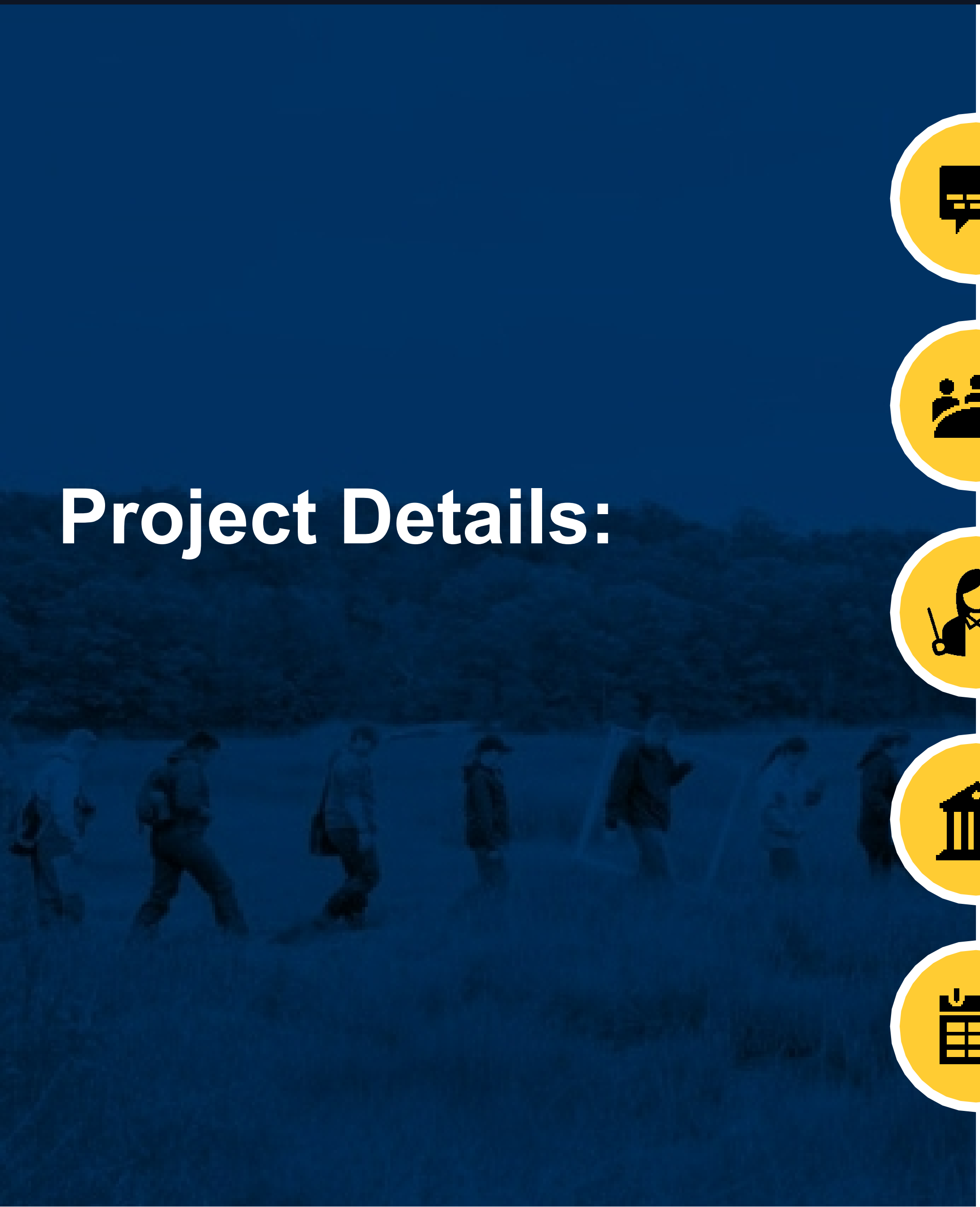
University of New Haven

TAGLIATELA COLLEGE OF ENGINEERING

EDU PREDICT TOOL
PREDICTING ENROLLMENT TRENDS IN HIGHER EDUCATION IN THE USA



Project Details:

Project Title: EDU PREDICT TOOL

Project Team: 01

Project Advisor: Dr. Ardiana Sula

MSDS Capstone – SP 25 DSCI 6051-07

Date of Presentation: 02-28-2025

EduPredict – Forecasting Higher Education Enrollment Trends

- **Goal:** Analyze and predict future enrollment patterns for international students in U.S. universities using data-driven techniques.
- **Outcome:** A **Power BI-based interactive dashboard** that provides enrollment trend forecasts under different scenarios (**Baseline, Growth, and Decline**).
- **Core Features:**
  - Machine learning-driven insights for **strategic academic planning**.
  - Customizable filters for **region, study level, and time period** to explore data dynamically.
- **Significance:**
  - Equips university officials with insights to **optimize resource planning and policy decisions**.
  - Supports institutions in **adapting to demographic and economic shifts** in student enrollment.

