Introduction to Machine Learning on IBM Cloud

IBM **Developer**

Upkar Lidder
> ulidder@us.ibm.com
> @lidderupk
> upkar.dev

http://bit.ly/ibm-cloud-summit-2019
http://bit.ly/upkar-autoai

Prerequisites

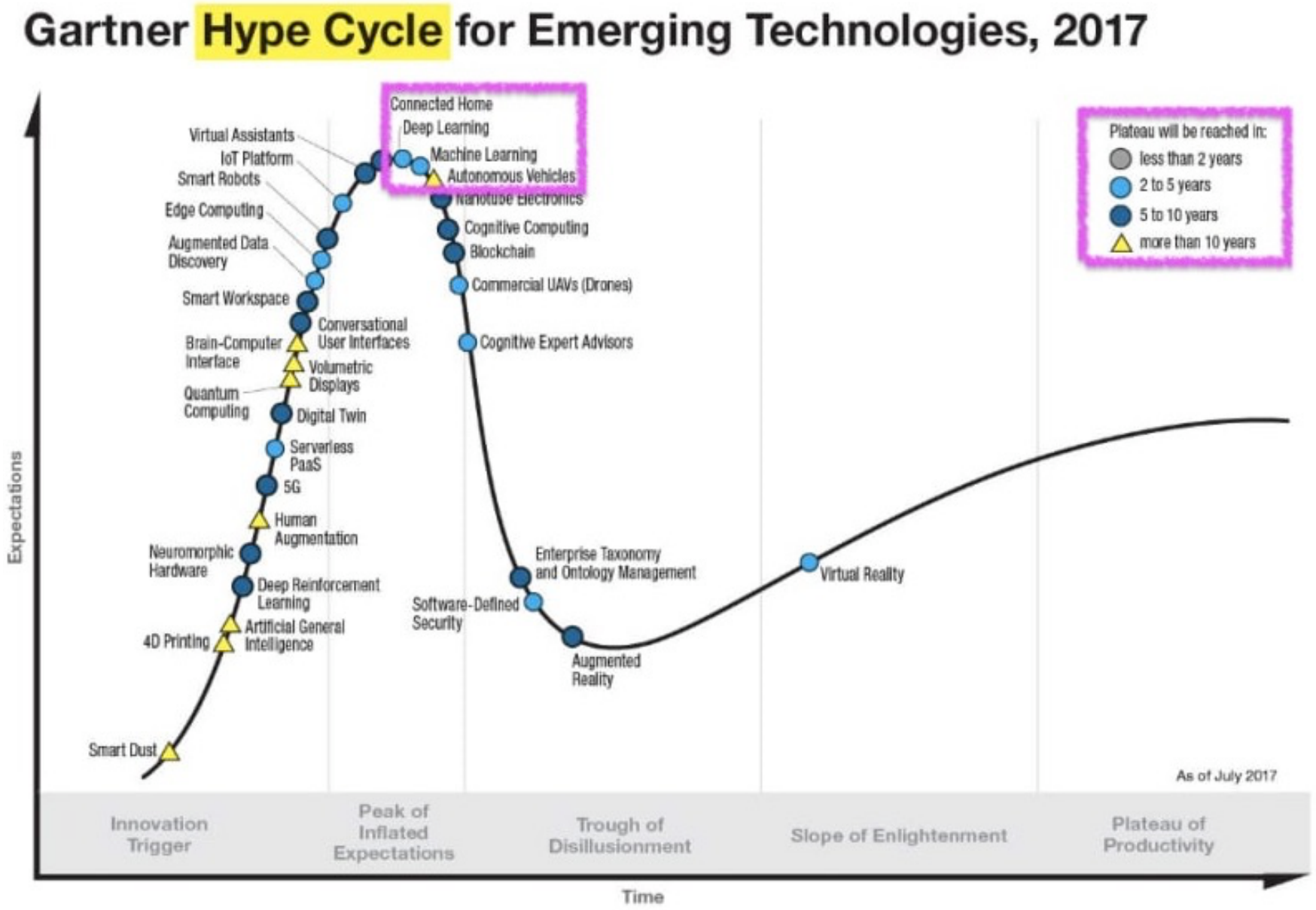
1. Create IBM Cloud Account using THIS URL

http://bit.ly/ibm-cloud-summit-2019

2. Check your email and activate your account. Once activated, log back into your IBM Cloud account using the link above.

3. If you already have an account, use the above URL to sign into your IBM Cloud account.

ML Hype



Source: Gartner (July 2017)

ML on IBM Cloud - Cognitive Services

Natural Language Processing

Watson Assistant
Lite • IBM • IAM-enabled

Watson Assistant lets you build conversational interfaces into any application, device, or channel.

Natural Language Understanding
Lite • IBM • IAM-enabled

Analyze text to extract meta-data from content such as concepts, entities, emotion, relations, sentiment and more.

Voice Agent with Watson
Lite • IBM • IAM-enabled

Create a cognitive voice agent that uses Watson services to speak directly with customers using natural language over the telephone

Discovery
Lite • IBM • IAM-enabled

Add a cognitive search and content analytics engine to applications.

Personality Insights
Lite • IBM • IAM-enabled

The Watson Personality Insights derives insights from transactional and social media data to identify psychological traits.

Language Translator
Lite • IBM • IAM-enabled

Translate text, documents, and websites from one language to another. Create industry or region-specific translations via the service's...

Speech to Text
Lite • IBM • IAM-enabled

Low-latency, streaming transcription

Text to Speech
Lite • IBM • IAM-enabled

Synthesizes natural-sounding speech from text.

Tone Analyzer
Lite • IBM • IAM-enabled

Tone Analyzer uses linguistic analysis to detect three types of tones from communications: emotion, social, and language. This insight can...

Visual Recognition

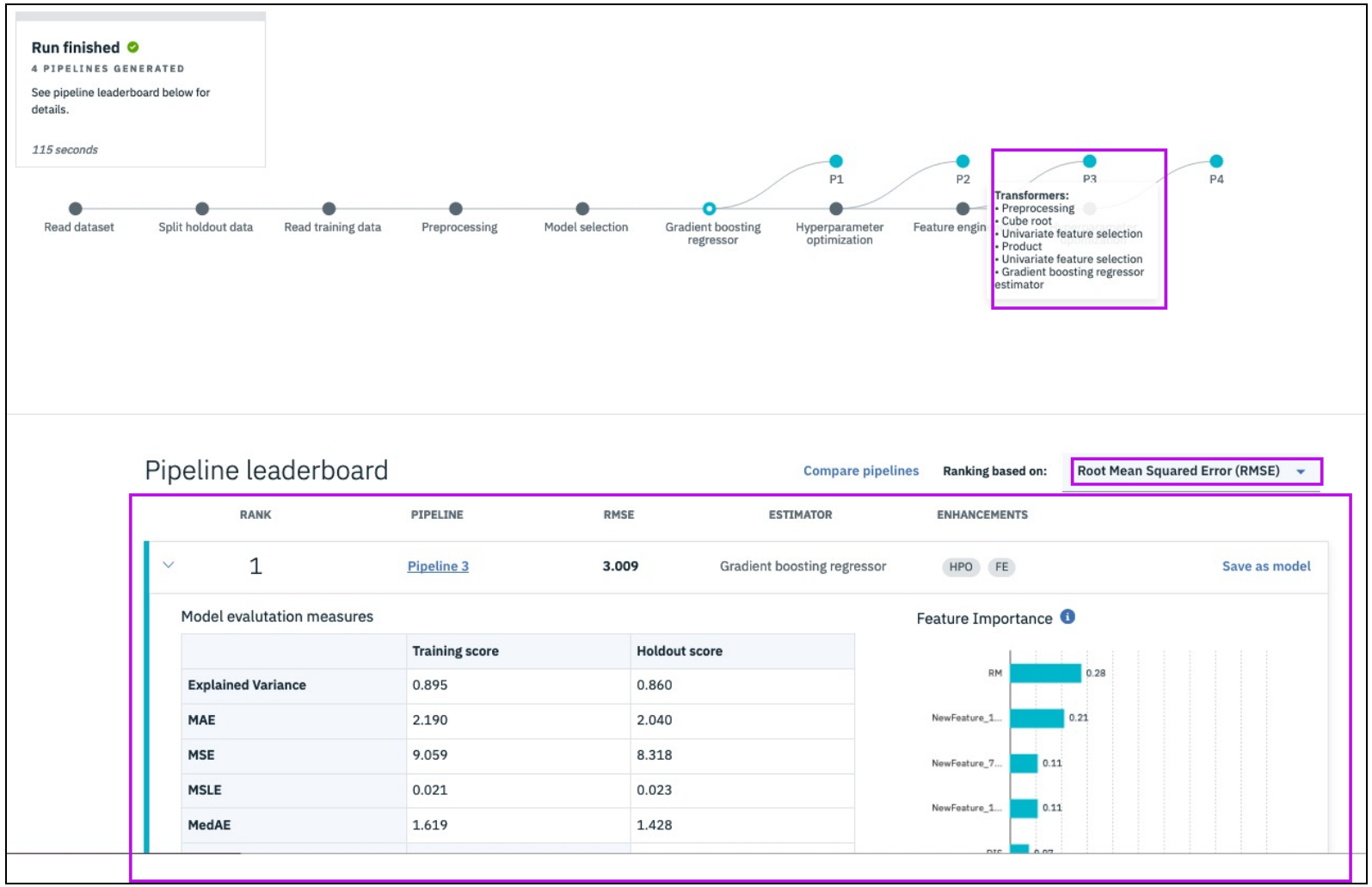
Visual Recognition
Lite • IBM • IAM-enabled

Find meaning in visual content! Analyze images for scenes, objects, faces, and other content. Choose a default model off the shelf, or create...

ML on IBM Cloud - Guided ML

To help simplify an AI lifecycle management, AutoAI automates:

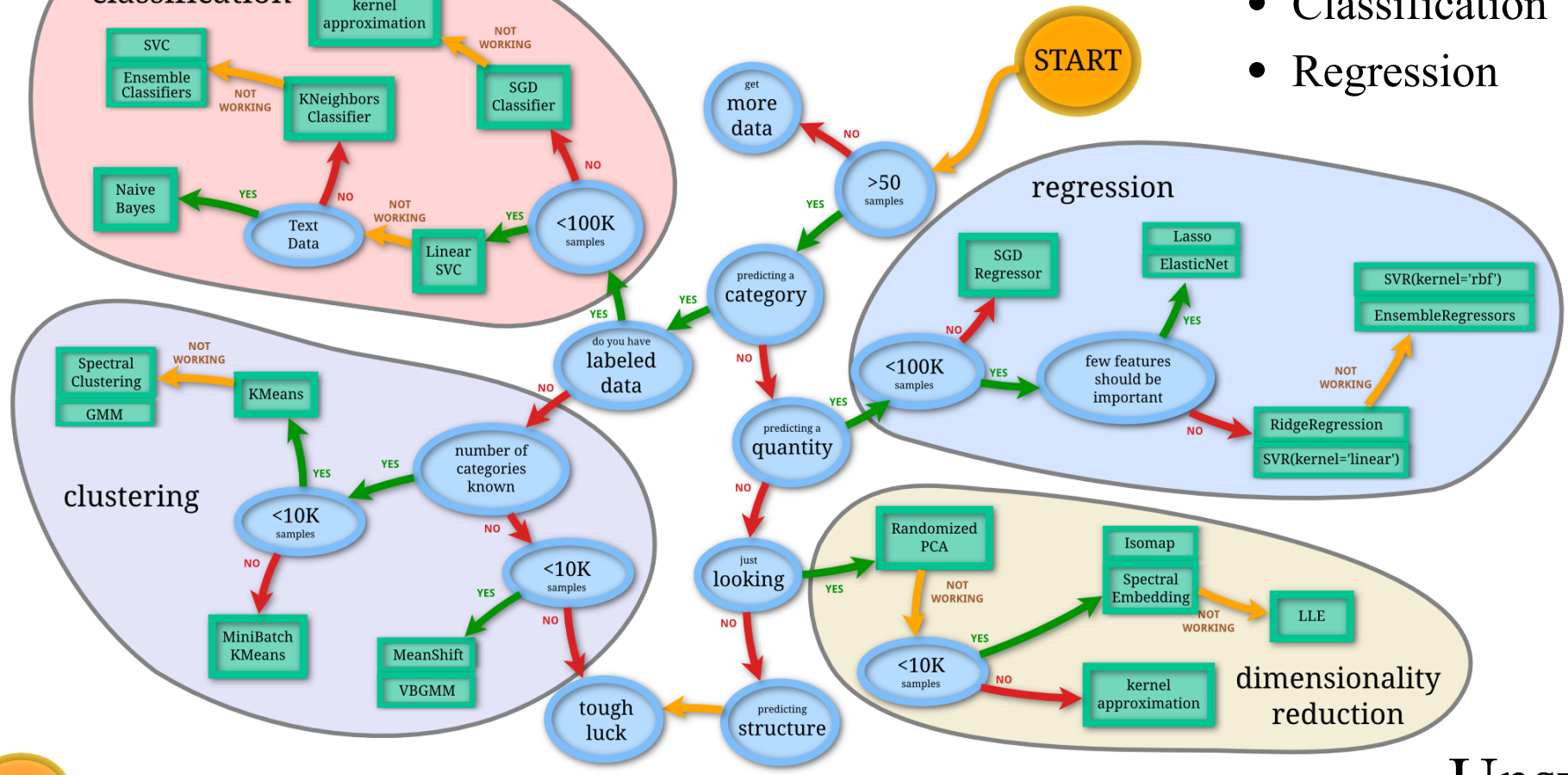
- Data preparation
- Model development
- Feature engineering
- Hyper parameter optimization



ML Map

Supervised Learning

- Classification
- Regression

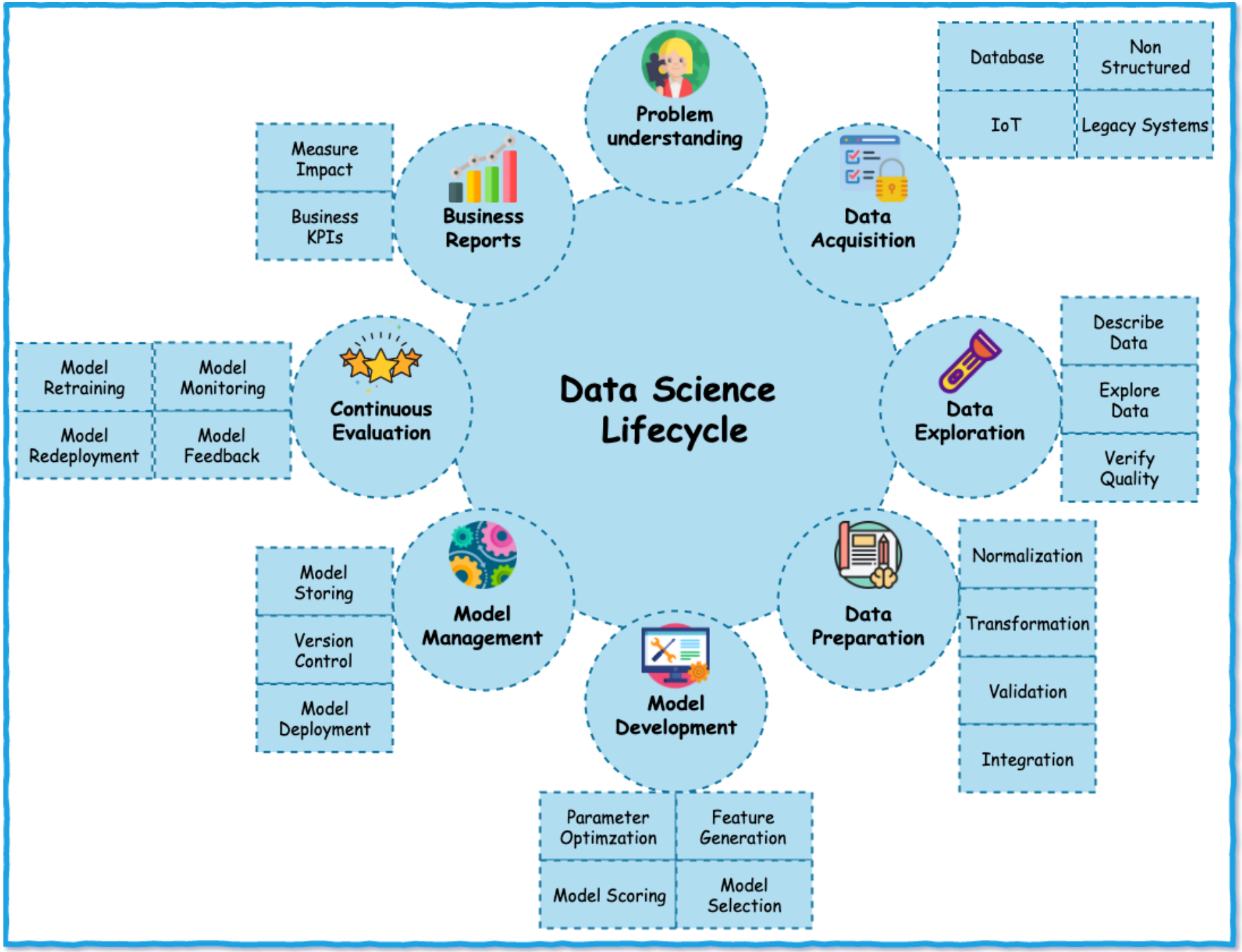


Unsupervised Learning

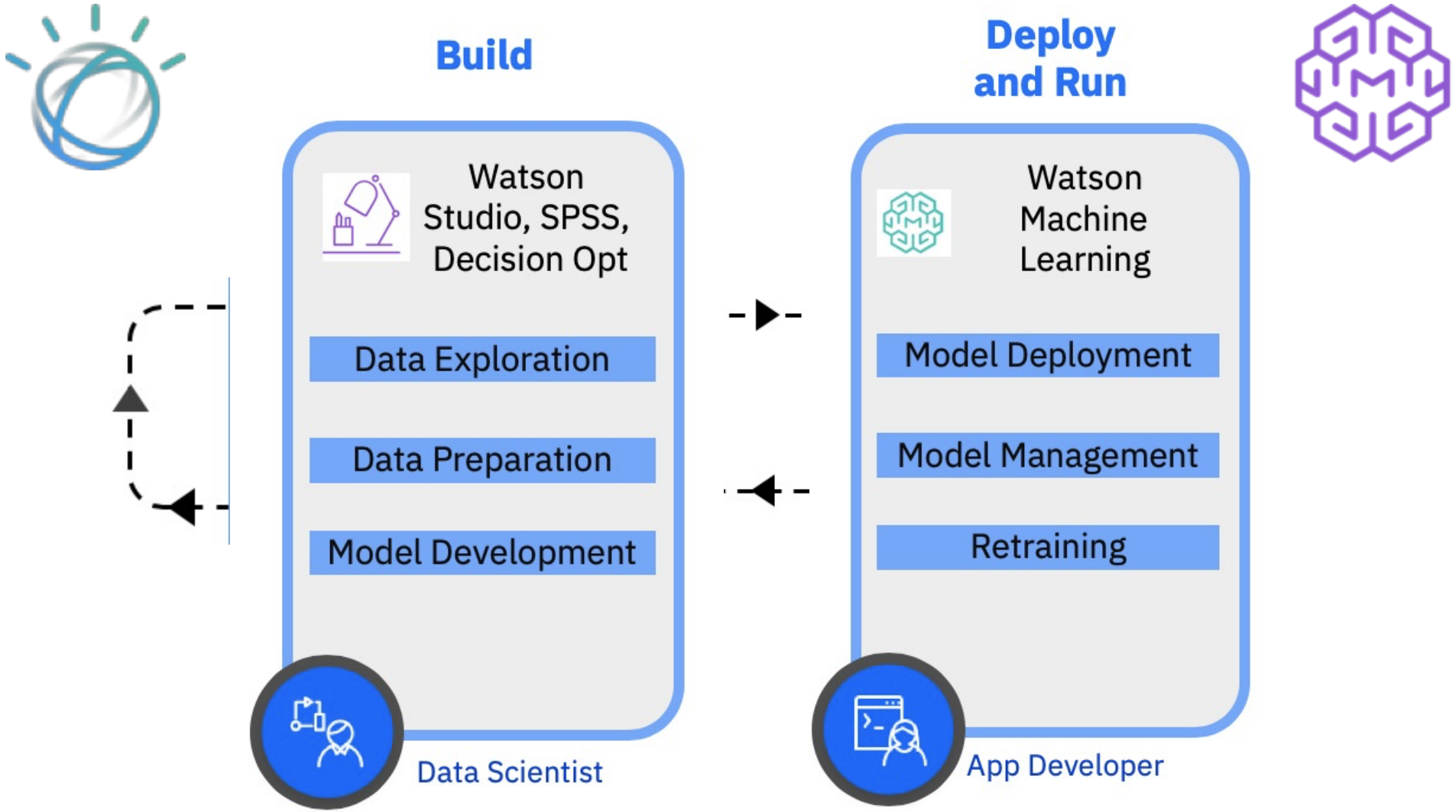
- Clustering
- Dimensionality Reduction

https://scikit-learn.org/stable/tutorial/basic/tutorial.html#machine-learning-the-problem-setting

