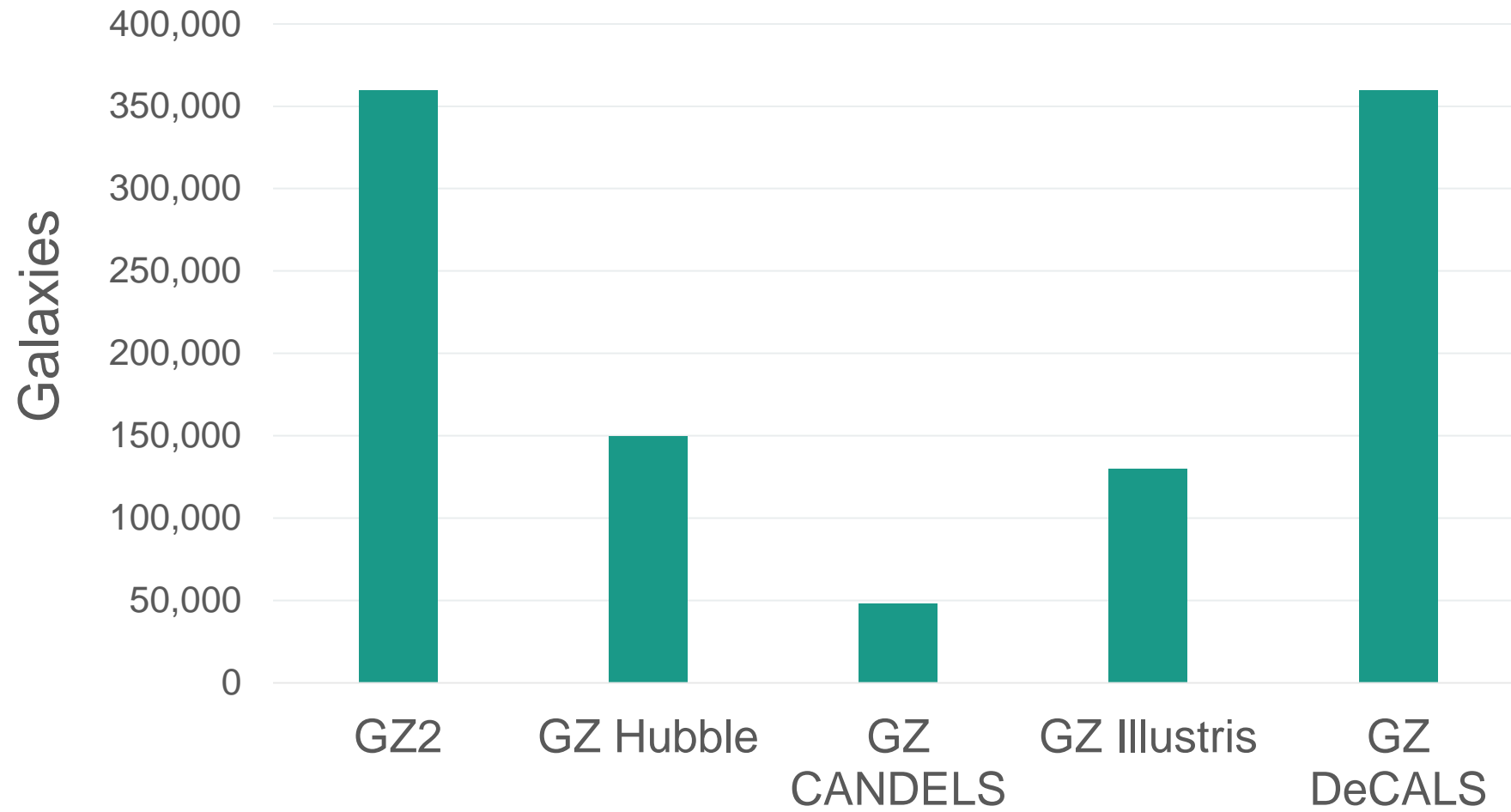


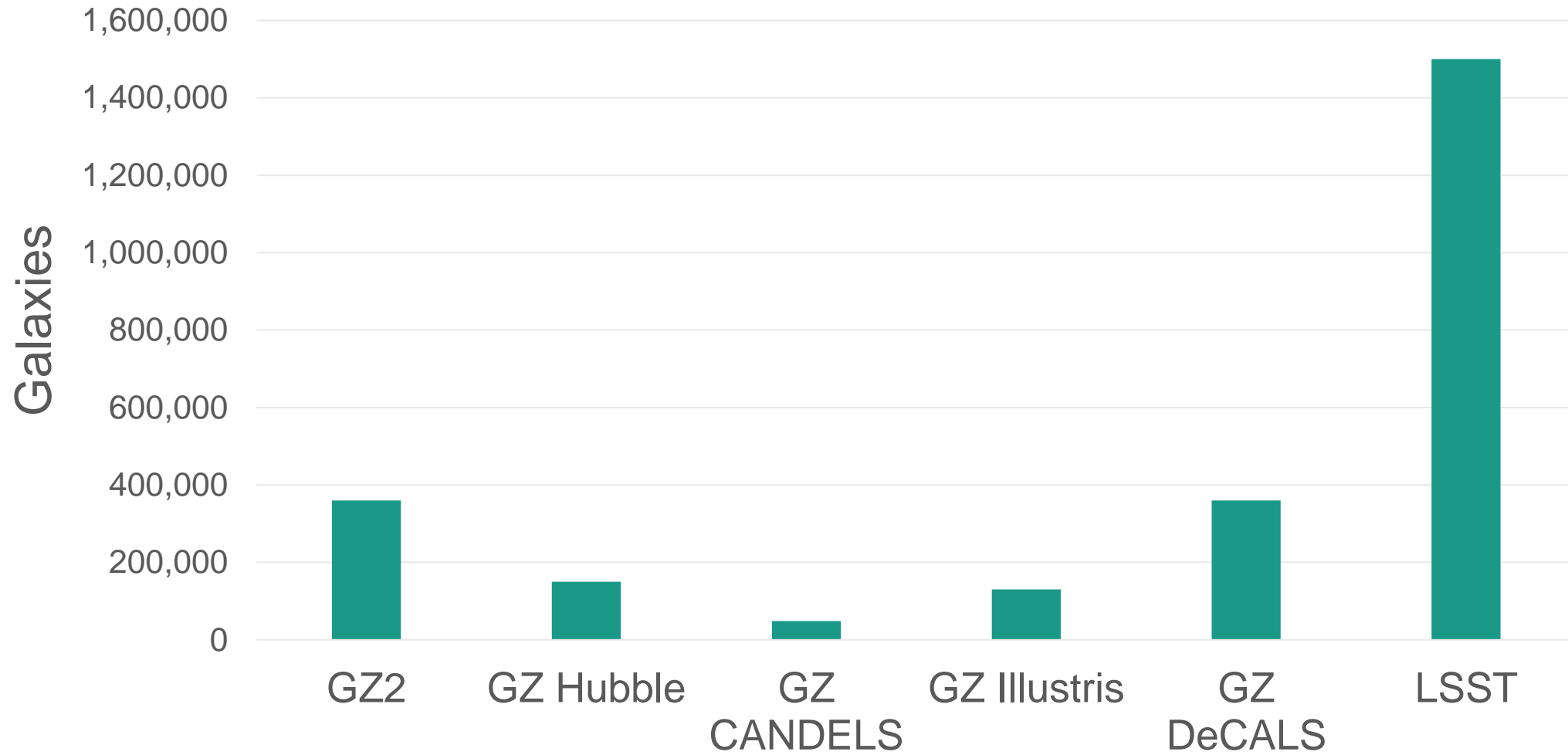
# Bayesian Active Learning for Probabilistic Galaxy Morphology

Mike Walmsley

*with Chris Lintott, Lewis Smith, Yarin Gal, et al*

University of Oxford







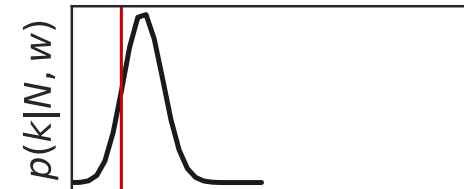
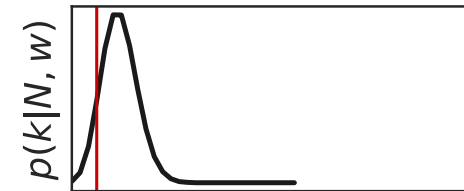
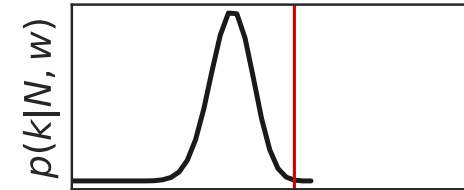
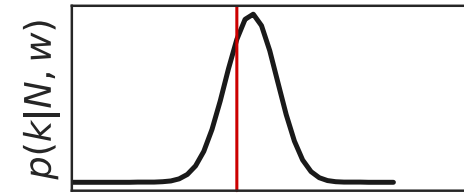
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## BCNN with Two Twists:

1. Embrace Label Uncertainty
2. Apply Active Learning

# Posteriors for Votes

- Our CNN can learn from uncertain labels and make probabilistic predictions  $p(k|w)$



