SPRING 2023-2024

GE 461: INTRODUCTION TO DATA SCIENCE

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FALL DETECTION
FOURTH PROJECT REPORT

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PART A)

We must do dimensionality reduction in order to determine if sensor data samples form segregated clusters in the space spanned by the sensor data since there are a lots of features. We extracted the top two principal components for this purpose, and here are the results:

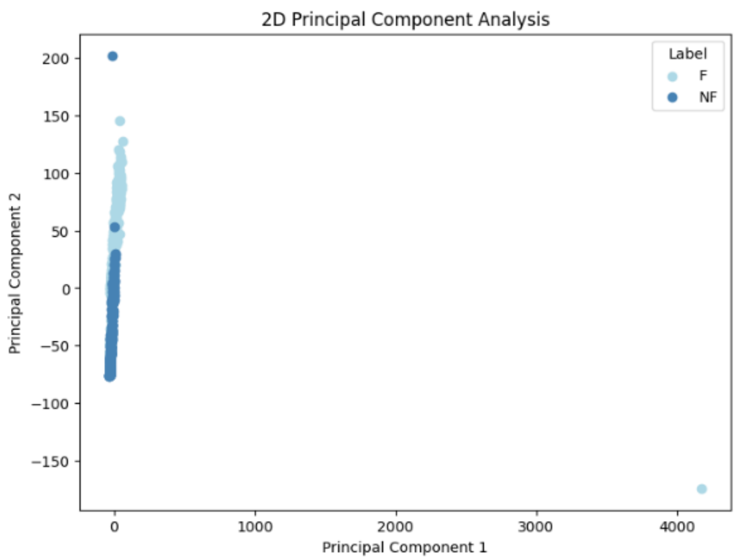

Fig. 1. Projected Data PCA Visualization with Labels

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Cumulative explained variance ratio:
PC 1: 75.31%
PC 2: 83.82%
```

Fig. 2. Cumulative Explained Variances by top 2 PC's

It is evident that two of the data points in Fig. 1 are outliers. It would be reasonable to eliminate these two points from our dataset because they are outliers and might have an impact on the analysis. The cumulative total of the variances for the first two components is displayed in Fig. 2. The first principal component alone accounts for 75.31% of the total variance, while the first and second principal components together account for 83.82% of it. MinMaxScaler is sensitive to outliers. Since we have removed them, we can apply MinMaxScaler to normalize the data. After we do it, here are the results of two principal components:

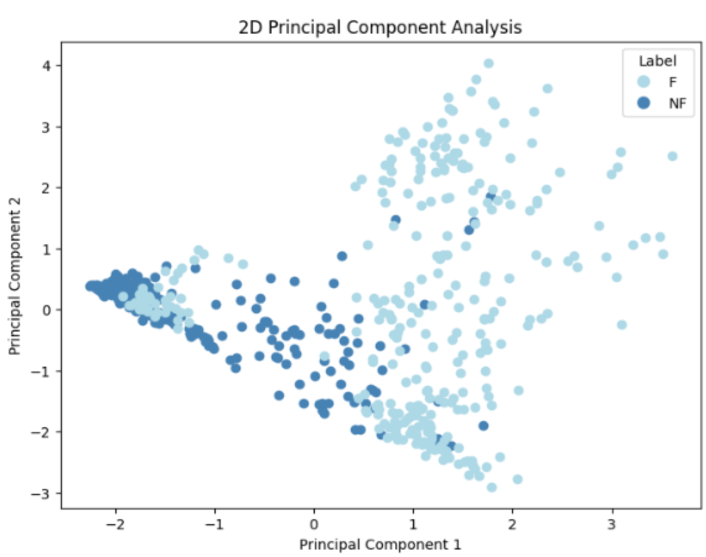
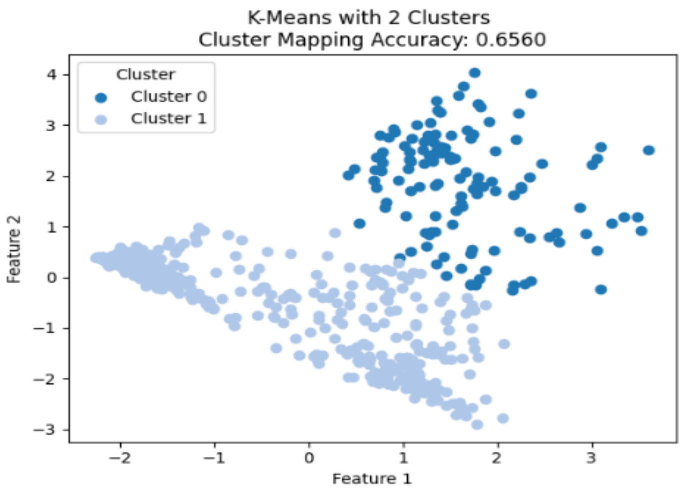


Fig. 3. Normalized Data PCA Visualization with Labels

```
Cumulative explained variance ratio:
PC 1: 26.65%
PC 2: 48.71%
```

Fig. 4. Cumulative Explained Variances by top 2 PC's

