GALAXY MORPHOLOGIES FOR THE DARK ENERGY SURVEY

From Convolutional Neural Networks and Domain Adaptation

l'Observatoire de Paris
Penn Arts & Sciences

Helena Domínguez Sánchez
Marc Huerta-Company
Mariangela Bernardi
Diego Tuccillo

EWASS — Prague — 29 June 2017

OBJECTIVE

Provide visual-like morphologies for galaxies in DES survey

- ✓ GZOO decision tree scheme & T-Type (Hubble sequence)
- ✓ Deep Learning based classification algorithm using CNN

(e.g., Galaxy Zoo, Dieleman+2015, CANDELS, Huertas-Company+2015)

OBJECTIVE

Provide visual-like morphologies for galaxies in DES survey

- ✓ GZOO decision tree scheme & T-Type (Hubble sequence)
- ✓ Deep Learning based classification algorithm using CNN

(e.g., Galaxy Zoo, Dieleman+2015, CANDELS, Huertas-Company+2015)

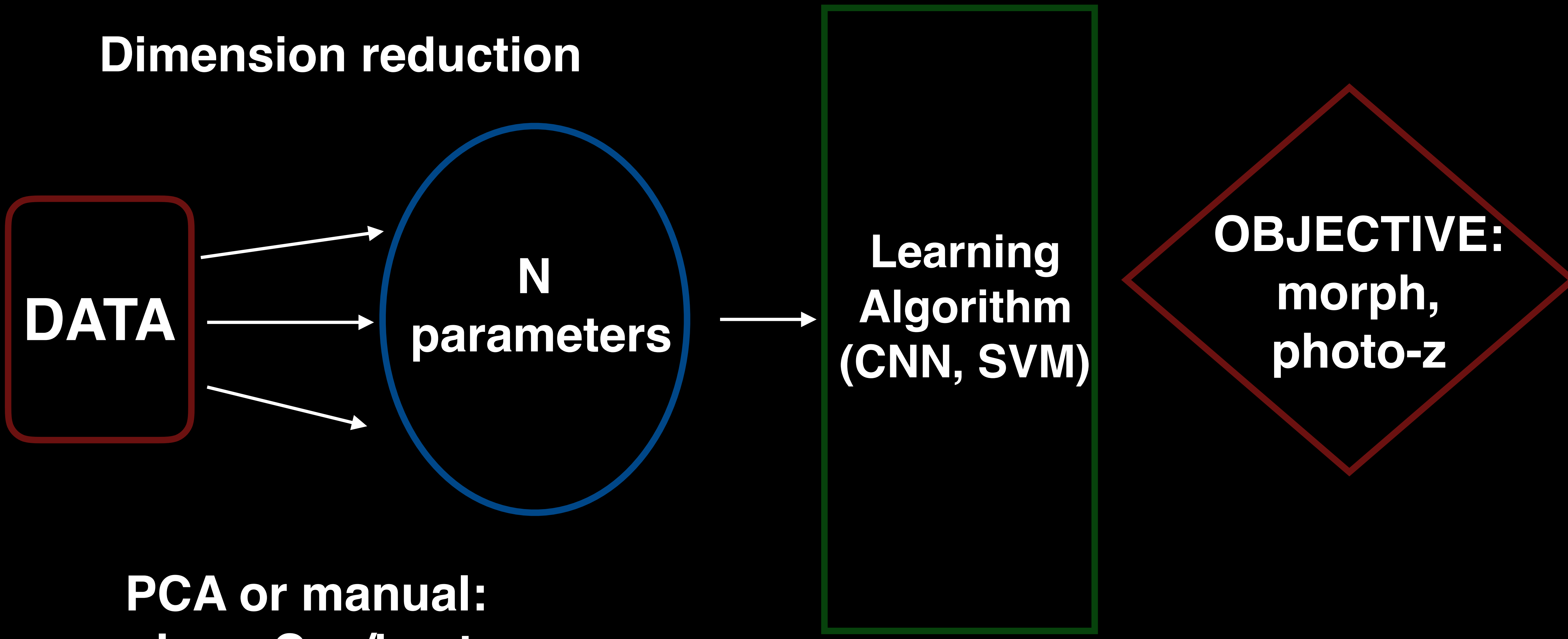
THE DARK ENERGY SURVEY

- ✓ 5000 deg2, southern skye, 525 obs. nights (5 years)
- ✓ DECam, Blanco 4-m telescope, Cerro Tololo (Chile)
- ✓ 300 mill. galaxies, 5 optical filters (*grizY*), mag(r) < 24.3

https://www.darkenergysurvey.org/

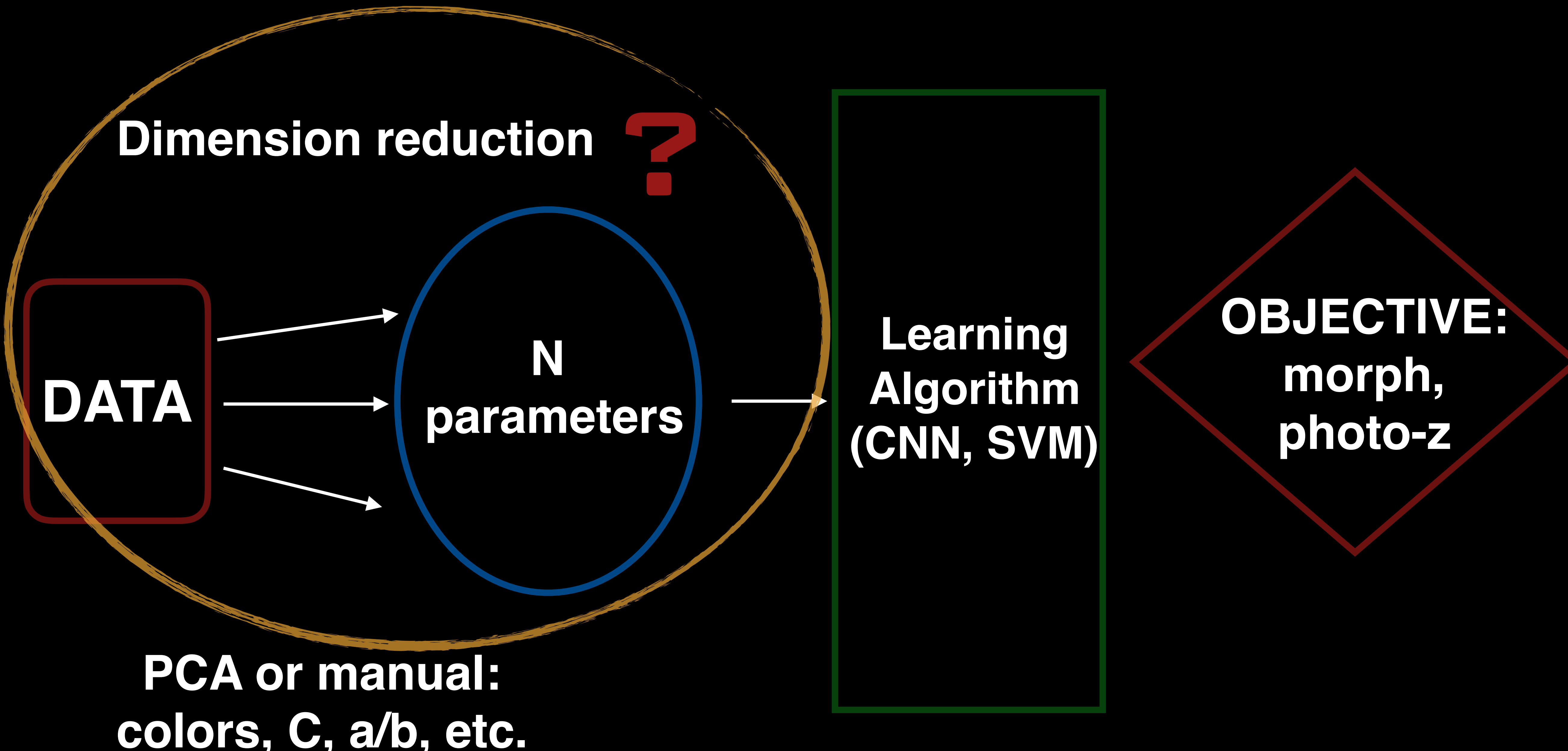
CLASSICAL MACHINE LEARNING

Dimension reduction

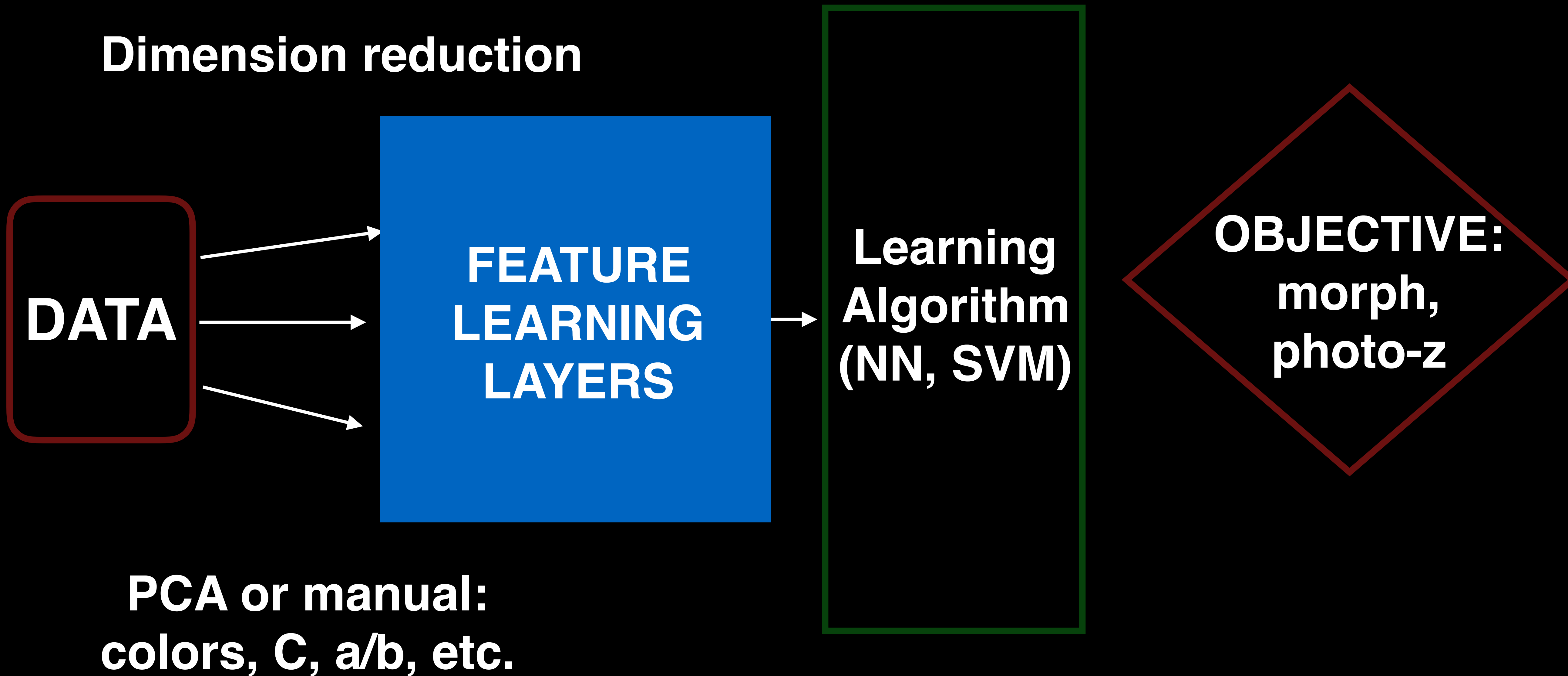


PCA or manual:
colors, C, a/b, etc.

