Domain Adaptation and Active Learning for SN photometric classification

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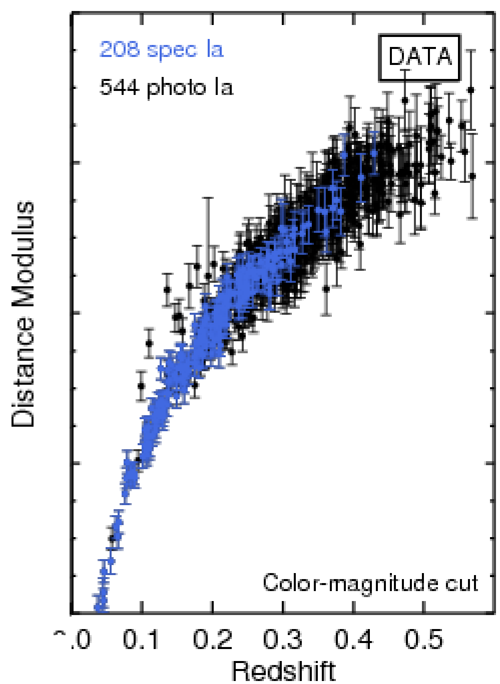
Goal:

Compensate for the fact that spectroscopic and photometric samples come from intrinsically different underlying distributions

Example:

Photometric samples go further in z



Covariate shift

$$P_{train}(Y) = \underline{P(Y|X)}\, P_{train}(X)$$

$$P_{test}(Y) = \underline{P(Y|X)}\, P_{test}(X)$$

$$P_{train}(Y) \neq P_{test}(X)$$

Solution:

Use the Kernel trick to re-weight the training sample *(Kernel Mean Matching - KMM)*

Plot from Campbell et al., 2013

Important remarks:

I am aware that

Selection cuts here imply very good epoch coverage

post-SNPCC data
-3 to +24 days in all filters

This is best-case scenario!

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This will be a very sad talk...

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Spoiler alert!

Domain Adaptation alone will not solve the problem.

We will need to re-think how
spectroscopic samples are built.

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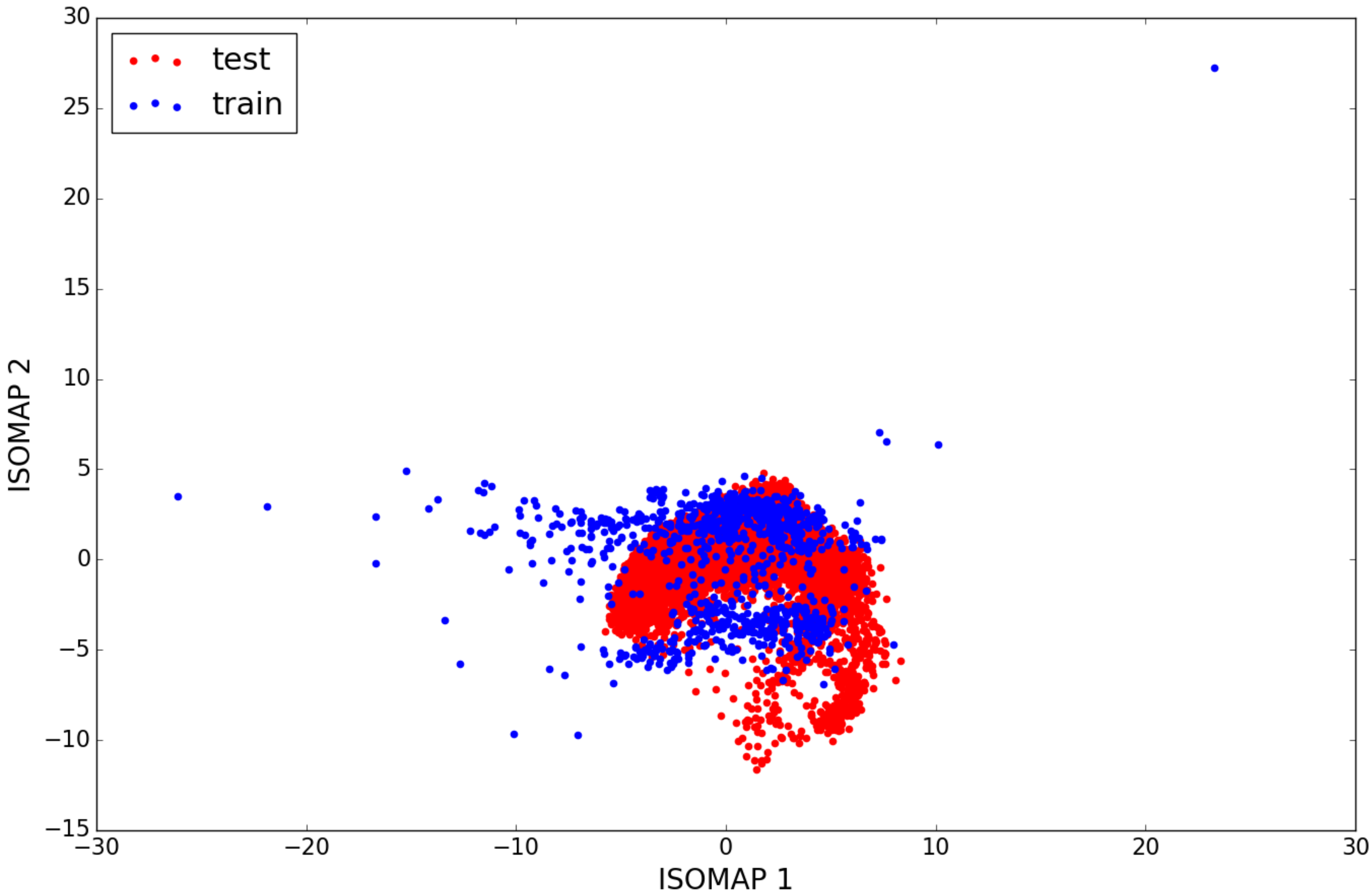

