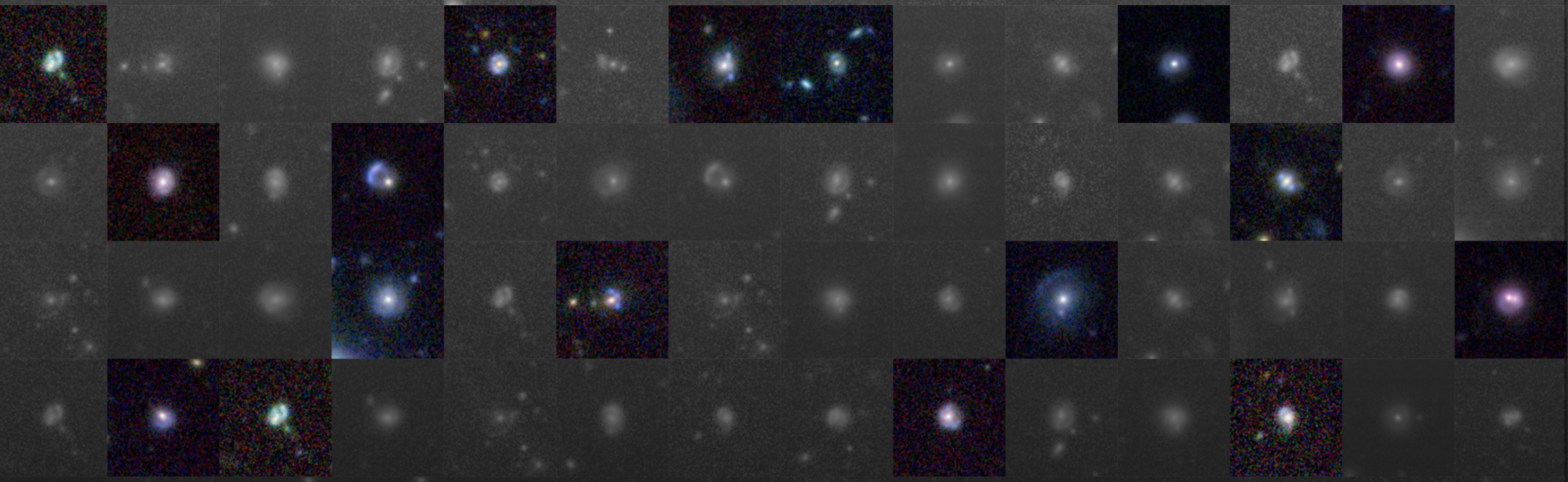

Finding rare objects in space: a class imbalance problem

Philippa Hartley
Jodrell Bank Centre for Astrophysics

Wednesday Nov 22nd 2017

4IR Workshop on Class Imbalance in Machine Learning

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esa LSST Large Synoptic Survey Telescope INTERNATIONAL SPACE SCIENCE INSTITUTE

Strong gravitational lenses

Science Objectives:

Cosmology: Hubble Constant

Galaxy structure and evolution

Dark matter substructure

Cosmic telescopes

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Euclid mission: Strong Lens Legacy Science Group

- ***white paper in prep.***

Current sample

~300 strong lenses

Expectations

~10 000 000 000 sources

~300 000 galaxy-galaxy lenses

~3000 cluster lenses

Where are they?

Support vector machines

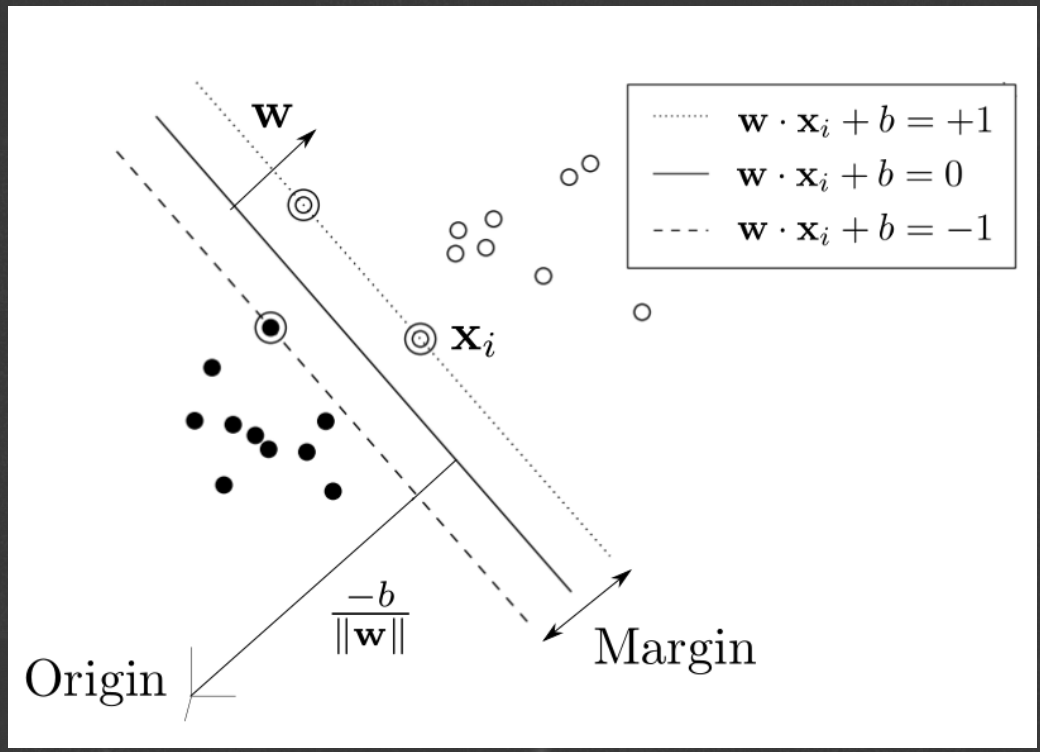
$$\{\mathbf{x}_i, y_i\}, \quad i = 1, \cdots, l, \quad y_i \in \{-1, 1\}, \quad \mathbf{x}_i \in \mathbf{R}^d$$

$$\mathbf{x}_i \cdot \mathbf{w} + b \geq +1 \quad \text{for } y_i = +1$$
$$\mathbf{x}_i \cdot \mathbf{w} + b \leq -1 \quad \text{for } y_i = -1$$

$$L_P \equiv \frac{1}{2}\|\mathbf{w}\|^2 - \sum_{i=1}^{l} \alpha_i y_i (\mathbf{x}_i \cdot \mathbf{w} + b) + \sum_{i=1}^{l} \alpha_i$$

$$\mathbf{w} = \sum_i \alpha_i y_i \mathbf{x}_i \qquad \sum_i \alpha_i y_i = 0.$$

$$L_D = \sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j \mathbf{x}_i \cdot \mathbf{x}_j$$



Vapnik et al. 1979, Cortes & Vapnik 1995

- Find optimal hyperplane separating two classes of data
- Optimisation depends only on dot products of support vectors, found on the edge of each class

Support vector machines

$$\{\mathbf{x}_i, y_i\}, \quad i = 1, \cdots, l, \quad y_i \in \{-1, 1\}, \quad \mathbf{x}_i \in \mathbf{R}^d$$

$$\mathbf{x}_i \cdot \mathbf{w} + b \geq +1 \quad \text{for } y_i = +1$$
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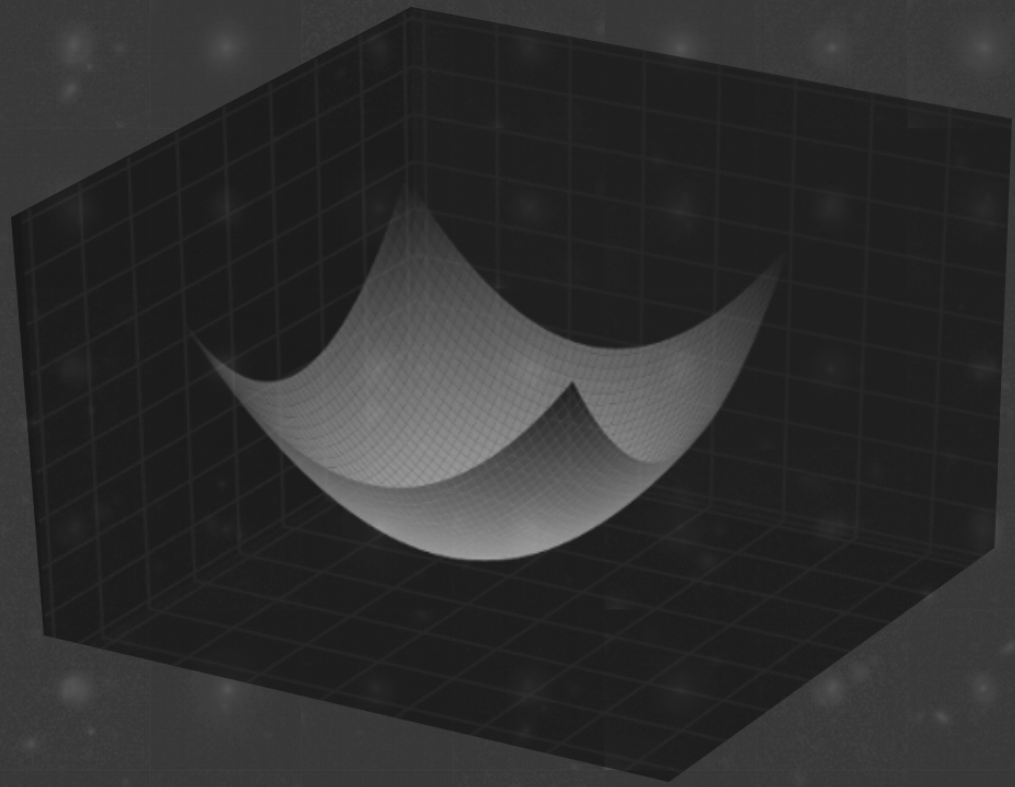


