



Is deployment the elephant in the room?

John McConnell

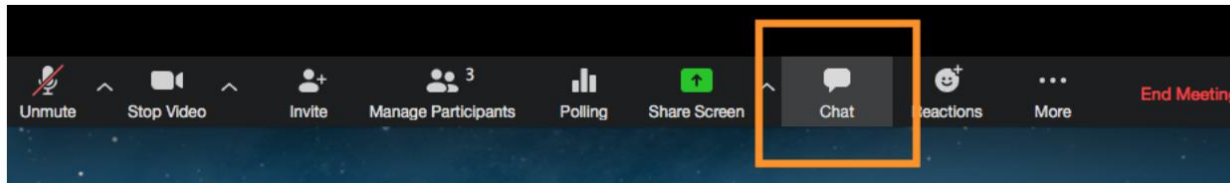
February 2026

www.sv-europe.com

A SELECT INTERNATIONAL COMPANY

FAQ's

- Is this session being recorded? Yes
- Can I get a copy of the slides? Yes, we'll email links to download materials after the session has ended.
- Can we arrange a re-run for colleagues? Yes, just ask us.
- How can I ask questions? All lines are muted so please use the chat panel
 - If we run out of time we will follow up with you.



Is there a problem?

- **WHAT OTHERS ARE SAYING**

“43% of Data Scientists say that 80%, or more, of their built models fail to deploy”

- Eric Siegel – KD Nuggets January 2024

According to Gartner analyst Nick Heudecker, over 85% of data science projects fail.

- Ryohei Fujimaki, DataNami 2020

- S&P Global Market Intelligence / 451 Research (Voice of the Enterprise), Oct 2025 Finds a big rise in “doesn’t reach production”: companies abandoning most AI initiatives before production increased from 17% to 42%, and the average organization scrapped 46% of proof-of-concept projects prior to production.

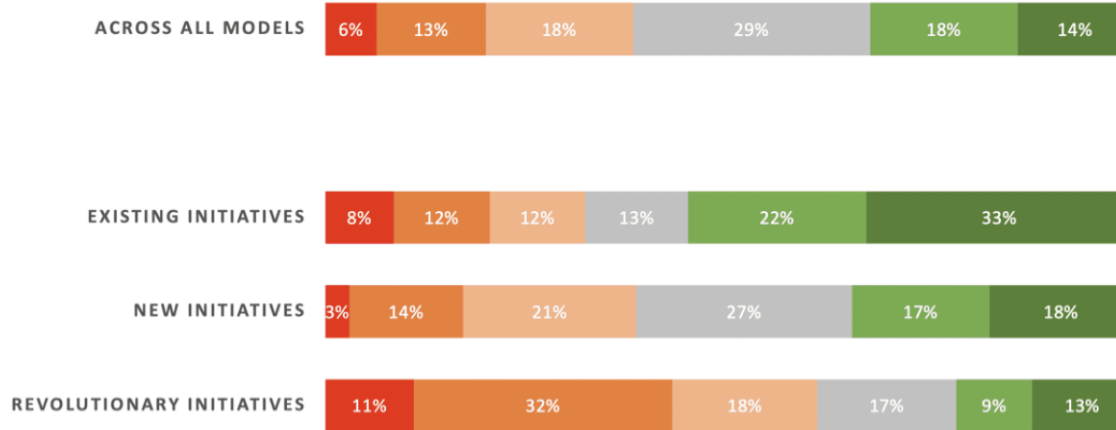
- **OUR OWN EXPERIENCE**

We don’t always succeed but have learned from our experiences

We see more use of platforms and pipelines and more joined-up teamwork across functions

PROPORTION OF MODELS THAT ARE DEPLOYED

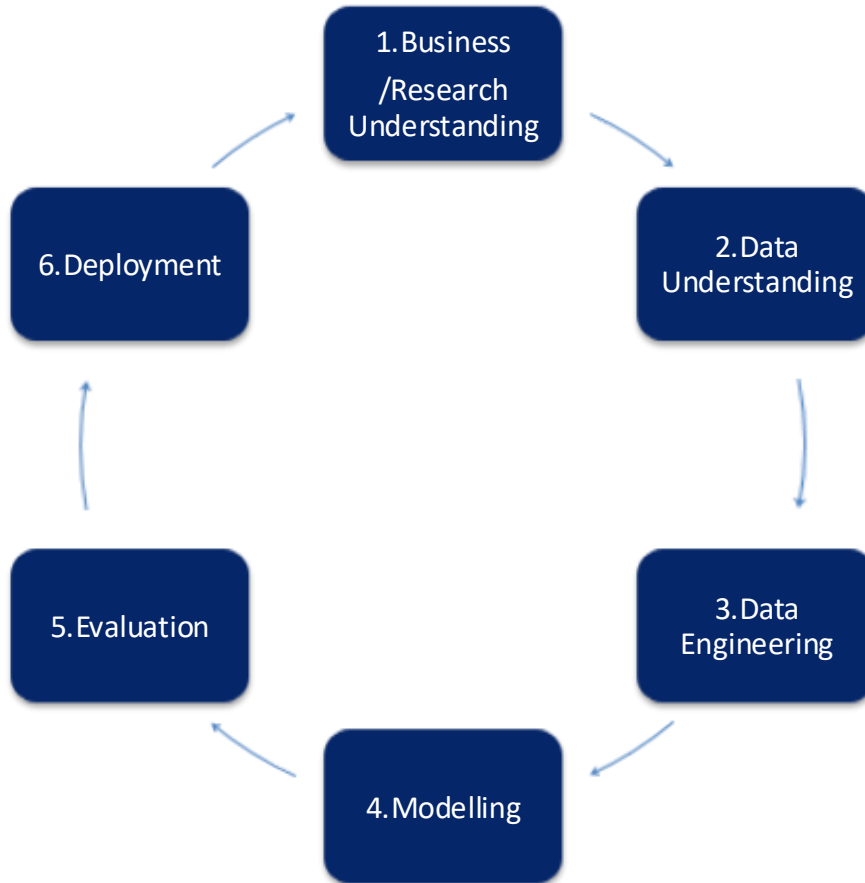
■ 0% ■ 1% -20% ■ 21% -40% ■ 41% - 60% ■ 61% -80% ■ 81% - 100%



Key:

- Existing initiatives:** Models developed to update/refresh an existing model that's already been successfully deployed
- New initiatives:** Models developed to enhance an existing process for which no model was already deployed
- Revolutionary initiatives:** Models developed to enable a new process or capability

The CRISP DM/DS process model

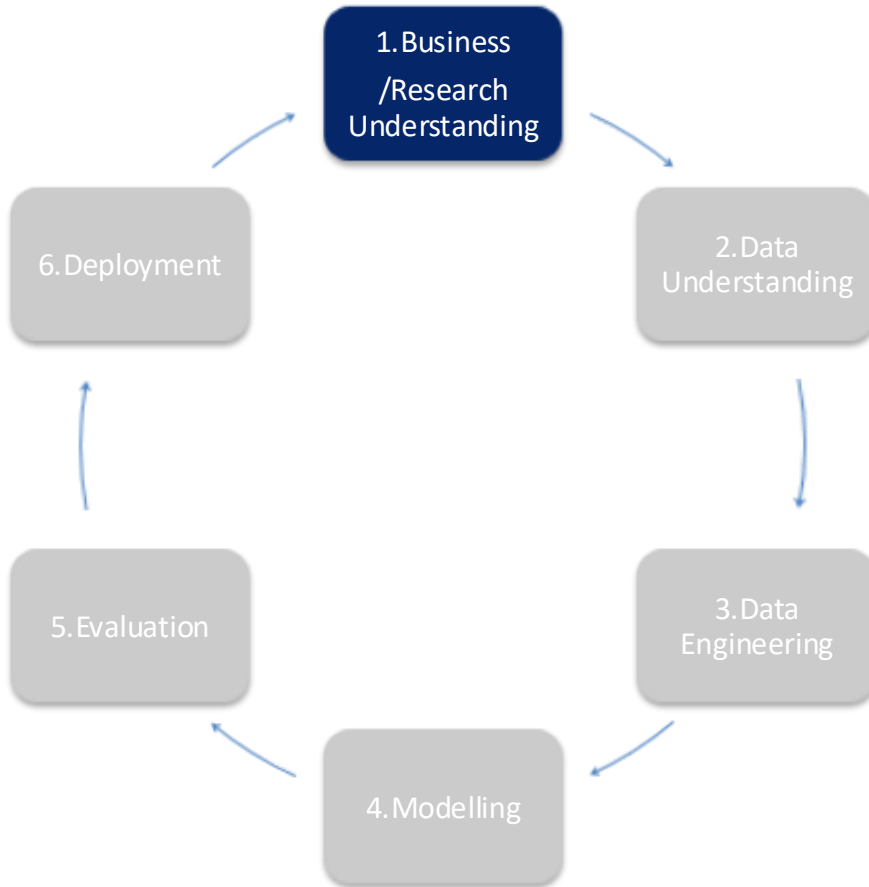


The Cross Industry Standard Process for Data Mining and Data Science.

