celiotomy retrospective analysis 2023

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#Model primary outcome of incisional infection vs variables that make sense:

```
## logistf(formula = incis_infect ~ enterot + bowel_resect + preop_antibio +
##     intraop_antibio + anes_time + recov_time + recov_qual, data = data)
##
## Model fitted by Penalized ML
## Coefficients:
##                          coef  se(coef) lower 0.95 upper 0.95      Chisq
## (Intercept)      -3.07028681 1.5848930 -8.0761574 -0.4334199 5.45704893
## enterotY          0.31639619 0.3473535 -0.3890697  1.0428758 0.76790682
## bowel_resectY     0.85271871 0.5160953 -0.2326142  1.9019128 2.39814349
## preop_antibioY   -0.06344311 0.3812145 -0.8673340  0.6931377 0.02593893
## intraop_antibioY  0.27488064 0.3604840 -0.4782285  0.9935478 0.53353307
## anes_time        -0.03215775 0.2452482 -0.5701393  0.4599259 0.01516658
## recov_time       -0.43064828 0.3624198 -1.2200117  0.3009104 1.25564089
## recov_qualfair    0.56984478 1.4575566 -1.6602129  5.4640992 0.16788863
## recov_qualgood    0.82158857 1.4424157 -1.3513259  5.7043849 0.38541124
## recov_qualpoor    0.55276356 1.5238535 -1.9517343  5.4977878 0.13903484
##                          p method
## (Intercept)      0.01948954      2
## enterotY         0.38086537      2
## bowel_resectY    0.12147934      2
## preop_antibioY   0.87204955      2
## intraop_antibioY 0.46512526      2
## anes_time        0.90198619      2
## recov_time       0.26247783      2
## recov_qualfair   0.68199510      2
## recov_qualgood   0.53472137      2
## recov_qualpoor   0.70924241      2
##
## Method: 1-Wald, 2-Profile penalized log-likelihood, 3-None
##
## Likelihood ratio test=7.147469 on 9 df, p=0.6217689, n=573
## Wald test = 242.8144 on 9 df, p = 0
```

##Note that none of the variables in the full model are significant. Backwards elimination removed all of the variables and resulted in a model of (incisional infection ~ 1). ## The next step would be to trial individual sets of variables that may be significant

First try enterotomy or resection:

```
## logistf(formula = incis_infect ~ enterot + bowel_resect, data = data)
```

```
##
## Model fitted by Penalized ML
## Coefficients:
##                    coef  se(coef) lower 0.95 upper 0.95    Chisq         p
## (Intercept)   -2.8986203 0.2777626 -3.4846616 -2.3863905      Inf 0.0000000
## enterotY       0.1969729 0.3320154 -0.4533046  0.8637653 0.350686 0.5537251
## bowel_resectY  0.6288751 0.3679076 -0.1316104  1.3306892 2.675592 0.1018975
##               method
## (Intercept)        2
## enterotY           2
## bowel_resectY      2
##
## Method: 1-Wald, 2-Profile penalized log-likelihood, 3-None
##
## Likelihood ratio test=2.816695 on 2 df, p=0.244547, n=608
## Wald test = 260.0242 on 2 df, p = 0
```

Antibiotic use:

```
## logistf(formula = incis_infect ~ preop_antibio + intraop_antibio,
##     data = data)
##
## Model fitted by Penalized ML
## Coefficients:
##                       coef  se(coef) lower 0.95 upper 0.95     Chisq         p
## (Intercept)      -2.6535176 0.2416686 -3.1600028 -2.2058539       Inf 0.0000000
## preop_antibioY   -0.1923760 0.3707555 -0.9570097  0.5159410 0.2720081 0.6019879
## intraop_antibioY  0.2232458 0.3571590 -0.5044835  0.9125981 0.3802123 0.5374896
##                  method
## (Intercept)           2
## preop_antibioY        2
## intraop_antibioY      2
##
## Method: 1-Wald, 2-Profile penalized log-likelihood, 3-None
##
## Likelihood ratio test=0.8727224 on 2 df, p=0.6463842, n=608
## Wald test = 263.0964 on 2 df, p = 0
```