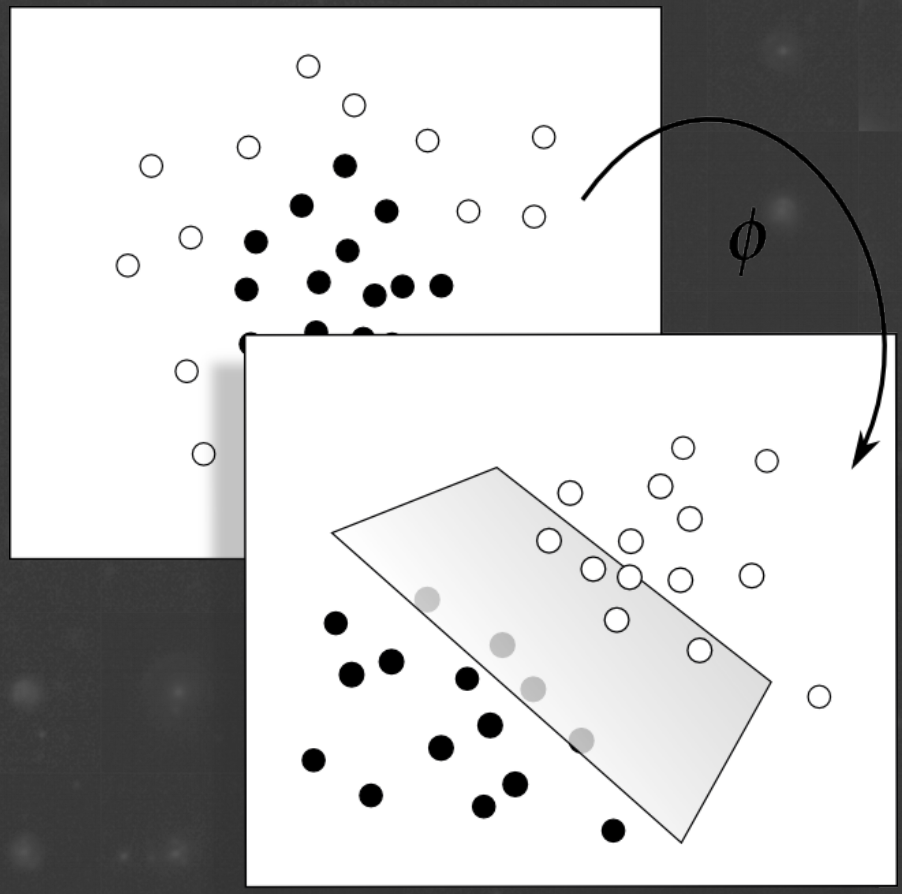
Vapnik et al. 1979, Cortes & Vapnik 1995

- Function is convex: every local solution is a global one – no local minima

Support vector machines

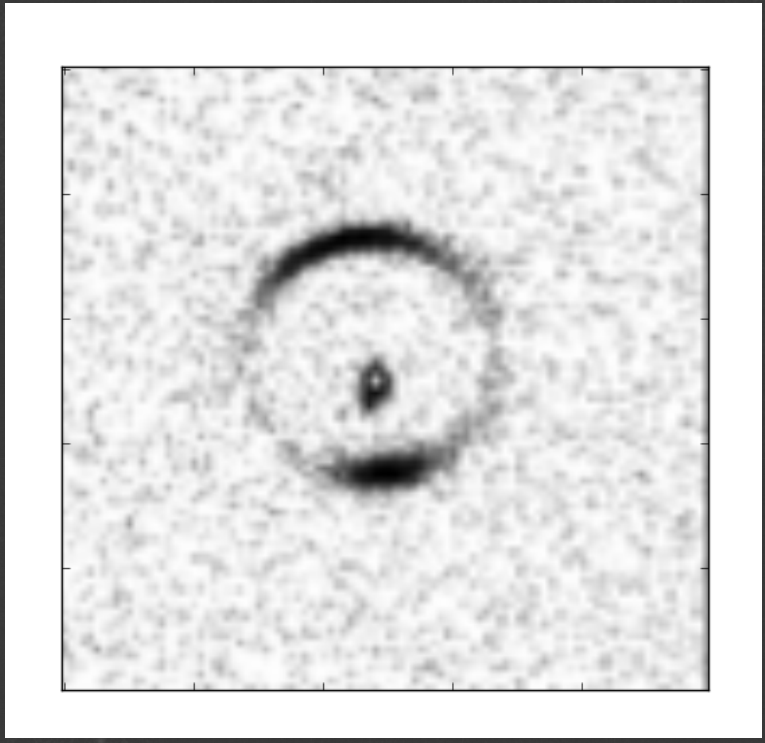
$$K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i) \cdot \phi(\mathbf{x}_j).$$

Boser et al. 1992

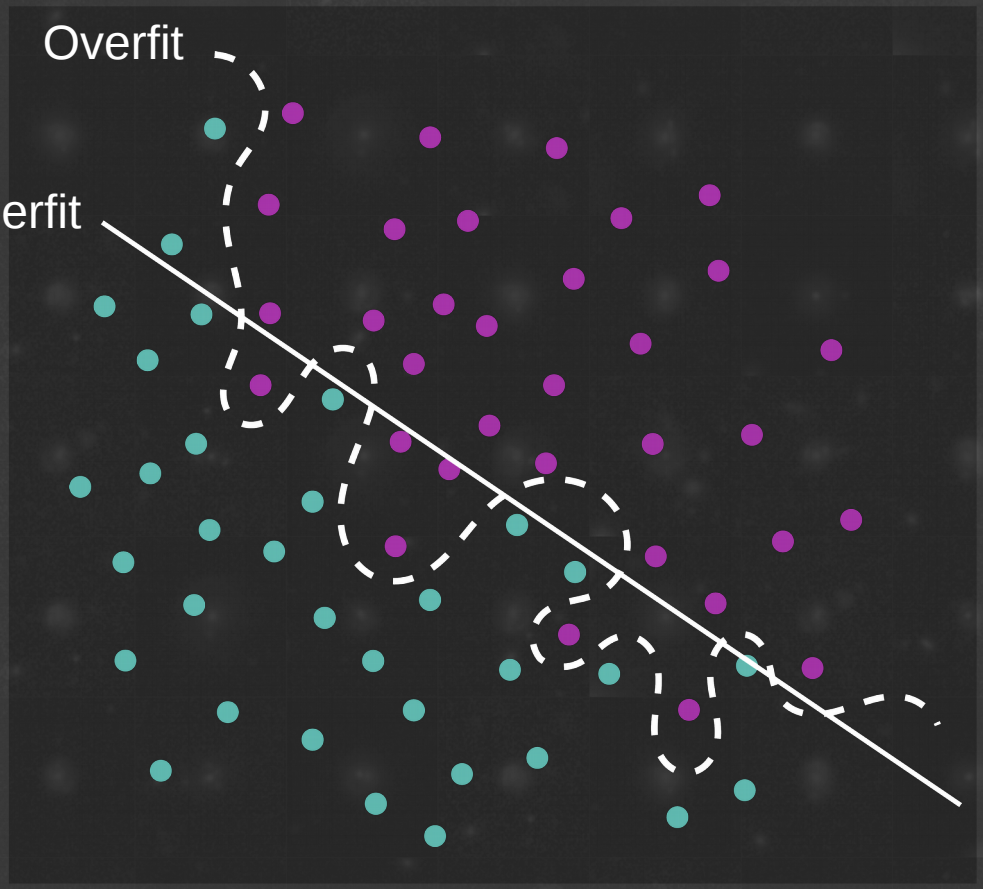


- Coordinate transformation can deal with non-linear separation
- Unknown kernel function replaces dot product

Feature extraction

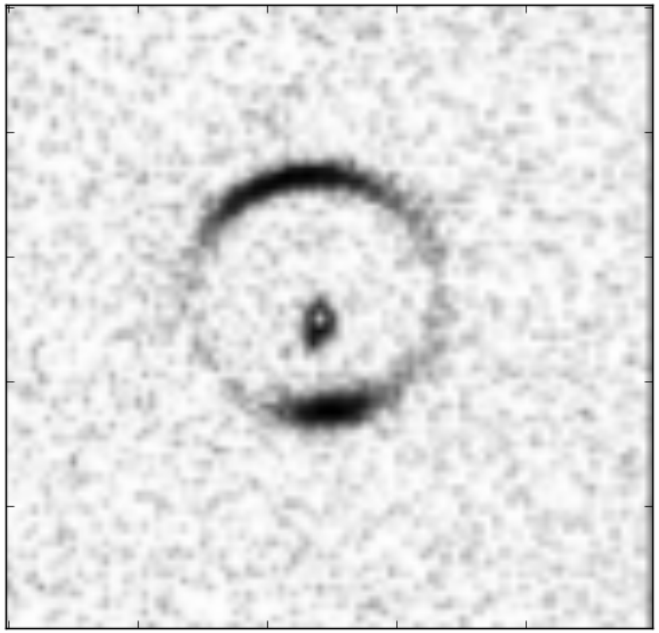


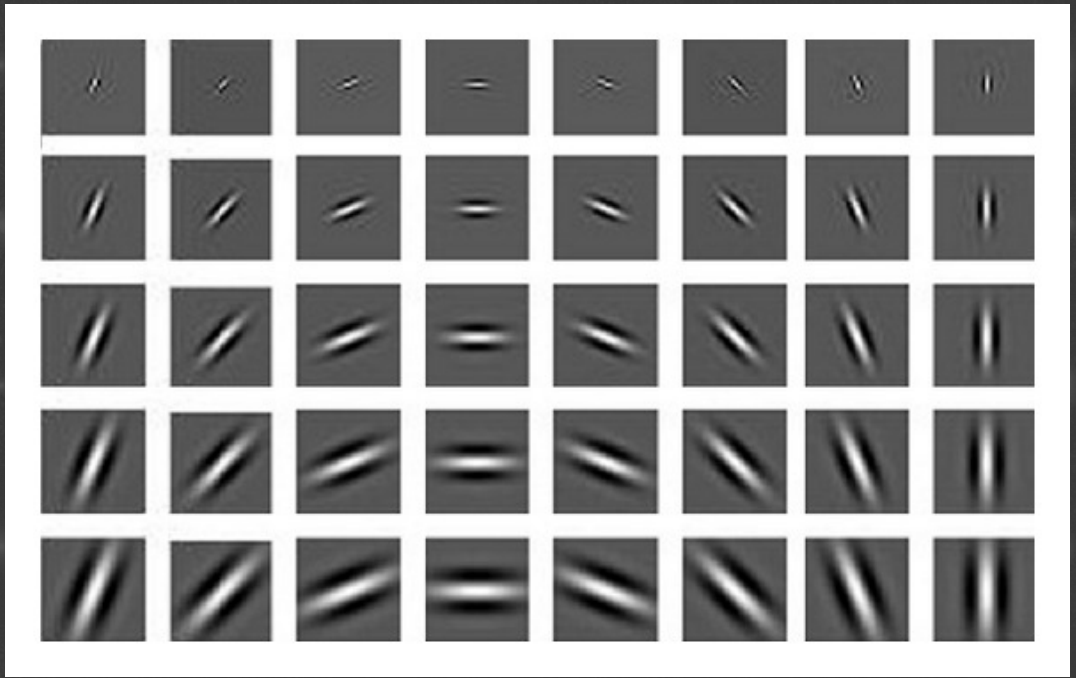
100 * 100 pixels = **10 000** features



Feature extraction

Apply **Gabor filters**: model the simple cells of the mammillian visual cortex (Marcelja 1980)

