Build an explainable AI model with AWS Sagemaker Clarify

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Topics

- Introduction to Explainable AI
- What is SHAPLEY
- How to build Explainable AI Model using Sagemaker Clarify
- How to build a model to explain Credit decision using Sagemaker Clarify in Sagemaker Studio.

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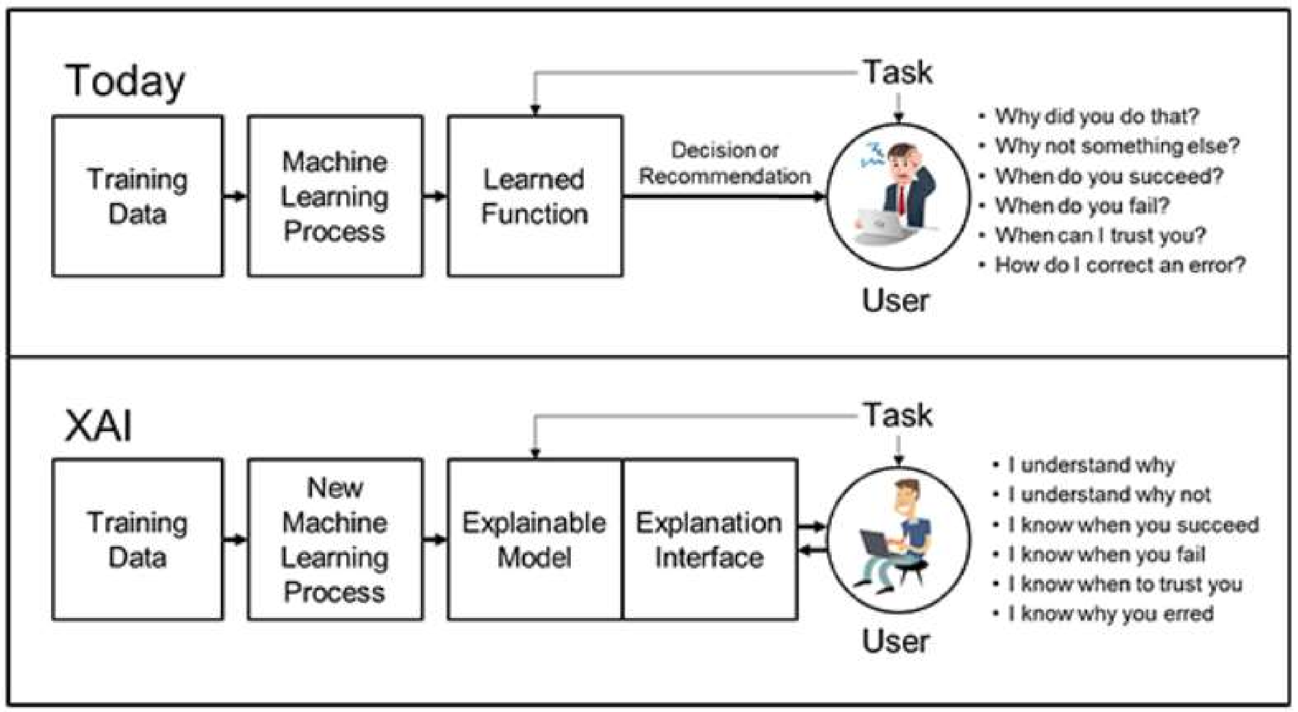
Understand How Machines Make Decision



The diagram Source: https://www.darpa.mil/program/explainable-artificial-intelligence

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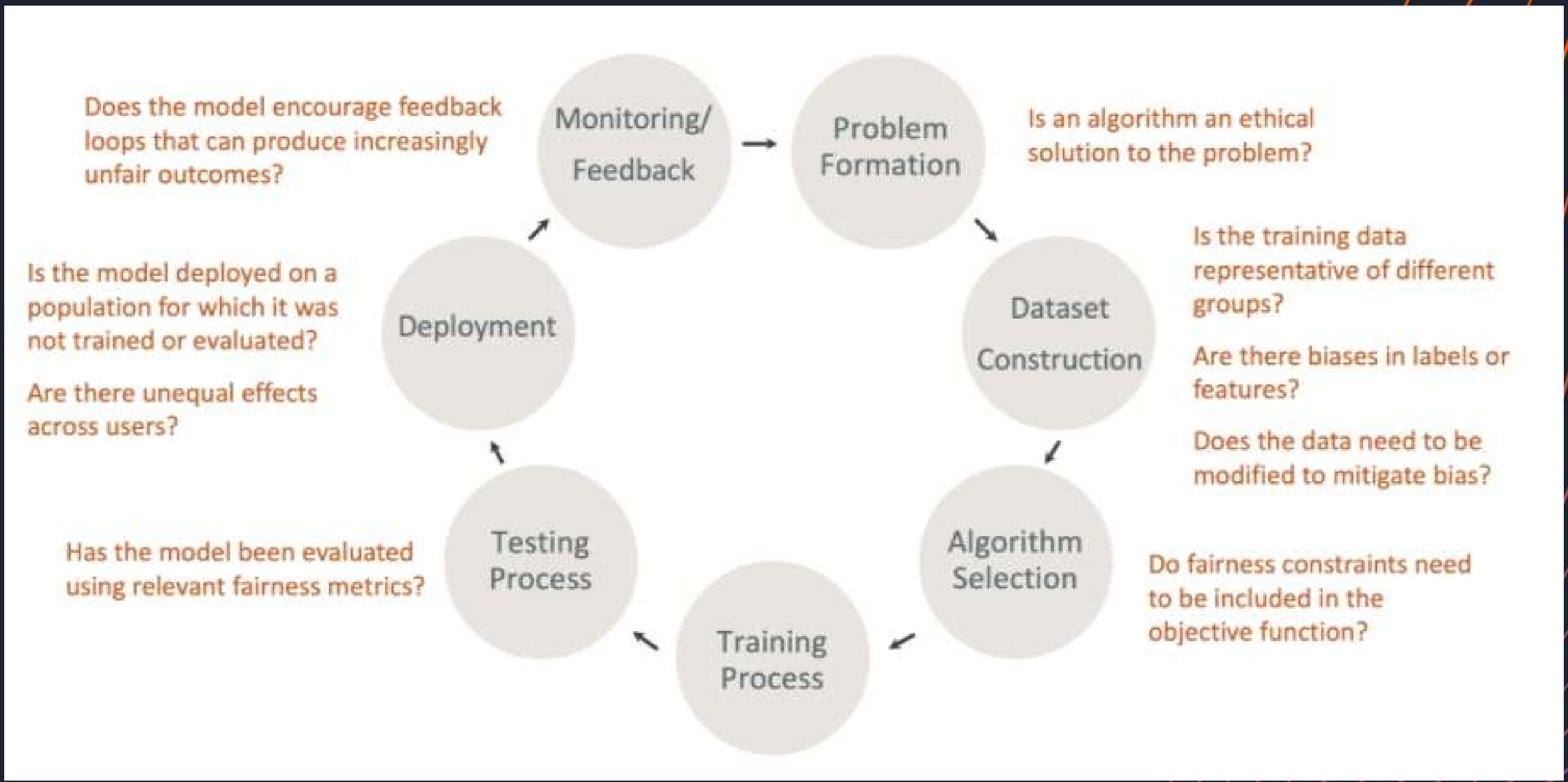
Understand How Machines Make Decision

AI-based systems are disrupting almost every industry – healthcare, finances, education, retail, media, marketing, social, economy, HR system, etc, etc. and helping us to make crucial decisions that are impacting millions of lives.

Hence it is important to understand how these decisions are made by the AI system.

Can we trust the Machine Learning, Deep Learning models, and their training algorithm?

Machine Learning Lifecycle



https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-fairness-and-explainability.html

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Explain the Model Decision

Simple Algorithms

- Bayesian classifiers,
- Decision trees,
- Linear Regression,
- Logistic Regression etc ..

