Data Science Final Project Presentation

Class: IBM IMVAI-1901

Team 2

Team Members

Allen Vincent Hui Kim Seng

Aung Pye Phyo

Chong Yul Chin (Eunice)

Law Tuan Lee (Jolene)

Lai Wei Jie

Agenda

Team Members	Roles & Responsibilities	Agenda
Eunice Chong	Product Owner Plans, defines the problem, builds hypothesis, and provides feedback	1) Introduction 2) Planning Analytics
Allen Vincent Hui Kim Seng	Data Analyst / Data Engineer Collects and analyzes data from operational systems and databases (e.g Kaggle, data.gov.sg) ; understands data and uses statistical method and analytical tool to interpret the data Uses computational notebook to perform data cleansing, and creates data visualization to make information more accessible and understandable	3) Descriptive Analytics 4) Diagnostic Analytics
Law Tuan Lee (Jolene)	Data Scientist Manages data by building, testing and transforming raw data into usable pipeline for machine learning. Extracts insights from data patterns; builds and tests the model to provide a prediction	5) Predictive Analytics

Agenda

Team Members	Roles & Responsibilities	Agenda
Lai Wei Jie	Data Scientist Takes inputs from prediction to deploy predictive models via machine learning. Make sure a satisfactory model has been developed before deploying into production environment. Provides recommendations to our user	6. Prescriptive Analytics
Aung Pye Phyo	Developer Enables models to be deployed and develop software application effectively that leverage the insights and data gathered from other data science team. Actively monitor the quality of model in production to detect performance degradation and model staleness. Research and implement best practices to enhance existing machine learning infrastructure.	7. Environment Check 8. Summary and Reflection

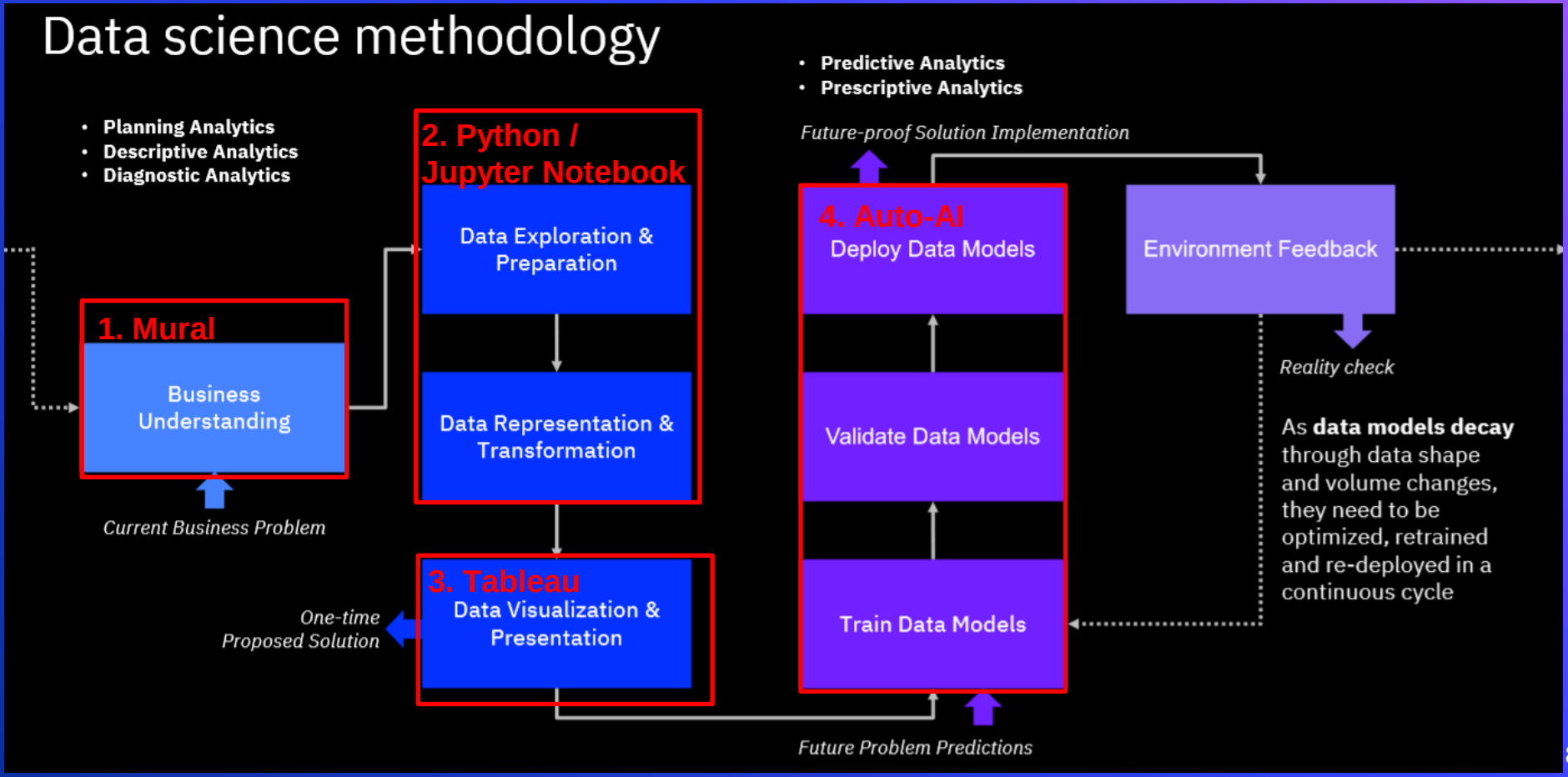
1. Introduction

Project Objectives

Using Data analytics Lifecycle and following the Data Science Methodology, our objective is to accurately predict health insurance charges and provide recommendations to our Users on what they do to avoid paying a higher health insurance charges than other Users with similar biometrics to achieve greater financial savings.

Data Analytics Lifecycle

Tools


Data science methodology
• Planning Analytics
• Descriptive Analytics
• Diagnostic Analytics
1. Mural
Business Understanding
Current Business Problem
2. Python / Jupyter Notebook
Data Exploration & Preparation
Data Representation & Transformation
3. Tableau
Data Visualization & Presentation
One-time Proposed Solution
• Predictive Analytics
• Prescriptive Analytics
Future-proof Solution Implementation
4. Auto-AI
Deploy Data Models
Validate Data Models
Train Data Models
Environment Feedback
Reality check
As data models decay through data shape and volume changes, they need to be optimized, retrained and re-deployed in a continuous cycle
Future Problem Predictions

2. Planning Analytics

Business Understanding

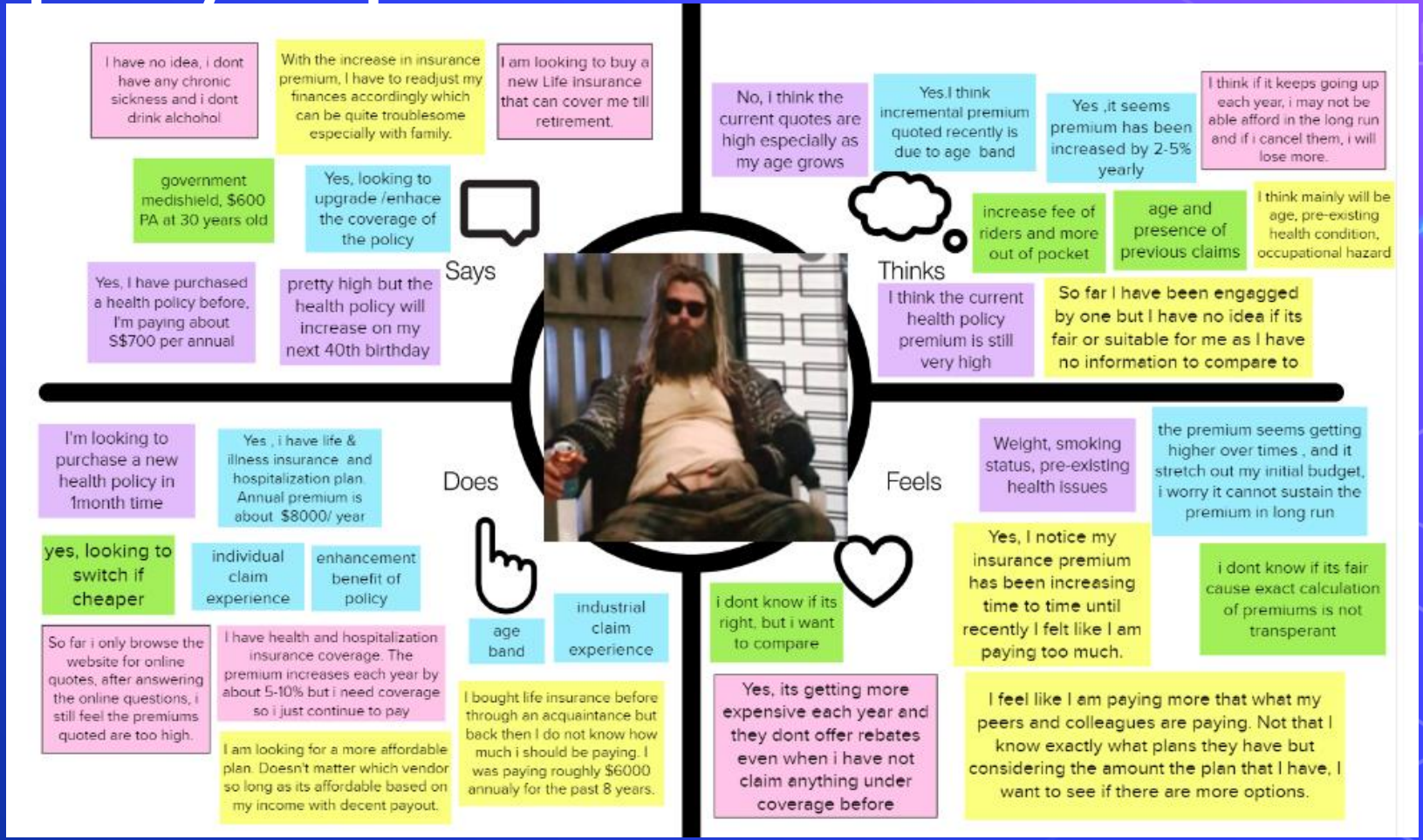
What is the business problem?

- Why the difference in health insurance charges for different customers and what one can do to avoid paying high charges

What is the business opportunity?

- What can health insurance company do to show transparency and promote self-discipline from customer to lead a more prudent life and be covered for the unexpected in life.

Empathy Map


I have no idea, i dont have any chronic sickness and i dont drink alchohol
With the increase in insurance premium, I have to readjust my finances accordingly which can be quite troublesome especially with family.
I am looking to buy a new Life insurance that can cover me till retirement.
government medishield, $600 PA at 30 years old
Yes, looking to upgrade /enhace the coverage of the policy
Says
Yes, I have purchased a health policy before, I'm paying about S$700 per annual
pretty high but the health policy will increase on my next 40th birthday
No, I think the current quotes are high especially as my age grows
Yes.I think incremental premium quoted recently is due to age band
Yes ,it seems premium has been increased by 2-5% yearly
I think if it keeps going up each year, i may not be able afford in the long run and if i cancel them, i will lose more.
increase fee of riders and more out of pocket
age and presence of previous claims
I think mainly will be age, pre-existing health condition, occupational hazard
Thinks
I think the current health policy premium is still very high
So far I have been engagged by one but I have no idea if its fair or suitable for me as I have no information to compare to
I'm looking to purchase a new health policy in 1month time
Yes , i have life & illness insurance and hospitalization plan. Annual premium is about $8000/ year
Does
yes, looking to switch if cheaper
individual claim experience
enhancement benefit of policy
So far i only browse the website for online quotes, after answering the online questions, i still feel the premiums quoted are too high.
I have health and hospitalization insurance coverage. The premium increases each year by about 5-10% but i need coverage so i just continue to pay
I am looking for a more affordable plan. Doesn't matter which vendor so long as its affordable based on my income with decent payout.
age band
industrial claim experience
I bought life insurance before through an acquaintance but back then I do not know how much i should be paying. I was paying roughly $6000 annualy for the past 8 years.
Weight, smoking status, pre-existing health issues
the premium seems getting higher over times , and it stretch out my initial budget, i worry it cannot sustain the premium in long run
Feels
Yes, I notice my insurance premium has been increasing time to time until recently I felt like I am paying too much.
i dont know if its fair cause exact calculation of premiums is not transperant
i dont know if its right, but i want to compare
Yes, its getting more expensive each year and they dont offer rebates even when i have not claim anything under coverage before
I feel like I am paying more that what my peers and colleagues are paying. Not that I know exactly what plans they have but considering the amount the plan that I have, I want to see if there are more options.

PainPoints

- I don’t know if its fair cause exact calculation of charges is not transparent
- The charges seem getting higher over times , and it has stretched my initial budget, I worry it cannot sustain the payment in long run
- Yes, it is getting more expensive each year and they don't offer rebates even when I have not claim anything under coverage before
- So far I have only browse the website for online quotes, after answering the online questions, I still feel the charges quoted are too high.

HMW Statement

How might we help people to avoid paying higher annual health

for insurance charges than their peers
people looking to purchase new plans

so that they can avoid being overcharged

Reframed HMW Statement

How might we understand what is the expected annual health insurance charges

for Individuals with comparable biometrics and lifestyles

so that they can ease the financial burden in the long run

Hill Statement

Who Thor, a middle age working Singapore

What wants to know the average health insurance charges paid by other policy holders with similar biometric and lifestyles

Wow to avoid not paying more than 5% than average health insurance charges paid by policy holders with similar demographics

Hypothesis

If we provide Thor

with a tool that enables him to enter his details to generate an average health insurance charges paid by others

We will observe

- Hypothesis 1: A higher charges paid if the user is having a higher BMI (i.e. If Thor has a high BMI)
- Hypothesis 2: A lower charges paid if the user is a non-smoker (i.e. If Thor is a smoker)

MVP

If we provide middle aged adults

With a model that enables him to compare health insurance charges paid by policy holders of similar demographics

We will address the risk of: individuals overpaying for their health insurance

By Measuring:

We'll know we've arrived when we observed:

- Users have a 70% successful purchase rate after getting their quote
- More than 85% download clicks rate of the recommendation generated

3. Descriptive Analytics

Approach

Step 1: Gather the appropriate data set and prepare for analysis.

kaggle

Step 2: Using Jupyter Notebook in Kaggle to perform

- Data Profile
- Data Cleansing
- Data Transformation

tableau

Step 3: Using Tableau to visualize preliminary cleansed data results and run summary statistics

Step 4: Create models using IBM Auto AI with Machine Learning service associated. With Auto AI, we can build and deploy a machine learning model with sophisticated training features and no coding.

Step 5: Determine the best model that can be used to predict health insurance charges based on the pipeline results and Deploy Import data using IBM Watson Studio service.

