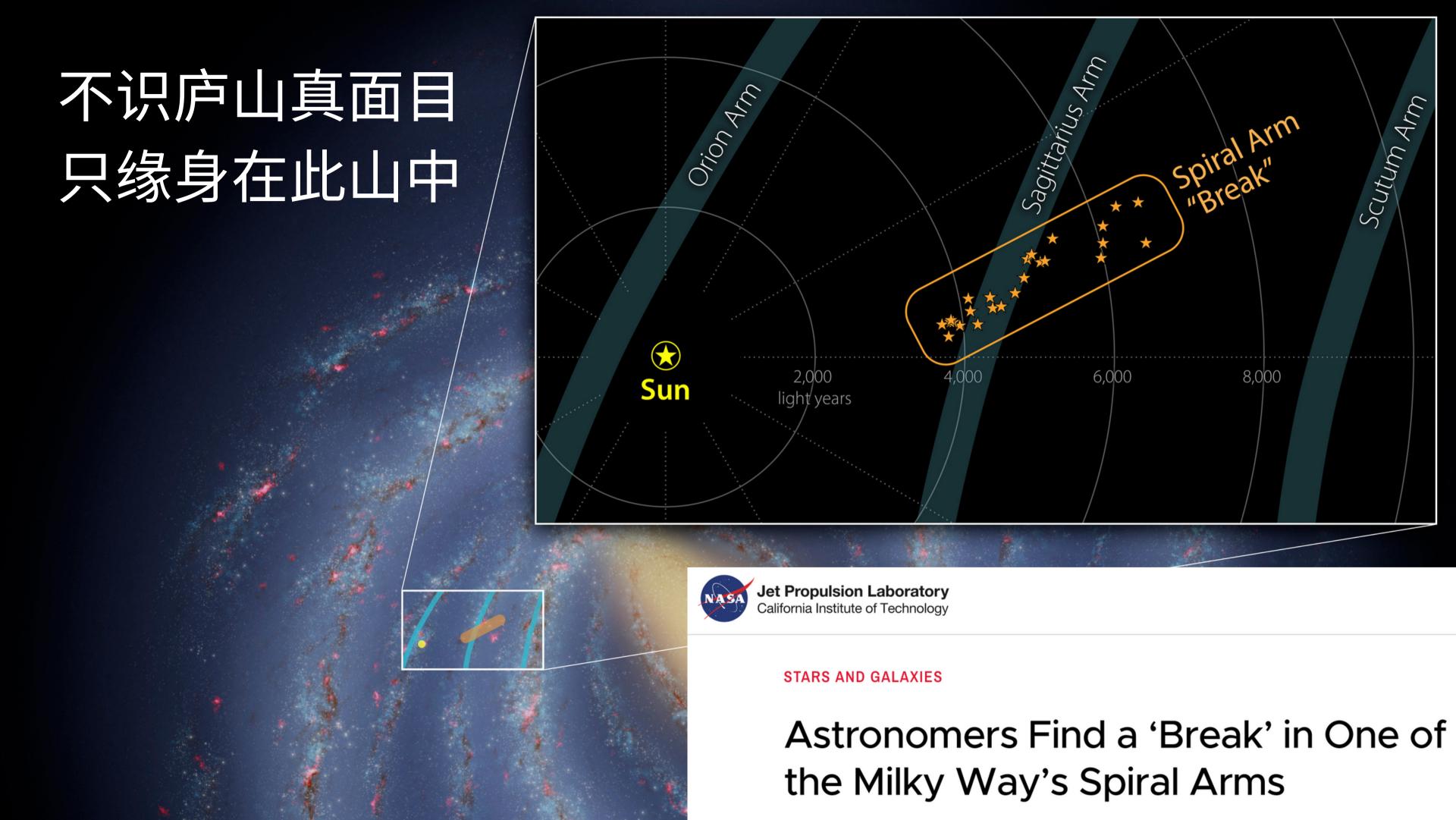
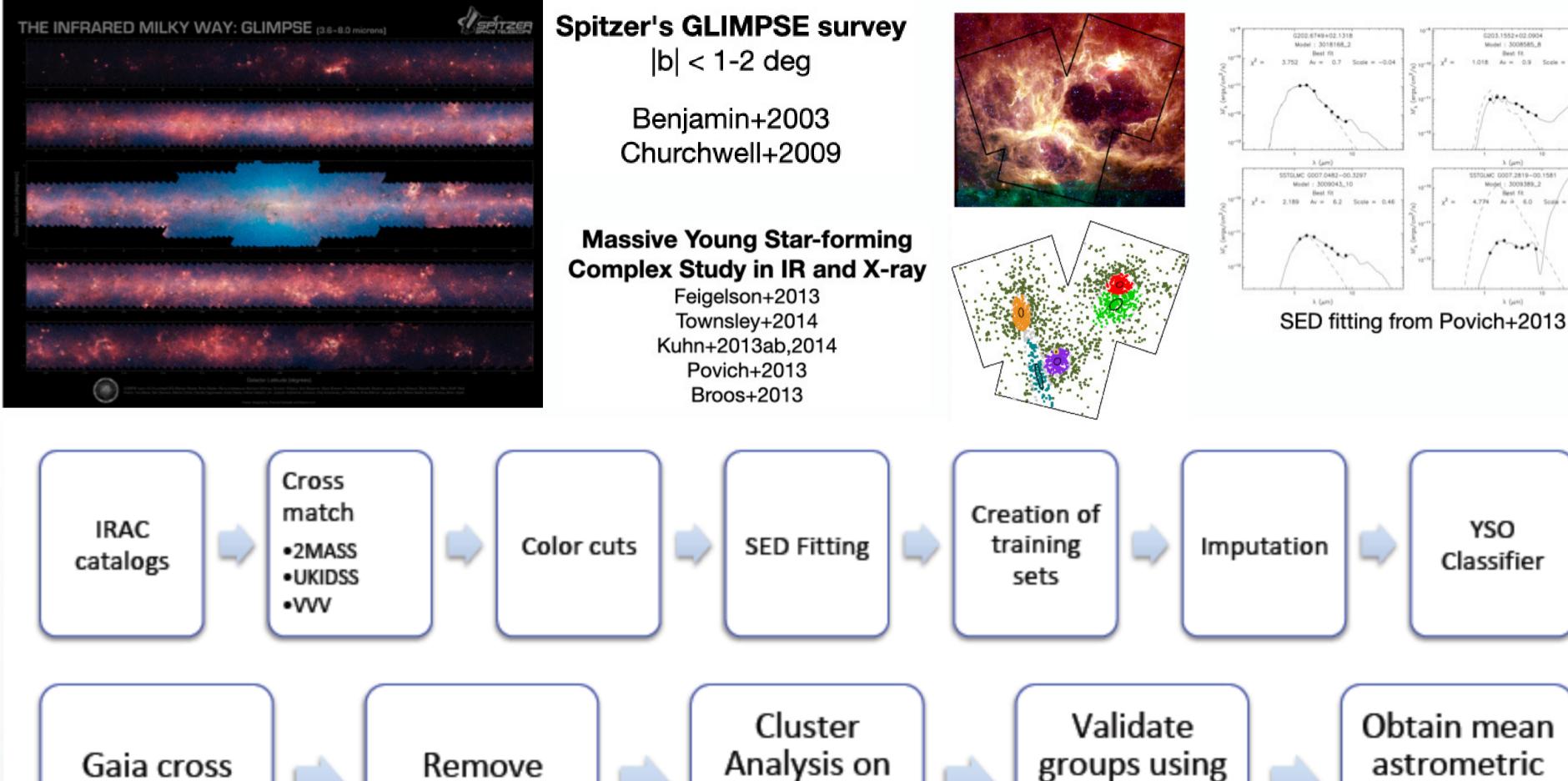


## ASTROSTATS TIPS OF THE DAY

Rafael S.de Souza Shanghai Astronomical Observatory Chair: The Cosmostatistics Initiative





duplicates

match

Spatial

Distributions

clustering in

PM/Plx

Obtain mean astrometric properties of groups

YSO

Classifier

#### THE ASTROPHYSICAL JOURNAL

SUPPLEMENT SERIES

#### SPICY: The Spitzer/IRAC Candidate YSO Catalog for the Inner Galactic Midplane

Michael A. Kuhn<sup>1</sup> D, Rafael S. de Souza<sup>2</sup> D, Alberto Krone-Martins<sup>3,4</sup> D, Alfred Castro-Ginard<sup>5</sup> D, Emille E. O. Ishida<sup>6</sup> D, Matthew S. Povich<sup>1,7</sup> D, Lynne A. Hillenbrand<sup>1</sup>, and for the COIN Collaboration

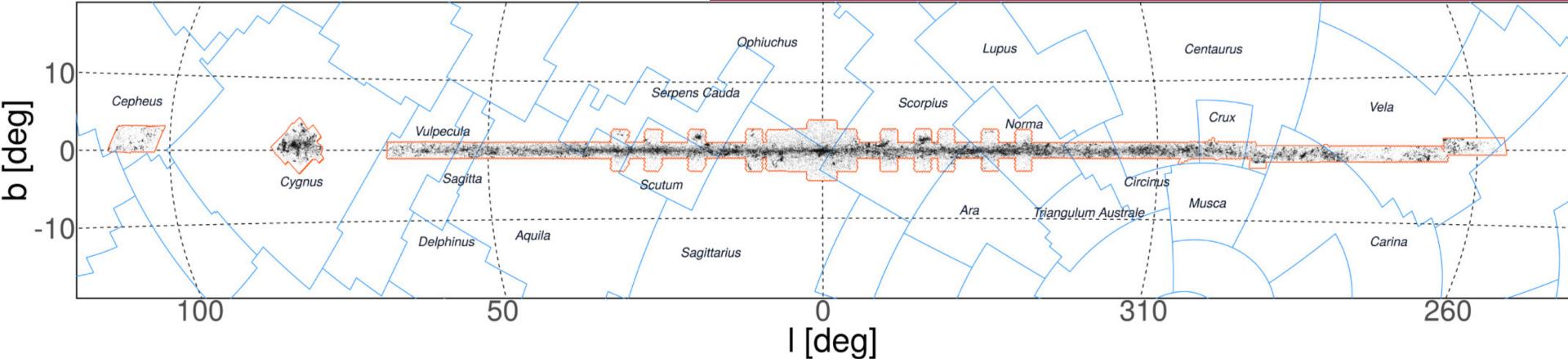
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The Astrophysical Journal Supplement Series, Volume 254, Number 2

Citation Michael A. Kuhn et al 2021 ApJS 254 33

### 120,000 new YSOs

The SPICY catalog is the largest homogeneous sample of YSO candidates available to date for the inner regions of the Milky Way

