The detection of transiting exoplanets by Gaia

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ABSTRACT

Context. The space telescope Gaia is mainly dedicated to performing high-precision astrometry but is also used to perform spectroscopy and epoch photometry, which can be used to study various types of photometric variability. One such variability type is exoplanetary transits. The photometric data accumulated so far have finally matured enough to allow the detection of some exoplanets.

Aims. In order to fully exploit the scientific potential of Gaia, we search its photometric data for the signatures of exoplanetary transits.

Methods. The search relies on a version of the box-fitting least-squares method, applied to a set of stars prioritized by machine-learning classification methods. An independent photometric validation was obtained using the public full-frame images of TESS. In order to validate the first two candidates, radial-velocity follow-up observations were performed using the spectrograph PEPSI of the Large Binocular Telescope.

Results. The radial-velocity measurements confirm that two of the candidates are indeed hot Jupiters. Thus, they are the first exoplanets detected by Gaia: Gaia-1b and Gaia-2b.

Conclusions. Gaia-1b and Gaia-2b demonstrate that the approach presented in this paper is indeed effective. This approach will be used to assemble a set of additional exoplanet candidates, to be released in the third Gaia data release, ensuring better fulfillment of the exoplanet detection potential of Gaia.

Key words. methods: data analysis – planets and satellites: detection – techniques: photometric – techniques: radial velocities

1. Introduction

Transit photometry is currently the most prolific method for detecting exoplanets, with more than 3000 discovered to date; space-based missions, such as Kepler (Borucki et al. 2010) and the Transiting Exoplanet Survey Satellite (TESS; Ricker et al. 2015), are most often used in this pursuit. These missions excel in detecting exoplanets thanks to their high-cadence, highly precise photometry and continuous sampling of large samples of stars. Nevertheless, there is still some chance that sparse low-cadence photometry, while far from being optimal for that purpose, would also be able to detect transiting exoplanets. In fact, the transits of two exoplanets that had been detected via radial velocities (RVs) – HD 209458b (Charbonneau et al. 2000) and HD 189733b (Bouchy et al. 2005) – were later found in the archived photometry of the first all-sky astrometric mission HIPPARCOS (Perryman et al. 1997). The HIPPARCOS photometric time series had fewer than 200 measurements each but still managed to sample the planetary transits (Robichon & Arenou 2000; Hébrard & Lecavelier Des Etangs 2006). These detections proved it was possible for such sparse and low-cadence observations to sample a meaningful number of transit events.

The current astrometric mission Gaia (Gaia Collaboration 2016) has already revolutionized astronomy with its high-precision astrometry for about 1.8 billion stars. On the other hand, similarly to HIPPARCOS, the photometry produced by Gaia is very sparse, with an irregular sampling scheme, which, as mentioned above, is suboptimal for detecting exoplanetary transits. Still, early on in its first two years of operation, Gaia did manage to capture some transits of previously known exoplanets, such as WASP 19b (Hebb et al. 2009) and WASP-98 b (Hellier et al. 2014). Dżigan & Zucker (2012) estimated that with 5 yr of Gaia photometry (which is more precise than that of HIPPARCOS) it should be possible to detect several hundred transiting Jovian exoplanets, as well as brown dwarfs (Holl et al. 2022).

As members of the Data Processing and Analysis Consortium (DPAC) of Gaia, we hereby present the approach taken by DPAC to exploit the potential of Gaia to detect transiting exoplanets. We have found 41 candidates and validated via RV follow-up observations the first two candidate planet host stars: Gaia EDR3 3026325426682637824 and Gaia EDR3 3026325426682637824

https://www.cosmos.esa.int/web/gaia/iow_20170209
Gaia EDR3 1107980654748582144, which we henceforth refer to as Gaia-1 and Gaia-2, respectively.

Section 2 describes the search procedure, including the validation by TESS photometry. Section 3 presents a detailed analysis of the two candidates that we validated with RV measurements. Finally, we conclude in Sect. 4 and put the results in the context of Gaia data releases.

