

# MACHINE LEARNING AND GAIA DR2, ON THE HUNT FOR OPEN STAR CLUSTERS

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Gaia RIA — February 18th



# PRE-GAIA VIEW OF THE OC POPULATION

- Census counted with around 3000 catalogued objects compiled from heterogeneous data sources [Dias+02][Kharchenko+13][Röser+16]
- Estimated number of OCs  $\sim 10^5$  [Binney&Tremaine 2008]
- Thought to be complete up to 1.8 kpc

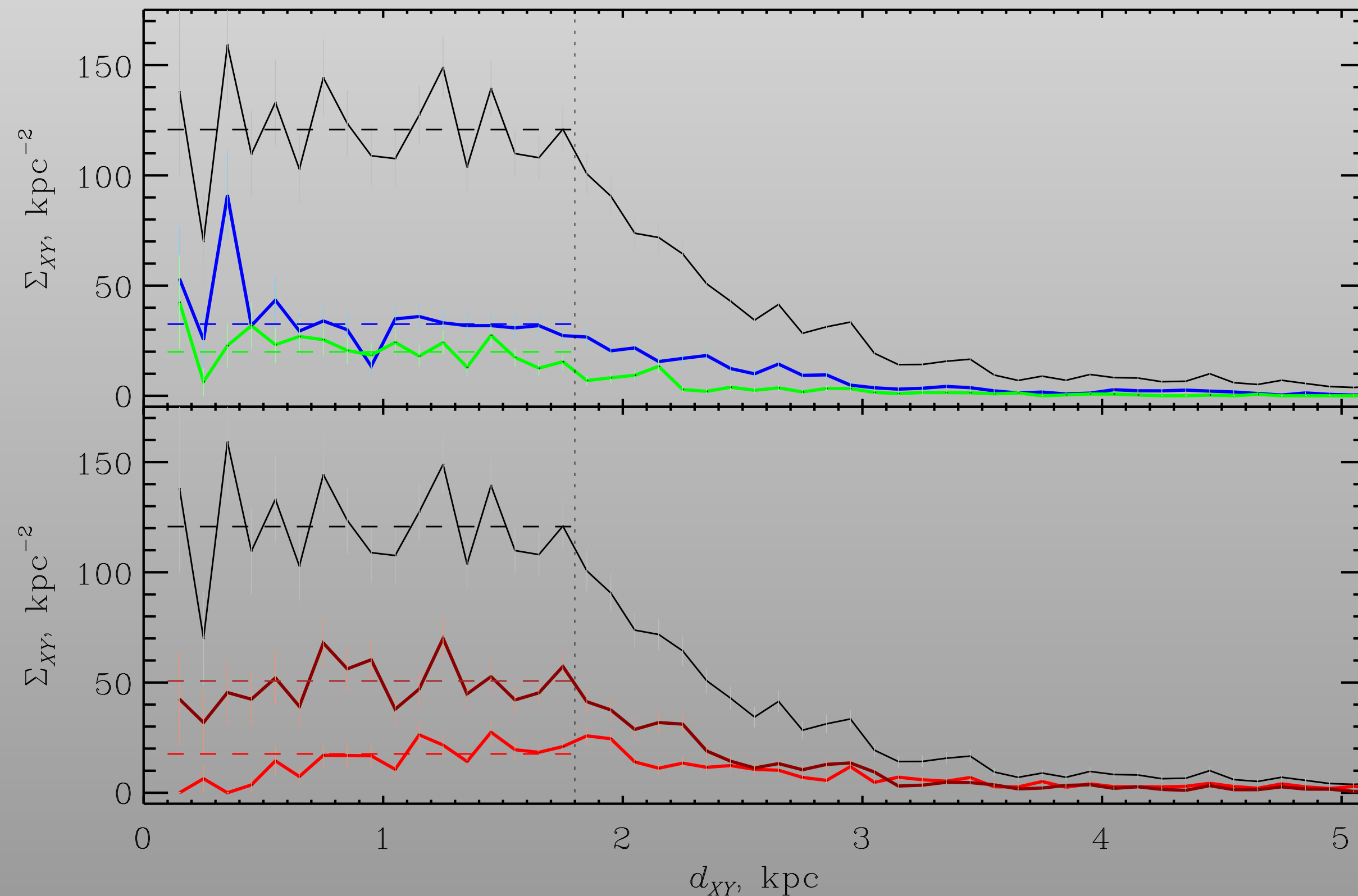


Fig. 4 from Kharchenko+13.

Space density of stellar clusters as a function of distance.

Adopted a completeness limit at 1.8 kpc

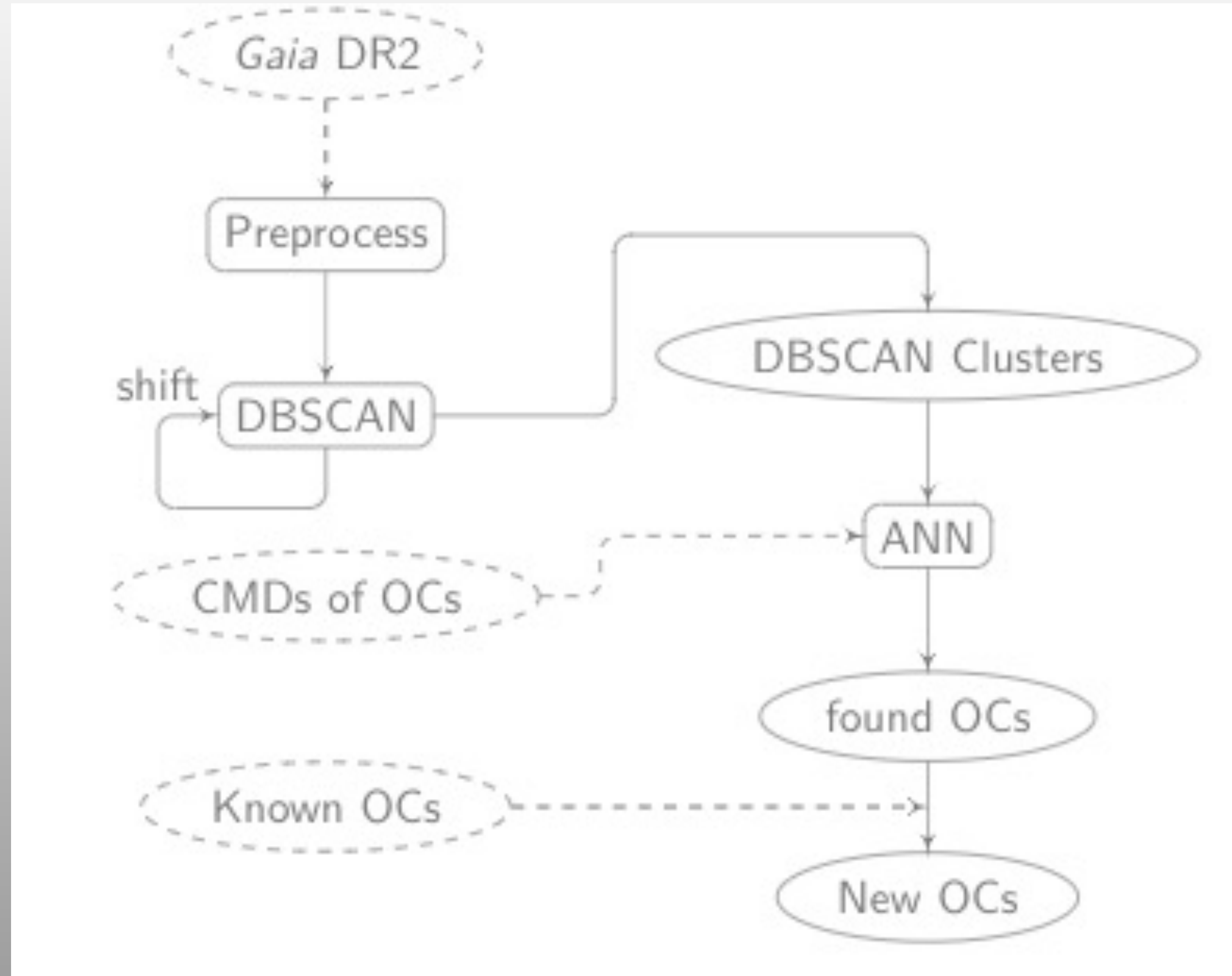
# AFTER GAIA DR2

- Trying to characterise the catalogued OCs with Gaia DR2, only 1169 objects were found and 60 new OCs were serendipitously detected [[Cantat-Gaudin...ACG+18](#)]
- The remaining clusters were either discarded or not seen by Gaia (too distant, IR...)
- Dedicated studies to search for unknown OCs:
  - • [[Castro-Ginard+18](#)]: 23 new objects found with TGAS (validated with Gaia DR2), most of them located in the disc within 1kpc
  - [[Cantat-Gaudin...ACG+19](#)]: 41 new objects in the Perseus direction
  - • [[Castro-Ginard+19](#)]: 53 OCs found with Gaia DR2 in the Galactic anti-centre
  - [[Sim+19](#)]: 207 OCs by visually inspecting proper motion diagrams
  - [[Liu&Pang19](#)]: 76 high quality OCs, FoF algorithm on 5-D astrometry
  - • [[Castro-Ginard+20](#)]: 582 new OCs in the Galactic disc (Big Data)

