

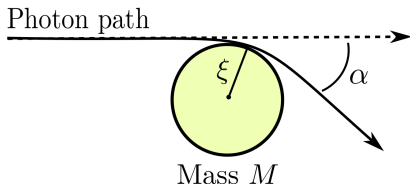
Intelligence artificielle pour la détection de lentilles gravitationnelles.

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

Journée Scientifique de l'OCA

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Small history of gravitational lenses

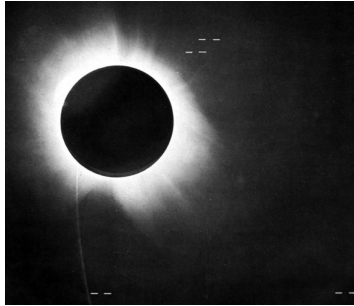


$$\alpha = \frac{4GM}{c^2\xi}$$

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]

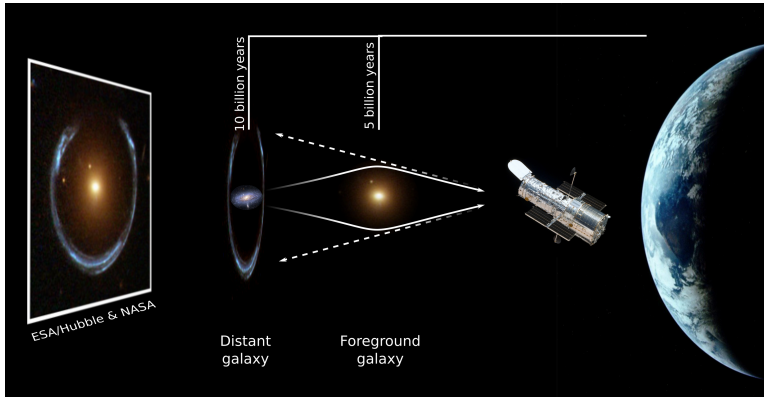
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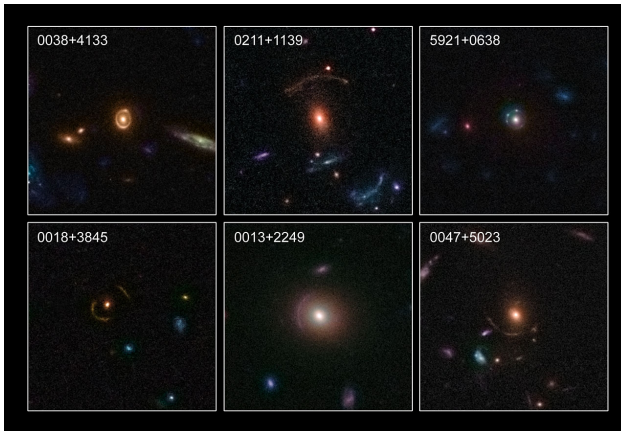
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Strong Gravitational lenses



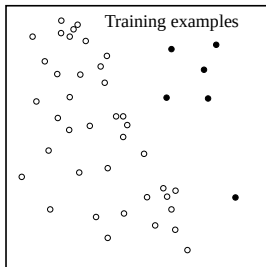
- Cosmic telescopes (magnification of far-off objects).
- 300 strong lenses currently known, detected by humans.
- Euclid mission [Laureijs et al., 2012], Strong Lens Legacy Science Group :
300 000 galaxy/galaxy lenses out of 10 billion sources. **How to find them ?**

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Supervised machine learning

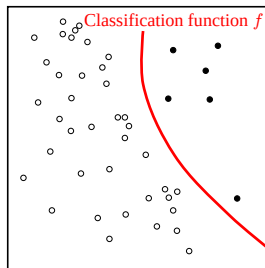
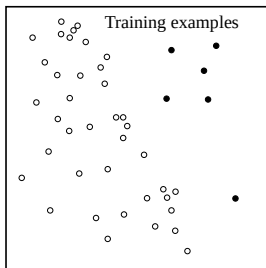


- Teach the machine to perform a given task.
- Give it n example of observations x and the corresponding prediction y .
- Optimization problem:

