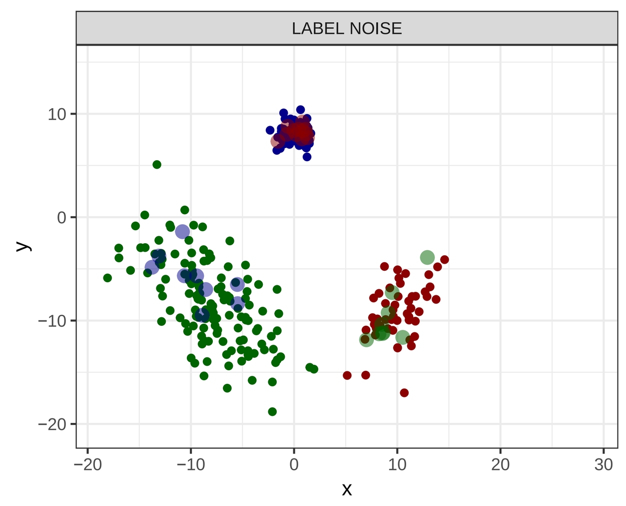
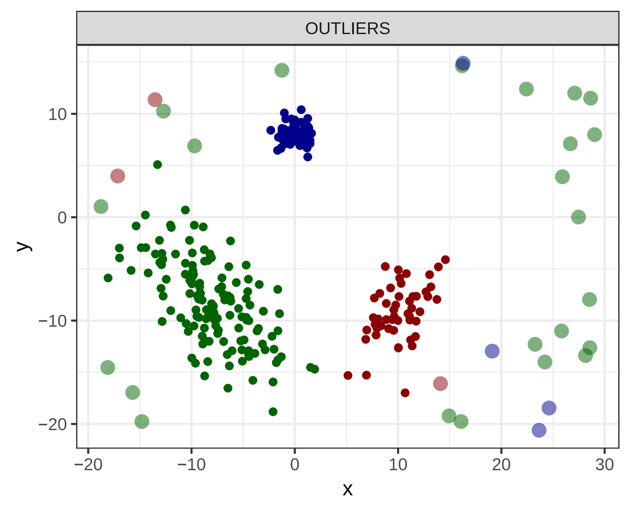
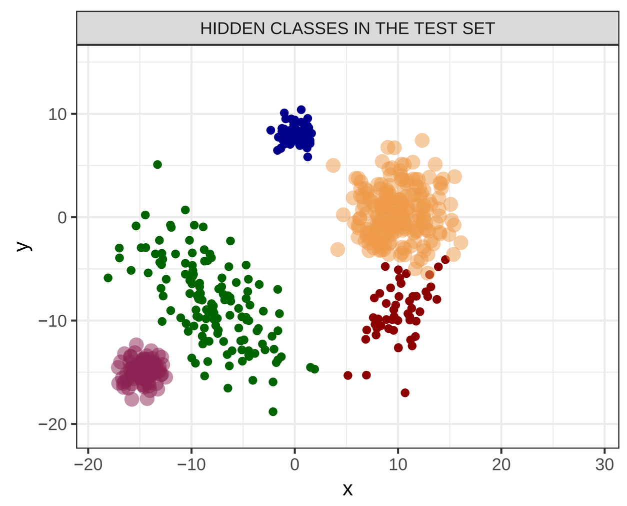
Supervised Learning in Presence of Outliers, Label Noise and Unobserved Classes

Andrea Cappozzo*, Francesca Greselin*, Thomas Brendan Murphy†
*Department of Statistics and Quantitative Methods, University of Milan-Bicocca, Milan, Italy
† School Of Mathematics & Statistics and Insight Research Centre, University College Dublin, Dublin, Ireland

Problem Framework: 3 main issues in Classification







- **Label Noise:** The class-membership is unreliable for some training observations
- **Outliers:** A proportion of observations might depart from the bulk of the data structure
- **Unobserved Classes:** Only a subset of classes might have been seen in the learning data

