Intelligence artificielle pour la détection de lentilles gravitationnelles.

Rémi Flamary, Philippa Hartley, Neal Jackson, Amit Tagore, Ben Metcalfe

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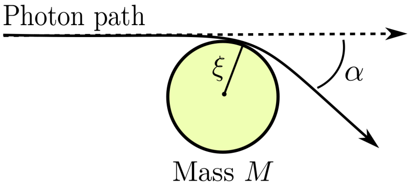
Small history of gravitational lenses



$$\alpha = \frac{4\mathrm{G}M}{c^2\xi}$$

Timeline

- **1704** Newton suspects gravitational deflection of light.
- **1915** General relativity predicts twice the deflection of Newton.
- **1919** Lensing effect observed by Arthur Eddington during a solar eclipse.
- **1979** Observation of the first strong lens : Twin Quasar Q0957+561A [Walsh et al., 1979]

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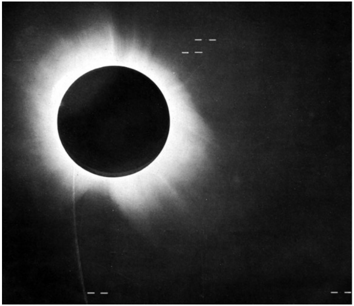

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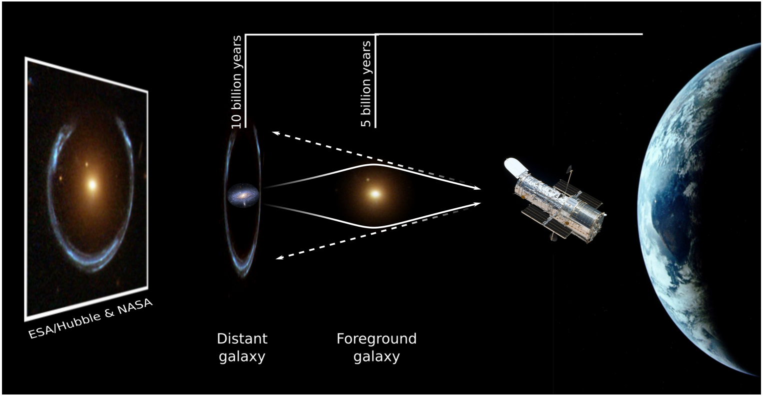
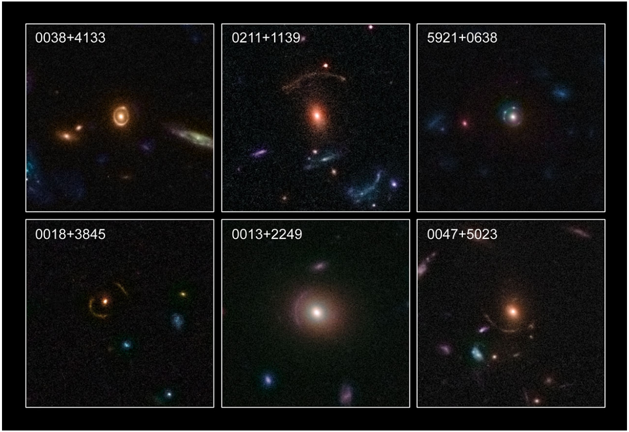


- Cosmic telescopes (magnification of far-off objects).
- 300 strong lenses currently known, detected by humans.
- Euclid mission [Laureijs et al., 2012], Strong Lens Legacy Science Group : 300 000 galaxy/galaxy lenses out of 10 billion sources. How to find them ?

Strong Gravitational lenses



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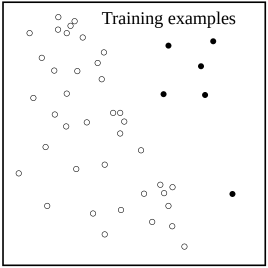
Supervised machine learning



- Teach the machine to perform a given task.
- Give it n example of observations x and the corresponding prediction y.
- Optimization problem:

$$\min_{f} \quad \frac{1}{n}\sum_{i=1}^{n} L(y_i, f(x_i)) \tag{1}$$

- We chose Support Vector Machines that work well on small datasets.

