Identifying galaxies, quasars, and stars with machine learning: A new catalogue of classifications for 111 million SDSS sources without spectra

A. O. Clarke, A. M. M. Scaife, R. Greenhalgh, and V. Griguta

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- The Legacy Survey of Space and Time (LSST) is expected to observe
  - 20 billion galaxies.
  - Produce 20 terabytes of data every night for ten years (60 petabytes)

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- Detailed spectroscopic observations are expensive and time-consuming.

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  - Using high-probability candidates for spectroscopic follow-up means we're not wasting resources on low-probability candidates.

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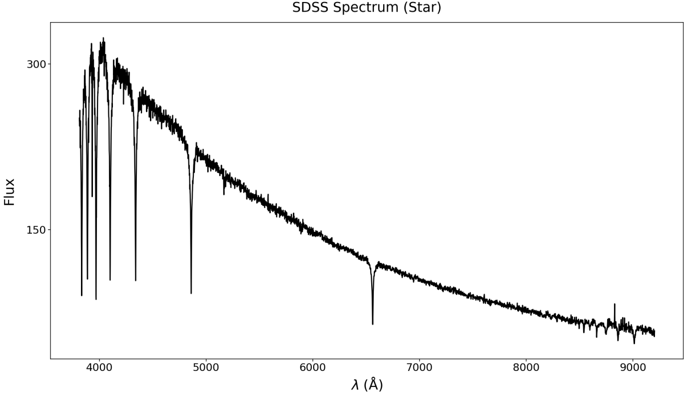
- Then use this model to classify 111 million unlabeled photometric sources as candidate quasars, galaxies, and stars.

Data Representations

- First, let's establish how ground-truth labels are typically assigned in astronomy.



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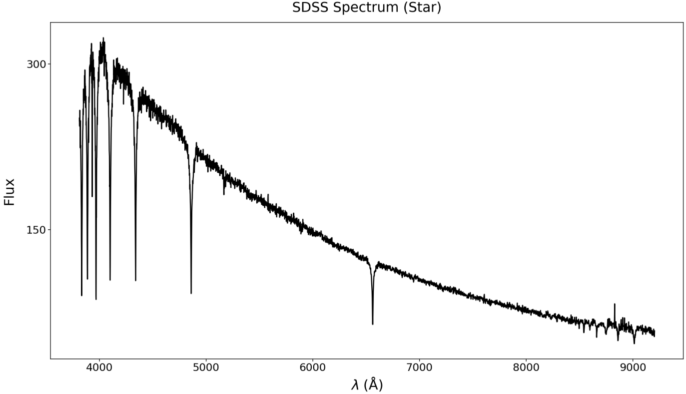

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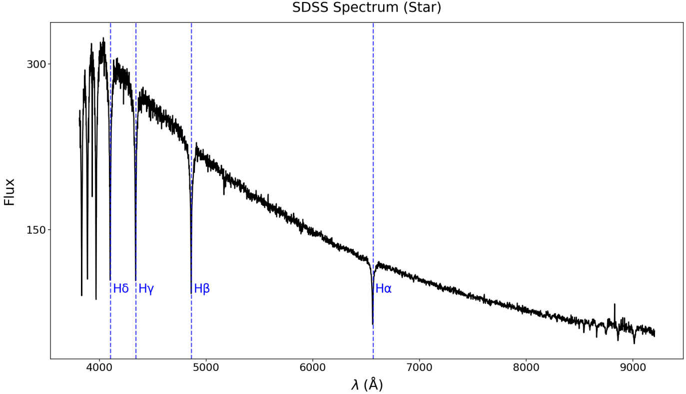

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  - `QSO`: Quasars have flat spectra with strong emission lines from AGNs around supermassive black holes.
  - There are other classes, e.g. white dwarfs and unknown objects, but this work focuses on the main three.

