dlPatientODonorO-IIM-B

1. Logistic correlations

1.1 Task description

In classification applications, it might be interesting to look for logistic dependencies between single input and single target variables. This task calculates the absolute values of the logistic correlation between all inputs and all targets. The logistic correlation is a numerical value between 0 and 1 that expresses the strength of the logistic relationship between a single input and output variables. When it is close to 1 it indicates a strong relationship. A value close to 0 indicates that there is no relationship.

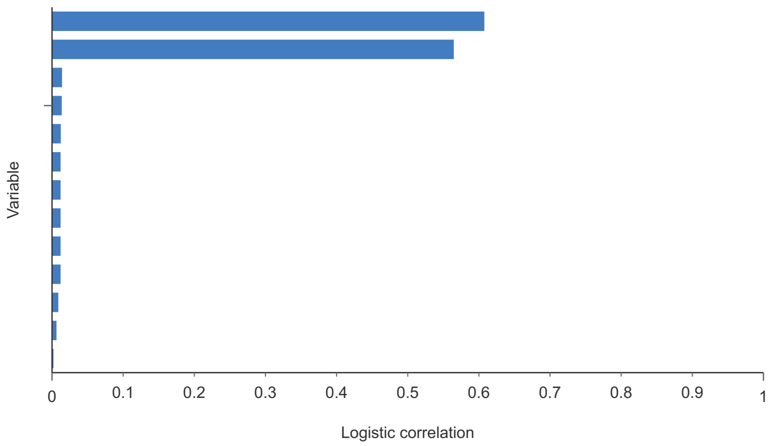
1.2 Logistic correlations

The following table shows the absolute value of the logistic correlations between all input and target variables. The maximum correlation (0.606263) is yield between the input variable Acceptable Survival Score(2 and less score=reject) and the target variable Accepted 1 or Rejected 0.

	Accep
Donor HLA-A	
Patient HLA-A	
A Match	
Donor HLA-B	
Patient HLA-B	
B Match	
Donor HLAA-DR	
Patient HLA-DR	
DR-Match	
Acceptable Survival Score(2 and less score=reject)	
Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)	
Donor=GovnOrPvtHospital(Govt=1, Pvt=0)	
PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)	

1.3 Accepted 1 or Rejected 0 bars chart

The next chart illustrates the dependency of the target Accepted 1 or Rejected 0 with all the input variables. The y-labels from greater to smaller correlations are: Acceptable Survival Score(2 and less score=reject), Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy), PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0), Patient HLA-A, DR-Match, Donor HLA-B, Donor HLA-A, Donor=GovnOrPvtHospital(Govt=1, Pvt=0), A Match, Donor HLAA-DR, Patient HLA-B, B Match, Patient HLA-DR.



2. Univariate outliers

2.1 Task description

Outliers are defined as observations in the data that are abnormally distant from the others. They may be due to variability in the measurement or may indicate experimental errors. This task uses the Tukey's method, which defines an outlier as those values of the data set that fall to far from the central point, the median. The maximum distance to the center of the data that is going to be allowed is defined by the cleaning parameter. As it grows, the test becomes less sensitive to outliers but if it is too small, a lot of values will be detected as outliers.

2.2 Univariate outliers results

The data has not outliers.

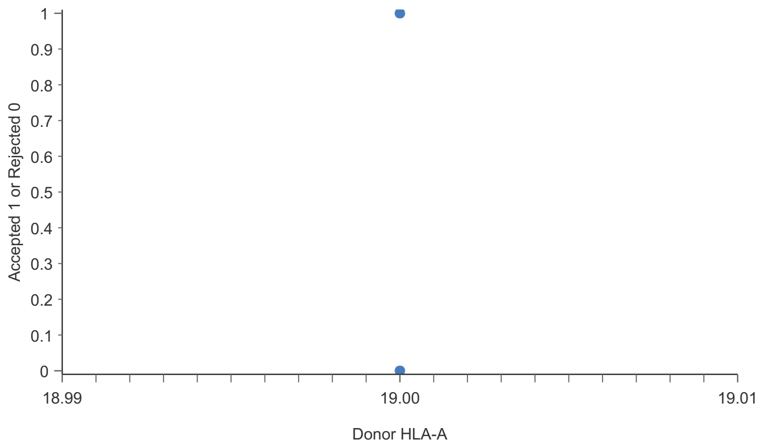
3. Scatter plot

3.1 Task description

This task plots graphs of all target versus all input variables. That charts might help to see the dependencies of the targets with the inputs.

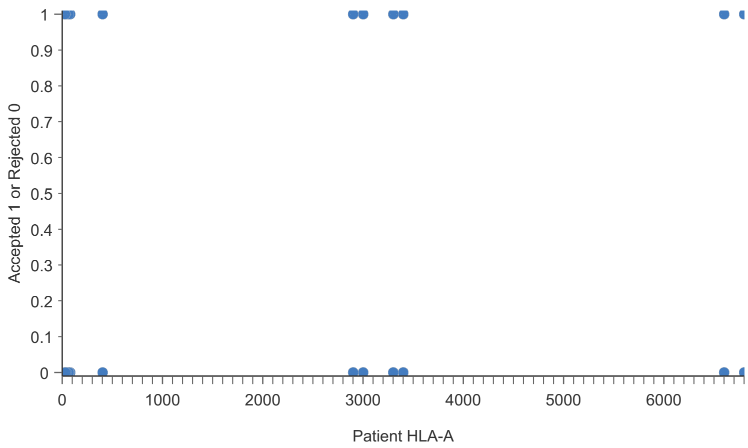
3.2 Accepted 1 or Rejected 0 scatter chart vs Donor HLA-A

The following chart shows the scatter plot for the input Donor HLA-A and the target Accepted 1 or Rejected 0.



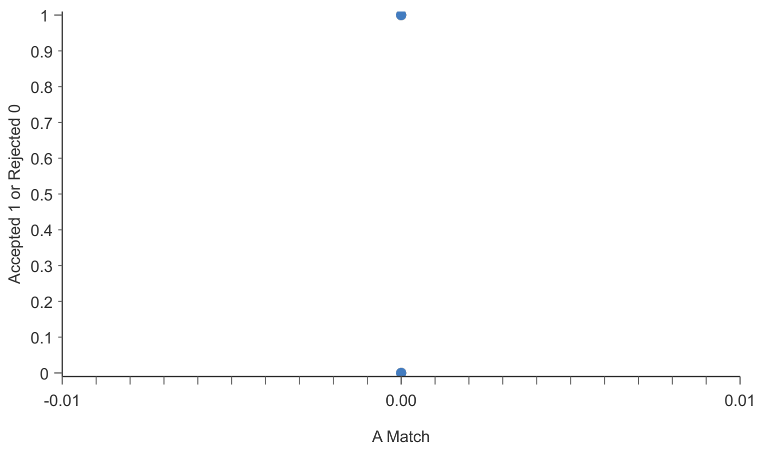
3.3 Accepted 1 or Rejected 0 scatter chart vs Patient HLA-A

The following chart shows the scatter plot for the input Patient HLA-A and the target Accepted 1 or Rejected 0.



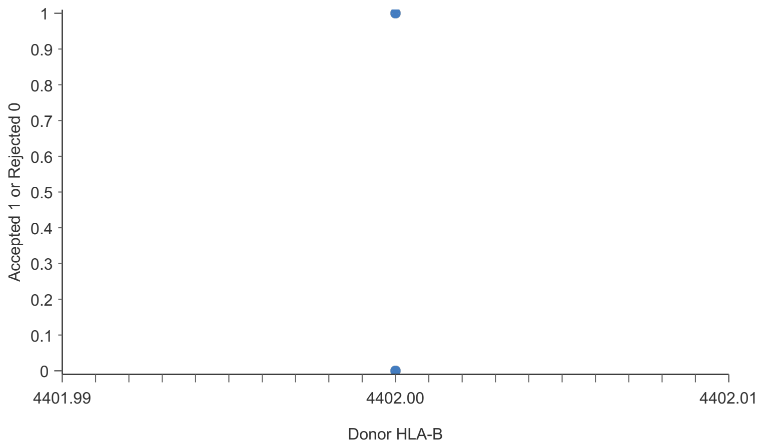
3.4 Accepted 1 or Rejected 0 scatter chart vs A Match

The following chart shows the scatter plot for the input A Match and the target Accepted 1 or Rejected 0.



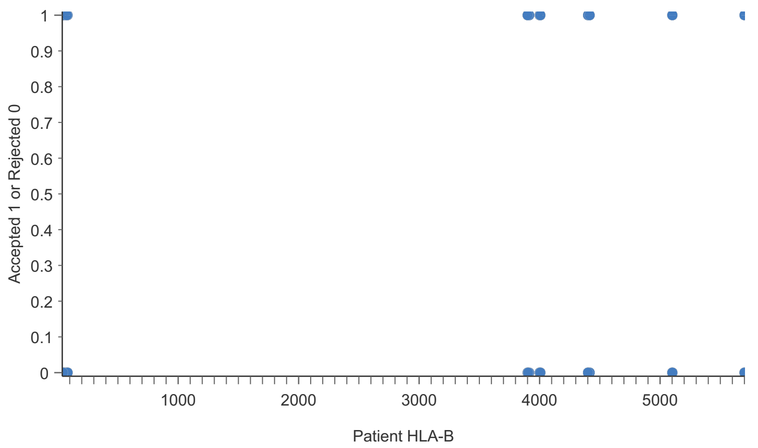
3.5 Accepted 1 or Rejected 0 scatter chart vs Donor HLA-B

The following chart shows the scatter plot for the input Donor HLA-B and the target Accepted 1 or Rejected 0.



