

# P8160 - Breast Cancer Diagnosis

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## 1. Objectives

Mammography is recognized as the most effective screening method for early breast cancer detection, but its accuracy remains limited. And as the number of variables that help predict breast cancer increases, doctors are forced to rely more on their subjective experiences to make decisions. The use of computer models can detect abnormalities in mammograms to aid radiologists in breast cancer diagnosis (Freer et al. 2001). The purpose of this study was to predict breast cancer benign/malignant status by quantitative modeling based on logistic regression, which may help radiologists manage the large amount of available information, make effective decisions to detect breast cancers and reduce unnecessary biopsy.

## 2. Background

The data given has 569 observations. The column ‘Diagnosis’ which identifies if the image is coming from cancer tissue or benign cases (M=malignant, B = benign) would be used as outcome for modeling. We denote malignant as 1 and benign cases as 0 for prediction. The other 30 columns correspond to mean, standard deviation and the largest values (points on the tails) of the distributions of the following 10 features computed for the cell nuclei:

- radius: mean of distances from center to points on the perimeter
- texture: standard deviation of gray-scale values
- perimeter: mean size of the core tumor
- area: mean area of the core tumor
- smoothness: local variation in radius lengths
- compactness:  $\text{perimeter}^2/\text{area} - 1.0$
- concavity: severity of concave portions of the contour
- concave points: number of concave portions of the contour
- symmetry: symmetry of the tumor
- fractal dimension: "coastline approximation" - 1

As exploring the breast cancer data, there are many predictors are highly correlated to each other as shown in the Figure 0, such as ‘area\_mean’, ‘perimeter\_worst’, ‘radius\_mean’ and so on, that could cause unstable parameter estimation as well as perplexing the interpretation of logistic model. While we could eliminate some correlated features for modeling as shown in the Figure B, regularized logistic regression also help to tackle with it, which would be further explore in the following parts.

## 2. Methods

### 2.1. Logistic Model

Logistic model measure the probability of an event taking place by having the log-odds for the event be a linear combination of one or more independent variables, and commonly used in classifying binary response variables.

Hereby, the variable “Diagnosis” is a binary response variable indicating if the image is coming from cancer tissue or benign cases (M = malignant, B = benign). In the following logistic regression model, the “Diagnosis” variable will be coded as 1 for malignant cases and 0 for benign cases.

Given  $n$  i.i.d. observations with  $p$  predictors, we consider a logistic regression model

$$P(Y_i = 1 \mid \mathbf{x}_i) = \frac{e^{\mathbf{x}_i^\top \beta}}{1 + e^{\mathbf{x}_i^\top \beta}}, \quad i = 1, \dots, n \quad (1)$$

where  $\beta = (\beta_0, \beta_1, \dots, \beta_p)^\top \in \mathbb{R}^{p+1}$  is the parameter vector,  $\mathbf{x}_i = (1, X_{i1}, \dots, X_{ip})^\top$  is the vector of predictors in the  $i$ -th observation, and  $Y_i \in \{0, 1\}$  is the binary response in the  $i$ -th observation. Let  $\mathbf{y} = (Y_1, Y_2, \dots, Y_n)^\top$  denote the response vector,  $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n)^\top \in \mathbb{R}^{n \times (p+1)}$  denote the design matrix. The observed likelihood of  $\{(Y_1, \mathbf{x}_1), (Y_2, \mathbf{x}_2), \dots, (Y_n, \mathbf{x}_n)\}$  is

$$L(\beta; \mathbf{y}, \mathbf{X}) = \prod_{i=1}^n \left[ \left( \frac{e^{\mathbf{x}_i^\top \beta}}{1 + e^{\mathbf{x}_i^\top \beta}} \right)^{Y_i} \left( \frac{1}{1 + e^{\mathbf{x}_i^\top \beta}} \right)^{1-Y_i} \right].$$

Maximizing the likelihood is equivalent to maximizing the log-likelihood function:

$$f(\beta; \mathbf{y}, \mathbf{X}) = \sum_{i=1}^n \left[ Y_i \mathbf{x}_i^\top \beta - \log(1 + e^{\mathbf{x}_i^\top \beta}) \right]. \quad (2)$$

The estimates of model parameters are

$$\hat{\beta} = \arg \max_{\beta} f(\beta; \mathbf{y}, \mathbf{X}),$$

and the optimization problem is

$$\max_{\beta} f(\beta; \mathbf{y}, \mathbf{X}). \quad (3)$$

Denote  $p_i = P(Y_i = 1 \mid \mathbf{x}_i)$  as given in (1) and  $\mathbf{p} = (p_1, p_2, \dots, p_n)^\top$ . The gradient of  $f$  is

$$\begin{aligned} \nabla f(\beta; \mathbf{y}, \mathbf{X}) &= \mathbf{X}^\top (\mathbf{y} - \mathbf{p}) \\ &= \sum_{i=1}^n (Y_i - p_i) \mathbf{x}_i \\ &= \begin{pmatrix} \sum_{i=1}^n (Y_i - p_i) \\ \sum_{i=1}^n (Y_i - p_i) X_{i1} \\ \vdots \\ \sum_{i=1}^n (Y_i - p_i) X_{ip} \end{pmatrix}. \end{aligned}$$