Intraoperative antibiotic type or timing?

```
## logistf(formula = incis_infect ~ intraop_antibio_type + intraop_antibio_time,
##     data = data)
##
## Model fitted by Penalized ML
## Coefficients:
##                                          coef se(coef) lower 0.95 upper 0.95
## (Intercept)                        -2.0276552 1.509804 -6.9492252  0.3590186
## intraop_antibio_typeenro            0.8521640 2.211057 -4.5867321  6.3228231
## intraop_antibio_typeenro pmx        3.1262675 2.224000 -0.7271235  9.0795130
## intraop_antibio_typegent           -0.1733553 1.696205 -3.2901247  4.8818982
## intraop_antibio_typegent cefa       0.4182173 2.163217 -4.9820754  5.8289444
## intraop_antibio_typegent cefa pmx   0.7752851 2.209802 -4.6611909  6.2410962
## intraop_antibio_typegent pmx        0.8780849 1.765815 -2.3676022  5.9894662
```

```
## intraop_antibio_typemetro         3.0878280 2.216076 -0.7434176  9.0296809
## intraop_antibio_typep             0.9290429 2.224000 -4.5274058  6.4200251
## intraop_antibio_typepen          -0.5397908 1.705466 -3.6837188  4.5200993
## intraop_antibio_typepen cefa      3.1262675 2.224000 -0.7271235  9.0795130
## intraop_antibio_typepen clinda    0.8137246 2.208963 -4.6221299  6.2799616
## intraop_antibio_typepen enro      0.8906035 2.216076 -4.5551141  6.3695499
## intraop_antibio_typepen gent     -0.3729802 1.545718 -2.8664714  4.5698953
## intraop_antibio_typepen gent pmx -1.2957788 2.063010 -6.6015610  4.0034149
## intraop_antibio_typepmx          -1.0430085 1.704269 -4.1811821  4.0115537
## intraop_antibio_typeppen enro     0.6599668 2.229826 -4.7993471  6.1500579
## intraop_antibio_time              0.1537578 0.322033 -0.8336830  0.7619085
##                                        Chisq         p method
## (Intercept)                      2.643998067 0.1039417      2
## intraop_antibio_typeenro         0.144969541 0.7033898      2
## intraop_antibio_typeenro pmx     2.467580700 0.1162167      2
## intraop_antibio_typegent         0.009898673 0.9207476      2
## intraop_antibio_typegent cefa    0.036626932 0.8482266      2
## intraop_antibio_typegent cefa pmx 0.120585065 0.7284008      2
## intraop_antibio_typegent pmx     0.264014843 0.6073752      2
## intraop_antibio_typemetro        2.433098745 0.1187979      2
## intraop_antibio_typep            0.169434250 0.6806151      2
## intraop_antibio_typepen          0.090372579 0.7637040      2
## intraop_antibio_typepen cefa     2.467580700 0.1162167      2
## intraop_antibio_typepen clinda   0.132711182 0.7156374      2
## intraop_antibio_typepen enro     0.157247850 0.6917031      2
## intraop_antibio_typepen gent     0.052235781 0.8192175      2
## intraop_antibio_typepen gent pmx  0.367328571 0.5444640      2
## intraop_antibio_typepmx          0.313089051 0.5757908      2
## intraop_antibio_typeppen enro    0.086070033 0.7692340      2
## intraop_antibio_time             0.170864602 0.6793445      2
##
## Method: 1-Wald, 2-Profile penalized log-likelihood, 3-None
##
## Likelihood ratio test=19.11204 on 17 df, p=0.3221394, n=167
## Wald test = 73.84055 on 17 df, p = 4.657713e-09
```

Anesthesia variables?

```
## logistf(formula = incis_infect ~ anes_time + recov_time + recov_qual,
##     data = data)
##
## Model fitted by Penalized ML
## Coefficients:
##                      coef  se(coef) lower 0.95 upper 0.95      Chisq
## (Intercept)    -3.7192307 1.5532395 -8.6806985 -1.2507024 10.2640622
## anes_time       0.2581382 0.1739744 -0.1153288  0.5988728  1.8955356
## recov_time     -0.4142717 0.3631276 -1.1915428  0.3032292  1.1893804
## recov_qualfair  0.8651348 1.4603742 -1.2984640  5.7471962  0.4341948
## recov_qualgood  1.1406629 1.4421388 -0.9523914  6.0096151  0.8563290
## recov_qualpoor  0.8098640 1.5277337 -1.6355198  5.7415443  0.3244785
##                          p method
## (Intercept)    0.001356467      2
## anes_time      0.168578877      2
```

```
## recov_time     0.275454567      2
## recov_qualfair 0.509937780      2
## recov_qualgood 0.354768046      2
## recov_qualpoor 0.568928574      2
##
## Method: 1-Wald, 2-Profile penalized log-likelihood, 3-None
##
## Likelihood ratio test=3.715463 on 5 df, p=0.5910646, n=573
## Wald test = 245.202 on 5 df, p = 0
```