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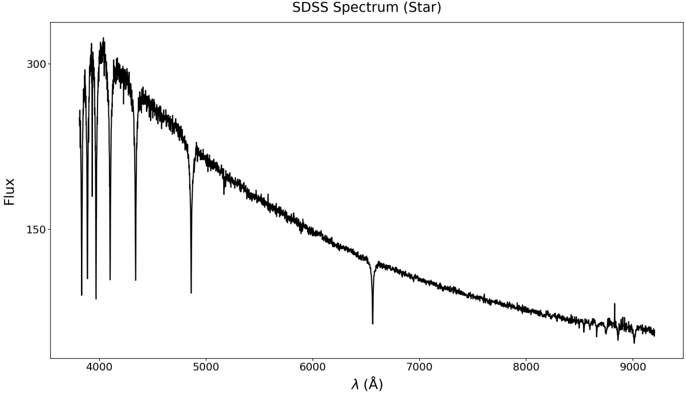

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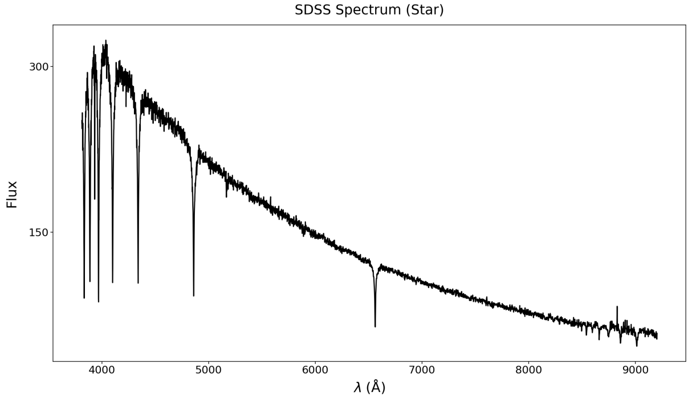

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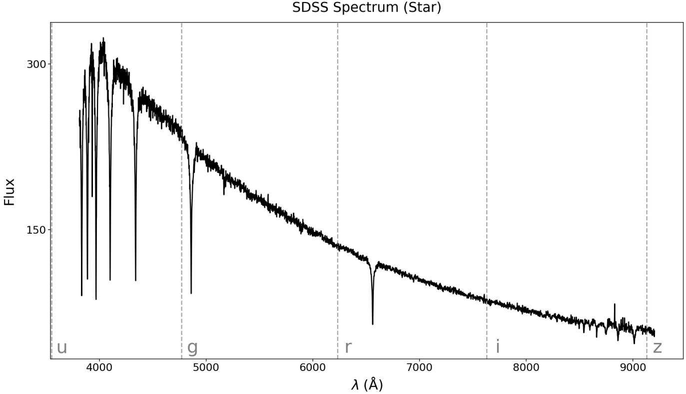

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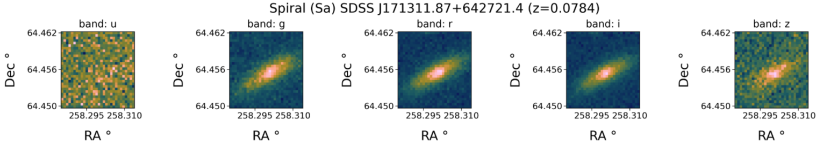
- Photometric data measures brightness in broad wavelength bands, in terms of the total flux magnitude. In other words, the sum of image pixels constrained by a fitting model.



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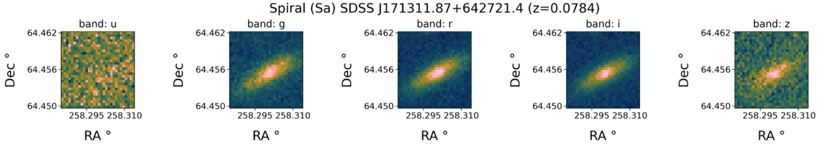

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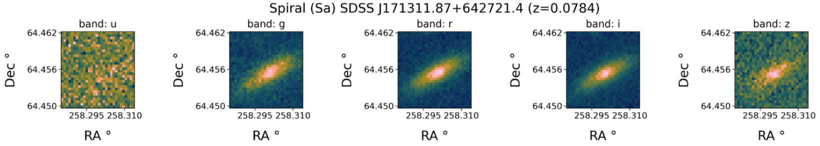

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Feature Engineering

- SDSS photometric data provides measurements in 5 bands:

Band	Wavelength (Å)	Color
u	3550	Ultraviolet
g	4770	Green
r	6230	Red
i	7620	Infrared
z	9130	Far Infrared

Table: Photometric Bands

Feature Engineering

- WISE photometric data provides measurements in 4 bands.:

Band	Wavelength (Å)
w1	34,000
w2	46,000
w3	120,000
w4	220,000

Table: Photometric Bands

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- When used as a feature for point objects, this represents the magnitude (the log of the flux)

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Extended Objects - de Vaucouleurs profile fit

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- $I(r) = I_0 \exp(-7.67(\frac{r}{r_{eff}})^{\frac{1}{4}} - 1))$
- where r_{eff} is the effective radius containing half the light.

