Large-scale Analysis and Comparison of Web Page Segmentation Approaches

Defense of Master's Thesis

Lars Meyer

January 28th, 2020

Watertown Daily Times
Serving the communities of Jefferson, St. Lawrence and Lewis counties, New York
In print daily. Online always.

"Bitten by Magic" by Kelly Ashley published today

By SEAN EWART
PUBLISHED: SATURDAY, SEPTEMBER 7, 2013 AT 4:30 AM

"Bitten by Magic," the second book in Kelly M. Ashley's Sisters of Fate series, is out today.

A follow up to her fantasy romance novel, "The Fur Flies," which was released in May, Mrs. Ashley's new book centers on the passion of Alexa, a witch, and Wilhelm, a vampire.

In "Bitten by Magic" Alexa is required to marry Wilhelm in order to settle a dispute.

"It's a paranormal romance," Mrs. Ashley, who writes under the pen name Kelliea Ashley, said. "If anybody likes the witches and the vampires and the werewolves that's what it is."

But Mrs. Ashley cautioned, "It's not 'Twilight,'" referring to the popular book and movie series. "My vampires don't sparkle."

Born in Gouverneur, Mrs. Ashley currently lives in Ogdensburg and said she draws inspiration from the north country as settings for her novels.

"All of my books have a north country feel," she said. "Even with the vampires and werewolves."

Mrs. Ashley said she originally intended to write the Sisters of Fate series as a trilogy, but was pushed by her editor at Breathless Press to explore the characters further and extend it.

"It's open ended," she said, so readers can expect more tales of forbidden love between witches, vampires and werewolves.

Mrs. Ashley said she has been writing since she was 13 but it was her husband, Joshua, who finally convinced her to find a publisher for her novels in 2012.

Her latest book is available as an e-book at breathlesspress.com, amazon.com, allromanceebooks.com, Apple I-Books and bookstrand.com.

"As long as [people] read them and get away from their everyday life, that's what I'm shooting," Mrs. Ashley said. "I'm not looking to get rich; I'm just looking to put my work out there."

Related Stories
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What is a segment?

"A segment is a part of a web page
containing the elements that belong together...

... visually,
semantically,
and in purpose."

Use cases

- accessibility enhancements
  - enhanced screen readers
    e.g.: Michael Cormier et al., "Towards an improved vision-based web page segmentation algorithm", 2017
  - adaptation to small screens
    e.g.: Shumeet Baluja, "Browsing on small screens: recasting web-page segmentation into an efficient machine learning framework", 2006
  - …
- information retrieval
  - content summarization
    e.g.: Chitra Pasupathi et al., "Web document segmentation using frequent term sets for summarization", 2012
  - page classification/ranking
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Approaches

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Visual	Cormier et al.	Web page	Cormier et al., "Purely vision-based segmentation of web pages for assistive technology", 2016
	MMDetection	Photo	Chen et al., "MMDetection: Open mmlab detection toolbox and benchmark", 2019
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Evaluation setup

Webis Web Segments 2020

- first crowd-sourced dataset for Web Page Segmentation

Kiesel et al., "Web Page Segmentation from First Principles", 2020

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  $\longrightarrow$ 42450 human segmentations

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- 8490 pages, 5 annotators per page
  ⟶ 42450 human segmentations
- Fusion of human segmentations for page based on area agreement ⟶ ground truth

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Evaluation metrics

Segments are regarded as **clusters of atomic elements**:

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$\longrightarrow$ *Precision* (P_{B^3}), *Recall* (R_{B^3}) and *F-score* (F_{B^3}) can be calculated between two segmentations

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$\longrightarrow$ different atomic elements cover variety of algorithm performance aspects

Kiesel et al., "Web Page Segmentation from First Principles", 2020

Terms

Precision: how many of the elements in an **algorithm segment** also belong to *one* segment in the ground truth?

Recall: how many of the elements in a **ground truth segment** are grouped *together* in *one* algorithm segment?

F-score: harmonic mean of precision and recall

Consistency and reproducibility

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- *Webis Web Segments 2020* based on *Webis Web Archive 17*

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⟶ Contribution: TypeScript/JavaScript port of VIPS

CSSBox (VIPS-Java)

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Safari

Summary: Methodology

Summary: Methodology

Webis Web Archive 17

Summary: Methodology

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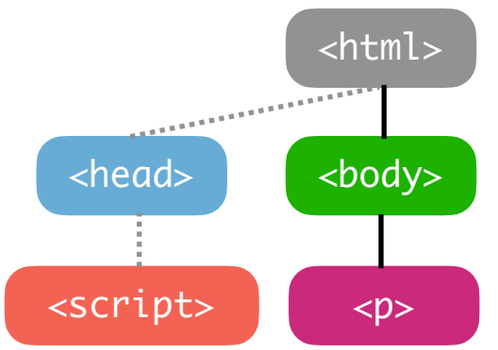
algorithm →

```
{
"id":000000,
"width":1366,
"height":750,
"segmentations":
{
"single":[[[[0,0],
[0,750],[1366,750],
[1366,0],[0,0]]]]
}
}
```

JSON

Summary: Methodology



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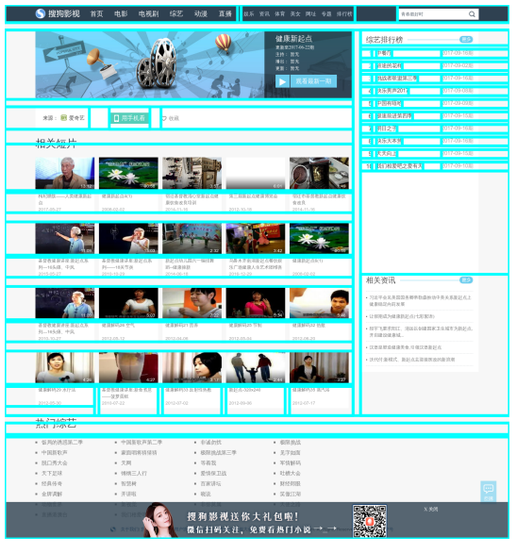
JSON

algorithm
segmentation



ground truth

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algorithm
segmentation

ground truth

P_{B^3}

R_{B^3}

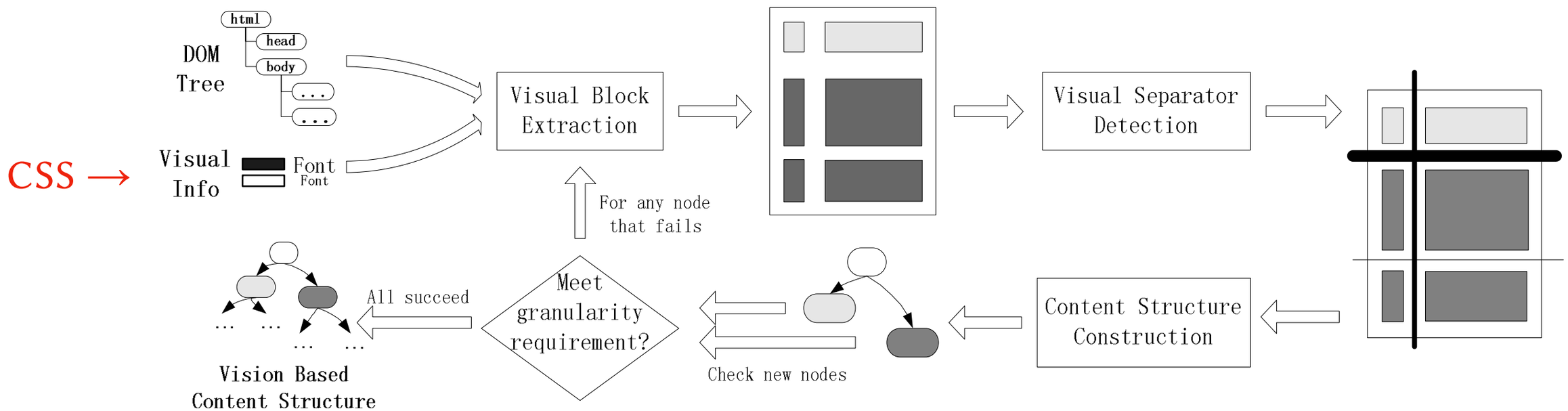
F_{B^3}

Approaches, Evaluations and Results

Overview

1. Evaluation of all algorithms + single-segment baseline against the ground truth
2. Parameter analyses: VIPS and Cormier et al.
3. Visual/hybrid segmentations fit to DOM nodes
4. Cross-evaluation (algorithm similarity)
5. *Min-vote* ensemble (combining algorithm segmentations)

DOM-only approach: VIPS



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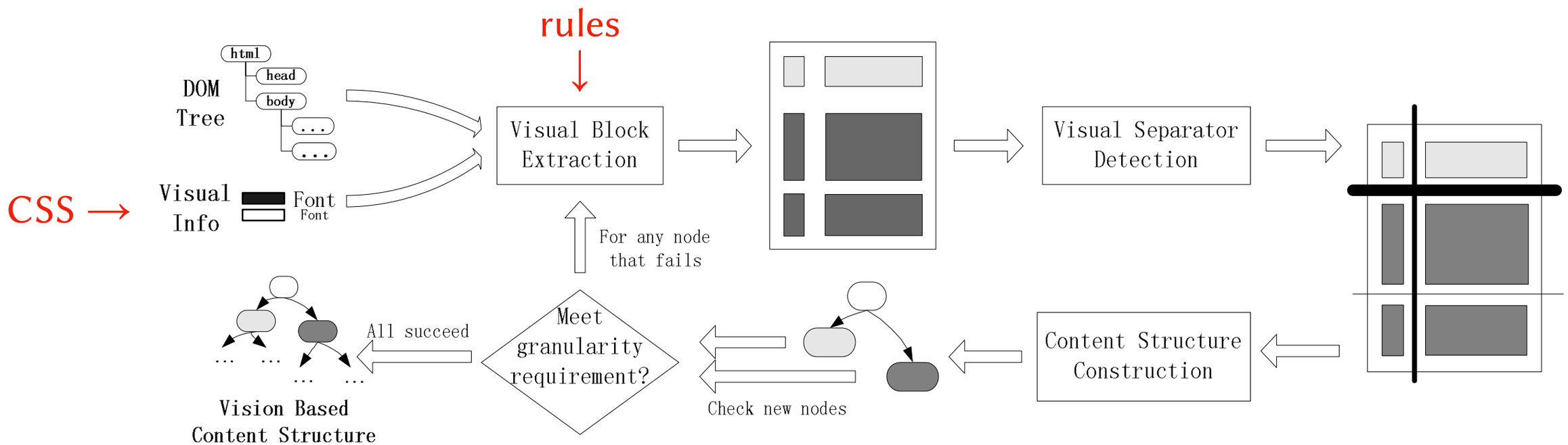

