## Capstone Oral Defense



# A Semi-supervised Machine Learning Approach for Open Star Cluster Member Determination

# Md Mahmudunnobe

Major: CS (Data Science) / NS (Atoms and Molecules)

## What: Hypothesis



- Past works mainly used unsupervised models
   (Agarwal et al. 2020, Cantat-Gaudin et al, 2020, etc.)
- A supervised model is more accurate and easier to validate (Jain et al, 1999, Reddy et al, 2018)
- Use of an additional supervised model increased the members (Gao, 2018b; Castro-Ginard et al. 2018, Mahmudunnobe et al, 2021)
- Hypothesis: Based on these evidences, I argue that a combination of unsupervised and a supervised model would be a better approach to detect members of open star clusters.

# **What: Specific Focus**



#### Goal of the Project:

- Develop a workflow to combine unsupervised and supervised models
- Develop or Suggest metrics to compare between different models
- Suggest the **best practices** for applying a specific model

(Chosen Model to Explore: GMM, Random Forest)

# Why: Why it matters now?



- GAIA provides the precise data for distances, positions, velocities of stars
- Having confirmed members allow further studies:
  - Understanding Star Formation
  - Understanding Galaxy Formation
  - Modeling Stellar Evolution

#### **How: Workflow**



N<sub>1</sub> **Features** Known Label (i.e. distance, velocity) **Unsupervised Model** (Binary: 0 or 1) Data from Smaller Region Train **Features Features Supervised Model** (i.e. distance, velocity) (i.e. distance, velocity) (Classification) Data from Larger Region Data from Smaller Region N2 Binary Output Membership Probability **Prediction** Member(1) or field(0) (number in range [0-1])

#### **How: Metrics**



## **Unsupervised Model**

- Members should be more compact (smaller SD)
- Modified Silhouette Score (MSS)

$$\frac{1}{K} \sum_{i=1}^{K} \frac{(SD_{i,field} - SD_{i,member})}{max(SD_{i,field}, SD_{i,member})}$$

## Supervised Model

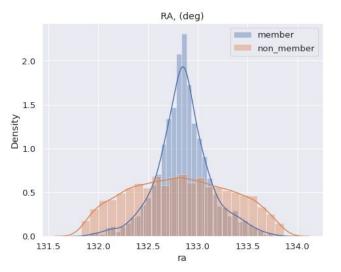
- Want to avoid false positive
- Precision

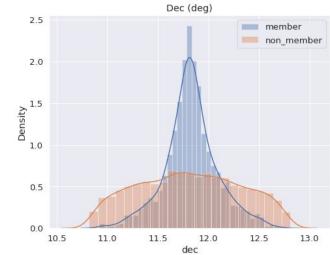
True Positive
True Positive + False Positive

# **GMM: Modified Replication**



- 1. **Feature Selection:** Remove ra and dec from the features
- As they overlap for a small search radius

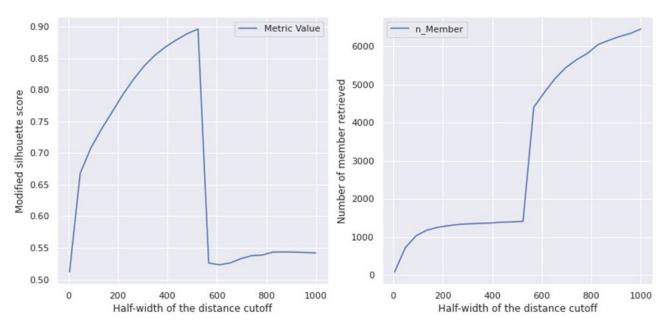




# **GMM: Modified Replication**



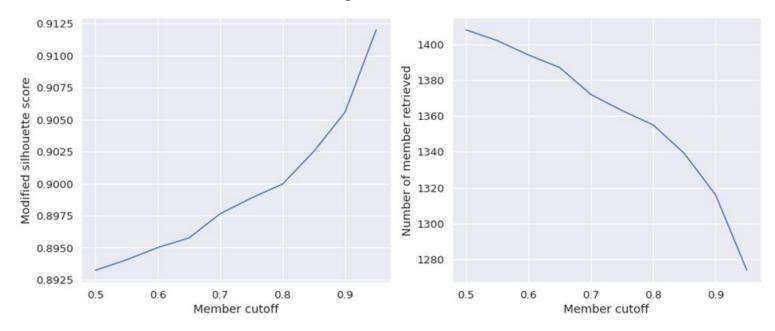
#### 2. Choose the **distance cutoff** using MSS and number of members



