





Machine Learning and Decision-Making

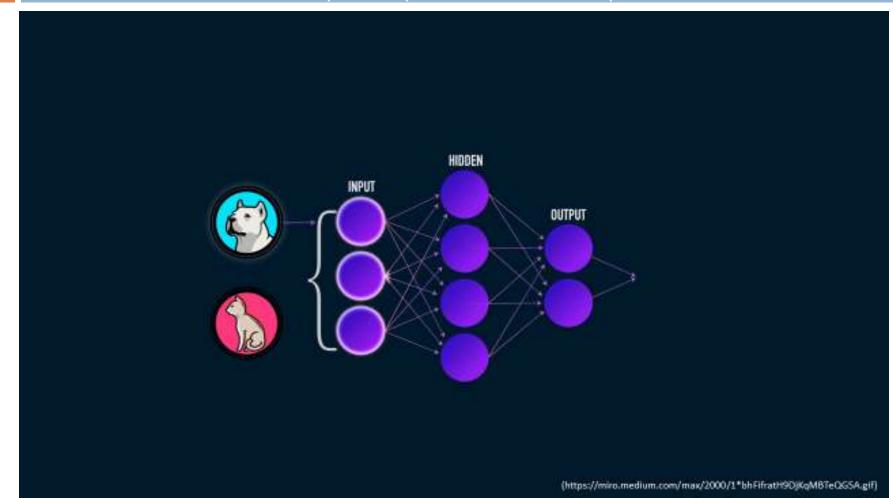
ADI @ LEI/3º, MiEI/4º - 2º Semestre Filipe Gonçalves, Inês Alves, Cesar Analide

- Artificial Neural Networks
- Multilayer Perceptron
- Workflow Pipeline
- Hands On

Neural Networks

Multilayer Perceptron

Workflow Pipeline



What about Artificial Neural Networks?

Neural Networks

Multilayer Perceptron

Workflow Pipeline

Hands On

We have already used several learning model techniques... But now let's try using Multilayer Perceptrons (MLPs), a class of Artificial Neural Networks (ANN)!

Artificial Neural Networks are a computational model that consists of several processing elements that receive inputs and deliver outputs based on their predefined activation functions.

Artificial Neural Networks can be applied both for Regression and Classification problems.

To implement our first Artificial Neural Network we will use:



Hands On

Why?

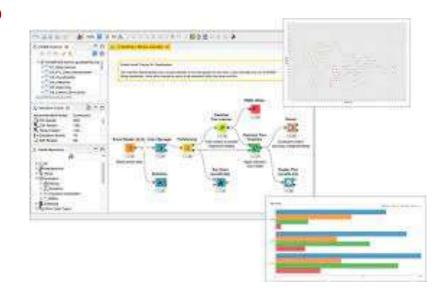
Open-source platform applied for data science

Strong and comprehensive platform for drag-and-drop analytics, machine & deep learning, statistics, and ETL

Tool of choice for data science starters

Also, no programming background required



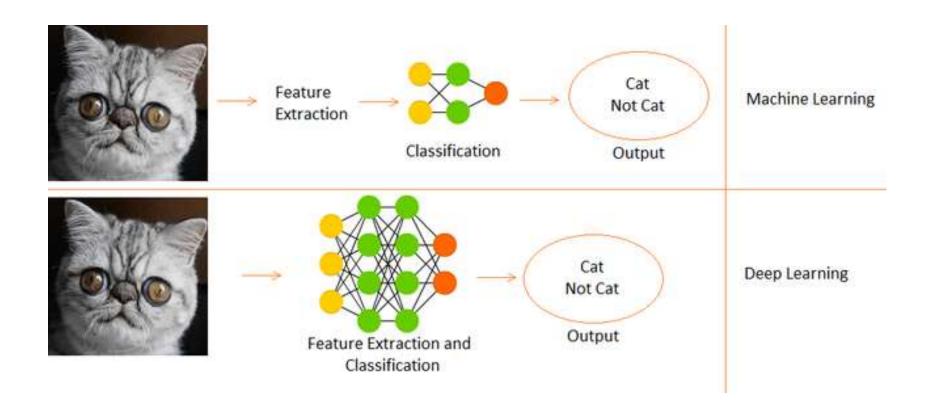


Machine Learning vs Deep Learning

Neural Networks

Multilayer Perceptron

Workflow Pipeline



ANN on Classification Problem

Neural Networks

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Hands On

Let's consider the development & testing of a learning model solution for a binary classification problem – classify as Moon or not Moon given its parameters

