



Exploiting auxiliary data: Random Forest Regression estimator

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Session 29

Stating the problem

- In addition to the survey sample, we have some additional data from an external source (administrative data, Big Data, ...)
- These data, A are linked to our population at statistical unit level
- We want to improve the estimations of our target variables exploiting A . The idea is $E(X|A)$ should have less variance than $E(X)$.
- That way, we can reduce the sample size and therefore the response burden.
- A machine learning approach is preferred, both to save the analyst's time and to avoid subjectivity.

The Random Forest Regression estimator

- Definition for simple stratified sampling:

$$\hat{X}_{RFRE} = \sum_{i=1}^N \hat{x}_i + \sum_{h=1}^L \sum_{i=1}^{n_h} N_h \frac{x_{hi} - \hat{x}_{hi}}{n_h}$$

- The out-of-bag prediction is used for in sample units.
- The formula also works for any bootstrap aggregated algorithm. We also know general unbiased model based estimators both for totals and its variance.
- Random Forest and similar algorithms are a good general purpose choice, since they are non linear and non parametric.

Properties

- The RFR estimator is approximately unbiased: it is an approximation of an unbiased estimator.
- An approximate estimator of its variance is

$$\hat{V}_{RFR} = \sum_{h=1}^L N_h^2 \left(1 - \frac{n_h}{N_h}\right) \frac{s_{e,h}^2}{n_h}$$

- This second approximation is not as good as the first one, so the bias is small but perceptible.
- We know an unbiased version of the estimators, but we currently do not have a fast enough implementation to run the simulations.

Synthetic data simulation (I)

Linear model

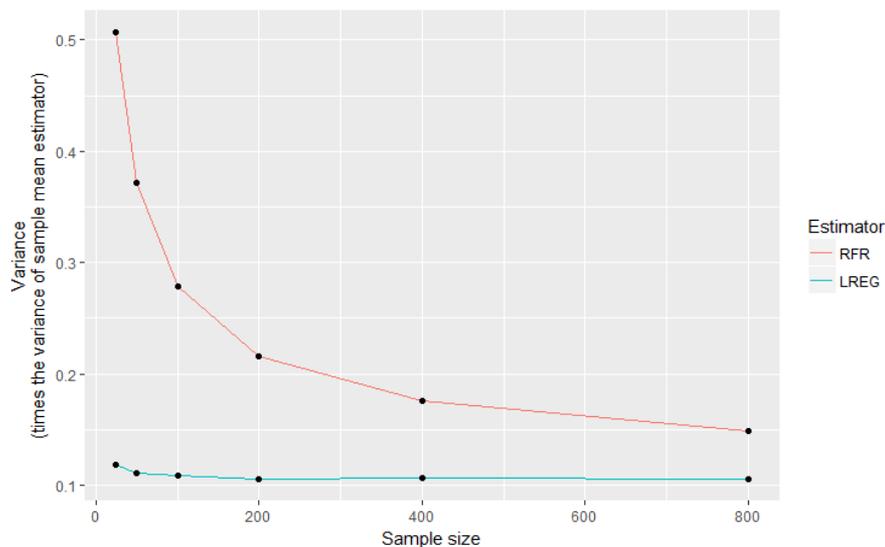
Estimator	RFRE	Linear Regression	Sample mean
Bias (estimator)	0.01	0.11	-0.07
Variance (estimator)	27.88	10.87	100
Bias (estimated variance)	-2.92	-3.33	0.59
Variance (estimated variance)	10.97	0.07	100

Linear model on logarithms

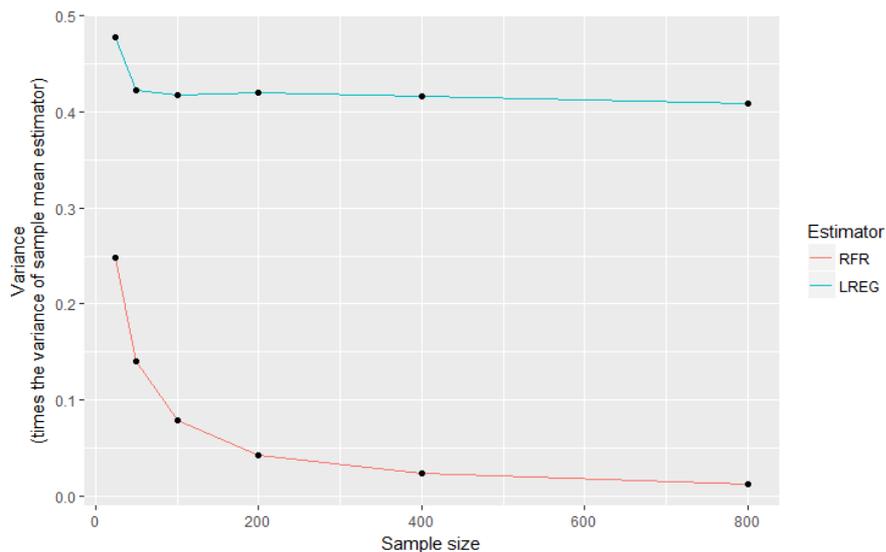
Estimator	RFRE	Linear Regression	Sample mean
Bias (estimator)	0.10	1292.15	-20.14
Variance (estimator)	7.86	41.70	100
Bias (estimated variance)	-4.86	-20.70	-0.20
Variance (estimated variance)	0.98	44.37	100

Synthetic data simulation (II)

Linear model



Linear model on logarithms



- The linear regression estimator learns faster and gets stuck.
- While the RFR estimator continues learning, its variance decreases faster than $O\left(\frac{1}{n}\right)$.

Simulation with real data (SBS)

Total Expenses, simple random sampling

Estimator	RFRE	Linear Regression	Sample mean
Bias (estimator)	0.24	2.77	0.32
Variance (estimator)	60.98	78.73	100
Bias (estimated variance)	-0.97	-24.02	1.83
Variance (estimated variance)	82.82	87.76	100

Total Personnel Expenses, stratified sampling, MV allocation

Estimator	RFRE str	Sample mean str	RFRE	Sample mean
Bias (estimator)	-0.08	0.01	-0.01	-0.04
Variance (estimator)	40.65	86.01	13.60	100
Bias (estimated variance)	-0.89	0.56	-2.05	-0.57
Variance (estimated variance)	2875.59	12300.93	29.88	100

Conclusions

- A good choice when the analyst has a lot of auxiliary data and little idea about how to use it (or little time).
- If the sample is big enough its performance will be similar to those of the *real model*.
- It might be advisable to use the unbiased formula for the variance. The bias is small but still noticeable.
- To preserve affine identities a multivalued version of the Random Forest can be used.
- Up to a certain degree it makes unnecessary the use of a complicated sampling design to improve accuracy.
- Possible additional uses: imputation, small areas, ...

Bibliography

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