After normalization, The outcome is simpler to comprehend and the data is better represented with the normalization. Following this, 26.65% and 22.06% of the variance are explained by the top two principal components, and total of 48.71% variance are explained. By this process, we can cluster data points effectively. Here are the results of K-means with 2 clusters:




```
Cluster 0: Falls - 122, Non-Falls - 4
Cluster 1: Falls - 190, Non-Falls - 248
```

Fig. 6. Cluster Memberships and Action Labels

Fig. 5. K-Means Algorithm with 2 Clusters

Utilizing two clusters for K-means clustering, we attain a 65.6% label mapping accuracy. Upon analyzing the cluster distributions, it can be observed that cluster 0 mostly consists of instances belonging to the 'Fall' class, indicating a high degree of accuracy in classifying them as such. On the other hand, cluster 1 shows a combination of "Fall" and "Non-Fall" occurrences. As a result, K-means clustering with just two clusters is too coarse to accurately forecast which classes will be in the "Fall" and which won't. To evaluate if our clusterings get better, we may experiment with other clusterings. The cluster numbers that are tested range from three to ten:

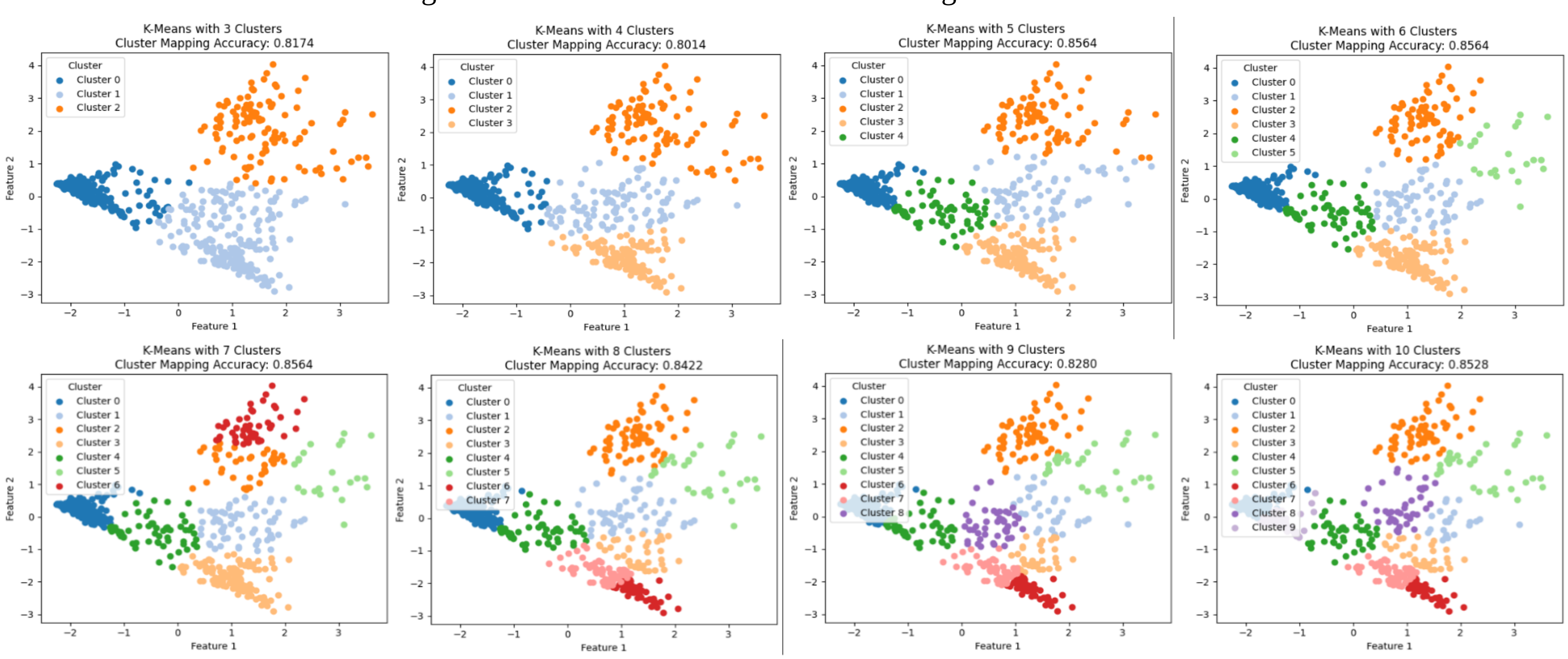


Fig. 7. K-Means with Different Number of Clusters

One can examine the accuracy results for various clusterings by zooming in on the graphs. The following conclusions may be drawn from the graphs when we examine them and contrast them with earlier research. First of all, we can observe that our approach for evaluating clustering accuracy has improved after the cluster count of five. The accuracy of this example has increased due to the inclusion of the green zone, which has made it easier to distinguish the light blue region, which mostly consists of 'Fall' instances. Nevertheless, accuracy stops improving after five clusters, suggesting that the model is overfitting. Thus, five clusters in all are considered adequate to determine if an activity is associated with a 'Fall' or not.

