

Anomaly Detection and Failure Prediction workshop

This workshop will teach you how to use OpenShift and the Red Hat OpenShift Data Science platform to examine and understand anomalies and predict failures in water pumps. We will work through the following agenda:

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1 Introduction

OpenShift Data Science is a cloud service that gives data scientists and developers a powerful AI/ML platform for building intelligent applications. Data scientists and developers can collaborate to quickly move from experiment to production in a consistent environment.

Available as an add-on cloud service to [Red Hat OpenShift Dedicated](#) and [Red Hat OpenShift Service on AWS](#) or as a self-managed software product, OpenShift Data Science allows data scientists to quickly develop, train, and test machine learning models using the JupyterLab interface. After models are developed, data scientists can use GitHub integration to trigger updated builds of OpenShift applications created by developers.

In this introductory workshop, you'll learn how to:

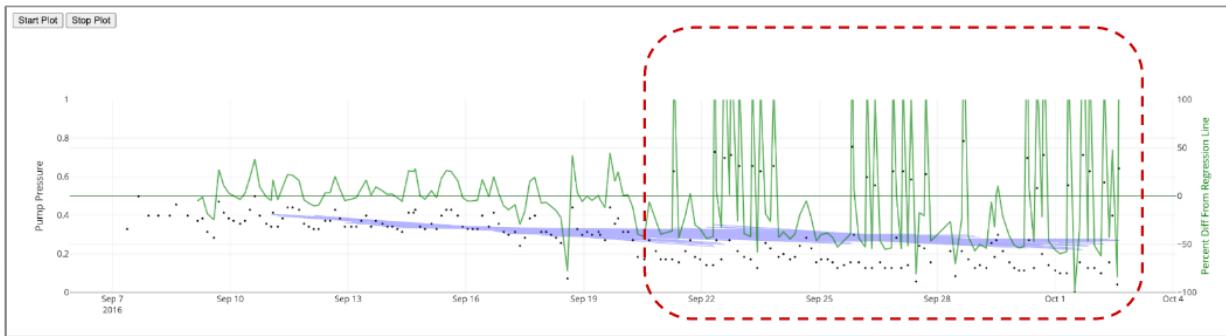
Use the Red Hat OpenShift Data Science platform to:

1. [Deploy an Anomaly Detection ‘containerized web application’](#) (in the Red Hat OpenShift platform) to display time series data which contains an anomaly.
2. [Generate Synthetic sensor data](#) to mimic real-time data generated by an Edge device. You will use this data in the next step.
3. [Deploy a Failure Prediction ‘containerized web application’](#) (in the Red Hat Openshift platform) and use the synthetic sensor data to predict the failure of a mechanical device.

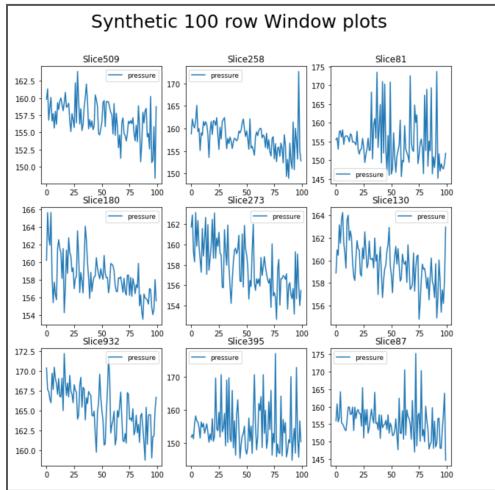
We'll start from a sensor dataset like this:

timestamp	sensor_25	sensor_11	sensor_36	sensor_34
2018-04-10 09:55:00	0.886128288849588	0.6936344767141810	0.21762059617623900	0.25318778143401500
2018-04-10 09:56:00	0.9204208188441080	0.7000403380548420	0.0968758054521226	0.2539990089674020
2018-04-10 09:57:00	0.9202596186121920	0.7037891972869380	0.09844494043538750	0.2719518531347420
2018-04-10 09:58:00	0.8767057041000580	0.7074345247993290	0.11346761648322900	0.26238610341377100
2018-04-10 09:59:00	0.907298589265789	0.7092217106877420	0.11872560793926700	0.24854953238656100
2018-04-10 10:00:00	0.9458851484833250	0.7088721741223050	0.12288425435926700	0.25818383654697300
2018-04-10 10:01:00	0.9458851484833250	0.7088721741223050	0.12288425435926700	0.25818383654697300
2018-04-10 10:02:00	0.8725669047299990	0.7112236359658490	0.12616730006050600	0.26549390466843700
2018-04-10 10:03:00	0.8795137723375100	0.7087605920157160	0.11858339137158600	0.2587340761266980
2018-04-10 10:04:00	0.8923600377327950	0.7036476602524060	0.126257236501765	0.27057234537967100

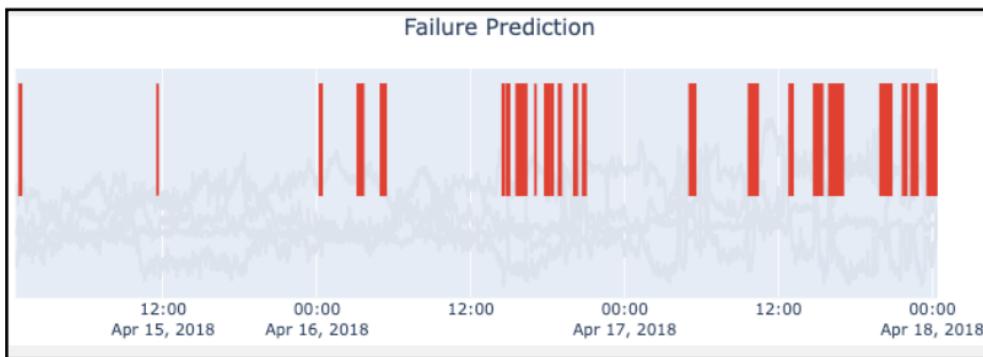
We will learn how to recognize anomalies in our data like this:



We will then generate synthetic data to mimic 'live' sensor data streaming from an Edge device connected to a Mechanical Pump. Plotted synthetic sensor data will look like this:



From this synthetic sensor data we will use our failure prediction model to predict when our mechanical device will fail based on sensor readings like this:



The failure prediction model will be accessible, via a Failure Prediction web application which we will deploy on the OpenShift (kubernetes) platform. We can do all of this without having to install anything on your computer, thanks to Red Hat OpenShift Data Science!

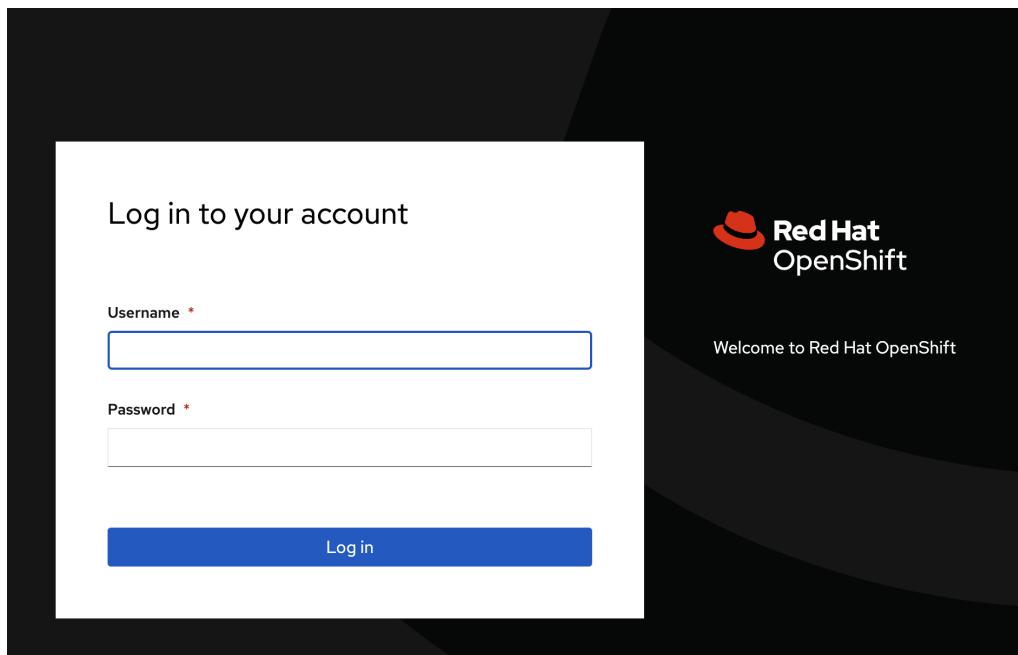
If you're ready, let's start!

2 Log into the Red Hat OpenShift Data Science Platform

Use the url, from your instructor, to access the Red Hat OpenShift Data Science platform. The url will look similar to the following example:

<https://console-openshift-console.apps.ieee.d7se.p1.openshiftapps.com>

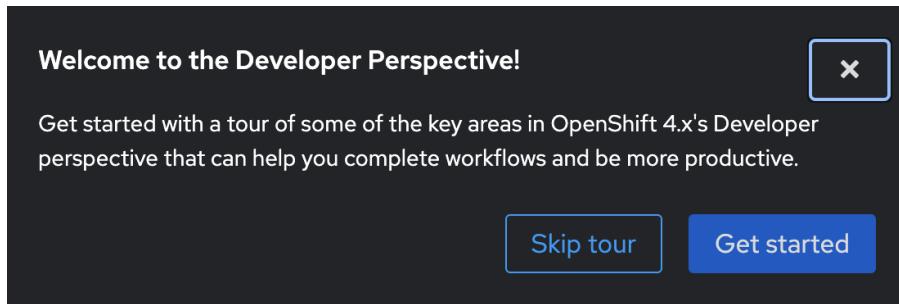
You will see the following login page appear.



Login in with your **username**: **user<#>** & **password**: **openshift**.

Note: your instructor will hand out usernames once the workshop starts.

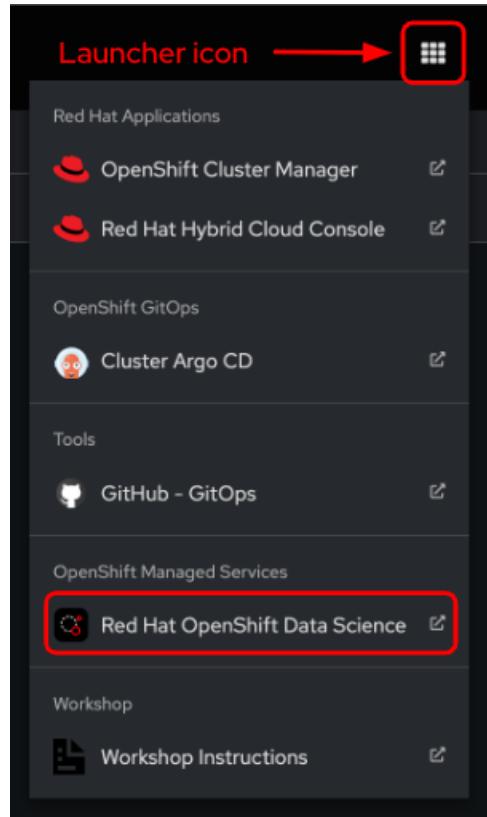
Upon successful login, you will see the **Red Hat OpenShift Dedicated** environment. You may also see a “Welcome to the Developer Perspective!” dialog box. Click “Skip tour” to close this box.



The **Red Hat OpenShift Dedicated platform** will be displayed. This is a **kubernetes platform** from which you can create **containerized applications**. We will come back to using OpenShift. We are going to first look at and use the **Red Hat OpenShift Data Science platform**.

A screenshot of the Red Hat OpenShift Data Science platform dashboard. The URL in the address bar is https://console-openshift-console.apps.cluster-vmx62.sandbox2256.opentlc.com/add/all-namespaces. The page title is "Welcome to the 'AI/ML Intelligent Applications for the Edge' Workshop". On the left is a sidebar with icons for Developer, Topology, Observe, Search, Builds, Pipelines, Environments, Helm, Project, ConfigMaps, and Secrets. The main area shows a table of projects. The table has columns: Name, Display name, Status, Requester, and Created. The data is as follows:

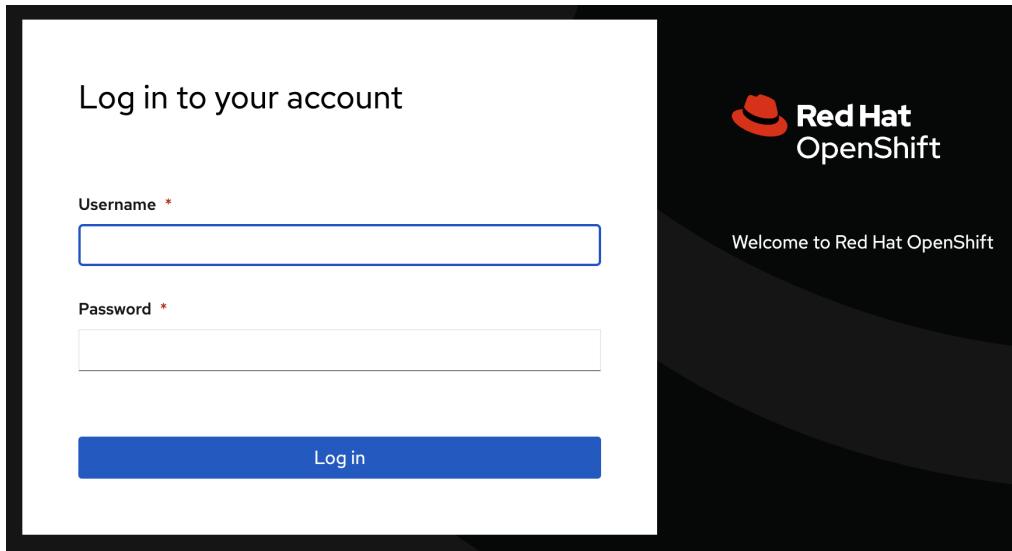
The **Red Hat OpenShift Data Science platform (dashboard)** is accessed by **selecting** the '*launcher icon*' in the upper right corner. **Select the option 'Red Hat OpenShift Data Science'**. See the following screenshot for the location of the Launcher icon.



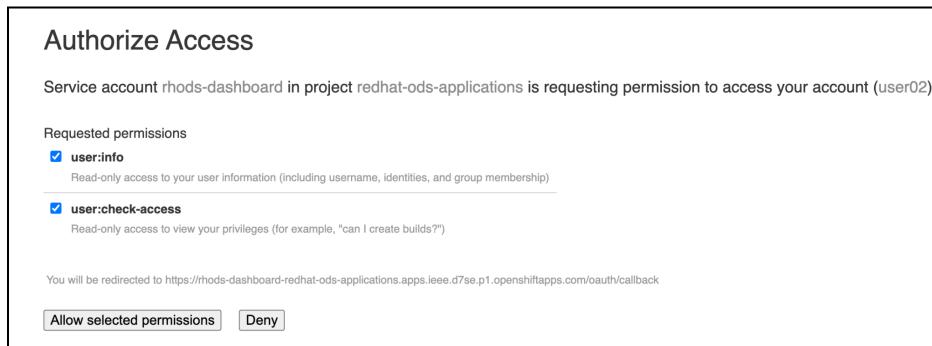
After selecting the '**Red Hat OpenShift Data Science**' option, a dialog box with a "**Log in with OpenShift**" button will appear. Click this button to proceed with logging into the Red Hat OpenShift Data Science (RHODS) dashboard.



You will encounter another Login page. Enter the username and password you were given at the beginning of the workshop, then click the 'Login' button.



You may see an 'Authorize Access' screen. Click the 'Allow selected permissions' button.

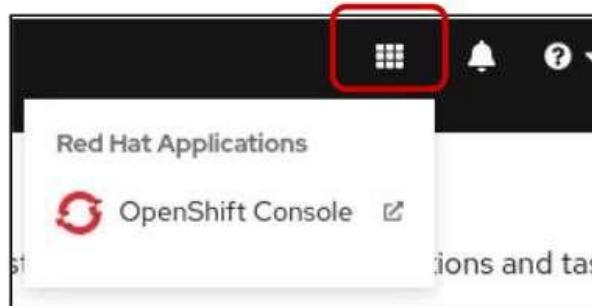


You will now be logged into the Red Hat OpenShift Data Science platform.

The platform, by default, displays all currently enabled applications. In this case, Jupyter is enabled.

The screenshot shows the Red Hat OpenShift Data Science platform. The left sidebar has a dark theme with white text. The 'Enabled' option is selected under the 'Applications' menu. The main content area is titled 'Enabled' and contains a card for the 'Jupyter' application. The card features a small icon, the text 'Jupyter', a 'Red Hat managed' badge, a brief description of its purpose, and a blue 'Launch application' button.

Note: you can always return to the **OpenShift Console** by using the launcher button (the black-and-white icon that looks like a grid), and choosing **OpenShift Console**.



Let's look at some of the menu items available in the Red Hat OpenShift Data Science platform:

1. Applications
2. Data Science Projects
3. Model Serving
4. Resources
5. Settings (note: this option is only seen and available to administrators)

1. The **Applications** menu option takes you to a variety of available applications.

These include:

- [Red Hat managed cloud services](#): Applications that have been developed by Red Hat, such as OpenShift Streams for Apache Kafka.
- [Partner managed services](#): Services created by one of Red Hat's external partners, such as Intel oneAPI AI Analytics Toolkit Container. These services are available to you in the OpenShift Data Science dashboard.
- [Self-managed software](#): Other types of software developed by one of our external partners, such as OpenVINO. This software is available to you in the Openshift Data Science dashboard.

The **Applications** menu items allows you to see already ‘Enabled’ applications. You can launch your enabled applications, view documentation, or get started with quick instructions and tasks.

The **Applications** menu item also allows you to ‘Explore’ all available applications by choosing the Explore menu item. In the Explore menu, you can add optional applications to your Red Hat OpenShift Data Science instance.