The proposed workflow shows how to create a Multilayer Perceptron with a softmax layer for classification

In this example the MLP is used to classify a simple dataset with two features

Dataset available:

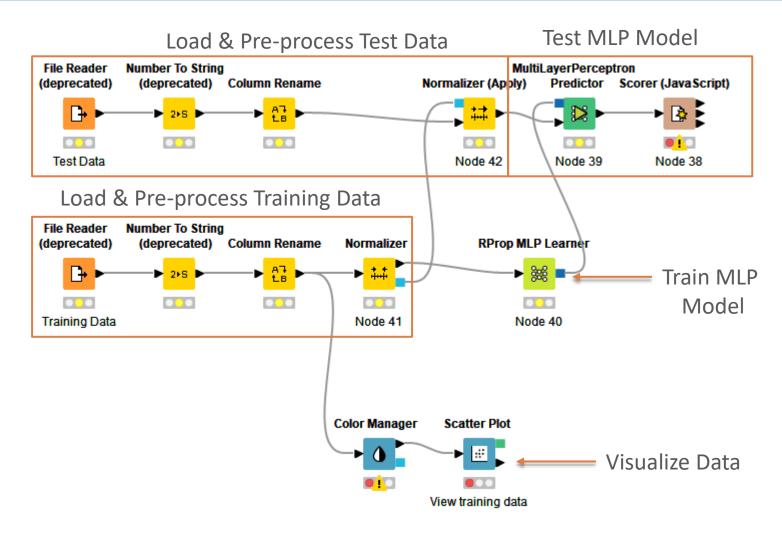
- Training Data: https://bit.ly/36NBOxo
- Test Data: https://bit.ly/3vcAuxd

ANN Workflow Pipeline

Neural Networks

Multilayer Perceptron

Workflow Pipeline



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Hands On

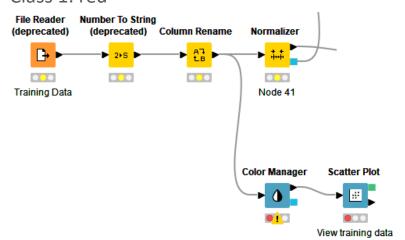
Start by loading and preparing Training Data:

- Col0: binary numeric class (convert to String)
- Col1, Col2: normalize double features

Visualize data distribution per class:

Class 0: blue

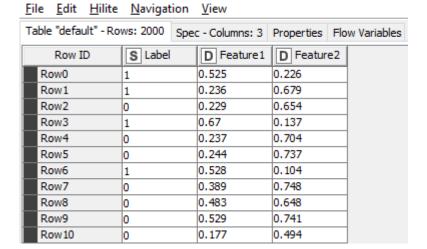
Class 1: red



L File Table - 3:1 - File Reader (deprecated) (Training Data)

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Ta	able "moon_data_	train.csv" - Row	s: 2000 Spec	- Columns: 3 P	roperties	Flow Variab
	Row ID	Col0	D Col1	D Col2		
Г	Row0	1	0.611	-0.46		
Г	Row1	1	-0.556	0.731		
Г	Row2	0	-0.585	0.663		
Г	Row3	1	1.198	-0.695		
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Г	Row7	0	0.06	0.911		
	Row8	0	0.443	0.648		
	Row9	0	0.629	0.893		
	Row10	0	-0.794	0.244		

🛕 Normalized table - 0:41 - Normalizer



Hands On

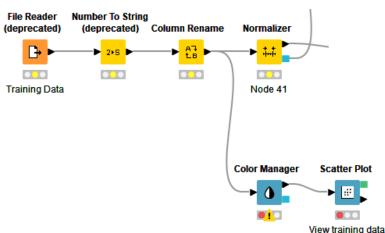
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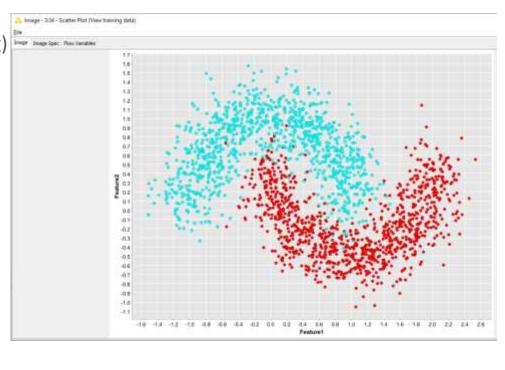
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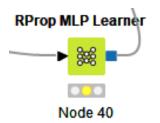