TEAM

Koteswar Enamadni

Ifra Naaz Mohammed

Krishnaveni Peesapati

Gnaneswari Vaddepalli

Chethan Chakradhar M

Karthik Vinnakota

The Problem

1

Unpredictable Enrollment Trends

- Universities struggle to accurately forecast student enrollments due to shifting demographics, changing student preferences, and external influences.

2

Impact of External Factors

- Enrollment is heavily influenced by **government policies, economic conditions, and global mobility trends**, making long-term planning difficult.

3

Data Fragmentation & Decision-Making Challenges

- Enrollment data is scattered across multiple sources, leading to incomplete insights and reactive rather than proactive strategic planning.

Project Goals & Objectives

Primary Goal: Develop a **predictive model** that estimates future **student enrollments** based on multiple factors.

Key Objectives:

- Integrate **historical datasets** on enrollment, demographics, and funding sources.
- Identify **patterns & trends** in student admissions across various academic levels.
- Build a **forecasting model** using machine learning.
- Deploy results via a **user-friendly Power BI dashboard** for dynamic analysis.

Data Collection & Sources

Title: Where Our Data Comes From

Content:

- **Dataset Breakdown:**
  - **Student Enrollment Trends** (By year, region, academic level).
  - **Demographics** (Gender, marital status, visa type).
  - **Funding Sources** (Self-funded, government-sponsored, institution grants).
- **Data Quality:**
  - Missing data handled using **forward fill & interpolation** techniques.
  - Cleaned, structured, and prepared for **model training**.

Exploratory Data Analysis (EDA)

