MS&E 226 Project Part 2

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1 Introduction

In Part 2 of this, we will continue to build on our observations from the prediction task utilizing the College Scorecard from Part 1 of the project.

2 Prediction on Test Set

In this section we will see how our models for the regression and classification task from Part 1 perform on the test data.

2.1 Regression Task utilizing Linear Regression Model

We ran the regression model that was obtained by running forward step-wise regression from Part 1. The model selected included 15 covariates. The RMSE from cross validation was 4796.309 from the training data. The cross validation RMSE test error was 4745.161. Generally the training error is lower than the test error since our model was built on the training data. In this case, the training error is slightly higher than the test error. However a lower test error may be due to a high sampling bias. Since we did not have control over which observations were going to be included in the training/test set, this may have led to "easier" to predict or less noisy observations in the test set resulting in a lower test error, and "harder" to predict or noisier observations in the training set. Though we did utilize cross validation to compute the RMSE, the split in data 80/20 may have led to the test set performing better by random.

2.2 Classification Task utilzing Logistic Regression Model

We ran the logistic model that was obtained by running forward step-wise regression from Part 1. The model selected includes 16 covariates. The 0-1 error rate (utilizing cross validation) was 10.1% from the training data. We obtained a 0-1 error rate (utilizing cross validation) of 11.6% when running the model on the held out test data. The training error is generally lower than the test error since our model was built on the training data. Overall, this slight (+1.5%) increase on the 0-1 error rate shows our training error rate was a good predictor of our test error rate.