- fixed set of rules down to element level

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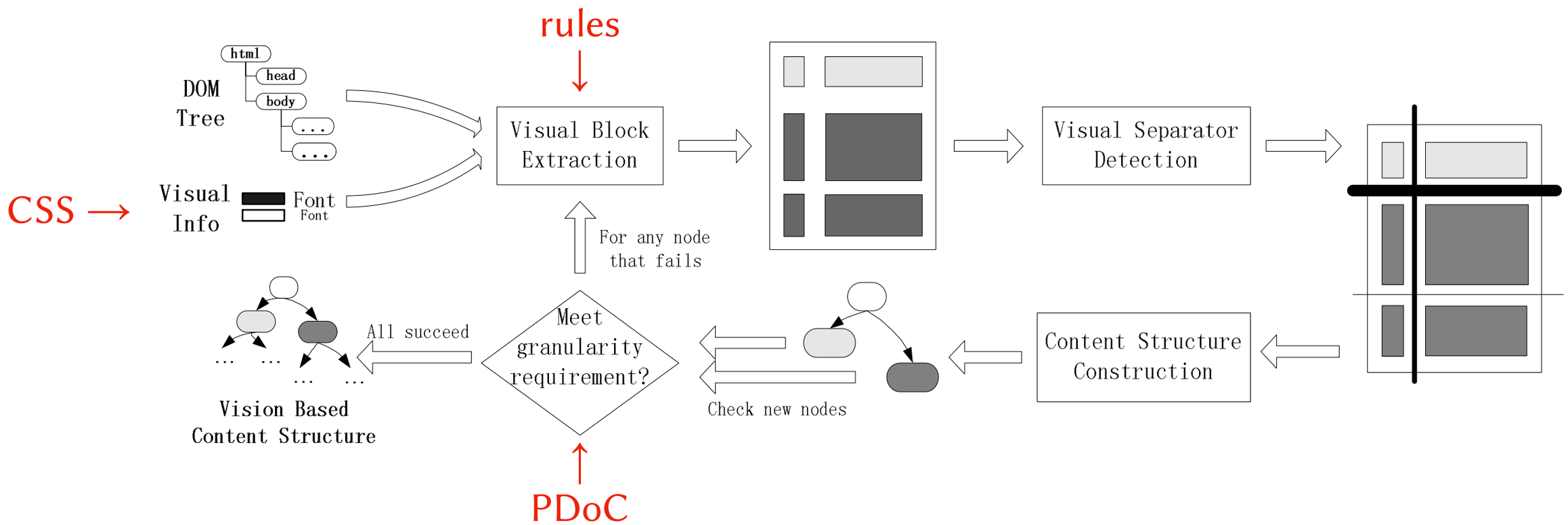

- fixed set of rules down to element level
- *Permitted Degree of Coherence* (PDoC) influences granularity

Deng Cai, Shipeng Yu, Ji-Rong Wen, Wei-Ying Ma,
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Results: VIPS

		pixels			*characters*		
PDoC	*# segments*	P_{B^3}	R_{B^3}	F_{B^3}	P_{B^3}	R_{B^3}	F_{B^3}
8	**80.2**	0.46	0.36	0.32	**0.93**	0.41	0.50
5	13.5	0.35	0.70	0.38	0.74	0.76	0.68
Δ	- 66.7	- 0.11	+ 0.34	+ 0.06	- 0.19	+ 0.35	+ 0.18

- oversegmentation (ground truth: 9.1 segments)

Results: VIPS

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- oversegmentation (ground truth: 9.1 segments)

$\longrightarrow$ high precision, low recall, low F-score

Results: VIPS

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Reason:

- PDoC > 6 applies rules targeting specific element types

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$\longrightarrow$ outdated, detrimental to segmentation quality

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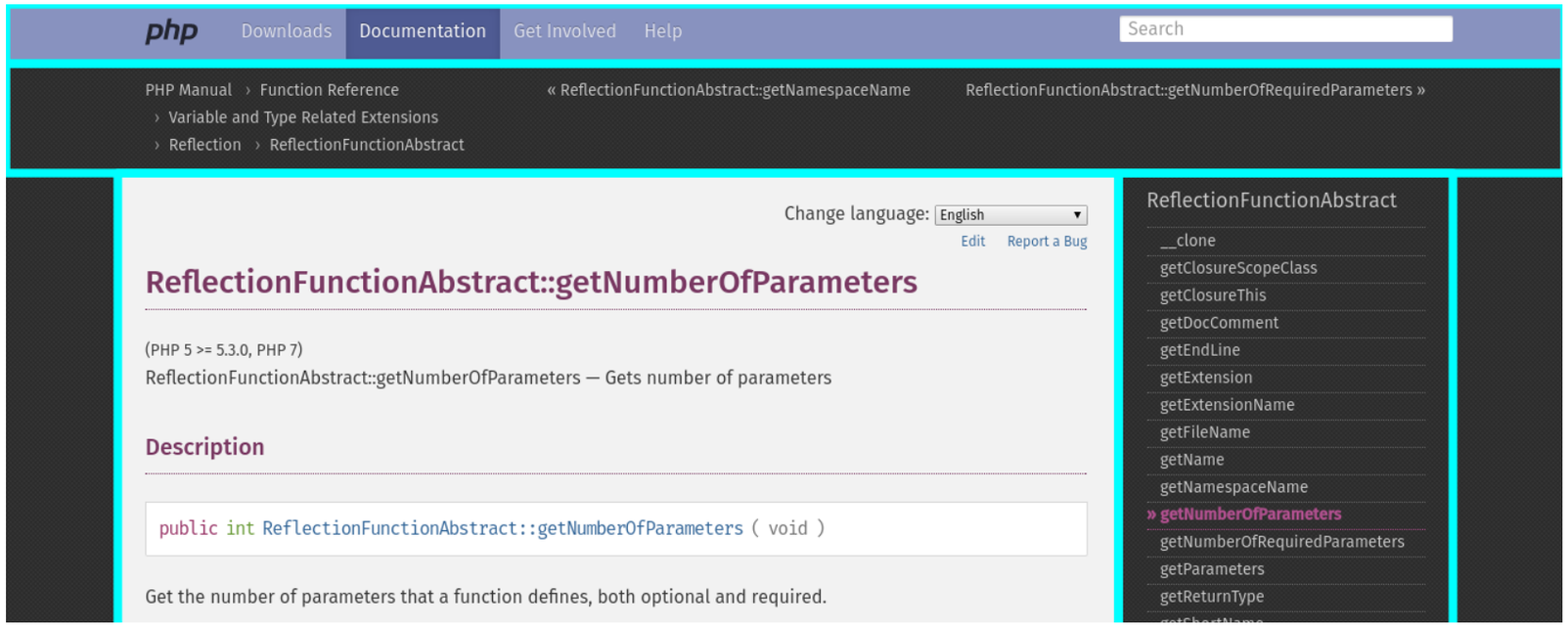

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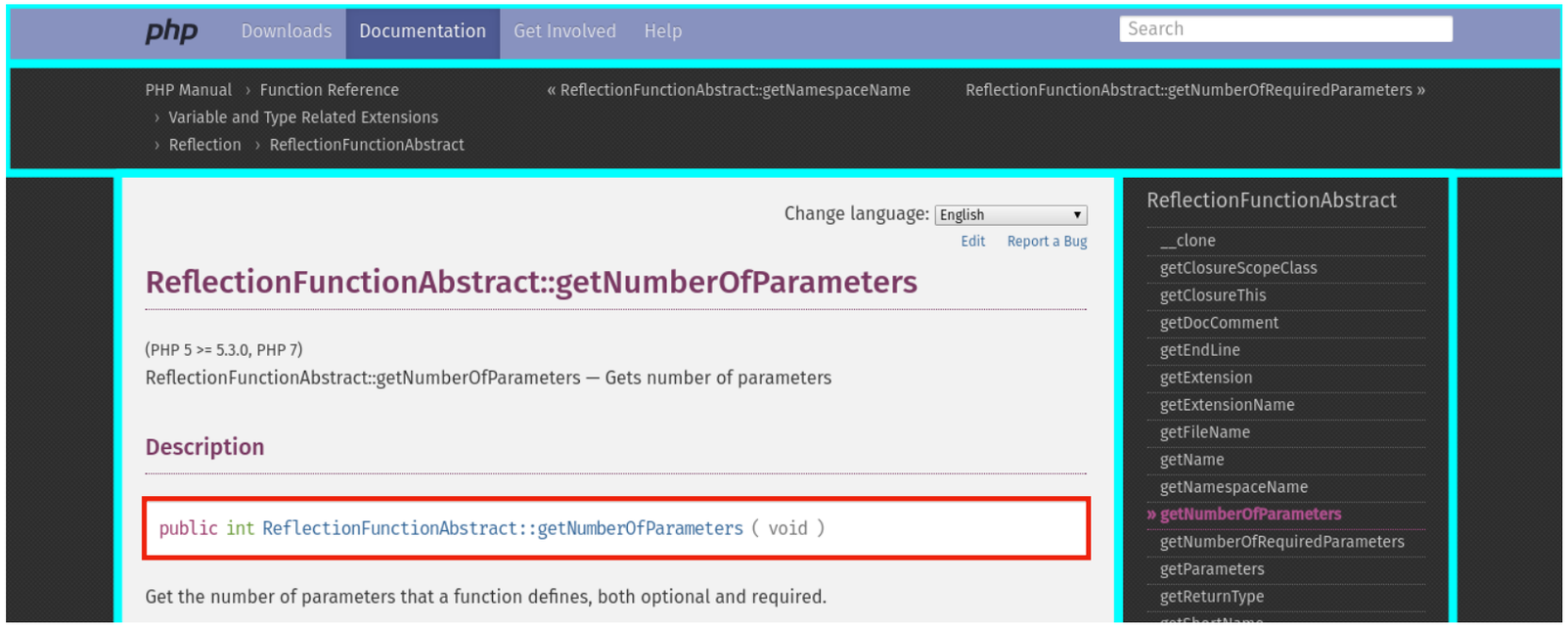

