in 30 slides!

GROBID

from PDF to structured documents





Patrice Lopez April 2015

GROBID

- GeneRation Of BIbliographic Data
- A text mining library for extracting bibliographical metadata at large - started in 2008 (first as a hobby ;)
- Problem:
 - → Modern digital libraries techniques require high quality metadata and full text, but we have PDF
- Goals:
 - Automatic metadata and structured content extraction from PDF
 - → State-of-the-art
 - → fast, robust, production-ready



GROBID

- Input:
 - Technical and scientific domains
 - Scholar documents, technical manuals and patents
 - Text with layout information (PDF) or raw text
- Machine learning approach: cascading of linear chain
 CRF
- Normalization of metadata
- Result and training data in TEI (Text Encoding Initiative)

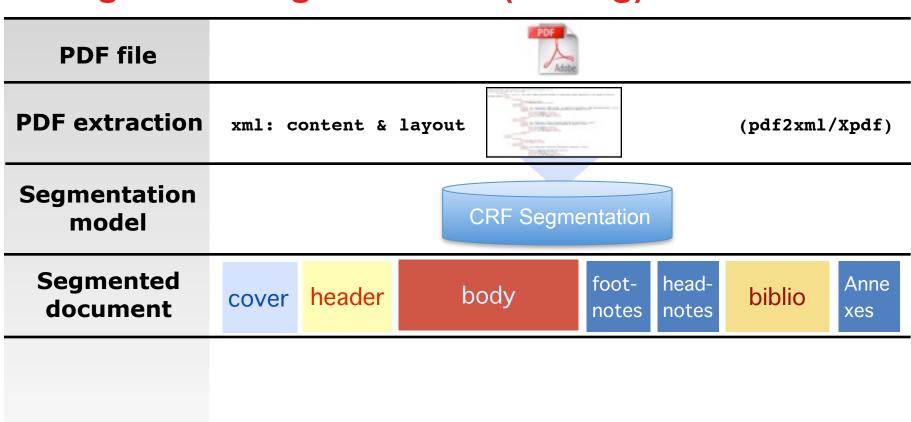


Approach

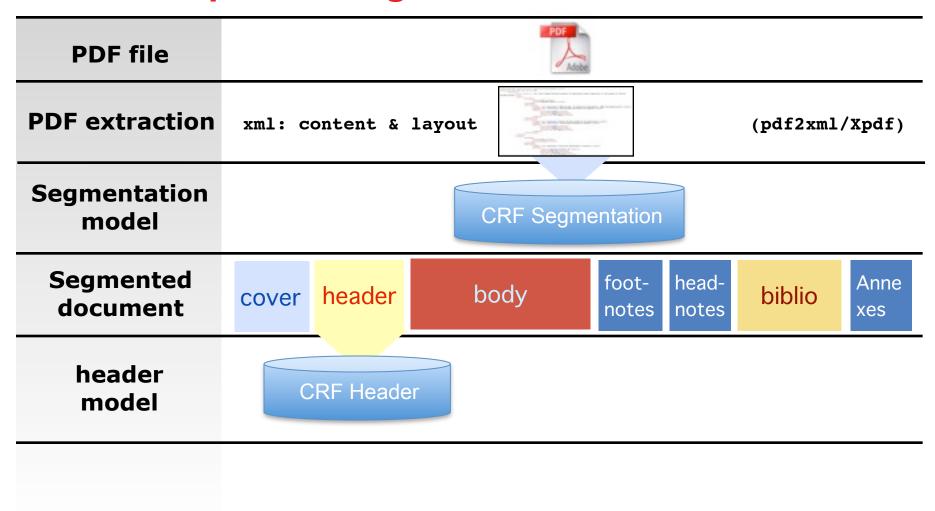
- GROBID is based on 11 different CRF models (2 for patents)
- Each model uses the same generic CRF-based framework covering training, evaluation, tokenization, decoding, etc.
- Each model has its own set of features, set of training data and normalization
- As features, exploitation of
 - → position information (begin/end of line, in the doc.)
 - → lexical information (vocabulary, large gazetteers)
 - → layout information (font size, block, etc.)



