Deblending in crowded star fields using convolutional neural networks

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Table of contents

The detection and deblending problems

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- Problem : source detection in crowded star fields

Figure 1: Example of crowded star field in the Milky Way (Image credit: NASA/ESA)

- Current method in SExtractor:
  - Matched filter :
    - Linear filter that maximizes the output SNR
    - Coming back to convolve the input
  - Multi thresholding

Sextractor method

- Background subtraction, matched-filtering, thresholding and deblending

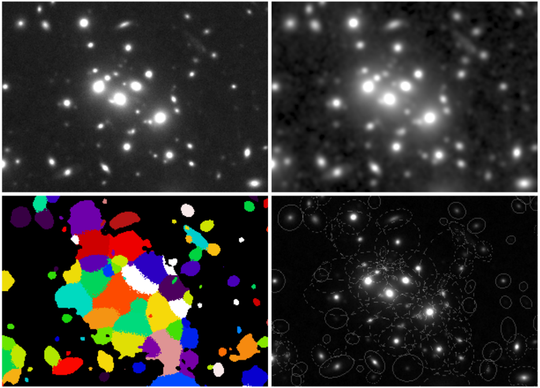

Figure 2: Example of SExtractor processing. Top left: source image, Top right: background subtraction and match-filtering, Bottom left: thresholding and deblending, Bottom right: final image with source shapes

Method limitations

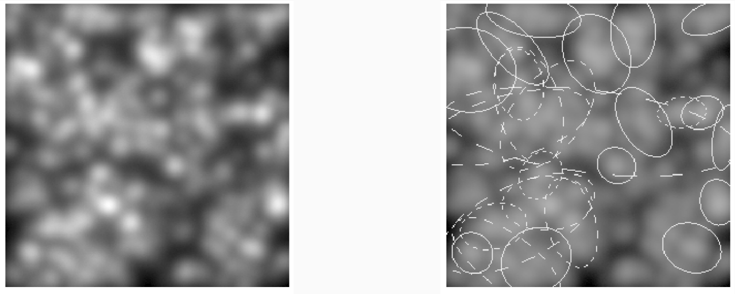

Figure 3: Example of SExtractor result using default parameters

- Lack of robustness regarding contaminants
- Heuristic-based filtering, thresholding and deblending

$\rightarrow$ Extending the heuristic-based method to convolutional neural networks for automatic "intelligent" image segmentation

Convolutional neural networks and deep learning

- Multilayer neural networks not usable with high dimension inputs like images
  $\rightarrow$ Use convolutions
  - Translation invariant processing using a small number of trainable parameters
  - Deep learning: stack these layers to capture more and more abstract input features

