

Benjamin Limoges

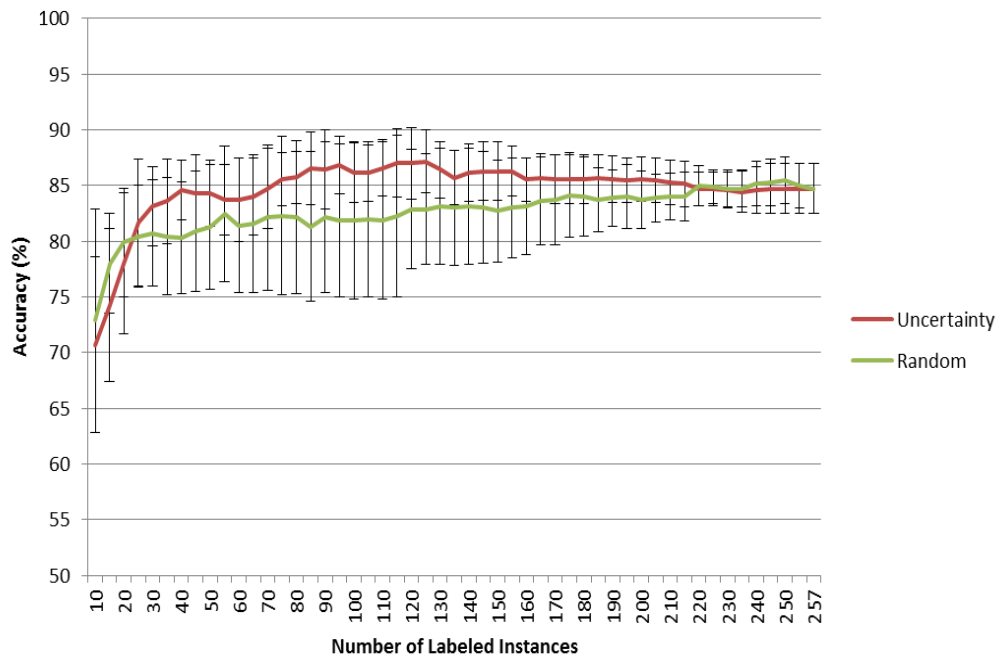
For both datasets, the uncertainty sampling started off slightly worse than random sampling, then uncertainty sampling became much better for a period, followed by tapering off when the two converged. Uncertainty sampling starts off worse most likely by random chance – after two requests (of 5 each) uncertainty sampling has some performance gains at $k = 5$ for both datasets. This is because the fuzziest points are being removed (and labeled) allowing the classifier to have a sharp increase in accuracy. The random does not cause there to be as sharp of an accuracy gain because it is not getting rid of this “fuzziness.”

Across different runs of k the two datasets acted differently. For all values of k , the accuracy gain is relatively constant for the Ecoli dataset. There is an initial boost, which tapers off. The random slowly but surely catches up. For the Ionosphere dataset, $k=7$ seems to get the largest gain in accuracy. The higher value k s are also dramatically improved under uncertainty sampling. I believe that this increase for larger values of k (in the Ionosphere dataset) was because the points are clustered together in several of the feature spaces (this is a conjecture and not verified). By having “too many” neighbors, the learner was needlessly confusing itself. So labeling data defined this boundary really quickly, giving the sharp performance gain.