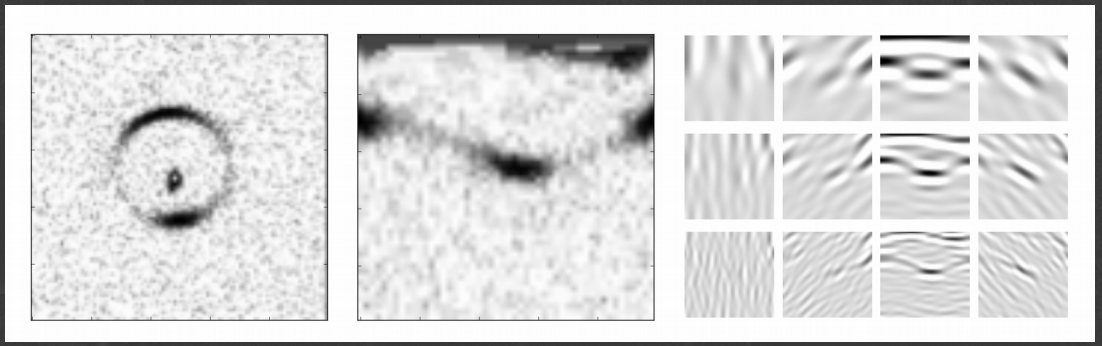




$$G_c[i,j] = Be^{-\frac{(i^2+j^2)}{2\sigma^2}} \cos\left(\frac{2\pi}{\lambda}(i\cos\theta + j\sin\theta)\right)$$

Feature extraction

Training sample → polar transform → Gabor filterbank → calculate moments

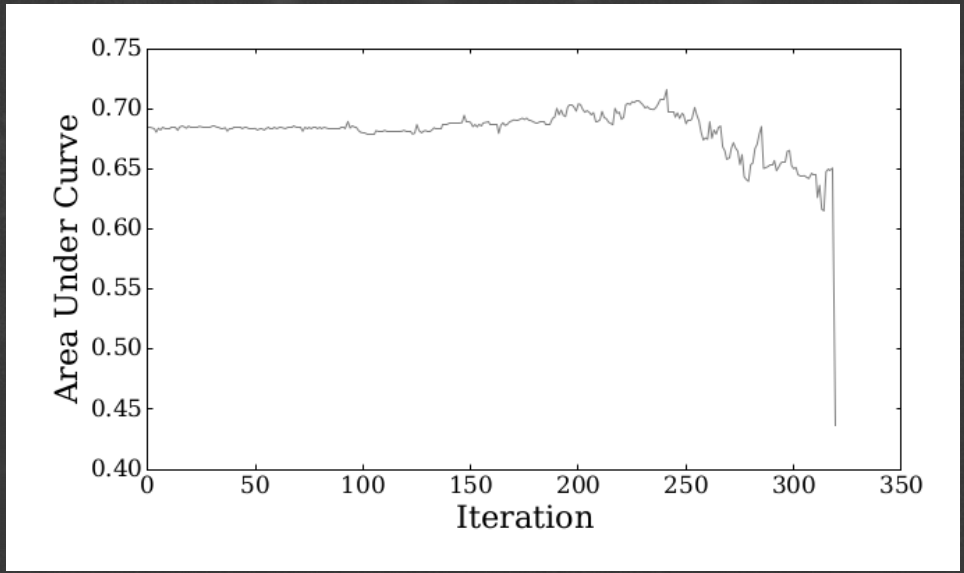


Mean	$\mu_1(x_1, \ldots, x_N) = \frac{1}{N} \sum_{j=1}^{N} x_j$
Variance	$\mu_2(x_1, \ldots, x_N) = \frac{1}{N-1} \sum_{j=1}^{N} (x_j - \mu_1)^2$
Skew	$\mu_3(x_1, \ldots, x_N) = \frac{1}{N} \sum_{j=1}^{N} \left[\frac{x_j - \mu_1}{\mu_2} \right]^3$
Kurtosis	$\mu_4(x_1, \ldots, x_N) = \left\{ \frac{1}{N} \sum_{j=1}^{N} \left[\frac{x_j - \mu_1}{\mu_2} \right]^4 \right\}$
Local energy	$E_s(x_1, \ldots, x_N) = \sum_{j=1}^{N} x_j^2$

Hartley et al. 2017 MNRAS

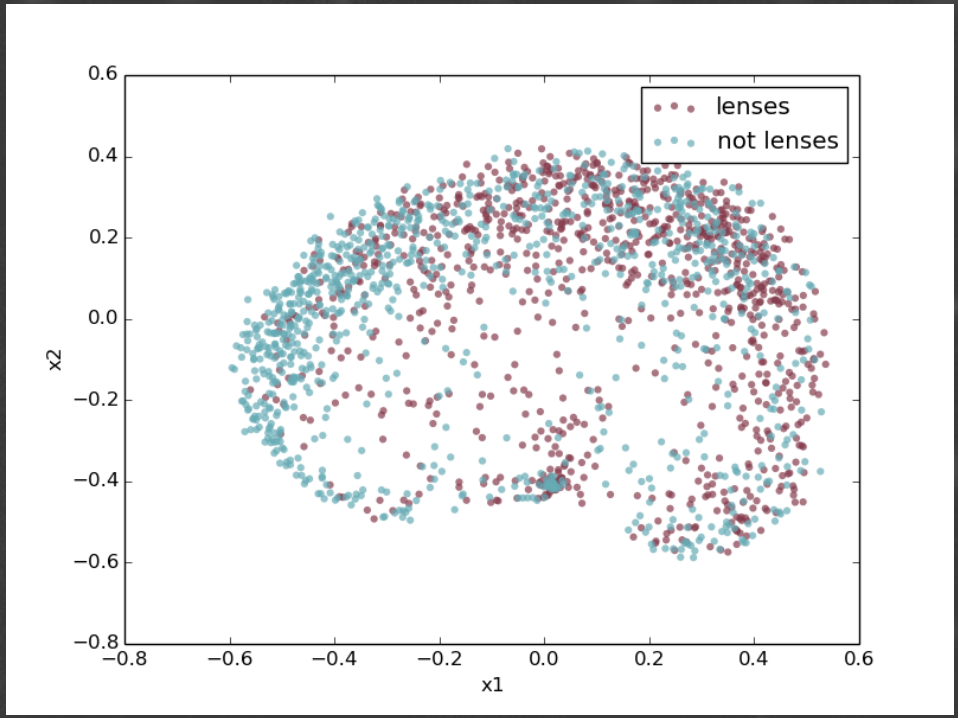
4 bands * 9 kernel frequencies * 7 kernel rotations * 5 moments = **1260** features

Feature selection



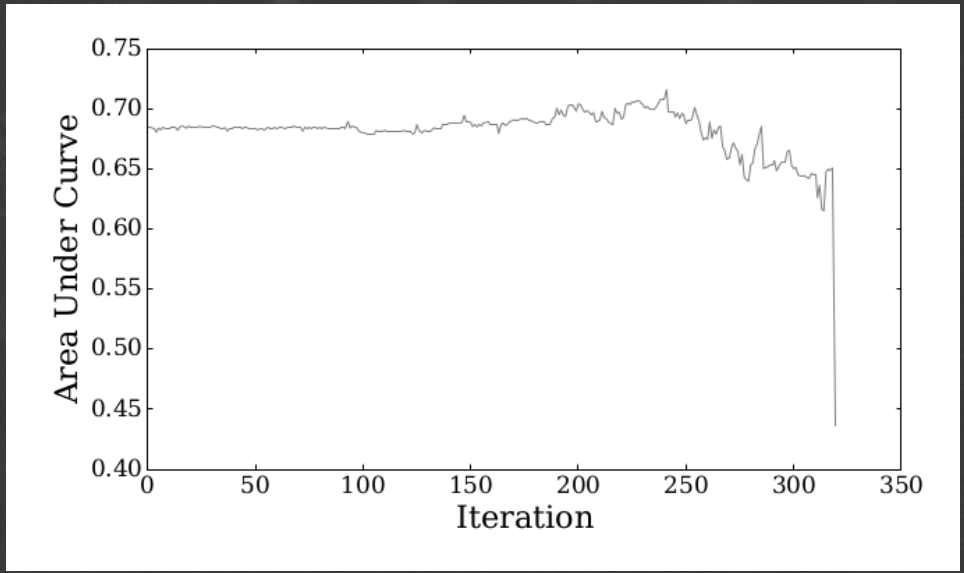
Recursive feature elimination

Simple, but can be unstable



Principle component analysis

Feature selection



Recursive feature elimination

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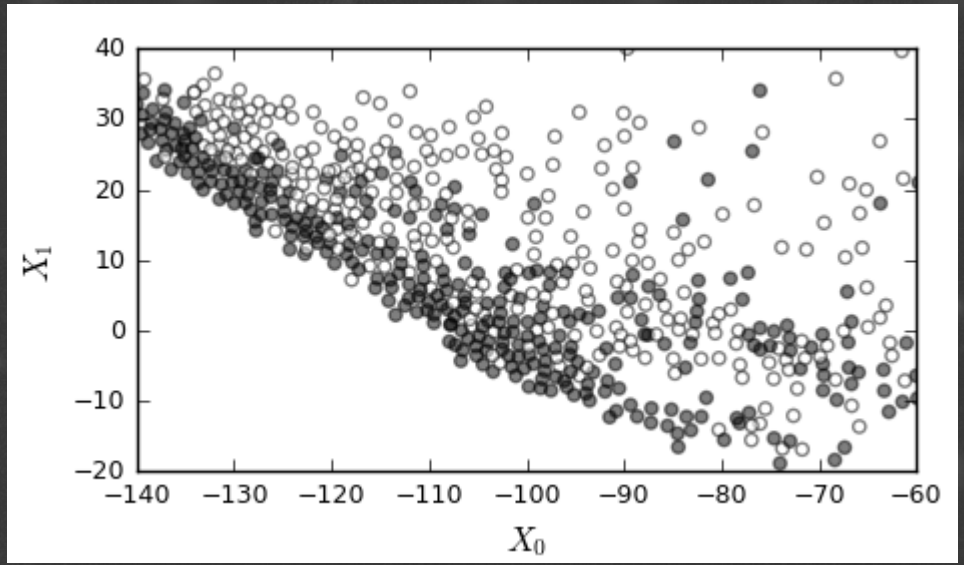