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- Used for galaxy colors, photometric redshift, ML classification

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- $\texttt{flux}_{cmodel} = \texttt{frac}_{dev} \times \texttt{flux}_{dev} + (1 - \texttt{frac}_{dev}) \times \texttt{flux}_{exp}$ where $\texttt{frac}_{dev}$ is the fraction of the `devMag` component in the fit.

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- $\texttt{resolved}_r = |\texttt{psf}_r - \texttt{cmodMag}_r|$

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$\texttt{psf}_u$, $\texttt{psf}_g$, $\texttt{psf}_r$, $\texttt{psf}_i$, $\texttt{psf}_z$, $\texttt{w1}$, $\texttt{w2}$, $\texttt{w3}$, $\texttt{w4}$, $\texttt{resolved}_r$

Three Samples of Different Classes

Galaxy	psf_u	psf_g	psf_r	psf_i	psf_z	$cmod_r$	$\lvert psf_r - cmod_r \rvert$
	23.49	22.09	20.10	19.29	19.07	19.51	0.59
	$w1$	$w2$	$w3$	$w4$	–	–	–
	14.69	14.44	12.36	8.76	–	–	–
Quasar	psf_u	psf_g	psf_r	psf_i	psf_z	$cmod_r$	$\lvert psf_r - cmod_r \rvert$
	17.99	17.82	17.81	17.78	17.68	17.72	0.08
	$w1$	$w2$	$w3$	$w4$	–	–	–
	14.12	13.03	10.21	7.46	–	–	–
Star	psf_u	psf_g	psf_r	psf_i	psf_z	$cmod_r$	$\lvert psf_r - cmod_r \rvert$
	16.88	15.77	15.81	15.87	15.88	15.81	0.00
	$w1$	$w2$	$w3$	$w4$	–	–	–
	15.17	15.17	12.66	9.18	–	–	–

Dataset - Training Data

- The dataset includes 3,238,003 unique sources which have been spectroscopically observed and assigned a class of `STAR`, `GALAXY`, or `QSO` (quasar), based on spectroscopic models described earlier. [2]

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- In total, 138,546 sources were removed.

Dataset - Features Optimization

- Different combinations of SDSS, WISE, and $\texttt{resolved}_r$ features were tested.
- The best performance was achieved using all features.

Zoom Out - Big Picture

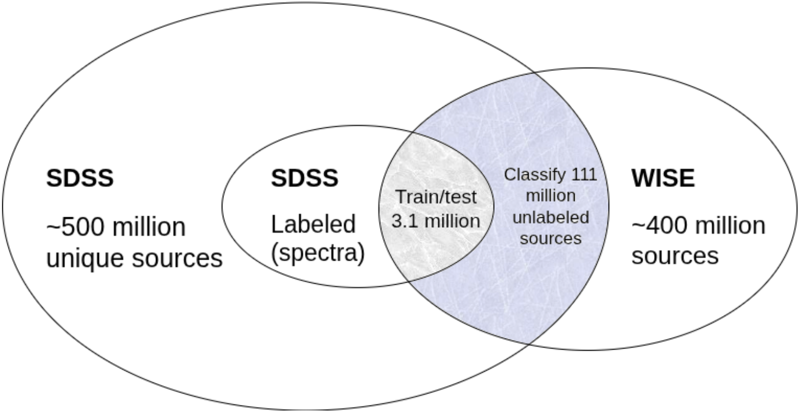

Figure: Venn Diagram of Data Overlap

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    - Each tree is trained on a random subset of both features and samples.
    - The predicted classification comes from a majority consensus classification across the full set of models from all trees in the forest.

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  - Effective at multi-class classification

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- Hyper-parameters in Random Forests:
  - Number of trees: *n_estimators*
  - Maximum number of features per decision tree: *max_features*
  - Minimum samples per leaf: *min_samples_leaf*

Hyper-parameters Optimization

- Used a 5-fold cross validation scheme to optimize hyper-parameters.

