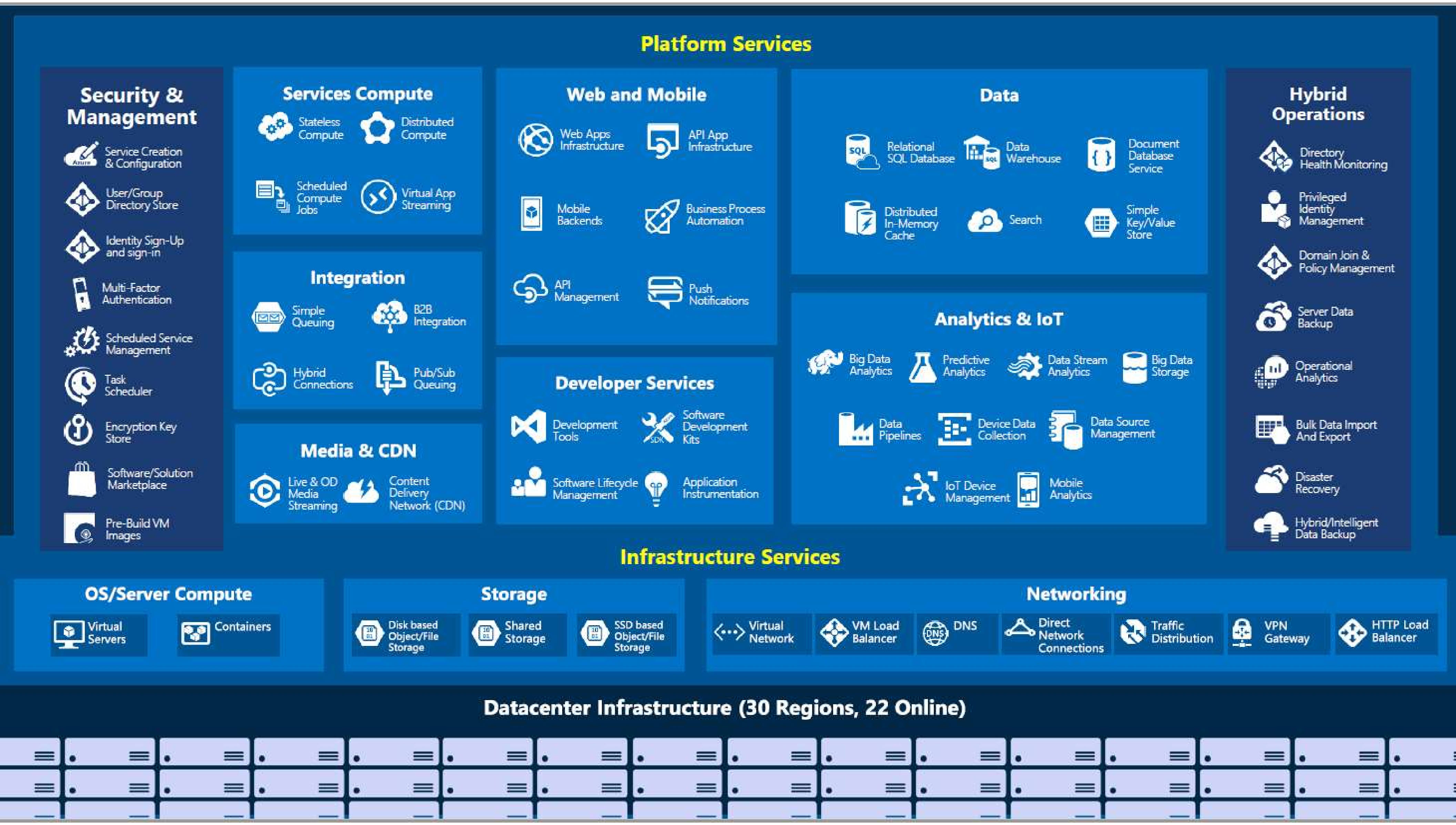
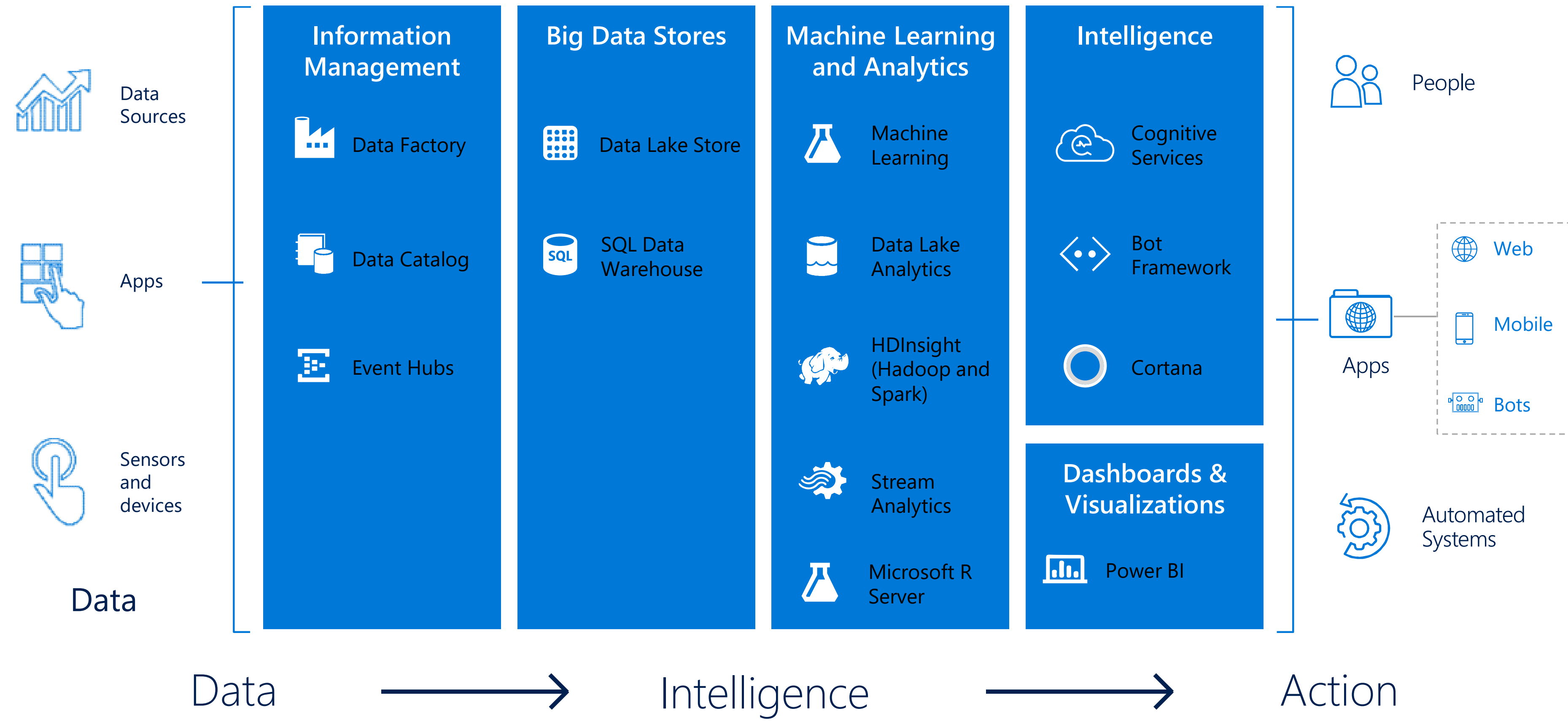

