## Supplemental Acknowledgements

Susan Buchbinder, Departments of Medicine, Epidemiology and Biostatistics, University of California, San Francisco; Edwin DeJesus, Orlando Immunology Center, Florida; Ian Frank, School of Medicine, University of Pennsylvania, Philadelphia; Spyros Kalams, Department of Pathology, Microbiology and Immunology, Vanderbilt University, Nashville, Tennessee; Michael C. Keefer, University of Rochester Medical Center, Rochester, New York; Mark J. Mulligan, New York University Langone Vaccine Center; Richard Novak, Division of Infectious Diseases, University of Illinois at Chicago; Beryl Koblin, Mailman School of Public Health, Columbia University, New York; Stephen Brown, AIDS Research Alliance, Los Angeles; Thomas B. Campbell, Division of Infectious Diseases,University of Colorado, Denver Colorado; Mamta K. Jain, UT Southwestern Medical Center, Dallas TX; Julie E. Ledgerwood, Clinical Trials Program NIAID/VRC, NIH, Bethesda MD; Kenneth H. Mayer, HIV Center for Clinical and Behavioral Studies, Columbia University, New York; Paul Goepfert, Alabama Vaccine Research Clinic, University of Alabama, Birmingham AL; Hana El-Sahly, Molecular Virology and Microbiology, Baylor College of Medicine, Houston TX; Benigno Rodriguez, Division of Infectious Diseases \& HIV Medicine, Case Western Reserve University, Cleveland OH; Lindsey R. Baden, Division of Infectious Diseases, Brigham and Women's Hospital, Boston MA; Donald M. Poretz, Clinical Alliance for Research and Education Infectious Disease, Annandale VA; Judith Aberg, Judith Aberg, Infectious Disease, Icahn School of Medicine at Mount Sinai, New York.

SOM Figure. 1 Distinct response rates and magnitude of antibody FcyRIla and FcyRIIIa binding to gp140, gp120 and V1V2 proteins. Antibody FcyRIla (A, C, E) and FcyRIIla (B, D, F) binding to an array of envelope glycoprotein gp140 and V1V2 proteins, gp41, gp120, V3 and p24 Gag proteins. Positivity was defined as exceeding the $95^{\text {th }}$ percentile of baseline, MFI>100, and participant-specific three-fold increase from baseline.

SOM Figure 2. IgG3 response magnitude and rate. Boxplots of MFI are displayed for antigens including vaccine matched gp140s, suptype consensus gp140s, Consensus gp140 and gp120 (A), as well as V1V2 conformational and sequence motifs, gp41, and p24 Gag (B). The mid-line of the box denotes the median and ends of the box denote the $25^{\text {th }}$ and $75^{\text {th }}$ percentiles, with whiskers extending to the most extreme data points. Positivity was defined as exceeding the $95^{\text {th }}$ percentile of baseline, MFI>100, and participant-specific three-fold increase from baseline.

SOM Figure 3. Sieve signatures based on distances of breakthrough viruses to Con $\mathbf{S}$ gp140 and B Con gp140. Boxplots of hamming distances of mindist sequences to ConS gp 140 (A,C,E) or B.con.env03 gp140 (B, D,F) by treatment group for three sets of Env-gp120 sites: (A,B) all Env-gp120 sites that could be aligned with confidence ( $\mathrm{n}=432$ ); (C,D) the 93 CD4bs antibody contact sites; and (E,F) 54 sites corresponding to the 4 k -mers overlapping the CD4bs where significant sieve effects were found (4). The mid-line of the box denotes the median and the ends of the box denote the $25^{\text {th }}$ and $75^{\text {th }}$ percentiles. The whiskers that extend from the top and bottom of the box extend to the most extreme data points that are no more than 1.5 times the interquartile range or if no value meets this criterion, to the data extremes. The dashed horizontal lines show hamming distances of the subtype $B$ vaccine strain to the gp140 antigen for the specified Env-gp120 site set. P-value reports the result of a 2 -sided Wilcoxon Test for a difference in distribution of the distances by treatment group.

