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# CAP 4628/5627 Affective Computing
# Project 1 – 3D Expression Recognition

## Project Report

**1. What are the classification results for each experiment? (Create a table of this sample template available at end of document)**

| Classifier/ Datatype | Original Data | | | Translated | | | Average(Rotated X \| Y \| Z) | | |
|---|---|---|---|---|---|---|---|---|---|
| **Metric** | **Accuracy** | **Precision** | **Recall** | **Accuracy** | **Precision** | **Recall** | **Accuracy** | **Precision** | **Recall** |
| **Random Forest** | 33.65 | 32.64 | 33.73 | 49.15 | 33.83 | 34.71 | 36.32 | 34.11 | 34.75 |
| **SVM** | 47.94 | 50.18 | 48.32 | 55.65 | 57.54 | 55.38 | 48.75 | 51.11 | 48.77 |
| **Decision Tree** | 28.76 | 27.89 | 28.34 | 36.72 | 36.56 | 38.42 | 27.54 | 26.87 | 27.61 |

**2. Which of the classifiers worked the best for each data type (original, translated, rotated)? Why? If multiple had the same, then why did this happen? Note: this question is left intentionally vague. What does work best mean? Which metric is best? Think about what we've talked about in class in regards to expressions and emotion.**

- SVM performed the best among the classifiers for all types of data: original, translated, and rotated. Translated data had the highest accuracy, followed closely by original and rotated data.
- SVM (Support Vector Machine) may have performed better due to its ability to effectively handle high-dimensional data, such as the 3D facial landmark features used in this project. SVM works by finding the optimal hyperplane that separates different classes in the feature space, maximizing the margin between the classes. It can capture complex relationships between facial landmarks and emotions while minimizing overfitting.
- Accuracy is a common metric, but when dealing with expressions and emotions, precision and recall might be more informative. Precision measures the proportion of correctly identified instances among the total instances identified as positive, while recall measures the proportion of correctly identified instances among all actual positive instances.

**3. For the top classifier, for each data type, describe the misclassification for each classifier. What was misclassified as what (e.g., sad looks like happy)? Based on your intuition about how expressions look, do the misclassifications make sense (i.e., do you think the expressions are similar – not based on any specific example)?**

**Top classifier is SVM:**
**Original Data:**
• A total of 3665 subjects related to “Angry” misclassified as “Sad.
• A total of 1284 subjects related to “Disgust” misclassified as “Fear”.
• A total of 1789 subjects related to “Fear” were misclassified as “Happy”.
• A total of 1404 subjects related to “Happy” were misclassified as “Fear”.
• A total of 2253 subjects related to “Sad” misclassified as “Angry”.
• A total of 1359 subjects related to “Surprise” were misclassified as “Fear”.

**Translated Data:**
• A total of 2857 subjects related to “Angry” misclassified as “Sad”.
• A total of 1672 subjects related to “Disgust” were misclassified as “Fear”.
• A total of 1419 subjects related to “Fear” were misclassified as “Happy”.
• A total of 1507 subjects related to “Happy” misclassified as “Fear”.
• A total of 2055 subjects related to “Sad” misclassified as “Angry”.
• A total of 896 subjects related to “Surprise” misclassified as “Fear”.

**RotatedX Data:**
• A total of 3611 subjects related to “Angry” misclassified as “Sad”.
• A total of 1197 subjects related to “Disgust” misclassified as “Fear”.
• A total of 1779 subjects related to “Fear” were misclassified as “Happy”.
• A total of 1441 subjects related to “Happy” misclassified as “Fear”.
• A total of 2177 subjects related to “Sad” misclassified as “Angry”.
• A total of 1321 subjects related to “Surprise” misclassified as “Fear”.

**RotatedY Data**
• A total of 3617 subjects related to “Angry” misclassified as “Sad”.
• A total of 1166 subjects related to “Disgust” misclassified as “Fear”.
• A total of 1753 subjects related to “Fear” misclassified as “Happy”.
• A total of 1439 subjects related to “Happy” were misclassified as “Fear”.
• A total of 2172 subjects related to “Sad” misclassified as “Angry”.
• A total of 1301 subjects related to “Surprise” misclassified as “Fear”.

