New catalogue of Pre-Main Sequence objects using AI

Miguel Vioque

University of Leeds

R. D. Oudmaijer (University of Leeds, UK), M. Schreiner (Desupervised, Denmark), D. Baines (ESAC, Spain), and R. Pérez-Martínez (Isdefe,Spain)

STARRY

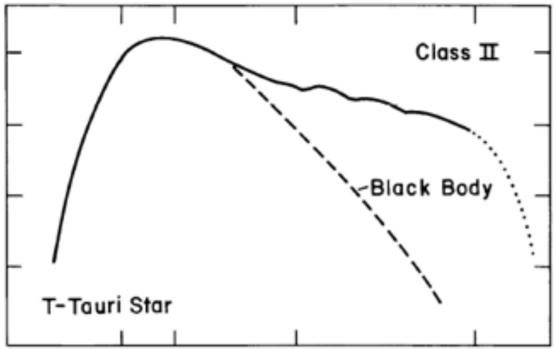
STARS THAT 'R' YOUNG

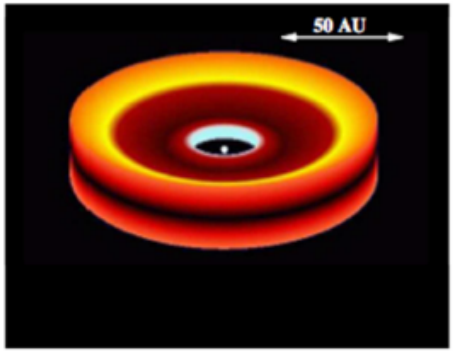
MARIE CURIE ACTIONS

Isdefe

Artificial Intelligence in Astronomy, Garching, 25th of July 2019

Looking for new High-Mass Pre-Main Sequence (PMS) objects

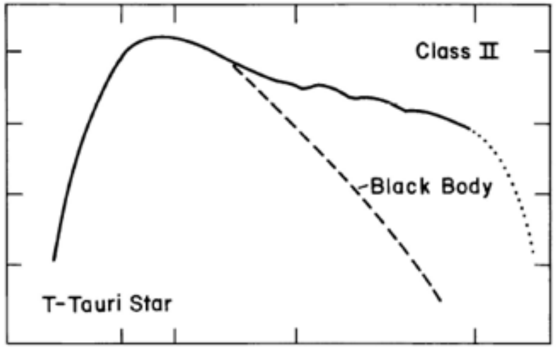


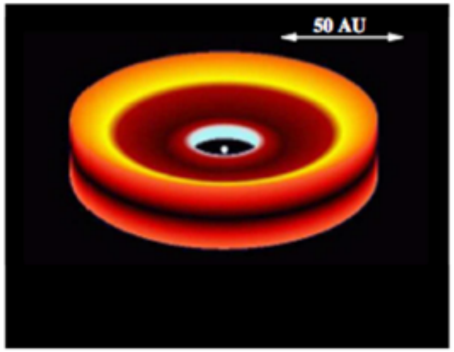


Main characteristics of PMS objects:

- Infrared excesses
- Hα emission
- Photometric variability

Looking for new High-Mass Pre-Main Sequence (PMS) objects



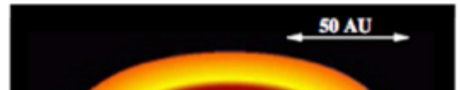


Main characteristics of PMS objects:

- Infrared excesses
- Hα emission
- Photometric variability

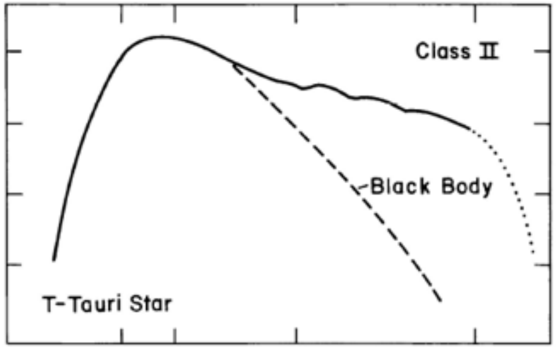
~250 high-mass PMS known at the moment

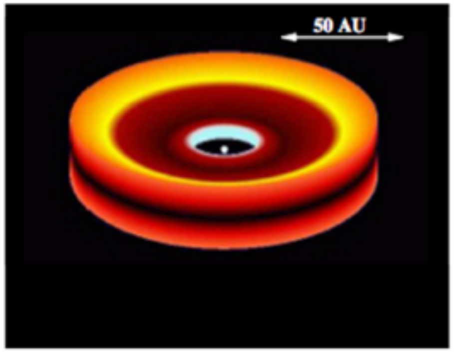
Looking for new High-Mass Pre-Main Sequence (PMS) objects



Perform an homogeneous selection, distance and position independent!

Looking for new High-Mass Pre-Main Sequence (PMS) objects

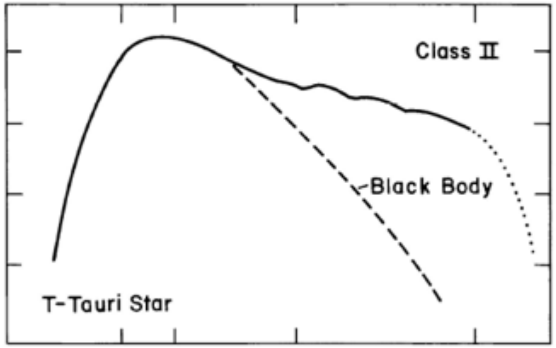


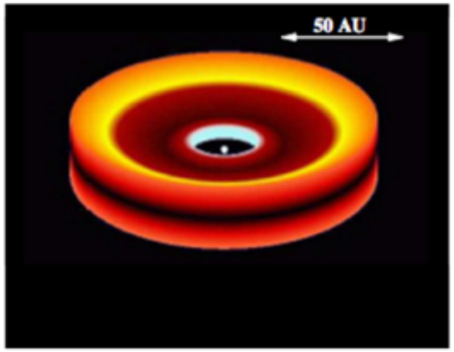


Main characteristics of PMS objects:

- Infrared excesses
- Hα emission
- Photometric variability

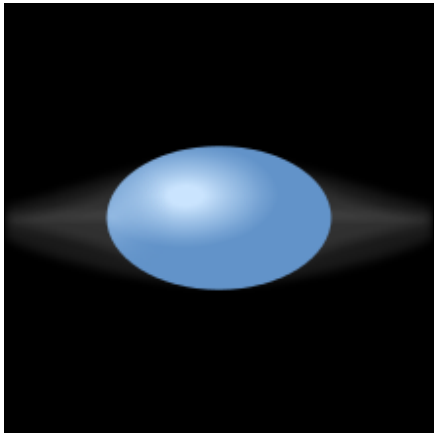
Looking for new High-Mass Pre-Main Sequence (PMS) objects





Main characteristics of PMS objects:

- Infrared excesses
- Hα emission
- Photometric variability



High mass PMS objects (Herbig Be stars) are very similar to **Classical Be stars**

We used an Artificial Neural Network

Selection of the **characteristics**:

- From Gaia: $\boldsymbol{B_p}, \boldsymbol{G}, \boldsymbol{R_p}$ and **2 variability indicators**
- From AllWISE: $\boldsymbol{J}, \boldsymbol{H}, \boldsymbol{K_s}, \boldsymbol{W1}, \boldsymbol{W2}, \boldsymbol{W3}, \boldsymbol{W4}$
- From IPHAS & VPHAS+: $\boldsymbol{r - H_\alpha}$

Create **all possible colours**

Remove all linear dependency (PCA)

Distance and position independent!

Cross-match Gaia DR2 x AllWISE x IPHAS and VPHAS+

Master Sample = 4,151,538 sources

Construction of the **Training Set** (**3 classes**):

- **848** Pre-Main Sequence objects
  - **163** are Herbig Ae/Be stars (high mass end, all available)
- **775** Classical Be stars (all available)
- **471,111** random sources with all the characteristics

Cross-match Gaia DR2 x AllWISE x IPHAS and VPHAS+

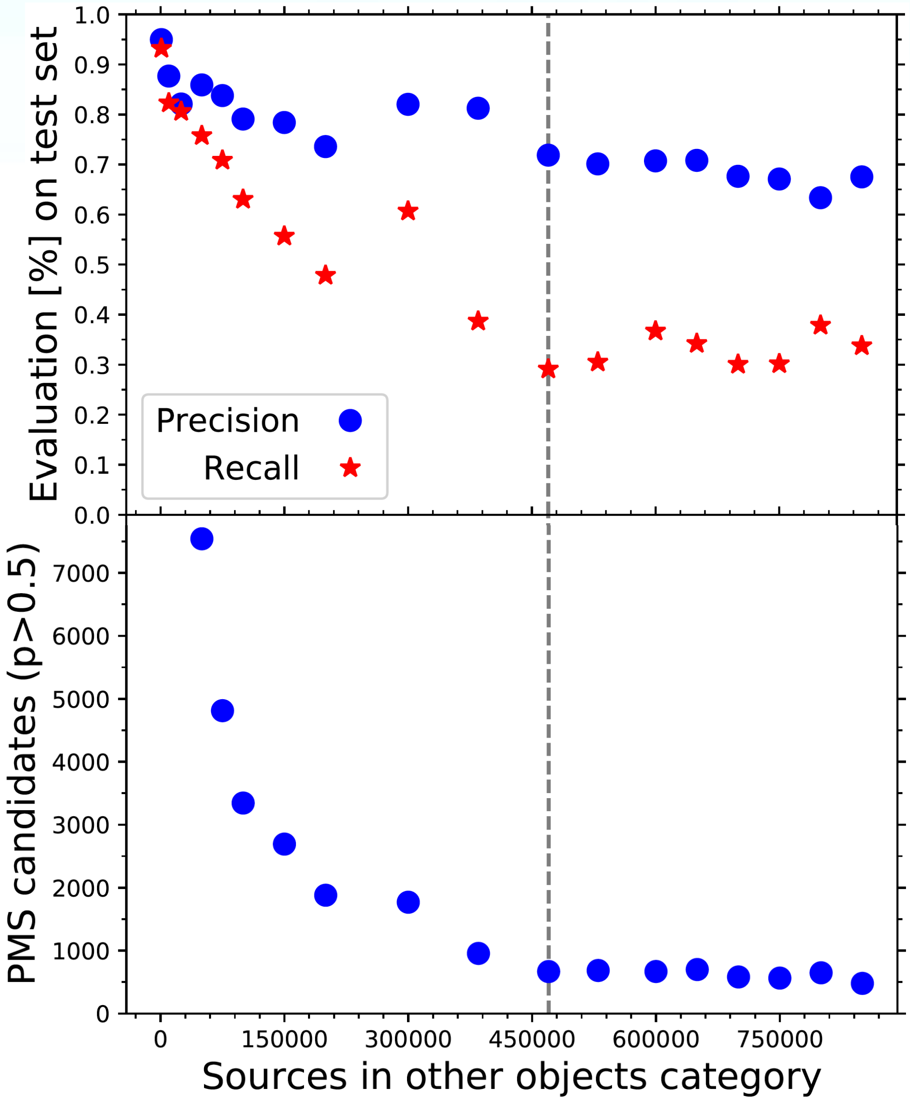
Master Sample = 4,151,538 sources

Construction of the **Training Set** (**3 classes**):

- **848** Pre-Main Sequence objects
  - **163** are Herbig Ae/Be stars
    (high mass end, all available)

- **775** Classical Be stars (all available)

- **471,111** random sources with all the characteristics



Size of other objects category

There is a stabilization point and after this the algorithm generalizes properly.

Cross-match Gaia DR2 x AllWISE x IPHAS and VPHAS+

Master Sample = 4,151,538 sources

Construction of the **Training Set** (**3 classes**):

- **848** Pre-Main Sequence objects
  - **163** are Herbig Ae/Be stars
    (high mass end, all available)
- **775** Classical Be stars (all available)
- **471,111** random sources with all the characteristics

Cross-match Gaia DR2 x AllWISE x IPHAS and VPHAS+

Master Sample = 4,151,538 sources

Construction of the **Training Set** (**3 classes**):

- **848** Pre-Main Sequence objects
  - **163** are Herbig Ae/Be stars
    (high mass end, all availa
- **775** Classical Be stars (all available)
- **471,111** random sources with all the characteristics

There is a large contamination between categories!

This algorithm cannot assess itself

Construction of the **Training Set** (**3 classes**):

- **848** Pre-Main Sequence objects
    - **163** are Herbig Ae/Be stars
      (high mass end, all availa

- **775** Classical Be stars (all availabl

- **471,111** random sources with all the characteristics

There is a large contamination between categories!