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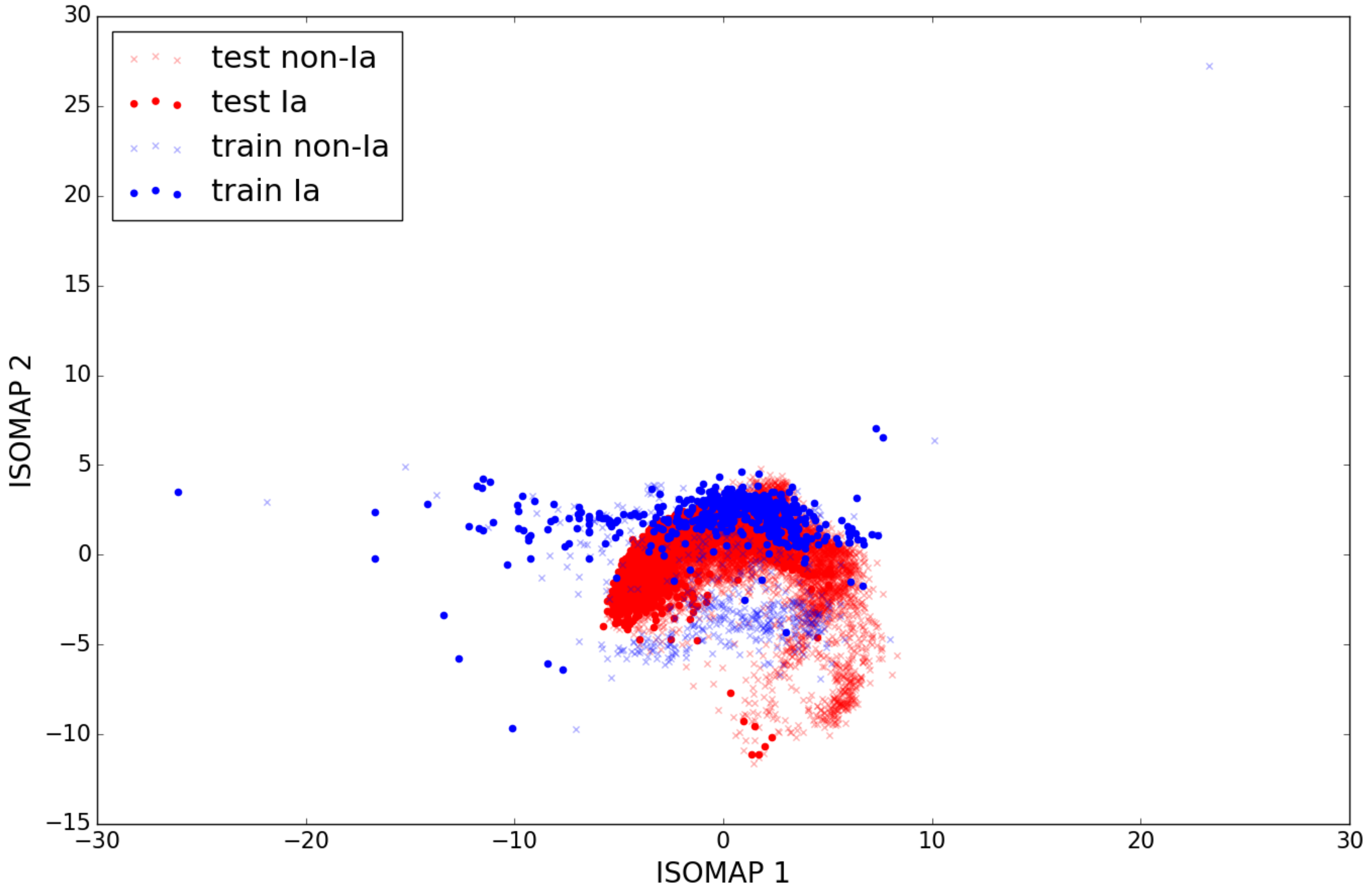

