Learning from Partial Information
(Two case studies)

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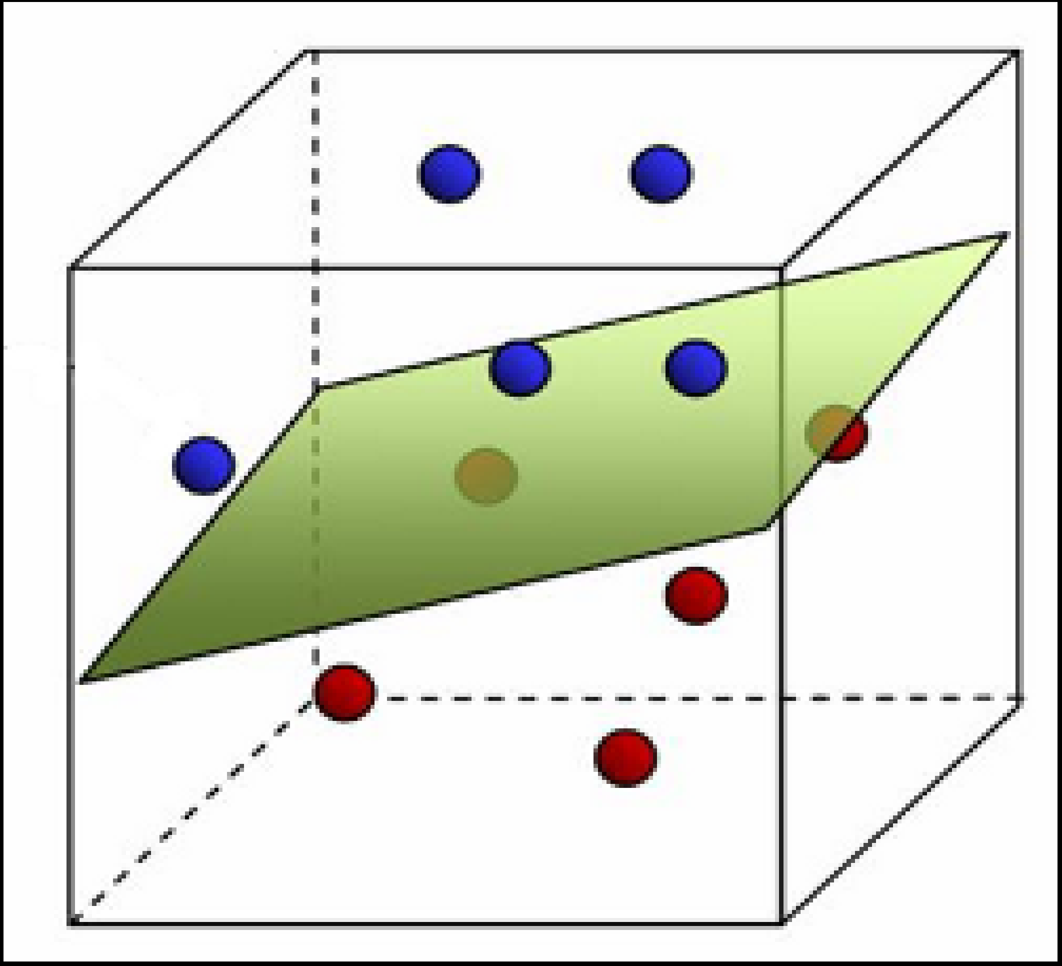
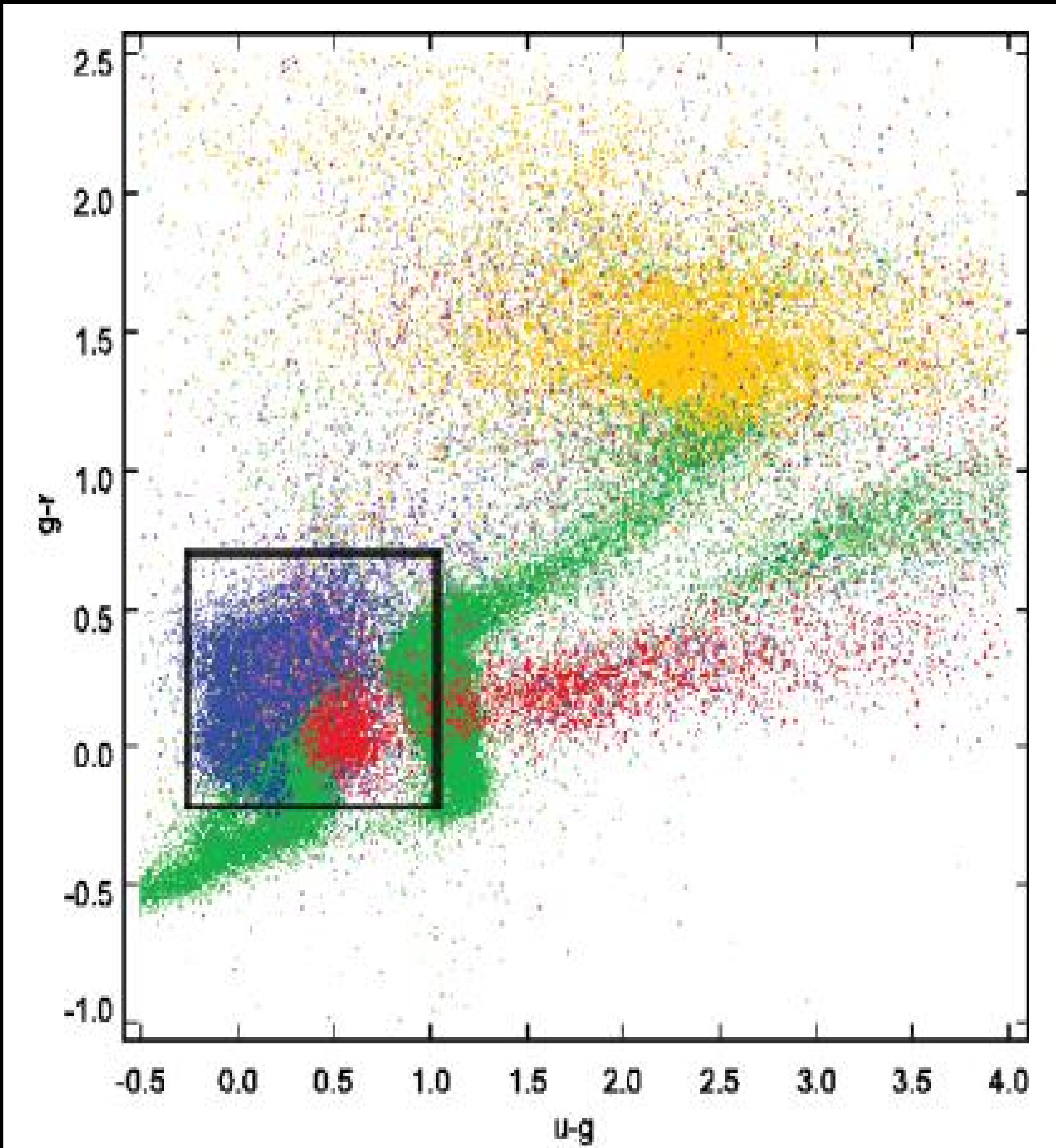
Automated Learning Methods

- All methods assume that the different types (classes) are separable in the feature space.



