Predicting Social Emotional Composite Scores

Alyssa Weber

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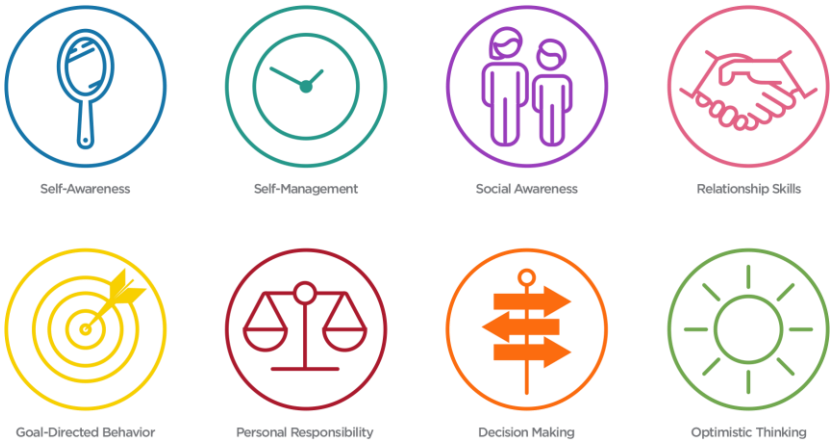
Introduction

Project Proposal

Since the COVID pandemic of 2020, there has been an observed increase of prioritization in education regarding Social Emotional Learning (SEL). The lockdowns of the pandemic isolated adolescents and this period significantly impacted changes in depressive symptoms, anxiety, and life satisfaction (Magson et al., 2021). I have been employed in the White Bear Lake District for eight years as a mathematics teacher. Our high school has set a building goal for the 2022-2023 school year stating that "100% of student and staff will feel their social emotional needs are being supported". Students are given a survey called DESSA (Devereux Student Strengths Assessment) using a company called Aperture Education to track student self-reported SEL scores in eight different strands, shown below. The survey this year was administered in late November and again in late March. White Bear Lake Area High School would like to know what features, other than survey scores, could be used as earlier predictors of social emotional wellbeing.



Dessa Survey Strands (9-12 sel, 2023)

Not only is this analysis on student SEL interesting, but it is also necessary. If educators could accurately predict at-risk students early on in their high school careers, we could implement earlier forms of intervention. Increasing student emotional well-being will lead to safer learning environments, higher levels of performance, and greater social connections. The only way that students can succeed as scholars and leaders in their communities is to make sure their crucial needs are being met first. The CDC (Center for Disease Control and Prevention) reports that the levels of trauma and distress among adolescents observed in the years of 2011-2021 requires action (CDC, 2003). The sooner interventions can take place, the better.

This project would directly support the students enrolled at my high school. Administrators, support staff, and educators are presently using data reactively, rather than proactively, to target students in need of support mid-year. Data for this analysis has been put together by the director of teaching and learning who is also a part of the research, evaluation, and assessment team. The data includes grade level, gender, resolved race/ethnicity, zip code, home language, special education tags, 504 support tags, English language learner tags, total college credits taken and the latest date in which they were taken. It also includes the target variable of fall SEC (Social-Emotional Composite) scores.

Model Proposal

Regression models will work best for the original dataset since it would be predicting numerical SEL scores. However, I also plan on converting the SEL scores into categorical data such as “needs support” and “typical” with the cutoff scores aligning with the DESSA survey scales. In this case I could create a logistic regression model and/or a decision tree. These models will be run using the sklearn packages including “LinearRegression”, “LogisticRegression”, and “DecisionTreeClassifier”. I plan on using cross-validation techniques or an 80/20 training and

testing split. Results for the linear regression can be evaluated using sklearn's accuracy tool which provides an r-squared value. This will help determine how much the given variables account for the variation of the target scores and how much variation is due to other variables. Results for the logistic regression and decision tree can be found using sklearn's accuracy score and confusion matrix which commonly uses accuracy, recall, precision, and F1 scores. I will specifically be using the confusion matrix to evaluate false positives and negatives.

Ethical Implications

I hope to gain more insight on the social emotional well-being of the secondary students in my district. Prioritizing strong relationships with our most at-risk youth and supporting their emotional needs helps create a fostering and productive classroom culture. Ethically, this data was collected from students in our district that staff work with daily, and the results will only be able to generalize to the students within the district. Conclusions will need to be interpreted accurately and presented thoughtfully as I talk about the mental health of our adolescents. False negative results (identifying a student as "does not need support", when in fact they do) will be more harmful than false positives. However, luckily for us, self-reported survey results will be not too far behind to continue to guide our work. As educators, we are intentional about not developing preconceptions about our students and maintaining a growth-mindset. Predicting a student's need for emotional support through background knowledge and algorithms can take away some of our natural instincts to initiate support. Lastly, there are student privacy data laws that will need to be taken seriously in this analysis. Reporting specific cases should only involve personnel that work directly with the student. Whole group data should be collected and presented with student anonymity as a top priority.

