# WordFences: Text Localization and Recognition

## ICIP 2017

**Andrei Polzounov (Universitat Politecnica de Catalunya, Barcelona, Spain),**

**Artsiom Ablavatski (A*STAR Institute for Infocomm Research, Singapore),**

**Dr Sergio Escalera (Universitat de Barcelona, Barcelona, Spain),**

**Dr Shijian Lu (A*STAR Institute for Infocomm Research, Singapore),**

**Dr Jianfei Cai (Nanyang Technological University, Singapore)**

# Sponsors

Institute for Infocomm Research

A*STAR

Institució CERCA

Centres de Recerca de Catalunya

- Institute for Infocomm Research (I[2]R), at Singapore's Agency for Science, Technology and Research (A*STAR)
- CERCA Program, Government of Catalonia

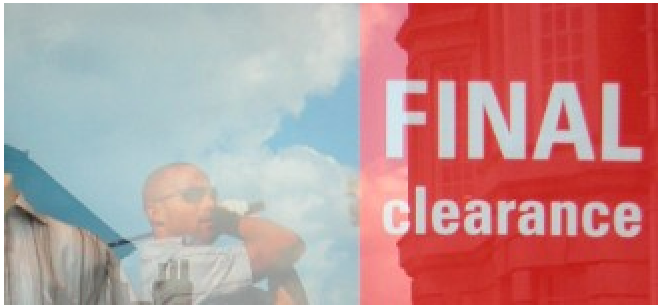
Generalitat de Catalunya

# Problem Description

- Text detection and recognition in natural scene imagery.
- Good test case problem for AI research and for uses in industry: mapping business from StreetView, translating menus or billboards, *etc.*

# Motivation

- OCR can be used on scanned text.
- Natural images have a ton of variety in fonts, scales, kerning and features.