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PDoC 5:

- applied rules target only coarse page divisions

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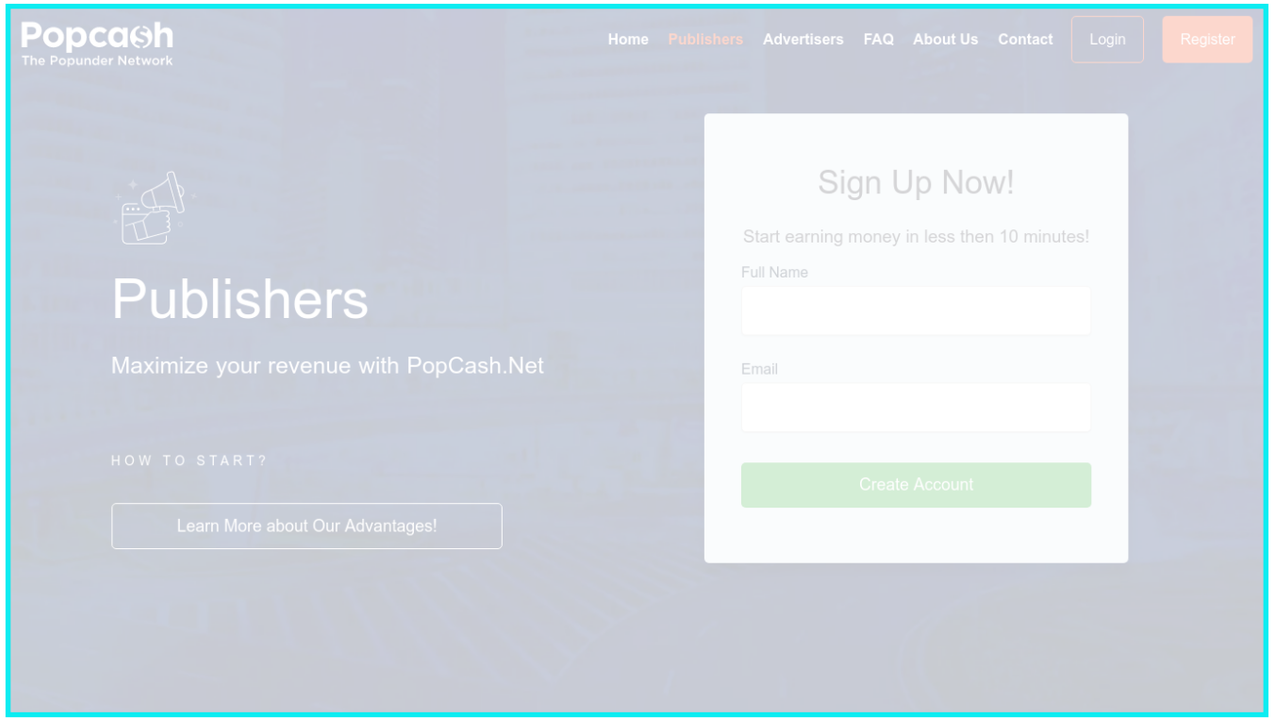
$\longrightarrow$ **VIPS (PDoC 5) is best single algorithm**

PDoC 8

PDoC 5

ground truth

Visual approach: Cormier et al.



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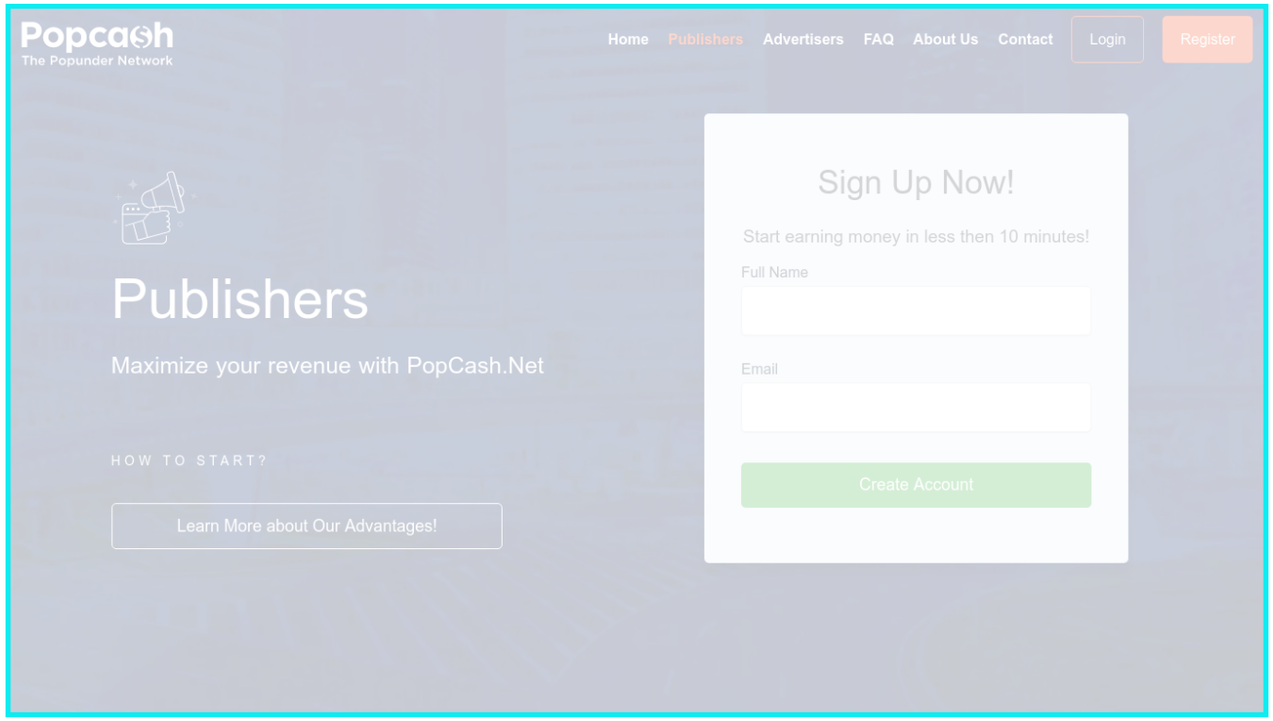

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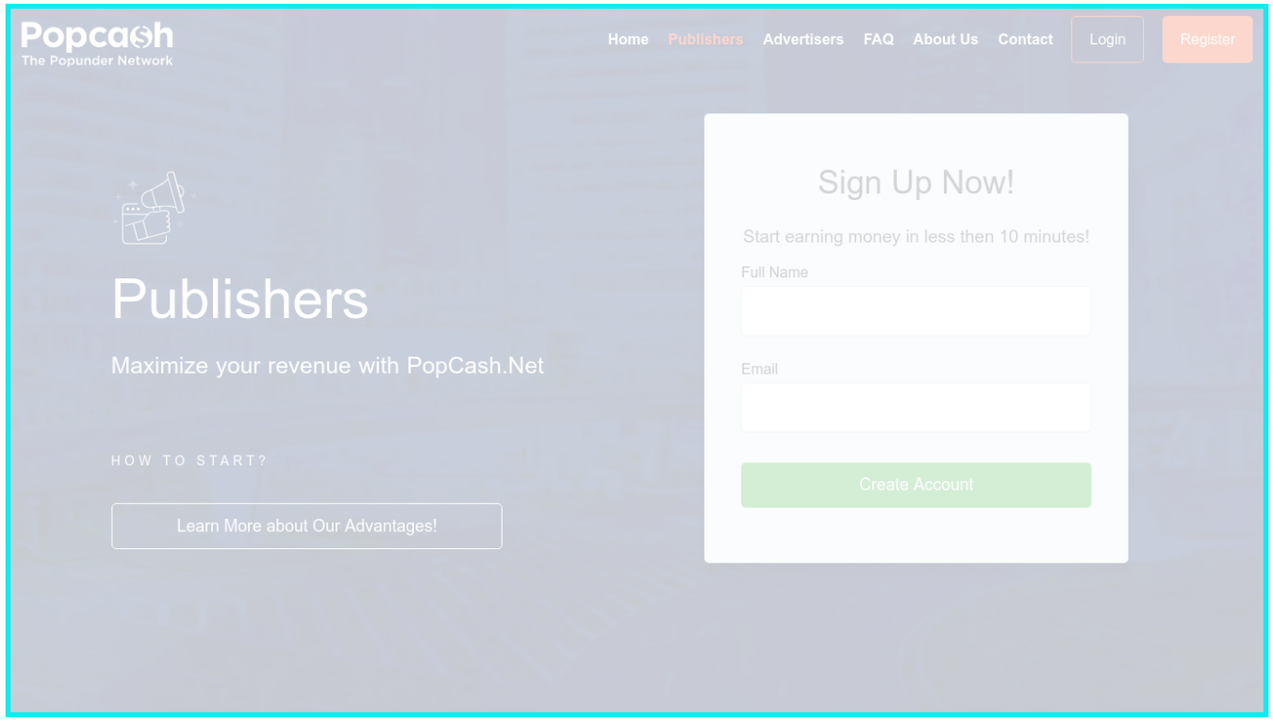