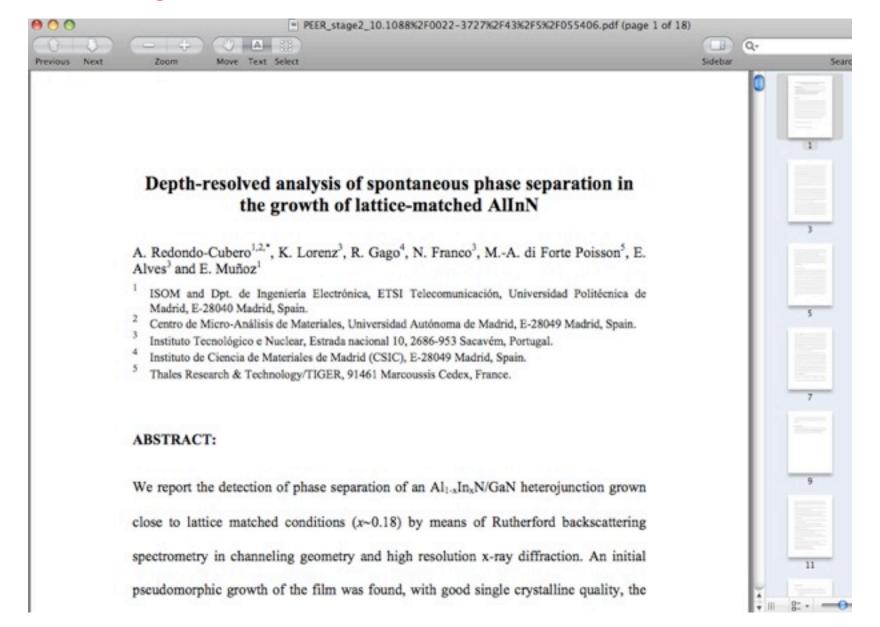
High-level segmentation (zoning)