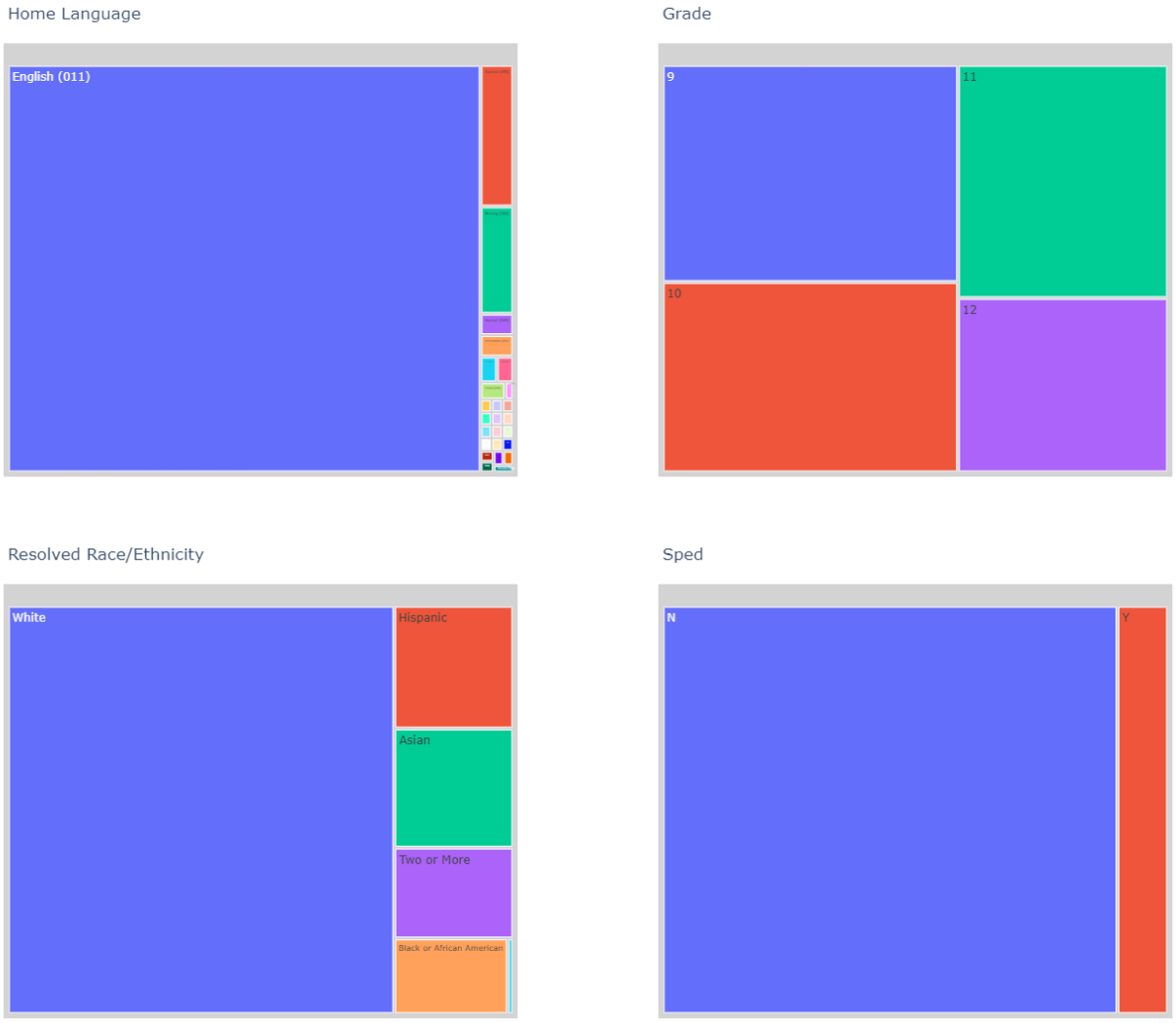
Method/Results

Data Exploration

I began the EDA process by making sure that the dataset was large and robust enough to provide insight on SEL scores for secondary students in my district. The data set originally started with 2,520 students. Since the model is going to be used to predict SEL scores, it is imperative that it only includes students who have a Fall SEC score. There were 1,052 students who did not take the fall survey and were therefore removed from the dataset. It would not be beneficial to fill scores with a mean value for a target variable. It is worrisome that the remaining scores may be biased against students who chose to participate in the survey. However, with the goal of identifying at risk students, 1,468 remaining instances should still provide adequate guidance.