➢ possess a certain degree of interpretability, traceability, visibility, and transparency in their decision-making process at the cost of the performance

Complex Algorithms

- PCA,
- Deep Neural Network,
- Ensemble methods,
- Random forests etc

➢ sacrifice their explainability to achieve high performance and accuracy

AWS Sagemaker clarify

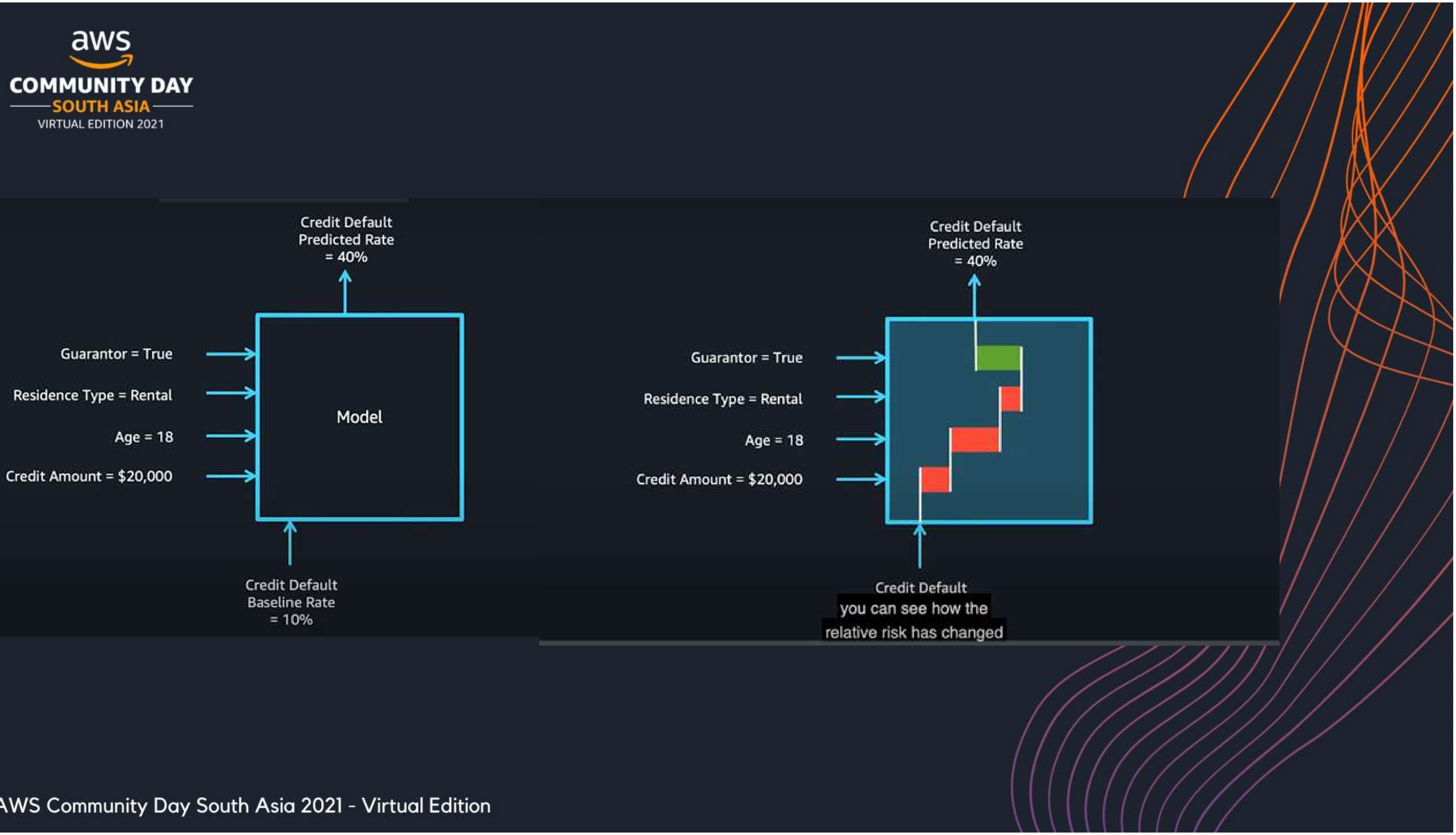
- Detecting dataset bias
  - ✓ Pre Training & Post Training Bias Detection
  - ✓ Measure bias using a various statistical metrics.
  - ✓ Help in early detection of bias in dataset
- Detecting model bias
  - ✓ Explain how feature values contribute to the predicted outcome, both for the model overall and for individual predictions.
  - ✓ Run a SageMaker Clarify analysis, which includes automatic deployment to a temporary endpoint, and computation of bias metrics using our model and dataset.
  - ✓ By computing these metrics, we can figure out if trained model has similar predictive behavior across groups.

Explain Credit Decision with Sagemaker Clarify

- Classify credit applications and predict whether the credit would be payed back or not
- Bank to Reduce the risk of losing money due to unpaid credits
- Also reduce the risk of denying trustworthy customers credit which has a set of negative impacts.

Explain Credit Decision with Sagemaker Clarify

- Explain specific failure cases in model predictions
- Explain risk factor for credit default
- Achieve the stakeholder's trust in model
- Identify potential bias in model
- Comply with “right for explanation” for users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Credit Default
Predicted Rate
= 40%
Guarantor = True
Residence Type = Rental
Age = 18
Credit Amount = $20,000
Model
Credit Default
Baseline Rate
= 10%
Credit Default
Predicted Rate
= 40%
Guarantor = True
Residence Type = Rental
Age = 18
Credit Amount = $20,000
Credit Default
you can see how the
relative risk has changed
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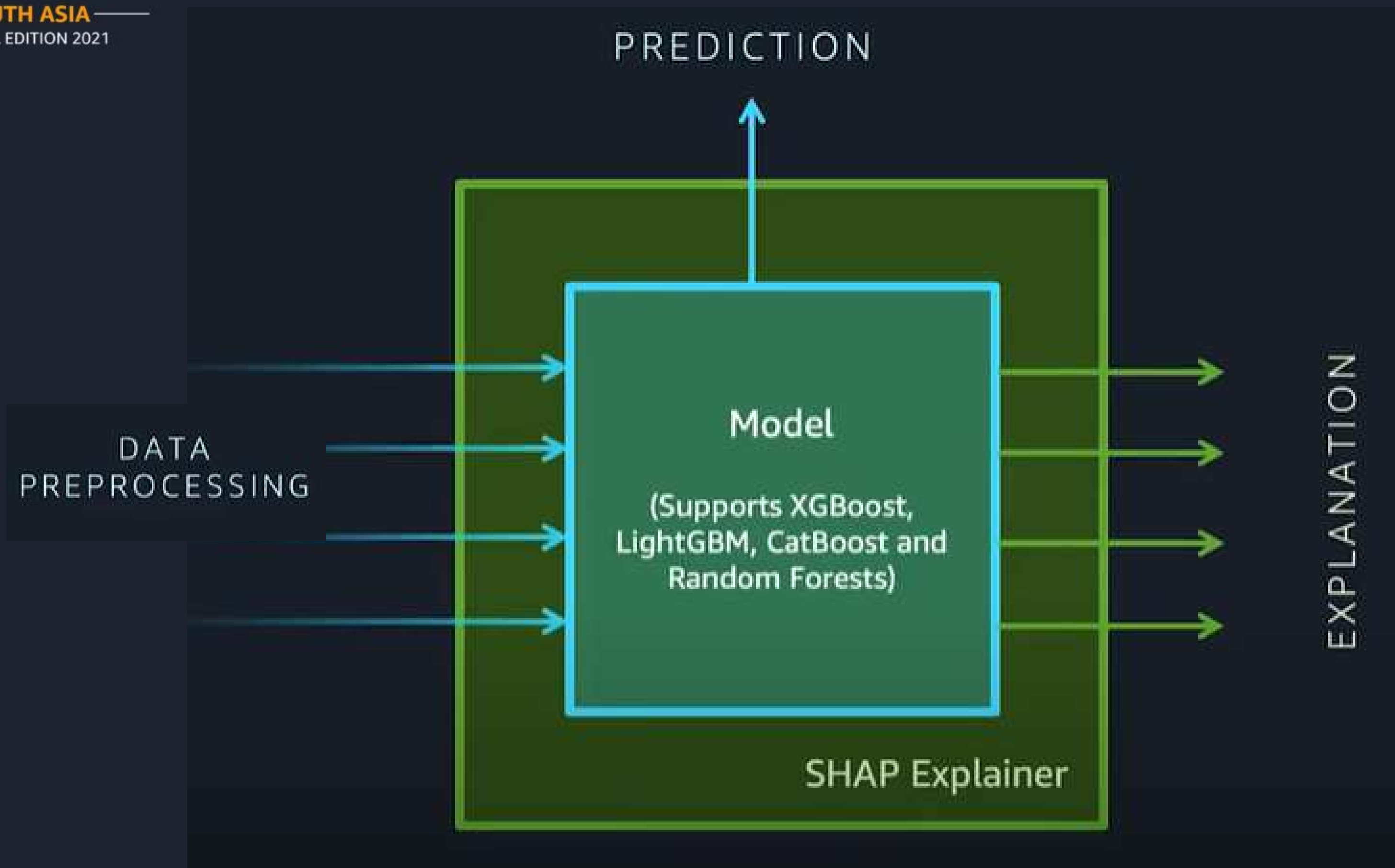
PREDICTION
DATA
PREPROCESSING
Model
(Supports XGBoost, LightGBM, CatBoost and Random Forests)
SHAP Explainer
EXPLANATION

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SHAPE

SHAP stands for SHapley Additive exPlanations. 'Shapley' relates to a game theoretic concept called Shapley values that is used to create the explanations.