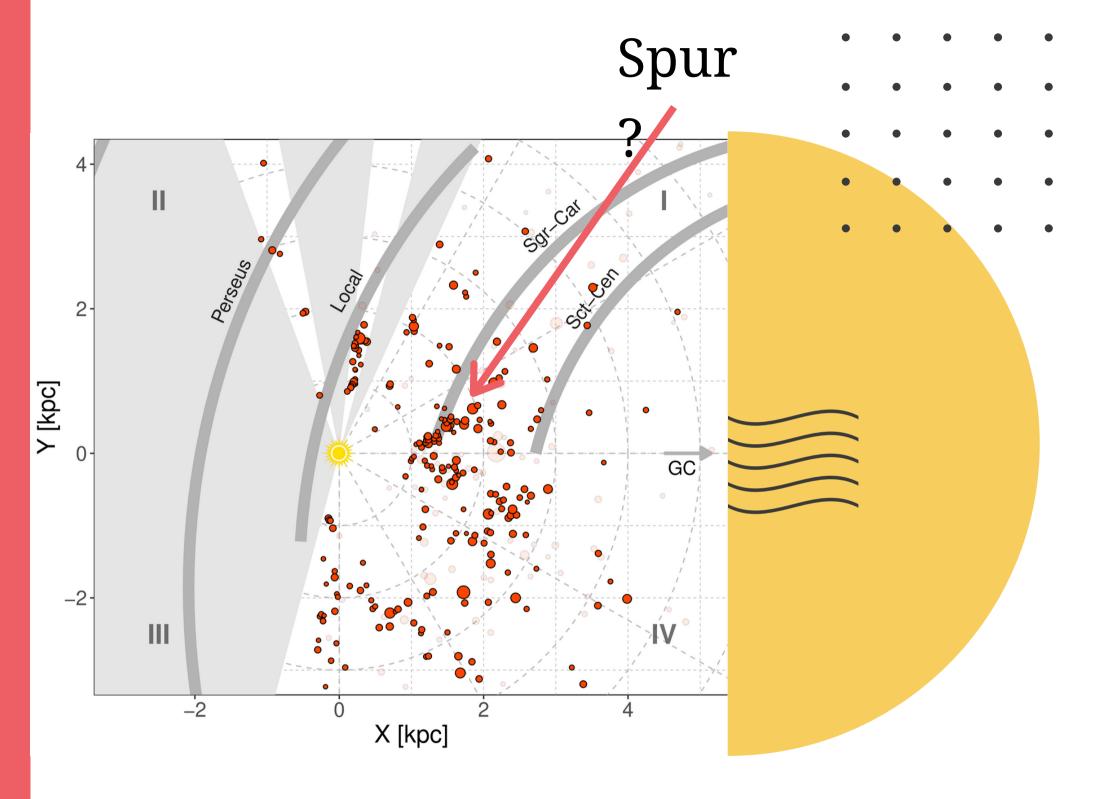


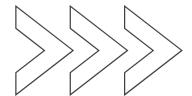
## Spatial distribution of YSO groups

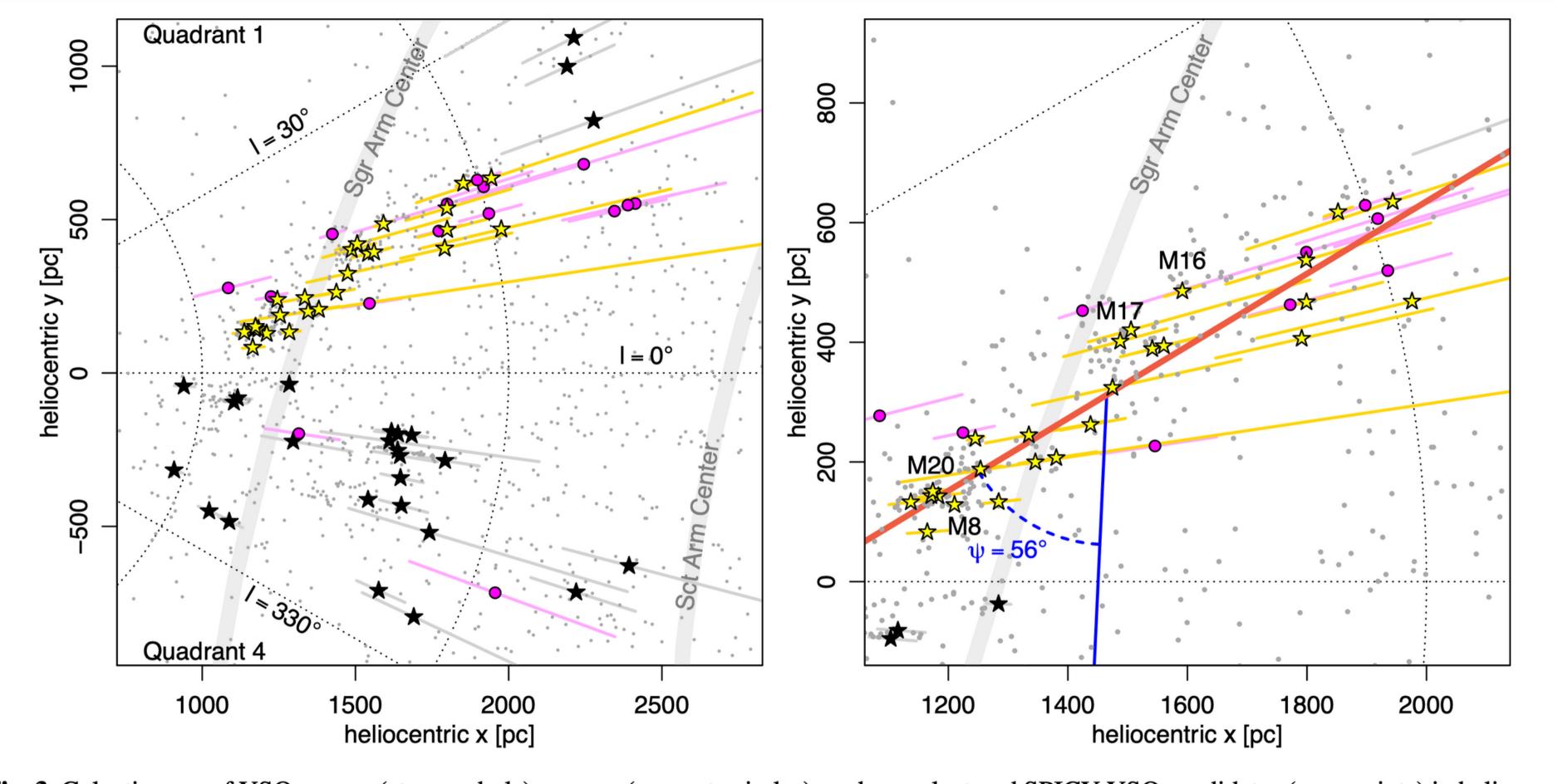
Good tracers of star forming regions and galactic structure



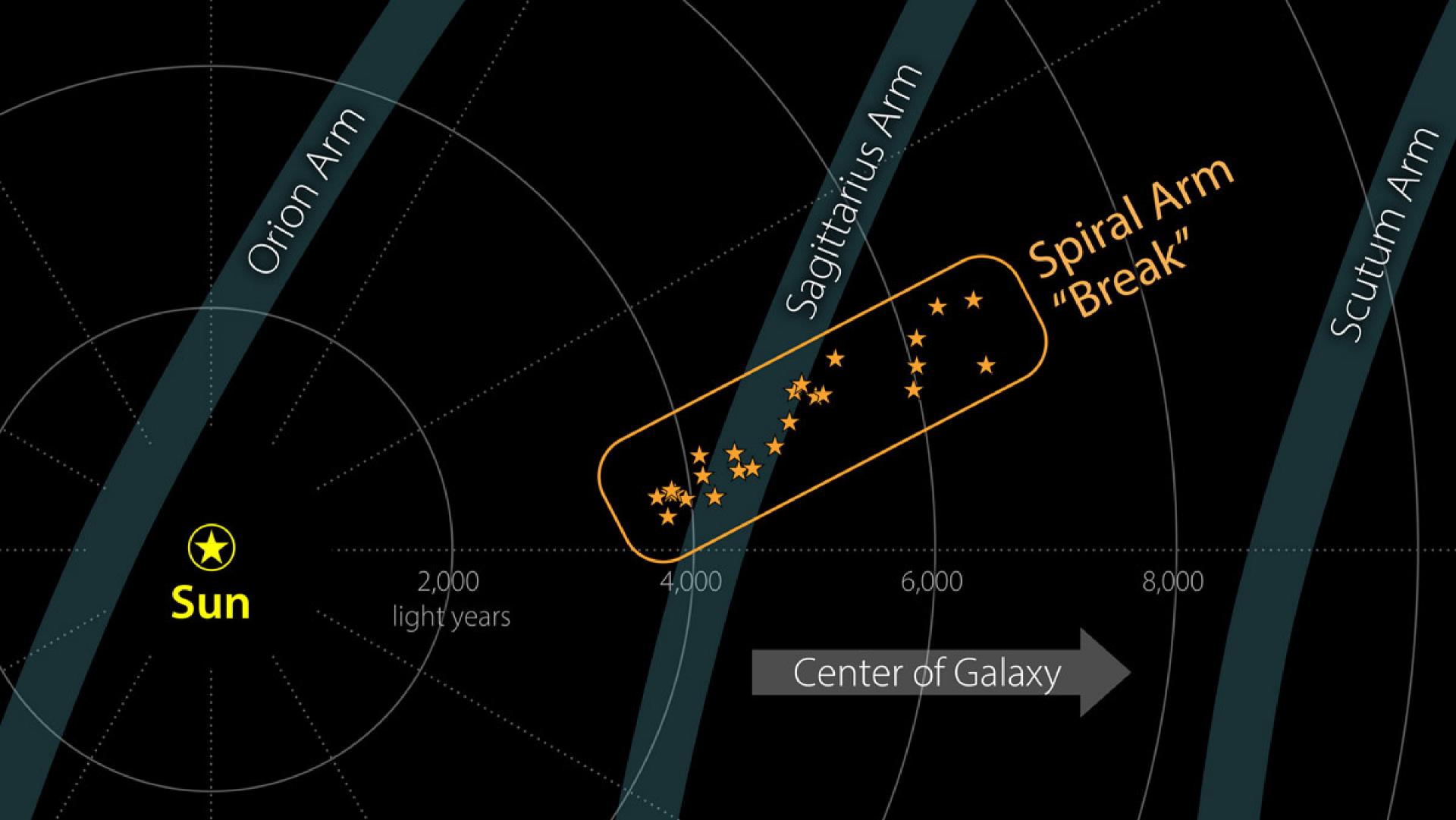
Independent probe of spiral arms structure



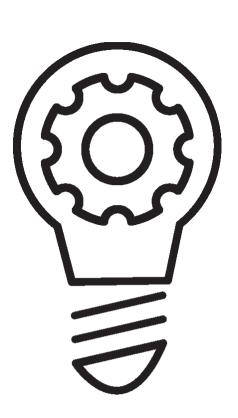




**Fig. 3.** Galactic map of YSO groups (star symbols), masers (magenta circles), and non-clustered SPICY YSO candidates (gray points) in heliocentric *xy* coordinates. The right panel shows a zoomed-in view. Groups associated with the structure are color-coded yellow, while others are black. The spiral-arm centers defined by Reid et al. (2019) are indicated by the grey bands. The red line indicates the major axis of the feature identified here with its 56° pitch angle illustrated in blue.