Architecture & Methodology

In order to deal with the **small Training Set** and **the large contamination**:

Bootstrap (x30)

Balanced class weights

Architecture & Methodology

In order to deal with the **small Training Set** and **the large contamination**:

Bootstrap (x30)
Balanced class weights

Chosen architecture:

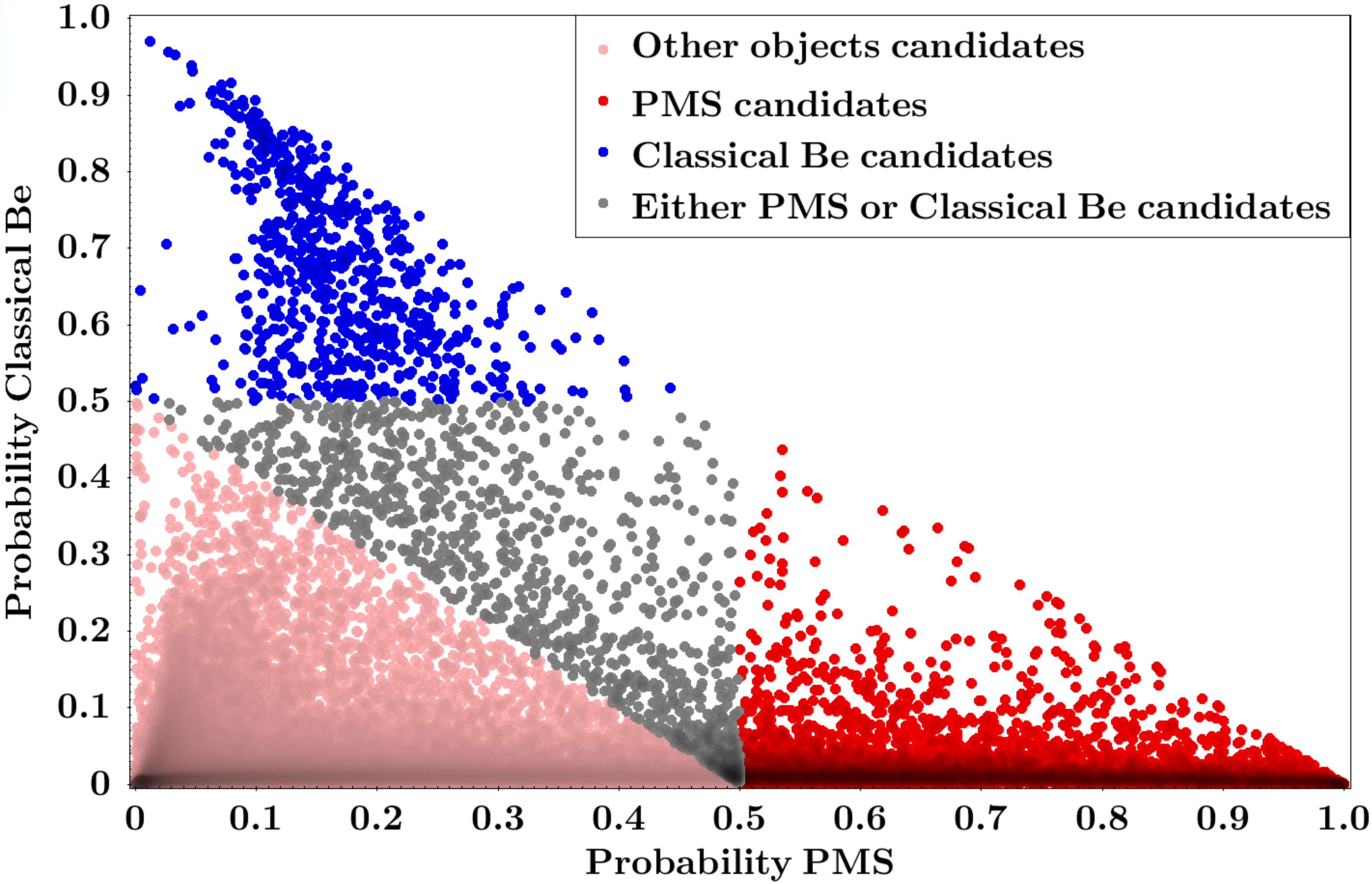
- 2 hidden layers of 580 neurons each
- L2 regularization (0.01) and 50% dropout
- Early-stopping when precision gets to a maximum (10% Cross-Validation)
- Test Set size is kept to 10%