Step 6: Run Model to predict results

Dataset Overview

- Data Source

https://www.kaggle.com/datasets/simranjain17/insurance

- Dataset Description

This is a basic Health Insurance Data where every row states details of one policy holder e.g. Gender, BMI and other characteristics

Dataset - Attributes

Attributes	Description	Data Type
Age	This is the age of the person.	Integer
Sex	This is the sex of the person.	String
BMI	This is the Body Mass Index of the person where: BMI = weight/ height in metres squared.	Decimal
Children	This is the number of children of the person.	Integer
Smoker	This is a value representing whether the person is a smoker.	String
Region	This is the location of where the person stays.	String
Charges	This is the amount the person is paying for their health insurance charges annually.	Decimal

Dataset - Attributes

Source: IBM Data Refinery

Data | Profile | Visualizations

	age Integer	sex String	bmi Decimal	children Integer	smoker String	region String	charges Decimal
1	19	female	27.9	0	yes	southwest	16884.924
2	18	male	33.77	1	no	southeast	1725.5523
3	28	male	33	3	no	southeast	4449.462
4	33	male	22.705	0	no	northwest	21984.47061
5	32	male	28.88	0	no	northwest	3866.8552

Data Exploration

insurance.csv (55.63 kB)

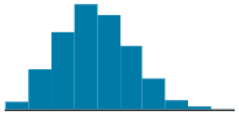
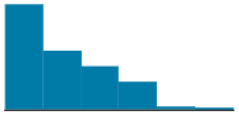
Detail | Compact | Column

7 of 7 columns

age	sex	bmi	children	smoker	region	charges
19	female	27.9	0	yes	southwest	16884.924
18	male	33.77	1	no	southeast	1725.5523
28	male	33	3	no	southeast	4449.462
33	male	22.705	0	no	northwest	21984.47061
32	male	28.88	0	no	northwest	3866.8552
31	female	25.74	0	no	southeast	3756.6216
46	female	33.44	1	no	southeast	8240.5896
37	female	27.74	3	no	northwest	7281.5056
37	male	29.83	2	no	northeast	6406.4107
60	female	25.84	0	no	northwest	28923.13692
25	male	26.22	0	no	northeast	2721.3208
62	female	26.29	0	yes	southeast	27808.7251

Data Exploration

This a Basic Health Insurance Data where Every Row states details of one policyholder.

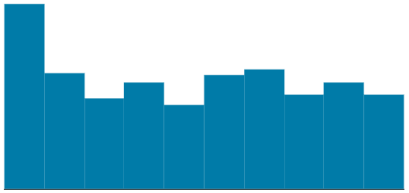
# age	A sex	# bmi	# children	✓ smoker	A region	# charges
The Age of the policyholder	The Gender of the policyholder	The Body Mass Index of the Policyholder	Number of Children of the Policyholder	A Column whether the Policyholder is Smoker or No Smoker	The Region where the Policyholder belongs to	The Premium Charged to the Policyholder
 18 64	male 51% female 49%	 16 53.1	 0 5	 true 274 20% false 1064 80%	southeast 27% southwest 24% Other (649) 49%	 1.12k 63.8k
19	female	27.9	0	yes	southwest	16884.924
18	male	33.77	1	no	southeast	1725.5523
28	male	33	3	no	southeast	4449.462
33	male	22.705	0	no	northwest	21984.47061
32	male	28.88	0	no	northwest	3866.8552
31	female	25.74	0	no	southeast	3756.6216

Data Exploration

Detail Compact Column 7 of 7 columns

age

The Age of the policyholder



Valid	1338	100%
Mismatched	0	0%
Missing	0	0%
Mean	39.2	
Std. Deviation	14	
Quantiles	18	Min
	27	25%
	39	50%
	51	75%
	64	Max

sex

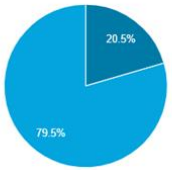
The Gender of the policyholder

male	51%
female	49%

Valid	1338	100%
Mismatched	0	0%
Missing	0	0%
Unique	2	
Most Common	male	51%

smoker

A Column whether the Policyholder is Smoker or No Smoker

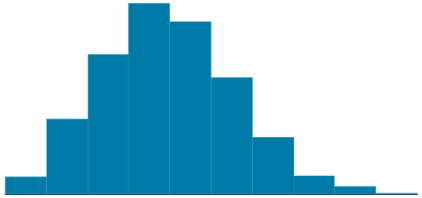


true	274 20%
false	1064 80%

Valid	1338	100%
Mismatched	0	0%
Missing	0	0%
True	274	20%
False	1064	80%

bmi

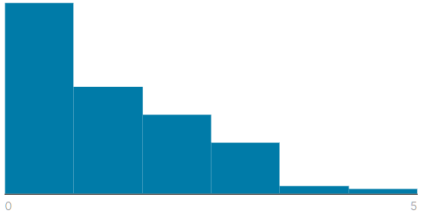
The Body Mass Index of the Policyholder



Valid	1338	100%
Mismatched	0	0%
Missing	0	0%
Mean	30.7	
Std. Deviation	6.1	
Quantiles	16	Min
	26.3	25%
	30.4	50%
	34.7	75%
	53.1	Max

children

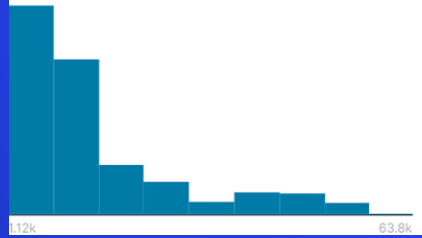
Number of Children of the Policyholder



Valid	1338	100%
Mismatched	0	0%
Missing	0	0%
Mean	1.09	
Std. Deviation	1.21	
Quantiles	0	Min
	0	25%
	1	50%
	2	75%
	5	Max

charges

The Premium Charged to the Policyholder



Valid	1338	100%
Mismatched	0	0%
Missing	0	0%
Mean	13.3k	
Std. Deviation	12.1k	
Quantiles	1.12k	Min
	4.74k	25%
	9.39k	50%
	16.7k	75%
	63.8k	Max

Data Prepation (Cleansing) with Python

Step #0: PROBLEM STATEMENT

Insurance.csv is a data listing the health insurance charges paid by individuals.

We would like to develop a model to predict the total dollar amount that customers are willing to pay given the following following attributes using Artificial Neural Networks

- Age
- Gender
- BMI
- Smoker

The model should be able to predict

- Health Insurance Premium Charges

STEP #1: IMPORT LIBRARIES/DATASETS

Data collected from https://www.kaggle.com/simranjain17/insurance

Data Prepation (Cleansing) with Python

[1]:

```
## Database Phase
import pandas as pd
import numpy as np

#Visualization Phase
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib as mpl
import matplotlib.pylab as pylab
%matplotlib inline
pd.set_option('display.max_columns', 500)
mpl.style.use('ggplot')
sns.set_style('white')
pylab.rcParams['figure.figsize'] = 12,8
```

+ Code + Markdown

[2]:

```
insurance = pd.read_csv('../input/insurance/insurance.csv')
insurance_copy=insurance.copy('../input/insurance/insurance.csv')
```

Data Prepation (Cleansing) with Python

[3]:
```
print ("The shape of the  data is (row, column):"+ str(insurance_copy.shape))
print (insurance_copy.info())
```

```
The shape of the  data is (row, column):(1338, 7)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1338 non-null   int64
 1   sex       1338 non-null   object
 2   bmi       1338 non-null   float64
 3   children  1338 non-null   int64
 4   smoker    1338 non-null   object
 5   region    1338 non-null   object
 6   charges   1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
None
```

+ Code + Markdown

[4]:
```
df = insurance_copy
```

Data Prepation (Cleansing) with Python

[5]:
```
insurance_csv = ('../input/insurance/insurance.csv')
insurance = pd.read_csv('../input/insurance/insurance.csv')
```

+ Code + Markdown

[6]:
```
df.head()
```

[6]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

[7]:
```
df.tail()
```

[7]:

	age	sex	bmi	children	smoker	region	charges
1333	50	male	30.97	3	no	northwest	10600.5483
1334	18	female	31.92	0	no	northeast	2205.9808
1335	18	female	36.85	0	no	southeast	1629.8335
1336	21	female	25.80	0	no	southwest	2007.9450
1337	61	female	29.07	0	yes	northwest	29141.3603

+ Code + Markdown

[8]:
```
insurance_copy.dtypes
```

[8]:
```
age           int64
sex          object
bmi         float64
children      int64
smoker       object
region       object
charges     float64
dtype: object
```

[9]:
```
#Checking out the statistical parameters
insurance_copy.describe()
```

[9]:

	age	bmi	children	charges
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.663397	1.094918	13270.422265
std	14.049960	6.098187	1.205493	12110.011237
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.296250	0.000000	4740.287150
50%	39.000000	30.400000	1.000000	9382.033000
75%	51.000000	34.693750	2.000000	16639.912515
max	64.000000	53.130000	5.000000	63770.428010

Data Representation and Transformation with Python

Attributes	Description	Original DataType	Transformed DataType
Age	This is the age of the person.	Integer	Integer
Sex	This is the sex of the person.	String	Changed to Boolean in Python. 1 = Male, 0 = Female.
BMI	This is the Body Mass Index of the person where: BMI = weight/ height in metres squared.	Decimal	Decimal
Children	This is the number of children of the person.	Integer	Integer
Smoker	This is a value representing whether the person is a smoker.	String	Changed to Boolean in Python. 1 = Yes, 0 = No
Region	This is the location of where the person stays.	String	String
Charges	This is the amount the person is paying for their health insurance charges annually.	Decimal	Decimal

1-Hot Encoding

Data Representation and Transformation with Python

```
#Checking out the categories and their respective counts in each feature
print("sex:",insurance_copy.sex.value_counts())
print("-"*40)
print("smoker:",insurance_copy.smoker.value_counts())
print("-"*40)
print("age:",insurance_copy.age.value_counts())
print("-"*40)
print("bmi:",insurance_copy.bmi.value_counts())
print("-"*40)
print("children:",insurance_copy.children.value_counts())
print("-"*40)
print("charges:",insurance_copy.charges.value_counts())
print("-"*40)
```

```
sex: male      676
female    662
Name: sex, dtype: int64
----------------------------------------
smoker: no     1064
yes     274
Name: smoker, dtype: int64
----------------------------------------
age: 18    69
19    68
50    29
51    29
47    29
46    29
45    29
20    29
48    29
52    29
22    28
49    28
54    28
53    28
21    28
26    28
24    28
25    28
28    28
27    28
23    28
```

```
23    28
43    27
29    27
30    27
41    27
42    27
44    27
31    27
40    27
32    26
33    26
56    26
34    26
55    26
57    26
37    25
59    25
58    25
36    25
38    25
35    25
39    25
61    23
60    23
63    23
62    23
64    22
Name: age, dtype: int64
----------------------------------
bmi: 32.300    13
28.310     9
30.495     8
30.875     8
31.350     8
          ..
```

```
          ..
46.200     1
23.800     1
44.770     1
32.120     1
30.970     1
Name: bmi, Length: 548, dtype: int64
----------------------------------------
children: 0    574
1    324
2    240
3    157
4     25
5     18
Name: children, dtype: int64
----------------------------------------
charges: 1639.56310     2
16884.92400    1
29330.98315    1
2221.56445     1
19798.05455    1
              ..
7345.08400     1
26109.32905    1
28287.89766    1
1149.39590     1
29141.36030    1
Name: charges, Length: 1337, dtype: int64
----------------------------------------
```

