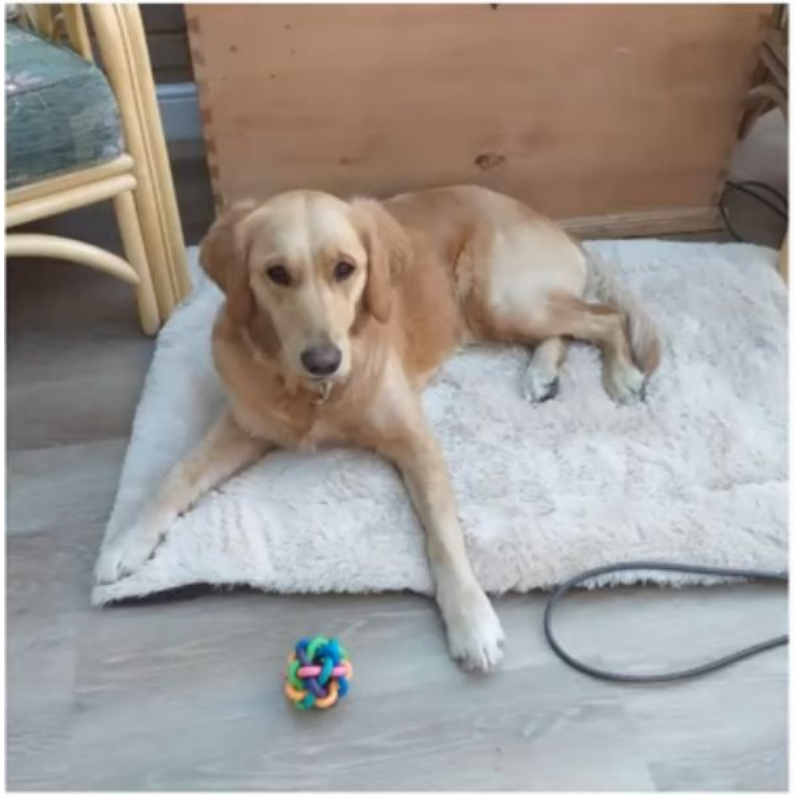
# Finding Radio Bursts Fast

Mike Walmsley, with CHIME and Galaxy Zoo collaborations

University of ~~Oxford~~ Manchester! Thanks Anna!