Association with NSAID use?

```
## logistf(formula = incis_infect ~ postop_nsaid_num + postop_nsaid_days,
##     data = data)
##
## Model fitted by Penalized ML
## Coefficients:
##                         coef  se(coef)  lower 0.95 upper 0.95      Chisq
## (Intercept)       -3.4935737 0.4604556 -4.42446188 -2.5968871 55.5636104
## postop_nsaid_num   0.1331680 0.3121734 -0.51657910  0.7320001  0.1740918
## postop_nsaid_days  0.1241185 0.0335200  0.06457981  0.2071685 21.3085348
##                              p method
## (Intercept)       9.048318e-14      2
## postop_nsaid_num  6.765006e-01      2
## postop_nsaid_days 3.909869e-06      2
##
## Method: 1-Wald, 2-Profile penalized log-likelihood, 3-None
##
## Likelihood ratio test=23.75979 on 2 df, p=6.928314e-06, n=604
## Wald test = 248.4323 on 2 df, p = 0
```

None of these produced significant independent predictors without possible confounding. The use of multiple days of NSAIDs is likely due to the infection, not the cause of the infection.

How about modeling postop reflux?

```
## logistf(formula = postop_reflux ~ anes_time + bowel_resect +
##     enterot + preop_antibio + intraop_antibio + postop_antibio_days +
##     postop_antibio_addnl + postop_nsaid_num + postop_nsaid_days +
##     postop_lido + postop_alpha2 + postop_butor + postop_ket,
##     data = data)
##
## Model fitted by Penalized ML
## Coefficients:
##                              coef   se(coef)  lower 0.95  upper 0.95
## (Intercept)           -5.08839704 0.88976713 -7.36033423 -3.56885514
## anes_time              0.17112722 0.15248573 -0.13104623  0.47402240
## bowel_resectY          0.11465795 0.33996989 -0.56567985  0.78166116
## enterotY               0.03485143 0.22016023 -0.39996262  0.47231700
## preop_antibioY        -0.02666645 0.24296885 -0.51297966  0.45072952
```

```
## intraop_antibioY       0.22887053 0.23872242 -0.24794233  0.69816697
## postop_antibio_days   -0.03488200 0.04368450 -0.12574426  0.04923036
## postop_antibio_addnlY  0.42085195 0.23112808 -0.03711106  0.87865840
## postop_nsaid_num       0.23346662 0.20263222 -0.17089144  0.63263670
## postop_nsaid_days      0.03338072 0.04378197 -0.05226941  0.12299927
## postop_lidoY           2.79537712 0.81316965  1.47836085  4.97921064
## postop_alpha2Y         0.21635780 0.24510746 -0.27021236  0.70225838
## postop_butorY          0.46184987 0.25292442 -0.03719759  0.96580061
## postop_ketY           -0.62276688 0.27170387 -1.17795137 -0.09731420
##                             Chisq            p method
## (Intercept)                   Inf 0.000000e+00      2
## anes_time              1.23598215 2.662468e-01      2
## bowel_resectY          0.11147317 7.384731e-01      2
## enterotY               0.02462709 8.752999e-01      2
## preop_antibioY         0.01182594 9.134031e-01      2
## intraop_antibioY       0.89502182 3.441201e-01      2
## postop_antibio_days    0.63706327 4.247762e-01      2
## postop_antibio_addnlY  3.24587273 7.160355e-02      2
## postop_nsaid_num       1.29201258 2.556774e-01      2
## postop_nsaid_days      0.57313642 4.490153e-01      2
## postop_lidoY          28.21790174 1.083974e-07      2
## postop_alpha2Y         0.76261416 3.825117e-01      2
## postop_butorY          3.28954797 6.972221e-02      2
## postop_ketY            5.43999167 1.968076e-02      2
##
## Method: 1-Wald, 2-Profile penalized log-likelihood, 3-None
##
## Likelihood ratio test=73.02386 on 13 df, p=2.217373e-10, n=602
## Wald test = 145.1962 on 13 df, p = 0
```

Some significant predictors. Will need to decrease complexity of the model by dropping least significant terms. Automatic selection dosn't work due to model separation, so will do backwards selection by hand.

The final model includes postoperative lidocaine and alpha-2 agonists as significant predictors:

```
## logistf(formula = postop_reflux ~ postop_lido + postop_alpha2,
##     data = data)
##
## Model fitted by Penalized ML
## Coefficients:
##                      coef  se(coef)  lower 0.95 upper 0.95     Chisq
## (Intercept)    -4.3872275 0.8243811 -6.56377151 -3.0916539       Inf
## postop_lidoY    3.0701106 0.8277834  1.76338778  5.2502984 39.125132
## postop_alpha2Y  0.4450261 0.2056487  0.04276427  0.8520088  4.704332
##                           p method
## (Intercept)    0.000000e+00      2
## postop_lidoY   3.974941e-10      2
## postop_alpha2Y 3.008669e-02      2
```

```
##
## Method: 1-Wald, 2-Profile penalized log-likelihood, 3-None
##
## Likelihood ratio test=47.97917 on 2 df, p=3.81466e-11, n=606
## Wald test = 139.41 on 2 df, p = 0
```

```
##                     or or.lower or.upper
## (Intercept)      0.012    0.001    0.045
## postop_lidoY    21.544    5.832  190.623
## postop_alpha2Y   1.561    1.044    2.344
```

