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NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

MACHINE LEARNING FOR ANALYSIS OF NAVY AVIATOR TRAINING

by

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ABSTRACT

This project investigated patterns in the training data of Navy aviators in an attempt to predict their success in training. With the help of the sponsor, we assembled a database from many sources of training data. This database covered 18,596 candidate and Naval Flight Officer candidates through their pretesting, classroom instruction, candidate training in generic aircraft, and candidate training in specialized aircraft. This data was a challenge to organize because it had incompatible formats and missing data. After standardizing the formats and fixing errors in the data, and aggregating sparse training records to a smaller set of average scores, we had 301 features for the candidates. We then correlated their features using both numeric-correlation and nonnumeric-association (class-characterization) methods. We identified 38 kinds of measures of success in the program and particularly focused on correlations involving those. We did confirm some early indicators of success and failure in the program, most of which were not surprising. We conclude that the Navy is doing a good job of identifying candidates likely to be successful.

I. INTRODUCTION AND PREVIOUS WORK

This project investigated methods of predicting pilot training performance from earlier data on them. The goal was to test features and combinations of them that were most helpful in guiding the Navy on investments in training of pilots and flight officers.

Military training assessment has many difficulties due to the expense of staging realistic exercises and the rarity of exceptional events for which warfighters must be ready (Salas, Milham, and Bowers, 2003; Schnell, Keller, and Poolman, 2008). Skills decay is an important issue for this kind of training (Schendel and Hagman, 1991; Foggliatto and Anzanello, 2011; Ebbatson et al, 2012). It is thus important to thoroughly exploit existing data through data-mining techniques to get early warning of potential problems (Dubey, 2016; Huggins, 2018; Gombolay, Jensen, and Son, 2019). An important subproblem is that of predicting future pilot performance, for which a variety of data-mining techniques have been tried (Kaplan, 1965; Hunger and Burke, 2009; McFarland, 2017).

Previous analysis of the Naval training data by the sponsor was regression analysis. However, many attribute values were missing in this data, and regression do not work well on incomplete data. Our previous work (Rowe, 2012) provided some more robust approaches. It examined records of carrier landings as graded by Landing Signal Officers. We were able to show the rate at which landing success and quality increased with experience, and we were able to correlate phrases in the comments on the landings with the degree of eventual success the candidate had.

II. ANALYSIS SETUP

A. SIMPLIFYING THE DATA

The sponsor sent us data in 143 Excel tables concerning Navy training performance by 18,596 training candidates. We first converted the tables into CSV (comma-separated-value) files to make them easier to manipulate with programs. The main categories of tables were:

- The ASTB_IFS_API_PRI_v2.1 table which reports data from early in training.
- The "Cumulative_All_Students_2012-2019" table giving basic information about trainee pilots such as their air wing and curricula.
- The API_DATA table which appears to cover additional scores to the preceding.
- "Academic" tables reporting test scores on written tests in training after API instruction. These we averaged for each pilot for each course as we will explain.
- The other tables reporting scores on flight performance by the pilot trainees (which we called "maneuver" tables). These we averaged for each pilot as we will explain.
- "1542" files which have some data not appearing in any other tables.

A traditional database design would keep the tables separate and do joins between the tables on their primary keys, the ID codes. See the database design discussion later. However, the total number of pilot trainees was small enough, with 18,596 explicit pilot ID codes, that it was simpler and more efficient to do the joins in advance and store a single flat file in main memory for analysis. When we did this, the file was 301 columns and 46.3 megabytes, a size that will not require much paging when stored in main memory since processing generally can operate on one candidate at a time.

We had to be careful about the joins because there was much missing data. Some tests are not used in some curricula; some candidates are authorized to skip certain tests; some candidates drop out of the program and lack data for the later stages of training; and some candidate data could not be located in the incomplete data we were given. For these reasons, it was important to do outer joins rather than the traditional inner joins to connect tables, meaning that unmatched values in one table were represented by null values for their columns in the join.

B. DATA CLEANUP

The sponsor sent us data of many types from several sources. Some of the data was numeric like traditional test scores; some was numeric in a limited range, such as grades of 1, 2, 3, 4, or 5 on flight tests; and some of it was nonnumeric, such as candidate race, the kind of previous flight training they had, and whether they had been given an exemption on a particular evaluation. Pilot names and other personally identifiable information were excluded.

There were many null values (blanks) in the data for measurements and features that did not apply to particular candidates, such as tests not taken in their curriculum. Null values were inferred for the empty string, a string consisting of a single space, “N/A”, “#N/A”, “NONE”, and “NULL”. These were replaced by the string “NULL” to regularize them. 4804 null values for candidate ID codes occurred in the ASTB_IFS_API_PRI_v2.1 table for records from 2000 to 2010; they were replaced with consecutive negative numbers since the rest of their rows contained significant information. Null values for numeric attributes generally meant missing values, so we excluded them from averages, but nulls for nonnumeric attributes were generally important, such as a null for the type of previous flight training which meant the candidate had no previous flight training.

We had to regularize other inconsistent formats. For instance, some grades were 0 and 1 and others were Y and N for the same test. Most training scores were the integers 0 to 100, but some were 10000 and had to be changed to 100 to avoid distorting averages. We also converted some nonnumeric values into numeric values when it appeared reasonable and helpful for analysis. For instance, pilot course status was rated as “Complete”, “Pass”, “Incomplete”, “Conditional Pass”, and “Pass”; to get averages for a pilot, we converted the first two to numeric value 1.0, the next two to 0.5, and the last to 0.0. Dates we converted to epoch time (seconds since January 1, 1970 at midnight) so they became numeric and easier to compare.

C. CONSOLIDATING FLIGHT TEST AND ACADEMIC DATA

The main challenge in data setup for this project were dealing with the many tables for specialized flight tests and academics (143 in all) in the later stages of training, many of which had multiple rows for the same pilot and many nulls in the flight tests. Our study of the tables indicated they could be combined horizontally in two circumstances. First, some tables were labeled “v2” which meant they were the second half of another table that exceeded the Excel size limit, so we combined those. Second, some tables were labeled with names of different training wings but covered the same skills, so we combined those. (We also considered combining some tables that were labeled “CH-1” and “CH-2”, but we decided against it because they had differences in the column names and we did not understand what they represented.) However, in seven cases of table pairs for flight tests of the two acceptable categories, the number of columns differed between the pair. We found this meant that some tests were not administered to the candidates listed in one table, so we added columns of nulls to that table to permit appending tables of equal length.

We further chose to aggregate the sparse data of the remaining flight-test tables into fewer columns since there were so many nulls. We normalized the grades by dividing them by the corresponding level-of-difficulty (MIF) values, then averaged them for each pilot for a particular skill. We then took the average for each pilot over all skills on which they were tested in a curriculum. This meant we had one average grade for each pilot and curriculum they took, and reduced the number of such tables to two, one for flight tests and one for academics. This averaging no longer allowed testing the correlations involving particular grades; however, the database implementation to be described did allow such queries.

III. ANALYSIS

A. CORRELATING PILOT FEATURES

Our analysis used programs we wrote in the Python programming language. Python is not subject to the size limits of Excel, and it could process the files quickly once they were converted to comma-delimited text format (CSV). Setup of the data took a few minutes, and the correlations to be described took a few hours on a single workstation.