# METHOD

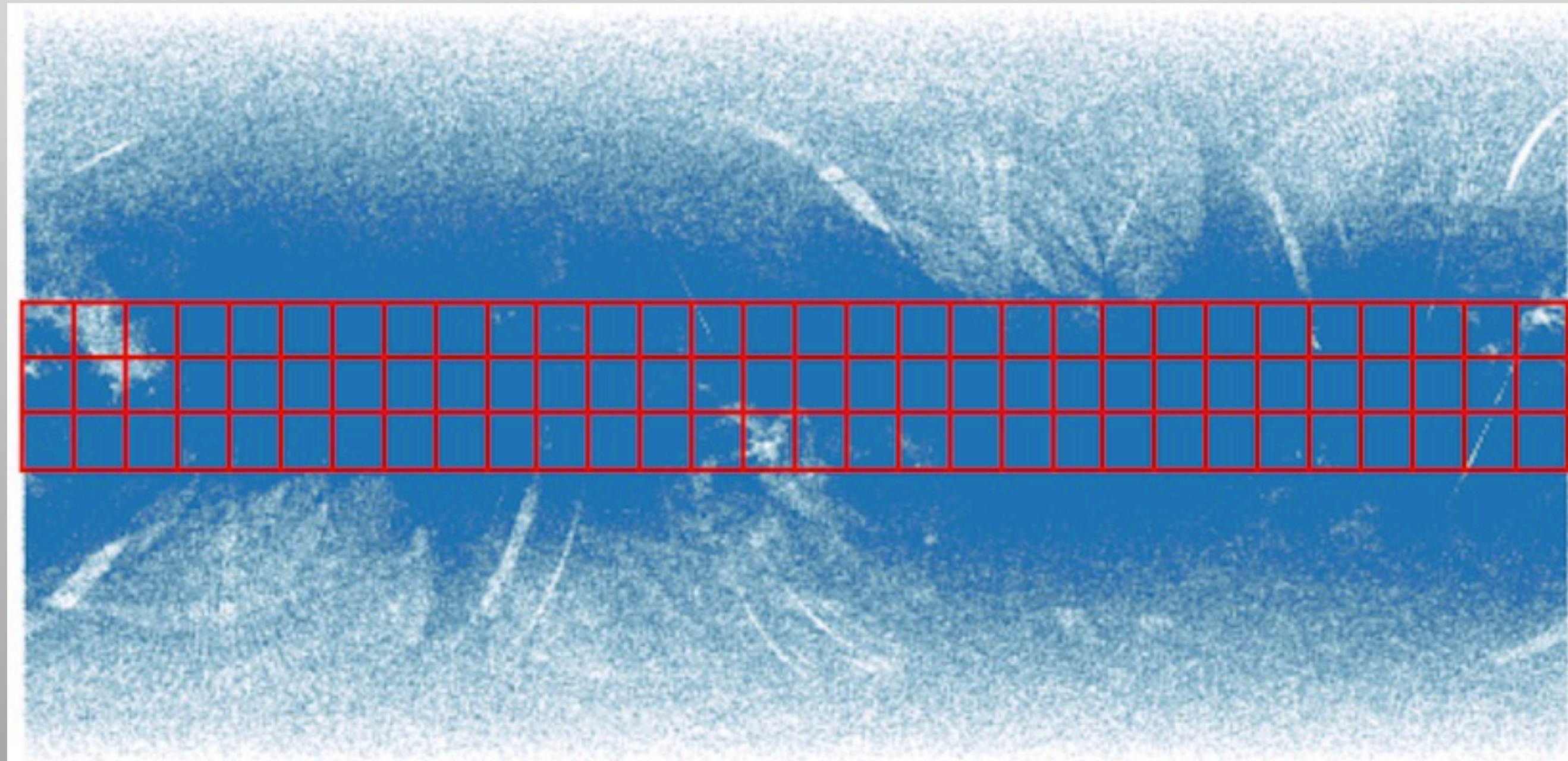
- Data mining methodology to automatically search OCs in the Gaia DR2 archive
- Method based on two combined machine learning algorithms:
  - Unsupervised learning: detection of over-densities in the 5-dimensional astrometric space (position, parallax and proper motions)
    - DBSCAN: density based space clustering
  - Supervised learning: classification of over-densities into real OCs or random statistical clusters
    - ANN: to detect isochrone patterns on a CMD

# FLOW CHART



# PREPROCESSING

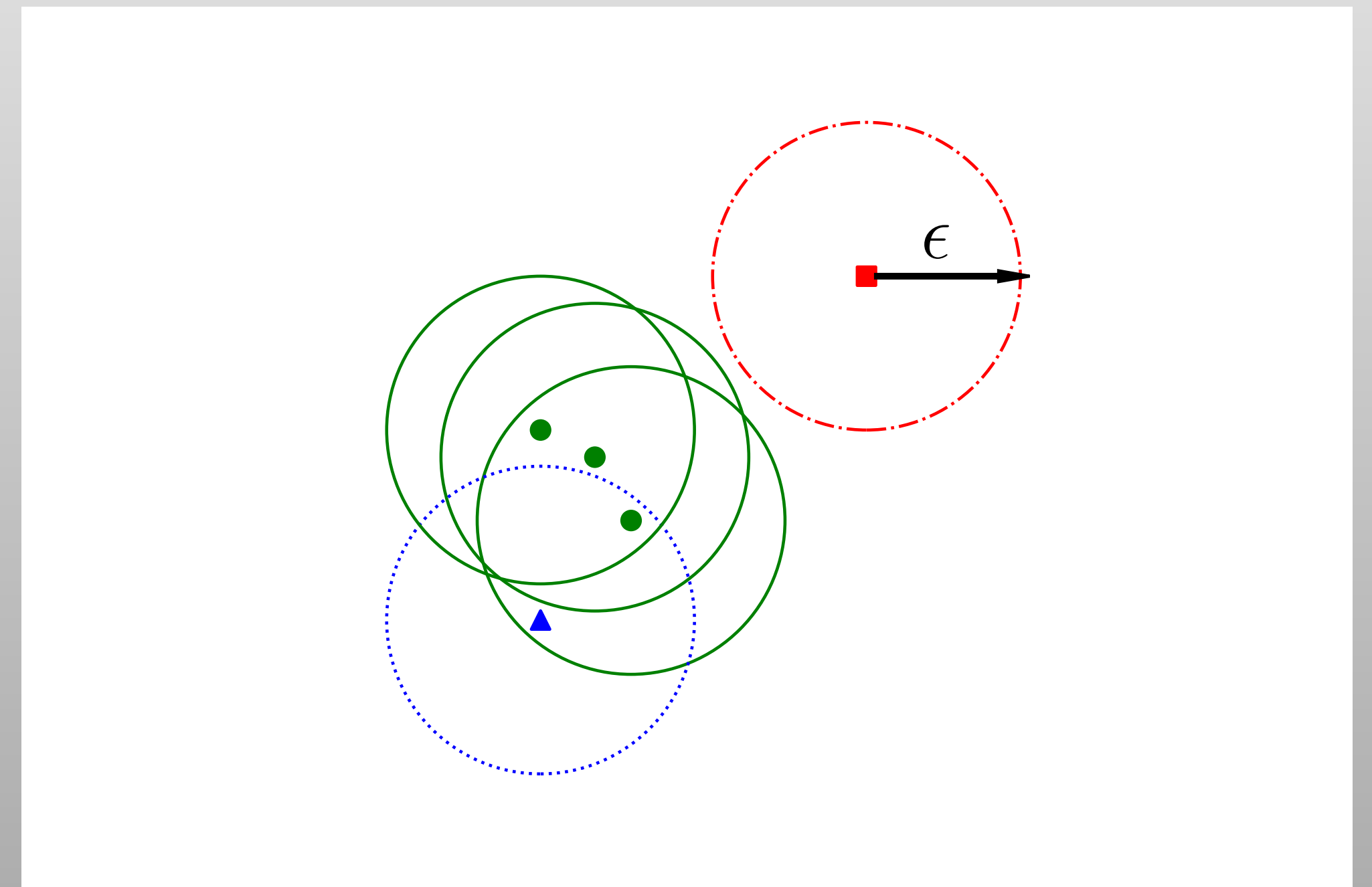
- Rejection of stars with high proper motion ( $>30$  mas/yr) or high parallax ( $> 7$  mas)
- Divide the area of study in rectangles of size  $L$  deg (to be optimised using simulated data). Consider only  $|b| < 10^\circ$  ( $\sim 95\%$  of the known clusters are in this region)
- Shift rectangles to account for the clusters in the border



# DBSCAN

Use a density based unsupervised algorithm to search for over-densities in the parameter space [Ester+96]

- No a priori knowledge of the number of clusters
- Finds arbitrary shaped clusters
- Need to define two parameters ( $\epsilon$ , minPts)



$$d(i, j) = \sqrt{(l_i - l_j)^2 + (b_i - b_j)^2 + (\varpi_i - \varpi_j)^2 + (\mu_{\alpha^*, i} - \mu_{\alpha^*, j})^2 + (\mu_{\delta, i} - \mu_{\delta, j})^2}$$

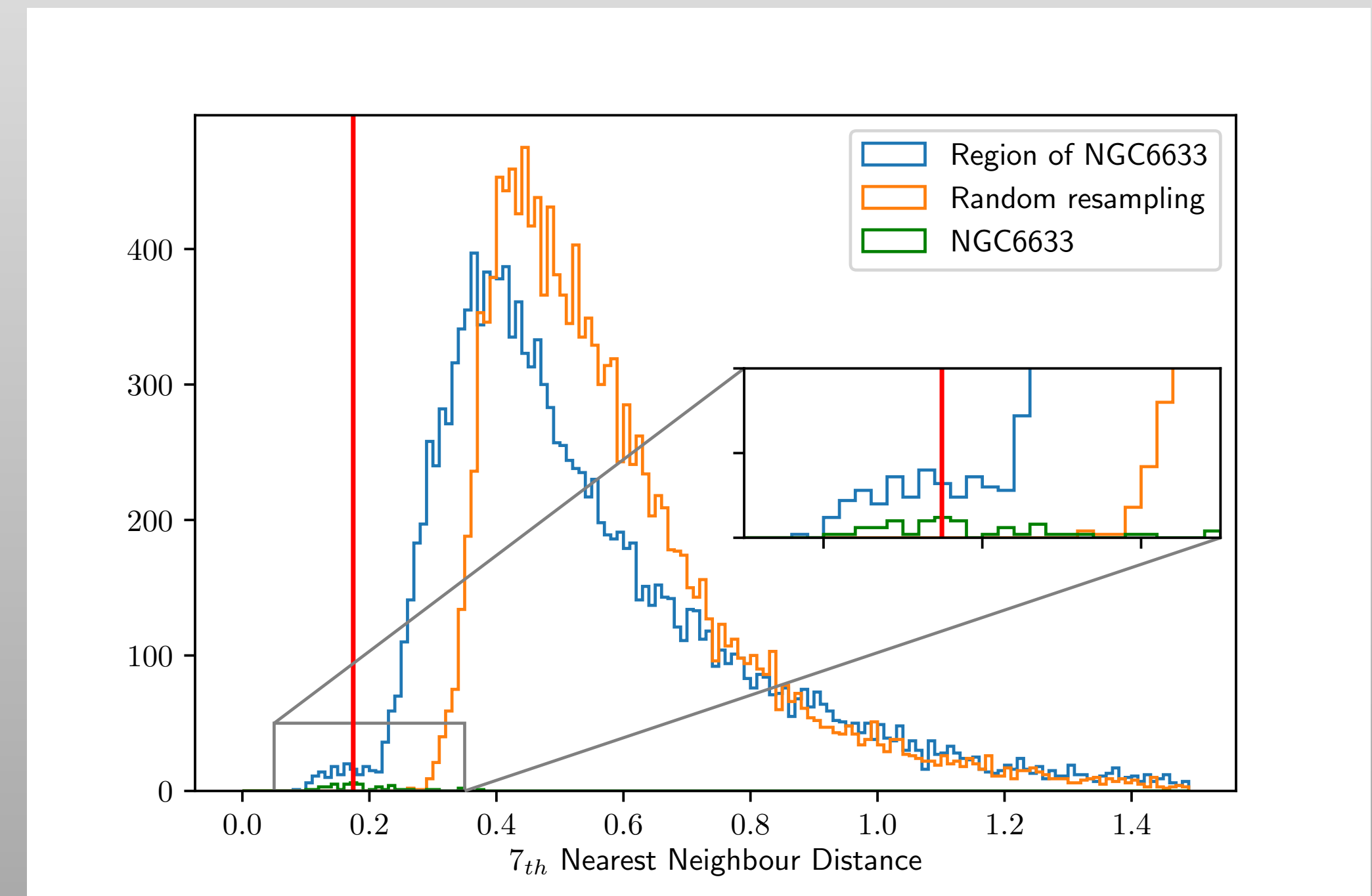
# DBSCAN — DETERMINATION OF EPSILON

Leave minPts to be optimised using simulated data (together with L)

For the determination of  $\epsilon$ :

- Distance between the  $k$ th nearest neighbours in a cluster should be smaller than the distance between stars belonging to the field
- Compute  $\epsilon$  as:

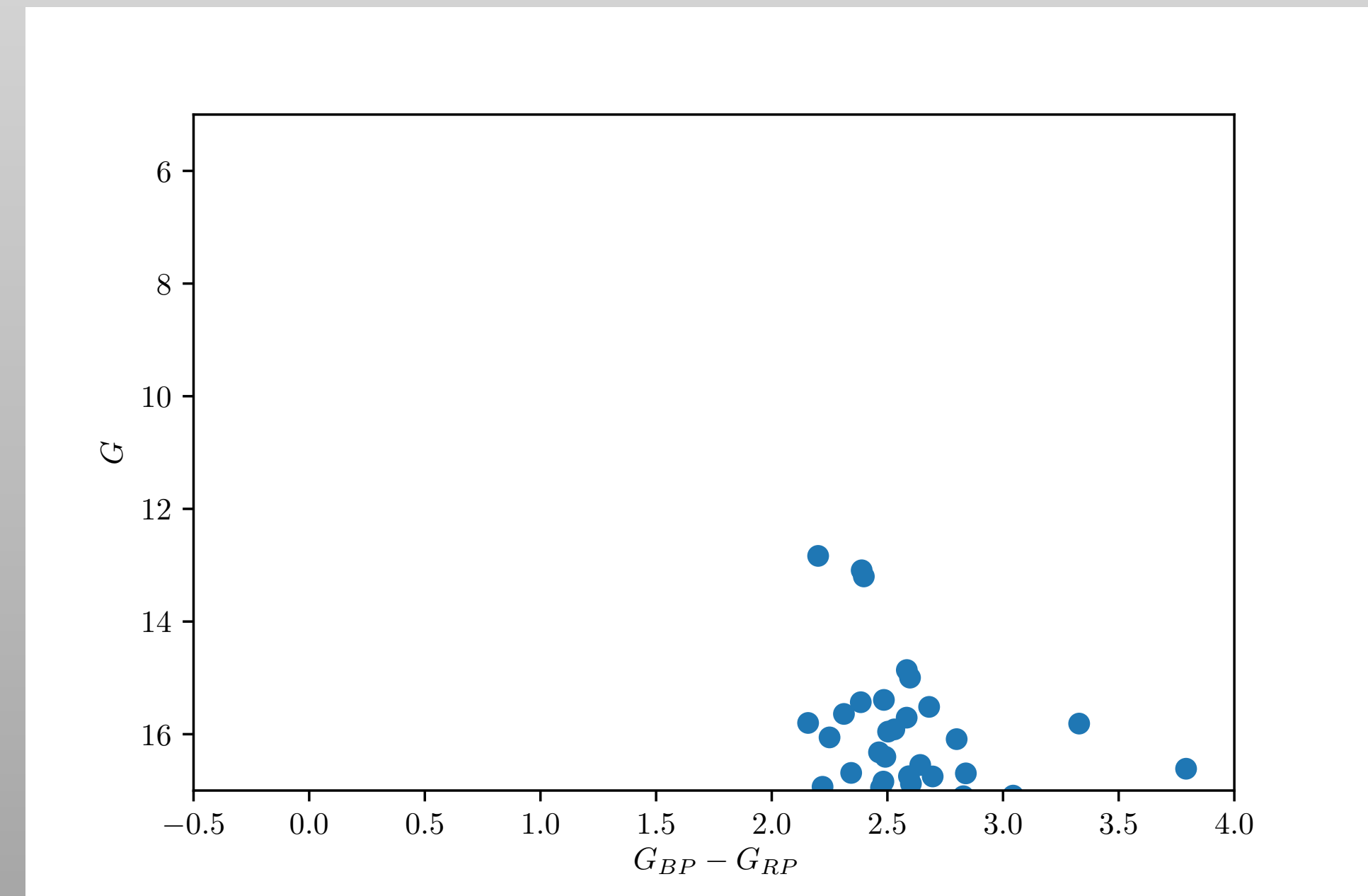
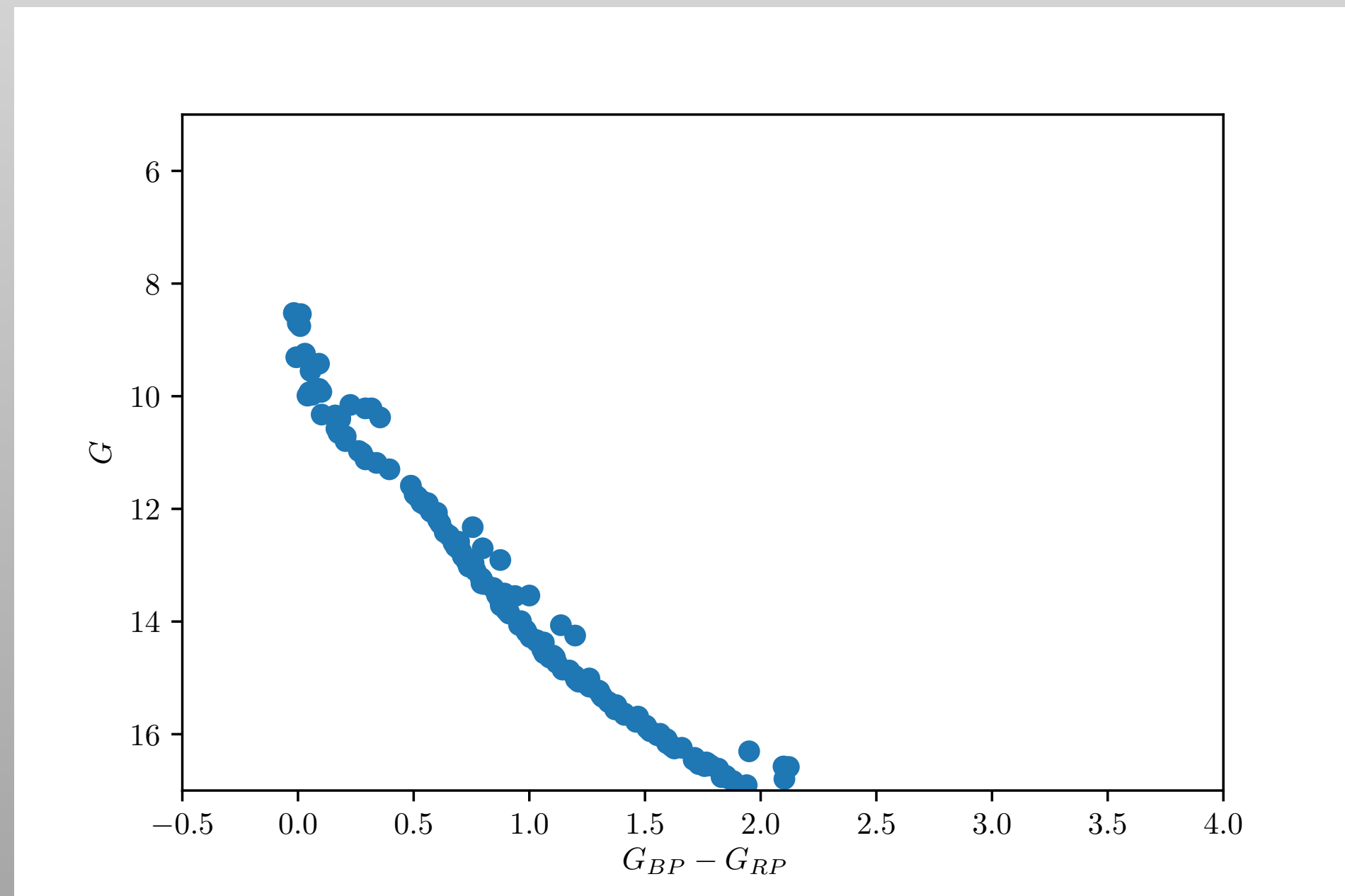
$$\epsilon = (\epsilon_{kNN} + \epsilon_{rand})/2$$



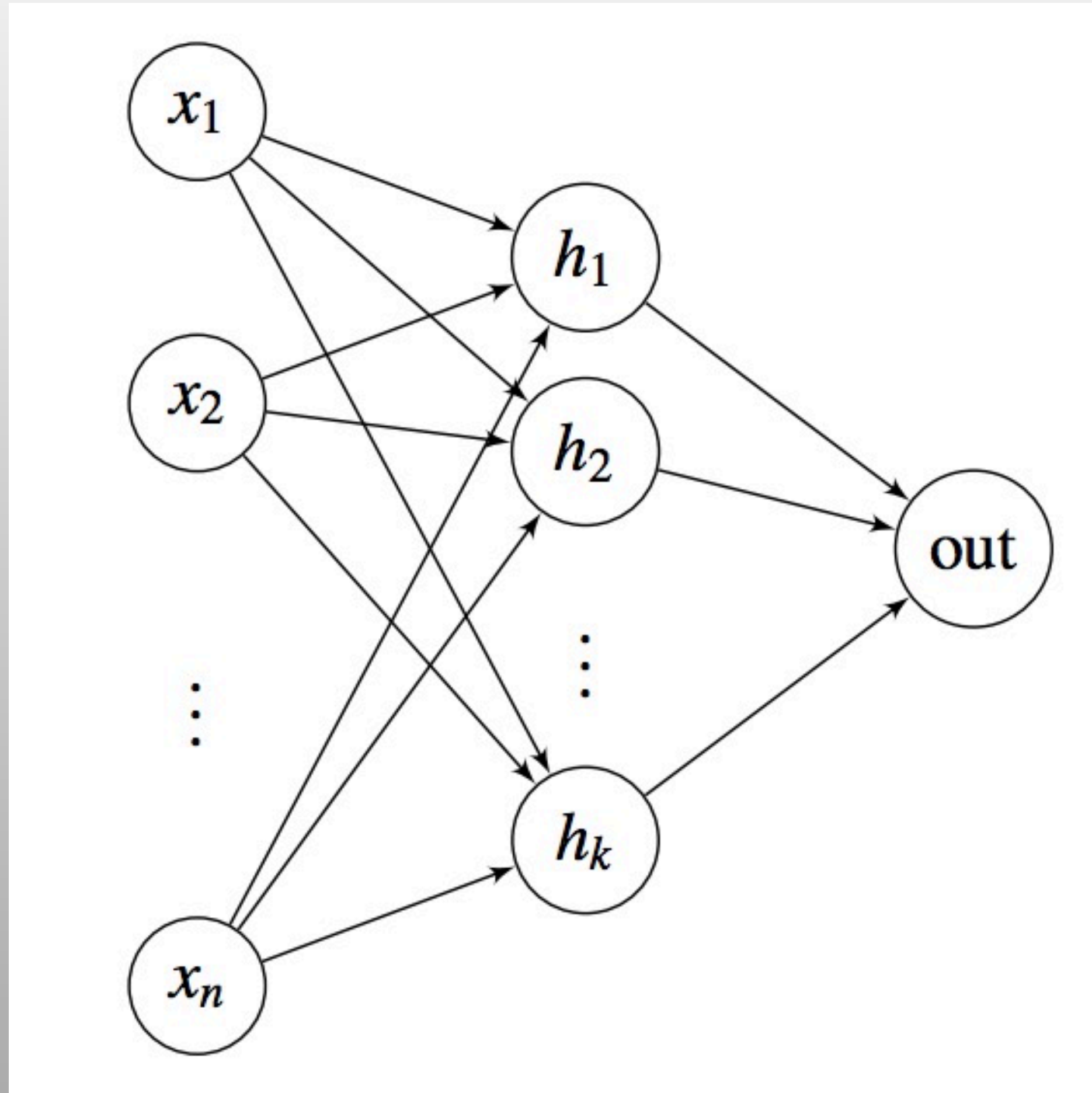


# REAL OCS VS. STATISTICAL CLUSTERS

- DBSCAN finds statistical clusters that may or may not correspond to physical OCs
- Distinguish between them using Gaia photometry: stars in an OC follow an isochrone in a CMD



