# Discovering Ultracool Dwarfs in Deep Surveys using Machine Learning Methods

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# Overview

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# What are Ultracool Dwarfs?

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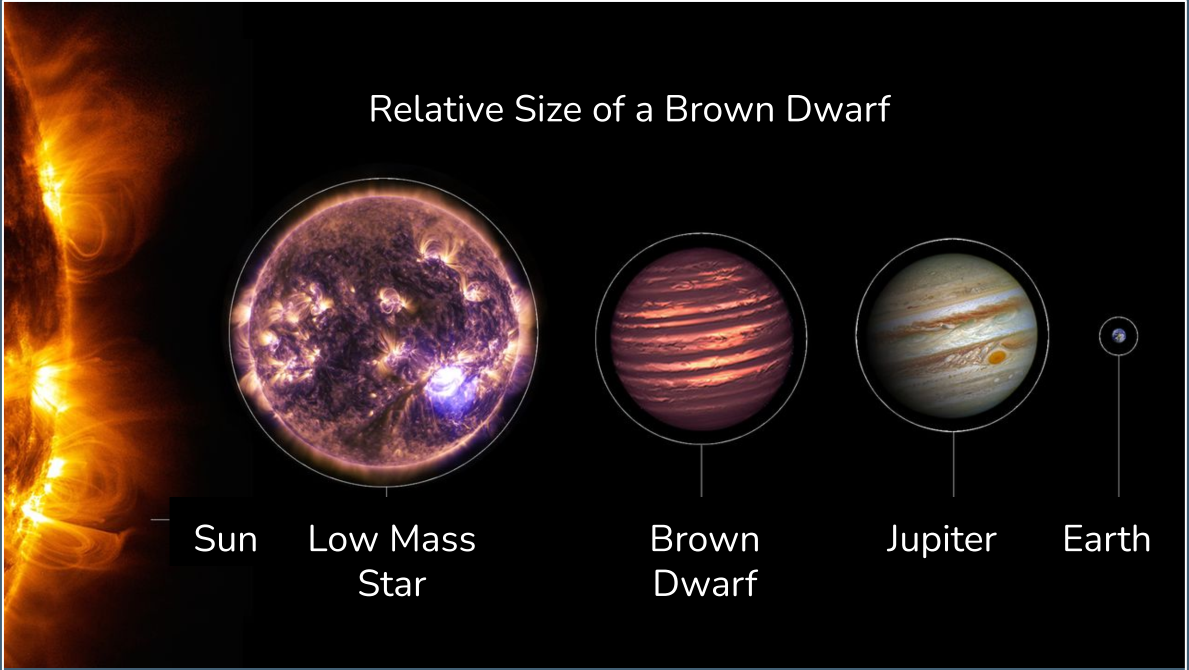


Artist rendition of relative size of a brown dwarf to the Sun, a low-mass star, Jupiter, and Earth with sizes to scale.

- Spectral class M6 and later (M, L, T, Y)
- Late L, T, & Y form below the hydrogen burning mass limit (brown dwarfs)
- Radiate in the infrared
- Common objects

$T_{eff} \leq 3000°K$
$Mass \leq 0.1\ M_\odot$

Image Credit: Jupiter: NASA, ESA, A. Simon (NASA, GSFC); Sun and Low-Mass Star: NASA, SDO; Brown Dwarf: NASA, ESA, JPL-Caltech; Earth: NASA; Infographic: NASA, E. Wheatley (STScI).

# Why do we want to find them?

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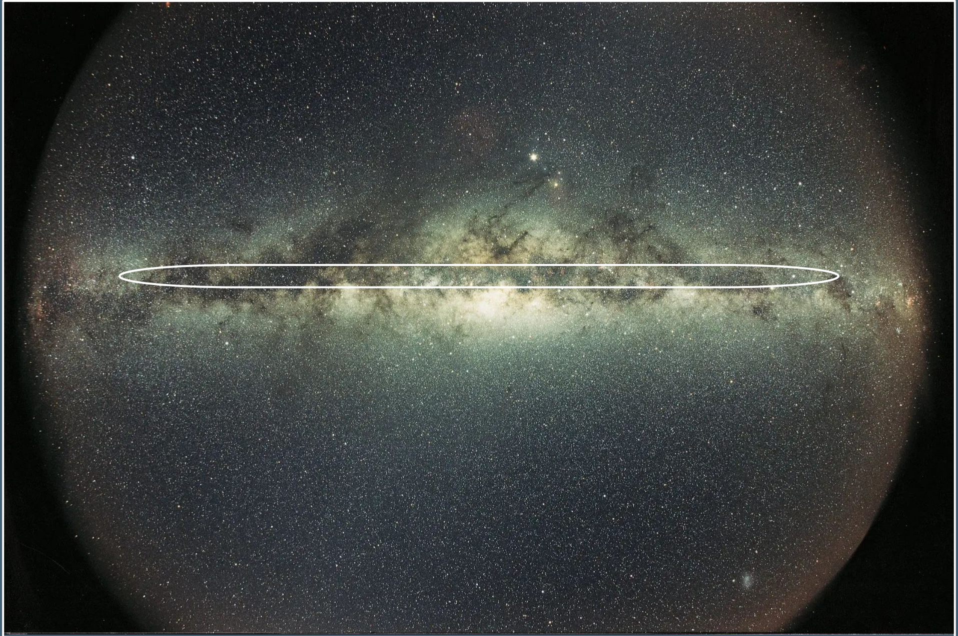
- Understanding differences between star and planet formation
- Improve current stellar models
- Increase known sources at further distances (> 100 parsecs)
- Improve measurement of Milky Way parameters such as thin disk scaleheight