A Shapley value describes the marginal contribution of each 'player' when considering all possible 'coalitions'.

Using this in a machine learning context, a Shapley value describes the marginal contribution of each feature when considering all possible sets of features.

'Additive' relates to the fact that these Shapley values can be summed together to give the final model prediction.

As an example, we might start off with a baseline credit default risk of 10%. Given a set of features, we can calculate the Shapley value for each feature. Summing together all the Shapley values, we might obtain a cumulative value of +30%. Given the same set of features, we therefore expect our model to return a credit default risk of 40% (i.e. 10% + 30%).

Shapeley Values

WITH GUARANTOR		WITHOUT GUARANTOR	
Guarantor = True	✓	Guarantor = ~~True~~ = False	✗
Residence Type = Rental	✓	Residence Type = Rental	✓
Age = 18	✓	Age = 18	✓
Credit Amount = $20,000	✓	Credit Amount = $20,000	✓
Credit Default Risk = 40%		Credit Default Risk = 60%	
		Effect of Guarantor = **-20%**	

WITH GUARANTOR		WITHOUT GUARANTOR	
Guarantor = True	✓	Guarantor = ~~True~~ = False	✗
Residence Type = ~~Rental~~ = Own	✗	Residence Type = ~~Rental~~ = Own	✗
Age = 18	✓	Age = 18	✓
Credit Amount = $20,000	✓	Credit Amount = $20,000	✓
Credit Default Risk = 10%		Credit Default Risk = 20%	
		Effect of Guarantor = **-10%**, -20%	

WITH GUARANTOR		WITHOUT GUARANTOR	
Guarantor = True	✓	Guarantor = ~~True~~ = False	✗
Residence Type = Rental	✓	Residence Type = Rental	✓
Age = ~~18~~ = 45	✗	Age = ~~18~~ = 45	✗
Credit Amount = $20,000	✓	Credit Amount = $20,000	✓
Credit Default Risk = 20%		Credit Default Risk = 35%	
		Effect of Guarantor = -15%, -10%, -20%	

Shapeley Values

WITH GUARANTOR		WITHOUT GUARANTOR	
Guarantor = True	✓	Guarantor = ~~True~~ = False	✗
Residence Type = ~~Rental~~ = Own	✗	Residence Type = ~~Rental~~ = Own	✗
Age = 18	✓	Age = 18	✓
Credit Amount = ~~$20,000~~ = $5,000	✗	Credit Amount = ~~$20,000~~ = $5,000	✗
Credit Default Risk = 20%		Credit Default Risk = 45%	

Effect of Guarantor = -25%, -5%. -15%, -15%, -10%, -20%

WITH GUARANTOR		WITHOUT GUARANTOR	
Guarantor = True	✓	Guarantor = ~~True~~ = False	✗
Residence Type = ~~Rental~~ = Own	✗	Residence Type = ~~Rental~~ = Own	✗
Age = ~~18~~ = 45	✗	Age = ~~18~~ = 45	✗
redit Amount = ~~$20,000~~ = $5,000	✗	Credit Amount = ~~$20,000~~ = $5,000	✗
Credit Default Risk = 5%		Credit Default Risk = 45%	

Effect of Guarantor = -10%, -15%, -25%, -5%. -15%, -15%, -10%, -20%

Overall Effect of Guarantor = SHAP Value for Guarantor = -17%

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AWS Services

As part of the solution, the following services are used:

AWS Lambda: Used to generate a synthetic credits dataset and upload to Amazon S3.

AWS Glue: Used to crawl datasets, and transform the credits dataset using Apache Spark.

Amazon S3: Used to store datasets and the outputs of the AWS Glue Job.

Amazon SageMaker Notebook: Used to train the LightGBM model.

Amazon ECR: Used to store the custom docker image with pre built Scikit-learn + LightGBM training environment. Used to train the model inside.

Amazon SageMaker Endpoint: Used to deploy the trained model and SHAP explainer.

Amazon SageMaker Batch Transform: Used to compute explanations in batch.

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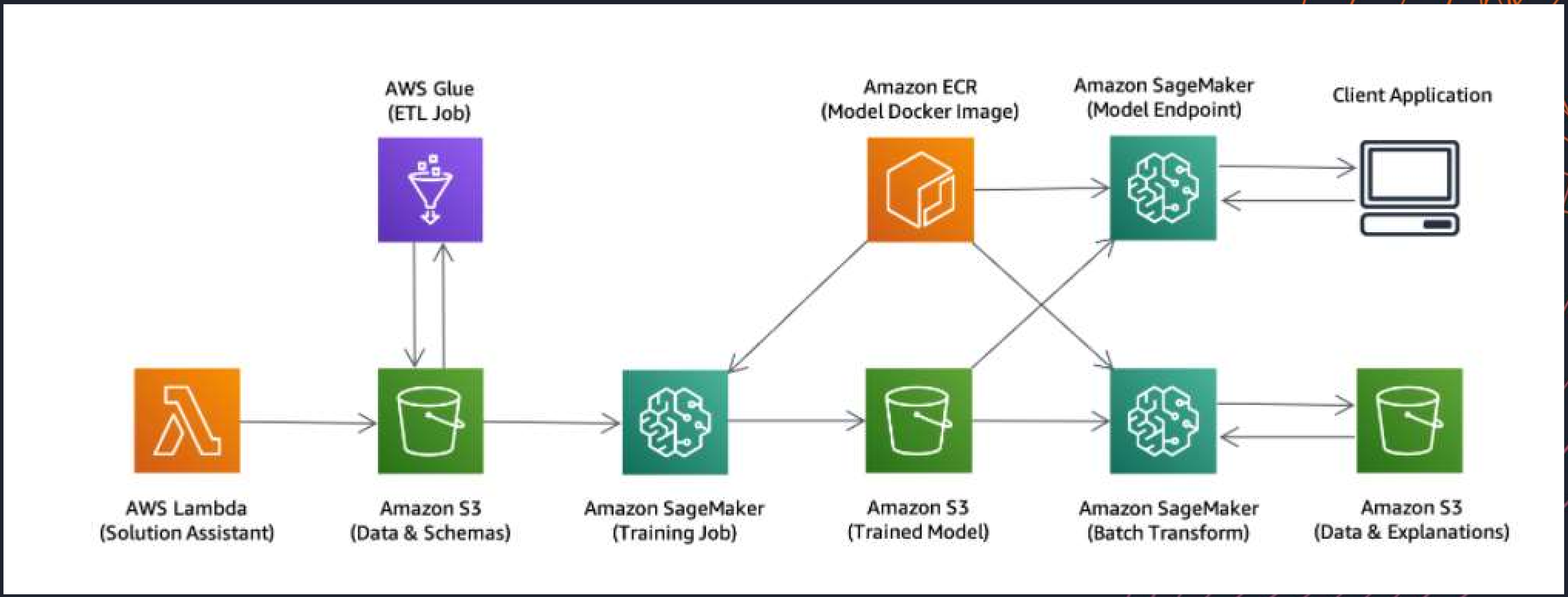
Architecture