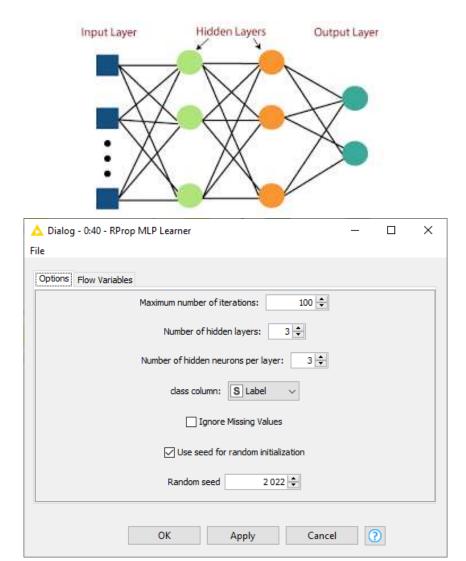
Hands On

Create a simple general purpose Multilayer
Perceptron consisting of three fully connected
(FC) layers

Parameters:

- Number of Iterations: 100
- Number of hidden layers: 3
- Number of hidden neurons per layer: 3
- Class Column: Label
- Random seed: 2022





Build & Train MLP

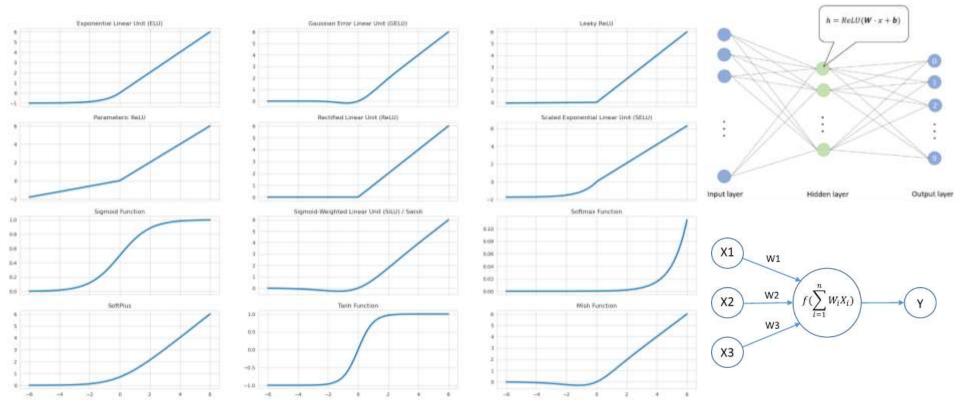
Neural Networks

Multilayer Perceptron

Workflow Pipeline

Hands On

Activation Functions



Neural Networks

Multilayer Perceptron

Workflow Pipeline

Hands On

Load and prepare Test Data (according to training Data):

- Col0: binary numeric class (convert to String)
- Col1, Col2: normalize double features

A Renamed/Retyped table - 3:36 - Column Rename									
<u>F</u> ile <u>E</u> dit <u>H</u> ilite	<u>N</u> avigation	<u>V</u> iew							
Table "default" - Rov	Flow Variables								
Row ID	S Label	D Feature 1	D Feature	:2					
Row0	0	-0.501	0.687						
Row1	1	0.19	-0.341						
Row2	0	0.995	0.663						
Row3	0	-1.031	0.342						
Row4	1	0.038	-0.837						
Row5	0	-0.114	0.74						
Row6	1	0.568	-0.376						
Row7	1	0.029	0.066						
Row8	1	1.971	0.274						
Row9	0	0.709	0.241						
Row10	1	0.37	-0.128						

△ Normalized output - 0:42 - Normalizer (Apply)

File Edit Hilite Navigation View

File Reader deprecated)	Number To String (deprecated)	Column Rename	Normalizer (Apply)
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Test Data			Node 42

