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SWEET-Cat update and MOOGme

A new minimization procedure for high quality spectra

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ABSTRACT

Aims.
Methods.
Results.

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1. Introduction

The study of extrasolar planetary systems is an established field of research. To date, over 3200 extrasolar planets have been discovered around solar-type stars[1]. Most of these have been found thanks to the incredible precision achieved in photometric transit and radial velocity. Especially the latest announcement from the *Kepler* space mission with 1284 confirmed exoplanets (Morton et al. 2016). The increasing number of exoplanets allow us to do statistical studies of the newfound worlds by analyzing their internal structure, atmospheric composition, with more.

A key aspect to this progress is the characterization of the planet host stars. For instance, precise and accurate stellar radii are critical if we want to measure oresice values of the radius of a transiting planet (see e.g. Torres et al. 2012). The determination of the stellar radius is in turn dependent on the quality of the derived stellar parameters such as the effective temperature.

2. MOOGme

MOOGme (acronym for MOOG made easy) is a new tool for analyzing spectra. MOOGme is written in Python and works as a wrapper around MOOG (Sneden 1973), and ARES (Sousa et al. 2015a) for an all-in-one tool. MOOG is a radiative transfer code under the assumption of local thermodynamic equilibrium (LTE). And ARES is a tool to measure equivalent widths (EW) automatically from a spectrum given a line list. MOOGme has four different functions: Measure EWs with ARES, synthetic fitting, EW method, and abundances, all described below.

[1] For an updated table we refer to http://ww.exoplanet.eu

2.1. EW measurements

EW measurements are important for the EW method and to obtain abundances. This can be done manually using a tool like IRAF, but often when dealing with a large sample of stars this is not a suitable way to deal with the problem. Therefore tools like ARES exists which can measure the EW of spectral lines automatically. To use this mode of MOOGme, ARES has to be installed and be in the PATH. Then MOOGme just need a spectrum (format should be 1D for ARES to read it) and a line list. For the latter, MOOGme is shipped with some line lists ready to use, in the format suitable for MOOGme. The output will be a line list in the format required for MOOG. The output can be used for either the EW method or the abundance method, both described below.

2.2. Synthetic fitting

FOR MARIA :)

2.3. EW method

This is the second standard method for obtaining parameters from stellar spectra. Here measured EWs are used to calculate abundances using a given stellar atmosphere model with a given set of atmospheric parameters, effective temperature ($T_{\rm eff}$), surface gravity ($\log g$), metallicity ([Fe/H], where iron often is used as a proxy), and the micro turbulence ($\xi_{\rm micro}$). By removing correlations between the measured abundances (through the measured EWs) and the excitation potential and reduced EW ($\log(EW/\lambda)$) we can constrain $T_{\rm eff}$ and $\xi_{\rm micro}$. By obtaining ionization balance between Fe I and Fe II, that is the average abundance of all Fe I lines are equal to the average abundance of all Fe II lines, we constrain $\log g$. Last, we change the input [Fe /H]

to match that of the average output [Fe/H]. Hence we have four criteria to minimize simultaneously:

1. The slope between abundance and excitation potential ($a_{\rm EP}$).
2. The slope between abundance and reduced EW ($a_{\rm RW}$).
3. The difference between the average abundances of Fe I and Fe II (ΔFe).
4. Input and output metallicity.

There exists many minimization routines available in Python. Most commonly known are the ones from the SciPy ecosystem[2]. There are some pros and cons with using proprietary minimization routines. Pros are that it is already written, and usually there are good documentation in libraries such as SciPy. Cons in this situation is, that most minimization routines are not able to handle multiple criteria at once. A work around is to combine the criteria into one single criteria by e.g. adding them quadratically and minimize that expression instead. The minimization routines are also not physical in the sense that they are not optimized for the problem. These two cons was incitement for writing a minimization optimized for our problem. Here is how it works.

1. Run MOOG once with a user defined initial parameters (default is solar) and calculate $a_{\rm EP}$, $a_{\rm RW}$, and ΔFe.
2. Change the atmospheric parameters ($T_{\rm eff}$, $\log g$, [Fe/H], $\xi_{\rm micro}$) according to the size of the indicator. A parameter is only changed if it is not fixed.
   - $a_{\rm EP}$: Indicator for $T_{\rm eff}$. If this value is positive, then increase $T_{\rm eff}$.
   - $a_{\rm RW}$: Same as above but for $\xi_{\rm micro}$.
   - ΔFe: Same as above but for $\log g$. Positive ΔFe means $\log g$ should be decreased.
3. For [Fe/H] it is changed to the output [Fe/H] in each iteration (if free).
4. If the new parameters have already been used in a previous, then change them slightly. This is done by drawing a random number from a Gaussian distribution with a mean at the previous value and a sigma equal to the absolute value of the indicator.
5. Calculate a new atmospheric model by interpolating a grid so we have the requested parameters and run MOOG once again.
6. For each iteration save the parameters used and the quadratic sum of the indicators. If we do not reach convergence, then return the best found parameters.

