Michael Smurfit Graduate School of Business
M.Sc. in Business Analytics
Capstone Presentation

Amazon Web Services Amazon SageMaker - An Exploratory Approach

Nguyen, Hang, BA. and Lalhlimpuii, Rosy, BE.

Supervisor: Dr. Michael MacDonnell

August 2020





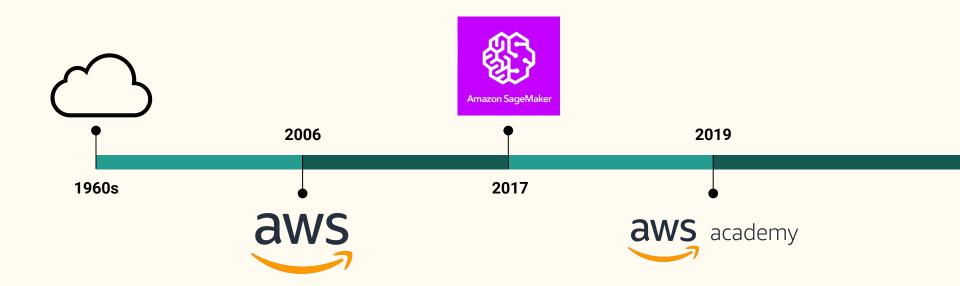
Contents

- 1. Capstone Project's Objectives
- 2. Introduction: AWS, AWS Academy, Amazon SageMaker
- 3. Use Case 1: Customer Churn Prediction using Amazon SageMaker Autopilot
- 4. Use Case 2: Stock Price Prediction using GluonTS and DeepAR algorithm
- 5. AWS Products Module Integration
- 6. Limitations and Recommendations
- 7. Learning and Takeaways

Capstone Project's Objectives

- Explore Amazon SageMaker by comparing among 3 approaches (Studio, Notebook Instance, Console) in 2 use cases (Autopilot, Built-in algorithm).
- Recommend AWS Products Module Integration

Introduction



What Amazon SageMaker offer?

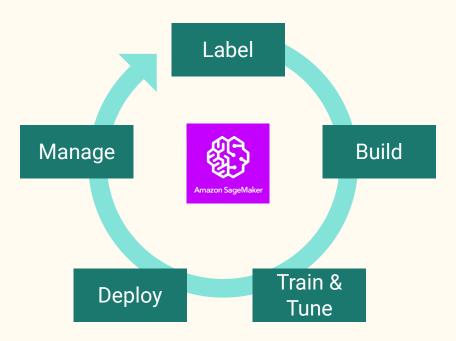
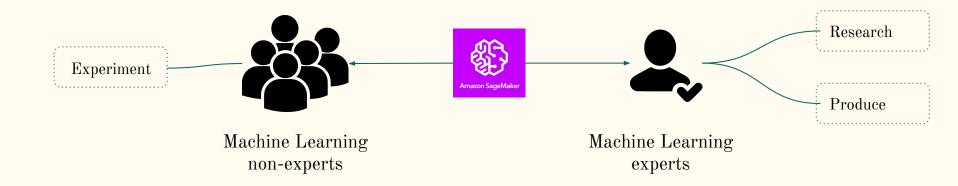
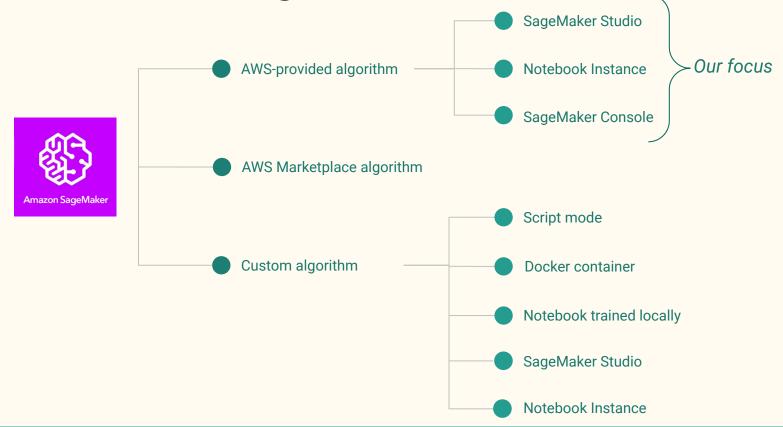


Fig. 1. Amazon SageMaker offerings

Who is Amazon SageMaker for?



