

Supporting Information

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SI Text

Text S1—Analysis of the Whole HA Protein. In order to further verify that our approach is capable of identifying functionally important sites, we conducted a second set of experiments in which the algorithm was provided with full HA sequences rather than the receptor-binding domain (RBD) alone. The HA sequences of the human pandemic and circulating human H1N1 strains were collected from the National Center for Biotechnology Information (NCBI) influenza database (1) following the same method described for the RBD analysis. The dataset consisted of 821 circulating human H1N1 and 673 pandemic H1N1 (pH1N1) sequences.

We hypothesized that a significant number of the detected sites would overlap with the sites selected when analyzing the RBD, and that in general, most discriminative sites would be in the RBD, taking into account that it consists of approximately 27% of the whole HA sequence (the whole HA sequence is approximately 560 amino acids long). Indeed, for the pH1N1 versus human seasonal H1N1 strains, 9 of the 18 most highly ranked positions of the whole HA analysis (i.e., 50%; Table S1) were in the RBD. Out of 10 highly ranked positions from the RBD analysis (Table 1), 7 appeared in the highly ranked set from the analysis of the entire HA. For the swine versus pH1N1 strains, 15 of the 32 (approximately 47%, Table S2) highly ranked positions in the full HA analysis were from the RBD sequence. Additionally, 11 out of the 13 (approximately 85%, Table 2) highly ranked positions from the RBD analysis were ranked highly in the analysis of the whole HA. These results demonstrate the power of the approach and its ability to identify the known functional regions and residues, even when provided with a very large set of features. Moreover, the analysis reinforces the importance of the highly ranked residues selected.

Text S2—Experimental Methods. Generation of viruses. The eight genes of the A/swine/NC/18161/02 (H1N1) virus were cloned into a dual-promoter plasmid, pHW2000. The HA of A/swine/NC/18161/02 was mutated with the QuikChange mutagenesis kit (Stratagene) following the instructions of the manufacturer. Reverse genetics (rg) viruses were generated by DNA transfection as described previously (2). Each viral HA segment was sequenced to confirm the identity of the virus.

Hemagglutination assay. Hemagglutination assays were performed as previously described (3). Six types of packed erythrocytes (Rockland) were used in different concentrations: 0.5% for turkey, chicken, and goose RBCs; 0.75% for guinea pig and human (group O) RBCs; and 1% for horse RBCs (4). We added 0.5% bovine serum albumin (Sigma) to the horse RBCs. Virus titers were normalized to $10^{6.25}$ egg 50% infective doses (eID₅₀) per milliliter prior to the hemagglutination assay. Turkey red blood cells were used to measure the eID₅₀s.

Mouse experiments. Six- to 8-wk-old female DBA/2J mice (Jackson Laboratory) were housed at St. Jude Children's Research Hospital according to the institution's Animal Care and Use Committee guidelines. The experiments were performed in compliance with relevant institutional policies of the National Institutes of Health and the Animal Welfare Act. Mice were sedated with 2,2,2-tribromoethanol (Avertin; Sigma) and intranasally inoculated with 30 μ L of virus diluted in phosphate buffer saline ($n = 5$ mice per group). The mice were monitored daily for survival and body weight loss over a period of 14 d. Any mouse

showing more than 30% of body weight loss was considered to have reached the experimental end point and was humanely euthanized. The mouse-lethal dose (MLD₅₀) was calculated using the method of Reed and Muench (5).

Text S3—Mutual Information Analysis with AVANA. We applied the AVANA (*Antigenic Variability Analyzer*) method (6), a software program that calculates entropy profiles from multiple sequence alignments, to the same input datasets used in our study (see *Computational Methods*). Specifically, we carried out two analyses with AVANA, comparing seasonal human H1N1 versus pH1N1, and swine H1N1 versus pH1N1 strains. For the human H1N1 versus pH1N1 dataset, AVANA selected 49 positions, which included 8 of the 10 highly ranked positions detected in our study (see *Results* in the main text and Table S5). When applied to the pH1N1 and swine H1N1 dataset, AVANA detected 14 positions, 6 of which overlapped with the 13 highly ranked positions from our approach (see *Results* in the main text and Table S6). Remarkably, position 133_A, which was detected as discriminative by our method and was shown to have a phenotypic effect in vivo (see *Results*), was not identified by AVANA, reinforcing the advantage of our method.

Text S4—Seasonal Human H1N1 Versus Swine H1N1 Strains. Swine and human seasonal H1N1 sequences were collected from the NCBI database (1), and a dataset was built as described in *Computational Methods* (main text). The resulting dataset consisted of 195 swine H1N1 and 525 human seasonal H1N1 sequences. We applied our computational approach to this set and obtained an overall mean test accuracy of 98% (with 50 runs of 10-fold cross-validation).

Text S5—Computational Methods. Two datasets were created as described in the main text (*Computational Methods*): pH1N1 sequences versus prior circulating human strains, and pH1N1 sequences versus classical swine strains. These datasets were analyzed using JBoost (<http://jboost.sourceforge.net/>) to identify positions in HA that distinguish “pH1N1” isolates from “human circulating” H1N1 isolates, as well as positions that distinguish pH1N1 from “swine” H1N1 isolates. JBoost is an open-source Java implementation of the Adaboost (7) machine-learning algorithm. This discriminative learning approach tries to identify the features that best distinguish between different data categories. Ultimately, classifiers in the form of decision trees called alternating decision trees (ADTs) (8) are generated. The ADT algorithm is an easily interpretable, boosting-based algorithm that is a generalization of decision trees and boosting using decision stumps. This algorithm also provides a measure of confidence, called a classification margin, for each prediction. An example of a decision tree created by the ADT method is presented in Fig. S3. The rectangles in the decision tree are the decision (or splitter) nodes, and the ovals are the prediction nodes; the values in each oval correspond to the contribution of that node to the prediction score. The number in each decision node represents the number of the iteration in which that feature was selected. In order to predict the label of a given example, we begin at the root of the decision tree and traverse the tree, using the decision nodes and summing the scores in the prediction nodes along the selected path.

In our setting each data instance is an influenza HA sequence, so the dimensionality of each data point is $N = 155$ for the receptor-binding site of the HA dataset. Each data instance consists

