The Completeness of Accreting Neutron Star Binary Candidates from the Chinese Space Station Telescope (Postprint)

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Abstract

Neutron stars (NS) have many extreme physical conditions, and one may obtain some important information about an NS via accreting neutron star binary (ANSB) systems. The upcoming Chinese Space Station Telescope (CSST) provides an opportunity to search for a large sample of ANSB candidates. Our goal is to check the completeness of the potential ANSB samples from CSST data. In this paper, we generate some ANSBs and normal binaries under the CSST photometric system by binary evolution and binary population synthesis method and use a machine learning method to train a classification model. Although the Precision (94.56%) of our machine learning model is as high as in previous studies, the Recall is only about 63.29%. The Precision/Recall is mainly determined by the mass transfer rate between the NSs and their companions. In addition, we also find that the completeness of ANSB samples from CSST photometric data by the machine learning method also depends on the companion mass and the age of the system. ANSB candidates with a low initial mass companion star (0.1 M to 1 M) have a relatively high Precision (94.94%) and high Recall (86.32%), whereas ANSB candidates with a higher initial mass companion star (1.1 M to 3 M) have similar Precision (93.88%) and quite low Recall (42.67%). Our results indicate that although the machine learning method may obtain a relatively pure sample of ANSBs, a completeness correction is necessary for one to obtain a complete sample.

Full Text

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Key words: stars: neutron – X-rays: binaries – methods: analytical

1. Introduction

The concept of a "neutron star" (NS) was proposed by Lev Davidovich Landau in 1932, but it was not until 1967 that Antony Hewish and Jocelyn Bell Burnell detected the first known NS (also a pulsar, Hewish et al. 1968). Because a NS possesses many extreme physical parameters, it serves as a unique laboratory that allows us to study the properties of dense matter. Several decades later, many breakthroughs in physics and astronomy have been achieved related to NSs, especially the first gravitational wave detection from the merging of two NSs (i.e., GW170817), which represents an "unprecedented joint gravitational and electromagnetic observation" and "marks the beginning of a new era of discovery" (Abbott et al. 2017).

However, some crucial information about NSs, such as their structure, equation of state, birth environment, and progenitor, remains vague (Lattimer 2012; Özel 2013; Smartt 2015). Accreting neutron star binaries (ANSBs) are a special class of binary systems where NSs accrete material from their normal companion stars through Roche lobe overflow (RLOF) or stellar wind accretion (Frank et al. 2002). The accreted material may form a disk around the NS and emit X-rays from the release of gravitational potential energy. Such binaries are called "X-ray binaries." Depending on the mass of companion stars, ANSBs are classified into three categories: low-mass X-ray binaries (LMXBs, companion star mass below 1 M), intermediate-mass X-ray binaries (IMXBs, companion star mass between 1 M and 10 M), and high-mass X-ray binaries (HMXBs, companion star mass higher than 10 M) (Degenaar & Suleimanov 2018). Some ANSBs are persistent X-ray sources, while others are transient X-ray sources (Degenaar et al. 2018).

As X-ray sources, ANSBs also emanate near-ultraviolet (NUV)/optical radiation with several different physical origins: thermal radiation from the accretion disk (Shakura & Sunyaev 1973; van Paradijs & McClintock 1995; Frank et al. 2002), X-ray reprocessing (Cunningham 1976; van Paradijs & McClintock 1994; Russell et al. 2006), interaction between the relativistic stellar wind of an NS and inflowing matter (Campana & Stella 2000), synchrotron radiation in the jet (Corbel & Fender 2002; Homan et al. 2005; Russell et al. 2006) and in the hot accretion flow (Veledina et al. 2012), and radiation from the companion star itself. In this paper, we mainly investigate the contributions from the accretion disk, X-ray reprocessing, and the companion star. We will consider other mechanisms step by step to complete our model in the future.

ANSBs play an important role in the theory of binary evolution and the formation of millisecond pulsars (MSPs). According to the recycling scenario, a slowly rotating NS in a binary system that obtains angular momentum by accreting material from its companion star can become an MSP (see Bhattacharya & van den Heuvel 1991 for a review). During the accretion phase, the ANSB manifests itself as an X-ray source, while the binary hosts a radio MSP after mass transfer stops. The discovery of coherent pulsations in the transient LMXB SAX J1808.4-3658 (Wijnands & van der Klis 1998) and transitional MSPs strongly supports the recycling scenario (Archibald et al. 2009; Papitto et al. 2013; Bassa et al. 2014). Therefore, ANSBs may provide key information on the formation of MSPs and binary evolution (e.g., Patterson 1984; Baillot d'Etivaux et al. 2019). However, the present small sample of ANSBs limits their role in providing sufficient information (e.g., Ritter & Kolb 2003; Liu et al. 2007; Avakyan et al. 2023). A complete sample of ANSBs is very important for constraining the formation of MSPs. The upcoming Chinese Space Station Telescope (CSST) could provide an opportunity to build such a sample. CSST is a 2 m space telescope planned for launch in a few years. The survey from CSST has seven photometric imaging bands covering 255–1000 nm, with a large field of view of 1 deg^2 and high spatial resolution of 0.15 (Cao et al. 2018; Gong et al. 2019).