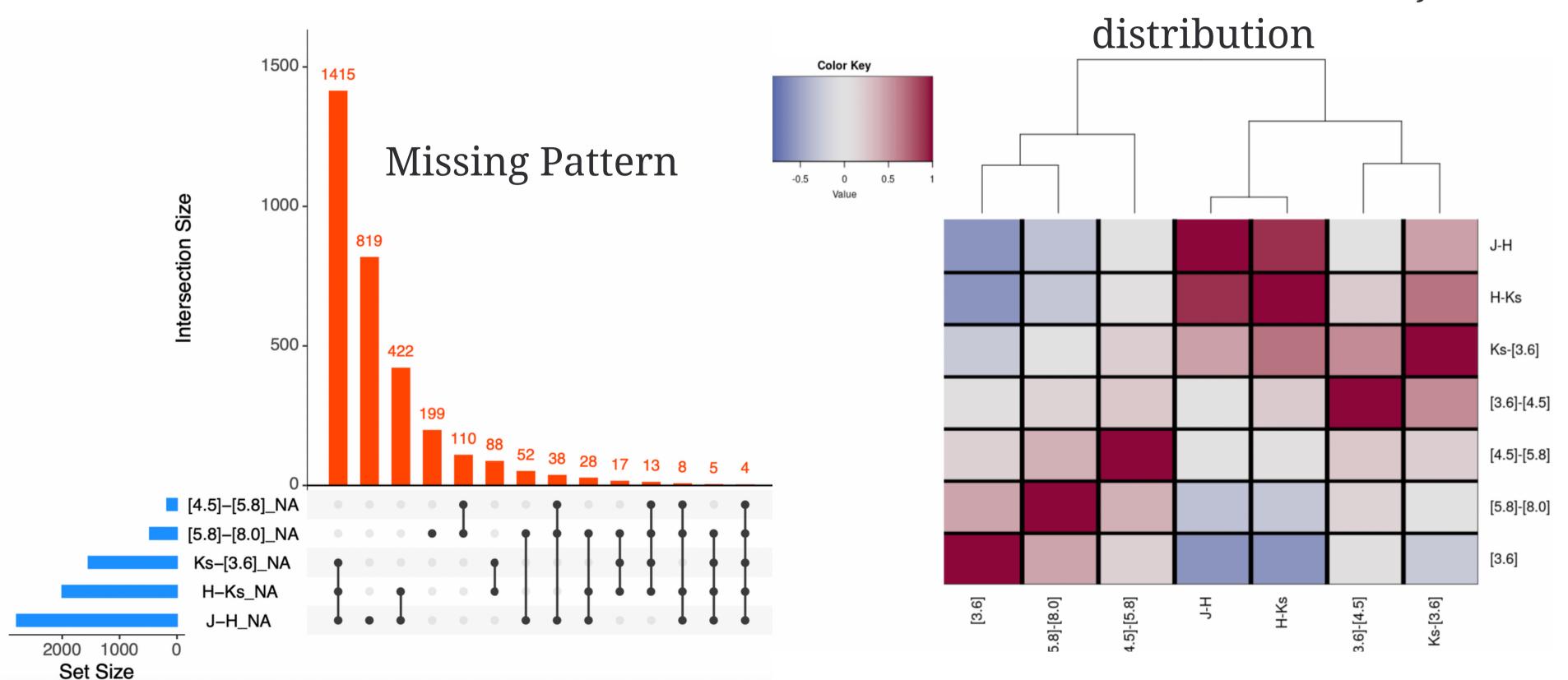
# Some common data issues and possible approaches



- Missing data Imputation techiques
- Measurement Errors Hierarchical Bayesian
- High-dimensionality Principal Component Analysis
- Non-linear maps Regression Tree models, etc.
- Non-Gaussianity Generalized Linear Models

## Missing data

Data is correlated -> Find a joint



Traditional approaches relying upon finding a joint distribution and sampling missing data from it.

Hard to find for highdimensional cases, Multivariate assumption may not hold.

#### Joint modelling imputation

#### Training sample



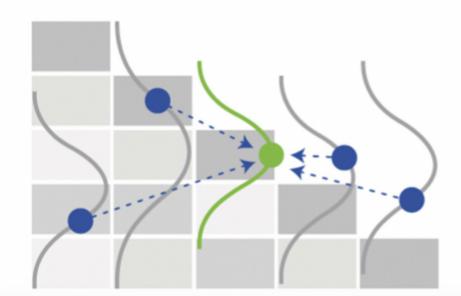
Estimate means and covariance of all predictors in the model using training data

#### Individual patient data



Identify missing variables given an individual patient

#### **Imputation**



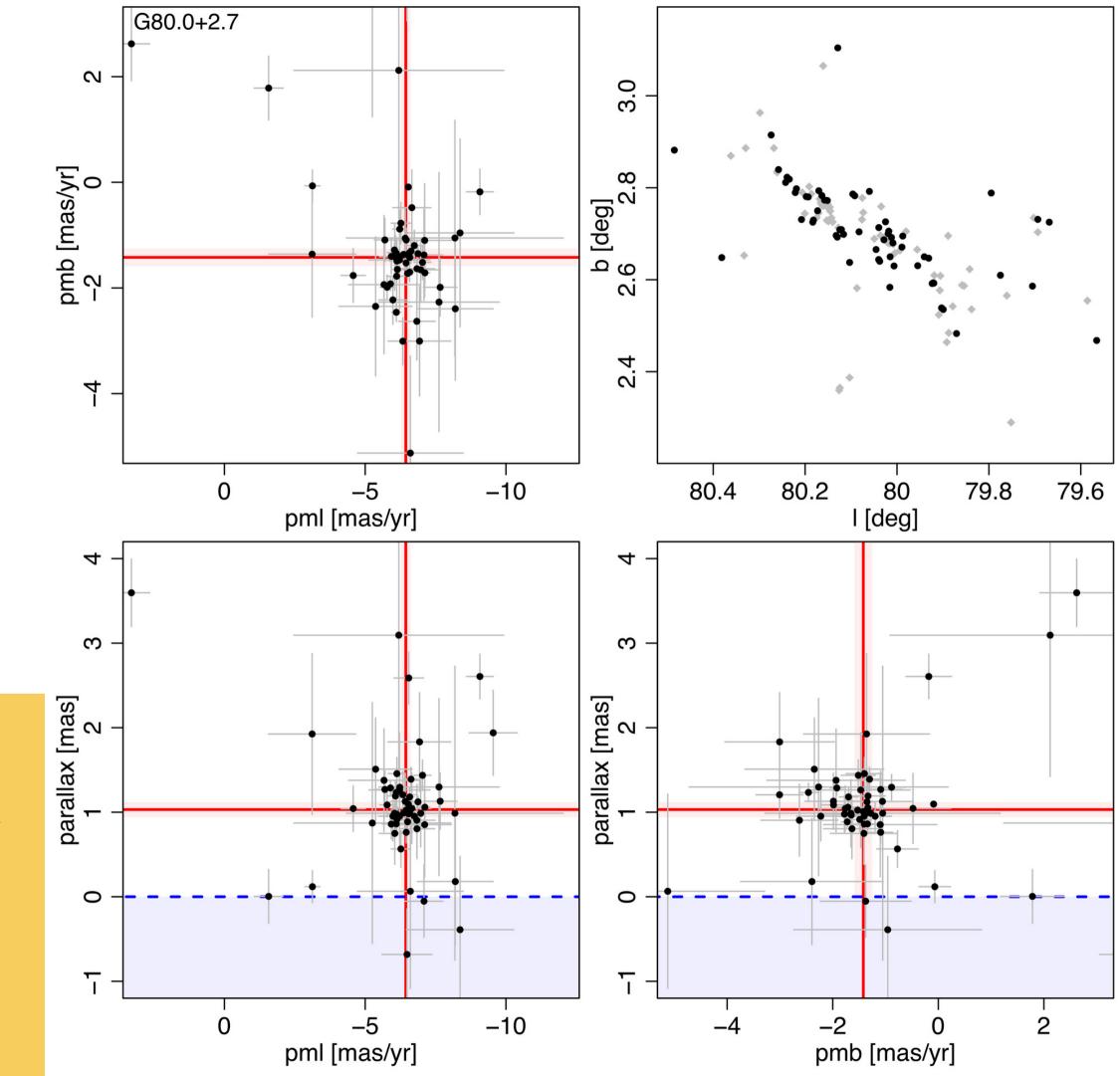
Use derived distribution to generate imputation for missing variable

## Hierarchical Bayesian Models

## ASTROMETRIC PROPERTIES OF THE STELLAR GROUPS

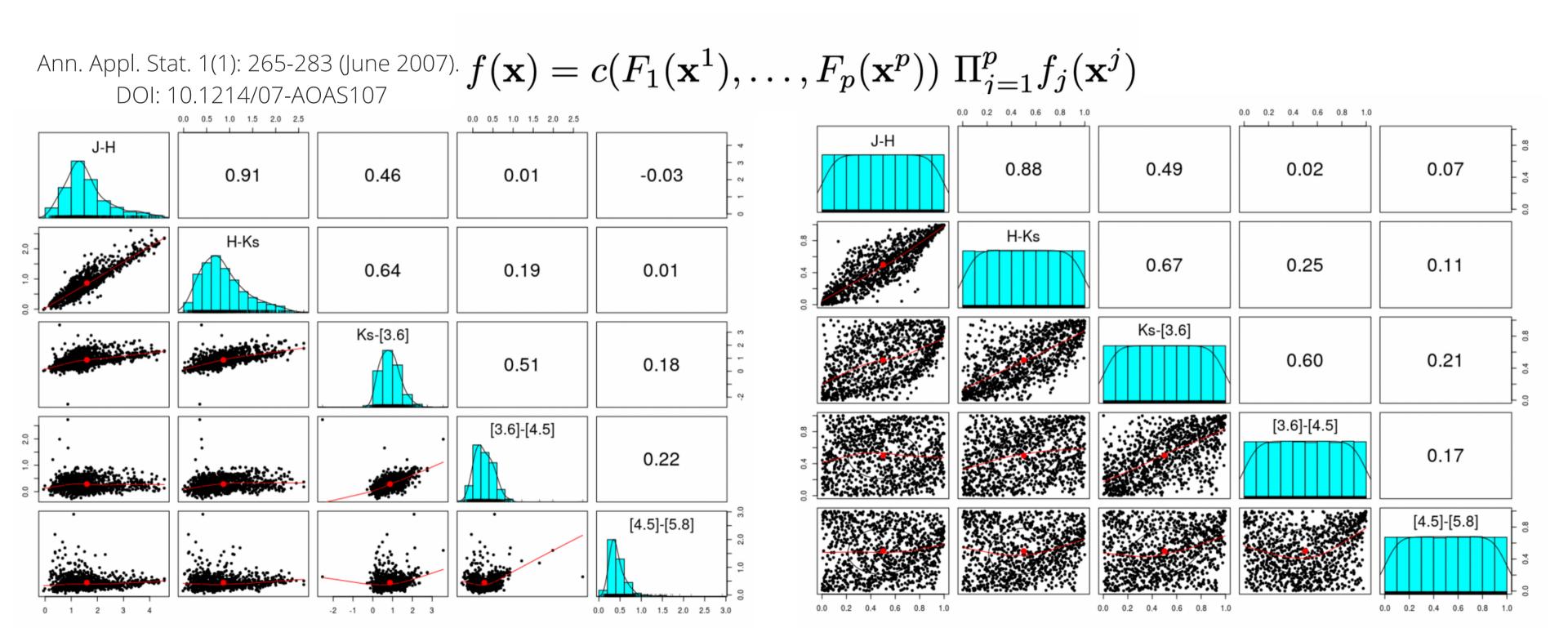
$$egin{aligned} arpi_{
m i} &\sim \mathscr{T}(1/\mathrm{d}_\odot, \sigma_{arpi_{
m i}}^2, 
u), \ 
u &\sim \Gamma(2, 0.1), \ 
d_\odot &\sim \mathrm{Uniform}(0, 25), \ 
i &= 1 \dots n_{\mathrm{Gaia}} \end{aligned}$$

- Heteroscedastic measurement errors, outliers, non-normality, etc.
- Principled statistics still needed



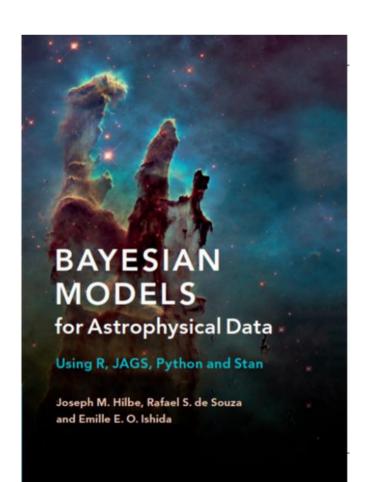
### Multiple Imputation via Gaussian Copulas

