STATISTICS
TEXAS A&M UNIVERSITY

Automated Variable Star Classification: Methods and Challenges

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Methodology: Statistical Classifiers

Methodology: CART Example with OGLE Data

Challenge 1: Selection of Training Data

Challenge 2: Classification versus Clustering

Outline

Data Sets are Large and Growing

- *Hipparcos* (1989–1993): 2712 periodic variables
  - Laurent Eyer and students classified all by eye.
- *OGLE* (1992–present): 100,000s
- *Gaia* (present): millions
- *LSST* (2020): billions

Classification Example

Data:

- $\approx 100,000$ variable sources (large J–stetson) in M33
- ≈ 30 observations / source in I–band
- mix of Miras (O–rich/C–rich), SRVs, Cepheids, non–periodic sources, junk, etc.

Goals:

- Find O–rich and C–rich Miras.
- Determine period–luminosity relationships for the Miras.

Overview of Statistical Classification

Key Terms:

- **training data:** lightcurves of known class
- **unlabeled data:** lightcurves of unknown class

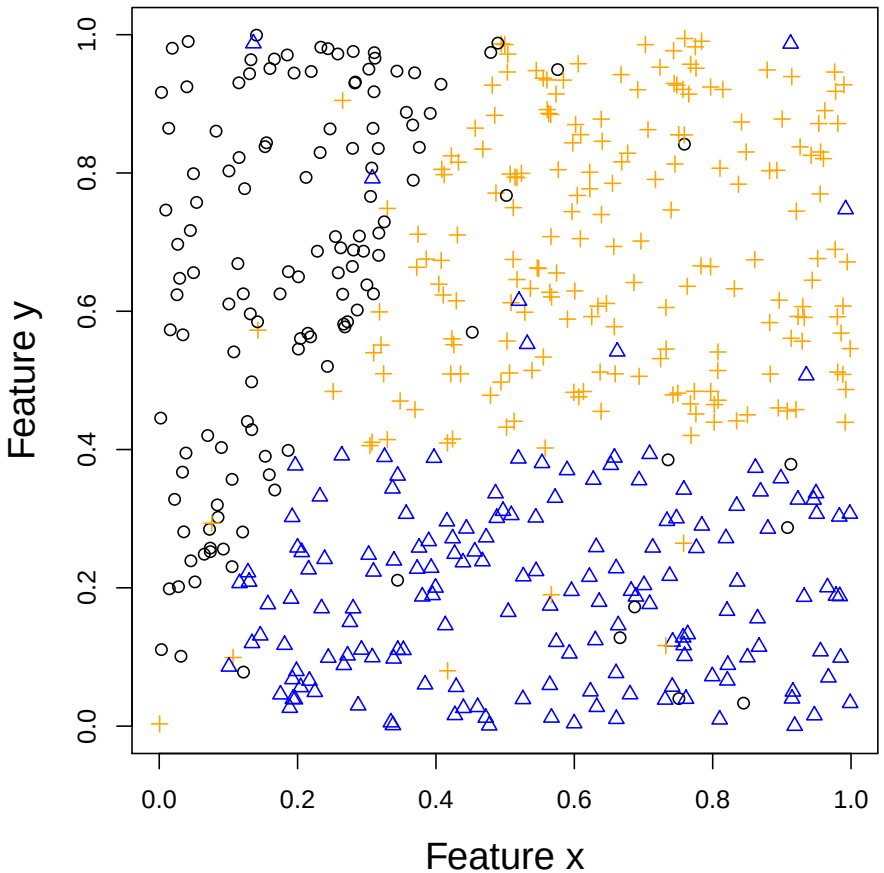
Steps in Classification:

1. **feature extraction:** derive quantities from light curves useful for separating classes, eg period, amplitude, derivatives, etc.
2. **classifier construction:** using training data, construct function

$$\widehat{\mathcal{C}}(\mathit{features}) \rightarrow \mathit{class}$$

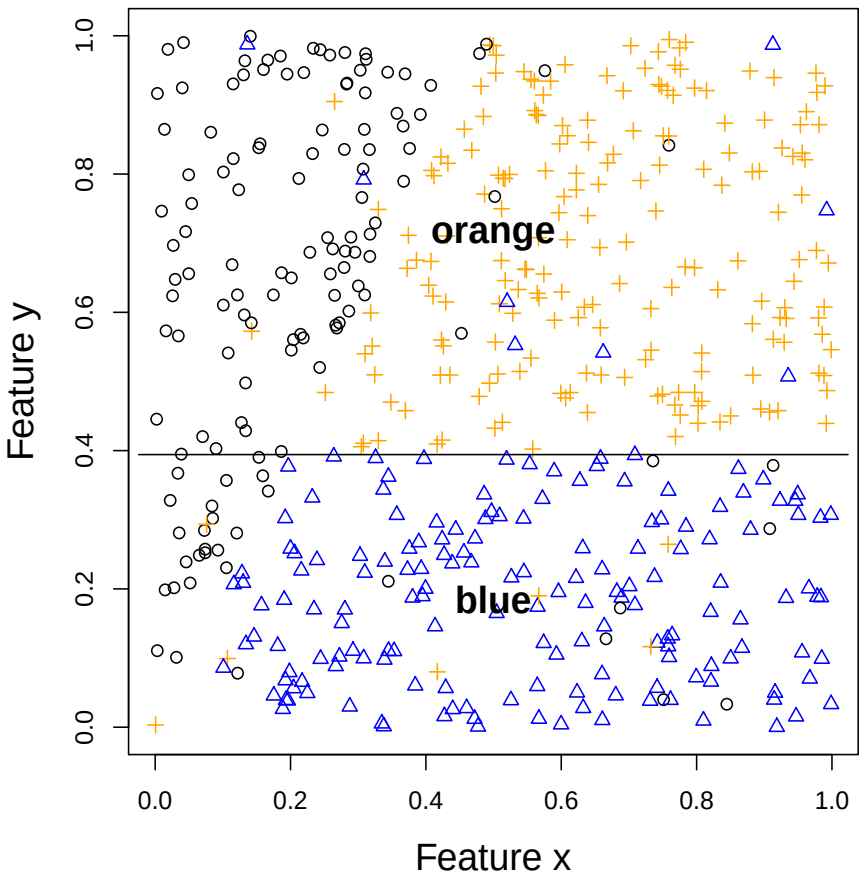
3. **apply classifier:** for unlabeled data, compute features and predict class using $\widehat{\mathcal{C}}$

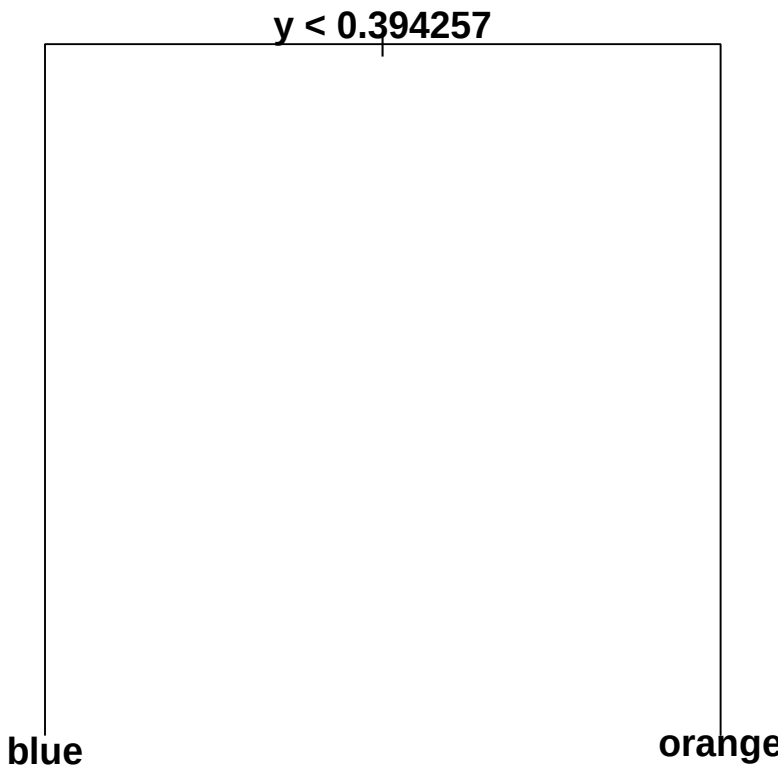
Classifier Construction using CART



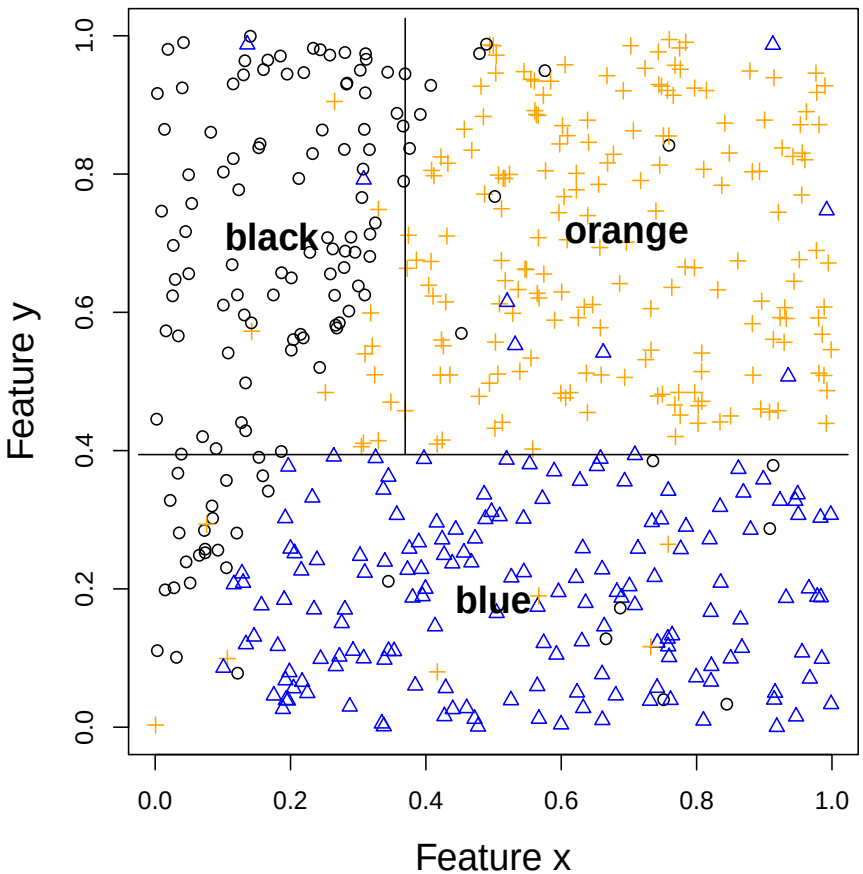
- CART developed by Breiman et al in 1980's [1]
- recursively partitions feature space
- partition represented by tree

