Final Project: Machine Learning Services
Student Name: CHEN TZU-AN (Can also call me ANN)
SMC ID: 1931977
CHEN_TZU-AN01@STUDENT.SMC.EDU

AWS Machine Learning Report

Choose any project that you are interested in doing. The main thing is to learn and to have fun doing it. Come up with an innovative idea related to the course material that you are interested in related to Machine Learning on Amazon Web Services. Requirements:

- Select at least one Machine Learning related service on AWS. It could be any ML service we did or did not cover in this course.
- In this project, I used SageMaker to create a deployable model, provide bias detection and explainability to analyze data, and understand prediction outcomes from the model.

- Implement a working cloud architecture using the selected ML service.
- For this project, I downloaded and explored the South German Credit dataset to analyze credit risk. The data was preprocessed using sklearn, followed by training a Gradient Boosting Machine model with XGBoost. I then built an inference pipeline that combined the sklearn preprocessing model and the XGBoost model to preprocess input data and generate predictions for each instance. To ensure transparency and fairness, a SageMaker Clarify job was run to obtain Kernel SHAP values for the model on both training and test datasets and to provide bias metrics, including pre-training bias metrics on the data.

- The total time spent on the project - including research, design, configuring, coding, testing, redesign, etc., should be around 10 - 15 hours.

Submit:

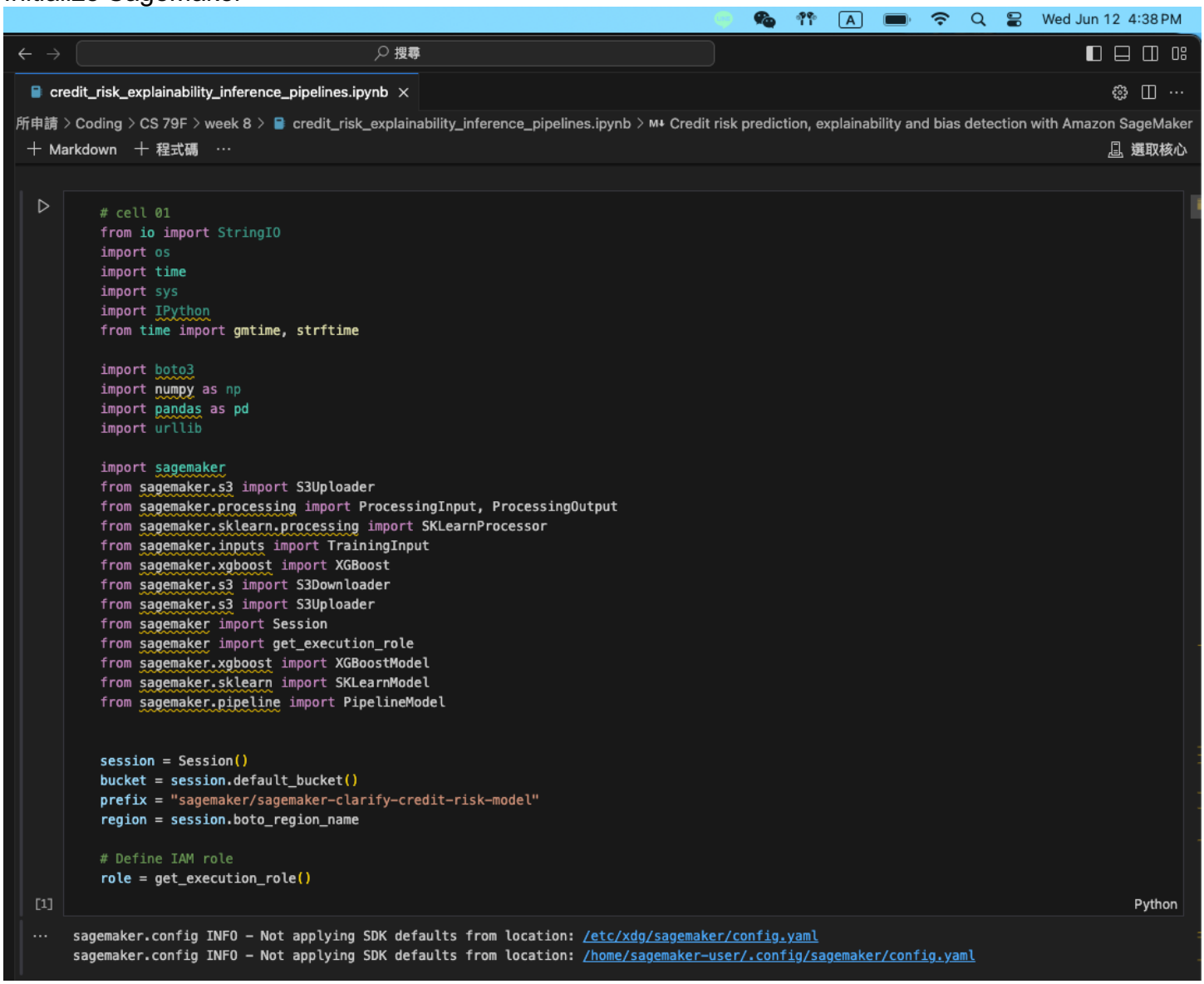
- 3 full-page written report detailing the project.
- Include screenshots in the report Appendix

[Appendix]

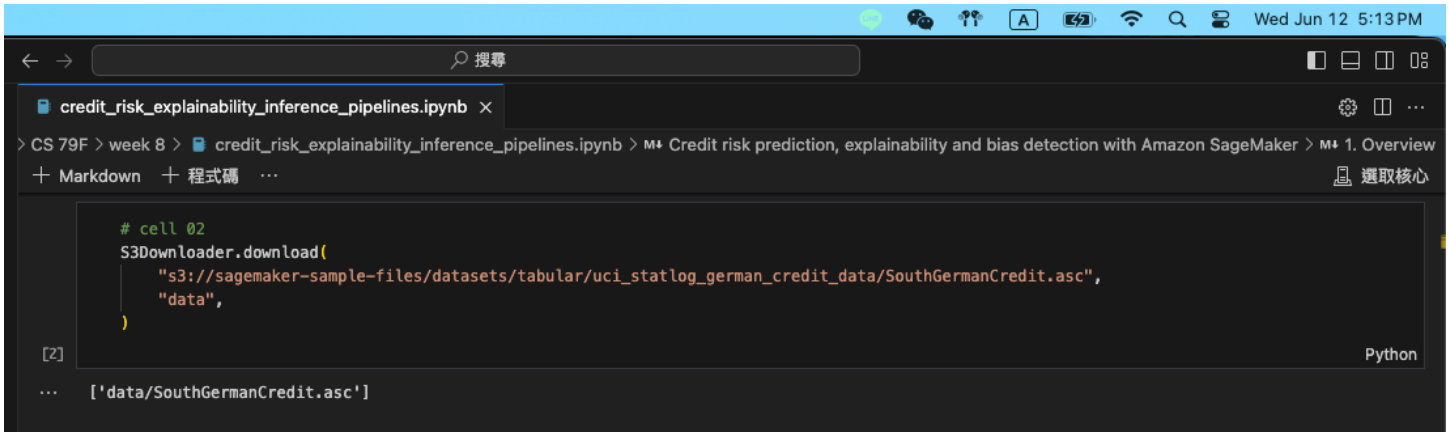
- South German Credit dataset source (https://archive.ics.uci.edu/dataset/573/south+german+credit+update)
- dataset source from Ulrike Grömping Beuth University of Applied Sciences Berlin (https://prof.beuth-hochschule.de/groemping/)
- A Unified Approach to Interpreting Model Predictions (https://papers.nips.cc/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf)
- Bias and Explainability-Tabular Data (https://catalog.us-east-1.prod.workshops.aws/workshops/63069e26-921c-4ce1-9cc7-dd882ff62575/en-US/lab5-bais-and-explainablity/lab-1)
- Host models along with pre-processing logic as serial inference pipeline behind one endpoint (https://docs.aws.amazon.com/sagemaker/latest/dg/inference-pipelines.html)
- aws/sagemaker-scikit-learn-container (https://github.com/aws/sagemaker-scikit-learn-container)
- aws/sagemaker-xgboost-container (https://github.com/aws/sagemaker-xgboost-container/blob/master/src/sagemaker_xgboost_container/encoder.py)
- Feature Attributions that Use Shapley Values (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-shapley-values.html)
- Use SageMaker Clarify to explain and detect bias (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-configure-processing-jobs.html)

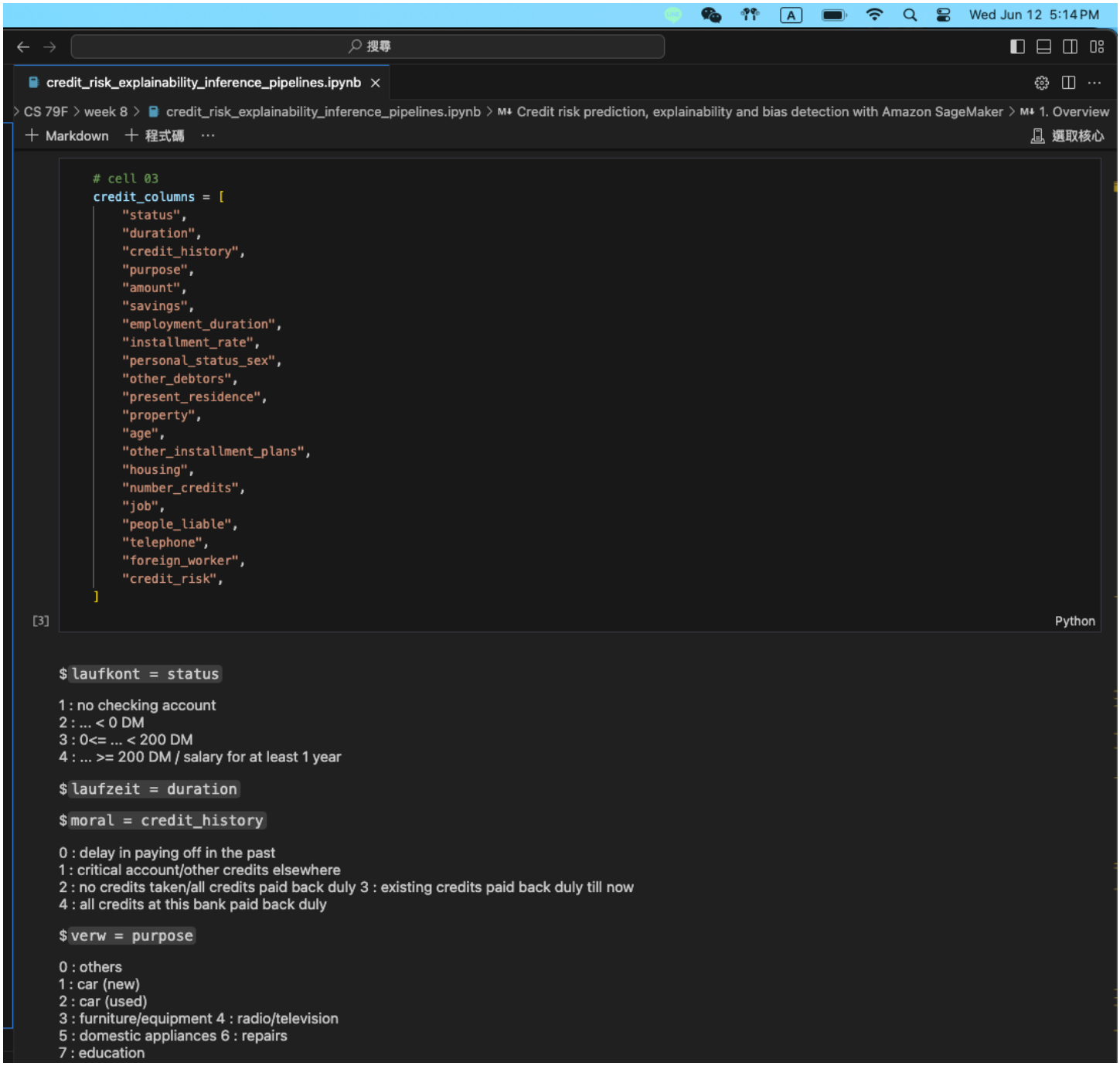
Credit risk prediction, explainability and bias detection with SageMaker

