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An Environment for Developing Incremental Learning Applications for Data Streams

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Abstract

Smart cities look to leverage technology, particularly sensors, and software to provide improved services for its citizenry and enhanced operational efficiencies. Cities look to develop applications that can process data from sensors and other sources to gain insights into operation, enable them to improve operations and inform city leadership. Such applications often need to process streams of data from sensors or other sources to provide city staff with insights into city operations. However, cities are faced with limited budgets and limited staff. The development of applications by third parties can be extremely expensive. One alternative is to identify tools for software development that city staff can use – where the development tools can simplify the development process.

This research addresses this challenge by looking at a graphical flow-based programming framework, Node-RED, as the foundation for a flexible application development environment that can accelerate and simplify the development of applications of interest to smart cities. Node-RED presents a visual programming framework composed of nodes and data flows. We look at extending Node-RED to incorporate nodes that hide the complexity of developing incremental machine learning applications by providing relatively simple and easy to use graphical interfaces. Nodes for a variety of learning methods are introduced and used for real-time analysis of data streams. Nodes providing different metrics have also been designed to enable the application developer to evaluate the trained models.

Keywords

Incremental machine learning, data stream processing, Internet of things, Node-RED

Summary for Lay Audience

With the new advances in wireless communication, more and more devices are connecting to the Internet to offer better services. It could be a refrigerator in a house or different facilities in the city, like sensors in parking spots. The growth in the number and popularity of these devices requires that people with different programming backgrounds start to contribute to developing applications that meet their needs. For many of these applications, it is important to try to predict an outcome; this makes use of machine learning methods. Machine learning is a collection of theories and methods that enables computers to learn from data and make predictions without being explicitly programmed to do. This research looks at methods and tools that can facilitate the development of applications that can use machine learning methods for such an environment.

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Chapter 1

Introduction

The main purpose of the internet of things (IoT) is connecting physical objects to the Internet. IoT helps physical objects to be able to sense, send and receive messages, perform computations and communicate with other physical objects through the Internet to achieve an objective [1]. IoT applications have been used in a variety of domains like enterprises, transportation, healthcare, communication, environment, and smart city. Being able to connect objects creates the power of decision making and control which results in huge benefits in many domains. Industries and governments are also investing a considerable amount of money in IoT. According to Castillo and Thierer [2], by 2025, the value of IoT technologies will be anywhere from $2.7 trillion to $14.4 trillion.

The continuous growth of IoT in every aspect of our lives has created the need to develop, control and maintain IoT applications. However, creating IoT applications has its own challenges. Heterogeneity of sensors, various protocols of communication, data management and developing user-friendly graphical interfaces for monitoring of data are some of the challenges of IoT development. These challenges are particularly significant in the emergence of smart cities. Cities have limited funding and limited staff for developing and maintaining applications. These difficulties make the development hard and delay the progress of IoT applications in smart cities. In order to make this process easier, we need platforms that can provide abstractions for the different layers of the development so that people with different technical knowledge are able to meet their needs by creating their own applications.

In order to be able to take advantage of the large amounts of data that is being produced by different sensors, platforms need to provide tools for data analysis. Machine learning is being used in many IoT applications, like in smart cities, to turn data into value and make decisions that help the system perform more efficiently and more effectively. The data generated by sensors are being used in a variety of smart city applications including being used to predict electricity load [3], estimate solid waste generation [4], controlling available parking slots [5] and many other applications.

In an IoT application sensors are continuously sensing their environment, producing data and sending them to a system, a server or an edge processor, for storage, analysis, and further distribution. In some applications, it is critical to make real-time decisions and be reflective of the latest changes in the data. Most of the existing IoT platforms have provided typical methods of machine learning that are only able to train on large batches of data and usually require an expert to develop such applications. These models are typically developed off-line. An alternative is to consider learning on streams of data. The method of learning that can train and adjust the model on continuous streams of data is called online machine learning or incremental machine learning.

Node-RED is a web-based visual programming tool that was first created by IBM for the rapid development of IoT applications. Node-RED has a flow-based programming model and connects data sources by “wiring” them together. Node-RED provides a rich set of tools for application development and it is designed in a way that people with different programming backgrounds can utilize its features to develop a data-intensive application.

Node-RED’s active community of developers has built tools for machine learning that can be easily added to Node-RED. However, all the existing training methods are typical machine learning algorithms that need the whole data (or large quantities of data) for training. In our work, we look at the feasibility of building a set of tools for Node-RED that enables users to have access to online machine learning methods and data preprocessing functions that are specifically designed for online machine learning settings.

The main contribution of this thesis is an environment for developing incremental learning solutions for data streams. This environment contains methods for training models, evaluating the models, and data preprocessing nodes. The environment has a user-friendly graphical interface that facilitates the development process which enables users with low programming knowledge to take advantage of the tools.

This thesis is structured as follows. In Chapter 2, we will look at a number of existing tools that are trying to facilitate the development of IoT applications and discuss their approaches for data analysis. Also, in this chapter, methods of incremental machine learning will be introduced and compared with the batch machine learning. In Chapter 3, we will explain Node-RED and the advantages that it offers for building IoT applications. Then we discuss our contributions to Node-RED that enable developing incremental machine learning solutions in simple steps. In Chapter 4, the provided approaches will be evaluated using various datasets and we will walk through the steps for building an incremental learning model using Node-RED. In Chapter 5, we provide a summary of the proposed approach and some future directions.

Chapter 2

Literature Review

IoT applications are now being used in many domains from medical and healthcare to smart cities and agriculture. The advent of communication technologies like 5G is also going to accelerate the growth of the number of devices that are connected to the Internet. This raises the necessity of having software platforms that make the development of IoT applications faster and easier. In this chapter, a number of IoT platforms, as well as their efforts for data stream analysis, will be discussed.

2.1 IoT Platforms

In order to develop a platform for IoT development, some requirements should be satisfied. Since IoT has a large number of applications, large amounts of users' data is transferred between various sources. Hence, there should be mechanisms to secure such an environment. IoT applications are being used in areas that need their systems to be as deterministic and real-time as possible. So IoT platform developers need to make sure to design systems that can work in real-time environments. IoT applications are needed to perform their tasks with the minimum help of humans so an important characteristic of an IoT platform is to enable building applications that are intelligent enough to work without human intervention.

The authors of the IoT framework IoTSuite [6] have designed and implemented a set of tools to make IoT development easier. They have tried to provide tools for different stages of developing an IoT application. Their first tool is an editor that lets the designers write high-level code that specifies the architecture of the application and deployment configurations. They provide a compiler that translates the high-level code to parser files. IoTSuite has a Mapper component that converts the high-level computational services like deployment specifications and architecture specifications into standardized data structures. Decision mappers use these data structures to create mapping files that are responsible to decide where each computational service will be deployed among the set of devices that are specified in the deployment specification. Then the Linker tool collects all the generated codes in different stages of parsing and creates packages that contain device-specific codes that prepare them to be deployed on the devices. Finally, the last tool is the Running system which is responsible to execute the codes on multiple devices in a distributed way. Although IoTSuite has provided a complete set of tools for IoT development, its high-level programming language is quite difficult to understand for people with a limited programming background.

RapIoT [7] is a software toolkit that tries to take care of the low-level details of IoT development so a developer can easily focus on application development. RapIoT helps non-experts to design an IoT prototype quickly by providing a set of primitives that are common among all IoT devices, so the user does not need to know any device-specific details. The architecture of RapIoT consists of three tools. The first tool is RapEmbedded that is an Arduino library to let developers define primitives for a sensor or device. An example of a primitive could be the location and the level of pollution for an air quality sensor. The second tool of RapIoT is RapMoblie that is a mobile app that acts as a gateway to gather the data from installed devices and communicate with the application that is on the cloud. The last tool is RapCloud that provides a set of APIs that lets developers create applications and deploy them in the cloud. The mobile app retrieves the primitives from the devices and sends them to the cloud. The app in the cloud performs the needed operations and sends back the results to the mobile app. The need to have access to a smartphone to be able to control the IoT devices and monitor the results has made RapIoT hard to use in areas like smart cities that need better ways of interacting with devices. However, it could be a very great choice for prototyping small IoT applications in areas like smart homes.

IoTLink [8] is another platform that aims to provide a set of tools that abstracts the complexities of implementing an IoT application. There are four layers in the platform. The first layer provides a high level and unified representation of connections between different physical sensors. The second layer stands on top of sensor readings to collect and aggregate the different sensors’ values and performs the required preprocessing. The third layer abstracts the objects or “things” with their attributes. The fourth layer prepares the objects for application logic by creating appropriate data formats and networking interfaces. Figure 1 depicts the aforementioned layers and their specific components in IoTLink's metamodel. IoTLink provides applications that are platform-independent, and they can be transferred into a specific platform like Java. However, one disadvantage of IoTLink over other platforms is the lack of a solution for the deployment of the developed applications.

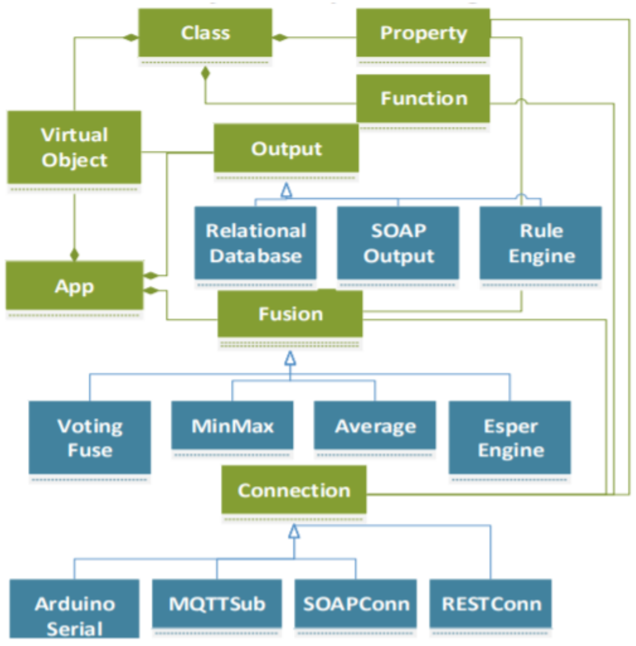


Figure 1: IoTLink abstraction layers' metamodel.

Another platform is DataTweet [9] where the goal of its designers is to develop a platform that eases the development of an IoT application. This platform has two main entities. The first entity is application logic and the second one is common service entity (CSE). The application logic is the part of the platform that IoT stakeholders interact with. They use it to design user interfaces and implement the logic of the application. The CSE takes care of common tasks among all IoT applications. Some of these common procedures provide modules that enable using popular IoT protocols like HTTP and MQTT. The other common services provided are the registration of new applications and devices, device configuration management, data processing, and security. The CSE provides abstractions in the lower IoT environment that helps the developers to focus on the application logic.

2.2 Real-Time analysis of IoT data

In IoT, data from heterogeneous sources are often streaming data to servers, and an IoT platform must be able to integrate these streams of data and provide tools for the discovery of knowledge and analysis of data. The large scale of the data and the dynamic environment of information are some of the challenges of real-time analysis of the data streams.

One of the efforts for analyzing the streams of data is complex event processing (CEP) [10]. CEP is a kind of stream processing system that performs queries on data without any need to store the data. After defining patterns for the CEP engine, it is capable of finding and matching those patterns in the continuous stream of data. CEP has a wide range of applications in areas like business activity monitoring, sensor networks and market data [11]. Esper [12] is a popular compiler and runtime environment for CEP that is available for Java and .NET.

Other open-source frameworks that enable analysis on streams of data include S4 [13], Apache Storm [14] and Apache Spark [15]. S4 [13] is a stream processing engine that has inspired by MapReduce to build a distributed platform. S4 uses Hadoop in order to have a MapReduce model for its engine. Using MapReduce helps to parallelize the tasks and run them on a cluster of nodes. A problem with S4 is that the engine does not perform the load balancing in the cluster automatically.

Apache Storm [14] is a real-time distributed stream processing engine that is able to perform computations for large amounts of data. Since Storm is running on a cluster of nodes, it is easily scalable by adding computational nodes. Running on a cluster of nodes has made Storm applications fault-tolerant because any failure of a node will be handled by other nodes in the cluster.

Currently, Apache Spark [15] is the most popular framework for big data analytics on clusters. Spark introduced a resilient distributed dataset (RDD) which is the fundamental data structure in Spark. RDDs are portioned across machines and if one of them fails other RDDs can rebuild the lost RDD which makes Spark fault-tolerant. RDDs have a caching process in memory that makes Spark 10 to 100 times faster than the Hadoop in some operations. Spark Streaming is a powerful library provided by Spark to process the continuous streams of data with high throughput and fault tolerance. Although Spark has interfaces for Scala, Python, Java, and R, it is still hard for people with low programming skills to set up a Spark environment, write programs and benefit the advantages of Spark.

Although frameworks like Apache Spark, Apache Storm, and S4 offer various tools for processing streams of data, they are not commonly used for other stages of IoT application development. We prefer to use frameworks that, besides being able to process streams of data, can integrate with heterogeneous data sources like MQTT, Kafka, TCP, and REST and also have compatibility with IoT hardware like Arduino, Raspberry Pi, or Android-based devices. In addition, platforms with visual programming interfaces make the development and management of IoT applications much more accessible for IoT application stakeholders.

2.3 Incremental learning

Nowadays, online users produce a huge amount of data every second from all around the world. Every second, Google receives about 63 thousand search queries, around 6 thousand tweets are published on Twitter, almost 58 thousand videos are viewed on YouTube, and around 280 transactions happen in Walmart. Companies analyze all these generated data to make the best customer experience and increase their revenue. We also have a similar situation in other areas, like smart cities. Sinaeepourfard, et al. [16] have done a study in the city of Barcelona. They performed an estimation of the amount of data that will be transmitted from sensors in the case of complete sensor coverage in the city. They measured that each day around 8 GB of data will be transmitted from sensors. This projection excludes the data that can be acquired from many other sources such as mobile devices, surveillance cameras, or web services.

Machine learning methods are used to take advantage of this huge amount of data to get insights about the behavior of the system. Classical machine learning approaches need the whole batch of data to perform their training. These methods are not suitable for an environment that the data is constantly updating since we need our models to be reflective of the new changes. With the arrival of new data, batch-learning methods need to do the whole training process again and discard the former model which is time-consuming and expensive regarding the computational resources.

In order to overcome the aforementioned problems, it is necessary to come up with ways to train models on streams of data. This approach would let the model be up to date and be representative of the latest changes in the data. Incremental or online learning is the name that is assigned to these models. These models continuously integrate the data into the model and spend less amount of time and space which makes them a suitable option for real-time learning of large amounts of data. The definition of an incremental learning algorithm is an algorithm that generates from a given stream of training data $s_1, s_2, \ldots\ s_t$ a sequence of models $h_1, h_2, \ldots h_t$. The model h_i only depends on h_{i-1} and the recent p examples $s_i, \ldots\ s_{i-p}$ with p being strictly limited.