Platform Services
Security & Management
Service Creation & Configuration
User/Group Directory Store
Identity Sign-Up and sign-in
Multi-Factor Authentication
Scheduled Service Management
Task Scheduler
Encryption Key Store
Software/Solution Marketplace
Pre-Build VM Images
Services Compute
Stateless Compute
Distributed Compute
Scheduled Compute Jobs
Virtual App Streaming
Integration
Simple Queuing
B2B Integration
Hybrid Connections
Pub/Sub Queuing
Media & CDN
Live & OD Media Streaming
Content Delivery Network (CDN)
Web and Mobile
Web Apps Infrastructure
API App Infrastructure
Mobile Backends
Business Process Automation
API Management
Push Notifications
Developer Services
Development Tools
Software Development Kits
Software Lifecycle Management
Application Instrumentation
Data
Relational SQL Database
Data Warehouse
Document Database Service
Distributed In-Memory Cache
Search
Simple Key/Value Store
Analytics & IoT
Big Data Analytics
Predictive Analytics
Data Stream Analytics
Big Data Storage
Data Pipelines
Device Data Collection
Data Source Management
IoT Device Management
Mobile Analytics
Hybrid Operations
Directory Health Monitoring
Privileged Identity Management
Domain Join & Policy Management
Server Data Backup
Operational Analytics
Bulk Data Import And Export
Disaster Recovery
Hybrid/Intelligent Data Backup
Infrastructure Services
OS/Server Compute
Virtual Servers
Containers
Storage
Disk based Object/File Storage
Shared Storage
SSD based Object/File Storage
Networking
Virtual Network
VM Load Balancer
DNS
Direct Network Connections
Traffic Distribution
VPN Gateway
HTTP Load Balancer
Datacenter Infrastructure (30 Regions, 22 Online)

Transform data into intelligent action



Microsoft

Microsoft & Machine Learning

17 years of realizing innovation

1999	2004	2005	2008	2010	2012	2014
Computers work on users behalf, filtering junk email	Microsoft search engine built with machine learning	SQL Server enables data mining	Bing Maps ships with ML traffic-prediction service	Microsoft Kinect can watch users gestures	Successful, real-time, speech-to-speech translation	Microsoft launches Azure Machine Learning

John Platt,
Distinguished scientist at
Microsoft Research

"Machine learning is pervasive throughout Microsoft products."

Microsoft Azure Machine Learning

Built for a cloud-first, mobile-first world

Fully managed

No software to install, no hardware to manage, and one portal to view and update.

Integrated

Simple drag, drop and connect interface for Data Science. No need for programming for common tasks.

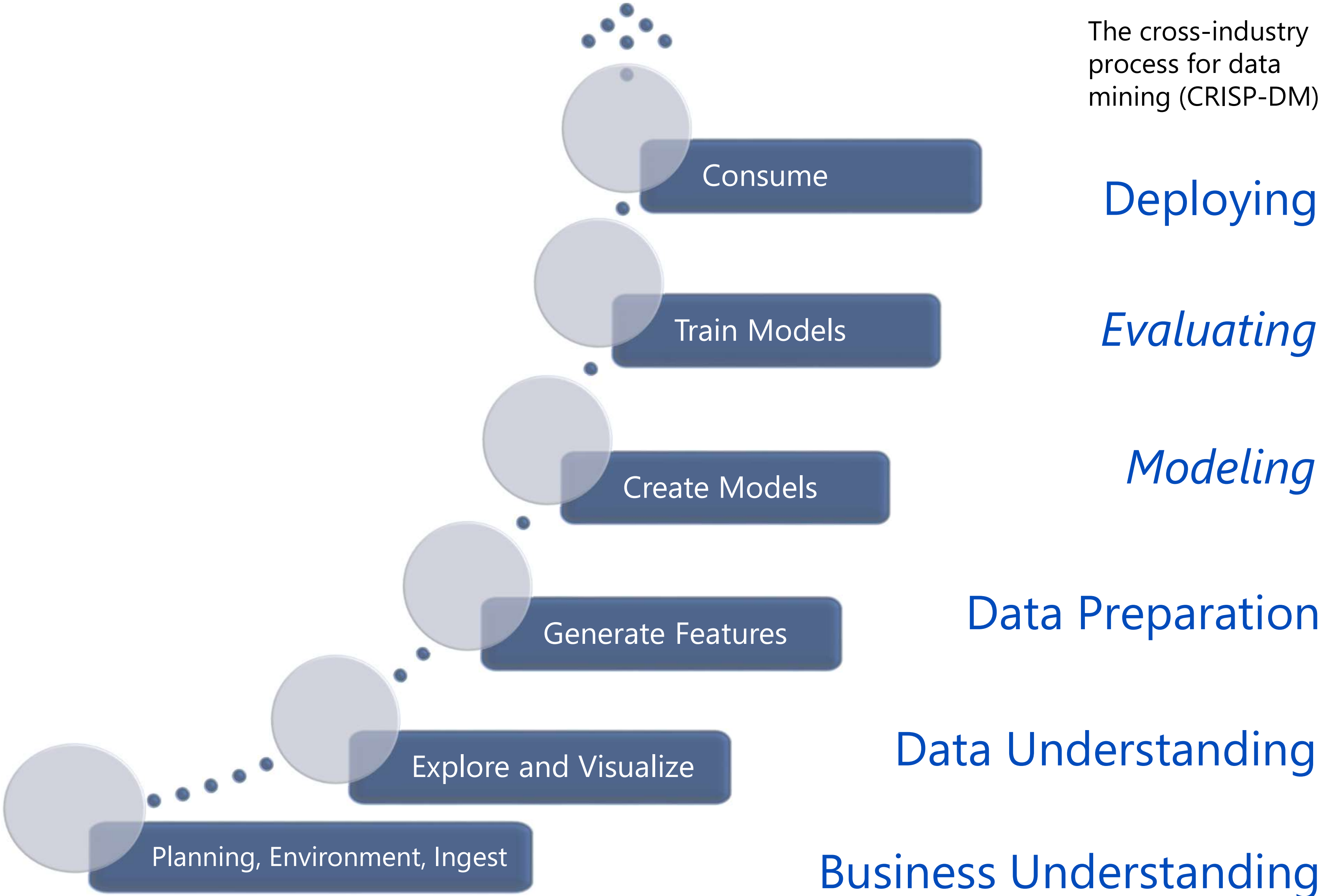
Best in Class Algorithms + R + Python

Built-in collection of best of breed algorithms. Support for R and Python.

Deploy in Seconds

Operationalize models with a single click. Retrain models programmatically.

Data Science Process



Everyday examples of predictive analytics

- Product recommendation – "customers who bought this item also bought"
- Mortgage applications – credit worthiness
- Pattern recognition – speech recognition on your smart phone, character recognition on postal mails, facial recognition on security systems
- Web search page result – display sequences to render on page
- Predictive Maintenance – used on things we can monitor: planes, elevators, cars, data centers, etc.
- Healthcare – determine patient outcomes and future care

Getting Started with Azure Machine Learning (First time setting up)

- Set up a Microsoft Azure Account
- One stop shop for Azure services -> portal.microsoft.com
- Set up an AzureML Workspace -> under Intelligence + analytics, choose Machine Learning Workspace
- Give a workspace name
- Set up a new Resource Group
- Set up a new Storage Account
- Set up a new Web Service Plan
- Launch AzureML Studio

Accessing Azure Machine Learning (Return visits)

