### Segmentation Of Layout-Based Documents Bachelor's Thesis

Albert-Ludwigs-Universität Freiburg

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Extracting text blocks from PDFs



#### Extracting text blocks from PDFs

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#### A Benchmark and Evaluation for Text Extraction from PDF

Hannah Bast University of Freiburg 79110 Freiburg, Germany bast@cs.uni-freiburg.de

#### ABSTRACT

Extracting the body text from a PDF document is an important but surprisingly difficult task. The reason is that PDF is a layout-based format which specifies the fonts and positions of the individual characters rather than the semantic units of the text (e.g., words or paragraphs) and their role in the document (e.g., body text or caption). There is an abundance of extraction tools, but their quality and the range of their functionality are hard to determine. Claudius Korzen University of Freiburg 79110 Freiburg, Germany korzen@cs.uni-freiburg.de

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- Only characters, their bounding boxes, and font information is stored

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- Only characters, their bounding boxes, and font information is stored
- Usually also no whitespace characters



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Character	bounding box	font name	font size
"А"	(75.8, 697.2), (87.9, 708.5)	Arial	17.2



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Character	bounding box	font name	font size
"А"	(75.8, 697.2), (87.9, 708.5)	Arial	17.2
"B"	(92.2, 697.2), (103.8, 708.4)	Arial	17.2



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Character	bounding box	font name	font size
,,A''	(75.8, 697.2), (87.9, 708.5)	Arial	17.2
"B"	(92.2, 697.2), (103.8, 708.4)	Arial	17.2
,,e"	(103.8, 697.1), (112.5, 704.8)	Arial	17.2



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Character	bounding box	font name	font size
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	:		

Reading order is also often difficult to detect



- Reading order is also often difficult to detect
- Especially, in documents featuring a two-column layout:



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### Problem definition



For each page of a given PDF, ...

- Our input is a list of characters. Each character comes with its bounding box and its font information.
- Our output is a list of text blocks sorted by reading order.





#### ■ We seperate our approach into two main steps



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- First, we use page segmentation to detect text blocks



- We seperate our approach into two main steps
- First, we use page segmentation to detect text blocks
- Second, we order the detected text blocks using a similar but more informed approach

#### Page segmentation



Page segmentation is the process of reassembling the characters of a layout-based document into semantic units like words, lines, or text blocks

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- We only focus on reassembling characters into text blocks
- We perform our segmentation using an XY-cut algorithm



An XY-cut algorithm can be used to group the characters of a page

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- It does so by applying vertical cuts (through the X-axis) and horizontal cuts (through the Y-axis) to the page

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- It does so by applying vertical cuts (through the X-axis) and horizontal cuts (through the Y-axis) to the page
- Diagonal cuts and cuts through characters are not allowed
- Cuts can also be used to detect reading order (more on that later)



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- Each cut divides a page into two parts
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Detecting text blocks also yields a preliminary reading order

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- This allows us to make use of information about the text blocks themselves:

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We predict the semantic roles of detected text blocks using a machine-learning model developed by Korzen

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- We predict the semantic roles of detected text blocks using a machine-learning model developed by Korzen
- We then use the XY-cut algorithm again but now choose cuts using a machine-learning model which also considers semantic roles

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- We then use the XY-cut algorithm again but now choose cuts using a machine-learning model which also considers semantic roles
- This way, we can correct potential mistakes in the preliminary reading order







■ We evaluate our approach on 1,750 randomly selected articles from arXiv.org



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- We compare text blocks using their bounding boxes

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Text block detection:

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- Reading order detection:
  - $\tau_n$  := the normalized Kendall- $\tau$ -correlation between expected and detected reading order



 $\mathbf{r}$  can be used to compare the order of a sequence of numbers to an ascending order

- $\bullet$   $\tau$  can be used to compare the order of a sequence of numbers to an ascending order
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#### $7,\,5,\,6,\,9$

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Concordant pairs: 0

7, 5, 6, 9 Discordant pairs: 0

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Concordant pairs: 0

 $\overline{7, 5}, 6, 9$ Discordant pairs: 1

 $\mathbf{r}$  can be used to compare the order of a sequence of numbers to an ascending order