**Sklar's Theorem:** Let F be a p-dimensional joint distribution function with marginals  $F1, \ldots, Fp$ . Then there exists a copula C with uniform marginals such that F(x1,...,xp) = C(F1(x1),...,Fp(xp)) ()



### Domain Specific Languages for Bayesian Analysis

- JAGS
- Stan
- Edward
- TensorFlow Probability
- Greta, ....



```
# Bayesian_plx_to_d
# Transform parallax into distance (kpc)
# INPUT:
# w - parallax (mas)
# errw - associated uncertainty (mas)
# Return heliocentric distance (kpc)
require(R2jags)
Bayesian_plx_to_d <- function(w,errw,nobs){</pre>
nobs = nobs
model.data <- list(w = w,</pre>
                                            # Parallax
                                            # Error in Parallax
                    errw = errw,
                    N = nobs
                                            # Sample size
NORM <- "
model{
# Likelihood
for (i in 1:N){
w[i] \sim dt(1/d,pow(errw[i],-2),nu)
#nu <- nuMinusOne + 1
\#nuMinusOne ~ dexp(1/29)
nu \sim dgamma(2,0.1)
# Weakly uniform prior for distance
d \sim dunif(0,25)
plx <- 1/d
params <- c("d","plx")</pre>
```

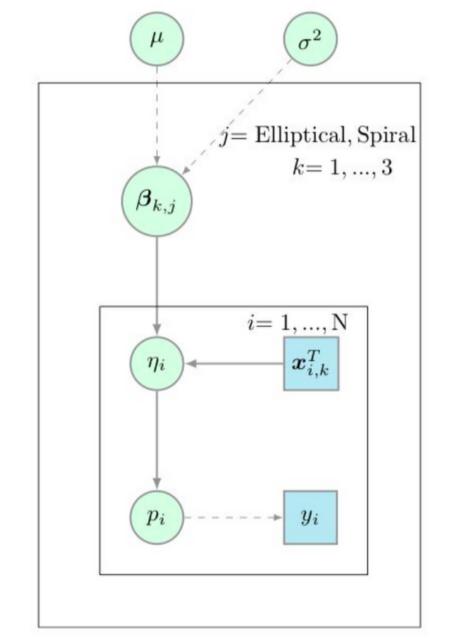
## JAGS (Just Another Gibbs Sample) language

Enables to create Hierarchical Bayesian Models for general regression purposed quite fast.

## Is the cluster environment quenching the Seyfert activity in elliptical and spiral galaxies?

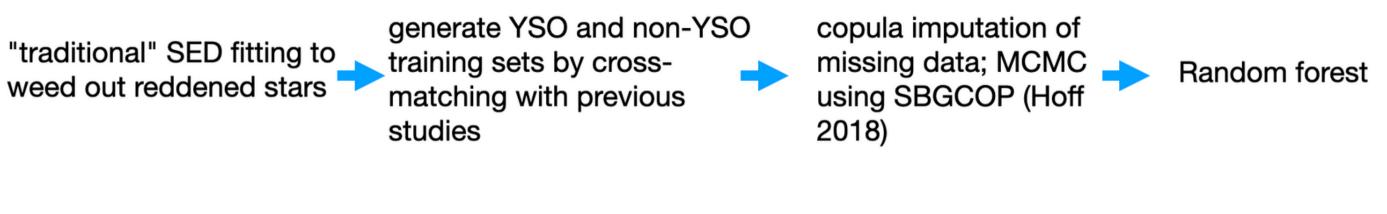
R. S. de Souza<sup>1\*</sup>, M. L. L. Dantas<sup>2</sup>, A. Krone-Martins<sup>3</sup>, E. Cameron<sup>4</sup>, P. Coelho<sup>2</sup>, M. W. Hattab<sup>5</sup>, M. de Val-Borro<sup>6</sup>, J. M. Hilbe<sup>7</sup>, J. Elliott<sup>8</sup> and A. Hagen<sup>9</sup>, for the COIN Collaboration

```
#Model
jags_model<-"model{
#Shared hyperpriors for beta
tau ~ dgamma(1e-3,1e-3) #Precision
mu \sim dnorm(0, 1e-3)
                         #mean
#Diffuse prior for beta
for(j in 1:2){
for(k in 1:3){
beta[k,j]~dnorm(mu,tau)
# Likelihood
for(i in 1:N){
Y[i] ~ dbern(pi[i])
logit(pi[i]) <- eta[i]
eta[i] <- beta[1,gal[i]]*X[i,1]+
beta[2,gal[i]]*X[i,2]+
beta[3,gal[i]]*X[i,3]
```

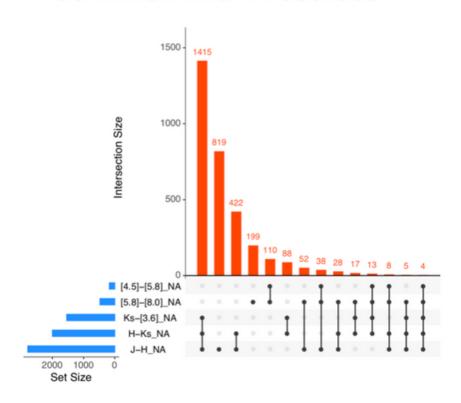


 $y_{i} \sim \text{Bernoulli}(p_{i})$   $\log \text{it}(p_{i}) = \eta_{i}$   $\eta_{i} = \boldsymbol{x}_{i,k}^{T} \beta_{k,j}$   $\boldsymbol{x}_{i,k}^{T} =$   $\begin{pmatrix} 1 & (\log M_{200})_{1} & (\frac{r}{r_{200}})_{1} \\ \vdots & \vdots & \vdots \\ 1 & (\log M_{200})_{N} & (\frac{r}{r_{200}})_{N} \end{pmatrix}$   $\beta_{k,j} \sim \text{Normal}(\mu, \sigma^{2})$   $\mu \sim \text{Normal}(0, 10^{3})$   $\tau \sim \text{Gamma}(10^{-3}, 10^{-3})$   $\sigma^{2} = 1/\tau$  j = Elliptical, Spiral k = 1, ..., 3 i = 1, ..., N

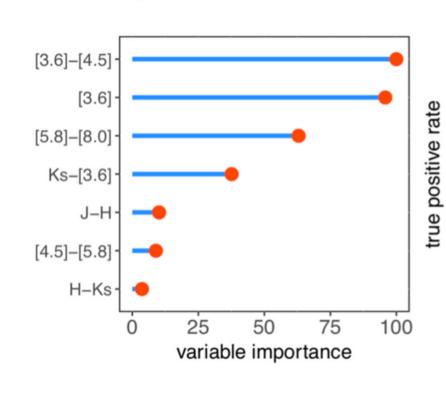
#### **Classification scheme**



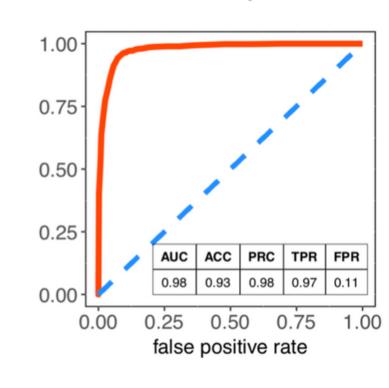


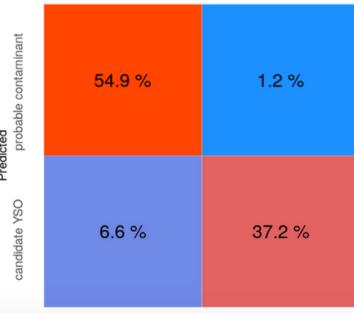


#### 117,446 YSO candidates



#### Classifier performance





#### THE ASTROPHYSICAL JOURNAL

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#### SPICY: The Spitzer/IRAC Candidate YSO Catalog for the Inner Galactic Midplane

Michael A. Kuhn<sup>1</sup> D, Rafael S. de Souza<sup>2</sup> D, Alberto Krone-Martins<sup>3,4</sup> D, Alfred Castro-Ginard<sup>5</sup> D, Emille E. O. Ishida<sup>6</sup> D, Matthew S. Povich<sup>1,7</sup> D, Lynne A. Hillenbrand<sup>1</sup>, and for the COIN Collaboration

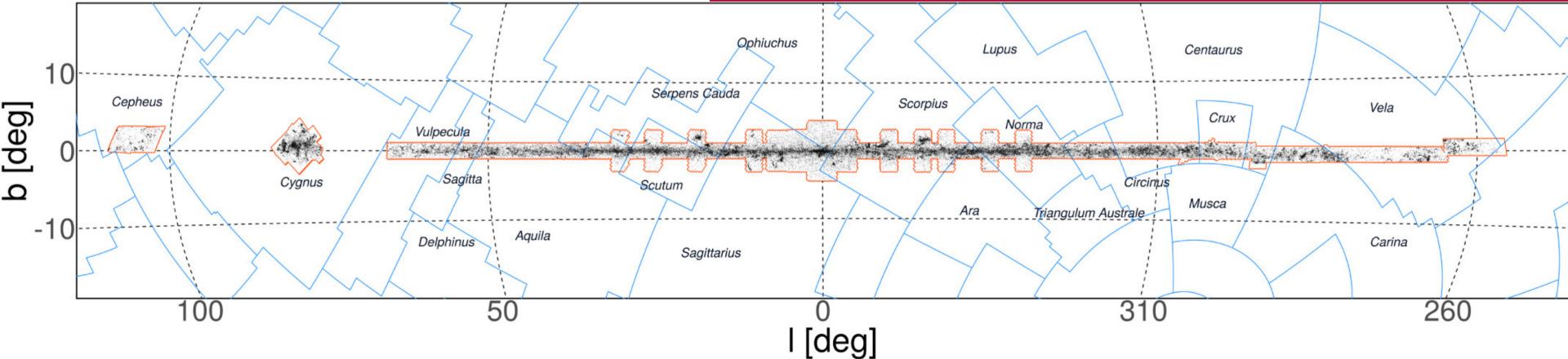
Published 2021 June 2 • © 2021. The American Astronomical Society. All rights reserved.