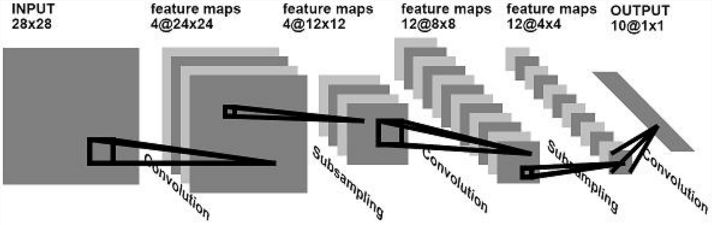

Figure 4: Example of convolutional neural network designed for MNIST

Object detection with deep learning

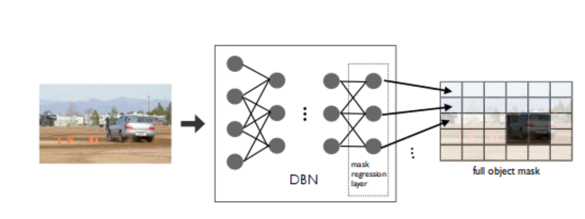

Figure 5: Deep neural networks for object detection

Figure 6: Learning to segment object candidates

Application to deblending in crowded star fields

Training data

- Data: simulated images using Skymaker

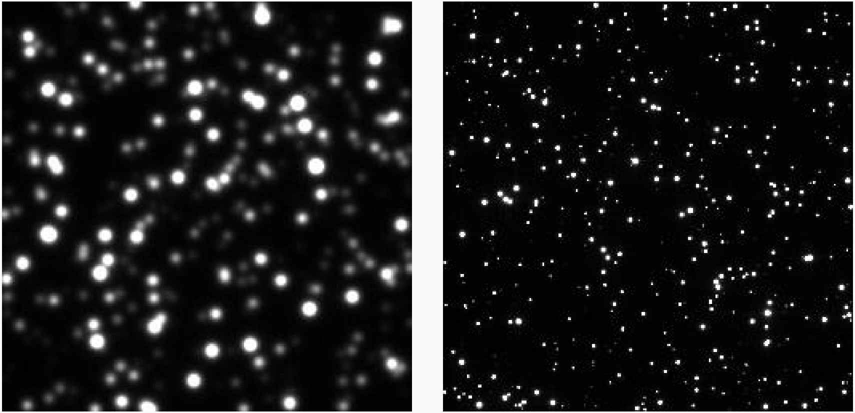

Figure 7: Examples of simulated images using Skymaker

Image preprocessing

- High dynamic inputs disturb neural network convergence
- $I' = \begin{cases} log(1+u) & \text{if } u > 0 \\ -log(1-u) & \text{if } u < 0 \end{cases}$ where $u = \frac{I - I_0}{k\sigma_{I-I_0}}$

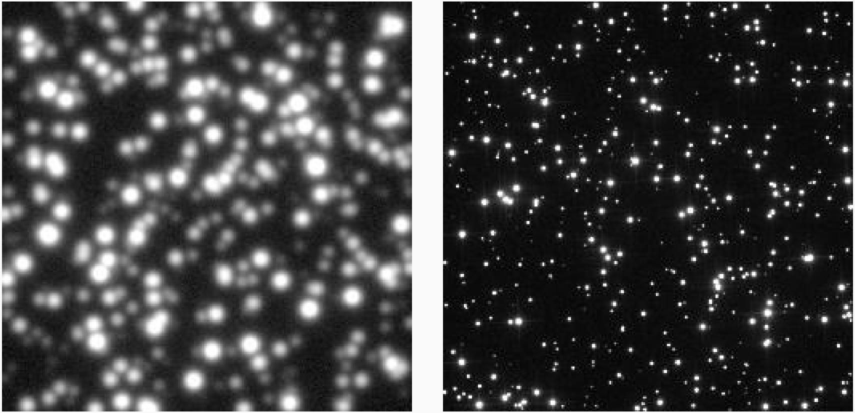

Figure 8: Preprocessed images

How to detect (blended) sources ?

- Neural network designed to find a mask where non-zero values are sources centroids

