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The Backyard Worlds: Cool Neighbors Citizen Science Project

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Abstract. Brown dwarfs represent astrophysical laboratories capable of yielding fundamental insights about planetary atmospheres and the process of star formation at low masses. Although observational and theoretical studies of brown dwarfs have progressed over the past ~25 years, the solar neighborhood census of such objects remains incomplete, especially for populations with the very lowest luminosities. The archival data set furnished by NASA's Wide-field Infrared Survey Explorer (WISE) has unrivaled potential to pinpoint the lowest luminosity brown dwarfs, but this vast archive has not yet been exhaustively explored. The existing Backyard Worlds: Planet 9 citizen science project has discovered hundreds of brown dwarfs through extensive visual inspection of WISE sky maps. However, the Backyard Worlds: Planet 9 interface is primarily optimized for discovery of hypothesized outer solar system planets rather than brown dwarfs. We describe the design and launch of Backyard Worlds: Cool Neighbors, which is optimized for discovery of extremely low luminosity brown dwarfs. Whereas Backyard Worlds: Planet 9 shows participants randomly selected sky patches, Backyard Worlds: Cool Neighbors is a targeted survey. Our candidate brown dwarf targets are selected from the CatWISE2020 catalog using a machine learning technique, then visually inspected by citizen scientists to reliably confirm or reject each candidate's motion, a telltale proxy for solar neighborhood membership. Discovering extreme brown dwarfs will enable the most exceptional and diverse set of isolated exoplanet analogs to be characterized spectroscopically during JWST's lifetime.

1. Introduction

What are the properties of giant exoplanet atmospheres, such as their water and cloud content? Is there a low-mass cutoff to the star formation process, and if so what is its value? How do the answers to these questions depend on variables such as age and metallicity? Brown dwarfs of extremely low luminosity play a central role in answering these important questions.

Y dwarfs, the coolest and least luminous known class of brown dwarfs, overlap in mass and temperature with giant exoplanets, but are free of contaminating glare from a much brighter host star. This makes Y dwarfs ideal laboratories for learning about giant exoplanet atmospheres, especially in the new era of JWST mid-infrared spectroscopy. Y dwarfs are predicted to harbor water ice clouds at temperatures below 450 K (Morley et al. 2014), and the local space density of Y dwarfs is a sensitive probe of star formation's cutoff (or lack thereof) at planetary masses ($M \lesssim 13\ M_{\rm Jup}$; e.g., Burgasser 2004; Kirkpatrick et al. 2019, 2021).

Late-type subdwarfs — ancient substellar objects of low metallicity — represent a second class of extremely low luminosity brown dwarfs. In the Sun's local Galactic neighborhood, L and T type subdwarfs are rarer than solar metallicity objects of the same spectral classes, making them difficult to detect. Identifying very cold ($T_{\rm eff} \lesssim 1{,}400$ K) T type subdwarfs inhabiting the solar neighborhood can tell us how commonly substellar objects formed during the early periods of the Milky Way's formation history.

Finding examples of Y dwarfs and late-type subdwarfs has posed a major bottleneck for all of these lines of inquiry. Such brown dwarfs are sufficiently faint that we can only hope to detect them very nearby (within ~20 pc for Y dwarfs and ~100 pc for T type subdwarfs). Thankfully, modern wide-area surveys like *WISE* (Wright et al. 2010) and its extension, NEOWISE (Mainzer et al. 2011), are sufficiently sensitive to detect these objects in the ~4-5 micron wavelength range where they emit most strongly. However, pinpointing extremely low luminosity brown dwarfs in the vast *WISE*/NEOWISE data stream, which contains billions of detections and trillions of pixels, represents an enormous technical challenge. These brown dwarfs are much rarer than common artifacts like detector noise and bright star diffraction spikes. Visual inspection campaigns to validate *WISE* brown dwarf candidates have required individual Ph.D. astronomers to scrutinize up to of order 1 million candidates each (e.g., Kirkpatrick et al. 2014; Schneider et al. 2016; Kirkpatrick et al. 2016). Citizen science and machine learning represent promising avenues to overcome this burdensome vetting bottleneck, by crowdsourcing the effort of visually approving/rejecting brown dwarf candidates and generalizing from labeled training samples to massive data sets.

