Supplementary 1.
Randomized Control Analysis Reveals the Effectiveness of Different Components of ICE

To understand the impact of the three components of ICE (C1: fuzzy clustering-based model generation, C2: instance-model association, and, C3: KNN-based model selection), we perform a randomized control experiment, where one or more of the components is replaced with comparable, randomized procedures. For a fair evaluation, we compare the ICE strategy with bagging (random subset) over a simple base learning – a single SVM with linear kernel. Here we set the number of fuzzy clusters to 100 (therefore 100 models in pool, and, the number of models per testing instance is much smaller in prediction; number of neighbors set to 10 in prediction); we set the number of bags for bagging to be 100 as well. To randomize C1 of ICE, the fuzzy clustering is replaced by bootstrapping instances, but the bags are made the same size as in the fuzzy clusters, therefore resulting in a slightly modified version of Bagging. To randomize C2, the decision table is shuffled row-wise, destroying the association of models to instances. Finally, to randomize C3, KNN is replaced with random selection of instances. Note that randomizing C2 or C3 (or both) are expected to have similar impact on the algorithm, which will essentially perform random model selection (and in most cases will choose many more models than real ICE due to independence of different rows of the randomized decision table).

Figure 1 shows the performance of ICE with different components randomized. Here, in order to show the effectiveness of each component of ICE, the parameter α and β are set to 0, effectively eliminating 'whole' model. Not surprisingly, when both the model generation and model selection components of ICE are randomized (columns 1-3 in Figure 1a), its performance gain is similar to that of Bagging. On the other hand, when only one component is randomized (columns 4-7), ICE can still perform better than standard Bagging, although not as effective as the complete ICE algorithm (column 8), indicating that both components of ICE played a role in effective learning.

Interestingly, with only C1 randomized, our algorithm is conceptually similar to dynamic model selection (Cruz et al. 2015), except that we replaced their learning-based model selection with simple KNN-based model selection. The fact that this version of ICE still outperforms dynamic model selection suggests that, with limited training data, KNN-based model selection can have more robust performance than learning-based. In addition, when C2 or C3 (or both) are randomized but C1 is not randomized (column 5-7), our algorithm is conceptually similar to bagging, except that the models in the ensemble are based on clusters of instances instead of random selection of instances. As shown, this version of ICE has significant performance gain over Bagging, suggesting that, at least in these datasets, clustering-based model generation, which implicitly diversifies the models, can be better than randomized model generation.

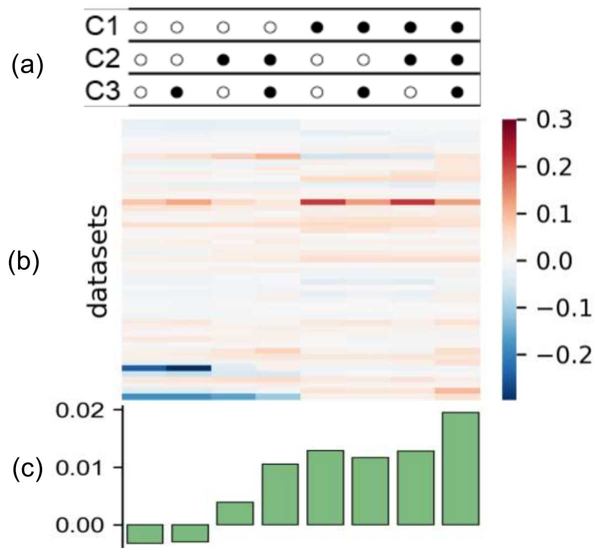

Figure 1

Component analysis of ICE. Each column indicates a randomized control experiment. (a) Marker '•' and '◦' represent standard component and random control. (b) Color indicates the AUC gain of ICE over Bagging. (c) Each bar shows the average AUC gain of ICE over Bagging.