# Using convolutional neural networks to identify strong lenses in Euclid and J-PAS


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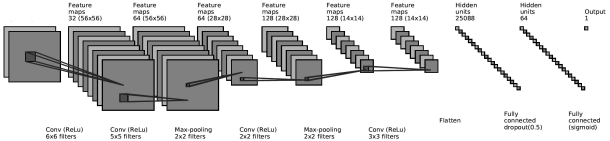
# Using Convolutional Neural Networks

Input images (N bands)


Flatten the data to a 1D-vector

Output

$0 \leq P_{\text{lens}} \leq 1$

Non-lens — Lens

Convolutional part: Feature extraction

Dense layers: Classification

Convolutional layer — Detects features on images

ReLu activation function — Introduces non-linearity $[f(x) = \max(0, x)]$

Pooling layer — Reduces the dimensionality

## Supervised learning

Loss function: binary-crossentropy

$$E = -\frac{1}{N}\sum_{i=1}^{N}[b_i \log(y_i) + (1 - b_i)\log(1 - y_i)]$$

Weights update

$$w'_{jk} = w_{jk} - \eta\frac{\partial E(w)}{\partial w_{jk}}$$

$$w'_{ki} = w_{ki} - \eta\frac{\partial E(w)}{\partial w_{ki}}$$

Backpropagation process

Adam optimization (learning rate: $\eta = 0.001$)
Batch size: 30
Epochs: 60 (early-stopping)
Data augmentation (rotations, zooms, flips, shifts)
Flux normalized to max value in each band

| True \ Predicted | Non lens | Lens |
|---|---|---|
| Non lens | TN | FP |
| Lens | FN | TP |

$$Recall \equiv TPR = \frac{TP}{P} = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{N} = \frac{FP}{TN + FP}$$

$$Accuracy \equiv Acc = \frac{TP + TN}{P + N} = \frac{TP + TN}{TP + TN + FP + FN}$$

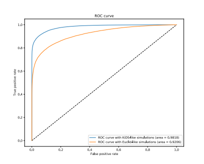
$$Precision \equiv Pre = \frac{TP}{TP + FP}$$

$$F_\beta = (1 + \beta^2)\frac{Pre \times Recall}{(\beta^2 Pre + Recall)}$$

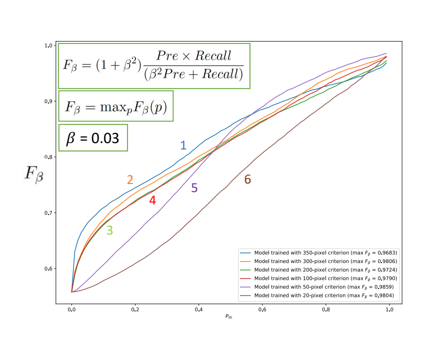
$$F_\beta = \max_p F_\beta(p)$$

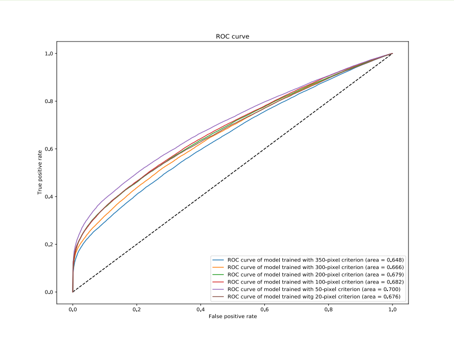
$$F_{\beta=0} = Pre$$

$\beta = 0.03$



We aim to find the model that is best able to distinguish between lenses and non-lenses in the 4-band Euclid-like simulations.