2. The Existing Backyard Worlds: Planet 9 Project

The Backyard Worlds: Planet 9 citizen science project (`https://backyardworlds.org`; Kuchner et al. 2017) was launched in 2017 February with the goal of crowdsourcing an all-sky visual search for moving objects within the full *WISE*/NEOWISE data set. To push fainter than prior *WISE*-based motion surveys, this project employed novel unWISE coadds (Lang 2014; Meisner et al. 2018b,c, 2019) that are stacked together in each six-monthly sky pass of *WISE* exposures. Searching for a theorized "Planet 9" in the outer solar system is a primary goal of Backyard Worlds: Planet 9, and Planet 9 would move by many arcminutes between successive *WISE* sky passes (Trujillo & Sheppard 2014; Batygin & Brown 2016). Backyard Worlds: Planet 9 therefore shows citizen scientists time series animated "flipbooks" (movies) covering large sky patches $10' \times 10'$ in extent. These sky regions are *randomly selected*, and are rendered as difference images that null out static sources, as Planet 9 moves fast enough to avoid self-subtraction (Meisner et al. 2017, 2018a). Users are asked to click the locations of potential moving objects they see within these difference images.

Motion selection is also a common technique used to discover nearby brown dwarfs, which appear to shift position relative to much more distant stars and galaxies. However, the Backyard Worlds: Planet 9 visual inspection workflow may not be ideal for brown dwarf discovery. Brown dwarfs in the solar neighborhood generally move at rates of only $\sim$0.1$''$/year to a few arcseconds per year. At the *WISE* angular resolution ($\sim$6$''$ FWHM), brown dwarfs are severely self-subtracted in Backyard Worlds: Planet 9 flipbooks, appearing merely as faint "dipoles", often with amplitudes smaller than background noise.

Nevertheless, Backyard Worlds: Planet 9 citizen scientists have discovered several hundred previously unrecognized moving objects that our team has spectroscopically confirmed to be cold brown dwarfs (e.g., Meisner et al. 2020a; Faherty et al. 2020; Schapera et al. 2022b). Backyard Worlds: Planet 9 has therefore demonstrated the efficacy of citizen science for brown dwarf discovery, and suggests that a new crowdsourced search optimized for brown dwarf discovery should uncover hundreds or thousands more substellar objects. Backyard Worlds: Planet 9 has also amassed over 74,000 registered users, including $\sim$300+ advanced "super users", a sizable community which can be leveraged to beta test and participate in future Backyard Worlds spin-off projects.

3. The Backyard Worlds: Cool Neighbors Project

Backyard Worlds: Planet 9 has already discovered several of the most extreme brown dwarfs yet known, including five Y dwarfs (among only a few dozen known; Meisner et al. 2020a; Bardalez Gagliuffi et al. 2020; Schneider et al. 2021) and the first extreme T type subdwarfs — T type subdwarfs with very low metallicity, [Fe/H] ≤ -1 (esdTs; Schneider et al. 2020; Meisner et al. 2021; Brooks et al. 2022). To build on these initial successes, we have created a spin-off citizen science project called Backyard Worlds: Cool Neighbors, which is optimized for discovery of extremely low luminosity brown dwarfs.