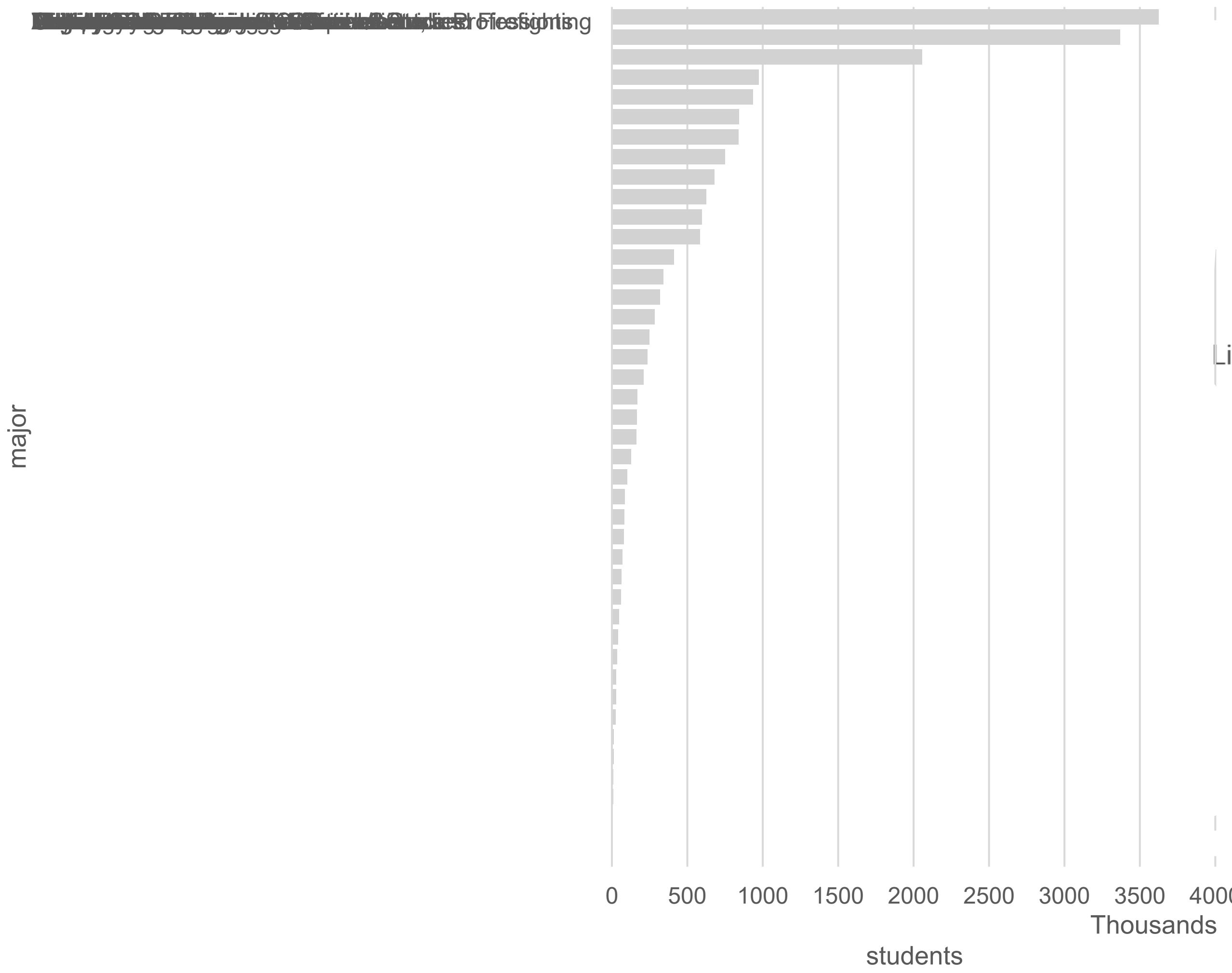
Title: Making Sense of the Data

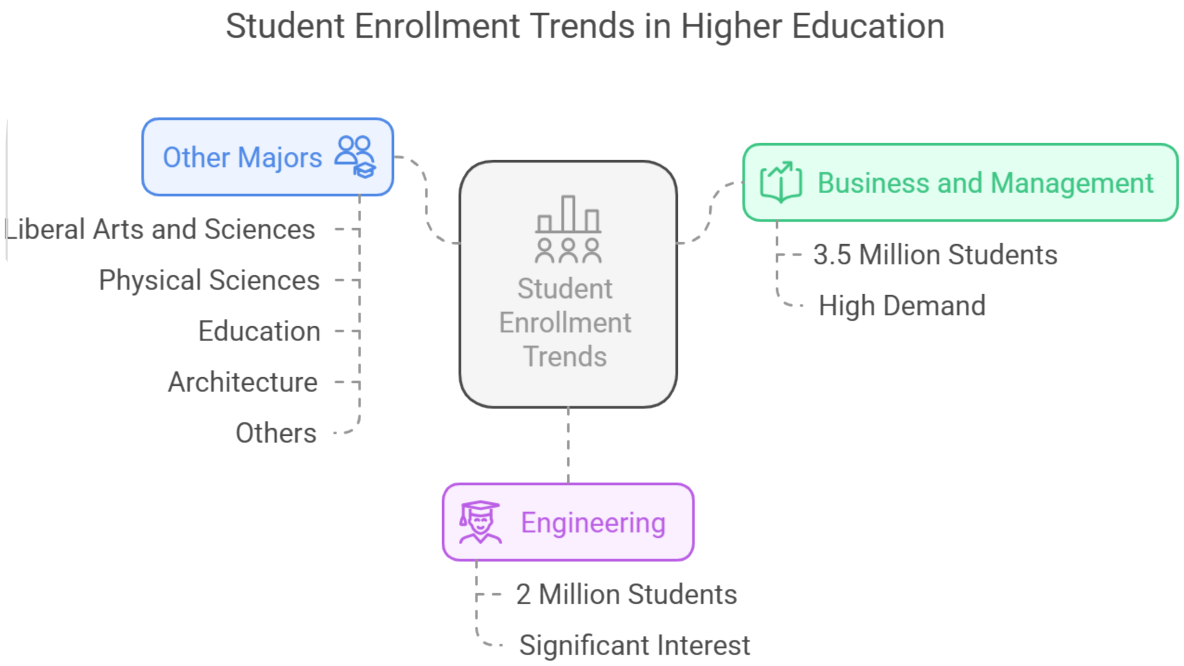
Content:

- **What We Did:**
  - Examined trends in **student enrollment across different years**.
  - Analyzed **regional student distribution** to identify dominant source countries.
  - Explored funding types to understand **how students finance their studies**.