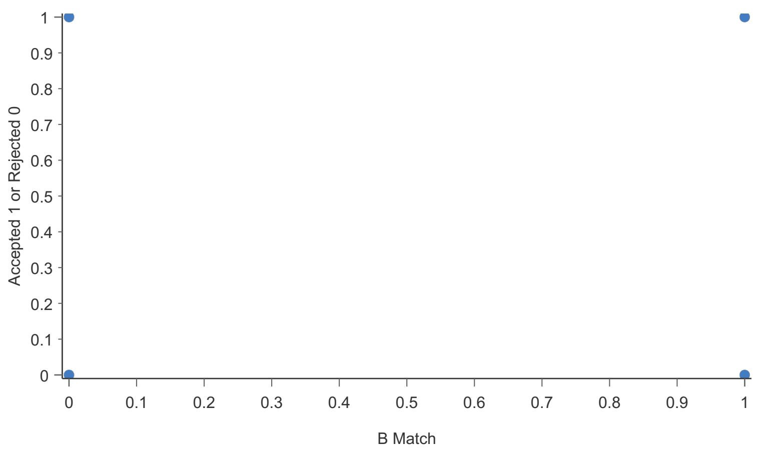
3.6 Accepted 1 or Rejected 0 scatter chart vs Patient HLA-B

The following chart shows the scatter plot for the input Patient HLA-B and the target Accepted 1 or Rejected 0.



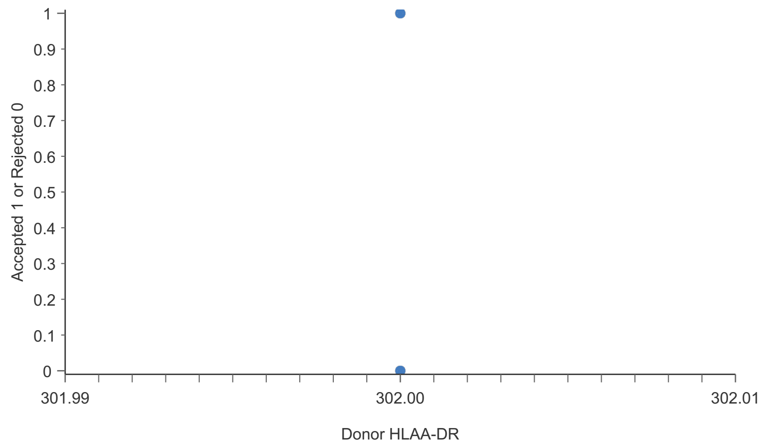
3.7 Accepted 1 or Rejected 0 scatter chart vs B Match

The following chart shows the scatter plot for the input B Match and the target Accepted 1 or Rejected 0.



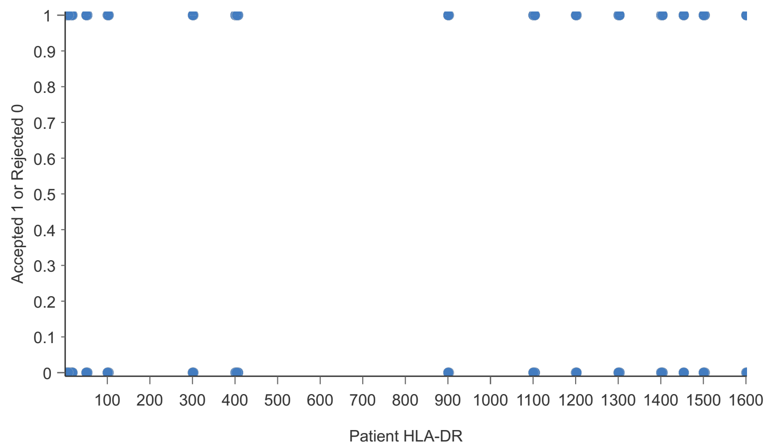
3.8 Accepted 1 or Rejected 0 scatter chart vs Donor HLAA-DR

The following chart shows the scatter plot for the input Donor HLAA-DR and the target Accepted 1 or Rejected 0.



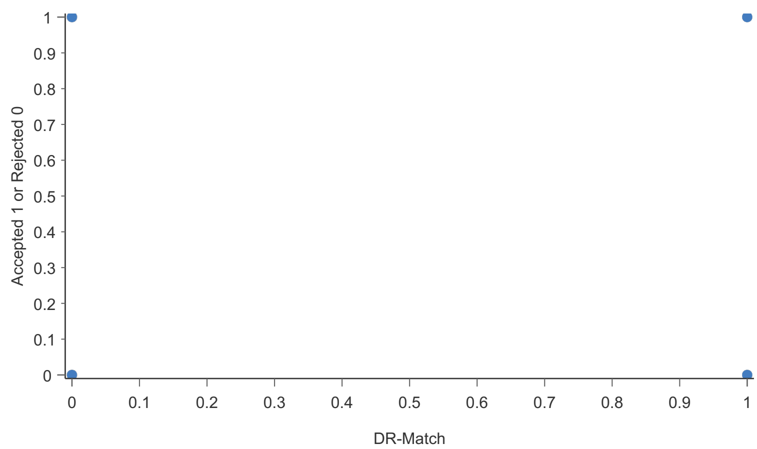
3.9 Accepted 1 or Rejected 0 scatter chart vs Patient HLA-DR

The following chart shows the scatter plot for the input Patient HLA-DR and the target Accepted 1 or Rejected 0.



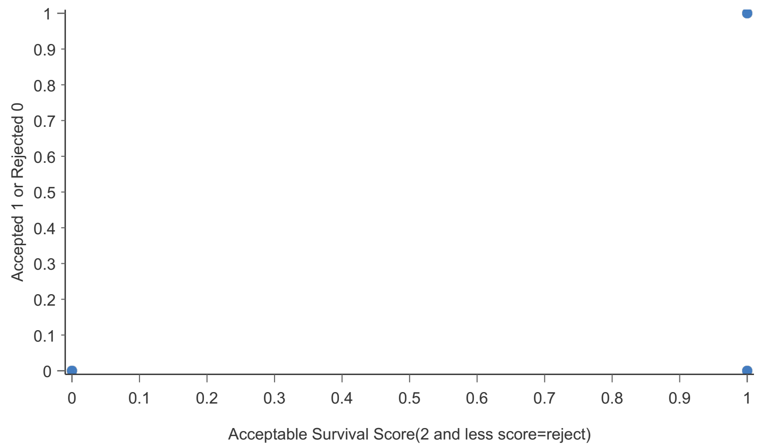
3.10 Accepted 1 or Rejected 0 scatter chart vs DR-Match

The following chart shows the scatter plot for the input DR-Match and the target Accepted 1 or Rejected 0.



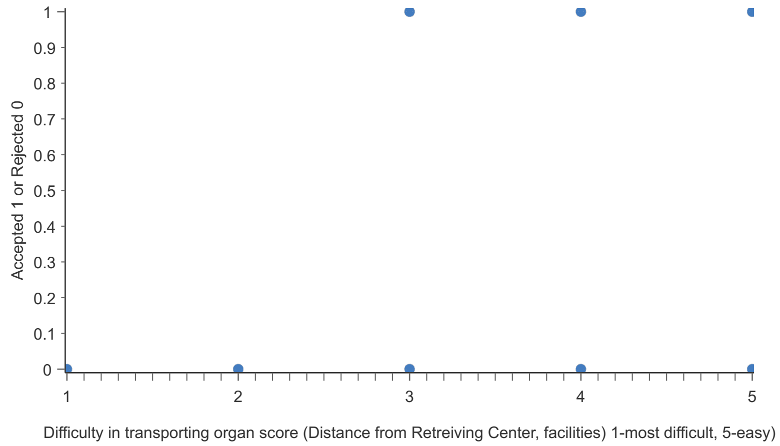
3.11 Accepted 1 or Rejected 0 scatter chart vs Acceptable Survival Score(2 and less score=reject)

The following chart shows the scatter plot for the input Acceptable Survival Score(2 and less score=reject) and the target Accepted 1 or Rejected 0.



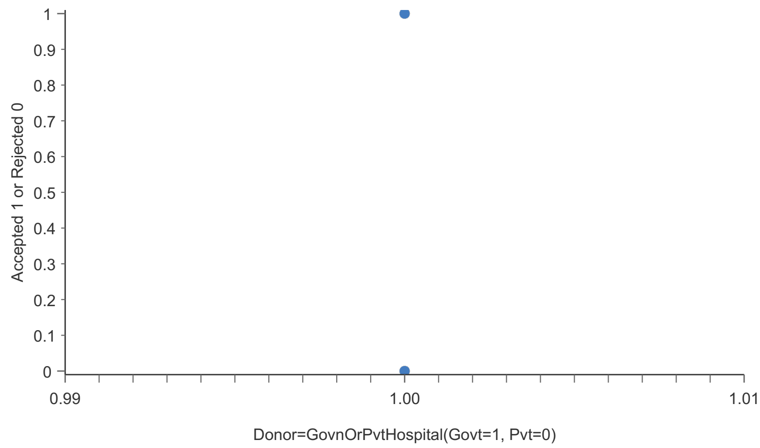
3.12 Accepted 1 or Rejected 0 scatter chart vs Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)

The following chart shows the scatter plot for the input Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy) and the target Accepted 1 or Rejected 0.



