

Machine Learning Techniques for Embedded Control Software

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Agenda

- Machine learning
- MATLAB
 - Classifier
 - Regressor
 - LSTM
- Control system
- Use cases
 - Bang bang controller
 - PID controller
 - Water tank controller

Machine Learning: Supervised, Unsupervised, Reinforcement learning and RNN

BACKGROUND

Machine Learning

- Machine learning represents a set of **statistical methods** to progressively improve the performance of an algorithm in identifying patterns in data

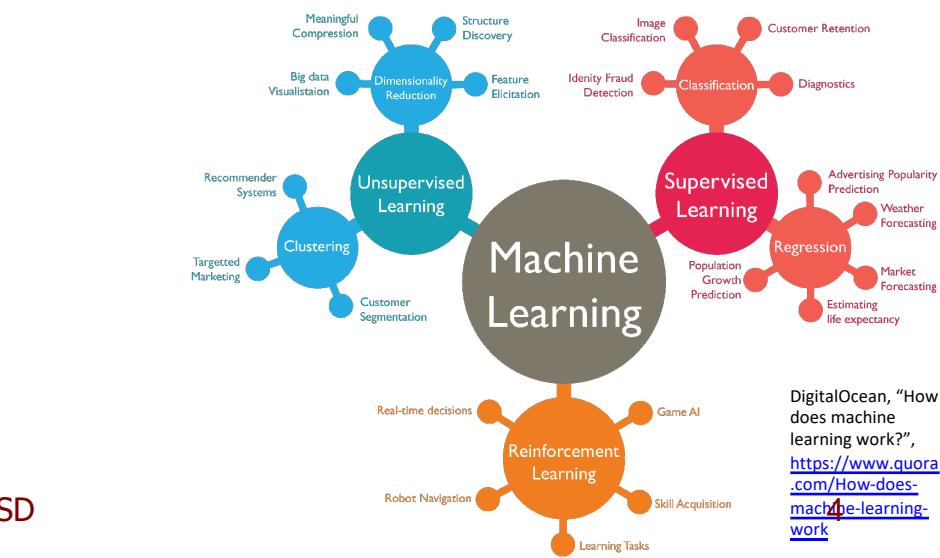
→ – Supervised:

– Unsupervised

– Reinforcement learning

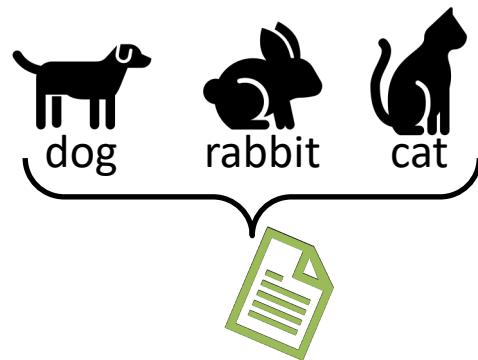
If you know an algorithm on how to solve a problem, just use it instead of using A.I.

We need a large data sets
↑



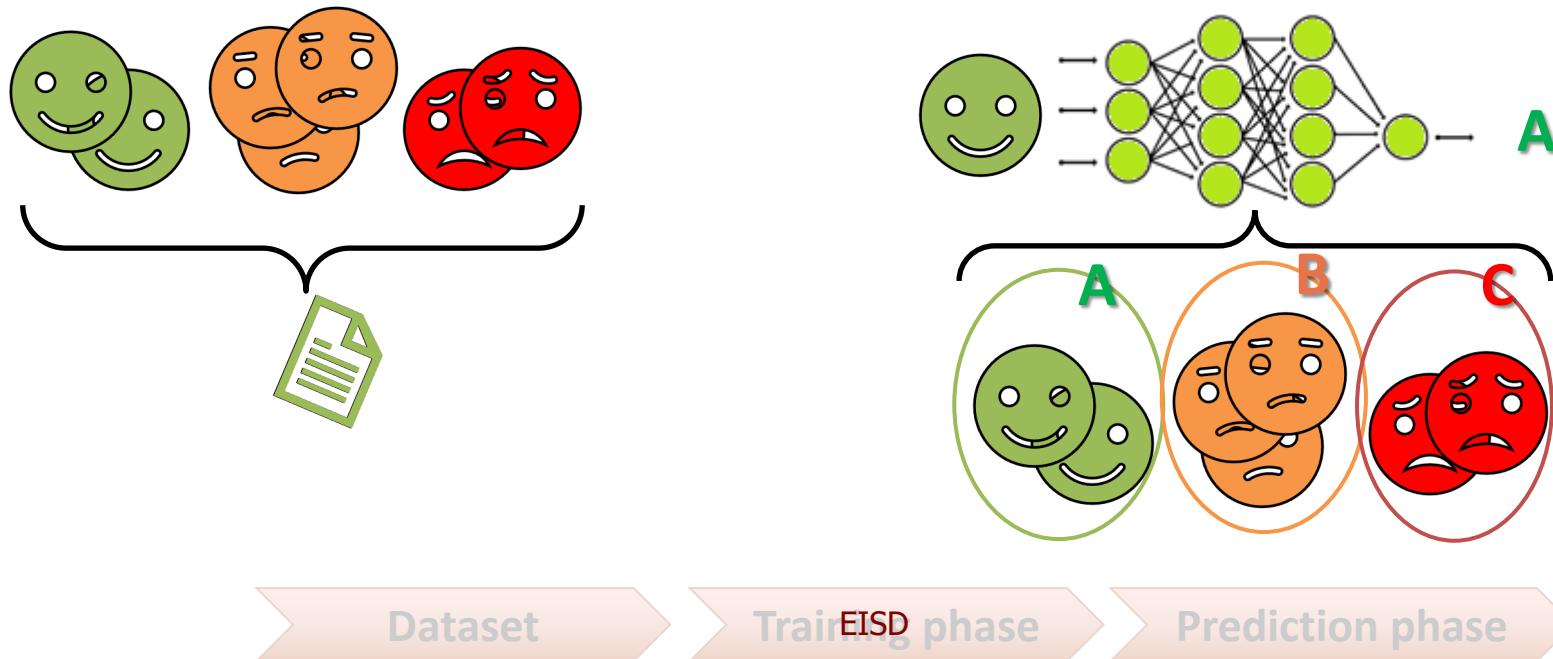
Machine Learning: Supervised

- Having **inputs** and related **outputs**, extract the **rule** that associates the inputs to the outputs
 - Classification
 - Regression



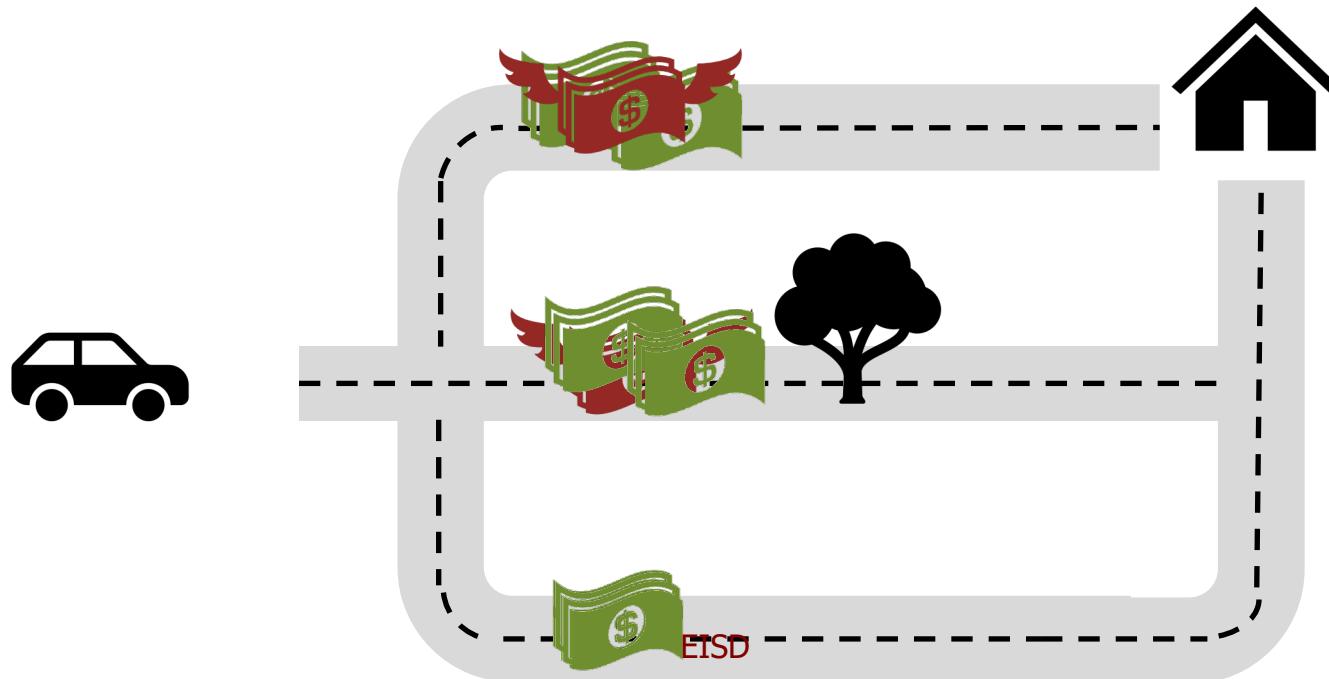
Machine Learning: Unsupervised

- Having unlabeled inputs, finding the structure
 - Clustering \Rightarrow Data is organized in different sets



Machine Learning: Reinforcement learning

- Allows the system to be able to learn and **adapt** to changes in the environment in which it is immersed



Artificial Intelligence

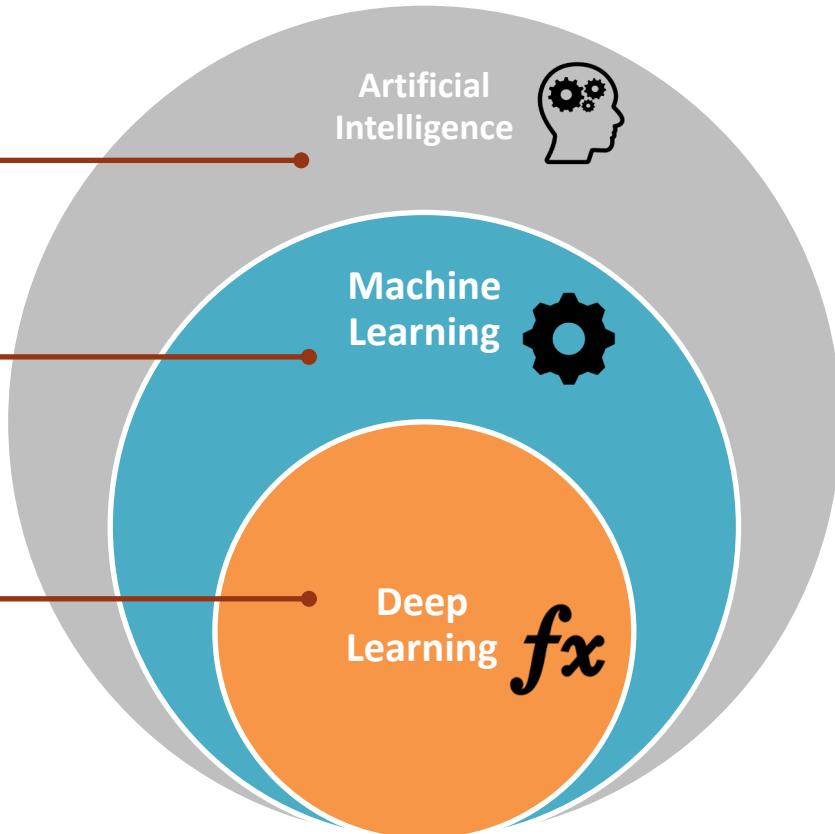
Any technique which enables computers to mimic human behavior

Machine Learning

Subset of AI techniques which use statistical methods to enable machines to improve with experience