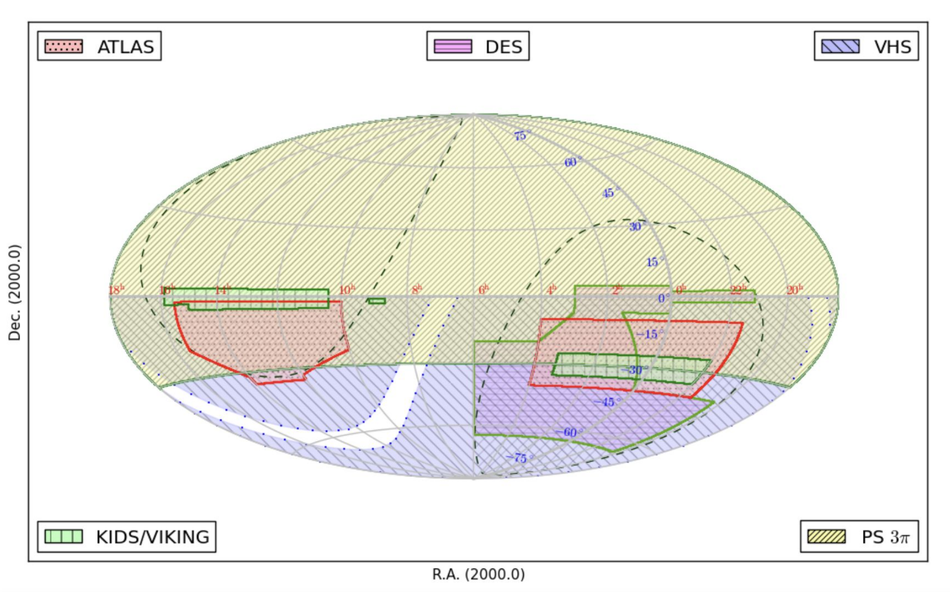


Milky Way with thin disk highlighted

Image Credit: © *Dirk Hoppe*

# Wide-Field Surveys

- PanSTARRS, Sloan Digital Sky Survey (SDSS), and ATLAS in the optical
- 2-Micron All Sky Survey (2MASS) in the near-infrared
- Wide-field Infrared Survey Explorer (WISE) catalogue




Coverage of Pan-STARRS in yellow, DES in purple, VHS in blue (Shanks 2016)

# Deep Sky Surveys

## Dark Energy Survey (DES)

- Search for galaxies and aims to constrain dark energy
- Depth: 21.7 in mags in near-infrared Y band
- 5,000 $deg^2$ coverage in South

## VISTA Hemisphere Survey (VHS)

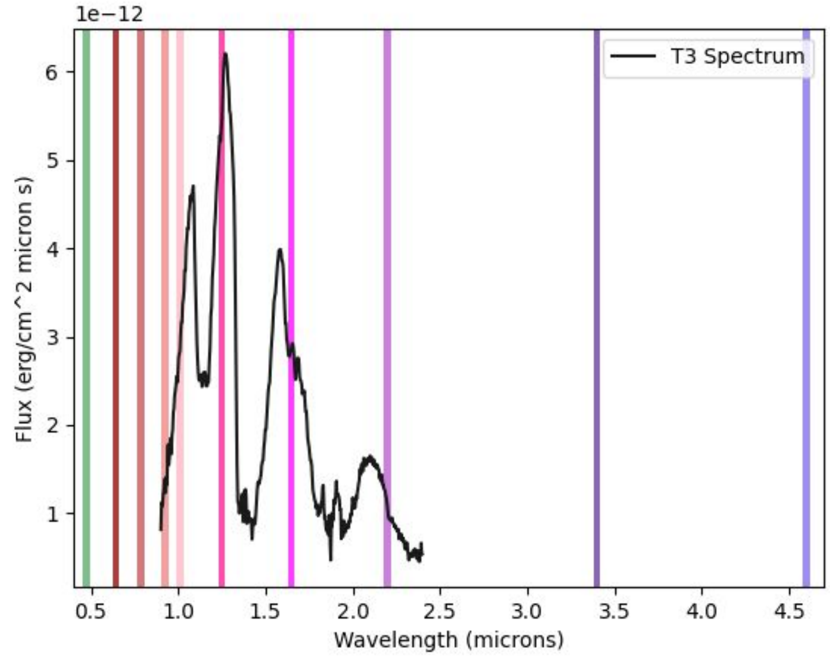
- Search for high-redshift quasars, low mass-stars
- 30 x deeper than 2MASS
- 21,000 $deg^2$ coverage in South