Denote  $w_i = p_i(1 - p_i) \in (0, 1)$  and  $\mathbf{W} = \text{diag}(w_1, \dots, w_n)$ . The Hessian matrix of  $f$  is given by

$$\begin{aligned} \nabla^2 f(\beta; \mathbf{y}, \mathbf{X}) &= -\mathbf{X}^\top \mathbf{W} \mathbf{X} \\ &= -\sum_{i=1}^n w_i \mathbf{x}_i \mathbf{x}_i^\top \\ &= -\begin{pmatrix} \sum_{i=1}^n w_i & \sum_{i=1}^n w_i X_{i1} & \cdots & \sum_{i=1}^n w_i X_{i1} X_{ip} \\ \sum_{i=1}^n w_i X_{i1} & \sum_{i=1}^n w_i X_{i1}^2 & \cdots & \sum_{i=1}^n w_i X_{i1} X_{ip}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{i=1}^n w_i X_{ip} & \sum_{i=1}^n w_i X_{ip} X_{i1} & \cdots & \sum_{i=1}^n w_i X_{ip}^2 \end{pmatrix}. \end{aligned}$$

Next, we show that the Hessian matrix  $\nabla^2 f(\beta; \mathbf{y}, \mathbf{X})$  is a negative-definite matrix if  $\mathbf{X}$  has full rank.

**Proof.** For any  $(p+1)$ -dimensional nonzero vector  $\alpha$ , given that  $\mathbf{X}$  has full rank,  $\mathbf{X}\alpha$  is also a nonzero vector. Since  $\mathbf{W}$  is positive-definite, we have

$$\begin{aligned} \alpha^\top \nabla^2 f(\beta; \mathbf{y}, \mathbf{X}) \alpha &= \alpha^\top (-\mathbf{X}^\top \mathbf{W} \mathbf{X}) \alpha \\ &= -(\mathbf{X}\alpha)^\top \mathbf{W} (\mathbf{X}\alpha) \\ &< 0. \end{aligned}$$

Thus,  $\nabla^2 f(\beta; \mathbf{y}, \mathbf{X})$  is negative-definite. □

Hence, the optimization problem (3) is a well-defined problem.

## 2.2. Newton-Raphson Algorithm

### 2.2.1 Algorithm Design

While derivative of the likelihood function with respect to the parameters is nonlinear and difficult to solve analytically for maximum likelihood, it requires Newton-Raphson iterations. The target function  $f$  given in task 1:

$$f(\beta; \mathbf{y}, \mathbf{X}) = \sum_{i=1}^n [Y_i \mathbf{x}_i^\top \beta - \log(1 + e^{\mathbf{x}_i^\top \beta})]. \quad (4)$$

We develop a modified Newton-Raphson algorithm including a step-halving step. *(we probably don't need to ensure that the direction of the step is an ascent direction, since in this example Hessian is always negative-definite. but Hessian could be computationally singular when the starting points are bad)*

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**Algorithm 1** Newton-Raphson algorithm including a step-halving step

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**Require:**  $f(\beta)$  - target function as given in (4);  $\beta_0$  - starting value

**Ensure:**  $\hat{\beta}$  such that  $\hat{\beta} \approx \arg \max_{\beta} f(\beta)$

$i \leftarrow 0$ , where  $i$  is the current number of iterations

$f(\beta_{-1}) \leftarrow -\infty$

**while** convergence criterion is not met **do**

$i \leftarrow i + 1$

$\mathbf{d}_i \leftarrow -[\nabla^2 f(\beta_{i-1})]^{-1} \nabla f(\beta_{i-1})$ , where  $\mathbf{d}_i$  is the direction in the  $i$ -th iteration

$\lambda_i \leftarrow 1$ , where  $\lambda_i$  is the multiplier in the  $i$ -th iteration

$\beta_i \leftarrow \beta_{i-1} + \lambda_i \mathbf{d}_i$

**while**  $f(\beta_i) \leq f(\beta_{i-1})$  **do**

$\lambda_i \leftarrow \lambda_i / 2$

$\beta_i \leftarrow \beta_{i-1} + \lambda_i \mathbf{d}_i$

**end while**

**end while**

$\hat{\beta} \leftarrow \beta_i$

---

### 2.2.2 Complete Separation Problem

However, the function does not converge when a complete separation occurs. A complete separation in a logistic regression, also referred as perfect prediction, which occurs whenever there exists some vector of coefficients  $\beta$  such that  $Y_i = 1$  whenever  $X_i^T \beta > 0$  and  $Y_i = 0$  whenever  $X_i^T \beta \leq 0$ . In other words, complete separation occurs whenever a linear function of predictors can generate perfect predictions of response.