Data Representation and Transformation with Python

[11]:
```
#Check for missing values in pandas dataframe using isnull() function
print('Data columns with null values:',insurance_copy.isnull().sum())
```

```
Data columns with null values: age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

[12]:
```
#Check for missing values in pandas dataframe using isna() function
df.isna().any()
```

[12]:
```
age         False
sex         False
bmi         False
children    False
smoker      False
region      False
charges     False
dtype: bool
```

Data Representation and Transformation with Python

[13]:
```
#Check for duplicate values, It returns a boolean series which is True only for Unique elements
df.duplicated()
```

[13]:
```
0       False
1       False
2       False
3       False
4       False
        ...
1333    False
1334    False
1335    False
1336    False
1337    False
Length: 1338, dtype: bool
```

[14]:
```
#Check how many rows have duplicate values
df.duplicated().sum()
```

[14]:
```
1
```

[15]:
```
# Extract duplicate rows
df.loc[df.duplicated(keep=False), :]
```

[15]:

	age	sex	bmi	children	smoker	region	charges
195	19	male	30.59	0	no	northwest	1639.5631
581	19	male	30.59	0	no	northwest	1639.5631

[16]:
```
# Remove duplicate row
df.drop_duplicates(inplace=True)
```

Data Representation and Transformation with Python

[17]:
```
#Prints information about the DataFrame.
#The information contains the number of columns, column labels, column data types, memory usage, range index, and the number of cells in each co
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1337 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1337 non-null   int64
 1   sex       1337 non-null   object
 2   bmi       1337 non-null   float64
 3   children  1337 non-null   int64
 4   smoker    1337 non-null   object
 5   region    1337 non-null   object
 6   charges   1337 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 83.6+ KB
```

+ Code + Markdown

[18]:
```
#Transform sex=male. It returns a boolean series and set it as 'True', else 'False'
df['sex'] == 'male'
```

1-Hot Encoding

[18]:
```
0       False
1        True
2        True
3        True
4        True
        ...
1333     True
1334    False
1335    False
1336    False
1337    False
Name: sex, Length: 1337, dtype: bool
```

Data Representation and Transformation with Python

1-Hot Encoding

[19]:
```
#Transform sex=male. It returns a value as '1' if True, else '0' if False
(df['sex'] == 'male').astype(int)
```

[19]:
```
0       0
1       1
2       1
3       1
4       1
       ..
1333    1
1334    0
1335    0
1336    0
1337    0
Name: sex, Length: 1337, dtype: int64
```

[20]:
```
df['sex'] = (df['sex'] == 'male').astype(int)
```

[21]:
```
#Transform smoker=yes. It returns a boolean series and set it as 'True', else 'False'
df['smoker'] == 'yes'
```

[21]:
```
0        True
1       False
2       False
3       False
4       False
        ...
1333    False
1334    False
1335    False
1336    False
1337     True
Name: smoker, Length: 1337, dtype: bool
```

Data Representation and Transformation with Python

[22]:
```
#Transform smoker=yes. It returns a value as '1' if True, else '0' if False
(df['smoker'] == 'yes').astype(int)
```

1-Hot Encoding

[22]:
```
0       1
1       0
2       0
3       0
4       0
       ..
1333    0
1334    0
1335    0
1336    0
1337    1
Name: smoker, Length: 1337, dtype: int64
```

+ Code + Markdown

[23]:
```
df['smoker'] = (df['smoker'] == 'yes').astype(int)
```

[24]:
```
#Returns the first 5 rows of the dataframe
df.head()
```

[24]:

	age	sex	bmi	children	smoker	region	charges
0	19	0	27.900	0	1	southwest	16884.92400
1	18	1	33.770	1	0	southeast	1725.55230
2	28	1	33.000	3	0	southeast	4449.46200
3	33	1	22.705	0	0	northwest	21984.47061