The data joined into a single table had 301 distinct columns and 18,596 rows representing pilot candidates. The columns are listed in Appendix B. To determine predictive ability, we could convert everything to numbers and run regressions. However, many numeric attribute values were missing, and regressions can be misled when too many variables are included, since the weaker factors may confound (interfere with the calculation of) the stronger factors. Thus we focused on comparing pairs of columns to find those that had statistically significant correlations on just nonnull numeric values. Once these are found, regressions can be done on only the statistically significant sets of pairs.

However, there are two issues. First, the data for the columns is generally acquired in a specific order, and we want to predict later data from earlier data. This meant only certain correlations of columns were useful. Studying the sponsor's diagrams, we obtained this sequence of training phases:

PRE – ASTB – IFS – API – PRI – PRI2 -- INT – ADVCORE -- ADV – FRS

Here "PRE" is our own phase label representing information about the candidate before they start any training such as their previous flight training, their grades in previous academic work, their gender, and their race. ASTB (Aviation Selection Test Battery) is represents initial testing, IFS (Initial Flight Screening) is initial flight school, API (Aviation Preflight Indoctrination) is academic work on basic aviation concepts, PRI (Primary Flight Training) is the first phase of flight experience in designated aircraft, INT (Intermediate Flight Training) is the second phase, ADV (Advanced Flight Training) is the third phase, and FRS (Fleet Replacement Squadron) is the graduate program. PRI2 represents later concepts in PRI, and ADVCORE represents earlier concepts in ADV.

Candidates increasingly differ in their training as they get more specialized training at the later stages, but still follow the same basic pattern above. The Naval Flight Officers in particular have many later courses different from those of the pilots.

Most attributes in our data are associated with particular phases. The file "Key for ATSB_IFS_API.xlsx" provided phase information on the 116 columns of ASTB_IFS_API_PRI_v2.1, and the names of the Academic Test and Maneuver Test files themselves indicated their phases. Phase names for the other columns we determined from background research.

Another issue is that some columns were numeric and others were nonnumeric categorical data like graduation status. Though most columns were numeric, some nonnumeric columns are quite important such as those relating to success of training. This meant we had to implement four cases in correlating columns:

- Two numeric columns, such as two test scores: We did a Pearson correlation and a linear regression from the earlier column to the later column. The correlation was a measure of statistical significance.

- An earlier categorical column and a later numeric column: We compared the mean in the later column for each categorical value in the earlier column. Degree of significance was the number of standard deviations from overall mean of the later column.

- An earlier numeric column and a later categorical column: We use the same method as the preceding in the reverse direction.

- Two categorical columns: We measured the statistical significance as the number of standard deviations of the frequency of the occurrence of the pair of values from the expected frequency of a Poisson distribution based on the occurrence rates of the values individuals. Specifically, if the value in the first column occurs n1 times out of N1 and the value in the second column occurs n2 times out of N2, and the pair of values occurred K times in the data, the number of standard deviations from the expected frequency is $\left|K - \left(\frac{n_1 n_2}{N_1}\right)\right| / \sqrt{\left(\frac{n_1 n_2}{N_1}\right)}|$.

Rows with nulls for numeric columns being correlated were ignored, but nulls for nonnumeric columns were useful and their rows retained, such as nulls for final grades indicating a candidate had dropped out.

We did not correlate some columns we considered uninteresting:

- Columns having only one value since we cannot conclude anything from them.

- Nonnumeric columns having more than 100 values since these were unlikely to show statistically significant trends.

- ID code number. This occurred several times in the join table because we were using outer joins.

- Raw test scores when normalized scores were available.

- Redundant data on sex and gender.

B. MEASURES OF CANDIDATE SUCCESS

We were primarily tasked to find factors indicating future success or failure of a candidate. 38 attributes could be relevant, both numeric and categorical:

- RetestStatus and ExamineeStatus attributes of the ATSB data

- IFS_DISENROLLMENT_DESCRIPTION, IFS_STATUS_NUM, and IFS_USNA_PFP in the ASTB_IFS_API_PRI_v2.1 table
- IFS_ACAD_FAIL and IFS_FLT_FAIL in the ASTB_IFS_API_PRI_v2.1 table
- API_NSS and API_Test_FAILS in the ASTB_IFS_API_PRI_v2.1 table
- Pri, Int, and Adv in the ASTB_IFS_API_PRI_v2.1 table, representing status of candidates in primary, intermediate, and advanced training
- NGCode in the ASTB_IFS_API_PRI_v2.1 table
- Number of ASTB1-5 and Number of ASTBE in the ASTB_IFS_API_PRI_v2.1 table
- SYL-ST (syllabus status) and STAT_RESN attributes in the Cumulative table
- NSS_UNSATS, OFFICIAL_NMU, NUM_RRU, IPC, FPC, and NSS in the Cumulative table, that all seem to be related to grading.
- FRS_TW1_Grade, FRS_TW2_Grade, FRS_TW3_Grade, FRS_TW4_Grade, FRS_TW5_Grade, and FRS_TW6_Grade from the FRS data.
- FRS_TW6_Status from the FRS data. This is the only FRS_Status attribute that was not null in our data.
- Counts that we calculated on the number of nonnull records for the candidate for each of the 10 phases. Unsuccessful candidates will be missing data for the later phases, although incomplete records mean some successful candidates are missing data for the earlier phases.
- Averages that we calculated for academic and flight-test grades for the PRI, INT, and ADV phases.

Table 1 summarizes correlation information for the these columns of the data with earlier data. (All columns are listed in Appendix B.) Positive Pearson correlations were considered greater than 0.1 and negative correlations were less than -0.1; correlations only compared non-null values. Other correlations had a threshold of significance of 5.0. Note the "Suitability for Prediction" does not include obvious correlations such as between different status measures. Note that for prediction purposes, it only makes sense to assess the effect on an attribute on an attribute at the same or a later phase.

Table 1: Possible measures of success of a candidate.

Success-related attribute and phase	Possible nonnull values	Nonnull occurrences	Suitability for prediction
RetestStatus (ASTB) (column 5)	Never, 30Days, 90Days,	8540	Positive correlations of "Never" with AQR_345 > 6.2, SAT_RAW_345 > 0.85, MCT_Z_ATBE

	180Days, Never1992, Resume		> 0.55, AQR_Z_ASTBE > 0.70, OAT_X_ASTBE > 0.70.
ExamineeStatus (ASTB) (column 9)	None	None	No nonnull data
IFS_STATUS (IFS) (column 76)	Complete, Disenroll, Closing	13844	Positive correlations of "Disenroll" with IFS_ACAD_FAIL > 0.30, IFS_FLT_FAIL > 0.08, IFS_USNA_PRP="PFP Completer"
IFS_STATUS_NUM (IFS) (column 78)	Numbers 0.0 to 1.0	13834	Mild (around 0.07) correlations with AQR, PFAR, FOFAR, OAR, SAT.
IFS_DISENROLLMENT_DESCRIPTION (IFS) (column 77)	String	5787	All nonnull values had significantly fewer previous flight hours. DOR and Performance disenrollment had significantly lower values on MST, RCT, MCT, ANIT, Personality3, 7, DOT, DLT, VTT, Skill, PFAR, FOFAR, OAR, and significantly higher on Personality1, 2, 4, 5, 6.
IFS_USNA_PFP (IFS) (column 98)	String	634	Value of PFP Attrite was significantly correlated with lower SAT, RCT, MCT, ANIT, Personality2, 3, 4, 5, 7, 8, 9, DOT, DLT, ATT, Skill, AQR, PFAR.
IFS_ACAD_FAIL (IFS) (column 93)	Number 0.0 to 1.0	13844	Significantly negatively correlated with AQR, PFAR, FOFAR, OAR, MST, RCT, MCT, ANIT, IFS_STATUS_NUM, less with flight-hours attributes
IFS_FLT_FAIL (IFS) (column 95)	Number 0.0 to 1.0	13844	Positive correlations (higher failure rates) for female, African, and Asian; pipeline of SNFO, IFS_DATE_ENROLLED, IFS_FPY_HRS_TO_FIRST_SOLO, IFS_WAIVED_HOURS_TO_SOLO. Negative correlations on HasFormalFlightInstr, MCT, ANIT, PFAR, TOTAL_SOLO_HOURS.
API_NSS (API) (column 106)	Integer	17401	Positive correlations on AQR, PFAR, FOFAR, OAR, SAT, ANI, MST, RCT, MCT, ANIT, DOTFactor, DLTFactor, AQR; positively correlated with IFS_STG_1, 3, IFS_EOC, IFS_FAA. Negative correlations on IRS_RPY_HRS_TO_FIRST_SOLO, IFS_ACAD_FAIL.
API_Test_FAILS (API) (column 107)	Integer	17446	Positive correlations (higher failure rates) on female, Afri, Hisp, PacIslander, Aircrew, and Training, pipeline SNFO, IFS_ACAD_FAIL.

