Automatically Inferring the Document Class of a Scientific Article

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Context

Document class: How the document will be structured and written once in PDF format





Associated document in PDF format

Several libraries and commands.

Among them: \documentclass{report} (The argument defines the selected document class)

LATEX source code

- Scientific style
- Mathematical formulas



Association for Computing Machinery (ACM)

American Astronomical Society (AAS)

aastex aastex61 aastex62

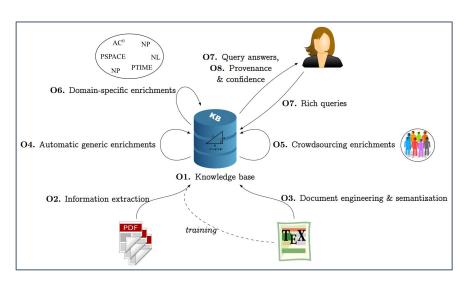


American Mathematical Society (AMS)

amsart amsproc

Applications

Systems extracting information from scholarly articles



The TheoremKB project https://github.com/PierreSenellart/theoremkb

Improve articles indexation in academic search engines



BASE search engine https://www.base-search.net/

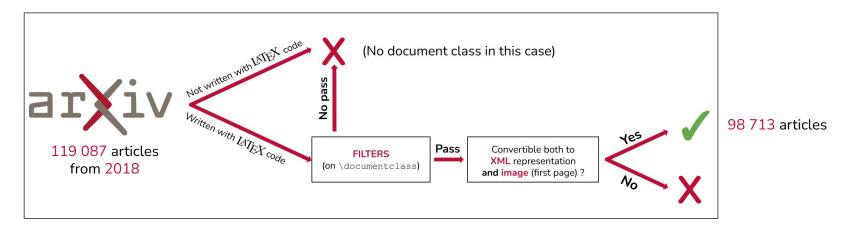


Google scholar search engine https://scholar.google.com/

Outline

Dataset and performance metrics
Statistical study
Random forest-based approach
CNN-based approach (deep learning)

Dataset and performance metrics



Among these 98713 articles → more than 1200 document class names. We kept the most frequent ones, and merged the most similar ones (amsart and amsproc for instance), ending in 33 document classes.

$$\operatorname{precision}_{i} = \frac{\operatorname{TP}_{i}}{\operatorname{TP}_{i} + \operatorname{FP}_{i}}$$

$$\operatorname{recall}_{i} = \frac{\operatorname{TP}_{i}}{\operatorname{precision}_{i} \times \operatorname{recall}_{i}}$$

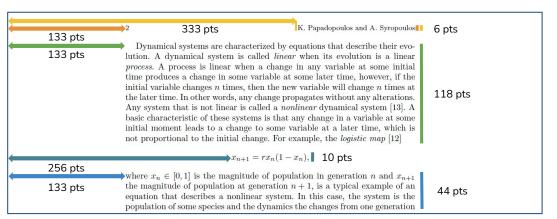
$$\operatorname{recall}_{i} = \frac{\operatorname{TP}_{i}}{\operatorname{precision}_{i} + \operatorname{recall}_{i}}$$

Why Macroscopic F1-Score?

- Macroscopic gives same weight to each document class
- F1-Score gives finer analysis for multiclass classification than accuracy

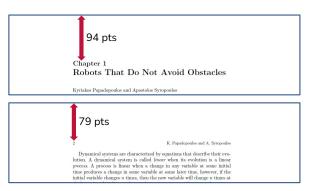
Construction of five (simple) hand-designed features (1)

1 point = $\frac{1}{72}$ inch



Weighted average left margin (lm)

$$\overline{m^{
m h}} = rac{\sum\limits_{i=1}^{N_b} m_i^{
m h} imes l_i}{\sum\limits_{i=1}^{N_b} l_i} egin{dcases} m_i^{
m h} & ext{Margin for i-th text block} \ l_i & ext{Vertical height of i-th text block} \ N_b & ext{Total number of blocks} \end{cases}$$