Ta	ble "default" - Ro	ws: 1000 Spec	c - Columns: 3	Properties Flo	w Vari
	Row ID	S Label	D Feature 1	D Feature2	
	Row0	0	0.25	0.663	
Г	Row1	1	0.421	0.271	
Г	Row2	0	0.62	0.653	
Г	Row3	0	0.119	0.531	
Г	Row4	1	0.383	0.083]
Г	Row5	0	0.346	0.683]
Г	Row6	1	0.514	0.258	1
	Row7	1	0.381	0.426	
	Row8	1	0.861	0.505	
	Row9	0	0.549	0.493	
	Dow 10	1	0.465	0.352	1

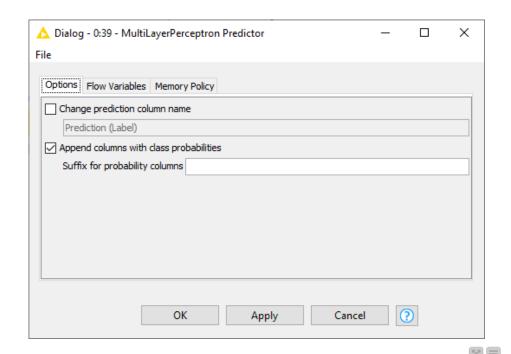
Multilayer Perceptron

Workflow Pipeline

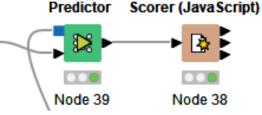
Hands On

After training is finished, we can use the MultiLayerPerceptron Predictor Node to create predictions

Apply the Scorer Node to evaluate the classification performance of the MLP model



MultiLayerPerceptron Predictor Sco



Scorer View

Confusion Matrix

	0 (Predicted)	1 (Predicted)	
0 (Actual)	426	71	85.71%
1 (Actual)	52	451	89.66%
	89.12%	86.40%	

Overall Statistics

Overall Accuracy	Overall Error	Cohen's kappa (ĸ)	Correctly Classified	Incorrectly Classified
87.70%	12.30%	0.754	877	123

Hands On

Regarding Artificial Neural Networks, take into consideration the following good practices:

- ANN are picky they prefer scaled data! Normalize whenever possible!
- Fine-tune the ANN parameters (e.g., number of iterations, number of hidden layers, number of hidden neurons per layer) using grid search methods
- Never forget to use a specific random seed (replicate learning model train/test)



Hands On

Neural Networks Multilayer Perceptron Workflow Pipeline Hands On



ANN on Classification Problem

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Hands On

Let's consider the development & testing of a learning model solution for a binary classification problem – classify as Moon or not Moon given its parameters

The proposed workflow shows how to create a Multilayer Perceptron with a softmax layer for Iraining Data: knime://knime.workflow/moon_data_train.csv
Test Data: knime://knime.workflow/moon_data_eval.csv
kflow Requirements:
NIME Deeplearning4J Integration classification

In this example the MLP is used to classify a simple dataset with two features

Dataset available:

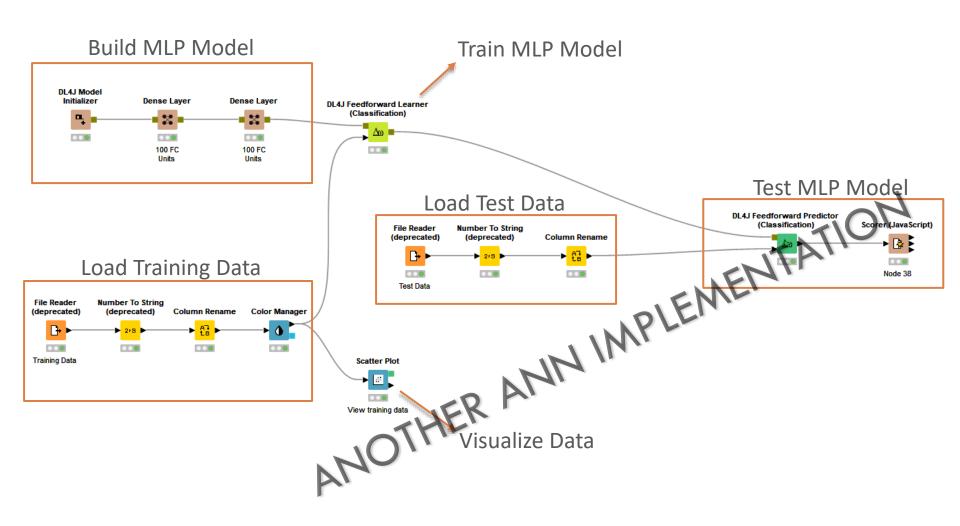
Workflow Requirements:

ANN Workflow Pipeline

Neural Networks

Multilayer Perceptron

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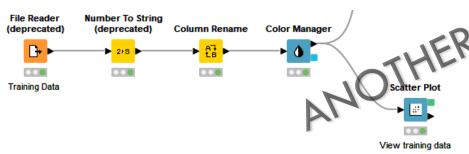
Hands On

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Hands On

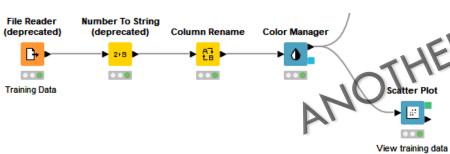
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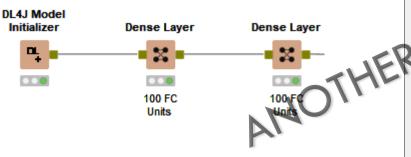


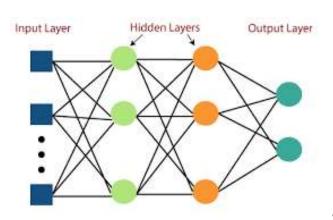
Hands On

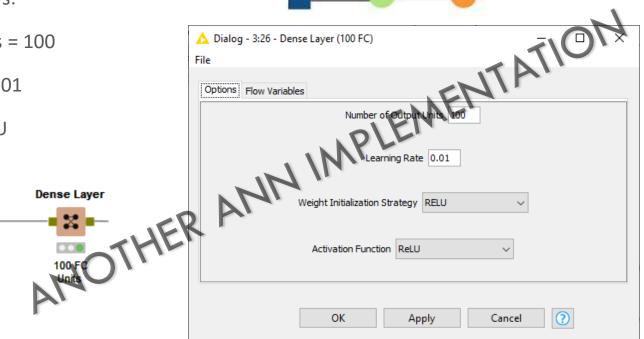
Create a simple general purpose Multilayer
Perceptron consisting of two fully connected
(FC) layers

Parameters for each FC layers:

- Number of Units / Nodes = 100
- Learning Rate: 10^-2 = 0.01
- Activation Function: ReLU







Neural Networks

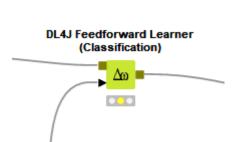
Multilayer Perceptron

Workflow Pipeline

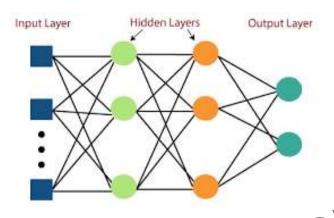
Hands On

Train the created network using the DL4J Feedforward Learner (Classification) Node

Take into consideration adjusting the **learning** parameters (e.g., Learning Parameter, Output Layer Parameters, Column Selection, etc.)







Important Parameters:

• Global Learning Rate (Global Parameters) configure the learner node to use the specified learning rate for all layers

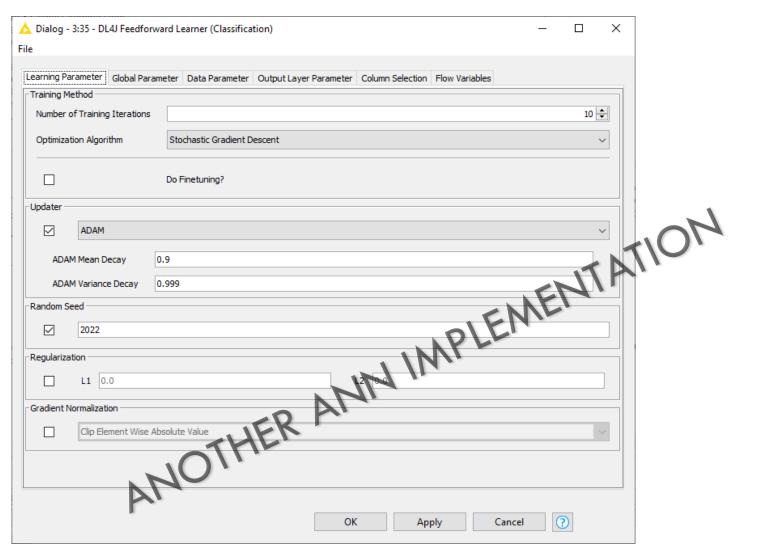
Output Layer Parameter: configure the loss function suitable for the learner node ('Negative Log Likelihood' paired with 'Softmax' is usually a good choice for classification)

