RoadRunner: a fast and flexible exoplanet transit model

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ABSTRACT
I present RoadRunner, a fast exoplanet transit model that can use any radially symmetric function to model stellar limb darkening while still being faster to evaluate than the analytical transit model for quadratic limb darkening by Mandel & Agol (2002). CPU and GPU implementations of the model are available in the PyTransit transit modelling package, and come with platform-independent parallelisation, supersampling, and support for modelling complex heterogeneous time series. The code is written in numba-accelerated Python (and the GPU model in OpenCL) without C or Fortran dependencies, which allows for the limb darkening model to be given as any Python-callable function. Finally, as an example of the flexibility of the approach, the latest version of PyTransit comes with a numerical limb darkening model that uses LDTk-generated limb darkening profiles directly without approximating them by analytical models.

Key words: Methods: numerical – Techniques: photometric – Planets and satellites

1 INTRODUCTION
An exoplanet transit model aims to reproduce the photometric signal caused by a planet crossing over the limb-darkened disk of its host star. Modelling the transit signal would be a simple problem were it not for stellar limb darkening (LD). A planetary transit over a uniform disk can be modelled simply by the area of the stellar disk subtracted by the intersection area of the stellar and planetary disks. However, the stellar surface brightness changes from the centre to the limb of the star (ignoring other effects such as gravity darkening, flares, and spots), and the true transit signal equals to the stellar surface brightness integrated over the stellar disk subtracted by the surface brightness integrated over the area occluded by the planet.

This integration can be carried out analytically for some simple LD models (Mandel & Agol 2002), using a series expansion for increased model flexibility (Giménez 2006), using model-specific analytical approximations (Maxted & Gill 2019), or using numerical integration (Nelson & Davis 1972; Kreidberg 2015; Maxted 2016). However, the low-order LD models with analytical solutions may fail to reproduce the true stellar surface brightness profile sufficiently well, and lead to biases in planet characterisation based on transit light curve analysis (Csizmadia et al. 2013; Espinoza & Jordan 2015). The transit model based on series expansion for the general LD model by Giménez (2006) allows in theory for LD models of unlimited complexity, but the computation speed becomes quickly prohibitively slow to reach an absolute precision required (or offered) by space-based photometry. The models based on approximations, such as the one by Maxted & Gill (2019), can be very powerful in a some volume of parameter space, but may become biased outside the parameter space they were designed for. In theory, numerical integration allows the use of any LD model with accuracy bound only by the floating point precision. However, the computation cost of a model based on numerical integration is generally significantly higher than for the analytical models.

Here I present RoadRunner, a fast transit model that can use any limb darkening model, reach ppm-precision, and still be faster to evaluate than the analytical transit model for quadratic LD by Mandel & Agol (2002). The model uses one-dimensional numerical integration approach similar to the EBOP (Popper & Etzel 1981), JKTEBOP (Southworth 2008), and BATMAN (Kreidberg 2015) packages, but separates the integral of the stellar surface brightness occluded by the planet into a product of the mean occluded surface brightness and the occluded surface area. This separation is beneficial because the occluded area is cheap to calculate analytically, while the mean stellar surface brightness can be precomputed into a relatively low-resolution interpolation table.

The model is implemented in PyTransit v2.1† (Parviainen 2015). The implementation is based on numba-accelerated Python code with no C or Fortran dependencies, what makes the installation of the package trivial and allows for painless parallelisation in computing environments where compiling parallelised code could be nontrivial. Also, due to the pure-Python implementation, the

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† https://github.com/hpparvi/PyTransit
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limb darkening model can be any Python callable that returns the stellar surface brightness as a function of $\mu^2$.

I describe the theory behind the model evaluation in all its simplicity in Sect. 2, detail the steps taken to make the theory into an efficient implementation in Sect. 3, give examples of the model usage in Sect. 4, discuss the model performance and scalability in Sect. 5, and finish with conclusions and discussion in Sect. 6.