The screenshot displays the Red Hat OpenShift Data Science interface. On the left, a sidebar menu includes 'Applications' (selected), 'Enabled' (highlighted), and 'Explore'. Below these are 'Data Science Projects', 'Model Serving', 'Resources', and 'Settings'. The main content area is titled 'Explore' with the sub-instruction 'Add optional applications to your Red Hat OpenShift Data Science instance.' It lists several applications categorized by source:

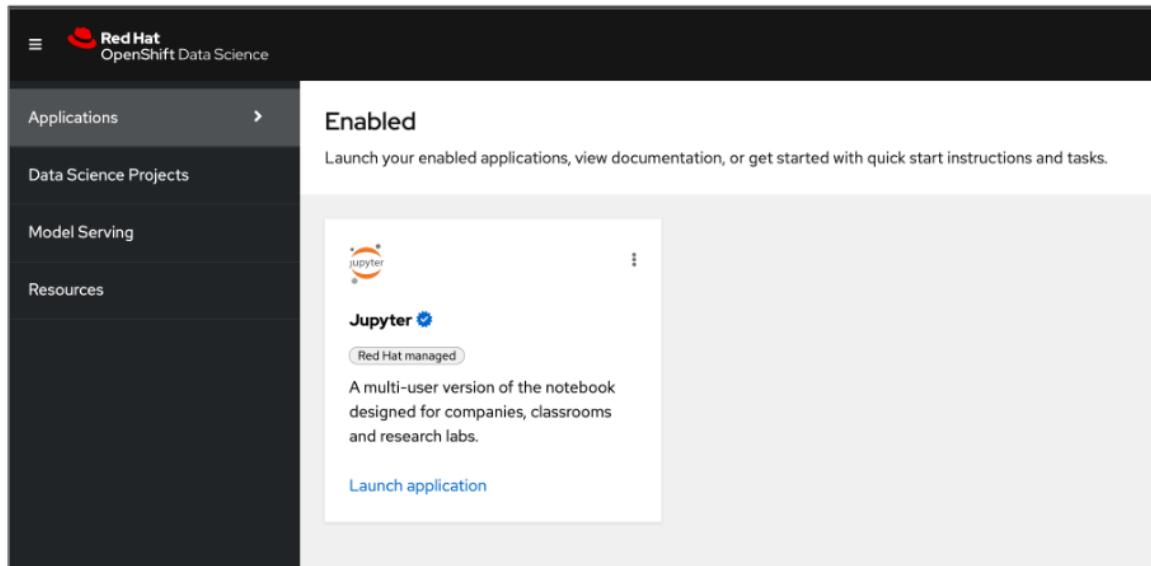
- Partner managed:**
 - Anaconda Professional (by Anaconda)
 - Jupyter (by Jupyter)
- Self-managed:**
 - IBM Watson Studio (by IBM)
 - OpenShift Streams for Apache Kafka (by Red Hat)
 - Intel® oneAPI AI Analytics Toolkit Container (by Intel®)
 - OpenVINO (by Intel®)
- Red Hat managed:**
 - OpenVINO (by Intel®)

2. The **Data Science Projects** menu option allows you to view your existing projects or create new projects. When you create a Data Science project you are able to add Workbenches, Cluster Storage, Data Connections, Models and Servers. This enables you to quickly access your work for various projects.
3. The **Model Serving** menu option allows you to view the health and performance of your deployed models.
4. The **Resources** menu option allows you to access all the learning resources for Red Hat OpenShift Data Science and supported applications.
5. *If you login as an admin*, you will see an additional **Settings** menu option. (The above screen capture comes from an admin user dashboard view.) The Settings option allows admins to:
 - a. Import, delete and modify Notebook Images
 - b. Update Cluster Settings (global settings for all users)
 - c. Manage Users by defining OpenShift group membership for Data Science administrators and users.

Let's start the lab by launching our Jupyter notebook server!

3 Start your Jupyter Image Notebook server

Let's launch the Jupyter Notebook server and customize options for your Jupyter Notebook server! Click the [Launch application](#) url at the bottom of the 'Jupyter' card..



Start a notebook server.

When you first gain access to Jupyter, a configuration screen gives you the opportunity to select a notebook server image and configure the deployment size and environment variables for your data science project.

You can customize the following options:

- Notebook image
- Deployment size
- Environment variables

Start a notebook server

Select options for your notebook server.

Notebook image

- VS Code Server v4.9.1 ⓘ
Coder Code Server v4.9.1
[▶ Versions](#)
- Standard Data Science 1.2 ⓘ
Python v3.8
[▼ Versions](#)
 - Version 2023.1 ⓘ ★ Recommended
 - Version 1.2 ⓘ
Python v3.8
- PyTorch 2023.1 ⓘ
Python v3.9, PyTorch v1.13
[▶ Versions](#)
- TrustyAI ⓘ
Python v3.9
- Minimal Python 2023.1 ⓘ
Python v3.9
[▶ Versions](#)
- CUDA 2023.1-cuda-11.8 ⓘ
Python v3.9
[▶ Versions](#)
- TensorFlow 2023.1-cuda-11.8 ⓘ
Python v3.9, TensorFlow v2.11
[▶ Versions](#)

Deployment size

Container Size

Demo / Workshop

Environment variables

[+ Add more variables](#)

[Start server](#)

[Cancel](#)

Start server in current tab

The following subsections list which prerequisite(s) you need to choose for this activity.

Notebook image

You can choose from a number of predefined images. When you choose a predefined image, your JupyterLab instance will then contain the associated libraries and packages that you need to do your work.

Available notebook images include:

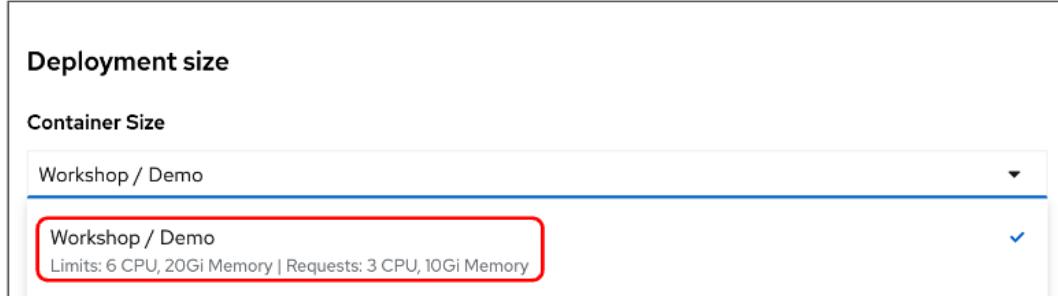
- VS Code Server
- **Standard Data Science**
- PyTorch
- TrustyAI
- Minimal Python
- CUDA
- Tensorflow

For this learning path, choose the **Standard Data Science** notebook image. Make certain you choose **Version 1.2 Python v3.8**.

Note: not sure what Notebook images contain? Click on the “?” beside each image to learn what packages/libraries are included within each image.

Deployment size

You can choose different deployment sizes (resource settings) based on the type of data analysis and machine learning code you are working on. Each deployment size is pre-configured with specific CPU and memory resources.



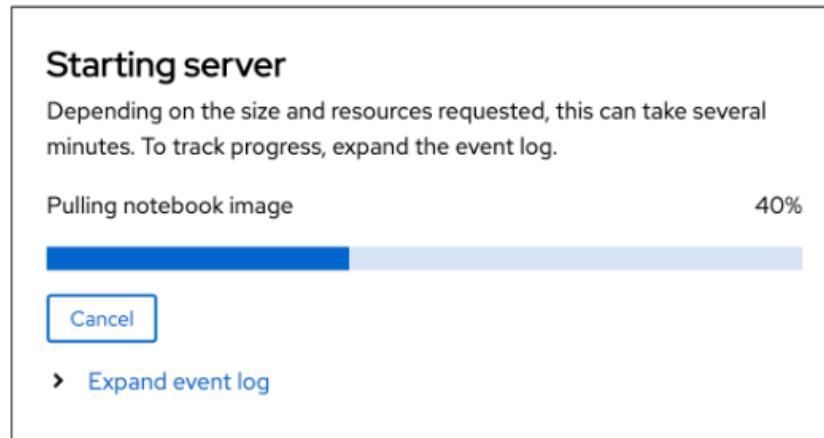
For this learning path, the container size has been pre-configured to 6 CPU, 20 Gi Memory

Environment variables

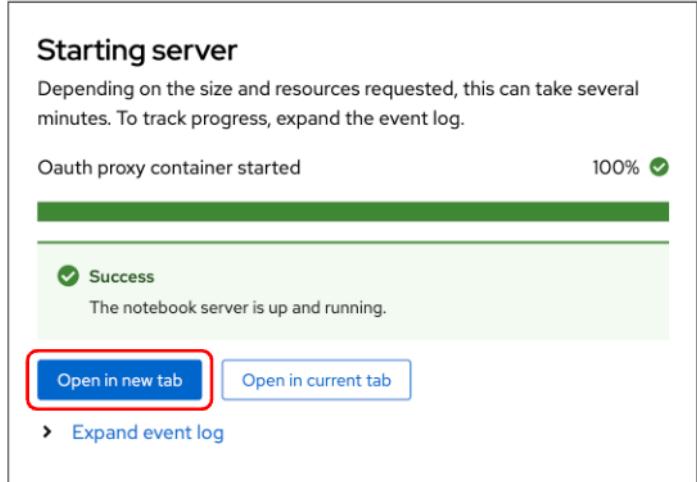
The environment variables section is useful for injecting dynamic information that you don't want to save in your notebook.

Note: This learning path does not use any environment variables.

If you are satisfied with your notebook server selections, click the **Start Server** button to start the notebook server. The following “Starting server” diaglog box will appear.

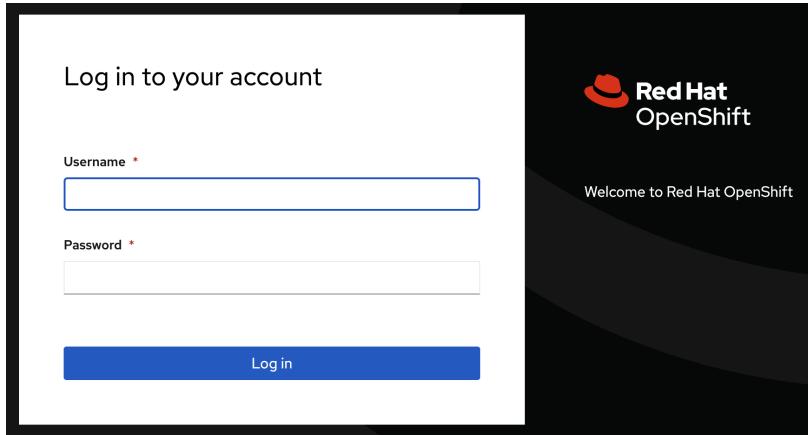


Your Notebook server may take a minute to spin up. If you are interested, you can click the “Expand event log” to see where in the process your Notebook Server is. Once your server is ready, you will see the progress bar turn green and reach 100%.



You can now choose to start your Jupyter Lab environment in the current tab or open the environment in a new tab. Click the '**'Open in new tab'** button to launch Jupyter Lab in a new tab.

You will see another Login page. Enter the username and password you were given at the beginning of the workshop, then click the 'Login' button.



After you log in, you may see an 'Authorize Access' screen. Click the 'Allow selected permissions' button to continue.

Authorize Access

Service account jupyter-nb-user3 in project rhods-notebooks is requesting permission to access your account (user3)

Requested permissions

user:info

Read-only access to your user information (including username, identities, and group membership)

user:check-access

Read-only access to view your privileges (for example, "can I create builds?")

You will be redirected to <https://jupyter-nb-user3-rhods-notebooks.apps.cluster-vmx62.sandbox2256.opentlc.com/oauth/callback>

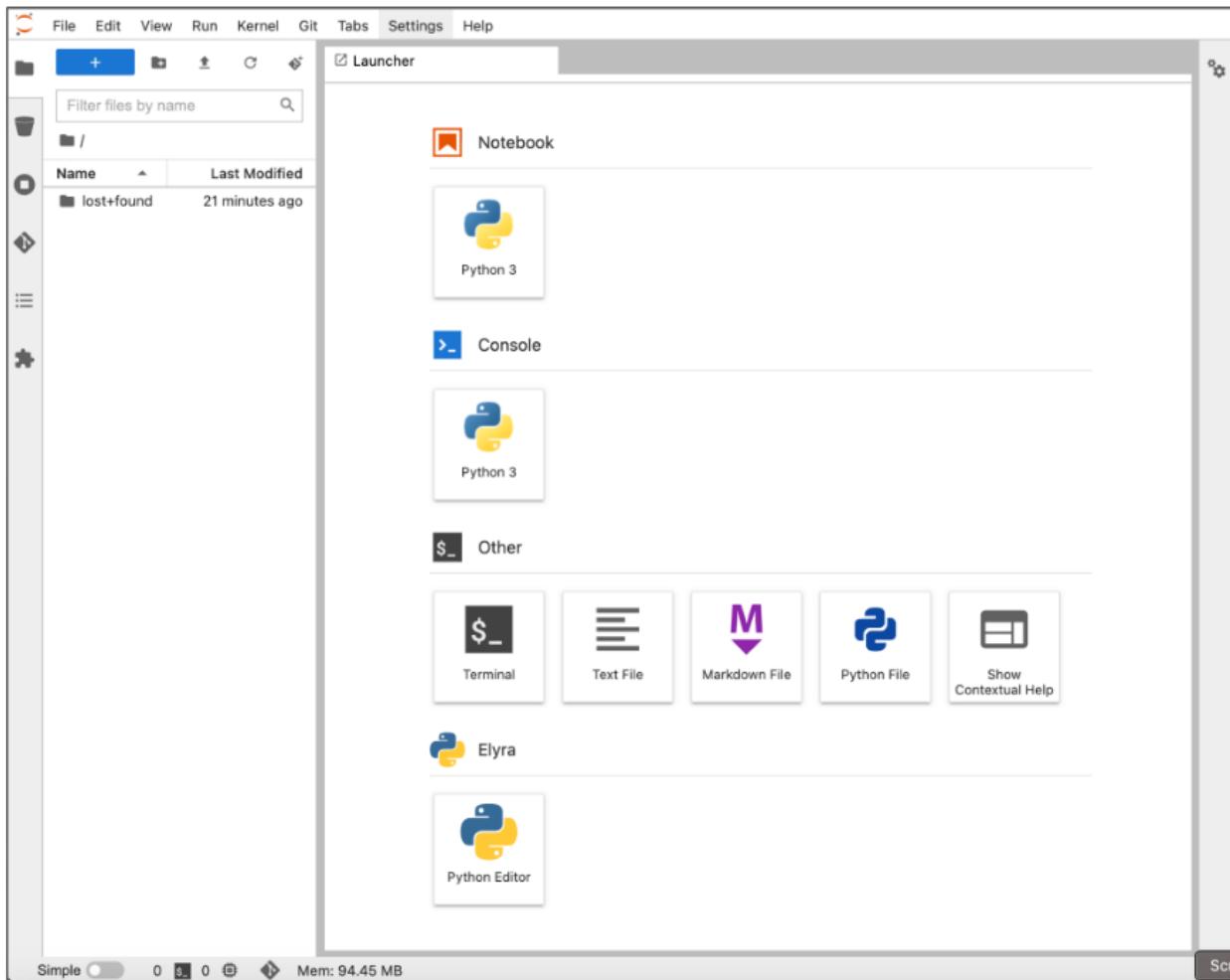
Allow selected permissions

Deny

If your login is successful, you will have started your Jupyter notebook server and will be taken into the Jupyter Lab Environment.

3a The Jupyter Lab Environment

You are now inside your Jupyter Lab environment. As you can see, it's a web-based environment, but everything you'll do here is in fact happening on the Red Hat OpenShift Data Science cluster. This means that without having to install and maintain anything on your own computer, and without disposing of lots of local resources like CPU and RAM, you can still conduct your Data Science work in this powerful and stable managed environment.



In the "file-browser" like window you're in right now, you'll find the files and folders that are saved inside your own personal space inside Red Hat OpenShift Data Science. It's

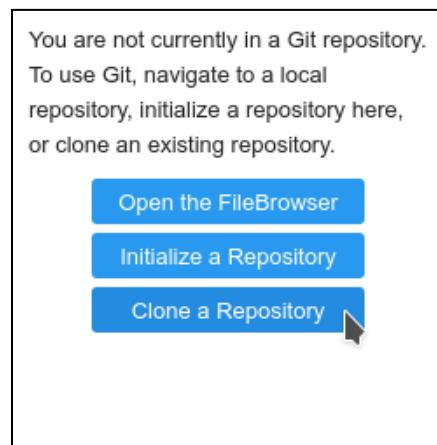
pretty empty right now though... So the first thing we will do is to bring the content of the workshop inside this environment.

3b Clone a github repository

- On the left toolbar, click on the Git icon:



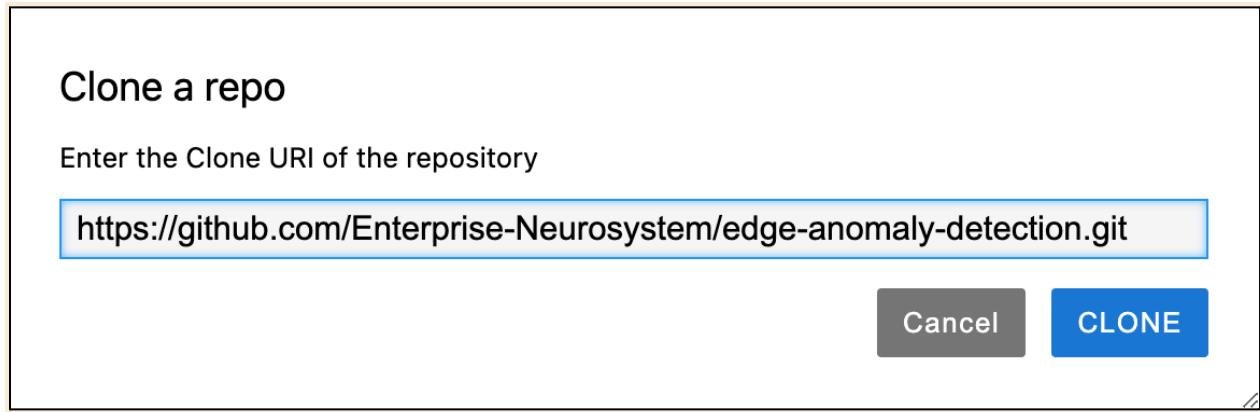
- Then click on Clone a Repository:



We are going to first look at Anomaly Detection. Therefore, enter the following git repo for Anomaly Detection.

- Enter Clone URI of the repository,

<https://github.com/Enterprise-Neurosystem/edge-anomaly-detection.git>, then
click the CLONE button.

