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ZTF IC 10 periodic variables and non-periodic variables catalog

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ABSTRACT

Transient studies on nearby starburst galaxy IC 10 can tell us how massive stars affect their environments. Identifying transients in IC 10 will guide us on which particular sources to closely look at. We choose to use time-series data from The Zwicky Transient Facility (ZTF) which has been observing IC 10 region for a few years. A novel methodology is purposed to examine the lightcurves in ZTF R and G band and pick up both periodic variables and non-periodic variables. A catalog of periodic variables and non-periodic variables in IC 10 is presented.

1. INTRODUCTION

A nearby galaxy called IC 10 is made of a large and diverse collection of massive stars, such as Luminous Blue Variables, Wolf-Rayet stars, High-Mass X-ray binaries. Studying the transients in IC 10 will help revealing how massive stars affect their environments.

In this work, Zwicky Transient Facility (ZTF) R band and G band data will be used to identify optical transients. Many work has been done to identify transients using ZTF data. Chen et al. (2020) published a ZTF catalog of periodic variable stars, discovering 781,602 periodic variables with 11 class labels; Cheung et al. (2021) further proposed a new model to better classify these periodic variables in Chen's catalog using a convolutional variational autoencoder and hierarchical random forest. However, in Chen's catalog, only one periodic variable star falls in the field of IC 10. Obviously, there should be more than only one interesting sources inside IC 10, therefore here we closely examine all ZTF sources within the IC 10 region to come up with a finer collection of periodic variable stars, as well as non-periodic variables.

Our methodology can be summarized in a flowchart (Figure 1). Instead of dump all sources straight into Lomb-Scargle analysis, we introduce a simple but effective way to pick out variable sources before touching their periodicity. This extra step enables us to get lists of both periodic variables and non-periodic variables, and makes the followup Lomb-Scargle and de-aliasing process much neater. Besides, we also included lightcurve shape indicators and machine learning powered classification to help locking on interesting sources.

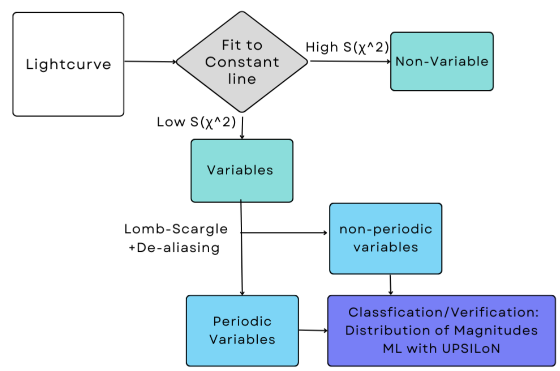

Figure 1. Visualization of our methodology

2. DATA

The Zwicky Transient Facility (ZTF) (Masci et al. 2018) is transient survey that is build on the legacy of the Palomar Transient Factory (PTF). ZTF has been observing IC 10 region almost every night during the past few years, making it a perfect dataset to work on. Here we use the ZTF DR 11 data in G band and R band, since they are two most sensitive ZTF bands. ZTF's G (green) band has a filter central wavelength of 4803 Å and FWHM of 1321 Å, ZTF's R (red) band has a filter central wavelength of 6434 Å and FWHM of 1557 Å. We do a radial query of 225″ around the center of IC 10 ($RA = 00:20:23.16,\ DEC = +59:17:34.7$ (Cotton et al. 1999)) to cover the optical size of IC 10 (Huchra et al. 1999). 2407 and 1334 ZTF labeled lightcurves are found in R and G band, respectively. These lightcurves are further grouped as the same source if their radial distance is smaller than 1″, to account for the fact that ZTF often have multiple labels for one same source. In cases of a grouped source with multiple ZTF labels, all labels goes through our variability analysis, but only the ZTF label with highest number of observations can qualify a source to be labeled as periodic variable or non-periodic variable. In addition, only clear observations without any flags are used in this work.

3. METHODOLOGY

3.1. *Variables with $S_k(\chi^2)$*

A source without any variability ideally gives a lightcurve of constant magnitude over time. By fitting the lightcurve with a line of constant value and look at how good the fit is, we can very effectively separate possible variable sources from non-variable sources. For a lightcurve with n observations of magnitudes m_i and errors in magnitude σ_i , the chi-square χ^2 of the best fitting constant magnitude m_C is

$$\chi^2 = \sum_{i=1}^{n} \frac{(m_i - m_C)^2}{\sigma_i^2} \tag{1}$$

We further measure the probability that an observed lightcurve matches the constant line model via survival function $S_k(\chi^2)$, the chance that a constant line fit "survives",

$$S_k(\chi^2) = 1 - F_k(\chi^2) \tag{2}$$

$F_k(\chi^2)$ is the cumulative density function (CDF) of a chi-squared distribution with degree of freedom k, and here $k = n - 1$. We define variable sources to be sources with 99% or higher chance being variable, that is, sources with $S_k(\chi^2)$ less than $1/(100 \times$ total number of lightcurves in each band). The rest are classified as non-variable sources. Note that the "variable sources" defined here simply means the lightcurve does not match a constant line, which could due to the source is intrinsically variable, but also could due to many other factors including unexpected noises, and limitations of specific observations. The distribution of $S_k(\chi^2)$ and its cutoff can be visualized in Figure 2.