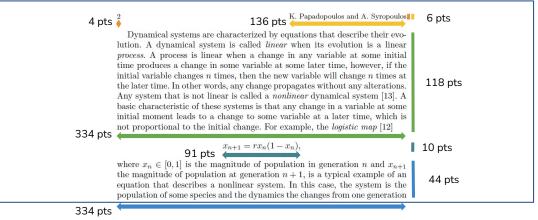


Average first top margin (tm)

$$\overline{m^{ ext{V}}} = rac{\sum\limits_{i=1}^{N_p} \min_j m_{i,j}^{ ext{V}}}{N_p} \hspace{0.5cm} egin{pmatrix} m_{i,j}^{ ext{V}} & ext{Distance between top of page of j-th block of i-th page} \ N_p & ext{Total number of pages} \ \end{pmatrix}$$

Construction of five (simple) hand-designed features (2)

1 point = $\frac{1}{72}$ inch



Weighted average column width (cw)

$$\overline{w} = rac{\sum\limits_{i=1}^{N_b} w_i imes l_i}{\sum\limits_{i=1}^{N_b} l_i} egin{cases} w_i & ext{Width of i-th text block} \ l_i & ext{Vertical height of i-th text block} \end{cases}$$

K. Papadopoulos and A. Syropoulos

Dynamical systems are characterized by equations that describe their evolution. A dynamical system is called *linear* when its evolution is a linear *process*. A process is linear when a change in any variable at some initial time produces a change in some variable at some later time, however, if the initial variable changes n times, then the new variable will change n times at the later time. In other words, any change propagates without any alterations. Any system that is not linear is called a *nonlinear* dynamical system [13]. A basic characteristic of these systems is that any change in a variable at some initial moment leads to a change to some variable at a later time, which is not proportional to the initial change. For example, the *logistic map* [12]

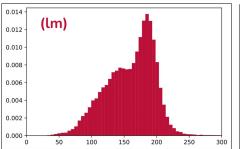
$$x_{n+1} = rx_n(1 - x_n),$$

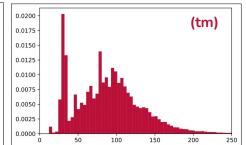
where $x_n \in [0,1]$ is the magnitude of population in generation n and x_{n+1} the magnitude of population at generation n+1, is a typical example of an equation that describes a nonlinear system. In this case, the system is the population of some species and the dynamics the changes from one generation

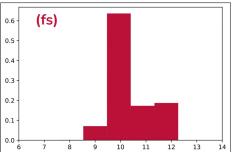
Most common font family (ff) Most common font size (fs)

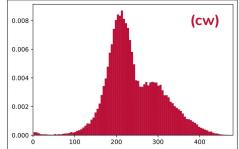
$$f_i = rac{\sum\limits_{s \in S_i} l_s imes h_s}{\sum\limits_{j=1}^{N_f} \sum\limits_{s \in S_j} l_s imes h_s} egin{cases} S_i & ext{Set of all tokens of i-th font} \ l_S & ext{Length of token s} \ h_S & ext{Height of token s} \end{cases}$$

Global distributions of the features

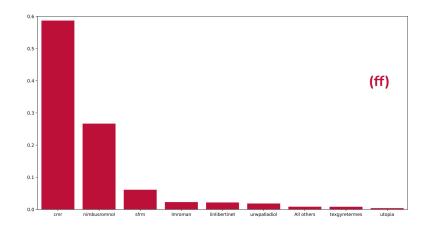








- Gaussian-like distributions for (lm), (tm) and (cw).
- Different values for (fs) and peak value for (tm).



Only a few font families (ff) are widely used.

We identify several characteristics that seem to be document-class specific, and therefore discriminative.

Comparison of distributions from two different document classes



SHABANI, SAMADFAM, SADEGHI: LOCAL VISUAL MICROPHONES

the speed of moving hot air or similar transparent fluids against a textured background. In material engineering, Davis et al. [9] used sub-pixel motion extraction to estimate certain material properties from a video [9]. In 3D video processing, motion detection is used to extract depth map from binocular images [8, 14].