Light profile of galaxies are different from that of stars

Homogeneous Features: Classification Problem

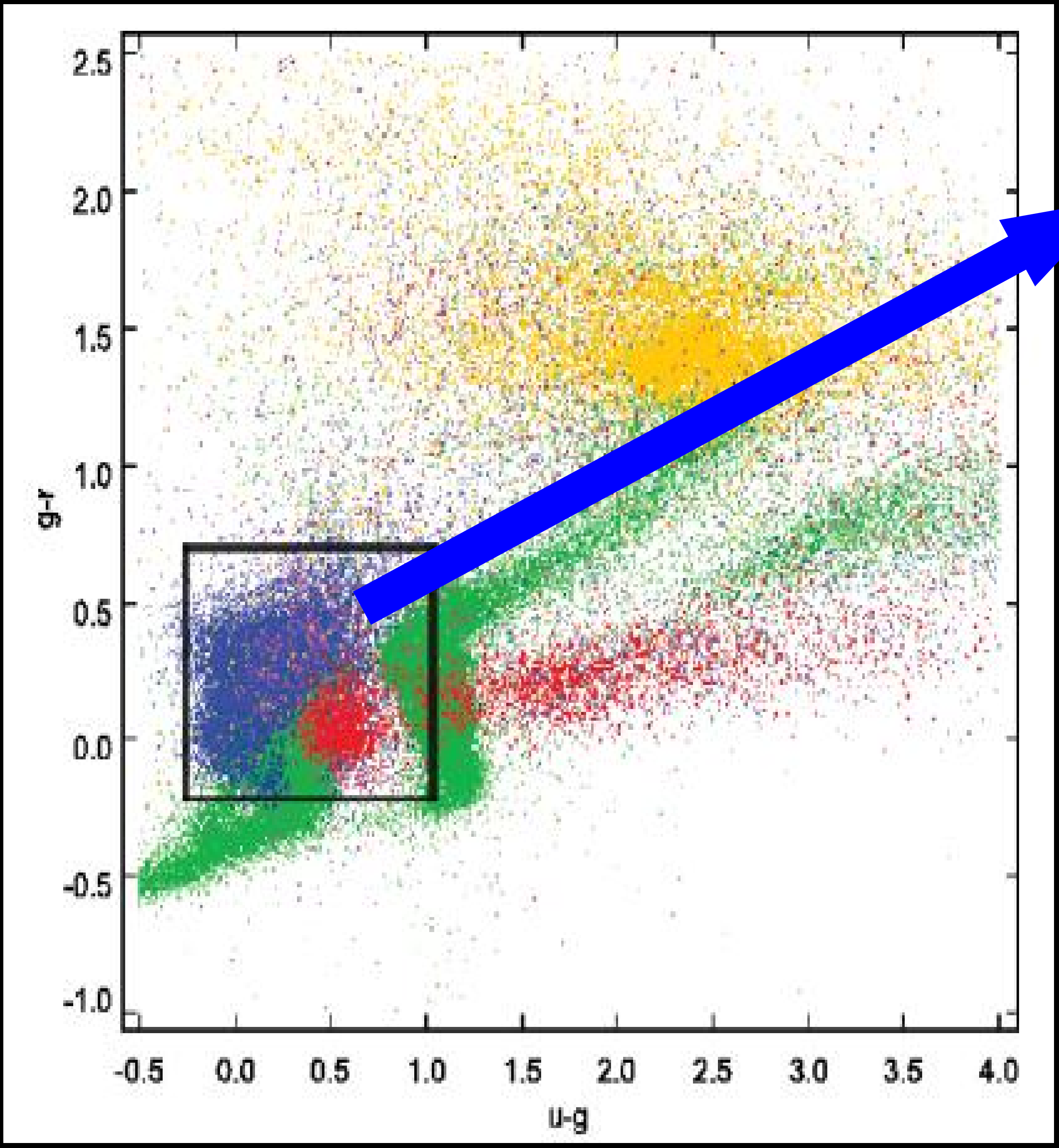


SDSS

colour-colour plot

Composed of about a million points showing clustering of Quasars (blue and red), main sequence stars (green), late type stars (yellow) and unresolved galaxies (pink) in a colour -colour plot of SDSS colours.

Classification



Blue are low redshift Quasars and our goal is to identify them and verify whether the actual number count match with the estimated values.