A


C


B


D


F


SOM Figure 2




SOM Table 1A. FcyRIla (H131) Antigen Specific Response Rates

| Antigen | Treatment <br> Arm | Response Rate | $95 \%$ CI |
| :---: | :--- | :--- | :--- |
| A1.con.env <br> 03 gp140CF | Vaccine | $113 / 146=77.4 \%$ | $(70.0 \%, 83.4 \%)$ |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
| AE.A244 <br> V1V2 Tags | Vaccine | $30 / 147=20.4 \%$ | $(14.7 \%, 27.6 \%)$ |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
| B.MN V3 <br> gp70 | Vaccine | $14 / 148=9.5 \%$ | $(5.7 \%, 15.3 \%)$ |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
| B.con.env03 <br> gp140 CF | Vaccine | $130 / 149=87.2 \%$ | $(80.9 \%, 91.7 \%)$ |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
| C.1086 <br> V2 tags | Vaccine | $0 / 150=0.0 \%$ | $(0.0 \%, 2.5 \%)$ |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
| C.1086C <br> V1V2 Tags | Vaccine | $37 / 149=24.8 \%$ | $(18.6 \%, 32.3 \%)$ |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
| C.con.env03 <br> gp140 CF | Vaccine | $110 / 145=75.9 \%$ | $(68.3 \%, 82.1 \%)$ |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
| Con 6 <br> gp120/B | Vaccine | $27 / 149=18.1 \%$ | $(12.8 \%, 25.1 \%)$ |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
| Con S gp140 <br> CFI | Vaccine | $147 / 149=98.7 \%$ | $(95.2 \%, 99.6 \%)$ |
| VRC A <br> gp140 | Vaccine | $147 / 150=98.0 \%$ | $(94.3 \%, 99.3 \%)$ |
| VRC B <br> gp140 | Vaccine | $145 / 148=98.0 \%$ | $(94.2 \%, 99.3 \%)$ |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
|  | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |  |
|  | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |  |


| Antigen | Treatment Arm | Response Rate | 95\% CI |
| :---: | :---: | :---: | :---: |
| VRC <br> C_gp140 | Vaccine | 146/150 = 97.3\% | (93.3\%, 99.0\%) |
|  | Placebo | $0 / 39=0.0 \%$ | (0.0\%, 9.0\%) |
| $\begin{aligned} & \text { VRC_A } \\ & \text { gp70V1V2 } \end{aligned}$ | Vaccine | 37/139 = 26.6\% | (20.0\%, 34.5\%) |
|  | Placebo | 0/37 = 0.0\% | (0.0\%, 9.4\%) |
| gp41 | Vaccine | 133/143 = 93.0\% | (87.6\%, 96.2\%) |
|  | Placebo | 0/37 = 0.0\% | (0.0\%, 9.4\%) |
| $\begin{gathered} \text { gp70_B. } \\ \text { CaseA2 } \\ \text { V1V2/169K } \end{gathered}$ | Vaccine | $45 / 142=31.7 \%$ | (24.6\%, 39.7\%) |
|  | Placebo | $0 / 39=0.0 \%$ | (0.0\%, 9.0\%) |
| gp70_B. CaseA V1V2 | Vaccine | 29/145 $=20.0 \%$ | (14.3\%, 27.2\%) |
|  | Placebo | $0 / 39=0.0 \%$ | (0.0\%, 9.0\%) |
| $\begin{gathered} \text { gp70_C. } 1086 \\ \text { V1V2 } \end{gathered}$ | Vaccine | 24/142 = 16.9\% | (11.6\%, 23.9\%) |
|  | Placebo | $0 / 39=0.0 \%$ | (0.0\%, 9.0\%) |
| p24 Gag | Vaccine | 60/147 = 40.8\% | (33.2\%, 48.9\%) |
|  | Placebo | $0 / 39=0.0 \%$ | (0.0\%, 9.0\%) |