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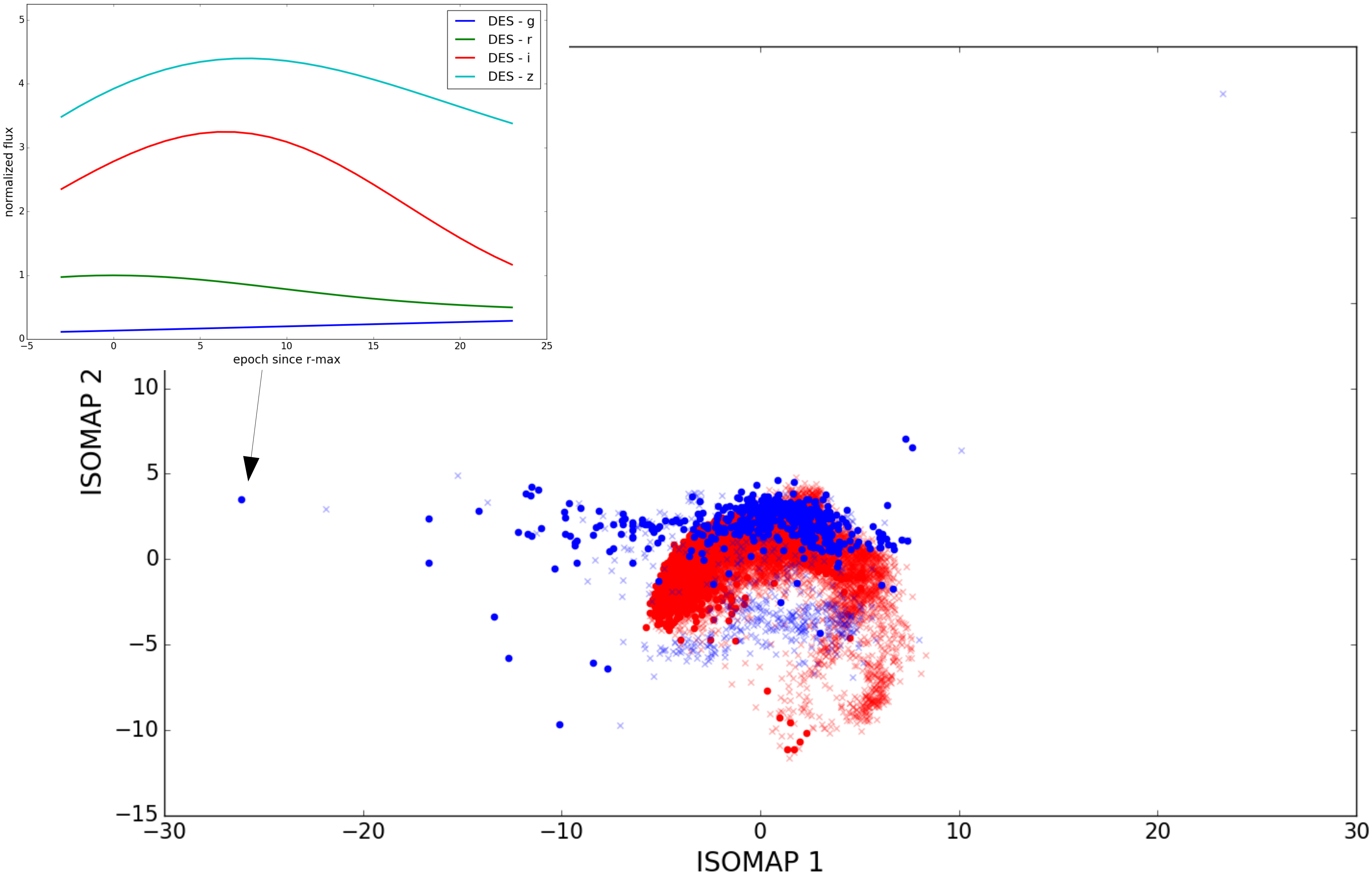

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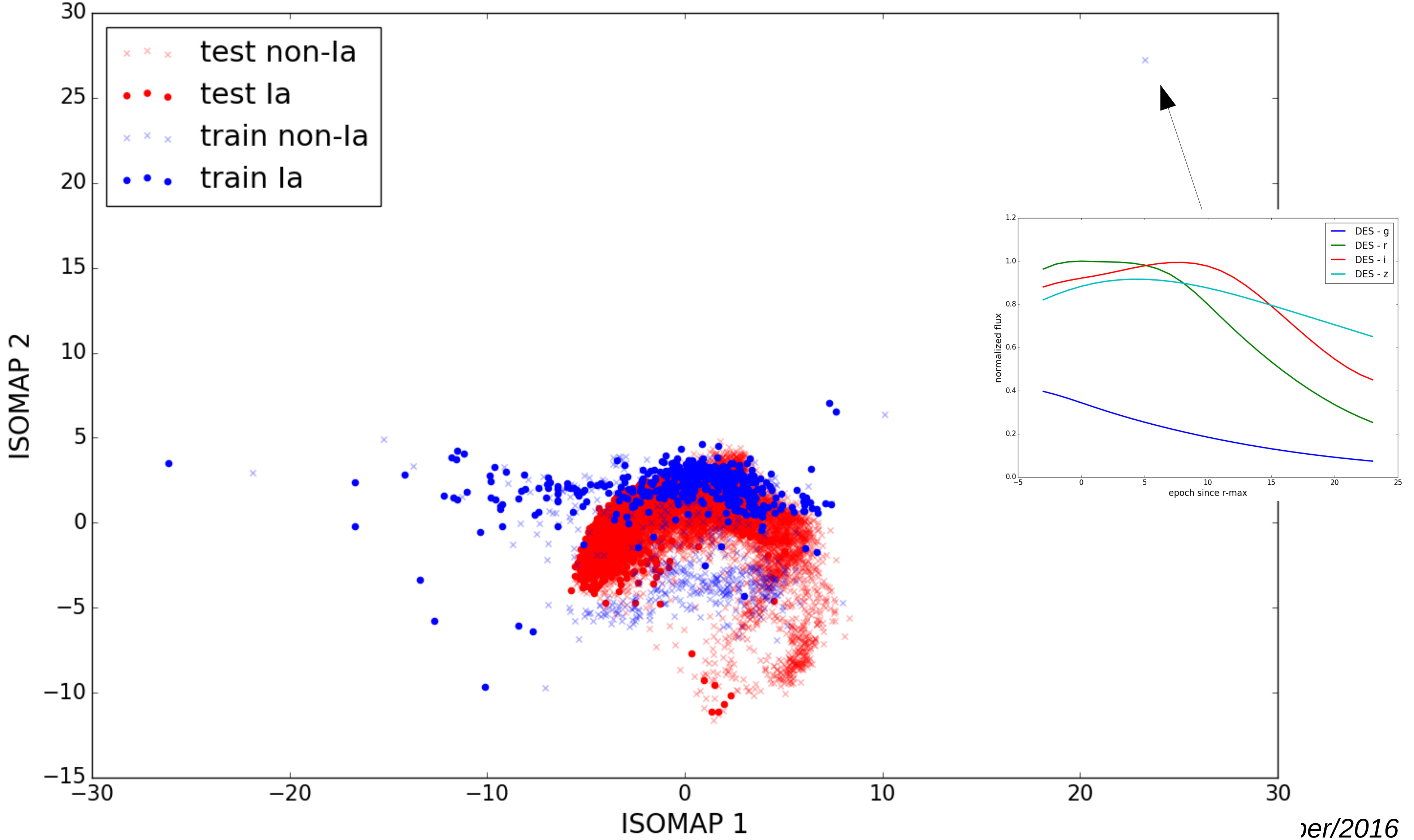