For New Initiatives we look at the whole cycle

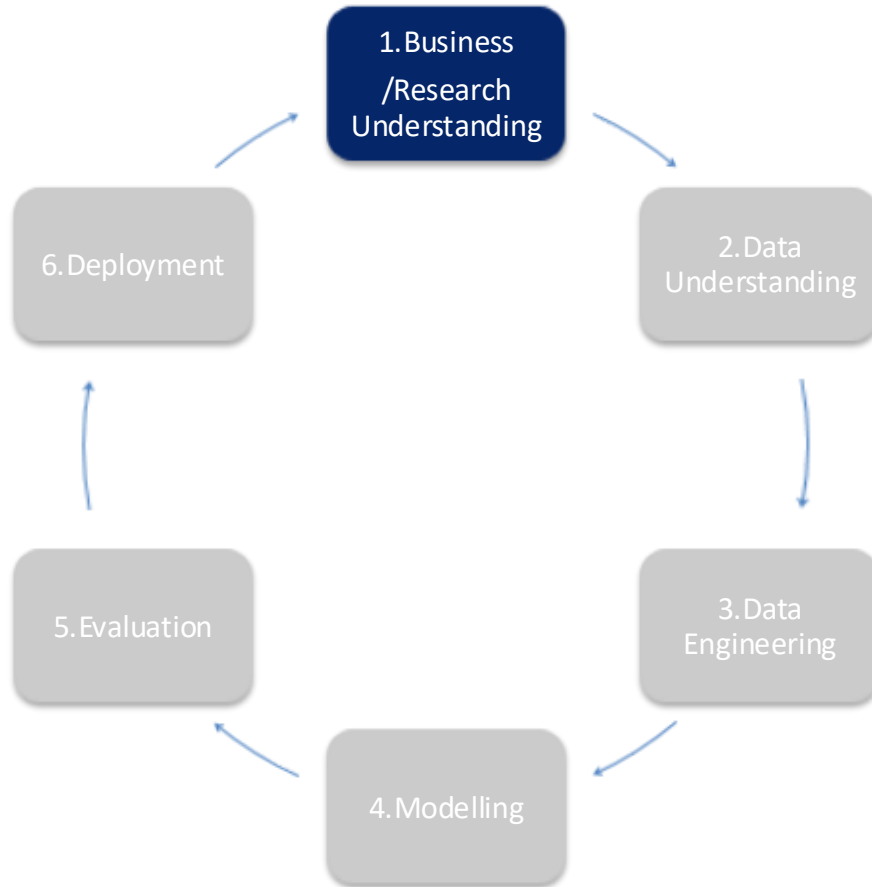
At the outset **Deployment** might seem somewhat far off ... something we can think about if/when we have arrived at a successful model

1. Business/Research Understanding



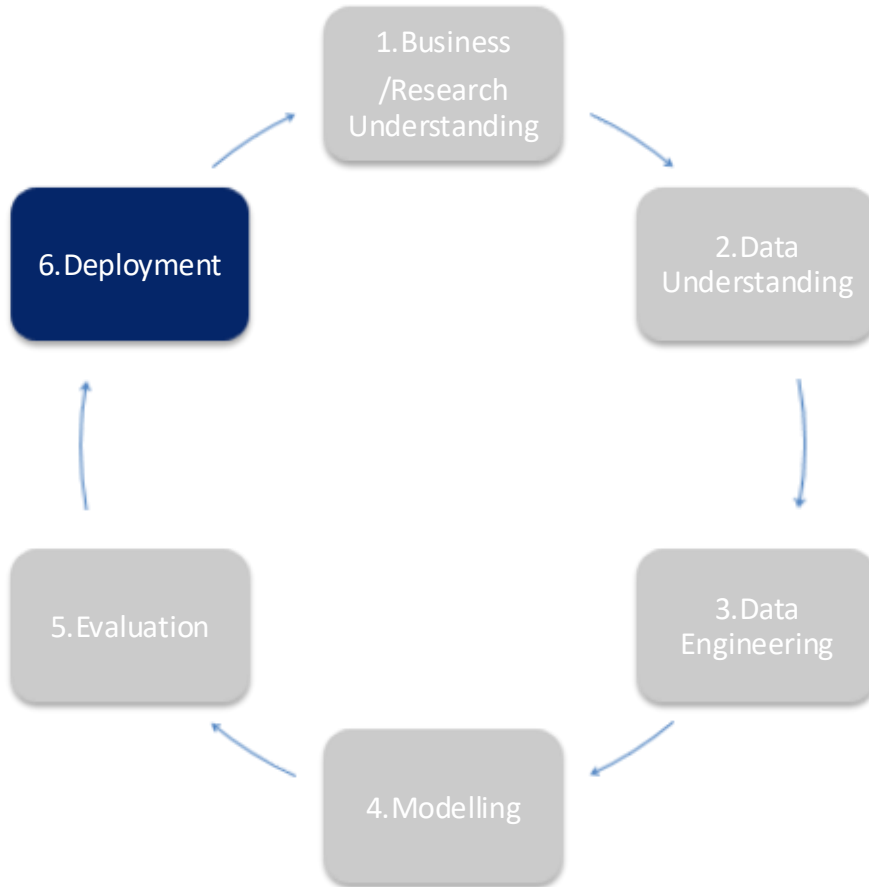
- We start with business/research conversations.
- Agree the objectives
- Understand the context
- Set success criteria
- Be sure to talk about “Deployment”

1. Agreeing Success Criteria



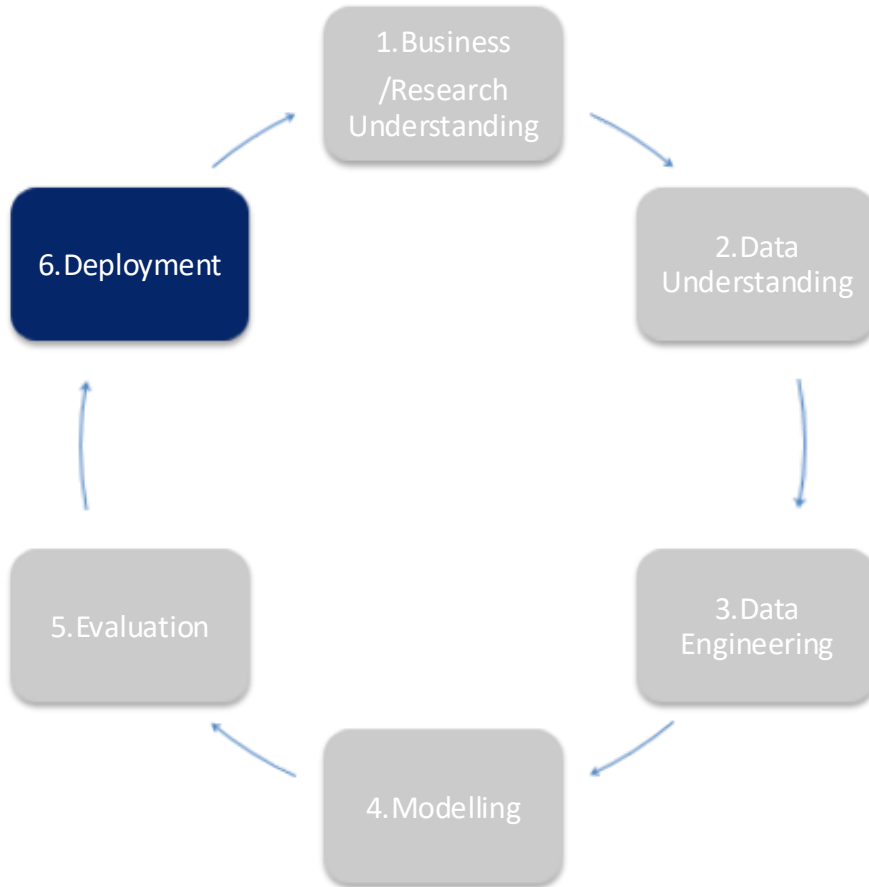
- An important step in the project where all stakeholders should align.
- For example, in a customer retention scenario, let's say we can only operationally intervene with 2,000 customer at a time
- So we might agree that we want our model to accurately identify 70% of customers who are likely to leave within the top 2,000 most "at risk" (of leaving)
 - If our churn rate is 20% that is likely to be a strong model