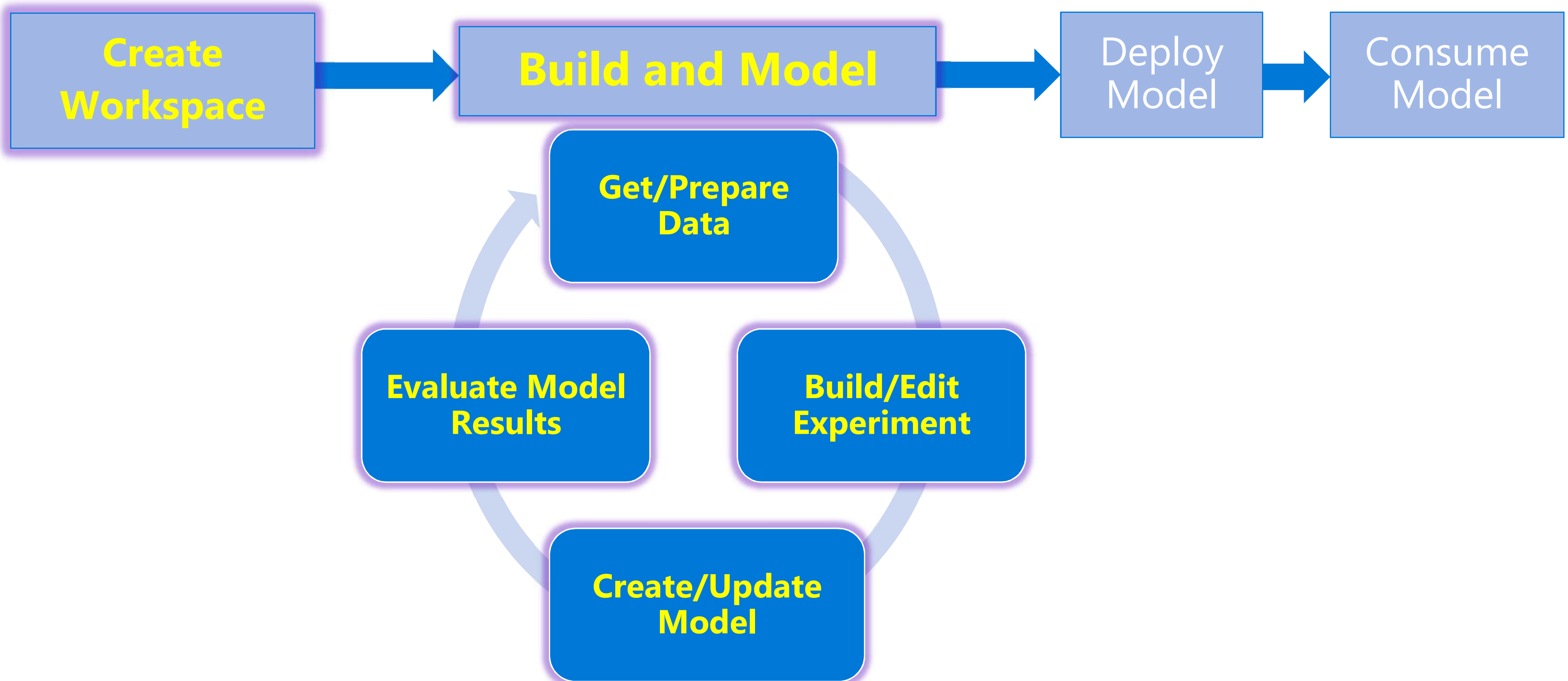
Option 1

- Log in to Azure portal -> portal.microsoft.com
- Select your AzureML workspace on the dashboard
- Launch AzureML Studio

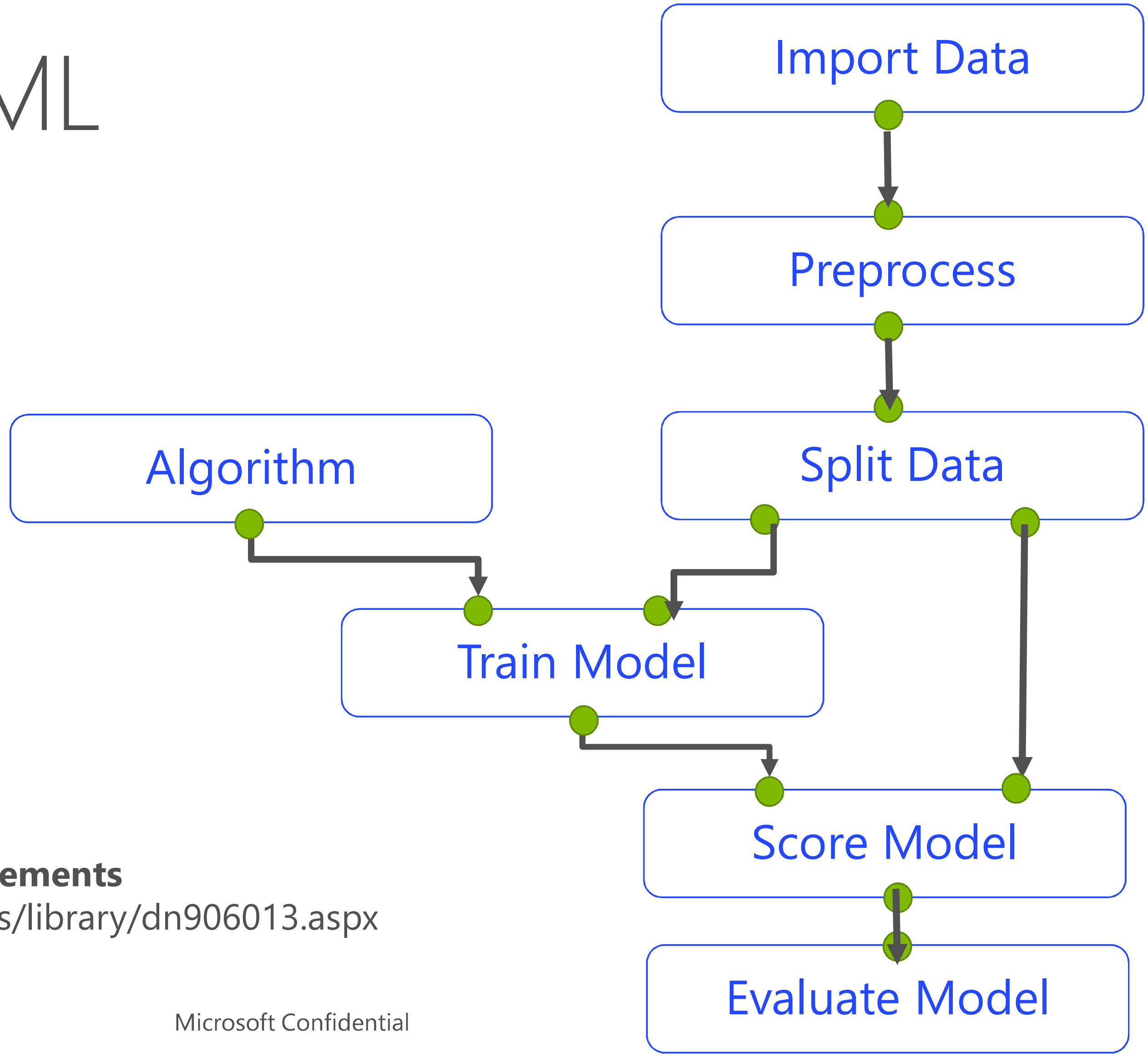
Option 2

- Log in directly to AzureML Studio -> studio.azureml.net

Creating an Experiment



Basic Azure ML Elements



Reference to all the AzureML Elements
https://msdn.microsoft.com/en-us/library/dn906013.aspx

Import Data

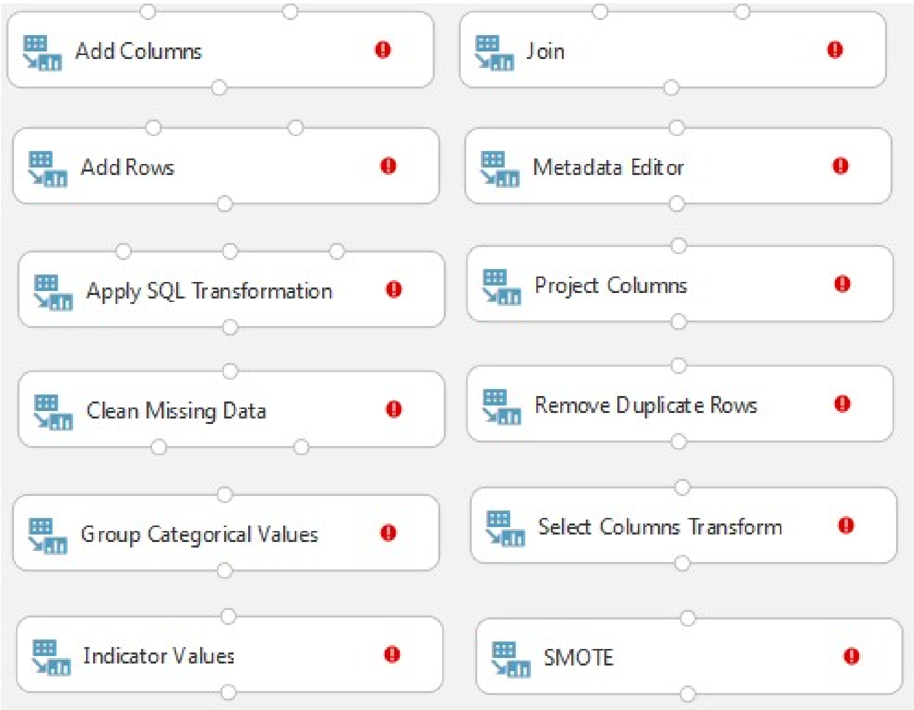
- Read data from:
  - Web URL
  - Hive query
  - Azure SQL database
  - Azure table
  - Azure blob storage