To further explain this problem, we prove that: if there exists a vector of coefficients  $\hat{\beta}$  such that  $Y_i = 1$  whenever  $\mathbf{x}_i^\top \hat{\beta} > 0$  and  $Y_i = 0$  whenever  $\mathbf{x}_i^\top \hat{\beta} \leq 0$ , there does not exist  $\beta^* \in \mathbb{R}^{(p+1)}$  such that  $\beta^* = \arg \max_{\beta} f(\beta)$ , where  $f$  is given in (4). Thus our Newton-Raphson algorithm does not converge.

**Proof.** Assume such  $\beta^*$  exists, then  $\forall \beta \in \mathbb{R}^{p+1}$ , we have  $f(\beta) \leq f(\beta^*)$ .

First, we prove that: there exists a vector of coefficients  $\tilde{\beta}$  such that  $Y_i = 1$  whenever  $\mathbf{x}_i^\top \tilde{\beta} > 0$  and  $Y_i = 0$  whenever  $\mathbf{x}_i^\top \tilde{\beta} < 0$ .

Let  $A_1 = \{i : Y_i = 1\} = \{i : \mathbf{x}_i^\top \hat{\beta} > 0\}$  and  $A_0 = \{i : Y_i = 0\} = \{i : \mathbf{x}_i^\top \hat{\beta} \leq 0\}$ . Then we have

$$\epsilon := \min_{i \in A_1} (\mathbf{x}_i^\top \hat{\beta}) > 0.$$

Let  $\tilde{\beta} = \hat{\beta} - (\epsilon/2, 0, \dots, 0)^\top$ . Given that  $X_{i0} = 1$  for all  $i$ , we have

$$\begin{aligned} \mathbf{x}_i^\top \tilde{\beta} &= \mathbf{x}_i^\top \hat{\beta} - \epsilon/2 \cdot 1 \geq \epsilon - \epsilon/2 = \epsilon/2 > 0, \quad \forall i \in A_1 \\ \mathbf{x}_i^\top \tilde{\beta} &= \mathbf{x}_i^\top \hat{\beta} - \epsilon/2 \cdot 1 \leq 0 - \epsilon/2 = -\epsilon/2 < 0, \quad \forall i \in A_0 \end{aligned}$$

Thus we have  $A_1 = \{i : Y_i = 1\} = \{i : \mathbf{x}_i^\top \tilde{\beta} > 0\}$  and  $A_0 = \{i : Y_i = 0\} = \{i : \mathbf{x}_i^\top \tilde{\beta} < 0\}$ .

Next, we prove that

$$\lim_{k \rightarrow \infty} f(k\tilde{\beta}) = 0. \quad (5)$$

$\forall k > 0$ , we have  $A_1 = \{i : \mathbf{x}_i^\top (k\tilde{\beta}) > 0\}$  and  $A_0 = \{i : \mathbf{x}_i^\top (k\tilde{\beta}) < 0\}$ .

Thus,

$$\begin{aligned} \lim_{k \rightarrow \infty} f(k\tilde{\beta}) &= \lim_{k \rightarrow \infty} \sum_{i \in A_1} \left[ Y_i \mathbf{x}_i^\top (k\tilde{\beta}) - \log \left( 1 + e^{\mathbf{x}_i^\top (k\tilde{\beta})} \right) \right] + \lim_{k \rightarrow \infty} \sum_{i \in A_0} \left[ Y_i \mathbf{x}_i^\top (k\tilde{\beta}) - \log \left( 1 + e^{\mathbf{x}_i^\top (k\tilde{\beta})} \right) \right] \\ &= \sum_{i \in A_1} \lim_{k \rightarrow \infty} \left[ k \mathbf{x}_i^\top \tilde{\beta} - \log \left( 1 + e^{k \mathbf{x}_i^\top \tilde{\beta}} \right) \right] + \sum_{i \in A_0} \lim_{k \rightarrow \infty} \left[ -\log \left( 1 + e^{k \mathbf{x}_i^\top \tilde{\beta}} \right) \right] \\ &= \sum_{i \in A_1} \lim_{z \rightarrow \infty} [z - \log(1 + e^z)] + \sum_{i \in A_0} (-\log 1) \\ &= 0 + 0 = 0. \end{aligned}$$

Last, we prove that: there exists  $\beta \in \mathbb{R}^{p+1}$  such that  $f(\beta) > f(\beta^*)$ , which is contradictory to the statement that  $\forall \beta \in \mathbb{R}^{p+1}, f(\beta) \leq f(\beta^*)$ .

Note that  $f(\beta) < 0$  holds for any  $\beta \in \mathbb{R}$ , then we have  $f(\beta^*) < 0$ .

Given that  $f(\beta^*) < 0$  and (5) holds, there exists  $N \in \mathbb{R}$  such that  $\forall k > N, f(k\tilde{\beta}) > f(\beta^*)$ .