4	32	1	28.880	0	0	northwest	3866.85520

[25]:
```
#Returns the last 5 rows of the dataframe
df.tail()
```

[25]:

	age	sex	bmi	children	smoker	region	charges
1333	50	1	30.97	3	0	northwest	10600.5483
1334	18	0	31.92	0	0	northeast	2205.9808
1335	18	0	36.85	0	0	southeast	1629.8335
1336	21	0	25.80	0	0	southwest	2007.9450
1337	61	0	29.07	0	1	northwest	29141.3603

Data Representation and Transformation with Python

[26]:
```
#To find which User paid lowest premium
df.charges.idxmin()
```

[26]:
```
940
```

[27]:
```
#Retrieve specific rows from Dataframe
df.iloc[940]
```

[27]:
```
age              50
sex               0
bmi           46.09
children          1
smoker            0
region      southeast
charges     9549.5651
Name: 941, dtype: object
```

+ Code + Markdown

[28]:
```
#Returns index of first occurrence of maximum over requested axis.
df.charges.idxmax()
```

[28]:
```
543
```

Data Representation and Transformation with Python

[29]:
```
#Retrieve specific rows from Dataframe
df.iloc[543]
```

[29]:
```
age                54
sex                 0
bmi             47.41
children            0
smoker              1
region      southeast
charges     63770.42801
Name: 543, dtype: object
```

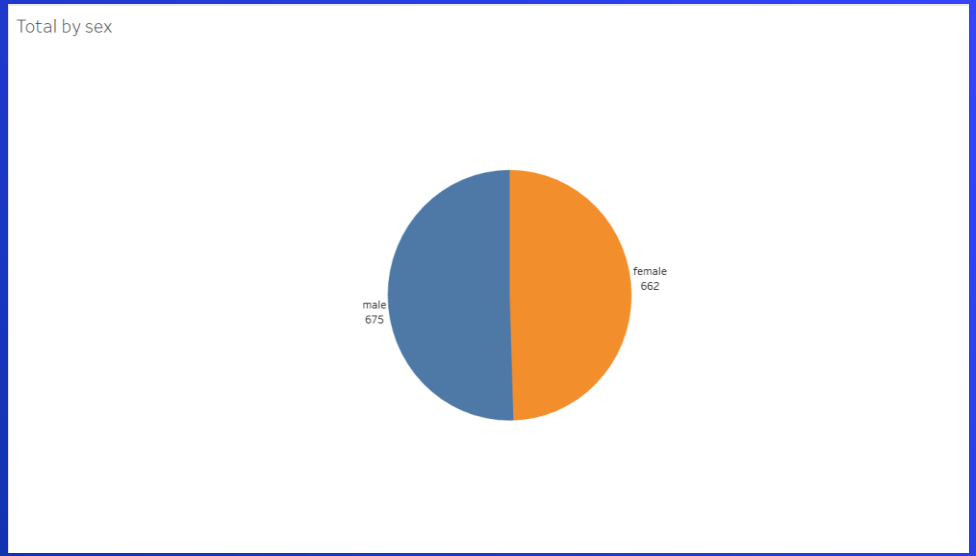
[30]:
```
#Retrieve specific rows from Dataframe
df.iloc[581]
```

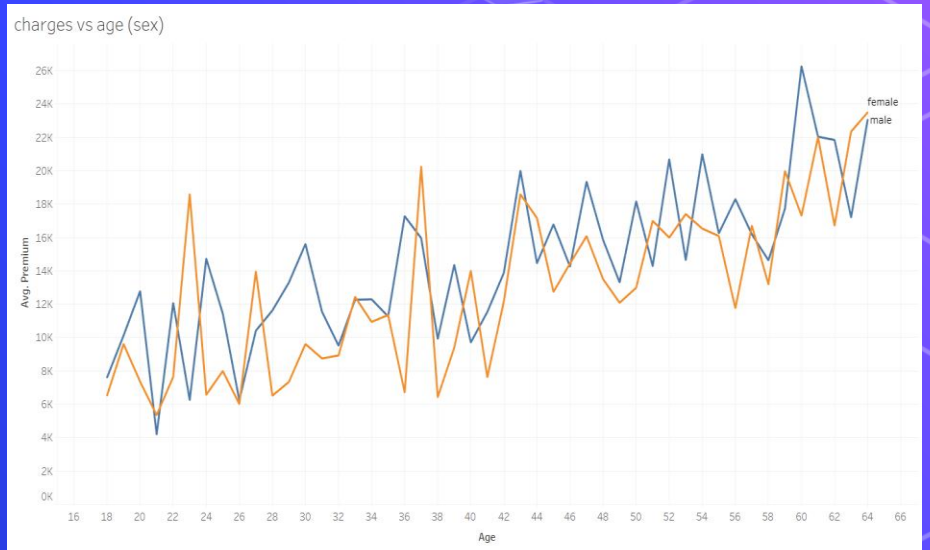
[30]:
```
age               39
sex                1
bmi            45.43
children           2
smoker             0
region     southeast
charges     6356.2707
Name: 582, dtype: object
```

[31]:
```
#Retrieve specific rows from Dataframe
df.iloc[195]
```

[31]:
```
age               19
sex                1
bmi            30.59
children           0
smoker             0
region     northwest
charges     1639.5631
Name: 195, dtype: object
```

Data Visualization with Tableau – What have we discovered from the data?





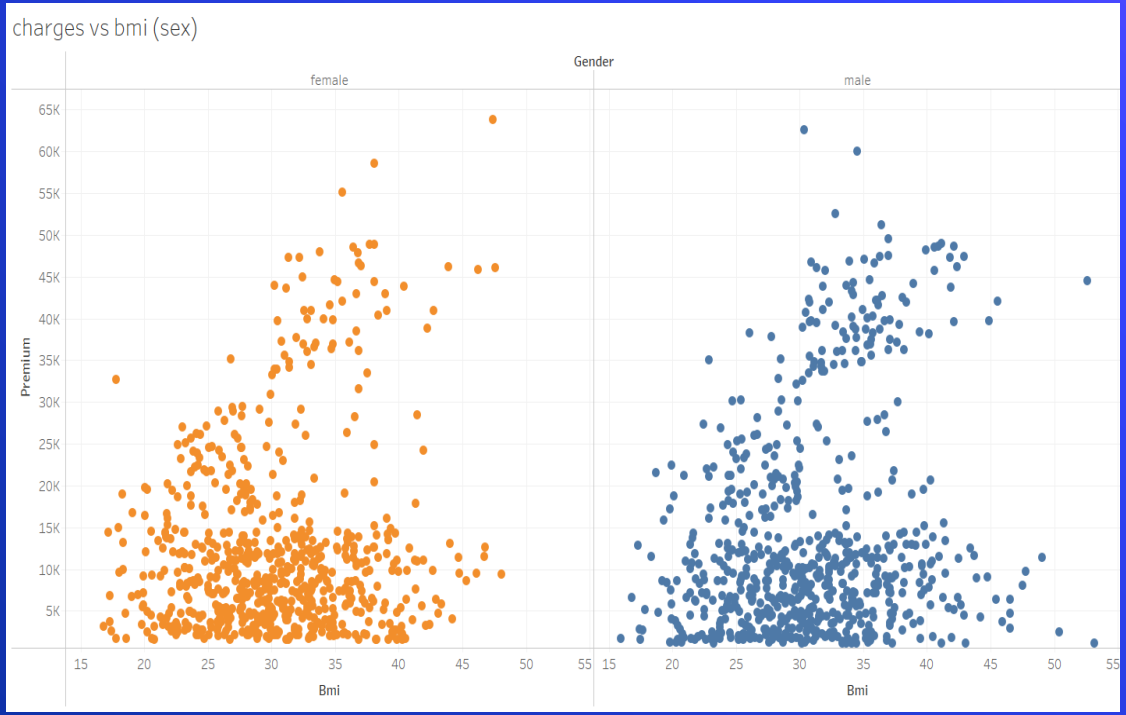
Total count of 1337 customers. sex breakdown is quite even.

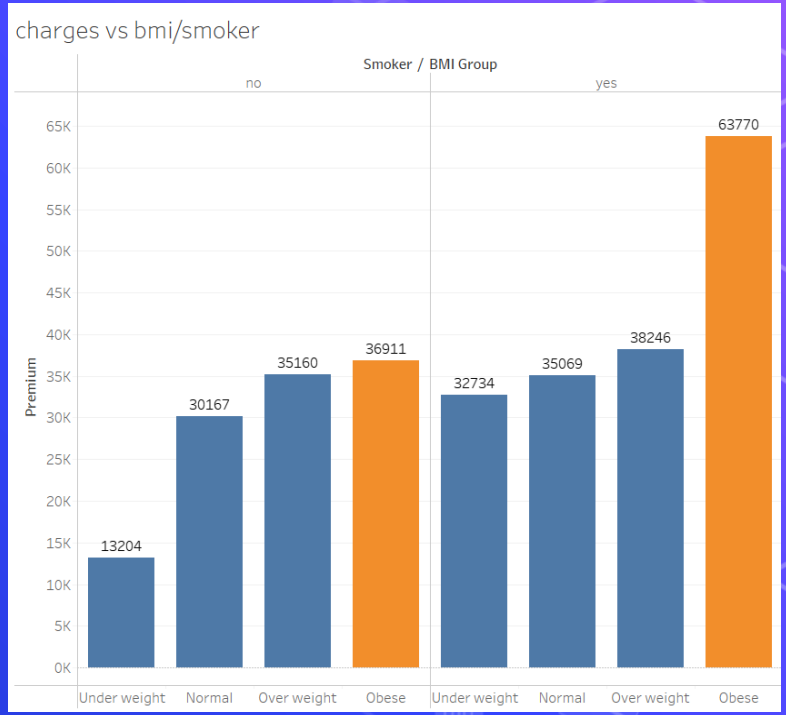
- 51% Male
- 49% Female

Positive Relationship between charges and age. Charges starts to go up as customer ages, regardless of sex. However, males do pay higher as they age.

Source: https://public.tableau.com/app/profile/allen.hui/viz/IMVAI1901-DS-Team2-Insurance-Final/DashboardforInsuranceCustomer?publish=yes

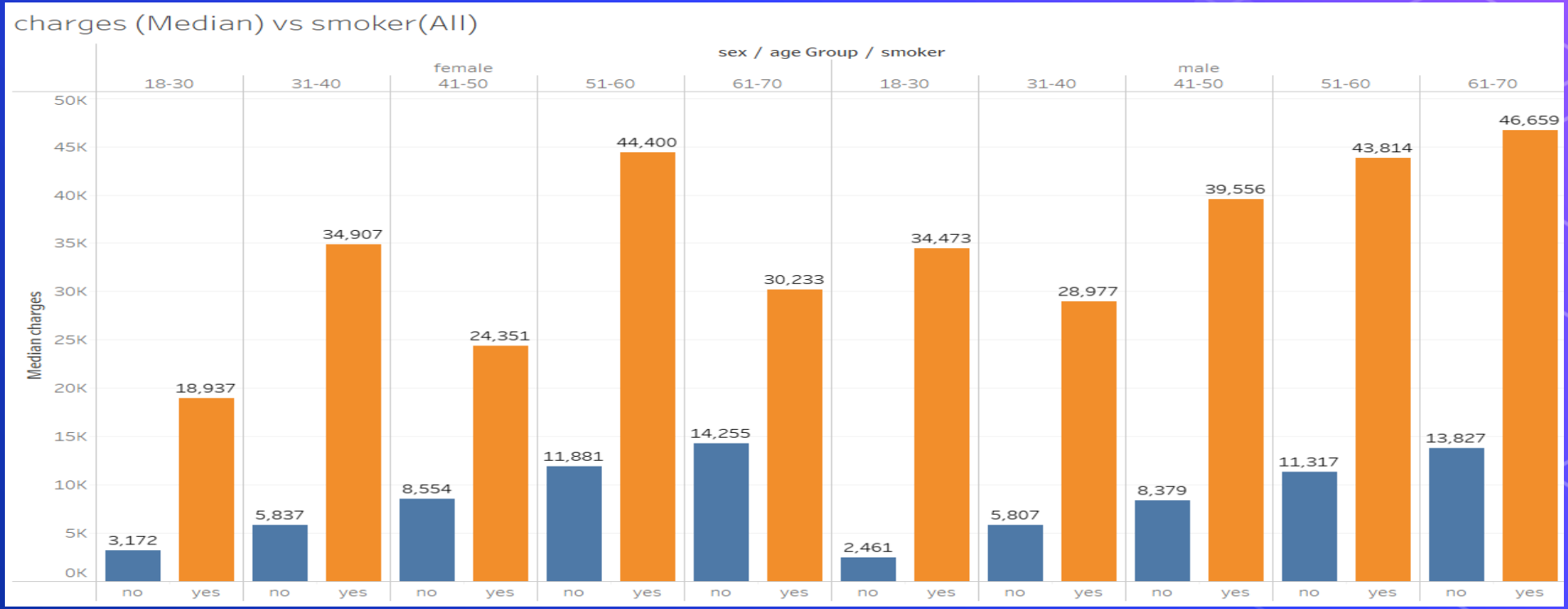
Data Visualization with Tableau - So, age does makes a difference. What about BMI?





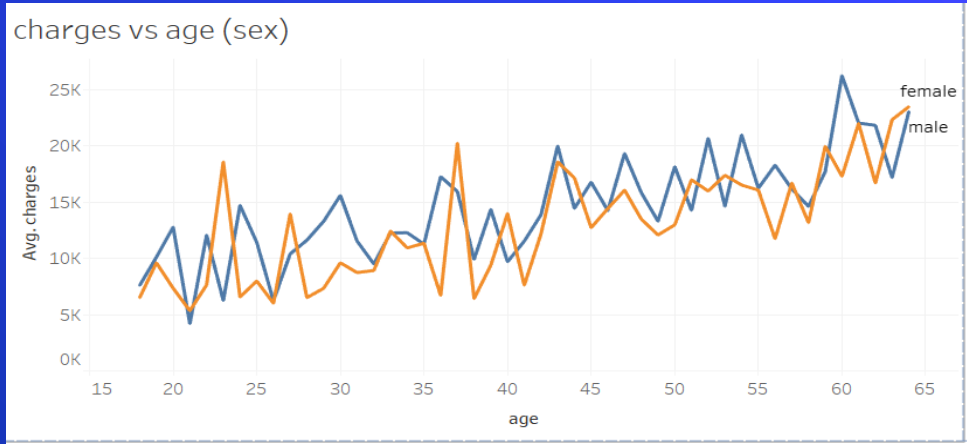
Charges paid by consumers with high BMI >30, tend to pay higher. But it is not always the truth based on the plot shown. But if BMI is high and smoking, charges paid is 74.3% higher then BMI high and non-smoker

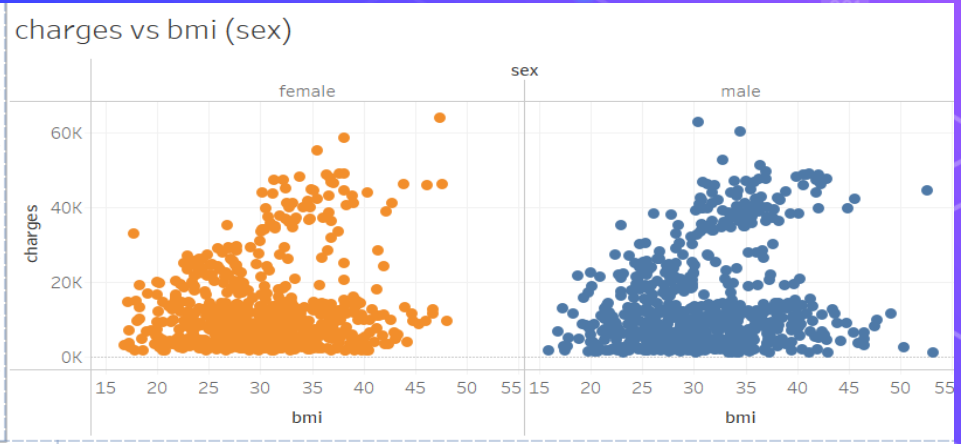
Data Visualization with Tableau - Since, age and BMI make a difference. What about smokers?

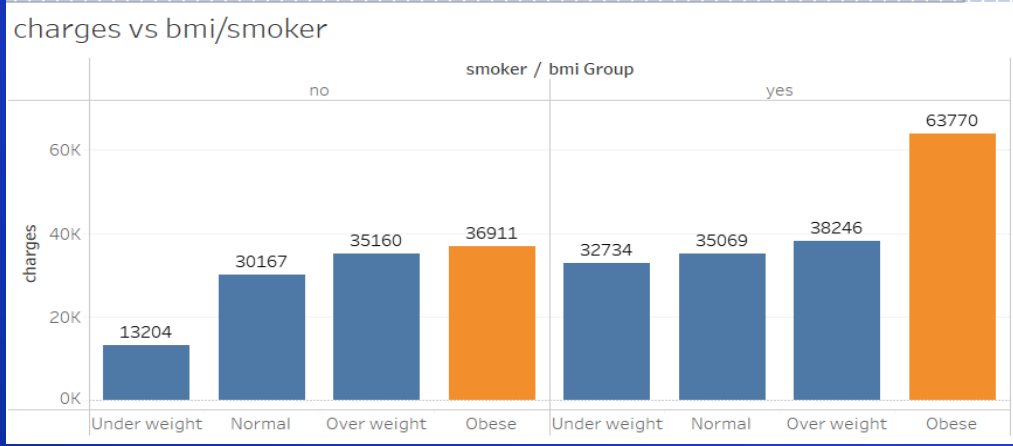


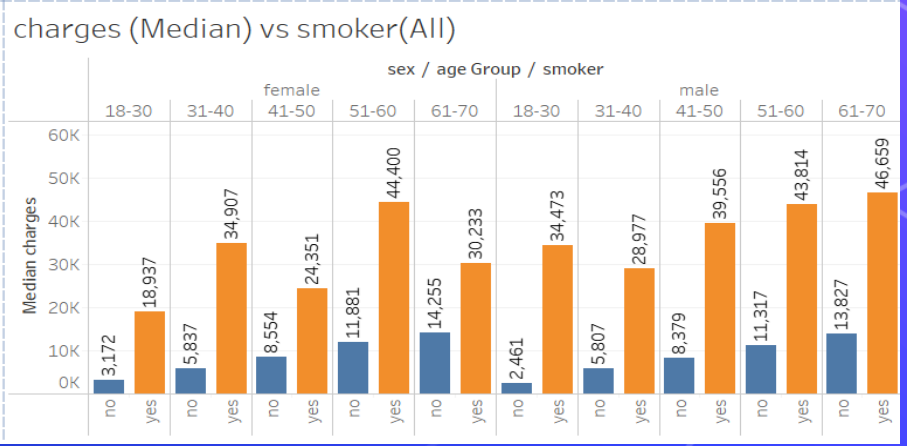
- Smokers across all ages and sex, pay higher than non-smokers.
- Male smoker pay over $32k more compared to non-smoker for age group 18-30, 61-70

DashBoard from Tableau









4. Diagnostic Analytics

Attribute Insights

With these findings, what can we conclude?

As evident by the analysis thus far, we can conclude that there is a strong relationship between charges charged and the various key variables. This has been explained by the health risk associated with high BMI readings and smoking habit. Thus charges are charged higher to consumers with such traits.

Key Variables	Affect Charges
Age ↑	✓
BMI ↑	✓
Smoker ✓	✓

Conclusion:
Anyone with BMI and smoke at the same time, will have to be prepared for high charges when buying a policy or renewal, this aligns with our hypothesis

5. Predictive Analytics