CLASSICAL MACHINE LEARNING



DEEP LEARNING



WHY IS IT SO EXCITING?

- ✓ Very **reduced human intervention**: features are automatically extracted, input “raw data” (e.g., pixels flux)
- ✓ **High level of abstraction**: very complex patterns can be extracted

WHY IS IT SO EXCITING?

- ✓ Very **reduced human intervention**: features are automatically extracted, input "raw data" (e.g., pixels flux)
- ✓ **High level of abstraction**: very complex patterns can be extracted

BUT...

- ✓ Need of a **large number of previously classified objects** for training (10000+)
- ✓ Can we **transfer knowledge** (domain adaptation) from one survey (SDSS) to another (DES)?

OBJECTIVE

Bright sample

- ✓ Transfer knowledge from SDSS
- ✓ Reproduce GZOO catalogue for SDSS sample (230,000 galaxies, $z < 0.2$, mag < 17)
- ✓ Test models on DES images (DECALS classification, DES-S82, 4000 galaxies, $z < 0.15$, mag < 19)

OBJECTIVE

Bright sample

- ✓ Transfer knowledge from SDSS
- ✓ Reproduce GZOO catalogue for SDSS sample (230,000 galaxies, z < 0.2, mag < 17)
- ✓ Test models on DES images (DECALS classification, DES-S82, 4000 galaxies, z < 0.15, mag < 19)

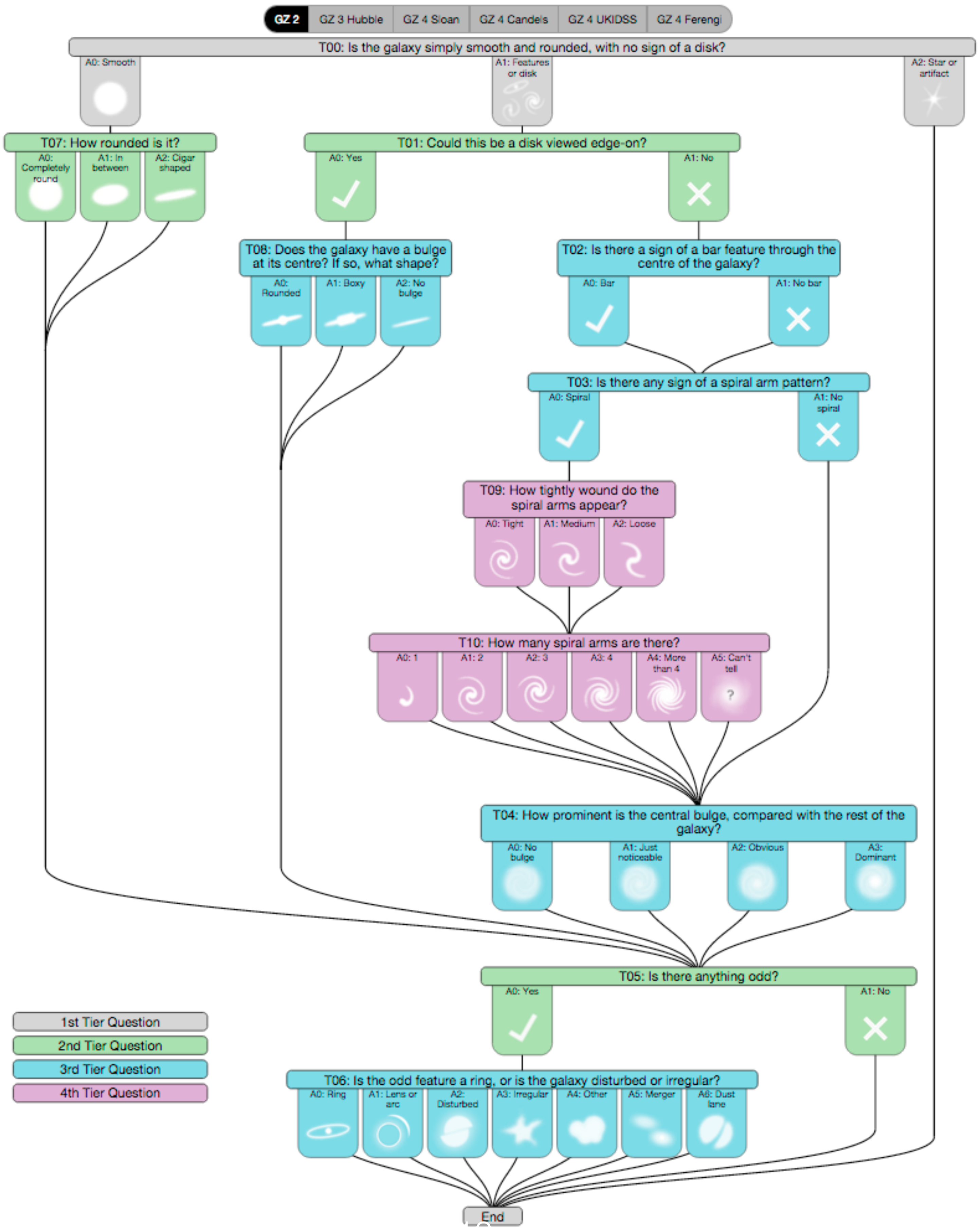
Faint sample

- ✓ Simulate high-z galaxies: train & test models
- ✓ Define redshift, magnitude and size limits for accurate classifications

METHODOLOGY

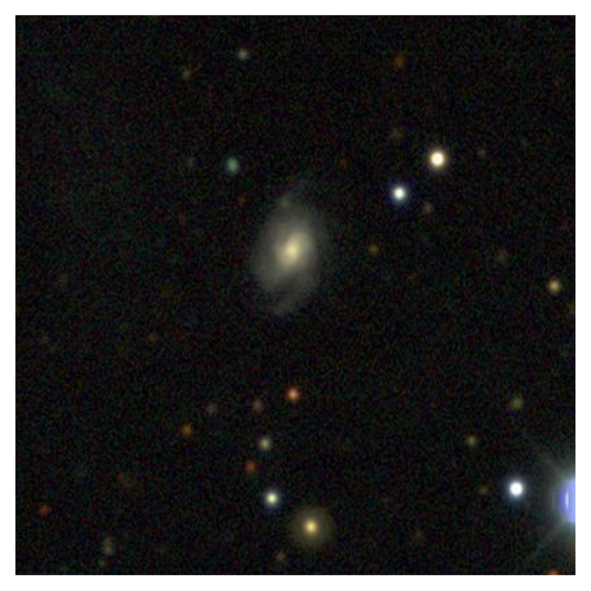
- ✓ **Train & test with SDSS survey** (GZOO catalogue)
  - Probabilities according to number of votes for each answer

Galaxy Zoo Decision Trees

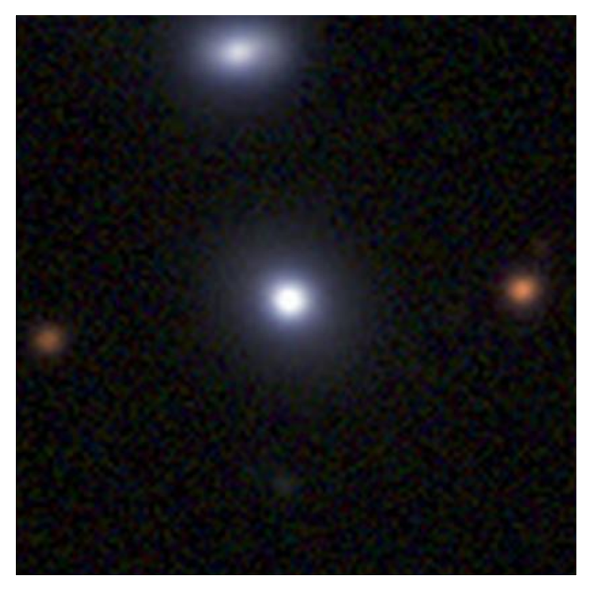


METHODOLOGY

- ✓ **Train & test with SDSS survey** (GZOO catalogue)
  - Probabilities according to number of votes for each answer
- ✓ **New approach** (different from Dielmann+2015):
  - Select well classified galaxies for training (P > 0.7 & votes > 5)
  - Train each question separately using binary classification



FEATURES/DISK



SMOOTH

METHODOLOGY

- ✓ **Train & test with SDSS survey** (GZOO catalogue for ~240,000 galaxies)

    - Probabilities according to number of votes for each answer

- ✓ **New approach** (different from Dielmann+2015):

    - Select well classified galaxies for training (P > 0.7 & votes > 5)

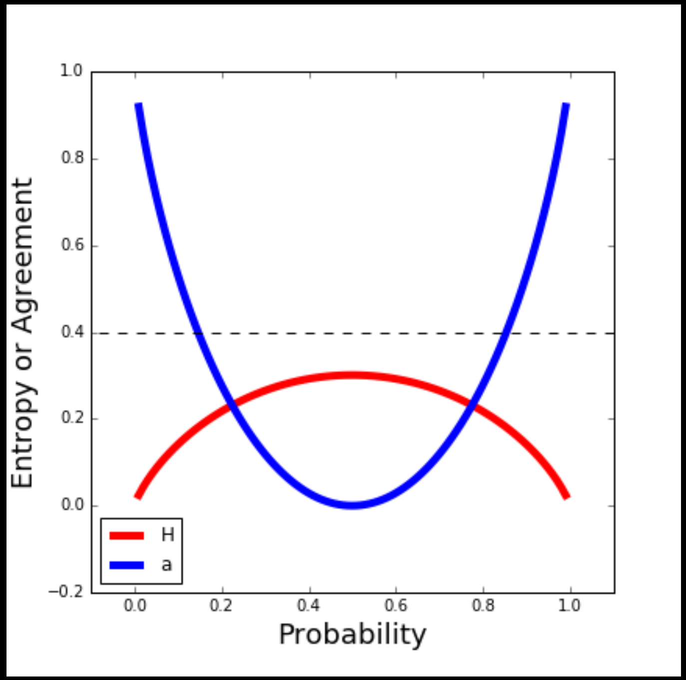
    - Train each question separately using binary classification

