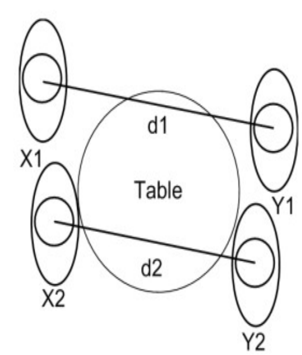
Summary.
Date: Sun, Nov 22, 2020.

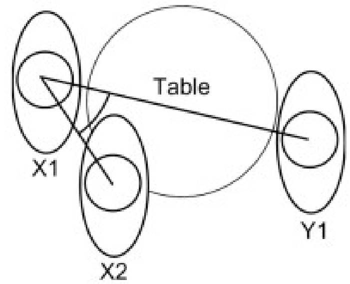
Baselines (Starting point):

1. Take a region of interest around the two tables in each frame to make sure only see the four people of interest.
2. Find the people in the image.
3. Create an eigenbackground from hand selected frames (empty)
4. Subtract the eigenbackground from the frame and threshold it
   - Result: Foreground blobs.
5. Cluster the segmented frame using k-means clustering.
   - Five clusters: 1/person and 1 for noisy pixels (background).
   - Centroids of the clusters (2D position of each person in the image plane).
   - ID of each person with their corresponding video data, hand labeled associations of the initial position of each cluster were used.
   - Tracking: looking for the closest corresponding cluster centroid in the previous frame.
   - Sanity check: newly found positions were very far from the previous ones?
     - If not, no update (previous positions = current).
   - Smoothed resulting position to cancel out some noise (sliding window width of 15 frames).

FEATURES

Position	**Description**	**Calculation/Values**
POSITION		
DIFANGLE	• Difference in the angle both persons have with the table. • Angular proximity between participants	0 to 180 deg
MOVEMENT		
DECRDIS	Difference between the average euclidean distance in the first n frames and the last n frames	 • x1 represents person x at the beginning of the date • x2 represents person x at the end of the date. • Same for person y. • **DECRDIS = d2 – d1.** • N = 250 (~12.5 sec). N w/ no

		impact on performance.

MOVDISTR	• How often someone moves in a
	• particular direction.
	• This direction is taken relative to the other person.
	• This feature is person dependent.
	• Include also movement distribution of the other person.
	• **Note:** Need to include how the person of interest moved but also how the other moved in the date?
		
		• Use two consecutive frames.
		• **x1** is the person of interest at the current frame
		• **y1** is the other person in the date at the current frame.
		• **x2** is the person of interest in the next frame.
		• The **distance between x1 and x2** is the distance traveled
		• **Angle between the vectors x1-x2 and x1-y1** is the direction with respect to the other person.
		  ○ This angle is the absolute angle (0..180 deg).
		    ■ 0 deg (moving towards the other person)
		    ■ 180 deg (moving away from the other person.
		  ○ Histogram is accumulated by calculating this angle at each frame, weighted by the euclidean distance between x1 and x2.
		    ■ Mean and Variance are taken from this histogram

	SYNCHRONY	
MOTIONSYNC	How often the two people move at the same time	• Calculate the amount of motion/ frame. (Difference in person's position between consecutive frames) → Need to accumulate it in a 1 sec window. • Note: slide window over the entire date (1 frame at a time) ==> Amount of motion per second.

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Make a 2-D histogram from couple in a date.
Histogram = 4 bins

Bin 1 = counts how often seconds of low activity occur at the same time
Bin 2 & 3 = how often a second of high activity in one person co-occurs with low activity in the other
Bin 4 = Checks how often seconds of high activity in one person co occur with seconds of high activity in the other.

Note: People interested on exchanging info will have higher values in BIN 4.
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<tr>
<td>MOTION-
REACTION</td>
<td>How they react to each other.
How the distance with a previous position of the other varies.</td>
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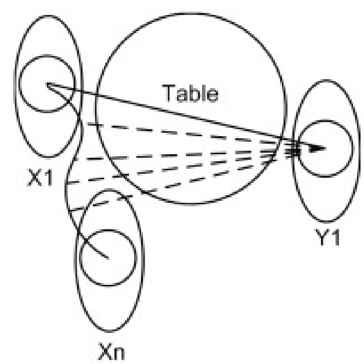

Window size = 1 sec.
Total frames used = 20.
Result = Distribution of 20 bins.
BIN 1: Distance between x and y at time t.
BIN 2: Distance between x at time t+1 and y at time t and so on.
Notes:
This is averaged over all 20-frame windows in the date.
By fixing the position of y, the change in distance is only based on the movement of x (Know how x reacts).
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- **Prediction Execution:**
  - Done through Supervised learning approach.
    - Support Vector Machine (SVM)
      - Use a radial basis function kernel.
    - k-nearest-neighbor (kNN).

        - kNN classifier: k = 3.
    - Split the classification task by gender.
    - Use leave-one-out cross validation. (All but one of the data points are used as training data).
    - Scale all features to have zero mean and unit variance.

- **Results:**
    - Experiments were carried out using all the features.
    - Tested the different categories by fusing all the features belonging to a category.
    - **Baseline:**
        - Calculated by labeling all test data points as the most frequent class.
        - Females (exchanging contact information task) is higher (females did not want to exchange contact information).

          Physical attraction task (Opposite). More males found their female date physically attractive.
    - **Prediction of Exchanging contact information:** labeled as not wanting to exchange contact information.
        - Positional information can be used to as predictor. Performance for males is better.\
        - Feature with best performance is the variance in distance for men (men want to exchange contact information more often in dates where there is a high variance in distance).
    - **Prediction of Physical attraction:** labeled as finding the other physically attractive.
        - Females are easier to predict than males.
        - Task movement features perform well.
        - Synchrony based features are above baseline in a few cases.
        - For females the average difference in angle with respect to the
        - table also gives good results (Female found the male physically attractive the average angle between them was smaller).
        - Variance in position also give good results.
            - Women move less when they are physically attracted to the other (45 pixels vs 76 pixels in variance, where the body width was approximately 80 pixels).
            - For males the variance in position of their female counterpart is also a good predictor.
        - Males are physically attracted: variance in position of the female is higher (67 pixels vs 47 pixels).
            - Females who are physically attracted tend to move less
            - Males tend to be physically attracted to females who move more
    - **Notes:**
        - Synchrony related features don’t seem to work when predicting exchanging contact information, they do perform well when predicting physical attraction.
        - Predicting attraction is a lot easier when looking at females.
        - Decision of exchanging contact information is more complex for females.
        - Wanting to exchange contact information could be an indication of romantic attraction, instead of physical.