ML Lifecycle



Watson Studio & Watson Machine Learning



Watson Studio

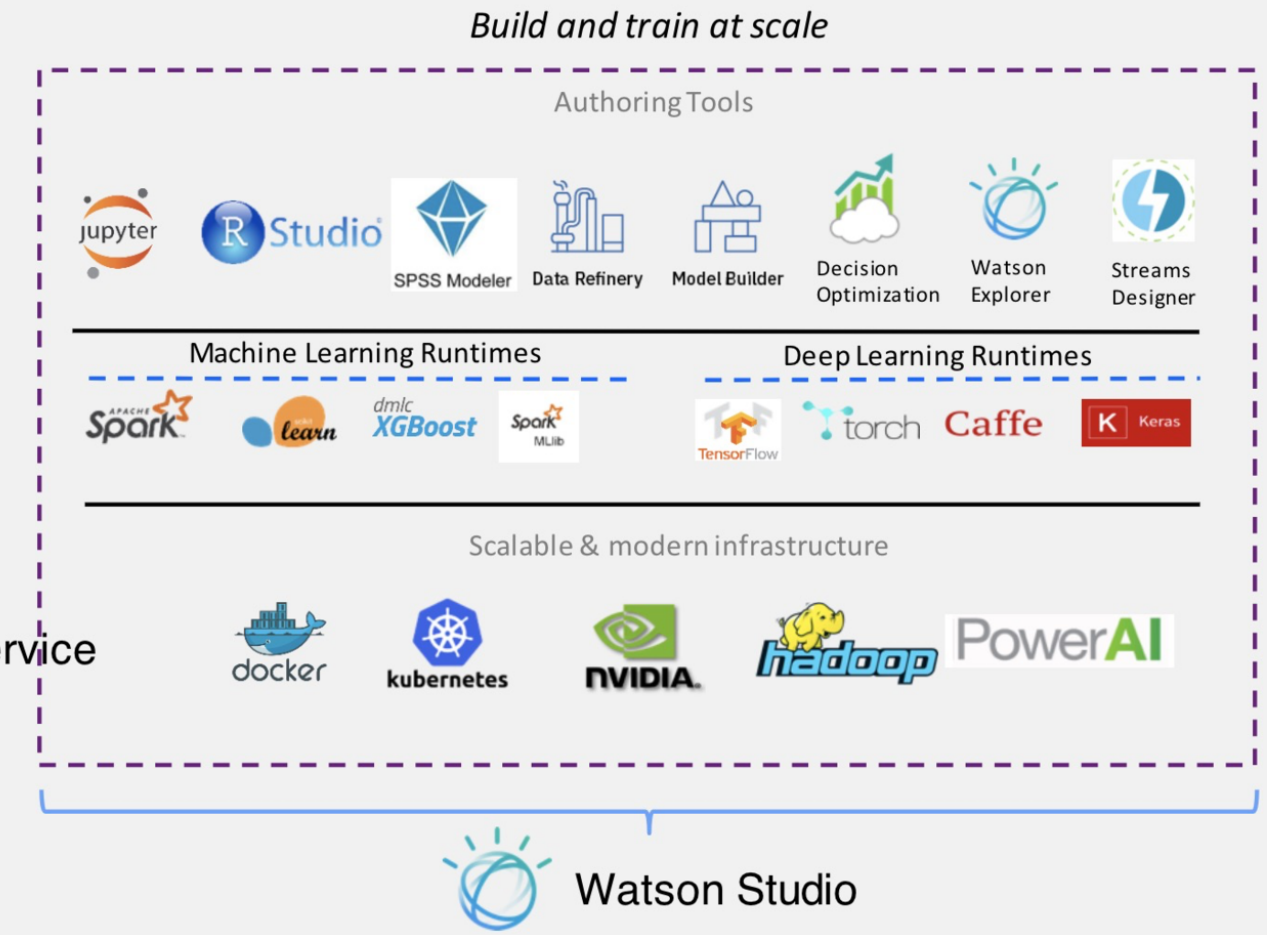
IBM Watson Studio

- Create, collaborate, govern and integrate
- Using best of breed - Open source & IBM tools
- Code (R, Python or Scala) and no-code/visual modeling tools

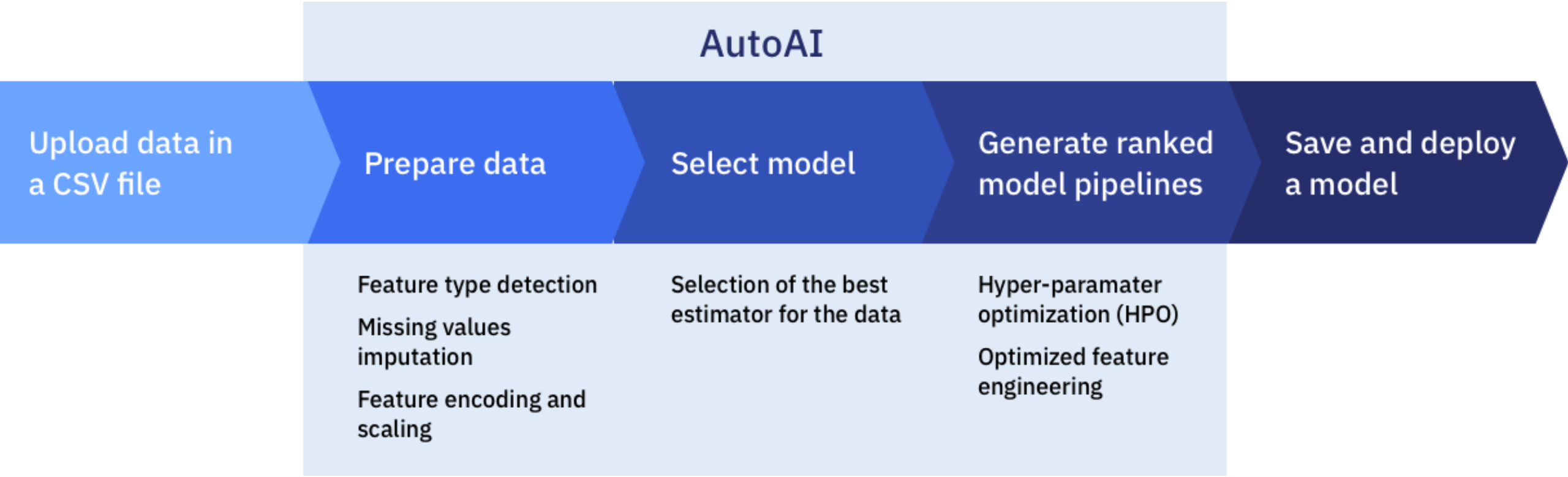
- Most popular open source frameworks
- IBM best-in-class frameworks
- Workflow driven data science

- Container-based resource management
- Elastic pay as you go cpu/gpu power
- Run on x86, Power, zLinux
- Integrate with Cloudera and HDP using Hadoop Integration service

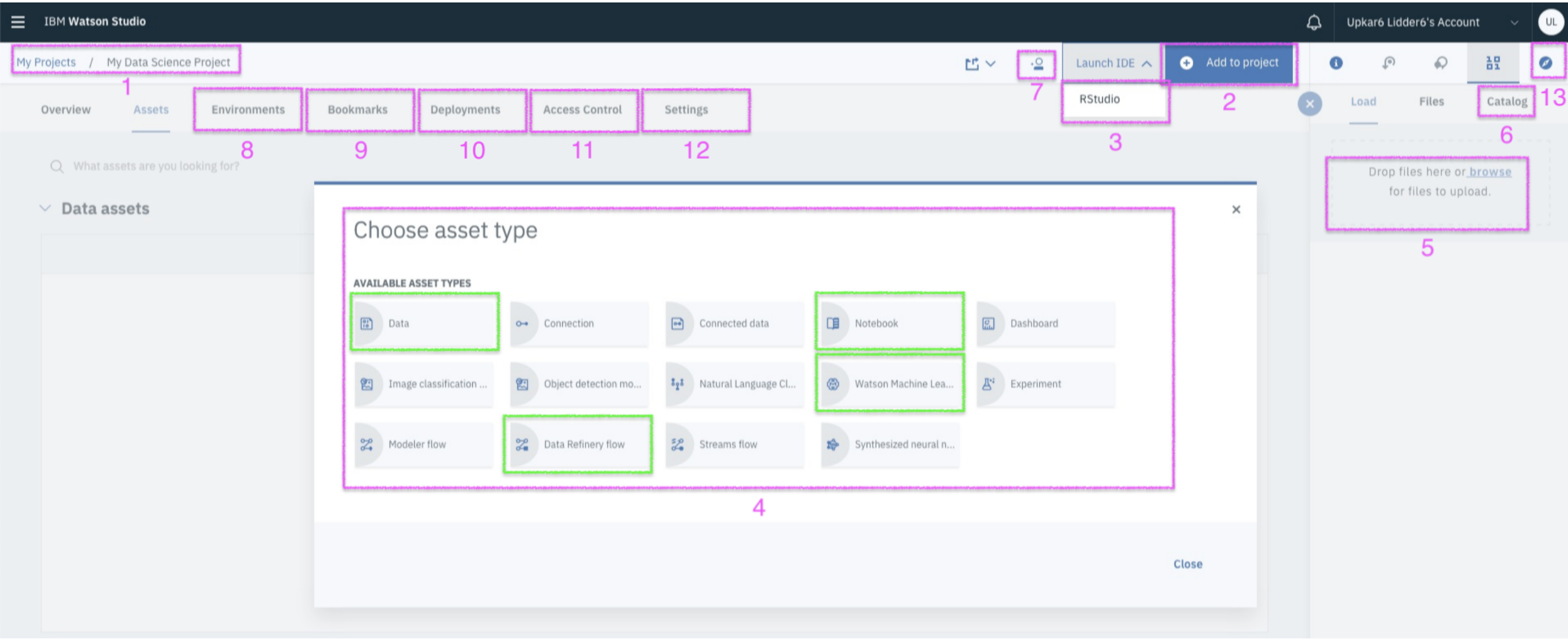
- Train and deploy where your data lives
  - As a Fully managed Service
  - In your Data center
  - On AWS, Azure, IBM Soft layer



AutoAI


AutoAI
Upload data in a CSV file
Prepare data
Select model
Generate ranked model pipelines
Save and deploy a model
Feature type detection
Missing values imputation
Feature encoding and scaling
Selection of the best estimator for the data
Hyper-paramater optimization (HPO)
Optimized feature engineering

IBM Watson Studio - project based development platform



Workshop - Goals

Successfully **Create**, **Store** and **Deploy** a Linear Regression Model on IBM Cloud using Watson Studio and Watson Machine Learning Services.

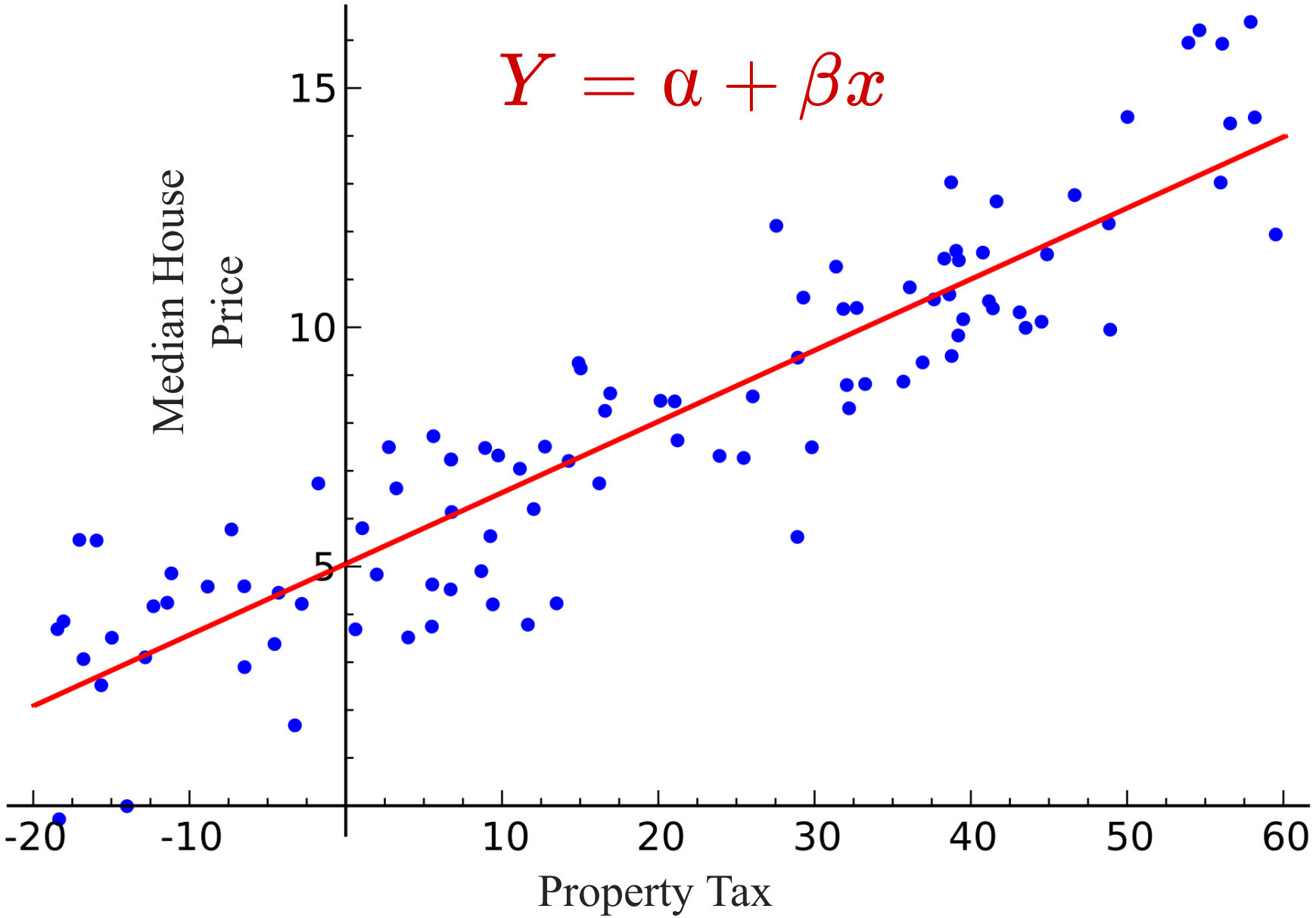
Question - predict median house price [MEDV] for Boston area

```
Boston House Prices dataset
===========================

Notes
------
Data Set Characteristics:

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive

    :Median Value (attribute 14) is usually the target

    :Attribute Information (in order):
        - CRIM     per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over 25,000 sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
        - NOX      nitric oxides concentration (parts per 10 million)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1940
        - DIS      weighted distances to five Boston employment centres
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax rate per $10,000
        - PTRATIO  pupil-teacher ratio by town
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
http://archive.ics.uci.edu/ml/datasets/Housing


This dataset was taken from the StatLib library which is maintained at Carnegie Mellon University.
```

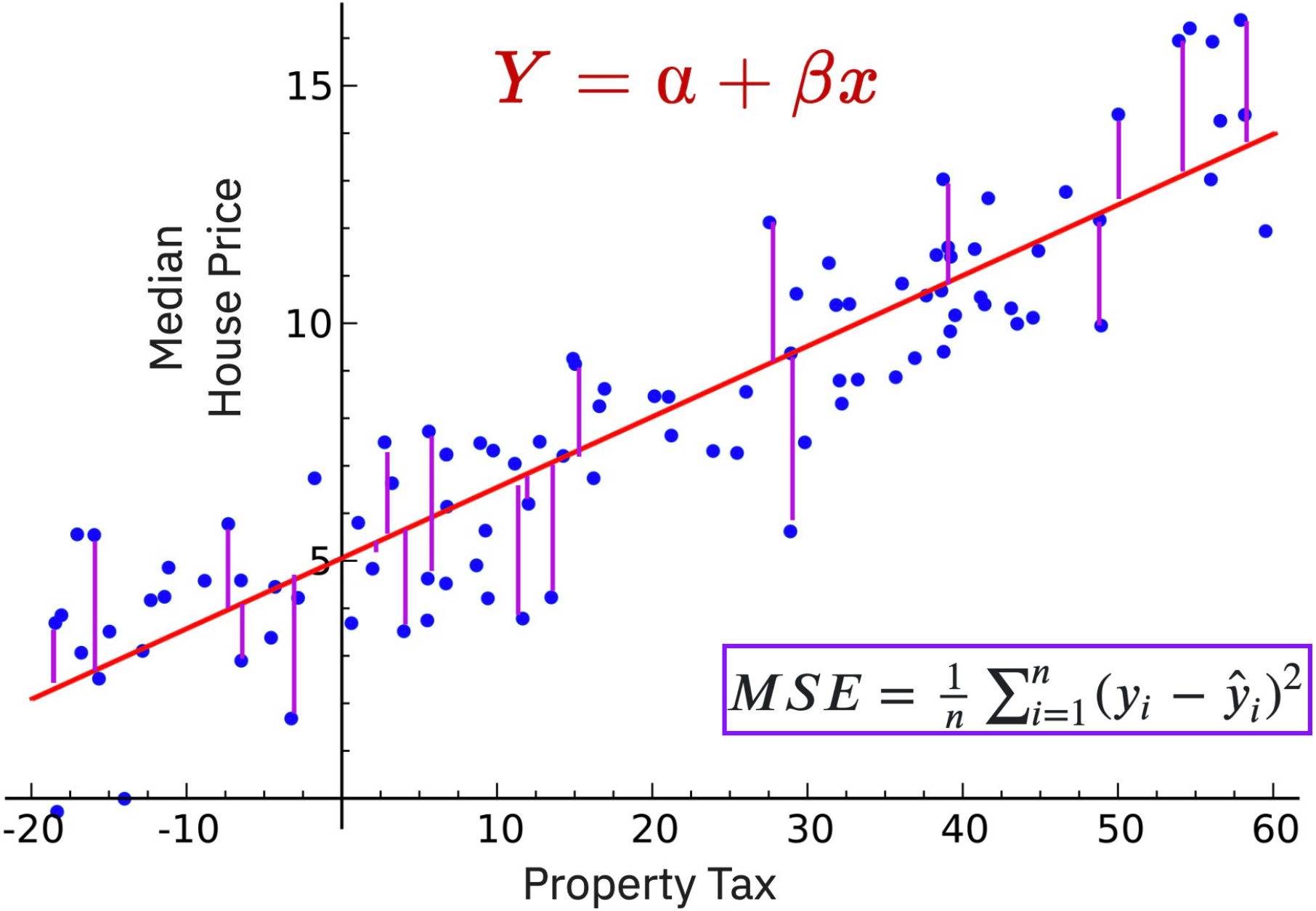
	0	1	2	3	4
CRIM	0.00632	0.02731	0.02729	0.03237	0.06905
ZN	18.00000	0.00000	0.00000	0.00000	0.00000
INDUS	2.31000	7.07000	7.07000	2.18000	2.18000
CHAS	0.00000	0.00000	0.00000	0.00000	0.00000
NOX	0.53800	0.46900	0.46900	0.45800	0.45800
RM	6.57500	6.42100	7.18500	6.99800	7.14700
AGE	65.20000	78.90000	61.10000	45.80000	54.20000
DIS	4.09000	4.96710	4.96710	6.06220	6.06220
RAD	1.00000	2.00000	2.00000	3.00000	3.00000
TAX	296.00000	242.00000	242.00000	222.00000	222.00000
PTRATIO	15.30000	17.80000	17.80000	18.70000	18.70000
B	396.90000	396.90000	392.83000	394.63000	396.90000
LSTAT	4.98000	9.14000	4.03000	2.94000	5.33000
MEDV	24.00000	21.60000	34.70000	33.40000	36.20000

http://bit.ly/boston-house-csv

Linear regression - try to fit a line



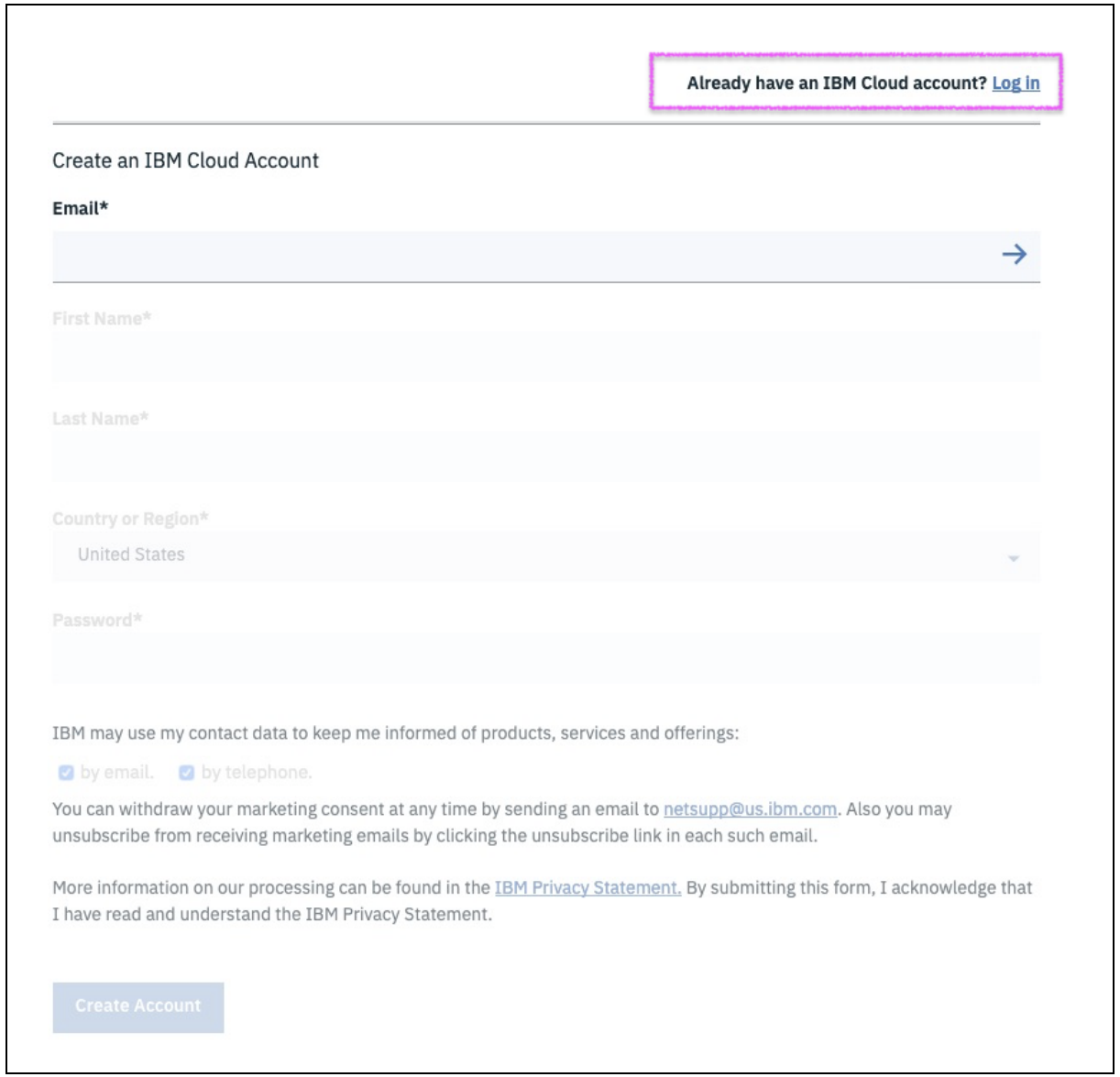
Linear regression - loss function to get best fit