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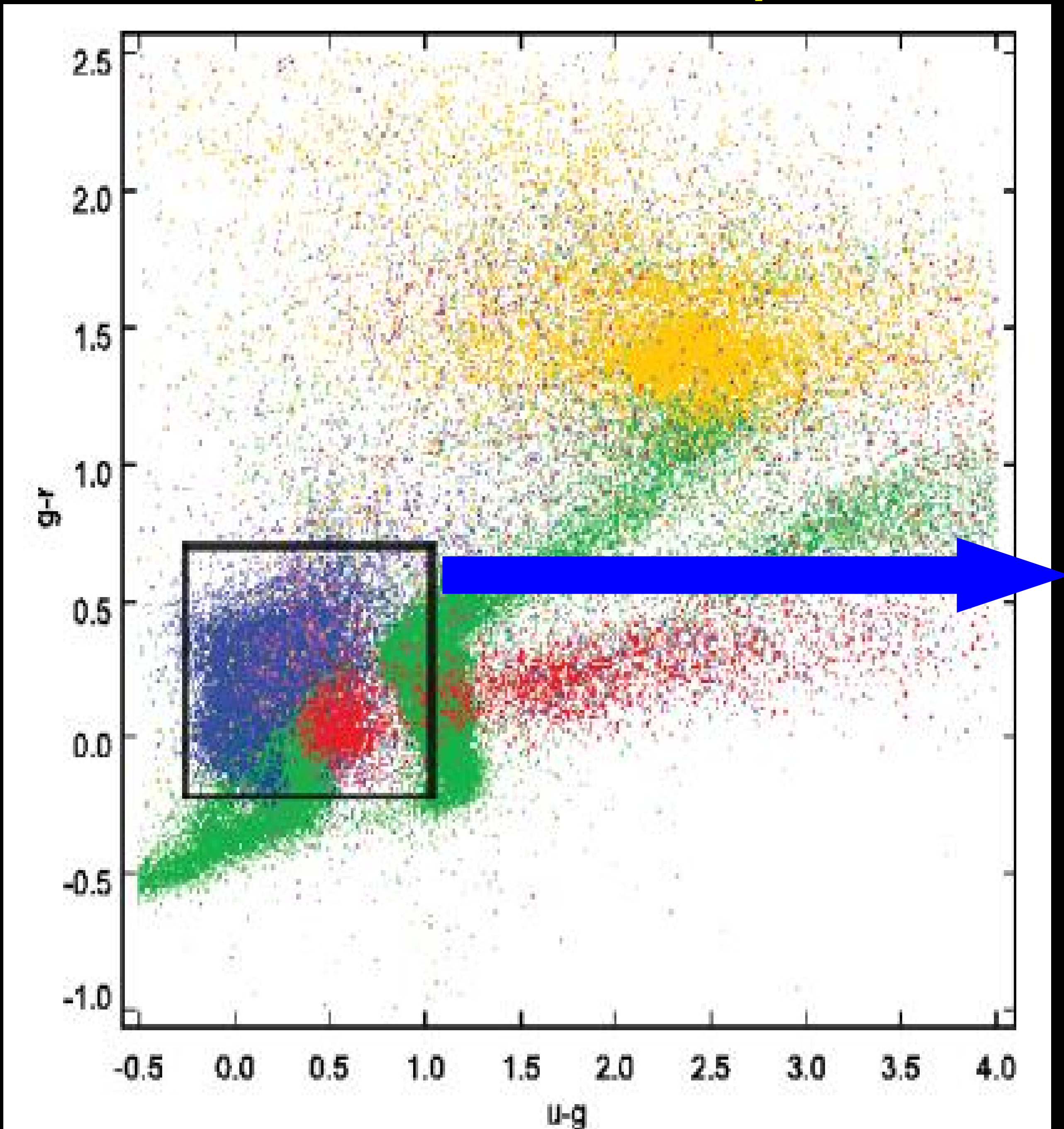
Learn from Examples



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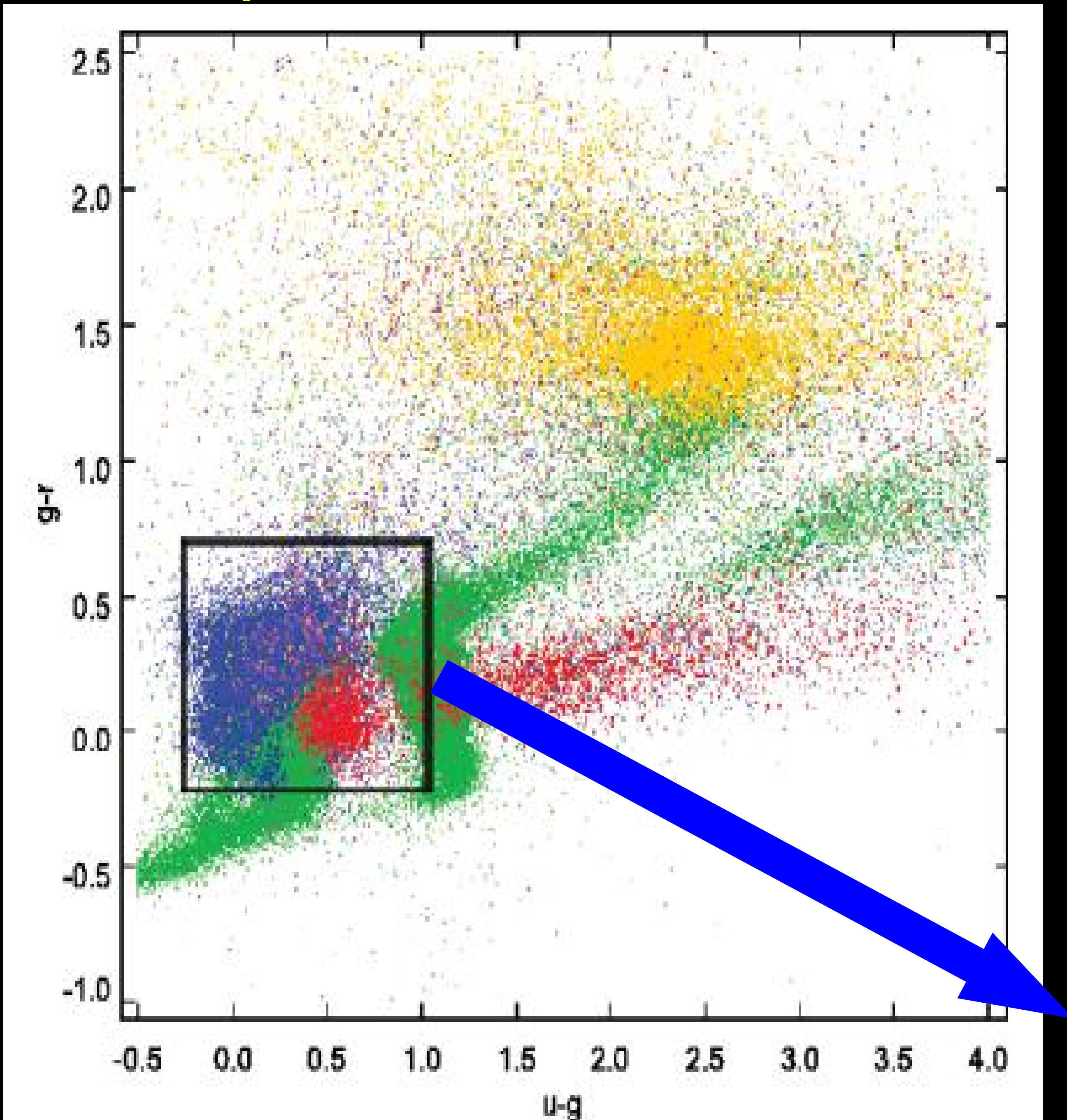
The region in the box has about 150,000 confirmed observations and about 6 million unconfirmed cases.