3.2. *Periodic variables with Lomb-Scargle*

Three Lomb–Scargle periodogram based criteria are used to determine if a variable source is probable to be a real periodic variable: FAP, Q_P, and Q_T. Their definitions and cutoffs are briefly summarized in Table 1. The details are presented in subsections below.

3.2.1. *FAP*

FAP, false alarm probability, is a quantity that is very widely used to look for periodic variables. FAP originates from the Lomb-Scargle periodogram, a commonly used tool to characterize periodic signals in unevenly spaced observations named after Lomb (1976) and Scargle (1982). A periodogram calculates the power on a frequency/period grid, and FAP gives the probability of measuring a peak at certain or higher power assuming Gaussian noise and non-periodic data. A smaller FAP hints that the sources is more likely to be periodic.

Here we use Python package *Astropy* (Astropy Collaboration et al. 2013; Price-Whelan et al. 2018) to calculate the Lomb-Scargle periodogram, and then *Astropy* further approximates the false alarm probabilities at Lomb-Scargle periodogram peak following Baluev (2008). The distribution of FAP in R and G band is shown in Figure 3. To get sources with 99% or higher probability of having a non-false alarm, we set FAP cutoffs at $1/(100 \times$ total number of lightcurves in each band). Specifically, we keep R band sources with FAP $< 4.15 \times 10^{-6}$ and G band sources with FAP $< 7.36 \times 10^{-6}$ as "low FAP" sources. Although FAP is one of the most effective criteria to detect periodic signals, it is vulnerable to aliasing. The nightly/quarter/yearly observation window pattern can create fake peaks and contaminate the real peak on the periodogram. The following two criteria are mainly devoted to the de-aliasing of low FAP sources.

3.2.2. Q_P

Q_P is the ratio of powers, P_{LS}/P_{window}, where P_{LS} is the Lomb-Scargle periodogram peak power, and P_{window} is the window function power. Window function refers to recalculating the Lomb-Scargle periodogram of a lightcurve by changing all magnitude to a constant value while keeping observation window the same. Window function power is the power at the period of the original Lomb-Scargle periodogram peak. $Q_P > 1$ indicates the period or frequency we found is more significant in the lightcurve of interest than in a straight line given same spacing in observations. An intrinsically non-periodic source could have a low FAP due to aliasing, but it not likely to have a $Q_P > 1$. Therefore such a cut will help removing aliasing. The distribution of Q_P for low FAP sources in both bands is shown in Figure 4.

3.2.3. C_T

C_T is the relative change in periods, $|T_{LS} - T_{window}|/T_{window}$, where T_{LS} is the period at Lomb-Scargle periodogram peak power, T_{window} is the period at window function peak power. C_T tells how close the period we found is to the aliasing period. We thus rule out sources with $C_T < 0.01$, i.e. period and aliasing period only differ by 1%. As Figure 5 shows, there is a suspicious spike between $C_T = 0.5$ and 1 in both bands. Due to the fact that ZTF make observations on a daily basis, most of sources have window function period $T_{window} = 1$ *day*. Aliases reappears following $\frac{1}{T_{\rm alias}} = \frac{1}{T_{\rm true}} + \frac{n}{T_{\rm window}}$ for integer values of n. In cases with no true period ($T_{\rm true} \to \infty$) and $T_{\rm window} = 1$ *day*,

