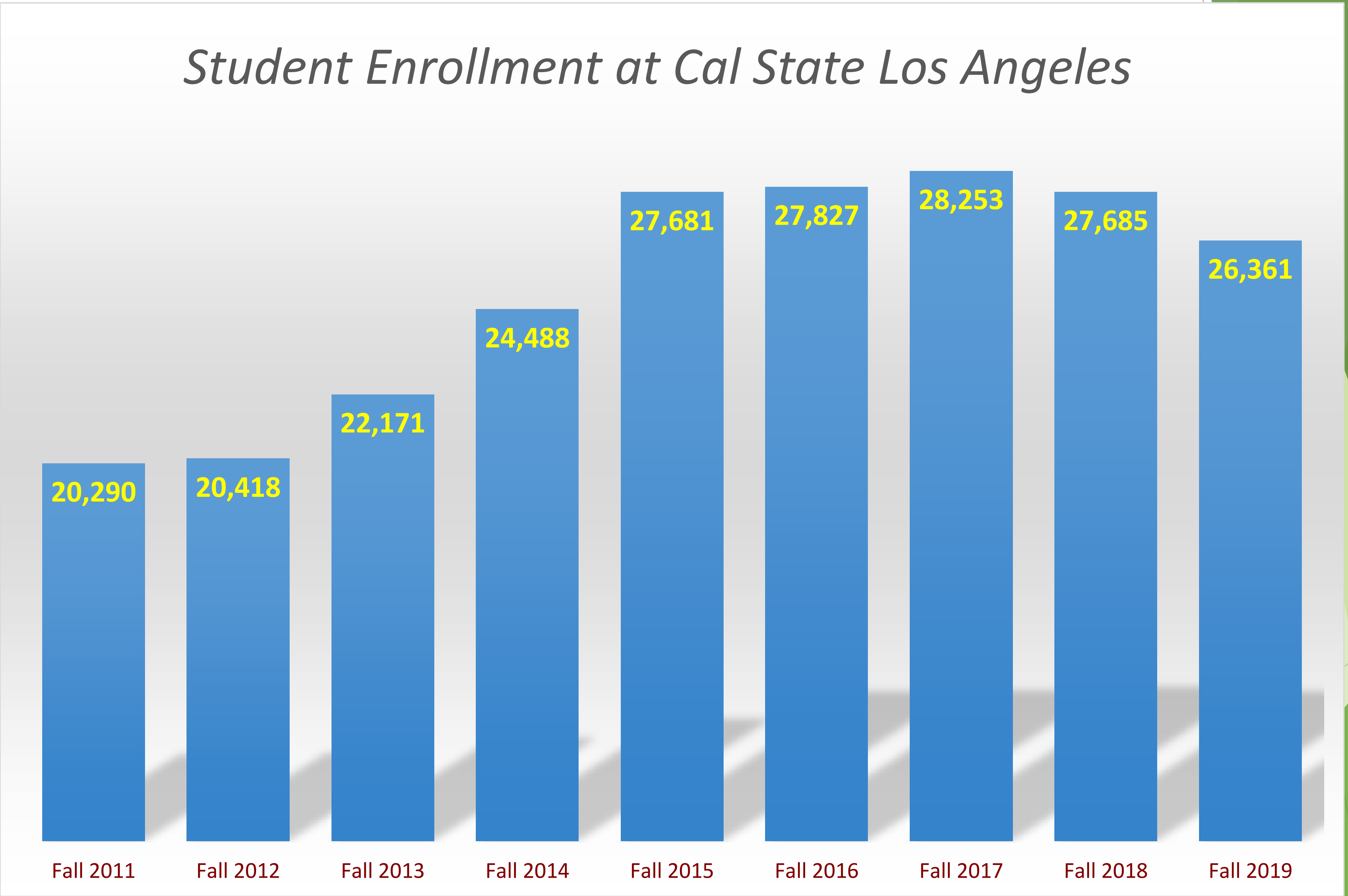
# Enrollment Modeling with Machine Learning Algorithms