Map features to Class



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The region in the box has about 150,000 confirmed observations and about 6 million unconfirmed cases.

All objects have known colours (partial information) but the confirmatory spectra and hence class is unknown.

Bayesian Model

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)}$$

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Feature Space

- SDSS provides 5 magnitudes for each object in bands u, g, r, i and z that can be used to construct a ten dimensional colour space.
- A subset of the 150,000 objects with confirmed spectroscopic classification can be used to estimate the likelihood.
- The classifier can be tested on remaining data to verify the accuracy of the model.

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The distribution is not smooth

The colour space need to be binned to approximate the distribution. Computing conditional likelihood of the binned high dimensional feature space is nearly impossible.

- The classifier can be tested on remaining data to verify the accuracy of the model.

Two issues with Bayesian Formalism

- How would you guess the True value of the Prior for each bin?

- Conditional dependency of the input feature space – likelihood is conditionally dependent on feature vectors - Naive Bayesian models that ignore conditional dependence fail on even simple XOR problems.

Bayesian Prior

- Ensemble methods: Multiple models, same data : many weak learners combined to form a strong learning model
- Bagging: each model in ensemble vote for the probable candidate
- Boosting: Emphasise the failing models with weights
- Bayesian Model Averaging (BMA): Sampling Hypothesis from Hypothesis Space
- Bayesian Model Combination (BMC): Seek combination of models closest to a distribution.

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Our Solution

- Estimating both Prior and Likelihood from data.
- Boosting: Emphasise the failing models with weights

Replace Prior by weights within the same model.

Likelihood estimation of Binned Space

- There may not be sufficient samples in each bin to estimate likelihood when conditional dependence constrains are imposed on them.

- We adopted an imposed conditional independence formula that approximate the likelihood for a conditionally dependent event as the product of the likelihood for pairs of input features.

Likelihood estimation of Binned Space

- There may not be sufficient samples to estimate likelihood when constrains on conditional dependence is imposed on them.

- We adopted an imposed conditional independence formula that approximate the likelihood for a conditionally dependent event.

Imposed Conditional Independence

The likelihood for a conditionally dependent event *A* is approximated as

- L(A|b,c,d,e,f) ~

  M*L(A|b,c)* L(A|b,d)* L(A|b,e)* L(A|b,f)* L(A|c,d) *L(A|c,e)* L(A|c,f)* L(A|d,e)* L(A|d,f)* L(A|e,f)

- Works better than Naive Bayes – no issue with XOR gate

Imposed Conditional Independence

The likelihood for a conditionally dependent event *A* can be approximated as the product of the likelihood of its paired inputs.

- L(A|b,c,d,e,f) ~

  M*L(A|b,c)* L(A|b,d)* L(A|b,e)* L(A|b,f)* L(A|c,d) *L(A|c,e)* L(A|c,f)* L(A|d,e)* L(A|d,f)* L(A|e,f)