6. Deployment



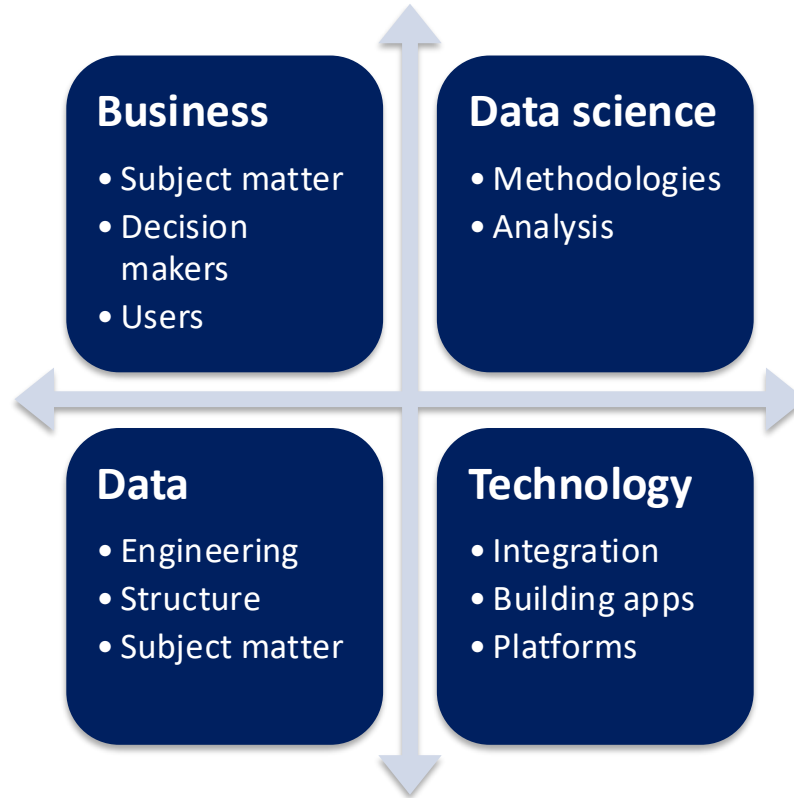
- The whole point of the exercise
- Can be about deploying, often strategic, insights that come from simpler (often statistical) models and statistical analyses
- More often about deploying models (and often the data engineering that feeds them)

6. Deployment



- Increasingly needs to be Real-Time
- Frequently needs to be scheduled
 - Typically processing batches
- Often integrated into operational systems
- Can be behind apps/platforms including
 - What-if? simulators
 - Decision Management tools

People (/ Roles)



BLOCKERS TO DEPLOYMENT SUCCESS

The Data

- We don't have enough (when we assess in Data Understanding)
- The quality is too low
- It is too difficult to access, clean or prepare
 - The “effort to insight” ratio is too high
- What was accessible to us when we built our model is not available when we deploy



The Model(s)

- The model does not meet our accuracy target
- OR
- It is essentially flawed
 - This could be data related, or issues in the data prep
 - We may not realise it is flawed until it is deployed and it does not deliver the results we expected



Stakeholder alignment (people, politics)

- May block us during the Evaluation
- Often happens as/after we deploy
- Decision making stakeholders may not “buy” the model
 - Especially when we start a new initiative they often want to how the model is working
- **End user stakeholders** may not know how to use the model
- They may not want the model
 - It can be seen as a threat
 - The use of the model may be perceived to be adding to their workload



Technical alignment

- This most often hits right at the point of deployment
- Simply put, we can't move our model into production for a technical reason e.g.
 - The data sources we need for the model are not reachable or reachable in time
 - The target platform cannot run the model(s) (or we don't have one)
 - IT governance e.g. concerns about open source



(TECHNICAL) DEPLOYMENT OPTIONS

**Option 1 – Recode the model into
something else**

Simple models can be (hand) coded

```
Call:
lm(formula = CONSUME ~ PRICE + INC + TEMP + PRICEINCI, data = datavar)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.0575279	-0.0163589	-0.0008483	0.0168662	0.0718922

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.1570203	0.2324673	0.675	0.5058
PRICE	-0.1636906	0.7438870	-0.220	0.8277
INC	0.0012301	0.0012133	1.014	0.3208
TEMP	0.0028231	0.0004171	6.769	5.31e-07 ***
PRICEINCI	-0.2786003	0.1344397	-2.072	0.0491 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.03094 on 24 degrees of freedom

Multiple R-squared: 0.7411, Adjusted R-squared: 0.698

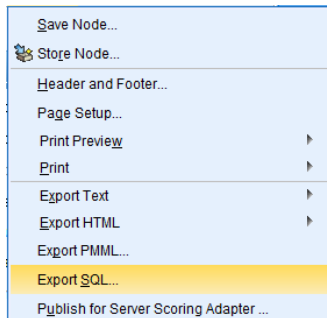
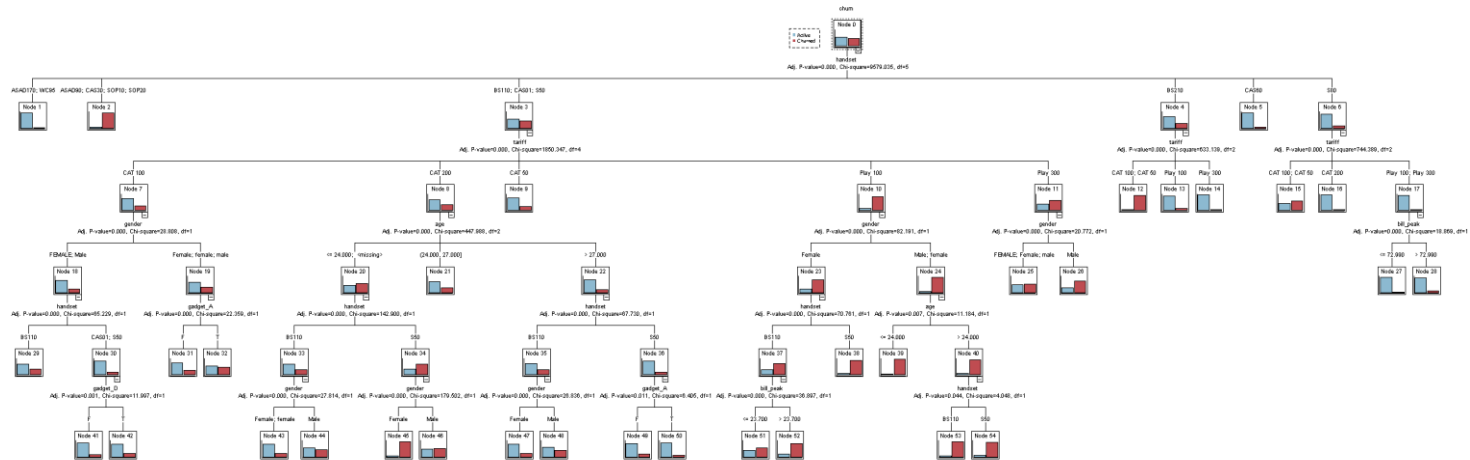
F-statistic: 17.18 on 4 and 24 DF, p-value: 8.968e-07

- Linear Regression models are a good example
- They fit easily into Excel formulae or into other code e.g. we've sometimes deployed models in SAP this way

Consume = 0.1570203 -0.1636906*PRICE + 0.0012301*INC + 0.0028231*TEMP -0.278600*PRICEINCI

**Option 2 – Export the model into a code
format that can be plugged into other
software**

Exporting SQL is one option (sometimes)



- Some tools support this. E.g. Python and R support it for some model types
- Caution around the **differences in SQL** between databases e.g. Oracle and IBM/DB2
- Some tools provide **target-specific SQL** which can sometimes be published into the database

PMML is the standard export/import format



www.dmg.org

Predictive
Model
Markup
Language

PMML 4.4.1 - General Structure

PMML uses XML to represent mining models. The structure of the models is described by an XML Schema. One or more mining models can be contained in a PMML document. A PMML document is an XML document with a root element of type PMML. The general structure of a PMML document is:

```
<?xml version="1.0"?>
<PMML version="4.4"
  xmlns="https://www.dmg.org/PMML-4_4"
  xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance">

  <Header copyright="Example.com"/>
  <DataDictionary> ... </DataDictionary>

  ... a model ...