The original dataset provided 17 features. I have removed the fall SEC percentile and the winter SEC percentile as they are not useful training or testing features. There is a column named "Fall SEC Description" that categorizes the fall SEC scores into three different sets; N- "Needs Support", T – "Typical", and S – "Strength". Since I am only interested in classifying students as either "Needs Support" or does not need support, I have changed all N values to 1, and both T and S values to 0. This column will be used for a classification model. The raw SEC score column will be used in a regression model. There are two columns that contain Winter SEC scores. I will keep these in the original data frame but will withhold them from now in the condensed modeling data frame.

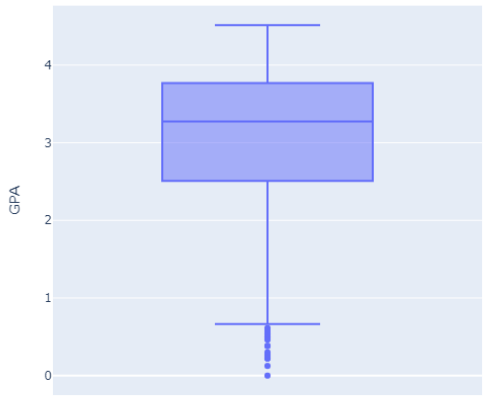
To explore the data, I used a variety of visualizations. To begin, I used tree maps for categorical features to verify that there was enough data in each subgroup to use in the modeling phase.

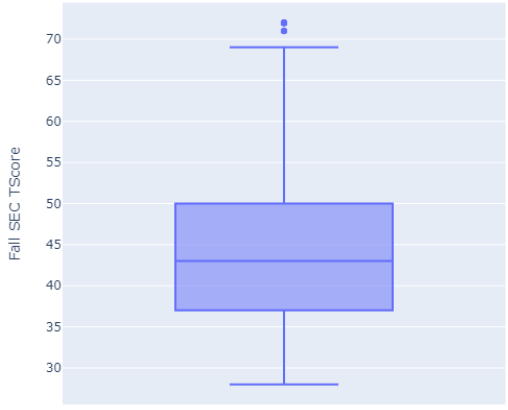


From this exploratory process, I decided to remove the “Home Language” column. 93% of the students in this dataset use English at home. 23 other subgroups had counts of less than five, making this feature not reliable for a test/training split. I ran into errors when trying to build visualizations for 504 Services and English Language Learners. For both features I found that over 93% of the data was missing in each column and therefore would also be removed. In this

process I also investigated two columns named “Latest College Credit Taken” and “Total College Credit Taken". Both columns appear to give similar information in a slightly different format. I have noted that only one should be used in the modeling phase.

To view the spread of numerical data I chose to use boxplots. For GPA I found that all the scores are between 0-4.5. 75% of the students had a GPA in the range of 2.5-4.5 with even spread. The first 25% of the GPA data was spread out between 0-2.5 with quite a few outliers. These outliers will be kept without change in the dataset due to accurate representations. I also viewed the spread of the Fall SEC scores. I found that my target variable is slightly skewed right with two upper outliers. It is likely that these students took the survey and answered every question with the highest rank. It is hard to determine whether these are accurate reflections of the students’ self-evaluation or not. These data points will also be kept in the dataset.





My final steps for cleaning the data were to fill NaN values in the “Total College Credit Taken” column with “0” since these students have not completed a college credit and to create dummy features for categorical data. I created two condensed data frames named “dessa_df_dummy” and “dessa_df_dummy_lin”. The original data frame was used for the categorical descriptions of

Needs Support vs Does Not Need Support, while the latter was used for the linear regression with the original SEC scores.