For sound detection, Zeev et al. [25] extracted speech signals by measuring the vibration of people's neck in a video. Davis et al. [10] used sub-pixel motion extraction to recover sound from silent video. They extract vibration separately in a number of scales and angles. Then they align signals temporally (to avoid destructive interference) and finally they take a weighted average among all orientations and scales.

bmvc2k document class

Source: https://doi.org/10.48550/arXiv.1801.09436

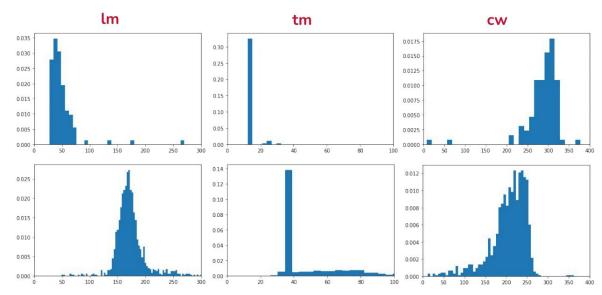
Mancuso et al.: Long-term evolution of the heliospheric magnetic field intensity

modulation parameter ϕ (Eq. 3) estimated as in Usoskin (Fig. 2c). (2006). We remark that the above relation (Eq. 3) has been

nT (Steinhilber et al. 2010). In the calculation of the 1σ (North GRIP) ice cores, based on the works of McCracken (68.27%) and 2σ (95.45%) confidence intervals for B_{HMF}, & Beer (2015) and Usoskin et al. (2015). An average comwe also propagated the uncertainty in τ ($\Delta \tau \approx 0.9$) and posite time series, $B_{[GCR]}$, was obtained by averaging tothe uncertainty in the relation expressing the expected 44Ti gether these two independent cosmogenic radionuclide reproduction rate Q in a stony meteorite as a function of the constructions in the common intervals from 1766 to 1982

In Fig. 2, we show the long-term evolution of $B_{\rm HMF}$ obtained assuming the LIS of Castagnoli & Lal (1980) in the obtained in this work along with the above three average

aa document class



This example shows that we can easily **separate** these two document classes with 3 features only.

This entire study indicates that using statistical learning should work pretty well ...

Random forest-based approach

Configuration and results

Random forest model: Ensemble method that uses statistical learning to train a lot of decision trees on different subparts of the training dataset.

Hyperparameters $\begin{cases} &\text{Minimum number of samples per leaf} \rightarrow \text{set to 0.01\% (risk of overfitting if too high)} \\ &\text{Number of decision trees} \rightarrow \text{set to 1000 to ensure stability of most common decisions} \end{cases}$

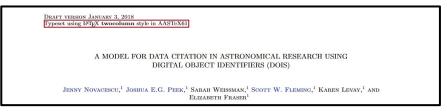
Features of the model: the five hand-designed features. Output: Predicted document class among 33 of them.

Model	Averaged precision	Averaged recall	Macroscopic F1-Score
Dummy	0.09%	3.03%	0.18 %
Random forest model	64 %	66 %	64 %

Simple modelization (no deep learning and only five, simple, features) \rightarrow Really promising results!

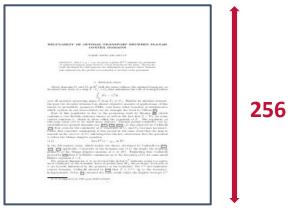
Input data

Text element specific to AAS document class



Source: https://arxiv.org/pdf/1801.00004.pdf

Example of input bitmap rendering



Some usual elements from ACM document class

ACM Reference Format

Antoine Gauquier and Pierre Senellart. 2023. Automatically Inferring the Document Class of a Scientific Article. In ACM Symposium on Document Engineering 2023 (DocEng '23), August 22–25, 2023, Limerick, Ireland. ACM, New York, NY, USA, 17 pages. https://doi.org/10.1145/3573128.3604894

1 INTRODUCTION

The majority of research papers in fields such as mathematics, physics and computer science are written using the BIEA document composition system. BIEA documents have a document class, which defines the type of document to be generated and how it is styled. The standard BIEA document classes include article, book and report, but many others have been defined and are included in modern BIEA distributions. In particular, many publishers of academic journals and conference proceedings created specific document classes, to define their own document structure standards, and to get a uniform style for all the papers in a given conference

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easy for a human being familiar with the various famous document classes to determine, given only the PDF of the paper, the document class used. However, this manual method cannot be scaled up to the use cases above. This motivates the current work, which explores automatic inference of the document class of a given scientific

There is a relatively rich literature on information extraction from scholarly articles. For instance, there is previous work on extraction of headers and meta-data [1, 6, 14], citations [19], acknowledgments [11] or figure meta-data [3].³ The exploitation of the layout and visual rendering of PDF documents to make inference about their content or structure has also been considered [10, 22, 23], especially for applications such as extraction of data from invoice-type documents. However, to the best of our knowledge, the specific task of BIEX document class inference from PDF articles has not been addressed to this date.

