SelfDocSeg: A Self-Supervised vision-based Approach towards Document Segmentation

Subhajit Maity*[1] **Sanket Biswas***[2] Siladittya Manna[3] Ayan Banerjee[2]
Josep Lladós[2] Saumik Bhattacharya[4] Umapada Pal[3]

[1]Technology Innovation Hub, Indian Statistical Institute, Kolkata, India

[2]Computer Vision Center, Universitat Autònoma de Barcelona, Spain

[3]CVPR Unit, Indian Statistical Institute, Kolkata, India

[4]Electronics and Electrical Communication Engineering, Indian Institute of Technology Kharagpur, India

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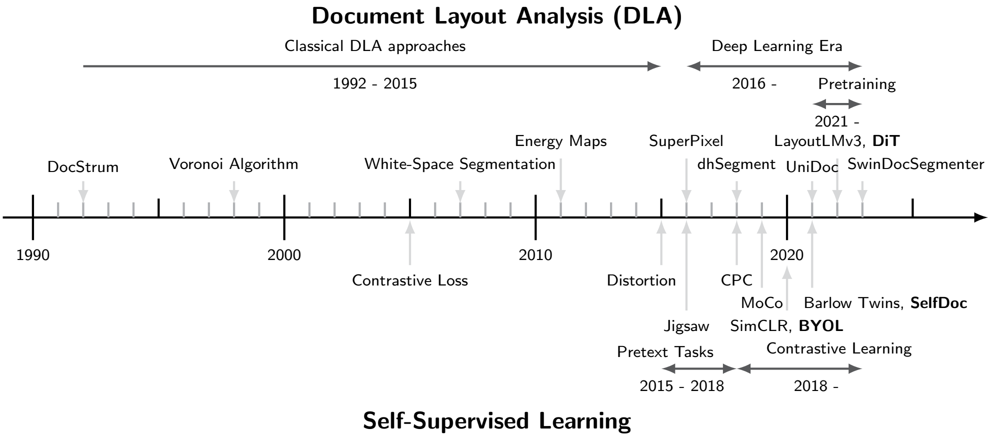
Outline

Going Back in Time



Coming back to the Present Day

Where DLA and Self-supervised Learning stand today?

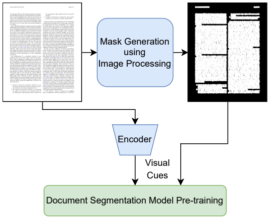
- The classical image processing techniques for DLA had long been lost.
- Modern self-supervision is bringing the classical algorithms, like Felzenszwalb, Normalized Cuts *etc*. back for guidance.
- The current document pre-training techniques for DLA use *multi-modal* approaches and *large-scaled* datasets.

What do we need?

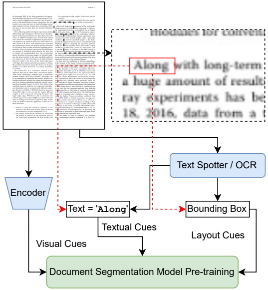
- A strategy to use the document images without annotations for DLA.
- A *data-efficient* pre-training strategy with *unlabelled* document images to alleviate the usual requirement of computational resources.

What's different from prior state-of-the-arts (SOTAs)?

- No textual cue or layout cue from trained OCR. Only visual cues are enough to capture global and local context.
- Superior data efficiency



(a) SelfDocSeg



(b) Existing Self-supervised SOTAs

Contributions

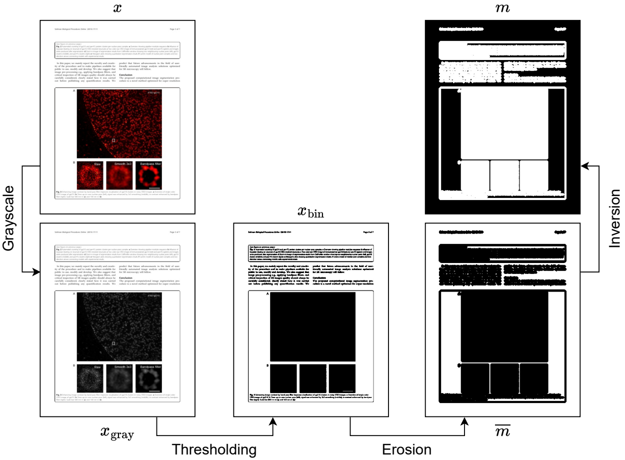
- A novel *vision-based self-supervised* framework, specifically designed to pre-train an image encoder for DLA task.
- A *pseudo physical layout guided strategy* for self-supervision in the region of interest localization for document segmentation.
- A *data-efficient pre-training strategy* to learn multiple document object representations simultaneously in the self-supervised setting