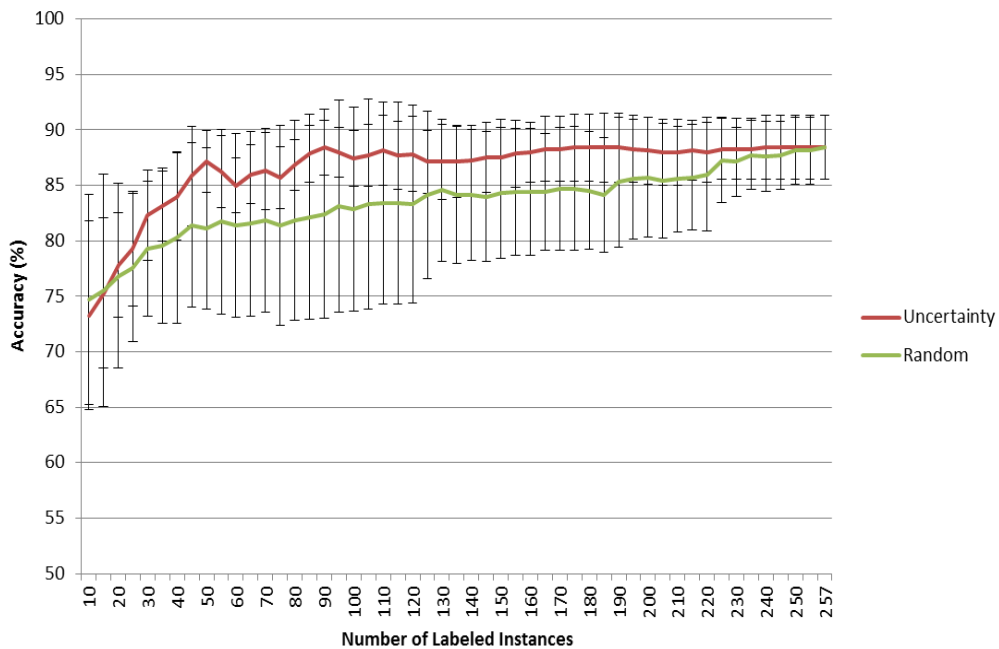
Ionosphere got a larger gain than Ecoli in performance from uncertainty sampling. I have two hypotheses for why this is true. The first is that Ionosphere is a binary class problem, whereas Ecoli is a 5 class problem. This means that with uncertainty sampling, for the Ionosphere dataset, the learner could quickly remove uncertain examples to get a large boost in accuracy. For Ecoli, the multiclass problem made it that the learner had to balance the distinction between 5 classes instead of two. So it may “spend” its 5 additional labels on clearing one boundary without improving performance with the other boundaries. Another issue with the Ecoli dataset was the minority class issue with class 7. This made it hard to pin down – the learner may have been constantly getting this class wrong until most of the datapoints were labeled.

The convergence of random sampling and uncertainty sampling as more labels were added is because the pool of unlabeled instances was becoming increasingly small. If there were an infinite pool of unlabeled instances to draw from, then the convergence would be much slower; by the end of the finite pool of unlabeled instances the two methods were drawing extremely similar sets of points to be labeled. In the asymptotic case with infinite data, the two would converge simply because the boundaries would become clearer and clearer, since the random draws will eventually include the “key” points that define the boundary between the classes – uncertainty sampling gets there quicker by defining the boundary immediately, whereas random sampling fills in the entire space.

