Algorithm Selection

The 3 algorithms I have chosen to test Fashion-MNIST on are: Naïve Bayes, Random Forests and SVM. I chose these algorithms as they each classify data differently. I chose to test Naïve Bayes to see how a probabilistic classifier performs for image classification as its typically intended probabilistic variables and not pixel postion data. I chose Random Forests to see how an ensemble learning method performs on the dataset and to see the effect of the number of trees had. SVM was chosen to see how well the data could be separated and to see the effects of overfitting. The hyperparameters selected for Naive Bayes where the different event models; Categorical, Gaussian, Complement, Bernoulli and Multinomial. As they assume distribution of features differently and individually Laplace smoothing had no effect on performance. For Random Forests I explored the effect the number of trees had on performance, the functions to measure the quality of a split in the tree (Gini impurity and entropy/information gain), max features (square root features or log2 features) and max depth of the tree. For SVM, I tested the different kernel functions as they separated the data differently and the regularisation parameter to see if the margins were being overfit and if they could be improved upon.

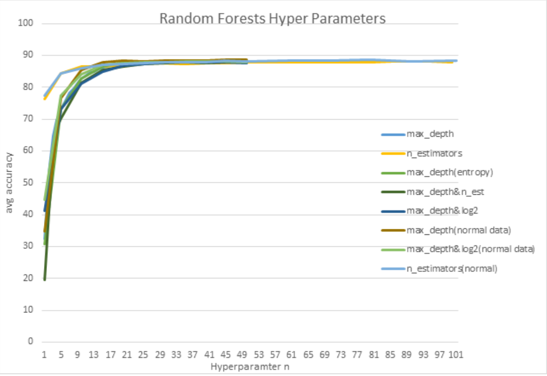
Methodology

To measure and test performance the algorithms learnt to fit the training set with the correct labels, then they were predicted against the testing set without the labels. These sets were split by the data set creators. Precision recall and F-1 score for each class (0-9) were collected, as well as an average of the entire prediction. They each represent different interpretations of accuracy so a combined average of all these results is used as main measurement of the overall accuracy of the prediction. The collection of precision recall and f1-score for each class also enabled me to explore how accuracy ranged over the classes and the different scores. The dataset was initially Binarized to increase speed and improve performance, but I was concerned how it might affect accuracy so used to it find optimal or best parameters and test further and compare it with the accuracy of the raw data set. To optimise parameters, if capable, for example with Random Forests, they were iteratively tested as well as tested in conjunction with other parameters. I also tested how the best performing of each parameter worked together. I also tested the default parameters as a comparison, to find out if they were necessary or optimal as the performance could plateau and waste computation time and resources. In some cases where an iterative testing was deemed too computationally long to find i.e., for SVM, the regulation parameter was optimised by seeing how a range of larger and smaller values would improve performance, then the values in-between was tested till an optimal value was found. For Naïve Bayes, the Laplacian smoothing had no effect on accuracy, so the different event models were tested with and without binarizing the data.

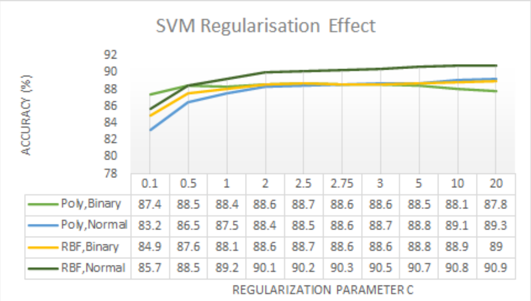
Results

With Naïve Bayes, as Laplacian smoothing had no effect on accuracy the only results that were recorded were the average accuracy for each event model. Categorical could not give results for the normal data set, however performed the best alongside Bernoulli for the binarized set: 71.4%. Bernoulli uses binary data and will convert normal data, so has been omitted as it will perform the same for both. Multinomial then gives the best accuracy for the normal data set:66.7%. Multinomial and Complement naïve bayes decreases in accuracy with binarized, complement NB is expected to follow suite as it is an adaption of multinomial NB suited for imbalanced data sets. Gaussian Distribution increases in accuracy with binary data.