0 20 40  
k 'Bar' votes, of  $N$  total

1 Model  
Mike \

# Probabilistic CNN

Volunteers  $N$   
Responses  $k$   
Typical vote prob.  $\rho$   
Galaxy  $x$   
CNN output  $f^w(x)$

$N$  volunteers and  $k$  responses  $\approx$   $N$  trials and  $k$  successes

Volunteer model:  $p(k \mid x, N) = \text{Bin}(k \mid \rho, N)$

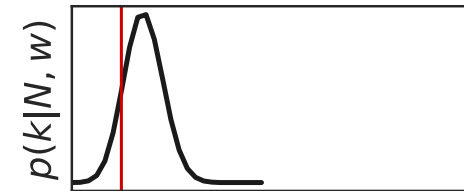
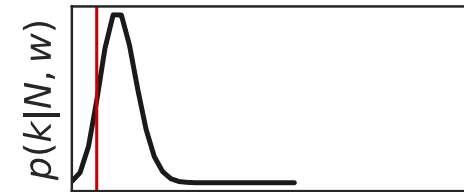
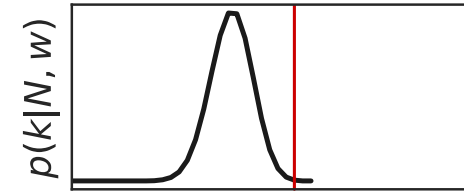
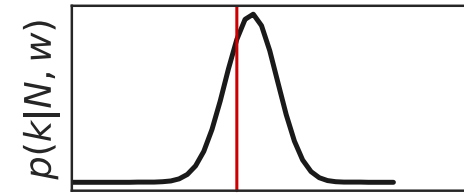
How likely is each  $\rho$  given observed  $k, N$ ?