# ANN — INTRODUCING PHYSICAL MEANING



- Need labeled data to train the network
- Train on CMD to recognise the isochrone pattern
  - For the 1229 OCs in [[Cantat-Gaudin... ACG+18](#)] plus data augmentation
  - Random field stars selected from the same region

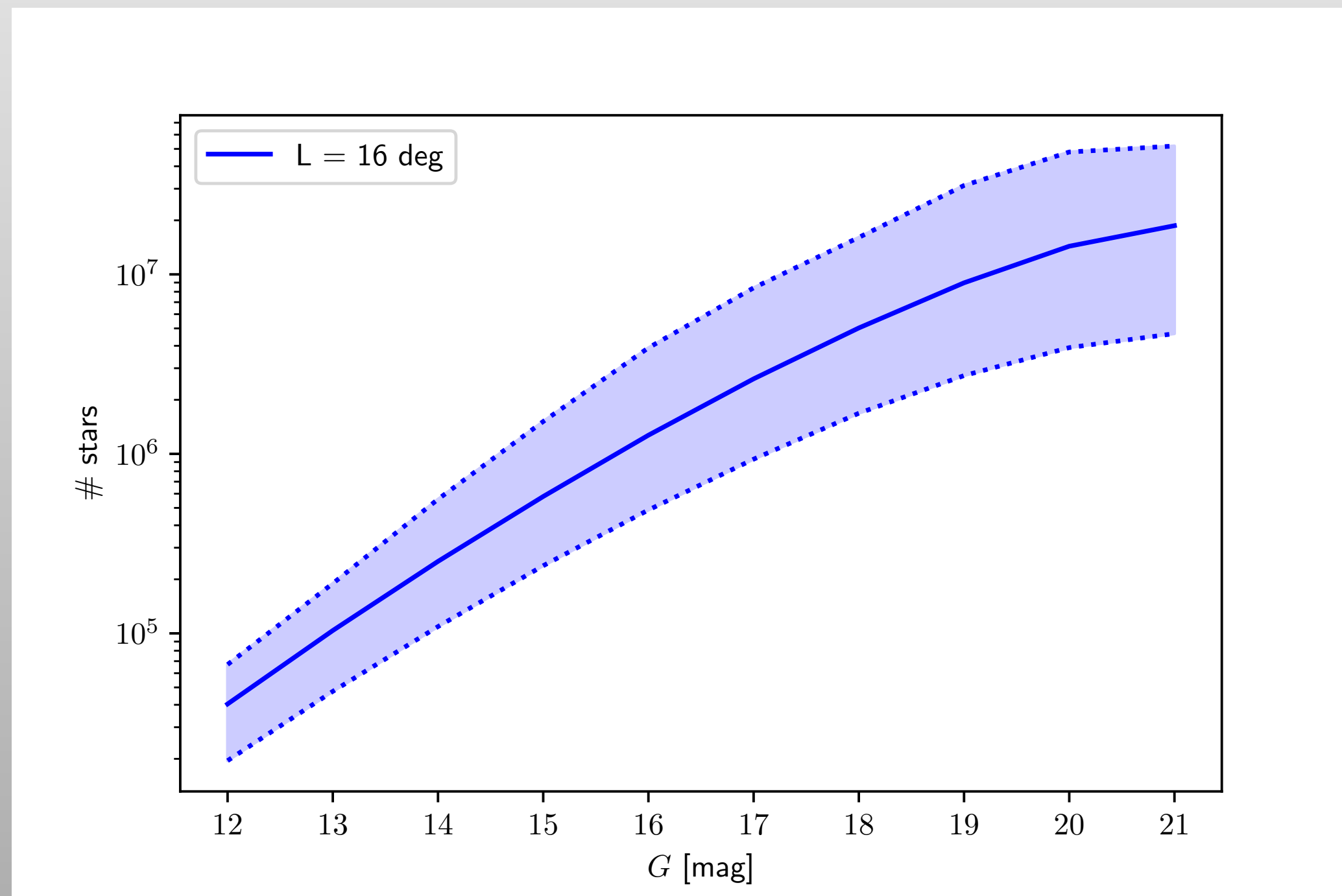
Training - test splits set to 67%-33%

Classify 90.27% of the cases to the right class

SO FAR, NO BIG DATA INVOLVED

# DBSCAN IN PARALLEL

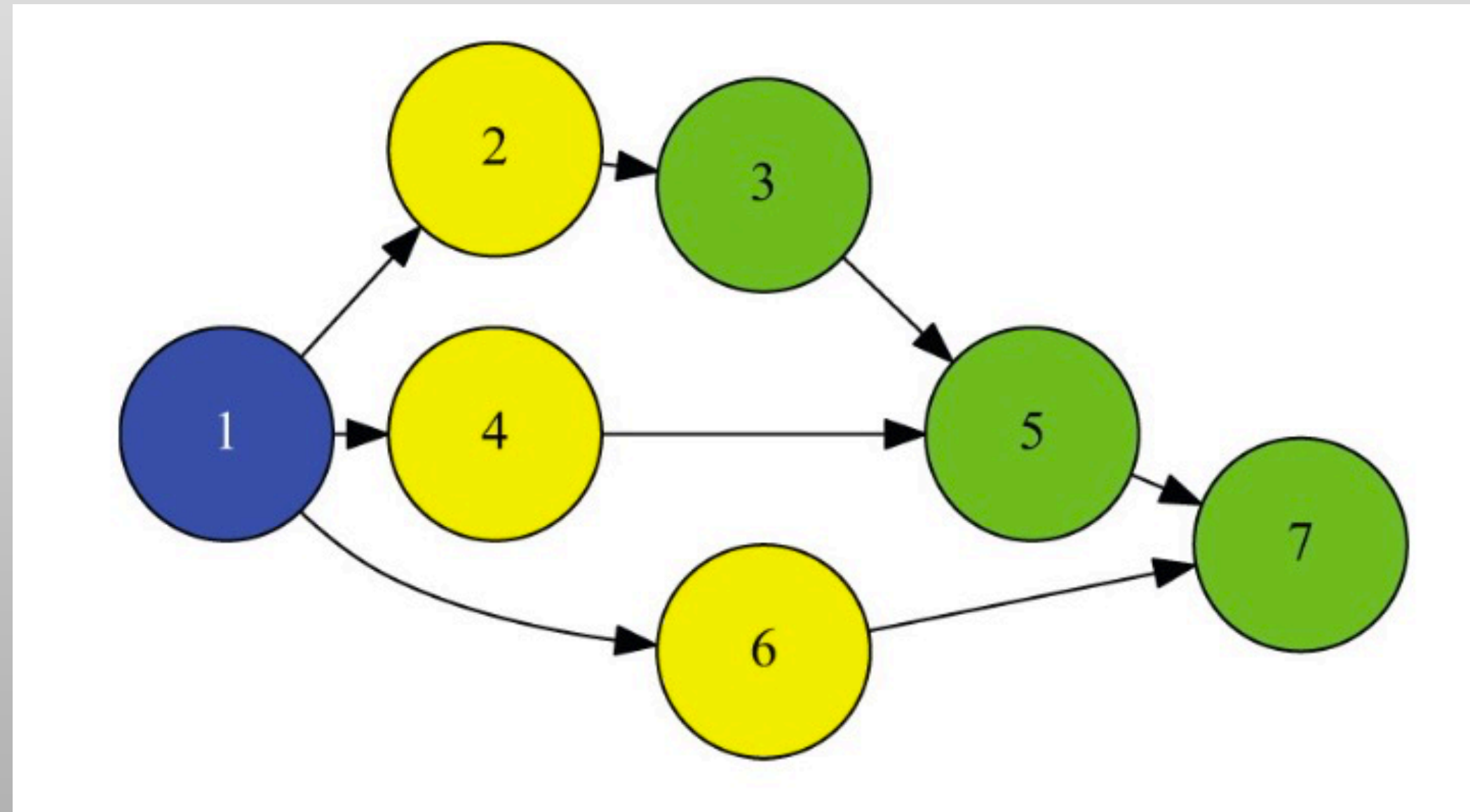
Run DBSCAN to the whole Galactic disc up to magnitude  $G = 17$  ( $10^8$  stars) [Castro-Ginard+20]



- DBSCAN on  $\sim 10^7$  stars in each box (large enough data)
- Two level parallelization
  - Computation of each box in parallel
  - Parallelization of the DBSCAN algorithm if needed

