

Supervised Classification of Emission Stars Spectra

Jaroslav Vazny, Petr Skoda

Astronomical Institute of the Academy of Sciences of the Czech Republic

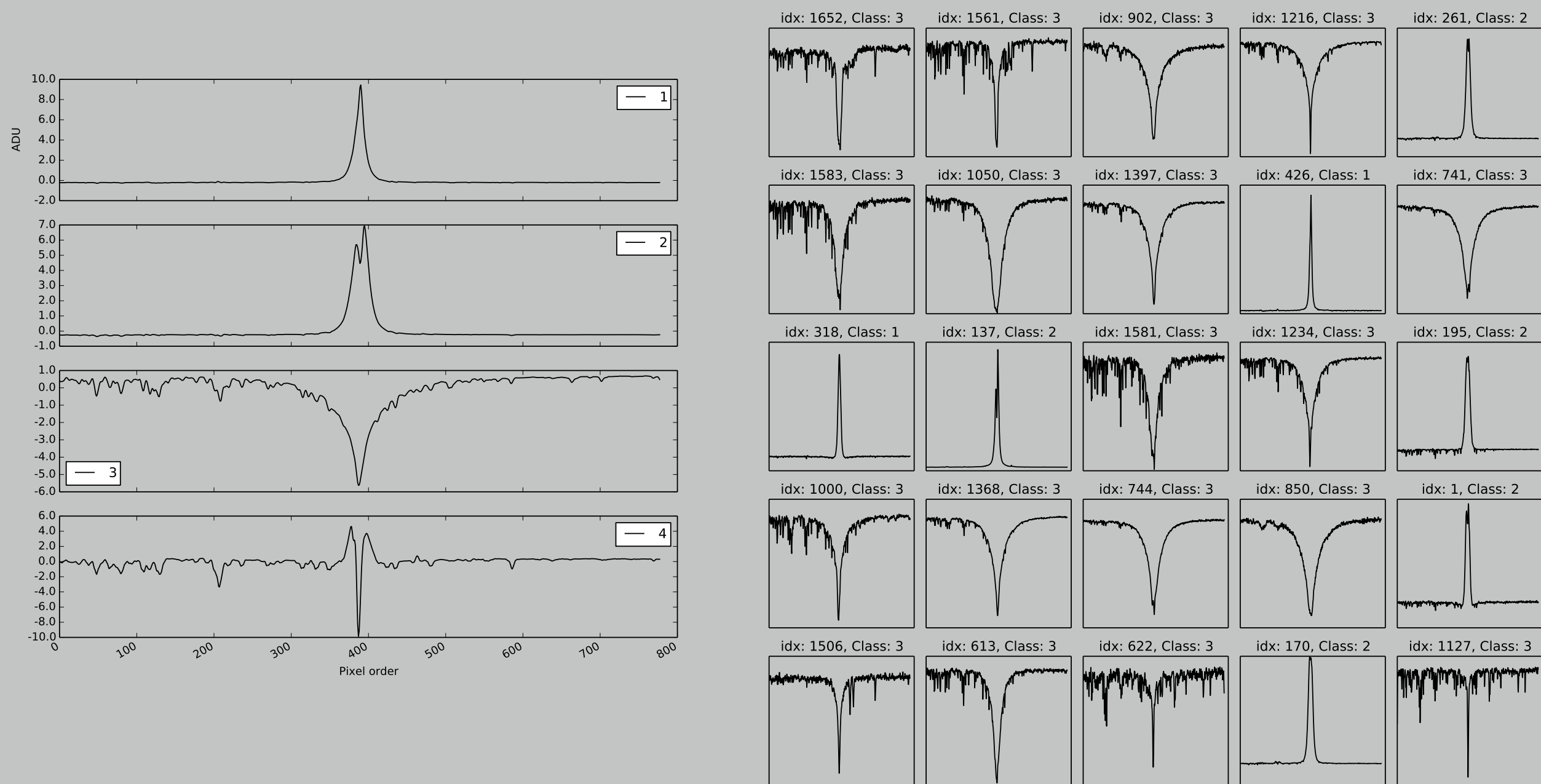


Objectives

- 1. Classify Emission star spectra based on H- α line profile.
- 2. Compare methods for dimensionality reduction.
- 3. Tune classifier parameters.