</PMML>
```

Standards-based, Open-source Middleware for Predictive Analytics Applications

Convert your fitted **Scikit-Learn**, **R** or **Apache Spark** models and pipelines into the standardized **Predictive Model Markup Language** (PMML) representation, and make quick and dependable predictions in your **Java/JVM** application.

Standardization enables automation, which in turn enables higher efficiency and higher quality business processes.

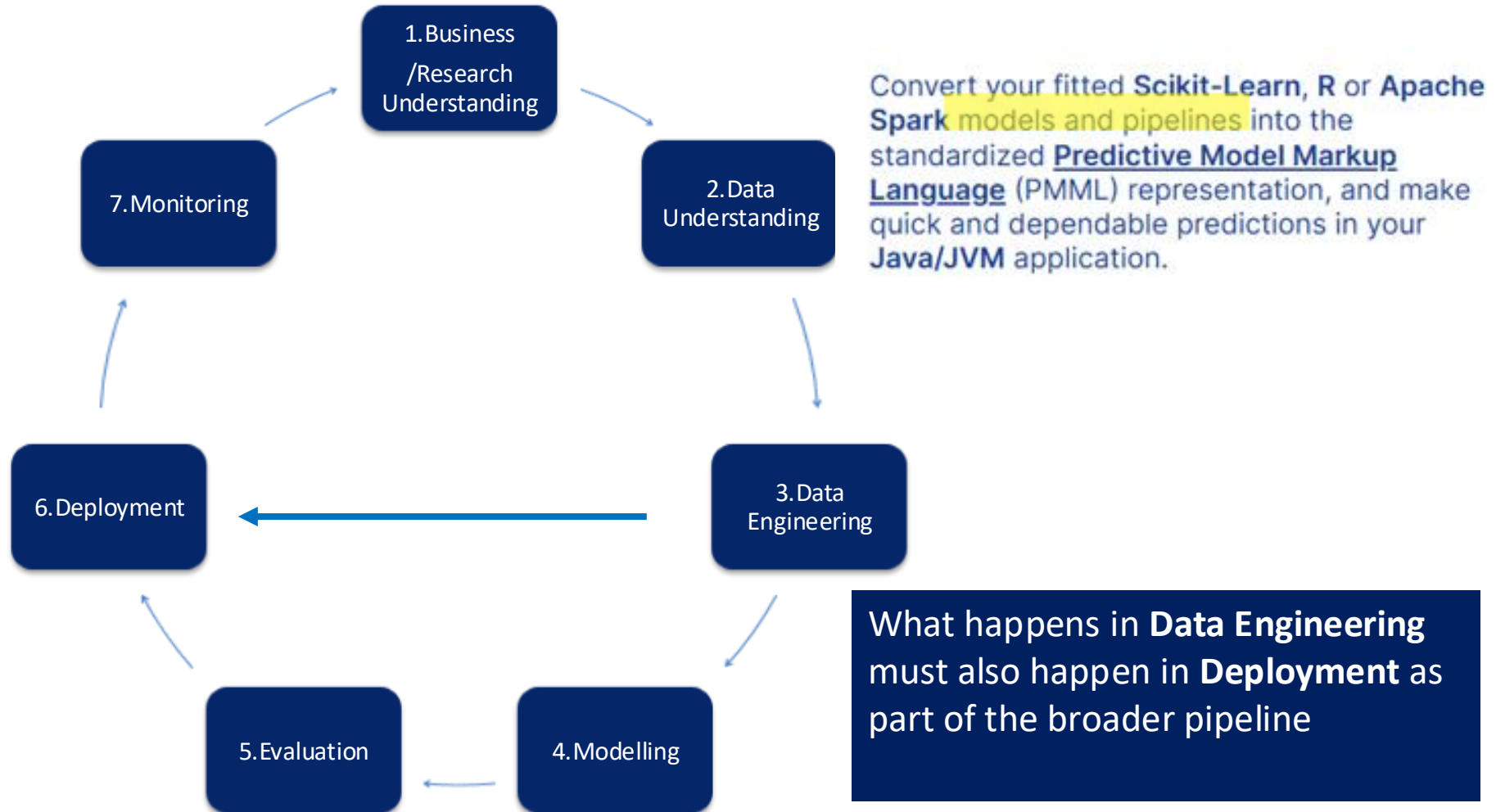
[GET STARTED NOW!](#)

<https://openscoring.io/>



Villu Russmann and his team have developed tools to make PMML work from the most commonly used advanced Python and Spark algorithms/models

Data preparation is also part of a Deployment pipeline



An Example Case

- In a recent project, we worked to develop a model to forecast operational customer satisfaction for a UK bank
- We tested multiple algorithms, including **ARIMAS** and various **Regressions**
- **XGBoost** was the most accurate
- The bank needed to deploy the model in a forecasting (What-if?) simulator in Excel
- In the end, we were not able to install any additional open-source engines ... for technical reasons
- Hence, the currently deployed model uses a combination of **Factor Analysis and Constrained Linear Regression**
 - — The accuracy is still acceptable, but we had to compromise it
- The Openscoring team has developed a working prototype to deploy XGBoost models into MS Excel
 - Supports Python's Pickle, R's RDS or Predictive Model Markup Language (PMML)

OpenScoring's Excel XLSBoost deployer

train

Search for tools, help, and more (Alt + Q)

JM

File Home Insert Share Page Layout Formulas Data Review View Automate Help Draw

H16

✕ ✓ f_x

 0

	A	B	C	D	E	F	G	H
1	Passenger	Survived	pclass	Name	Sex	age	sibsp	parch
2	1	0	3	Braund, Mr. Owen Harris	male	22	1	
3	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Tilden)	female	38	1	
4	3	1	3	Heikkinen, Miss. Laina	female	26	0	
5	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	
6	5	0	3	Allen, Mr. William Henry	male	35	0	
7	6	0	3	Moran, Mr. James	male		0	
8	7	0	1	McCarthy, Mr. Timothy J	male	54	0	
9	8	0	3	Palsson, Master. Gosta Leonard	male	2	3	
10	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27	0	
11	10	1	2	Nasser, Mrs. Nicholas (Adele Achem Nasser)	female	14	1	
12	11	1	3	Sandstrom, Miss. Marguerite Rut	female	4	1	
13	12	1	1	Bonnell, Miss. Elizabeth	female	58	0	
14	13	0	3	Saunders, Mr. William Henry	male	20	0	
15	14	0	3	Andersson, Mr. Anders Johan	male	39	1	
16	15	0	3	Vestrom, Miss. Hulda Amanda Adolfina	female	14	0	
17	16	1	2	Hewlett, Mrs. (Mary D Kingcome)	female	55	0	
18	17	0	3	Rice, Master. Eugene	male	2	4	
19	18	1	2	Williams, Mr. Charles Eugene	male		0	
20	19	0	3	Vander Planke, Mrs. Julius (Emelia Maria)	female	31	1	
21	20	1	3	Masselmani, Mrs. Fatima	female		0	
22	21	0	2	Fynney, Mr. Joseph J	male	35	0	
23	22	1	2	Beesley, Mr. Lawrence	male	34	0	
24	23	1	3	McGowan, Miss. Anna "Annie"	female	15	0	
25	24	1	1	Sloper, Mr. William Thompson	male	28	0	
26	25	0	3	Palsson, Miss. Torborg Danira	female	8	3	
27	26	1	3	Asplund, Mrs. Carl Oscar (Selma Augusta)	female	38	1	

< > ≡ to_score +

XLSBoost Add-in

...

XGBoostTitanic

Schema

- Reads 8 columns
- Writes 3 columns

Options

☒ Validate input values

Apply Predictive Model

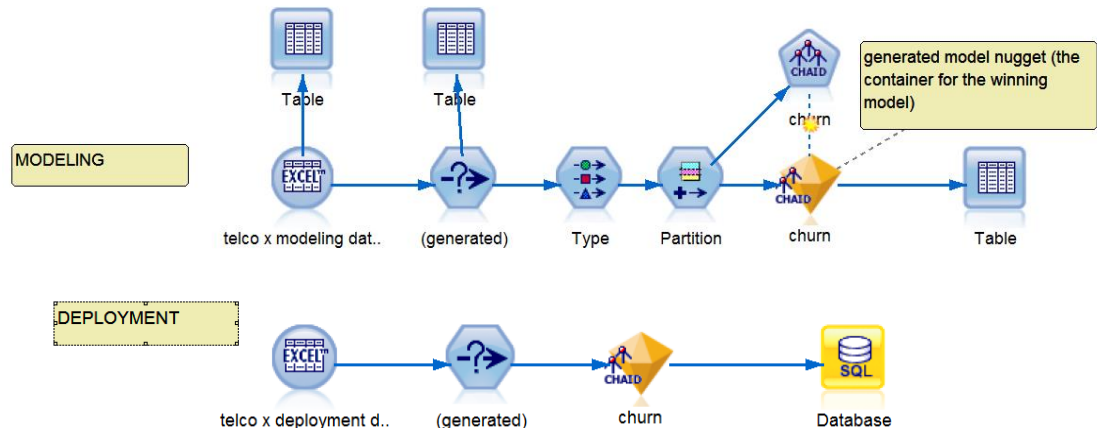
Ready! Select a range and click the "Apply Predictive Model" button.