# Why do we need an ML Club?

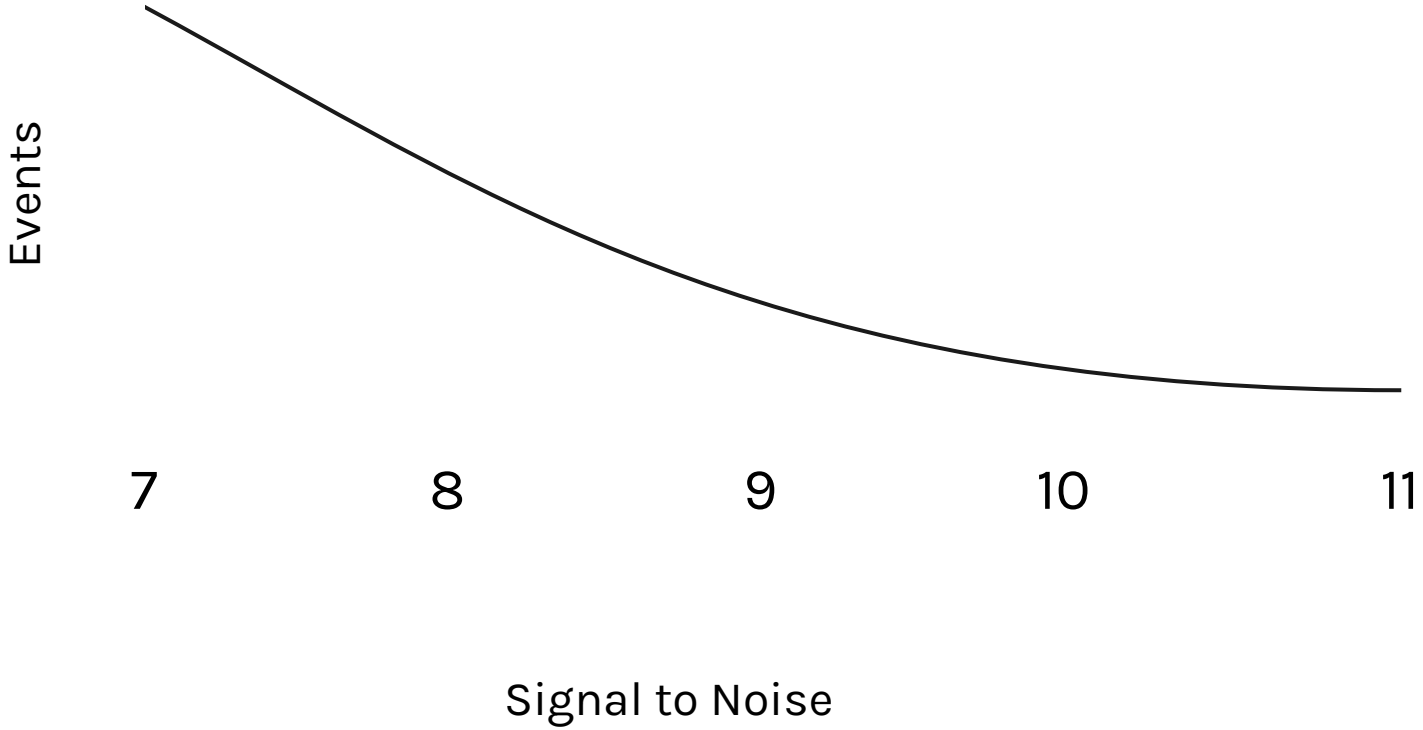


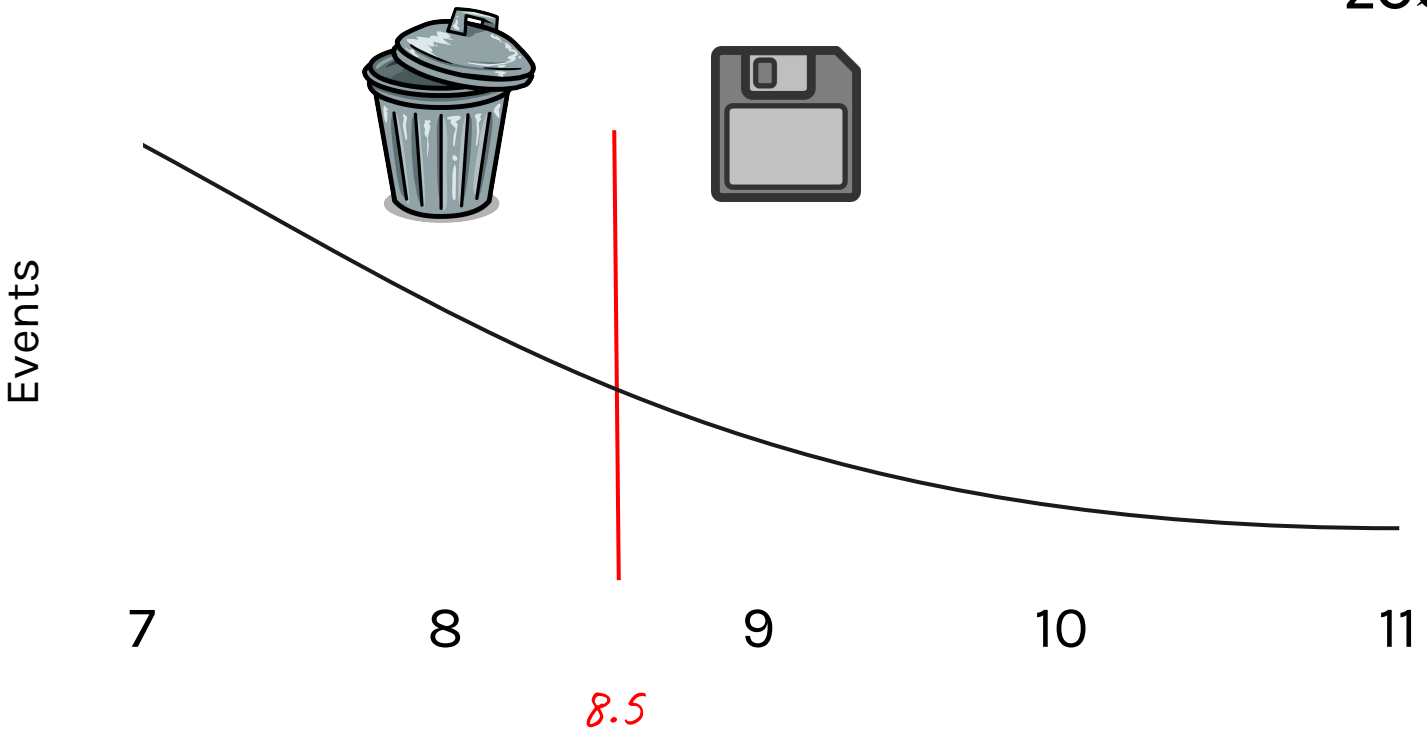
ZOONIVERSE

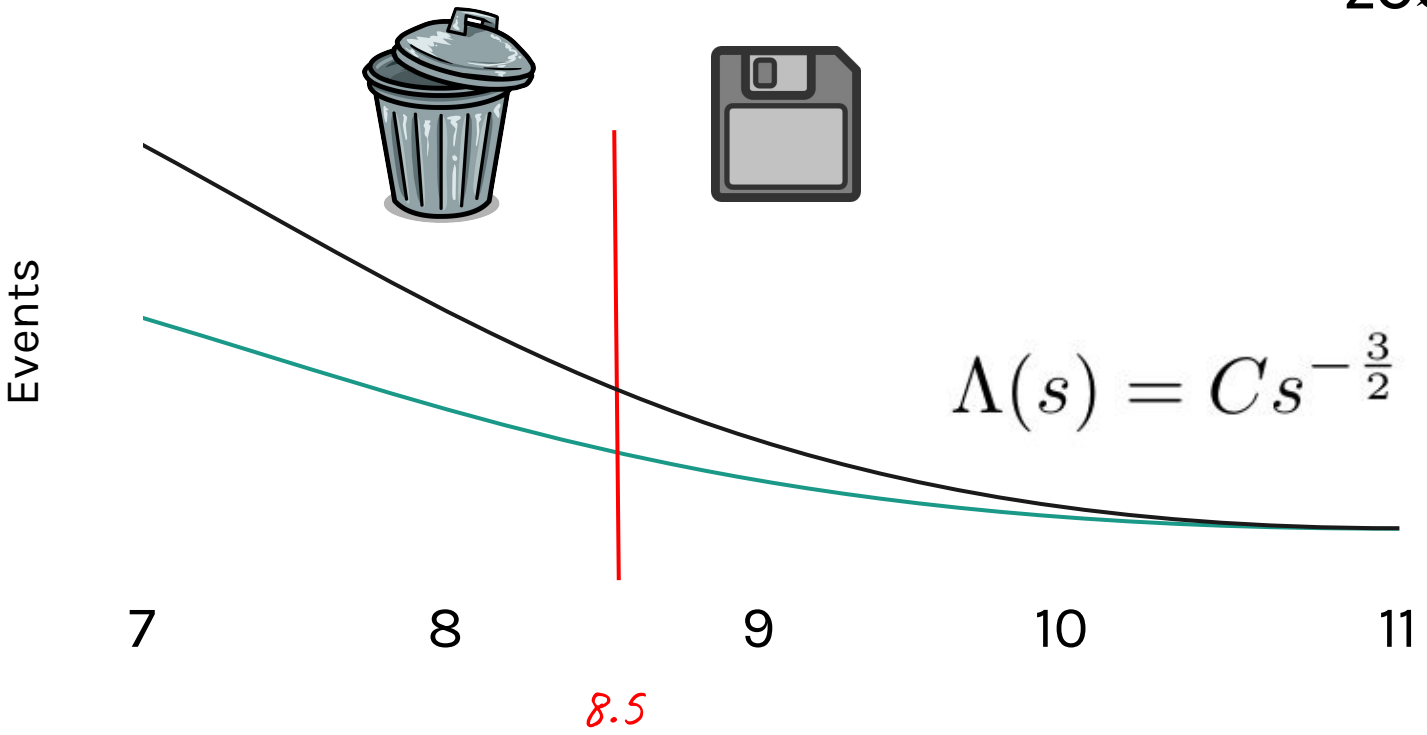
1. CHIME FRB: Shortcuts

2. Galaxy Zoo: Uncertainty and Information

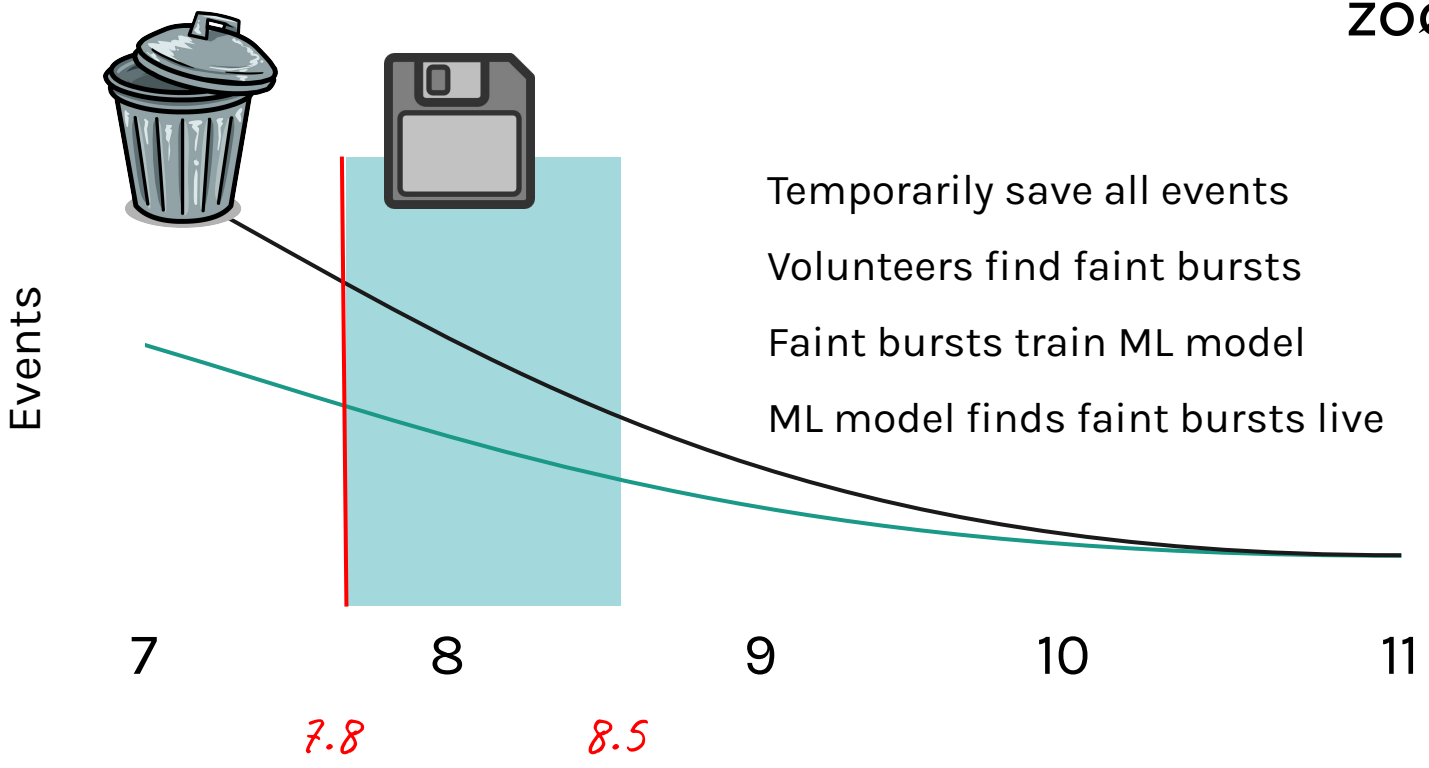
3. Now what?