Hyper-parameter	Optimal Value	Comments
n_estimators	200	Best performance/running time tradeoff
max_features	3	Increasing this will improve F_1 score, but will lead to overfitting. Used the default value of `Int`($\sqrt{n\_features}$)
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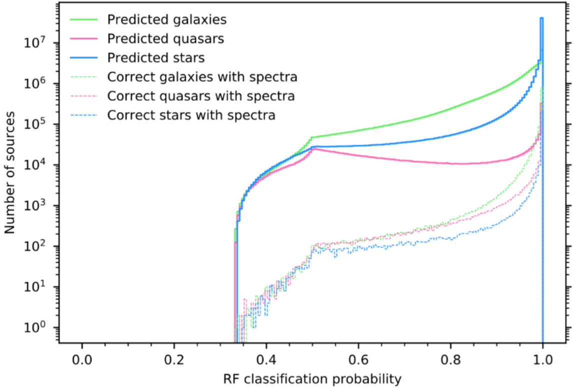
- Precision: TP / (TP + FP).
- Recall: TP / (TP + FN).
- F1 Score: 2 * (Precision * Recall) / (Precision + Recall). The F1 Score is a harmonic mean of precision and recall. This metric balances precision and recall.
  - Galaxies: 0.991
  - Quasars: 0.952
  - Stars: 0.978

Test Results on Unlabeled Data

- 50,417,547 galaxies classified, 70% with *pred_prob* > 0.9



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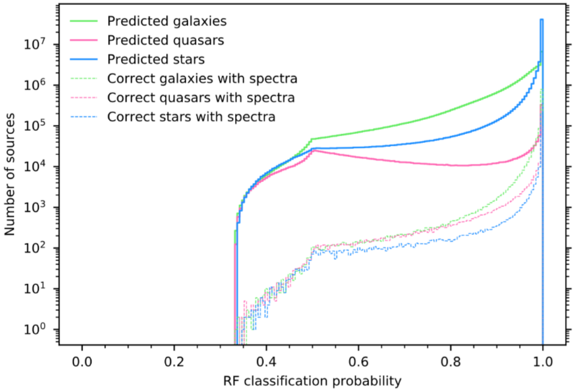

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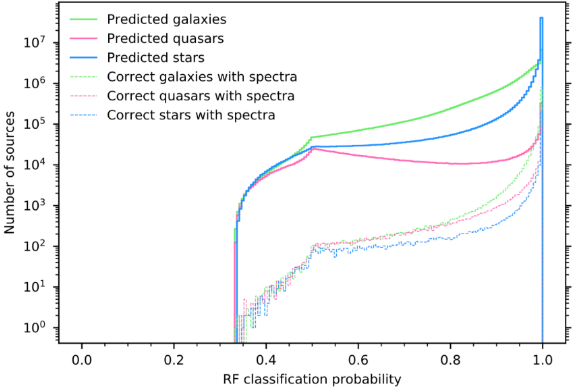

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Test Results on Unlabeled Data

- A non-linear dimension reduction technique (UMAP) was used to reduce the number of features from 10 to 2. This provided a 2-D visualization of the feature space, and was used for clustering visualizations.

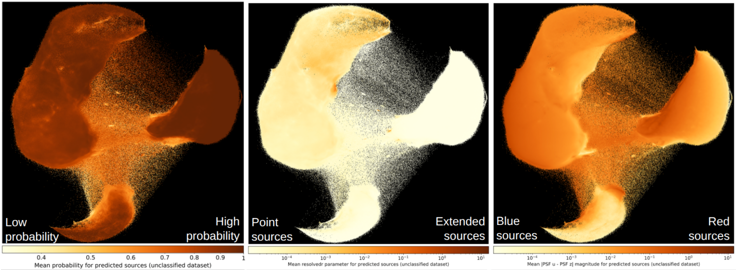

Figure: UMAP projections of photometric features.

Key Takeaways

- The number of catalogued quasars, according to this model's predictions, increased by a factor of 4.

So What?

- A spectroscopic follow-up survey targeting quasars with high classification probabilities using the model and data is the natural next step.[4]

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  - Perform spectroscopic follow-up observations to confirm quasar nature.
  - Use confirmed quasars for cosmological studies and surveys, such as mapping large-scale structure or studying quasar evolution.

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References

[1] Clarke et al. (2020), "Identifying galaxies, quasars, and stars with machine learning: A new catalogue of classifications for 111 million SDSS sources without spectra", *Astronomy and Astrophysics*, Volume 639, A84.