Log Likelihood  $\mathcal{L} = \log[ \text{Bin}(k \mid \rho, N) ] = k \log(\rho) + (N - k) \log(1 - \rho) + C$

Predict  $f^w(x) = \hat{\rho}$  and maximise likelihood of  $\hat{\rho}$

# Posteriors for Votes

- Our CNN can learn from uncertain labels and make probabilistic predictions  $p(k|w)$



0 20 40  
k 'Bar' votes, of  $N$  total

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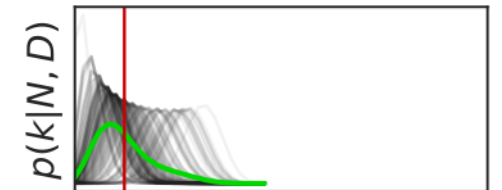
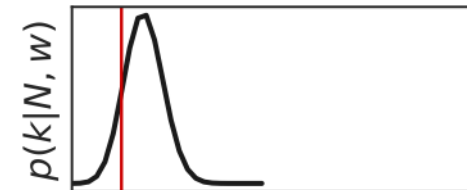
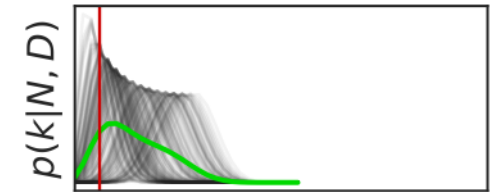
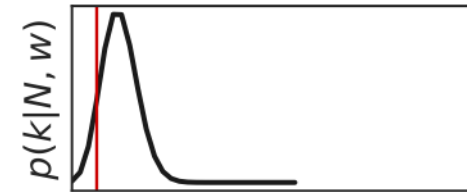
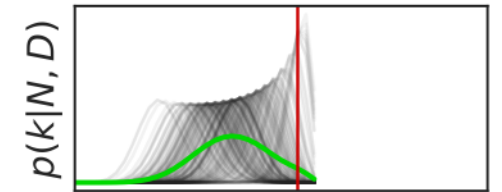
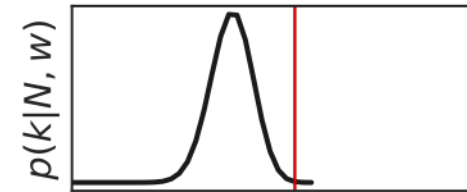
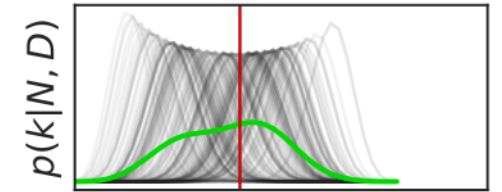
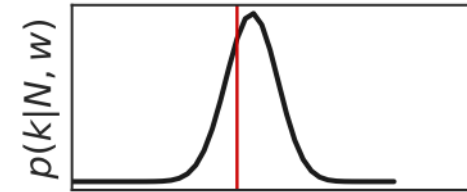


For details on BCNN, see Y. Gal (2016)

# Posteriors for Votes

- Our CNN can learn from uncertain labels and make probabilistic predictions  $p(k|w)$
- Marginalising over weights (BCNN) lets us predict votes over all CNN we might have trained

$$p(k|D) = \int p(v|w) p(w|D) dw$$



1 Model  
Miki

30 "Models" (BCNN)