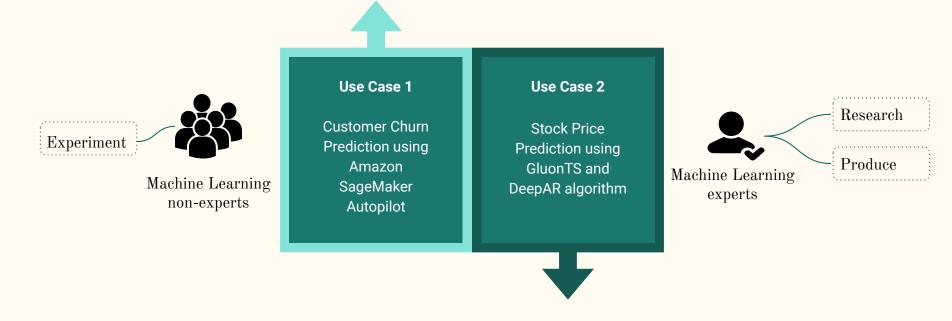
How to use Amazon SageMaker?



We explore 3 Approaches

01	SageMaker Studio	 fast, fully integrated IDE for machine learning single, web-based visual interface notebooks, automatic model creation, etc.
02	Notebook Instance	 one-click Jupyter notebooks fully elastic compute resources easy sharing with others
03	SageMaker Console	 SageMaker main interface process, train, deploy without any code Ground Truth, Augmented Al and AWS Marketplace.

We explore 2 Use cases



Use Case 1: Customer Churn Prediction using Amazon SageMaker Autopilot

SageMaker StudioNotebook Instance



Use Case 1: Customer Churn Prediction using Amazon SageMaker Autopilot



University of California Irvine
Repository of Machine Learning
Datasets, consisting profile of
customers of an unknown US mobile
operator, collected by Daniel T.
Larose and mentioned in
Discovering Knowledge in Data



Amazon SageMaker SDK library



AWS built-in algorithms

- XGBoost
- Linear-Learner

Experiment with SageMaker Autopilot

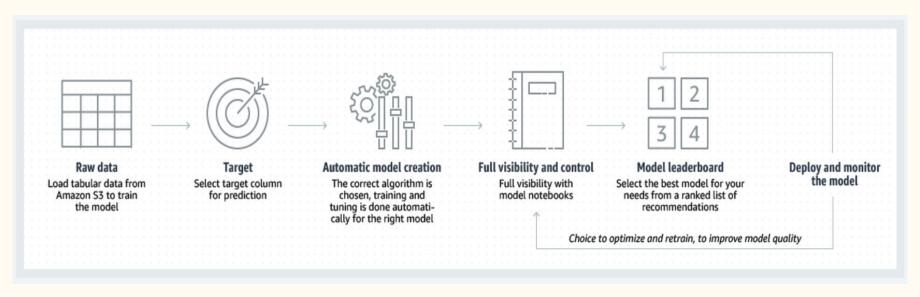
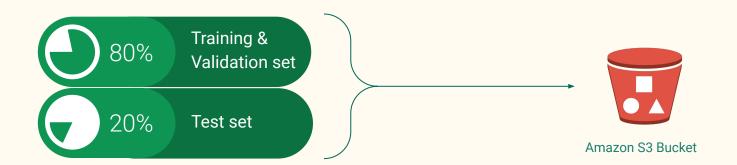


Fig. 2. Amazon SageMaker Autopilot workflow







NOTE: Autopilot automatically split Training and Validation set with default ratio = 0.8/0.2

SageMaker Studio



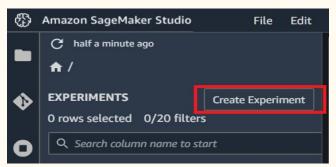


Fig. 3. Create an Autopilot Experiment

SageMaker Studio **Deployment Data Preparation Autopilot Setup Pre-processing & Training Test & Cleanup** Studio Notebook Studio Studio Studio Studio Notebook Open candidate generation notebook Open data exploration notebook **EXPERIMENT: AUTOML-TRIAL** Feature Engineering Model Tuning Completed Analyzing Data Amazon SageMaker Autopilot is extracting features from your dataset. If experiment is taking too long to run, you can stop the experiment You can always return to this page later by choosing this experiment on the Experiments tab in the navigation panel. Trials Job profile You don't have any trials running.