Su Seon Yang & Sunny Moon

Institutional Effectiveness

California State University, Los Angeles


Student Enrollment at Cal State Los Angeles
20,290
20,418
22,171
24,488
27,681
27,827
28,253
27,685
26,361
Fall 2011
Fall 2012
Fall 2013
Fall 2014
Fall 2015
Fall 2016
Fall 2017
Fall 2018
Fall 2019

| Prediction | | |
|---|---|---|
| New | FTF | 2) New Student Model |
| | Transfers | |
| | PB | |
| | Graduate | |
| Returning | UG | |
| | PB | |
| | Graduate | |
| Transitory | UG | |
| | PB | |
| | Graduate | |
| Continuing | UG | 1) Continuing Student Model |
| | PB | |
| | Graduate | |

# 1) Continuing Student Enrollment Predictive Model

# 1-1. Design of Continuing Student Enrollment Modeling

Fall semester | Spring semester | Fall semester

**Demographic info**

Gender
Race/Ethnicity
Residence
Age
First Generation

**Retention Status**
**1 - Retained,**
**0 - Not Retained**

**Academic info**

Full-time/Part-Time
Matriculation
Enrollment Type
Current GPA
Cumulative GPA
Total Cumulative Units
College → College Change

Department Change
Plan Change
Enrollment Status
Apply for Graduation

**Financial info**

# of Pell received since matriculation

# 1-2. Steps of Continuing Student Enrollment Modeling

- Data used: Fall 2017 students (28,253) and their Spring 2018 information
- Dependent variable: Retention status (1: Yes, 0: No) at Fall 2018
- Data preprocessing:
  - Dummy variable creation for categorical variables
  - Missing data imputation using MICE – 41 Matriculation info are replaced
  - Feature scaling using Min-Max Scalar
  - Oversampling using SMOTE (1: 65.8% / 0: 34.2%)
- Feature (Independent Variable) Selection
  - Univariate selection
  - Recursive feature elimination
  - Boruta
  - In-built feature importance (using Tree-based)
- Predictive Model Development
  - Logistic Regression
  - XGBoost
  - Random Forest
  - Neural Network
- Model Evaluation: Receiver Operating Characteristic (ROC) Curve

# 1-3. Feature (Independent Variable) Selection

## 1. Univariate selection

| Variable | Score |
|---|---|
| APPLY_GRADUATION_YES | 5558.937264 |
| ENR_SP_NOT-ENROLLED | 2751.930063 |
| ENR_TYPE_New transfer | 571.435326 |
| FTPT_PART-TIME | 316.071119 |
| ENR_TYPE_First-time freshman | 226.951868 |
| ENR_TYPE_Continuing UG | 138.038118 |
| ENR_TYPE_New GRAD | 111.795063 |
| TOT_CUMULATIVE | 111.436214 |
| C_PELL | 102.566199 |
| RACE_ETH_WHITE | 56.696445 |
| ENR_TYPE_Transitory UG | 44.406907 |
| AGE | 30.244531 |
| COLL_ED | 23.383476 |
| RACE_ETH_HISP | 19.403433 |
| FIRST_GEN_Unknown | 17.647793 |
| COLL_ET | 16.093830 |
| CUR_GPA | 15.327322 |
| MAJ_CHANGE_NO CHANGE | 11.456142 |
| FIRST_GEN_Parent Graduated College | 10.389122 |
| DEPT_CHANGE_NO CHANGE | 9.070429 |
| ENR_TYPE_Continuing PB | 8.672398 |
| COLL_HHS | 8.172547 |
| RACE_ETH_BLACK | 8.051507 |
| COLL_UN | 7.880994 |
| COLL_BE | 6.584027 |
| CUM_GPA | 5.748966 |
| RACE_ETH_UNK | 4.307901 |
| ENR_TYPE_Returning PB | 3.456677 |
| RACE_ETH_INTERNATIONAL | 2.716553 |
| COLL_CHANGE_NO CHANGE | 2.436400 |
| RACE_ETH_PACIF | 1.522056 |
| COLL_NSS | 0.860046 |
| ENR_TYPE_Returning UG | 0.821817 |
| ENR_TYPE_New PB | 0.787612 |
| RESIDENCE Resident | 0.460874 |