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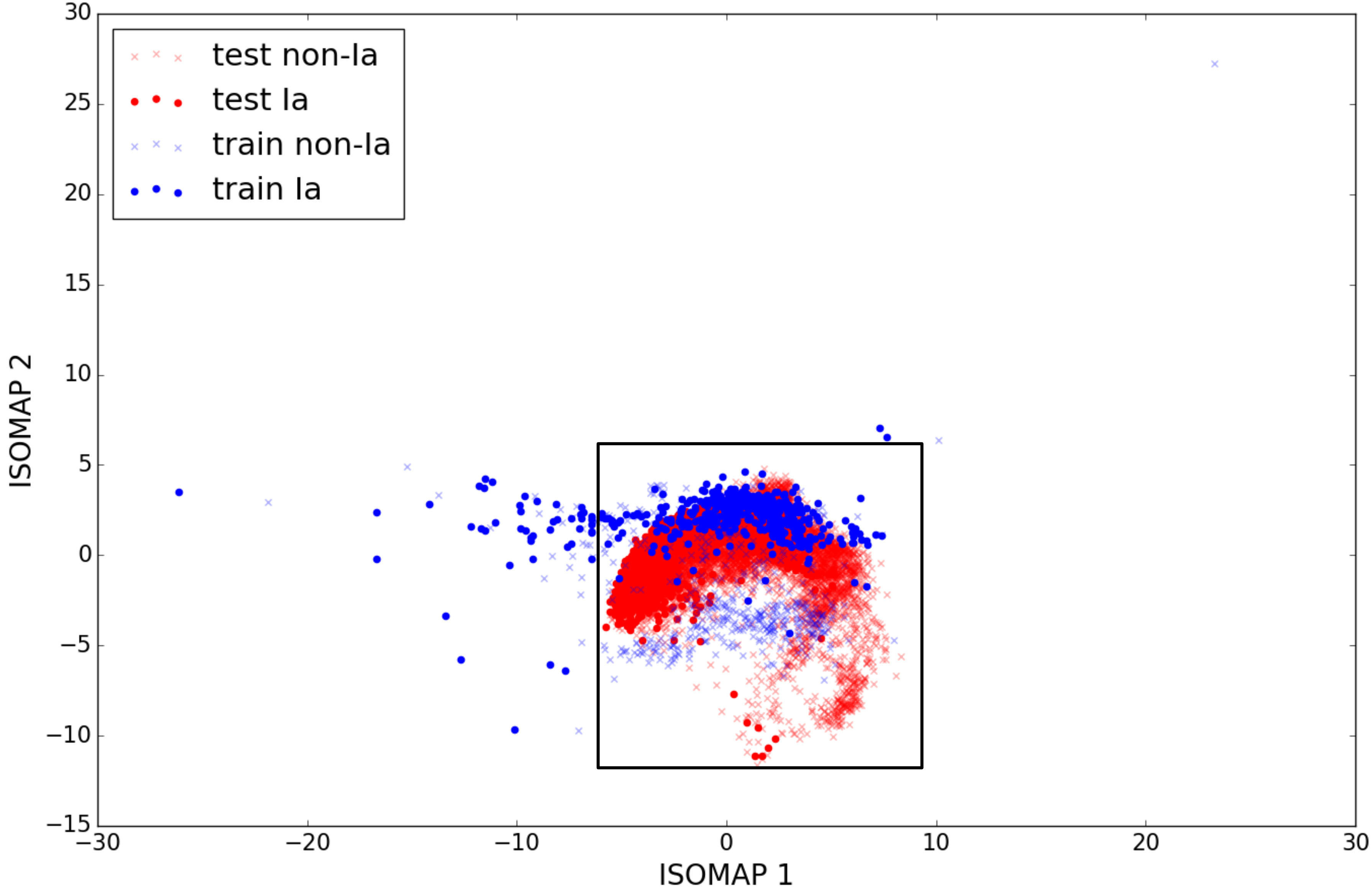
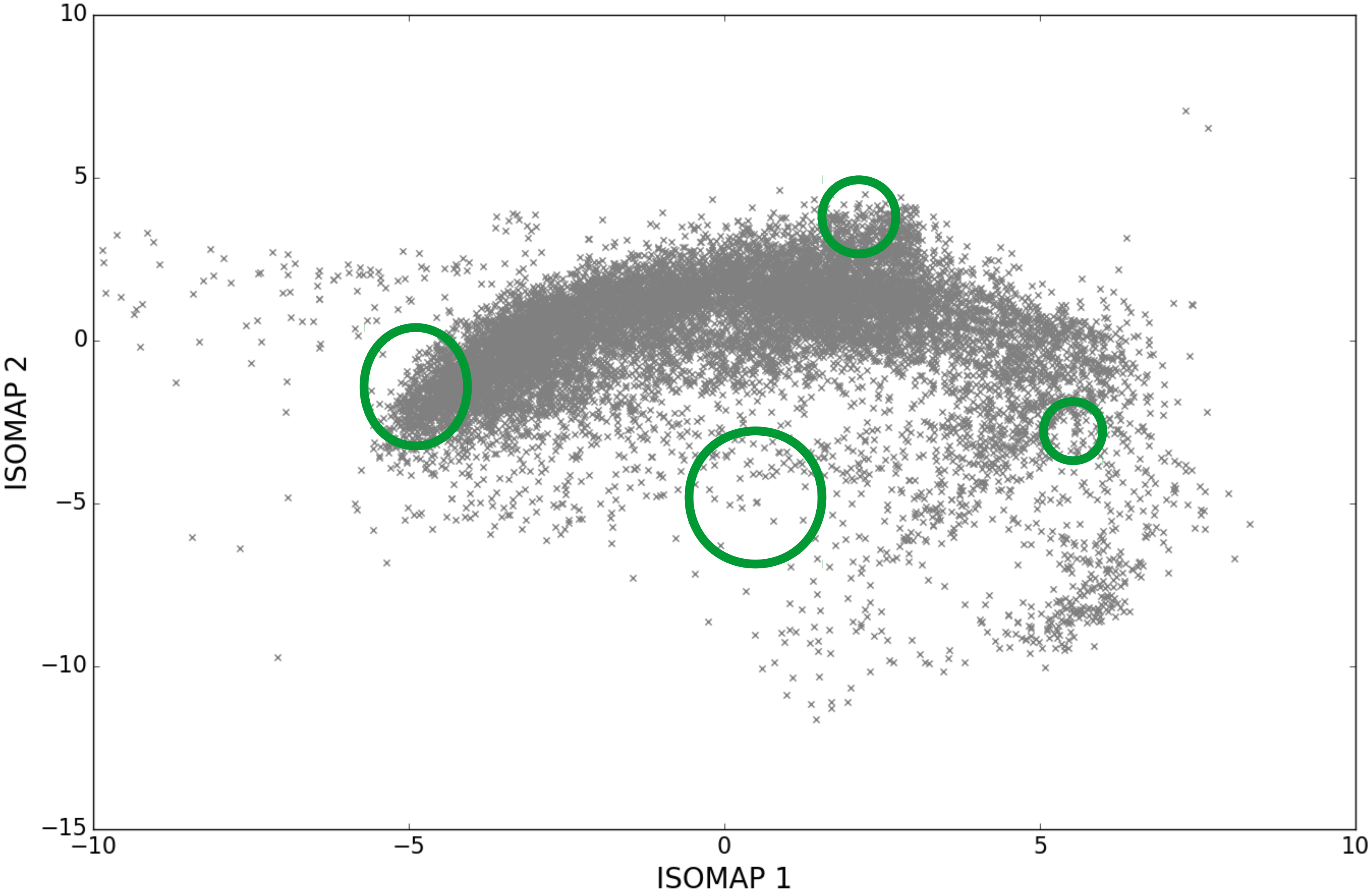