- Load a collection of images from blob storage for use in image classification tasks

Preprocess Data

Prepare data for Machine Learning

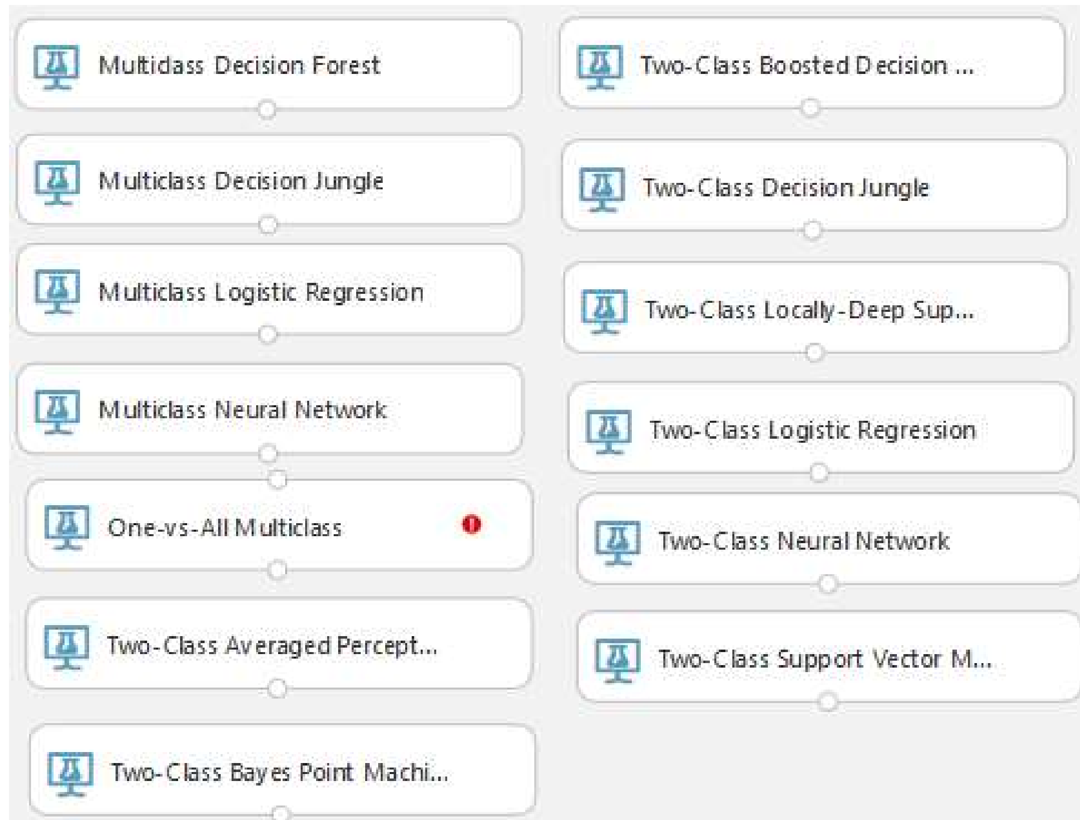
- Merging datasets
- Grouping and summarizing data
- Converting values to another type
- Checking for missing values and replacing them with appropriate values
- Flagging columns as features (for example, labels)