PART B)

Since the 'Fall' class is so important in our situation, I also looked at the models' recall values and accuracy scores. False negatives, or Type 2 mistakes, are often seen as more serious than false positives, or Type 1 errors, in healthcare applications. This also applies to our situation. Mislabeling "Non-Fall" as "Fall" can have catastrophic consequences because falls can cause major injuries to the elderly. As such, it is crucial to include recall values in our analysis.

SVM

Parameters for hypertuning SVM is shown below

```
c_values = [0.001, 0.01, 0.1, 1.0, 10.0]
kernel_types = ["rbf", "linear", "sigmoid", "poly"]
gamma_values = ["scale", "auto"]
degrees = [0,1,2,3,4,5]
```

Fig. 8. Parameters for Hypertuning SVM Model

Note that only the poly kernel is impacted by the degree parameter. To avoid calculating different kernels with varying degrees again and again, the calculations for poly and other kernels have been divided into distinct sections of the code. The regularization parameter, denoted as C, is inversely correlated with the degree of regularization. Gamma modifies the kernel coefficient of the kernels we have chosen.

After the hypertuning, we tried all combinations with Grid Search. Detailed results can be seen in Table-1 below. If we look the results, two combinations gave the best performance on the validation set, which splitted as 70%-15%-15%.

	C	Kernel Type	Gamma	Recall %	Accuracy %
1	1	poly(degree=3)	auto	79.25	83.53
2	10	rbf	scale	79.25	83.53

Therefore, I tried both combinations on test set and here are the results:

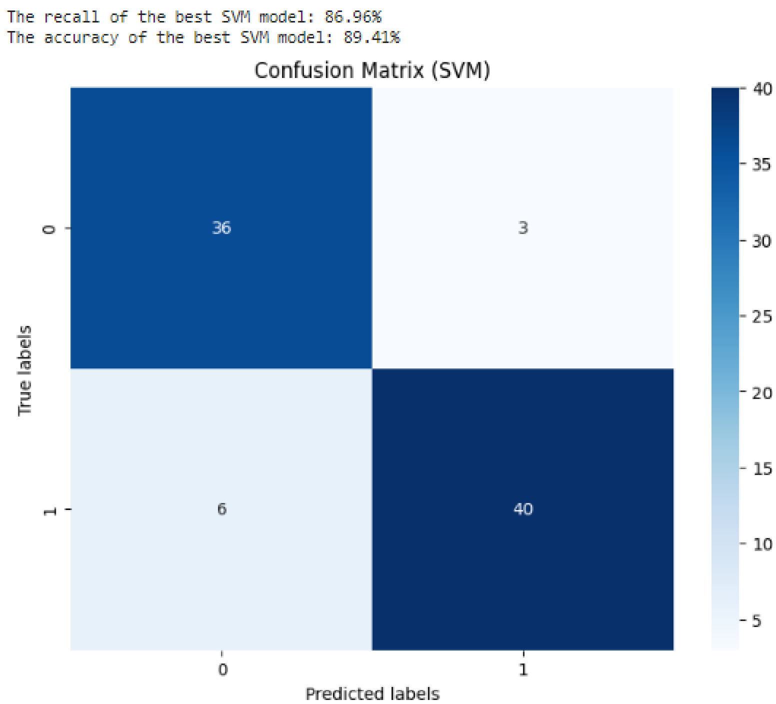


Fig. 9. Results of SVM (First Combination)

As one can see, in the test set, the first combination of SVM resulted in an accuracy of 89.41% and a recall of 86.96%. We are labeling 40 falls out of 46, missing 6 falls. Here are the results of second combination:

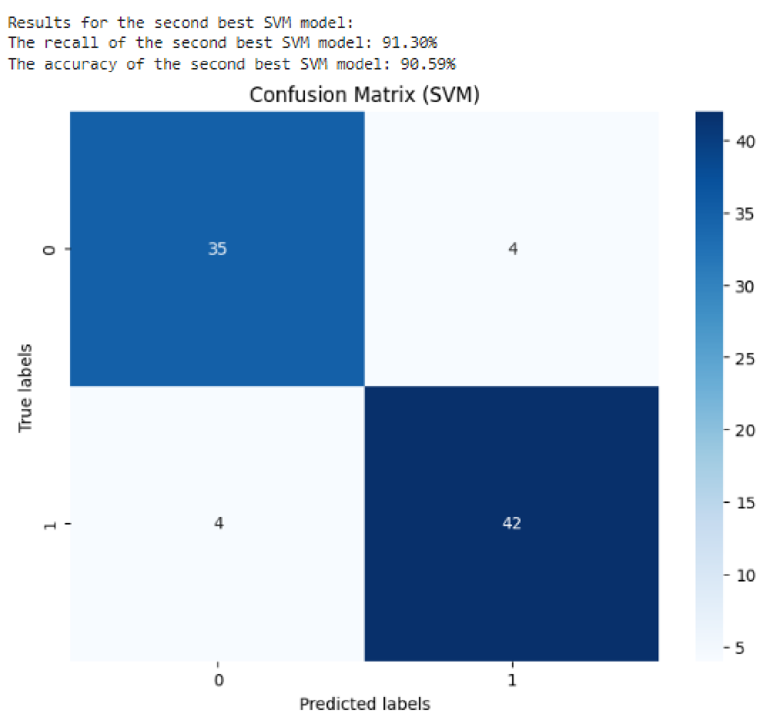


Fig. 10. Results of SVM (Second Combination)

Second combination dominated first in both metrics. The accuracy value is 90.59% and recall value is 91.3%. Hence, for SVM, model parameters are shown below:

C = 10

Kernel Type = rbf

Gamma = scale

MLP

Parameters for hypertuning MLP is shown below

```
alphas = [1, 0.1, 0.01, 0.001]
hidden_layer_sizes = [(8, 8, 8), (16, 16), (32, 32), (64, 64)]
solvers = ["adam", "sgd", "lbfgs"]
activation_functions = ["relu", "logistic", "tanh"]
```

Fig. 11. Parameters for Hypertuning MLP

When designing a Multi-Layer Perceptron (MLP) neural network, certain hyperparameters are essential. Regularization is controlled by the alpha parameter, the architecture is determined by hidden_layer_sizes, which varies the number of neurons in each layer; optimization algorithms such as Adam, SGD, and L-BFGS are used as solvers for weight updates; and non-linearity is introduced by activation_functions, which include ReLU, logistic sigmoid, and hyperbolic tangent. In order to get the most performance and generalization out of the neural network model, certain hyperparameters must be tuned.

After the hypertuning, again, we tried all combinations with Grid Search. Detailed results can be seen in Table-2 below. If we look the results, contrary to SVM, only one gave the best performance on the validation set, which splitted as 70%-15%-15.