Events
7
8
9
10
11
Signal to Noise

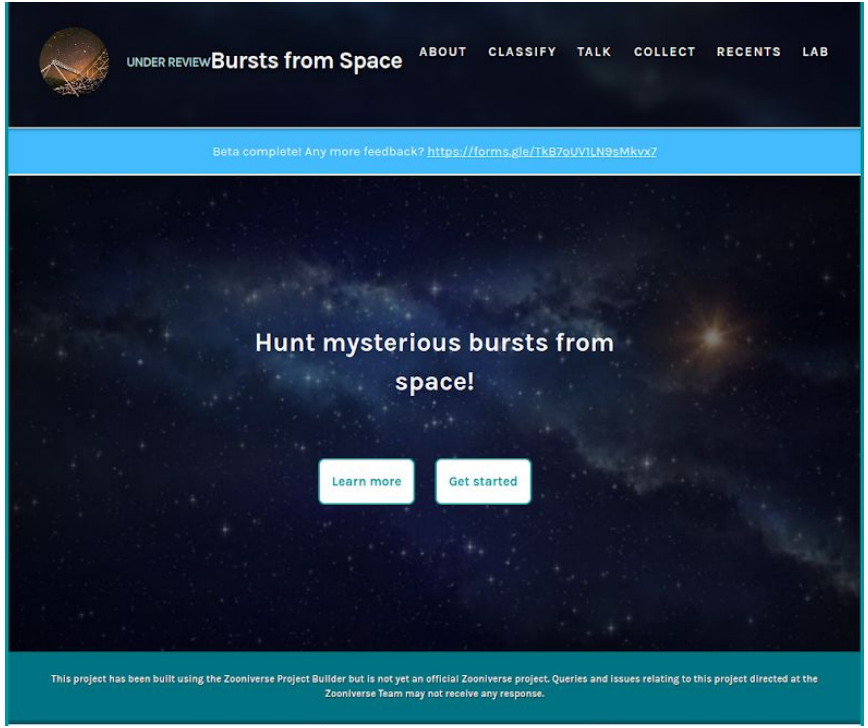

Events
7
8
9
10
11
8.5
Signal to Noise

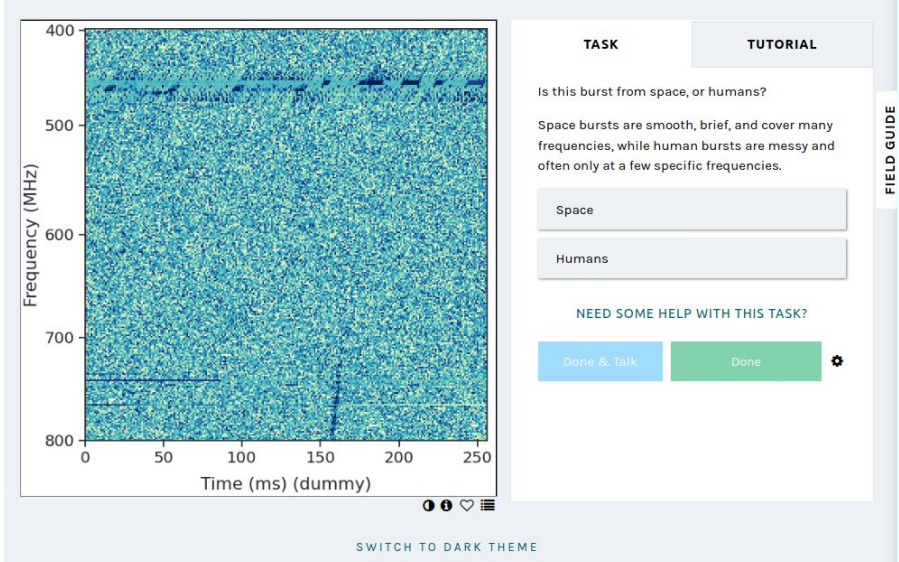

Events
$\Lambda(s) = Cs^{-\frac{3}{2}}$
7
8
9
10
11
8.5
Signal to Noise

ZOONIVERSE




Mike Walmsley et al




http://bit.ly/burstsfromspace

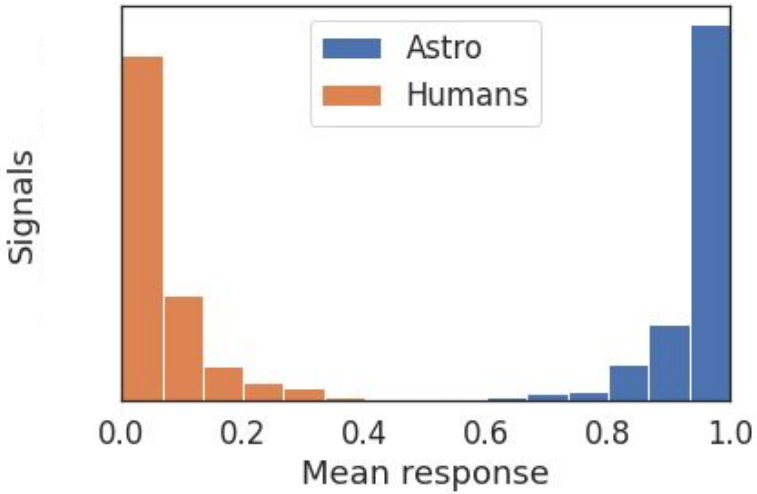
# Beta Results - Performance

13,000 classifications from 116 volunteers

- Average of more than 100 per person

99.3% agreement with CHIME experts when asking 15+ volunteers

- 99.1% with 10 volunteers
- 98.6% with 5 volunteers



ZOONIVERSE

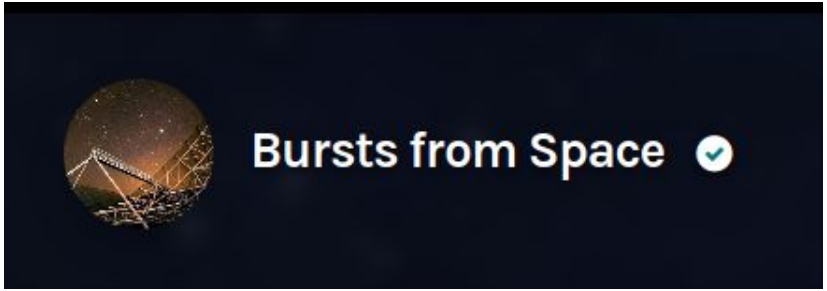
**Project Launched - Oct. 30th 2020**

New Data Weekly

19,689 Candidates

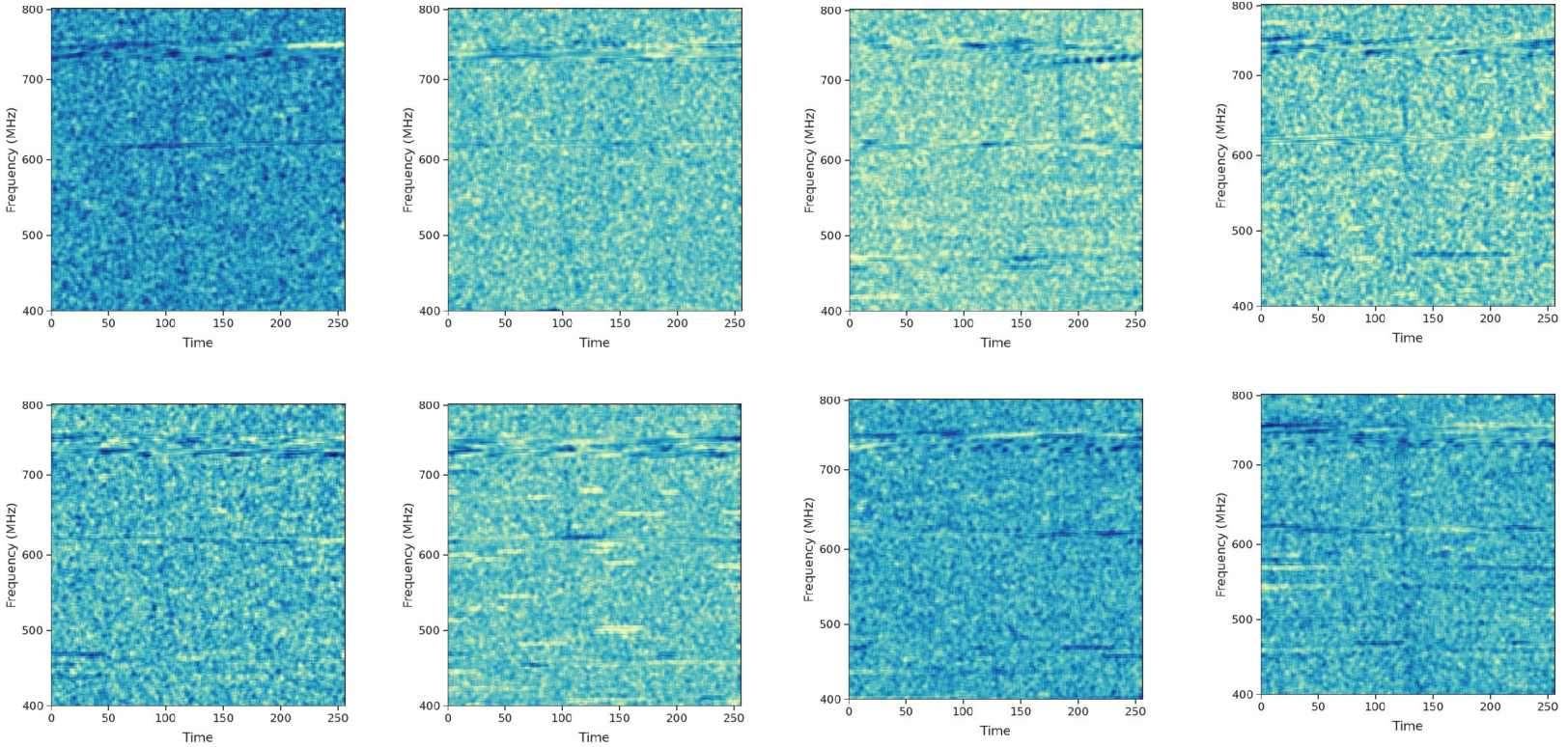
304,071 Classifications

Many hundreds of FRB-like signals

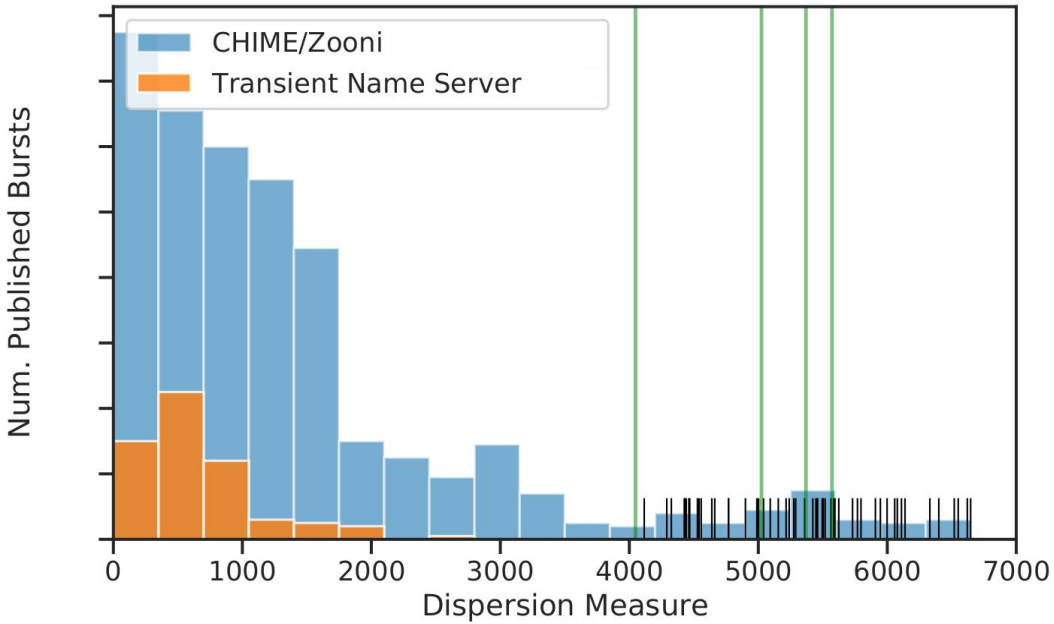


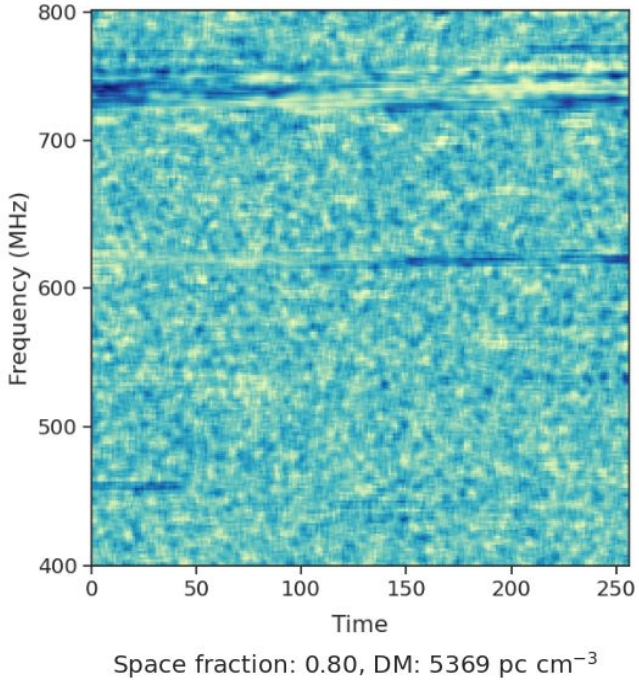

bit.ly/burstsfromspace

ZOONIVERSE




Mike Walmsley et al

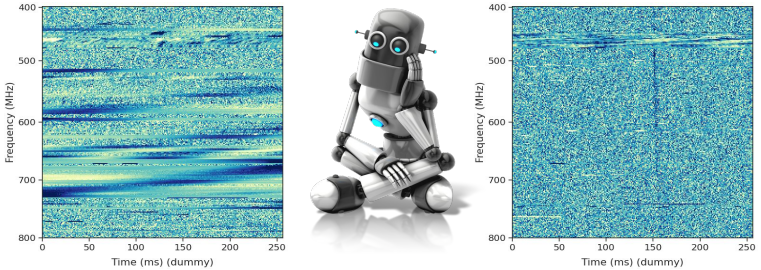

CHIME/Zooni
Transient Name Server
Num. Published Bursts
0
1000
2000
3000
4000
5000
6000
7000
Dispersion Measure


800
700
600
500
400
Frequency (MHz)
0
50
100
150
200
250
Time
Space fraction: 0.80, DM: 5369 pc cm$^{-3}$

ZOONIVERSE

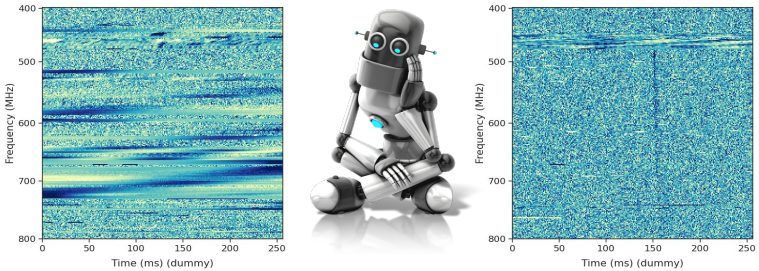
# Can ML identify **faint** FRBs?