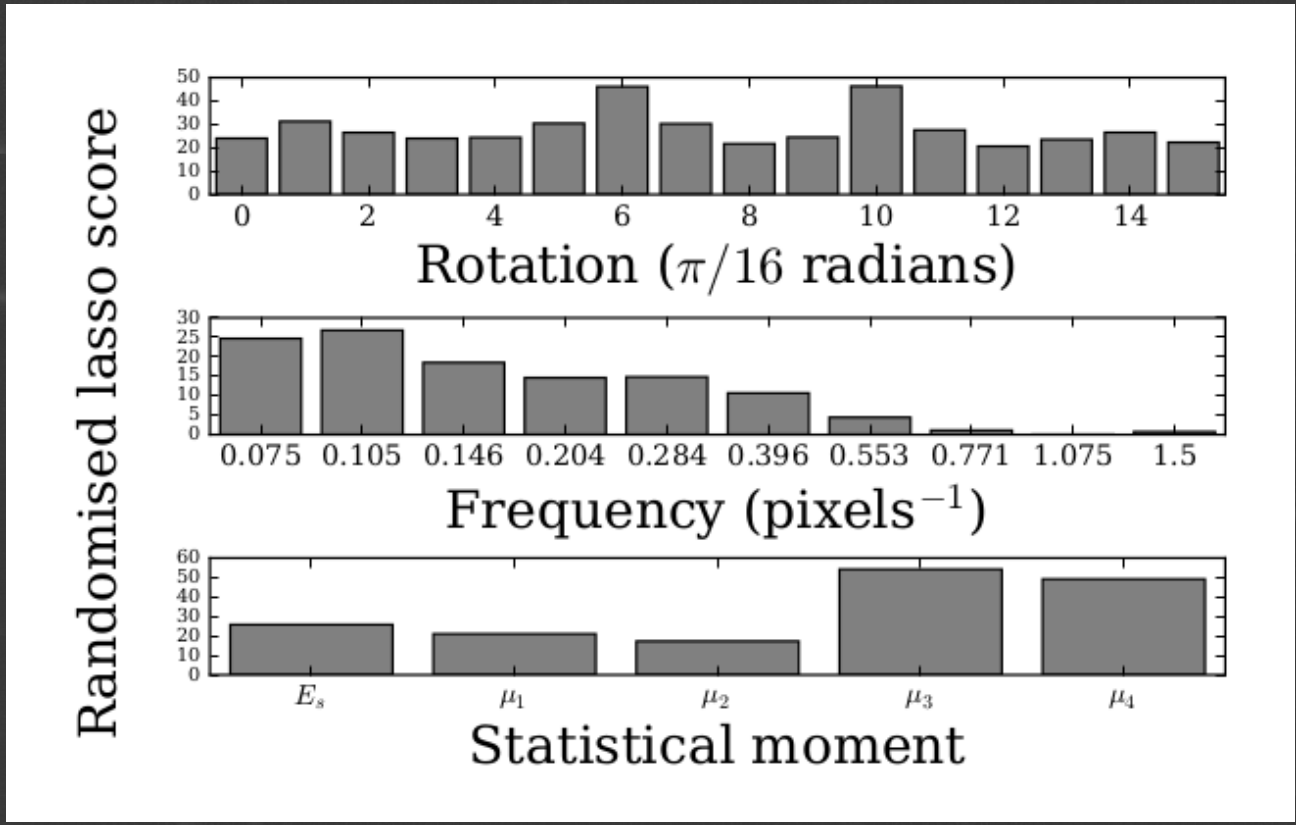
t-distributed stochastic neighbour embedding (t-SNE)

Like principle component analysis but able to respresent non-linear relationships

Feature selection

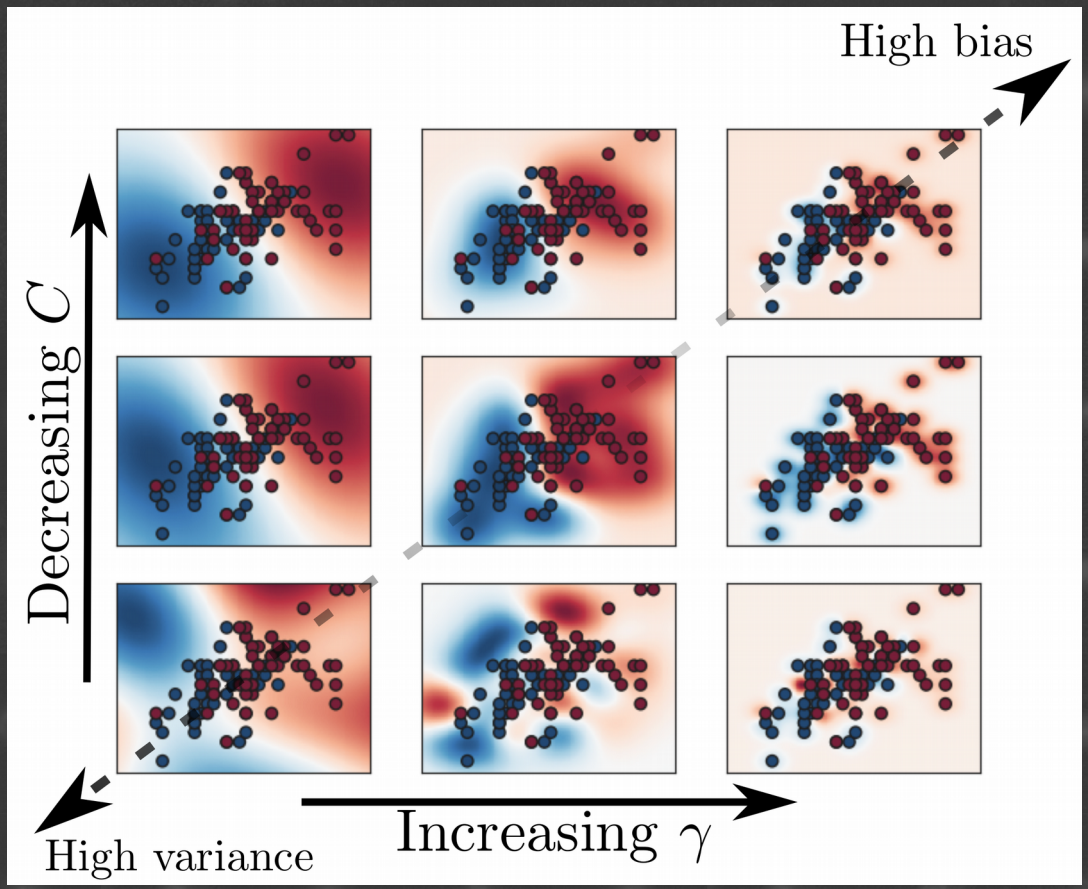
Stability selection:

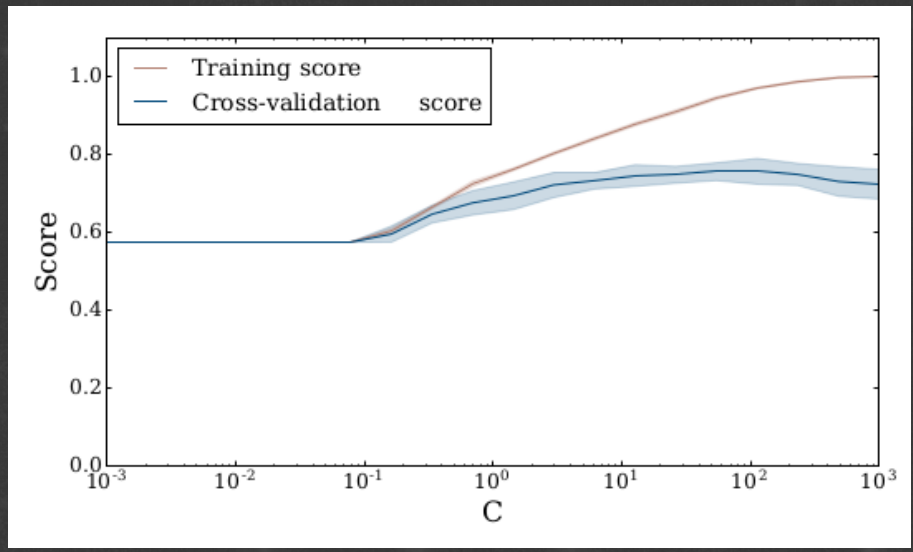
Features are subsampled and perfomance evaluated

