1 Introduction

To improve health management, accurately predicting body fat percentage has become crucial. This project aims to develop a simple, accurate, and robust model with clinical indicators, and provide users with a friendly interface that enables people to track their body fat index.

2 Data Processing

The target variable, body fat, follows a normal distribution $N(18.9, 7.75)$; its extreme values are 0% and 45.1%, both of which are abnormal. For these two outliers, we replace them with the average body fat within ±5 years of age of the corresponding samples. Similarly, we use z-score with a threshold of 3 to detect other outliers and impute them in the same way. Next, we split the whole set at an 8:2 ratio and randomly select an equal number of samples from three age groups, [20-40), [40-60) and [60, 81], as the test set; then the rest becomes the training set.

3 Final Model Statement

$$\begin{aligned}\text{BODYFAT} = {} & 0.7684 \cdot \text{ADBOMEN} - 0.2623 \cdot \text{CHEST} - 0.3255 \cdot \text{HIP} + \\ & 0.3044 \cdot \text{THIGH} + 0.0345 \cdot \text{AGE} - 13.2971 \qquad (*)\end{aligned}$$

3.1 Usage Example

A man aged 40 with abdomen, chest, hip, and thigh circumferences(cm) of 86.6, 97, 92.6, and 55.9 respectively is expected to have a body fat of 16.06% based on our model; His 95% prediction interval is 11.71% and 20.41%.

3.2 Interpretation

Estimated coefficients are shown by $(*)$ in the units of centimeters for all circumferences and years for age. This means that for each year increase in age while all the other measurements remain constant, the model predicts that body fat will increase, on average, by 0.0345%.

4 Relevant Statistical Analysis

4.1 Model Selection

4.1.1 Selection Criteria

We develop the selection criteria in terms of accuracy, simplicity, and robustness. For model accuracy, we consider the root mean square error(RMSE) and the coefficient of determination(R^2) on the training set. A lower RMSE indicates that the model fits training data well; A R^2 closer to 1 indicates a better degree of fit. For model simplicity, we count how many predictors are included, and evaluate whether the rationale is easy to interpret. For robustness, we consider RMSE and R^2 on the test set. Since the test set is unseen during training, a good performance suggests that the model is generalizable and adaptive for new inputs.

4.1.2 Candidate Models

We have proposed four candidate models in total:

(1) Baseline. A basic linear regression model involving only height and weight.
(2) Ridge regression. Linear regression with ridge penalty and all the 14 predictors[1].
(3) Lasso regression with 5-fold cross-validation(CV). Among features with the largest absolute coefficients, we pick five most common ones to fit again from scratch. The final model involves age, chest, abdomen, hip, and thigh circumstances.
(4) An SVM regression model involving the same five predictors as the candidate model (3).

4.1.3 Comparison

From Table 1, although (1) is the simplest, it performs the worst. We do not want to sacrifice accuracy too much for simplicity. (2), (3), and (4) result in similar accuracy and robustness. Despite a slightly better accuracy, (2) includes 14 predictors, which is too many to be further generalized. (4) applies a complex methodology that is not friendly for comprehension and performs worse than (3). So we choose (3) as our final model. (3) contains five common

[1]Age, height, wight, Adioposity, and ten circumferences (neck, chest, abdomen, hip, thigh, knee, ankle, biceps, forearm, wrist).

predictors and performs well; its rationale is also intuitive. It should be noted that we made this decision only based on our criteria and did not consider the process of model construction.

Since coefficients returned by lasso are biased, we cannot conduct standard significance testing. However, CV results show that (3) performs similarly on training and test sets, which confirms its robustness and implies that it can explain about 63% of the body fat variance.