Thus our assumption must be false.  $\square$

### 2.3. Logistic-LASSO Model

Regularization is the common approach for variable selection, in which LASSO is to add L-1 penalty to the objective function. In the context of logistic regression, we turn to maximize the penalized log-likelihood as following:

- Log-likelihood  $f$  of logistic regression:

$$f(\beta; \mathbf{y}, \mathbf{X}) = \sum_{i=1}^n \left[ Y_i \mathbf{x}_i^\top \beta - \log \left( 1 + e^{\mathbf{x}_i^\top \beta} \right) \right].$$

- LASSO estimates the logistic model parameters  $\beta$  by optimizing a penalized loss function:

$$\min_{\beta} -\frac{1}{n} f(\beta) + \lambda \sum_{k=1}^p |\beta_k|. \quad (6)$$

where  $\lambda \geq 0$  is the tuning parameter. Note that the intercept is not penalized and all predictors are standardized.

Then we could develop a path-wise coordinate descent algorithm to the penalized weighted-least-squares problem with a sequence of nested loops:

**OUTER LOOP** In the outer loop, we compute the solutions of the optimization problem (6) for a decreasing sequence of values for  $\lambda$ :  $\{\lambda_1, \dots, \lambda_m\}$ , starting at the smallest value  $\lambda_1 = \lambda_{max}$  for which the estimates of all coefficients  $\hat{\beta}_j = 0, j = 1, 2, \dots, p$ , which is

$$\lambda_{max} = \max_{j \in \{1, \dots, p\}} \left| \frac{1}{n} \sum_{i=1}^n X_{ij} (Y_i - \bar{Y}) \right|, \quad (7)$$

**Algorithm 2** Path-wise coordinate-wise optimization algorithm

**Require:**  $g(\beta, \lambda) = -\frac{1}{n}f(\beta) + \lambda \sum_{k=1}^p |\beta_k|$  - target function, where  $f(\beta)$  is given in (4);  $\beta_0$  - starting value;  $\{\lambda_1, \dots, \lambda_m\}$  - a sequence of descending  $\lambda$ 's, where  $\lambda_1 = \lambda_{max}$  is given in (7);  $\epsilon$  - tolerance;  $N_s$ ,  $N_t$  - maximum number of iterations of the middle and inner loops

**Ensure:**  $\hat{\beta}(\lambda_r)$  such that  $\hat{\beta}(\lambda_r) \approx \arg \min_{\beta} g(\beta, \lambda_r)$ ,  $r = 1, \dots, m$

$\tilde{\beta}_0(\lambda_1) \leftarrow \beta_0$

OUTER LOOP

**for**  $r \in \{1, \dots, m\}$ , where  $r$  is the current number of iterations of the outer loop, **do**

$s \leftarrow 0$ , where  $s$  is the current number of iterations of the middle loop

$g(\tilde{\beta}_{s-1}(\lambda_r), \lambda_r) \leftarrow \infty$

MIDDLE LOOP

**while**  $t \geq 2$  and  $s < N_s$  **do**

$s \leftarrow s + 1$

Update  $\tilde{w}_i^{(s)}$ ,  $\tilde{z}_i^{(s)}$  ( $i = 1, \dots, n$ ), and thus  $\ell_s(\beta)$  as given in (8) based on  $\tilde{\beta}_{s-1}(\lambda_r)$

$t \leftarrow 0$ , where  $t$  is the current number of iterations of the inner loop

$\tilde{\beta}_s^{(0)}(\lambda_r) \leftarrow \tilde{\beta}_{s-1}(\lambda_r)$

$h_s(\tilde{\beta}_s^{(-1)}(\lambda_r), \lambda_r) \leftarrow \infty$ , where  $h_s(\beta, \lambda) = -\frac{1}{n}\ell_s(\beta) + \lambda \sum_{k=1}^p |\beta_k|$

INNER LOOP

**while**  $\left| h_s(\tilde{\beta}_s^{(t)}(\lambda_r), \lambda_r) - h_s(\tilde{\beta}_s^{(t-1)}(\lambda_r), \lambda_r) \right| > \epsilon$  and  $t < N_t$  **do**

$t \leftarrow t + 1$

$\tilde{\beta}_0^{(t)}(\lambda_r) \leftarrow \sum_{i=1}^n \tilde{w}_i^{(s)} \left( \tilde{z}_i^{(s)} - \sum_{k=1}^p X_{ik} \tilde{\beta}_k^{(t-1)}(\lambda_r) \right) / \sum_{i=1}^n \tilde{w}_i^{(s)}$

**for**  $j \in \{1, \dots, p\}$  **do**

$\tilde{\beta}_j^{(t)}(\lambda_r) \leftarrow S \left( \frac{1}{n} \sum_{i=1}^n \tilde{w}_i^{(s)} X_{ij} \left( \tilde{z}_i^{(s)} - \sum_{k < j} X_{ik} \tilde{\beta}_k^{(t)}(\lambda_r) - \sum_{k > j} X_{ik} \tilde{\beta}_k^{(t-1)}(\lambda_r) \right), \lambda_r \right) / \frac{1}{n} \sum_{i=1}^n \tilde{w}_i^{(s)} X_{ij}^2$

**end for**

**end while**

$\tilde{\beta}_s(\lambda_r) \leftarrow \tilde{\beta}_s^{(t)}(\lambda_r)$

**end while**

$\hat{\beta}(\lambda_r) \leftarrow \tilde{\beta}_s(\lambda_r)$

$\tilde{\beta}_0(\lambda_{r+1}) \leftarrow \hat{\beta}(\lambda_r)$

**end for**

where  $\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$ . For tuning parameter value  $\lambda_{k+1}$ , we initialize coordinate descent algorithm at the computed solution for  $\lambda_k$  (warm start). Apart from giving us a path of solutions, this scheme exploits warm starts, and leads to a more stable algorithm.