  - Correlation analysis to detect **relationships between key factors**.
- **Key Insights:**
  - **Business & STEM fields** are the most popular.
  - **Asia contributes the highest number** of international students.
  - Enrollment growth has **gradually increased over the years**.

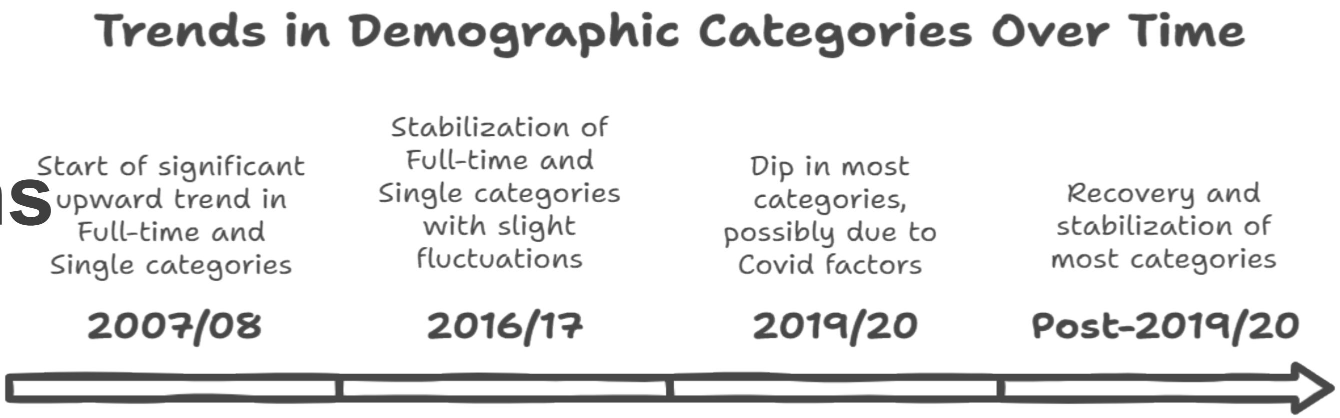
Key EDA Visualizations

'major': Business and Management and Engineering have noticeably higher 'students'.