In a previous related work, Lan et al. (2022) compiled ANSBs and normal binary stars to investigate whether machine learning can efficiently search for ANSB candidates under the CSST photometric system. Their classification results indicated that machine learning can efficiently select ANSB candidates from the background of normal stars. However, the ANSBs in their model were obtained through binary evolution simulations, and the parameter space of these ANSBs may not cover the entire range. They also did not check the completeness of ANSBs in CSST data. In this work, we extend the parameter space of the generated ANSBs to check the completeness of ANSBs obtained from CSST photometric data and to determine which ANSB parameters mainly affect the completeness of the sample. The paper is organized as follows: In Section 2, we describe our methods. We present the machine learning classification results in Section 3. Discussions and conclusions are given in Sections 4 and 5, respectively.

2. Method

The main aim of this paper is to check Precision and Recall from CSST photometric data using a machine learning method. Several basic methods are similar to those in Lan et al. (2022). For example, following Lan et al. (2022), we assume that the observed optical emission from an ANSB system is mainly contributed by its accretion disk and companion star. While Lan et al. (2022) only considered main sequence stars as companions, this paper also includes red giant branch (RGB) and asymptotic giant branch (AGB) stars. The details of our method follow.

We used binary population synthesis to generate background stars ranging in age from 1 Myr to 14 Gyr, with initial masses ranging from 0.5 M to 10 M and solar metallicity, in which all systems are evolving binaries, based on Hurley's rapid binary evolution code (Hurley et al. 2000, 2002). The basic assumptions for the binary population synthesis are similar to those in Meng et al. (2009) and Meng & Podsiadlowski (2017).

We generate ANSB samples in our model by setting several independent variables (the mass of the NS, the initial mass and age of the companion star, and the mass transfer rate). We assume that the NS in an ANSB system is a point mass, i.e., we neglect radiation from the surface of the NS and the spin of the NS. We generate NSs with masses ranging from 1.4 M to 2 M using a Monte Carlo method. We focus on cases where the companions fill their Roche lobes, i.e., we focus on LMXBs and IMXBs, since HMXBs are mainly formed through wind accretion (Frank et al. 2002). Because there is a rough boundary of 3 M for the properties of X-ray binary systems (Zhang et al. 2023), based on models from Ge et al. (2010, 2015), the companions in the ANSBs are generated with discrete initial masses ranging from 0.1 M to 3 M , with ages evenly distributed throughout their lifetimes. The mass transfer rates are also randomly generated, with the lower limit set to be much lower than that from wind accretion, while the upper limit is set to the typical thermal timescale mass transfer rate (Ge et al. 2010). Considering that the companions are filling their Roche lobes, we set the binary separation a following the equation in Eggleton (1983), where R_2 is the radius of the companion star. The orbital inclination has a great influence on the observed optical flux from the accretion disk (see Frank et al. 2002), and we set as randomly distributed between 0° and 90°.

The other methods used to obtain the total magnitudes of ANSBs, including the systematic error of the CSST photometric system, are the same as those in Lan et al. (2022). In particular, the radiation from the disk includes contributions from both the multi-color disk and the irradiated accretion disk, as in Lan et al. (2022). We also use the same machine learning process as in Lan et al. (2022) to compare our results with theirs.

In Figure 1 [Figure 1: see original paper], we show all the ANSBs we generated (colored dots) in the color–magnitude diagram (CMD), where different colors represent different initial masses of companion stars. For comparison, single stars with different masses and an age of 1 Gyr are also shown. The ANSBs cover a large range in the CMD because the systems have different NS masses, companion masses, ages, and mass transfer rates. The positions of ANSBs in the CMD are strongly dependent on mass transfer rates. For a given companion, ANSBs with higher mass transfer rates appear brighter and bluer, while ANSBs with lower mass transfer rates are located close to normal single stars in the CMD, as depicted by the discrete curves for low-mass stars. In Figure 1, there is a clear upper boundary for the brightness of ANSBs, which results from our treatment that there is an upper limit of the mass transfer rate of 10^{-6} M yr^{-1}.