Overall Algorithmic Overview of SelfDocSeg

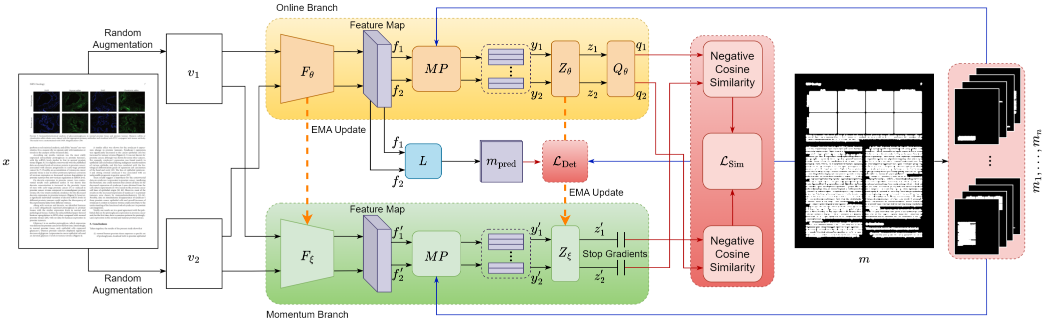
1. First, an approximate layout mask m is generated.
2. The image encoder is pre-trained with the help of m as visual cues in a non-weight-shared two-branch network similar to BYOL [28].
3. The encoder pre-training is done with two objectives - *(a) localization* and *(b) representation* of layout objects.
4. Localization objective is optimized using a detection loss $\mathcal{L}_{\text{Det}}$.
5. Layout object representations are extracted by *mask pooling* operation on encoded feature-maps for each object.
6. Representation objective is learnt via a similarity loss $\mathcal{L}_{\text{Sim}}$.

Mask Generation

1. **Grayscale Conversion:** CIE grayscale conversion on the document image x
2. **Thresholding:** Global thresholding with value 239 for 8-bit integer pixels
3. **Erosion:** 5×5 rectangular kernel
4. **Inversion:** pixel values subtracted from 255 to get the layout mask m



Architecture



Architecture Details

Online Branch

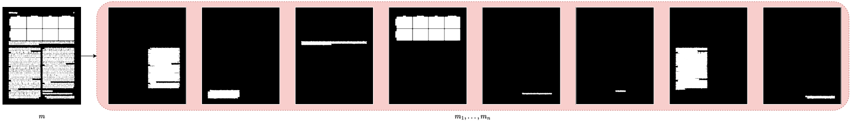
The online branch has an encoder F_θ, a projector Z_θ and a predictor Q_θ. It is updated using backpropagation.

Momentum Branch

The momentum branch has an encoder F_ξ and a projector Z_ξ. It is updated using an exponentially moving average (EMA).

Layout Objects for Mask Pooling

The layout object masks $m_1, \ldots, m_n$ are separated from mask m as separate contours.



Preliminaries

Mask Pooling

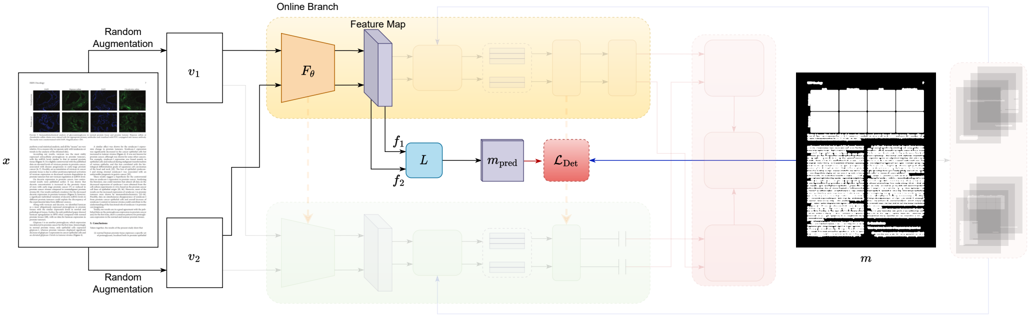
Mask pooling [35] is used for extracting layout object representation from encoded feature maps. It is just an average pooling inside each contour masked by m.

$$y^{(k)} = \frac{1}{\sum_{i,j} m_k[i,j]} \sum_{i,j} m_k[i,j] f[i,j]$$

Weight Updates

$$\textbf{Online Branch:} \quad \theta \leftarrow \text{optimizer}\left(\theta, \nabla_\theta \mathcal{L}_{\text{total}}, \eta\right)$$
$$\textbf{Momentum Branch:} \quad \xi \leftarrow \tau\xi + (1-\tau)\,\theta$$