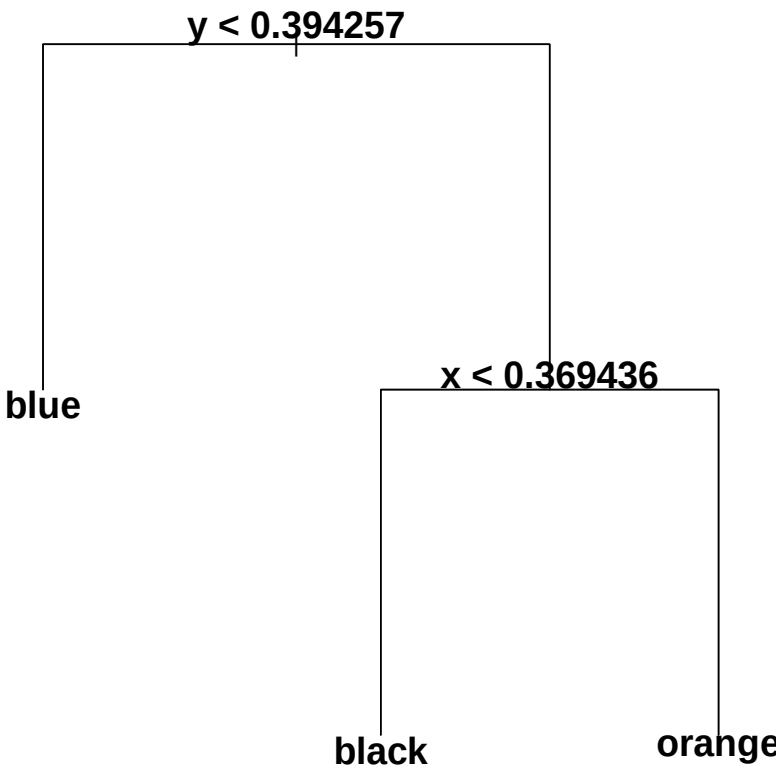
Building CART Tree . . .



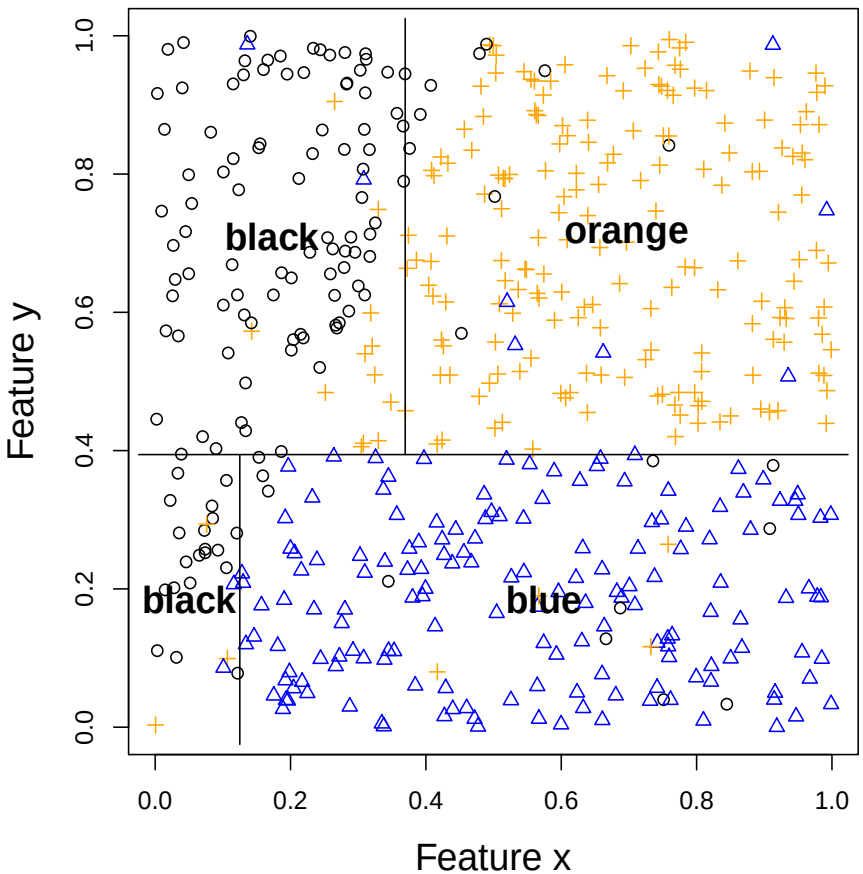


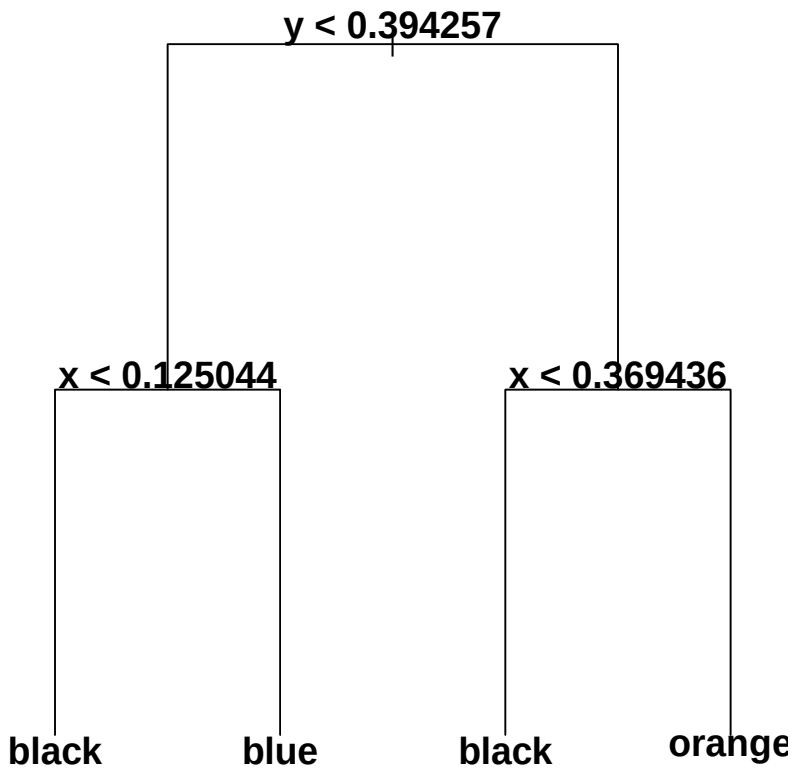
Building CART Tree . . .



