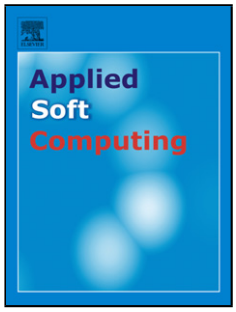

Title: Predicting body fat percentage from anthropometric and laboratory measurements using artificial neural networks

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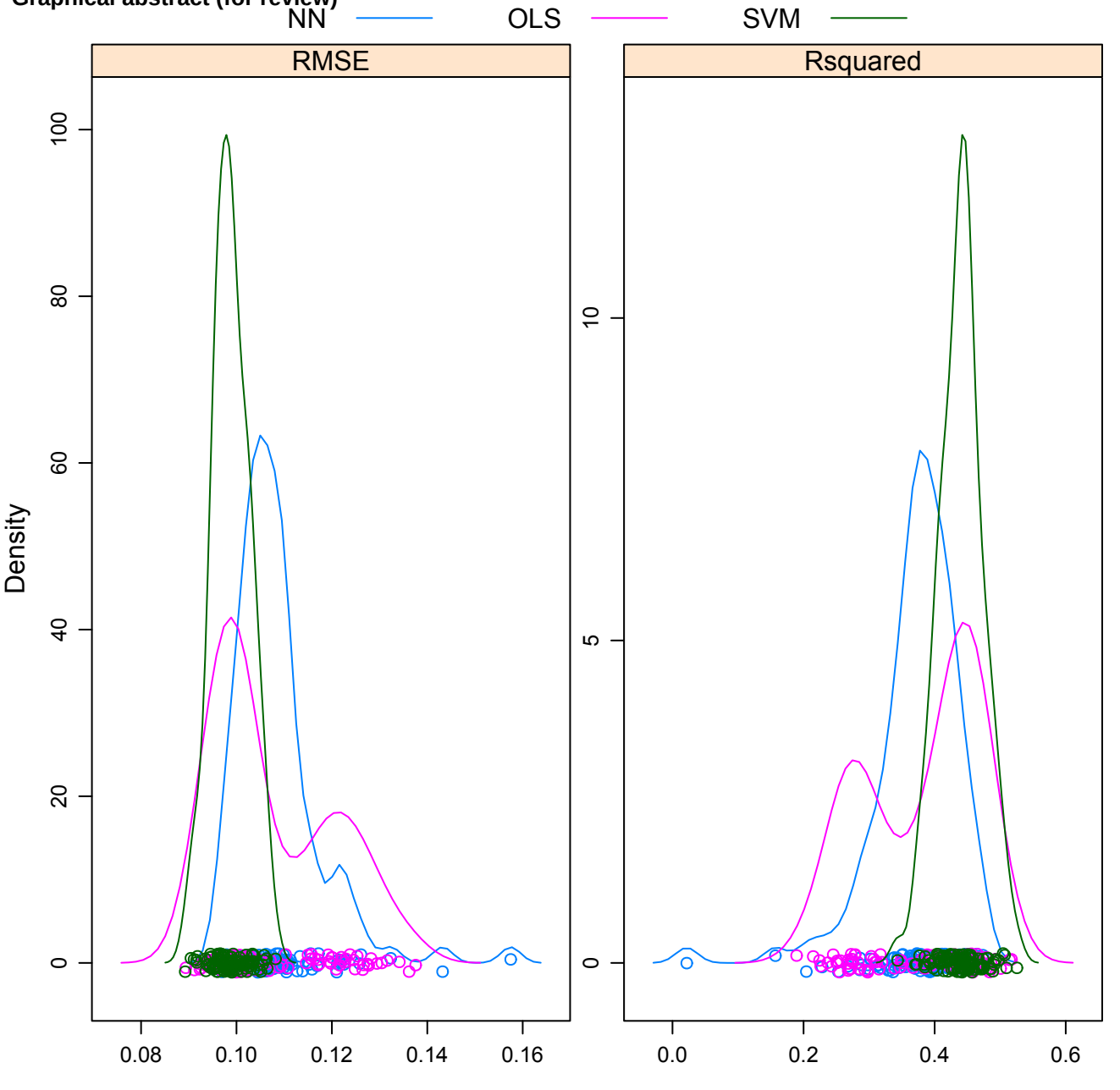
Highlights

- Body fat percentage is predicted from easily measurable data to quantify obesity risk.
- Linear regression, neural networks and support vector machines are used.
- Models built on empirical data from a representative US health survey (n=862).
- Optimal parameters are chosen and bootstrap validation is used.
- Linear regression is slightly outperformed by support vector machines, but not neural networks.

*Graphical abstract (for review)



Predicting body fat percentage from anthropometric and laboratory measurements using artificial neural networks

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Abstract

Purpose of the research: Obesity is a major public health problem with rapidly growing prevalence and serious associated health risks. Characterized by excess body fat, the accurate measurement of obesity is a non-trivial question. Widely used indicators, such as the body mass index often poorly predict actual risk, but the direct measurement of body fat mass is complicated. The aim of the present research is to investigate how well can body fat percentage be predicted from easily measureable data: age, gender, weight, height, waist circumference and different laboratory results. For that end, linear regression, feedforward neural networks and support vector machines are applied on the data of a representative US health survey ($n = 862$) using adult males. Optimal parameters are chosen and bootstrap validation is used to get realistic error estimates. Results: No methods can well predict the body fat percentage, but support vector machines slightly outperformed feedforward neural networks and linear regression (root mean square error 0.0988 ± 0.00288, 0.108 ± 0.00928 and 0.107 ± 0.012 respectively). Conclusion: Even this best performance means that soft computing methods had an R^2 of 44%, but this slight advantage it is balanced by the fact that regression models are clinically interpretable.

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Keywords: Obesity, body composition, body fat percentage, prediction, neural network, support vector machine.

1. Introduction

Obesity [1] is widely considered to be one the most important current public health problems due to its continuously increasing prevalence in the developed world (affecting both adults [2, 3] and children [4, 5]) on the one hand, and the seriousness of the health risks it gives rise to on the other hand. Increased risk of a number of diseases have been casually linked to obesity, including type 2 diabetes mellitus, hypertension, ischaemic heart disease, stroke, infertility, osteoarthritis, liver and gallbladder disease and certain tumors [6]. Not surprisingly, obesity also increases all-cause mortality [7] and poses a significant economical burden as well [8, 9].

Screening for the disease and accurate tracking of the severity for the already ill both underline the importance of the exact measurement of obesity. This is, however, not a trivial question: the definition of obesity ("condition of excess body fat" [1, p. 3]) does not directly give rise to any quantitative metric. Weight is a straightforward proxy for body fat and is easy to measure but is almost meaningless without information on the overall stature of the person. Usually height is used for that purpuse, leading to indicators such as body mass index (BMI) [10], which is so widely used that even the definition of obesity is sometimes linked to it, and is endorsed by the World Health Organization [11].

It is, however, well-known that these indicators, even though stature is taken into account, often perform poorly [12] in predicting health outcomes because they don't measure body fat itself, much less its distribution (which is also known to be prognostic: visceral fat, i.e. abdominal obesity is especially associated with negative outcome [13]), among others. Methods such as waist circumference or waist-to-hip ratio measurement try to correct for this aspect [14].

A much better approach would be the direct measurement of body fat mass itself, or body fat percentage (BFP), i.e. body fat mass divided by body weight,

but it is hindered by the fact that its measurement is difficult, unfit for wider use. (Precise methods include dual energy X-ray absorptiometry (DXA), bioelectrical impedance analysis (BIA) and air displacement plethysmography [15].)

It would be therefore important if BFP could be predicted from easily measurable parameters such as basic sociodemographic data (age, gender), basic anthropometric data (weight, height, waist circumference) and basic laboratory parameters obtained from routine blood drawing. The rationale of this last component is that obesity is associated with a systemic inflammation state [16] and is demonstrated to be associated with changes in clinical chemistry parameters [17]. It is therefore appealing intuitively to include these parameters too.

The aim of the present research is to investigate how well BFP can be predicted from these parameters. That is, clinical prediction models [18] were built and validated from these variables using an empirical database (where BFP was measured with BIA as gold standard).

