

04/13 update

- Preliminary results on a small, **balanced** subsample (5000 cases, 5000 controls).
- Training set of 9000 IDs, test set of 1000 IDs.
- Imputed missing variables with median.
- Lab data (blood tests, FOBT) and colonoscopies converted to longitudinal summaries (mean,max,min,...).
- Lab data restricted to time interval from ‘indexdate - 3 years’ to ‘indexdate - 1 year’.
- No ICD code information, no medication information, no smoking status records (smoking status at index is in demographic variables).
- Logistic regression.

Predictors ($p = \#$ of predictors)	Training AUC	Test AUC
Demographic ($p = 10$)	0.814	0.818
Charlson ($p = 18$)	0.705	0.693
Demographic + Charlson ($p = 28$)	0.863	0.862
Labs ($p = 210$)	0.824	0.824
Demographic + Charlson + Labs ($p = 238$)	0.913	0.910

04/20 update

- Preliminary results on a small, **balanced** subsample (5000 cases, 5000 controls).
- Training set of 9000 IDs, test set of 1000 IDs.
- Imputed missing variables with median.
- **Sets of predictors:**
 - Demographic data includes race, age, weight, etc. (**Demographic**).
 - Charlson score inputs plus GERD diagnosis (**Charlson**).
 - Lab data (blood tests, FOBT) and colonoscopy data converted to longitudinal summaries (mean,max,min,...) (**Labs**).
 - Medication (H2R and PPI) converted to longitudinal summaries (mean,max,...) (**Meds**).
- Lab and medication data restricted to time interval from ‘indexdate - 3 years’ to ‘indexdate - 1 year’.
- Logistic regression.

Predictors ($p = \#$ of predictors)	Training AUC	Test AUC
Demographic ($p = 10$)	0.814	0.818
Charlson ($p = 18$)	0.705	0.693
Meds ($p = 10$)	0.604	0.598
Demographic + Charlson + Labs + Meds ($p = 240$)	0.915	0.912

04/27 update

- Baseline logistic regression on entire sample (no blood labs, no medication data).
- Full sample contains $n = 6,649,108$ observations, with $n_{\text{control}} = 6,637,713$ and $n_{\text{case}} = 11,395$.
- Imputed numeric variables with medians, imputed smoking status at random, proportional to non-missing in sample (45% current, 41% former, 14% never).

Predictors ($p = \#$ of predictors)	Training AUC	Test AUC
Demographic ($p = 10$)	0.670	0.675
Charlson ($p = 18$)	0.684	0.705
Demographic + Charlson ($p = 28$)	0.760	0.770

Smoking status missingness.

In the entire sample:

Smoking Status	Current	Former	Never	Missing
Count	1696052	1521806	537727	2893523
Probability	0.26	0.23	0.08	0.44

Among cases:

Smoking Status	Current	Former	Never	Missing
Count	3901	3546	594	3354
Probability	0.34	0.31	0.05	0.29

Among controls:

Smoking Status	Current	Former	Never	Missing
Count	1692151	1518260	537133	2890169
Probability	0.25	0.23	0.08	0.44

05/04 update

- Preliminary results on a balanced **random sample** of 5000 cases and 5000 controls.
- Most missing variables imputed with their median, SmokeStatus imputed at random proportional to non-missing.
- Training on 9000 observations, testing on 1000 observations.
- Baseline logistic regression fit with subsets of predictors, and all predictors.
- Random forest fit with all predictors.

Model/predictors ($p = \#$ of predictors)	Training AUC	Test AUC
Logistic regression	-	-
Demographic ($p = 10$)	0.669	0.676
Charlson ($p = 18$)	0.689	0.659
Meds ($p = 10$)	0.515	0.513
Colonoscopies ($p = 2$)	0.513	0.502
Labs ($p = 200$)	0.671	0.621
All ($p = 240$)	0.814	0.778
Random forest	-	-
All ($p = 240$)	0.985	0.844

Random forest variable importance. Most important blood lab measurements (all means of measurements over the 2 year window):

1. Hematocrit value (CBC labs)
2. MCH value (CBC labs)
3. ALT value (LFT labs)
4. Alk. Phos. value (LFT labs)
5. AST value (LFT labs)
6. White blood cells (WBC) value (CBC labs)
7. Glucose value (BMP labs)

Next steps:

- Better approaches to impute missing variables (esp. SmokeStatus).
- Improved non-linear classifiers for subsample.
- Logistic regression baselines for the full sample of 6M observations.

05/11 update

- Baseline logistic regression on full sample (no medication data).
- $n = 6,649,108$ observations, with $n_{\text{control}} = 6,637,713$ and $n_{\text{case}} = 11,395$.
- Most missing variables imputed with their median, SmokeStatus imputed at random proportional to non-missing.
- For lab information, only means of each measurement, no longitudinal information so far.
- **05/27 update:** Charlson and Demographic+Charlson updated to exclude Cancer and Metastatic Carcinoma.

Model/predictors ($p = \#$ of predictors)	Training AUC	Test AUC
Demographic ($p = 10$)	0.670	0.675
Charlson ($p = 16$)	0.684	0.705
Demographic + Charlson ($p = 26$)	0.760	0.770
Colonoscopies ($p = 2$)	0.511	0.504
Labs ($p = 34$)	0.604	0.601
Meds ($p = 10$)	0.523	0.512

Next steps:

- Process medication data.
- Approaches to impute missing variables (esp. SmokeStatus).
- Non-linear classifiers for subsample, plots/graphics to interpret predictor effects.

05/18 update

- Medication data processed for full sample, new line (red) added to last week's table of baseline logistic regression AUCs.
- Gradient boosting implemented for the random sample of 5000 cases and 5000 controls.

Model/predictors ($p = \#$ of predictors)	Training AUC	Test AUC
Logistic regression	-	-
All ($p = 240$)	0.814	0.778
Random forest	-	-
All ($p = 240$)	0.985	0.844
Gradient boosting	-	-
All ($p = 240$), no interactions	0.900	0.847
All ($p = 240$), 2-way interactions	0.924	0.857
All ($p = 240$), 3-way interactions	0.937	0.864

Same gradient boosting results without Charlson score inputs or GERD at index:

Model/predictors ($p = \#$ of predictors)	Training AUC	Test AUC
Gradient boosting	-	-
No Charlson inputs ($p = 222$), no interactions	0.881	0.811
No Charlson inputs ($p = 222$), 2-way interactions	0.898	0.820
No Charlson inputs ($p = 222$), 3-way interactions	0.909	0.817

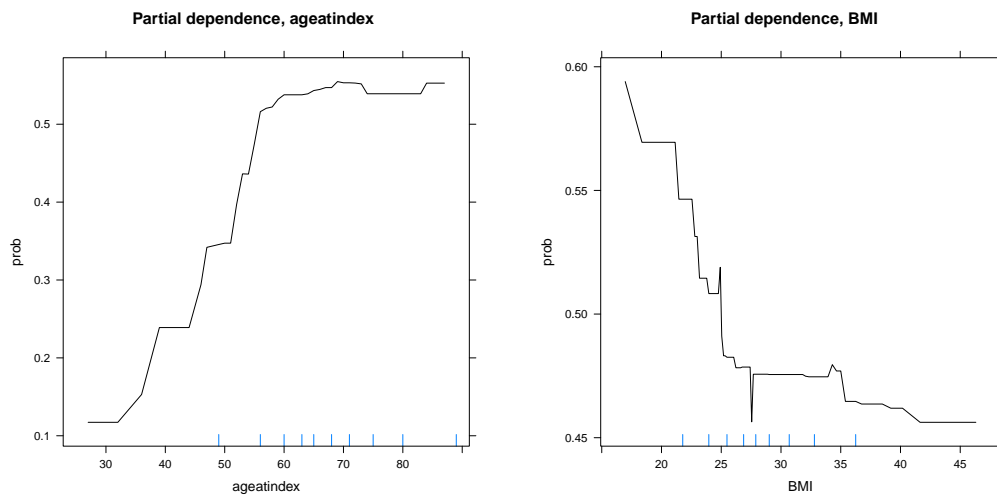
Next steps

- Scaling up gradient boosting, dealing with unbalanced classes in full sample.
- Plots/graphics to interpret black box models.

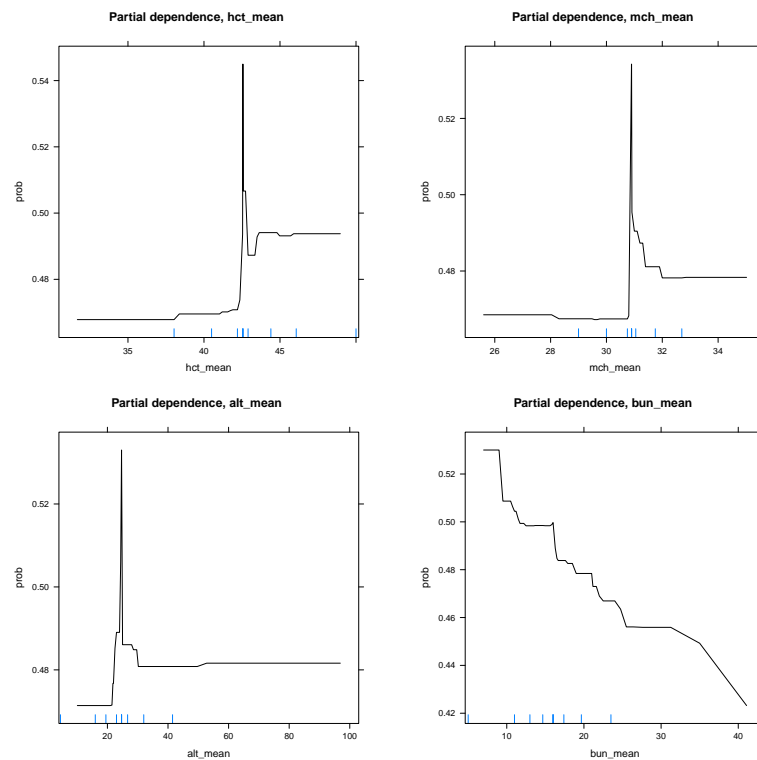
05/25 update

- Results now without Cancer and Metastatic Carcinoma inputs to Charlson score.
- Implemented scalable **xgboost** model, test AUC **0.860**.

Partial dependence plots (from xgboost model). Demographic variables:



Most influential blood lab variables:



Missingness rates for blood lab variables (where ‘missing’ means zero measurements of that variable in the 2 year window):

Proportion missing	controls	cases
A1c_mean (A1C Labs)	0.51	0.52
bun_mean (BMP Labs)	0.17	0.30
hct_mean (CBC Labs)	0.20	0.50
CRP_mean (CRP Labs)	0.95	0.94
alkphos_mean (LFT Labs)	0.23	0.47
chol_mean (Lipid Labs)	0.19	0.32

08/20: now with the new data, 4 year window from index-1 to index-5

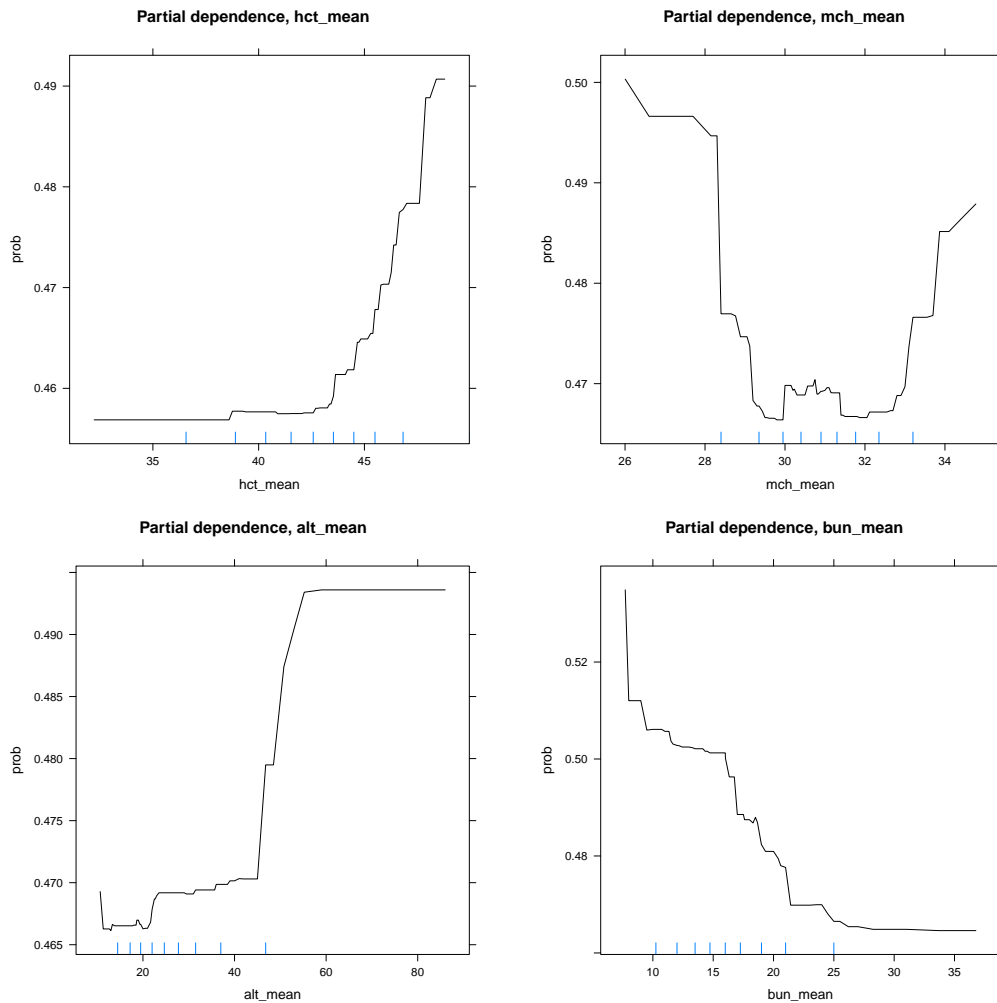
Proportion missing	controls	cases
A1c_mean (A1C Labs)	0.43	0.47
bun_mean (BMP Labs)	0.11	0.26
hct_mean (CBC Labs)	0.12	0.46
CRP_mean (CRP Labs)	0.93	0.91
alkphos_mean (LFT Labs)	0.15	0.42
chol_mean (Lipid Labs)	0.12	0.29

uniformly fewer missing, but rates are not cut in half, moreover heterogeneity of missingness between cases and controls is not fixed.

06/08 update

- Re-coded BMI/weight measurements?
- Re-run xgboost on balanced subsample with NAs, test AUC **0.880**, but it is using missing values to identify cases.
- Source of missingness? More detailed breakdown for LFT Labs.

Updated partial dependence plots for blood lab variables. Using new xgboost model on subsample.



Detailed breakdown of missingness for LFT labs. (Prediction window is second and third years before index)

Mean # of labs	controls	cases
First year before index	1.87	2.42
Second year before index	1.47	1.52
Third year before index	1.42	1.34

Detailed breakdown for the prediction window (index minus 3 years to index minus 1 year):

Proportion	controls	cases
At least 1 lab	0.83	0.69
At least 2 labs	0.67	0.59
At least 3 labs	0.45	0.44
At least 4 labs	0.30	0.31
At least 5 labs	0.18	0.21

Next Steps:

- Imputation with xgboost
- Implement xgboost for entire sample

06/22 update

- Set up code on GitLab (waljee-zhu-ml-projects/hosea-project).
- Received updated sample with recoded BMIs. BMIs are more likely to be missing for cases (14%) than controls (8%).
- Continuing to code imputation following Deng and Lumley (2021).

BMI comparison on the original sample data:

Original BMI	< 20	$\in (20, 25]$	$\in (25, 30]$	$\in (30, 35]$	$\in (35, 40]$	> 40
$\mathbb{P}(\textit{Control} \textit{BMI})$	0.9960	0.9978	0.9985	0.9985	0.9986	0.9986
$\mathbb{P}(\textit{Case} \textit{BMI})$	0.0040	0.0022	0.0015	0.0015	0.0014	0.0014

With the re-coded sample data:

New BMI	< 20	$\in (20, 25]$	$\in (25, 30]$	$\in (30, 35]$	$\in (35, 40]$	> 40
$\mathbb{P}(\textit{Control} \textit{BMI})$	0.9983	0.9985	0.9985	0.9984	0.9981	0.9979
$\mathbb{P}(\textit{Case} \textit{BMI})$	0.0017	0.0015	0.0015	0.0016	0.0019	0.0021

06/29 update

- Now using updated data (new BMIs, Charlson scores).
- For subsample, comparison of baseline logistic regression and xgboost models for different imputation approaches:
 1. **No imputation:** leave NAs in the data, learn a classification for subjects with missing data (only compatible with xgboost).
 2. **Median imputation:** impute all variables with median/most common class.
 3. **Regression imputation:** impute by (linear) regression of each predictor variable on the others (similar to MICE).
 4. **Random sample imputation:** impute each predictor by sampling at random from the non-missing entries.

AUC results for xgboost/logistic regression for different imputation approaches. Results still on balanced subsample.

Imputation method/model	Training AUC	Test AUC	Test AUC (complete records)
No imputation	-	-	-
xgboost	0.977	0.942	0.643
Median imputation	-	-	-
logistic regression	0.834	0.810	0.585
xgboost	0.970	0.857	0.623
Regression imputation	-	-	-
logistic regression	0.805	0.760	0.557
xgboost	0.948	0.815	0.705
Random sample imputation	-	-	-
logistic regression	0.724	0.689	0.724
xgboost	0.919	0.729	0.745

Regression imputation still has ‘regression to mean’ effect for imputed values, imputed values have smaller variance than the true values (with observation error). Maybe try a version that imputes a rank then resamples from observed values.

07/06 update

- Source of missingness in the data? About 85% of cases missing Charlson score inputs (compared to about 47% of controls).
- Missingness in test set/use case?
- Updated (in red) last weeks results with a test set of 1000 complete records (226 cases, 774 controls).
 - Poor generalization to complete cases for no imputation, median imputation implies that those models are fitting to the missingness, patterns won't continue to hold with fully observed data.
 - Regression imputation still has 'regression to mean' effect for imputed values, imputed values have smaller variance than the observed values (observation error).
 - Good generalization of random sample imputation implies that there is no bias introduced from training on data with missingness.

07/13 update

- Should we evaluate the model on complete records or missing/imputed records?
- Recall: previous results with an additional test set of 1000 complete records (226 cases, 774 controls).
 - New comparison for **multiple** random sample imputation: imputes by sampling from non-missing entries several times (reps) for each missing value, training on the multiple imputed records.
- Memory issues fitting xgboost on the full data, implementing “batched” training.

AUC’s for xgboost/logistic regression for different imputation approaches. Results still on balanced subsample.

Imputation method/ prediction model	Training AUC	Test AUC (imputed records)	Test AUC (complete records)
No imputation	-	-	-
xgboost	0.977	0.942	0.643
Median imputation	-	-	-
logistic regression	0.834	0.810	0.585
xgboost	0.970	0.857	0.623
Regression imputation	-	-	-
logistic regression	0.805	0.760	0.557
xgboost	0.948	0.815	0.705
Random sample imputation	-	-	-
logistic regression	0.724	0.689	0.724
xgboost	0.919	0.729	0.745
Multiple rand. samp.	-	-	-
xgboost, 10 reps	0.909	0.742	0.781
xgboost, 20 reps	0.939	0.765	0.820
xgboost, 30 reps	0.948	0.768	0.781

Final two columns suggest two different evaluation metrics, ensuring the model performs well on **both** (A) new patients with imputed data and (B) new patients with fully observed blood labs, etc.

07/20 update

- Continuing to test/tune imputation approaches.
- Notes on decision curve analysis.

Imputation method/ prediction model	Training AUC	Test AUC (imputed records)	Test AUC (complete records)
Separate class	-	-	-
xgboost	0.977	0.942	0.643
Median	-	-	-
logistic regression	0.834	0.810	0.585
xgboost	0.970	0.857	0.623
Regression	-	-	-
logistic regression	0.805	0.760	0.557
xgboost	0.948	0.815	0.705
Regression v2	-	-	-
logistic regression	0.769	0.706	0.564
xgboost	0.928	0.722	0.764
Random sample	-	-	-
logistic regression	0.724	0.689	0.724
xgboost	0.919	0.729	0.756
Multiple rand. samp.	-	-	-
xgboost, 10 imputes \times 50 trees	0.909	0.742	0.781
xgboost, 20 imputes \times 25 trees	0.906	0.750	0.778
xgboost, 30 imputes \times 20 trees	0.909	0.765	0.788
xgboost, 100 imputes \times 5 trees	0.898	0.762	0.806

07/27 update

- Continuing to tweak regression imputation approaches.
- Comparing parameters/number of imputations needed for multiple sample imputation.
- Notes on decision curve analysis.

Next steps:

- Re-process new data when available

Imputation method/ prediction model	Training AUC	Test AUC (imputed records)	Test AUC (complete records)
Separate class	-	-	-
xgboost	0.977	0.942	0.643
Median	-	-	-
logistic regression	0.834	0.810	0.585
xgboost	0.970	0.857	0.623
Regression	-	-	-
logistic regression	0.759	0.704	0.657
xgboost	0.902	0.742	0.757
Single rand. samp.	-	-	-
logistic regression	0.724	0.689	0.724
xgboost	0.919	0.729	0.756
Multiple rand. samp.	-	-	-
xgboost, 10 imputes	0.909	0.742	0.781
xgboost, 20 imputes	0.906	0.750	0.778
xgboost, 30 imputes	0.909	0.765	0.788
xgboost, 100 imputes	0.898	0.762	0.806

08/03 update

- Received new data, loading/processing files
- Still issues with missing Charlson scores (0's vs NAs), relationship between CaseControl indicator and number of visits.

08/17 update

- Processed longitudinal summaries for BMP labs. Missingness rates down but still different for cases and controls. Continuing to process new blood lab data.
- Incidence rates for some example Charlson inputs: Peptic Ulcer Disease, Renal Disease, GERD. Full tables for all inputs are on the next page.

Variable (ignoring NA's)	Among cases	Among controls
pu	6.8% (120/1762)	3.8% (142821/3803451)
RD	11.8% (208/1762)	12.1% (460302/3803451)
GERD	-	-

Variable (impute NA's as 0's)	Among cases	Among controls
pu	1.1% (120/11395)	2.2% (142821/6637713)
RD	1.8% (208/11395)	6.9% (460302/6637713)
GERD	17.9% (2044/11395)	15.7% (1039206/6637713)

Cross-classified by number of BMP lab results (0, 1 or 2+):

Peptic Ulcer Disease, **controls**:

Number of BMP labs	0	1	NA
0	29.3%	0.9%	69.8%
1	32.2%	0.9%	66.8%
2+	61.5%	2.5%	36.0%

Peptic Ulcer Disease, **cases**:

Number of BMP labs	0	1	NA
0	8.6%	0.7%	90.8%
1	10.7%	0.4%	88.8%
2+	17.0%	1.3%	81.7%

Full tables for all Charlson indicators (**red** indicates these variables have been dropped from past models):

Variable (ignoring NA's)	Among cases	Among controls
CANCER	30.5% (538/1762)	18.3% (695558/3803451)
CHF	12.3% (217/1762)	11.8% (450090/3803451)
CTD	2.9% (51/1762)	3.0% (115492/3803451)
DEM	1.4% (24/1762)	2.3% (85704/3803451)
DIAB_C	15.5% (273/1762)	13.8% (525226/3803451)
HIV	0.3% (6/1762)	0.8% (30507/3803451)
MET_CAR	6.6% (117/1762)	1.3% (47696/3803451)
MLD	9.1% (160/1762)	8.0% (305462/3803451)
MSLD	0.7% (13/1762)	0.8% (29495/3803451)
PARA	1.9% (33/1762)	1.9% (72051/3803451)
RD	11.8% (208/1762)	12.1% (460302/3803451)
cd	16.3% (287/1762)	15.3% (582328/3803451)
copd	43.1% (759/1762)	35.9% (1365577/3803451)
diab_nc	44.6% (786/1762)	44.8% (1702629/3803451)
mi	9.1% (161/1762)	7.0% (264731/3803451)
pud	6.8% (120/1762)	3.8% (142821/3803451)
pvd	20.1% (354/1762)	16.0% (609425/3803451)
GERD	-	-

Variable (impute NA's as 0's)	Among cases	Among controls
CANCER	4.7% (538/11395)	10.5% (69558/6637713)
CHF	1.9% (217/11395)	6.8% (450090/6637713)
CTD	0.4% (51/11395)	1.7% (115492/6637713)
DEM	0.2% (24/11395)	1.3% (85704/6637713)
DIAB_C	2.4% (273/11395)	7.9% (525226/6637713)
HIV	0.1% (6/11395)	0.5% (30507/6637713)
MET_CAR	1.0% (117/11395)	0.7% (47696/6637713)
MLD	1.4% (160/11395)	4.6% (305462/6637713)
MSLD	0.1% (13/11395)	0.4% (29459/6637713)
PARA	0.3% (33/11395)	1.1% (72051/6637713)
RD	1.8% (208/11395)	6.9% (460302/6637713)
cd	2.5% (287/11395)	8.8% (582328/6637713)
copd	6.7% (759/11395)	20.6% (1365577/6637713)
diab_nc	6.9% (786/11395)	25.6% (1702629/6637713)
mi	1.4% (161/11365)	4.0% (264731/6637713)
pud	1.1% (120/11395)	2.2% (142821/6637713)
pvd	3.1% (354/11395)	9.2% (609425/6637713)
GERD	17.9% (2044/11395)	15.7% (1039206/6637713)

08/31 update

- Re-fit xgboost models on new subsampled data (compare to 07/27 results).
 $n_{\text{train}} = 9000$, $n_{\text{test}} = 1000$, $n_{\text{complete.test}} = 1000$.
- Compare (xgboost) model performance with different groups of variables included.
- Ongoing: a proxy for number of visits to better impute Charlson ICD codes?