3 Inference

3.1 Significant Covariates

In our chosen linear regression model, 15 covariates were used to build our selected model. As noted in figure 1, we will consider p-values with "*", "**", or "***" as statistically significant at an $\alpha = 0.05$ cutoff. The statistically significant p-values represent the probability that we would end up with data that shows us the estimated $\hat{\beta}_j$ given the null was true i.e. $\hat{\beta}_j = 0$. In inference for our linear regression model, we assume the population model is linear, our errors are normally distributed, and errors are i.i.d. with mean 0. Under these assumptions, we can only believe there is an associative relationship (correlation in the population model) for the significant covariates and our outcome. For instance, a larger proportion of students make over 25k post-grad can be associated with higher expected earnings, but we cannot make establish causality based simply on which covariates are significant.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	3.918e+03	2.106e+03	1.861	0.062878	.
gt_25k_p6	5.696e+04	8.040e+02	70.841	< 2e-16	***
UGDS_ASIAN	3.437e+04	2.151e+03	15.982	< 2e-16	***
PREDDEGBachelor	1.400e+03	3.008e+02	4.653	3.39e-06	***
PREDDEGCertificate	-9.378e+02	2.644e+02	-3.548	0.000394	***
STABBRAL	4.238e+03	2.084e+03	2.033	0.042093	*
STABBRAR	3.930e+03	2.092e+03	1.878	0.060400	.
STABBRAZ	1.316e+03	2.030e+03	0.648	0.516779	
STABBRCA	8.127e+02	1.966e+03	0.413	0.679398	
STABBRCO	2.686e+03	2.023e+03	1.328	0.184261	
STABBRCT	3.571e+03	2.056e+03	1.737	0.082465	.
STABBRDC	5.842e+03	2.459e+03	2.375	0.017580	*
STABBRDE	2.008e+03	2.455e+03	0.818	0.413499	
STABBRFL	1.926e+03	1.979e+03	0.973	0.330651	
STABBRGA	2.914e+03	2.013e+03	1.448	0.147833	
STABBRHI	-7.314e+03	2.360e+03	-3.099	0.001954	**
STABBRIA	1.016e+03	2.048e+03	0.496	0.619825	
STABBRID	2.622e+03	2.241e+03	1.170	0.242060	
STABBRIL	2.066e+03	1.982e+03	1.042	0.297319	
STABBRIN	1.864e+03	2.017e+03	0.924	0.355691	
STABBRKS	1.359e+03	2.047e+03	0.664	0.506749	
STABBRKY	2.313e+03	2.048e+03	1.129	0.258776	
STABBRLA	3.508e+03	2.048e+03	1.713	0.086790	.