Predictive Analytics - What Happens next?

- Using descriptive data accumulated over time to find explanatory variables, we are able to build statistical models that can be applied to other data points for which we're to predict the outcome.
- Our Team **identified an issue** where Users are not aware which factors has the most weightage affecting the calculation of their health insurance charges
- **Discovered** that the issue is causing Users not knowing what action they can take to have greater financial savings, i.e. pay lesser charges

We need to:

- **Predict** the expected health insurance charges that the Users need to pay given their biometrics demographic and make recommendations accordingly.

Our team decided to use AutoAI for this section.

What is Auto AI?

Automated machine learning (AutoML) is the process of automating the manual tasks that data scientists must complete as they build and train machine learning models (ML models).

These tasks include

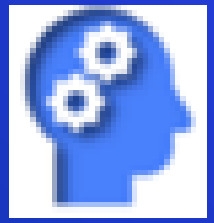
- feature engineering and selection,
- choosing the type of machine learning algorithm;
- building an analytical model based on the algorithm;
- hyperparameter optimization,
- training the model on tested data sets and
- running the model to generate scores and findings.

AutoAI is a variation of AutoML. It extends the automation of model building to the entire AI lifecycle.

Like AutoML, AutoAI applies intelligent automation to the steps of building predictive machine learning models.

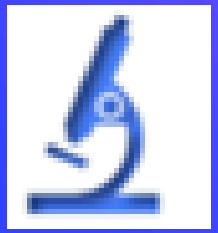
Why we choose to use Auto AI?

Build Models Faster

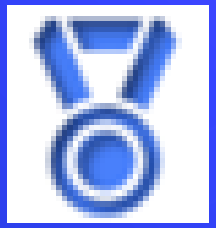


Jump The skills gap

Discover more use cases



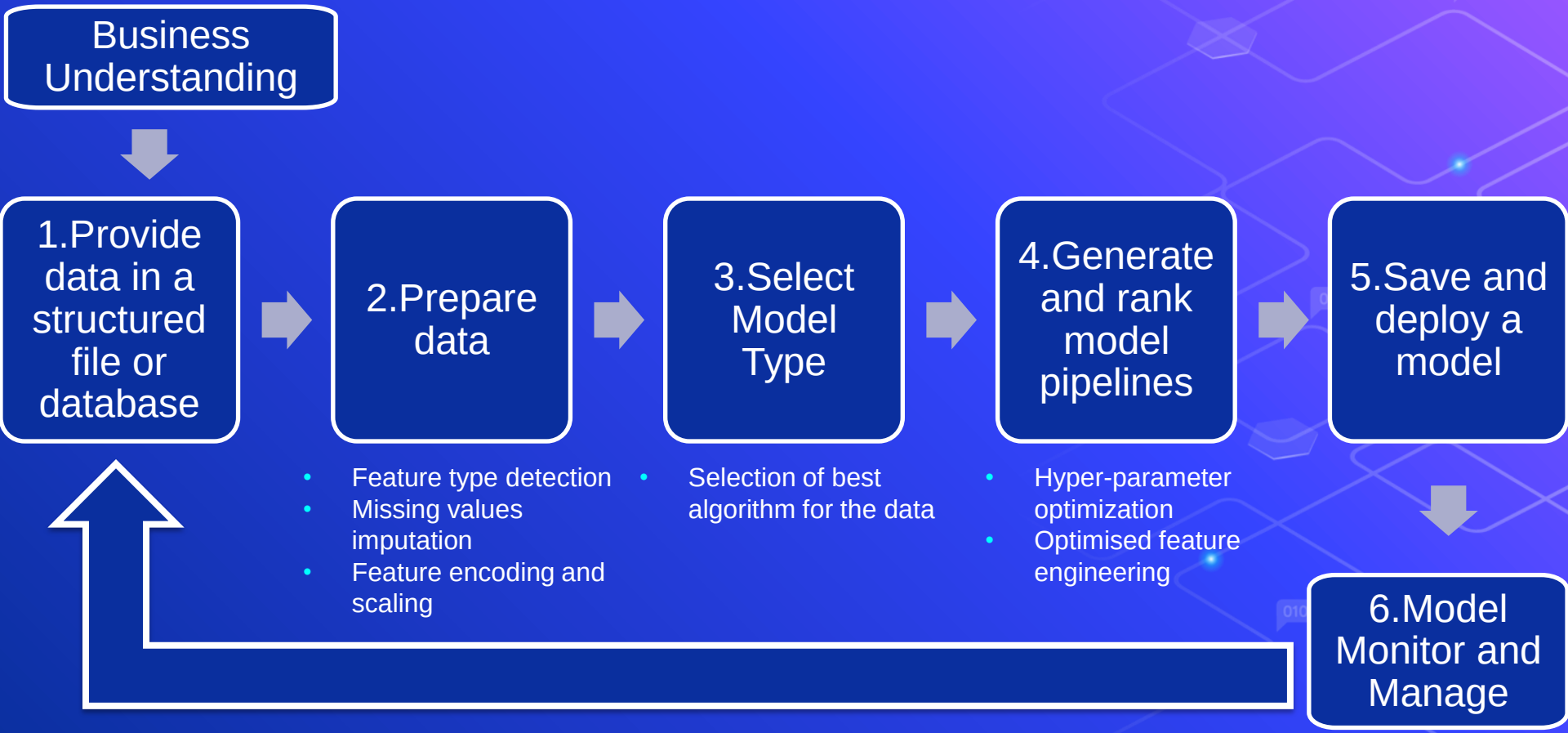
Find signal from noise



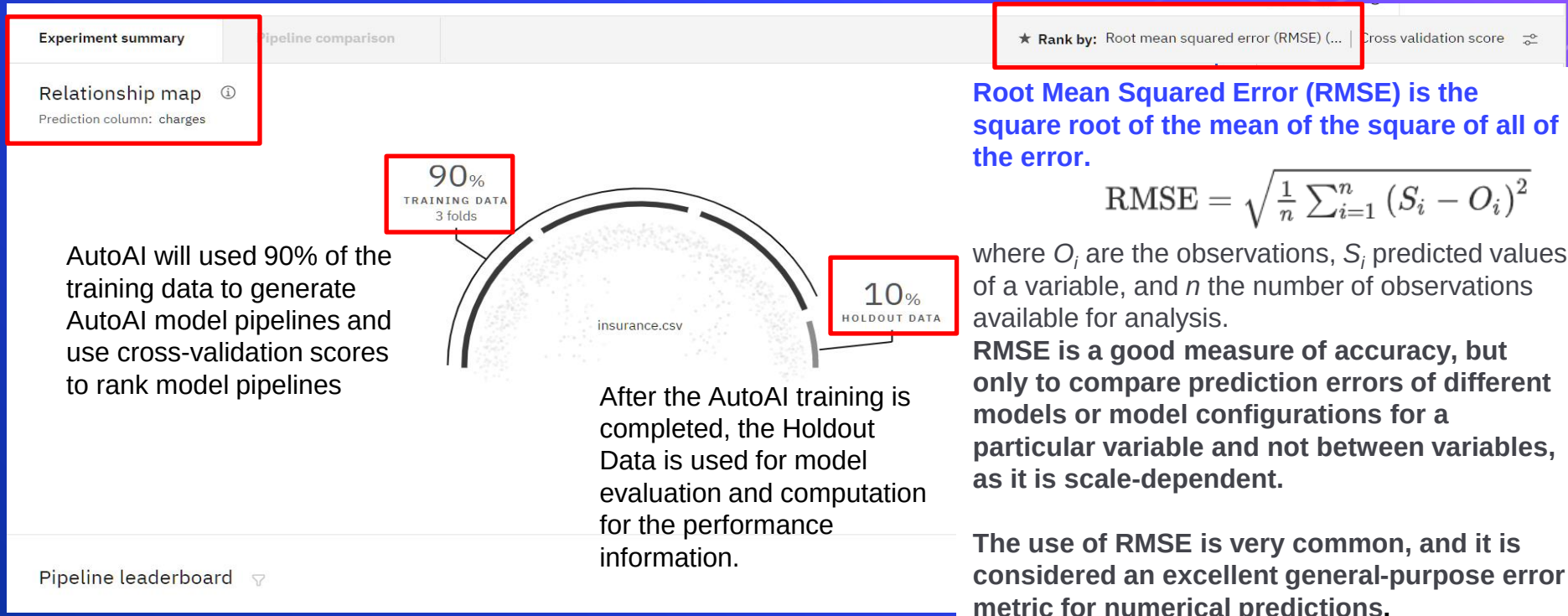
Rank and explore models

Ready, set, deploy

Auto-AI process



Train Data Models with Auto AI



AutoAI will used 90% of the training data to generate AutoAI model pipelines and use cross-validation scores to rank model pipelines

After the AutoAI training is completed, the Holdout Data is used for model evaluation and computation for the performance information.

Root Mean Squared Error (RMSE) is the square root of the mean of the square of all of the error.

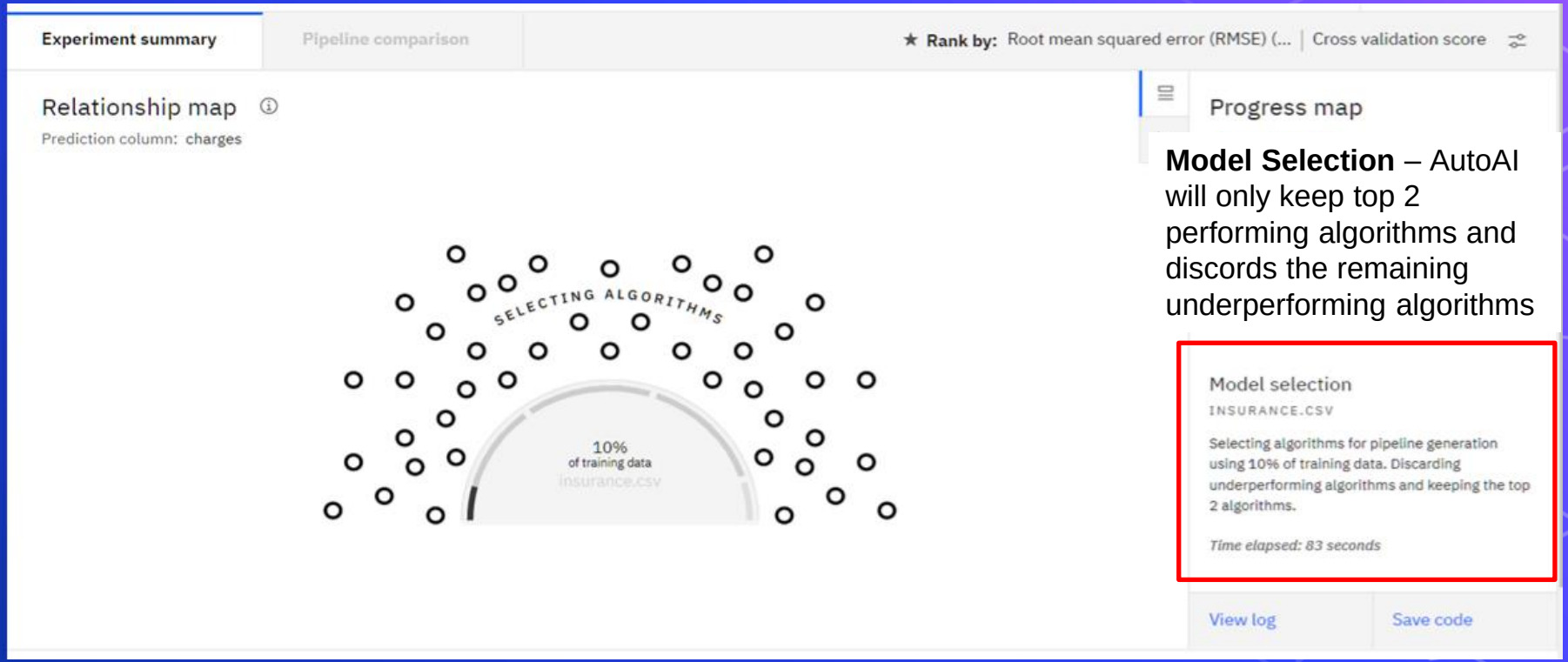
$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2}$$

where O_i are the observations, S_i predicted values of a variable, and n the number of observations available for analysis.

RMSE is a good measure of accuracy, but only to compare prediction errors of different models or model configurations for a particular variable and not between variables, as it is scale-dependent.

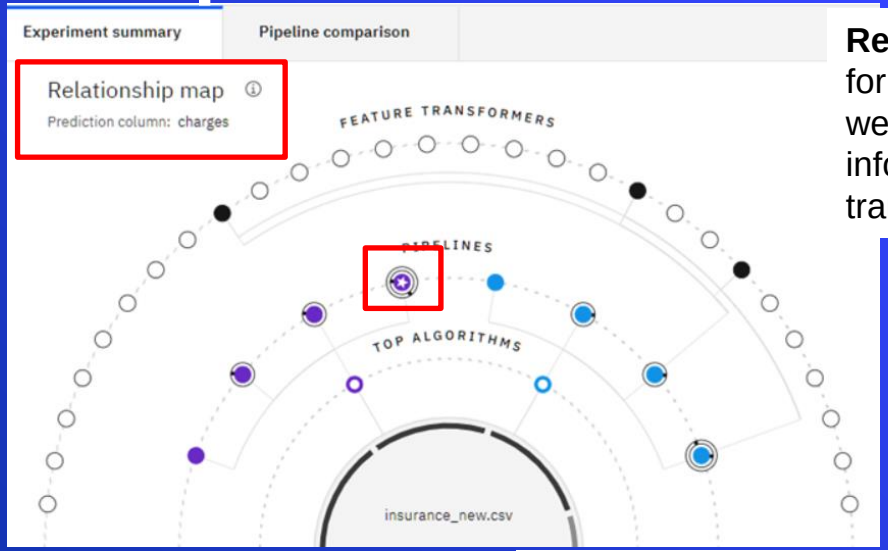
The use of RMSE is very common, and it is considered an excellent general-purpose error metric for numerical predictions.

Train Data Models with Auto AI



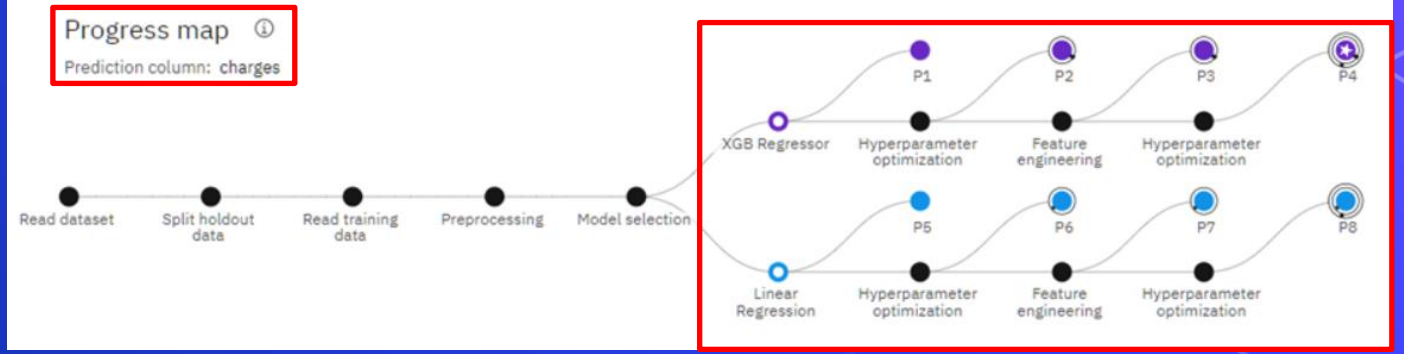
Model Selection – AutoAI will only keep top 2 performing algorithms and discords the remaining underperforming algorithms

Pipeline Transformations

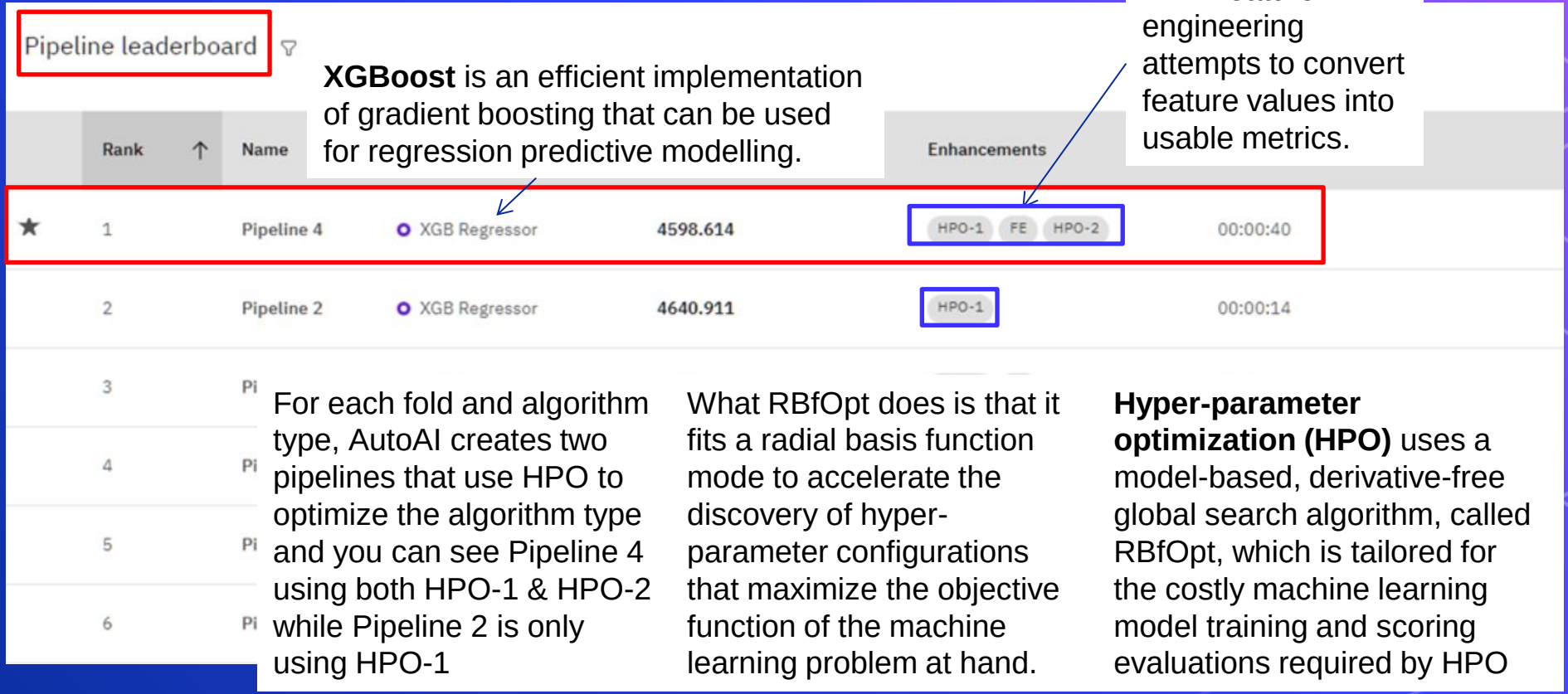


Relationship map view is useful for specific pipeline view where we can hover over a node in the infographic to view the feature transformations for that pipeline

Progress Map view is useful to show the overview of the entire AutoAI process, which are the top 2 algorithms kept; and if any Hyperparameter optimization or feature engineering was performed for the pipeline.



Pipeline Leaderboard

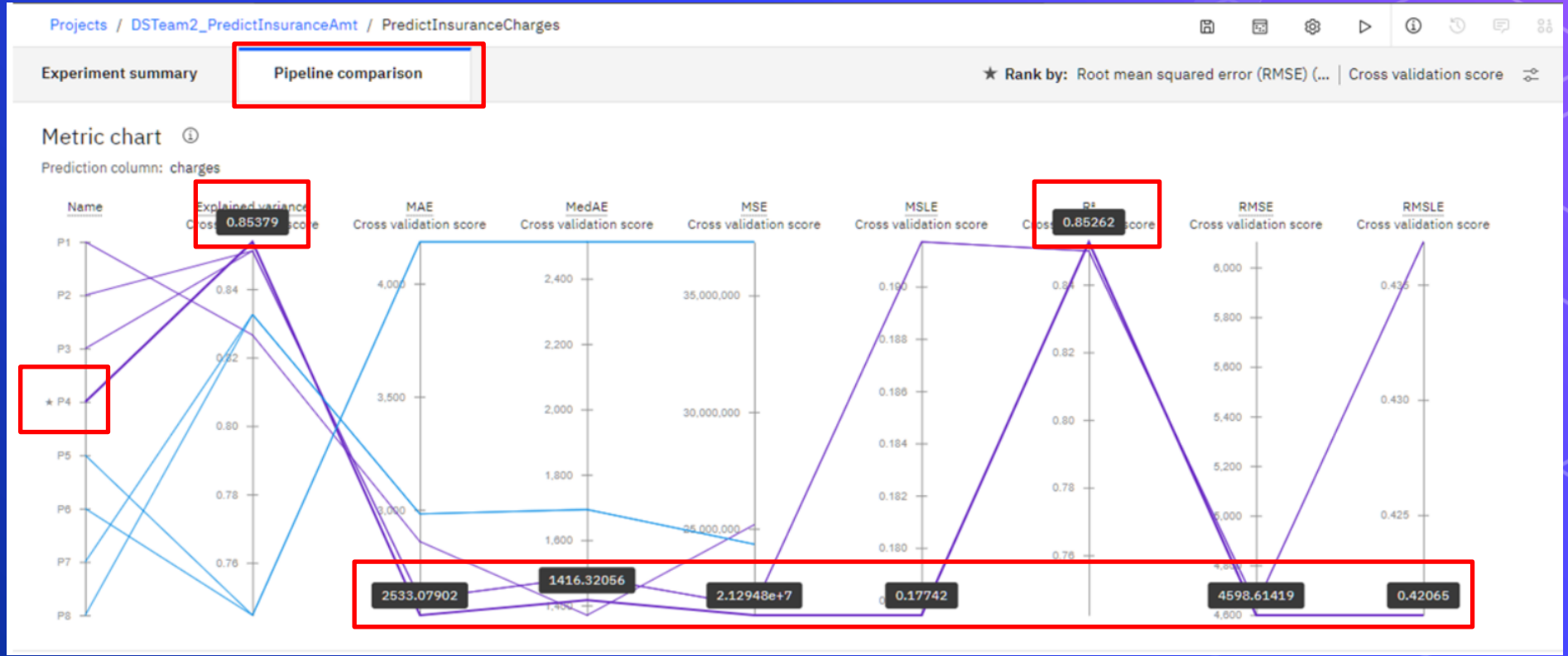


For each fold and algorithm type, AutoAI creates two pipelines that use HPO to optimize the algorithm type and you can see Pipeline 4 using both HPO-1 & HPO-2 while Pipeline 2 is only using HPO-1