By using the indicators like this, we can relative fast reach convergence. There are some interdependencies among the indicators. E.g. by changing $T_{\rm eff}$ all indicators will be affected, however the effect is strongest for $a_{\rm EP}$.

2.3.1. Options

It is possible to run the EW method with a set of different options which will be described here.

model Change which type of model atmosphere to use. Currently the following are available: Kurucz 95, Marcs, and Kurucz from APOGEE.

weights Calculate the slopes with an weight based on the distance from the mean.

fixteff Fix $T_{\rm eff}$. Same is available for $\log g$ (fixlogg), [Fe/H] (fixfeh), and $\xi_{\rm micro}$ (fixvt).

iterations The maximum number of iterations (160 by default).

EPcrit The criteria for $a_{\rm EP}$ to reach convergence (0.001 by default).

RWcrit The criteria for $a_{\rm RW}$ to reach convergence (0.003 by default).

ABdiffcrit The criteria for ΔFe to reach convergence (0.01 by default).

MOOGv The version of MOOG being used (2014 by default).

outlier Remove outliers after the first run with the minimization routine and restarting the minimization from the previous best parameters. The options are to remove all outliers above 3σ once or iteratively, or remove one outlier above 3σ once or iteratively.

autofixvt If the minimization routine does not converge and $\xi_{\rm micro}$ is close to 0 or 10 with a significant $a_{\rm RW}$, then fix $\xi_{\rm micro}$.

teffrange This is a special option for two of the line list shipped with MOOGme. The ones from Sousa et al. (2015b) and Tsantaki et al. (2013). The latter is a subset of the former optimized for cooler stars. If this option is set, and the former line list is used for a cool star ($T_{\rm eff}$ found after the minimization), then remove the lines from the used line list to match the latter line list and rerun the minimization routine.

refine After the minimization is done, run it again from the best found parameters but with more strict criteria. If this option is set, it will always be the last step (after removal of outliers and the use of teffrange).

If $\xi_{\rm micro}$ is fixed it is changed at each iteration according to an empirical relation. For dwarfs it follows the one presented in Tsantaki et al. (2013) and for giants it follows the one presented in Adibekyan et al. (2015) (THIS IS NOT TRUE. NOT RIGHT REFERENCE FOR VARDAN).

2.4. Abundance method

We made a mode to calculate abundances for different elements based on the measured EW. Here we require a line list with the EW of the elements and the corresponding atmospheric parameters for the star of interest. We provide a line list with XXX elements ready to use. The results are saved to a table.

3. New spectroscopic parameters for 65 planet hosts

Here we present the sample of 66 stars. We were unable to derive parameters for HD77065. This is a spectroscopic binary according to Pourbaix et al. (2004).

The remaining 65 stars are presented in Table 1

4. Conclusion

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[2] `http.scipy.org`

Table 1. The derived parameters for the 65 stars in our sample.