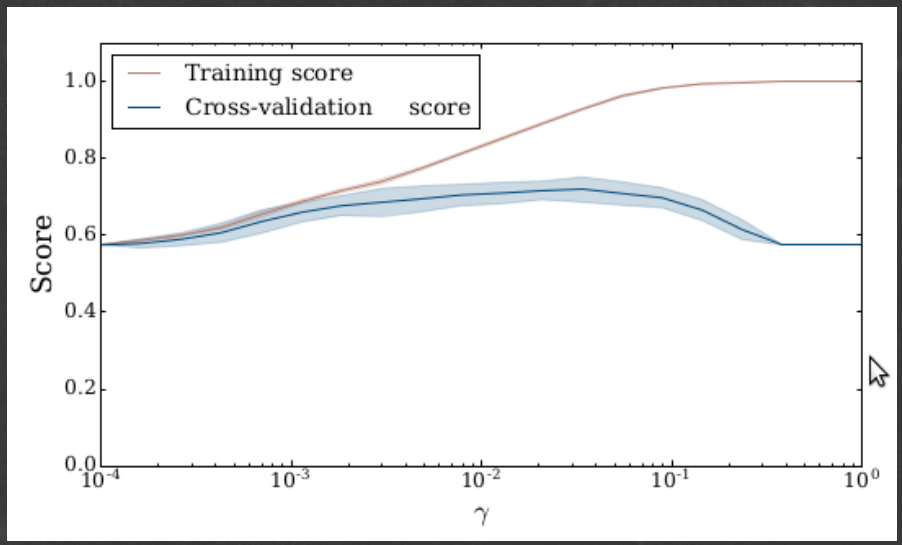


Model tuning

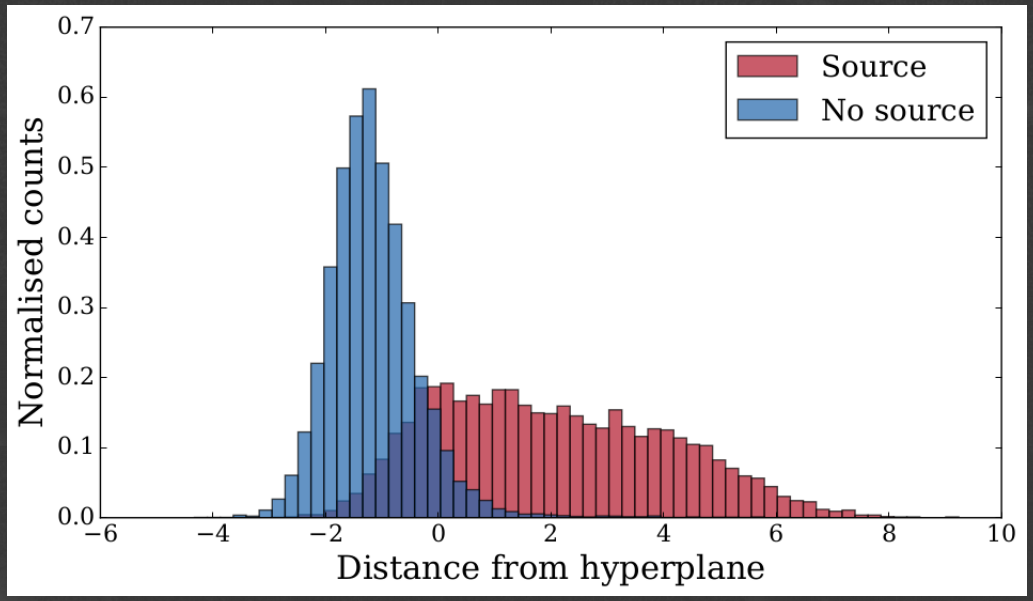
Regularisation parameters



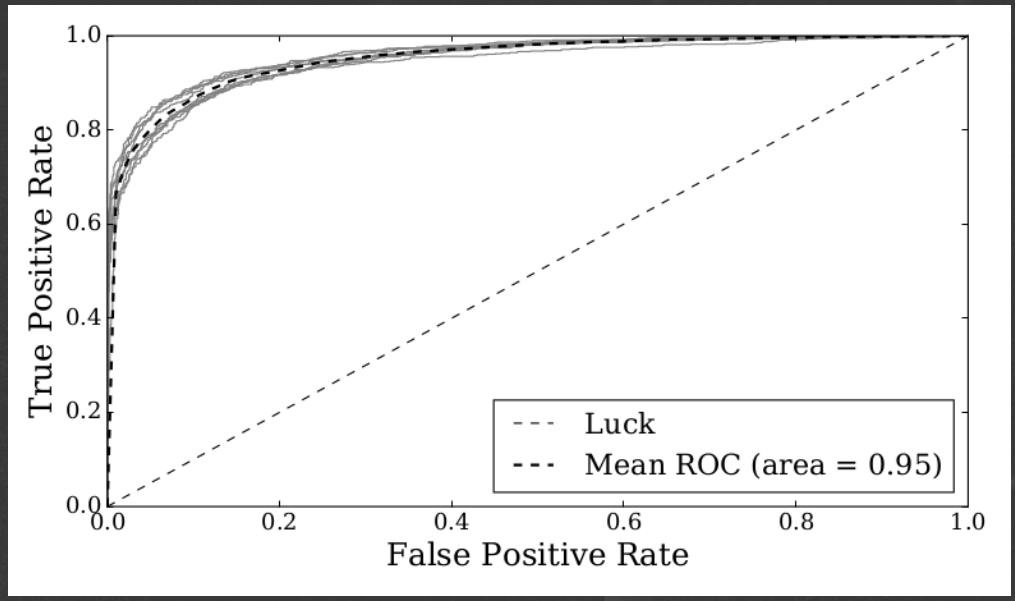




Results

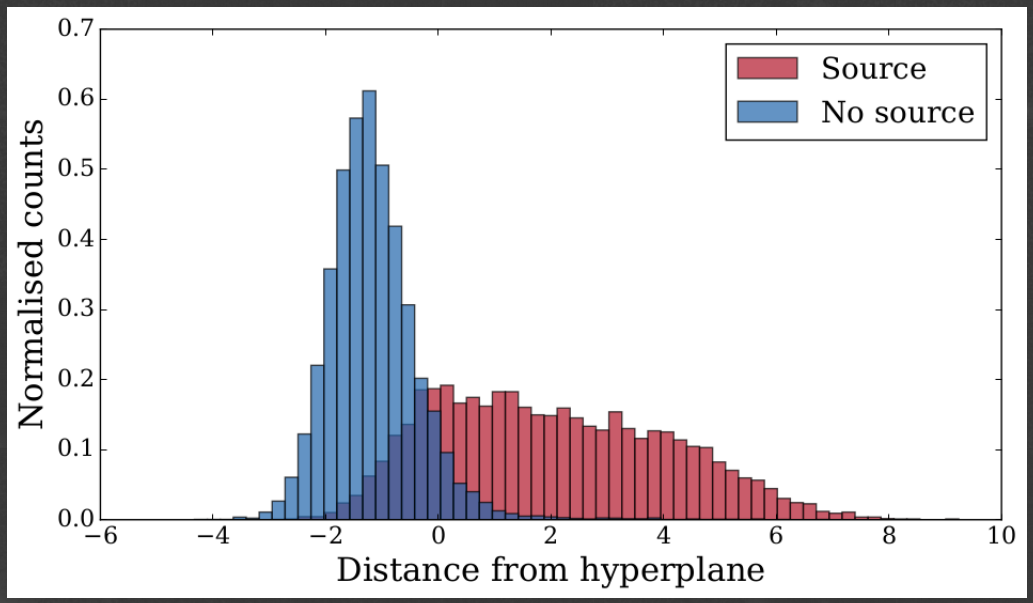


Raw score from SVM

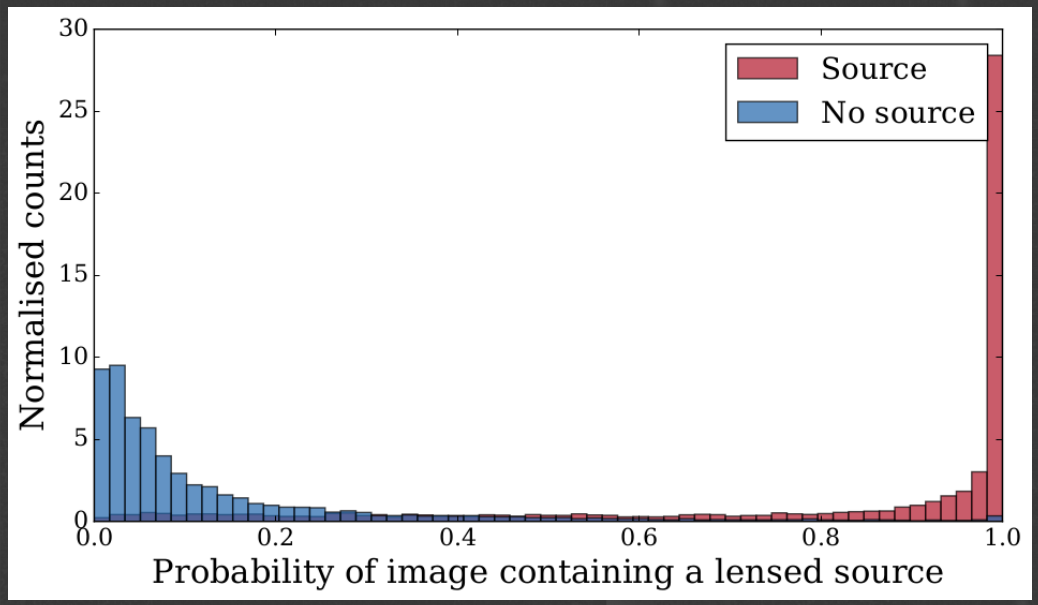


Receiver operating characteristic (ROC) curve

Results: Platt scaling

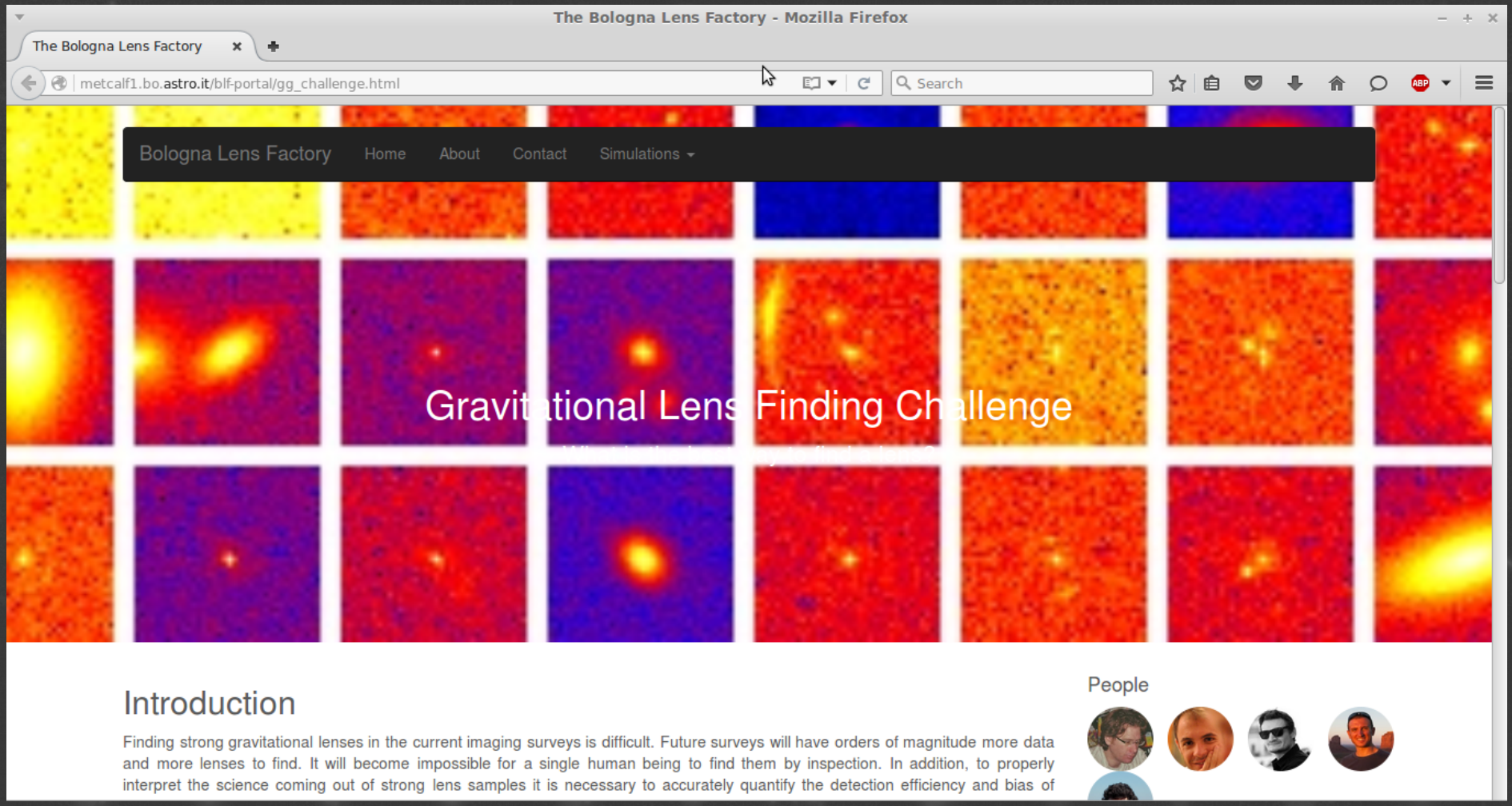


Raw score from SVM



