IEOR160 Project

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Contents

1 Part 1

1a Four Most Significant Variables

The four most significant variables are BMI, S5, Sex, BP in order of increasing p-value. Each of these variables has a p-value below 0.05 which is a widely used significance level. This p-value is testing the null hypothesis that the coefficient is equal to 0 (there is no relation between the given variable and response variable). Thus, the smaller the p-value the more confidence we have in rejecting the null hypothesis, which indicates that there is a significant relationship between the given variable and response variable. The code for this part shows the coefficients and statistics with just these four variables used.

Error	R^2
772097	0.455053

1b Best Combination of Four Independent Variables

With the given heuristic of using the variables with the five lowest p-values and using a subset of size four, we find that the subset that uses Sex, BMI, BP and S5 has the highest R^2 value as shown in the table below. The coefficients, SSE and R^2 value are all shown in the second table. These are the four features with the least p-value so it makes sense that they have the minimum SSE and R^2 value.

Subset of Variables	Error	R^2
$\{BMI, BP, S5, S6\}$	778372	0.450624
$\{Sex, BP, S5, S6\}$	874717	0.382623
$\{Sex, BMI, S5, S6\}$	774756	0.453176
$\{Sex, BMI, BP, S6\}$	862701	0.391104
$\{Sex, BMI, BP, S5\}$	772097	0.455053

Best Subset	Error	R^2	B_{sex}	B_{BMI}	B_{BP}	B_{S5}
$\{Sex, BMI, BP, S5\}$	772097	0.455053	-155.447	597.687	213.927	600.31

1c Lasso Regularization

The Lasso Regularization employs an L1 penalty to penalize for large coefficient values and to select features (drives coefficient of insignificant features to zero). The first table shows the error and corresponding R^2 values for each of the different lambda values. As lambda increases, we penalize more and, thus, the error increases and R^2 decreases. This is because more weight is being placed on the penalty term in the loss function and less weight is being placed on minimizing the original least squares term. The tradeoff is that as the λ term increases, the model becomes simpler as fewer variables are selected.

In this case, the optimal value of lambda was 200 and the regression coefficients and R^2 are shown in the second table. In this case BMI, BP, S3, S5, and S6 were selected via lasso regularization.

λ	Error	R^2
200	802793	0.433387
220	810566	0.427902
240	819078	0.421893
260	828331	0.415363
280	838324	0.40831
300	849057	0.400734
320	860531	0.392636
340	871720	0.384739
360	881977	0.377499
380	892820	0.369846
400	904250	0.361779

λ	200
Error	802793
R^2	0.433387
B_{AGE}	0
B_{sex}	0
B_{BMI}	455.688
B_{BP}	65.6527
B_{S1}	0
B_{S2}	0
B_{S3}	66.4006
B_{S4}	0
B_{S5}	455.892
B_{S6}	55.8544

1d Mixed-integer Optimization

Using Mixed-integer Optimization, the regression coefficients, error and R^2 are shown in the table below. This modeled as a mixed-integer optimization problem that uses at most 4 variables. In this case, BMI, BP, S1, and S5 are chosen. This subset did not appear under the heuristic method used in part b.

Error	755094
R^2	0.467054
B_{AGE}	0
B_{sex}	0
B_{BMI}	603.681
B_{BP}	200.878
B_{S1}	-267.699
B_{S2}	0
B_{S3}	0
B_{S4}	0
B_{S5}	711.644
B_{S6}	0

1e Comparison of Results

Looking at the accuracy of each method, the heuristic selection method had the least out-of-sample error, however the mixed integer optimization method is very close in second place. The lasso regularization method does the worst in terms of out-of-sample accuracy.

Method	Error
Heuristic Selection	579396.8559607414
Lasso Regularization	693913.9388466905
Mixed Integer Optimization	583706.7341750131

2 Part 2

2a Lasso with Second Order Interactions

We used a regularization parameter of 9.57 while implementing lasso regression with second order interactions. Using 9.57 as the regularization parameter we obtained the following values of the coefficients :

Coefficients for linear terms(β_i) =

1. -46.3591,
2. -226.708
3. 534.415
4. 230.201,
5. 316.992
6. 0
7. 12.5382
8. 204.877
9. 582.585
10. 160.929

Coefficients for quadratic terms (β_{jk}) =

0	0	0	0	0	0	0	0	0	0
.	0	0	0	0	0	0	0	0	0
.	.	0	0	0	0	0	0	0	0
.	.	.	0	0	0	0	0	0	0
.	.	.	.	0	0	0	0	0	0
.	.	.	.	.	0	0	0	0	0
.	.	.	.	.	.	0	0	0	0
.	.	.	.	.	.	.	0	0	0
.	.	.	.	.	.	.	.	0	0
.	.	.	.	.	.	.	.	.	102.204

We used the value of regularization parameter 9.57 as that enables us to select 10 independent variables out of the 65 possible variables available to us.