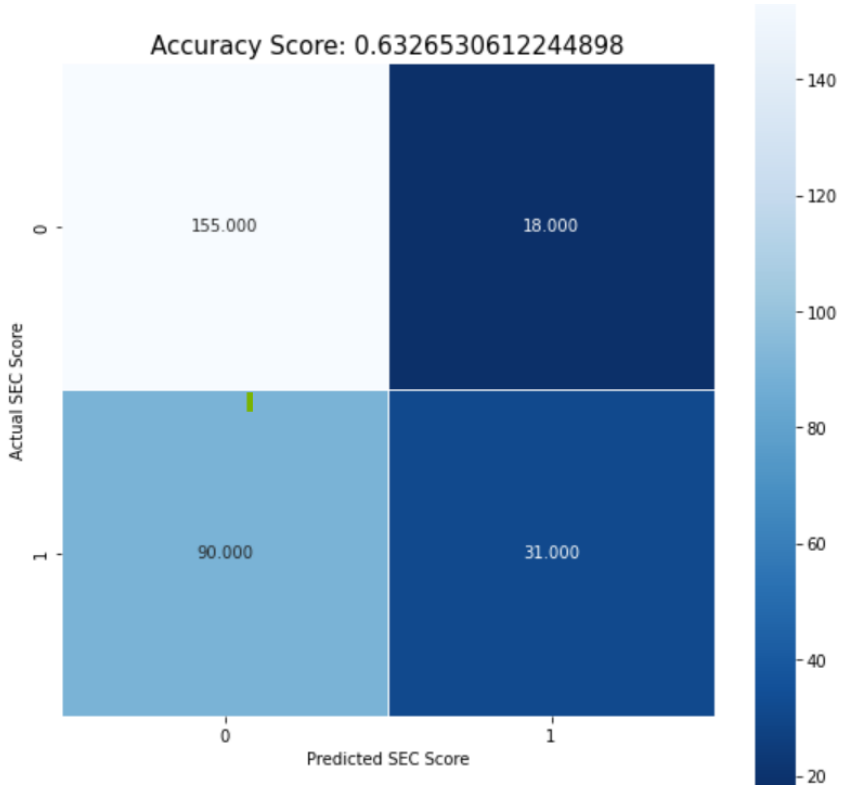
The final data frame to be used in the modeling phase consists of:

- Categorical dummy features including:
    - Grade
    - Gender
    - Resolved Race/Ethnicity
    - Home ZIP Code
    - Sped
- Numerical features including:
    - GPA
    - Total College Credit Taken
- Target Variable:
    - Fall SEC Score (Numerical)
    - Fall SEC Description (Categorical)

Logistic Regression Model

To perform the logistic model, I first split the data into an 80% training and 20% testing set with the Fall SEC Description as the target feature. I then created the Logistic Regression Model using the sklearn package for both the modeling and the classification reports. The Logistic Regression Model produced an accuracy score of 63% on the holdout data. To analyze if

these results were meaningful or not, I produced both a confusion matrix and ran a classification report.



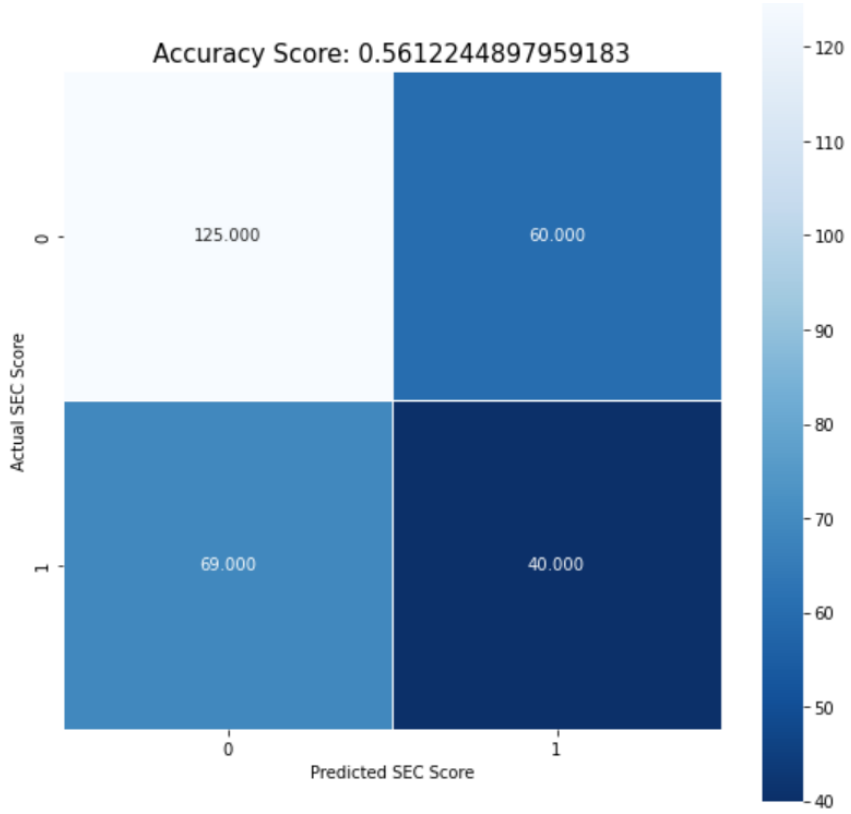
The accuracy of the logistic regression model was 63%. Meaning that the model predicted the SEL description as "Needs Support" or "Does Not Need Support" 63% of the time. This model only produced 18 false positives, indicating the model thought a student would need support, when in fact they did not. Many of the inaccurate results were false negatives, implying the model predicted that students would not need support, when in fact they did.

