

# Optimized Warehouse Management System Web Application

a final report,  
submitted in complete fulfillment.

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conducted by the SmartBridge.

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# Chapter 1: Introduction

## 1.1. Overview

The entire setup of the Web Application has been created to assist the user, which in our particular case, will be the owner or employees of the food delivery chain. The projected web application contains 4 essential parts or tabs.

The essential tabs gradually and almost with utmost certainty, help the user glide through the desired process of predicting future number of order, also keeping in mind some additional benefits, such as keeping a check on a sound mental health, staying updated with the events in and around the world in general and the business in particular.

The 4 tabs of the web application are as follows,

- **About tab** : This is the first tab that the user is navigated to once he or she decides to open and use the web application.
- **Assistance tab** : This is the second tab that the user might use. Contains the chat bot, named The Czar bot.
- **Predictions tab** : This is the third and the most important part of our web application. This part is the reason behind building this web application. Uses backend ML model to predict outcomes.
- **Dashboard tab** : This is the last yet most visually appealing tab in the web application. Contains charts, graphs and tables depicting the relations between target and non target attributes.

## 1.2. Purpose

The purpose of the web application is ultimately, to predict the number of orders, for a particular center and a particular deliverable consumable good, not only for a given week but also for the upcoming 10 weeks, for anticipated storage purpose. Although the main function of the web application is prediction, there are numerous other add on services added onto the very web app to make it more user friendly and to keep a user engaged for as long as possible.

The varying purposes of each of the tabs are mentioned as follows,

- **About tab** : The about tab is the first tab that our user is navigated to once the user opens

the web application. The About tab, as the name suggests, provides the user with a variety of information through the various widgets that it has. The widgets being, as follows,

**Our Motivation Widget**, gives the user, an insight to the cause or thought that went behind the creation of such a web application. It also goes onto inform the user about the current global standing of India in the hunger index.

**Essential info Widget**, provides the user with essential data required during the prediction, i.e. center id and meal id. It becomes impractical for the user to remember these unique datas or to carry large documents for the same, thus for the convenience of the user these have been hosted on the web app.

**News Widget**, provides the user with news regarding the various happenings in the world in general, and food news in particular.

**Youtube Widget**, provides the user with colourful food related videos, solely for the user's entertainment.

- **Assistance tab** : This tab contains the chat bot, named The Czar bot. The Czar bot has been programmed to answer all the queries of the user, both through an output displayed in a text form and through audio form. Apart from a few general queries and greetings, the Czar bot is also capable of,
  - intercepting and appropriately reciprocating to both positive and negative feedback, since mental health is important.
  - answering queries, related to food business in general and governmental policies regarding the same, through a smart document understanding system embedded within the Czar bot.
  - giving updated stock lists of the Czar's warehouse items.
  - telling jokes and giving tips, month wise, for the user to understand and better utilise the seasonal changes to his/her benefit, and store sufficient stocks without the risk of spoilage.
- **Prediction tab** : This tab has an Machine Learning Regression algorithm model running in the back end. The purpose of this tab is to give predictions in the form of number of orders, for a particular center and consumable item, for a given week and 10 week ahead.
- **Dashboard tab** : This tab contains the visua representations of the dependencies between the target and non target attributes. A better insight to the relationship between the attributes and their variations accordingly, through graphs and tables is provided.

## **Chapter 2: Literature Survey**

### **2.1. Existing Problem**

A food delivery service has to deal with a lot of perishable raw materials which makes it all, the most important factor for such a company is to accurately forecast daily and weekly demand. Too much inventory in the warehouse means more risk of wastage, and not enough could lead to out-of-stocks - and push customers to seek solutions from your competitors. The replenishment of majority of raw materials is done on weekly basis and since the raw material is perishable, the procurement planning is of utmost importance.

So, the need of the hour is a method to predict the prospective demand amounts in the not so distant future so that the supply chain can stock and meet every incoming demand of the customer.

### **2.2. Proposed Solution**

According to the UN's Food and Agricultural Organization, a massive one third of the total amount of food produced globally is wasted, which is worth over \$750 billion. India currently ranks 7th in terms of overall food wastage. Thus, pre predicted number of orders would significantly reduce the wastage during procurement. The software solution to the problem solution being:

- IBM Watson Machine Learning instance: Helps predict the desired number of orders as per the changing independent variables, using algorithms. Connected through REST APIs and storing metadata in Cloudant DB.
- News feed: Using iframe source code to embed e-newspaper in the Web Application. It helps the user get a better understanding of the food world.
- Youtube Videos: Keeps the user interested in the Web App through colourful display of vibrant food items.
- IBM Watson Cognos Embed: Connected through shareable preview link, this creates and hosts a live interactive dashboard, using uploaded datasets, enhances the understanding of the user.
- IBM Watson Assistant: Connected through REST APIs, this helps create and host Chat bots in Web App.
- NODE RED: Visual Flow editor, used to host the Web Application.