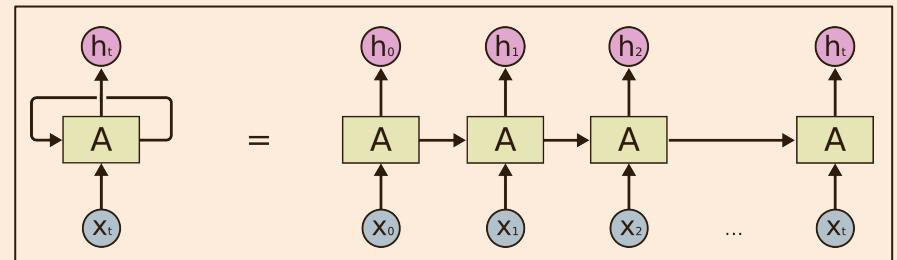
Deep Learning

Subset of ML which make the computation of multi-layer neural networks feasible



RNN: LSTM

- Recurrent neural networks (RNN) are networks **with loops** in them
 - Allow the persistence of information
- Variety of problems
 - speech recognition
 - language modeling
 - Translation
 - image captioning
 - ...
- Look at recent information to perform the present task



U → If more context is needed → LSTM

Long Short Term Memory networks (LSTMs) are a special kind of RNN, capable of learning long-term dependencies 9

How to build a classifier

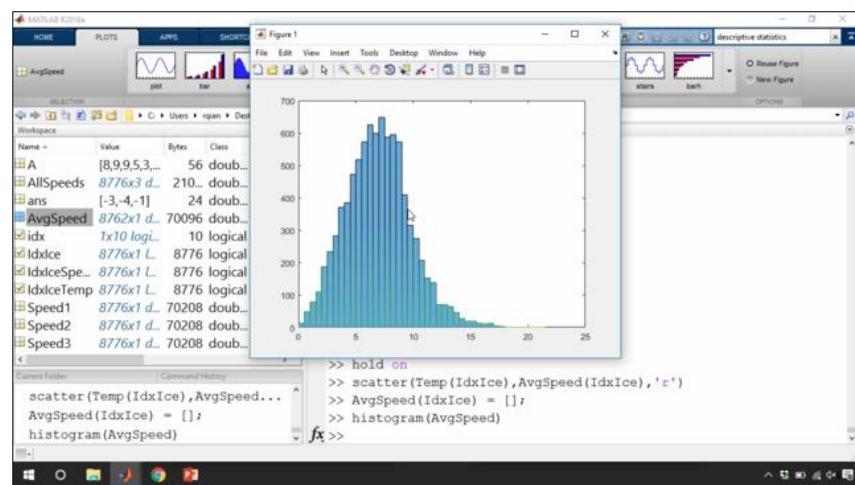
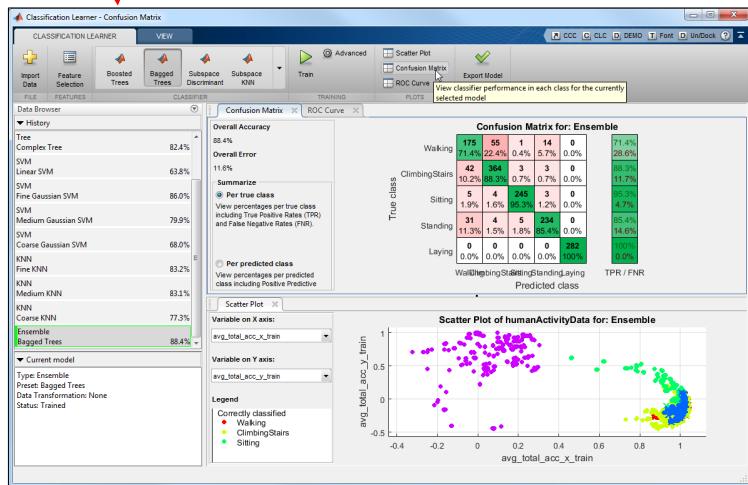
How to build a regressor

How to build a LSTM

MACHINE LEARNING IN MATLAB

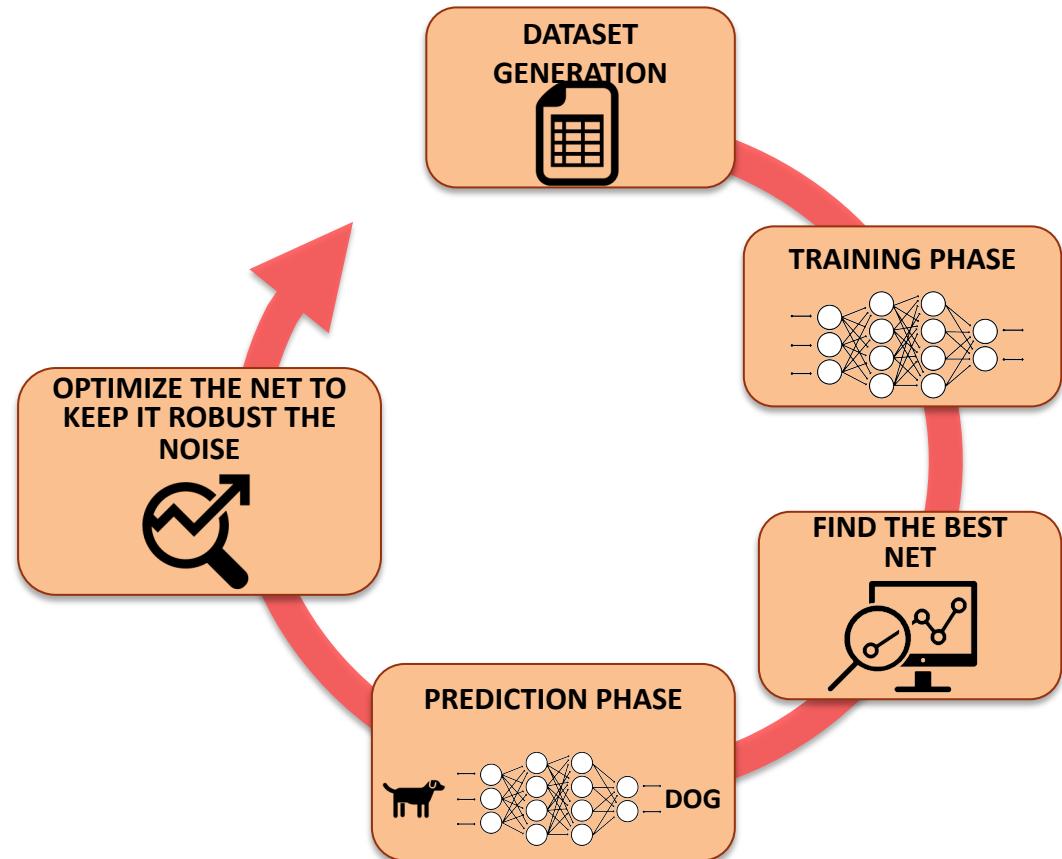
Development environment

- The **MATLAB** environment
 - Is an environment for numerical calculation and statistical analysis
 - Allows the use of machine learning techniques → *Unsupervised techniques*
 - Classification Learner App
 - Regression Learner App



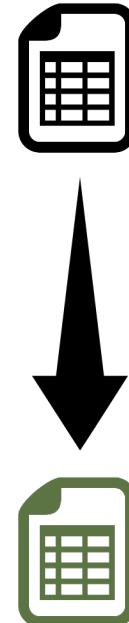
How to build a NET in MATLAB

- Main steps are:
 - Dataset generation
 - Build of the trained NET
 - Prediction phase
 - Optimize the NET



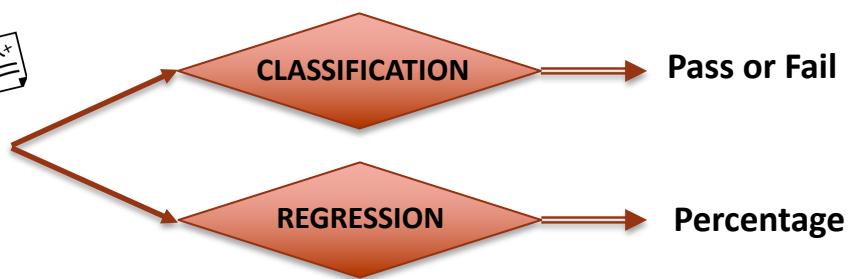
MATLAB: Dataset generation

- Preprocess the data
 - Normalizing the data
 - Remove ambiguities
- Extract features
 - Find the minimum of features that will capture the essential patterns in the data

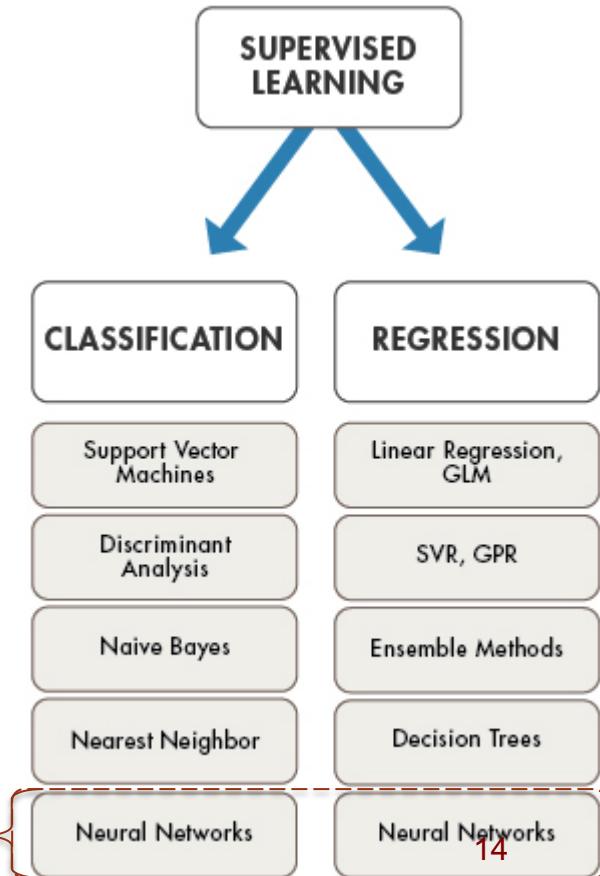


MATLAB: Training phase

- Supervised Learning
 - CLASSIFICATION techniques predict *categorical* response
 - Support Vector Machines, Discriminant Analysis, Naive Bayes, Nearest Neighbor, Neural Networks
 - REGRESSION techniques predict *continuous* response
 - Linear Regression, Generalized Linear Models(GLM), Support Vector Machine Regression(SVR), Gaussian Process Regression(GPR), Ensemble Methods, Decision Trees, Neural Networks



EISD Neural Network Toolbox™



MATLAB: Training phase for classifier

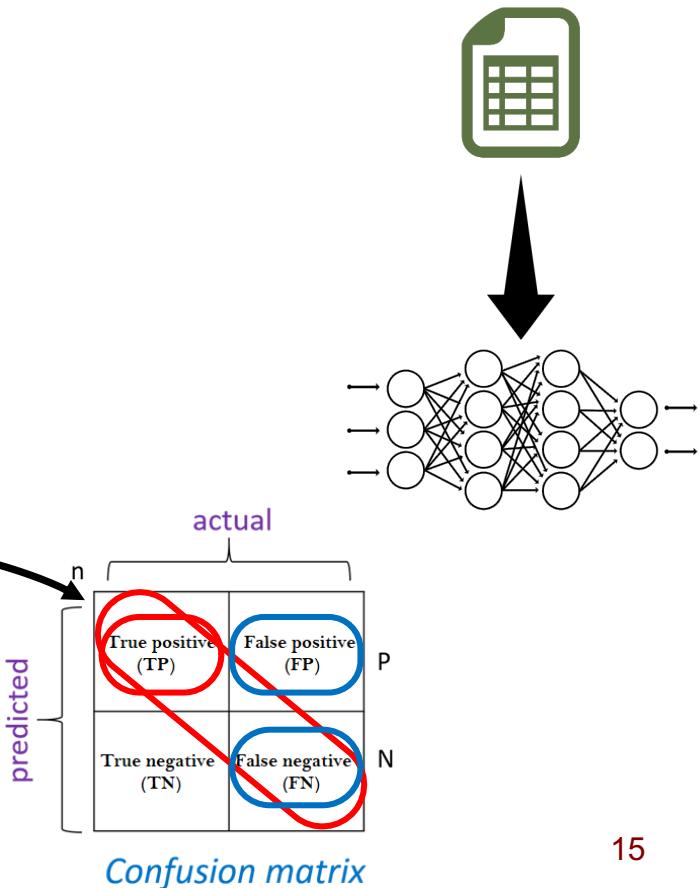
- Two ways
 - Manual method
 - Automatic method
 - *Classification Learner App*
- How to choose the best classifier:
use ***confusion matrix*** —

$$- \text{Accuracy} = \frac{\sum_i \text{ConfusionMatrix}[i][i] * 100}{\# \text{observation}}$$

$$- \text{precision} = \frac{TP}{TP + FP}$$

$$- \text{recall} = \frac{TP}{TP + FN}$$

EISD



MATLAB: Training phase

Manual method

fitcsvm, fitcecoc,
fitckernel ...

