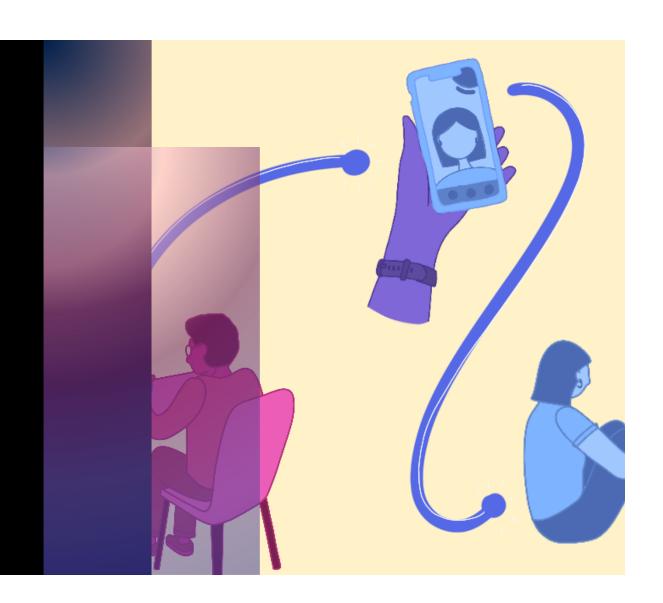
Speed Dating Predictions

A prediction model with an analysis of what drives people to choose a mate.



Business Idea: Speed Dating Match Prediction.

Importance: We find this as an interesting topic since there are already serval dating apps

that show potential matches based on individual needs, likes and dislikes. It will also give us insight into human behaviour and understand what factors

are important to people when it comes to choosing potential mates.

Data Resources: For this project we are using a dataset that was compiled by Columbia

Business School professors Ray Fisman and Sheena Iyengar for their

paper Gender Differences in Mate Selection: Evidence From a Speed Dating

Experiment.

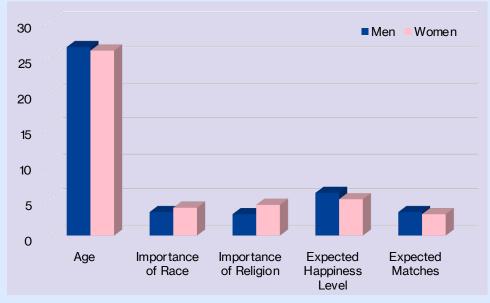
As part of their study the subjects were asked to fill a survey when they signed up for the Speed Dating Event and fill a scorecard on various attributes on each of their potential matches. At the end of the night subjects were matched with potential partners if both persons said yes. This experiment was conducted on various days with different groups of people and collated into one dataset.

Our goal is to predict the result of matching as "Yes" or "No"

Distribution of Gender 50.10% ■ Men ■ Women Match Distribution 16.50% 83.50% ■Yes ■No