# How would you classify?

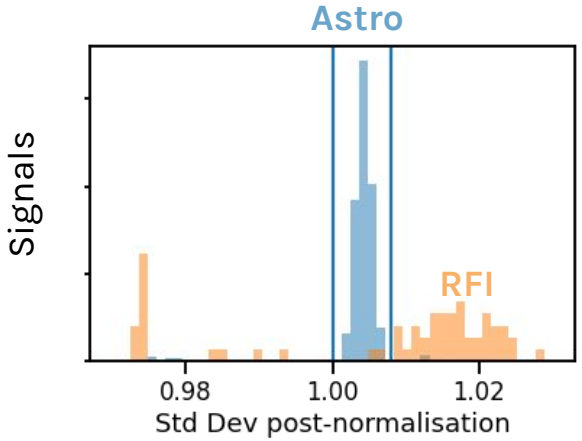



CHIME's classifier - **99% accurate**

# How would you classify?

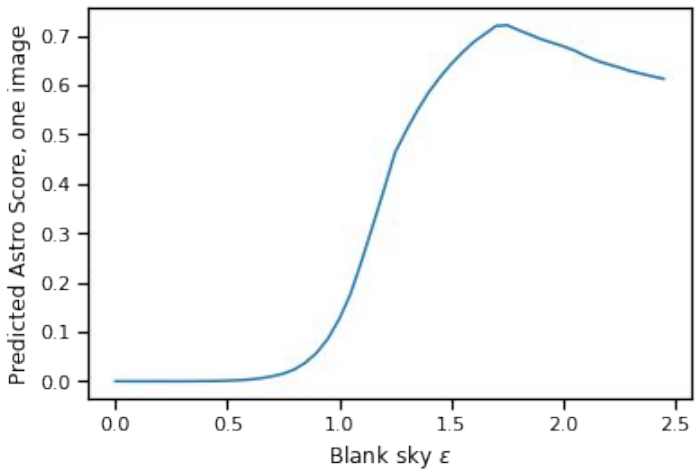


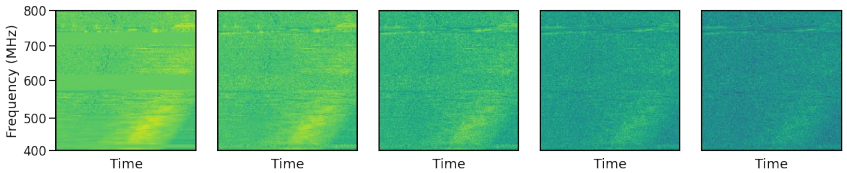

CHIME's classifier - **99% accurate**



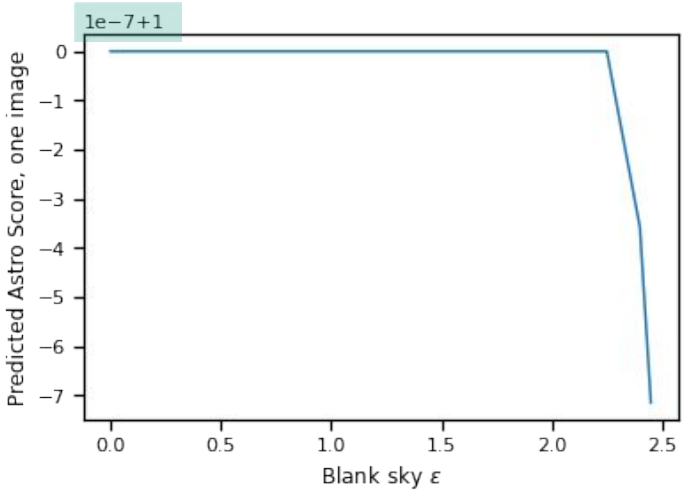

Standard deviation **only** - **93% accurate**

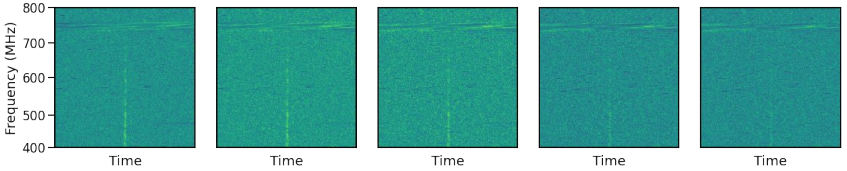
## RFI + ε Blank Sky



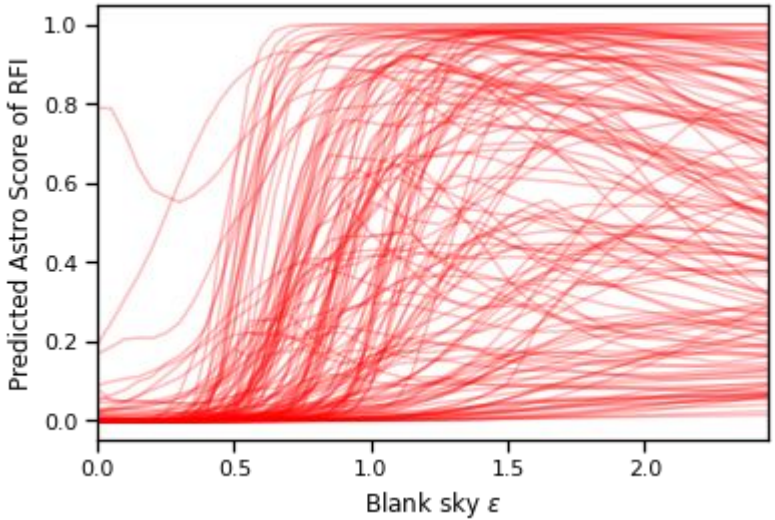




## Astro + ε Blank Sky

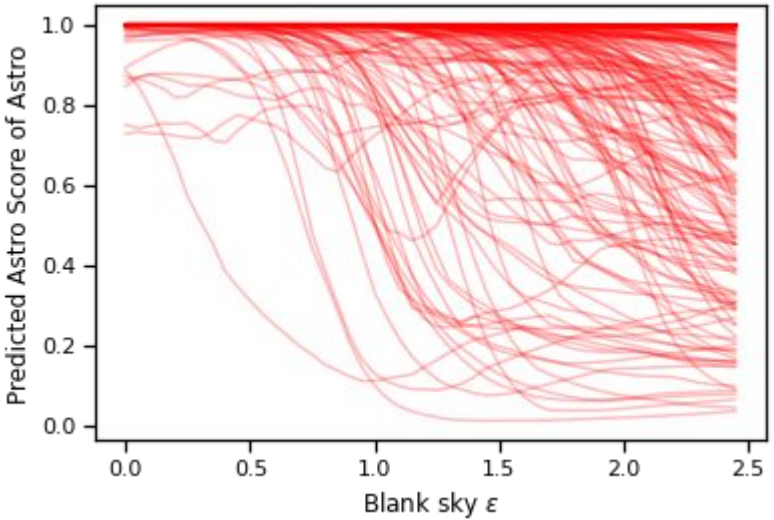


## RFI + ε Blank Sky




## Astro + ε Blank Sky



ZOONIVERSE

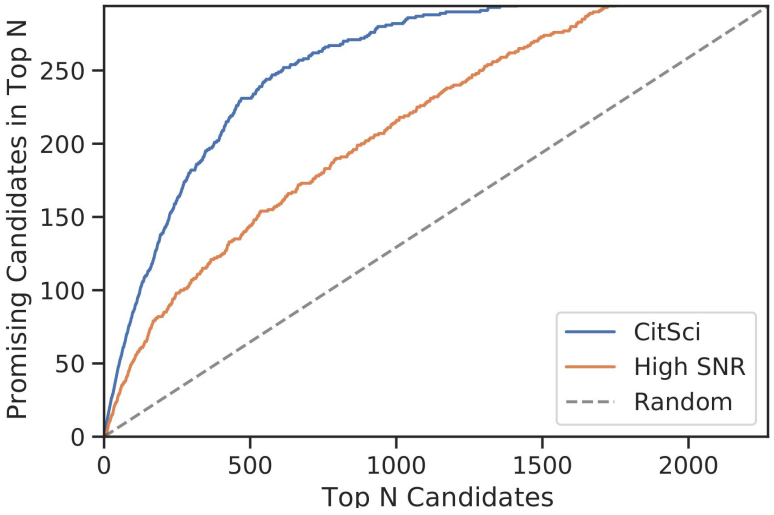
# Retraining

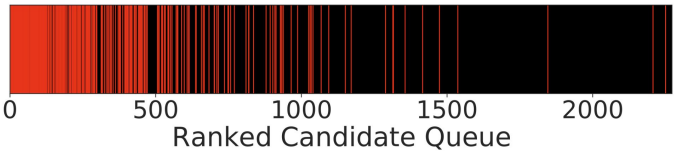
Classifier calls faint signals astro

**Fails to generalise**

Retrain on citizen scientist labels

**Performs far better**



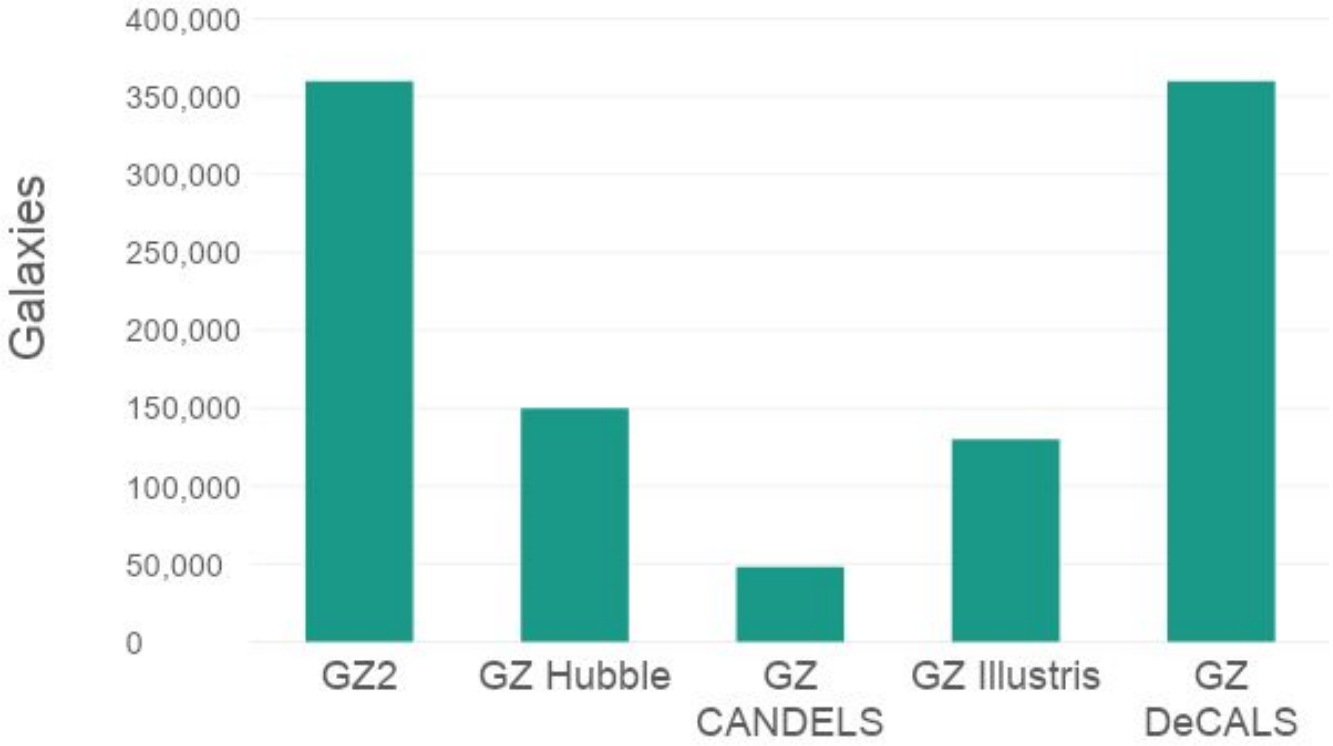