Training the Neural Network

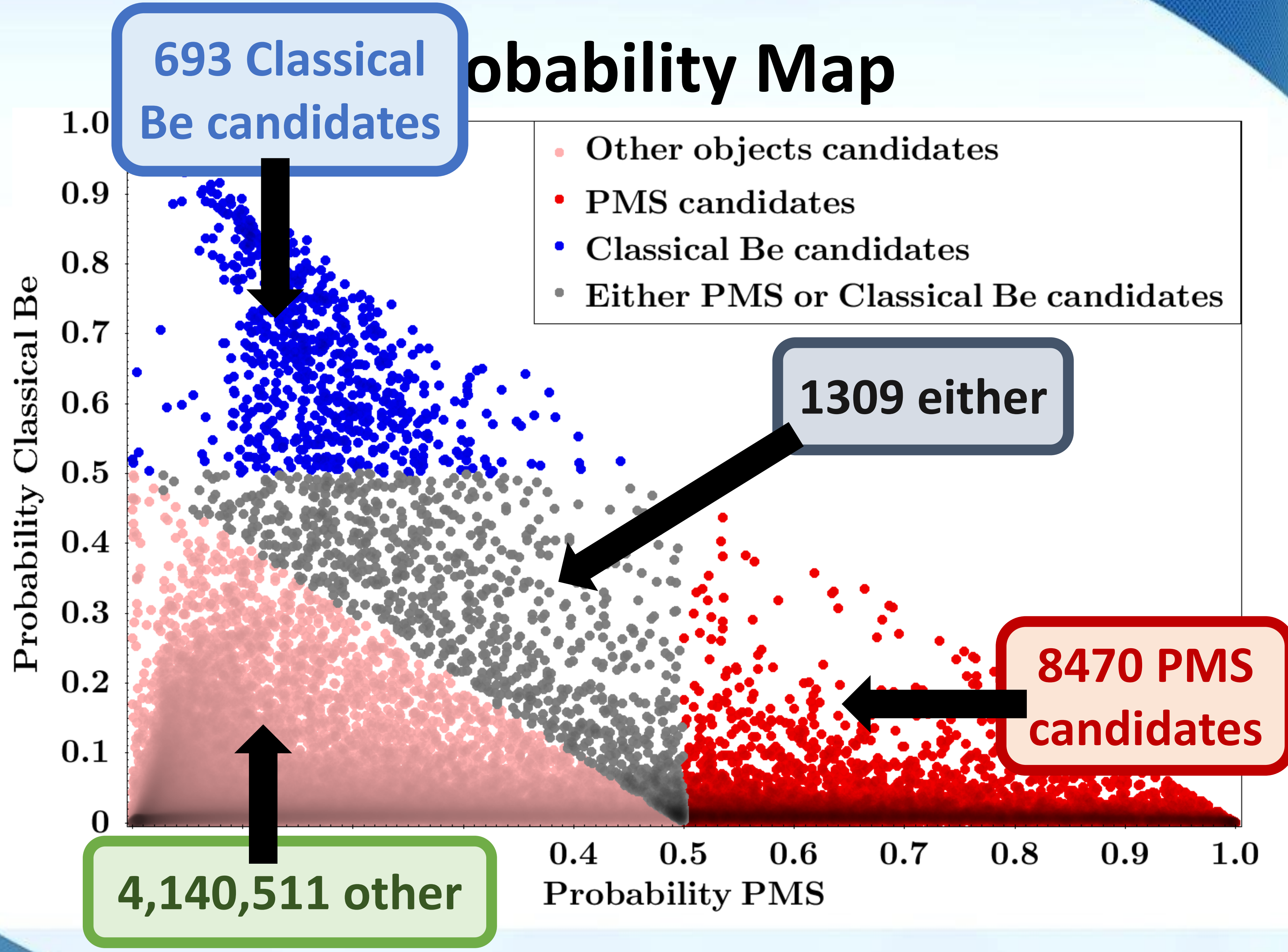
Trained Neural Network

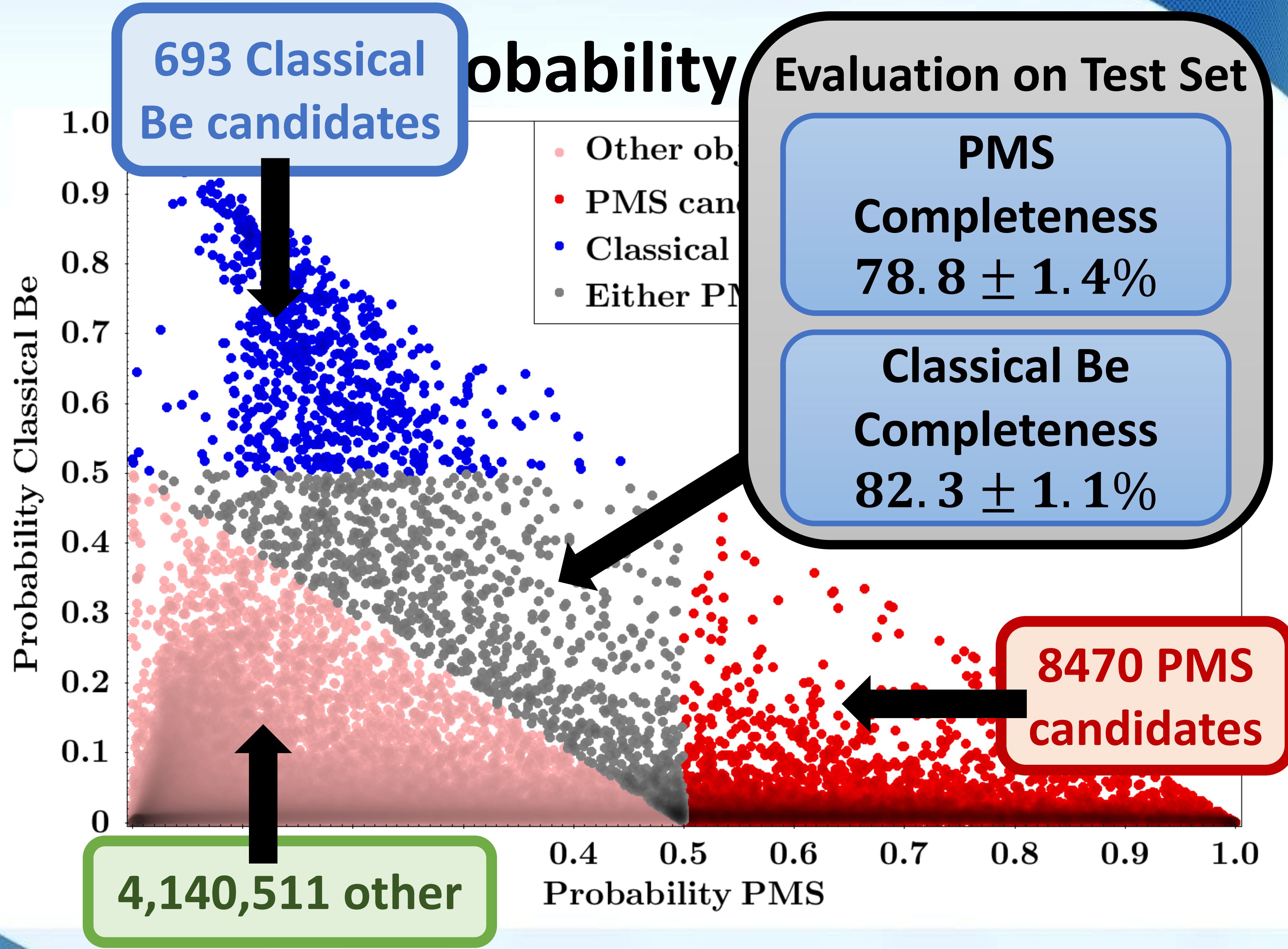
Master Sample = 4,151,538 sources

Probability Map



obability Map

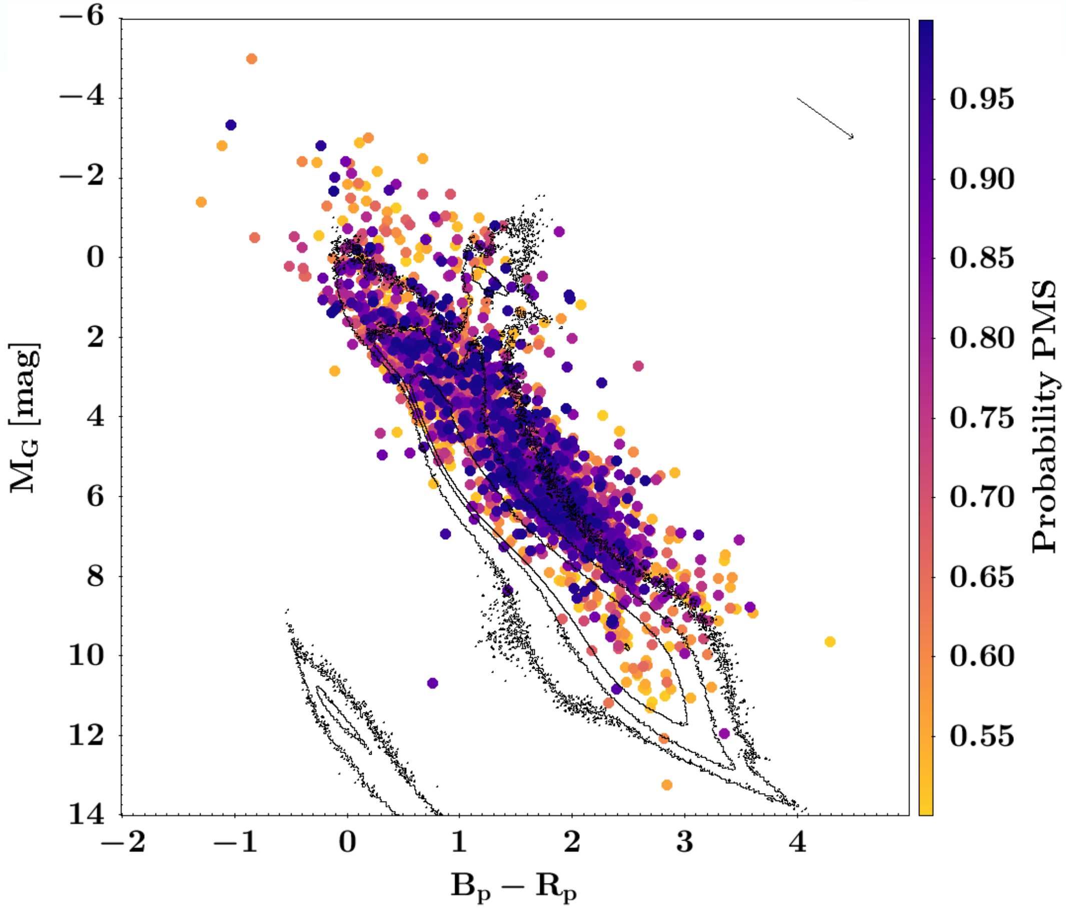




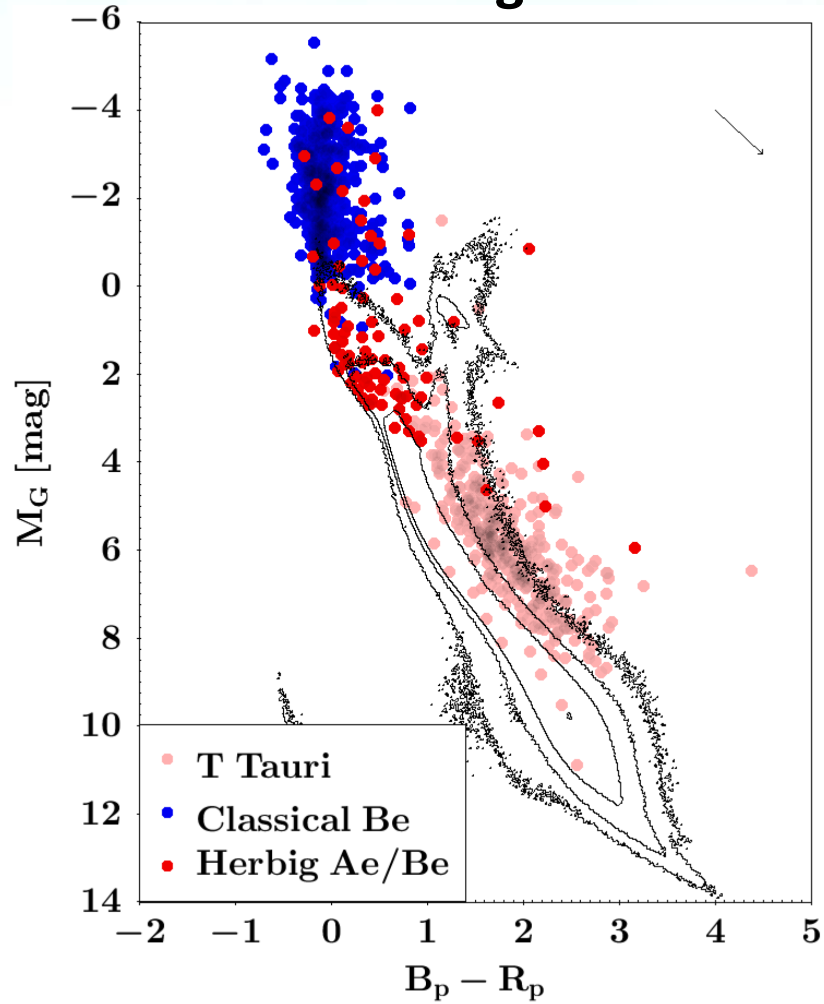
obability
693 Classical Be candidates
Evaluation on Test Set
PMS Completeness
78.8 ± 1.4%
Classical Be Completeness
82.3 ± 1.1%
Other obj
PMS can
Classical
Either PM
8470 PMS candidates
4,140,511 other
Probability Classical Be
Probability PMS
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
0.4
0.5
0.6
0.7
0.8
0.9
1.0