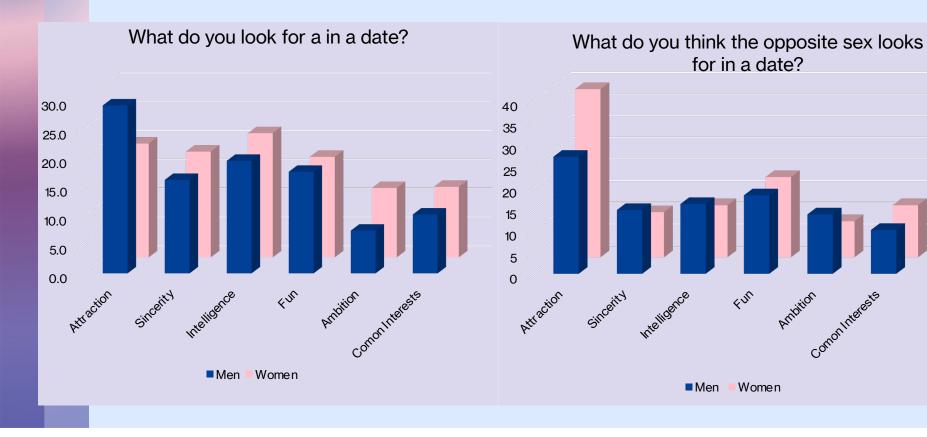
Some Information About our Data

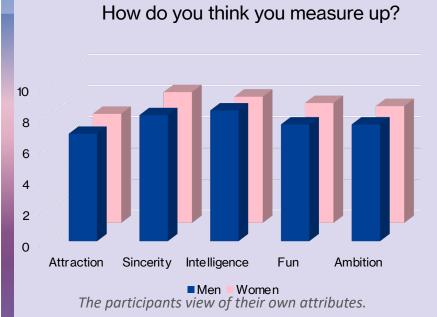
- 84 attributes and 1 target(match) column
- 76 columns with null values and 7 object type columns.
- We will eventually drop columns with more than 20% missing values and fill the remaining null values with the mean of the column and create dummy variables using one hot encoding in Data Processing Part I.



Gender Differences in Views & Perception

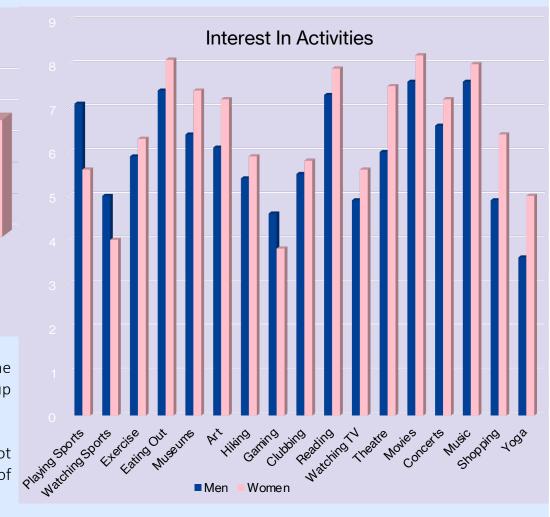
The Participants were asked to distribute 100 points across the below attributes in response to each question.





All this information was collected from the participants as part of the signing up process before the event.

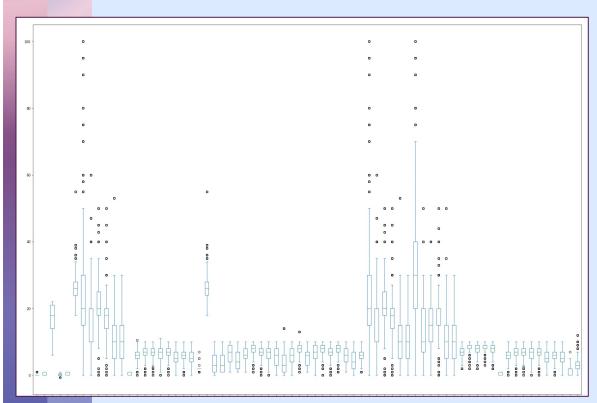
The participants chose to match or not with the person they met at the end of their 4-minute speed date.



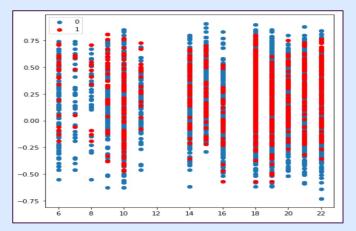
Having explored our data we then checked for any outliers that could cause our model to be overfit and/or underperform.

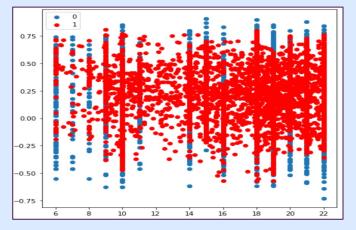
After Dealing with the outliers using Isolation Forest we began the process of fitting our models and tuning them.