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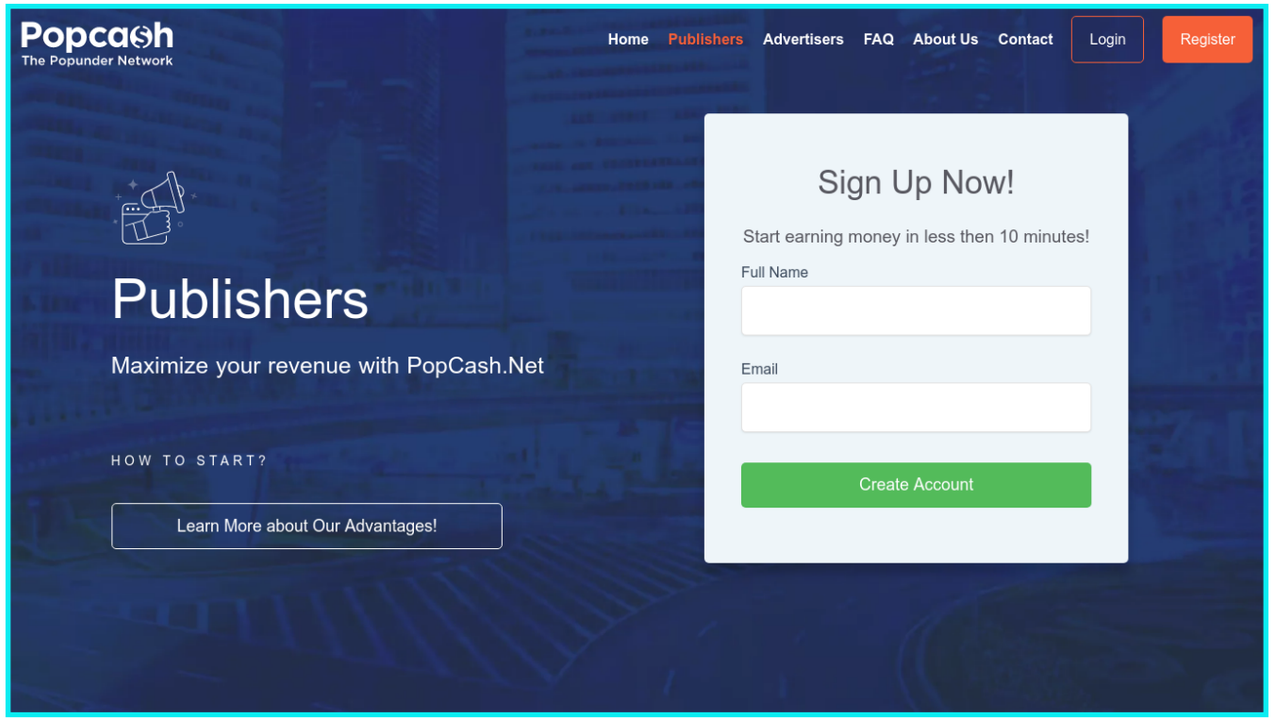

Visual approach: Cormier et al.

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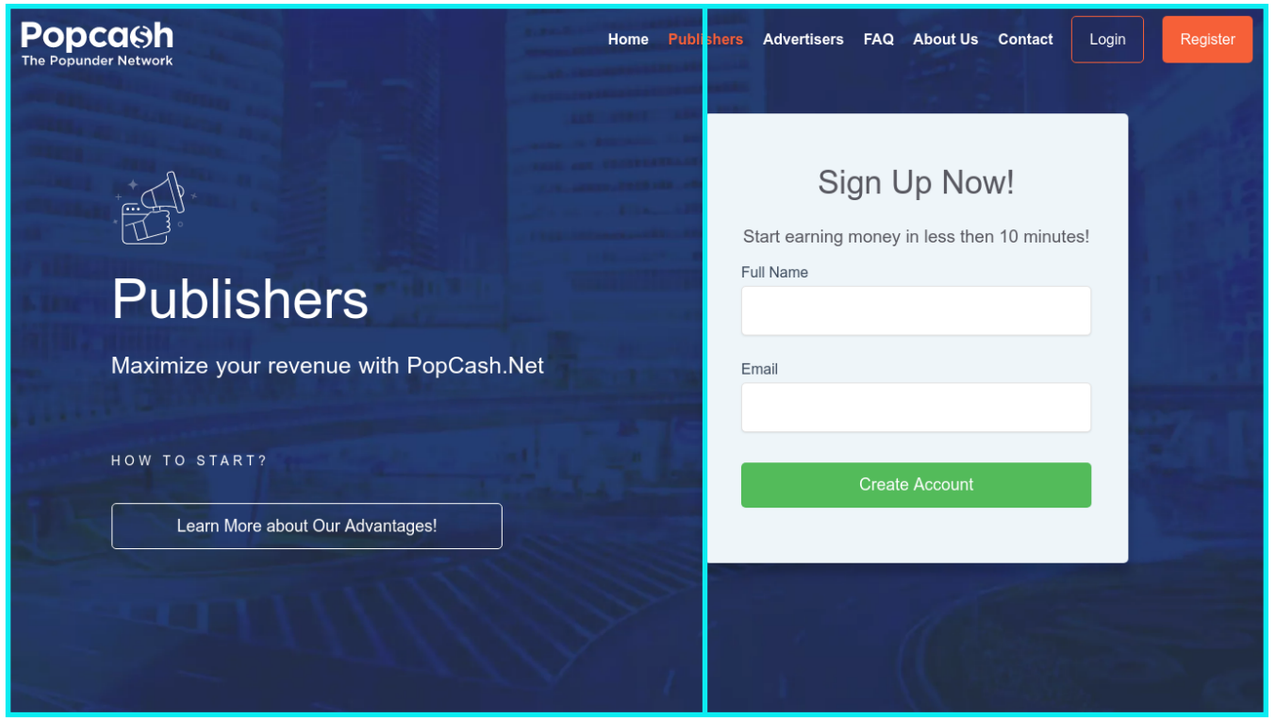

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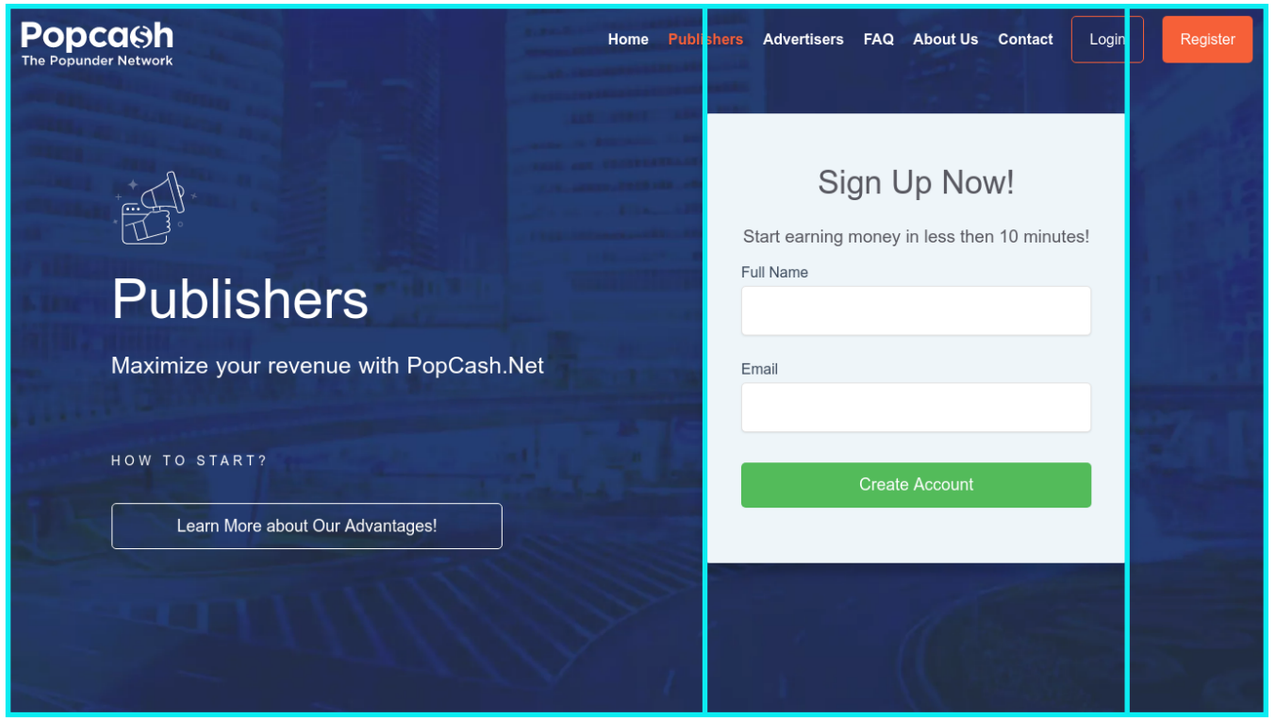

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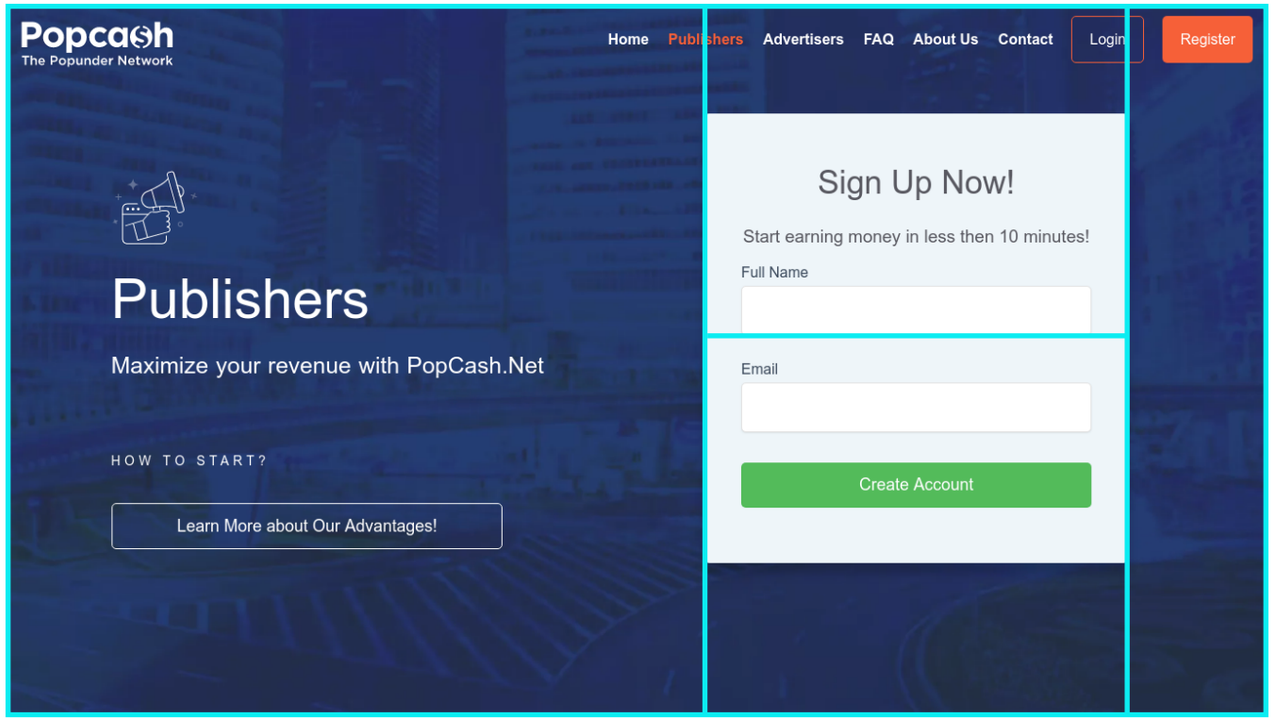