**MIDDLE LOOP** In the middle loop, we find the estimates of  $\beta$  by solving the optimization problem (6) for a fixed  $\lambda$ . For each iteration of the middle loop, based on the current parameter estimates  $\tilde{\beta}$ , we form a quadratic approximation to the log-likelihood  $f$  using a Taylor expansion:

$$\begin{aligned} f(\beta) &\approx \ell(\beta) = f(\tilde{\beta}) + (\beta - \tilde{\beta})^\top \nabla f(\tilde{\beta}) + \frac{1}{2} (\beta - \tilde{\beta})^\top \nabla^2 f(\tilde{\beta}) (\beta - \tilde{\beta}) \\ &= f(\tilde{\beta}) + [\mathbf{X}(\beta - \tilde{\beta})]^\top (\mathbf{y} - \tilde{\mathbf{p}}) - \frac{1}{2} [\mathbf{X}(\beta - \tilde{\beta})]^\top \tilde{\mathbf{W}} \mathbf{X}(\beta - \tilde{\beta}) \\ &= f(\tilde{\beta}) + \sum_{i=1}^n (Y_i - \tilde{p}_i) \mathbf{x}_i^\top (\beta - \tilde{\beta}) - \frac{1}{2} \sum_{i=1}^n \tilde{w}_i [\mathbf{x}_i^\top (\beta - \tilde{\beta})]^2 \\ &= -\frac{1}{2} \sum_{i=1}^n \tilde{w}_i \left\{ [\mathbf{x}_i^\top (\tilde{\beta} - \beta)]^2 + 2 \frac{Y_i - \tilde{p}_i}{\tilde{w}_i} [\mathbf{x}_i^\top (\tilde{\beta} - \beta)] \right\} + f(\tilde{\beta}) \\ &= -\frac{1}{2} \sum_{i=1}^n \tilde{w}_i \left[ \mathbf{x}_i^\top (\tilde{\beta} - \beta) + \frac{Y_i - \tilde{p}_i}{\tilde{w}_i} \right] + \frac{1}{2} \sum_{i=1}^n \tilde{w}_i \left( \frac{Y_i - \tilde{p}_i}{\tilde{w}_i} \right)^2 + f(\tilde{\beta}), \end{aligned}$$

where  $\tilde{\mathbf{p}} = (\tilde{p}_1, \dots, \tilde{p}_n)^\top$  and  $\tilde{\mathbf{W}} = \text{diag}(\tilde{w}_1, \dots, \tilde{w}_n)$  are the estimates of  $\mathbf{p}$  and  $\mathbf{W}$  based on  $\tilde{\beta}$ . We rewrite the function  $\ell(\beta)$  as follows:

$$\ell(\beta) = -\frac{1}{2} \sum_{i=1}^n \tilde{w}_i (\tilde{z}_i - \mathbf{x}_i^\top \beta)^2 + C(\tilde{\beta}), \quad (8)$$

where

$$\tilde{z}_i = \mathbf{x}_i^\top \tilde{\beta} + \frac{Y_i - \tilde{p}_i}{\tilde{w}_i}$$

is the working response,  $\tilde{w}_i$  is the working weight, and  $C$  is a function that does not depend on  $\beta$ .

**INNER LOOP.** In the inner loop, we find the estimates of  $\beta$  by solving a modified optimization problem of (6). With fixed  $\tilde{w}_i$ 's,  $\tilde{z}_i$ 's, and a fixed form of  $\ell$  based on the estimates of  $\beta$  in the previous iteration of the middle loop, we use coordinate descent to solve the penalized weighted least-squares problem

$$\min_{\beta} -\frac{1}{n} \ell(\beta) + \lambda \sum_{k=1}^p |\beta_k|, \quad (9)$$

and update the estimates of  $\beta$ . For each iteration of the inner loop, suppose we have the current estimates  $\tilde{\beta}_k$  for  $k \neq j$  and we wish to partially optimize with respect to  $\beta_j$ :

$$\min_{\beta_j} \frac{1}{2n} \sum_{i=1}^n \tilde{w}_i \left( \tilde{z}_i - X_{ij} \beta_j - \sum_{k \neq j} X_{ik} \tilde{\beta}_k \right)^2 + \lambda |\beta_j| + \lambda \sum_{k \neq j} |\tilde{\beta}_k|.$$