**RotatedZ Data:**
• A total of 3621 subjects related to “Angry” misclassified as “Sad”.
• A total of 1131 subjects related to “Disgust” misclassified as “Fear”.
• A total of 1739 subjects related to “Fear” misclassified as “Happy”.
• A total of 1476 subjects related to “Happy” misclassified as “Fear”.
• A total of 2187 subjects related to “Sad” were misclassified as “Angry”.
• A total of 1282 subjects related to “Surprise” misclassified as “Fear”.

The misclassification makes sense because facial expressions associated with different emotions may share similar facial features or expressions. For example, anger and sadness can both involve furrowed brows or downturned mouth corners, making them difficult to distinguish based on facial landmarks. Similarly, the emotions "disgust" and "fear" can share some characteristics, such as wide-open eyes and a wrinkled nose, which can lead to misclassification in some cases.

**4. Why do you think you got the results that you got for each of the different data types/classifiers (i.e., why are they different, or why are they the same)? For example, if SVM and RF have different results, why are they different? If they are the same – why are they the same?**

Comparing the result on classifiers:

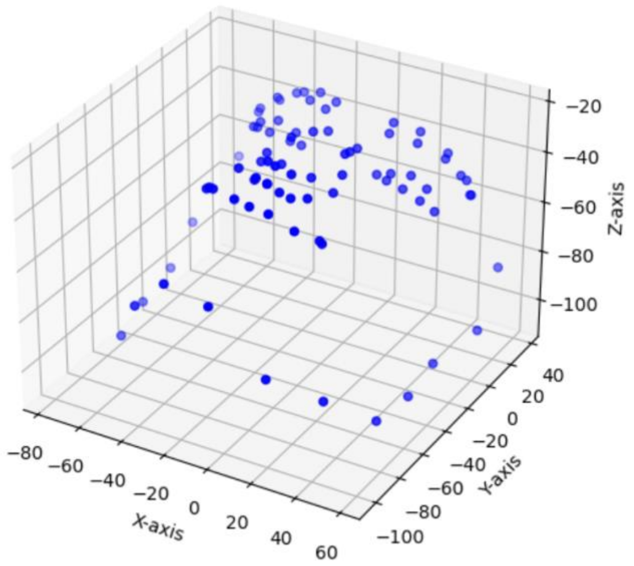
- SVMs are effective in high-dimensional spaces, which is beneficial when dealing with datasets like 3D facial landmarks where each sample has a large number of features (249 in this case).
- Random Forest might not have performed as well as SVM due to its ensemble nature, which relies on multiple decision trees. In some cases, decision trees may struggle to capture complex relationships in the data compared to SVM's optimization for finding the optimal hyperplane.
- SVMs with non-linear kernel can capture complex patterns in the data by mapping the input features into a higher-dimensional space. This allows SVMs to learn intricate decision boundaries that might not be achievable with simple decision trees.
- SVMs are less prone to overfitting compared to decision trees, especially when the number of features is large. Decision trees tend to overfit the training data.

Comparing the result on data types:

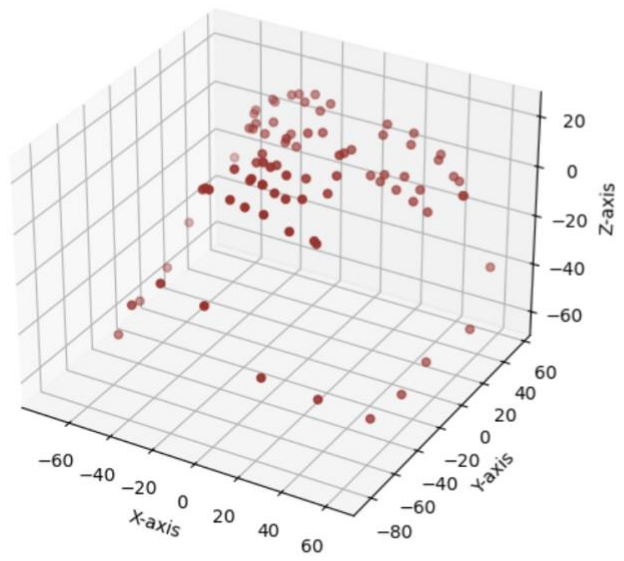
- The accuracy for translated data is higher than rotated data and original data.
- Translating the data to the origin (0, 0, 0) effectively normalizes positional variations across different samples. This normalization process can enhance the separability of different classes and improve classification accuracy.
- Rotating the data or using the original coordinates may introduce additional complexity or non-linearity that could impact classifier performance negatively.