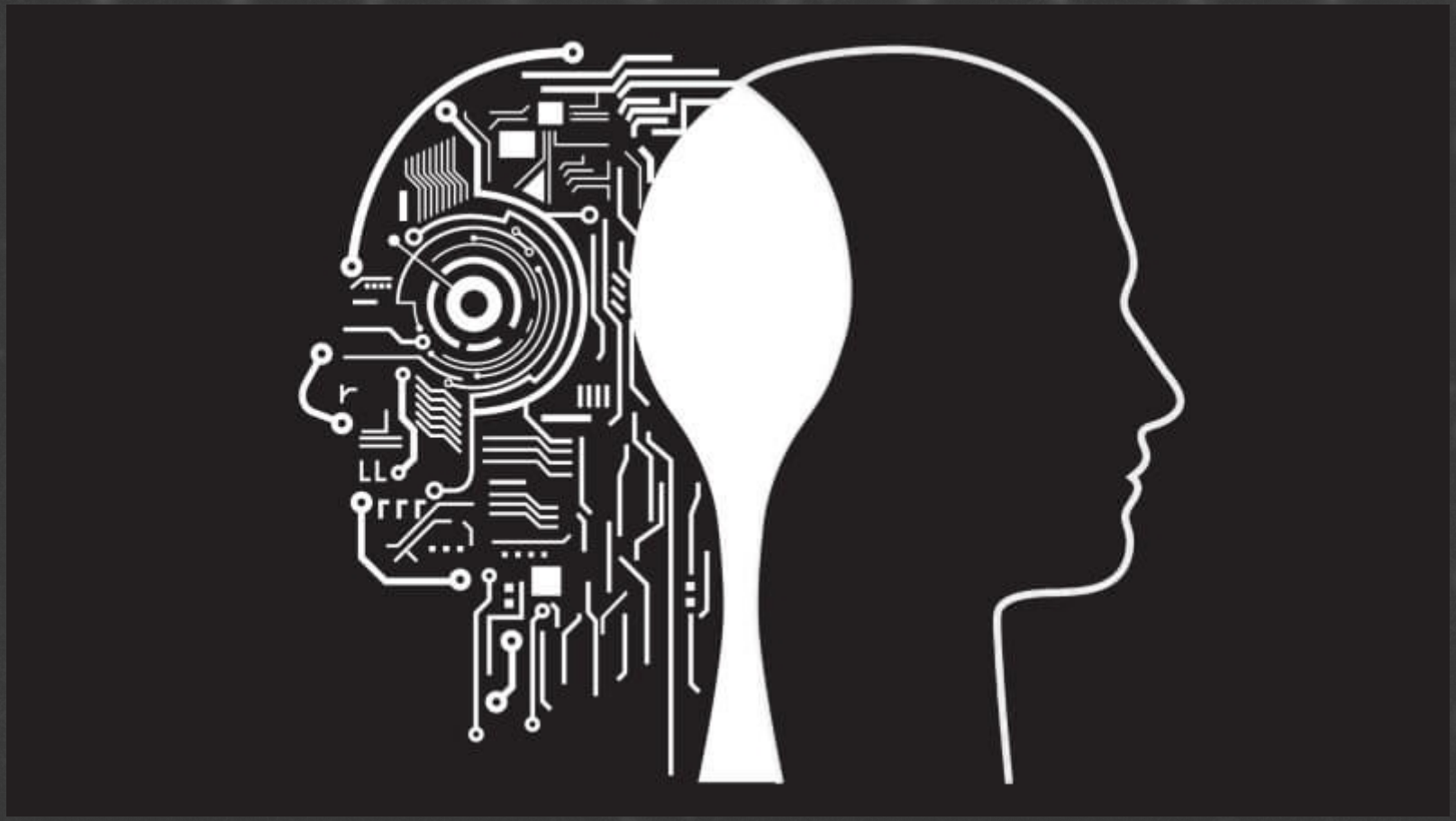
Convert output into calibrated probabilities

Lens Finding Challenge



Metcalf et al., in preparation 2017

Machine vs human



100 000 simulated images, 48 hours

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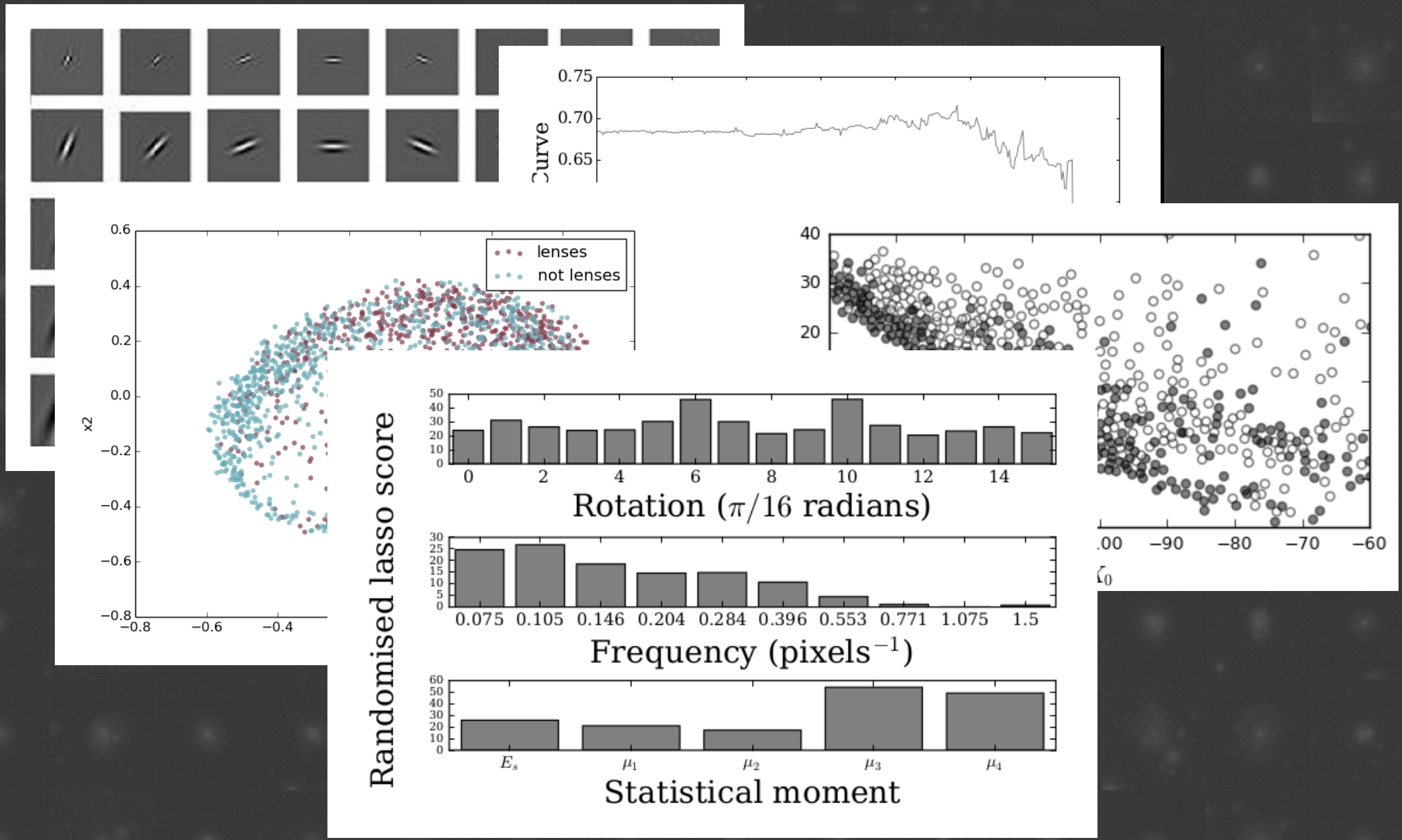
Lens Finding Challenge



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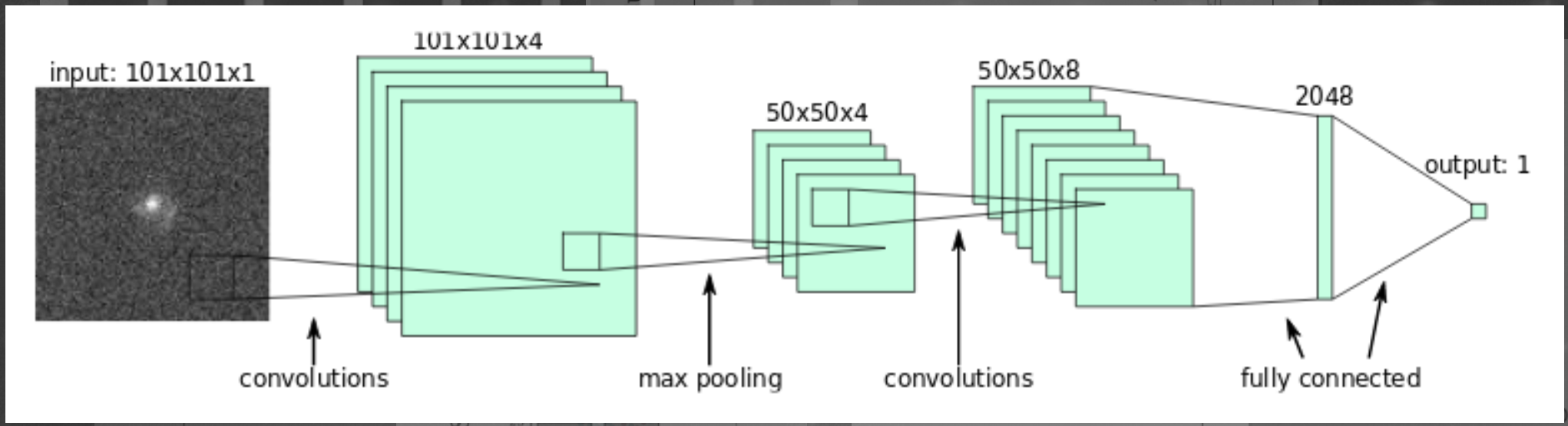