			Negative correlations on AQR, PFAR, FOFAR, OAR, MST, RCT, EOC, FAA.
Pri (status in training) (PRI) (column 109)	G, UI, NG, AT, TG, UA	14461	Positive correlations of graduate status with FormalFlightInstrHours, SAT, Personality9, AQR, IFS_STATUS value Complete. Negative correlations on IFS_FLT_FAIL, API_Test_FAILS.
Int (status in training) (INT) (column 110)	G, AT, UI, NG, MA, J	5530	Higher API_NSS for graduates versus non-graduates of this phase, and fewer API_Test_FAILS.
Adv (status in training) (ADV) (column 111)	G, AT, UI, NG, UU, TG, SQ, UIT	16005	Very similar to INT.
NGCode (PRE) (column 113)	12 strings	1761	Too many values for useful correlation.
Number of ASTB1-5 (ASTB) (column 114)	Floating point	14477	Significantly higher values for female versus male, African and Hispanic versus Caucasian, Aircrew or Training experience, negative correlations with AQR, PFAR, FOFAR, OAR, MST, RCT, and MCT.
Number of ASTBE (ASTB) (column 115)	Floating point	4564	Very similar correlations to Number of ASTB1-5.
SYL_ST (syllabus status) (ADV) (column 124)	Comp-lete, Active, Attrite	6292	Higher attrition rates for Adv_Helo, E-2/C-2, 44USCG, Tiltrotor, and USN_P3_P8, and lower rates for Adv_Stk and CV12ADV_TILT.
STAT_RESN (reason for syllabus status) (ADV) (column 125)	20 strings	260	Too many values for useful correlation.
NSS_UNSATS (ADV) (column 127)	Number	3012	Significantly higher for SYL_ST value Attrite. No correlations possible with ASTB and IFS tests because no candidates have data for both.
OFFICIAL_NMU (ADV) (column 129)	Number	3012	Values strongly positively correlated with NSS_UNSATS. Same comments as for NSS_UNSATS.

NUM_RRU (ADV) (column 130)	Number	3012	Values positively correlated with NSS_UNSATS. Same comments as for NSS_UNSATS.
IPC (ADV) (column 131)	Number	3012	Not significantly correlated with anything.
FPC (ADV) (column 132)	Number	3012	Positively correlated with NSS_UNSATS, ALL_NMU, and OFFICIAL_NMU.
NSS (ADV) (column 133)	Floating point	5221	Positive correlations on SYL_ST value Attrite. Negative correlations on NSS_UNSATS, ALL_NMU, and OFFICIAL_NMU.
FRS_TW6_ Grade (FRS) (there were no grades for TW1, 2, 3, 4, or 5) (column 151)	Number	1274	Positive correlations on DOTFactor, IFS_FAA, IFS_ACAD_FAIL, API_FY, PRI_TW-5_166A_CH-1_Academics grade, NFO_TW-6_171_MPR_E6_CH-1 grade, PRI_166B_Academics grade, PRI_166A_CH-1_Academics grade, PRI_166A_CH-2_Academics grade, AER2, API_COUNT, PRI_COUNT. Negative correlations on female, Hisp race, lSNP pipeline, PFP Attrite, Pri, Adv; significantly higher for Afri race; HasFormalFlightInstr, Personality5, Personality8, IFS_STG_1, 2, 3, IFS_PRIOR_HRS_2_IFS, NFO_TW-6_171_Core_Academics grade, NFO_TW-6_155C_157B_Int grade, NFO_TW-6_158F_CH-1_Fighter grade, NFO_TW-6_158F_CH-1_Strike grade, NFO_TW-6_164A_CH-1 grade, NFO_TW-6_164 grade, NFO_TW-6_171_E2_MPR_E6 grade, INT_COUNT, ADV_COUNT
FRS_TW6_Status (FRS) (column 152)	Number 0.0 to 1.0	7682	Positively correlations on ADV_R_TW-5_156D_Academics, ADV-R_TW-5_156D_GTN650_CN_Academics, ADV-S_TW-1_167A_CH-1_Academics, INT-J-167A_Academics, INT-J_167_CH-2_Academics, NFO_TW-6_158F_CH-1_Fighter_Academics, NFO_TW-6_162_Pri1_Academics, NFO_TW-6_162_Pri2_Academics, NFO_TW-6_164A_CH-1_Academics, NFO_TW-6_171_Core_Academics, NFO_TW-6_171_Core_CH-1_Academics, NFO_TW-6_171_E2_CH1_Academics, NFO_TW-6_171_E2_MPR_E6_Academics, PRI_166A_CH-1_Academics, PRI_166A_CH-

			2_Academics, ADV-E2_176 grade, ADV-R_TW-5_156D_GTN650 grade, ADV-R_TW-5_156D grade, INT-J_167A grade, NFO_TW-6_155C_157B_Int grade, NFO_TW-6_155C_Primary grade, NFO_TW-6_158F_CH-1_Strike grade, NFO-TW-6_162A_Pri2 grade, NFO_TW-6_162_Pri1 grade, NFO_TW-6_163 grade, NFO_TW-6_164A_CH-1 grade, NFO_TW-6_164 grade, NFO_TW-6_164 grade, NFO_TW-6_171_Core grade, NFO_TW-6_171_E2_CH1 grade, NFO_TW-6_171_E2_MPR_E6 grade, PRI_166A_CH-2 grade, PRI_TW-5_166A_TOP-offs_CH-1 grade, PRI_TW-5_166B grade, AER2, AWX1. Negative correlations on ADV-E2_TW-4_147G_T-44A_Academics, INT-J_167_CH-2_Academics, NFO_TW-6_164A_Academics, PRI_166B_Academics, NFO_TW-6_163A grade, PRI_166A_CH-1 grade, INT_COUNT.
Count of nonnull values for the API phase (API) (column 288)	Floating point	18596	Positive correlations on MCT, AQR, PFAR, FOFAR, OAR, IFSFISCAL_YEAR; negative correlations on IFS_TOTAL_FLIGHT_TIME. Negative correlations on SNP and SNFO pipelines, Disenroll for IFS_STATUS, IRS_STG_1, 2, 3.
Count of nonnull values for the PRI phase (PRI) (column 289)	Floating point	18596	Positive correlations on MCT, AQR, PFAR, FOFAR, OAR, SNA pipeline, IFS_STATUS_NUM, IFS_STG_1, 2, 3, PRI_166A_CH-1_Academics grade, NFO_TW-6_162A_Pri1 grade, NFO_TW-6_162_Pri1 grade, PRI_TW-5_166A_Top-offs_CH-1 grade, API_COUNT. Negative correlation on PRI_166A_CH-2_Academics grade.
PRI academic average (column 290)	Floating point	13555	Positively correlations on “Never”, “180Days”, and “Resume” in RetestStatus, AQR, PFAR, FORAR, OAR, MST, RCT, ANIT, IFS_EOC, IFS_FAA, API_NSS, AER1, AER2, AWX1, ENG1, FRR1, NAV1. Negative correlations on HasFormalFlightInstr, IFS_PILOT_SCHOOL of Trident Gulf Shores, IFS_ACAD_FAIL, API_Test_FAILS, PRI_COUNT.
PRI flight average (column 291)	Floating point	10664	Positive correlations on HasFormalFlightInstr, AQR, PFAR, FOFAR, OAR, SAT, ANI, MCT, ANIT, DOTFactor, IFS_EOC, IFS_FAA,