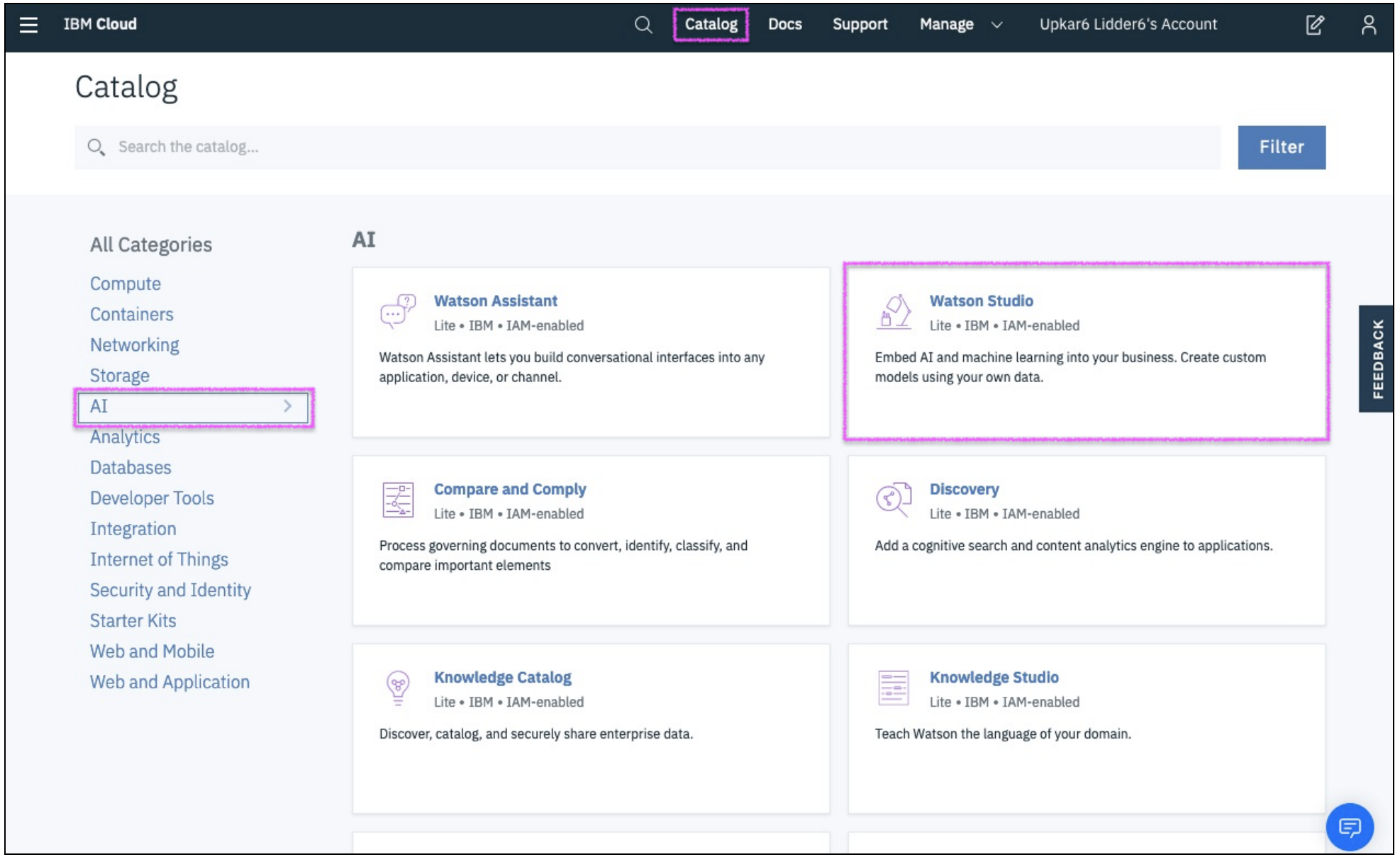
Steps

1. Sign up / Log into *IBM Cloud* - http://bit.ly/ibm-cloud-summit-2019
2. Create *Watson Studio Service*.
3. Sign into Watson Studio and create a new *Data Science Project*. It also creates a *Cloud Object Store* for you.
4. Upload csv *data* to your project.
5. Add a new *AutoAI Experiment* to your project.
6. Create a *ML Model* and *save* it to IBM Cloud.
7. Create a new *deployment* on IBM Cloud.
8. *Test* your model !

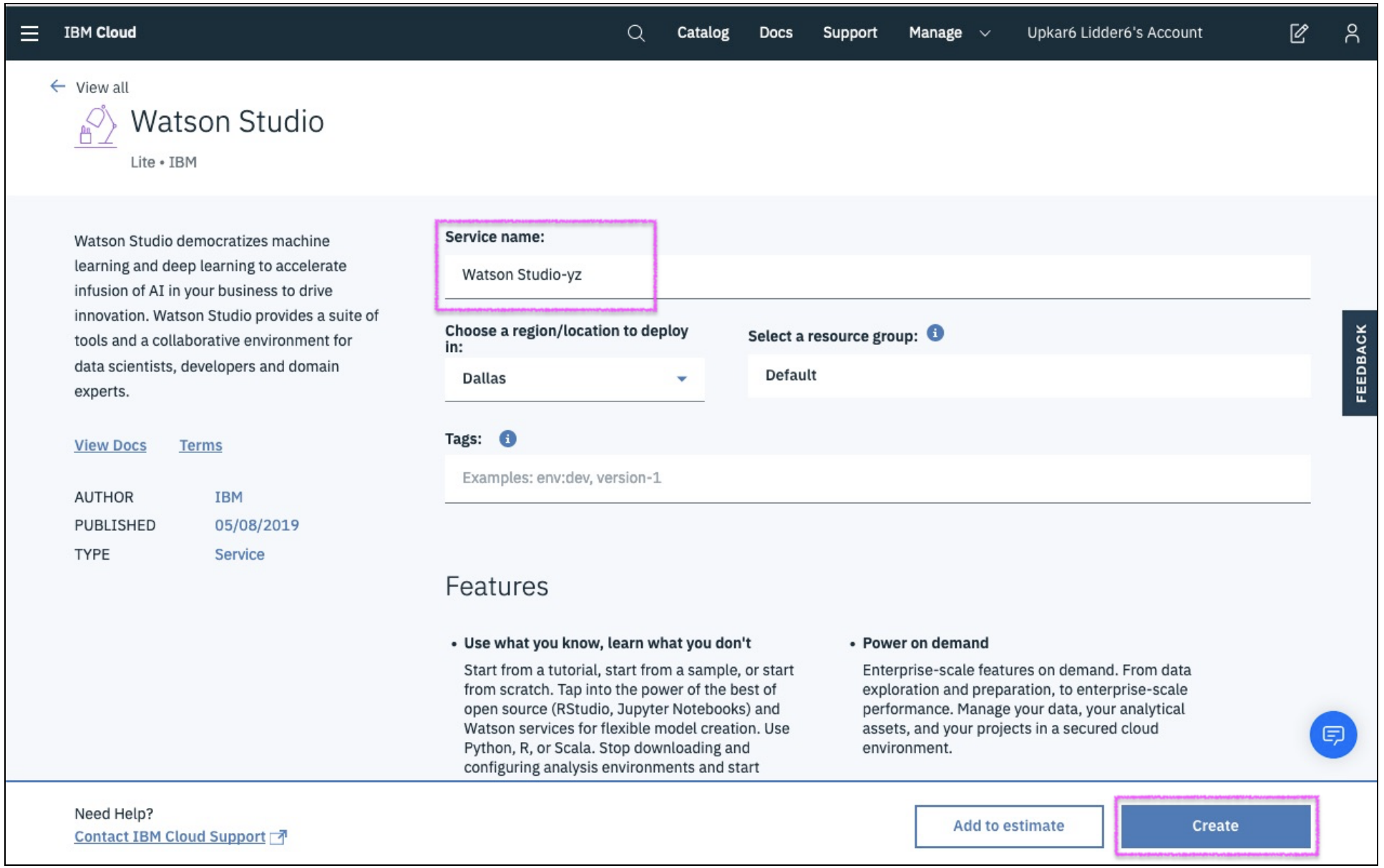
Step 1 - sign up/ log into IBM Cloud



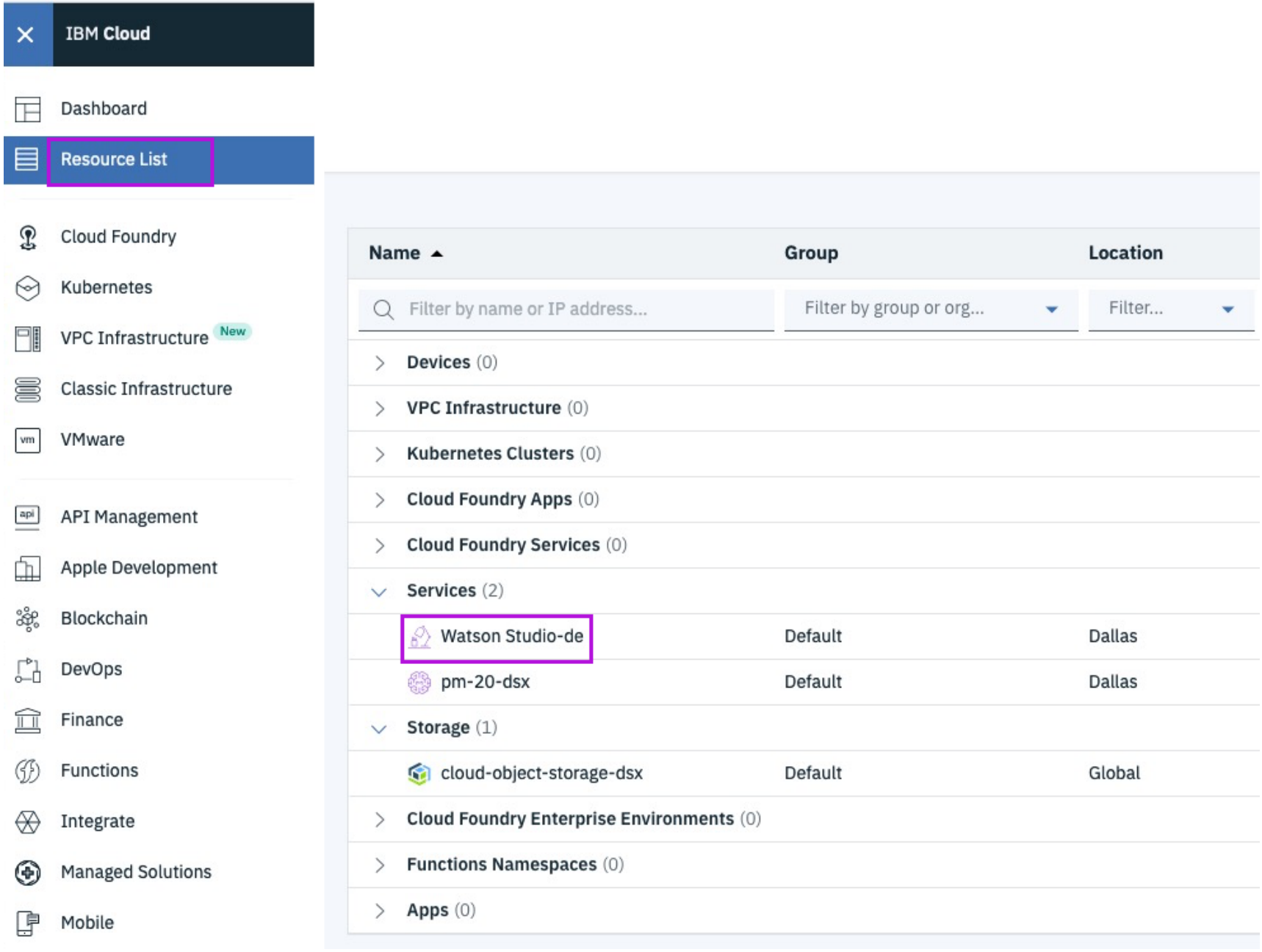
Step 2 - locate Watson Studio in Catalog



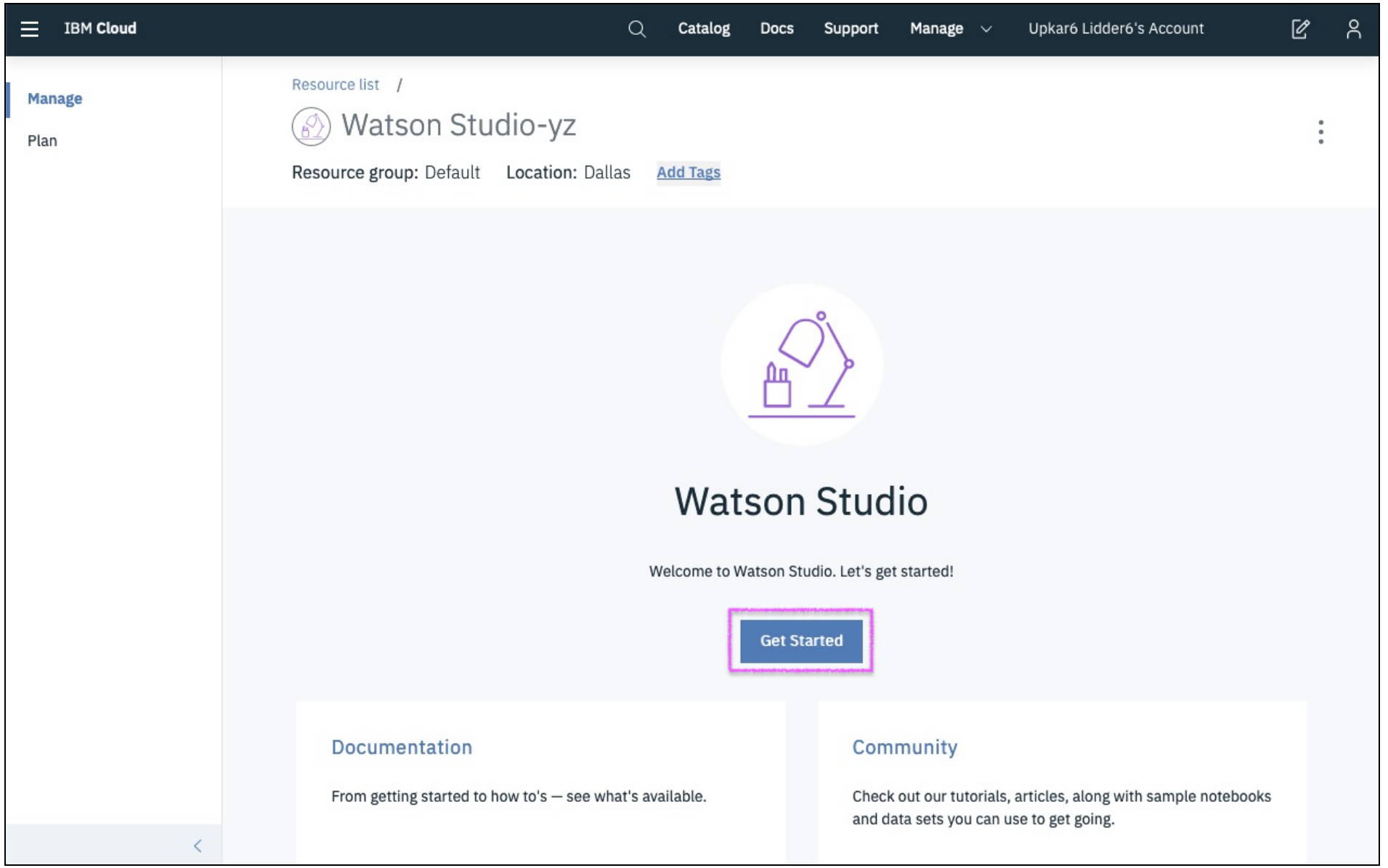
Step 3 - create Watson Studio instance



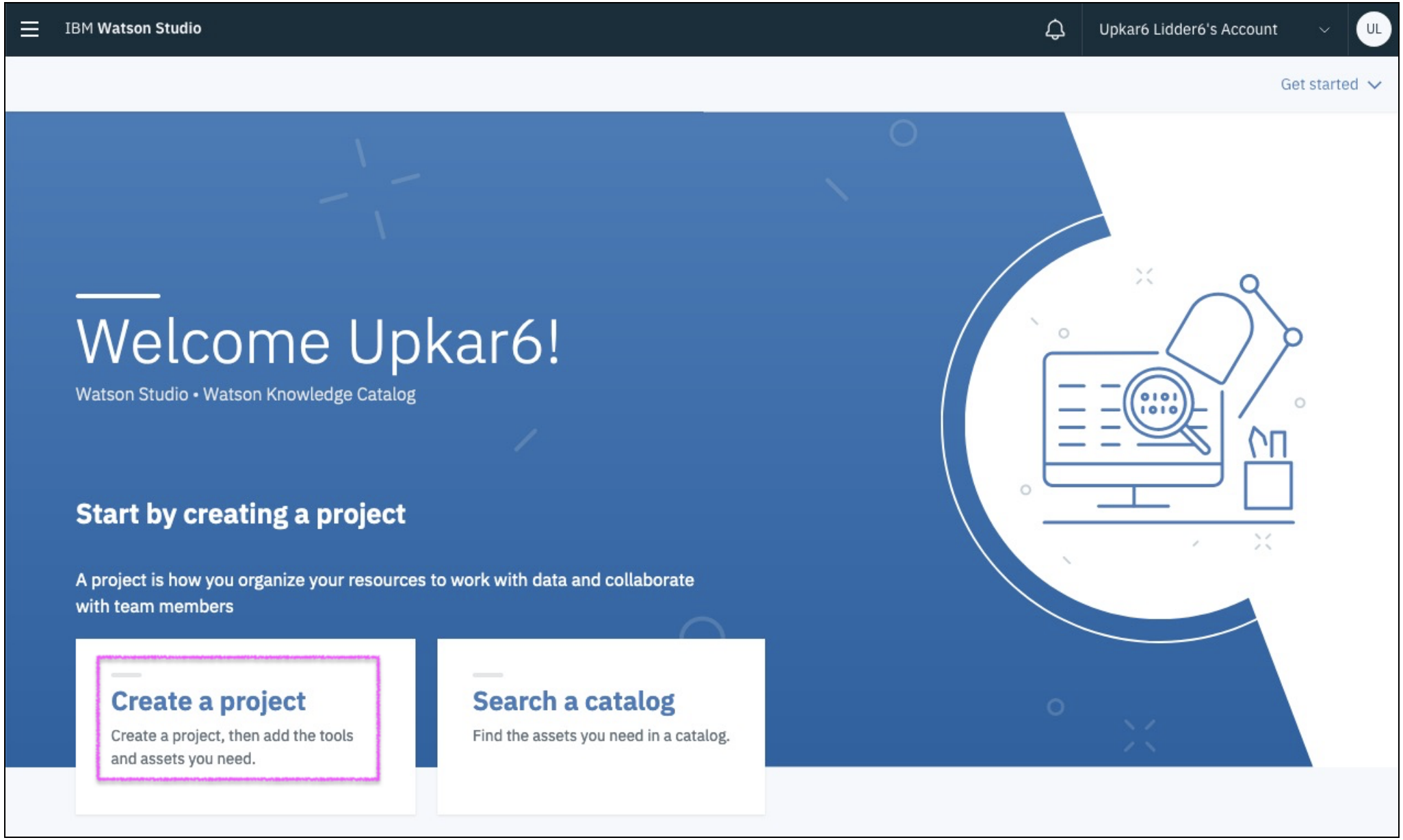
Step 3 - already have Watson Studio? Find it in **Resources**