	Avg Accuracy	
NB Model	normal	binary
Categorical	N/A	**71.4**
Gaussian	59.1	66.4
Complement	60.7	56
Bernoulli	**N/A**	**71.4**
Multinomial	**66.7**	59.3



With Random Forests I wanted to establish which parameters have greater effect on the accuracy and what their optimal values are. I established comparison accuracies using default parameters and with some parameters changed, e.g., criterion, max features. And conjunction of the highest accuracies of max depth and n estimators (no. trees). I also plotted the results of the parameters that were iterable (max depth, n estimators). We can see the accuracy for all parameters plateau at around 88% with 0.5% deviation, binarizing the data, the criterion and max features have no considerable effect. From the graph we can see that the number of trees has less effect on the accuracy than the depth of the trees. However, from the tests optimal parameters can be established; max_depth of the trees being 40 and n_estimator of 85 trees. Using these optimal parameters has the potential of having a better time complexity and better use of resources in comparison to using the default values especially for estimators. Binarizing the data has no considerable effect on accuracy but has a better time to compute.



	0.1	0.5	1	2	2.5	2.75	3	5	10	20
Poly,Binary	87.4	88.5	88.4	88.6	88.7	88.6	88.6	88.5	88.1	87.8
Poly,Normal	83.2	86.5	87.5	88.4	88.5	88.6	88.7	88.8	89.1	89.3
RBF,Binary	84.9	87.6	88.1	88.6	88.7	88.6	88.6	88.8	88.9	89
RBF,Normal	85.7	88.5	89.2	90.1	90.2	90.3	90.5	90.7	90.8	90.9

With SVM, I established using binary data which out of the 4 kernels (Radial Basis function RBF, SVCLinear, Polynomial, Sigmoid) performed better. Sigmoid had considerably lower accuracy whilst RBF and Poly got similar accuracies throughout the different classes and measurements and an average accuracy variance of 0.3%. Using only RBF and Poly kernel SVM, I optimised the regularisation parameters for both binary and normal data, 1 being the default parameter. The poly kernel was used to get a range of testing parameters hence why the parameters are not uniform. The poly kernel with binarized data has a max of 88.7% at C=2, with normal data it has a max of 89.3% with C=20. RBF with binary data has a max of 89% at C=20. With normal data it has a max of 90.9% at C=20 also. From the graph we can see there is a plateau for all 4 at C=2-5. From the graph it shows that with the normal dataset and RBF kernel, SVM at its default values of 1 overfits and benefits from a higher regularisation parameter, showing that RBF & C=20 with the normal data set are the optimal parameters.

Conclusion

Naïve Bayes performed considerably worse than SVM and random forests by 16.6%, whilst SVM and random forest performed very similarly of around 88%, however with proper optimisation the regularisation parameter and using the right Kernels i.e., RBF or Poly, you can achieve higher accuracies of 89-90.9%. With Random Forests the parameters reached a plateau of 88% where no change to data or parameters has no effect, however we were able to optimise the parameters to max depth= 40 and n estimators being 85, which could improve time complexity and resource use whilst giving the same results as the default parameters. With Naïve Bayes Laplacian smoothing had no effect but using different event models we were able to improve performance to 71.4%. I think SVM gave the highest accuracy as how the kernel functions can learn to separate the classes, having a choice of kernels that separate the data in varying different ways and being able to adjust the overfitting of the hyperplanes with the regularisation parameter. It gives you more chance to improve upon the results. RBF groups classes into radial clusters, where polynomial kernel tries to fit the hyper plane around the classes. Due to this RBF tends to be more closely "fitting". Naïve Bayes gives the worst as it predicts classes based off the probability distribution of pixel positions. Random Forests is a close competitor to SVM though, with how decision trees work it is a good choice for the data set. As several of the classes like Bags, sandals and sneakers are more unique looking where T-shirt/top, shirts, pullovers are more similar looking and are often misclassified, which seems to be a limiting factor on the accuracy of the methods even though a high accuracy can be learnt.