Backyard Worlds: Cool Neighbors asks citizen scientists to look for motion within animated time series image blinks composed of unWISE coadds, with each frame being a two-color composite showing the W1 (3.4μm, rendered as blue) and W2 (4.6μm, rendered as red) channels (see Figure 1). Backyard Worlds: Cool Neighbors image blinks have five critical differences relative to those of Backyard Worlds: Planet 9:

1. Each Backyard Worlds: Cool Neighbors image blink is centered on a pre-selected Y dwarf or subdwarf candidate, not a random sky location. See §3.1-3.2 for brown dwarf candidate selection details.
2. No difference imaging is applied, allowing Backyard Worlds: Cool Neighbors to avoid loss of signal-to-noise due to brown dwarf self-subtraction.
3. The Backyard Worlds: Cool Neighbors image blinks each cover a relatively small sky region, only 2′ on a side, a 25× narrower sky area. This "zoomed in" view maximizes volunteers' ability to assess each pre-selected brown dwarf candidate.
4. The 'classification' task is relatively simple, requesting only a binary "yes"/"no" rating for each brown dwarf candidate as to whether the citizen scientist does or doesn't believe it is a bona-fide moving astrophysical source (as opposed to noise, an artifact, or a stationary source).
5. Backyard Worlds: Cool Neighbors incorporates an additional five years of NEOWISE imaging (2017-2021), a 125% increase in the total number of *WISE* sky passes presented to volunteers relative to Backyard Worlds: Planet 9.

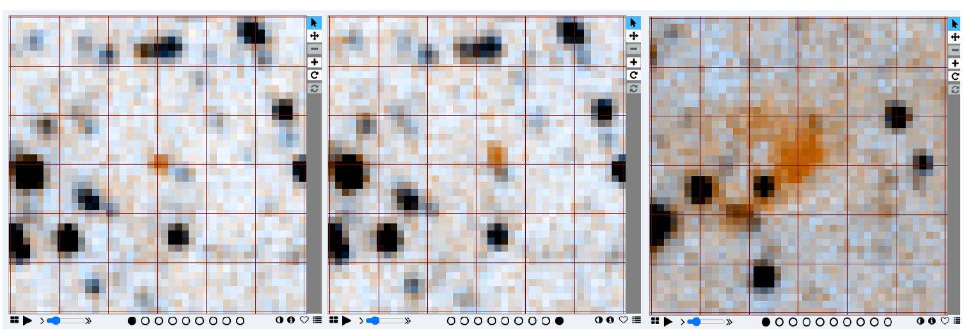

Figure 1. Backyard Worlds: Cool Neighbors Zooniverse classification interface example. The left and middle unWISE cutouts show the visually perceptible motion of a faint brown dwarf (orange source, moving toward the upper right over time). The right unWISE cutout shows a spurious moving object candidate caused by a bright star optical ghost.

3.1. Capitalizing on CatWISE

The CatWISE2020 catalog is currently the largest and deepest mid-infrared proper motion data set (Eisenhardt et al. 2020; Marocco et al. 2021). With ~2 billion unique sources, CatWISE2020 contains more than twice as many objects as its predecessor AllWISE (Cutri et al. 2013). By virtue of incorporating five years of NEOWISE data (through calendar year 2018), CatWISE2020 also boasts a time baseline ~15× longer than AllWISE, yielding > 10× more accurate motions. Because of the vast brown dwarf discovery space newly accessible with CatWISE2020, we use this novel catalog to pre-select Y dwarf and subdwarf targets for Backyard Worlds: Cool Neighbors citizen scientists to visually inspect.