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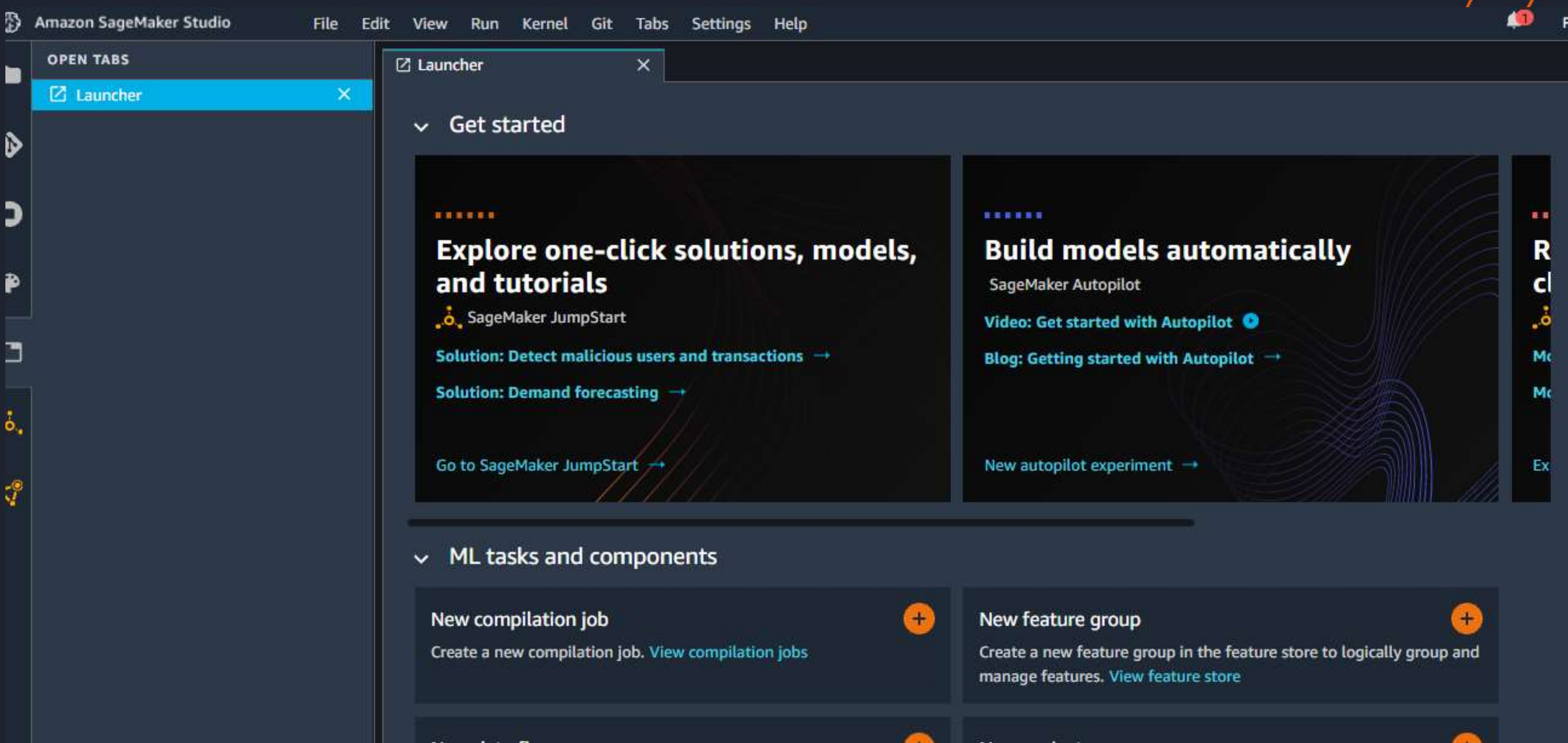
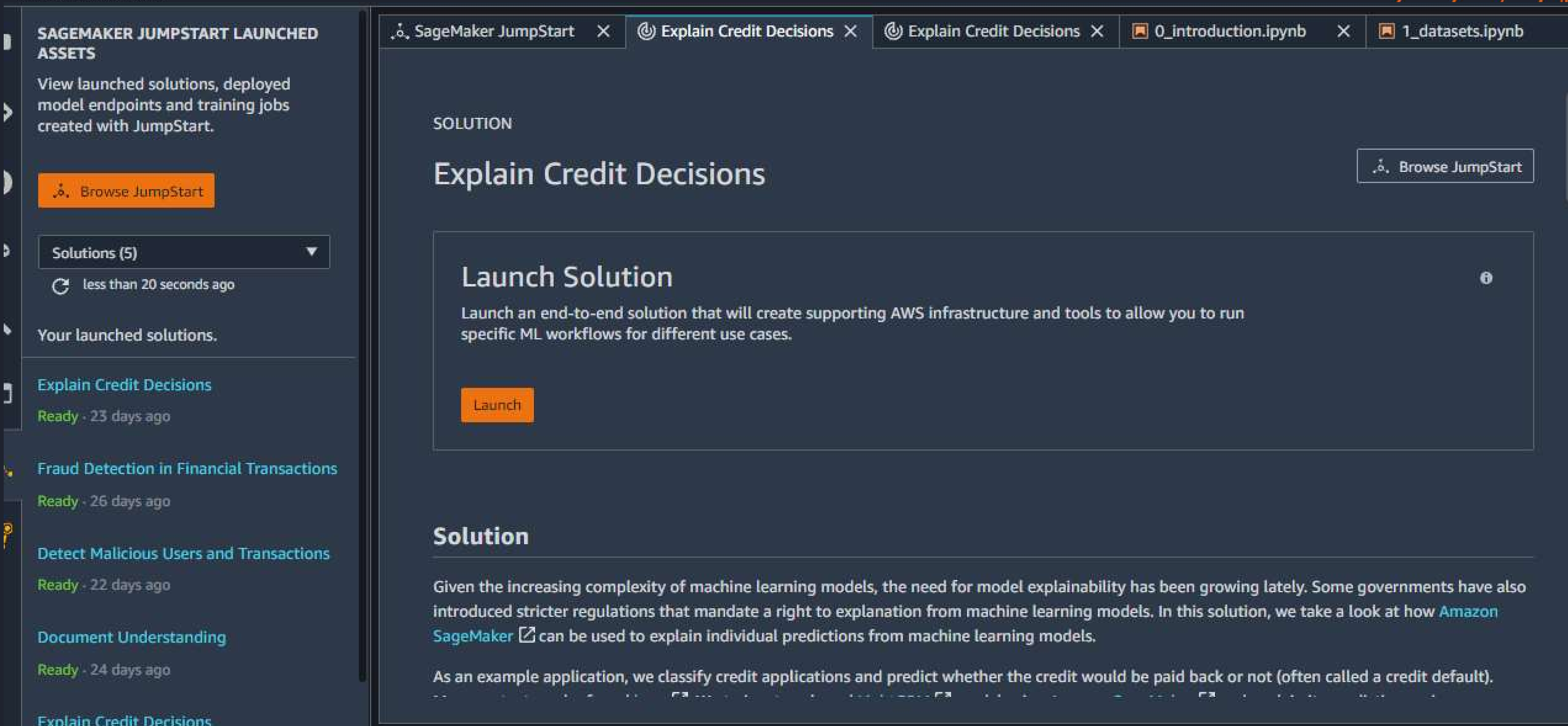
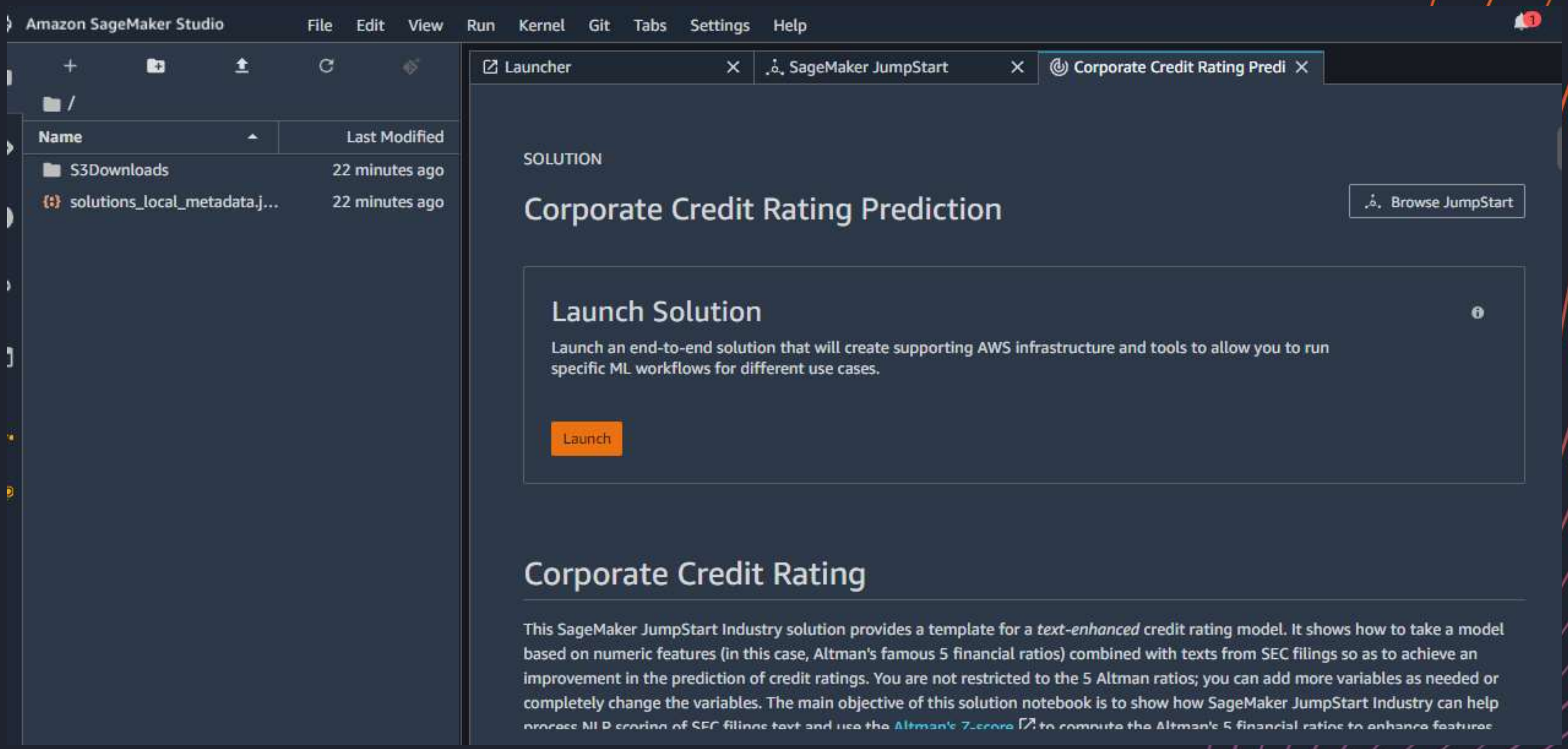
Demo