According to the number p which is the number of instances that the model trains at once, we can have either batch-incremental (p>1) or instance-incremental (p=1) learning. In batch-incremental learning, every p example of data forms a batch and a classical batch-learning method trains on the batch. Each training on each batch creates a model. In this method, depending on the size of the window (p), we might end up having a large number of models. Due to storage limitations, we may be forced to delete the older models to have storage space for the new models. Then a voting method decides the prediction based on all the results that have been achieved from all the existing models. This method has significant disadvantages. First, the model needs to wait for a batch to get full then it will start learning the new examples. The second problem happens when parts of data that have been trained by the deleted models are somehow discarded from our training process. Lastly, different voting schemes would have to be analyzed and tested to find the one that best fits the problem.

On the other hand, instance-incremental methods train on every instance of data as it arrives. These methods have solved some of the problems of batch-incremental methods, however, they also have their own disadvantages. There are fewer algorithms available for instance-incremental learning and not every classical machine learning algorithm can be modified to train on instances. When learning on instances, at the beginning of the training process, we cannot expect the model to have relatively accurate predictions and depending on the data, the model needs to see a minimum number of instances before starting to perform well.

Authors in [17] investigated a variety of methods for both batch-based and instance-based methods of incremental learning for classification. They considered Support Vector Machines, Decision Trees, and Logistic Regression for batch-incremental learning, and Naive Bayes, Hoeffding Tree ensembles, and Stochastic Gradient Descent for instance incremental learning. Then they carried out an extensive number of experiments by training on both synthetic and real data. After comparing the results, they concluded that instance-incremental methods perform as well as their equivalent batch-learning methods while using fewer time and memory resources.

Chapter 3

Approach

In this Chapter, I will walk through the proposed approach for building incremental learning solutions that are easy to develop in an IoT environment. First, we discuss what is Node-RED as a flow-based IoT tool and how its features have made the development of IoT products much easier. Then Python's incremental library Creme [18] will be introduced. I will then explain how I used Creme to build a set of essential tools in Node-RED, in order to solve a good range of machine learning problems for a data stream environment.

3.1 Node-RED

Node-RED is an open-source tool for building Internet of Things (IoT) applications. Node-RED is web-based and provides browser-based editor. It uses predefined blocks of codes that are called nodes and wire these nodes together to perform a specific task (Figure 2). There are three kinds of nodes: input nodes, processing nodes, and output nodes. A set of connected nodes that carry out a specific task creates a 'flow'. In addition to IoT, Node-RED has been used in a wide range of applications which has resulted in a large user base and an active developer community.

Node-RED was first created by IBM researchers Nick O'Leary and Dave Conway-Jones and was released as an open-source project in 2013. IBM built Node-RED because they were "looking for a way to simplify the process of hooking together systems and sensors when building proof-of-concept technologies for customers". Node-RED now is part of the OpenJS Foundation.

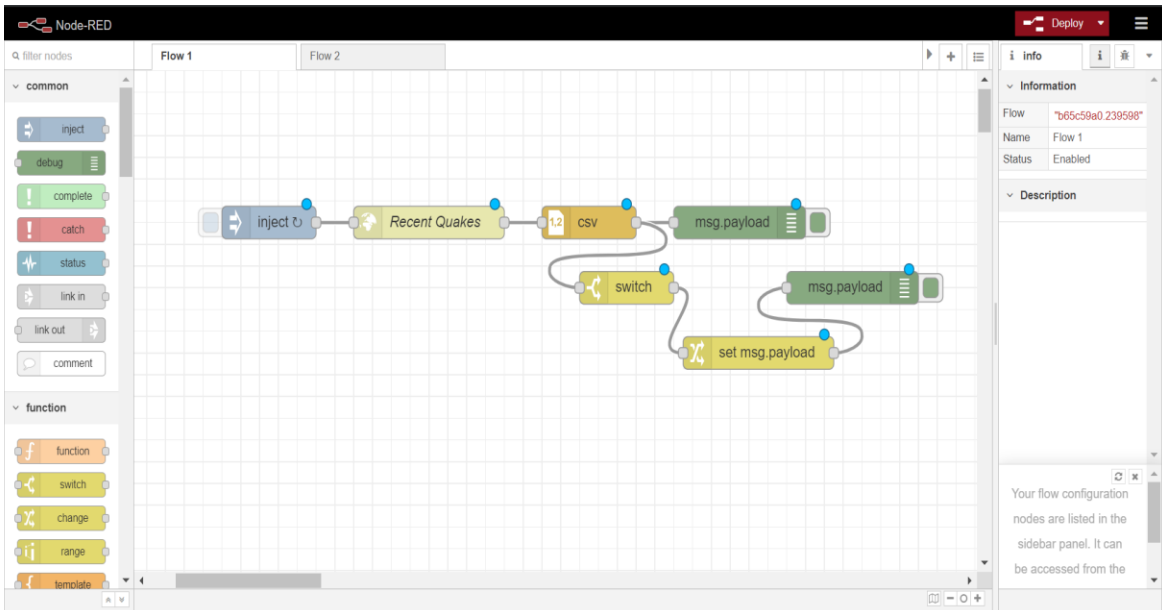


Figure 2: An example of a flow in Node-RED's browser-based editor.

The set of built-in nodes that Node-RED offers, which are accompanied by the visual representation, have hidden the complexity of developing lots of tasks. Developers can quickly put these nodes together to create flows. Node-RED has also an active developer community that works on the core code or to design new nodes and flows to publish in the Node-RED library. They keep developing new nodes and share them with other developers. Node-RED also provides a function node that allows a user to write their own functions using JavaScript. The ease of use that hides the programming details, the growing set of predefined nodes by the developer community, and the flexibility in defining new nodes and functions have made Node-RED a strong tool for the development of IoT applications. In this project, Node-RED version 1.0.0 has been used.

3.1.1 Node-RED's editor components

Node-RED's editor has four components that are shown in Figure 3.

3.1.1.1 Palette

Palette shows the list of the installed nodes in Node-RED (Figure 4) and it's located on the left side of the editor. These nodes are grouped by their categories. Node-RED has a set of default nodes that will be installed with Node-RED. In version 1.0.0 the existing categories are common nodes, function, network, sequence, parser, and storage.

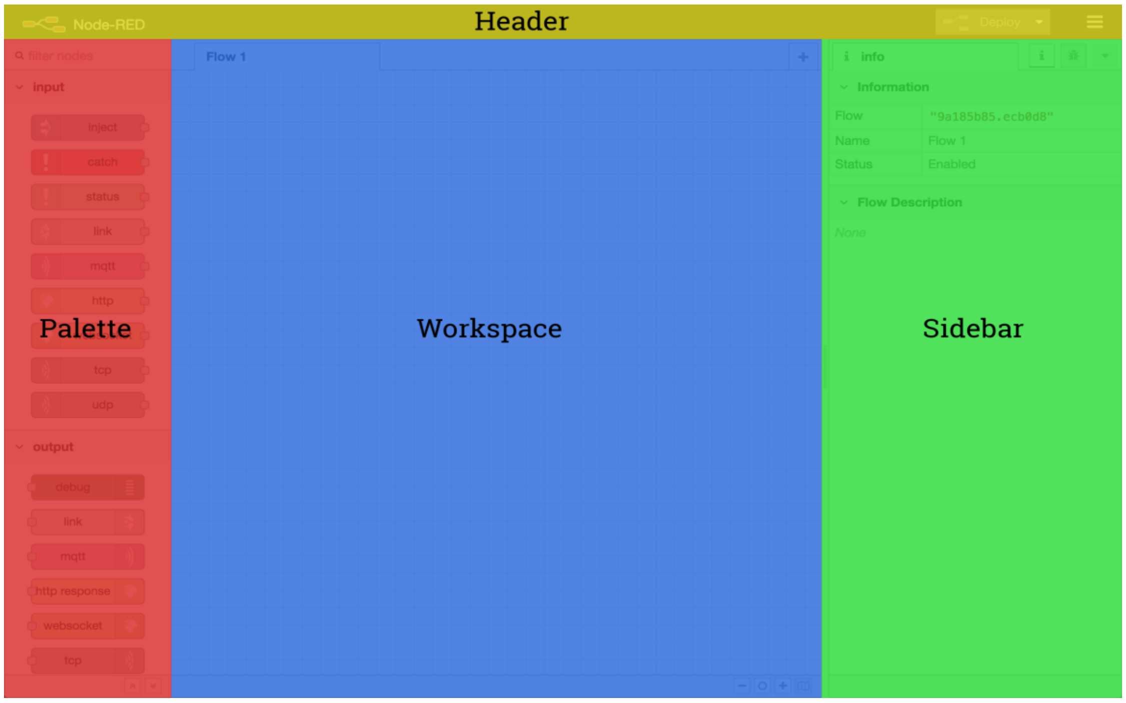


Figure 3: Node-RED's editor components **[19]**.

3.1.1.2 Workspace

Workspace is in the middle of the editor. Users drag the nodes to the workspace and wire them together to create and design flows. A user can have multiple flows in one workspace and also can create multiple workspace tabs (Figure 5Figure **5**)

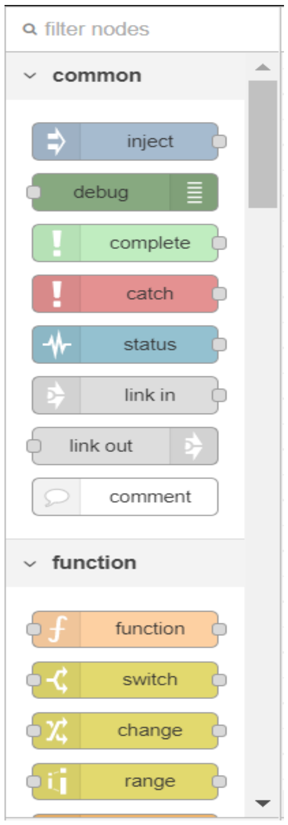


Figure 4: Node-RED's palette.

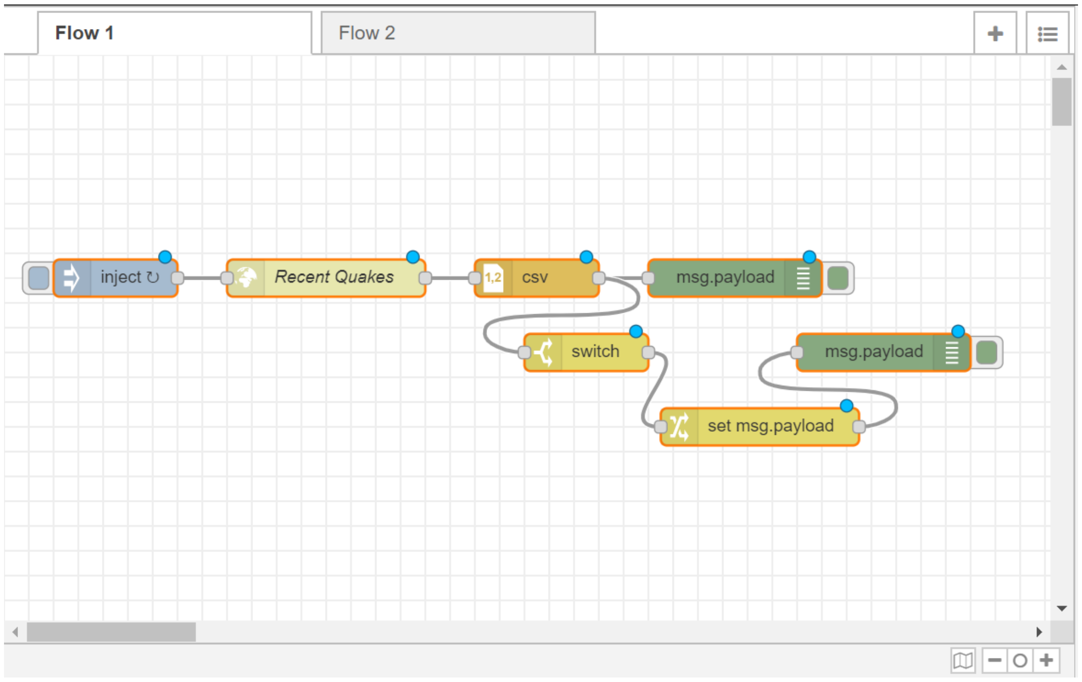
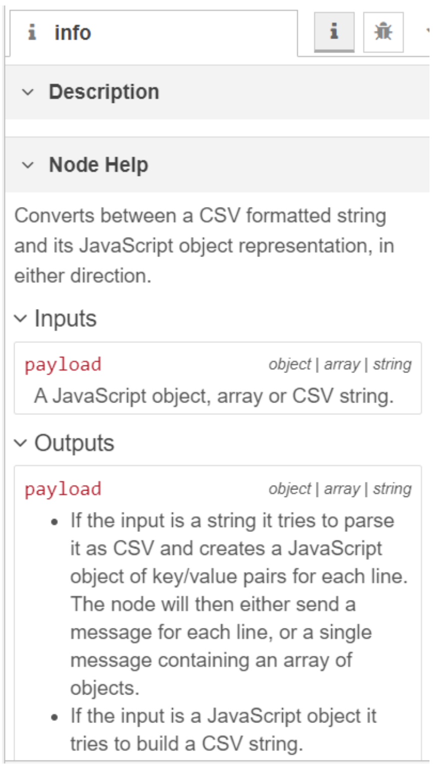


Figure 5: Node-RED's workspace.

3.1.1.3 Sidebar

The sidebar is located at the right side of the editor and contains four sub-panels: node information panel, debug panel, configuration panel and context panel. When a node is selected, the node's information bar shows the node's help information. Figure 6 shows a part of the information sidebar for the CSV node. It explains the functionality of the node, inputs, and outputs.

The other panel in the sidebar is the debug message panel that is responsible for displaying the logs in the flow. It shows messages that have passed through Node-RED's debug nodes. By default, the debug message displays all the debug nodes' messages, but it is possible to filter them to only see the messages of the selected nodes. Figure 7 shows the debug sidebar displaying the messages that have been received by the debug node.



Converts between a CSV formatted string and its JavaScript object representation, in either direction.