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

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

Supervised machine learning

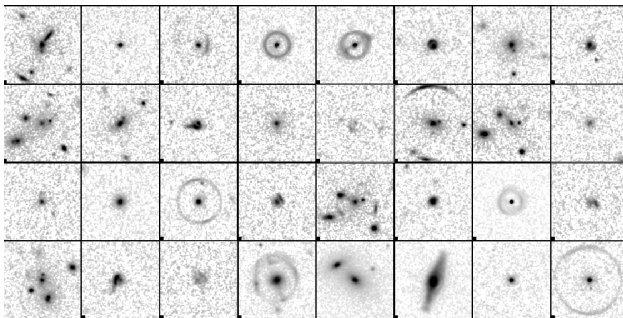


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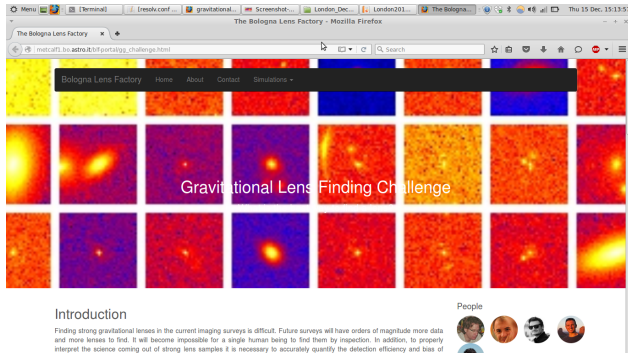
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Training dataset



- 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
CMU-DeepLens-Resnet-Voting	Ground-Based	0.98	0.02	0.10	CNN
LASTRO EPFL	Ground-Based	0.97	0.07	0.11	CNN
CAS Swinburne Melb	Ground-Based	0.96	0.02	0.08	CNN
AstrOmatic	Ground-Based	0.96	0.00	0.01	CNN
Manchester SVM	Ground-Based	0.93	0.22	0.35	SVM / Gabor
Manchester-NA2	Ground-Based	0.89	0.00	0.01	Human Inspection
ALL-star	Ground-Based	0.84	0.01	0.02	edges/gradients 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 TPR₀.

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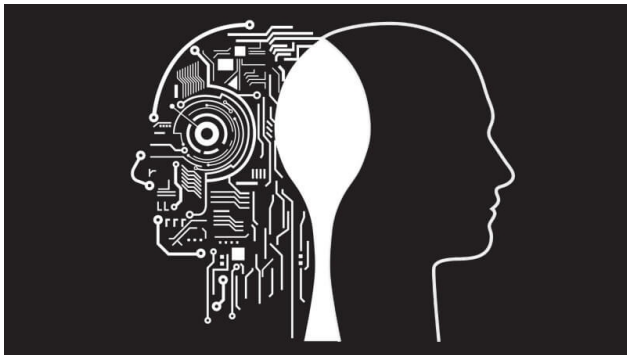
Competition results in TPR_0

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Results

- 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



Results

- 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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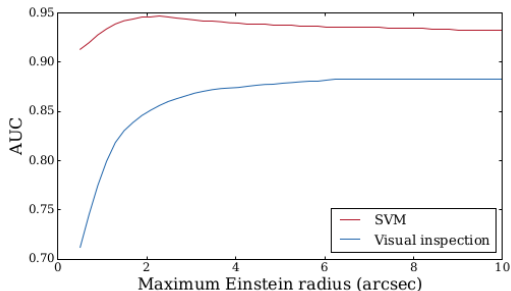
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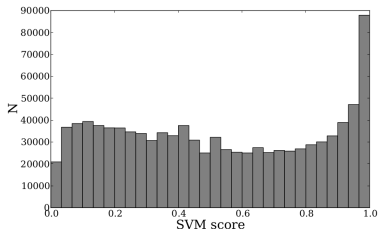
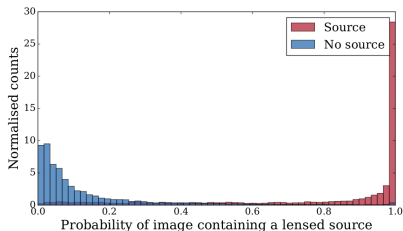
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Real data: Kilo Degree Survey



- 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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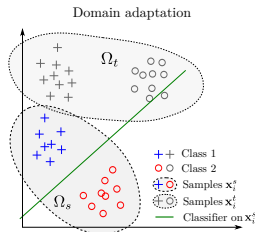
Conclusions

- 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?

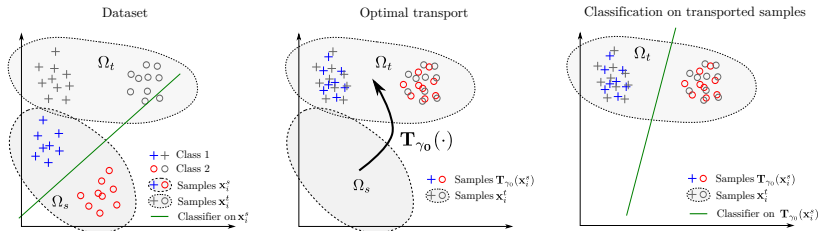
The future : Domain adaptation



Domain adaptation (special case of transfer 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?
- Use of Optimal Transport theory to adapt between domains [Courty et al., 2016, Damodaran et al., 2018].

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Thank you





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