2. Methods

Transit-finding algorithms, such as the box-fitting least-squares (BLS) algorithm (Kovács et al. 2002), have a typical time complexity of $O(N \cdot N_p)$, where $N$ is the number of points in the light curve and $N_p$ is the number of trial periods scanned. Gaia Early Data Release 3 (EDR3) is the result of analyzing the data of the first 34 months of Gaia operation, and scanning for periods in a range of $[0.5, 100]$ days would require about $O(10^4)$ trial periods. With 1.8 billion stars in the Gaia database, and a few dozen measurements for each star, applying the conventional search algorithms to all of them would be prohibitively time-consuming and impractical. Therefore, we decided not to perform an exhaustive transit search on all the observed stars, focusing instead on stars that passed an initial examination as part of a general classification step that used machine-learning methods to classify Gaia time series into variability classes (Sect. 2.3).

2.1. Gaia photometry

The light curves we scanned included the combined epoch photometry from all three photometric bands of Gaia – $G$, $G_{BP}$, and $G_{RP}$ – after independently subtracting their median magnitudes. We combined the three bands in an effort to increase the number of samples in each light curve, assuming the transit effect to be achromatic (to a first approximation) and therefore similar in all three bands. We searched for outliers based on their distance from the median magnitude, in terms of the standard deviation, $\sigma$, and excluded samples that were $2\sigma$ brighter or $5\sigma$ fainter than the median.

2.2. Training set

We compiled a training set consisting of Gaia light curves with noticeable transits of previously known exoplanets. We applied a dedicated version of the BLS algorithm we developed to the Gaia light curves of all known transiting exoplanets in order to find these transits. This version scans a restricted range in the parameter space of the three temporal transit parameters: period, mid-transit time, and duration. We followed a very similar approach in another study in which we used Gaia photometry to test for false positives in the TESS detections due to blends with background binaries (Panahi et al., in prep.). The scan only covered a range of $\pm 3\sigma$ for each transit parameter, as published in the NASA exoplanet archive (Akeson et al. 2013). At the end of each run, a set of preliminary transit parameters was obtained, along with a statistic we dub the transit signal-to-noise ratio ($SNR_T$):

$$SNR_T = \frac{d}{\sigma_{OOT}} \sqrt{N_{IT}},$$

where $d$ is the transit depth found by BLS, $\sigma_{OOT}$ is the standard deviation of the out-of-transit (OOT) measurements (as a proxy to the random variability of the whole light curve), and $N_{IT}$ is the number of in-transit (IT) points. We visually inspected the folded light curves of the stars that had $SNR_T > 6$ and selected the ones with a clear transit-like signal, resulting in 77 sources to be used as the training set.

2.3. Classification

A general supervised classification module was applied to all variability types (Rimoldini et al., in prep.); it included a generic computationally efficient period search method, the generalized Lomb-Scargle (GLS) method (Zechmeister & Kürster 2009), although it was not necessarily optimal for all classes. Given the weak signal of exoplanetary transits and the likely unreliable period GLS obtained for them, the classifier was designed to attempt an initial identification of this class from simple epoch photometry statistics in the three Gaia bands, without the important test of periodicity.

Consequently, the initial set of 77 training sources was further trimmed down to enhance the clarity of the signal and thus the chances of detection. For example, sources with negative $G$-band standardized skewness (in magnitude) were excluded, as noise fluctuations on the bright side of the time series were larger than the transit signal in those cases. Eventually, only 66 sources were used to train classifiers for exoplanetary transits, among a training set of almost 60 000 objects and 40 classes (before the selection of publishable classes).

Random forest (Breiman 2001) and eXtreme Gradient Boosting (XGBoost; Chen & Guestrin 2016) classification methods were used to model the training set with a list of attributes defined in Sect. 10.3.3 of Rimoldini et al. (2022). The XGBoost classifier was distinctively more effective than random forest in naturally identifying these rare training objects, and it was thus adopted for predicting exoplanetary transits. This resulted in a total number of 18 383 candidates.

2.4. Initial candidates

We applied to the 18 383 initial candidates a dedicated implementation of the BLS algorithm – SparseBLS (Panahi & Zucker 2021) – which we had developed especially for Gaia photometry. Unlike the BLS version that we used to compile the training set (Sect. 2.2), SparseBLS scans only an array of trial periods and estimates the mid-transit time and transit duration from the actual data timestamps, as opposed to a predetermined grid. SparseBLS is especially suitable for sparse light curves that contain hundreds of measurements or fewer, since the run time depends quadratically on the number of samples in the light curve.