## CatWISE2020 Catalogue

- Known for discovering brown dwarfs
- Depth: W1 = 17.7 mag and W2 = 17.5 mag

# Photometric Bands

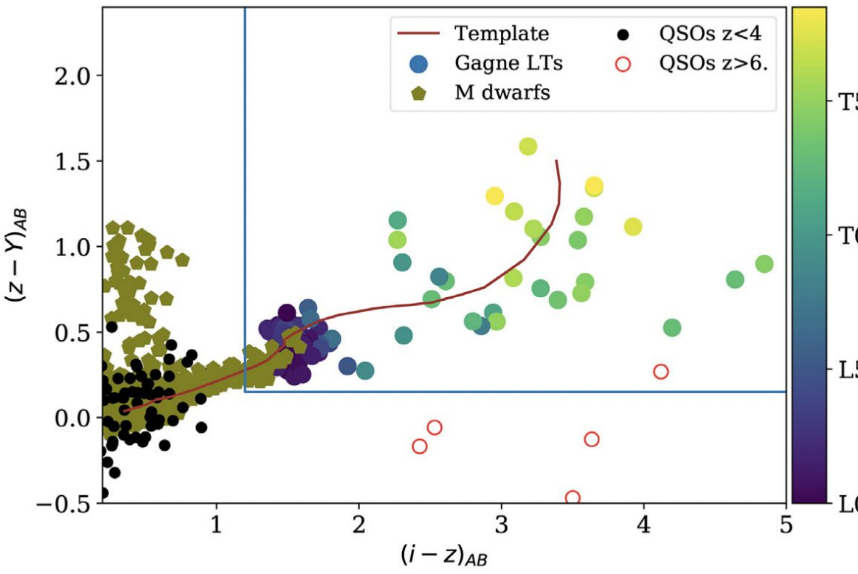
- PanSTARRS and DES survey use grizY bands
- VHS has many sources in J and $K_s$ bands, analogous to 2MASS J and $K_s$
- CatWISE has W1, W2 bands




In order of highlights: g, r, i, z, Y, J, H, $K_s$, W1, and W2 bands overlaid on a T3 Spectrum

# Previous Research

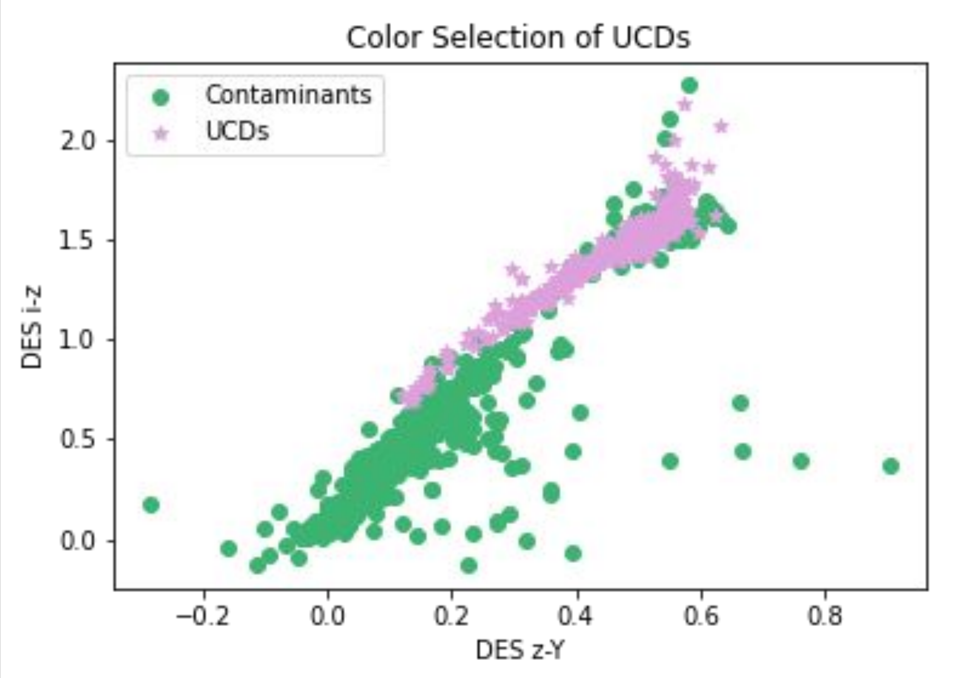
- Carnero Rosell et al. 2019 created a catalogue of 11,745 brown dwarfs of type L0 to T9 using DES, VHS, and WISE photometry
- Used photometric color selection to identify possible candidates
- Spectral classification based on color templates
- Measured thin disk scale height to be 450 pc