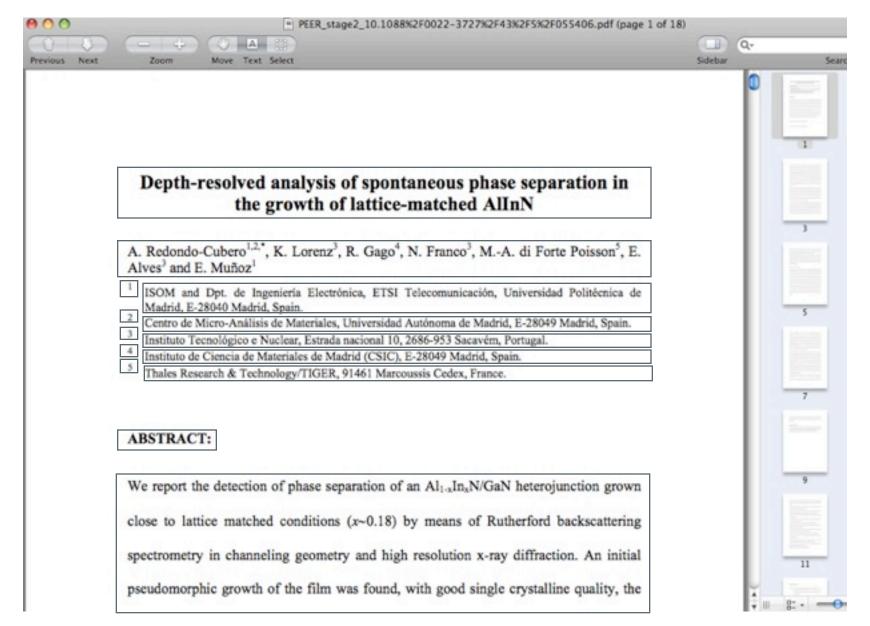


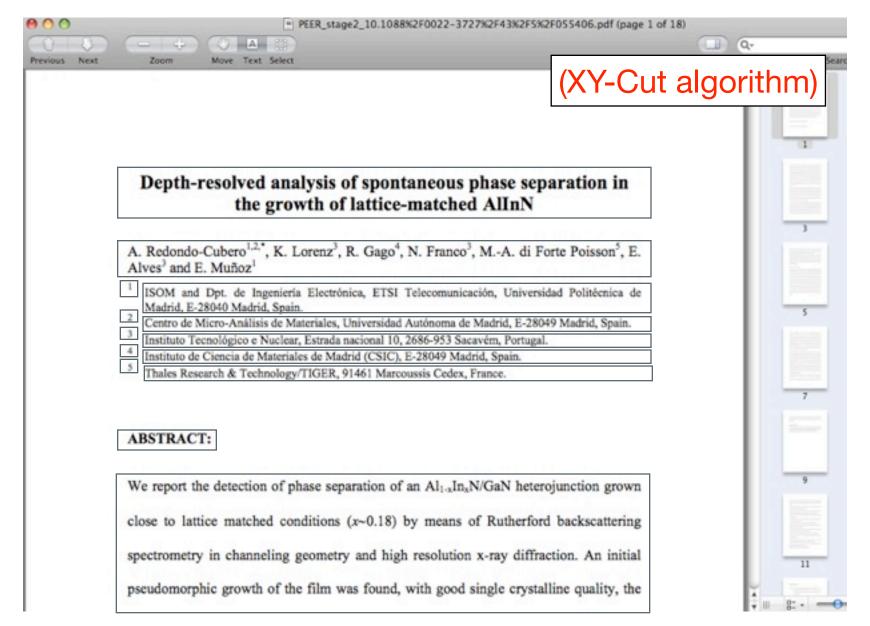


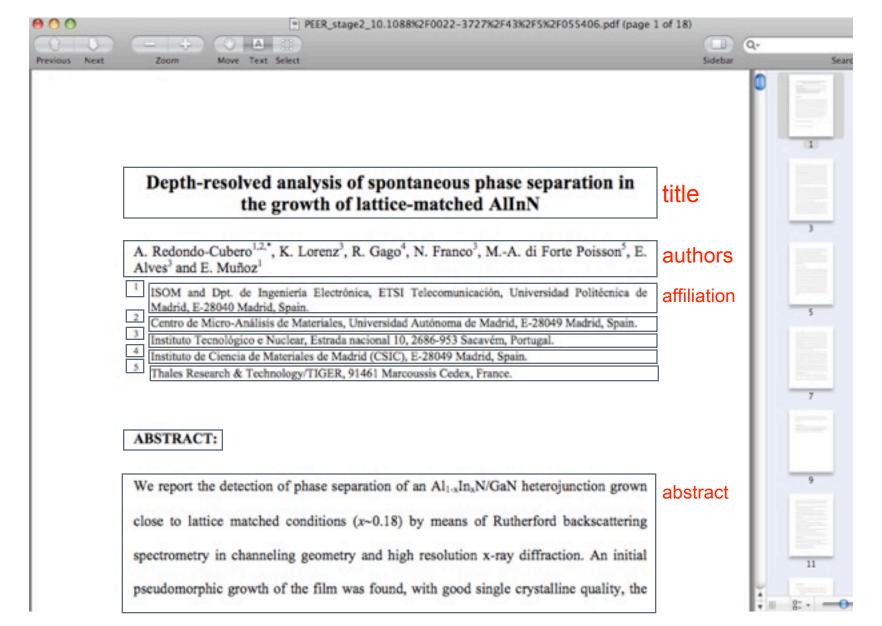


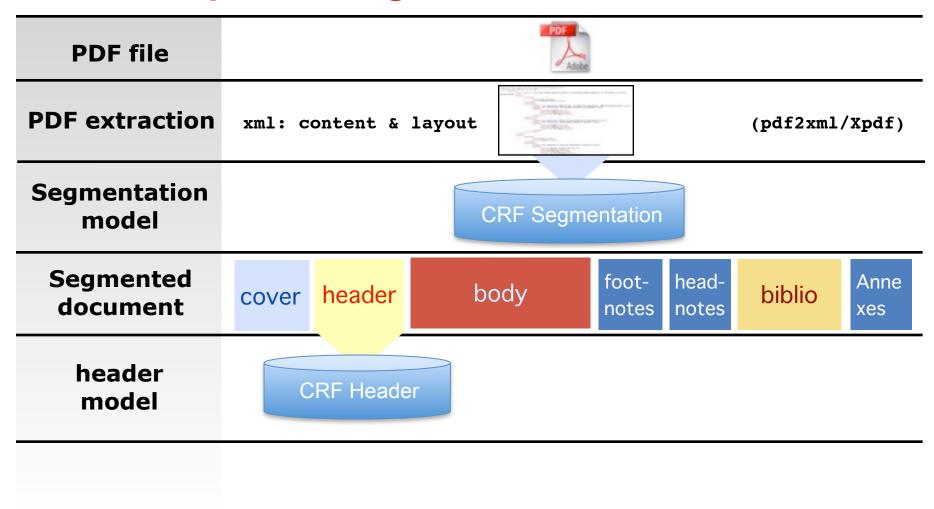




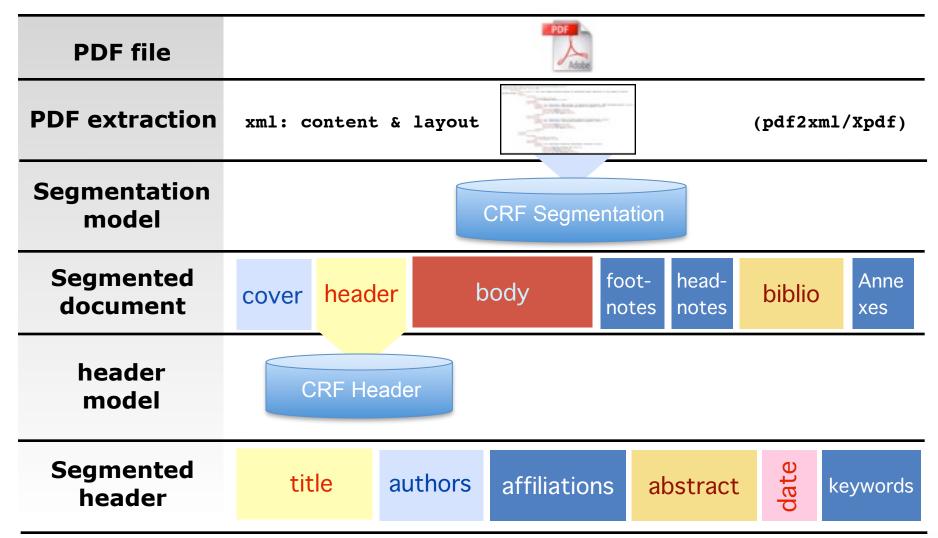




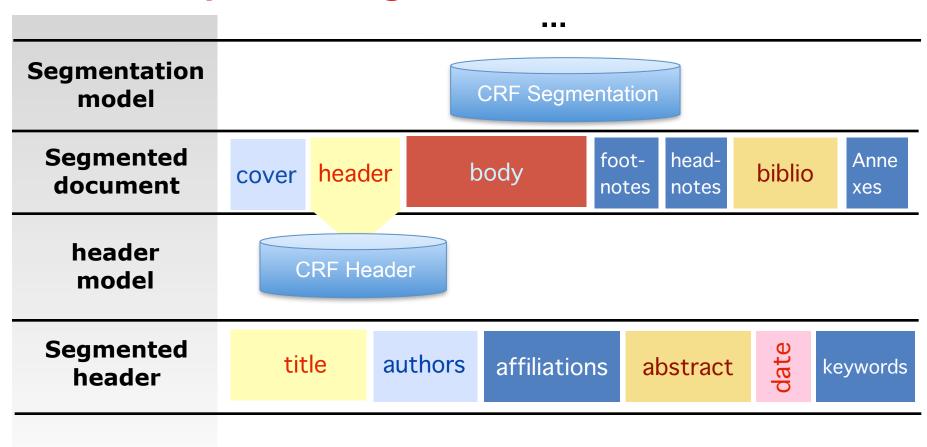




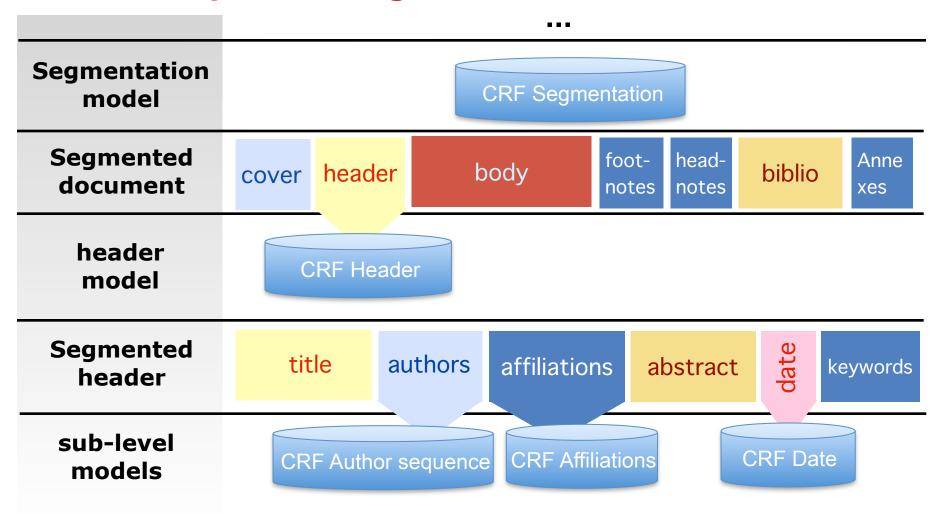






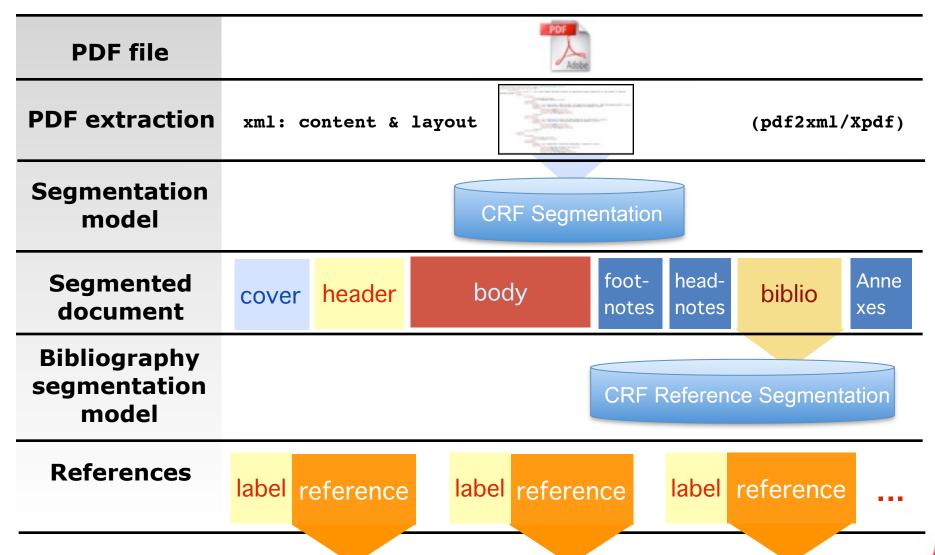








Bibliographical reference parsing





Bibliographical reference parsing



MPG S S·F·X

Cascading models

- Advantages of a cascading approach:
 - → hierarchical structure from "flat" linear chain CRF
 - → a way to manage fine-grained structures (55 final labels,
 14 intermediary labels in total in 9 models for full texts)
 - → modularity: reuse of models (dates, names)
 - speed: number of labels and features for each model remains relatively low
 - training data: examples limited to one level of information



Cascading models

- Managing propagation of errors in the cascading:
 - → we assume that invalid text segments for a particular level will have to be processed
 - ➡ training data in each model can include noisy input
 - ⇒ spurious text segments from the upper level are "neutralized" with a dedicated label
 - → still to be evaluated and tuned...