The value of R^2 for this problem = 0.498677

2b Mixed Integer Optimization with Second Order Interactions

Linear regression coefficients (β_i) =

1. 0
2. -233.553
3. 595.908
4. 263.431
5. -327.887
6. 0
7. 0
8. 242.18
9. 561.239
10. 121.949

Coefficients for quadratic terms (β_{jk}) =

$$
\begin{array}{cccccccccc}
0 & 0 & 0 & 3540.81 & 0 & 0 & 0 & 0 & 0 & 0 \\
. & 0 & 4250.64 & 0 & 0 & 0 & -3850.05 & 0 & 0 & 0 \\
. & . & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
. & . & . & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
. & . & . & . & 0 & 0 & 0 & 0 & 0 & 0 \\
. & . & . & . & . & 0 & 0 & 0 & 0 & 0 \\
. & . & . & . & . & . & 0 & 0 & 0 & 0 \\
. & . & . & . & . & . & . & 0 & 0 & 0 \\
. & . & . & . & . & . & . & . & 0 & 0 \\
. & . & . & . & . & . & . & . & . & 0
\end{array}
$$

The value of R^2 for this problem = 0.523882

2c Comparison of Results with Second Order Interactions

Out of sample error in part (f) = 573404.8630648409

Out of sample error in part(g) = 573285.4410441783

We observe that the mixed integer programming method of regression gives us a higher accuracy than the Lasso regression method when 10 independent variables are considered.

3 Appendix: The Code

Listing 1: 1a Code

```
option solver minos; # No integer programming here

##########################################################################

reset;

data reg_data.dat;

print "Looking at the p-values, we should use BMI, S5, Sex, S6"; # Features from
    p-values

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
    mat[i, Y])^2; # We need to minimize sum of squared errors
subject to not_use_S1: coeffs[S1] = 0; # Use only the 4 features mentioned above
subject to not_use_S2: coeffs[S2] = 0; # Use only the 4 features mentioned above
subject to not_use_S3: coeffs[S3] = 0; # Use only the 4 features mentioned above
subject to not_use_S4: coeffs[S4] = 0; # Use only the 4 features mentioned above
subject to not_use_AGE: coeffs[AGE] = 0; # Use only the 4 features mentioned above
subject to not_use_BP: coeffs[BP] = 0; # Use only the 4 features mentioned above

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs; # Displaying results
```

Listing 2: 1b Code

```
option solver minos;

###########################################################################

reset;

data reg_data.dat;

print "Leaving out SEX";

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
    mat[i, Y])^2; # We need to minimize the sum of squared errors
subject to not_use_S1: coeffs[S1] = 0; # Use only the features mentioned above
subject to not_use_S2: coeffs[S2] = 0; # Use only the features mentioned above
subject to not_use_S3: coeffs[S3] = 0; # Use only the features mentioned above
subject to not_use_S4: coeffs[S4] = 0; # Use only the features mentioned above
subject to not_use_AGE: coeffs[AGE] = 0; # Use only the features mentioned above
subject to not_use_SEX: coeffs[SEX] = 0; # Use only the features mentioned above

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs; # Displaying results

###########################################################################
```

```
reset;

data reg_data.dat;

print "Leaving out BMI";

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
    mat[i, Y])^2; # We need to minimize the sum of squared errors
subject to not_use_S1: coeffs[S1] = 0; # Use only the features mentioned above
subject to not_use_S2: coeffs[S2] = 0; # Use only the features mentioned above
subject to not_use_S3: coeffs[S3] = 0; # Use only the features mentioned above
subject to not_use_S4: coeffs[S4] = 0; # Use only the features mentioned above
subject to not_use_AGE: coeffs[AGE] = 0; # Use only the features mentioned above
subject to not_use_BMI: coeffs[BMI] = 0; # Use only the features mentioned above

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs; # Displaying results

##########################################################################

reset;

data reg_data.dat;

print "Leaving out BP";
```

```
var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith feature

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i, Y])^2; # We need to minimize the sum of squared errors
subject to not_use_S1: coeffs[S1] = 0; # Use only the features mentioned above
subject to not_use_S2: coeffs[S2] = 0; # Use only the features mentioned above
subject to not_use_S3: coeffs[S3] = 0; # Use only the features mentioned above
subject to not_use_S4: coeffs[S4] = 0; # Use only the features mentioned above
subject to not_use_AGE: coeffs[AGE] = 0; # Use only the features mentioned above
subject to not_use_BP: coeffs[BP] = 0; # Use only the features mentioned above

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i, Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs; # Displaying results

##########################################################################

reset;

data reg_data.dat;

print "Leaving out S5";

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith feature

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
```

```
    mat[i, Y])^2; # We need to minimize the sum of squared errors
subject to not_use_S1: coeffs[S1] = 0; # Use only the features mentioned above
subject to not_use_S2: coeffs[S2] = 0; # Use only the features mentioned above
subject to not_use_S3: coeffs[S3] = 0; # Use only the features mentioned above
subject to not_use_S4: coeffs[S4] = 0; # Use only the features mentioned above
subject to not_use_AGE: coeffs[AGE] = 0; # Use only the features mentioned above
subject to not_use_S5: coeffs[S5] = 0; # Use only the features mentioned above

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs; # Displaying results

##########################################################################

reset;

data reg_data.dat;

print "Leaving out S6";

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
    mat[i, Y])^2; # We need to minimize the sum of squared errors
subject to not_use_S1: coeffs[S1] = 0; # Use only the features mentioned above
subject to not_use_S2: coeffs[S2] = 0; # Use only the features mentioned above
subject to not_use_S3: coeffs[S3] = 0; # Use only the features mentioned above
subject to not_use_S4: coeffs[S4] = 0; # Use only the features mentioned above
```

```
subject to not_use_AGE: coeffs[AGE] = 0; # Use only the features mentioned above
subject to not_use_S6: coeffs[S6] = 0; # Use only the features mentioned above

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs; # Displaying results
```