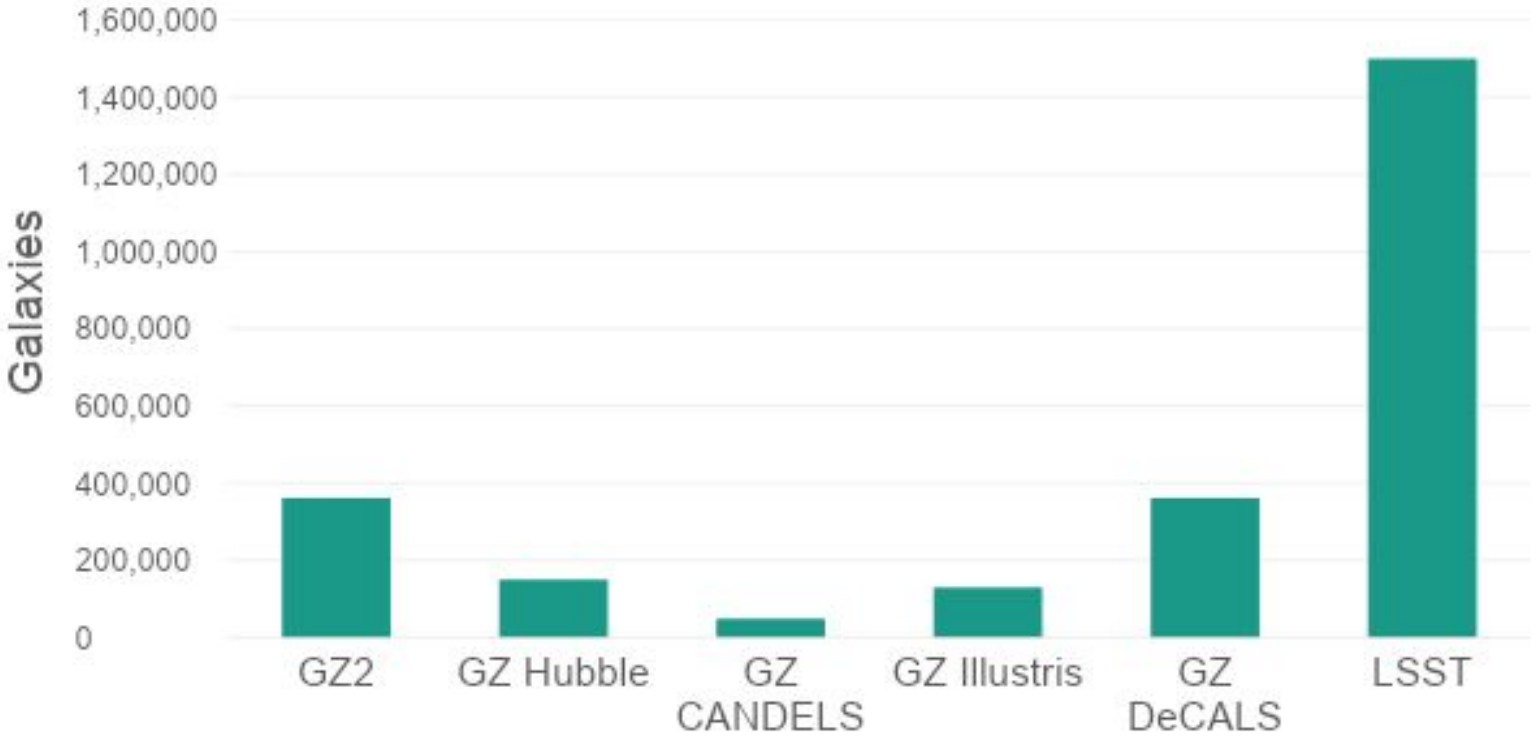
ZOONIVERSE

1. Fast Radio Bursts: Shortcuts

2. Galaxy Zoo: Uncertainty and Information

3. Now what?


Galaxies
400,000
350,000
300,000
250,000
200,000
150,000
100,000
50,000
0
GZ2
GZ Hubble
GZ CANDELS
GZ Illustris
GZ DeCALS

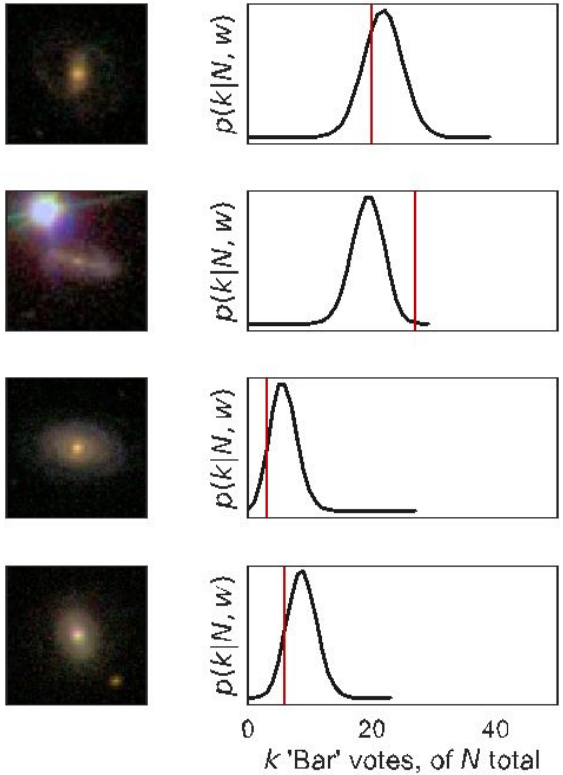



Mike Walmsley et al


Mike Walmsley et al

**Posteriors for Votes**

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




1 Model

# Probabilistic CNN

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

N volunteers and k responses ≈ N trials and k successes

How fair might the coin be? $\mathrm{Beta}(\rho|\alpha,\beta)$

Toss N times, get k heads $\mathrm{Bin}(k|\rho,N)$

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

$$\mathcal{L} = \int \mathrm{Beta}(\rho|\alpha,\beta)\mathrm{Bin}(k|\rho,N)d\alpha d\beta$$