2 THEORY

The transit signal is caused by a planet occluding a part of the limb-darkened stellar surface. If the stellar surface brightness can be presented as a radially symmetric function of a normalised distance from the stellar centre, $z$, (that is, if we can ignore gravitation darkening and other effects breaking the radial symmetry) the transit signal is

\[ I = \int_{A_\star} I(z) \, dA - \int_{A_p} I(z) \, dA \]

\[ = 2\pi \int_0^1 z I(z) \, dz - \int_{A_p} I(z) \, dA, \]

where $A_\star$ stands for the area of the star and $A_p$ stands for the stellar surface area occluded by the planet. The first term can be calculated analytically for most limb darkening models, and efficiently numerically for any model that might not have an analytical form available. The second term is more complicated since the integration needs to be carried out over the stellar surface area covered by the planet. However, thanks to the radial symmetry, this integration can also be carried out in one dimension, as detailed in Kreidberg (2015).

The integrals above can also be expressed as products of mean intensities and areas as

\[ I = \hat{I}_\star \hat{A}_\star - \hat{I}_p \hat{A}_p. \]

Now, by normalising the stellar radius and out-of-transit flux both to unity, we get

\[ I = \frac{\pi \hat{I}_\star - \hat{I}_p \hat{A}_p}{\pi \hat{I}_\star} = \frac{I_\star - \hat{I}_p \hat{A}_p}{I_\star}, \]

where $I_\star = \pi \hat{I}_\star$. The area occluded by the planet, $A_p$, is fast to compute analytically, and the only factor that cannot be calculated analytically is the mean surface brightness over the area occluded by the planet.

The mean occluded surface brightness can be estimated given a planet-star radius ratio $k$, the normalised planet-star centre distance $c$, and the limb darkening model $l(\mu)$ by first discretising the stellar radius from 0 to 1\(^2\) calculating a weight vector $\mathbf{w}$ where the weights equal to the areas of the annuli occluded by the planet divided by the total area occluded by the planet, and calculating a stellar brightness profile vector $\mathbf{l}$ by evaluating the limb darkening model at the bin centres, as illustrated in Fig. 1. Now, the mean occluded surface brightness is given by weighted average that can be computed as a dot product of $\mathbf{w}$ and $\mathbf{l}$.

\[ \hat{I}_p = \frac{A_p}{\hat{A}_\star}. \]

\[ g = \frac{c}{1 + k}. \]

\[ \hat{l} = \mu_\mathbf{w} \cdot \mathbf{l}. \]

\[ (5) \]

where $\mu$ is the foreshortening angle and $\gamma$ is the normalised distance from the centre of the stellar disk.

\[ (4) \]

Finally, the transit model for a given $k$, $c$, and limb darkening profile can be evaluated as

\[ I = \frac{l_\star - (\mathbf{w} \cdot \mathbf{I}) \times a(c, k)}{l_\star}, \]

where $a$ is the circle-circle intersection area. That is, the transit model evaluation reduces to a dot product of the weight and limb darkening profile vectors multiplied by the area occluded by the planet.

\[ (5) \]

\[ \hat{I}_\star \]

\[ \hat{A}_\star \]

\[ \mu_\mathbf{w} \cdot \mathbf{l} \]

\[ (4) \]

\[ (5) \]

\[ MNRAS 000, 1–7 (2020) \]
3 IMPLEMENTATION

3.1 Basic implementation

While Eq. (5) can be used to directly evaluate the transit model, some simple optimisations can be used to significantly decrease the computational cost of the model in real-life use cases. In the most basic typical case a single transit model evaluation considers a single stellar brightness profile, a single radius ratio, and up to hundreds of thousands of star-planet separation $c$ values. The computation of the weight array separately for each $c$ would be rather expensive, and can be avoided by precomputing it into a 2d weight vector interpolation table for a set of grazing values $g = c / (1 + k)$ for $g = [0..1]$. I parameterise the array with a grazing value rather the star-planet distance $c$ because this simplifies the interpolation in the case we want to precompute the weight array also as a function of $k$, giving us a 3d weight vector interpolation table, and then interpolate the weight vector in the $(k, g)$-space, as detailed later in Sect. 3.1.2.