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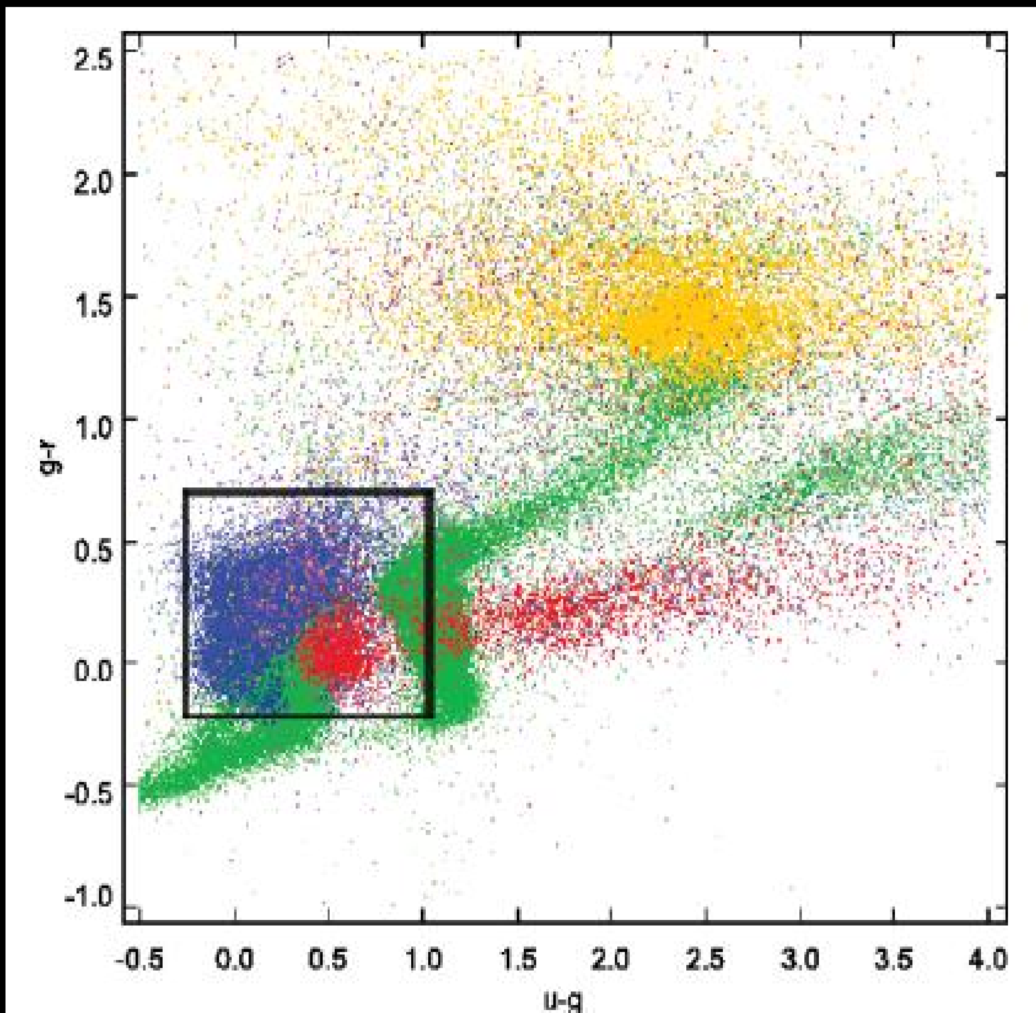
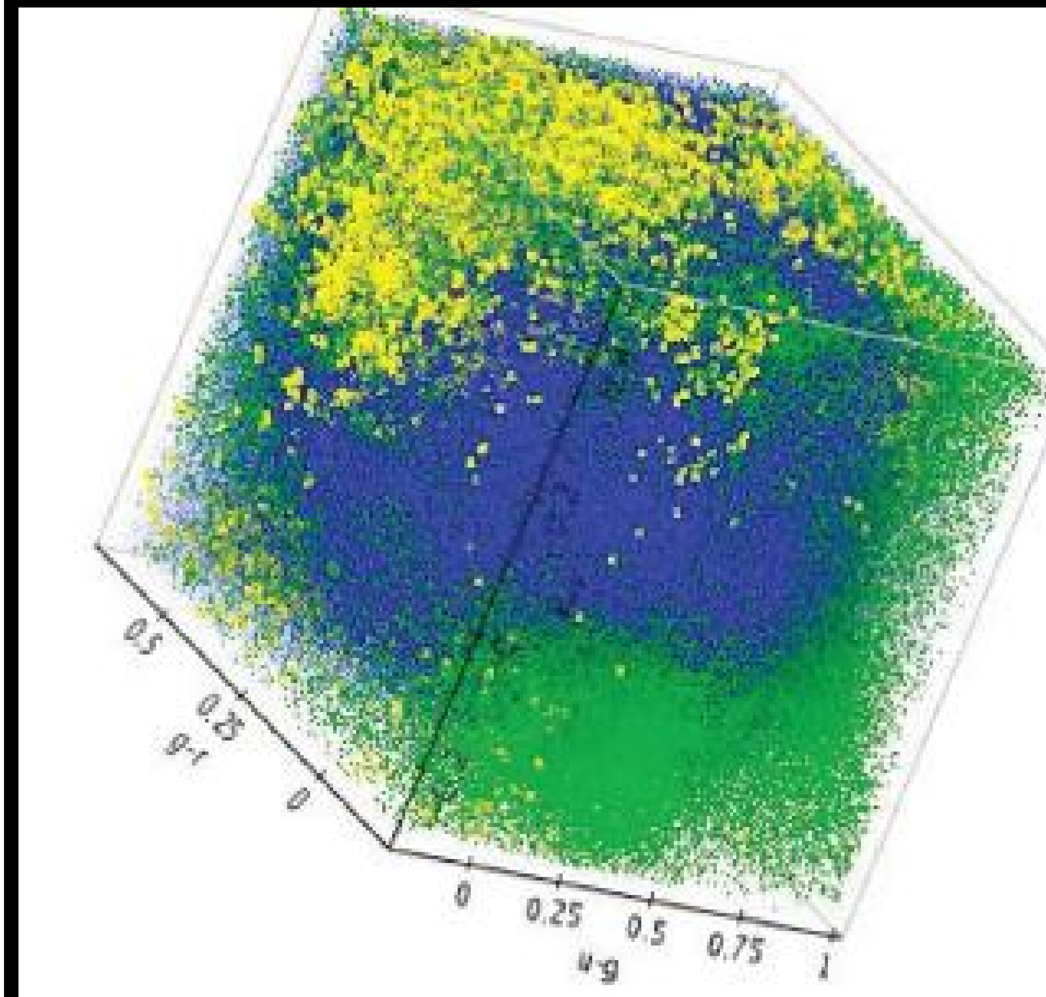
Classification of the 6 million Objects





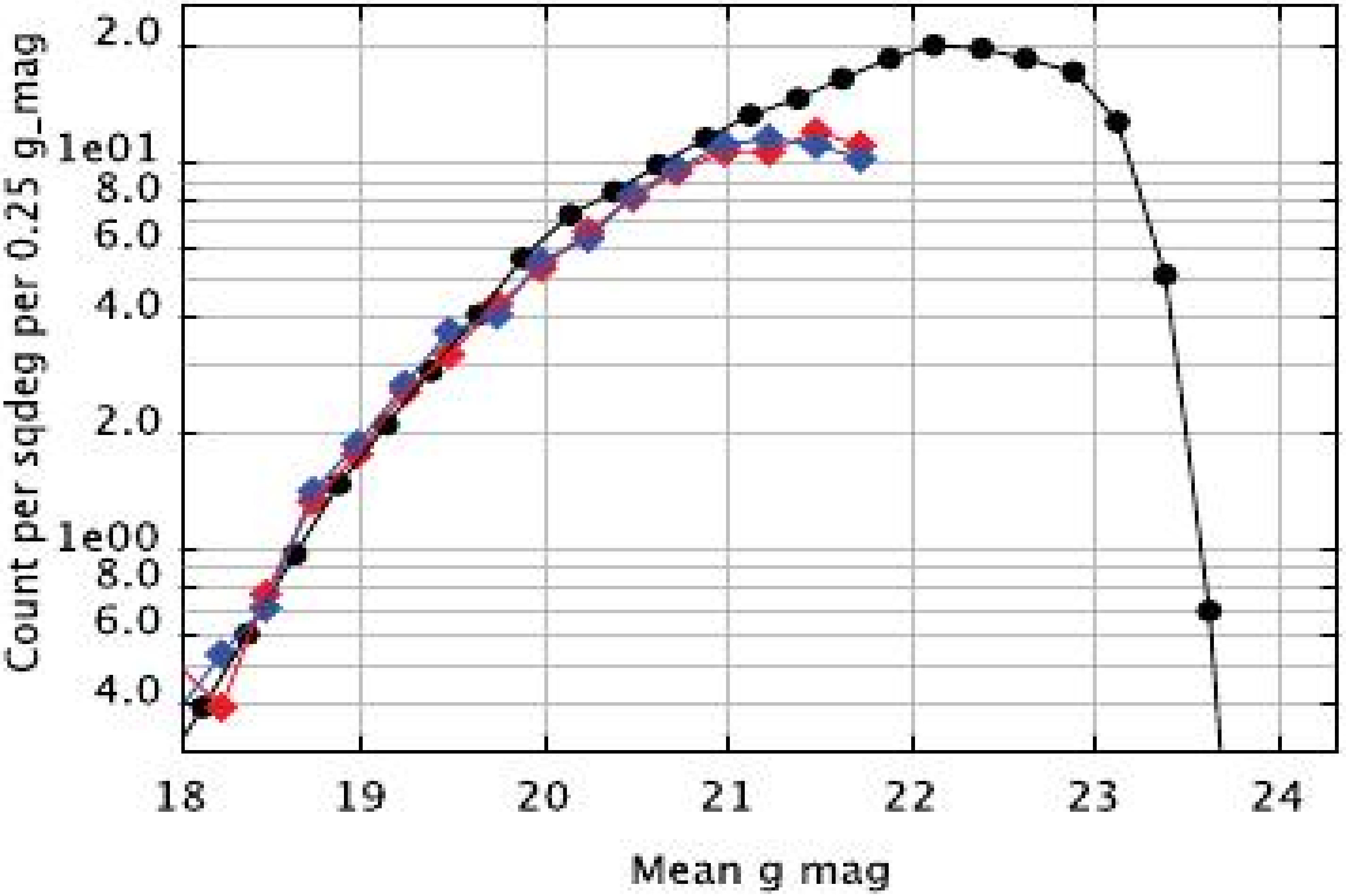
Blue are Quasars, Yellow are unresolved Galaxies and Green are main sequence Stars