STABBRMA	4.001e+03	2.000e+03	2.001	0.045494	*
STABBRMD	4.221e+03	2.057e+03	2.052	0.040250	*
STABBRME	2.710e+03	2.163e+03	1.253	0.210324	
STABBRMI	3.372e+03	2.003e+03	1.683	0.092384	.
STABBRMN	1.219e+03	2.009e+03	0.607	0.543940	
STABBRMO	2.451e+03	2.006e+03	1.222	0.221849	
STABBRMS	3.367e+03	2.133e+03	1.579	0.114488	
STABBRMT	1.191e+03	2.421e+03	0.492	0.622719	
STABBRNC	2.365e+03	2.018e+03	1.172	0.241266	
STABBRND	1.221e+02	2.251e+03	0.054	0.956760	
STABBRNE	1.475e+03	2.118e+03	0.696	0.486258	
STABBRNH	2.793e+03	2.265e+03	1.233	0.217615	
STABBRNJ	4.717e+03	2.012e+03	2.345	0.019092	*
STABBRNM	3.222e+03	2.151e+03	1.498	0.134187	
STABBRNV	5.132e+02	2.164e+03	0.237	0.812519	
STABBRNY	4.760e+03	1.974e+03	2.412	0.015914	*
STABBROH	2.521e+03	1.980e+03	1.273	0.202970	
STABBROK	1.090e+03	2.047e+03	0.532	0.594543	
STABBROR	1.992e+03	2.051e+03	0.971	0.331487	
STABBRPA	3.743e+03	1.976e+03	1.894	0.058326	.
STABBRPR	4.556e+03	2.202e+03	2.069	0.038592	*
STABBRRI	3.199e+03	2.266e+03	1.412	0.158088	
STABBRSC	2.616e+03	2.048e+03	1.278	0.201466	
STABBRSD	4.048e+02	2.265e+03	0.179	0.858174	
STABBRTN	3.202e+03	2.015e+03	1.589	0.112127	
STABBRTX	2.438e+03	1.973e+03	1.236	0.216597	
STABBRUT	2.130e+03	2.101e+03	1.014	0.310799	
STABBRVA	2.221e+03	2.009e+03	1.105	0.269064	
STABBRVT	2.642e+03	2.287e+03	1.155	0.248030	
STABBRWA	1.229e+03	2.028e+03	0.606	0.544444	
STABBRWI	1.940e+03	2.029e+03	0.957	0.338878	
STABBRWV	4.842e+03	2.190e+03	2.211	0.027081	*
STABBRWY	3.002e+03	2.420e+03	1.240	0.214906	
PPTUG_EF	-3.357e+03	4.361e+02	-7.698	1.77e-14	***
GRAD_DEBT_MDN_SUPP	9.070e-02	1.786e-02	5.077	4.02e-07	***
PCTFLOAN	-3.956e+03	6.703e+02	-5.902	3.91e-09	***
CONTROLPrivate NonProfit	-6.848e+02	2.952e+02	-2.320	0.020416	*
CONTROLPublic	-1.659e+03	3.067e+02	-5.411	6.68e-08	***
UGDS_WHITE	-1.285e+03	4.702e+02	-2.733	0.006311	**
UGDS_NRA	8.848e+03	2.886e+03	3.066	0.002182	**
DISTANCEONLY	3.198e+03	1.402e+03	2.281	0.022622	*
UG25abv	1.150e+03	5.591e+02	2.057	0.039725	*
PCTPELL	-2.008e+03	8.255e+02	-2.432	0.015058	*
UGDS_2MOR	5.730e+03	3.147e+03	1.821	0.068714	.
RPY_3YR_RT_SUPP	-1.153e+03	8.038e+02	-1.434	0.151534	