Introduction

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

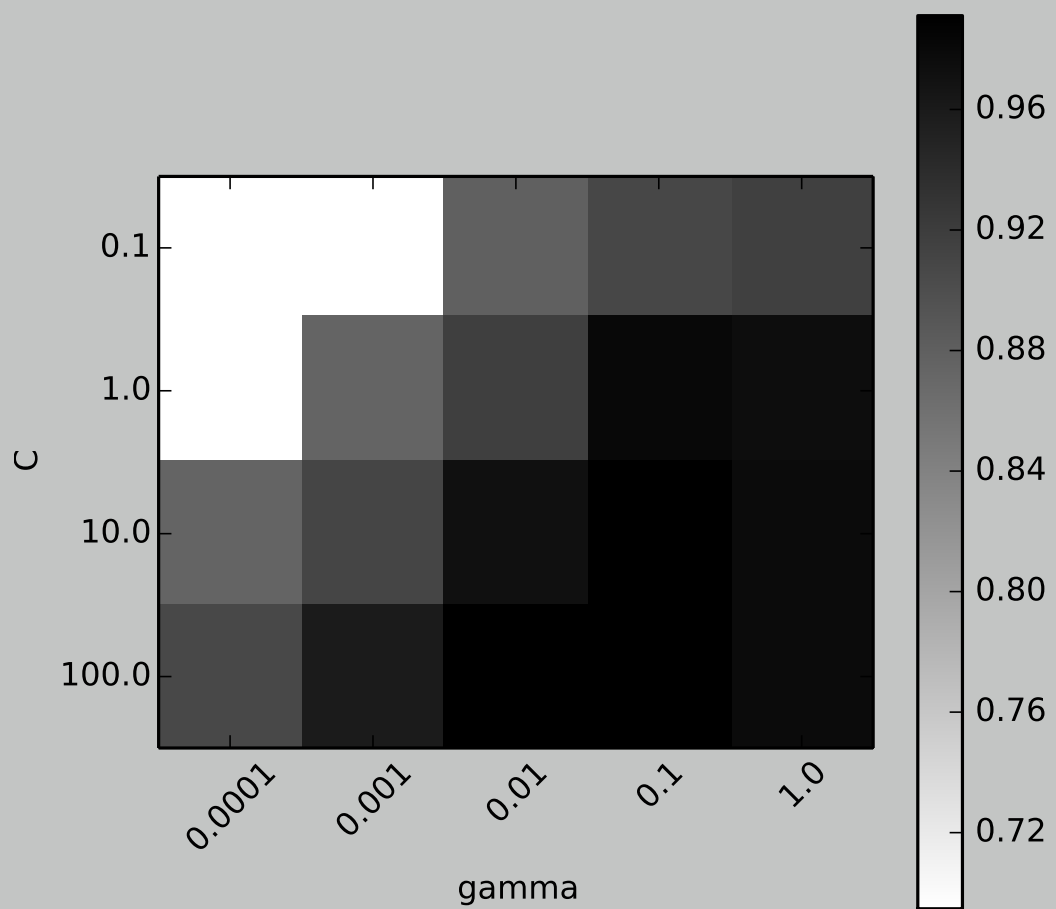


Dimensionality Reduction

- Each spetrum has 778 points. Different approaches were tested for dimensionlity 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) classificator with rbf kernal ($\exp(-\gamma|\mathbf{x} - \mathbf{x}'|^2)$) was used. Grid search is used to find optimal values for \mathbf{C} and γ parameters. There is an exaple of heatmap for optimal parameters for data reduced by Isomap method.



Classification

- Data were splited into training (75%) and testing (25%) sample. Reports for different reduction aprouches are show below compared to non-reduced data sample.