HR diagram

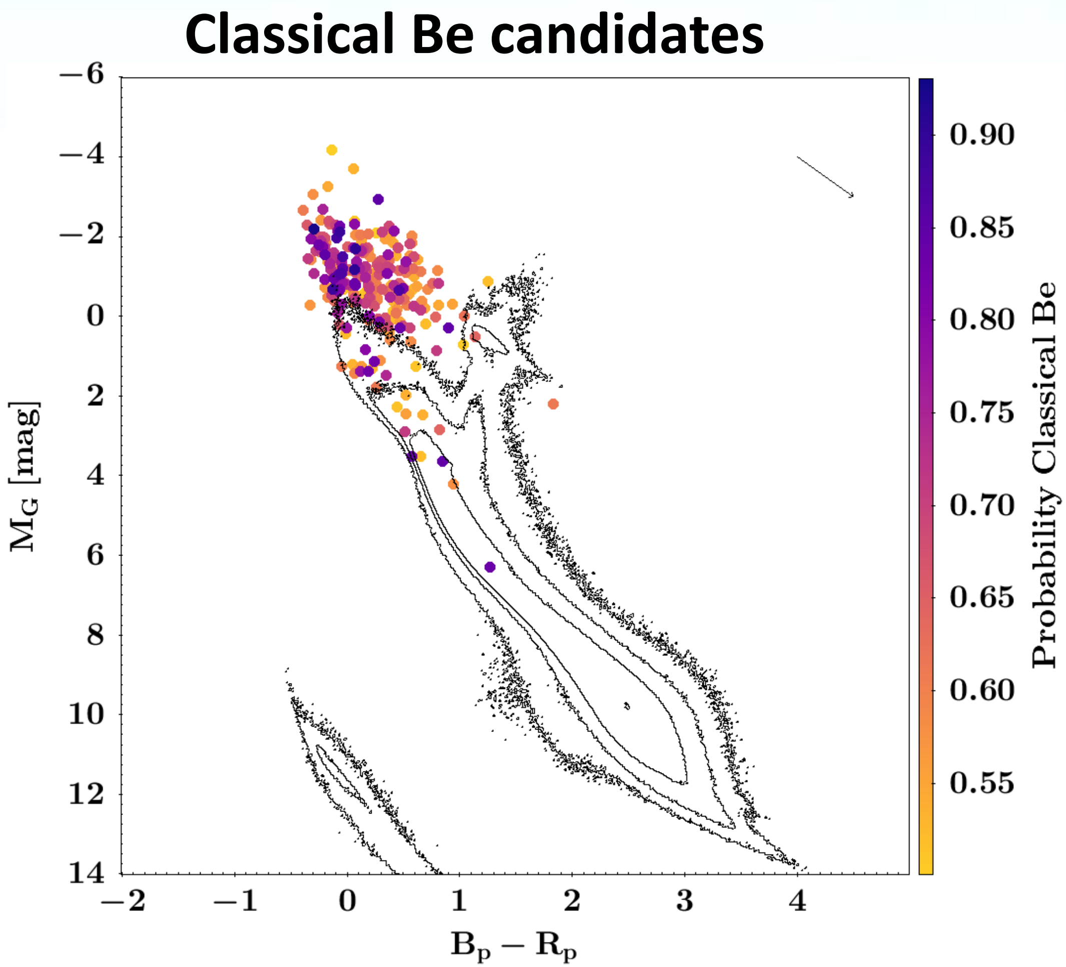
PMS candidates

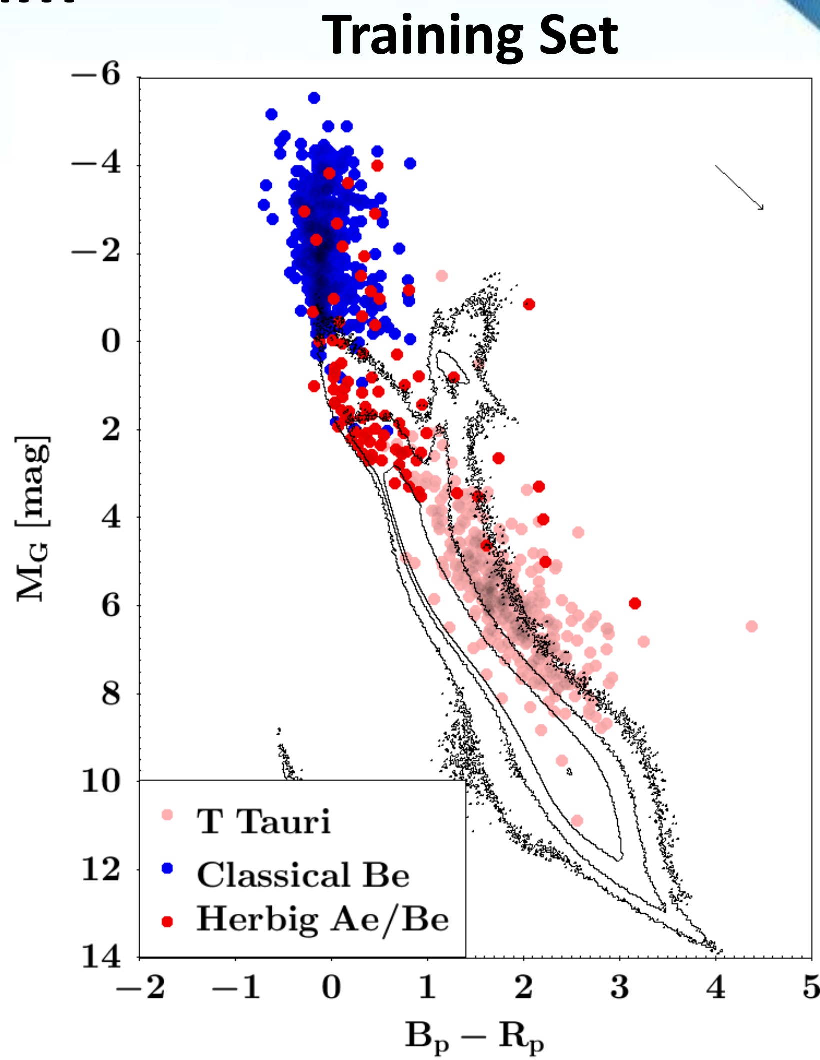


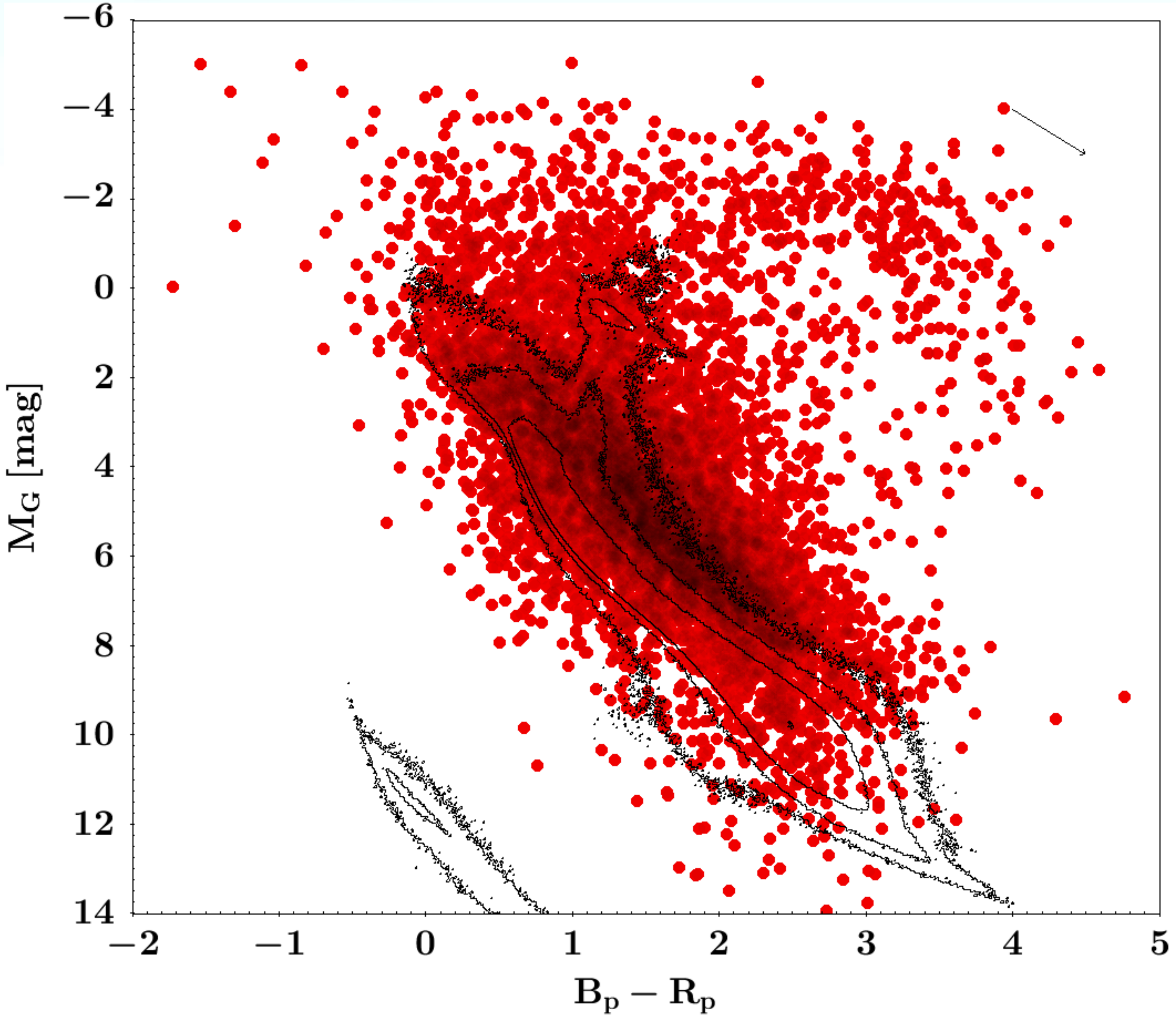
Training Set



HR diagram

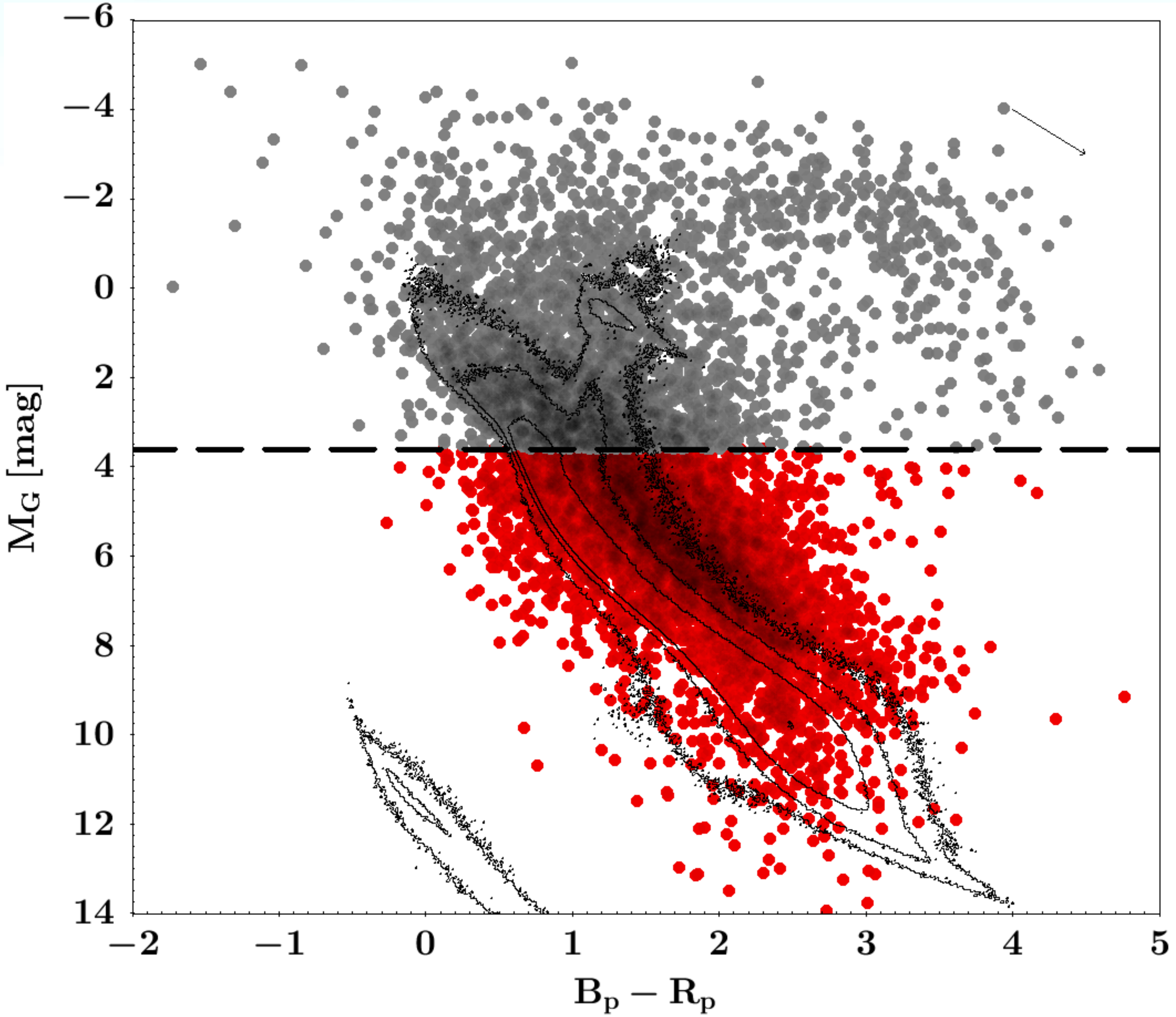

Classical Be candidates
−6
−4
−2
0
2
4
6
8
10
12
14
−2
−1
0
1
2
3
4
M_G [mag]
$B_p - R_p$
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
Probability Classical Be


Training Set
−6
−4
−2
0
2
4
6
8
10
12
14
−2
−1
0
1
2
3
4
5
M_G [mag]
$B_p - R_p$
T Tauri
Classical Be
Herbig Ae/Be

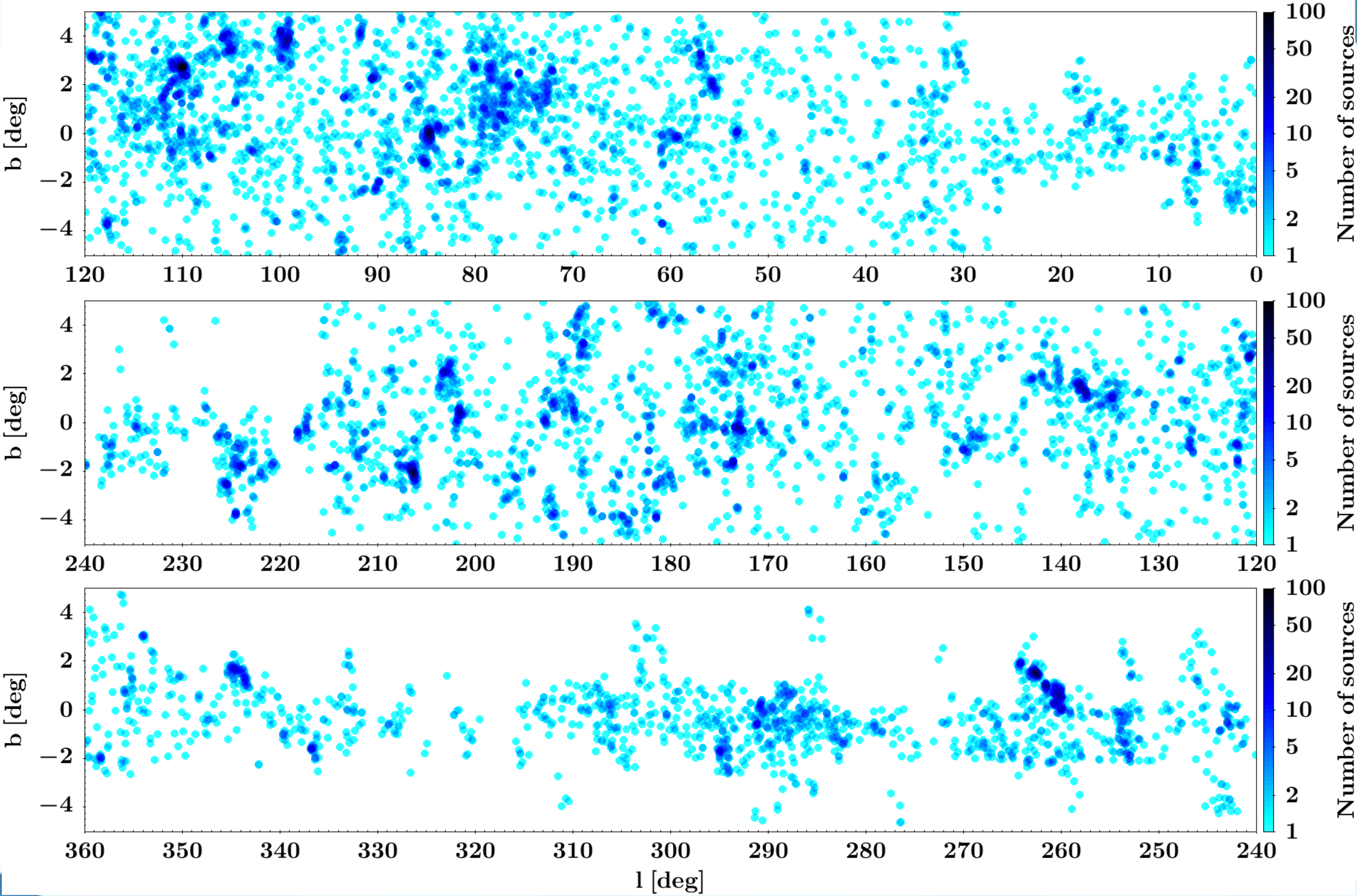


−6
−4
−2
0
2
4
6
8
10
12
14
M_G [mag]
−2
−1
0
1
2
3
4
5
$B_p - R_p$

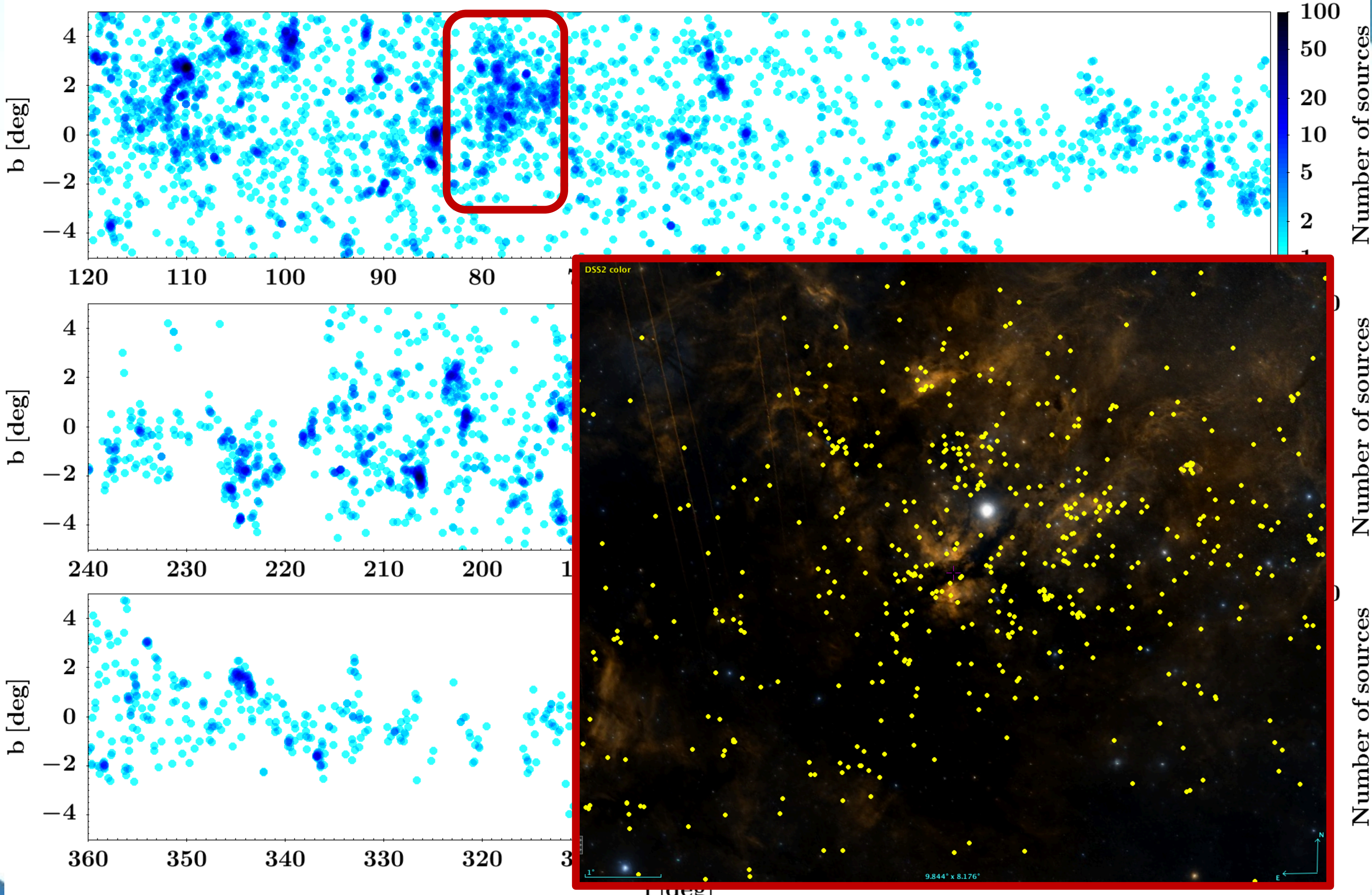
3131 potential high mass (**682** with good Gaia solution)