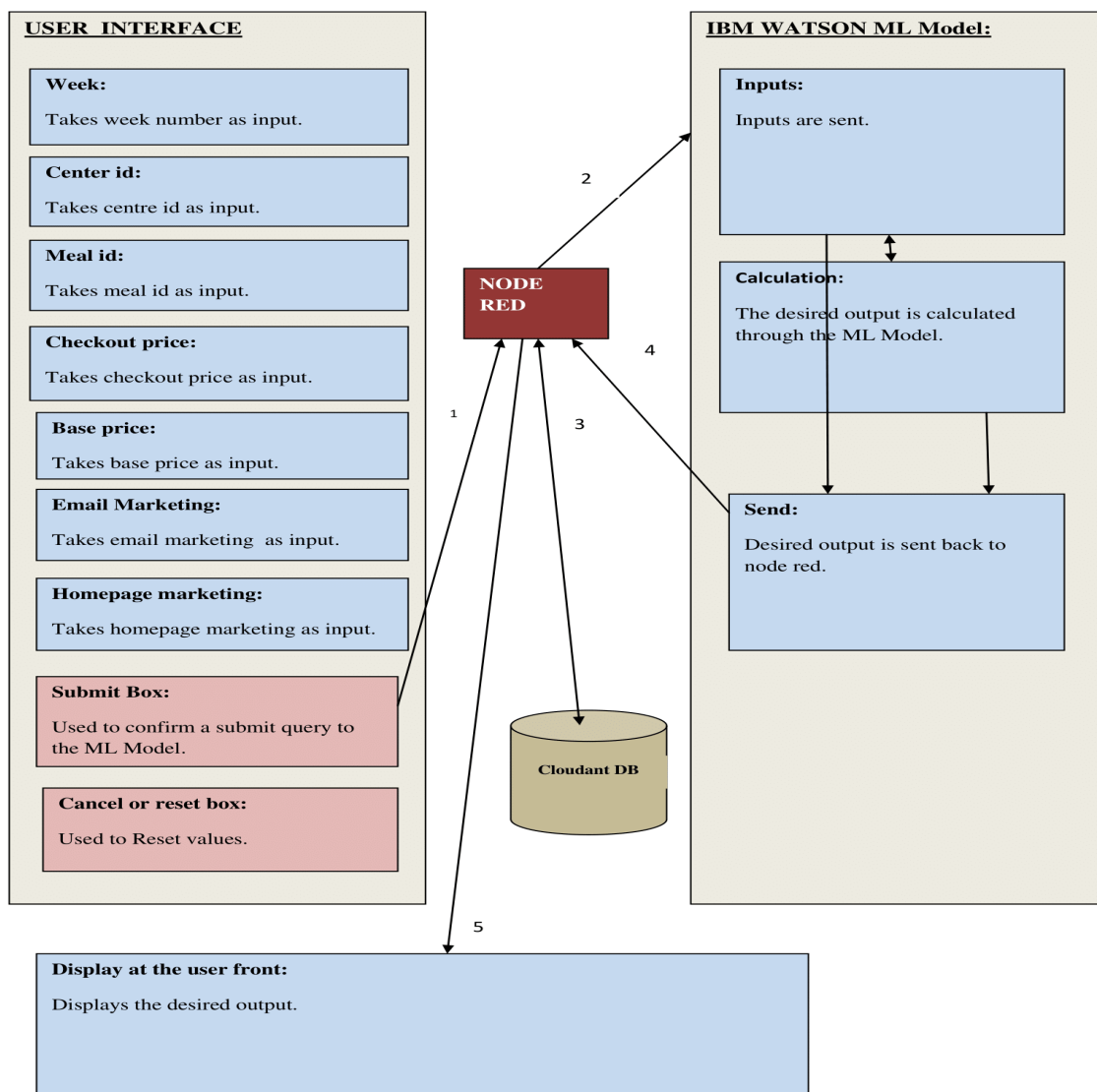
## Chapter 3: Theoretical Analysis

### 3.1. Block Diagram

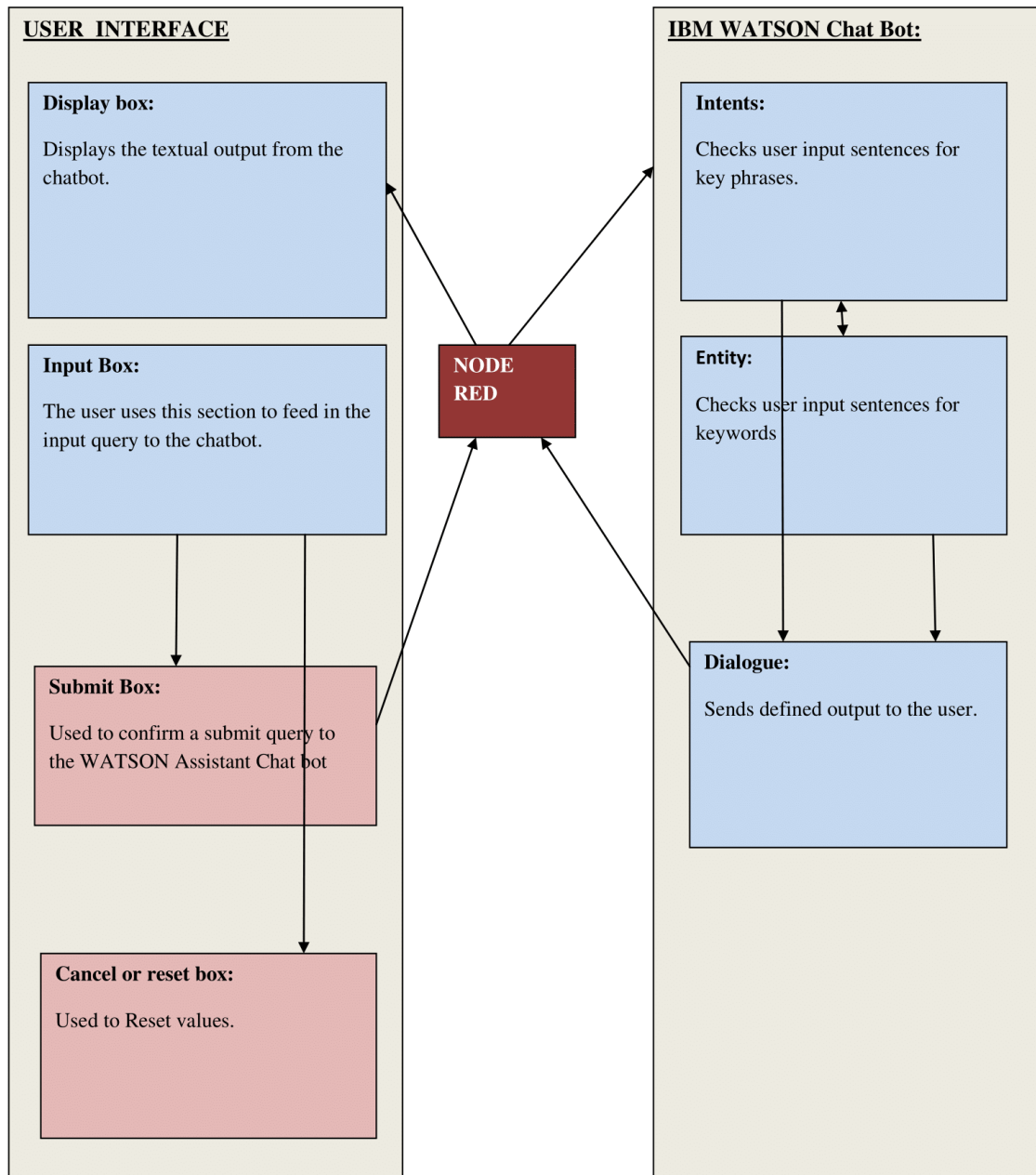
Although there are several small components in the entire web application, but the two main parts which form the bulk of the functioning and almost all of the interactive user interface, are,

- The Machine Learning model running in the backend.
- The Chat bot.

The working of the ML Model block diagram,



The Chat bot working block diagram is as follows,



## 3.2. Software Design

### Technology Stack used:

o IBM Watson Studio Machine Learning instance:

1. Server type: REST
2. Programming Language: Python
3. App: Jupyter Notebook
4. Hosted: NODE RED
5. Database: Cloudant DB
6. API Endpoints: Mentioned in service credentials

o IBM Watson Assistant:

1. Server type: REST
2. Programming Language: Python
3. App: Chat Bot
4. Hosted: NODE RED
5. Database: Cloudant DB
6. Algorithms used: Fuzzy logic, Natural Language Processing, Speech Processing.
7. API Endpoints: Mentioned in service credentials

o IBM Discovery Services:

1. Server type: REST
2. Programming Language: Python
3. App: Smart Document understanding imparted to the chat bot
4. Hosted: NODE RED
5. Database: Cloudant DB
6. Algorithms used: Fuzzy logic, Natural Language Processing.
7. API Endpoints: Mentioned in service credentials



o IBM Watson-Cognos Embed:

1. Server type: REST
2. Programming Language: Python
3. App: Dashboard
4. Hosted: NODE RED
5. Database: Cloudant DB
6. API Endpoints: Mentioned in service credentials

o NODE RED:

1. Server type: NodeJS Project (Web-APP + REST Server)
2. Programming Language: Python, HTML, PHP, CSS, Javascript.
3. App: NODE RED
4. Database: Cloudant DB

### **Implementation Details:**

- Module 1: IBM Watson Studio Machine Learning Instance:

Creation:

The Machine Learning model is the heart of our project, since the central idea of predicting the number of orders and thereby reducing the wastage will be computed by the Machine Learning Model. Therefore, the model has be fitted with a dataset, and different pipelines have to be tested in order to select the best pipeline. The best pipeline being that which has the maximum accuracy, in our case, the maximum accuracy being that of 76.2%. The algorithm in use being **Random Forest Regressor**.