Comparing different imputation approaches and prediction models:

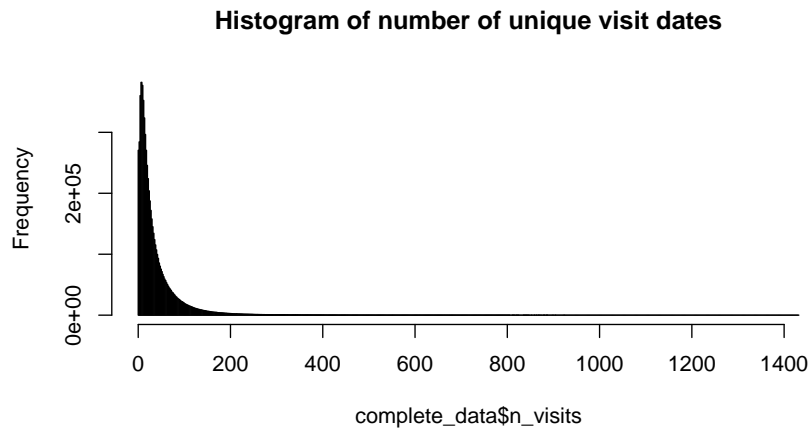
Imputation method/ prediction model	Training AUC	Test AUC (imputed records)	Test AUC (complete records)
Separate class	-	-	-
xgboost	0.985	0.962	0.582
Median	-	-	-
logistic regression	0.853	0.846	0.583
xgboost	0.963	0.911	0.618
Regression	-	-	-
logistic regression	0.772	0.726	0.651
xgboost	0.911	0.750	0.798
Single rand. samp.	-	-	-
logistic regression	0.739	0.695	0.703
xgboost	0.916	0.780	0.833
Multiple rand. samp.	-	-	-
xgboost, 10 imputes	0.942	0.824	0.885
xgboost, 20 imputes	0.935	0.820	0.872
xgboost, 30 imputes	0.943	0.810	0.879
xgboost, 100 imputes	0.931	0.824	0.891

Comparing different included variables (imputing with single random sampling, fit with xgboost):

Variables included	Training AUC	Test AUC (imputed records)	Test AUC (complete records)
Demographic ($p = 11$)	0.743	0.700	0.663
Charlson + GERD ($p = 16$)	0.600	0.542	0.530
Medications ($p = 10$)	0.594	0.501	0.539
Labs ($p = 202$)	0.903	0.687	0.829

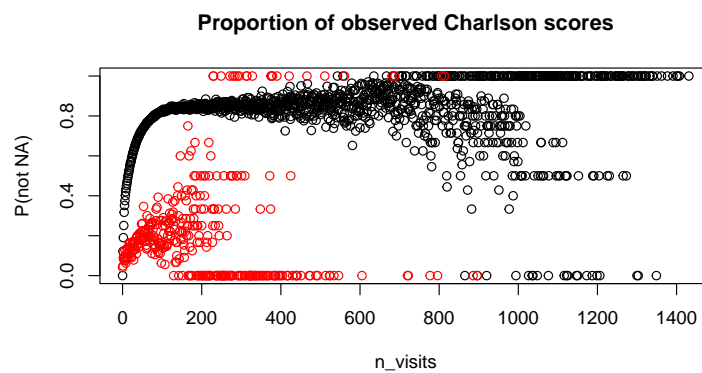
09/21 update

Overall missingness of Charlson score inputs. A histogram of the total number of visits in the 4-year prediction window:

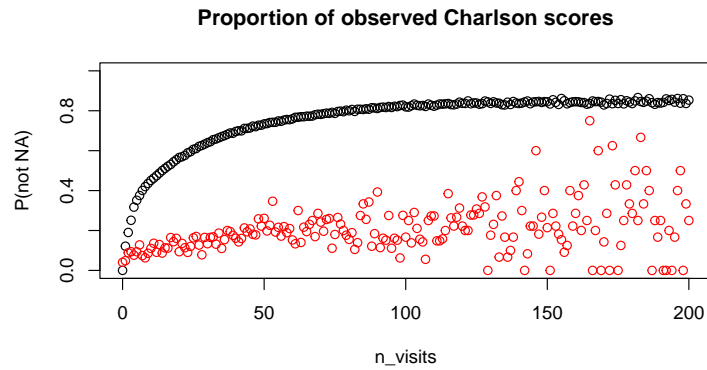


The median control has 22 visits, while the median case has 33 visits.

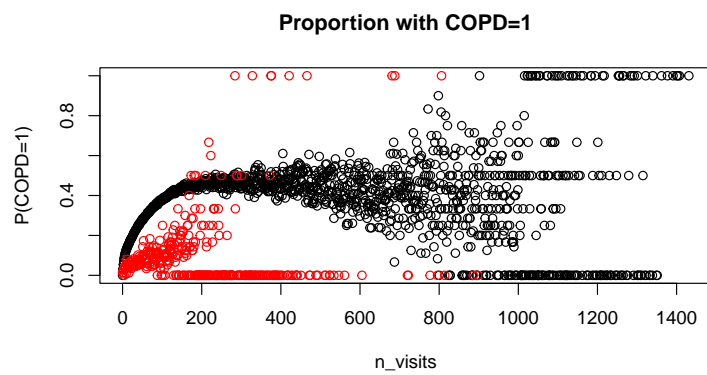
Proportion of observed Charlson scores plotted against number of visits, separating controls (black) and cases (red):



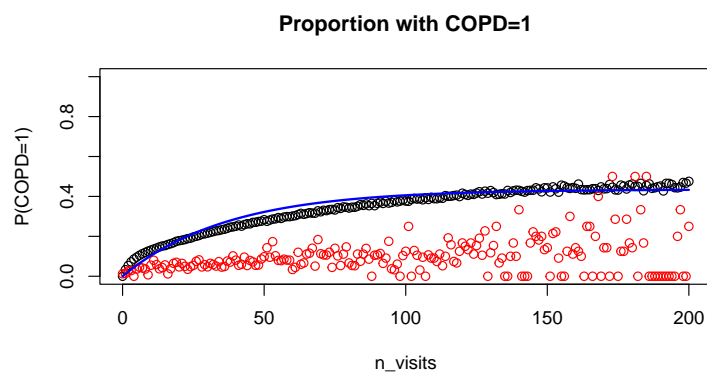
The same plot restricted to ≤ 200 visits.



Example: missingness of COPD. Proportion of patients coded COPD=1, plotted against number of visits, separating controls (black) and cases (red):



The same plot restricted to ≤ 200 visits. The blue line is a model-based estimate of $\mathbb{P}(\text{COPD} = 1 | n.\text{visits})$ using pooled case and control data.

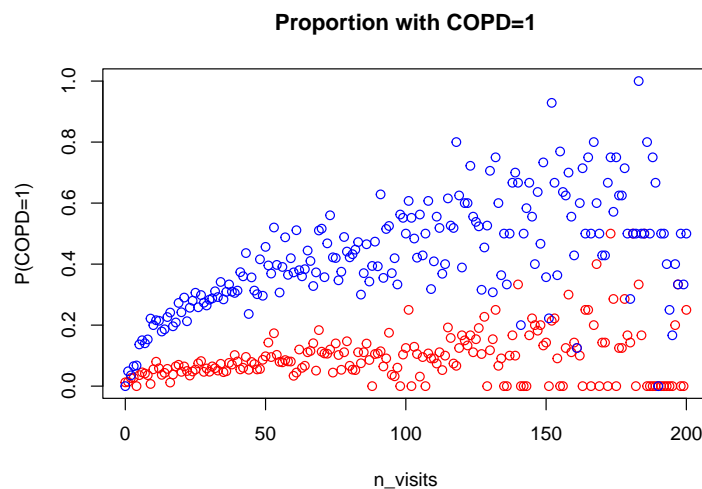


For cases only, created a new COPD indicator based on the 'alldxscx' table. For ICD9, 1 means you have a code '49x', for ICD10, 1 means you have a code starting with 'J44'.

Cross-classification of old and new indicator for total of 11,395 cases (overall proportions in parentheses).

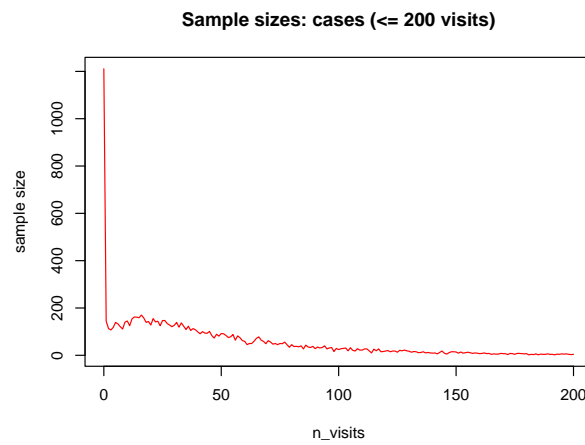
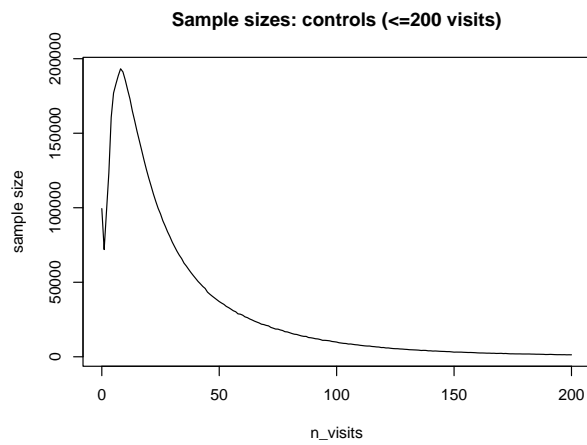
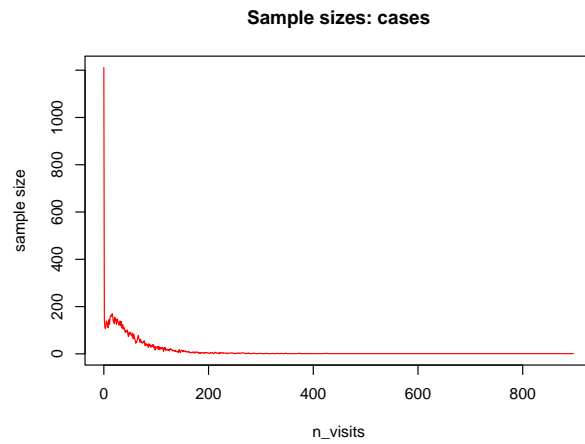
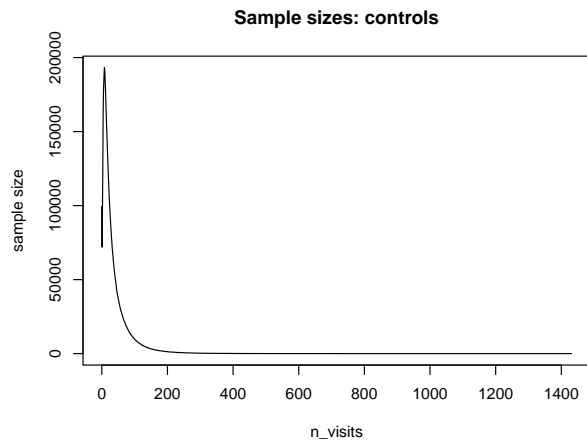
	New COPD=1	New COPD=0/NA
Old COPD=1	7845 (0.688)	2791 (0.245)
New COPD=0/NA	160 (0.014)	599 (0.053)

Proportion of patients with COPD=1 plotted against number of visits, restricted to ≤ 200 visits, with the old indicator in red and the new indicator in blue.



Next steps: similarly code a new indicator for controls, see if it changes results. Generalize to other Charlson inputs (or other entirely new ICD codes), and look at ways to impute by incorporating n_visits.

Sample sizes for controls and cases for calculating the proportions in the above plots.



09/28 update

- Implemented new train/valid/test scheme
 - Imputed records results are not exactly comparable
 - Complete records results are comparable
- Experimentation with regression imputation
- Experimentation with `xgboost` tuning parameters
- Currently working on multiple random sample with new train/valid/test scheme

Imputation method	Training AUC	Test AUC (imputed records)	Test AUC (complete records)
Separate class	0.974 (0.985)	0.953 (0.962)	0.607 (0.582)
Median	0.979 (0.963)	0.939 (0.911)	0.649 (0.618)
Regression	0.952 (0.911)	0.739 (0.750)	0.770 (0.798)
1 rand. samp.	0.987 (0.916)	0.783 (0.780)	0.890 (0.833)
10/04 update			
2 rand. samp.	1.000	0.801	0.918
5 rand. samp.	0.977	0.807	0.928
10 rand. samp.	1.000 (0.942)	0.818 (0.824)	0.915 (0.885)
20 rand. samp.	0.953 (0.935)	0.804 (0.820)	0.909 (0.872)
50 rand. samp.	0.978	0.814	0.912
100 rand. samp.	0.975 (0.931)	0.822 (0.824)	0.925 (0.891)

*all with `xgboost` prediction model; AUCs in parentheses denote previous results.

10/04 update

- Implemented new train/valid/test scheme with multiple imputation
- Updated table on previous page with result with multiple imputation
- Some improvement with a single random simpling imputation
- Some improvement compared to previous results, mostly for “complete records” test set
- Next step: utilize all of the data

10/12 update

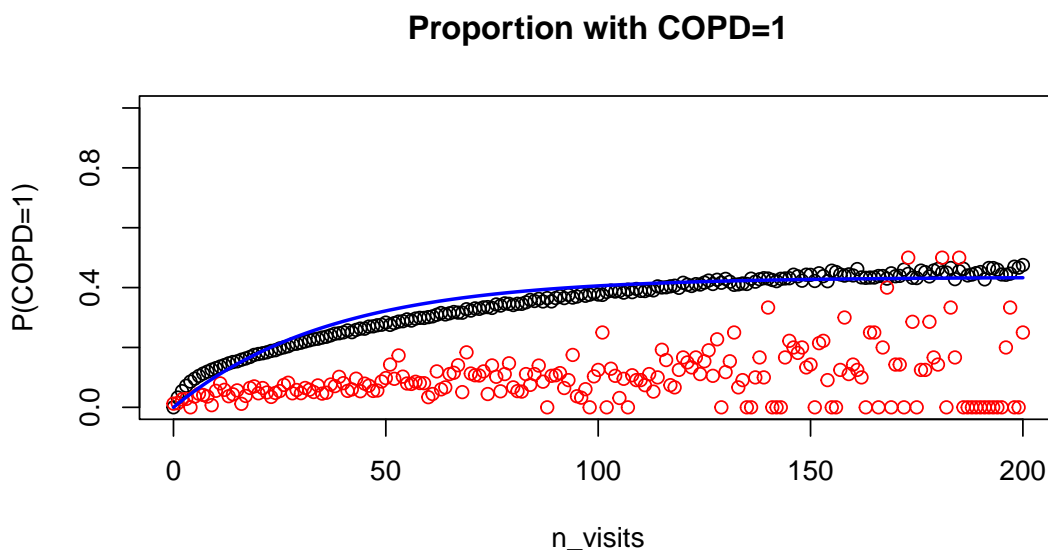
- Redo analysis with various Charlson variable treatments:
 - no Charlson
 - sampling from observed values (what was done previously)
 - imputing a probability using number of visit (see Peter’s proposed Geometric model)
 - imputing by sampling using the fitted probability
- Results:
 - see table below
 - dropping Charlson leads to a small decrease in testing performance for both imputed and “complete” records
 - sampling with fitted probability has similar performance compared to the previous methods
 - imputing the fitted probability leads to a huge improvement in performance
- Currently examining where this large improvement comes from, still suspicious
- Try the same with multiple random samples
- Working on utilizing all data ...

Imputation method	Training AUC	Test AUC (imputed)	Test AUC (complete)
Separate class	0.974	0.953	0.607
Median	0.990	0.941	0.674
Simple random sample			
no Charlson	0.988	0.771	0.873
random Charlson	0.999	0.786	0.905
proba. Charlson	1.000	0.906	0.975
proba.-weighted random Charlson	0.997	0.795	0.896

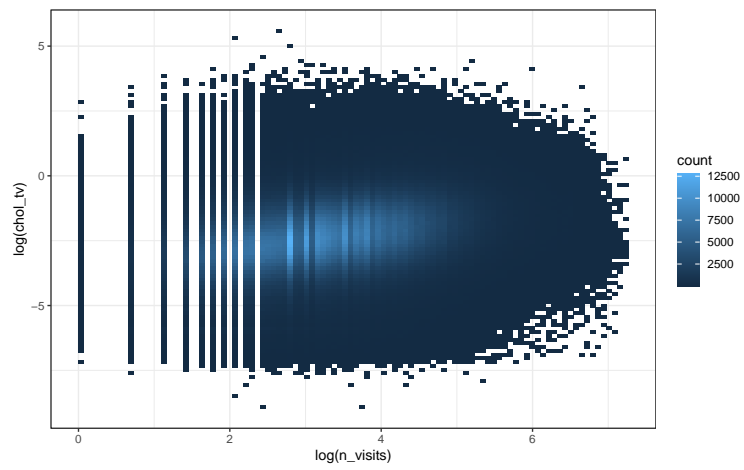
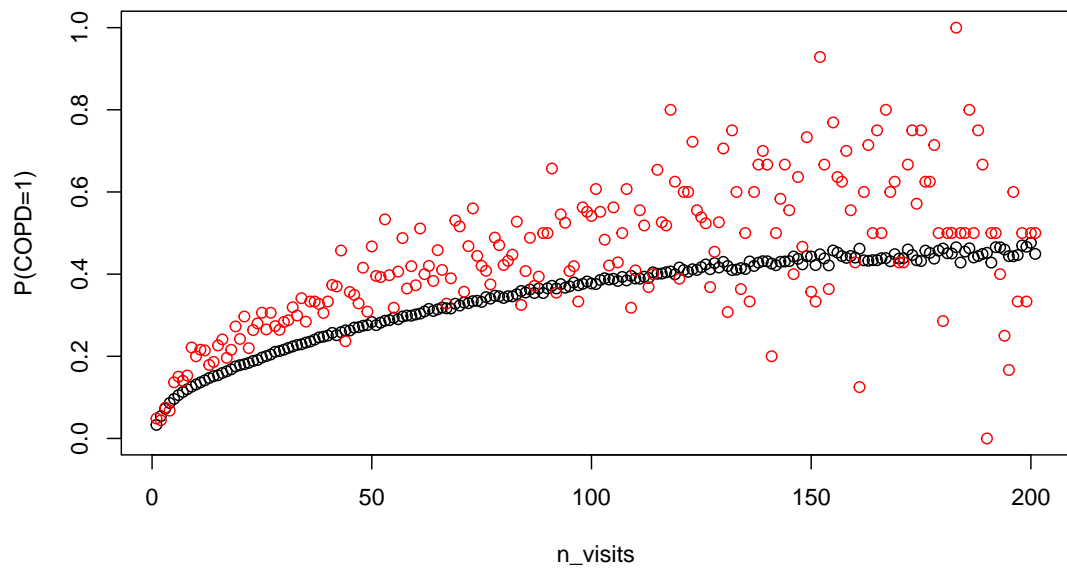
10/26 update

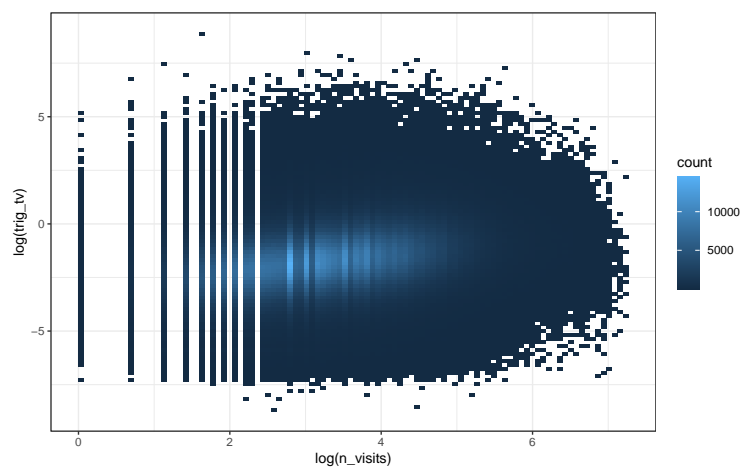
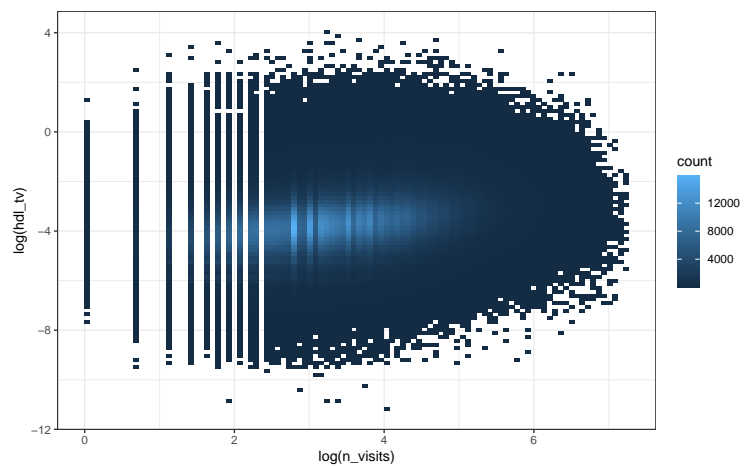
Some follow-ups:

- Using number of visits to impute Charlson/GERD variables:
 - Imputing probabilities is not a good idea as it is easy to spot missing values (between 0 and 1) from observed values (0/1)
 - randomizing using the probability does not improve performance
 - preferable to have a unified treatment
- ICD codes recoding for cases comparing before and after
 - we no longer see the large discrepancy between cases and control
 - see COPD graphs below
- Does the “tv” lab summaries contain some information about the number of measurements?
 - there were some concern that variability would be associated with number of measurements
 - see density plots for “chol”, “hdl” and “trig” below
 - “tv” stands for “total variation” and is the average absolute change between measurement (standardized by time between measurements)
 - there does not seem to be strong associations



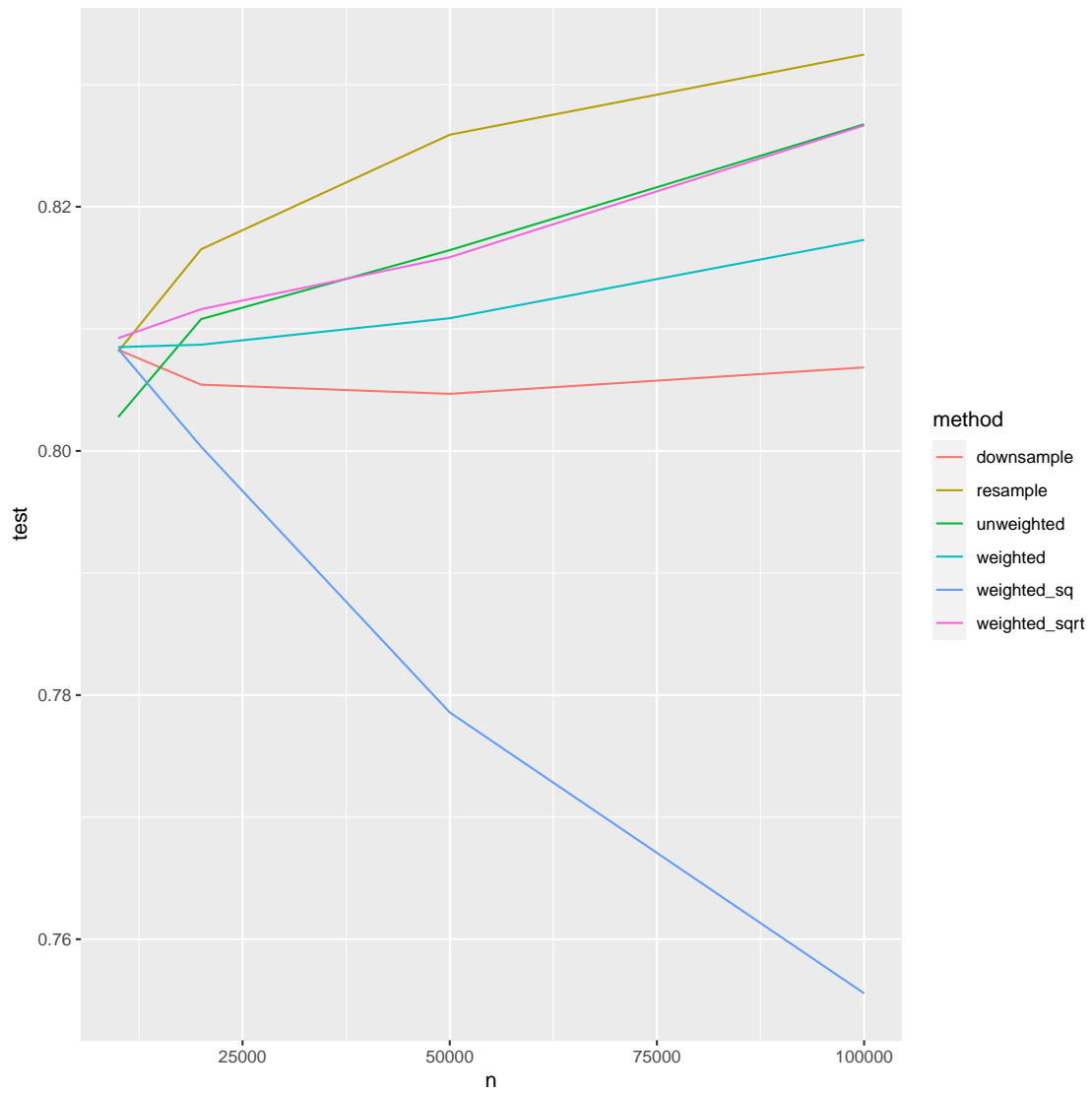
Proportion with COPD=1

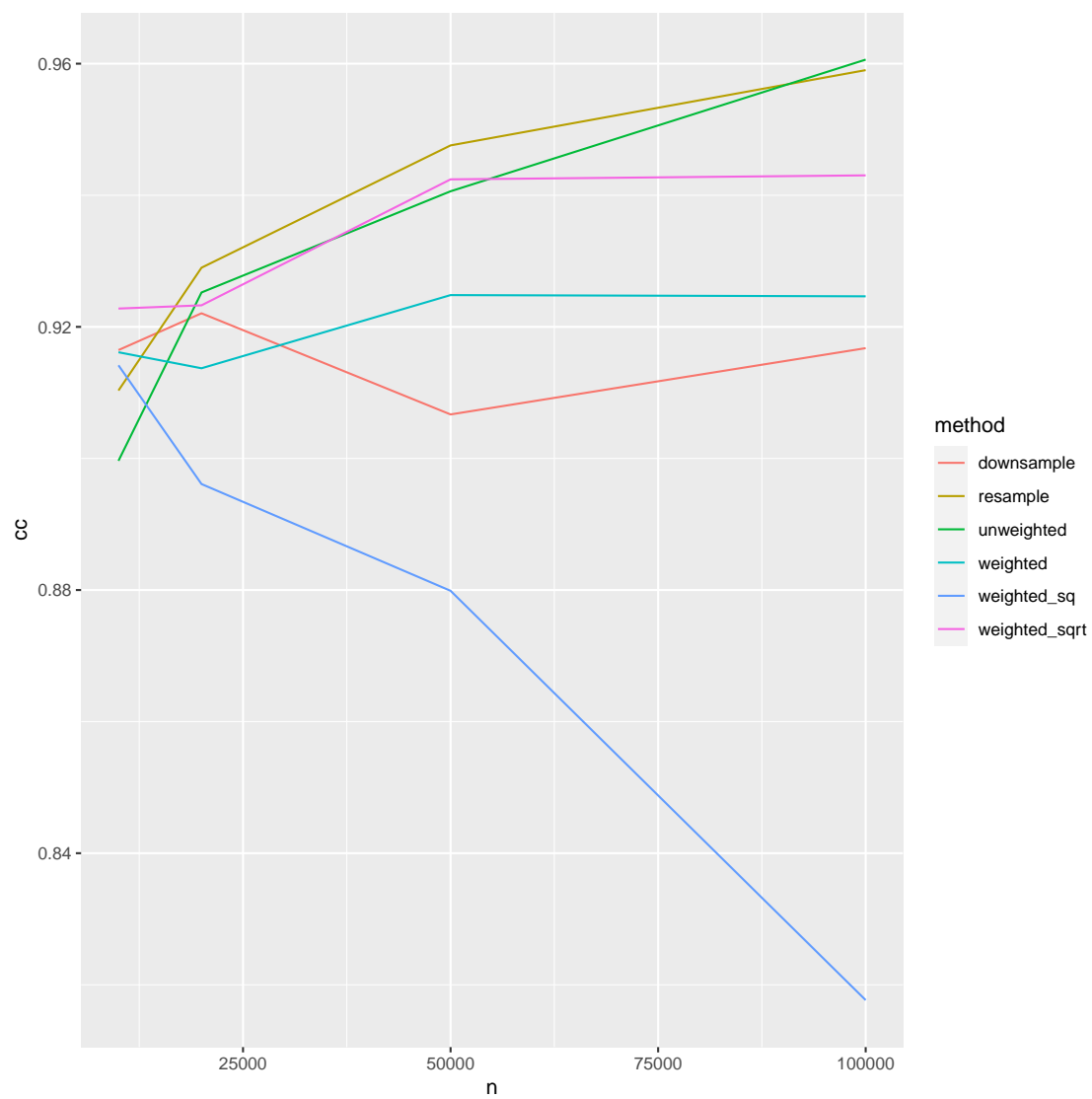




Using all data:

- Scalability study
- Sample 1M controls, keep all 11.4K cases (1M/11.4K)
- Train-test split 75-25 stratified
 - Fixed test set (250K/2.8K)
 - Training using increasing subsets of (750K/8.5K)
- Working training set consisting of downsampling the controls
 - $n = 10K, 20K, 50K, 100K$
 - keeping all 8.5K cases
 - as n increases, the training set becomes more and more unbalanced
 - $n = 10K$ is close to balanced
- Validation set: stratified 2-1
 - Model/imputation trained on 67%, validation/model selection on 33%
- Extra testing set: “complete cases” (same as before, 710/290)
 - small, with possible overlap
 - not a super reliable testing set
- Methods (e.g. with 100K/8.5K \rightarrow 66.7K/5.7K)
 - Unweighted: do nothing special
 - Downsample: sample controls to get a balance training set (5.7K/5.7K)
 - Resample: resample cases to get a balance training set (66.7K/66.7K)
 - Weighted: cases’ loss reweighted by $w = 66.7/5.7$
 - Weighted_sqrt: by \sqrt{w}
 - Weighted_sq: by w^2





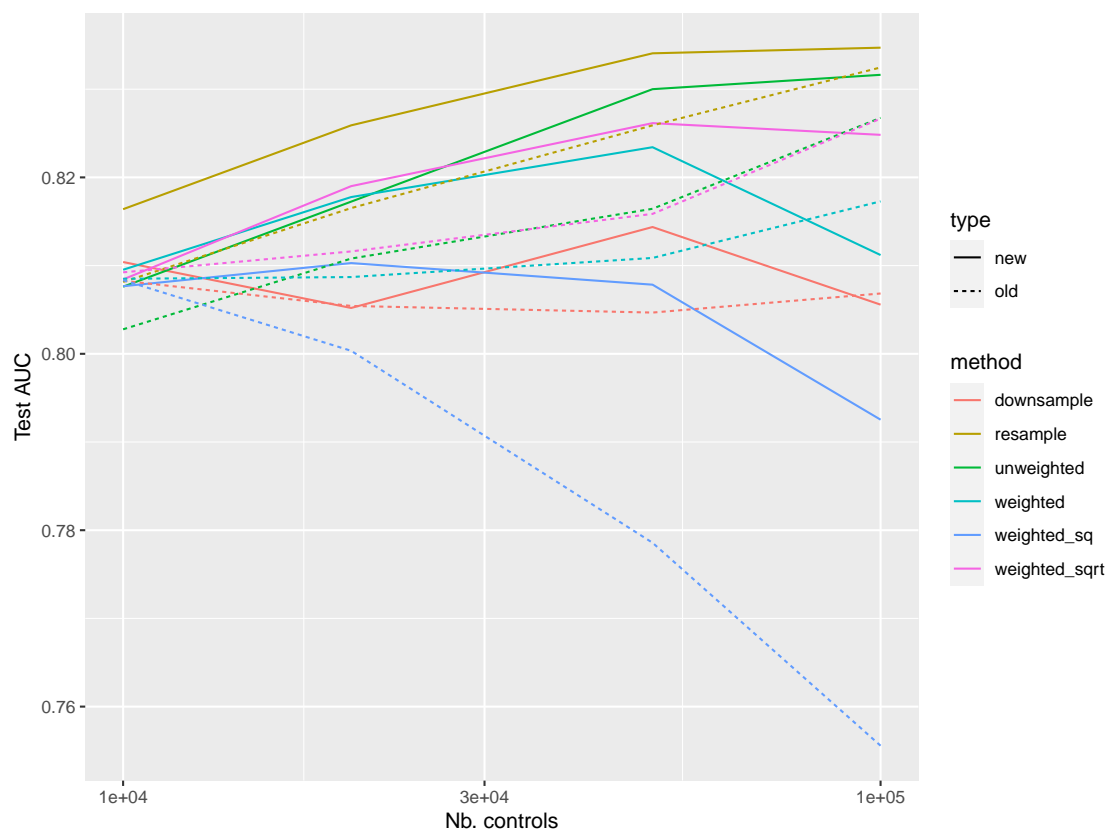
11/02 update

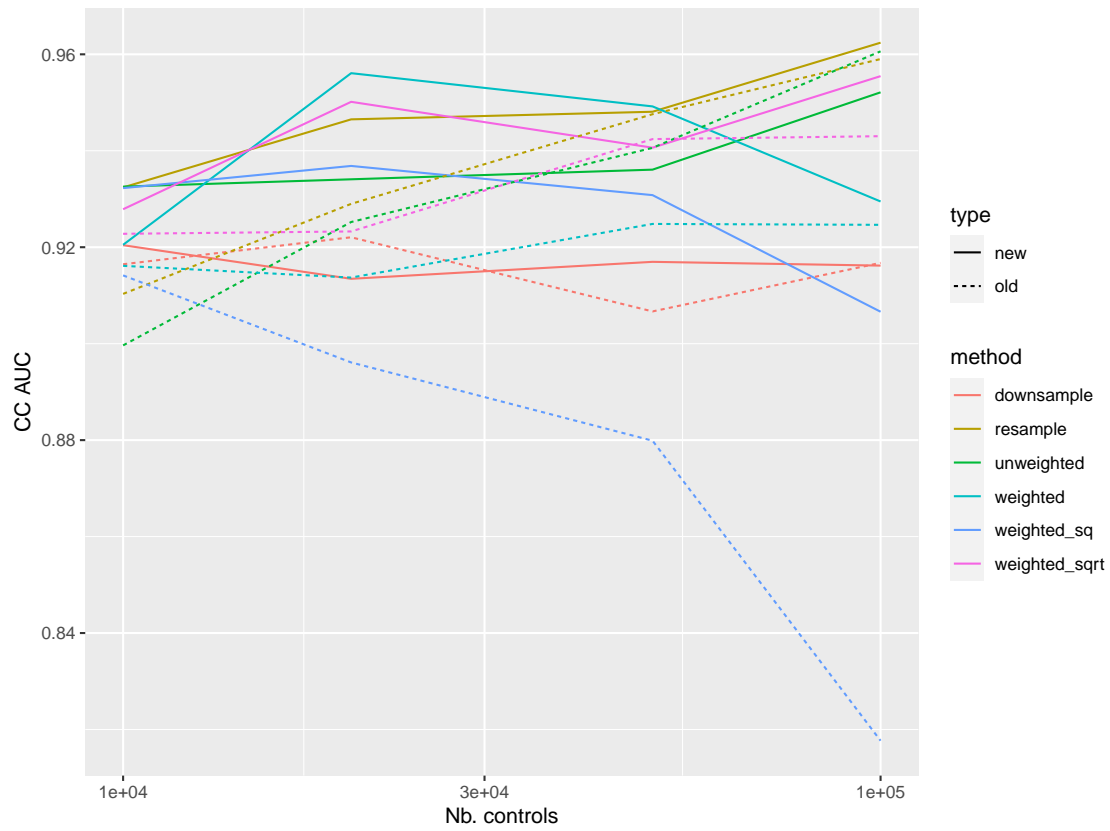
Tuning

- subsampling each iteration, learning rate, tree depth
- Some improvement is still possible
- Dependent on the training set size
 - Tuned on small sample size, improvements don't necessarily carry to larger sample size
 - prohibitive to tune on large dataset

Training set size

- Training becomes *very* slow
- Early results show improvement beyond 100K
- Exploring ways to speed up training (lightgbm, catboost)





11/09 update

Training set size

- Added results for $> 100K$ controls
- Goal:
 - Harness all data
 - Study how the increasing case/control imbalance affects results
- Similar train/valid/test split as before
 - 2M control + 11K cases (increased from 1M previously to allow the 1M case)
 - All splits are stratified (cases/control proportion preserved)
 - test: 25%, train+valid: 75%
 - N : number of controls in train+valid
 - subsample train+valid controls down to N
 - train: 67%, valid: 33%
 - NB: test set is fixed with N , validation set increases with N
- Imputation:
 - Simple random sampling from the training set into validation and testing sets
- xgboost parameters:
 - Default values, except:
 - `subsample` = 0.5
 - `max_depth` = 5
 - `eta` = 0.5 (stepsize)
 - NB: these values are represented with vertical dashed lines in the following “Tuning” section
- Methods:
 - downsample** sample controls down to the number of cases
 - resample** sample (w/ replacement) the cases up to the number of controls (note that controls appearing more than once get different imputation)
 - unweighted** no resample, no reweighting
 - weighted** no resampling, cases upweighted by $n_{\text{controls}}/n_{\text{cases}}$
 - weighted_sqrt** no resampling, cases upweighted by $\sqrt{n_{\text{controls}}/n_{\text{cases}}}$

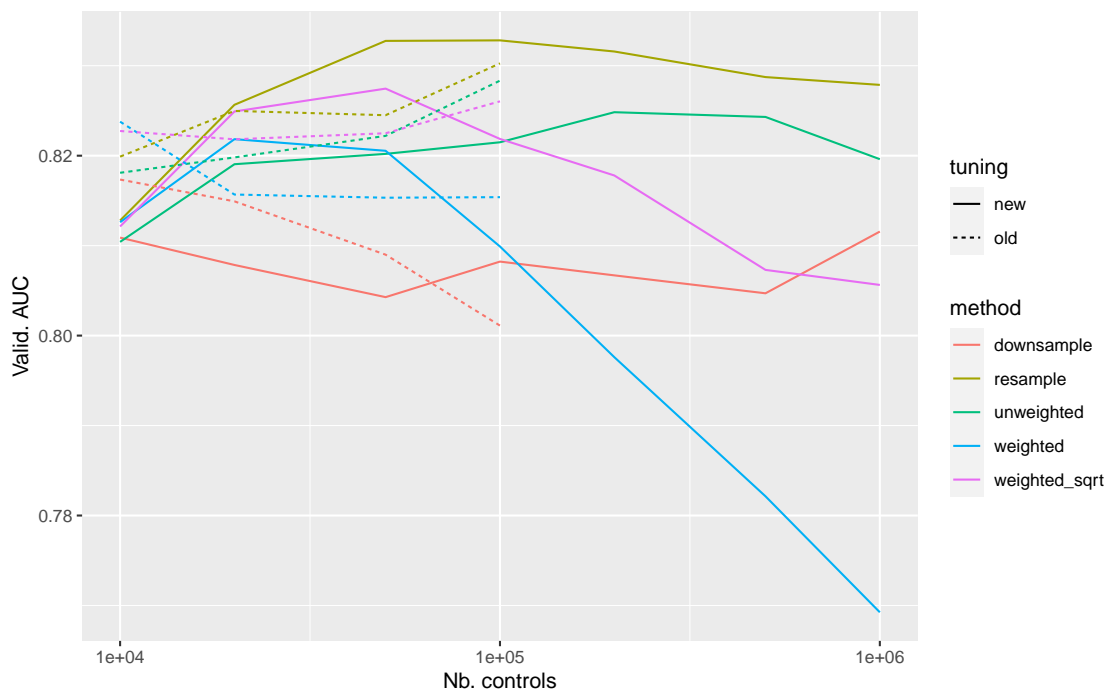
weighted_sq no resampling, cases upweighted by $(n_{\text{controls}}/n_{\text{cases}})^2$ (dropped from graph because much worse values and changed the scale too much to see others well)

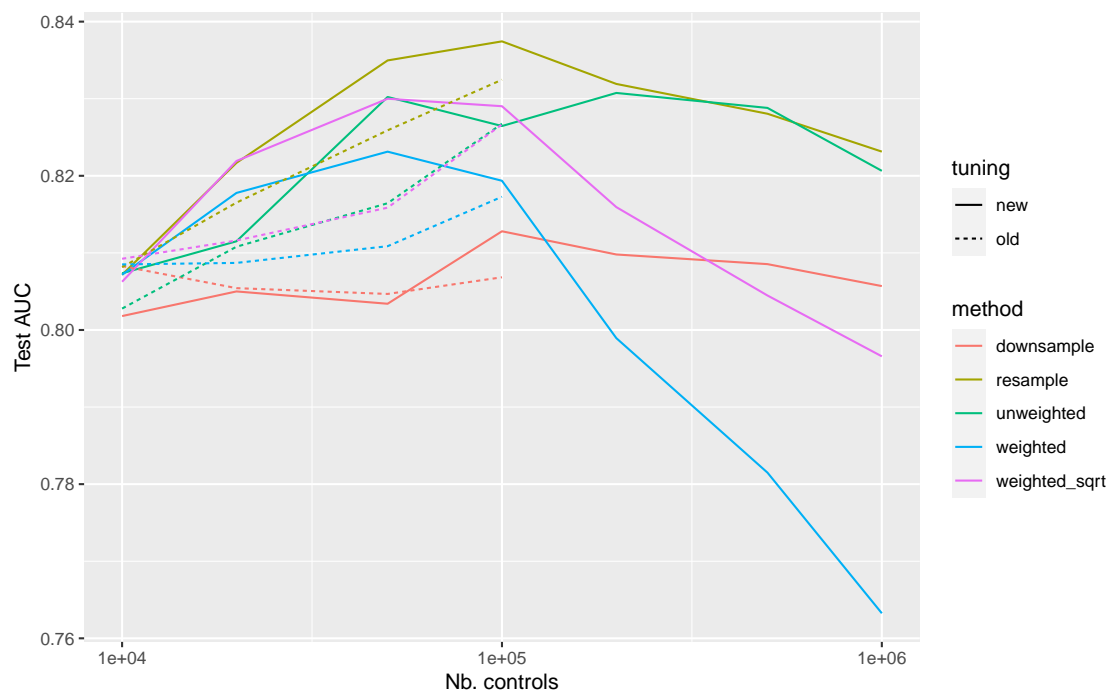
- Plots:

- y-axis: Test set AUC and Validation set AUC
- x-axis: Nb. of controls before train/valid split
- colors: which method is used to deal with imbalance
- linetype: new vs. old tuning. The new tuning was performed manually with 100K controls; the old tuning with 10K controls. For more on tuning, see next section.

- Results and analysis:

- Single repetition, so there is some variability due to the sampling. To get a sense of the scale of the variability, the “downsample” method should be the same across the range. I might do multiple repetitions in the future, but this gets very long for large N , so I am avoiding it for now.
- The “resampling” method seems to be the best across the board
- The “unweighted” method seems more stable?
- Not much to gain beyond 50K-100K (decrease? within variability?). The best tuning parameters might not be the same for larger datasets, as is apparent between old/new tuning curves.



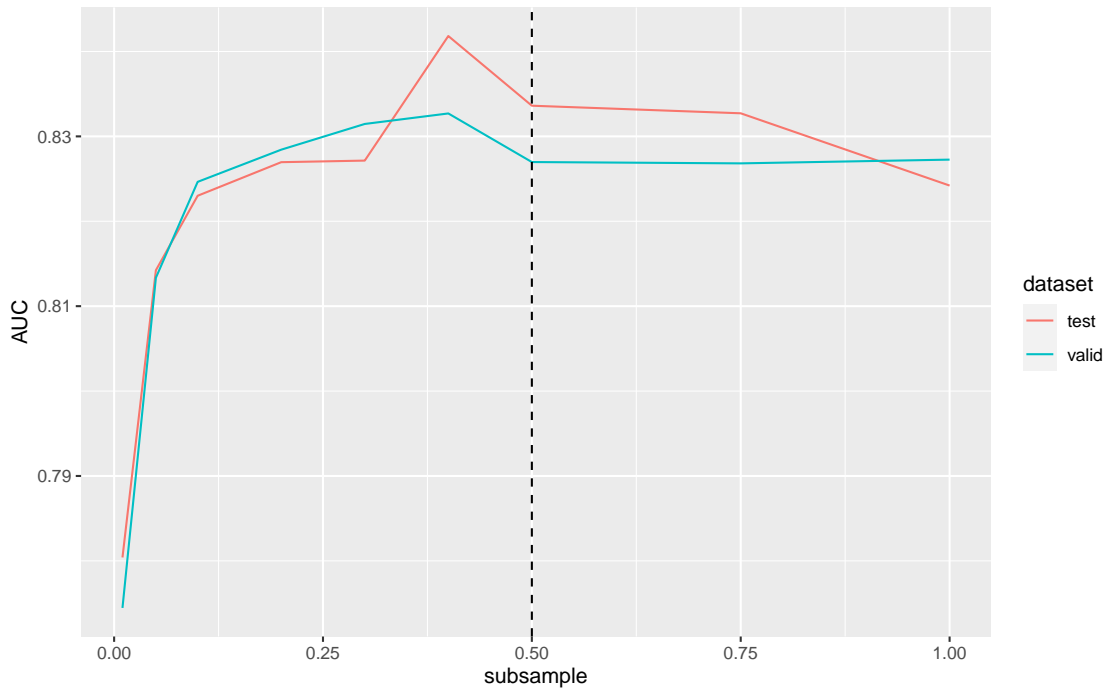
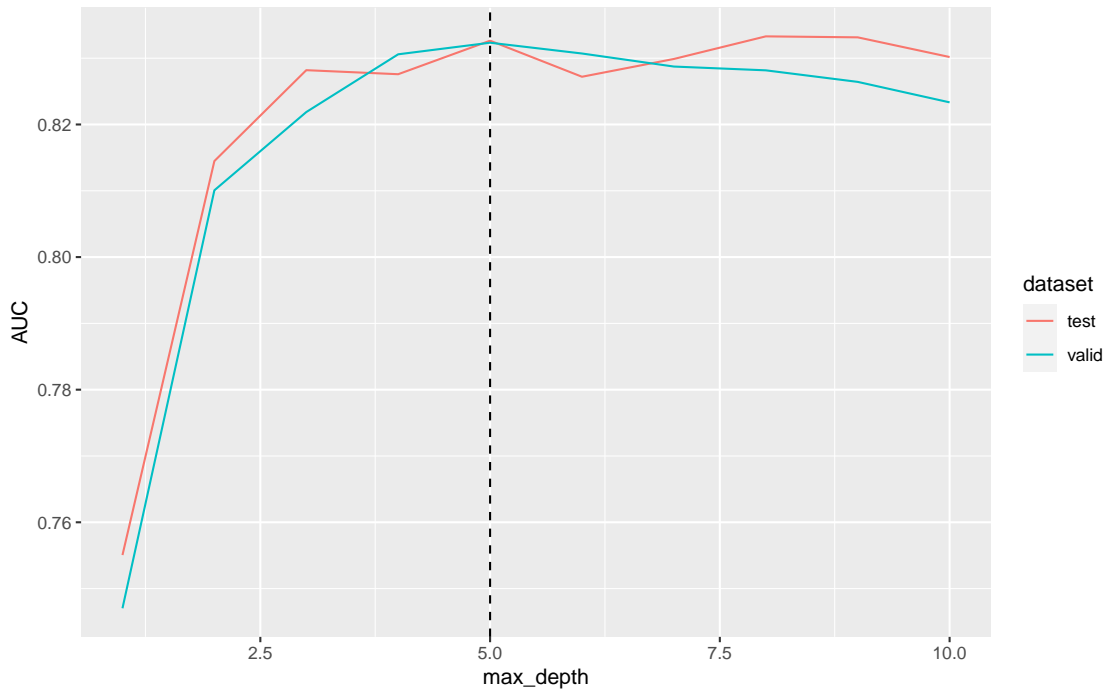


Tuning

- Protocol:
 - Same as above, except:
 - * Fix Nb. controls to $N = 100K$
 - * Use “resample” method only
 - Fix all parameters to their default value stated above (and blotted with a vertical dashed line), vary one parameter along a plausible range
- Parameters:
 - max_depth** Control the complexity of the tree added at each iteration (deeper trees have more explanatory power, but can overfit)
 - subsample** Determines what percentage of the training set is used to fit the next tree (more subsampling prevents overfitting but slows down fitting and may lead to under-fitting)
 - eta** (step-size) controls how much the new tree contributes to the model (small step-size prevents overfitting, but slows down fitting)
- Results and analysis:
 - max_depth** Above depth 4-5, not much variation on valid/test AUCs; some improvement on train/cc AUCs
 - subsample** Except for small proportions, not much variation for all 4 datasets; best seems to be around 0.4-0.75
 - eta** waiting for results ...

Next steps

- Tuning for larger number of controls
- Alternative metrics



11/16/2021 update

Tuning:

- AUROC, N=100K controls
- step-size: added results, see graph below
- for small eta, I didn't reach the stopping criterion, so take results with a grain of salt
- Seems like the “default” values I was using were mostly good
- Working on N=1M (*very slow...*)

Multiple tests sets:

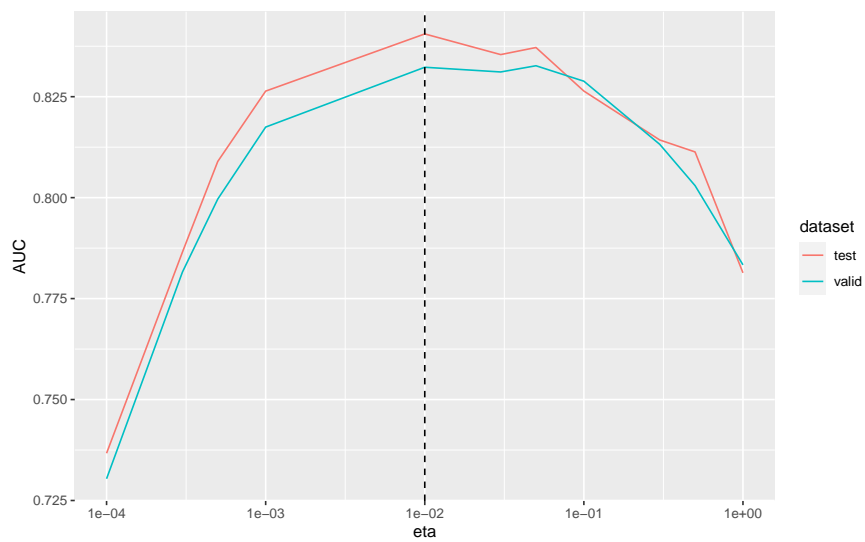
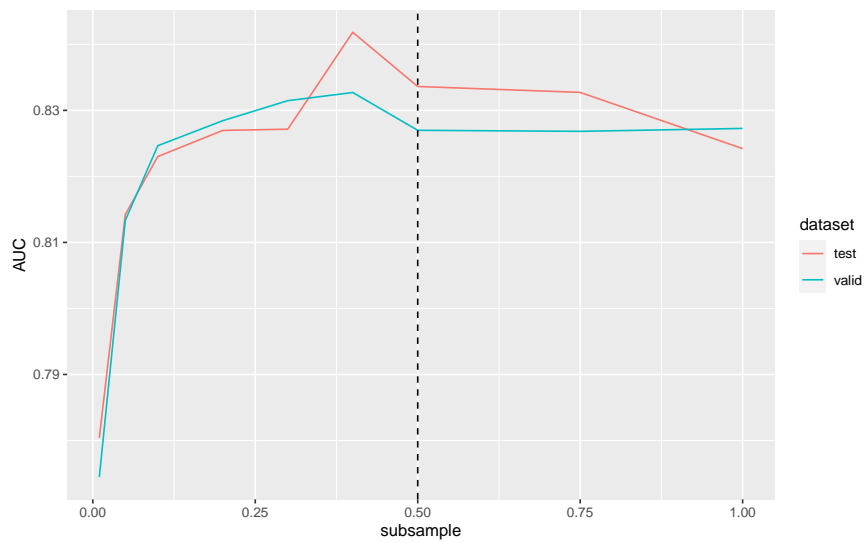
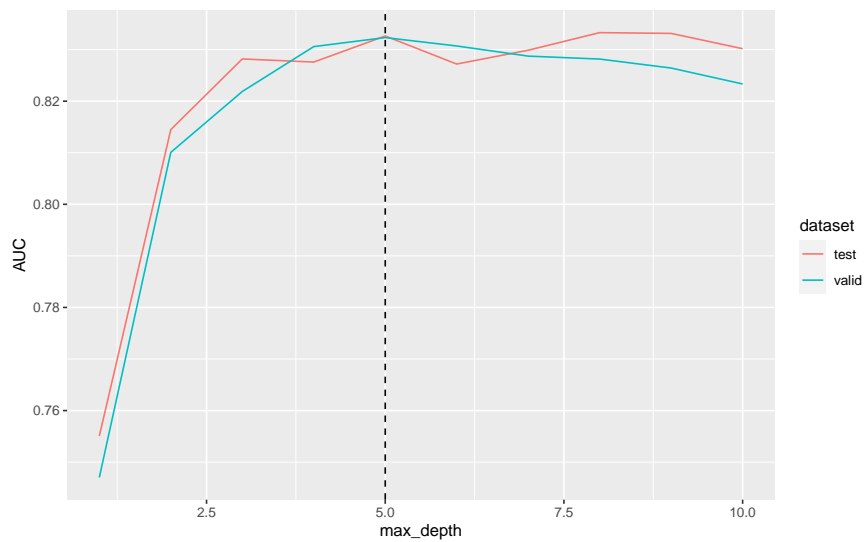
- All: original test set
- Complete cases: subset to only complete observations
- x-y% missing: subset to observations with (x,y]% of missing values
- AUROC graph below (resampling cases):
 - Seems to stabilize beyond 100K
 - 10-30% missing values have much larger AUC
 - Complete cases is much more variable since smaller