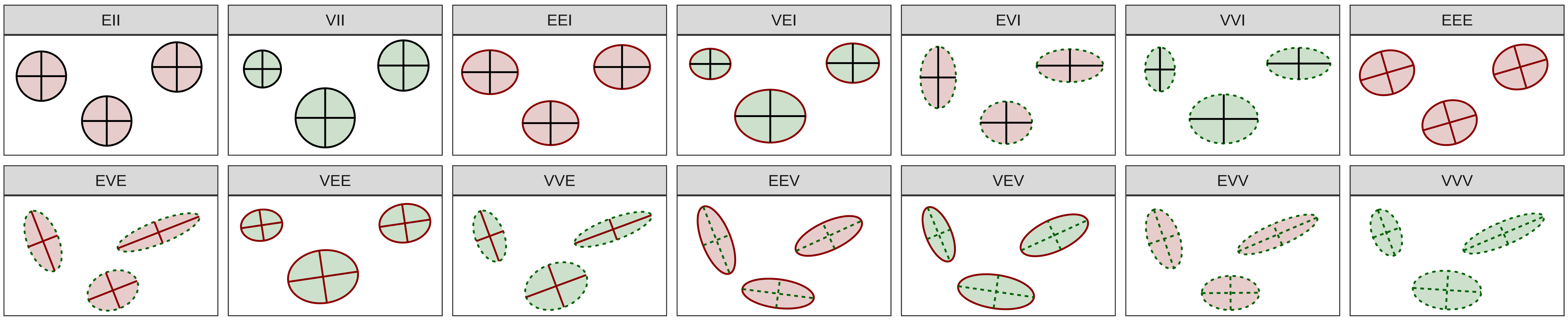
Proposed Solution: RAEDDA Model

The **Robust Adaptive Eigenvalue Decomposition Discriminant Analysis (RAEDDA)** generalizes the *AMDA* model [2] by:

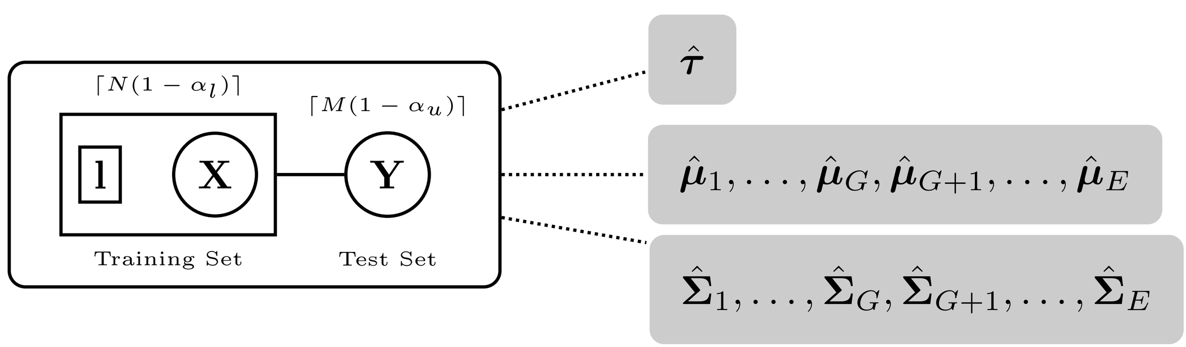
- Accounting for both attribute and class noise [6], employing impartial trimming [4]
- Considering a more flexible class of learners with the parsimonious parametrization based on the eigen-decomposition $\boldsymbol{\Sigma}_g = \lambda_g \boldsymbol{D}_g \boldsymbol{A}_g \boldsymbol{D}_g^{'}$
- Enforcing a constrained parameter estimation to avoid convergence to degenerate solutions and to protect the estimates from spurious local maximizers

Given a sample of N training and M test data, we construct a procedure for maximizing the *trimmed observed-data log-likelihood:*