    - Test with sample not used for training

    - Much better output agreement

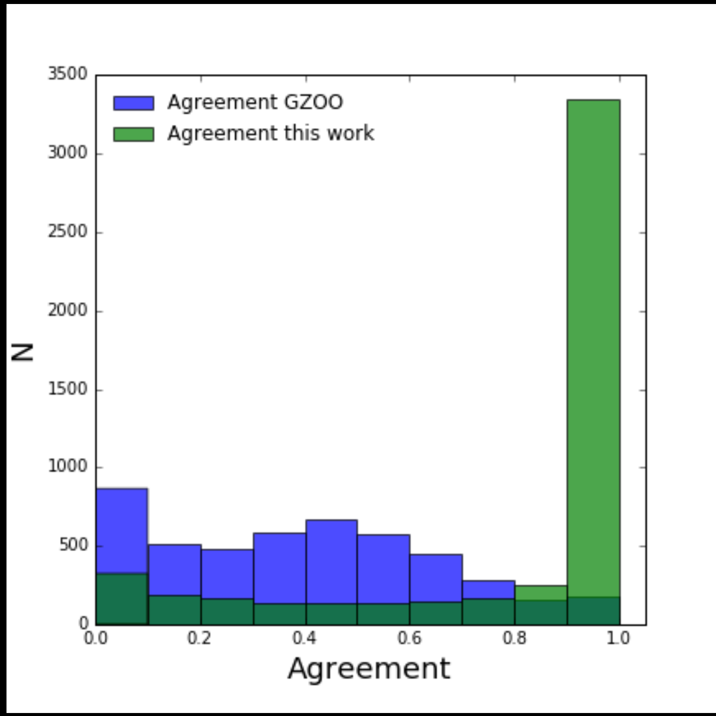
$$H(p) = -\sum_{i=1}^{n} p(x_i) \log p(x_i).$$

$$a(p) = 1 - \frac{H(p)}{\log(n)}.$$



METHODOLOGY

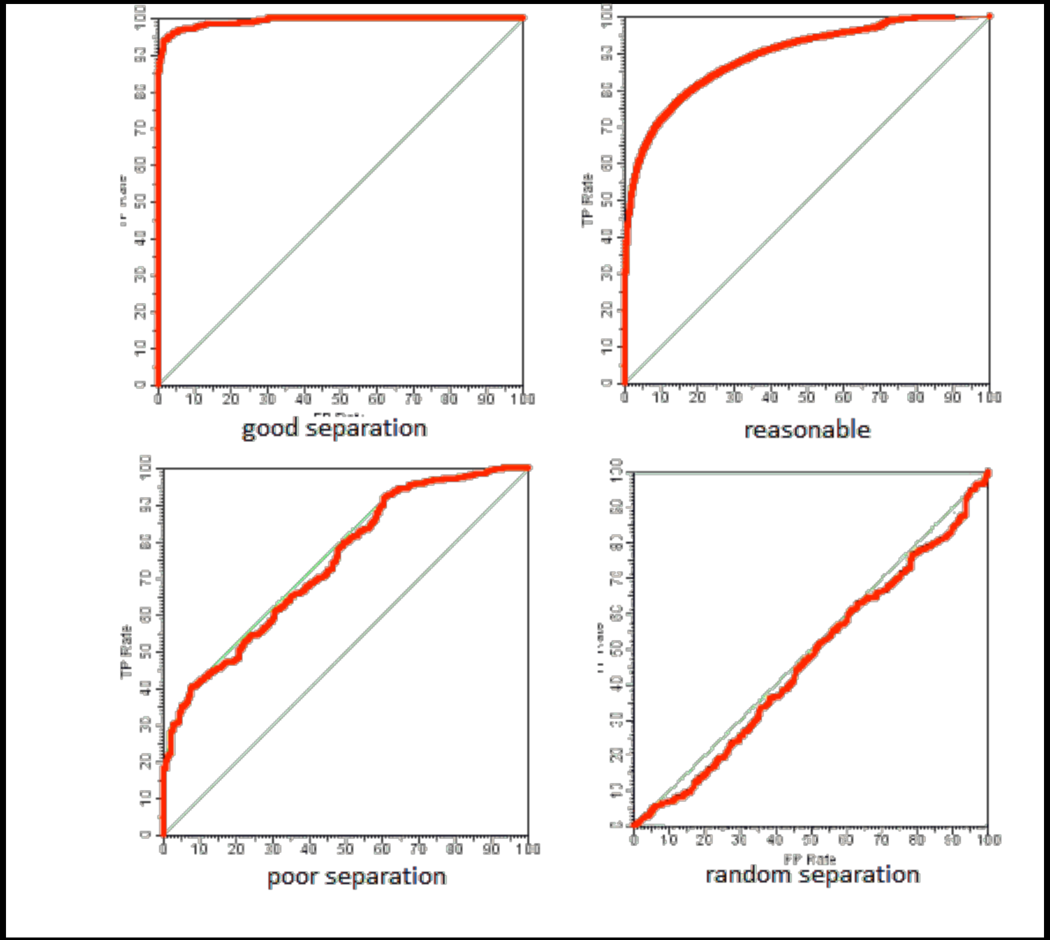
- ✓ **Train & test with SDSS survey** (GZOO catalogue)
    - Probabilities according to number of votes for each answer
- ✓ **New approach** (different from Dielmann+2015):
    - Select well classified galaxies for training (P > 0.7 & votes > 5)
    - Train each question separately using binary classification
    - Test with sample not used for training
    - Much better output agreement



TESTING MODELS

Actual Class

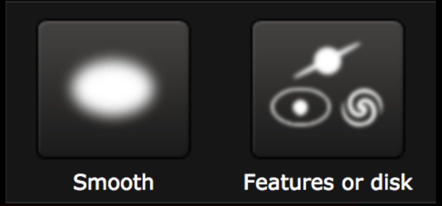
Predicted Class		p	n
	Y	True Positives	False Positives
	N	False Negatives	True Negatives
Totals:		P	N



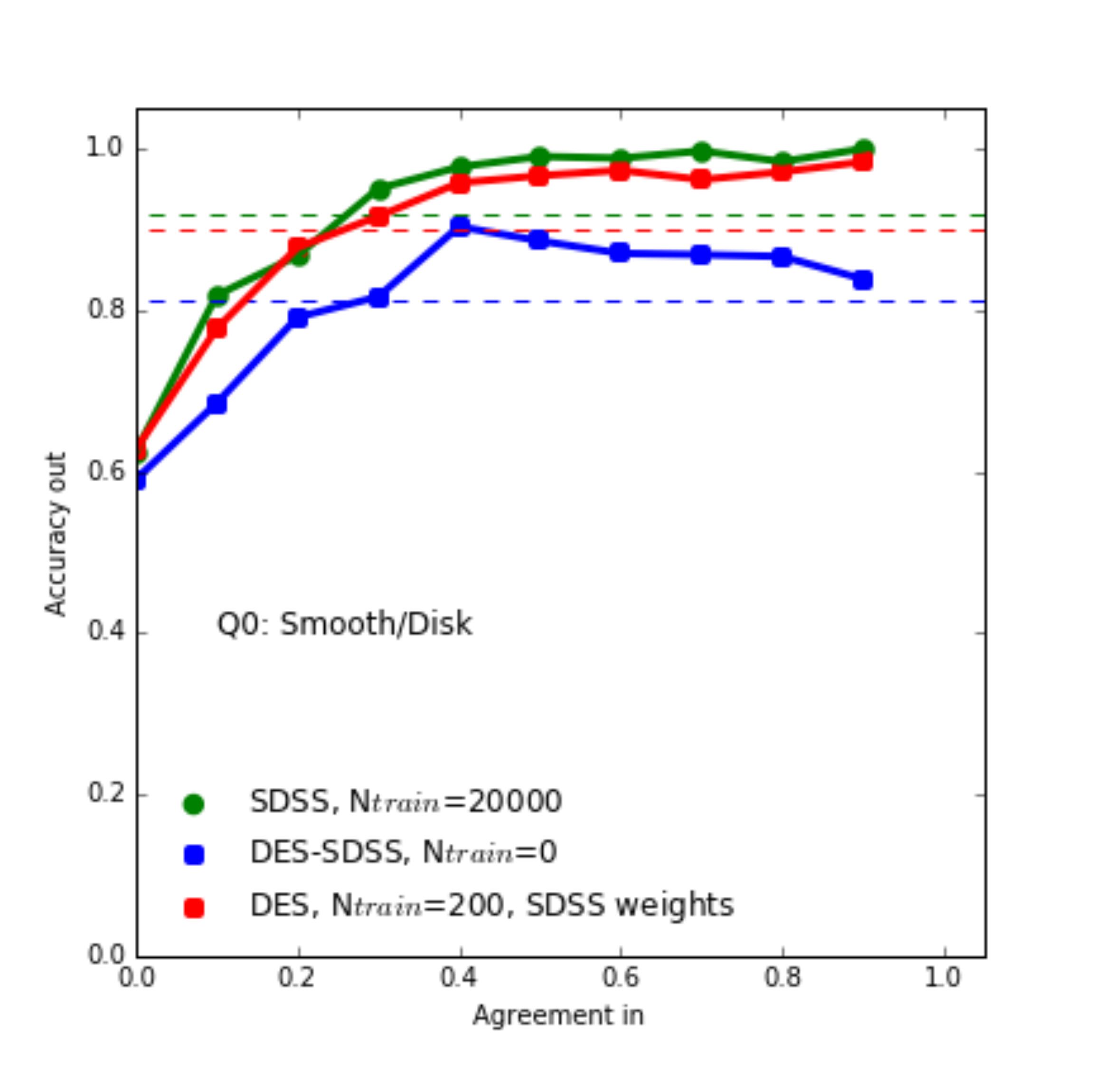
- Accuracy=TP+TN/(P+N)
- TPR=TP/P
- FPR=FP/N
- Precision=TP/(TP+FP)