Amazon SageMaker Studio
File
Edit
View
Run
Kernel
Git
Tabs
Settings
Help
OPEN TABS
Launcher
Launcher
Get started
Explore one-click solutions, models, and tutorials
SageMaker JumpStart
Solution: Detect malicious users and transactions
Solution: Demand forecasting
Go to SageMaker JumpStart
Build models automatically
SageMaker Autopilot
Video: Get started with Autopilot
Blog: Getting started with Autopilot
New autopilot experiment
ML tasks and components
New compilation job
Create a new compilation job. View compilation jobs
New feature group
Create a new feature group in the feature store to logically group and manage features. View feature store


SAGEMAKER JUMPSTART LAUNCHED ASSETS
View launched solutions, deployed model endpoints and training jobs created with JumpStart.
Browse JumpStart
Solutions (5)
3 minutes ago
Your launched solutions.
Explain Credit Decisions
Ready · 23 days ago
Fraud Detection in Financial Transactions
Ready · 26 days ago
Detect Malicious Users and Transactions
Ready · 22 days ago
Document Understanding
Ready · 24 days ago
Explain Credit Decisions
Launcher
SageMaker JumpStart
about 1 hour ago
SageMaker JumpStart
Discover and deploy one-click solutions, pretrained models, and example notebooks
Search
Featured content
Corporate Credit Rating Prediction
Financial Services
Use multimodal data to predict corporate credit rating.
RoBERTa-SEC-WIKI-Large
Community Model · Text
Task: Text Embedding
Pre-training Dataset: S&P 500 10-K/10-Q (2010-2019) and WikiPedia
Fine-tunable: No
Source: Gluon NLP
SEC Filings Retrieval w/ Summarizer and Scoring
Financial Services
This notebook shows how Amazon SageMaker JumpStart Industry hel deploy a simple solution to retrieve SEC filings and construct a datafra of mixed tabular-and-text (TabText) data.


SAGEMAKER JUMPSTART LAUNCHED ASSETS
View launched solutions, deployed model endpoints and training jobs created with JumpStart.
Browse JumpStart
Solutions (5)
less than 20 seconds ago
Your launched solutions.
Explain Credit Decisions
Ready · 23 days ago
Fraud Detection in Financial Transactions
Ready · 26 days ago
Detect Malicious Users and Transactions
Ready · 22 days ago
Document Understanding
Ready · 24 days ago
Explain Credit Decisions
SageMaker JumpStart
Explain Credit Decisions
Explain Credit Decisions
0_introduction.ipynb
1_datasets.ipynb
SOLUTION
Explain Credit Decisions
Browse JumpStart
Launch Solution
Launch an end-to-end solution that will create supporting AWS infrastructure and tools to allow you to run specific ML workflows for different use cases.
Launch
Solution
Given the increasing complexity of machine learning models, the need for model explainability has been growing lately. Some governments have also introduced stricter regulations that mandate a right to explanation from machine learning models. In this solution, we take a look at how Amazon SageMaker can be used to explain individual predictions from machine learning models.
As an example application, we classify credit applications and predict whether the credit would be paid back or not (often called a credit default).

AWS Sagemaker Studio



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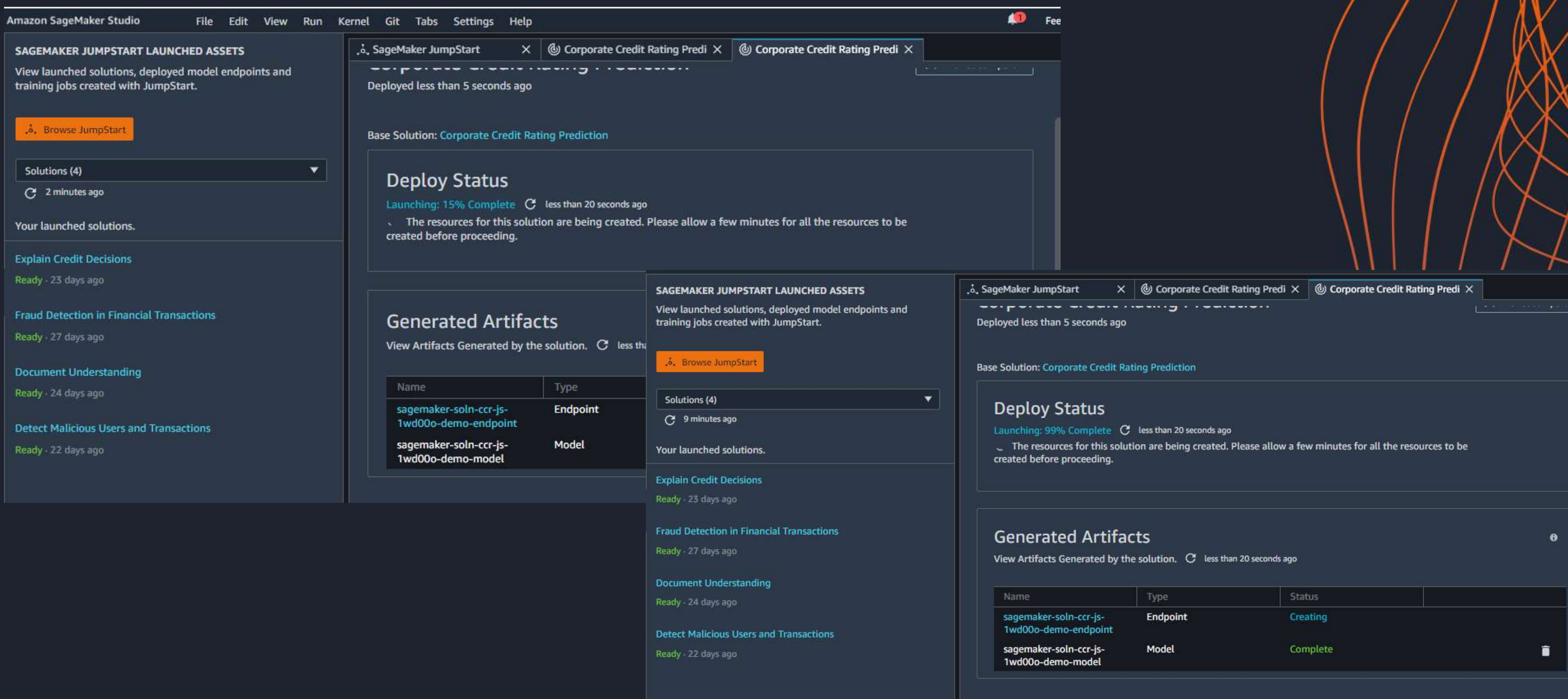