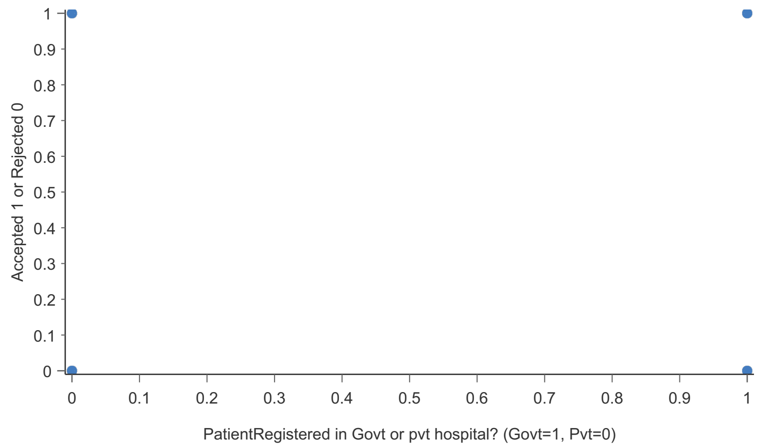
3.13 Accepted 1 or Rejected 0 scatter chart vs Donor=GovnOrPvtHospital(Govt=1, Pvt=0)

The following chart shows the scatter plot for the input Donor=GovnOrPvtHospital(Govt=1, Pvt=0) and the target Accepted 1 or Rejected 0.



3.14 Accepted 1 or Rejected 0 scatter chart vs PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)

The following chart shows the scatter plot for the input PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0) and the target Accepted 1 or Rejected 0.



4. Neural network

4.1 Task description

The neural networks represents the predictive model. In Neural Designer neural networks allow deep architectures, which are a class of universal approximator.

4.2 Inputs

The number of inputs is 13. The next table depicts some basic information about them, including the name, the units and the description.

	Name	Units	Description
1	Donor HLA-A		
2	Patient HLA-A		
3	A Match		
4	Donor HLA-B		
5	Patient HLA-B		
6	B Match		
7	Donor HLAA-DR		
8	Patient HLA-DR		
9	DR-Match		
10	Acceptable Survival Score(2 and less score=reject)		
11	Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)		
12	Donor=GovnOrPvtHospital(Govt=1, Pvt=0)		
13	PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)		

4.3 Scaling layer

The size of the scaling layer is 13, the number of inputs. The scaling method for this layer is the MinimumMaximum. The following table shows the values which are used for scaling the inputs, which include the minimum, maximum, mean and standard deviation.

	Minimum
Donor HLA-A	[illegible]
Patient HLA-A	[illegible]
A Match	[illegible]
Donor HLA-B	[illegible]
Patient HLA-B	[illegible]
B Match	[illegible]
Donor HLAA-DR	[illegible]
Patient HLA-DR	[illegible]
DR-Match	[illegible]
Acceptable Survival Score(2 and less score=reject)	[illegible]
Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)	[illegible]
Donor=GovnOrPvtHospital(Govt=1, Pvt=0)	[illegible]
PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)	[illegible]

4.4 Neural network

The number of layers in the neural network is 2. The following table depicts the size of each layer and its corresponding activation function. The architecture of this neural network can be written as 13:3:1.

	Inputs number	Neurons number	Activation function
1	13	3	Logistic
2	3	1	Logistic

4.5 Neural network parameters

The following table shows the statistics of the parameters of the neural network. The total number of parameters is 46.

	Minimum	Maximum	Mean	Standard deviation
Statistics	-0.968	0.999	0.108	0.565

4.6 Probabilistic layer

The size of the probabilistic layer is 1, the number of outputs. The probabilistic method for this layer is the probability.

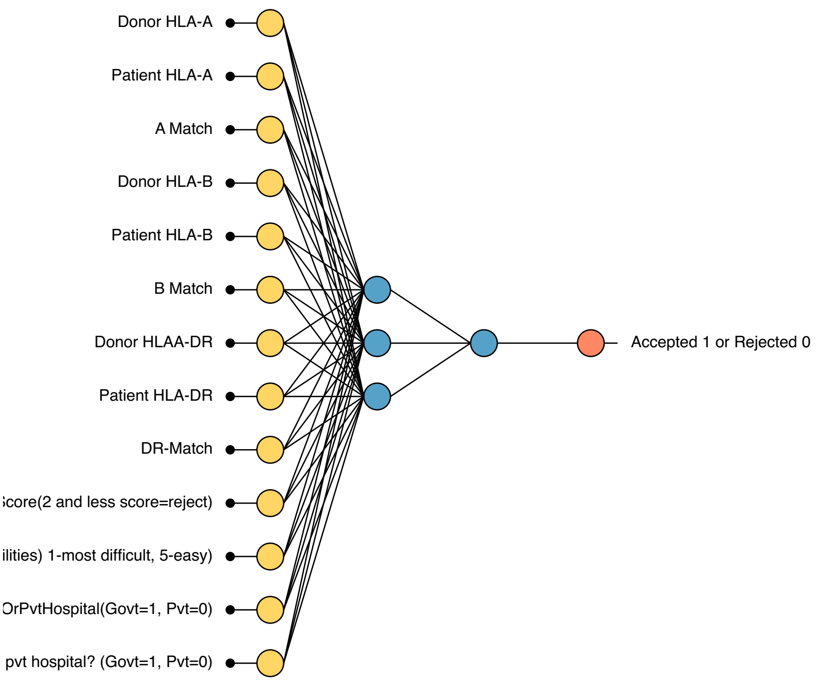
4.7 Outputs table

The number of outputs is 1. The next table depicts some basic information about them, including the name, the units and the description.

	Name	Units	Description
1	Accepted 1 or Rejected 0		

4.8 Neural network graph

A graphical representation of the network architecture is depicted next. It contains a scaling layer, a neural network and a probabilistic layer. The yellow circles represent scaling neurons, the blue circles perceptron neurons and the red circles probabilistic neurons. The number of inputs is 13, and the number of outputs is 1. The complexity, represented by the numbers of hidden neurons, is 3.



5. Neural network

5.1 Task description

The neural networks represents the predictive model. In Neural Designer neural networks allow deep architectures, which are a class of universal approximator.

5.2 Inputs

The number of inputs is 13. The next table depicts some basic information about them, including the name, the units and the description.

	Name	Units	Description
1	Donor HLA-A		
2	Patient HLA-A		
3	A Match		
4	Donor HLA-B		
5	Patient HLA-B		
6	B Match		
7	Donor HLAA-DR		
8	Patient HLA-DR		
9	DR-Match		
10	Acceptable Survival Score(2 and less score=reject)		
	Difficulty in transporting organ score (Distance		

11	from Retreiving Center, facilities) 1-most difficult, 5-easy)		
12	Donor=GovnOrPvtHospital(Govt=1, Pvt=0)		
13	PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)		

5.3 Scaling layer

The size of the scaling layer is 13, the number of inputs. The scaling method for this layer is the MinimumMaximum. The following table shows the values which are used for scaling the inputs, which include the minimum, maximum, mean and standard deviation.

	Minimum
Donor HLA-A	[illegible]
Patient HLA-A	[illegible]
A Match	[illegible]
Donor HLA-B	[illegible]
Patient HLA-B	[illegible]
B Match	[illegible]
Donor HLAA-DR	[illegible]
Patient HLA-DR	[illegible]
DR-Match	[illegible]
Acceptable Survival Score(2 and less score=reject)	[illegible]
Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)	[illegible]
Donor=GovnOrPvtHospital(Govt=1, Pvt=0)	[illegible]
PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)	[illegible]

5.4 Neural network

The number of layers in the neural network is 4. The following table depicts the size of each layer and its corresponding activation function. The architecture of this neural network can be written as 13:5:4:3:1.

	Inputs number	Neurons number	Activation function
1	13	5	Logistic
2	5	4	Logistic
3	4	3	Logistic
4	3	1	Logistic

5.5 Neural network parameters

The following table shows the statistics of the parameters of the neural network. The total number of parameters is 113.

	Minimum	Maximum	Mean	Standard deviation
Statistics	-0.997	0.974	-0.0942	0.557

5.6 Probabilistic layer

The size of the probabilistic layer is 1, the number of outputs. The probabilistic method for this layer is the probability.