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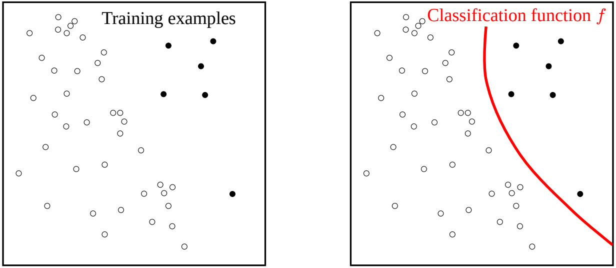

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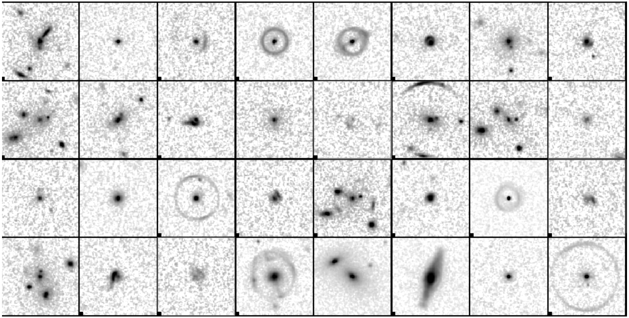
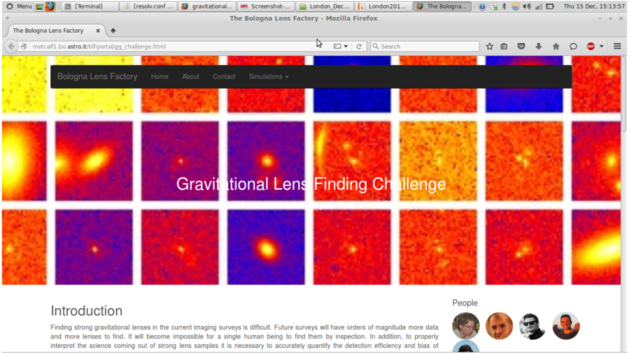
Training dataset



- Use training data from the lens finding challenge [Metcalf et al., 2018].
- Simulated with Bologna Lens factory.
- 20 k Ground observation (4 wavelengths) and 20k images Space observations.
- Simulated following Kilo degree Survey (Kids) and Euclid observation models.
- Validation on part of the dataset suggest 96% and 88% AUC.

Gravitational lens finding challenge



Competition [Metcalf et al., 2018]

- Training dataset presented earlier.
- 100 000 simulated test images, 48 hours for classifying.
- Performances measured with Area Under the ROC Curve (AUC) and the ratio of correctly classified lenses before a false positive occur (TPR_0).

Competition results in AUC

Name	type	AUROC	TPR_0	TPR_{10}	short description
CMU-DeepLens-ResNet-ground3	Ground-Based	0.98	0.09	0.45	CNN
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LASTRO EPFL	Ground-Based	0.97	0.07	0.11	CNN
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ALL-star	Ground-Based	0.84	0.01	0.02	edges/gradiants and Logistic Reg.
CAST	Ground-Based	0.83	0.00	0.00	CNN / SVM
YattaLensLite	Ground-Based	0.82	0.00	0.00	SExtractor

Results

- 3 family of submissions:
    - Convolutional neural networks (CNN).
    - Support vector Machines (us).
    - Human Annotator (us).
- AUC is ability to separate the classes in average.
- CNN works best in AUC, well in TPR_0.

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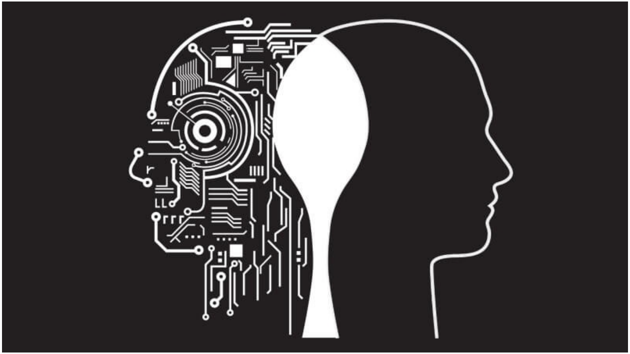
- TPR_0 is the ratio of detected lenses before a false positive occur when sorted by classifier scores.
- Measure of trust for the highest predicted scores, better for retrieval.
- SVM work far better in TPR_0 for space data.
- CNN work better on space data.
- None of the methods is designed to optimize this criterion.