Convolutional neural network
Credit: Schaefer et al. 2017

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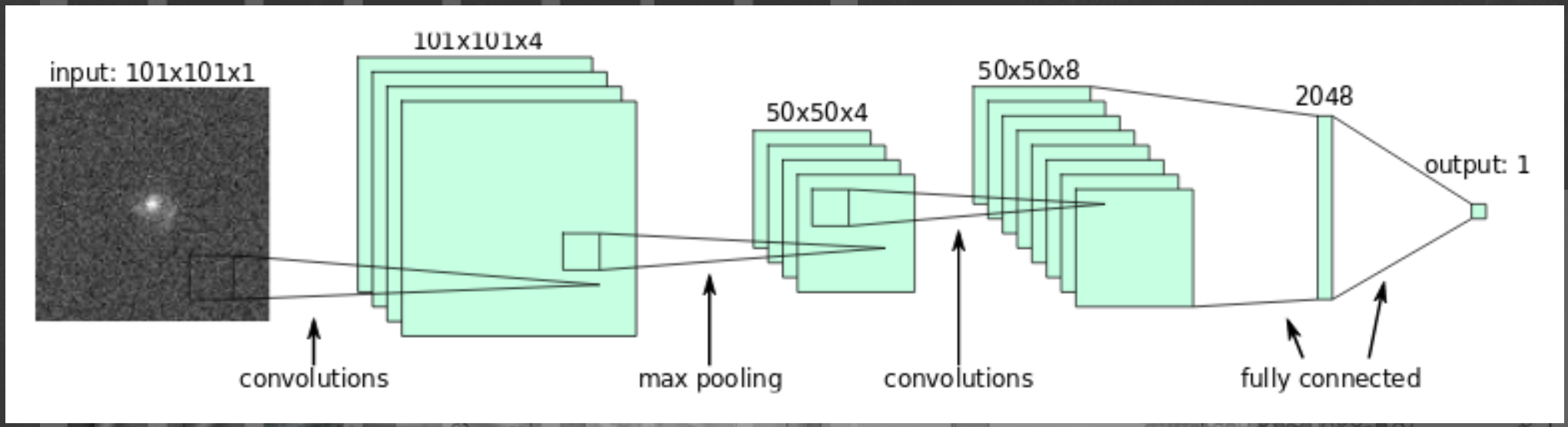
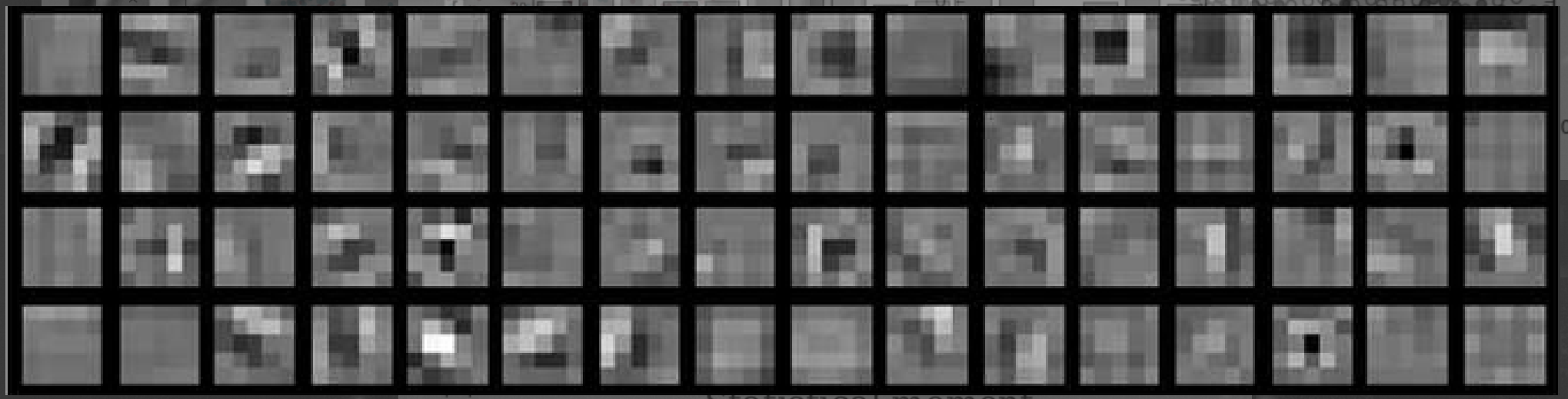
Lens Finding Challenge

Credit: Schaefer et al. 2017





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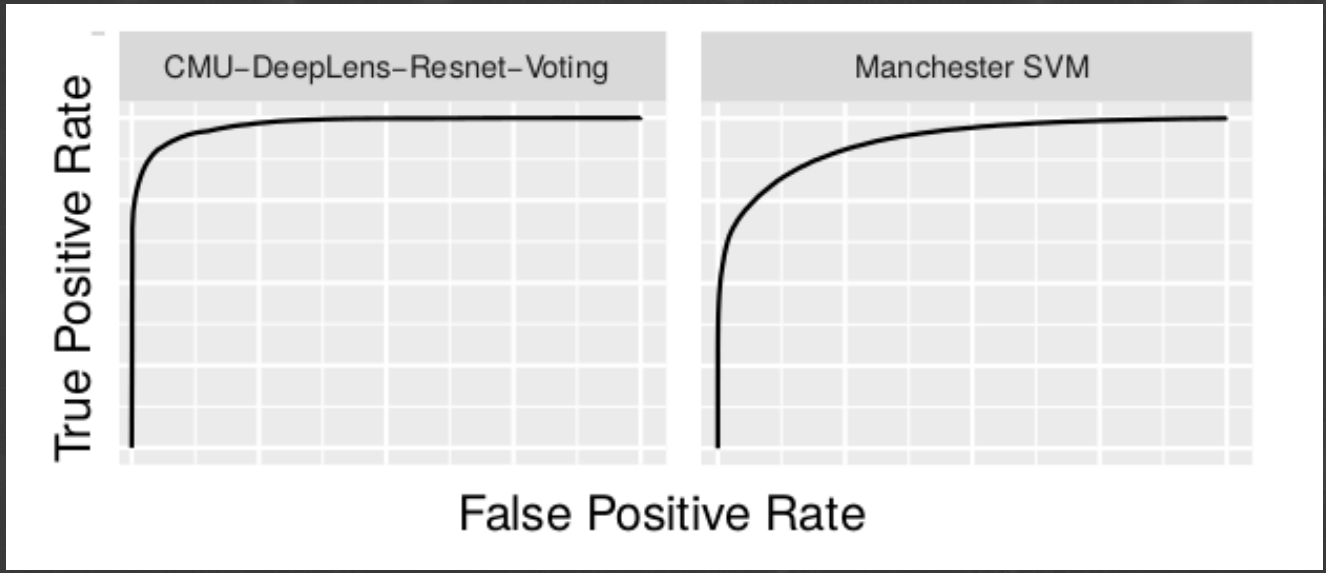
Lens Finding Challenge: results

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/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



Metcalf et al., in preparation 2017

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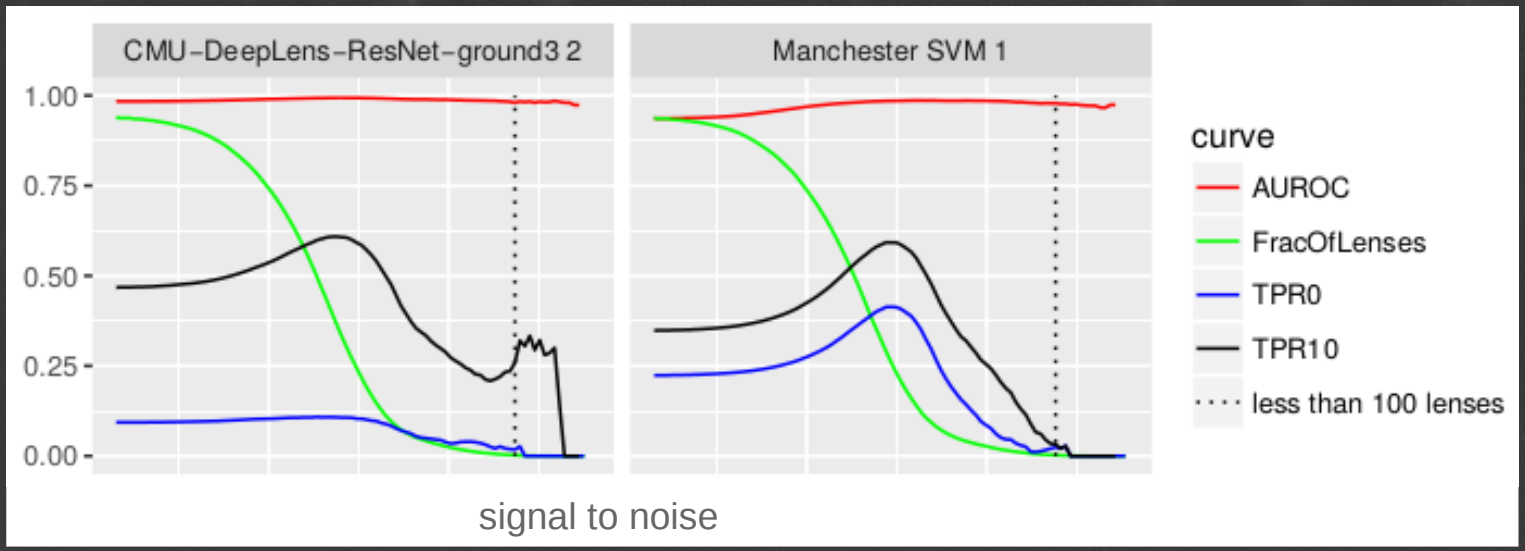