Hosting:

After selecting the desired Machine Learning Model, the next step is to host it in the Web Application. This process is accomplished through the NODE RED flow editor, using various nodes such as, Form node. http in node. http request node. Function node. Debug node. Template node. After the successful configuration of the aforementioned nodes in a required manner, the

flow needs to be deployed in order to see the web app in action.

Process flow:

The user feeds the User interface input option with essential data so as to get the requisite number of orders for subsequent 10 weeks and the given week. After the data is filled and submitted, the data is fed to the Model, using NODE RED API Connections and the subsequent output generated is displayed in the UI of the web app.

- Module 2: IBM Watson Assistant:

Objective:

For the user to have a better experience while using the Web Application, inclusion of an interactive chat bot was crucial. The Chat bot not only helps the user get a better experience through inputs of business related data, but it also gives feedback to the user and itself acknowledges feedback, shares jokes and is appreciative of human interaction, since, our goal has also been to promote mental health.

Creation:

The Watson Assistant Skill section has intents to analyze user input sentences, entities to analyze user input key words and dialogs, to reciprocate an output. It all depends upon an individual, as to how and where to drive the anticipated conversation, using fuzzy logic, NLP and SP.

The Czar bot is also endowed with a smart document understanding capability, therefore, it can understand and answer several queries generated regarding the food business, known and unknown competition and related government policies. This capability is courtesy the Watson Discovery Services.

Hosting:

The Czar bot is hosted using APIs entered in the NODE RED flow, containing the Chat bot Node, along with a variety of function, template and audio nodes, and a form node.

Process Flow:

As the user submits the enquiry through the user interface on the chat bot widget in the Web

App, the NODE RED sends the enquiry to the Chat bot and reverts back with a prompt reply along with an audio reply of the same.

- Module 3: IBM Watson Cognos Embed:

Creation:

A live interactive dashboard is created for the user to get a better understanding of the dataset. The dataset used to create the Machine Learning model, is uploaded to the dashboard and subsequent charts and flows, depicting the relation between the target attribute to the independent attributes, are designed and implemented.

There are two parts to the dashboard,

- o The Basic interpretation tab is for the user to begin to understand the nature of the dependencies.
- o The Advanced interpretation is for a user who has already developed an understanding for the aforesaid dataset.

Hosting:

The NODE RED Template node, along with the shareable preview link of the Cognos dashboard is used to embed the dashboard into the Web Application.

- Module 4: Web App: User Interface:

Our Motivation:

This section contains an article depiction from a popular and trusted newspaper, used to solidify the user's knowledge base and thereby get a better understanding of the business in general and our objective in particular.

Essential info:

Used to feed the user with essential data that he might need for computation of the predictions using the ML model, which otherwise would've been cumbersome to memorize.

News feed:

Provides a daily dosage of Global news in general and food related news and recipes in particular.

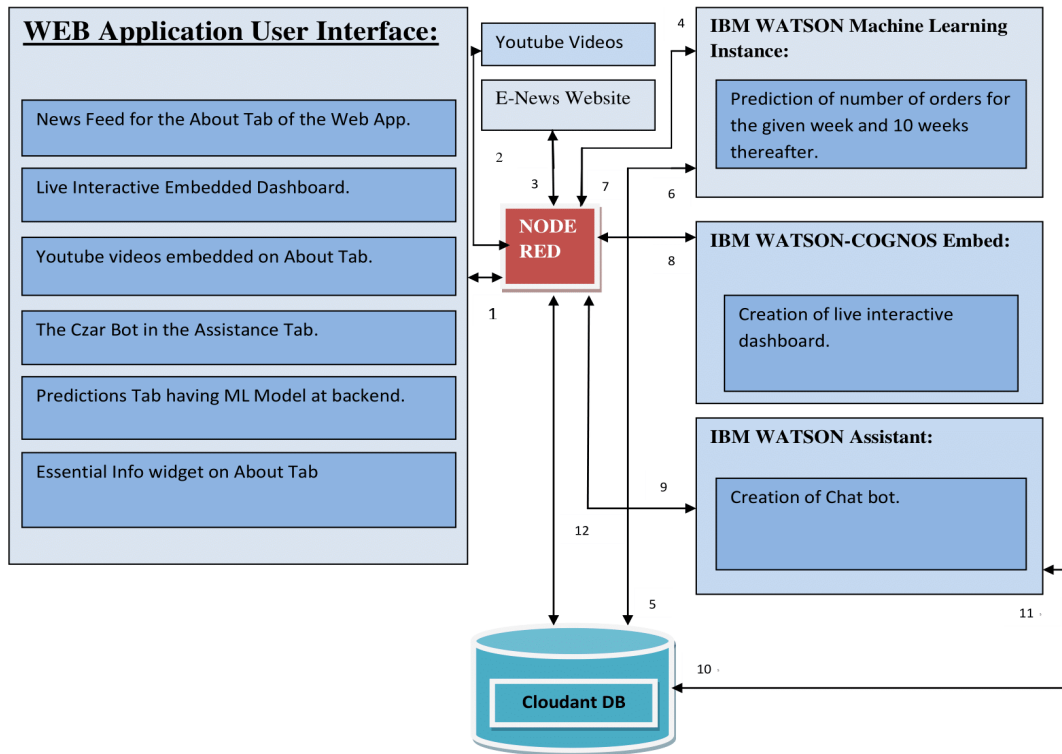
Youtube Video:

Used for users who don't read much news and are more drawn towards audio visual representation.

# Chapter 4

## 4.1. Flowchart

This flowchart goes on to depict the working of the entire web application.



### INDEX

1. Sending Requests from User Interface to the NODE RED Flow, using input options.
2. Youtube Videos iframe Sources for embedding the videos in Web APP.
3. News feed iframe Sources for embedding the news articles in Web APP.
4. Sending essential data to the Machine Learning instance in the backend to get the desired output.
5. Computing, storing and retrieving data from Cloudant Database.
6. Sending the results back to the ML instance.
7. Sending the outputs to NODE RED flows for display using REST APIs.
8. Embedded Dashboard displayed through shareable preview link.
9. Input to The Czar bot (Chat bot) through the input options.
10. Sending query to Cloudant Database for fetching the required data for analysis and output.
11. Data sent to IBM Assistant Chat bot.
12. Computation and sending data to NODE RED flow for display using REST APIs.

## 4.2. Experimental Investigation

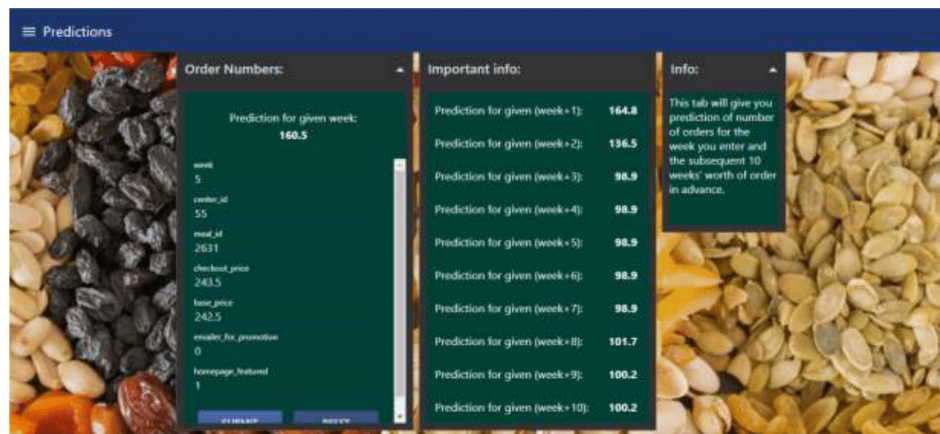
Experimental investigation done over a wide range of experimental data and subsequent output only go on to show that,

- Meal-id 2290, has the highest number of orders almost throughout the year, in almost all of the centers, whereas Meal-id 177 has the lowest number of orders in almost all of the centers and that too throughout the year.
- Center-id 10 has the highest rating amongst the other centers available for this food delivery chain, whereas, Center-id 186 has the lowest rating.
- Spending a substantial amount on advertising an item, both through email and by featuring it on the web page, increases the sales of that item by a significant margin. Thus advertising is important.
- There is a surge of delivery orders towards the middle or end of every month, a carefully and meticulously dedicated lineup and workforce can deal with the periodic surge gracefully.