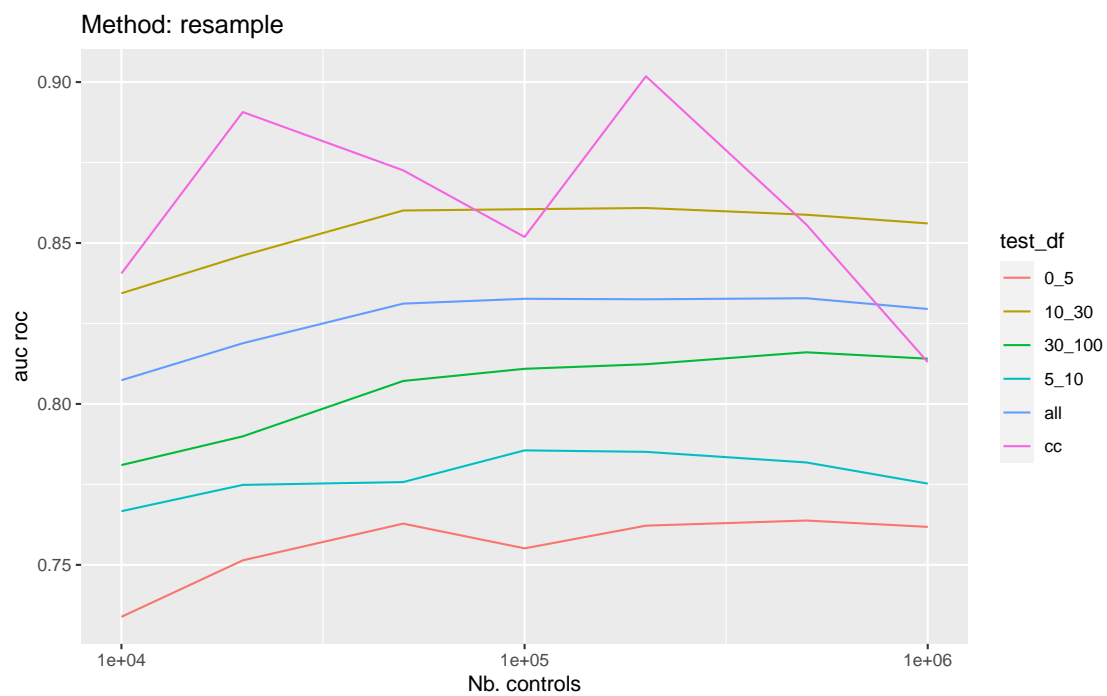
Test set	Sample size	Nb. cases	% cases
All	502849	2849	0.56%
Complete cases	1571	12	0.76%
0-5% missing	83640	286	0.34%
5-10% missing	133194	369	0.28%
10-30% missing	163377	1122	0.69%
30-100% missing	121067	1060	0.86%

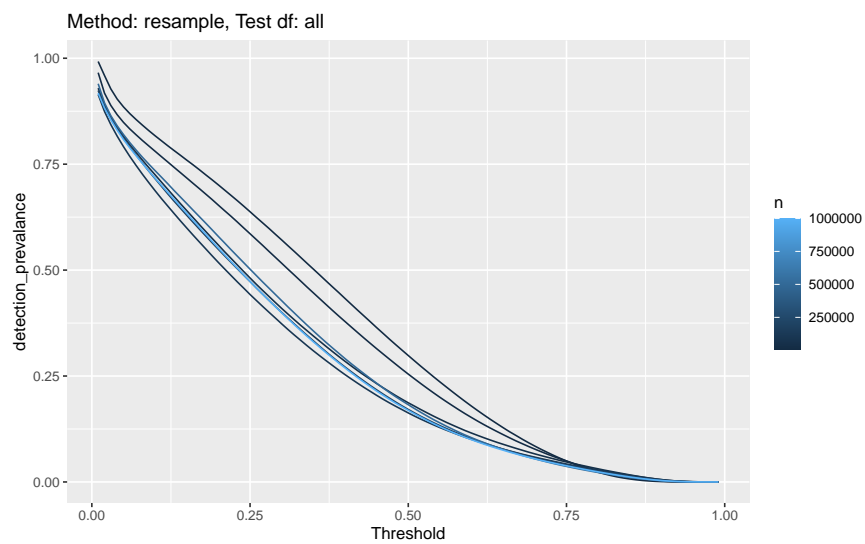
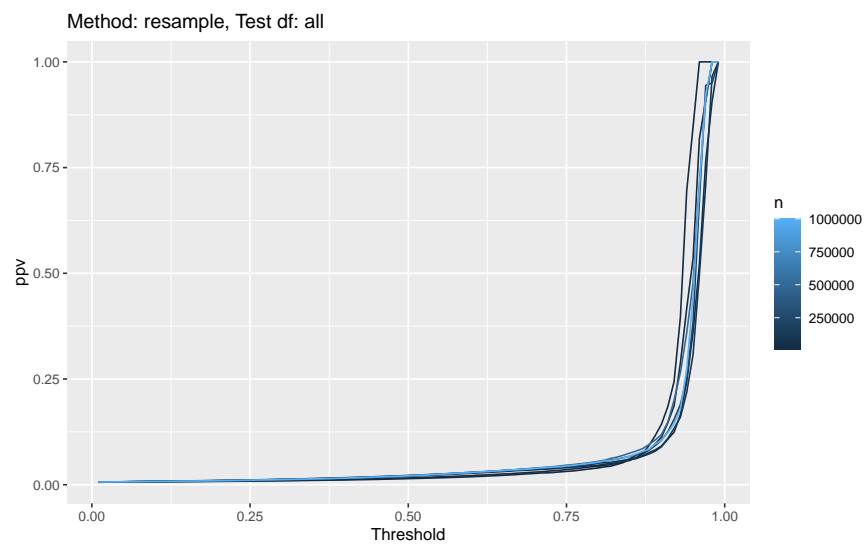
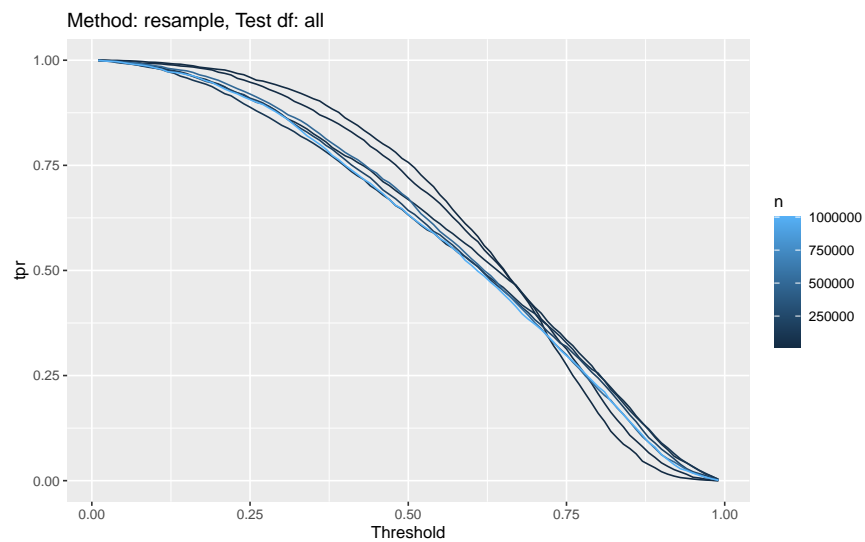
Metrics:

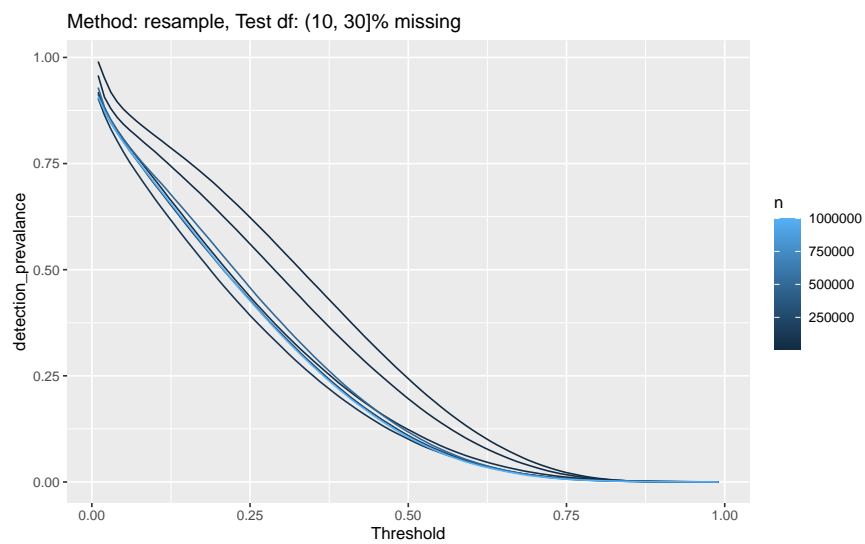
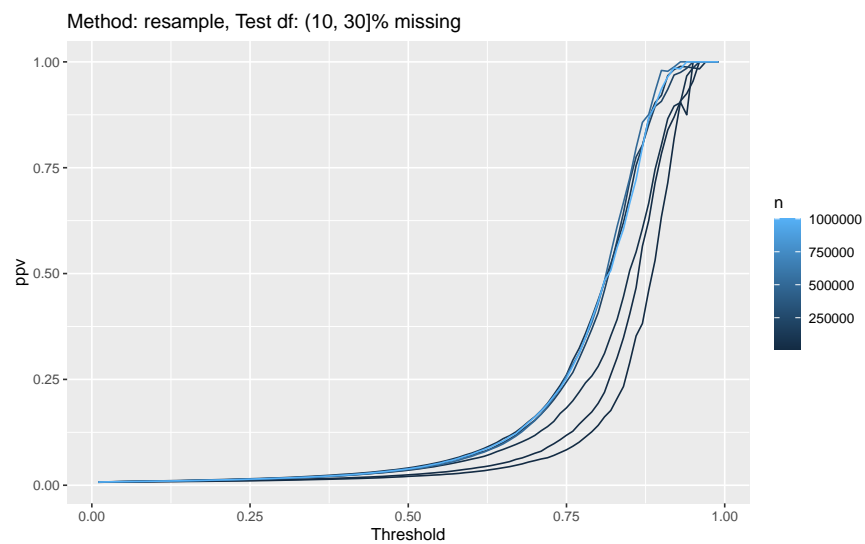
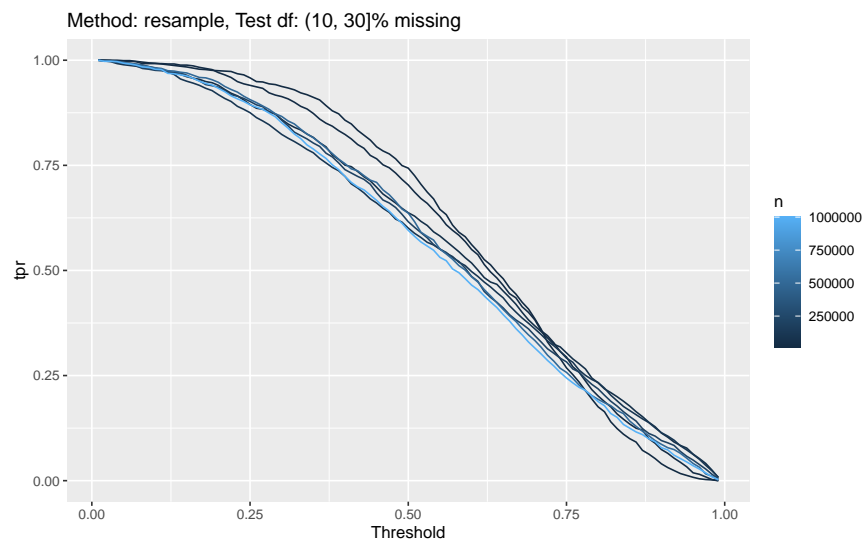
- AUC ROC: area under the ROC curve (sens, 1-spec)
- AUC PRC: area under the precision-recall curve (prec, rec)

- TPR: true positive rate (*recall*, *sensitivity*, TP/P , “% of cases that would be tested”)
- PPV: positive predictive value (*precision*, TP/DP , “% of cases among those tested”)
- Detection prevalence: (DP/N) , “% of patients tested”)









11/23/2021 update

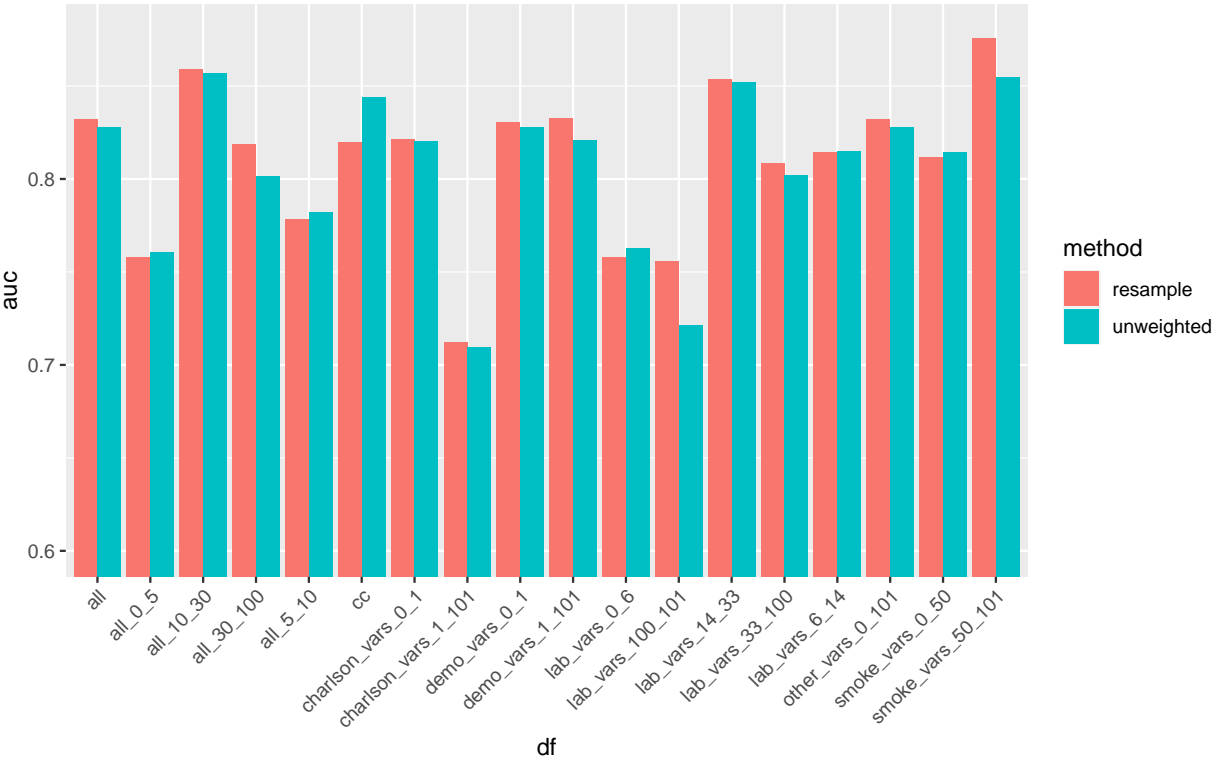
Missing values

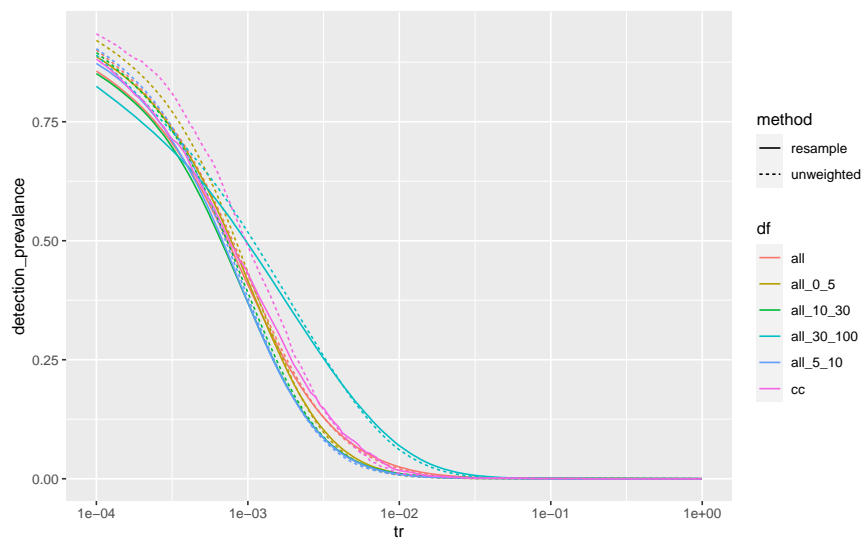
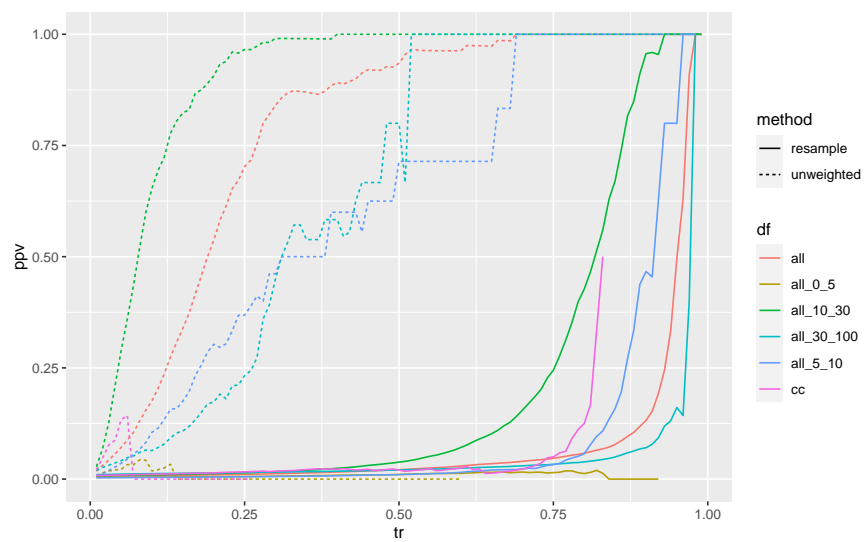
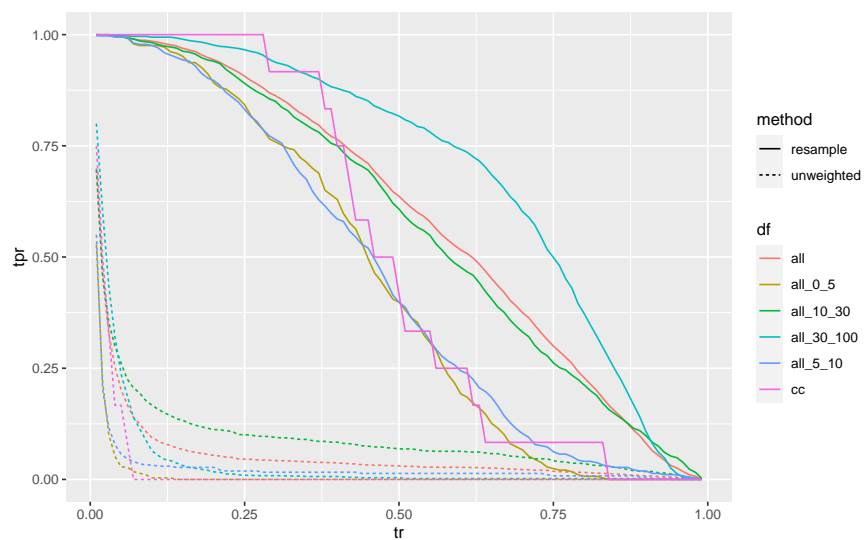
- Last week: split test set by proportion of missing values
- New: split test set by proportion of missing values within groups of variables
- Better for: 10-30% of missing values, 14-33% of missing lab variables, missing smoking variables
- Worse for: 0-10% of missing values, 1-100% missing charlson variables, 0-6 and 100% missing lab variables
- NB: high case % for missing charlson scores (but smaller total observations); higher case % for 100% missing lab variables

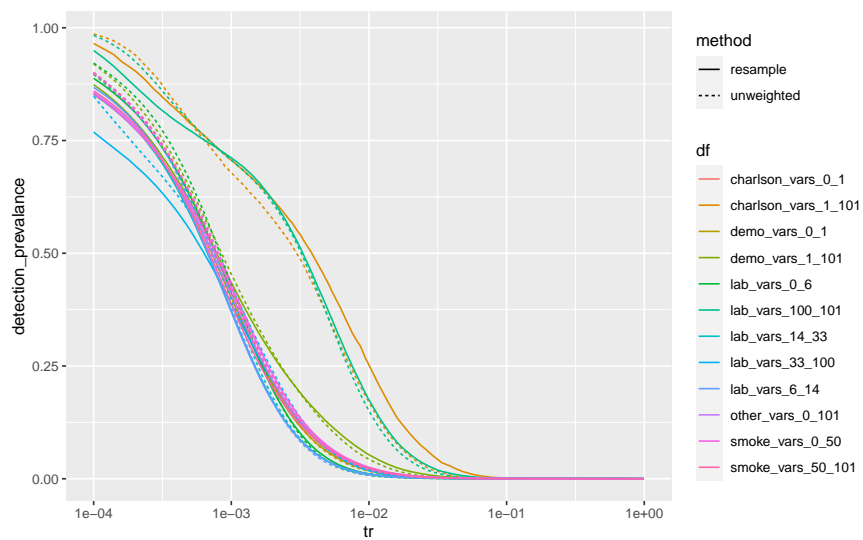
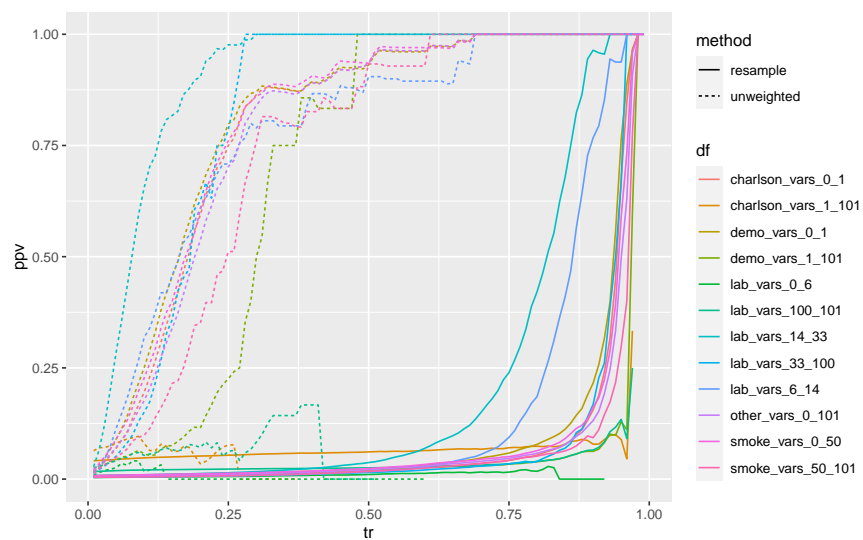
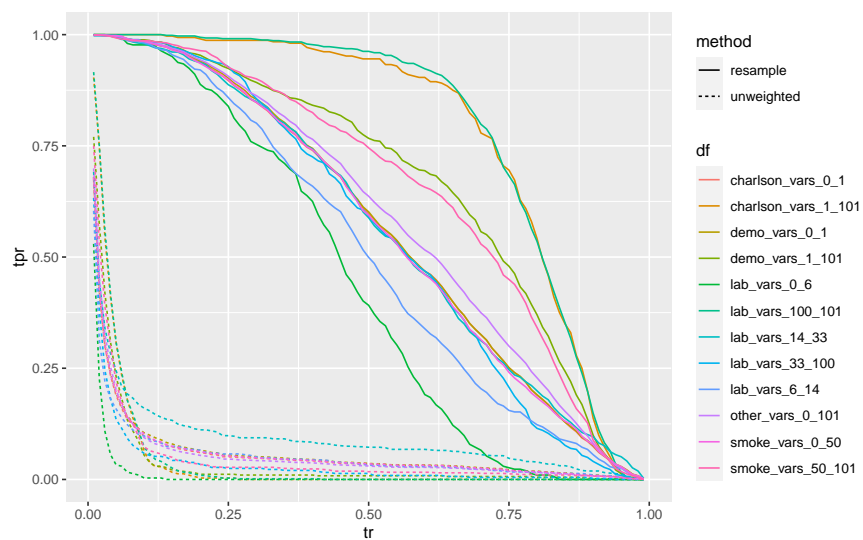
Calibration