## 2. RFE

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(1, 'APPLY_GRADUATION_YES'),
(1, 'CUM_GPA'),
(1, 'CUR_GPA'),
(1, 'ENR_SP_NOT-ENROLLED'),
(1, 'ENR_TYPE_Continuing UG'),
(1, 'ENR_TYPE_New transfer'),
(1, 'ENR_TYPE_Returning UG'),
(1, 'ENR_TYPE_Transitory UG'),
(1, 'TOT_CUMULATIVE'),
(2, 'ENR_TYPE_First-time freshman'),
(3, 'ENR_TYPE_New GRAD'),
(4, 'ENR_TYPE_Returning GRAD'),
(5, 'MAJ_CHANGE_NO CHANGE'),
(6, 'COLL_CHANGE_NO CHANGE'),
(7, 'ENR_TYPE_Continuing PB'),
(8, 'RACE_ETH_PACIF'),
(9, 'COLL_ED'),
(10, 'C_PELL'),
(11, 'DEPT_CHANGE_NO CHANGE'),
(12, 'COLL_UN'),
(13, 'COLL_BE'),
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(15, 'AGE'),
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(17, 'ENR_TYPE_Returning PB'),
(18, 'RACE_ETH_ASIAN'),
(19, 'RACE_ETH_TWO RACES'),
(20, 'RACE_ETH_HISP'),
(21, 'RACE_ETH_UNK'),
(22, 'RACE_ETH_BLACK'),
(23, 'RACE_ETH_INTERNATIONAL'),
(24, 'COLL_HHS'),
(25, 'MATRIC'),
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(27, 'SEX_M'),
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## 3. Boruta