3.1.1 Interpolation in $g$

First, the stellar disk is discretised into concentric annuli (bins) during the model initialisation. The model uses a discretisation strategy where the stellar disk is divided into an inner and outer region divided at $z_{\text{cut}}$, as shown in Fig. 1. The bin width is constant in $z$ in the inner region and constant in $\mu$ in the outer region. The use of bins with constant $\Delta z$ in the inner region ensures that the central regions of the stellar disk are sampled well, and the use of bins with constant $\Delta \mu$ in the outer region ensures that the limb of the star where the surface brightness changes rapidly is also sampled well. The inner and outer region resolution and the dividing $z$ value can be optimised automatically given a limb darkening model and an allowed error threshold.

The discretisation yields two arrays storing the $z$ values of the bin edges and means, and an array containing the $\mu$ values corresponding to the mean $z$ values can be calculated for the limb darkening model evaluation since the limb darkening models are generally expressed as functions of $\mu$. In PYTHON, the model is initialised as

```python
ze, zm = create_z_grid(zcut, nzin, nzlimb)
mu = sqrt(1 - zm*zm)
```

where $z_{\text{cut}}$ is the radius that defines the inner and outer areas of the stellar disk, and $n$zin and $n$zlimb the inner and outer region resolutions.

After the initialisation, the model can be evaluated for an array of planet-star centre distances, $c$, given a radius ratio, $k$, limb darkening model $1$model, limb darkening model parameters, $1$par, the integrated stellar brightness, $i$star, and the $g$-discretisation resolution, $n$g, as

```python
dg, w = calculate_weights(k, ze, ng)
dp = lmodel(mu, 1dpar)
dl = dot(w, dp)
```

for $iz$ in range($n$z):

```python
g = z[iz] / (1+k)
i = int(floor(g/dg))
a = g/dg - i
ip = (1-a)*dlw[i] + a*dlw[i+1]
ap = ccc_intersection_area(k, z)
f[iz] = (istar - ip * ap) / istar
```

The model evaluation will be rather slow if implemented in pure PYTHON. However, the speed will be close to C of Fortran performance if the loop and all the main functions are accelerated using NUMBA.

3.1.2 Interpolation in $k$ and $g$

The previous approach calculates the weight array for each new planet-star radius ratio $k$. This can be avoided by precomputing a 3D weight array during the model initialisation so that the weight vector can be interpolated as a function of $k$ and $g$. For this, we need to give the model the minimum and maximum radius ratio limits and the radius ratio resolution. Now, the weight calculation is moved to the model initialisation

```python
ze, zm = create_z_grid(zcut, nzin, nzlimb)
dk, dg, w = calculate_weights_3d(nk, k0, k1, ze, ng)
mu = sqrt(1 - zm*zm)
```

and the only required modification to the model evaluation is one additional interpolation

```python
ldp = lmodel(mu, 1dpar)
nk = (k - k0) / dk
ik = int(floor(nk))
ak = nk - ik
ldw = (1-ak)*dot(w[ik], ldp) + ak*dot(w[ik+1], ldp)
for iz in range(nz):
...
```

While promising in theory, the performance gain offered by interpolating in $k$ and $g$ is rather insignificant what comes to the total evaluation speed of the transit model when including also the Keplerian orbit computations, etc. Both approaches are implemented in PyTRANSIT, interpolation in $g$ only (from here named as direct model) is the default setting, and the model using $(g, k)$ interpolation (from here named as interpolated model) can be switched on in the model initialisation easily.