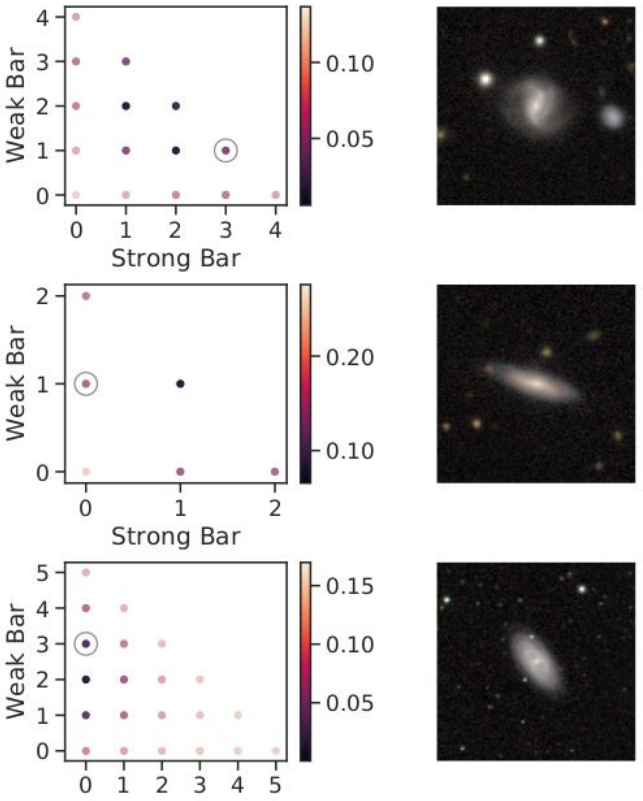
Predict $f^w(x) = \alpha,\beta$ and maximise the likelihood of $\alpha,\beta$

# Multiple Answers

$$\mathcal{L} = \int \text{Beta}(\rho|\alpha,\beta)\text{Bin}(k|\rho,N)d\alpha d\beta$$

Add a few dimensions…

$$\mathcal{L}_q = \int \text{Dirichlet}(\vec{\rho}|\vec{\alpha})\text{Multi}(\vec{k}|\vec{\rho},N)d\vec{\alpha}$$



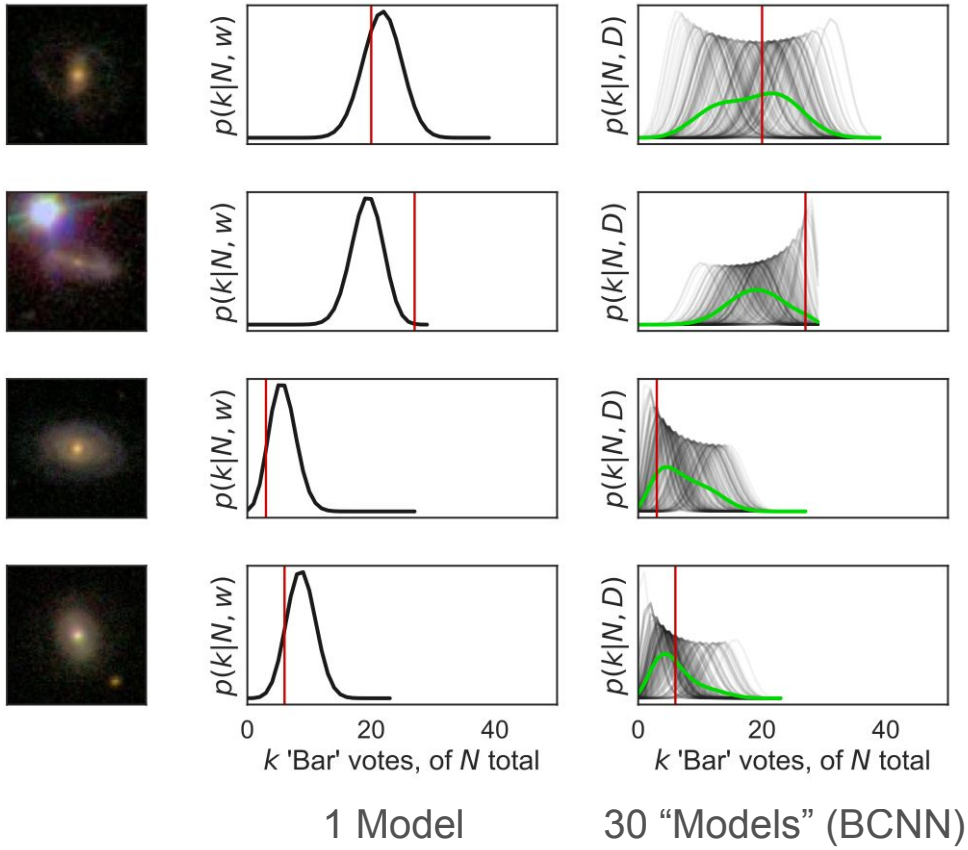
# Posteriors for Votes

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

- 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*

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



Galaxy $x$
CNN weights $w$
Training data $D_{train}$
CNN output $f^w(x)$
Dropout dist. $q_\theta^*$
Forward pass t of T

**Probabilistic to Bayesian CNN**

What about the models we might have trained, but didn't?

$$p(y = c|\, x, D_{train}) = \int f^w(x)\, p(w\,|D_{train})\, dw$$

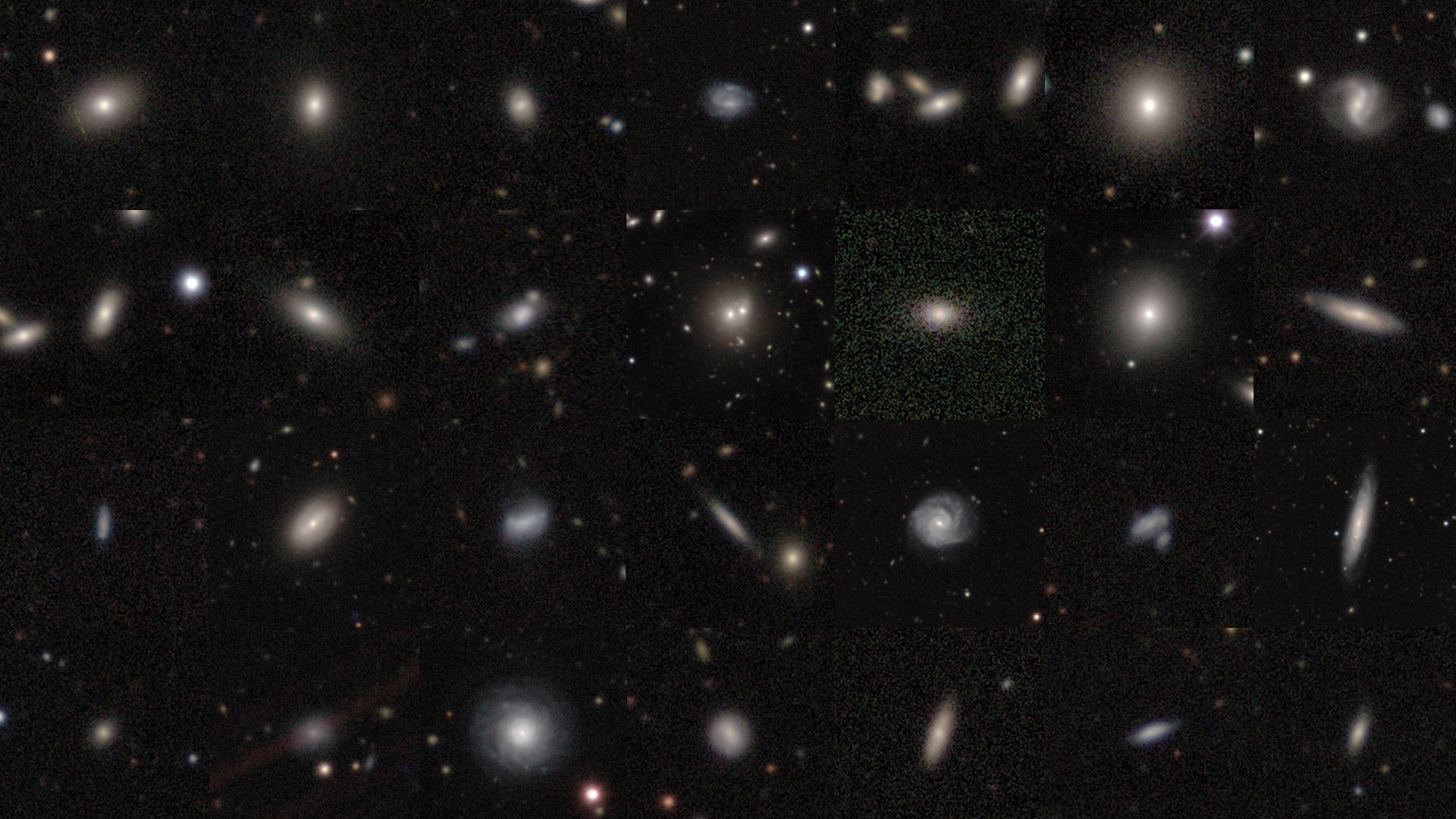
Unknown!

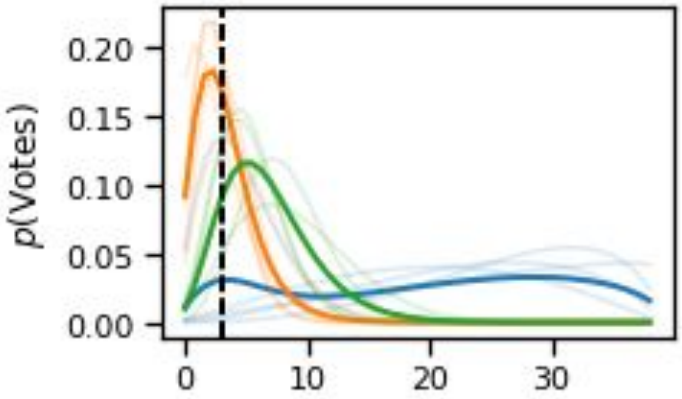
Approximate $p(w\,|D_{train})$ with Dropout

$$\approx \int q_\theta^*(w)\, dw$$

$$\approx \frac{1}{T}\sum_{t=1}^{T} f^{w_t}(x)$$

See Y. Gal et al (2016)






