Outline: **Unbalanced Supervised Problems**
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Statistical Methods for Large, Complex Data

A reference article on subsampling in unbalanced classification problems:

The Annals of Statistics
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LOCAL CASE-CONTROL SAMPLING: EFFICIENT SUBSAMPLING IN IMBALANCED DATA SETS

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For classification problems with significant class imbalance, subsampling can reduce computational costs at the price of inflated variance in estimating model parameters. We propose a method for subsampling efficiently for logistic regression by adjusting the class balance locally in feature space via an accept–reject scheme. Our method generalizes standard case-control sampling, using a pilot estimate to preferentially select examples whose responses are conditionally rare given their features. The biased subsampling is corrected by a post-hoc analytic adjustment to the parameters. The method is simple and requires one parallelizable scan over the full data set.

Standard case-control sampling is inconsistent under model misspecification for the population risk-minimizing coefficients θ^*. By contrast, our estimator is consistent for θ^* provided that the pilot estimate is. Moreover, under correct specification and with a consistent, independent pilot estimate, our estimator has exactly twice the asymptotic variance of the full-sample MLE—even if the selected subsample comprises a miniscule fraction of the full data set, as happens when the original data are severely imbalanced. The factor of two improves to $1+\frac{1}{c}$ if we multiply the baseline acceptance probabilities by $c>1$ (and weight points with acceptance probability greater than 1), taking roughly $\frac{1+c}{2}$ times as many data points into the subsample. Experiments on simulated and real data show that our method can substantially outperform standard case-control subsampling.

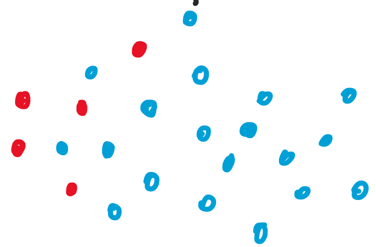
Some more references

Dubey, Rashmi et al. “Analysis of sampling techniques for imbalanced data: An n = 648 ADNI study.” *NeuroImage* vol. 87 (2014): 220-41. doi:10.1016/j.neuroimage.2013.10.005

Menardi, Torrelli (2010) “Training and assessing classification rules with unbalanced data”. Working Paper 2-2010. Dipartimento B. De Finetti, Universita’ di Trieste.

Imbalanced Learning tools, MIT (includes SMOTE)
https://imbalanced-learn.org/stable/index.html

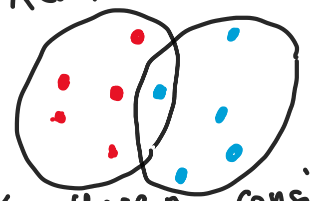
The data in feature space



"scarce" class n_R

"abundent" class n_B

(1) Reduce the abundant class



Keep these n_R fixed

consider only n_R of these at random

... can "repeat"

Form one, or several, datasets of size $2n_R < n_R+n_B$.

The red points are always the same.

(1B) A variant

Bootstrap the red points (resampling with replacement)

Sub-bootstrap the blue points (Select n_R blue points at random with replacement)

... can "repeat" both

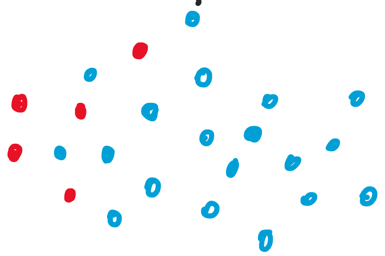
Form one, or several, datasets of size $2n_R < n_R+n_B$

The red points are bootstrapped too.

... MAKES MORE SENSE STATISTICALLY

we simulate sampling from the two populations.

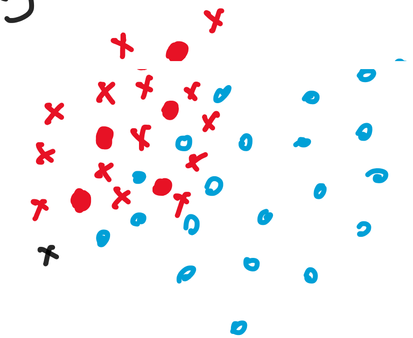
The data in feature space



"scarce" class n_R

"abundent" class n_B

② Augment the scarce class



● = actual red points

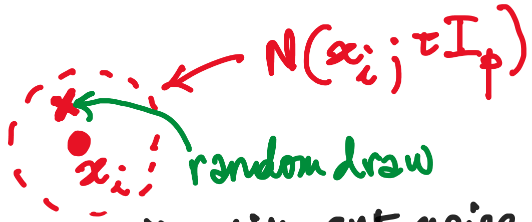
x = artificial red points

Form a dataset of size

$2n_B > n_R + n_B$

How do we create the artificial points? some options

(i) Over-bootstrap the red points (select n_B red points at random with replacement) ADDING NOISE to each draw



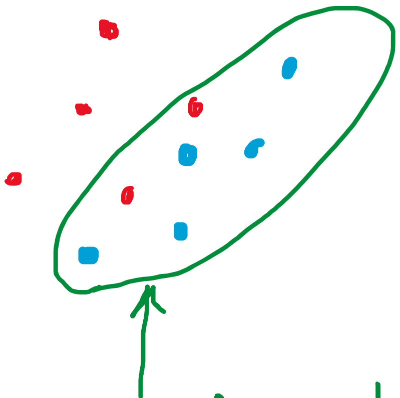
(can specify different noise models)

(ii) n_B times over: select at random two red points and a point between them

(can "localize" the selection of the red points, e.g., first at random, second at random among its closest red neighbors)

Localizing the reduction or the augmentation

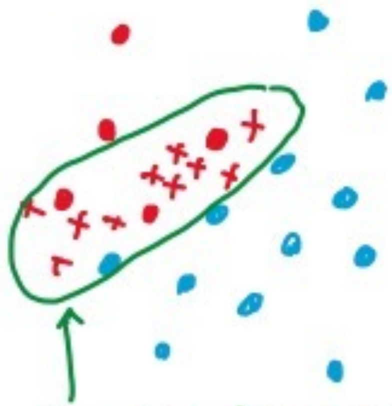
preserve the abundant class where it is harder to discriminate, i.e., close to the red points



localize subsampling here

Focus the augmentation of the scarce class where it is harder to discriminate, i.e., close to the blue points.

... MAKES MORE SENSE STATISTICALLY



localize/focus augmentation here