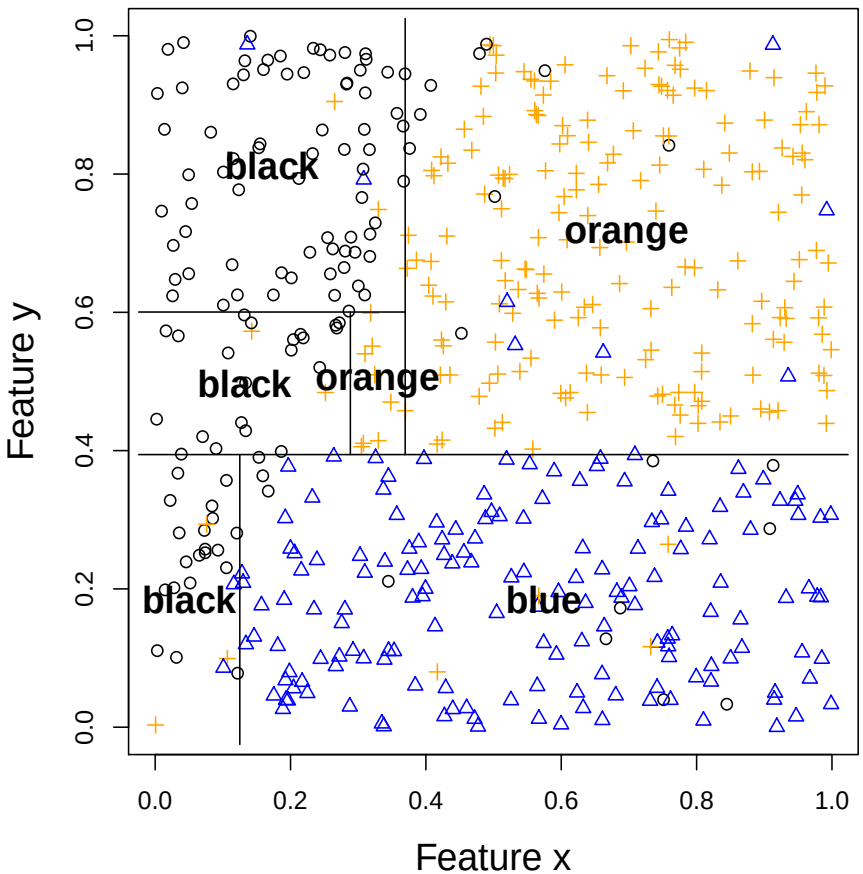


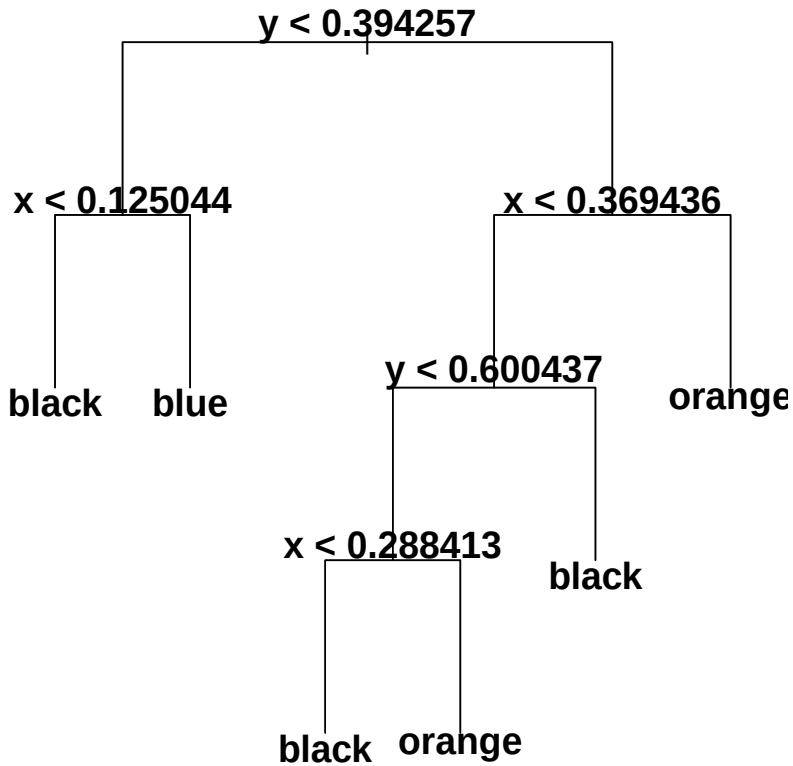
Building CART Tree . . .





Resulting Classifier





Apply Classifier to Test Data

Test Data: Data used to evaluate classifier accuracy. Test data is not used to construct classifier.

Confusion Matrix: Rows are true class of test data. Columns are predicted class of test data. Entries are counts.

	Predicted		
Truth	black	blue	orange
black	23	1	7
blue	2	30	2
orange	3	1	31

Outline

OGLE Classification Example

Classes

- Mira O–rich
- Mira C–rich
- Cepheid
- RR Lyrae AB
- RR Lyrae C

Features

- period (of best fitting sinusoid)
- amplitude = 95^{th} percentile mag - 5^{th} percentile mag
- skew of magnitude measurements
- p2p_scatter (used by Dubath)

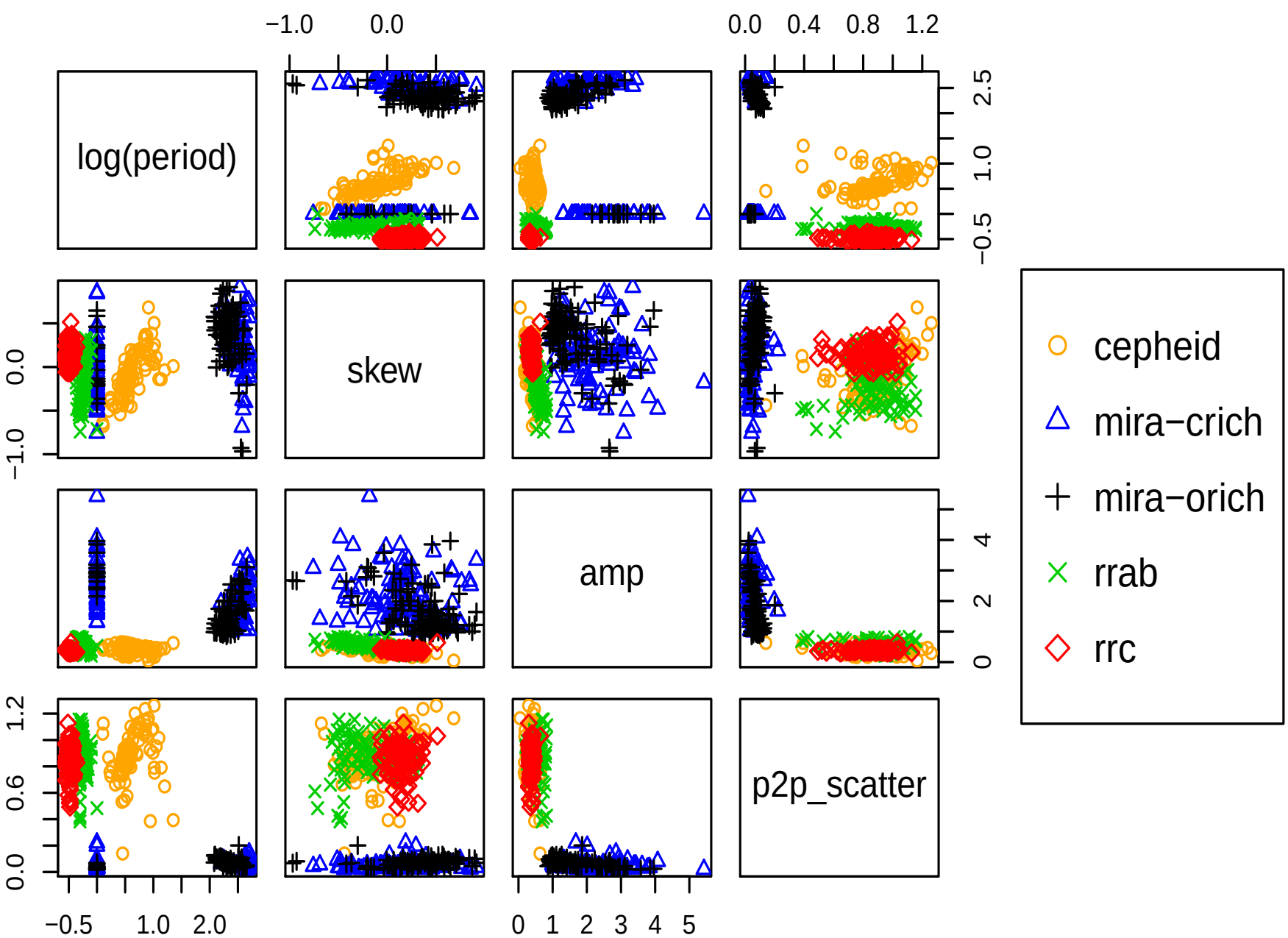
First 6 Rows of Feature–Class Dataframe

period	skew	amp	p2p_scatter	class
1.6128497	-0.5009063	0.56050	0.8672024	cepheid
0.6394983	0.3022388	0.35675	0.7523166	rrab
0.6433533	0.3200730	0.33730	0.8554517	rrab
0.4954661	-0.2053132	0.42000	0.7560226	rrab
0.3540801	0.1361693	0.34340	0.9215426	rrc
0.5460332	-0.3863142	0.69600	1.0682803	rrab

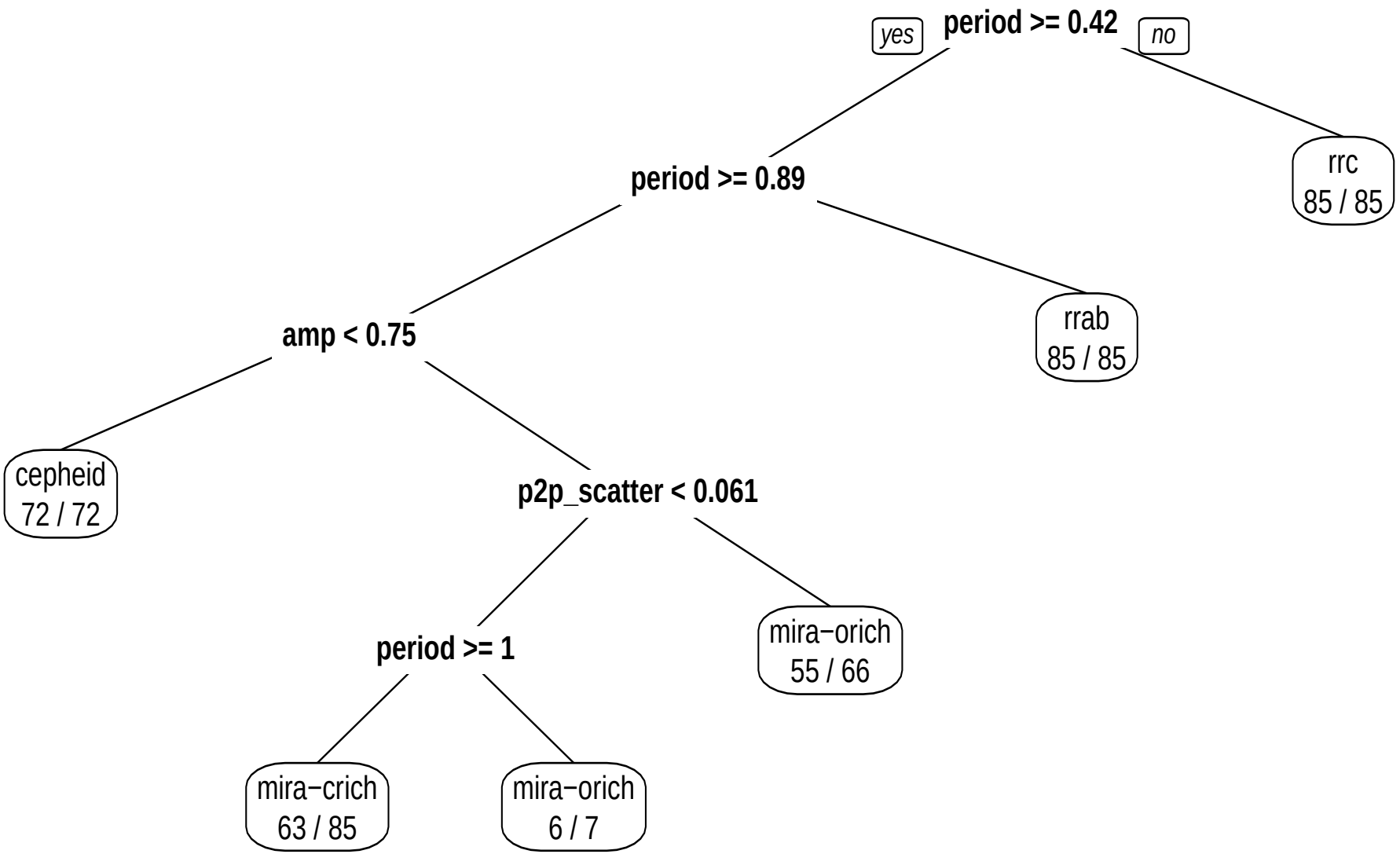
500 total rows. 5 classes.