Star	$T_{\rm eff}$ (K)	$\log g$ (dex)	[Fe/H] (dex)	$\xi_{\rm micro}$ (km/s)	$\xi_{\rm micro}$ fixed?
WASP-762	6347 ± 52	4.29 ± 0.08	0.36 ± 0.04	1.73 ± 0.06	no
WASP-822	6563 ± 55	4.29 ± 0.10	0.18 ± 0.04	1.93 ± 0.08	no
WASP-882	6450 ± 61	4.24 ± 0.06	0.03 ± 0.04	1.79 ± 0.09	no
WASP-952	5799 ± 31	4.29 ± 0.05	0.22 ± 0.03	1.18 ± 0.04	no
WASP-972	5723 ± 52	4.37 ± 0.07	0.31 ± 0.04	1.03 ± 0.08	no
WASP-992	6324 ± 89	4.70 ± 0.11	0.27 ± 0.06	1.83 ± 0.12	no
HATS-12	5969 ± 46	4.61 ± 0.06	−0.04 ± 0.04	1.06 ± 0.08	no
Qatar-22	4637 ± 316	4.23 ± 0.61	0.09 ± 0.17	0.63 ± 0.83	no
WASP-442	5612 ± 80	4.47 ± 0.30	0.17 ± 0.06	1.32 ± 0.13	no
HAT-P-462	6421 ± 121	4.53 ± 0.14	0.16 ± 0.09	1.67 ± 0.18	no
WASP-522	5197 ± 83	4.47 ± 0.30	0.15 ± 0.05	1.16 ± 0.14	no
WASP-722	6570 ± 85	4.71 ± 0.13	0.15 ± 0.06	2.30 ± 0.15	no
WASP-752	6203 ± 46	4.42 ± 0.22	0.24 ± 0.03	1.45 ± 0.06	no
HAT-P-422	5903 ± 66	4.29 ± 0.10	0.34 ± 0.05	1.19 ± 0.08	no
HATS-52	5383 ± 91	4.40 ± 0.22	0.08 ± 0.06	0.91 ± 0.14	no
HD2855072	4620 ± 126	4.42 ± 0.61	0.04 ± 0.06	0.74 ± 0.43	no
HR2282	5042 ± 42	3.30 ± 0.09	0.07 ± 0.03	1.14 ± 0.04	no
SAND3642	4457 ± 104	2.26 ± 0.20	−0.04 ± 0.06	1.60 ± 0.11	no
Aldebaran	5279 ± 223	4.53 ± 0.40	0.14 ± 0.12	3.05 ± 0.41	no
Gl785	5087 ± 48	4.30 ± 0.10	−0.01 ± 0.03	0.69 ± 0.10	no
HD120084	4969 ± 40	2.94 ± 0.14	0.12 ± 0.03	1.41 ± 0.04	no
HD192263	4946 ± 46	4.43 ± 0.14	−0.05 ± 0.02	0.66 ± 0.12	no
HD207229	4957 ± 49	2.83 ± 0.09	0.04 ± 0.04	1.49 ± 0.05	no
HD219134	4767 ± 70	4.32 ± 0.17	−0.00 ± 0.04	0.59 ± 0.24	no
HD81688	4870 ± 30	2.50 ± 0.14	−0.26 ± 0.03	1.50 ± 0.03	no
HD82886	5124 ± 22	3.30 ± 0.05	−0.25 ± 0.02	1.15 ± 0.03	no
HD85503	4605 ± 94	2.61 ± 0.26	0.25 ± 0.06	1.64 ± 0.11	no
HD87883	4917 ± 68	4.34 ± 0.19	0.02 ± 0.03	0.46 ± 0.21	no
HIP11915	5770 ± 14	4.47 ± 0.03	−0.06 ± 0.01	0.95 ± 0.02	no
omiUma	5499 ± 52	3.36 ± 0.07	−0.01 ± 0.05	1.98 ± 0.06	no
11Com	4911 ± 38	2.68 ± 0.08	−0.20 ± 0.03	1.56 ± 0.04	no
HD102272	5351 ± 135	3.92 ± 0.33	−0.34 ± 0.11	1.16 ± 0.20	no
HD104985	4809 ± 48	2.73 ± 0.08	−0.26 ± 0.04	1.65 ± 0.05	no
HD114762	6058 ± 83	4.71 ± 0.09	−0.78 ± 0.05	0.00 ± 0.23	no
HD114762	6061 ± 83	4.70 ± 0.08	−0.78 ± 0.05	0.02 ± 0.26	no
HD136512	4915 ± 33	2.74 ± 0.08	−0.14 ± 0.03	1.57 ± 0.04	no
HD152581	5355 ± 82	3.65 ± 0.18	−0.39 ± 0.07	0.60 ± 0.15	no
HD155358	5917 ± 51	4.12 ± 0.08	−0.55 ± 0.04	1.06 ± 0.08	no
HD170693	4547 ± 55	2.23 ± 0.10	−0.31 ± 0.03	1.54 ± 0.05	no
HD220842	6027 ± 30	4.35 ± 0.05	−0.08 ± 0.03	1.19 ± 0.04	no
HD221345	4797 ± 44	2.58 ± 0.11	−0.23 ± 0.03	1.58 ± 0.04	no
HD233604	4925 ± 44	2.79 ± 0.11	−0.15 ± 0.03	1.62 ± 0.05	no
HD37124	5468 ± 32	4.28 ± 0.04	−0.43 ± 0.03	0.67 ± 0.07	no
HD81688a	4906 ± 29	2.69 ± 0.06	−0.21 ± 0.02	1.60 ± 0.03	no
HD82886	5252 ± 66	3.67 ± 0.13	−0.41 ± 0.06	0.06 ± 0.10	no
HD97658	5182 ± 43	4.50 ± 0.12	−0.29 ± 0.03	0.77 ± 0.11	no
Kepler-444	5163 ± 40	4.41 ± 0.11	−0.50 ± 0.03	0.78 ± 0.10	no
WASP-100	6853 ± 209	4.15 ± 0.26	−0.30 ± 0.12	1.87 ± 0.02	yes
HAT-P-242	6470 ± 181	4.75 ± 0.26	−0.41 ± 0.10	1.40 ± 0.03	yes
HAT-P-392	6745 ± 236	4.91 ± 0.46	−0.21 ± 0.12	1.53 ± 0.04	yes
WASP-612	6265 ± 168	4.21 ± 0.21	−0.38 ± 0.11	1.44 ± 0.02	yes
HD70573	5889 ± 186	4.32 ± 0.27	−0.42 ± 0.13	1.14 ± 0.01	yes

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Appendix A: An appendix