SOM Table 1B. FcyRIIla (F158) Antigen Specific Response Rates

| Antigen | Treatment <br> Arm | Response Rate | $\mathbf{9 5 \% ~ C I}$ |
| :---: | :--- | :--- | :--- |
| A1.con.env0 <br> 3 gp140CF | Vaccine | $89 / 149=59.7 \%$ | $(51.7 \%, 67.3 \%)$ |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
| AE.A244 <br> V1V2 Tags | Vaccine | $16 / 150=10.7 \%$ | $(6.7 \%, 16.6 \%)$ |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
| B.MN V3 <br> gp70 | Vaccine | $6 / 150=4.0 \%$ | $(1.8 \%, 8.5 \%)$ |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
| B.con.env03 <br> 140 CF | Vaccine | $104 / 149=69.8 \%$ | $(62.0 \%, 76.6 \%)$ |


|  | Placebo | $0 / 39=0.0 \%$ | (0.0\%, 9.0\%) |
| :---: | :---: | :---: | :---: |
| C. 1086 <br> V2 tags | Vaccine | 0/150 $=0.0 \%$ | (0.0\%, 2.5\%) |
|  | Placebo | 0/ $39=0.0 \%$ | (0.0\%, 9.0\%) |
| C.1086C <br> V1V2 Tags | Vaccine | 25/149 $=16.8 \%$ | (11.6\%, 23.6\%) |
|  | Placebo | 0/ $39=0.0 \%$ | (0.0\%, 9.0\%) |
| $\begin{aligned} & \text { C.con.env03 } \\ & \text { gp140CF } \end{aligned}$ | Vaccine | 73/141 = 51.8\% | (43.6\%, 59.9\%) |
|  | Placebo | 0/ $39=0.0 \%$ | (0.0\%, 9.0\%) |
| Con 6 gp120 | Vaccine | 12/149 = 8.1\% | (4.7\%, 13.5\%) |
|  | Placebo | 0/ $39=0.0 \%$ | (0.0\%, 9.0\%) |
| Con S gp140 CFI | Vaccine | 144/150 = 96.0\% | (91.5\%, 98.2\%) |
|  | Placebo | 0/ $39=0.0 \%$ | (0.0\%, 9.0\%) |
| VRC A gp140 | Vaccine | 146/150 = 97.3\% | (93.3\%, 99.0\%) |
|  | Placebo | 0/ $39=0.0 \%$ | (0.0\%, 9.0\%) |
| VRC B <br> gp140 | Vaccine | 132/140 = 94.3\% | (89.1\%, 97.1\%) |
|  | Placebo | 0/ $39=0.0 \%$ | (0.0\%, 9.0\%) |
| VRC C gp140 | Vaccine | 122/140 = 87.1\% | (80.6\%, 91.7\%) |
|  | Placebo | 0/ $39=0.0 \%$ | (0.0\%, 9.0\%) |
| $\begin{aligned} & \text { VRC_A } \\ & \text { gp70 V1V2 } \end{aligned}$ | Vaccine | $34 / 150=22.7 \%$ | (16.7\%, 30.0\%) |
|  | Placebo | 0/ $39=0.0 \%$ | (0.0\%, 9.0\%) |
| gp41 | Vaccine | 134/150 = 89.3\% | (83.4\%, 93.3\%) |
|  | Placebo | $0 / 39=0.0 \%$ | (0.0\%, 9.0\%) |
| $\begin{gathered} \text { gp70_B. } \\ \text { CaseA2 } \\ \text { V1V2/169K } \end{gathered}$ | Vaccine | 24/149 = 16.1\% | (11.1\%, 22.8\%) |
|  | Placebo | 0/ $39=0.0 \%$ | (0.0\%, 9.0\%) |
| $\begin{gathered} \text { gp70_B. } \\ \text { CaseAV1V2 } \end{gathered}$ | Vaccine | 15/149 = 10.1\% | (6.2\%, 15.9\%) |
|  | Placebo | 0/ $39=0.0 \%$ | (0.0\%, 9.0\%) |


| gp70_C.1086 <br> $\overline{\mathrm{V} 1 / \mathrm{V} 2}$ | Vaccine | $19 / 149=12.8 \%$ | $(8.3 \%, 19.1 \%)$ |
| :---: | :--- | :--- | :--- |
|  | Placebo | $0 / 39=0.0 \%$ | $(0.0 \%, 9.0 \%)$ |
| p24 Gag | Vaccine | $29 / 143=20.3 \%$ | $(14.5 \%, 27.6 \%)$ |
|  | Placebo | $0 / 37=0.0 \%$ | $(0.0 \%, 9.4 \%)$ |