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(1, 'AGE'),
(1, 'APPLY_GRADUATION_YES'),
(1, 'CUM_GPA'),
(1, 'CUR_GPA'),
(1, 'C_PELL'),
(1, 'DEPT_CHANGE_NO CHANGE'),
(1, 'ENR_SP_NOT-ENROLLED'),
(1, 'ENR_TYPE_Continuing UG'),
(1, 'ENR_TYPE_First-time freshman'),
(1, 'ENR_TYPE_New GRAD'),
(1, 'ENR_TYPE_New transfer'),
(1, 'FTPT_PART-TIME'),
(1, 'MAJ_CHANGE_NO CHANGE'),
(1, 'MATRIC'),
(1, 'TOT_CUMULATIVE'),
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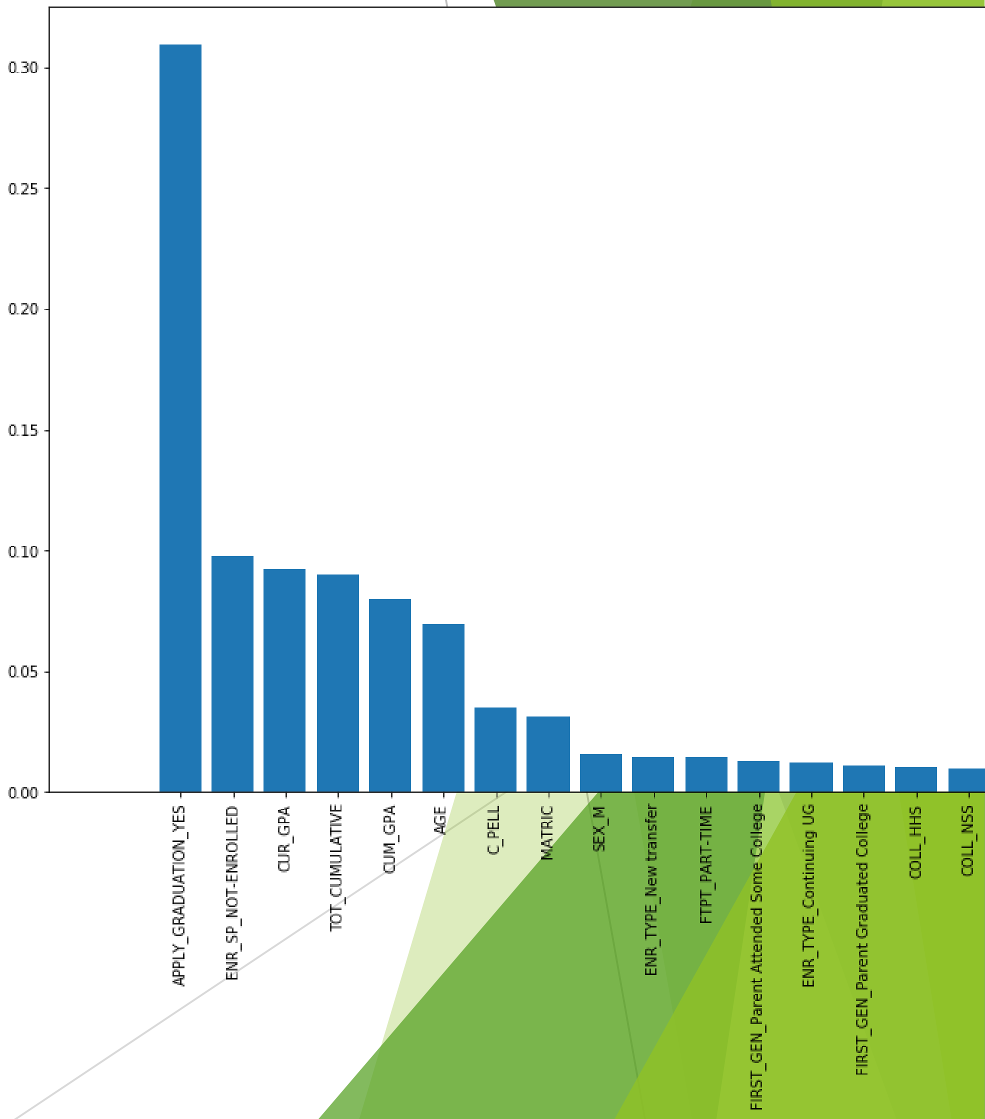
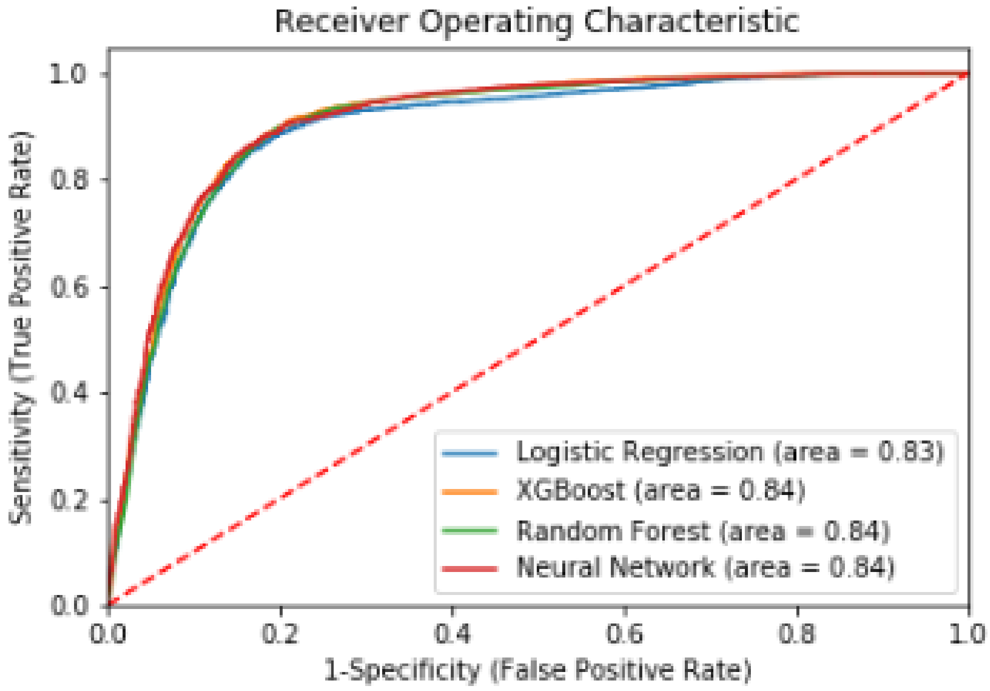
## 4. In-built feature selection



# 1-4. Model Evaluation for Fall 2018 Prediction




W/ Standardization,
Feature selection by Boruta (*k* = 15)

# 1-5. Fall 2019 Prediction Result

- Note that Matriculation plays an important role in this prediction model.
- Out of 27,685 Fall 2018 FTF, 62 students have missing Matriculation. Thus, they are excluded in this prediction.