**5. You must plot one sample of each data type – original, translated, rotated (1 each for x, y, and z). In total, you will have 5 figures/plots. Note: if you are unsure how to do this, look up 3D scatter plot in python.**

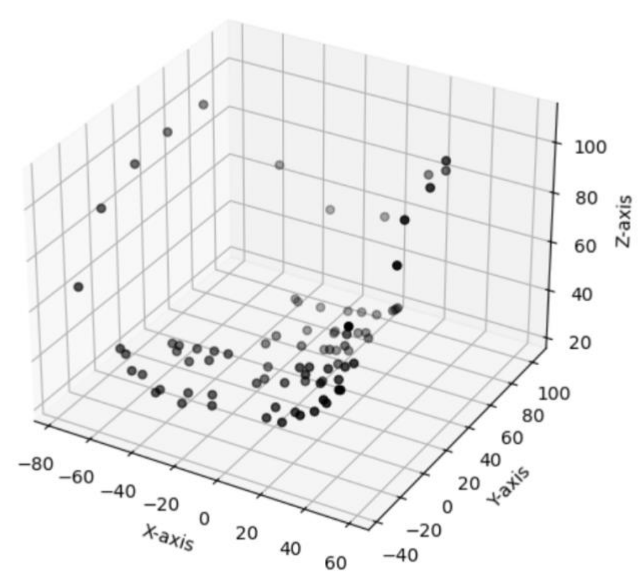
Sample 18179: Original



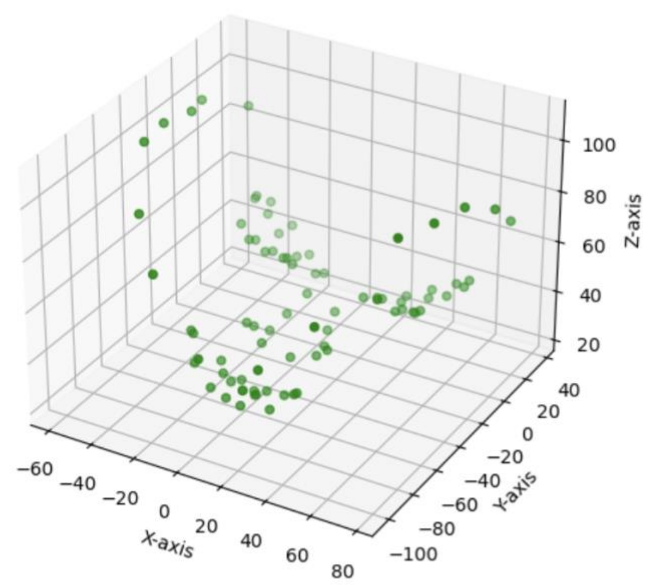

Sample 18179: Translated

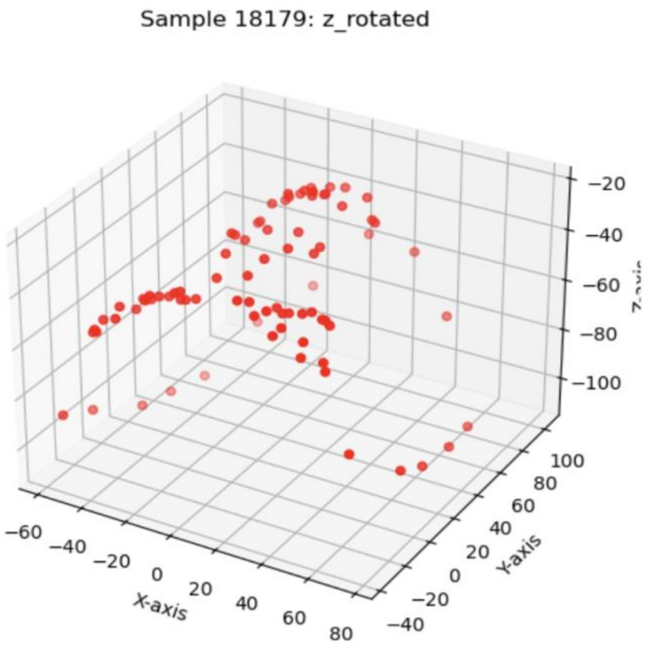


Sample 18179: x_rotated




Sample 18179: y_rotated

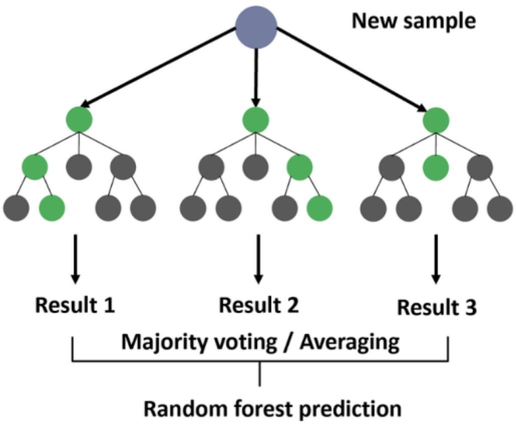





**6. (CAP 5627 only) Describe, in your own words, what Random Forest, SVM, and Decision Tree classifiers are/how they work. You may need to look this information up. Your description should be approximately 100-150 words in length for each classifier**

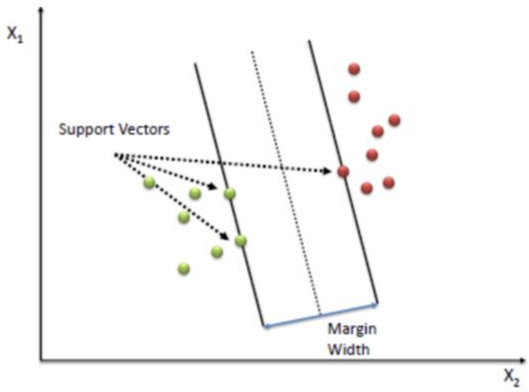
**Random Forest Classifier(RF):**

Random Forest is an ensemble learning technique used for classification and regression tasks. It constructs multiple decision trees during training, each trained on a random subset of the training data using bootstrapping. At each node, a random subset of features is considered for splitting, introducing diversity among the trees. During prediction, the class with the most votes (classification) or the average prediction (regression) from all trees is chosen. This approach reduces overfitting and improves generalization compared to individual decision trees. Random Forest is favoured for its high accuracy, robustness, and ability to handle high-dimensional data. Additionally, it provides insights into feature importance, aiding in feature selection, making it a valuable tool across various domains for tasks such as classification, regression, and feature selection.




**Support Vector Machine Classifier(SVM):**

Support Vector Machine (SVM) is a powerful supervised machine learning algorithm used for both classification and regression tasks. It works by finding the hyperplane that best separates the data points of different classes in the feature space. This hyperplane is chosen such that it maximizes the margin, which is the distance between the hyperplane and the nearest data points of each class, also known as support vectors. In classification, SVM aims to find the optimal hyperplane that maximizes the margin while correctly classifying the training data. If the data is not linearly separable, SVM can use a technique called the kernel trick to map the input data into a higher-dimensional space where it becomes separable. SVM is its ability to handle high-dimensional data efficiently, making it suitable for applications with a large number of features. Additionally, SVM has regularization parameters that help prevent overfitting by balancing the margin size and classification error.