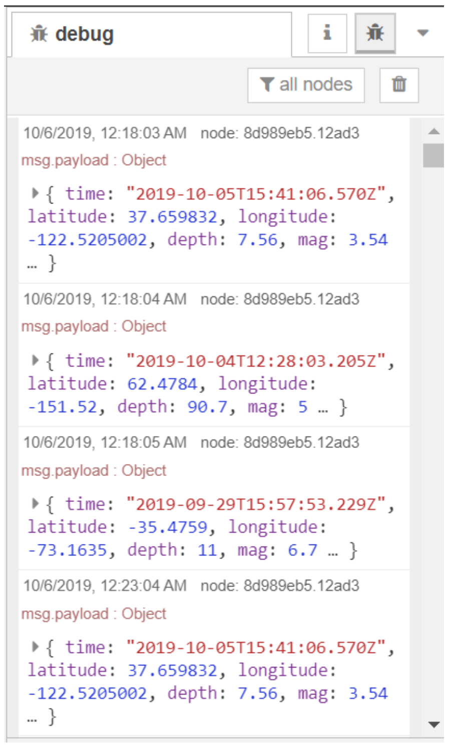
Inputs

payload object | array | string
A JavaScript object, array or CSV string.

Outputs

payload object | array | string
- If the input is a string it tries to parse it as CSV and creates a JavaScript object of key/value pairs for each line. The node will then either send a message for each line, or a single message containing an array of objects.
- If the input is a JavaScript object it tries to build a CSV string.

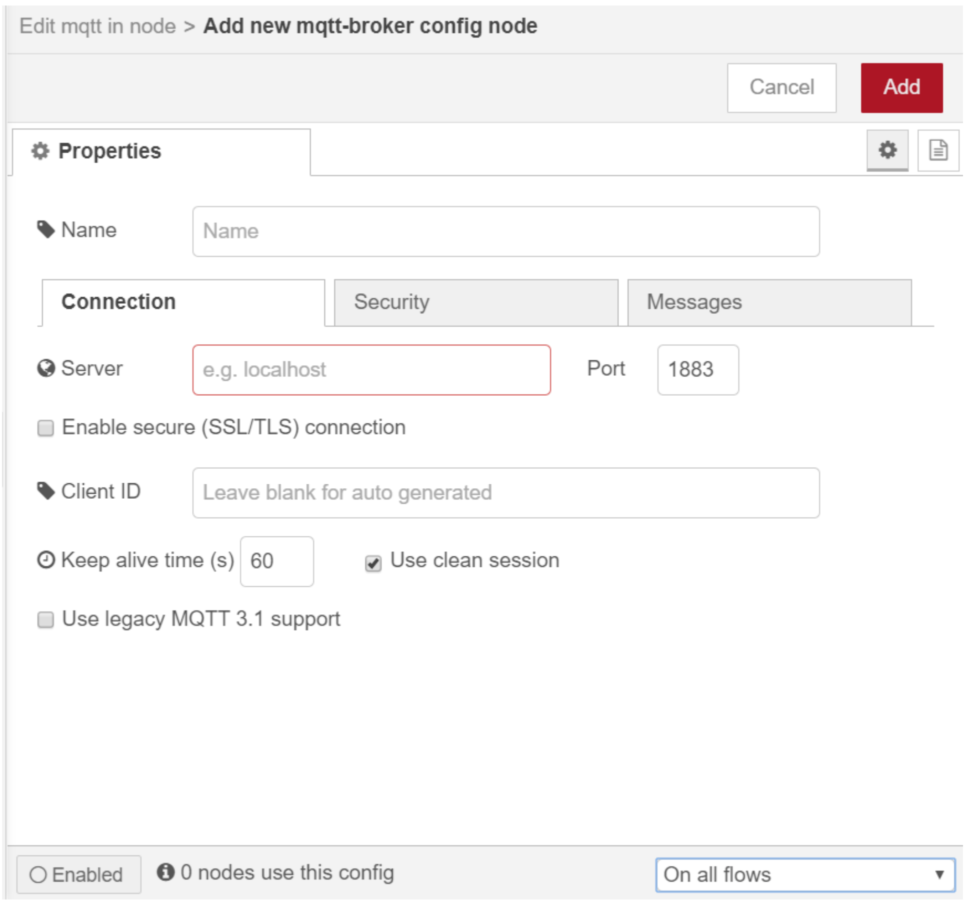
Figure 6: Information sidebar for the CSV node.



```
10/6/2019, 12:18:03 AM   node: 8d989eb5.12ad3
msg.payload : Object
▸{ time: "2019-10-05T15:41:06.570Z",
latitude: 37.659832, longitude:
-122.5205002, depth: 7.56, mag: 3.54
… }
10/6/2019, 12:18:04 AM   node: 8d989eb5.12ad3
msg.payload : Object
▸{ time: "2019-10-04T12:28:03.205Z",
latitude: 62.4784, longitude:
-151.52, depth: 90.7, mag: 5 … }
10/6/2019, 12:18:05 AM   node: 8d989eb5.12ad3
msg.payload : Object
▸{ time: "2019-09-29T15:57:53.229Z",
latitude: -35.4759, longitude:
-73.1635, depth: 11, mag: 6.7 … }
10/6/2019, 12:23:04 AM   node: 8d989eb5.12ad3
msg.payload : Object
▸{ time: "2019-10-05T15:41:06.570Z",
latitude: 37.659832, longitude:
-122.5205002, depth: 7.56, mag: 3.54
… }
```

Figure 7: Debug message sidebar.

The configuration node allows the nodes to create and share a specific configuration to other nodes. For instance, the “MQTT in” node can share the configurations for connecting to the MQTT broker with the node “MQTT out” since they are both using the same MQTT broker. Configurations are globally scoped by default which means they can be used in different flows. Figure **8** shows the configuration node for the node “MQTT in”.


Edit mqtt in node > **Add new mqtt-broker config node**

Cancel | Add

Properties

Name: Name

Connection | Security | Messages

Server: e.g. localhost   Port: 1883

☐ Enable secure (SSL/TLS) connection

Client ID: Leave blank for auto generated

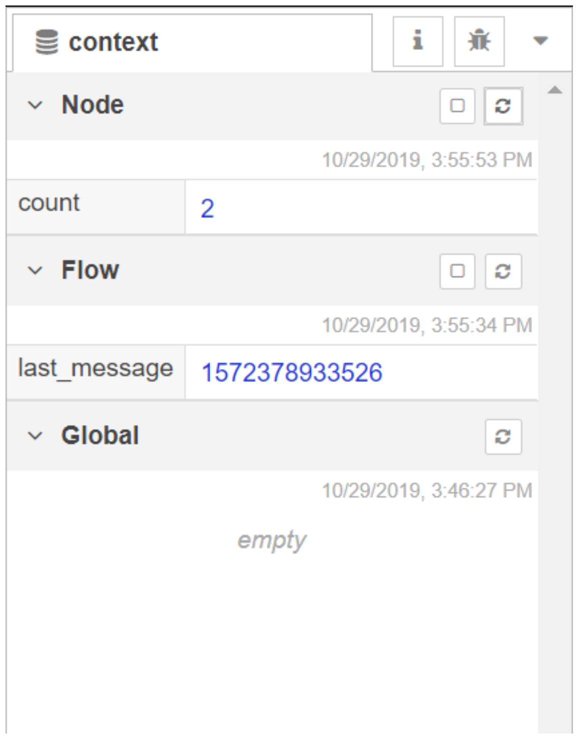
Keep alive time (s): 60   ☑ Use clean session

☐ Use legacy MQTT 3.1 support

Enabled   0 nodes use this config   On all flows

Figure 8: configuration node for the node MQTT.

In Node-RED, messages are not the best place for storing variables because when a new message arrives it will be replaced with the former message and we lose the former message information. Node-RED has created context variables for storing information. Every context variable has a scope. The scopes are node, flow and global. The node scope means that only the node that has set the value of the context variable has access to that variable. Flow scope means when a node puts value in a context variable, all the nodes in the same flow have access to that context variable. And finally, the global scope means all the nodes in all the flows have access to the context variable. Figure 9 pictures the context panel of the sidebar. In the context panel, we can see the list of context variables grouped by their scope.



10/29/2019, 3:55:53 PM

count	2

10/29/2019, 3:55:34 PM

last_message	1572378933526

10/29/2019, 3:46:27 PM

empty

Figure 9: Context panel

The palette manager and the edit dialog are two other important components in Node-RED that need to be explained.

3.1.1.4 Palette Manager

The other important section of the Node-RED's editor is the palette manager (Figure 10) that can be accessed by clicking the palette tab in the user settings. Under the nodes tab, we can see the installed nodes. Users can disable or remove a specific node through this window. The other tab is the install tab that gives the ability to search through the repository of nodes in the Node-RED library and add them to the Node-RED's local set of nodes by installing them.

3.1.1.5 Edit Dialog

By double-clicking a node in the workspace, edit dialog will pop up. Edit dialog has three tabs:

- The Properties tab shows the features and parameters of a node that can be changed by the developer. Figure 11 shows the properties of a CSV node.
- The Description tab allows the developer to write any explanation about the node. This description will be displayed in the sidebar.
- The Appearance tab allows the developers to have small modifications in the appearance of a node like a node's icon.

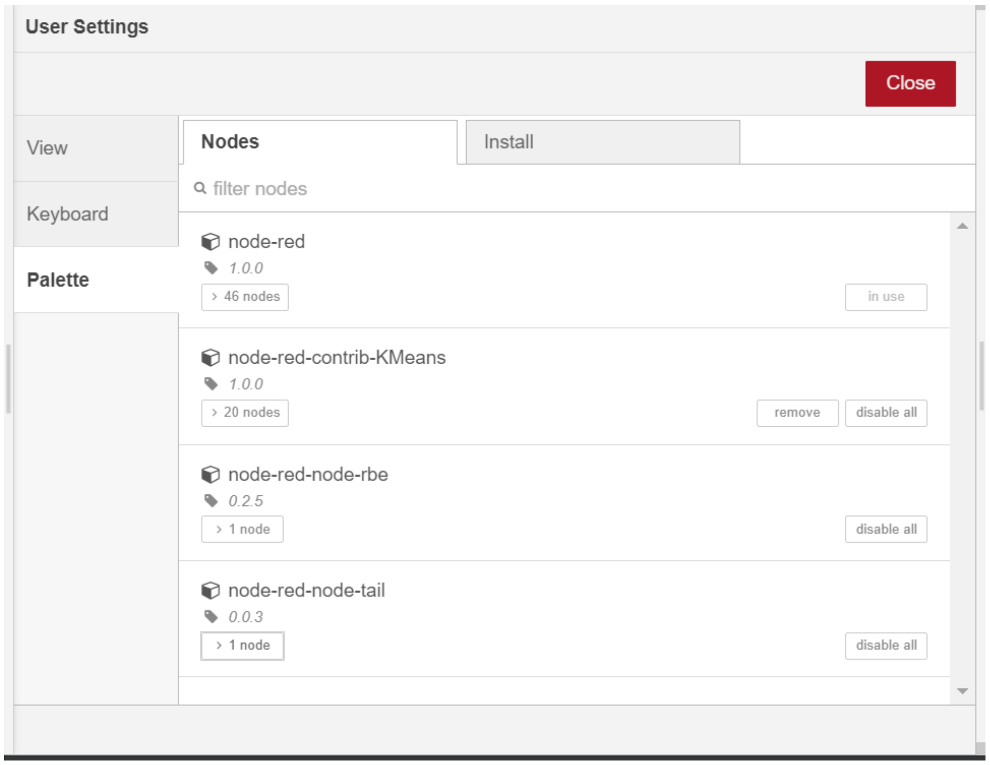
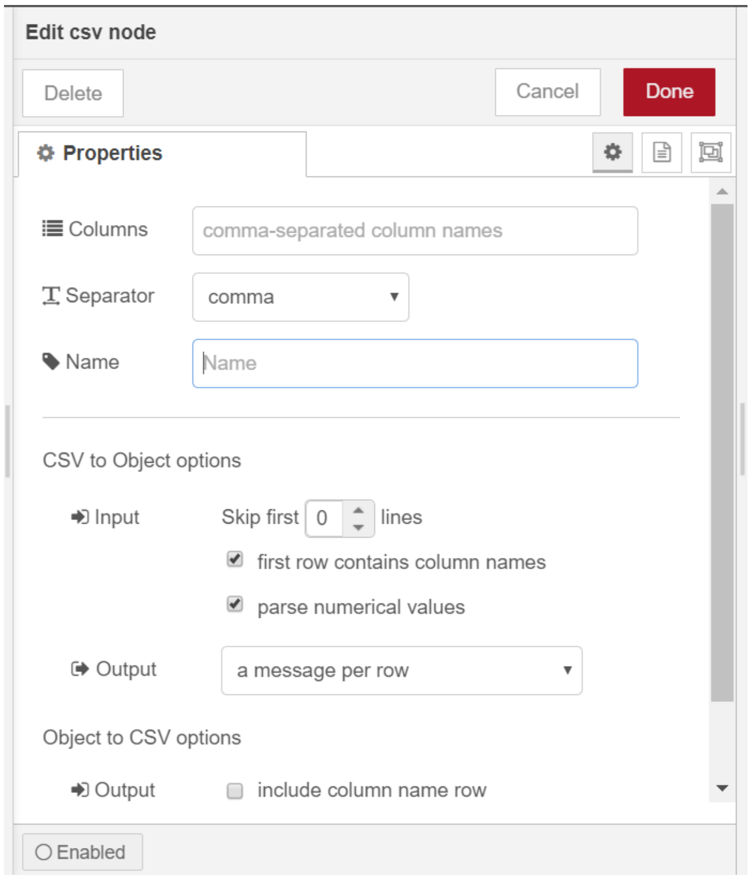


Figure 10: Node-RED's palette manager.


Edit csv node

Columns: comma-separated column names

Separator: comma

Name: Name

CSV to Object options

Input: Skip first 0 lines

✓ first row contains column names

✓ parse numerical values

Output: a message per row

Object to CSV options

Output: include column name row

Figure 11: properties of a CSV node.

3.1.2 Node-RED programming model

A more detailed look at the Node-RED’s flow-based programming model will be considered in this section. The main components such as messages, nodes, and flows will be explained to get a better understanding of the Node-RED’s architecture.

3.1.2.1 Nodes

Nodes are small predefined functions that carry out a specific task. Just like functions, they receive input, perform a process and then return the outputs. Each node can have at most one input. An input to a node is a message that has been generated by another node. In a node implementation, each node is made of two files. An HTML file that specifies the appearance of a node such as its color, icon, name, node configurations and the information window that explains the node and the parameters of the node. The other file is a JavaScript file that contains the code that runs the node and its specific function.

When the address of the Node-RED is accessed in the browser, the codes for each node are loaded in the browser.

There are three types of nodes:

- Input nodes: These nodes initialize the start of a flow and generate the initial message. An external stimulator like an HTTP request, a click by a user, or a TCP message triggers the input node and causes the flow to start. Input nodes do not have connecting points on the left side which means they cannot have inputs from other nodes.