Verification using Heterogeneous Surveys

Table 5. Summary of the matching of our catalogue predictions with some existing catalogues.

Cat. code	DBNN predictions Quasar	Galaxy	Star	Failures as per catalogue Quasar	Galaxy	Star	Accuracy (per cent)	i mag range	Ref
2DF	5976	238	1535	122	0	52	98	17.0–22.0	1
XBH	212	0	0	0	0	0	100	15.8–20.5	2
ASFS	1088	12	31	0	12	31	96	14.5–22.1	3
BATCS	21	0	0	3	0	0	86	18.1–20.5	4
CGRBS	265	1	0	0	1	0	100	14.7–21.5	5
DLyaQ	21	0	1	0	0	1	95	16.5–19.4	6
F2QZ	186	1	3	0	1	3	98	16.6–21.0	7
KFQS	144	2	13	3	1	7	94	16.8–20.6	8
LQAC	61 504	17	267	0	17	267	100	14.7–22.3	9
LQRF	60 280	14	219	0	14	219	100	14.7–21.7	10
BZC	249	4	2	0	4	2	98	15.0–21.0	11
PCS	53	0	2	0	0	2	96	15.1–18.5	12
ROSA	1134	0	1	0	0	1	100	15.5–20.5	13
SQ13	65 223	55	395	0	55	395	99	14.7–22.8	14
SQR13	7	0	21	7	0	0	75	16.3–20.3	14
DR7Q	79 140	17	341	0	17	341	100	14.9–21.8	15
SSSC	82	2	1171	82	2	0	93	14.9–21.5	16
SSA13	5	0	1	0	0	0	83	17.8–20.8	17
XMMSS	37	0	5	1	0	2	93	14.9–20.7	18
SDSS/XMM	580	0	0	0	0	0	100	15.2–20.5	19
RASS/2MASS	6	0	0	0	0	0	100	15.5–18.4	20
CAIXA	16	0	0	0	0	0	100	15.1–17.8	21
WDMB	20	0	106	20	0	0	84	15.3–20.5	22
PMS	639	6	19 596	639	6	0	97	14.8–20.2	23
GLQ	2	0	0	0	0	0	100	18.8–19.1	24

Comparison with expected number counts



Further Information


Monthly Notices of the ROYAL ASTRONOMICAL SOCIETY

Mon. Not. R. Astron. Soc. **419,** 80–94 (2012) doi:10.1111/j.1365-2966.2011.19674.x

A photometric catalogue of quasars and other point sources in the Sloan Digital Sky Survey

Sheelu Abraham,[1★] Ninan Sajeeth Philip,[1★] Ajit Kembhavi,[2★] Yogesh G. Wadadekar[3★] and Rita Sinha[4★†]

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[2] *Inter-University Centre for Astronomy and Astrophysics, Post Bag 4, Ganeshkhind, Pune 411007, India*
[3] *National Centre for Radio Astrophysics, TIFR, Post Bag 3, Ganeshkhind, Pune 411007, India*
[4] *Elviraland 194, 2591 GM The Hague, the Netherlands*

The Predicted Catalogue

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Keywords Back
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Simple Target | List Of Targets
Fast Xmatch with large catalogs or Simbad

Target Name (resolved by Sesame) or **Position**: Target dimension:
Clear J2000 2 arcmin
Radius Box size

J/MNRAS/419/80 Photometric Classification Catalogue of SDSS DR7 (Abraham+, 2012) Similar Catalogs ReadMe+ftp
Post annotation

1.J/MNRAS/419/80/catalog Photometric catalogue based on SDSS DR7 (a sample is published as Table 4) *(6038247 rows)*

A more complex situation

- What if all input features are not known?

Straightforward solution : Compute the inverse probability for the missing feature just as you handle missing values.

Not so easy situation: What if we do not have a training data with all features for computing inverse probability?