3. Results

There are several metrics for classification results in machine learning. Among them, Precision represents the proportion of examples classified as positive cases that are actually positive, while Recall represents the proportion of all positive cases that are correctly classified and measures the model's ability to recognize positive cases. Recall may represent the completeness of ANSBs identified from observational data. Here, True Positive (TP) means a positive example that is correctly predicted, i.e., the true value of the data is positive and the predicted value is also positive. True Negative (TN) means a negative example that is correctly predicted. False Positive (FP) means a negative example that is incorrectly predicted. False Negative (FN) means a positive example that is incorrectly predicted.

For the whole machine learning sample, the Precision is 94.56%, similar to that in Lan et al. (2022). In other words, almost all of the ANSB candidates identified from the CSST photometric data may be real ANSBs. However, the Recall is only 63.29%, which means that many ANSBs may be missed by the machine learning method. As is well known, there is a competition between Precision and Recall for a machine learning model, in which a key threshold between 0 and 1 is designed to balance this trade-off. In our model, the threshold is set to 0.5. We performed a test with a threshold of 0.3 and found that Precision decreased to 89.42% and Recall increased to 66.67%, as expected. Table 1 shows the classification results of our model.

As we can see in Figure 1, whether an ANSB is recognized by the machine learning method could be mainly determined by the mass transfer rate between the NS and its companion. In Figure 2 [Figure 2: see original paper], we show the Precision and Recall of ANSBs as a function of mass transfer rate, where other parameters are randomly distributed within the range of values we set. For ANSBs with a given companion star, the higher the mass transfer rate, the higher the Precision and Recall. In the upper panel of Figure 2, we show the Precision and Recall of ANSB systems with companion stars of 1 M as a function of mass transfer rate. For ANSB systems with 1 M companion stars, our model cannot identify samples with mass transfer rates less than $10^{-9} M_{\odot}\mathrm{yr}^{-1}$. While our model is very good at identifying samples with mass transfer rates higher than $10^{-8} M_{\odot}\mathrm{yr}^{-1}$, these samples have Precision and Recall close to 1. For comparison, we show in the lower panel of Figure 2 the Precision and Recall of ANSB systems with 3 M companion stars as a function of mass transfer rate. Our model cannot efficiently identify samples with mass transfer rates less than $10^{-8}M_{\odot}\mathrm{yr}^{-1}$. Samples with mass transfer rates higher than $10^{-7}M_{\odot}\mathrm{yr}^{-1}$ can be well identified, but about one fifth of their completeness is missing. In other words, for a given companion, Precision/Recall reaches an almost constant value when the mass transfer rate is high enough. This results from the fact that when the mass transfer rate is sufficiently high, the radiation from the accretion disk of an ANSB dominates the observable optical flux, i.e., the radiation from the companion star is negligible compared to that from the accretion disk. These results indicate that the CSST photometric system could be sensitive to those ANSBs with thermal-timescale mass transfer.

As affirmed in Figure 2, our model can easily identify ANSB systems with high mass transfer rates, but the completeness is affected by the initial masses of companion stars. In Figure 3 [Figure 3: see original paper], we show the Precision and Recall of ANSBs as a function of the initial mass of the companion star, where other parameters are randomly distributed within the range of values we set. Throughout the entire interval of companion mass, the Precision remains almost constant at about 94%, with a slightly higher value for stars less massive than 1 M compared to more massive stars. As discussed by Lan et al. (2022), the high Precision derives from the fact that the flux of a normal binary is roughly the superposition of two blackbody spectra, whereas the flux from our ANSB model is roughly the superposition of an accretion disk spectrum and a blackbody spectrum. This huge flux difference determines the high Precision. Moreover, a more massive companion star makes its spectrum more similar to that of an accretion disk, as shown in Lan et al. (2022), which results in a slight decrease in Precision with companion mass. However, Recall is highly dependent on companion mass. For cases with companions less massive than 1 M , Recall is significantly higher than for cases with companions more massive than 1 M (86.32% versus 42.67%). In particular, Recall decreases with increasing companion mass for cases with companions more massive than 0.71 M . This occurs because the greater the initial mass of a companion star, the brighter the companion star becomes, and the flux from the companion star may dominate over the flux from the accretion disk.

The age of an ANSB, which is determined by the companion star age, could also affect Precision and/or Recall. The upper panel of Figure 4 [Figure 4: see original paper] presents Precision and Recall of ANSBs as a function of the ANSB system age, where their companion stars have the same initial mass (1 M) and other parameters are randomly distributed within the range of values we set. For the entire evolutionary stage, we obtain an overall result of Precision = 97.32% and Recall = 70.95%. For different ages of ANSB systems, Precision is maintained at a high value (>95%) with small fluctuations. This is because the radiation of a normal binary system comes from two blackbodies, while the radiation of an ANSB system comes from a blackbody and an accretion disk. Recall remains in the range of about 0.7–0.75 for 95% of the time and drops below 0.7 in the last 5% of the time when the companion star is in the main sequence stage and Hertzsprung gap, resulting in minimal changes in brightness and color (see lower panel).