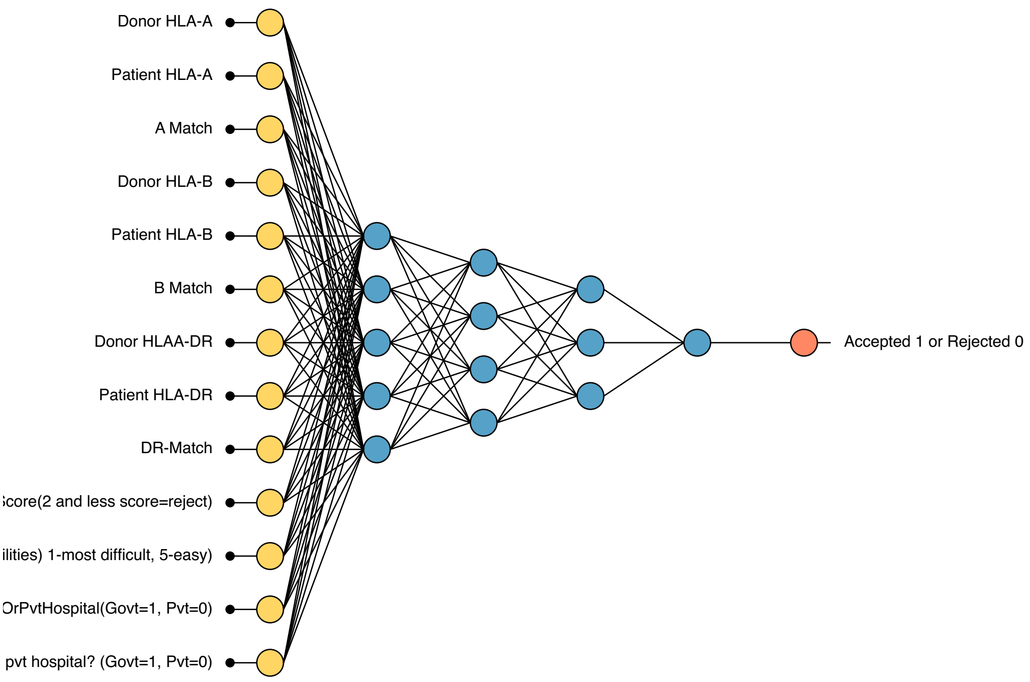
5.7 Outputs table

The number of outputs is 1. The next table depicts some basic information about them, including the name, the units and the description.

	Name	Units	Description
1	Accepted 1 or Rejected 0		

5.8 Neural network graph

A graphical representation of the network architecture is depicted next. It contains a scaling layer, a neural network and a probabilistic layer. The yellow circles represent scaling neurons, the blue circles perceptron neurons and the red circles probabilistic neurons. The number of inputs is 13, and the number of outputs is 1. The complexity, represented by the numbers of hidden neurons, is 5:4:3.



6. Neural network

6.1 Task description

The neural networks represents the predictive model. In Neural Designer neural networks allow deep architectures, which are a class of universal approximator.

6.2 Inputs

The number of inputs is 13. The next table depicts some basic information about them, including the name, the units and the description.

	Name	Units	Description
1	Donor HLA-A		
2	Patient HLA-A		
3	A Match		
4	Donor HLA-B		
5	Patient HLA-B		
6	B Match		
7	Donor HLAA-DR		
8	Patient HLA-DR		
9	DR-Match		
10	Acceptable Survival Score(2 and less score=reject)		
11	Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)		
12	Donor=GovnOrPvtHospital(Govt=1, Pvt=0)		
13	PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)		

6.3 Scaling layer

The size of the scaling layer is 13, the number of inputs. The scaling method for this layer is the MinimumMaximum. The following table shows the values which are used for scaling the inputs, which include the minimum, maximum, mean and standard deviation.

	Minimum
Donor HLA-A	(
Patient HLA-A	(
A Match	(
Donor HLA-B	(
Patient HLA-B	(
B Match	(
Donor HLAA-DR	(
Patient HLA-DR	(
DR-Match	(

Acceptable Survival Score(2 and less score=reject)	(
Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)	(
Donor=GovnOrPvtHospital(Govt=1, Pvt=0)	(
PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)	(

6.4 Neural network

The number of layers in the neural network is 4. The following table depicts the size of each layer and its corresponding activation function. The architecture of this neural network can be written as 13:5:4:3:1.

	Inputs number	Neurons number	Activation function
1	13	5	Logistic
2	5	4	Logistic
3	4	3	Logistic
4	3	1	Logistic

6.5 Neural network parameters

The following table shows the statistics of the parameters of the neural network. The total number of parameters is 113.

	Minimum	Maximum	Mean	Standard deviation
Statistics	-0.997	0.974	-0.0942	0.557

6.6 Probabilistic layer

The size of the probabilistic layer is 1, the number of outputs. The probabilistic method for this layer is the probability.

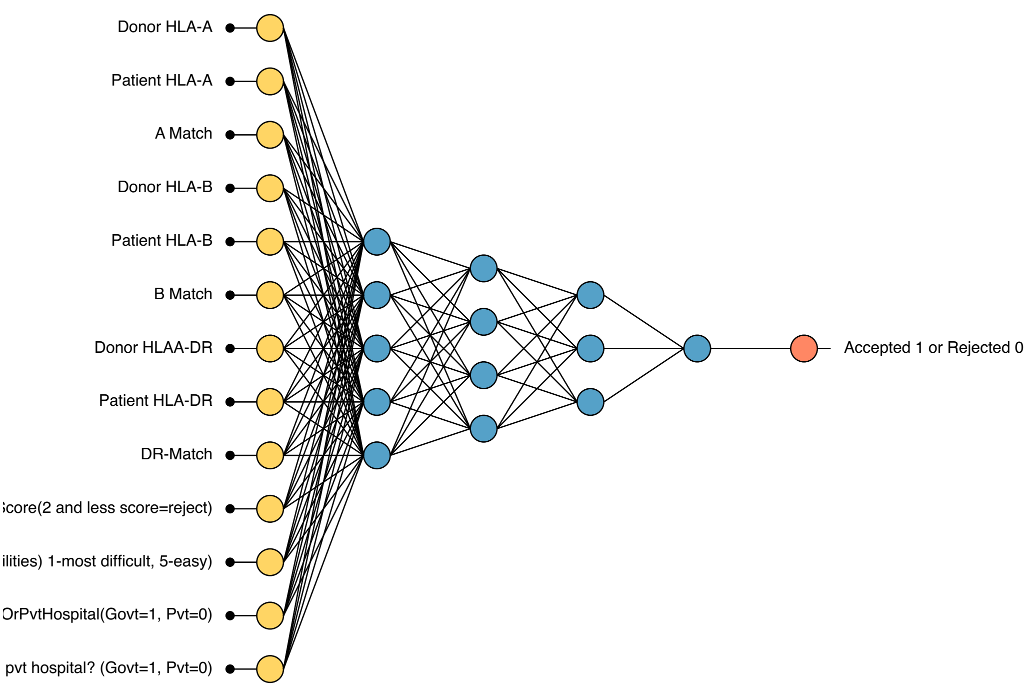
6.7 Outputs table

The number of outputs is 1. The next table depicts some basic information about them, including the name, the units and the description.

	Name	Units	Description
1	Accepted 1 or Rejected 0		

6.8 Neural network graph

A graphical representation of the network architecture is depicted next. It contains a scaling layer, a neural network and a probabilistic layer. The yellow circles represent scaling neurons, the blue circles perceptron neurons and the red circles probabilistic neurons. The number of inputs is 13, and the number of outputs is 1. The complexity, represented by the numbers of hidden neurons, is 5:4:3.



7. Neural network

7.1 Task description

The neural networks represents the predictive model. In Neural Designer neural networks allow deep architectures, which are a class of universal approximator.

7.2 Inputs

The number of inputs is 13. The next table depicts some basic information about them, including the name, the units and the description.

	Name	Units	Description

1	Donor HLA-A		
2	Patient HLA-A		
3	A Match		
4	Donor HLA-B		
5	Patient HLA-B		
6	B Match		
7	Donor HLAA-DR		
8	Patient HLA-DR		
9	DR-Match		
10	Acceptable Survival Score(2 and less score=reject)		
11	Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)		
12	Donor=GovnOrPvtHospital(Govt=1, Pvt=0)		
13	PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)		

7.3 Scaling layer

The size of the scaling layer is 13, the number of inputs. The scaling method for this layer is the MinimumMaximum. The following table shows the values which are used for scaling the inputs, which include the minimum, maximum, mean and standard deviation.

	Minimum
Donor HLA-A	(
Patient HLA-A	(
A Match	(
Donor HLA-B	(
Patient HLA-B	(
B Match	(
Donor HLAA-DR	(
Patient HLA-DR	(
DR-Match	(
Acceptable Survival Score(2 and less score=reject)	(
Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)	(
Donor=GovnOrPvtHospital(Govt=1, Pvt=0)	(
PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)	(

7.4 Neural network

The number of layers in the neural network is 4. The following table depicts the size of each layer and its corresponding activation function. The architecture of this neural network can be written as 13:5:4:3:1.

	Inputs number	Neurons number	Activation function
1	13	5	Logistic
2	5	4	Logistic
3	4	3	Logistic
4	3	1	Logistic

7.5 Neural network parameters

The following table shows the statistics of the parameters of the neural network. The total number of parameters is 113.

	Minimum	Maximum	Mean	Standard deviation
Statistics	-0.997	0.974	-0.0942	0.557

7.6 Probabilistic layer

The size of the probabilistic layer is 1, the number of outputs. The probabilistic method for this layer is the probability.