```
The settings of the best MLP model: size=(8, 8, 8), alpha=0.001, solver=lbfgs, activation_function=tanh
The best validation recall: 96.23%
The best validation accuracy: 91.76%
```

According to the results, MLP classifier dominated SVM on the validation set. Hence, best parameters for MLP is shown as:

Hidden Unit Size = (8, 8, 8)

alpha = 0.001

solver = lbfgs

Activation Function = tanh

After hypertuning, I tested the model on the test set. Here are the results:

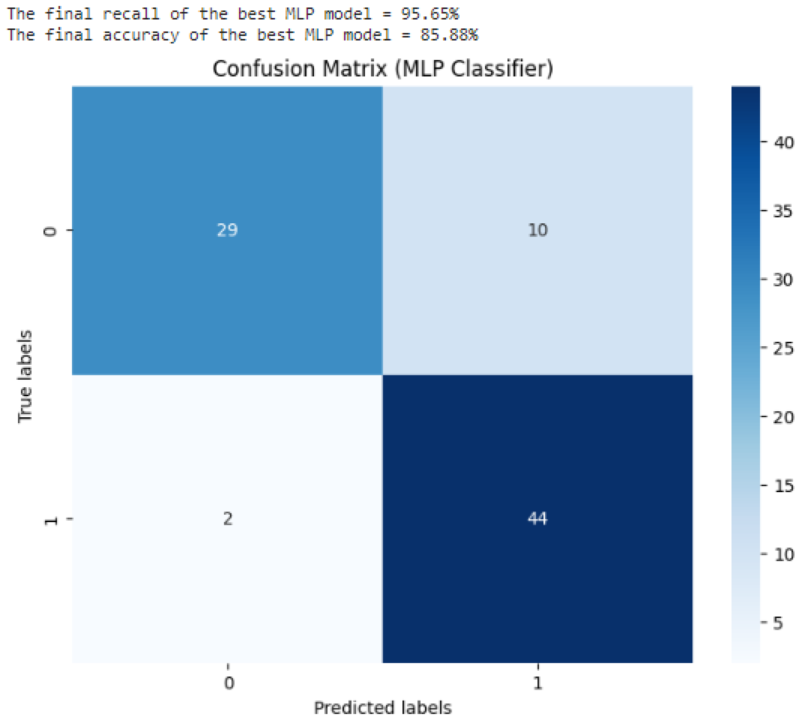


Fig. 12. Results of MLP

The MLP model’s accuracy is 85.88% and recall value is 95.65% on the test set. Although recall value is pretty high, accuracy value is remarkably lower than previous models. It is caused by mislabeling “Non-Fall” instances as “Fall”.

Finally, the SVM model achieved the maximum accuracy, while the MLP model had the highest recall. As a result, the decision between these models is determined by the application's specific requirements. If the cost of a Type 2 error is high, the MLP model may be a better option. However, for optimal overall performance, the SVM model is recommended. Ultimately, the 'optimal' model is determined by the application's specific requirements and goals. Below, you can see detailed results of hypertuning phase of both SVM and MLP models:

Table-1 (SVM):

C	Kernel Type	Gamma	Recall %	Accuracy %
1	poly(degree=3)	auto	79.25	83.53
10	rbf	scale	79.25	83.53
0.1	rbf	auto	79.25	82.35
10	rbf	auto	79.25	82.35
0.1	poly(degree=3)	auto	77.36	82.35

1	poly(degree=3)	scale	77.36	82.35
1	poly(degree=5)	scale	77.36	82.35
10	poly(degree=3)	auto	77.36	82.35
0.1	poly(degree=5)	auto	75.47	82.35
1	poly(degree=5)	auto	75.47	82.35
1	rbf	scale	77.36	81.18
1	rbf	auto	77.36	81.18
0.01	poly(degree=3)	scale	73.58	81.18
0.1	poly(degree=5)	scale	73.58	81.18
0.001	poly(degree=3)	auto	71.70	80.00
10	poly(degree=5)	scale	71.70	80.00
0.1	rbf	scale	79.25	78.82
0.01	poly(degree=3)	auto	81.13	77.65
0.01	poly(degree=5)	auto	81.13	77.65
10	poly(degree=5)	auto	81.13	77.65
0.01	linear	scale	81.13	76.47
0.01	linear	auto	81.13	76.47
0.01	sigmoid	scale	81.13	76.47
0.01	sigmoid	auto	81.13	76.47
0.01	poly(degree=1)	scale	81.13	76.47
0.01	poly(degree=1)	auto	81.13	76.47
0.1	linear	scale	81.13	76.47
0.1	linear	auto	81.13	76.47
0.1	sigmoid	scale	81.13	76.47
0.1	poly(degree=1)	scale	81.13	76.47
0.1	poly(degree=3)	scale	81.13	76.47
0.1	poly(degree=1)	auto	81.13	76.47
1	linear	scale	81.13	76.47