Color cut displaying UCDs and quasars

# Color Selection

- Color: magnitudes in two photometric bands subtracted from each other
- The color-color plot shows some overlap between UCDs and our contaminant sample
- ML can help find patterns of all color combinations to identify UCDs




z-Y color plotted against i-z color for UCDs and contaminants

# Limitations

01
## Color cut

Have to pre-determine expected color

02
## Large data

Time–consuming to test several cuts on large datasets

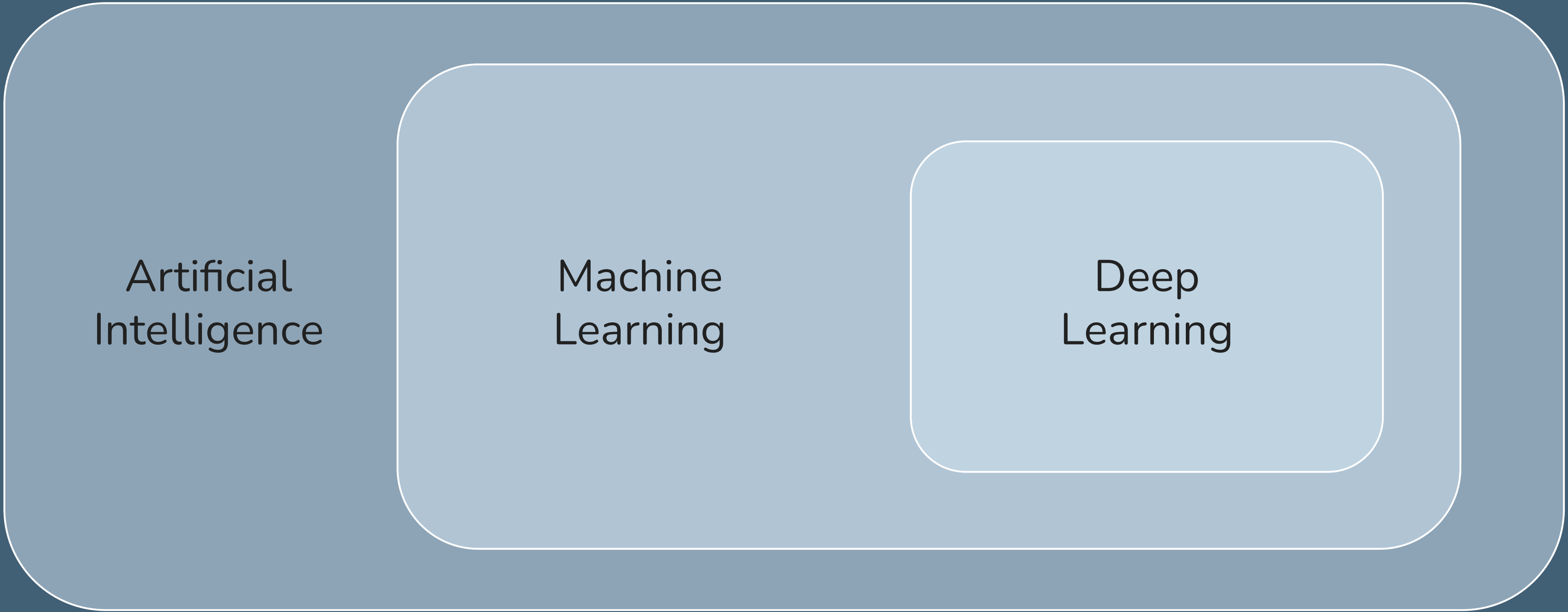
03
## Limited photometry

Hard to incorporate many bands and quickly add new photometry

04
## Contaminants

Can improve on methods used to extract contaminants

# What is Machine Learning?



# What is Machine Learning?

Artificial Intelligence

Machine Learning

- Set of algorithms and statistical models that identify patterns in data
- Includes Random Forests

# What are Random Forests (RF)?

A set of decision trees that is built on “features” and outputs “labels”

| | |
|---|---|
| Training | Subset of pre-classified data used to identify most accurate decision trees |
| Test | separate subset of pre-classified data used to determine tree performance |

