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Factors and Techniques for Projecting Enrollment

Accurate enrollment forecasting is crucial for effective fiscal and program planning at any higher education institution that relies on revenue generation from student enrollment. Scholars have identified different factors and techniques for forecasting student enrollment. The purpose of this report is to list some of those factors and techniques to provide guidance to the UMass Boston leaders in choosing the factors and a technique that would be appropriate for the institution.

Enrollment projection models are intricate as there are many different factors to consider and techniques to choose from for an accurate estimation. Factors may vary based on the type of the institution (private vs. public), the purpose of the enrollment prediction (budgeting vs. staffing), the types of enrollment (full-time vs. part-time), and so on. Techniques may vary based on the data availability, purpose, population sub-group that behaves differently, an acceptable level of accuracy, and so on. Appropriateness of the factors and techniques may vary from state to state, school to school, or even in different schools in the same city. A list of the underlying factors that drive the quantitative methods of enrollment projection modeling is presented below.

Unmanageable and Manageable Factors

Brinkman & McIntyre (1997)[1] classified the factors affecting enrollment into two primary groups: those that are manageable and those that are not. Unmanageable factors are those "outside the institution that are typically associated with demand analysis," i.e., external environment (Table 1). Manageable factors are the internal actions that are normally in the control of the institution (Table 1).

Table 1: Unmanageable and Manageable Factors

Unmanageable Factors		
Demographic Factors - Population's age structure - Racial and ethnic composition - Skill levels - Prior education experience - Total inhabitants - Shifts in the location and existence of geographical constraints on transportation for the commuter schools	**Economic Factors** - Disposable incomes of potential students - Unemployment rates - The general economic returns to college education - The demand for, and return to, training in specific areas - Economic cycle - Institutions budget	**Action of Competitors** - Substitute institutions' manageable factors, e.g., tuition and fees, financial aid, admissions policies, changes in programs, and when and where they deliver services
Social and Cultural Factors - Change in the role of women in the society - Generational differences in test scores, use of technology, and learning styles	**Public Policy** - Legislatively set tuition and fees - Admissions criteria - Degree requirements - Other policies that alter the public's preferences for higher education generally or for specific institutions	

Manageable Factors		
Pricing - Tuition - Fees - Residence hall costs - Financial aid **Quality of Education** - Student outcome obtained from: - Employment data after graduation - Institution's rating	**Institutional Policies** - Marketing effort - Admission policies and practices - Registration and course enrollment - Academic probation and dismissal policies - Curriculum - Addition and deletion of programs and courses - Length of programs - Location and scheduling of programs	**Campus Climate** - Student and other support services, such as counseling and placement - Adequacy of facilities - The appearance of the campus - The general academic and social environment in which students undergo their college experiences - Anything that may affect how students evaluate the investment and consumption benefits of attending an institution can influence their decisions to attend (or to stay enrolled)

Source: Brinkman, P. T., & McIntyre, C. (1997). Methods and techniques of enrollment forecasting

Other Common Factors

Retention: past trend in retention[2,3] is one of the must-have components as the retained students make up the highest percentage of enrollment.[4] Retention may vary in different colleges in the same institution or different majors within the same college. One model uses a cohort retention method to project the number of returning undergraduate students for upcoming years by using trend analyses that includes predicting the number of continuing students who—1) will be promoted to the next year-in-school, 2) will return in the same year-in-school, and 3) return to the institution after an absence of more than the previous summer session,[5] i.e., re-admitted students.

The Number of High School Graduates: the number of high school graduates[6,7] has an impact on college enrollment. Historical trends and projections of future graduates have been used[8] for enrollment projection. Racial/ethnic categories should be carefully examined for private and public school graduates as they may significantly depend on the population of a region.

Past trends in recruitment[9] and migration statistics such, as state and regional net in-migration and out-migration of students affect student enrollment.[10] The rate of increase in college tuition relative to the growth in family income, trends in federal and state financial aid, and employment prospects of recent graduates are responsible for changing enrollment patterns.[11] The list of factors affecting enrollment can become longer and more complex when various uncertain external factors occur. For example, anti-immigration policies affecting the children from the families of the undocumented immigrants[12] or domestic or international crises and changes in federal or state government policies affecting a given institution.[13]

Commonly Used Techniques

Curve-fitting (trend analyses) and causal models (explanatory, structural, and econometric) are the two quantitative approaches most commonly used for projecting enrollment.[14] The curve-fitting technique has been widely used, especially by the state forecasters, as this technique requires only the historical data, that is, historical information about enrollment patterns (Table 2).[15]

Curve-fitting techniques or trend analyses assume that the effect of political, social and economic trends in student enrollment in the previous years will continue to affect in the future by viewing enrollment as a function of time alone.[16] Although using this technique to find "patterns" is useful when conditions are expected to be alike for example, continuous growth,[17] the causal model is more accurate as it takes the cause and effect relationships between independent factors and enrollment patterns into account (Table 4).[18]

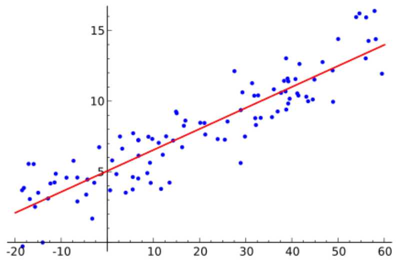
Table 2: List of Commonly Used Curve-Fitting Techniques

Curve-fitting Techniques		
Technique	**Description**	**Limitations and Assumptions**
Simple averages	Uses the mean of past enrollments as the enrollment forecast for the next time period. Depending on the availability of past enrollment data, the average can be based on long or short time periods.	Generally not a good choice because enrollment is not consistent from year to year.
Moving averages	This is similar to simple averages technique, except that a fixed number of past enrollment figures are used to estimate future enrollments.	Appropriate for short-range forecasting: less rigid than simple averages. As enrollment trends become more pronounced, fewer data points should be included. In times of continued expansion (or contraction) of enrollments, moving-average technique is inappropriate.
Exponential smoothing	ls a variation of averaging techniques; most recent historical enrollment figure is weighted most heavily and each successively earlier data point is weighted less than the previous one.	Appropriate for short-range forecasting; similar difficulties as averaging techniques during periods of continued expansion (or contraction) of enrollment.
Polynomial models	Uses a standard least squares estimation for three orders of polynomials; linear, quadratic, or some more complex order.	No guarantee that the curve will not change shape substantially for the forecast years. Numbers of data points must be at least equal to the number of parameters to be estimated. Difficult to determine beforehand appropriate polynomial order.
Exponential models	Parameters are multiplied together rather than added.	Reflects more accurately some situations in which rate of growth or shrinkage of enrollment is constant.
Spectral analysis	Is a special form of the polynomial model using trigonometric functions (sine and cosine) to replace "t".	Usually inappropriate for enrollment projections because it requires a minimum or approximately 25 historical data points.

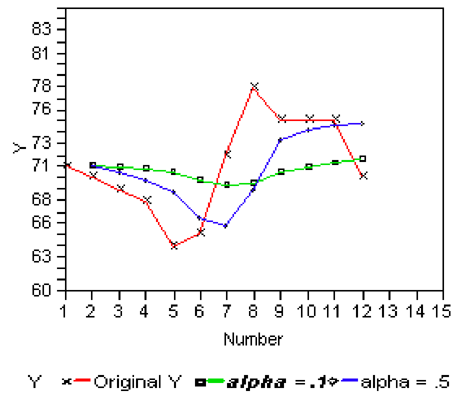
Source: copied from Kraetsch, G. A. (1979). Methodology and Limitations of Ohio Enrollment