Learning to Localize Layout Objects



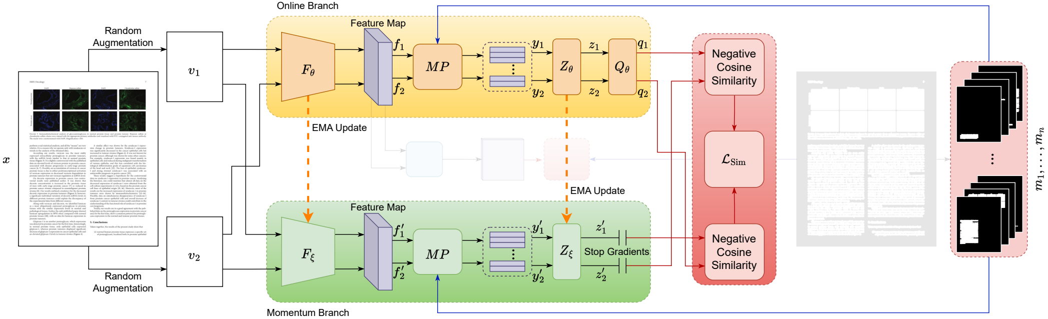
Localization Pre-training Objective

- The mask predictor module L is used to predict the layout mask m_{pred}.
- m_{pred} translates to the pixel-level probability of a layout object being present.
- We formulate this prediction objective as an imbalanced classification task and use Focal Loss [43] $\mathcal{L}_{\text{Det}}$ for the same.

Detection Loss

$$\mathcal{L}_{\text{Det}} = -\frac{\alpha}{\sum_{i,j} m[i,j]} \cdot \sum_{i,j} (m[i,j](1 - m_{\text{pred}}[i,j])^{\gamma} \log m_{\text{pred}}[i,j]$$
$$+ (1 - m[i,j]) m_{\text{pred}}[i,j]^{\gamma} \log(1 - m_{\text{pred}}[i,j]))$$

Learning to Recognize Layout Objects



Representation Pre-training Objective

- Representation of each layout object is extracted from feature maps of encoders F_θ and F_ξ in the online and the momentum branches using masked pooling.
- The encoder is trained using cosine similarity loss [28] $\mathcal{L}_{\text{Sim}}$ between online predictor Q_θ and momentum projector Z_ξ.

Similarity Loss

$$\mathcal{L}_{\text{Sim}} = 4 - 2\left(\frac{\langle q_1, z_2' \rangle}{\|q_1\|_2 \cdot \|z_2'\|_2} + \frac{\langle q_2, z_1' \rangle}{\|q_2\|_2 \cdot \|z_1'\|_2}\right)$$

Experimental Setup

Pre-training Dataset:

- DocLayNet [51]

Fine-tuning Dataset:

- DocLayNet [51]
- PubLayNet [63]
- PRImA [2]
- Historic Japanese [54]

Our Backbone:

- ResNet 50 [34]

Competitors:

- DocSegTr [8]
- LayoutParser [55]
- Biswas *et al.* [9]
- Mask RCNN [33] (Fully supervised)
- LayoutLMv3$_{\text{Base}}$ [36]
- UDoc [29]
- DiT$_{\text{Base}}$ [40]

Our Detector:

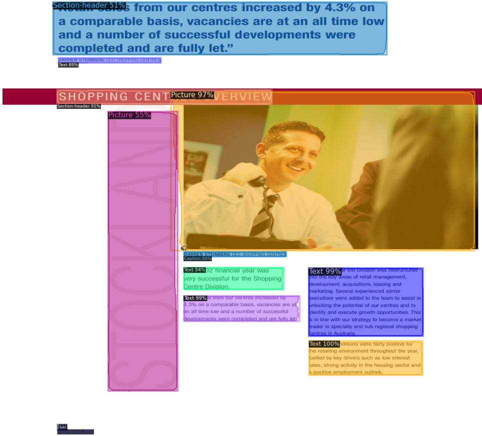
- Mask RCNN [33]

Frameworks: PyTorch, OpenCV, PyTorch Lightning, Lightly, Detectron2
Source code: `https://github.com/MaitySubhajit/SelfDocSeg`

Results - Quantitative

Methods	Cues V	Cues L	Cues T	# Data	DocLayNet mAP	PubLayNet mAP	PRImA mAP	HJ mAP
DocSegTr [8]	✓	✗	✗	-	-	90.4	42.5	**83.1**
LayoutParser [55]	✓	✓	✓	-	-	86.7	**64.7**	81.6
Biswas *et al.* [9]	✓	✗	✗	-	-	89.3	56.2	82.0
Mask RCNN [33]	✓	✗	✗	-	72.4	88.6	56.3	80.1
$\text{LayoutLMv3}_{\text{Base}}$ [36]	✓	✓	✓	11M	-	**95.1**	40.3	82.7
UDoc[29]	✓	✓	✓	1M	-	93.9	-	-
DiT_{Base} [40]	✓	✗	✗	42M	-	93.5	-	-
BYOL [28]	✓	✗	✗	81k	63.5	79.0	28.7	59.8
SelfDocSeg	✓	✗	✗	81k	**74.3**	89.2	52.1	78.8