The Astrophysical Journal Supplement Series, Volume 254, Number 2

Citation Michael A. Kuhn et al 2021 ApJS 254 33

### 120,000 new YSOs

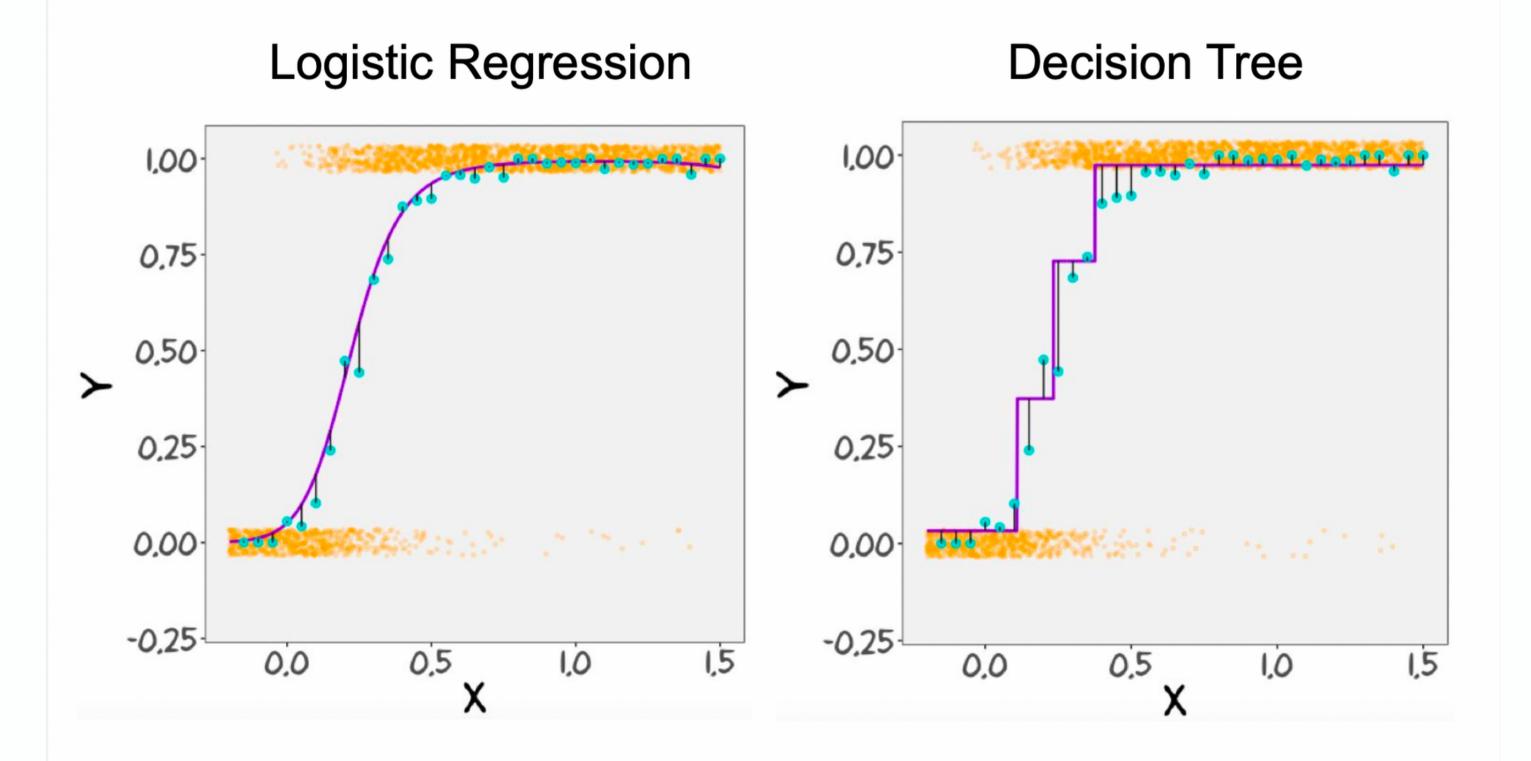
The SPICY catalog is the largest homogeneous sample of YSO candidates available to date for the inner regions of the Milky Way



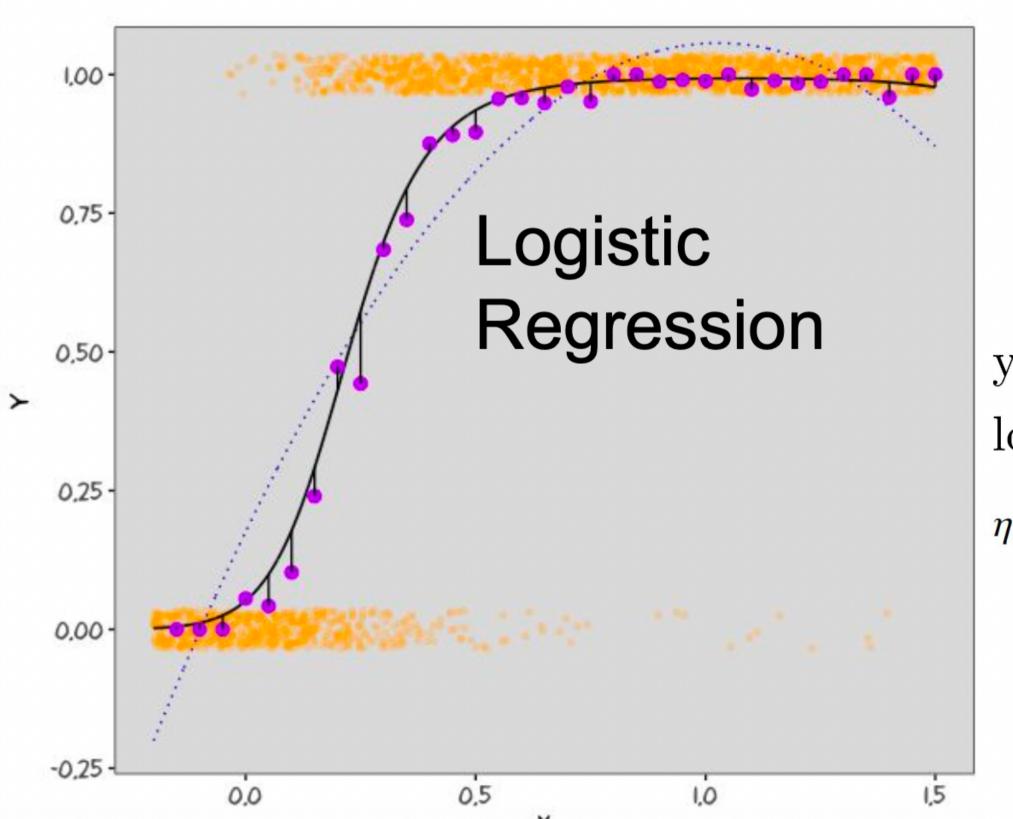


### Logistic regression "vs" Decision Tree

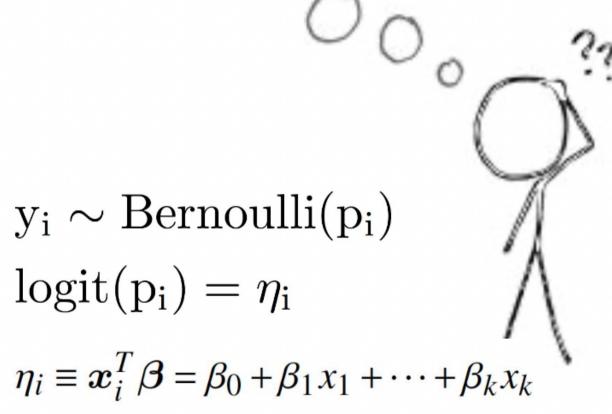
Caveat: You get what you ask for



## Gaussian Models Limitations



#### Binary data



#### A high occurrence of nuclear star clusters in faint Coma galaxies, and the roles of mass and environment

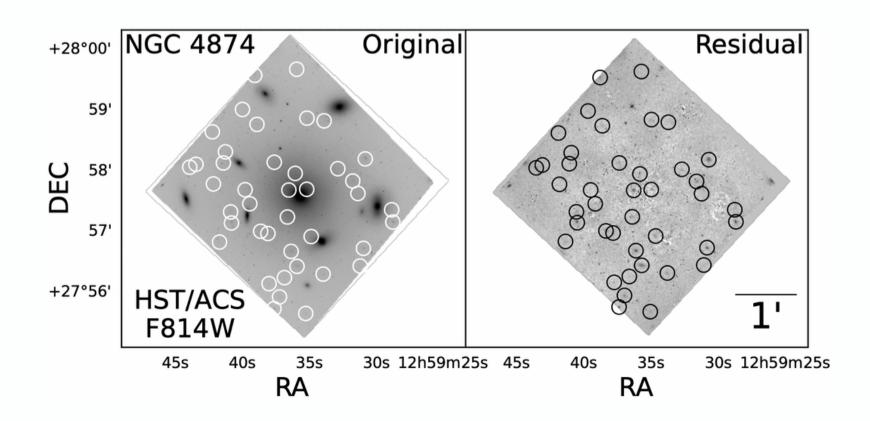
<u>Emílio Zanatta</u> ™, Rubén Sánchez-Janssen, Ana L Chies-Santos, Rafael S de Souza, John P Blakeslee

Monthly Notices of the Royal Astronomical Society, stab2348,

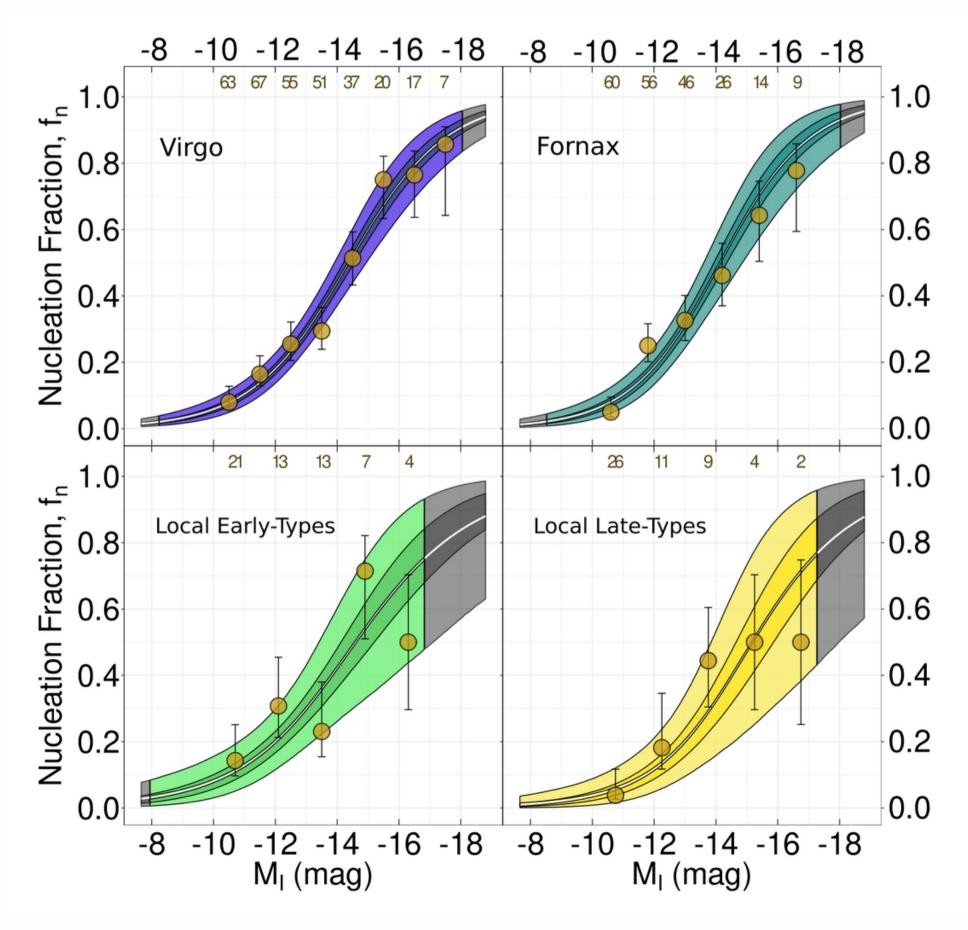
https://doi.org/10.1093/mnras/stab2348

Published: 23 August 2021

NSCs are the densest known star clusters in the Universe. With apparent magnitudes between -14 and -10 mag in the infrared, they are on average 40 times brighter than globular clusters, although their effective radii are not larger than 2 to 5 parsecs.