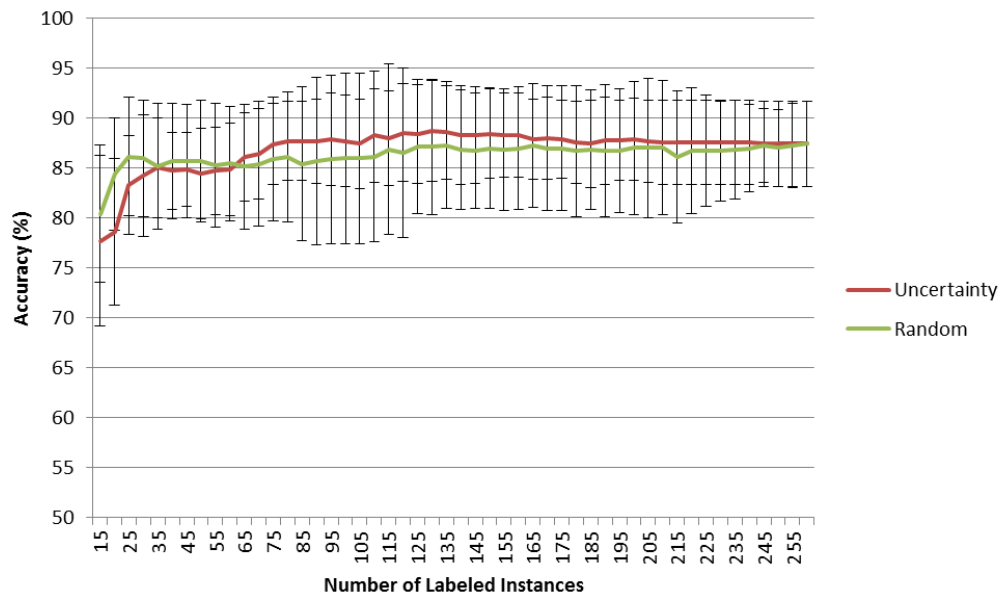
Ecoli, K = 3



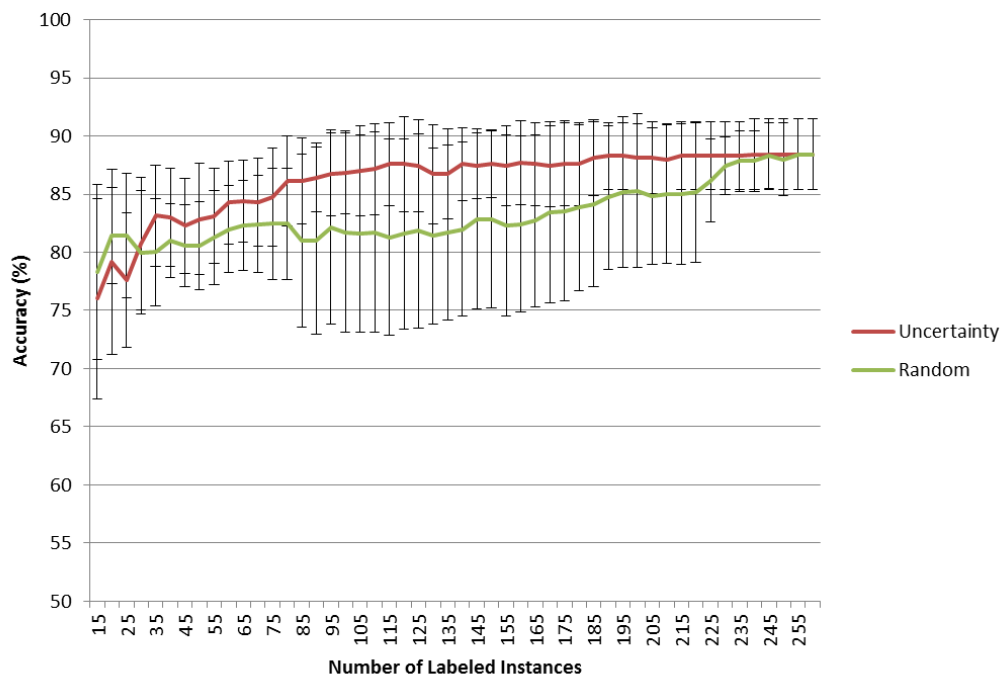
Ecoli, K = 5



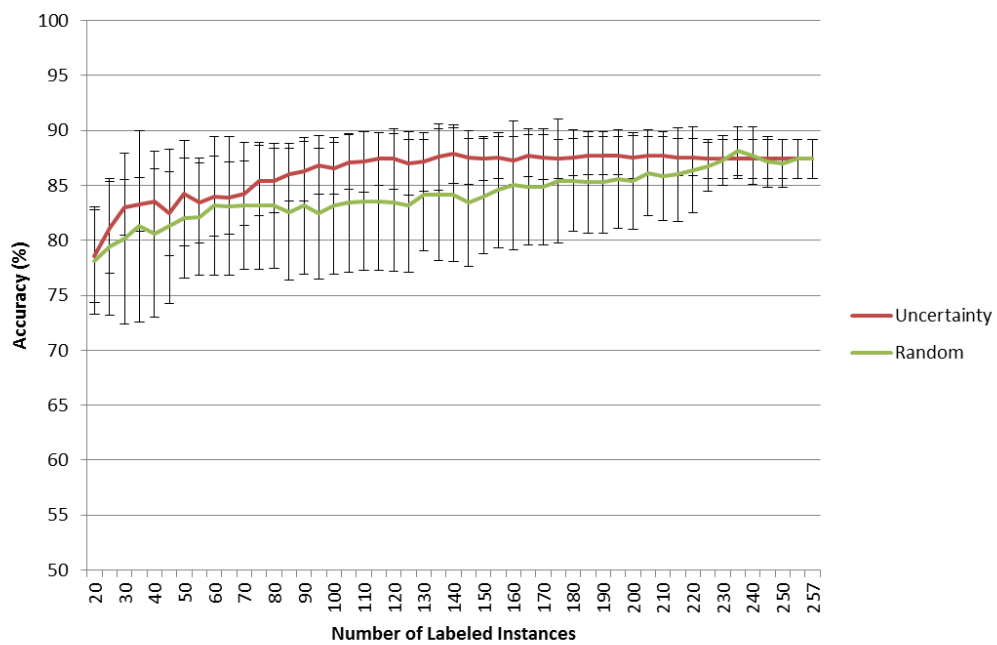