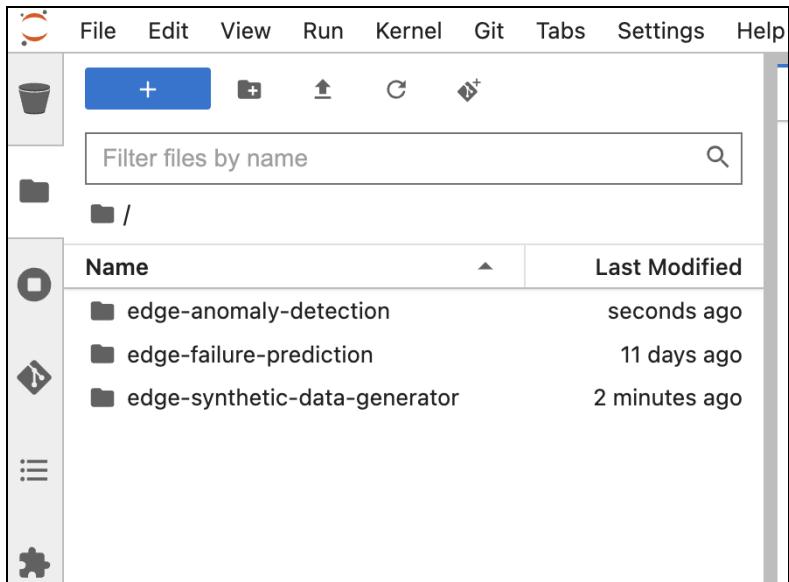


- It takes a few seconds, after which you can view the newly-created folder, `edge-anomaly-detection`

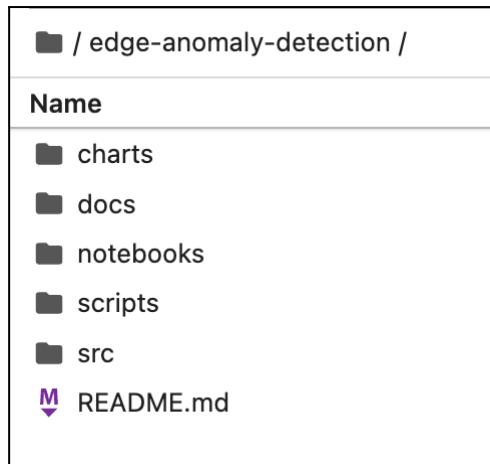
Note: After you have cloned the `edge-anomaly-detection` repository, proceed with cloning the following 2 repositories that will be used later in this workshop.

1. <https://github.com/Enterprise-Neurosystem/edge-synthetic-data-generator.git>
2. <https://github.com/Enterprise-Neurosystem/edge-failure-prediction.git>

After you've cloned the repositories, the `edge-anomaly-detection`, `edge-synthetic-data-generator` and `edge-failure-prediction` folders will appear under the **Name** pane.



Let's open up the edge-anomaly-detection folder by double clicking on the edge-anomaly-detection folder name.



The folder should contain the following sub-folders:

- charts
- docs
- notebooks
- scripts
- src

Change into the notebooks sub-folder. You will see the following 2 files: 01-sandbox.ipynb & 02-anomaly-detection-notebook.ipynb

If you have not worked with Jupyter Notebooks before, continue to the next section - [Introduction to Jupyter Notebooks](#).

If you are familiar with Jupyter Notebooks, continue to the section - [Anomaly Detection](#).

3c Introduction to Jupyter Notebooks

This section provides a small introduction on how to use Jupyter Notebooks. If you're already at ease with Jupyter, you can directly head to the next section - [Anomaly Detection](#).

What's a notebook?

- A notebook is an environment where you have *cells* that can display formatted text, or code.

This is an empty cell:

A screenshot of a Jupyter Notebook cell. The cell identifier 'In []:' is visible on the left. The main area of the cell is empty, showing only the top edge of the browser window.

And a cell where we have entered some code:

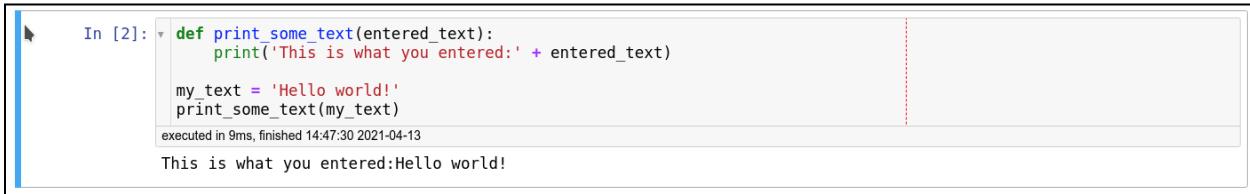
A screenshot of a Jupyter Notebook cell containing Python code. The code defines a function 'print_some_text' that prints the user-entered text. It then creates a variable 'my_text' with the value 'Hello world!' and calls the function with this variable. The code is syntax-highlighted in blue and red.

- Code cells contain Python code that can be run interactively. That means you can modify the code, then run it. The code will not run on your computer or in the browser, but directly in the environment you are connected to, Red Hat OpenShift Data Science in our case.
- To run a code cell, just select it (click in the cell, or on the left side of it), and click the Run/Play button from the toolbar (you can also press CTRL+Enter to run a cell, or Shift+Enter to run the cell and automatically select the following one).

The Run button on the toolbar:



Our cell after pressing Run:



In [2]:

```
def print_some_text(entered_text):
    print('This is what you entered:' + entered_text)

my_text = 'Hello world!'
print_some_text(my_text)
```

executed in 9ms, finished 14:47:30 2021-04-13

This is what you entered:Hello world!

As you can see, you have the result of the code that was run in that cell, as well as information on when this particular cell has been run.

- When you save a notebook, the code as well as the results are saved! So you can always reopen it to look at the results without having to run all the program again, while still having access to the code.

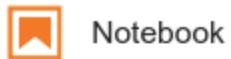
Notebooks are so named because they are just like a physical Notebook: it's exactly like if you were taking notes about your experiments (which you will do), along with the code itself, including any parameters you set. You see the output of the experiment inline (this is the result from a cell once it's run), along with all the notes you want to take (to do that, switch the cell type from the menu from `Code to Markup`).

Time to play

Now that we have covered the basics, just give it a try!

- In your Jupyter environment (the file explorer-like interface), there is a file called `01-sandbox.ipynb`. Double-click on it to launch the notebook (it will open another tab in the content section of the environment). Please feel free to experiment, run the cells, add some more and create functions. You can do what you want - it's your environment, and there is no risk of breaking anything or impacting other users. This environment isolation is also a great advantage brought by Red Hat OpenShift Data Science.
- You can also create a new notebook by selecting `File->New->Notebook` from the menu on the top left, then select a Python 3 kernel. This instructs Jupyter that we want to create a new notebook where the code cells will be run using a Python 3 kernel. We could have different kernels, with different languages or versions that we can run into notebooks, but that's a story for another time...

- You can also create a notebook by simply clicking on the icon in the launcher:



- If you want to learn more about notebooks, head to [this page](#). Now that you're more familiar with notebooks, you're ready to go to the next section - [Anomaly Detection](#).

4 Anomaly Detection

4a Examine time series data for anomalies

If you have not already done so, change into the notebooks sub-folder. You will see the following 2 files: 01-sandbox.ipynb,

02-anomaly-detection-notebook.ipynb.

Double click 02-anomaly-detection-notebook.ipynb to open the notebook.

The screenshot shows a Jupyter Notebook interface with two tabs open: "01-sandbox.ipynb" and "02-anomaly-detection-notebook.ipynb". The "02-anomaly-detection-notebook.ipynb" tab is active, showing the following code:

```
[ ]: # first, execute pip installs to ensure we have the correct packages
!pip install matplotlib==3.4.1
!pip install pandas==1.2.4

[ ]: import matplotlib.pyplot as pl
import numpy as np
import pandas as pd
import matplotlib.dates as mdates
import datetime as dt

# %matplotlib

[ ]: # Read data from csv file. Assumes that data is in two columns: datetime and pressure.
# Datetime values are assumed to be in the form: '%m/%d/%Y %H:%M'
# Returns two lists: first list is datetimes, second list is pressures
def generateData():
    plungerData = pd.read_csv("../src/static/data/casing.csv")
    times = plungerData.iloc[:, 0].tolist()
    pressures = plungerData.iloc[:, 1].tolist()
    return times, pressures

The data we will be using (casing1.csv) has 2 columns timestamp and pressure. This data has already been refactored. If you wish to look at the non-refactored data, open file static/data/casing_NotRefactored.csv. The dataset is from a gas pump that is slowly failing overtime. Let's plot this data to see what it looks like. Can we see an anomaly in the visible data?

[ ]: # plot the dataset to see what it looks like
times, pressures = generateData()
fig = pl.figure()
fig.set_figwidth(10)
fig.set_figheight(4)
pl.scatter(times, pressures)
pl.show()
```

We can see from the above plot that the pressure decreases over time and towards the end we observe some pressure

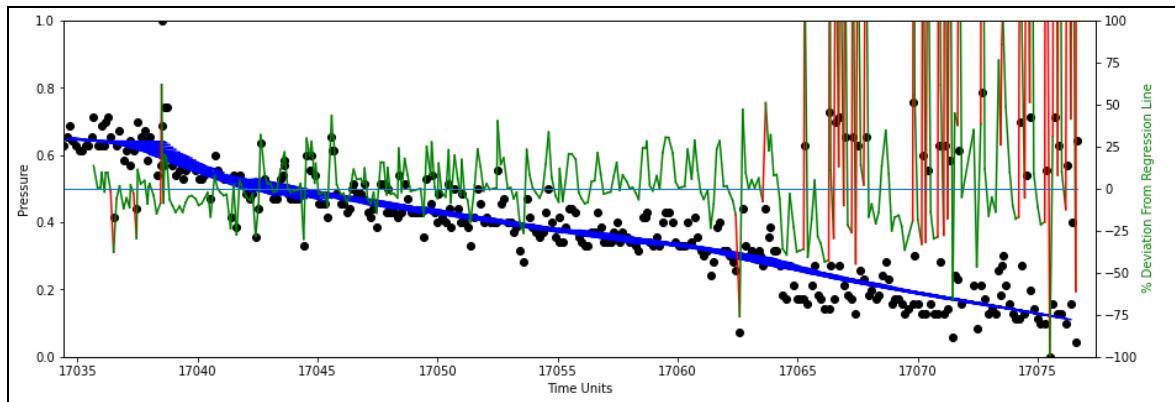
At the bottom of the interface, status information includes: Simple, 0, 2, Initialized (additional servers needed), Python 3 | Idle, Mem: 220.45 MB, Mode: Command, Ln 1, Col 1, 02-anomaly-detection-notebook.ipynb.

In this notebook, we'll explore a very small data set (2 columns consisting of timestamp and pressure) so that you can see what 'sensor' data looks like. The dataset is in csv file format.

You will work through this notebook, reading the explanations and executing the notebook's cells. You will examine the data and understand how we determine the data

shows an anomaly by using Linear Regression. Do this now. When you are finished we will discuss the data and what we expect when looking for anomalies.

The last notebook cell you execute will produce the following Anomaly Detection plot.



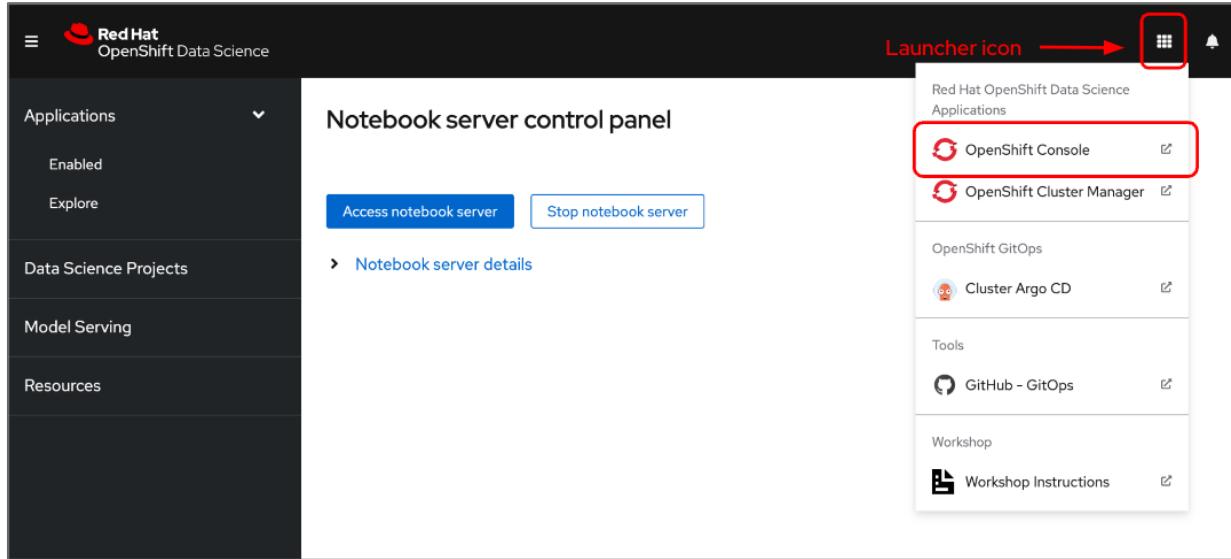
In this plot, the far right hand side of the plot is not only an anomaly, it is also the failure of a mechanical pump. Hypothesis: If we can detect anomalies we can then use this knowledge to predict when a mechanical pump will fail.

Let's take the web application developed for Anomaly Detection and deploy it using containerization. Go to the next section: Deploy the Anomaly Detection model & web application as a container

4b Deploy the Anomaly Detection model & web application as a container

We need to containerize and deploy the Anomaly Detection Web Application code. We will package the code as a container image and run it directly in OpenShift as a Web Application.

From the Red Hat OpenShift Data Science platform choose the **Launcher**. From the Launcher drop down menu select “**OpenShift Console**”



Note: The Launcher tool (icon) is also visible in the OpenShift console. **You can use this tool to move between the Red Hat OpenShift Data Science Platform and the Red Hat OpenShift Dedicated platform.**

Once you are in the OpenShift console, make certain you are in ‘Developer’ mode.

The screenshot shows the Red Hat OpenShift Dedicated web interface. The left sidebar has a dropdown menu set to 'Developer'. Below it, there are links for 'Monitoring', 'Search', 'Builds', and 'Helm'. The main area is titled 'Add' and says 'Select a Project to start adding to it or [create a Project](#)'. It includes a search bar and a table listing projects. One project, 'areznik-dev', is shown with details: Name (PR areznik-dev), Display name (areznik-dev), Status (Active), Requester (areznik), and Created (Oct 18, 2023).

Change to Developer mode. You will see a number of projects listed. Check if you can find the following listed projects as we will be using them in the lab.

1. edge-anomaly-detection
2. edge-failure-prediction
3. user<#> <- your user project. **You will be working in your project user<#>**

This screenshot is similar to the one above but includes additional annotations. A red box highlights the 'Toggle between Developer & Administrator roles' link in the sidebar. A red arrow points to the 'Search by name...' input field in the main search bar, which contains the placeholder text 'Enter the name of a Project you wish to select. As you type, the matching project names will populate the list. Once you see the project you wish to use, double click on the project name.'

The main table lists several projects:

Name	Display name	Status	Requester	Created
PR edge-anomaly-detec...	Edge Detection Workshop	Active	No requester	May 17, 2023, 9:45 AM
PR edge-failure-predicti...	Edge Prediction Workshop	Active	system:admin	May 17, 2023, 9:45 AM
PR edge-synthetic-data...	Edge Data Gen Workshop	Active	No requester	May 17, 2023, 9:45 AM
PR group-project	The Allen Parsons Project	Active	No requester	May 17, 2023, 9:49 AM
PR sandbox	Sandbox	Active	No requester	May 17, 2023, 9:45 AM
PR user1	Start Here - user1	Active	No requester	May 17, 2023, 9:45 AM

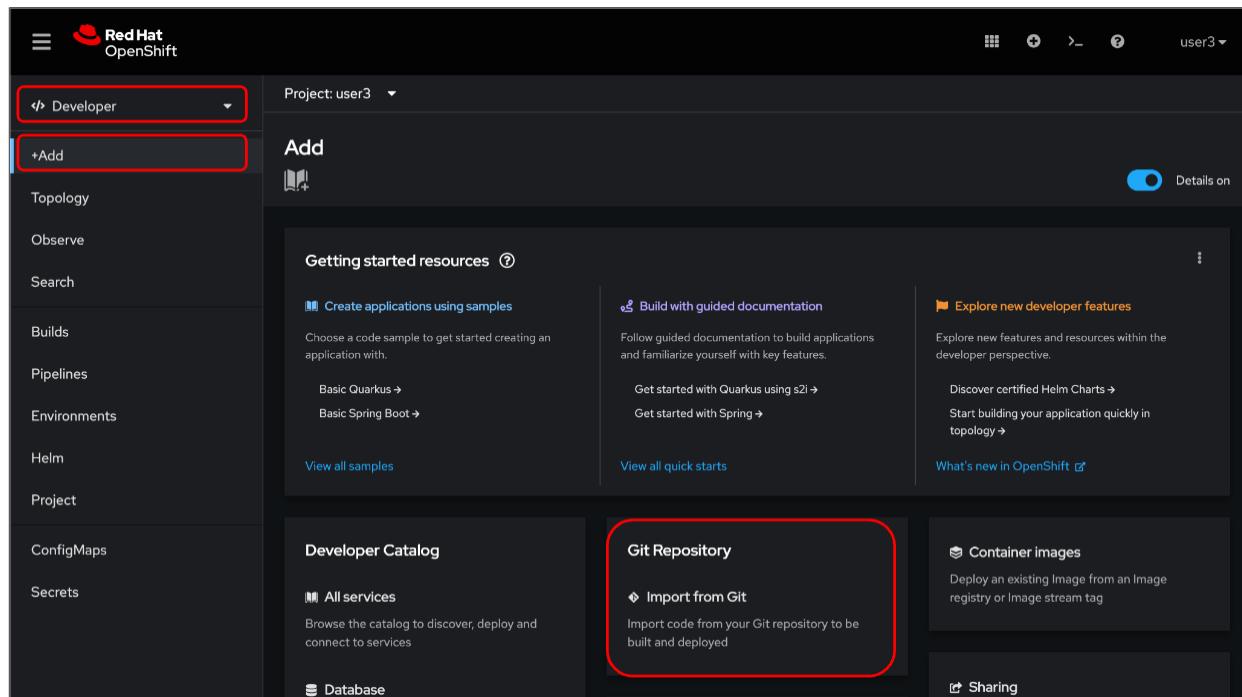
Hint: you can type in the name of a project and search for it in the '*Search by name...*' field!

During the workshop, if you do not have time to create containers in your own project, the projects **edge-anomaly-detection** & **edge-failure-prediction** will contain (pre-created) containers which you can view and run.

Make certain that you are in the 'Project' that is assigned to you (user<#>).

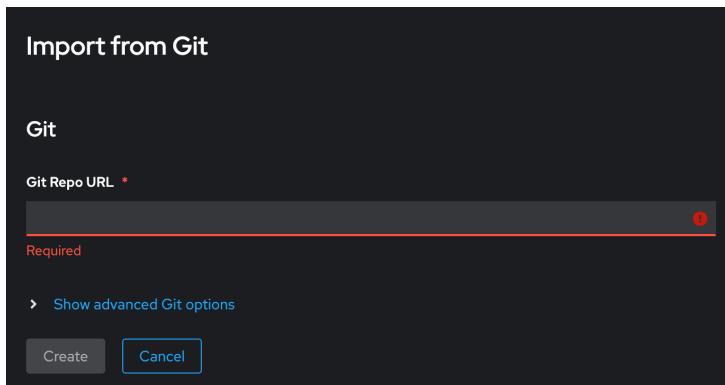
Project user<#>' is your work area (namespace) within OpenShift. This project name will be your userid that you were given at the beginning of the workshop. In the following screenshot, the project name is: user3. Click your project user<#>.