We have also resampled our data using Synthetic Minority Oversampling Technique (SMOTE)



Data Processing Part II





Principal Component Analysis Results

Logistic Regression			Decision Tree Classifier				Naïve Bayes Classifier				KNN Classifier								
Classification	report: precision	recall	f1-score	support	Classification	report: precision	recall	f1-score	support	Classification	report: precision	recall	f1-score	support	Classificatio	n report: precision	recall	f1-score	support
0 1	0.83 0.13	0.69 0.24	0.76 0.17	1722 323	0 1	0.83 0.16	0.76 0.23	0.79 0.19	1703 342	0 1	0.83 0.30	1.00 0.01	0.91 0.02	1695 350	0 1	0.83 0.38	0.99 0.03	0.90 0.06	1683 362
accuracy macro avg weighted avg	0.48 0.72	0.47 0.62	0.62 0.46 0.66	2045 2045 2045	accuracy macro avg weighted avg	0.50 0.72	0.49 0.67	0.67 0.49 0.69	2045 2045 2045	accuracy macro avg weighted avg	0.56 0.74	0.50 0.83	0.83 0.46 0.75	2045 2045 2045	accuracy macro avg weighted avg	0.60 0.75	0.51 0.82	0.82 0.48 0.75	2045 2045 2045
Confusion mate [[1194 528] [244 79]]	rix:				Confusion matr [[1289 414] [263 79]]	rix:				Confusion mate [[1688 7] [347 3]]	rix:				Confusion mat [[1665 18] [351 11]]				
Classificatio	n report: precision	recall	f1-score	support	Classification	n report: precision	recall	f1-score	support	Classificatio	n report: precision	recall	f1-score	support	Classificatio	n report: precision	recall	f1-score	support
0 1	0.83 0.00	1.00 0.00	0.91 0.00	1524 306	0 1	0.83 0.15	0.81 0.17	0.82 0.16	1532 298	0 1	0.85 0.25	1.00 0.00	0.92 0.01	1546 284	0 1	0.84 0.00	1.00 0.00	0.91 0.00	1538 292
accuracy macro avg weighted avg	0.42 0.69	0.50 0.83	0.83 0.45 0.76	1830 1830 1830	accuracy macro avg weighted avg	0.49 0.72	0.49 0.71	0.71 0.49 0.71	1830 1830 1830	accuracy macro avg weighted avg	0.55 0.75	0.50 0.84	0.84 0.46 0.77	1830 1830 1830	accuracy macro avg weighted avg	0.42 0.71	0.50 0.84	0.84 0.46 0.77	1830 1830 1830
Confusion mat [[1524 0] [306 0]]					Confusion mat [[1240 292] [246 52]]	rix:				Confusion mat [[1543 3] [283 1]]	rix:				Confusion mat [[1537 1] [292 0]]	rix:			