Listing 3: 1c Code

```
reset;
reset options;

option solver cplex;

data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature
var z{1..n_features}; # z[i] is the absolute value of coeffs[i]

print "Lambda =", lambdas[1]; # Setting lambda

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
    mat[i, Y])^2 + sum{k in 1..n_features}lambdas[1]*z[k]; # We need to minimize the
    sum of squared errors + the regularization penalty
subject to abs_1 {j in 1..n_features}: z[j] >= coeffs[j]; # To implement the absolute
    value l1-penalty
subject to abs_2 {j in 1..n_features}: z[j] >= -coeffs[j]; # To implement the
    absolute value l1-penalty
```

```
solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs, z;

###############################################################################

reset;
reset options;

option solver cplex;

data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature
var z{1..n_features}; # z[i] is the absolute value of coeffs[i]

print "Lambda =", lambdas[2]; # Setting lambda

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
    mat[i, Y])^2 + sum{k in 1..n_features}lambdas[2]*z[k]; # We need to minimize the
    sum of squared errors + the regularization penalty
subject to abs_1 {j in 1..n_features}: z[j] >= coeffs[j]; # To implement the absolute
    value l1-penalty
subject to abs_2 {j in 1..n_features}: z[j] >= -coeffs[j]; # To implement the
    absolute value l1-penalty

solve;
```

```
var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs, z;

################################################################################

reset;
reset options;

option solver cplex;

data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature
var z{1..n_features}; # z[i] is the absolute value of coeffs[i]

print "Lambda =", lambdas[3]; # Setting lambda

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
    mat[i, Y])^2 + sum{k in 1..n_features}lambdas[3]*z[k]; # We need to minimize the
    sum of squared errors + the regularization penalty
subject to abs_1 {j in 1..n_features}: z[j] >= coeffs[j]; # To implement the absolute
    value l1-penalty
subject to abs_2 {j in 1..n_features}: z[j] >= -coeffs[j]; # To implement the
    absolute value l1-penalty

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
```

```
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs, z;

###############################################################################

reset;
reset options;

option solver cplex;

data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature
var z{1..n_features}; # z[i] is the absolute value of coeffs[i]

print "Lambda =", lambdas[4]; # Setting lambda

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
    mat[i, Y])^2 + sum{k in 1..n_features}lambdas[4]*z[k]; # We need to minimize the
    sum of squared errors + the regularization penalty
subject to abs_1 {j in 1..n_features}: z[j] >= coeffs[j]; # To implement the absolute
    value l1-penalty
subject to abs_2 {j in 1..n_features}: z[j] >= -coeffs[j]; # To implement the
    absolute value l1-penalty

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
```

```
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs, z;

##############################################################################

reset;
reset options;

option solver cplex;

data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature
var z{1..n_features}; # z[i] is the absolute value of coeffs[i]

print "Lambda =", lambdas[5]; # Setting lambda

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
    mat[i, Y])^2 + sum{k in 1..n_features}lambdas[5]*z[k]; # We need to minimize the
    sum of squared errors + the regularization penalty
subject to abs_1 {j in 1..n_features}: z[j] >= coeffs[j]; # To implement the absolute
    value l1-penalty
subject to abs_2 {j in 1..n_features}: z[j] >= -coeffs[j]; # To implement the
    absolute value l1-penalty

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
```

```
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs, z;

#############################################################################

reset;
reset options;

option solver cplex;

data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature
var z{1..n_features}; # z[i] is the absolute value of coeffs[i]

print "Lambda =", lambdas[6]; # Setting lambda

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
    mat[i, Y])^2 + sum{k in 1..n_features}lambdas[6]*z[k]; # We need to minimize the
    sum of squared errors + the regularization penalty