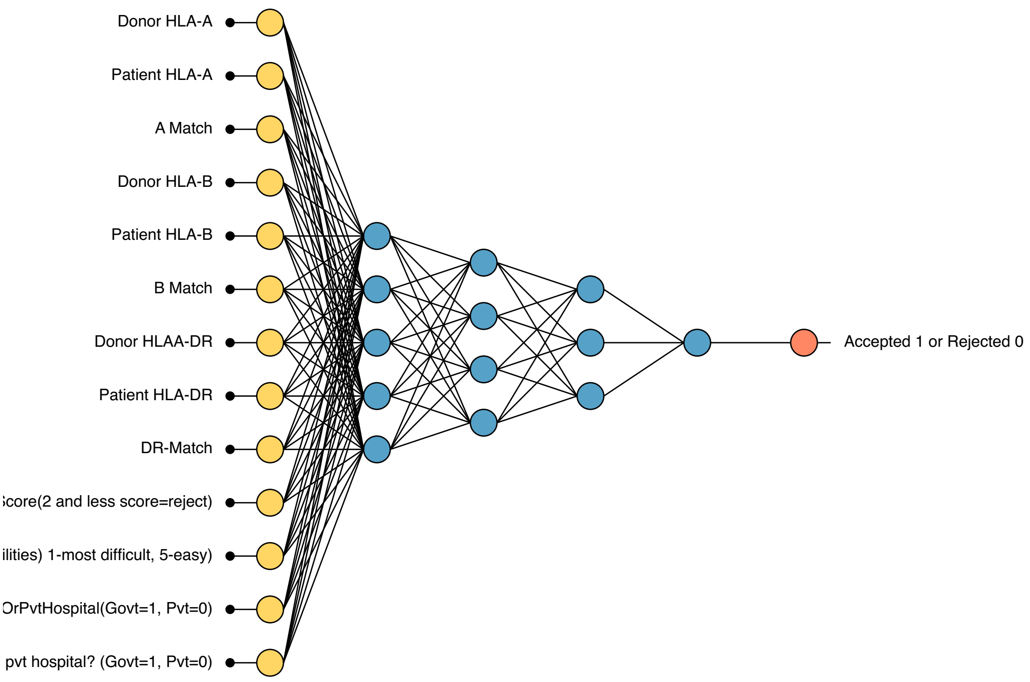
7.7 Outputs table

The number of outputs is 1. The next table depicts some basic information about them, including the name, the units and the description.

	Name	Units	Description
1	Accepted 1 or Rejected 0		

7.8 Neural network graph

A graphical representation of the network architecture is depicted next. It contains a scaling layer, a neural network and a probabilistic layer. The yellow circles represent scaling neurons, the blue circles perceptron neurons and the red circles probabilistic neurons. The number of inputs is 13, and the number of outputs is 1. The complexity, represented by the numbers of hidden neurons, is 5:4:3.



8. Neural network

8.1 Task description

The neural networks represents the predictive model. In Neural Designer neural networks allow deep architectures, which are a class of universal approximator.

8.2 Inputs

The number of inputs is 13. The next table depicts some basic information about them, including the name, the units and the description.

	Name	Units	Description
1	Donor HLA-A		
2	Patient HLA-A		
3	A Match		
4	Donor HLA-B		
5	Patient HLA-B		
6	B Match		
7	Donor HLAA-DR		
8	Patient HLA-DR		
9	DR-Match		
10	Acceptable Survival Score(2 and less score=reject)		
11	Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)		
12	Donor=GovnOrPvtHospital(Govt=1, Pvt=0)		
13	PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)		

8.3 Scaling layer

The size of the scaling layer is 13, the number of inputs. The scaling method for this layer is the MinimumMaximum. The following table shows the values which are used for scaling the inputs, which include the minimum, maximum, mean and standard deviation.

	Minimum
Donor HLA-A	(
Patient HLA-A	(
A Match	(
Donor HLA-B	(
Patient HLA-B	(
B Match	(
Donor HLAA-DR	(
Patient HLA-DR	(
DR-Match	(

Acceptable Survival Score(2 and less score=reject)	(
Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)	(
Donor=GovnOrPvtHospital(Govt=1, Pvt=0)	(
PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)	(

8.4 Neural network

The number of layers in the neural network is 4. The following table depicts the size of each layer and its corresponding activation function. The architecture of this neural network can be written as 13:5:4:3:1.

	Inputs number	Neurons number	Activation function
1	13	5	Logistic
2	5	4	Logistic
3	4	3	Logistic
4	3	1	Logistic

8.5 Neural network parameters

The following table shows the statistics of the parameters of the neural network. The total number of parameters is 113.

	Minimum	Maximum	Mean	Standard deviation
Statistics	-0.997	0.974	-0.0942	0.557

8.6 Probabilistic layer

The size of the probabilistic layer is 1, the number of outputs. The probabilistic method for this layer is the probability.

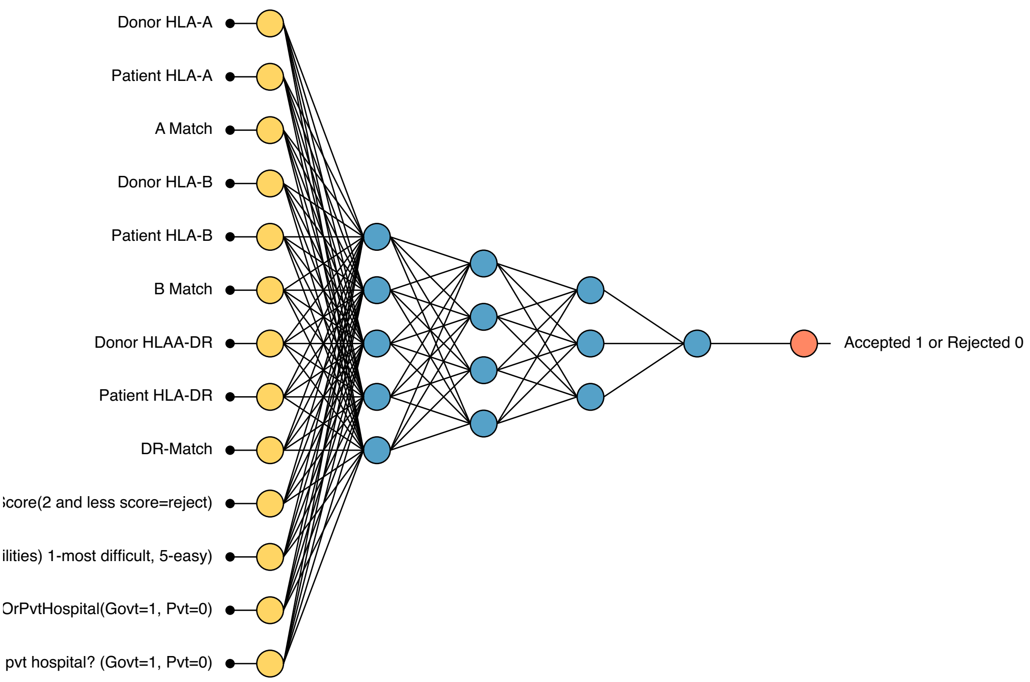
8.7 Outputs table

The number of outputs is 1. The next table depicts some basic information about them, including the name, the units and the description.

	Name	Units	Description
1	Accepted 1 or Rejected 0		

8.8 Neural network graph

A graphical representation of the network architecture is depicted next. It contains a scaling layer, a neural network and a probabilistic layer. The yellow circles represent scaling neurons, the blue circles perceptron neurons and the red circles probabilistic neurons. The number of inputs is 13, and the number of outputs is 1. The complexity, represented by the numbers of hidden neurons, is 5:4:3.



9. Loss index

9.1 Task description

The loss index plays an important role in the use of a neural network. It defines the task the neural network is required to do, and provides a measure of the quality of the representation that it is required to learn. The choice of a suitable loss index depends on the particular application.

9.2 Error method

The weighted squared error is used here as the error method.

9.3 Error method

The weighted squared error is used here as the error method. This is especially useful when the data set has unbalanced targets. That is, there are too few positives when compared to the negatives, or vice versa. The following table shows the exponent in the error betwen the outputs from the neural network and the targets in the data set.

	Value
Positives weight	1.77
Negatives weight	1

9.4 Regularization method

The neural parameters norm is used as the regularization method. Is is applied to control the complexity of the neural network by reducing the value of the parameters. The following table shows the weight of this regularization term in the loss expression.

	Value
Neural parameters norm weight	0.001

10. Training strategy

10.1 Task description

The procedure used to carry out the learning process is called training (or learning) strategy. The training strategy is applied to the neural network in order to obtain the best possible loss.

10.2 Training algorithm

The quasi-Newton method is used here as training algorithm. It is based on Newton's method, but does not require calculation of second derivatives. Instead, the quasi-Newton method computes an approximation of the inverse Hessian at each iteration of the algorithm, by only using gradient information.