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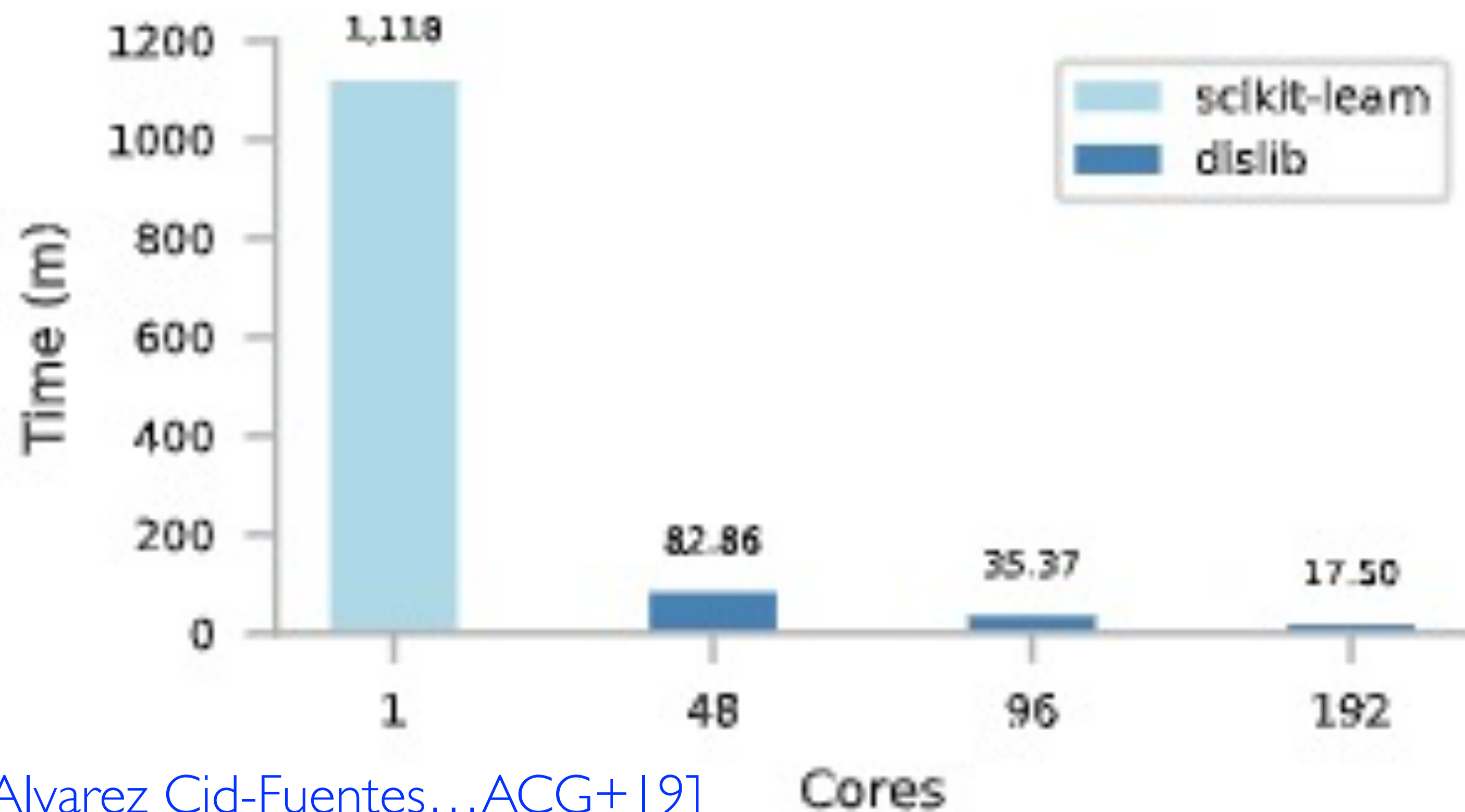
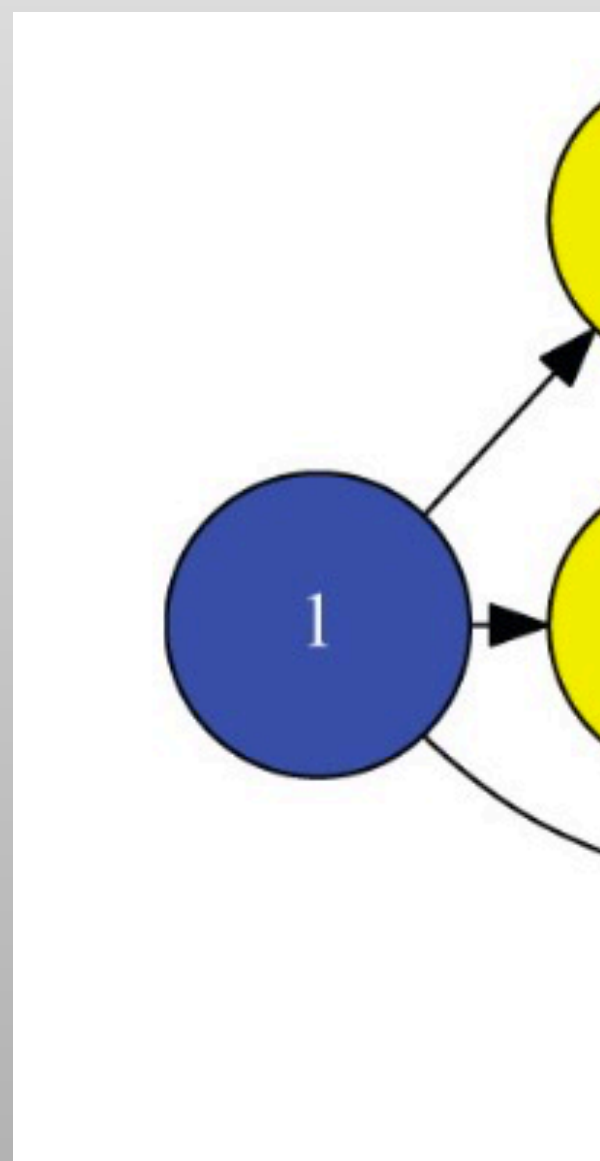
Use PyCOMPSs framework [Tejedor+15]



- Exploit parallelism of applications at task level
- Task — decorated python function
- Builds a task graph taking into account data dependencies
- Schedule and execute application in the distributed environment based on the graph

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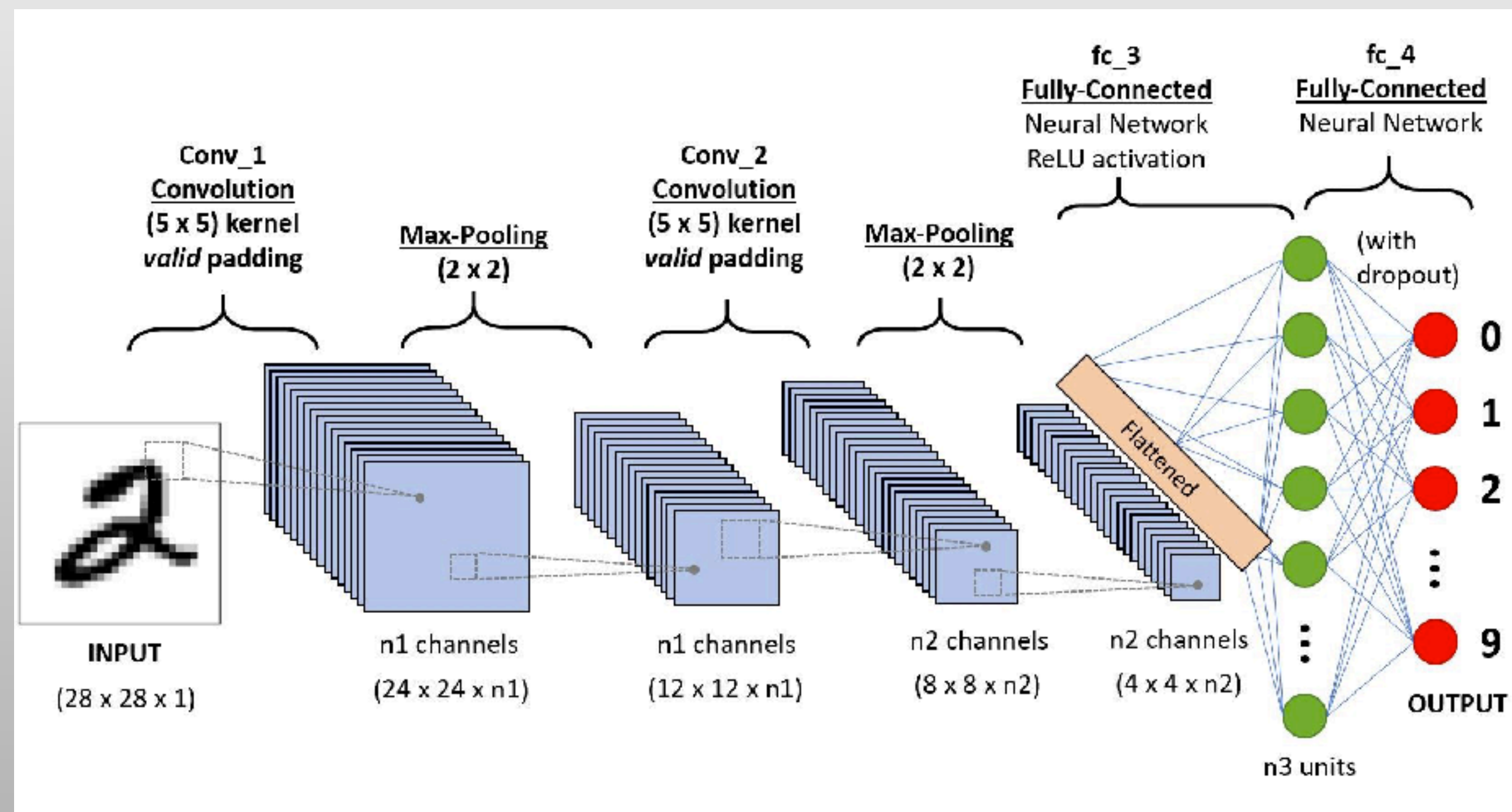
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[Alvarez Cid-Fuentes...ACG+19]

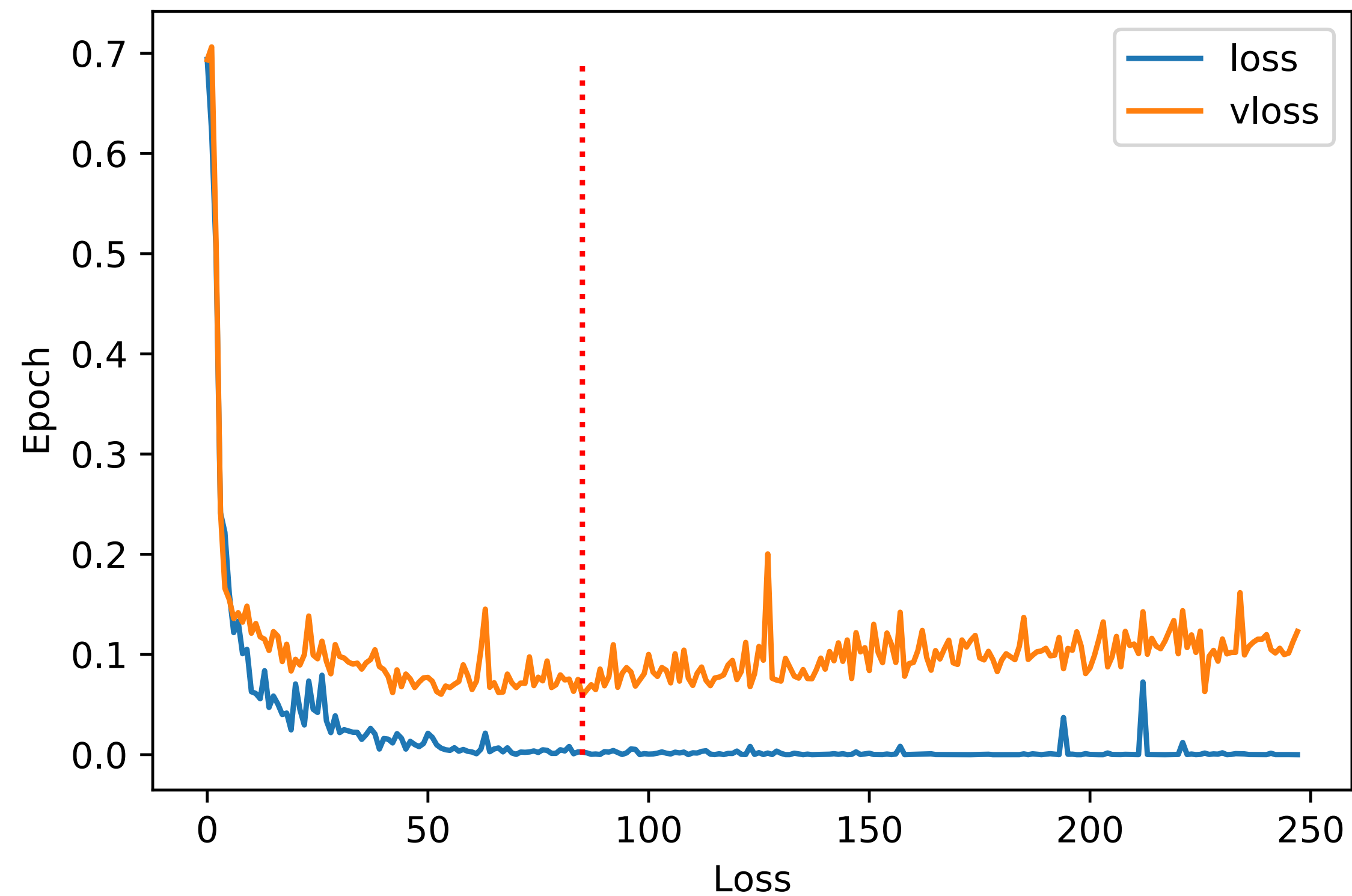
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# DEEP LEARNING FOR OC RECOGNITION