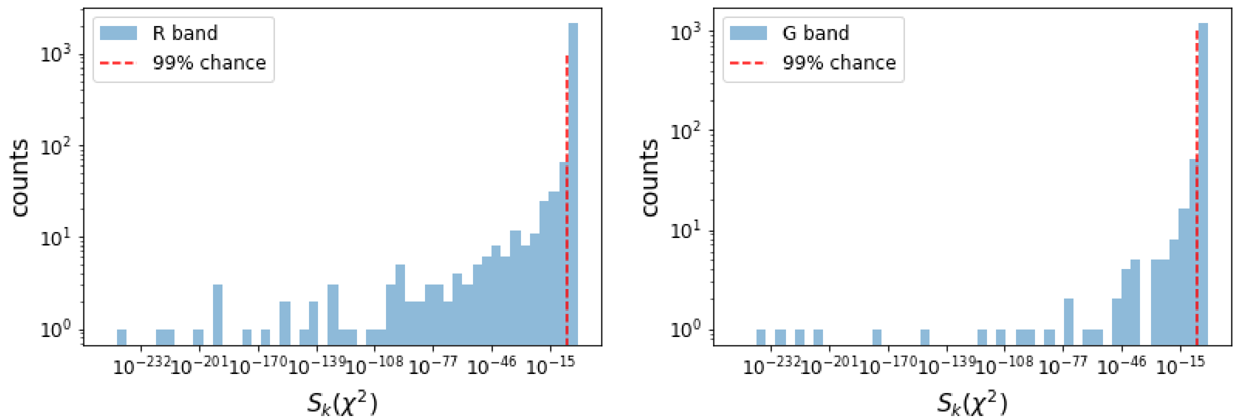

Figure 2. Distribution of $S_k(\chi^2)$ for all sources in ZTF R and G band. Sources left to the red dotted line has 99% or more chance to be variable.

	Definition	Cutoff in R band	Cutoff in G band
FAP	False alarm probability from Lomb-Scargle	FAP $< 4.15 \times 10^{-6}$	FAP $< 7.36 \times 10^{-6}$
Q_P	$P_{\rm LS}/P_{\rm window}$	$Q_P > 1$	$Q_P > 1$
C_T	$\lvert T_{\rm LS} - T_{\rm window}\rvert / T_{\rm window}$	$C_T > 0.01$	$C_T > 0.01$
		$C_T < 0.49,\ C_T > 0.91$	$C_T < 0.49,\ C_T > 0.91$

Table 1. Periodic variable criteria

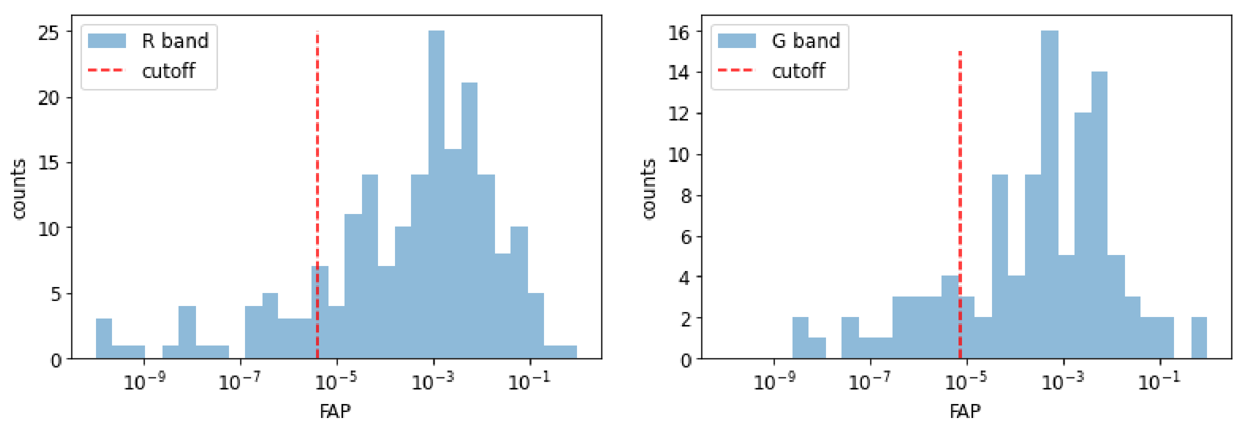

Figure 3. Distribution of FAP for periodic variable suspects in ZTF R and G band. We keep sources left to the red dotted line as low FAP sources.

we get $T_{\rm alias} = 1, 1/2, 1/3, 1/4, ...$ These aliasing period will return $C_T = 1/2, 2/3, 3/4, ...$, exactly where the spike is located. To resolve such aliasing, we rule out sources with $0.49 < C_T < 0.91$, accounting n up to 10, since higher n will have very weak aliasing effect. To prevent removing real periodic sources with periods lower than 0.5 days, we preserve sources that has extremely low FAP (FAP $< 10^{-30}$). Finally, only sources with more than 50 clear observations will be included in the final catalog.