<https://xlsboost.com/>

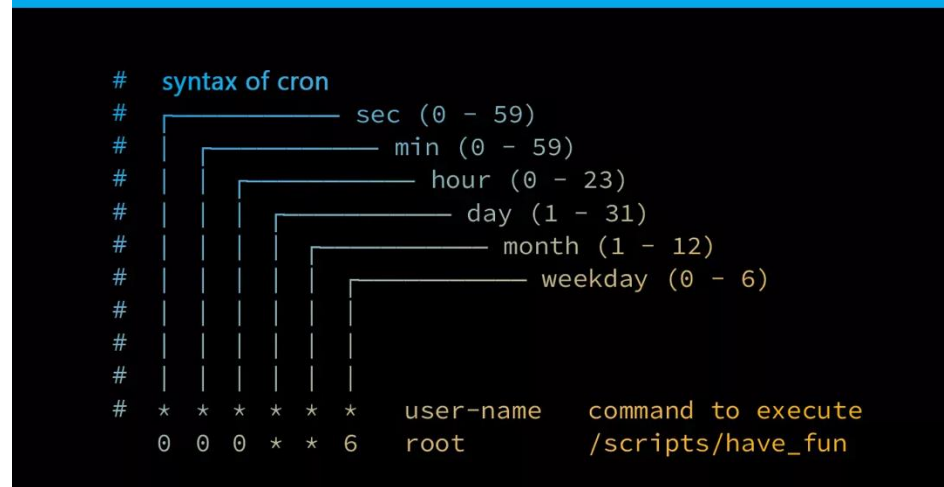
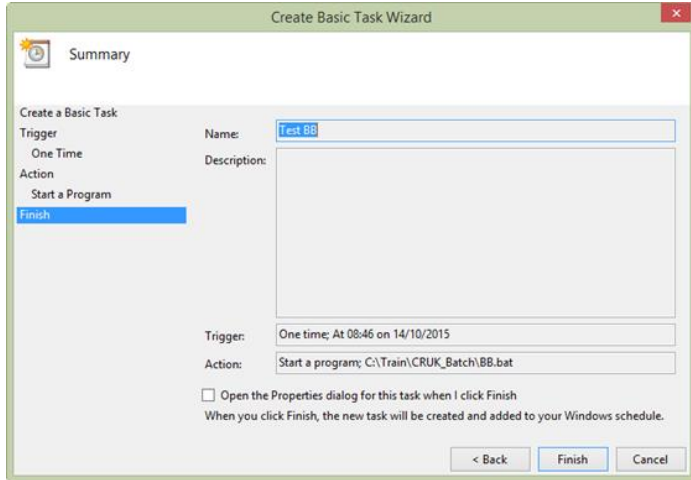
**Option 3 – Using the same engine to build
(train) and deploy**

The basic idea

- A. Start with the modelling “pipeline/job”
 - You typically need to adapt it to create a deployment/scoring version
 - Usually a simplified version
- B. Install the software on a deployment machine; R, Python, SAS, SPSS, WPS, etc.
 - Or use the same machine
- C. Periodically run new data through the job and send the scores/predictions to an operational target



Which means we can usually schedule easily



As long as the analytical tool/engine allows **batch execution** (usually via the command line) we can use standard scheduling tools in the OS e.g. Windows Task Scheduler or CRON to run at a given time/periodically

Real-time would require more engineering

Option 4 – Use a Data Science/ML platform

Platform essentials

Support for low/no-code

- Visual interfaces
- May optionally generate code

And code

- Scripts
- Notebooks

Support collaboration

- Roles
- Within functions
- Between functions

Auto ML

- Algorithm selection
- Algorithm settings optimisation
- Feature selection

Ease of deployment

- Scheduled (batches)
- Real-time

Post deployment life cycle managment

- Monitoring
- Reporting/Alerting
- Model refreshing
- Model retirement

MLOps support

- Enables integration and scaling of deployments across operational environments e.g. Digital, CRM, Finance, Sales, Contact centre, etc.

Platform nice-to-haves

Recommendations

- Auto ML +
- Data engineering
 - Feature extraction/creation

Advanced stuff

- Simulation
- Optimisation
- Deep learning

SDKs and APIs

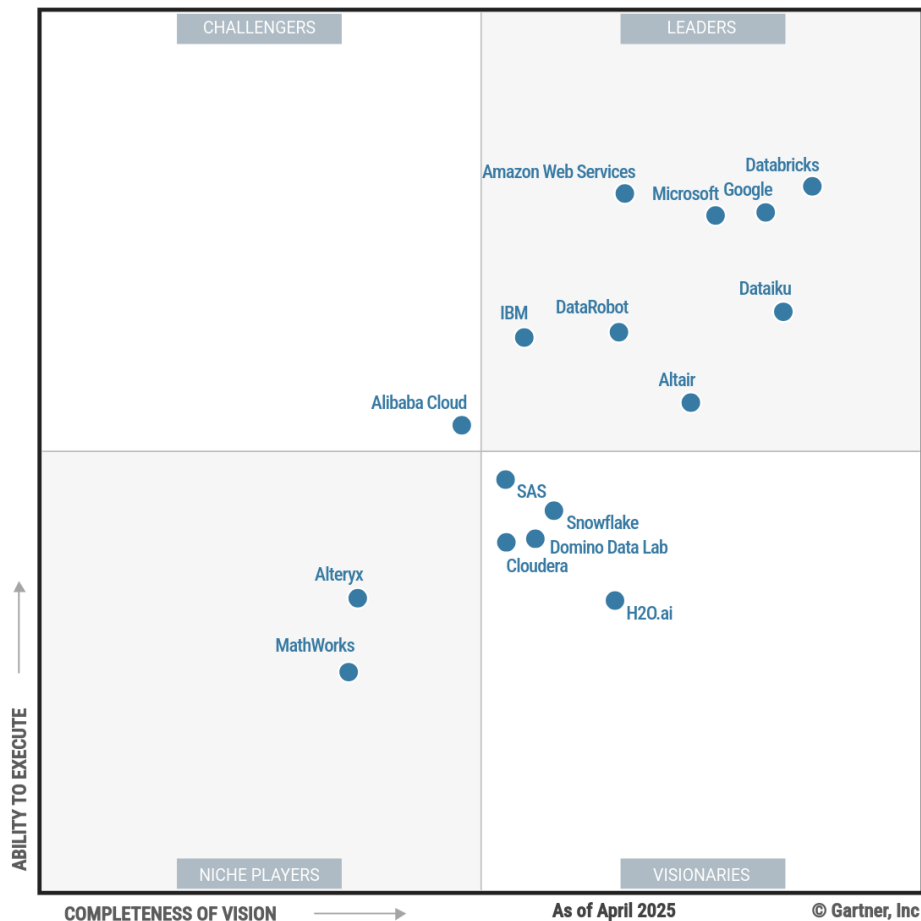
- Support more programmatic code-based model development
 - C, Java, etc.
- API into platform

Model interpretability

- Tools to help understand models better
 - Many algorithms produce opaque models

Support for GenAI

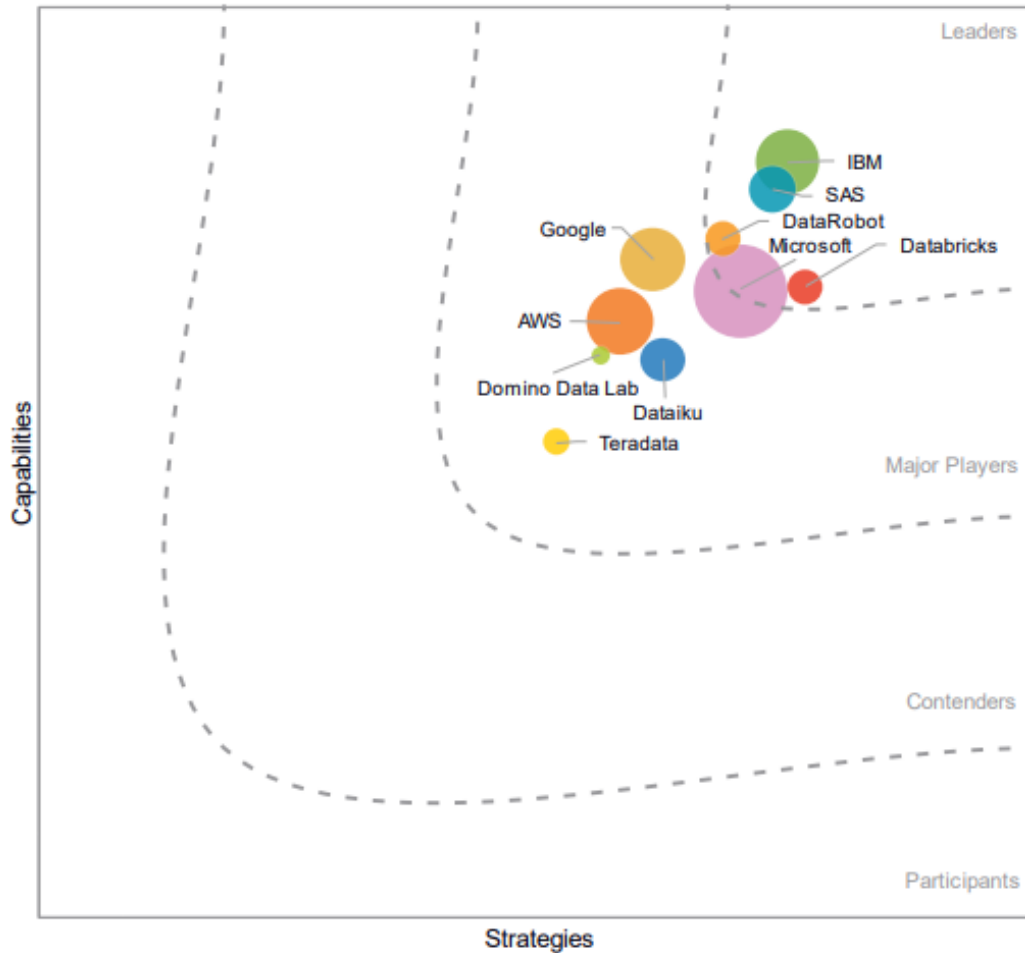
- Access to LLMs
 - E.g. for RAG
- Agentic support
- Foundation models



Magic Quadrant for Data Science and Machine Learning Platforms

[Gartner MQ 2025](#)

- DS/ML Specialists
 - Dataiku, DataRobot, DataBricks, SAS, Altair, H2O
- Broader Cloud Platforms
 - Microsoft, Amazon, Google, IBM, Alibaba
- Open source alternatives exist beyond Anaconda e.g. Airflow and MLOps



IDC MarketScape Worldwide Machine Learning Operations Platforms Vendor Assessment

[IDC Marketplace 2024](#)

Canvass for Low/No-code



AI Package Tracker

[Feedback](#)

[Visit SageMaker Canvas](#)

Model accuracy results

Current model accuracy

95.673%



Great job!

Your model's prediction score is higher than the target of 80%!

Modify the feature values to see how they affect the On-time prediction in real time.

Feature	Feature importance	Value
Total items	<div><div></div></div> 77%	200
U.S. ZIP code	<div><div></div></div> 11%	15203
Temperature	<div><div></div></div> 9%	0°C
Humidity	<div><div></div></div> 3%	20%

On time prediction

On time

Delayed

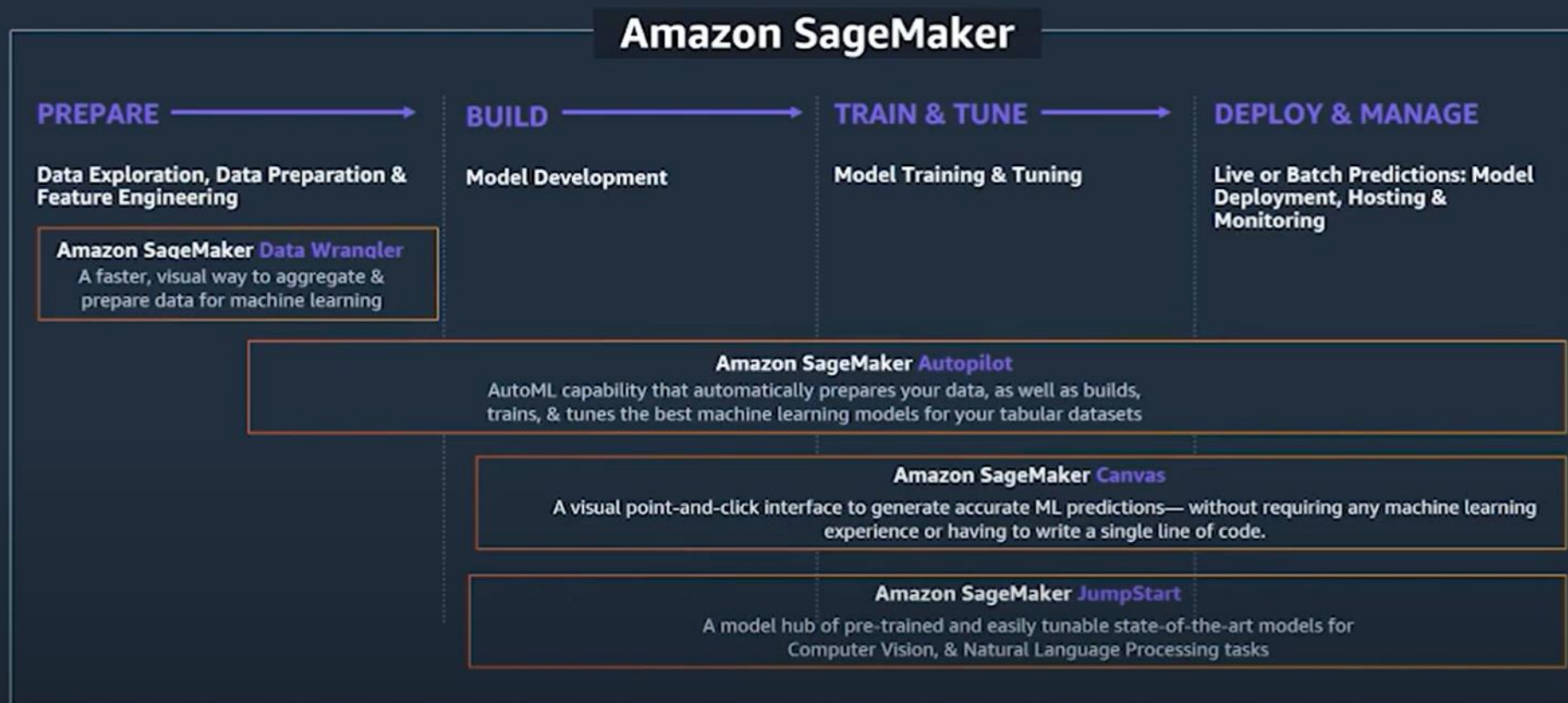
 9% ⓘ

 91% ⓘ

[Back](#)


[Complete the demo](#)

Low-Code Machine Learning on AWS













AWS Sagemaker support Low-Code ML through to deployment and monitoring

Notebooks etc. for Code

 jupyter Smarty_Bot Last Checkpoint: a few seconds ago (autosaved)

File Edit View Insert Cell Kernel Widgets Help

         Code  nbdiff

