

Daniel@FinTOC-2019 Shared Task : TOC Extraction and Title Detection



Emmanuel Giguet ¹ Gaël Lejeune ²

September 30th, 2019

¹Normandie Univ, UNICAEN, ENSICAEN, CNRS, GREYC UMR 6072 – Caen, France

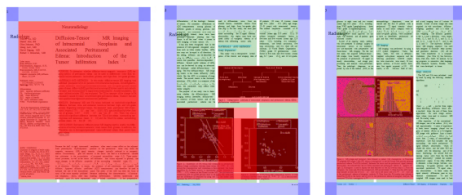
²Sorbonne University, STIH, EA 4509, – Paris, France

1. Introduction
2. TOC Detection
3. Title Detection
4. Conclusion

Introduction

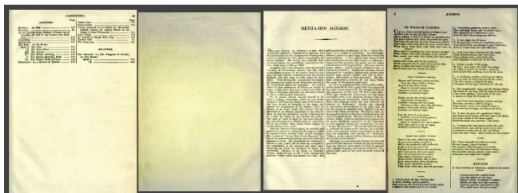
1. RESURGENCE : Structure Extraction from Biomedical Articles

- **Corpus:** 300 Biomedical Articles from Medline
- **Documents:** 5 to 20 pages
- **Hierarchy:** Section, subsection, subsection
- **Tasks:** Document Layout Analysis, Document Structure Extraction, Information Extraction (Authors, Affiliations, Keywords, Figures, ...)



2. Several Participations to INEX “Book Structure Extraction”

- **Corpus:** 2,000 Books (Microsoft and Internet Archives)
- **Document size:** Hundreds of pages
- **Hierarchy:** Book, Part, Chapter, Psalm, Sonnet, Sermon, ...
- **Task:** Document Structure Extraction from Whole Content



The FinTOC-2019 Corpus

- A few dozen of financial prospectuses
- Document size: About hundred pages
→ larger than scientific articles, smaller than books

Document characteristics

- May contain a table of contents, and parts → like books
- May contain small sections → like articles
- May contain large tables → more corpus specific

Document layout and formatting

- No Professional Editing Guidelines, no Controlled Stylesheet
- Manual Formatting instead of Styling Rules leads to inconsistencies
 - ⇒ between the ToC and the Document Structure
 - ⇒ between headings level and Formatting effects

TOC Detection

TOC Detection: Principles

- Our method is based on the ToC Detection and Analysis
 - ⇒ “Do not deny the obvious” principle :
 - ⇒ If there is a ToC, try to use it.
- And a Fallback when no ToC is found
 - ⇒ Major Headings are detected from Shallow Document Analysis
 - ⇒ We do not focus on the Whole Document Analysis, unlike our participations to Inex/ICDAR
- Our expectations: good precision and low recall
 - ⇒ Headings in the ToC are supposed to be good
 - ⇒ Some documents don't have a ToC
 - ⇒ Some headings may not be in the TOC
- The input: the raw PDF documents
 - ⇒ In order to control the whole processing chain

1. Locating the ToC Pages
2. Building the ToC Entries
3. Inferring the Hierarchy
4. Computing PDF Page Numbers

TOC Detection: Method (I)

1. **Locating the ToC Pages** at the beginning
 - Search-space: the first third of the document
 - Invariant Pattern: A right-aligned increasing sequence of integers
 - Size: The ToC may spread on up to three contiguous pages
2. **Building the ToC Entries:** A sequential pattern
 - Toc Entry Parts: Level Number, Title*, Leader line, Page Number
 - Only the title is mandatory. It may spread over multiple lines.
 - Some title may have no Page Number → Contrast Detection based on Line Spacing and Character effects variations
3. Inferring the Hierarchy
4. Computing PDF Page Numbers

TOC Detection: Method (II)

1. Locating the ToC Pages
2. Building the ToC Entries: A sequential pattern
3. **Inferring the Hierarchy** from Contrastive Effects
 - Line spacing → Larger for major headings
 - Formatting character effects → bold, character set, font-size
 - Indentation → Positive for lower-level subheadings
 - Numbering Character Sets → Uppercase for major headings
 - Multi-level numbering structure → For lower-level subheadings
4. **Computing PDF Page Numbers**
 - Computing the shift between PDF and printed page numbers

TOC Detection: Results

| | Run | F-measure |
|-----------|-----|-----------|
| Daniel | 1 | 42.72 |
| IHSMarkit | 1 | 39.41 |