3.2. Machine Learning Brown Dwarf Candidate Selection

Conventional *WISE* brown dwarf searches have relied on all-sky queries that implement hard cuts on catalog quantities such as color (with red W1−W2 color indicating cold temperature), total proper motion, and artifact flags. Recently, astronomers have turned to machine learning techniques when performing brown dwarf selections with catalogs such as AllWISE and CatWISE (Marocco et al. 2019; Meisner et al. 2020b; Gong et al. 2022). The Backyard Worlds: Cool Neighbors project uses a custom machine learning algorithm to select its targets (Kota et al. 2022). In brief, decision-tree-based, supervised classifiers are constructed using the XGBoost machine learning software package (Chen & Guestrin 2016) in order to rank the probability that each catalog object is a brown dwarf. The method uses samples of known brown dwarfs as "training data", and customized classifier variants can be produced by training on different subsamples of known objects, such as Y dwarfs or T-type subdwarfs. These XGBoost classifiers have shown a remarkable capacity for selecting extreme objects missed by prior searches (e.g., Marocco et al. 2019; Meisner et al. 2020b). The XGBoost machine learning framework incorporates information from numerous catalog columns simultaneously, whereas conventional searches only examine a few specific columns related to color/motion/flags.

We have trained one customized XGBoost classifier to select promising Y dwarf candidates, and a second to select promising T subdwarf candidates. We then select the 15,000 highest-ranking CatWISE2020 candidates from each classifier for visual inspection vetting by Backyard Worlds: Cool Neighbors citizen scientists, to check for motion and weed out artifacts. Based on initial tests, we estimate that ~0.5% of the XGBoost classifier candidates will be real, previously undiscovered brown dwarfs, suggesting a total yield of ~150 new Backyard Worlds: Cool Neighbors brown dwarf discoveries. While most of these discoveries will be "field" T dwarfs, we expect to nearly double the number of known T type subdwarfs (see Figure 2). At present, our subject sets retain previously discovered moving objects, as these can be useful in assessing the accuracy of participant responses. In future iterations of Backyard Worlds: Cool Neighbors, we will consider removing previously discovered moving objects flagged by our machine learning classifiers.

3.3. Crowdsourcing via Zooniverse Project Builder

For each of our 30,000 brown dwarf candidates, we produce a $2' \times 2'$ time series image blink centered on the target. Each frame in the image blink represents one coadded sky pass worth of *WISE* imaging, and the typical image blink contains 18 such frames[1] displayed in chronological order. Time-ordering allows linear motion, such as that signifying a brown dwarf in the solar neighborhood, to be readily perceived by the human eye.

[1]One frame for each *WISE* sky coverage during the 2010-2021 time interval, with a gap between early 2011 and late 2013 due to the *WISE* hibernation period.

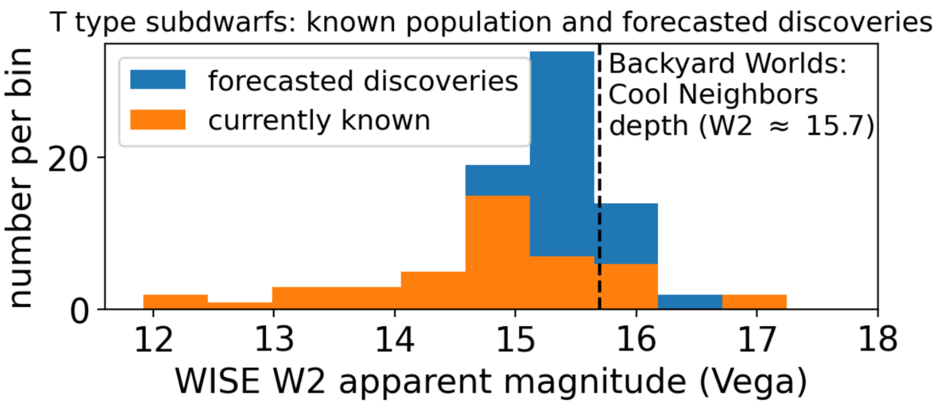

Figure 2. Assuming a conservative Backyard Worlds: Cool Neighbors completeness limit of W2 = 15.7 (see Meisner et al. 2020a), we expect our discoveries to nearly double the number of known T type subdwarfs.