The age of a star heavily depends on its initial mass, so we must consider the influence of initial mass. Similar to Figure 4, the upper panel of Figure 5 [Figure 5: see original paper] illustrates Precision and Recall of ANSBs as a function of age, while their companion stars have an initial mass of 3 M . For the entire evolutionary stage, we obtain an overall result of Precision = 83.58% and Recall = 41.47%. Precision initially fluctuates in the range of 0.7–0.8 (from age 0 to age 70), then stabilizes close to a value of 1 (from age 70 to age 100). This behavior is attributed to the high surface temperature of a star with an initial mass of 3 M during its main sequence stage (age 0 to age 70, see lower panel), because ANSB systems with high-temperature companion stars are relatively easily identified as hot background stars. However, Recall rises first and then stays around 0.5. This occurs because from age 0 to age 65, as the surface temperature of the companion star decreases, the radiation from the ANSB system can exhibit both components from the accretion disk and the companion star, rather than just a single hot component. From age 65 to age 70, the brightness of the companion star increases, and the radiation from the companion star may partially cover the radiation from the accretion disk, leading to a decrease in Recall, i.e., the systems may be easily identified as single stars by our machine learning model. Eventually, from age 70 to age 100, the companion star becomes a giant, and Recall remains stable.

4. Discussion

In this paper, we examine how the completeness of potential ANSB candidates from future CSST photometric data depends on the properties of ANSBs, investigating three parameters: mass transfer rates, initial masses, and the ages of companions.

First, we find that the mass transfer rate has a decisive effect on the recognition results of our model. For ANSB systems with low mass transfer rates, our model is almost unable to identify them. For ANSB systems with sufficiently high mass transfer rates, our model can identify them well, and the recognition results achieve both high Precision and high Recall. This means that there is a high probability that X-ray emission can be observed in the ANSB systems identified by our model. Mass transfer rate is the dominant parameter that affects Recall from a machine learning method because this value directly determines the flux from the accretion disk in an ANSB system (Lan et al. 2022). However, the initial mass of the companion star also impacts the identification results. A higher mass transfer rate "threshold" is required to produce good identification results when the initial mass of the companion star is larger. Conversely, a lower upper limit of Recall is associated with a greater initial mass of the companion star. These results indicate that the CSST photometric system could be quite sensitive to ANSB systems in which mass transfer occurs on a thermal timescale.

In addition, we find that the initial mass of the companion star has little effect on Precision but a significant effect on Recall. For different initial masses of companion stars, Precision remains almost constant (94%). As discussed by Lan et al. (2022), the high Precision is due to the fact that the flux from a normal binary star is the superposition of two blackbody spectra, while the flux from an ANSB is the superposition of an accretion disk spectrum and a blackbody spectrum. However, the initial mass of the companion star significantly affects Recall because the initial mass determines the brightness of the companion star, which affects the flux contribution from the companion star in an ANSB system. Considering the effect of the mass transfer rate, the systems identified from the CSST photometric system are more likely to be LMXBs, which could be observed by X-ray observations.

Finally, we should point out that the ANSBs in our model are produced based on some simple assumptions. For example, we only consider the radiation from the accretion disk and the companion star, while the corona of the NS and the heating of the companion star are ignored (e.g., Harlaftis et al. 1997; Markoff et al. 2005; Romani & Sanchez 2016). Some physical processes that we neglected could become important in special ANSBs, such as jets (Russell et al. 2006, 2007). We also do not consider the effect of emission lines from the disk, which could affect the accuracy of the classification model (a double-peaked Hα emission line perhaps supports the existence of an accretion disk, Wang et al. 2009). In the future, we will add these effects step by step. Perhaps the slitless spectroscopy module of CSST might be helpful to improve our model.

We also explored the effect of the companion star age on Precision and Recall, finding that the more massive the companion, the more significant the effect of age on Precision and/or Recall. This is because the higher the initial mass of the companion star, the greater its luminosity.

5. Conclusions

In this paper, we produced ANSBs and background stars to investigate whether the completeness of ANSB candidates in CSST data depends on the properties of the potential ANSB systems. We obtain overall results of Precision = 94.56% and Recall = 63.29%. We find that the mass transfer rate has a decisive influence on the identification results of our model. For ANSB systems with high mass transfer rates, our model is able to obtain good identification results (high Precision and high Recall). The initial mass and age of the companion star also impact the identification results. Our results indicate that ANSB systems with less massive companions and thermal-timescale mass transfer rates are more likely to be identified by the CSST photometric system and would have better completeness.

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Note: Figure translations are in progress. See original paper for figures.