1	linear	auto	81.13	76.47
1	poly(degree=1)	scale	81.13	76.47
1	poly(degree=1)	auto	81.13	76.47
10	linear	scale	81.13	76.47
10	linear	auto	81.13	76.47
10	poly(degree=1)	scale	81.13	76.47
10	poly(degree=1)	auto	81.13	76.47
0.001	poly(degree=5)	auto	66.04	76.47
0.01	rbf	auto	83.02	75.29
0.01	rbf	scale	81.13	75.29
0.1	sigmoid	auto	81.13	75.29
0.001	linear	scale	83.02	74.12
0.001	linear	auto	83.02	74.12
1	poly(degree=4)	auto	62.26	74.12
10	poly(degree=4)	scale	62.26	74.12
10	poly(degree=4)	auto	62.26	74.12
0.1	poly(degree=4)	auto	58.49	71.76
1	poly(degree=4)	scale	58.49	71.76

0.01	poly(degree=4)	auto	56.60	70.59
0.1	poly(degree=4)	scale	56.60	70.59
0.1	poly(degree=2)	scale	58.49	69.41
0.1	poly(degree=2)	auto	58.49	69.41
1	poly(degree=2)	scale	58.49	69.41
1	poly(degree=2)	auto	58.49	69.41
10	poly(degree=2)	scale	58.49	69.41
10	poly(degree=2)	auto	58.49	69.41
0.01	poly(degree=5)	scale	52.83	69.41
0.01	poly(degree=2)	scale	60.38	67.06
0.01	poly(degree=2)	auto	50.94	67.06
0.001	poly(degree=4)	auto	47.17	67.06
0.01	poly(degree=4)	scale	41.51	63.53
0.001	rbf	scale	100.00	62.35
0.001	rbf	auto	100.00	62.35
0.001	sigmoid	scale	100.00	62.35
0.001	sigmoid	auto	100.00	62.35
0.001	poly(degree=0)	scale	100.00	62.35
0.001	poly(degree=1)	scale	100.00	62.35
0.001	poly(degree=2)	scale	100.00	62.35
0.001	poly(degree=3)	scale	100.00	62.35
0.001	poly(degree=4)	scale	100.00	62.35
0.001	poly(degree=5)	scale	100.00	62.35
0.001	poly(degree=0)	auto	100.00	62.35
0.001	poly(degree=1)	auto	100.00	62.35
0.001	poly(degree=2)	auto	100.00	62.35
0.01	poly(degree=0)	scale	100.00	62.35
0.01	poly(degree=0)	auto	100.00	62.35
0.1	poly(degree=0)	scale	100.00	62.35
0.1	poly(degree=0)	auto	100.00	62.35
1	poly(degree=0)	scale	100.00	62.35
1	poly(degree=0)	auto	100.00	62.35
10	poly(degree=0)	scale	100.00	62.35
10	poly(degree=0)	auto	100.00	62.35
1	sigmoid	scale	62.26	61.18
10	sigmoid	scale	58.49	57.65
1	sigmoid	auto	56.60	56.47
10	sigmoid	auto	52.83	52.94

Table-2 (MLP):

Hidden Layer Size	Activation Function	Solver	Alpha	Recall %	Accuracy %
(8, 8, 8)	tanh	lbfgs	0.001	96.23	91.76
(16, 16)	relu	lbfgs	0.1	90.57	89.41
(32, 32)	relu	adam	0.1	88.68	88.24
(16, 16)	relu	lbfgs	1	86.79	88.24
(16, 16)	tanh	lbfgs	1	86.79	88.24
(16, 16)	tanh	adam	0.01	86.79	88.24
(16, 16)	tanh	adam	0.001	86.79	88.24
(32, 32)	tanh	lbfgs	1	86.79	88.24
(32, 32)	tanh	adam	0.01	86.79	88.24
(32, 32)	tanh	adam	0.001	86.79	88.24
(64, 64)	relu	lbfgs	1	86.79	88.24
(8, 8, 8)	relu	lbfgs	0.01	90.57	87.06