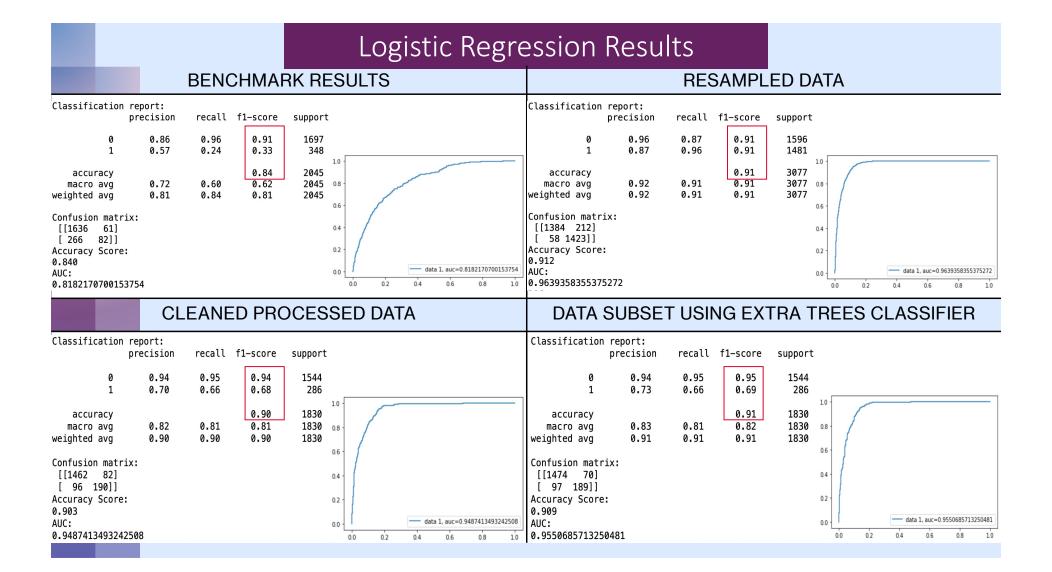
Our Process

We used four machine learning models to classify our data into match and no match. We ran each of our models using four versions of our data to get the best model and accuracy.

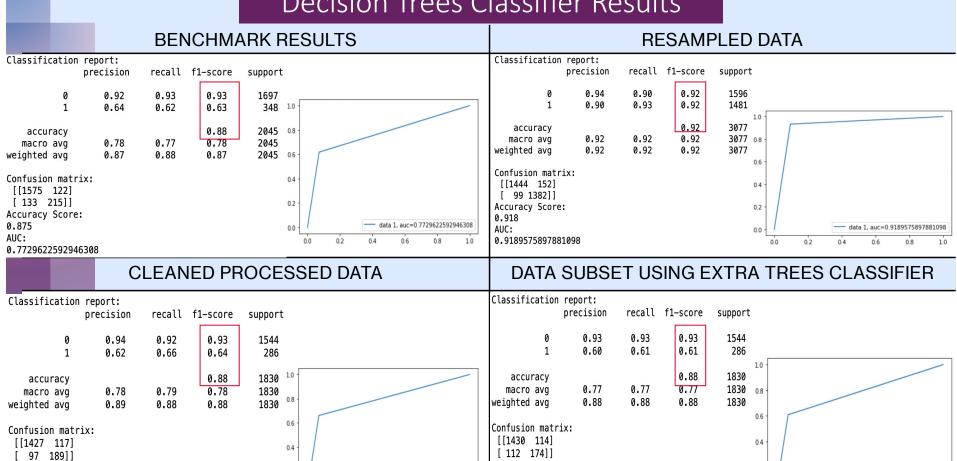
Logistic Regression Decision Trees Classifier Naïve Bayes Classifier

K Nearest Neighbors

- **1. Benchmark Data:** This data is the original dataset in which we have not dropped any columns or rows.
- 2. Cleaned & Processed Data: In this set we dropped columns and rows with logically and those with large volumes of null values (20% & above) and treated our dataset for outliers.
- 3. Resampled Data: We resampled our dataset using Synthetic Minority Oversampling Technique (SMOTE)
- **4. Data using Extra Trees Classifier as a feature selection method:** Using this method we got the top 12 attributes which we then used for our machine learning models.



Decision Trees Classifier Results



0.2

0.0

Accuracy Score:

0.792530979383311

0.883

AUC:

Accuracy Score:

0.7672787057502083

0.877

AUC:

data 1. auc=0.792530979383311

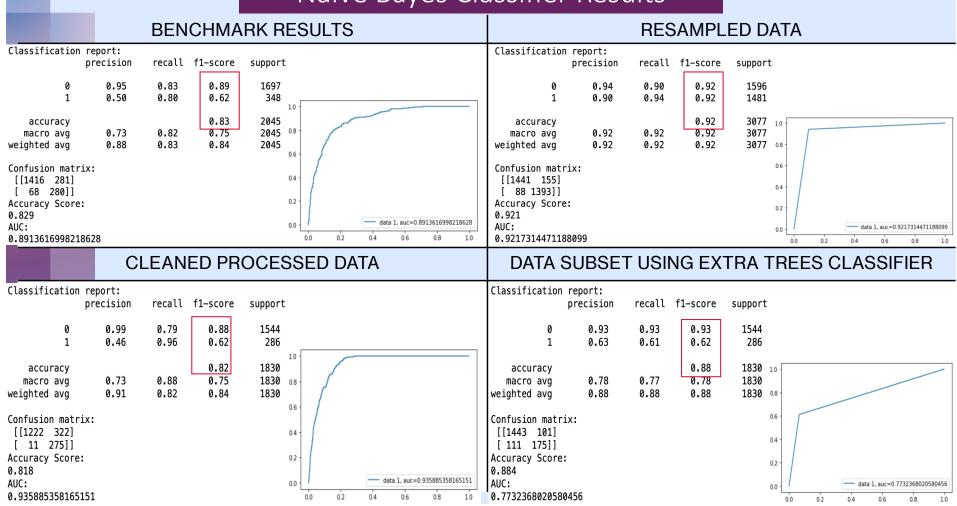
0.2

0.0

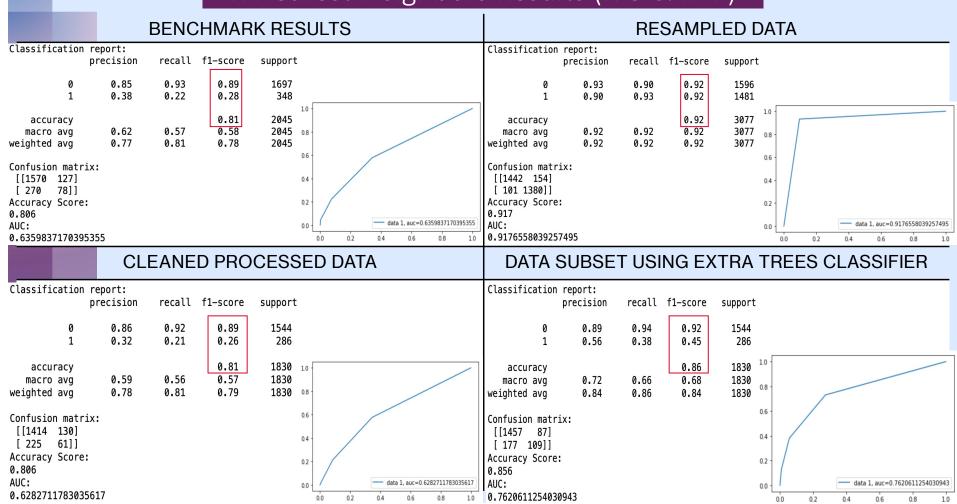
data 1, auc=0.7672787057502083

1.0

Naïve Bayes Classifier Results



K Nearest Neighbors Results (K-3 & K=7)



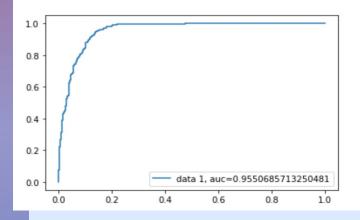
Selected Model & Results

Classification	report: precision	recall	f1-score	support		
0 1	0.94 0.73	0.95 0.66	0.95 0.69	1544 286		
accuracy macro avg weighted avg	0.83 0.91	0.81 0.91	0.91 0.82 0.91	1830 1830 1830		

Confusion matrix: [[1474 70] [97 189]] Accuracy Score: 0.909 AUC:

0.9550685713250481

ROC:



Winning Model: Logistic regression

Winning Dataset: Data Subset Using decision trees Classifier

Top features:

'int_corr': correlation between participant's and partner's ratings of interests

'age_o' : age of partner

'pf o att', 'pf o int', 'pf o fun', 'pf o amb', 'pf o sha':

Partner's stated preference for attraction, intelligence, fun,

ambition, shared interest

'attr_o', 'sinc_o', 'intel_o', 'fun_o', 'amb_o', 'shar_o' :

Rating by partner the night of the event, for attraction,

intelligence, fun, ambition, shared interest

'like_o': partners rating of like

'dec': decision of participant

'attr': attractiveness of partner

'intel', 'fun', 'amb', 'shar', 'like': Participants rating on

intelligence, fun, ambition, shared interest and like

'prob': How probable do you think it is that this person will

say 'yes' for you

#