#### Logistic Regression



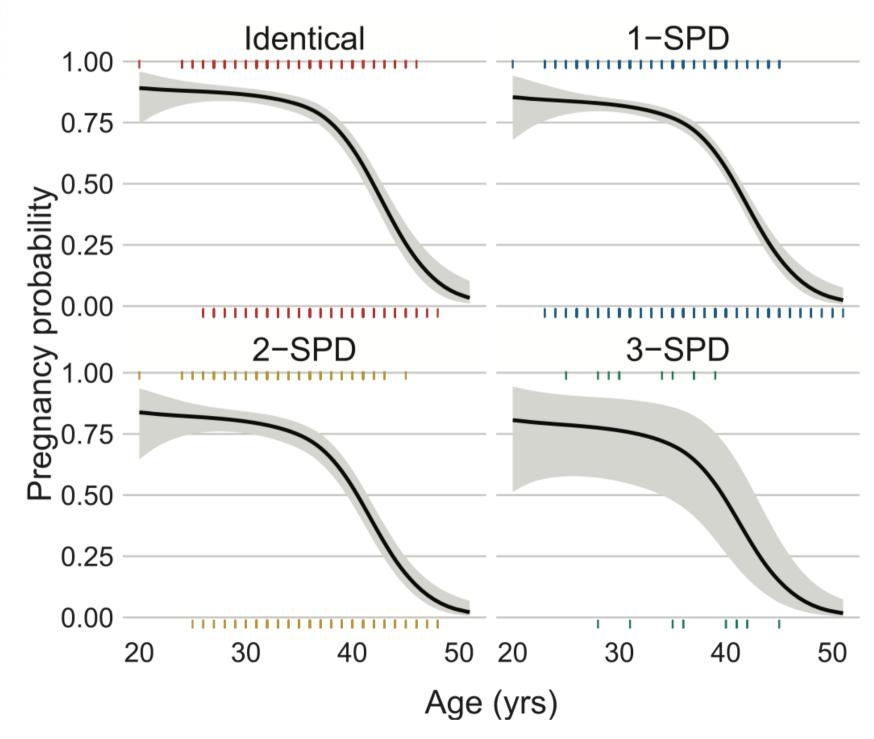
#### Statistical Methods in Medical Research

Fallopian tube anatomy predicts pregnancy and pregnancy outcomes after tubal reversal surgery

Rafael S de Souza , Gary S Berger First Published July 7, 2021 | Research Article | Find in PubMed | Check for updates https://doi.org/10.1177/09622802211023543

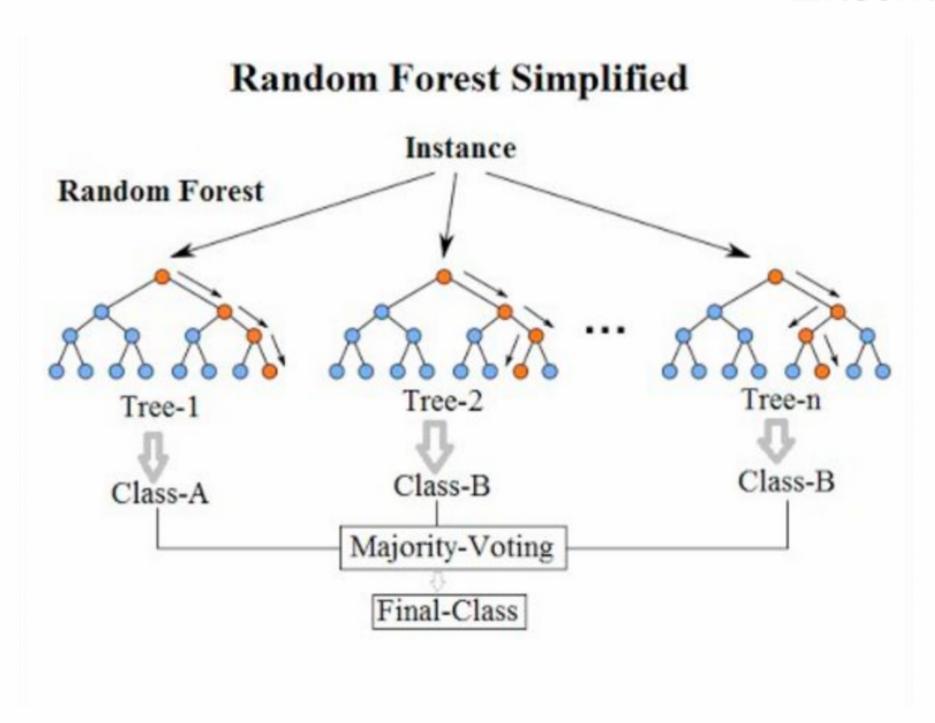
Article information

## Logistic Regression again



## Random Forests

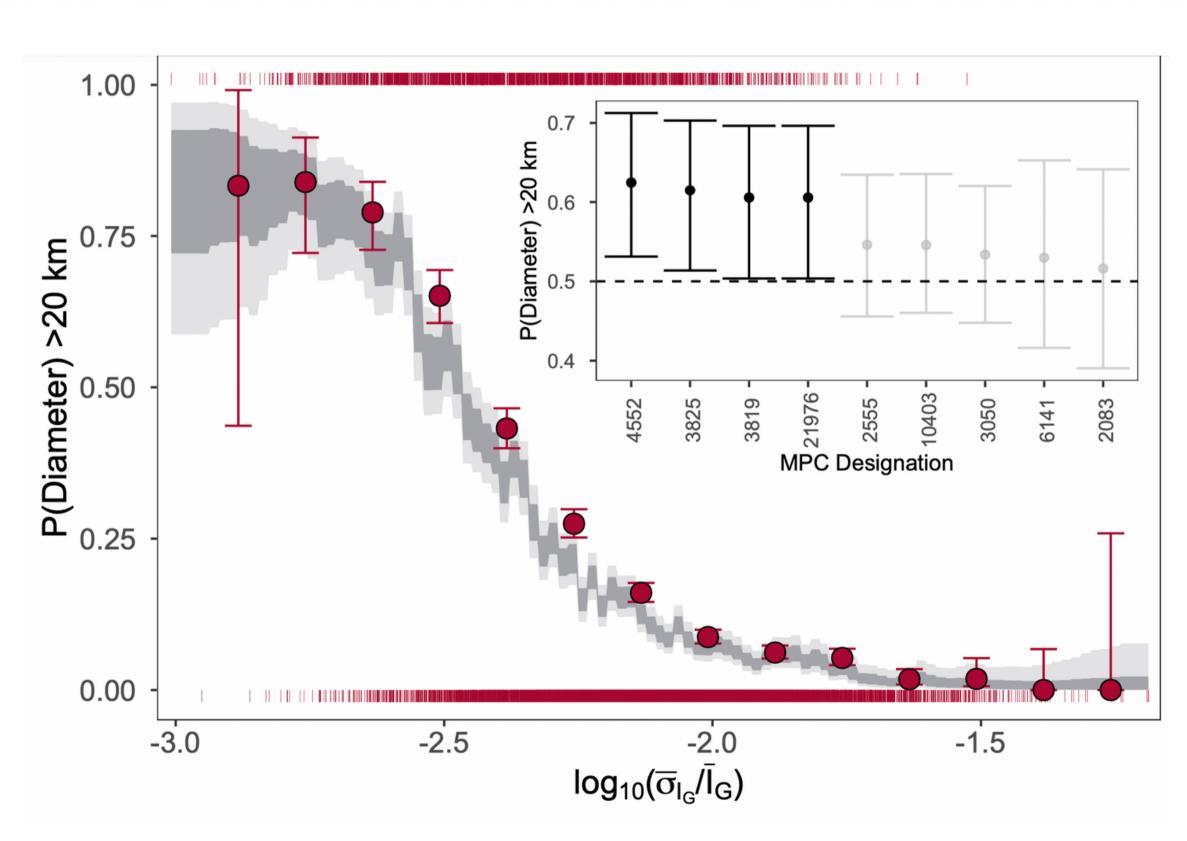
Ensemble method

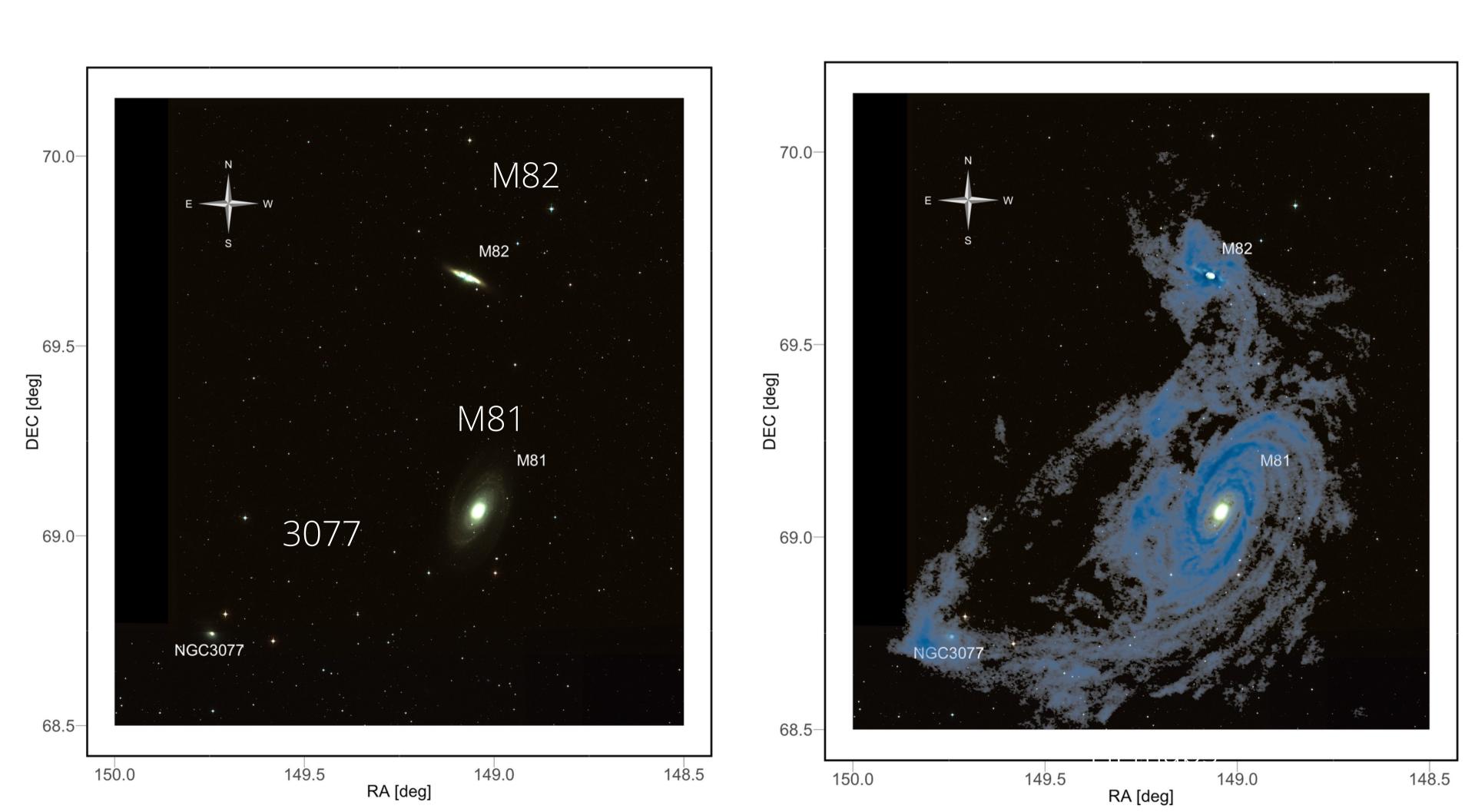


#### Probabilistic modeling of asteroid diameters from Gaia DR2 errors

Rafael S. de Souza , Alberto Krone-Martins , Valerio Carruba , Rita de Cassia Domingos , E. E. O. Ishida , Safwan Alijbaae , Mariela Huaman Espinoza , and William Barletta