3.3. *Extra classification and verification*

3.3.1. *Distribution of magnitudes*

Periodic variables and non-periodic variables can be variable in very different ways: periodic sines, periodic eclipsing dips, sudden flares, step-wise change of magnitudes... Although looking at the lightcurves directly is probably the most intuitive and accurate way to figure out where the variability comes from, it would be unrealistic to manually check all the lightcurves. Instead, the shape of the distribution of magnitudes for

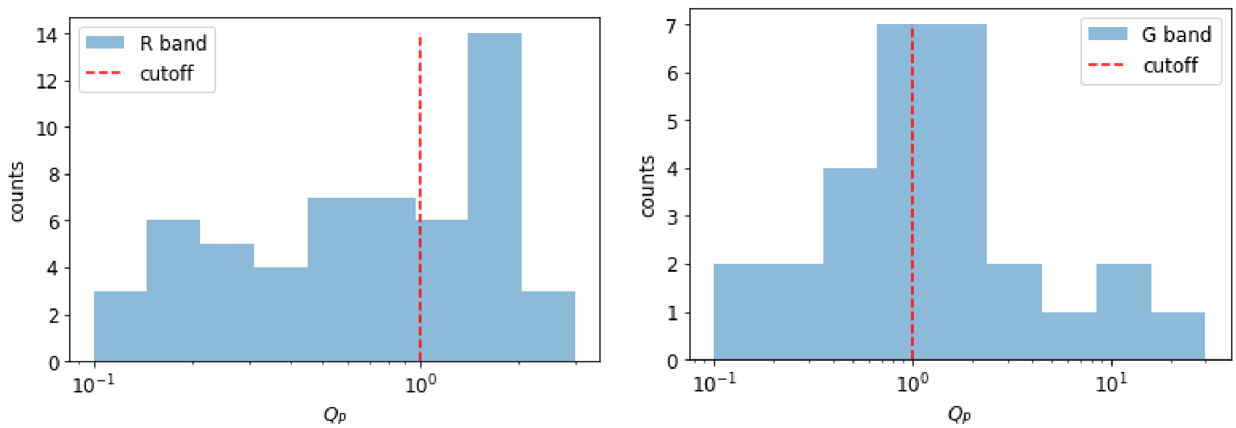

Figure 4. Distribution of Q_P for low FAP sources in ZTF R and G band. We keep sources right to the red dotted line, remove the ones on the left.

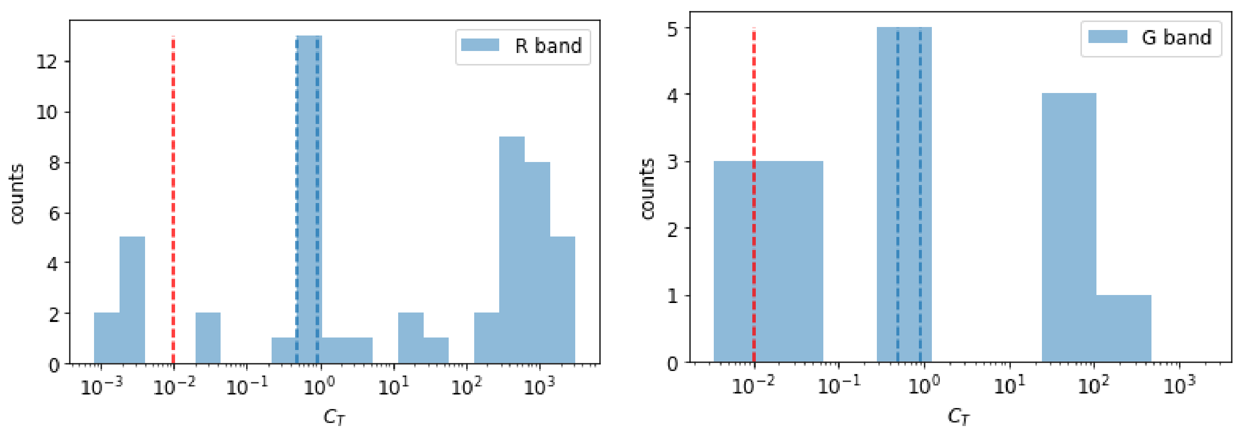

Figure 5. Distribution of C_T for low FAP sources in ZTF R and G band. We cut sources left to the red dotted line, and sources in between blue dotted lines, with exception of extremely low FAP.

each lightcurve would imply the actual shape of the lightcurve. Ideally, when the magnitudes are evenly sampled from every phase of a lightcurve, we would expect for a non-varying star, the distribution of magnitudes to be a Gaussian with standard deviation equal to the error in magnitude measurements, for a sine-like periodic variable, the distribution of magnitudes would be close to a plateau plus Gaussian noise, for eclipsing periodic variable, the distribution magnitudes would be close to a tilted Gaussian... Practically, we looked at typical histogram of magnitudes and found that most of them falls into either a one Gaussian, two Gaussian (close to the plateau + Gaussian noise case), and Gumbel distribution (close to tilted Gaussian). By looking at which of the three distributions fits the distribution of magnitudes relatively better, we can have some idea about what the actually lightcurve looks like. Note that the shape of magnitudes distribution is a nice indicator of the lightcurve's shape, but having certain shape of magnitudes distribution does not decisively guarantee a particular shape of the lightcurve. Magnitudes distribution heavily depends on how the magnitude measurements are distributed among different phases of the lightcurve, if all phases are completely covered by the measurements, and how the magnitudes are binned when plotting the histogram (here for all sources their magnitudes are placed in 10 evenly spaced bins).