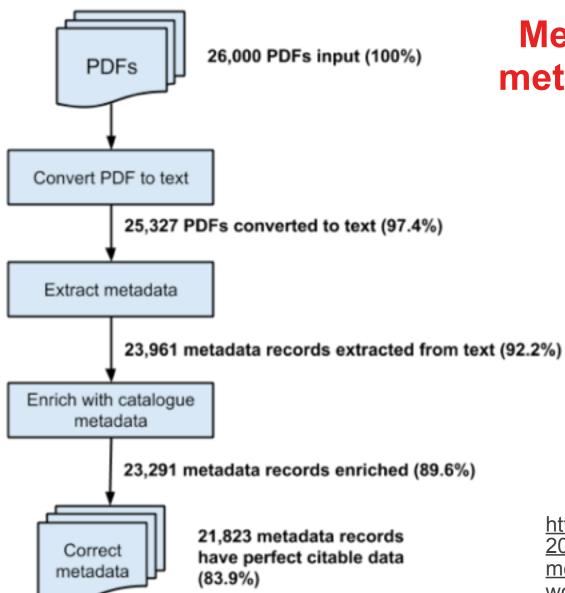
Header metadata extraction

Table 2. Results (A₁₀₀: First evaluation setup with 100 articles, B₁₀₀: Second evaluation setup with 100 articles, B₁₁₅₃: Second evaluation setup with 1,153 articles)

	Title		Authors			Authors' last names	Abstract		Year				
	A_{100}	${\bf B}_{100}$	B ₁₁₅₃	A ₁₀₀	${\bf B}_{100}$	B ₁₁₅₃	${\bf B}_{100}$	B ₁₁₅₃	A ₁₀₀	${\bf B}_{100}$	B ₁₁₅₃	${\bf B}_{100}$	B ₁₁₅₃
GROBID	N/A	0.92	0.92	N/A	0.83	0.83	0.90	0.91	N/A	0.75	0.74	0.64	0.69
Mendeley Desktop	N/A	0.84	0.82	N/A	0.72	0.70	0.78	0.77	N/A	N/A	N/A	0.23	0.26
ParsCit	0.59	0.52	0.54	0.47	0.29	0.31	0.36	0.37	0.49	0.31	0.26	0.06	0.07
PDFSSA4MET	0.13	0.21	0.18	0.05	0.02	0.01	0.20	0.18	N/A	N/A	N/A	N/A	N/A
PDFMeat	0.60	N/A	N/A	0.6	N/A	N/A	N/A	N/A	0.14	N/A	N/A	N/A	N/A
SciPlore Xtract	0.76	0.81	0.78	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
SVMHeaderParse	0.50	0.57	0.61	0.64	0.70	0.73	0.74	0.76	0.37	0.64	0.64	0.21	0.20

from (Lipinski et al., 2013)





Mendeley's header metadata extraction evaluation

https://krisjack.wordpress.com/ 2015/03/12/how-well-doesmendeleys-metadata-extractionwork/



Evaluation again PubMedCentral: Header

1943 PDF from 1943 journals (2011)

Fields	Precision		Recall		f-score					
title	72.16	83.46	89.79	68.39	79.1	85.1	70.23	81.22	87.38	
authors	61.41	69.27	80.24	58.26	65.72	76.13	59.79	67.45	78.13	
first author	90.53	93.98	92.72	85.6	88.87	87.67	88	91.35	90.13	
abstract	16.32	48.97	80.11	14.93	44.79	73.29	15.6	46.79	76.55	
keywords	54.78	61.59	84.67	42.23	47.48	65.28	47.69	53.62	73.72	
	59.89	72.61	85.64	54.73	66.35	78.26	57.19	69.34	81.79	r
all fields	59.04	71.45	85.51	53.88	65.19	77.49	56.26	68.09	81.18]

strict

soft: ignore punctuation, case and spaces

purple:
Levenshtein distance
≥ 0.8

micro average

macro average

Inria

Evaluation again PubMedCentral: Header

1943 PDF from 1943 journals (2011)

Instance-level results				
Total expected instances	1943			
Total produced instances	1933			
	130	strict		
Total correct instances	385	soft		
Total correct instances	815	Levenshtein		
	602	Ratcliff-Obershelp		
	6.73	strict		
Instance level recall	19.92	soft		
Instance-level recall	42.16	Levenshtein		
	31.14	Ratcliff-Obershelp		

Matching
strict
soft: ignore punctuation, case and spaces
purple: Levenshtein distance ≥ 0.8
grey: Ratcliff- Obershelp similarity ≥ 0.95