training data: 400 randomly selected rows
test data: remaining 100 rows

Feature Distributions



CART Model Fit To Training Data



Confusion Matrix using Test Data

	Predicted				
Truth	cepheid	mira-crich	mira-orich	rrab	rrc
cepheid	24	0	0	0	0
mira-crich	0	15	10	0	0
mira-orich	0	5	12	0	0
rrab	1	0	0	14	0
rrc	0	0	0	1	14

Conclusion: Develop features to better separate O/C–rich Mira.

Notes on Existing Classification Literature

- **"On machine learning classification of variable stars" Richards J. et al. 2011 [5]**
  - mix of OGLE and Hipparcos data
  - extract 50+ features
  - test several classifiers, Random Forest works best
- **"Random forest automated supervised classification of Hipparcos periodic variable stars" Dubath et al. 2011 [2]**
  - Hipparcos data
  - extract $\sim$ 10 features
  - use random Forest
- **"Modeling Light Curves for Improved Classification" Faraway, J. Mahabal, A. et al. 2014 [3]**
  - model light curve variation using Gaussian processes
  - extract features from Gaussian process fit
  - improve classification accuracy over simplier features used in [5]

Outline

What Training Data To Use?

Unlabeled Data: Light curves with 20 photometric measurements.

Two Options for Training Data

1. High SN: Many photometric measurements / light curve

- Pros: Accurately estimate features (eg period estimates correct)
- Cons: Training "looks different" than unlabeled data.

2. Training resembles Unlabeled: 20 photometric measurements

- Pros: Training "looks the same" as unlabeled.
- Cons: Features estimated incorrectly.

What Training Data To Use?

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2. Training resembles Unlabeled: 20 photometric measurements
   - Pros: Training "looks the same" as unlabeled.
   - Cons: Features estimated incorrectly.

Training Data Should Resemble Unlabeled Data

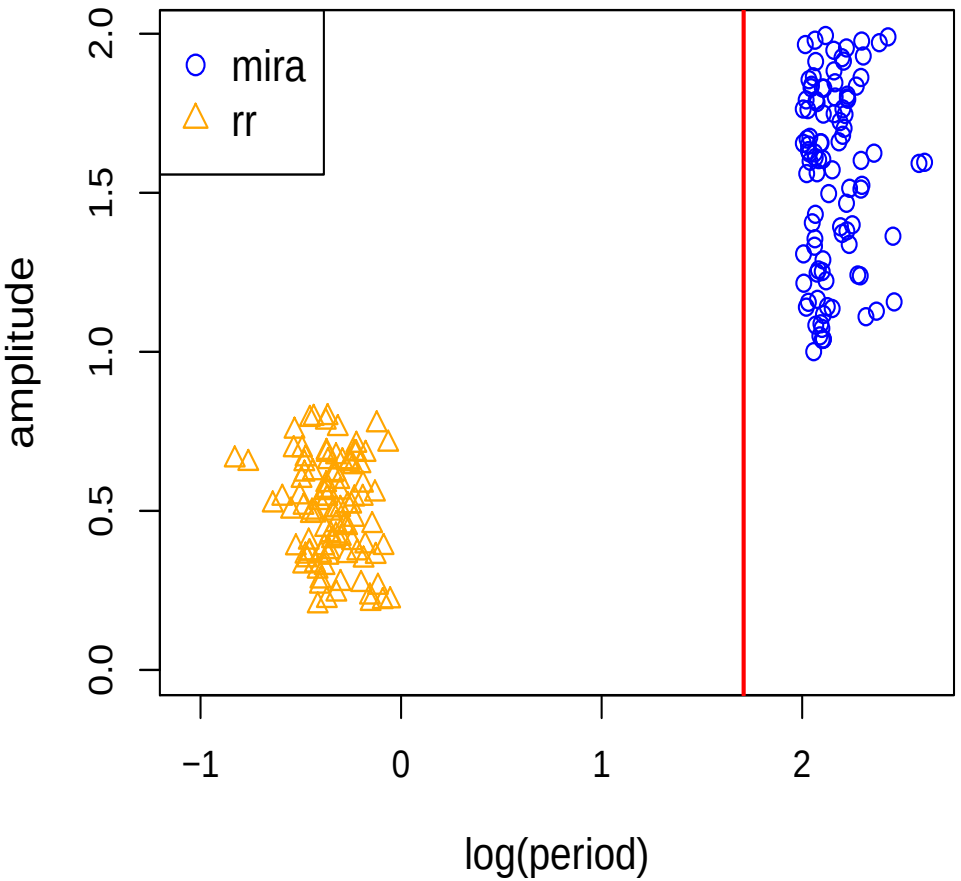
Hypothetical Example:

- Unlabeled Data: RR Lyrae and Miras with 20 **photometric measurements**
- Features: period and amplitude.

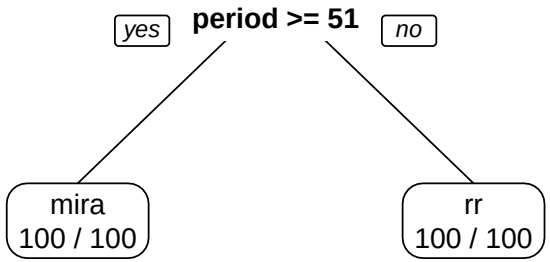
- Training 1: Light curves with > 100 photometric measurements
- Training 2: Light curves with 20 photometric measurements