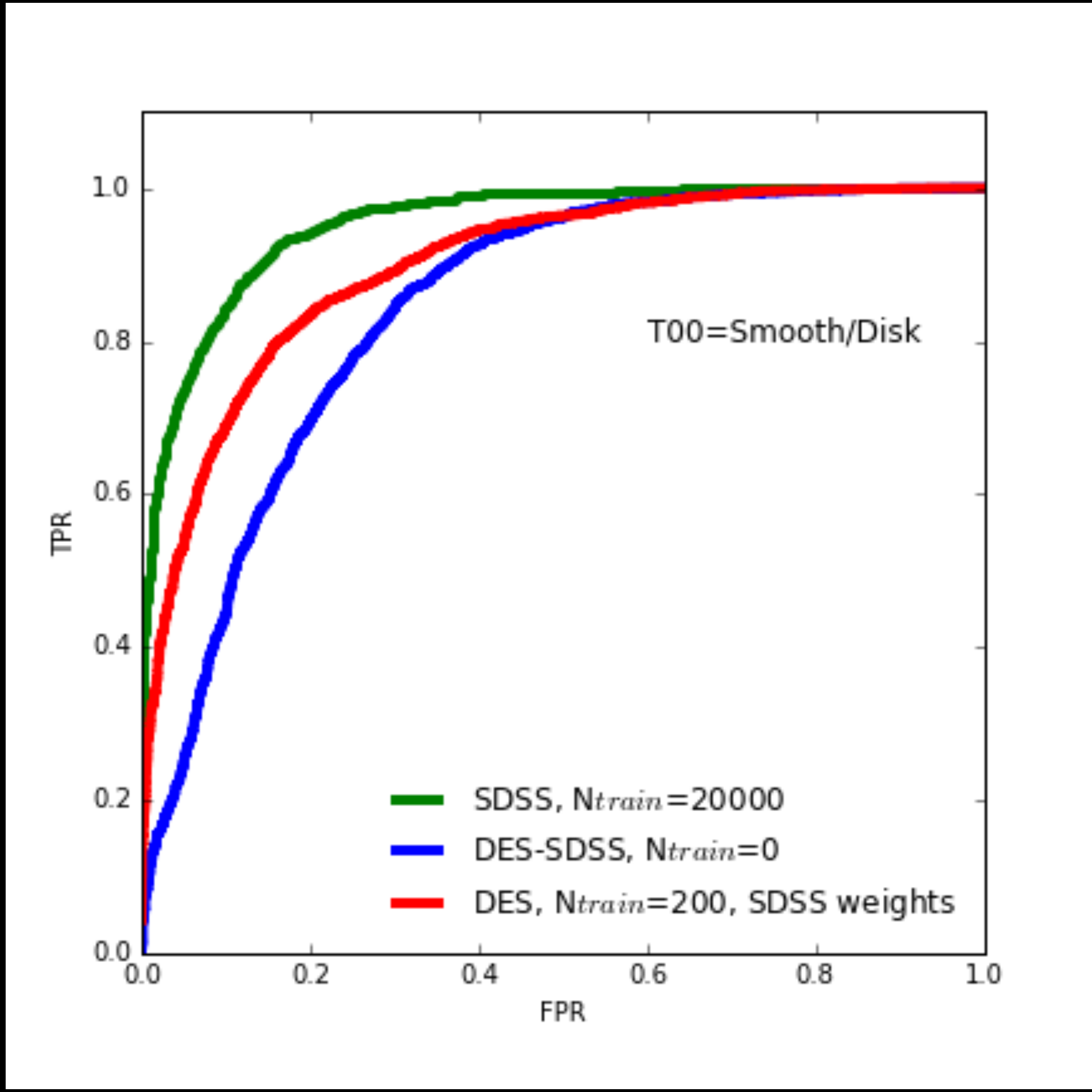
- ROC= TPR vs FPR
  (for different P_{thresh})