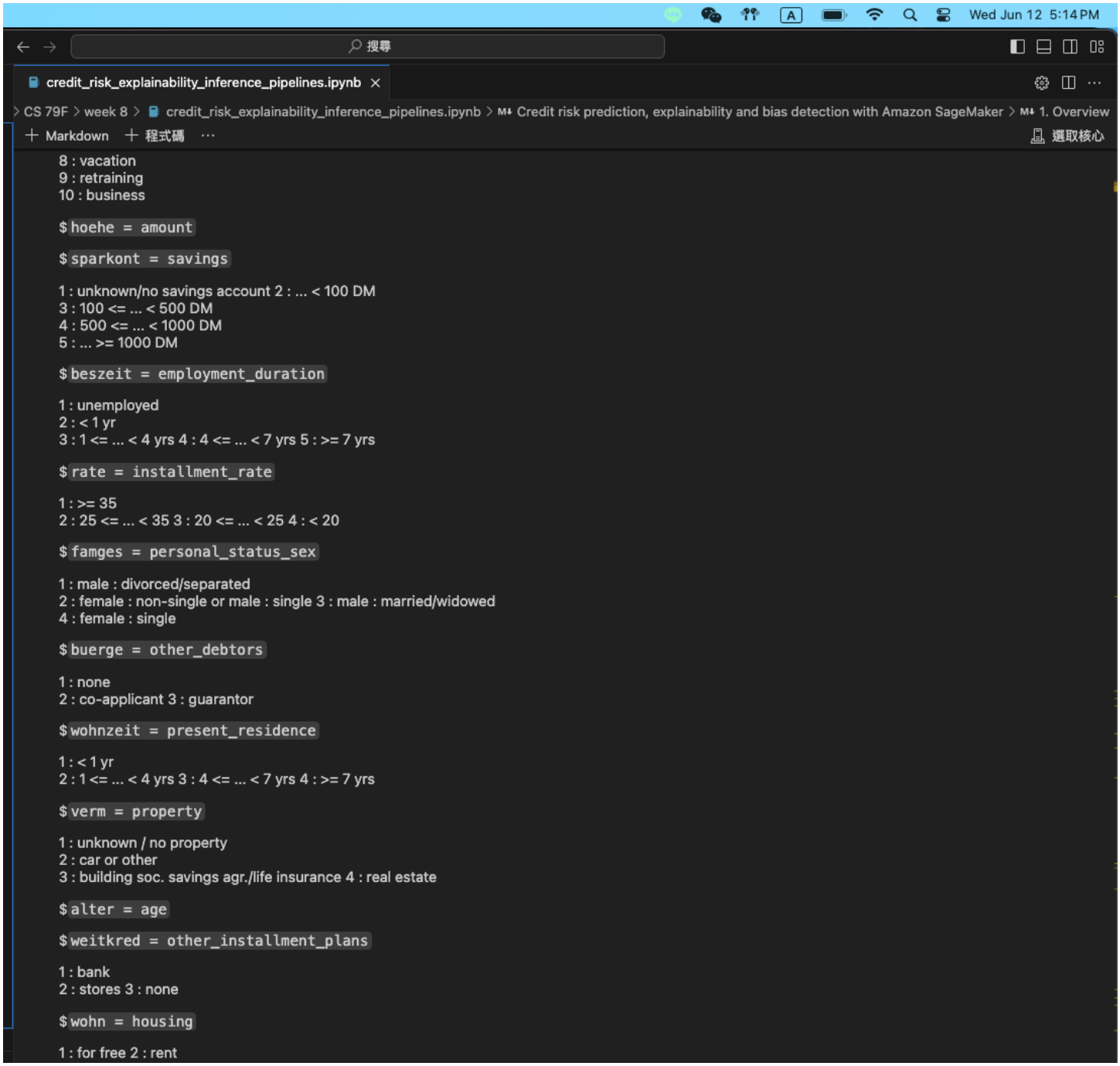
Step 1:
Initialize SageMaker

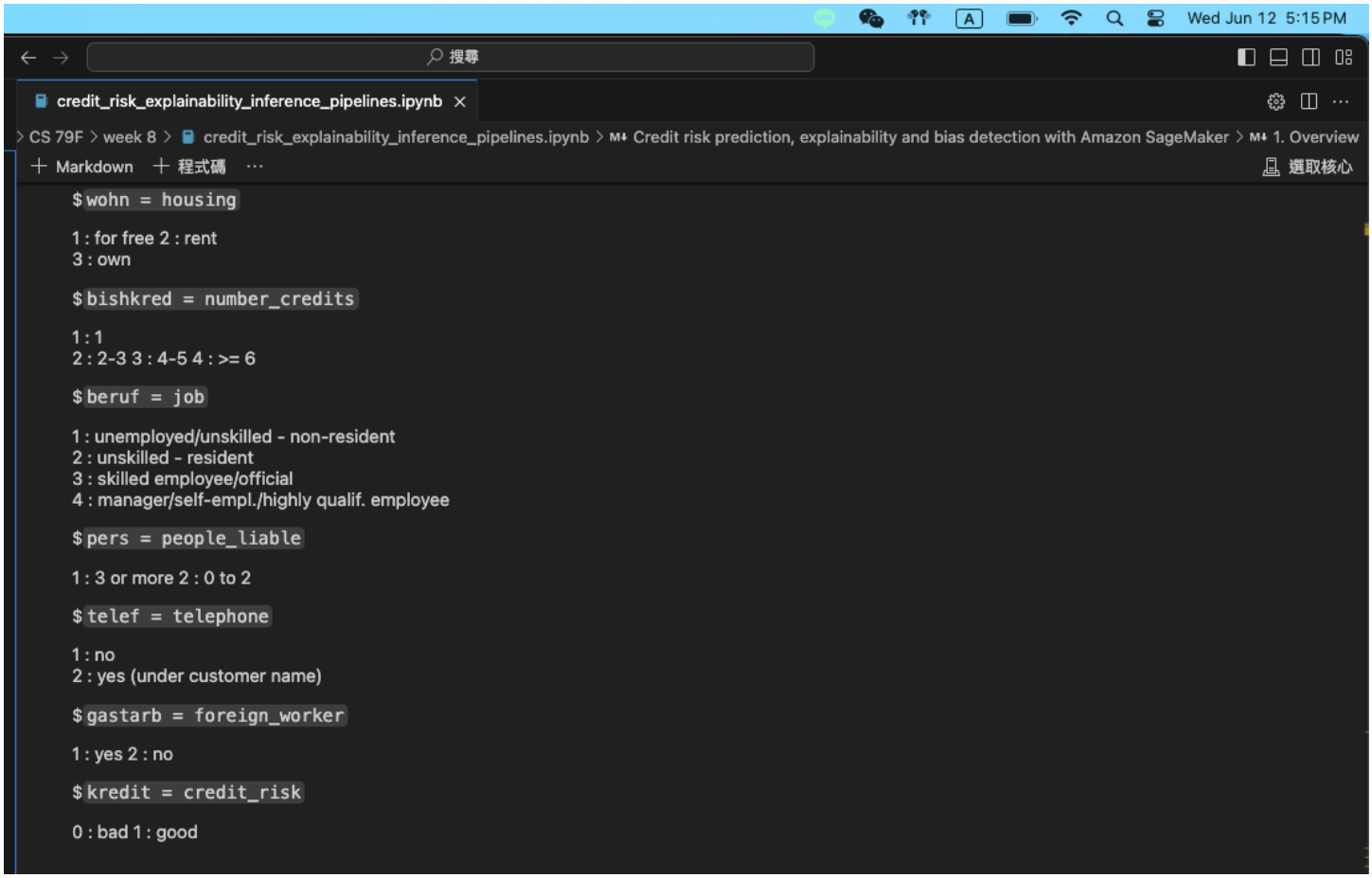


Step 2:
Download data

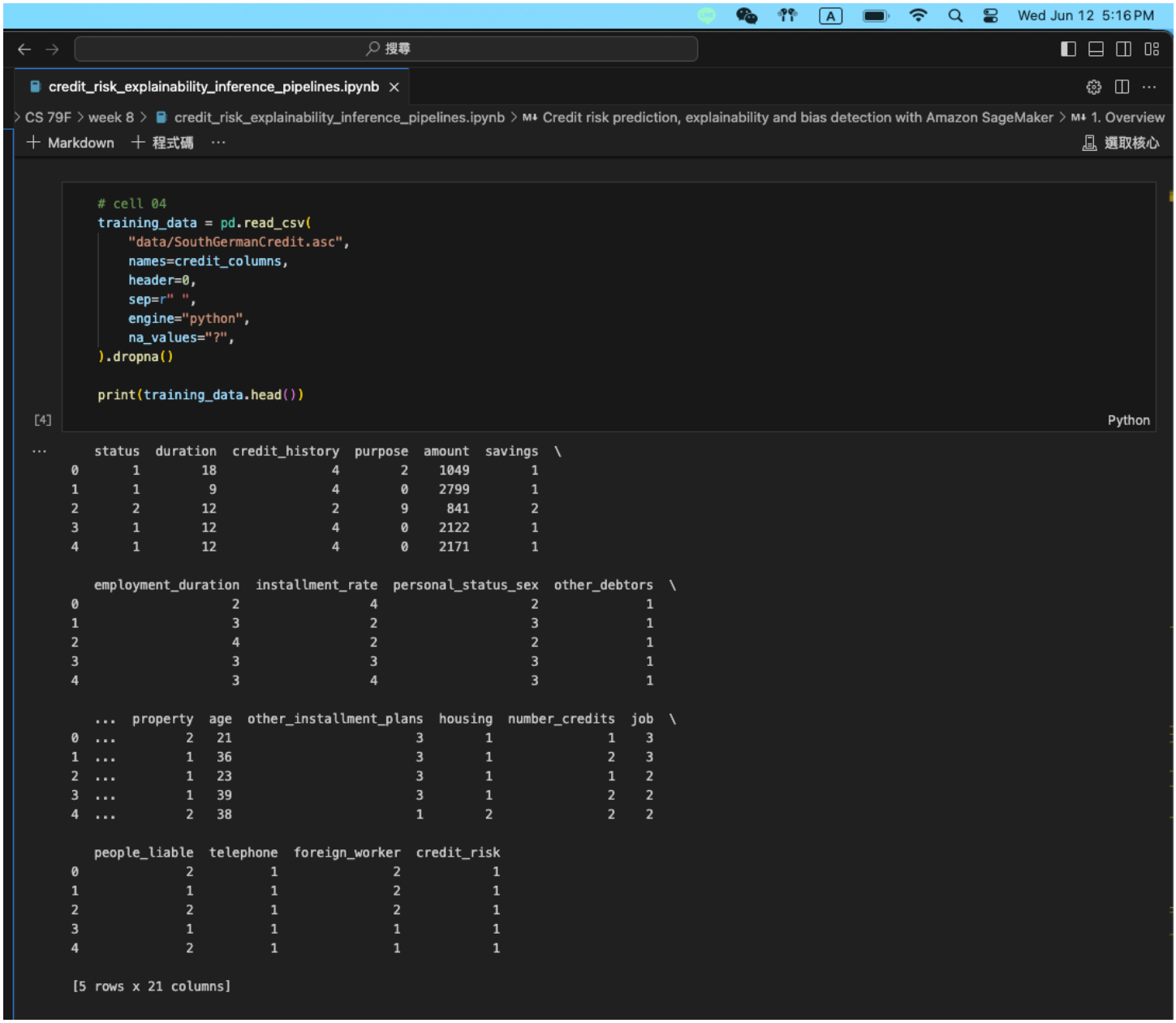



Wed Jun 12 5:14 PM
搜尋
credit_risk_explainability_inference_pipelines.ipynb
CS 79F > week 8 > credit_risk_explainability_inference_pipelines.ipynb > Credit risk prediction, explainability and bias detection with Amazon SageMaker > 1. Overview
Markdown
程式碼
選取核心
# cell 03
credit_columns = [
"status",
"duration",
"credit_history",
"purpose",
"amount",
"savings",
"employment_duration",
"installment_rate",
"personal_status_sex",
"other_debtors",
"present_residence",
"property",
"age",
"other_installment_plans",
"housing",
"number_credits",
"job",
"people_liable",
"telephone",
"foreign_worker",
"credit_risk",
]
[3]
Python
$laufkont = status
1 : no checking account
2 : ... < 0 DM
3 : 0<= ... < 200 DM
4 : ... >= 200 DM / salary for at least 1 year
$laufzeit = duration
$moral = credit_history
0 : delay in paying off in the past
1 : critical account/other credits elsewhere
2 : no credits taken/all credits paid back duly 3 : existing credits paid back duly till now
4 : all credits at this bank paid back duly
$verw = purpose
0 : others
1 : car (new)
2 : car (used)
3 : furniture/equipment 4 : radio/television
5 : domestic appliances 6 : repairs
7 : education

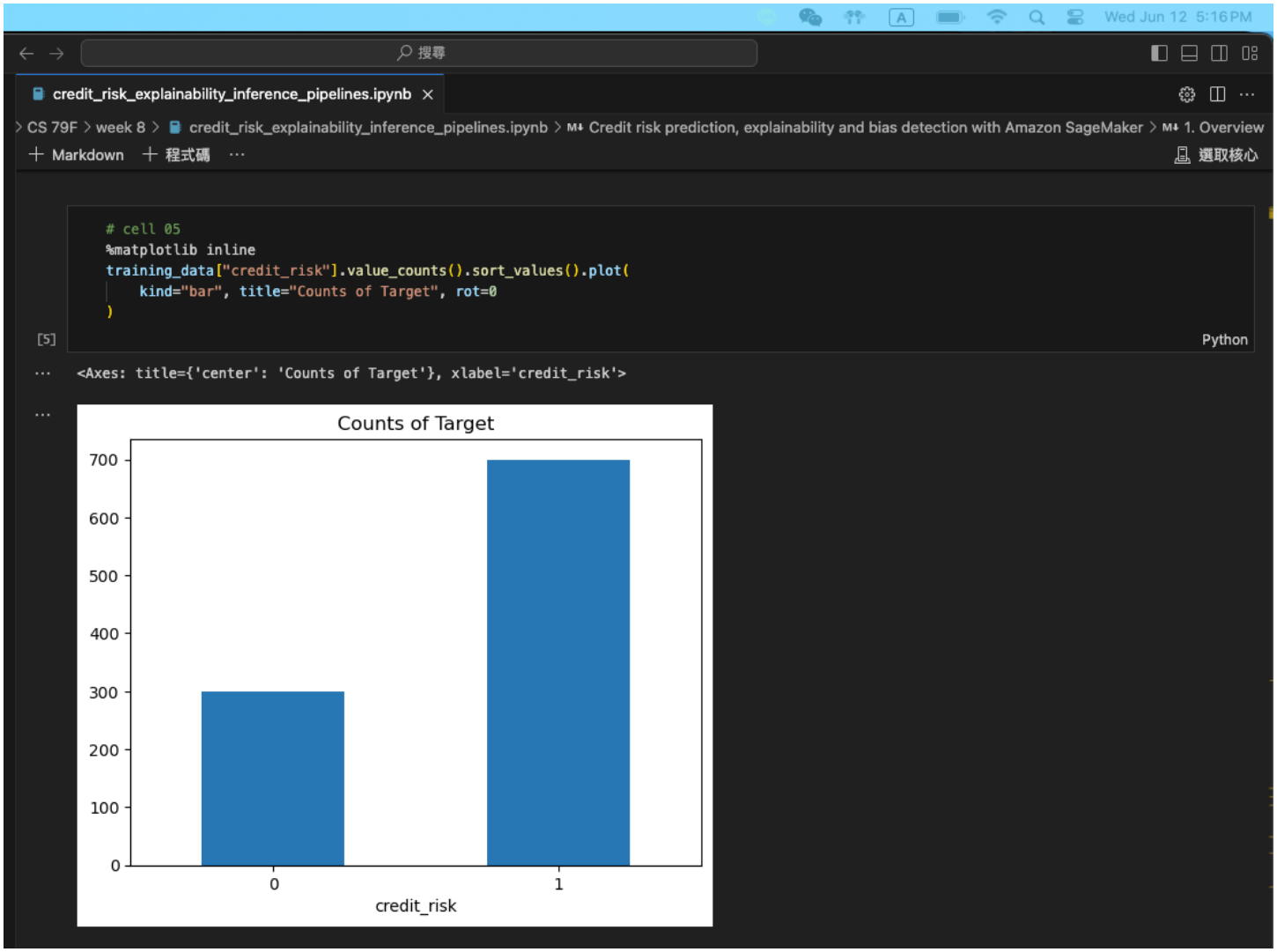

Wed Jun 12 5:14 PM
搜尋
credit_risk_explainability_inference_pipelines.ipynb
CS 79F > week 8 > credit_risk_explainability_inference_pipelines.ipynb > Credit risk prediction, explainability and bias detection with Amazon SageMaker > 1. Overview
Markdown
程式碼
選取核心
8 : vacation
9 : retraining
10 : business
$hoehe = amount
$sparkont = savings
1 : unknown/no savings account 2 : ... < 100 DM
3 : 100 <= ... < 500 DM
4 : 500 <= ... < 1000 DM
5 : ... >= 1000 DM
$beszeit = employment_duration
1 : unemployed
2 : < 1 yr
3 : 1 <= ... < 4 yrs 4 : 4 <= ... < 7 yrs 5 : >= 7 yrs
$rate = installment_rate
1 : >= 35
2 : 25 <= ... < 35 3 : 20 <= ... < 25 4 : < 20
$famges = personal_status_sex
1 : male : divorced/separated
2 : female : non-single or male : single 3 : male : married/widowed
4 : female : single
$buerge = other_debtors
1 : none
2 : co-applicant 3 : guarantor
$wohnzeit = present_residence
1 : < 1 yr
2 : 1 <= ... < 4 yrs 3 : 4 <= ... < 7 yrs 4 : >= 7 yrs
$verm = property
1 : unknown / no property
2 : car or other
3 : building soc. savings agr./life insurance 4 : real estate
$alter = age
$weitkred = other_installment_plans
1 : bank
2 : stores 3 : none
$wohn = housing
1 : for free 2 : rent