**Training:**

- **6: 20-pixel** (15,771): $\mu_{eff} \geq 4.0 \;\&\; n_{im} > 0 \;\&\; n_{pix} > 20$
- **5: 50-pixel** (14,450): $\mu_{eff} \geq 4.0 \;\&\; n_{im} > 0 \;\&\; n_{pix} > 50$
- **4: 100-pixel** (12,840): $\mu_{eff} \geq 4.0 \;\&\; n_{im} > 0 \;\&\; n_{pix} > 100$
- **3: 200-pixel** (10,868): $\mu_{eff} \geq 4.0 \;\&\; n_{im} > 0 \;\&\; n_{pix} > 200$
- **2: 300-pixel** (9,802): $\mu_{eff} \geq 4.0 \;\&\; n_{im} > 0 \;\&\; n_{pix} > 300$
- **1: 350-pixel** (9,441): $\mu_{eff} \geq 4.0 \;\&\; n_{im} > 0 \;\&\; n_{pix} > 350$

**Testing:**

**assessable 1** (88,910)

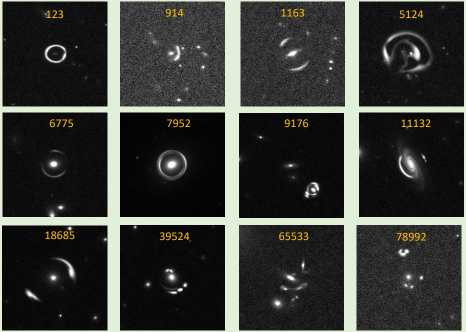
Lenses
$\mu_{eff} \geq 1.6 \;\&\; n_{im} > 0 \;\&\; n_{pix} > 20$

Non-lenses
the rest except those with $1 < \mu_{eff} < 1.6$

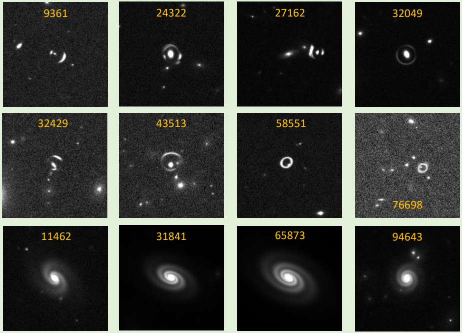
# Results with 4-band Euclid-like data

88,910 candidates → model 50-pixel → 9057 candidates with $P_{lens} > 0.9$

8837 True Positives




220 False Positives → **48 lenses recognizable by eye**



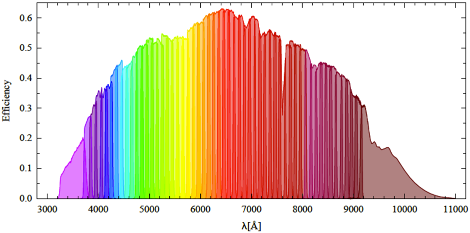

**Reminder:** Criteria for defining the lenses in the test data set → $\mu_{eff} \geq 1.6 \; \& \; n_{im} > 0 \; \& \; n_{pix} > 20$

# Using convolutional neural networks to identify lensed quasars in J-PAS

The Javalambre-Physics of the Accelerating Universe Astrophysical Survey (J-PAS) will cover $\geq 8000\ \mathrm{deg}^2$ of the northern hemisphere in $\sim 5$ years.

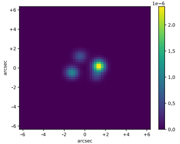

*Astrophysical Observatory of Javalambre* (Teruel, Spain)

- 54 narrow band filters in the visible
- Expected measures for $14\times10^6$ LRGs and over 1/2 million quasars
- A significant number of them will be lensed

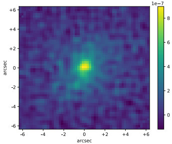


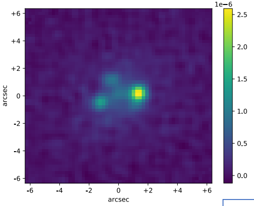
# Lensing simulations. Training and test datasets.

