Sequence based course recommender for personalised curriculum planning

Chris Wong cwon7609@uni.sydney.edu.au
School of Information Technology

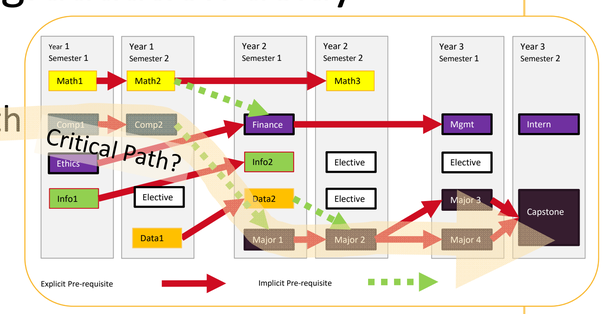
Motivation

Help students navigate their degrees

- Influence student success via course advice
- Minimise degree completion time
- Maximise results - Grade Point Average (GPA)
- This study focuses on institutional (structural/operational) factors rather than personal background factors
  ….e.g. preparedness, medical, employment, social/friendship, financial…

Critical paths could result in graduation delay

- Not just poor choices
  …Even with pre-defined pathways
- Failure or deferment on critical path could lead to cascading delays
  … but not all critical paths are explicitly known…



Other issues affecting choice:

- Structural: Sequencing, concurrency (*compulsory, pre-requisites, …*)
- Operational: constraints (*course availability, scheduling, class quotas …*)
- Individual: context (*intended career, jobs, interests , accreditation …*)

➔ increase complexity of decision making

Advisers are key sources of pathways

- Sources are academic advisors, peers, online, friends, social media
- Using their Implicit/tacit knowledge?
- Not scalable, inconsistent, outdated or inaccurate advice.

Related Work

Existing systems

- Course catalogues, handbooks/calendars, study plan templates, enrolment systems, integrated with student management systems

Machine learning for educational data science

- Educational data mining:
  … used for analysis and prediction [3,6](grades, failure risk)
- Educational recommenders[8] becoming common:
  … for career choice/degree/major, learning objects[1] using collaborative filtering, content based approaches or association mining[2].

Deep Learning (Recurrent Neural Networks)

- RNN now being used for sequence prediction[4], learning analytics[9], student performance prediction[5] & contextual recommendations[7]

Data

10 years of student records

- 2.1 million transcript results[11]
- 30 degrees, 14 majors, 400+ courses, 72000 graduation records
- ➔ use subset for experiment – Engineering and IT records

Preparation

- Data wrangling, cleansing (*anomalies, missing data, …)*
- Normalisation (*due to part-time, absences, double degrees, transfers, credit transfer …*)
- k-anonymised, de-identified
- Human ethics approval[12]!

Attributes to be used:

- Degree/major, course, year/semester, grades/marks, classification information e.g. gender, status
- Courses *may* be annotated by topics & learning objectives

Methodology

Exploratory Data Analysis

- Use Machine Learning – clustering (k-means) , predictive modelling (regression, decision tree, neutral network, random forest) → detect patterns & make observations
- Analyse by cohorts e.g. engineering majors, IT

Develop Baseline Recommender

- Results are used for implementing classical recommender → becomes “baseline” for evaluation

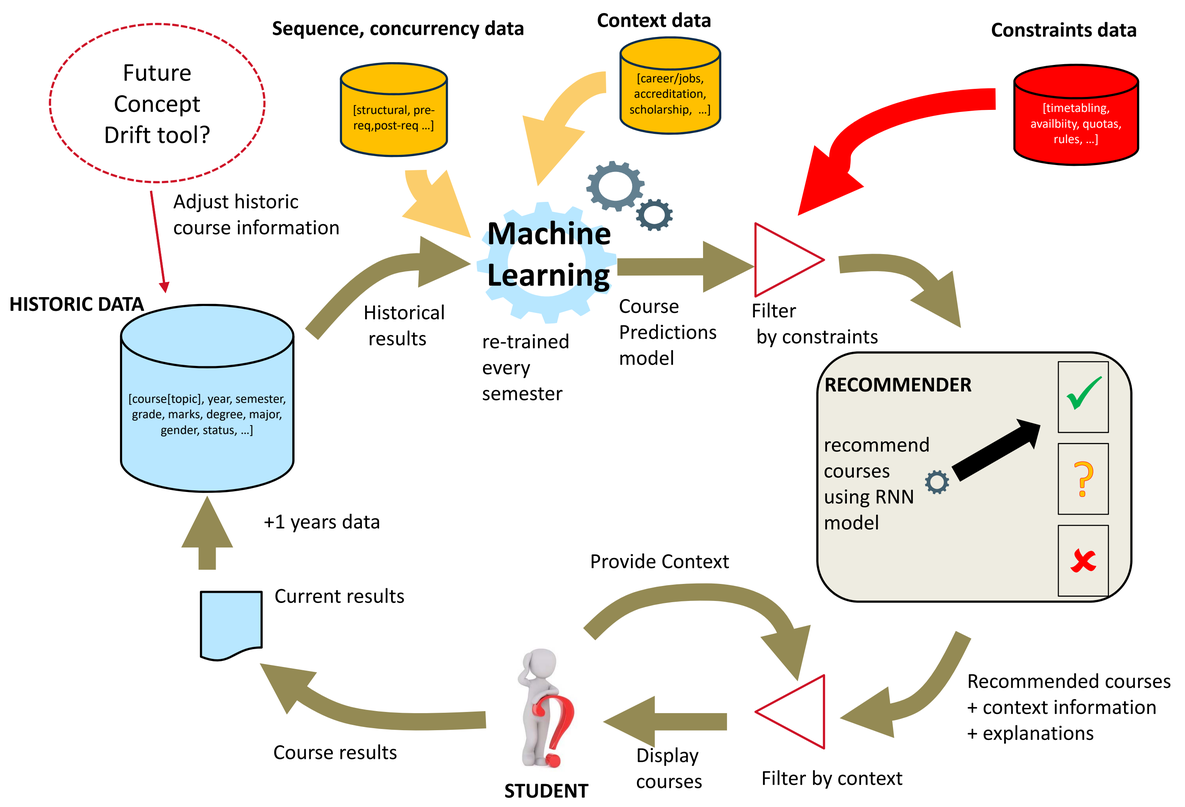
Prototype & test Initial deep learning recommender

- Train & tune Recurrent Neural Network & compare to baseline
  (objective function: hybrid of duration and GPA, add sequence , context and constraint filters)
- Evaluate – using split (90:10) and 10-fold cross validation
- Prototype user interface options (including HCI, formatting, explainability, warnings)

Experiment & evaluation

(see below..)

Proposed Solution



Experiment

Pilot prototype on focus group

- Select focus group users – pre& post pilot qualitative/quantitative surveys, workshop on prototype. Ensure appropriate mix of 1st, 2nd, 3rd & final year students and faculty/admin users.
- These students will use prototype to choose courses.
- Compare baseline (i.e. simulation of other peer students)
- Adjust database for concept drift as courses may have changed.
- Attempt multi-semester → retrain deep learning model based on student results.

Issues

Ethical

- Monitor focus group users – do no harm!

User interface

- How to design and present recommendations?
- How to provide explanations of recommendations?

Concept Drift[10] automation

- Needs further research – e.g. topic mining course descriptions/outlines, develop heuristics, adjust historic data?

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