Fitcdiscr, ...

Fitcnb, ...

Fitcknn, ...

SUPERVISED LEARNING

CLASSIFICATION

REGRESSION

Support Vector
Machines

Linear Regression,
GLM

Discriminant
Analysis

SVR, GPR

Naive Bayes

Ensemble Methods

Nearest Neighbor

Decision Trees

Neural Networks

Neural Networks

MATLAB: Training phase for classifier

Manual method

Import Data

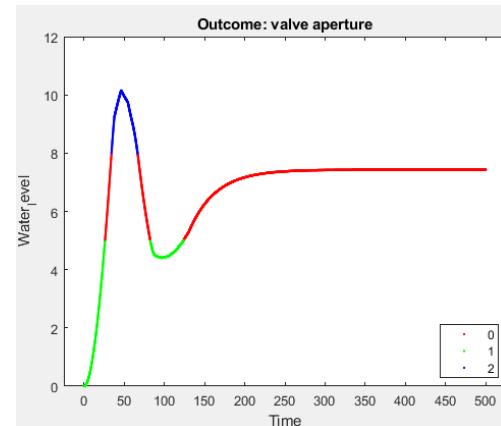
```
waterTank = ImportData('dataser.csv');
% Response
Y = waterTank.OPEN_CLOSE;
% Predictor
X = waterTank.WATER_LEVEL;
```

Partition the data into training set (60%) and test set (40%)

```
cv = cvpartition(length(waterTank), 'holdout', 0.40);
% Training set and Test set
Xtrain = X(training(cv), :); Xtest = X(test(cv), :);
Ytrain = Y(training(cv), :); Ytest = Y(test(cv), :);
```

Build the various classifiers with their confusion matrix, for example

```
%% Linear Discriminant Analysis
lda = fitcdiscr(Xtrain,Ytrain);
%lda is trained model of type ClassificationDiscriminant
Y_lda = lda.predict(Xtest);
C_lda = confusionmat(Ytest,Y_lda)
C_lda = bsxfun(@rdivide,C_lda,sum(C_lda,2)) * 100
```



MATLAB: Training phase for classifier

Manual method

Compare the confusion matrices graphically

Calculate accuracy

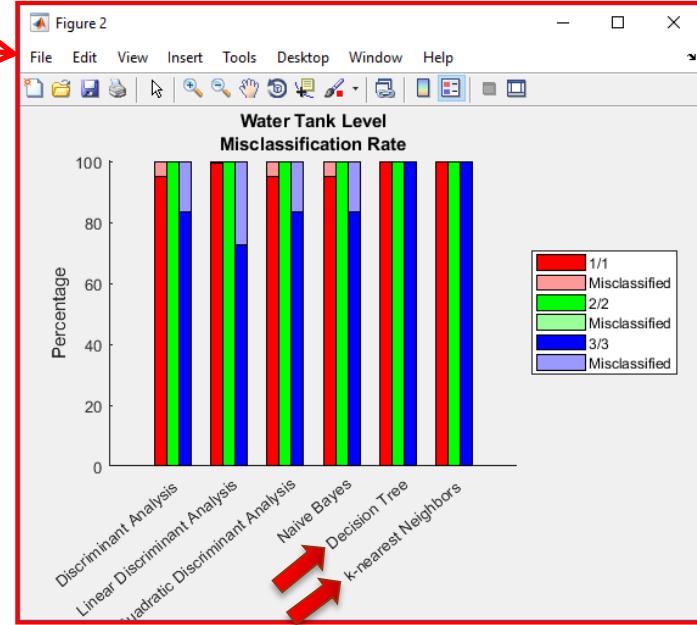
```
summ = 0;
for i = 1:3
    summ = summ + C_lda(i,i);
end
accuracy_lda= summ*100/3;
```

Calculate precision

```
precision_0 = (C_lda(2,2)+C_lda(2,3)+C_lda(3,2)+C_lda(3,3))
              / (C_lda(1,2)+C_lda(1,3)+C_lda(2,2)
                  +C_lda(2,3)+C_lda(3,2)+C_lda(3,3));
precision_1 = ...
precision_2 = ...
precision = precision_0 + precision_1 + precision_2;
```

Calculate recall

```
recall_0 = (C_lda(1,1))/(C_lda(1,1)+C_lda(2,1)+C_lda(3,1));
recall_1 = ...
recall_2 = ...
recall = recall_0 + recall_1 + recall_2;
```



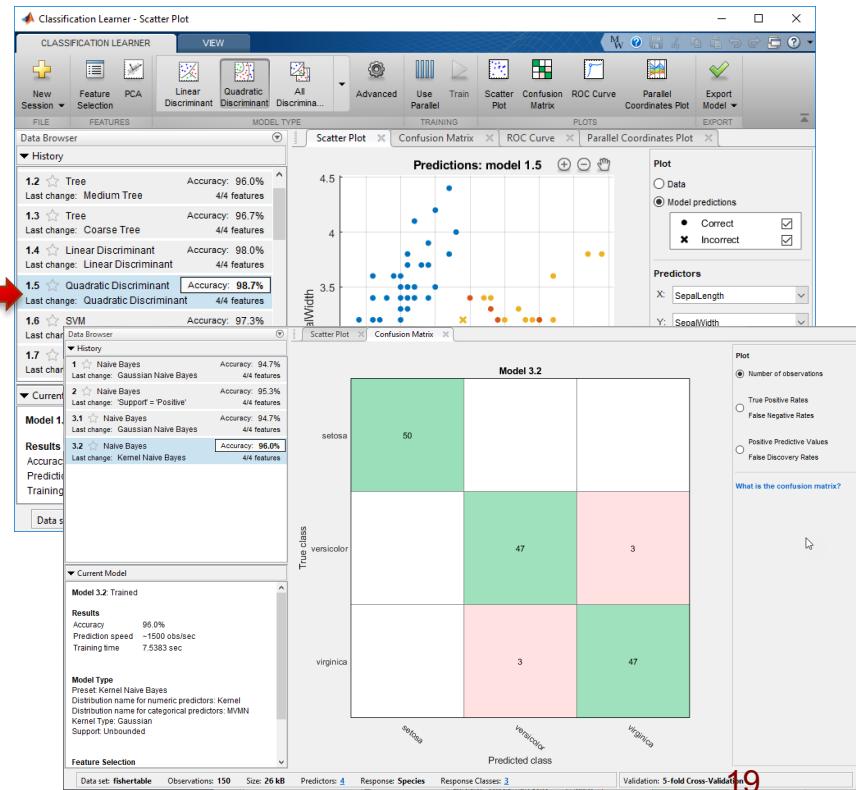
And then choose the best classifier to save in a MAT-file

MATLAB: Training phase for classifier

Automatic method

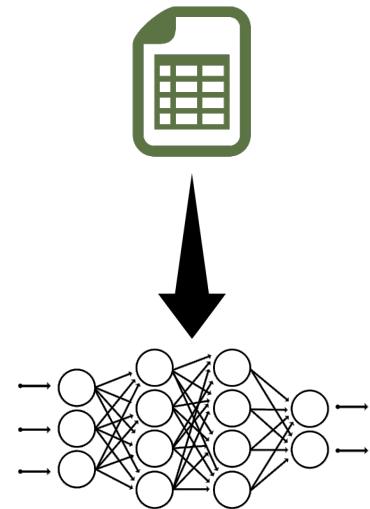
- Import dataset
- Try it on all types of classifiers
- Choose the best classifier
 - Only accuracy is calculated automatically
- Export it in a MAT-file

Precision and recall are very important as well!



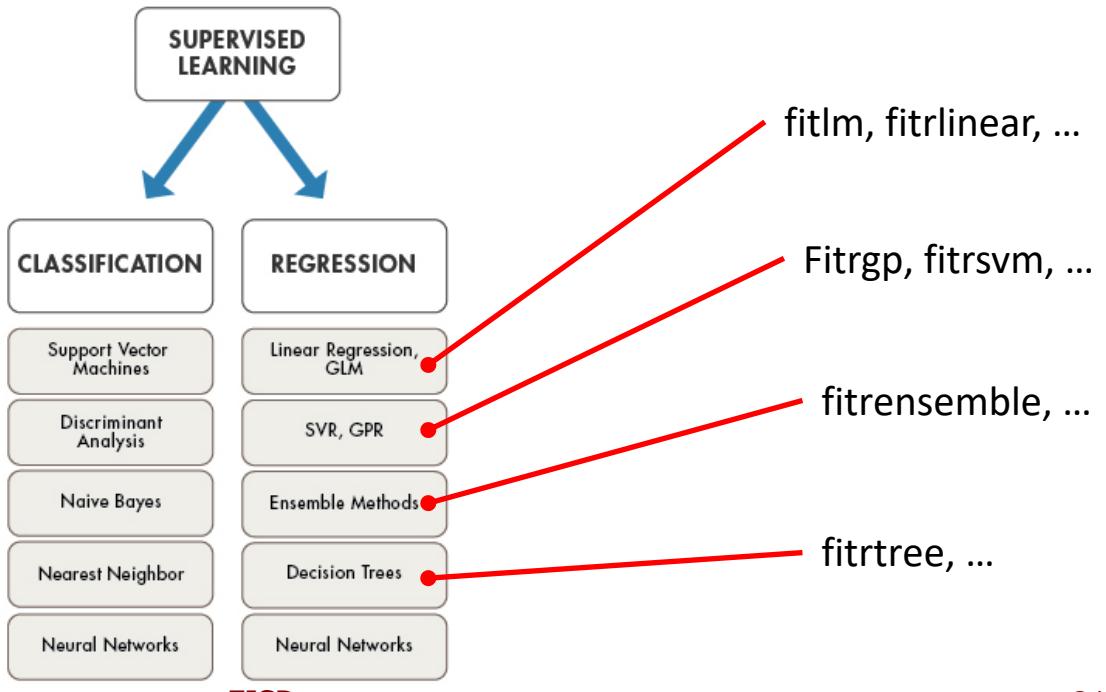
MATLAB: Training phase for regressor

- Two ways
 - Manual method
 - Automatic method
 - *Regression Learner App*
- How to choose the best regressor:
use root-mean-square error (RMSE)
$$RMSE = \sqrt{\sum(Dates - Scores)^2} / Dates$$



MATLAB: Training phase

Manual method

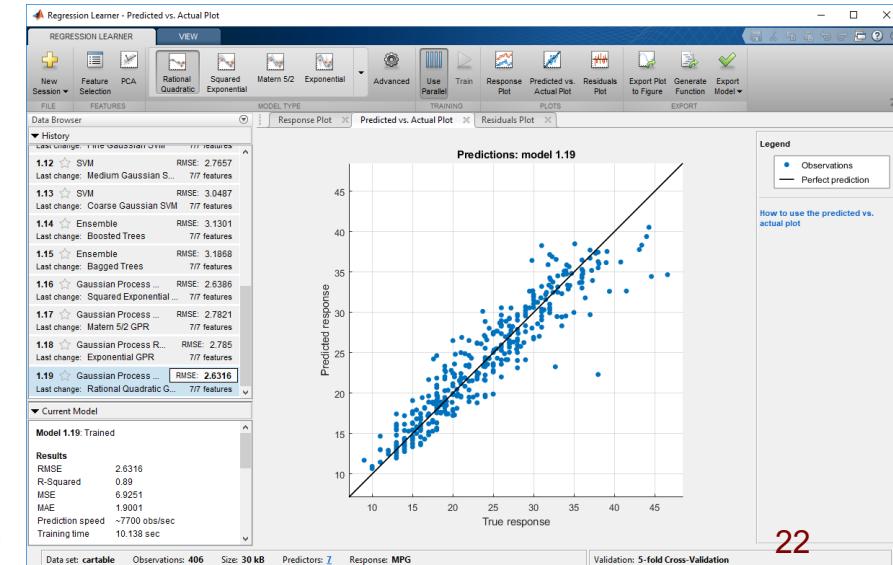


MATLAB: Training phase for regressor

Automatic method

Regression Learner App

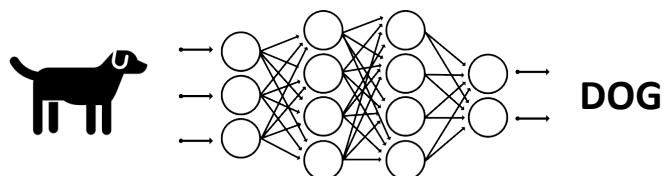
- Import dataset
- Try it on all types of classifiers
- Choose the best classifier
 - Only **root-mean-square error (RMSE)** is calculated automatically
- Export it in a MAT-file