- Processing nodes: these nodes perform a specific task on each message. They have a connecting dot at the left side of the node that allows them to get inputs from other nodes. After receiving the message, they execute the function and modify the message. Then the updated message will be passed to the node that is connected to the connecting dot on the right side of the processing node. Some of the built-in processing nodes can join, split, switch and change data. If Node-RED does not have a processing node that someone is looking for, it is possible to implement a custom processing node. The function node in Node-RED allows implementing any function by writing a JavaScript code.

- Output nodes: These nodes send the final message outside the Node-RED flow either to the debug console, a device, or as a Kafka message it can send them to the Kafka broker. Output nodes do not have connecting dots on their right side which means they do not send messages to other nodes and they end a flow.

3.1.2.2 Messages

The information that passes through the nodes in Node-RED is called a “message”. A message is simply a JavaScript object with some properties. The most important property of a message is msg.payload that contains the data we are trying to pass from a node to another node. The payload property can contain data of any type like string, Boolean, number, JavaScript object, etc. The other property of a message is msg._msgid that can be used to assign an id to the message which is useful for debugging process. The other property is msg.topic that allows assigning a topic to the message to increase the readability and understanding the purpose of the message. Below we can see an example of a message.

```
{
    _msgid: '1db99c6d.e24664',
    topic: '',
    payload: {}
};
```

Node-RED does not restrain the users and let them add custom properties to their message. Since msg.payload can get modified when a message passes through nodes, we can use custom properties to pass specific data to a certain node.

3.1.2.3 Flows

A flow is a set of connected nodes that exchange messages to perform a specific task. Under the hood, Node-RED stores flows as JavaScript objects that describe how the nodes are connected and what each node configuration looks like.

3.1.3 Building a node in Node-RED

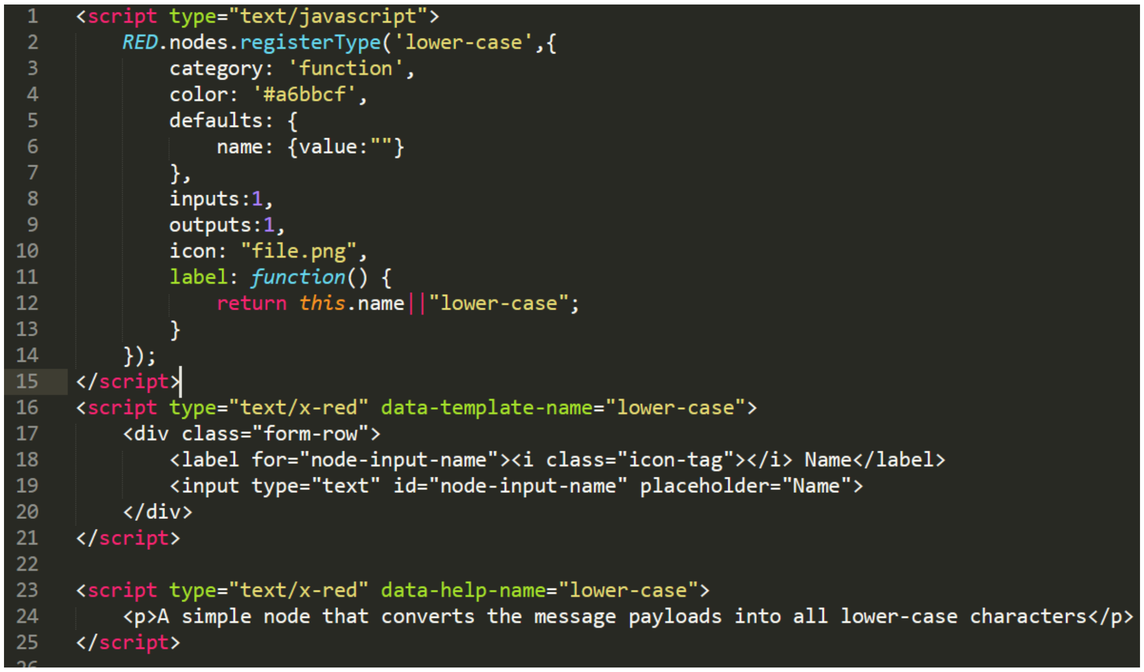
In order to define a new node, three files must be created. An HTML file that specifies the node's appearance, a JavaScript file that defines the functionality of a node, and a JSON file that prepares a node to be installed with Node.JS package manager npm. Since Python is used to take advantage of its capabilities in online machine learning, each node usually has a Python file as well as the other three files. An overview of the structure of each file will be presented in the following.

3.1.3.1 HTML file

The HTML file consists of three sections where each is inside a <script> tag. Figure **12** is the HTML file for a node called "lower-case" that can show these sections. This node converts all the characters of the message payload to lower case characters.

1. The first section registers a node in Node-RED's list of local nodes. The default values of a node's parameters, the node's icon, its color, and the category that it belongs are defined in this section.

2. The second segment which is defined under the type “text/x-red” with “data-template-name” defines the node’s name and specifies the properties of the node that can be edited by the users and their input type.
3. The help segment which is identified by assigning the “data-help-name” to the node’s name, allows the developer to write a help description for the node to explain any information about the node.



```
<script type="text/javascript">
    RED.nodes.registerType('lower-case',{
        category: 'function',
        color: '#a6bbcf',
        defaults: {
            name: {value:""}
        },
        inputs:1,
        outputs:1,
        icon: "file.png",
        label: function() {
            return this.name||"lower-case";
        }
    });
</script>
<script type="text/x-red" data-template-name="lower-case">
    <div class="form-row">
        <label for="node-input-name"><i class="icon-tag"></i> Name</label>
        <input type="text" id="node-input-name" placeholder="Name">
    </div>
</script>

<script type="text/x-red" data-help-name="lower-case">
    <p>A simple node that converts the message payloads into all lower-case characters</p>
</script>
```

Figure 12: The HTML file of a node called “lower-case”

3.1.3.2 JavaScript file

The JavaScript file defines the logic and behavior of a node. Some of the main parts of the JavaScript file are:

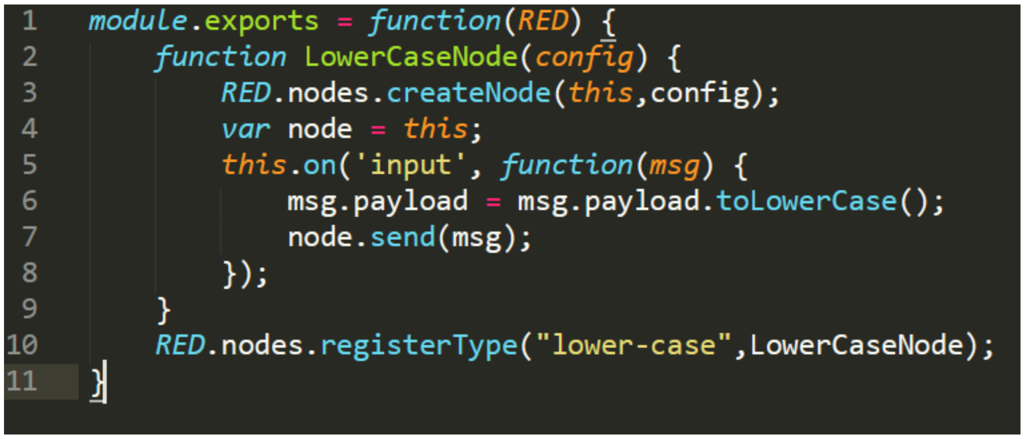
1. Constructor: it is responsible to create an instance of the node. It receives the parameters that are set by the user in the edit dialog and assigns them to the node’s instance.

2. Message listener: an event listener will be registered to hear the messages that are arriving at the node and perform a specific operation upon receiving the message.

In addition, we can listen to the errors that might happen during the process of handling a message.

3. Sending a message: after processing the input message, the node can send a message to the connected nodes.

Figure 13 shows the aforementioned sections in the Javascript file of the lower-case node.

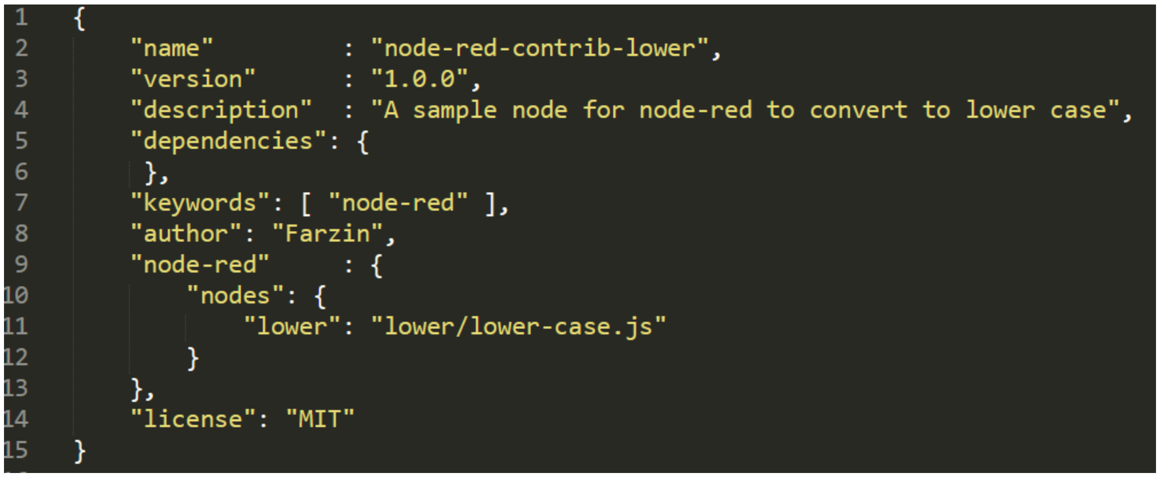


```
module.exports = function(RED) {
    function LowerCaseNode(config) {
        RED.nodes.createNode(this,config);
        var node = this;
        this.on('input', function(msg) {
            msg.payload = msg.payload.toLowerCase();
            node.send(msg);
        });
    }
    RED.nodes.registerType("lower-case",LowerCaseNode);
}
```

Figure 13: Javascript code of an example node called “lower-case”

3.1.3.3 Package.json file

Like any other module in NodeJS, in order to install a node, a package.json file is needed to describe the module. Information like the list of nodes in the module, the given name to the list of nodes, authors’ names, and the license are mentioned in this file. Figure 14 shows the json file for the lower-case node.



```
{
    "name"          : "node-red-contrib-lower",
    "version"       : "1.0.0",
    "description"   : "A sample node for node-red to convert to lower case",
    "dependencies": {
     },
    "keywords": [ "node-red" ],
    "author": "Farzin",
    "node-red"      : {
        "nodes": {
            "lower": "lower/lower-case.js"
        }
    },
    "license": "MIT"
}
```

Figure 14: JSON file for the lower-case node.

3.1.4 Deployment of a Node-RED application

Since we are running Node-RED in the terminal, Node-RED is a child process of the shell. This means that when we shut down the terminal, the Node-RED application will be also terminated. In order to keep the Node-RED application running, we need to detach the process from the terminal. We can use the *screen* command for detaching a process from the terminal. The details of using this command for attaching and detaching a process can be found in [20]. As an example, the flow shown in Figure 15 is an application that publishes the current timestamp as a Kafka message. A python application was also programmed to consume Kafka messages. After running the application, I detached the Node-RED process from the terminal and closed the terminal. We can even close the Node-RED editor in the browser and the application keeps running. Figure 16 shows the messages received by the consumer while I had closed the terminal and Node-RED editor. We might also consider deploying our application in a remote machine. We can use a cloud-computing platform like Amazon Web Services for hosting our application. Amazon EC2 provides virtual machines that can be rented and be used to host our application. First, we need to install Node-RED in the remote virtual machine. Then we need to use a process manager like PM2 [21] to run Node-RED on boot and to ensure that it is always running in the background.

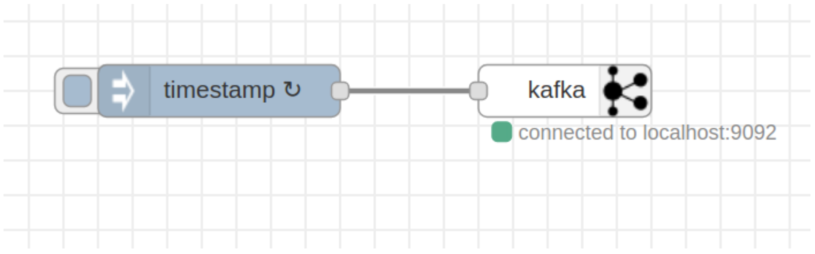
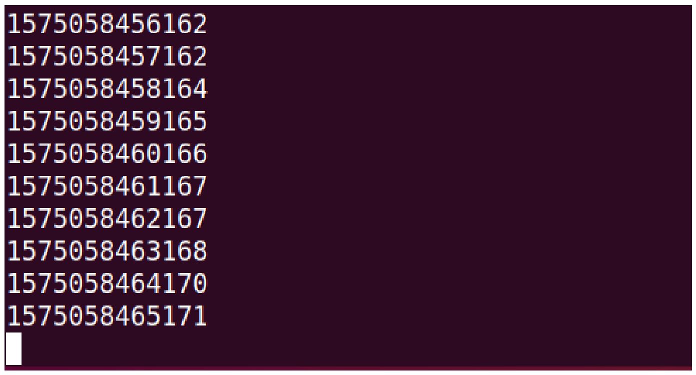


Figure 15: The flow for publishing the current timestamp



```
1575058456162
1575058457162
1575058458164
1575058459165
1575058460166
1575058461167
1575058462167
1575058463168
1575058464170
1575058465171
```

Figure 16: The messages received by Kafka consumer

3.2 Incremental learning with Creme

Creme is an online machine learning library for Python. It is written with Python and the style of APIs is inspired by Python's machine learning library Scikit-learn [22]. Creme can train on streams of data. In contrast to batch learning that needs to have access to the entire data, Creme has been designed to train machine learning models by receiving one instance of data at a time.

Creme provides different sets of tools for developing an online machine learning model and they are continuously adding more features to their library. Binary and multi-class classifiers, regressors, unsupervised clustering, ensemble learning, and tools for data preprocessing and feature extraction are some of the main parts of their library.

For some operations like scaling the data, the model needs the whole data to compute the mean and variance. However, receiving the data in a stream format creates the need for creating new methods to compute these statistics. Creme has developed a set of functions called “running statistics” that compute an online version of operations like mean, variance, entropy, correlation, etc. These functions are also used to build some of the training methods. For instance, KMeans uses the running mean to update its centers and clusters.