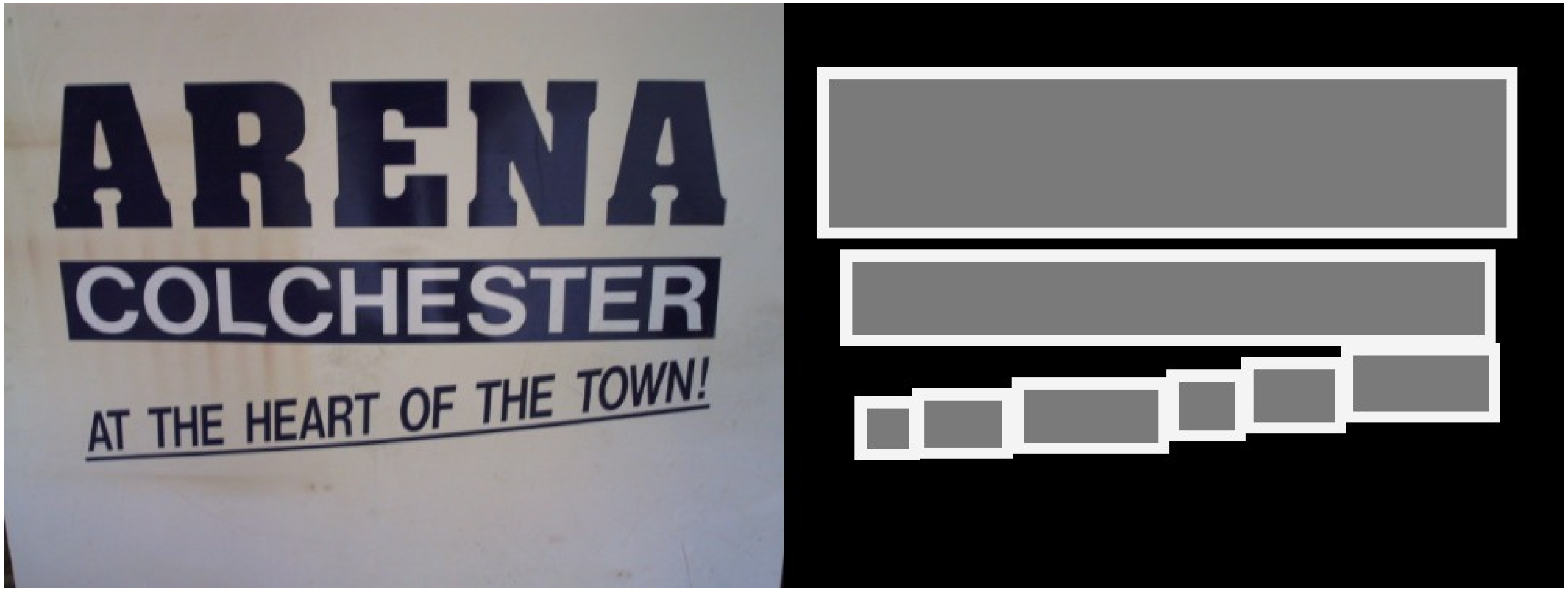


# Proposed Solution

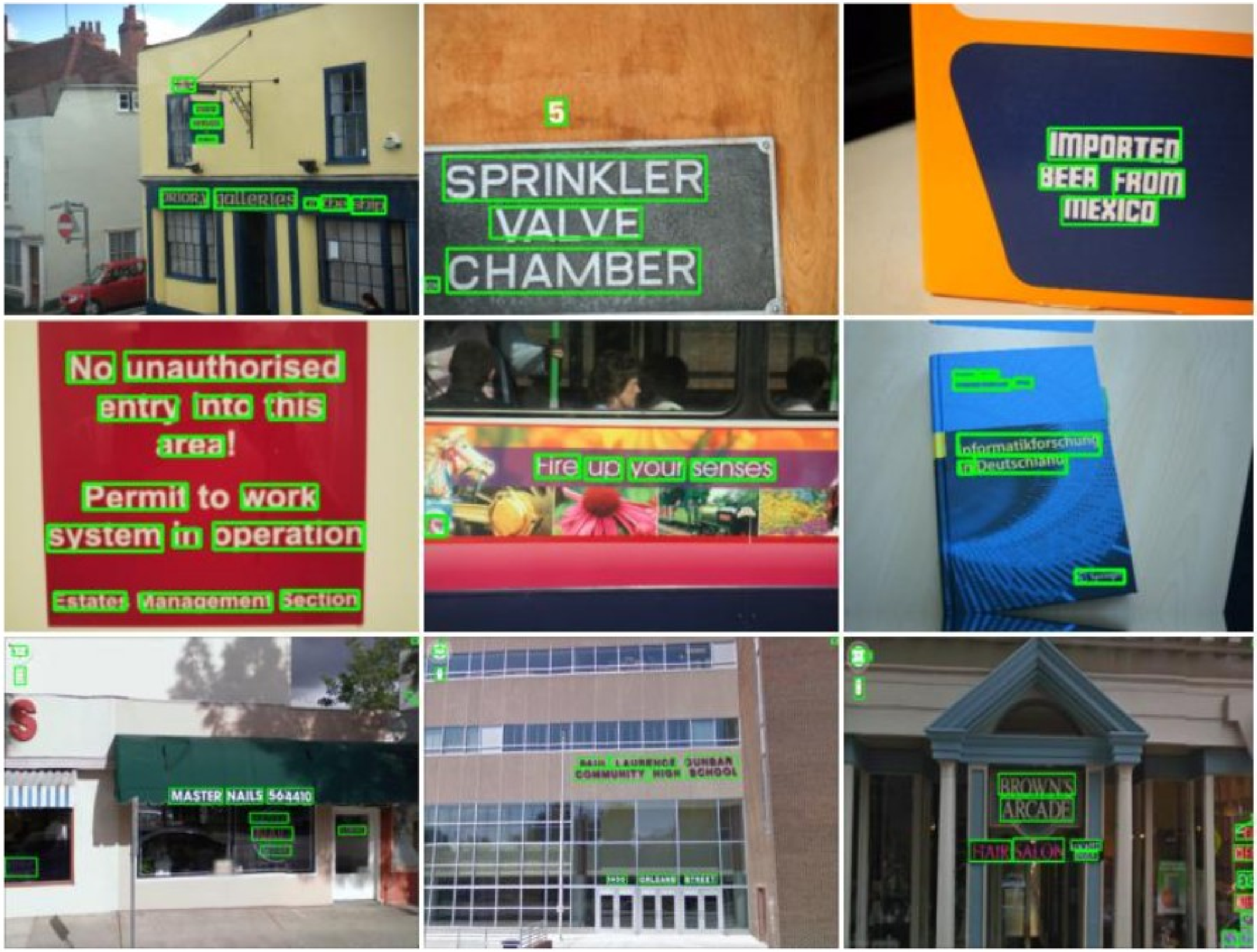
- 2-stage deep learning network
    - Find locations/ROIs (text localization) with CNN.
    - Detect characters (end-to-end text recognition) with RNN.
- 1st stage is the more difficult one. It is related to object recognition and semantic segmentation problems in Computer Vision.