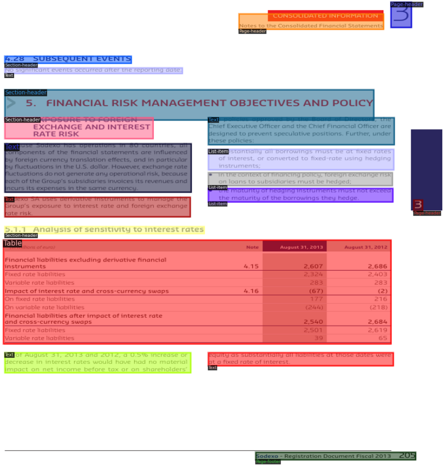
Results - Visual Comparison with Ground-truth



Left: Prediction

Right: Ground-truth

Results - Visual Comparison with Ground-truth



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Results - Visual Comparison with Ground-truth

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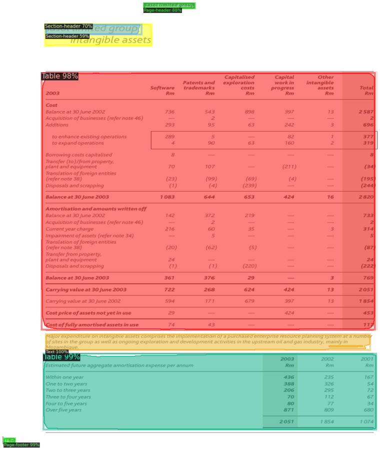

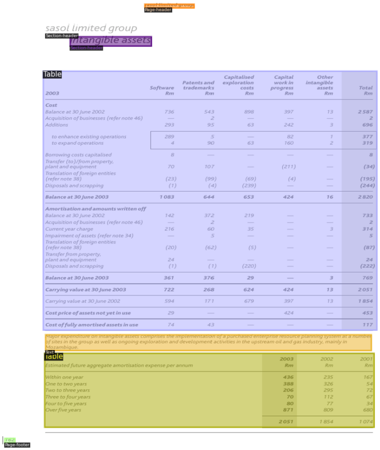

Left: Prediction

Right: Ground-truth

Discussion & Further Insights

Generalizability & Effectiveness of Pre-training

Experimented with fewer annotations in a semi-supervised setting for fine-tuning.

% Annotations	mAP
10%	41.3
50%	65.1
100%	74.3

Contribution of Detection & Representation Objectives

Experimentation with $\mathcal{L}_{\text{Det}}$ and $\mathcal{L}_{\text{Sim}}$ in strip-down style.

Loss	mAP
w/o $\mathcal{L}_{\text{Sim}}$	39.1
w/o $\mathcal{L}_{\text{Det}}$	69.7
Combined ($\mathcal{L}_{\text{total}}$)	74.3

The Story so far

- **SelfDocSeg** being a *OCR-free pertaining strategy* is computationally less expensive, as large-scale OCR systems are difficult and time-consuming to train.

- Ideally **SelfDocSeg** provides a *wide range of flexibility with backbones and detectors* and can achieve better performance with a stronger backbone.

- **SelfDocSeg** is *data-efficient* compared to state-of-the-art pre-training methods for DLA and can *generalize quickly over different domains* in the fine-tuning stage.

What's Next?

- Although being a superior pre-training strategy in terms of data efficiency, **SelfDocSeg** is not yet tested for data-hungry models like LayoutLMv3 or DiT.
- Following the recent trends to promote performance improvement, the scope of exploration remains in multi-domain and multi-lingual pre-training for introducing data variety.
- **SelfDocSeg** is particularly designed to cater to DLA. Thus, pre-training and fine-tuning for multi-task settings in downstream with vision-based self-supervision can be explored.

Conclusion

- **SelfDocSeg** is *self-supervised* and *vision based* and is motivated by recent self-supervised works in computer vision.
- Self-supervision for documents is possible in a unimodal setting without dependency on OCR or textual knowledge.
- The complete visual representation approach of **SelfDocSeg** facilitates superior understanding and encoding of the visual modality in the layout-guided document understanding paradigm.

To Know More

arXiv: `https://arxiv.org/abs/2305.00795`

Code: `https://github.com/MaitySubhajit/SelfDocSeg`

Project Page: `https://maitysubhajit.github.io/SelfDocSeg`