MATLAB: Prediction phase

- After train, predict responses using **predict**

```
y = myClassifier.predict(feature1);
```



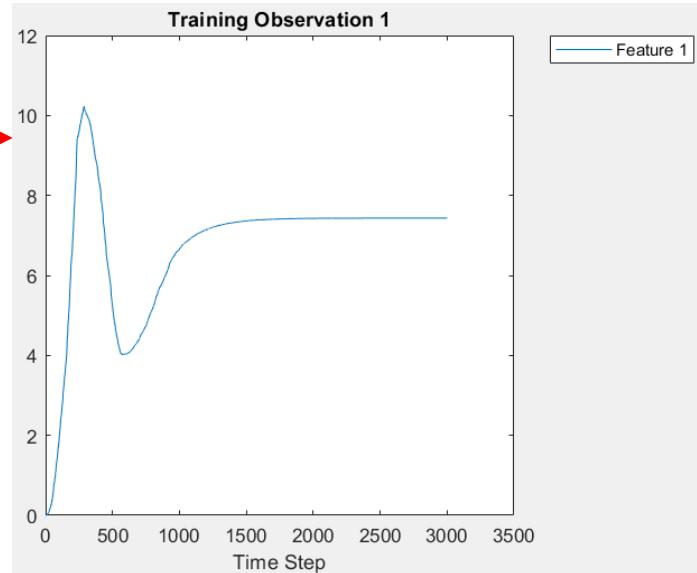
How to build a LSTM

Import Data

```
dataset = csvread("dataset_openclose.csv");
% Response
Y = dataset(:,3); %OPEN_CLOSE
% Predictor
X = dataset(:,2); %WATER_LEVEL
```

Partition the data into training set (60%) and test set (40%)

```
cv = cvpartition(length(dataset_openclose), 'holdout', 0.40);
% Training set and Test set
Xtrain = X(training(cv),:); XTrain = num2cell(XTrain);
XTest = X(test(cv),:); XTest = num2cell(XTest);
YTrain = categorical(Y(training(cv),:));
YTest = categorical(Y(test(cv),:));
```



How to build a LSTM

Build network

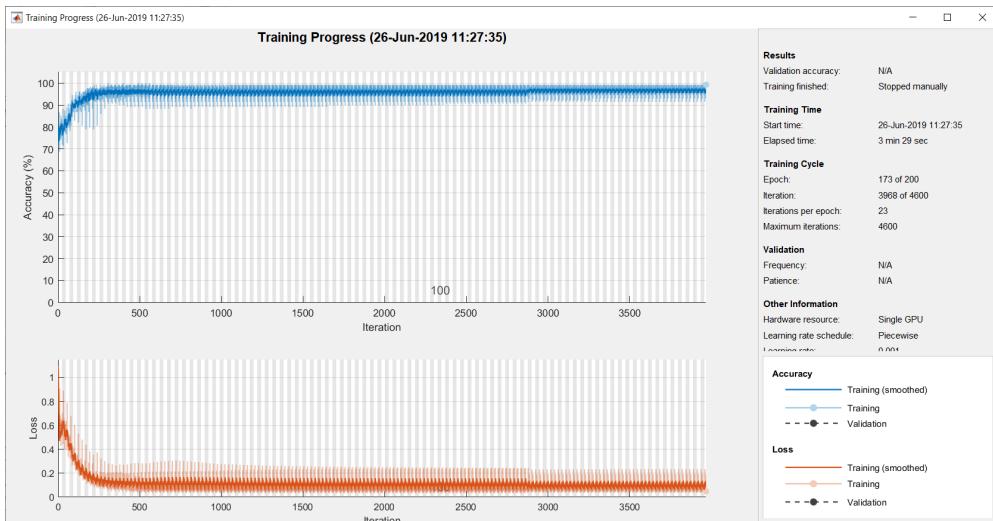
```
%% Define LSTM Network Architecture
inputSize = 1;
numHiddenUnits = 100;
numClasses = 3; % number of categories

layers = [ ...
    sequenceInputLayer(inputSize)
    bilstmLayer(numHiddenUnits, 'OutputMode', 'last')
    fullyConnectedLayer(numClasses)
    softmaxLayer
    classificationLayer] %regressionLayer

maxEpochs = 100;
miniBatchSize = 27;

options = trainingOptions('rmsprop', ...
    'MaxEpochs',200, ...
    'GradientThreshold',1, ...
    'InitialLearnRate',0.005, ...
    'LearnRateSchedule','piecewise', ...
    'LearnRateDropPeriod',125, ... % default 10
    'LearnRateDropFactor',0.2, ... % default 0.1
    'Verbose',0, ...
    'Plots','training-progress')
```

```
%% Train LSTM Network
net = trainNetwork(XTrain,YTrain,layers,options);
```



How to build a LSTM

Prediction phase

```
%% Prediction
YPred = classify(net,XTest, ...
    'MiniBatchSize',miniBatchSize, ...
    'SequenceLength','longest');
```

Calculate accuracy

```
%% Calculate the classification accuracy of the
% predictions
accuracy = sum(YPred == YTest)./numel(YTest)
```

accuracy =

0.9590

>> tabulate(YPred)

Value	Count	Percent
0	1571	78.55%
1	290	14.50%
2	139	6.95%

>> tabulate(YTest)

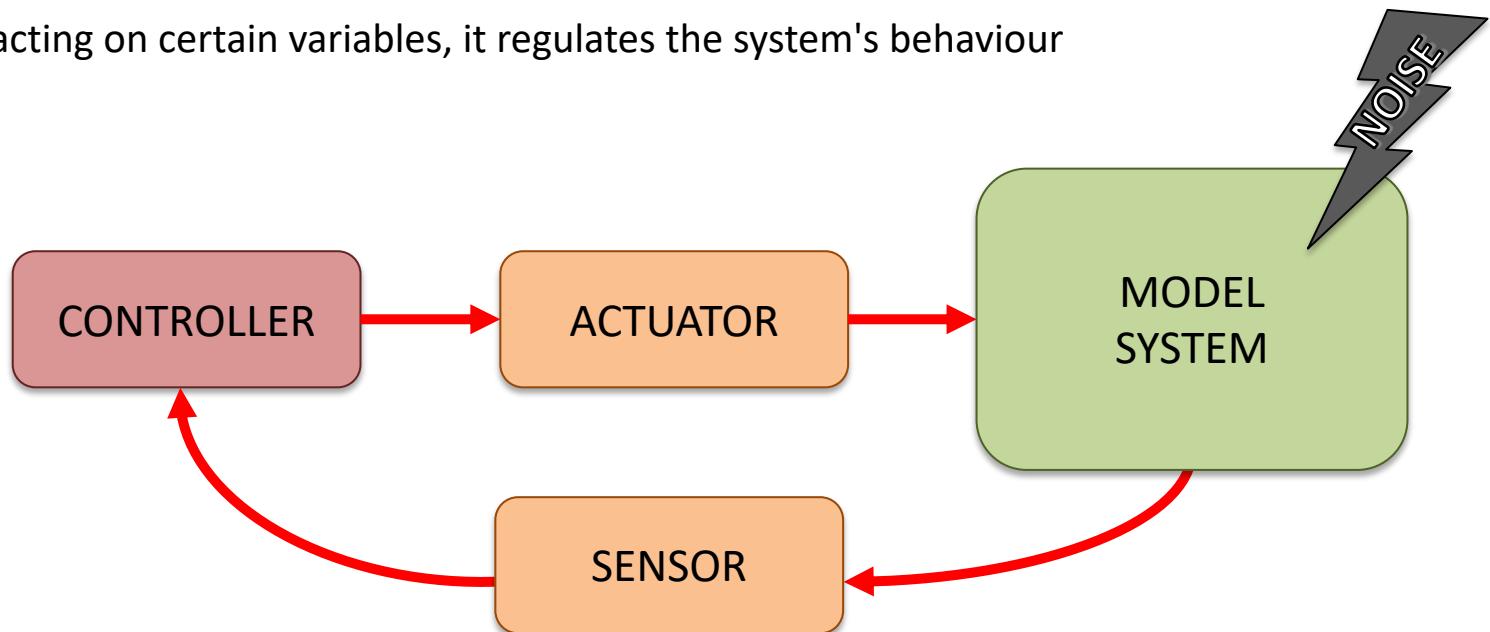
Value	Count	Percent
0	1557	77.85%
1	304	15.20%
2	139	6.95%

Methodology

MACHINE LEARNING IN CONTROL SYSTEM

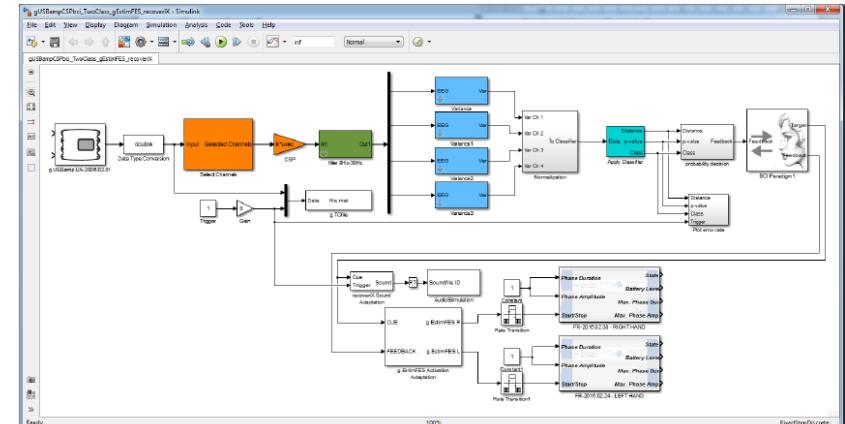
Control system

- A control system manages, commands, directs, or regulates the behavior of other devices or systems using control loops
 - acting on certain variables, it regulates the system's behaviour



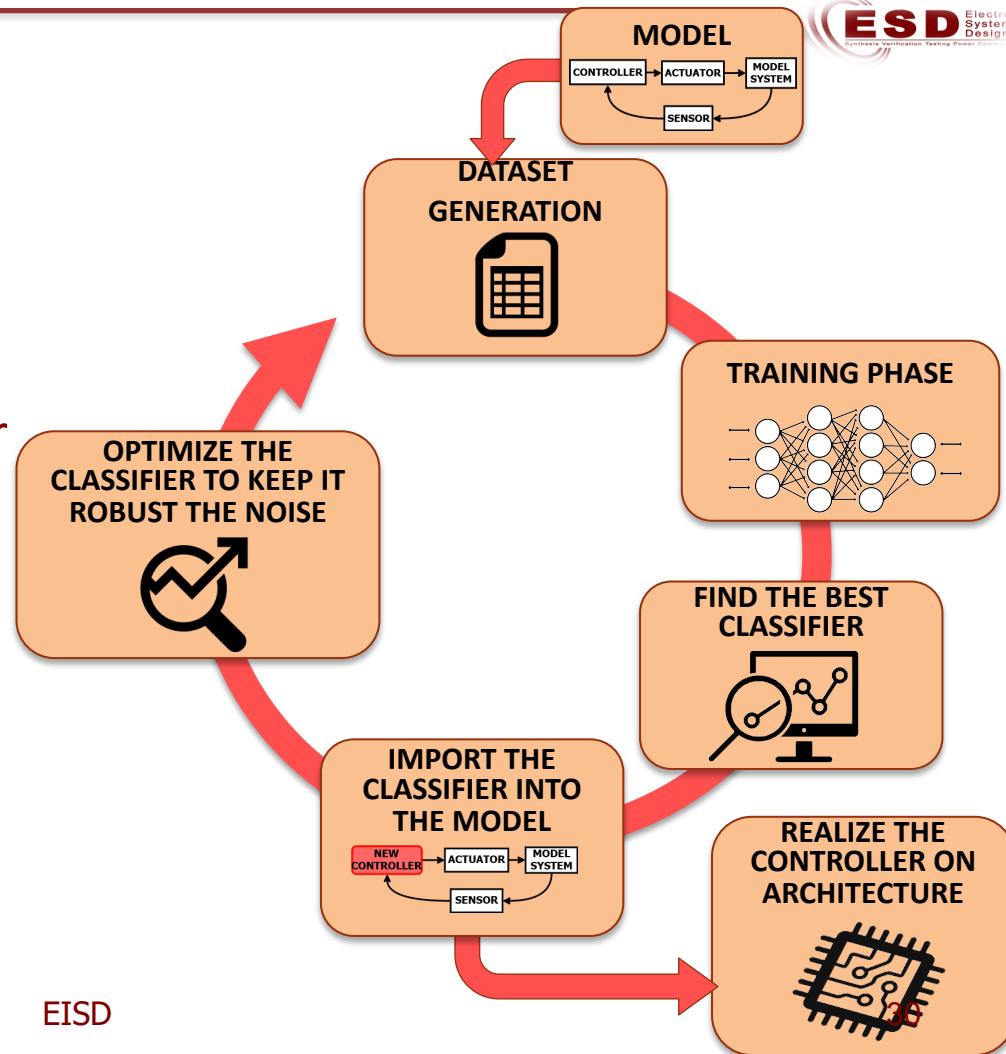
Development environment

- The **Simulink** environment
 - Allows construction of the simulation environment for the hardware and software design of an system
 - Is closely integrated with MATLAB