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Evaluation again PubMedCentral: Citations

1943 PDF from 1943 journals (2011)

Fields	Precision	Recall	f-score
title	87.3	74.49	80.39
authors	79.12	64.08	70.81
first author	86.17	69.64	77.03
date	90.66	72.87	80.79
inTitle	81.6	73.92	77.57
volume	91.6	76.57	83.41
page	89.33	74.03	80.96
all fields	86.46	72.13	78.65
ali litius	86.54	72.23	78.71

Matching

soft: ignore punctuation, case and spaces

micro average macro average



Evaluation again PubMedCentral: Citation

1943 PDF from 1943 journals (2011)

Instance-level results				
Total expected instances	89,688			
Total produced instances	87,337			
	30,617	strict		
Tatal as we at in atom as a	42,368	soft		
Total correct instances	46,059	Levenshtein		
	42,167	Ratcliff-Obershelp		

Precision	Recall	f-score	
35.06	34.14	34.59	strict
48.51	47.24	47.87	soft
52.74	51.35	52.04	Levenshtein
48.28	47.02	47.64	Ratcliff-Obers.

Matching
strict
soft: ignore punctuation, case and spaces
purple: Levenshtein distance ≥ 0.8
grey: Ratcliff- Obershelp similarity ≥ 0.95



Metadata consolidation

- Exploitation of external bibliographical databases for correcting/completing results based on extraction results
- Crossref: The full bibliographical record can be obtained based on either:
 - → DOI
 - → Journal title, volume, first page
 - → Title + author first name → frequent!
- Provides ~10% improvement on header metadata extract
- Price to pay for real time processing: online requests
- Ideally use "in house" database and bibliographic deduplication techniques: ResearchGate, Mendeley, EPO
- Used at the EPO: Summon API



Training data

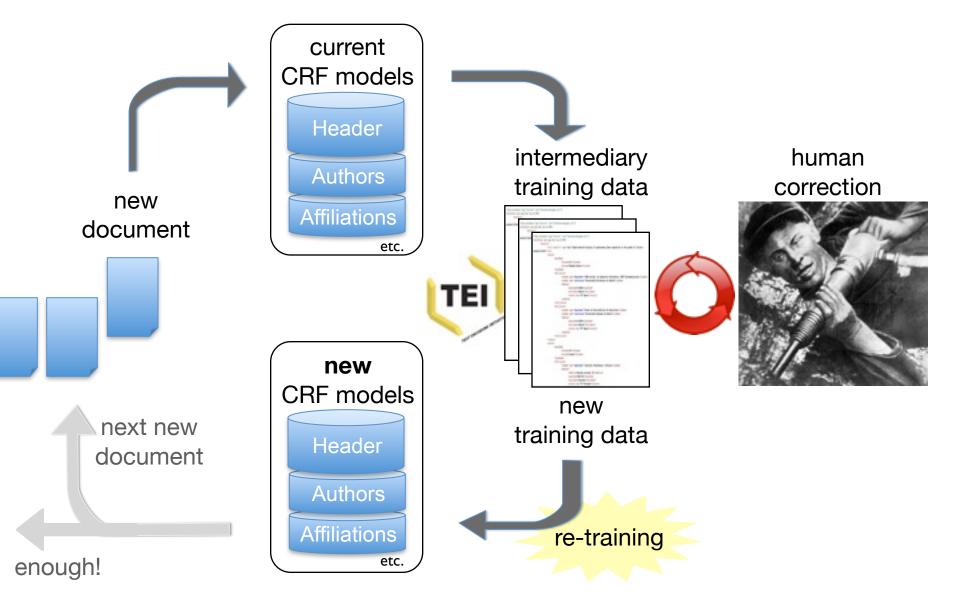
Models	# examples	exploit layout info
segmentation	121	X
header	3971	X
affiliation-address	1064	
names (header)	1297	
names (citation)	253	
date	619	
reference-segmenter	17	X
citation	4150	
fulltext (body)	8 (+13 abstracts)	X

insufficient training data

(+ 2 models for patent not included here)