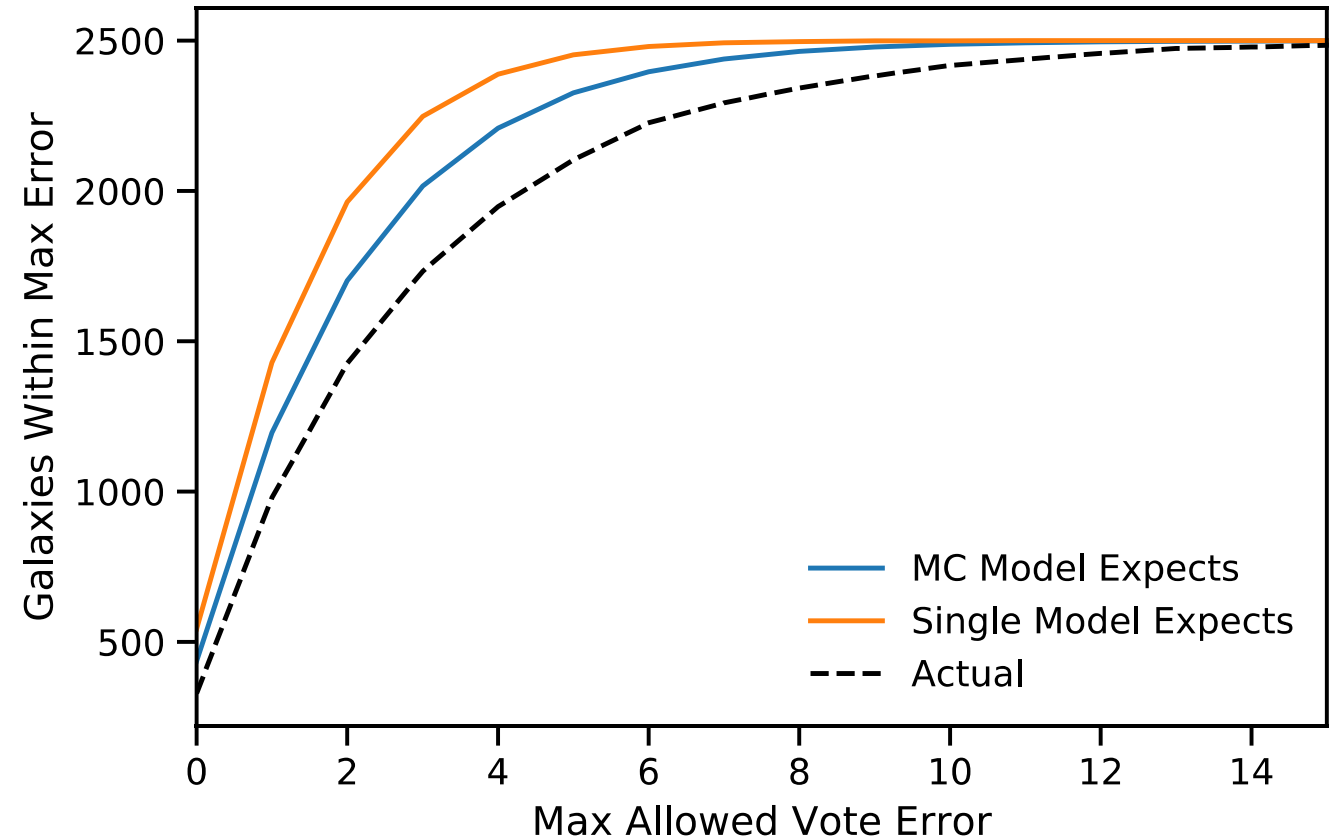
# Posteriors for Votes

- Marginalising over weights (BCNN) lets us predict votes *over all CNN we might have trained*

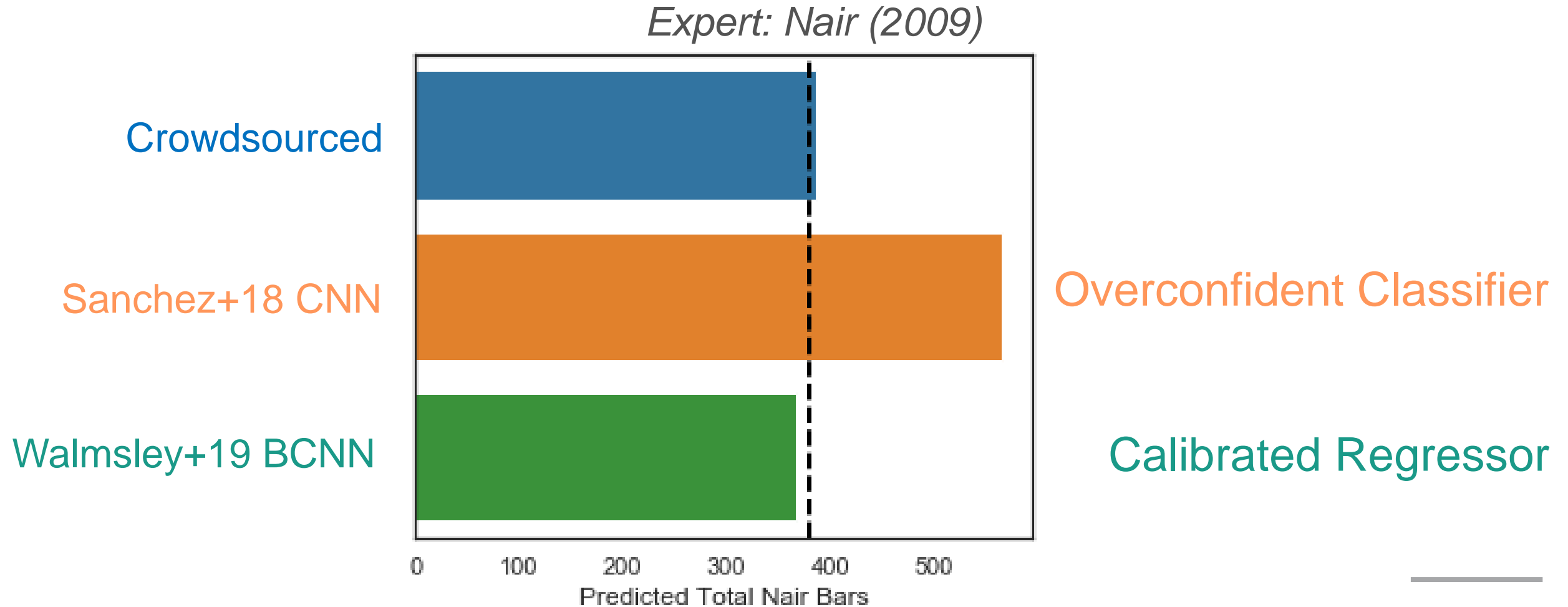
$$p(k|D) = \int p(v|w) p(w|D) dw$$

- BCNN posteriors are much better calibrated

**Result: Morphology catalog with trustworthy uncertainties**



# Uncertainty Matters – Predicting Expert Opinion



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# BCNN with Two Twists:

Predictions must be uncertain:

1. Embrace Label Uncertainty  
allowing models to classify unknowns by qualifying errors

2. Apply Active Learning



## Principles for Choosing Data

Mutual Information  $I[X, Y] = H[p(X)] - E_{p(Y)} H[P(X|Y)]$

Information Gain  $U(x) = H[p(\theta|D)] - E_{p(y|x, D)} H[p(\theta|D, x, y)]$

## Principles for Choosing Data

Information Gain

$$\begin{aligned}
 U(x) &= H[p(\theta|D)] - E_{p(y|x, D)} H[p(\theta|D, x, y)] \\
 &= I[\theta, y | D, x] \\
 &\quad \dots \text{rearrange by symmetry of } I \dots \\
 &= I[y, \theta | D, x] \\
 &= H[p(y|x, D)] - E_{p(\theta|D)} H[p(y|x, \theta)]
 \end{aligned}$$

# Mutual Information

Mutual Information  $I$   
 Entropy  $H$   
 Votes  $k$   
 Weights  $\theta$   
 Training data  $D$

Pick galaxies where the models **confidently** disagree.

$$I = - \int H[p(k|\theta)] p(\theta|D) d\theta + H \left[ \int p(k|\theta) p(\theta|D) d\theta \right]$$

↑  
 Each model is confident...

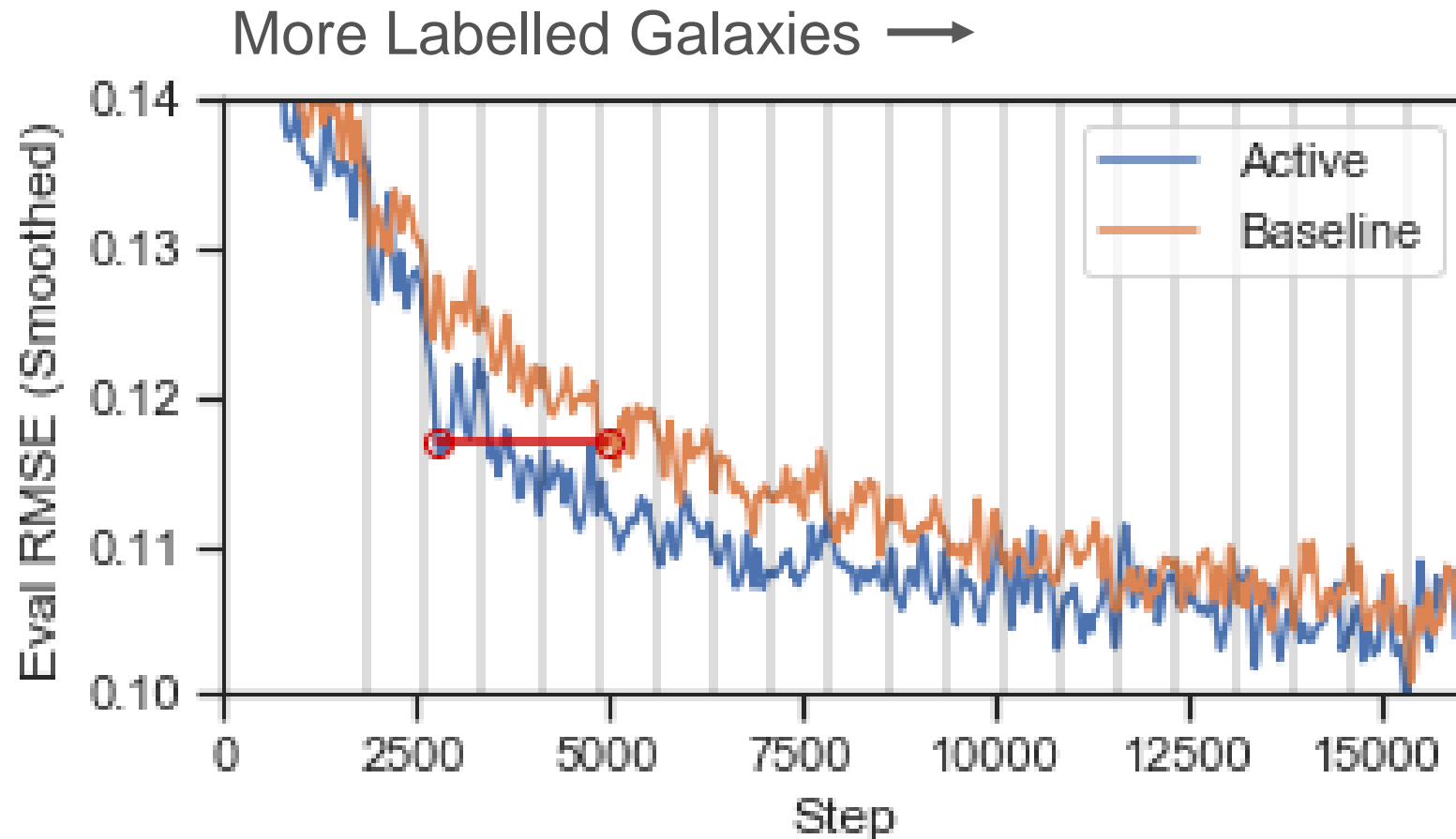
↑  
 ...but they give different answers

Only possible because we:

- Think about labels probabilistically,  $p(k|\theta)$
- Approximate training many models with BCNN,  $p(\theta|D)$