7, 5, 6, 9

- To compute  $\tau$ , we count concordant and discordant pairs in a given sequence
- Let's look at an example:

Concordant pairs: 0

Discordant pairs: 2
$\mathbf{r}$  can be used to compare the order of a sequence of numbers to an ascending order

7. 5. 6. 9

- To compute  $\tau$ , we count concordant and discordant pairs in a given sequence
- Let's look at an example:

Disco

Concordant pairs: 1

Discordant pairs: 2

 $\mathbf{r}$  can be used to compare the order of a sequence of numbers to an ascending order

7, 5, 6, 9

- To compute  $\tau$ , we count concordant and discordant pairs in a given sequence
- Let's look at an example:

Concordant pairs: 2

Discordant pairs: 2

- $\mathbf{r}$  can be used to compare the order of a sequence of numbers to an ascending order
- To compute  $\tau$ , we count concordant and discordant pairs in a given sequence
- Let's look at an example:

Concordant pairs: 3

7,  $\overline{5}$ ,  $\overline{6}$ ,  $\overline{9}$ Discordant pairs: 2

- $\mathbf{r}$  can be used to compare the order of a sequence of numbers to an ascending order
- To compute  $\tau$ , we count concordant and discordant pairs in a given sequence
- Let's look at an example:

7, 5,  $\overline{6, 9}$ Discordant pairs: 2

Concordant pairs: 4

October 20, 2021

Assuming the sequence does not contain duplicates, we can define  $\tau$  as

$$\tau = \frac{\#con - \#dis}{\#con + \#dis}$$



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For our example, we obtained #con = 4 and #dis = 2 yielding

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 $\mathbf{\tau}$  takes values between -1 and 1, so we normalize it using

$$au_n = rac{ au+1}{2}$$



## Evaluation results



### Average metric values on our evaluation dataset:

$B_G^=$	$B_A^=$	$B_G^+$	$B_A^-$	$ au_n$	$ au_n^f$
51.4%	46.7%	12.9%	14.7%	0.873	0.994

## Input format

```
1
         "glyphs": [{
2
              "char": "A".
3
              "font size": "11pt",
4
              "bounding box": [1, 4, 2.5, 6]
5
           },
6
7
              "char": "4".
8
              "font size": "11pt",
9
              "bounding box": [1, 1, 3, 3]
10
           }]
11
     }
12
```



## Some important remarks

- The example omitted some important aspects:
  - How do we compute potential cuts algorithmically?
    ising projection profiles of bounding boxes
  - How do we decide which cut to choose?
    - $\implies$  based on cut size
  - When do we stop cutting?
    - $\implies$  after cut size falls below a certain size threshold

### Text block postprocessing Raw detected block



#### 1.1 Kinds of semantic information

In the following, we briefly describe the kind of semantic information that we investigate in this paper.

**Word identification.** This is crucial for applications like search: a word that has not been identified correctly will not be found. Word identification in a PDF is non-trivial and challenging for a number of reasons. The spacing between letters can vary from line to line and even within a line, and there is no fixed rule to

### Text block postprocessing Splits applied in postprocessing



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### Text block postprocessing Split down into words



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$$\#exp = 8, #det = 9$$





$$#exp = 8, #det = 9, #cor = 4$$





$$#exp = 8, #det = 9, #cor = 4$$

$$B_{G}^{=} = \frac{\#cor}{\#exp} = \frac{4}{8} = 0.5 \stackrel{\frown}{=} 50\%$$
$$B_{A}^{=} = \frac{\#cor}{\#det} = \frac{4}{9} = 0.\overline{4} \stackrel{\frown}{=} 44.\overline{4}\%$$















$$\#exp = 8, #det = 9$$





$$#exp = 8, #det = 9, #stm = 2$$





$$#exp = 8, #det = 9, #stm = 2, #stl = 1$$





$$#exp = 8, #det = 9, #stm = 2, #stl = 1$$

$$B_G^+ = \frac{\#stm}{\#exp} = \frac{2}{8} = 0.25 \stackrel{\frown}{=} 25\%$$
$$B_A^- = \frac{\#stl}{\#det} = \frac{1}{9} = 0.\overline{1} \stackrel{\frown}{=} 11.\overline{1}\%$$