Distribution of magnitudes are fitted into one Gaussian, two Gaussian, and and Gumbel distribution, and the three models are compared using chi-square error and F-test. One Gaussian and Gumbel distribution both have three fitting parameters, and they are compared with each other by chi-square error, $\chi^2_k = \sum_i \frac{M_{measured}-M_{model}}{k}$, where k is the degree of freedom. Two Gaussian, having 6 fitting parameters are treated with extra care via F-test. P-value is calculated to quantify how much two Gaussian is statistically better than one Gaussian or Gumbel distribution. Only if for a magnitude distribution, two Gaussian is statistically 90% better than the chi-square error winner between one Gaussian and Gumbel, the magnitude distribution is tagged by "two Gaussian" shape, otherwise it is tagged by "one Gaussian" or "Gumbel" depends one which has a smaller chi-square error. Besides, we also ask the location of "two Gaussian"'s two peaks to be more separated than the sum of two standard deviations, and the standard deviations themselves can not be smaller than the mean error of magnitude measurements, so that the "two Gaussian" has two real separated peaks, instead of being a pseudo one Gaussian. The shape of magnitude distribution is included in the catalog, and more discussion on shapes is presented in section 4.

3.3.2. *UPSILoN, machine learning classification*

To cross check the effectiveness of our methodology, we use a different approach to look for periodic variables. UPSILoN (AUtomated Classification of Periodic Variable Stars using MachIne LearNing) is a machine learning driven algorithm to identify and classify periodic variables in any optical survey developed by Kim & Bailer-Jones (2015). UPSILoN extracts key features of a lightcurve and then machine learning deploys these key feature to classify the lightcurve into classes including non-variable, δ Scuti, RR Lyrae, Cepheid, Type II Cepheid, eclipsing binary, long-period variable, as well as their subclasses. We run UPSILoN on all sources within IC 10 field. The detailed subclasses output of UPSILoN is included in our catalog. For the purpose of cross-checking, as shown in section 4, we treat any source that is not classified as "non-variable", and is not flagged "suspicious" as a periodic variable identified by UPSILoN.

4. CATALOG DEMOGRAPHICS

4.1. *General demographics*

A brief view of how many sources are variables, periodic variables, and non-periodic variables can be found in Table 2. Note here the number of "sources" is presented, but not number of "lightcurves", since some of the lightcurves belong to the same source, as mentioned in section 2. As shown in the table, there are more sources observed, or exclusively observed in R band than in G band, because sources in this work are typically $\sim$ 1 magnitude ($\sim$ 2.5 times) brighter in R band than in G band, making R band more sensitive. Looking at the percentages, in both bands, roughly 11-12% of the sources show some variability, and 1-2% is periodic. These percentages roughly drops by half for "Both R and G" case. The only exception is that only 0.2% sources are periodic in both R and G band, but such lack of R and G common periodic sources could partially due to nearly half (15 out of 32) R band periodic source are never observed in G band. Besides, for those exclusively observed in G band, there seems to be an unexpected high number of variable sources, which might be worth investigating.

4.2. *Magnitude distribution shapes*

Table 3 demonstrates how shape of magnitude distribution varies depending on if the source is variable or periodic. Among non-variable sources, there a significantly lower number of "2 Gaussian" shapes as expected, since the magnitude distribution of non-variable sources by definition should not be spread out enough to have two separate peaks. For periodic variables, however, we can see a clear increase of "two Gaussian" shapes in R band, since this is the expected shape for typical sine-like periodic lightcurves. Such increase is not as obvious in G band, probably due to the extremely small sample size (only 9). Looking across different bands, the shape percentages are generally similar for both R and G band under a same category, as expected. The shape information can hint us that "2 Gaussian" periodic variables are most likely to be sinusoidal periodic sources, while "Gumbel" and "1 Gaussian" periodic variable are more likely to be periodic eclipsing sources, or sinusoidal periodic sources with a gentler change in magnitude. "2 Gaussian" non-periodic variables could suggest that the sources are changing their magnitude for a significant amount of duration, while for "Gumbel" and "1 Gaussian" non-periodic variables, such change in magnitude might last for a shorter and shorter time.