subject to abs_1 {j in 1..n_features}: z[j] >= coeffs[j]; # To implement the absolute
    value l1-penalty
subject to abs_2 {j in 1..n_features}: z[j] >= -coeffs[j]; # To implement the
    absolute value l1-penalty

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared
```

```
display sse, error, y_hat, ss_tot, r_sq, coeffs, z;

#############################################################################

reset;
reset options;

option solver cplex;

data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith feature
var z{1..n_features}; # z[i] is the absolute value of coeffs[i]

print "Lambda =", lambdas[7]; # Setting lambda

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i, Y])^2 + sum{k in 1..n_features}lambdas[7]*z[k]; # We need to minimize the sum of squared errors + the regularization penalty
subject to abs_1 {j in 1..n_features}: z[j] >= coeffs[j]; # To implement the absolute value l1-penalty
subject to abs_2 {j in 1..n_features}: z[j] >= -coeffs[j]; # To implement the absolute value l1-penalty

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i, Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs, z;
```

```
#############################################################################

reset;
reset options;

option solver cplex;

data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith feature
var z{1..n_features}; # z[i] is the absolute value of coeffs[i]

print "Lambda =", lambdas[8]; # Setting lambda

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i, Y])^2 + sum{k in 1..n_features}lambdas[8]*z[k]; # We need to minimize the sum of squared errors + the regularization penalty
subject to abs_1 {j in 1..n_features}: z[j] >= coeffs[j]; # To implement the absolute value l1-penalty
subject to abs_2 {j in 1..n_features}: z[j] >= -coeffs[j]; # To implement the absolute value l1-penalty

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i, Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs, z;

#############################################################################
```

```
reset;
reset options;

option solver cplex;

data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith feature
var z{1..n_features}; # z[i] is the absolute value of coeffs[i]

print "Lambda =", lambdas[9]; # Setting lambda

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i, Y])^2 + sum{k in 1..n_features}lambdas[9]*z[k]; # We need to minimize the sum of squared errors + the regularization penalty
subject to abs_1 {j in 1..n_features}: z[j] >= coeffs[j]; # To implement the absolute value l1-penalty
subject to abs_2 {j in 1..n_features}: z[j] >= -coeffs[j]; # To implement the absolute value l1-penalty

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i, Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs, z;

##############################################################################

reset;
reset options;
```

```
option solver cplex;

data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature
var z{1..n_features}; # z[i] is the absolute value of coeffs[i]

print "Lambda =", lambdas[n_features]; # Setting lambda

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
    mat[i, Y])^2 + sum{k in 1..n_features}lambdas[n_features]*z[k]; # We need to
    minimize the sum of squared errors + the regularization penalty
subject to abs_1 {j in 1..n_features}: z[j] >= coeffs[j]; # To implement the absolute
    value l1-penalty
subject to abs_2 {j in 1..n_features}: z[j] >= -coeffs[j]; # To implement the
    absolute value l1-penalty

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs, z;

##############################################################################

reset;
reset options;

option solver cplex;
```

```
data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature
var z{1..n_features}; # z[i] is the absolute value of coeffs[i]

print "Lambda =", lambdas[11]; # Setting lambda

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] -
    mat[i, Y])^2 + sum{k in 1..n_features}lambdas[11]*z[k]; # We need to minimize the
    sum of squared errors + the regularization penalty
subject to abs_1 {j in 1..n_features}: z[j] >= coeffs[j]; # To implement the absolute
    value l1-penalty
subject to abs_2 {j in 1..n_features}: z[j] >= -coeffs[j]; # To implement the
    absolute value l1-penalty

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display sse, error, y_hat, ss_tot, r_sq, coeffs, z;

##############################################################################
```