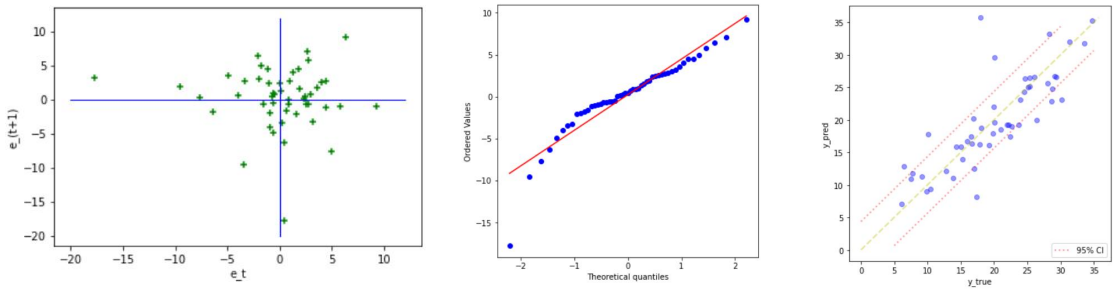
Table 1. Comparison among Candidate Models

Criteria / Candidate Model	Accuracy (Training set)		Simplicity		Robustness (Test set)	
	RMSE	R^2	#Parameters	Methodology	RMSE	R^2
(1) Baseline: Linear regression	5.4799	0.4445	2	Linear regression	5.0462	0.5154
(2) Ridge regression	4.2354	0.6682	14	Linear regression	4.3720	0.6363
(3) LassoCV regression	4.4722	0.6300	5	Linear regression	4.3568	0.6388
(4) SVM regression	4.5940	0.6096	5	SVM regression	4.4429	0.6244

4.2 Model Diagnostics

4.2.1 Residual Analysis

Results are shown in Figure 1. There is no obvious trend in Figure 1(a), meaning that the residuals are irrelevant. Except for a few outliers, most residuals are normally distributed (Figure 1(b)); Most true values are located in the 95% confidence interval of predicted ones.



(a) (b) (c)

Figure 1. Residual Analysis.

(a): Residual Plot. (b). Q-Q Plot of the Residuals. (c) Scatter Plot of predicted and true values on the test set.

4.2.1 Outlier Analysis

We check the outlier with the largest residual value(Table 2). It turns out that its original body fat is an outlier and the imputed one used is very far from the original. However, the prediction provided by our model falls between the two, balancing this difference to some extent. This shows that our model is able to adjust for aberrant values and again confirms its robustness.

Table 2. Outlier Analysis for the Largest Residual

Body Fat - Original	Body Fat - imputed	Body Fat - predicted	Age	Chest	Abdomen	Hip	Thigh
45.1	17.98	35.74	51	119.8	122.1	112.8	62.5

5 Discussion

5.1 Model Strengths and Weaknesses

Compared with other candidates, our final model reduces the number of predictors from 14 to 5 and achieves the best overall performance. However, the R^2 on the test set is 0.6388, which is acceptable but not convincing enough for a mature product. This could be improved with a larger dataset and a more powerful methodology.

5.2 Conclusions

To find the best model for body fat, we have compared four regression models and chosen the one with lasso regularization and CV. This model shows good accuracy and robustness on both training and test sets, although limitations still exist. We believe it can be better polished with superior techniques if time permits.

References

[1] Scikit-learn: Machine Learning in Python, Pedregosa et al., JMLR 12, pp. 2825-2830, 2011.

Contribution Table

Contributions	Shan Leng	Siyan Wang	Ruotong Zhang
Presentation	Reviewed, edited, and provided feedback on all slides.	Responsible for slides.	Reviewed, edited and provided feedback on all slides.
Summary	Responsible for final model statement, relevant statistical analysis and model diagnostics; Reviewed and edited all sections.	Responsible for discussion and provided feedback on whole document.	Responsible for introduction and data processing; Provided feedback on whole document.
Code	Responsible for model construction and diagnostics code.	Reviewed code.	Responsible for data cleaning code.
Shiny App	Provided feedback on Shiny app.	Responsible for Shiny app.	Reviewed Shiny app.