- TPR —> Completeness
- Precision—> Purity

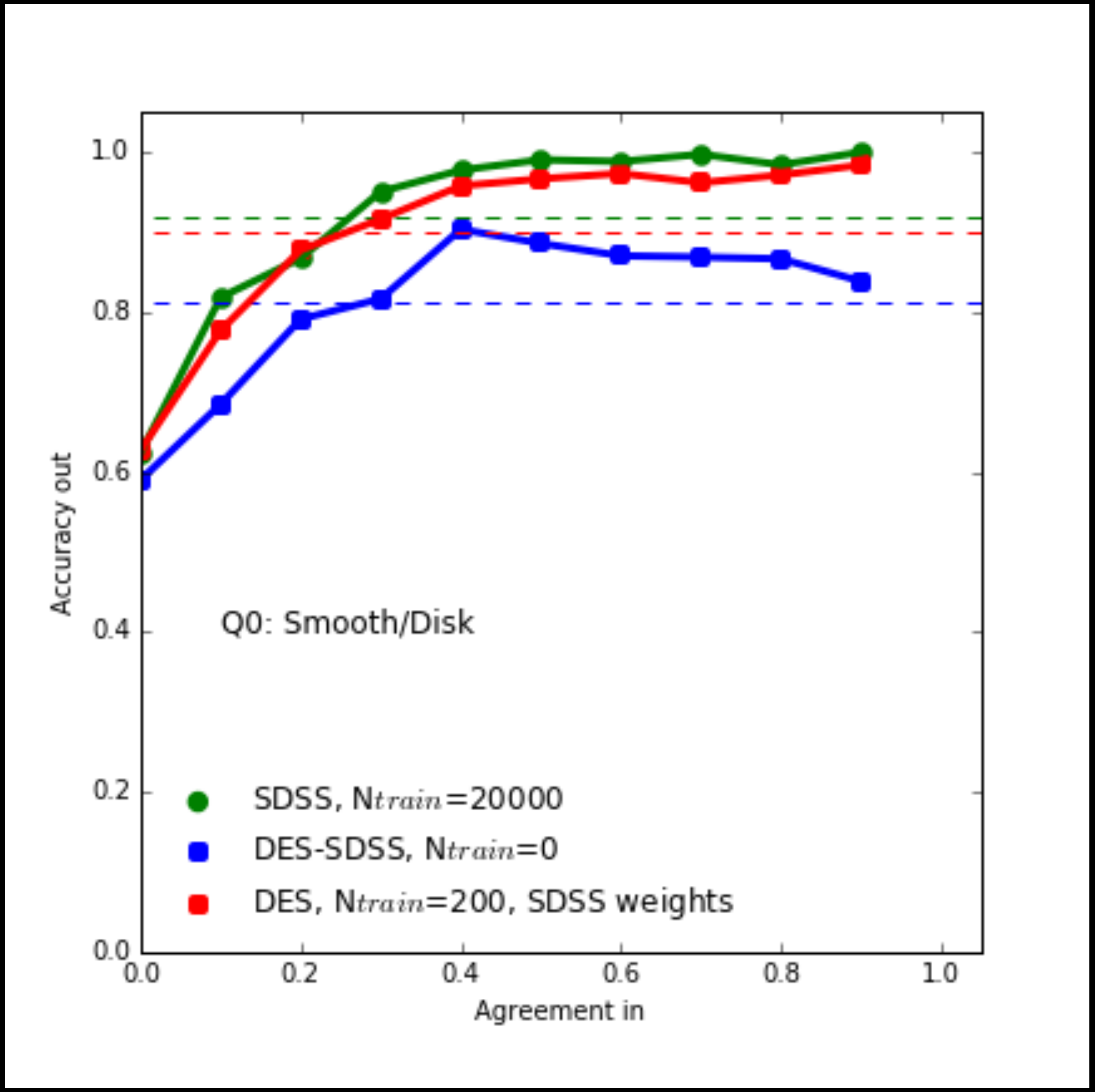


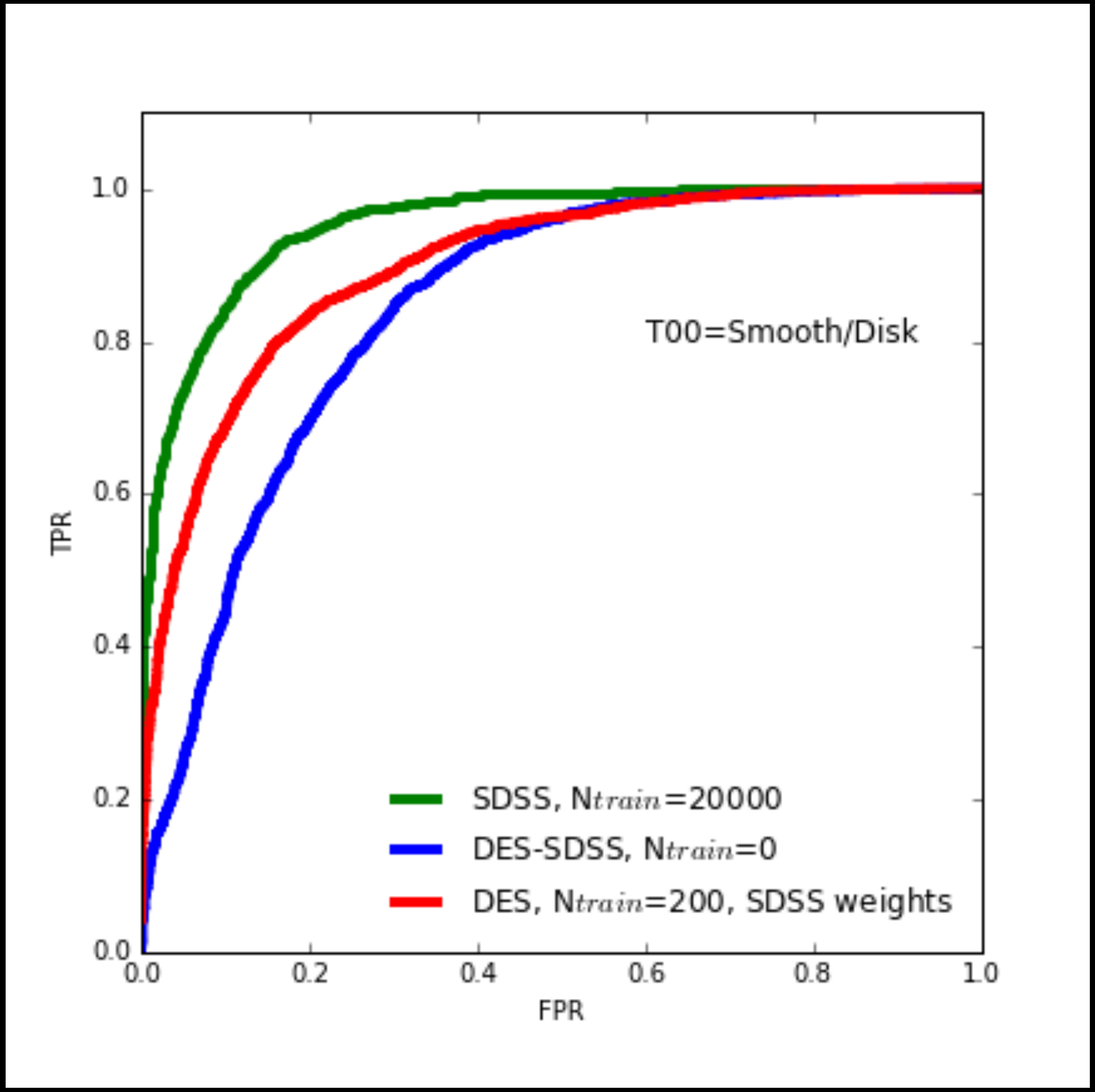
RESULTS: SMOOTH VS FEATURES





RESULTS: SMOOTH VS FEATURES





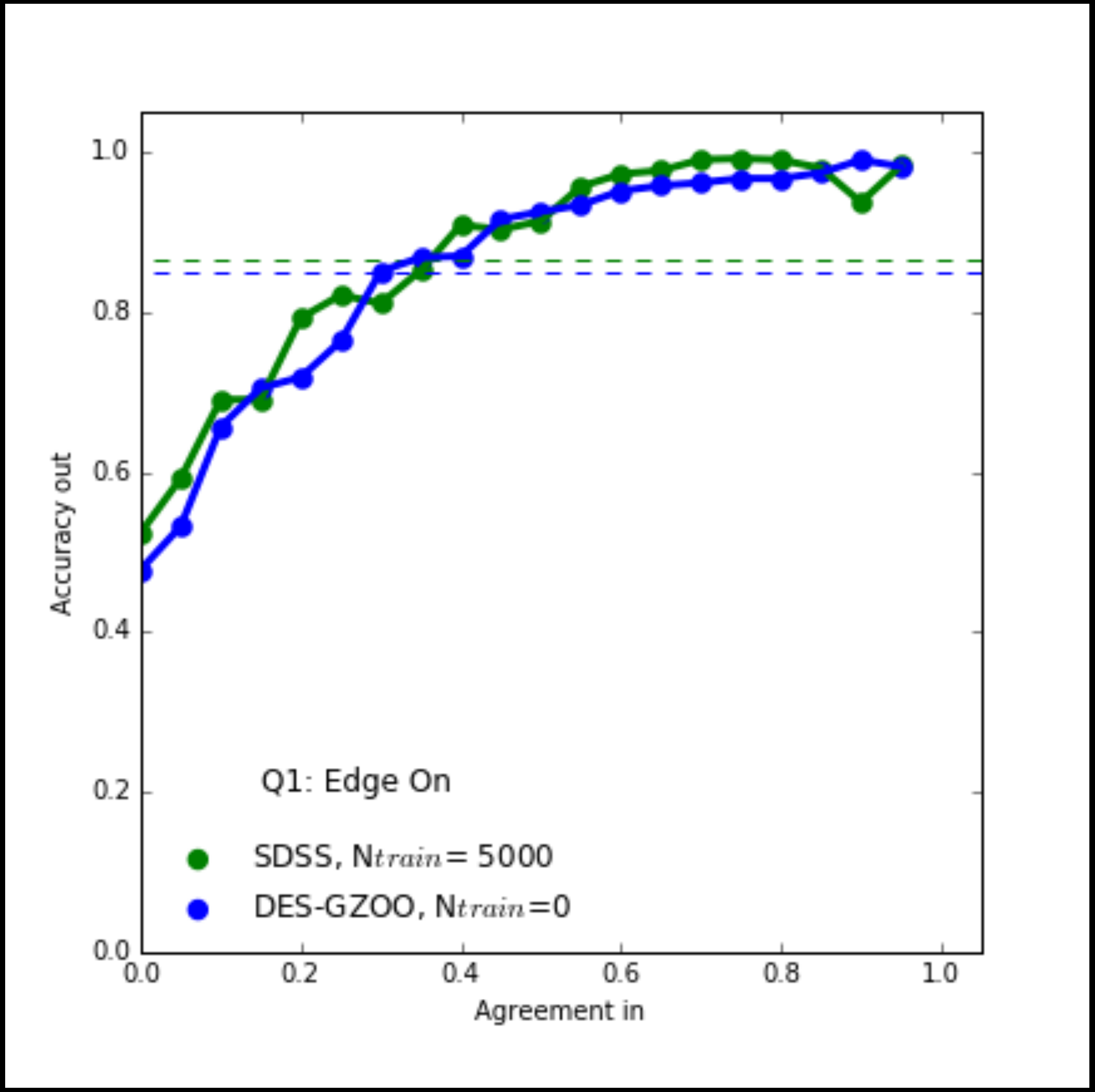
	TPR	P	Acc.
SDSS:	0.95	0.99	0.99
DES no train:	0.40	0.99	0.77
DES train	0.95	0.96	0.97