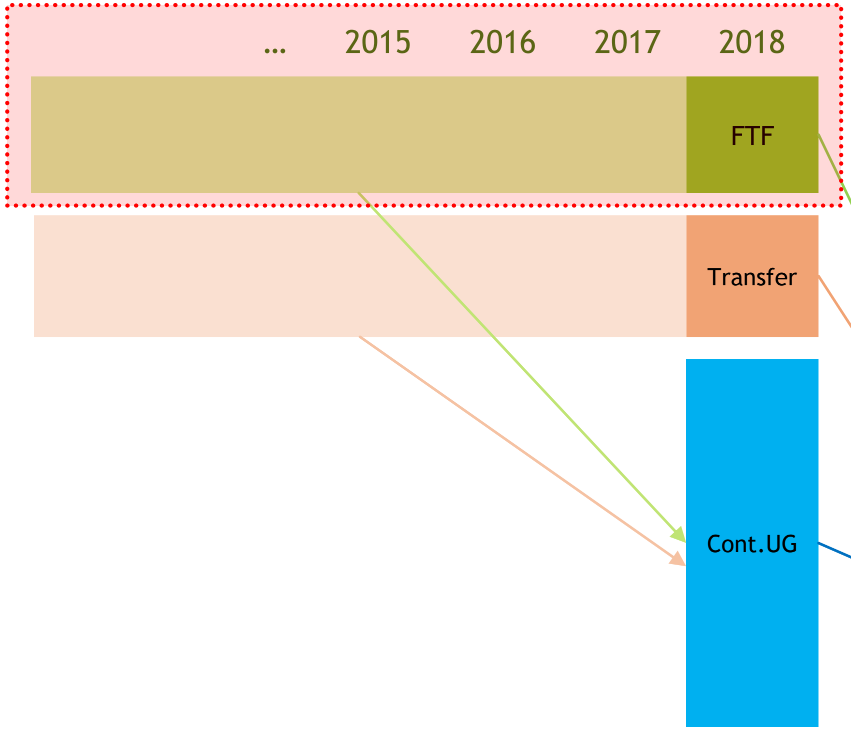
| Metric (Y=1) | Logistic Regression | XG Boost | Random Forest | Neural Network |
|---|---|---|---|---|
| Precision | 0.85 | 0.86 | 0.85 | 0.85 |
| Recall | 0.96 | 0.78 | 0.92 | 0.97 |
| F1 | 0.90 | 0.82 | 0.88 | 0.90 |
| FP rate | 0.30 | 0.23 | 0.30 | 0.31 |

| Student Level | Fall 19 Census Data | Logistic Regression | XG Boost | Random Forest | Neural Network |
|---|---|---|---|---|---|
| UG | 16,069 | 17,839 | 15,284 | 17,204 | 17,895 |
| PB | 458 | 596 | 288 | 552 | 649 |
| Graduate | 1,858 | 1,571 | 583 | 1,495 | 1,642 |
| Total | 18,385 | 20,006 (108.8%) | 16,155 (87.9%) | 19,251 (104.7%) | 20,186 (109.8%) |

# 1-6. Limitations

- Student groups in continuing-type enrollment model are too broad.
  - It is very hard to determine independent variables, which play an important role over all student groups.
- Next Step
  - Separate student groups into sub-groups: FTF, Transfer, PB and Graduate
  - Add independent variables for each sub-group (ex. FTF)
    - Pre-College: SAT, High School GPA
    - Academic: Unit-load (per 1year), GPA trend, etc.