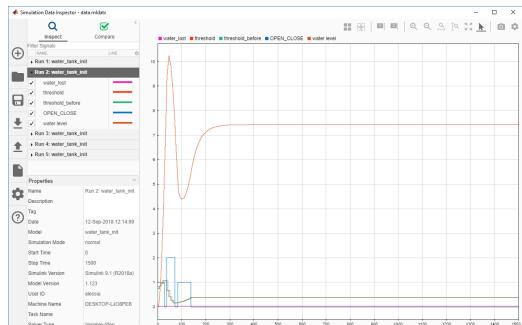
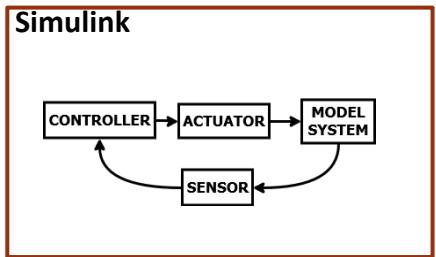
Methodology

- Main steps are:
 - Export the dataset
 - Build of the trained classifier
 - Implement in system
 - Optimize the classifier
 - Generate the code



Export dataset

- Use Simulation Data Inspector
 - Observe the interested signals
 - Export and save them in the Matlab workspace
 - Export the data in a CSV-file



Simulation Data Inspector



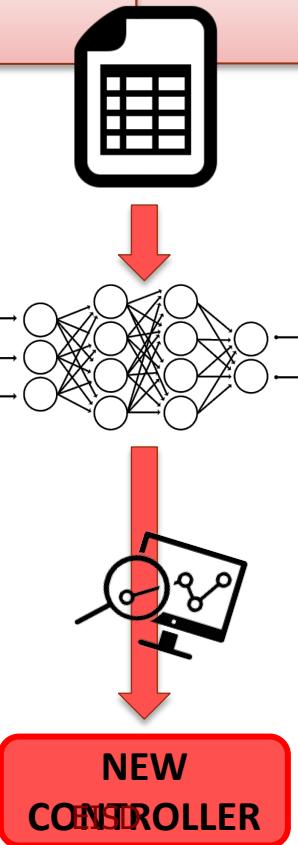
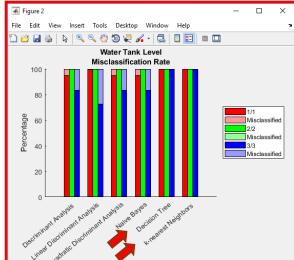
File .csv

Build the trained classifier

Manual method

Statistics and Machine Learning Toolbox

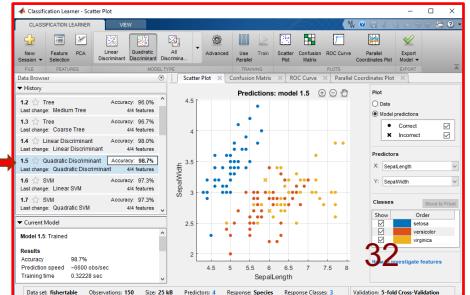
- Import Dataset
- Build the various classifiers with their confusion matrix
- Compare the confusion matrices graphically
- Or calculate accuracy, precision and recall and choose the best classifier



Automatic method

Classification Learner App

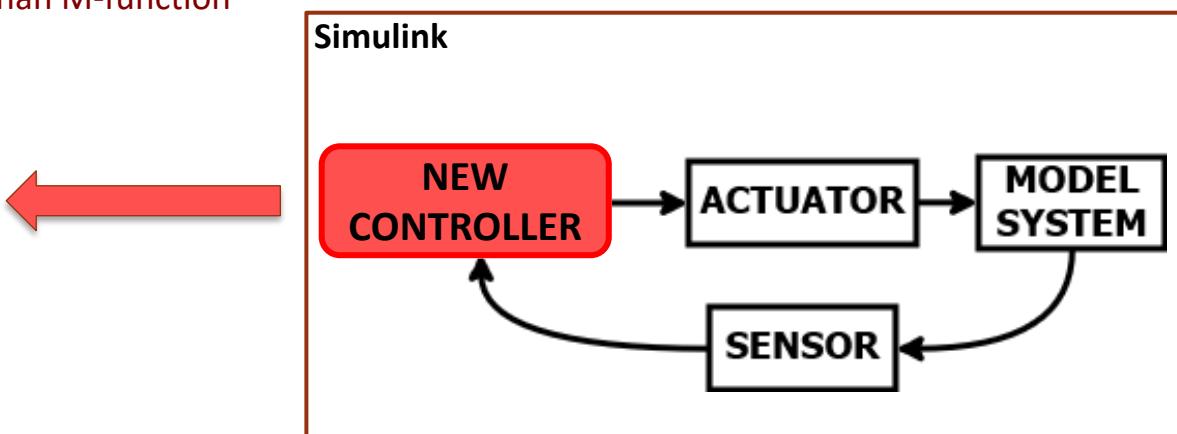
- Import dataset
- Try it on all types of classifiers
- Choose the best classifier



Implementation in the system

- Put the classifiers in
 - **M-function** blocks
 - **S-function** blocks
 - Simulating the **same result** is obtained with the M-functions
 - The S-function is **faster** than M-function

```
function OPEN_CLOSE = fcn(u1, u2, ...)  
persistent mdl;  
if isempty(mdl)  
    mdl = loadCompactModel('my_classifier.mat');  
end  
OPEN_CLOSE = int8(predict(mdl, [u1, u2, ...]));  
end
```



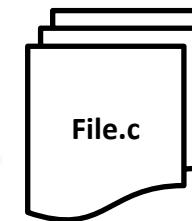
Code generation

- From M-file to C-file
 - MATLAB Coder
 - Simulink Coder

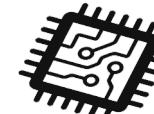
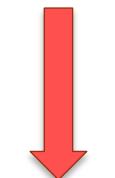
```
function OPEN_CLOSE = fcn(u1, u2, ...)  
persistent mdl;  
if isempty(mdl)  
    mdl = loadCompactModel('my_classifier.mat');  
end  
OPEN_CLOSE = int8(predict(mdl, [u1, u2, ...]));  
end
```

classifyX.m

- MATLAB Coder
- Simulink Coder



File.c

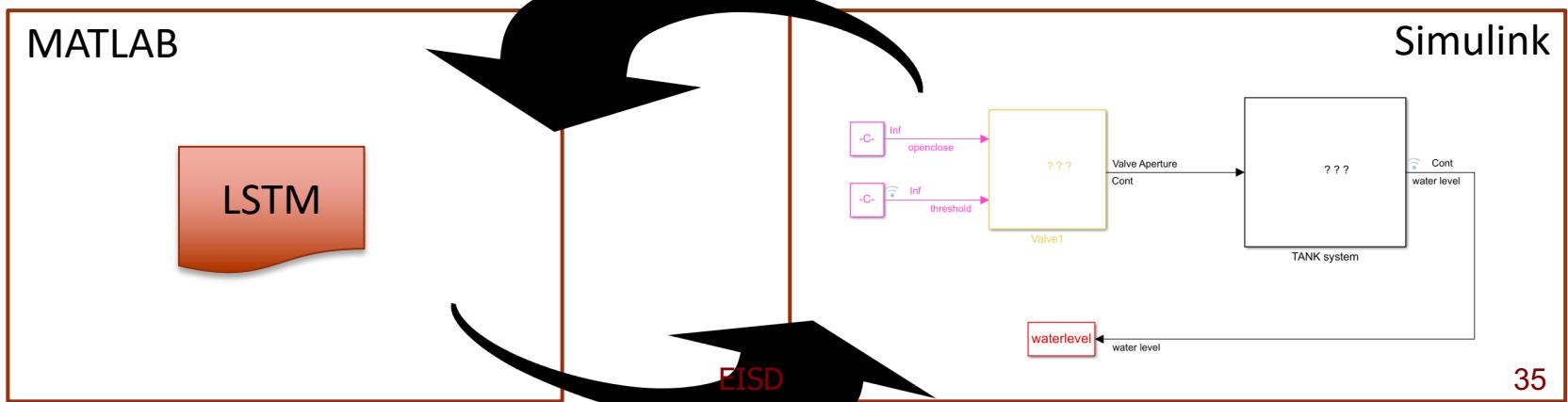


LSTM limitations in MATLAB

- LSTM in MATLAB code
 - cannot be imported in Simulink
 - cannot be exported in C/C++



IDEA:

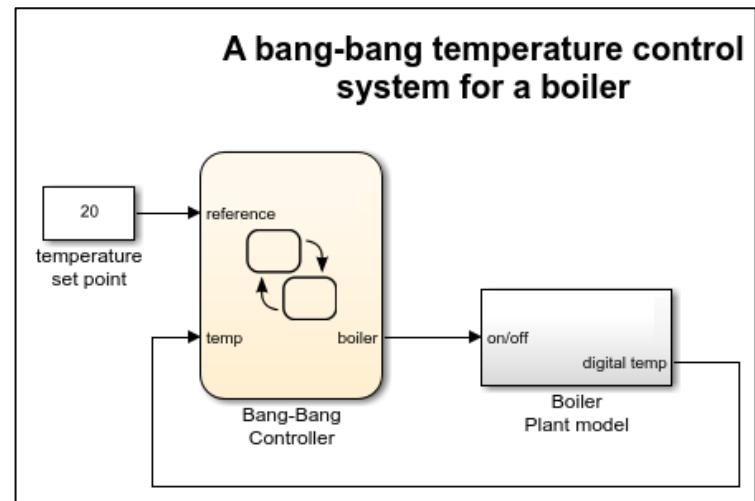


1. Bang bang controller
2. PID controller
3. Water tank controller

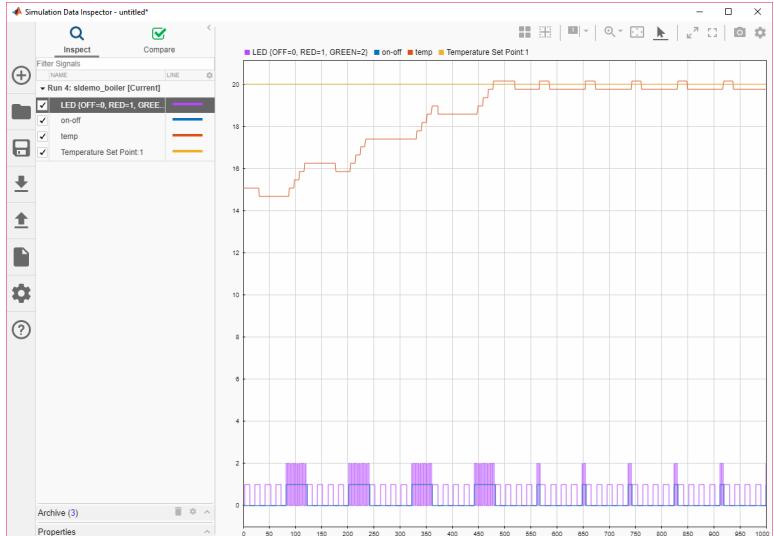
EXPERIMENTAL RESULTS

Bang bang controller

- The Bang-Bang control-boiler model is composed of
 - **Controller**
 - Inputs
 - Temperature set point
 - Digital temperature
 - Outputs
 - ON-OFF $\begin{cases} 0 & \text{the boiler is activated to warm up} \\ 1 & \text{the boiler is switched off} \end{cases}$
 - **Boiler plant model**