	Description	Value
Inverse Hessian approximation method	Method used to obtain a suitable training rate.	BFGS
Training rate method	Method used to calculate the step for the quasi-Newton training direction.	BrentMethod
Training rate tolerance	Maximum interval length for the training rate.	0.005
Minimum parameters increment norm	Norm of the parameters increment vector at which training stops.	1e-09
Minimum loss increase	Minimum loss improvement between two successive iterations.	1e-12
Performance goal	Goal value for the loss.	1e-12
Gradient norm goal	Goal value for the norm of the objective function gradient.	0.001
Maximum selection loss increases	Maximum number of iterations at which the selection loss increases.	100
Maximum iterations number	Maximum number of iterations to perform the training.	1000
Maximum time	Maximum training time.	3600
Reserve parameters norm history	Plot a graph with the parameters norm of each iteration.	false
Reserve loss history	Plot a graph with the loss of each iteration.	true
Reserve selection loss history	Plot a graph with the selection loss of each iteration.	true
Reserve gradient norm history	Plot a graph with the gradient norm of each iteration.	false

11. Training

11.1 Task description

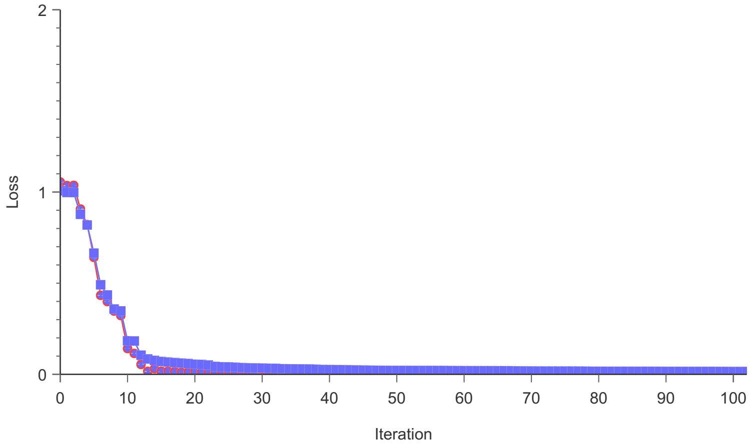
The procedure used to carry out the learning process is called training (or learning) strategy. The training strategy is applied to the neural network in order to obtain the best possible loss. The type of training is determined by the way in which the adjustment of the parameters in the neural network takes place.

11.2 Training algorithm

The quasi-Newton method is used here for training. It is based on Newton's method, but does not require calculation of second derivatives. Instead, the quasi-Newton method computes an approximation of the inverse Hessian at each iteration of the algorithm, by only using gradient information.

11.3 Quasi-Newton method losses history

The following plot shows the losses in each iteration. The initial value of the training loss is 1.00661, and the final value after 102 iterations is 0.0153078. The initial value of the selection loss is 1.05501, and the final value after 102 iterations is 0.000694378.



11.4 Quasi-Newton method results

The next table shows the training results by the quasi-Newton method. They include some final states from the neural network, the loss functional and the training algorithm.

	Value
Final parameters norm	14.7
Final loss	0.0153
Final selection loss	0.000694
Final gradient norm	0.000646
Iterations number	102
Elapsed time	15
Stopping criterion	Gradient norm goal

12. Confusion

12.1 Task description

In the confusion matrix the rows represent the target classes and the columns the output classes for the testing target data set. The diagonal cells in each table show the number of cases that were correctly classified, and the off-diagonal cells show the misclassified cases.

12.2 Confusion table

The following table contains the elements of the confusion matrix. The element (0,0) contains the true positives, the element (0,1) contains the false positives, the element (1,0) contains the false negatives, and the element (1,1) contains the true negatives for the variable Accepted 1 or Rejected 0. The decision threshold is 0.5. The number of correctly classified instances is 998, and the number of misclassified instances is 1.

	Predicted positive	Predicted negative
Actual positive	357	0
Actual negative	1	641

13. Binary classification tests

13.1 Task description

The following parameteres are used for testing the loss of a classification problem with two classes

13.2 Binary classification tests

The next table lists the binary classification tests for this application.

	Description	Value
Classification accuracy	Ratio of instances correctly classified	0.998999
Error rate	Ratio of instances misclassified	0.001001
Sensitivity	Portion of actual positive which are predicted positive	1
Specificity	Portion of actual negative predicted negative	0.998442
Precision	Portion of predicted positive which are actual positive	0.997207
Positive likelihood	Likelihood that a predicted positive is an actual positive	642
Negative likelihood	Likelihood that a predicted negative is an actual negative	0
F1 score	Harmonic mean of precision and sensitivity	0.998601
False positive rate	Portion of actual negative which are predicted positive	0.00155763
False discovery rate	Portion of predicted positive which are actual negative	0.0027933
False negative rate	Portion of actual positive which are predicted negative	0
Negative predictive value	Portion of predicted negative which are actual negative	1
Matthews correlation	Correlation between the targets and the outputs. It takes a value between -1 and +1	0.997824

Youdens index	Probability that the prediction method will make a correct decision as opposed to guessing	0.998442
Markedness	Probability of predicting the classifier labels from the real classes	0.995649

14. Binary classification tests

14.1 Task description

The following parameteres are used for testing the loss of a classification problem with two classes

14.2 Binary classification tests

The next table lists the binary classification tests for this application.

	Description	Value
Classification accuracy	Ratio of instances correctly classified	0.998999
Error rate	Ratio of instances misclassified	0.001001
Sensitivity	Portion of actual positive which are predicted positive	1
Specificity	Portion of actual negative predicted negative	0.998442
Precision	Portion of predicted positive which are actual positive	0.997207
Positive likelihood	Likelihood that a predicted positive is an actual positive	642
Negative likelihood	Likelihood that a predicted negative is an actual negative	0
F1 score	Harmonic mean of precision and sensitivity	0.998601
False positive rate	Portion of actual negative which are predicted positive	0.00155763
False discovery rate	Portion of predicted positive which are actual negative	0.0027933
False negative rate	Portion of actual positive which are predicted negative	0
Negative predictive value	Portion of predicted negative which are actual negative	1
Matthews correlation	Correlation between the targets and the outputs. It takes a value between -1 and +1	0.997824
Youdens index	Probability that the prediction method will make a correct decision as opposed to guessing	0.998442
Markedness	Probability of predicting the classifier labels from the real classes.	0.995649

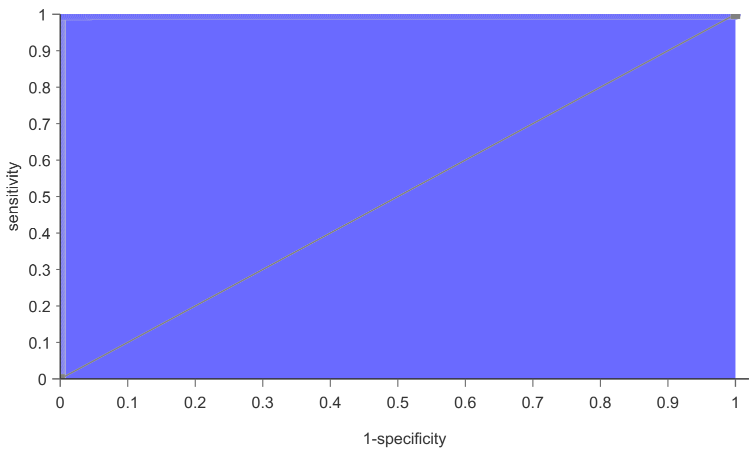
15. ROC curve

15.1 Task description

A good way to study the loss is to plot a ROC (Receiver Operating Characteristic) curve. This method is a graphical illustration of how well the classifier discriminates between the two different classes. This capacity of discrimination is measured by calculating area under curve (AUC).

15.2 ROC chart

By varying the value of the threshold, it can be obtained a family of different binary classifiers and, for each of them, we can calculate their sensitivity and its specificity. The ROC curve is a graph which plots in the x-axis 1.0-specificity and in the y-axis the sensitivity calculated for every different threshold. In order to calculate the points of the curve, the threshold will vary along the output probability of the testing instances in ascending order. If we have a perfect model, that can correctly classify all the instances, the ROC curve will pass through the upper left corner which is the point in which the sensitivity and specificity take the value 1. The closer to the upper left corner that the ROC curve passes, the better its discrimination capacity. The base line represents the ROC curve for a random classifier.



15.3 Area under curve

As a perfect classifier passes through the upper left corner, i.e., the point (0,1), the area under curve for it would be 1. A random classifier, represented by the base line, has an area under curve of 0.5. If the area under curve takes a value lower than 0.5, means that it worse than randomness. In practice, this measure should take a value between 0.5 and 1.0. The closer to 1 area under curve, the better the classifier.

	Value
Area under curve	1

15.4 Optimal threshold

Optimal threshold is computed by finding the point of the ROC curve that is the nearest one to the upper left corner. The threshold which corresponds to that point is called optimal threshold and is the one that best discriminates between the two different classes.

	Value
Optimal threshold	0.946

16. Neural network outputs

16.1 Task description

A neural network produces a set of outputs for each set of inputs applied. The outputs depend, in turn, on the values of the parameters.