Classifier built on Training 1 Data

Feature Distribution



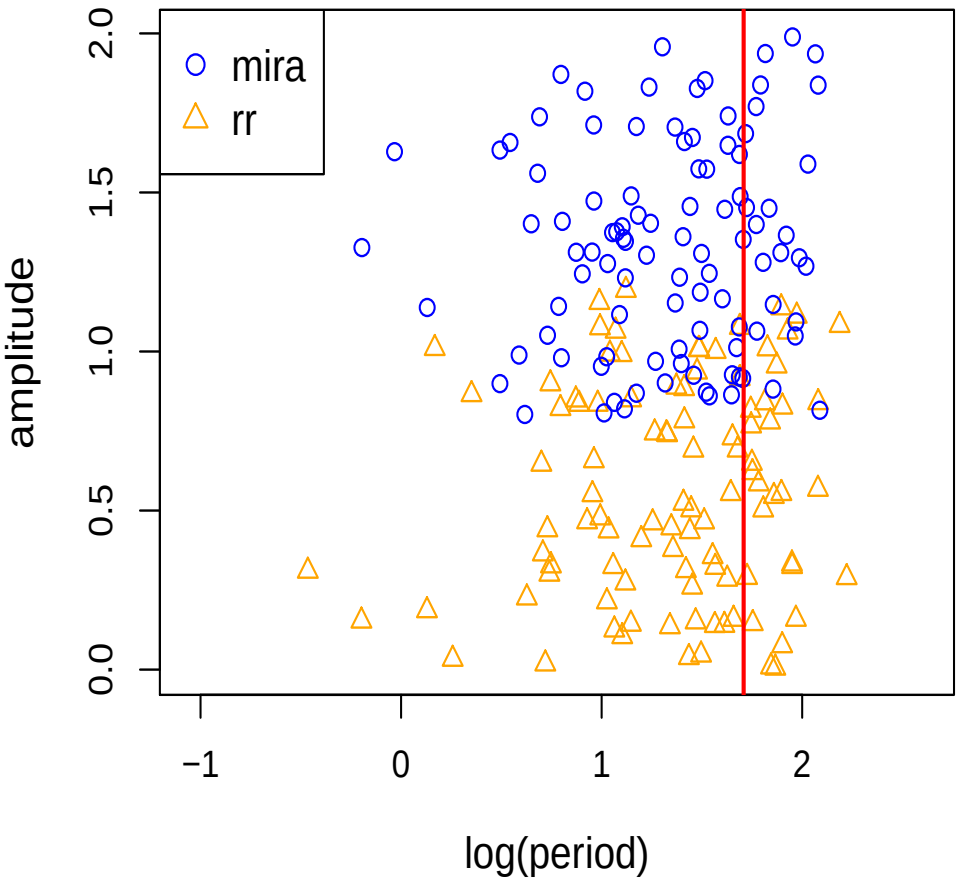
CART Tree



Conclusion: Seemingly Perfect Classification

Apply Classifier to Unlabeled Data

Feature Distribution



Confusion Matrix

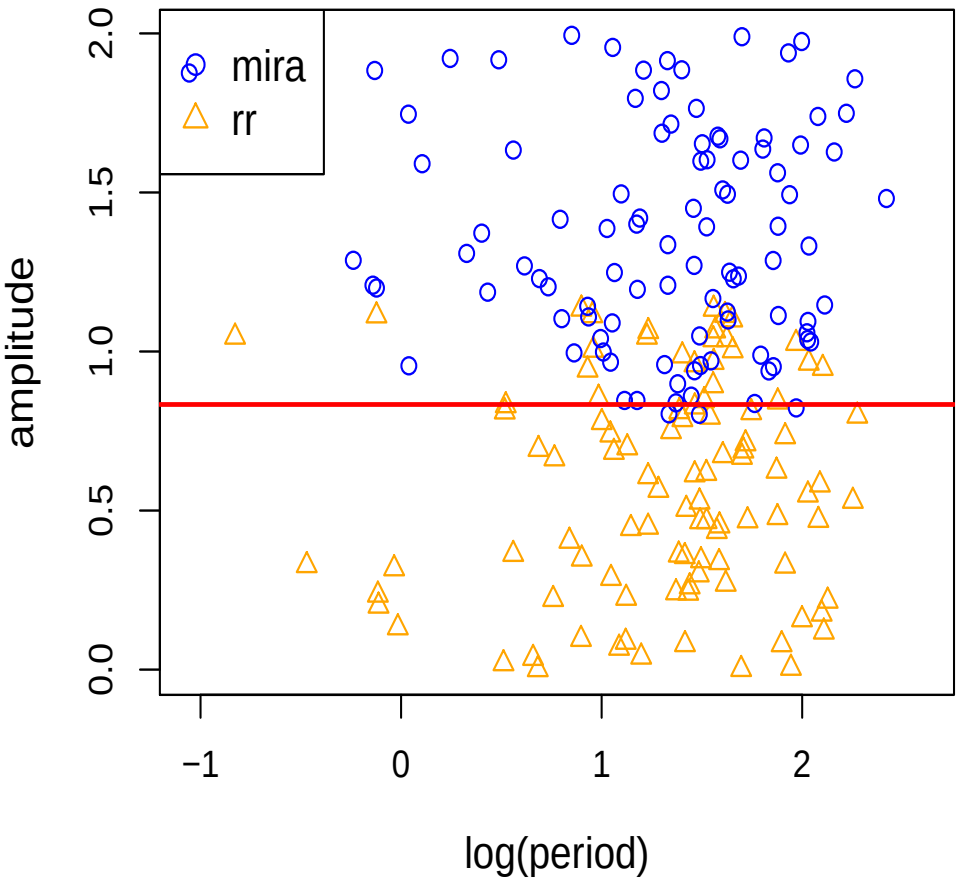
Truth	Predicted mira	Predicted rr
mira	22	78
rr	28	72

Observations

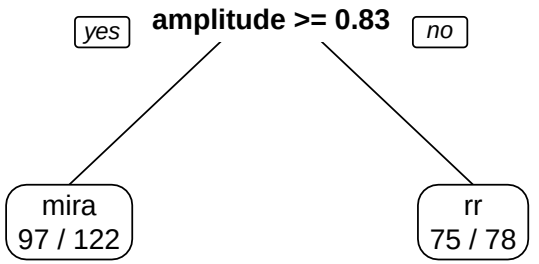
- Classifier constructed using Training Data 1 used period to separate classes.
- For poorly sampled unlabeled data, period does not separate classes (cannot compute period accurately).
- But amplitude is still useful for separating classes.

Classifier built on Training 2 Data

Feature Distribution

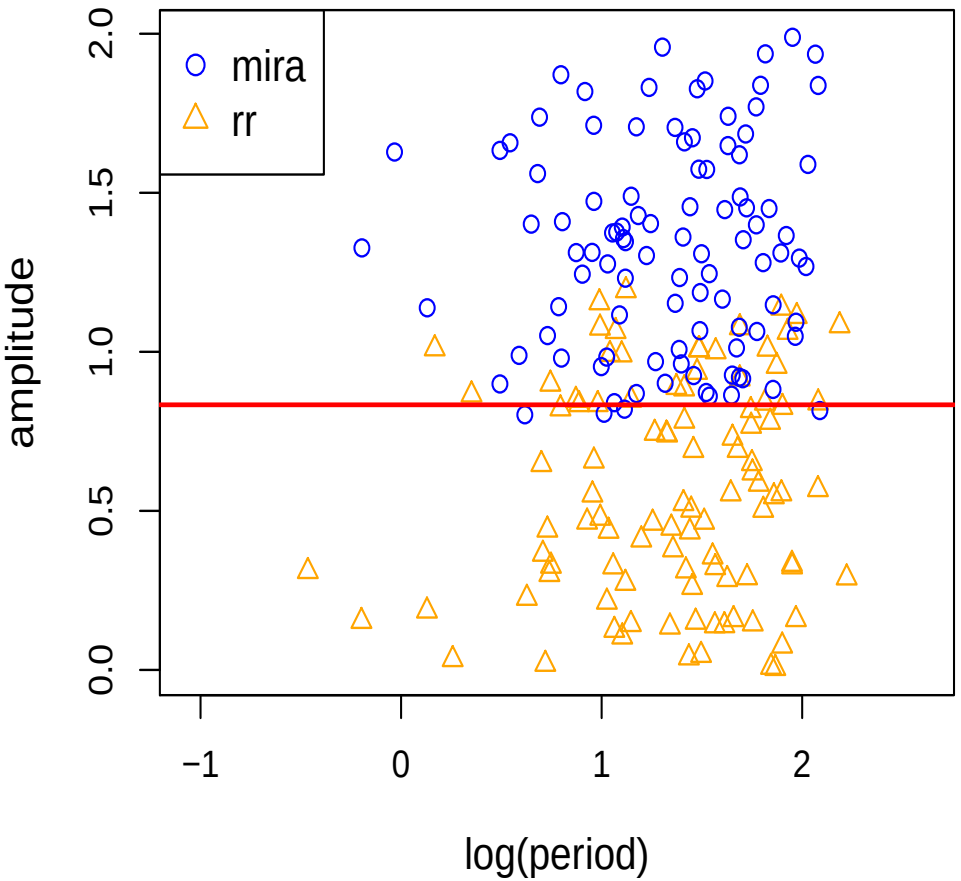


CART Tree



Apply Train 2 Classifier to Unlabeled Data

Feature Distribution



Confusion Matrix

	Predicted	
Truth	mira	rr
mira	96	4
rr	29	71

Conclusion: Much better performance.

Summary of Training Data Selection

- Classifiers constructed on high SN data find class boundaries in high SN feature space.
- These boundries may not exist for low SN unlabeled data.
- Downsampling high SN data to match unlabeled data SN can improve classifier performance.
- See Long et al. [4] for extensive discussion / methodology.

Outline

Recall Classification Example

Data:

- $\approx 100,000$ variable sources (large J–stetson) in M33
- ≈ 30 observations / source in I–band
- mix of Miras (O–rich/C–rich), SRVs, Cepheids, non–periodic sources, junk, etc.

Goals:

- Find O–rich and C–rich Miras.
- Determine period–luminosity relationships for the Miras.

Building Classifier for M33 is Difficult

OGLE Training Data

- downsample to match M33 cadence / photometric error
- select OGLE classes which match classes in M33

Evaluating Classifier Performance

- straightforward to measure error rate on training data
- but our goal is to determine period–luminosity relationships