SOM Table 2. Weights of summary of immune response markers when calculating the first (PC1) and second (PC2) principal component, otherwise known as loadings. The markers that most substantially contribute to each principal component are in bold.

|  | PC1 | PC2 |
| :--- | ---: | ---: |
| Cd8.env.poly | 0.224 | $\mathbf{0 . 5 6 6}$ |
| IgG env | $\mathbf{0 . 4 5 0}$ | -0.006 |
| IgG V2 | 0.301 | -0.040 |
| IgG gp41 | $\mathbf{0 . 4 1 1}$ | -0.083 |
| ADCP1 | $\mathbf{0 . 4 0 1}$ | 0.038 |
| FcyRIla | $\mathbf{0 . 4 2 8}$ | -0.056 |
| IgA env | 0.173 | $\mathbf{- 0 . 7 9 2}$ |
| IgG3 Env | $\mathbf{0 . 3 3 7}$ | $\mathbf{0 . 2 0 0}$ |

SOM Table 3. Weights of individual immune response markers when calculating the first (PC1) and second (PC2) principal component.

|  | Target | PC1 | PC2 |
| :---: | :---: | :---: | :---: |
| ADCP | Phagocytosis of Con S gp140 | 0.177 | 0.127 |
| CD8 | Polyfunctionality | 0.090 | 0.004 |
| $\lg A$ | AE A244 V1V2 Tags | 0.009 | -0.014 |
| IgG | ABDM HVTN505 gp41 ID | 0.096 | -0.011 |
|  | AE A244 V1V2 Tags | 0.082 | -0.035 |
|  | Bio V3 B | 0.128 | -0.051 |
|  | C HVTN505 gp41 ID | 0.106 | -0.032 |
|  | C Con gp140 | 0.180 | -0.118 |
|  | Con S gp140 | 0.185 | -0.175 |
|  | gp41 | 0.177 | -0.098 |
|  | VRC A gp140 | 0.195 | -0.184 |
|  | VRC B gp140 | 0.164 | -0.162 |
|  | VRC C gp140 | 0.197 | -0.151 |
| IgG3 | A1 Con gp140 | 0.165 | 0.275 |
|  | B Con gp140 | 0.168 | 0.316 |
|  | C Con gp140 | 0.158 | 0.329 |
|  | Con 6 gp140 | 0.083 | 0.141 |
|  | Con S gp140 | 0.160 | 0.334 |
|  | gp41 | 0.174 | 0.190 |
|  | VRC A gp140 | 0.162 | 0.259 |
|  | VRC B gp140 | 0.160 | 0.300 |
|  | VRC C gp140 | 0.139 | 0.323 |
| FcyRIla | A1 Con gp140 | 0.202 | -0.116 |
|  | B Con gp140 | 0.212 | -0.094 |
|  | C Con gp140 | 0.207 | -0.074 |
|  | gp41 | 0.189 | -0.084 |
|  | p24 | 0.041 | -0.028 |
|  | VRC_A_gp70V1V2_avi | 0.101 | -0.005 |
|  | VRC A gp140 | 0.187 | -0.168 |
|  | VRC B gp140 | 0.202 | -0.157 |
|  | VRC C gp140 | 0.203 | -0.123 |
| FcyRIIIa | A1 Con gp140 | 0.193 | -0.076 |
|  | B Con gp140 | 0.206 | -0.044 |
|  | C Con gp140 | 0.194 | -0.025 |
|  | Con S gp140 | 0.214 | -0.065 |
|  | p24 | 0.039 | -0.028 |
|  | VRCBgp140 | 0.209 | -0.108 |