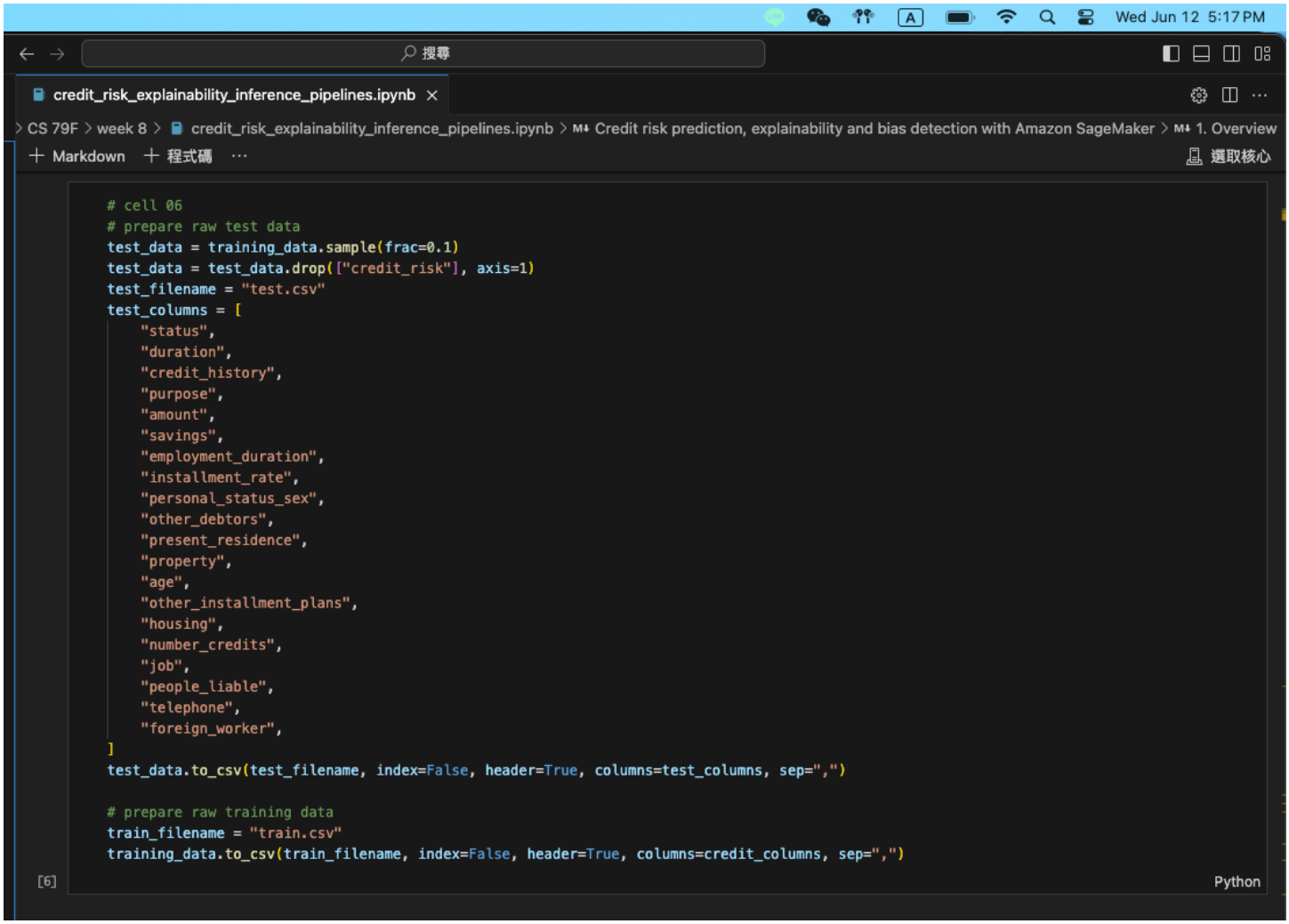
Step 3:
Data inspection



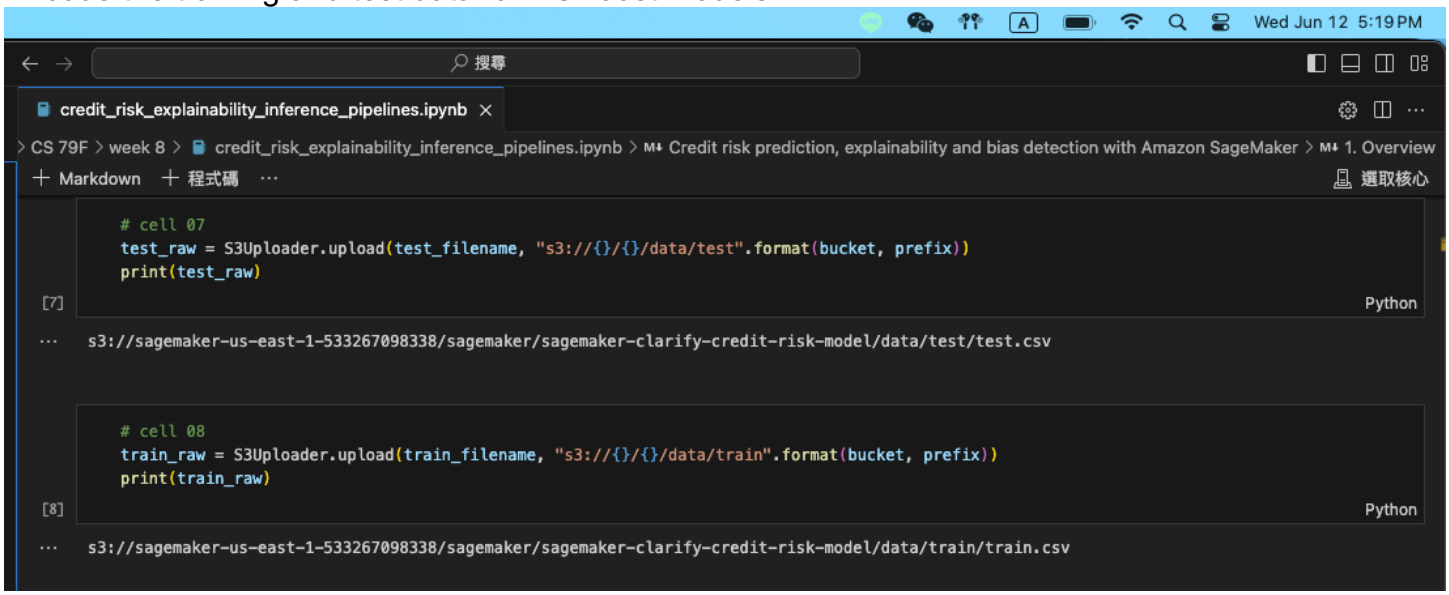
Step 4:
Plotting histograms for the distribution of the different features to visualize the data.



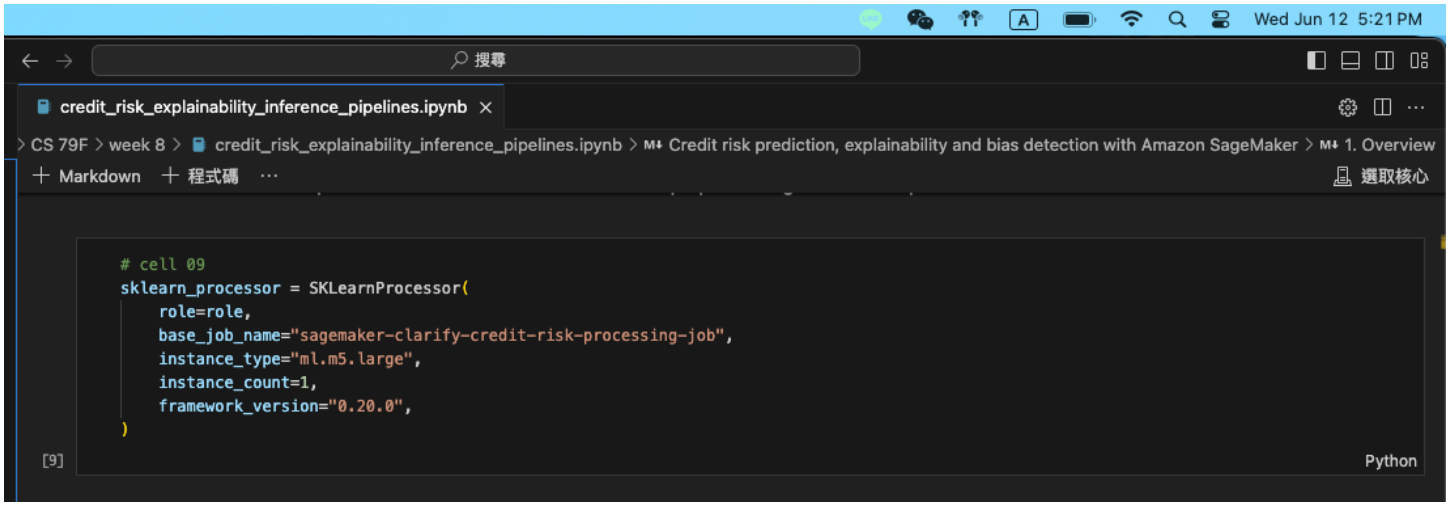
Step 5:
Create the raw training and test CSV files



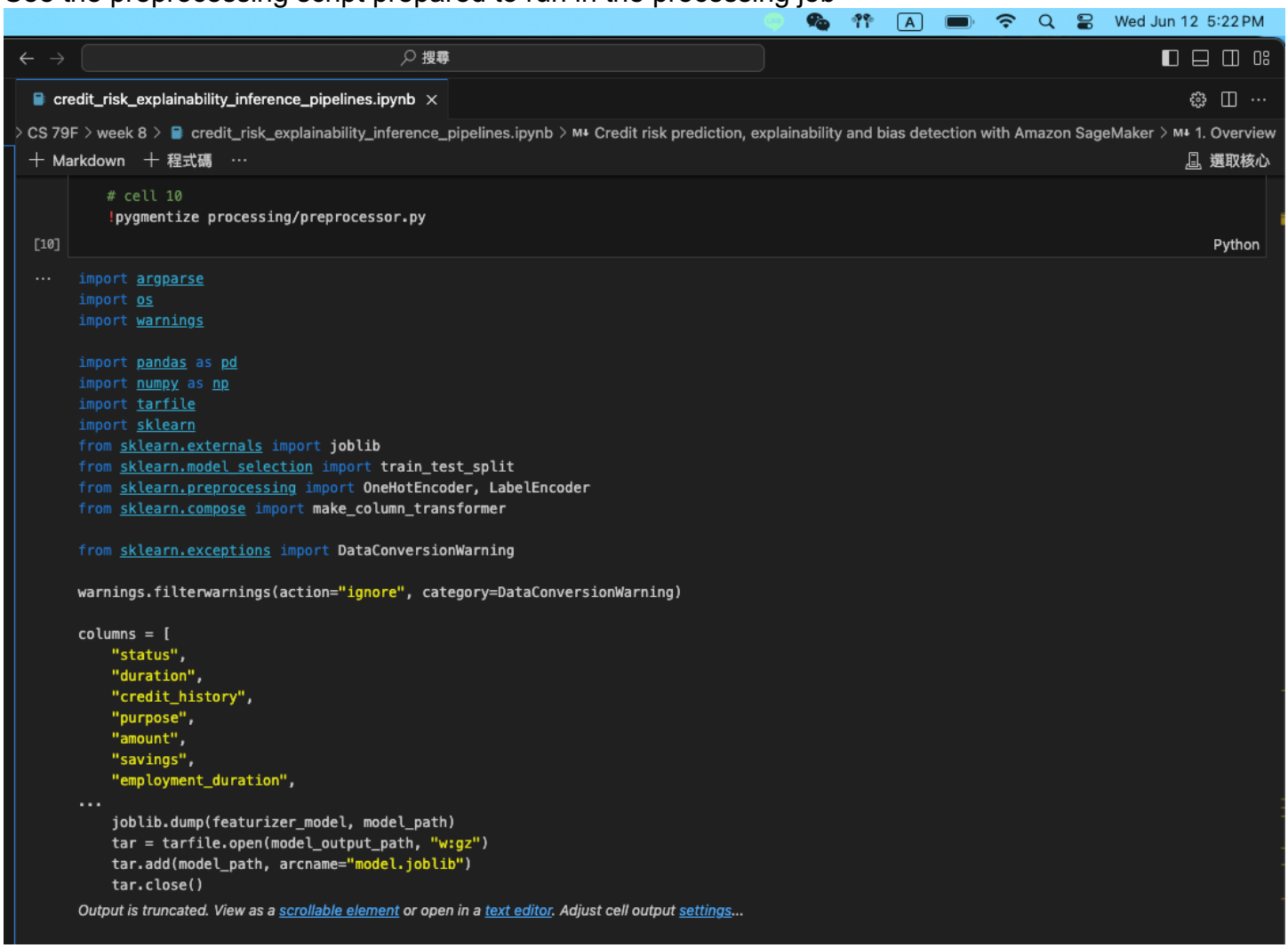
Step 6:
Encode the training and test data for XGBoost models.

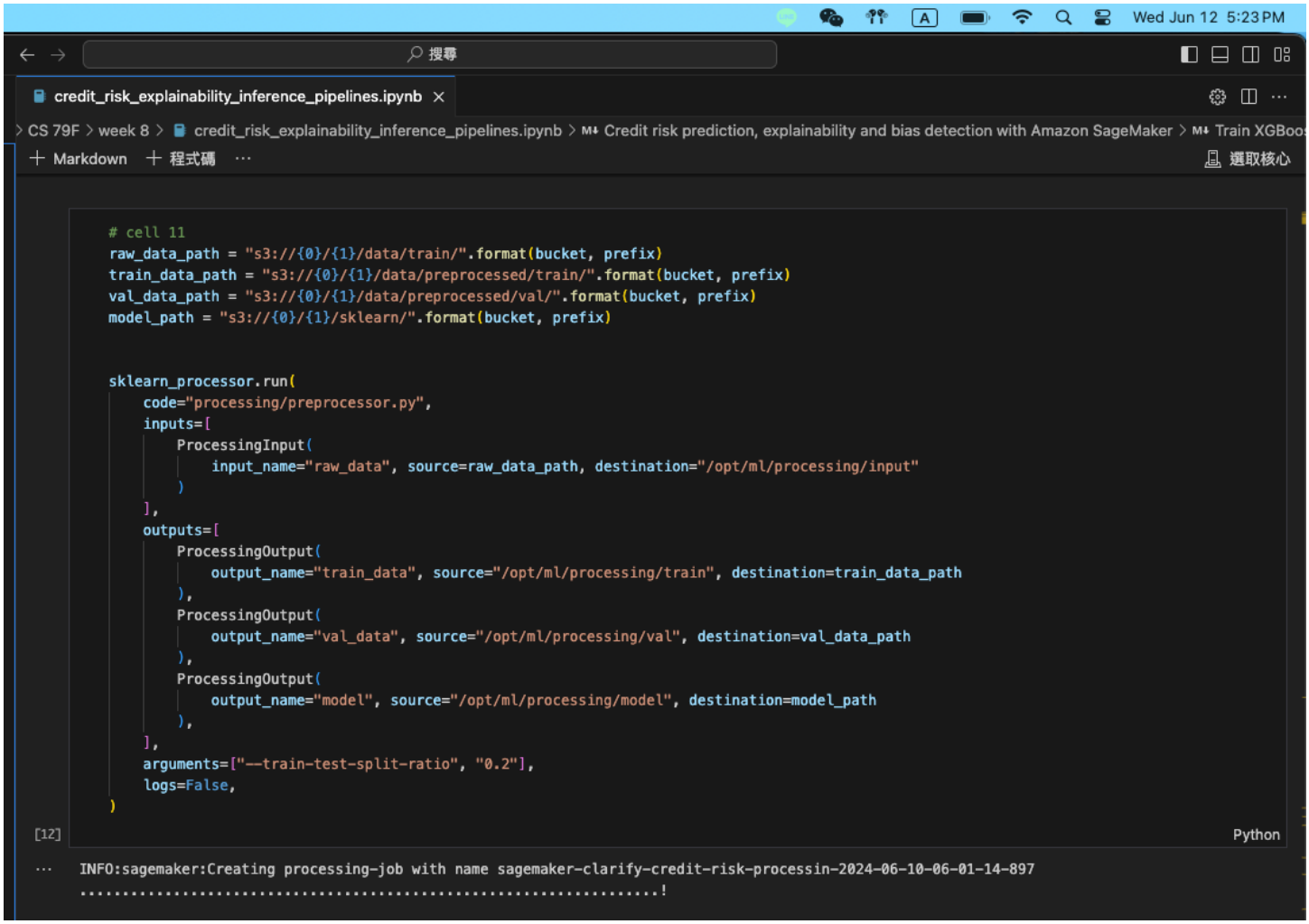


Step 7:
Use SageMaker Processing jobs to perform the preprocessing on the raw data. Output a sklearn model that can be used for preprocessing inference requests.