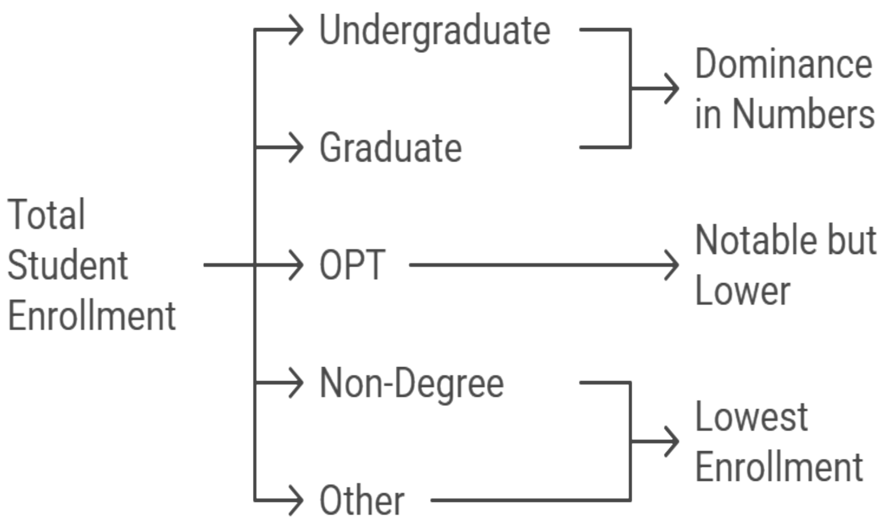


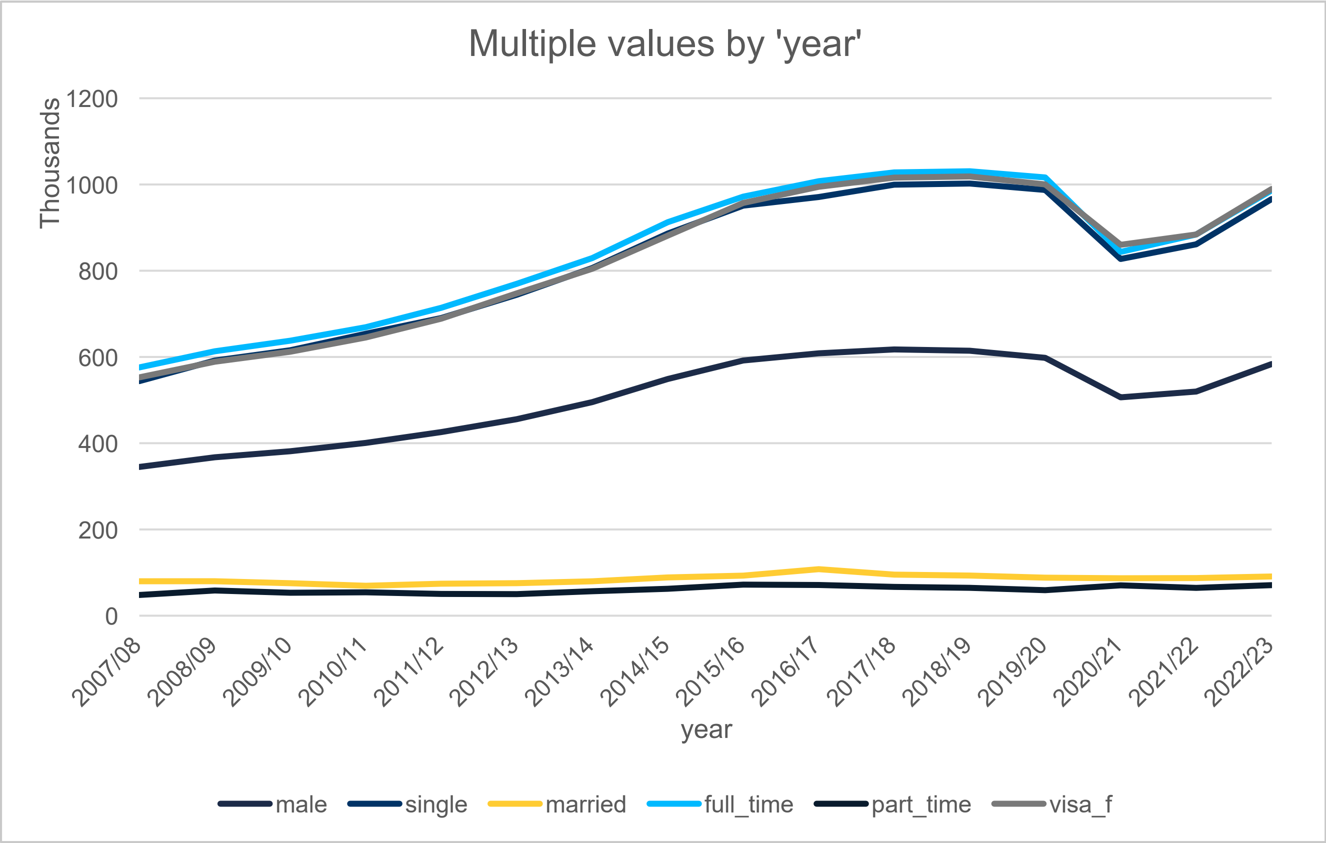


Key EDA Visualizations



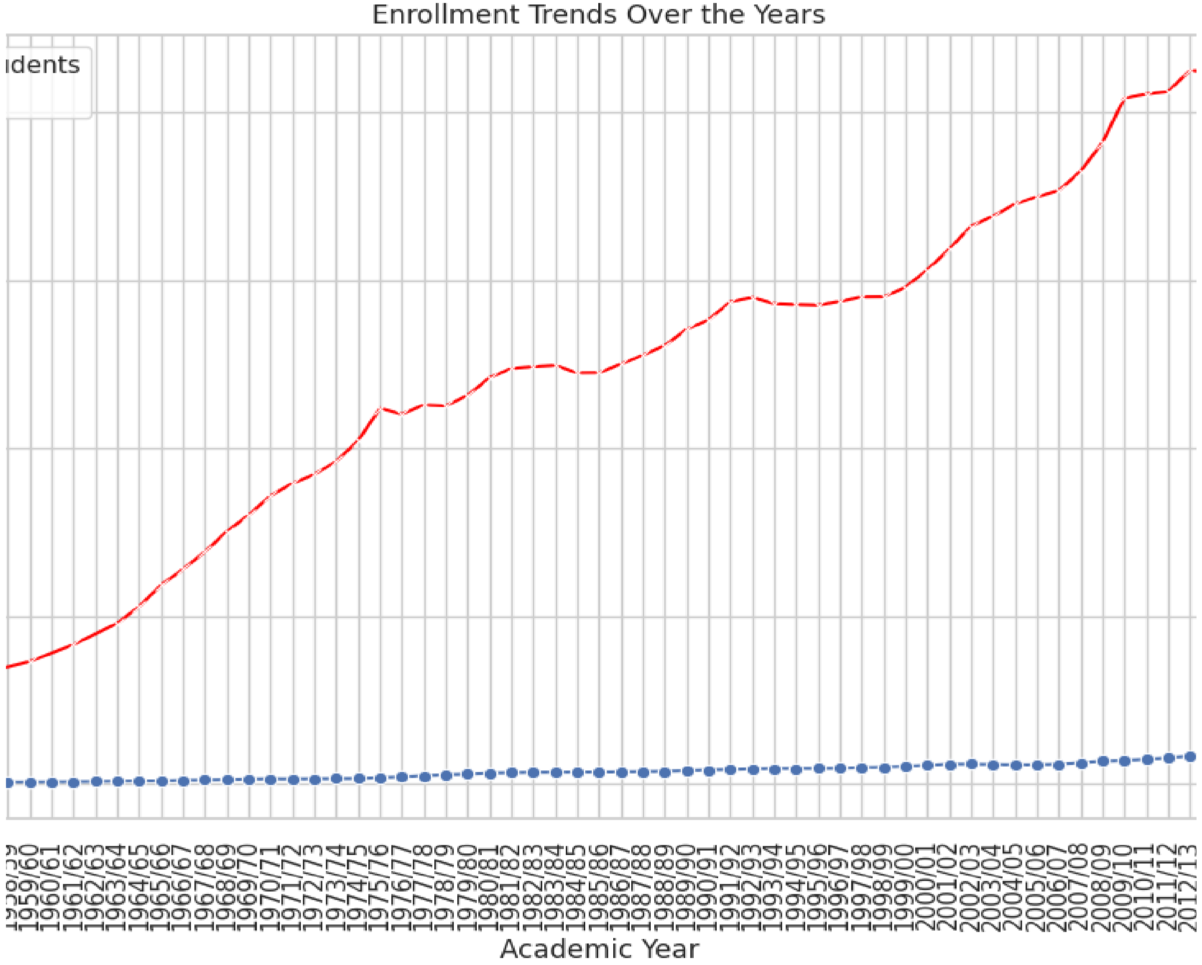