4.3. *Color-magnitude Diagrams*

Figure 6 shows the magnitude and color distribution across sources of different variability. For reference, the distance modulus (m-M) of galaxy IC 10 is generally agreed to be around 24 (Sakai et al. 1999; Ovcharo & Nedialkov 2005; Kim et al. 2009). All these observed sources are very bright, the bottom bars in both bands are most likely to be giants, and the upper ones are more likely to be supergiants. Variable sources are well separated in color and brightness, leaving us a complete and diverse variable star sample to study. Table 4 gives a more detailed view on how much the color and magnitude is changing. Variables generally have greater changes in magnitude and color, as expected. To have a sense of the actual change of brightness of these stars with typical values of $< \Delta_{max} m >$ and $< \sigma_m >$, 1 mag-

	R band	G band	Both R and G	Only detected in R	Only detected in G
All Sources	1516 (100%)	864 (100%)	821 (100%)	695 (100%)	43 (100%)
Variables	188 (12.4%)	101 (11.7%)	43 (5.2%)	85 (12.2%)	18 (41.9%)
Periodic Variables	32 (2.1%)	9 (1.0%)	2 (0.2%)	15 (2.2%)	0 (0%)
Non-Periodic Variables	156 (10.3%)	92 (10.6%)	36 (4.4%)	70 (10.1%)	18 (41.9%)

Table 2. General statistics of the catalog. Column name "R/G band" means the sources are observed in R/G band, and is variable/periodic/non-periodic in R/G band; "Both R and G" means the sources are observed in both R and G band, and is variable/periodic/non-periodic in both R and G band; "Only detected in R/G" means the sources are only observed in R/G band, never seen in the other(G/R) band, and is variable/periodic/non-periodic in R/G band. The percentages mark the percentage inside each column.

	Total		1 Gaussian		Gumbel		2 Gaussian	
	R	G	R	G	R	G	R	G
Non-Variables	1328 (100%)	763 (100%)	973 (73.3%)	542 (71.0%)	303 (22.8%)	176 (23.1%)	52 (4.0%)	45 (6.0%)
Periodic Variables	32 (100%)	9 (100%)	14 (43.8%)	8 (88.9%)	4 (12.5%)	0 (0%)	14 (43.8%)	1 (11.1%)
Non-Periodic Variables	156 (100%)	92 (100%)	105 (67.3%)	53 (57.6%)	25 (16.0%)	24 (26.1%)	26 (16.7%)	15 (16.3%)

Table 3. The shape statistics of magnitude distributions. The percentages show the percentage in each row, with R and G band separated.

nitude smaller is 2.5 times brighter, and a 0.2 magnitude change is roughly 20% change in brightness.

4.4. *Compare to UPSILoN*

Additionally, we compare our periodic variable samples to the ones found by machine learning powered UPSILoN. Both this work and UPSILoN found more periodic stars in R band than in G band, and both found very few sources that are periodic in both bands, again since R band has more and brighter sources. A reasonable amount of sources are identified periodic under both methods, especially the two sources that are periodic in both R and G band. Figure 7 is a typical example when a source is identified as a periodic variable by UPSILoN but is not identified as periodic variable by the criteria outlines in this paper. This particular source does look promising on the folded lightcurve, however, it does not pass the survival function $S_k(\chi^2)$ cut. As shown in the lightcurve, the error in magnitude is comparable to the change in magnitude, thus a non-varying magnitude model can not be fully ruled out. On the other hand, Figure 8 is a typical example where we find a source as periodic variable but UPSILoN missed that source. This source definitely looks variable from its lightcurve, and shows some periodicity at around 238 days from its folded lightcurve. We do not know the exact reason why UPSILoN rejected this source, but since the ZTF data used here and the data where UPSILoN is trained on inevitably have different characteristics such as band, observing window, instrument, and so on, it is not surprising that UPSILoN will not be always correct.

4.5. *Compare to Chen et al.*

As mentioned in the introduction, Chen et al. (2020)'s catalog of periodic variable stars contains one source within the field of IC 10. This particular periodic variable source is re-discovered in this work. The lightcurve is shown in Figure 9 It is identified as periodic variable in R band, while in G band it does not pass our survival function test. This source is identified as periodic in both bands by UPSILoN.

4.6. *Compare to SIMBAD database*

A query of identified variable sources' locations is conducted in SIMBAD. The nearest (if there is any) object within 2 arcsec radius is treated as matched counterparts. An overview of the matched statistics is shown in Table 6,the detailed matched information including identifier name, identified type, and distance is include in our catalog. Among matched SIMBAD sources, we re-discovered variable sources including Wolf-Rayet stars, X-ray sources, emission-line stars, carbon stars, supernova remnants,cluster of stars, HII regions, and radio sources.