# Contributions

- Two main contributions:
  - Use a word separator – a „WordFence“ for deliniating individual words.
  - Using a novel weighted pixelwise softmax function for training the semantic segmentation.

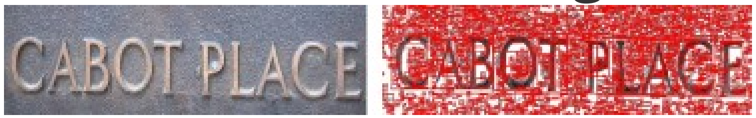


# Sample Detections



# Related Work (CV)

- Maximally Stable Extremal Regions by Huang *et al.*(2014) – works by first using an MSER transform and then training a CNN.




- Stroke Width Transform by Epshtein et al. (2010) – an edge detection method, that relies on the fact that a given text font should have similar width/thickness for each stroke in a character.

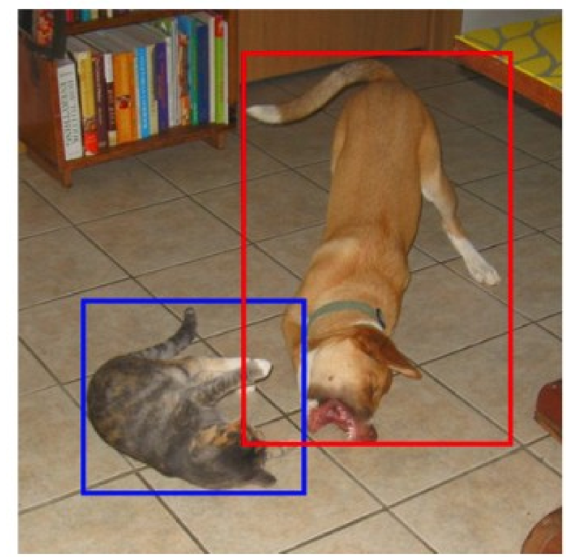
- Edge Boxes by Zitnick and Dollár (2014) – simple object score based on the number of edges within a given sliding window. Sparse and fast to evaluate, but results could be better.

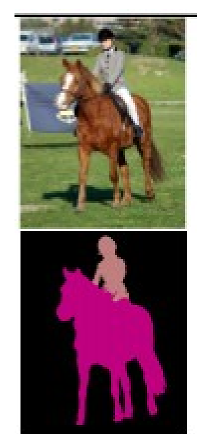
# Related Deep Learning

- Single shot ROI detection: YOLO (2015) by Redmon *et al.* and SSD: Multibox (2015) by *Liu et al.* - both of these work by splitting image into grid and calculating probabilities

- Fully convolutional networks (2015) by Long and Shelhamer – replace fully connected layers with deconv.