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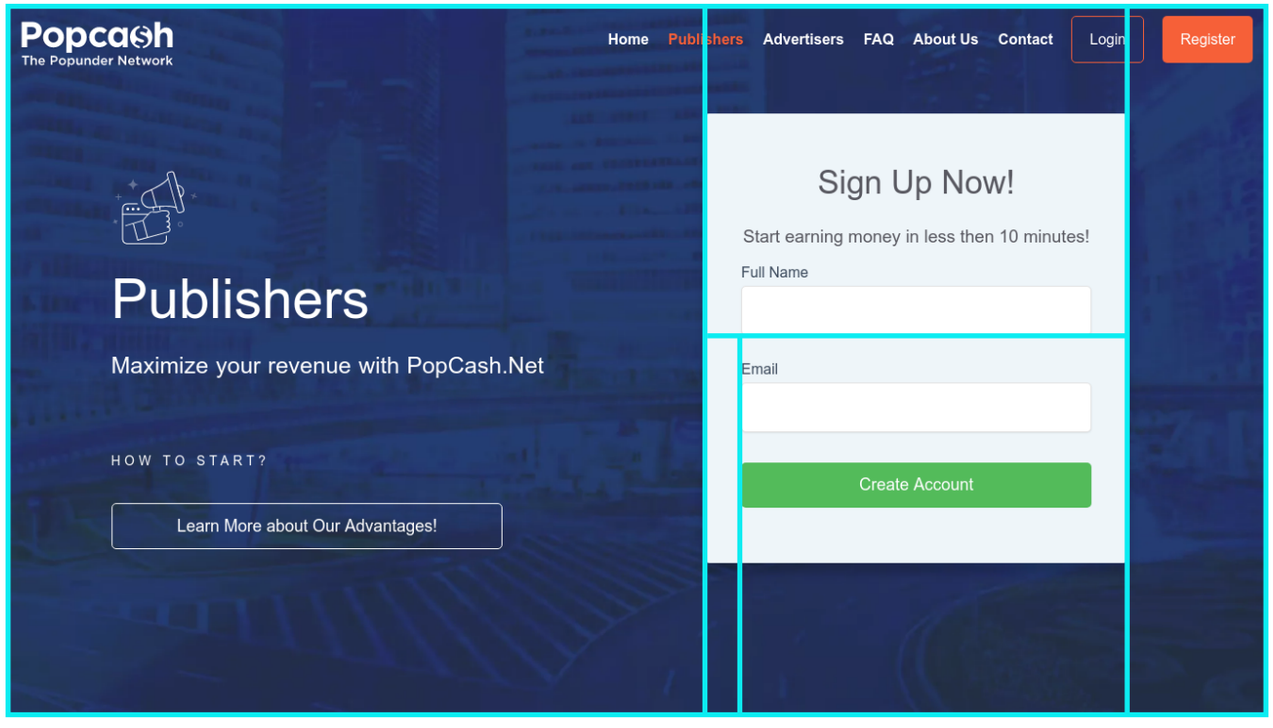

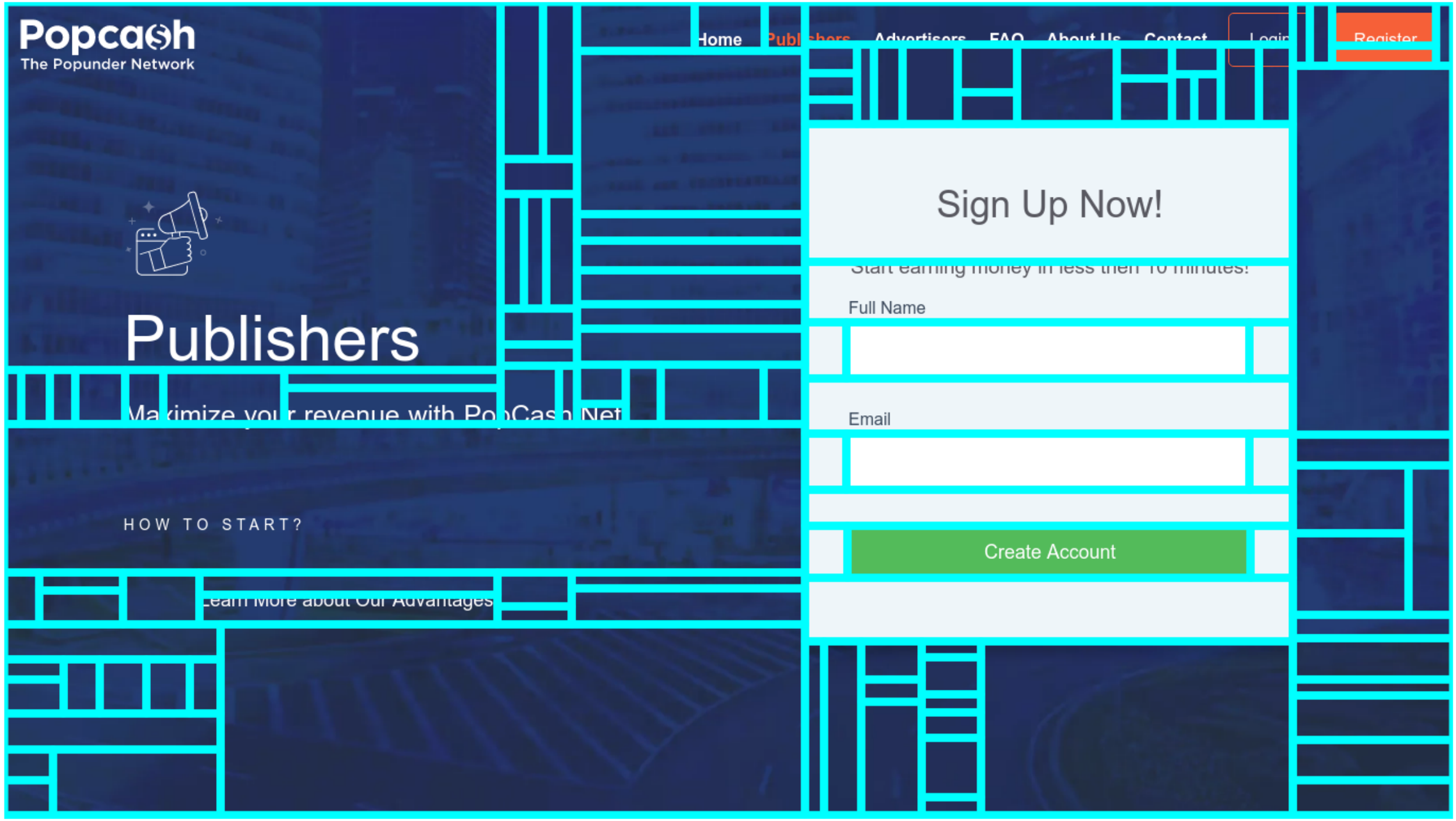

Cormier et al.

$(s_{min} = 45,\ t_l = 512)$

Results: Cormier et al.

			pixels			*characters*		
	Parameters	*# segments*	P_{B^3}	R_{B^3}	F_{B^3}	P_{B^3}	R_{B^3}	F_{B^3}
(worst)	s_{min} = 90 px t_l = 256 px	18.4	0.29	0.86	0.35	0.60	0.87	0.63
(best)	s_{min} = 45 px t_l = 512 px	**38.0**	0.34	0.77	**0.36**	0.67	0.78	0.62
	Δ	+ 19.6	+ 0.05	- 0.09	+ 0.01	+ 0.07	- 0.09	- 0.01
	VIPS (PDoC 5)	13.5	0.35	0.70	0.38	0.74	0.76	0.68

Primary observations:

- Purely visual approach comes close to VIPS' performance

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Primary observations:

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- but: needs more than **3x** segment count to come close

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Primary observations:

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- but: needs more than **3x** segment count to come close

$\longrightarrow$ expresses fundamentally different operation (visual vs. DOM-based)

Results: Cormier et al.