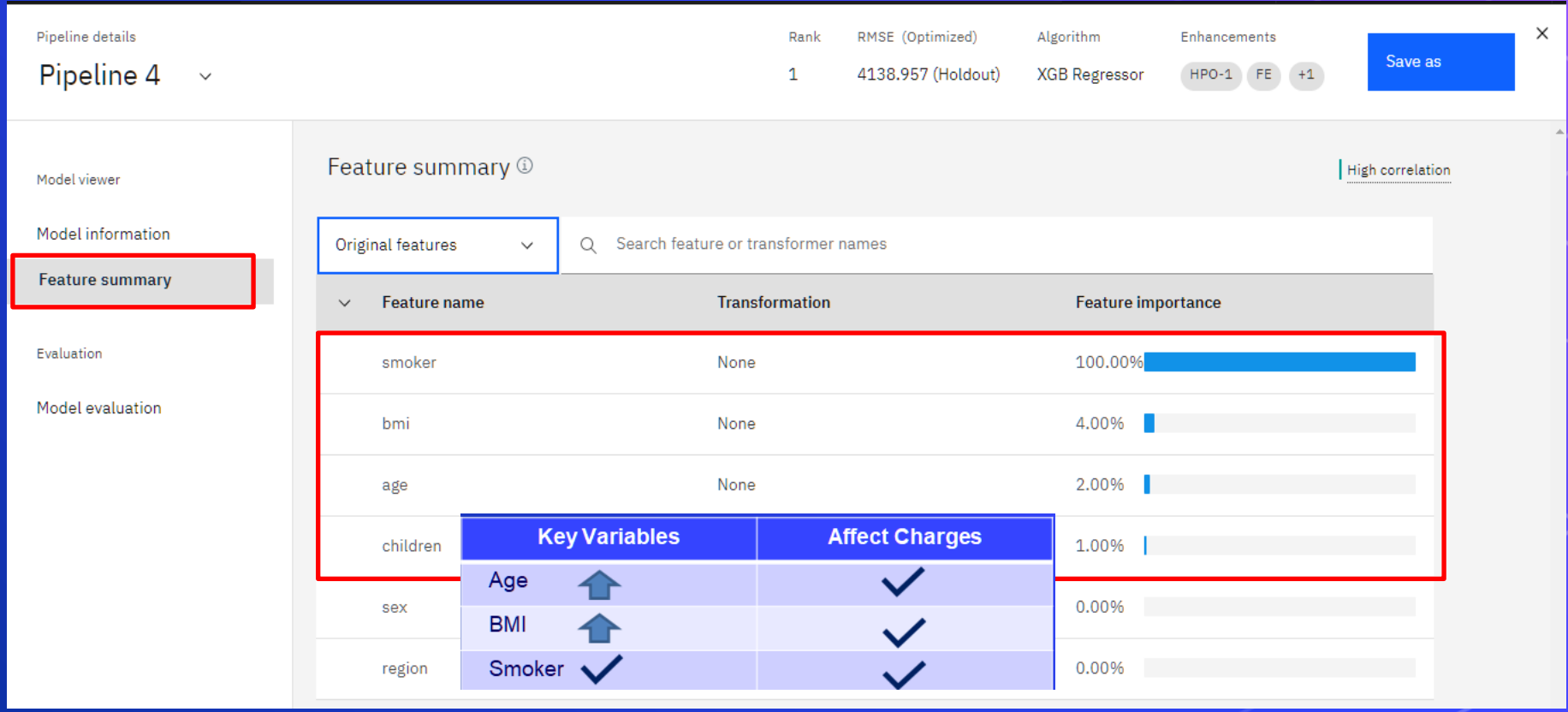
What RBfOpt does is that it fits a radial basis function mode to accelerate the discovery of hyper-parameter configurations that maximize the objective function of the machine learning problem at hand.

Hyper-parameter optimization (HPO) uses a model-based, derivative-free global search algorithm, called RBfOpt, which is tailored for the costly machine learning model training and scoring evaluations required by HPO

Metric Chart



Pipeline Details – Feature Summary



Pipeline Details – Model Evaluation

Pipeline details

Pipeline 4

Rank	RMSE (Optimized)	Algorithm	Enhancements
1	4138.957 (Holdout)	XGB Regressor	HPO-1 FE +1

Save as

Model viewer

Model information

Feature summary

Evaluation

Model evaluation

Model evaluation

Model evaluation measure

Measures	Holdout score	Cross validation score
Root mean squared error	4138.957	4598.614
R squared	0.895	0.853
Explained variance	0.895	0.854
Mean squared error	17130968.000	21294802.667
Mean squared log error	0.202	0.177
Mean absolute error	2347.269	2533.079
Median absolute error	1533.956	1416.321
Root mean squared log error	0.449	0.421

6. Prescriptive Analytics

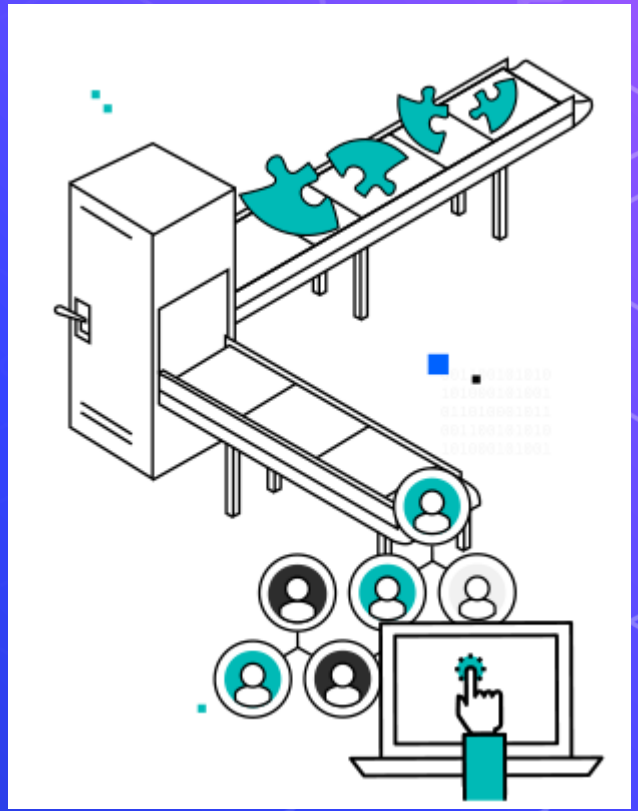
Prescriptive Analytics – What should you do?

- Prescriptive analytics take the inputs from prediction and combined with rules and constraint-based optimization, this enables better decisions about what to do.
- If we want to change the way we do business, first we need to be able to predict future outcomes and variables that may impact those outcomes.
- Now that we've identified what's going to happen, we need to determine what to do, in order to overcome operational obstacles and achieve continuous improvement

Before Model Deployment

Questions to answer:

- What are my deployment requirements?
- How will I evaluate the model's performance in production?
- Have I minimized the trap of overfitting my model?
- How frequently do I plan on re-training my model?
- What are the data preprocessing needs?
- Will the format of the production input data differ drastically from the model training data?
- Will it come in batches or as a stream?
- Do I need to run the model offline?



Models are normally deployed in a limited way until their performance has been fully evaluated. Deployment may be as simple as generating a report with recommendations, or as involved as embedding the model in a complex workflow and scoring process managed by a custom application.

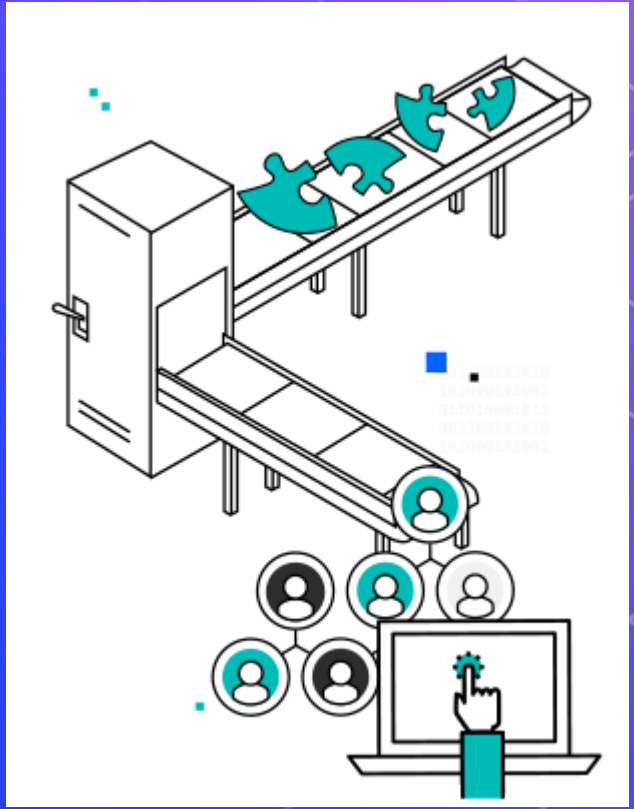
Model Deployment

Once a satisfactory model has been developed and is approved by the business sponsors, we are now ready to deploy it into the production environment or a comparable test environment.

While deploying a model into an operational business process is usually an IT function, the process is not as simple as simply handing the model off to the IT team.

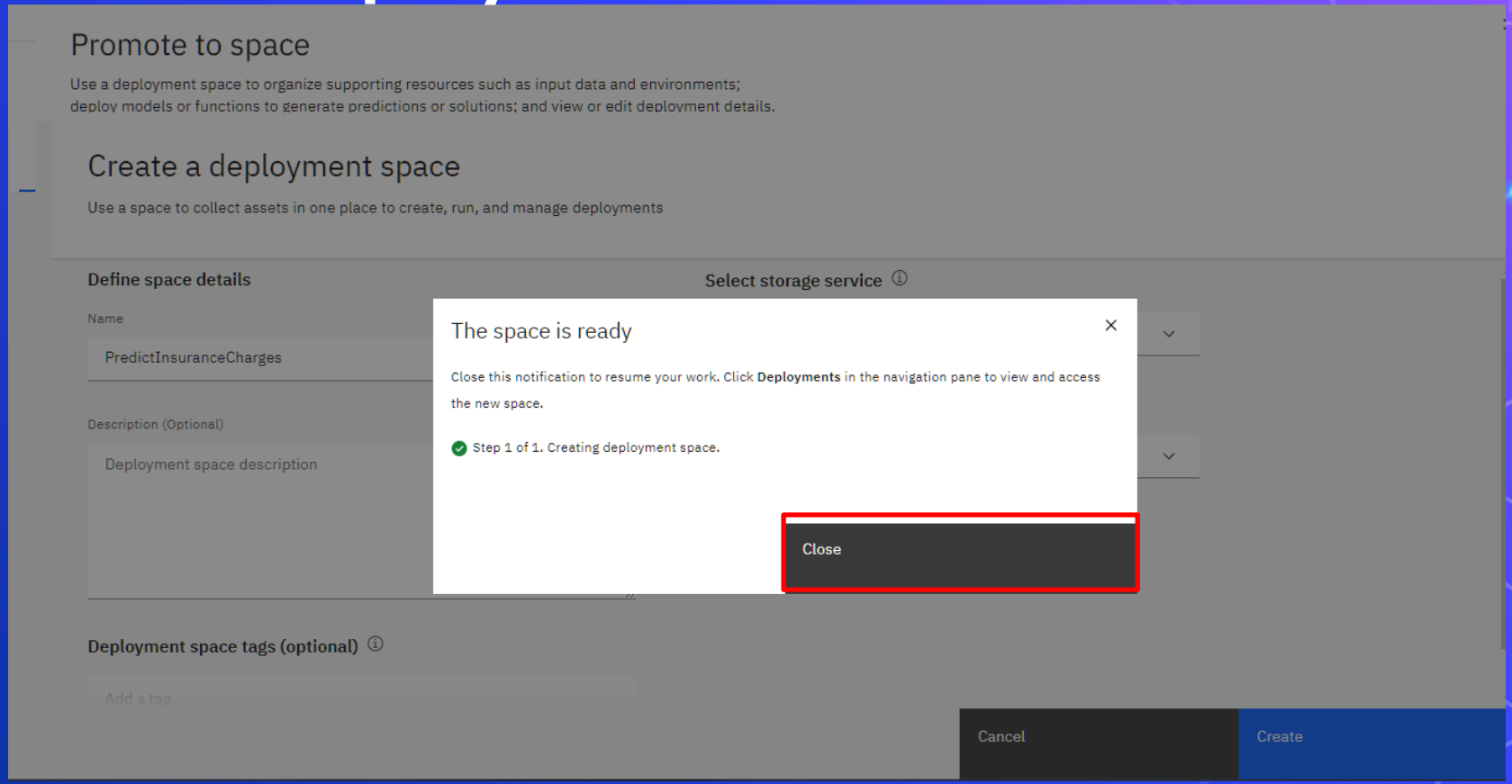
Testing the model prior to deployment is necessary to identify any dependencies in the production environment.

We also need to ensure models are able to receive correct production data and send the scores to the right place, and that the system must be set up for monitoring and scalability post deployment.

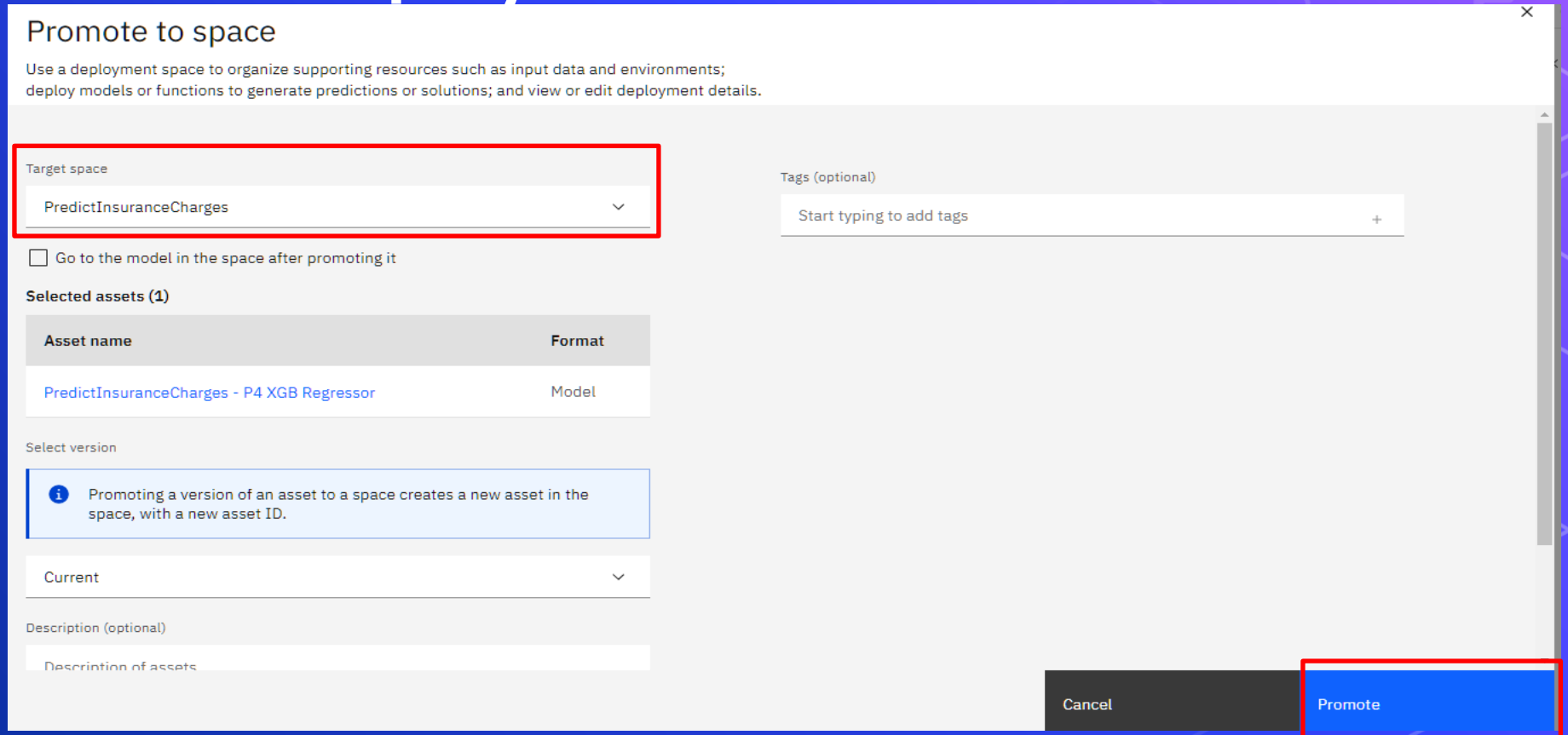


Model Deployment

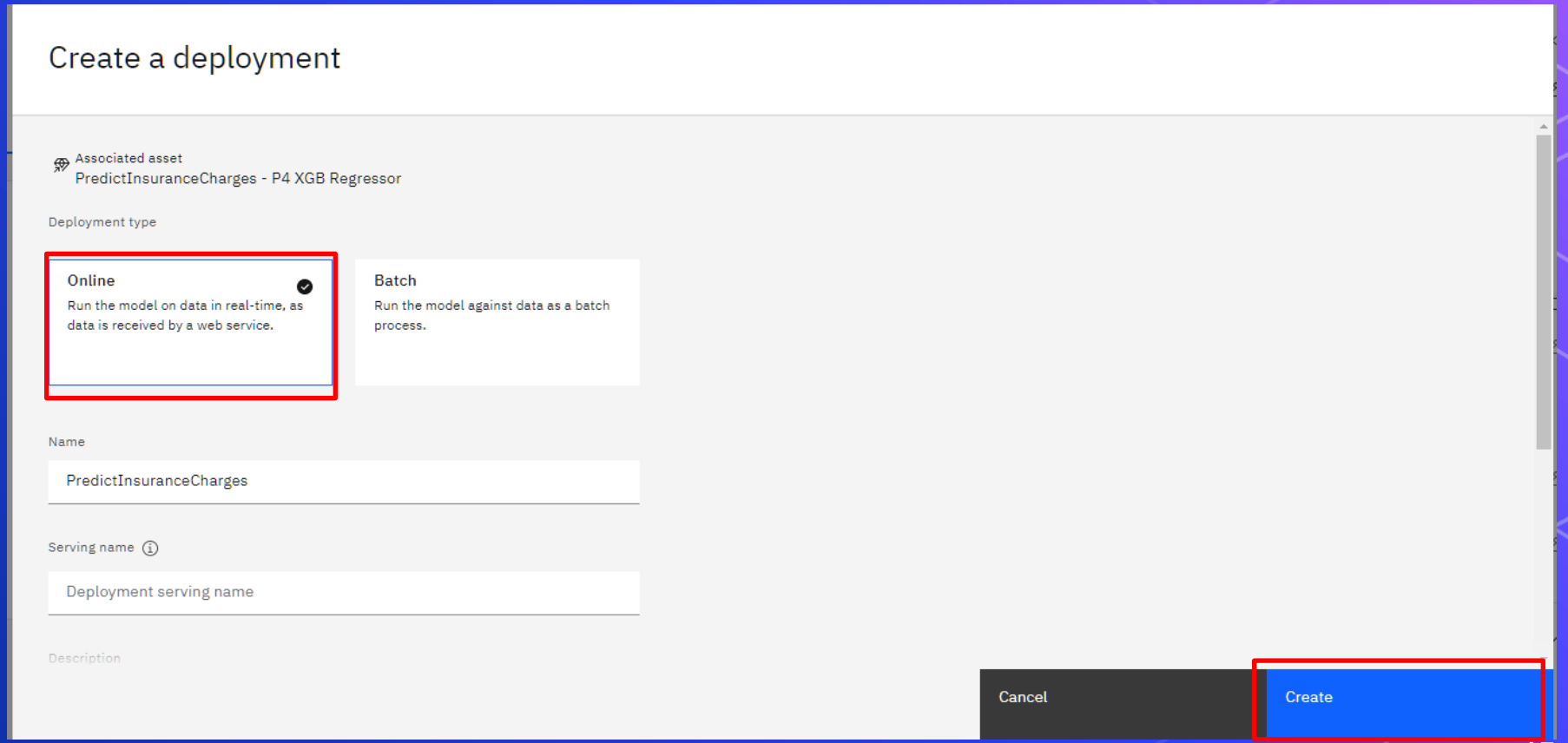
Model Deployment



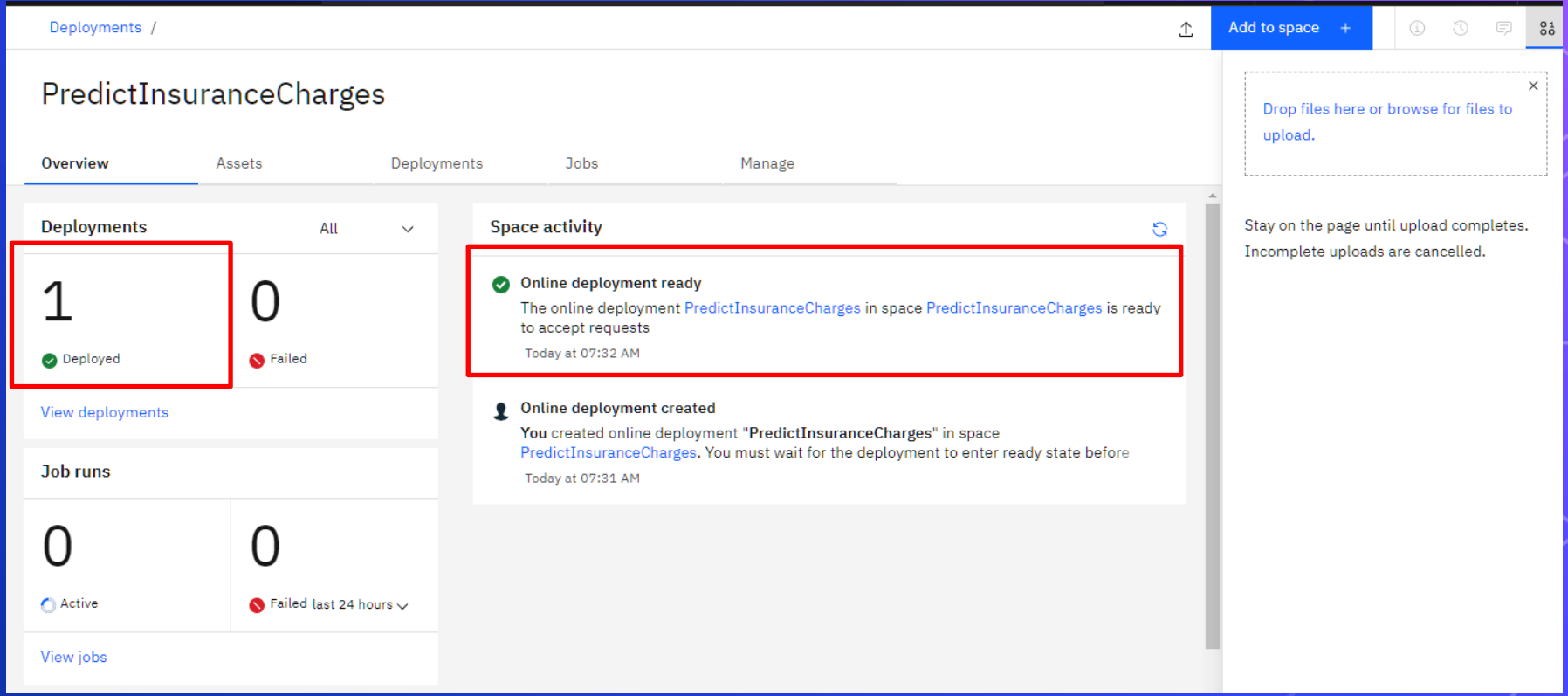
Model Deployment



Model Deployment



Model Deployment



Model Deployment

PredictInsuranceCharges Deployed Online

API reference | Test

Direct link

Endpoint

https://us-south.ml.cloud.ibm.com/ml/v4/deployments/abfdf0b9-238e-42ce-ae7b-b8486e513b1e/predic

Bearer <token>

IAM

Code snippets

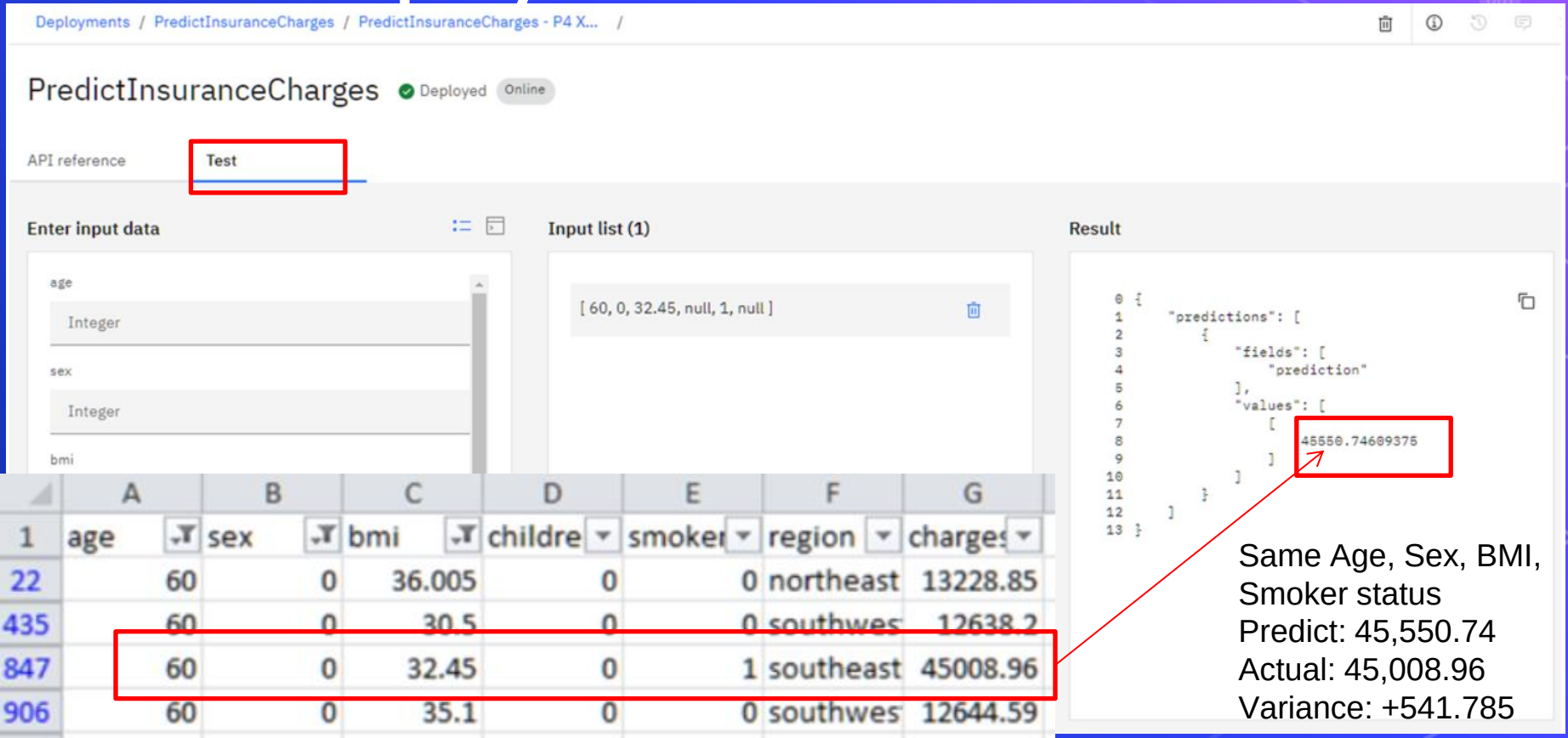
cURL | Java | JavaScript | **Python** | Scala