Once you have selected your project (e.g. user<#>), you can begin the process to create your container. Click the +Add menu. A number of options will appear.



We are going to create a containerized web application. We will be using the source code found in the **edge-anomaly-detection** **github repository** to create the containerized web application. To do this we use the **Git Repository**, '*Import from Git*' option.

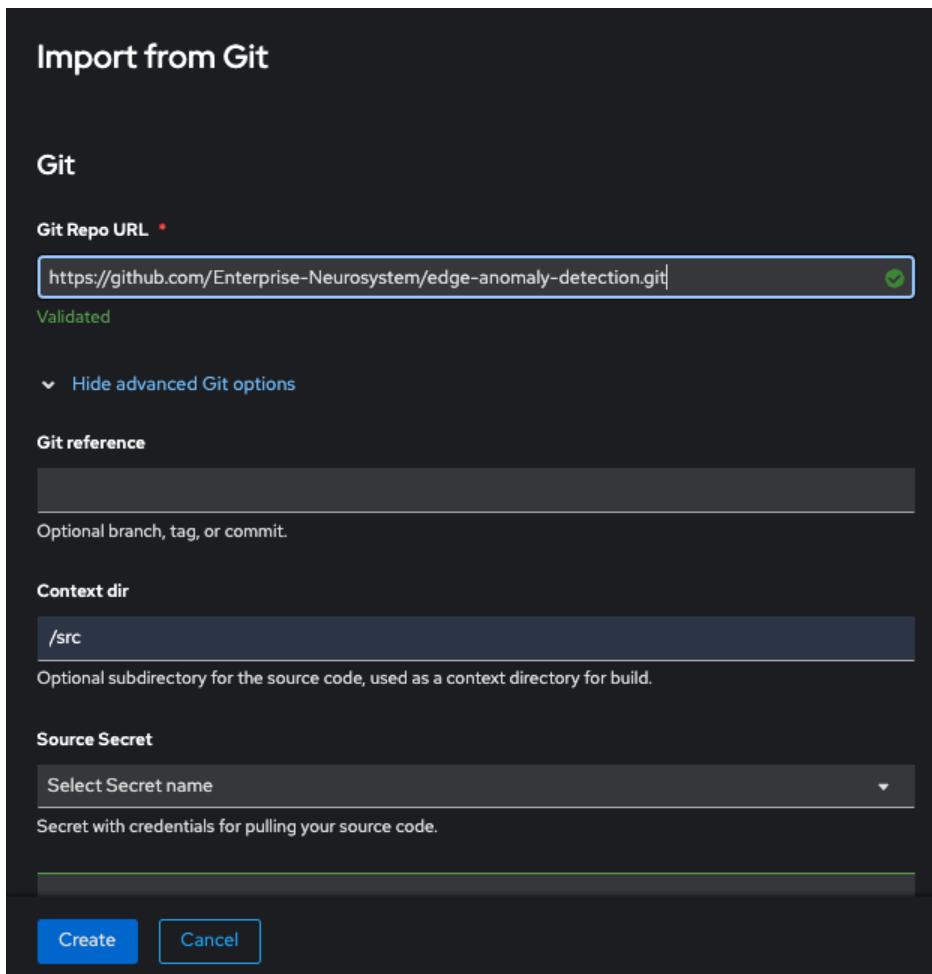
Click the ‘Git Repository’ option. The Import from Git page will appear.



In the Git Repo URL Field, enter:

`https://github.com/Enterprise-Neurosystem/edge-anomaly-detection.git`

The Git Repo URL will be validated. Once validated, further options are available.



Next you will need to:

1. Open “Show advanced Git Options”
2. Set “Context dir” to “src”

If you continue to scroll down the page, you will see that everything is automatically selected to create a deployment of your application, as well as a route through which you will be able to access the application.

Make certain to name your app. For example, *app-anomaly-detection*. Now we are ready to press the ‘Create’ button to create our containerized application. Press the ‘Create’ button.

The automated process will take a few minutes. Some alerts may appear if OpenShift tries to deploy the application while the build is still running, but that’s OK. Eventually, OpenShift will deploy the application (rollout), and in the topology view, you should see a screen similar to the following screen capture.

Click inside the topology icon (outer circle) to display the Resources tab

D edge-anomaly-detection-git Actions ▾

Health checks Container edge-anomaly-detection-git does not have health checks to ensure your application is running correctly. [Add health checks](#)

Details Resources Observe

Pods

Waiting for the build Waiting for the first build to run successfully. You may temporarily see "ImagePullBackOff" and "ErrImagePull" errors while waiting.

Show waiting pods with errors

No Pods found for this resource.

Builds

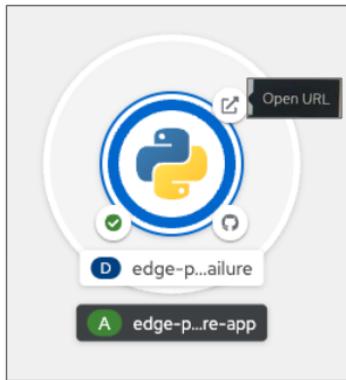
edge-anomaly-detection-git Start Build

Build #1 is running (Just now) View logs

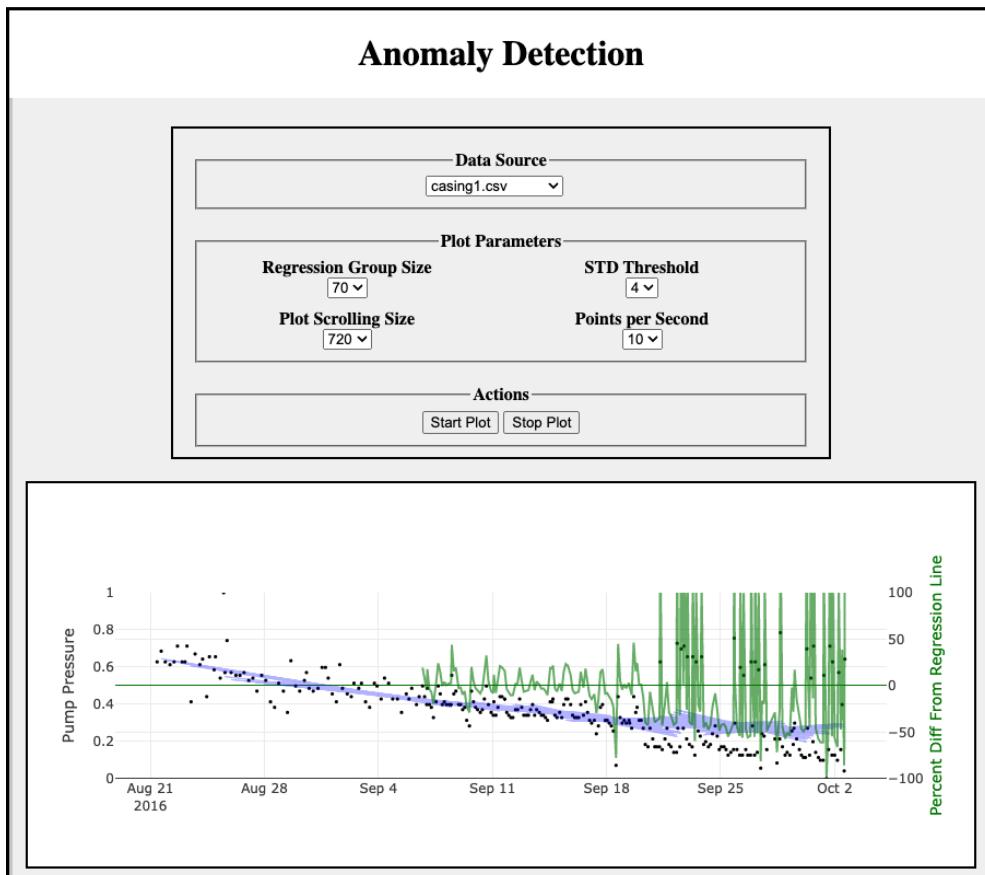
Services

edge-anomaly-detection-git Service port: 8080-tcp → Pod port: 8080

Now we can head back to our ‘Developer’ view and display our containerized application in a browser by clicking on the URL icon in the Topology view.



Your containerized Anomaly Detection application will appear in your browser window.
In this example we have gone ahead and executed the application.



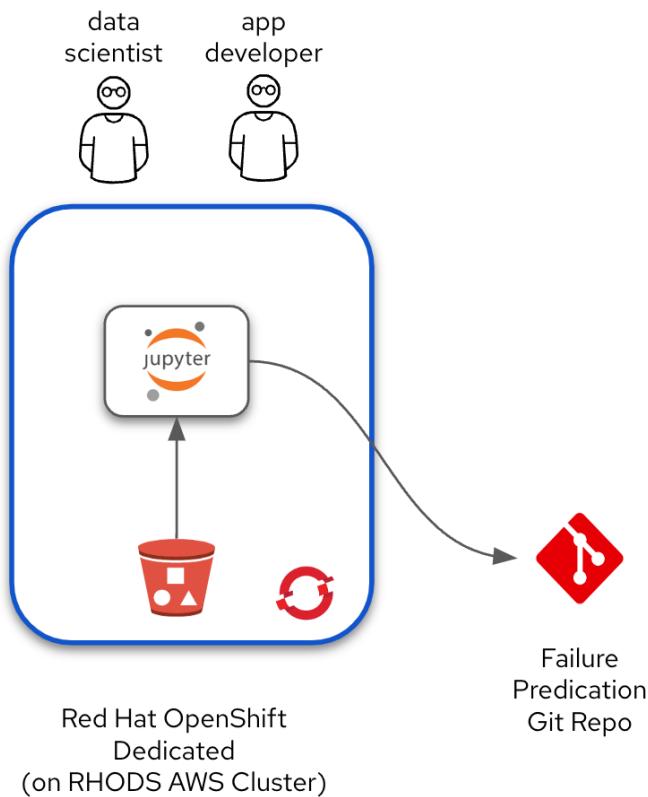
Try re-running the application with different plot parameters to see what happens.

Now that you have an idea of what sensor anomalies look like and how to detect them, let's take a look at how we can predict failures. Continue to the next section, [Failure Prediction Web Application](#).

5. Failure Prediction Web Application

5a Business Background & Architecture

Let's discuss the architecture that makes up the Failure Prediction Web application.



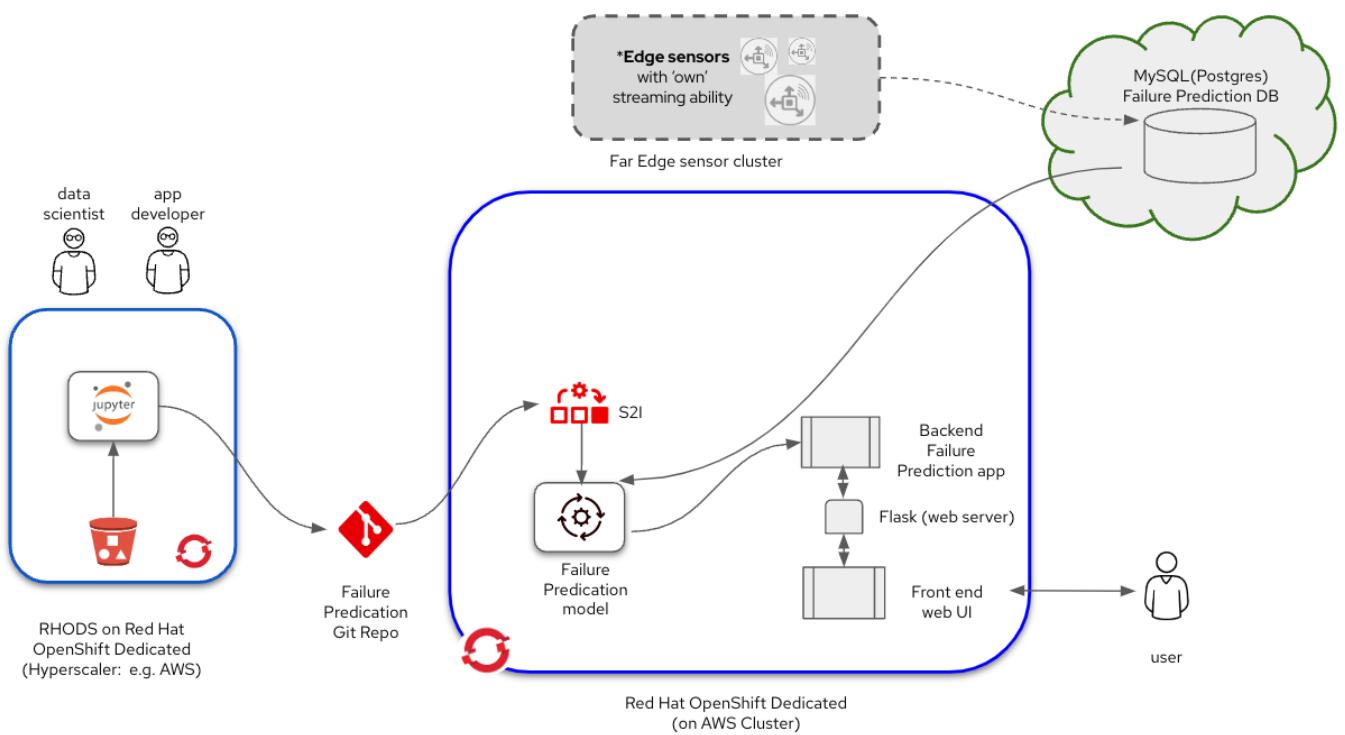
Here we have the DS and App Developer working and saving their work (python files) to a central github repository.

This is important to understand. Because we will then use the OpenShift platform that will take that repository and models, web UI and underlying business logic (services) and containerize them.

Once containerized we can then deploy the containerized image to be access by a URL (entry to our Failure Prediction model analysis)

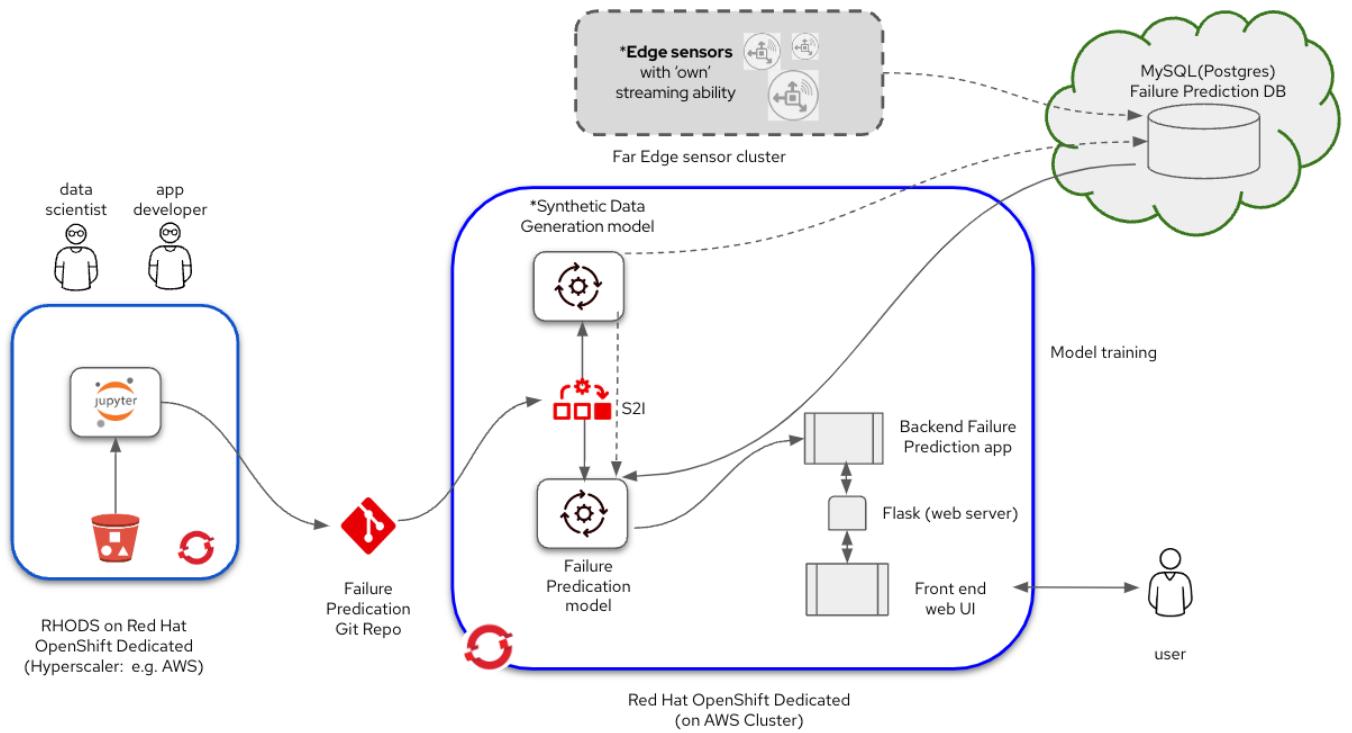
We envisioned the following scenario where data was generated by sensors, and placed into a database located outside of our network.

The fact is that some companies will save most of the time series data in order to train future models on that data..