Figure 1: Linear Regression Output for Training Data

When we run the same model on our test data, we observe different results as seen in Figure 2. As we examine our p-values, we are still operating under the null hypothesis that $\hat{\beta}_j = 0$. We notice that quite a few of our covariate are no longer significant when using the test data. Our failure to reject the null can be due the fact we don't have enough data. Since our data was split 80/20, this can be particularly relevant when looking at the State covariate. We may not had enough of a particular State in our test set to get enough evidence to reject the null. To further explore this, we could try another random 80-20 split or gather more data for the test set.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	5.955e+03	3.519e+03	1.692	0.0910	.
gt_25k_p6	5.822e+04	1.722e+03	33.803	< 2e-16	***
UGDS_ASIAN	1.322e+04	3.345e+03	3.953	8.34e-05	***
PREDDEGBachelor	1.242e+03	6.032e+02	2.058	0.0399	*
PREDDEGCertificate	-9.543e+02	4.955e+02	-1.926	0.0545	.
STABBRAL	-9.626e+02	3.436e+03	-0.280	0.7794	
STABBRAR	2.011e+02	3.470e+03	0.058	0.9538	
STABBRAZ	-1.461e+03	3.340e+03	-0.438	0.6619	
STABBRCA	-4.318e+02	3.270e+03	-0.132	0.8950	
STABBRCO	-1.440e+03	3.389e+03	-0.425	0.6711	
STABBRCT	-7.777e+02	3.449e+03	-0.225	0.8217	
STABBRDC	7.963e+03	3.801e+03	2.095	0.0365	*
STABBRDE	-1.091e+03	4.128e+03	-0.264	0.7916	
STABBRFL	-6.819e+02	3.296e+03	-0.207	0.8362	
STABBRGA	-6.896e+02	3.353e+03	-0.206	0.8371	
STABBRHI	-9.711e+03	4.018e+03	-2.417	0.0159	*
STABBRIA	-2.351e+03	3.514e+03	-0.669	0.5037	
STABBRID	-2.555e+02	3.929e+03	-0.065	0.9482	
STABBRIL	-1.577e+02	3.300e+03	-0.048	0.9619	
STABBRIN	-3.525e+03	3.495e+03	-1.009	0.3133	
STABBRKS	-3.858e+03	3.401e+03	-1.135	0.2569	
STABBRKY	-1.123e+03	3.397e+03	-0.331	0.7411	
STABBRLA	-1.742e+03	3.516e+03	-0.496	0.6204	
STABBRMA	-5.282e+01	3.325e+03	-0.016	0.9873	
STABBRMD	1.805e+02	3.423e+03	0.053	0.9580	
STABBRME	1.669e+03	3.607e+03	0.463	0.6437	
STABBRMI	-3.205e+02	3.318e+03	-0.097	0.9231	
STABBRMN	-4.372e+03	3.405e+03	-1.284	0.1995	
STABBRMO	-1.564e+03	3.342e+03	-0.468	0.6398	
STABBRMS	4.278e+02	3.676e+03	0.116	0.9074	
STABBRMT	-3.974e+03	3.939e+03	-1.009	0.3134	
STABBRNC	-8.383e+02	3.334e+03	-0.251	0.8015	
STABBRND	-5.429e+03	4.147e+03	-1.309	0.1908	
STABBRNE	-1.623e+03	3.533e+03	-0.459	0.6460	
STABBRNH	-2.968e+03	3.565e+03	-0.833	0.4053	
STABBRNJ	2.249e+03	3.375e+03	0.666	0.5053	
STABBRNM	1.107e+01	3.502e+03	0.003	0.9975	
STABBRNV	-3.030e+02	3.650e+03	-0.083	0.9339	
STABBRNY	-1.519e+03	3.295e+03	-0.461	0.6449	
STABBROH	-2.738e+03	3.283e+03	-0.834	0.4046	
STABBROK	-3.399e+03	3.470e+03	-0.979	0.3276	
STABBROR	-9.182e+01	3.473e+03	-0.026	0.9789	
STABBRPA	-1.214e+02	3.275e+03	-0.037	0.9704	
STABBRPR	1.852e+03	3.494e+03	0.530	0.5961	
STABBRSC	-1.940e+02	3.357e+03	-0.058	0.9539	
STABBRSD	-3.936e+03	3.709e+03	-1.061	0.2890	
STABBRTN	-1.849e+03	3.385e+03	-0.546	0.5851	
STABBRTX	-8.287e+02	3.269e+03	-0.253	0.7999	
STABBRUT	6.023e+02	3.835e+03	0.157	0.8753	
STABBRVA	-2.808e+03	3.334e+03	-0.842	0.3999	
STABBRVT	-1.096e+03	3.944e+03	-0.278	0.7811	
STABBRWA	-2.928e+03	3.401e+03	-0.861	0.3896	
STABBRWI	-2.799e+03	3.435e+03	-0.815	0.4154	
STABBRWV	-2.703e+02	3.514e+03	-0.077	0.9387	
PPTUG_EF	-3.449e+03	8.584e+02	-4.018	6.38e-05	***
GRAD_DEBT_MDN_SUPP	6.931e-02	3.447e-02	2.011	0.0447	*
PCTFLOAN	-1.102e+03	1.253e+03	-0.879	0.3796	
CONTROLPrivate NonProfit	-1.131e+03	5.628e+02	-2.010	0.0448	*
CONTROLPublic	-1.040e+03	6.004e+02	-1.733	0.0835	.
UGDS_WHITE	-1.393e+03	9.120e+02	-1.527	0.1270	
UGDS_NRA	1.296e+04	5.312e+03	2.440	0.0149	*
DISTANCEONLY	-2.968e+03	2.330e+03	-1.273	0.2032	
UG25abv	1.062e+03	1.071e+03	0.992	0.3213	
PCTPELL	-2.954e+03	1.556e+03	-1.899	0.0579	.
UGDS_2MOR	1.155e+04	6.598e+03	1.750	0.0804	.
RPY_3YR_RT_SUPP	3.024e+02	1.603e+03	0.189	0.8504	