Landmark selection:

Build less complex models

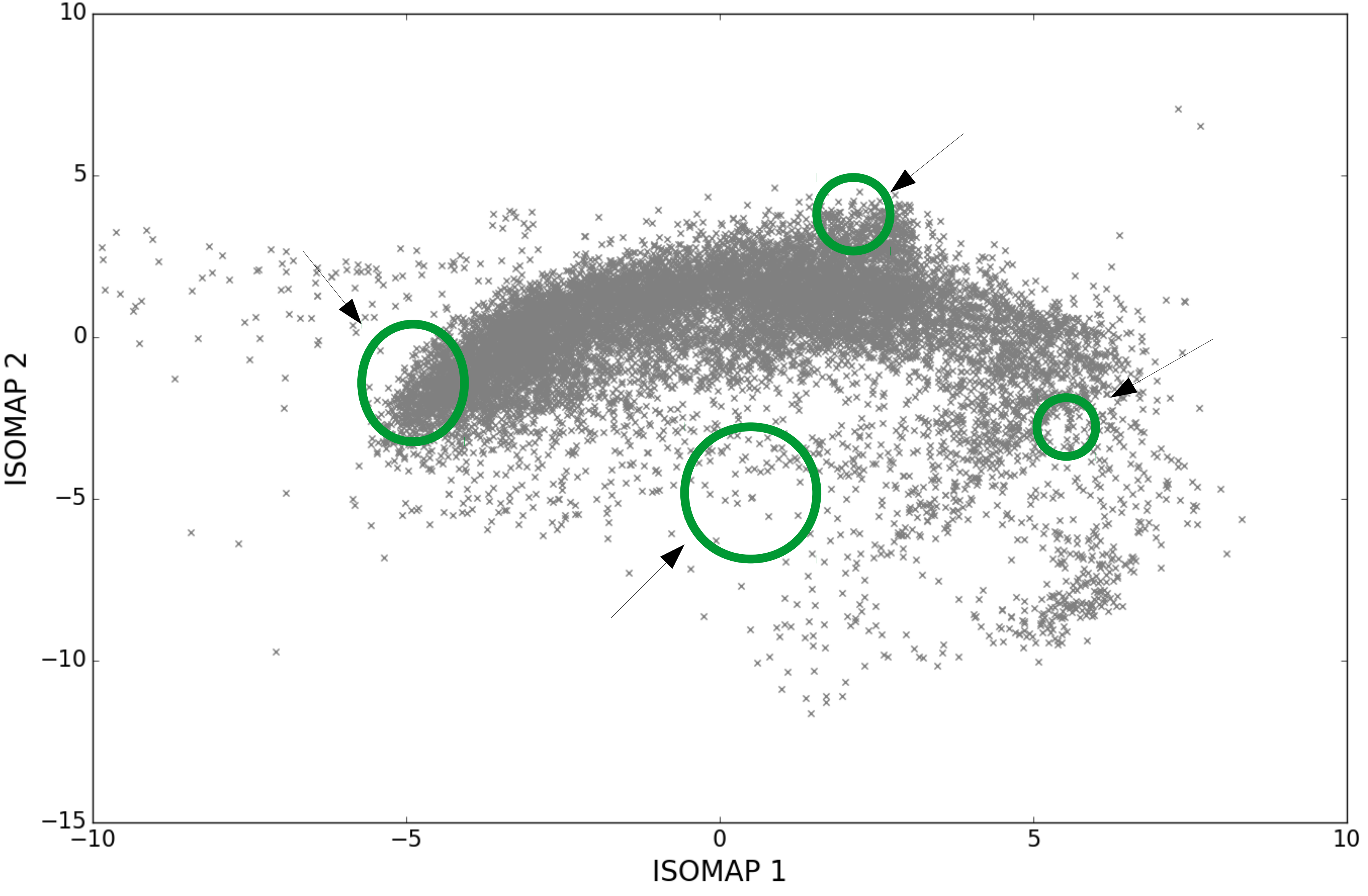
Forget spec/sample distinction:

Landmark clustering



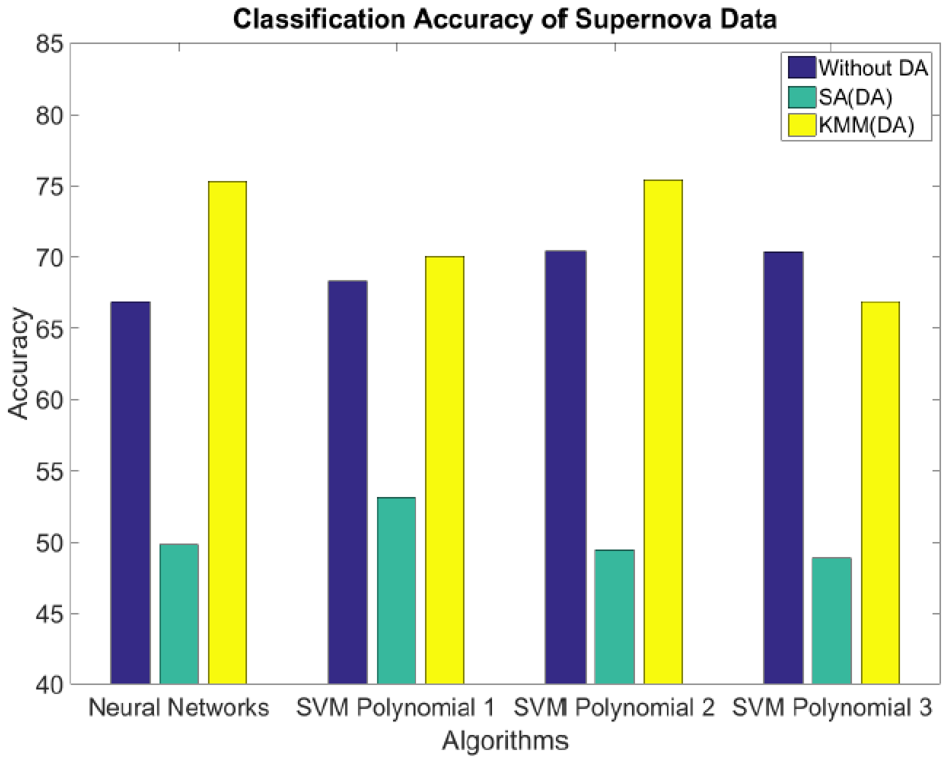
Forget spec/sample distinction:

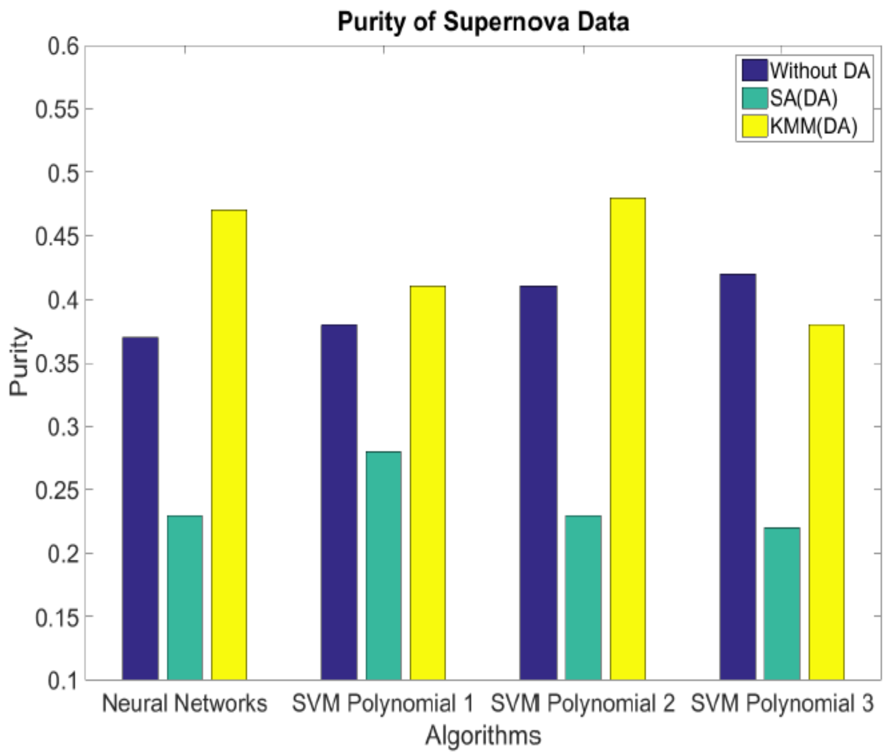
Train the model locally +
Apply the weights



Preliminary results from post-SNPCC data:

At least 3 observed epochs (for all filters)
At least one epoch before -3 and 1 epoch after +24 days since max (for all filters)
Light curve fit using Gaussian Process regression





Plot by Ricardo Vilalta

Problem:

Sometimes there are no training points in a group!

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Active learning: ask!

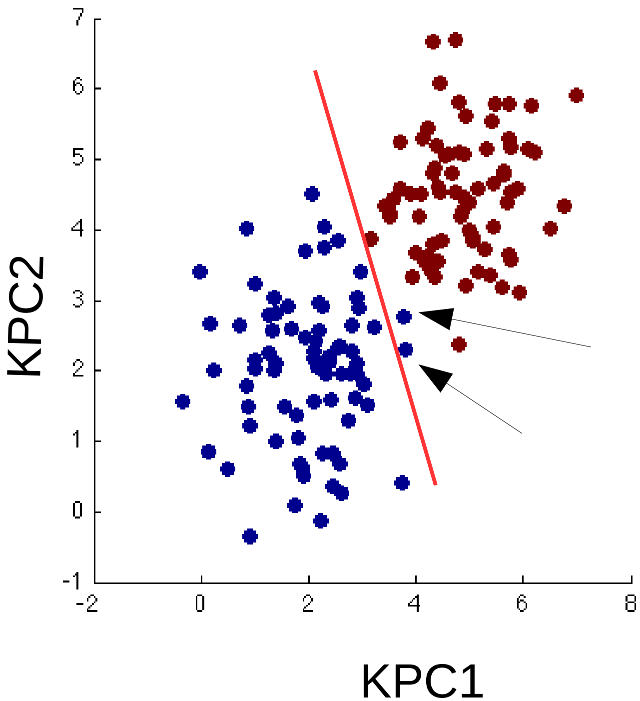
Assume a minimum number of training in each group.

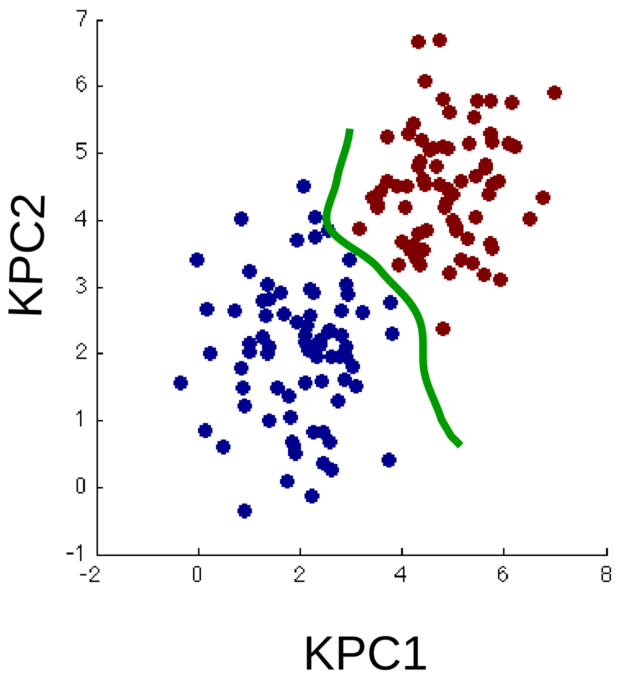
Make a query.