The current aim was not the analysis of the relationships between the predictor variables and the response aimed to provide new clinical knowledge, rather the building of a purely predictive model. This allowed us to use modern tools of soft computing (machine learning) which are black-box in that sense, but might provide better predictions. Neural networks were chosen as an example, in particular ordinary multi-layer feedforward neural networks [19] and support vector machines [20]. As a comparison, linear regression was used, illustrating the more traditional biostatistical approach.

2. Material and methods

2.1. Database

National Health and Nutrition Examination Survey (NHANES) is now a continuous American public health program, with results published in biannual cycles [21]. It is a nation-wide survey aimed to be representative for the whole civilian non-institutionalized US population, by employing a complex, stratified

multi-stage probability sampling plan. The amount of collected data is tremendous (although sometimes varying from cycle to cycle), including demographic data, physical examination, collection of clinical chemistry parameters, and a thorough questionnaire concentrating on anamnesis and lifestyle.

In contrast to the predictor variables, BFP is unfortunately not easily accessible from the NHANES data. While DXA is used in the last two decade, BFP-containing results are only available up to 2006, and even those are more complex because they were imputed to account for the non-negligible and non-random missingness. To simplify the analysis from this aspect we therefore chose BIA, which was measured last in the 1999/2000 cycle [22], and is directly available (`BIDPFAT` variable of the `BIX` dataset).

To account for the survey design of the NHANES, weighting has to be used, but as not every machine learning methods necessarily accomodates it easily, we decided – as a further simplification – to neglect it for the purposes of this demonstration.

In addition to age and gender (from the `DEMO` dataset) and weight, height and waist circumference (from the `BMX` dataset), C-reactive protein (`LAB11`), variables from the standard biochemistry profile & hormones (`LAB18`) and from the complete blood count with 5-part differential – whole blood (`LAB25`). Together, they include 39 variables; they will be addressed by abbreviations, internationally used ones, wherever possible.

To achieve more homogeneity, the database was filtered to males, aged > 18 years.

Every subject with missing value was removed (resulting in a database without missing values); leaving the final sample size at $n = 862$.

2.2. Prediction models

2.2.1. Linear regression

As a reference for comparison, BFP was modelled with simple linear regression estimated with ordinary least squares (OLS). No interaction was assumed among the variables, every variable was entered in a linear form, and no pena-

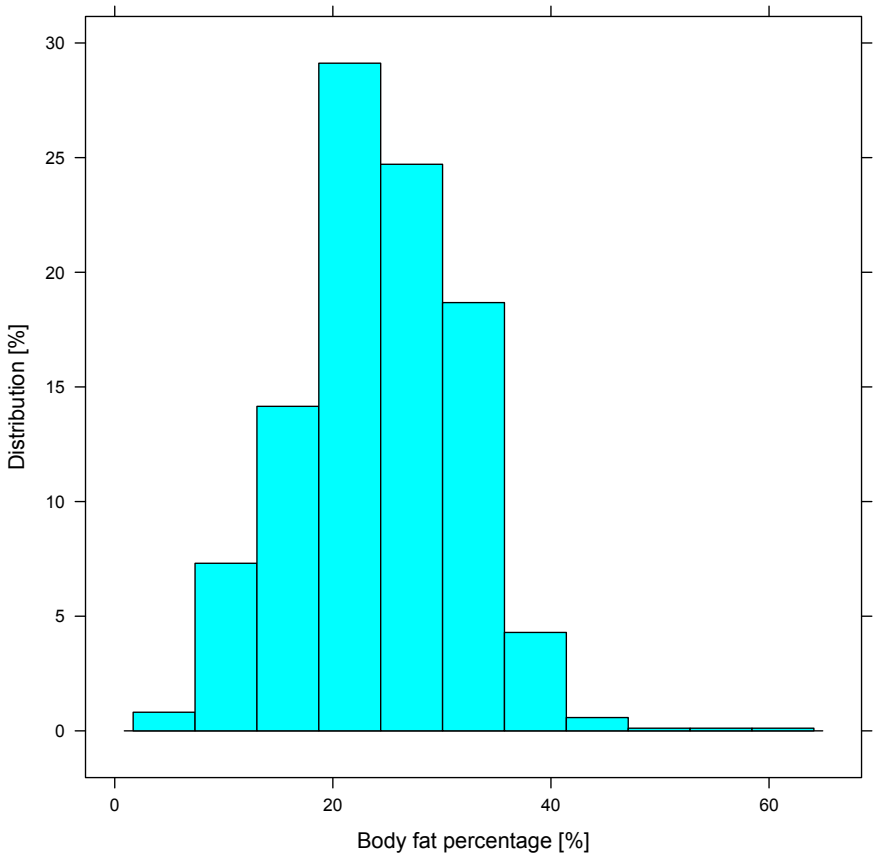


Figure 1: Histogram of BFP values in the database.

lization was applied. These are very likely poor choices [23], but nevertheless represent a typical solution in the biomedical literature.

BFP is not a continuous variable so the above approach is strictly speaking not correct. However, BFP values are so far from the limits (Figure 1) that it represents no major practical problem, so we made no correction for this (such as using GLM or applying a transformation like the logit-transform).

2.2.2. Neural network

Ordinary feedforward neural network. Feedforward neural network (NN) with logistic activation function, sum of squared error error function and two hidden layers – and varying number of neurons in each layer: 2, 3, 5 and 10 – were used. Training was done with resilient backpropagation with weight backtracking [24].

Support vector machine. Support vector machine with Gaussian radial basis kernel function in 'epsilon-svr' configuration was used. ε was fixed at 0.1, but C (cost) and the σ parameter was varying: the former from 0.1 to 1 in 0.1 steps, and then from 1 to 30 in unit steps, the latter took the values of 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 10^{0} and 10^{1}.

2.3. Modelling strategy

All variables were scaled to the $[0, 1]$ interval prior to modelling.

Optimal parameters were investigated with grid- (i.e. exhaustive) search. For each parameter-combination, a bootstrap validation with 100 bootstrap replicates was performed to obtain a realistic estimate of model performance (to show generalizability). Root mean square error (RMSE) and R^2 metrics were used to characterize the error.

Results are statistically compared using a t-test (appropriate as the sample size is large enough to justify normality due to the central limit theorem) with p-values and confidence intervals adjusted with Bonferroni correction for the multiple comparisons situation [25, 26].

2.4. Implementation

The investigation was carried out under the `R` statistical program package [27] version 3.3.2, using a custom script developed for the purpose that is available at `https://github.com/tamas-ferenci/BFPprediction`.

The whole workflow was managed with the `caret` library [28], version 6.0-73. Linear regression was handled with the `rms` library [29]. Feedforward neural networks were implemented with the `neuralnet` library [30], support vector machines were implemented with the `kernlab` library [31].

Visualization was performed with the `lattice` library [32].

3. Results

The results of the linear regression for the whole database are shown on Figure 2.

This illustrates that this model is interpretable, i.e. a clinical meaning can be associated with its results. (But note that it is the model for the whole dataset, without validation.)

Results of the parameter search, and the fitted vs. actual plot of the best model can be seen on Figure 3. for the ordinary feedforward neural network and on Figure 4. for the support vector machine. As the Figures show, the optimal parameter-combination for NN was 2 neuron in both hidden layers, for SVM the optimal was $C = 20$ and $\sigma = 0.001$.

The error measures for all 100 bootstrap replicates are shown on Figure 5.

4. Discussion

Results obtained with modern soft computing techniques were not convincingly better than linear regression.

Only SVM was able to clearly outperform simple regression, but this was rather an advantage in terms of stability of the results across bootstrap replicates and not substantially improved average value (RMSE: 0.0988 ± 0.00288 vs. 0.107 ± 0.012). Feedforward neural networks had an average performance nearly identical to regression with only minimally improved stability (RMSE: 0.108 ± 0.00928). These are all well illustrated on Figure 5. Overall, SVM was able to achieve an average R^2 of 44%.

Difference was – statistically – insignificant between linear regression and neural networks ($p = 1$ after correction both for RMSE and R^2), but it was significant between support vector machines and both other methods ($p < 0.0001$ in both case).

