Photometric Detection of Quasars

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Understanding

Analysis

Archives

Data

Universe

Objective

Illustration of Machine Learning Applications in Astronomy

Using SDSS data Archive





Quasar Colours



Difference Boosting Neural Network

Object types are identified on the basis of subtle differences in features.

What is Bayes Rule?

Suggests to update your belief on the basis of evidences in 3 steps.

Prior P(A) : Initial belief

Evidence B : Make an Observation

P(A|B) : Update Prior with a posterior

Repeat until the confidence is acceptable

How to compute the Posterior Probability?



P(A) is prior belief that the outcome is A
P(A|B) is the updated belief about the outcome
P(B|A) is the likelihood for B to cause A
P(B): probability for B to occur.

Iterative learning

$$\begin{split} P(C_k \mid U) &= \frac{\prod_m \hat{P}(U_m \cap C_k) W_m}{\sum_j \prod_m \hat{P}(U_m \cap C_j) W_m}. \\ \Delta W_m &= \alpha \left[1 - \frac{P_k}{P_k^*} \right] \end{split} \label{eq:deltaWm}$$
 Where P_k stands for the posterior for the actual class and P_k for that of the predicted class.

Start with a small and equal value for W_m initially and as each new data is seen, update W_m along the negative gradient of the probability estimates – which in effect is the difference of their posterior estimates.

Training data

Since the entire learning process depends upon the data, it is important that the data used for training has all the features to be expected in the problem domain. Iterative identification of Principal Samples

Randomly pick up just one example from each class and train the network on it. Test the network on the remaining data

Look for the example that has failed with maximum posterior probability from each class and add it to the training data.

REPEAT THE PROCESS UNTIL ALL EXAMPLES ARE CORRECTLY CLASSIFIED.

Optimal Data Selection



Classification Results

Name	SDSS	DBNN	%
Star	72449	68747	94.89
Galaxy	1868	238	12.74
Quasar	90363	88290	97.7
HizQSO	3702	3289	88.86
Star-Late	759	184	24.24
Total	169141	160748	95.03

Histogram of x33\$Confidence



Distribution of Passed and Failed Cases



R Graphics: Device 2 (ACTIVE)

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Distribution of Passed and Failed Cases



Distribution of Passed and Failed Cases



Distribution of Passed and Failed Cases

Distribution of Passed and Failed Cases



What caused failures?



Colors of quasars and stars are indistinguishable at some redshift patches

What caused failures?

🞽 Xpdf: HowGoodIsSpecClassification0.pdf

Preview image (click to go to Navigate tool)



Object Type (type): GALAXY

Magnitudes:

Ultraviolet (u):	19.09 ± 0.04
Green (g):	17.73 ± 0.01
Red (r):	16.96 ± 0.00
Infrared - 7600 Å (i):	16.49 ± 0.00
Infrared - 9100 Å (z):	16.24 ± 0.01

Preview spectrum (click for a larger version)



Spectral classification (specClass): QSO

Redshift Data:

Redshift (z):

3.61262

_ 0 X

Quit

Get spectrum as CSV

Incorrect Spectroscopic classifications

Object ID (objID): 587722982287802775 Right ascension (ra):

Declination (dec):

204.76416145

-0.71141558

Image Data (What does it look like?)

iew image (click to go to Navigate tool)



Spectrum Data (What does its spectrum look like?)

Preview spectrum (click for a larger version)



Object Type (type): STAR

Spectral classification (specClass): QSO

What caused failures?

Object ID (objID):

Right ascension (ra):

Declination (dec):

587730773876604962

331.48760872

12.21102915

Image Data (What does it look like?)

iew image (click to go to Navigate tool)



Spectrum Data

version)





Object Type (type): STAR

Spectral classification (specClass): QSO

Incorrect Spectroscopic Classification





Spectral Classification Statistics

Total Number of Failed Objects with Spectra : 1647

Objects with wrong classification labels : 283

How to reduce failures?

Define training samples with accurate labels

Increase the parameter space with multiwavelength observations

Build a hybrid spec-photo network

Usefulness of the method

Object ID (objID):

Right ascension (ra):

Declination (dec):

587726033846075436

150.11433595

2.99756903

Image Data (What does it look like?)

iew image (click to go to Navigate tool)



Preview spectrum (click for a larger version)

Spectrum Data

(What does its spectrum look

like?)





Object Type (type): STAR

Spectral classification (specClass): QSO

Outliers detection – objects with peculiar colors are automatically assigned low confidence values by DBNN.

Usefulness of the method

Object ID (objID):

Right ascension (ra):

Declination (dec):

588007005806854207

252.17182864

41.28061611

Image Data (What does it look like?)

iew image (click to go to Navigate tool)



Preview spectrum (click for a larger version)

Spectrum Data

(What does its spectrum look

like?)



Object Type (type): STAR

Spectral classification (specClass): QSO

Outliers detection – objects with peculiar colors are automatically assigned low confidence values by DBNN.

RA=30.15249, DEC= 0.76370, MJD=51871, Plate= 403, Fiber=587



RA=234.15093, DEC= 4.69084, MJD=54567, Plate=1836, Fiber=270



Object ID (objID):

Right ascension (ra):

Declination (dec):

587730022261129248

234.15093049

4.69083722

Image Data (What does it look like?)

iew image (click to go to Navigate tool)



(What does its spectrum look like?) Preview spectrum (click for a larger

Spectrum Data

Preview spectrum (click for a larger version)



Object Type (type): STAR

Spectral classification (specClass): QSO

Objects with Interesting Spectra

Objects with interesting spectra in the list of failed 1647 objects: 119

Usefulness of the method

Most suited for candidate selection for follow up observations

The assigned probability can be used to compromise between completeness and contamination on trained networks

Very fast – can classify a million objects in one second on a modern PC

Question Time

Thank You

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