# What if we focus on FTF in Continuing Student Enrollment Model?




| Prediction | |
|---|---|
| FTF | New |
| Other UG | New |
| PB | New |
| Graduate | New |
| UG | Returning |
| PB | Returning |
| Graduate | Returning |
| UG | Transitory |
| PB | Transitory |
| Graduate | Transitory |
| UG | Continuing |
| PB | Continuing |
| Graduate | Continuing |

# Fall 19 Prediction Result (FTF focus)

- SAT score plays an important role in this prediction model.
- Out of 3,862 Fall 2018 FTF, 6 students have missing SAT score. Thus, they are excluded in this prediction.

| Retention Status | XG Boost | Random Forest | Actual Data |
|---|---|---|---|
| 1 (Yes) | 2,834 | 3,040 (98.6%) | 3,084 |
| 0 (No) | 1,022 | 816 | 772 |

# 2) New Student Enrollment Predictive Model

# 2-1. Design of New Student Enrollment Modeling

Application cycle

Fall semester

**Demographic info**

Gender
Race/Ethnicity
Local/Non-local
Age
First Generation
Commuting Distance to Campus

**Enrollment Status**
**1 - Enrolled,**
**0 - Not Enrolled**

**Academic info**

Student Type
College
Department
Study of Field

Admission Decision

ECD

Orientation

**Financial info**

Pell Eligibility

# 2-2. Steps of New Student Enrollment Modeling

- Data used: Fall 2018 Application data (*n* = 67,256)
- Dependent variable: Enrollment status (1: Yes, 0: No) at Fall 2018
- Goal is to *predict as many enrolled students as possible (high sensitivity) while to reduce false-positive rate*.
- Data preprocessing:
  - Dummy variable creation for categorical variables
  - Missing data imputation using MICE
  - Feature scaling using Min-Max Scalar
  - Oversampling using SMOTE (1: 13% / 0: 87%)
- Feature (Independent Variable) Selection
  - Univariate selection
  - Boruta
  - In-built feature importance (using Tree-based)
- Predictive Model Development
  - Logistic Regression
  - XGBoost
  - Random Forest
  - Neural Network
- Model Evaluation
  - Receiver Operating Characteristic (ROC) Curve
  - Confusion Matrix

# 2-3. Feature (Independent Variable) Selection

## 1. Univariate selection

| Variable | Score |
|---|---|
| ORIENTATION_Y | 26586.499933 |
| ECD_Y | 22110.252919 |
| ADMITTED_Y | 3198.119305 |
| LOCAL_FLAG_Y | 1797.766336 |
| PELL_ELIG_Y | 1573.632203 |
| ADMITTED_Not Available | 640.306725 |
| ECD_Not Available | 640.306725 |
| LOCAL_FLAG_Not Available | 505.903662 |
| COLL_ED | 451.014388 |
| STUDY_FIELD_EDUCATION. | 428.490543 |
| DEPT_EDUCD | 407.006231 |
| STDNT_TYPE_New GRAD | 278.500345 |
| DEPT_AASE | 194.553631 |
| STDNT_TYPE_New PB | 181.214030 |
| STDNT_TYPE_Returning UG | 157.291724 |
| FIRST_GEN_Parent Graduated College | 83.345275 |
| DEPT_COMD | 71.817559 |
| DEPT_EDCI | 71.326500 |
| DEPT_CFS | 70.473077 |
| RACE_ETH_HISP | 67.036327 |
| STDNT_TYPE_New transfer | 66.823601 |
| FIRST_GEN_Unknown | 61.824399 |
| DIST | 59.128706 |
| STUDY_FIELD_PUBLIC ADMINISTRATION AND SOCIAL S... | 57.888482 |
| RACE_ETH_BLACK | 57.859243 |
| RACE_ETH_WHITE | 56.935698 |
| STUDY_FIELD_PSYCHOLOGY. | 52.098972 |
| DEPT_PSY | 51.761239 |
| DEPT_EDD | 49.031463 |
| COLL_NSS | 46.596511 |