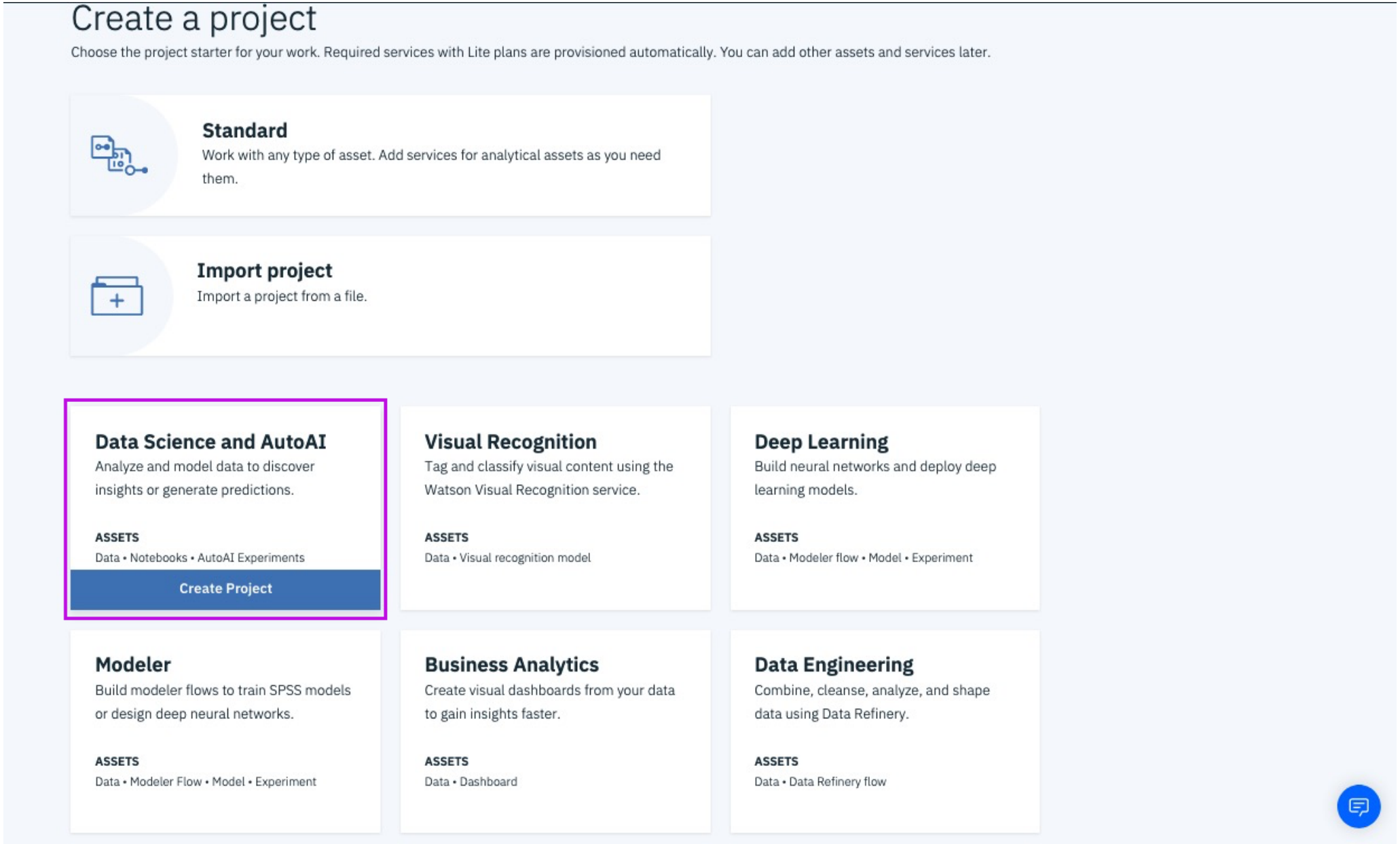
Step 4 - launch Watson Studio



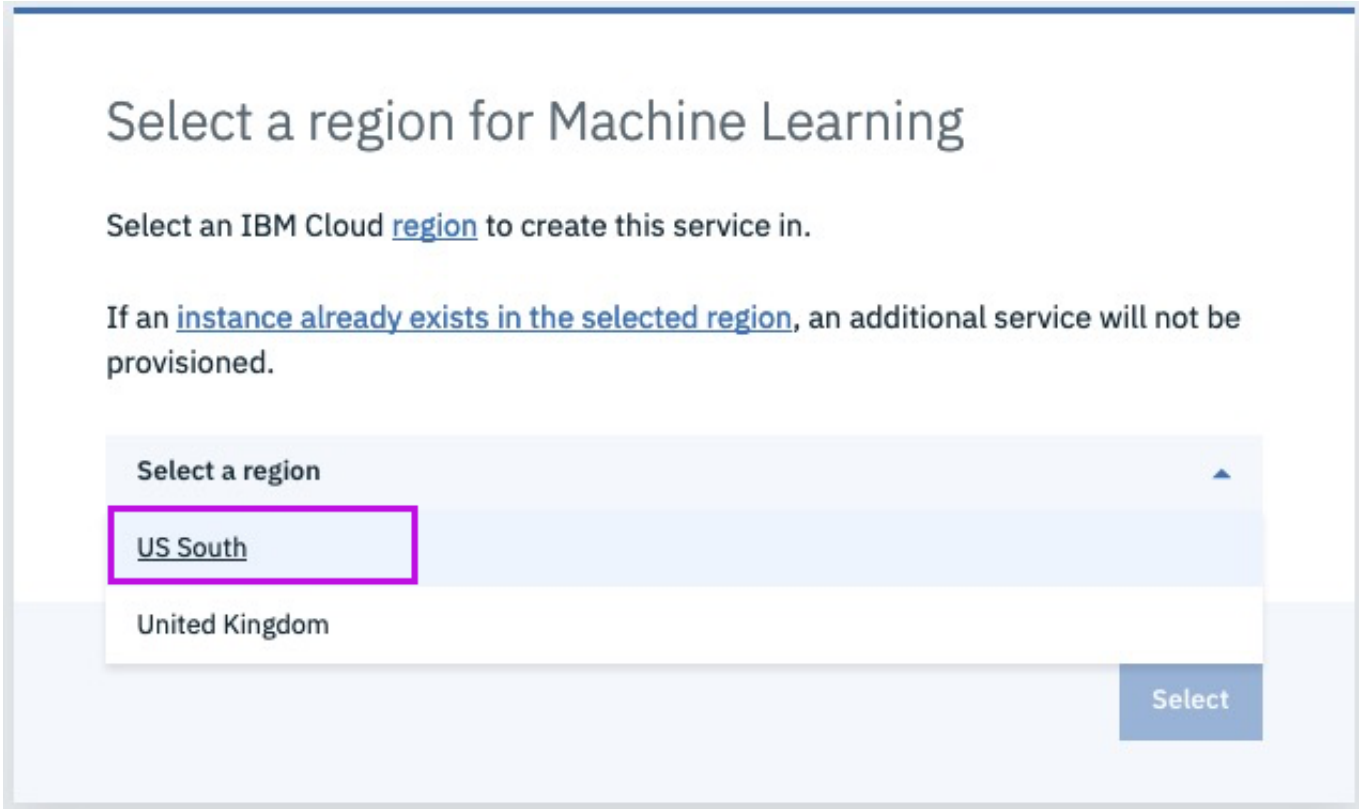
Step 5 - create a new project



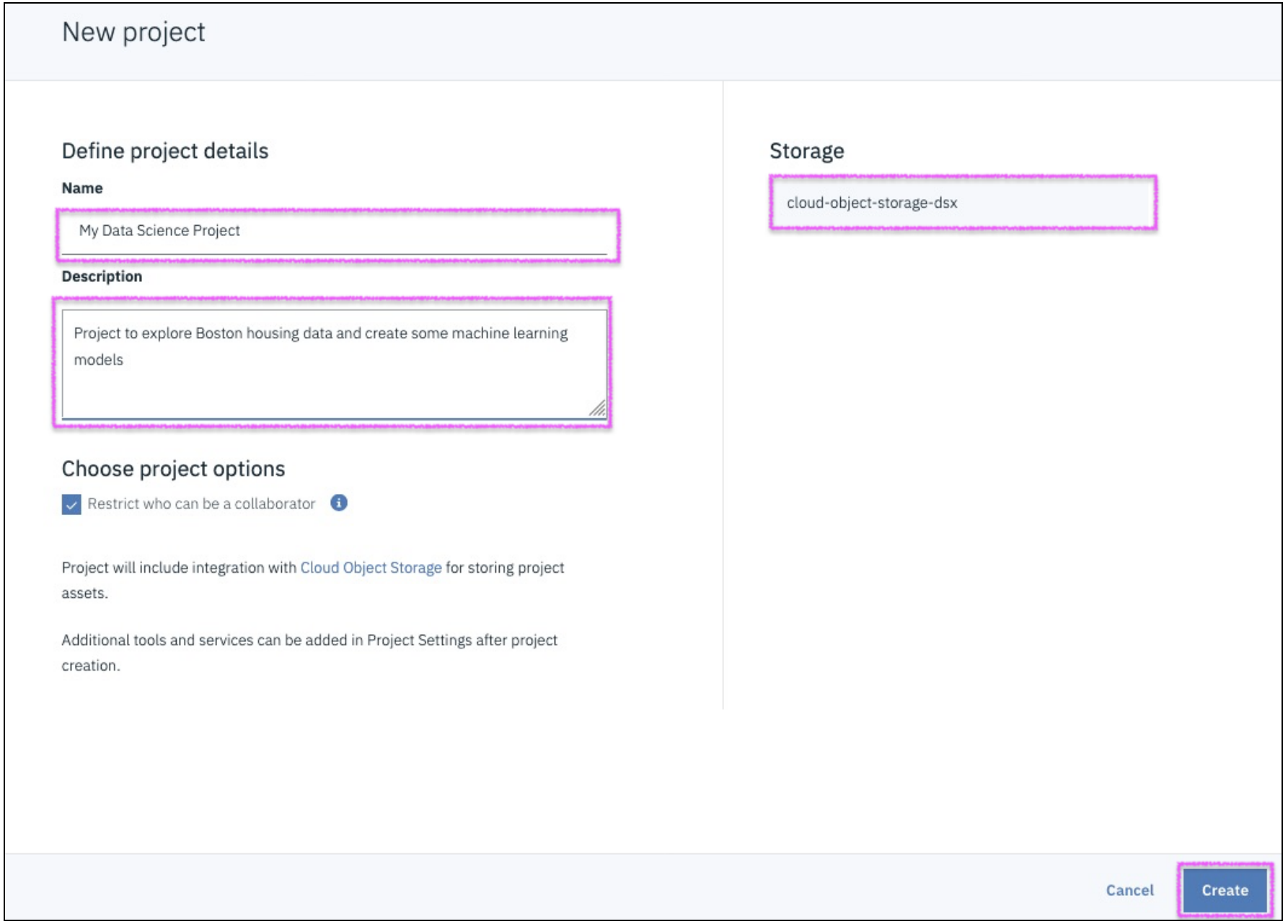
Step 6 - pick Data Science starter



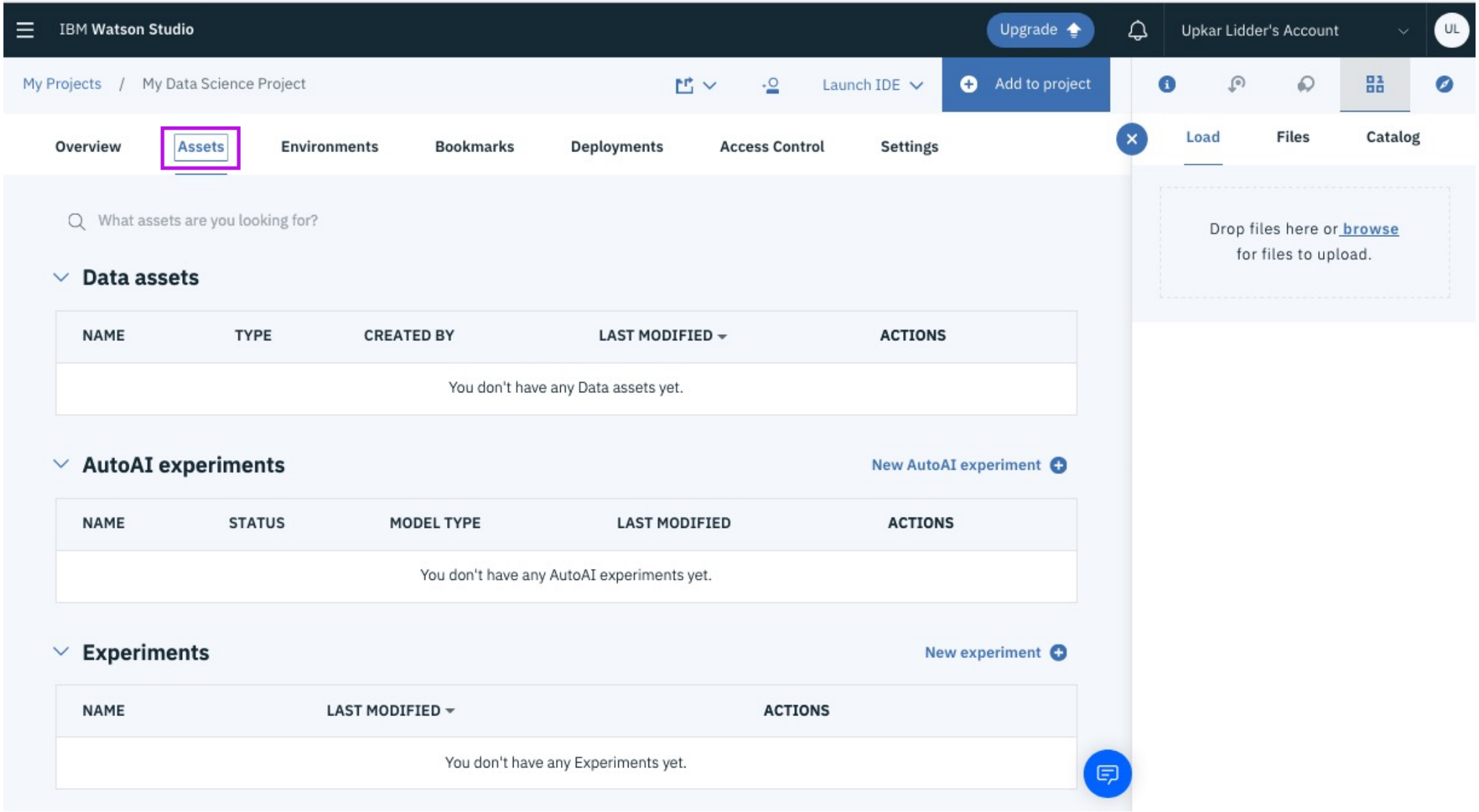
Step 6a - pick region [US South]



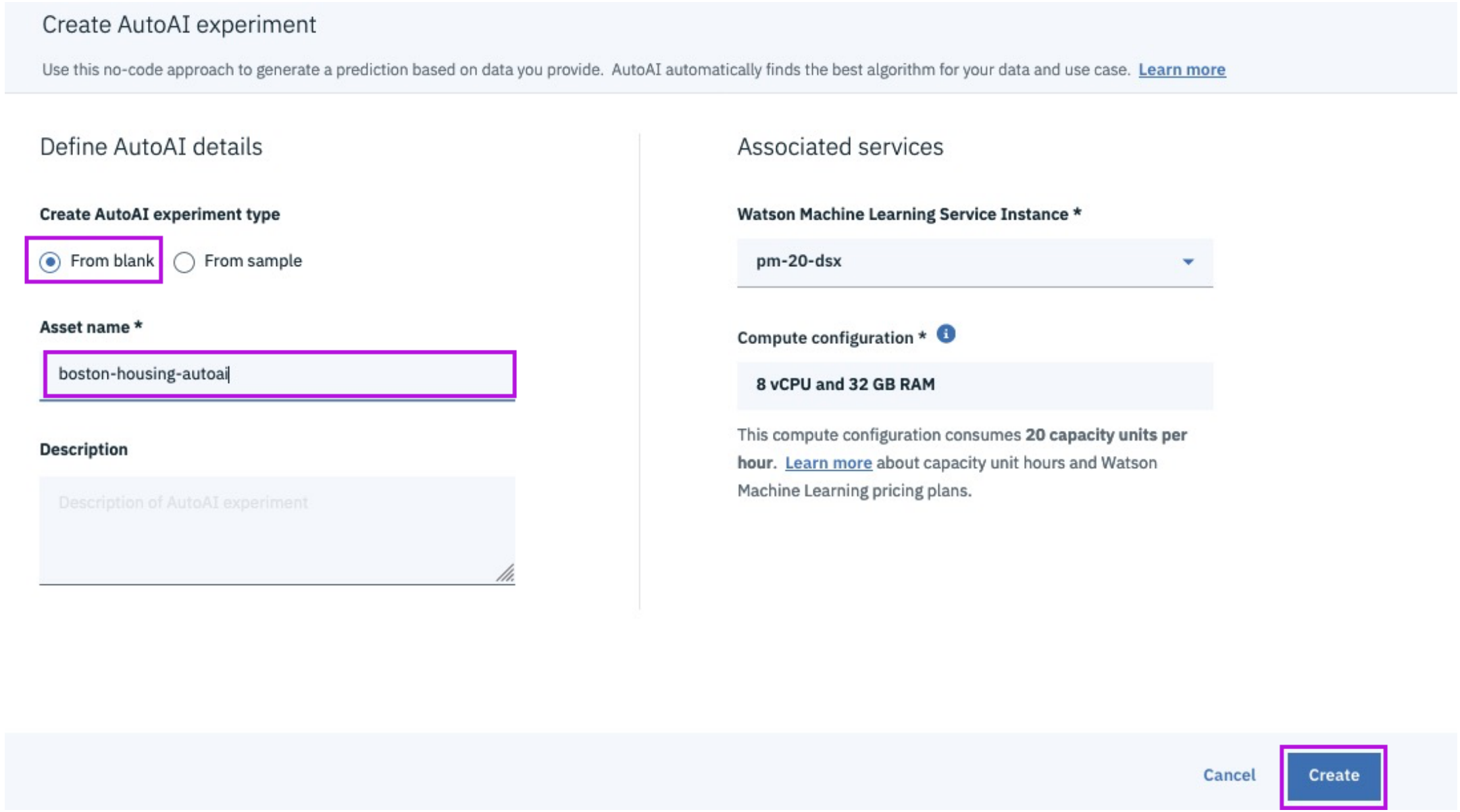
Step 7 - give the project a name and assign COS



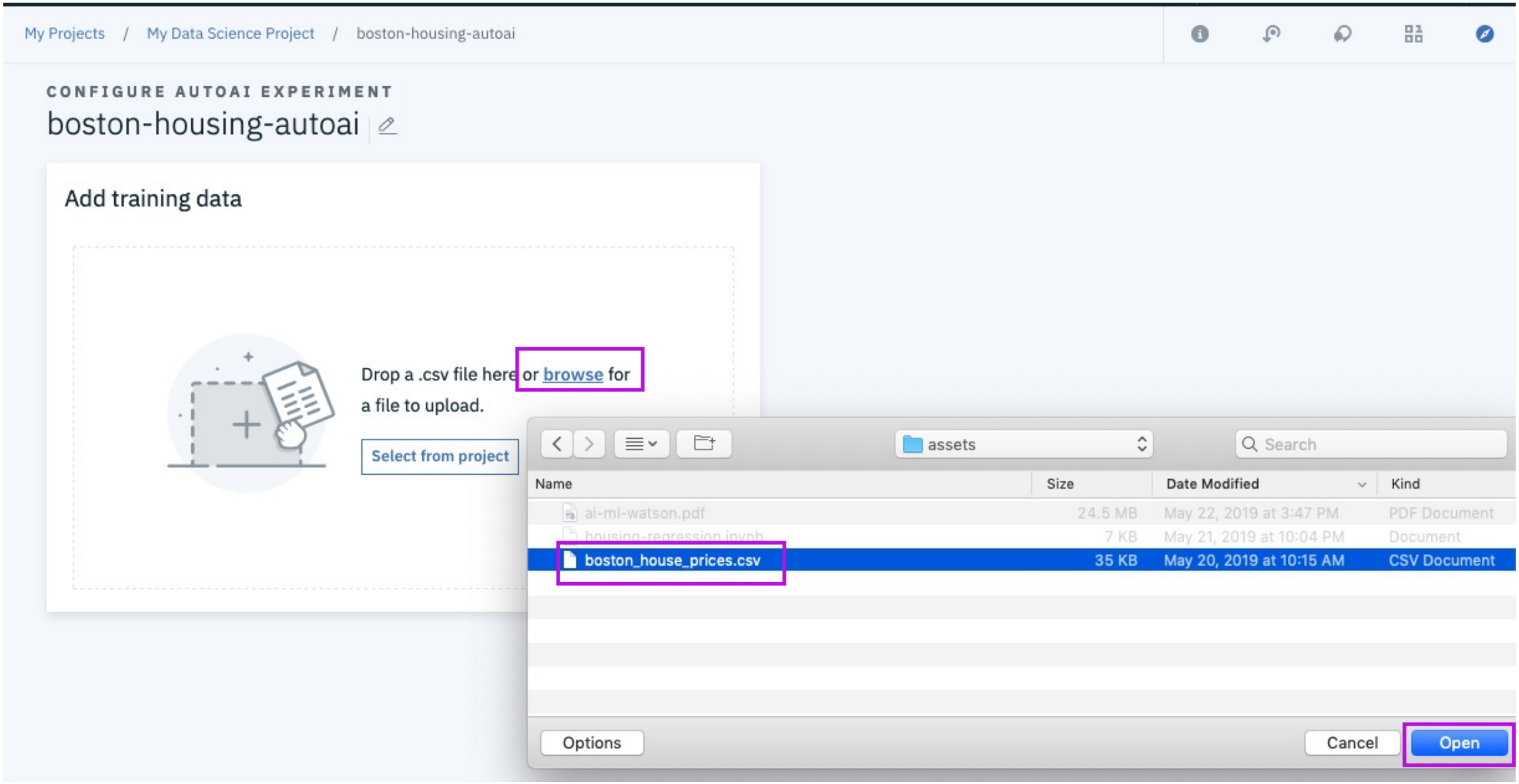
Step 8 - open asset tab, this is your goto page!