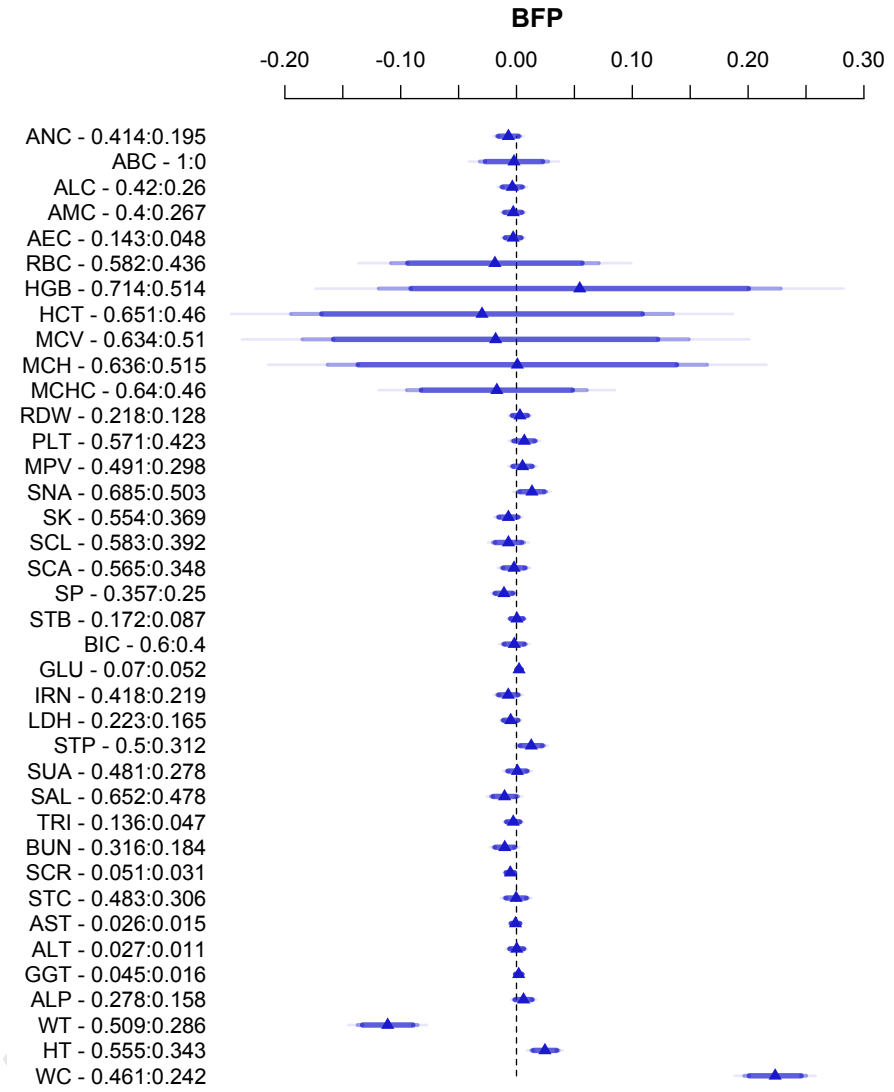
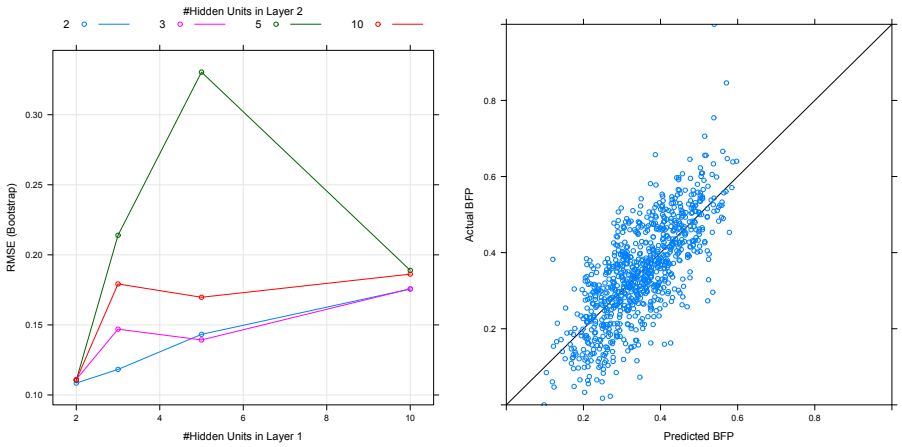
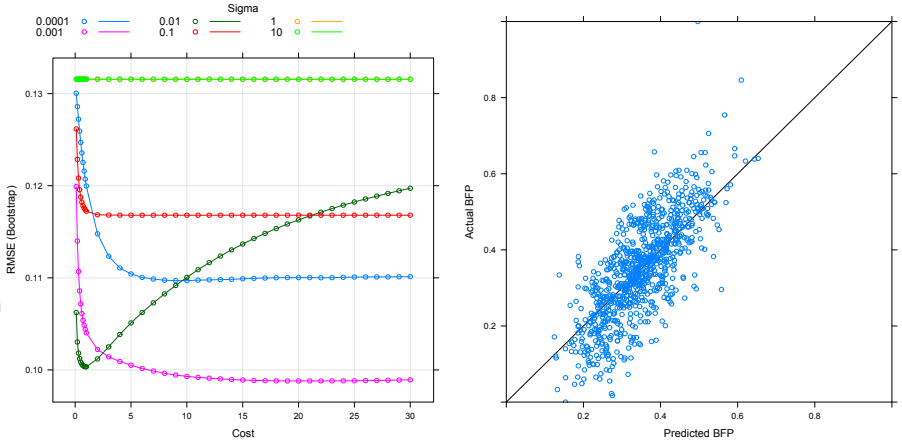


Figure 2: Results of the linear regression model: estimated $\widehat{\beta}$ regression coefficients – for 1 interquartile range increase – with 90, 95 and 99% confidence intervals



(a) Results for all parameter-combination. (b) Fitted vs. actual plot of the best model.

Figure 3: Results of the modeling with ordinary feedforward neural networks.



(a) Results for all parameter-combination. (b) Fitted vs. actual plot of the best model.

Figure 4: Results of the modeling with support vector machine.

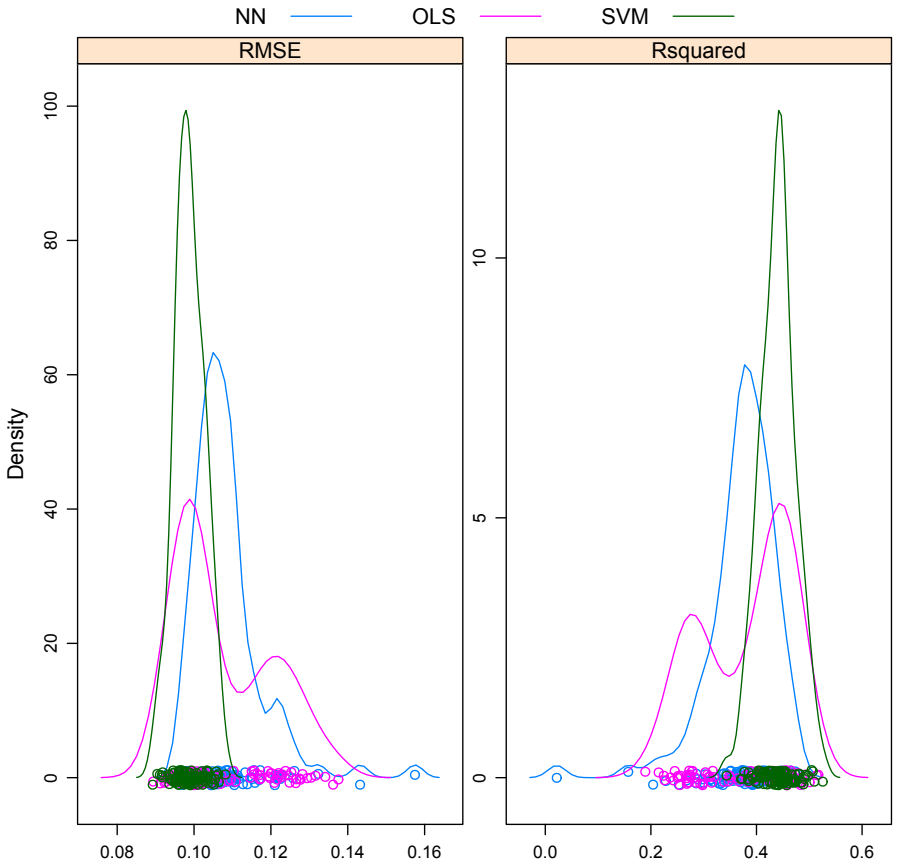
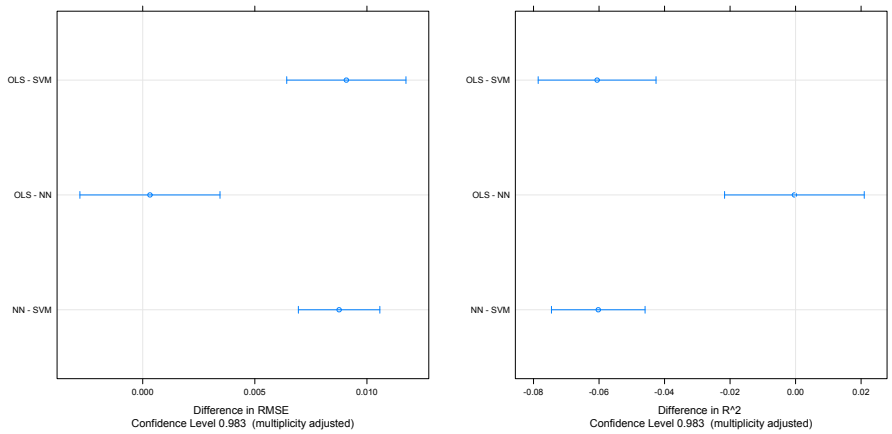