# Chapter 5

## 5.1. Result

Results for Machine Learning model, from the debug section of NODE RED flow.



6/23/2020, 10:44:38 AM	node: 8c567e73.a0032	msg.payload : number	98.9
6/23/2020, 10:44:39 AM	node: ab1cd012.881ac	msg.payload : number	98.9
6/23/2020, 10:44:40 AM	node: 9f8e0b81.a694e8	msg.payload : number	98.9
6/23/2020, 10:44:41 AM	node: 6242d160.0f3f1	msg.payload : number	101.7
6/23/2020, 10:44:42 AM	node: c6d6b36c.86877	msg.payload : number	136.5
6/23/2020, 10:44:43 AM	node: ed0a1f91.a3fdf	msg.payload : number	98.9
6/23/2020, 10:44:43 AM	node: 1ee96199.edbcbe	msg.payload : number	160.5

6/23/2020, 10:44:43 AM	node: 1ee86199.edbcbe
msg.payload : number	
164.8	
6/23/2020, 10:44:43 AM	node: 33531c07.e4fbb4
msg.payload : number	
160.5	
6/23/2020, 10:44:43 AM	node: 3a704c20.75ae94
msg.payload : number	
100.2	
6/23/2020, 10:44:43 AM	node: f3aa5a82.2e5a78
msg.payload : number	
98.9	
6/23/2020, 10:44:43 AM	node: 33664ed8.4f1fb2
msg.payload : number	
100.2	

Chat bot results from NODE RED Debug section.

```

6/23/2020, 10:15:36 AM node: d7517e5d.682f9
msg.payload : Object
  ▾ object
    ▾ intents: array[1]
      ▸ 0: object
    ▾ entities: array[1]
      ▸ 0: object
    ▾ input: object
      text: "hi"
    ▾ output: object
      ▾ generic: array[1]
        ▾ 0: object
          response_type: "text"
          text: "Hello! Go on, ask me for a joke."
      ▸ text: array[1]
      ▸ nodes_visited: array[2]
      log_messages: array[0]
    ▸ context: object

```



```

msg.payload : Object
  ▼ object
  ▼ intents: array[1]
    ▼ 0: object
      intent: "General_Jokes"
      confidence: 1
  ▼ entities: array[1]
    ▸ 0: object
  ▸ input: object
  ▼ output: object
    ▼ generic: array[1]
      ▼ 0: object
        response_type: "text"
        text: "Question: What is the longest word in the English language? Answer: "Smiles". Because there is a mile between its first and last letters!"
    ▼ text: array[1]
      0: "Question: What is the longest word in the English language? Answer: "Smiles". Because there is a mile between its first and last letters!"
  ▸ nodes_visited: array[1]
  log_messages: array[0]
  ▸ context: object

```

```

msg.payload : Object
  ▼ object
  ▸ intents: array[1]
  ▼ entities: array[1]
    ▸ 0: object
  ▼ input: object
    text: "how are you Czar bot?"
  ▼ output: object
    ▼ generic: array[1]
      ▸ 0: object
    ▼ text: array[1]
      0: "I am doing just fine. Thank you so much for asking! How are you doing?"
  ▸ nodes_visited: array[1]
  log_messages: array[0]
  ▸ context: object

```

## 5.2. Advantages & Disadvantages

- **Advantages**

- i. The web app predicts the number of orders for the upcoming weeks in advance, with utmost accuracy, thus decreasing the wastage of consumables while stocking up.
- ii. The web app takes the mental well being of the user into consideration and acts on it through the Czar bot, also keeping a routine tab on the same.
- iii. The web app shells out preliminary legal and corporate counselling through the smart document understanding system and general Q & A embedded within the Czar bot.
- iv. The web app gives a better understanding of entity relations and dependencies to the user through the intricately designed interactive dashboard.

- **Disadvantages**

- i. Although the web app provides preliminary solution to almost any problems that an user is expected to encounter, for more advanced stages of the same or different problems, the user might have to search beyond the scope of this web app.

## 5.3 Conclusion

It can be safely and economically concluded that, the web application has served its purpose of predicting the number of orders, categorically for each combination of center and meal id, for atleast 11 weeks, i.e. for the given week and 10 weeks ahead of it. The accuracy is a stunning 76.2%

The web app also takes into account the much debated and essential mental healthcare and has initiated a willful step towards championing the cause of the same. The interactive dashboard and extensive business and governmental policy tips and updates, provide a whole new dimensional experience for the user, who might find it ever so more engaging to work with the web app.

The news feed section, combined with the videos and about section keeps the user updated on the new happenings all around the globe. Through the web app, apart from availing the core functionality of prediction, the user can avail these spectacular and interactive add ons and thus keep himself/herself engaged for a longer period of the business hours with much ease.

## 5.4. Future Scope

Although the current web application uses NODE RED UI platform when it comes to hosting, in the not so distant future, a flask app would seem more appropriate for the same, given the greater visual appeal of a flask app when compared to its NODE RED contemporary.

The Machine learning algorithm can also be switched with a more advanced algorithm of deep learning or AI, such as Recurrent Neural Networks or Time series forecasting, for better accuracy and smoother experience. The chatbot can be upgraded with more functionalities.

## Bibliogarchy

1. SmartBridge Bootcamp on the various related topics of the project.
2. NODE RED discussion forum.
3. IBM Documents, regarding the services in use, the user manuals.
4. IBM Cognitive Classes.

## Appendix

### A.1. Source code for the Machine Learning Notebook:

```
1 1. Set Up
2 In [ ]:
3 try:
4     import autoai_libs
5 except Exception as e:
6     import subprocess
7     out = subprocess.check_output('pip install
    autoai_libs'.split(' '))
8     for line in out.splitlines():
9         print(line)
10    import autoai_libs
11 import sklearn
12 try:
13     import xgboost
14 except:
15     print('xgboost, if needed, will be installed and imported
    later')
16 try:
17     import lightgbm
18 except:
19     print('lightgbm, if needed, will be installed and
```

```

imported later')
20 from sklearn.cluster import FeatureAgglomeration
21 import numpy
22 from numpy import inf, nan, dtype, mean
23 from autoai_libs.sklearn.custom_scorers import CustomScorers
24 import sklearn.ensemble
25 from autoai_libs.cognito.transforms.transform_utils import
    TExtras, FC
26 from autoai_libs.transformers.exportable import *
27 from autoai_libs.utils.exportable_utils import *
28 from sklearn.pipeline import Pipeline
29 known_values_list=[]
30 In [ ]:
31 # compose a decorator to assist pipeline instantiation via
    import of modules and installation of packages
32 def decorator_retries(func):
33     def install_import_retry(*args, **kwargs):
34         retries = 0
35         successful = False
36         failed_retries = 0
37         while retries < 100 and failed_retries < 10 and not
            successful:
38             retries += 1
39             failed_retries += 1
40             try:
41                 result = func(*args, **kwargs)
42                 successful = True
43             except Exception as e:
44                 estr = str(e)
45                 if estr.startswith('name ') and
                    estr.endswith(' is not defined'):
46                     try:
47                         import importlib
48                         module_name = estr.split("'")[1]
49                         module =
                            importlib.import_module(module_name)
50                         globals().update({module_name:

```

```

module}))
51         print('import successful for ' +
module_name)
52         failed_retries -= 1
53         except Exception as import_failure:
54             print('import of ' + module_name + '
failed with: ' + str(import_failure))
55             import subprocess
56             if module_name == 'lightgbm':
57                 try:
58                     print('attempting pip install
of ' + module_name)
59                     process =
subprocess.Popen('pip install ' + module_name, shell=True)
60                     process.wait()
61                     except Exception as E:
62                         print(E)
63                         try:
64                             import sys
65                             print('attempting conda
install of ' + module_name)
66                             process =
subprocess.Popen('conda install --yes --prefix {sys.prefix} -c
powerai ' + module_name, shell = True)
67                             process.wait()
68                             except Exception as
lightgbm_installation_error:
69                                 print('lightgbm
installation failed!' + lightgbm_installation_error)
70                             else:
71                                 print('attempting pip install of
' + module_name)
72                                 process = subprocess.Popen('pip
install ' + module_name, shell=True)
73                                 process.wait()
74                                 try:
75                                     print('re-attempting import of '

```

```

+ module_name)
76                                     module =
importlib.import_module(module_name)
77                                     globals().update({module_name:
module})
78                                     print('import successful for ' +
module_name)
79                                     failed_retries -= 1
80                                     except Exception as
import_or_installation_failure:
81                                     print('failure installing and/or
importing ' + module_name + ' error was: ' + str(
82 import_or_installation_failure))
83                                     raise
(ModuleNotFoundError('Missing package in environment for ' +
module_name +
84                                     '? Try
import and/or pip install manually?'))
85                                     elif type(e) is AttributeError:
86                                     if 'module ' in estr and ' has no
attribute ' in estr:
87                                     pieces = estr.split(" ")
88                                     if len(pieces) == 5:
89                                     try:
90                                     import importlib
91                                     print('re-attempting import
of ' + pieces[3] + ' from ' + pieces[1])
92                                     module =
importlib.import_module('.' + pieces[3], pieces[1])
93                                     failed_retries -= 1
94                                     except:
95                                     print('failed attempt to
import ' + pieces[3])
96                                     raise (e)
97                                     else:
98                                     raise (e)

```

```

99             else:
100                 raise (e)
101             if successful:
102                 print('Pipeline successfully instantiated')
103             else:
104                 raise (ModuleNotFoundError(
105                     'Remaining missing imports/packages in
environment? Retry cell and/or try pip install manually?'))
106             return result
107         return install_import_retry
108 2. Compose Pipeline
109 In [ ]:
110 # metadata necessary to replicate AutoAI scores with the
pipeline
111 __input_metadata = {'target_label_name': 'num_orders',
'learning_type': 'regression', 'run_uid':
'94f92dbf-657b-42a7-bc44-3edd70d2fea2', 'pn': 'P3',
'cv_num_folds': 3, 'holdout_fraction': 0.1,
'optimization_metric': 'neg_root_mean_squared_error',
'pos_label': None, 'random_state': 33, 'data_source': ''}
112
113 # define a function to compose the pipeline, and invoke it
114 @decorator_retries
115 def compose_pipeline():
116     import numpy
117     from numpy import nan, dtype, mean
118     #
119     # composing steps for toplevel Pipeline
120     #
121     __input_metadata = {'target_label_name': 'num_orders',
'learning_type': 'regression', 'run_uid':
'94f92dbf-657b-42a7-bc44-3edd70d2fea2', 'pn': 'P3',
'cv_num_folds': 3, 'holdout_fraction': 0.1,
'optimization_metric': 'neg_root_mean_squared_error',
'pos_label': None, 'random_state': 33, 'data_source': ''}
122     steps = []

```



```

123     #
124     # composing steps for preprocessor Pipeline
125     #
126     preprocessor__input_metadata = None
127     preprocessor_steps = []
128     #
129     # composing steps for preprocessor_features
    FeatureUnion
130     #
131     preprocessor_features_transformer_list = []
132     #
133     # composing steps for
    preprocessor_features_categorical Pipeline
134     #
135     preprocessor_features_categorical__input_metadata =
    None
136     preprocessor_features_categorical_steps = []
137
    preprocessor_features_categorical_steps.append(('cat_column_s
    elector',
    autoai_libs.transformers.exportable.NumpyColumnSelector(column
    ns=[0, 1, 2, 5, 6])))
138
    preprocessor_features_categorical_steps.append(('cat_compress
    _strings',
    autoai_libs.transformers.exportable.CompressStrings(activate_
    flag=True, compress_type='hash', dtypes_list=['float_int_num',
    'float_int_num', 'float_int_num', 'float_int_num',
    'float_int_num'], missing_values_reference_list=['', '-', '?',
    nan], misslist_list=[[], [], [], [], []])))
139
    preprocessor_features_categorical_steps.append(('cat_missing_
    replacer',
    autoai_libs.transformers.exportable.NumpyReplaceMissingValues
    (filling_values=100001, missing_values=[])))
140
    preprocessor_features_categorical_steps.append(('cat_unknown_

```

```

replacer',
autoai_libs.transformers.exportable.NumpyReplaceUnknownValues
(filling_values=100001, filling_values_list=[100001, 100001,
100001, 100001, 100001], known_values_list=[[1.0, 2.0, 3.0,
4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 11.0, 12.0, 13.0, 14.0,
15.0, 16.0, 17.0, 18.0, 19.0, 20.0, 21.0, 22.0, 23.0, 24.0,
25.0, 26.0, 27.0, 28.0, 29.0, 30.0, 31.0, 32.0, 33.0, 34.0,
35.0, 36.0, 37.0, 38.0, 39.0, 40.0, 41.0, 42.0, 43.0, 44.0,
45.0, 46.0, 47.0, 48.0, 49.0, 50.0, 51.0, 52.0, 53.0, 54.0,
55.0], [10.0, 11.0, 13.0, 14.0, 17.0, 20.0, 23.0, 24.0, 26.0,
27.0, 29.0, 30.0, 32.0, 34.0, 36.0, 39.0, 41.0, 42.0, 43.0,
50.0, 51.0, 52.0, 53.0, 55.0, 57.0, 58.0, 59.0, 61.0, 64.0,
65.0, 66.0, 67.0, 68.0, 72.0, 73.0, 74.0, 75.0, 76.0, 77.0,
80.0, 81.0, 83.0, 86.0, 88.0, 89.0, 91.0, 92.0, 93.0, 94.0,
97.0, 99.0, 101.0, 102.0, 104.0, 106.0, 108.0, 109.0, 110.0,
113.0, 124.0, 126.0, 129.0, 132.0, 137.0, 139.0, 143.0,
145.0, 146.0, 149.0, 152.0, 153.0, 157.0, 161.0, 162.0,
174.0, 177.0, 186.0], [1062.0, 1109.0, 1198.0, 1207.0,
1216.0, 1230.0, 1247.0, 1248.0, 1311.0, 1438.0, 1445.0,
1525.0, 1543.0, 1558.0, 1727.0, 1754.0, 1770.0, 1778.0,
1803.0, 1847.0, 1878.0, 1885.0, 1902.0, 1962.0, 1971.0,
1993.0, 2126.0, 2139.0, 2290.0, 2304.0, 2306.0, 2322.0,
2444.0, 2490.0, 2492.0, 2494.0, 2539.0, 2569.0, 2577.0,
2581.0, 2631.0, 2640.0, 2664.0, 2704.0, 2707.0, 2760.0,
2826.0, 2867.0], [0.0, 1.0], [0.0, 1.0]],
missing_values_reference_list=['', '-', '?', nan]))
141
preprocessor_features_categorical_steps.append(('boolean2float
_transformer',
autoai_libs.transformers.exportable.boolean2float(activate_flag
=True)))
142
preprocessor_features_categorical_steps.append(('cat_imputer'
,
autoai_libs.transformers.exportable.CatImputer(activate_flag=T
rue, missing_values=100001, sklearn_version_family='20',
strategy='most_frequent'))))