- Introduction of deep learning architecture for a more robust classification (feature extraction)
- Training with real OCs + simulated data (isochrones from Padova [Bressan+12]) —  $\sim 20,000$  samples
- Training in two steps
  - Minimise validation loss
  - Minimise false positives from [Castro-Ginard+19]

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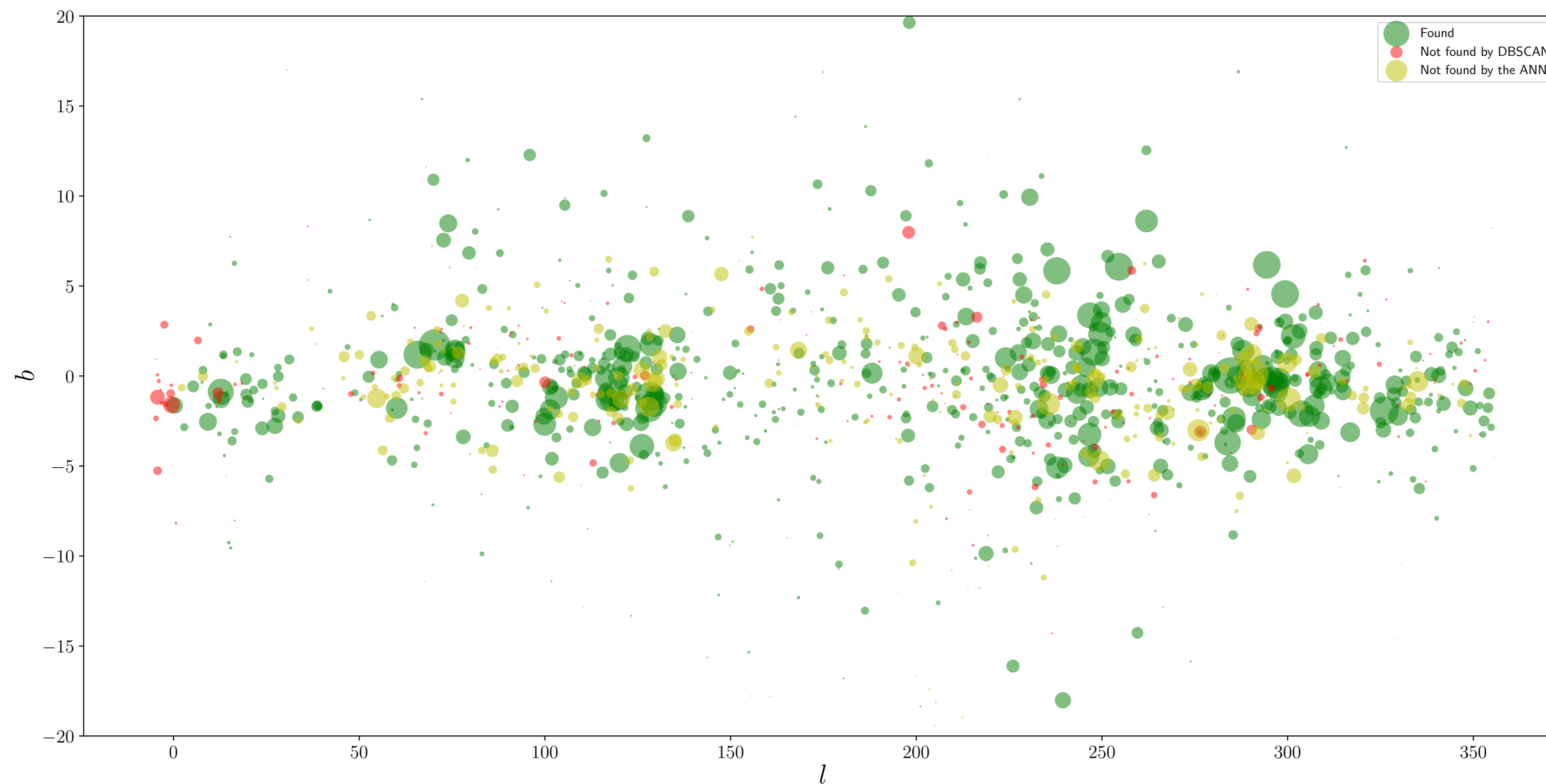


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# METHOD LIMITATIONS

- Detection limited to the most compact cluster in a given  $L \times L$  area.
- Only clusters with well-defined CMD.

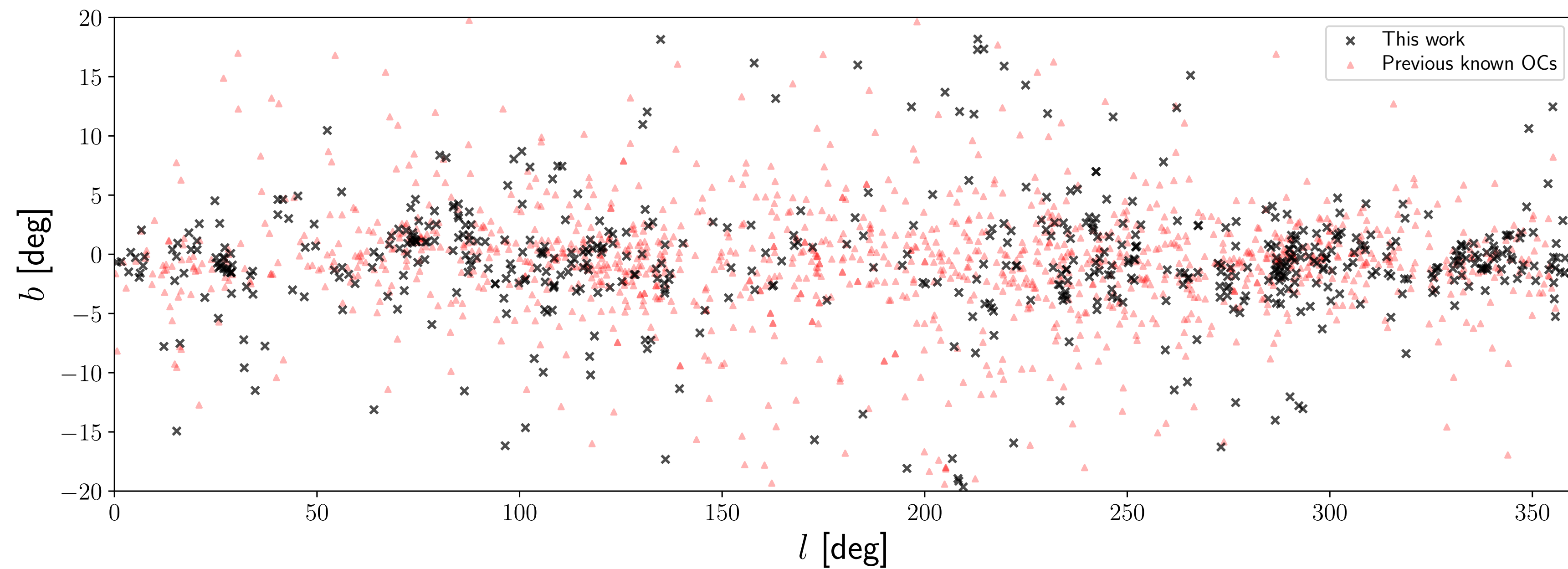


# SOME RESULTS

- More than 650 UBC clusters.