```
In [5]: import streamlit as st
        from gtts import gTTS
        from PyPDF2 import PdfReader
        #from langchain.embeddings import GPT4AllEmbeddings
        from langchain_community.embeddings import GPT4AllEmbeddings

In [6]: #from langchain.vectorstores import Chroma
        from langchain_community.vectorstores import Chroma
        #from langchain.embeddings import HuggingFaceInstructEmbeddings
        from langchain_community.embeddings import HuggingFaceInstructEmbeddings

In [ ]: #from langchain.LLms import HuggingFaceHub
        from langchain_community.llms import HuggingFaceHub
        from langchain.memory import ConversationBufferMemory, ConversationBufferWindowMemory
        from langchain.chains import ConversationalRetrievalChain, LLMChain
        from langchain.text_splitter import RecursiveCharacterTextSplitter
        from langchain_core.prompts import PromptTemplate
        #from langchain.memory.chat_message_histories import StreamlitChatMessageHistory
        from langchain_community.chat_message_histories import StreamlitChatMessageHistory
        #from langchain.retrievers.multi_query import MultiQueryRetriever
        import chromadb
        from langchain_core.prompts import ChatPromptTemplate
        from langchain.retrievers.multi_query import MultiQueryRetriever
        import sagemaker, boto3, json
        from sagemaker.session import Session

In [8]: from langchain_community.embeddings import HuggingFaceEmbeddings
        from langchain_core.prompts import ChatPromptTemplate
        from langchain_community.llms import Bedrock
        from langchain_community.embeddings import BedrockEmbeddings

In [9]: sagemaker_session = Session()
        aws_role = sagemaker_session.get_caller_identity_arn()
        aws_region = boto3.Session().region_name
        sess = sagemaker.Session()
        client = boto3.client('sagemaker')
        Bedrockclient = boto3.client("bedrock-runtime")
        import torch
        device = "cuda" if torch.cuda.is_available() else "cpu"
        print(f"Using device: {device}")