- DeepLab (2015) Liang-Chieh *et al.* - and ResNet101 (2016) by He *et al.* are the bases for this work.



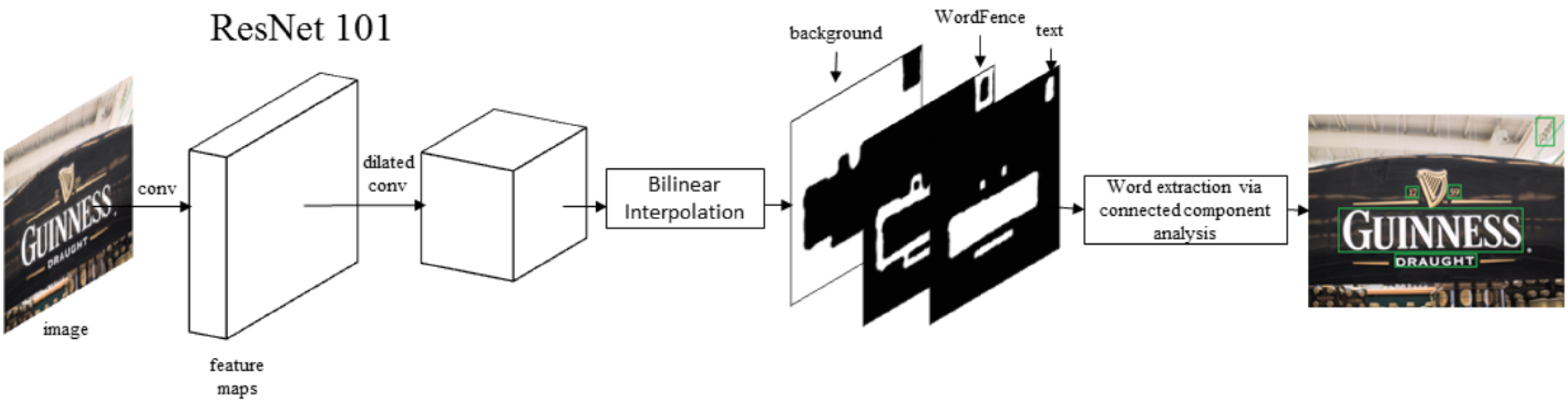


# Related Text Detection

- SynthText (2016) by Gupta, Vedaldi, and Zisserman. Synthetic dataset for text recognition and one-shot box approach to learning.