It is interesting that both lidocaine and alpha-2s significantly increased the odds of postop reflux. However, it is quite possible that the distribution of the data causes issues with the modeling. For example, if you look at the frequency table for lidocaine and reflux, there was only one patient that was refluxing but didn't receive lidocaine, but there were 126 that continued to reflux while still on IV lidocaine...

```
##        lidocaine   N   Y
## reflux
## N                104 375
## Y                  1 126
```

The numbers for lidocaine plus alpha-2s are better distributed, so I find it likely that continued administration of alpha-2 agonists is associated with more patients refluxing - but it is also likely that these patients were more painful or needed to be sedated more for continued treatments.

```
##                 alpha2   N   Y
## reflux lidocaine
## N      N                74  30
##        Y               201 174
## Y      N                 1   0
##        Y                53  73
```

In the end, I'm not sure that any of these predictors are truly valid indicators.

For other complications, the full model wasn't particularly interesting, but after backwards selection by hand again recovery quality, enterotomy (yes), the addition of additional antibiotics postoperatively (other than pen/gent), and the number of types of NSAIDs were all predictive:

```
## logistf(formula = other_comp ~ recov_qual + enterot + postop_antibio_addnl +
##     postop_nsaid_num, data = data)
##
## Model fitted by Penalized ML
```

```
## Coefficients:
##                             coef  se(coef)  lower 0.95  upper 0.95     Chisq
## (Intercept)           -2.1112440 0.6854658 -3.60802714 -0.84540701 11.337611
## recov_qualfair         0.9465681 0.6453026 -0.23980348  2.37372994  2.389457
## recov_qualgood         0.6973747 0.6368062 -0.47025977  2.11153570  1.302378
## recov_qualpoor         1.5445097 0.6760613  0.29138150  3.01997105  5.956893
## enterotY              -0.4484703 0.1806113 -0.80488000 -0.09504569  6.192212
## postop_antibio_addnlY  1.2883861 0.1816850  0.93464868  1.64797993 52.212199
## postop_nsaid_num       0.3781191 0.1749325  0.03552929  0.72394280  4.680692
##                                  p method
## (Intercept)           7.595296e-04      2
## recov_qualfair        1.221561e-01      2
## recov_qualgood        2.537794e-01      2
## recov_qualpoor        1.465985e-02      2
## enterotY              1.283137e-02      2
## postop_antibio_addnlY 4.981571e-13      2
## postop_nsaid_num      3.050347e-02      2
##
## Method: 1-Wald, 2-Profile penalized log-likelihood, 3-None
##
## Likelihood ratio test=80.60572 on 6 df, p=2.664535e-15, n=590
## Wald test = 90.03383 on 6 df, p = 0
```

```
##                         or2 or.lower2 or.upper2
## (Intercept)           0.121     0.027     0.429
## recov_qualfair        2.577     0.787    10.737
## recov_qualgood        2.008     0.625     8.261
## recov_qualpoor        4.686     1.338    20.491
## enterotY              0.639     0.447     0.909
## postop_antibio_addnlY 3.627     2.546     5.196
## postop_nsaid_num      1.460     1.036     2.063
```

While good and fair recoveries were not predictive (as opposed to excellent), I had to leave them in the model because poor recoveries were associated with an increase in the incidence of 'other' complications. Enterotomies decreased the incidence of these other complications by almost half.

Finally, nothing in the model was particularly predictive of survival to dismissal, but the number of days in the hospital was weakly associated (possibly)...

```
## logistf(formula = surv_dismis ~ days_hosp, data = data)
##
## Model fitted by Penalized ML
## Coefficients:
##                   coef   se(coef)   lower 0.95 upper 0.95     Chisq
## (Intercept) 1.36807035 0.21931100  0.921721633  1.7976957 35.553865
## days_hosp   0.05637523 0.03459238 -0.006925352  0.1314929  2.957072
##                        p method
## (Intercept) 2.480943e-09      2
## days_hosp   8.550262e-02      2
```

```
##
## Method: 1-Wald, 2-Profile penalized log-likelihood, 3-None
##
## Likelihood ratio test=2.957072 on 1 df, p=0.08550262, n=608
## Wald test = 226.7517 on 1 df, p = 0
```

```
##                or3 or.lower3 or.upper3
## (Intercept) 3.928     2.514     6.036
## days_hosp   1.058     0.993     1.141
```