Mock qso 186535

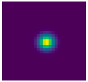



Galaxy 2406-4867




Lensed QSO image (630 nm)



Softened isothermal ellipsoids

$$\kappa(\boldsymbol{\theta}) = \theta_E \frac{\boldsymbol{\theta}^2 + 2\theta_c^2}{2(\boldsymbol{\theta}^2 + \theta_c^2)^{3/2}}$$

$$\boldsymbol{\alpha}(\boldsymbol{\theta}) = \frac{1}{\pi} \int \kappa(\boldsymbol{\theta}') \frac{\boldsymbol{\theta} - \boldsymbol{\theta}'}{|\boldsymbol{\theta} - \boldsymbol{\theta}'|^2} d^2\theta'$$

J-PAS: 0.2267 arcsec/pixel

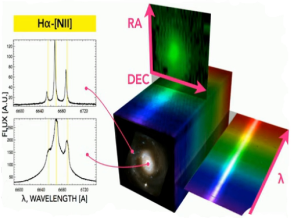
Characteristics of the training/test datasets: **80% train / 20% test**

- 3920 galaxies found in a $\sim 1$ deg$^2$ area surveyed.
- 10567 mock qsos close to galaxies ($3'' < \theta < 6''$)
- 5820 mock non-lensed qsos

→ Non-lensing examples

- 12749 mock lensed qsos → Lensing examples

Convolving real SDSS spectra (DR12 quasar catalog Pâris et al., 2017), with the JPAS photometric passbands, and adding J-PAS-like noise.



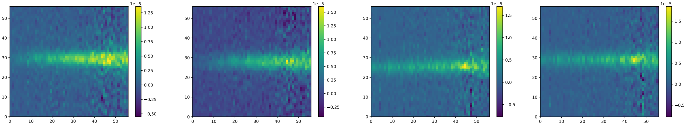

Credit to Sara Cazzoli (IAA, CSIC)

# Examples of pseudo-spectra

Lensed QSO

Gal 2406-5039 – QSO 252530

Gal 2241-4779 – QSO 167627



Pseudo-spectrum along $x$-axis

Pseudo-spectrum along $y$-axis

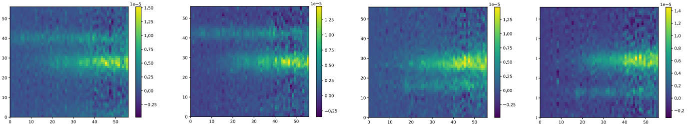
Pseudo-spectrum along $x$-axis

Pseudo-spectrum along $y$-axis

Non-lensed (galaxy near QSO)

Gal 2470-14560 – QSO 2625

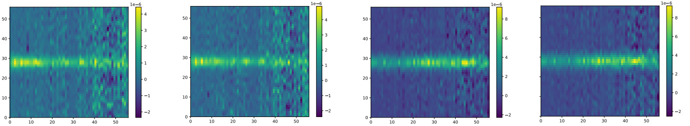
Gal 2406-2679 – QSO 157164



Non-lensed (QSO)

QSO 247110

QSO 252350



# Current results

Difference between training models using the full cube (56 J-PAS band images) or the 2 pseudo-spectra.

Training: 29136    Test: 12721

**Model trained using 56 images (J-PAS filters)**

| True \ Predicted | Non-lens | Lens |
|---|---|---|
| Non-lens | 8431 (99.5%) | 39 (0.5%) |
| Lens | 39 (0.9%) | 4212 (99.1%) |

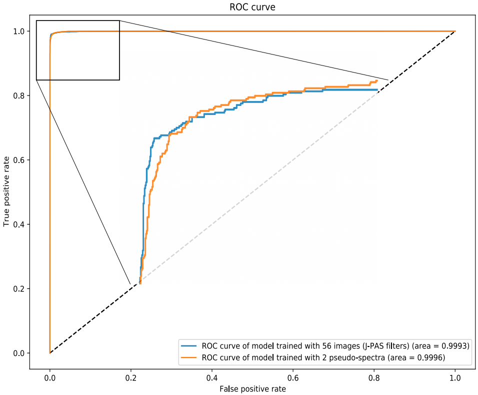
**Model trained with the 2 pseudo-spectra**

| True \ Predicted | Non-lens | Lens |
|---|---|---|
| Non-lens | 8429 (99.5%) | 41 (0.5%) |
| Lens | 50 (1.2%) | 4201 (98.8%) |

The pseudo-spectra contain all the relevant information about the morphological and spectral features.

It helps to reduce in a factor 25 the size of the data

Pending of checking results with proper cross-validation




Manjón-García et al (in prep)