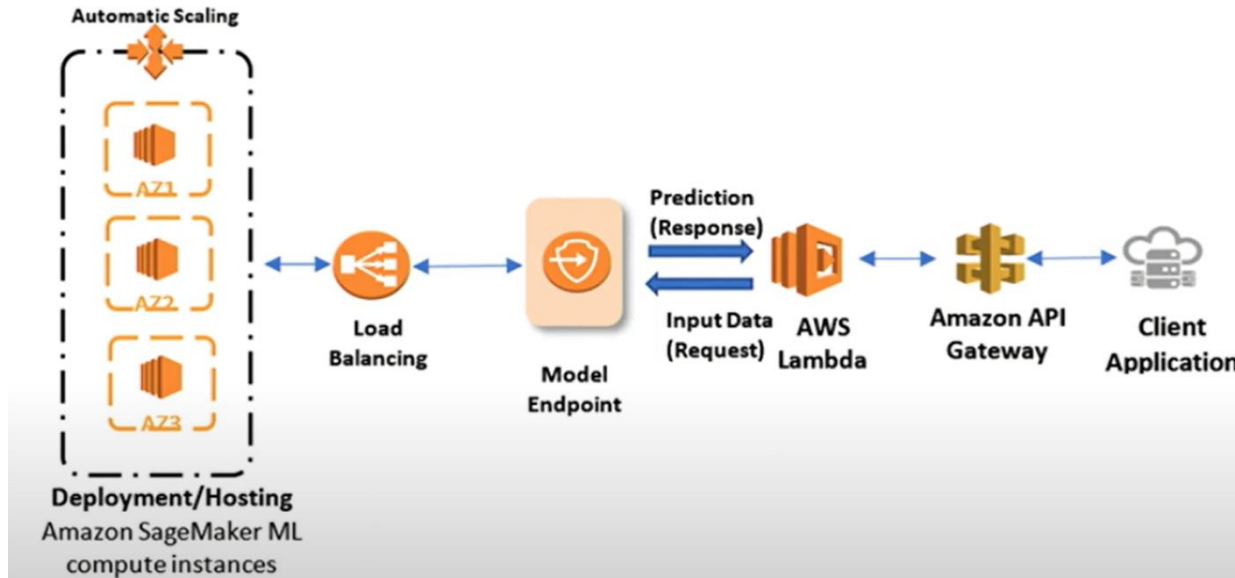
Using device: cpu
```

Real-time deployment from code

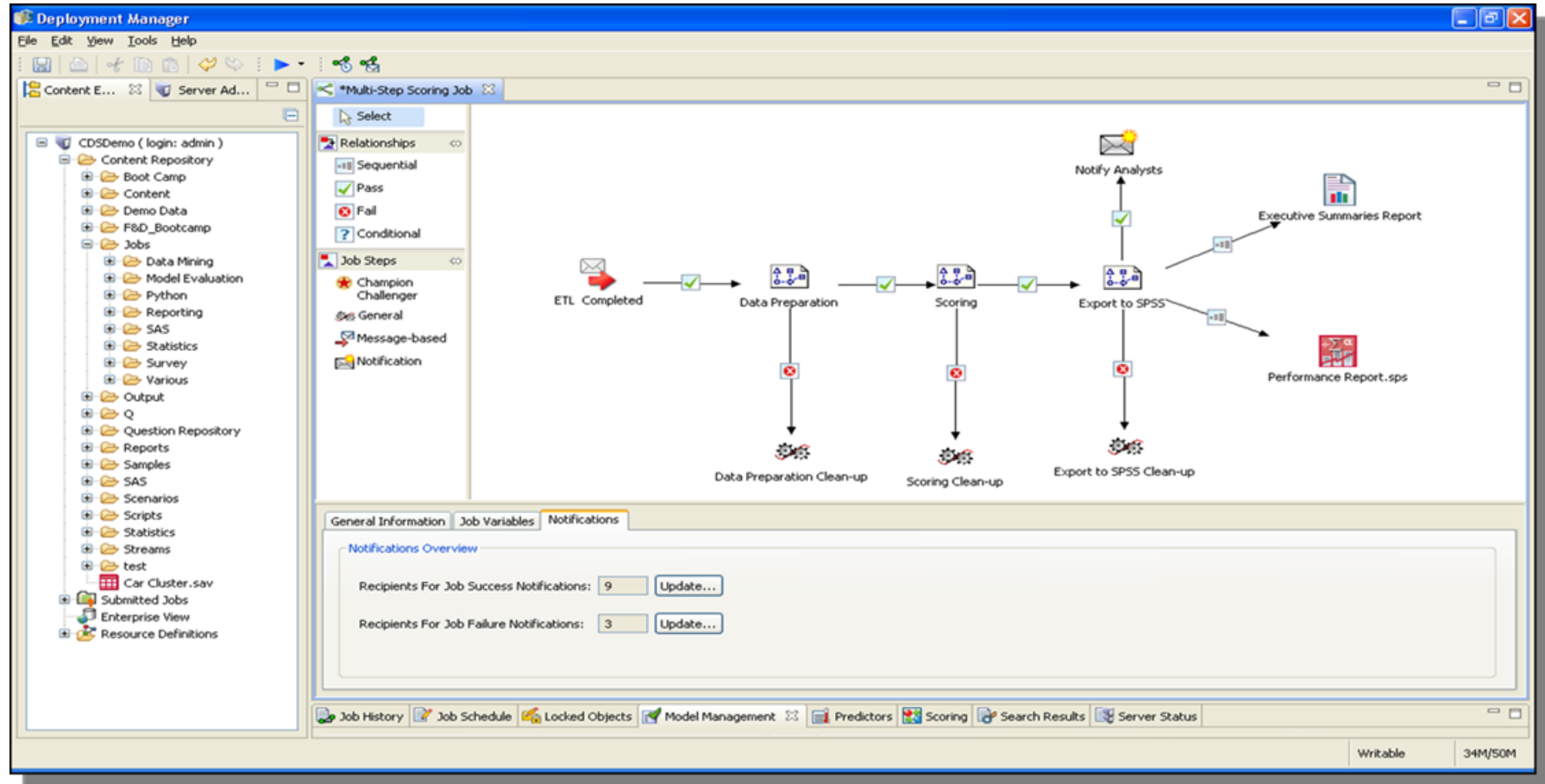
Hosting / Inference

Once the training is done, we can deploy the trained model as an Amazon SageMaker real-time hosted endpoint. This will allow us to make predictions (or inference) from the model. Note that we don't have to host on the same type of instance that we used to train. Because instance endpoints will be up and running for long, it's advisable to choose a cheaper instance for inference.

```
In [23]: text_classifier = bt_model.deploy(initial_instance_count = 1, instance_type = 'ml.m4.xlarge')
-----!
```

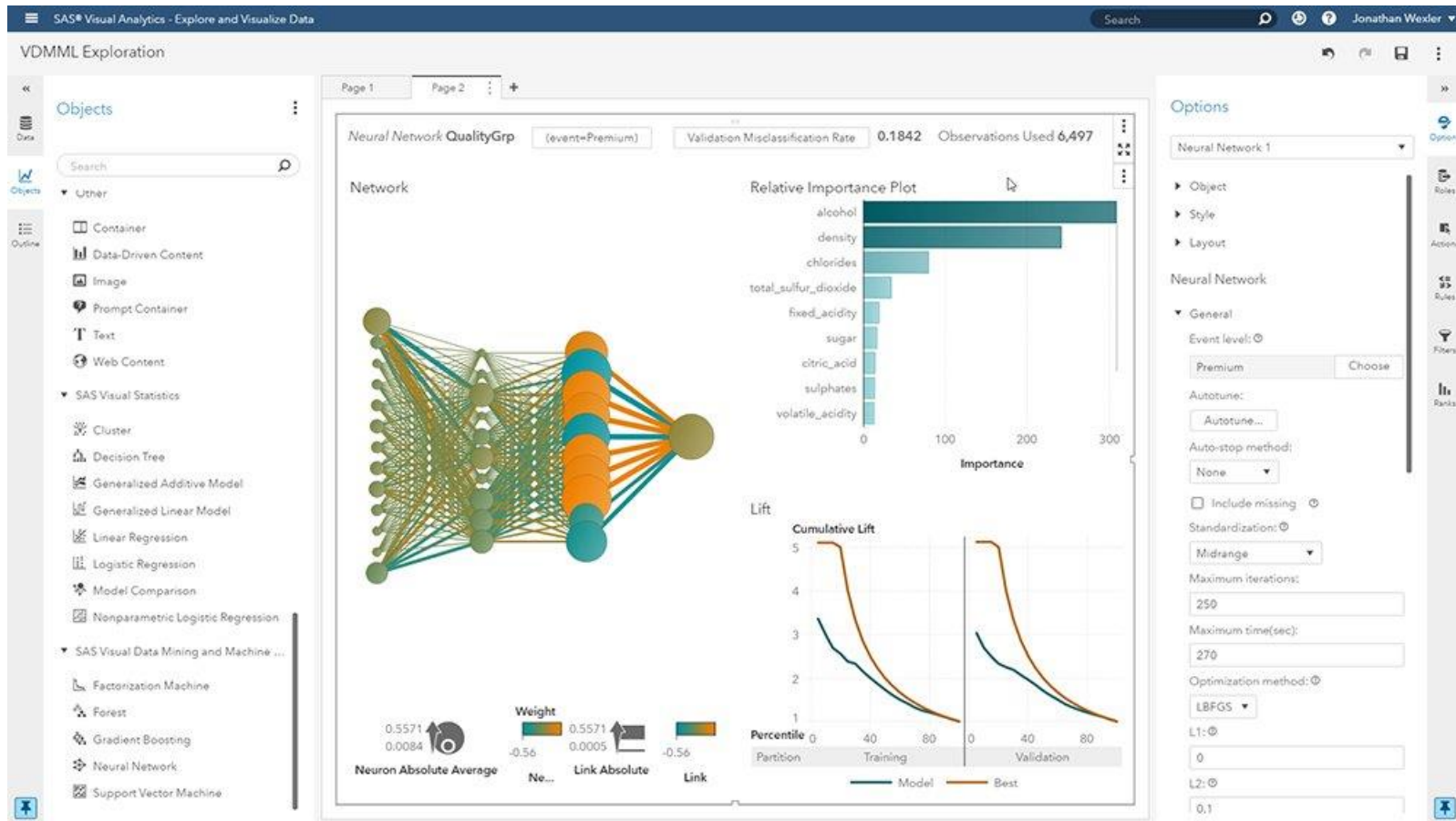


Premised platforms are also available



IBM/SPSS Collaboration & Deployment Services

Premised platforms are also available



SAS Viya is cloud native but it can be installed on-prem using containers

Premised platforms are also available

Dashboard

Home

My Jobs/Workflows

Compare Jobs/Workflows/Scenarios

Admin Space

Add/Edit User

Edit teams/groups & permissions

Explore database

Manage database

New/Edit tool

New/Edit workflow

File paths management

Import tools and workflows

Usage Statistics

My Account

Account Info

Log out

Demo

CAD + Image

3D animation + Video

Web tool

PDF viewer

FUNIS

MATOFX SPDM™

Create

Project

Scenario

Job

Custom Workflow

Job Search

Search for Jobs

Simulation Approvals

No pending approvals.

Tutorials

MATOFX SPDM tutorial

Workflow Job Status

Job ID	Tool	Date Created	Date Completed	Job Status	Scenario
<input type="checkbox"/>	74 Heat Transfer Model	2026-01-19 07:56:53	None	New	Quicklaunch of Material Properties to Heat Transfer_9
<input type="checkbox"/>	73 Material Properties Calculator	2026-01-19 07:56:53	2026-01-19 07:57:	Complete	Quicklaunch of Material Properties to Heat Transfer_9
<input type="checkbox"/>	68 Heat Transfer Model	2026-01-16 11:50:44	2026-01-16 11:51:	Complete	Quicklaunch of Material Properties to Heat Transfer_8
<input type="checkbox"/>	67 Material Properties Calculator	2026-01-16 11:50:44	2026-01-16 11:51:	Complete	Quicklaunch of Material Properties to Heat Transfer_8
<input type="checkbox"/>	60 Material Properties Calculator	2026-01-15 14:35:05	None	New	Quicklaunch of Test Custom Workflow_5
<input type="checkbox"/>	59 Heat Transfer Model	2026-01-15 14:35:05	None	New	Quicklaunch of Test Custom Workflow_5
<input type="checkbox"/>	58 Heat Transfer Model	2026-01-15 14:34:58	None	New	Quicklaunch of Material Properties to Heat Transfer_7


Job Status

Job ID	Tool	Date Created	Date Completed	Job Status	Scenario
<input type="checkbox"/>	96 Heat Transfer Model	2026-01-26 13:26:07	None	New	Quicklaunch of Heat Transfer Model_16
<input type="checkbox"/>	95 Material Properties Calculator	2026-01-22 08:39:15	None	Denied	Quicklaunch of Material Properties Calculator_24
<input type="checkbox"/>	94 Material Properties Calculator	2026-01-22 08:38:36	None	Denied	Quicklaunch of Material Properties Calculator_23
<input type="checkbox"/>	93 Material Properties Calculator	2026-01-22 07:38:25	2026-01-22 07:39:09	Complete	Quicklaunch of Material Properties Calculator_22
<input type="checkbox"/>	92 Material Properties Calculator	2026-01-22 07:37:22	None	New	Quicklaunch of Material Properties Calculator_21
<input type="checkbox"/>	91 Material Properties Calculator	2026-01-22 07:25:35	2026-01-22 07:31:47	Failed	Quicklaunch of Material Properties Calculator_20
<input type="checkbox"/>	90 Material Properties Calculator	2026-01-22 07:16:44	None	Denied	Quicklaunch of Material Properties Calculator_19

Projects


Project Name	Objective	Date Created	Owner	View Permissions	Number of Scenarios
<input type="checkbox"/> Project Eureka	Test project	2026-01-16 12:03:05	Robert Cordina	Test User 1, Test User 3, T	0
<input type="checkbox"/> Proj 2	Proj 2	2026-01-16 10:08:43	Test User 1	World	1
<input type="checkbox"/> Project 5	Proj 5	2026-01-12 10:31:13	Robert Cordina	Test User 1	1
<input type="checkbox"/> Project 4	Proj 4	2026-01-12 10:08:39	Robert Cordina	Test User 2	1
<input type="checkbox"/> Project 3	Proj 3	2026-01-12 10:02:48	Robert Cordina	World	1
<input type="checkbox"/> Project 2	Test Proj 2	2026-01-12 09:59:31	Robert Cordina	World	1
<input type="checkbox"/> Project 1	Test project	2026-01-12 09:56:13	Robert Cordina	World	66

Automated Workflow Quick Access

 **Material Properties to Heat Transfer**
Automated workflow consisting of Material Properties Calculator, Heat Transfer Model

Launch in existing project


Launch in new project

 **Test Custom Workflow**
Automated workflow consisting of Heat Transfer Model, Material Properties Calculator

Launch in existing project


Launch in new project

Single Tool Quick Access

 **Material Properties Calculator**
Calculate material properties based on formulation.


Launch in existing project

Launch in new project

 **Heat Transfer Model**
Simulate the heat transfer through a 2D rectangular object.


Launch in existing project

Launch in new project

 **Colour Check and Transformation**
Check the colours in an image and transform it.

Launch in existing project

Launch in new project

 **Material Properties Calculator - Repeat**
MatProp Calculator using repeat simulation function.

Launch in existing project

Launch in new project

[MATOFX SPDM](#) from Funis Consulting is a tool agnostic simulation workflow platform

IBM Watson X - Auto AI RAG Experiment progress map

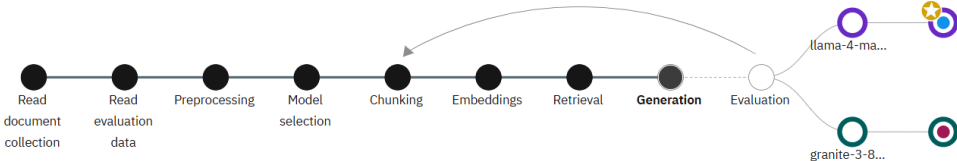
Experiment summary

Setting importance

Pattern comparison

★ Rank by: Answer correctness | Mean

Progress map ⓘ



Experiment status

Experiment in progress

Text generation completed

View Log

RAG Pattern leaderboard ▾

Rank	↑	Name	Model name	Answer correctness (Optimized)	Retrieval method	Hybrid ranker strategy	Number of chunks	Chunk size
★ 1		Pattern 1	llama-4-maverick-17b-128e-instruct-fp8 slate-125m-english-rtvr-v2	<div></div> 0.918	Window Size: 3	N/A	5	2048

IBM Watson X - API endpoint of deployed AI Service

Pattern 3: SPSS_SYNTAX_Auto_AI_RAG_Build_31_Jul... ✓ Deployed Online

API reference

Test

Preview

Endpoints for inferencing ⓘ

Private endpoint

https://eu-gb.ml.cloud.ibm.com/ml/v4/deployments/0f2eb07b-5931-442b-8a53-469c62329ce8/ai_service?version=2021-05-01

https://eu-gb.ml.cloud.ibm.com/ml/v4/deployments/0f2eb07b-5931-442b-8a53-469c62329ce8/ai_service_stream?version=2021-05-01

Public endpoint

https://eu-gb.ml.cloud.ibm.com/ml/v4/deployments/0f2eb07b-5931-442b-8a53-469c62329ce8/ai_service?version=2021-05-01

https://eu-gb.ml.cloud.ibm.com/ml/v4/deployments/0f2eb07b-5931-442b-8a53-469c62329ce8/ai_service_stream?version=2021-05-01

[Learn more](#) about the 2021-05-01 version query parameter

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 (https://eu-gb.dataplatform.cloud.ibm.com/docs/content/wsj/analyze-data/ml-authentication).
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}
```

