College students are enrolled at each semester with either part-time or full-time status. While most of the students keep an overall constant enrollment status during their education period, some of them may frequently change their status between full time and part time from one semester to the next. The goal of this research is to exploit the historic patterns to estimate and categorize students’ strategy in three different groups of part time, full time and mixed, investigate the educational features of each group and compare their performance. Enrollment strategy refers to the student’s mindset for enrolment plan and in one way can be captured from the student’s historic enrollment status. Data is collected from the University of Central Florida from 2008 to 2017 and Hidden Markov Model is applied to identify different types of student strategy. Results show that students with Mixed Enrollment Strategy (MES) have features (ex. time to graduation and graduation/leaving ratio) and performances (ex. cumulative GPA) relatively between students with Full-time Enrollment Strategy (FES) and students with Part-time Enrollment Strategy (PES).
Table 1: Example enrollment status’ over academic career and corresponding enrollment strategies

| student number | enrollment status | enrollment strategy |
|----------------|-------------------|---------------------|
| 1              | F,P,F,F,F        | F,F,F,F,F           |
| 2              | F,P,F,P,P        | M,M,M,M,M           |
| 3              | P,F,P,F,P,P      | P,P,P,P,P           |
| 4              | P,F,F,P,F,P,P    | M,M,M,P,P,P         |

Legend: FT=F, PT=P, FES=F, MES=M, PES=P

college students that attend college utilizing a combination of part-time and full-time enrollment are less likely to drop out and more likely to complete degrees when compared to full-time students.

In this study, we seek to find a more comprehensive means of identifying and clustering students with regards to their enrollment strategy (e.g. part-time, full-time, etc). Unlike a single-period model in which the students’ strategy is equivalent to the observed student status (part-time or full-time), we make use of a multi-period dynamic approach using the Hidden Markov Models. Through application of the model we are able to provide a richer understanding of enrollment strategies, by extending our traditional notions to include not only full-time and part-time enrollment strategies, but also a mixed enrollment strategy. Students who use a mixed enrollment strategy regularly alternate between full-time and part-time status. After categorizing students into three groups of full-time, part-time and mixed enrolment strategy, we examine the student outcomes such as GPA and graduation rate associated with each strategy.

2 Problem statement

We consider the problem of classifying students according to their enrollment strategy as opposed to their enrollment status during any given semester. For many students the distinction between enrollment strategy and actual enrollment is minor. At the University of Central Florida a student is considered as full time student in a given semester if he or she takes more than 12 credits in that semester. For approximately 35% of the student-body at the University of Central Florida, their enrollment status is consistently full-time throughout their academic career, meaning they employ a strategy of enrolling full-time. In contrast, the case for so-called part-time students it is not so clear. In any given semester, about 30% of enrollments are part-time, and yet only 7% of students consistently enroll part-time over their academic career. Enrolling part-time in any given semester is not equivalent to the strategy of consistently enrolling part-time. It follows that just because a student enrolls in a single semester part-time, that does not mean they bear similarity to student’s who consistently enroll part-time.

The goal of this paper is to recognize and report the distinction between a student’s enrollment strategy and enrollment status, and to find a more meaningful way to classify students over their academic career. More specifically, this paper develops a model that takes as its input a sequence of enrollment statuses and returns a sequence of estimated strategies applied over the same time-frame. In recognition that students apply a greater diversity of strategies then just a full-time enrollment strategy (FES) or part-time enrollment strategy (PES), we introduce the notion of a mixed enrollment strategy (MES). For a mixed enrollment strategy, students alternate between part-time and full-time enrollments. Table 1 provides examples of the enrollment status of four different students over their academic career along with the corresponding enrollment strategies. For example, enrollment strategies for student number 1 through number 3 are FES, MES, and PES respectively.