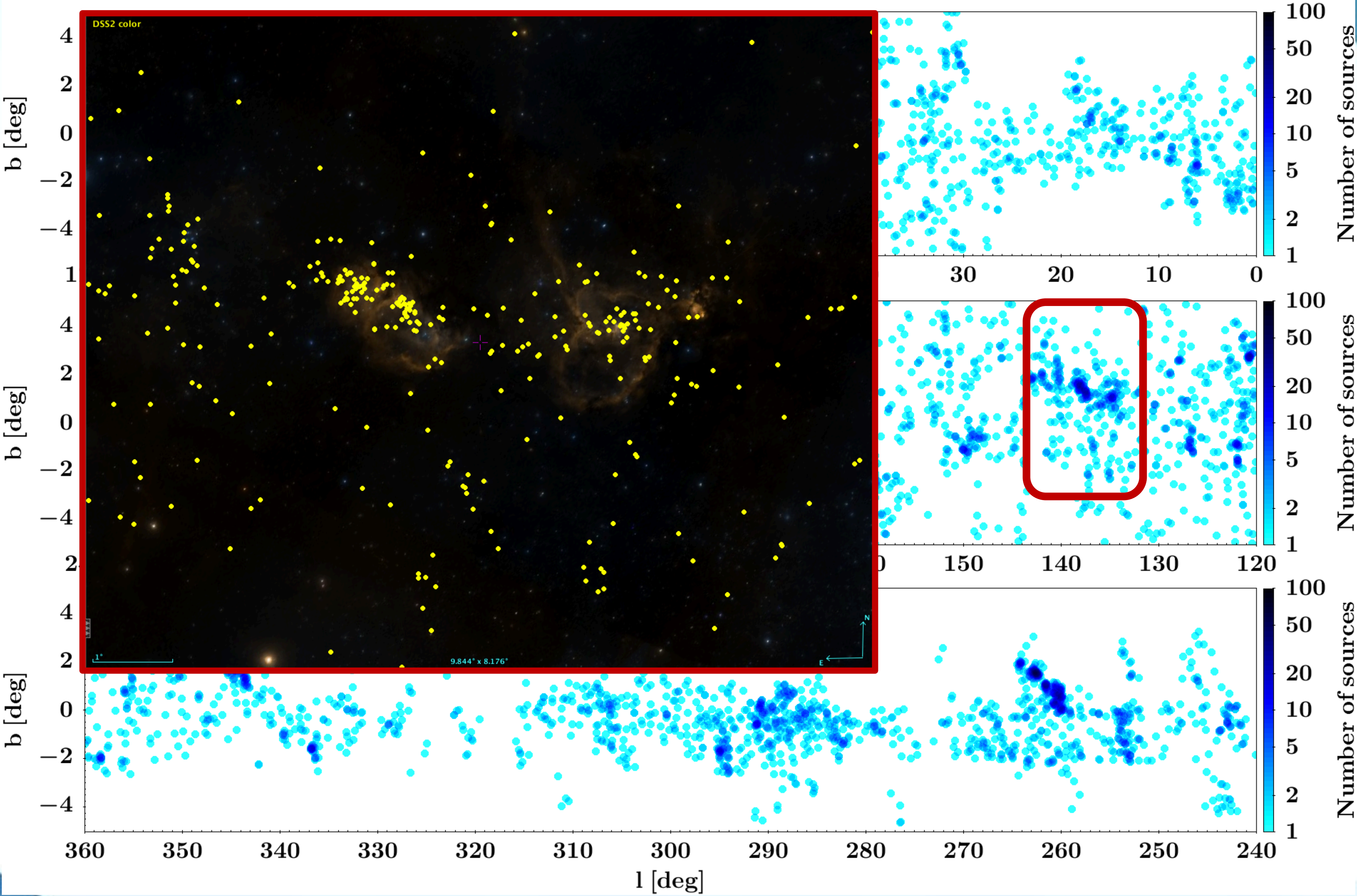
Coordinates



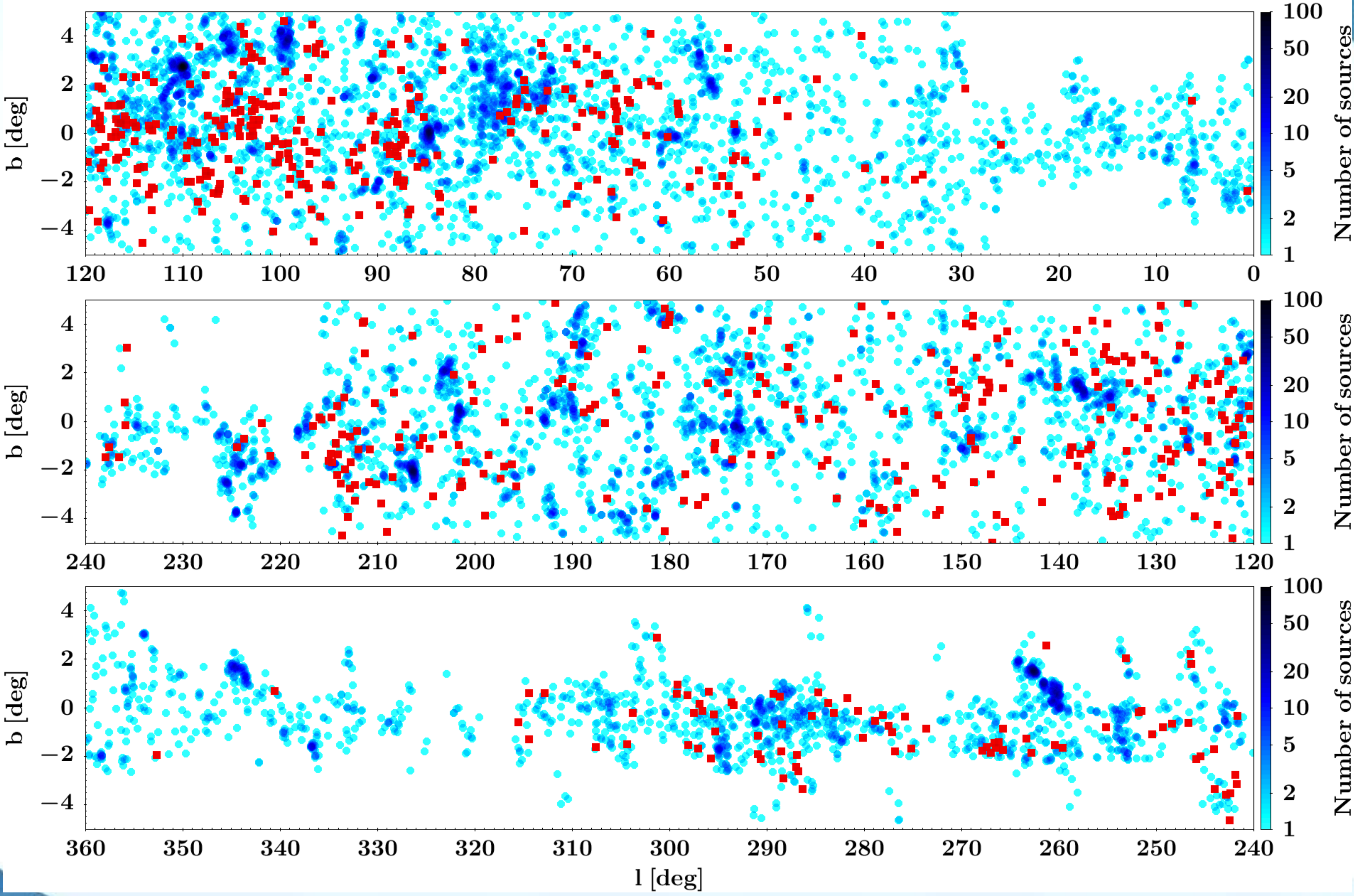
Coordinates



Coordinates

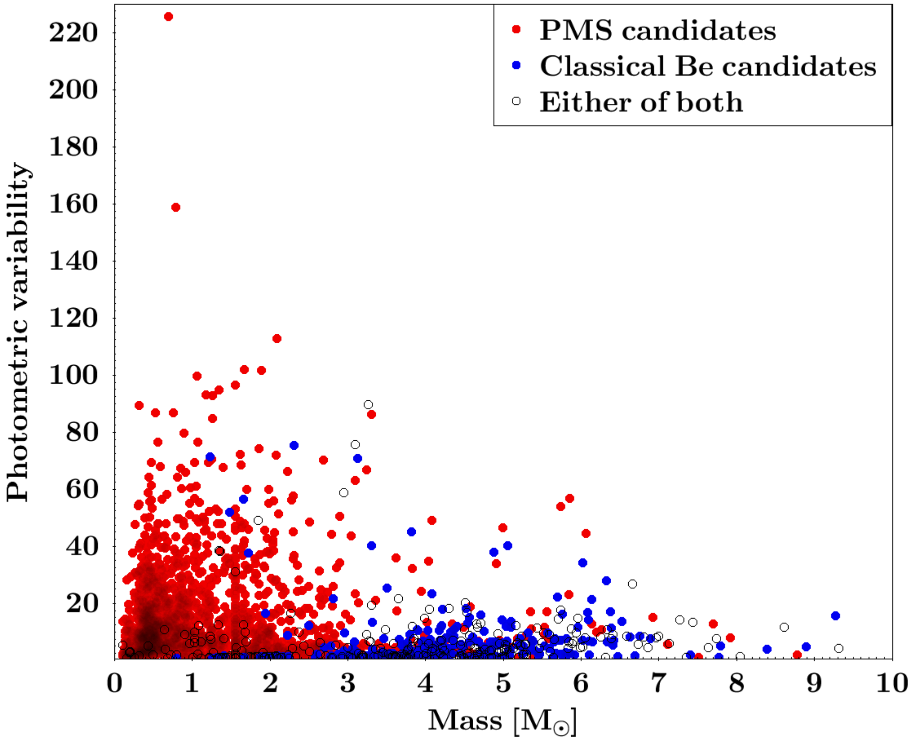


Coordinates

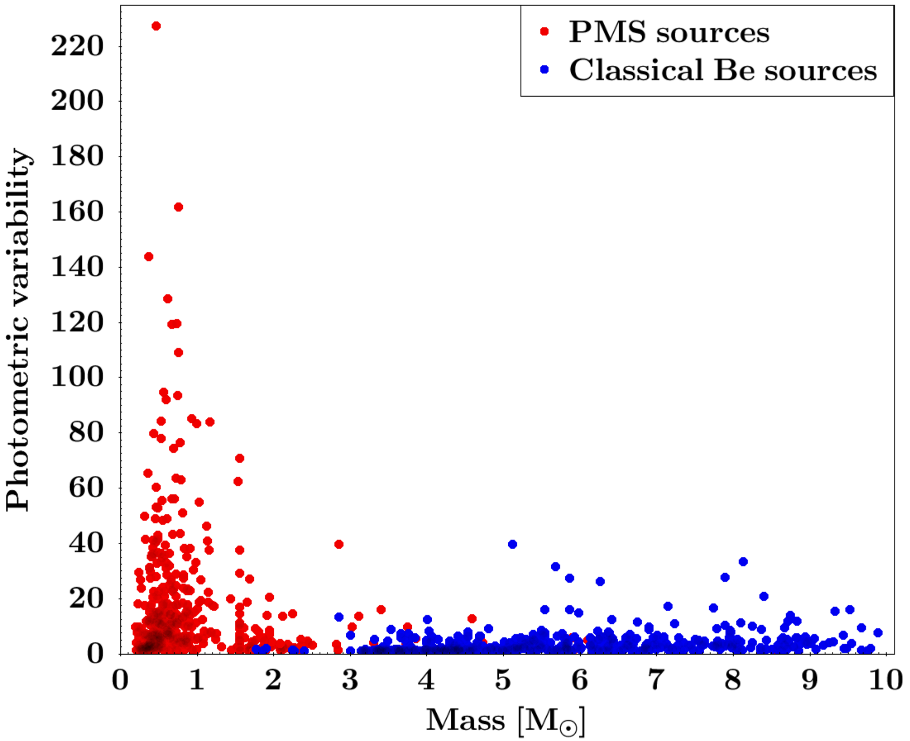


Variability vs. Masses (lower limits)