Figure 5: Distribution of the boostrap-validated error metrics for the three models, visualized with rugged density plot.



(a) RMSE metric. (b) R^2 metric.

Figure 6: Differences between the methods with 95% confidence intervals (after adjustment for multiple comparisons) for both performance metrics.

Numerical differences between the methods with 95% confidence intervals are shown on Figure 6.

Using age, gender and basic anthropometric data – especially BMI – for the prediction of BFP is not novel, quite to the contrary: the earliest reports on this question go back to the early '90s (see e.g. the work of Deurenberg et al [33]). These studies [33, 34, 35, 36, 37, 38] reported R^2s about 65-90% of which our results fell short.

Our linear regression was inferior in a sense that we assumed no interaction between weight and height, thus the model was unable to capture a construct like BMI which was given as an input in the previous examples. Neural networks, however, specifically have the advantage of being able to find even such possibly non-linear functional forms, so this cannot explain our findings. A much more likely explanation is that those studies analyzed males and females together. As their BFP very markedly differs (and can be simply captured by including gender as an explanatory variable) such models have a huge advantage in terms of R^2, as the overall variance is larger and that increase can be well desribed by

the gender variable. In contrast our model was focused solely on males, which inevitably led to worse R^2, but a more realistic estimate of how the model works for a particular gender.

Few studies examined the application of machine learning tools, such as neural networks or support vector machines in predicting body fat percentage from anthropometric and/or laboratory data. Kupusinac et al [39, 40] investigated neural networks for the very same task, Almeida et al [41] used further anthropometric variables, while Shao [42] applied hybrid approaches, however, we could not find any studies that incorporated laboratory results. This underlines the novelty of the present research, but also shows that – despite the current findings – further research using soft computing methods is warranted to have a more comprehensive picture.

Naturally, our study has several limitations. We have no data on the dynamics of these variables – predictors and BFP as well – as we have used a cross-sectional database, with no follow-up. Thus, we cannot infer on how the changes of BFP are followed by the changes in the predictors (or vice versa). Also, while we performed a rather careful internal validation – through bootstrap –, there was no external validation. Temporal external validation is an attractive option, limited by the availability (and differences in the measurement) of BFP in the NHANES cycles. Using databases from other countries is also a feasible option that can also shed light on potential genetic differences. Finally, some of the predictor variables might be subject to some degree of subjectivity when measurement is concerned (differences in definitions and measurement methods, possible measurement errors etc.), which was not a problem within the framework of a single, and very well-regulated study, but might be a problem when several different data sources are used.

5. Conclusions

The soft computing methods investigated in the present study were not able to substantially outperform simple linear regression. While support vec-

tor machine did exhibit some advantage (but even it had an R^2 of 44%), it is overall balanced by the fact that regression models are clinically interpretable, i.e. "white-box". While for some modern methods of machine learning, exploration of the models is a possibility, we aimed to focus on very well established, classical methods. Inclusion of other soft computing methods is an interesting and relevant possible research direction.

A further possible future research direction is the investigation of variable (predictor) importance, with different models. Knowing what variables are important in the prediction of BFP might give important insight; however, the measurement of variable importance is not trivial, especially when multiple – fundamentally different – models are involved, and their results should be compared [43].

The present investigation was unable to replicate the studies that reported R^2 over 60-70% for similar tasks, even with laboratory parameters included, the likely reason of which is the inclusion of only one gender.

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Author declaration

There are no conflicts of interest associated with this publication and there has been no financial support for this work that could have influenced its outcome.