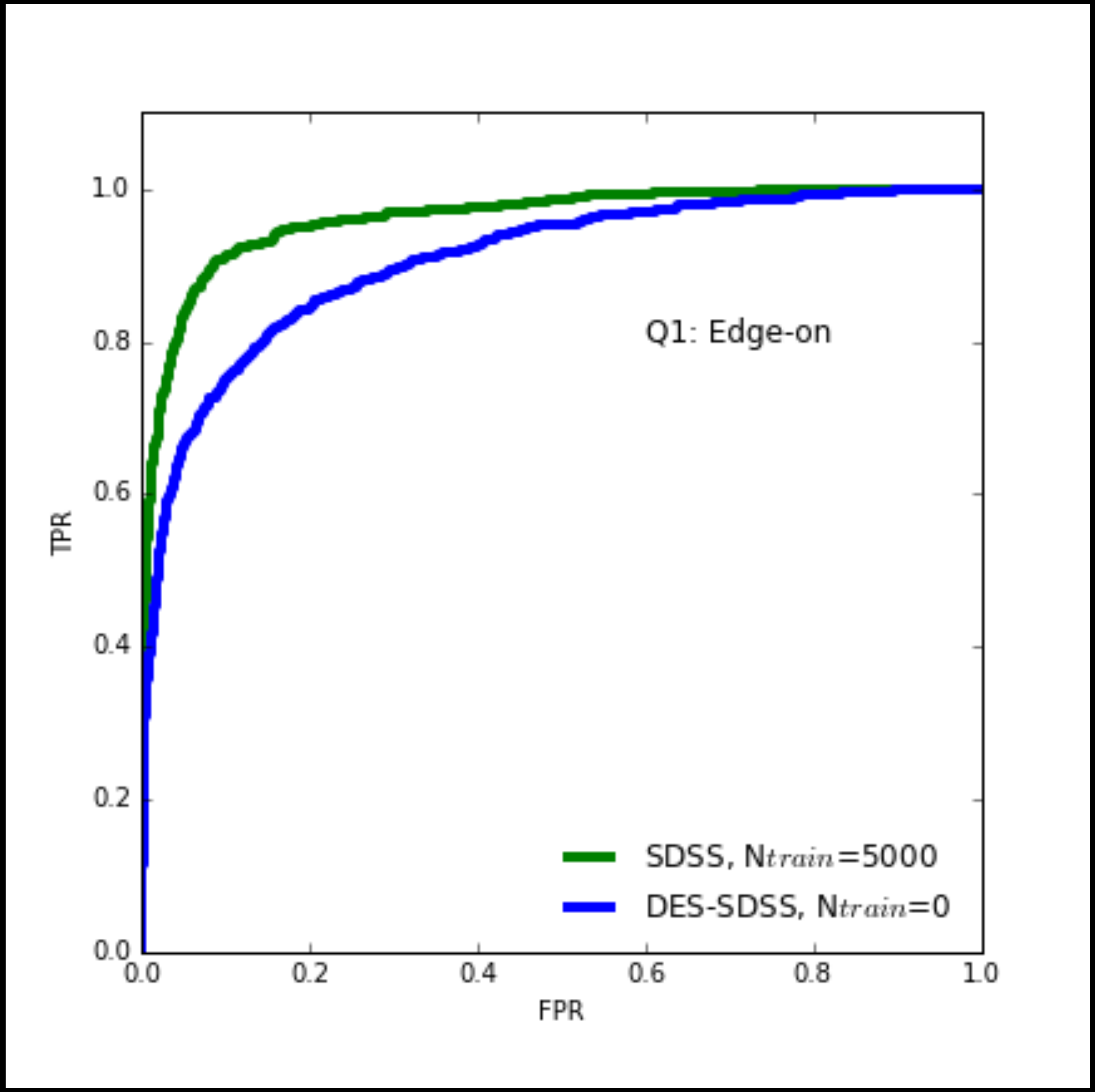
Agreement > 0.4

RESULTS: FEATURES EXAMPLES

RESULTS: SMOOTH EXAMPLES

Results: Edge On

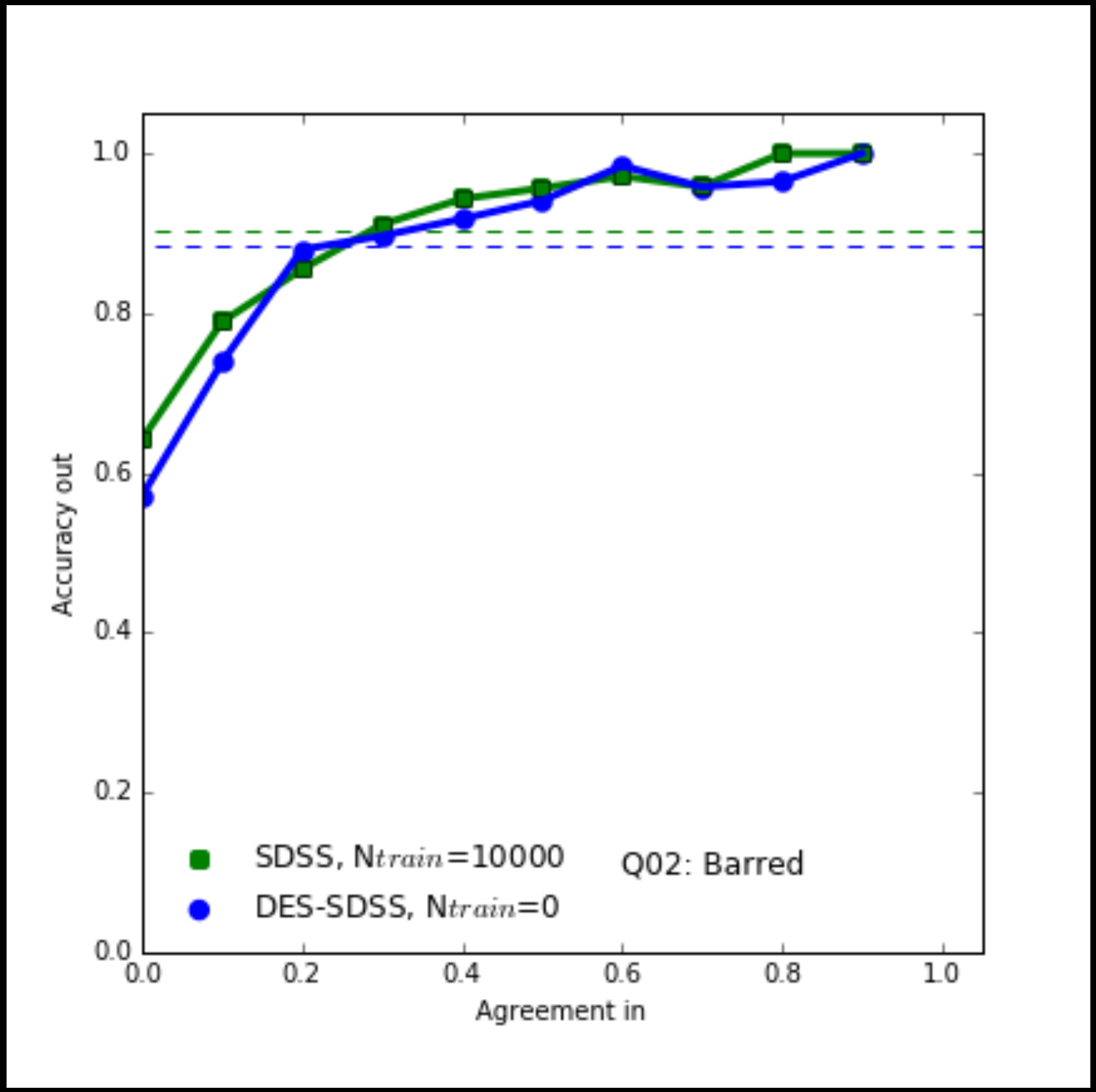


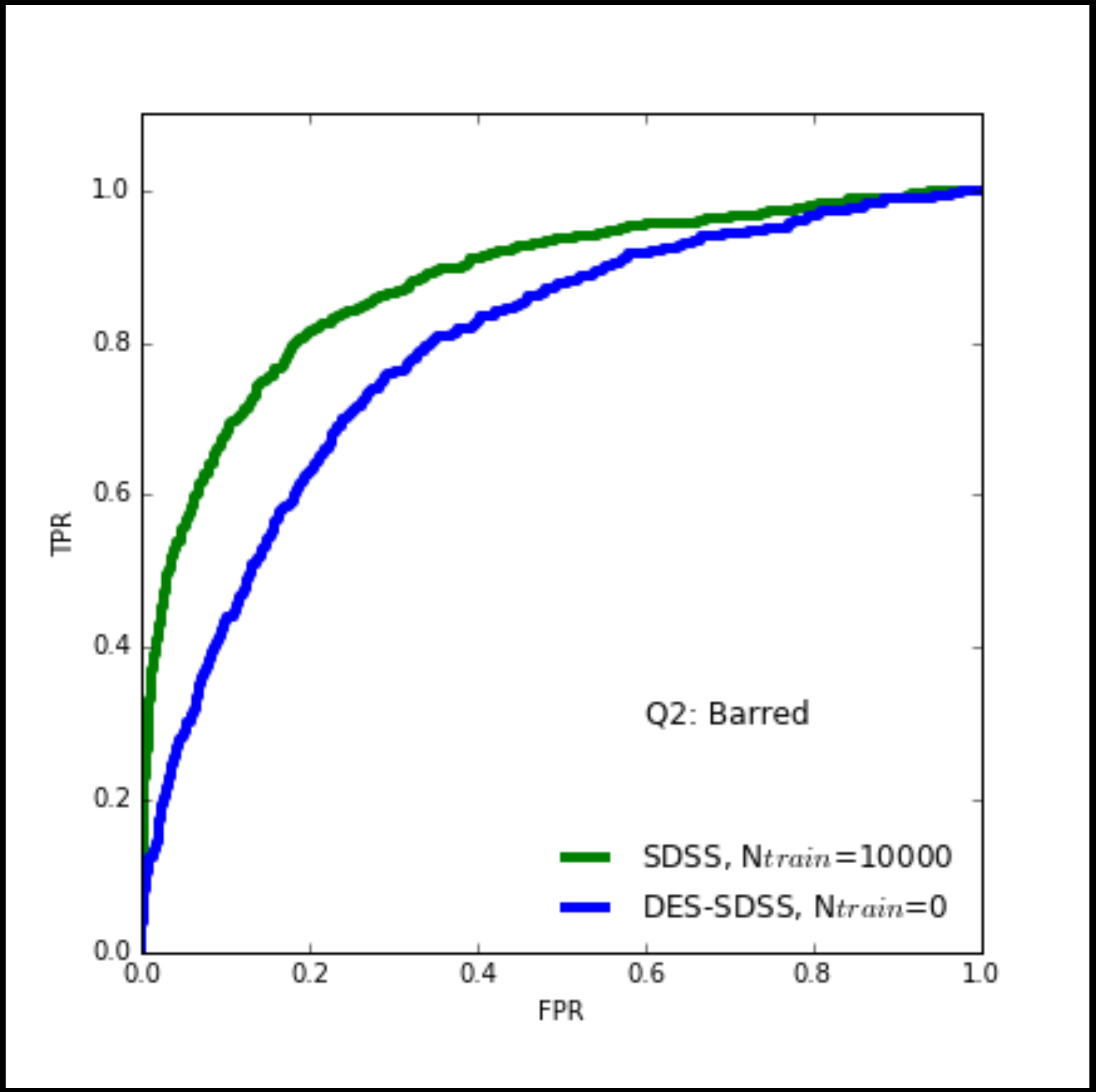


	TPR	P	Acc.
SDSS:	0.99	0.85	0.97
DES no train:	0.92	0.83	0.96

RESULTS: EDGE ON EXAMPLES

RESULTS: BARRED GALAXIES





	TPR	P	Acc.
SDSS:	0.81	0.81	0.97
DES no train:	0.65	0.25	0.96

Low statistics:

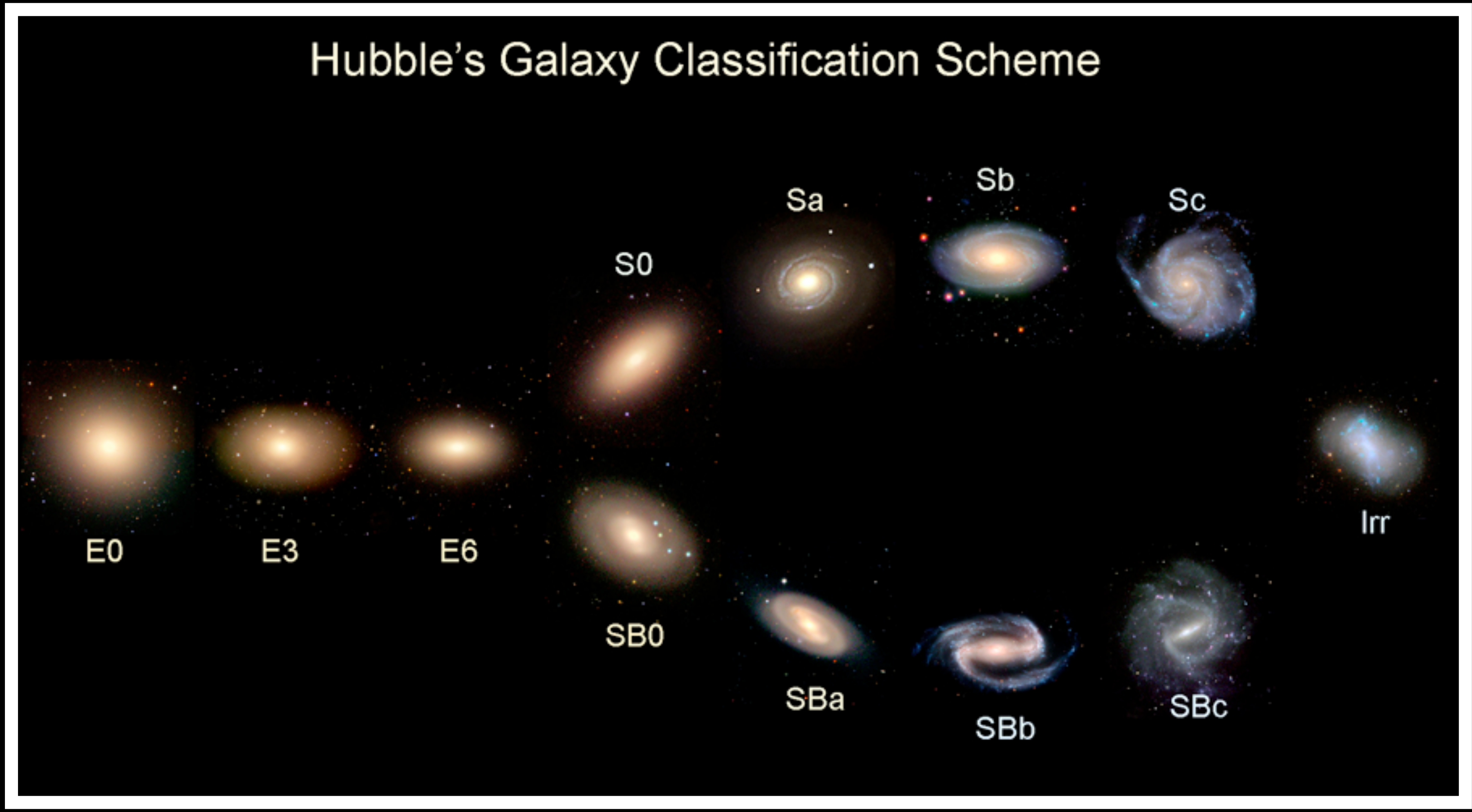
Only 20/1270 barred galaxies

TP=13 FP=39

TN=1211 FN=7

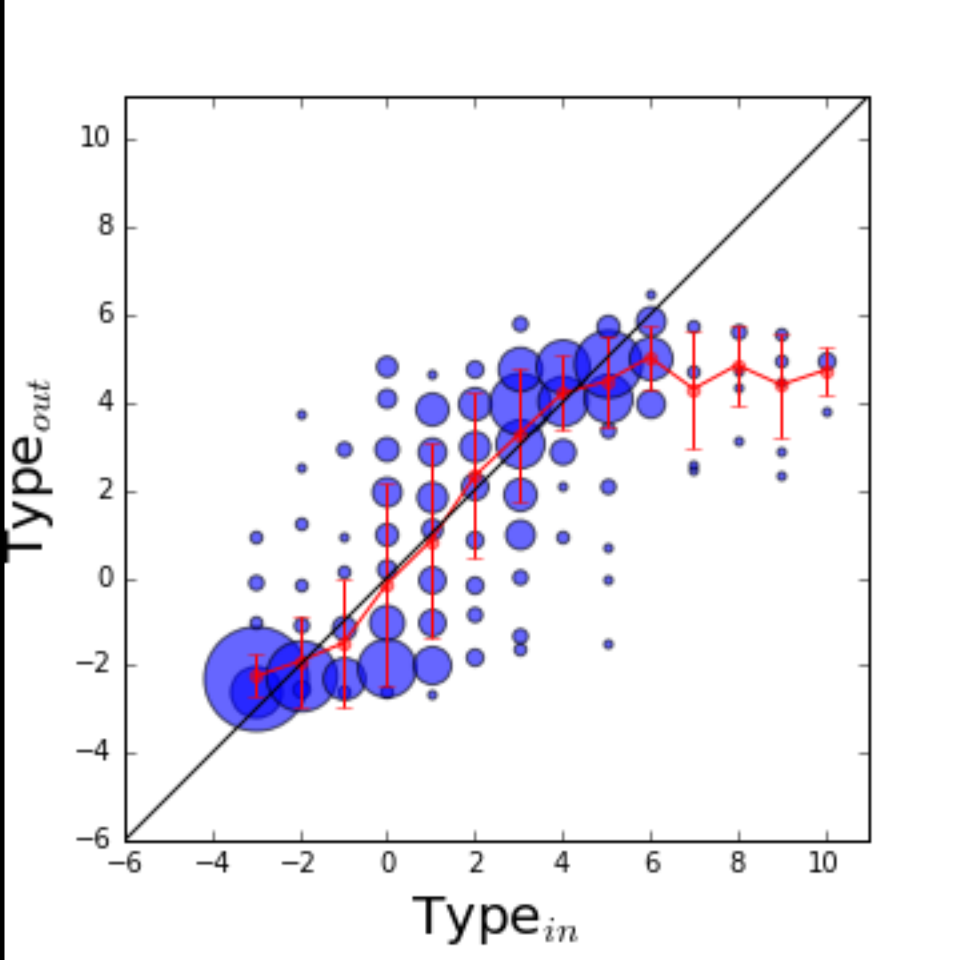
Results: Barred examples

Results: T-Type

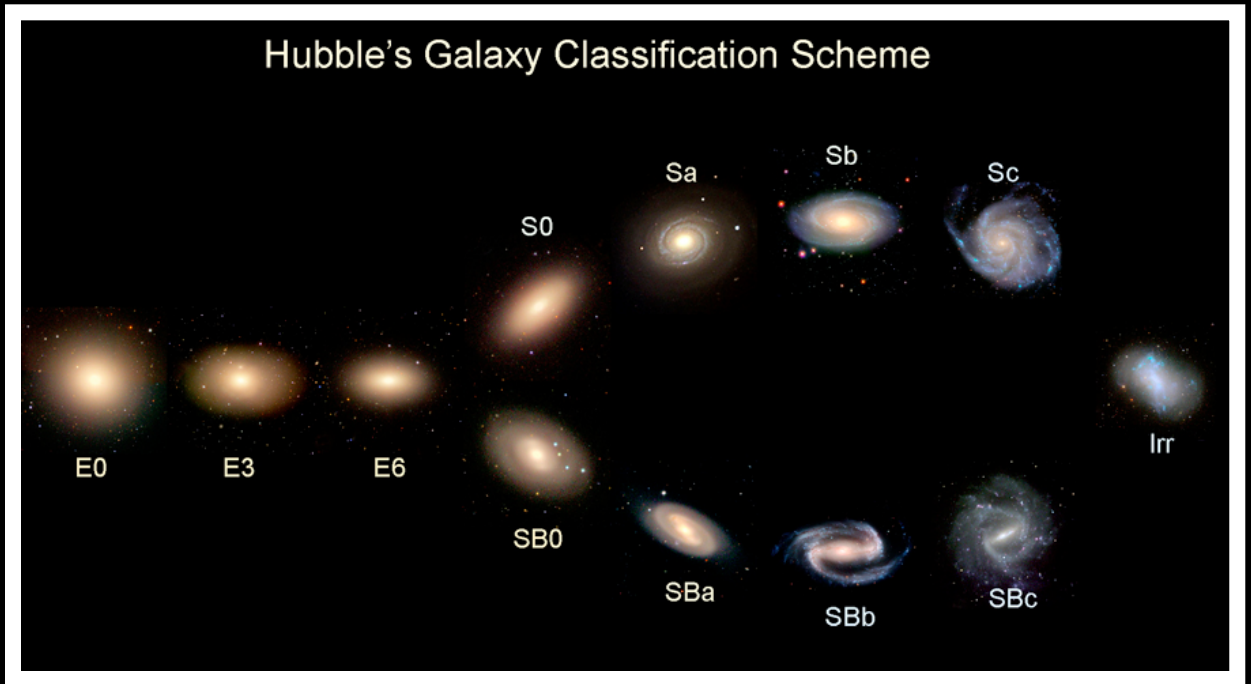


-3 -2 -1 0 2 4 6 10

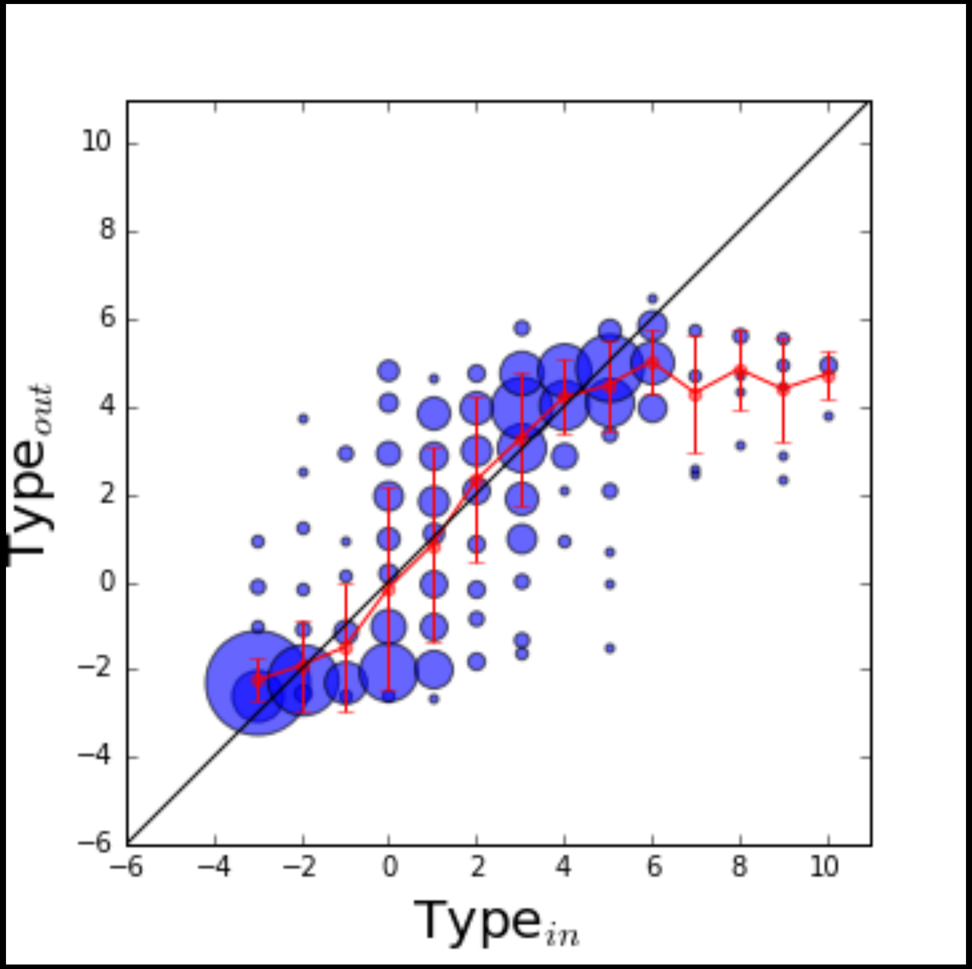
Results: T-Type



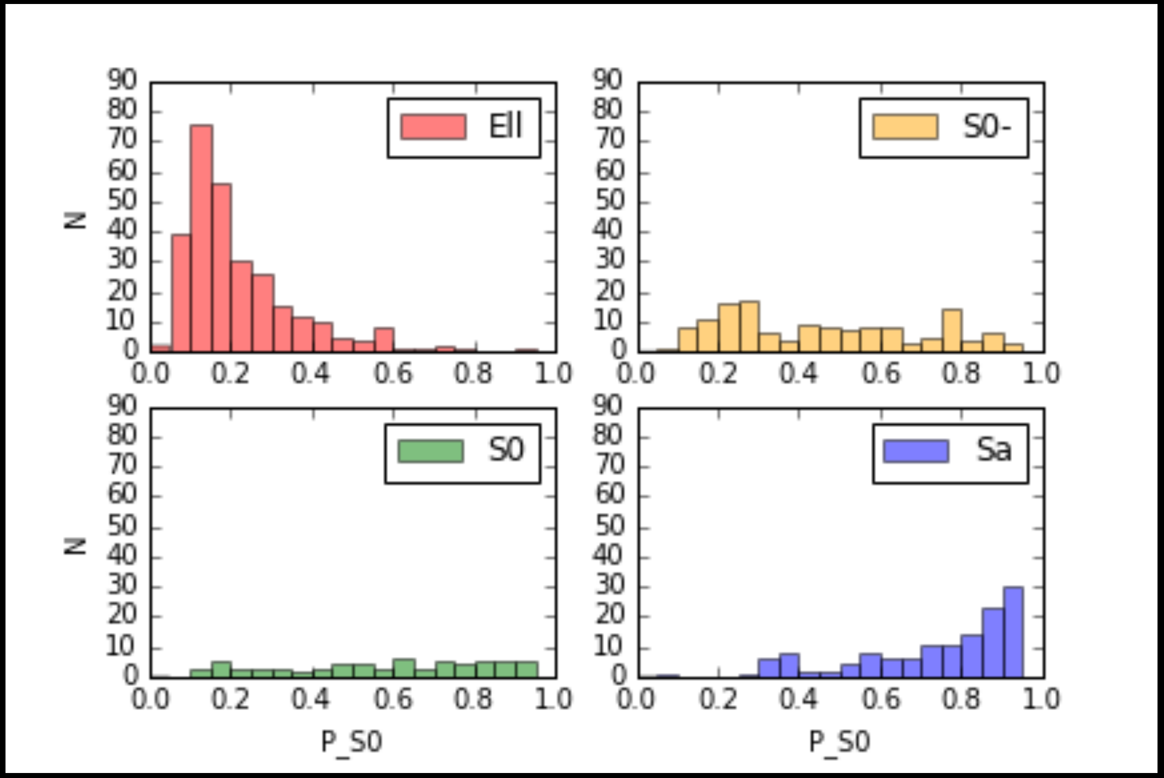
- Trained with Nair+ 2010 catalogue (14000 galaxias, SDSS)
- Better than previous classifications (e.g. SVM, Huertas-Company +2011)
- Further model to separate S0/ETGs
- Testing on DES Sample



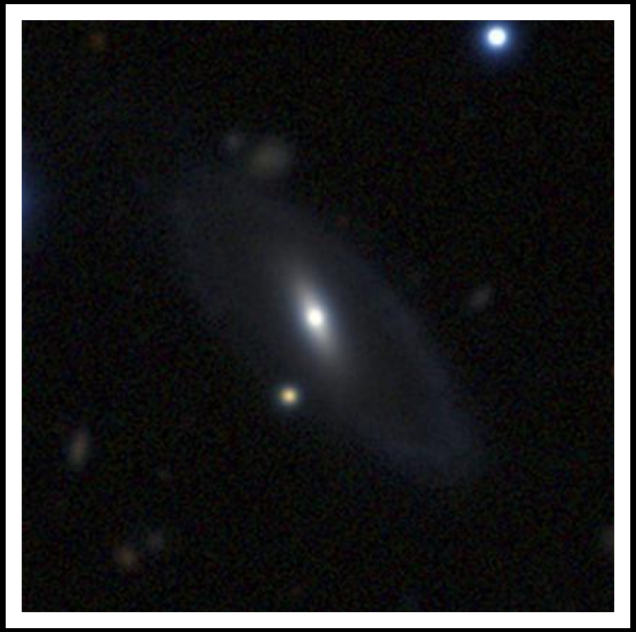
Results: T-Type



- Trained with Nair+ 2010 catalogue (14000 galaxias, SDSS)
- Better than previous classifications (e.g. SVM, Huertas-Company +2011)
- Further model to separate S0/ETGs
- Testing on DES Sample