Candidates

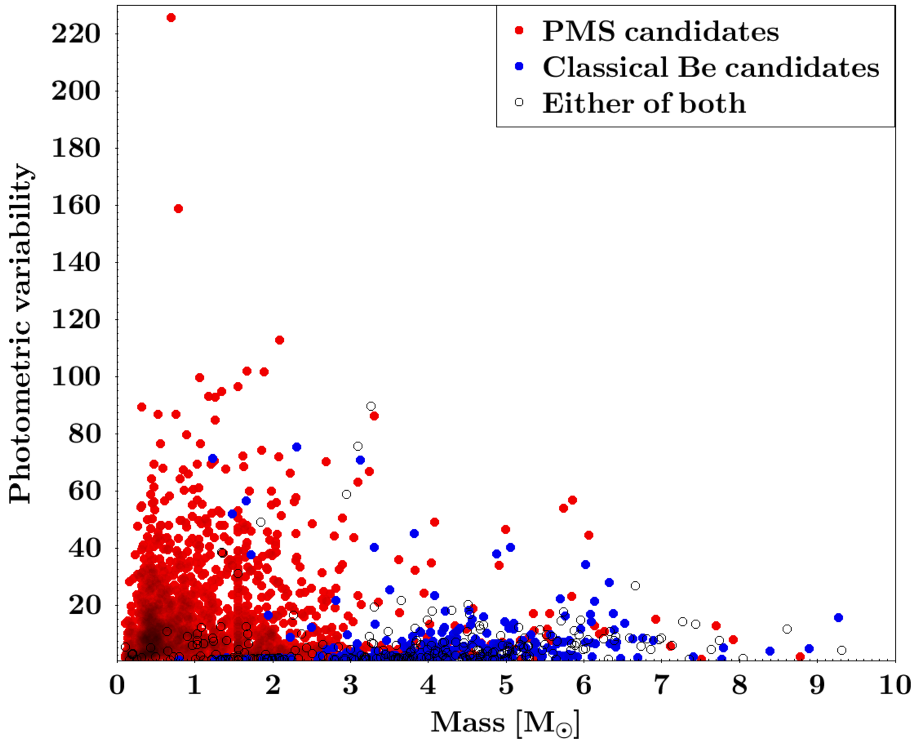


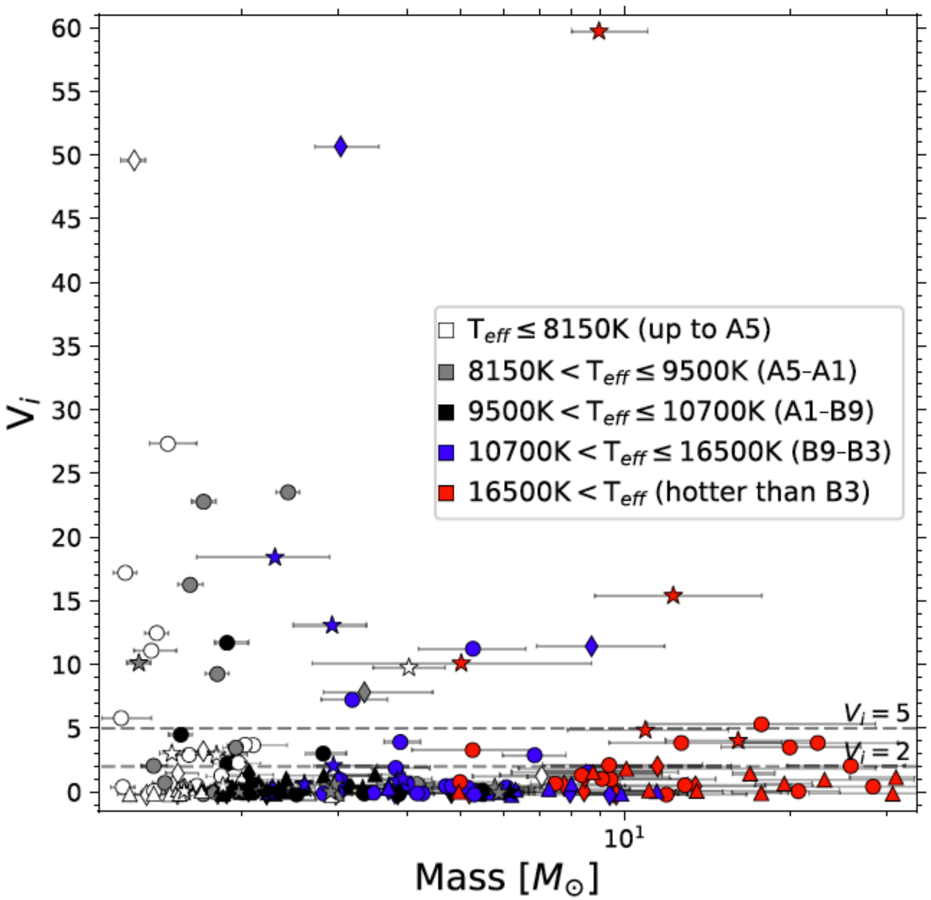
Training Set



Variability vs. Masses (lower limits)

Candidates





Vioque et al. 2018

Results:

- We retrieve **8470 new PMS candidates. 3131 (682) potential high-mass ones** (~250 known at the moment).

- We retrieve **693 new Classical Be stars candidates.**

- We retrieve **1309** candidates of belonging to either one of the two categories.

Completeness
$\mathbf{78.8 \pm 1.4\%}$

Completeness
$\mathbf{82.3 \pm 1.1\%}$

Near- and mid- infrared excesses are the most important characteristics followed by Hα and variability **which are equaly important**

Architecture & Methodology

In order to deal with the **small Training Set** and **the large contamination**:

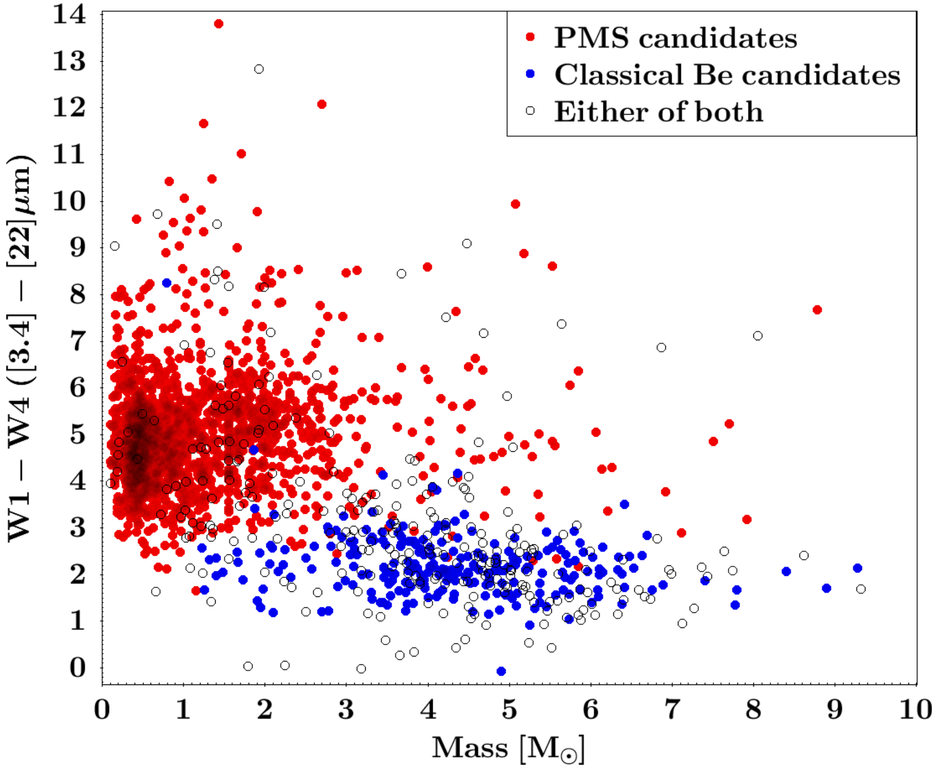
Bootstrap (x30)

Balanced class weights

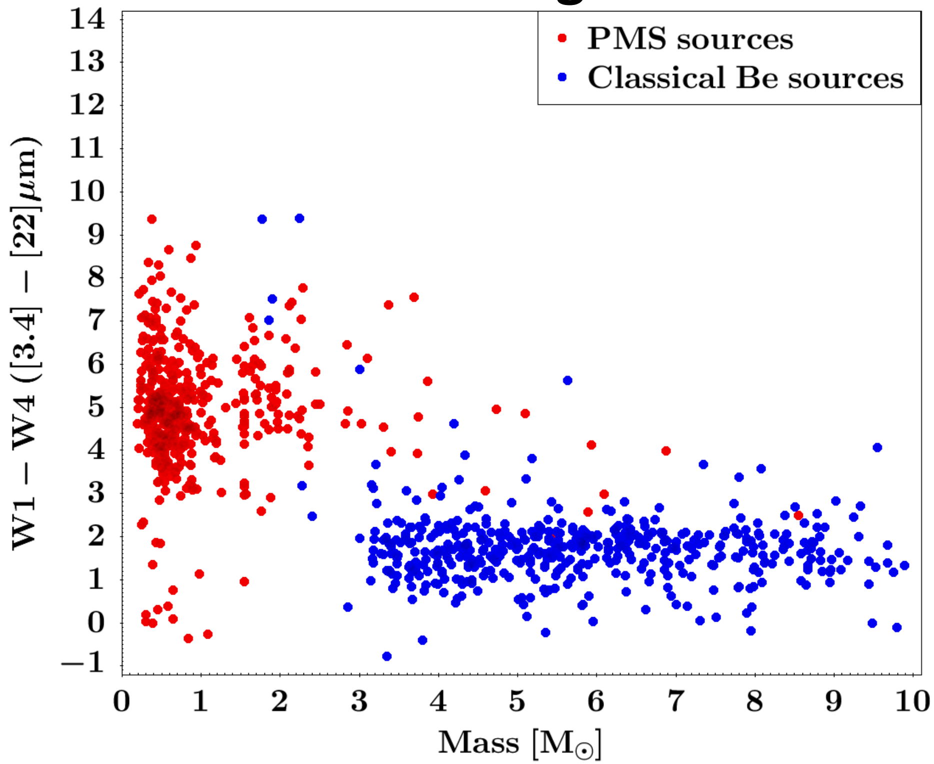
Original Dataset	1	2	3	4	5	6	7	8	9	10
Bootstrap 1	8	6	2	9	5	8	1	4	8	2
Bootstrap 2	10	1	3	5	1	7	4	2	1	8
Bootstrap 3	6	5	4	1	2	4	2	6	9	2

Mid-IR excess vs. Masses (lower limits)