(8, 8, 8)	relu	lbfgs	0.001	90.57	87.06
(8, 8, 8)	tanh	lbfgs	1	88.68	87.06
(32, 32)	relu	adam	0.001	88.68	87.06
(8, 8, 8)	relu	adam	0.1	86.79	87.06
(8, 8, 8)	relu	adam	0.01	86.79	87.06
(8, 8, 8)	relu	adam	0.001	86.79	87.06
(32, 32)	relu	lbfgs	1	86.79	87.06
(64, 64)	tanh	lbfgs	1	86.79	87.06
(64, 64)	tanh	adam	0.1	86.79	87.06
(64, 64)	tanh	adam	0.01	86.79	87.06
(64, 64)	tanh	adam	0.001	86.79	87.06
(32, 32)	tanh	adam	0.1	84.91	87.06
(16, 16)	logistic	lbfgs	0.1	88.68	85.88
(32, 32)	logistic	lbfgs	0.1	88.68	85.88
(32, 32)	relu	adam	0.01	88.68	85.88
(64, 64)	relu	adam	0.1	88.68	85.88
(64, 64)	logistic	lbfgs	0.1	88.68	85.88
(16, 16)	relu	lbfgs	0.01	84.91	85.88
(16, 16)	tanh	adam	0.1	83.02	85.88
(16, 16)	relu	adam	0.01	83.02	85.88
(8, 8, 8)	logistic	lbfgs	0.1	88.68	84.71
(64, 64)	relu	adam	0.01	88.68	84.71
(64, 64)	relu	adam	0.001	88.68	84.71
(64, 64)	relu	lbfgs	0.001	88.68	84.71
(8, 8, 8)	relu	lbfgs	1	86.79	84.71
(8, 8, 8)	logistic	lbfgs	0.01	86.79	84.71
(16, 16)	tanh	lbfgs	0.1	84.91	84.71
(32, 32)	tanh	lbfgs	0.001	88.68	83.53

(32, 32)	relu	lbfgs	0.01	86.79	83.53
(32, 32)	tanh	lbfgs	0.01	86.79	83.53
(32, 32)	logistic	lbfgs	0.001	86.79	83.53
(64, 64)	tanh	lbfgs	0.1	84.91	83.53
(8, 8, 8)	relu	sgd	1	79.25	83.53
(16, 16)	relu	adam	0.001	79.25	83.53
(64, 64)	relu	adam	1	79.25	83.53
(16, 16)	logistic	lbfgs	0.01	84.91	82.35
(16, 16)	tanh	lbfgs	0.01	84.91	82.35
(8, 8, 8)	relu	lbfgs	0.1	83.02	82.35
(32, 32)	tanh	lbfgs	0.1	83.02	82.35
(16, 16)	relu	lbfgs	0.001	81.13	82.35
(32, 32)	relu	lbfgs	0.1	81.13	82.35
(16, 16)	logistic	lbfgs	1	79.25	82.35
(32, 32)	logistic	lbfgs	1	79.25	82.35
(64, 64)	logistic	lbfgs	1	79.25	82.35
(8, 8, 8)	relu	adam	1	77.36	82.35
(8, 8, 8)	logistic	lbfgs	0.001	88.68	81.18
(16, 16)	logistic	lbfgs	0.001	86.79	81.18
(32, 32)	logistic	lbfgs	0.01	84.91	81.18
(64, 64)	tanh	lbfgs	0.01	84.91	81.18
(8, 8, 8)	tanh	lbfgs	0.1	83.02	81.18
(64, 64)	relu	lbfgs	0.1	83.02	81.18
(64, 64)	tanh	lbfgs	0.001	83.02	81.18
(8, 8, 8)	relu	sgd	0.1	79.25	81.18
(8, 8, 8)	relu	sgd	0.01	79.25	81.18
(8, 8, 8)	relu	sgd	0.001	79.25	81.18
(16, 16)	relu	adam	0.1	79.25	81.18
(64, 64)	relu	lbfgs	0.01	79.25	81.18
(8, 8, 8)	tanh	adam	1	77.36	81.18
(8, 8, 8)	tanh	adam	0.1	77.36	81.18
(8, 8, 8)	logistic	adam	0.01	77.36	81.18
(8, 8, 8)	tanh	adam	0.01	77.36	81.18
(8, 8, 8)	logistic	adam	0.001	77.36	81.18
(8, 8, 8)	tanh	adam	0.001	77.36	81.18
(16, 16)	relu	adam	1	77.36	81.18
(16, 16)	tanh	adam	1	77.36	81.18
(32, 32)	relu	adam	1	77.36	81.18