Updates:

$$\begin{aligned} \tilde{\beta}_0 &\leftarrow \frac{\sum_{i=1}^n \tilde{w}_i (\tilde{z}_i - \sum_{k=1}^p X_{ik} \tilde{\beta}_k)}{\sum_{i=1}^n \tilde{w}_i}, \\ \tilde{\beta}_j &\leftarrow \frac{S\left(\frac{1}{n} \sum_{i=1}^n \tilde{w}_i X_{ij} (\tilde{z}_i - \sum_{k \neq j} X_{ik} \tilde{\beta}_k), \lambda\right)}{\frac{1}{n} \sum_{i=1}^n \tilde{w}_i X_{ij}^2}, \quad j = 1, \dots, p \end{aligned}$$

where  $S(z, \gamma)$  is the soft-thresholding operator with value

$$S(z, \gamma) = \text{sign}(z)(|z| - \gamma)_+ = \begin{cases} z - \gamma, & \text{if } z > 0 \text{ and } \gamma < |z| \\ z + \gamma, & \text{if } z < 0 \text{ and } \gamma < |z| \\ 0, & \text{if } \gamma \geq |z| \end{cases}$$

We can then update estimates of  $\beta_j$ 's repeatedly for  $j = 0, 1, 2, \dots, p, 0, 1, 2, \dots$  until convergence.

- Note: Care is taken to avoid coefficients diverging in order to achieve fitted probabilities of 0 or 1. When a probability is within  $\epsilon = 10^{-5}$  of 1, we set it to 1, and set the weights to  $\epsilon$ . 0 is treated similarly.

## 2.4. Five-fold Cross Validation for LASSO

Since the Logistic-Lasso model depend on penalty term  $\lambda$  for selection, we further develop 5-fold cross validation to select the parameter  $\lambda$  to obtain the optimized result.

For the initial  $\lambda$  range, which is a sequence of descending  $\lambda$ 's, where  $\lambda_1 = \lambda_{max}$ . We set  $\lambda_{min} = \frac{\lambda_{max}}{e^6}$ , and create 30  $\lambda$  candidates on a log scale.

To select the optimal tuning parameter  $\lambda$ , the original data is randomly shuffled and split into five equally sized groups. One of the groups is used as a test set, while the remaining groups are used as training data. The path-wise coordinate-wise optimization algorithm is then applied to the training data, and AUC scores are calculated for each  $\lambda$  using the test data. This process is repeated until each of the five groups has been used as the test set, and the mean AUC for each  $\lambda$  is computed.

We select the best  $\lambda$  in two ways. One way is that we wrote a function to do the 5-fold cross-validation and the other way is to use the `cv.glmnet` function from the popular package `caret`.

Here we take the  $\lambda$  with the greatest mean AUC as the best  $\lambda$ . Further, we look at the predictors that the best  $\lambda$  choose and take them to re-fit the logistic regression model on the training data which is the 'optimal' model. We also run the training data by Newton-Raphson algorithm to get the 'full' model. After that, we compare the two models' prediction performance on the test data in specificity, sensitivity, and AUC.

## 3. Results

### Five-fold CV for Logistic-LASSO

Both our cross-validation function and `cv.glmnet` function reach the greatest mean AUC when  $\lambda = 0.0099322$ , thus this is the best  $\lambda$  we choose. As for the predictors, when  $\lambda = \lambda_{best}$ , both methods select ten same predictors, which are `texture_mean`, `concave.points_mean`, `radius_se`, `fractal_dimension_se`, `radius_worst`, `texture_worst`, `smoothness_worst`, `concavity_worst`, `concave.points_worst`, and `symmetry_worst`.

### Model Comparison

The ten selected predictors are used to re-fit the logistic regression model as the 'optimal' model, which is then compared with the 'full' model generated by Newton-Raphson algorithm. The result turns out that the two models differ in prediction performance. The 'optimal' model out-performed the 'full' model with higher specificity, sensitivity, larger AUC, and fewer predictors.

## 4. Discussion

The main conclusion is that Lasso-logistic model performed better than the full logistic model in this case. Recall that our goal is to build a predictive model to classify each patient's cancer diagnosis accurately according to the information extracted from the images. The specificity and sensitivity should be as high as possible.

For the future work, now that we have selected the ten predictors, we want to know why do these ten matter. What's the interpretation of this model? Do these predictors have any clinical significance? These questions may need to be answered by a cancer expert.



## **Group Contributions**

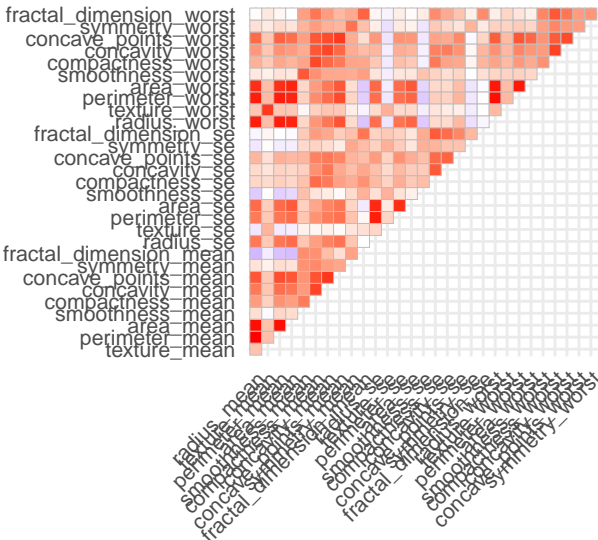
## References

Freer, Timothy W., and Michael J. Ulissey. "Screening mammography with computer-aided detection: prospective study of 12,860 patients in a community breast center." *Radiology* 220.3 (2001): 781-786.