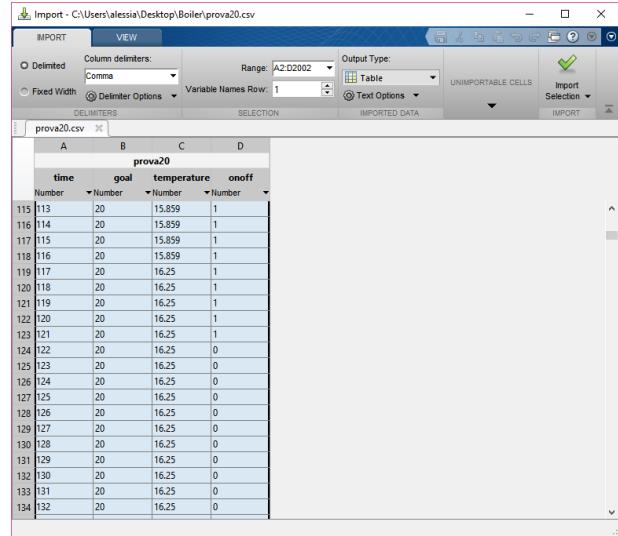


Bang bang controller



Simulation Data Inspector

csvwrite()

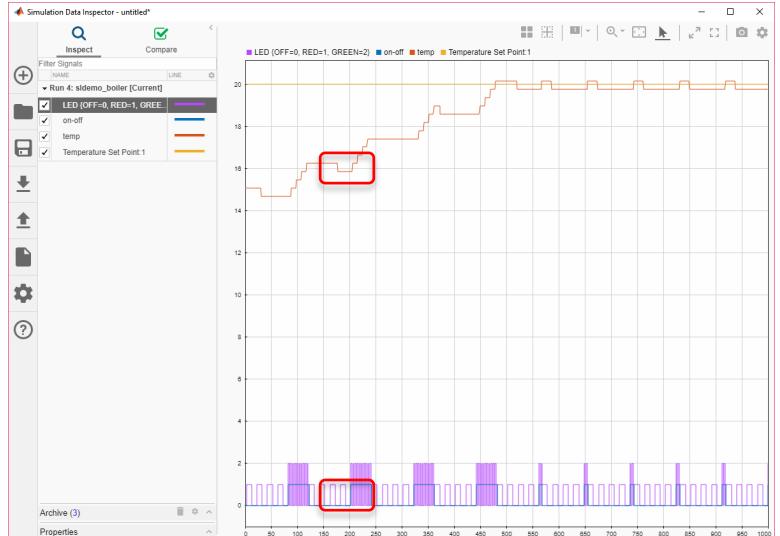
The figure shows the EISD Import dialog with a CSV file named "prova20.csv" loaded. The dialog has tabs for IMPORT, VIEW, and TEXT. Under IMPORT, the "Delimited" option is selected with "Comma" as the column delimiter. The "Range" is set to A2:D2002 and the "Output Type" is set to "Table". The "Import Selection" checkbox is checked. The imported data is displayed in a grid with four columns: time, goal, temperature, and onoff. The data consists of 134 rows, each containing a number from 115 to 132 for the first three columns and either 1 or 0 for the onoff column.

	A	B	C	D
	time	goal	temperature	onoff
Number	Number	Number	Number	Number
115	113	20	15.859	1
116	114	20	15.859	1
117	115	20	15.859	1
118	116	20	15.859	1
119	117	20	16.25	1
120	118	20	16.25	1
121	119	20	16.25	1
122	120	20	16.25	1
123	121	20	16.25	1
124	122	20	16.25	0
125	123	20	16.25	0
126	124	20	16.25	0
127	125	20	16.25	0
128	126	20	16.25	0
129	127	20	16.25	0
130	128	20	16.25	0
131	129	20	16.25	0
132	130	20	16.25	0
133	131	20	16.25	0
134	132	20	16.25	0

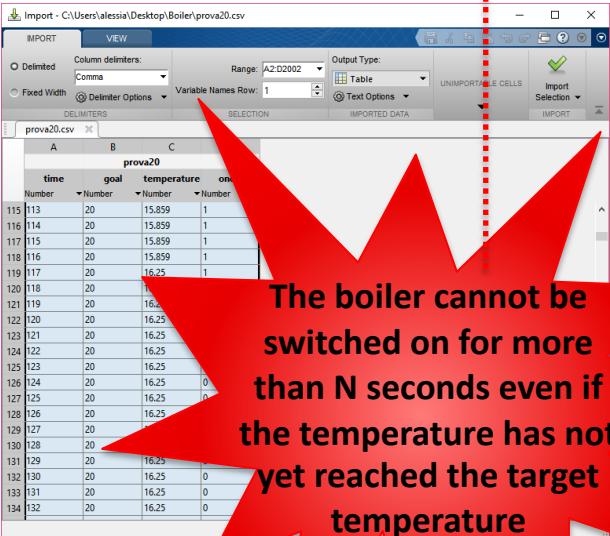
File.csv

Bang bang controller

- Problem n. 1



csvwrite()



Import - C:\Users\alesia\Desktop\Boiler\prova20.csv

IMPORT VIEW

Column delimiters: Comma Range A2:D2002 Output Type: Table

Fixed Width Delimiter Options Variable Names Row: 1 Text Options IMPORTED DATA

DELIMITERS SELECTION IMPORTED DATA

prova20.csv

	A	B	C	prova20
time	goal	temperature	on/off	
115	113	20	15.859	1
116	114	20	15.859	1
117	115	20	15.859	1
118	116	20	15.859	1
119	117	20	16.25	1
120	118	20	16.25	1
121	119	20	16.25	1
122	120	20	16.25	1
123	121	20	16.25	1
124	122	20	16.25	1
125	123	20	16.25	1
126	124	20	16.25	0
127	125	20	16.25	0
128	126	20	16.25	0
129	127	20	16.25	0
130	128	20	16.25	0
131	129	20	16.25	0
132	130	20	16.25	0
133	131	20	16.25	0
134	132	20	16.25	0

it looks like the boiler is off for 80 seconds, then turns on for up to 40 seconds and then back off for another 80 seconds

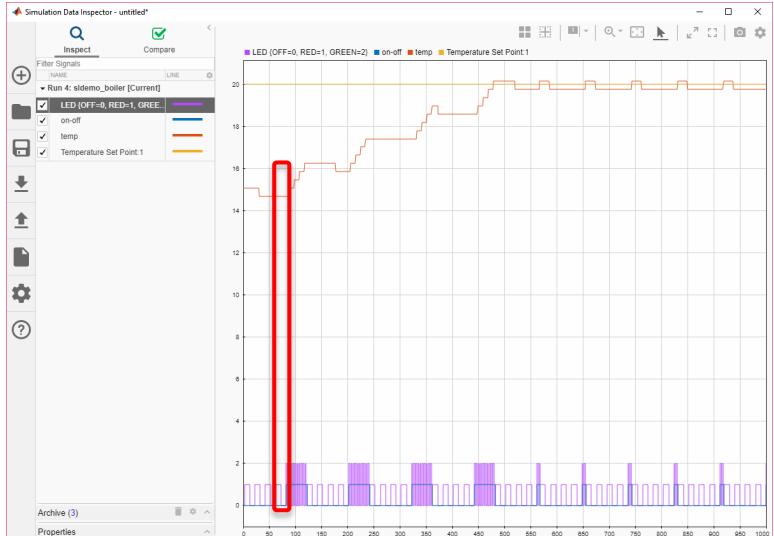
The boiler cannot be switched on for more than N seconds even if the temperature has not yet reached the target temperature

For CSV

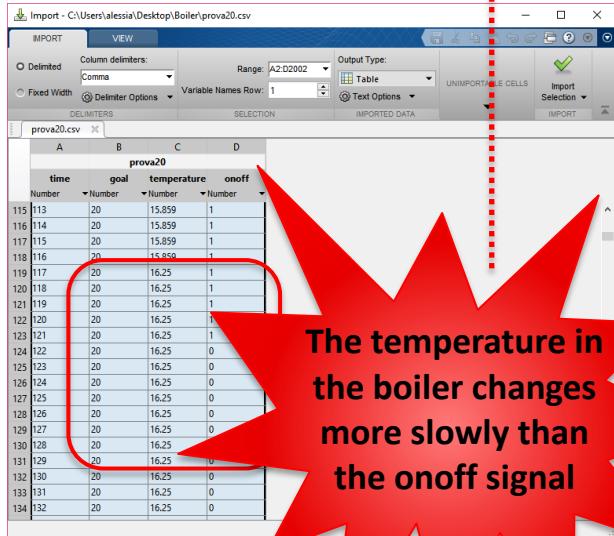
Simulation Data Inspector

Bang bang controller

- Problem n. 2



csvwrite()



Import - C:\Users\alesia\Desktop\Boiler\prova20.csv

IMPORT VIEW

Column delimiters: Comma Range A2:D2002 Output Type: Table

Fixed Width Delimiter Options Variable Names Row: 1 Text Options Import Selection UNIMPORTABLE CELLS Import Import

prova20.csv

A	B	C	D	
time	goal	temperature	onoff	
115	113	20	15.859	1
116	114	20	15.859	1
117	115	20	15.859	1
118	116	20	15.859	1
119	117	20	16.25	1
120	118	20	16.25	1
121	119	20	16.25	1
122	120	20	16.25	1
123	121	20	16.25	1
124	122	20	16.25	0
125	123	20	16.25	0
126	124	20	16.25	0
127	125	20	16.25	0
128	126	20	16.25	0
129	127	20	16.25	0
130	128	20	16.25	0
131	129	20	16.25	0
132	130	20	16.25	0
133	131	20	16.25	0
134	132	20	16.25	0

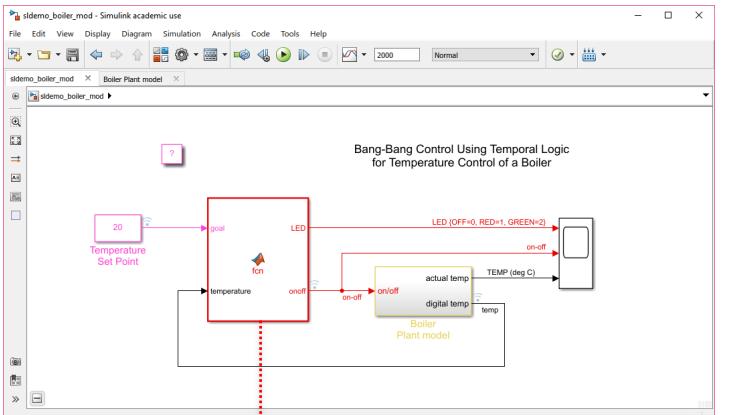
File .sv

When goal = 20 and temperature = 16.25, onoff signal is 1 or 0?

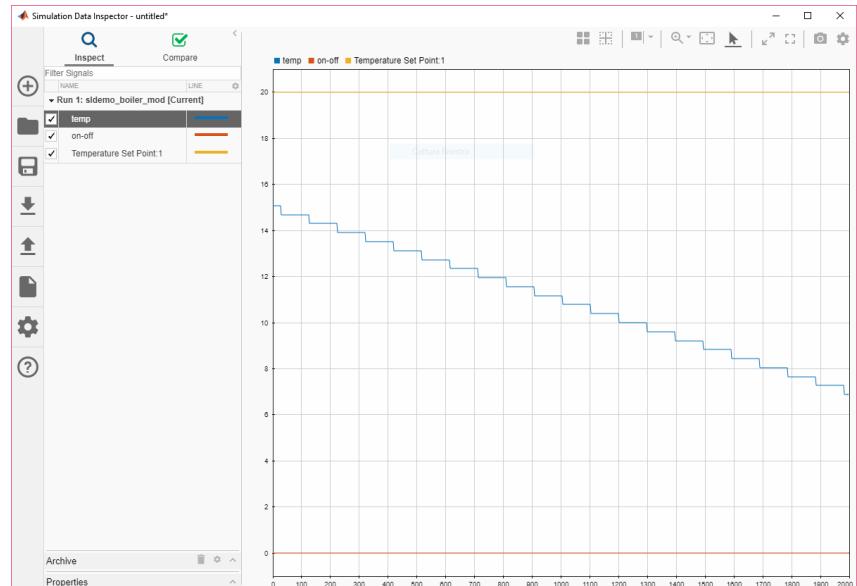
Simulation Data Inspector

Bang bang controller

- It is necessary to build an ad hoc dataset otherwise it does not work!