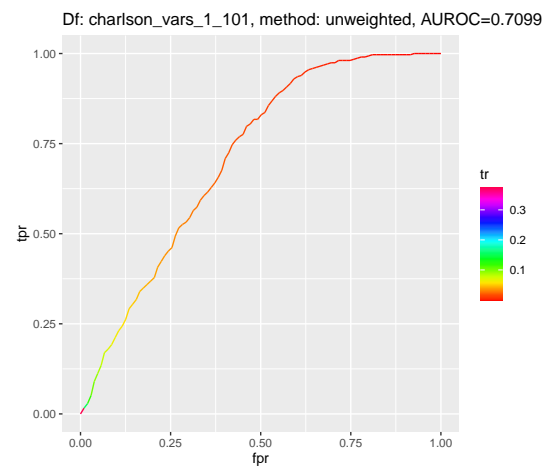
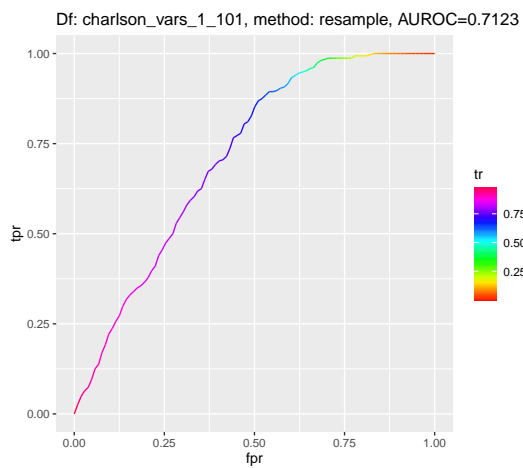
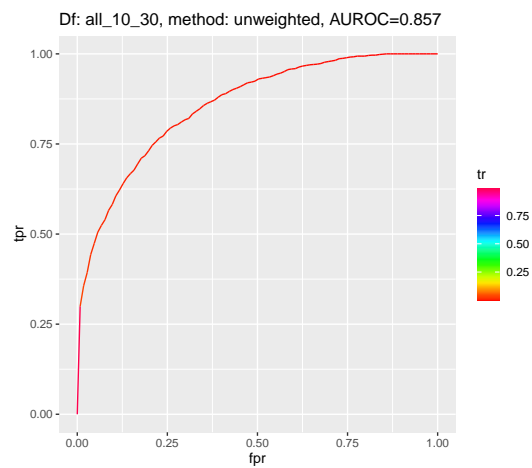
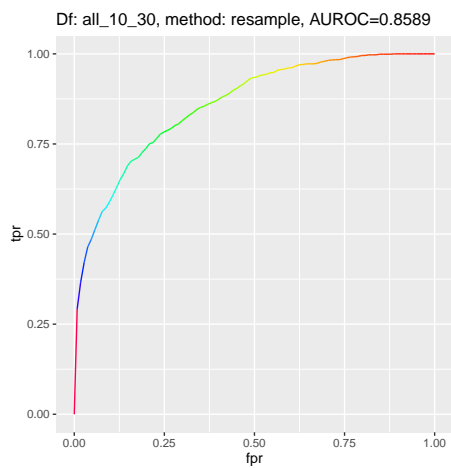
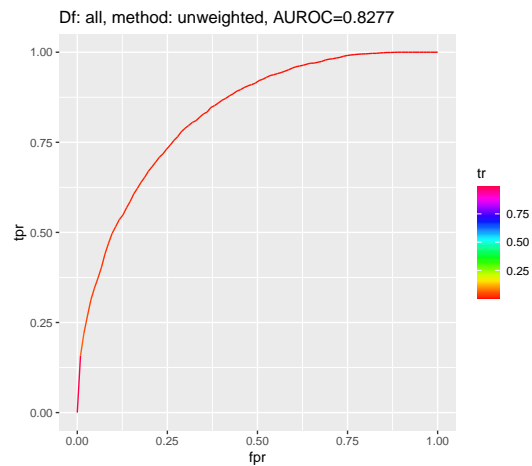
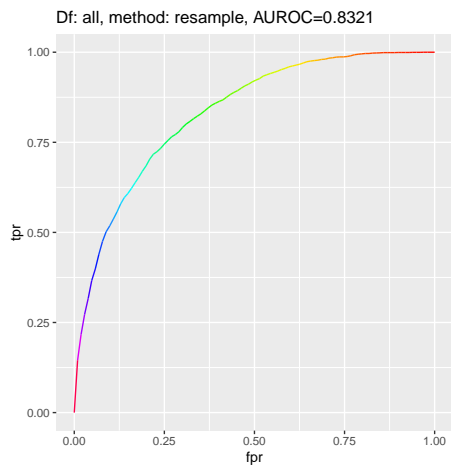
- Using the “resample” technique centers the scores around 50%, but the probabilities become uncalibrated (need to be careful with the interpretation)
- For “unweighted” the model is calibrated for the case proportion in the training set (0.5%)
- weight/resample to case incidence?
- Optimal threshold around 30-70% for “resample”; around 1-5% for “unweighted”
- Note that AUC only depends on the rank of the predicted probabilities, not on the probabilities themselves

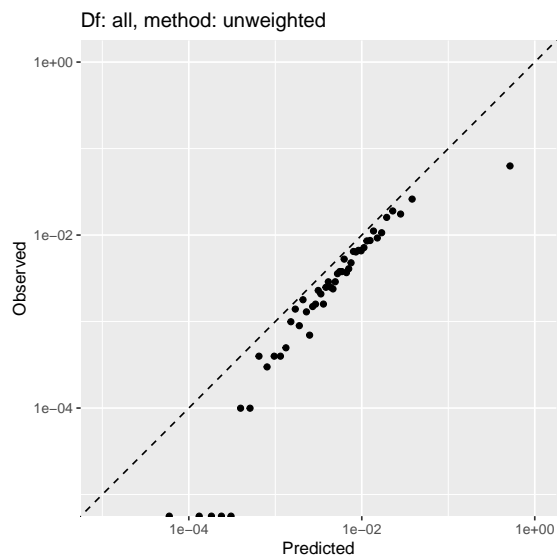
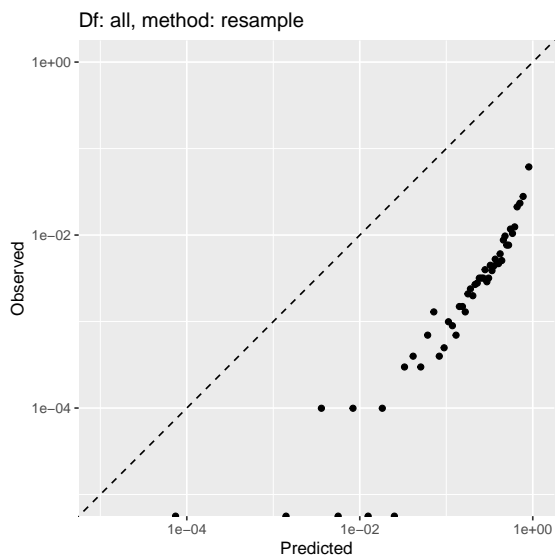
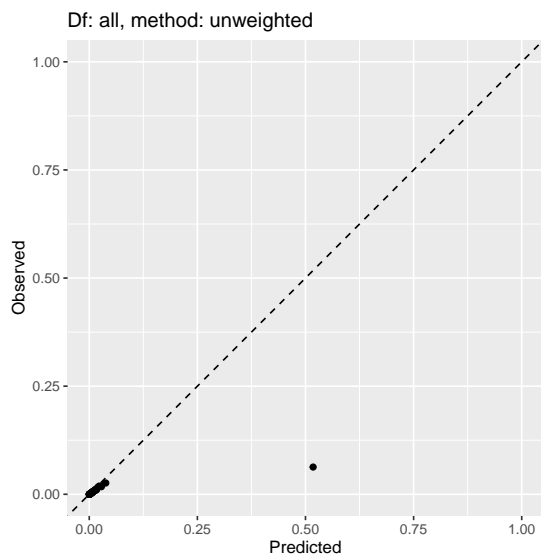
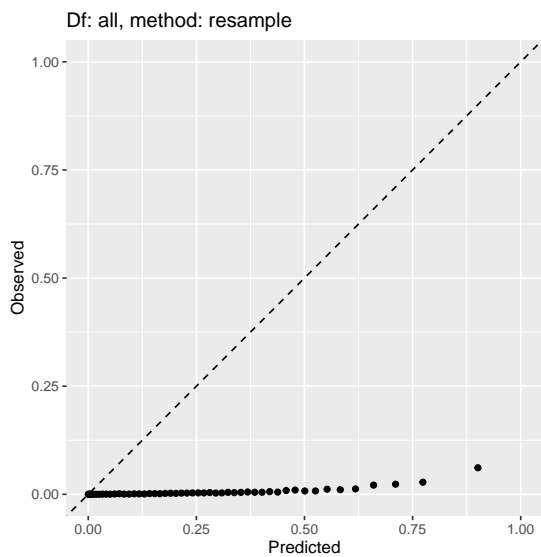
Test set	Sample size	Nb. cases	% cases
all	502849	2849	0.57%
cc	1571	12	0.76%
all_0_5	83640	286	0.34%
all_5_10	133193	369	0.28%
all_10_30	163373	1122	0.69%
all_30_100	121072	1060	0.88%
lab_vars_0_6	89372	304	0.34%
lab_vars_6_14	165220	593	0.36%
lab_vars_14_33	120373	843	0.70%
lab_vars_33_100	88946	444	0.50%
lab_vars_100_101	38938	665	1.71%
charlson_vars_0_1	495273	2537	0.51%
charlson_vars_1_101	7576	312	4.12%
demo_vars_0_1	416583	2244	0.54%
demo_vars_1_101	86266	605	0.70%
other_vars_0_101	502849	2849	0.57%
smoke_vars_0_50	284455	2044	0.72%
smoke_vars_50_101	218394	805	0.37%

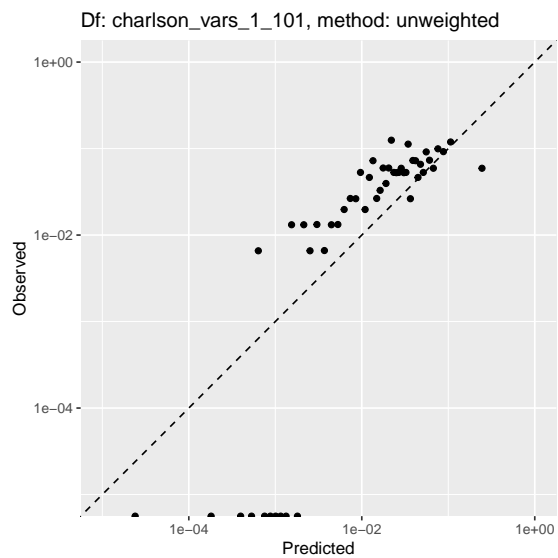
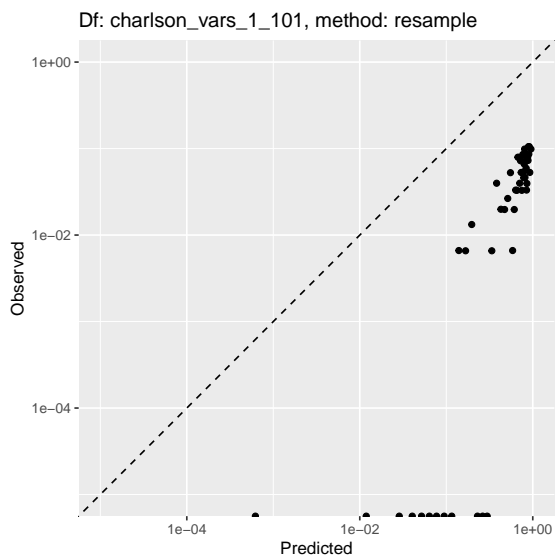
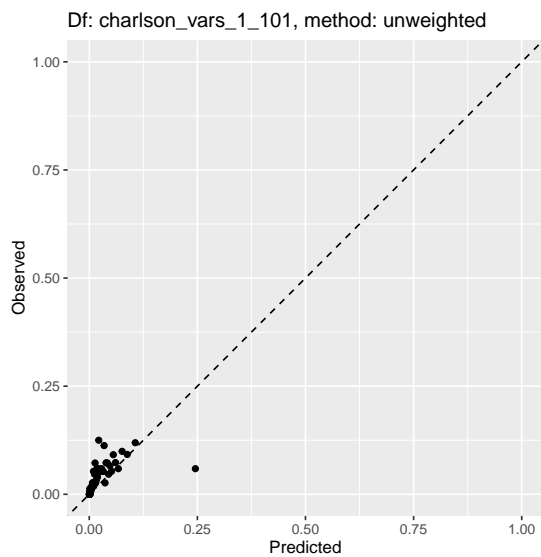
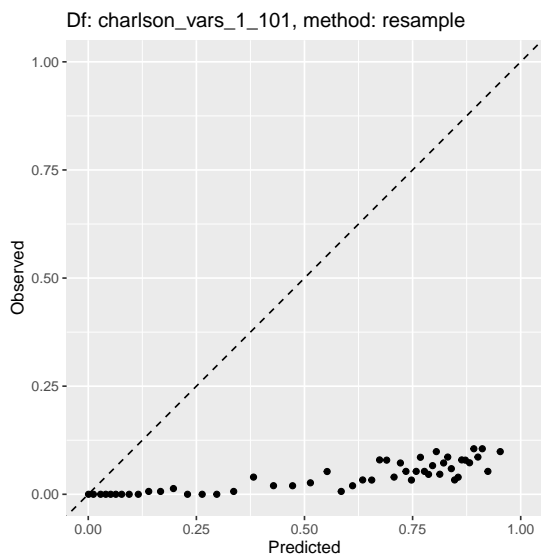








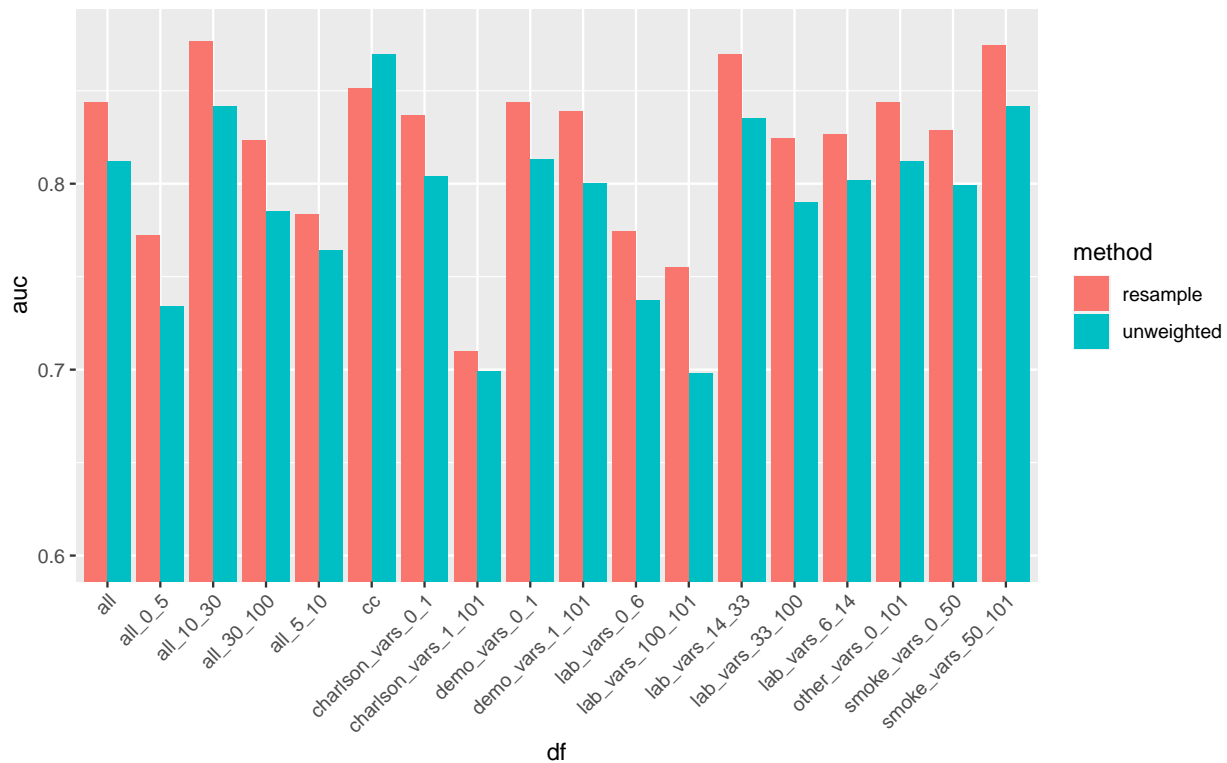


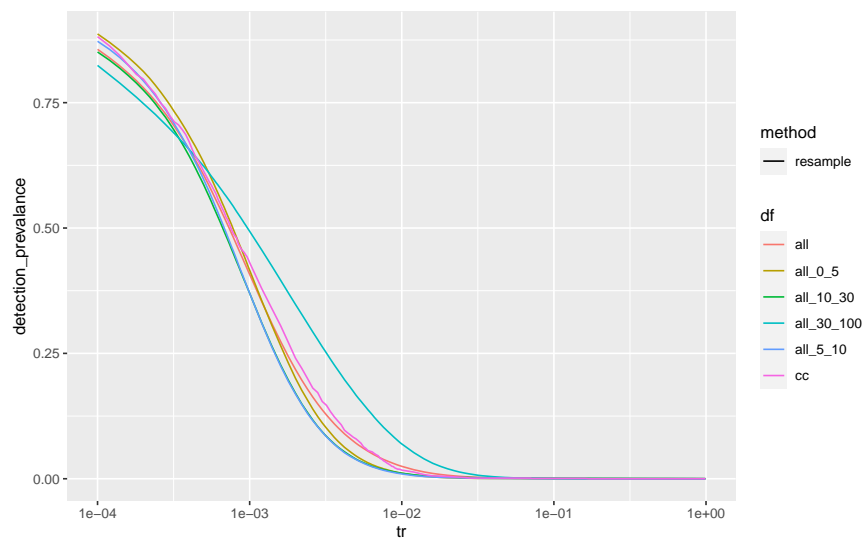
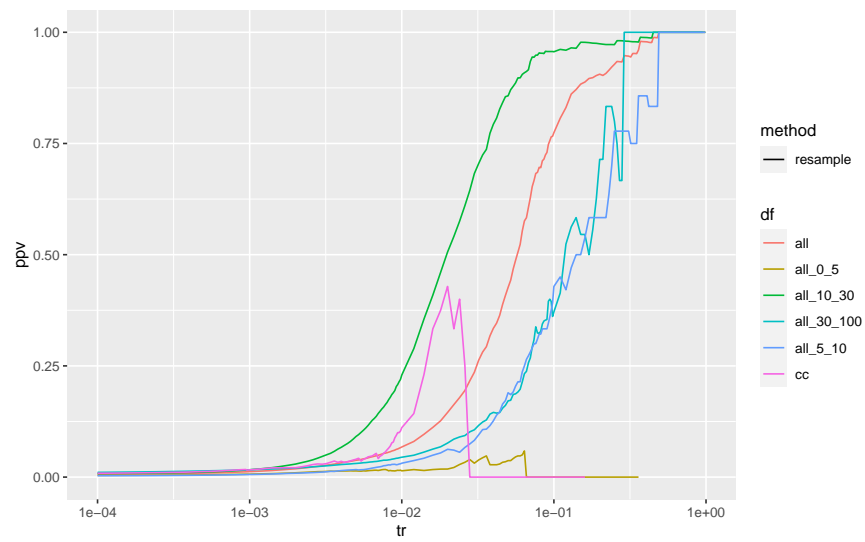
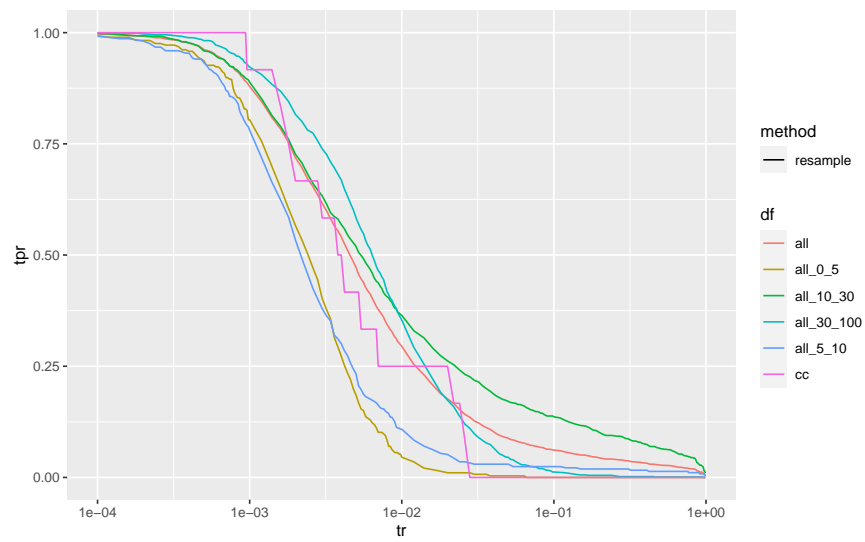


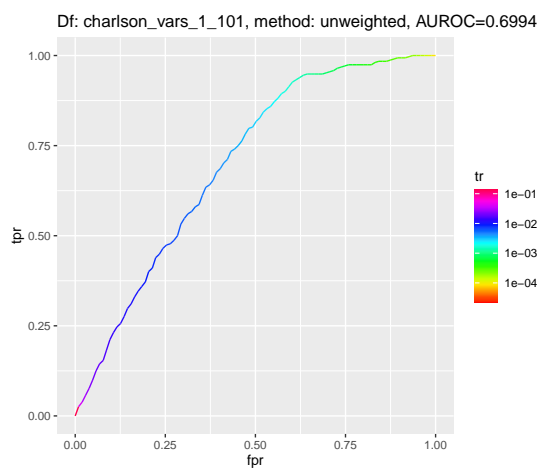
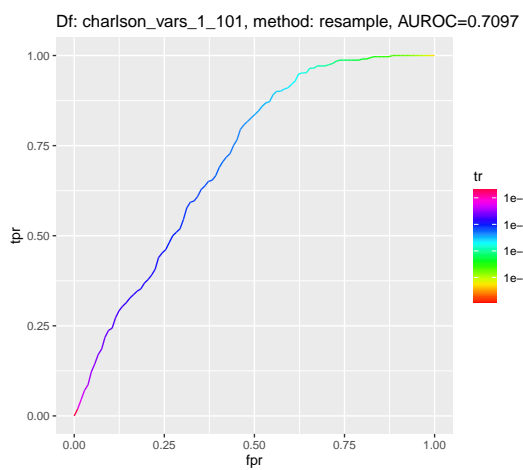
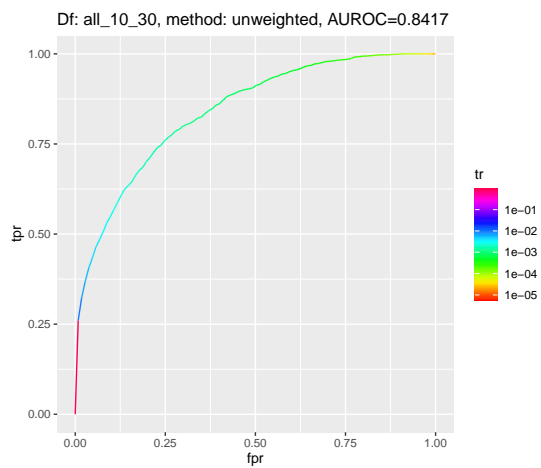
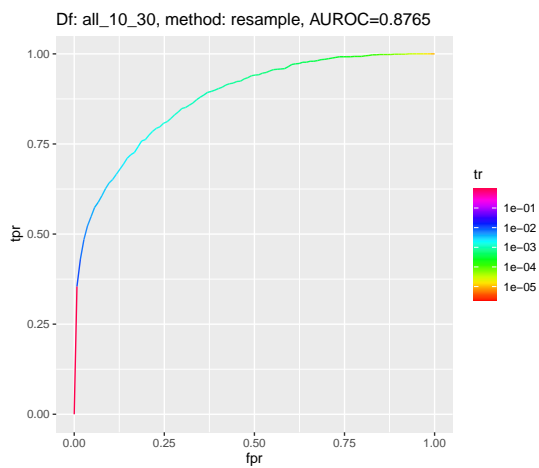
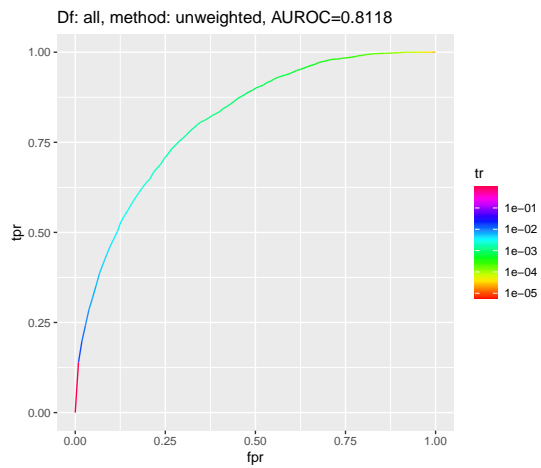
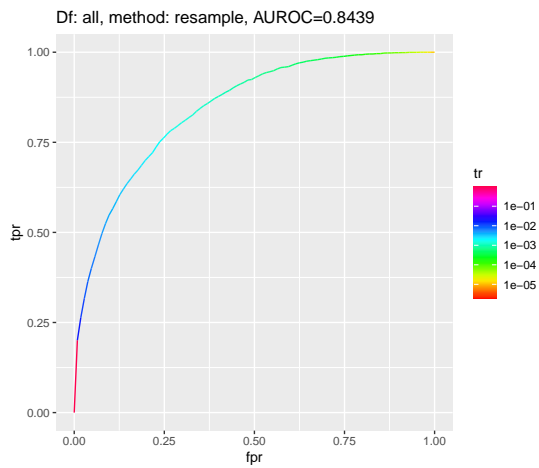
11/30/2021 update