We use the Zooniverse Project Builder Tool as the crowdsourcing platform for our citizen science visual inspection campaign. We upload each of our 30,000 ‘subjects’ (image blinks) to Zooniverse for classification by volunteers. The classification task presented to users requests that they provide a binary label for each subject, indicating “yes”/“no” whether they believe that the candidate at center is a moving brown dwarf as opposed to an artifact or stationary source. The Zooniverse TALK forum functionality provides citizen scientists with a way to pursue further discussion/deliberation related to each subject, both with fellow citizen scientists and our team of professional researchers. There is also a so-called “Move-in Form” online questionnaire available which will allow motivated citizen scientists to report any particularly exciting finds directly to the Cool Neighbors science team.

Because of the simple binary nature of our classification task, we select the Zooniverse “enable on mobile” option to reach the largest possible set of participants. We set the retirement number (number of independent single-user classifications required to consider each subject completed) to seven, the same value used successfully by Backyard Worlds: Planet 9. This means that the initial Backyard Worlds: Cool Neighbors project will be 100% complete upon receiving 30,000 × 7 = 210,000 classifications. For comparison, the Backyard Worlds: Planet 9 project has already received more than 8 million classifications.

3.4. unWISE to Zooniverse Pipeline: unWISE-verse

For our 30,000 brown dwarf candidates to be uploaded to Zooniverse in a convenient and efficient manner, an automated data pipeline between unWISE and Zooniverse was necessary. The unWISE-verse[2] (Schapera et al. 2022a) data pipeline was created to serve this purpose. unWISE-verse is a Python module that takes as input a comma separated value (CSV) file of (RA, Dec) coordinates, downloads the corresponding unWISE time series cutouts via the WiseView (Caselden et al. 2018) API, and then uploads these

[2]This code can be accessed via a public GitHub repository: `https://github.com/coolneighbors/unWISE-verse`

unWISE images to Zooniverse as subject sets using the Panoptes Client. unWISE-verse has a convenient graphical user interface (GUI) frontend built with Tkinter, pictured in Figures 3 and 4.

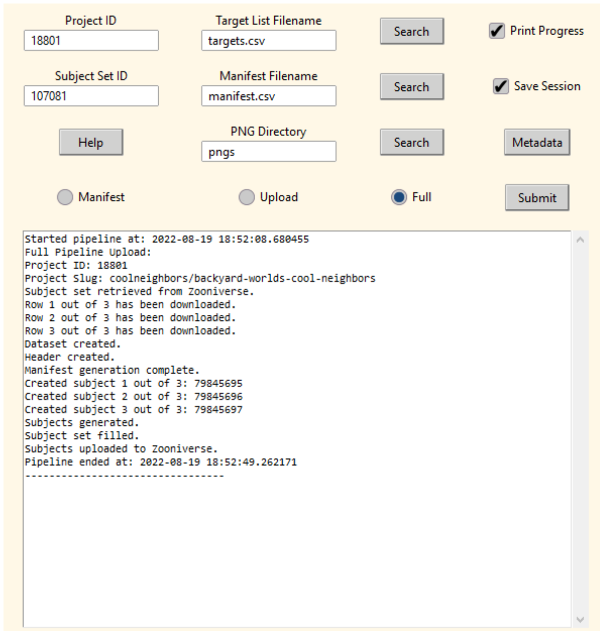

Figure 3. unWISE-verse data pipeline interface example.

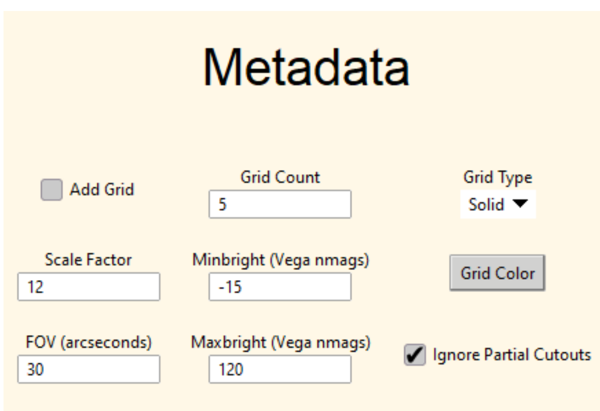

Figure 4. unWISE-verse data pipeline metadata window.