Listing 4: 1d Code

```
reset;
reset options;

data reg_data.dat;
```

```
var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature
var used{1..n_features} binary; # used[i] is 1 if the ith feature is used, 0 otherwise

minimize sse: sum{i in 1..n_train}(mat[i,Y] - sum{j in
    1..n_features}(coeffs[j]*mat[i,j]))^2; # We need to minimize the sum of squared
    errors
subject to sum_of_coeffs_constraint: sum{j in 1..n_features}used[j] <= 4; # Can use
    at most 4 features
subject to binary1{j in 1..n_features}: coeffs[j] <= first_order_coeff_bound*used[j];
    # To make sure that coeffs[j] is not nonzero when used[j] is zero
subject to binary2{j in 1..n_features}: coeffs[j] >=
    -first_order_coeff_bound*used[j]; # To make sure that coeffs[j] is not nonzero
    when used[j] is zero

option solver cplex;

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}coeffs[j]*mat[i,j] - mat[i,
    Y])^2; # The SSE with coeffs
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
    calculation
var r_sq = 1 - error/ss_tot; # Formula for r-squared

display r_sq, coeffs, used;
```

Listing 5: 1e Code

```
n_features = 10 # The number of features
n_train = 250 # The number of training samples

def get_predictions(beta, X):
  Y_pred = [] # List to store the predicitions
  for x in X: # Going through all the data
    y_pred = 0
```

```
    for i in range(n_features):
      y_pred += beta[i] * x[i] # simulating the dot product
    Y_pred.append(y_pred) # Adding the prediction to the list
  return Y_pred # Returning the list

def sse(beta, X, Y_actual):
  Y_pred = get_predictions(beta, X) # Getting the predictions
  squared_differences = [(Y_actual[i] - Y_pred[i])**2 for i in range(len(Y_pred))] #
      Calculating the sum of squared errors
  return sum(squared_differences) # Returning the SSE

def read_data(filename):
  X = [] # List to store all the data points
  Y = [] # List to store all the target variables
  with open(filename) as f: # Opening the file containing the data (NOT necessarily
      .dat)
    lines = f.readlines() # Reading all the lines in the file
    lines = lines[n_train + 1:] # Skipping the first n_train + 1 lines since we need
        out-of-sample error and the first line is just feature names
    for line in lines: # Going through all lines
      if "AGE" in line: # Checking if the word "AGE" is in the line
        continue # Skipping if the word "AGE" is in the line because if it is, the
            line is just feature names, not an actual sample
      numbers = line.split() # Splitting the string
      numbers = [float(number) for number in numbers] # Converting strings to numbers
      y = numbers[-1] # Extracting the target variable
      x = numbers[0:-1] # Extracting the features
      X.append(x) # Adding the sample
      Y.append(y) # Adding the target variable
  return X, Y # returning the data points and target variables

X, Y_actual = read_data('data.txt') # Getting the data points as X and target
    variables as Y
# X[i] is the ith sample. X[i][j] is the jth feature of the ith sample
# Y[i] is the ith target variable

coeffs_given = [-59.6, -241.6, 535.1, 241.7, -844.9, 407.4, -224.3, 285.2, 762.4,
```

```
    169.6] # The coefficients given to us
print("SSE All 10: {0}".format(sse(coeffs_given, X, Y_actual))) # The SSE using the
    coefficients given

coeffs_part_a = [0, -153.335, 610.97, 0, 0, 0, 0, 0, 588.782, 188.019] # The
    coefficients from part (a)
print("SSE Part 1A: {0}".format(sse(coeffs_part_a, X, Y_actual))) # The SSE using the
    coefficients from part (a)

coeffs_part_b = [0, -155.447, 597.687, 213.927, 0, 0, 0, 0, 600.31, 0] # The
    coefficients from part (b)
print("SSE Part 1B: {0}".format(sse(coeffs_part_b, X, Y_actual))) # The SSE using the
    coefficients from part (b)

coeffs_part_c = [0, 0, 405.494, 0.000540696, 0, 0, 0, 0, 414.866, 23.1162] # The
    coefficients from part (c)
print("SSE Part 1C: {0}".format(sse(coeffs_part_c, X, Y_actual))) # The SSE using the
    coefficients from part (c)

coeffs_part_d = [0, 0, 603.681, 200.878, -267.699, 0, 0, 0, 711.644, 0] # The
    coefficients from part (d)
print("SSE Part 1D: {0}".format(sse(coeffs_part_d, X, Y_actual))) # The SSE using the
    coefficients from part (d)
```