```

```

143     preprocessor_features_categorical_steps.append(('cat_encoder'
,
autoai_libs.transformers.exportable.CatEncoder(activate_flag=T
rue, categories='auto', dtype=numpy.float64,
encoding='ordinal', handle_unknown='error',
sklearn_version_family='20'))))
144     preprocessor_features_categorical_steps.append(('float32_trans
former',
autoai_libs.transformers.exportable.float32_transform(activate
_flag=True)))
145     # assembling preprocessor_features_categorical_
Pipeline
146     preprocessor_features_categorical_pipeline =
sklearn.pipeline.Pipeline(steps=preprocessor_features_categor
ical_steps)
147     preprocessor_features_transformer_list.append(('categorical',
preprocessor_features_categorical_pipeline))
148     #
149     # composing steps for preprocessor_features_numeric
Pipeline
150     #
151     preprocessor_features_numeric__input_metadata = None
152     preprocessor_features_numeric_steps = []
153     preprocessor_features_numeric_steps.append(('num_column_selec
tor',
autoai_libs.transformers.exportable.NumpyColumnSelector(colum
ns=[3, 4])))
154     preprocessor_features_numeric_steps.append(('num_floatstr2float
_transformer',
autoai_libs.transformers.exportable.FloatStr2Float(activate_fl
ag=True, dtypes_list=['float_num', 'float_num'],

```

```

missing_values_reference_list=[]))
155     preprocessor_features_numeric_steps.append(('num_missing_repl
acer',
autoai_libs.transformers.exportable.NumpyReplaceMissingValues
(filling_values=nan, missing_values=[]))
156     preprocessor_features_numeric_steps.append(('num_imputer',
autoai_libs.transformers.exportable.NumImputer(activate_flag=T
rue, missing_values=nan, strategy='median'))
157     preprocessor_features_numeric_steps.append(('num_scaler',
autoai_libs.transformers.exportable.OptStandardScaler(num_sca
ler_copy=None, num_scaler_with_mean=None,
num_scaler_with_std=None, use_scaler_flag=False))
158     preprocessor_features_numeric_steps.append(('float32_transform
er',
autoai_libs.transformers.exportable.float32_transform(activate
_flag=True))
159     # assembling preprocessor_features_numeric_Pipeline
160     preprocessor_features_numeric_pipeline =
sklearn.pipeline.Pipeline(steps=preprocessor_features_numeric
_steps)
161     preprocessor_features_transformer_list.append(('numeric',
preprocessor_features_numeric_pipeline))
162     # assembling preprocessor_features_FeatureUnion
163     preprocessor_features_pipeline =
sklearn.pipeline.FeatureUnion(transformer_list=preprocessor_f
eatures_transformer_list)
164     preprocessor_steps.append(('features',
preprocessor_features_pipeline))
165     preprocessor_steps.append(('permuter',
autoai_libs.transformers.exportable.NumpyPermuteArray(axis=0,
permutation_indices=[0, 1, 2, 5, 6, 3, 4]))
166     # assembling preprocessor_Pipeline

```

```

167     preprocessor_pipeline =
168         sklearn.pipeline.Pipeline(steps=preprocessor_steps)
169     #
170     # composing steps for cognito Pipeline
171     #
172     cognito__input_metadata = None
173     cognito_steps = []
174     cognito_steps.append(('0',
175         autoai_libs.cognito.transforms.transform_utils.TA1(fun=numpy.
176             tan, name='tan', datatypes=['float'],
177             feat_constraints=[autoai_libs.utils.fc_methods.is_not_categorical],
178             tgraph=None, apply_all=True, col_names=['week',
179                 'center_id', 'meal_id', 'checkout_price', 'base_price',
180                 'emailer_for_promotion', 'homepage_featured'],
181             col_dtypes=[dtype('float32'), dtype('float32'),
182                 dtype('float32'), dtype('float32'), dtype('float32'),
183                 dtype('float32'), dtype('float32')],
184             col_as_json_objects=None)))
185     cognito_steps.append(('1',
186         autoai_libs.cognito.transforms.transform_utils.FS1(cols_ids_must_keep=range(0, 7),
187             additional_col_count_to_keep=8,
188             ptype='regression')))
189     cognito_steps.append(('2',
190         autoai_libs.cognito.transforms.transform_utils.TA1(fun=numpy.
191             sin, name='sin', datatypes=['float'],
192             feat_constraints=[autoai_libs.utils.fc_methods.is_not_categorical],
193             tgraph=None, apply_all=True, col_names=['week',
194                 'center_id', 'meal_id', 'checkout_price', 'base_price',
195                 'emailer_for_promotion', 'homepage_featured', 'tan(week)',
196                 'tan(center_id)', 'tan(meal_id)', 'tan(checkout_price)',
197                 'tan(base_price)'], col_dtypes=[dtype('float32'),
198                 dtype('float32'), dtype('float32'), dtype('float32'),
199                 dtype('float32'), dtype('float32'), dtype('float32'),
200                 dtype('float32'), dtype('float32'), dtype('float32'),
201                 dtype('float32'), dtype('float32')],

```

```

col_as_json_objects=None)))
177     cognito_steps.append(('3',
    autoai_libs.cognito.transforms.transform_utils.FS1(cols_ids_m
ust_keep=range(0, 7), additional_col_count_to_keep=8,
ptype='regression'))))
178     cognito_steps.append(('4',
    autoai_libs.cognito.transforms.transform_utils.TA1(fun=numpy.
rint, name='round', datatypes=['numeric'],
feat_constraints=[autoai_libs.utils.fc_methods.is_not_categor
ical], tgraph=None, apply_all=True, col_names=['week',
'center_id', 'meal_id', 'checkout_price', 'base_price',
'emailer_for_promotion', 'homepage_featured', 'tan(meal_id)',
'tan(base_price)', 'sin(week)', 'sin(meal_id)',
'sin(checkout_price)', 'sin(base_price)',
'sin(tan(center_id))', 'sin(tan(meal_id))'],
col_dtypes=[dtype('float32'), dtype('float32'),
dtype('float32'), dtype('float32'), dtype('float32'),
dtype('float32'), dtype('float32'), dtype('float32'),
dtype('float32'), dtype('float32'), dtype('float32'),
dtype('float32')], col_as_json_objects=None)))
179     cognito_steps.append(('5',
    autoai_libs.cognito.transforms.transform_utils.FS1(cols_ids_m
ust_keep=range(0, 7), additional_col_count_to_keep=8,
ptype='regression'))))
180     # assembling cognito_ Pipeline
181     cognito_pipeline =
    sklearn.pipeline.Pipeline(steps=cognito_steps)
182     steps.append(('cognito', cognito_pipeline))
183     steps.append(('estimator',
    sklearn.ensemble.forest.RandomForestRegressor(bootstrap=True,
criterion='mse', max_depth=None, max_features='auto',
max_leaf_nodes=None, min_impurity_decrease=0.0,
min_impurity_split=None, min_samples_leaf=1,
min_samples_split=2, min_weight_fraction_leaf=0.0,
n_estimators=10, n_jobs=2, oob_score=True, random_state=33,
verbose=0, warm_start=False)))