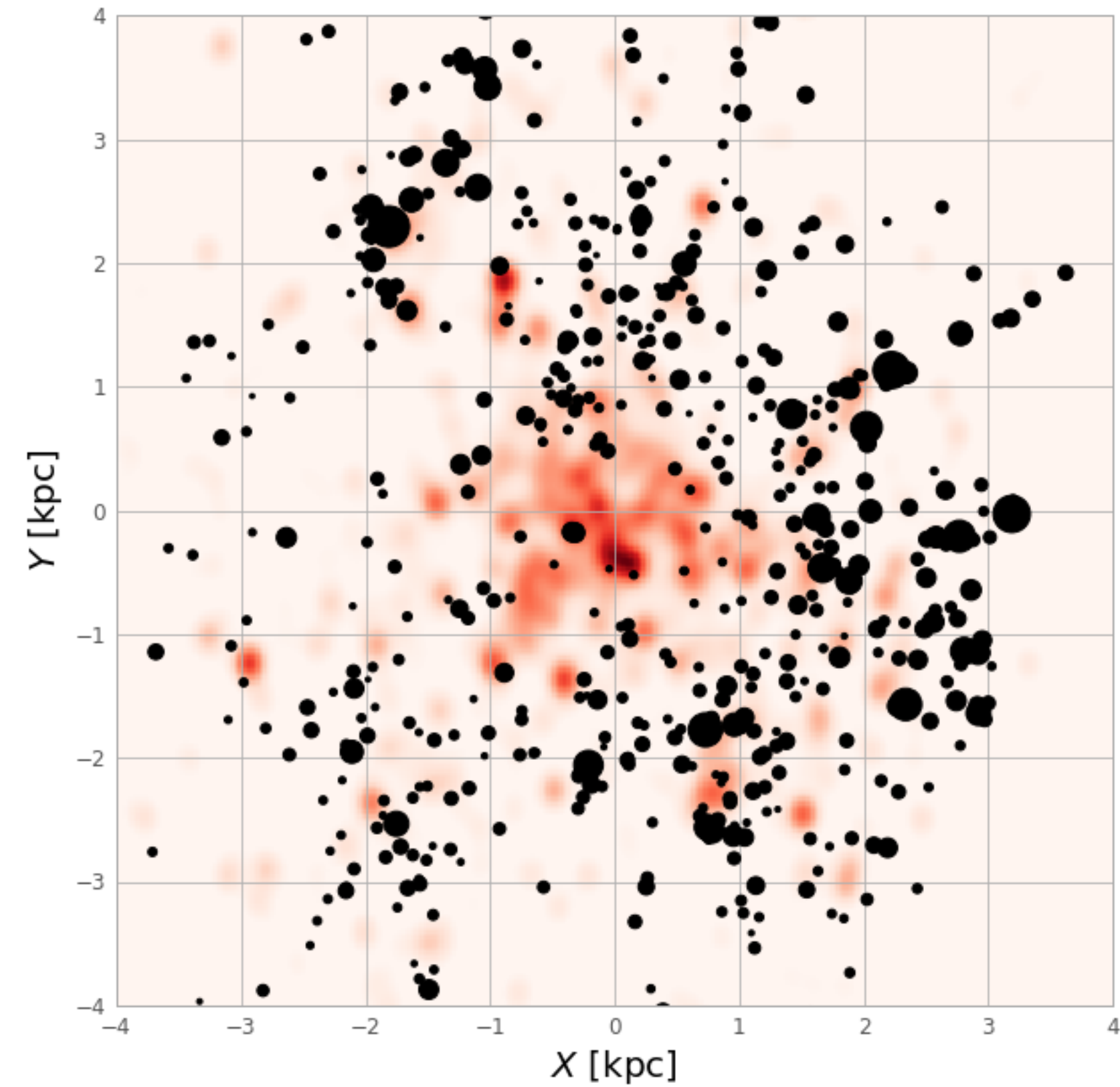
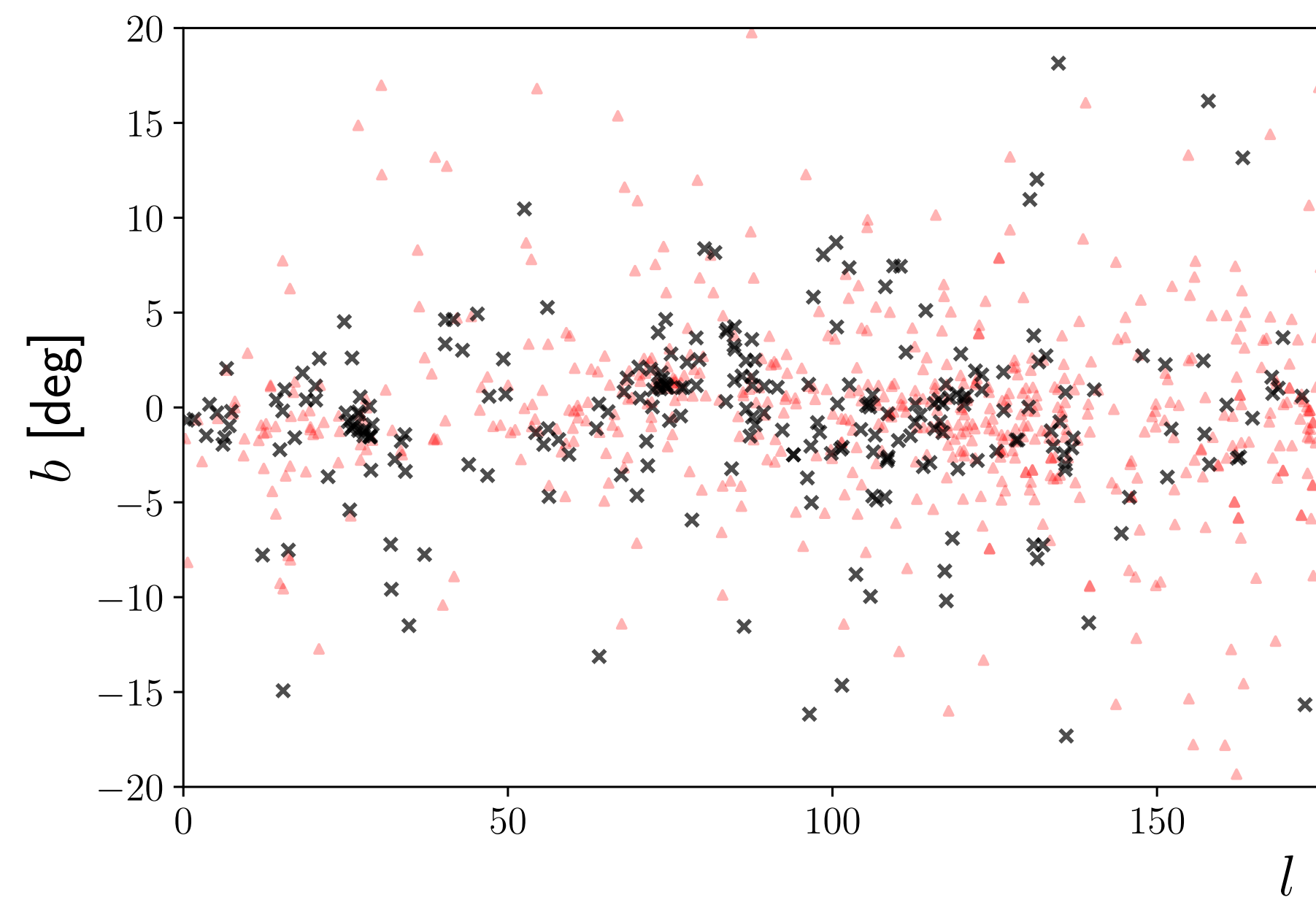
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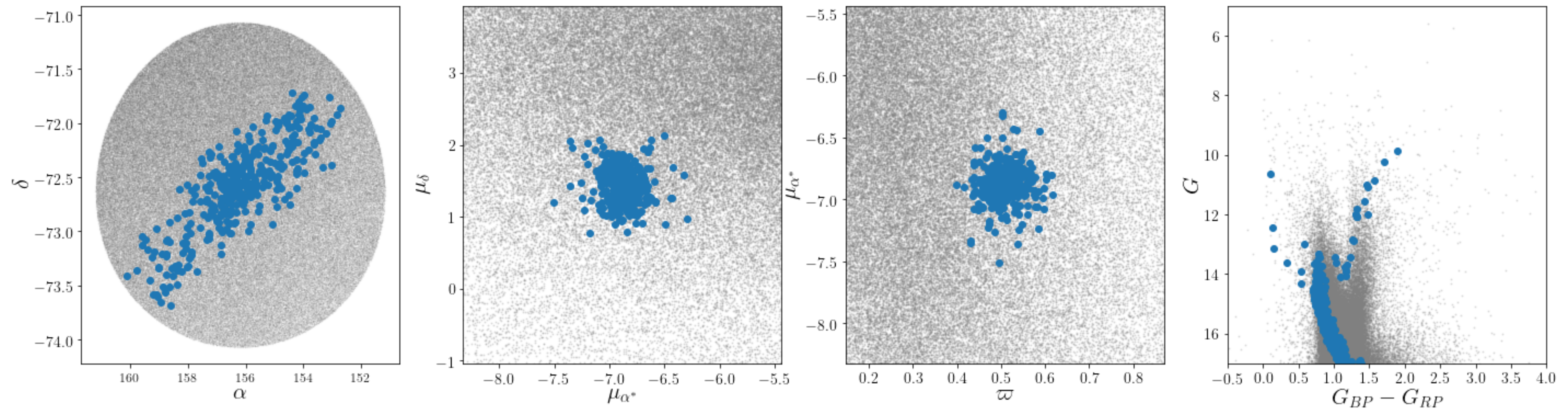