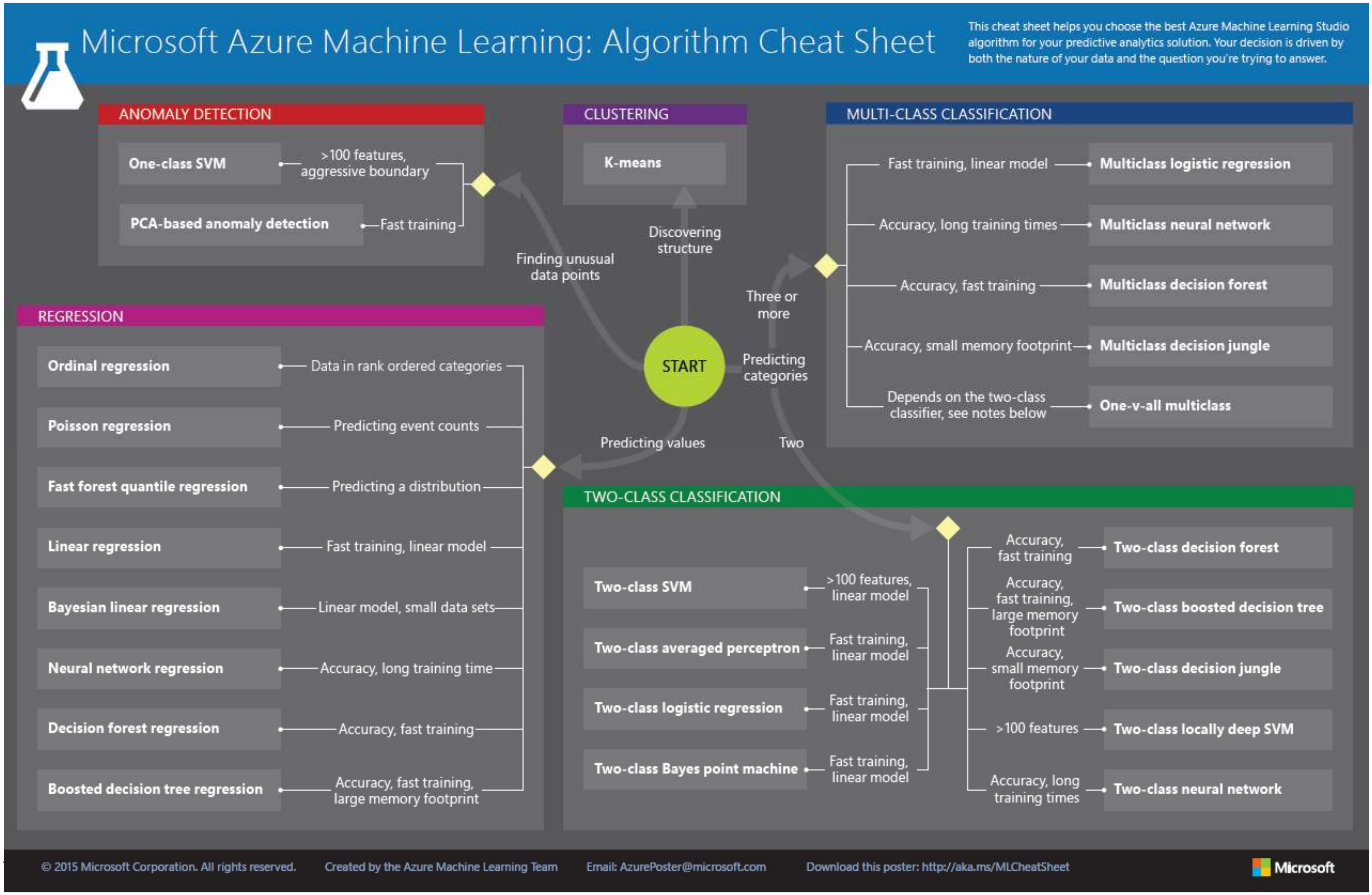


Choosing a Model

Initialize Model – Classification

- Predict the class or category for data





Microsoft Azure Machine Learning: Algorithm Cheat Sheet
This cheat sheet helps you choose the best Azure Machine Learning Studio algorithm for your predictive analytics solution. Your decision is driven by both the nature of your data and the question you're trying to answer.
ANOMALY DETECTION
One-class SVM
>100 features, aggressive boundary
PCA-based anomaly detection
Fast training
CLUSTERING
K-means
MULTI-CLASS CLASSIFICATION
Fast training, linear model
Multiclass logistic regression
Accuracy, long training times
Multiclass neural network
Accuracy, fast training
Multiclass decision forest
Accuracy, small memory footprint
Multiclass decision jungle
Depends on the two-class classifier, see notes below
One-v-all multiclass
Finding unusual data points
Discovering structure
Three or more
Predicting categories
START
Predicting values
Two
REGRESSION
Ordinal regression
Data in rank ordered categories
Poisson regression
Predicting event counts
Fast forest quantile regression
Predicting a distribution
Linear regression
Fast training, linear model
Bayesian linear regression
Linear model, small data sets
Neural network regression
Accuracy, long training time
Decision forest regression
Accuracy, fast training
Boosted decision tree regression
Accuracy, fast training, large memory footprint
TWO-CLASS CLASSIFICATION
Two-class SVM
>100 features, linear model
Two-class averaged perceptron
Fast training, linear model
Two-class logistic regression
Fast training, linear model
Two-class Bayes point machine
Fast training, linear model
Accuracy, fast training
Two-class decision forest
Accuracy, fast training, large memory footprint
Two-class boosted decision tree
Accuracy, small memory footprint
Two-class decision jungle
>100 features
Two-class locally deep SVM
Accuracy, long training times
Two-class neural network
© 2015 Microsoft Corporation. All rights reserved.
Created by the Azure Machine Learning Team
Email: AzurePoster@microsoft.com
Download this poster: http://aka.ms/MLCheatSheet
Microsoft

Machine Learning Algorithms

Split into two main categories:

- Supervised learning
  - Labels provided
  - Predicting the future
  - Learn from known past examples to predict future

- Unsupervised learning
  - Labels not provided
  - Understanding the past and making sense of data
  - Learning the structure of data

Supervised learning – example

Data Input Features (Vectors)

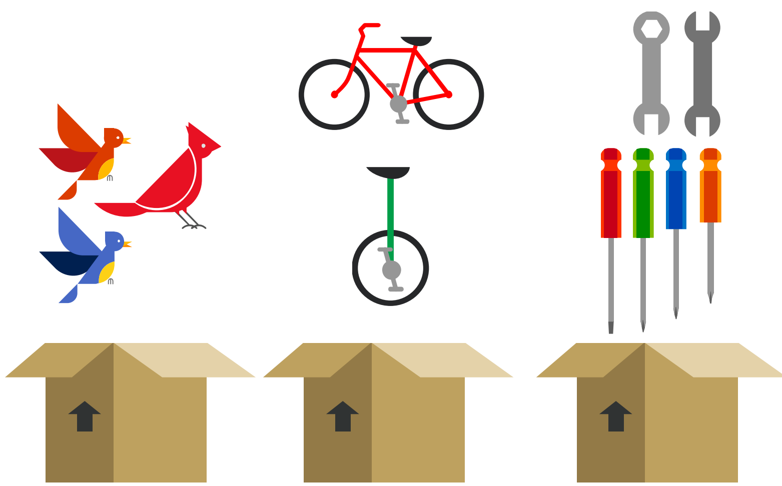
Known Outcomes

age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	hours-per-week	income
39	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Not-in-family	White	Male	60	<=50K
38	State-gov	Doctorate	16	Married-civ-spouse	Prof-specialty	Husband	White	Male	45	>50K
38	Private	Some-college	10	Divorced	Exec-managerial	Not-in-family	White	Female	50	<=50K
38	Private	Assoc-voc	11	Married-civ-spouse	Craft-repair	Husband	Black	Male	40	<=50K
66	Private	11th	7	Married-civ-spouse	Craft-repair	Husband	White	Male	20	<=50K
26	Private	Bachelors	13	Married-civ-spouse	Sales	Wife	Black	Female	40	>50K
50	Private	9th	5	Divorced	Transport-moving	Not-in-family	White	Male	50	<=50K
53	Private	HS-grad	9	Married-civ-spouse	Craft-repair	Husband	White	Male	40	<=50K
28	Private	HS-grad	9	Never-married	Transport-moving	Unmarried	White	Male	55	<=50K
28	Private	HS-grad	9	Never-married	Exec-managerial	Not-in-family	White	Male	40	<=50K

Machine Learning Capabilities

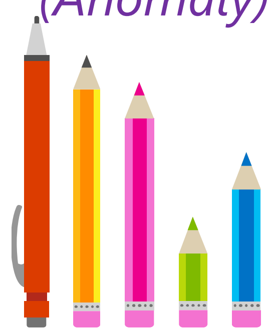
SUPERVISED

Which category
(Classification)



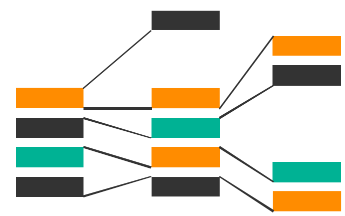
How much/many
(Regression)

Is it odd
(Anomaly)



UNSUPERVISED

Which group
(Clustering, Recommender)



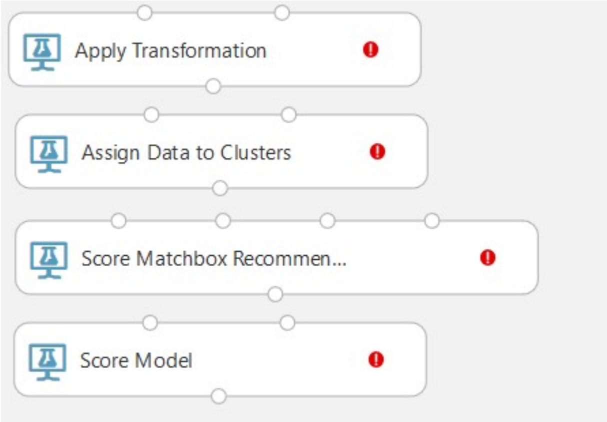
Testing the Model

Apply a trained model to the test data to get:

- Estimates of projected demand, volume, or other numeric quantity, for regression models
- Cluster assignments
- A predicted class or outcome, for classification models
- Probability scores associated with these outputs

Train

Score



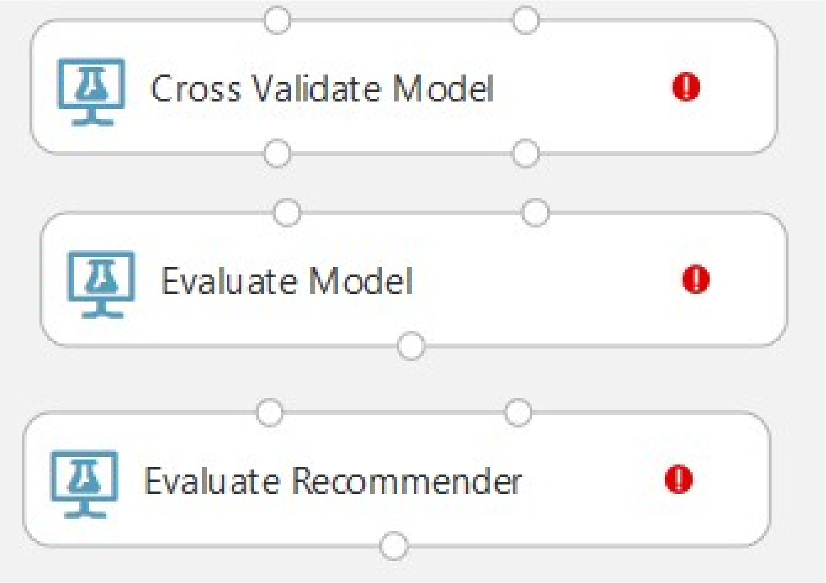
Evaluating the Model

Metrics for Classification Models

- Accuracy
- Recall
- Precision
- F-Score
- AUC
- Average Log Loss
- Training Log Loss