Ecoli, K = 7



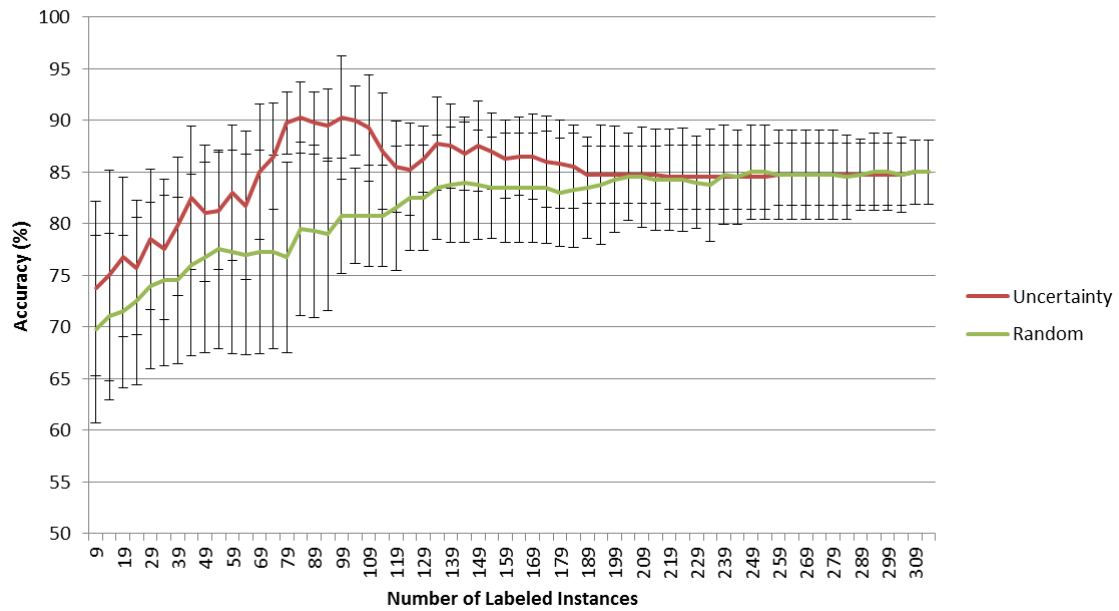
Ecoli, K = 9



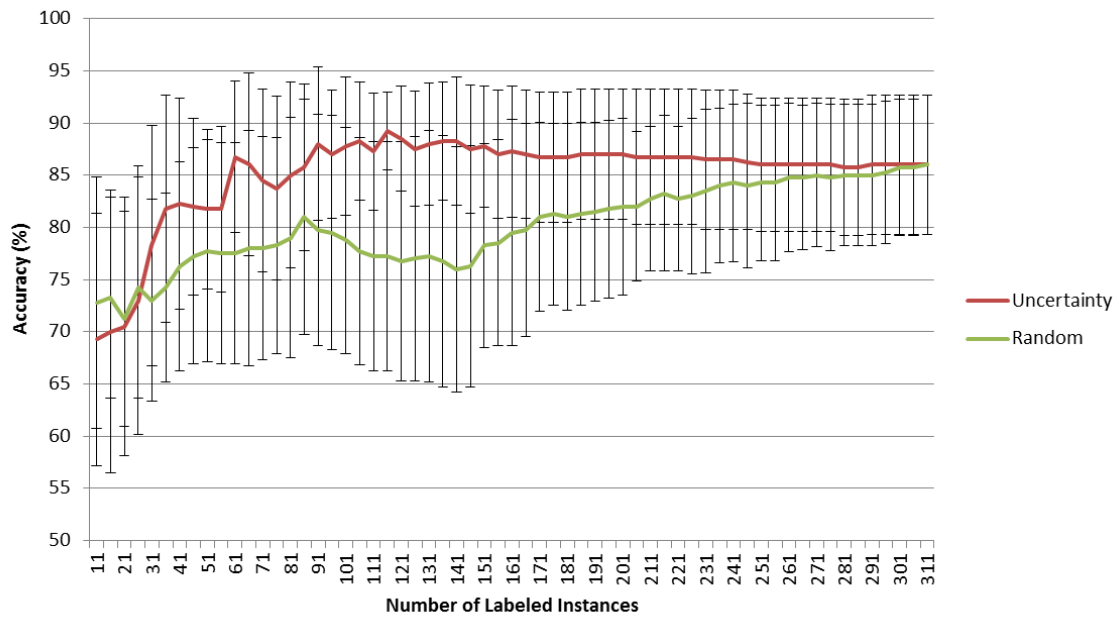
Ecoli, K = 11



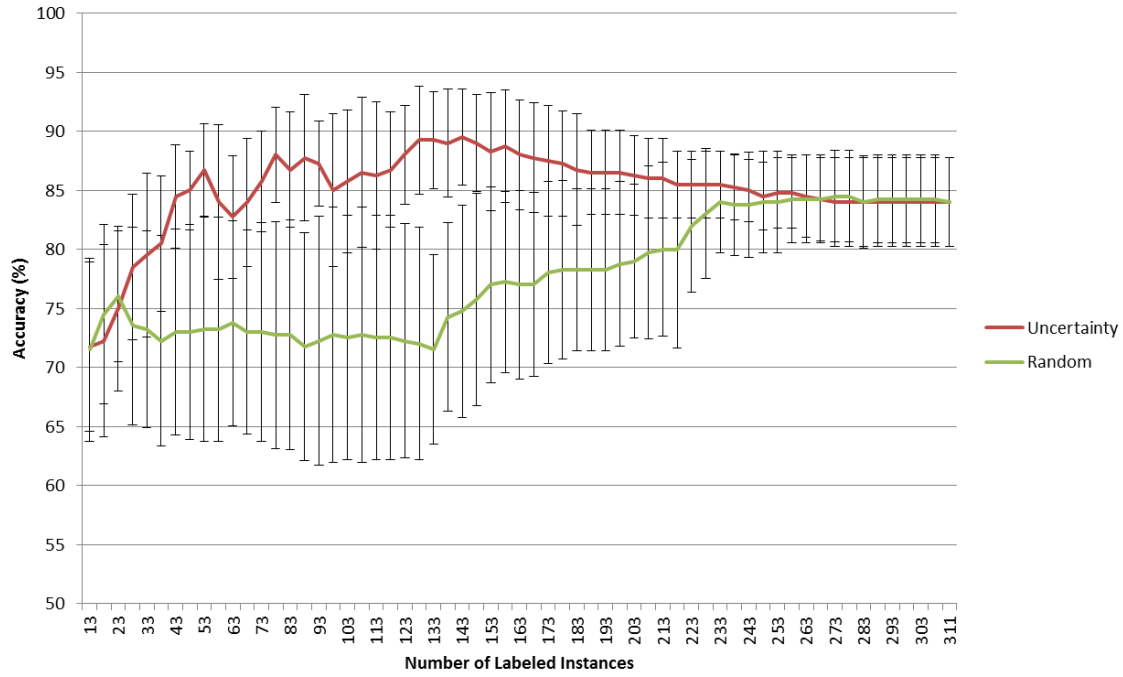