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Figure1

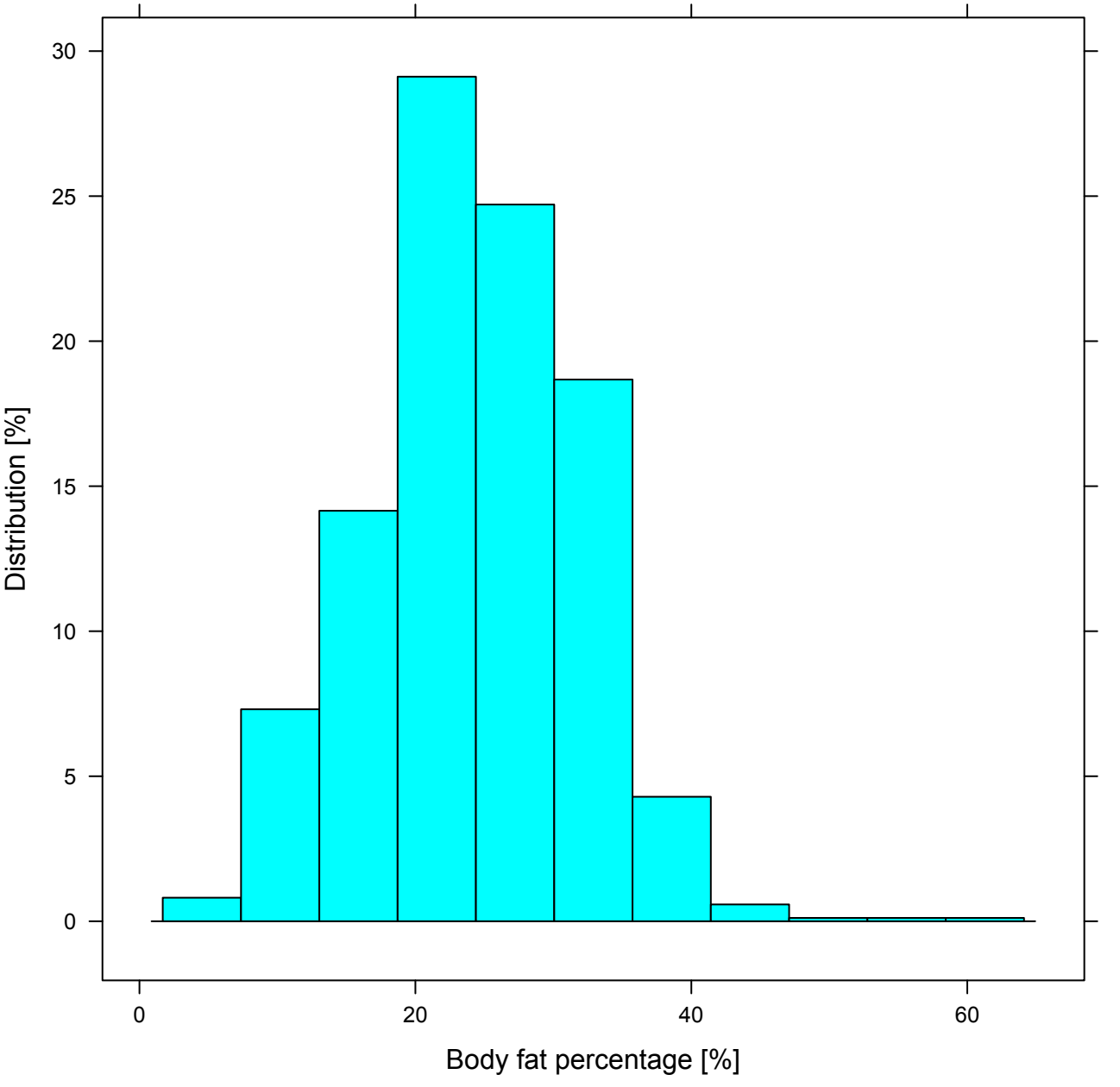


Figure2

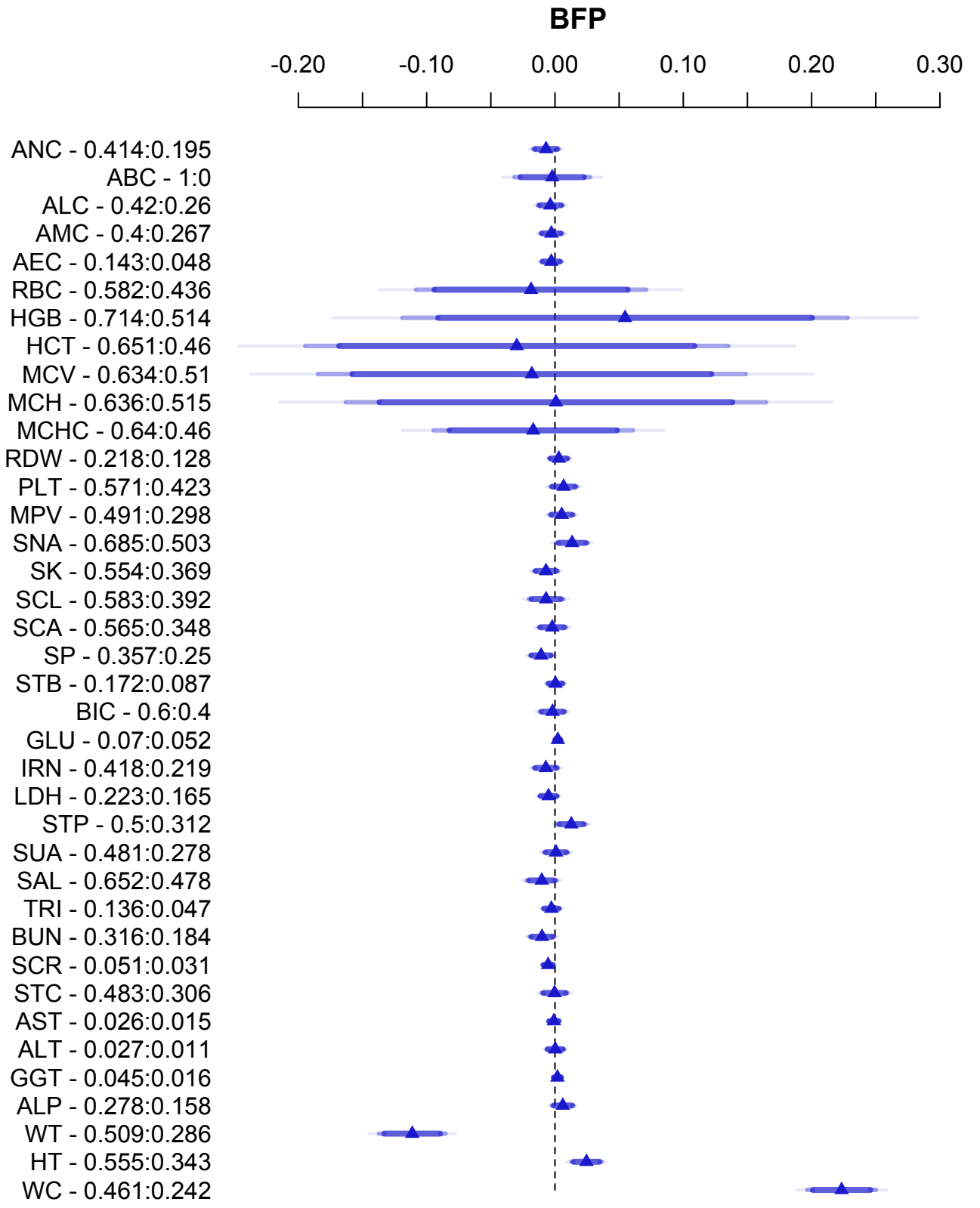

BFP
-0.20
-0.10
0.00
0.10
0.20
0.30
ANC - 0.414:0.195
ABC - 1:0
ALC - 0.42:0.26
AMC - 0.4:0.267
AEC - 0.143:0.048
RBC - 0.582:0.436
HGB - 0.714:0.514
HCT - 0.651:0.46
MCV - 0.634:0.51
MCH - 0.636:0.515
MCHC - 0.64:0.46
RDW - 0.218:0.128
PLT - 0.571:0.423
MPV - 0.491:0.298
SNA - 0.685:0.503
SK - 0.554:0.369
SCL - 0.583:0.392
SCA - 0.565:0.348
SP - 0.357:0.25
STB - 0.172:0.087
BIC - 0.6:0.4
GLU - 0.07:0.052
IRN - 0.418:0.219
LDH - 0.223:0.165
STP - 0.5:0.312
SUA - 0.481:0.278
SAL - 0.652:0.478
TRI - 0.136:0.047
BUN - 0.316:0.184
SCR - 0.051:0.031
STC - 0.483:0.306
AST - 0.026:0.015
ALT - 0.027:0.011
GGT - 0.045:0.016
ALP - 0.278:0.158
WT - 0.509:0.286
HT - 0.555:0.343
WC - 0.461:0.242

Figure3a

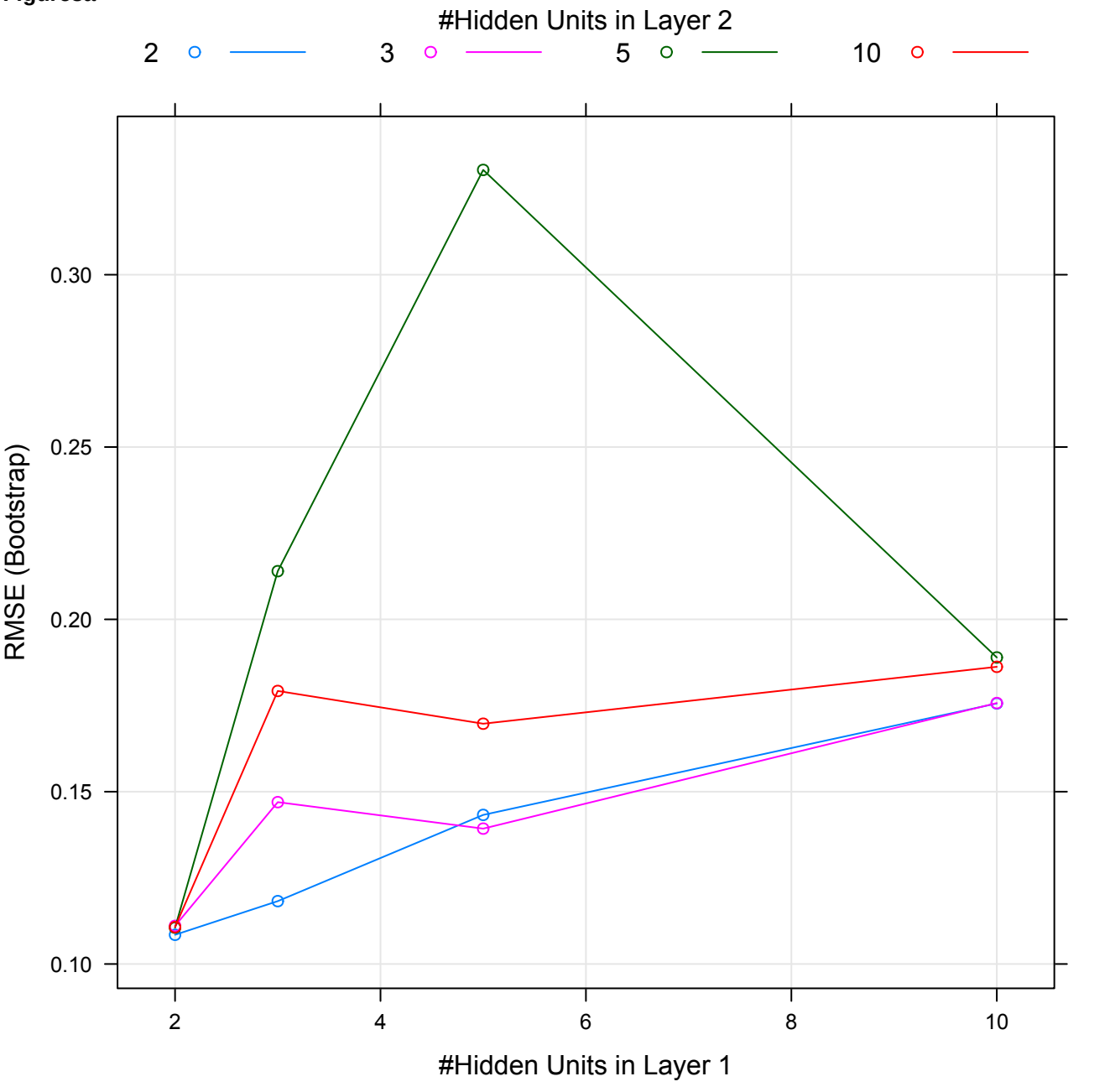

#Hidden Units in Layer 2
2
3
5
10
RMSE (Bootstrap)
0.10
0.15
0.20
0.25
0.30
2
4
6
8
10
#Hidden Units in Layer 1