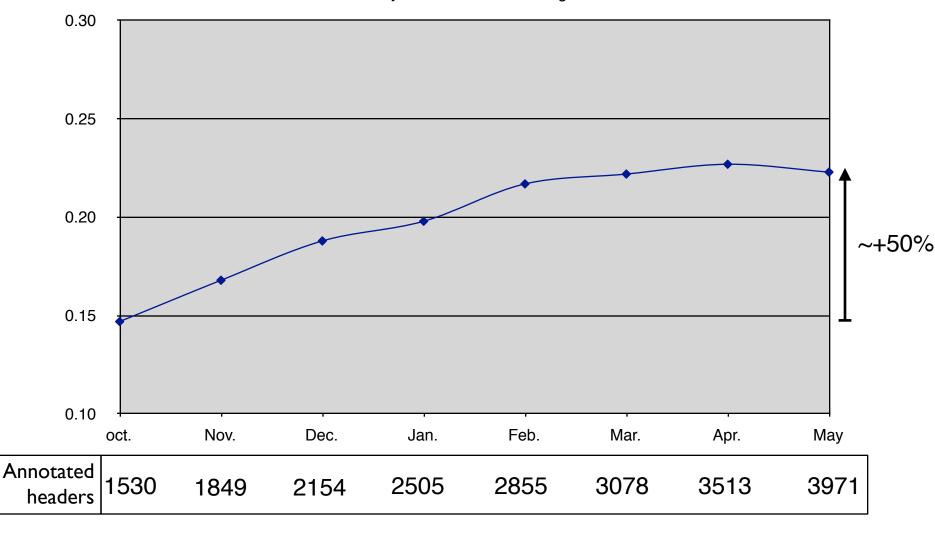


Assisted generation of training data



EPO project: Augmentation of training data for headers (2013-14)

Instance level accuracy of header extraction against the October set



Technical details

- GROBID is Open Source since 02.2011 https://github.com/kermitt2/grobid
- Apache 2.0 license
- JNI integration of the CRF libraries (CRF++, Wapiti)
- Batch, API Java & RESTful interface (with console)
- Thread-safe at parser-level
- Documentations: wiki pages, web service manual, annotation guidelines



Speed / Scaling

GROBID REST Service:

- Header: 3 PDF/s, 1 thread (MacBook)
- Citations: 12 PDF/s, 1M PDF/day on a Xeon 10 CPU E5-2660 and 10 GB memory, 3GB used in average, 9 threads (INIST)
- Full process (header, citation, fulltext): 0.6 PDF/s,1 thread (MacBook)



Performance

Robustness:

- for scholar literature, between 1 and 2% of the PDF parsing are failing, usually due to timeout at 20s
- an additional 1-2% of all coming PDF do not provide a usable text layer (PDF is bitmap only or the textual layer is encrypted)

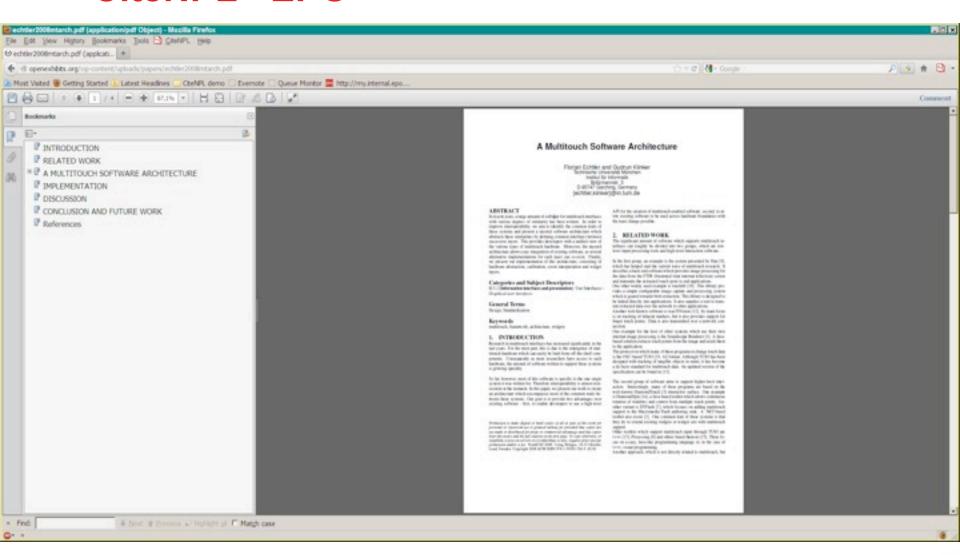


Use case 1: Self-archiving of PDF

- Problem: users need to input the full bibliographical information when self-archiving or uploading a PDF
- Solution: metadata are automatically extracted from header and a pre-filled form is simply checked by the user
- This is an online usage of GROBID taking advantage of the sub-second PDF processing for header metadata
- In production at ResearchGate, Mendeley, HAL (French national OA archive) and EPO
- Success rate for full metadata after enrichment: 70-80%

