and PC-CB

B. Results

Table III lists notable results. As expected, the rule-based method (PC-RB) yields high precision with a cost of low recall. Using machine learning techniques (PC-ML), the overall performances (in terms of F1) are improved. The combine method (PC-CB) of PC-RB and a majority voting of LMT, Random Forest, and RIPPER classification models§ performs the best in terms of F1, improving the performance over the state-of-the-art (the rule based method) by 16.98% (The recall is improved by 22.6%, while the precisions are on par.).

C. Impact of Ensemble Methods

It is worth noting that the ensemble methods result in a greater improvement compared to only using base classifiers. Figure 7 compares the performances (in terms of F1) between the ensemble methods and the best base classifiers for PC-ML (MLR†) and PC-CB (LMT‡). The X-axis denotes the first k base classifiers, ranked by their *F1* scores, used in each ensemble method. We conclude that the ensemble methods are useful for these specific problems, when the best base classifiers are combined. However, the performance of the ensemble methods can decrease as the number of classifiers grows. This might be because bad classifiers can impede the collective decision of the good ones. Unlike traditional document classification techniques wherein feature space can grow large as the number of documents increases (to handle the pattern and lexical diversity, etc.), all of our proposed methods scale well with document growth as the feature size is fixed.

VI. CONCLUSIONS

We have presented three methods for detecting pseudo-codes in scholarly documents: rule based (PC-RB), machine learning based (PC-ML), and combine (PC-CB) methods. Our *PC-RB* method extends the state-of-the-art approach. The *PC-ML* method employs machine learning techniques to extract sparse boxes from a document and classifies each of them whether it is a pseudo-code using a novel set of 47 features. The *PC-CB* capture the benefits of the both former methods. The best performance in terms of F1 is achieved by the *PC-CB* method with the combination of the rule-based method and the majority vote of LMT, RF, and RIPPER classifiers. Moreover, we present an analysis of the performance increase using the ensemble methods. Future work could investigate scalability for large datasets such as the over 2 million documents in Citeseer^X repository, and to employ the co-training [18] technique to expand the training data with unlabeled data.

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