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	Parameters	*# segments*	P_{B^3}	R_{B^3}	F_{B^3}	P_{B^3}	R_{B^3}	F_{B^3}
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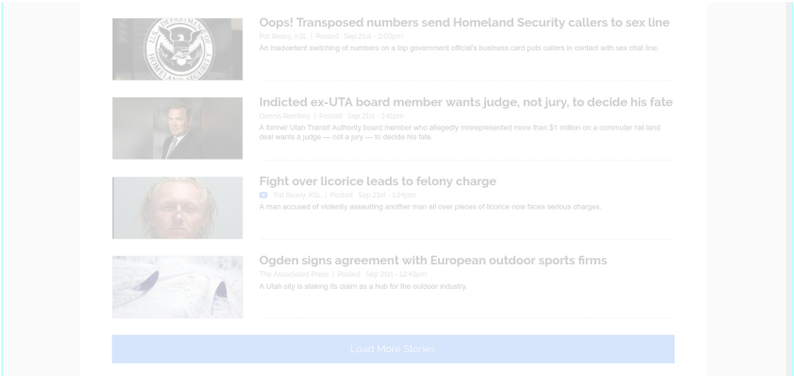
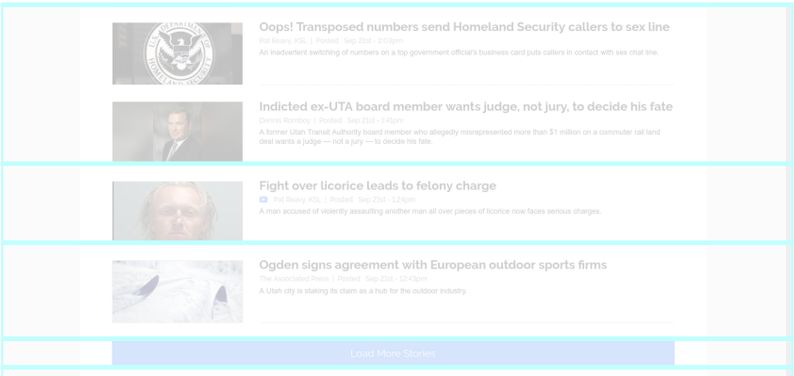
Parameters:

- t_l (max. line length for probability estimation) $\in \{256, 512\}$ px
- increasing t_l finds extended lines across larger gaps



(a) $s_{min} = 45, t_l = 256$ px



(b) $s_{min} = 45, t_l = 512$ px

Results: Cormier et al.

			pixels			*characters*		
	Parameters	*# segments*	P_{B^3}	R_{B^3}	F_{B^3}	P_{B^3}	R_{B^3}	F_{B^3}
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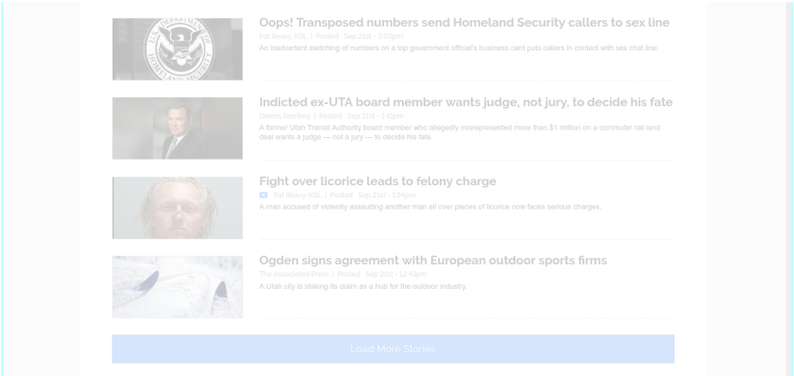

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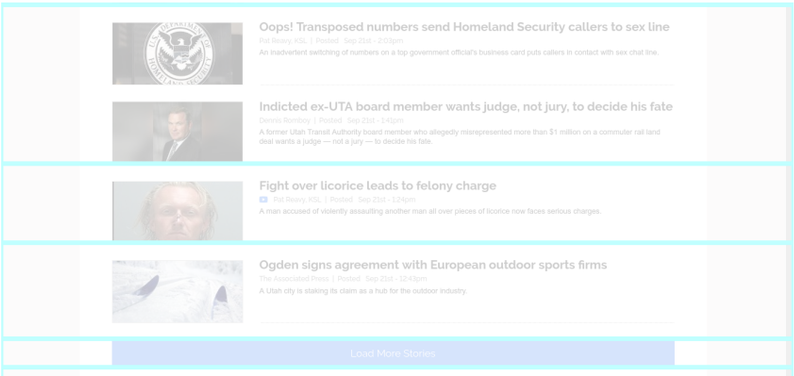

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Results: Cormier et al.

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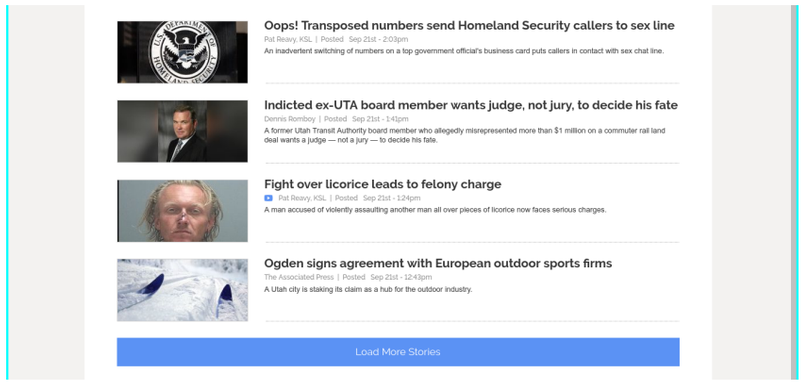

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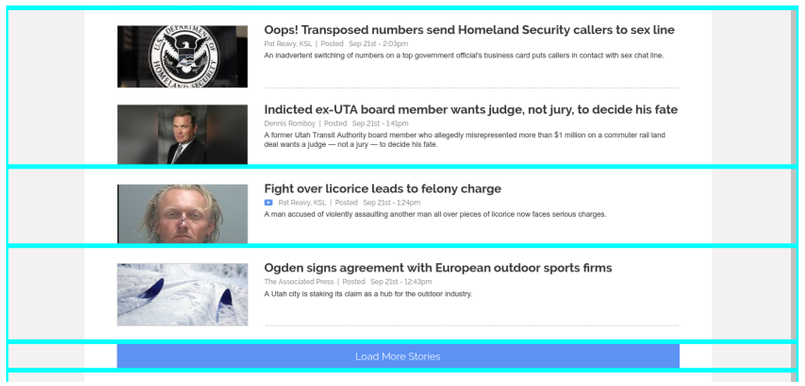

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Results: Cormier et al. - DOM fitting

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- primary culprit: blank space
- correct segmentation of blank space important for some uses (e.g. design mining), irrelevant for others (e.g. text extraction tasks)
- can be somewhat mitigated by *fitting to DOM nodes*

Results: Cormier et al. - DOM fitting

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- human segmentations are fit to DOM nodes (containment threshold θ_c = 0.75)

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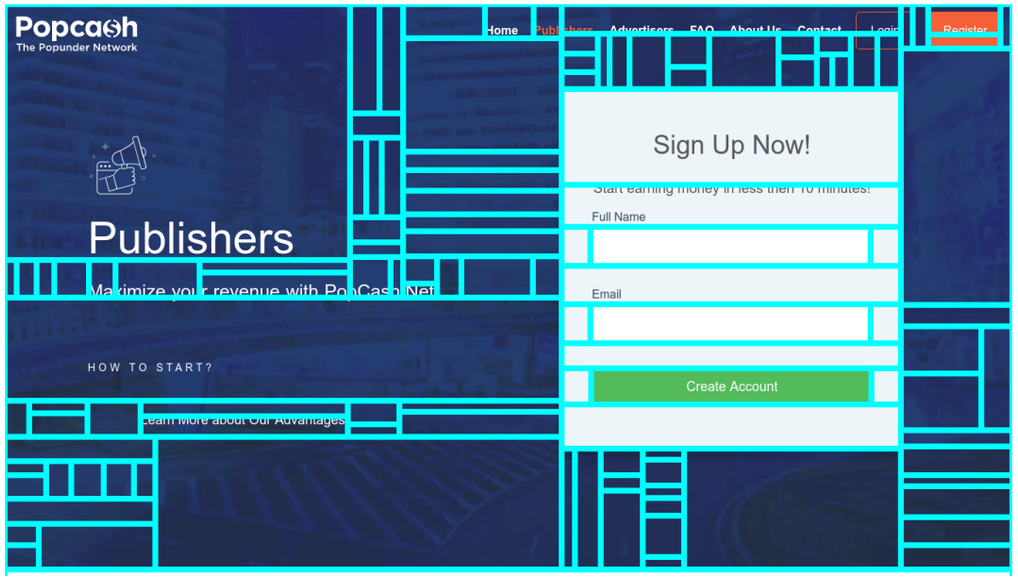
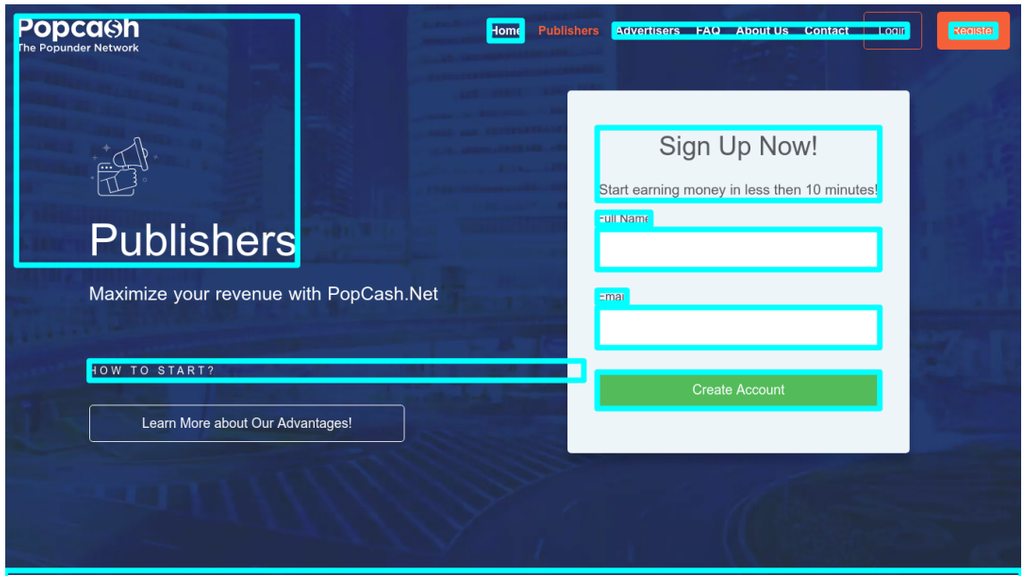
$\longrightarrow$ fair treatment: fit visual/hybrid algorithms to DOM nodes, too

DOM fitting: example



original



fitted

Results: Cormier et al. - DOM fitting

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- Reduced oversegmentation **and** increased precision (*pixels*) and recall (*characters*)

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- Reduced oversegmentation **and** increased precision (*pixels*) and recall (*characters*)

$\longrightarrow$ F_{B^3} matches VIPS for *pixels* and comes closer for *characters*

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$\longrightarrow$ transfer to Web Page Segmentation possible?