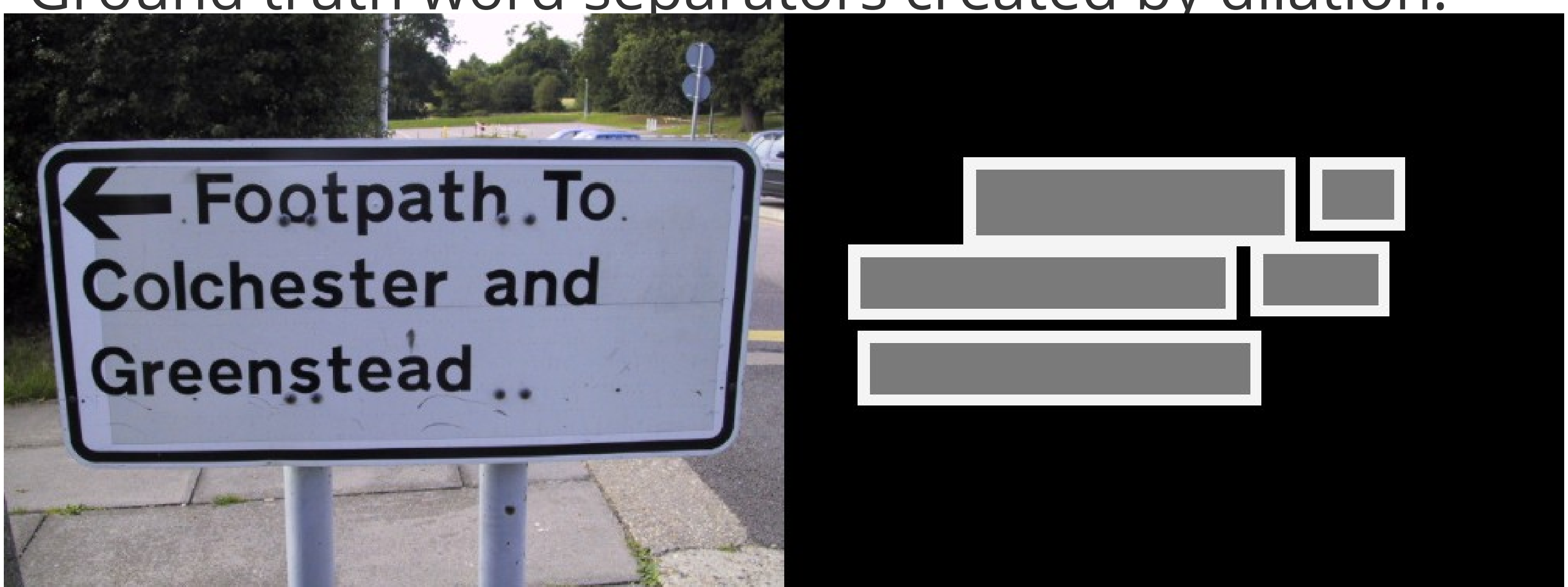

- Jaderberg *et al.* (2014) – used CNN to generate high number of proposals and filter with Random Forest (HoG).
- He *et al.* (2016) – cascaded CNN with false positive rejection to detect textlines (no split).

# Model Overview



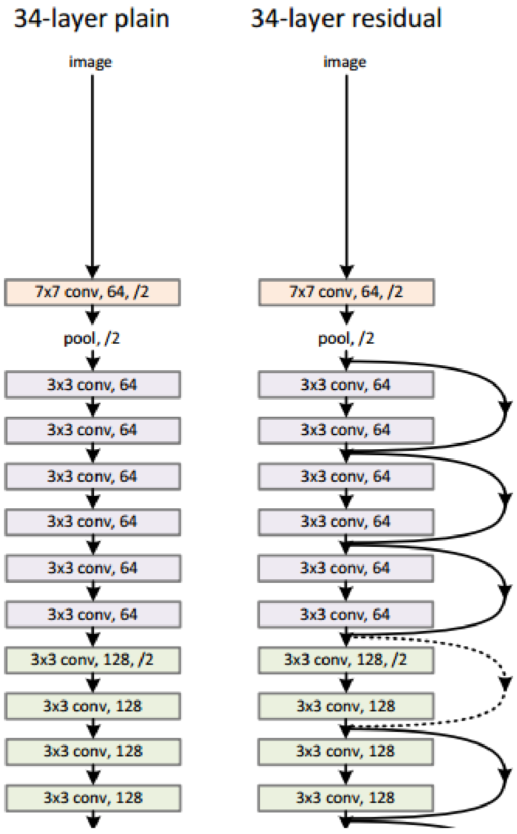
# Word Localization as Semantic Segmentation

- Semantic segmentation is a well known problem.
- Able to handle different scales using wide fields of view and multi-scale inference.
- Ground truth word separators created by dilation.



# ResNet of Exponential Receptive Fields

- ResNets help to train huge networks without a vanishing gradient.
- Receptive fields can be enlarged using convolutional dilations in the ConvNets.
- Deep network + exponential receptive fields = effective multi-scale detection of different sized text.



# Weighted Pixelwise Softmax Loss

- Background pixels are the majority. More emphasis for text and WordFence pixels is needed.

