Making ends meet: Projecting demand for class seats at a major American university

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Springboard Data Science Career Track
Capstone #2 Presentation Slides

Introduction

- One of the biggest challenges facing university administrators and department heads: Meeting student needs
- As a business, university success = student success
  - Ease, availability of required classes
  - Graduation rates
- Course, seat availability is part of the university's product students pay for
  - If the product is sparse or difficult to obtain, students will go elsewhere

Introduction

- Providing seats in balanced, economical way requires calculation
  - Need to balance student-to-instructor ratio with not “over-offering”

- Seat projection requires attention to detail
  - Entry-level or advanced course? Which semester?
  - Specificity facilitates both accuracy and user experience

- **In the current project**, I will:
  - Demonstrate how different factors—i.e. semester type—modulate enrollment patterns expected for a given course
  - Use data-science techniques to show how these patterns can be computationally modelled

The scope

- University of Arizona
  - One of three major public universities in Arizona
  - Current undergraduate population: 35,123
- Seat projections as a service
  - Dashboard with prompts to specify course parameters needed for projection
- Project goals:
  - Demonstrate how course-specific factors can modulate enrollment patterns
  - Exemplify how such a projection tool could be valuable to those responsible for course scheduling, planning

The data

- 30 years of enrollment data for ENGL101
  - 100-level, general-education course required for bachelor's degree of any kind
  - Taken early in undergraduate career to facilitate sign-up in more advanced courses
  - Volume of students must be accounted for
- Data is deidentified
  - Aggregated at the level of class enrollment; cannot be traced back to any particular student
- Fall-, summer-, and spring-semester data
  - ENGL101 not offered in winter during 30-year period
- Cleaning largely unnecessary
  - Data pulled from university database by me, as an analyst at UAIR
  - No rows with null values

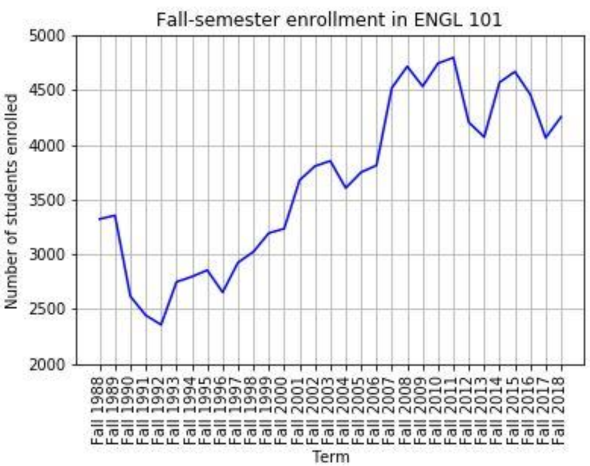
The application

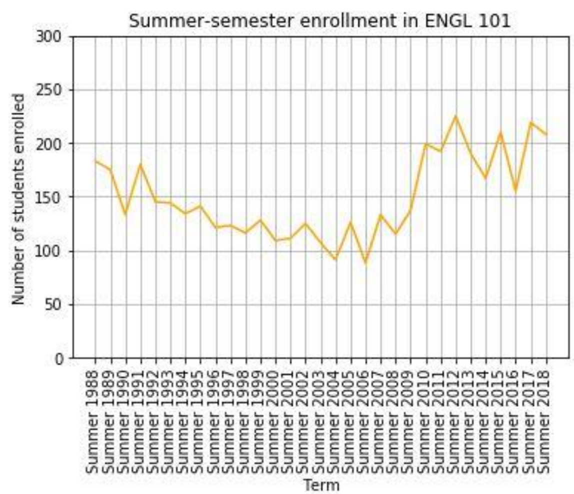
- Dashboard as user interface
  - Course facilitators able to enter course-specific parameters in prompts (i.e. semester type, specific course catalog number)

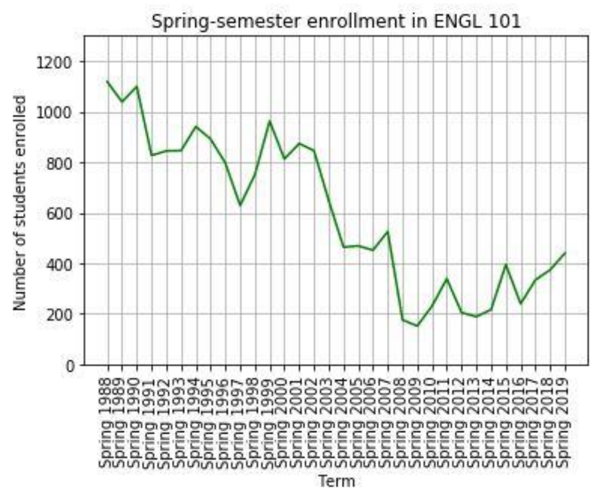
- By-semester projection capability necessitates subsetting data by semester
  - Improved model accuracy, reduced noise
  - In future, extend tool to other courses, i.e. different course types

Exploratory data analysis

- Data subsetted, read into pandas for wrangling
- Visualizations for fall, summer, spring ENGL101 data







Model selection

- Univariate time-series
  - OLS inappropriate: Enrollment is count data, cannot be fraction or negative value
- Step 1: AR, auto-regressive, model

$$X_t = \delta + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-1} + A_t$$

- Assumptions:
  - Stationarity: Calculate means, variances to determine equality
    - Not met; Data need to be differenced until stationarity is achieved
  - Normality: Shapiro-Wilks test
    - Met
  - Trend: Autocorrelation plots
    - Points related but not strong correlation