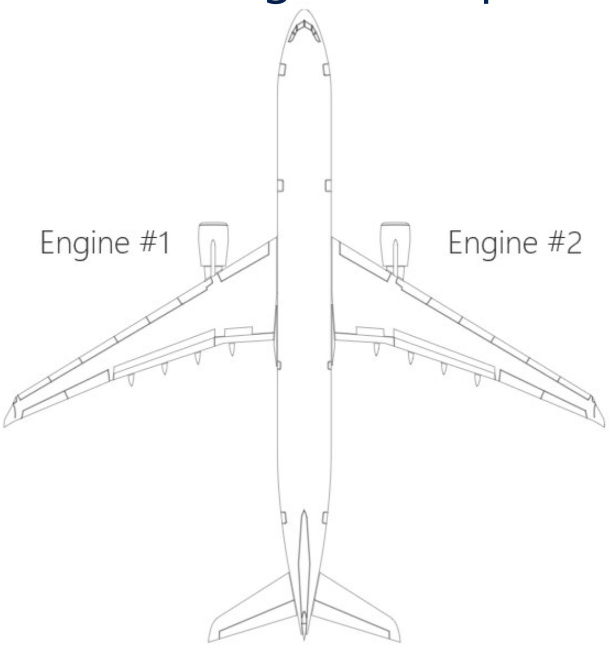
Metrics for Regression Models

- Mean absolute error (MAE)
- Root mean squared error (RMSE)
- Relative absolute error (RAE)
- Relative squared error (RSE)
- Coefficient of determination



Azure Machine Learning – Aerospace Predictive Maintenance

Predict the time-to-failure of aircraft engine components.



Data – sensor readings from plane engines

Sample training data

~20k rows,
100 unique engine id

id	cycle	setting1	setting2	setting3	s1	s2	s3	...	s19	s20	s21
1	1	-0.0007	-0.0004	100	518.67	641.82	1589.7		100	39.06	23.419
1	2	0.0019	-0.0003	100	518.67	642.15	1591.82		100	39	23.4236
1	3	-0.0043	0.0003	100	518.67	642.35	1587.99		100	38.95	23.3442
...	...										
1	191	0	-0.0004	100	518.67	643.34	1602.36		100	38.45	23.1295
1	192	0.0009	0	100	518.67	643.54	1601.41		100	38.48	22.9649
2	1	-0.0018	0.0006	100	518.67	641.89	1583.84		100	38.94	23.4585
2	2	0.0043	-0.0003	100	518.67	641.82	1587.05		100	39.06	23.4085
2	3	0.0018	0.0003	100	518.67	641.55	1588.32		100	39.11	23.425
...	...										
2	286	-0.001	-0.0003	100	518.67	643.44	1603.63		100	38.33	23.0169
2	287	-0.0005	0.0006	100	518.67	643.85	1608.5		100	38.43	23.0848

s1 – s21 are raw features.

a1 – a21 and sd1 – sd21 are aggregated features, they represent moving average and standard deviation of sensor values in the most recent 5 cycles.

Building a regression model (part 1 of 2)

- Data Input and Output -> Import training data
  - Web URL via HTTP
  - http://azuremlsamples.azureml.net/templatedata/PM_step1output_train.csv
  - Csv with header
- Data Transformation -> Manipulation -> Select Columns in dataset
  - Select all columns except for label1 and label2
- Data Transformation -> Manipulation -> Edit Metadata
  - Change RUL to label
- Feature Selection -> Filter Based Feature Selection
  - Feature scoring method: Pearson correlation
  - select RUL as target column
  - Number of desired features -> set to 35

Building a regression model (part 2 of 2)

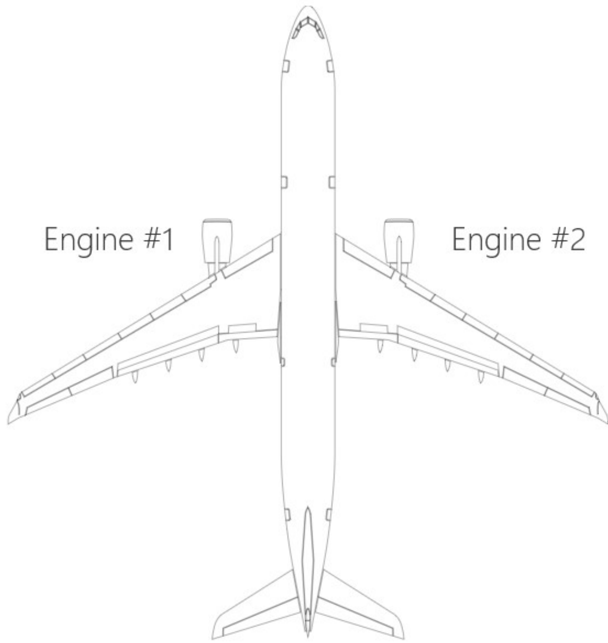
- Machine Learning -> Initialize Model -> Regression -> Decision Forest Regression
  - Leave parameters as defaults
- Machine Learning -> Initialize Model -> Regression -> Linear Regression
  - Leave parameters as defaults
- Machine Learning -> Train -> Train Model
  - Set it for both models
  - Select RUL as column name
- Machine Learning -> Score -> Score Model
  - Set it for both models
- Machine Learning -> Evaluate -> Evaluate Model
- Data Input and Output -> Import training data
  - Web URL via HTTP
  - http://azuremlsamples.azureml.net/templatedata/PM_step1output_test.csv
  - Csv with header
  - Connect to second port of the Score Model module
- Run the model

Evaluating regression models

- What features are used?
  - Select Visualize from “Filter Based Feature Selection”
- What are the predicted numeric outcomes?
  - Select Visualize from “Score Model”
- What are the evaluation indicators?
  - Mean Absolute Error
  - Root Mean Squared Error
  - Relative Absolute Error
  - Relative Squared Error
  - Coefficient of Determination

Azure Machine Learning – Aerospace Predictive Maintenance

Predict if an asset will fail within certain time frame (e.g. days).



Building a classification model (part 1 of 2)

- Re-use your regression model template
  - Save As -> New Name
- Re-use the same data for train and test
- Data Transformation -> Manipulation -> Select Columns in dataset
  - Make sure you select label1 as well, and exclude RUL and label2
- Data Transformation -> Manipulation -> Edit Metadata
  - Change label1 to label
- Feature Selection -> Filter Based Feature Selection
  - Feel free to try another feature scoring method
  - select label1 as target column
  - Number of desired features -> set to any number you like

Building a classification model (part 2 of 2)

- Try FOUR different two-class classification algorithms
- Evaluate all FOUR models
  - Evaluate Model module compares takes at most two models as inputs, so you will need two Evaluate Model modules
- Data Transformation -> Manipulation -> Add Rows
  - Join both Evaluate Model Modules
  - This step will append the evaluation metrics and stack them into one single table for all four models
- R Language Modules -> Execute R Script
  - Keep the first line and last line
  - Delete the rest, and add the following code to the body
  - Give the descriptions of your models, from left to right

```
a <- c("Logistic Regression", "Boosted Decision Tree", "Decision Forest", "Neural Network")
data.set <- cbind(a, dataset)
names(data.set)[1] <- c("Algorithms")
```

Evaluating classification models (part 1 of 2)