3.3 Building incremental learning nodes for Node-RED

Node-RED’s developer community has designed various machine learning nodes for Node-RED, however, all the nodes are only designed for batch-oriented machine learning. These methods usually store the whole data in a file and then train a model on that data. IoT data is usually in the form of a stream so it is important to have learning methods that can handle stream data and find the patterns in real-time. I used Python and the Creme library to build a set of nodes for Node-RED that makes it possible to perform online machine learning tasks in Node-RED.

A typical approach to train a machine learning model consists of preparing the data, picking the right model, training, evaluating the results, and then using the trained model to perform predictions on the new data. I have developed a set of nodes that are considered essential tools for covering a normal range of machine learning problems, including models for both supervised and unsupervised learning and different tasks such as classification, regression, and clustering.

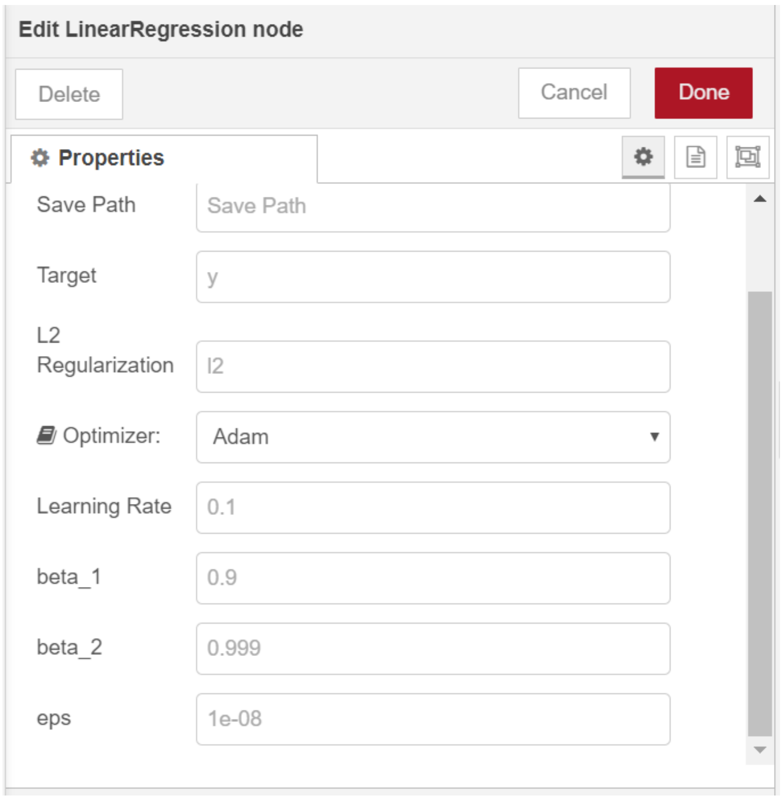
3.3.1 Training

Different nodes for training machine learning models have been implemented. Any training node follows three steps after receiving an instance of the data. In the first step, before training on the new data, the model predicts the target based on the existing model. This gives us the opportunity to see how the model performs and to evaluate the model at every single step. It helps us to monitor the progress of the model’s performance from the very beginning of the training process. This way there is no need to split some part of the data for validation because for any instance of the training data a validation test happens. In the second step, the model trains on the data based on the true value of the target, and at the last step, it saves the updated model as a file.

Now different types of training models will be discussed.

3.3.1.1 Regression

Linear regression is a common approach for data analysis and building predictive models. Developers need to specify some parameters of the model in the editor, otherwise, default values will be assigned. One of the parameters is the optimization technique. Developers can pick from AdaBound [23], AdaDelta [24], AdaGrad [25], Adam [26], Momentum [27], NestrovMomentum [27], RMSProp [27], VanillaSGD [28], and FTRLProximal [29]. Any of these optimizers have their own set of parameters that can be set. For example, if we pick Adam, as we can see in Figure 17, the parameters that are needed for Adam's optimization will pop up. The other parameters that are needed for linear regression are L2 regularization amount, address to save the model, and the target value's name.



Save Path	Save Path
Target	y
L2 Regularization	l2
Optimizer:	Adam
Learning Rate	0.1
beta_1	0.9
beta_2	0.999
eps	1e-08

Figure 17: Example of Linear Regression's node properties.

3.3.1.2 Binary classification

Binary classification is a type of problem where the target can only have two possible values. For this type of machine learning problem, a logistic regression node has been implemented. The logistic regression node's parameters are the path to store the model, L2 regularization, name of the target index, and the optimization technique.

3.3.1.3 Multi-class classification

Machine learning problems where the target value has a range of more than two classes are called multi-class classifications. This is a generalization of binary classification problems. The first node that has been implemented to solve these problems is the multinomial logistic regression which is a generalization of logistic regression for multi-class classification. The parameters of multinomial logistic regression are the same as logistic regression.

The other classifier implemented is one-vs-rest classifier. This method assigns a binary classifier for each class of the target value. For stream data, since we may not know the number of classes in the beginning, the one-vs-rest classifier can be suitable because it generates a classifier on the fly for each new class. The parameters are the same as logistic regression since each of the independent binary classifiers is a logistic regression classifier.

The third classifier is the decision tree classifier that is implemented based on the work of Domingos et al. [30]. The parameters are *patience*, which is the timeout parameter between split attempts [31], maximum tree depth, the minimum number of child samples, confidence, and tie threshold. Those developers who do not have enough information about the parameters can leave them blank so the default values would be assigned.

The last classifier for multi-class classification is Gaussian naive Bayes. This method assigns a gaussian distribution for each class of the target. The parameters are model save path and the target name.

3.3.1.4 Unsupervised clustering

Unsupervised clustering refers to problems in machine learning where the aim is to divide unlabeled data into clusters with similar features. For this purpose, a KMeans node has been implemented. For KMeans the user needs to specify the number of clusters, half-life, mu, and sigma. In incremental KMeans, each instance is assigned to the closest cluster and then the center of the cluster will move toward the new instance. The half-life parameter determines the amount that the center of the cluster will move toward the new assigned instance. *Mu* and *sigma* are the mean and standard deviation of the normal distribution that instantiates the cluster positions.

3.3.2 Metrics

Two metric nodes are designed for evaluating the results of the training nodes. After every training node, a metric node can be used to compute the performance of the model. Metric nodes need the predicted value and the true value as their inputs. A classification metric node and a regression metric node have been implemented. Classification metric node contains some of the popular metrics for classification problems. With the classification metric node, a developer can pick any method from the options accuracy, cross-entropy, macro F1, macro precision, macro recall, micro F1, micro precision, and micro recall.

Accuracy is the percentage of the correct predictions. Cross-entropy is the other metric that for a classification problem with 2 classes can be calculated as:

$$-(y\log(p) + (1-y)\log(1-p)) \ .$$

Where y is the binary class of the target value (0 or 1), and p is the predicted probability of the class.

F1, precision, and recall are also widely used for evaluating the results of a classification problem. Below we can see how each of these metrics is calculated.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$F1 = 2\ \times \frac{Precision *\ Recall}{Precision +\ Recall}$$

The macro average of each of these metrics for a dataset with two classes is calculated as below:

$$Macro\ Precision = \frac{Precision1 +\ Precision2}{2}$$

$$Macro\ Recall = \frac{Recall1 +\ Recall2}{2}$$

$$Macro\ F1 = 2\ \times \frac{Macro\ Precision *\ Macro\ Recall}{Macro\ Precision +\ Macro\ Recall}$$

And we compute the micro averages of these metrics with the following equations:

$$Micro\ Precision = \frac{True\ Positive1 + True\ Positive\ 2}{True\ Positive1 + False\ Positive1 + True\ Positive2 + False\ Positive2}$$

$$Micro\ Recall = \frac{True\ Positive1 +\ True\ Positive2}{True\ Positive1 + False\ Negative1 +\ True\ Positive2 + False\ Negative2}$$

$$Micro\ F1 = 2\ \times \frac{Micro\ Precision *\ Micro\ Recall}{Micro\ Precision +\ Micro\ Recall}$$

Each of these metrics has its own advantages and depending on the application we might consider different choices. In the macro versions of the above metrics each class has an equal weight in calculating the final value of the metric, however, in the micro version, we aggregate the contributions of each class to compute the final value of the metric. For datasets with imbalanced data, the results of the above approaches might be very different.

The other metric node is a regression metric that computes the performance of regression problems. The methods that regression metric node covers are mean absolute error

(MAE), mean squared error (MSE), root mean squared error (RMSE), root mean squared logarithmic error (RMSLE), and symmetric mean absolute percentage error (SMAPE).

3.3.3 Prediction and Evaluation

The predict node loads a trained model from a given address and performs prediction for the new data. The Predict node has only one parameter and that is the model path.

The evaluation node loads a saved model and performs prediction on the data. The difference between the evaluation node and predict node is that we use the evaluation node when we know the true value of the target value. Based on the predicted value and the true value of the data we can evaluate how the model is performing.

3.3.4 Utility Nodes

In the process of training on a data stream, we might need nodes that perform preprocessing operations. Scaling the data before training is one of the most common preprocessing operations. There are datasets that have features with a large range of magnitudes among the values. Sometimes, having widely varying scales of data can be misleading as some machine learning methods are sensitive to the variance in range and it affects their performance. The Standard Scaler node has been implemented to scale a specified feature in the dataset. It computes the running mean and running variance of the feature and transforms every sample to make the mean 0 and variance 1. The trained scaler model can be saved to be used for scaling the test data in the prediction.

Chapter 4

Experiments and Results

In this Chapter, different experiments are presented to illustrate the use of the nodes added to Node-RED, to show how they can simplify the process of creating applications for analyzing streaming data, and to provide evaluations of the implemented nodes. First, we need to generate streams of data to simulate an IoT environment in which sensors are collecting data and sending them to a central server for analysis. Then we will use the incremental learning nodes to perform learning and prediction on the data streams.

4.1 Stream Data Simulation

In order to evaluate the performance of the incremental learning nodes, we need to have streams of data for the input. Apache Kafka is a popular stream processing platform that offers a real-time and distributed messaging queue. We can use Kafka to publish messages and any number of subscribers can receive the messages with no data loss. I have created a server program that reads the data from a CSV file and publishes each record in the dataset with a specific topic using Kafka. In Node-RED there are nodes for receiving inputs from a Kafka publisher and subscribing to a specific topic.

4.2 Linear regression

For evaluating the linear regression node, we use the Boston housing dataset [32]. It contains information about 506 houses. For each house, there are 13 features and the goal is to train and predict the price of a house. Some of the features in the dataset are per capita crime rate, nitric oxide concentration, the average number of rooms per resident, index of accessibility to radial highways and so on. In the Kafka server, each record of the dataset gets converted to a JSON object and published with the topic named “LR”.

In Figure 18, we can see the flow of nodes for linear regression. In this flow, the nodes Standard Scaler, Linear Regression, and Regression Metric are the new implemented nodes, and the rest of the nodes already exist in Node-RED. We walk through the steps that have resulted in this flow for linear regression prediction.

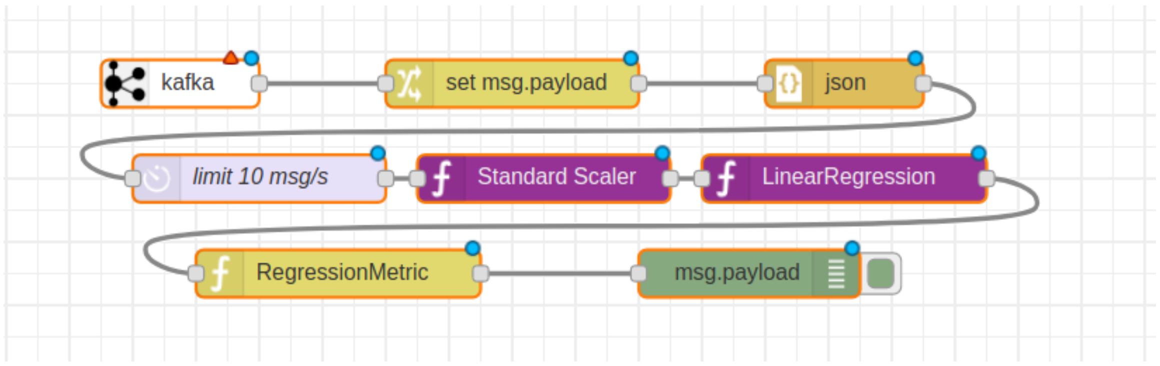
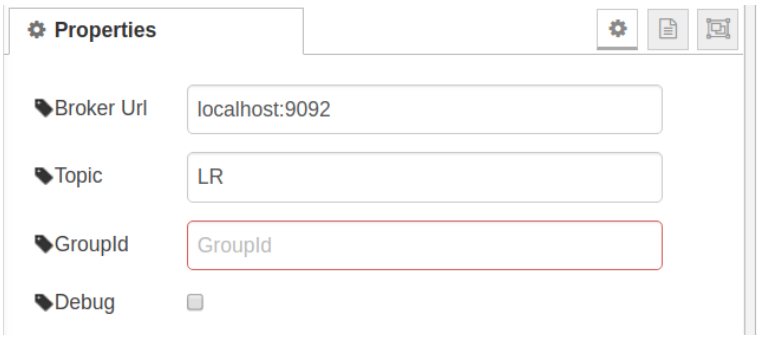


Figure 18: Linear regression training flow.

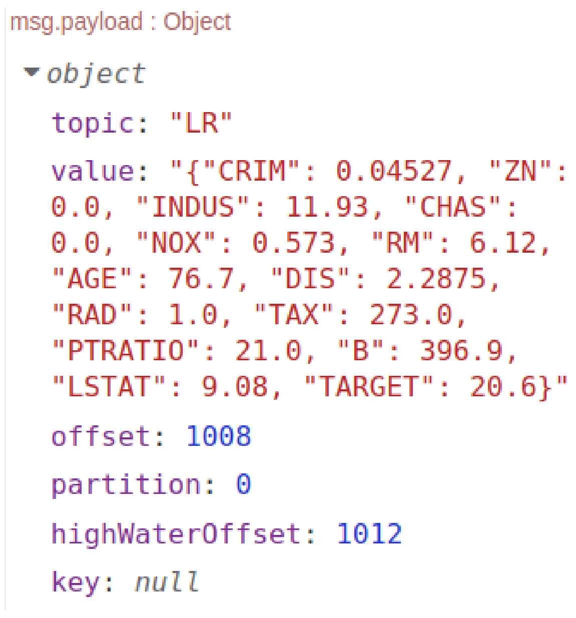
As we can see in Figure 18, we first make use of the Kafka input node to receive the messages from Kafka broker. Figure 19 shows the parameters of the Kafka input node: the Kafka broker URL and the topic of the message for subscription are set. The Group Id is for assigning a Kafka consumer to a specific group. We just leave the group id blank since we are not using any group.