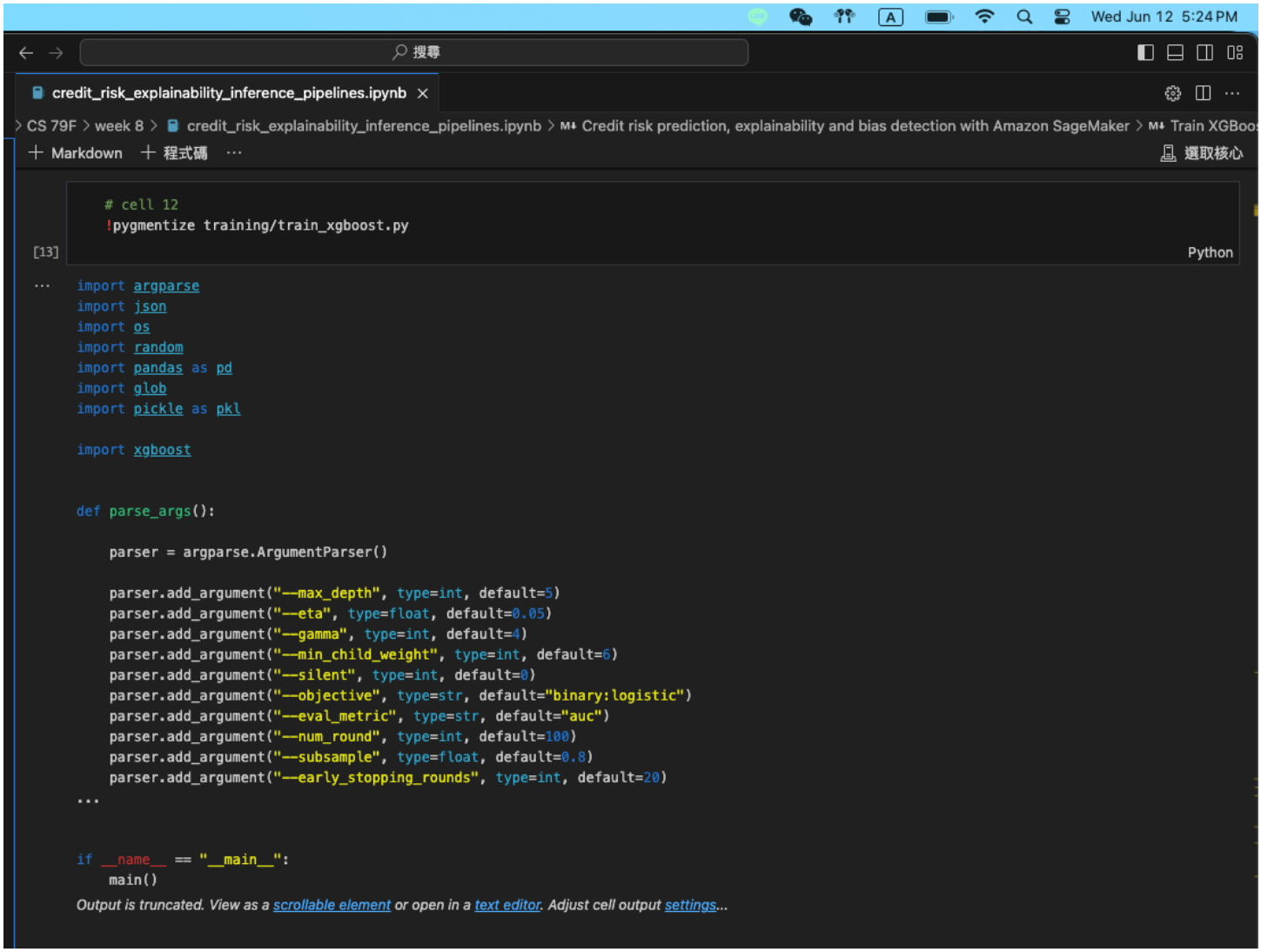


Step 8:
See the preprocessing script prepared to run in the processing job

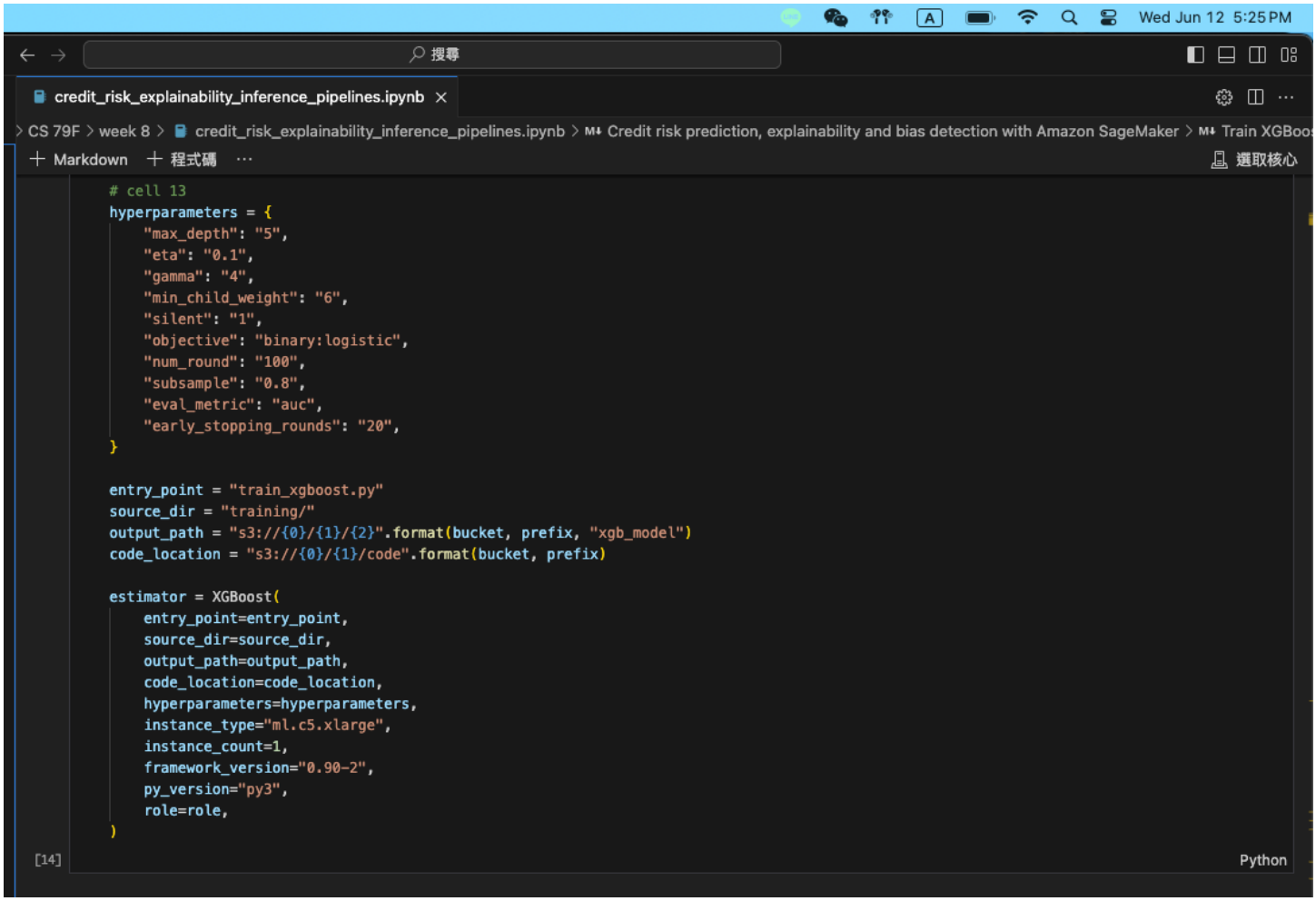




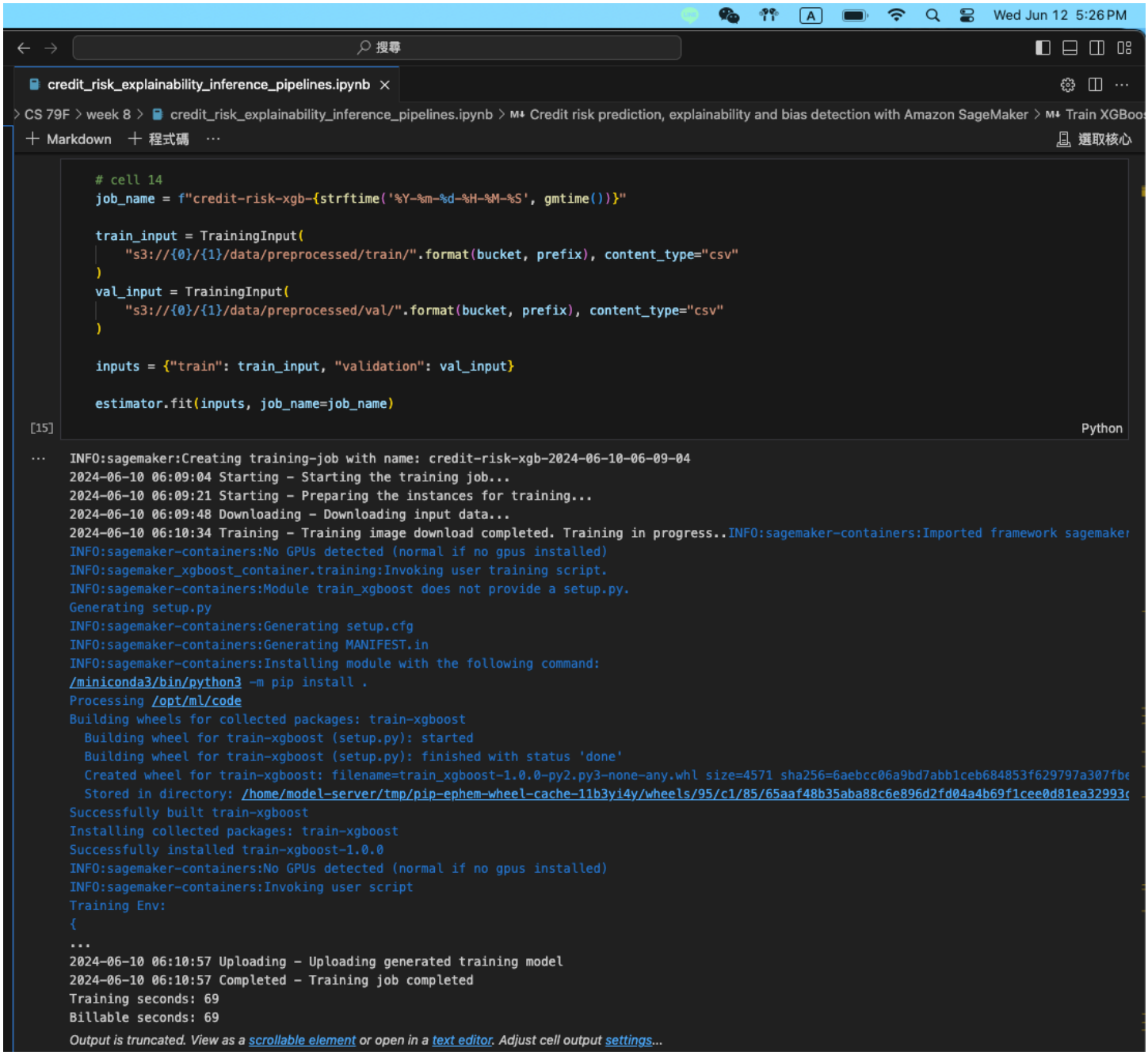
Step 9:
Train XGBoost Model on the preprocessed data.



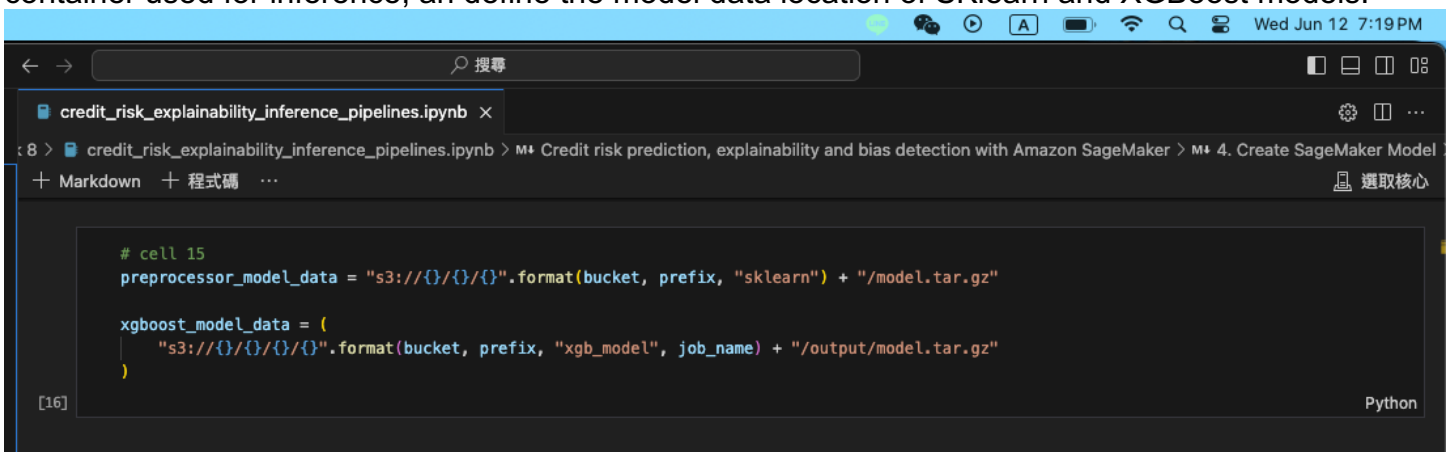
Step 10:
Set up XGBoost Estimator and pre-defined values for Hyperparameters for XGBoost algorithm



Step 11:
Train the model

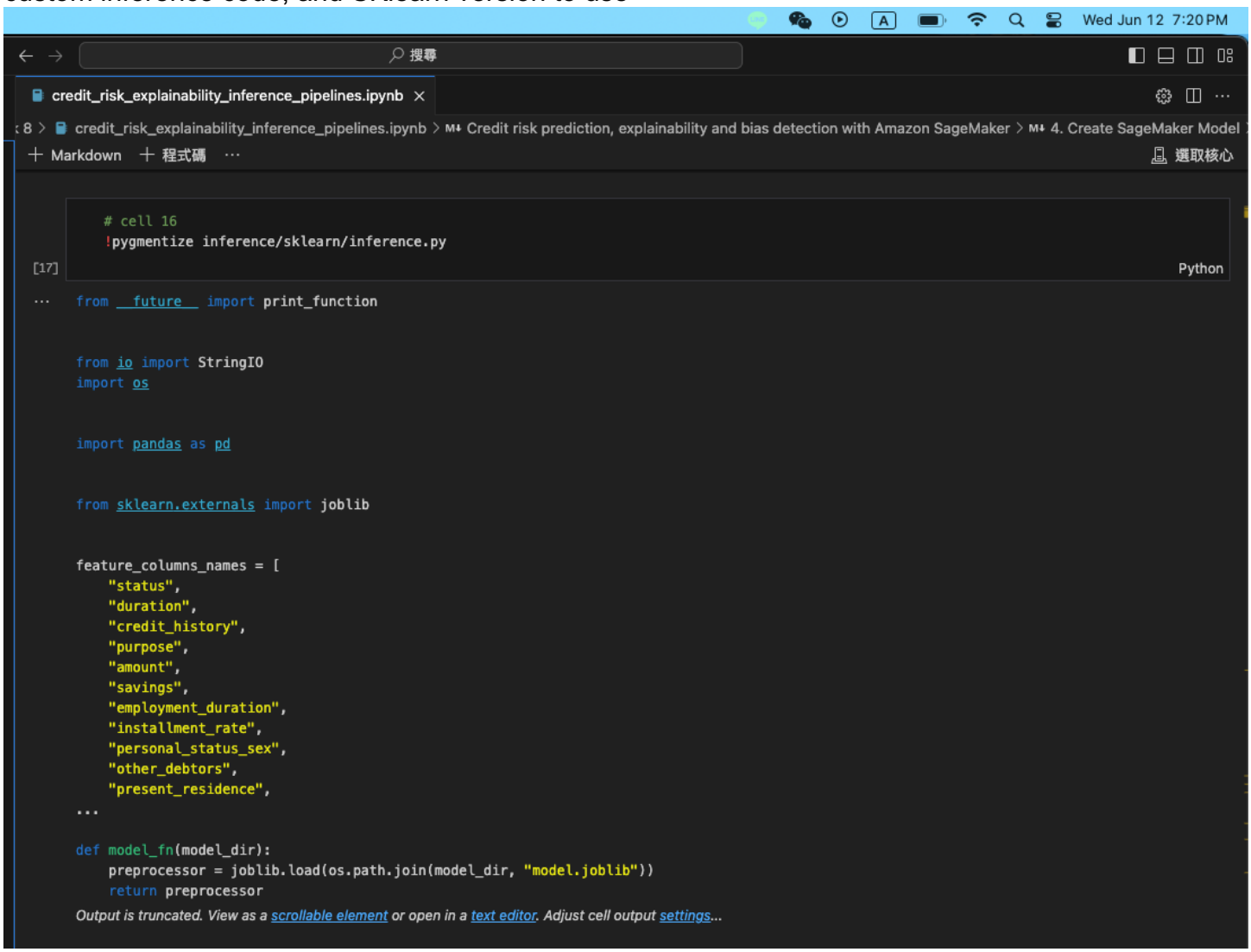


Step 12:
Create two SageMaker Model objects, which associate the artifacts of training (to the Docker container used for inference, an define the model data location of SKlearn and XGBoost models.