Fig.4. Data Exploration notebook and Candidate Generation notebook in Studio Autopilot Experiment

SageMaker Studio



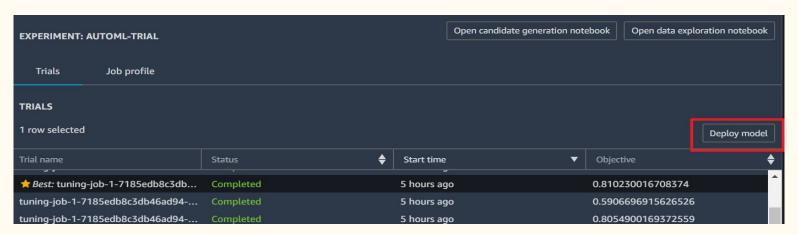
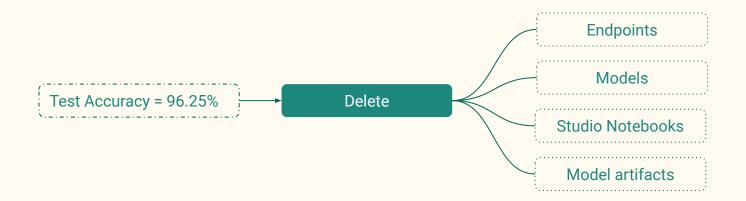


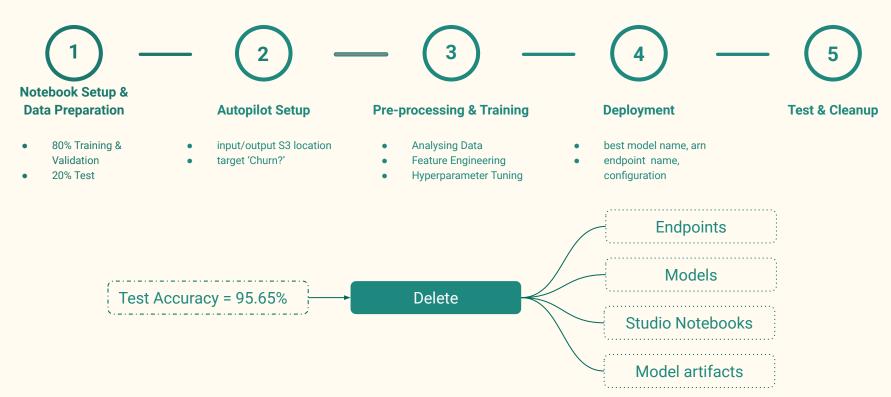
Fig. 5. Autopilot automatically chooses the best model after Training jobs











NOTE: Autopilot automatically split Training and Validation set with default ratio = 0.8/0.2

SageMaker Studio

OR

02

Notebook Instance

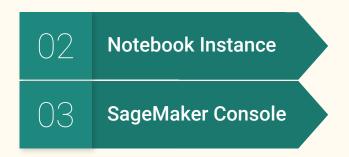
for Autopilot Job

		SageMaker Studio	Notebook Instance	Details
1	Accuracy	96.25%	95.65%	
2	Time	/	X	Starting a Studio notebook is typically faster than launching an notebook instance
3	Interpretability	/	X	- Data Exploration notebook from Studio helps users explore the descriptive statistics with no code needed - Trial Component list allows users to compare the metrics among trial models via CloudWatch
4	Transparency	/	X	- Candidate Generation notebook from Studio helps users examine candidates' hyperparameters - Trial Component list: all of model's parameters, configurations and results.

NOIE.