## 2. Boruta

```
(1, 'ADMITTED_Not Available'),
(1, 'ADMITTED_Y'),
(1, 'AGE'),
(1, 'COLL_ED'),
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(1, 'COLL_NSS'),
(1, 'DEPT_AASE'),
(1, 'DEPT_COMD'),
(1, 'DEPT_EDSC'),
(1, 'DEPT_EDUCD'),
(1, 'DIST'),
(1, 'ECD_Not Available'),
(1, 'ECD_Y'),
(1, 'FIRST_GEN_Parent Graduated College'),
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(1, 'LOCAL_FLAG_Y'),
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(1, 'PELL_ELIG_Y'),
(1, 'RACE_ETH_BLACK'),
(1, 'RACE_ETH_HISP'),
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(1, 'STDNT_TYPE_New transfer'),
(1, 'STDNT_TYPE_Returning UG'),
(1, 'STUDY_FIELD_EDUCATION.'),
(1, 'STUDY_FIELD_PUBLIC ADMINISTRATION AND SOCIAL SERVICE PROFESSIONS.'),
```
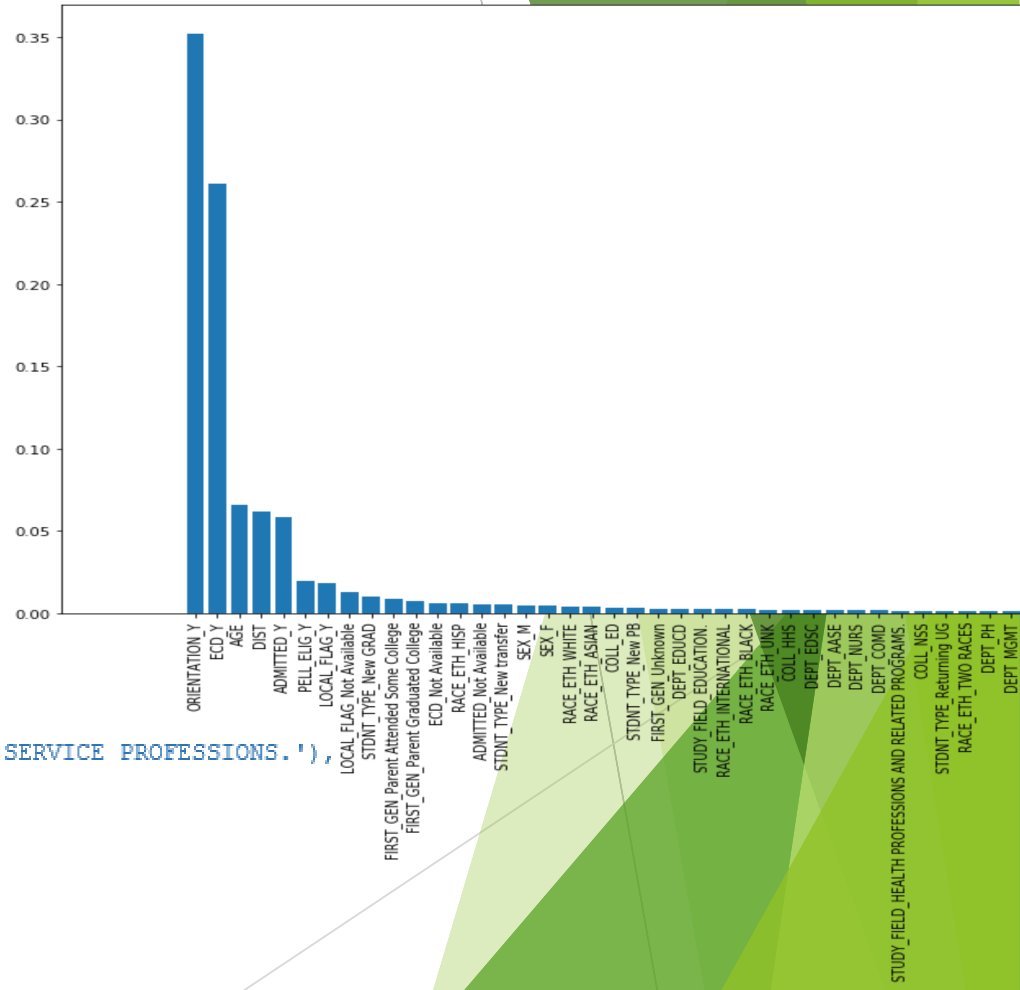
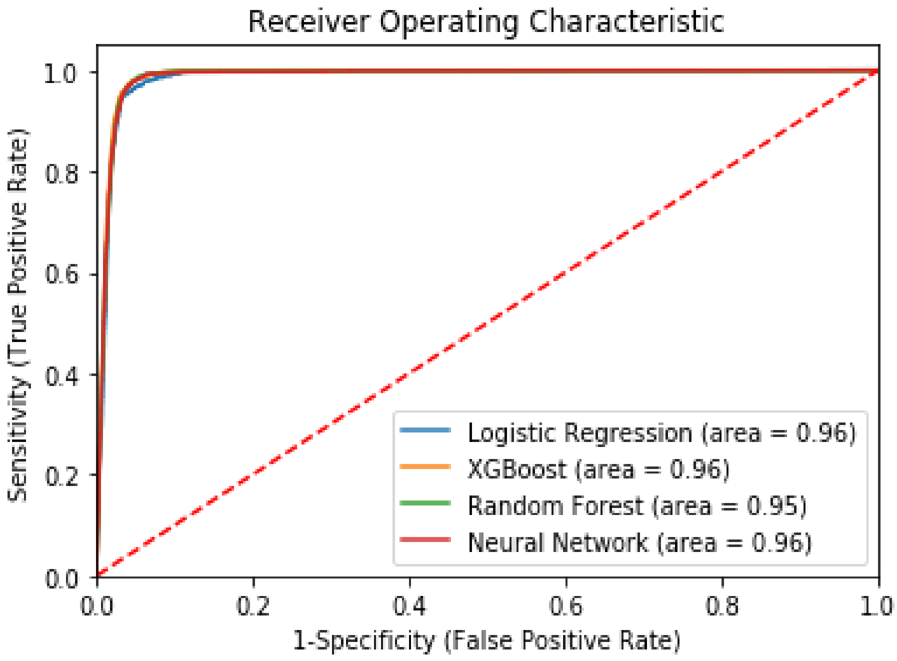