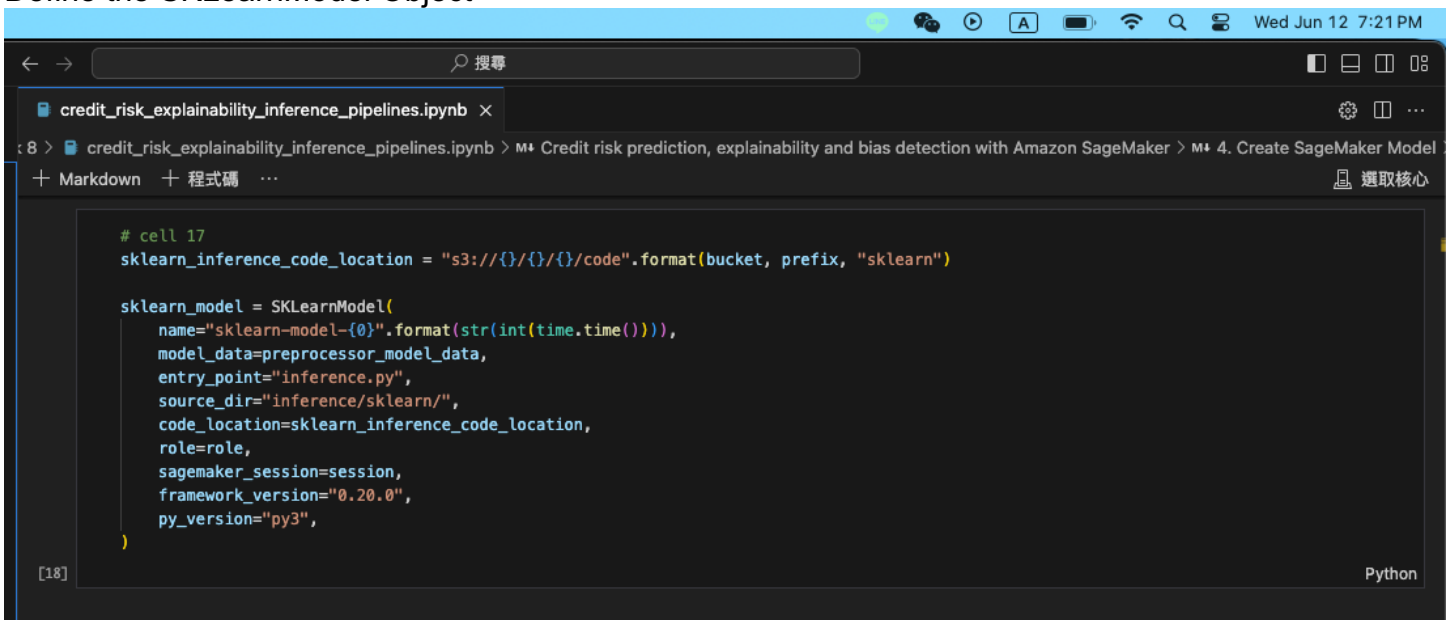


Step 13:

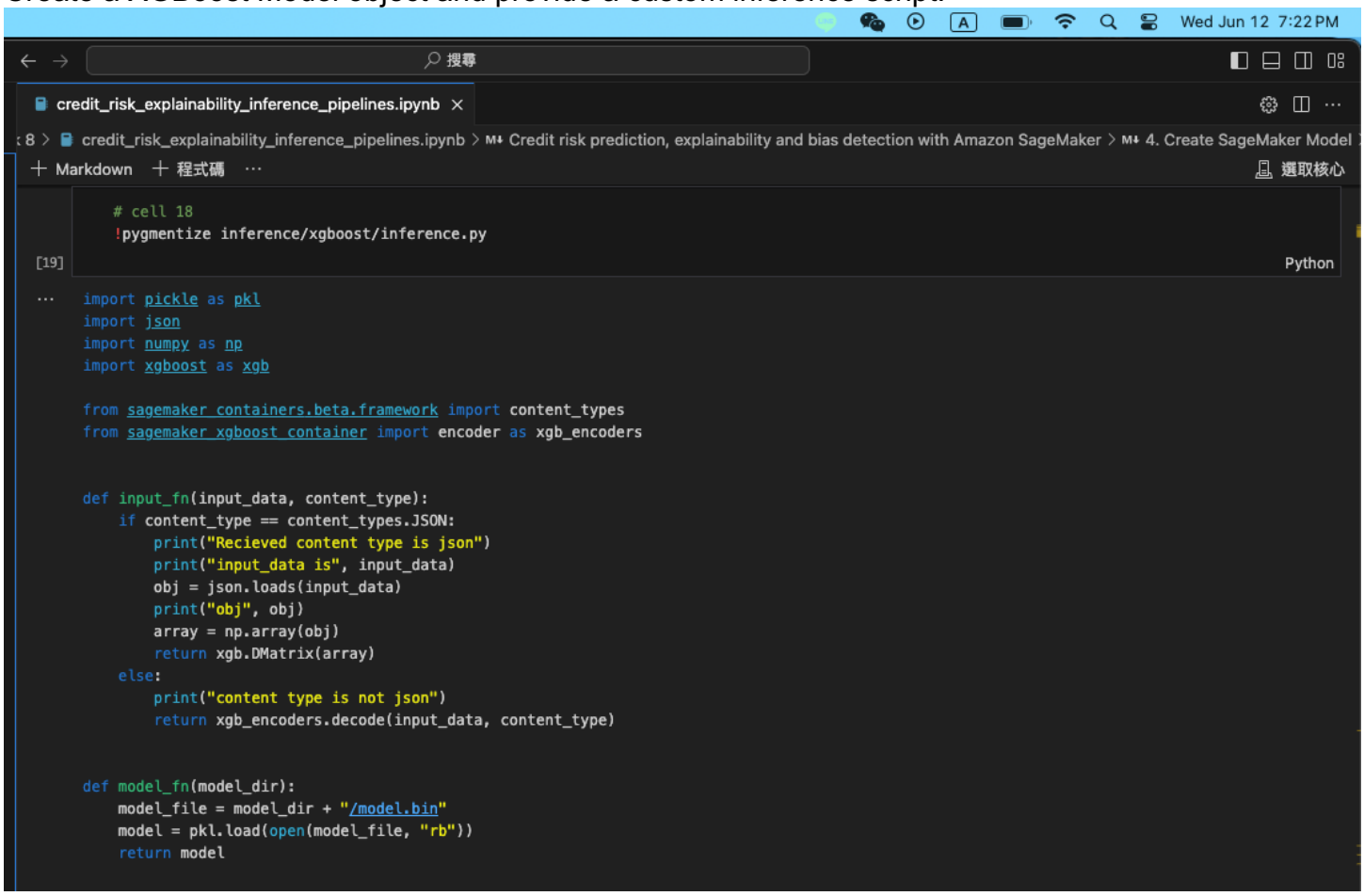
Create a SageMaker SKlearn Model Object which will contain the location of the sklearn model data, custom inference code, and SKlearn version to use



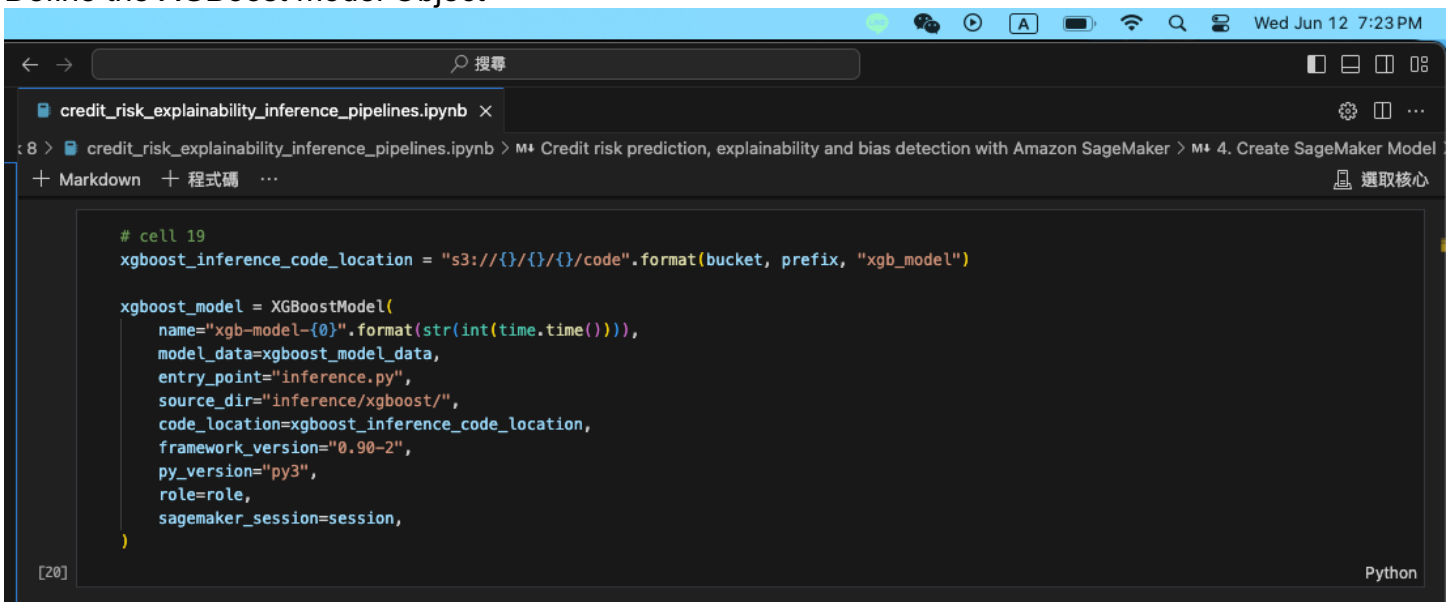
Step 14:
Define the SKLearnModel Object



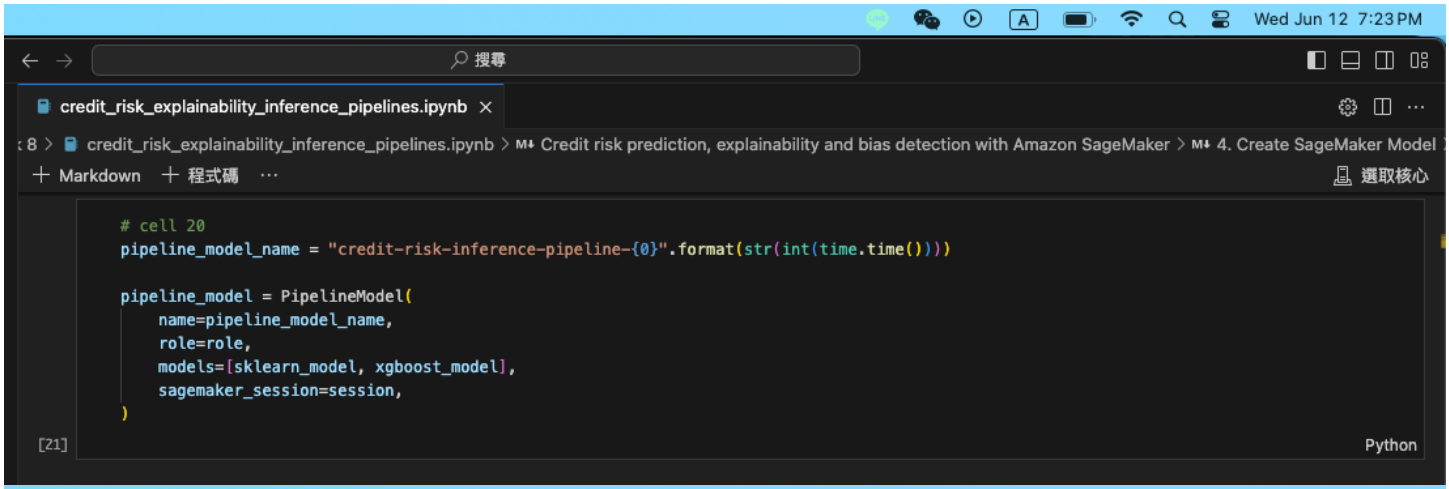
Step 15:
Create a XGBoost Model object and provide a custom inference script.