Figure3b

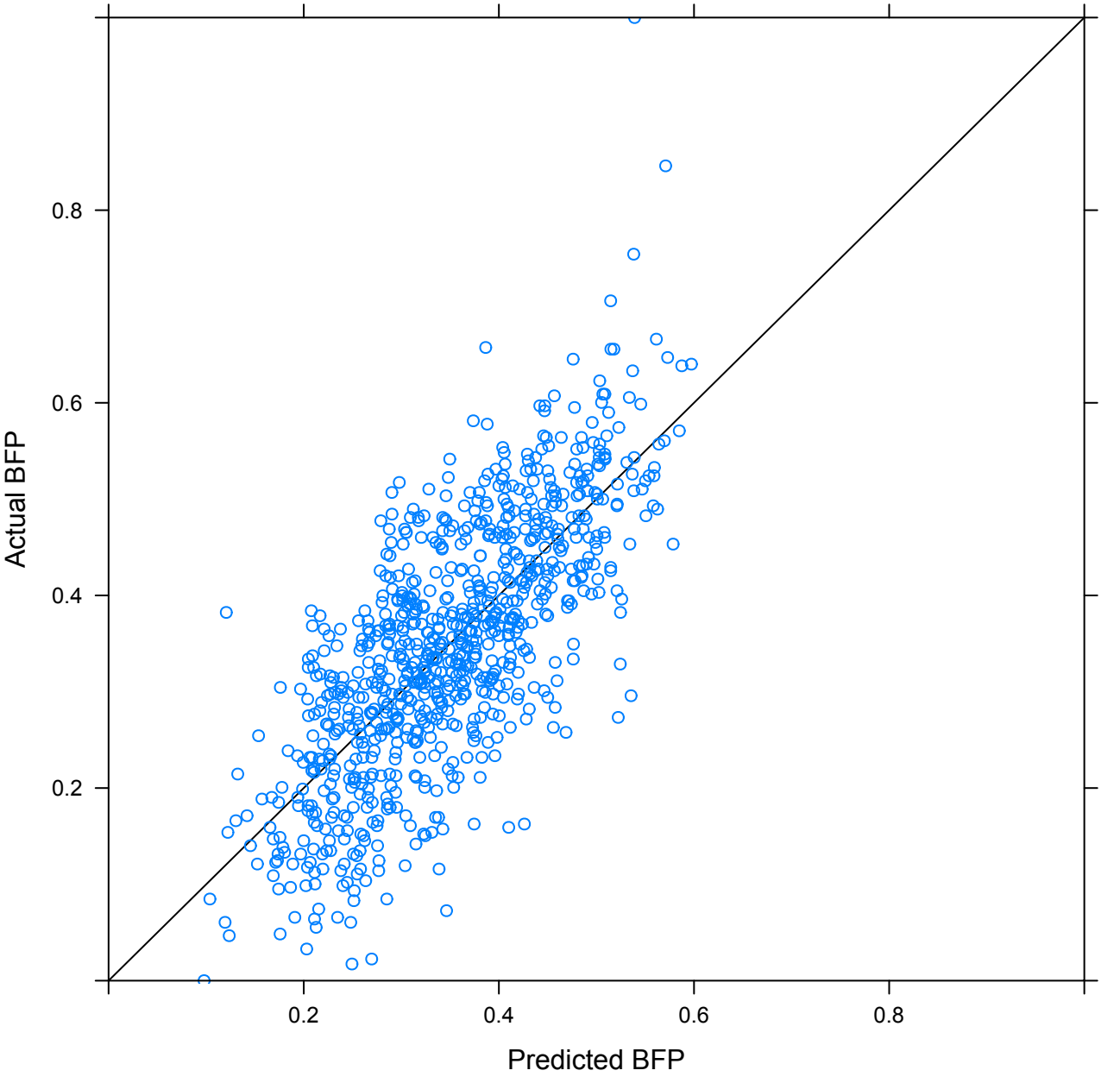


Figure4a

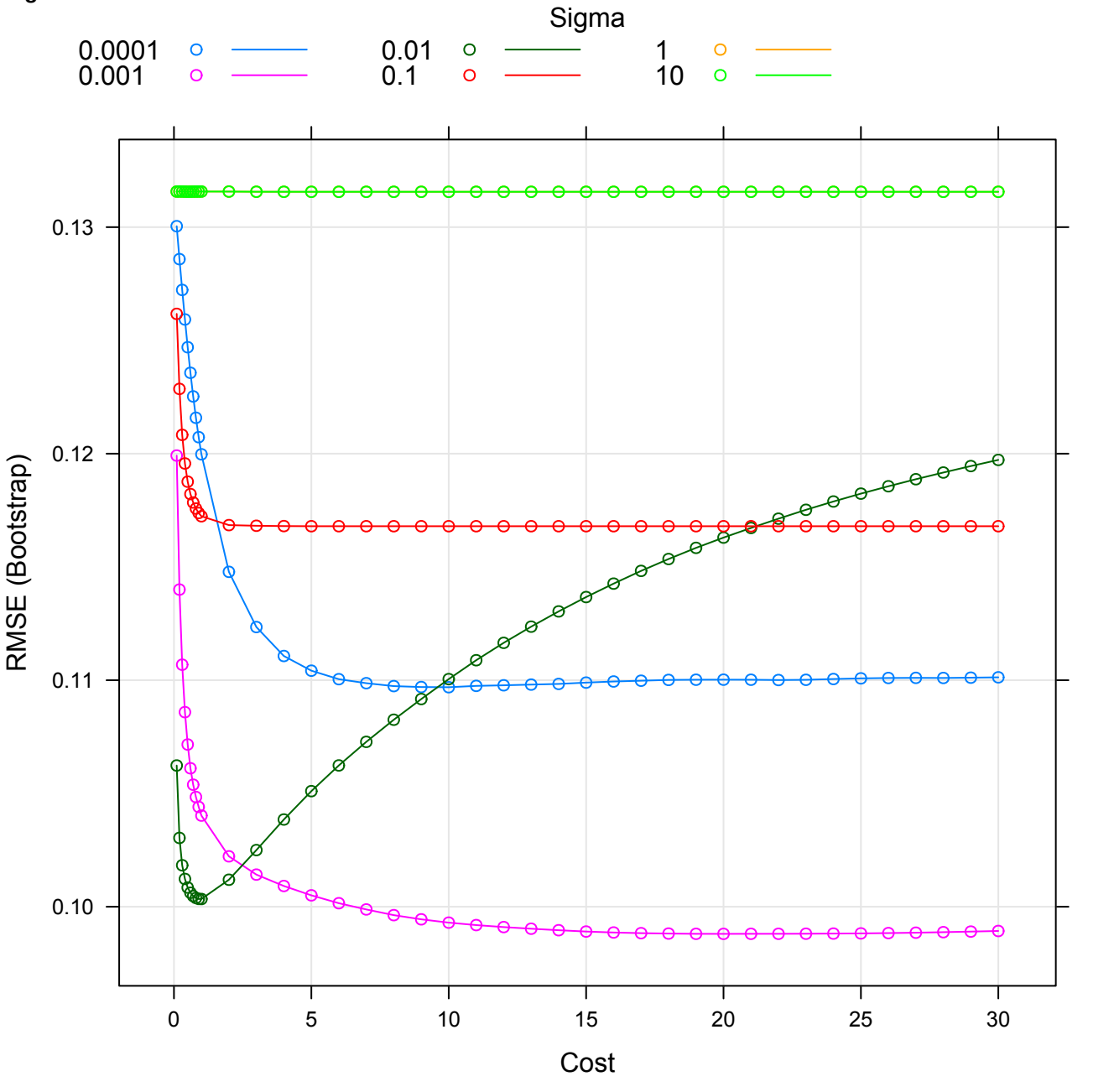

Sigma
0.0001
0.001
0.01
0.1
1
10
RMSE (Bootstrap)
0.13
0.12
0.11
0.10
0
5
10
15
20
25
30
Cost