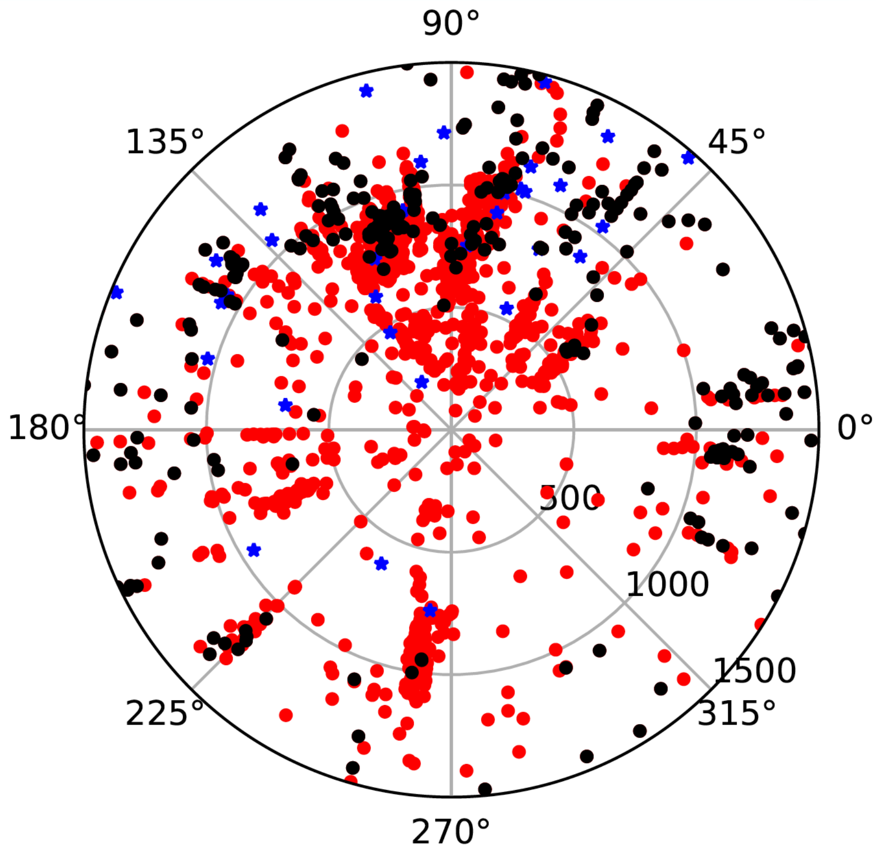
Candidates



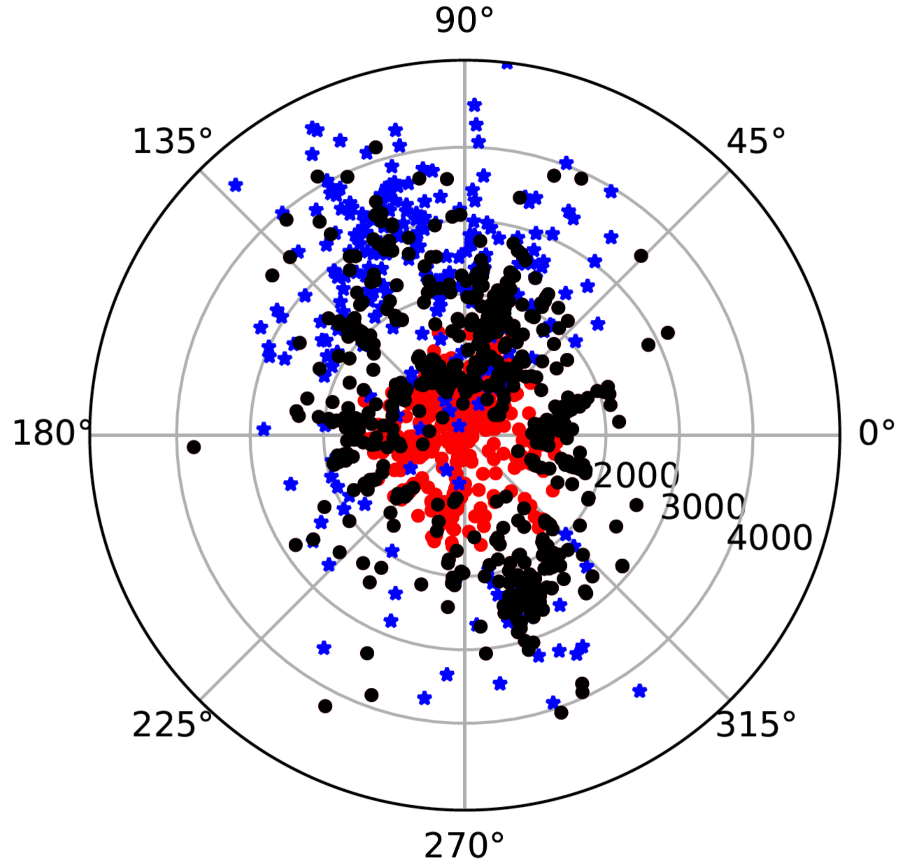
Training Set



Spatial distribution

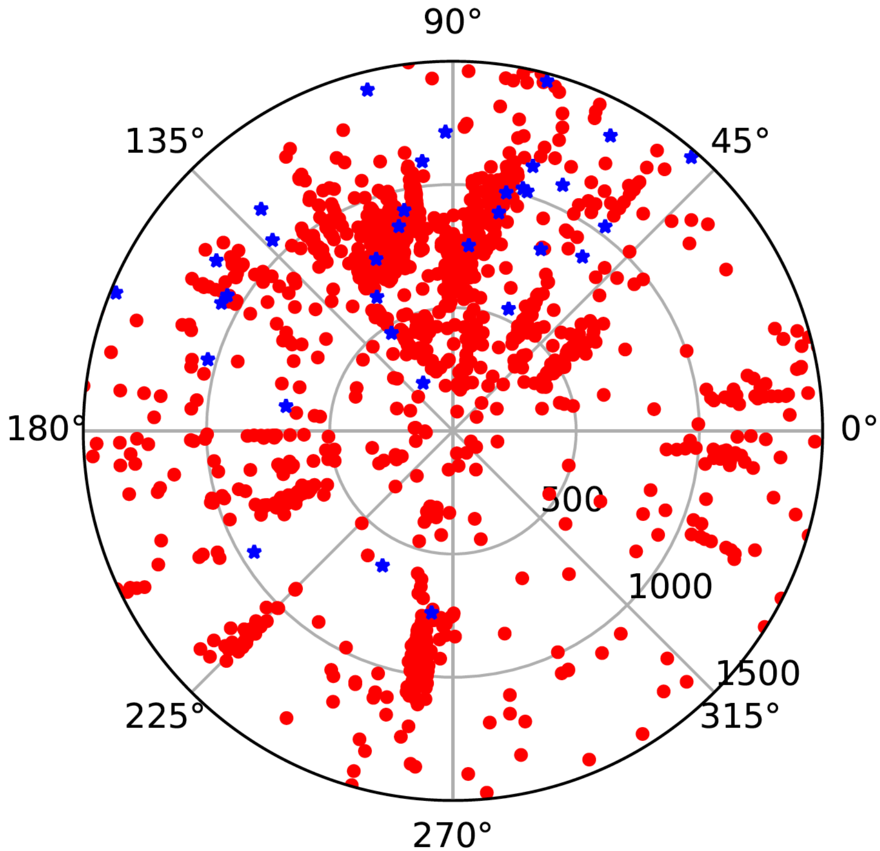


Within 1.5 Kpc

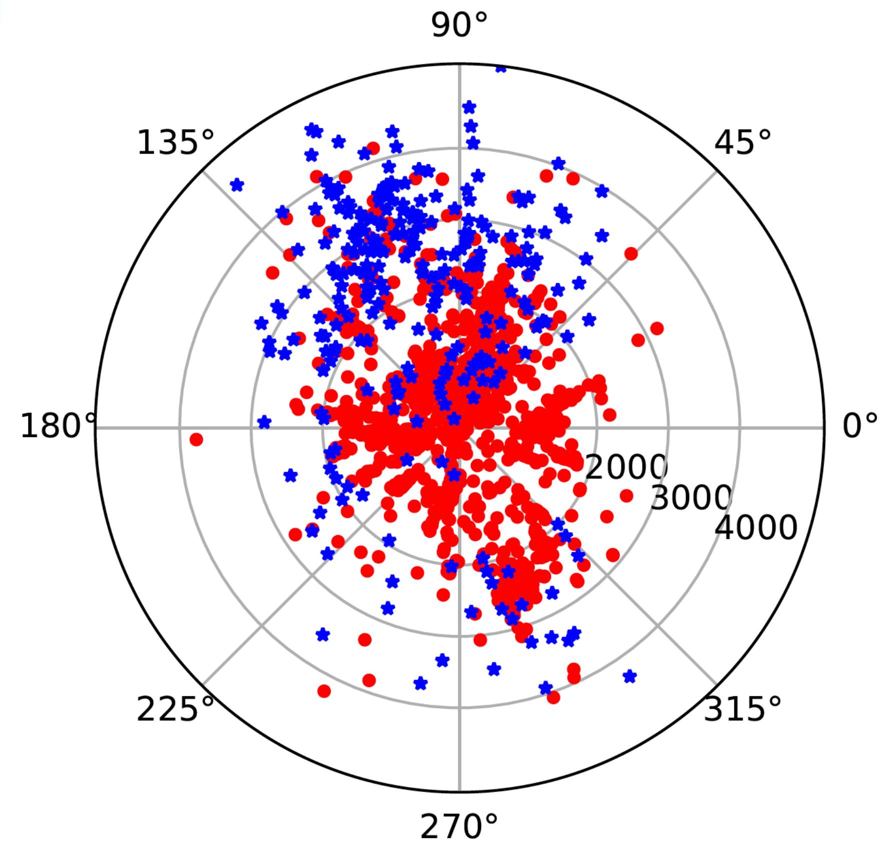


All (up to 5 Kpc)

Spatial distribution

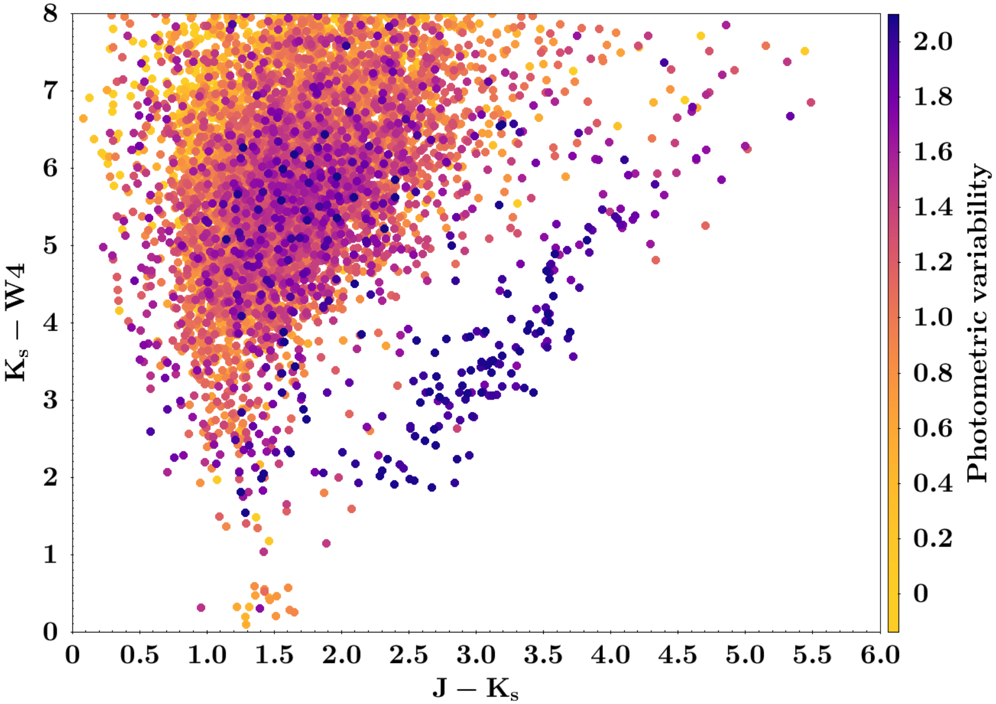


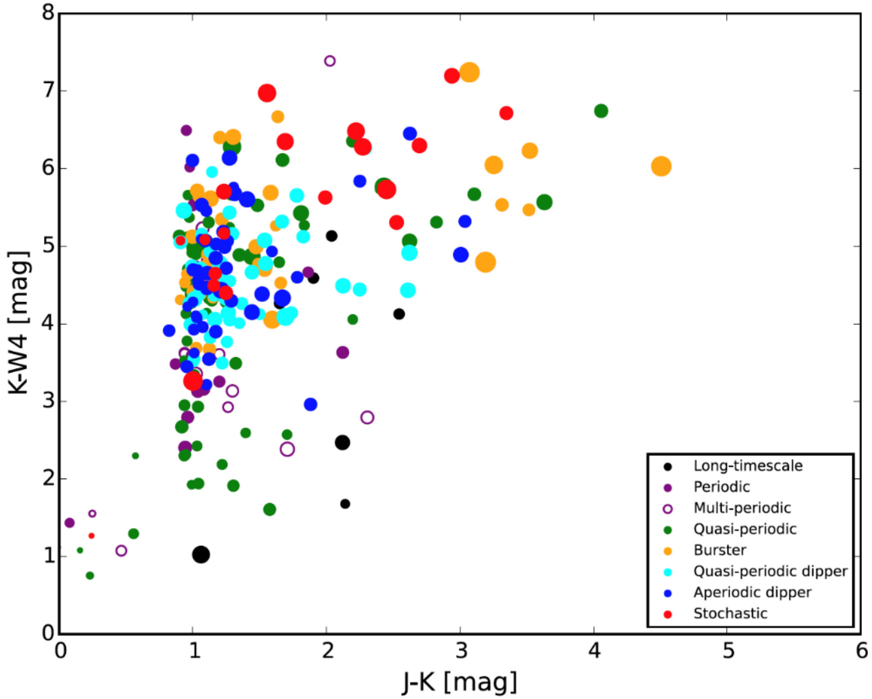
Within 1.5 Kpc



All (up to 5 Kpc)