3.2 Limb darkening

3.2.1 Named limb darkening models

The limb darkening model is chosen in the transit model initialisation, and can be one of the named limb darkening models built in to PyTRANSIT or a Python callable. The built-in models are

- uniform
- linear
- quadratic
- triangular quadratic
- general
- nonlinear
- logarithmic
- exponential
- power-2
- power-2-pm

and are all integrated analytically over the stellar disk to get an exact normalisation factor.

4 See Mandel & Agol (2002), Giménez (2006), Parviainen & Aigrain (2015), and Kreidberg (2015) for overviews of the analytical forms. The triangular quadratic is an alternative parametrisation to the quadratic model by Kipping (2013), and the power-2-pm model is an alternative parametrisation to the power-2 model by Maxted (2018).
3.2.2 Custom limb darkening model

The RoadRunner model can model limb darkening by any Python callable that returns an array of surface brightness values when given an array of $\mu$ values and a parameter vector. If the model is given a single callable rather than an LD model name in the initialisation, the normalisation factor is integrated numerically with a minor performance loss. If the model is given a tuple containing two callables, the second one is assumed to calculate the normalising integral in an optimised fashion for a given set of LD parameters.

3.2.3 LDTk limb darkening model

Since the limb darkening is not restricted to be an analytical function of any sort, we can, for example, use numerical limb darkening profiles created by stellar atmosphere models directly. PyTransit takes advantage of this possibility and offers an LDTk-based (Parviainen & Aigrain 2015) limb darkening model to be used with the RoadRunner transit model. The LDTk limb darkening model creates a sample of limb darkening profiles given a set of transmission functions defining the passbands and a set of stellar parameters and their uncertainties. Each model evaluation draws a random profile from the sample and interpolates the brightness values for the given $\mu$ values from the tabulated specific intensity spectra.

The LDTk limb darkening model uses PHOENIX-calculated stellar spectra by Husser et al. (2013), but the approach can be extended to use any stellar spectra calculated for a set of $\mu$ values. The approach of using modelled stellar spectra directly is similar to setting LDTk-calculated priors on the limb darkening coefficients but we do not need to worry about how well the chosen LD model can reproduce the true LD profile, and the final model will have a smaller number of free parameters since the limb darkening is parameter (coefficient) free. However, introducing additional uncertainty (to account for possible biases in the stellar atmosphere models) becomes difficult.

3.3 Accuracy

The accuracy of the model can be tuned by modifying the $g$, $z_{\text{in}}$, and $z_{\text{limb}}$ resolutions and the $z_{\text{cut}}$ location. The model shows no asymptotic biases and a sub-ppm error level can be achieved while still keeping a practical performance (although this sort of accuracy is unlikely necessary in the near future). Figure 2 shows the direct model error as a function of the grazing value for quadratic limb darkening for four radius ratios and three integration resolution setups. The errors are computed against the analytic quadratic limb darkening model by Mandel & Agol (2002). Since the lowest-resolution setup already yields maximum errors in the range of 5 ppm, the resolution can still be significantly reduced for most current scientific use cases.

3.4 Optimisations

3.4.1 Selection of the implementation

Many variables outside the basic computation algorithm can affect the execution speed of the code. The processor, operating system, and size of the simulated dataset can all affect whether, for example, parallel or serial computation is the optimal approach. Multi-threading can increase the execution speed with modern multicore computers significantly, but comes with internalisation overheads that can decrease the overall evaluation speed if the problem is not large enough to justify them. In our case, because the transit model is very cheap to compute, the per-call parallelisation overhead can be many times larger than the actual transit model computation time if the number of points to evaluate the model at is small (smaller than some thousands of in-transit datapoints).

PyTransit implements several versions of the model (parallel, serial, simplified) and chooses the best implementation after the model has been set up by making a quick trial run with each and selecting the fastest. This is invisible to the end user, generally takes some fractions of a second, and should ensure that the optimal model is chosen always.

3.4.2 Small-planet approximation

If the planet is small enough, the weighted average can be replaced with the limb darkening value evaluated at the centre of the planet. The small-planet approximation radius ratio threshold can be set at the model initialisation.