			API_NSS, AER1, AER2, AWX1, ENG1, FRR1, NAV1. Negative correlations on IFS_ACAD_FAIL, IFS_FLT_FAIL, API_Test_FAILS.
Count of nonnull values for the INT phase (INT) (column 293)	Floating point	18596	Positive correlations on License for previous training, AQR, PFAR, FOFAR, OAR, SAT, ANIT, MCT, ATTFactor, SNA pipeline, API_NSS, PRI_166A_CH-1_Academics grade, PRI_166A_CH-2_Academics grade, PRI_166B_Academics grade, NFO_TW-6_155C_Primary grade, NFO_TW-6_162A_Pri1 grade, NFO_TW-6_162A_Pri2 grade, PRI_166A_CH-1 grade, PRI_166A_CH-2 grade, PRI_166B grade, AER1, AER2 AWX1, ENG1, NAV1, PRE_COUNT, PRI_COUNT. Negative correlations on female, any race but Cauc, Aircrew for previous training, IFS_TOTAL_FLIGHT_TIME, API_Test_FAILS, NFO_TW-6_155C_157B_Int grade, NFO_TW-6_155C_157B_Int_Academics grade, NFO_TW-6_162A_Pri1_Academics grade, NFO_TW-6_162_Pri1_Academics grade
INT academic average (column 294)	Floating point	8153	Positive correlations on AQR, PFAR, FOFAR, OAR, ANI, MST, RCT, ANIT, Personality8, AQR, IFS_STG_1, IFS_STG_3, IFS_EOC, IFS_FAA, AER1, AER3, AWX1, ENG1, FRR1, NAV1, PRI_ACADEMIC_AV, PRI_FLIGHT_AV. Negative correlations on IFS_ACAD_FAIL, API_test_FAILS, Number of ASTB1-5, Number of ASTBE.
INT flight average (column 295)	Floating point	3301	Positive correlations on DLTFactor, Number of ASTBE, PRI_TW-5_166A grade, PRI_TW-5_166A_Top-offs_CH-1 grade, API_COUNT, PRI_COUNT, PRI_FLIGHT_AV. Negative correlations on HasFormalFlightInstr, MCT, ANIT, ATTFactor, AQR, OAR, IFS_PRIOR_HRS_2_IFS, PRI_166A_CH-1 grade, PRI_166A_CH-2 grade, PRI_166B grade, ENG1.
Count of nonnull values for the ADV phase (ADV) (column 297)	Floating point	18,596	Positive correlations on female, any race other than Cauc, Pri graduation, Int graduation, ADV-E2-176_Academics grade, ADV-E2-176_CN_Academics grade, NFO_TW-6_164A_CH-1_CN_Academics grade, NFO_TW-6_171_Core_Academics grade,

			PRI_166A_CH-1_Academics grade, PRI_166A_CH-2_Academics grade, ADV_E2_TW-1_176_CN grade, INT-J_167_CH-2 grade, NFO_TW-6_155C_Primary grade, NFO_TW-6_158F_CH-1_Fighter grade, NFO_TW-6_158F_CH-1_Strike grade, NFO_TW-6_162A_Pri1 grade, NFO_TW-6_162A_Pri2 grade, NFO_TW-6_162_Pri1 grade, NFO_TW-6_163 grade, NFO_TW-6_164A_CH-1_CN_Feb_18 grade, NFO_TW-6_171_Core grade, PRI_166A_CH-1 grade, PRI_166A_CH-2 grade, PRI_TW-5_166A_top-offs_CH-1 grade, PRE_COUNT, API_COUNT PRI_COUNT, PRI2_COUNT, ADVCORE_COUNT. Negative correlations on ANIT, ATTFactor, PFAR, ADV-E2_176_CN_Academics grade, NFO_TW-6_164A_Academics grade, INT-J_167A grade, NFO_TW-6_164A grade, NFO_TW-6_164 grade, PRI_TW-4_166A_CH-2 grade, PRI_166B grade.
ADV academic average (column 298)	Floating point	9712	Positive correlations on PFAR, FOFAR, OAR, MST, RCT, MCT, ANIT, AQR, IFS_EOC, IFS_FAA, API_NSS, AER1, AER2, AWX1, ENG1, FRR1, PRI2_COUNT, INT_COUNT, INT_ACADEMIC_AV, INT_FLIGHT_AV, NAV1. Negative correlations on IFS_ACAD_FAIL, API_Test_FAILS, Int nongraduate, API_COUNT,
ADV flight average (column 299)	Floating point	4593	Positive correlations on AQR, PFAR, FOFAR, OAR, MST, MCT, ANIT, IFS_TOTAL_FLIGHT_TIME, IFS_EOC, API_NSS, INT-J_167_CH-2_Academics_RAW_SCORE_DV, NFO_TW-6_155C_157B_Int_Academics, NFO_TW-6_155C_Primary_Academics, NFO_TW-6_162A_Pri1_Academics, NFO_TW-6_162A_Pri2_Academics, NFO_TW-6_162_Pri2_Academics, NFO_TW-6_155C_Primary grade, NFO_TW-6_157B_Int grade, NFO_TW-6_162A_Pri1 grade, NFO_TW-6_162A_Pri2 grade, NFO_TW-6_162_Pri1 grade, PRI_166A_CH-1 grade, AER1, AER2, AWX1, ENG1, FRR1, NAV1, API_COUNT,