## Statistical Analysis Plan for Superlearner CoR Analysis of Month 7 Markers in HVTN 505

April 19, 2019

## Analysis Notes Specific to Superlearner Supervised Learning

- Keep for CoR analysis individual variables that are matched to vaccine antigens. For vaccinemismatched biomarkers, if there is only one vaccine-mismatched variable in a set, use it, otherwise use the scores PC1 and/or mdw. If PC1 and mdw have Spearman rank r>0.9, only keep PC1. The HVTN505: var.super object contains this set of variables. For every variable in this list, there is also a dichotomized version, whose name has a suffix _bin at the end.
- Pre-scale each variable to have mean 0 and sd 1 in the vaccine arm (both quantitative and binary variables)
- Given there are only 25 total HIV infected cases, only allow learning algorithms to have a maximum of 4 immune response variables. Also use leave-one-out cross-validation and negative log-likelihood loss, which some studies have shown tend to perform well in small sample size settings.
- Include learning algorithms with and without lasso pre-screening (with default tuning parameter selection), and perhaps with and without logistic regression univariate 2 -sided $p$-value screening (at levels p < 0.01, < 0.05, < 0.10)
- Another screen to use with Superlearner would be to only include markers with a certain 'dynamic range,' knowing that biologically-relevant inter-vaccinee variability majorly impacts power. Exclude variables such that the $20^{\text {th }}$ percentile of the readout equals the $80^{\text {th }}$ percentile of the readout in vaccine recipients. In addition, for each variable in a set (i.e., vaccine-matched, PC1, MDWS), compute the 'dynamic range' score as the standard deviation of the marker in vaccinees divided by the standard deviation of the marker in placebo recipients. One screen that is used only includes variables in the top half of dynamic range scores.
- Do high-correlation screening, not allowing any pair of immune response variables to have $r$ > 0.9
- Include easy-to-interpret models in Superlearner and include models that study pairwise interactions of variables
- Run the Superlearner averaging over 10 random seeds
- The output may include CV-AUC forest plots similar to Ted Westling's tutorial (http://faculty.washington.edu/peterg/SanofiPasteurCorrelatesRTraining.2018.html) and Magaret et al. 2019. An important aspect of the results to communicate is the quality of classification accuracy obtained via different variable sets. Therefore, the forest plots include best models based on different combinations of assays, assuming there are too many (assay $x$ antigen) combinations to adequately display. This has important upstream effects of how to set up the library of learners. Looking at Ted's example, there are models presented for " $\lg A, \lg G$, Both, Neither." Conceptually, we want the same thing, but there are more assay categories. Note that models with $\operatorname{Ig} G$ and $\lg A$ also include $\log \lg A / \lg G$ ratio variables. The classes to use (with legend labels) are as follows:

1. None (No Month 7 markers - only the baseline variables in every model - BMI, age, risk score)
2. IgG+lgA (considering all antigens)
3. $\lg G 3$ (IgG subclass associated with functional responses)
4. T cells (ICS CD4 and CD8 T cells) (considering all antigens)
5. Fx Ab (Functional Ab variables "phago", "fcrR2a", "fcrR3a", "Tier 1 nAb") (considering all antigens)
6. $1+2+3(\lg G+\lg G 3+\lg A)$
7. $1+2+4$ (IgG+IgA+T cells)
8. $1+2+3+4(\operatorname{lgG}+\operatorname{lgG} 3+\lg A+T$ cells $)$
9. $1+2+3+5(\lg G+\lg G 3+\lg A+F x A b)$
10. $1+4+5$ ( T cells +Fx Ab )
11. All $(\operatorname{lgG}+\operatorname{lgG} 3+\lg A+T$ cells $+F x$ Ab)

Technically, only phago is a purely functional readout. We consider FcR a function but it is still a biophysical measurement, IgG3 is binding but is associated with function in a number of studies in the literature.

In terms of display, if results are shown for each algorithm type and screen, then there would be too many results to display. Only the SL and the top few performing models will be shown for each.

- Apply the usual nested cross-validation to be able to estimate cross-validated risk to appropriately characterize the classification accuracy (free of overfitting) of the Superlearner model and the other models.
- The output may include a plot of the distribution of estimated risk of HIV-1 infection (fitted values), and overlay on the plot an estimate of the overall HIV-1 infection risk of placebo recipients between Month 7 and 24.