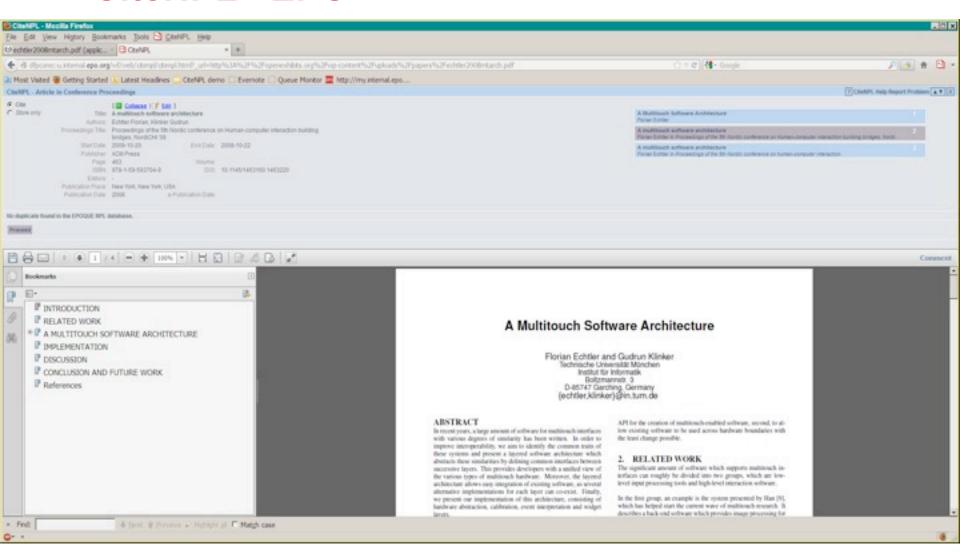


CiteNPL - EPO



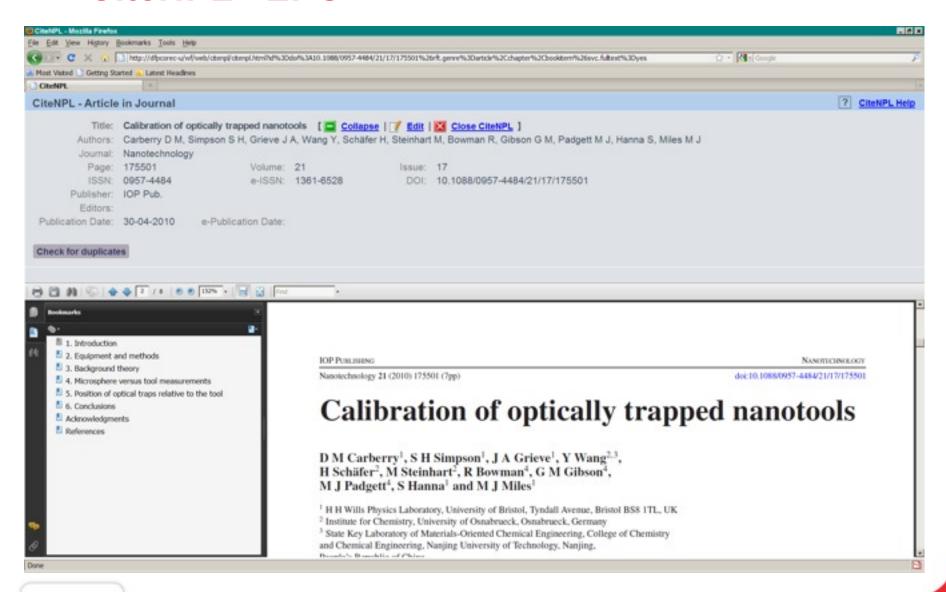


CiteNPL - EPO





CiteNPL - EPO





Use case 2: Citation extraction at ResearchGate

- Every days, thousands of PDF are loaded either by RG users or by crawlers on OA archives
- The "acquisition" document workflow integrates Grobid for citation extraction:
 - 300K PDF are processed every months on a Hadoop cluster of 16 machines
 - Extracted citations are matched against an internal biblio. DB
- Services:
 - citation notifications for researchers
 - relevance ranking in search
- ResearchGate reported an overall Grobid failure rate of 1% on user's self-uploaded PDF





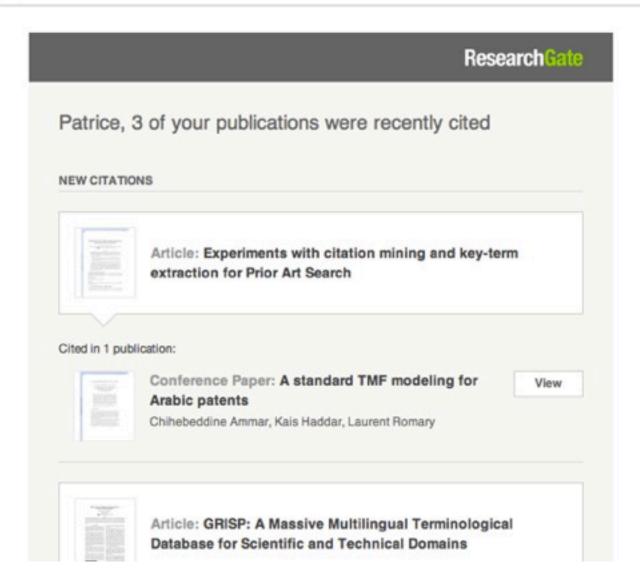


Hide

From: ResearchGate <no-reply@researchgate.net>

Subject: Patrice, 3 of your publications were recently cited Date: November 20, 2014 12:48:19 PM GMT+01:00

To: Patrice Lopez



On-going and future works

Ongoing projects:

- Citation extraction with INIST (France): production of training data
- CJK support, work with WIPO (Switzerland)
- Improvement of full text body restructuring

Future efforts:

- Confidence scores (with additional regression models)
- Two-stage CRF
- Document and citation classification