```

```

184     # assembling Pipeline
185     pipeline = sklearn.pipeline.Pipeline(steps=steps)
186     return pipeline
187 pipeline = compose_pipeline()
188 3. Extract needed parameter values from AutoAI run
    metadata
189 In [ ]:
190 # Metadata used in retrieving data and computing metrics.
    Customize as necessary for your environment.
191 #data_source='replace_with_path_and_csv_filename'
192 target_label_name = _input_metadata['target_label_name']
193 learning_type = _input_metadata['learning_type']
194 optimization_metric =
    _input_metadata['optimization_metric']
195 random_state = _input_metadata['random_state']
196 cv_num_folds = _input_metadata['cv_num_folds']
197 holdout_fraction = _input_metadata['holdout_fraction']
198 if 'data_provenance' in _input_metadata:
199     data_provenance = _input_metadata['data_provenance']
200 else:
201     data_provenance = None
202 if 'pos_label' in _input_metadata and learning_type ==
    'classification':
203     pos_label = _input_metadata['pos_label']
204 else:
205     pos_label = None
206 4. Create dataframe from dataset in Cloud Object Storage
207 In [ ]:
208 # @hidden_cell
209 # The following code contains the credentials for a file in
    your IBM Cloud Object Storage.
210 # You might want to remove those credentials before you
    share your notebook.
211 credentials_0 = {
212     'ENDPOINT':
        'https://s3-api.us-geo.objectstorage.softlayer.net',
213     'IBM_AUTH_ENDPOINT':

```

```

    'https://iam.bluemix.net/oidc/token/',
214     'APIKEY':
        '_wsK86uTdRgevFlmjANKlp0tzMyuvUut6s7ddVqjLYKj',
215     'BUCKET': 'optfood-donotdelete-pr-tpuulakeaudnfv',
216     'FILE': 'FoodProj.csv',
217     'SERVICE_NAME': 's3',
218     'ASSET_ID': '1',
219     }
220 In [ ]:
221 # Read the data as a dataframe
222 import pandas as pd
223
224 csv_encodings=['UTF-8','Latin-1'] # supplement list of
    encodings as necessary for your data
225 df = None
226 readable = None # if automatic detection fails, you can
    supply a filename here
227
228 # First, obtain a readable object
229 # Cloud Object Storage data access
230 # Assumes COS credentials are in a dictionary named
    'credentials_0'
231
232 credentials = df = globals().get('credentials_0')
233 if readable is None and credentials is not None :
234     try:
235         import types
236         import pandas as pd
237         import io
238         import os
239     except Exception as import_exception:
240         print('Error with importing packages - check if
        you installed them on your environment')
241     try:
242         if credentials['SERVICE_NAME'] == 's3':
243             try:
244                 from botocore.client import Config

```



```

245         import ibm_boto3
246     except Exception as import_exception:
247         print('Installing required packages!')
248         !pip install ibm-cos-sdk
249         print('accessing data via Cloud Object
Storage')
250     try:
251         cos_client =
ibm_boto3.resource(service_name=credentials['SERVICE_NAME'],
252         ibm_api_key_id=credentials['APIKEY'],
253         ibm_auth_endpoint=credentials['IBM_AUTH_ENDPOINT'],
254         config=Config(signature_version='oauth'),
255         endpoint_url=credentials['ENDPOINT'])
256     except Exception as cos_exception:
257         print('unable to create client for cloud
object storage')
258     try:
259         cos_client.meta.client.download_file(Bucket=credentials['BUCKET'],
Filename=credentials['FILE'], Key=credentials['FILE'])
260     except Exception as cos_access_exception:
261         print('unable to access data object in
cloud object storage with credentials supplied')
262     try:
263         for encoding in csv_encodings:
264             df = pd.read_csv(credentials['FILE'],
encoding = encoding, sep = None, engine = 'python')
265             os.remove(credentials['FILE'])
266             print('Data loaded from cloud object
storage with encoding ' + encoding)
267             break
268     except Exception as cos_object_read_exception:
269         print('unable to access data object from

```

```

    cos object with encoding ' + encoding)
270         elif credentials['SERVICE_NAME'] == 'fs':
271             print('accessing data via File System')
272             try:
273                 df = pd.read_csv(credentials['FILE'], sep
    = None, engine = 'python')
274             except Exception as FS_access_exception:
275                 print('unable to access data object in
    File System with path supplied')
276         except Exception as data_access_exception:
277             print('unable to access data object with
    credentials supplied')
278
279     # IBM Cloud Pak for Data data access
280     project_filename = globals().get('project_filename')
281     if readable is None and 'credentials_0' in globals() and
    'ASSET_ID' in credentials_0:
282         project_filename = credentials_0['ASSET_ID']
283     if project_filename != 'None' and project_filename != '1':
284         print('attempting project_lib access to ' +
    str(project_filename))
285         try:
286             from project_lib import Project
287             project = Project.access()
288             storage_credentials =
    project.get_storage_metadata()
289             readable = project.get_file(project_filename)
290         except Exception as project_exception:
291             print('unable to access data using the project_lib
    interface and filename supplied')
292
293
294     # Use data_provenance as filename if other access
    mechanisms are unsuccessful
295     if readable is None and type(data_provenance) is str:
296         print('attempting to access local file using path and
    name ' + data_provenance)

```

```

297     readable = data_provenance
298
299     # Second, use pd.read_csv to read object, iterating over
    list of csv_encodings until successful
300     if readable is not None:
301         for encoding in csv_encodings:
302             try:
303                 df = pd.read_csv(readable, encoding=encoding,
    sep = None, engine = 'python')
304                 print('successfully loaded dataframe using
    encoding = ' + str(encoding))
305                 break
306             except Exception as exception_csv:
307                 print('unable to read csv using encoding ' +
    str(encoding))
308                 print('handled error was ' +
    str(exception_csv))
309         if df is None:
310             print('unable to read file/object as a dataframe
    using supplied csv_encodings ' + str(csv_encodings))
311             print(f'Please use \'insert to code\' on data
    panel to load dataframe.')
312             raise(ValueError('unable to read file/object as a
    dataframe using supplied csv_encodings ' +
    str(csv_encodings)))
313
314     if isinstance(df, pd.DataFrame):
315         print('Data loaded succesfully')
316
317     5. Preprocess Data
318     In [ ]:
319     # Drop rows whose target is not defined
320     target = target_label_name # your target name here
321     if learning_type == 'regression':
322         df[target] = pd.to_numeric(df[target],
    errors='coerce')
323     df.dropna('rows', how='any', subset=[target],