(32, 32)	tanh	adam	1	77.36	81.18
(64, 64)	tanh	adam	1	77.36	81.18
(64, 64)	logistic	adam	0.001	77.36	81.18
(64, 64)	logistic	lbfgs	0.01	83.02	80.00
(16, 16)	logistic	adam	1	81.13	80.00

(16, 16)	relu	sgd	1	81.13	80.00
(16, 16)	tanh	sgd	1	81.13	80.00
(16, 16)	logistic	adam	0.1	81.13	80.00
(16, 16)	relu	sgd	0.1	81.13	80.00
(16, 16)	tanh	sgd	0.1	81.13	80.00
(16, 16)	logistic	adam	0.01	81.13	80.00
(16, 16)	relu	sgd	0.01	81.13	80.00
(16, 16)	tanh	sgd	0.01	81.13	80.00
(16, 16)	logistic	adam	0.001	81.13	80.00
(16, 16)	relu	sgd	0.001	81.13	80.00
(16, 16)	tanh	sgd	0.001	81.13	80.00
(32, 32)	logistic	adam	1	81.13	80.00
(32, 32)	tanh	sgd	1	81.13	80.00
(32, 32)	logistic	adam	0.1	81.13	80.00
(32, 32)	tanh	sgd	0.1	81.13	80.00
(32, 32)	logistic	adam	0.01	81.13	80.00
(32, 32)	tanh	sgd	0.01	81.13	80.00
(32, 32)	logistic	adam	0.001	81.13	80.00
(32, 32)	tanh	sgd	0.001	81.13	80.00
(64, 64)	logistic	adam	0.1	81.13	80.00
(64, 64)	logistic	adam	0.01	81.13	80.00
(8, 8, 8)	tanh	sgd	1	79.25	80.00
(8, 8, 8)	tanh	sgd	0.1	79.25	80.00
(8, 8, 8)	tanh	sgd	0.01	79.25	80.00
(8, 8, 8)	tanh	sgd	0.001	79.25	80.00
(64, 64)	relu	sgd	1	79.25	80.00
(64, 64)	logistic	adam	1	81.13	78.82
(64, 64)	tanh	sgd	1	81.13	78.82
(64, 64)	tanh	sgd	0.1	81.13	78.82
(64, 64)	tanh	sgd	0.01	81.13	78.82
(64, 64)	tanh	sgd	0.001	81.13	78.82
(64, 64)	logistic	lbfgs	0.001	81.13	78.82
(32, 32)	relu	sgd	1	79.25	78.82
(32, 32)	relu	sgd	0.1	79.25	78.82
(32, 32)	relu	sgd	0.01	79.25	78.82
(32, 32)	relu	sgd	0.001	79.25	78.82
(64, 64)	relu	sgd	0.1	79.25	78.82
(64, 64)	relu	sgd	0.01	79.25	78.82
(64, 64)	relu	sgd	0.001	79.25	78.82
(8, 8, 8)	tanh	lbfgs	0.01	81.13	77.65
(32, 32)	relu	lbfgs	0.001	77.36	77.65
(16, 16)	tanh	lbfgs	0.001	77.36	76.47
(8, 8, 8)	logistic	adam	1	100.00	62.35

(8, 8, 8)	logistic	sgd	1	100.00	62.35
(8, 8, 8)	logistic	lbfgs	1	100.00	62.35
(8, 8, 8)	logistic	adam	0.1	100.00	62.35
(8, 8, 8)	logistic	sgd	0.1	100.00	62.35
(8, 8, 8)	logistic	sgd	0.01	100.00	62.35
(8, 8, 8)	logistic	sgd	0.001	100.00	62.35
(16, 16)	logistic	sgd	1	100.00	62.35
(16, 16)	logistic	sgd	0.1	100.00	62.35
(16, 16)	logistic	sgd	0.01	100.00	62.35
(16, 16)	logistic	sgd	0.001	100.00	62.35
(32, 32)	logistic	sgd	1	100.00	62.35
(32, 32)	logistic	sgd	0.1	100.00	62.35
(32, 32)	logistic	sgd	0.01	100.00	62.35
(32, 32)	logistic	sgd	0.001	100.00	62.35
(64, 64)	logistic	sgd	1	100.00	62.35
(64, 64)	logistic	sgd	0.1	100.00	62.35
(64, 64)	logistic	sgd	0.01	100.00	62.35
(64, 64)	logistic	sgd	0.001	100.00	62.35