SageMaker Studio is good for Autopilot job, but it is still not matured enough for complicated tasks (research and production)

Use Case 2: Stock Price Prediction using GluonTS and DeepAR algorithm



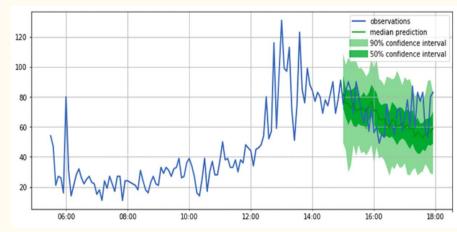


Fig. 6. DeepAR Inference visualisation*

^{*} Gasthaus, J. et al. (2019), Creating neural time series models with Gluon Time Series, AWS Machine Learning Blog. URL

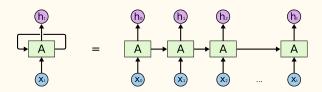
Use Case 2: Stock Price Prediction using GluonTS and DeepAR algorithm



Deutsche Börse Public Dataset - Xetra, consisting of daily trading data (Jul 2017 - Oct 2018)



GluonTS library



AWS built-in algorithm

- Autoregressive Recurrent Network
- High accuracy, global model from all-time series

Notebook Setup

Notebook Instance



Data Preparation and Preprocessing

Example: bucket-name-1, bucket-name-2, bu

Comma delimited. ARNs, "*" and "/" are not supported.

Allow users that have access to your notebook instance access to any bucket



Feature Selection

Registry (5 actions) A 1 warning

Service EC2 Container Registry

Q Filter actions

▶ ☐ List

Manual actions (add actions)

▼ Write (5 selected)

BatchDeletelmage

✓ CompleteLaverUpload

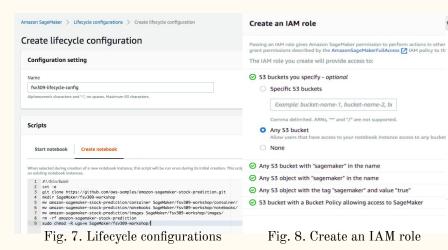
✓ CreateRepository ⑦

Actions Specify the actions allowed in EC2 Container Registry

All EC2 Container Registry actions (ecr.*)

Train & Deploy Test & Cleanup

Notebook instance settings





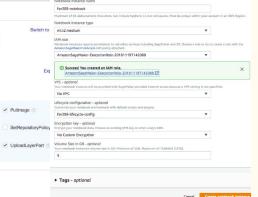


Fig. 9. Add new policy

DeleteRepository [

✓ InitiateLaverUpload

DeleteRepositoryPolicy

Fig. 10. Create notebook instance



- Download data to local files in Notebook Instance
- Pre-process data:
 - Filter top 100 stocks, by trading volume
 - \circ Delete instance with trading volumes = 0
 - Delete instance outside trading hours
- Resample data according to Month, Week, Day, Hour intervals
- Save and upload data to S3 Bucket

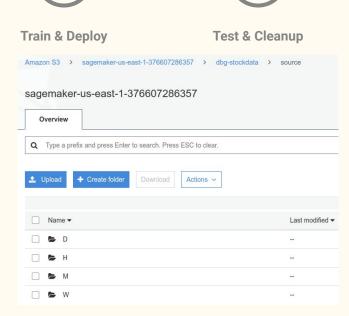
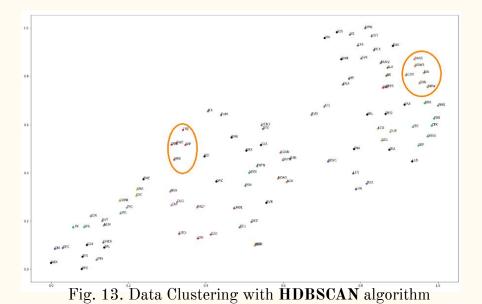