We scanned with SparseBLS periods in the range $[0.5, 100]$ days, with a frequency step of $\Delta f = 10^{-5} \text{d}^{-1}$. This resulted in preliminary transit parameters, including period, time of mid-transit, and transit depth, along with other BLS statistics, such as the signal detection efficiency (SDE; Kovács et al. 2002; Alcock et al. 2000), which quantifies the prominence of the periodogram peak. Similarly to BLS, SparseBLS uses the signal residue (SR) score for its periodogram. The SR is the part of the sum of squared residuals in a least-square fit that depends on the attempted model. For this score, the SDE is simply defined as

$$SDE = \frac{\text{SR}_{\text{peak}} - \langle \text{SR} \rangle}{\text{sd}(\text{SR})},$$

where $\text{SR}_{\text{peak}}$ is the highest value of the periodogram, $\langle \text{SR} \rangle$ is the SR mean value, and sd(SR) is the standard deviation of the SR values in the periodogram.

\footnote{To be made public with Gaia Data Release 3 (DR3).}
In order to narrow down the list of final candidates, we applied the following cuts to the resulting parameters: (i) $SNR_T > 7.5$; (ii) SparseBLS SDE $>6$; and (iii) transit depth $<40$ mmag. The last criterion was an attempt to avoid cases of eclipsing binaries, or Jovian exoplanets around M dwarfs, which usually have depths greater than 40 mmag. Those cases should be detectable by other tasks that focus on eclipsing binaries. We visually inspected the remaining 130 candidates to look for clear transit-like features. We excluded 41 candidates that did not meet the following criteria: (i) the host star is a main-sequence star; (ii) the achromatic transit is seen in $G$ and $G_{RP}$; (iii) the transit is not V-shaped; (iv) there is no visible OOT variability; (v) there is no visible secondary eclipse; and (vi) there is no visible odd-even difference in TESS photometry.

2.5. Photometric validation

In order to photometrically validate the remaining 89 candidates, we searched for their light curves in the full-frame image (FFI) photometry of TESS. About half of them (48) were found more likely to be eclipsing binaries or exhibited no transit in the TESS data. Within the remaining 41 candidates (to be published in Gaia DR3, along with 173 known exoplanets with visible transits in the photometry of Gaia; (Eyer et al. 2022))\(^3\), we were able to find significant transit-like signals in the FFI data for 21 stars. For these 21 stars, we used the FFI data to refine the transit parameters we had calculated during the preparation of the initial candidate set.

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3. Confirmed planets

We selected two of our leading candidates for confirmation by RV follow-up observations. Figures 1 and 2 show the normalized and combined photometry of Gaia and TESS for these two candidates, Gaia-1 and Gaia-2, along with the best fitting models (Sect. 3.3), with 68% confidence intervals. We detrended the Gaia light curves using a simple linear fit. For the TESS light curves, we used the Python packages Lightkurve (Lightkurve Collaboration 2018) and tesscut (Brasseur et al. 2019) to acquire the TESS FFI photometry, and the flatten\(\circ\) method to detrend the raw data.

The combined light curve of Gaia-1 contains 117 Gaia measurements (in all three bands) and 952 TESS measurements. We note the slight dilution in the TESS light curve of Gaia-1. This may be due to the relatively large point spread function (PSF) of TESS\(^4\), where the dilution is caused by the blended light of nearby stars included in the PSF. Gaia-2 is much brighter than its close neighbors, and the blending effect is unnoticeable.

In the case of Gaia-2, we decided to exclude one measurement from the Gaia G band that resided, after phase folding, in the middle of the transit, with a normalized flux of $f_{\text{norm}} = 0.9965$. A closer look at this specific measurement reveals several indications of possible saturation. Furthermore, the $G_{RP}$ and $G_{BP}$ measurements, taken at almost the same time, do agree with the transit model. Therefore, and thanks to the validation by TESS photometry, we were confident that this point was

\(4\) In fact, the relevant size in TESS is the pixel response function. See Sect. 6 of the TESS Instrument Handbook.