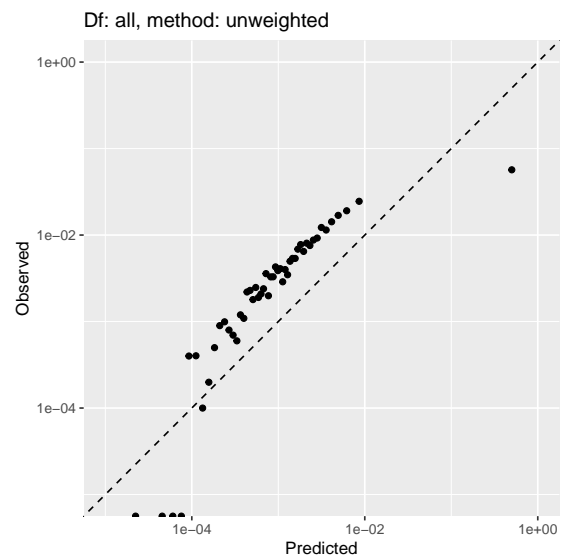
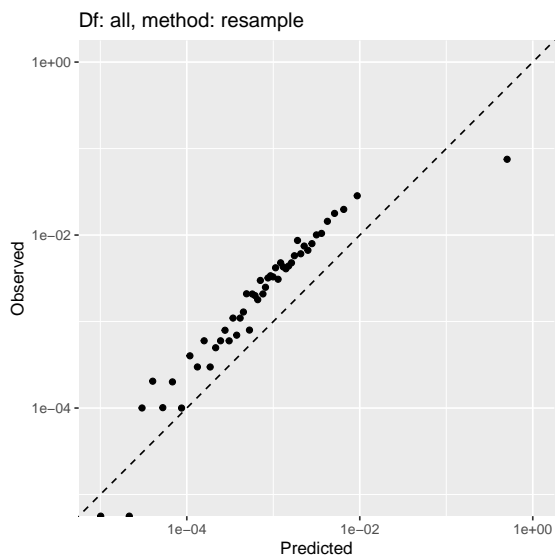
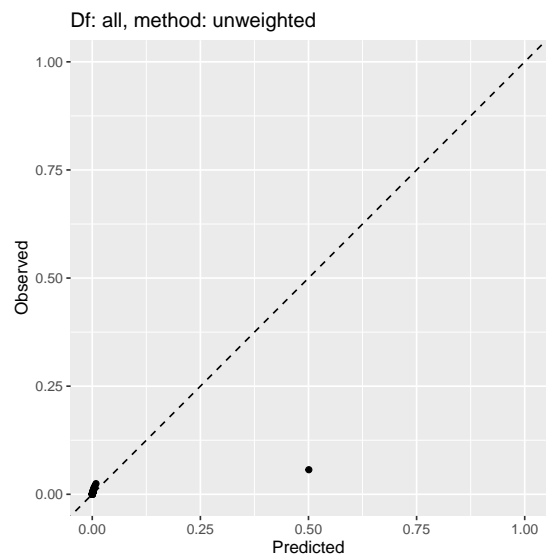
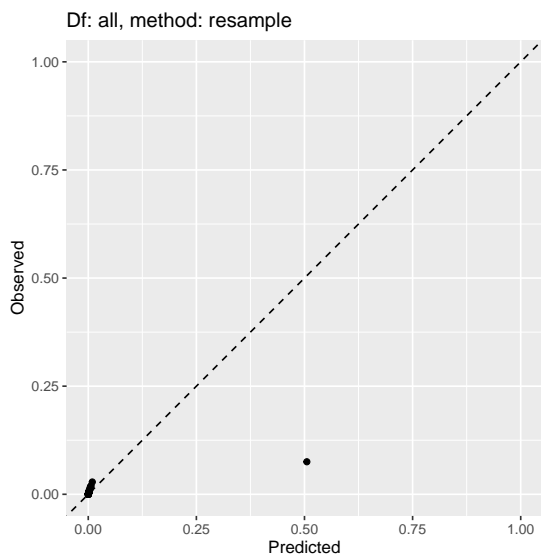
Recalibration

- “resample”: upsample cases up to a balanced training set; downweight cases so they have the same total weight as the original dataset
 - Example
 - original training set: 1M controls + 5K cases
 - after resampling: 1M controls + 1M cases
 - reweighting: controls(1M, 1) and cases(1M, 11K/6M)
- “unweighted”: reweight cases to have the same weight as in the original dataset
 - reweighting: controls(1M, 1) and cases(5K, 1M*11K/5K/6M)
- Same simulations as last week but with twice as many controls
- Note that the fitted models are calibrated for the 11K/6M proportion but that is not what the testing sets are (2.5K/500K), so we expect some miscalibration on the test sets (there’s a factor of ~ 3 between the two)





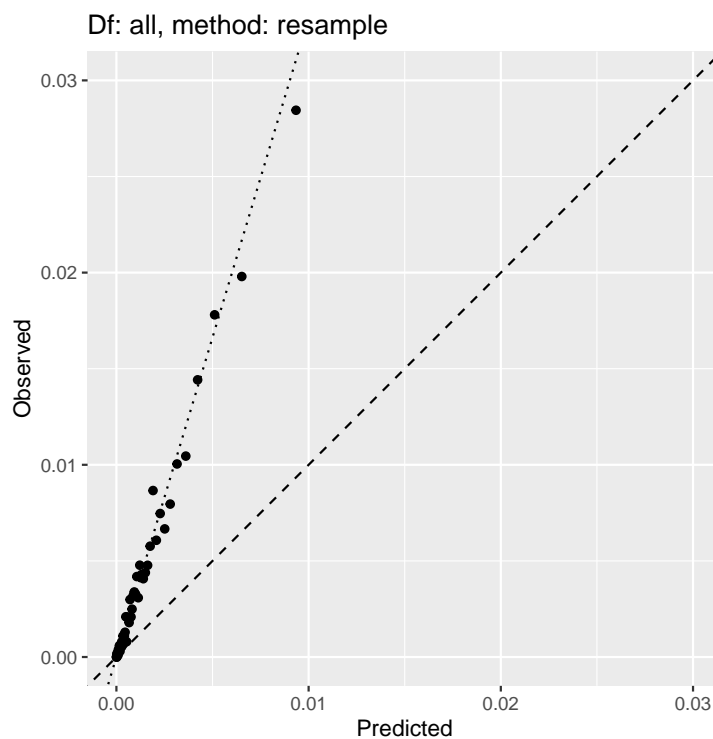




12/07/2021 update

More on calibration

- Inspection of the miscalibration observed last week showed that it is due to the miscalibration in the testing set.
- See plot below. The dotted line has slope $6.6\text{M}/2\text{M}$ which is exactly the ratio between the testing set and the calibration



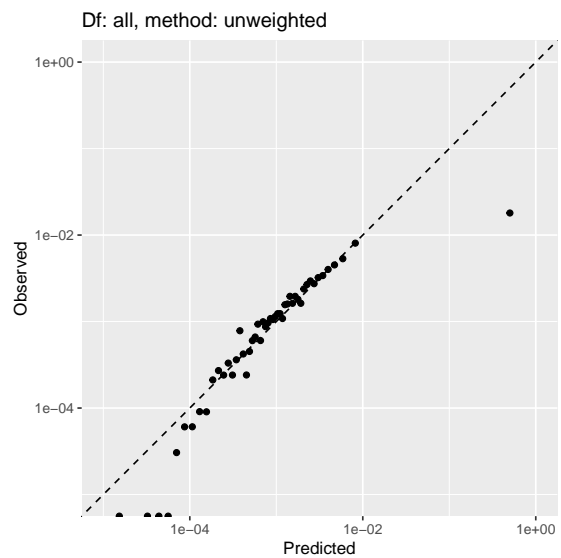
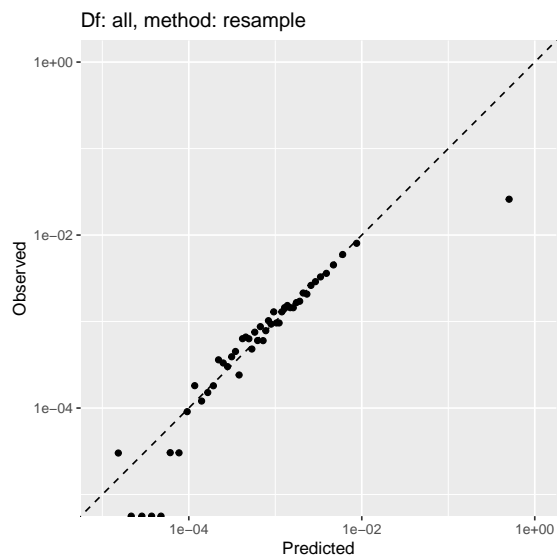
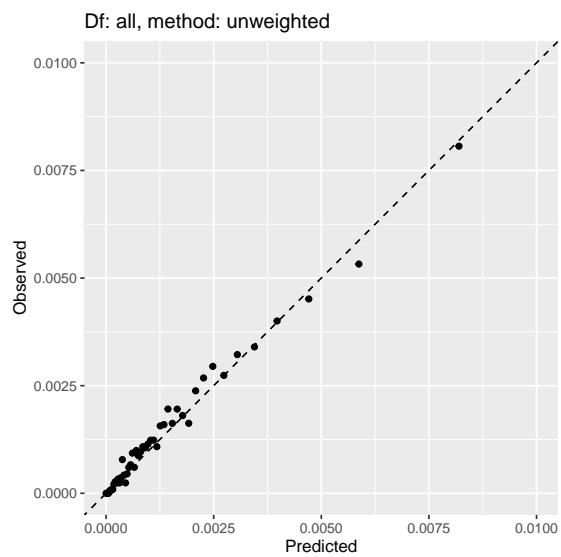
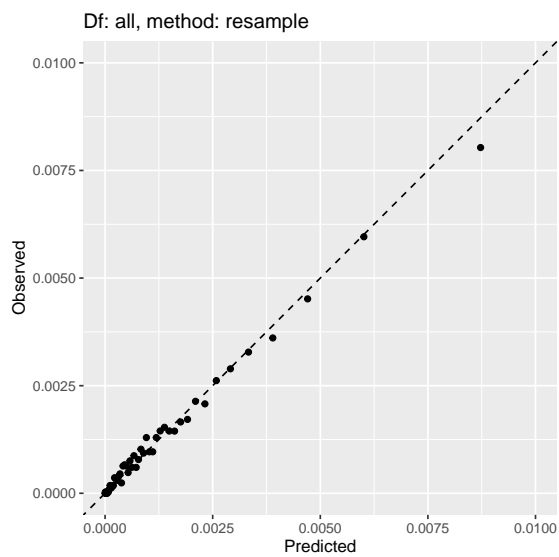
- Training on the whole data set is currently running: we should get correct calibration
- Below is the calibration table depending on the threshold

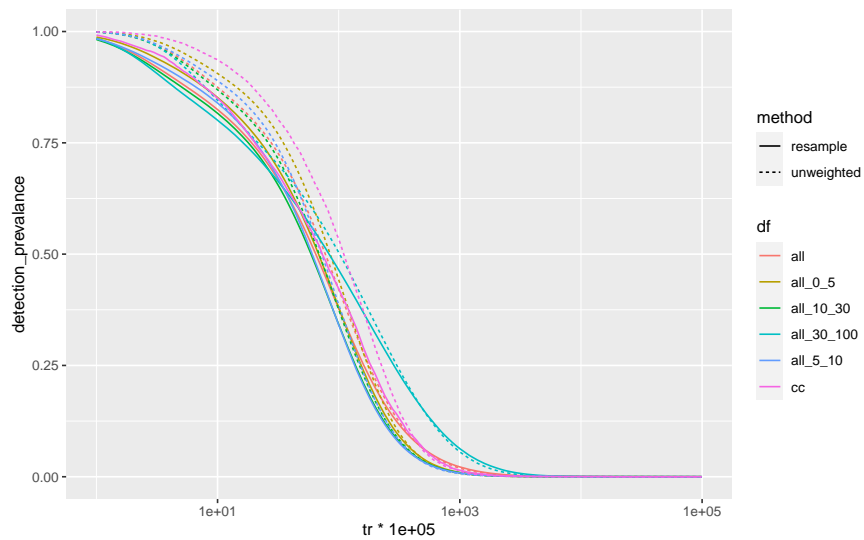
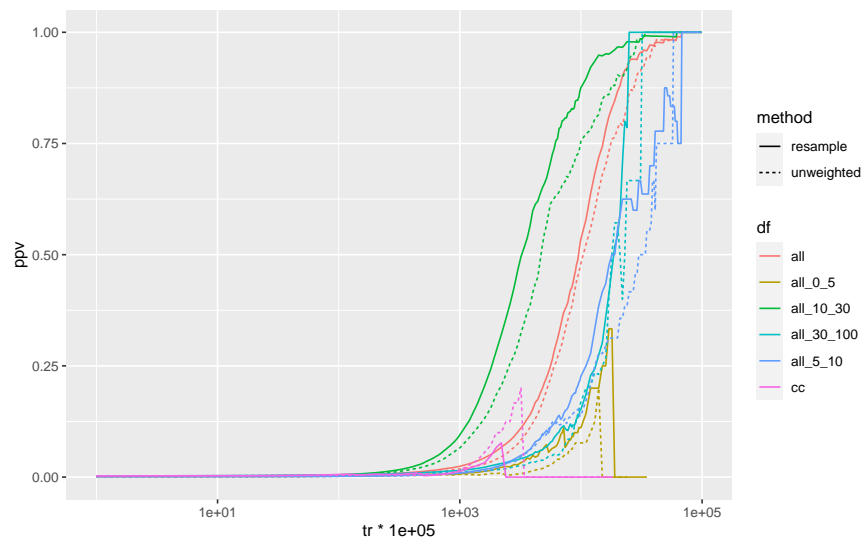
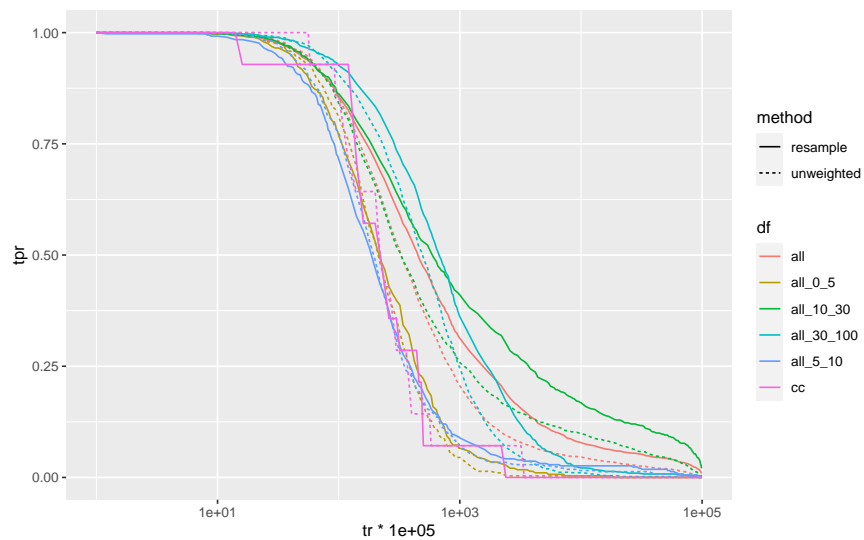
*Threshold in /100000, values in %, using miscalibrated model (6.6M/2M), rule of thumb:
multiply threshold by 3.2*

Threshold	TPR	PPV	Det. prev.	Threshold	TPR	PPV	Det. prev.
10	99.72	0.66	85.64	80	91.65	1.10	47.41
12	99.61	0.67	83.93	82	91.33	1.11	46.66
14	99.51	0.68	82.33	84	91.08	1.12	45.94
16	99.44	0.70	80.80	86	90.70	1.14	45.24
18	99.30	0.71	79.38	88	90.17	1.15	44.56
20	99.19	0.72	77.98	90	89.93	1.16	43.90
22	99.05	0.73	76.64	92	89.36	1.17	43.23
24	98.84	0.74	75.31	94	89.08	1.18	42.61
26	98.84	0.76	73.99	96	88.77	1.20	41.96
28	98.60	0.77	72.76	98	88.31	1.21	41.34
30	98.46	0.78	71.48	100	87.89	1.22	40.75
32	98.35	0.79	70.24	120	84.49	1.35	35.34
34	98.21	0.81	69.07	140	80.94	1.48	30.94
36	97.93	0.82	67.92	160	78.31	1.62	27.34
38	97.82	0.83	66.80	180	75.36	1.76	24.32
40	97.65	0.84	65.69	200	71.85	1.87	21.81
42	97.44	0.85	64.60	220	69.71	2.01	19.68
44	97.19	0.87	63.53	240	67.22	2.13	17.87
46	96.98	0.88	62.50	260	65.39	2.27	16.29
48	96.67	0.89	61.47	280	63.53	2.41	14.93
50	96.21	0.90	60.47	300	61.60	2.54	13.74
52	96.00	0.91	59.46	320	59.99	2.67	12.71
54	95.86	0.93	58.50	340	58.23	2.80	11.79
56	95.68	0.94	57.51	360	56.55	2.93	10.95
58	95.37	0.96	56.55	380	55.46	3.07	10.22
60	94.91	0.97	55.62	400	54.12	3.20	9.57
62	94.66	0.98	54.73	420	52.51	3.32	8.95
64	94.38	0.99	53.85	440	51.07	3.43	8.43
66	94.10	1.01	52.98	460	49.74	3.54	7.96
68	93.86	1.02	52.12	480	48.51	3.66	7.51
70	93.33	1.03	51.31	500	47.24	3.78	7.08
72	92.98	1.04	50.50	600	41.87	4.33	5.48
74	92.49	1.05	49.71	700	37.77	4.91	4.35
76	92.35	1.07	48.92	800	34.40	5.48	3.56
78	92.07	1.08	48.17	900	31.59	6.07	2.95

12/14/2021 update

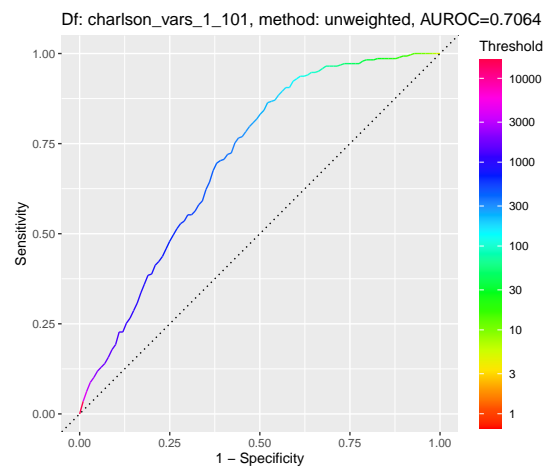
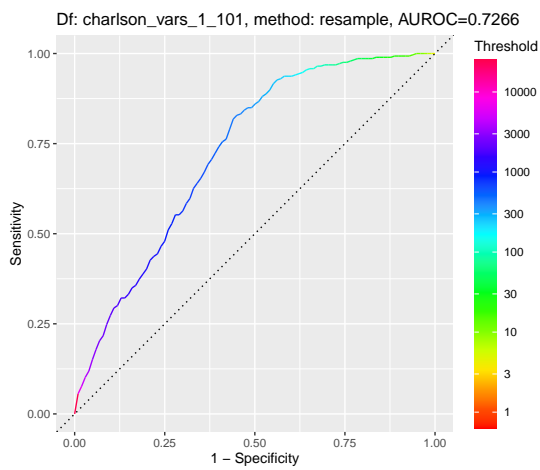
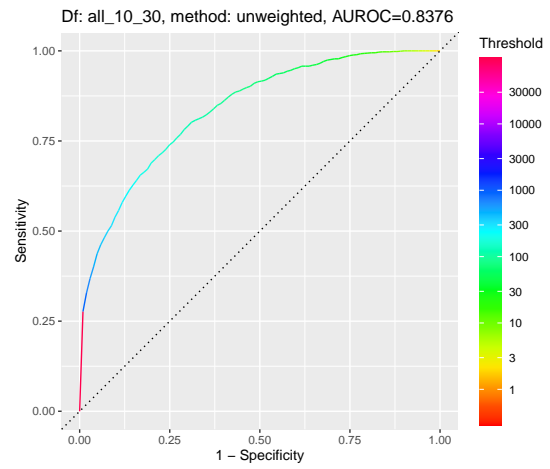
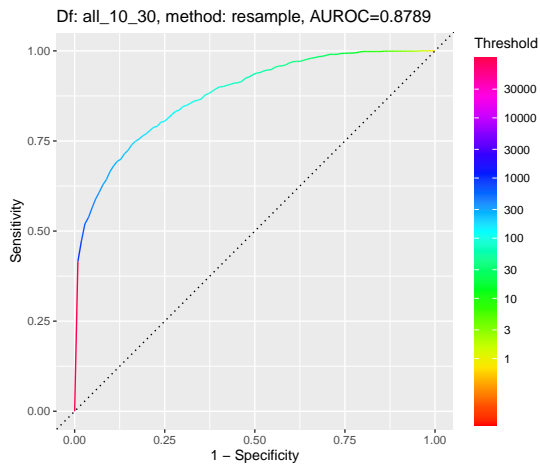
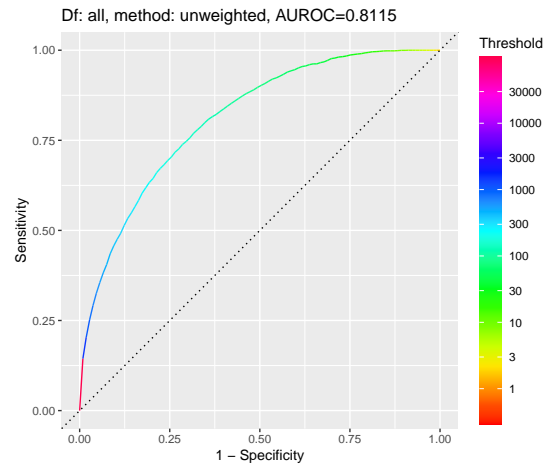
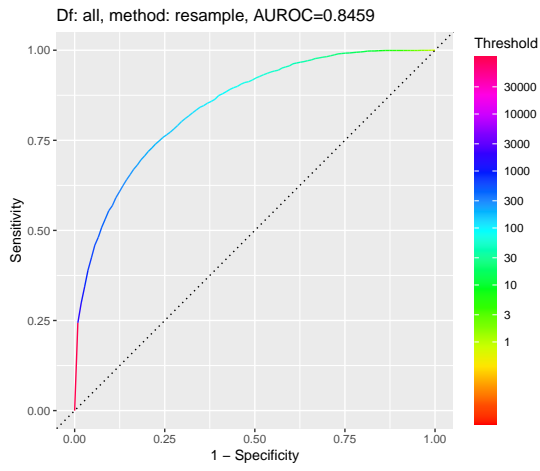
- Follow-up on last week:
 - We were unsure why the miscalibration was in the observed direction
 - Solution: we needed to remember that the testing sets contained 3x too many cases compared to the training set
 - This explains why the observed proportion was 3x higher than expected
 - The fitted probabilities were correct, but the case incidence in the testing set was incorrect
- Results using all 6M controls are in!
- Essentially the same as before with slightly improved AUC (0.8459 vs 0.8439); calibration in the testing set is improved
- We have the same proportion on all sets (training, validation, testing) which makes the model calibrated to the correct incidence and the evaluation uses the correct incidence as well.
- Threshold selection: similar evaluation metrics except ppv/3

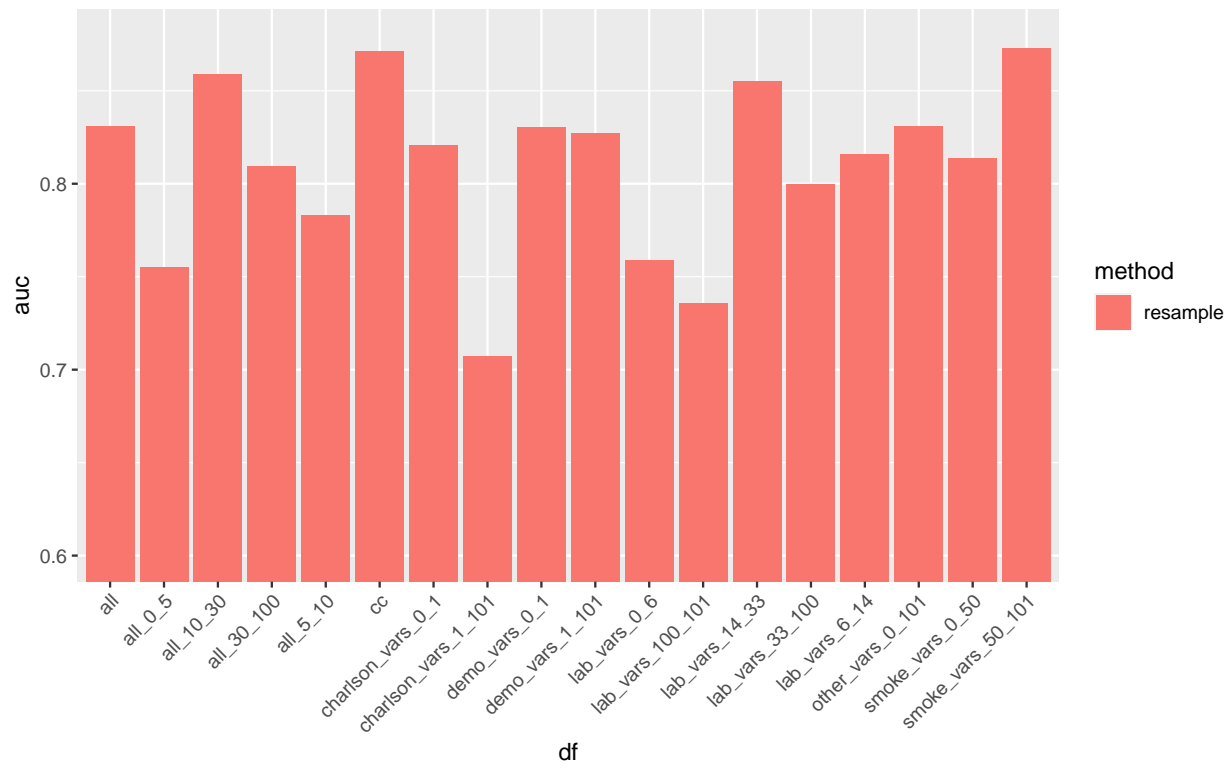




Threshold	TPR	PPV	Det. prev.
10	99.79	0.21	82.47
12	99.68	0.21	80.65
14	99.51	0.22	78.94
16	99.33	0.22	77.34
18	99.23	0.22	75.82
20	99.12	0.23	74.37
22	98.91	0.23	72.96
24	98.56	0.24	71.60
26	98.28	0.24	70.27
28	98.07	0.24	68.99
30	97.86	0.25	67.72
32	97.61	0.25	66.51
34	97.30	0.26	65.33
36	96.91	0.26	64.16
38	96.77	0.26	63.03
40	96.60	0.27	61.91
42	96.28	0.27	60.83
44	95.75	0.27	59.77
46	95.37	0.28	58.72
48	95.05	0.28	57.69
50	94.49	0.29	56.70
52	94.28	0.29	55.71
54	94.03	0.29	54.76
56	93.72	0.30	53.81
58	93.37	0.30	52.91
60	92.91	0.31	52.00
62	92.56	0.31	51.14
64	92.31	0.31	50.28
66	91.79	0.32	49.45
68	91.30	0.32	48.64
70	91.19	0.33	47.84
72	90.91	0.33	47.06
74	90.59	0.34	46.30
76	90.14	0.34	45.56
78	89.79	0.34	44.82

Threshold	TPR	PPV	Det. prev.
80	89.61	0.35	44.11
82	89.26	0.35	43.41
84	88.94	0.36	42.73
86	88.49	0.36	42.06
88	88.03	0.36	41.41
90	87.71	0.37	40.77
92	87.43	0.37	40.14
94	87.05	0.38	39.54
96	86.38	0.38	38.95
98	86.00	0.38	38.37
100	85.68	0.39	37.80
120	82.59	0.43	32.72
140	78.98	0.47	28.58
160	76.20	0.52	25.18
180	73.82	0.57	22.37
200	71.29	0.61	20.00
220	68.87	0.66	18.01
240	66.80	0.70	16.30
260	64.55	0.75	14.84
280	62.48	0.79	13.57
300	60.62	0.83	12.46
320	58.97	0.88	11.50
340	57.04	0.92	10.65
360	56.02	0.97	9.89
380	54.62	1.02	9.21
400	53.32	1.06	8.61
500	47.31	1.28	6.33
600	42.86	1.51	4.87
700	39.24	1.74	3.86
800	36.57	2.00	3.14
900	33.17	2.18	2.61
1000	31.27	2.43	2.20
2000	21.83	5.87	0.64
5000	11.51	21.28	0.09
10000	7.83	53.61	0.03





01/04/2022 update

Some follow-ups

- Patient data importance:
 - Smoking status (current: 121/239, former:52/239)
 - HIV indicator (231/239)
- Calibration metrics
 - resampling, using all data (50-25-25 split)
 - Create 51 bins with equal number of observations
 - * i.e., every 2nd percentile
 - * i.e., the 0.00, 0.02, ..., 0.98, 1.00 quantiles
 - * n.b., the last bin is very large [0.0106, 1.0000] and causes problem to compute “expected” counts
 - Using all 51 bins:
 - * Pearson correlation (0.920, 95% c.i. [0.864,0.954])
 - * Spearman correlation (0.988)
 - * Hosmer-Lemeshow (H=30593, df=49, $p < 2.2e-16$)
 - Using all but last bin:
 - * Pearson correlation (0.997, 95% c.i. [0.995, 0.998])
 - * Spearman correlation (0.988)
 - * Hosmer-Lemeshow (H=42.7, df=48, $p=0.690$)

Comparison to Kunzmann

- “Esophageal condition”:
 - I could only match GERD and H2R
- Their cohort has much fewer smokers (US vs UK?, 40% missing?)
- Estimated OR compared to theirs
 - Age & Sex seem to have similar effect
 - BMI and smoking seem to have a weaker effect (smoking status has a lot of missing values, so SRS imputation should hide effect)
 - Esophageal condition, despite the mismatch, seem to have a similar effect

Variable	No EAC	EAC	Kunzmann OR (CI)	OR
Age				
0-50	1,094,536	187	–	0.20
50-55	435,106	400	1.00 (reference)	1.00
55-60	563,542	1,097	1.99 (1.11–3.65)	2.19
60-65	792,624	2,053	2.76 (1.60–4.74)	2.96
65+	2,082,924	4,770	4.03 (2.36–6.89)	3.18
Sex				
Female	346,096	50	1.00 (reference)	1.00
Male	4,632,189	8496	5.16 (3.58–7.44)	6.60
BMI				
0-25	1,024,990	1,531	1.00 (reference)	1.00
25-30	1,753,719	2,640	1.50 (1.02–2.21)	1.00
30-35	1,135,392	1,841	1.91 (1.25–2.94)	1.16
35+	664,785	1,310	2.97 (1.79–4.94)	1.57
Smoking				
Never	405,221	502	1.00 (reference)	1.00
Former	2,031,897	3,705	2.03 (1.47–2.80)	1.05
Current	2,253,878	4,083	3.83 (2.59–5.66)	1.35
Esophagal condition				
No	346,096	50	1.00 (reference)	1.00
Yes	4,632,189	8496	1.88 (1.39–2.54)	1.44

Sensitivity analyses

- 2–5:
 - 4 years of data, predicting 1 years ahead
 - usual analysis
- 4–5:
 - 2 years of data, predicting 3 years ahead
 - i.e., using year -5 and -4 to predict outcome
- same pipeline as before, using 100K controls
- AUCs: 0.7837 (2–5) vs 0.7565 (4–5)
- Models are miscalibrated, needs to be improved ...