The goal of this work is to propose relatively simple, scalable, tractable, and effective methods to achieve this classification task. We propose a supervised machine learning approach to this classification problem, each class corresponding to one (or several related) document classées). A first idea is to engineer discriminant features

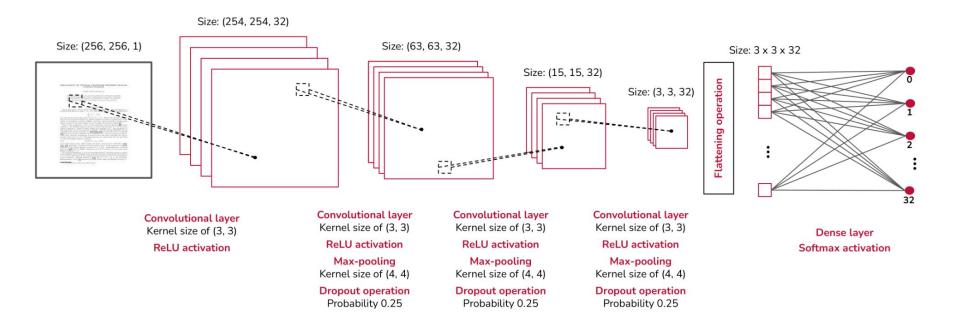
1https://scholar.google.com/ 2https://www.base-search.net/

³More examples can be found on the CiteSeerX webpage https://csxstatic.ist.psu.edu/

- ACM Reference Format
- Rights and information about the article

Source: https://arxiv.org/pdf/1806.06252.pdf

Architecture



Results and comparison with state-of-the-art

Architecture	Macro F1-Score	Number of parameters	FLOPS (in billions)
Our architecture	92.31 %	38 177	1.36
ResNet50V2	92.28 %	23 632 417	9.13
NASNetMobile	91.31 %	4 304 597	1.50
EfficientNetV2B0	93.43 %	4 091 844	0.80

Analysis:

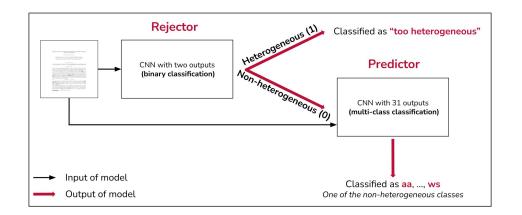
- → 100 times less parameters than other models
- → Almost as performant, above 92% of F1-Score
- → Number of floating operations at inference time slightly above EfficientNetV2B0

Separating heterogeneous document classes with reject option (1)

Document class	Precision	Recall	F1-Score
book	56.84 %	21.39 %	31.09 %
report/wlscirep	52.09 %	77.69 %	62.37 %
other (including article)	69.17 %	65.00 %	67.02 %

Common ground of theses classes: they are widely customizable, and thus embed a great **heterogeneity** of renderings.

What about directly putting apart these heterogeneous classes before applying classifier? This is **reject option**.



Separating heterogeneous document classes with reject option (2)

Model	Precision	Recall	F1-Score
Rejector	90.55 %	89.15 %	89.04 %
Classifier	96.94 %	96.73 %	96.83 %

Improvement in the classifier performance (more than 4.50% in averaged F1-Score). However ...

The rejector has lower performance \rightarrow overall system not necessarily better!

Still very useful for applications where we know that **heterogeneous classes are not frequently observed or relevant** (for instance, articles from conference proceedings or journals).

Recall for non-heterogeneous class of rejector is above 98 %: non-heterogeneous classes are almost always classified as so.

Conclusion and perspectives

- It is statistically relevant to discriminate document classes on the basis of features from PDF rendering.
- A (relatively) simple classification method on a set of 5 simple features gives promising results.
- Using a computer-vision based approach (CNN) gives really good performance, comparable to state-of-the-art models with way more parameters.
- We can even improve these results by putting apart heterogeneous classes, which are not related to a specific conference or journal.

- The experiment was conducted on a « small » subset of ArXiV (only 2018): what happens on a larger time frame?
- Dependency on ArXiV: we don't know any dataset where document class is readily available.
- We did show that using document class helps detecting mathematical environments (TheoremKB). But finding an
 efficient way maximising performance is still in progress.



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Thank you for your attention! Any questions?

https://github.com/AntoineGauquier/inferring_document_class_of_scientific_article/

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