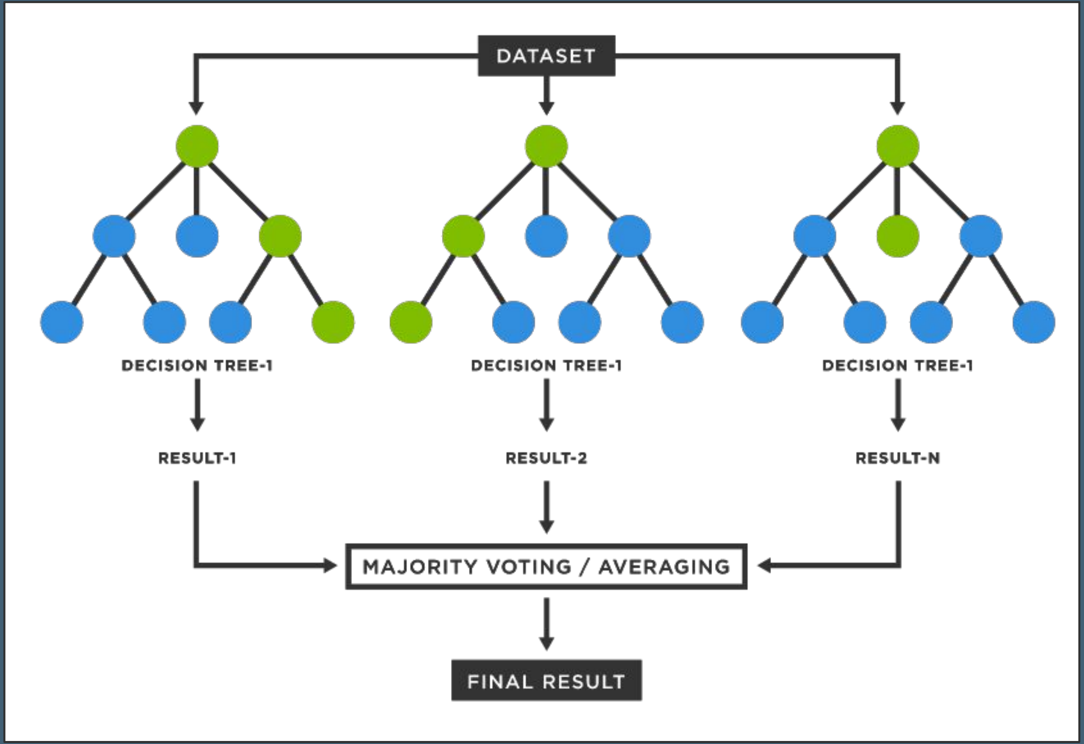



Image Credit: https://www.tibco.com/reference-center/what-is-a-random-forest

# Inputs and Outputs

| $f_1$ | $f_2$ | $f_3$ | Label |
|---|---|---|---|
| 1 | 3 | 5 | 0 |
| 2 | 4 | 6 | 1 |
| 5 | 6 | 9 | 0 |
| 7 | 8 | 0 | 1 |
| 4 | 6 | 8 | ? |

Training

Test

Features

| Prediction |
|---|
| 0 |
| 1 |
| 0 |
| 0 |
| 1 |

# Measuring RF Performance

| | |
|---|---|
| True Positives (TP) | False Positives (FP) |
| False Negatives (FN) | True Negatives (TN) |

| | | |
|---|---|---|
| **Precision** | Measure of misclassified objects of one class | $\frac{TP}{TP + FP}$ |
| **F1 Score** | Balanced measure of model performance | $\frac{TP}{TP + \frac{1}{2}(FP + FN)}$ |

# Why RFs?

01

## Multiple Data Points

Can investigate all colors to identify objects and rank their importance

02

## Efficiency

ML methods can sort through millions of sources at a time

03

## Contaminants

Filter galactic and high-redshift objects

04

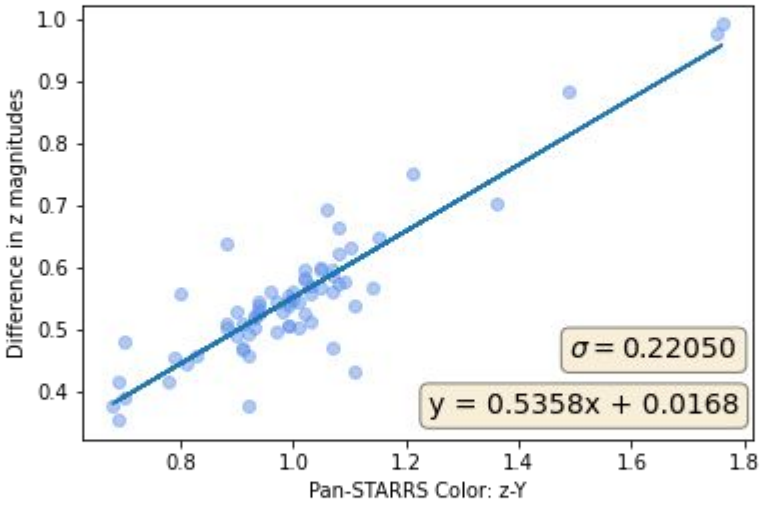
## Previous Research

RFs can identify brown dwarf candidates based on photometric colors and indices (Aganze et al. 2022, Gong et al. 2022)

# Photometric Correction

| | | |
|---|---|---|
| PanSTARRS | ⇨ | DES |
| 2MASS | ⇨ | VHS |
| AllWISE | ⇨ | CatWISE |

# Photometric Correction




Correction of DES z-band magnitudes

- All photometry in the Ultracool Sheet is photometrically corrected to deep sky surveys using linear regression based on color
- MSE of fits: 0.0083 - 0.0019

