Predicting Students Engagement Using Machine Learning Techniques

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ABSTRACT

Through over 1,000 surveys and, this study examined academic support and course level engagement among students using Likert scale survey data in both remote and in-person settings. Students from 19 courses junior and sophomore level classes in electrical and mechanical engineering at a large public research institution reported present and preferred levels of academic support and engagement within in-person and remote learning settings.

Machine learning algorithm and models were used to predict five students' academic support and engagement scales. Evaluation criteria was to measure the MSE, and the results shows that among all approaches used in this study only three machine learning methods worked best to predict the mean square error. This study will help to predict how student demographics will predict instructional and engagement support, and this information will benefit educators and education institutions to build plans and resources to provide students with the best learning environment.

DATA INFORMATION

This study is part of a larger, single-institution research project that evaluated the connections between various forms of support (from faculty, TAs, and peers) and multiple forms of course-level engagement (attention, participation, effort, positive and negative emotional engagement) both in traditional and remote learning settings. The study used quantitative data analysis methods of both nominal and ordinal data to compare student perceptions of peer support across traditional classroom settings and the remote learning settings necessitated by the pandemic.

Participants

The study includes a student population of 1328 undergraduate students recruited across four engineering majors and 19 separate classes at the sophomore and junior levels in both traditional and remote learning settings. Self-reported ethnicity was Asian (43.3%), Black (2.9%), Hispanic (3.1%), White (40.7%), Pacific-Islander (less than 1%), Native American (less than 1%), and Other (2.6%). A number of students were mixed race (6.7%) among which White-Asian was most common (73%). Approximately 25.7% of the original sample was female, with 73.8% male and less than 1% reporting as non-binary. Students also reported their status as U.S. citizens (78.4%), Permanent Residents (5.1%), or International (16.3%) with the most common countries of origin being China (16.2%) or India (4.2%). Preliminary data analyses for all the scales indicated no emerging differences between permanent residents and citizens, so these groups were combined in the final analyses, accounting for 83.5% of the sample population. Similarly, all international students were combined into a single group (16.3% of the sample population) as supported by the preliminary analyses of all the measurement scales. The final demographic characteristics of the student population are summarized in Table 1.

12 courses were surveyed during remote learning in Spring of 2020 and 7 courses were surveyed during traditional learning between 2016 and 2018. As a result, 45.7% of survey respondents reported their experiences in remote learning while 54.3% reported their experiences in traditional college classrooms. Of the 19 courses studied, 7 were taught in both remote and traditional learning and three (ME1, ME2, EE4) were taught by the same instructor in both settings (Table 2).

Procedures

IRB (Internal Review Board) approval (STUDY00000378) was obtained to recruit and survey undergraduate students for this study. All participation was voluntary, and students were informed that their survey responses would remain confidential.

Table 1: Population Characteristics

	Asian	Black	Latino	Native American	Pacific Islander	White	Other	Total
Total	567	39	40	3	4	533	34	1220
Gender								
Male	416	30	31	3	4	399	24	976
Female	149	9	9	0	0	128	10	340
Country of Origin								
U.S. Citizen	313	34	37	3	4	520	23	934
Permanent Resident	50	3	1	0	0	9	4	67
International Students	199	1	1	0	0	4	7	212
Learning Environment								
Remote	272	13	17	0	0	236	11	549
Traditional	295	26	23	3	4	297	23	671

In several courses, students were incentivized with a nominal amount of extra credit for the course in which they were recruited. In one traditional learning course (EE1), students completed a paper-and-pencil copy of the survey while in all remaining courses, students completed an electronic survey online and outside of class.

Table 2: Courses Studied

Course	**Level**	**Setting**	**Topic**	**Enrolled**	**Participants (*N*)**
ME1	Sophomore Junior Senior	Traditional	Visualization & CAD	179	140
		Remote		155	73
ME2	Sophomore	Traditional	Engineering Statics	69	20
		Remote		92	6
ME3	Sophomore	Traditional	Kinematics and Dynamics	263	218
		Remote		184	143
EE1	Sophomore	Traditional	Introduction to Electrical Engineering	223	175
		Remote		105	73
EE2	Sophomore	Traditional	Circuit Theory	91	70
		Remote		69	57
EE3	Sophomore	Traditional	Continuous Time Linear Systems	84	63
		Remote		86	70
EE4	Sophomore	Traditional	Digital Circuits and Systems	41	35
		Remote		37	27
EE5	Junior	Remote	Devices and Circuits I	56	49
EE6	Junior	Remote	Devices and Circuits II	36	25
EE7	Junior	Remote	Discrete Time Linear Systems	47	37
EE8	Junior	Remote	Energy Systems	71	37
EE9	Junior	Remote	Applied Electromagnetics	15	10