Neural Networks

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Multilayer Perceptron

Workflow Pipeline



Neural Networks

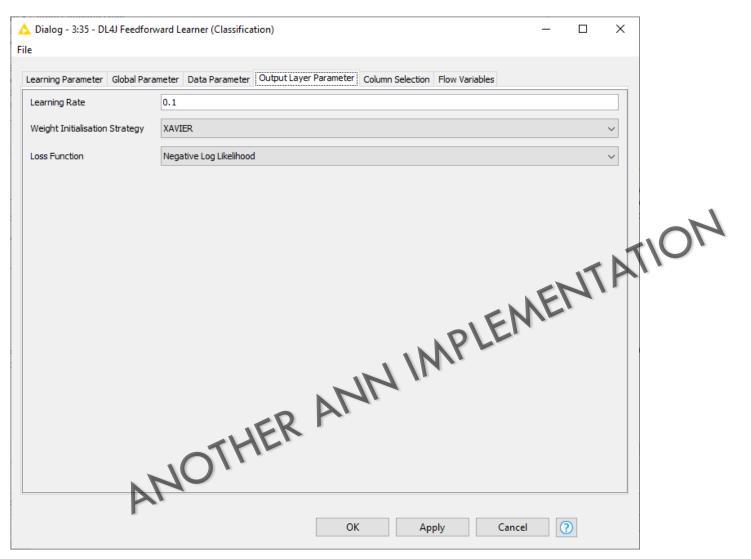
Multilayer Perceptron

Workflow Pipeline

Dialog - :	3:35 - DL4	J Feedforward L	earner (Classifica	tion)			-		×
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Global Lear	ning Rate								
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Global Drop	o-Out Rate	<u> </u>							
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Global Bias								TE	**
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Neural Networks Multilayer Perceptron Workflow Pipeline Hands On

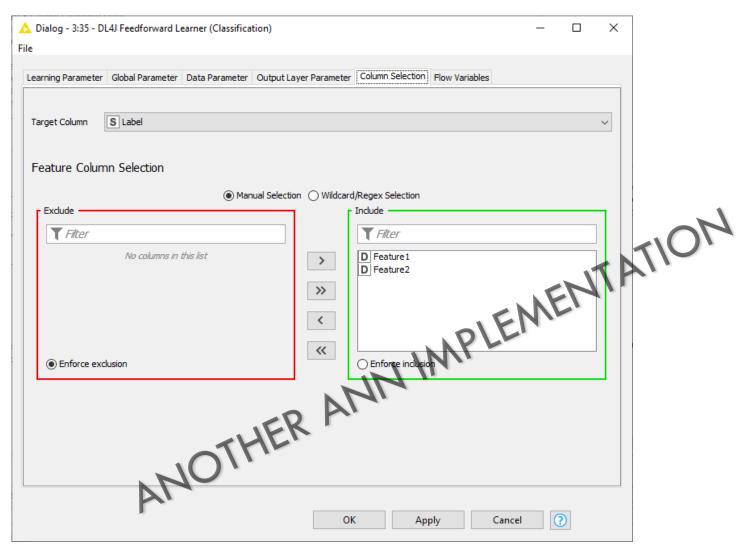


Neural Networks

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Multilayer Perceptron

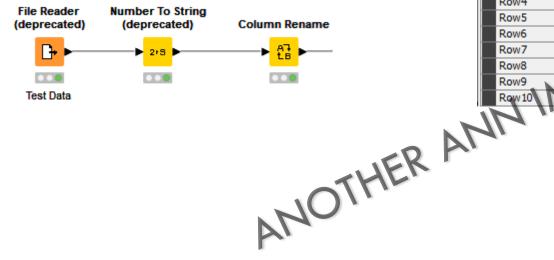
Workflow Pipeline



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