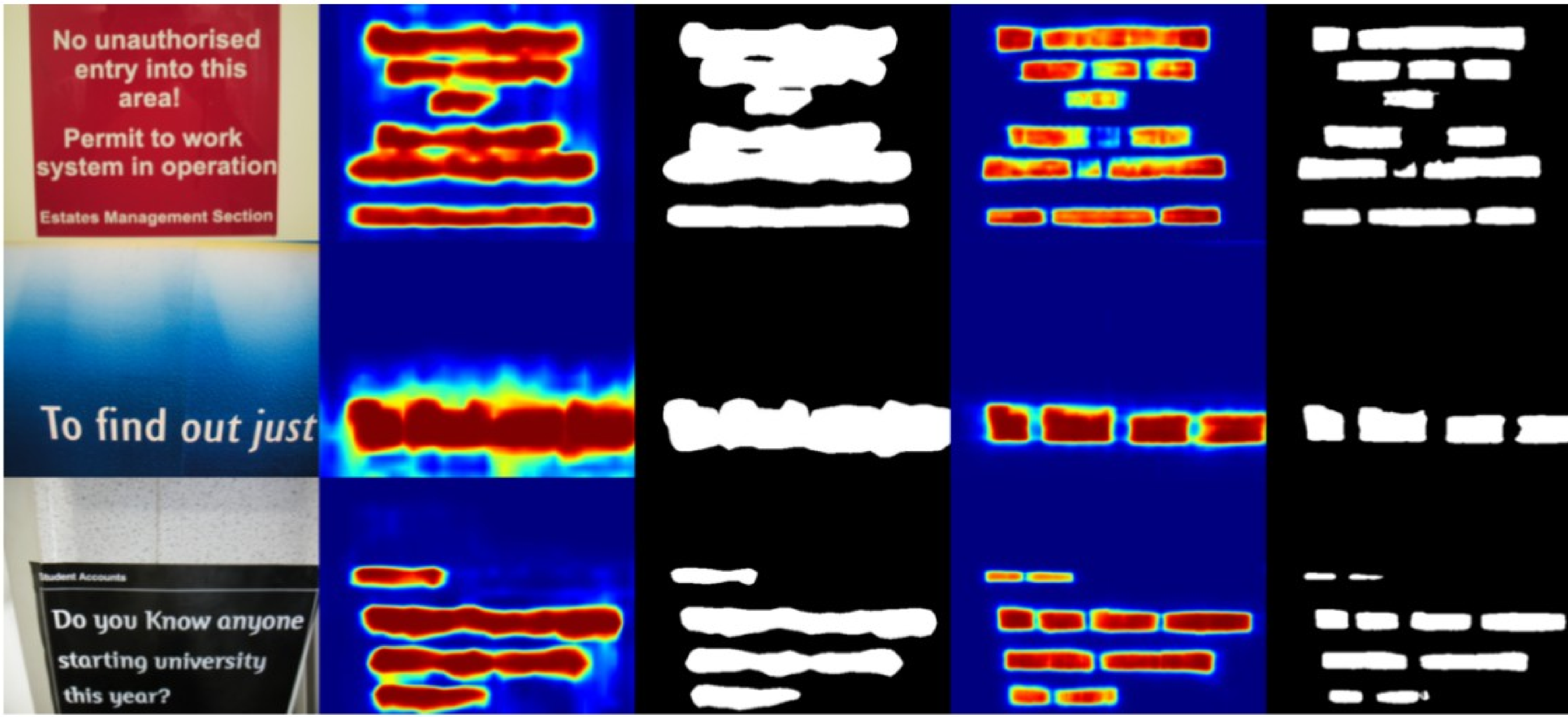
**Algorithm 1** Pixelwise Weighted Softmax Loss

**Require:** Predicates after fusion $\mathbf{Pr}$, ground truth labels $\mathbf{L}$

1: $probs \leftarrow Softmax(\mathbf{Pr})$ ▷ pixel probabilities
2: $m \leftarrow NumberOfUniqueLabels(\mathbf{L})$
3: $n_1, n_2, \ldots, n_m \leftarrow CountsOfUniqueLabels(\mathbf{L})$ ▷ get counts of each label on a ground truth image
4: $loss \leftarrow -\sum \frac{1}{n_{gt}} \log(probs_{gt})$ ▷ weighted loss calculation
5: $Backpropagate(loss, \frac{1}{n_1}, \frac{1}{n_2}, \ldots, \frac{1}{n_m})$ ▷ loss backpropagation with normalization factors

- Algorithm allows us to rebalance per image weights on the fly.