Listing 6: 2f Code

```
reset;
reset options;

option solver cplex;

data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature
var coeffs_second_order{j in 1..n_features, k in j..n_features}; # coeffs[i,j] is the
    regression coefficient for the second order interaction between the ith and jth
    feature
```

```
var z_coeffs{1..n_features}; # z[i] is the absolute value of coeffs[i]
var z_coeffs_second_order{j in 1..n_features, k in j..n_features}; # z[i,j] is the
    absolute value of coeffs_second_order[i,j]

print "Lambda =", lambda_part_2;

minimize sse: sum{i in 1..n_train} (sum{j in 1..n_features}(coeffs[j]*mat[i,j]) +
    sum{j in 1..n_features, k in j..n_features}(mat[i, j] * mat[i, k] *
    coeffs_second_order[j,k]) - mat[i, Y])**2 + sum{k in
    1..n_features}lambda_part_2*z_coeffs[k] + sum{j in 1..n_features, k in
    j..n_features} lambda_part_2*z_coeffs_second_order[j,k]; # We need to minimize
    the sum of the squared errors + the regularization penalty
subject to abs_1 {j in 1..n_features}: z_coeffs[j] >= coeffs[j]; # To implement
    absolute value function
subject to abs_2 {j in 1..n_features}: z_coeffs[j] >= -coeffs[j]; # To implement
    absolute value function
subject to abs_3{j in 1..n_features, k in j..n_features}: z_coeffs_second_order[j,k]
    >= coeffs_second_order[j,k]; # To implement absolute value function
subject to abs_4{j in 1..n_features, k in j..n_features}: z_coeffs_second_order[j,k]
    >= -coeffs_second_order[j,k]; # To implement absolute value function
solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}(coeffs[j]*mat[i,j]) + sum{j
    in 1..n_features, k in j..n_features}(mat[i, j] * mat[i, k] *
    coeffs_second_order[j,k]) - mat[i, Y])^2; # The SSE with coeffs and
    coeffs_second_order
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
var r_sq = 1 - error/ss_tot; # r-squared
var adj_r_sq = r_sq - (1-r_sq)*(2/247);

display sse, error, y_hat, ss_tot, r_sq, coeffs, coeffs_second_order;
```

Listing 7: 2g Code

```
reset;
reset options;
```

```
data reg_data.dat;

var coeffs{1..n_features}; # coeffs[i] is the regression coefficient for the ith
    feature
var coeffs_second_order{j in 1..n_features, k in j..n_features}; # coeffs[i,j] is the
    regression coefficient for the second order interaction between the ith and jth
    feature
var used{1..n_features} binary; # used[i] is 1 if the ith feature is used, 0 otherwise
var used_second_order{j in 1..n_features, k in j..n_features} binary; #
    used_second_order[i,j] is 1 if the second order interaction between the ith and
    jth feature is used, 0 otherwise

minimize sse: sum{i in 1..n_train}(mat[i,Y] - sum{j in
    1..n_features}(coeffs[j]*mat[i,j]) - sum{j in 1..n_features, k in
    j..n_features}(mat[i,j]*mat[i,k]*coeffs_second_order[j,k]))^2; # We need to
    minimize the sum of squared errors
subject to sum_of_coeffs_constraint: sum{j in 1..n_features}used[j] + sum{j in
    1..n_features, k in j..n_features} used_second_order[j,k] = n_features; # Use at
    most n_features features
subject to binary1{j in 1..n_features}: coeffs[j] <= first_order_coeff_bound*used[j];
    # To make sure that coeffs[i] is not nonzero when used[i] is 0
subject to binary2{j in 1..n_features}: coeffs[j] >=
    -first_order_coeff_bound*used[j]; # To make sure that coeffs[i] is not nonzero
    when used[i] is 0
subject to binary3{j in 1..n_features, k in j..n_features}: coeffs_second_order[j,k]
    <= second_order_coeff_bound*used_second_order[j,k]; # To make sure that
    coeffs[i,j] is not nonzero when used[i,j] is 0
subject to binary4{j in 1..n_features, k in j..n_features}: coeffs_second_order[j,k]
    >= -second_order_coeff_bound*used_second_order[j,k];
option solver cplex; # To make sure that coeffs[i,j] is not nonzero when used[i,j] is
    0

solve;

var error = sum{i in 1..n_train} (sum{j in 1..n_features}(coeffs[j]*mat[i,j]) + sum{j
    in 1..n_features, k in j..n_features}(mat[i, j] * mat[i, k] *
```

```
    coeffs_second_order[j,k]) - mat[i, Y])^2; # The SSE with coeffs and
    coeffs_second_order
param y_tot = sum{i in 1..n_train} mat[i,Y]; # Sum of all y
param y_hat = y_tot/n_train; # Mean of all y
param ss_tot = sum{i in 1..n_train}(mat[i,Y] - y_hat)^2; # Denominator in r-squared
var r_sq = 1 - error/ss_tot; # r-squared
var adj_r_sq = r_sq - (1-r_sq)*(2/247);

display sse,r_sq, error, coeffs,coeffs_second_order, used, used_second_order;
```