Ionosphere, K = 3



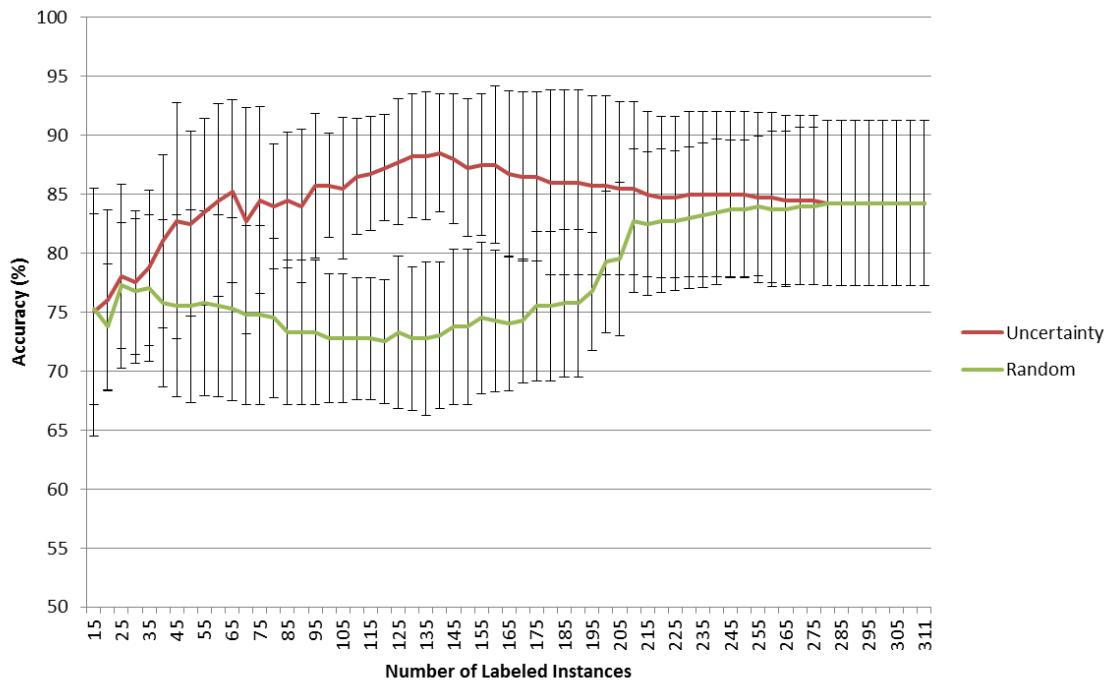
Ionosphere, K = 5



Ionosphere, K = 7



Ionosphere, K = 9



Ionosphere, K = 11