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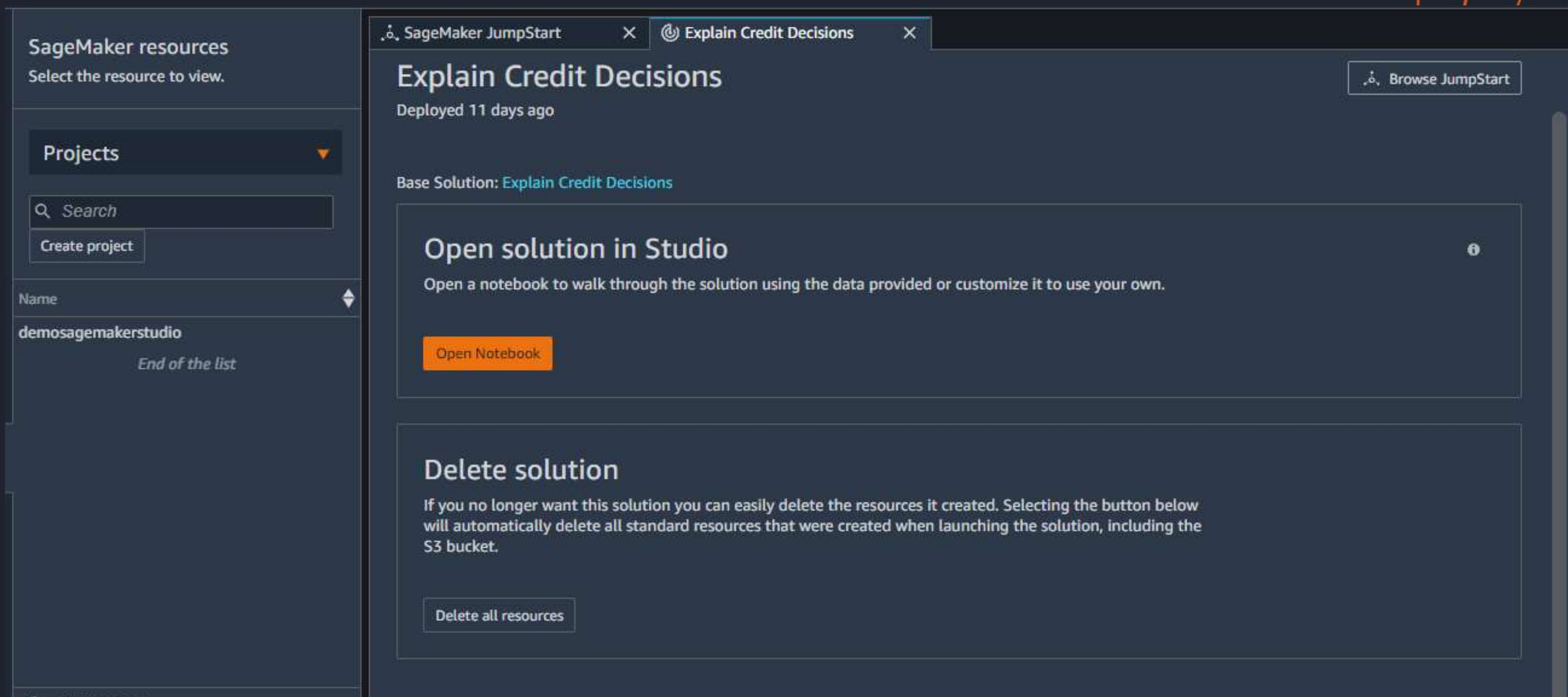
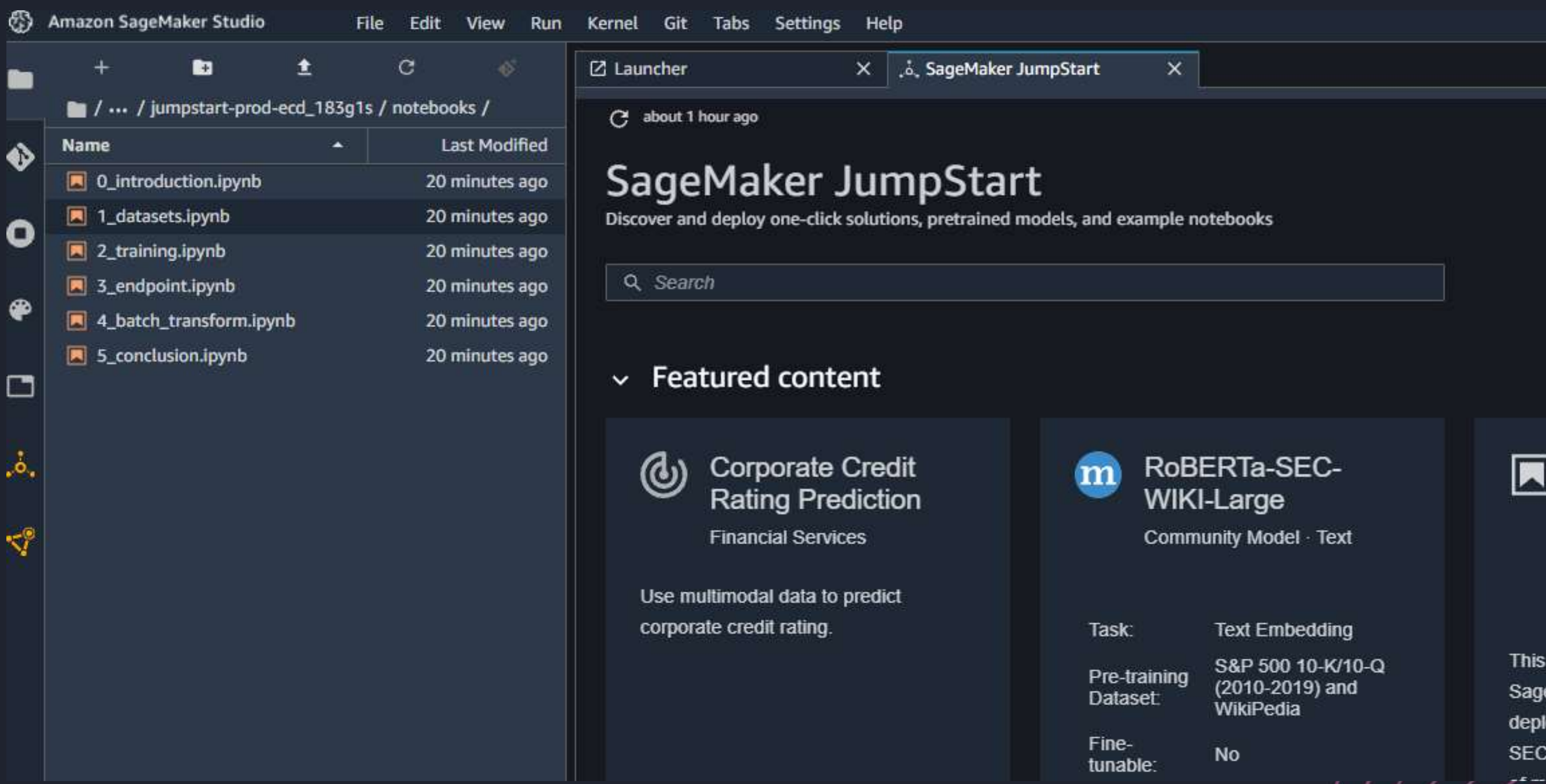
AWS Sagemaker Studio