Step 9 - create a new AutoAI experiment

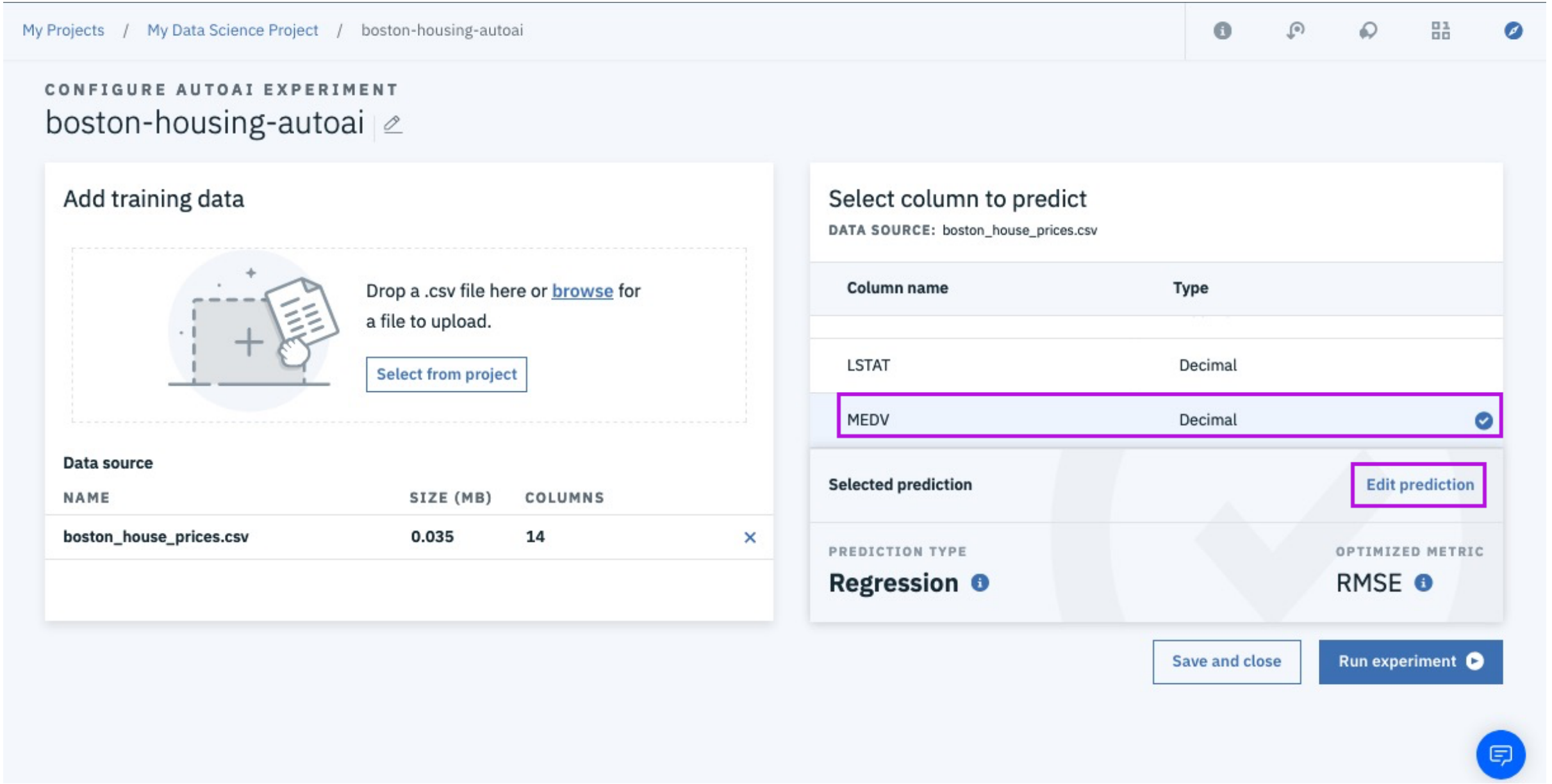


Step 10 - adding training data

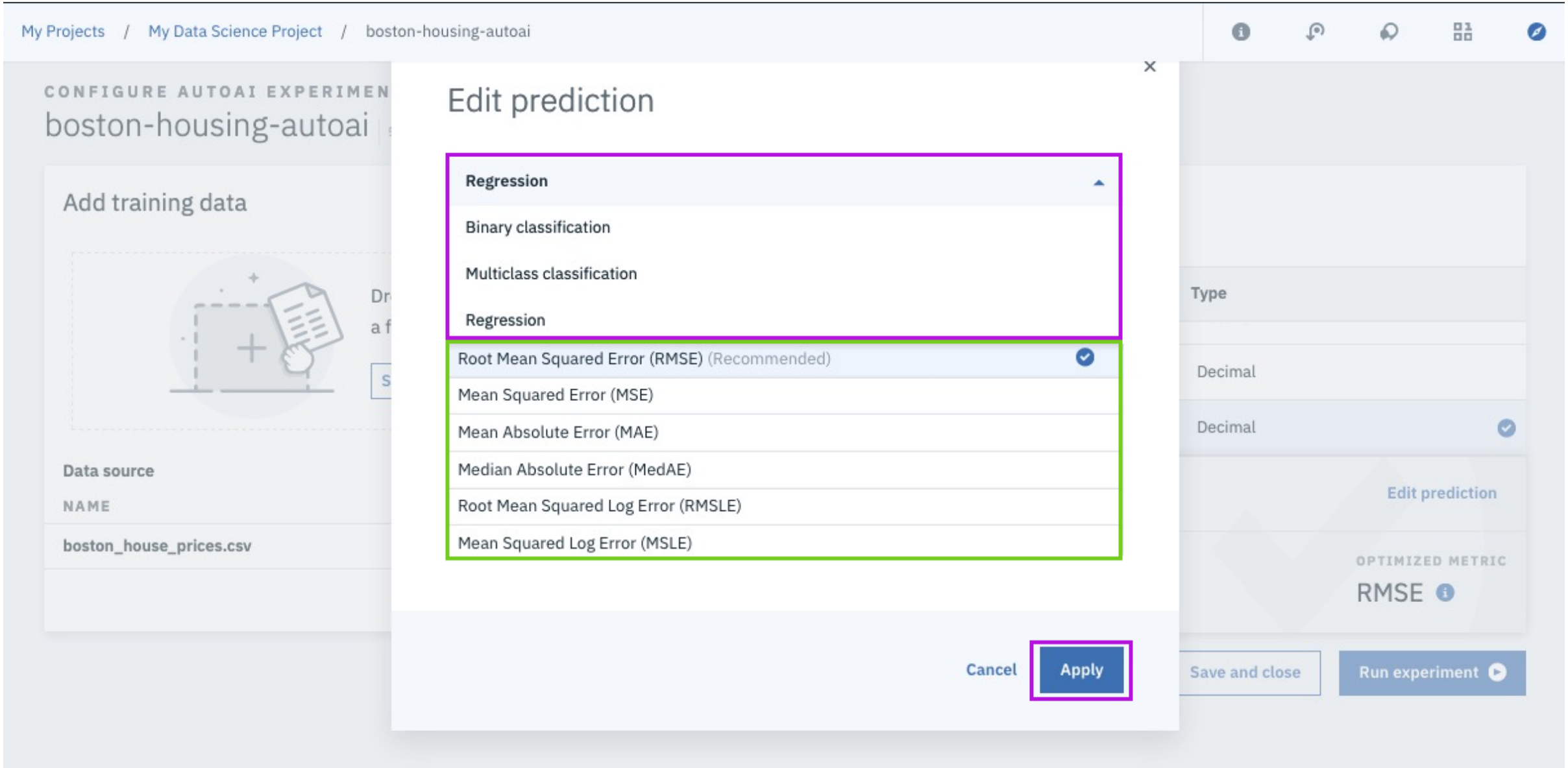


http://bit.ly/boston-house-csv

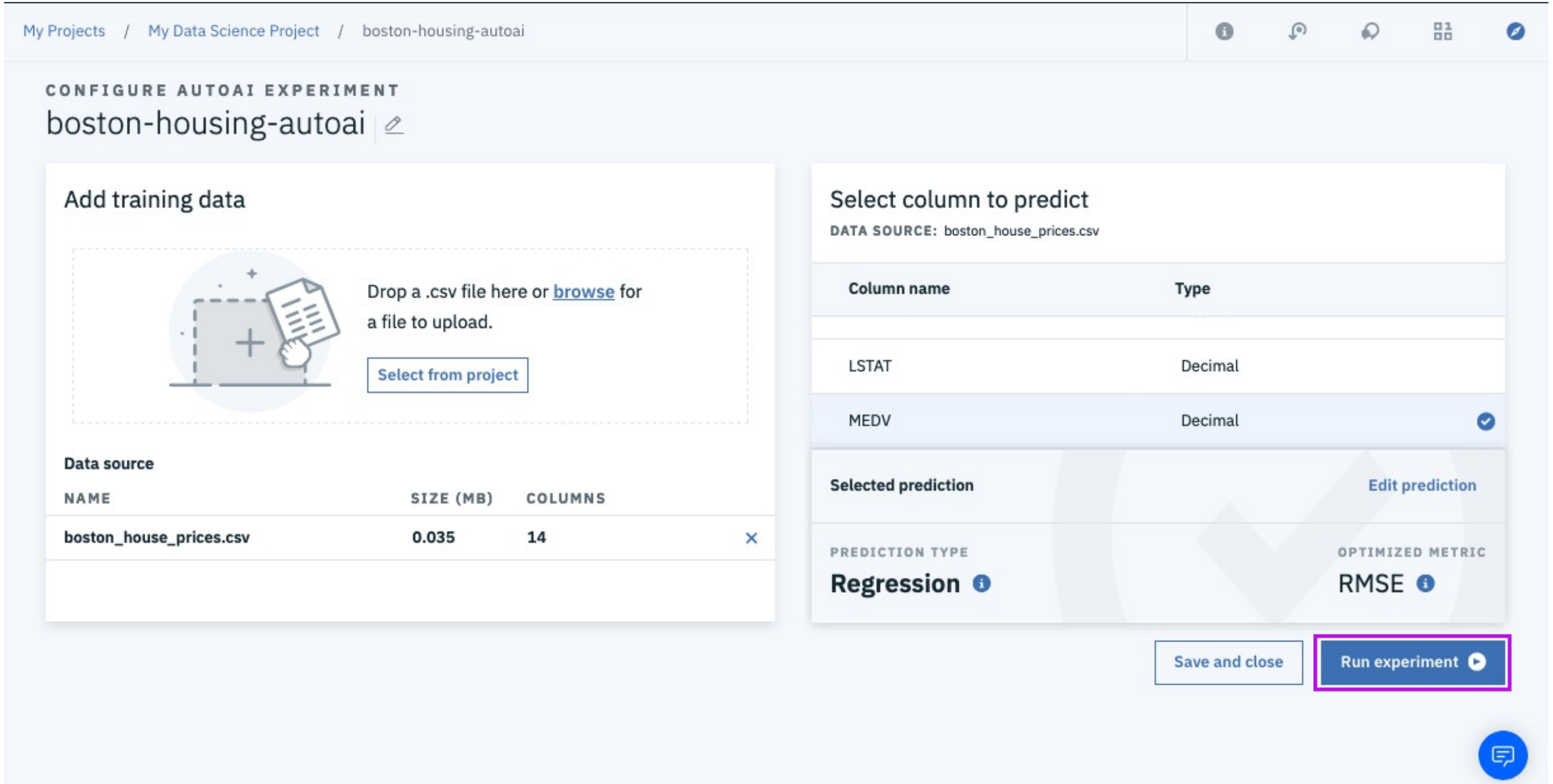
Step 11 - pick target column to predict [MEDV]



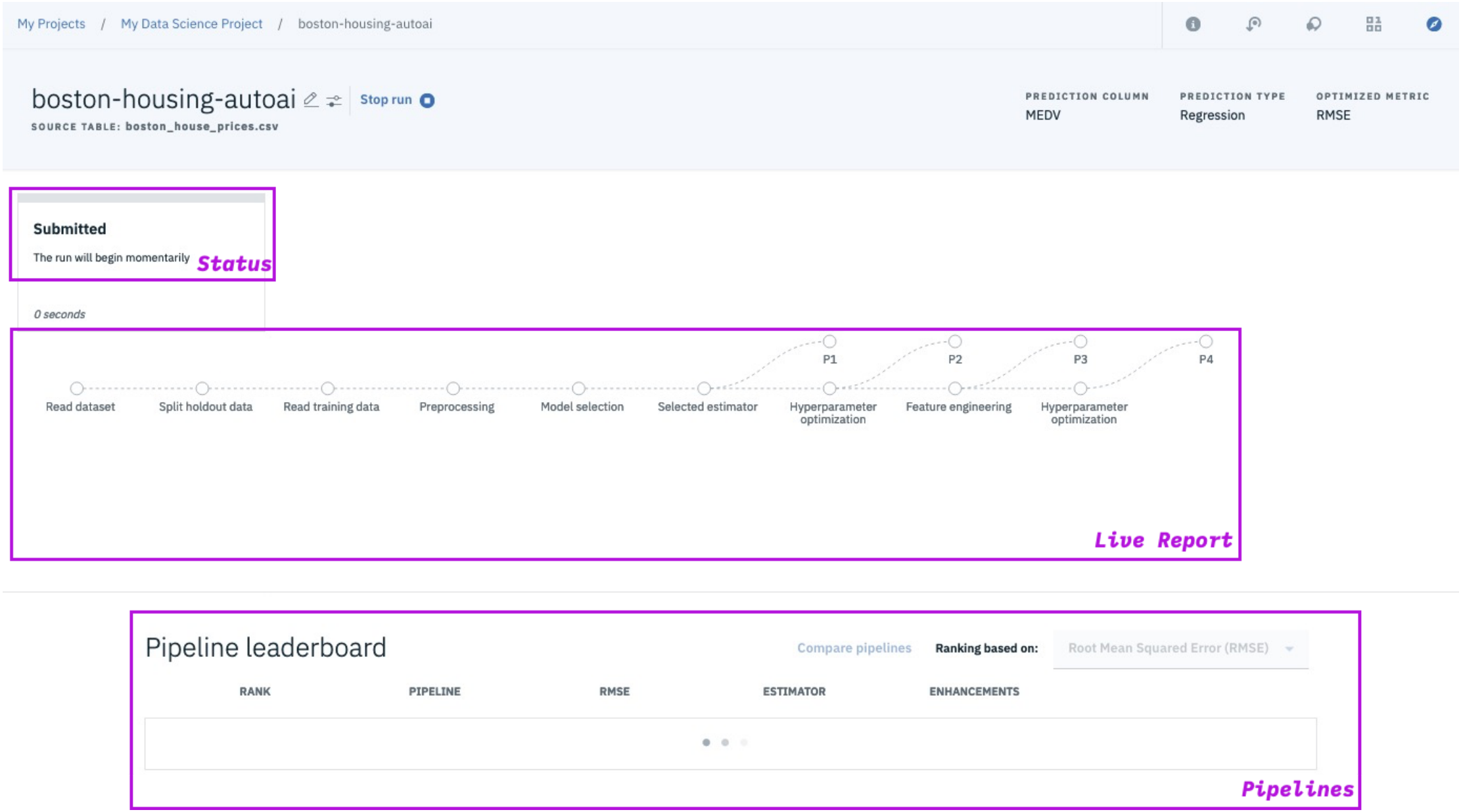
Step 11a - change model and metric if needed



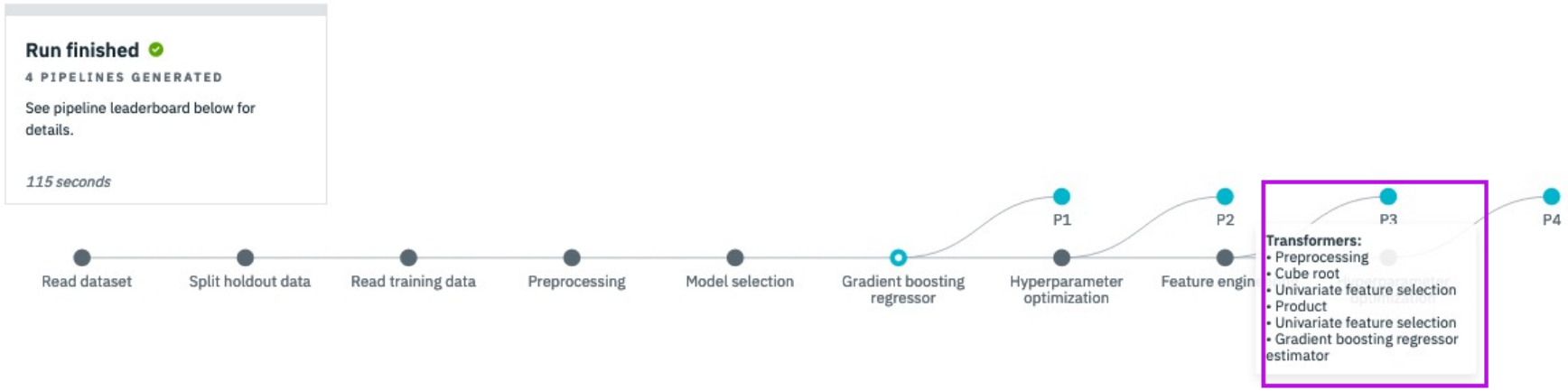
Step 12 - run experiment

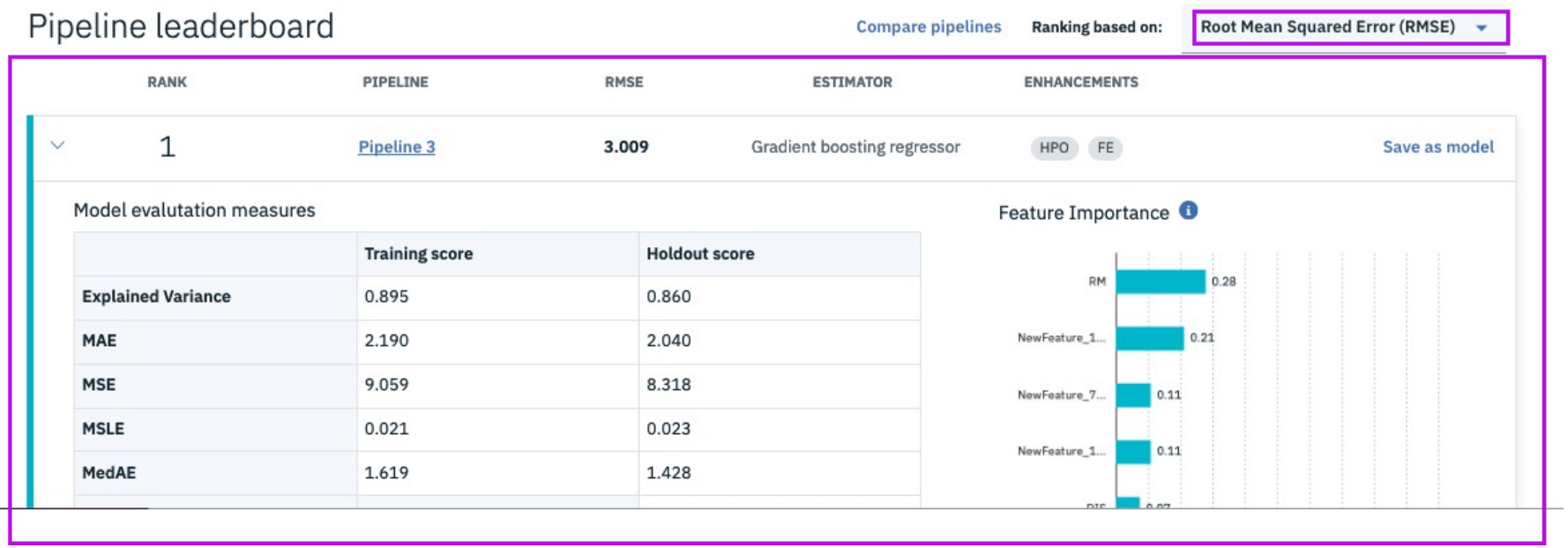


Step 13a - sit back and relax!

