Predicting Risk of Being Victims of Bullying for High School Students using Artificial Neural Network

Ziyue Zhang

Abstract—**This study aims to 1) examine the predictors of the victims of bullying at high school 2) build a predictive model for victims of bullying using artificial neural network and compare its performance to logistic regression model. Youth Risk Behavior Surveillance System (YRBSS) 2015 data were used for this study. The YRBSS was developed in 1990 to monitor priority health risk behaviors that contribute markedly to the leading causes of death, disability, and social problems among youth and adults in the United States. All the participants who were eligible were randomly assigned into 2 groups: training sample and testing sample. Two models were built using training sample: artificial neural network and logistic regression, and later used to predict the risk of being victims of bullying in the testing sample. Receiver operating characteristic (ROC) were calculated and compared for these two models for their discrimination capability and a curve using predicted probability versus observed probability were plotted to demonstrate the calibration measure for these two models. In this study, we identified several important predictors for being a victim of bullying at high school e.g., sex orientation, smoking, drinking, or being Hispanic or Latino. This provided important information for educators as well as parents provide timely intervention. We built a predictive model using artificial neural network as well as logistic regression to provide a tool for early detection. As to performance of these two models, logistic regression had a better discriminating capability as well as a better calibration between predicted probability and observed probability.**

Index terms—**Bully, attempt to intimidate someone with strength, logistic model, regression model with categorical dependent variable, predictive model, process predicting outcome using data mining, variable, factor affecting risks of being victims.**

I. INSTRUCTION

Between 1 in 4 and 1 in 3 U.S. students say they have been bullied at school. Many fewer have been cyberbullied. Most bullying happens in middle school. The most common types are verbal and social bullying. There is growing awareness of the problem of bullying. In 2014, the Centers for Disease Control and Department of Education released the first federal uniform definition of bullying for research and surveillance. [2] The core elements of the definition include: unwanted aggressive behavior; observed or perceived power imbalance; and repetition of behaviors or high likelihood of repetition.

Bullying can happen in any number of places, contexts, or locations. Sometimes that place is online or through a cellphone. Bullying that occurs using technology (including but not limited to phones, email, chat rooms, instant messaging, and online posts) is considered electronic bullying and is viewed as a context or location. Electronic bullying or cyberbullying involves primarily verbal aggression (e.g., threatening or harassing electronic communications) and relational aggression (e.g., spreading rumors electronically).

Kids who are bullied are more likely to experience: 1) Depression and anxiety, increased feelings of sadness and loneliness, changes in sleep and eating patterns, and loss of interest in activities they used to enjoy. These issues may persist into adulthood. 2) Decreased academic achievement—GPA and standardized test scores—and school participation. They are more likely to miss, skip, or drop out of school. There is not a single profile of a young person involved in bullying. Youth who bully can be either well connected socially or marginalized, and may be bullied by others as well. Similarly, those who are bullied sometimes bully others. Youth who both bully others and are bullied are at greatest risk for subsequent behavioral, mental health, and academic problems. [1]

In this study, we aim to 1) examine the predictors of the victims of bullying at high school 2) build a predictive model for victims of bullying using artificial neural network and compare its performance to logistic regression model.

II. 2 DATA AND METHODS:

A. Data

Youth Risk Behavior Surveillance System (YRBSS) 2015 data were used for this study.

The YRBSS was developed in 1990 to monitor priority health risk behaviors that contribute markedly to the leading causes of death, disability, and social problems among youth and adults in the United States. These behaviors, often established during childhood and early adolescence, include: 1)behaviors that contribute to unintentional injuries and violence, 2) sexual behaviors related to unintended pregnancy and sexually transmitted infections, including HIV infection, 3)alcohol and other drug use, 4)tobacco use, 5) unhealthy dietary behaviors, 6)inadequate physical activity.

In addition, the YRBSS monitors the prevalence of obesity and asthma and other priority health-related behaviors plus sexual identity and sex of sexual contacts. From 1991 through 2015, the YRBSS has collected data from more than 3.8 million high school students in more

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than 1,700 separate surveys.

B. Models

Artificial neural netwrok consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. In more practical terms neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. Using neural networks as a tool, data warehousing firms are harvesting information from datasets in the process known as data mining. The difference between these data warehouses and ordinary databases is that there is actual anipulation and cross-fertilization of the data helping users makes more informed decisions.