4. Backyard Worlds: Cool Neighbors Beta Test

All citizen science projects formally endorsed by Zooniverse are required to undergo a "beta testing" phase, to receive and incorporate initial feedback from early users. We have designed a custom Zooniverse subject set for the Cool Neighbors beta test. The breakdown of target classes is listed in Table 1.

Table 1. Beta Test Target Class Breakdown

Target Class	Number of Beta Test Subjects
Machine Learning Selected Brown Dwarf Candidates	175
Known Brown Dwarfs	30
Random Sky Locations	35
Known Quasars	35
Total	275

The 175 machine learning selected brown dwarf candidates are representative of the (much larger) sample of brown dwarf candidates that will be incorporated into the final version of Cool Neighbors. The known brown dwarfs are a 'truth' sample meant to understand the rates of true positives and false negatives among Zooniverse participant classifications. The random sky locations are intended to assess the rates of false positives and true negatives. The known quasars are meant to asses the rate of false positives that arise when participants encounter sources that are relatively red (in W1-W2) but are stationary extragalactic objects.

5. Outlook and Future Work

We have built the Zooniverse interface for a new citizen science project called Backyard Worlds: Cool Neighbors. The Cool Neighbors beta test recently took place from 2022 August 23-30, and analysis of the associated classifications remains ongoing. We will incorporate user feedback received through our beta test, make any necessary updates to our methodology/interface, and then proceed to formal launch of the Backyard Worlds: Cool Neighbors project. We expect the project will reveal hundreds of previously undiscovered brown dwarfs in the solar neighborhood.

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References

Bardalez Gagliuffi, D. C., Faherty, J. K., Schneider, A. C., et al. 2020, ApJ, 895, 145, doi: 10.3847/1538-4357/ab8d25

Batygin, K., & Brown, M. E. 2016, AJ, 151, 22, doi: 10.3847/0004-6256/151/2/22

Brooks, H., Kirkpatrick, J. D., Caselden, D., et al. 2022, AJ, 163, 47, doi: 10.3847/1538-3881/ac3a0a

Burgasser, A. J. 2004, ApJS, 155, 191, doi: 10.1086/424386

Caselden, D., Westin, Paul, I., Meisner, A., Kuchner, M., & Colin, G. 2018, WiseView: Visualizing motion and variability of faint WISE sources, Astrophysics Source Code Library, record ascl:1806.004. http://ascl.net/1806.004

Chen, T., & Guestrin, C. 2016, arXiv e-prints, arXiv:1603.02754. https://arxiv.org/abs/1603.02754

Cutri, R. M., Wright, E. L., Conrow, T., et al. 2013, Explanatory Supplement to the AllWISE Data Release Products, Tech. rep.

Eisenhardt, P. R. M., Marocco, F., Fowler, J. W., et al. 2020, ApJS, 247, 69, doi: 10.3847/1538-4365/ab7f2a

Faherty, J. K., Goodman, S., Caselden, D., et al. 2020, ApJ, 889, 176, doi: 10.3847/1538-4357/ab5303

Gong, Z., Nava Vega, A., Gauna Gutierrez, E., et al. 2022, Research Notes of the American Astronomical Society, 6, 74, doi: 10.3847/2515-5172/ac6521

Kirkpatrick, J. D., Schneider, A., Fajardo-Acosta, S., et al. 2014, ApJ, 783, 122, doi: 10.1088/0004-637X/783/2/122

Kirkpatrick, J. D., Kellogg, K., Schneider, A. C., et al. 2016, ApJS, 224, 36, doi: 10.3847/0067-0049/224/2/36

Kirkpatrick, J. D., Martin, E. C., Smart, R. L., et al. 2019, ApJS, 240, 19, doi: 10.3847/1538-4365/aaf6af