3.4.3 Transmission spectroscopy

The passband-dependent variations in the radius ratio are small compared to the average radius ratio and have an insignificant effect on the limb darkening weights. Thus, for transmission spectroscopy, we can use a single limb darkening weight array calculated for the mean radius ratio rather than calculating the weight array separately for each passband. This approach reduces the computation cost of the model for transmission spectroscopy.

3.4.4 GPU computation

The RoadRunner transit model evaluation is so computationally cheap that using a GPU just for the evaluation of a single transit model does not bring forth any significant speed benefits, and can actually be slower due to the need to copy data between the main memory and the GPU. However, GPU evaluation can increase the evaluation speeds significantly (10-20 times) when we increase the computational burden of a single datapoint evaluation (such as when using supersampling), and when we want to evaluate the model for a large set of parameters simultaneously, such as when using emcee (Foreman-Mackey et al. 2013) for Markov Chain Monte Carlo sampling. PyTransit implements the RoadRunner model for GPUs using OpenCL, and the GPU version can be used as a drop-in replacement for the CPU implementation without any modifications. However, the GPU version is limited to 32 bit floating point precision and may not be suitable when extreme precision is required.

4 MODEL USAGE

4.1 Basic usage

The model is prepared for use by initialising an instance of the RoadRunnerModel class and giving the model a set of arrays defining the modelled light curves.

```python
from pytransit import RoadRunnerModel
tm = RoadRunnerModel('power -2')
tm.set_data(times)
```
The `RoadRunnerModel.set_data` method takes at minimum an array of mid-exposure values to evaluate the model at, here given in the `times` array, but it can also be given the model supersampling factor and exposure time of individual exposures when modelling long-cadence observations (from *Kepler* or *TESS*, for example, Kipping 2010)

\[
\text{tm.set_data}(\text{times}, \text{nsamples}=10, \text{exptimes}=0.02)
\]

The model is ready to be evaluated after the setup

\[
\text{flux} = \text{tm.evaluate}(k, 1dc, t\theta, p, a, i, e, w)
\]

where `k` is a float or a 1D or 2D array containing radius ratios, `1dc` is a 2D array containing limb darkening parameters (coefficients), and `t\theta, p, a, i, e, w` are either floats or 1D arrays containing the orbital parameters (zero epoch, period, normalised semi-major axis, inclination, eccentricity, and argument of periastron, respectively).

If the radius ratio and orbital parameters are floats, the model is evaluated for this set of scalar parameters, and the returned flux array will be one-dimensional with a shape `(npt)`, where `npt` is the number of mid-exposure times to evaluate the model at. However, if the radius ratios and orbital parameters are given as one-dimensional arrays of size `npv`, the model will be evaluated for all the given parameters in parallel, and the returned flux array will be two-dimensional with a shape `(npv, npt)`. The parallelised evaluation can lead to very significant performance boost when using a global optimisation or MCMC method that benefits from parallelised code.

### 4.2 Heterogeneous light curves

The mid-exposure times are the minimal amount of information required by the model, but more can be given when modelling heterogeneous light curves. Now, the modelled dataset consists of several light curves with (possibly) different passbands, exposure times, and required supersampling rates, and the radius ratio and limb darkening coefficients can be treated as passband-dependent variables. The full form of `RoadRunnerModel.set_data` is

\[
\text{tm.set_data}(\text{times}, \text{lcids}, \text{pbids}, \text{nsamples}, \text{exptimes})
\]

where `lcids` is an integer array of size `npv` containing the per-exposure light curve indices that map each exposure into a single light curve, `pbids` is an integer array of size `nc` containing the per-light-curve passband indices that map each light curve into a single passband, where `nc` is the number of separate light curves, and `nsamples` and `exptimes` can be also given as arrays setting

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Figure 2. The RoadRunner model error as a function of the grazing value \((z/(1+k))\) in parts per million for quadratic limb darkening for \(k\) values of 0.01, 0.05, 0.1, and 0.5, \(n_z\) of 60, 12, and 18, and \(n_g\) of 100, 150, and 200. The y-scale is the same for all columns in a single row, but varies from row to row. The error is computed against the analytical quadratic limb darkening model by Mandel & Agol (2002).