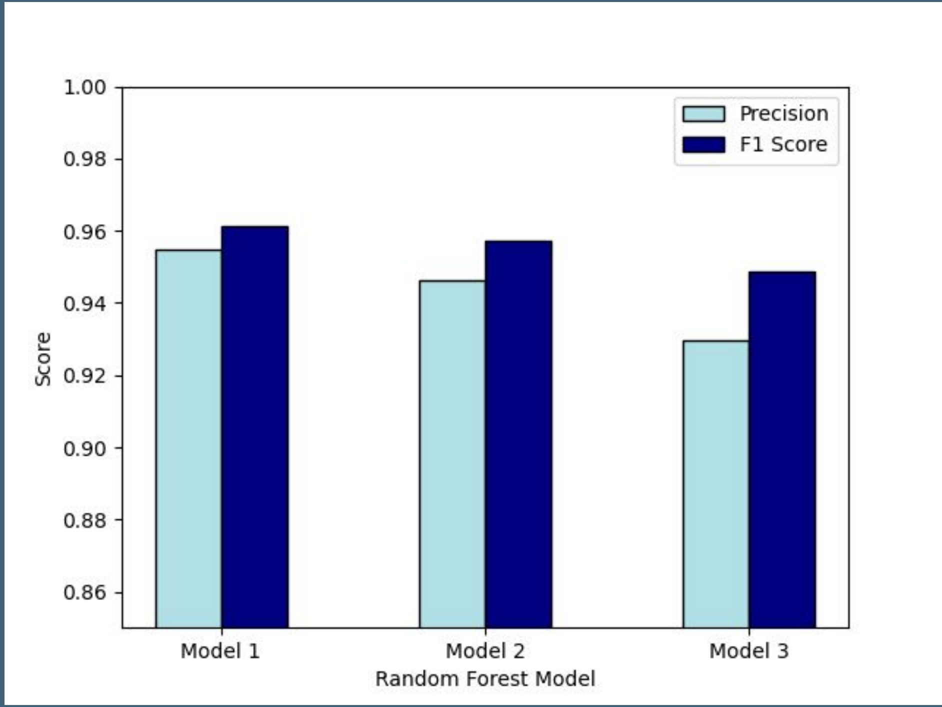
# Binary Classification Models

- Training/testing data for UCDs are from the UltracoolSheet
- “Contaminants” are queried to represent a standard sample of sky
- 864 UCDs (label: 1) and 796 Contaminants (label: 0) form the training set

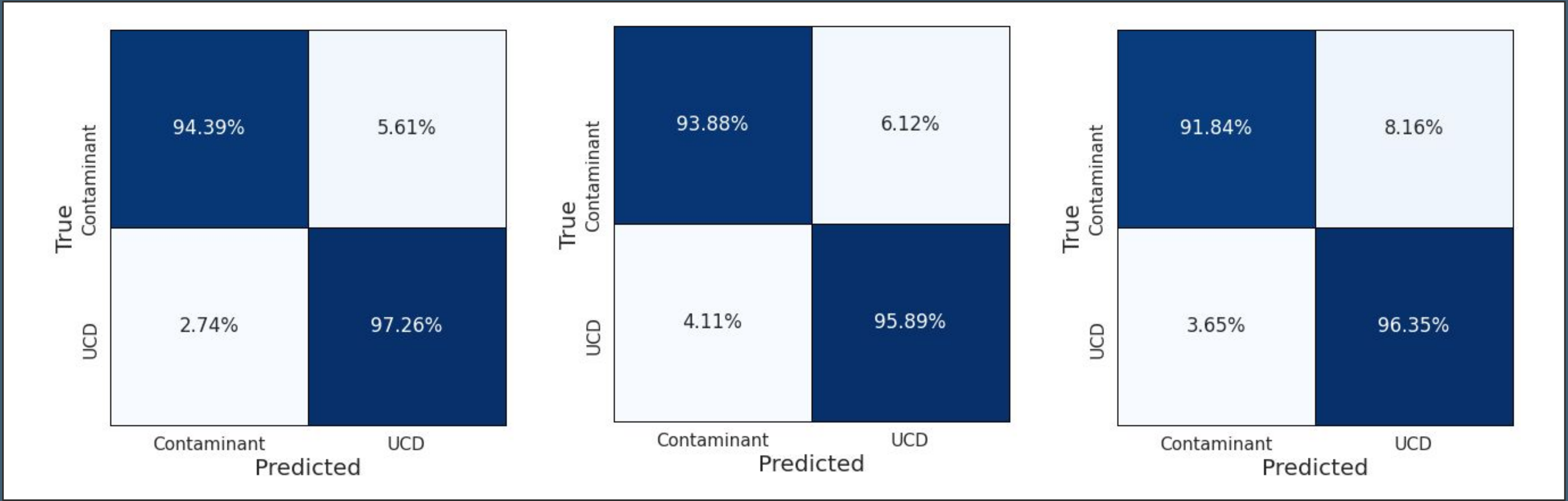
| **Model 1** | **Model 2** | **Model 3** |
| --- | --- | --- |
| Uses optical and infrared (rizYJ$K_s$W1W2) magnitudes and proper motions | Removes proper motions, only has rizYJ$K_s$W1W2 magnitudes | Based only on color from r-i to W1-W2 |

# Results: Binary Models

- Slight dip in performance from Model 1 to Model 2 when proper motions are removed
- Proper motions were the least important feature - included as close UCDs have larger motions
- Training just on colors still performs well