Listing 8: 2h Code

```
n_features = 10 # The number of features (first order)
n_train = 250 # The number of training samples

def get_predictions(beta, beta_matrix, X):
  Y_pred = [] # List to store the predicitions
  for x in X: # Going through all the data
    y_pred = 0
    for i in range(n_features):
      y_pred += beta[i] * x[i] # simulating the dot product
    for i in range(n_features):
      for j in range(i, n_features):
        y_pred += beta_matrix[i][j]*x[i]*x[j] # including second order interactions
    Y_pred.append(y_pred) # Adding the prediction to the list
  return Y_pred # Returning the list

def sse(beta, beta_matrix, X, Y_actual):
  Y_pred = get_predictions(beta, beta_matrix, X) # Getting the predictions
  squared_differences = [(Y_actual[i] - Y_pred[i])**2 for i in range(len(Y_pred))] #
     Calculating the sum of squared errors
  return sum(squared_differences) # Returning the SSE

def read_data(filename):
  X = [] # List to store all the data points
  Y = [] # List to store all the target variables
  with open(filename) as f: # Opening the file containing the data (NOT necessarily
     .dat)
```

```
    lines = f.readlines() # Reading all the lines in the file
    lines = lines[n_train + 1:] # Skipping the first 251 lines since we need
        out-of-sample error and the first line is just feature names
    for line in lines: # Going through all lines
      if "AGE" in line: # Checking if the word "AGE" is in the line
        continue # Skipping if the word "AGE" is in the line because if it is, the
            line is just feature names, not an actual sample
      numbers = line.split() # Splitting the string
      numbers = [float(number) for number in numbers] # Converting strings to numbers
      y = numbers[-1] # Extracting the target variable
      x = numbers[0:-1] # Extracting the features
      X.append(x) # Adding the sample
      Y.append(y) # Adding the target variable
  return X, Y # returning the data points and target variables

X, Y_actual = read_data('data.txt') # Getting the data points as X and target
    variables as Y
# X[i] is the ith sample. X[i][j] is the jth feature of the ith sample
# Y[i] is the ith target variable

coeffs_part_a = [-46.3591,-226.708, 534.415, 230.201, -316.992, -4.3493e-08, 12.5382,
    204.877, 582.585, 160.929] # coefficients for first order features in Part 2f
coeffs_part_a_matrix= [[1.09417e-06, 0.000102456, 1.09665e-07, 4.80696e-07,
    1.91375e-08, -2.53955e-08, 1.98485e-08, 8.45594e-08, 3.59663e-07, 1.69066e-07],
[0,-1.80499e-08, 2.86425e-07, 4.22607e-07, 9.68603e-08, -2.63781e-10, -1.32483e-07,
    -3.07998e-08, 1.38711e-07, 7.5646e-08],
[0, 0, 1.46462e-07, 1.92339e-07, 6.51947e-08, 9.46737e-08, 7.90349e-08, 1.8639e-07,
    8.70322e-08, 4.95379e-07],
[0,0, 0, 7.47294e-08,-1.63143e-08, -4.19059e-09, 2.81844e-08, 5.16799e-08,
    5.4629e-08, 1.00506e-07],
[0,0,0,0,3.59483e-08,5.64592e-09, -6.18133e-08, -5.2328e-08, 5.35758e-08,7.07302e-08],
[0,0,0,0,0,-5.44664e-08, -8.03162e-09, -1.5056e-08, 1.33778e-07, 7.95601e-08],
[0,0,0,0,0,0,4.66955e-08, 3.47648e-08, -4.29466e-08, 8.84204e-08],
[0,0,0,0,0,0,0,4.1884e-08, -1.03307e-09, 2.61773e-07],
[0,0,0,0,0,0,0,0,-1.75994e-08, 2.13799e-07],
[0,0,0,0,0,0,0,0,0,102.204]] # coefficients for second order features in Part 2f
print("SSE Part 2F: {0}".format(sse(coeffs_part_a,coeffs_part_a_matrix, X, Y_actual)))
```

```
coeffs_part_b = [0,-233.553, 595.908, 263.431, -327.887 ,0, 0, 242.18 ,561.239,
    121.949] # coefficients for first order features in Part 2g
coeffs_part_b_matrix= [[0,0,0, 3540.81, 0, 0, 0, 0, 0, 0],
[0, 0, 4250.64, 0, 0, 0, -3850.05,0,0,0],
[0,0,0,0,0,0,0,0,0,0],
[0,0,0,0,0,0,0,0,0,0],
[0,0,0,0,0,0,0,0,0,0],
[0,0,0,0,0,0,0,0,0,0],
[0,0,0,0,0,0,0,0,0,0],
[0,0,0,0,0,0,0,0,0,0],
[0,0,0,0,0,0,0,0,0,0],
[0,0,0,0,0,0,0,0,0,0]] # coefficients for second order features in Part 2g
print("SSE Part 2G: {0}".format(sse(coeffs_part_b,coeffs_part_b_matrix, X, Y_actual)))
```