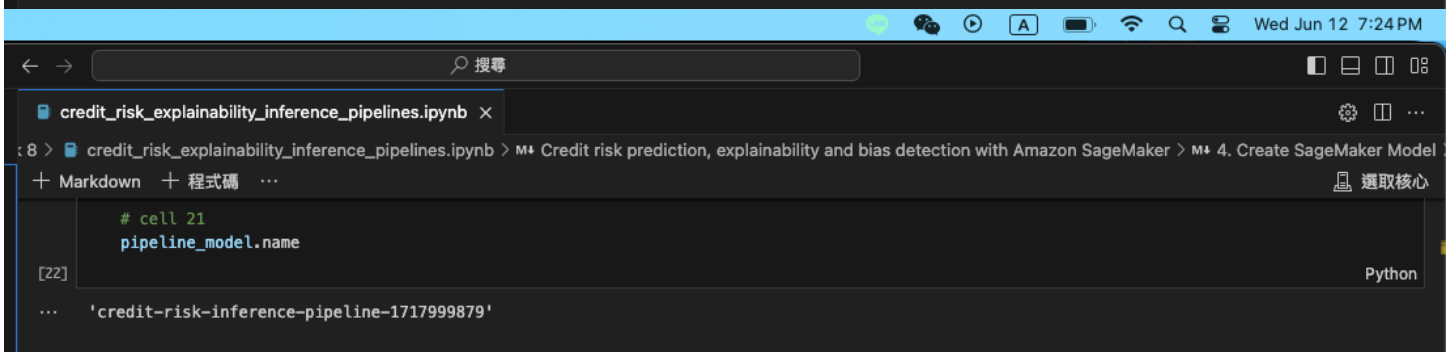


Step 16:
Define the XGBoost model Object

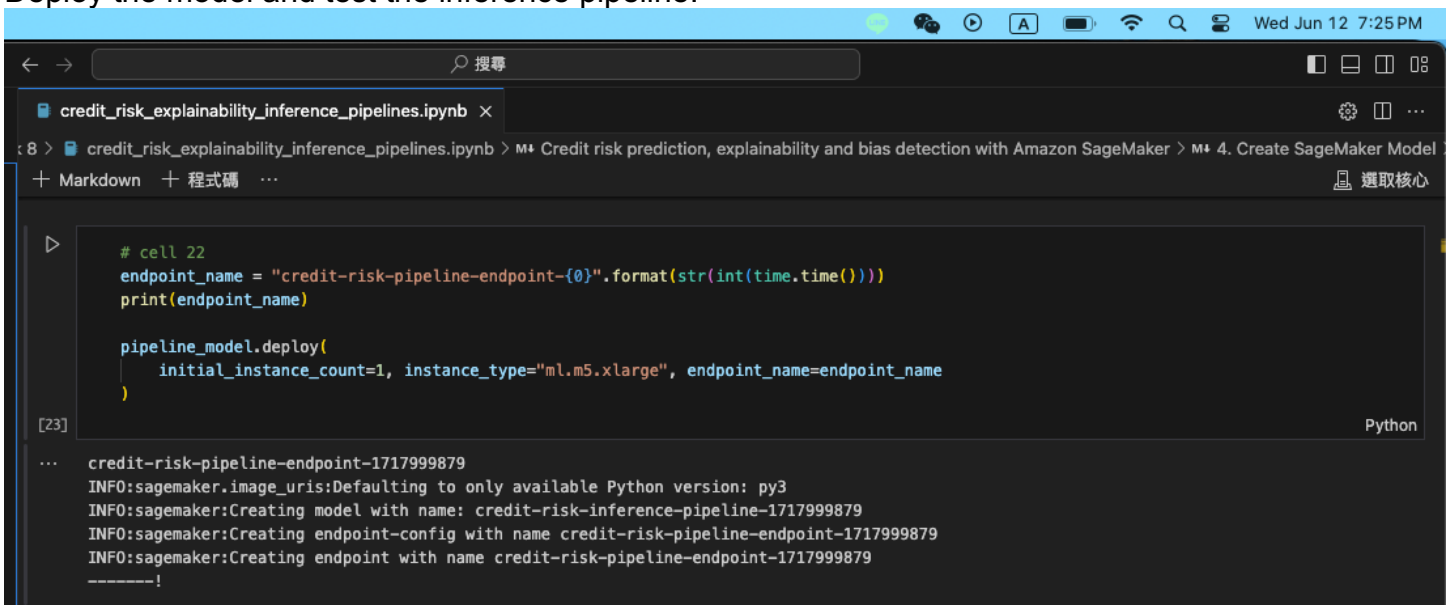


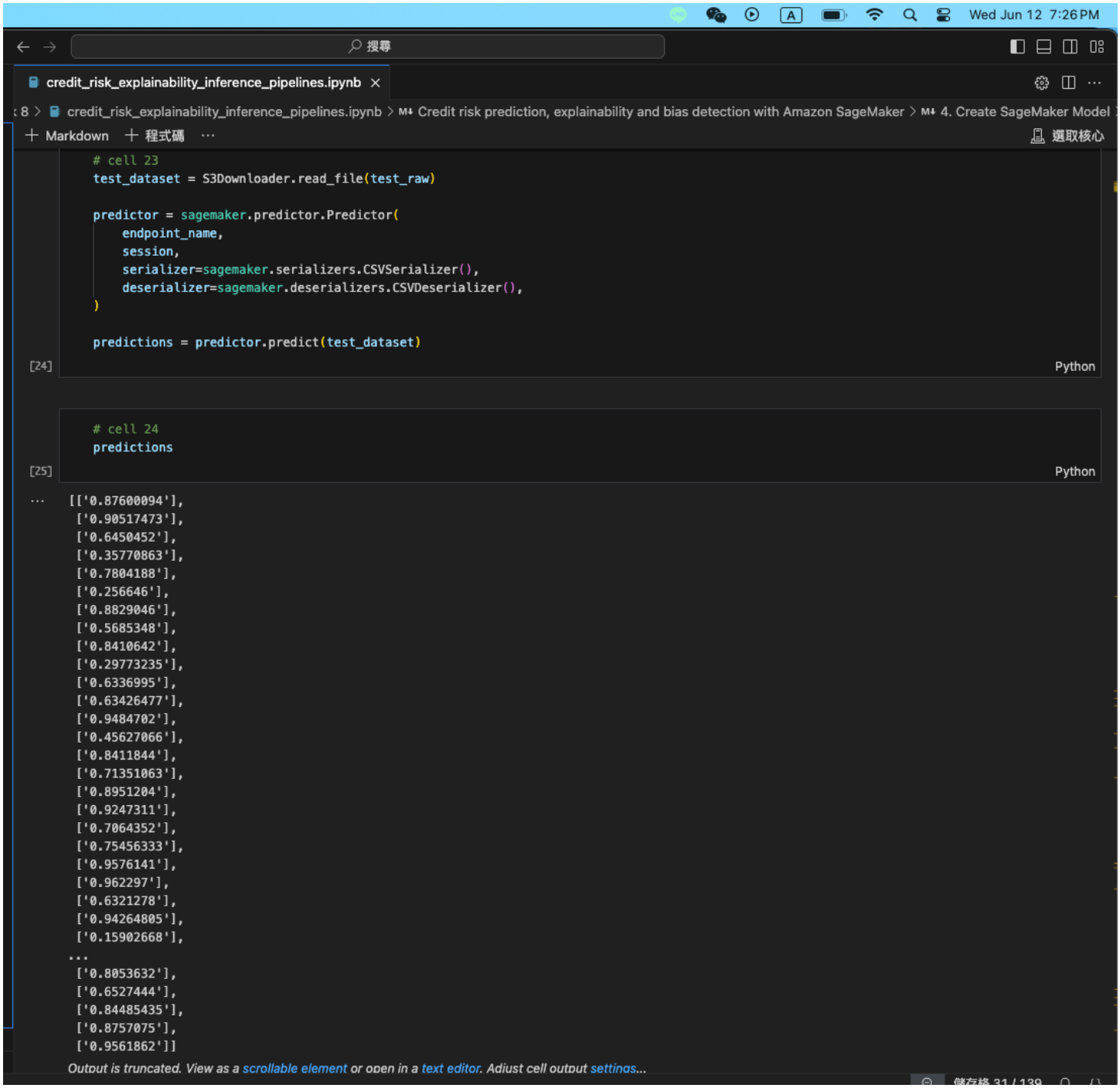
Step 17:
Deploy the models in a pipeline by building a PipelineModel object and calling the deploy() method.



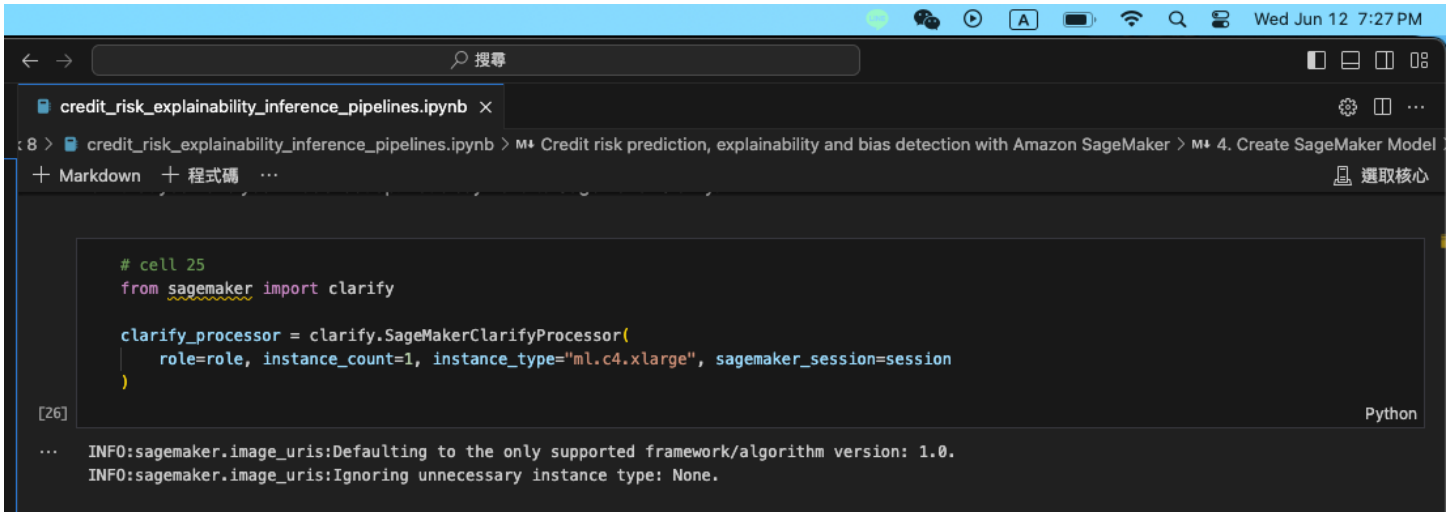


Step 18:
Deploy the model and test the inference pipeline.