*Featured?*

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

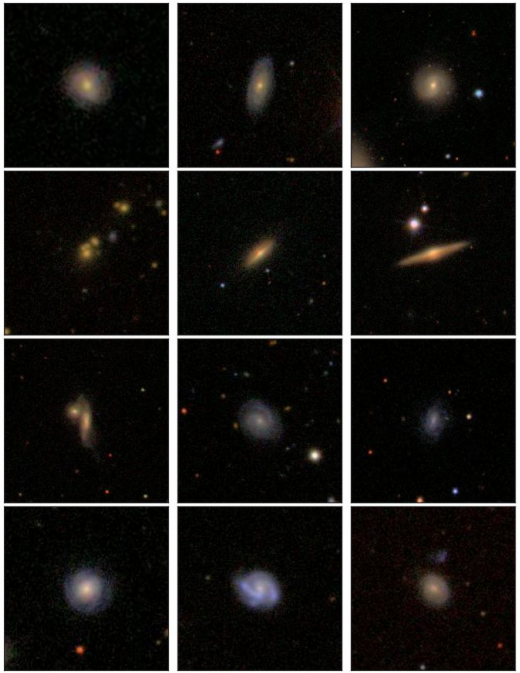
$$I = -\int H[p(k|w)]\; p(w|D)\; dw + H\left[\int p(k|w)\, p(w|D)\; dw\right]$$

Each model is confident…

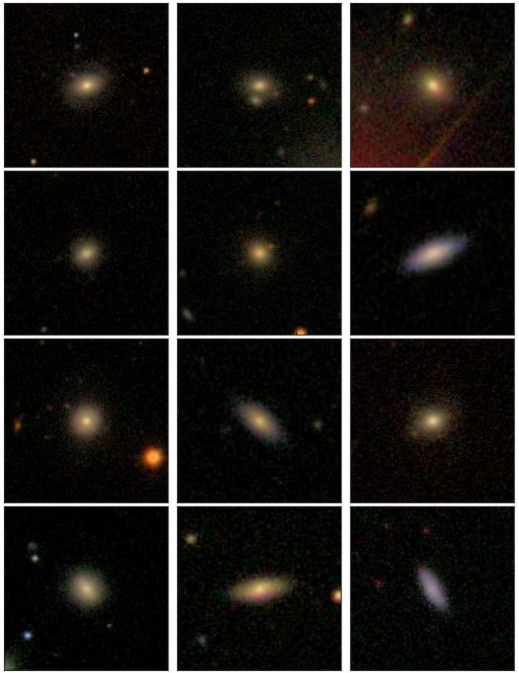
…but they give different answers

Mutual Information $I$
Entropy $\mathrm{H}$
Votes $k$
Weights $w$
Training data $D$

# Selected Galaxies for “Smooth?”

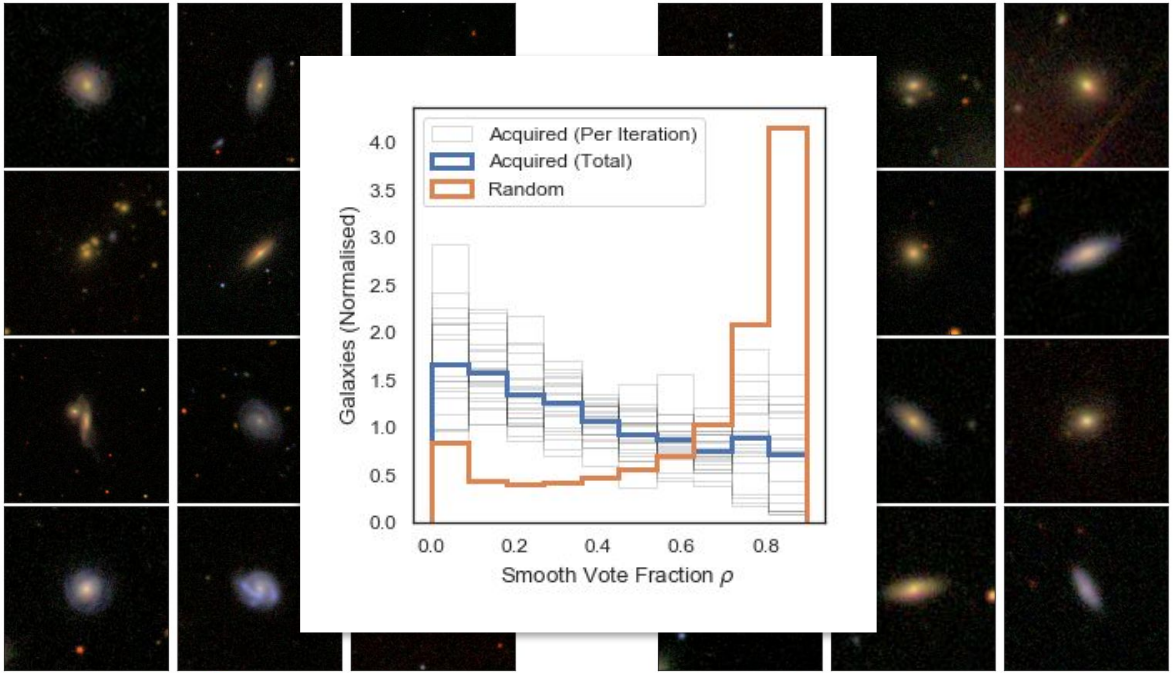


**High** mutual information



**Low** mutual information

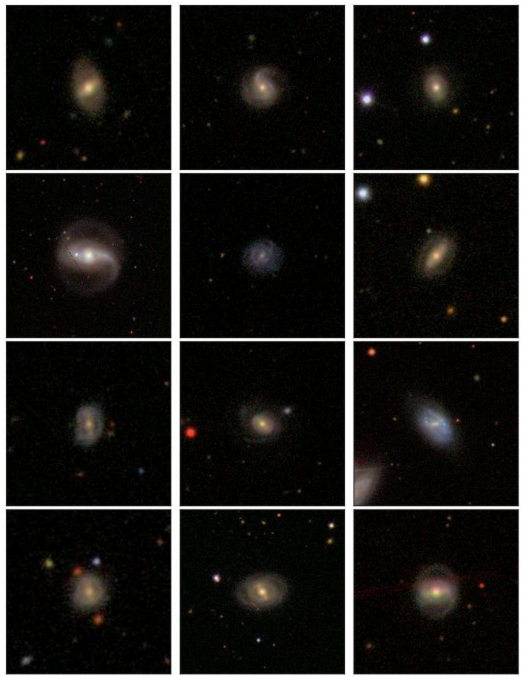
# Selected Galaxies for “Smooth?”