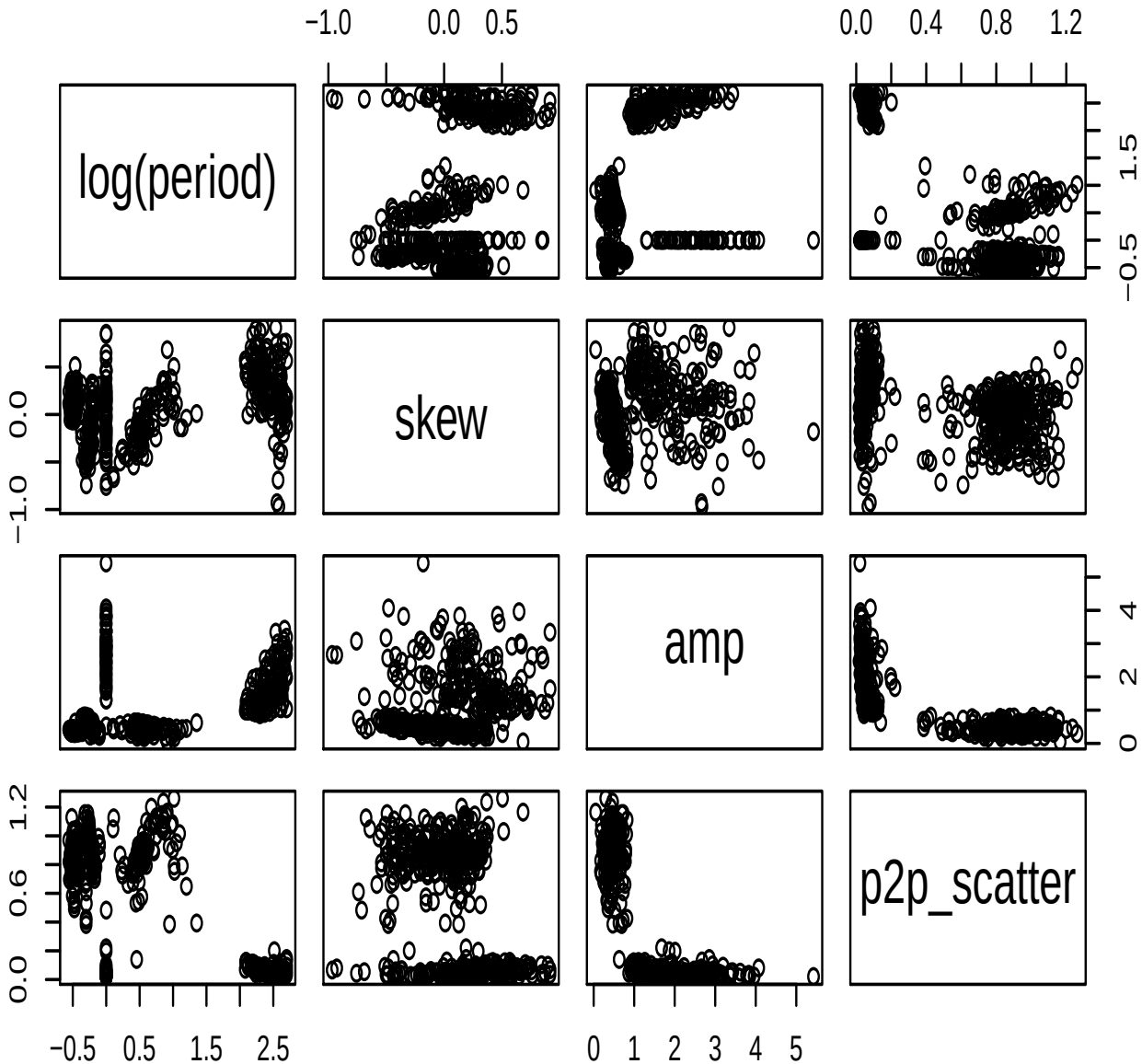
A Different Approach: Clustering

clustering: find groups (ie clusters) of objects in feature space

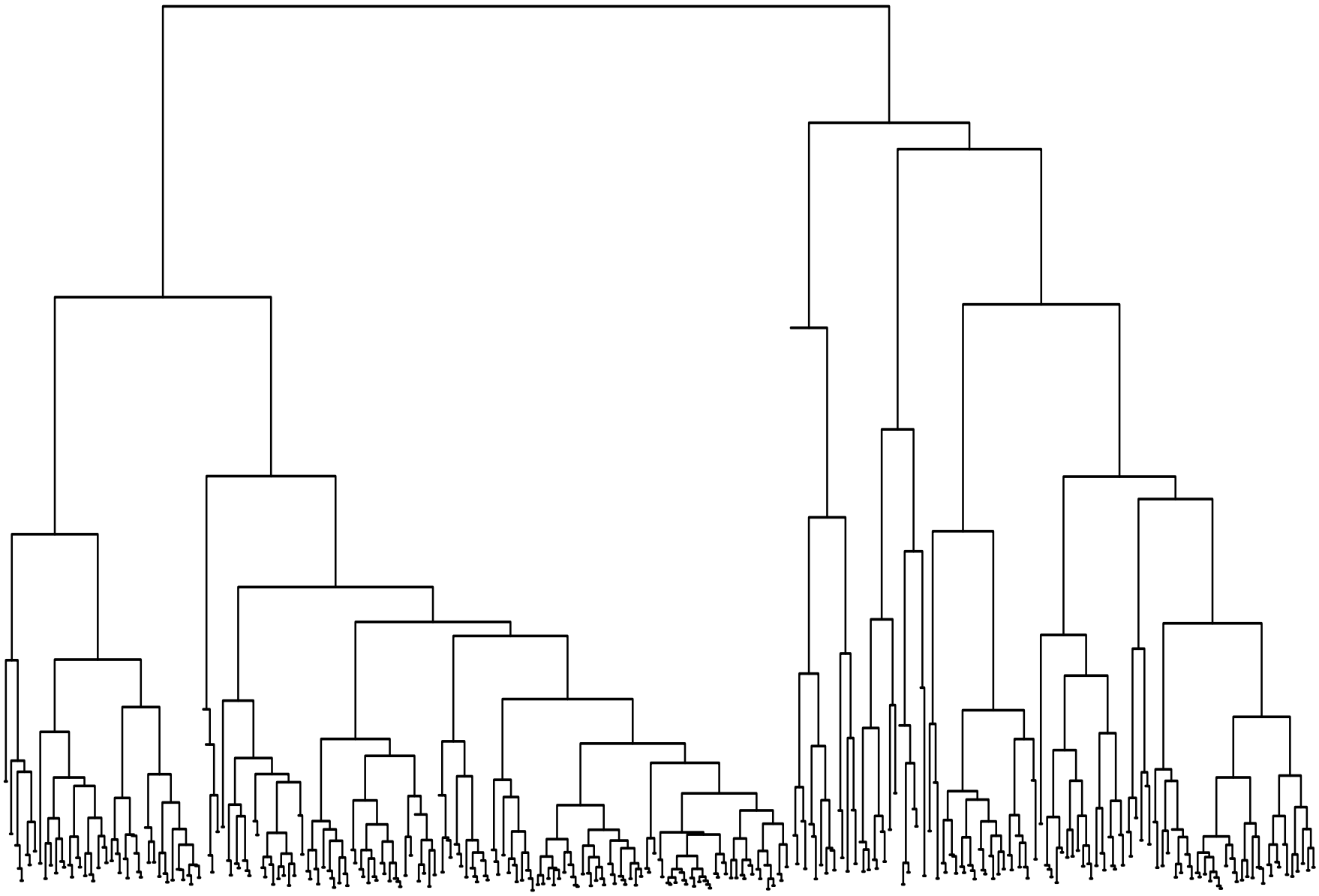
- compute feature distance between all objects
- find clusters where:
  - distance between objects within cluster is small
  - distance between objects in different clusters is large

clustering is different than classification: No training data. No objective measure of success.

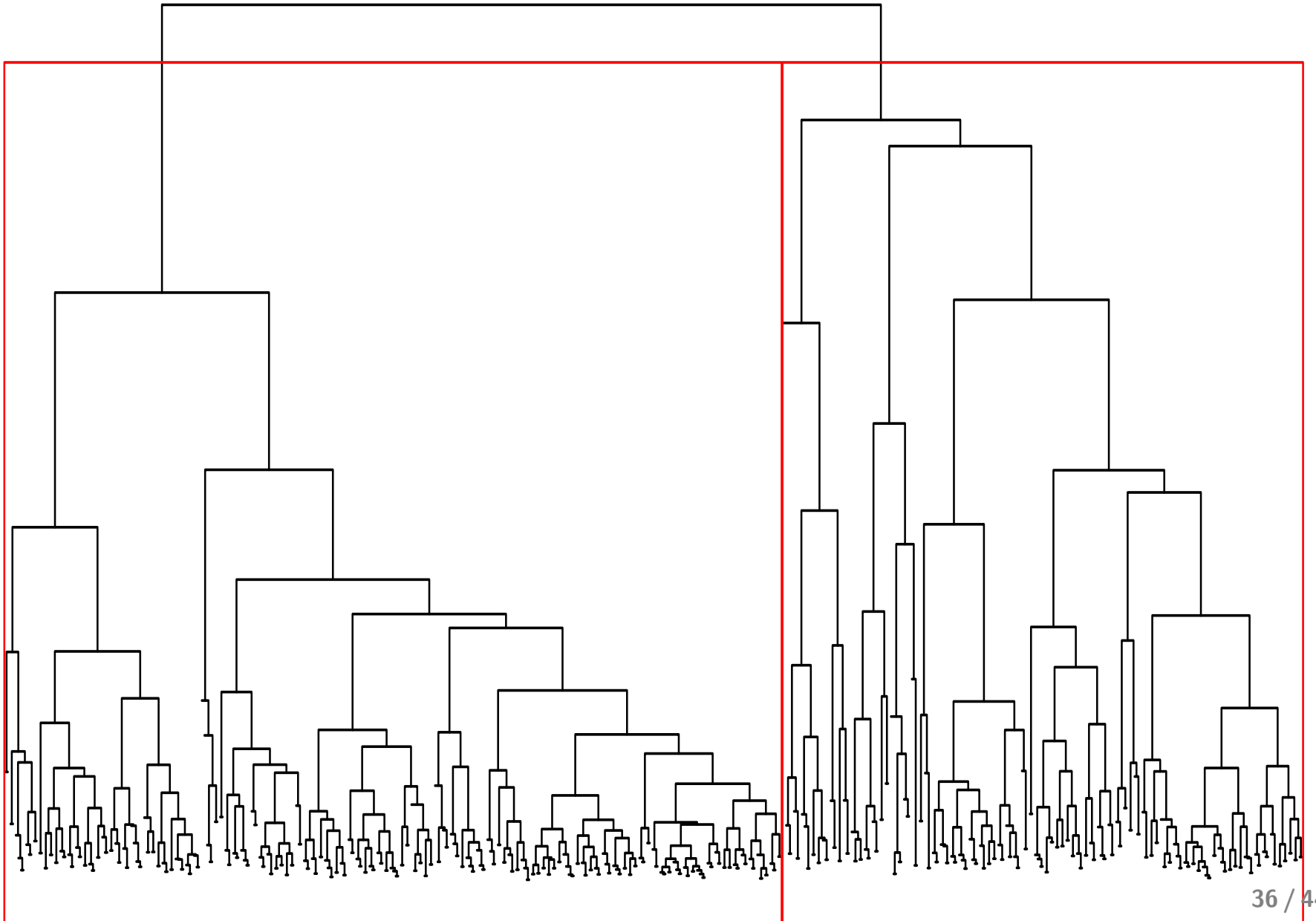
OGLE Data


log(period)
skew
amp
p2p_scatter
−1.0
0.0
0.5
0.0
0.4
0.8
1.2
−0.5
0.5
1.5
2.5
0
1
2
3
4
5