Bearer <token> ⓘ

IAM

About this deployment

Name

Pattern 3:
SPSS_SYNTAX_Auto_AI_RAG_Build_31_Ju
...

Description

No description provided.

Deployment Details

Deployment ID: 0f2eb07b-5931-44...

Serving name:

No serving name

Software specification:

[runtime-24.1-py3.11](#) ⓘ

Hardware specification:

Extra extra small: 1 CPU and 2 GB RAM

Copies:

1

Tags

wx-autoai-rag

Associated asset

[Pattern 3: SPSS_SYNTAX_Auto_AI_RA...](#)
5b51ff4b-84c6-43d3-86cc-09b359cab643

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📁 All Bookmarks

CONVERSATIONS

▼ Can SPSS run SARIMA?

Can SPSS run SARIMA

DOCUMENT REFERENCES

IBM_SPSS_Statistics_Core_System_User_G...

IBM_SPSS_Forecasting.pdf

IBM_SPSS_Statistics_Command_Syntax_Re...

Python_Reference_Guide_for_IBM_SPSS_S...

<https://chatspss.com/>

🔊

MODEL

main model

+

SEND FEEDBACK

EXPORT PDF

LOG OUT

PRIVACY

SMARTVISION

Can SPSS run SARIMA?

Here are the main points to answer the question:

- IBM SPSS Statistics can estimate SARIMA models using the ARIMA command.
- The ARIMA command supports both nonseasonal and seasonal univariate ARIMA models.
- The MODEL subcommand is used to specify the SARIMA model, including the order of the autoregressive, differencing, and moving average components, as well as the seasonal components [S2].

To access the ARIMA procedure in SPSS, you can use the following menu path: *Analyse > Forecasting > Create Models*

Here's an example of how to specify a SARIMA model using the ARIMA command in SPSS Syntax:

```
ARIMA SALES  
/MODEL=(0,1,1)(0,1,1).
```

This example estimates a SARIMA(0,1,1)(0,1,1) model for the SALES series [S2].

↑

+

new conversation

Blocker	Mitigations
Technical	Involve technical colleagues early Figure out the technical path to get there Automate that
Data	Improving data quality is a broad project often leading to a Data Lake/Warehouse to support Data Science Tactically assess quality and look to clean what we can and only use data of Assess if this will be sufficient to hit our targets
Stakeholder buy-in	To get alignment we need to agree what a good outcome is Agree the criteria in a less technical way e.g. Lift, gain, profit Keep them involved/informed where possible
End user buy-in	Engage early. Get feedback. Make sure there are benefits e.g. productivity, and communicate them
Model does not work in training. It isn't accurate enough or other success criteria are not hit	Need to clearly agree what "work" means with stake holders. Is any model better than no model? This is the "art+science" of building ML models which can be solved with more/better data, more feature engineering, algorithmic choices and tuning
Model works in training but not in deployment	Add a QA process Peer reviews

In summary

- There are many ways to deploy
- Deployment planning is key
 - Make sure we have a plan to deploy assuming for model success
 - Make sure we set expectations ... we don't always get to where we want
- Get communication/alignment with stakeholders early and often ... don't forget end user stakeholders who may be a broad group who become involved post deployment
- Involve technical colleagues early too
- Depending on where you are in your deployment journey think about the next level of automation
 - The more automated the less work ... the less likely errors
- Platforms are definitely not for all use cases/contexts
 - Depends on scale and availability
 - Platforms/automation do not eliminate blockers on their own ... but they help
- Did we say plan deployment from the beginning?

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Thank you