	Event=Positive	Event=Negative	Events
Predicted Positive	True Positive(TP)	False Positive(FP)	TP+FP
Predicted Negative	False Negative(FN)	True Negative(TN)	FN+TN
Observations	TP+FN	FP+TN	Te

Accuracy
- Ratio of correctly predicted observations
- Accuracy=(TP+TN)/Te
- Good for even distribution of data say 50/50

Precision
- What percentage of Predicted observation were correct
- Precision=(TP)/(TP+FP)
- Good for uneven distribution

Recall
- What percentage of positive events were correctly predicted(sensitivity)
- Recall=TP/(TP+FN)
- Good for uneven distribution

F1 Score
- Weighted average of Precision and Recall
- F1 Score=2*(Recall*Precision)/(Recall + Precision)
- Better way to show uneven distribution

Data Set	Events=Positive	Events=Negative	Events
Predicted Positive	2894	994	3888
Predicted Negative	643	11750	12393
Observations	3537	12744	16281

Total Events=16281

Accuracy=(2894+1750)/16281=~90%

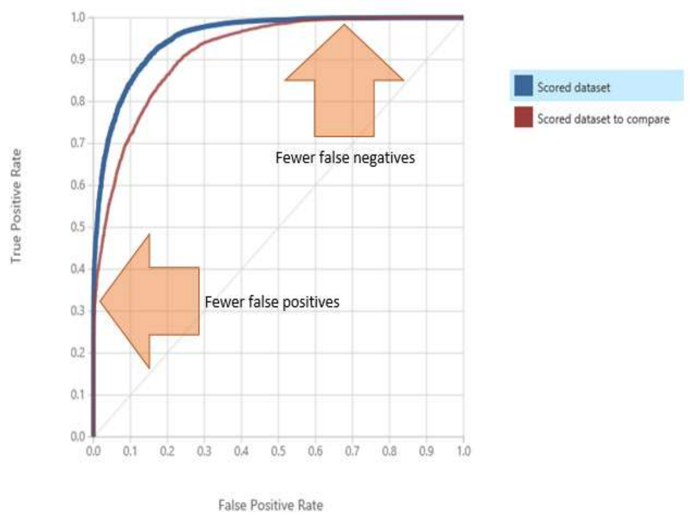
Precision=2894/3537=~82%

Recall=2894/3888=~74%

F1 Score= 2*(0.74*0.82)/(0.74+0.82)=~78%

Evaluating classification models (part 2 of 2)