Figure 2: Linear Regression Output for Test Data

3.2 Bootstrap

1,000 bootstrap samples were drawn to create a confidence interval for each of the regression coefficients. The model selected from Part 1 of the project was ran on each sample (drawn with replacement from the training data). To compute a 95% confidence interval, the estimate from the original sample was utilized $\hat{\beta_j}$. From the bootstrap samples, we computed the standard error, which can be approximated as the sample standard deviation of the bootstrap sample. The confidence interval was computed as [$\hat{\beta_j}$ - 1.96 x SE, $\hat{\beta_j}$ + 1.96 x SE]. From observation, the bootstrap samples appeared normally distributed and so the confidence intervidence interval was computed utilizing the standard error.

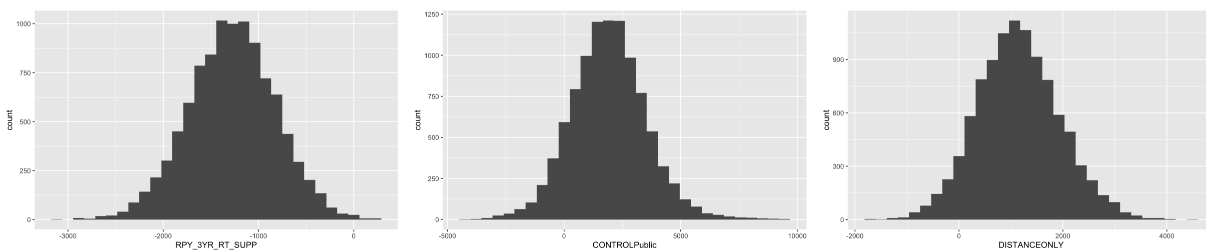

Figure 3: Bootstrap Confidence Intervals

3.2.1 95% Confidence Intervals for lm() and bootstrapped samples (reduced version – see Appendix for full list of covariates)

```
##             VARNAME  LOWER_LM   UPPER_LM LOWER_BOOT UPPER_BOOT
## 66      UGDS_ASIAN 30155.228 38585.4960 33689.7001 35051.0235
## 57        STABBRUT -1988.384  6248.2866 -1008.1139  5268.0161
## 41        STABBRNE -2676.712  5626.7369 -1674.6842  4624.7095
## 19        STABBRDC  1021.622 10661.8872  4152.4274  7531.0815
## 3    CONTROLPublic -2260.465 -1058.2827 -4837.9882  1519.2402
## 38        STABBRMT -3554.103  5936.6866 -2145.7182  4528.3023
## 58        STABBRVA -1717.063  6158.8910 -1259.5547  5701.3826
## 47        STABBROH -1359.451  6401.6100 -1254.3155  6296.4747
## 53        STABBRSC -1397.336  6629.7505  -689.6585  5922.0728
## 12 RPY_3YR_RT_SUPP -2728.491   422.4588 -2044.1831  -261.8487
```

As seen in the results, the bootstraps used to compute the confidence interval led to different results in than the R output. Some bootstrapped samples led to similar confidence intervals from the R output. However, the bootstrap one generally had a higher standard error, thus resulting in a wider confidence interval. The differing results could be due to a number of different factors. One issue may have arisen from the large amount of categories in the state variable. For a given bootstrap sample, it may be expected that this sample may look nothing like the original such as omission of a state or heavy clustering. A possible alternative to this would be to bootstrap states proportional to the number in the original sample or stratified sampling. The distribution in the state variables may have led to a sample that is not reflective of the original sample.

3.3 Post Selection Inference

Since many of the selected covariates in our model were significant, this could have been a result of how the model was built. From Part 1, we utilized forward step wise regression to select our predictor variables. This method of selecting covariates greedily picks which covariates to add to the model based on some criterion (p-values, AIC). As a result, we have favorably biased which p-values we would see as significant. Though we were able to test our model on the test set, the structure of the data made it difficult to reject the null in some cases since there is a possibility that the test set did not include values that were in the training set. This could mean we do not have enough data, thus low power. A way to further validate that our covariates are significant is to possibly gather more data that is more representative of the training set.

3.4 Collinearity

Some other issues may also arise due to collinarity. Collinarity is an issue because we will be unsure how a covariate will affect the outcome. For instance 'PCTPELL' and 'RPY_3YR_RT_SUPP' are collinear with each other because they are highly correlated with each other, as we examined in Part 1 of the project. In the training data, we notice 'PCTPELL' is significant. But in the test data, it is no longer significant. This may have due to collinarity issues. A possible way to further explore this would be to run the model without 'RPY_3YR_RT_SUPP' to see if 'PCTPELL' remains significant in both cases.

4 Discussion

This project sought to better understand the College Scorecard data set by building a predictive models as well as utilizing inference to better understand the population model. This model would be good for both prediction and inference purposes. On one hand, this model could be adapted to predict the median potential earnings of students at a given university given a set of factors As well, this model could be adapted to predict the potential earnings for a given time point. On the other hand, this model could also be used to understand how median earning for a given university are influenced by different factors of the university attended. This model could be useful to determining the amount a bank should loan a student given the university they go to or the starting financial aid a student receives at a given university.

As a result of the constant shifting state of higher education this model should be run on a frequent basis. The covariates as well as the outcome variables can face dramatic shifts outside due to the state of the world outside of our model's control. This could include the fluctuating job market (geographic location, job demand for certain job), difficulty getting loans for certain institution types, or shifts in admission rates.

One question that arose in the Part 1 of the project is whether the incomes were adjusted for inflation. It may be beneficial to have both data sets, one adjusted and one unadjusted, for local inflation. Because the cost of living may be higher in one area, it may make sense to utilize the adjusted income to better understand how geographic location explains income levels. A few other covariates that may have been of use to this data analysis includes admissions rate, cost of tuition, and average financial aid awarded.

One of the surprisingly challenging aspects of the project was dealing with the State covariate. The unique levels made it difficult to utilize in the prediction task and even more in the inference task. If I tackle this dataset again, I may have tried categorizing these variables into broader categories such as geographic region (Pacific Northwest, South, New England). This may have made techniques such as cross validation and bootstrap more manageable as well as the final model more interpretable.