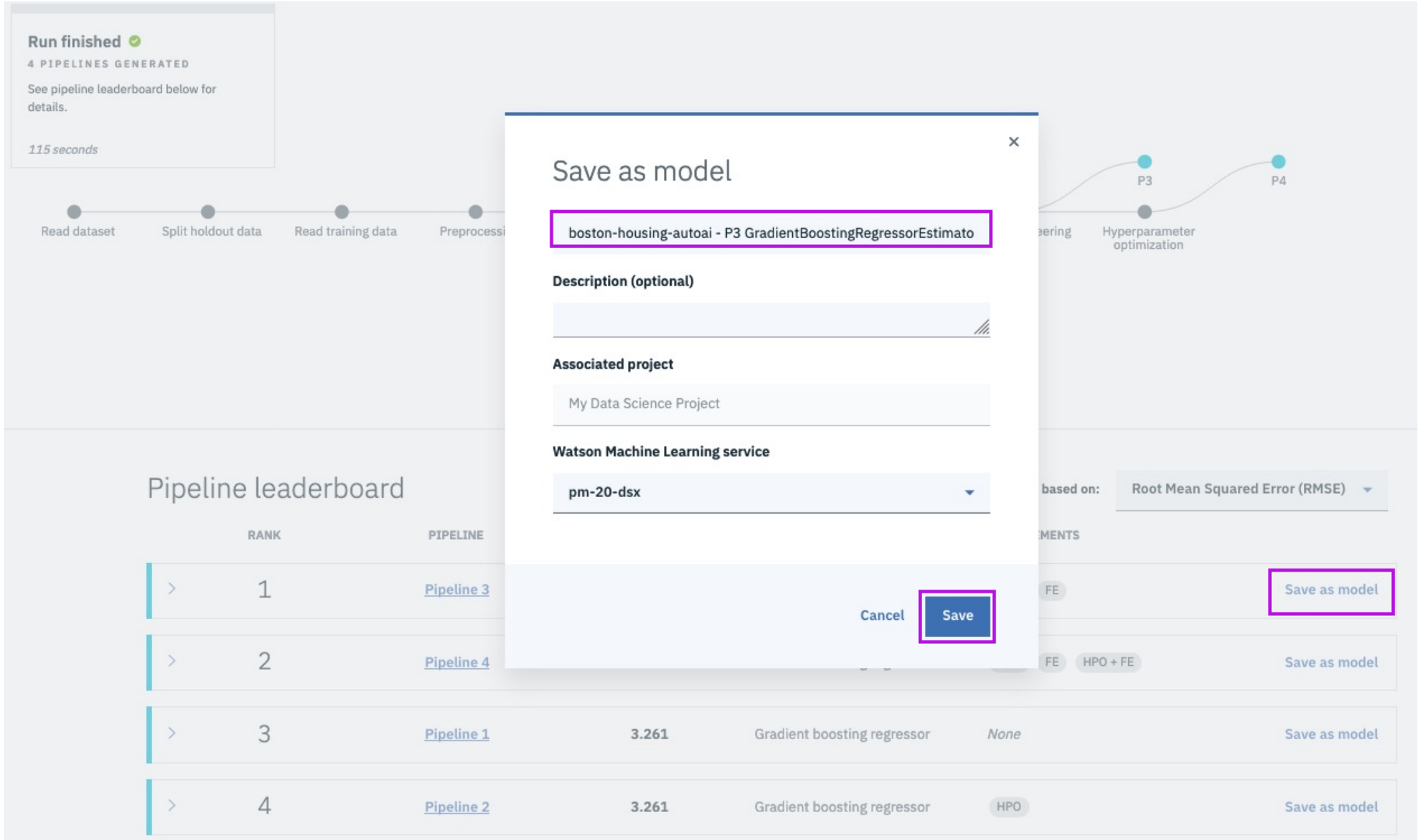


Step 13b - explore different models in the pipeline

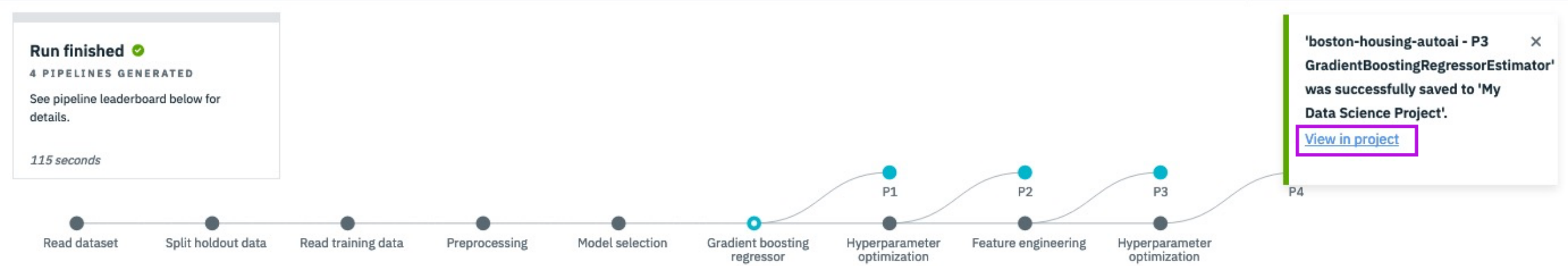




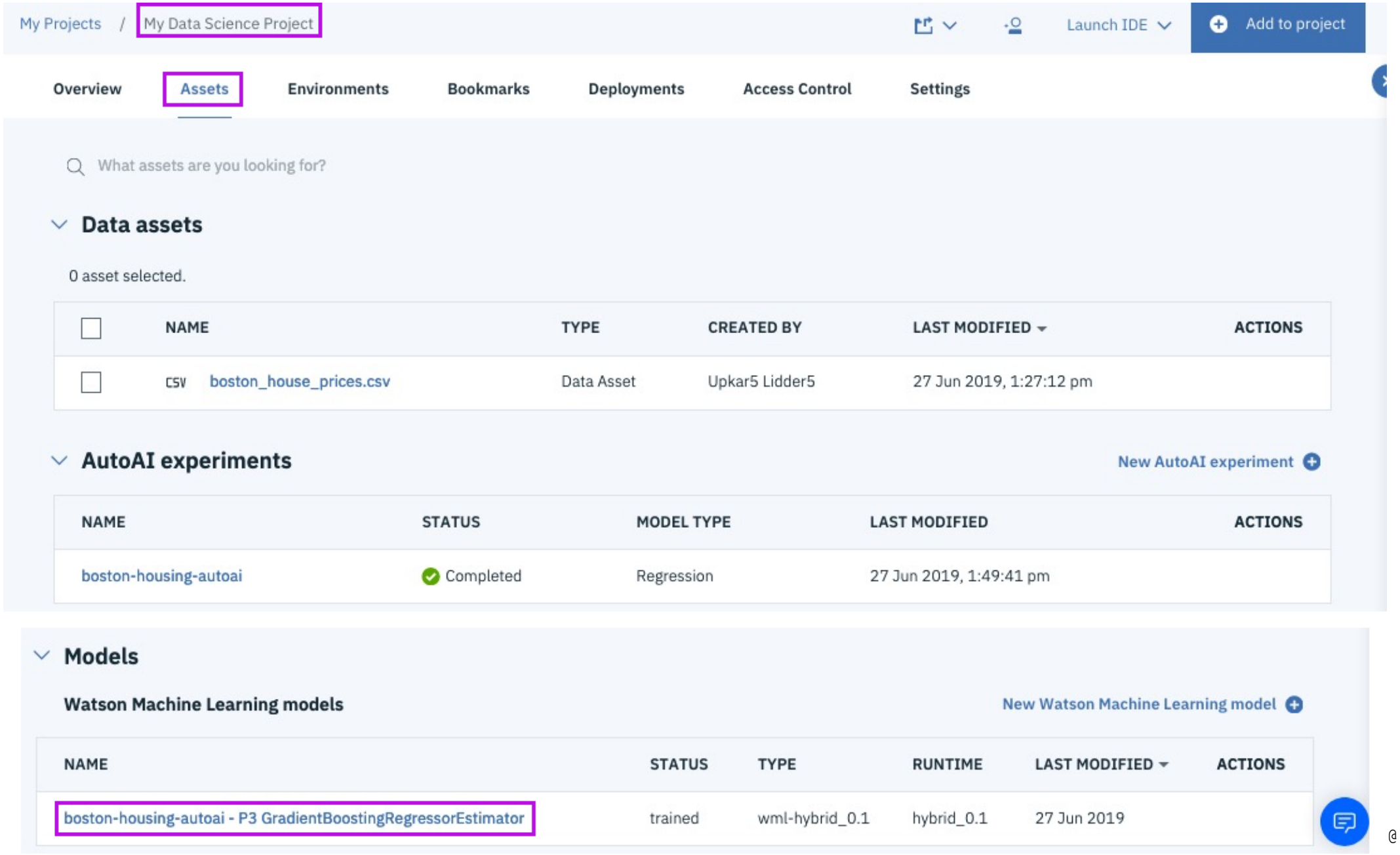
Step 14 - save the best model



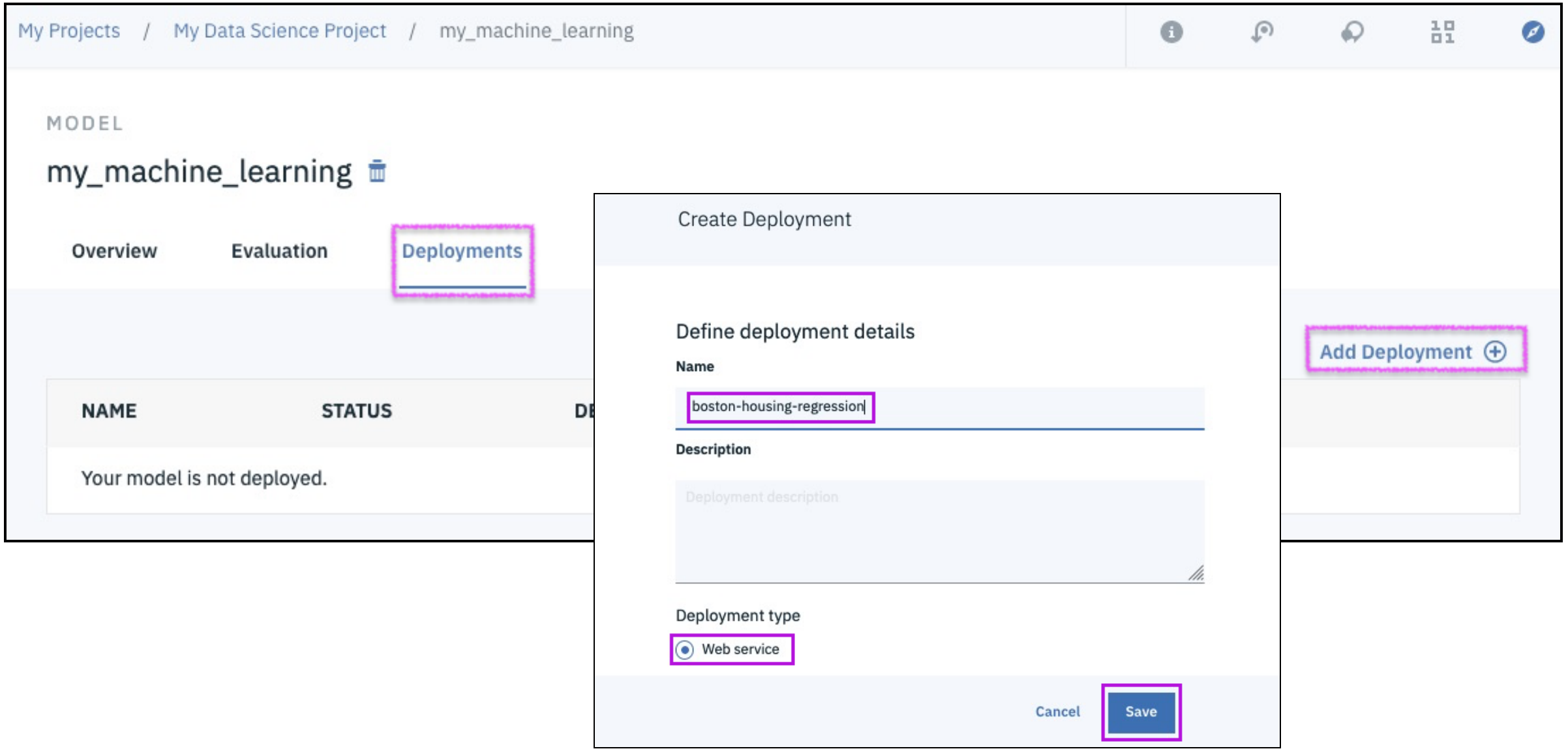
Step 15a - view the model



Step 15b - view the model, another way

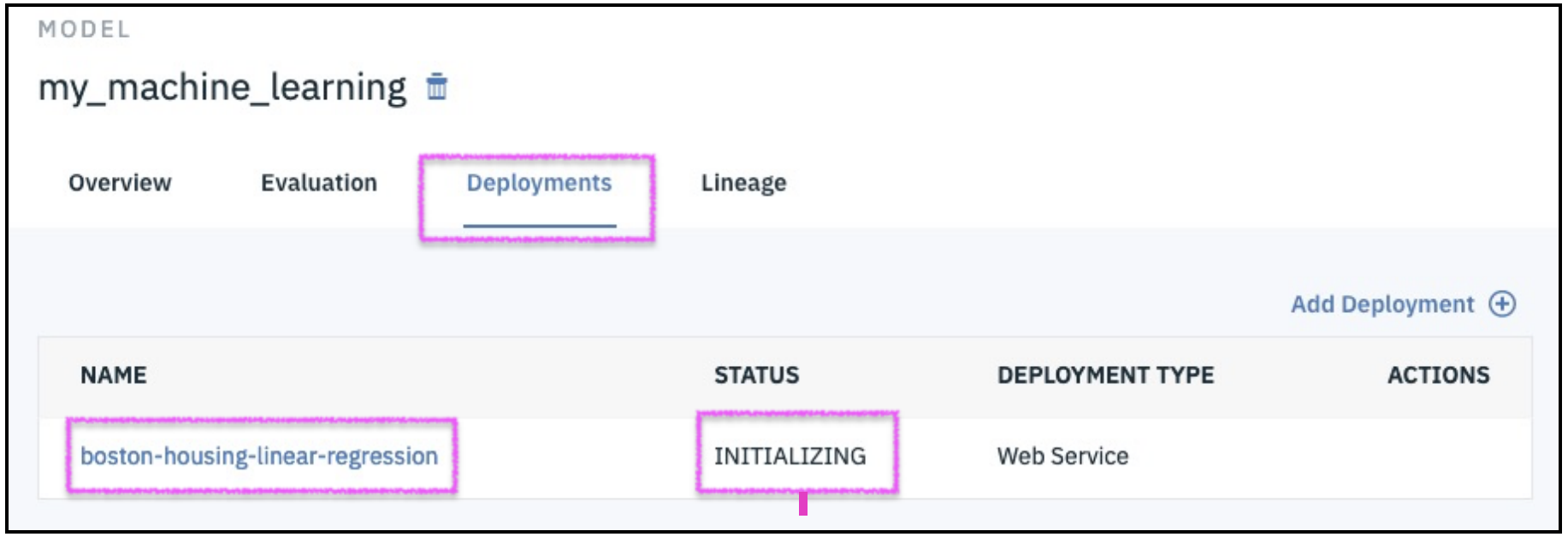


Step 16 - add a new deployment

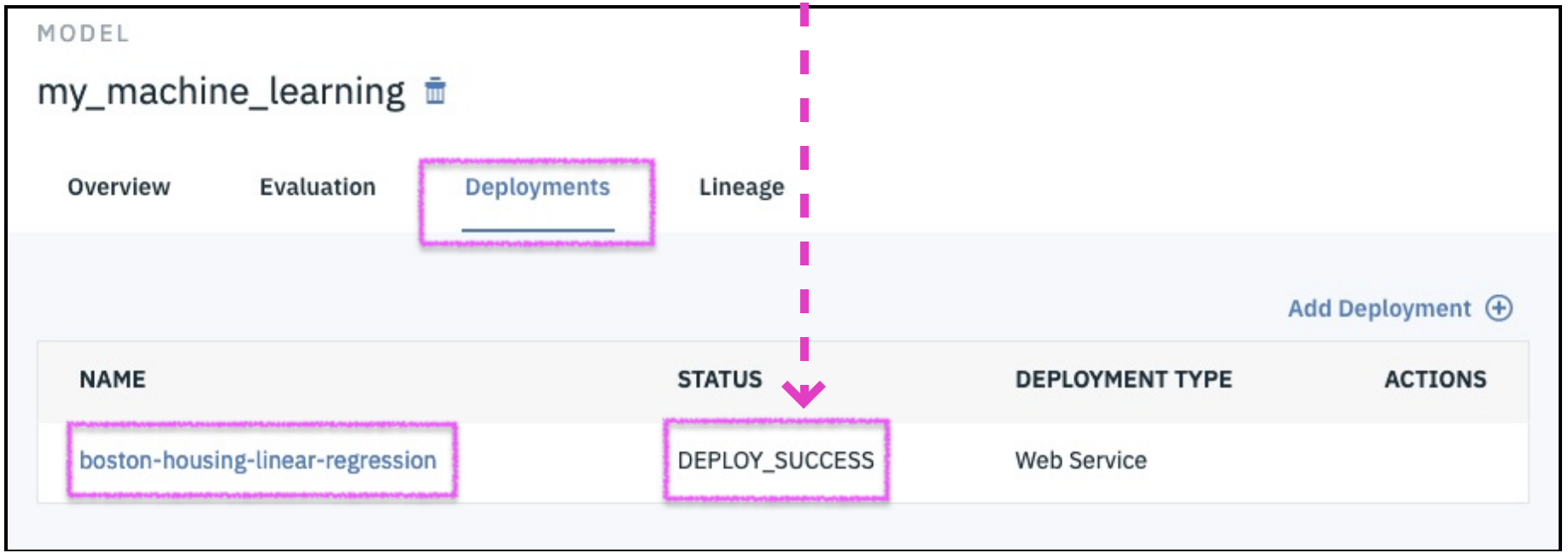


Step 17 - ensure that deployment is successful with **ready** status

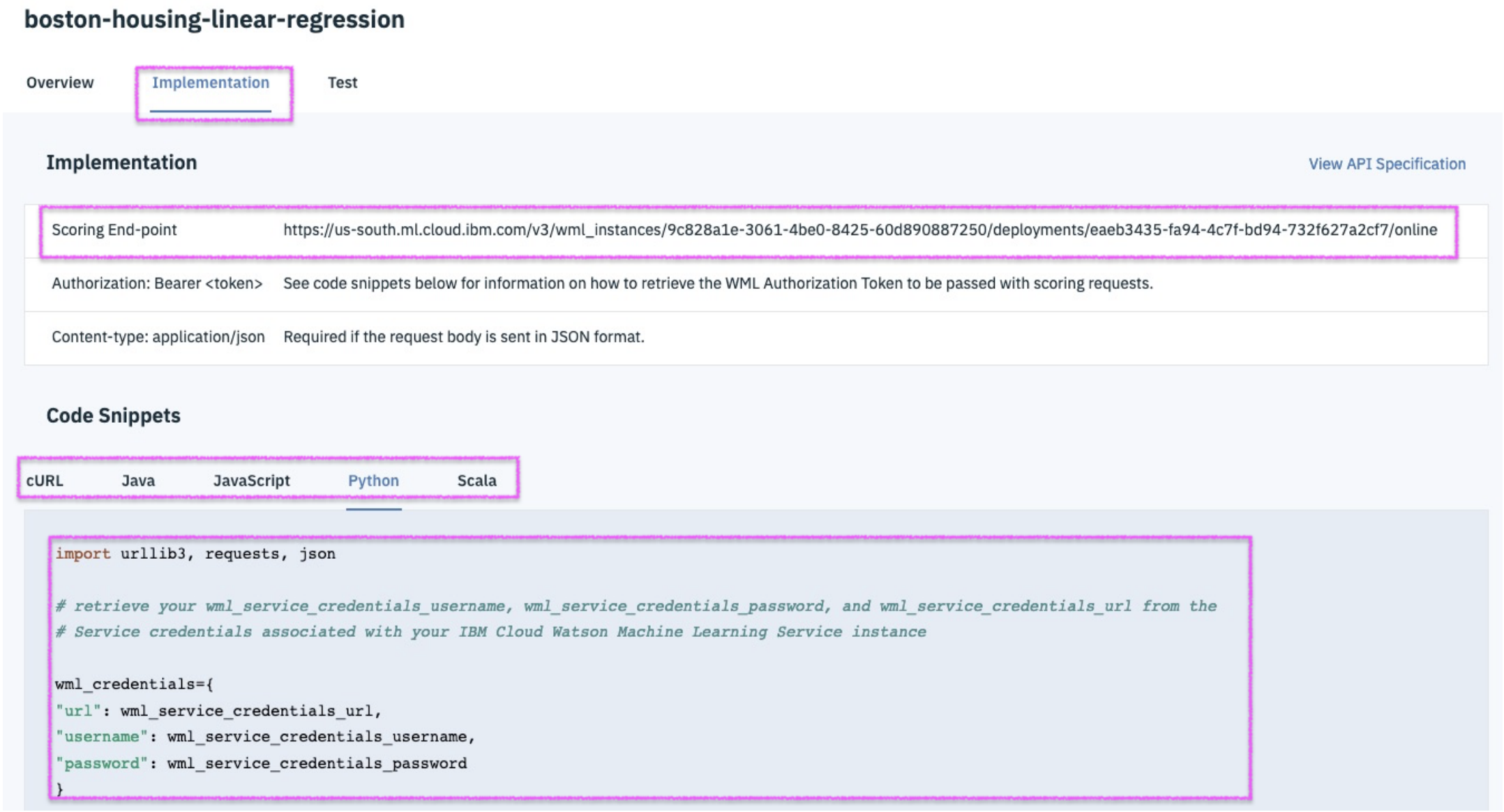
1



2



Step 18a - implementation / test the deployed model



Step 18b - implementation / test the deployed model

```
{"input_data":[{
        "fields": ["CRIM","ZN","INDUS","CHAS","NOX","RM","AGE","DIS","RAD","TAX","PTRATIO","B","LSTAT"],
        "values": [[0.00632,18,2.31,0,0.538,6.575,65.2,4.09,1,296,15.3,396.9,4.98]]
}]}
```

AutoAI - Behind the scenes

Data pre-processing

- analyze, clean and prepare raw data for ML
- automatically detects and categorizes features based on data type
- missing value imputation
- feature encoding
- feature scaling

Automated model selection

- test and rank candidate estimators
- select the best performing estimator with the ranking choice made by the user

Automated Feature Engineering

- transform raw data into combination of features that best fit the model

Hyperparameter Optimization

- refine the best performing model

AutoAI - Supported Estimators

http://bit.ly/autoai-estimators

Classification
AdaBoost Classifier
Bernoulli Naïve Bayes Classifier
Calibrated Classifier with Cross-Validation
Decision Tree Classifier
Extra Trees Classifier
Gaussian Naïve Bayes Classifier
Gaussian Process Classifier
Gradient Boosted Tree Classifier
Nearest Neighbor Analysis (KNN) Classifier
Label Propagation
Label Spreading
LGBM Classifier
Linear Discriminant Analysis
Linear Support Vector Classifier
Logistic Regression with Cross-Validation
Logistic Regression
MLP Classifier
Multinomial Naïve Bayes Classifier
Nearest Centroid
Nu Support Vector Classifier
Passive Aggressive Classifier
Perceptron
Quadratic Discriminant Analysis
Radius Neighbors Classifier
Random Forest Classifier
Ridge Classifier with Cross-Validation
Ridge Classifier
SGD Classifier
Support Vector Classifier
XGBoost Classifier

Regression	
AdaBoost Regression	Orthogonal Matching Pursuit with Cross-Validation
ARD Regression	Orthogonal Matching Pursuit
Bayesian Ridge Regression	Passive-Aggressive Regression
CCA	PLS Canonical
Decision Tree Regression	PLS Regression
Extra Trees Regression	Radius Neighbors Regression
Elastic Net with Cross-Validation	Random Forest Regression
Elastic Net	RANSAC Regression
Gaussian Process	Ridge with Cross-Validation
Gaussian Process Regression	Ridge
Gradient Boosting Regression	SGD Regression
Huber Regression	Support Vector Regression
Nearest Neighbor Analysis (KNN)	Theil-Sen Regression
Kernel Ridge	XGBoost Regression
Lars with Cross-Validation	
Lars	
Lasso with Cross-Validation	
Lasso	
Lasso Lars with Cross-Validation	
Lasso Lars	
Lasso Lars IC	
LGBM Regression	
Linear Regression	
Linear Support Vector Regression	
MLP Regression	
MultiTask Elastic Net CV	
MultiTask Elastic Net	
Multi Task Lasso CV	
Multi Task Lasso	
Nu SVR	

Watson Machine Learning

WML - Supported Frameworks as of 06.21.19

TensorFlow

- Version 1.5
- Version 1.11 in an Anaconda 5.2.0 environment

Spark MLlib

Spark 2.1

Caffe

Version 1.0

Predictive Model Markup Language (PMML)

Version 3.0 to 4.3

XGBoost

- XGBoost 0.6a2 and 0.71 in an Anaconda 4.2.x environment with scikit-learn 0.17 and Python 3.5
- XGBoost 0.80 in an Anaconda 5.0.1 environment with scikit-learn 0.19 and Python 3.5

scikit-learn

- scikit-learn 0.17 on Anaconda 4.2.x for Python 3.5 Runtime
- scikit-learn 0.19 on Anaconda 5.0.0 for Python 3.5 Runtime

PyTorch

Versions: 0.3, 0.4.1, 1.0

Keras

- Version 2.1.3 with Tensorflow version 1.5
- Version 2.2.4 with TensorFlow version 1.11 in an Anaconda 5.2.0 environment

IBM SPSS Modeler

- IBM SPSS Modeler 17.1
- IBM SPSS Modeler 18.0

IBM Watson Machine Learning

Embed Machine Learning and Deep Learning in your Business

Push analytics to Data

ML close to data for faster and secure insights

- Connect to remote Hadoop and Spark clusters to train ML models at scale
- Move analytics to the data, access data from Hadoop and combine it with RDBMS to expand data access and optimize performance.
- Simplify big data analysis for analysts and business users.
- Mix and match deployment options

Deploy & Manage

Manage models and versions

- Save models on a central repository with version control built in
- Portable models – deploy in the cloud, on devices or on premise
- Import models trained somewhere else and deploy in WML
- Transfer models to connected devices (e.g. Core ML, Tensorflow Lite)
- Deployment flexibility: Shiny apps, scripts, decision optimization and WEX models

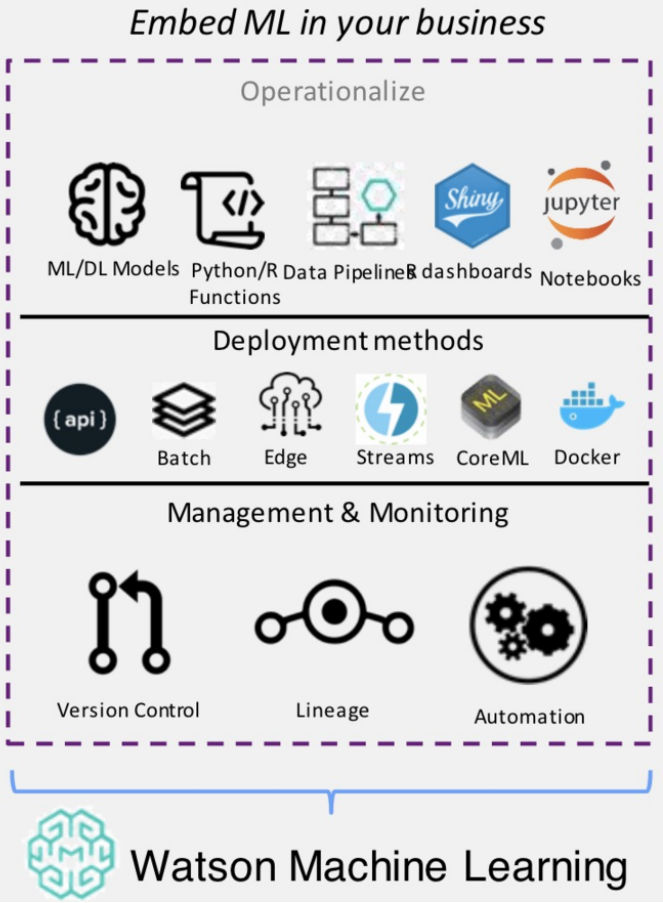
Automate ML

Your models always learning with a feedback loop

- Automate the retraining of models with feedback loop capabilities
- Automate the deployment of models in products
- Automate the Hyperparameter Optimization and Feature Engineering to rapidly train models
- A/B testing of models and performance Monitoring

Fully Managed on IBM Cloud

Deploy it on Private or Public Cloud



IBM Watson Machine Learning Client

Welcome to watson-machine-learning-client's documentation!

`watson-machine-learning-client` is a python library that allows to work with Watson Machine Learning service on IBM Cloud. Test and deploy your models as APIs for application development, share with colleagues using this python library.