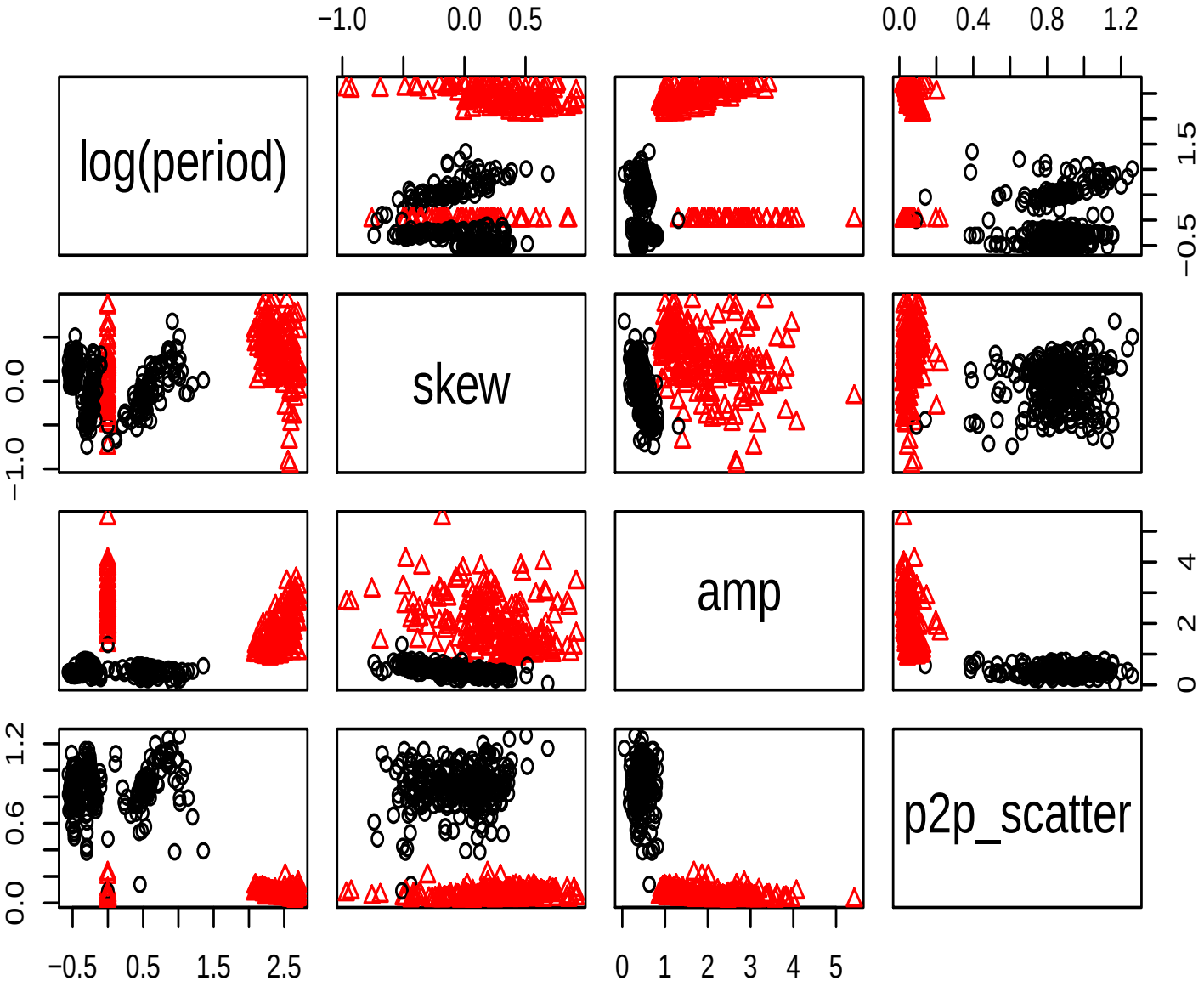
Clustering Dendogram of OGLE Data



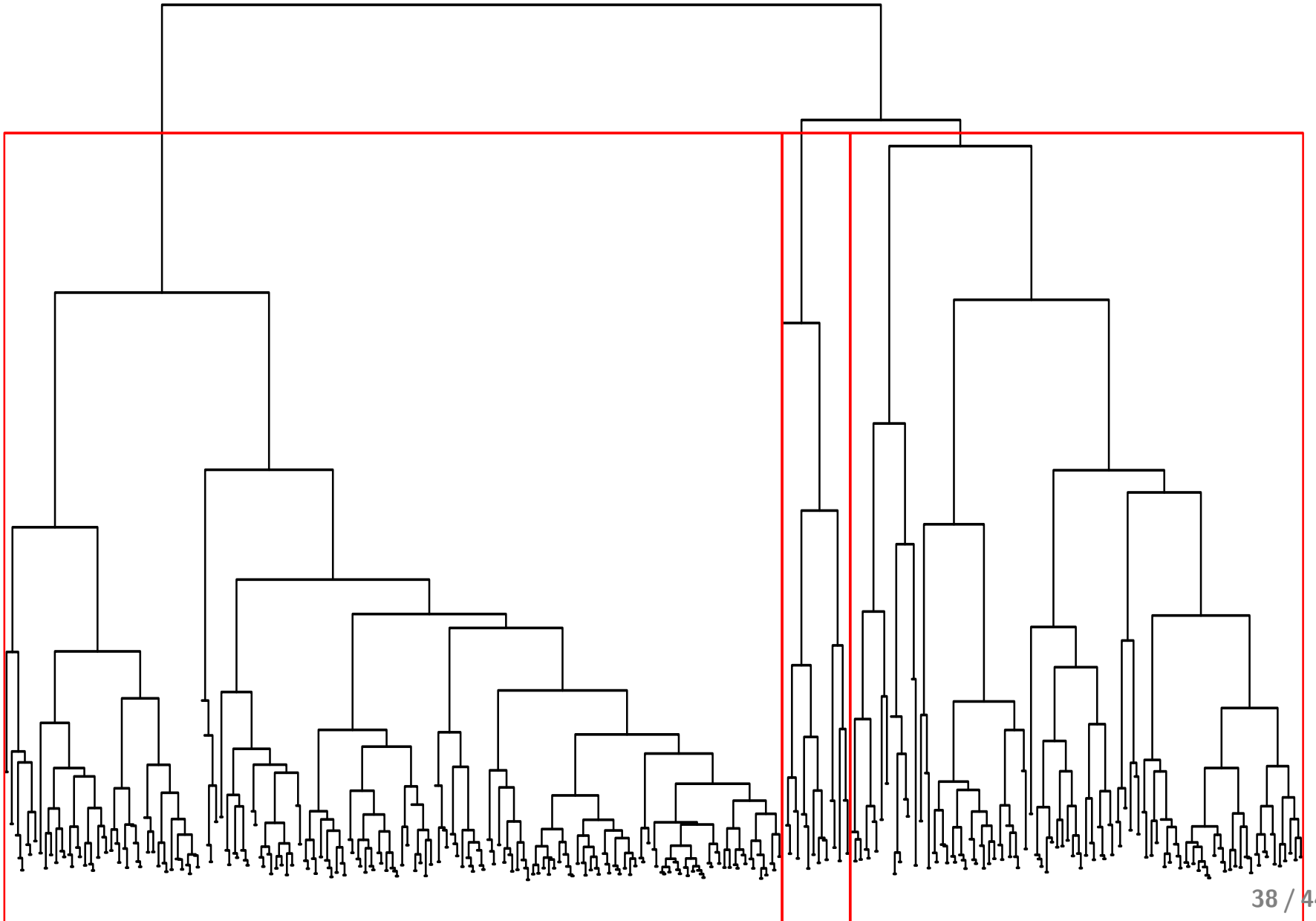
Two Clusters



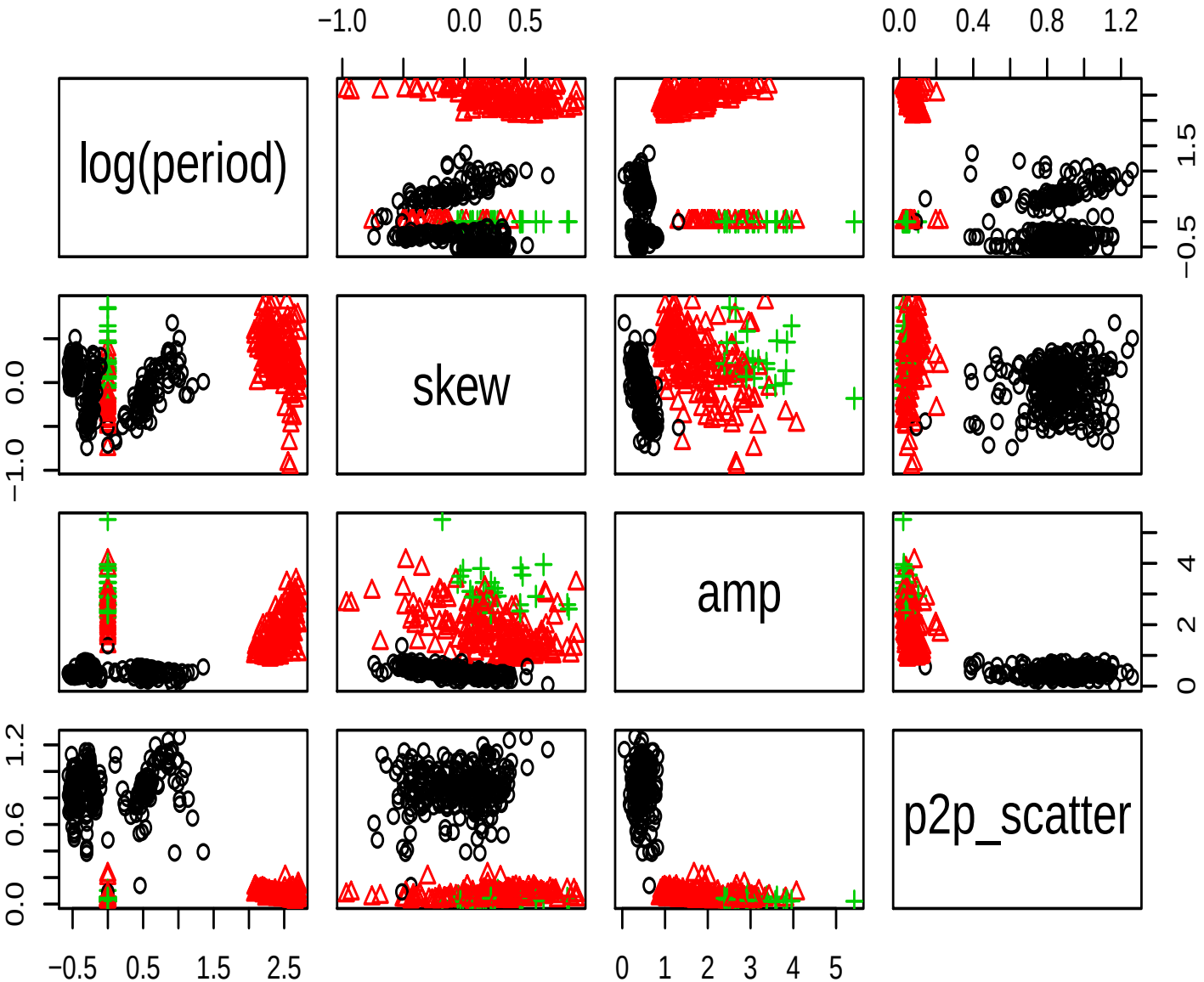
Two Clusters



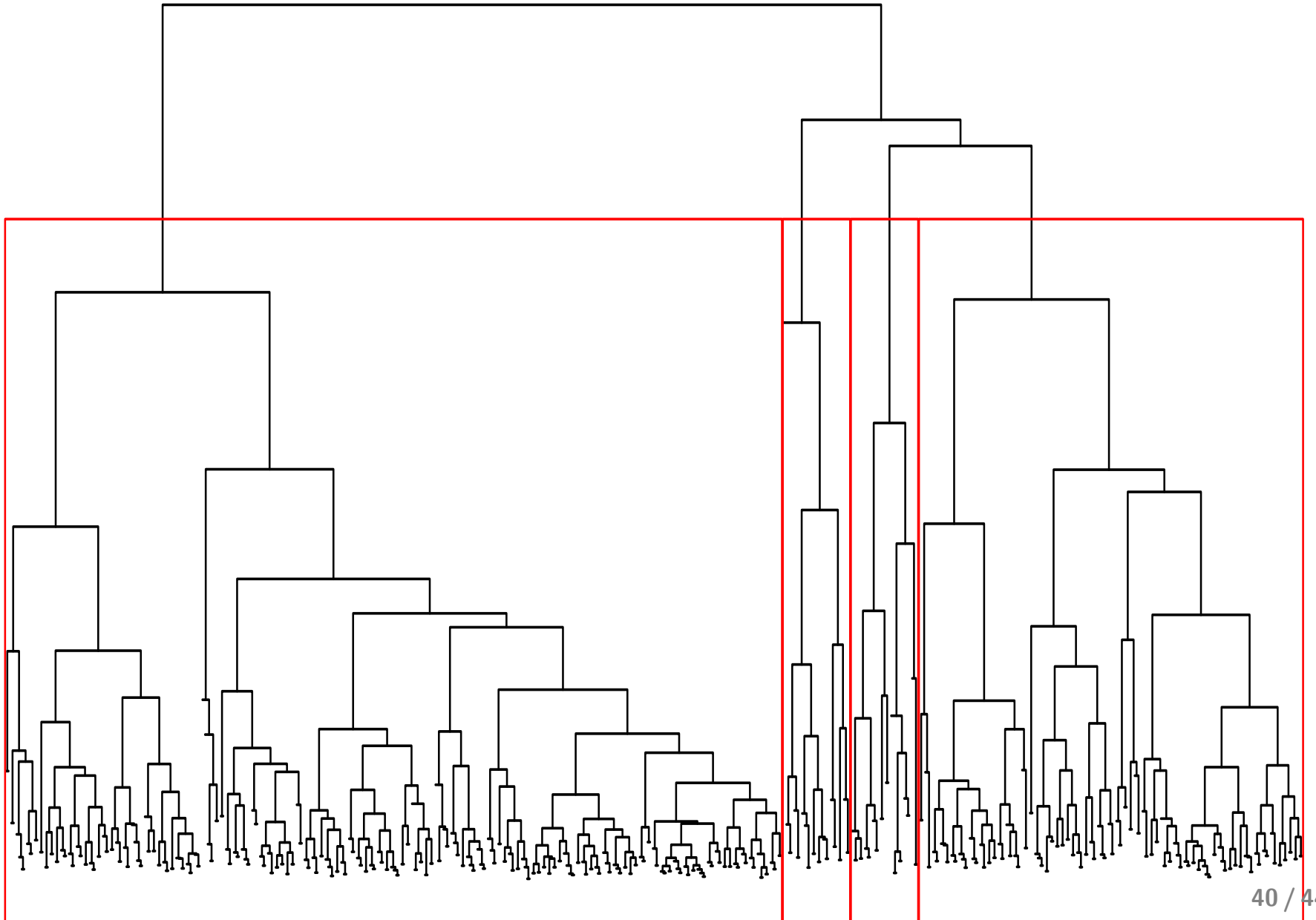
Three Clusters



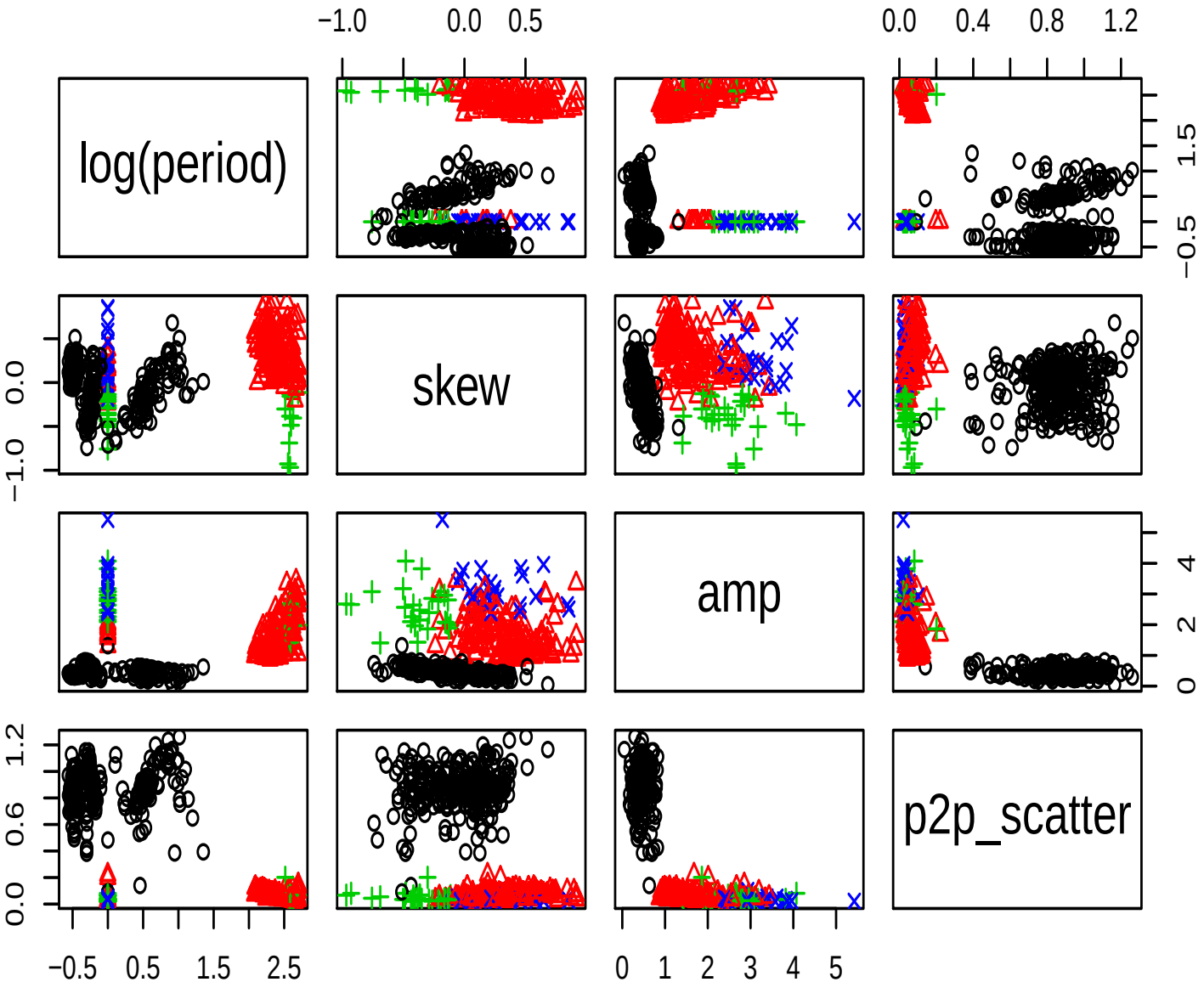
Three Clusters



Four Clusters



Four Clusters



More on Clustering

- many "knobs" in clustering methods
  - features
  - distance metric between features
  - hierarchical clustering, k–means, model based, etc.
- hard to statistically quantify successful clustering
  - may explain popularity of classification
- opinion: variable star "classification" is between the statistical concepts of clustering and classification

Conclusions

- statistical classification
  1. select training data
  2. extract features
  3. build classifier
  4. apply classifier to unlabeled data
- training data should "look like" unlabeled data
- classification as practiced in statistics does not always fit perfectly with what astronomers want to do

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