Kirkpatrick, J. D., Gelino, C. R., Faherty, J. K., et al. 2021, ApJS, 253, 7, doi: 10.3847/1538-4365/abd107

Kota, T., Kirkpatrick, J. D., Caselden, D., et al. 2022, AJ, 163, 116, doi: 10.3847/1538-3881/ac4713

Kuchner, M. J., Faherty, J. K., Schneider, A. C., et al. 2017, ApJ, 841, L19, doi: 10.3847/2041-8213/aa7200

Lang, D. 2014, AJ, 147, 108, doi: 10.1088/0004-6256/147/5/108

Mainzer, A., Bauer, J., Grav, T., et al. 2011, ApJ, 731, 53, doi: 10.1088/0004-637X/731/1/53

Marocco, F., Caselden, D., Meisner, A. M., et al. 2019, ApJ, 881, 17, doi: 10.3847/1538-4357/ab2bf0

Marocco, F., Eisenhardt, P. R. M., Fowler, J. W., et al. 2021, ApJS, 253, 8, doi: 10.3847/1538-4365/abd805

Meisner, A., Bromley, B. C., Nugent, P. E., et al. 2017, AJ, 153, 65, doi: 10.3847/1538-3881/153/2/65

Meisner, A. M., Bromley, B. C., Kenyon, S. J., & Anderson, T. E. 2018a, AJ, 155, 166, doi: 10.3847/1538-3881/aaae70

Meisner, A. M., Lang, D., Schlafly, E. F., & Schlegel, D. J. 2019, PASP, 131, 124504, doi: 10.1088/1538-3873/ab3df4

Meisner, A. M., Lang, D., & Schlegel, D. J. 2018b, AJ, 156, 69, doi: 10.3847/1538-3881/aacbcd

Meisner, A. M., Lang, D. A., & Schlegel, D. J. 2018c, Research Notes of the American Astronomical Society, 2, 202, doi: 10.3847/2515-5172/aaecd5

Meisner, A. M., Faherty, J. K., Kirkpatrick, J. D., et al. 2020a, ApJ, 899, 123, doi: 10.3847/1538-4357/aba633

Meisner, A. M., Caselden, D., Kirkpatrick, J. D., et al. 2020b, ApJ, 889, 74, doi: 10.3847/1538-4357/ab6215

Meisner, A. M., Schneider, A. C., Burgasser, A. J., et al. 2021, ApJ, 915, 120, doi: 10.3847/1538-4357/ac013c

Morley, C. V., Marley, M. S., Fortney, J. J., et al. 2014, ApJ, 787, 78, doi: 10.1088/0004-637X/787/1/78

Schapera, N., Humphreys, A., & Meisner, A. 2022a, coolneighbors/unWISE-verse: unWISE-verse: An Integrated WiseView and Zooniverse Data Pipeline, v1.0.0, Zenodo, doi: 10.5281/zenodo.6864030

Schapera, N., Caselden, D., Meisner, A. M., et al. 2022b, Research Notes of the AAS, 6, 189, doi: 10.3847/2515-5172/ac9141

Schneider, A. C., Greco, J., Cushing, M. C., et al. 2016, ApJ, 817, 112, doi: 10.3847/0004-637X/817/2/112

Schneider, A. C., Burgasser, A. J., Gerasimov, R., et al. 2020, ApJ, 898, 77, doi: 10.3847/1538-4357/ab9a40

Schneider, A. C., Meisner, A. M., Gagné, J., et al. 2021, ApJ, 921, 140, doi: 10.3847/1538-4357/ac1c75

Trujillo, C. A., & Sheppard, S. S. 2014, Nat, 507, 471, doi: 10.1038/nature13156

Wright, E. L., Eisenhardt, P. R. M., Mainzer, A. K., et al. 2010, AJ, 140, 1868, doi: 10.1088/0004-6256/140/6/1868