			PRI_COUNT, PRI_ACADEMIC_AV, PRI_FLIGHT_AV, INT_FLIGHT_AV. Negative correlations on FormalFlightInstrHours, IFS_ACAD_FAIL, API_Test_FAILS, Pri nongraduate, INT_J_167A_Academics, NFO_TW-6, PRI_166A_CH-1_Academics, INT-J_167A grade, NFO_TW-6_155C_157B_Int grade.
Count of nonnull values for the FRS phase (FRS) (column 300)	Floating point	18,596	Positive correlations on female, Cauc race, AQR, PFAR, FOFAR, IFS_STG_1, IFS_STG_2, IFS_STG_3, Pri graduate, Int graduate, Adv graduate, NFO_TW-6_155C_157B_Int_Academics grade, NFO_TW-6_162_Pri1_Academics grade, NFO_TW-6_164A_Academics grade, NFO_TW-6_164_Academics grade, NFO_TW-6_171_Core_Academics grade, PRI_166A_CH-1_Academics grade, PRI_166A_CH-2_Academics grade, PRI_166B_Academics grade, ADV-E2_176 grade, INT-J_167A grade, INT-J_167_CH-2 grade, NFO_TW-6_155C_Primary grade, NFO_TW-6_162_Pri1 grade, NFO_TW-6_163A grade, NFO_TW-6_163 grade, NFO_TW-6_164A_CH-1_CN_Feb_18 grade, NFO_TW-6_164A_CH-1 grade, NFO_TW-6_164A grade, NFO_TW-6_171_Core grade, PRI_TW-5_166A grade, PRE_COUNT, API_COUNT, PRI_COUNT, INT_COUNT, ADVCORE_COUNT, ADV_COUNT. Negative correlations on Aircrew and Winged training, DOTFactor, IFS_TOTAL_FLIGHT_TIME, ADV-S_167A_CH-1_Academics grade, INT-J_167_CH-2_Academics grade, INT-J_167A_Academics grade, PRI_166A_CH-1_Academics grade, ADV-R_TW-5_156D_GTN560 grade, INT-J_167A grade, NFO_TW-6_164 grade, NFO_TW-6_171_E2_CH-1 grade, PRI_166A_CH-1 grade, PRI_166A_CH-2 grade.

C. DISCUSSION

The reliability of these correlations was hampered by the low counts of candidates who drop out of the training program. For instance, IFS_STATUS recorded 13,460 candidates who completed and only 374 who were disenrolled; SYL_ST had 5369 who were complete and 260 who were attrited. Data were specifically sparse for the flight tests since there were so many specialized curricula; the aggregation we did was essential to make sense of the data. It is difficult to do useful machine learning when there is such a strong bias in one direction, in this case success in the program.

Nonetheless, we did see some interesting trends. Note that since correlations were only calculated on pairs of values where both values were non-null, correlations on later phases did not include people who attrited at earlier phases.

- There were some strong correlations of success with increasing dates, but these are likely spurious due to having more complete data for recent candidates.
- There were some strong correlations of success with number of flight hours. However, "Formal flight instruction hours" correlated negatively with several measures of final success. It may be that weaker candidates are attrited, get more remedial instruction, or that formal flight instruction on different aircraft confuses candidates.
- Female gender and minority race showed relatively more failures early in training but relatively fewer failures later in training.
- Several ASTB test results correlated well with success in IFS, Primary, Intermediate, and FRS; we gather that the ASTB has been designed to do this. However, ASTB metrics were not helpful in predicting success in the Advanced training, by which time many additional skills have been learned.
- Several Primary, Intermediate and Advanced training grades correlated positively with both success in Advanced training and FRS. We gather these are useful metrics that should be preserved. However, some of the advanced-training grades correlated negatively with success, and these should be investigated further. Perhaps the grades tend to be recorded more for "makeup" activities for candidates who have failed in other skills, or perhaps the training associated with those skills is counterproductive.
- Some of the strong correlations to phase counts may be due to policy rather than candidate aptitude, as when candidates are attrited if they fail to score sufficiently well on a metric or fail a benchmark too many times. We are not familiar with Navy policy and cannot guess what the attrition conditions are. However, being attrited in the next phase after a test score is probably a good indicator of aptitude rather than policy because a policy on that test score would have attrited them earlier.

IV. DESIGN OF A DATABASE

An alternative way to store the data is in a traditional database, and this offers more flexibility in running queries on it. We built a prototype with Oracle XE for Laptops since the Navy has an Oracle license. The SQL Developer (SQLD) interface tool was used to access Oracle XE and run SQL queries. After all the data preparation is completed on the laptop, the final schema was moved (using SQLD) to an Oracle 19c Database residing on the campus Network Operations Center. SQLD has a tool to load an Excel spreadsheet into a database table which loaded the files. Access the database was over port 1521 as setup by the Network Operations staff.

The main tables needed for a traditional database design are a student table, a curriculum table, a score table, a student-curriculum linking table, and a student-score linking table. There will be many scores for each student, so there needs to be an auxiliary data structure holding links to the score records for each student. Additional tables were sent us beyond those mentioned earlier, and they could be helpful in database queries. Examples are the list of curricula and their names, the descriptions of the coded values, and the descriptions of the column labels.

An Oracle database has data and metadata constraints we had to address including:

- Column name length: Database column names usually have limits. Fortunately in the 19c version the limits have been increased beyond the 30 character limit in previous versions.
- Non-alphabetic characters in column names: A database column name cannot have a hyphen so this was replaced by an underscore. Other characters that had to be replaced were "(", ")" , ".", and "/".
- Values that were spaces: These needed to be replaced by nulls since that is what they meant.
- Dates and times: Most formats used were either "MM-DD-YYYY" (Date) or "MM-DD-YYYY HH24:MI" (Timestamp). Some date values did not fit either format, and were loaded as a Character type and cleaned up later. All dates were converted to epoch time as described in section II.
- As with the previously described analysis, missing ID_CODE values were replaced with sequential negative numbers.

A problem with doing outer joins with the ID_CODE attribute is that its values will occur twice in the columns of the result. The usual to do the outer join using SQL would be:
CREATE TABLE T3 AS SELECT * FROM T1 FULL OUTER JOIN T2 ON T1.ID_CODE = T2.ID_CODE

The problem with this is that the “*” (select all columns) will confuse the SQL as the ID_CODE column is in both tables. One option is the write out all the column names instead of the “*” but that would be a tedious as we have tables with hundreds of columns. One option is to rename (in SQLDEVELOPER) the ID_CODE column to ID_CODE1 (in table T1) and ID_CODE2 (in table T2). So now the OUTER JOIN “SELECT *” would generate 2 ID_CODE columns (ID_CODE1 & ID_CODE2), and the rest of the columns. Now to combine the two ID_CODE columns we had to first create 2 separate tables using SQL,“CREATE TABLE T5 AS (SELECT * FROM T2 where T3.ID_CODE2 = NULL)”, followed by DROP COLUMN of ID_CODE2. Next we created a table T6 with ID_CODE2. Next the columns ID_CODE1 & ID_CODE2 (in tables T5 & T6) were renamed to ID_CODE (SQLDEVELOPER). Finally the 2 tables were merged into one table (ID_CODE column) using the SQL, “CREATE TABLE T7 AS (SELECT * FROM T5) UNION (SELECT * FROM T6)”. This process was repeated for all tables one by one till a FULL OUTER JOIN (of all tables) was generated.

The ML_ADV_E2_TW_1_176_ACADEMICS table has scores each time a test was taken by a student, so to get an average value the SQL used was:

SELECT IC_CODE, SUM(RAW_SCORE_DV)/COUNT(RAW_SCORE_DV) as
RAW_SCORE_DV_AVG
GROUP BY ID_CODE
ORDER BY ID_CODE”.

To take into account the “Degree of Difficulty” a similar SQL query was used where the score was divided by the MIP column value.

V. CONCLUSIONS

Our results identified quite a few factors helpful in predictions, some that were obvious and some that were not. We did not see any obvious factors in performance that the Navy is not acting upon. What factors we measured as significant such as previous flight training, gender, and race are not ones the Navy can control practically or legally. Overall, we conclude that the Navy is doing a good job predicting performance of candidate candidates from their multistage testing program.

