# When They Will Pay: Understand Deposit Decisions in College Admission

## Introduction

Motivation Recruitment of new students is a challenging task of enrollment management for many institutions of higher education, since they need to meet revenue goals, ensure academic ability and promote diversity of the student body (Adams-Johnson et al. 2019; Maldonado, Armelini, and Guevara 2017). The recruitment process includes several general stages, searching and answering inquries of propsective applicants, reviewing application materials and making admission decisions, encouraging admitted students to pay deposits, and assisting with students' matriculation. This project focuses on the deposit stage where students' choices play an important role. Understanding students' decision to pay deposits can help institutions to design marketing and recruitment strategies (DesJardins 2002; Johnson 2019).

Summary of previous studies Previous studies have provided valuable insights on improving recruitment efforts by investigating various factors which could affect admission outcome. DesJardins (DesJardins 2002) used predictive models to segment students, so enrollment managers could focused on student groups of interest who have similar probabilities to enroll or not. Maldonado et al. (Maldonado, Armelini, and Guevara 2017) developed nested logit models to predict students' enrollment probabilities, and the decision makers utilized the models to allocate resources for admission activities. Goenner and Pauls (Goenner and Pauls 2006) predicted the enrollment probabilities of inquirers to help University of North Dakota allocate recruitment efforts by geographic areas. Braunstein et al. (Braunstein, McGrath, and Pescatrice 1999) focused on the factors related to student financials on enrollment decisions of admitted students, so the particular institution can understand the effects of various financial aids and how they affect students differently from various socio-economic backgrounds. Johnson (Johnson 2019) studied various factors associated with enrollment decisions of out-of-state students with multiple potential destinations and provided insights on why the students accepted their offer of admission or chose another instittion.

Difference from previous studies The previous studies however made two implicit assumptions. One was all factors had time independent values, and the other

was all factors had time independent effects. Indeed, many factors related to admission process are time independent, e.g., racial ethnicity and HS GPA, but others may easily violate the assumption, e.g., institutional financial aid offered and student loan borrowed. On the other hand, even time independent factors could have time varying effects. For example, Pell eligible students are more likely to pay deposit when they had to, i.e., when deposit deadline approaches, so Pell eligibility does not matter in the early admission season but is important later. As a result, the colleagues of the Admission Office want to understand not only whether a factor could affect students' decisions, but also how the factor affect decisions in different time periods. Moreover, the Admission Office pay a lot of attention to deposit paid before considering about matriculating students, so it is useful to model students' decision to pay deposit, rather than modeling enrollment decisions directly.

Contribution of this study This study provides new insights in factors affecting admission outcome to help with recruitment efforts. First, we model students' journey from being admitted to deciding to pay deposit. Event history analysis is used to model the admission journey, similar to those modeling students' journey from matriculation to graduation (Gross, Torres, and Zerquera 2013; Zhan, Xiang, and Elliott III 2018; Chen and Hossler 2017). However, instead of using the popular proportional hazard models, we developed stepwise exponential models to accommodate time varying factors and time varying effects. We further introduce Bayesian Hierarchical framework to event history analysis. The framework provides balance between overfitting and underfitting, so true timevaring effects are not exaggerated by noise in observed data or ignored by model assumptions. Second, we model deposit decisions instead of enrollment decisions. Although enrollment decision is the final outcome of interest, in practice the Admission Office need to work sequentially to encourage paying deposits and then to prevent withdrawal of deposits (which they call "summer melt"). They would like a tool to understand whether/how factors affect deposit decisions. Third, we include student activities as surrogates of students' interests to the admission offers, in addition to the factors usually included in previous research such as demographic characteristics, socio-economic background, high school academic performance and student financials. More specifically, we investigate the effects of factors related to students' activities on the admission websites and campus visits.

Summary of results In this paper, we implement Bayesian hierarchical event history analysis

# Theoretical Backgound and Pratical Application

#### **Admission Funnel**

An admission funnel invovles six processes, prospects, inquiries, applicants, admits, deposits and enrolls (**stonybrook?**). In the prospect stage, the admission office search for high school students who might be interested to the institution. In

the inquiry stage, the admission office communicate with students who expressed interest, attempt to further enhance their interest, and encourage them to apply. In the applicant stage, the admission office notify students with incomplete application forms, process and review completed applications. In the admit stage, the admission office make decisions to offer admission, put students on a wait list, or reject applications. In the deposit stage, the admission office prepare financial aid packages and collaborate with other offices to interact with admitted students in campus tours and other programs, in order to encourge the students to accept the offers. In the enroll stage, the admission office continue to engage with students and collaborate with other offices to help with new student orientation, course registration and on-campus residency. There are several important rates to monitor in the admission funnel, conversion rate, selection rate, yield rate and melt rate (ruffalonl?). Conversion rate is The proportion of applicants from inquiries. Selection rate is the proportion of admits from applicants. Yield rate is the proportion of deposits from admits. Melt rate is the proportion of enrolls from deposits. With melt rate typically closed to 1 or 100% at the University of Delaware, the deposit stage or yield rate largely determines the number of new students we will have.