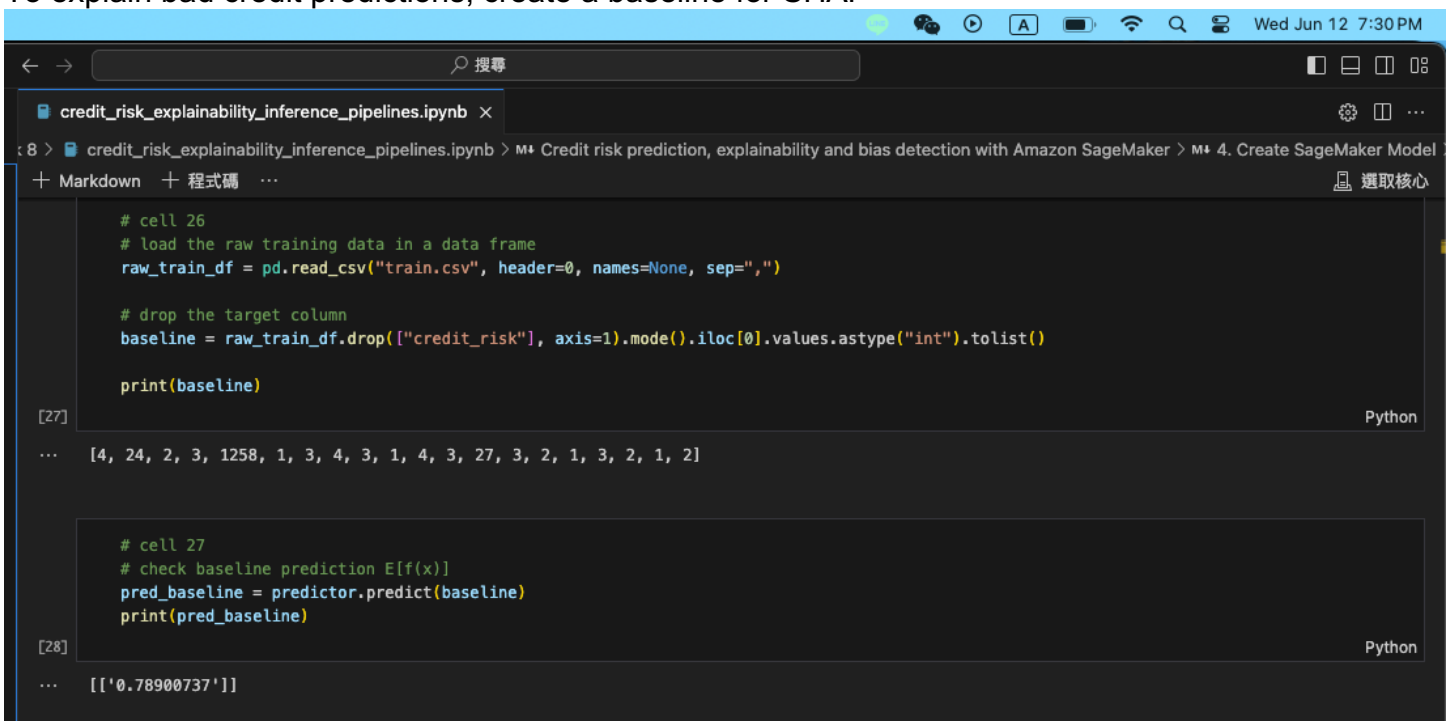




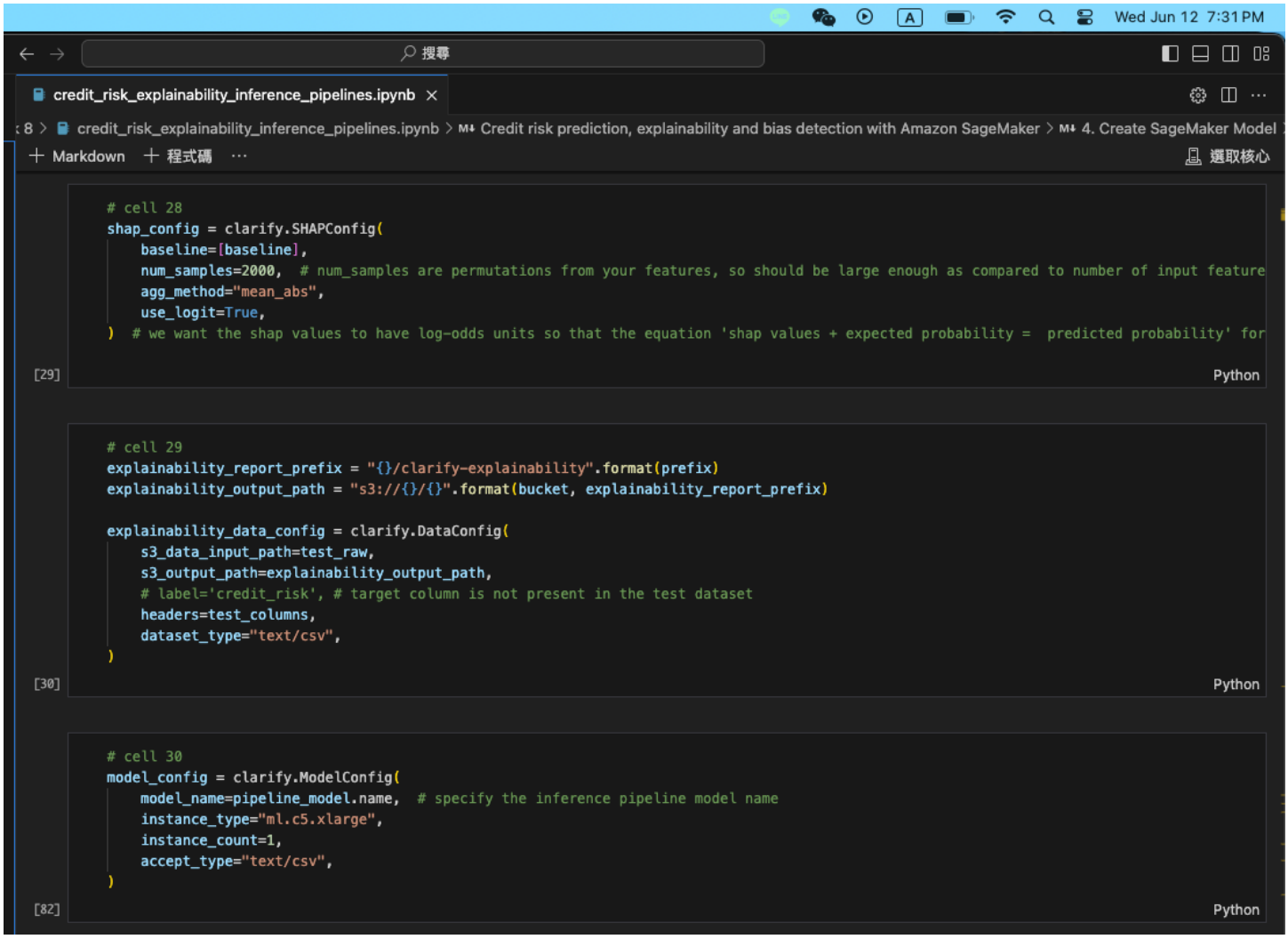
Step 19:
SageMaker Clarify



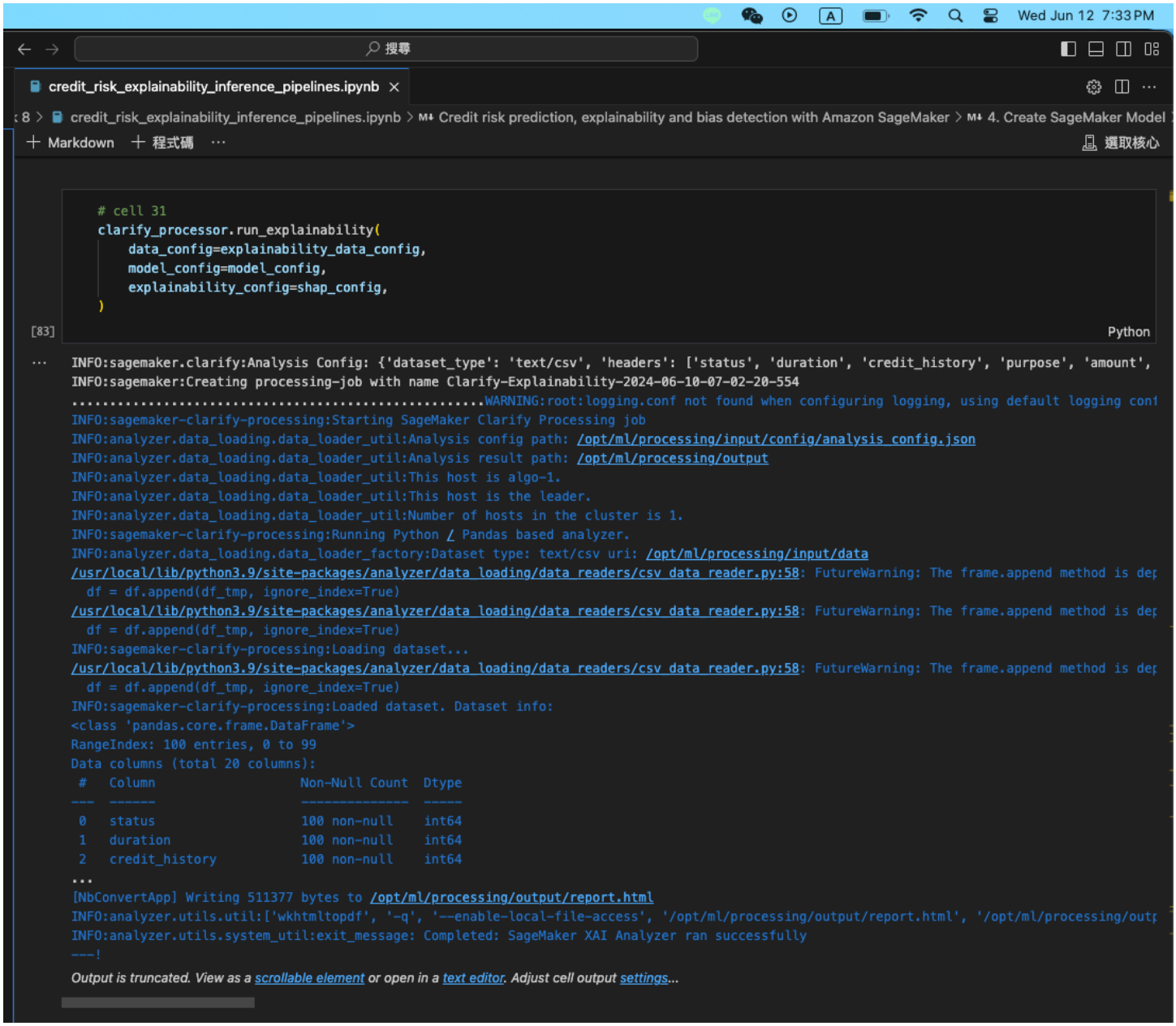
Step 20:
To explain bad credit predictions, create a baseline for SHAP



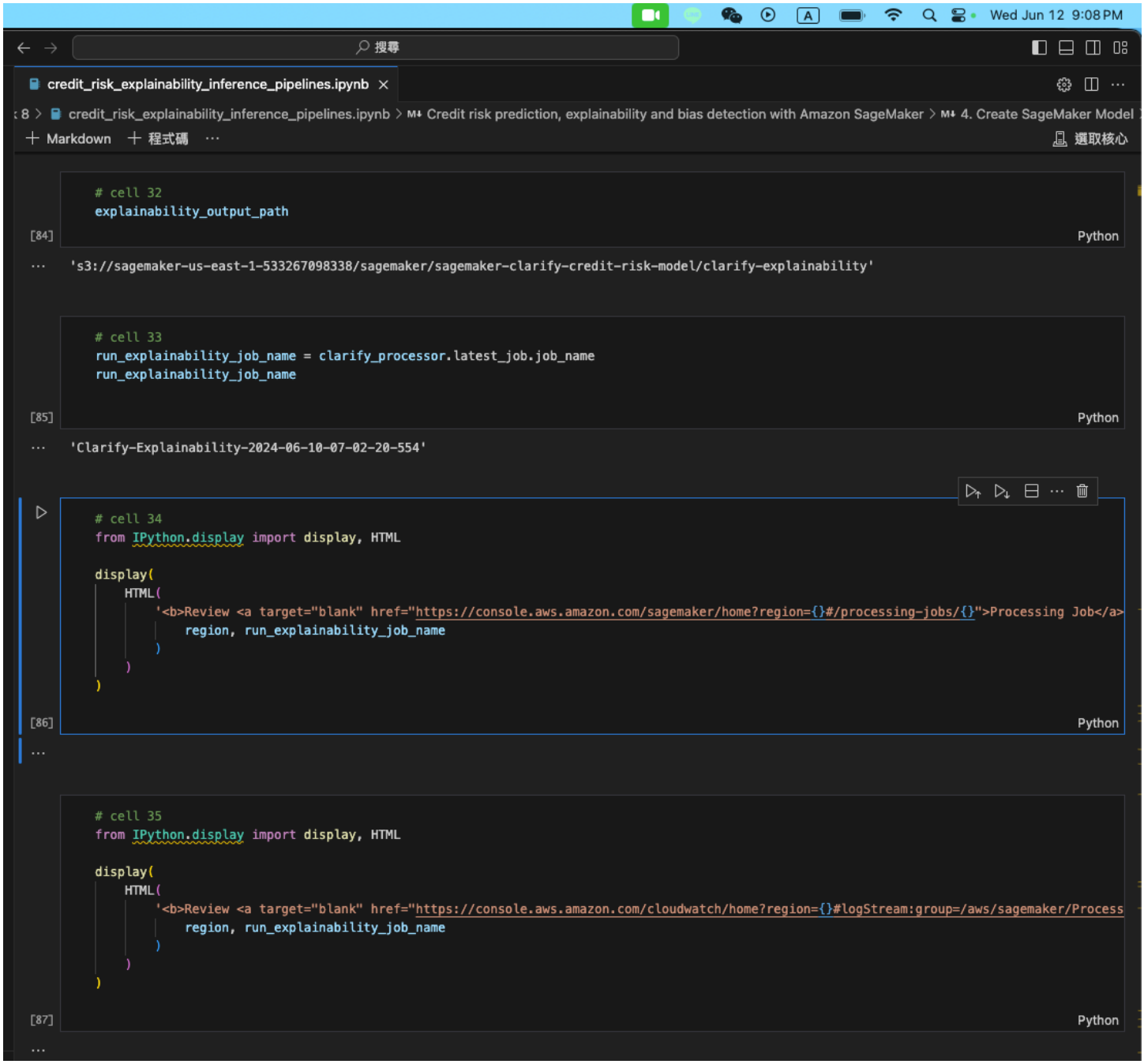
Step 21:
Setup configurations (SHAPConfig, DataConfig, ModelConfig) to start the explainability analysis by Clarify

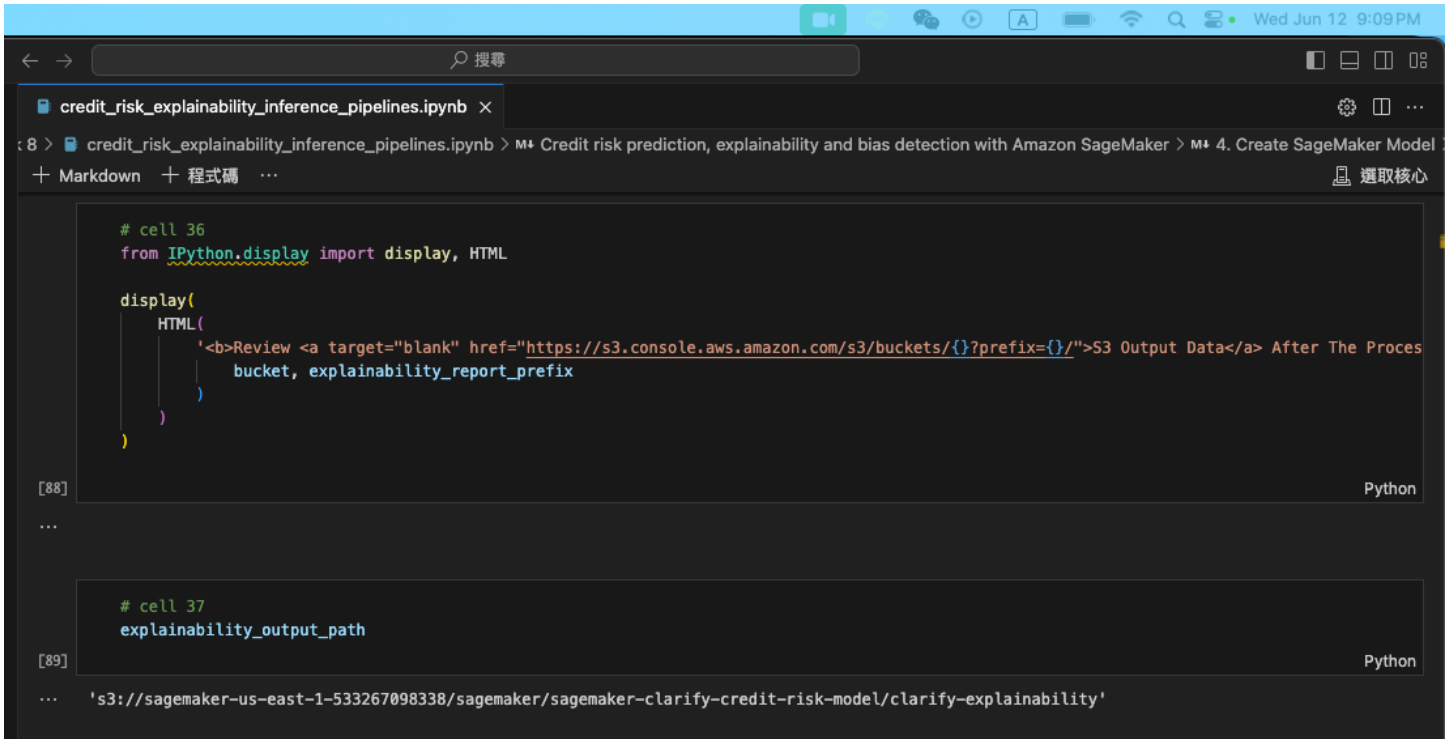


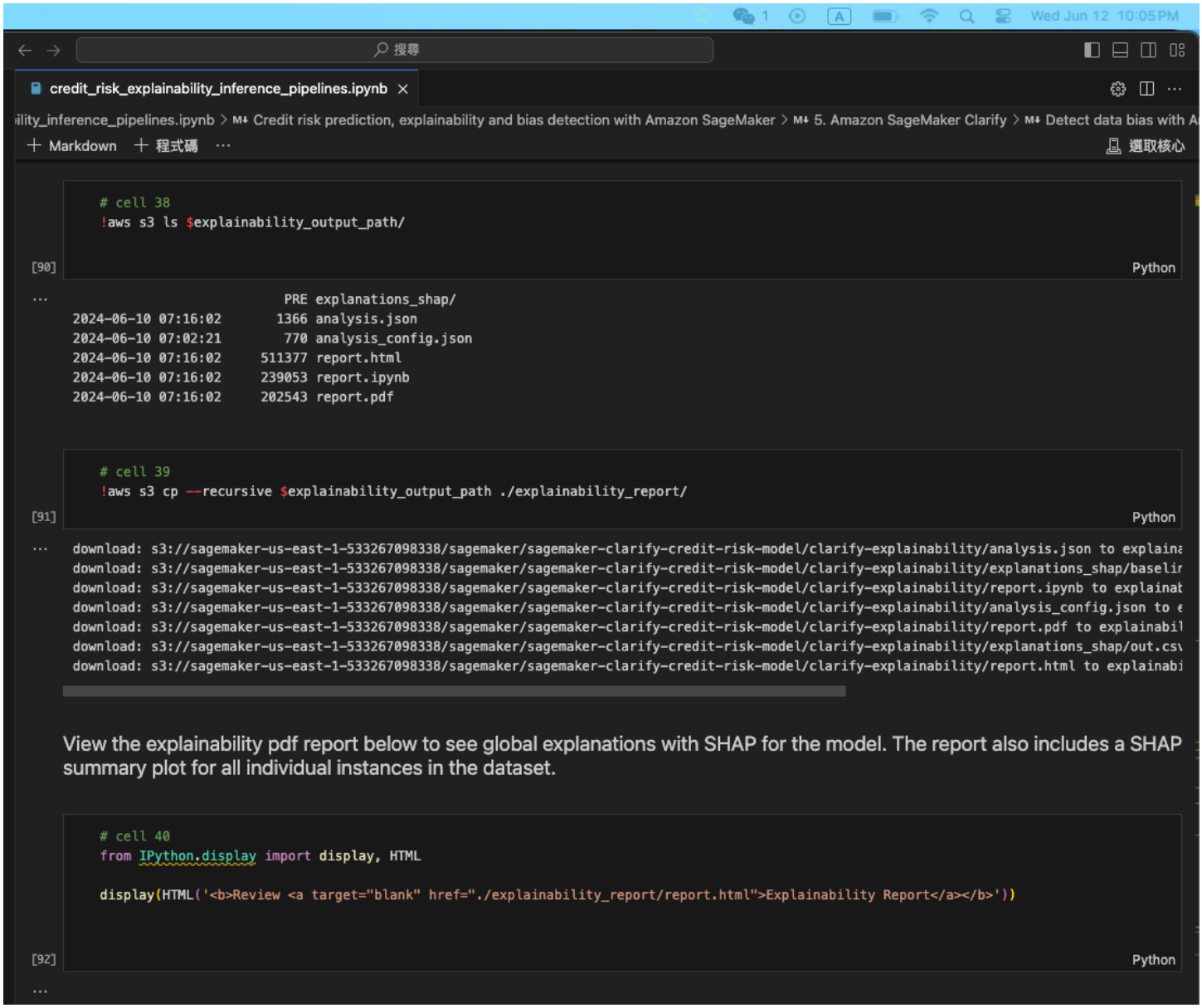
Step 22:
Run SageMaker Clarify Explainability job which spins up an ephemeral SageMaker endpoint, performs inference and calculate explanations on that endpoint