Heterogeneous Input Features

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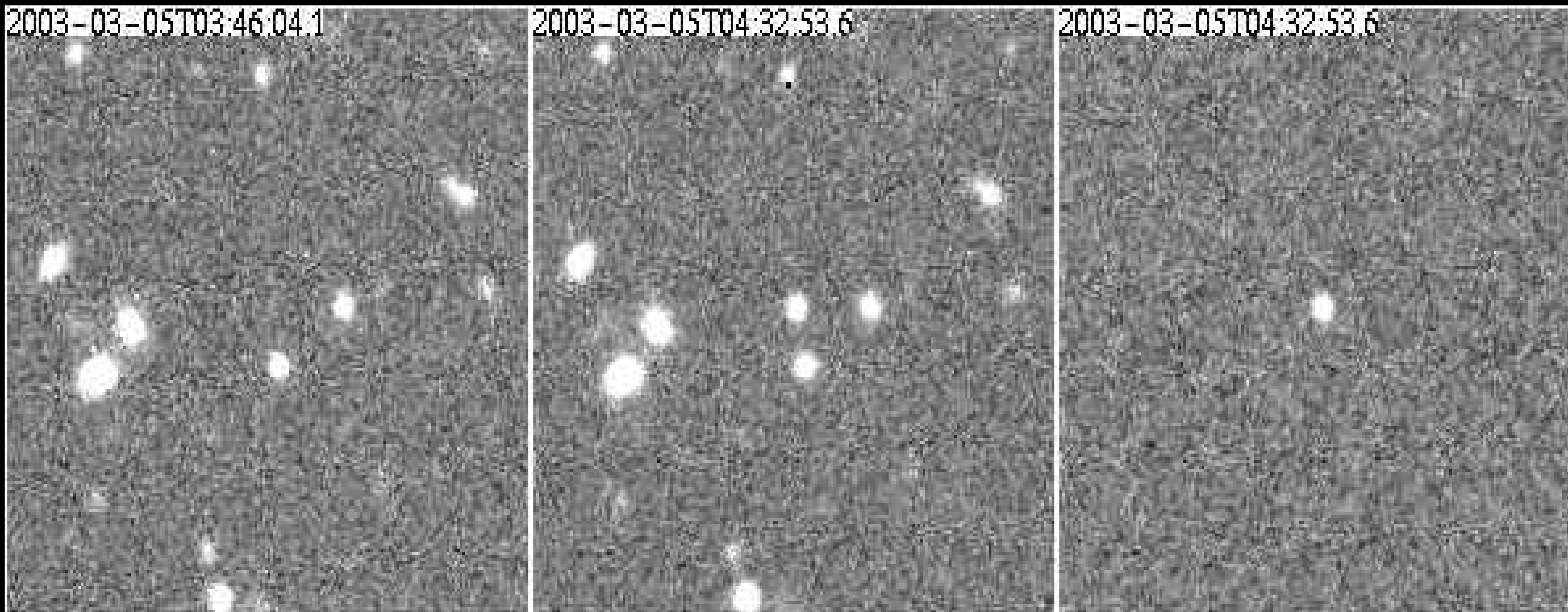
A Challenging Problem



CRTS Catalina Real-Time Transient Survey

A Challenging Problem

Generate alerts on optical transient detections

Minimize false alarms

Customize alarms to user demands

Send the alarms immediately – given minimal or sometime very little information about it.

Example : Nearest distance to a galaxy or star

: Distance to nearest known radio object

: Distance to nearest known x-ray detections

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Each survey may use a different unit for their catalogues – need to be considered separately

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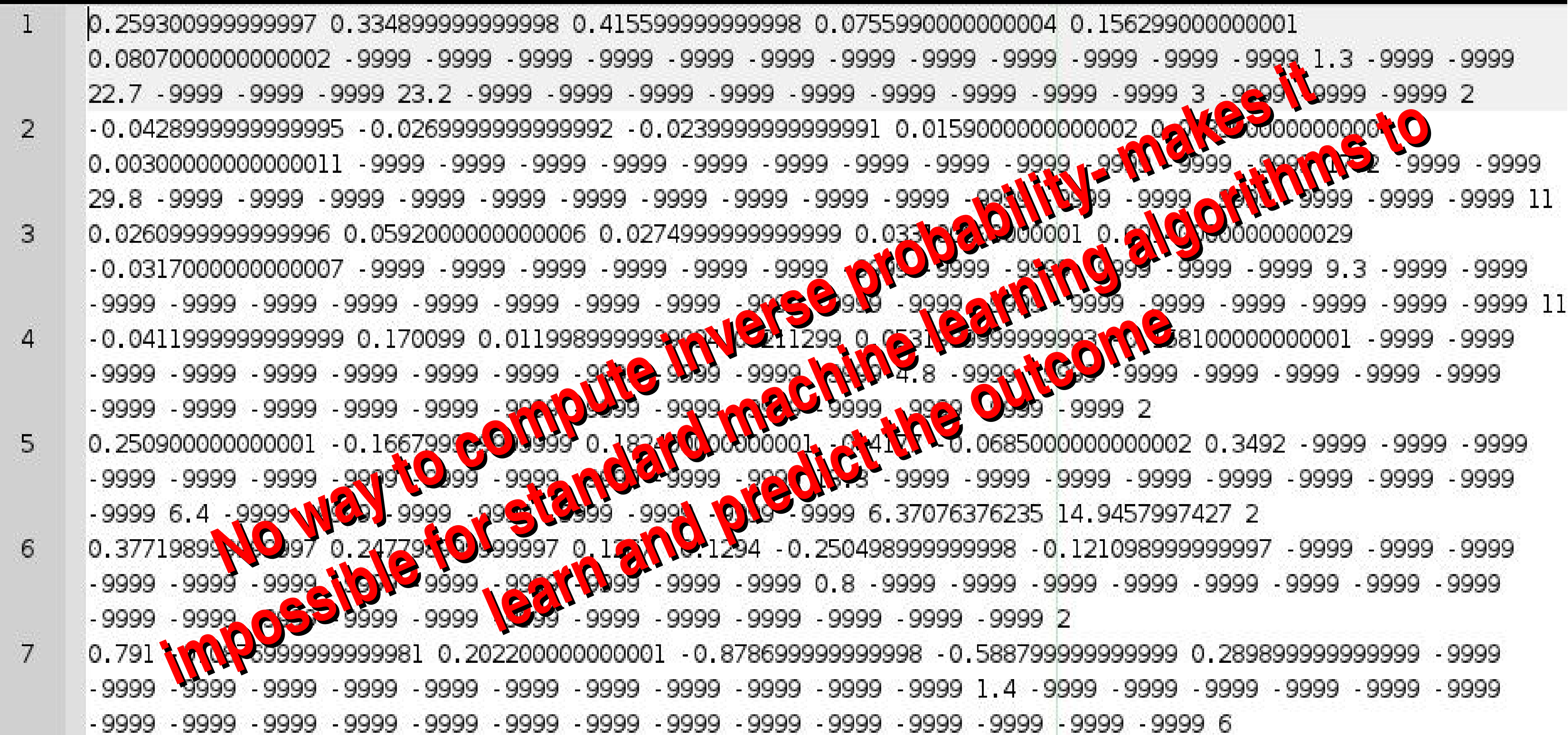
Missing Data Values

```
1  0.259300999999997 0.334899999999998 0.415599999999998 0.0755990000000004 0.156299000000001
   0.0807000000000002 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 1.3 -9999 -9999
   22.7 -9999 -9999 -9999 23.2 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 3 -9999 -9999 -9999 2
2  -0.0428999999999995 -0.0269999999999992 -0.0239999999999991 0.0159000000000002 0.0189000000000004
   0.0030000000000011 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 17.2 -9999 -9999
   29.8 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 11
3  0.0260999999999996 0.0592000000000006 0.0274999999999999 0.0331000000000001 0.0014000000000029
   -0.0317000000000007 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 9.3 -9999 -9999
   -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 11
4  -0.0411999999999999 0.170099 0.0119989999999994 0.211299 0.0531989999999993 -0.15810000000001 -9999 -9999
   -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 4.8 -9999 -9999 -9999 -9999 -9999 -9999 -9999
   -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 2
5  0.250900000000001 -0.166799999999999 0.182400000000001 -0.4177 -0.0685000000000002 0.3492 -9999 -9999 -9999
   -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 13.3 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999
   -9999 6.4 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 6.37076376235 14.9457997427 2
6  0.377198999999997 0.247798999999997 0.1267 -0.1294 -0.250498999999998 -0.121098999999997 -9999 -9999 -9999
   -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 0.8 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999
   -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 2
7  0.791 -0.0876999999999981 0.202200000000001 -0.878699999999998 -0.588799999999999 0.289899999999999 -9999
   -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 1.4 -9999 -9999 -9999 -9999 -9999 -9999
   -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 6
```