Table 3: Examples of Curve-Fitting Techniques

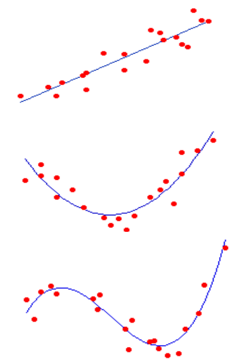
Linear



Exponential Smoothing: Original and Smoothed Values



Polynomial Model Order: Linear, Quadratic and Cubic



Source: Google Images

Table 4: List of Commonly Used Causal Models

Causal Models		
Technique	**Description**	**Limitations and Assumptions**
Cohort-survival techniques	Identifies a group of individuals with common traits, such as grade level or year of birth. This group is aged through the educational system by the: -grade-progression or class-succession method; or -age-survival method.	Assumes that net migration, mortality, and school attendance patterns will remain stable over time.
Ratio methods	Uses time series data to calculate the ratio between the total population by age groups. These extrapolated values of ratios are then used for enrollment projections.	Less accurate than cohort-survival techniques because the ratios are insensitive to recent changes which are compiled with historical data.
Markov transition model	Uses a transition matrix to estimate numbers of students enrolled at each level in the next time period. Model is applied successively for forecasting purposes.	Assumes that enrollments in one year are dependent only on enrollments of the previous year. Can design student flow models.
Multiple correlation and regression methods	Determines relationship between enrollments (dependent variable) and one or more independent variables, such as high school graduates, per capita income, ethnic background, and student demand estimation. Includes autocorrelation and multicollinearity techniques.	Permits development of econometric models of student behavior patterns (e.g., income, tuition, draft laws).
Path-analytical models	Extension of multiple correlation and regression models, except uses *a priori* identification of causal relationships.	Best suited for student demand, and not direct enrollment projections.
Systems of equations	Uses a series of equations to link different parameters of interest, such as optimization, simulation, or student flow models.	Few models developed.

Source: copied from Kraetsch, G. A. (1979). Methodology and Limitations of Ohio Enrollment Projections

Time Series Analysis

Box-Jenkins (ARIMA): auto-regressive integrated moving average (ARIMA) involves three basic parameters: 1) the amount of autocorrelation, 2) the level of systematic change over time, and 3) the component for including a moving average of the time based points. This model requires longitudinal data with a minimum of forty-five or sixty data points to achieve highly accurate forecasting.[19]

Fuzzy time series: this model can be constructed for a nonlinear pattern of enrollment forecasts in which the values of the time series are linguistic terms represented by fuzzy sets. It is more of a data mining approach that is more frequently used to forecast enrollment rather than offers the explanation of enrollment changes.[20]

Qualitative methods and **subjective judgment** have also been used for forecasting student enrollment where the subjective estimates of influential factors can be implemented when an objective or mathematical model is unavailable[21]. Lastly, many higher education institutions use a **combination of quantitative and qualitative** approaches for forecasting enrollment.

Linear Trend Analyses for UMass Boston Enrollment Projection

Dr. James J. Hughes, Associate Provost for Institutional Research, Assessment, and Planning created a pilot model for projecting enrollment in Fall 2016. This model employed three widely used techniques for trend analyses: linear (i.e., a straight line of best fit to time series historical data using the method of least squares), smoothed linear (i.e., moving averages technique added to the linear model for reducing or smoothing out the effect of random variations or irregular roughness in the time series data), and adjusted trends (adjusted for seasonal components such as spring enrollment as a percent of fall enrollment and trend component such as underlying techniques like averaging). This pilot model used these curve-fitting techniques at various levels of disaggregation of student types as well as took a number of factors that influence student enrollment at UMass Boston into account. Nevertheless, these techniques have produced a misleadingly optimistic enrollment projection.

We believe that the factors and techniques presented above have strong potentials for improving the current pilot model.

This list is compiled by the OIRAP Research Analyst Fatema Binte Ahad from the existing literature.

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[20] ibid
[21] ibid