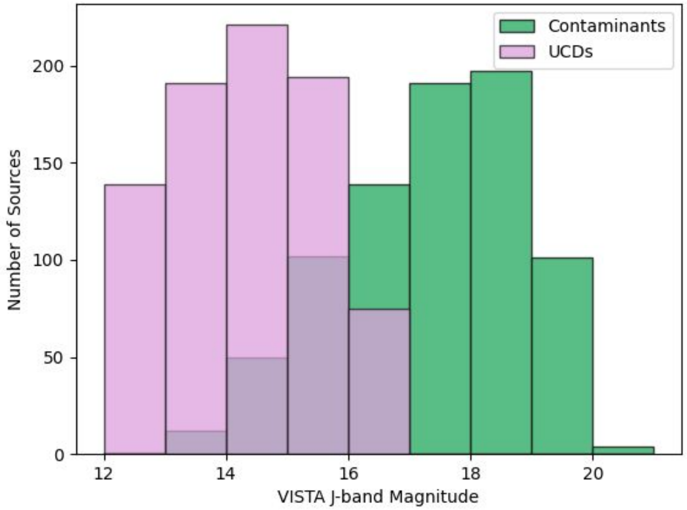


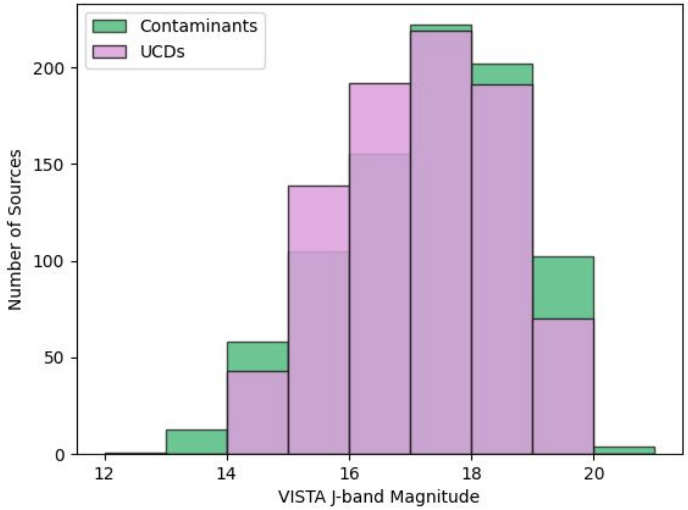
# Results: Binary Models




Model 1 | Model 2 | Model 3

# Brightness Bias

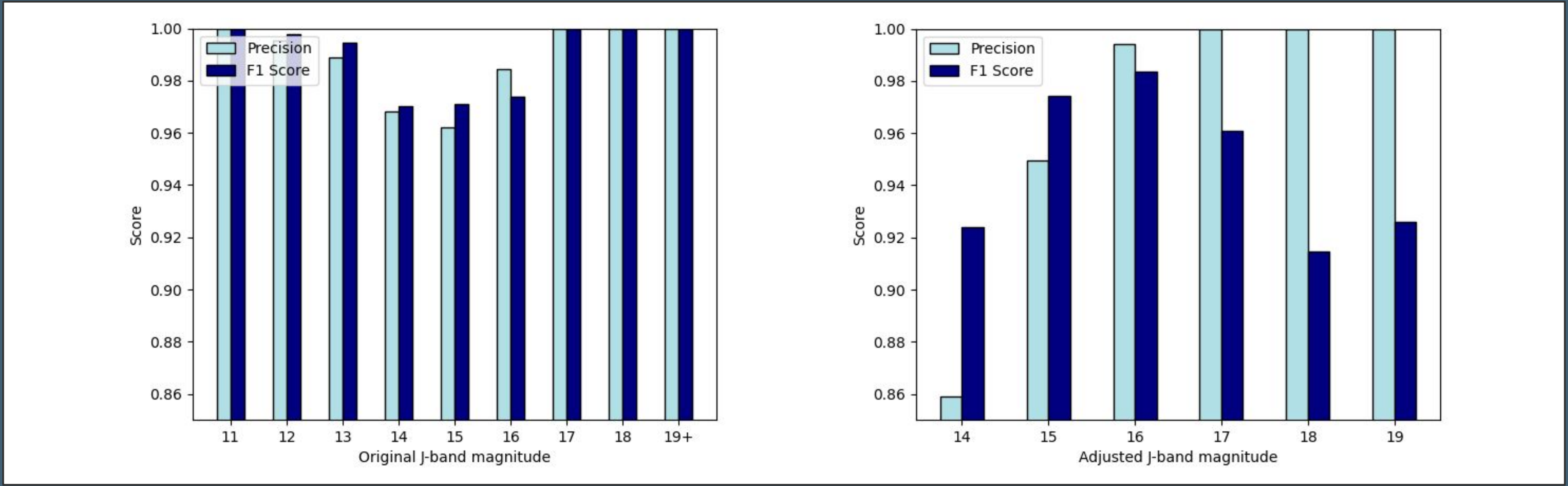



Adjusting VHS J-band photometry of sources to prevent brightness from biasing the classification