AWS Sagemaker Studio



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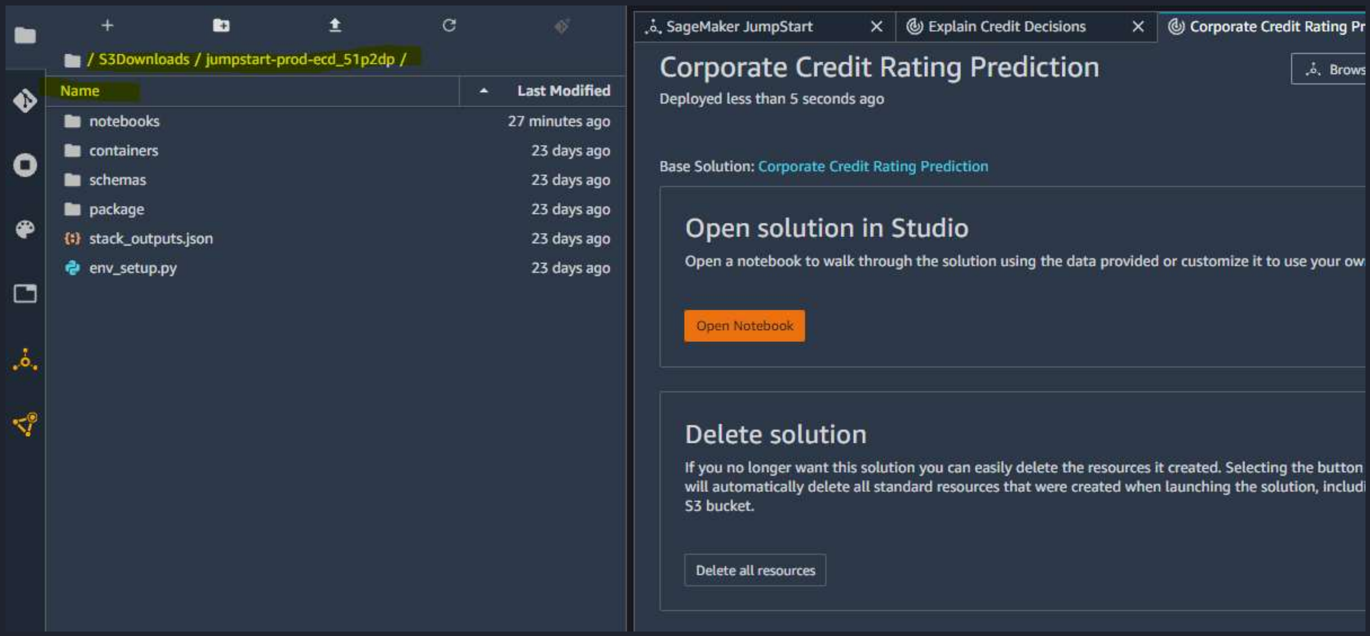
AWS Sagemaker Studio



Once the solution is launched the notebooks are run in order notebook_1 to notebook_5 and Code directory structure is created in Sagemaker Studio as shown above. Source codes are available in container folder. These codes are required when we will customize the solution for our own data or model.

Stages

- Our solution is split into the following stages, and each stage has it's own notebook:
- Introduction: We take a high-level look at the solution components.
- Datasets: We prepare a dataset for machine learning using AWS Glue.
- Training: We train a LightGBM model using Amazon SageMaker, so we have an example trained model to explain.
- Endpoint: We deploy the model explainer to a HTTP endpoint using Amazon SageMaker and visualize the explanations.
- Batch Transform: We use Amazon SageMaker Batch Transform to obtain explanations for our complete dataset.
- Dashboard: We develop a dashboard for explanations using Amazon SageMaker and Streamlit.
- Conclusion: We wrap things up and discuss how to clean up the solution.

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Model Deployment

- Once the SageMaker training job is completed, a number of trained model artifacts are stored in S3 bucket
- Retrieve the model data (i.e. model.tar.gz) from the most recent trained model
- Define the model using SKLearnModel() to deploy which includes the explainer logic.
- Calling model.deploy() will start a container to host the model.
- Entities are used ->

```
entities = [
    'data',
    'features',
    'descriptions',
    'prediction',
    'explanation_shap_values',
    'explanation_shap_interaction_values'
]
```

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Model Explaination

- Call explainer.predict with features (for a credit application) to obtain a prediction and explanation.
- Visualize Explanations with bokeh & waterfall chart.
- A waterfall chart can be used to show the cumulative effect of each feature.
- Green arrows indicate that the feature *decreased* the predicted credit default risk for the individual credit application.
- While red arrows indicate that the feature *increased* the predicted credit default risk for the individual credit application.
- After all features have been considered, we reach the final predicted credit default risk (at the top of the chart).

Solution Code & Explanation

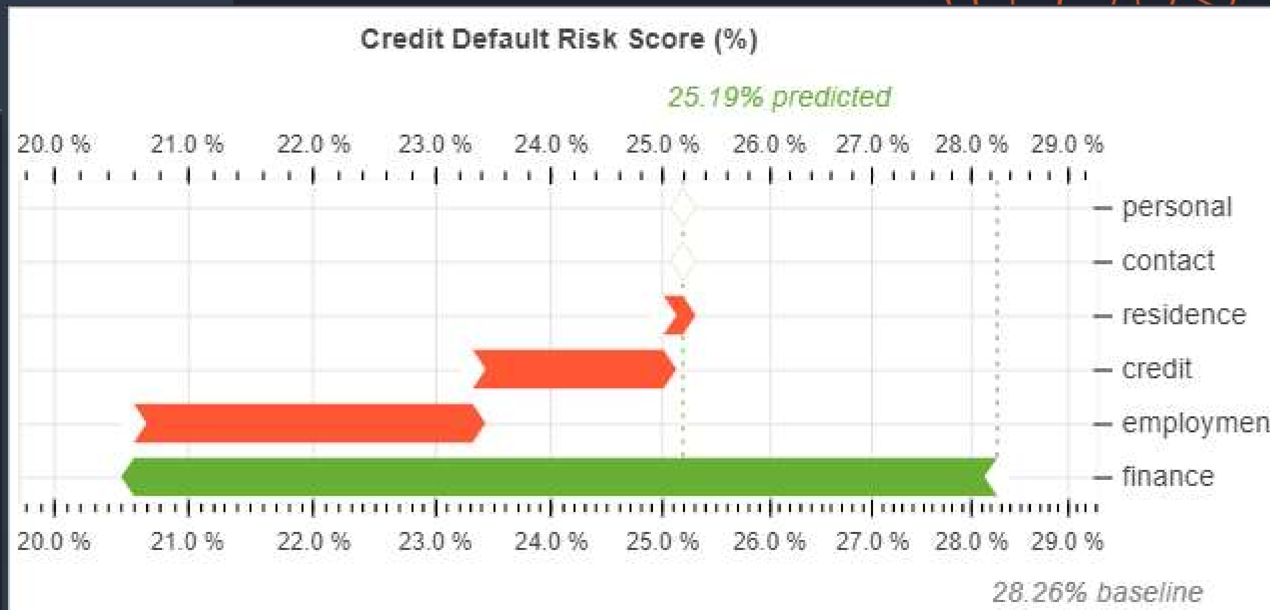
Please refer the reference slide for the link of:

- Youtube : Explaining Credit Decisions with Amazon SageMaker – Webinar by Solution Developer
- AWS Lab github links