# WordFence vs No-WordFence




- WordFences act as penalization for merged words.

# Text Datasets

- ICDAR 2011 and ICDAR 2013 – International Conference on Document Analysis and Recognition
- COCO-Text – subset of the popular MS-COCO dataset for object recognition (21 classes)
- SVT – Google Street View data
- SynthText – synthetic text mixed with scene images from Gupta *et al.*

# Localization Results

| Model | PASCAL VOC IoU = 0.5 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | ICDAR11 | | | ICDAR13 | | | SVT | | |
| | P | R | F | P | R | F | P | R | F |
| Tian *et al.* [32] | 0.89 | 0.79 | 0.84 | 0.93 | 0.83 | **0.88** | - | - | - |
| Gupta *et al.* [5] | 0.78 | 0.63 | 70.0 | 0.78 | 0.63 | 0.70 | 0.47 | 0.45 | 0.46 |
| Jaderberg *et al.* [11]* | 0.89 | 0.68 | 77.4 | 0.89 | 0.68 | 0.77 | 0.59 | 0.49 | 0.54 |
| Gupta *et al.* [5]* | **0.94** | 0.77 | **0.85** | **0.94** | 0.76 | 0.84 | **0.65** | 0.60 | **0.62** |
| **WDN (ours)** | 0.64 | **0.92** | 0.75 | 0.65 | **0.92** | 0.76 | 0.47 | **0.63** | 0.54 |

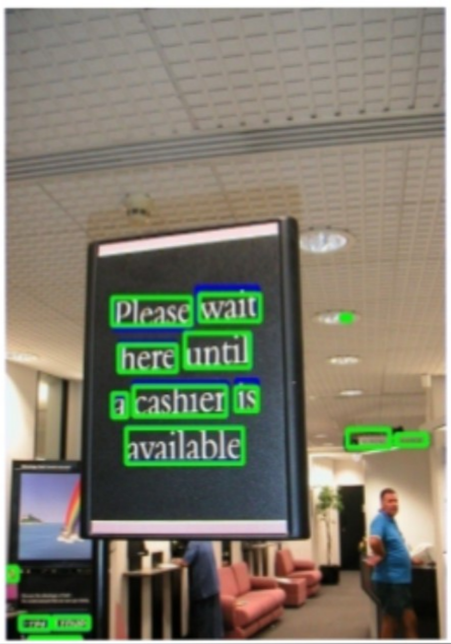
- Methods marked with * use multi-stage false-positive detectors.