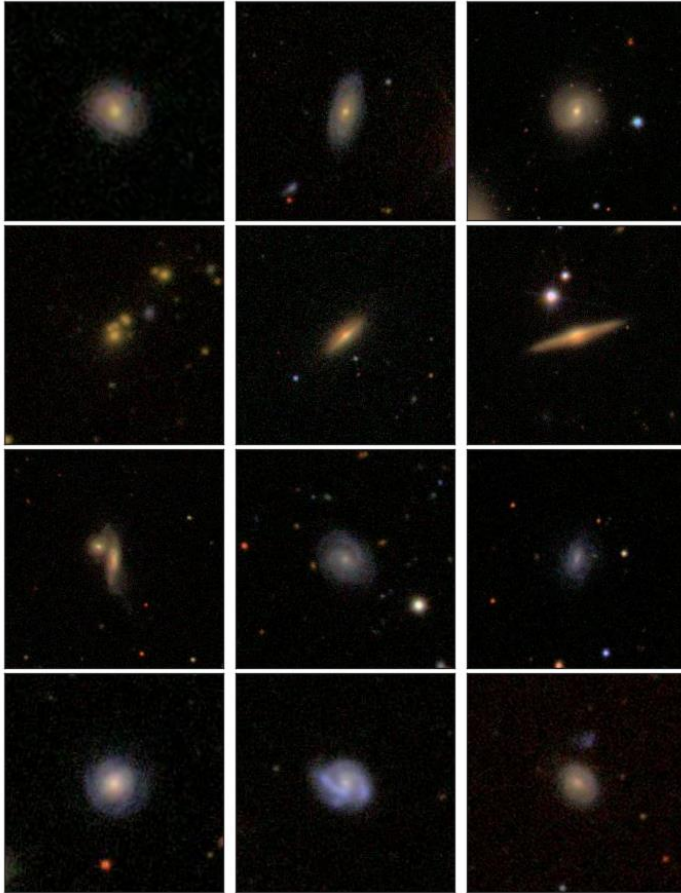
$$H = - \sum_i^N p(k = i) \log p(k = i)$$