```
import requests

# NOTE: you must manually set API_KEY below using information retrieved from your IBM Cloud account.
API_KEY = "<your API key>"
token_response = requests.post('https://iam.cloud.ibm.com/identity/token', data={"apikey":
 API_KEY, "grant_type": 'urn:ibm:params:oauth:grant-type:apikey'})
mltoken = token_response.json()["access_token"]

header = {'Content-Type': 'application/json', 'Authorization': 'Bearer ' + mltoken}
```

Model Deployment



	A	B	C	D	E	F	G
1	age	sex	bmi	childre	smoker	region	charges
22	60	0	36.005	0	0	northeast	13228.85
435	60	0	30.5	0	0	southwes	12638.2
847	60	0	32.45	0	1	southeast	45008.96
906	60	0	35.1	0	0	southwes	12644.59

Same Age, Sex, BMI, Smoker status
Predict: 45,550.74
Actual: 45,008.96
Variance: +541.785

Model Comparison using Python

```python
# Import Libraries and DataSet
import numpy as np
import pandas as pd

dataset = pd.read_csv('../input/insurance-new2/insurance_new2.csv')
```

+ Code + Markdown

```python
# Display dataset
print (dataset.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1338 non-null   int64
 1   sex       1338 non-null   int64
 2   bmi       1338 non-null   float64
 3   children  1338 non-null   int64
 4   smoker    1338 non-null   int64
 5   charges   1338 non-null   float64
dtypes: float64(2), int64(4)
memory usage: 62.8 KB
None
```

+ Code + Markdown

```python
# Create Dataframe
df = dataset

# Specify which columns for input variables
X = dataset.iloc[:, :5]

# Specify which column is the target or predict column
y = dataset.iloc[:, 5]
```

```python
# Training model using linear regression
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X.values,y)

# Testing Model for a Age=60, Sex=0, BMI=32.45, Smoker=1
# Predict output for Charges to be $45,008.96
print(regressor.predict([[60, 0, 32.45, 0, 1]]))
```

```
[37695.74856522]
```

```python
# Training model using XGBRegressor (Similar Algorithm as Auto AI)
from xgboost import XGBRegressor
my_model = XGBRegressor()
my_model.fit(X.values, y)

# Testing Model for a Age=60, Sex=0, BMI=32.45, Smoker=1
# Predict output for Charges to be $45,008.96

print(my_model.predict([[60, 0, 32.45, 0, 1]]))
```

```
[45044.88]
```

Result

```
{
    "predictions": [
        {
            "fields": [
                "prediction"
            ],
            "values": [
                [
                    45550.74609375
                ]
            ]
        }
    ]
}
```

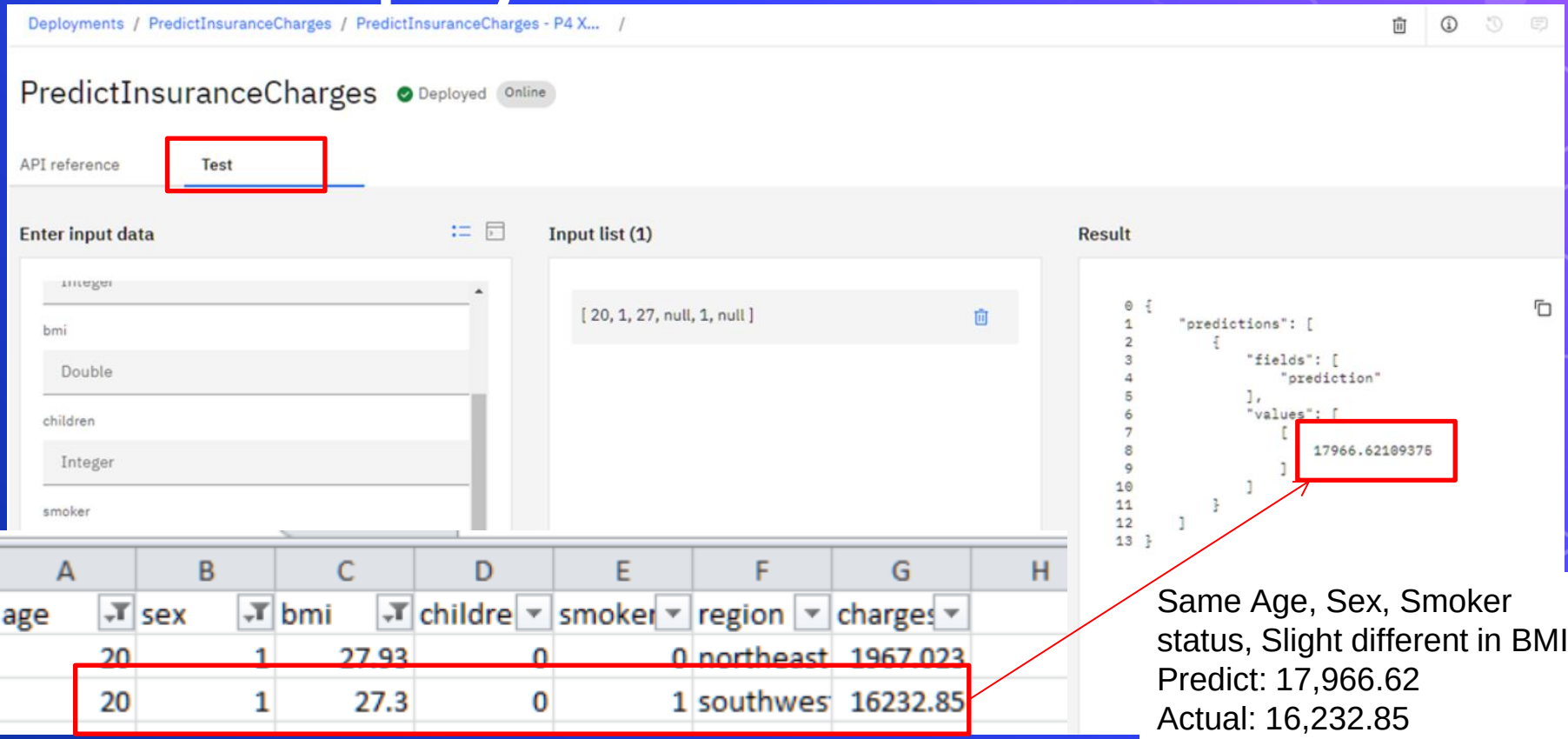
Actual: $45,008.96

Python
Linear Regression: $37,695.75
XGB Regressor: $45,044.88**

Auto AI
XGB Regressor :$45,550.74

Conclusion:
Both machine learning methods provides similar results if similar algorithms are used. Auto AI provides the convenience to automate the testing of 8 algorithms and ranking the best performing algorithm pipeline which otherwise, we will need to do manually like this example. However, it will be useful if Auto AI can display all 8 algorithms so that we are aware which 6 algorithms are discarded from the entire list of 11 regression algorithms.

Model Deployment



A	B	C	D	E	F	G	H
age	sex	bmi	childre	smoker	region	charges	
20	1	27.93	0	0	northeast	1967.023	
20	1	27.3	0	1	southwes	16232.85	

Same Age, Sex, Smoker status, Slight different in BMI
Predict: 17,966.62
Actual: 16,232.85
Variance: +1,733.77

Model Deployment

PredictInsuranceCharges ● Deployed Online

age	sex	bmi	smoker	charges	Predict	Variance
48	1	32.3	0	8,765.25	9,804.94	1,039.69
50	1	32.3	1	41,919.10	42,749.02	829.92
50	1	32.3	0	9,630.40	10,010.84	380.44

Interactive Recommendation:
Assuming the User is a 48years male smoker with BMI 32.3, besides displaying the current prediction of $42,339.88 at age 48.

An AI recommendation will also display to the user that while maintaining his current BMI; if his maintain his current smoking habit, the charges will increase slightly in 2 years time to $42,749.02.

However, he could have at least $32,000 in cost savings if he decides to gives up smoking at age 50 and only pay $10,010.84. Thus, encouraging the user to make a healthy change in his lifestyle NOW to enjoy greater financial benefits later.

[50, 1, 32.3, null, 1, null]

[50, 1, 32.3, null, 0, null]

[48, 1, 32.3, null, 1, null]

[48, 1, 32.3, null, 0, null]