Of course we didn't have live sensors so we had to add a synthetic data generator which we will see in the next diagram

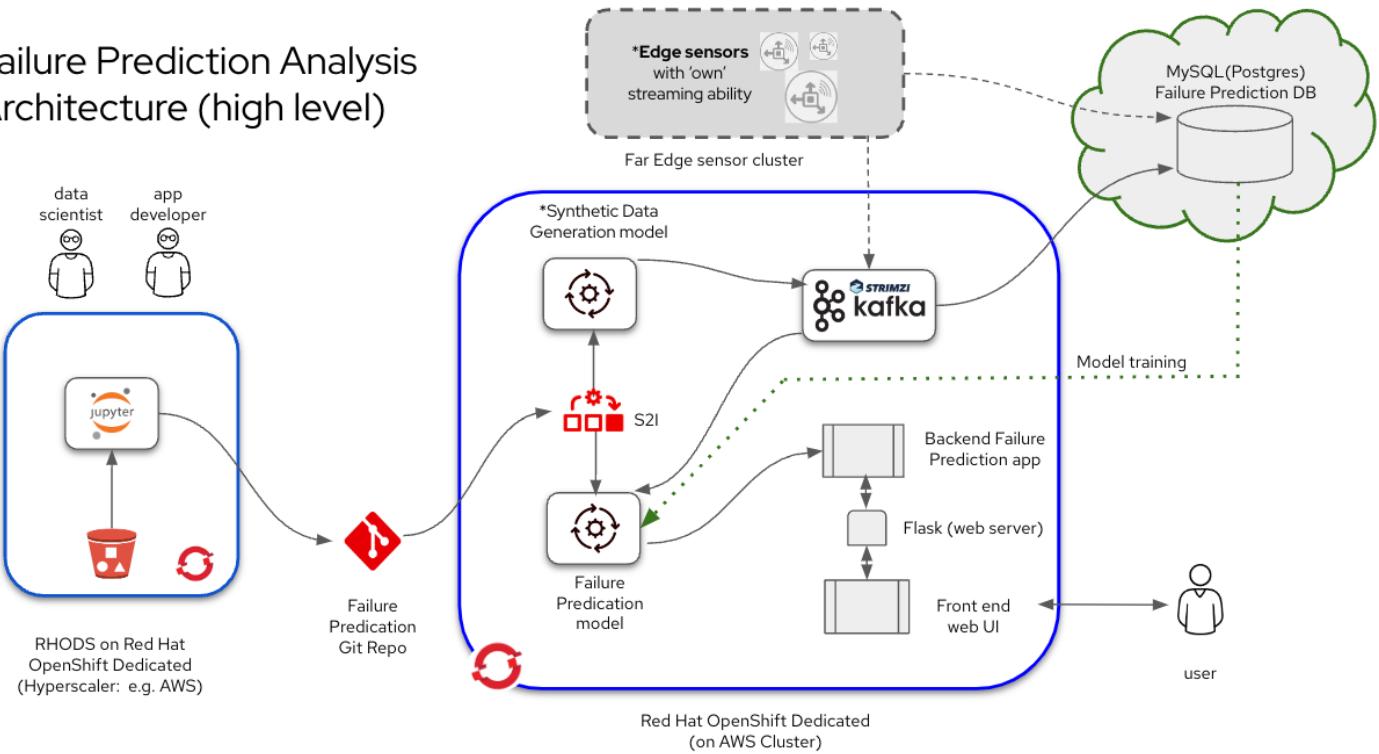
The addition of the Synthetic data generator was containerized and deployed via S2I. This allowed us to create data for consumption by our model and also store data in an external database residing in S3 storage in AWS



This looks good but we then needed a service to stream the data to the database and the model. That's where we introduced the Apache Kafka streaming service.

With the Apache Kafka streaming service we can take the synthetic data we generate, save it to the database and also stream the data to our failure prediction model for analysis.

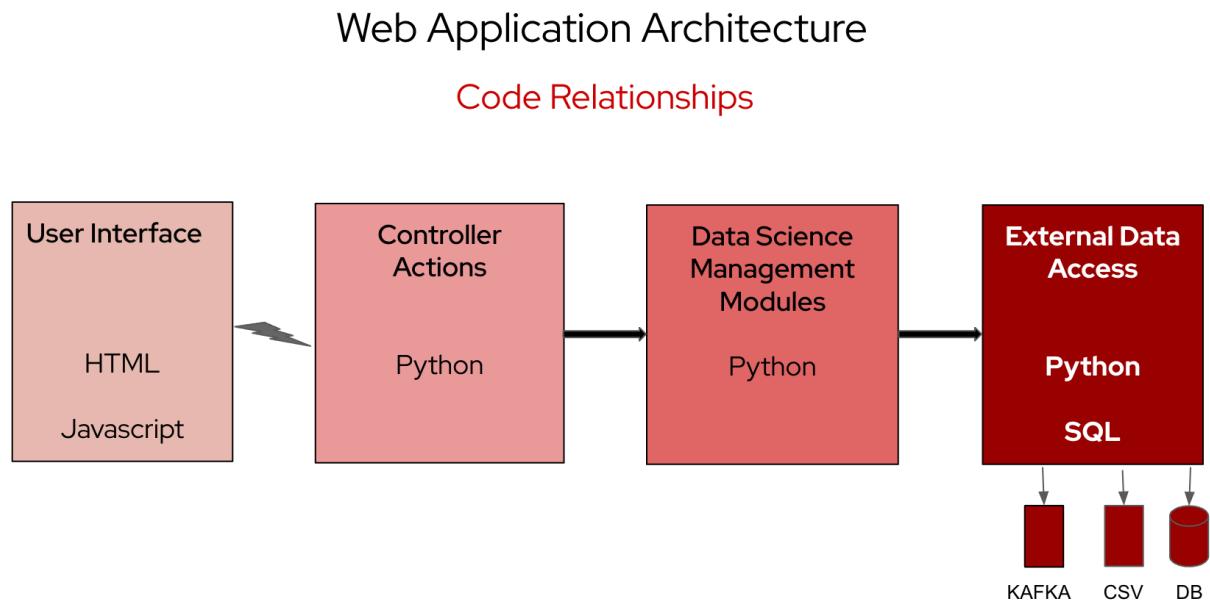
Failure Prediction Analysis Architecture (high level)



Note: in the future we can use the stored data to re-train our failure prediction model.

Analysis from the failure prediction model is then accessed through the web ui where it is displayed in plot format to our users.

5b Web Application Architecture



<class discussion>, after which we will discuss re-shaping time series data to work with an LSTM model.

5c Reshaping Time Series Data

Original Time Series Data

X1	X2	X3	X4	Y
x ₁₁	x ₁₂	x ₁₃	x ₁₄	y ₁
x ₂₁	x ₂₂	x ₂₃	x ₂₄	y ₂
x ₃₁	x ₃₂	x ₃₃	x ₃₄	y ₃
x ₄₁	x ₄₂	x ₄₃	x ₄₄	y ₄
x ₅₁	x ₅₂	x ₅₃	x ₅₄	y ₅
x ₆₁	x ₆₂	x ₆₃	x ₆₄	y ₆
x ₇₁	x ₇₂	x ₇₃	x ₇₄	y ₇
x ₈₁	x ₈₂	x ₈₃	x ₈₄	y ₈
...
x _{n1}	x _{n2}	x _{n3}	x _{n4}	y _n

Name: [Alexander Laskorunsky](#)

URL: <https://medium.com/mlearning-ai/lstm-with-keras-data-reshaping-in-many-to-one-architecture-c7d3669e3a5c>

This is what data would look like in a supervised model where you are trying to make a prediction from the rows of data.

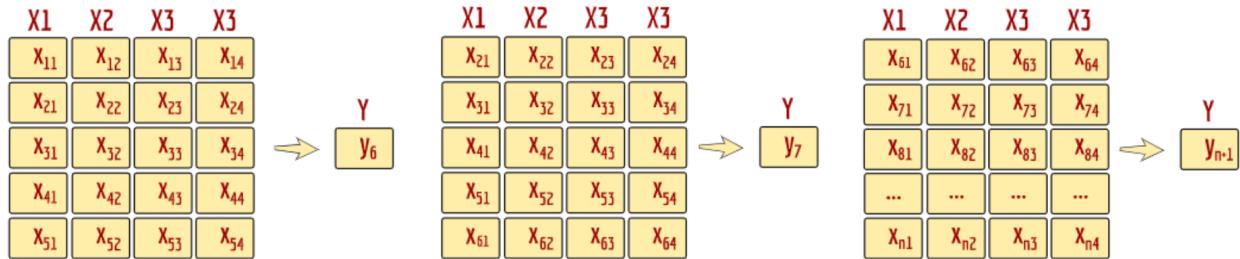
- Diagram shows 4 feature-xs (x14) and one target value (y)

Each column represents some value (e.g. diabetes, body mass index, gender, glucose level etc) The target is diabetes Y or N

The model can be a simple neural network which we can readily train with this data in the present form.

This is the typical data you come across, and if you want to make a prediction you supply 4 features to the model once it has been trained. Prediction is then simple.

Time Series to LSTM reshape



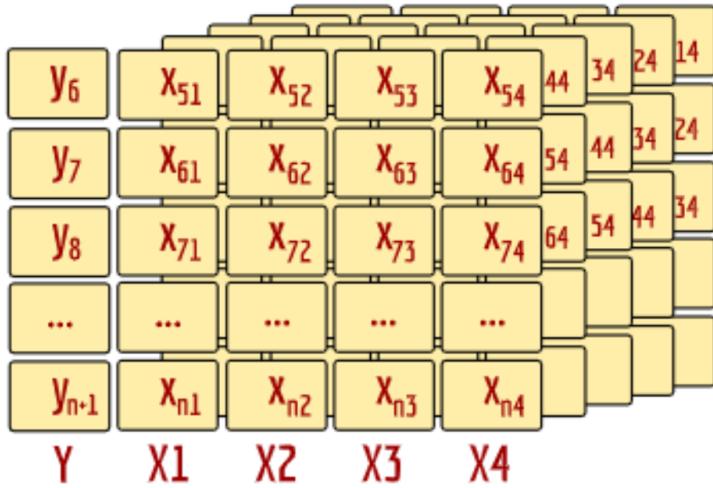
Name: [Alexander Laskorunsky](#)

URL: <https://medium.com/mlearning-ai/lstm-with-keras-data-reshaping-in-many-to-one-architecture-c7d3669e3a5c>

We have 4 features and a target output value. Each row represents a data point in a time series. We don't show the actual time values because we don't care what they are when we train the model. We assume that all of the time deltas between each data point are the same.

In the above example, we are using 5 data points to make a prediction for the 6th data point. Therefore we stack the above slices to make a 3D array.

Final 3D array for LSTM



Name: [Alexander Laskorunsky](#)

URL: <https://medium.com/mlearning-ai/lstm-with-keras-data-reshaping-in-many-to-one-architecture-c7d3669e3a5c>

Think of each of the groups of 5 features that we were looking at as a 2D array. In this chart each group is stacked one behind the other.

We use these 2D numpy arrays to train our model. We feed the model one array at a time. (E.g) feed one card at a time to the model

That's how we take a time series and reshape it so that it can be used in an LSTM model. For prediction, we create a buffer (programmatically) that holds 5 data points at a time. And we can't start predicting until the buffer has 5 data points in it. The buffer behaves as a queue, and we pop the bottom one off so that we can maintain a buffer size of 5 (in this case).

Now that we have seen the architectural overview, let's start building the failure prediction app. As usual, we start with the data. That is, we will examine and curate the data so that it can be readily used by our model.

We can see that the original shape of the time series was $(n_rows, 5)$ where 5 denotes the number of features.

The final shape is: $(n_rows - prediction_size - 1, prediction_size, num_features)$

- E.g. $(n_rows - 5 - 1, 5, 5)$

5d Data Preparation

We want to do the following steps for data preparation/curation:

1. Obtain sensor Data
2. Plot the data
3. Convert the Machine Status (text) to numeric values. (This column will become the model label)
4. Examine Nulls & determine which columns to drop
5. Discover the Failure times
6. Split data by Failure times into Training, Test, Validation
7. Mind the mean of the Training data
8. Replace the NaNs & blanks with the mean of the Training data
9. Create a MinMaxScaler for Training data
10. Transform all data using MinMaxScaler that was fit to Training data
11. Fit & Transform the Training data using PCA
12. Transform the Test and Validation data using the fitted PCA
13. Create a ranked list of the Principle Components. (This ranked list will now become the model features)

We placed all the data prep into one notebook - 10-pump-data-discovery.ipynb. Let's take a look at this notebook.

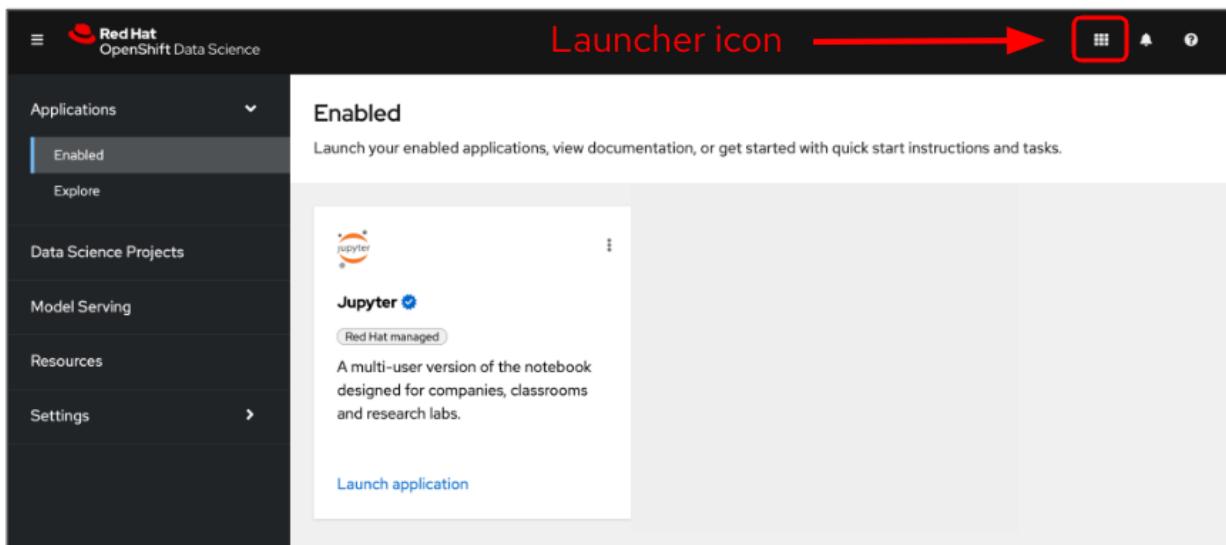
/ edge-failure-prediction / notebooks /		
Name	Last Modified	
scratch	4 hours ago	
00-connect-to-database.ipynb	4 hours ago	
01-data-cleaning.ipynb	4 hours ago	
02-principal-component-analysis.ipynb	4 hours ago	
03-examine-annotations.ipynb	4 hours ago	
04-graph-annotations.ipynb	4 hours ago	
10-pump-data-discovery.ipynb	4 hours ago	
requirements.txt	4 hours ago	

Now that we have seen how to curate the data, we will turn our attention to the Failure Prediction Web application which will incorporate what we learned.

5e Containerize & Run the Failure Prediction Web Application

Let's start by containerizing and deploying the Failure Prediction Web Application code. We will package the code as a container image and run it directly in OpenShift as a Web Application.

From the Red Hat OpenShift Data Science platform choose the Launcher Tool and **Select “OpenShift Console”**



Within the OpenShift console, make certain you are in ‘Developer’ mode.

Note: The Launcher Icon is also visible in the OpenShift console. You can use this icon to move between the Red Hat OpenShift Data Science Platform and the Red Hat OpenShift Dedicated platform.

Project: All Projects

Add

Select a Project to start adding to it or [create a Project](#).

Name	Display na...	Status	Requester	Created
PR areznik-dev	areznik-dev	Active	areznik	Oct 18, 2023

While you are in Developer mode, click on the ‘Topology’ menu item. You will see 6 projects:

Welcome to the 'AI/ML Intelligent Applications for the Edge' Workshop

Project: All Projects

Topology

Select a Project to view the topology or [create a Project](#).

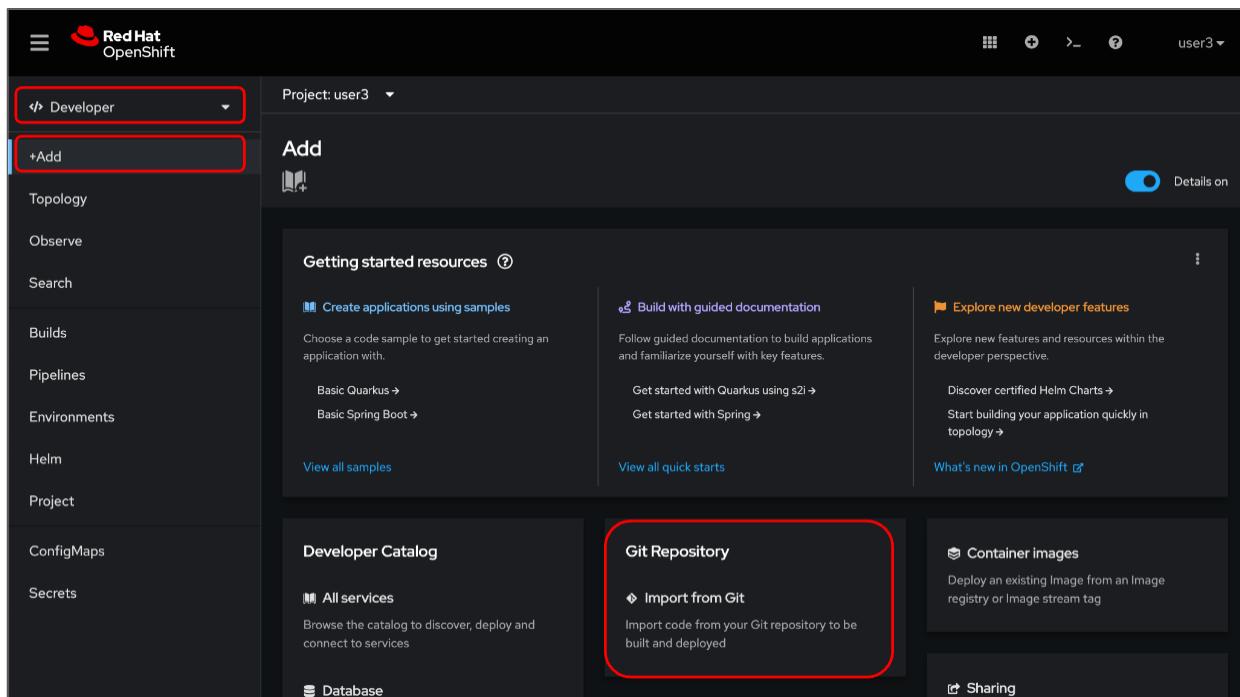
Name	Display name	Status	Requester	Created
PR edge-anomaly-detect...	Edge Detection Workshop	Active	No requester	May 6, 2023, 3:28 PM
PR edge-failure-prediction	Edge Prediction Workshop	Active	No requester	May 6, 2023, 3:28 PM
PR edge-synthetic-data-...	Edge Data Gen Workshop	Active	No requester	May 6, 2023, 3:28 PM
PR group-project	The Allen Parsons Project	Active	No requester	May 6, 2023, 3:32 PM
PR sandbox	Sandbox	Active	No requester	May 6, 2023, 3:28 PM
PR user3	Start Here - user3	Active	No requester	May 6, 2023, 3:28 PM

1. Edge-anomaly-detection
2. Edge-failure-prediction
3. Edge-synthetic-data-generator
4. Group-project
5. Sandbox
6. user<#>

You will begin by working in your project user<#>.