Model training

- AR model: 70/30 train-test split
  - Enormous MSE, poor accuracy suggest model is severely underfit

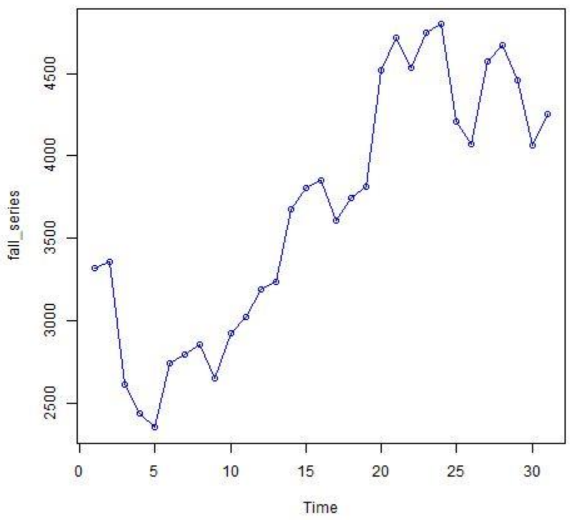
- ARIMA (auto-regressive, integrated, moving-average) may be a better fit for data we know not to be random (AR models typically used to model random processes)
  - ARIMA accommodates non-stationarity via differencing

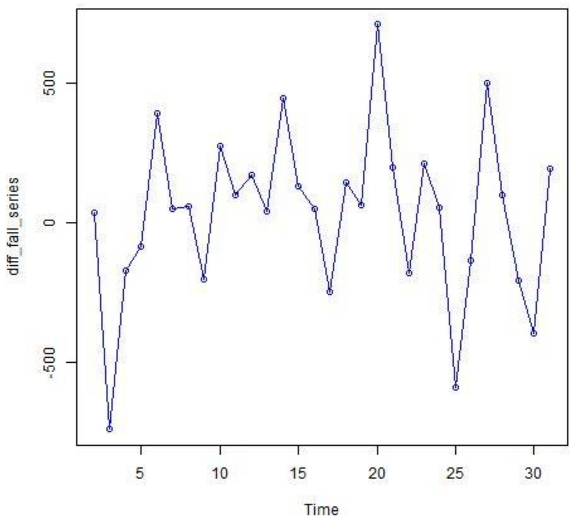
$$y_t = \delta + \{\phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p}\} + \{\theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q}\} + \epsilon_t$$

$$\implies y_t = \delta + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t$$

ARIMA, by hand

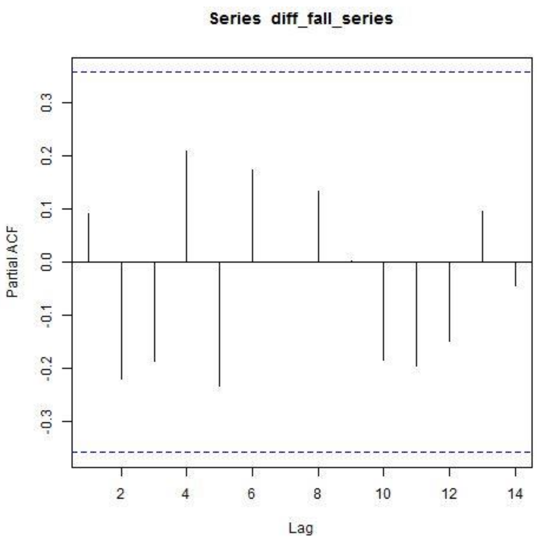
- “I” parameter *(D)* = number of differences needed to achieve stationarity
  - *1 differencing for fall data* → *d = 1*

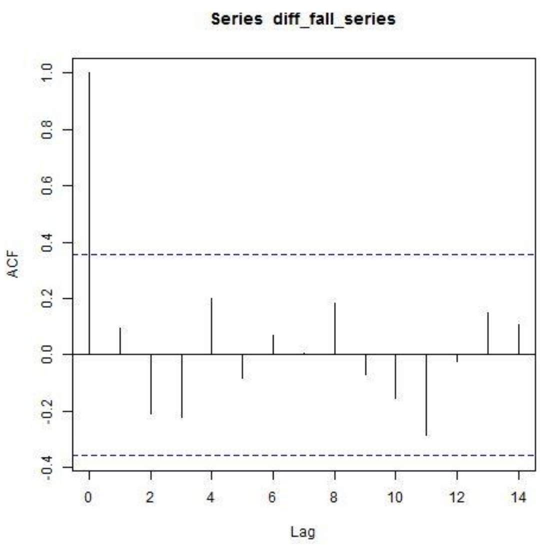




ARIMA, by hand (cont.)

- "AR" parameter *(P)* = PACF
  - Drop-off after 1 lag; $p = 1$
- "MA" parameter *(Q)* = ACF
  - Drop-off after 1 lag; $q = 1$





Model evaluation

- ARIMA, by-hand*:
  - Best fall model: ARIMA(1,1,0)
  - Best summer model: ARIMA(0,1,1)
  - Best spring model: ARIMA(0,1,0)

  *AIC used as measure of model quality

- ARIMA, automated (“forecast” package in R)
  - Best fall model: ARIMA(0,1,0)
  - Best summer model: ARIMA(1,1,0)
  - Best spring model: ARIMA(0,1,0)

Conclusion

- Automated model selection provides rigorous search through all parameter combinations
- Stepping through model-construction process an instructive exercise
  - Offers better understanding of mathematical influences
- Computers best-suited for tasks involving speed and iteration
- Humans best-suited for questions of “why”, application of computer-generated solutions

Thank you!

Questions can be addressed to nyssabulkes at gmail dot com

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