Student Enrollment Trends and Patterns



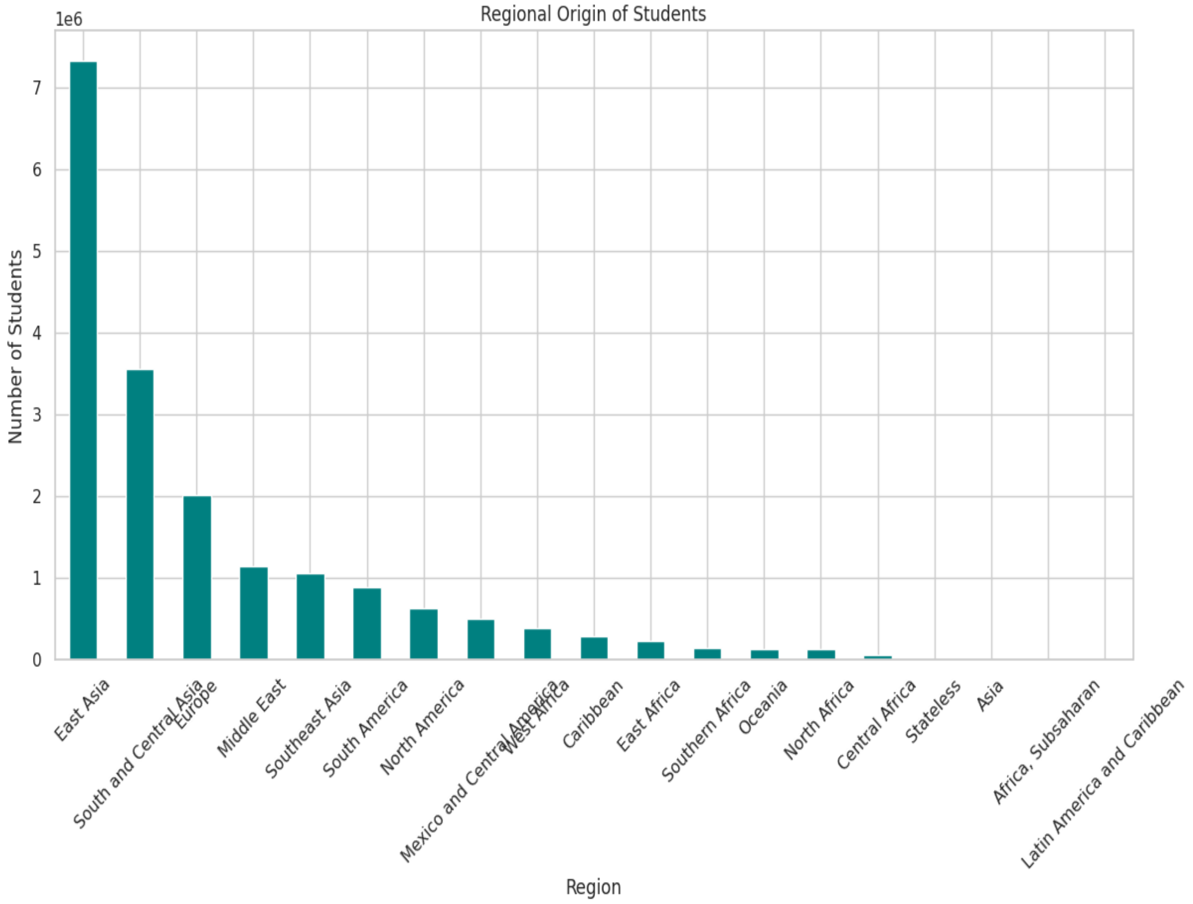


Key EDA Visualizations

Trend Analysis: Growth in **international vs. U.S. students** over time.