```

```

        inplace=True)
323 In [ ]:
324 # extract X and y
325 df_X = df.drop(columns=[target])
326 df_y = df[target]
327 In [ ]:
328 # Detach preprocessing pipeline (which needs to see all
    training data)
329 preprocessor_index = -1
330 preprocessing_steps = []
331 for i, step in enumerate(pipeline.steps):
332     preprocessing_steps.append(step)
333     if step[0]=='preprocessor':
334         preprocessor_index = i
335         break
336 #if len(pipeline.steps) > preprocessor_index+1 and
    pipeline.steps[preprocessor_index + 1][0] == 'cognito':
337     #preprocessor_index += 1
338
    #preprocessing_steps.append(pipeline.steps[preprocessor_index
    ])
339 if preprocessor_index >= 0:
340     preprocessing_pipeline =
        Pipeline(memory=pipeline.memory, steps=preprocessing_steps)
341     pipeline =
        Pipeline(steps=pipeline.steps[preprocessor_index+1:])
342 In [ ]:
343 # Preprocess X
344 # preprocessor should see all data for cross_validate on
    the remaining steps to match autoai scores
345 known_values_list.clear() # known_values_list is filled
    in by the preprocessing_pipeline if needed
346 preprocessing_pipeline.fit(df_X.values, df_y.values)
347 X_prep = preprocessing_pipeline.transform(df_X.values)
348 6. Split data into Training and Holdout sets
349 In [ ]:
350 # determine learning_type and perform holdout split

```

```

        (stratify conditionally)
351  if learning_type is None:
352      # When the problem type is not available in the
        metadata, use the sklearn type_of_target to determine whether
        to stratify the holdout split
353      # Caution: This can mis-classify regression targets
        that can be expressed as integers as multiclass, in which
        case manually override the learning_type
354      from sklearn.utils.multiclass import type_of_target
355      if type_of_target(df_y.values) in ['multiclass',
        'binary']:
356          learning_type = 'classification'
357      else:
358          learning_type = 'regression'
359      print('learning_type determined by type_of_target
        as:', learning_type)
360  else:
361      print('learning_type specified as:', learning_type)
362
363  from sklearn.model_selection import train_test_split
364  if learning_type == 'classification':
365      X, X_holdout, y, y_holdout = train_test_split(X_prep,
        df_y.values, test_size=holdout_fraction,
        random_state=random_state, stratify=df_y.values)
366  else:
367      X, X_holdout, y, y_holdout = train_test_split(X_prep,
        df_y.values, test_size=holdout_fraction,
        random_state=random_state)
368  7. Generate features via Feature Engineering pipeline
369  In [ ]:
370  #Detach Feature Engineering pipeline if next, fit it, and
        transform the training data
371  fe_pipeline = None
372  if pipeline.steps[0][0] == 'cognito':
373      try:
374          fe_pipeline = Pipeline(steps=[pipeline.steps[0]])
375          X = fe_pipeline.fit_transform(X, y)

```

```

376         X_holdout = fe_pipeline.transform(X_holdout)
377         pipeline.steps = pipeline.steps[1:]
378     except IndexError:
379         try:
380             print('Trying to compose pipeline with some of
cognito steps')
381             fe_pipeline = Pipeline(steps =
list([pipeline.steps[0][1].steps[0], pipeline.steps[0][1].step
s[1]]))
382             X = fe_pipeline.fit_transform(X, y)
383             X_holdout = fe_pipeline.transform(X_holdout)
384             pipeline.steps = pipeline.steps[1:]
385         except IndexError:
386             print('Composing pipeline without cognito
steps!')
387         pipeline.steps = pipeline.steps[1:]
388 8. Additional setup: Define a function that returns a
scorer for the target's positive label
389 In [ ]:
390 # create a function to produce a scorer for a given
positive label
391 def make_pos_label_scorer(scorer, pos_label):
392     kwargs = {'pos_label':pos_label}
393     for prop in ['needs_proba', 'needs_threshold']:
394         if prop+'=True' in scorer._factory_args():
395             kwargs[prop] = True
396     if scorer._sign == -1:
397         kwargs['greater_is_better'] = False
398     from sklearn.metrics import make_scorer
399     scorer=make_scorer(scorer._score_func, **kwargs)
400     return scorer
401 9. Fit pipeline, predict on Holdout set, calculate score,
perform cross-validation
402 In [ ]:
403 # fit the remainder of the pipeline on the training data
404 pipeline.fit(X, y)

```

```

405 In [ ]:
406 # predict on the holdout data
407 y_pred = pipeline.predict(X_holdout)
408 In [ ]:
409 # compute score for the optimization metric
410 # scorer may need pos_label, but not all scorers take
    pos_label parameter
411 from sklearn.metrics import get_scorer
412 scorer = get_scorer(optimization_metric)
413 score = None
414 #score = scorer(pipeline, X_holdout, y_holdout) # this
    would suffice for simple cases
415 pos_label = None # if you want to supply the pos_label,
    specify it here
416 if pos_label is None and 'pos_label' in _input_metadata:
417     pos_label=_input_metadata['pos_label']
418 try:
419     score = scorer(pipeline, X_holdout, y_holdout)
420 except Exception as e1:
421     if pos_label is None or str(pos_label)=='':
422         print('You may have to provide a value for
    pos_label in order for a score to be calculated.')
423         raise(e1)
424     else:
425         exception_string=str(e1)
426         if 'pos_label' in exception_string:
427             try:
428                 scorer = make_pos_label_scorer(scorer,
    pos_label=pos_label)
429                 score = scorer(pipeline, X_holdout,
    y_holdout)
430                 print('Retry was successful with pos_label
    supplied to scorer')
431             except Exception as e2:
432                 print('Initial attempt to use scorer
    failed. Exception was:')

```

```

433             print(e1)
434             print('')
435             print('Retry with pos_label failed.
Exception was:')
436             print(e2)
437         else:
438             raise(e1)
439
440     if score is not None:
441         print(score)
442 In [ ]:
443 # cross_validate pipeline using training data
444 from sklearn.model_selection import cross_validate
445 from sklearn.model_selection import StratifiedKFold, KFold
446 if learning_type == 'classification':
447     fold_generator = StratifiedKFold(n_splits=cv_num_folds,
random_state=random_state)
448 else:
449     fold_generator = KFold(n_splits=cv_num_folds,
random_state=random_state)
450 cv_results = cross_validate(pipeline, X, y,
cv=fold_generator, scoring={optimization_metric:scorer},
return_train_score=True)
451 import numpy as np
452 np.mean(cv_results['test_' + optimization_metric])
453 In [ ]:
454 cv_results

```

## A.2. Source Code for the main NODE RED flow:

```

1 [{"id":"42e7756f.e5d5fc","type":"ui_template","z":"aab06066.8
dbcb","group":"bd20e955.8237f8","name":"","order":0,"width":0
,"height":0,"format":"<p>\n    This tab will give you
prediction of number of orders for the week you enter and the

```



subsequent 10 weeks' worth of order in

```
advance.\n</p>", "storeOutMessages":true, "fwdInMessages":true,
"resendOnRefresh":true, "templateScope":"local", "x":720, "y":12
20, "wires":[[]]}, {"id":"bd20e955.8237f8", "type":"ui_group", "z
":"","name":"Info:", "tab":"8cee228d.c1fbc", "order":4, "disp":t
rue, "width":"3", "collapse":true}, {"id":"8cee228d.c1fbc", "type
":"ui_tab", "z":"","name":"Predictions", "icon":"dashboard", "or
der":3, "disabled":false, "hidden":false}]
```