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the oversampling rate and exposure time separately for each light curve.

As a dummy example, a heterogeneous time series consisting of three light curves observed in two different passbands would be set up as

```python
times = [0, 1, 2, 3, 4, 5]
lcids = [0, 0, 0, 1, 1, 1, 2]
 pbids = [0, 1, 0]
tm.set_data(times, lcids=lcids, pbids=pbids)
```

After the setup, the model can be evaluated either assuming a chromatic (passband-independent) radius ratio

```python
tm.evaluate(k=0.10,
    ldc=[[0.2, 0.1, 0.5, 0.1]],
    t0=0.0, p=1.0, a=3.0, i=0.5*pi)
```

chromatic (passband-dependent) radius ratio

```python
tm.evaluate(k=[0.10, 0.11],
    ldc=[[0.2, 0.1, 0.5, 0.1]],
    t0=0.0, p=1.0, a=3.0, i=0.5*pi)
```

or either but for a number of parameter sets simultaneously

```python
tm.evaluate(k=[[0.10, 0.12], [0.11, 0.13]],
    ldc=[[0.2, 0.1, 0.5, 0.1],
        [0.4, 0.2, 0.6, 0.2]],
    t0=[0.0, 0.01],
    p=[1.1, 1.2],
    a=[3.0, 2.0],
    i=[0.5*pi, 0.49*pi])
```

where in the last case \(k\) is a 2D array of shape \((n_{pv}, n_{pb})\), the limb darkening parameters \((ldc)\) are given as a 2D array of shape \((n_{pv}, n_{pb} \times n_{ldc})\), \(n_{pb}\) is the number of passbands, and \(n_{ldc}\) is the number of limb darkening model parameters. I have omitted the eccentricity and argument of periastron above because they are optional and default to zero (circular orbit) if not given.

### 4.3 LDTk model

The LDTk-based limb darkening model presented in Sect. 3.2 can be set up with minimal effort by initialising it with the passbands, stellar parameters and their uncertainties, number of samples to use, and whether to initially “freeze” the model (assuming LDTk is installed, of course).

```python
from pytransit import RoadRunnerModel, LDTkLD
from ldtk import sdds_r, sdds_i
ld = LDTkLD(sdds_r, sdds_i, teff=(3425, 50),
    logg=(4.6, 0.1),
    z=(0.0, 0.1),
    samples=10000,
    frozen=True,
    lowres=True)
```

```python
tm = RoadRunnerModel(ld)
tm.set_data(...) 
```

A frozen LD model returns values from the mean limb darkening profile rather than a profile drawn randomly from the sample. This is important during the model optimisation since a randomly drawn LD profile would confuse the optimiser. After the optimisation and before the MCMC sampling, however, the model should be released (thawed) to marginalise over the limb darkening profiles. The final option \((\text{lowres}=\text{True})\) tells LDTk to use light-weight low-resolution spectra binned from the original Husser et al. (2013) models to 5 nm spectral resolution. This should suit most exoplanet transit modelling needs but reduces the sizes of the downloaded spectra to 2% from the original.

### 5 PERFORMANCE

I show the performance of the different RoadRunner transit model implementations and an optimised quadratic model in Fig. 3. The direct serial RoadRunner model is faster than the quadratic model when the number of in-transit points is larger than 400, and the interpolated RoadRunner model is faster always. The interpolated model offers an advantage over the direct model when the number of in-transit points is smaller than 10^5. After this, the model evaluation time dominates the total evaluation time, and the additional per-call time to calculate the limb darkening tables becomes irrelevant. However, the interpolated model should never be slower than the direct model, and it’s only disadvantages are a small reduction in accuracy and the necessity to know the allowed minimum and maximum radius ratios.