A package called "neuralnet" in R was used to conduct neural network analysis. The package neuralnet focuses on multi-layer perceptrons (MLP, Bishop, 1995), which are well applicable when modeling functional relationships. The underlying structure of an MLP is a directed graph, i.e. it consists of vertices and directed edges, in this context called neurons and synapses. The neurons are organized in layers, which are usually fully connected by synapses. In neuralnet, a synapse can only connect to subsequent layers. The input layer consists of all covariates in separate neurons and the output layer consists of the response variables. The layers in between are referred to as hidden layers, as they are not directly observable. Input layer and hidden layers include a constant neuron relating to intercept synapses, i.e. synapses that are not directly influenced by any covariate. Neural networks are fitted to the data by learning algorithms during a training process. Neuralnet focuses on supervised learning algorithms.

The backward propagation of errors or backpropagation, is a common method of training artificial neural networks and used in conjunction with an optimization method such as gradient descent. The algorithm repeats a two phase cycle, propagation and weight update. When an input vector is presented to the network, it is propagated forward through the network, layer by layer, until it reaches the output layer. The output of the network is then compared to the desired output, using a loss function, and an error value is calculated for each of the neurons in the output layer. The error values are then propagated backwards, starting from the output, until each neuron has an associated error value which roughly represents its contribution to the original output.

We also used logistic regression models to calculate the predicted risk. Logistic regression is a part of a category of statistical models called generalized linear models, and it allows one to predict a discrete outcome from a set of variables that may be continuous, discrete, dichotomous, or a combination of these. Typically, the dependent variable is dichotomous and the independent variables are either categorical or continuous.

The logistic regression model can be expressed with the formula:

$$\ln(P/P-1) = \beta0 + \beta1*X1 + \beta2*X2 + ...+ \beta n*Xn$$

C. Model Evaluation

The two criteria to assess the quality of a classification model are discrimination and calibration. Discrimination is a measure of how well the two classes in the data set are separated; calibration determines how accurate the model probability estimated is to the true probability. To provide an unbiased estimate of a model's discrimination and calibration, these values have to be calculated from a data set not used in the model building process. Usually, a portion of the original data set, called the test or validation set, is put aside for this purpose. In small data sets, there may not be enough data items for both training and testing. In this case, the whole data set is divided into n pieces, n_1 pieces are used for training, and the last piece is the test set. This process of n-fold cross-validation builds n models; the numbers reported are the averages over all n test sets. An alternative to cross-validation is bootstrapping, a process by which training sets are sampled with replacement from the original data sets.

The discriminatory ability – the capacity of the model to separate cases from non-cases, with 1.0 and 0.5 meaning perfect and random discrimination, respectively– was determined using receiver operating characteristic (ROC) curve analysis. ROC curves are commonly used to summarize the diagnostic accuracy of risk models and to assess the improvements made to such models that are gained from adding other risk factors. Sensitivity, specificity, and accuracy will be also calculated and compared. For all these measures, there exist statistical tests to determine whether one model exceeds another in discrimination ability.

The contingency table can derive several evaluation "metrics" (see infobox). To draw a ROC curve, only the true positive rate (TPR) and false positive rate (FPR) are needed (as functions of some classifier parameter). The TPR defines how many correct positive results occur among all positive samples available during the test. FPR, on the other hand, defines how many incorrect positive results occur among all negative samples available during the test.

A ROC space is defined by FPR and TPR as x and y axes respectively, which depicts relative trade-offs between true positive (benefits) and false positive (costs). Since TPR is equivalent to sensitivity and FPR is equal to 1 − specificity, the ROC graph is sometimes called the sensitivity vs (1 − specificity) plot. Each prediction result or instance of a confusion matrix represents one point in the ROC space.

The best possible prediction method would yield a point in the upper left corner or coordinate (0,1) of the ROC space, representing 100% sensitivity (no false negatives) and 100% specificity (no false positives). The (0,1) point is also called a perfect classification. A random guess would give a point along a diagonal line (the so-called line of no-discrimination) from the left bottom to the top right corners (regardless of the positive and negative base rates). An intuitive example of random guessing is a decision by flipping coins. As the size of the sample increases, a random classifier's ROC point migrates towards the diagonal line. In the case of a balanced coin, it will migrate to the point (0.5, 0.5).