Properties

Broker Url: localhost:9092
Topic: LR
GroupId: GroupId
Debug: ☐

Figure 19: Kafka input node parameters.

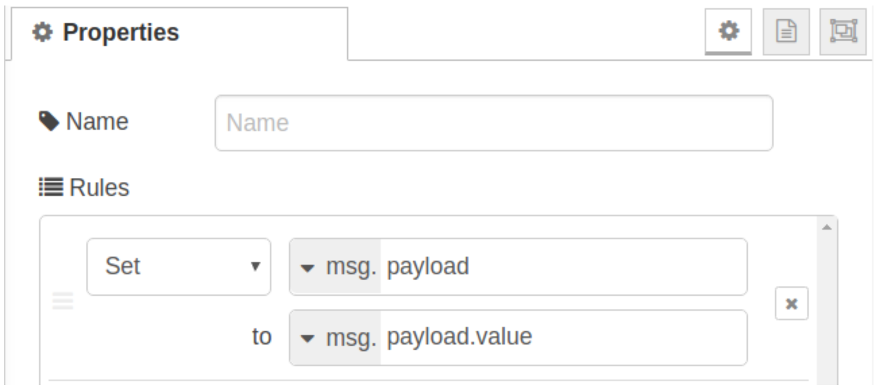
Figure 20 shows a message that has been received from the Kafka input node. This object message has different properties, but we only need the value property for our training because it contains a record of the dataset.



```
msg.payload : Object
▾object
  topic: "LR"
  value: "{"CRIM": 0.04527, "ZN":
  0.0, "INDUS": 11.93, "CHAS":
  0.0, "NOX": 0.573, "RM": 6.12,
  "AGE": 76.7, "DIS": 2.2875,
  "RAD": 1.0, "TAX": 273.0,
  "PTRATIO": 21.0, "B": 396.9,
  "LSTAT": 9.08, "TARGET": 20.6}"
  offset: 1008
  partition: 0
  highWaterOffset: 1012
  key: null
```

Figure 20: Kafka object message with topic LR.

Then we use the node “set msg.payload” to extract the value property of the message and pass it to the next node. Figure 21 shows the parameters of this node. As we can see, it updates the payload of the message to the value property of the message payload.



Properties

Name: Name

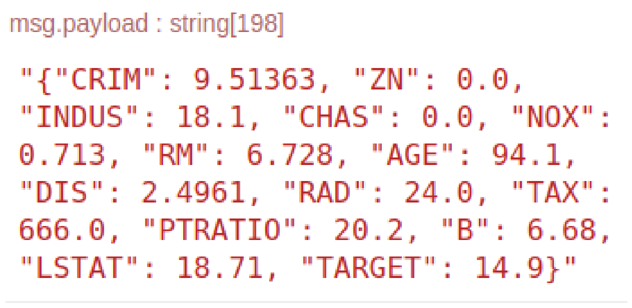
Rules

Set msg. payload

to msg. payload.value

Figure 21: Parameters of the “set msg.payload” node.

As we can see in Figure 22, the output of the “set payload.msg” node is a string that only contains the data that we need for training.

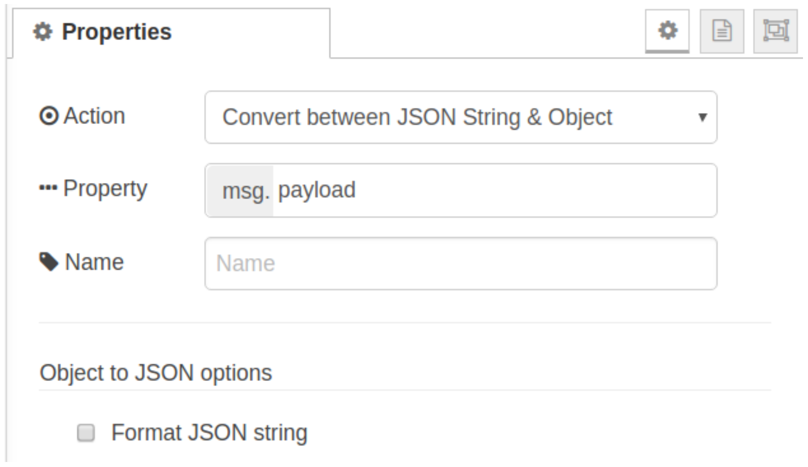


```
msg.payload : string[198]

"{"CRIM": 9.51363, "ZN": 0.0,
"INDUS": 18.1, "CHAS": 0.0, "NOX":
0.713, "RM": 6.728, "AGE": 94.1,
"DIS": 2.4961, "RAD": 24.0, "TAX":
666.0, "PTRATIO": 20.2, "B": 6.68,
"LSTAT": 18.71, "TARGET": 14.9}"
```

Figure 22: The output of the “set msg.payload” node

All the implemented training nodes need to receive their input in the form of a JSON object so we need to convert the string message to a JSON object. For this purpose, I have used the “json” node. Figure 23 shows the parameters of this node.



Properties

Action: Convert between JSON String & Object

Property: msg. payload

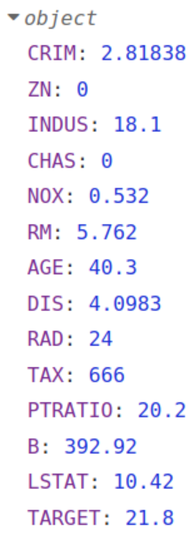
Name: Name

Object to JSON options

☐ Format JSON string

Figure 23: Parameters of the “json” node.

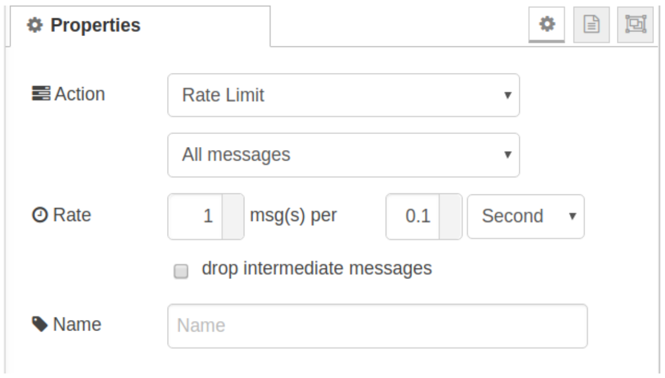
Figure 24 shows the output of the “json” node and we can see that the message has been converted to a JSON object.



```
▾object
  CRIM: 2.81838
  ZN: 0
  INDUS: 18.1
  CHAS: 0
  NOX: 0.532
  RM: 5.762
  AGE: 40.3
  DIS: 4.0983
  RAD: 24
  TAX: 666
  PTRATIO: 20.2
  B: 392.92
  LSTAT: 10.42
  TARGET: 21.8
```

Figure 24: Output of the "json" node.

The next node that has been used is the "limit" node. This node acts as a buffer and controls the speed and the rate of the incoming messages. I have set the limit to 10 messages per second in order to give some time to the training node to get updated. This limit can be increased or decreased depending on the training method. Figure 25 depicts the parameters of this node.



Action: Rate Limit

All messages

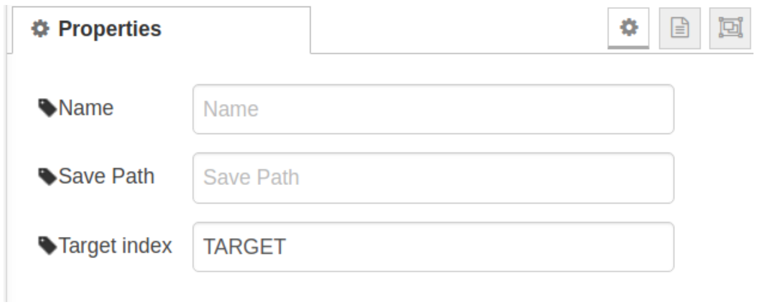
Rate: 1 msg(s) per 0.1 Second

☐ drop intermediate messages

Name: Name

Figure 25: Parameters of the "limit" node.

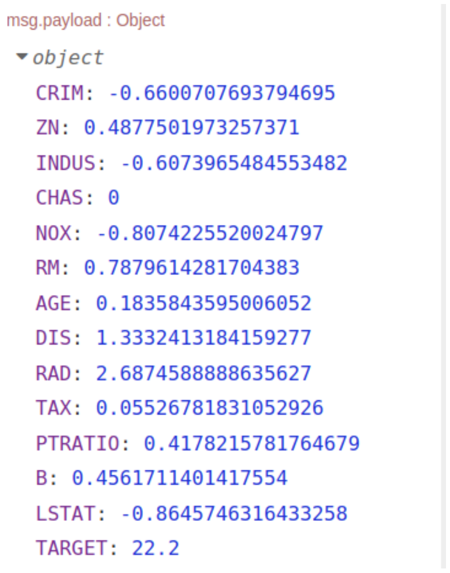
Linear regression performs better when the training data is scaled. In order to scale the data, we use the implemented "Standard Scaler" node. Figure 26 shows the parameters of this node. We need to clarify the target value name to the node so it will exclude that from scaling.



```
Name           Name
Save Path      Save Path
Target index   TARGET
```

Figure 26: Parameters of the “Standard Scaler” node

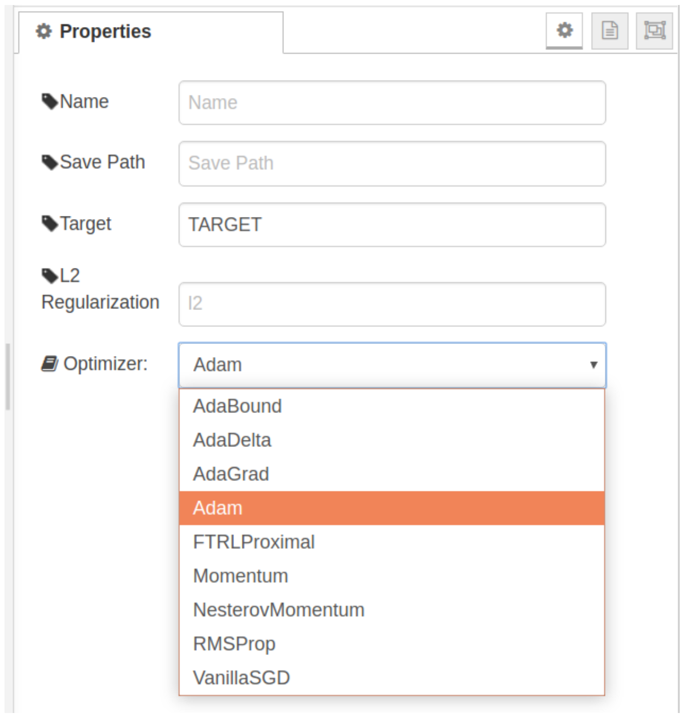
Figure 27 shows the scaled data. As we can see all the properties are scaled except the target value.



```
msg.payload : Object
▾object
  CRIM: -0.6600707693794695
  ZN: 0.4877501973257371
  INDUS: -0.6073965484553482
  CHAS: 0
  NOX: -0.8074225520024797
  RM: 0.7879614281704383
  AGE: 0.1835843595006052
  DIS: 1.3332413184159277
  RAD: 2.6874588888635627
  TAX: 0.05526781831052926
  PTRATIO: 0.4178215781764679
  B: 0.4561711401417554
  LSTAT: -0.8645746316433258
  TARGET: 22.2
```

Figure 27: The output of the “Standard Scaler” node.

Now the data is ready to be fed to the “Linear Regression” node for training. Figure 28 presents the available parameters for this node. I have left model save path, and L2 regularization blank so they will be assigned to their default value. “Target” is the name of the property that the model needs to train. We can also pick the optimizer from various options. The default optimizer for Linear regression is VanillaSGD.

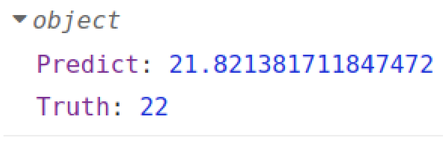


Name: Name
Save Path: Save Path
Target: TARGET
L2 Regularization: l2
Optimizer: Adam

AdaBound
AdaDelta
AdaGrad
Adam
FTRLProximal
Momentum
NesterovMomentum
RMSProp
VanillaSGD

Figure 28: Parameters of the “Linear Regression” node

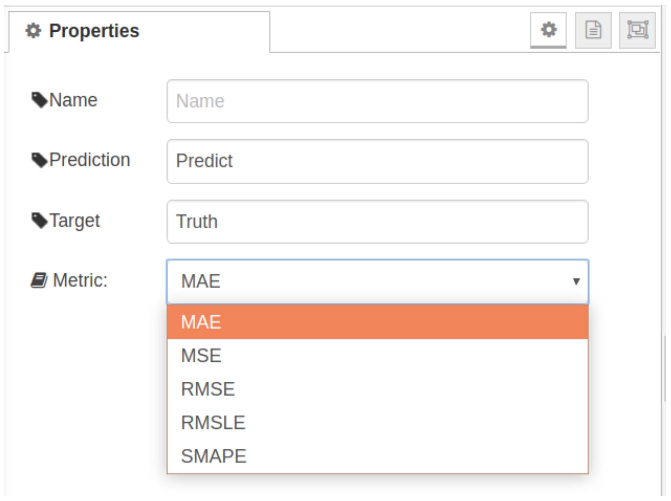
When the “Linear Regression” node receives an instance of data, before training on the data, it performs a prediction based on the existing model. Figure 29 shows the prediction of the linear regression for a specific instance before training the true value.



```
▾object
  Predict: 21.821381711847472
  Truth: 22
```

Figure 29: Output of the “Linear Regression” node for a specific training instance.

In order to evaluate the prediction results, we need to use the node “Regression Metric” that contains some of the popular metrics for a regression problem. This node computes the running metric for the model and gets updated after every prediction. Figure 30 shows the parameters of this node. We need to specify the name of the predict and true value properties and pick a metric method from the provided options. The default metric is MAE.


Properties

Name: Name
Prediction: Predict
Target: Truth
Metric: MAE

Figure 30: The parameters of the “Regression Metric” node.

Figure 31 shows the output of the regression metric at some point during the training.

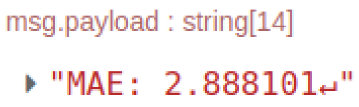

```
msg.payload : string[14]
▸ "MAE: 2.888101↵"
```

Figure 31: The output of the “Regression Metric” node.

Figure 32 shows the MAE during the training. We can observe that at the beginning, it shows high variance then it becomes more stable. In the end, the final MAE is almost 3.0 which is acceptable for a target value that ranges from 5 to 50.