Threading initialisation adds a significant overhead to the parallelised implementations and the parallelised versions are faster than the serial ones only when we reach tens of thousands of points. However, this applies only to the evaluation of the transit model itself, what is relatively cheap for both the RoadRunner and quadratic model. Parallelising the whole light curve calculation including the calculation of the normalised planet to star distance for eccentric orbits and supersampling increases the computational burden for a single modelled photometry observation, and benefits from parallelisation (either multithreading or GPU computation) significantly earlier.

### 6 CONCLUSIONS AND DISCUSSION

I have presented RoadRunner, a fast exoplanet transit model that can be used with any radially symmetric limb darkening model. The CPU and GPU implementations of the model available in PyTransit 2.1 have been tested thoroughly and offer an unified interface that is simple but still flexible enough to model complex heterogeneous time series observed in different passbands, and supersampling requirements. The model offers similar or higher performance to the analytical quadratic transit model by Mandel & Agol (2002), but allows complete flexibility to what comes to the stellar limb darkening. The model can use numerical limb darkening models just as well as analytical ones, what allows it to be paired, for example, with LDTk to use limb darkening profiles created by stellar atmosphere models directly.

The model already performs well, but future may show further possibilities for optimisation and improvement. Especially, while

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5 I am not showing the performance tests considering parallelising the whole light curve computation here because a) it is the same for all transit models, and b) it would deviate from the main focus of the paper.
the OpenCL implementation of the RoadRunner model is fully functional and can accelerate the computation speed 10-20 fold, its performance can likely be improved further. Also, the OpenCL implementation is limited to 32 bit floating point precision, which means that it cannot be directly used with observations requiring ppm precision. Some mixed CPU and GPU approaches could however allow to overcome the precision issue while still offering an improvement in the model performance (for example, calculating the normalised distances and the mean absolute error of 0.3 ppm).

The PyTransit package containing the implementation of the RoadRunner model has been under continuous development since 2010, and contains CPU implementations of six transit models and GPU implementations of four, all with an unified application interface (API). Version 2 moved to use numba-accelerated model implementations over the Fortran implementations of PyTransit 1, which allowed for easy installation in every Python-enabled computation environment and platform-independent parallelisation. The near future of the package will contain further stability testing to ensure that all the implemented transit models work robustly, and the slightly further future will see performance and usability optimisations, especially focusing on improving the performance of the GPU implementations.

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DATA AVAILABILITY

There are no new data associated with this article.

REFERENCES

Csizmadia S., Pasternacki T., Dreyer C., Cabrera J., Erikson A., Rauer H., 2013, A&A, 549, A9
Espinoza N., Jordan A., 2015, MNRAS, 450, 1879
Foreman-Mackey D., Hogg D. W., Lang D., Goodman J., 2013, Publ. Astron. Soc. Pacific, 125, 306
Giménez A., 2006, A&A, 450, 1231
Husser T.-O., Wende-von Berg S., Dreizler S., Homeier D., Reiners A., Barman T., Hauschildt P. H., 2013, A&A, 553, A6
Kipping D. M., 2010, MNRAS, 408, 1758
Kipping D. M., 2013, MNRAS, 435, 2152
Kreidberg L., 2015, ArXiv, 1507.08285
Mandel K., Agol E., 2002, ApJ, 580, L171
Maxted P. F., 2016, A&A, 591, 1
Maxted P. F. L., 2018, A&A, 616, A39
Maxted P. F. L., Gill S., 2019, A&A, 622, A33
Nelson B., Davis W. D., 1972, Astrophys. J., 174, 617
Parviainen H., 2015, MNRAS, 450, 3233
Parviainen H., Aigrain S., 2015, MNRAS, 453, 3822
Pepper D. M., Etzel P. B., 1981, Astron. J., 86, 102
Southworth J., 2008, MNRAS, 386, 1644

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