CSE 343 Machine Learning
Final Project Presentation

Students' Adaptability Level Prediction in Online Education

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Motivation

- Increasing importance of online education since Covid-19
- Factors affecting adaptability level in online education
- Different students faced different difficulties
- Predicting the adaptability level beforehand helps improve it to get an optimal level

Literature Review

- Impact of technology on virtual learning system
- Multiple research papers published to study different factors
- Researchers studied the improvement of online education model
- Comparison between offline and online education system
- Similar trends in on-campus vs off-campus performances

Literature Review

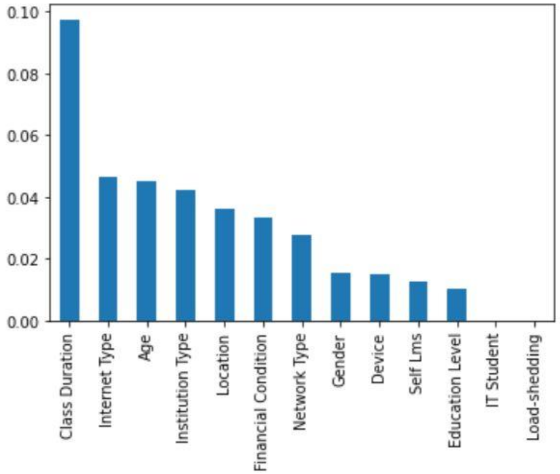
- Impact of pandemic on the global education system
- Difficulties faced in online education systems
- Rural areas vs Urban Areas : The former faced more challenges
- Lots of barriers : technological, communication, financial, etc.
- According to one research, better learning in online education systems

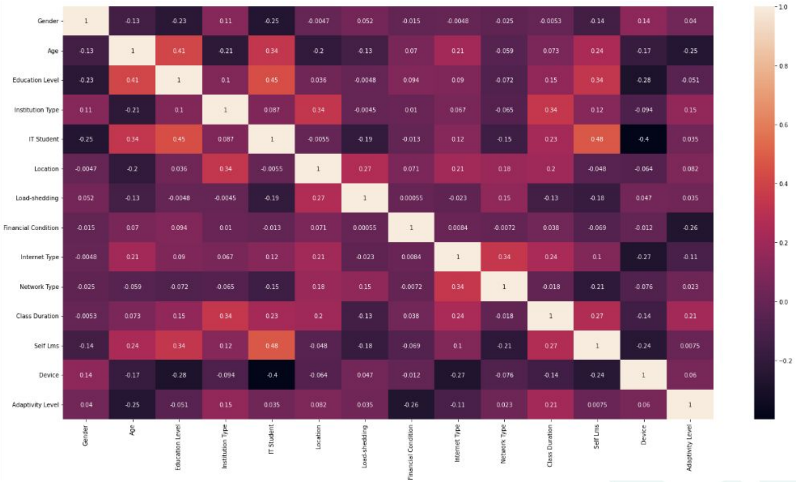
Dataset Description

- The dataset contains categorical data, having 13 features and 1 target variable.
- Some of the features contains binary values for e.g. yes/no, boy/girl etc. while some contain multiple values.
- There are 1205 samples in the dataset.
- As our data is categorical, no outlier is observed.

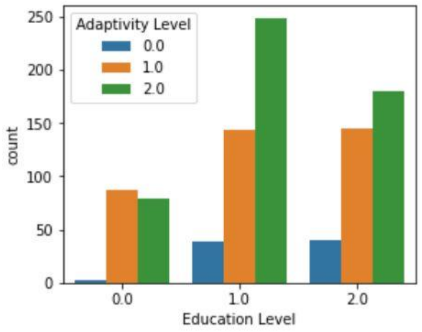
Dataset Preprocessing

- No null values observed
- String values in the dataset have been scaled to integers.
- Features like 'Load shedding' and 'Self Lms' have very low correlation w.r.t target variable and low information gain and hence are dropped while selecting features to improve model performance

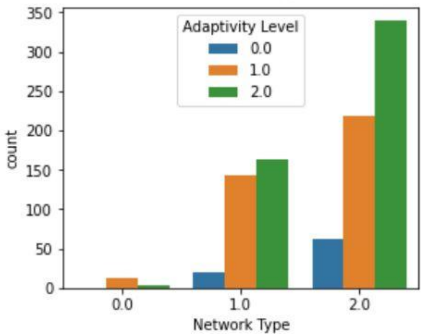




Dataset Analysis



- From this countplot we can observe that the students with moderate adaptivity are maximum from school while the students having high adaptivity are lowest in college.



- Similarly, from this countplot it is evident that with faster internet connectivity adaptivity level in online education increases.

Methodology

After preprocessing the data, we have used the following methods to predict the adaptability levels based on features in samples:

- Logistic Regression
- Gaussian Naive Bayes
- Random Forest Classifier
- Decision Trees
- Support Vector Machine
- K- Nearest Neighbors
- Artificial Neural Networks

Results

Performance of different classifiers on the dataset :

- Gaussian Naive Bayes :- Gave an accuracy of around 63.1% which was lowest amongst all the other classification models.

- Logistic Regression :- Gave an accuracy of about 64.7%, which was close to NB and much lower than other models.

- Random Forest :- Gave the best accuracy, i.e. 86.7%, highest among all the models.

- Decision Trees:- Gave an accuracy of about 82.98%

- Support Vector Machine:- Gave an accuracy of about 86%, which was the second highest.

- K-Nearest Neighbours:- Gave an accuracy of about 81.74%.

- Artificial Neural Networks:- Gave an accuracy of about 82.57%.

Hence, Random Forest Classifier works the best for the given dataset.

Conclusion

- Tried to forecast the student’s adaptability level using ML models.
- Used classifiers such as LR, Gaussian NB, DT, RF, SVM, ANN, and KNN.
- Since the data is categorical so decision trees work well and hence Random Forest (ensemble learning of DTs) works the best for the given dataset.
- Work done would be beneficial for the educational decision makers to improve the quality of education

Team members' contributions

- **Dataset description:** Aditya & Harshit
- **Model training :** Aditya & Harshit
- **Analysis :** Aditya, Harshit, Vaibhav & Vasu
- **Report:** Aditya, Harshit, Vaibhav & Vasu
- **Literature Review & Slides**: Vasu & Vaibhav

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