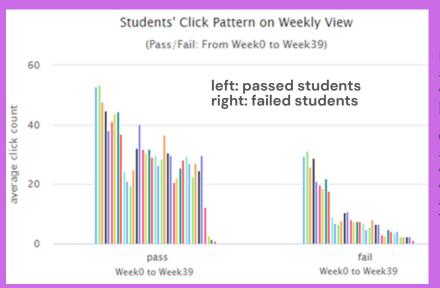
# Machine Learning modelling: student performance prediction

This research project analyses university students' baheviour patterns of those passed and failed groups using clickstream data. The comparison leads to a prediciton on students' final course results. The methodology and models can serve as possible solution to optimise student retention and advise future program improvement.

### **EXPLORATORY ANALYSIS**

- Goals: to explore click behaviour patterns between students who passed and failed the course
- Achievements: time and activity features are extraced and well trained for next-setp feature engineering



#### **Time**

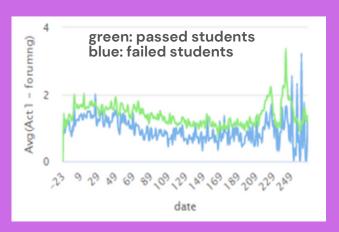
Passed and failed students have different click patterns over time.

(e.g. left figure shows 'pass' group over time has compariably higher average click count than 'fail' group)

#### **Activity category**

Click behaviours on the *forum*, learning content, subpage, homepage, quiz activity categories show different patterns between students who passed and failed over time.

(e.g. right figure shows forum clicks of passed students are clearly higher than failed students)



## PREDICTIVE MODELLING

- Goals: to build accurate predictive models
- Achievements: 60 models were trained using
  - 6 datasets by time frequency of 5341 students 6 machine learning algorithms
  - with/without a feature selection method
  - 10-fold cross validation

### Feature selection

- using all features (no feature selection method)
- using Infomation Gain to select features

10-fold cross

validation

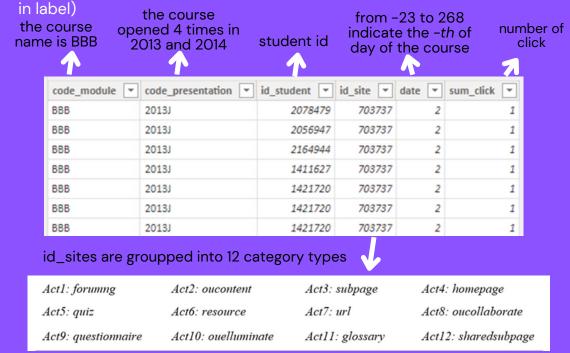
- 6 datasets
- S1-WEE S1-MON
- S2-WEE
- S2-MON
- S3-WEE S3-MON
- Machine learning algorithms Logistic Regression (LR)
- K-Nearest Neighbors (k-NN)
- Random Forest (RF) Gradient Boosting Tree (GBT)
- 1D Convolutional Neural Network
- (1D-CNN)
- Long short-term memory (LSTM)

# MODEL VALIDATION AND RESULTS WRAP-UP

- Goals: to evaluate and validate best performing model, and summarise final results
- Achievements:
  - models were evaluated using accuracy, F1-score, AUC
  - the best model was <u>LSTM + S3-WEE + using all features</u>, achieved up to accuracy of 90.22%, F1-score of 93.33% and AUC of 92.65%
  - feature engineering Strategy 3 performed the best
  - week-based performed better than month-based datasets
  - LSTM stood out among all the algorithms
  - LSTM + using all the features performed the best. Therefore, feature selection methods could be optional when using LSTM

# DATA PREPARATION

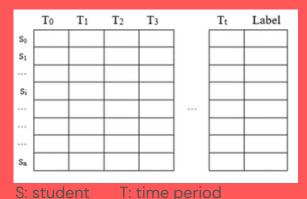
- Goals: to clean raw data (students' clickstream data from Learning Management System for a course) and merge it into the prediction label (students' final results of the course)
- Achievements: click data of 5341 students, 32% 'fail', 68% 'pass' (2 classes



# FEATURE ENGINEERING

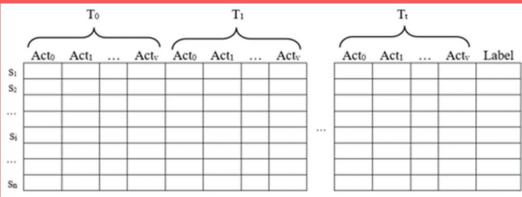
- Goals: to transform data to generate core features for predictive
- Achievements: 3 strategies to generate features; each strategy involves click count aggregation by different mix of time frequency (e.g. weekly and monthly) and activity categories, 6 datasets were generated

### Strategy 1: time periods as features



- each row indicate each student • each column indicate click number in each time period (each week or month)
  - Two datasets: S1-WEE S1-MON

### Strategy 2: time periods & activity categories as features



Act: activity categor

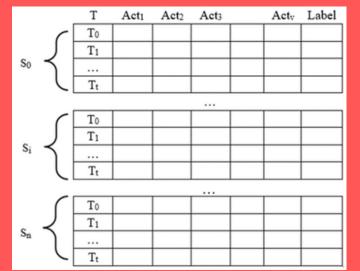
- each row indicate each student
- each column indicate each combination of each time period (week or month) and each activity type (12 types in total)

Two datasets: • S2-WEE S2-MON

# Strategy 3: panel data

Each panel represents each student; each panel is a matrix of time and activity

Act: activity category



T: time period

- For one panel (one student), each row indicates each time period (week or month), each columnn indicates click numbers on each activity type • There are 5521 panels
- (students)

Two datasets: S3-WEE S3-MON



Goals: to produce insightful suggesiton on how teachers best support students with pass as ultimate performance goal

S: student

Achievements: core aspects trained under feature engineering indicate as below are the key to optimise students' course performance:

- the importance of time period: week 0-3, week 38-39 < weeks 4-37 < weeks 22-35</li>
- important activity categories include homepage, subpages, forum, resources
- It is suggested to provide support to 'at-risk' students (i.e. students who are likely to fail the course) based on different activity categories in different course periods (see left figure)