Listing 9: data file

```
reset;
param n_samples >= 0; # Total number of samples. In this case, 442
param n_features >= 0; # Total number of features. In this case, 10
param n_train >= 0; # Total number of training samples. In this case, 250
param first_order_coeff_bound; # Upper limit on any first order coefficient
param second_order_coeff_bound; # Upper limit on any second order coefficient
param mat{1..n_samples, 1..n_features+1}; # mat[i,j] is the jth feature of the ith
    sample. If j=11, it is the target variable of the ith sample
param AGE; # number to refer to AGE feature
param SEX; # number to refer to SEX feature
param BMI; # number to refer to BMI feature
param BP; # number to refer to BP feature
param S1; # number to refer to S1 feature
param S2; # number to refer to S2 feature
param S3; # number to refer to S3 feature
param S4; # number to refer to S4 feature
param S5; # number to refer to S5 feature
param S6; # number to refer to S6 feature
param Y; # number to refer to target variable
param lambdas{1..11}; # All possible lambda values for Part I as a list
param lambda_part_2; # Lambda value for Part II
```

```
data;
param n_samples := 442;
param n_train := 250;
param n_features := 10;
param first_order_coeff_bound := 1000;
param second_order_coeff_bound := 5000;
param AGE := 1;
param SEX := 2;
param BMI := 3;
param BP := 4;
param S1 := 5;
param S2 := 6;
param S3 := 7;
param S4 := 8;
param S5 := 9;
param S6 := 10;
param Y := 11;
param lambdas := 1 200 2 220 3 240 4 260 5 280 6 300 7 320 8 340 9 360 10 380 11 400;
param lambda_part_2 := 9.57;
param mat: 1 2 3 4 5 6 7 8 9 10 11 :=
1 0.038075906 0.05068012 0.0616962065 2.187235e-02 -0.044223498 -3.482076e-02
    0.043400846 -0.0025922620 0.0199084209 -0.017646125 -1.1334842
2  -0.001882017 -0.04464164 -0.0514740612 -2.632783e-02 -0.008448724 -1.916334e-02
    -0.074411564 -0.0394933829 -0.0683297436 -0.092204050 -77.1334842
3   0.085298906 0.05068012 0.0444512133 -5.670611e-03 -0.045599451 -3.419447e-02
    0.032355932 -0.0025922620 0.0028637705 -0.025930339 -11.1334842
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    0.036037570 0.0343088589 0.0226920226 -0.009361911 53.8665158
5   0.005383060 -0.04464164 -0.0363846922 2.187235e-02 0.003934852 1.559614e-02
    -0.008142084 -0.0025922620 -0.0319914449 -0.046640874 -17.1334842
6  -0.092695478 -0.04464164 -0.0406959405 -1.944209e-02 -0.068990650 -7.928784e-02
    -0.041276824 -0.0763945038 -0.0411803852 -0.096346157 -55.1334842
7  -0.045472478 0.05068012 -0.0471628129 -1.599922e-02 -0.040095640 -2.480001e-02
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8   0.063503676 0.05068012 -0.0018947058 6.662967e-02 0.090619882 1.089144e-01
    -0.022868635 0.0177033545 -0.0358167281 0.003064409 -89.1334842
9   0.041708445 0.05068012 0.0616962065 -4.009932e-02 -0.013952536 6.201686e-03
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   0.013947743 -0.0763945038 -0.0629129499 -0.034214553 -51.1334842
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   -0.044958462 -0.0394933829 -0.0307512099 -0.042498767 26.8665158
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