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- More than 650 UBC clusters.
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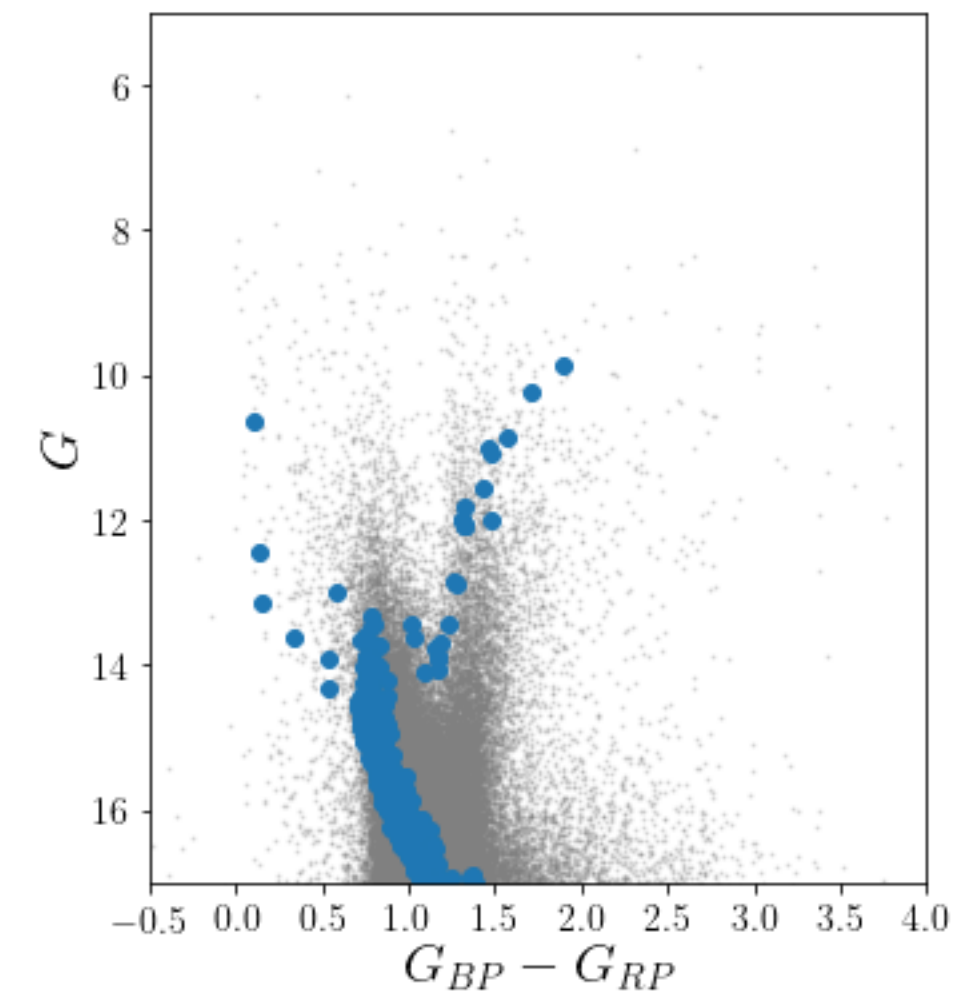
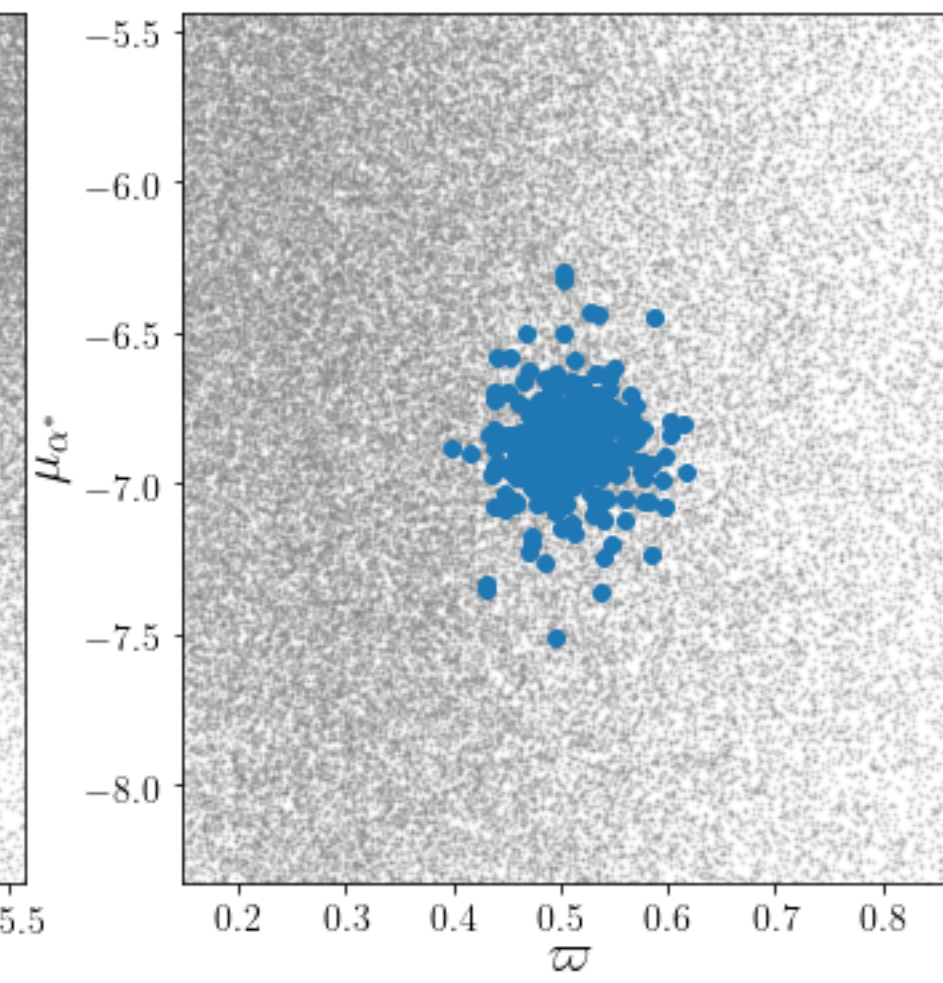
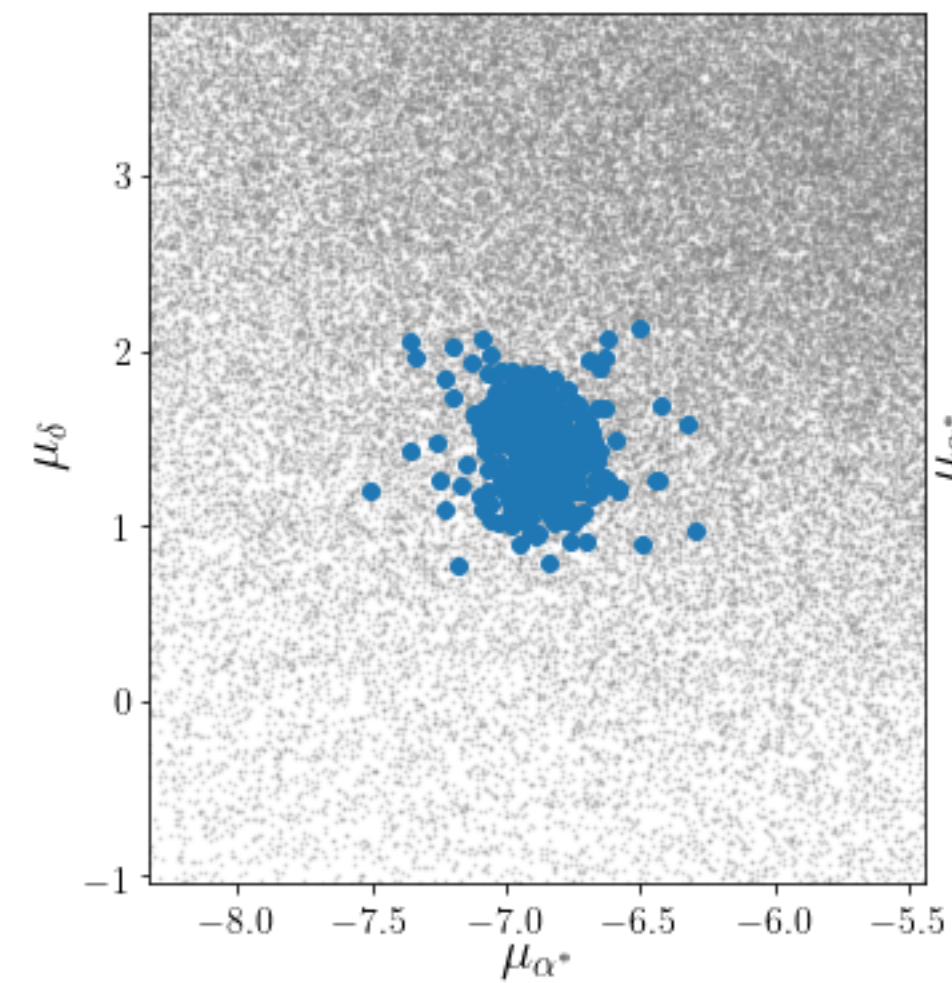
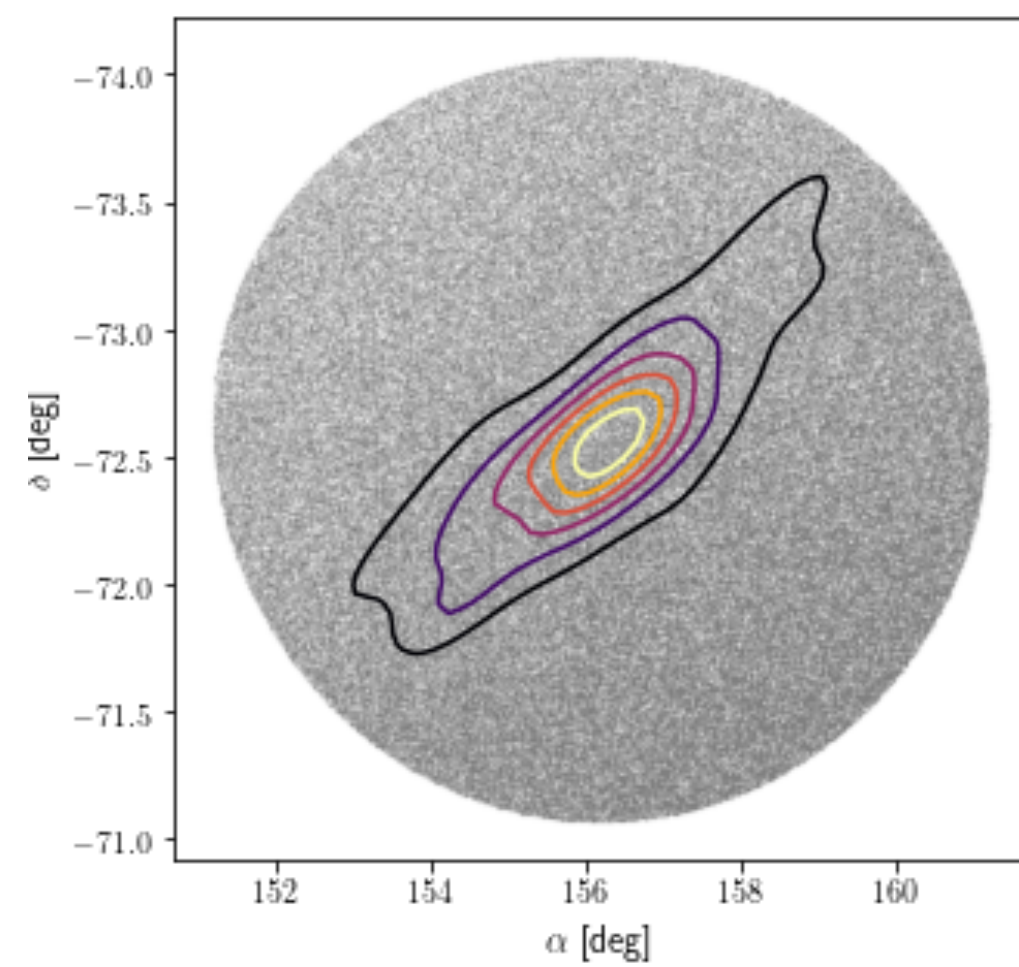
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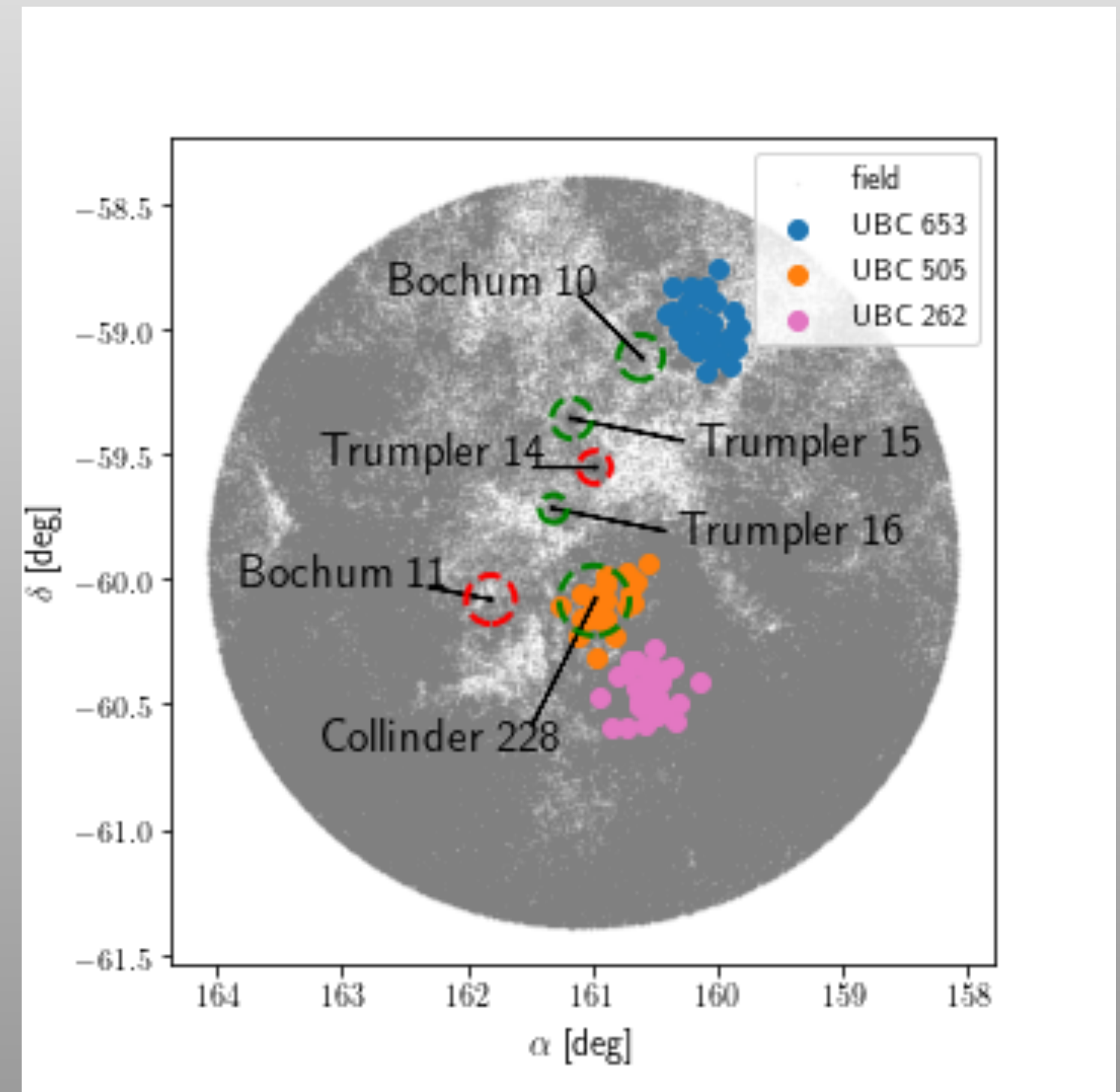
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