 $\tau_n$ 



#### Detected sequence:



#### Detected sequence: 7



### Detected sequence: 7, 5



### Detected sequence: 7, 5, 6



### **Detected sequence:** 7, 5, 6, 9

B



Detected sequence: 7, 5, 6, 9 #con = 4



Detected sequence: 7, 5, 6, 9 #con = 4, #dis = 2



Detected sequence: 7, 5, 6, 9 #con = 4, #dis = 2  $\tau = \frac{1}{3}$ 



Detected sequence: 7, 5, 6, 9 
$$\#con = 4, \#dis = 2$$
  $\tau = \frac{1}{3}$ 

We obtain

$$\tau_n = \frac{\tau+1}{2}$$



Detected sequence: 7, 5, 6, 9 
$$\#con = 4, \#dis = 2$$
  $\tau = \frac{1}{3}$ 

■ We obtain

$$\tau_n = \frac{\tau + 1}{2} = \frac{1/3 + 1}{2}$$



Detected sequence: 7, 5, 6, 9 
$$\#con = 4, \#dis = 2$$
  $\tau = \frac{1}{3}$ 

We obtain

$$\tau_n = \frac{\tau+1}{2} = \frac{1/3+1}{2} = \frac{4/3}{2}$$


Detected sequence: 7, 5, 6, 9 
$$\#con = 4, \#dis = 2$$
  $\tau = \frac{1}{3}$ 

We obtain

$$au_n = rac{ au+1}{2} = rac{1/3+1}{2} = rac{4/3}{2} = rac{2}{3}$$

#### Model architecture

Hidden Hidden Hidden Output Input layer layer layer layer layer  $I_1$  $H_1$  $H_1$  $H_1$  $I_2$  $I_3$  $O_1$  $\overset{\bullet}{H_{64}}$  $H_{256}$  $H_{256}$  $I_F$ 

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### Model input/output



The input is a matrix whose rows correspond to feature representations of cuts



- The output of the model is a score vector
- We then choose the cut with highest score

# Training data format

raining data	format					SURG
# name	page num	width,height	subpage	depth	dir	5
example.pdf	42	612,796	0,0,360,640	2	Χ	
# cut	left/upper s	emantic roles	right/lower set	mantic roles	label	
([530, 550], <b>Y</b> )	heading		paragraph		1	
([270, 290], <b>Y</b> )	paragraph		paragraph		0	
([170, 175], <b>X</b> )	-		-		0	
example.pdf	43	612,796	0,0,612,796	1	-	
([720,740], <b>Y</b> )	marginal		heading,parag	raph	0	
([680, 685], <b>Y</b> )	-		-		0	
([420, 430], <b>Y</b> )	table,parage	raph	formula, capti	on	0	
([296, 316], <b>X</b> )	heading,tab	le,caption	marginal,parag	graph,formula	1	

October 20, 2021

#### PdfAct comparison



	$B_G^=$	$B_A^{=}$	$B_G^+$	$B_A^-$	$ au_n$	$ au_n^f$
Thesis	51.4%	46.7%	12.9%	14.7%	0.873	0.994
PdfAct	66.5%	54.3%	10.1%	7.5%	0.859	0.985

### Full reading order results

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7 🕼	
9. BU 🕅	m
	<b>– 2</b> Ш
	<b>~</b> ~

.

strategy	$ au_n$	$ au_n^f$
Largest cut	0.872	0.993
Weighted-largest cut	0.863	0.983
Parameter cut	0.865	0.984
LogisticRegressor	0.873	0.994
BatchClassifier	0.872	0.992
Transformer	0.860	0.978
PdfAct	0.859	0.985

# XY-cut limitations for reading order





■ Wang et al.'s LayoutReader shows a way to overcome these limitations