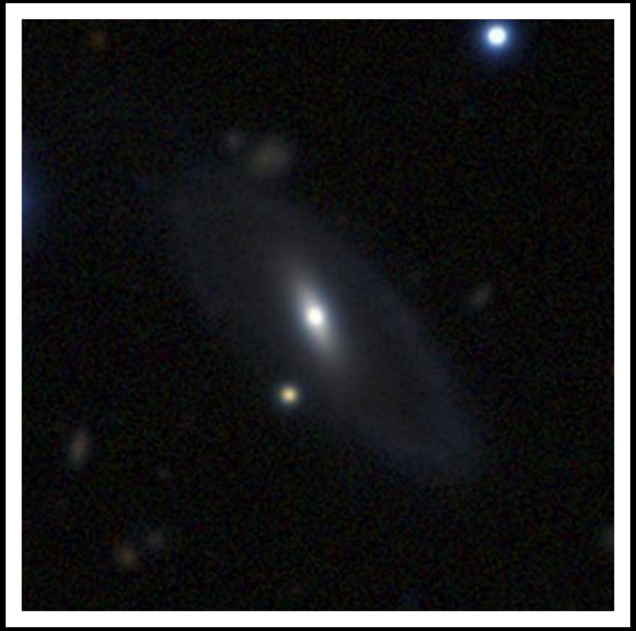


MAGNITUDE LIMIT



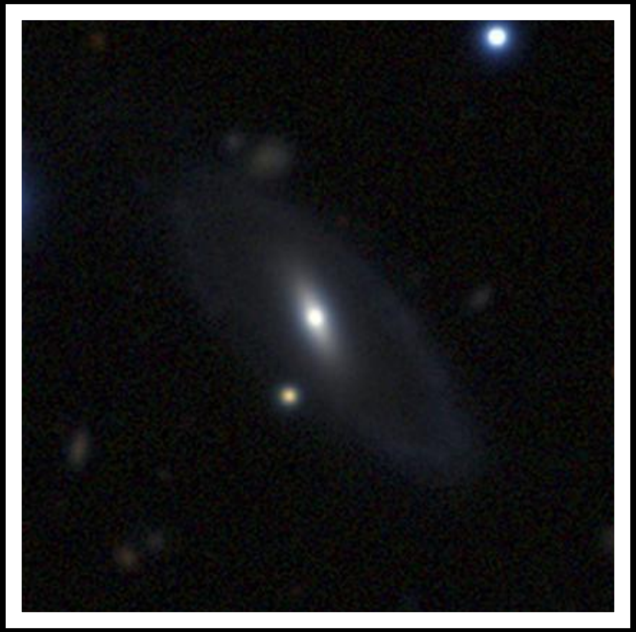
- ✓ Magnitude (redshift) affect model performance
- ✓ Difficult to classify even by visual inspection
- ✓ Well classified galaxy sample to simulate mag/redshift
- ✓ Test mag/redshift limits for accurate classification

MAGNITUDE LIMIT

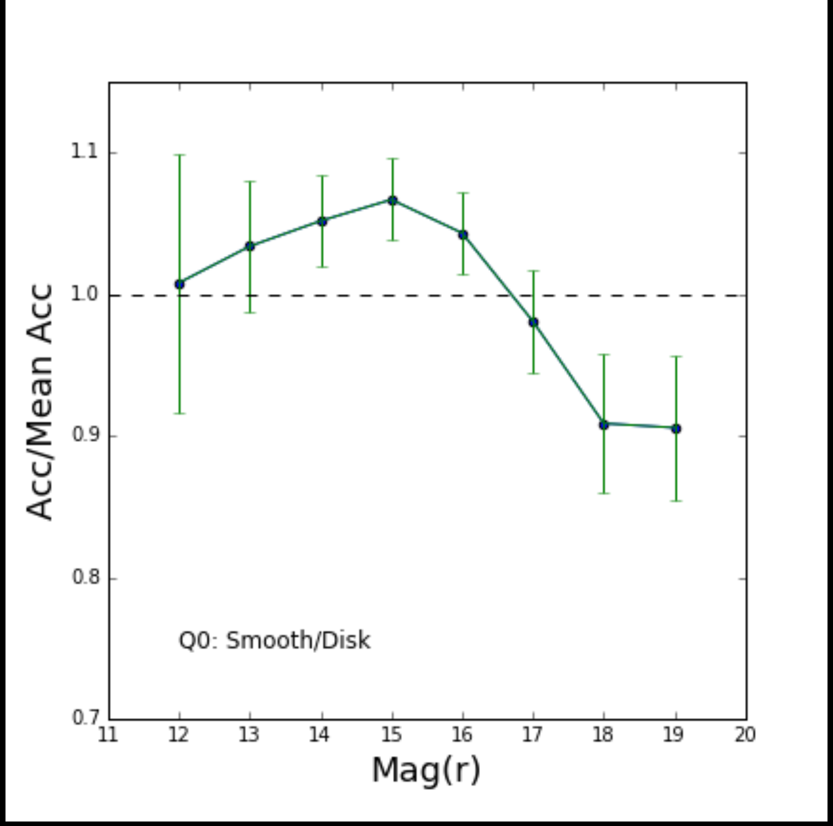


- ✓ Magnitude (redshift) affect model performance
- ✓ Difficult to classify even by visual inspection
- ✓ Well classified galaxy sample to simulate mag/redshift
- ✓ Test mag/redshift limits for accurate classification

MAGNITUDE LIMIT

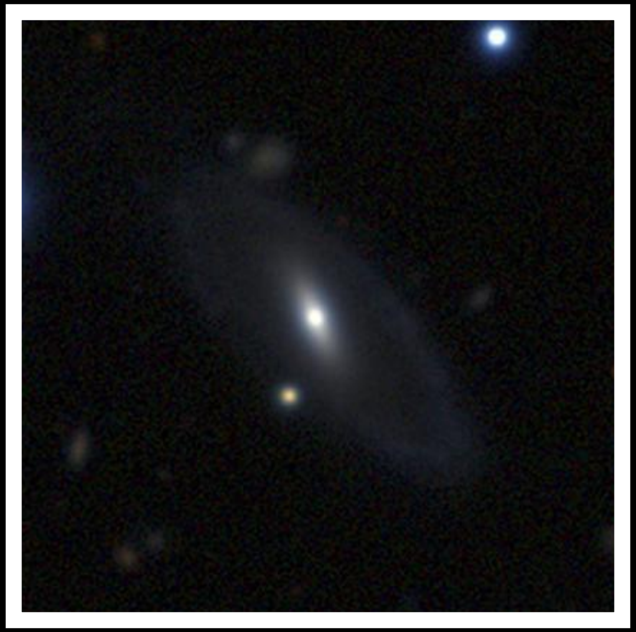


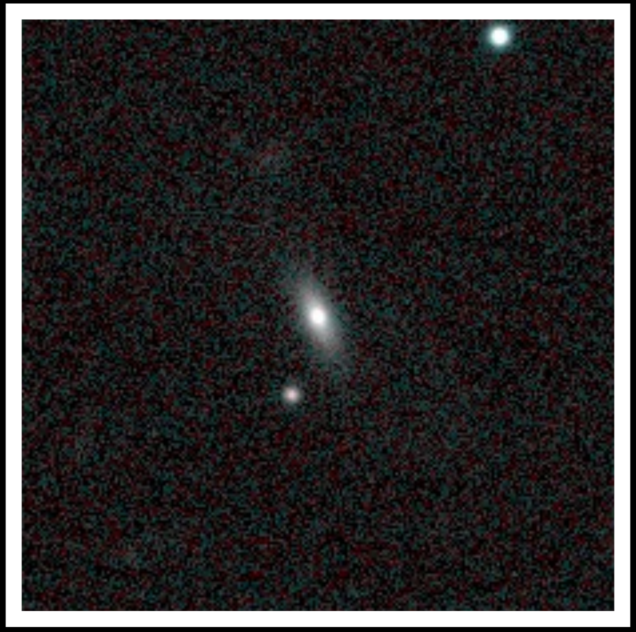
- Magnitude (redshift) affect model performance
- Difficult to classify even by visual inspection
- Well classified galaxy sample to simulate mag/redshift
- Test mag/redshift limits for accurate classification



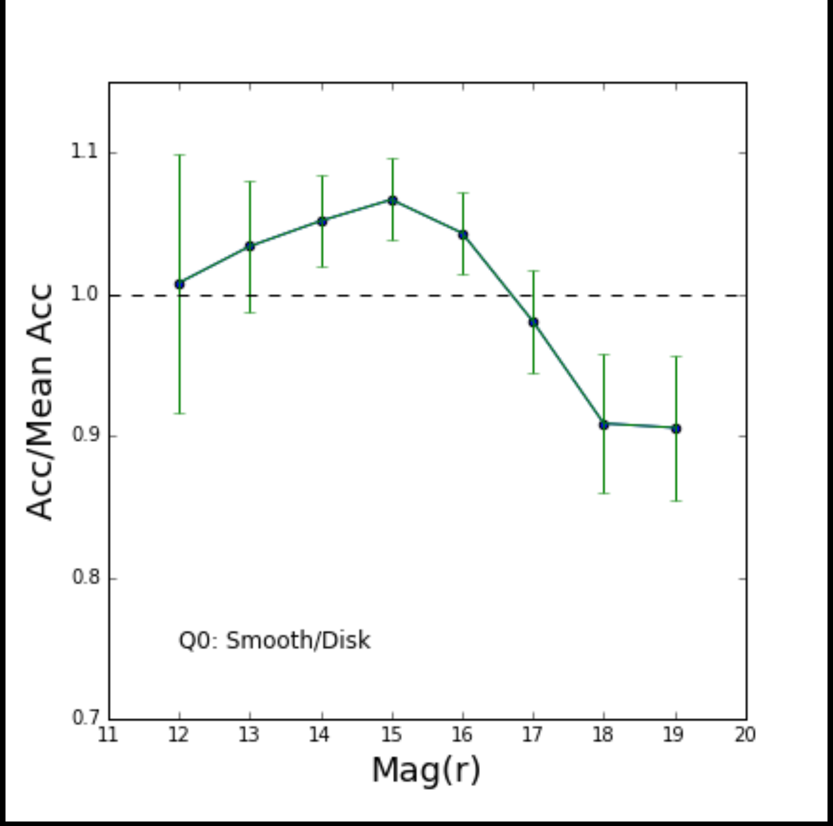
Test sample:
2400 DECALS galaxies
(mag < 19)

MAGNITUDE LIMIT





- Magnitude (redshift) affect model performance
- Difficult to classify even by visual inspection
- Well classified galaxy sample to simulate mag/redshift
- Test mag/redshift limits for accurate classification



Test sample:
2400 DECALS galaxies
(mag < 19)

QUESTIONS?

Helena Domínguez Sánchez

helenads@ucm.es