# RT 1: Clustering

To cluster the Covertype dataset subset with k-means and a Gaussian Mixture Model (GMM), I made specific choices regarding scaling, initialization, and other parameters to enhance stability and performance without using any class label information. Here is the rationale behind these choices:  
I scaled the data using StandardScaler before running k-means and GMM. Since features in the Covertype dataset have varying ranges, standardizing them ensures that each feature contributes equally to distance calculations in both algorithms. This is particularly important for k-means, which relies on Euclidean distances, and beneficial for GMM, as scaling can improve convergence in multimodal distributions.  
For the k-means algorithm, I used the k-means++ initialization to enhance clustering quality. The k-means++ method spreads out the initial cluster centers, reducing the likelihood of poor convergence and often leading to a more stable result than random initialization. This initialization should require fewer iterations to converge compared to random. Additionally, I set n\_init=10 since running the algorithm multiple times with different centroid seeds reduces the likelihood of convergence to suboptimal solutions.  
For GMM, I once again chose the k-means++ initialization for init\_params rather than random to leverage k-means clustering to initialize cluster centers more accurately. This decision was made for similar reasons as before. I set n\_init=10 for similar reasons as explained above, and decided to keep the default covariance\_type=full, to properly model the full covariance matrix for each component. I kept max\_iter=300 (the default) to balance sufficient iteration time with computational efficiency, and tol=1e-3 (the default again) as a convergence threshold to ensure that the model refines its cluster probabilities until there’s minimal improvement, since it balances precision and efficiency for convergence. I thought about including warm\_start but I ended up omitting it because, given the scope and scale of this coursework, iterative fitting would not be necessary (especially given the fact that we are supposed to make reasonable choices for this part of the coursework, and not deeply evaluate our models).  
By setting a random\_state=42 for both k-means and GMM, I ensured that the algorithms produce consistent results, allowing for reliable analysis of cluster performance across multiple runs. In a coursework setting, this reproducibility is advantageous as it enables clear assessment and comparison without relying on or affecting class label information.

Through these configurations, I selected initialization methods and parameters that are suited for clustering without label information, thereby achieving reproducibility and stable clustering quality suitable for unsupervised learning tasks.

# RT 2: Clustering

The total number of pairs of datapoints with the same class labels was 18840016, k-means had 13804797 errors, GMM had 13419928 errors, and random baseline had 16150142.

# RT 3: Clustering

The first thing to note about these errors is that they are much higher than expected for all models. It is of course possible to fine-tune and optimise k-means and GMM based on these results, but I did not opt to perform any of this given the instructions for this coursework. It is also noteworthy that the errors themselves also depends quite heavily on the random subset that has been chosen, and can vary quite a bit between runs.

The random baseline produces the highest number of errors, as expected, due to its random uniform clustering which fails to capture relationships between datapoints. Interestingly, however, it performs much closer to the other models than I expected for many runs, suggesting that likely separating classes based solely on feature space is inherently challenging in this dataset. I expected GMM to outperform K-means by quite a bit, especially given its ability to capture more nuanced and complex cluster structures through its use of Gaussian Distributions, and the ability to alter the covariances, but the two models had a similar number of errors for most runs. This could be due to the number of clustering challenges posed by the high dimensionality of the Covertype data set (curse of dimensionality), which makes Euclidean distances (used by K-means) less meaningful, coupled with the fact that the data may not fit Gaussian Distributions, or spherical clusters. The marginally better performance of the GMM could be due to K-means struggling with outliers, while full covariance gives GMM better flexibility.

# RT 4: Classification

Although training an SVM classifier on the Covertype dataset seems like a good choice due to the data’s high dimensionality, it would prove quite difficult, and would pose several challenges:

**1. Computational Complexity:** First of all, kernel-based methods would be computationally expensive due to the large size of the dataset (hundreds of thousands of data), and given the fact that their time complexity can range from quadratic to cubic. Even with a very efficient implementation, SVMs might run into memory or time constraints. The choice of kernel would feed into this, since using linear kernels (which are computationally cheaper) would lead to underfitting, but using nonlinear ones (e.g. RBF) would be much more computationally expensive.

**2. Class Imbalance:** The Covertype dataset contains 7 classes, which are likely imbalanced. In the case of imbalances, SVM’s margin optimisation would likely favor the majority class, performing poorly on minority classes. This is something that can be mitigated using the class\_weight parameter, but it would require very careful tuning and management of hyperparameters, which adds extra complexity to the training process.