Other updates

- Currently working on wrapping everything in a R package for simpler/easier usage and deployment.
- Also, implementation of some functions making sensitivity analyses easier (i.e., automating the data preprocessing)
- Starts with the assumptions that the user would input the same file as we got (patient info, medication, codes, labs)

01/04/2022 update follow-up

Sample sizes

- Training set (75%): 4,986,831 observations, 8,546 cases, 4,978,285 controls
 - Further split in training + validation
 - Training set (50%): 3,324,554 observations, 5,697 cases 3,318,857 controls
 - Validation set (25%): 1,662,277 observations, 2,849 cases 1,659,428 controls
- Testing set (25%): 1,662,277 observations, 2,849 cases, 1,659,428 controls

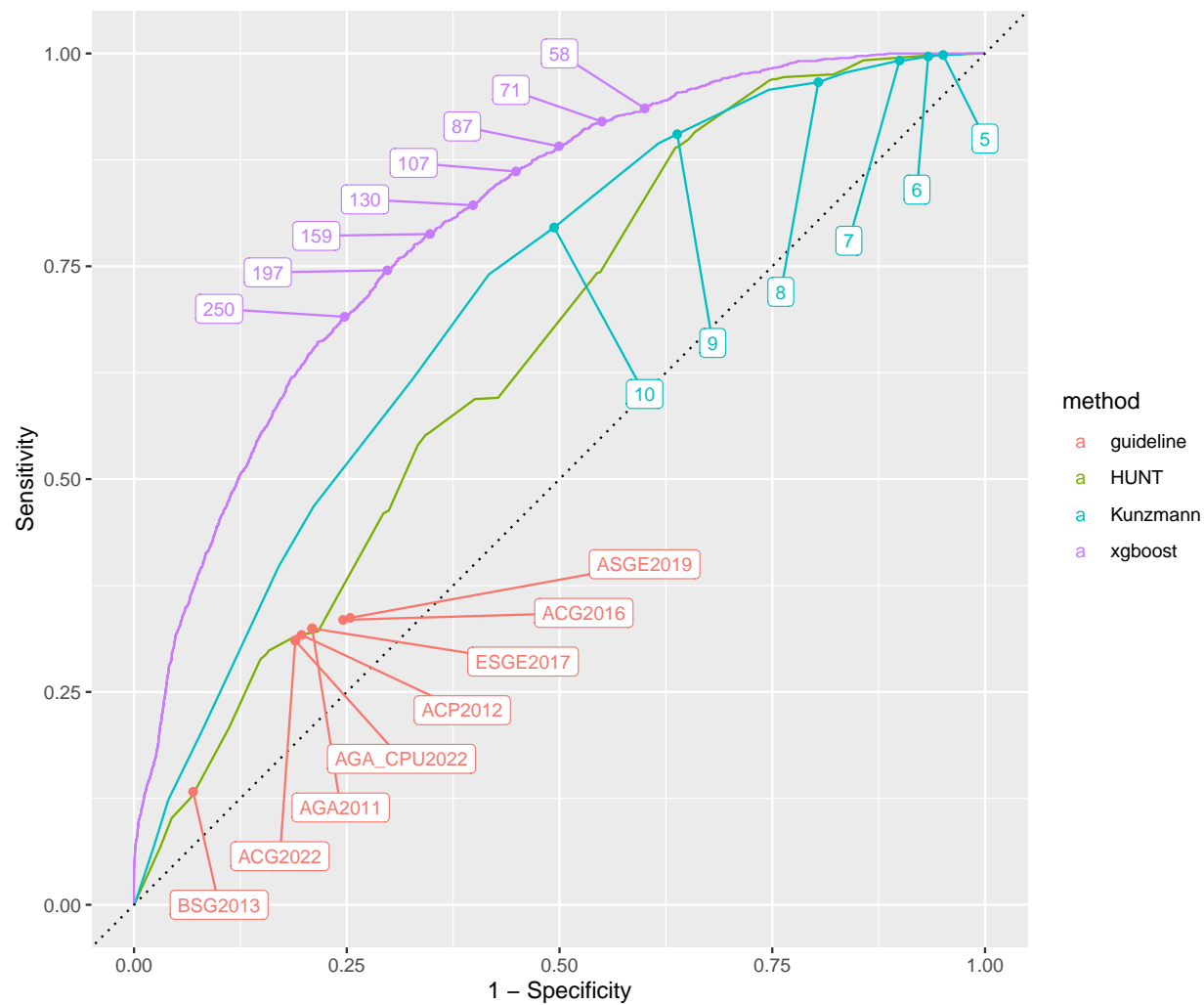
HUNT method

- This is not a logistic regression model so there is not really an “intercept” per se, only a baseline hazard when all variables are turned off. The baseline hazard seems to be 3.6.
- In any case, this does not really matter for computing AUC and plotting the ROC curve as we would only multiply all rates by some factor and this would produce the same results
- I will not be providing classification metrics (sensitivity, specificity, etc.) as this would require choosing a threshold. Let me know if you’d like to have them anyway.

Comparison to HUNT and Kunzmann

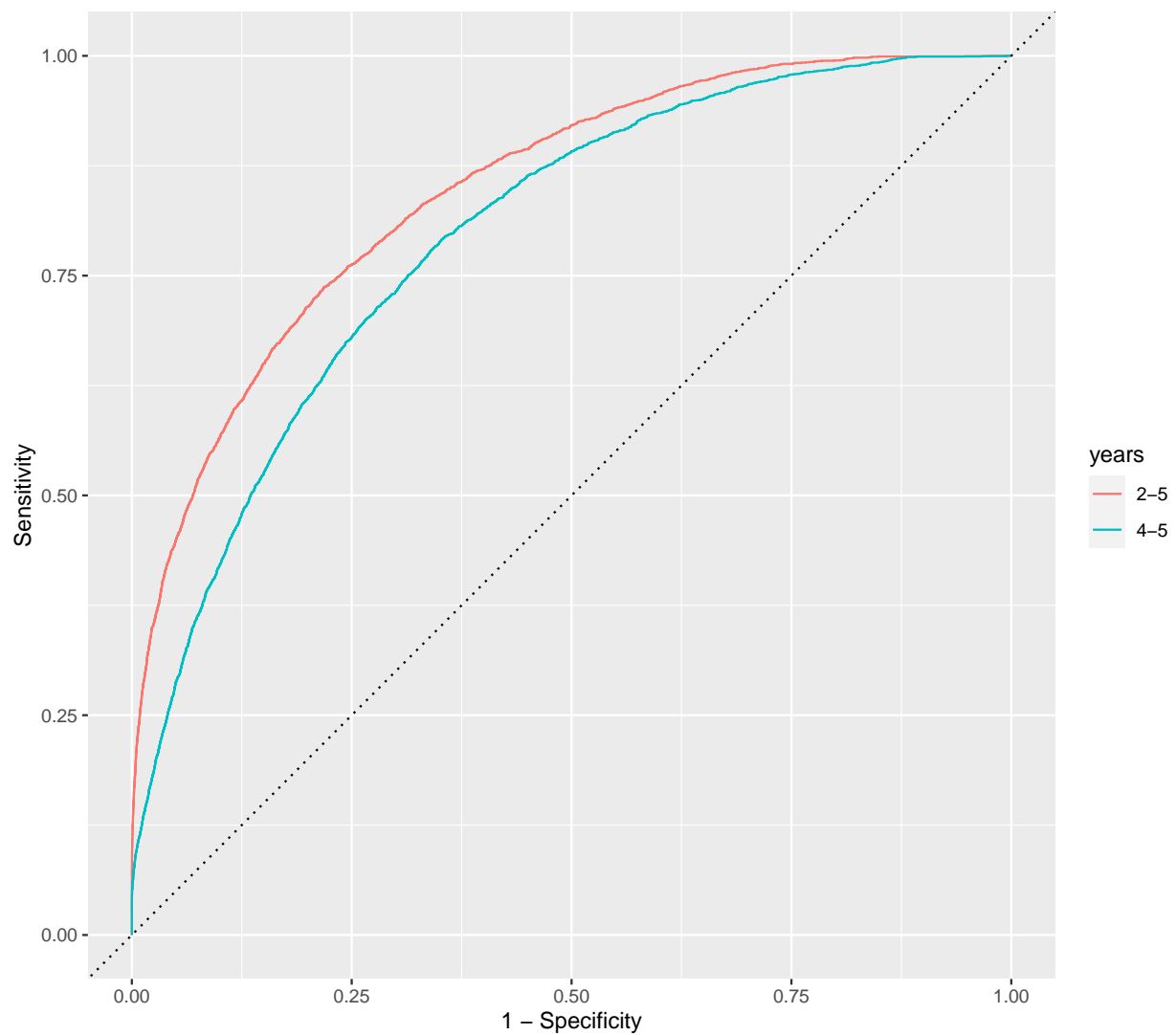
- Take the original testing set (25%: 2,849 cases, 1.66M controls)
- Subset to observations that are complete for both HUNT and Kunzmann (i.e., with observed age, sex, bmi, smoking status, GERD, H2R, PPI)
- Bin variables in the same way as original papers; construct the same indicators (smoking and esophageal condition)
- Resulting test set: 1,816 cases, 872,093 controls
- Used to compute a score using all three methods (xgboost, HUNT, Kunzmann)
- Plot ROC curves, and compute AUC
 - xgboost: 0.7869407
 - HUNT: 0.6500223

– Kunzmann: 0.7046042



Window comparison

- Years 2–5 vs 4–5 to predict outcome
- Same patients in both test sets (same test set as previously: 2.8K cases, 1.66M controls)
- Model: trained on 2–5 data
- AUCs:
 - 2–5: 0.8468027
 - 4–5: 0.7950466



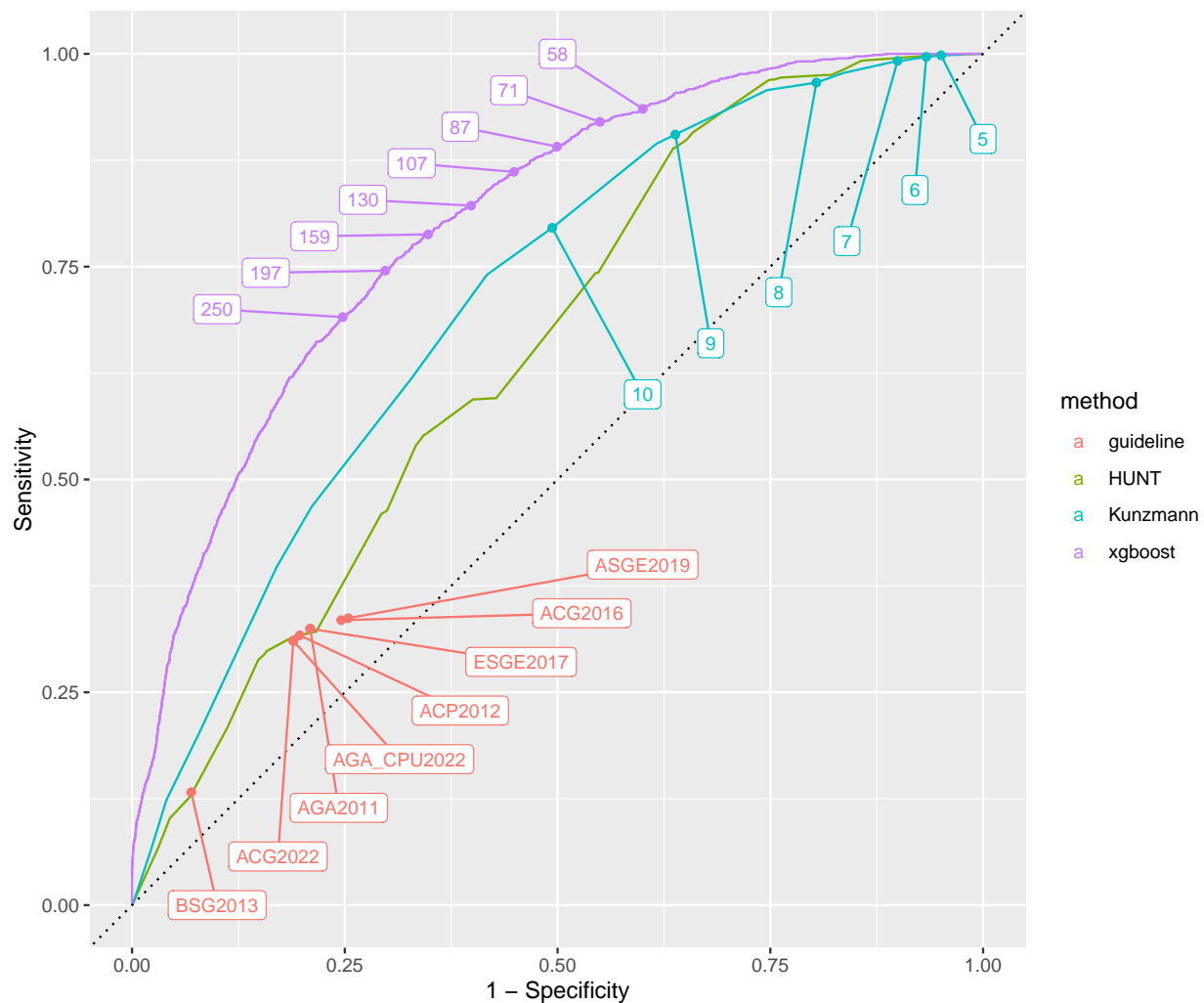
01/11/2022 update

- Server maintenance over the last few days ...
- Sensitivity analyses:
 - Data preparation for any prediction window (fewer years, later prediction, etc.)
 - * e.g. 5-1 to predict 0, 5-4 to predict 0, 2-1 to predict 0, etc.
 - * The R package will allow to construct these dataset very easily (just change parameters)
 - EAC vs EGJAC:
 - * how to get this information? (ICD 10: C15.x vs C15.5?; ICD9: 150.x vs 150.2/5?)
 - * We were always working with ‘CaseControl’ which was precomputed
 - * Goal: Compare whether separate models does better than a single model?
 - * Compare to HUNT & Kunzmann to check if this explain the big discrepancy?
- Implementation:
 - Working on an R package (hosted on GitLab)
 - Input: SAS files structured as before containing info for a set of patients
 - Read SAS Files, construct standardized data frame, use xgboost model to obtain predictions (averaged over multiple SRS for missing values)
 - Output: (ID, risk score). Format?
 - Standard R package documentation

01/18/2022 update

Added screening guidelines to ROC plot (see below)

- Kunzmann uses more BMI and age bins than HUNT
- Kunzmann uses medication data in addition to GERD
- The guidelines uses even less information and simpler combination
- NB: we cannot have the exact Kunzmann given our data, especially the ‘esophageal condition’ indicator is incomplete
- NB: similarly for guidelines, we are missing family history and other clinical information



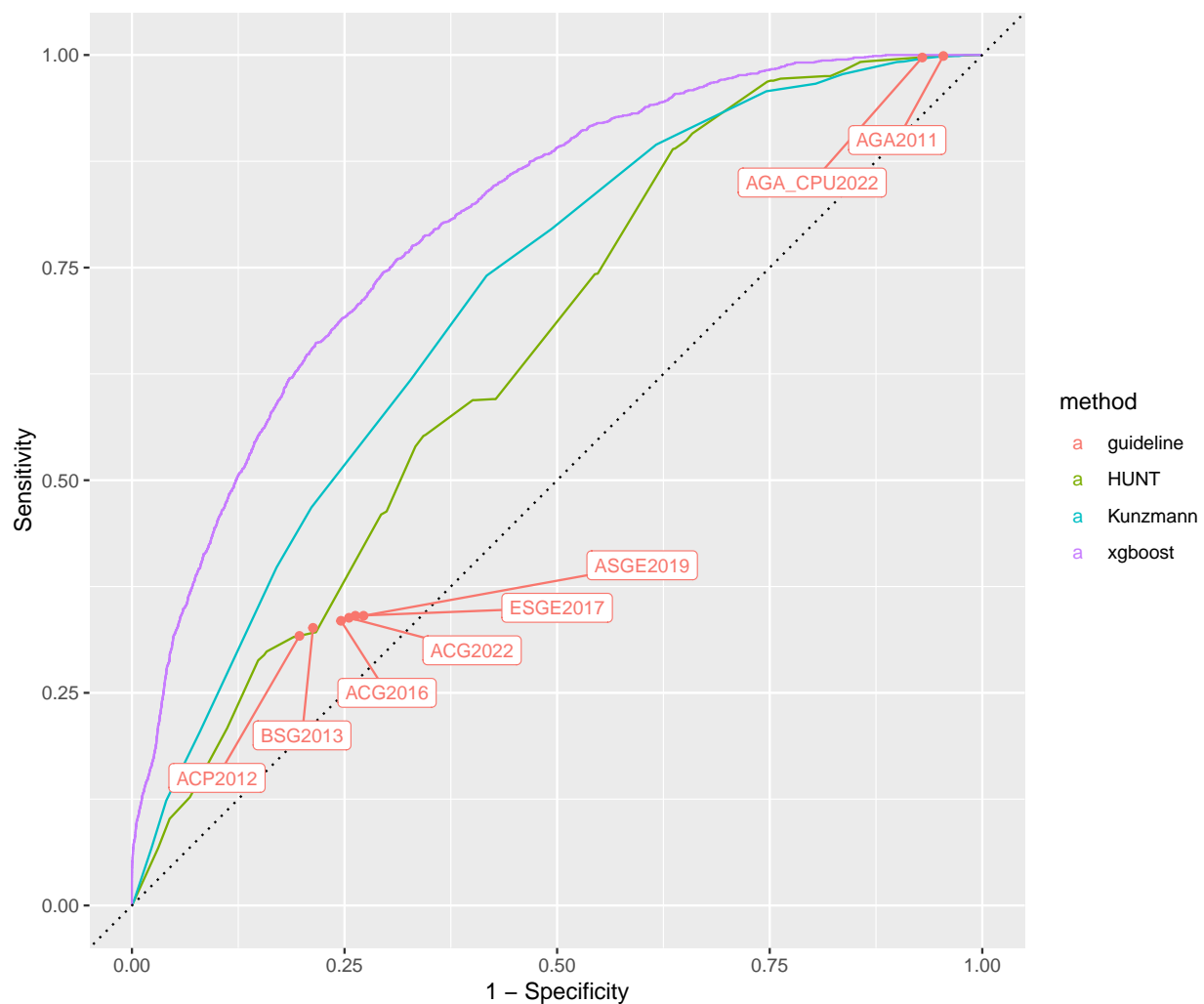
Other updates

- Waiting on EAC/EGJAC indicators
- R package:
 - Data processing functions complete
 - Next: use model to obtain scores and output
- Prediction window sensitivity analyses:
 - Takes a long time to preprocess the data
 - Ran into a small bug, could not finish processing
 - Once processing is done, easy to get performance

01/25/2022 update

Last week follow-up

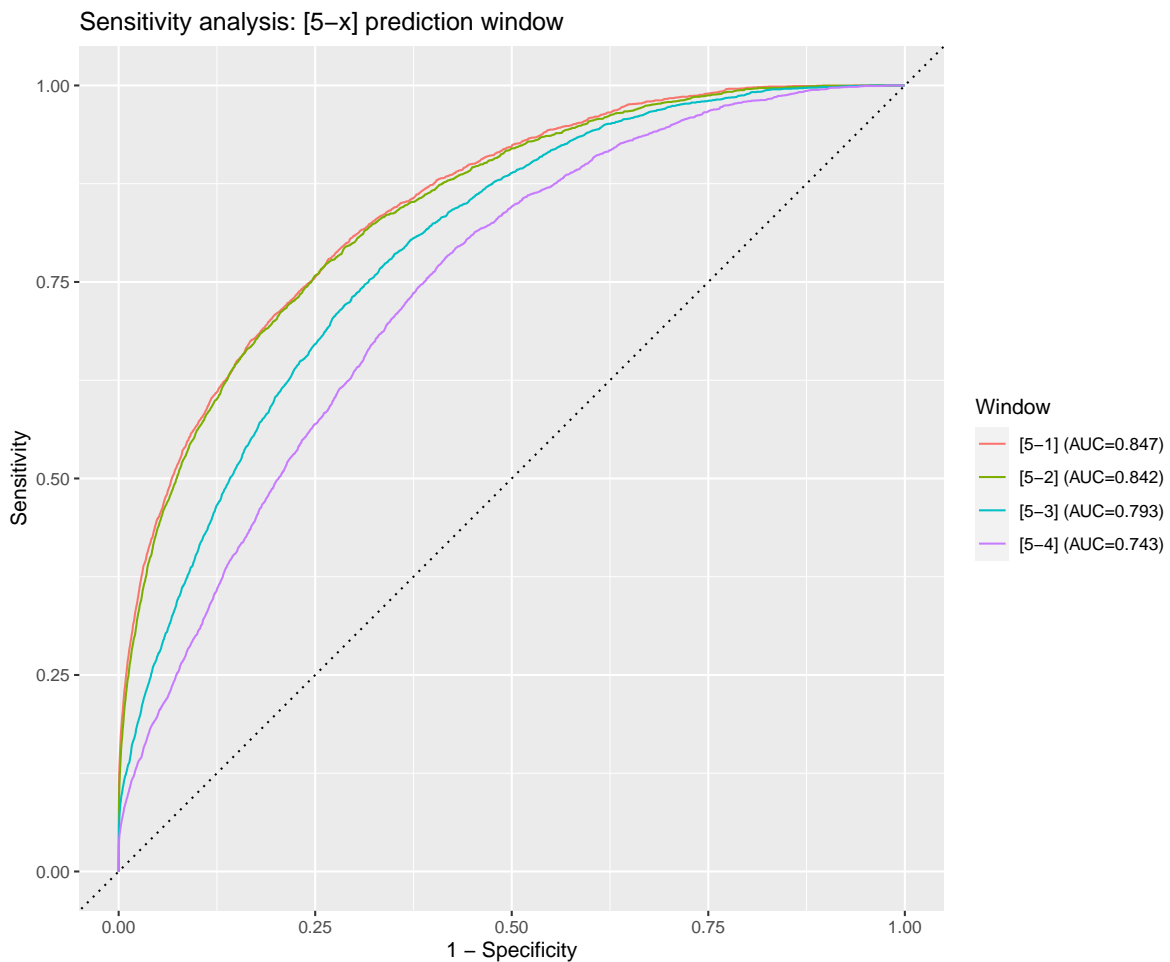
- There was a slight logical error in my calculation of the screening guideline
- Still essentially the same results, except two are pushed to top right
- Any guideline requiring GERD is capped
 - Prevalance is around 34% in cases
 - This means Sensitivity can be at most 34% for those guidelines
 - Prevalance around 27% in controls; other risk factors reduce the FPR a bit

