Sparse Integer Regression

Hao Liu Keivan Sadeghzadeh Cynthia Rudin

 $\mathrm{May}\ 2,\ 2017$

Problem

- Given n data points $(\mathbf{x}_i, y_i), \mathbf{x}_i \in \mathbb{R}^p, y_i \in \mathbb{R}$
- ② hope to find a linear relationship between \mathbf{x}_i and y_i , i.e. $y_i \approx \boldsymbol{\beta}^T \mathbf{x}_i, \, \boldsymbol{\beta} \in \mathbb{R}^p$
- **③** Integer Regression: find $\beta \in \mathbb{Z}^p$, that minimize the L2 loss $\sum_{i=1}^n (y_i \beta^T \mathbf{x}_i)^2$, or $\|Y X\beta\|^2$, where $Y \in \mathbb{R}^n$, $X \in \mathbb{R}^{n \times p}$

Ellipsoidal Hypersurface

- 1 Two forms of an ellipsoid
 - 1. $(X-U)^T Q(X-U) = 1$, $Q = RDR^T$, R is the rotation, D is the diameter, U is the center of X, Q is the transformation matrix
 - 2. $X^T A X + B^T X + C = 0$
- ② After solving it, we get $Q = RDR^T = \frac{A}{(B^TA^{-1}B)/4-C}$

Randomization

- Fact: An ellipsoid is a transformed ball, and the transformation matrix $Q = RDR^T$
- Generating m random points in the unit ball P(0,1)
- Using E = PDR + U, we can transform these points to the ellipsoid E(U,Q)

Algorithm setup

- Objective: minimize error function over integer coefficient sets inside the high dimension ellipsoidal hypersurface to reach optimal integer solution
- $F = ||Y X\beta||^2 = (Y X\beta)^T (Y X\beta)$ $\to \beta^T X^T X \beta - 2\beta^T X^T Y + Y^T Y - F = 0$
- We can get an ellipsoid with β on its border and β_{LS} at its center.
- This ellipsoid is like a counter line for the error function. Once we get a β , we can get this ellipsoid, all the β on the border of it have the same error F, and all the possible better solutions lie inside the ellipsoid.
- So we only need to sample inside the ellipsoid and eliminate the solution space outside the ellipsoid.
- Let $A = X^TX$, $B = -2X^TY$, $C = Y^TY F$, we can calculate the $Q = \frac{A}{(B^TA^{-1}B)/4-C}$, where Q is the transformation matrix of the ellipsoid. By using Q, we can sample in a unit ball, and transform them to the ellipsoid.

Algorithm Description

• We want to minimize the error function $F = ||Y - X\beta||^2$. And we observe that in the solution space(β space), all the β with the same F lies on a ellipsoid centered at β_{LS} . A bigger F correspond to a ellipsoid with larger size. Once we get a β , we can get this ellipsoid with all the possible better solutions lie inside it. So we can sample inside it, and once we get a better solution, which means a β with smaller F, we can draw another ellipsoid with the same center(β_{LS}), rotation and shape but a smaller size. Then we only need to sample inside this smaller ellipsoid. Continue this procedure, we can eventually get a series of ellipsoid with the same center(β_{LS}), rotation and shape but different sizes and a good integer solution to this problem.

Algorithm Procedure

Algorithm 1: Sparse Integer Regression

Data: $(\mathbf{x}_i, y_i), \mathbf{x}_i \in \mathbb{R}^p, y_i \in \mathbb{R}$ initialization:

- 1. calculate the least square error solution, $\boldsymbol{\beta}_{LS} = (X^TX)^{-1}X^TY$;
- 2. calculate $\tilde{\beta} = round(\beta_{LS})$ as the initial integer solution;

while true do

- 3. set current best Least Square error $F_{ellip} = F(\tilde{\beta}) = \sum_{i=1}^{n} (Y_i \tilde{\beta}X_i)^2$;
- 4. use $\tilde{\beta}$ to determine the current transformation matrix Q ;
- 5. sample M solutions (points) in the unit ball, and transform them to the ellipsoid centered at $\beta_{LS},$ with Q as the transformation matrix ;
- 6. round the solution;
- 7. calculate each solutions' least square error, and find the solution with the \min loss;
- if $min\ loss < F_{ellip}(current\ best\ loss)$ then set $\tilde{\beta}$ equal to that solution ;

$_{ m else}$

sample again/ enumerate all the remaining solution/ break the loop ;

Future work

• Try more data

Sparsity

- Add regulariz
 - Add regularizer into the objective function
 - Back Elimination
- Get a bound on how much space we eliminate if the objective reduce by some percent