Metcalf et al., in preparation 2017

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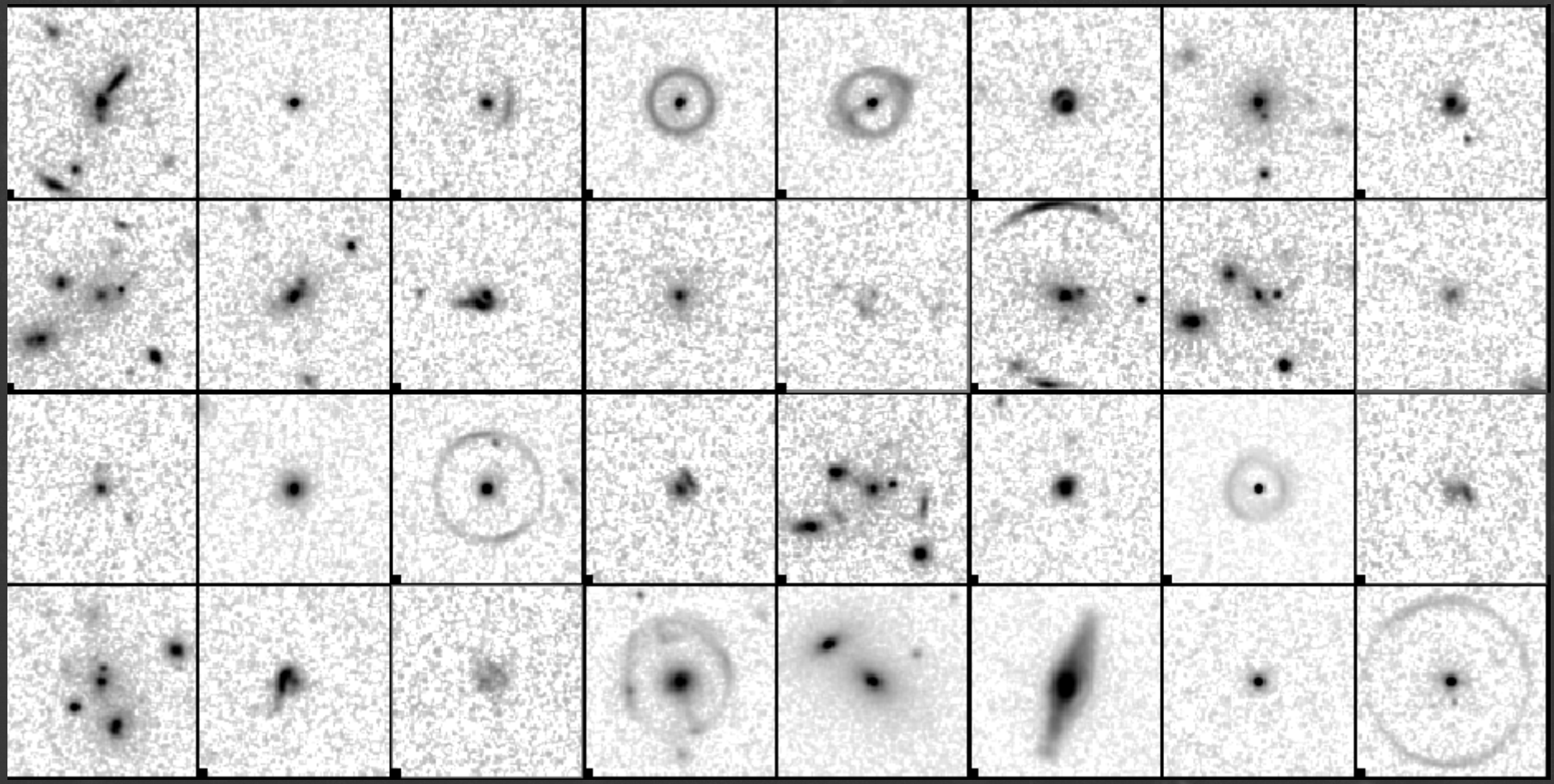
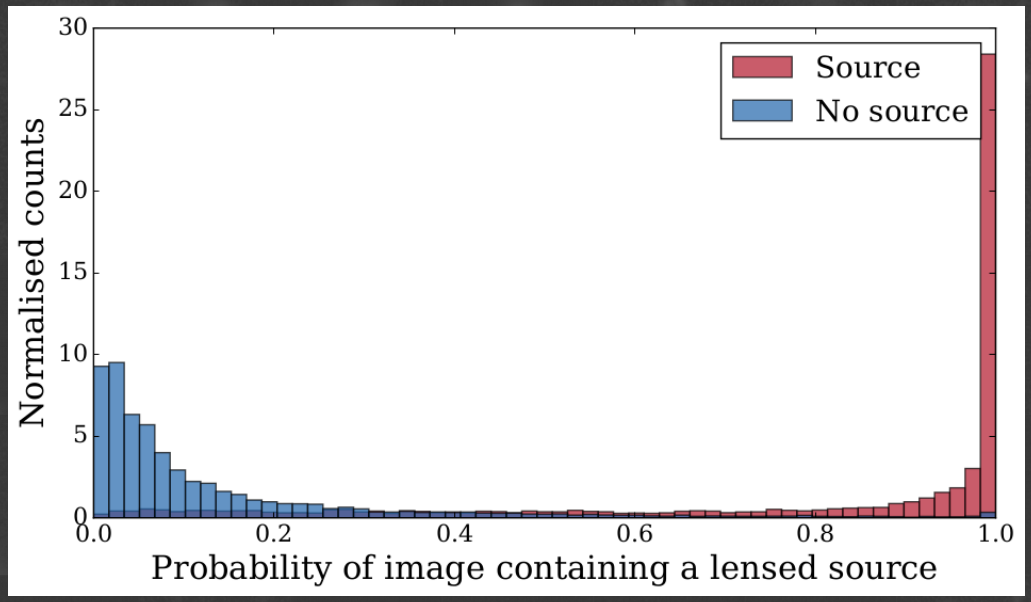
Real life data: Kilo Degree Survey

Domain adaptation

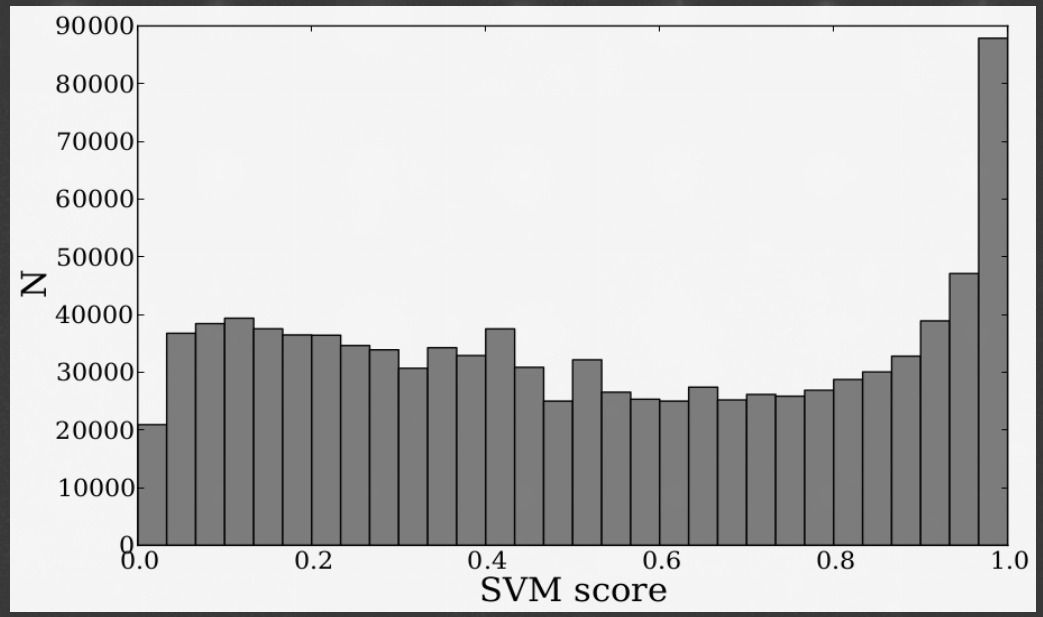


Real data: Kilo Degree Survey

1 000 000 real images after pre-selection



Classification of test mock data



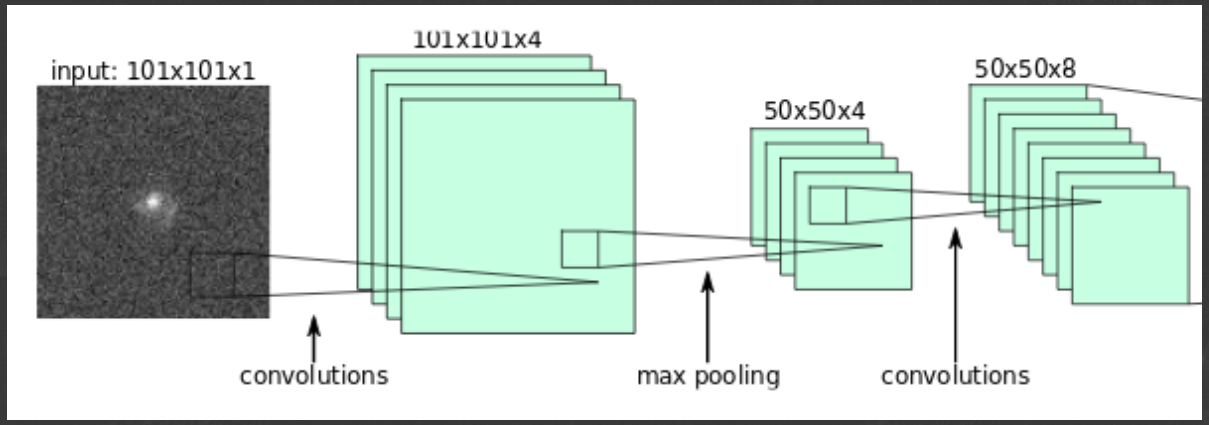
Classification of KiDS real data

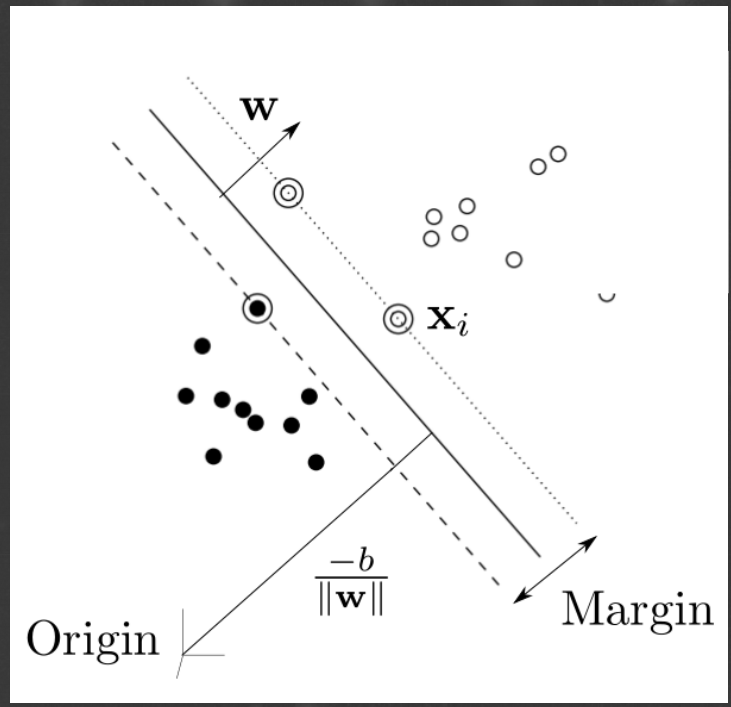
Real life data: Kilo Degree Survey

Hartley et al. 2017 MNRAS

Conclusions

- Machines by far surpass humans in this case
- Surprising strength of SVMs when false postives are a problem
- Domain adaption: limited by quality of training data
- The best architecture might be: CNN +SVM





P. Hartley, R. Flamary, N. Jackson, A. S. Tagore, R. B. Metcalfe, MNRAS 471 (3): 3378-3397, 2017

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