5 Appendix

5.1 Bootstrap Code

```
set.seed(4)
sample_coef <- NULL
boots = data.frame(summary(model_train)$coefficients[, 1])[-1]
boots = rownames_to_column(boots, "VAR_NAME")

for (i in 1:10000) {
    sample = train[sample(1:nrow(train), nrow(train), replace = TRUE),
        ]
    model_boot = lm(formula = md_earn_wne_p10 ~ gt_25k_p6 + UGDS_ASIAN +
        PREDDEG + STABBR + PPTUG_EF + GRAD_DEBT_MDN_SUPP + PCTFLOAN +
        CONTROL + UGDS_WHITE + UGDS_NRA + DISTANCEONLY + UG25abv +
        PCTPELL + UGDS_2MOR + RPY_3YR_RT_SUPP, data = sample)

    coeff = data.frame(summary(model_boot)$coefficients[, 1])
    colnames(coeff)[1] <- paste0("sample", i)
    coeff = rownames_to_column(coeff, "VAR_NAME")
    boots = merge(boots, coeff, by.x = "VAR_NAME", by.y = "VAR_NAME",
        all.y = TRUE)
}
```

5.2 95% Confidence Intervals for Linear Regression Coefficients

```
ci
```

```
##                    VARNAME      LOWER_LM      UPPER_LM   LOWER_BOOT UPPER_BOOT
## 1              (Intercept) -2.092700e+02  8044.9557440    393.00116  7442.6846
## 2  CONTROLPrivate NonProfit -1.263453e+03  -106.1682966  -3825.44423  2455.8225
## 3            CONTROLPublic -2.260465e+03 -1058.2827062  -4837.98820  1519.2402
## 4             DISTANCEONLY  4.496500e+02  5945.4554872   1647.56832  4747.5372
## 5       GRAD_DEBT_MDN_SUPP  5.568909e-02     0.1257198  -3139.42425  3139.6057
## 6                gt_25k_p6  5.537977e+04 58531.4251076  56295.97422 57615.2163
## 7                 PCTFLOAN -5.269971e+03 -2642.5130935  -7548.85429  -363.6300
## 8                  PCTPELL -3.625915e+03  -389.7681684 -10526.09133  6510.4081
## 9                 PPTUG_EF -4.211790e+03 -2502.2583347  -7124.97881   410.9304
## 10          PREDDEGBachelor  8.100610e+02  1989.1741729  -3460.90097  6260.1362
## 11       PREDDEGCertificate -1.456003e+03  -419.6876948   -937.88951  -937.8013
## 12          RPY_3YR_RT_SUPP -2.728491e+03   422.4587876  -2044.18306  -261.8487
## 13                STABBRAL  1.528064e+02  8323.2500026   2248.80499  6227.2514
## 14                STABBRAR -1.706375e+02  8030.5328413   2174.68803  5685.2073
## 15                STABBRAZ -2.662065e+03  5293.9738060   -664.81154  3296.7207
## 16                STABBRCA -3.041234e+03  4666.6450877   -129.83416  1755.2454
## 17                STABBRCO -1.278427e+03  6651.0253284   1993.30458  3379.2933
## 18                STABBRCT -4.583566e+02  7600.0600386   3065.73973  4075.9638
## 19                STABBRDC  1.021622e+03 10661.8871903   4152.42742  7531.0815
## 20                STABBRDE -2.804073e+03  6819.7990956           NA         NA
## 21                STABBRFL -1.953686e+03  5805.0978464  -1351.51835  5202.9299
```

```
## 22                     STABBRGA -1.031483e+03  6858.6194867   -269.99226  6097.1288
## 23                     STABBRHI -1.193894e+04 -2688.6099126 -10453.26977 -4174.2824
## 24                     STABBRIA -2.998343e+03  5030.7757703  -2243.89665  4276.3295
## 25                     STABBRID -1.770373e+03  7014.7237027   -707.03346  5951.3840
## 26                     STABBRIL -1.818698e+03  5950.3698302  -2951.46833  7083.1398
## 27                     STABBRIN -2.090607e+03  5817.6847358           NA         NA
## 28                     STABBRKS -2.653484e+03  5372.3225923  -1727.13146  4445.9703
## 29                     STABBRKY -1.700655e+03  6326.1618050   -827.30913  5452.8158
## 30                     