

# Supervised Classification of Emission Stars Spectra

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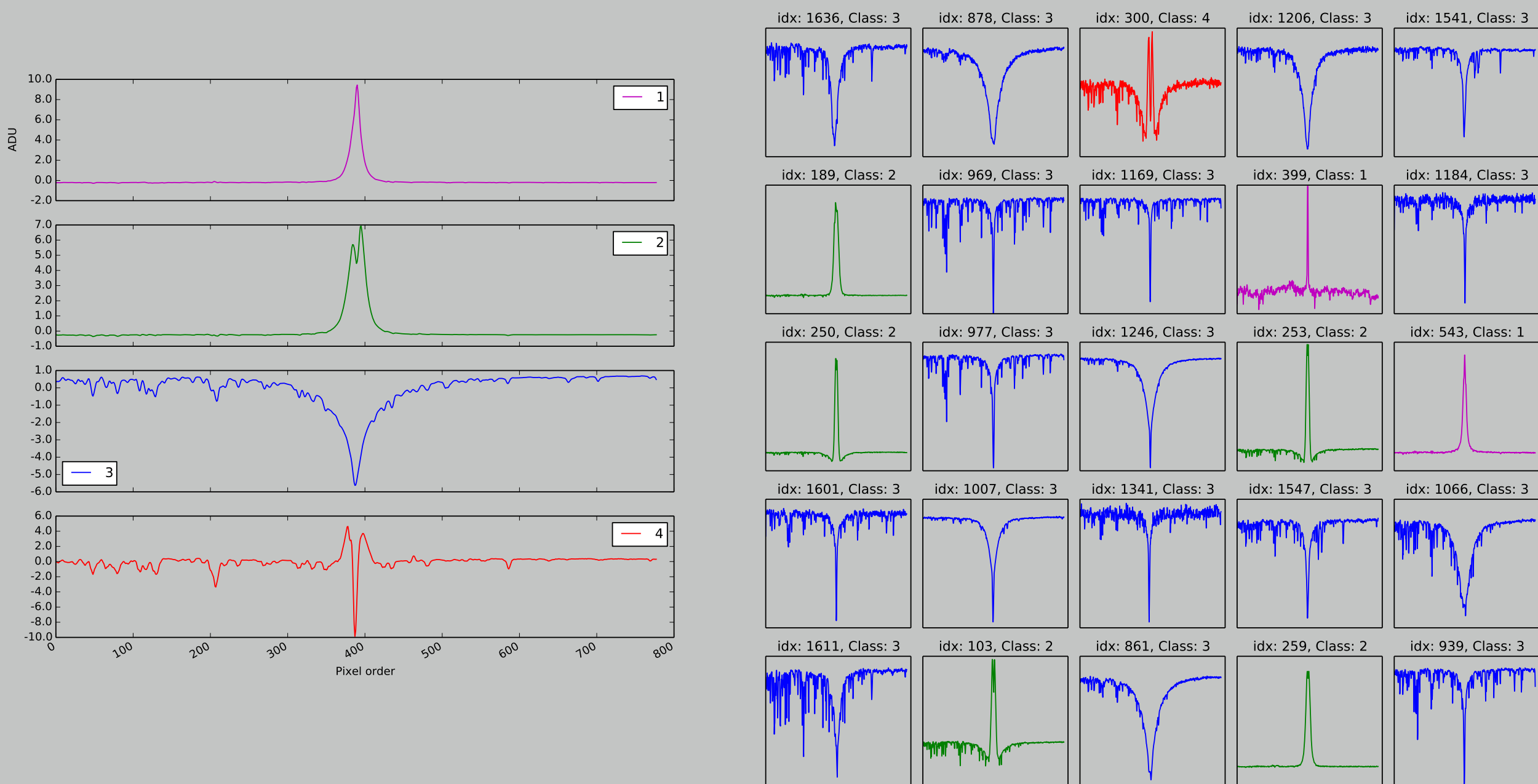


## Objectives

- 1. Classify emission star spectra based on H- $\alpha$  line profile.
- 2. Compare methods for dimensionality reduction.
- 3. Tune classifier parameters.

## Introduction

- There are 1805 manually classified spectra from Ondřejov observatory divided into 4 categories based on profile of the H- $\alpha$  line. We want to train a SVM classifier to automatically categorize the rest. Figure on the left shows the average spectrum in each category and on the right there are samples of individual spectra.