**3. Feature Scaling:** SVMs rely on distance metrics for optimisation, and are sensitive to feature magnitudes. To efficiently run SVM’s on this dataset, one would need to scale the features in an optimal manner, otherwise features with larger magnitudes would dominate the optimisation process, skewing the decision boundaries. This, of course, is possible, but it adds another layer of complexity.

Thus, given the dataset’s size, class imbalances, and nonlinear relationships, in order to use SVMs, one would need to make big decisions regarding optimisation and performance, likely needing to sacrifice one for the other at points. Given the dataset characteristics, it can be much more sensible to tackle a problem such as this with an ensemble method (e.g. Random Forest) to get more efficient modeling of feature relationships instead of opting for SVMs.

# RT 5: Classification

I maintained random\_state=42 for all models, in order to make empirical testing easier, increasing reproducibility.

**1. Logistic Regression:** First of all, I scaled the features fed into the logistic regression. I chose to do this since logistic regression relies on distance metrics during optimisation, and unscaled features could dominate the optimisation process, leading to poor convergence. I set solver=’lbfgs’ because it is efficient for multiclass classification problems and performs well on large datasets. I also tried ‘liblinear’ and ‘newton-cg’, but they were both outperformed by lbfgs. Additionally, I set max\_iter=1000 to allow the solver enough iterations to converge. I initially tested lower values, starting from 100, and also tested larger values up to 5000, but 1000 seemed to be the sweet spot. I decided to leave the rest of the settings on the defaults because alternate values did not seem to grant much of a performance or overhead boost.

**2. Decision Tree Classifier:** Feature scaling was not necessary for the decision tree because it is less sensitive to it, and thus I used the unscaled data. I set max\_depth=None, which is the default. I was surprised at first due to the test set accuracy (~93%), and thought some form of strange overfitting might be occurring, but after employing some cross-validation to test the results, it truly seems like this is the ideal value (cross validation still got ~92-93%). I tried many values, and anything under 10 introduced underfitting, while values over 15 still appeared to perform worse on the test set.. I left the rest of the settings on default, including using the gini index because there was no noticeable gain in tweaking them (I tried entropy, but there was no noticeable gain), and model efficiency was higher using them.

**3. Ensemble Method:** I trained both a Random Forest and a Gradient Boost ensemble method on the Covertype dataset, but I settled on the Random Forest due to its much more computationally efficient nature, coupled with its ability to model nonlinear relationships. This choice was reinforced given that Gradient Boosting’s sequential training process was significantly slower on this large dataset. Similarly to the decision tree, I used the unscaled data for this model, and set n\_estimators=100 to maximise performance. Setting it to anything less was a bit faster, but the results were slightly worse, and anything over this value gave very marginal to no improvements, but significantly increased training time. I set max\_depth=None for similar reasons as above, cross-validating these results as well, and I used max\_features=’sqrt’ to introduce randomness in feature selection and reduce overfitting. I also tested ‘log2’ and None, but the former reduced accuracy, and the latter increased overfitting.

# RT 6: Classification

There were quite significant differences in the performance of the three classifiers. Logistic Regression performed the worst, achieving the lowest accuracy of the three models (~72.4 for most runs). This result is consistent with the model’s assumption of linear decision boundaries, which does not effectively represent the dataset. Thus, Logistic Regression is not well-suited for high-dimensional, nonlinear datasets such as this one, as expected.

On the other hand, both the Decision Tree (~93.8%) and Random Forest (~95.5%) models performed very well on the test set, with Random Forest outperforming Decision Tree, as expected. This reflects both the model’s ability to capture nonlinear relationships, while setting max\_depth=None allowed all trees to grow fully, capturing the complex dataset structure. However, given how high these numbers are, the model’s tendency to overfit must be considered. Although both models performed excellently on both the training and test datasets, it is possible that they will fail to generalise to unseen data. Cross-validation was used to test this, however, and they both scored very close to their test set performance across the board (~93.2 and ~95.0 respectively), indicating that they likely generalise well, and overfitting might be minimal. The reason Random Forest outperforms Decision Tree is likely due to the fact that it mitigates overfitting better (bagging, feature randomness due to ‘sqrt’), and that it aggregates predictions from multiple trees to further emphasise its robustness.

# RT 7: Regression

# RT 8: Regression

# RT 9: Regression

# RT 10: HMM