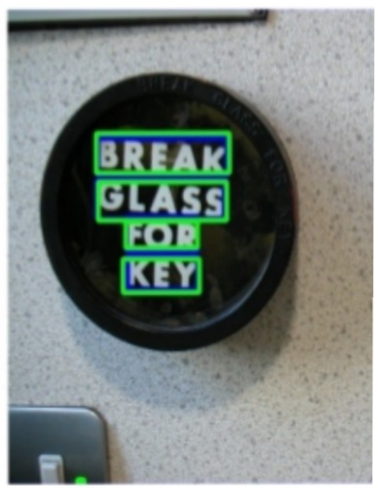
# Recognition Results

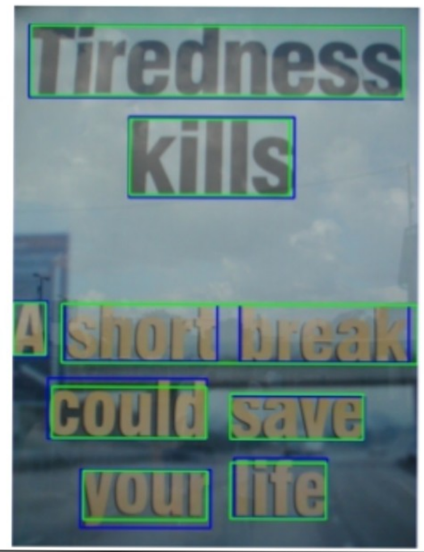
| Model | Year | IC11 | IC13 |
|---|---|---|---|
| Neumann *et al.* [20] | 2013 | 0.45 | - |
| Jaderberg *et al.* [11] | 2015 | 0.69 | 0.76 |
| Gupta *et al.* [5] | 2015 | **0.84** | 0.85 |
| **WDN** | 2016 | **0.84** | **0.86** |

- The recognition stage uses proposals given from the detection network.
- Recognition stage is based on the CRNN network by Shi *et al.* (2016).

# ICDAR 2011



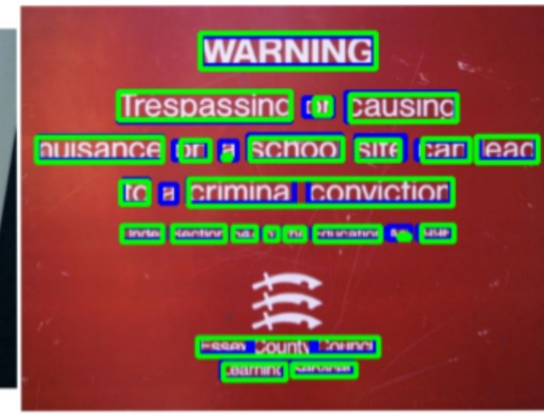



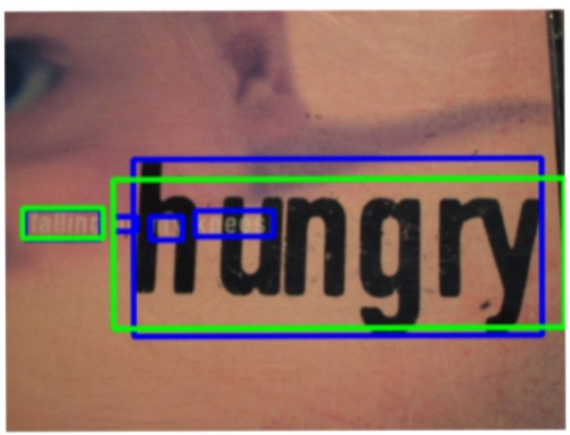


| | |
|---|---|
| P=0.875, R=0.778, F=0.824 | P=0.625, R=1.000, F=0.769 |
| "short break" not split correctly | Some false positives |

# ICDAR 2013


| | |
|---|---|
| P=1.000, R=0.889, F=0.941 | P=0.833, R=0.714, F=0.769 |
| | Some overlaps are <0.5 IoU |





| | |
|---|---|
| P=1.000, R=0.400, F=0.571 | P=0.300, R=0.750, F=0.429 |
| Challenging case - word is within another word | Too much word splitting, due to tricky font and spacing |

# Problems Encountered

- Going from segmentations to bounding boxes.
- Noisy detections and many false positives:
  - Many small detected regions.
  - Camera artifacts such as glare.
  - Need for balancing precision vs recall.

# Conclusion

- Text recognition as semantic segmentation
- WordFences as penalization
- SOTA recall on detection, which provides high quality samples to the recognition stage (which in itself is able to throw away false positives).
- SOTA F-scores on recognition

# Future Work

- WDN relies on visual information to split words.
- Humans also use word semantics and memory.
    - “Raeding wrods with jubmled letetrs“.
- A smarter system would be able to read text directly from images without a midpoint CV representation.
    - Learn directly from neural net to a dictionary word output?

# Questions?

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

UNIVERSITAT ROVIRA I VIRGILI

Universitat de Barcelona

Institute for Infocomm Research

A*STAR