# Active Learning Results

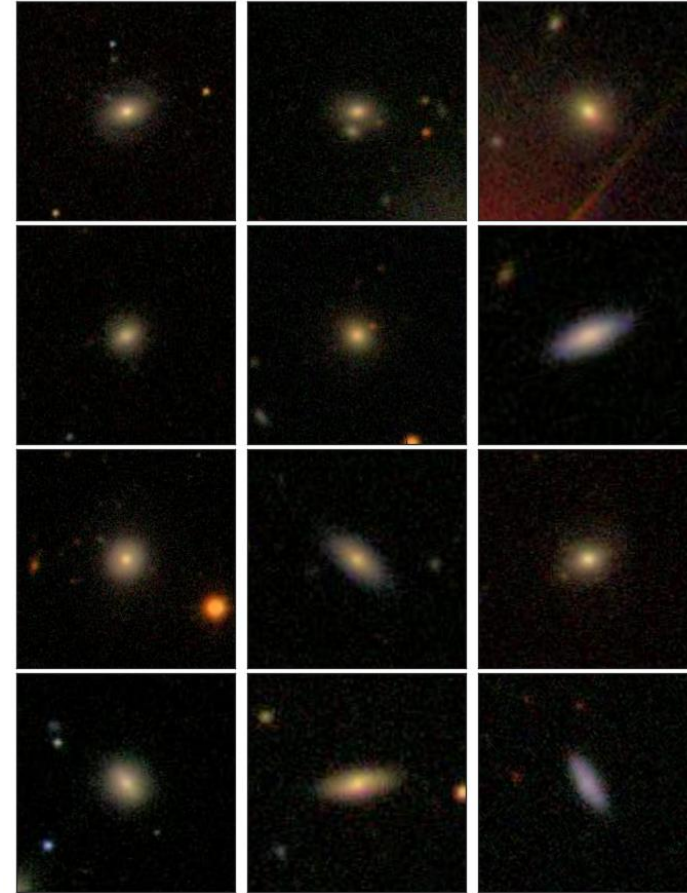




## Selected Galaxies for “Smooth?”

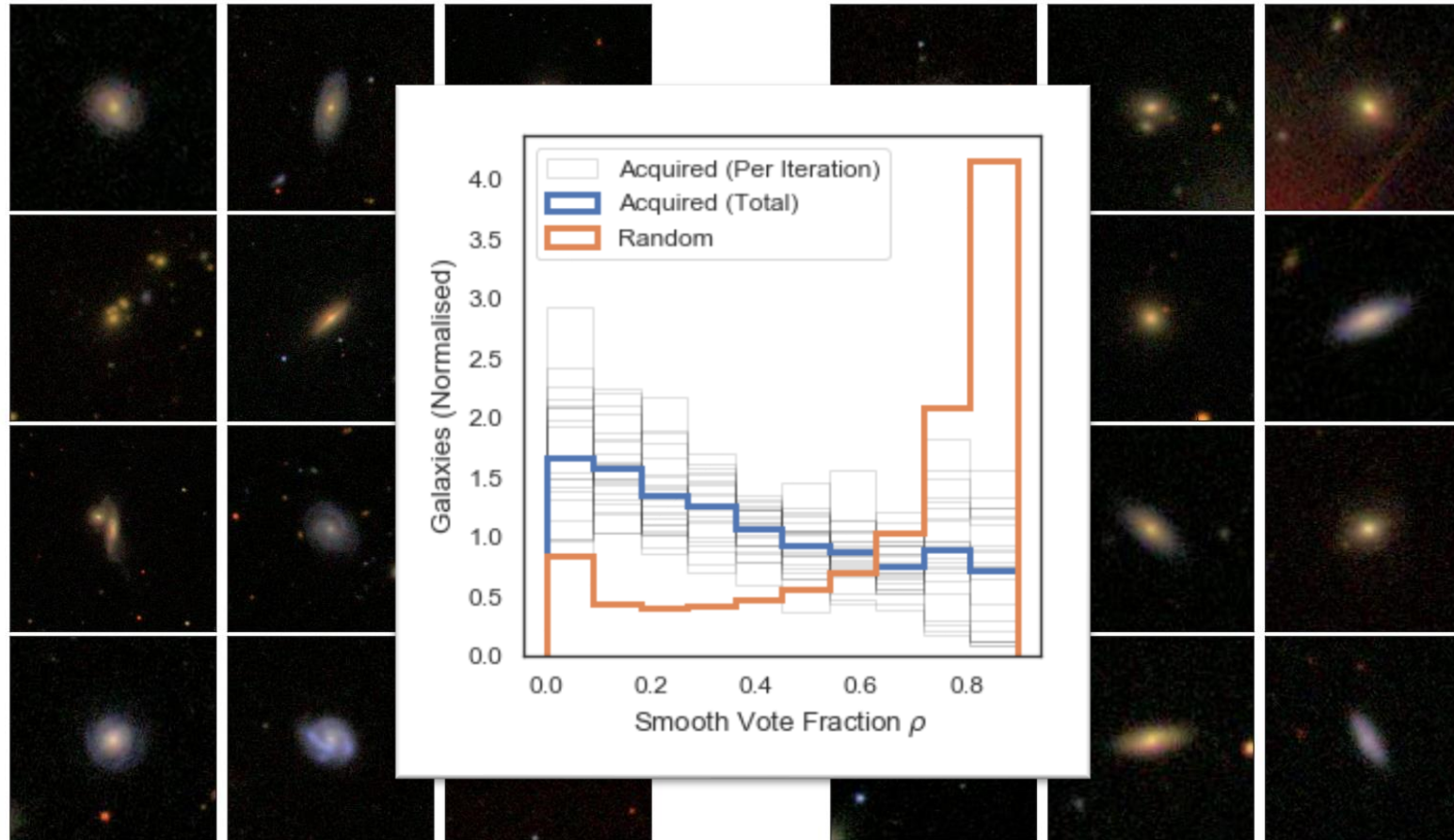


**High** mutual information



**Low** mutual information

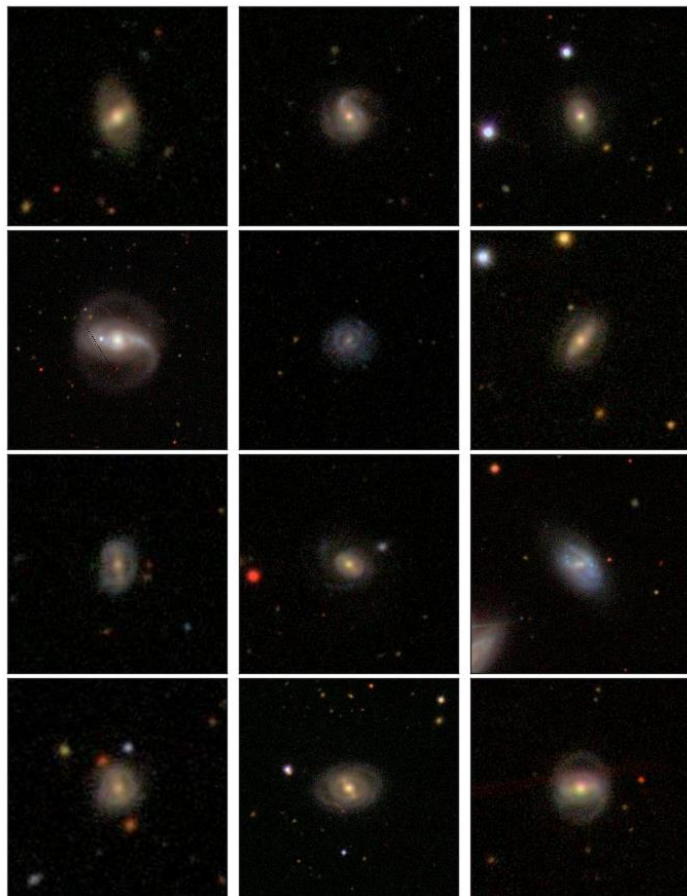
## Selected Galaxies for “Smooth?”