Some students were present in more than one class; since survey questions referred to a specific class ("this class"), duplicate surveys were retained for analysis. All results were cross-sectional.

The instrument used to collect data for this study was a survey which asked students to report their perceptions of various items related to peer support, engagement, belonging, peer harassment, task value, self-efficacy, TA and faculty support, and TA and faculty interactions as well as multiple demographic items.

Table 3: Faculty and Peer Support Measures

Measure	*Sample Items*
Perceptions of Faculty Support 5-point Likert-scale (α = 0.92)	The professor this class is willing to spend time outside of class to discuss issues that are of interest and importance to me. The professor in this class treats me with respect. The professor has clearly explained course goals and requirements. The professor (primary instructor) is often funny or interesting.
Perceptions of Peer Support 5-point Likert-scale (α = 0.87)	In this class, other students are friendl me. In this class, other students are helpfu me. In this class, other students are suppor In this class, other students are a reli resource to me.

Two examples of Likert scale items are mentioned to measure perception of faculty support and peer support (Table 3). The faculty support scale was developed using items from previous studies in K-12 [1] and higher education [2] and is described in more detail in by Wilson, Summers, and Wright [3]. Peer support includes elements of informational support (e.g., ‘students are a reliable resource for me’) and nurturant support (e.g. ‘students are friendly to me’) consistent with the multiple facets of peer support developed by Thompson & Mazer [4]. Similarly, other academic support and engagement scales are created.

APPROACH/MODELS

In this study, to predict the students’ academic support and course level engagement in both traditional and remote learning environment we used machine learning methods. As a baseline Ordinary Least Squares method of linear regression is used for comparison which will be less likely to overfit and will provide a sense to go for a complex modelling. The evaluation criteria will be based on the mean square error for the test data.

Machine learning models and algorithm used in this study are explained below briefly:

1. Ordinary Least Squares: It is one of the simplest methods of linear regression. The goal of OLS is to closely "fit" a function with the data. It does so by minimizing the sum of squared errors (a difference between observed values and predicted values) from the data.

2. Ridge regression: It solves some of the challenges faced by OLS by placing a penalty on the size of the coefficient. The ridge coefficients diminish the penalized residual sum of the squares:

$$\min_{w} ||Xw - y||_2^2 + \alpha ||w||_2^2$$

3. Lasso regression: It estimates sparse coefficients. It is useful in some situations because of its ability to choose solutions with fewer non-zero coefficients, thereby decreasing the number of features on which the solution depends. Mathematically, this consists of a linear model with an added regularization term[https://scikit-learn.org/stable/modules/linear_model.html#lasso]:

$$\min_{w} \frac{1}{2n_{\text{samples}}} ||Xw - y||_2^2 + \alpha ||w||_1$$

4. Elastic regression: It is a linear regression model trained with both the L1 and L2-norm regularization of the coefficients. This combination makes it possible to learn a sparse model where few weights are required. In this case, the objective function to minimize is

$$\min_{w} \frac{1}{2n_{\text{samples}}} ||Xw - y||_2^2 + \alpha\rho ||w||_1 + \frac{\alpha(1-\rho)}{2} ||w||_2^2$$

5. Generalized Linear Regression (Poisson): Predicted values $\hat{y}$ are linked to a linear

combination of input variables X using an inverse link function h.

$$\hat{y}(w, X) = h(Xw).$$

The squared loss function is replaced by the unit deviation of the distribution in the exponential family (or, more specifically, the reproductive exponential dispersion model) (EDM). If the target values are counts (non-negative integer valued) or relative frequencies (non-negative), the log-link deviance of Poisson may be used.

6. Generalized Linear Regression (Gamma): If the target values are positive valued and skewed then Gamma deviance with log-link can be used.