Future work should definitely try to obtain more complete data on the candidates, as many potentially useful comparisons such as between cumulative metrics such as NMU, RRU, IPC, FPC, and NSS lacked sufficient data for us. Further work could investigate additional metrics for predicting performance by additional testing; combinations of factors could show new trends. An approach of combining factors with a set-covering machine-learning approach to optimize statistical significance is promising and should be explored.

APPENDIX A: DELIVERABLES

Besides output files, we are sending to the sponsor the programs (in the Python programming language) we created:

- pilotscript2.py: Runs overall analysis script.
- extract_labels_from_csv.py: Used to remove columns labels from CSV (comma separated value) files and store them in a separate file. The results are "_nolabels.csv" and "_labels.txt" files.
- bettersplit.py: This splits rows in delimited files carefully, taking into account quotation marks and carriage returns within entries.
- count_all_nonnull_column_values: Counts the number of values not null in a given column of a given table. Useful since there are so many nulls in this data.
- append_and_extract_labels_from_csv: Combines two academic or flight-test files that contain similar data.
- append_and_extract_labels_from_csv: Combines all pairs of academic or flight-test files where either (1) one of the pair is "v2" of the other, or (2) the data is the same curriculum for different training wings.
- aggregate_academic_data_all.py: Aggregates all the files with classroom grades (with "Academic" in their names).
- aggregate_maneuver_data_all.py: Aggregates all the files with flight-test grades.
- aggregate_manever_data.py: Aggregates data for a single flight-test file for both multiple grades of a single pilot on a single skill and on all skills in a particular curriculum.
- join_files_out_pilots.py: Does an outer join of two tables on specified column numbers, with columns separated by a given delimiter, and stores the result in a specified file.
- setup_earlyfile.py: Replaces null ID codes with negative numbers in the ASTB_IFS_API_PRI_v2.1 table.
- get_time_patterns.py: Counts the number of records for each phase of training for each pilot.
- join_files_outer_pilots.py: Does an outer join between two tables in CSV form, also joining the column labels files. A join matches rows in two tables based on attribute values in a column of each table. An outer join inserts nulls for values in one table that do not match anything in the other table; this was important for our data because many candidate records were missing information.
- correlate_table_columns.py: Compares columns of a CSV file by doing tests of statistical significance as described. Currently it focuses on the "success" metrics described previously.
- jekamp_nolabels.csv and jekamp_labels.txt: Comma-separated join of all the relevant data, including some aggregated data, and the labels for the columns.
- jekamp_nolabels_unarystats.txt: Statistics on each column of jekamp, with average and standard deviation of the nonnull values for numeric and date columns, and the possible values for nonnumeric columns.

- jekamp_nolabels_binarystats.txt: Statistics on the correlation of each column measuring success in one way or another with all the other columns, as explained in the discussion of correlation in this document.

APPENDIX B: ATTRIBUTES ANALYZED

Table 2 lists the attributes of the complete join of all the tables. For Type, N=numeric, S=string, and U=uninteresting or unused. Dates and yes/no attributes are converted into numbers. The last columns 285-300 were calculated by us from the other data as additional metrics of candidate success. Note the duplicate ID_CODE columns are necessary when combining data from candidates not appearing in all tables since we are doing outer joins rather than inner joins and the ID code may not appear in all tables joined.

Table 2: Complete list of attributes in the full join of all tables.

	Attribute name	Type	Phase
0	ID_CODE	U	PRE
1	Examineeid	U	PRE
2	Gender	S	PRE
3	Race	S	PRE
4	AviationTraining	S	PRE
5	RetestStatus	S	ASTB
6	HasFormalFlightInstr	N	PRE
7	FormalFlightInstrDesc	S	PRE
8	FormalFlightInstrHours	N	PRE
9	ExamineeStatus	S	ASTB
10	TestID	S	ASTB
11	DesignTestID	U	ASTB
12	StartDt	N	ASTB
13	EndDT	N	ASTB
14	Form	N	ASTB
15	AQR_RAW_345	N	ASTB
16	AQR_345	N	ASTB
17	PFAR_RAW_345	N	ASTB
18	PFAR_345	N	ASTB
19	FOFAR_RAW_345	N	ASTB
20	FOFAR_345	N	ASTB
21	OAR_RAW_345	N	ASTB
22	OAR_345	N	ASTB
23	MCT_RAW_345	N	ASTB
24	SAT_RAW_345	N	ASTB
25	ANI_RAW_345	N	ASTB
26	ANI_345	N	ASTB
27	MST_RAW_345	N	ASTB
28	MST_345	N	ASTB
29	RCT_RAW_345	N	ASTB
30	RCT_345	N	ASTB
31	Status_345	S	ASTB
32	RecruitingBranch_A	S	PRE
33	ExamineeStatus_A	S	PRE
34	MST_Z_ASTBE	N	ASTB
35	RCT_Z_ASTBE	N	ASTB
36	MCT_Z_ASTBE	N	ASTB
37	ANIT_Z_ASTBE	N	ASTB

38	Personality1_Z_ASTBE	N	ASTB
39	Personality2_Z_ASTBE	N	ASTB
40	Personality3_Z_ASTBE	N	ASTB
41	Personality4_Z_ASTBE	N	ASTB
42	Personality5_Z_ASTBE	N	ASTB
43	Personality6_Z_ASTBE	N	ASTB
44	Personality7_Z_ASTBE	N	ASTB
45	Personality8_Z_ASTBE	N	ASTB
46	Personality9_Z_ASTBE	N	ASTB
47	DOTFactor_Z_ASTBE	N	ASTB
48	DLTFactor_Z_ASTBE	N	ASTB
49	ATTFactor_Z_ASTBE	N	ASTB
50	VTTFactor_Z_ASTBE	N	ASTB
51	SkillFactor_Z_ASTBE	N	ASTB
52	AQR_Z_ASTBE	N	ASTB
53	AQR_Stanine_ASTBE	U	ASTB
54	PFAR_Z_ASTBE	N	ASTB
55	PFAR_Stanine_ASTBE	U	ASTB
56	FOFAR_Z_ASTBE	N	ASTB
57	FOFAR_Stanine_ASTBE	U	ASTB
58	OAR_Z_ASTBE	N	ASTB
59	OAR_T_ASTBE	N	ASTB
60	IFS_LOCATION	S	IFS
61	IFS_PILOT_SCHOOL	S	IFS
62	IFSFISCAL_YEAR	N	IFS
63	IFS_BRANCH	S	IFS
64	IFS_TRAINING_PIPELINE	S	IFS
65	IFS_DATE_ENROLLED	N	IFS
66	IFS_DATE_COMPLETED_OR_DISENROLLED	N	IFS
67	IFS_DAYS_ENROLLED	N	IFS
68	IFS_DAYS_PENDING	N	IFS
69	IFS_TOTAL_FLIGHT_TIME	N	IFS
70	IFS_TOTAL_DUAL_HOURS	N	IFS
71	IFS_TOTAL_SOLO_HOURS	N	IFS
72	IFS_TOTAL_LANDINGS	N	IFS
73	IFS_NIGHT_HOURS	N	IFS
74	IFS_COMPLETED_CROSS_COUNTRY	N	IFS
75	IFS_FPY_HRS_TO_FIRST_SOLO	N	IFS
76	IFS_STATUS	S	IFS
77	IFS_DISENROLLMENT_DESCRIPTION	S	IFS
78	IFS_STATUS_NUM	N	IFS
79	IFS_WAIVED_HOURS_TO_SOLO	N	IFS
80	IFS_WAIVED_DAYS_TO_SOLO	N	IFS
81	IFS_WAIVED_DAYS_TO_COMPLETE	N	IFS
82	IFS_CLASS_NO	S	IFS
83	IFS_SUPERVISORS_COMMENTS	S	IFS
84	IFS_DATE_OF_LAST_FLIGHT	N	IFS
85	IFS_GENDER	U	IFS
86	IFS_RACE	U	IFS
87	IFS_ETHNICITY	U	IFS
88	IFS_STG_1	N	IFS
89	IFS_STG_2	N	IFS
90	IFS_STG_3	N	IFS