The diagonal divides the ROC space. Points above the diagonal represent good classification results (better than random), points below the line represent poor results (worse than random). Note that the output of a consistently poor predictor could simply be inverted to obtain a good predictor.

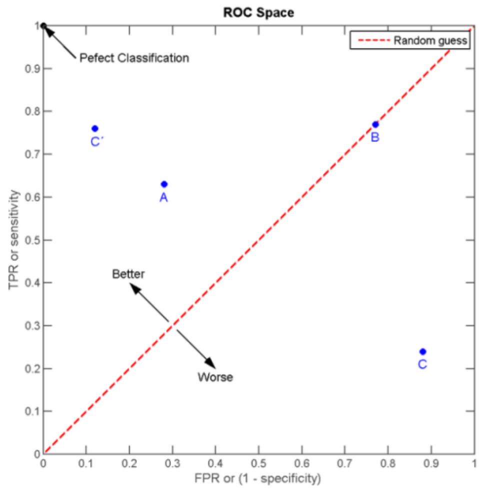

Fig. 1 . ROC curve for random guess.

Calibration is a measure of how close the predictions of a given model are to the real underlying probability. Almost always, the true underlying probability is unknown and can only be estimated retrospectively by verifying the true binary outcome of the data being studied. Calibration thus measures the similarity between two different estimates of a probability. One of the ways to assess calibration is to take the difference between the average observation and the average outcome of a given group as a measure of discalibration. A more refined way to measure calibration requires dividing the sample into smaller groups sorted by predictions, calculating the sum of predictions and sum of outcomes for each group, and determining whether there are any statistically significant differences between the expected and observed numbers by a simple method.

D. Variables

The outcome variable is being victims of bullying based on Q24 During the past 12 months, have you ever been bullied on school property and Q25 During the past 12 months, have you ever been electronically bullied? (Count being bullied through e-mail, chat rooms, instant messaging, websites, or texting.) Students who answered either one with YES were considered as victims of bullying.

Variables used in this study include age, sex, whether the students are Hispanic or Latino, race, height, weight, experience with cigarette smoking, alchohol drinking, marijuana using and/or sexual intercourse, sexual orientation, involvement in sports team, hours of sleep and whether the students have been physically and/or electronically bullied.

III. RESULTS

About 26.9% of 6771 students were victims of bully at high school, about 33.5% among the female and 20.1% among the male.

Basically, a corrgram is a graphical representation of the cells of a matrix of correlations. The idea is to display the pattern of correlations in terms of their signs and magnitudes using visual thinning and correlation-based variable ordering. Moreover, the cells of the matrix can be shaded or colored to show the correlation value. The positive correlations are shown in blue, while the negative correlations are shown in red; the darker the hue, the greater the magnitude of the correlation.

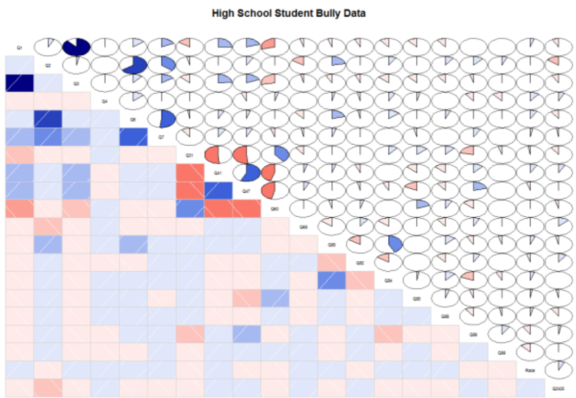

Fig. 2. Matrix of correlations between variables.

According to the logistic regression, female were more likely to be a victim of bullying than male. Students in 10th, 11th, or 12th grades were less likely to be a victim than those in 9th. Hispanic or Latino students were more likely to be a victim than those not. African American students were the one least likely to be a victim of bullying. Students weighted more were more likely to be a victim. Students who smoked or drank were more likely to be victims than those not. Bisexual students were more likely to be a victim than heterosexual. Students who played video games for 4 hours or more were likely to be a victim than those not playing video games.

TABLE II: LOGISTIC REGRESSION FOR BEING VICTIMS OF BULLYING AMONG HIGH SCHOOL STUDENTS

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-0.119	0.713	-0.166	0.868	
Q1	-0.060	0.053	-1.137	0.256	
factor(Q2) 2	-0.624	0.083	-7.492	0.000	***
factor(Q3) 2	-0.290	0.096	-3.005	0.003	**
factor(Q3) 3	-0.333	0.133	-2.501	0.012	*
factor(Q3) 4	-0.499	0.174	-2.861	0.004	**
factor(Q3) 5	-11.242	160.169	-0.070	0.944	
factor(Q4) 2	0.503	0.080	6.278	0.000	***
factor(Race)2	-0.176	0.204	-0.866	0.386	
factor(Race)3	-0.791	0.181	-4.372	0.000	***
factor(Race)4	0.178	0.279	0.636	0.525	
factor(Race)5	0.101	0.152	0.665	0.506	
Q6	-0.355	0.428	-0.830	0.407	
Q7	0.005	0.002	2.313	0.021	*
factor(Q31	-0.246	0.076	-3.230	0.001	**

)2					
factor(Q41)2	0.305	0.091	3.365	0.001	***
factor(Q41)3	0.397	0.091	4.351	0.000	***
factor(Q41)4	0.335	0.113	2.970	0.003	**
factor(Q41)5	0.319	0.125	2.561	0.010	*
factor(Q41)6	0.429	0.143	3.001	0.003	**
factor(Q41)7	0.375	0.150	2.503	0.012	*
factor(Q47)2	-0.044	0.110	-0.400	0.689	
factor(Q47)3	-0.003	0.113	-0.024	0.981	
factor(Q47)4	0.028	0.145	0.193	0.847	
factor(Q47)5	-0.165	0.156	-1.058	0.290	
factor(Q47)6	-0.038	0.161	-0.238	0.812	
factor(Q47)7	-0.304	0.125	-2.427	0.015	*
factor(Q60)2	-0.168	0.071	-2.345	0.019	*
factor(Q68)2	0.276	0.214	1.294	0.196	
factor(Q68)3	0.741	0.110	6.732	0.000	***
factor(Q68)4	0.239	0.167	1.430	0.153	
factor(Q80)2	-0.088	0.143	-0.618	0.537	
factor(Q80)3	0.118	0.123	0.960	0.337	
factor(Q80)4	0.108	0.119	0.910	0.363	
factor(Q80)5	0.218	0.120	1.814	0.070	.
factor(Q80)6	0.120	0.114	1.050	0.294	
factor(Q80)7	0.048	0.140	0.345	0.730	
factor(Q80)8	-0.035	0.110	-0.318	0.750	
factor(Q82)2	-0.064	0.113	-0.569	0.569	
factor(Q82)3	0.121	0.115	1.048	0.295	
factor(Q82)4	0.108	0.106	1.020	0.308	
factor(Q82)5	0.165	0.108	1.530	0.126	
factor(Q82)6	0.435	0.117	3.725	0.000	***
factor(Q82)7	0.498	0.097	5.153	0.000	***
factor(Q84)2	0.161	0.075	2.131	0.033	*
factor(Q84)3	0.160	0.089	1.801	0.072	.
factor(Q84)4	0.274	0.101	2.719	0.007	**
factor(Q85)2	-0.312	0.100	-3.131	0.002	**
factor(Q85)3	-0.290	0.133	-2.176	0.030	*
factor(Q88)2	-0.095	0.134	-0.709	0.478	
factor(Q88)3	-0.266	0.122	-2.180	0.029	*
factor(Q88)4	-0.467	0.121	-3.855	0.000	***
factor(Q88)5	-0.503	0.127	-3.955	0.000	***

factor(Q88)6	-0.322	0.167	-1.930	0.054	.
factor(Q88)7	-0.457	0.262	-1.743	0.081	.
factor(Q89)2	0.180	0.070	2.549	0.011	*
factor(Q89)3	0.109	0.089	1.217	0.224	
factor(Q89)4	0.488	0.155	3.144	0.002	**
factor(Q89)5	-0.015	0.265	-0.058	0.954	
factor(Q89)6	0.419	0.392	1.069	0.285	
factor(Q89)7	0.094	0.196	0.482	0.630	
factor(Q99)2	0.009	0.094	0.092	0.926	
factor(Q99)3	0.117	0.393	0.297	0.766	
factor(Q99)4	-0.208	0.574	-0.362	0.718	

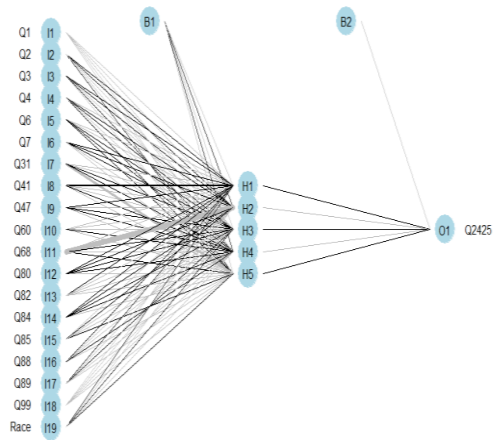

Fig. 3. Artificial neural network in training sample.

In above plot, line thickness represents weight magnitude and line color weight sign (black = positive, grey = negative). The net is essentially a black box so we cannot say that much about the fitting, the weights and the model. Suffice to say that the training algorithm has converged and therefore the model is ready to be used.

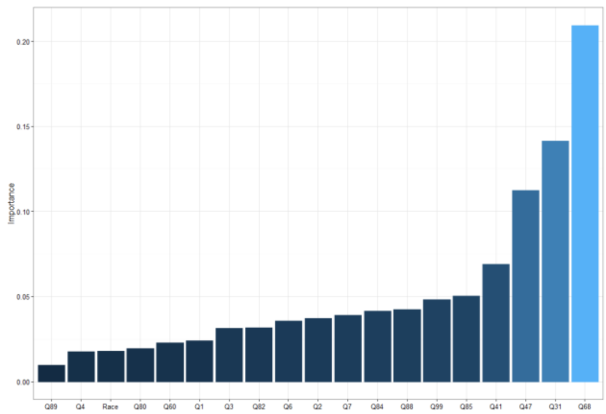

Fig. 4. Variable importance in artificial neural network.

According to this neural network, the top 5 most important predictors were Q85 (Have you ever been tested for HIV, the virus that causes AIDS), Q41 (During your life, on how many days have you had at least one drink of alcohol), Q47 (During your life, how many times have you used marijuana), Q31 (Have you ever tried cigarette smoking, even one or two puffs), Q68 (sexual orientation).

For training sample, the ROC was 0.67 for the Logistic regression and 0.75 for the artificial neural network. Artificial neural network performed better clearly. However in testing sample, the ROC was 0.66 for the Logistic regression and 0.61 for the artificial neural network. Artificial neural network had worse performance.

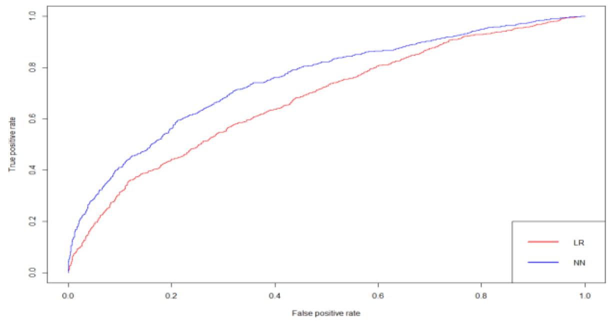

Fig. 5. ROC in training sample for logistic regression (Red) vs neural network (Blue).

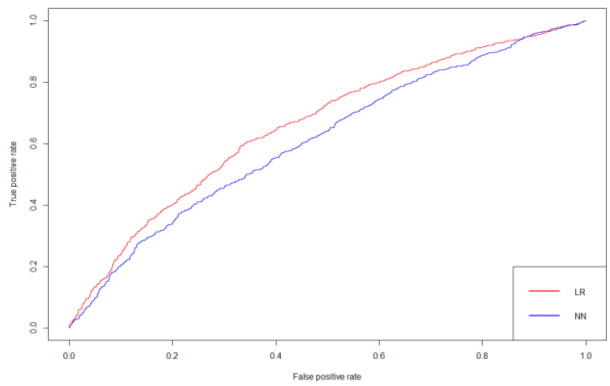

Fig. 6. ROC in testing sample for logistic regression (Red) vs neural network (blue).

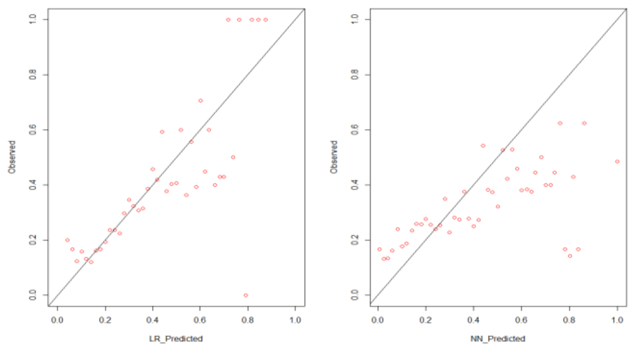

Fig. 7. Predicted probability vs. observed probability in testing sample for logistic regression (Red) vs neural network (Blue), sorted by predicted probability.

By visually inspecting the plot we can see that the predictions made by the neural network are (in general) less concentrated around the line (a perfect alignment with the line would indicate an ideal perfect calibration) than those made by the Logistic model.

IV. Discussions

No single known factor puts a child at risk of being bullied or bulling others. Bullying can happen anywhere—cities, suburbs, or rural towns. Depending on the environment, some groups—such as lesbian, gay, bisexual, or transgender (LGBT) youth, youth with disabilities, and socially isolated youth—may be at an increased risk of being bullied. Kids who are bullied can experience negative physical, school, and mental health issues.

In this study, we identified several important predictors for being a victim of bullying at high school e.g., sex orientation, smoking, drinking, or being Hispanic or Latino. This provided important information for educators as well as parents provide timely intervention. However, solutions to bullying are not simple. Bullying prevention approaches that show the most promise confront the problem from many angles. They involve the entire school community—students, families, administrators, teachers, and staff such as bus drivers, nurses, cafeteria and front office staff—in creating a culture of respect. Zero tolerance and expulsion are not effective approaches. Studies also have shown that adults, including parents[2], can help prevent bullying by keeping the lines of communication open, talking to their children about bullying, encouraging them to do what they love, modeling kindness and respect, and encouraging them to get help when they are involved in bullying or know others who need help [3]. We believe that the factors we identified here can help the educators and parents to identify the issue early.

To have an open communication and discussion on this matter as soon as possible, we further provide a predictive model using artificial neural network as well as logistic regression as a tool for early detection. As to performance of these two models, logistic regression had a better discriminating capability as well as a better calibration between predicted probability and observed probability.

There are limitations of this study. Some known factors which might predict of being a victim of bully were not available in this study, like low popularity, low self-esteem. Further we did not test the external validity neither for logistic regression nor for the ANN. However, we did a comprehensive split-sample validation with both strategies. Future studies could use outside data and test the performance of the outputs from these two models in this study.

A predictive model would be an extremely useful tool to detect bully victim among high school students. As long as the variables included in our tool are available, the risk to be a victim of bullying could be easily predicted. Early detection and intervention could be made available for the students at high risk being victim of bully. It is worth noting that our proposed model and the specific development method – either logistic regression or neural networks – must be evaluated and validated in an independent population.

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Ziyue (Amy) Zhang is a current 12th grade high school student at Peddie School in Hightstown, New Jersey, U.S. Growing up in Nanning and Shenzhen, China, she spent her first 15 years in the two places and later discovered her passion during high school. As a person who has been interested in developmental psychology and sociology, she sought to combine these two fields with data analysis in this particular project. Besides this examination of the predictors of victims of high school bullying, she independently conducted research on the effects of Child Sexual Abuse (CSA) on young victims' physical and intellectual development during her high school career. Moreover, in the summer after she finished junior year (11th grade), she worked as the only high school research assistant in Empathy Development Lab and The Tomasello Lab at Duke University for six weeks and studied topics such as the link between parenting styles and children's self-regulation abilities and the origin of social bonding through shared experience in infants and great apes. Working in the labs under Duke Child Studies, she was honored to exchange ideas with Professor Michael Tomasello and Professor Margarita Svetlova and further her passion in a more professional setting. In her future, Ziyue plans to continue pursuing her passion in related fields, while exploring other potential areas of interest as well. Hoping to use research as a tool, she hopes to address issues including but not limited to the effects of supportive immediate surroundings on young victims' recovery from early adversity in near future.