\(5\) $t = 1841.3424606$ (BJD – 2455197.5), marked with a green square in the top panel of Fig. 2.
Table 1. Stellar parameter estimates for Gaia-1 and Gaia-2.

| Parameter Units | Value | Source |
|-----------------|-------|--------|
| **Gaia source ID** | 3026325426682637824 | **Gaia-1** |
| **Gaia source ID** | 1107980654748582144 | **Gaia-2** |
| **TIC ID** | 11755687 | **Gaia EDR3** |
| RA deg | 90.6436666838 ± 3.4 × 10^{-9} | **Gaia EDR3** |
| RA deg | 110.7353331726 ± 2.2 × 10^{-9} | **Gaia EDR3** |
| Dec deg | −0.5771154808 ± 3.0 × 10^{-9} | **Gaia EDR3** |
| G mag | 12.99192 ± 0.00055 | **Gaia** |
| G mag | 11.20014 ± 0.00043 | **Gaia** |
| G mag | 13.38862 ± 0.00051 | **Gaia** |
| G mag | 11.54127 ± 0.00026 | **Gaia** |
| G mag | 12.41065 ± 0.00051 | **Gaia** |
| G mag | 10.69055 ± 0.00028 | **Gaia** |
| G mag | 13.242 ± 0.092 | **TIC** |
| G mag | 11.277 ± 0.008 | **Gaia EDR3** |
| Parallax mas | 2.715 ± 0.015 | **Gaia EDR3** |
| Parallax mas | 4.826 ± 0.023 | **Gaia EDR3** |
| Teff K | 5470 ± 110 | **isochrones** |
| Teff K | 5720 ± 84 | **isochrones** |
| M_s M_⊙ | 0.949 ± 0.066 | **isochrones** |
| M_s M_⊙ | 1.000 ± 0.095 | **isochrones** |
| R_s R_⊙ | 0.952 ± 0.025 | **isochrones** |
| R_s R_⊙ | 1.064 ± 0.031 | **isochrones** |
| ρ S M^{-3} | 1558 ± 170 | **isochrones** |
| ρ S M^{-3} | 1170 ± 160 | **isochrones** |
| Teff K | 5370 ± 140 | **TIC** |
| Teff K | 5720 ± 130 | **TIC** |
| M_s M_⊙ | 0.93 ± 0.12 | **TIC** |
| M_s M_⊙ | 1.02 ± 0.13 | **TIC** |
| R_s R_⊙ | 0.962 ± 0.054 | **TIC** |
| R_s R_⊙ | 1.088 ± 0.053 | **TIC** |
| ρ S M^{-3} | 1480 ± 310 | **TIC** |
| ρ S M^{-3} | 1120 ± 220 | **TIC** |

The host stars Gaia-1 and Gaia-2 are listed in the TESS Input Catalog (TIC; Stassun et al. 2018) with mass and radius estimates. We also used Gaia data to estimate these values independently, using the Python package isochrones (Morton 2015). This tool uses stellar evolution models, which are based on the distance and observable magnitudes in multiple bands. We used the Gaia parallax and the three magnitudes (G, GBP, and GBP) and obtained similar estimates, as listed in Table 1.

Table 2. PEPSI RV measurements of Gaia-1 and Gaia-2, extracted with SPARTA.

| Time (BJD − 2455197.5) | RV_{Blue} (m s^{-1}) | RV_{Red} (m s^{-1}) |
|-------------------------|----------------------|---------------------|
| 4009.231299             | 159 ± 89             | 262 ± 55            |
| 4025.149340             | 52 ± 44              | 39 ± 32             |
| 4025.378759             | −111 ± 40            | −67 ± 30            |
| 4027.127925             | 273 ± 81             | 64 ± 51             |
| 4035.150587             | −200 ± 40            | −220 ± 30           |
| 4035.256314             | −243 ± 38            | −201 ± 29           |
| 4035.296691             | −181 ± 40            | −180 ± 29           |
| 4053.139787             | −243 ± 72            | −380 ± 45           |
| 4053.176891             | −257 ± 48            | −242 ± 33           |
| 4053.218314             | −296 ± 43            | −250 ± 30           |
| 4009.242638             | −111 ± 30            | −89 ± 26            |
| 4025.160356             | 55 ± 26              | 50 ± 14             |
| 4025.405016             | 90 ± 25              | 86 ± 14             |
| 4035.167108             | −67 ± 25             | −48 ± 14            |
| 4035.278306             | −2 ± 25              | −21 ± 14            |
| 4035.156642             | −144 ± 27            | −164 ± 14           |
| 4053.197203             | −147 ± 25            | −141 ± 14           |
| 4053.238726             | −140 ± 25            | −128 ± 14           |

Notes. Systemic velocities of the circular orbits were removed (see Table 4).