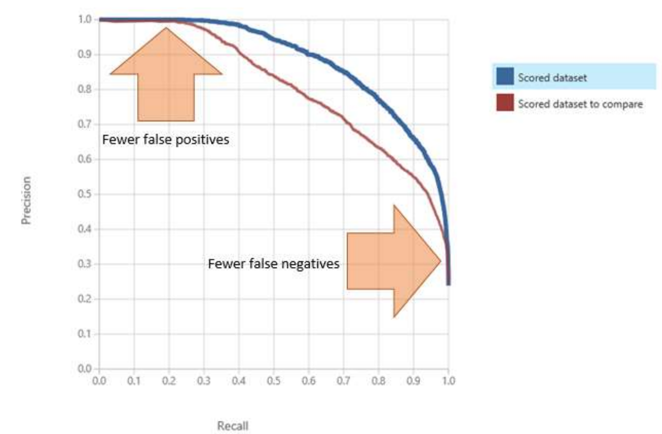
ROC- Receiver operating characteristics



AUC- Area under the curve

- Between 0 and 1, ideally should be close to 1

Precision / Recall Plot



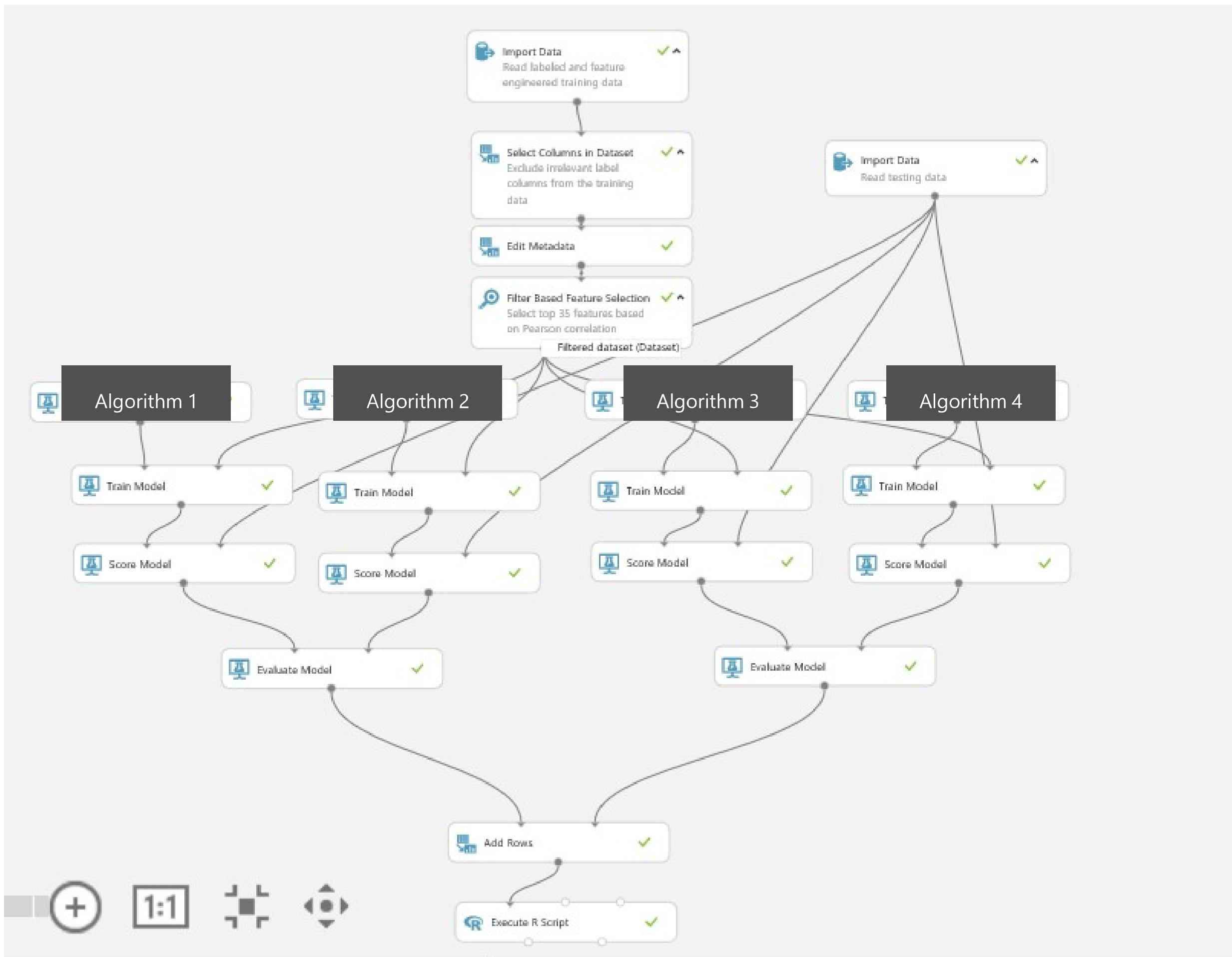
Threshold

- Optimize based on cost of False positive vs False negatives

Let the game begin…

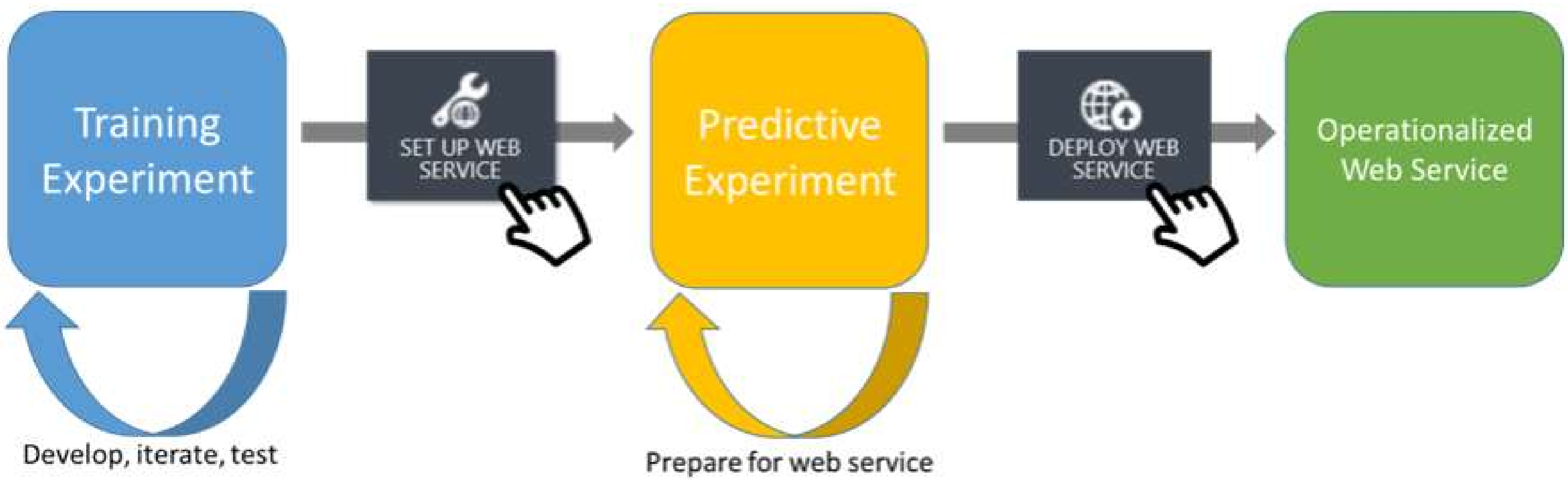
- Please choose one final champion model.
- Metrics in order of importance for this game:
    - AUC
    - Accuracy
    - Precision
    - Recall
    - F1 Score

Sample experiment in AzureML



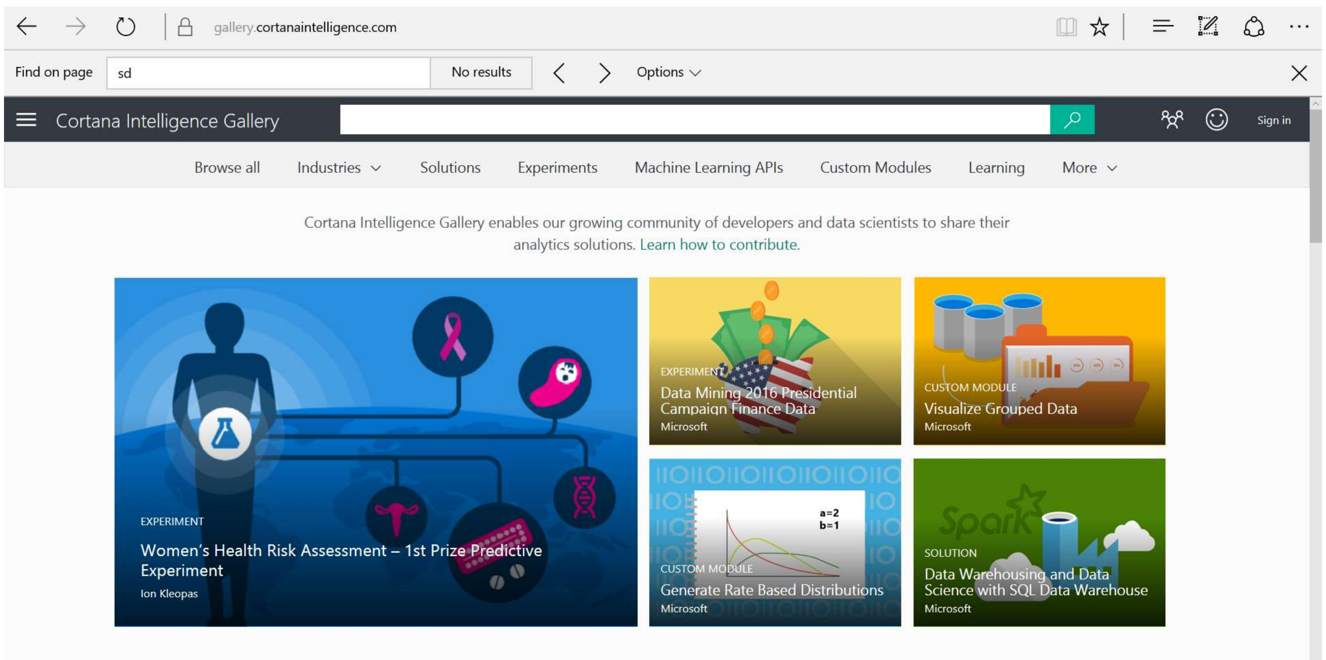
Operationalize your model as a web service

Here are the stages that a typical solution follows as you develop and deploy it using AzureML



Cortana Intelligence Gallery

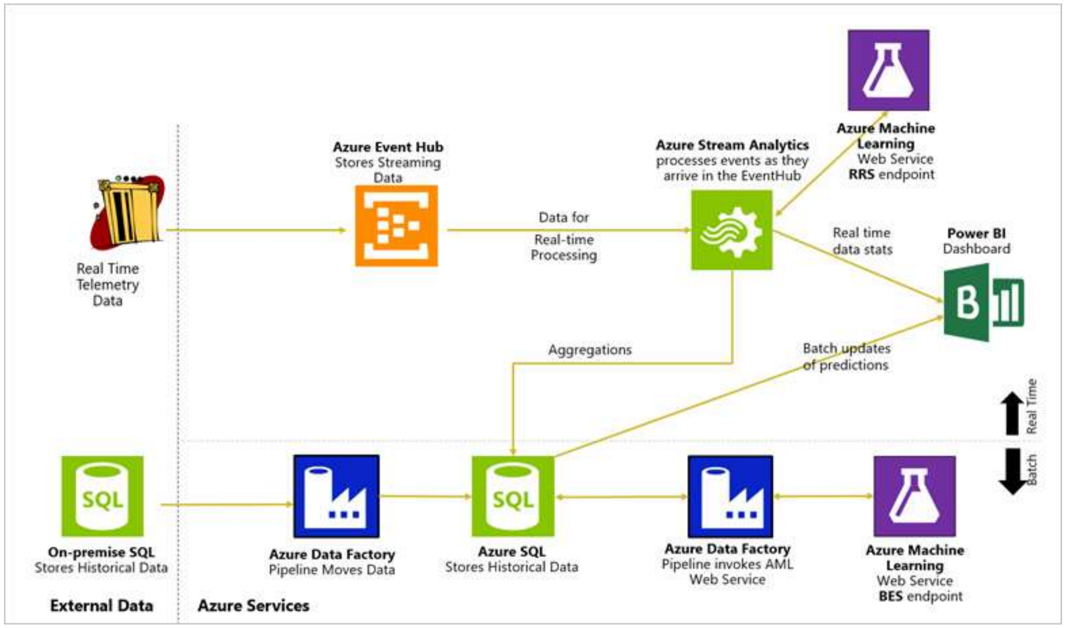
- Preconfigured machine learning templates and solutions -> https://gallery.cortanaintelligence.com/



Azure IoT Suite

Preconfigured Azure IoT solutions -> azureiotsuite.com

The following diagram outlines the logical components of the preconfigured solution:



Export data for later use

- Data Input and Output -> Export Data
  - Azure Blob Storage
  - Authentication Type - Account
  - Put in storage name (obtained from your storage service)
  - Put in account key (obtained from your storage service)
  - Put in container and blob name (obtained from your storage service) – put it in this format container/blob.csv