The training data itself has missing data values.

Note: The accuracy of the actual observation is not beyond one or two decimal places. The double precision is used here only to reduce round off error while rescaling the data during the processing.

Missing Values



Our Approach

The likelihood for a conditionally dependent event *A* can be approximated as the product of the likelihood of its paired inputs.

- L(A|b,c,d,e,f) ~

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- Estimate approximate Likelihood based on whatever information available and use it for training and testing.

Dynamic Learning

- With lot of missing values in the observations, each input data has partial information about the features associated to an outcome.

- Learn as we go... use Bayesian update rule to update the belief in each input feature and its consequences.

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Dynamic Addition of Features

- We want to use all available information about the detections as and when they become available.
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Dreaming Computers

- We now have many input features but not so many examples to learn from. This can lead to over-fitting the data and Memorising rather than generalising the situation.

- Dreams are synthetic inputs our brain uses to teach us how to react to plausible situations. Can we create dreams for computers?

Dreaming Computers

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- Hypothesis: Dreams are synthetic inputs our brain uses to teach us how to react to plausible situations. Can we create dreams for computers?

Information from Error Bars

- Error bars tell us that the nature of the object remains same even if the measurement value is perturbed within the range of the error bar – can be used to generate new data

DBNN Annotator

A collaborative project with Ashish Mahabal (Caltech), IUCAA, Pune and the CRTS Team with funding from IUSSTF and ISRO.

CRTS Predictions

	[1]	[2]	[3]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[16]	Total
[1]	273	3	4	1	1	0	1	3	3	3	0	1	293
[2]	4	402	3	0	4	1	3	2	0	1	1	0	421
[3]	0	0	34	0	0	0	0	0	0	0	0	0	34
[5]	0	0	0	60	0	0	0	0	1	0	0	0	61
[6]	0	0	0	0	126	0	0	0	0	0	0	0	126
[7]	0	0	0	0	0	32	0	0	0	0	0	0	32
[8]	0	0	0	0	0	0	6	0	0	0	0	0	6
[9]	0	0	0	0	0	0	0	18	0	0	0	0	18
[10]	0	0	0	0	0	0	0	0	12	0	0	0	12
[11]	0	0	0	0	0	0	0	0	0	43	0	0	43
[12]	0	0	0	0	0	0	0	0	0	0	5	0	5
[16]	0	0	0	0	0	0	0	0	0	0	0	1	1
Total	277	405	41	61	131	33	10	23	16	47	6	2	1052

1,"Cataclysmic Variable"
2,"Supernova"
3,"other"
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6,"AGN Variability"
7,"UVCeti Variable"
8,"Asteroid"
9,"Variable"
10,"Mira Variable"
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[7]	0	0	0	0	0	32	0	0	0	0	0	0	32
[8]	0	0	0	0	0	0	6	0	0	0	0	0	6
[9]	0	0	0	0	0	0	0	18	0	0	0	0	18
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Recall → 273/277 =98.5%

False Alarms → (293-273)/293 = 7%

But..

	[1]	[2]	[3]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[16]	Total
[1]	352	202	29	39	53	9	3	13	13	96	3	3	815
[2]	103	673	50	29	114	23	13	19	3	21	2	2	1052
[3]	1	3	39	0	0	3	0	2	0	0	0	0	48
[5]	0	0	1	44	1	0	0	0	1	0	0	0	47
[6]	22	37	14	8	166	11	1	5	5	4	1	0	274
[7]	1	0	0	0	0	66	0	0	0	0	1	0	68
[8]	0	0	0	0	0	0	3	0	0	0	0	0	3
[9]	0	0	0	0	0	0	0	2	0	0	0	0	2
[10]	0	0	0	0	0	0	0	0	1	0	0	0	1
[11]	0	1	1	0	0	0	0	0	0	66	0	0	68
[12]	0	0	0	0	0	0	0	0	0	0	3	0	3
[16]	0	0	0	0	0	0	0	0	0	0	0	1	1
[]													
	479	916	134	120	334	112	20	41	23	187	10	6	2382

Better than saying “could be anything”

Predictions 1-4 Actual BP1 BP2

- 1 2 0 11 2 69.16 % <-Failed 30.84 %
- 1 2 0 11 2 50.41 % <-Failed 49.59 %
- 1 2 0 11 2 50.41 % <-Failed 49.59 %
- 2 7 6 1 7 99.95 % <-Failed 0.05 %
- 2 1 0 6 1 72.45 % <-Failed 27.38 %
- 2 1 0 11 1 50.94 % <-Failed 49.06 %
- 2 1 0 11 11 98.06 % <-Failed 1.94 %
- 2 6 1 0 9 63.54 % <-Failed 25.86 %
- 2 1 0 6 1 96.13 % <-Failed 3.75 %
- 2 6 1 11 6 63.56 % <-Failed 27.91 %
- 6 2 1 0 1 33.84 % <-Failed 33.61 %
- 1 2 0 11 5 60.20 % <-Failed 39.80 %
- 1 2 0 6 2 50.69 % <-Failed 49.31 %
- 1 2 0 6 2 50.44 % <-Failed 49.56 %

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Thank You