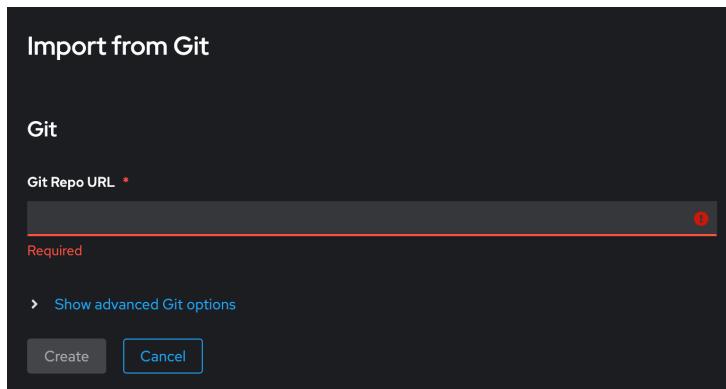
Make certain that you are in the ‘Project’ that is assigned to you (user<#>). Project user<#> is your work area within OpenShift. This project name will be your userid that you were given at the beginning of the workshop. In the following screenshot, the project name is: user3. Click your project user<#>. You will see the following screen where ‘No resources found’. This is ok as we are going to create your first containerized resource.

Once your project (e.g. user<#>) is opened, you can begin the process to create your container. Click the +Add menu. A number of options will appear.



We are going to create a containerized web application. We will be using the source code found in the edge-failure-prediction repository to create the web application. To do this we use the Git Repository, Import from Git option.

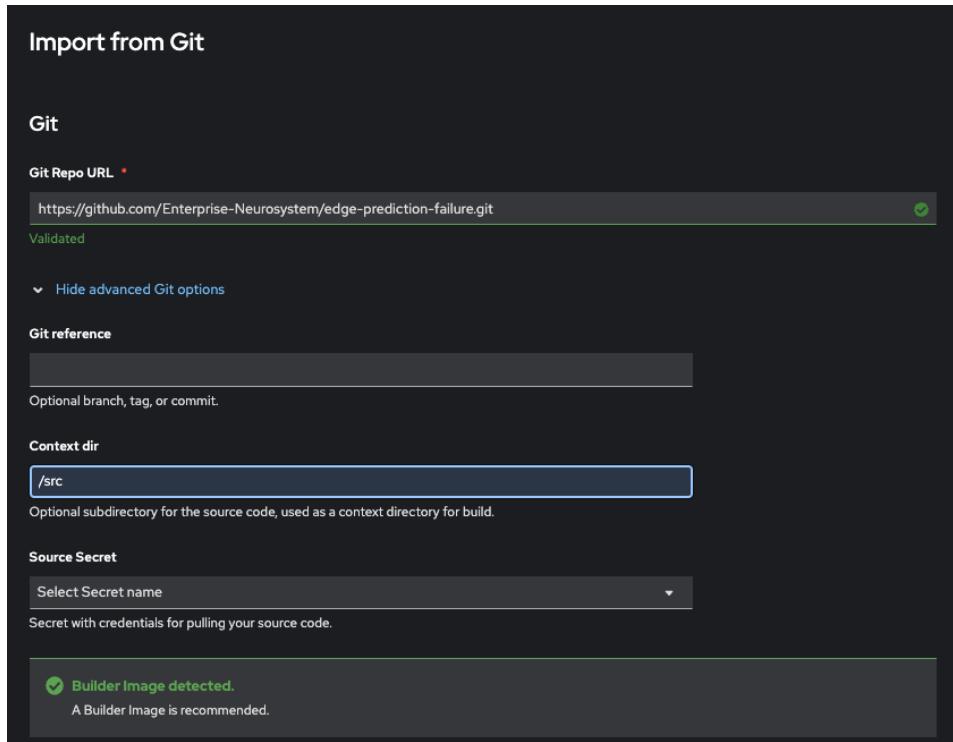
Click the ‘Git Repository option. An Import from Git page will appear.



In the Git Repo URL Field, enter:

<https://github.com/Enterprise-Neurosystem/edge-failure-prediction.git>

Note that the Git Repo URL will be validated. Once validated, further options are available.

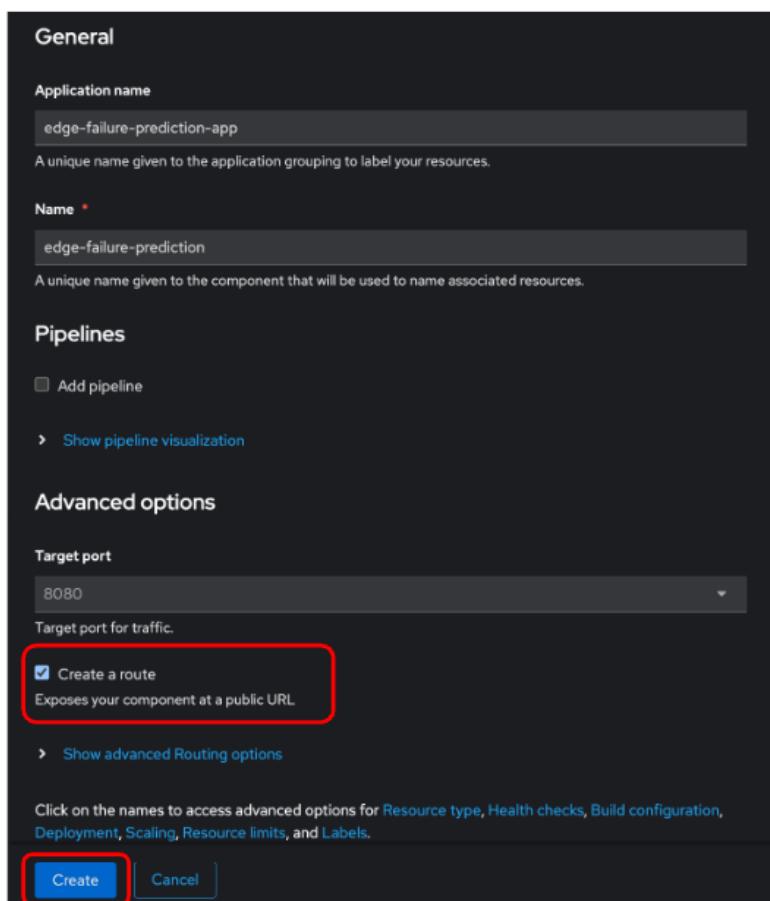


Next you will need to:

3. Open “Show advanced Git Options”
4. Set “Context dir” to “src”

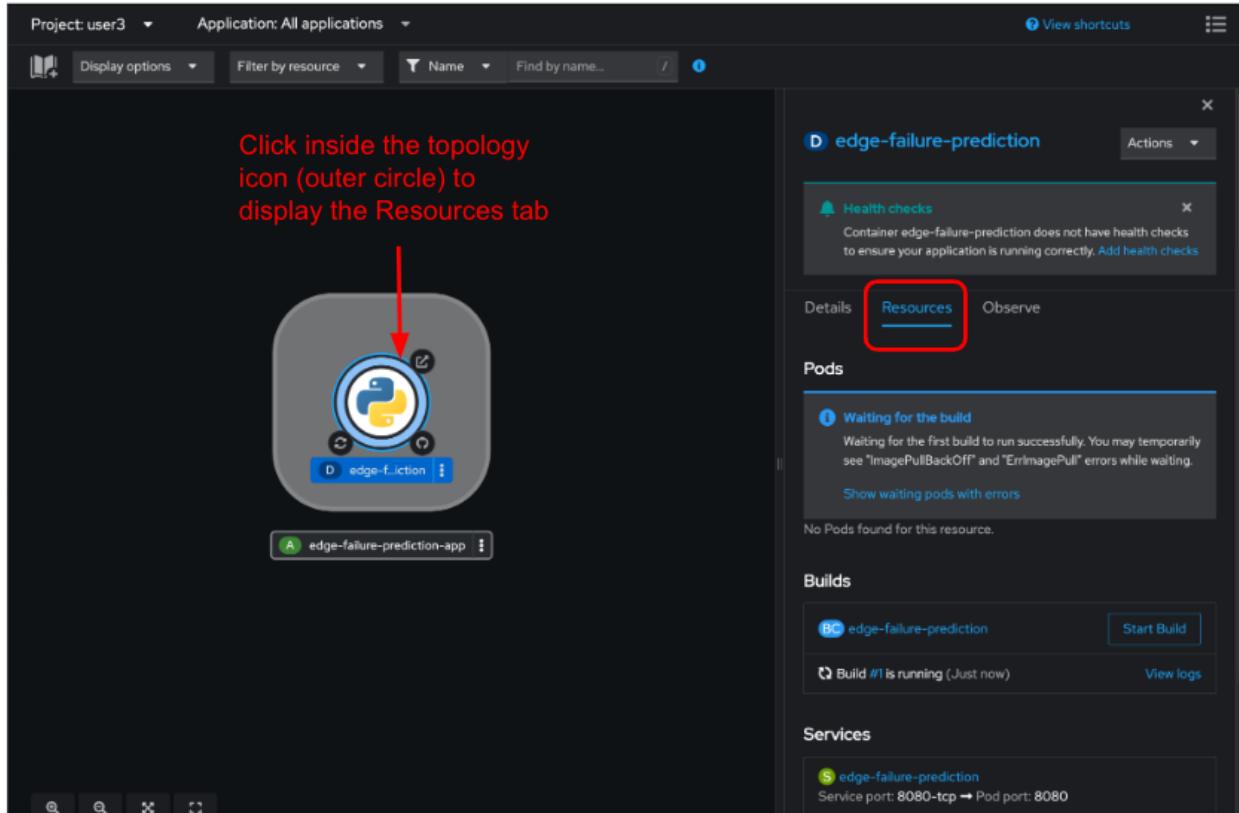
If you continue to scroll down the page, you will see that everything is automatically selected to create a deployment of your application, as well as a route through which you will be able to access the application.

Make certain to name your app. For example, app-failure-prediction. Now we are ready to press the ‘Create’ button to create our containerized application. Press the ‘Create’ button.

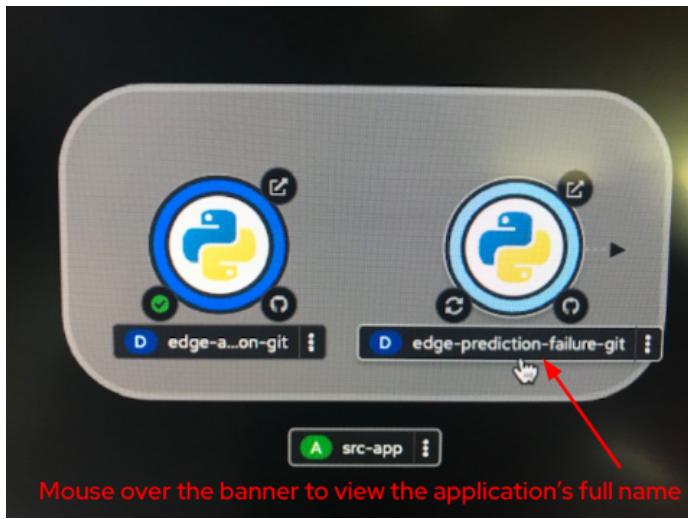


The automated process will take a few minutes. Some alerts may appear if OpenShift tries to deploy the application while the build is still running, but that's OK.

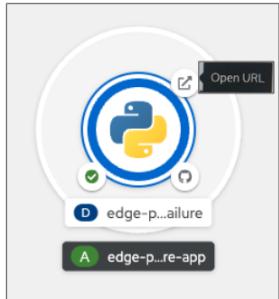
Eventually, OpenShift will deploy the application (rollout), and in the topology view, you should see a screen similar to the following screen capture.



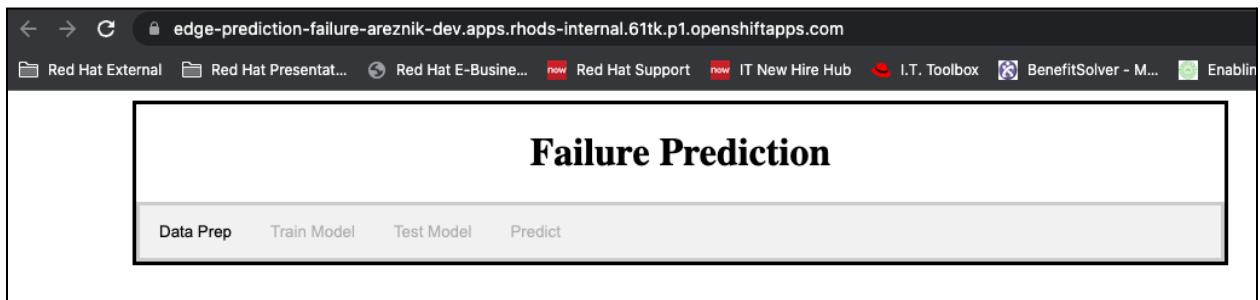
Note: if you gave the Failure Prediction application the same application name as the Anomaly Detection application (e.g. src-app) you will see both applications within the same container. See following screen capture.



Let's head back to our 'Developer' view and display our containerized application in a browser by clicking on the URL icon in the Topology view.



Your containerized Failure Prediction application will now appear in a browser window.



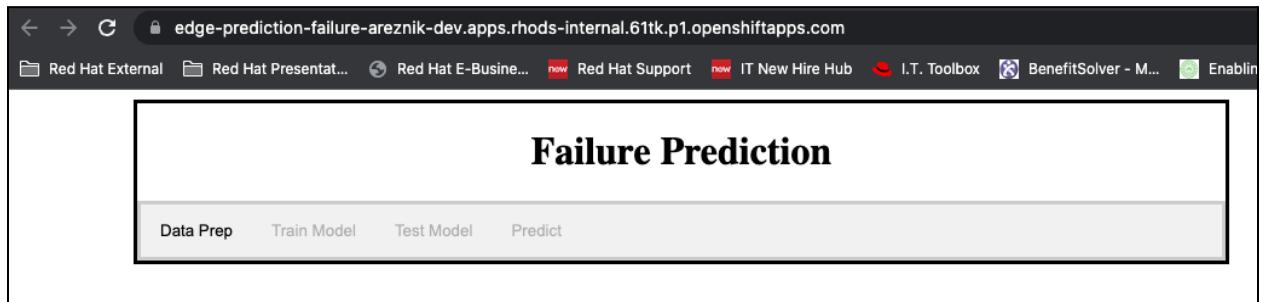
This application serves as a wizard that allows the user to:

- Prepare data for training, testing and prediction
- Train the model
- Test the model
- Make predictions on data that the user chooses

The goal of this application is to ultimately use a trained model that has learned what failures look like to specify there is a possibility of an imminent failure.

Opening Screen

When you first open the application, you will see **tabs**, some of which are initially disabled:



This user interface will guide you through all the processes from Data Preparation through Predictions and will make sure that you perform all processes in the correct order, just like a wizard.

The gray bar with the labels Data Prep, Train Model, Test Model, Predict serve as navigation tabs. When you click on a tab, the relevant screen will appear. Think of the tabs as menu selections that change the interface to suit the job at hand.

We don't have time in this lab to set up the database and database connections which contain water pump data that we will be curating. Therefore since you now know how to create a

containerized application, you will switch projects from <user># to edge-failure-prediction.

Switch to the **edge-failure-prediction** project.

The screenshot shows the Red Hat OpenShift web interface. The top navigation bar includes the Red Hat logo, 'OpenShift', and user information ('admin'). The main header shows 'Project: edge-failure-prediction' and 'Application: All applications'. The left sidebar has a 'Developer' section with a '+Add' button, followed by 'Topology', 'Observe', 'Search', 'Builds', 'Pipelines', 'Environments', 'Helm', 'Project', 'ConfigMaps', and 'Secrets'. The central area displays a cluster diagram with two pods: 'predict-db' (Postgres database with kaggle data) and 'predict'. The 'predict' pod has a red box around its URL in the browser address bar and another red box around its icon. The right panel shows the 'predict' pod details, including a 'Health checks' section with a warning message: 'Container predict does not have health checks to ensure your application is running correctly. Add health checks', and tabs for 'Details', 'Resources', and 'Observe'. The 'Pods' section lists the 'predict' pod as 'Running'. The 'Builds' section shows a build named 'predict' with a 'Start Build' button.

You will see the containerized postgres database and containerized edge-failure-prediction application. Go ahead and click the URL for the edge-failure-prediction application.

Data Preparation

When the application first loads in your browser, a large amount of data is loaded.

Click on the Data Prep tab.

If you click on the Data Prep tab before all the data has been loaded, you will see:

The screenshot shows a web-based application titled "Failure Prediction". At the top, there is a navigation bar with four tabs: "Data Prep" (which is highlighted in purple), "Train Model", "Test Model", and "Predict". Below the navigation bar, the main content area is titled "Data Preparation". Within this area, there is a section labeled "Data Preparation Action" containing two buttons: "Start Data Prep" and "Stop Data Prep". A message below the buttons states "Loading data....Takes about 20 sec". The entire interface is enclosed in a light gray border.

The message: **Loading data....** means that you cannot proceed past this page until the data are loaded. Notice that the Start Data Prep button is disabled, and will stay disabled until the data are loaded.

Once loaded, the **Start Data Prep** button will be enabled.

The screenshot shows the 'Failure Prediction' application interface. At the top, there are tabs for 'Data Prep', 'Train Model', 'Test Model', and 'Predict'. The 'Data Prep' tab is selected. Below the tabs, the title 'Data Preparation' is centered. Underneath it is a box labeled 'Data Preparation Action' containing 'Start Data Prep' and 'Stop Data Prep' buttons. A message below the buttons says 'Data is loaded. Press 'Start Data Prep' Btn'. In the center of the screen, there is a section titled 'Feature Choices' which is divided into four boxes:

- Sensor Name Sum Nulls** (Table):

Sensor Name	Sum Nulls
sensor_00	10208
sensor_01	369
sensor_02	19
sensor_03	19
sensor_04	19
sensor_05	19
sensor_06	4798
sensor_07	5451
- Dropped Sensors** (Table):

Dropped Sensors
sensor_00
sensor_15
sensor_50
sensor_51
- PC Name Ranked Variance** (Table):

PC Name	Ranked Variance
pc1	59.3%
pc2	16.5%
pc3	6.6%
pc4	3.7%
pc5	2.1%
pc6	1.6%
pc7	1.2%
- PC In Model** (Table):

PC In Model
pc1
pc2
pc3
pc4
pc5
pc6
pc7
pc8

The information that you see in the box labeled **Feature Choices** refers to what you discovered in the start of the workshop. That is, you did some data discovery. The box in the upper left shows how many nulls were found in each sensor column. That is why, for example, the box in the upper right shows a list of the sensors that will be dropped, including `sensor_00`.

The box in the lower left shows a list of results from the **Principal Component Analysis (PCA)** that you found in the data discovery. In the original data there were about 52 sensors. We would like to shorten this list to make the model training take less time. Instead of going through a long process of deciding which sensors to keep, we use the PCA that finds which linear combinations of all the sensors gives the most variance. The linear combinations are denoted by `pc1`, `pc2`, `pc3`, ..., (called Principal

Components) where pc1 is the first ranked. We then take however many pc's we need so that the sum of their ranked variances is at least 95%. In our case it takes 12 pc's to reach that goal. We then use those 12 pc's to represent a transformation of our original 52 sensors when we train the model.

Now that we have all the data loaded and the PCA transformation is complete, we are ready to proceed with preparing the data.