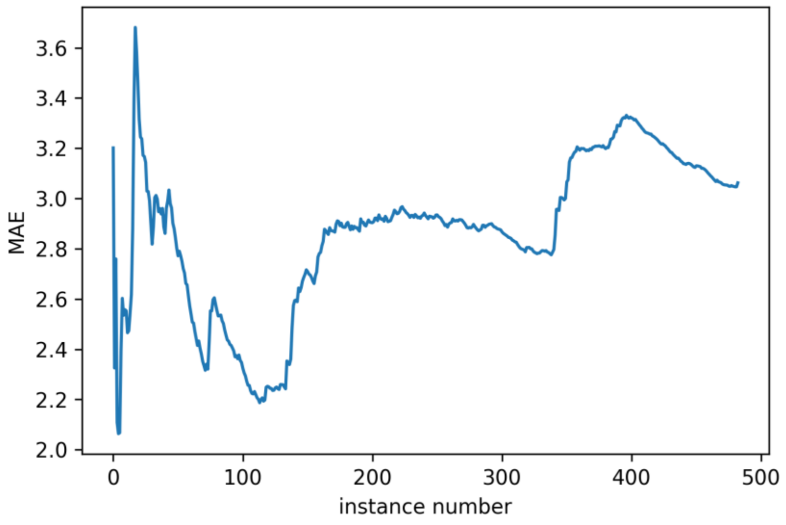


Figure 32: MAE of the linear regression model

4.3 Binary Classification

The New South Wales electricity data [33] has been used to evaluate the logistic regression node. This dataset contains 45,312 instances collected between May 1996 and December 1998 in 30-minutes intervals. Each instance consists of five features, the day of the week, the time stamp, the New South Wales electricity demand, the Victoria electricity demand, the scheduled electricity transfer between states, and a class label of either up or down. The goal is to predict whether the price will go up or down comparing to a moving average of the last 24 hours.

Figure 33 pictures the architecture of the flow for this training. The Kafka node subscribes to the topic “Log_reg” and receives the instances one by one. The nodes “set msg”, “json” and “limit” perform similarly to those used for linear regression. The node logistic regression performs the training, and the classification metric computes and reports the accuracy of the model.

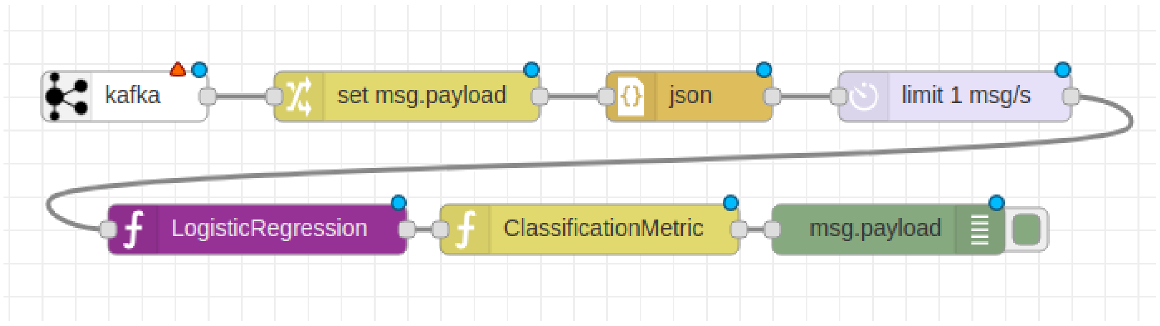


Figure 33: The flow of logistic regression training.

Figure 34 shows the accuracy of the model during training. After the initial high variance, the accuracy becomes stable and grows gradually. The final accuracy is around 71 percent. Bifet et al. [34] have used Naïve Bayes with an adaptive sliding window approach to train on this data and they have reached the accuracy of 72 percent which pretty close to our result.

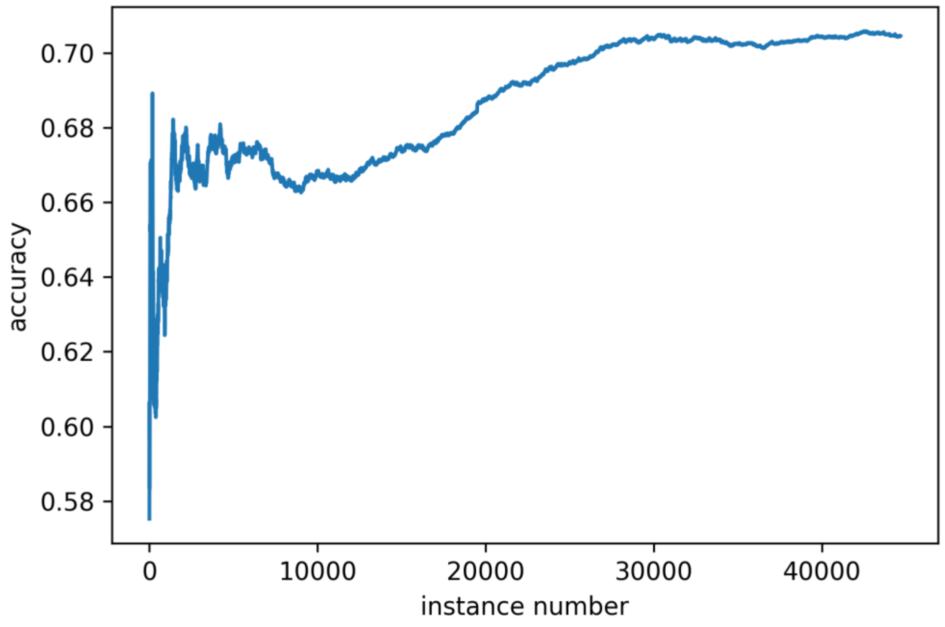


Figure 34: Accuracy of the logistic regression model.

4.4 Multiclass Classification

The dataset used for this type of learning is the Iris flower dataset. This data contains three classes that each of them has 50 instances assigned to them. Each of these classes is a type of iris flower and has four features including sepal length, sepal width, petal length, and petal width. The naive approach of picking a random class as our prediction gives us almost 33 percent accuracy which can be used as a baseline for our training results.

The first method that is used for training on the dataset is multinomial logistic regression. Figure 35 shows the flow of this training. The Kafka input node has subscribed to the topic IrisData and receives the messages. The accuracy of the trained model is depicted in Figure 36. We can understand from the plot that the model has an overall increasing trend in the accuracy and in the end it has reached an accuracy of 62 percent.

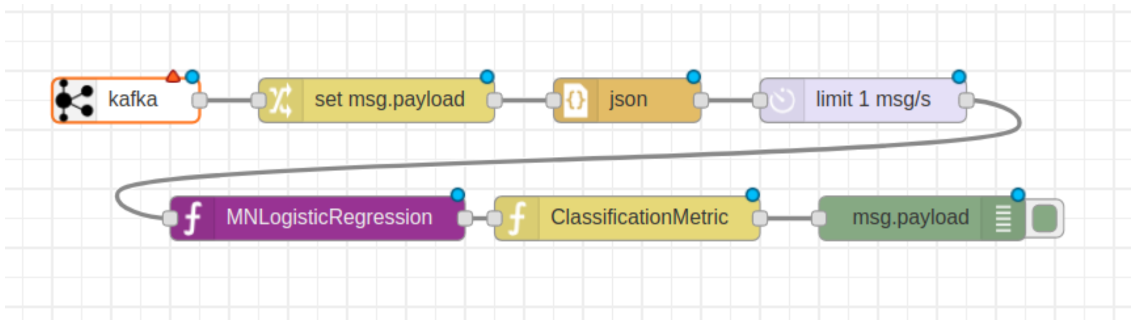


Figure 35: Flow of training with multinomial regression.

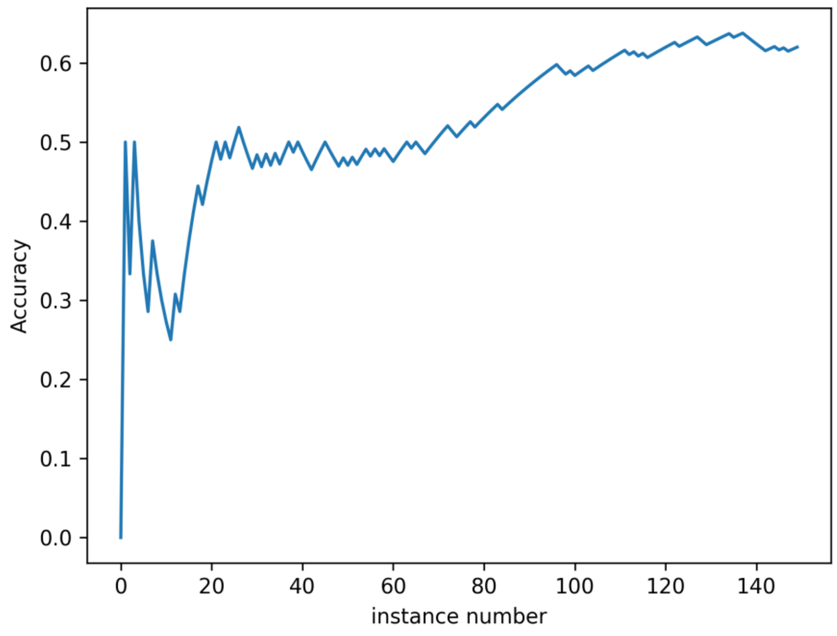


Figure 36: Accuracy of the multinomial regression model

The second method that has been used for the Iris classification is the one-vs-rest classification. Figure 37 shows the flow of the designed architecture. The Kafka input node subscribes to the topic IrisData to receive the messages from Kafka broker. Figure 38 is the plot that shows the accuracy of the model during the training process. The results are presenting a similar behavior to the results achieved with the multinomial regression. However, the final accuracy for multinomial regression is 3 percent higher.

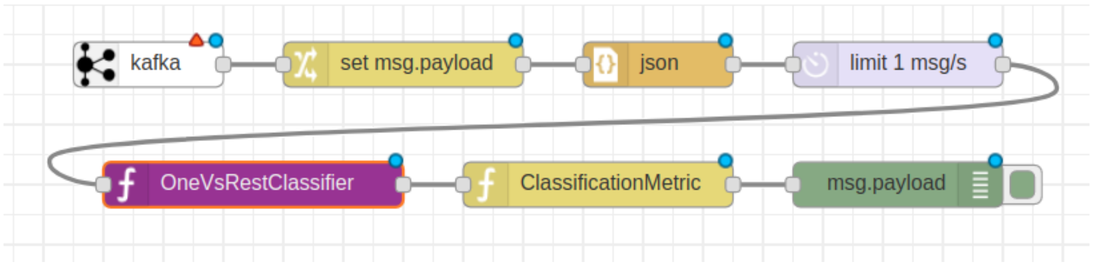


Figure 37: Flow of the one-vs-rest classification.

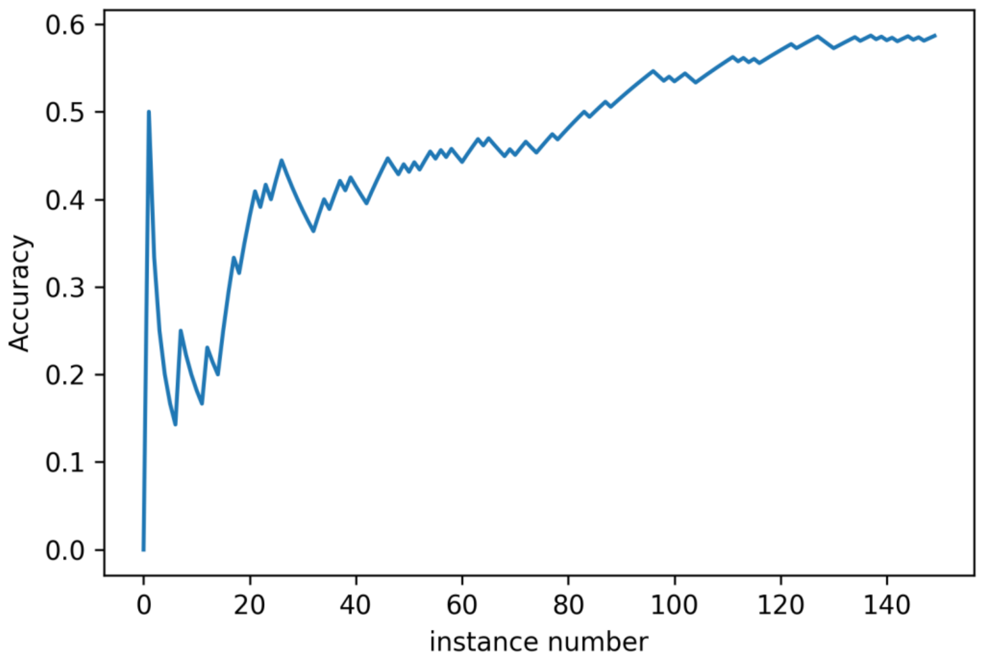


Figure 38: accuracy of the one-vs-rest classification.

The other multi-class classification method that has been used for training is the decision tree. Figure 39 shows the flow of this training. Despite the multinomial classifier and one-vs-rest classifier, as we can see in Figure 40, the decision tree has not performed well on the Iris dataset. The final accuracy achieved with the decision tree model is 27 percent which is lower than the baseline. Apparently, the decision tree is not the best option for this dataset.

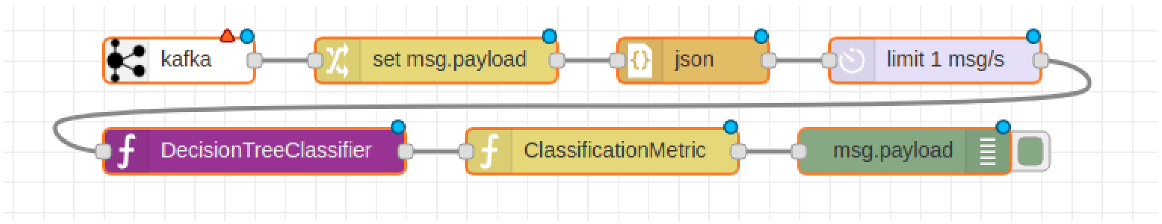


Figure 39: Flow of the Decision tree classification.