```
{
    "predictions": [
        {
            "fields": [
                "prediction"
            ],
            "values": [
                [
                    42749.01953125
                ],
                [
                    10010.841796875
                ],
                [
                    42399.8828125
                ],
                [
                    9804.947265625
```


Age 50

Age 48

Similar, if the user is currently a non-smoker, we will display in the UI a recommendation for user to continue his good non-smoker habit to avoid the need to pay additional $32,000 charges in 2 years time.

Environment Feedback (Reality Check)

- Collecting results from the implemented model allows organizations to gets feedback on the model's performance.
- **Analysing** the feedback enables the data scientist to **refine**, increase **accuracy** and its **usefulness**. (yields substantial additional benefits if it is undertaken as part of the overall process)
- Through feedback, refinement and redeployment, a model should continually **adapt to conditions**, allowing both the model and the work behind it to provide **value to the organization**.
- This methodology shows the **iterative nature** of the problem-solving process. Meaning we have to build, refine and improve the project through continuous testing and revise until we reach to a satisfactory level.

Environment Feedback (Reality Check)

- We need to avoid the most common problem in machine learning and data science – Overfitting.

- **Overfitting** refer to when a model that works well on training data but performs badly on new data, i.e. our model does not generalize well from our training data to unseen data.

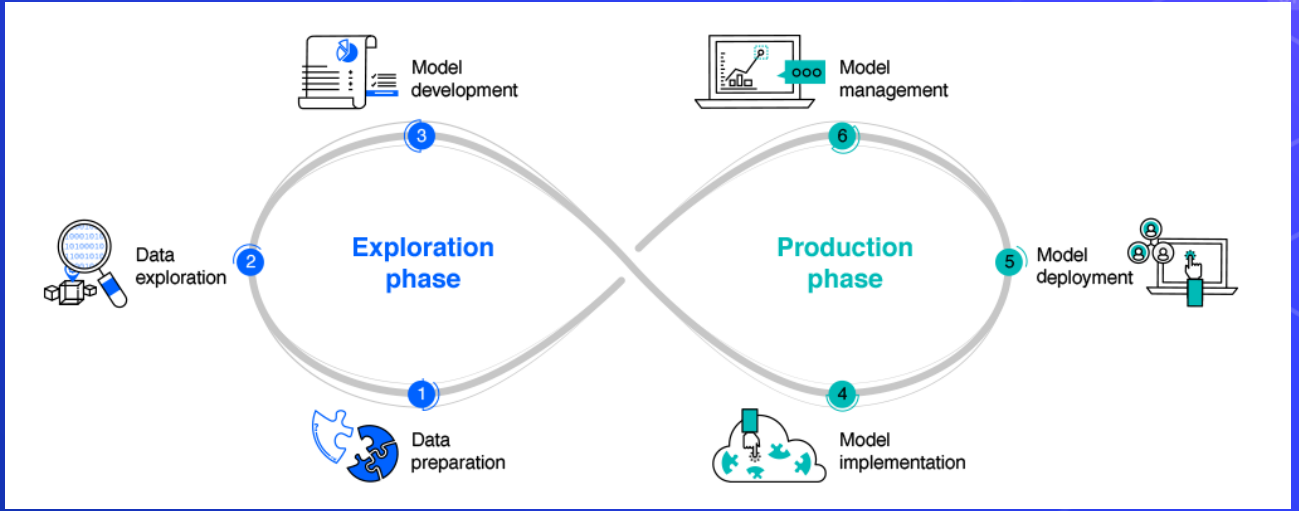
How to prevent Overfitting?

- Through **Model Management**

Environment Feedback (Reality Check)

Continuous Learning

- Using **continuous learning** paradigm, the data scientist can easily re-deploy and re-train the model pipeline using new data that may result in a better aligned prediction.



Environment Feedback (Reality Check)

- **Model management** must be a continuous process to ensure optimal performance over time. i.e. knowing exactly where each model is in the lifecycle, how old the model is, who developed it, and who is using it for which application.

- **Model version control**, such as event logging and change tracking to understand how the model evolves over time, is another critical requirement.

- Data science must also be concerned with **model decay**, and **continuously gather metrics** to determine when a model should be refreshed or replaced.

7. Summary and Reflection

Constraints and Challenges

Constraints	Challenges
Need to create multiple trial accounts due to limited available CU in AutoAI.	Short project timeline from choosing what data should be to analysed to creating a working model.
Multiple tools needed to be explored, in order to choose the right tool for the project. Group members need to learn and compare tools.	Not everyone is proficient in Python thus making it challenging for some of the group members.
Not easy to locate more similar dataset to further test the model (i.e. unseen data)	Takes time to choose the right visualization method/ tools to present the data.
Unable to open new IBM cloud Account due to failing IBM verification and old account being deactivated	Need to learn multiple platforms e.g. Python coding, Tableabu, AutoAI and data refinery within a short time frame is challenging

Future Enhancement

- Able to compare premium charges across different providers
- Able to suggest or show the benefit of staying with current provider or sign a new with another (in dollar terms)
- Able to pinpoint which criteria / underlying conditions causes the higher premium after generating a quote.
- Able to input additional parameters that could affect the insurance charges. Currently, user only given limited option to input personal data and underlying health conditions are not factored in and there is always a deviation from expected premium.
- Able to link to other apps that can help users monitor their health and lifestyle to that they can potentially keep their insurance premium to a minimum.

Conclusion

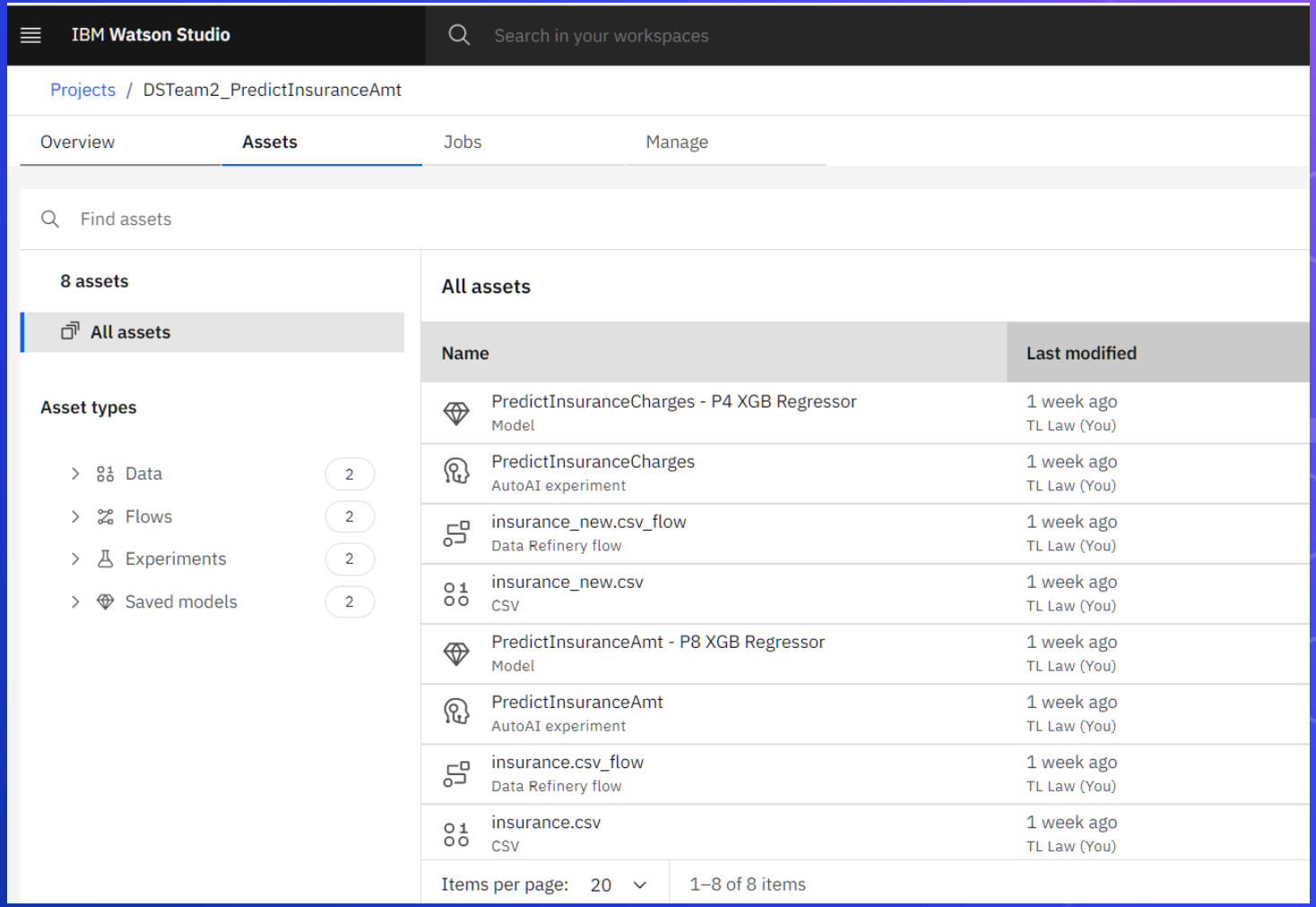
- Data Science isn't just about frameworks, data sources and pipelines — it's also about people. So, having a team with diverse knowledge is vital to a successful project
- Following Data Science methodology steps helps us to handle and produce insights using the data in our hands to generate meaningful AI solutions.
- Practicing the Data Science lifecycle from data exploration to deployment and model management allows us to understand and utilize available data into affective business model faster and more accurately.
- Exploring various visualization tools that are available, not only Watson Studio, but also other platforms such as Tableau, Matplotlib, etc. is important as different tools have different pros and cons.

The Journey Takeaways

- There is no 1 size fit all tool but it gives us opportunity to learn multiple tools.
- Using the right tool enables us to create the right model that reinforce our hypothesis.
- Understanding the data gives us the opportunity to create new business models.
- Having seen the power of diverse team brings different perspectives, skills and talents to this group project.
- Taking advantage of the strengths and weaknesses of our team mates allows us to be effective in creating the final outcome
- Every member of the team should learn basic coding to improve efficiency and also to be dynamic in using different tools.
- Prepare multiple trial accounts before hand and test out the accounts to make sure there are no errors.

The Journey Takeaways

- We should spend more time exploring available datasets with additional data to include more parameters to make the prediction more accurate.
- Team members should take time to test out the datasets from refinery stage to deploying of model so that not only everyone understand the project but also get to explore tools and learn the differences and apply them accordingly.


IBM Watson Studio
Search in your workspaces
Projects / DSTeam2_PredictInsuranceAmt
Overview
Assets
Jobs
Manage
Find assets
8 assets
All assets
Asset types
Data 2
Flows 2
Experiments 2
Saved models 2
All assets
Name
Last modified
PredictInsuranceCharges - P4 XGB Regressor
Model
1 week ago
TL Law (You)
PredictInsuranceCharges
AutoAI experiment
1 week ago
TL Law (You)
insurance_new.csv_flow
Data Refinery flow
1 week ago
TL Law (You)
insurance_new.csv
CSV
1 week ago
TL Law (You)
PredictInsuranceAmt - P8 XGB Regressor
Model
1 week ago
TL Law (You)
PredictInsuranceAmt
AutoAI experiment
1 week ago
TL Law (You)
insurance.csv_flow
Data Refinery flow
1 week ago
TL Law (You)
insurance.csv
CSV
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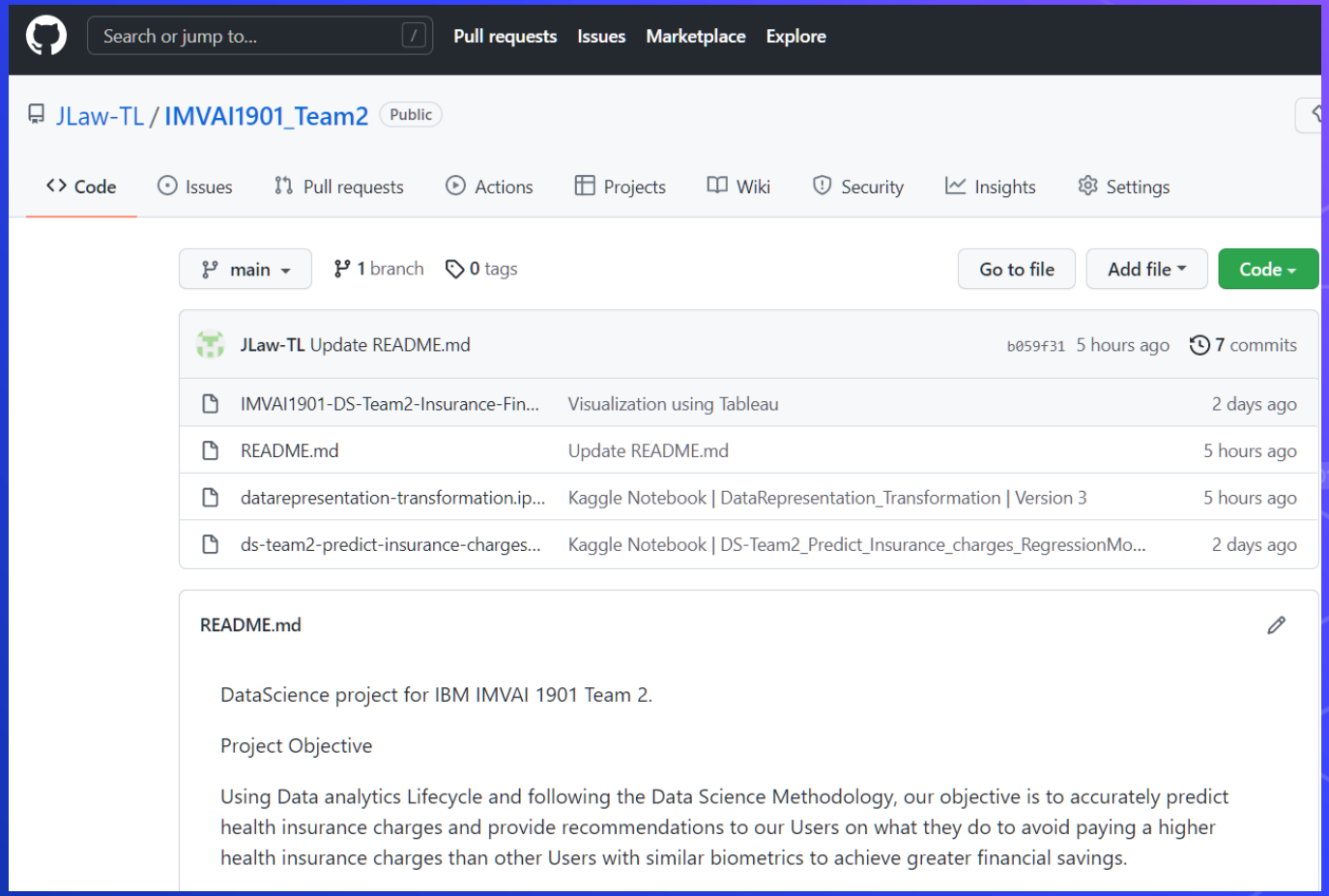
Items per page: 20
1–8 of 8 items



https://github.com/JLaw-TL/IMVAI1901_Team2

Thanks!

Special thanks to Suhaimi