**Friends-edges:**

1. Model Call: `ergm(formula = net ~ edges)` shows the ERGM formula used to fit the model, which in this case includes only the `edges` term. This is the most basic ERGM, modeling the overall density of the network without considering any other structural effects or nodal attributes.

2. Edges:

- Estimate: -2.86275

- Standard Error: 0.03564

- z value: -80.31

- P-Value: < 0.0001 (\*\*\*)

- Interpretation: The negative estimate for `edges` indicates that the likelihood of an edge (a tie between two nodes) is lower than what would be expected in a random graph of the same size. This suggests that the network has a lower density of ties than a random network. The extremely small p-value indicates this result is statistically significant, which means the network is likely sparse.

3. Deviance Information:

- Null Deviance: The goodness-of-fit measure for a model with no predictors, just the network structure (21349 on 15400 degrees of freedom).

- Residual Deviance: The goodness-of-fit for your model (6474 on 15399 degrees of freedom).

- The drop from null to residual deviance shows that the `edges` term explains a significant amount of the network structure. However, since this is a simple model, it's the only term considered.

4. AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion):

- Both are measures for model comparison, with lower values indicating a better balance between the goodness-of-fit and complexity of the model.

- AIC: 6476

- BIC: 6484

- In this case, the AIC and BIC are quite low, suggesting a model that fits well without unnecessary complexity.

5. MCMC %: This indicates the percentage of the Monte Carlo Markov Chain (MCMC) samples used to estimate the models that were discarded as burn-in. A value of 0% means no burn-in was used, which is appropriate for a simple model like this.

Conclusion:

The model indicates that the network is sparse, meaning that students do not tend to form friendships at a high rate relative to the number of possible friendships. This is a common finding in real-world social networks.

However, since the model only includes the `edges` term, it does not account for any potential complexities or additional structural tendencies within the network. To get a deeper understanding of the network, you might consider adding more terms to the model, such as nodal attributes (e.g., grade level, gender), structural tendencies (e.g., triadic closure), or interactions between nodes based on shared attributes.

**House\_friends:**

Model Summary

- Model Call: This restates the model you fitted: `net ~ edges + nodematch("House", diff = FALSE)`. This model is assessing the impact of general connectivity in the network (edges) and the effect of nodes being in the same "House" (nodematch for "House").

Maximum Likelihood Results

These results are key to understanding the network's dynamics:

- Edges (-3.61003): The estimate for `edges` is negative and highly significant (p < 0.0001), indicating a general low propensity for tie formation in the network. The coefficient of -3.61003 suggests that the log odds of any given pair of nodes forming a tie is low, reflecting a sparse network.

- Nodematch.House (1.39786): The positive and highly significant coefficient for `nodematch("House")` indicates that nodes within the same "House" are much more likely to form ties than nodes from different Houses. The magnitude of 1.39786 for the log odds ratio means that the presence of a shared "House" attribute increases the likelihood of a tie substantially.

Statistical Significance

- Significance Codes: Both coefficients are marked with `\*\*\*`, denoting p-values less than 0.001, which suggests that these effects are statistically robust.

Model Fit Statistics

- Null Deviance (42213 on 30450 degrees of freedom): This is a measure of how well a model with no predictors (only an intercept) fits the data. It acts as a baseline against which to compare the fitted model.

- Residual Deviance (9394 on 30448 degrees of freedom): This is the deviance from your model with predictors. A lower residual deviance compared to the null deviance indicates that your model provides a significantly better fit to the data than the null model.

- Degrees of Freedom: This decreased slightly from the null model to your model, reflecting the addition of model terms.

Information Criteria

- AIC (9398) and BIC (9415): These are information criteria used to evaluate the model fit considering the complexity of the model. Lower values typically indicate a better fit. Comparing these values across different models can help you select the best model among a set of candidates.

Interpretation and Implications

The results indicate that "House" plays a significant role in the formation of ties within this network, supporting the idea of homophily (the tendency for similar individuals to form connections). The strong effect seen in `nodematch("House")` implies that interventions or policies targeting specific Houses could be more effective due to the dense connections within these groups. The sparse overall connectivity suggested by the `edges` term might indicate isolated clusters or a need for initiatives to foster broader networking.

This analysis provides a robust framework for understanding the network's structure, which can inform strategic decisions or further academic research. If you have specific aspects of the results you'd like to explore further or additional questions about the network, feel free to ask!

**Participants\_perc\_academic:**

The output from the **ergm** function you provided does look structurally correct, and it indicates that the model has been successfully fitted to your network data. Let's interpret the components of this output:

**Interpretation of the ERGM Summary:**

1. **Estimate for Edges**:
   * **Value**: -4.01884
   * **Interpretation**: The negative estimate indicates a tendency towards fewer edges than expected in a random network. In simpler terms, nodes tend not to form ties as frequently as they would in a random network, suggesting a sparser network structure.
   * **Statistical Significance**: Extremely significant (p < 0.0001), as denoted by the three stars (\*\*\*).
2. **Estimate for Nodecov (Perc\_Academic\_Norm)**:
   * **Value**: -0.05313
   * **Interpretation**: This coefficient represents the effect of the normalized academic performance on the likelihood of forming ties. The negative value suggests that higher academic performance (as normalized) slightly decreases the likelihood of forming ties, but...
   * **Statistical Significance**: Not statistically significant (p = 0.207), implying that the influence of academic performance on tie formation in this model is not statistically distinguishable from zero at conventional significance levels.
3. **Standard Error**:
   * Measures the standard deviation of the estimated effects, indicating the level of uncertainty around these estimates. Lower values suggest more precise estimates.
4. **Z-Value**:
   * Derived by dividing the estimate by its standard error, used to determine the significance of the effect. A higher absolute value generally indicates stronger evidence against the null hypothesis (which would typically state that there is no effect).
5. **P-Values**:
   * Used to decide whether to reject the null hypothesis. Here, only the edges effect is significant.
6. **Deviance Information**:
   * **Null Deviance vs. Residual Deviance**: The null deviance shows how well the model with only the intercept (no predictors) fits the data, whereas the residual deviance shows how well the model with predictors fits the data. The closer these values are, the better the model fits.
   * **Degrees of Freedom**: Shows the number of degrees of freedom left after fitting the model. It's calculated as the number of observations minus the number of parameters estimated.
7. **AIC and BIC**:
   * **AIC (Akaike Information Criterion)** and **BIC (Bayesian Information Criterion)** are measures used to compare models. Both criteria penalize the likelihood based on the number of parameters, aiming to balance model fit with complexity. Lower values are better.

**Conclusion:**

While your model is structurally sound and the fitting process itself seems successful, the actual impact of normalized academic performance (**nodecov.Perc\_Academic\_Norm**) on network formation does not appear to be significant. This might suggest that either **Perc\_Academic** isn't a strong predictor in this context, or that other factors not included in the model may be influencing the network structure more significantly.

**Perc academic effort influential:**

The output you've posted for your ERGM model looks structurally correct and it seems to have executed without issues. Here's a breakdown and interpretation of your model results:

Model Summary Interpretation:

1. Edges:

- Estimate: -4.02045

- Standard Error: 0.06243

- z value: -64.396

- Pr(>|z|): < 0.0001

- Interpretation: The negative estimate for `edges` indicates that the likelihood of edges forming in the network is lower than would be expected by chance alone. The highly significant p-value (<0.0001) strongly supports this finding, suggesting a sparse network.

2. Nodecov: Perc\_Academic\_Norm:

- Estimate: -0.07573

- Standard Error: 0.04815

- z value: -1.573

- Pr(>|z|): 0.116

- Interpretation: This coefficient is negative, suggesting that higher normalized academic performance might slightly decrease the likelihood of forming ties, though this effect is not statistically significant (p = 0.116). It indicates that as academic performance increases, the tendency to form connections decreases, albeit not strongly enough to be statistically conclusive.

3. Nodecov: Perc\_Effort\_Norm:

- Estimate:0.04602

- Standard Error:0.04802

- z value: 0.958

- Pr(>|z|):0.338

- Interpretation: This positive coefficient suggests a slight increase in the likelihood of forming ties with higher effort levels, although this effect is also not statistically significant (p = 0.338). It suggests that greater effort might be associated with slightly more connections, but like academic performance, this isn't a strong or statistically significant effect.

Additional Model Statistics:

- Null Deviance and Residual Deviance: The null deviance compared to the residual deviance shows how much better the model with predictors (your covariates) performs compared to a model without any predictors. The decrease is substantial, indicating that the model explains some of the variation in the network.

- AIC and BIC: Both are measures of model fit that penalize for the number of parameters. The lower these values, the better. Your values indicate a decent model fit but could potentially be improved with either model simplification or by including additional relevant predictors.

Considerations:

- Significance: None of the node covariates are statistically significant, which might suggest that either these factors are not strong predictors in this network context, or other unmodeled factors may be influencing tie formation.

**Feedback\_effort\_academic percentage**:

The results you've obtained from the ERGM using the `net\_2\_Feedback` dataset with attributes `Perc\_Academic\_Norm` and `Perc\_Effort\_Norm` indicate a statistically significant influence of both academic performance and effort on the formation of feedback ties within your network. Here’s a detailed breakdown and interpretation of your results:

ERGM Output Interpretation:

1. Edges:

- Estimate: -4.61405

- Standard Error: 0.07777

- Z-Value: -59.333

-P-Value: < 0.0001 (\*\*\*)

- Interpretation: The negative and highly significant estimate for edges suggests that the probability of any given tie existing in the network is quite low, indicating a sparse network. This is a typical finding in many real-world networks where connections between entities are less frequent than not.

2. Nodecov: Perc\_Academic\_Norm:

- Estimate: 0.12723

- Standard Error: 0.05678

- Z-Value: 2.241

- P-Value: 0.02505 (\*)

- Interpretation: The positive and statistically significant coefficient for normalized academic performance suggests that individuals with higher academic performance are more likely to form feedback ties compared to their lower-performing counterparts. The significance at the 0.05 level indicates a reliable effect within the model's context.

3. Nodecov: Perc\_Effort\_Norm:

- Estimate: 0.16154

- Standard Error: 0.05888

- Z-Value: 2.744

- P-Valu: 0.00608 (\*\*)

- Interpretation: Similarly, the positive and more significant coefficient for effort indicates that greater effort is associated with a higher likelihood of forming feedback ties. This effect is stronger and more statistically significant than that of academic performance.

Additional Statistics:

- Null Deviance and Residual Deviance: The large drop from null deviance to residual deviance shows that your model explains a significant portion of the network's structure compared to a model without any predictors.

- AIC and BIC: The values here are meant to help compare different models. Lower values typically indicate a better fit to the data, considering the number of parameters used.

Conclusion:

The model shows that both academic performance and effort significantly influence feedback relationships in your network, which suggests that these attributes are important in how individuals interact within the context of giving and receiving feedback. This could imply that individuals who perform better academically and those who put in more effort are more central or more engaged in feedback processes, which might be due to their more active or visible roles in the academic environment.

Is This Good?

Yes, the results are good in terms of statistical significance and the meaningful interpretation they offer regarding the network dynamics. They provide clear evidence that both academic performance and effort matter in the formation of feedback ties in your specific network setting.

**Growthmindset- moretime:**

The output from the **ergm** function is a summary of the fitted Exponential Random Graph Model for your network. Let's break down what each part of the output indicates:

**ERGM Summary Interpretation:**

1. **Edges**:
   * **Estimate**: -4.250933
   * **Standard Error**: 0.234554
   * **z value**: -18.123
   * **P-Value**: < 0.0001 (\*\*\*)
   * **Interpretation**: The negative and highly statistically significant coefficient for **edges** indicates that the likelihood of a tie existing between any two students is lower than would be expected if ties were formed at random. This suggests a sparse network where connections between students are less frequent.
2. **nodecov.GrowthMindset**:
   * **Estimate**: 0.008864
   * **Standard Error**: 0.016007
   * **z value**: 0.554
   * **P-Value**: 0.58
   * **Interpretation**: The coefficient for **nodecov.GrowthMindset** represents the effect of the growth mindset attribute on the formation of ties. Its positive sign suggests a very slight tendency for students with higher growth mindset scores to form more ties. However, the effect is not statistically significant (p = 0.58), which implies that within the context of this model, the growth mindset score does not have a significant impact on the likelihood of students choosing to spend more time with each other.

**Additional Model Statistics:**

* **Null Deviance vs. Residual Deviance**: The null deviance is the goodness-of-fit measure for a model with no predictors (only the network structure), while the residual deviance is for your model with predictors. The difference between the null and residual deviance shows how much better your model explains the network structure compared to the null model. The large decrease in deviance suggests that your model (including the **GrowthMindset** attribute) explains the network structure substantially better than the null model.
* **AIC and BIC**: These are measures of the model fit that take into account the number of parameters estimated. The lower these numbers, the better the balance between model fit and complexity. The AIC and BIC provided suggest that the model is relatively parsimonious, balancing model complexity and fit effectively.

**Conclusion:**

While the model structure appears to be good in terms of explaining the network (as indicated by the large decrease in deviance from null to residual), the specific attribute of interest (**GrowthMindset**) does not seem to have a significant influence on the formation of ties based on the desire to spend more time together in this particular network. The network's sparsity is well-captured, but **GrowthMindset** as operationalized might not be a driving factor in this context—or the model may need additional attributes or interaction terms to better capture the complexities of these social relationships.

**Advice- perc academic both source and target:**

The output from the **ergm()** function provides the results of fitting an Exponential Random Graph Model (ERGM) to your network. This model includes the effect of academic performance scores from both the source and target nodes on the likelihood of advice-seeking ties forming between them. Let's break down the results:

**ERGM Summary Explanation**

1. **Model Formula**:
   * **ergm(formula = net ~ edges + nodecov("Source\_Perc\_Academic") + nodecov("Target\_Perc\_Academic"))**
   * This formula indicates that the model includes the basic network structure (edges) and tests the influence of academic performance scores of both the source and target nodes on these edges.
2. **Parameter Estimates**:
   * **Edges**: The coefficient for **edges** is -3.8786 with a standard error of 0.2111. The very negative coefficient with a highly significant p-value (**<1e-04**) suggests a lower-than-expected number of ties compared to a random network of similar size. This indicates the network is sparse, meaning ties are less frequent than in a completely random distribution.
   * **nodecov.Source\_Perc\_Academic**: The coefficient is -0.0045 with a standard error of 0.0015, and it is statistically significant (**p = 0.0027**). This suggests that higher academic scores of source nodes are associated with a slightly lower probability of them initiating advice-seeking ties. This could imply that higher-performing students might be less likely to seek advice, possibly because they rely more on their own resources or have fewer queries.
   * **nodecov.Target\_Perc\_Academic**: The coefficient is 0.000165 with a standard error of 0.001635, which is not statistically significant (**p = 0.9194**). This suggests that the academic performance of target nodes does not significantly influence the likelihood of them being chosen for advice. Their academic performance, in this model, does not seem to impact their centrality as advice receivers.
3. **Deviance Information**:
   * **Null Deviance**: Measures the goodness-of-fit of a model with no predictors, just the network structure itself. Here, it's 35267 on 25440 degrees of freedom.
   * **Residual Deviance**: Measures the goodness-of-fit of the model with the included predictors. It is significantly lower at 3771 on 25437 degrees of freedom, indicating that the model with the predictors provides a substantially better fit than the null model.
4. **Model Fit (AIC and BIC)**:
   * **AIC (Akaike Information Criterion)**: 3777
   * **BIC (Bayesian Information Criterion)**: 3802
   * Both values are for model comparison, where lower values are better. The difference in deviance and these indices suggests the model fits the data well relative to its complexity.

**Conclusion and Implications**

* The significant negative effect of source academic performance suggests potential self-sufficiency or fewer perceived needs for academic advice among higher-performing students.
* The non-significant effect of target academic performance implies that, in this context, being academically strong does not necessarily make a student a more likely target for receiving advice, which might challenge assumptions about academic reputation influencing advice networks.
* These insights can inform educational strategies, potentially highlighting the need for encouraging more inter-peer engagement and advice-seeking among high performers or addressing why certain students are not perceived as go-to individuals for advice despite strong academic performance.

This analysis helps in understanding the underlying dynamics of advice-seeking behavior in educational settings and can guide interventions aimed at enhancing academic support networks.

**Disrespect\_attendance:**

The output from the **summary(model)** function provides the results of your Exponential Random Graph Model (ERGM), which was fitted to understand how attendance influences involvement in disrespect-related interactions within the school network. Let's analyze the results in relation to your research question and hypotheses.

**Model Summary Interpretation**

1. **Edges**:
   * **Estimate:** -4.900642
   * **Standard Error:** 1.679101
   * **z value:** -2.919
   * **P-value:** 0.00352
   * **Interpretation:** The negative estimate indicates that, overall, ties in the network are less likely than would be expected by chance alone, suggesting that disrespect interactions are not frequent or widespread. The significance of this coefficient (p < 0.01) underscores the sparsity of the network, meaning disrespect interactions are notably infrequent.
2. **nodecov.Source\_Attendance**:
   * **Estimate:** -0.011041
   * **Standard Error:** 0.005363
   * **z value:** -2.059
   * **P-value:** 0.03954
   * **Interpretation:** This coefficient is statistically significant and negative, indicating that higher attendance rates for the source nodes (those initiating disrespect) are associated with a slightly decreased likelihood of engaging in disrespect. This finding supports **Hypothesis 1**, suggesting that students who attend school more regularly are less likely to initiate disrespect, potentially due to better integration into the school community or adherence to school norms.
3. **nodecov.Target\_Attendance**:
   * **Estimate:** 0.014886
   * **Standard Error:** 0.008075
   * **z value:** 1.844
   * **P-value:** 0.06524
   * **Interpretation:** This coefficient is positive and marginally significant, suggesting a trend where students with higher attendance rates might be slightly more likely to be targeted for disrespect. This result is intriguing and aligns somewhat with **Hypothesis 2**, indicating that more frequently attending students may be more visible or more integrated, potentially making them more noticeable targets for disrespect. However, this result is not statistically significant at the conventional 0.05 level, indicating that more data or further study might be needed to confirm this trend.

**Deviance Information**

* **Null Deviance vs. Residual Deviance**: The substantial drop from the null deviance (6504.5) to the residual deviance (770.3) after including the predictors indicates that the model explains a significant portion of the network's variability. This confirms that attendance is a relevant factor in understanding the structure of disrespect interactions.

**Model Fit (AIC and BIC)**

* **AIC:** 776.3
* **BIC:** 795.7
* Both the AIC and BIC values indicate that the model fits the data reasonably well, with a good balance between accuracy and complexity.

**Conclusions and Implications**

The results suggest that attendance plays a nuanced role in disrespect interactions within the school:

* **For Initiators (Source):** More consistent attendance decreases the likelihood of being a source of disrespect, highlighting the potential benefits of engaging students more deeply in the school environment.
* **For Targets (Target):** Higher attendance may marginally increase the likelihood of being a target, possibly due to increased social exposure or conflicts.

These insights can inform targeted interventions, such as fostering positive engagement for regular attenders to leverage their influence in promoting respectful interactions and examining the social dynamics that lead to disrespect among students with high attendance. Further research could also explore other factors that may interact with attendance to influence these dynamics, such as peer relationships, teacher-student interactions, or school climate.