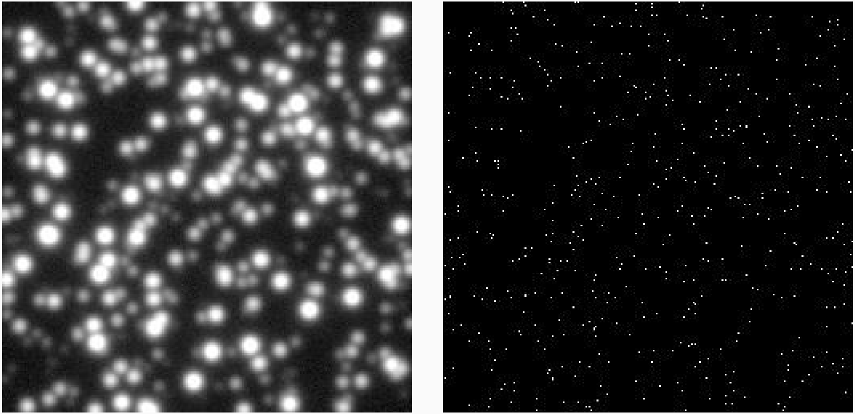

Figure 9: Example of input/output for the neural network

Model architecture

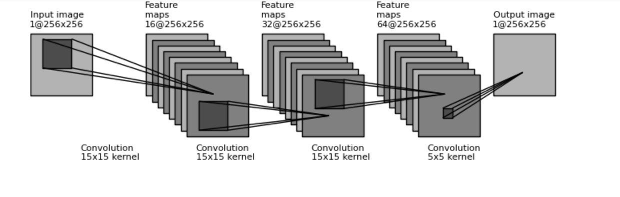

Figure 10: Neural network architecture for deblending

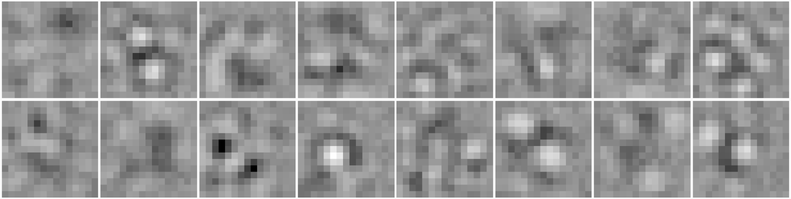

Figure 11: First convolutional layer kernels after training

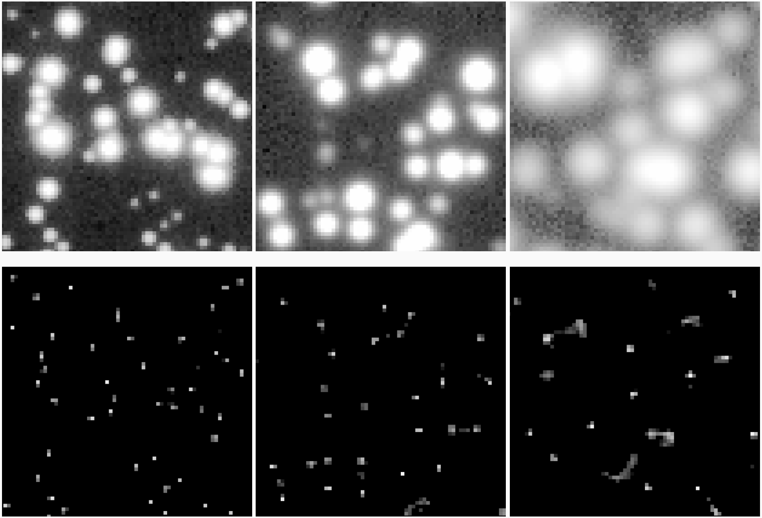

Figure 12: Example of 3 input/output results

Performance

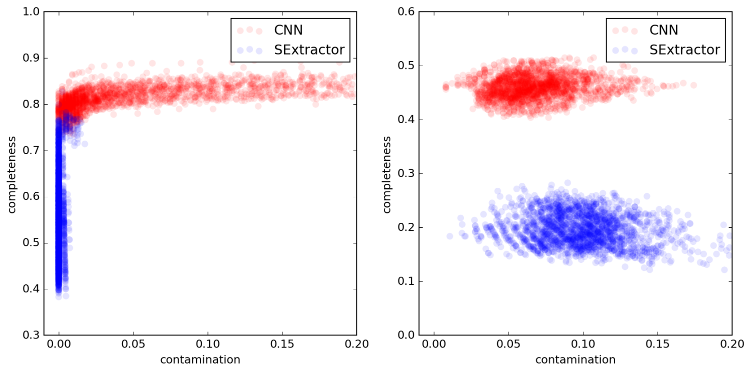

Figure 13: Completeness vs contamination for different detection thresholds. Blue: SExtractor, Red: CNN. Left: good seeing (0.1 arcsec), Right: bad seeing (1.5 arcsec)

- First approach competitive with the state of the art

Future prospects

- LAB/CNES PhD: *Robust detection of astronomical sources using convolutional neural networks*
  → **Universal** method and **Robustness** regarding contaminants (SExtractor-minded)

- Euclid: probe dark matter, dark energy and the expanding universe
  - Precise shear measurements
  - Wide and deep fields observations
  - Multi-channel detection (visible and infrared)
- Cosmic-DANCe: identify all members of young solar neighborhood
  - Precise astrometry in nearby clusters
  - Combine different observations with various features
  - Multi-channel detection (visible and near-infrared)
- Include a CNN-based detection module in SExtractor++
  - Developed by Euclid members
    - ISDC, Geneva
    - USM, Munich
    - CNES, Toulouse