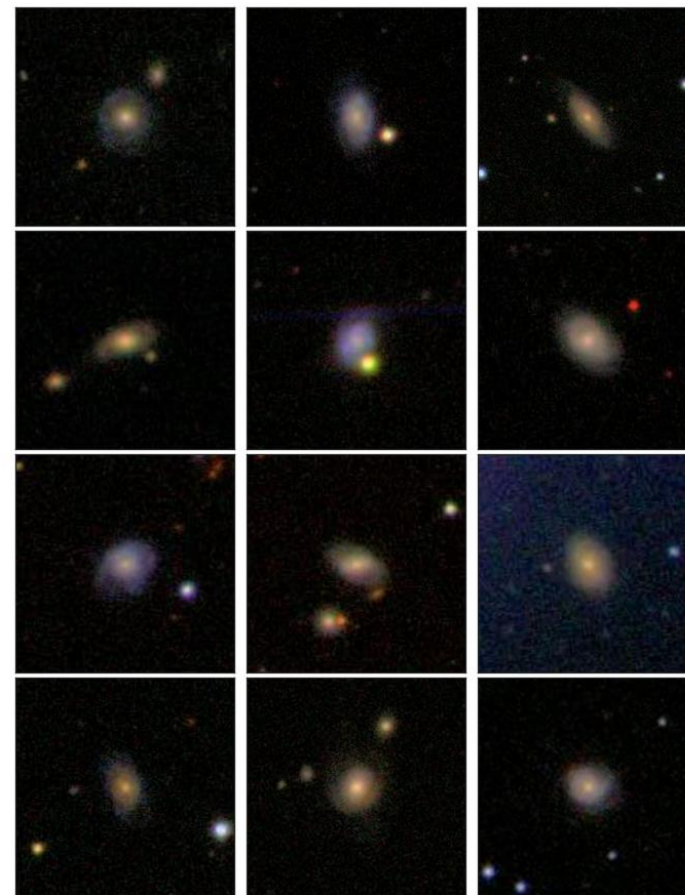
High mutual information

Low mutual information

## Selected Galaxies for “Bar?”



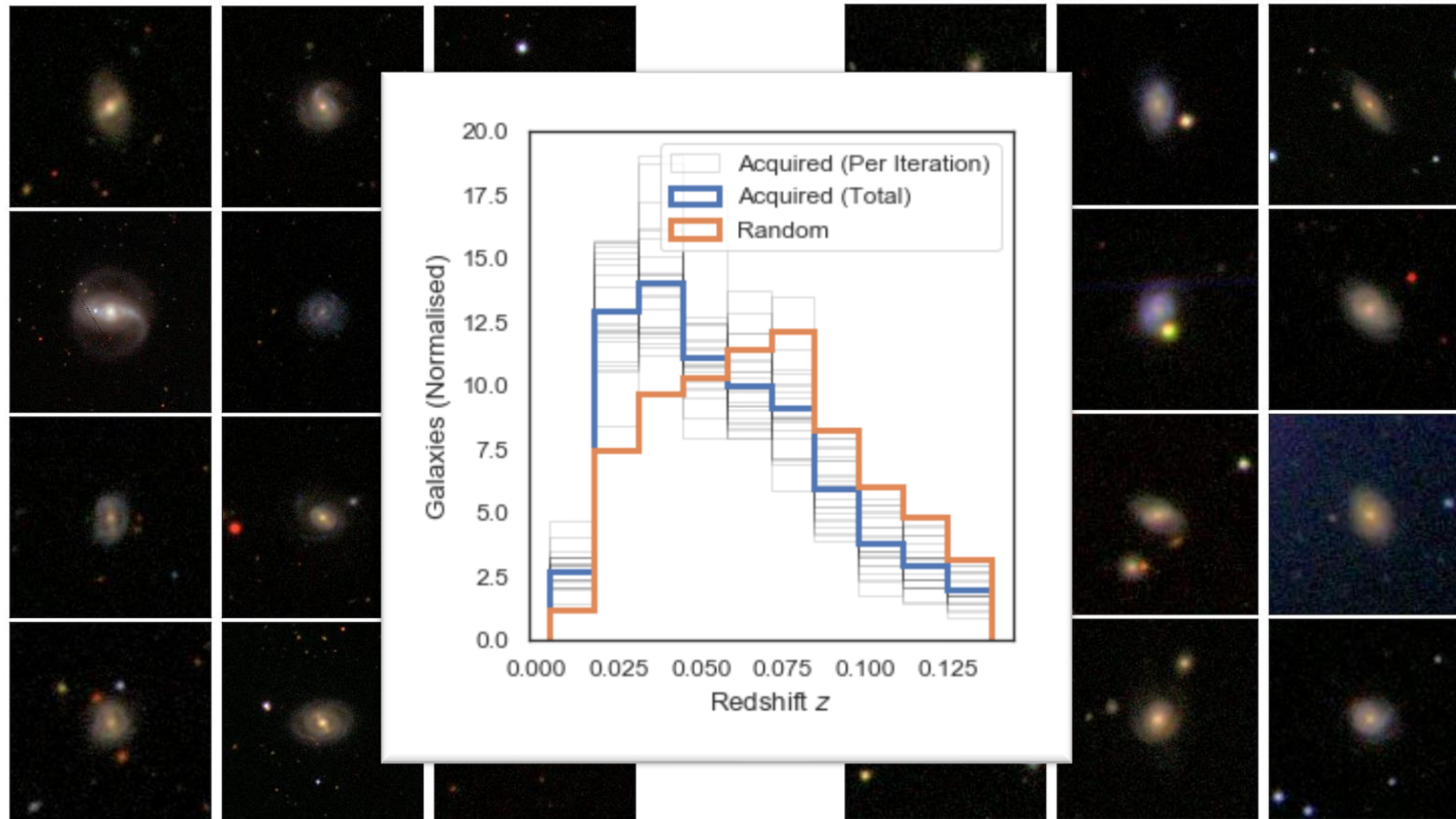
**High** mutual information



**Low** mutual information



## Selected Galaxies for “Bar?”



High mutual information

Low mutual information

## Live on Galaxy Zoo

Model retrains and requests  
new classifications weekly

New surveys get classified in  
weeks, not years

Every galaxy seen by at least 3  
volunteers

[PROJECTS](#)[ABOUT](#)[GET INVOLVED](#)[TALK](#)

# Galaxy Zoo



**Get started** ↓

Choose 'Enhanced' to see those galaxies we most

Classic

Enhanced

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arxiv: 1905.07424

 @mike\_w\_ai

 @chrislintott

 @yaringal

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