3.3. Analysis

We performed joint analyses, incorporating the Gaia and TESS photometry together with the RV data of the red and blue arms.
of PEPSI, which we treated as two different instruments, and using the Python package juliet (Espinoza et al. 2019). This package uses batman (Kreidberg 2015) to model the transit light curve and radvel (Fulton et al. 2018) to model the RV curve. It also uses several parametrization schemes that allow the parameter space to be sampled while maintaining the physical validity of the model. Espinoza (2018) and Kipping (2013) provide additional details of the sampling schemes and the parametrization. We used the dynamic nested sampling method (dynesty; Speagle 2020) to get parameter posterior estimates along with the Bayesian log evidence (lnZ) for each model, which is useful for comparing different models. According to Trotta (2008), a difference of $\Delta \ln Z < 1$ means the two models should be considered statistically indistinguishable, while $\Delta \ln Z > 5$ suggests strong evidence in favor of the model with the larger value of $\ln Z$. Besides selecting dynesty for the sampling method, all other parameters of the fit() method of juliet were left in their default values. Convergence is achieved when the program fails to improve its lnZ value by 0.5 in one complete iteration.

Given the relatively low number of RV measurements, we decided to assume a circular orbit and fix the eccentricity to zero, as expected for planets with such short periods (e.g., Wu 2003). We used similar priors for the various parameters as those used by Espinoza et al. (2020), which we detail in Table 3. We set all jitter terms, $\sigma_{\omega}$, and the flux offset terms, $M$, to zero since we used normalized light curves in this analysis. The mean values for the priors of the period and time of mid-transit were estimated based on the results of the preliminary analysis of the photometry.

The posterior medians and 68% confidence intervals of the system parameters resulting from the juliet analyses are detailed in Table 4, accompanied by corner plots (Foreman-Mackey 2016) for the main parameters in Figs. 3 and 4. We also used 68% confidence intervals for the RV models in Figs. 5 and 6. All two-dimensional histograms in the corner plots have four contour lines that represent levels of (0.5, 1.0, 1.5, 2.0) sigmas.

### 3.4. Gaia-1b

The RVs of Gaia-1 seem to closely trace a sine curve (Fig. 5), as expected for a circular Keplerian orbit. Based on the estimated stellar parameters, we estimate the mass and radius of the transiting object to be $M_p = 1.68 \pm 0.11M_J$, $R_p = 1.229 \pm 0.021R_J$, consistent with a possibly inflated hot Jupiter. For completeness, we tried to fit an eccentric orbit, but found no statistical evidence supporting an eccentric model ($\Delta \ln Z < 1$). When comparing to a model with no planet, we got a value of $\Delta \ln Z = 109$, which is strong evidence for the existence of Gaia-1b. The residuals in Fig. 1 show a possible systematic variation, suggesting some OOT variability, possibly due to a more massive companion. No such variability was observed in the photometry of TESS. Furthermore, the scatter does not seem to be consistent among the three bandpasses of Gaia photometry, and the joint RV and photometry analysis suggests a planetary companion. We therefore concluded there was no substantial evidence for this variability.

### Table 3. Prior distributions for the joint photometry and RV analysis of Gaia-1b and Gaia-2b.

| Parameter | Description | Units | Gaia-1b | Gaia-2b |
|-----------|-------------|-------|---------|---------|
| $P$       | Period      | days  | $N(3.052503, 0.01^2)$ | $N(3.691508, 0.01^2)$ |
| $T_0$     | Time of mid-transit | BJD - 2455197.5 | $N(3271.23705, 0.1^2)$ | $N(3646.43546, 0.1^2)$ |
| $K$       | Semi-amplitude of the radial velocity | m s$^{-1}$ | $U(0, 500)$ | $U(0, 500)$ |
| $e$       | Eccentricity | 0–fixed | 0–fixed; $U(0, 0.95)^{10}$ |
| $\omega$  | Argument of periastron | degrees | 0–fixed; $U(0, 3.60)^{10}$ |
| $\rho_*$  | Stellar mass mean density | kg m$^{-3}$ | $N(1558, 170^2)$ | $N(1173, 164^2)$ |
| $r_1, r_2$| Parametrization of $p, b^{(i)}$ | – | $U(0, 1)$ | $U(0, 1)$ |
| $q_1,Gaia$, $q_2,Gaia$ | Limb-darkening parametrization$^{10(i)}$ for Gaia | – | $U(0, 1)$ | $U(0, 1)$ |
| $D_{Gaia}$| Dilution factor for Gaia | 0–fixed | 0–fixed | $U(0, 1)$ |
| $q_1,TESS$, $q_2,TESS$ | Limb-darkening parametrization$^{10(i)}$ for TESS | 1–fixed | 1–fixed | $U(0, 1)$ |
| $D_{TESS}$| Dilution factor for TESS | – | $U(0.1, 1.0)$ | $U(0.1, 1.0)$ |
| $\gamma$ | Relative center-of-mass velocity for PEPSI$^{10(i)}$ | m s$^{-1}$ | $U(500, 500)$ | $U(500, 500)$ |