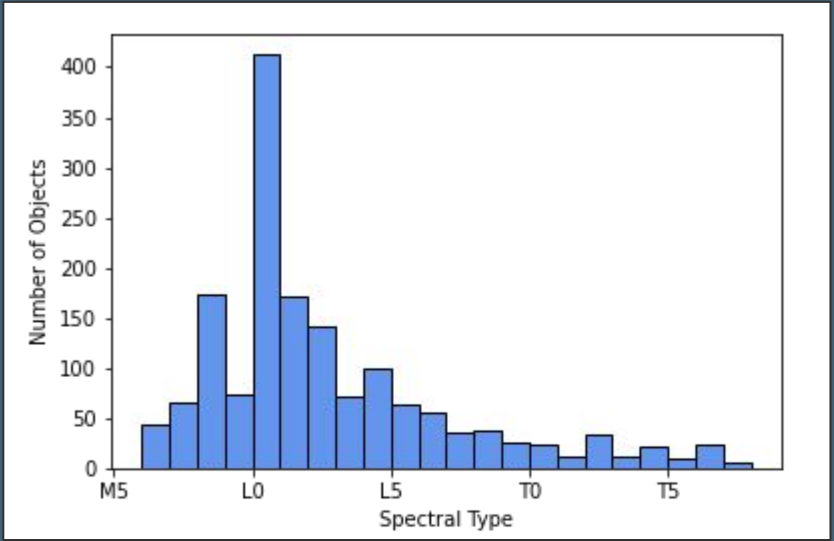
# Results: Magnitude Adjustment

- All sources in the training set are oversampled to 1000 using photometric uncertainty as noise for RF model testing
- Separated into bins 1 magnitude wide and tested through RF model 2



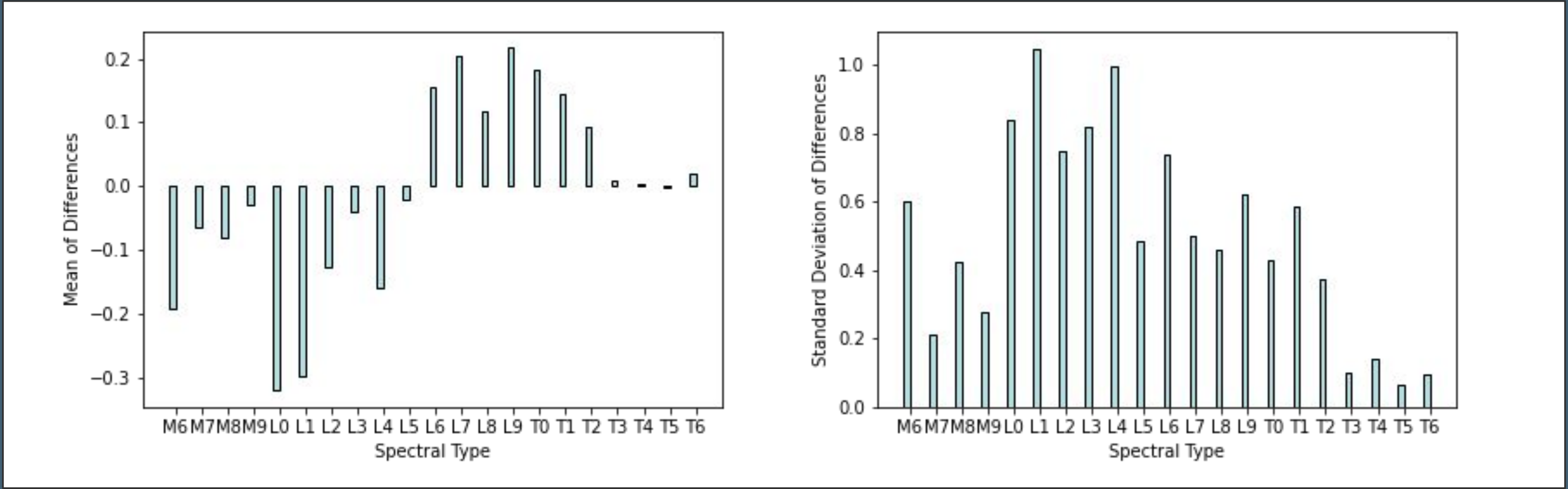
# Spectral Type

- The UltracoolSheet has very few T dwarfs with photometry, only 1 T9
- Oversampling with noise based on spectral type to increase T dwarf population
- Balanced all types to 1000 each



# Spectral Classification

- RF regression model trained on photometric colors from UltracoolSheet using z, Y, J, $K_s$, W1 and W2 bands
- Classification from M6 to T6



# Summary

- RF methods work accurately and quickly
- Still have limitations: need full photometry, potential for overfitting
- Broadly applicable to color-based/photometric selection of any type of source
- Can aid in creating a robust method of classification

# Future Work

- Further contaminant search of possible galactic sources
- RF parameter optimization
- Search for candidates in DES and running sources through our RF models
- Use population simulation models to measure Milky Way structure parameters

# Acknowledgements

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Dr. Adam Burgasser

Dr. Chris Theissen

ASTRO DATALAB

Cool Star Lab

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# Thanks!

# Questions?

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