91	IFS_EOC	N	IFS
92	IFS_FAA	N	IFS
93	IFS_ACAD_FAIL	N	IFS
94	IFS_ACAD_FAIL_BINARY	U	IFS
95	IFS_FLT_FAIL	N	IFS
96	IFS_FLT_FAIL_BINARY	U	IFS
97	IFS_PRIOR_HRS_2_IFS	N	IFS
98	IFS_USNA_PFP	S	IFS
99	API_FY	N	API
100	API_Service	S	API
101	API_Program	N	API
102	API_Desig	N	API
103	API_Source	S	API
104	API_StartCls	S	API
105	API_EndCls	S	API
106	API_NSS	N	API
107	API_Test_FAILS	N	API
108	Trawing	S	API
109	Pri	S	PRI
110	Int	S	INT
111	Adv	S	ADV
112	Select	S	PRI
113	NGCode	S	PRE
114	Number of ASTB1-5	N	ASTB
115	Number of ASTBE	N	ASTB
116	WING	S	PRE
117	SQDN	S	PRE
118	PHASE_NAME	S	PRE
119	ID_CODE	N	PRE
120	BRANCH	S	PRE
121	SYLLABUS	S	PRE
122	VERSION	S	PRE
123	SYL_TRACK	S	PRE
124	SYL_ST	S	ADV
125	STAT_RESN	S	ADV
126	SYL_STAT_DATE	N	PRE
127	NSS_UNSATS	N	ADV
128	ALL_NMU	N	ADV
129	OFFICIAL_NMU	N	ADV
130	NUM_RRU	N	ADV
131	IPC	N	ADV
132	FPC	N	ADV
133	NSS	N	ADV
134	ID_CODE	U	PRE
135	ADV-E2_TW-1_176_Academics_RAW_SCORE_DV	N	ADV
136	ADV-E2_TW-1_176_CN_Academics_RAW_SCORE_DV	N	ADV
137	ADV-E2_TW-4_147G_T-44A_Academics_RAW_SCORE_DV	N	ADV
138	ADV-R_TW-5_156D_Academics_RAW_SCORE_DV	N	ADV
139	ADV-R_TW-5_156D_GTN650_CN_Academics_RAW_SCORE_DV	N	ADV
140	ADV-R_TW-5_156D_GTN650_CN_CH-1_Academics_RAW_SCORE_DV	N	ADV
141	ADV-S_167A_CH-1_Academics_RAW_SCORE_DV	N	ADV
142	ADV-S_TW-2_167A_Academics_RAW_SCORE_DV	N	ADV

143	FRS_TW1_Grade	N	FRS
144	FRS_TW1_Status	U	FRS
145	FRS_TW2_Grade	N	FRS
146	FRS_TW2_Status	U	FRS
117	FRS_TW4_Grade	N	FRS
148	FRS_TW4_Status	U	FRS
149	FRS_TW5_Grade	N	FRS
150	FRS_TW5_Status	U	FRS
151	FRS_TW6_Grade	N	FRS
152	FRS_TW6_Status	S	FRS
153	INT-E2_TW-4_175_Academics_RAW_SCORE_DV	N	INT
154	INT-J_167A_Academics_RAW_SCORE_DV	N	INT
155	INT-J_167_CH-2_Academics_RAW_SCORE_DV	N	INT
156	INT-T_TW-5_161_Academics_RAW_SCORE_DV	N	INT
157	INT-T_TW-5_161_CH-1_Academics_RAW_SCORE_DV	N	INT
158	INT-T_TW-5_161_CH-2_Academics_RAW_SCORE_DV	N	INT
159	INT-T_TW-5_161_CH-2_GTN650_CN_Academics_RAW_SCORE_DV	N	INT
160	INT-T_TW-5_161_CH-2_GTN650_CN_CH-1_Academics_RAW_SCORE_DV	N	INT
161	NFO_TW-6_155C_157B_Int_Academics_RAW_SCORE_DV	N	INT
162	NFO_TW-6_155C_Primary_Academics_RAW_SCORE_DV	N	PRI
163	NFO_TW-6_157B_Int_Academics_RAW_SCORE_DV	N	INT
164	NFO_TW-6_158F_CH-1_ATM_Academics_RAW_SCORE_DV	N	ADV
165	NFO_TW-6_158F_CH-1_Fighter_Academics_RAW_SCORE_DV	N	ADV
166	NFO_TW-6_158F_Strike_CH-1_Academics_RAW_SCORE_DV	N	ADV
167	NFO_TW-6_162A_Pri1_Academics_RAW_SCORE_DV	N	PRI
168	NFO_TW-6_162A_Pri2_Academics_RAW_SCORE_DV	N	PRI2
169	NFO_TW-6_162B_Academics_RAW_SCORE_DV	N	ADV
170	NFO_TW-6_162_Pri1_Academics_RAW_SCORE_DV	N	PRI
171	NFO_TW-6_162_Pri2_Academics_RAW_SCORE_DV	N	PRI2
172	NFO_TW-6_164A_Academics_RAW_SCORE_DV	N	ADV
173	NFO_TW-6_164A_CH-1_Academics_RAW_SCORE_DV	N	ADV
174	NFO_TW-6_164A_CH-1_CN_Academics_RAW_SCORE_DV	N	ADV
175	NFO_TW-6_164_Academics_RAW_SCORE_DV	N	ADV
176	NFO_TW-6_171_Core_Academics_RAW_SCORE_DV	N	ADVCORE
177	NFO_TW-6_171_Core_CH-1_Academics_RAW_SCORE_DV	N	ADVCORE
178	NFO_TW-6_171_E2_CH1_Academics_RAW_SCORE_DV	N	ADV
179	NFO_TW-6_171_E2_MPR_E6_Academics_RAW_SCORE_DV	N	ADV
180	NFO_TW-6_171_E6_CH-1_Academics_RAW_SCORE_DV	N	ADV
181	NFO_TW-6_171_MPR_CH-1_Academics_RAW_SCORE_DV	N	ADV
182	NFO_TW-6_171_MPR_E6_CH-1_Academics_RAW_SCORE_DV	N	ADV
183	PRI_166A_CH-1_Academics_RAW_SCORE_DV	N	PRI
184	PRI_166A_CH-2_Academics_RAW_SCORE_DV	N	PRI
185	PRI_166B_Academics_RAW_SCORE_DV	N	PRI
186	PRI_TW-5_166A_Academics_RAW_SCORE_DV	N	PRI
187	PRI_TW-5_166A_Top-offs_CH-1_Academics_RAW_SCORE_DV	N	PRI
188	ID_CODE	N	PRE
189	1542.147GT44AAdvE2C2_DATA_COUNT	N	PRE
190	1542.147GT44AAdvE2C2_DATA_GRADE	N	PRE
191	1542.176CNATRANOTEJUNE19_DATA_COUNT	N	PRE
192	1542.176CNATRANOTEJUNE19_DATA_GRADE	N	PRE
193	1542.176_DATA_COUNT	N	PRE
194	1542.176_DATA_GRADE	N	PRE
195	ADV-E2_176_COUNT	N	ADV