Man vs machine



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- Eyeball inspection of the 100 000 simulated test images.
- 5 level confidence score.
- Done by Neal jackson and Amit Tagore (5000/2000 imgs/h).

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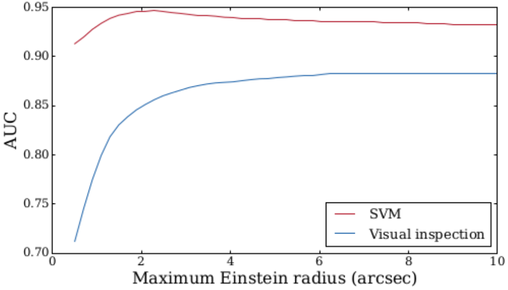

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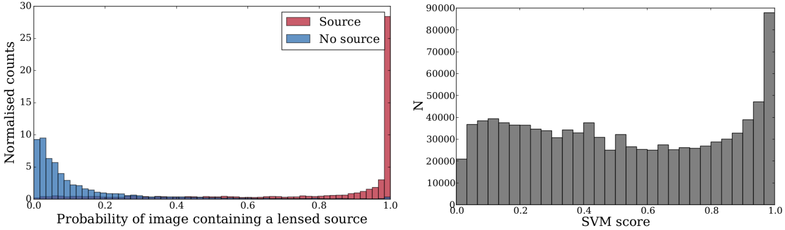
Real data: Kilo Degree Survey



- Apply our classifier on 1 million images from Kilo Degree Survey (KiDS).
- Classification score far more uncertain (simulation $\neq$ real life).
- Look at images with larger scores.
- Kept 213 object that range from possibly to very likely lenses.

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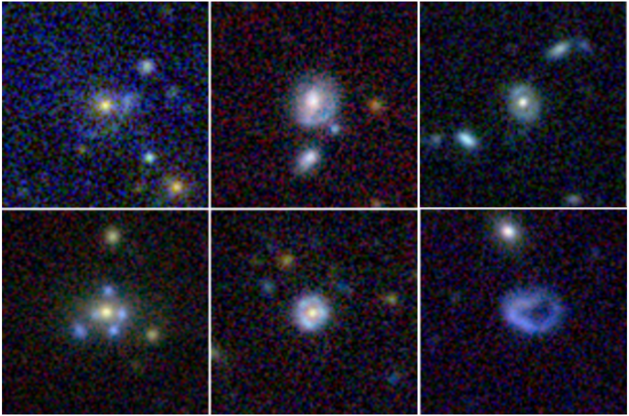

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Conclusion

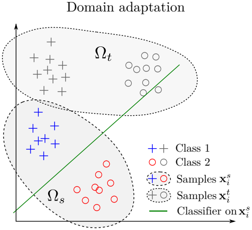
Conclusions

- We need automatic procedure to detect strong gravitational lenses.
- Machines now surpass humans in finding lenses.
- Strength of SVMs when false positives are a problem.
- CNN better approach (they learn the Gabor filters).

Best strategy?

- Use CNN but encode expert knowledge (polar representation, ...)
- Design dedicated objective to minimize false positives (neyman-pearson classification)
- Discrepancy between training and test data?

The future : Domain adaptation



Domain adaptation (special case of tranfer learning)

- Problem: New data is different from training data.
- In astronomy: Simulated data is always different from real life data.
- How to train on simulated data but still work on real data?
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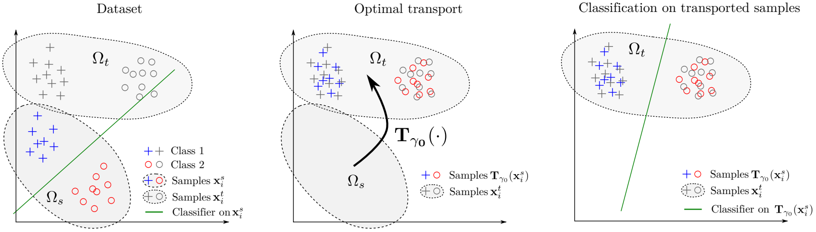

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Thank you

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