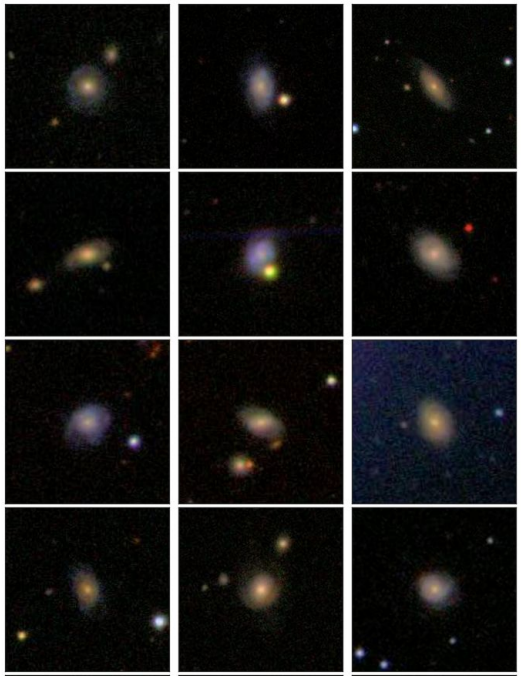

**High** mutual information

**Low** mutual information

# Selected Galaxies for “Bar?”

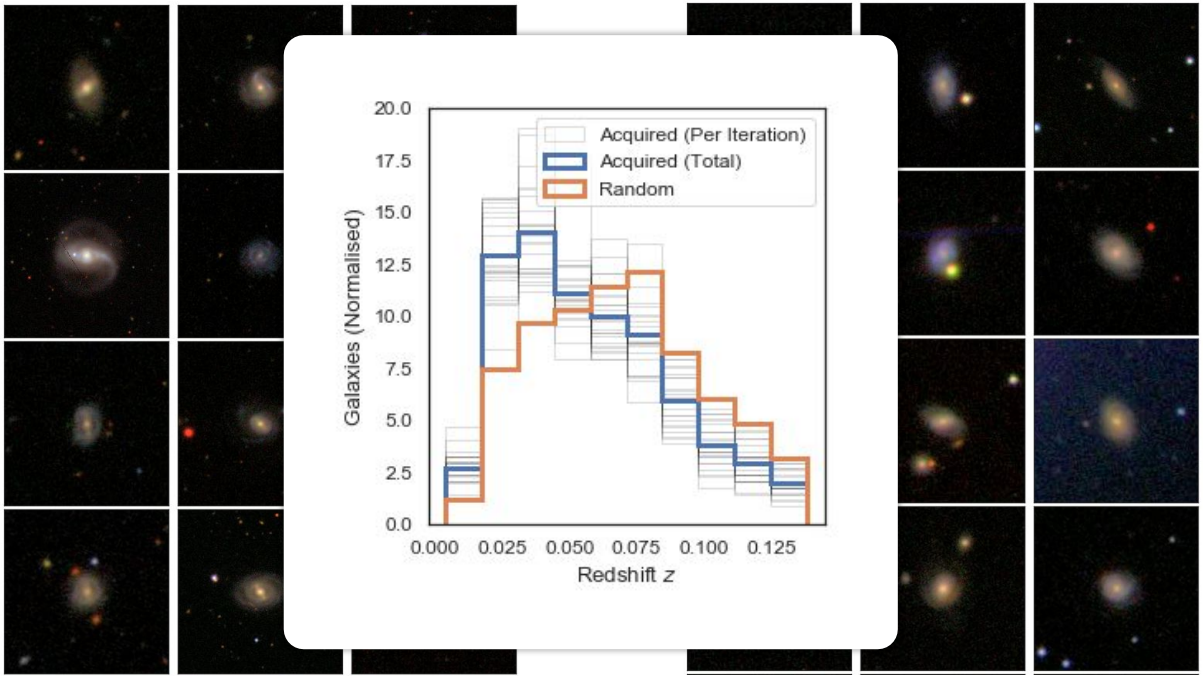


**High** mutual information



**Low** mutual information

# Selected Galaxies for “Bar?”




**High** mutual information

**Low** mutual information

# Performance

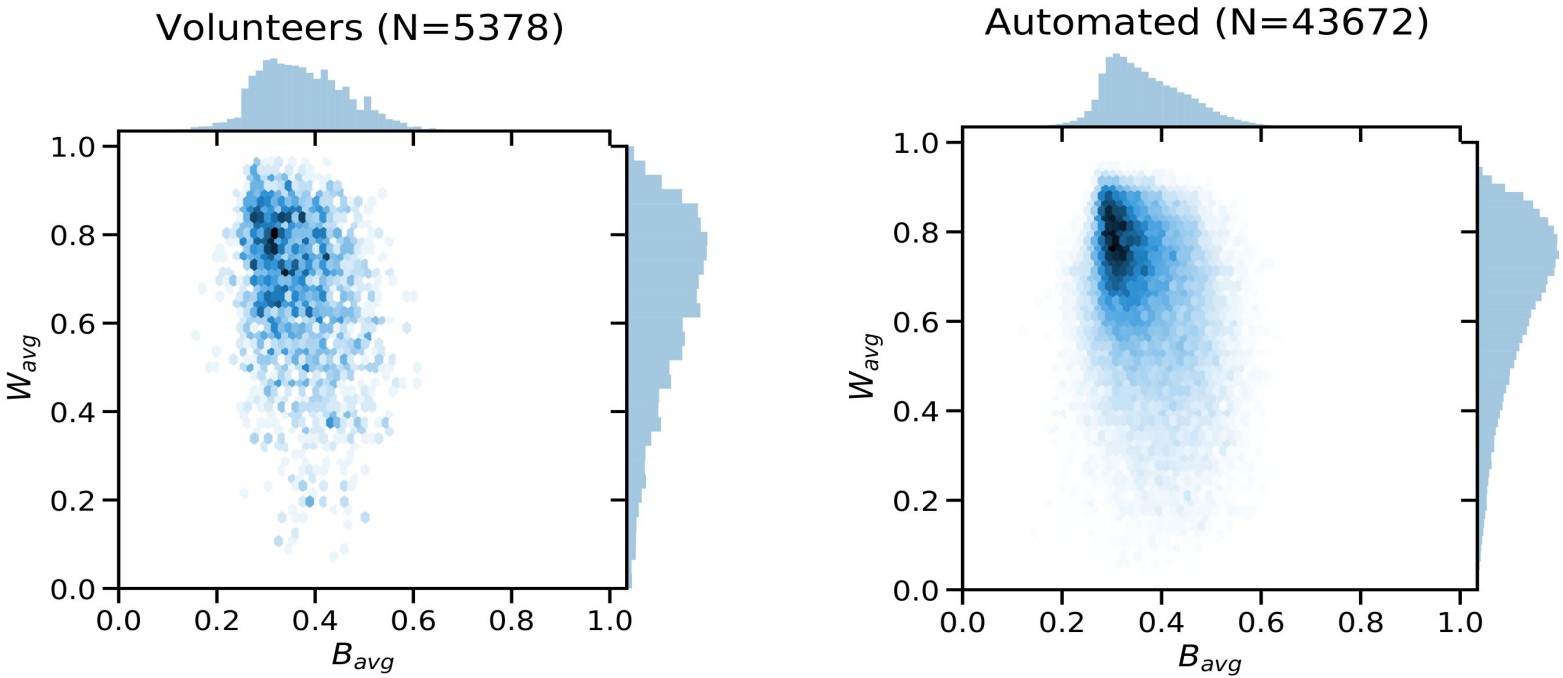
~ 99% accurate on every question for galaxies where the volunteers are confident

| Question | Count | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|---|
| Smooth Or Featured | 3495 | 0.9997 | 0.9997 | 0.9997 | 0.9997 |
| Disk Edge On | 3480 | 0.9980 | 0.9980 | 0.9980 | 0.9980 |
| Has Spiral Arms | 2024 | 0.9921 | 0.9933 | 0.9921 | 0.9924 |
| Bar | 543 | 0.9945 | 0.9964 | 0.9945 | 0.9951 |
| Bulge Size | 237 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| How Rounded | 3774 | 0.9968 | 0.9968 | 0.9968 | 0.9968 |
| Edge On Bulge | 258 | 0.9961 | 0.9961 | 0.9961 | 0.9961 |
| Spiral Winding | 213 | 0.9906 | 1.0000 | 0.9906 | 0.9953 |
| Spiral Arm Count | 659 | 0.9863 | 0.9891 | 0.9863 | 0.9871 |
| Merging | 3108 | 0.9987 | 0.9987 | 0.9987 | 0.9987 |

Classification metrics on confident galaxies

# Live Demo

https://bit.ly/decals_viz




Winding angle vs. bulge size, measured by volunteers or deep learning

https://zenodo.org/record/4196267

ZOONIVERSE

1. Fast Radio Bursts: Shortcuts

2. Galaxy Zoo: Uncertainty and Information

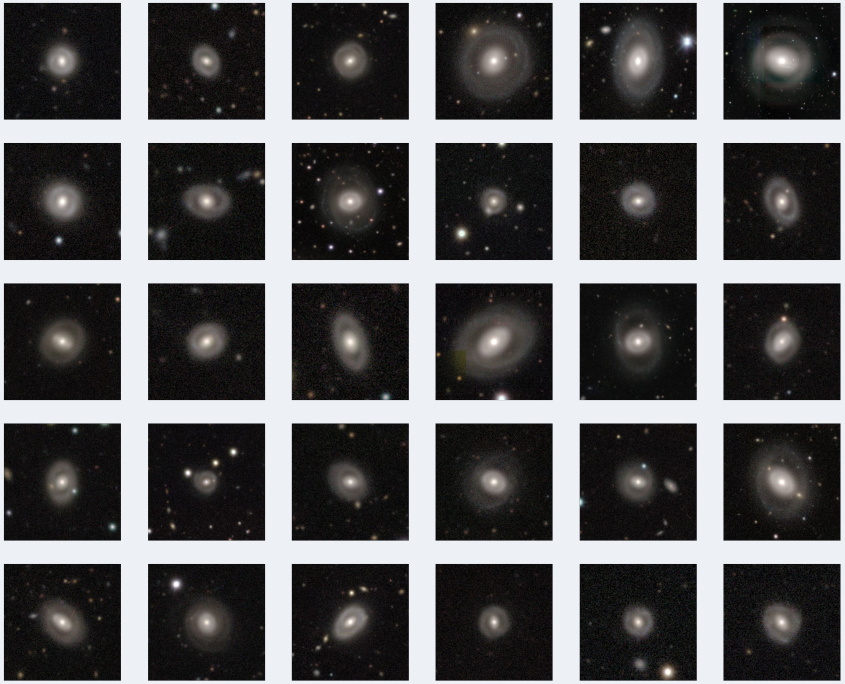
3. Now what?

# Live Demo #2!

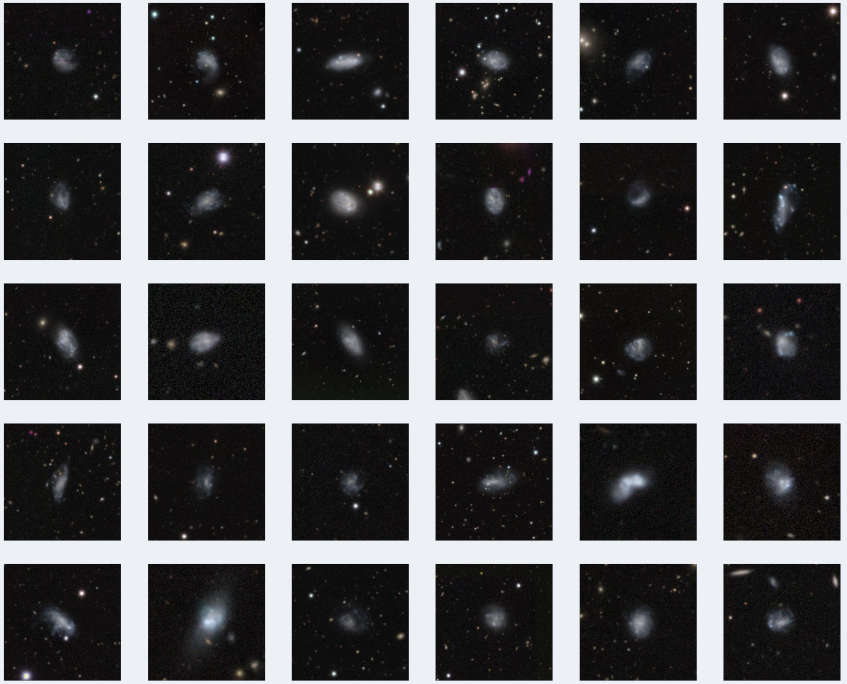
https://bit.ly/decals_similarity

# Transfer Learning

*Automatic selection cuts: featured > 0.6, face-on > 0.7, has spiral arms < 0.5.*
*Training set: 212 positive rings*



*Max prob. “ring”, validation set*



*Min prob. “ring”, validation set*

**Zoobot**

Navigation

Components
Finetuning Guide
Training from Scratch

data_utils
estimators
training
predictions
schemas
label_metadata

Quick search

Go



# Zoobot Documentation

## Guides

Zoobot makes it easy to train a state-of-the-art deep learning classifier to solve your galaxy morphology problem. For example, you can train a classifier to find ring galaxies in under 200 lines of code.

*Ring galaxies found using Zoobot and 212 labelled examples.*

You do not need to be a machine learning expert to use Zoobot. Zoobot includes components for common tasks like loading images, managing training, and making predictions. You simply need to assemble these together.

You will only need a small amount of labelled images; a few hundred is a good starting point. This is because Zoobot includes a classifier already trained to answer Galaxy Zoo questions for DECaLS galaxies. Retraining (finetuning) this model requires much less time and labels than starting from scratch.

If you do want to start from scratch, to reproduce or improve upon the pretrained classifier, Zoobot can do that as well.

No experience required

zoobot.readthedocs.io

github.com/mwalmsley/zoobot

ZOONIVERSE

@mike_walmsley_

CHIME:
bit.ly/burstsfromspace

Active Learning:
arxiv: 1905.07424

DECaLS:
arxiv: 2102.08414
zenodo: 4196267

Similarity:
bit.ly/decals_similarity

Transfer learning:
github.com/mwalmsley/zoobot