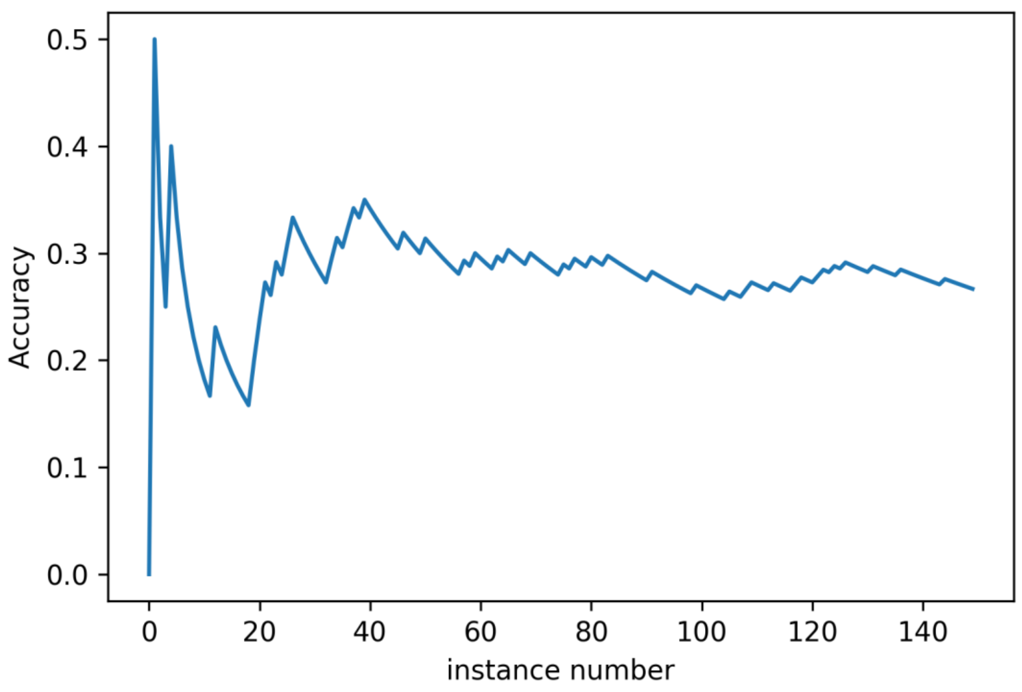


Figure 40: accuracy of the decision tree model.

The last method that has been trained on the Iris dataset is Gaussian naive Bayes. Figure 41 shows the flow of this training. This method provided the best accuracy among all the methods that were trained on the Iris dataset. As shown in Figure 42, the final accuracy is around 93 percent which is much higher than all the other three methods.

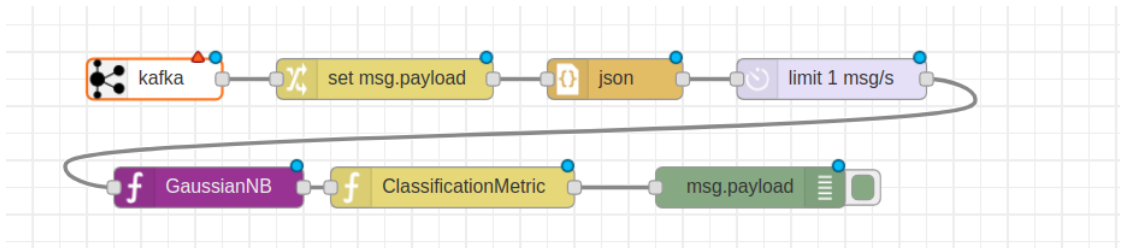


Figure 41: Flow of the Gaussian naive Bayes classification.

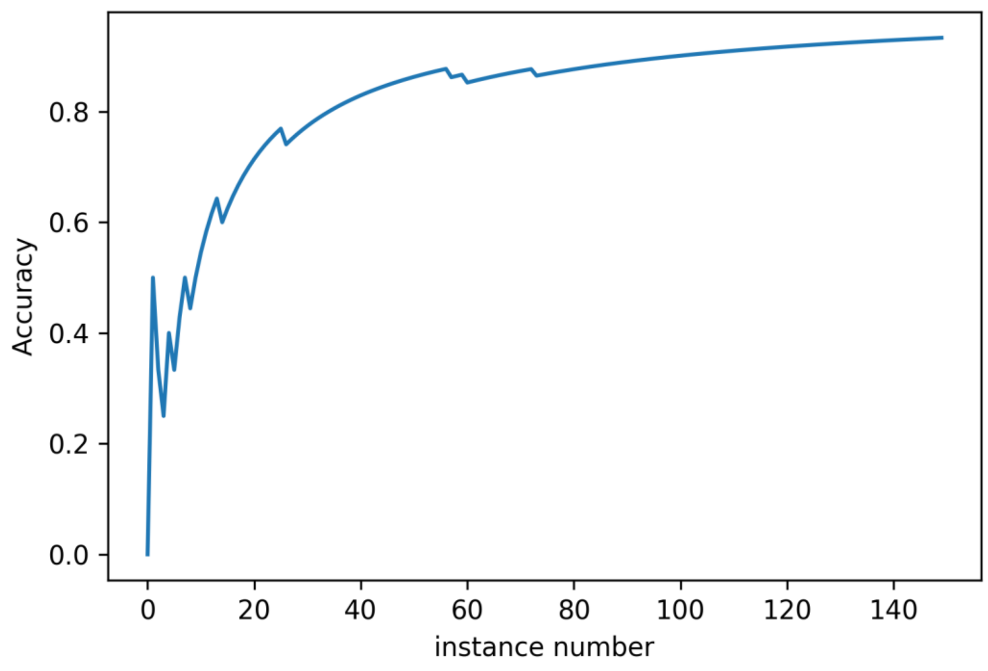


Figure 42: accuracy of the Gaussian naive Bayes classification.

In order to compare the results of the incremental Gaussian naive Bayes with a traditional batch Gaussian naive Bayes, I conducted another experiment. I trained a typical batch Gaussian naïve Bayes model using Scikit-learn on the Iris dataset. I used a 10-fold cross-validation approach and the mean of the accuracies was 94.66 percent. It means that our incremental method is almost as good as the typical batch version of itself.

We can observe that all the four methods that have been used for classifying the Iris problem have very similar flows. In fact, the only differences are the topic of the Kafka input node and the training method node. This means we have been able to try 4 learning algorithms on our data stream with only a few modifications on the flow that we have designed.

4.5 Clustering

In order to evaluate the implemented KMeans node, a synthetic unlabeled dataset is created. I used a python function to create three blobs of samples with 1000 instances. Each instance has two features. Figure 43 shows the scatter plot of the instances.

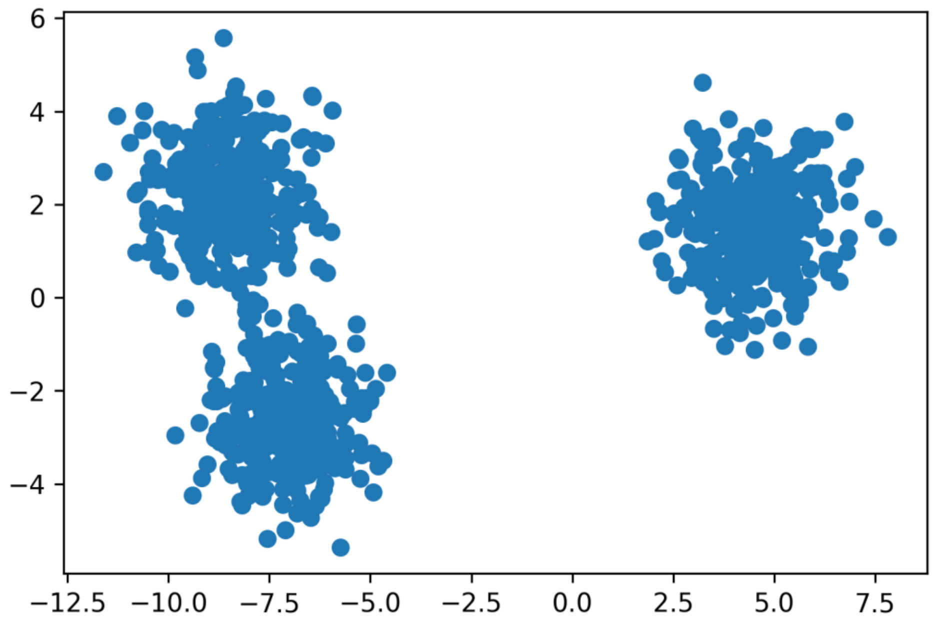


Figure 43: The generated dataset for clustering.

The flow of the nodes for clustering is shown in Figure 44. The Kafka input receives the message and passes it to the json node. Then json node converts the string payload to a json object and passes it to KMeans for training. I have specified the number of clusters which is 3 as a parameter for KMeans. Figure 45 shows the instances and the clusters that each instance has been assigned after training. We can infer that some instances in the green cluster are incorrectly labeled as class blue probably at the beginning of the training, but the model has learned the clusters after some time.

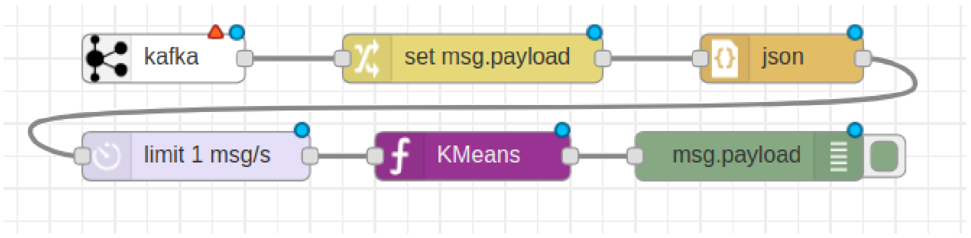


Figure 44: flow the clustering with KMeans.

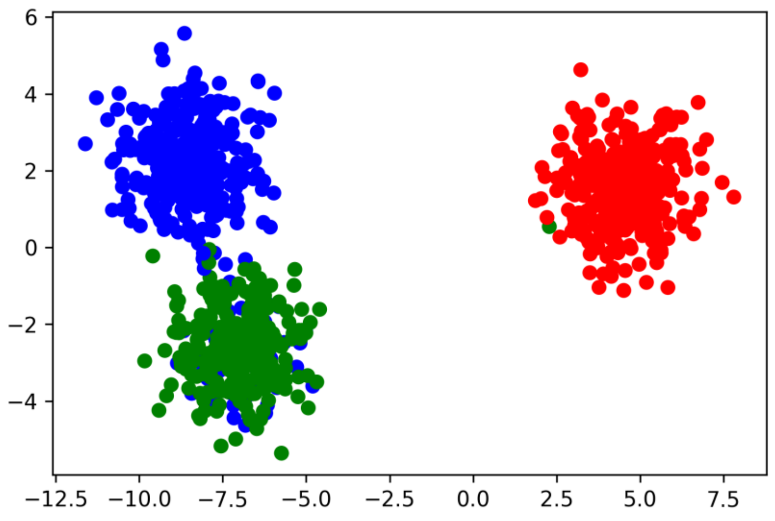


Figure 45: Labeled instances by KMeans.

A typical batch version of KMeans was also trained on the same dataset. The resulting clusters are shown in Figure 46. We can observe that the errors in incremental version are solved in the batch version of KMeans and that’s because the batch version iterates all the instances as many times as there is no change in the centroids. This iterative process increases the accuracy of clustering but it has its own disadvantages. Iterating the data more than once could be very time and resource-consuming when the training data becomes large. Also for some environments like smart city applications, we prefer models that are able to reflect the latest data changes into their decision makings.

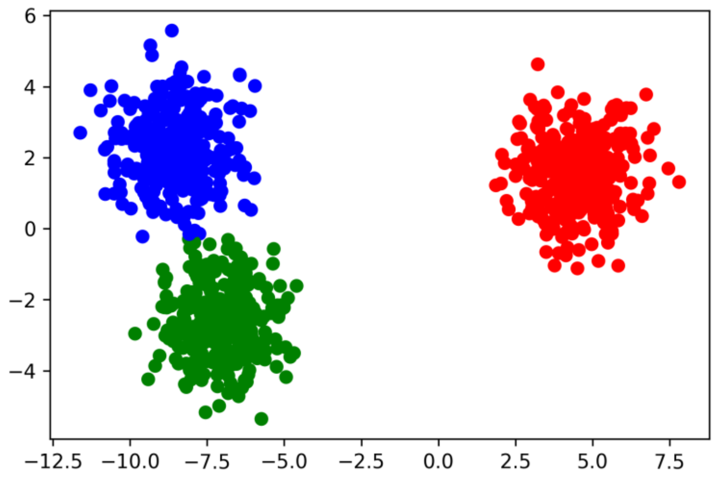


Figure 46: Result of typical batch KMeans

4.6 Summary

In this Chapter, we illustrate the use of the implemented nodes as well as nodes that already exist in Node-RED to solve different machine learning problems. We went through the steps that are needed to ingest the data, prepare the data, train on the data, and finally evaluate the trained models. The predefined nodes make the development of incremental machine learning algorithms much easier and much faster. We were able to try four leaning classification methods for the Iris dataset classification by small modifications in one flow. Our implemented nodes handled the training and evaluation part of the solution and we utilized the built-in nodes in Node-RED for ingesting and preparing the data for training.

The results achieved from the incremental learning methods are very close to their typical batch versions. We also saw that usually as the models receive more data, the predictions get more accurate. Having access to multiple methods for solving a problem like multi-class classification allowed us to have the flexibility for trying different methods and finding the best option for the problem.

Chapter 5

Conclusion

5.1 Summary

In this research, we looked at designing an environment that facilitates the development of applications for processing streams of data. These tools were developed in particular for use in the development of applications for processing the data of sensors, but they can also be utilized in any area that generates streams of data. After reviewing the existing platforms for IoT application development, we selected Node-RED as a tool that is aligned with our research goal of facilitating the development of stream processing applications.

In order to get deep insights from the data, we sought ways to incorporate machine learning algorithms into the applications so that they are able to train on streams of data and perform predictions. The best types of learning algorithms for such an environment are incremental machine learning algorithms that are able to train models by feeding the data instance by instance. We used Python to build a set of nodes for Node-RED to fulfill the need for incremental learning methods. These nodes cover a variety of machine learning methods encompassing both supervised and unsupervised methods. We conducted experiments that showed how we can easily build learning solutions for data streams by taking advantage of the implemented training nodes and the nodes that already exist in Node-RED.

The main contribution of this thesis was designing an environment for developing incremental machine learning tools for data streams. This environment has made the development of data stream analysis applications easier and users with low programming knowledge can also take advantage of the provided methods.

5.2 Future Work

There is still work that needs to be done for Node-RED to make it more powerful for building IoT applications. We can extend the training nodes and preprocessing nodes.

Developing deep learning methods that are able to train on data streams is one potential area that is necessary for specific types of problems like object recognition in images. Building nodes that are able to create plots and diagrams and tools for the creation of dashboards can also be useful additions.

When training on data streams, there might be cases that patterns of data start to change in certain periods of time. In such scenarios, it would be necessary to be able to reset a model and retrain a training node. Therefore, future work should consider adding an option to the training nodes to drop a model after a period of time or under certain circumstances and then retrain to capture the new patterns in the data.

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