Friedman J, Hastie T, Tibshirani R. Regularization Paths for Generalized Linear Models via Coordinate Descent. *J Stat Softw.* 2010;33(1):1-22. PMID: 20808728; PMCID: PMC2929880.

Appendices

A



B

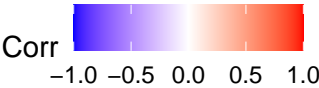
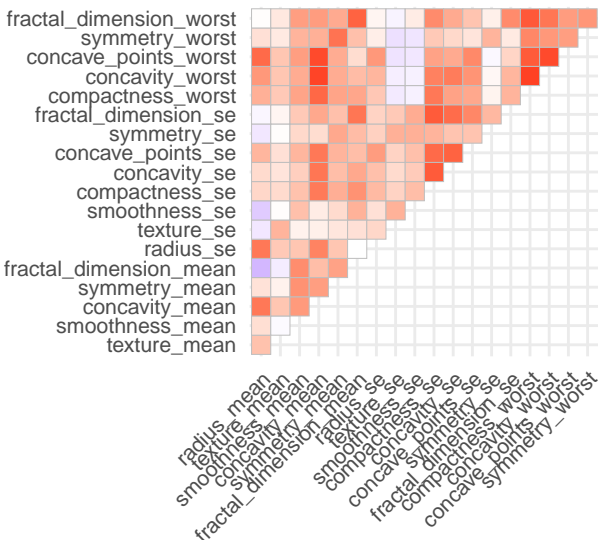


Figure 0: Correlation Table

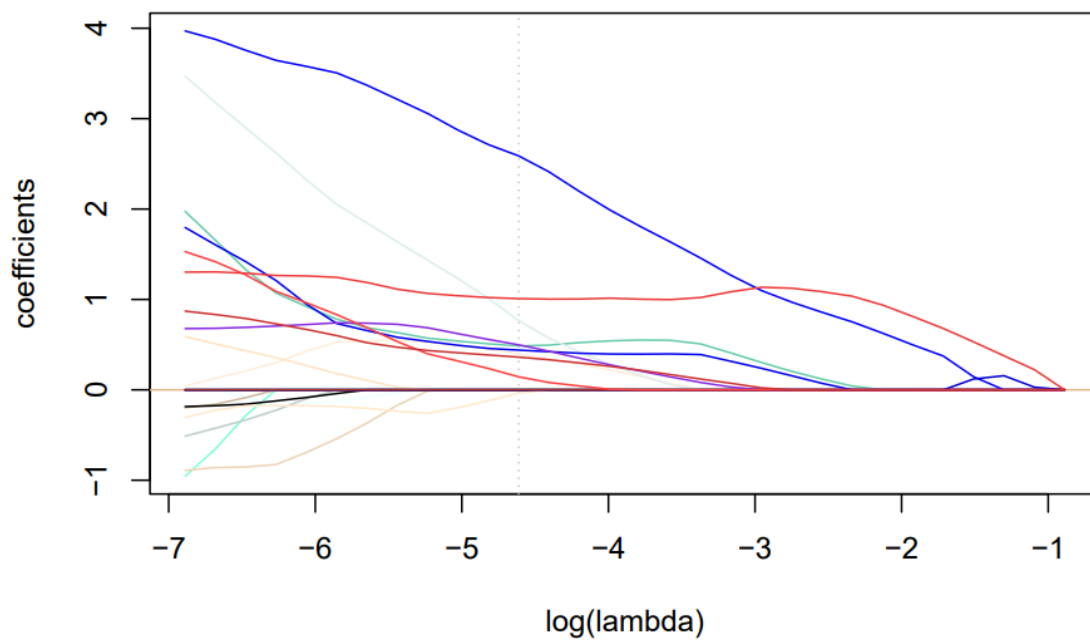


Figure 1: Task 4 Coefficients Shrinkage

lambda	ours_AUC	cv.glmnet_AUC
0.4115445	0.5000000	0.5000000
0.3346284	0.9760054	0.9725915
0.2720876	0.9796678	0.9787526
0.2212355	0.9816903	0.9817053
0.1798874	0.9828852	0.9834002
0.1462671	0.9841071	0.9847216
0.1189303	0.9853029	0.9850192
0.0967027	0.9861031	0.9858166
0.0786293	0.9872060	0.9873215
0.0639338	0.9885875	0.9887026
0.0519848	0.9893408	0.9892575
0.0422691	0.9895397	0.9894566
0.0343691	0.9898394	0.9896556
0.0279457	0.9903360	0.9902522
0.0227227	0.9903354	0.9901527
0.0184759	0.9903346	0.9904508
0.0150229	0.9903347	0.9903518
0.0122151	0.9904332	0.9904501
0.0099322	0.9905325	0.9906491
0.0080759	0.9905317	0.9904501
0.0065665	0.9905324	0.9905479
0.0053393	0.9902345	0.9903485
0.0043414	0.9893390	0.9893569
0.0035300	0.9887423	0.9889618
0.0028703	0.9880447	0.9880654
0.0023338	0.9881480	0.9881674
0.0018976	0.9875518	0.9877693
0.0015430	0.9875498	0.9876669
0.0012546	0.9867502	0.9867649
0.0010201	0.9863500	0.9865655