Train the model (+weights), project the test data and classify.
Use a method which gives you full posteriors.

Choose the ones you trust less.

Make a query.





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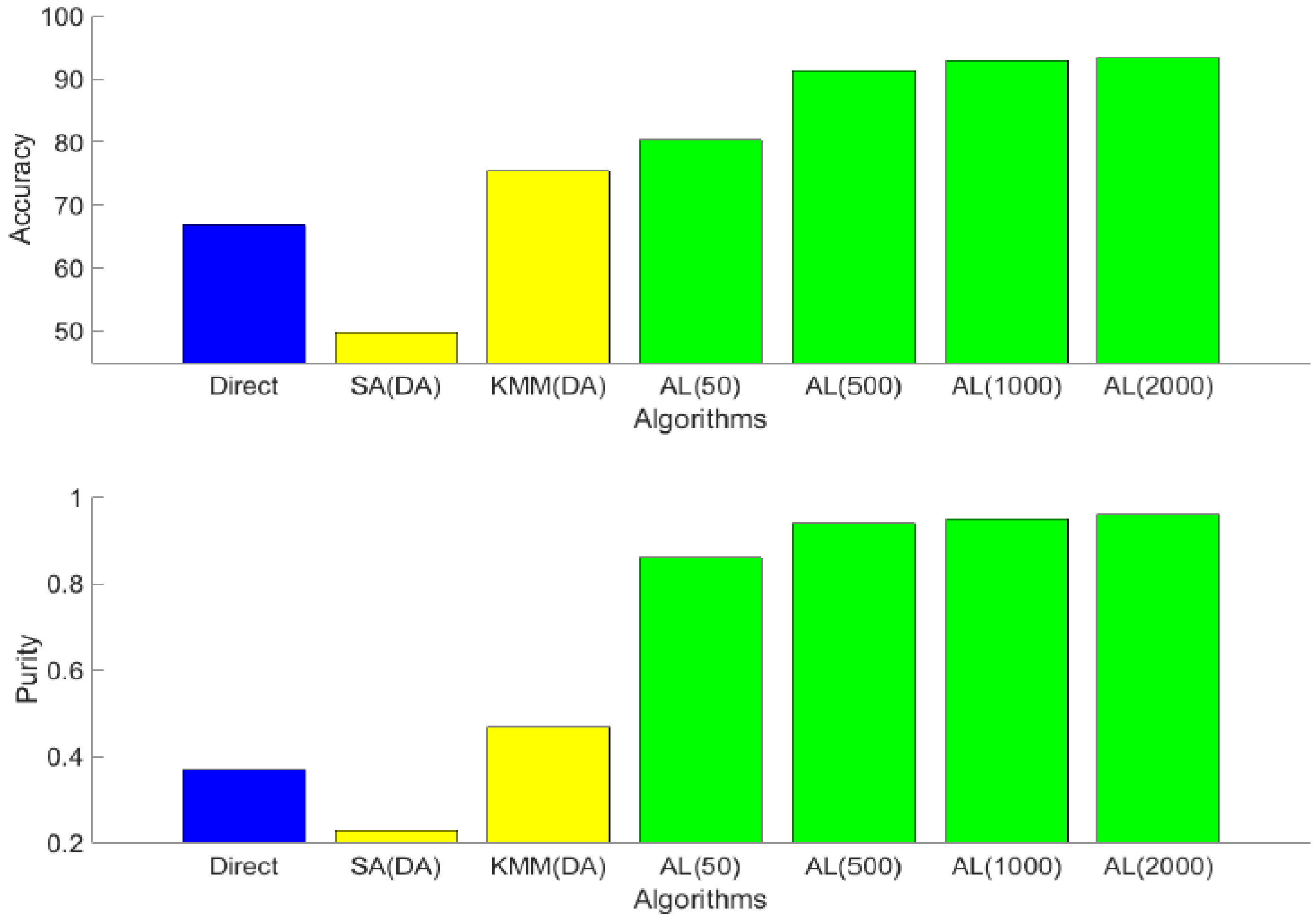

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Take away message:

Domain differences need to be addressed

Results are dependent on feature extraction
(what about missing data?)

Use active learning in pre-max data or
simulations for follow-up strategies -
But this requires simulations...

Change dynamics in the construction of the
spectroscopic sample

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Change dynamics in the construction of the
spectroscopic sample

I would build the photometric sample first!

References:

Dataset shift in Machine Learning, by Joaquin Quinonero-Candela, Masashi Sugiyama, Anton Schwaighofer and Neil D. Lawrence, 2009, MIT Press

Covariate shift by Kernel Mean Matching, by Arthur Gretto (CMU), http://www.cs.cmu.edu/~arthurg/talks.html

Resources on Active Learning, http://active-learning.net/