7. Epsilon Support vector Regression: The approach is based on libsvm. The free parameters of the model are C and epsilon.

8. Nu SVM: It uses a parameter nu to control the number of support vectors.

9. Stochastic Gradient Descent: In this linear model, the SGD minimizes the regularized empiric loss. It is especially useful when the number of samples (and the number of features) is very high.

Non-linear methods like neural network and decision tree were explored

Proposed approach outline:

- For this study, 134 features and 1053 samples were used. Numerical and discrete variables are identified in the input data. The missing values in the discrete value allocated as nan (special string) and the missing numeric value identified as 0.

- Splitting the data into 80% train and 20% test data.

- One hot encoding was used for transforming discrete features into binary features.

- Standard scaling is used to normalize the features by subtracting the mean and dividing by standard deviation (Centering and scaling happen independently on each feature).

- For feature selection, Mutual Information and Correlation based methods were used in order to select k best features. k best features based on mutual information produced best results with k=all. Correlation based method produced best results with k=810 but it failed measurably on test data. I decided to go ahead with all the features.

- Model Selection: First baseline model was used to predict the measure scales and then complex machine learning models and algorithm were used. Jupyter Notebook was used to implement the model for this project using python language.

- For hyper parameter tuning, Gridsearch cross validation was used, it implements fit and score methods. This method exhaustively considers all parameter combinations. It uses default as 5-fold cross validation which an iterable yielding (train, test) splits as arrays of indices.[5]

EXPERIMENTAL RESULTS

After applying various models and algorithms to predict academic support and engagement scale, we found that some methods worked better than others, the full list of methods vs. measured scale is summarized in Table 4.

Results show that the ridge regression model better performed for the Effort scale and faculty support scale by providing 0.7125 MSE for effort scale and 0.5328 for faculty support scale. Fig 1 shows the color coding used for indicating the type of method applied for all the scales. Fig 2 and Fig 3 shows the graph between the predicted and validation samples for effort and faculty support scale.

Table 4: MSE result table

ML methods \ Scales	*Effort*	*Belonging*	*Faculty support*	*Peer support*	*Positive Emotional Engagement*
OLS	0.7639	0.6079	0.5553	0.6740	0.6384
Ridge	0.7125	0.5857	0.5328	0.6767	0.6314
Lasso	0.7598	0.5941	0.5432	0.6851	0.7339
Elastic	0.7254	0.6015	0.5432	0.6851	0.7339
GLR (Poisson)	0.7183	0.5830	0.5425	0.6803	0.6303
GLR (Gamma)	0.7229	0.6216	0.5430	0.6768	0.6402
Epsilon SVM	0.7601	0.5942	0.5454	0.6851	0.7427
Nu SVM	0.7598	0.5942	0.5455	0.6850	0.7380
Stochastic Gradient Descent	0.7539	0.6120	0.5437	0.6750	0.6911

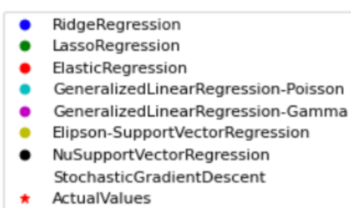

Fig 1. Color coding for all machine learning methods

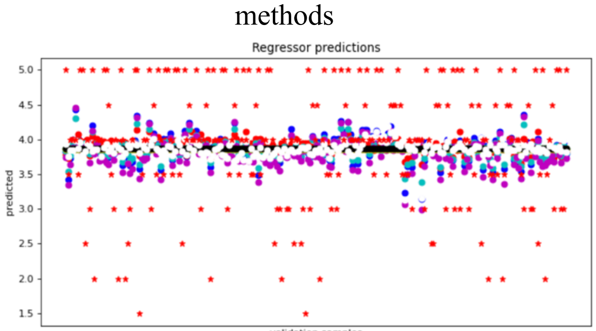

Fig 2. Effort scale predicted Vs actual values

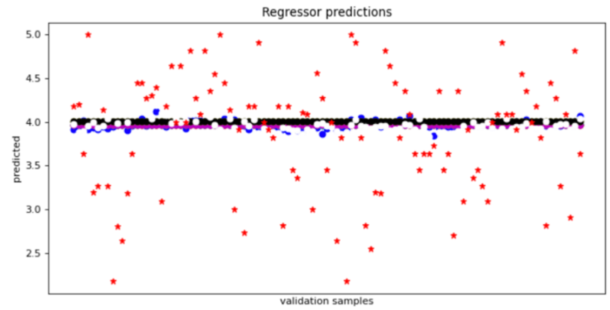

Fig 3. Faculty support scale predicted Vs actual values

In case of belonging (best MSE 0.5830) and positive emotional engagement scale (best MSE 0.6303), generalized linear regression was used with Poisson distribution showed.