Click on the Start Data Prep button.

Each row of data that we will use has a timestamp together with the 12 pc's that we will now call **model features**. Data that is ordered by time is called a **Time Series**.

In the background, the application is reshaping the time series data so that it will be put into a form that the model understands. While this processing is taking place you will see:

Failure Prediction

Data Prep Train Model Test Model Predict

Data Preparation

Data Preparation Action

Start Data Prep Stop Data Prep

30%

Feature Choices

Sensor Name	Sum Nulls
sensor_00	10208
sensor_01	369
sensor_02	19
sensor_03	19
sensor_04	19
sensor_05	19
sensor_06	4798
sensor_07	5451

Dropped Sensors	
sensor_00	
sensor_15	
sensor_50	
sensor_51	

PC Name	Ranked Variance
pc1	59.3%
pc2	16.5%
pc3	6.6%
pc4	3.7%
pc5	2.1%
pc6	1.6%
pc7	1.2%

PC In Model	
pc1	
pc2	
pc3	
pc4	
pc5	
pc6	
pc7	
pc8	

The progress bar will start slowly and at about 50% will speed up. When the data preparation is complete, a message will appear and the next tab, **Train Model** tab will be enabled:

Failure Prediction

Data Prep Train Model Test Model Predict

Data Preparation

— Data Preparation Action —

Data is prepared. Ready to train

Feature Choices

Sensor Name	Sum Nulls
sensor_00	10208
sensor_01	369
sensor_02	19
sensor_03	19
sensor_04	19
sensor_05	19
sensor_06	4798
sensor_07	5451

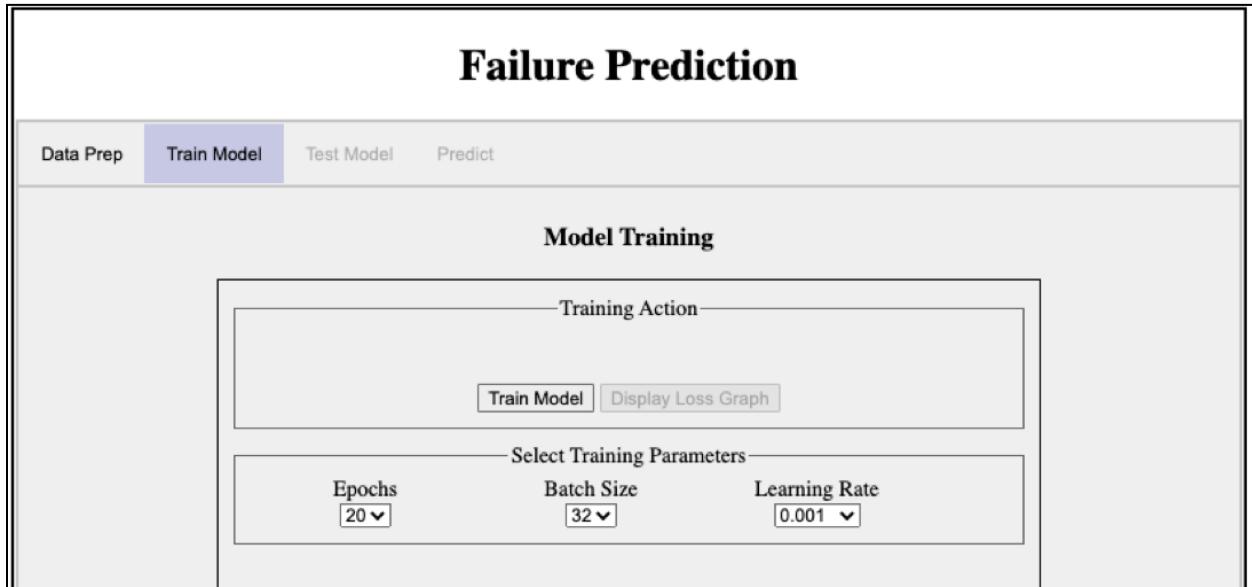
Dropped Sensors
sensor_00
sensor_15
sensor_50
sensor_51

PC Name	Ranked Variance
pc1	59.3%
pc2	16.5%
pc3	6.6%
pc4	3.7%
pc5	2.1%
pc6	1.6%
pc7	1.2%

PC In Model
pc1
pc2
pc3
pc4
pc5
pc6
pc7
pc8

Training the Model

Click on the Train Model tab.



The training process of a model is sometimes called the **learning process**. This learning process is iterative. A model is a numerical approximation of an entity, and the training data are used to calculate coefficients of the approximation. The training data contain values for the features (input) together with values for the target (output). So during one pass (called an **epoch**) on the data, small samples of the training data (called a **batch**) are used to update the model's coefficients.

During training, a parameter called the **learning rate** is used to determine the “pace” of the iterative steps used to update the coefficients. If the learning rate is too large, then the model may step over a critical part of the updating process. If too small, the updates may cause the model to converge too quickly and possibly miss the optimal approximation. In this training session, the learning rate starts as the value in the pull down, but after 10 epochs its value is divided by a factor of 10.

The default values in the pull downs are better left alone for this workshop.

Click on the Train Model button to start the training.

During training, there is no progress feedback. This is because the fit() function only gives progress in the form of text displayed in a terminal console. Since a web application has no console, there is no progress feedback available.

Failure Prediction

Data Prep **Train Model** Test Model Predict

Model Training

Training Action

Train Model [Display Loss Graph](#)

Select Training Parameters

Epochs <input type="button" value="20 ▾"/>	Batch Size <input type="button" value="32 ▾"/>	Learning Rate <input type="button" value="0.001 ▾"/>
---	---	---

Working...For 20 Epochs expect about 40 seconds

When the training is finished you will see:

Failure Prediction

Data PrepTrain ModelTest ModelPredict

Model Training

—Training Action—

—Select Training Parameters—

Epochs
Batch Size
Learning Rate

Training is finished. Click on Display Loss Graph Btn.

Notice that the Display Loss Graph button is now enabled.

Click on the Display Loss Graph button and we will see a graph showing the Loss Graph:

Failure Prediction

Data Prep Train Model Test Model Predict

Model Training

Training Action

Select Training Parameters

Epochs <input type="button" value="20 ▾"/>	Batch Size <input type="button" value="32 ▾"/>	Learning Rate <input type="button" value="0.001 ▾"/>
---	---	---

Cross-Entropy Loss

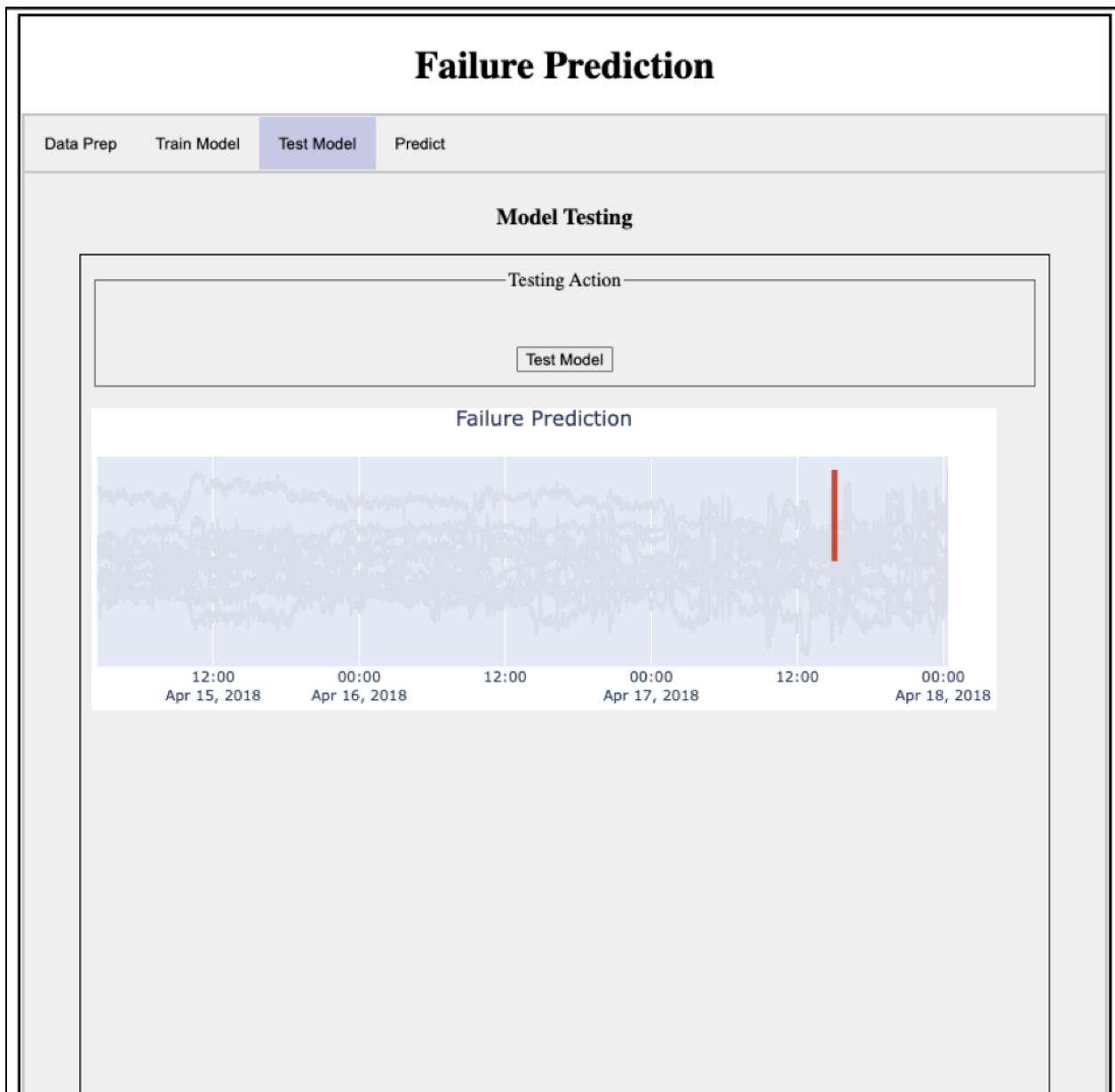
Epoch	Loss
0.0	0.35
2.5	0.08
5.0	0.05
7.5	0.03
10.0	0.01
12.5	0.005
15.0	0.002
17.5	0.001

Besides the graph you will notice that the two tabs labeled Test Model and Predict have been enabled. We will run the Test first, although at this point we could just as well run a prediction.

Testing the Model

Click on the Test Model tab. The Test Model tab is sparse because there are no parameters to define for training.

Just **click on the Test Model button.** The result is something like:



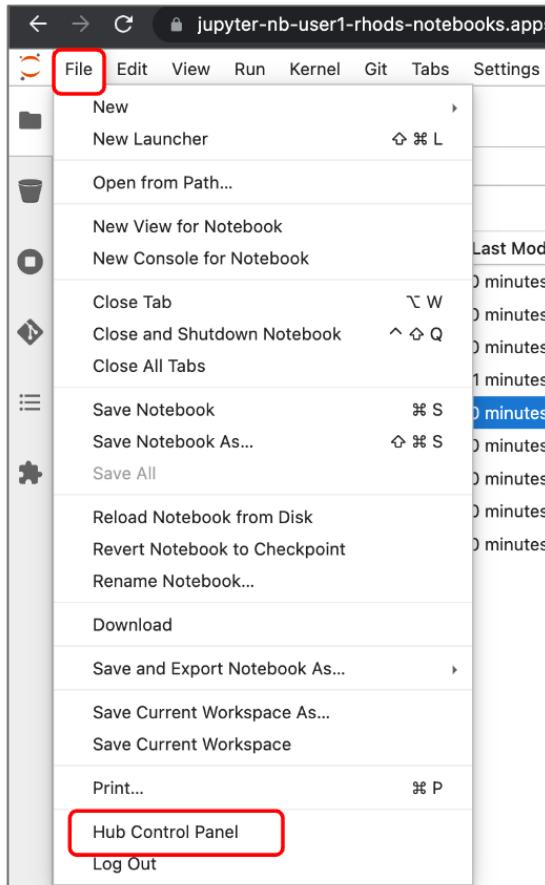
Do not be surprised if your neighbor gets a slightly different result. This is because of all the moving parts of the process, that is, because of the stochastic nature of training the model. Remember that a model is an approximation and the training involves uncertainties and randomness in order to make the approximation.

Before we can look at predicting mechanical pump failures in real time, we need to have real time mechanical pump sensor data to work with. For this workshop, we will not be connecting to a real time mechanical pump. Therefore; to **simulate real time mechanical pump sensor data, we created a synthetic data generator**. This generator will allow you to create real-time synthetic data that our failure prediction model can ingest and determine if a mechanical failure is imminent. Let's look at how we generate Synthetic Data. Continue to the next section - [Generate Synthetic Data](#).

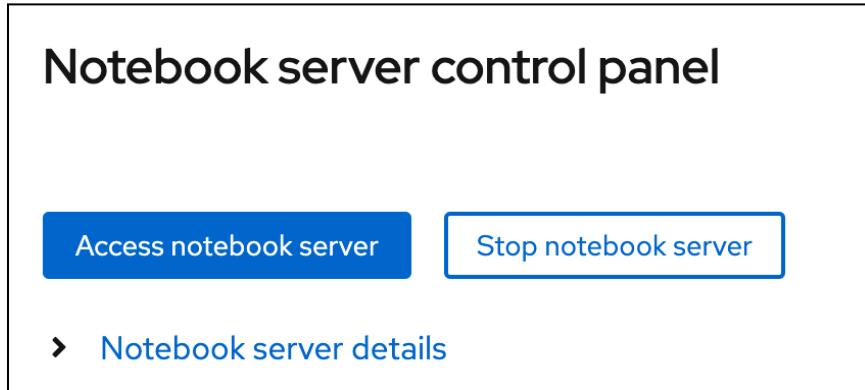
5f Generate Synthetic Data

We are now going to generate synthetic data that we will use in our Failure Prediction Model. **Navigate back to your JupyterLab environment.** We need to change the Notebook server image from 'Standard Data Science' to 'PyTorch'.

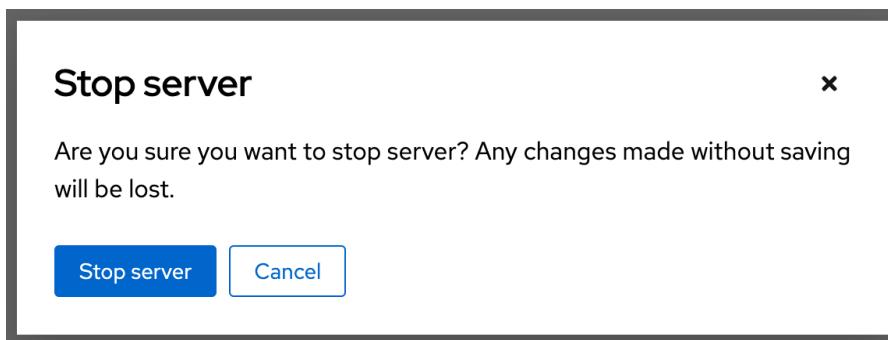
From the '*File*' menu, choose '*Hub Control Panel* option'.



The ‘Notebook server control panel’ page will appear. Click the ‘Stop notebook server’ option.



The Stop server dialog will appear. Choose the ‘Stop server’ option.



The ‘Start a Notebook Server’ options page will appear. This page should look familiar to you.

Start a notebook server

Select options for your notebook server.

Notebook image

- VS Code Server v4.9.1 ⓘ
Coder Code Server v4.9.1
[▶ Versions](#)
- Standard Data Science 2023.1 ⓘ
Python v3.9
[▶ Versions](#)
- PyTorch 1.2 ⓘ
Python v3.8, PyTorch v1.8
[▼ Versions](#)
 - Version 2023.1 ⓘ ★ Recommended
 - Version 1.2 ⓘ
Python v3.8, PyTorch v1.8
- TrustyAI ⓘ
Python v3.9

Deployment size

Container Size

Demo / Workshop

Environment variables

[+ Add more variables](#)

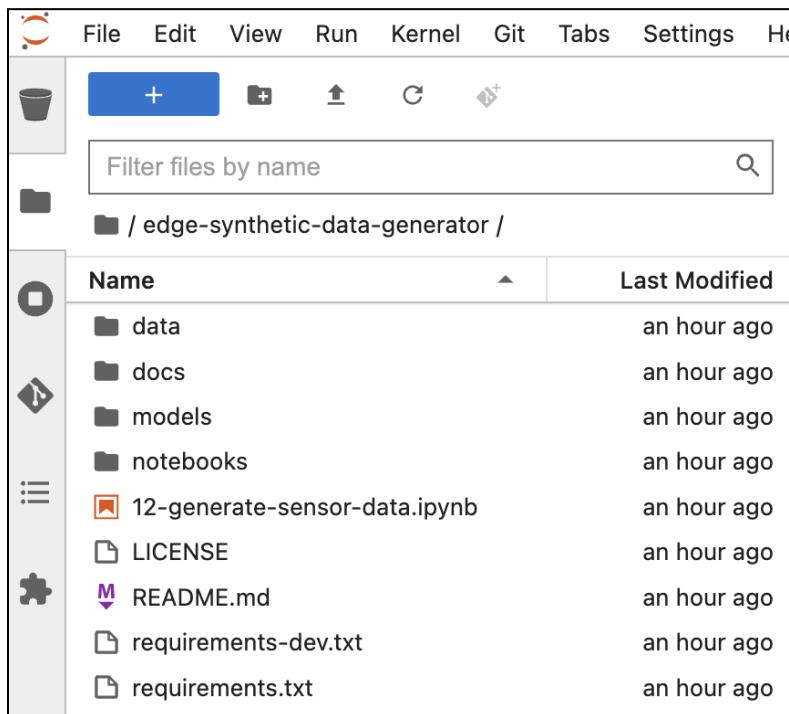
[Start server](#) [Cancel](#)

In the ‘Start a Notebook’ server page, choose ‘PyTorch 1.2 Version 1.2’, ‘Demo/Workshop’ container size. Then press the “Start Notebook” server button.

Once the server spins up you will be taken to the Jupyter Lab environment.

Previously you have already done a ‘git clone’ operation for the ‘edge-synthetic-data-generator’ git repo.

Let’s open up the edge-synthetic-data-generator folder by double clicking on the edge-synthetic-data-generator folder name.



The folder should contain the following sub-folders:

- data
- docs
- models
- notebooks

We will be working with the `12_generate_sensor_data.ipynb` jupyter notebook. Double click on the notebook name to open the notebook.

You will be running each of the cells, one at a time, in this notebook.