Results: MMDetection

		pixels			*characters*		
Variant	*# segments*	P_{B^3}	R_{B^3}	F_{B^3}	P_{B^3}	R_{B^3}	F_{B^3}
original	**252.2**	0.47	0.41	0.33	0.80	0.44	0.48
fitted	14.7	0.67	0.38	0.35	0.80	0.54	0.56
Δ	- 237.5	+ 0.20	- 0.03	+ 0.02	-	+ 0.10	+ 0.08
VIPS (PDoC 5)	13.5	0.35	0.70	0.38	0.74	0.76	0.68

- Real-world image segmentation does not directly transfer well

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- Real-world image segmentation does not directly transfer well
- *massive* oversegmentation

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Reasons:

Results: MMDetection

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Reasons:

- segmenting real-world objects found in images on web pages
- neural network model not trained on web pages

Results: MMDetection - DOM fitting

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- **94.2%** reduction in segment count
- **best precision** for *pixels* across all single algorithms
- F_{B^3} approaches VIPS for *pixels*

Further experiments

Algorithm cross-evaluation

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- F_{B^3} expresses segmentation *similarity*
  (interpreted as quality when comparing to ground truth)

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F_{B^3}	S			
S^*	**VIPS**	**HEPS**	**Cormier**	**MMDet.**
VIPS	1.00	0.41	**0.51**	0.31
HEPS	0.41	1.00	0.50	0.31
Cormier	**0.51**	0.50	1.00	0.37
MMDet.	0.31	0.31	0.37	1.00

pixels

F_{B^3}	S			
S^*	**VIPS**	**HEPS**	**Cormier**	**MMDet.**
VIPS	1.00	0.48	**0.60**	0.41
HEPS	0.48	1.00	0.43	0.36
Cormier	**0.60**	0.43	1.00	0.40
MMDet.	0.41	0.36	0.40	1.00

characters

Min-vote ensemble

- Applying segmentation fusion (used in ground truth creation) to algorithm segmentations

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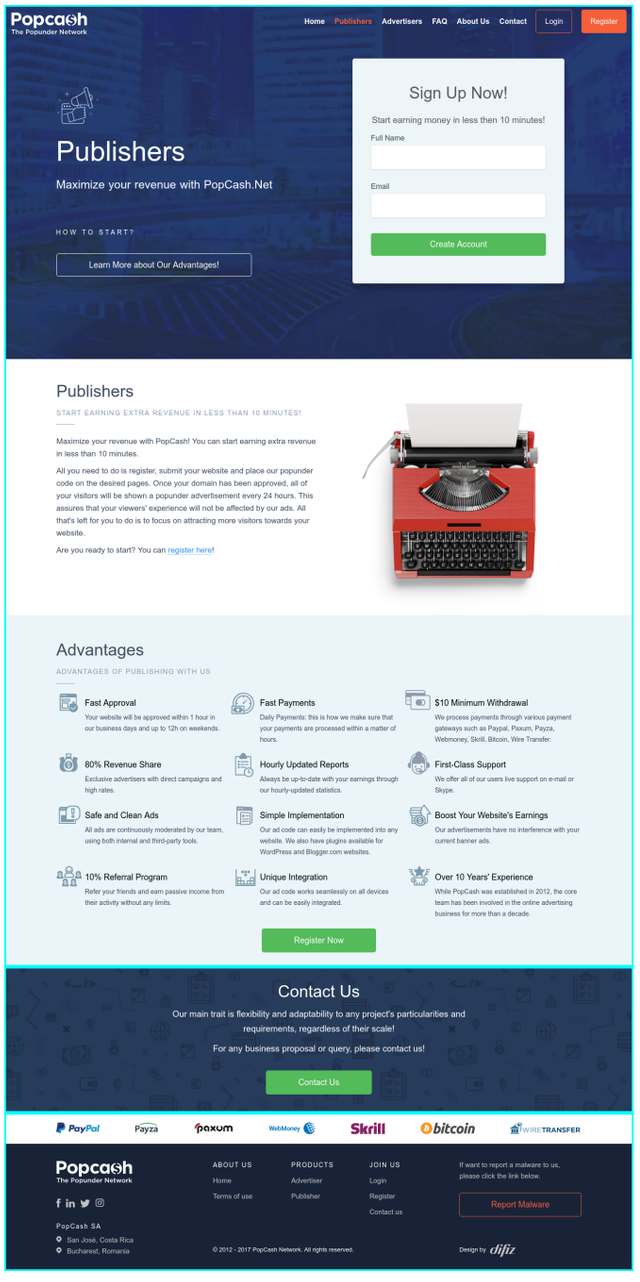
- *Min-vote@n*, $n \in [1, 2, 3, 4]$ = number of algorithm segmentations that put a given element in a segment
- Initially evaluated for paper with unoptimized parameters
- now: optimized parameters, fitted segmentations $\longrightarrow$ what improvements do we see?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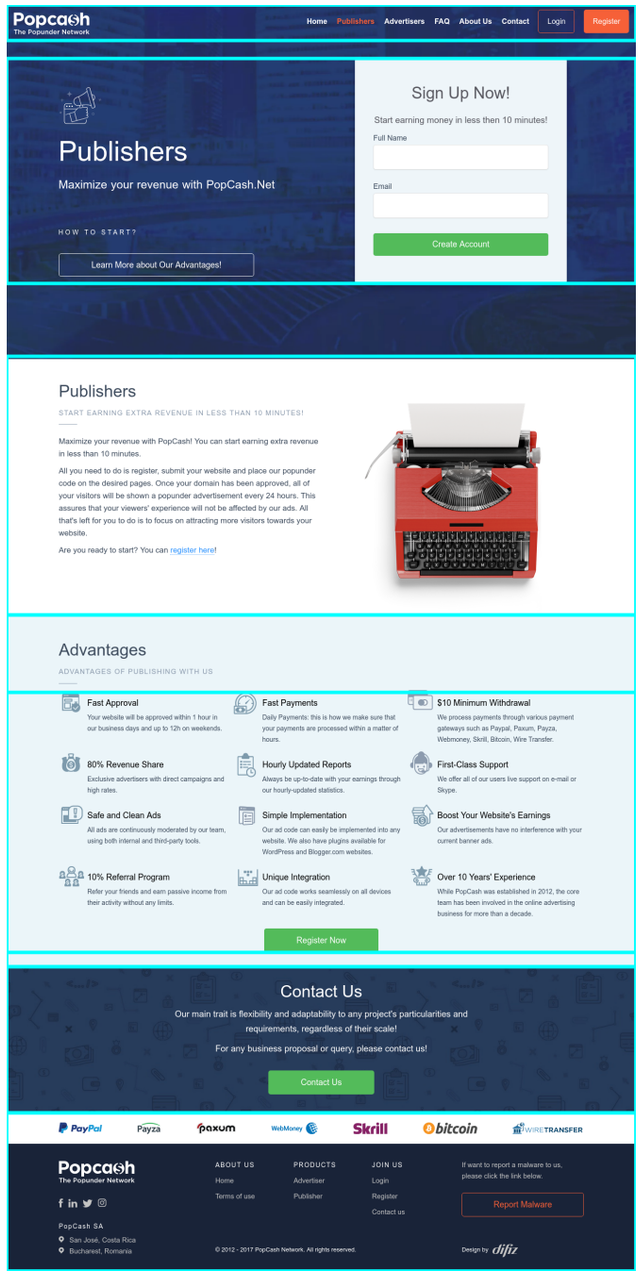
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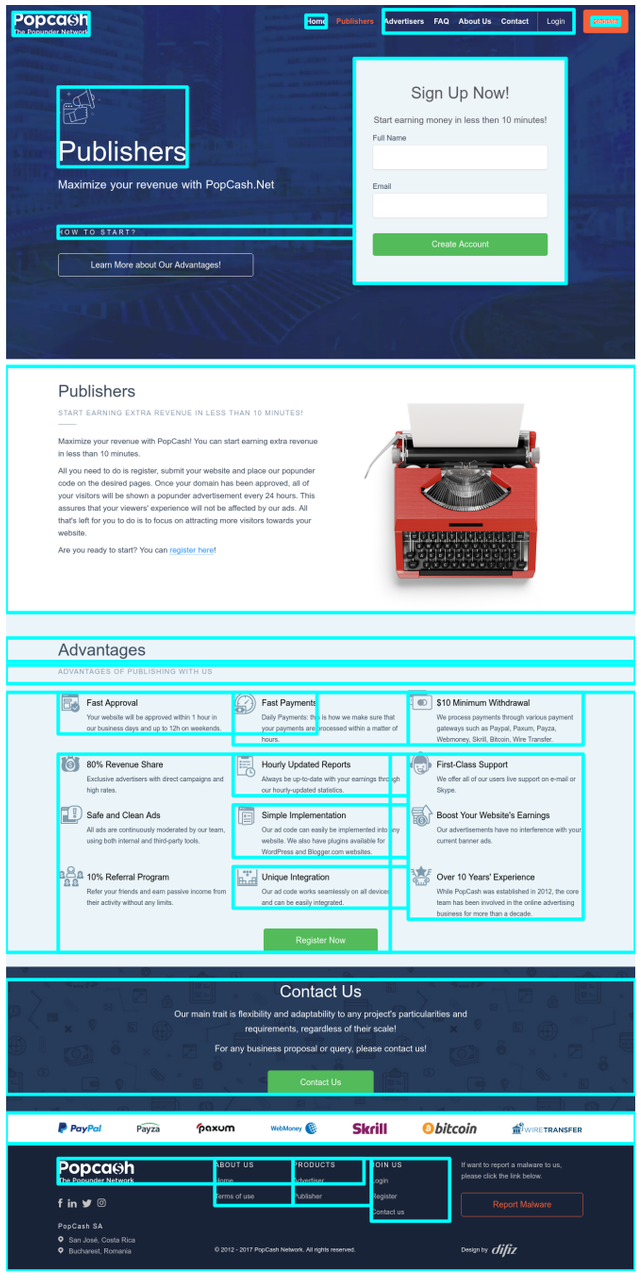
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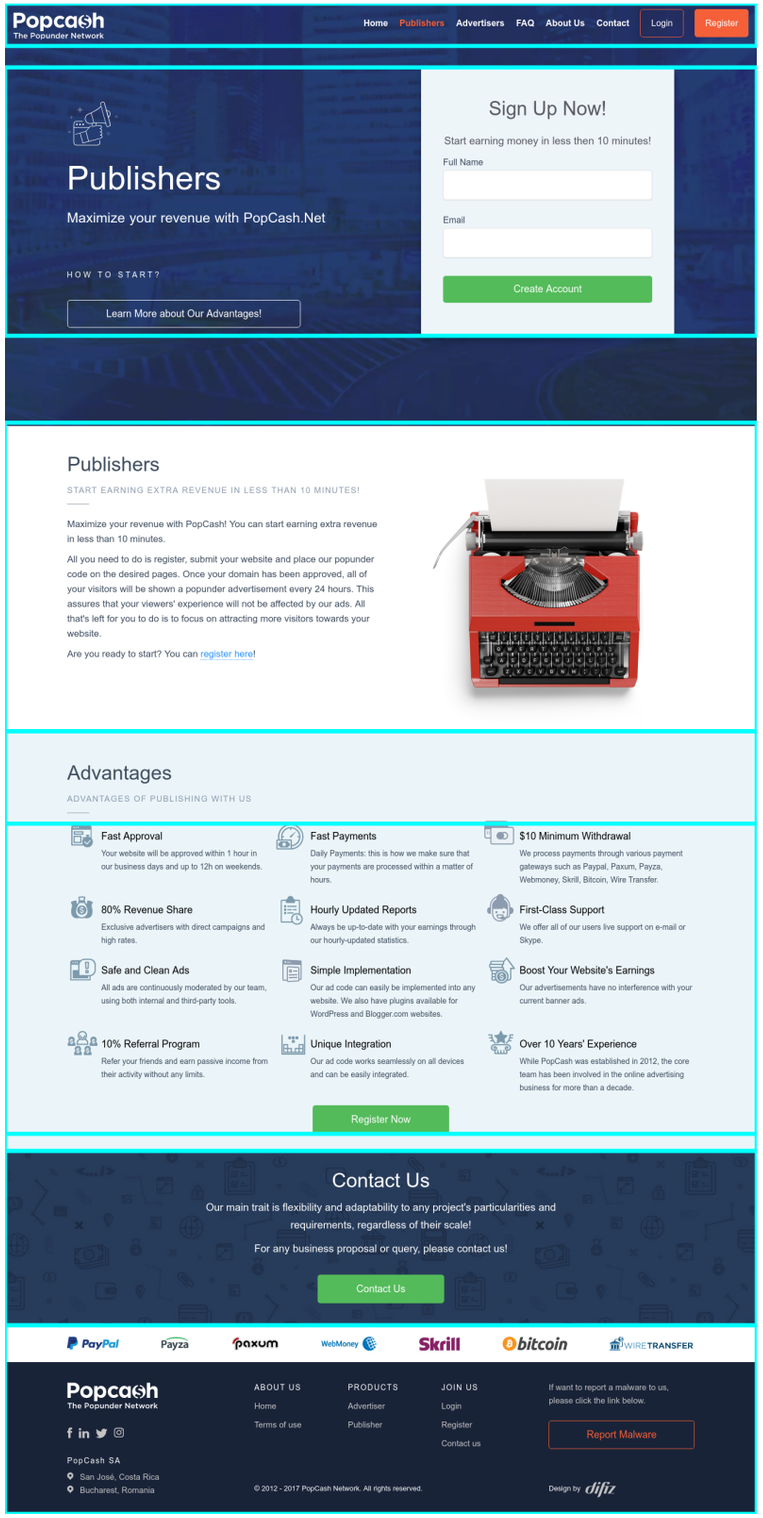