5. INTERESTING INDIVIDUALS

6. CONCLUSION

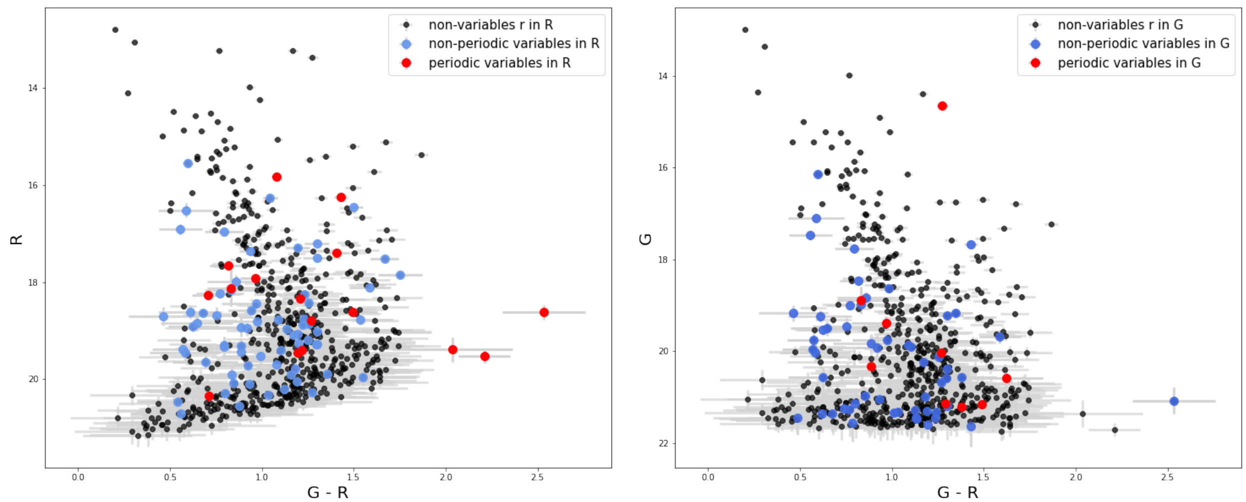

Figure 6. The color magnitude diagram. On horizontal axis is the mean G-R color, and on vertical axis is the mean R or G magnitude. Grey lines denotes 1σ in color and magnitude. Sources included in this plot are all observed in both R and G band to have a meaningful G-R color.

	$< \Delta_{max} m >$	$< \sigma_m >$	$< \Delta_{max}(G-R) >$	$< \sigma_{(G-R)} >$
Non-variables in R	0.667	0.095	0.859	0.163
Non-Periodic variables in R	0.998	0.134	0.986	0.179
Periodic Variables in R	0.786	0.136	0.840	0.140
Non-variables in G	0.897	0.156	0.856	0.161
Non-Periodic variables in G	1.332	0.218	1.066	0.203
Periodic Variables in G	1.465	0.230	1.395	0.204

Table 4. A closer look at the change in magnitude and G-R color. The Columns from left to right in order gives the average maximum change in magnitude (in R or G band, depending on the row located), the average standard deviation in magnitude (in R or G band, depending on the row located), the average maximum change in color, and the average standard deviation in color.

	This Work	UPSILoN	Overlaps
Periodic in R	32	35	23
Periodic in G	9	15	3
Periodic in both R and G	2	4	2

Table 5. Periodic sources found by machine-learning-driven UPSILoN compared to periodic sources found by the methodology outlined in this paper. An overlap is when both UPSILoN and our catalog mark the same source as periodic.

	This work	Simbad matches
Periodic variables in R	32	14
Periodic variables in G	9	3
Non-Periodic variables in R	156	43
Non-Periodic variables in G	92	28

Table 6. Number of SIMBAD matches within 2 arcsec radius.

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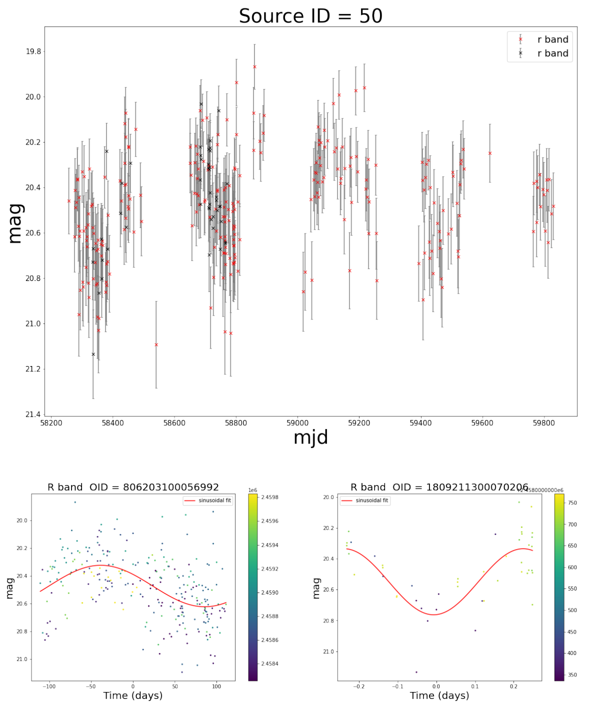