**Notes.** We denote uniform distributions between $a$ and $b$ as $U(a, b)$ and normal distributions with mean $\mu$ and variance $\sigma^2$ as $N(\mu, \sigma^2)$. $^{10}$ Separate analysis, allowing eccentricity. $^{10(i)}$ Described by Espinoza (2018); $p = R_p/R_s$ is the planetary to stellar radius ratio, and $b = (a/R_s)\cos i$ is the impact parameter. $^{10}$ Described by Kipping (2013). $^{10}$ Around a middle value of −37750 for Gaia-1b and −36000 for Gaia-2b.

**Fig. 3.** Gaia-1b: corner plot of the posterior distributions of the main system parameters, assuming circular orbit.
therefore performed an additional analysis allowing nonzero 
RV curve seems to suggest a potentially eccentric orbit. We 
mal (Fig. 6), especially around phase zero, and the phase-folded 
Gaia 

Table 4. Posterior estimates for Gaia-1b and Gaia-2b.

| Parameter | Units | Gaia-1b | Circular orbit | Gaia-2b | Eccentric orbit |
|-----------|-------|---------|----------------|---------|----------------|
| \( P \)  | days  | 3.052524 ± 1.7 \times 10^{-5} | 3.6915224 ± 3.9 \times 10^{-6} | 3.6915237 ± 3.5 \times 10^{-6} |
| \( T_0 \) | BJD - 2455197.5 | 3271.18524 ± 5.7 \times 10^{-4} | 3646.48875 ± 1.9 \times 10^{-4} | 3646.48731 ± 2.5 \times 10^{-4} |
| \( r_1 \)  | – | 0.773 ± 0.028 | 0.806 ± 0.015 | 0.816 ± 0.015 |
| \( r_2 \)  | – | 0.124 ± 0.0023 | 0.1277 ± 0.0013 | 0.1282 ± 0.0013 |
| \( q_1,\text{Gaia} \) | – | 0.24 ± 0.14 | 0.125 ± 0.125 | 0.138 ± 0.123 |
| \( q_2,\text{Gaia} \) | – | 0.42 ± 0.34 | 0.39 ± 0.33 | 0.43 ± 0.31 |
| \( q_1,\text{TESS} \) | – | 0.64 ± 0.30 | 0.67 ± 0.16 | 0.64 ± 0.18 |
| \( q_2,\text{TESS} \) | – | 0.36 ± 0.22 | 0.24 ± 0.13 | 0.20 ± 0.12 |
| \( D,\text{TESS} \) | – | 0.767 ± 0.036 | 0.966 ± 0.019 | 0.969 ± 0.018 |
| \( \rho, \) | kg m⁻³ | 1460 ± 160 | 848 ± 50 | 1080 ± 140 |
| \( \gamma, \text{Blue} \) | m s⁻¹ | -37675 ± 18 | -35994 ± 9 | -35999 ± 10 |
| \( \gamma, \text{Red} \) | m s⁻¹ | -37915 ± 14 | -35967 ± 6 | -35971 ± 6 |
| \( K \) | m s⁻¹ | 243 ± 16 | 1071 ± 6.2 | 108.0 ± 5.6 |
| Inclination | degrees | 85.73 ± 0.47 | 85.21 ± 0.25 | 85.66 ± 0.31 |
| \( a, \) (semi-major axis) | AU | 0.04047 ± 9.4 \times 10^{-4} | 0.0467 ± 0.0015 | 0.0467 ± 0.0015 |
| \( e \) | – | – | – | – |
| \( \omega \) | degrees | – | – | – |
| \( M_p \) | \( M_J \) | 1.68 ± 0.11 | 0.817 ± 0.047 | 0.773 ± 0.041 |
| \( R_p \) | \( R_J \) | 1.229 ± 0.021 | 1.322 ± 0.013 | 1.327 ± 0.014 |
| \( \ln Z \) | – | 5518.7 | 8237.3 | 8285.6 |
| \( \ln Z \) without a planet | – | 5409.6 | 8104.3 | – |

Fig. 4. Gaia-2b: corner plot of the posterior distribution of the main system parameters, assuming circular orbit.