## 3. In-built feature selection



# 2-4. Model Evaluation for Fall 2018 Prediction




W/ Standardization,
Oversampling,
Feature selection by Boruta (*k* = 27)

| Metric (Y=1) | Logistic Regression | XG Boost | Random Forest | Neural Network |
|---|---|---|---|---|
| Precision | 0.79 | 0.81 | 0.82 | 0.81 |
| Recall | *0.96* | *0.96* | *0.93* | *0.95* |
| F1 | 0.86 | 0.88 | 0.87 | 0.88 |
| FP rate | *0.04* | *0.03* | *0.03* | *0.03* |

# 2-5. Fall 2019 Prediction Result

| Metric (Y=1) | Logistic Regression | XG Boost | Random Forest | Neural Network |
|---|---|---|---|---|
| Precision | 0.86 | 0.86 | 0.87 | 0.86 |
| Recall | *0.87* | *0.88* | *0.87* | *0.88* |
| F1 | 0.87 | 0.87 | 0.87 | 0.87 |
| FP rate | *0.02* | *0.02* | *0.02* | *0.02* |

| Enrollment Status | Student Level | Fall 19 Census Data | XG Boost | Neural Network |
|---|---|---|---|---|
| New | FTF | 2,480 | 2,794 | 2,762 |
| | Transfer | 1,734 | 1,948 | 1,969 |
| | PB | 197 | 116 | 106 |
| | Graduate | 413 | 111 | 89 |
| Returning | UG | 157 | 172 | 171 |
| | PB | 10 | 17 | 11 |
| | Graduate | 58 | 20 | 16 |
| Transitory | UG | 10 | 19 | 22 |
| | PB | 2 | 2 | 2 |
| | Graduate | 0 | 0 | 0 |
| Total | | 5,061 | 5,199 (102.7%) | 5,148 (101.7%) |

# Comparison and Future Steps

## Enrollment Model using Machine Learning Algorithm

- Separate student groups into sub-groups: FTF, Transfer, PB and Graduate
- Add independent variables for each sub-group (ex. FTF)
  - Pre-College: SAT, High School GPA
  - Academic: Unit-load (per 1year), GPA trend, etc.

## Traditional Model #1

- Aggregate Model
  - Based on trend of previous year
  - Matriculation Type
  - Currently used

## Traditional Model #2

- Aggregate Model: Matriculation Decay
  - Based on trend of previous year
  - Matriculation Type
  - Matriculation Term