# **GMM: Modified Replication**

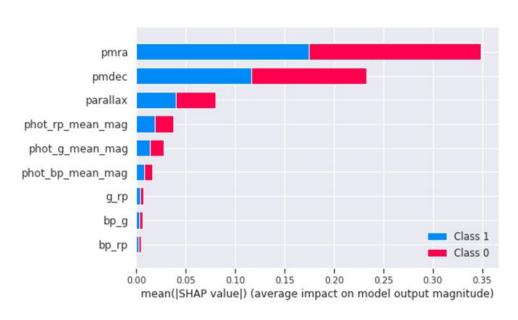


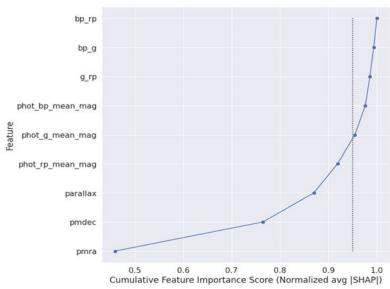
3. Choose the **member threshold** using MSS and number of members





#### 1. **Feature Selection**: SHAP feature importance







- 2. Divide into test and training data
  - for unbiased performance evaluation
  - Stratified split for maintaining class distribution

#### Propostion of class:

original target data:

- 1 0.501605
- 0 0.498395

#### test targets:

- 1 0.501538
- 0 0.498462

#### train\_targets:

- 1 0.501633
- 0 0.498367



#### 3. Optimize Hyperparameter using Cross Validation

N_estimators (Number of decision trees)	500, 1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500, 5000, 5500, 6000, 6500, 7000, 7500, 8000, 8500, 9000, 9500, 10000	
max_features (Number of features in each tree)	'sqrt', 1, 2, 3, 4,, n_feature	
max_depth (Maximum depth of the tree)	10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, None	
min_samples_leaf (Minimum samples required for a leaf node)	1, 2, 4	
min_samples_split (Minimum samples required to split a node)	2, 5, 10	
bootstrap (Whether bootstrapping the samples)	True, Faise	

```
{'n_estimators': 500,
  'min_samples_split': 5,
  'min_samples_leaf': 4,
  'max_features': 'sqrt',
  'max_depth': 20,
  'bootstrap': True}
```



#### 3. Optimize Hyperparameter using Cross Validation

N_estimators (Number of decision trees)	500, 1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500, 5000, 5500, 6000, 6500, 7000, 7500, 8000, 8500, 9000, 9500, 10000	
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```

# Result

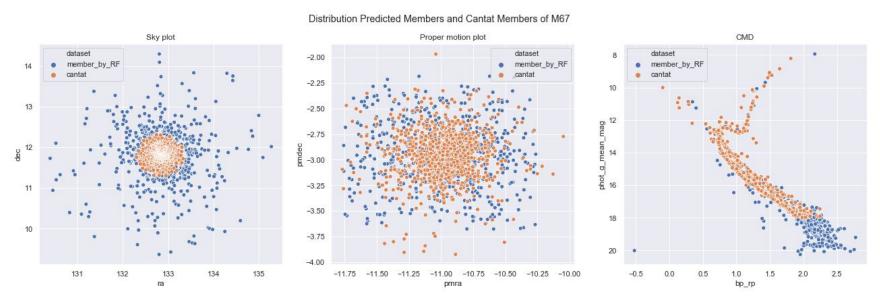


	Direct Replication M67	Modified Replication M67	NGC 3766
MSS (GMM) @ 0.6	0.70	0.89	0.61
MSS (GMM) @ 0.95	0.73	0.91	0.78
Precision (RF)	1.00	1.00	1.00
Number of Members	1377 (0.95)	1423 (0.95)	7640 (1)

Cantat-Gaudin paper (2020)	M67	NGC 3766
Number of Members	845	1368

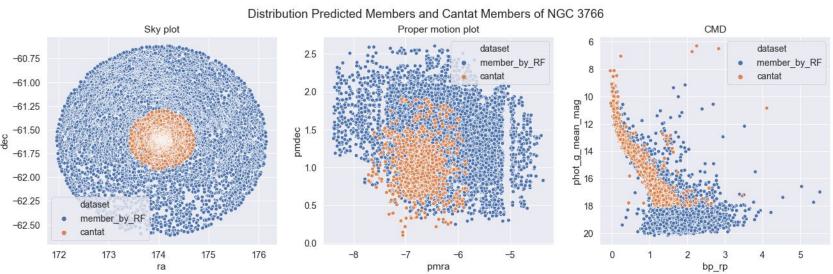
## **Result: Cantat Benchmark**





## **Result: Cantat Benchmark**





#### **Conclusion**



- More members can be found at the outer sky region and fainter magnitudes
- Need to compare between a number of model using these metrics to find the optimal model
- For unsupervised model, MSS can be used for feature selection and hyperparameter optimization.
- For supervised model, SHAP feature importance for feature selection and cross-validation for optimizating parameter.