Figure 2: Task 4 Lambda

predictor	ours_coef	cv.glmnet_coef
(Intercept)	-0.6138280	-0.6048659
radius_mean	0.0000000	0.0000000
texture_mean	0.3958698	0.3811372
perimeter_mean	0.0000000	0.0000000
area_mean	0.0000000	0.0000000
smoothness_mean	0.0000000	0.0000000
compactness_mean	0.0000000	0.0000000
concavity_mean	0.0000000	0.0000000
concave.points_mean	0.4850029	0.4476499
symmetry_mean	0.0000000	0.0000000
fractal_dimension_mean	0.0000000	0.0000000
radius_se	0.7660262	0.8379136
texture_se	0.0000000	0.0000000
perimeter_se	0.0000000	0.0000000
area_se	0.0000000	0.0000000
smoothness_se	0.0000000	0.0000000
compactness_se	0.0000000	0.0000000
concavity_se	0.0000000	0.0000000
concave.points_se	0.0000000	0.0000000
symmetry_se	0.0000000	0.0000000
fractal_dimension_se	-0.0364481	-0.0368622
radius_worst	2.5878169	2.5734608
texture_worst	0.4394404	0.4590245
perimeter_worst	0.0000000	0.0000000
area_worst	0.0000000	0.0000000
smoothness_worst	0.4980005	0.4945458
compactness_worst	0.0000000	0.0000000
concavity_worst	0.1437060	0.1253231
concave.points_worst	1.0087922	1.0692685
symmetry_worst	0.3617036	0.3641634
fractal_dimension_worst	0.0000000	0.0000000

Figure 3: Task 4 Selected Predictors

Model	specificity	sensitivity	AUC
full	0.9268293	0.9305556	0.9661130
optimal	0.9545455	0.9855072	0.9983389

Figure 4: Task 4 Two Model Comparison

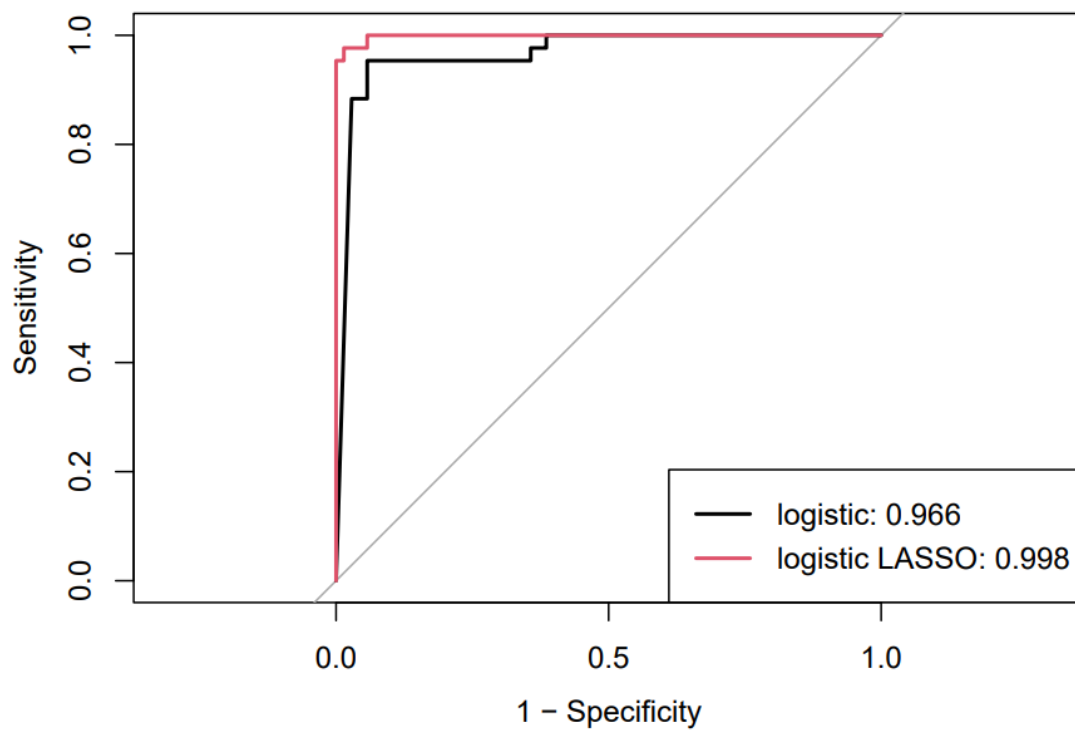


Figure 5: Task 4 ROC Curve