Model Explaination

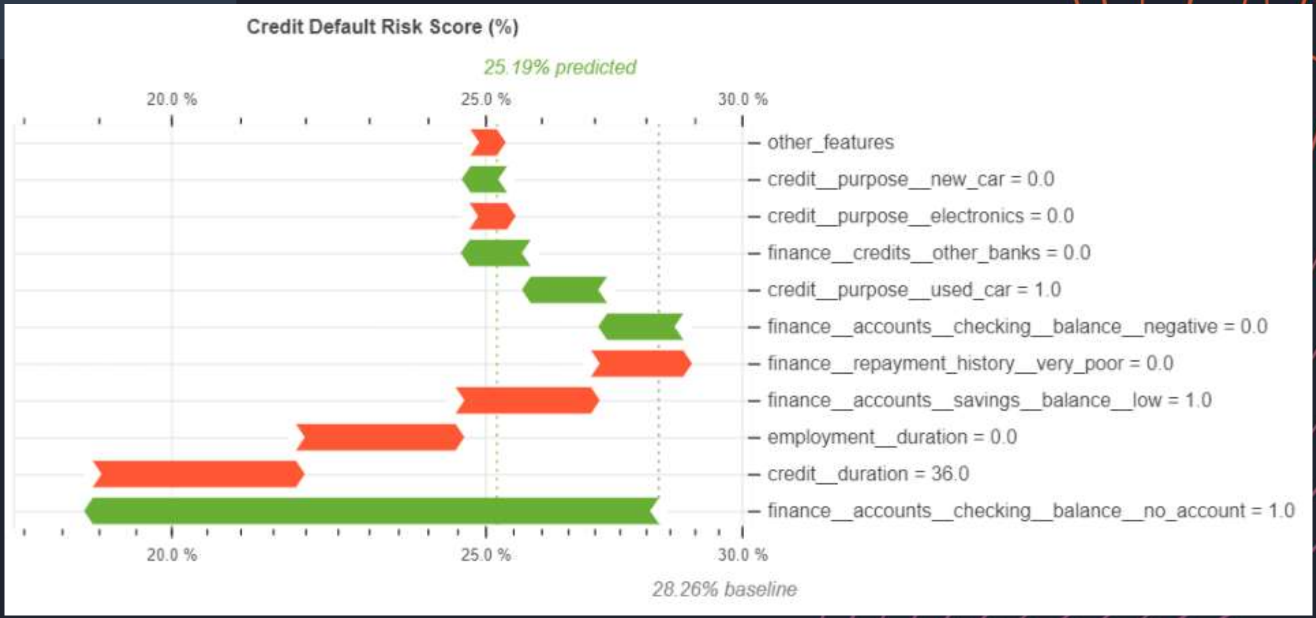
```
x_axis_label = 'Credit Default Risk Score (%)'
summary_waterfall = visuals.WaterfallChart(
    baseline=explanation_summary['expected_value'],
    shap_values=explanation_summary['shap_values'],
    names=explanation_summary['feature_names'],
    descriptions=explanation_summary['feature_descriptions'],
    max_features=10,
    x_axis_label=x_axis_label,
)
summary_waterfall.show()
```

We can see from the summary waterfall chart that features related to finance have the largest combined effect on the credit default risk.
Although features related to finance reduce the credit default risk, the features related to employment bring the risk back up again to a certain degree.



Explain Prediction

```
detailed_waterfall = visuals.WaterfallChart(
    baseline=explanation['expected_value'],
    shap_values=explanation['shap_values'],
    names=explanation['feature_names'],
    feature_values=explanation['feature_values'],
    descriptions=explanation['feature_descriptions'],
    max_features=10,
    x_axis_label=x_axis_label
)
detailed_waterfall.show()
```



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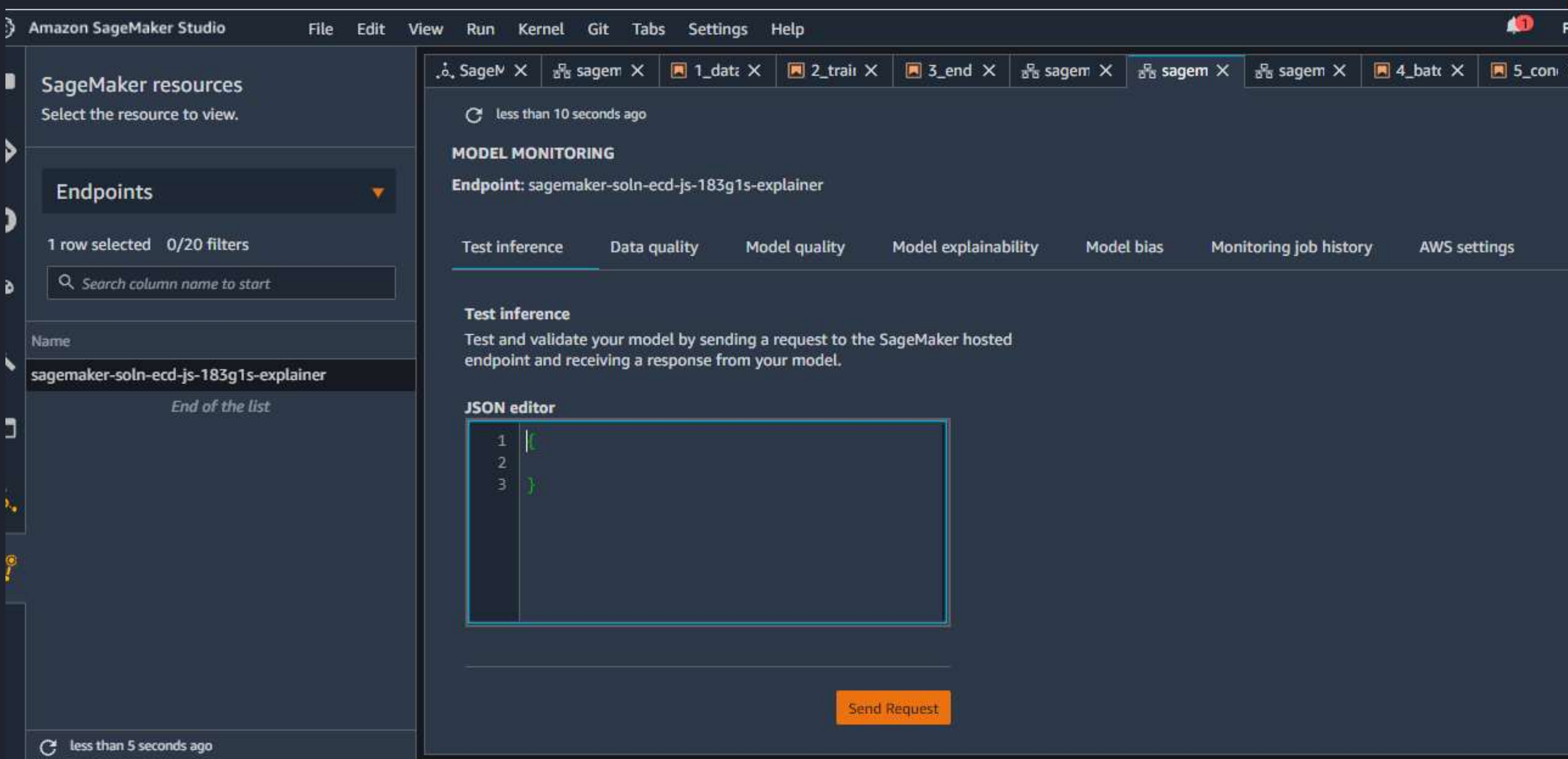
Explain Prediction

- Detailed waterfall chart shows that
  - Not having a checking account with the same bank indicates a lower credit default risk.
  - The credit to purchase a used car is associated with a lower credit default risk
  - After this we see a number of features that increase the credit default risk:
    - A credit amount of 6000 EUR, a lack of employment and a credit duration of 36 months.
    - Another potential area for investigation, would be related to the repayment history feature.
    - Not having a very poor repayment history is associated with a higher credit default risk score.

Counterfactual Example

```
counter_sample = dict(sample)
counter_sample['finance__accounts__checking__balance'] = 'negative'  # from 'no_account'
counter_output = explainer.predict(counter_sample)
counter_explanation = visuals.detailed_explanation(counter_output)
visuals.WaterfallChart(
    baseline=counter_explanation['expected_value'],
    shap_values=counter_explanation['shap_values'],
    names=counter_explanation['feature_names'],
    feature_values=counter_explanation['feature_values'],
    descriptions=counter_explanation['feature_descri
    max_features=10,
    x_axis_label=x_axis_label,
).show()
```

Endpoint Example



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Counterfactual Example

- Now let's switch the value of the checking account balance of the applicant from no account to negative.
- We can then see how the overall prediction of the model changes, and also see the updated contribution of this feature.
- Clearly, this application has become substantially more risky.

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References

Youtube : Explaining Credit Decisions with Amazon SageMaker – Webinar
https://www.youtube.com/watch?v=Nlwz4cU68T8&t=1204s
by AWS Solution Developer

AWSLABS : https://github.com/awslabs/sagemaker-explaining-credit-decisions

My Github link : https://bit.ly/3BzAsQT

My Linkedin : https://www.linkedin.com/in/sarbani-maiti-35b89111/

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Thank You