Figure 7. An example source that identified as periodic in R band by UPSILoN but not identified as periodic in R band by our catalog. Top panel shows the lightcurve with error in magnitude as error bar. Red and black represents two ZTF labeled OIDs, but the two OIDs essentially corresponds to the same source. Bottom panel are the folded lightcurve of the two OIDs, fitted with a sine function, and color-coded by mjd. This source is not identified as periodic variable by our catalog because it did not pass the survival function $S_k(\chi^2)$ cut, that is, the lightcurve is not variable enough to rule out a constant line model.

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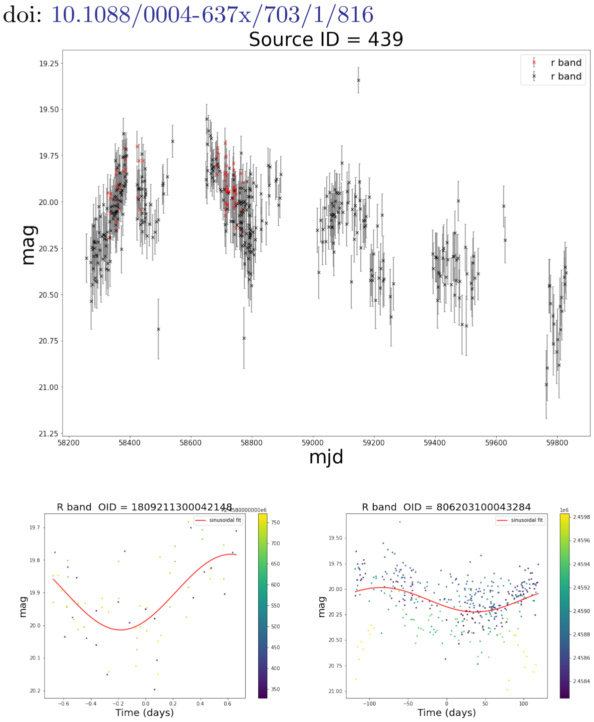

Figure 8. An example source that is identified as periodic in R band by our catalog but missed by UPSILoN. Top panel shows the lightcurve with error in magnitude as error bar. Red and black represents two ZTF labeled OIDs, but the two OIDs essentially corresponds to the same source. Bottom panel are the folded lightcurve of the two OIDs, fitted with a sine function, and color-coded by mjd.

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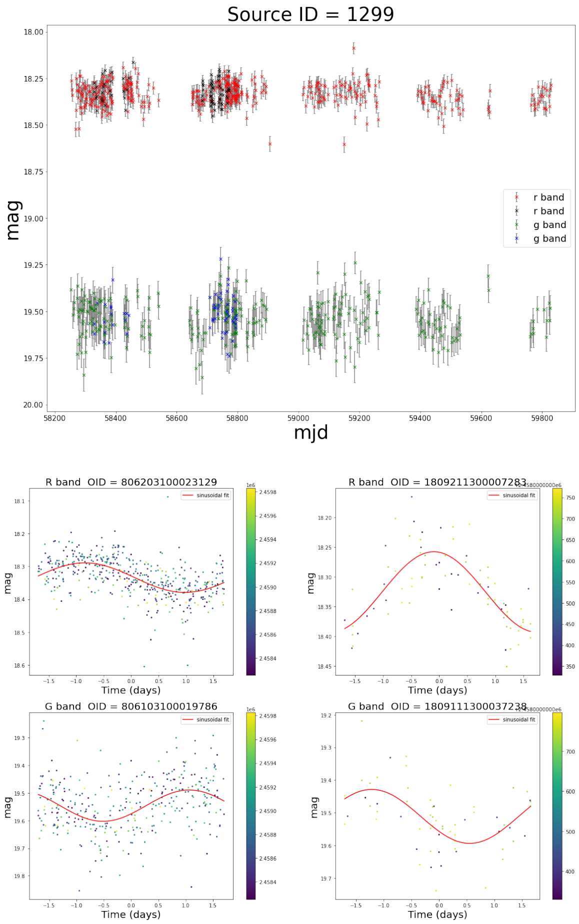

Figure 9. The periodic variable source found by Chen et al. in IC 10. This source is identified as variable in R by our algorithm, but did not pass the survival function test in G band due the relatively large error in G band magnitude measurements.