196	ADV-E2_176_GRADE	N	ADV
197	ADV-E2_TW-2_176_CN_COUNT	N	ADV
198	ADV-E2_TW-2_176_CN_GRADE	N	ADV
199	ADV-R_TW-5_156D_GTN650_CH-1_COUNT	N	ADV
200	ADV-R_TW-5_156D_GTN650_CH-1_GRADE	N	ADV
201	ADV-R_TW-5_156D_GTN650_COUNT	N	ADV
202	ADV-R_TW-5_156D_GTN650_GRADE	N	ADV
203	ADV-R_TW-5_156D_COUNT	N	ADV
204	ADV-R_TW-5_156D_GRADE	N	ADV
205	ADV_E2_TW-1_176_CN_COUNT	N	ADV
206	ADV_E2_TW-1_176_CN_GRADE	N	ADV
207	INT-E2_TW-4_175_COUNT	N	INT
208	INT-E2_TW-4_175_GRADE	N	INT
209	INT-J_167A_COUNT	N	INT
210	INT-J_167A_GRADE	N	INT
211	INT-J_167_CH-2_COUNT	N	INT
212	INT-J_167_CH-2_GRADE	N	INT
213	INT-T_TW-5_161_CH-2_GTN650_CH-1_COUNT	N	INT
214	INT-T_TW-5_161_CH-2_GTN650_CH-1_GRADE	N	INT
215	INT-T_TW-5_161_CH-2_GTN650_COUNT	N	INT
216	INT-T_TW-5_161_CH-2_GTN650_GRADE	N	INT
217	INT-T_TW-5_161_CH-2_COUNT	N	INT
218	INT-T_TW-5_161_CH-2_GRADE	N	INT
219	NFO_TW-6_155C_157B_Int_COUNT	N	INT
220	NFO_TW-6_155C_157B_Int_GRADE	N	INT
221	NFO_TW-6_155C_Primary_COUNT	N	PRI
222	NFO_TW-6_155C_Primary_GRADE	N	PRI
223	NFO_TW-6_157B_Int_COUNT	N	INT
224	NFO_TW-6_157B_Int_GRADE	N	INT
225	NFO_TW-6_158F_CH-1_ATM_COUNT	N	ADV
226	NFO_TW-6_158F_CH-1_ATM_GRADE	N	ADV
227	NFO_TW-6_158F_CH-1_Fighter_COUNT	N	ADV
228	NFO_TW-6_158F_CH-1_Fighter_GRADE	N	ADV
229	NFO_TW-6_158F_CH-1_Strike_COUNT	N	ADV
230	NFO_TW-6_158F_CH-1_Strike_GRADE	N	ADV
231	NFO_TW-6_162A_Pri1_COUNT	N	PRI
232	NFO_TW-6_162A_Pri1_GRADE	N	PRI
233	NFO_TW-6_162A_Pri2_COUNT	N	PRI2
234	NFO_TW-6_162A_Pri2_GRADE	N	PRI2
235	NFO_TW-6_162B_COUNT	N	ADV
236	NFO_TW-6_162B_GRADE	N	ADV
237	NFO_TW-6_162_Pri1_COUNT	N	PRI
238	NFO_TW-6_162_Pri1_GRADE	N	PRI
239	NFO_TW-6_163A_COUNT	N	ADV
240	NFO_TW-6_163A_GRADE	N	ADV
241	NFO_TW-6_163_COUNT	N	ADV
242	NFO_TW-6_163_GRADE	N	ADV
243	NFO_TW-6_164A_CH-1_CN_Feb_18_COUNT	N	ADV
244	NFO_TW-6_164A_CH-1_CN_Feb_18_GRADE	N	ADV
245	NFO_TW-6_164A_CH-1_COUNT	N	ADV
246	NFO_TW-6_164A_CH-1_GRADE	N	ADV
247	NFO_TW-6_164A_COUNT	N	ADV
248	NFO_TW-6_164A_GRADE	N	ADV

249	NFO_TW-6_164_COUNT	N	ADV
250	NFO_TW-6_164_GRADE	N	ADV
251	NFO_TW-6_171_Core_CH-1_COUNT	N	ADVCORE
252	NFO_TW-6_171_Core_CH-1_GRADE	N	ADVCORE
253	NFO_TW-6_171_Core_COUNT	N	ADVCORE
254	NFO_TW-6_171_Core_GRADE	N	ADVCORE
255	NFO_TW-6_171_E2_CH1_COUNT	N	ADV
256	NFO_TW-6_171_E2_CH1_GRADE	N	ADV
257	NFO_TW-6_171_E2_MPR_E6_COUNT	N	ADV
258	NFO_TW-6_171_E2_MPR_E6_GRADE	N	ADV
259	NFO_TW-6_171_E6_CH-1_COUNT	N	ADV
260	NFO_TW-6_171_E6_CH-1_GRADE	N	ADV
261	NFO_TW-6_171_MPR_CH-1_COUNT	N	ADV
262	NFO_TW-6_171_MPR_CH-1_GRADE	N	ADV
263	NFO_TW-6_171_MPR_E6_CH-1_COUNT	N	ADV
264	NFO_TW-6_171_MPR_E6_CH-1_GRADE	N	ADV
265	PRI_166A_CH-1_COUNT	N	PRI
266	PRI_166A_CH-1_GRADE	N	PRI
267	PRI_166A_CH-2_COUNT	N	PRI
268	PRI_166A_CH-2_GRADE	N	PRI
269	PRI_166B_COUNT	N	PRI
270	PRI_166B_GRADE	N	PRI
271	PRI_TW-5_166A_COUNT	N	PRI
272	PRI_TW-5_166A_GRADE	N	PRI
273	PRI_TW-5_166A_Top-offs_CH-1_COUNT	N	PRI
274	PRI_TW-5_166A_Top-offs_CH-1_GRADE	N	PRI
275	PRI_TW-5_166A_Top-offs_COUNT	N	PRI
276	PRI_TW-5_166A_Top-offs_GRADE	N	PRI
277	ID_CODE	U	PRE
278	AER1	N	API
279	AER2	N	API
280	AWX1	N	API
281	ENG1	N	API
282	FRR1	N	API
283	NAV1	N	API
284	ID_CODE	U	PRE
285	PRE_COUNT (calculated)	N	PRE
286	ASTB_COUNT (calculated)	N	ASTB
287	IFS_COUNT (calculated)	N	IFS
288	API_COUNT (calculated)	N	API
289	PRI_COUNT (calculated)	N	PRI
290	PRI_ACADEMIC_AV (calculated)	N	PRI
291	PRI_FLIGHT_AV (calculated)	N	PRI
292	PRI2_COUNT (calculated)	N	PRI2
293	INT_COUNT (calculated)	N	INT
294	INT_ACADEMIC_AV (calculated)	N	INT
295	INT_FLIGHT_AV (calculated)	N	INT
296	ADVCORE_COUNT (calculated)	N	ADVCORE
297	ADV_COUNT (calculated)	N	ADV
298	ADV_ACADEMIC_AV (calculated)	N	ADV
299	ADV_FLIGHT_AV (calculated)	N	ADV
300	FRS_COUNT (calculated)	N	FRS

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