The screenshot shows a Jupyter Notebook interface. On the left is a file browser with a tree view of a directory named 'edge-synthetic-data-generator'. The current file is '12_generate_sensor_data.ipynb', which was modified 'a minute ago'. The notebook title is 'Generate Sensor Data'. The content includes a text block about generating synthetic data from real sensor data, mentioning DoppelGANger and its GitHub repository. Below is a code cell containing pip installation commands for torch, git, numpy, and kafka-python, along with imports for pandas, numpy, matplotlib.pyplot, matplotlib.dates, and specific modules from gretel-synthetics. A second code cell shows imports for torch, gretel-synthetics.timeseries_dgan.dgan, and gretel-synthetics.config.

Run the first cell to install the required packages for this workshop by selecting it and clicking on the run button or press the <shift><enter> keys on your keyboard.

The screenshot shows the same Jupyter Notebook interface. The 'Run the selected cells and advance' button is highlighted with a red box. The notebook title is 'Generate Sensor Data'. The content includes a text block about generating synthetic data from real sensor data, mentioning DoppelGANger and its GitHub repository. Below is a code cell containing pip installation commands for torch, git, numpy, and kafka-python, along with imports for pandas, numpy, matplotlib.pyplot, matplotlib.dates, and specific modules from gretel-synthetics.

Next, in the following cell, replace ‘None’ with the GROUP_ID number that is part of your username. E.g. user3: GROUP_ID = 3

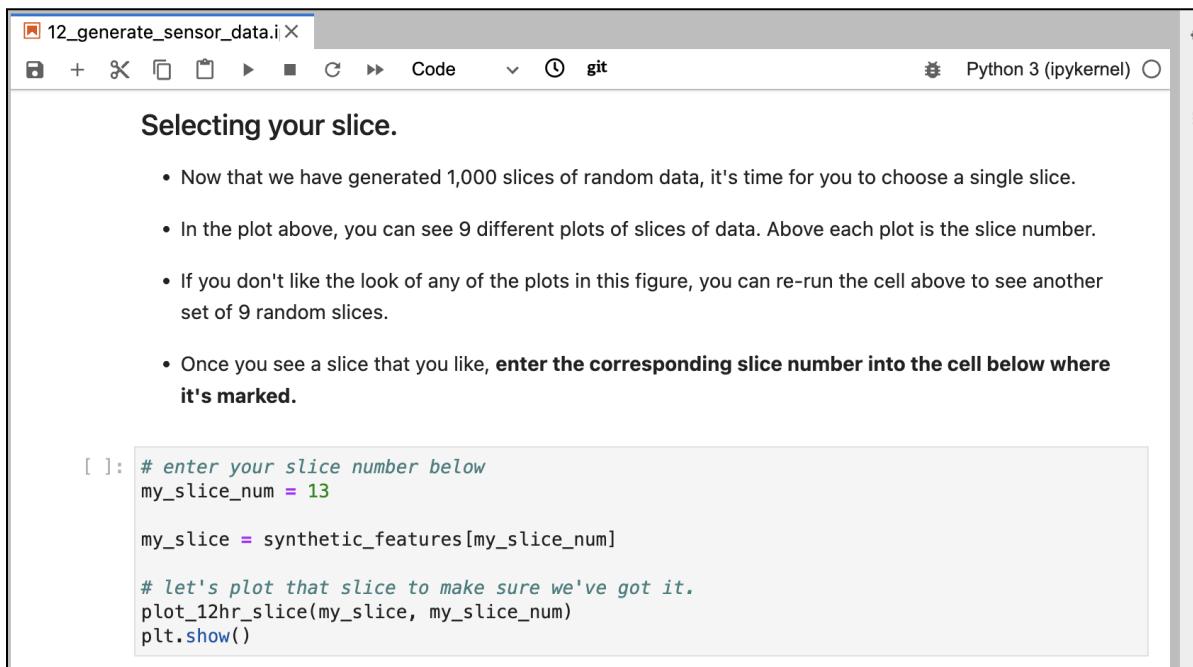


```
[ ]: GROUP_ID = None
```

Afterwards, select and run cells 3-7 to generate synthetic data from a pre-trained model and plot some slices of the data.

i) Select a data slice

Once you have run the first 7 cells and reach the section titled ‘Selecting your slice’, enter in the slice number in the following cell. For example, if your slice number is 13, your code should resemble the following:



Selecting your slice.

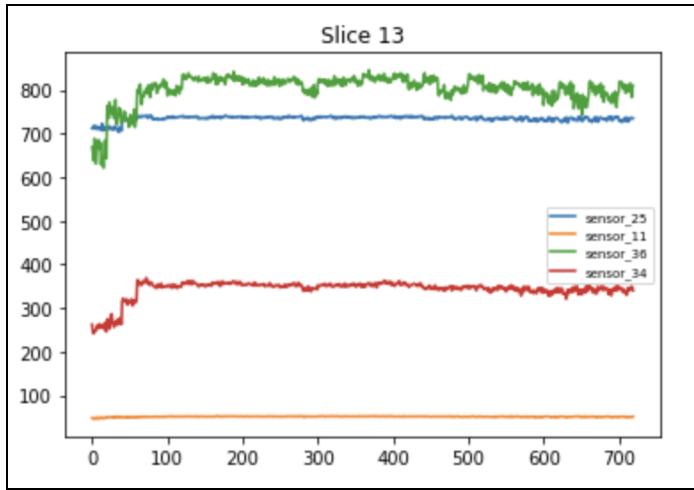
- Now that we have generated 1,000 slices of random data, it's time for you to choose a single slice.
- In the plot above, you can see 9 different plots of slices of data. Above each plot is the slice number.
- If you don't like the look of any of the plots in this figure, you can re-run the cell above to see another set of 9 random slices.
- Once you see a slice that you like, **enter the corresponding slice number into the cell below where it's marked.**

```
[ ]: # enter your slice number below
my_slice_num = 13

my_slice = synthetic_features[my_slice_num]

# let's plot that slice to make sure we've got it.
plot_12hr_slice(my_slice, my_slice_num)
plt.show()
```

After inputting your slice number, run the cell to plot the sensor data for that slice:



Next we will prepare our sensor data, for streaming by Kafka, by running cells 9-11.

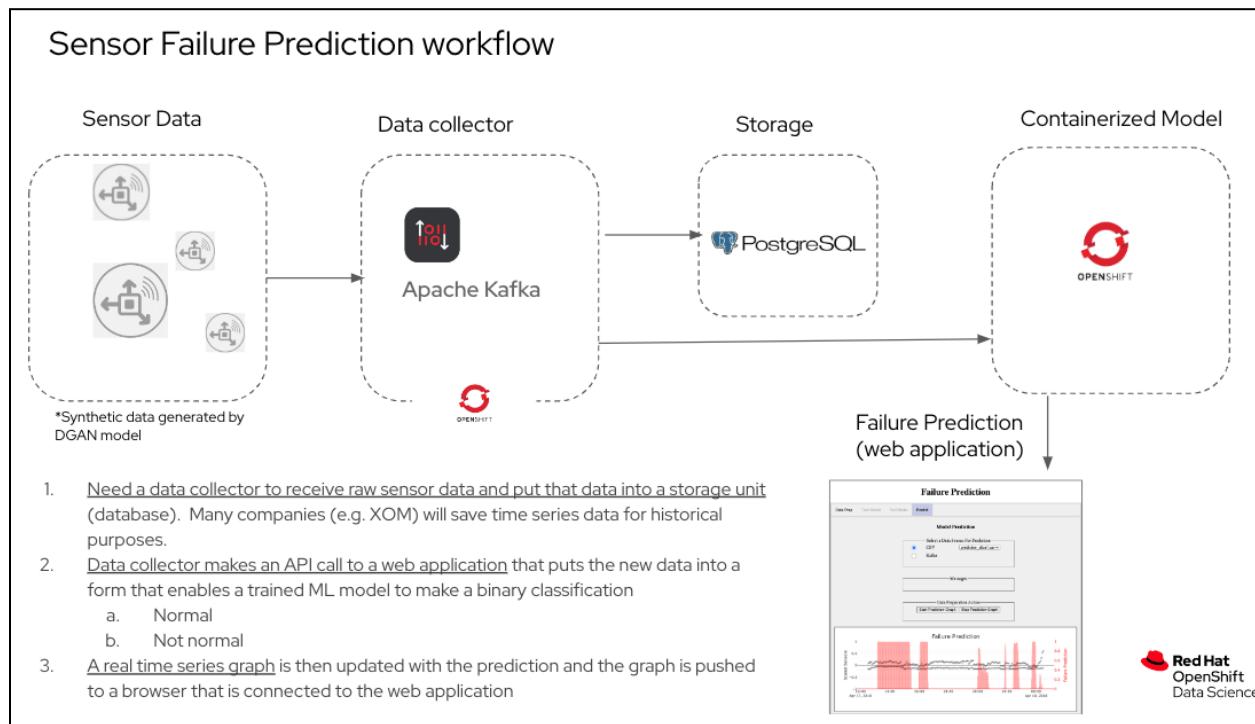
Stop at the following warning message:

WARNING: Don't run these last two cells until the failure prediction app is running and you have pressed the Start Prediction Graph button.

```
[ ]: def produce_data(sensor_slice):
    # create the producer
    producer = KafkaProducer(
        bootstrap_servers=[KAFKA_BOOTSTRAP_SERVER],
        security_protocol=KAFKA_SECURITY_PROTOCOL,
        sasl_plain_username=KAFKA_USERNAME,
        sasl_plain_password=KAFKA_PASSWORD,
        api_version_auto_timeout_ms=30000,
        max_block_ms=90000,
        request_timeout_ms=450000,
        acks="all",
        key_serializer=str.encode,
    )

    # sending our data 10 rows per second
    for row_index in range(0, 720, 10):
        # select our 10 rows
        ten_rows = sensor_slice[row_index : row_index + 10, :]
        # wait a second
        sleep(1)
        for i in range(10):
            one_row = ten_rows[i].tolist()
            jsonpayload = json.dumps(
                {
                    "timestamp": one_row[0],
                    "sensor_data": one_row[1:-1],
                    "machine_status": one_row[-1],
                }
            )
            producer.send(KAFKA_TOPIC, jsonpayload.encode("utf-8"), key=str(GROUP_ID))
    producer.flush() # Important, especially if message size is small
```

Before you run the remaining 2 cells, let's take a look at the Sensor Failure Prediction workflow so that we understand what is happening with our sensor data and in particular why we use Kafka.



When we generate our synthetic data, it needs a service to push it to our model for failure prediction. The service that we use is called **Apache Kafka Streaming**. This service takes our generated synthetic data and pushes it to our deployed (and containerized) Failure Prediction web application.

We didn't have time in this workshop for you to set up this streaming service. Therefore we have set up the Kafka service for you.

Now that you understand what role the generated synthetic data plays, and what role Kafka plays, we will leave this notebook. Don't close it, as we will come back to the notebook to perform the actual data streaming. We will turn our attention back to the [Failure Prediction Web Application](#) that will be using our data.

ii) Run the Failure Prediction

Click on the Prediction tab:

The screenshot shows a user interface titled "Failure Prediction". At the top, there are four tabs: "Data Prep", "Train Model", "Test Model", and "Predict". The "Predict" tab is highlighted with a blue background. Below the tabs, the main content area is titled "Model Prediction". It contains three sections: "Select a Data Source For Prediction" with two radio button options ("CSV" and "Kafka"), "Messages" (an empty input field), and "Data Preparation Action" with two buttons ("Start Prediction Graph" and "Stop Prediction Graph"). A large, empty rectangular area is located below these sections.

Before we can make a prediction, we must first select a data source for the prediction data. There are two options:

1. Use a CSV file which will be streamed one point at a time, simulating real time generation. The data in the CSV file is taken from the original Kaggle data source as test data.
2. Use a data stream of Synthetic data with the help of Apache Kafka that also simulates the production of real time data.

NOTE: You cannot run a prediction if no data source has been selected. If you attempt to click on the Start Prediction Graph before selecting a data source you will get a red message:

The screenshot shows the 'Failure Prediction' interface. At the top, there are tabs: Data Prep, Train Model, Test Model, and Predict. The Predict tab is highlighted. Below the tabs, there's a section titled 'Model Prediction' with the sub-instruction 'Select a Data Source For Prediction'. Two radio buttons are shown: 'CSV' and 'Kafka'. The 'Kafka' button is selected. Below this is a 'Messages' section containing the error message 'No data source has been selected' in red. At the bottom is a 'Data Preparation Action' section with two buttons: 'Start Prediction Graph' and 'Stop Prediction Graph'.

We will use the Kafka Data Source for Prediction. **Select the Kafka radio button, enter the Group Id** that is the number in your username e.g. <user>#. This Group Id allows your browser session to pull out messages that you were identified with.

Failure Prediction

Data Prep Train Model Test Model **Predict**

Model Prediction

Select a Data Source For Prediction

CSV
 Kafka Group Id

Messages

Prediction Action

We have selected the 'Kafka' Data Source, and entered '3' as we are logged in with username: 'user3'.

Hint: The purpose of the button labeled **Stop Prediction Graph** is to allow you to stop a prediction process before it is finished. You can use this button if you wish to choose another data source and run the prediction again before the last prediction process has finished.

Click on the Start Prediction Graph button.

Head back to the Jupyter notebook where you generated synthetic data and run the remaining 2 cells which will (1) connect to the Kafka cluster based on the credentials you defined in the previous step, (2) initialize a KafkaProducer object, (3) stream your data to the sensor failure prediction model

The screenshot shows a Jupyter Notebook interface with a single cell containing Python code. The code defines a function `produce_data` that creates a `KafkaProducer` object and streams data from a `sensor_slice` DataFrame. The code is highlighted with a red border.

```
[ ]: def produce_data(sensor_slice):
    # create the producer
    producer = KafkaProducer(
        bootstrap_servers=[KAFKA_BOOTSTRAP_SERVER],
        security_protocol=KAFKA_SECURITY_PROTOCOL,
        sasl_plain_username=KAFKA_USERNAME,
        sasl_plain_password=KAFKA_PASSWORD,
        api_version_auto_timeout_ms=30000,
        max_block_ms=900000,
        request_timeout_ms=450000,
        acks="all",
        key_serializer=str.encode,
    )

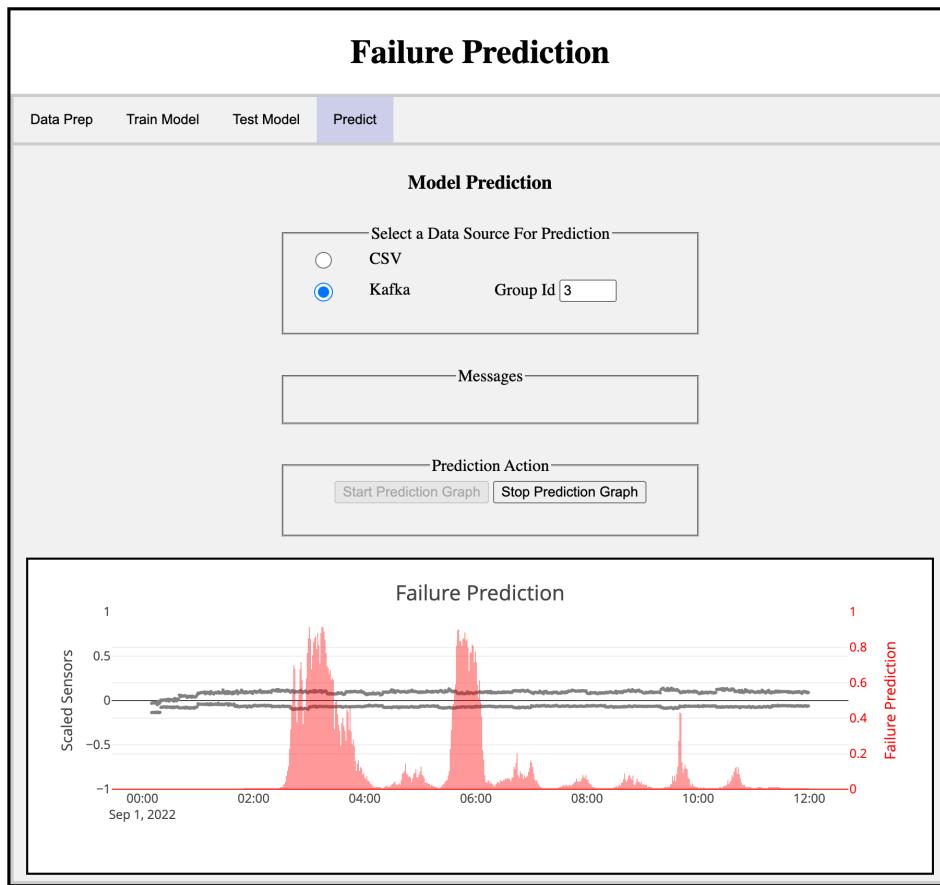
    # sending our data 10 rows per second
    for row_index in range(0, 720, 10):
        # select our 10 rows
        ten_rows = sensor_slice[row_index : row_index + 10, :]
        # wait a second
        sleep(1)
        for i in range(10):
            one_row = ten_rows[i].tolist()
            jsonpayload = json.dumps(
                {
                    "timestamp": one_row[0],
                    "sensor_data": one_row[1:-1],
                    "machine_status": one_row[-1],
                }
            )
            producer.send(KAFKA_TOPIC, jsonpayload.encode("utf-8"), key=str(GROUP_ID))
    producer.flush() # Important, especially if message size is small

[ ]: produce_data(my_slice)
```

Circle back to the web app to see your prediction graph updating as Kafka is streaming the synthetic data that you generated to your model.

There will be a pause while the data stream is prepared. Then you will see points from the prediction data source as well as a red prediction alarm if the model predicts failure is imminent.

Note: that the prediction data is only available 12 hours before failure.



The graph in your browser is interactive, so you can move your cursor to display the times.

If you are interested in how real time data is pushed from the server to the browser and then rendered in the browser, feel free to have a look at the following github repository.

- [GitHub - guiderae/WorkingDemos-RealTimeGraph1](https://github.com/guiderae/WorkingDemos-RealTimeGraph1)

6 Enablement Team Skills Set

6a Data Scientist

- Analyze and prepare data for training/testing
- Develop, test, train model
- Develop algorithm for preparing prediction data
- Develop algorithm for supplying prediction results
- Work with MLOps and Software Engineer to develop APIs to be used in delivered product

6b ML Ops

- Create and maintain the infrastructure that supports the development and deployment of the product which will involve:
 - CI/CD Pipeline (Including version control management)
 - Configuration Management
 - Deployment Automation, Containers
- Work with Data Scientist and Software Engineer to ensure smooth model integration

6c Software Engineer (Full Stack Developer)

- Design and implement the application architecture which includes:
 - Design and implement the database to meet application requirements
 - Integrate the database access with the application
 - Integrate the ML model with the application for training, testing and prediction
 - Design and implement the user interface to satisfy functionality requirements which will include re-training of the model
- Maintain application dependency list
- Work with Data Scientist to ensure training and testing are efficient
- Work with MLOps to monitor application performance

7 Model Serving in RHODS (demo with Guillaume Moutier)