	precision	recall	f1-score	support
0	0.63	0.90	0.74	173
1	0.63	0.26	0.36	121
accuracy			0.63	294
macro avg	0.63	0.58	0.55	294
weighted avg	0.63	0.63	0.59	294

In the table above, we can see that the F-1 score for Does Not Need Support (0) is 0.74, while the score for Needs Support (1) is 0.36. This shows us that this model works best for classifying students who do not need support.

Decision Tree Model

I built a decision tree next with sklearn's DecisionTreeClassifier package with the hopes of raising accuracy and dropping the false negative rate. I used a new 80/20% training testing split. This model gave me a decreased accuracy score of 56%.



The confusion matrix above shows more false positives than the previous model and less false negatives. Although this seems good at first glance, it is troublesome for the White Bear Lake District in trying to make predictions. This model would end up targeting 100 students to receive interventions, when only 40 of them needed them. The previous model only targeted 49

students, but 31 students did in fact need intervention. The logistic model would be a better allocation of resources and funding as the goal is to accurately target a subgroup of students who could use early intervention.

	precision	recall	f1-score	support
0	0.64	0.68	0.66	185
1	0.40	0.37	0.38	109
accuracy			0.56	294
macro avg	0.52	0.52	0.52	294
weighted avg	0.55	0.56	0.56	294

The classification report for the Decision Tree shows that the F-1 scores again favor this model for predicting students who do not need support (0). Since the accuracy went down and the false positives rose dramatically, this model will not be presented to the district.

Linear Regression

I also ran a Linear Regression Model using a new 80/20% training/test split on the data frame containing the raw SEC scores. All the variables listed in the data exploration section were used to predict the SEC numerical score. To measure its performance, I started with the r^2 score which reported at a measly 0.11. This quantity, being closer to 0 than 1, suggests that this linear model only explains 11% of the variation in SEC scores. I did not pursue this model further after this result. The district is not as concerned anyways with the exact score of each student, but rather if the student needs support or not.

Conclusion

Students are experiencing higher levels of social-emotional distress which is impacting their education. In this study of White Bear Lake Area secondary students, I have explored three

models to determine the best one for predicting students SEC scores or levels in the hopes of deploying a model that could help our district identify at risk students earlier within the school year. I have learned that this is not a task to be taken lightly, and that the details of the results impact the decision-making process the most. Based off my analysis, I would suggest that the district deploy the logistic model at the start of the year before the surveys are taken. All students predicted to need support should be given early intervention opportunities.

Ethically, this model inherently has false positive and negative results that need to be taken into consideration. Survey biases need to be kept at the forefront of decision making when it comes to self-reported mental health states. Luckily for the district, it is only trying to increase early interventions, rather than reallocate resources involving this matter. It is likely that <10% of the students will be labeled as needing support, when in fact they do not. It will not be harmful for students who do not need social-emotional intervention to be given intervention tasks that help build overall well-being. It is a priority for the district, however, that the students correctly categorized begin the process as soon as possible. Based on the model results of this year's data, we will miss many students who still need support.

My further recommendation to the district is to follow up with the Dessa Survey scores in November to target the rest of the students that need intervention. I would like to continue to monitor and adjust the model as we collect further years of data.

References

Aperture Education. (2023, February 28). *9-12 sel*. Social and Emotional Learning - Aperture Education. Retrieved March 26, 2023, from https://apertureed.com/9-12-student-portal/

Centers for Disease Control and Prevention. (2023, April 27). *YRBSS Data Summary & Trends*. Centers for Disease Control and Prevention. https://www.cdc.gov/healthyyouth/data/yrbs/yrbs_data_summary_and_trends.htm

Magson, N. R., Freeman, J. Y. A., Rapee, R. M., Richardson, C. E., Oar, E. L., & Fardouly, J. (2021, January). *Risk and protective factors for prospective changes in adolescent mental health during the COVID-19 pandemic*. Journal of youth and adolescence. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7590912/