Contents

WML - create scikit-learn linear regression model

```
1  from sklearn.linear_model import LinearRegression
2  from sklearn.datasets import load_boston
3  import matplotlib.pyplot as plt
4  from sklearn.model_selection import train_test_split
5  from sklearn.metrics import mean_squared_error, r2_score
6
7  boston = load_boston()
8  X_train, X_test, y_train, y_test = train_test_split(boston.data, boston.target)
9
10 # Create a new Linear Regression Model
11 LR_model = LinearRegression()
12
13 # Train the model
14 LR_model.fit(X_train, y_train)
15
16 # store actual and predited data to draw chart
17 predicted = LR_model.predict(X_test)
18 actual = y_test
19
20
21 # The coefficients
22 print('Coefficients: \n', LR_model.coef_)
23 # The mean squared error
24 print("Mean squared error: %.2f"
25       % mean_squared_error(actual, predicted))
26 # Explained variance score: 1 is perfect prediction
27 print('Variance score: %.2f' % r2_score(actual, predicted))
```

Output

```
Coefficients:
 [ -1.05001380e-01   3.29973196e-02   3.09915520e-02   2.74529793e+00
  -2.00482943e+01   4.60880933e+00  -1.36509230e-03  -1.27392294e+00
   2.69375701e-01  -1.12477385e-02  -9.48125356e-01   8.76288422e-03
  -4.24918821e-01]
Mean squared error: 33.77
Variance score: 0.67
```

WML - create scikit-learn linear regression model

```
1  from sklearn.linear_model import LinearRegression
2  from sklearn.datasets import load_boston
3  import matplotlib.pyplot as plt
4  from sklearn.model_selection import train_test_split
5  from sklearn.metrics import mean_squared_error, r2_score
6
7  boston = load_boston()
8  X_train, X_test, y_train, y_test = train_test_split(boston.data, boston.target)
9
10 # Create a new Linear Regression Model
11 LR_model = LinearRegression()
12
13 # Train the model
14 LR_model.fit(X_train, y_train)
15
16 # store actual and predited data to draw chart
17 predicted = LR_model.predict(X_test)
18 actual = y_test
19
20
21 # The coefficients
22 print('Coefficients: \n', LR_model.coef_)
23 # The mean squared error
24 print("Mean squared error: %.2f"
25       % mean_squared_error(actual, predicted))
26 # Explained variance score: 1 is perfect prediction
27 print('Variance score: %.2f' % r2_score(actual, predicted))
```

Output

```
Coefficients:
 [ -1.05001380e-01   3.29973196e-02   3.09915520e-02   2.74529793e+00
  -2.00482943e+01   4.60880933e+00  -1.36509230e-03  -1.27392294e+00
   2.69375701e-01  -1.12477385e-02  -9.48125356e-01   8.76288422e-03
  -4.24918821e-01]
Mean squared error: 33.77
Variance score: 0.67
```

WML - create scikit-learn linear regression model

```
1  from sklearn.linear_model import LinearRegression
2  from sklearn.datasets import load_boston
3  import matplotlib.pyplot as plt
4  from sklearn.model_selection import train_test_split
5  from sklearn.metrics import mean_squared_error, r2_score
6
7  boston = load_boston()
8  X_train, X_test, y_train, y_test = train_test_split(boston.data, boston.target)
9
10 # Create a new Linear Regression Model
11 LR_model = LinearRegression()
12
13 # Train the model
14 LR_model.fit(X_train, y_train)
15
16 # store actual and predited data to draw chart
17 predicted = LR_model.predict(X_test)
18 actual = y_test
19
20
21 # The coefficients
22 print('Coefficients: \n', LR_model.coef_)
23 # The mean squared error
24 print("Mean squared error: %.2f"
25       % mean_squared_error(actual, predicted))
26 # Explained variance score: 1 is perfect prediction
27 print('Variance score: %.2f' % r2_score(actual, predicted))
```

Output

```
Coefficients:
 [ -1.05001380e-01   3.29973196e-02   3.09915520e-02   2.74529793e+00
  -2.00482943e+01   4.60880933e+00  -1.36509230e-03  -1.27392294e+00
   2.69375701e-01  -1.12477385e-02  -9.48125356e-01   8.76288422e-03
  -4.24918821e-01]
Mean squared error: 33.77
Variance score: 0.67
```

WML - create scikit-learn linear regression model

```
1  from sklearn.linear_model import LinearRegression
2  from sklearn.datasets import load_boston
3  import matplotlib.pyplot as plt
4  from sklearn.model_selection import train_test_split
5  from sklearn.metrics import mean_squared_error, r2_score
6
7  boston = load_boston()
8  X_train, X_test, y_train, y_test = train_test_split(boston.data, boston.target)
9
10 # Create a new Linear Regression Model
11 LR_model = LinearRegression()
12
13 # Train the model
14 LR_model.fit(X_train, y_train)
15
16 # store actual and predited data to draw chart
17 predicted = LR_model.predict(X_test)
18 actual = y_test
19
20
21 # The coefficients
22 print('Coefficients: \n', LR_model.coef_)
23 # The mean squared error
24 print("Mean squared error: %.2f"
25       % mean_squared_error(actual, predicted))
26 # Explained variance score: 1 is perfect prediction
27 print('Variance score: %.2f' % r2_score(actual, predicted))
```

Output

```
Coefficients:
 [ -1.05001380e-01   3.29973196e-02   3.09915520e-02   2.74529793e+00
  -2.00482943e+01   4.60880933e+00  -1.36509230e-03  -1.27392294e+00
   2.69375701e-01  -1.12477385e-02  -9.48125356e-01   8.76288422e-03
  -4.24918821e-01]
Mean squared error: 33.77
Variance score: 0.67
```

WML - create scikit-learn linear regression model

```
1  from sklearn.linear_model import LinearRegression
2  from sklearn.datasets import load_boston
3  import matplotlib.pyplot as plt
4  from sklearn.model_selection import train_test_split
5  from sklearn.metrics import mean_squared_error, r2_score
6
7  boston = load_boston()
8  X_train, X_test, y_train, y_test = train_test_split(boston.data, boston.target)
9
10 # Create a new Linear Regression Model
11 LR_model = LinearRegression()
12
13 # Train the model
14 LR_model.fit(X_train, y_train)
15
16 # store actual and predited data to draw chart
17 predicted = LR_model.predict(X_test)
18 actual = y_test
19
20
21 # The coefficients
22 print('Coefficients: \n', LR_model.coef_)
23 # The mean squared error
24 print("Mean squared error: %.2f"
25       % mean_squared_error(actual, predicted))
26 # Explained variance score: 1 is perfect prediction
27 print('Variance score: %.2f' % r2_score(actual, predicted))
```

Output

```
Coefficients:
 [ -1.05001380e-01   3.29973196e-02   3.09915520e-02   2.74529793e+00
  -2.00482943e+01   4.60880933e+00  -1.36509230e-03  -1.27392294e+00
   2.69375701e-01  -1.12477385e-02  -9.48125356e-01   8.76288422e-03
  -4.24918821e-01]
Mean squared error: 33.77
Variance score: 0.67
```

WML - create scikit-learn linear regression model

```
1  from sklearn.linear_model import LinearRegression
2  from sklearn.datasets import load_boston
3  import matplotlib.pyplot as plt
4  from sklearn.model_selection import train_test_split
5  from sklearn.metrics import mean_squared_error, r2_score
6
7  boston = load_boston()
8  X_train, X_test, y_train, y_test = train_test_split(boston.data, boston.target)
9
10 # Create a new Linear Regression Model
11 LR_model = LinearRegression()
12
13 # Train the model
14 LR_model.fit(X_train, y_train)
15
16 # store actual and predited data to draw chart
17 predicted = LR_model.predict(X_test)
18 actual = y_test
19
20
21 # The coefficients
22 print('Coefficients: \n', LR_model.coef_)
23 # The mean squared error
24 print("Mean squared error: %.2f"
25       % mean_squared_error(actual, predicted))
26 # Explained variance score: 1 is perfect prediction
27 print('Variance score: %.2f' % r2_score(actual, predicted))
```

Output

```
Coefficients:
 [ -1.05001380e-01   3.29973196e-02   3.09915520e-02   2.74529793e+00
  -2.00482943e+01   4.60880933e+00  -1.36509230e-03  -1.27392294e+00
   2.69375701e-01  -1.12477385e-02  -9.48125356e-01   8.76288422e-03
  -4.24918821e-01]
Mean squared error: 33.77
Variance score: 0.67
```

WML - evaluation metrics

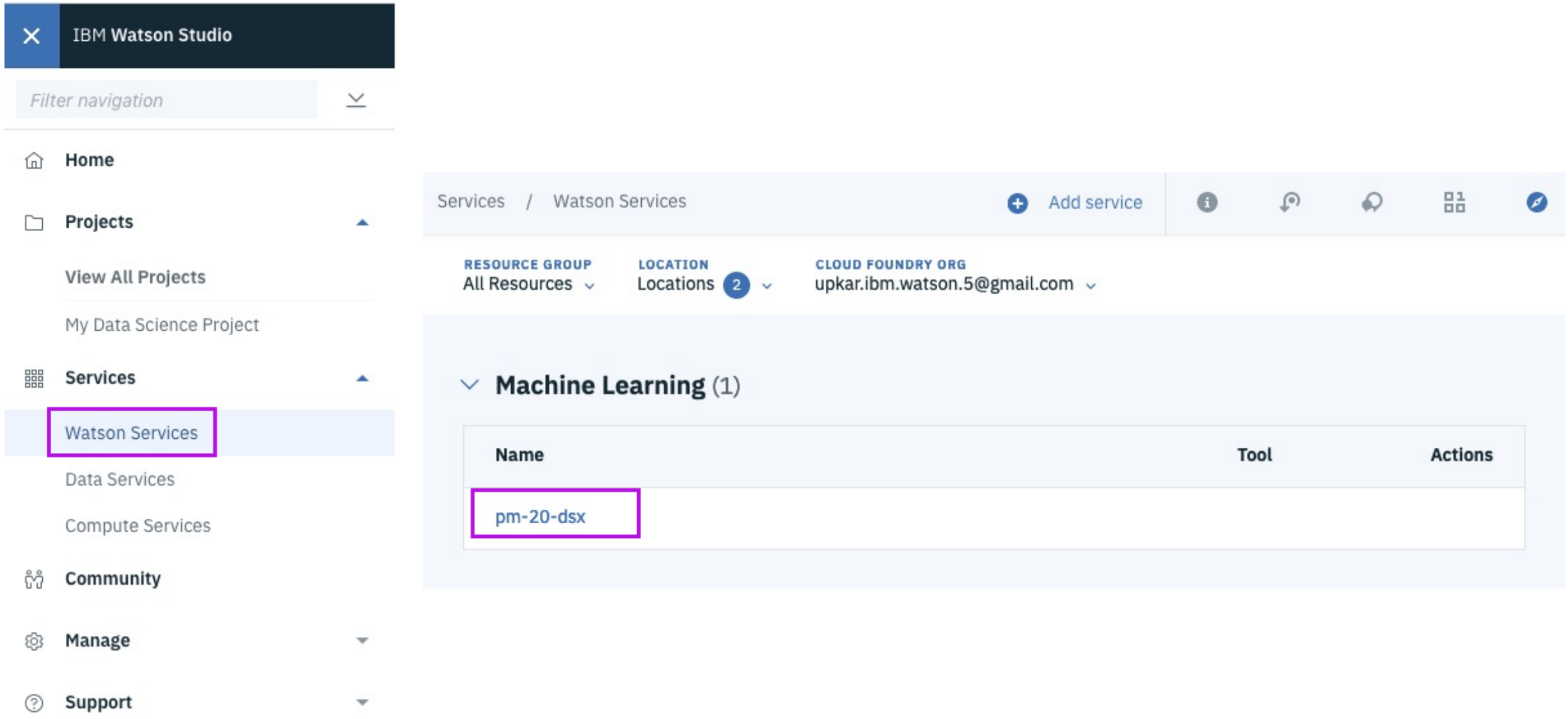
AutoAI

Name	Root Mean Squared Error (RMSE) (optimized)	Explained Variance	Mean Absolute Error (MAE)	Mean Squared Error (MSE)	Mean Squared Log Error (MSLE)	Median Absolute Error (MedAE)	Root Mean Squared Log Error (RMSLE)	R^2	Created At
P1	3.261	0.876	2.222	10.657	0.022	1.607	0.148	0.875	6/27/2019, 3:29:38 PM
P2	3.261	0.876	2.222	10.657	0.022	1.607	0.148	0.875	6/27/2019, 3:29:38 PM
P3	3.017	0.894	2.137	9.122	0.021	1.600	0.144	0.894	6/27/2019, 3:30:39 PM
P4	3.017	0.894	2.137	9.122	0.021	1.600	0.144	0.894	6/27/2019, 3:30:59 PM

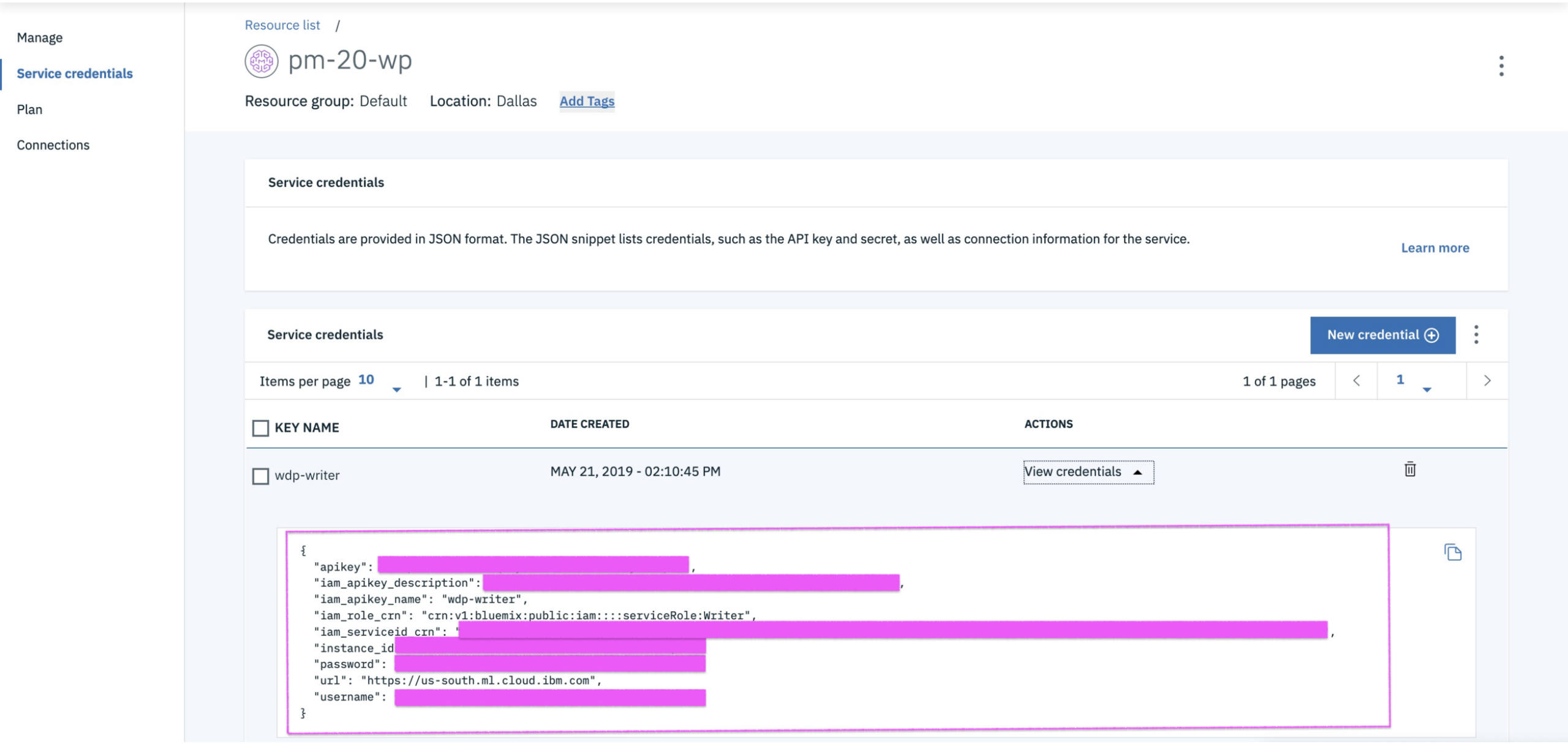
Notebook

```
Coefficients:
 [ -1.05001380e-01   3.29973196e-02   3.09915520e-02   2.74529793e+00
  -2.00482943e+01   4.60880933e+00  -1.36509230e-03  -1.27392294e+00
   2.69375701e-01  -1.12477385e-02  -9.48125356e-01   8.76288422e-03
  -4.24918821e-01]
Mean squared error: 33.77
Variance score: 0.67
```

WML - get Machine Learning service credentials



WML - get Machine Learning service credentials



WML - save scikit-learn linear regression model

```
# we will use WML to work with IBM Machine Learning Service
from watson_machine_learning_client import WatsonMachineLearningAPIClient

# Grab your credentials from the Watson Service section in Watson Studio or IBM Cloud Dashboard
wml_credentials = {
}

# Instantiate WatsonMachineLearningAPIClient
from watson_machine_learning_client import WatsonMachineLearningAPIClient
client = WatsonMachineLearningAPIClient( wml_credentials )

# store the model
published_model = client.repository.store_model(model=LR_model,
                                                meta_props={'name':'upkar-housing-linear-reg'},
                                                training_data=X_train, training_target=y_train)
```

WML - save scikit-learn linear regression model

```
# we will use WML to work with IBM Machine Learning Service
from watson_machine_learning_client import WatsonMachineLearningAPIClient

# Grab your credentials from the Watson Service section in Watson Studio or IBM Cloud Dashboard
wml_credentials = {
}

# Instantiate WatsonMachineLearningAPIClient
from watson_machine_learning_client import WatsonMachineLearningAPIClient
client = WatsonMachineLearningAPIClient( wml_credentials )

# store the model
published_model = client.repository.store_model(model=LR_model,
                                                meta_props={'name':'upkar-housing-linear-reg'},
                                                training_data=X_train, training_target=y_train)
```

WML - save scikit-learn linear regression model

```
# we will use WML to work with IBM Machine Learning Service
from watson_machine_learning_client import WatsonMachineLearningAPIClient

# Grab your credentials from the Watson Service section in Watson Studio or IBM Cloud Dashboard
wml_credentials = {
}

# Instantiate WatsonMachineLearningAPIClient
from watson_machine_learning_client import WatsonMachineLearningAPIClient
client = WatsonMachineLearningAPIClient( wml_credentials )

# store the model
published_model = client.repository.store_model(model=LR_model,
                                                meta_props={'name':'upkar-housing-linear-reg'},
                                                training_data=X_train, training_target=y_train)
```

WML - save scikit-learn linear regression model

```
# we will use WML to work with IBM Machine Learning Service
from watson_machine_learning_client import WatsonMachineLearningAPIClient

# Grab your credentials from the Watson Service section in Watson Studio or IBM Cloud Dashboard
wml_credentials = {
}

# Instantiate WatsonMachineLearningAPIClient
from watson_machine_learning_client import WatsonMachineLearningAPIClient
client = WatsonMachineLearningAPIClient( wml_credentials )

# store the model
published_model = client.repository.store_model(model=LR_model,
                                                meta_props={'name':'upkar-housing-linear-reg'},
                                                training_data=X_train, training_target=y_train)
```

WML - deploy scikit-learn linear regression model

```
import json

# grab the model from IBM Cloud
published_model_uid = client.repository.get_model_uid(published_model)

# create a new deployment for the model
model_deployed = client.deployments.create(published_model_uid, "Deployment of scikit model")

#get the scoring endpoint
scoring_endpoint = client.deployments.get_scoring_url(model_deployed)
print(scoring_endpoint)

#use the scoring endpoint to predict house median price some test data
scoring_payload = {"values": [list(X_test[0]), list(X_test[1])]}
predictions = client.deployments.score(scoring_endpoint, scoring_payload)
print(json.dumps(predictions, indent=2))
```

WML - deploy scikit-learn linear regression model

```
import json

# grab the model from IBM Cloud
published_model_uid = client.repository.get_model_uid(published_model)

# create a new deployment for the model
model_deployed = client.deployments.create(published_model_uid, "Deployment of scikit model")

#get the scoring endpoint
scoring_endpoint = client.deployments.get_scoring_url(model_deployed)
print(scoring_endpoint)

#use the scoring endpoint to predict house median price some test data
scoring_payload = {"values": [list(X_test[0]), list(X_test[1])]}
predictions = client.deployments.score(scoring_endpoint, scoring_payload)
print(json.dumps(predictions, indent=2))
```

WML - deploy scikit-learn linear regression model

```
import json

# grab the model from IBM Cloud
published_model_uid = client.repository.get_model_uid(published_model)

# create a new deployment for the model
model_deployed = client.deployments.create(published_model_uid, "Deployment of scikit model")

#get the scoring endpoint
scoring_endpoint = client.deployments.get_scoring_url(model_deployed)
print(scoring_endpoint)

#use the scoring endpoint to predict house median price some test data
scoring_payload = {"values": [list(X_test[0]), list(X_test[1])]}
predictions = client.deployments.score(scoring_endpoint, scoring_payload)
print(json.dumps(predictions, indent=2))
```