Simulation



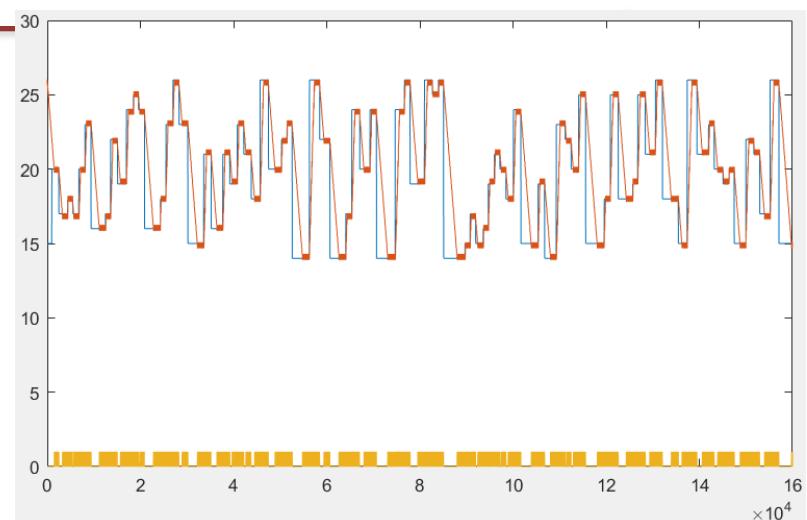
```
function [LED, onoff] = fcn(goal, temperature)
persistent mdl;
mdl = loadCompactModel('fineTree882.mat');
u = [goal double(temperature)];
LED = int8(0);
onoff = int8(predict(mdl,u));
end
```

Training dataset

- Build initial dataset, by observing the signals
 - Temperature goal signal
 - Actual temperature signal
 - Onoff signal
- Then, the training dataset is composed as follows
 - Count_0: how much the on-off signal is 0
 - Count_1: how much the on-off signal is 1
 - $\begin{cases} diff: \text{actualtemperature} - \text{goal} \\ signdiff: \begin{cases} -1 & \text{if } \text{actualtemperature} - \text{goal} < 0 \\ 1 & \text{otherwise} \end{cases} \end{cases}$
 - Onoff: Controller's output

Rows: 160000

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Number	count_0	count_1	diff	onoff	Number	count_0	count_1	sign_diff	onoff
75	0	-0.234	0	0	75	0	-1	0	0
76	0	-0.234	0	0	76	0	-1	0	0
77	0	-0.234	0	0	77	0	-1	0	0
78	0	-0.234	0	0	78	0	-1	0	0
79	0	-0.234	0	0	79	0	-1	0	0
80	0	-0.234	1	1	80	0	-1	1	0
0	1	-0.234	1	1	0	1	-1	1	0
0	2	-0.234	1	1	0	2	-1	1	42
0	3	-0.234	1	1	0	3	-1	1	0
0	4	-0.234	1	1	0	4	-1	1	0

Classifiers C.L.App and dataset with sign

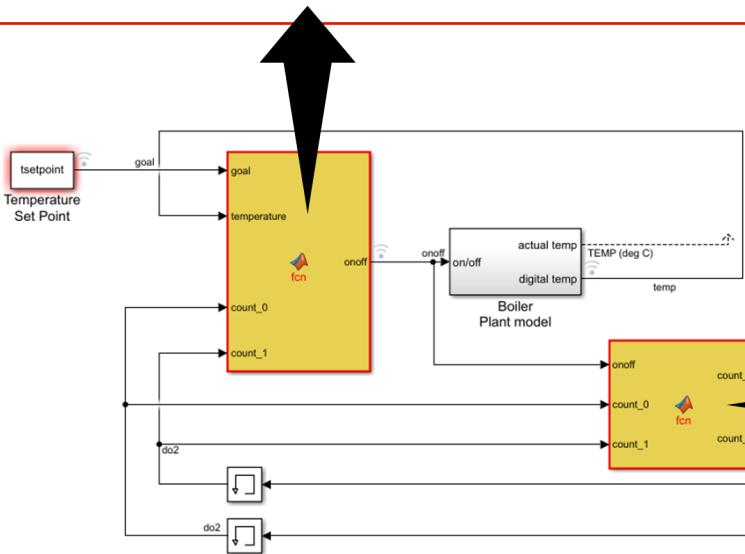
```

function onoff = fcn(goal, temperature, count_0, count_1)

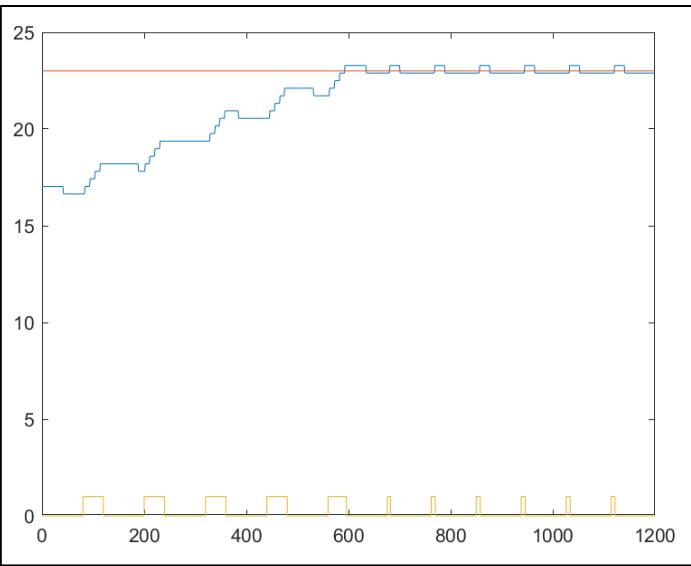
persistent mdl;
u = [double(count_0), double(count_1), sign(double(temperature)-goal)];
if isempty(mdl)
  mdl = loadCompactModel('classifier.mat'); %Boosted Trees
end
onoff = int8(predict(mdl,u));

end

```



EISD



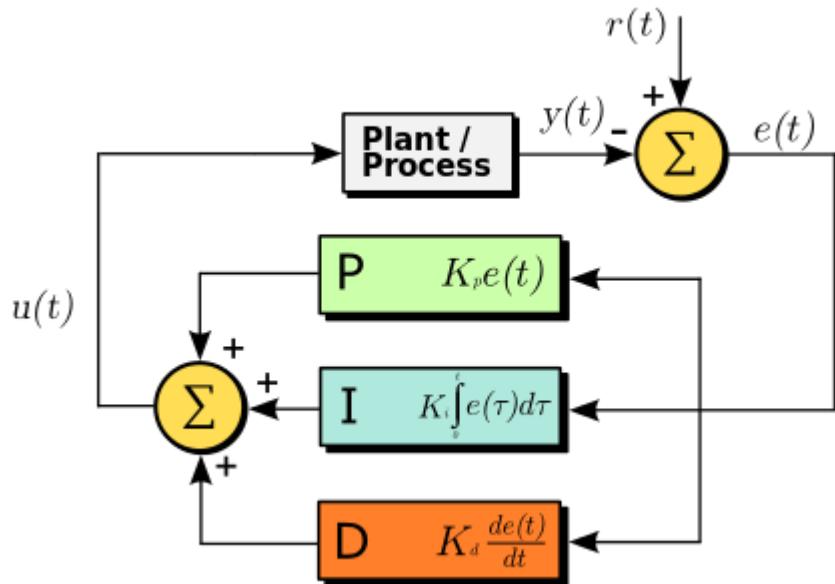
```

function [count_0, count_1] = fcn(onoff, count_0, count_1 )
  if onoff == 0
    count_0 = count_0 + 1;
    count_1 = 0;
  else
    count_0 = 0;
    count_1 = count_1 + 1;
  end
end

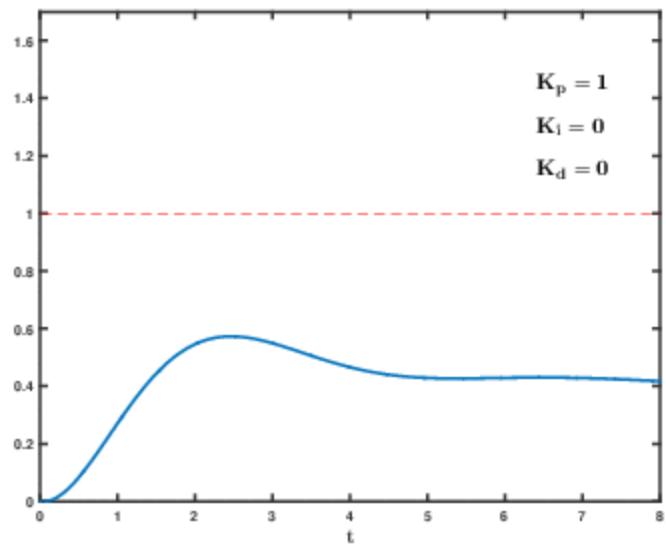
```

PID

- The **proportional–integral–derivative (PID) controller** acquires a value as input from a process and compares it with a reference value. The difference, the so-called error signal, is then used to determine the value of the controller output variable, which is the manipulable variable of the process.

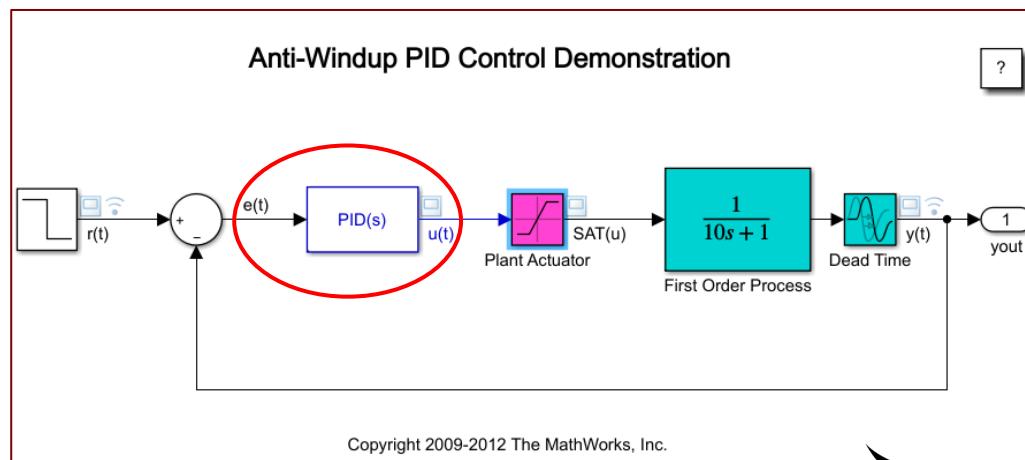


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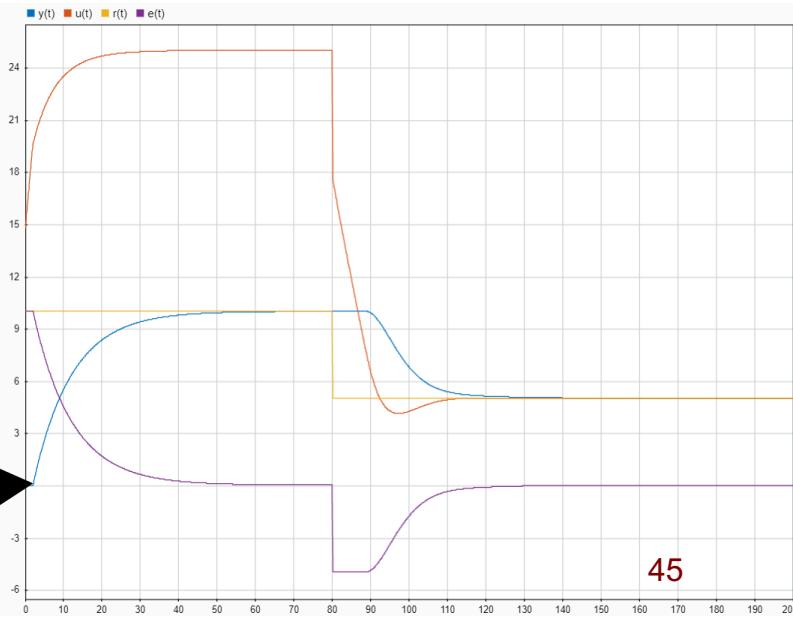