Candidates

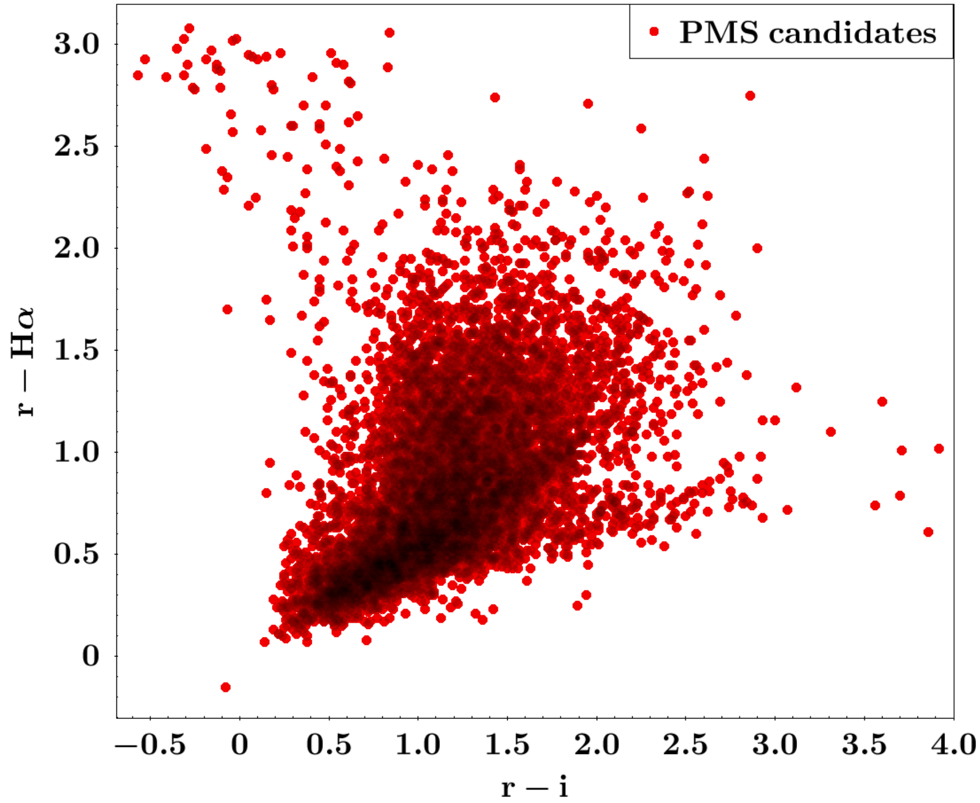


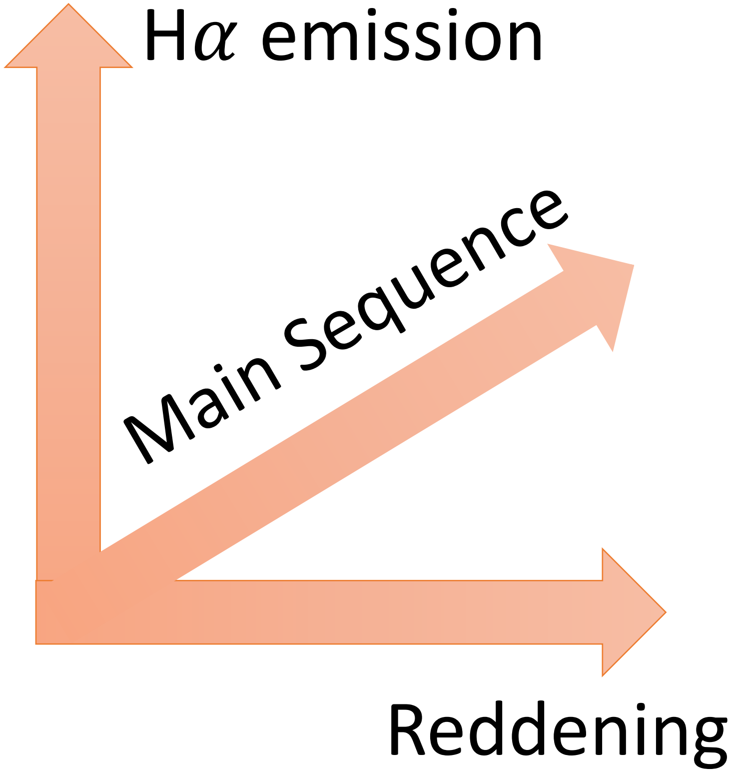


Cody & Hillenbrand, 2018

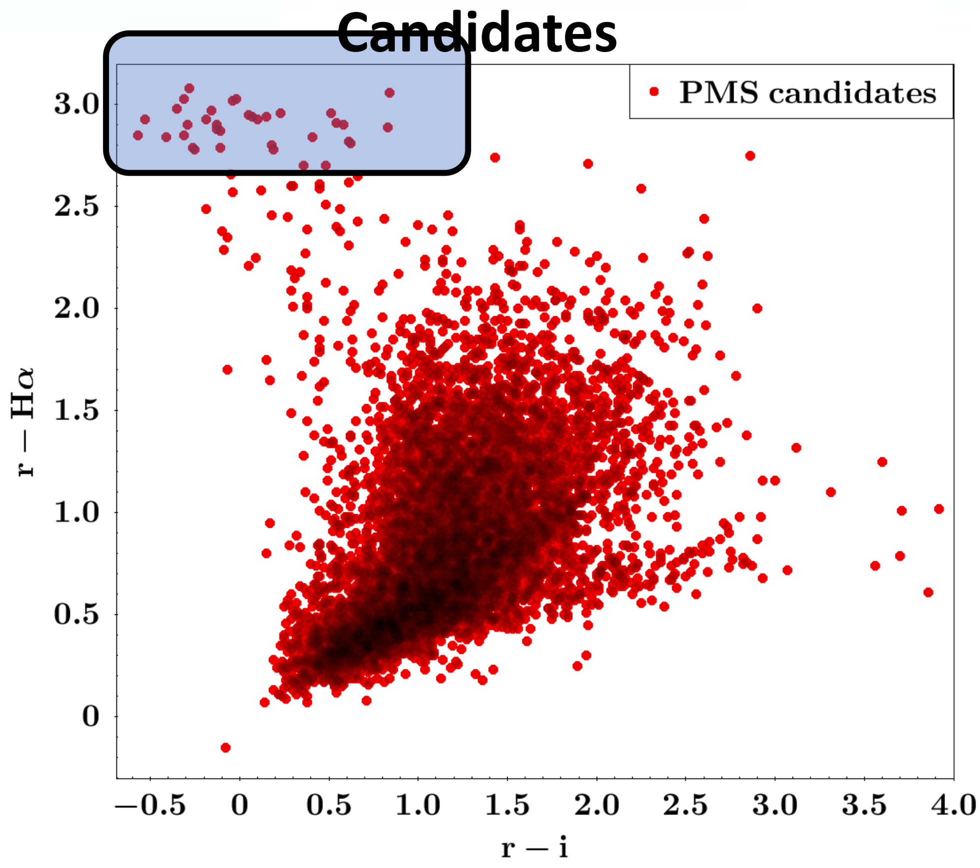
Caveats

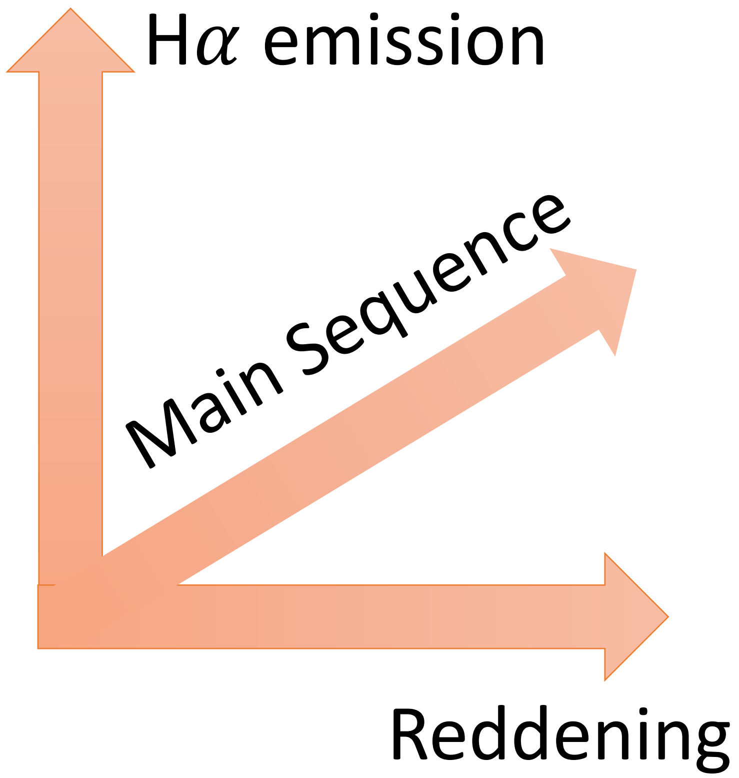
Candidates



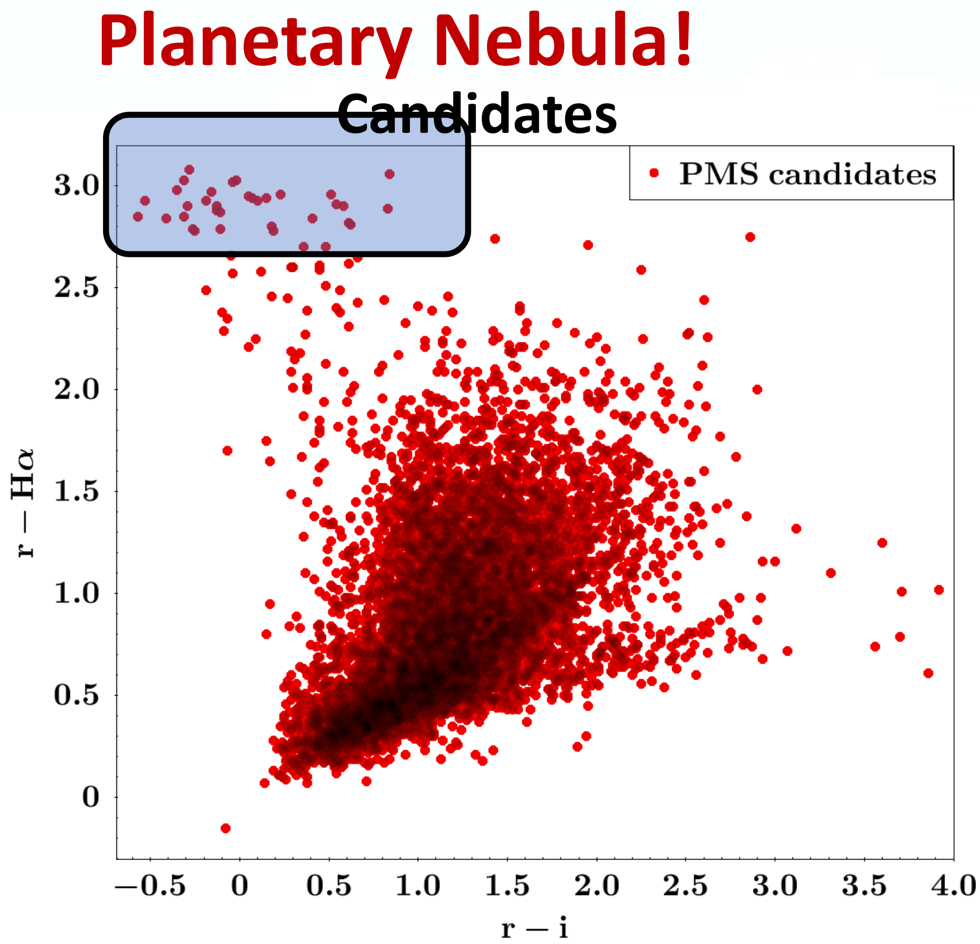


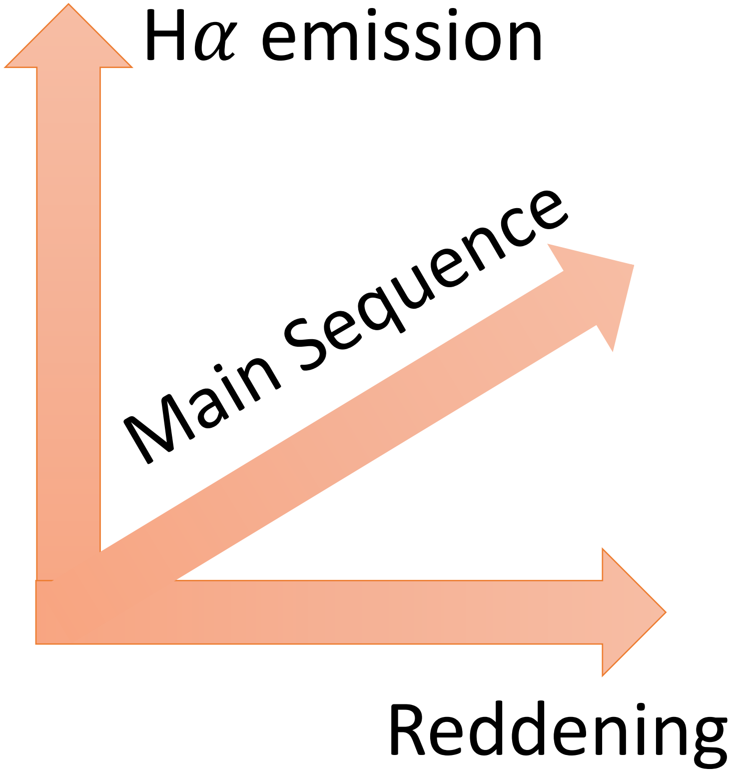
Caveats


Candidates
PMS candidates
r − Hα
r − i
3.0
2.5
2.0
1.5
1.0
0.5
0
−0.5
0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0


Hα emission
Main Sequence
Reddening

Caveats


Planetary Nebula!
Candidates
PMS candidates
r − Hα
r − i
3.0
2.5
2.0
1.5
1.0
0.5
0
−0.5
0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0


Hα emission
Main Sequence
Reddening