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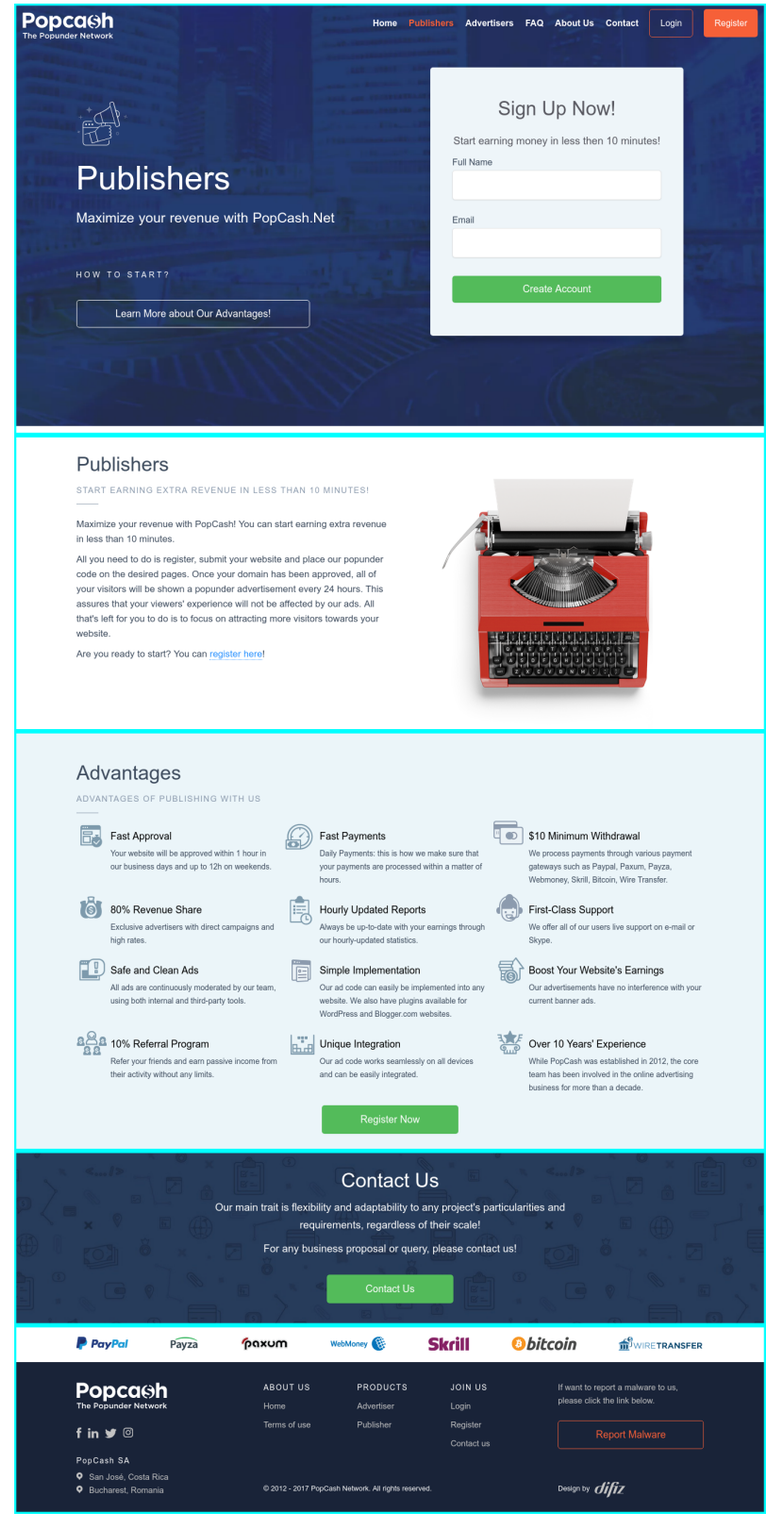

ground truth

Results: *Min-vote* ensemble

		pixels			*characters*		
Variant	*# segments*	P_{B^3}	R_{B^3}	F_{B^3}	P_{B^3}	R_{B^3}	F_{B^3}
unoptimized $n = 2$	32.9	0.39	0.64	0.38	0.76	0.68	0.65
optimized $n = 2$	16.0	0.37	0.77	**0.40**	0.71	0.80	**0.69**
Δ	- 16.9	- 0.02	+ 0.13	+ 0.02	- 0.05	+ 0.12	+ 0.04
VIPS (PDoC 5)	13.5	0.35	0.70	0.38	0.74	0.76	0.68

- influence of optimized parameters and **fitting**

Results: *Min-vote* ensemble

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- influence of optimized parameters and **fitting**
- segment count cut in half, only minor losses in precision
- **Min-vote@2** beats VIPS, provides **best overall results**

Summary - Ranking

		pixels			*characters*		
Approach / Variant	*# segments*	P_{B^3}	R_{B^3}	F_{B^3}	P_{B^3}	R_{B^3}	F_{B^3}
Min-vote@2 (optimized)	16.0	0.37	**0.77**	**0.40**	0.71	**0.80**	**0.69**
VIPS (PDoC 5)	13.5	0.35	0.70	**0.38**	0.74	0.76	**0.68**
Cormier et al. (s_{min} = 45 px, t_l = 512 px, **fitted**)	16.8	0.42	**0.77**	**0.38**	0.68	**0.81**	0.65
MMDetection (**fitted**)	14.7	**0.67**	0.38	0.35	**0.80**	0.54	0.56
HEPS	35.8	0.39	0.54	0.32	0.72	0.50	0.50
Meier et al. (**fitted**)	7.0	0.56	0.39	0.26	0.66	0.48	0.42

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		pixels			*characters*		
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Summary - Ranking

		pixels			*characters*		
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		pixels			*characters*		
Approach / Variant	*# segments*	P_{B^3}	R_{B^3}	F_{B^3}	P_{B^3}	R_{B^3}	F_{B^3}
Min-vote@2 (optimized)	16.0	0.37	**0.77**	**0.40**	0.71	**0.80**	**0.69**
VIPS (PDoC 5)	13.5	0.35	0.70	**0.38**	0.74	0.76	**0.68**
Cormier et al. (s_{min} = 45 px, t_l = 512 px, **fitted**)	16.8	0.42	**0.77**	**0.38**	0.68	**0.81**	0.65
MMDetection (**fitted**)	14.7	**0.67**	0.38	0.35	**0.80**	0.54	0.56
HEPS	35.8	0.39	0.54	0.32	0.72	0.50	0.50
Meier et al. (**fitted**)	7.0	0.56	0.39	0.26	0.66	0.48	0.42

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- New hybrid approaches combining visual segmentation strategies with DOM information

Thank you!