Machine Learning Topic 3

Error Estimation

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Error Estimation

- Definition of **empirical error**: slide 1
 - Empirical error may be misleading when $g = g_n$ is a data-based classifier, e.g. a data-based classifier may demonstrate 0 empirical error which is not representative of the true error of the classifier.
- LLN for $R_n(g)$: slide 1
- ullet CLT for empirical deviation from true risk: slide 1
- Proof of Chebyshev: slide 2
- Typical deviations from expected values: slide 3
 - Chernoff Bounds: slide 4
 - * Prime example for Chernoff Bounds: slide 5
 - Hoeffding's Lemma: slide 5
 - Hoeffding's Inequality: slide 5
 - Bernstein's Inequality: slide 6
 - * Use to pick classifier from class of size N: slide 6
 - Bound on the true risk of data-based classifier from the empirical risk: slide 7
 - Bound on the true risk of data-based classifier from the best in class: slide 7
 - Proof the empirical risk minimizier is PAC: bottom of slide 7-8
- Definition of the empirical risk minimizer g_n : slide 7
- Bound on the true risk of data-based classifier when empirical risk is 0 and best in class is 0: slide 9
- Description of other error estimator (i.e. when all training data is used): slide 10
 - Leave-one-out, k-cross validation: slide 11

Notes

- Bounding of sums of random variables minus their expected values is used for bounding $|R_n(g) R(g)|$: $R_n(g)$ is binomial a sum of n bernoullis, and R(g) is it's expected value
- CLT gives bounds of the order $\frac{1}{\sqrt{n}}$
- Chebyshev gives us that typical deviations are of the order $\frac{\sigma}{\sqrt{n}}$
- Chernoff gives us something an exponentially decreasing upper bound that is non-asymptotic
- Hoeffding / Bernstein gives us something that is non-asymptotic and distribution-free