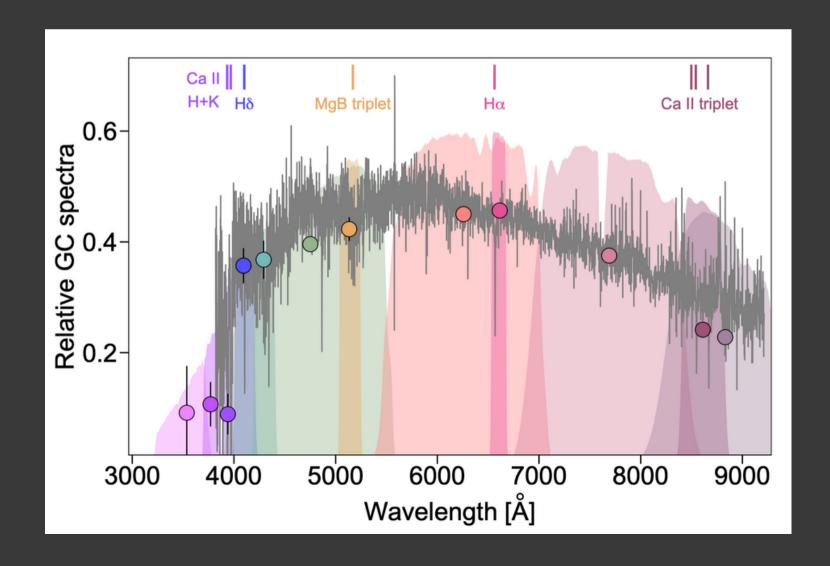
Logistic Bayesian Additive Regression Trees

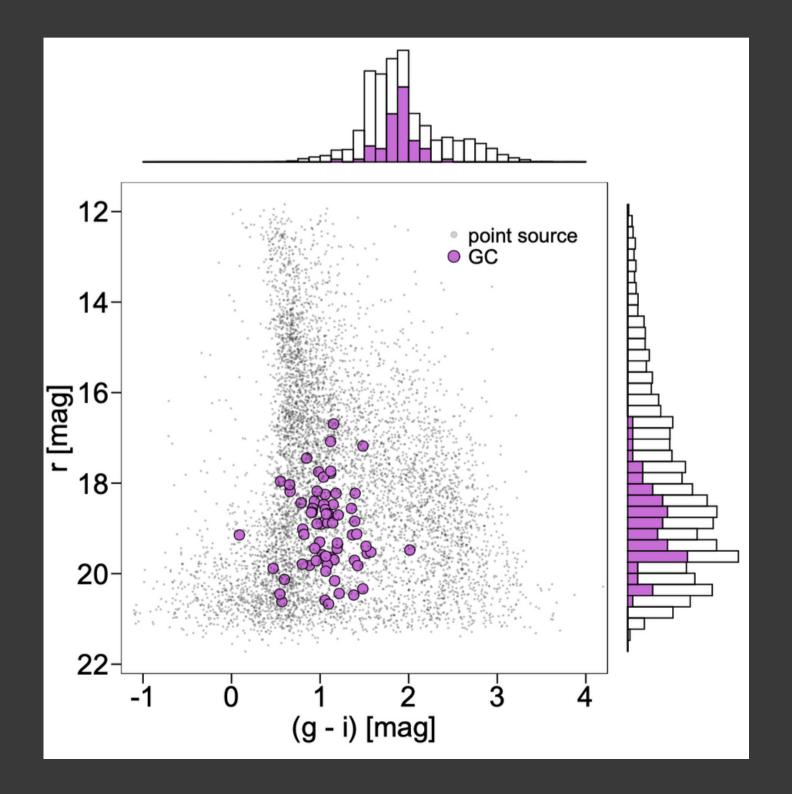




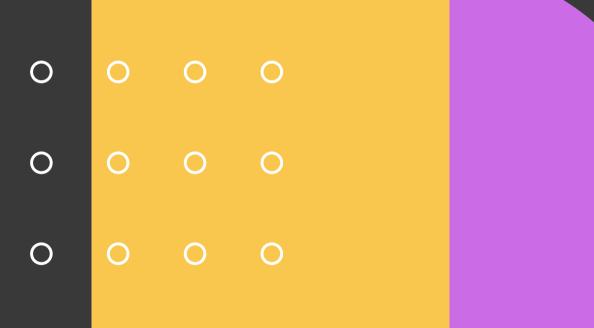
## J-PLUS PHOTOMETRY

For 7.2K point sources plus 73 confirmed GCs





# General Statistical pipeline

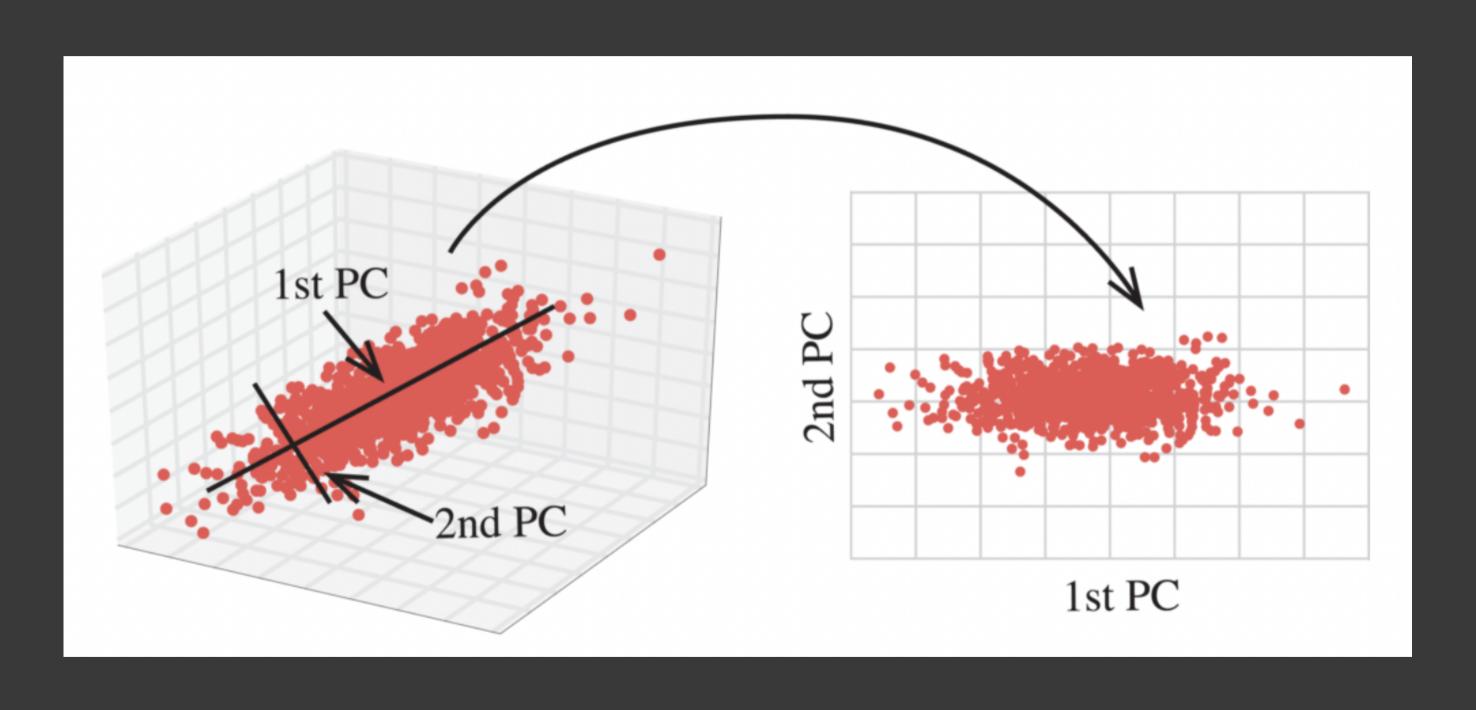


Copula Imputation for missing data

**Uncertainty aware PCA** 

Search for GC twins via Propensity Score matching

## Quick reminder

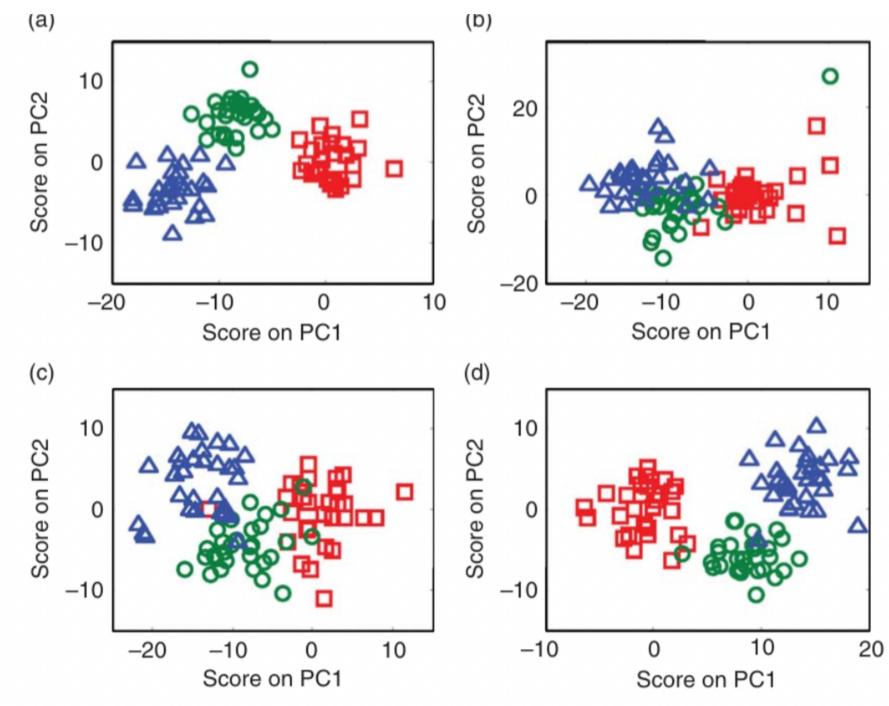


## 2.25 Other Topics in Soft-Modeling: Maximum Likelihood-Based Soft-Modeling Methods

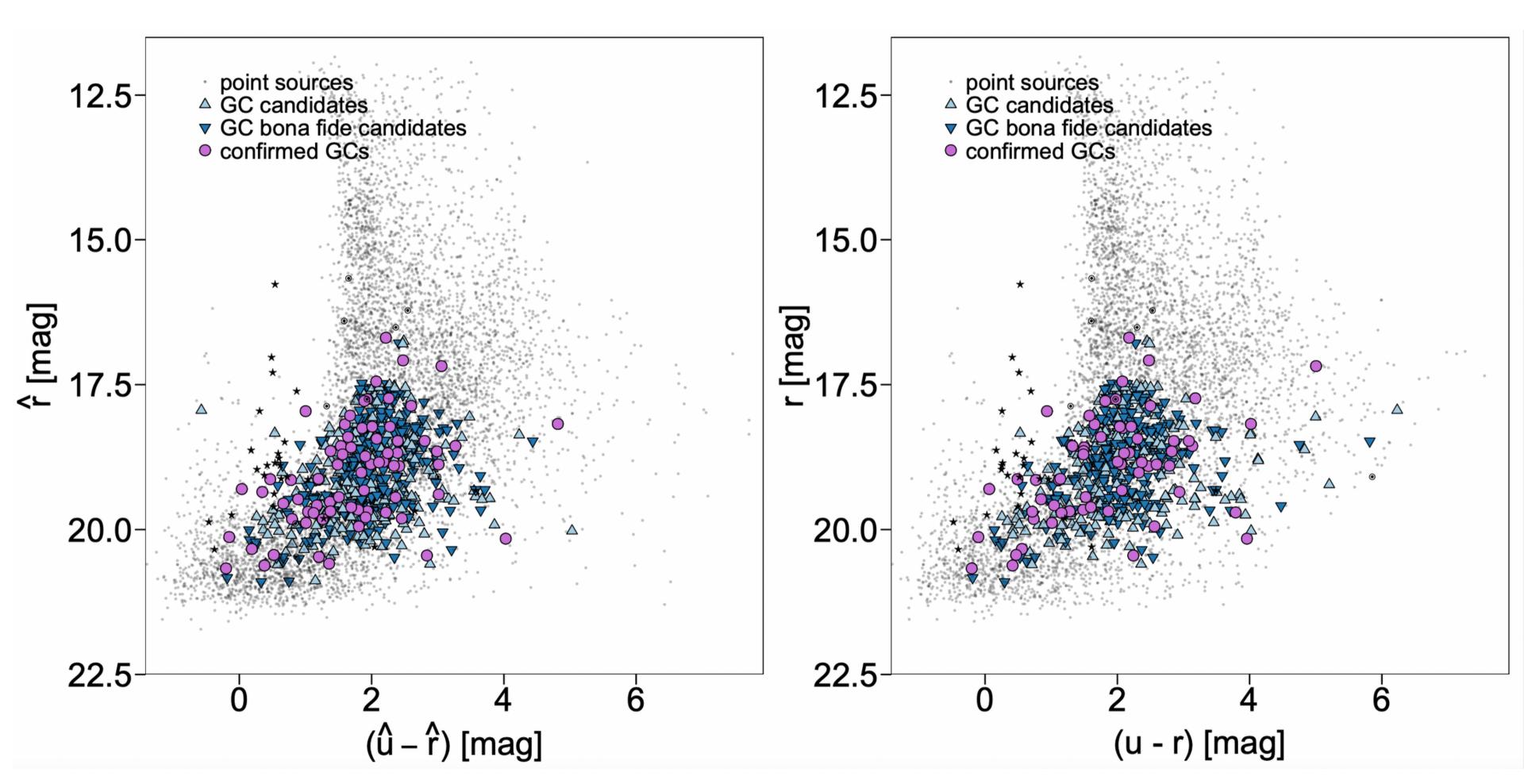
P. D. Wentzell, Dalhousie University, Halifax, NS, Canada