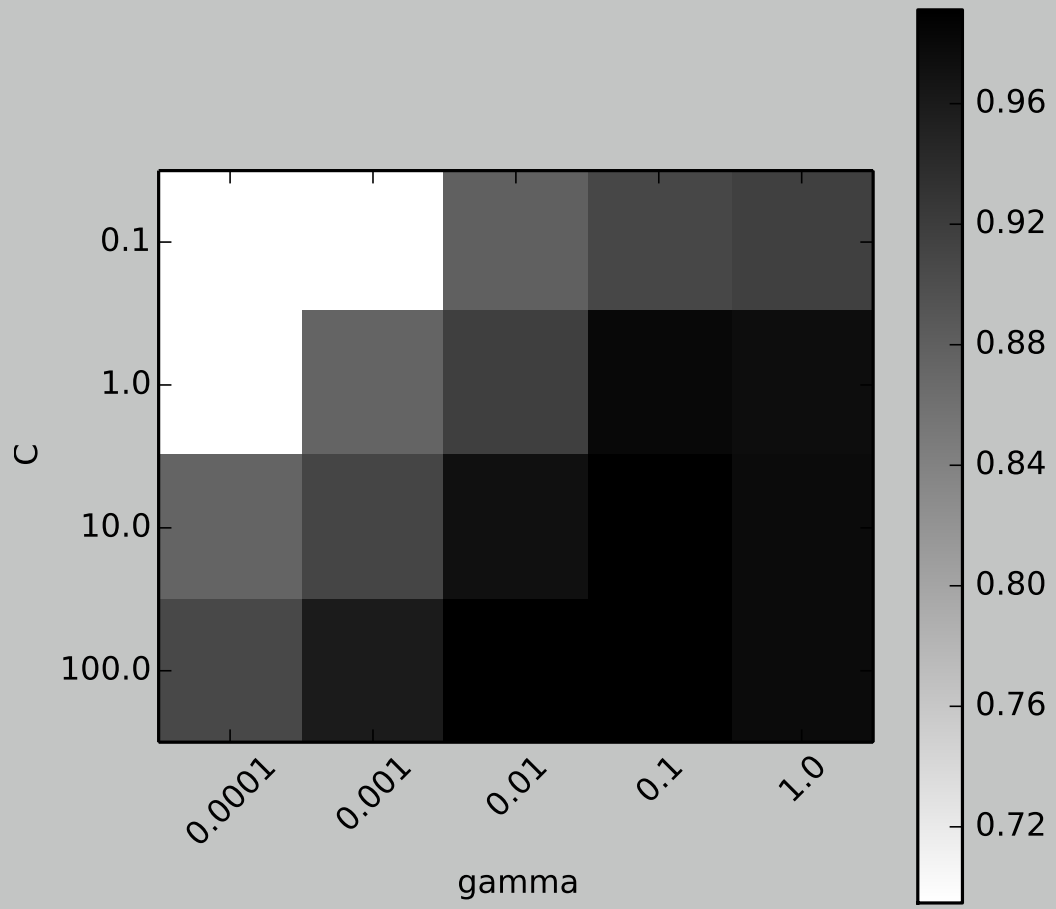


## Dimensionality Reduction

- Each spectrum has 778 points. Different approaches were tested for dimensionality reduction.
  - PCA: Principal component analysis. Linear dimensionality reduction using Singular Value Decomposition of the data and keeping only the most significant singular vectors to project the data to a lower dimensional space.
  - Isomap: Isometric Mapping. Can be viewed as an extension of Multi-dimensional Scaling (MDS) or Kernel PCA. Isomap seeks a lower-dimensional embedding which maintains geodesic distances between all points.
  - LLE: Locally linear embedding seeks a lower-dimensional projection of the data which preserves distances within local neighborhoods. It can be thought of as a series of local Principal Component Analyses which are globally compared to find the best non-linear embedding.

## Parameters tuning

- Support Vector Machines (SVM) was used as a classifier with Radial Basis Function (RBF) kernel ( $\exp(-\gamma|\mathbf{x} - \mathbf{x}'|^2)$ ). Grid search was used to find optimal values for  $C$  and  $\gamma$  parameters. There is an example of heatmap for optimal parameters for data reduced by Isomap method.



## Contact Information

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## Classification

- Data were split randomly into training (75%) and testing (25%) sample. Reports for different reduction approaches are shown below compared to non-reduced data sample. Precision =  $tp / (tp + fp)$ , recall =  $tp / (tp + fn)$ , f1-score =  $2 * (precision * recall) / (precision + recall)$  where tp is true positive, fp false negative and fn false negative.