Figure4b

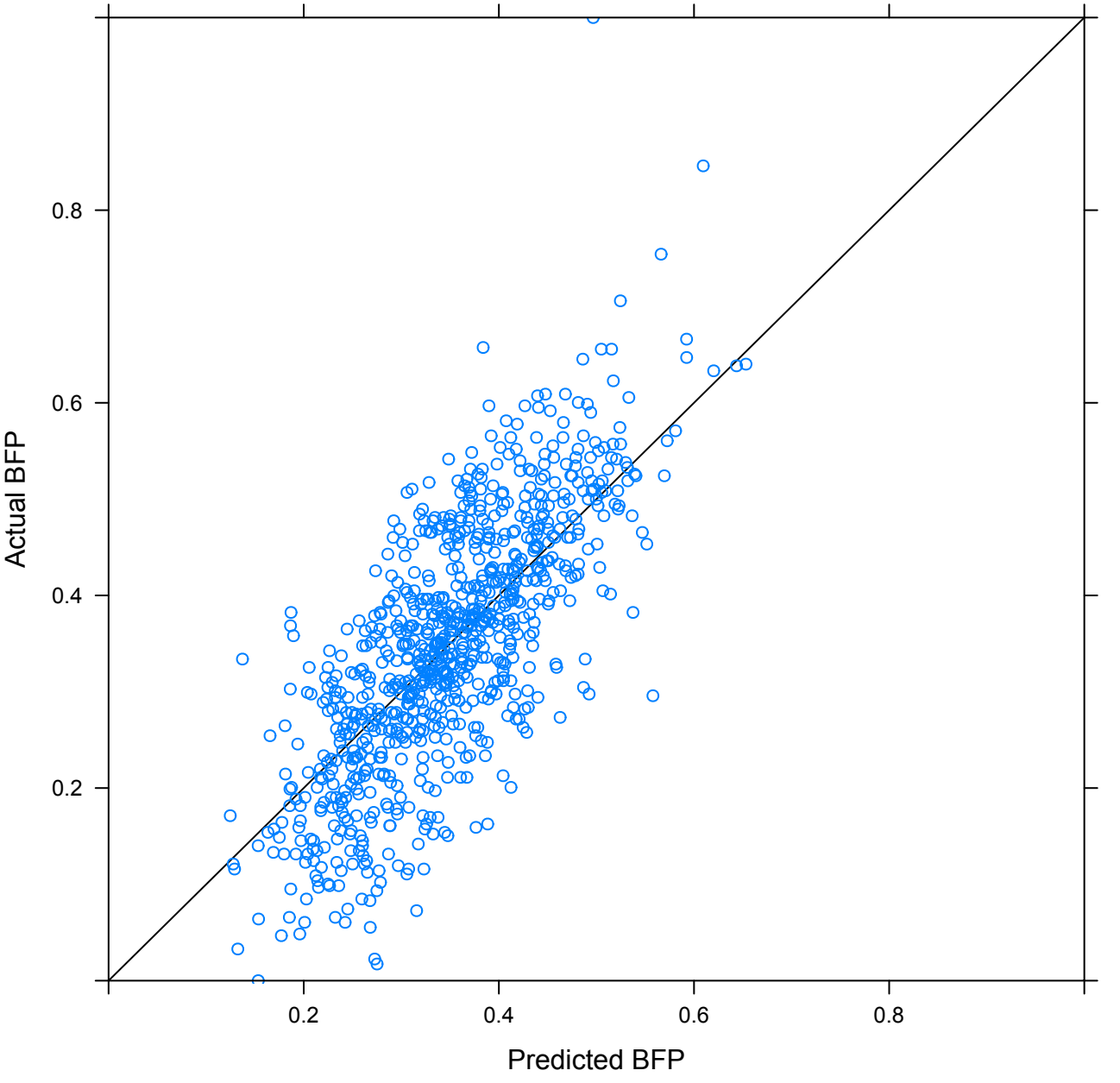


Figure5

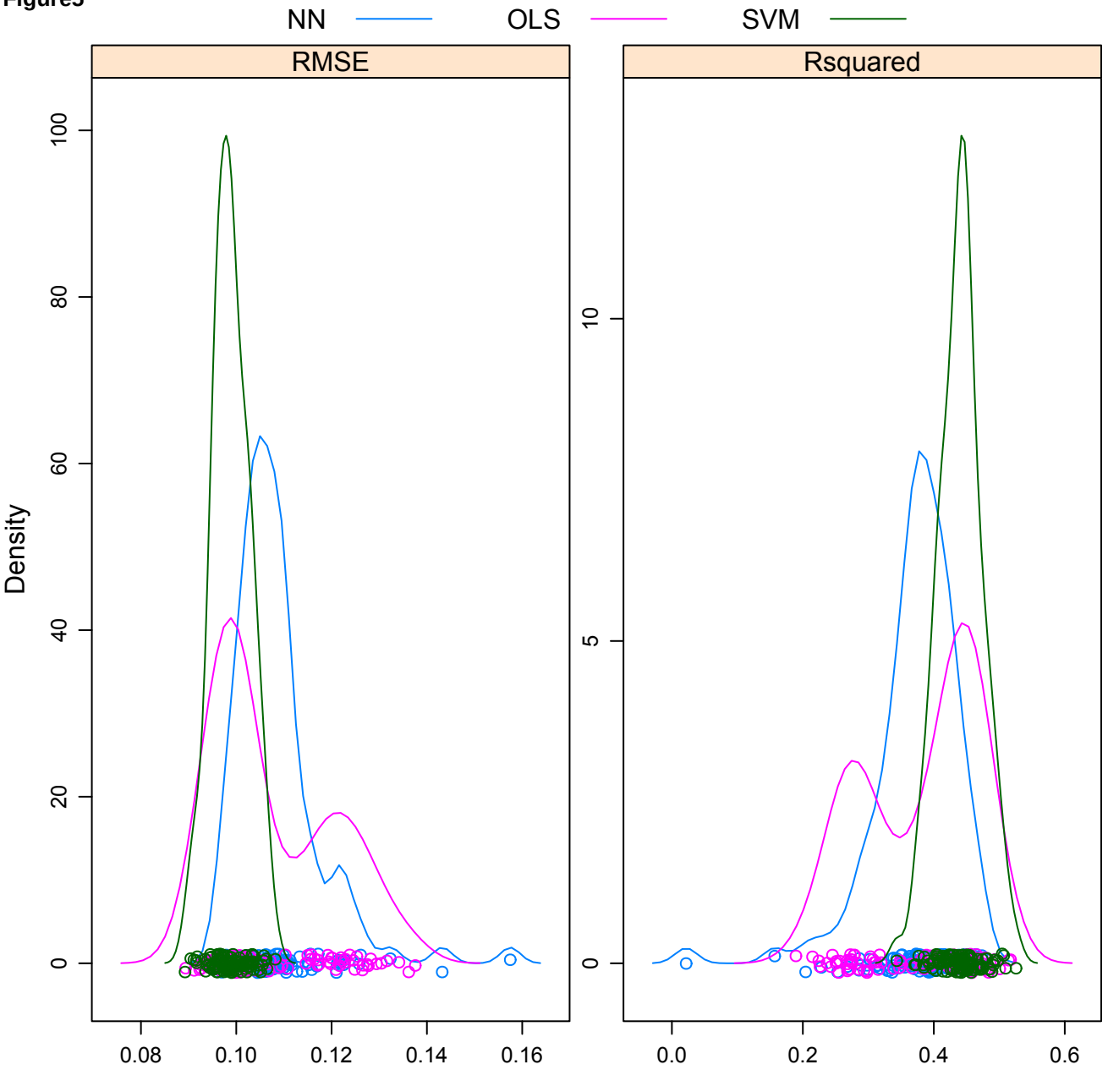

NN
OLS
SVM
RMSE
Rsquared
Density
0
20
40
60
80
100
0
5
10
0.08
0.10
0.12
0.14
0.16
0.0
0.2
0.4
0.6