Fig.11. Processed data on S3 bucket

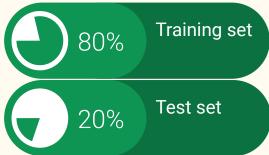


Fig.12. Data exploration





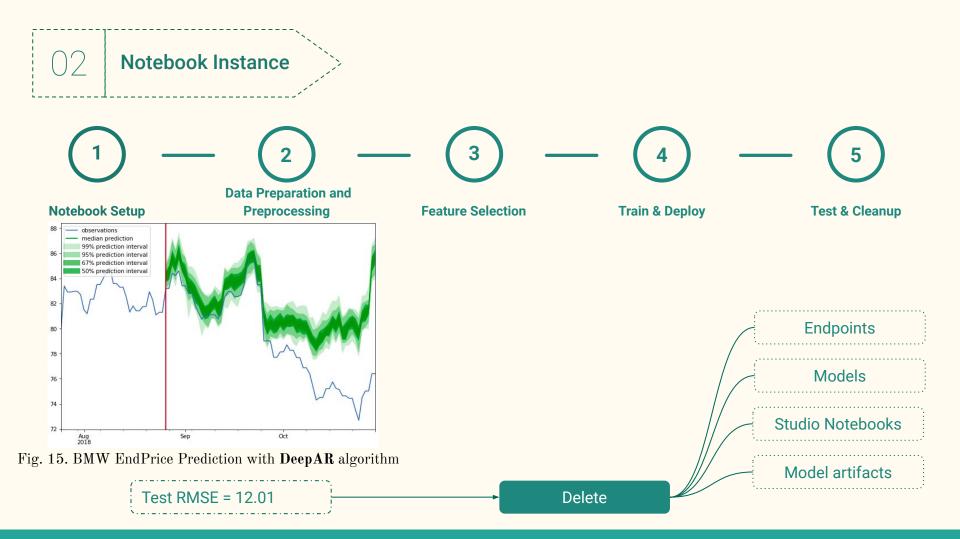






NOTE: We don't use hyperparameter tuning for DeepAR algorithm as the default hyperparameters are good enough for fast solutions

Fig. 14. Training loss per epoch



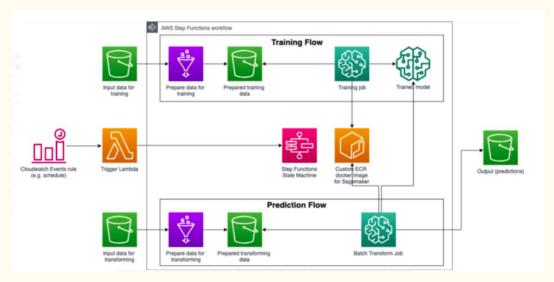


Fig. 16. Suggested Machine learning workflow for production*

- Amazon S3: storage service
- Amazon ECR: Docker container registry
- AWS Step Functions: serverless workflow

- Amazon CloudWatch: metrics recording
- AWS Glue: data extract, transform, and load
- AWS Lambda: automatic computing

^{*} Correa, R. F., (2019), Building an AWS Serverless ML Pipeline with Step Functions, OLX Group Engineering. URL