16.2 Inputs-outputs table

The next table shows the input values and their corresponding output values. The input variables are Donor HLA-A, Patient HLA-A, A Match, Donor HLA-B, Patient HLA-B, B Match, Donor HLAA-DR, Patient HLA-DR, DR-Match, Acceptable Survival Score(2 and less score=reject), Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy), Donor=GovnOrPvtHospital(Govt=1, Pvt=0) and PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0); and the output variable is Accepted 1 or Rejected 0.

	Value
Donor HLA-A	
Patient HLA-A	
A Match	
Donor HLA-B	
Patient HLA-B	
B Match	
Donor HLAA-DR	
Patient HLA-DR	
DR-Match	
Acceptable Survival Score(2 and less score=reject)	
Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)	
Donor=GovnOrPvtHospital(Govt=1, Pvt=0)	
PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)	
Accepted 1 or Rejected 0	0.003543

17. Neural network outputs

17.1 Task description

A neural network produces a set of outputs for each set of inputs applied. The outputs depend, in turn, on the values of the parameters.

17.2 Inputs-outputs table

The next table shows the input values and their corresponding output values. The input variables are Donor HLA-A, Patient HLA-A, A Match, Donor HLA-B, Patient HLA-B, B Match, Donor HLAA-DR, Patient HLA-DR, DR-Match, Acceptable Survival Score(2 and less score=reject), Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy), Donor=GovnOrPvtHospital(Govt=1, Pvt=0) and PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0); and the output variable is Accepted 1 or Rejected 0.

	Value
Donor HLA-A	
Patient HLA-A	
A Match	
Donor HLA-B	
Patient HLA-B	
B Match	
Donor HLAA-DR	
Patient HLA-DR	
DR-Match	
Acceptable Survival Score(2 and less score=reject)	
Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)	
Donor=GovnOrPvtHospital(Govt=1, Pvt=0)	
PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)	
Accepted 1 or Rejected 0	0.9961

18. Mathematical expression

18.1 Task description

The predictive model takes the form of a function of the outputs with respect to the inputs. The mathematical expression represented by the model can be used to embed it into another software, in the so called production mode.

18.2 Expression

The mathematical expression represented by the neural network is written below. It takes the inputs Donor HLA-A, Patient HLA-A, A Match, Donor HLA-B, Patient HLA-B, B Match, Donor HLAA-DR, Patient HLA-DR, DR-Match, Acceptable Survival Score(2 and less score=reject), Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy), Donor=GovnOrPvtHospital(Govt=1, Pvt=0) and PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0) to produce the output Accepted 1 or Rejected 0. For classification problems, the information is propagated in a feed-forward fashion through the scaling layer, the perceptron layers and the probabilistic layer.

```
scaled_Donor_HLA_A=2*(Donor_HLA_A-0)/(19-0)-1;
scaled_Patient_HLA_A=2*(Patient_HLA_A-0)/(6802-0)-1;
scaled_A_Match=2*(A_Match-0)/(1-0)-1;
scaled_Donor_HLA_B=2*(Donor_HLA_B-0)/(4402-0)-1;
scaled_Patient_HLA_B=2*(Patient_HLA_B-0)/(5703-0)-1;
scaled_B_Match=2*(B_Match-0)/(1-0)-1;
scaled_Donor_HLAA_DR=2*(Donor_HLAA_DR-0)/(302-0)-1;
```

```
scaled_Patient_HLA_DR=2*(Patient_HLA_DR-0)/(1602-0)-1;
scaled_DR_Match=2*(DR_Match-0)/(1-0)-1;
scaled_Acceptable_Survival_Score_2_and_less_score=reject_=2*(Acceptable_Survival_Score_2_and_less_score=reject_-0)/(1-0)-1;
scaled_Difficulty_in_transporting_organ_score__Distance_from_Retreiving_Center,_facilities__1_most_difficult,_5_easy_=2*(Diff
scaled_Donor=GovnOrPvtHospital_Govt=1,_Pvt=0_=2*(Donor=GovnOrPvtHospital_Govt=1,_Pvt=0_-0)/(1-0)-1;
scaled_PatientRegistered_in_Govt_or_pvt_hospital?__Govt=1,_Pvt=0_=2*(PatientRegistered_in_Govt_or_pvt_hospital?__Govt=1,_Pvt=
y_1_1=Logistic(-0.0879638
-0.260873*scaled_Donor_HLA_A
-0.309749*scaled_Patient_HLA_A
+0.00719491*scaled_A_Match
+0.00756205*scaled_Donor_HLA_B
+0.220424*scaled_Patient_HLA_B
+0.37075*scaled_B_Match
-0.093289*scaled_Donor_HLAA_DR
-0.214307*scaled_Patient_HLA_DR
+0.454286*scaled_DR_Match
+0.690212*scaled_Acceptable_Survival_Score_2_and_less_score=reject_
+0.74048*scaled_Difficulty_in_transporting_organ_score__Distance_from_Retreiving_Center,_facilities__1_most_difficult,_5_easy
-0.351087*scaled_Donor=GovnOrPvtHospital_Govt=1,_Pvt=0_
-0.573368*scaled_PatientRegistered_in_Govt_or_pvt_hospital?__Govt=1,_Pvt=0_);
y_1_2=Logistic(-0.167891
+0.299736*scaled_Donor_HLA_A
+0.317569*scaled_Patient_HLA_A
-0.58901*scaled_A_Match
-0.221755*scaled_Donor_HLA_B
-0.39706*scaled_Patient_HLA_B
-0.555177*scaled_B_Match
+0.523443*scaled_Donor_HLAA_DR
-0.207293*scaled_Patient_HLA_DR
-0.529751*scaled_DR_Match
-1.30001*scaled_Acceptable_Survival_Score_2_and_less_score=reject_
-1.04203*scaled_Difficulty_in_transporting_organ_score__Distance_from_Retreiving_Center,_facilities__1_most_difficult,_5_easy
+0.295424*scaled_Donor=GovnOrPvtHospital_Govt=1,_Pvt=0_
+0.0438063*scaled_PatientRegistered_in_Govt_or_pvt_hospital?__Govt=1,_Pvt=0_);
y_1_3=Logistic(-0.677572
-0.52084*scaled_Donor_HLA_A
+0.458933*scaled_Patient_HLA_A
+0.5046*scaled_A_Match
-0.194936*scaled_Donor_HLA_B
+0.323266*scaled_Patient_HLA_B
+0.0914631*scaled_B_Match
-0.776802*scaled_Donor_HLAA_DR
+0.520244*scaled_Patient_HLA_DR
+0.317702*scaled_DR_Match
-0.00416717*scaled_Acceptable_Survival_Score_2_and_less_score=reject_
+0.376296*scaled_Difficulty_in_transporting_organ_score__Distance_from_Retreiving_Center,_facilities__1_most_difficult,_5_eas
-0.806743*scaled_Donor=GovnOrPvtHospital_Govt=1,_Pvt=0_
-0.0760654*scaled_PatientRegistered_in_Govt_or_pvt_hospital?__Govt=1,_Pvt=0_);
y_1_4=Logistic(-0.496666
-0.396444*scaled_Donor_HLA_A
-0.0502326*scaled_Patient_HLA_A
+0.681284*scaled_A_Match
-0.438962*scaled_Donor_HLA_B
+0.132839*scaled_Patient_HLA_B
-0.677745*scaled_B_Match
+0.0478939*scaled_Donor_HLAA_DR
+0.010341*scaled_Patient_HLA_DR
-0.354408*scaled_DR_Match
+1.74727*scaled_Acceptable_Survival_Score_2_and_less_score=reject_
+2.87039*scaled_Difficulty_in_transporting_organ_score__Distance_from_Retreiving_Center,_facilities__1_most_difficult,_5_easy
-0.902147*scaled_Donor=GovnOrPvtHospital_Govt=1,_Pvt=0_
+0.0585006*scaled_PatientRegistered_in_Govt_or_pvt_hospital?__Govt=1,_Pvt=0_);
y_1_5=Logistic(0.0823388
-0.585287*scaled_Donor_HLA_A
+0.147526*scaled_Patient_HLA_A
+0.958377*scaled_A_Match
-0.696793*scaled_Donor_HLA_B
-0.262506*scaled_Patient_HLA_B
+0.167484*scaled_B_Match
-0.0785645*scaled_Donor_HLAA_DR
-0.0425606*scaled_Patient_HLA_DR
-0.208792*scaled_DR_Match
+2.37661*scaled_Acceptable_Survival_Score_2_and_less_score=reject_
+4.01164*scaled_Difficulty_in_transporting_organ_score__Distance_from_Retreiving_Center,_facilities__1_most_difficult,_5_easy
-0.47934*scaled_Donor=GovnOrPvtHospital_Govt=1,_Pvt=0_
+0.0442989*scaled_PatientRegistered_in_Govt_or_pvt_hospital?__Govt=1,_Pvt=0_);
y_2_1=Logistic(0.212231
-0.338729*y_1_1
-0.524431*y_1_2
-0.474994*y_1_3
-0.580099*y_1_4
-1.18787*y_1_5);
y_2_2=Logistic(0.210087
+0.173585*y_1_1
+0.53582*y_1_2
-0.232054*y_1_3
-0.578334*y_1_4
-1.90079*y_1_5);
y_2_3=Logistic(1.15445
-0.710031*y_1_1
+1.59004*y_1_2
-0.271465*y_1_3
-2.03613*y_1_4
-2.96868*y_1_5);
y_2_4=Logistic(-0.793419
+0.36148*y_1_1
-1.08411*y_1_2
-0.250952*y_1_3
+1.81443*y_1_4
+2.36309*y_1_5);
y_3_1=Logistic(-0.403441
+1.29855*y_2_1
+1.51672*y_2_2
+3.15785*y_2_3
-3.71308*y_2_4);
y_3_2=Logistic(-1.4304
+0.0515124*y_2_1
-0.738264*y_2_2
-0.938553*y_2_3
+0.0223018*y_2_4);
y_3_3=Logistic(0.679392
-1.12459*y_2_1
-1.63446*y_2_2
-2.40928*y_2_3
+2.46758*y_2_4);
non_probabilistic_Accepted_1_or_Rejected_0=Logistic(1.22716
-7.78893*y_3_1
```

```
+0.50205*y_3_2
+4.73017*y_3_3);
(Accepted_1_or_Rejected_0) = Probability(non_probabilistic_Accepted_1_or_Rejected_0);

Logistic(x){
    return 1/(1+exp(-x))
}

Probability(x){
    if x < 0
        return 0
    else if x > 1
        return 1
    else
        return x
}
```