Figure6a

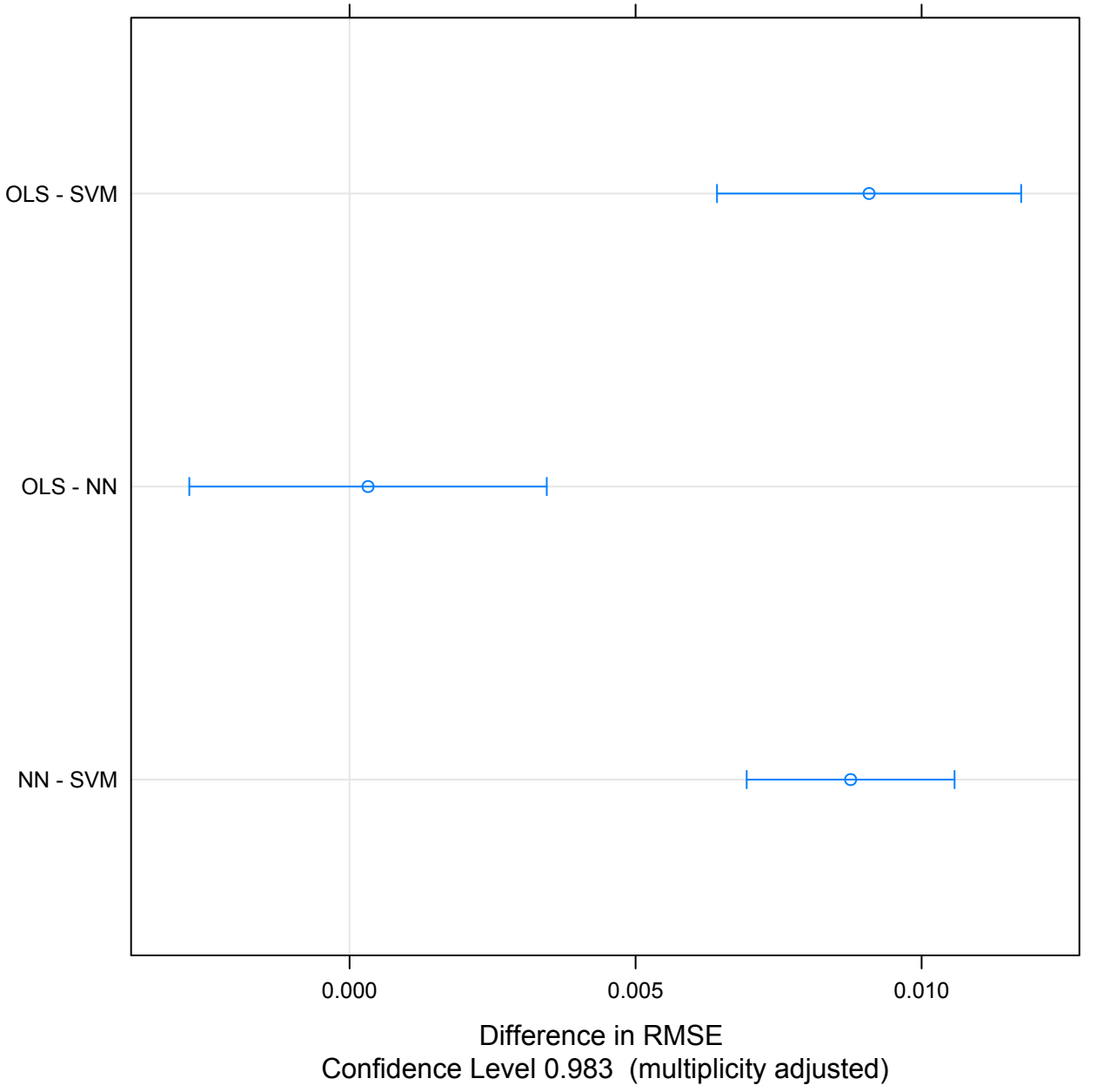
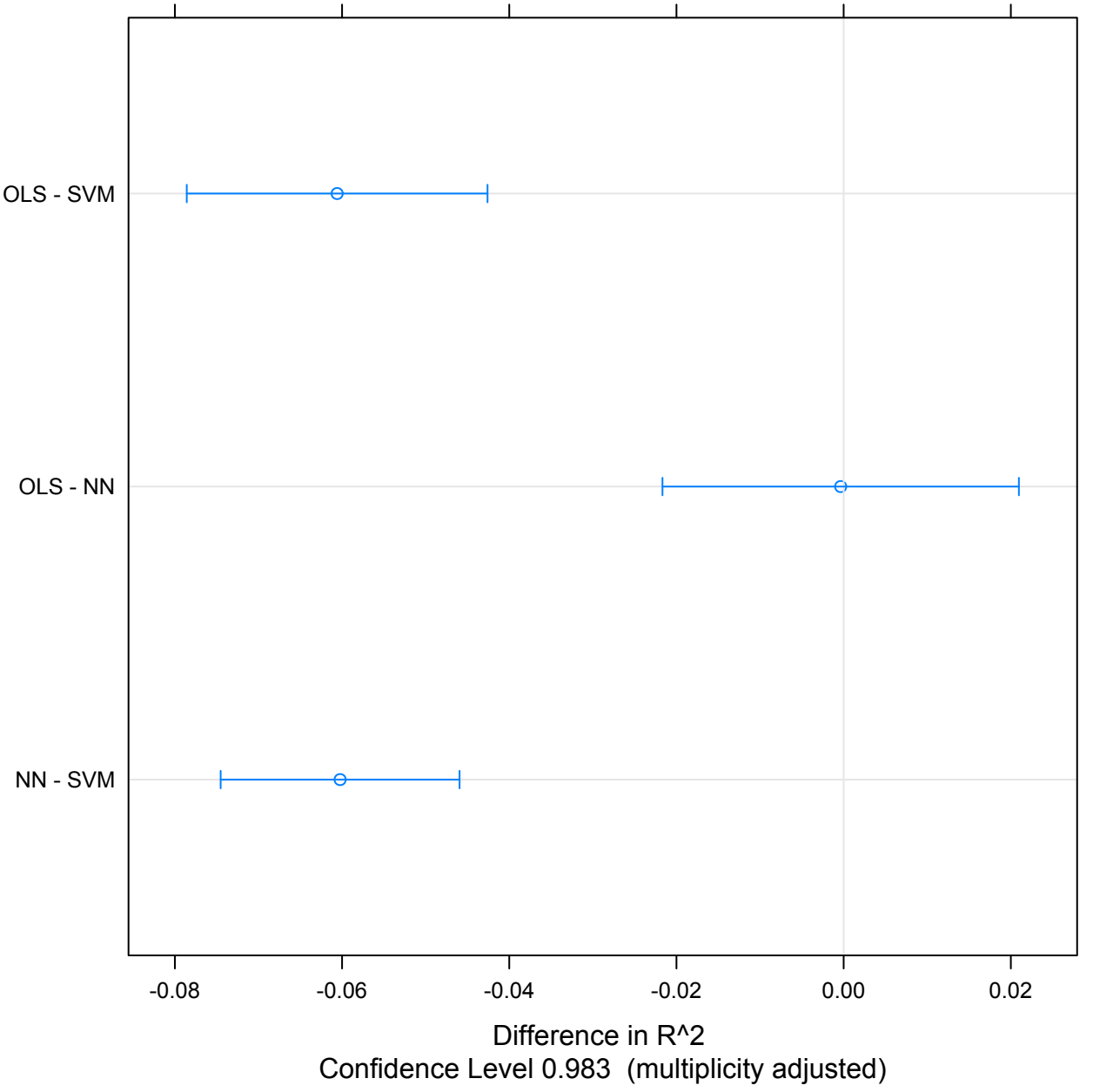

OLS - SVM
OLS - NN
NN - SVM
0.000
0.005
0.010
Difference in RMSE
Confidence Level 0.983 (multiplicity adjusted)

Figure6b


OLS - SVM
OLS - NN
NN - SVM
-0.08
-0.06
-0.04
-0.02
0.00
0.02
Difference in R^2
Confidence Level 0.983 (multiplicity adjusted)