PID

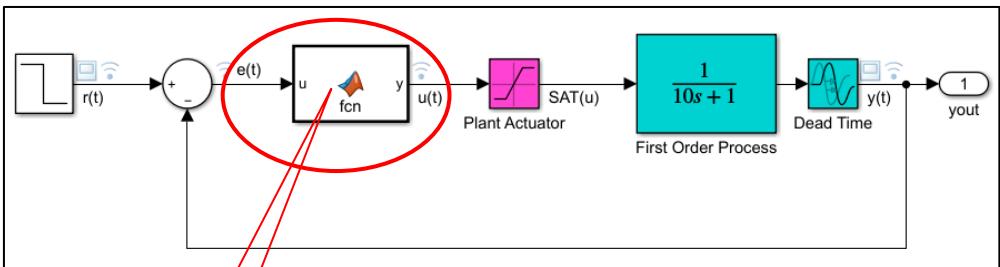
- This example shows how to use anti-windup schemes to prevent integration wind-up in PID controllers when the actuators are saturated
 - <https://it.mathworks.com/help/simulink/slref/anti-windup-control-using-a-pid-controller.html>



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PID example: PID controller



```
function y = fcn(u)
mdl = loadCompactModel('myRegressor.mat');
y = predict(mdl,u);
```

**Bagged tree
regressor with
Regression
Learner App**

EISD

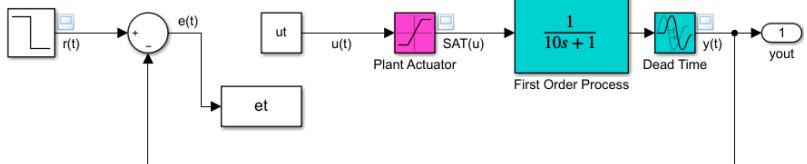


PID simulation

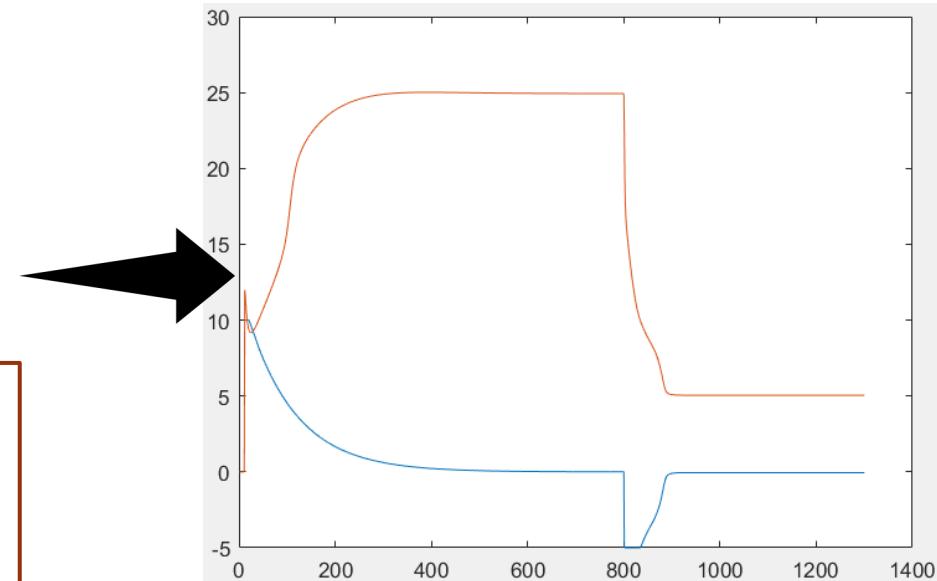
MATLAB

LSTM

Simulink

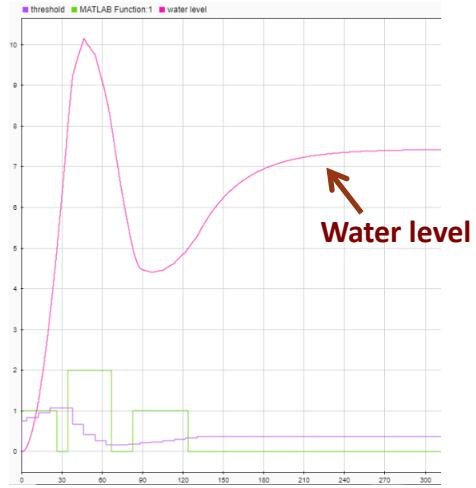
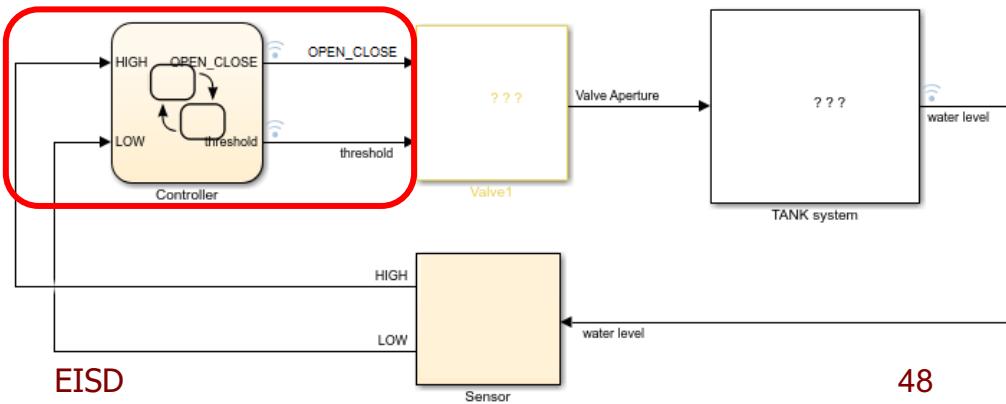
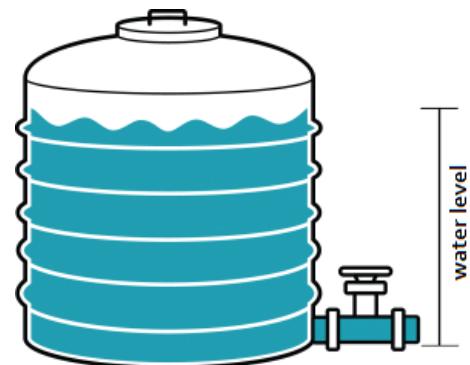


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Water tank

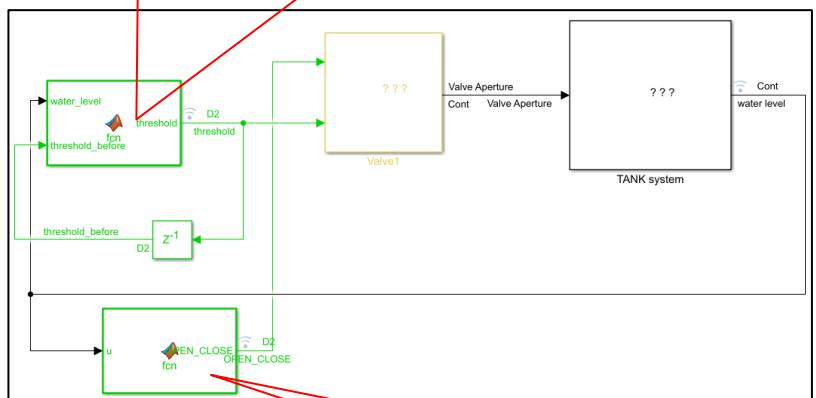
- Water tank is a tank that leaks water
- Controller manages the opening of the valve
 - Water level is between two values
 - The signals to be managed are
 - OPEN_CLOSE $\begin{cases} 0 & 5.5 \leq \text{waterLevel} \leq 8 \\ 1 & \text{waterLevel} < 5.5 \\ 2 & \text{waterLevel} > 8 \end{cases}$
 - Threshold → maximum valve opening value



Water tank simulation with regressor

```

function threshold = fcn(water_level, threshold_before)
persistent mdl;
init_threshold = 0.75;
if isempty(mdl)
  mdl = loadCompactModel('medTree0018.mat');
  threshold = init_threshold;
else
  X = [water_level threshold_before];
  threshold = double(mdl.predict(X));
end
end
  
```



```

function OPEN_CLOSE = fcn(u)
persistent mdl;
if isempty(mdl)
  mdl = loadCompactModel('my_classifierOC.mat');
end
OPEN_CLOSE = int8(predict(mdl,u));
end
  
```

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Water tank simulation with LSTM

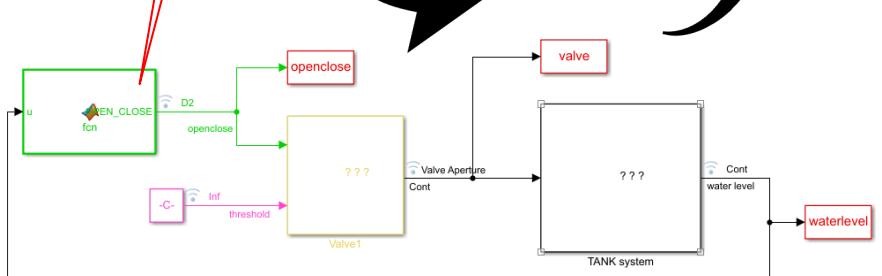
```

function OPEN_CLOSE = fcn(u)
persistent mdl;
if isempty(mdl)
    mdl = loadCompactModel('myClassifier.mat');
end
OPEN_CLOSE = int8(predict(mdl,u));
end
  
```

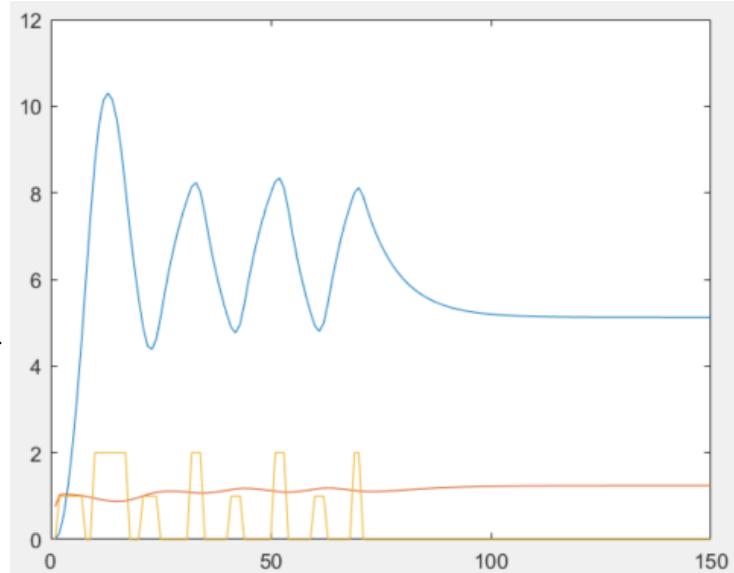
MATLAB

LSTM
for threshold

Simulink



EISD



Objectives

- Assumptions
 - Machine learning is often used in those fields of computer science where designing and programming explicit **algorithms is impractical**
 - **Building a control system is not easy** and it is necessary to have a engineer specializing who has an extensive knowledge in all areas of engineering, and an overview of the physical laws
 - The controller **code** of a system is **not always accessible**
- PROPOSED SOLUTION
 - Replicate the behavior of an embedded control system that is not known how it works, with **supervised** machine learning techniques

Objectives

- Assumptions
 - The **MATLAB/Simulink** environment allows
 - [Simulink] construction of the simulation environment for the hardware and software design of an embedded system
 - [Matlab] use of machine learning techniques
- Is it possible to implement a controller with machine learning techniques in MATLAB/Simulink environment?



References

- "*Understanding LSTM Networks*", <https://colah.github.io/posts/2015-08-Understanding-LSTMs/>
- The MathWorks, Inc., "Generate Code Using Simulink® Coder™",
<https://it.mathworks.com/help/rtw/examples/generating-code-using-simulink-coder.html>