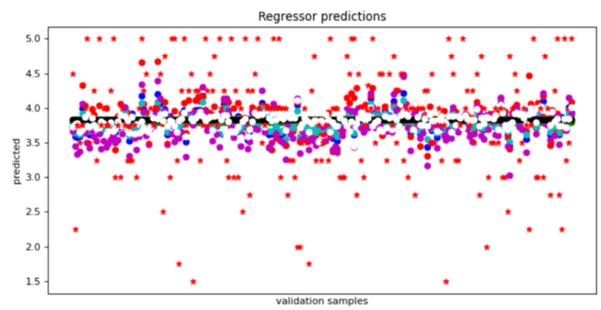

Fig 4. Belonging scale predicted Vs actual values

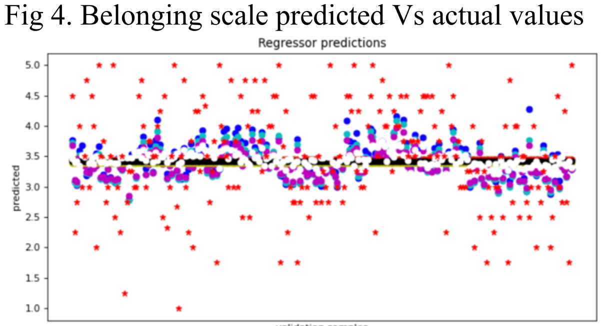

Fig 5. Positive emotional engagement scale predicted Vs actual values

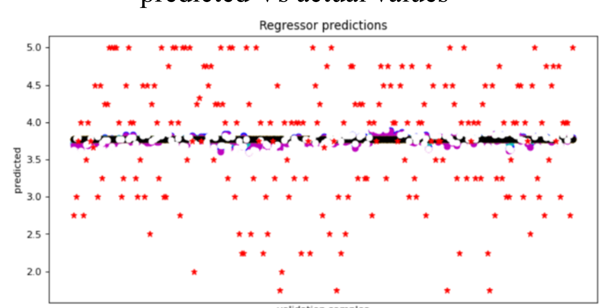

Fig 6. Peer support scale predicted Vs actual values

The predicted vs actual value graph for the above scales are shown in Fig 3 and Fig 4. On the contrary, peer support showed best results with simple baseline model (best MSE 0.6740).

CONCLUSION

This paper summarized the results of a study on. predicting student academic support and engagement scale based on data reported by students through surveys in remote and traditional learning environments using machine learning techniques. After using nine machine learning methods, we found that the ridge regression approach best provided MSE for effort and faculty support scale, while the generalized linear regression using Poisson distribution demonstrated the best MSE for belonging and positive engagement scale. Surprisingly, the OLS baseline model gave the best MSE for peer support. Non-linear models were also used in this analysis, e.g. neural network and decision tree, but none predicted good MSE. Feature selection (Mutual Information and Correlation) approaches were used to pick the best k functions. These techniques, however, failed to work measurably on test data. Overall, some of the methods predicted better outcomes than others. We have learned from the results that both traditional and remote learning settings had substantially different distributions of student responses. Unfortunately, the massive change in learning has had an effect on student support and engagement and, as a result, we infer that the expected outcomes are 20% off the actual values.

LIMITATION

The study focused on the student experience at a single institution and in a limited number of majors (primarily electrical and mechanical engineering), therefore the generalizability to other academic settings may be limited. Further, the remote learning data were collected in the first full term of remote learning and do not reflect longer term adjustments that students may have made as remote learning extended into the 2020-2021 academic year. The data available both in traditional and remote learning environment was limited therefore performance of the model is not as good as expected. Despite the limitations, the results of this study offer a rich perspective regarding predicted values for students' academic support and engagement.

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