Table 1: Results for the ToC Generation Task (test set)

| Xrx-measure Links | | | | Title | |
|-------------------|------|------|------|-------|------------|
| Doc | Prec | Rec | F1 | Acc | book id |
| 0 | 97.7 | 48.6 | 64.9 | 84.5 | 1252823262 |
| 1 | 87.2 | 51.9 | 65.1 | 96.5 | 1139920265 |
| 2 | 22.2 | 40.0 | 28.6 | 91.9 | 0881817786 |
| 3 | 90.5 | 12.3 | 21.7 | 85.7 | 1150262910 |
| 4 | 100 | 10.4 | 18.9 | 42.4 | 0992626050 |
| 5 | 83.3 | 2.9 | 5.6 | 59.7 | 0949250459 |
| 6 | 100 | 12.4 | 22.1 | 94.6 | 1151059737 |

Table 2: Results for the ToC Generation Task on the test set

Title Detection

Title Detection : Corpus

| | IS TITLE | IS NOT |
|---------|----------------|-----------|
| # Seg. | 10,271 | 65 354 |
| Ratio | (13.6%) | 86.4% |
| avg. | 29.8 | 203.4 |
| std. | ± 23 | ± 446 |
| min:max | 2 : 242 | 1 : 6,607 |

(a) Stats Train Set, size in chars

| | IS TITLE | IS NOT |
|------------|-----------|-----------|
| # Seg. | 888 | 13 928 |
| Ratio | 6% | 94% |
| avg.(std.) | 32.3 | 98.7 |
| std. | ± 24 | ± 280 |
| min:max | 5 : 232 | 1 : 6,586 |

(b) Stats Test Set, size in chars

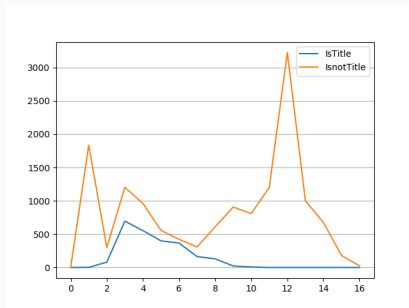


Figure 1: Number of instances with respect to their size in characters

Features (baseline)

- **basic features** BEGINSWITHNUMBERING, ISBOLD, ISITALIC, ISALLCAPS, BEGINSWITHCAP, PAGENUMBER
- **length** of the segment (in characters)
- **stylometry** Relative frequency of each punctuation sign, numbers and capitalized letters

Features (main system)

- Character n-grams with various sizes
- n_{min} and n_{max} in $[1 : 10]$
- (and $n_{min} \leq n \leq n_{max}$)

Title detection : Results (DT10 classifier)

Weighted F-1 measure

| | Cross-valid | Test-set |
|---|-------------|-------------|
| B1 (basic features) | 83.2 | 92.9 |
| B2 (basic + length) | 85.4 | 93.6 |
| B3 (stylo) | 85.4 | 93.2 |
| B4 (stylo+basic) | 90.4 | 94.2 |
| B5 (stylo+length) | 90.0 | 93.7 |
| B6 (stylo+basic+length) | 90.6 | 95.1 |
| n-grams ($1 \leq n \leq 1$) | 94.0 | 94.6 |
| n-grams ($1 \leq n \leq 2$) | 94.2 | 94.5 |
| n-grams ($1 \leq n \leq 3$) | 94.3 | 94.8 |
| n-grams ($1 \leq n \leq 4$) | 93.5 | 95.0 |
| n-grams ($1 \leq n \leq 5$) | 93.1 | 95.1 |

What we learned

- stylometric features worked well
- ... and even better than character n-grams
- 1-grams were sufficient to build an efficient classifier ($> 94\%$).
- with $n_{min} > 1$ or $n_{max} > 5$ the results drop significantly

What we learned

- stylometric features worked well
- ... and even better than character n-grams
- 1-grams were sufficient to build an efficient classifier ($> 94\%$).
- with $n_{min} > 1$ or $n_{max} > 5$ the results drop significantly
- Performs better on the test set (underfitting ?)
- 95% is not enough (roughly 65% on the **real task**)

Conclusion

Conclusion: Task 1

Interesting features we overlooked

- "Prefixes" : REGEX patt for first 3 chars of a line (*To9* → *Aa1*)
- "Suffixes" : REGEX patt for last 3 chars of a line (id.)
- Font Type
- Font Size

Title Detection

- **Pros:** simple method (characters and stylometry)
- **Cons:** ranked last, more feature engineering is needed
- **Future Directions:** Syntactic structure and/or LSTMs

Conclusion: Task 2

- **Pros:** Good precision, Simple and fast, Multilingual → no Lexicon
- **Cons:** Low recall (prospectuses without ToC) problem with headings not in the ToC
- **Future Directions:** Deeper Analysis of the Whole Document → not Straightforward to handle Manual Text Formatting and Unnumbered Headings
- **Open for collaborations:** Document Structure Extraction, Table Extraction, Information Extraction... from PDF documents

Comments, questions ?



Contacts

Emmanuel Giguet – Emmanuel.Giguet@unicaen.fr

Gaël Lejeune – gael.lejeune@sorbonne-universite.fr