3 Methodology

In this study, we generate and apply a Hidden Markov Model (HMM) to identify students’ enrollment strategy, and to characterize the impact of enrollment strategy on student outcomes. HMM is a statistical model which most application is in speech recognition and image processing [11, 19, 7, 21]. The use of HMM is not new to educational data mining and modeling. Previously it have been used to investigate students’ sequential behaviors, decision-making, and performance [12, 18, 5, 13, 16, 9]. As an example Falakmasir et al. [9], classified students into low-performing and high-performing groups and applied and trained two hidden Markov models for each group separately. For each HMM, they used forward algorithms to compute log-likelihoods for the observation sequences. They continued by applying a linear regression model to explain the difference between the computed log-likelihoods so as to predict post-test scores for the low-performing and high-performing students. Other papers have used HMMs in order to model sequential student behavior. Beal et al [5] colleagues modeled high school students’ actions and behaviors using HMMs. By
estimating HMM parameters with the Baum-Welch algorithm for each student, the authors clustered the students based on the individual transition matrices to assess differences in behavior and achievement of different clusters.

As depicted in Figure 1, similar to ordinary Markov Models, a HMM represents the dynamics of a system as it moves between operating states or modes (e.g. Modes 1, 2, and 3 in the figure). When operating within a state or mode, the system generates state-related output \( O_i \) at each time-step. Unlike Markov Models, in the case of the HMM problem the states are not always directly observable, and as such they can only be estimated by observing a sequence of outputs. For the problem under consideration here, the hidden state corresponds to the enrollment strategy of a student (e.g. full-time enrollment strategy, mixed enrollment strategy, part-time enrollment strategy), and the observations refer to the actualized enrollment in any given semester in the student academic history.

To give a formal definition of Hidden Markov models, we must begin with the following notations: \( Q = \{q_1, q_2, \ldots, q_N\} \) represents the set of \( N \) possible states in the system; \( A = [a_{ij}] \in \mathbb{R}^{N \times N} \) is a transition matrix, where each \( a_{ij} \) denotes the probability of transitioning from state \( i \) to \( j \) at any given time-step; \( O = o_1, o_2, \ldots, o_T \) represents a sequence of observations of length \( T \), each drawn from the set of \( M \) possible observations \( V = \{v_1, v_2, \ldots, v_M\} \); and \( \pi \) represents the distribution of the initial state the system begins in. When a system is operating in a specific state \( q_i \), the output \( o_t \) at any given time \( t \) is generated according to a unique probability distribution denoted as \( B = b_i(o_t) \), the emission probability. In order to generate a HMM to represent student enrollment strategies, we must learn the optimal model parameters \( \lambda = (A, B, \pi) \) that reproduce known observations. The process of learning \( \lambda \) is based on the Baum-Welch algorithm, which is an iterative process that requires calculating the likelihood of any sequence of observations given \( \lambda \), and decoding relationships between observations and hidden variables. As the model is iteratively updated, the likelihood calculations and the decoding is updated.

### 4 Student data records

The study presented in this paper makes use of processed undergraduate student records collected from the University of Central Florida, a large public university in the southeast United States, between the years of 2008 to 2017. The total data-set amounts to approximately 170,000 records. The data set contains a wide variety of information about students at UCF, including but not limited to: (1) demographic information, (2) admission information for students who have been admitted and enrolled, (3) degrees awarded (for bachelor level), (4) courses taken by student at UCF, and (5) family income. Some of the demographic information along with the fraction of students who enroll as full-time and part-time, and admission type (FTIC and transfer) are provided in Tables 2 through 5.

The processed student data includes a unique identifier, along with the student’s observed academic load for semester they enrolled. Synthetic examples are shown in Table 1. For each student their enrollment sequence is ordered from their first observed enrollment to their last observed enrollment without making note of the semester or year. The data
set includes both partial, halted, and graduated enrollment sequences within the indicated 10 years date-range. For the purposes of this study we restrict the problem to enrollment during Fall and Spring semesters, as such information regarding Summer enrollment is excluded when constructing the HMM. It is worth noting that the data-set includes both first-time-in-college students and transfer students.

5 Applying HMM to student data

In applying the HMM model to our problem, we begin by identifying the set of hidden states corresponding to three different enrollment strategies: full-time enrollment strategy (FES), part-time enrollment strategy (PES), and mixed enrollment strategy (MES). The probability a student changes his or her enrollment strategy from one semester to the next is represented using a probability transition matrix $A$. While the probability of observing an enrollment status while using a specific enrollment strategy is given by the emission matrix $B$. Finally, $\pi$ is the probability distribution over the students’ enrollment strategy during their first enrolled semester.

Beginning with an initial guess for $A$, $B$, and $\pi$, the Baum-Welch algorithm is applied to estimate the true model parameter set ($\lambda$). Converging after 20 iterations, the following values for $A$, $B$, and $\pi$ are generated:

$$A = \begin{bmatrix} 0.898 & 0.05 & 0.052 \\ 0.168 & 0.74 & 0.092 \\ 0.007 & 0.12 & 0.873 \end{bmatrix} \quad (1)$$

$$B = \begin{bmatrix} 0.974 & 0.026 \\ 0.611 & 0.389 \\ 0.061 & 0.939 \end{bmatrix} \quad (2)$$

$$\pi = [0.718 \quad 0.113 \quad 0.169] \quad (3)$$

For any two subsequent semesters $t$ and $t + 1$, the rows in the transition matrix $A$ correspond to states FES, MES and PES at semester $t$, while the columns correspond to states FES, MES and PES at semester $t + 1$. Based on the estimated transition matrix $A$, most of the students maintain their enrollment strategy with high probabilities from one semester to the next. Reading the diagonal of the matrix, with 0.898 probability a student employing a FES will continue employing a FES, similarly 0.74 for PES and 0.873 for MES. This indicates that most students maintain a static enrollment strategy, even if it is a mixed one.

For emission matrix $B$, each row corresponds to the probability of full-time and part-time enrollment status in a semester for a given enrollment strategy. Result indicate that students employing FES register full-time with probability 0.974 and as part-time with probability 0.026. While students employing a PES only register full-time with probability 0.061 versus part-time at 0.939. Most interesting are students with MES, as their full-time and part-time enrollment is split between 0.611 and 0.389. The initial probabilities matrix $\pi$ indicates that most of the undergraduate students start their first semester with full-time enrollment strategy (with probability 0.718). Moreover, the probability of being at PES and MES at the first semester are 0.169 and 0.113 respectively.

Table 4: Students admission type distribution at UCF over 10 years

| First-Time-in-College | Transfer |
|-----------------------|----------|
| Percentage            | 39.5%    | 60.5%    |
Table 5: Enrollment type distribution for different semesters at UCF over 10 years

| Semester | Full-time | Part-time |
|----------|-----------|-----------|
| Fall     | 72.4%     | 27.6%     |
| Spring   | 70.6%     | 29.4%     |
| Summer   | 10.0%     | 90.0%     |

Figure 2: Distribution students’ enrollment strategy

6 Results

After estimating model parameters, the next step is to find the strategies (hidden states) for each student in the data set at each semester with the Viterbi algorithm. Based on the estimated hidden states, students are classified into four groups, three of which corresponds to the students who maintain a consistent strategy of FES, PES or MES during their education. The last group corresponds to students who employee a combination of FES, MES and PES over their academic career. Figure 2 shows how students are distributed among these four groups.

Based on Figure 2, most of the students maintain their enrollment strategy during their educational career (Sum of Blue, grey and brown slices, approx. 73.4%). The most prevalent consistent enrollment strategy is FES, followed by PES and MES groups. For those students that change strategies at some point in the academic career, 73% change from FES to PES, and 15% move from PES to MES. For virtually all cases of FES to PES, the majority of students adjust their enrollment strategy during their last two semesters. Anecdotally, it appears this shift is due to course scheduling inefficiencies and early entrance into the work place through co-op placements.

Furthermore, Table 6 represents percentage of different enrollment strategies for male and female students. The percentage of FES, MES, and PES groups for female students are 56.4%, 4.0%, and 15.5% respectively. These ratios for male students are 52.9%, 3.9%, and 14.5% respectively. Proportion hypothesis test is conducted to see if gender impacts students enrollment strategy at UCF. P-values of the tests show that female students are more likely to have full-time enrollment strategy compared to male students. On the other hand, male students statistically have higher chances to apply combinations of all the enrollment strategies (the Other strategy). Also, for MES and PES students, there is no statistical differences between male and female ratios. In fact, For these students, gender is not a influential factor on their enrollment strategies.

Table 7 indicating how students with different ethnicity are distributed among the three enrollment strategy groups. As the table shows, the ratio of students with full-time enrollment strategy for Hispanic and black ethnicity are close together and differs from the ratio for white students. Hypothesis $t$-tests are conducted to assess statistical significance of these differences and the p-value is close to 0, implying the difference in the ratios are statistically considerable.

Clustering of the students based on enrollment strategy (FES, PES, MES), a number of descriptive statistics are calculated. They include family income, average cumulative GPA, graduation rate, and DFW rate. The impact of the family financial status on student enrollment strategy in each group is compared in Figure 3. Based on the result, students with lower family income are more likely to have part-time enrollment strategy compared to students with high family income. Kolmogorov-Smirnov (K-S) test is applied in order to assess if there is statistically significant difference.
Table 6: Female and male ratios for students with different enrollment strategies

| Gender | FES | MES | PES | Other | Population size |
|--------|-----|-----|-----|-------|-----------------|
| Male   | 52.9% | 3.9% | 14.5% | 28.7% | 62157           |
| Female | 56.4% | 4.0% | 15.5% | 24.1% | 68135           |

Table 7: Ethnicity ratios for students with different enrollment strategies

| Ethnicity  | FES | MES | PES | Other | Population size |
|------------|-----|-----|-----|-------|-----------------|
| White      | 56.5% | 3.5% | 13.6% | 26.4% | 71739           |
| Hispanic   | 52.0% | 4.5% | 17.4% | 26.1% | 30843           |
| Black      | 52.9% | 4.4% | 17.8% | 24.9% | 14553           |
| Other race | 53.8% | 4.1% | 14.5% | 27.6% | 13178           |

in family income distribution for students with different enrollment strategy. As shown in Table 8, the hypothesis test results p-values are close to zero for all three group pairs of indicating significant difference in annual family income between students with different enrollment strategies.

The average GPA for each strategy cluster is shown in Figure 4. Results show that the FES group has the highest average GPA. The lowest GPA corresponds to the PES group, while the MES group’s GPA lies in between. To assess if the average GPA for each group are statistically different from the other groups, statistical hypothesis t-tests are conducted. The result shows that the p-values for all the hypothesis tests are nearly to 0, indicating that the average GPA for each group is statistically different from others. The results are summarized in Table 9.

Figure 5 represents average GPA for FES, MES, and PES groups for transferred and FTIC students. FES groups have the highest average GPAs, followed by MES, and PES respectively. Conducted KS2 tests show that for both FTIC and transferred students, GPA distribution for FES, MES, and PES groups statically differ from each other.

Furthermore, inside each strategy cluster, the average GPA during full-time and part-time semesters are calculated. As indicated in Figure 6 (FTIC students), for the FES group, the average GPA for full-time semesters is higher than part-time semesters (3.1 vs 2.82). This indicates that students employing a full-time enrollment strategy, tend not to perform as well when registering part-time. Of interest however, is that for students employing a mixed-enrollment strategy hypothesis tests indicate there is no statistical difference in means between the average GPAs of full-time and part-time semesters; in other words, the semester enrollment status for MES students does not significantly impact their GPAs. While the GPA reductions observed for students employing a full-time enrollment strategy appear reasonable, the lack of GPA drop for mix enrollment strategy students is somewhat surprising, it suggests potential value in encouraging
Table 8: Results for the family income hypothesis tests

| Pair of groups | P-value       |
|----------------|--------------|
| FES and PES    | 0            |
| FES and MES    | $4.4 \times 10^{-95}$ |
| MES and PES    | $2.5 \times 10^{-20}$ |

Figure 4: Average GPA for different enrollment strategies

Table 9: Results for the GPA hypothesis tests

| Pair of groups | P-value       |
|----------------|--------------|
| FES and PES    | 0            |
| FES and MES    | $6.5 \times 10^{-84}$ |
| MES and PES    | $1.82 \times 10^{-86}$ |

Figure 5: Average GPA for FTIC and transferred students with different enrollment strategies
part-time students to occasionally enroll full-time. The same conclusion is observed for students in the PES group, that is, there is no statistical difference in means between the average GPAs of full-time and part-time semesters. In Figure 7 we analyze the same kind of analysis just for transferred students. Based on the figure, FES and PES students have higher GPA when register as full-time compared to when part-time (2.95 > 2.89 and 2.81 > 2.6). However for MES group, there is no statistical difference between GPA for full-time and part-time semesters.

We compare DFW rate for students with different enrollment strategies because it is another indicator of student performance. DFW rate is defined as the number of courses with D, F, and W grades over total number of courses taken by a student. An example of computing DFW rate is provided in appendix. DFW rate whisker plots are shown in Figure 8 for FTIC and transferred students. As the figures show, for both FTIC and transferred students, PES groups have the highest rate of DFW, followed by MES and FES respectively and the differences are statistically significant. Apart from, Figure 9 represent DFW rate that is broken to D, F, and W for FTIC and transferred students separately. Based on the figure, FES students have the lowest rates of D, F, and W grades when compared with MES and PES students.

The next analysis for FTIC and transferred students in term of academic performance is graduation rates. The approach that American universities use to compute graduation rate is six-year graduation rate. Based on federal definition, a program’s graduation rate is the percentage of FTIC students who complete the program within 150% of the standard enrollment time to degree [12]. For example, for a four-year program, students who earn degrees within 6 years are
considered as graduates. In this paper we use two more additional methods to compute graduation rate for two reasons: first, since PES students each semester take less courses compared to FES and MES students, it is more likely for them to finish their program in more than 6 years in comparison to FES and MES students, hence we compute six-year halt rate for FTIC students that is the percentage of FTIC students who halt enrollment at UCF in 6 years. Second, both the six-year graduation and halt rates are defined only for FTIC students, therefore in order to tackle this problem, we use absorbing Markov chain method which can compute graduation rate for both FTIC and transferred students. This approach is explained in appendix as well.

Table ?? shows result of six-year graduation and halt rates for FTIC student who start their education in Fall 2008, 2009, and 2010. Based on the table, PES students have higher six-year halt rate compared to FES and MES students.

Table ?? and ?? show graduation rate and time to finish school (either graduate or halt) for both FTIC and transferred students with different types of enrollment strategies. For each enrollment strategy, column G rate represents graduation rate for students of different academic levels. As we see in the table ?? for FTIC students with any enrollment strategy, higher academic levels correspond to higher graduation rates. For example Senior students have higher graduation rate compared to Junior, Sophomore, and Freshman students. Furthermore, FES students have the highest graduation rate, followed by MES and PES respectively.
Table 10: Graduation rate and time to finish school for FTIC students with different enrollment strategies

| Strategy | States   | G rate | Time to finish |
|----------|----------|--------|----------------|
| FES      | New student | 0.6589 | 9.23           |
|          | Freshman  | 0.6306 | 8.44           |
|          | Sophomore | 0.7773 | 7.59           |
|          | Junior    | 0.9    | 5.96           |
|          | Senior    | 0.9653 | 3.61           |
| MES      | New student | 0.4947 | 9.01           |
|          | Freshman  | 0.4343 | 8.23           |
|          | Sophomore | 0.6360 | 7.97           |
|          | Junior    | 0.7661 | 6.41           |
|          | Senior    | 0.9324 | 4.49           |
| PES      | New student | 0.1242 | 5.02           |
|          | Freshman  | 0.0608 | 3.84           |
|          | Sophomore | 0.1456 | 3.1            |
|          | Junior    | 0.3765 | 4.84           |
|          | Senior    | 0.8235 | 4.82           |

Table 11: Graduation rate and time to finish school for transferred students with different enrollment strategies

| Strategy | States | G rate | Time to finish |
|----------|--------|--------|----------------|
| FES      | New student | 0.7427 | 6.2            |
|          | Freshman  | 0.5752 | 6.12           |
|          | Sophomore | 0.6201 | 6.12           |
|          | Junior    | 0.7317 | 5.36           |
|          | Senior    | 0.8894 | 3.68           |
| MES      | New student | 0.7272 | 7.22           |
|          | Freshman  | 0.6732 | 6.91           |
|          | Sophomore | 0.6445 | 7.26           |
|          | Junior    | 0.7083 | 6.48           |
|          | Senior    | 0.8511 | 4.57           |
| PES      | New student | 0.3571 | 5.79           |
|          | Freshman  | 0.2645 | 4.61           |
|          | Sophomore | 0.1737 | 3.96           |
|          | Junior    | 0.2893 | 4.82           |
|          | Senior    | 0.6063 | 4.82           |

Column *Time to finish* in Table 10 explains expected time that takes for students to finish their school. For example, students in FES group, need on average 9.23 semesters to finish their academic careers (65.89% of these students will graduate and remaining will halt). Time to finish school for PES group is dramatically shorter than FES and MES groups. These can be explained because graduation rate for PES student is 12.42% and most of these students halt with a freshman academic level (Time to halt decreases the *Time to finish*). One the other hand, for students with senior academic levels, given that these students have high graduation rate, *Time to finish* for PES students is greater than FES and MES students (PES student takes fewer course in a given period of time in comparison to MES and FES). Table 11 represents the same indicators in Table 10 but for transferred students. For both FTIC and transferred groups, FES students have the highest graduation rate, followed by MES, and PES respectively. These results are shown in Figure 10.

7 Discussion

In the previous section, we showed that on average, FES students have better academic performance compared to MES and PES students. In this section we validate the results based on students who are classified as *other* students. As mentioned earlier, some students change their enrollment strategies during their academic periods and therefore do not fall in any of the FES, MES, and PES categories.
Graduation rate results showed that PES students are more likely to leave university before graduation. For students who change their enrollment from FES to PES, a question that might arise is whether this change could be a sign of dropout? In order to answer to this question, we compare students persistence of students who switch from FES to PES with students who stay FES. To do this comparison, we have selected students in same colleges with having similar GPA. Results show that for college of science students, from 62 of students who have switched after three FES semesters to PES, 10 students have not registered at UCF after switching (16% dropout). However for students who stay as FES students in the same length period, only 21 out of 3246 have not registered (less than 1% dropout). Results for other colleges are summarized in Table 12. Based on these results, students who switch from FES to PES are more likely to dropout compared to students who stay FES. In fact, switching from FES to PES can be considered as an indication of dropout.

Next, changes in GPA is compared between students who switch their enrollment strategies from FES to PES with students who stay FES. In fact we have two groups of student, students in the first group change their enrollment strategies after three FES semesters to PES, while students in second group keep their enrollment strategies as FES. Students in both groups are selected from same colleges and have similar GPAs at the end of the third semester, that is the semester in which the first group of students change their enrollment strategies to PES. For both groups, we compute the difference between the GPA of the fourth semesters and the average GPA for the first three semesters. For FTIC students, mean of this difference for students who switch from FES to PES is -0.64 and for students who stay FES is +0.44 (Negative means students GPA are decreased after switching to PES). These amounts for transferred students are +0.28 and -0.42 respectively. Figure 11 compares these differences for FTIC and transferred students separately.

There are two approaches to see if the changes in GPA for the both groups is significant. First, hypotheses t-test for mean of GPA before and after switching; and second, two ways ANOVA test. P-value for hypotheses t-tests show that for both FTIC and transferred students, the difference between average GPA of the first three semesters and fourth semester is statistically significant. Also, two ways ANOVA test is conducted to investigate impact of switching enrollment strategy and college on changes in GPA. Linear regression model with interaction is fitted in which the dependent variable is the difference between fourth semester GPA and average GPA for first three FES semesters. This model has two independent variables which are college and switching. Variable switching for a student is equal to 1 if the
Figure 11: comparing changes in GPA between students who switch from FES to PES and students who stay FES for FTIC and transferred students

Table 13: Analysis of variance for the linear regression model for FTIC students

| Source                | DF | Adj SS | Adj MS  | F-Value | P-Value |
|-----------------------|----|--------|---------|---------|---------|
| College               | 7  | 6.388  | 0.9125  | 1.11    | 0.367   |
| Switching             | 1  | 19.995 | 19.9952 | 24.41   | 0.000   |
| College*Switching     | 7  | 9.219  | 1.317   | 1.61    | 0.152   |
| Error                 | 56 | 45.875 | 0.8192  |         |         |
| Total                 | 71 | 82.442 |         |         |         |

The long-term vision of this research is to help identifying strategies that engender student success. Towards that end, this paper examined different enrollment strategies students apply over their academic career. Through application of Hidden Markov Models on a large student data set, we noted three dominant consistent strategies: full-time enrollment strategy, part-time enrollment strategy, and mixed enrollment strategy. The resulting HMM and its application leads to the conclusion that most of the students have a full-time enrollment strategy. When assessing different features of the three different enrollment strategies, we observe that the average GPA for FES students is the highest, followed by MES and PES students. While graduation rates indicate that students employing the PES are more at risk of not

Table 14: Analysis of variance for the linear regression model for transferred students

| Source                | DF | Adj SS | Adj MS  | F-Value | P-Value |
|-----------------------|----|--------|---------|---------|---------|
| College               | 7  | 3.548  | 0.5068  | 0.55    | 0.797   |
| Switching             | 1  | 9.485  | 9.4854  | 10.2    | 0.002   |
| College*Switching     | 7  | 1.747  | 0.2496  | 0.27    | 0.964   |
| Error                 | 62 | 57.639 | 0.9297  |         |         |
| Total                 | 77 | 72.420 |         |         |         |
graduating college. Also, financial analysis shows that there is statistically significant difference between family income distributions for students with different enrollment strategies.

The major contributions of this research is twofold. Firstly, we provide a powerful tool for identifying students enrollment strategy as FES, PES or MES, based on their historical enrollment status. Secondly, our multi-aspect assessments on each group of students, emphasizes the vulnerability of the PES group, while encouraging university to policy-makers identify such students early during their studies and help them shift towards a mixed enrollment strategy by providing them with financial, educational, and social support.

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Table 15 shows the way by which DFW rate is calculated. DFW rate for each student is defined as the number of courses with D, F, and W grades over total number of courses taken by the student.

Table 15: Some examples for calculating DFW rate

| Student | Num. of courses with DFW | Num. of all courses | DFW rate |
|---------|--------------------------|---------------------|-----------|
| 1       | 0                        | 10                  | 0/10      |
| 2       | 4                        | 20                  | 4/20      |
| 3       | 8                        | 30                  | 8/30      |

As it is mentioned earlier, we applied absorbing Markov model to compute graduation rate. This approach is a type of Markov chain in which number of states is finite. Each absorbing Markov chain with t transient states and r absorbing states has a canonical form that is presented in matrix $P$, where $I$ is an $r \times r$ identity matrix, $O$ is a $r \times t$ zero matrix, $R$ is a $t \times r$ matrix that represents transition from the transient states to the absorbing states, and $Q$ is a $t \times t$ matrix that expresses transitions between the transient states.

$$P = \begin{bmatrix} I & O \\ R & Q \end{bmatrix} \quad (4)$$

Each absorbing Markov Chain has two important characteristics which are expected time until absorption ($U$) and probabilities of absorption ($B$) to the absorbing states. These characteristics are computed with Equations 5 and 6.

$$U = N \times 1 \quad (5)$$

$$B = N \times R \quad (6)$$

where

$$N = (I - Q)^{-1}$$

In this problem, the transient states include one dummy state denoting new students and four academic level states consisting Freshman, Sophomore, Junior, and Senior. The two absorbing states are graduate and halt enrollment. Each student first goes to the new student state and then based on his academic level goes to the next corresponding state (For instance, a transferred student who starts his education at UCF with the junior academic level has a transition from new student state to junior state). A transition will be occurred at end of each semester based on students performance during the semester. These transitions are shown on Figure 12.
Figure 12: Markov chain transitions