03

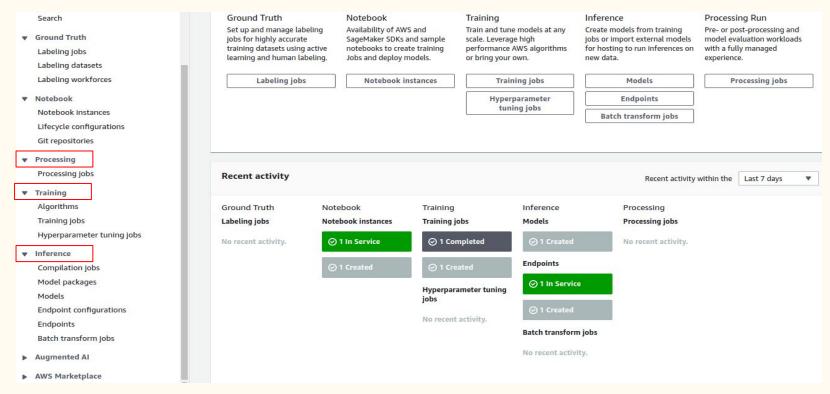


Fig. 17. SageMaker Console

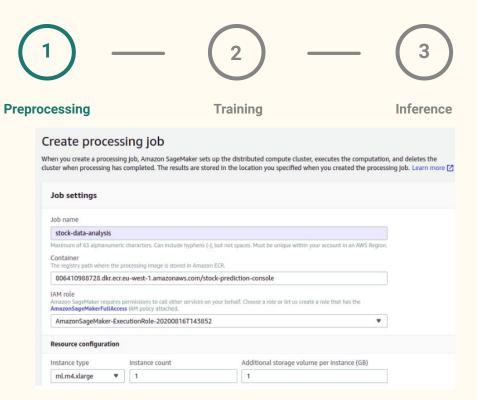


Fig. 18. Create a processing job from Console

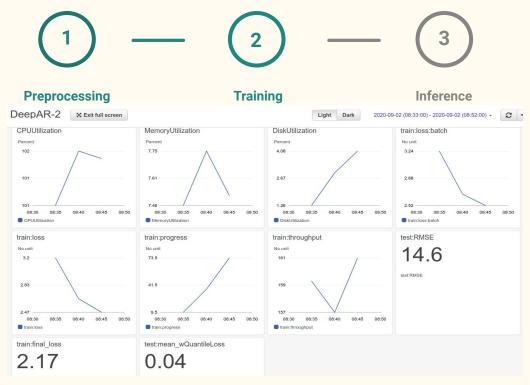


Fig. 19. Train/Test metrics

03

SageMaker Console



Test RMSE = 14.6

Prediction on an entire dataset

Batch Transforms without create an endpoint

Real-time prediction on large scale datasets

Create an endpoint configuration and an HTTPS endpoint

	Notebook Instance	SageMaker Console
1 RMSE	12.01	14.6
2 Code	conda-installedother data science packages	 process, train and deploy with one click
3 Research workflow	data explorationexecute and share 'technical' papers	 create Lifecycle Configuration, IAM, VPC, and label data
4 Production workflow	need advanced infrastructures (e.g. Netflix) to use at scale	 suit for script mode, docker container when using at scale

AWS Products - Module Integration

Module	AWS Product	
MIS41150: Introduction to Business An-	AWS Cloud Security	
alytics		
MIS41110: Programming for Analytics	AWS Developer Tools	
MIS41130: Statistics & Simulation	AWS Analytics	
Methods		
MIS41090: Advanced Operations Re-	AWS Machine Learning	
search		
MIS41270: Data Management & Mining	AWS Machine Learning	
MIS41040: Business Intelligence & Vi-	Amazon QuickSight	
sual Analytics		
MIS41050: Consulting Change & Project	AWS IoT, AWS Management and Governance	
Management		
MIS41120: Statistical Learning	AWS Machine Learning	

Tab. 1. AWS Products - Module Integration

Limitations and Recommendations

Limitations of SageMaker

- Complicated connection with other AWS services and in-progress pipeline development.
- Local mode is only available in Notebook Instance, not in Studio Notebook.
- Data pre-processing and Cross-validation are not well-supported.
- Detailed permissions system is needed when starting notebook instance and when onboarding to Studio.
- Python SDK is incomplete and some algorithms are not open-sourced.

Recommendations for SageMaker practitioners

- In-depth research on other AWS services (S3, ECR, Step Functions, CloudWatch, Glue, Lambda)
- Keep up-to-date with AWS SageMaker newly-launched features and libraries

Limitations and Recommendations

Capstone Project Limitations

- Do not cover all AWS Machine Learning services (Augmented AI, Forecast, Fraud Detector, Personalize, Rekognition, etc.) and approaches (script mode, docker container, AWS Marketplace and local model training).
- Have not fully explore Inference/Test step in Use Case 2.

M.Sc. in Business Analytics Capstone Presentation

Amazon Web Services

Amazon SageMaker - An Exploratory Approach

Learning and Takeaways

- Accelerate Machine Learning with Cloud Computing
 - Big Data infrastructure
 - High-quality models with minimal effort and machine learning expertise
 - ---- O Automated deployment and inference





Nguyen, Hang, BA. and Lalhlimpuii, Rosy, BE. Supervisor: Dr. Michael MacDonnell

Supervisor: Dr. Michael MacDonnell Sponsor contact: Ivan Obarski, AWS

August 2020