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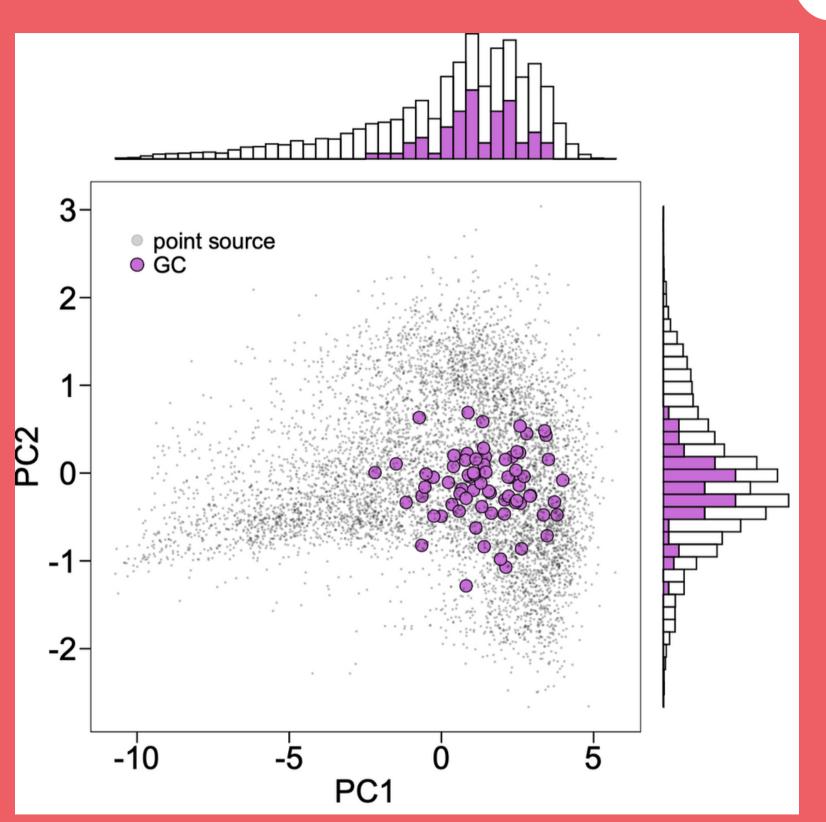
Uncertainty Aware Principal Components Analysis

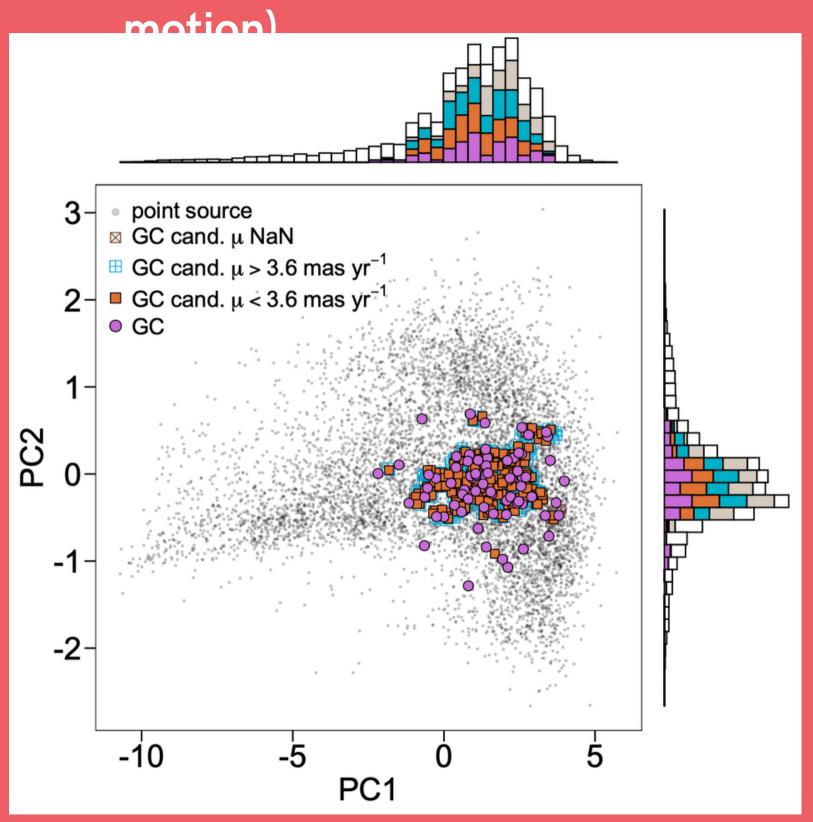


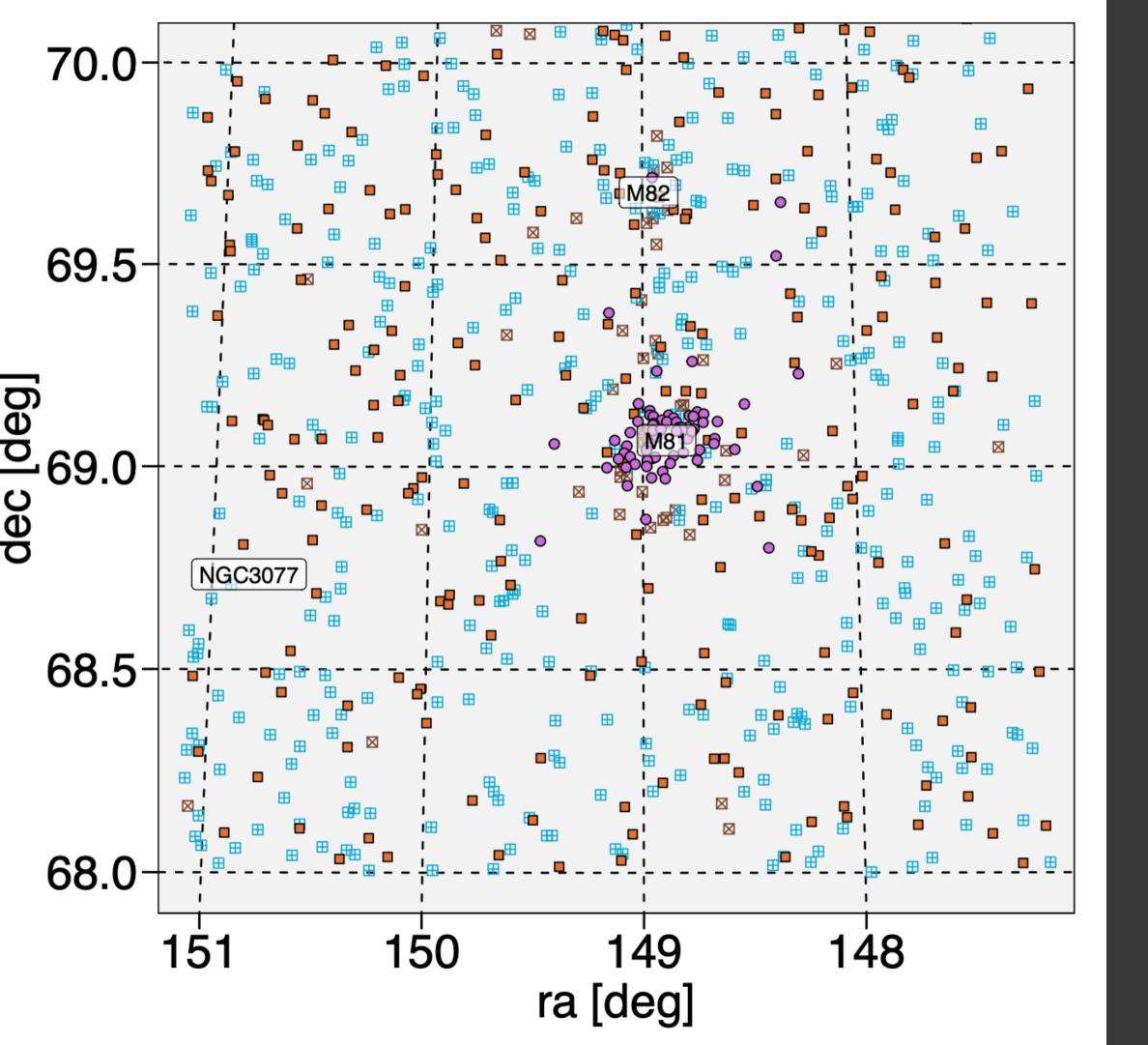
**Figure 16** Application of PCA and MLPCA to simulated clustered data with heteroscedastic noise: (a) PCA results for noise-free measurements, (b) PCA results for noisy measurements, (c) MLPCA results for noisy measurements with true measurement variances, and (d) MLPCA results with 'buffered' measurement variances.



640 GC candidates
310 bona fide (i.e. low proper





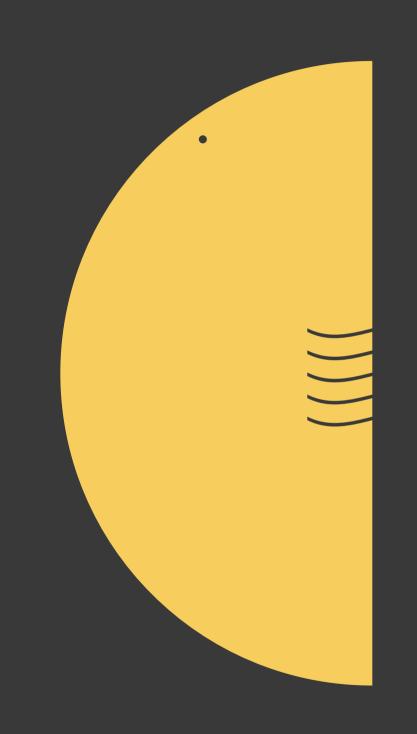


## Spatial distribution of 640 candidates 310 bonafide

The largest list of GCs around the triplet to date. The next step is to expand the search, and get spectra.

Sit down before fact as a little child, be prepared to give up every preconceived notion, follow humbly wherever and to whatever abysses nature leads...

Thomas Huxley



## References

- Copulas:
- Uncertainty Aware PCA:
- Hierarchical Bayesian Models: