Greenspace Team 3 - Therapeutic Alliance Week 6 Team Report

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- Team progress compared to the project plan and milestones

In our planned timeline, between June 2nd and June 8th, we aimed to complete the following tasks: Key Features Identification, Key Features Verification, and Model Prediction Accuracy Test. Prior to this, we had undertaken extensive data cleaning and attempted to build a model to predict the therapeutic alliance score. However, the model results did not allow us to successfully identify significant predictors for the therapeutic alliance score, and the model's performance was unsatisfactory. Consequently, we had to adjust our direction and timeline.

After discussions with several professors, we decided to pursue a different modeling approach based on the match logic provided by Greenspace. Our revised approach focused on the following four tasks:

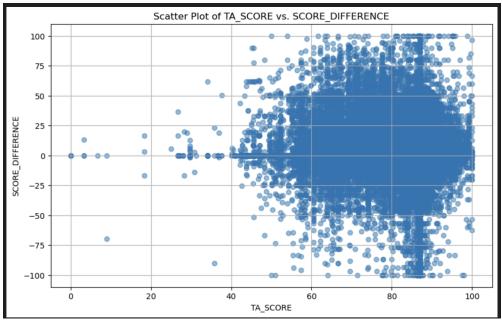
- 1. Compared the initial TA score and the final TA score of patients to identify which therapist had the most (or least) improvement in TA scores and tried to uncover any useful patterns.
- 2. Calculated the improvement rate for each therapist with different patient and assessment combinations to inform future models and determine the therapist's specialty (expertise in specific areas or assessments).
- 3. Identified the most frequently assigned assessments by each therapist to determine their specialties.
- 4. Calculated the caseload for each therapist.

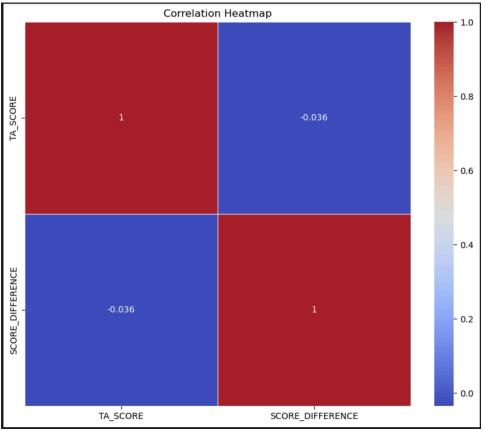
Next, we will investigate recommendation algorithms for therapist matching. We have developed our initial therapist-patient matching algorithms, but these are just preliminary attempts. Since this is beyond the scope of what we learned in our previous courses, we need further understanding and testing.

Results:

We uncovered an issue in our database where some therapists were assigned an unreasonable number of patients, or have assigned too many assessments. Moving forward, we will need to establish a threshold to filter out these illegitimate cases, ensuring the integrity of our data and the effectiveness of our matching system.

Regarding the score difference (the change between the initial and final TA scores of patients), it appears this feature is not as useful as previously thought. The scatterplot, along with a collinearity value of 0.036, supports this conclusion.





The results from our recommendation system appear not bad. Utilizing a Hybrid Recommender System, which combines Collaborative Filtering and Content-Based Filtering, the model demonstrated strong predictive performance. Specifically, in the test set, the model correctly predicted the first choice of therapist by patients 46.47% of the time. Furthermore, it correctly identified one of the top five therapists 91.51% of the time, and one of the top ten therapists 98.07% of the time. However, as we are relatively new to this algorithm, we are currently working to fully understand the implications of these percentages and determine if the performance is as impressive as it appears.

- The individual contributions on what they have done in previous week

Group Member	Contribution	Challenges
Kohsin	 Used SQL to extract data for calculating caseloads Tried to identify caseloads for every therapist. Tried using PHQ-9, GAD-7 and WSAS as input for random forest and neural network to calculate match scores. Studied for recommendation system algorithms. 	Some therapists had unreasonable active patient counts.
Zerui	 Found the most frequently assigned assessment by each therapist, which then was used to determine the specialty of therapists. Cleaned and merged data to prepare for the matching model input. 	 Need to filter out therapists who have assigned too many assessments. The most frequently assigned assessment is likely not a good

	Studied recommendation system approaches.	indicator for therapist expertise.
Zheng	 Determined the proportion of patients who show improvement under each therapist for different assessment and defined therapist's special. Tried KNN model for therapist recommendation 	 Using the highest improvement ratio to determine a therapist's specialization may not be effective for therapists with fewer patients. Limited data of the therapists to determine the matching rate.
Bingshen	 Find which therapist helps with TA improvement the most with the score difference feature. Tried Hybrid Recommender Systems for therapist recommendation 	For new patients or new therapists, the system lacks sufficient historical data to make accurate recommendations. The interaction data between patients and therapists is sparse, so the recommendation system may not be able to fully learn the preference relationships between users and items.

- Team communication and collaboration

- 1. We schedule regular team meetings every Wednesday and Saturday, with occasional additional meetings on Thursday, to discuss progress, challenges, and next steps.
- 2. We share regular updates on everyone's progress during these meetings.
- 3. We discuss insights from our meetings with Greenspace and split our tasks accordingly.

- Clear work plan with tasks assigned to each person for the next week

Group Member Next Week Tasks Assigned

Kohsin	Try recommendation algorithm, using therapeutic alliance scores as match scores.
Zerui	Build recommendation system using score improvement as criterion for good match.
Zheng	Find more columns that would affect matching scores, adjust the model by adding more attributes.
Bingshen	We need to evaluate the results of the current hybrid recommendation algorithm. If the performance metrics are indeed as strong as they appear, we can finalize the model. However, if the results fall short of expectations, further adjustments to the algorithm will be necessary.