#### College Choice

## Conceptual Framework

Our conceptual framework is developed from the theory of college choice (Chapman 1979: Hossler, Braxton, and Coopersmith 1989). The studies tried to understand students' enrollment decisions with their individual characteristics and preferences. Students decide whether to pay deposit, according to economic, sociological, and psychological factors (Paulsen 1990). Based on the theory of human capital (Becker 2009), the economic factors help students evaluate whether an institution provides the highest potential benefit versus cost. From sociological perspective, students choose the best institution for status attainment (Hossler, Schmit, and Vesper 1999), and the choice is affect by their sociological background (Johnson 2019). The psychological factors impact students' opinions on institutional environment and climate, and students decide whether it is a good fit to the institution (Paulsen 1990). We hypothesis that these factors not only affect students' decision to pay deposit, but also when they would like to pay deposit, i.e., these factors could also affect students' speed to make decisions. For admitted students, they are willing to pay deposits sooner than later if they are admitted to an institution with the best potential investment, status attainment, and/or student-institution fit.

With the guidance of the college choice theory and previous studies, we form the variable pool to reflect the three kinds of factors. The economic factors include institutional financial aid offered, Pell eligibility, expected family contribution (EFC), and time spent on student finance service (SFS) websites. Financial aids affect students' choice by reducing the cost of attendence. The grants and scholarships can be from federal, state or institution. We do not include

federal grants, because few students obtained federal grants by the end of deposit deadline. We do not include state scholarships, because they do not apply to non-Delawarean students. Pell eligibility is a good indicator for federal grants, because most Pell eligible students eventually obtain the federal Pell grants. In addition, both Pell eligibility and EFC indicate students' sensitivity to cost and financial aids. The time spent on SFS websites reflects students' efforts to evaludate the economic impact to attend the institution. The sociological factors include gender and ethnicity. The psychological factors include the period to receive admission offer, whether admitted to the Honor College, whether applied major and admitted major are different, loan borrowed, time spent on major finder websites, whether attended recruitment events, and whether postpone to review admission decision.

#### Data and Variables

Admit, deposit and yield trend Data for this study were pulled from a data reporting platform of the University of Delaware (UD), a public research university (Carnegie classification: R1) with a population of about 18,000 undergraduate students. We collected the weekly admission data of out-of-state applicants between late February and early May from Fall 2012 to Fall 2019. We chose late February as the starting point, because most admission decisions were made by the Admission Office by then and the Budget Office began to review the budget plan for the coming fiscal year. Most students paid deposit in early May if they accepted UD's offer, so we used it as the end point. Table 1 shows the number of admits and deposits by May 1 of each year. The number of admitted out-of-state students gradually increased from about 12,500 to about 15,000 from 2012 to 2019, and the number of deposited out-of-state students fluctuated between 2200 and 2900. Figure 1 shows yield by week for Fall 2017, Fall 2018 and Fall 2019. Week 11 always represents May 1, and Week 1 represents 70 days before May 1, which is in late Feburary. For all three falls, the yields increase slowly in early weeks in February and March, increase faster in April, and jump in the last week of April. The yield trends are more similar between Fall 2017 and Fall 2018, and the gap is larger between the trends of Fall 2018 and Fall 2019. Overall the sequence of week is a strong predictor for yield, and thus is used as an independent variable in the models.

Student attributes In addition to the sequence of week, student attributes are also included in the initial list of variables to predict yields. Table 2 describes the dependent and indepent variables in the models, and Table 3 shows the descriptive statistics of the variables. The depedent variable is whether a student will pay deposit. The independent variables include the student's demographic information, high school information, financial background, financial aid information. We further include interaction between financial aid and some other variables such as the interaction between institutional aid rate and estimated family contribution (EFC) rate, because we suspect the effect of institutional aid rate can be affected by other variables.

## Variable Selection

From the initial list of predictors, we select a subset with consistently high predictive powers and use them as input of the subsequent models. First, we randomly draw samples with replacement from a fall's data with date being May 1. Second, we fit LASSO regression to predict yield and record which variables are selected and the corresponding coefficients. Third, we repeat the previous two steps 200 times, so we can calculate the probability of each variable being selected for the fall. The higher the probability is, the higher predictive power a variable has. Fourth, we repeat the previous three steps for each fall, so we know which variables tend to have high predictive powers over years. We select Yield from major, HS GPA, Feeder HS, Institutional aid rate, EFC rate, African American, Asian, White, and Inst\*EFC. Fifth, we exclude variables with high variance of coefficients. Even a variable is selected for each fall, the high variance of coefficient indicates the predictive power is not consistent, so it will hurt the predictive performance when a trained model is applied to a test dataset. In this case, we calculate the average coefficients for selected variables from last step for each fall, and the calculate the standard deviation of the average coefficients. All variables show relatively small standard deviation except Yield from major which has standard deviation larger than 1, so we exclude Yield from major. Therefore, the final list of predictors are HS GPA, Feeder HS, Institutional aid rate, EFC rate, African American, Asian, White, and Inst\*EFC.

#### Statistical Model

The statistical model is a combination of an expential survival model and a logistic regression model. Equations (1) to (3) describe the prior distribution of unknown coefficients  $\alpha_t$ ,  $\beta_t$  and  $\beta_j$ , where j is from 1 to 8.

$$\alpha_{t} \sim \text{Normal}(\mu_{\alpha}, \sigma_{\alpha})$$

$$(1) \qquad \beta_{t} \sim \text{Normal}(\mu_{\beta}, \sigma_{\beta})$$

$$(2) \qquad \beta_{j} \sim \text{Normal}(\mu_{j}, \sigma_{j})$$

$$(3) \qquad \theta_{i} = exp(\beta_{t} * (week_{i} - \alpha_{t})) * (1/(1 + exp(-\Sigma_{j}(\beta_{j} * X_{ij}))))$$

$$(4) \qquad y_{i} \sim \text{Bernoulli}(\theta_{i})$$

$$(5)$$

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