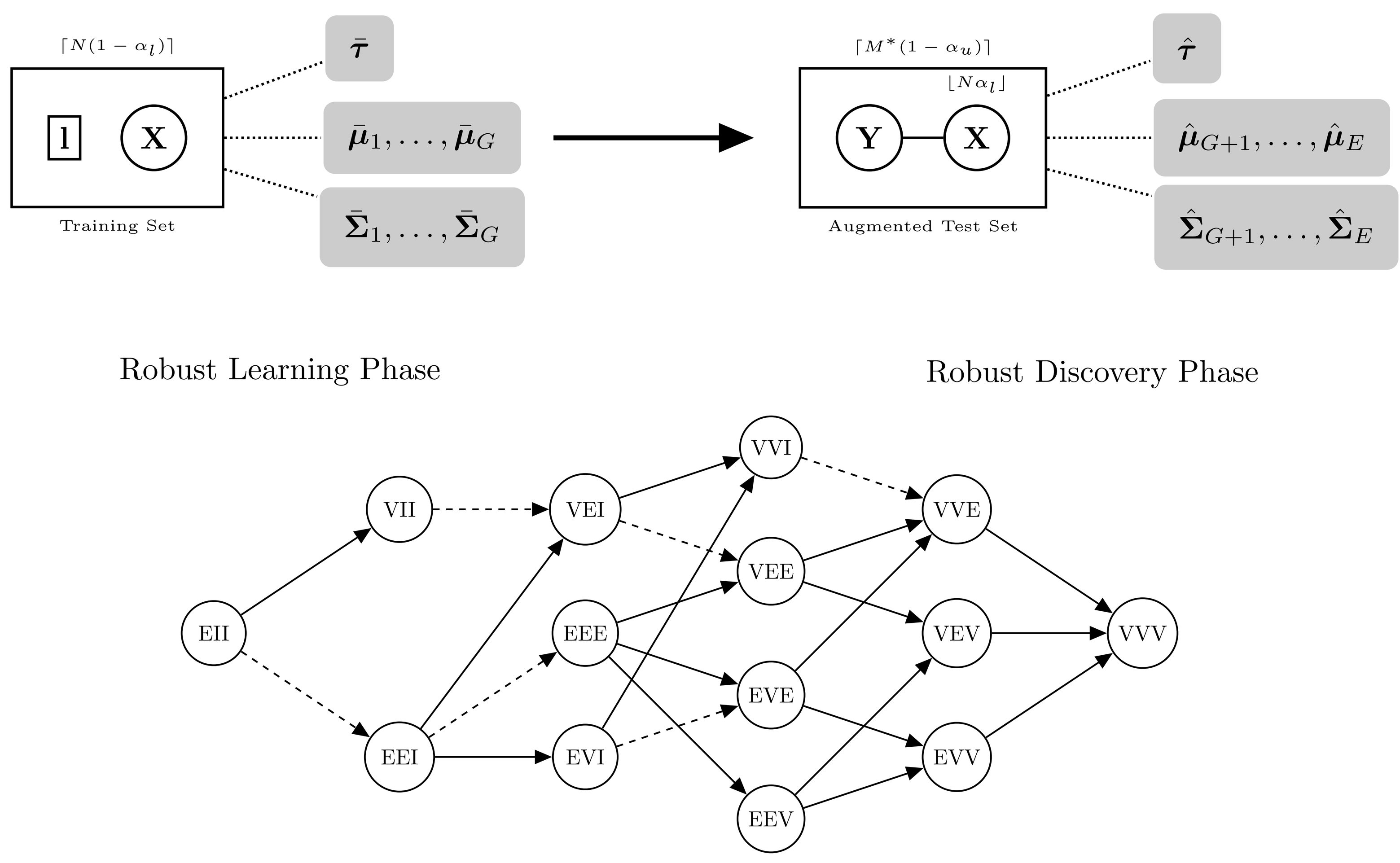
$$\ell_{trim}(\boldsymbol{\tau}, \boldsymbol{\mu}, \boldsymbol{\Sigma} | \mathbf{X}, \mathbf{Y}, \mathbf{l}) = \sum_{n=1}^{N} \zeta(\mathbf{x}_n) \sum_{g=1}^{G} \mathrm{l}_{ng} \log\left(\tau_g \phi(\mathbf{x}_n; \boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g)\right) + \sum_{m=1}^{M} \varphi(\mathbf{y}_m) \log\left(\sum_{g=1}^{E} \tau_g \phi(\mathbf{y}_m; \boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g)\right)$$