3.5. Gaia-2b

The phase coverage of the Gaia-2 RV measurements is suboptimal (Fig. 6), especially around phase zero, and the phase-folded RV curve seems to suggest a potentially eccentric orbit. We therefore performed an additional analysis allowing nonzero eccentricity, with a uniform prior distribution \( \mathcal{U}(0, 0.95) \), resulting in an estimate for the eccentricity of \( e = 0.346 ± 0.023 \) with \( \Delta \ln Z = 48 \) over the circular orbit. The RVs with the eccentric model are shown in Fig. 7, and the posterior distributions and estimates for the main orbital parameters are given in Fig. 8 and
Table 4. Despite the strong statistical evidence, such an eccentric orbit would be very surprising given the proximity of the planet to its host star. We therefore attempted to also fit a circular orbit with a constant slope in the RV curve, using a uniform prior distribution $\mathcal{U}(-300, 300) \text{ m s}^{-1} \text{ d}^{-1}$, which resulted in an estimate for the RV slope of $R_{\text{slope}} = -2.9 \pm 0.39 \text{ m s}^{-1} \text{ d}^{-1}$ with $\Delta \ln Z = 18$ over the no-slope, circular model. Statistically, the eccentric orbit seems to be preferable, but given the small number of measurements and their uncertainties, we decided to keep the more plausible circular orbit and wait for future RV measurements to better constrain this system.

We thus estimate the mass and radius of the transiting object to be $M_p = 0.817 \pm 0.047 M_J$, $R_p = 1.322 \pm 0.013 R_J$, which is also consistent with a potentially inflated hot Jupiter. When comparing to a model with no planet, we got a value of $\Delta \ln Z = 133$, strong evidence for the existence of Gaia-2b.

4. Conclusions

In this paper we have described the method used by DPAC to find the first batch of transiting exoplanet candidates based on Gaia photometry. For the first batch of candidates, we aimed at detecting the easiest cases, namely hot Jupiters – giant planets that orbit their stars in short periods of a few days at most. Transiting hot Jupiters are relatively easy to detect because they exhibit relatively deep transits and the transit duty cycles are large. For the reasons mentioned in Sect. 2, the presented search does not pretend to be exhaustive, and it does not come close to exploiting the full detection capability of Gaia. We therefore do not attempt to estimate the completeness of this search, since its statistical value is limited at this early stage.

However, even at this point it is clear that the circumstances of the future data releases (DR4 and DR5) will allow more detections of transiting exoplanets. First, the training set used to train the classifier will be based on more data, leading to a better selection of initial candidates. More importantly, since the number of measurements in each light curve will be larger, Gaia photometry is bound to capture more transits, thus significantly enhancing the ability of the BLS approach to identify them. Given the longer observation time baseline and the larger number of observations, one can predict that DR4 and DR5 will include larger sets of candidates, possibly also covering a wider range of orbital periods.
The confirmation of the two planets Gaia-1b and Gaia-2b serves to validate the presented search methodology. For Gaia-2b, we could not rule out a more eccentric orbit, or an additional massive object that induces an RV slope, due to insufficient phase coverage, but this will probably be resolved by future RV measurements. Even without a detectable RV slope, an eccentric orbit can potentially still be the result of the presence of a third massive object in the system, which would induce a nonzero eccentricity of the planet (Mazeh & Shaham 1979). In any case, even when allowing for eccentricity or an RV slope in our fits, the estimated mass of the transiting object is always less than 1.5 $M_J$, well within the planetary regime.

The capability of Gaia to photometrically detect transiting exoplanets has often been questioned. Nevertheless, recognizing its potential, several authors have tried to estimate Gaia yields of transiting exoplanets (Hog 2002; Robichon 2002; Dzigan & Zucker 2012) based on assumptions concerning Galactic models, planet frequency, and Gaia photometric performance. The Gaia mission has been given indicative approval for an extension through the end of 20256, which will likely significantly increase its detection potential. TESS is currently performing its own all-sky survey for transiting exoplanets, but its mode of operation focuses on short-period transits. Gaia is monitoring a larger sample of stars than TESS, and with the longer observing time span it can potentially detect long-period planets. Thus, having established that it can detect planetary transits, Gaia will complement the capabilities of TESS.

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