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

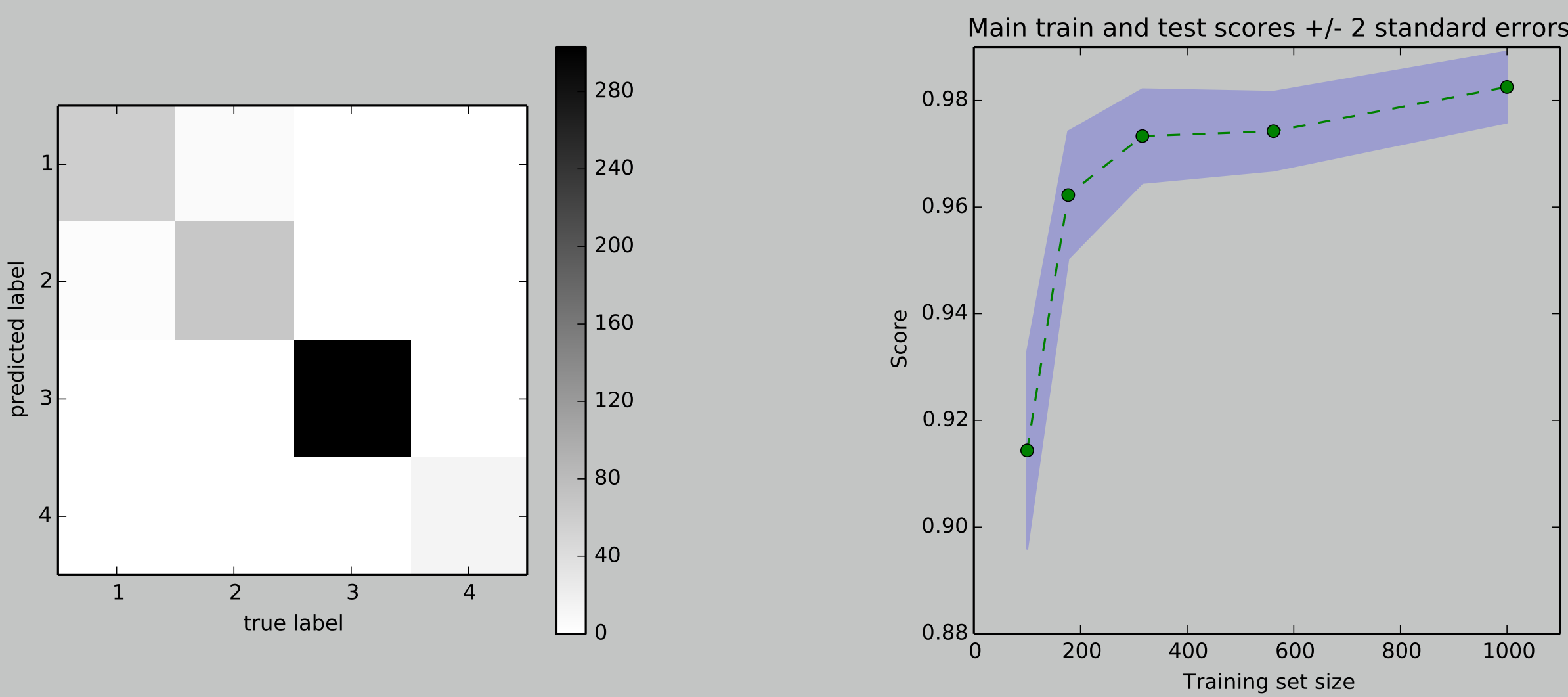
Table 2: ISOMAP Classification report

Category	Precision	Recall	f1-score	Support
1.0	0.97	1.00	0.98	61
2.0	1.00	0.97	0.99	74
3.0	0.99	1.00	1.00	303
4.0	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	0.91	1.00	0.95	61
2.0	0.99	0.92	0.95	74
3.0	1.00	1.00	1.00	303
4.0	0.92	0.86	0.89	14
avg/total	0.98	0.98	0.98	452

Table 4: LLE Classification report



Conclusion

- It is possible to dramatically reduce the number of dimension of spectra in classification problem (here from 778 to 10).
- PCA, Isomap, LLE and has similar effects in this concrete 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.

[3] Ž. Ivezić, A.J. Connolly, J.T. Vanderplas, and A. Gray. *Statistics, Data Mining and Machine Learning in Astronomy*. Princeton University Press, 2014.

Contact Information

- Web: http://physics.muni.cz/~vazny/wiki/index.php/Main_Page
- Email: jaroslav.vazny@gmail.com
- Phone: +42 606 77 65 64