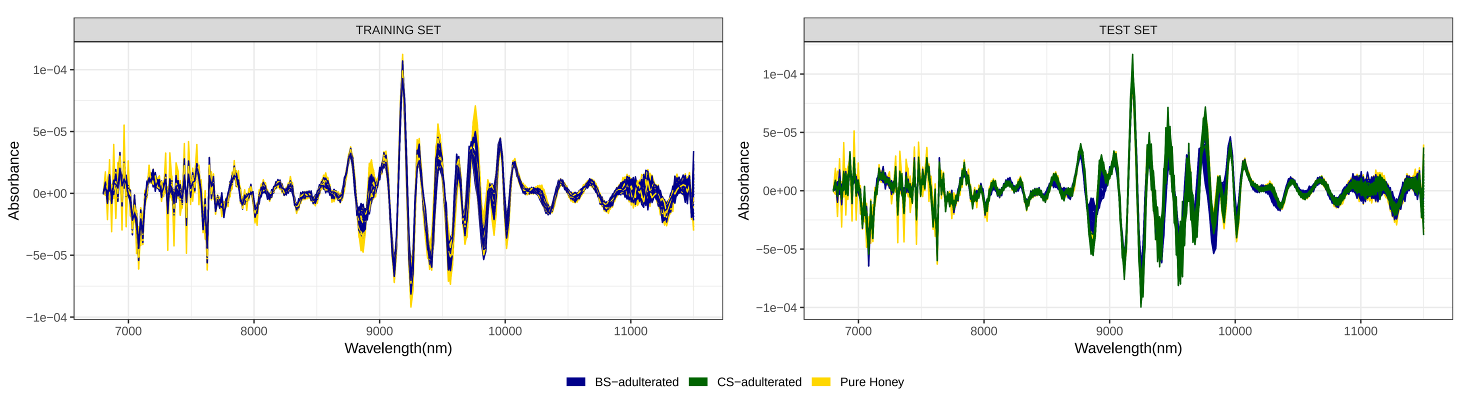
Parameters Estimation: Transductive Approach



Parameters Estimation: Inductive Approach



Experimental Results: Honey Dataset [5]



- 10% of *BS-adulterated* in the training set wrongly labelled as *Pure Honey*
- *CS-adulterated* group not present in the training set

	MclustDA [1]	RMDA [3]	AMDAt [2]	AMDAi [2]	RAEDDAt	RAEDDAi
ARI	0.321	0.317	0.633	0.451	0.843	0.831

References

[1] H. Bensmail and G. Celeux. Regularized Gaussian discriminant analysis through eigenvalue decomposition. *Journal of the American Statistical Association*, 91(436):1743–1748, dec 1996.
[2] C. Bouveyron. Adaptive mixture discriminant analysis for supervised learning with unobserved classes. *Journal of Classification*, 31(1):49–84, 2014.
[3] C. Bouveyron and S. Girard. Robust supervised classification with mixture models: Learning from data with uncertain labels. *Pattern Recognition*, 42(11):2649–2658, nov 2009.
[4] A. Gordaliza. Best approximations to random variables based on trimming procedures. *Journal of Approximation Theory*, 64(2):162–180, 1991.
[5] J. D. Kelly, C. Petisco, and G. Downey. Application of Fourier transform midinfrared spectroscopy to the discrimination between Irish artisanal honey and such honey adulterated with various sugar syrups. *Journal of Agricultural and Food Chemistry*, 54(17):6166–6171, 2006.
[6] X. Zhu and X. Wu. Class noise vs. attribute noise: A quantitative study. *Artificial Intelligence Review*, 22(3):177–210, nov 2004.