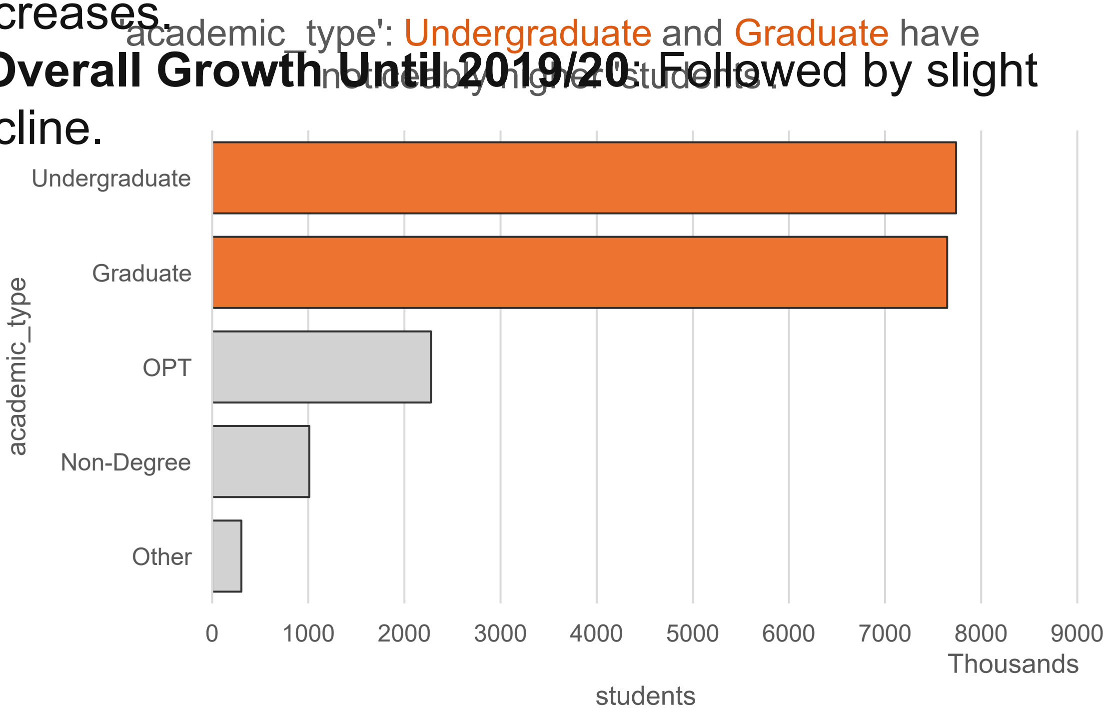


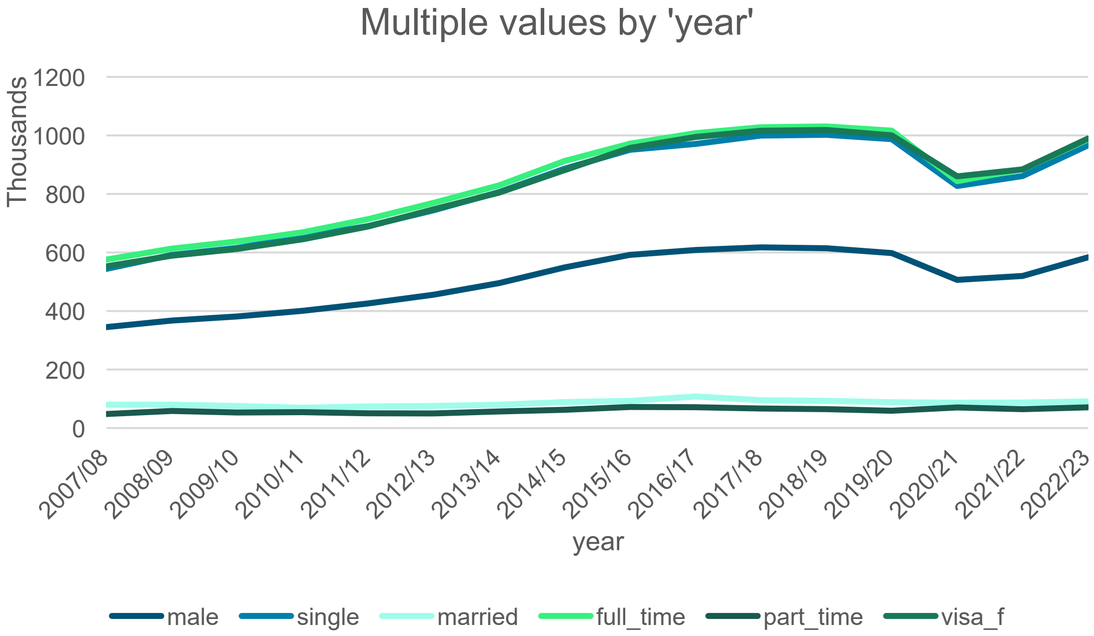
Regional Breakdown: Top contributing countries & continents for international students.



Key EDA Visualizations

1. **Full-time, Married Increase**: These categories show upward trends.
2. **Male, Part-time, Visa_f Stable**: Little to no change over time.
3. **Single Declines**: Peaks around 2017/18, then decreases.
4. **Overall Growth Until 2019/20**: Followed by slight decline.





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Trends in Employment Categories

Full-time Growth

Significant upward trend observed from 2007/08 to 2016/17.

Male Growth

Slower upward trend compared to full-time and single categories.

Married Stability

Remains relatively flat throughout the observed period.

Observations Summary

Highlights notable growth and external factors affecting trends.

Single Growth

Notable increase from 2007/08 to 2016/17, stabilizing afterward.

Part-time Growth

Shows an upward trend but at a slower rate.

Visa_f Increase

Slight increase over the years, lowest among all categories.

Handling Missing Data

Title: Ensuring Data Accuracy

Content:

- **Challenges:**
    - Some datasets had missing values, particularly in **older academic years**.
- **Solutions Implemented:**
    - **Forward Fill:** Used to maintain **continuity in time-series data**.
    - **Linear Interpolation:** Applied to estimate missing records based on known values.
    - **Outlier Detection:** Cleaned inconsistent data to avoid skewing results.
- **Outcome:**
    - A well-structured, **high-quality dataset** for training predictive models.

Modeling Approach

Title: Choosing the Right Prediction Models

Content:

- **Forecasting Techniques Used:**
  - **ARIMA**: For traditional time-series forecasting.
  - **Prophet**: Captures seasonality and event-driven changes.
  - **XGBoost**: Handles complex interactions in **demographic and financial factors**.
- **Trade-Offs:**
  - ARIMA works well for **time-dependent trends** but lacks flexibility.
  - Prophet helps with **seasonal patterns** but needs additional tuning.
  - XGBoost is **highly accurate** but computationally expensive.

Baseline & Progress [02-26-2025 to 03-02-2025]

Title: What We Have Done So Far

Content:

- **Reviewed past submissions** and finalized project scope.
- **Conducted detailed EDA** to understand **key trends & data gaps**.
- **Handled missing data** using **forward-fill and interpolation**.
- **Developed the first baseline forecasting model (ARIMA)** to test initial predictions.
- **Refined feature selection** to improve model accuracy.