**Decision Tree Classifier(DT):**

A Decision Tree is a supervised machine learning algorithm used for both classification and regression tasks. It works by recursively partitioning the data into subsets based on the values of input features. The partitioning process is guided by a set of decision rules learned from the training data. At each node of the tree, the algorithm selects the feature that best splits the data into subsets that are as pure as possible with respect to the target variable. The decision tree continues to split the data into subsets until a stopping criterion is met, such as reaching a maximum tree depth, having a minimum number of samples in a node, or when further splitting does not improve the model's performance. Once the tree is built, it can be used to make predictions by traversing the tree from the root node to the leaf nodes, where each leaf node corresponds to a predicted class (for classification) or a predicted value (for regression).

**Confusion Matrices for the top classifier:**

**SVM with Original Data:**

| **Emotion** | **Angry** | **Disgust** | **Fear** | **Happy** | **Sad** | **Surprise** |
|---|---|---|---|---|---|---|
| **Angry** | 5742 | 2373 | 1339 | 1026 | 3665 | 1221 |
| **Disgust** | 643 | 4044 | 1284 | 799 | 183 | 841 |
| **Fear** | 741 | 1481 | 3415 | 1789 | 1089 | 1634 |
| **Happy** | 211 | 556 | 1404 | 5467 | 84 | 118 |
| **Sad** | 2253 | 809 | 1239 | 531 | 4868 | 752 |
| **Surprise** | 532 | 915 | 1359 | 354 | 254 | 5388 |

**SVM with Translated Data:**

| **Emotion** | **Angry** | **Disgust** | **Fear** | **Happy** | **Sad** | **Surprise** |
|---|---|---|---|---|---|---|
| **Angry** | 6489 | 2095 | 1159 | 1219 | 2857 | 999 |
| **Disgust** | 581 | 4988 | 1672 | 717 | 162 | 627 |
| **Fear** | 684 | 1365 | 3809 | 1419 | 687 | 1286 |
| **Happy** | 1099 | 703 | 1507 | 6045 | 47 | 261 |
| **Sad** | 2055 | 578 | 992 | 387 | 6330 | 835 |
| **Surprise** | 218 | 451 | 896 | 188 | 46 | 5949 |

**SVM with Data rotated across X axis:**

| **Emotion** | **Angry** | **Disgust** | **Fear** | **Happy** | **Sad** | **Surprise** |
|---|---|---|---|---|---|---|
| **Angry** | 5941 | 2327 | 1341 | 1012 | 3611 | 1216 |
| **Disgust** | 653 | 3950 | 1197 | 778 | 90 | 803 |
| **Fear** | 774 | 1523 | 3470 | 1779 | 1101 | 1699 |
| **Happy** | 118 | 619 | 1441 | 5515 | 58 | 90 |
| **Sad** | 2177 | 823 | 1278 | 543 | 5036 | 759 |
| **Surprise** | 452 | 931 | 1321 | 346 | 248 | 5382 |

**SVM with Data rotated across Y axis:**

| **Emotion** | **Angry** | **Disgust** | **Fear** | **Happy** | **Sad** | **Surprise** |
|---|---|---|---|---|---|---|
| **Angry** | 5970 | 2358 | 1348 | 1009 | 3617 | 1221 |
| **Disgust** | 663 | 3904 | 1166 | 736 | 94 | 793 |
| **Fear** | 790 | 1566 | 3540 | 1753 | 1090 | 1715 |
| **Happy** | 91 | 613 | 1439 | 5598 | 45 | 87 |
| **Sad** | 2172 | 847 | 1252 | 545 | 5052 | 761 |
| **Surprise** | 434 | 879 | 1301 | 340 | 243 | 5370 |

**SVM for Data rotated across Z axis:**

| **Emotion** | **Angry** | **Disgust** | **Fear** | **Happy** | **Sad** | **Surprise** |
|---|---|---|---|---|---|---|
| **Angry** | 5989 | 2345 | 1356 | 1008 | 3621 | 1220 |
| **Disgust** | 664 | 3912 | 1131 | 731 | 100 | 784 |
| **Fear** | 781` | 1587 | 3572 | 1739 | 1081 | 1715 |
| **Happy** | 82 | 624 | 1476 | 5626 | 41 | 89 |
| **Sad** | 2187 | 854 | 1236 | 539 | 5065 | 761 |
| **Surprise** | 421 | 849 | 1282 | 330 | 234 | 5379 |