Category	Precision	Recall	f1-score	Support
1	0.95	0.95	0.95	61
2	0.96	0.96	0.96	74
3	1.00	1.00	1.00	303
4	0.93	0.93	0.93	14
avg/total	0.98	0.98	0.98	452

Table 1: Classification report without dimensionality reduction

Category	Precision	Recall	f1-score	Support
1	0.89	0.95	0.92	61
2	0.96	0.91	0.93	74
3	1.00	1.00	1.00	303
4	1.00	0.93	0.96	14
avg/total	0.98	0.98	0.98	452

Table 2: ISOMAP Classification report

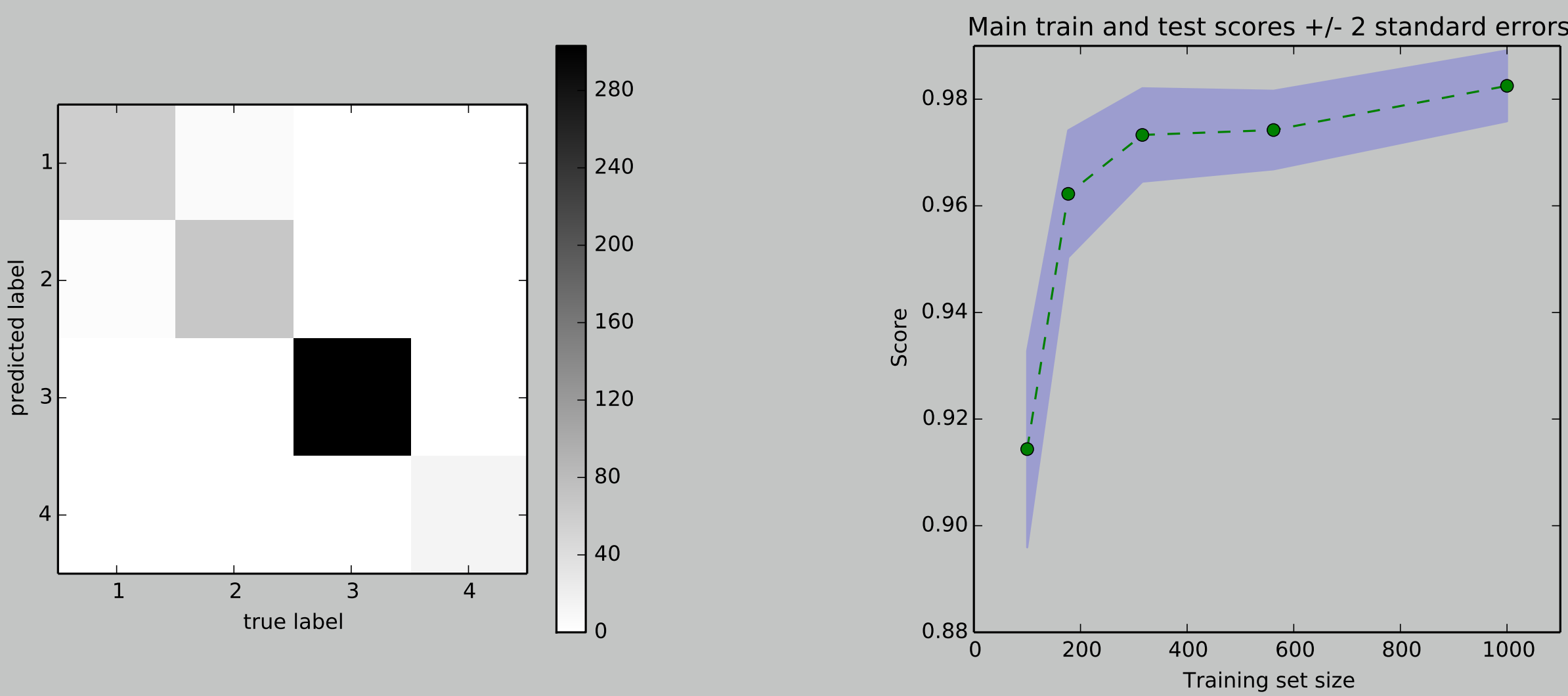
Category	Precision	Recall	f1-score	Support
1	0.97	1.00	0.98	61
2	1.00	0.97	0.99	74
3	0.99	1.00	1.00	303
4	1.00	0.86	0.92	14
avg/total	0.99	0.99	0.99	452

Table 3: PCA Classification report

Category	Precision	Recall	f1-score	Support
1	0.91	1.00	0.95	61
2	0.99	0.92	0.95	74
3	1.00	1.00	1.00	303
4	0.92	0.86	0.89	14
avg/total	0.98	0.98	0.98	452

Table 4: LLE Classification report

The left figure shows classification confusion matrix. Graph on the right is a learning curve.



## Conclusion

- It is possible to dramatically reduce the number of dimensions of spectra in classification problem (here from 778 to 10).
- PCA, Isomap, LLE and has similar effects in this classification problem.
- It is always important to tune corresponding hyperparameters.

## References

- [1] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.
- [2] Scott F Daniel, Andrew Connolly, Jeff Schneider, Jake Vanderplas, and Liang Xiong. Classification of stellar spectra with local linear embedding. *The Astronomical Journal*, 142(6):203, 2011.