STABBRLA -5.057988e+02  7522.6826175  -1120.92689  8137.8107
## 31                     STABBRMA  8.146303e+01  7920.7451694    751.43122  7250.7770
## 32                     STABBRMD  1.890427e+02  8252.8217892    705.72936  7736.1351
## 33                     STABBRME -1.529481e+03  6949.5462739   -389.28811  5809.3532
## 34                     STABBRMI -5.541111e+02  7298.5875393    161.03329  6583.4432
## 35                     STABBRMN -2.718195e+03  5156.6807032  -1970.61059  4409.0961
## 36                     STABBRMO -1.480583e+03  6381.9796917   -754.21321  5655.6097
## 37                     STABBRMS -8.131366e+02  7546.6831393    155.43034  6578.1162
## 38                     STABBRMT -3.554103e+03  5936.6865811  -2145.71820  4528.3023
## 39                     STABBRNC -1.590367e+03  6321.2763212   -911.99487  5642.9042
## 40                     STABBRND -4.289690e+03  4533.7914823  -3261.77204  3505.8735
## 41                     STABBRNE -2.676712e+03  5626.7368510  -1674.68419  4624.7095
## 42                     STABBRNH -1.646684e+03  7233.5584194   -347.04002  5933.9144
## 43                     STABBRNJ  7.741230e+02  8660.7544435   1535.27849  7899.5990
## 44                     STABBRNM -9.934142e+02  7437.8053890    -73.19240  6517.5835
## 45                     STABBRNV -3.727821e+03  4754.3058497  -2903.64346  3930.1282
## 46                     STABBRNY  8.920738e+02  8628.5759920   1536.64081  7984.0090
## 47                     STABBROH -1.359451e+03  6401.6099537  -1254.31547  6296.4747
## 48                     STABBROK -2.922374e+03  5101.5762779  -2281.77170  4460.9745
## 49                     STABBROR -2.028262e+03  6012.9931739  -1695.26322  5679.9946
## 50                     STABBRPA -1.307779e+02  7616.3154804    513.04821  6972.4894
## 51                     STABBRPR  2.405355e+02  8870.5691916   1364.51342  7746.5912
## 52                     STABBRRI -1.242305e+03  7641.3010541   -256.06423  6655.0607
## 53                     STABBRSC -1.397336e+03  6629.7505223   -689.65853  5922.0728
## 54                     STABBRSD -4.034725e+03  4844.3131243  -2722.68867  3532.2768
## 55                     STABBRTN -7.472845e+02  7150.3798802     44.63633  6358.4590
## 56                     STABBRTX -1.428796e+03  6305.5191328   -730.50121  5607.2244
## 57                     STABBRUT -1.988384e+03  6248.2865841  -1008.11394  5268.0161
## 58                     STABBRVA -1.717063e+03  6158.8910017  -1259.55470  5701.3826
## 59                     STABBRVT -1.839982e+03  7123.6084946   -966.56751  6250.1939
## 60                     STABBRWA -2.745996e+03  5204.9606656  -1960.31152  4419.2766
## 61                     STABBRWI -2.035720e+03  5916.5422288  -1743.38902  5624.2110
## 62                     STABBRWV  5.500850e+02  9133.0325301   1627.48753  8055.6300
## 63                     STABBRWY -1.741550e+03  7745.5185723   -106.08961  6110.0578
## 64                      UG25abv  5.441846e+01  2246.2772578  -5539.16520  7839.8609
## 65                    UGDS_2MOR -4.379302e+02 11897.3186481  -2246.04918 13705.4376
## 66                   UGDS_ASIAN  3.015523e+04 38585.4959849  33689.70008 35051.0235
## 67                     UGDS_NRA  3.192613e+03 14503.8388407   5462.07388 12234.3782
## 68                   UGDS_WHITE -2.206567e+03  -363.3523734  -4706.85119  2136.9315
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