Bi-Weekly Key Milestones Report

Title: Tracking Our Progress

Content:

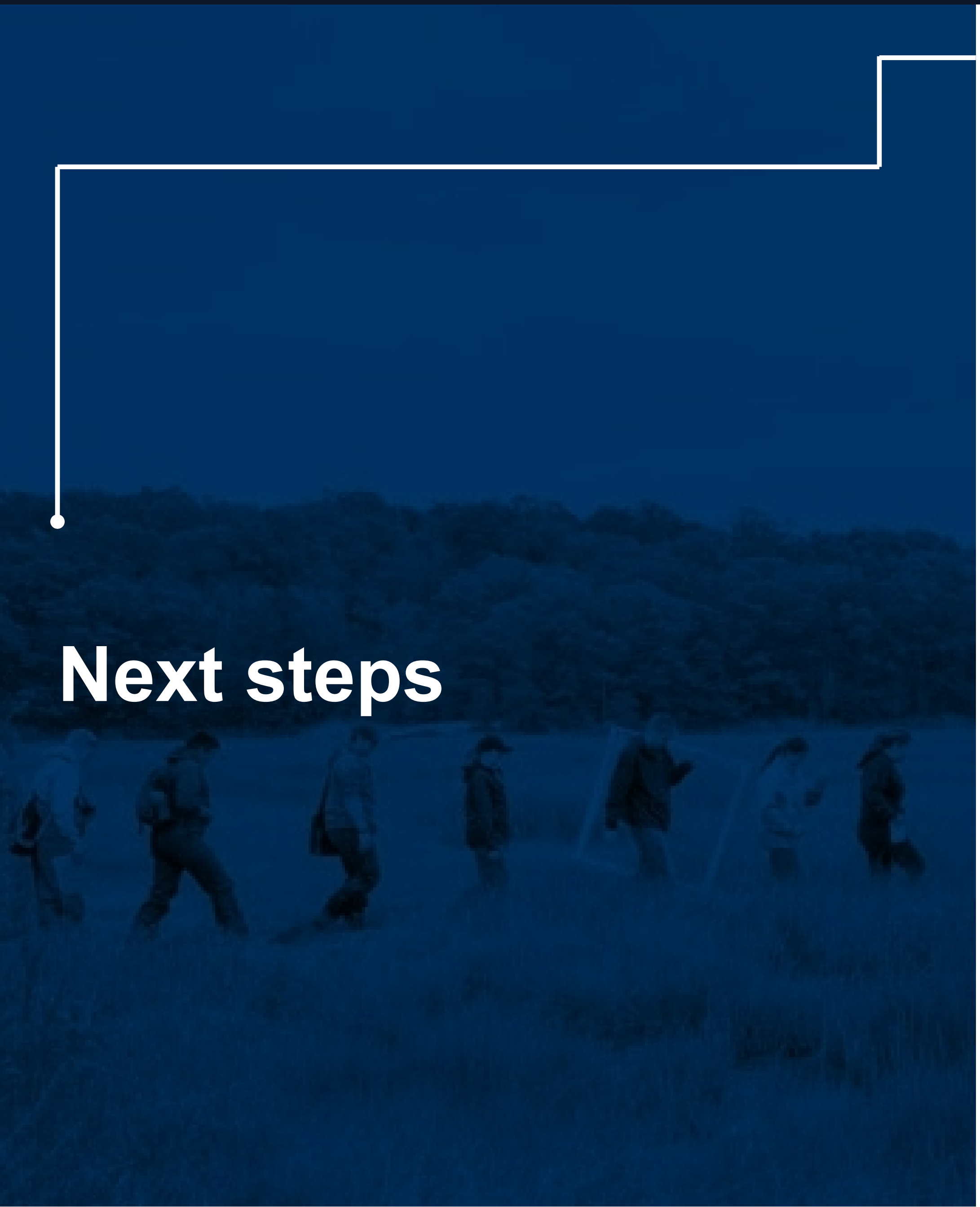
- **Week 1 Progress:**
  - Reviewed **project scope and data sources**.
  - Conducted **data cleaning & preprocessing**.
  - Built **initial visualization reports** for trend analysis.
- **Next Steps:**
  - Enhance **model accuracy** using hyperparameter tuning.
  - Explore **alternative models** for better forecasting.
  - Start integrating insights into **Power BI dashboard**.

Implementation & Deployment

FeatureEngineering: Categorical encoding, normalizing numerical features.

Model Optimization: Hyperparameter tuning to **increase predictive accuracy**.

Deployment Strategy: Integrating forecasts into an **interactive Power BI dashboard &** Enabling **user-driven filtering** for customized trend analysis.



Next steps

Refine our EDA to enhance trend interpretation.

Improve model accuracy with fine-tuned parameters.

Test different machine learning models for better performance.

Build a user-friendly dashboard for interactive data visualization.

Document insights for reporting and final project submission.

THANK YOU

Please let us know if you have any further suggestions or improvements.

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POWER ON