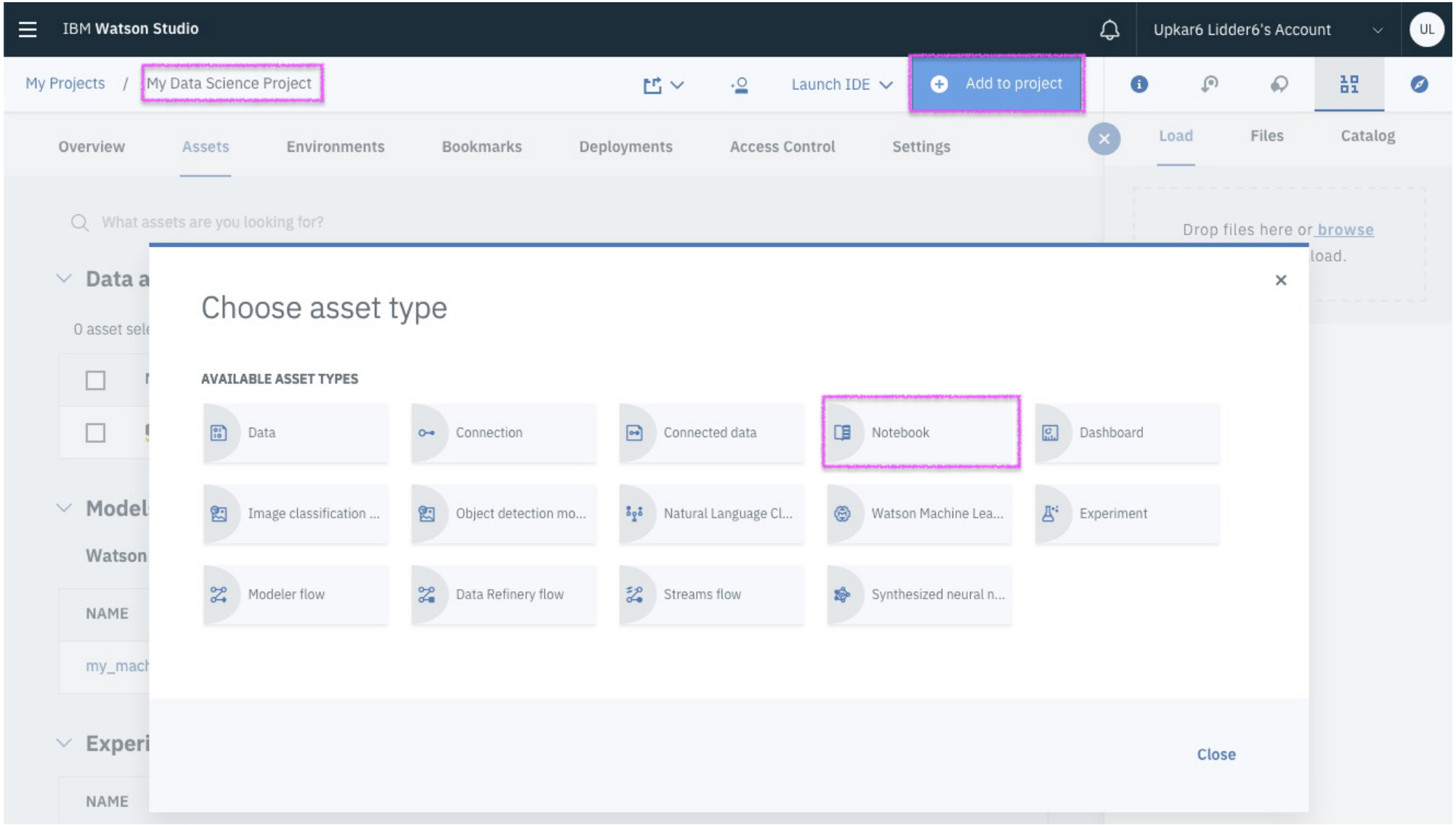
WML - deploy scikit-learn linear regression model

```
import json

# grab the model from IBM Cloud
published_model_uid = client.repository.get_model_uid(published_model)

# create a new deployment for the model
model_deployed = client.deployments.create(published_model_uid, "Deployment of scikit model")

#get the scoring endpoint
scoring_endpoint = client.deployments.get_scoring_url(model_deployed)
print(scoring_endpoint)

#use the scoring endpoint to predict house median price some test data
scoring_payload = {"values": [list(X_test[0]), list(X_test[1])]}
predictions = client.deployments.score(scoring_endpoint, scoring_payload)
print(json.dumps(predictions, indent=2))
```

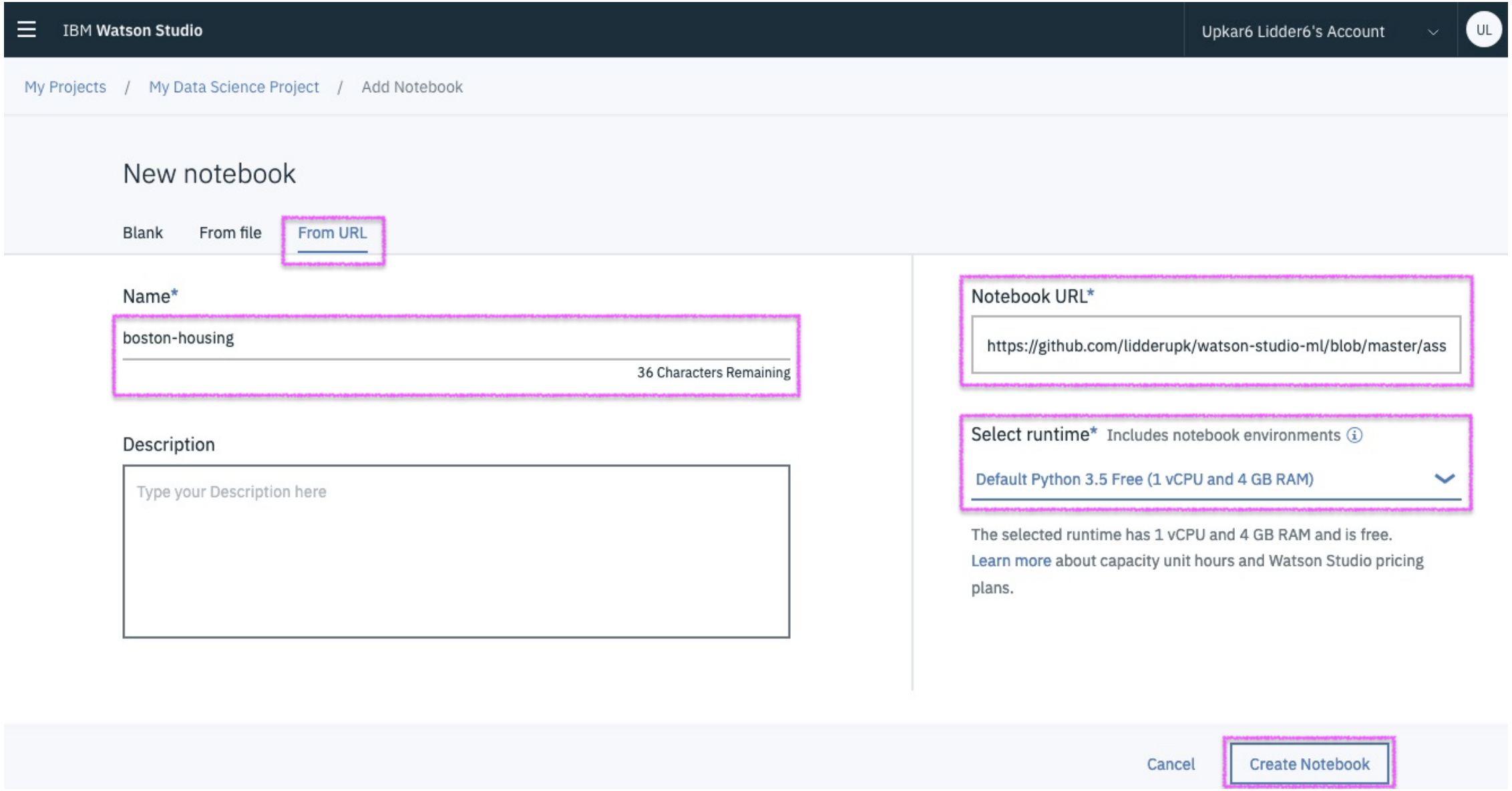
WML - deploy scikit-learn linear regression model

```
#######################################################################################

Synchronous deployment creation for uid: [redacted]' started

#######################################################################################


INITIALIZING
DEPLOY_SUCCESS


------------------------------------------------------------------------------------------------
Successfully finished deployment creation, deployment_uid='[redacted]'
------------------------------------------------------------------------------------------------


https://us-south.ml.cloud.ibm.com/v3/wml_instances/[redacted]/online
{
  "values": [
    [
      10.750284346772386
    ],
    [
      17.59893318342104
    ]
  ],
  "fields": [
    "prediction"
  ]
}
```

WML - try it out on your own ! Step1 - Sign into IBM Cloud

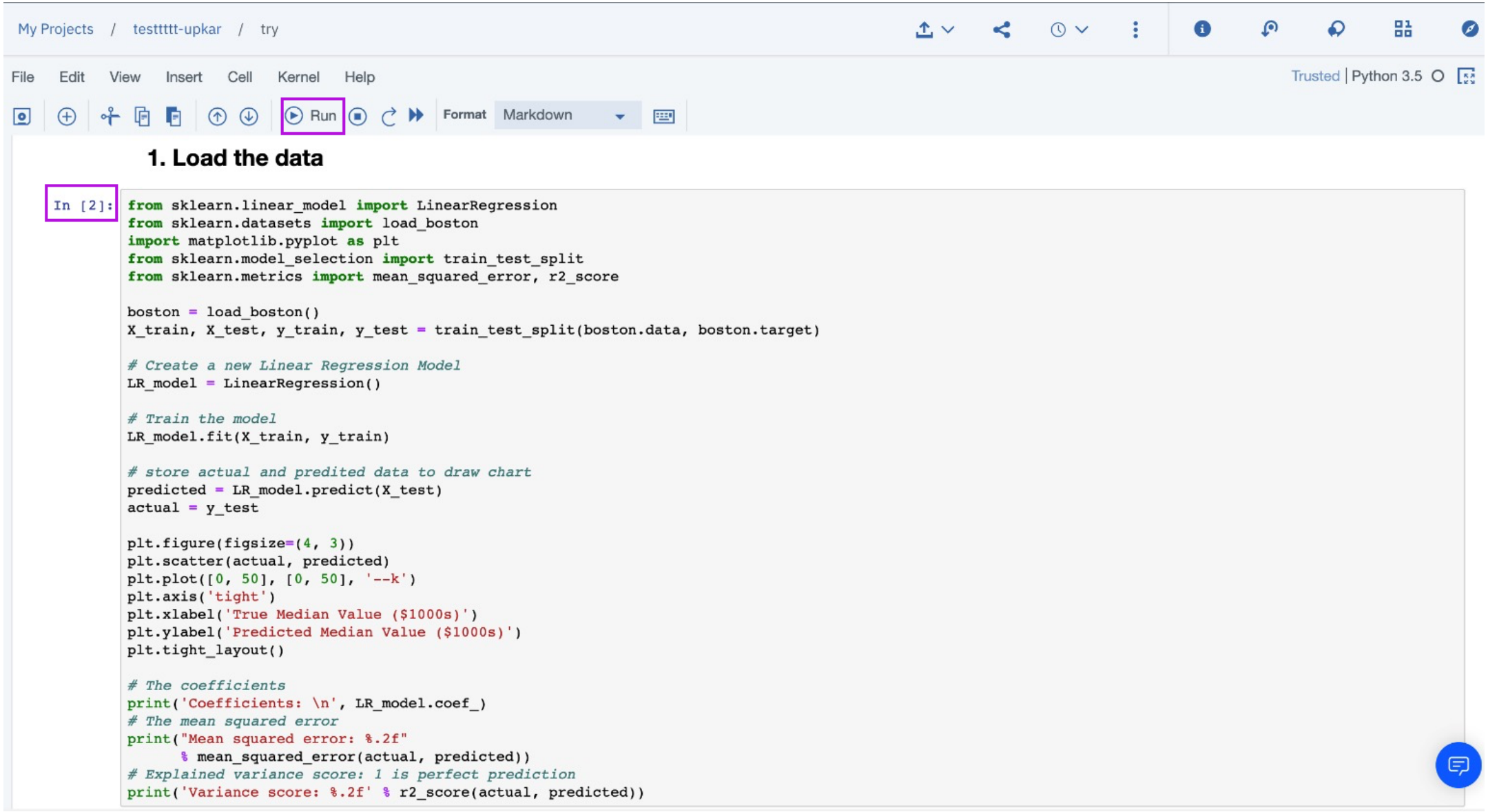


Step2 - create a new notebook from URL



Grab the FULL URL from : http://bit.ly/boston-house-notebook

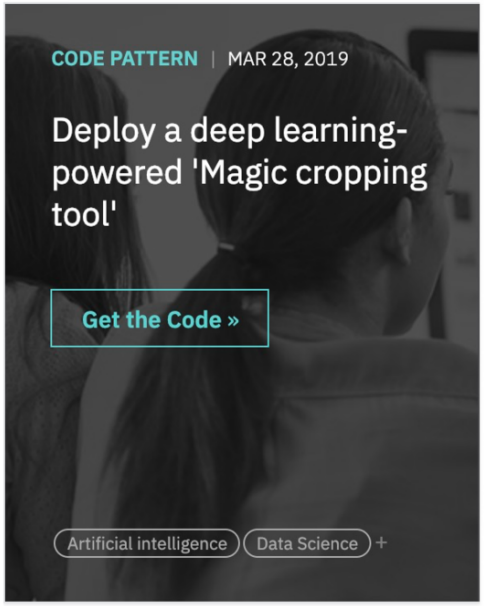
Step3 - paste your WML credentials and run each cell!

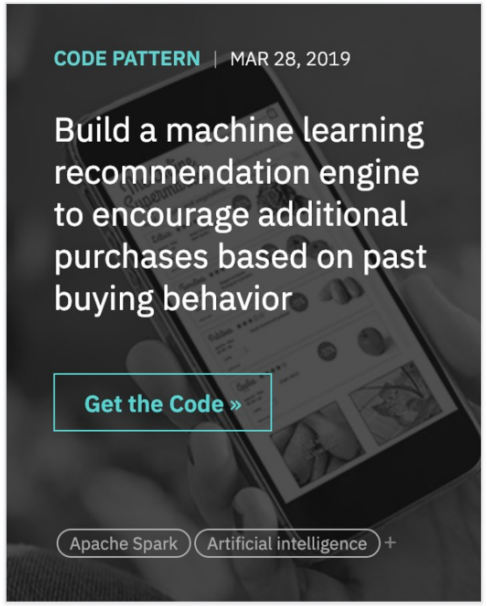


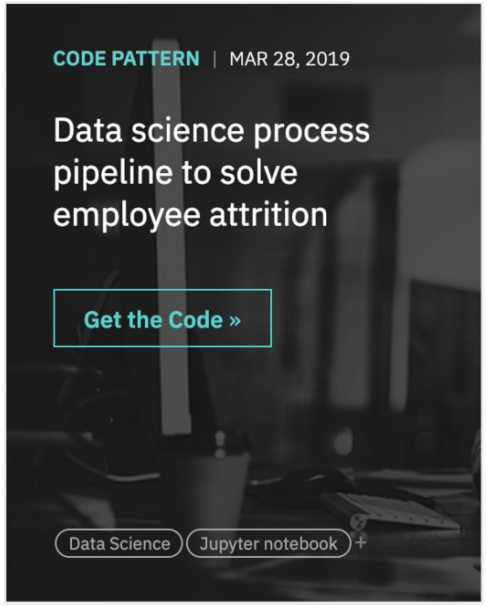
Grab the FULL URL from : http://bit.ly/boston-house-notebook

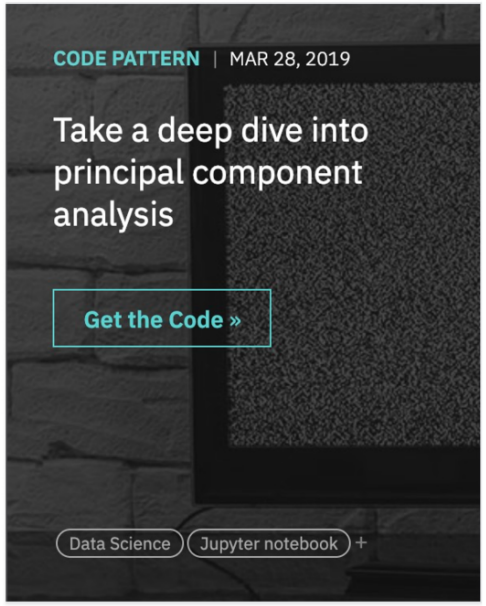
IBM Code Patterns

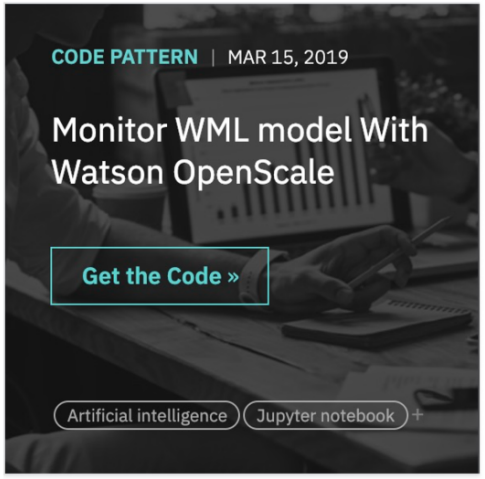
Machine Learning ×

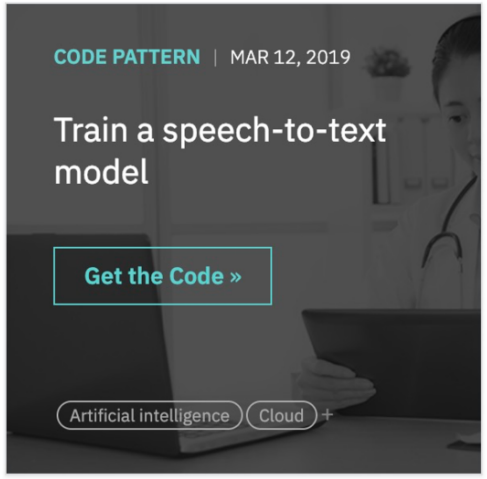


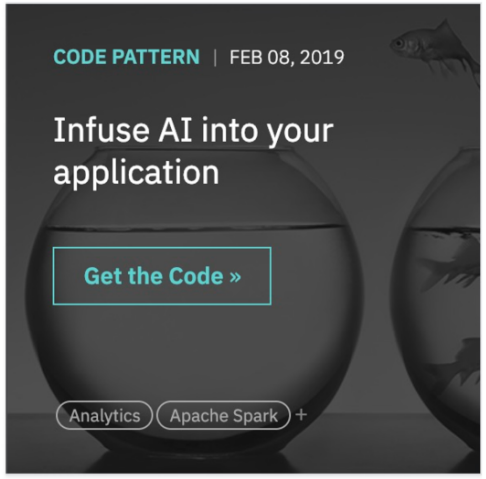












Thank you

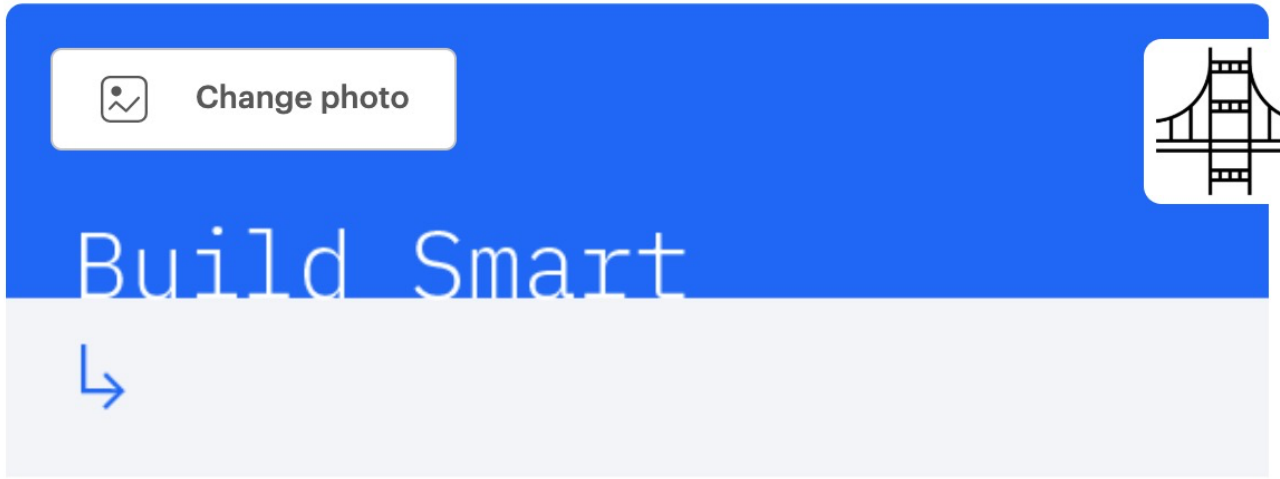
Let's chat !

Upkar Lidder, IBM

@lidderupk

https://github.com/lidderupk/

ulidder@us.ibm.com



Part of **IBM Developer – 29 groups**

IBM Developer SF Bay Area

San Francisco, CA

7,164 members · Public group

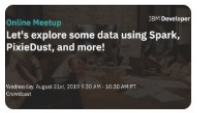
Organized by **Angie K** and **6 others**

IBM **Developer**

Share:

WED, AUG 21, 9:30 AM

Online Meetup: Let's explore some data using Spark, PixieDust, and more!



Needs a location

RSVP on Crowdcast NOW! https://www.crowdcast.io/e/8u3d6q3c ❗ Please do not forget to register on Crowdcast and join us using Chrome browser via Crowdcast on the event date! Spark and PixieDust! What cool names! They also happen to be two of my favorite open source tools t...

40 attendees Manage Going

THU, AUG 22, 12:00 PM

Lunch & Learn: A Tale of Two Disciplines-How Designers & Developers Co-Create

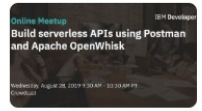
44 Tehama St

Two worlds collide – Design and Development. Will they destroy each other? Or will they peacefully co-exist and thrive, creating a beautiful new world! Join IBM Developer SF's lunch and learn to discover how IBM Cloud Garage designers and developers collaborate and co-create...

66 attendees Manage Attend

WED, AUG 28, 9:30 AM

Online Meetup: Build serverless APIs using Postman and Apache OpenWhisk



Needs a location

RSVP on Crowdcast NOW! https://www.crowdcast.io/e/lvaejjgs ❗ Please do not forget to register on Crowdcast and join us using Chrome browser via Crowdcast on the event date! IBM and Postman are partnering up to show you how to use open source tools to create and test scalabl...

36 attendees Manage Going

IBM Partners

Enabling Independent Software Vendors (ISVs) and tech companies for growth

Target audience

- ISVs and tech companies building and selling cloud solutions
- New to IBM Cloud
- Startups who aspire to build and sell their own solutions

Offers to help you get started

Build with up to $12,000 of free IBM Cloud™ credits ($1,000 per month for 12 months)

Integrate your solutions with leading-edge IBM Cloud technologies to deliver more innovation and value to your clients. Access more than **130 unparalleled services** including Watson™, Analytics and Security.

Build with 10TB of IBM Cloud Object Storage at no charge

Build data capability into your offering. IBM Cloud Object Storage is designed for high durability, resiliency and security.

Build with IBM Watson Assistant with a 1-year free trial

Receive access to 100K API calls per month plus 10 workspaces. Build and deploy chatbots quickly and efficiently with IBM Watson Assistant's advanced capabilities and seamless interface.

Get started

Experience IBM's countless partner benefits. Start building and selling with IBM today.

Learn more and access offers at ibm.com/partners/start

Build with IBM Cloud Kubernetes Service with a 1-year free trial

Containerize your solution with 1TB of block storage. Ship all your applications in one agile, well-defined structure with IBM Cloud Kubernetes Service.

Build with IBM Blockchain with a 6-month free trial

Build a network with up to 3 organizations to prototype. Build a secure business transaction network for your clients using blockchain and smart contracts.

Finished building and testing? Go-to-market with IBM

Access Provider Workbench, attend an orientation session and join the premier network of over 400 partners who are already listing their solutions on the IBM Marketplace.

Is your business a Startup? Build with up to $120,000 in IBM Cloud credits

If your business revenue in the last 12 months is less than $1M and you've been in business for fewer than five years, then you may qualify for Startup with IBM.