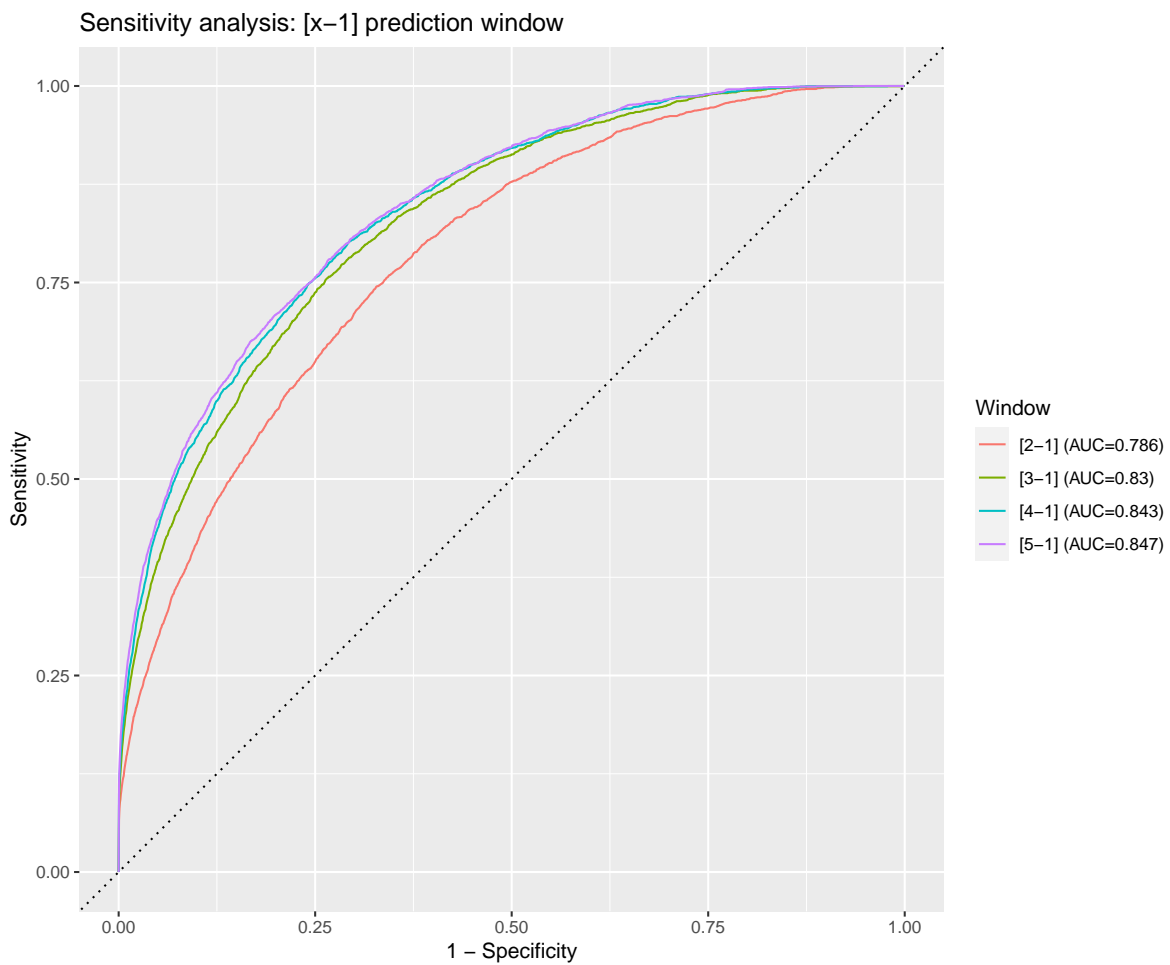


Nb. of risk factors	Controls		Cases	
	N	%	N	%
0	1,853	0.2	0	0.0
1	9,410	1.2	1	0.1
2	44,871	5.6	4	0.2
3	160,169	20.1	110	6.5
4	313,723	39.5	635	37.6
5	217,734	27.4	731	43.3
6	47,169	5.9	207	12.3
	794,911	100.0	1,688	100.0

Sensitivity analysis on prediction window

- I finally have the results!
- Predicting from farther away (+ decreasing aggregation window)
 - Removing the latest year has essentially no effect
 - Removing the last two years or more has a noticeable effect
- Decreasing aggregation window (still predicting 1 year later)
 - Dropping the first year has almost no effect on performance
 - Having only 1 year leads to a large gap





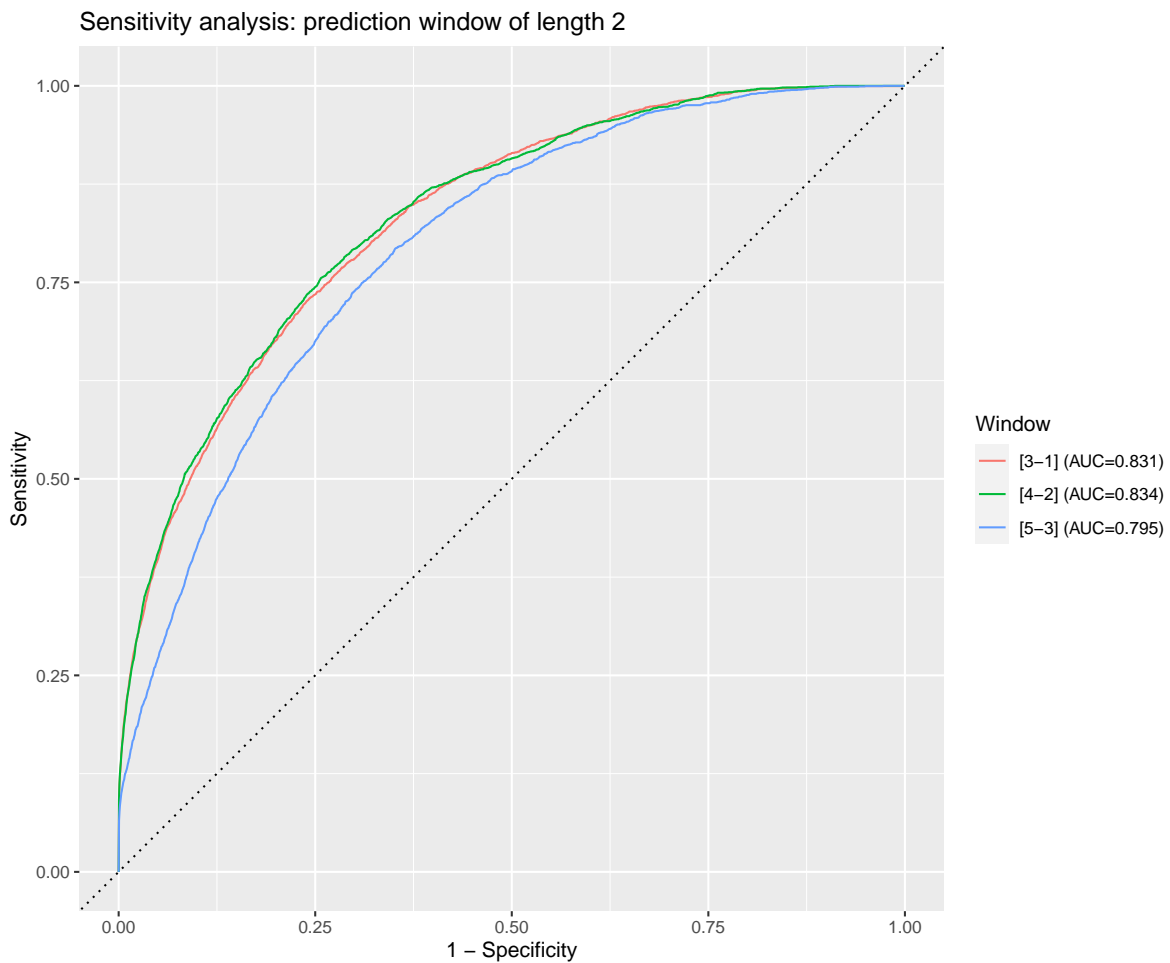
Next steps

- EAC v EGJAC
- Finalizing R package
- Study multiple imputations (effect on performance, variance of predicted risk by % of missing values and which values are missing)

02/01/2022 update

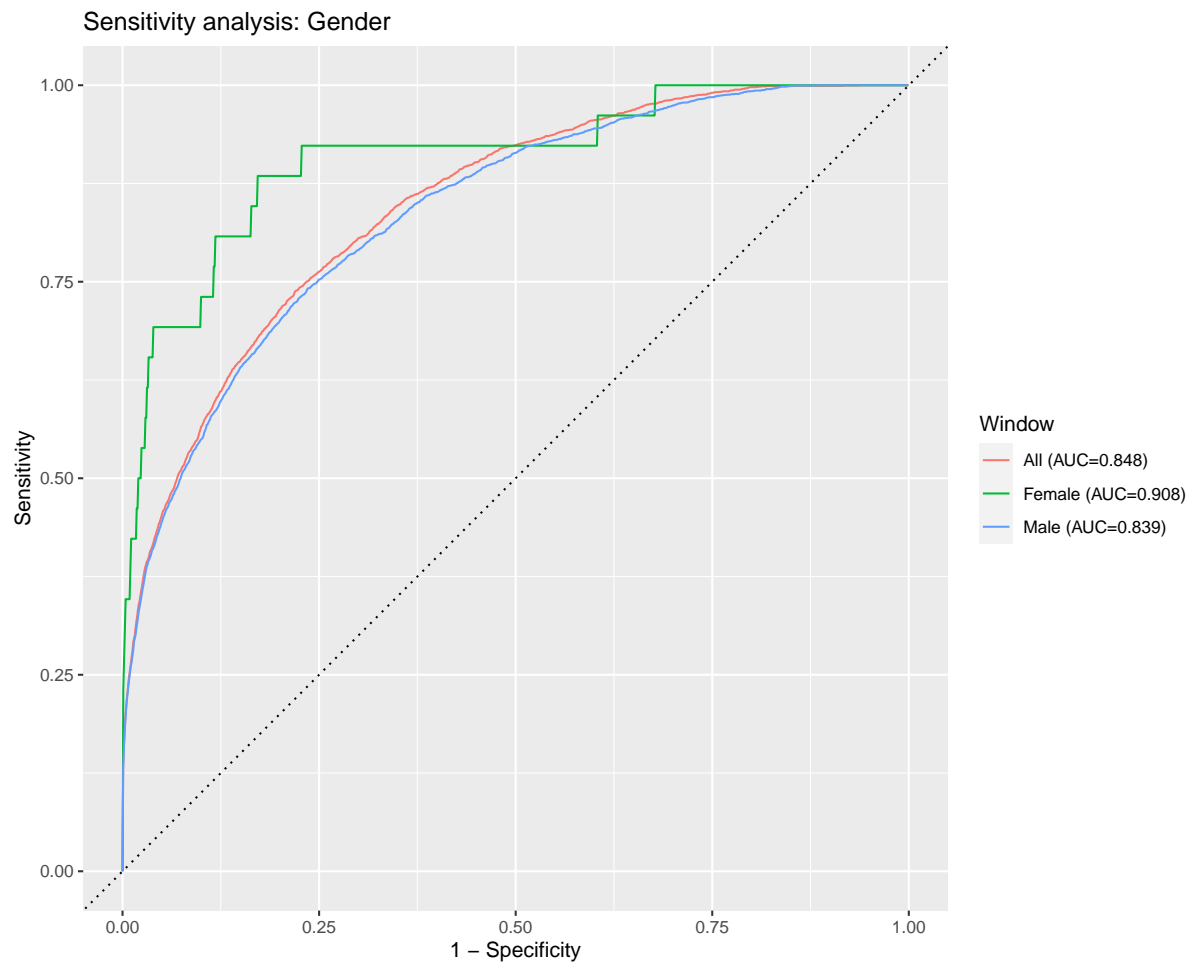
Follow-up on last week

- Fairer comparison when predicting farther in the future
- Prediction window of length 2, slides over the 5y period
- All observations have similar amount of data, but prediction is farther and farther back in time (1, 2, 3 years prior)
- No difference between years 1 and 2, but a significant drop at the 3rd year
- Similar conclusion as last week

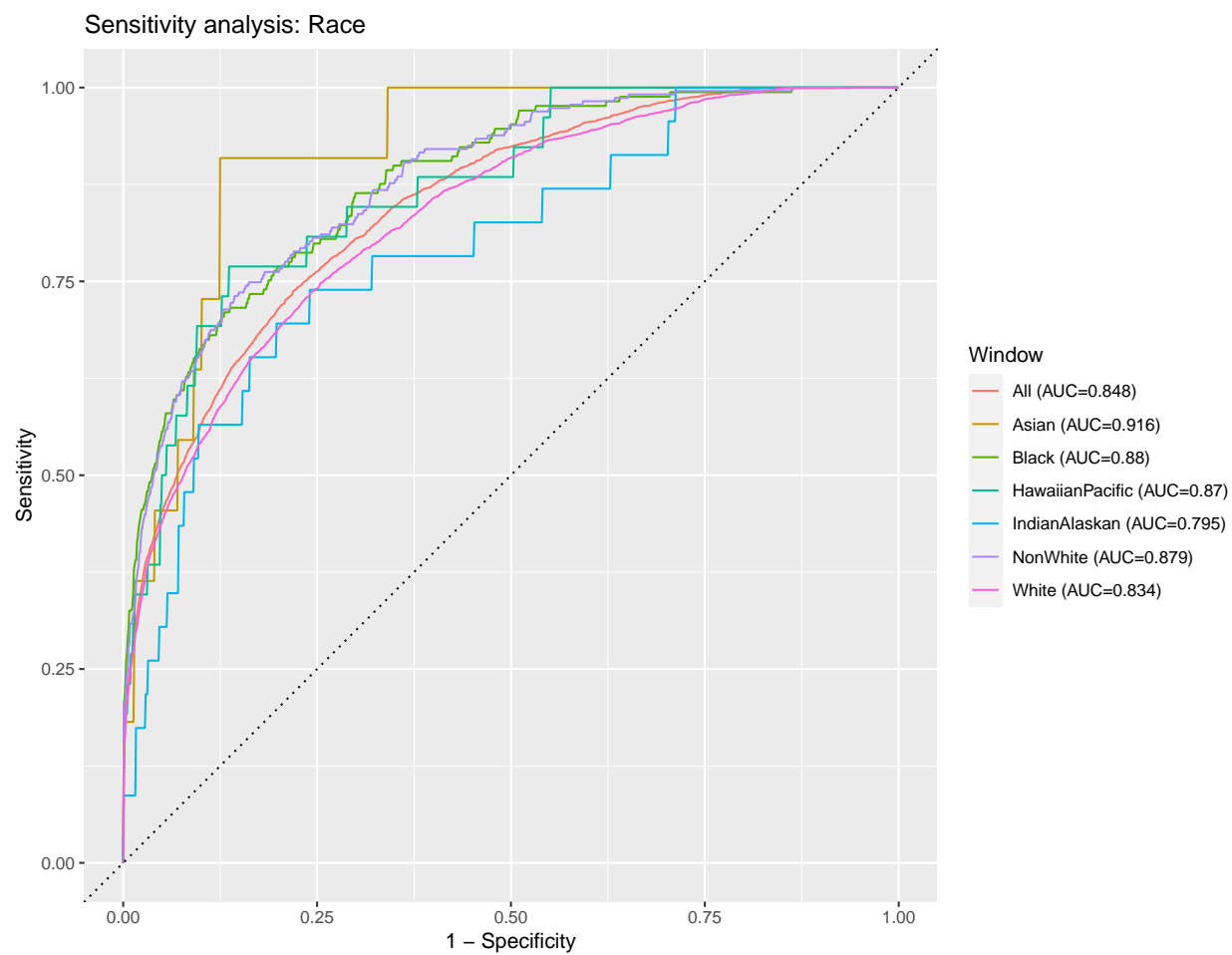


Performance on identity-defined test subsets

- Same test set as before (1.5M Controls, 3K cases)
- Gender:
 - 93% Male, 7% Female
 - Female: 26/115K cases/control

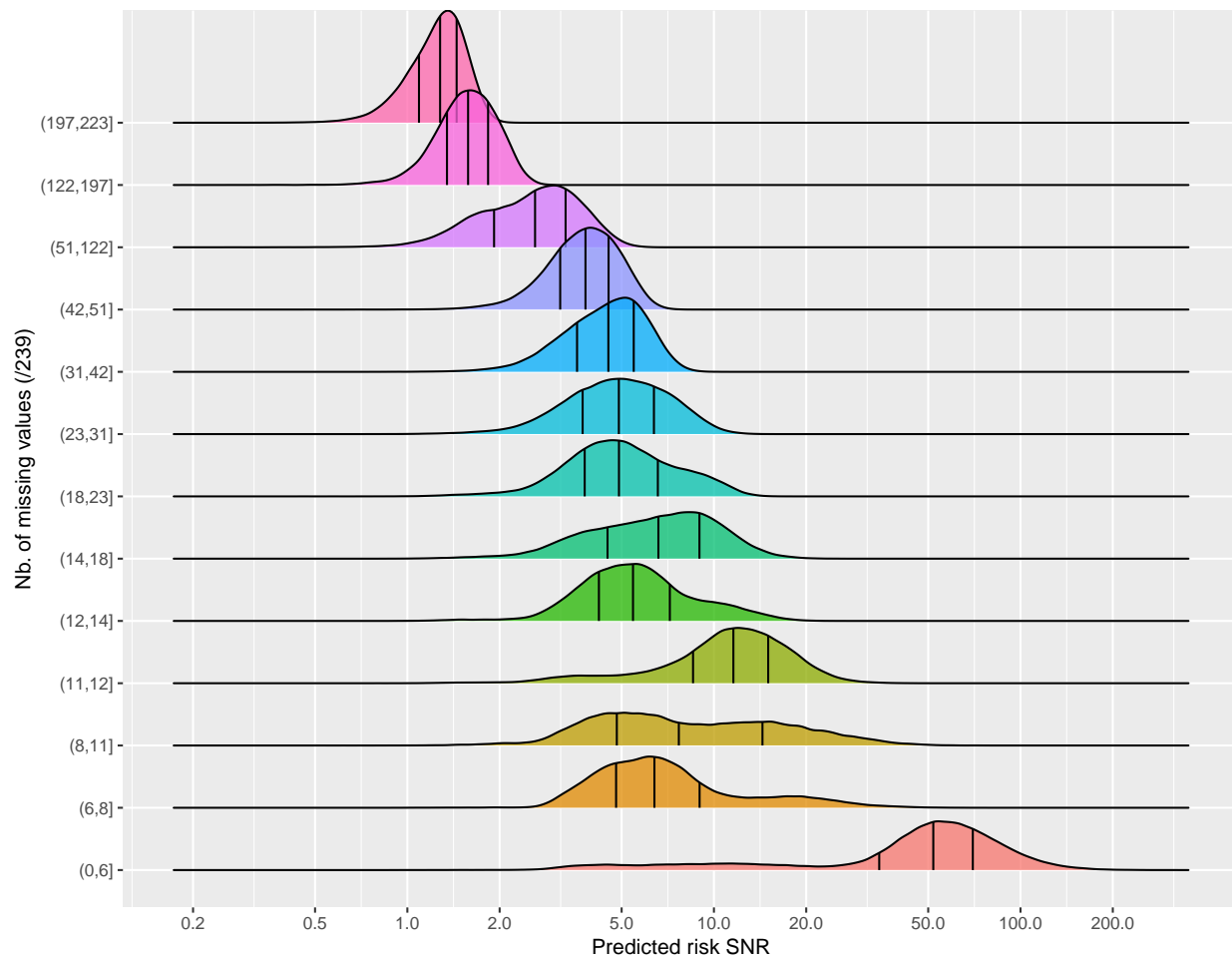


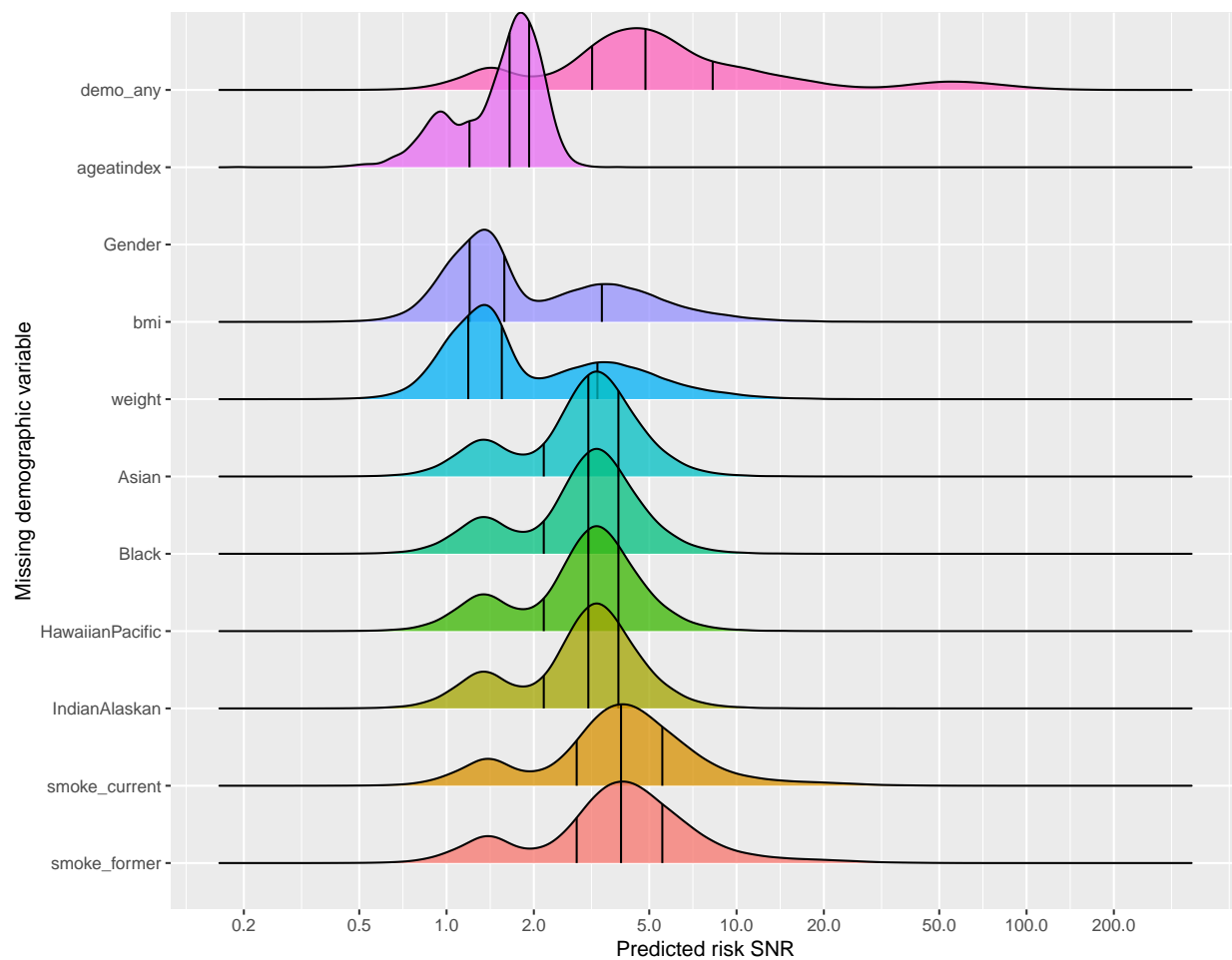
- Race:
 - 80% White, 1% Asian, 17% Black, 1% Hawaiian/Pacific, 1% Indian/Alaskan



Sensitivity analysis: missing values

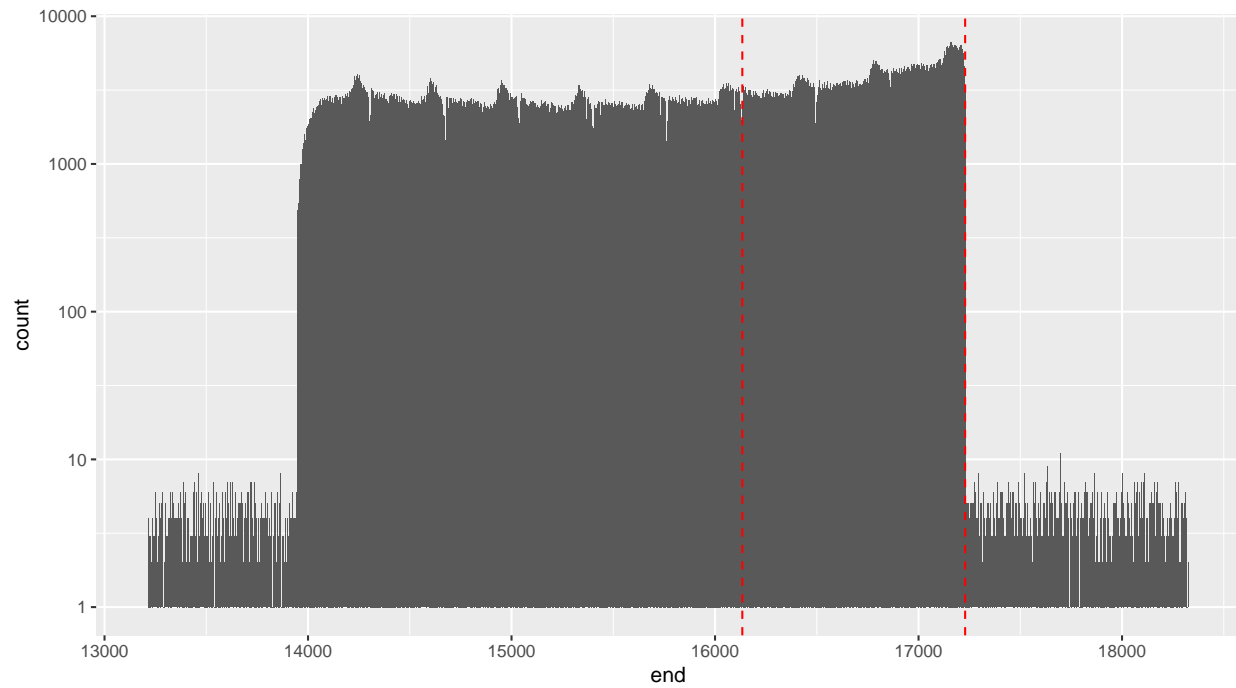
- For each observation:
 - Get 100 imputations
 - Get predicted risk for each imputation
 - Compute signal-to-noise ratio over the 100 risks
- High SNR means that the predicted risk does not change much with imputed values; small SNR means high dependence on the imputed values
- Partition the test set by the number of missing values
- Subsets defined by whether each demographic variable is missing





Sensitivity analysis: ICD10

- Data processed, results to come
- I settled on using 17229 as the last end date (then use -3 to -1 year)



Sensitivity analysis: Cancer type

- Trained separate models, comparison to come