19. Data set

19.1 Task description

The data set contains the information for creating the predictive model. It comprises a data matrix in which columns represent variables and rows represent instances. Variables in a data set can be of three types: The inputs will be the independent variables; the targets will be the dependent variables; the unused variables will neither be used as inputs nor as targets. Additionally, instances can be: Training instances, which are used to construct the model; selection instances, which are used for selecting the optimal order; testing instances, which are used to validate the functioning of the model; unused instances, which are not used at all.

19.2 Data preview table

The next table shows a preview of the data matrix contained in the file sub-patientO-DonorOdatasetNeuralNormalPriorityFinal-2.xlsx. Here, the number of variables is 14, and the number of instances is 4999.

	Donor HLA-A	Patient HLA-A	A Match	Donor HLA-B	Patien
1	19	19	1	4402	
2	19	26	0	4402	
...	...	...	...	...	
4999	0	0	0	0	

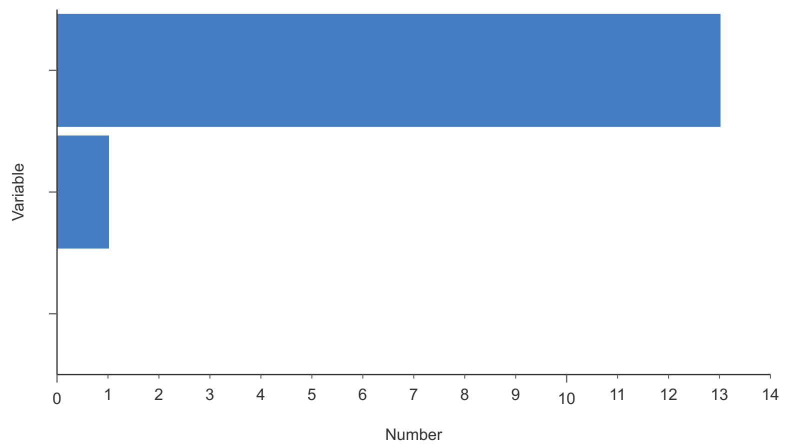
19.3 Variables table

The following table depicts the names, units, descriptions and uses of all the variables in the data set. The numbers of inputs, targets and unused variables here are 13, 1, and 0, respectively.

	Name
1	Donor HLA-A
2	Patient HLA-A
3	A Match
4	Donor HLA-B
5	Patient HLA-B
6	B Match
7	Donor HLAA-DR
8	Patient HLA-DR
9	DR-Match
10	Acceptable Survival Score(2 and less score=reject)
11	Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)
12	Donor=GovnOrPvtHospital(Govt=1, Pvt=0)
13	PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)
14	Accepted 1 or Rejected 0

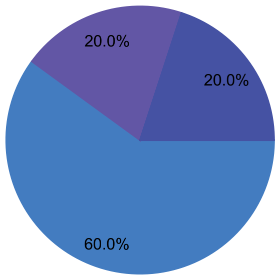
19.4 Variables bars chart

The next chart illustrates the variables use. It depicts the numbers of inputs (13), targets (1) and unused variables (0).



19.5 Instances pie chart

The following pie chart details the uses of all the instances in the data set. The total number of instances is 4999. The number of training instances is 3001 (60%), the number of selection instances is 999 (20%), the number of testing instances is 999 (20%), and the number of unused instances is 0 (0%).



19.6 Missing values results

There are not missing values in the data set.

20. Data set

20.1 Task description

The data set contains the information for creating the predictive model. It comprises a data matrix in which columns represent variables and rows represent instances. Variables in a data set can be of three types: The inputs will be the independent variables; the targets will be the dependent variables; the unused variables will neither be used as inputs nor as targets. Additionally, instances can be: Training instances, which are used to construct the model; selection instances, which are used for selecting the optimal order; testing instances, which are used to validate the functioning of the model; unused instances, which are not used at all.

20.2 Data preview table

The next table shows a preview of the data matrix contained in the file sub-patientO-DonorOdatasetNeuralNormalPriorityFinal-2.xlsx. Here, the number of variables is 14, and the number of instances is 4999.

	Donor HLA-A	Patient HLA-A	A Match	Donor HLA-B	Patien
1	19	19	1	4402	
2	19	26	0	4402	
...	...	...	...	...	
4999	0	0	0	0	

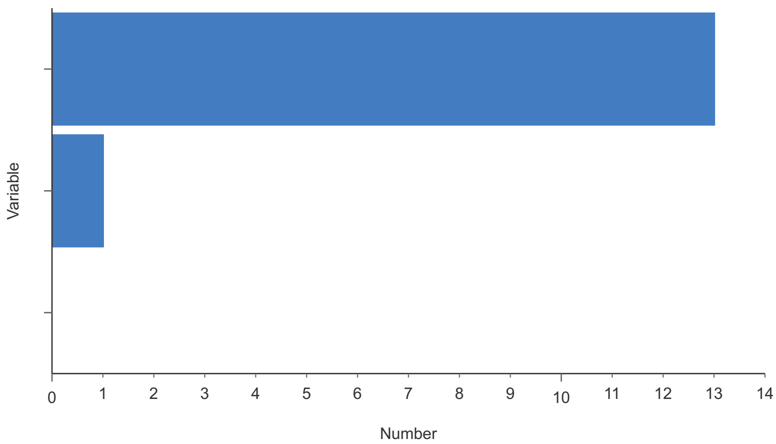
20.3 Variables table

The following table depicts the names, units, descriptions and uses of all the variables in the data set. The numbers of inputs, targets and unused variables here are 13, 1, and 0, respectively.

	Name	
1	Donor HLA-A	
2	Patient HLA-A	
3	A Match	
4	Donor HLA-B	
5	Patient HLA-B	
6	B Match	
7	Donor HLAA-DR	
8	Patient HLA-DR	
9	DR-Match	
10	Acceptable Survival Score(2 and less score=reject)	
11	Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)	
12	Donor=GovnOrPvtHospital(Govt=1, Pvt=0)	
13	PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)	
14	Accepted 1 or Rejected 0	

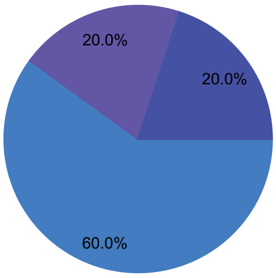
20.4 Variables bars chart

The next chart illustrates the variables use. It depicts the numbers of inputs (13), targets (1) and unused variables (0).



20.5 Instances pie chart

The following pie chart details the uses of all the instances in the data set. The total number of instances is 4999. The number of training instances is 3001 (60%), the number of selection instances is 999 (20%), the number of testing instances is 999 (20%), and the number of unused instances is 0 (0%).



20.6 Missing values results

There are not missing values in the data set.

21. Python expression

21.1 Task description

The predictive model takes the form of a function of the outputs with respect to the inputs. The mathematical expression represented by the model can be exported to different programming languages, in the so called production mode. The Python programming language expression has been saved in the following file: /Users/andreabrianc/Documents/deepLearningKidneyAllocationIIM/DeepLearninKidneyAllocationModel.py

22. Data statistics

22.1 Task description

Basic statistics are a very valuable information when designing a model, since they might alert to the presence of spurious data. It is a must to check for the correctness of the most important statistical measures of every single variable.

22.2 Data statistics results

The table below shows the minimums, maximums, means and standard deviations of all the variables in the data set.

	Minimum
Donor HLA-A	(
Patient HLA-A	(
A Match	(
Donor HLA-B	(
Patient HLA-B	(
B Match	(
Donor HLAA-DR	(
Patient HLA-DR	(
DR-Match	(
Acceptable Survival Score(2 and less score=reject)	(
Difficulty in transporting organ score (Distance from Retreiving Center, facilities) 1-most difficult, 5-easy)	(
Donor=GovnOrPvtHospital(Govt=1, Pvt=0)	(
PatientRegistered in Govt or pvt hospital? (Govt=1, Pvt=0)	(
Accepted 1 or Rejected 0	(