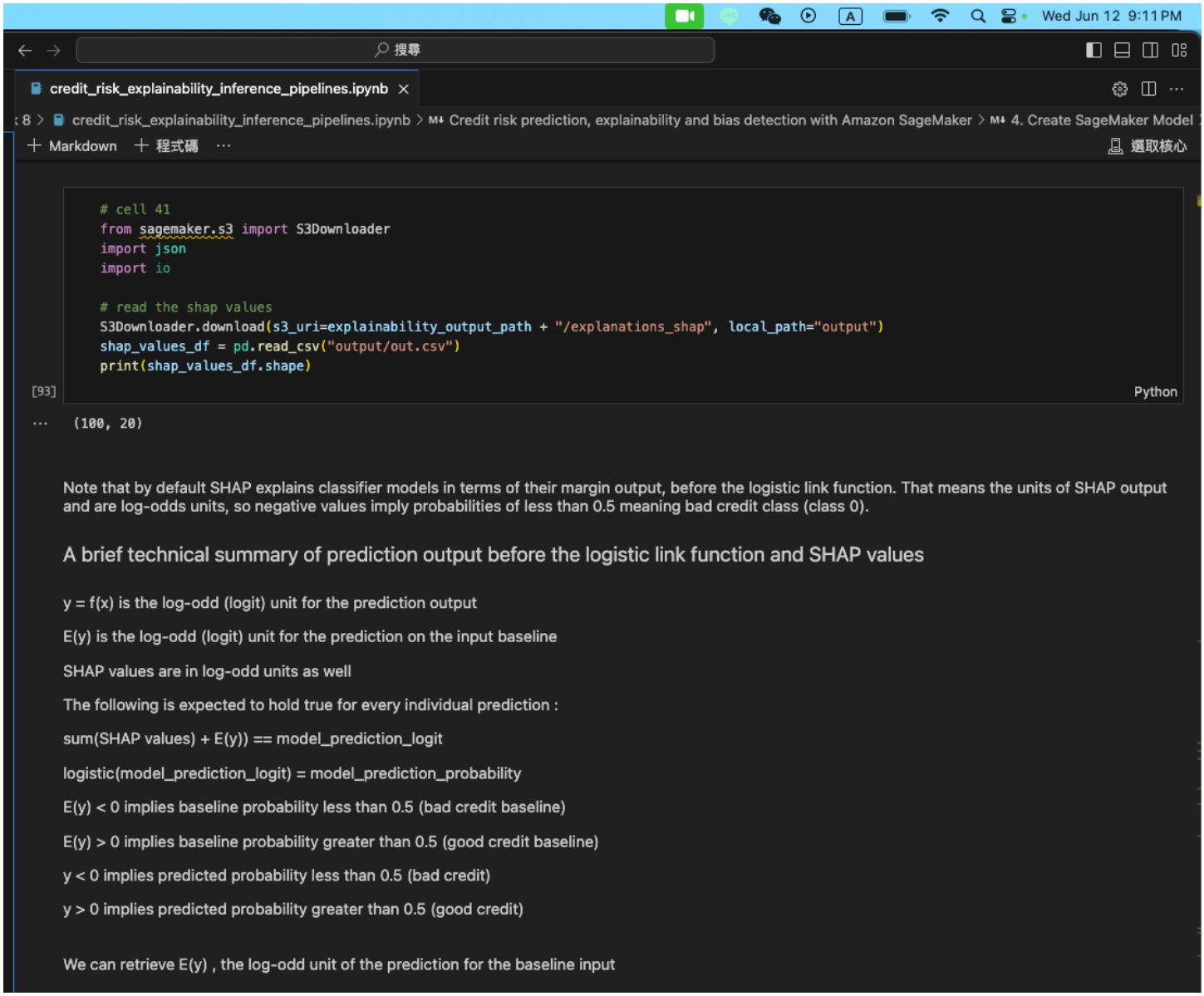
Step 23:
See the explainability report

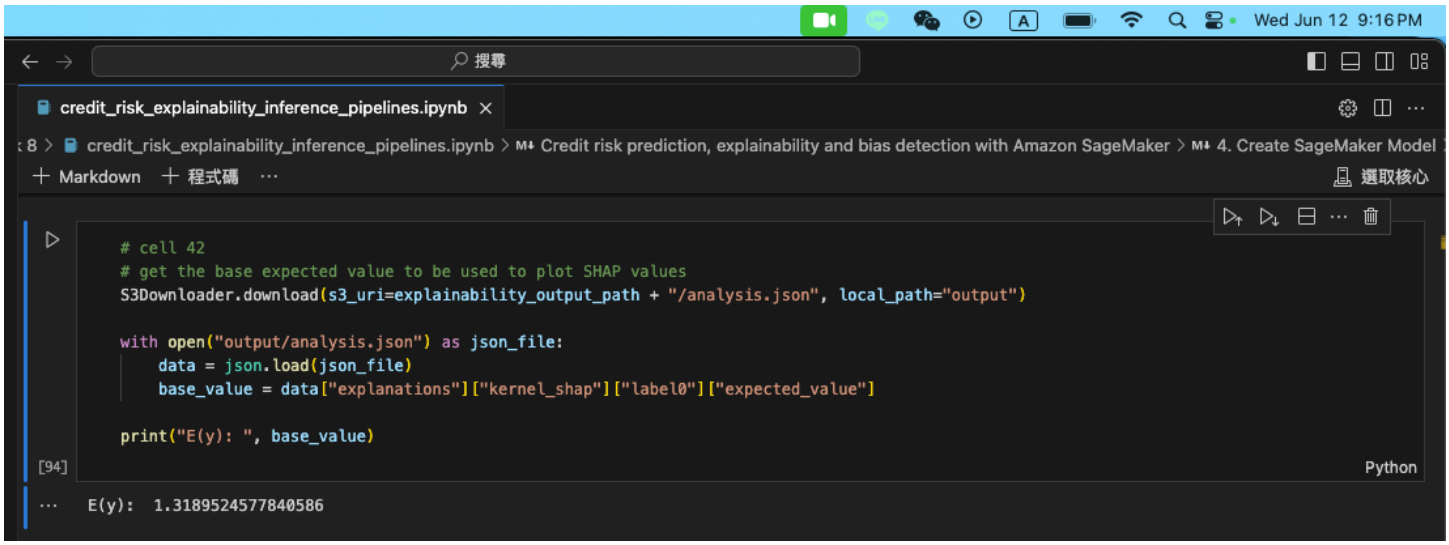

Wed Jun 12 9:08 PM
搜尋
credit_risk_explainability_inference_pipelines.ipynb
8 > credit_risk_explainability_inference_pipelines.ipynb > Credit risk prediction, explainability and bias detection with Amazon SageMaker > 4. Create SageMaker Model
Markdown
程式碼
選取核心
cell 32
explainability_output_path
[84]
Python
's3://sagemaker-us-east-1-533267098338/sagemaker/sagemaker-clarify-credit-risk-model/clarify-explainability'
# cell 33
run_explainability_job_name = clarify_processor.latest_job.job_name
run_explainability_job_name
[85]
Python
'Clarify-Explainability-2024-06-10-07-02-20-554'
# cell 34
from IPython.display import display, HTML
display(
HTML(
'<b>Review Processing Job
region, run_explainability_job_name
)
)
)
[86]
Python
# cell 35
from IPython.display import display, HTML
display(
HTML(
'<b>Review <a target="blank" href="https://console.aws.amazon.com/cloudwatch/home?region={}#logStream:group=/aws/sagemaker/Process
region, run_explainability_job_name
)
)
)
[87]
Python


Wed Jun 12 9:09 PM
搜尋
credit_risk_explainability_inference_pipelines.ipynb
8 > credit_risk_explainability_inference_pipelines.ipynb > Credit risk prediction, explainability and bias detection with Amazon SageMaker > 4. Create SageMaker Model
Markdown
程式碼
選取核心
# cell 36
from IPython.display import display, HTML
display(
HTML(
'<b>Review S3 Output Data After The Proces
bucket, explainability_report_prefix
)
)
)
[88]
Python
cell 37
explainability_output_path
[89]
Python
's3://sagemaker-us-east-1-533267098338/sagemaker/sagemaker-clarify-credit-risk-model/clarify-explainability'



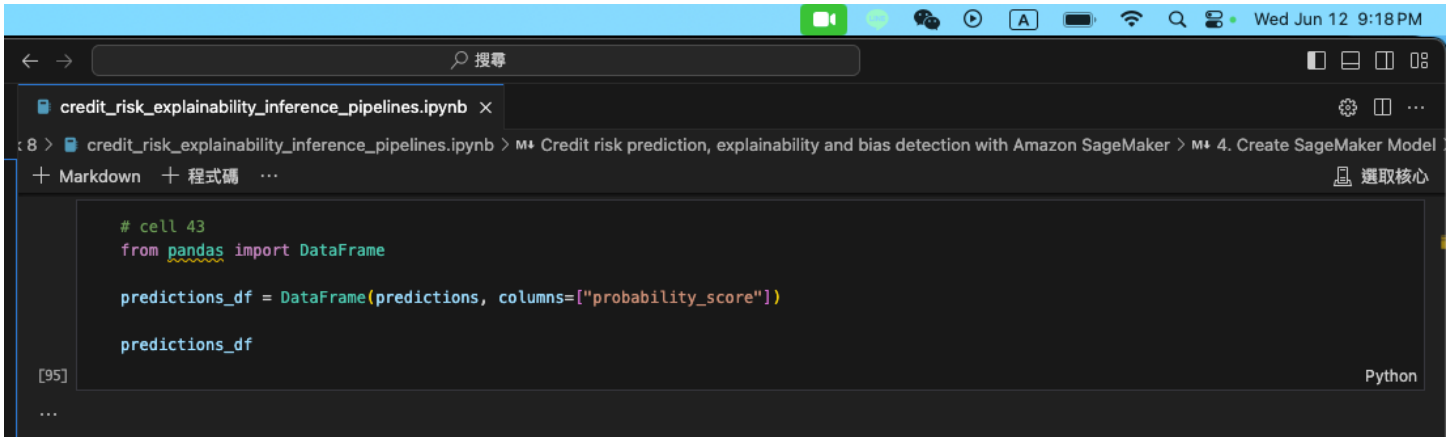
Step 24:
Clarify produces a CSV file which contains the SHAP value for each feature per prediction



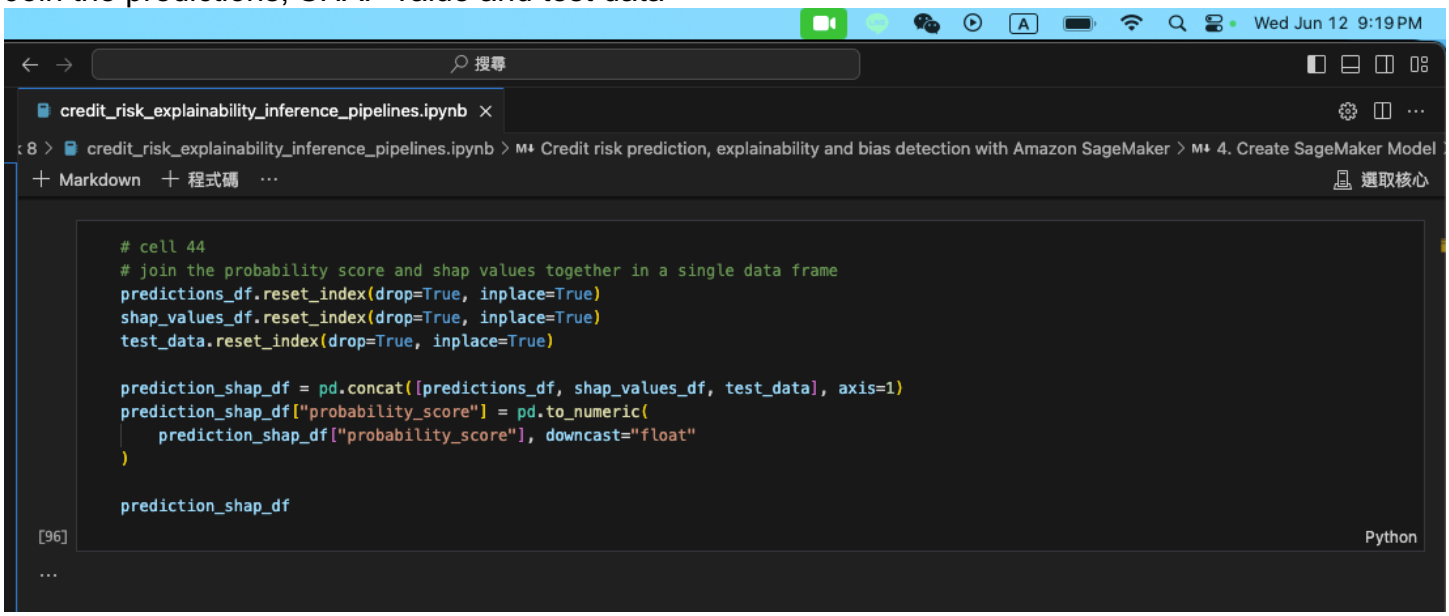


E(y) > 0 implies baseline probability greater than 0.5 (good credit baseline)

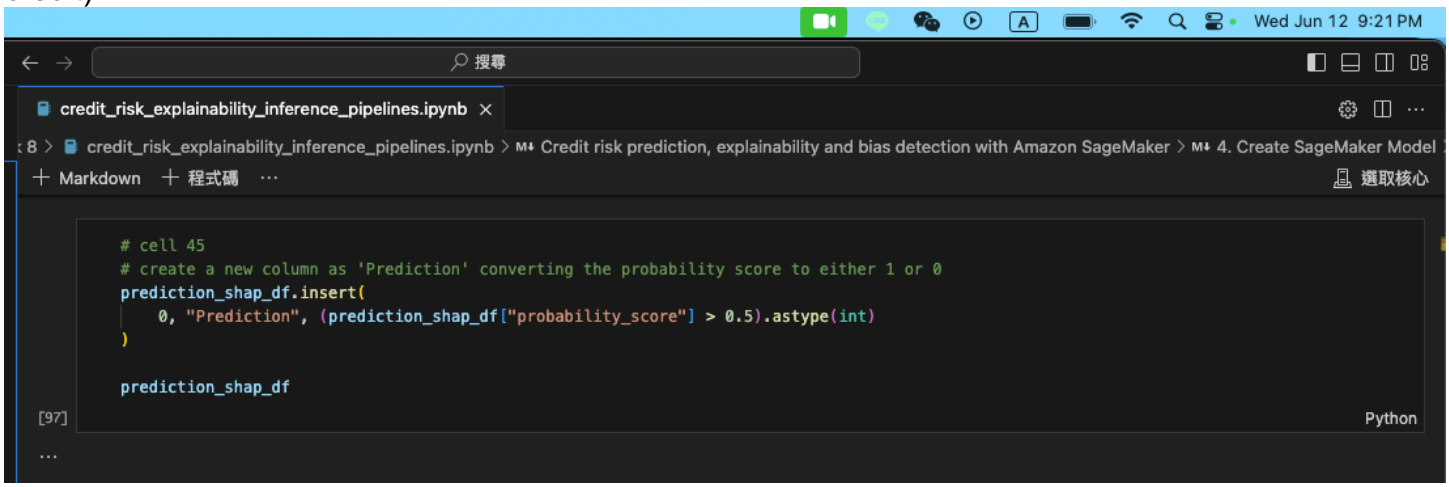
Step 25:
Create a dataframe containing the model predictions generated earlier during inference



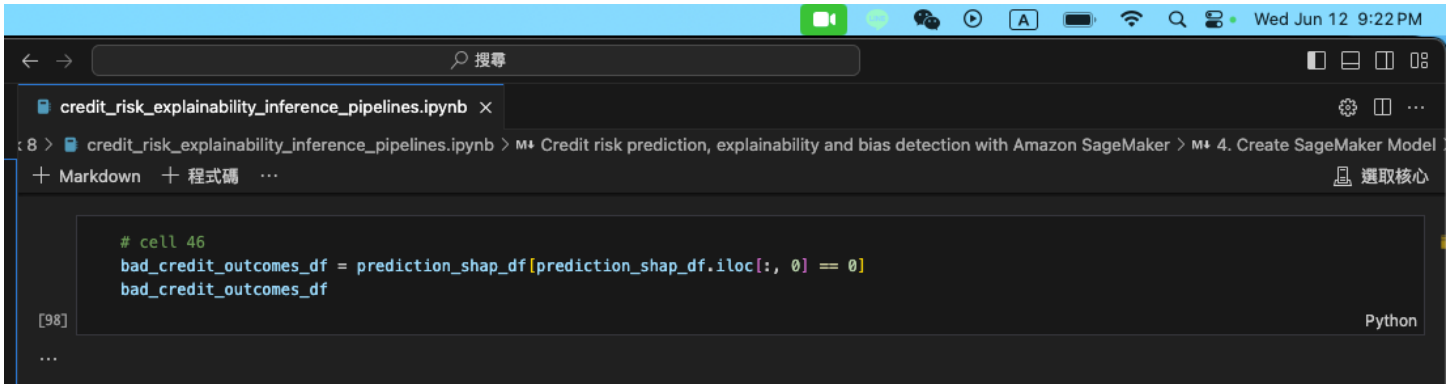
Step 26:
Join the predictions, SHAP value and test data



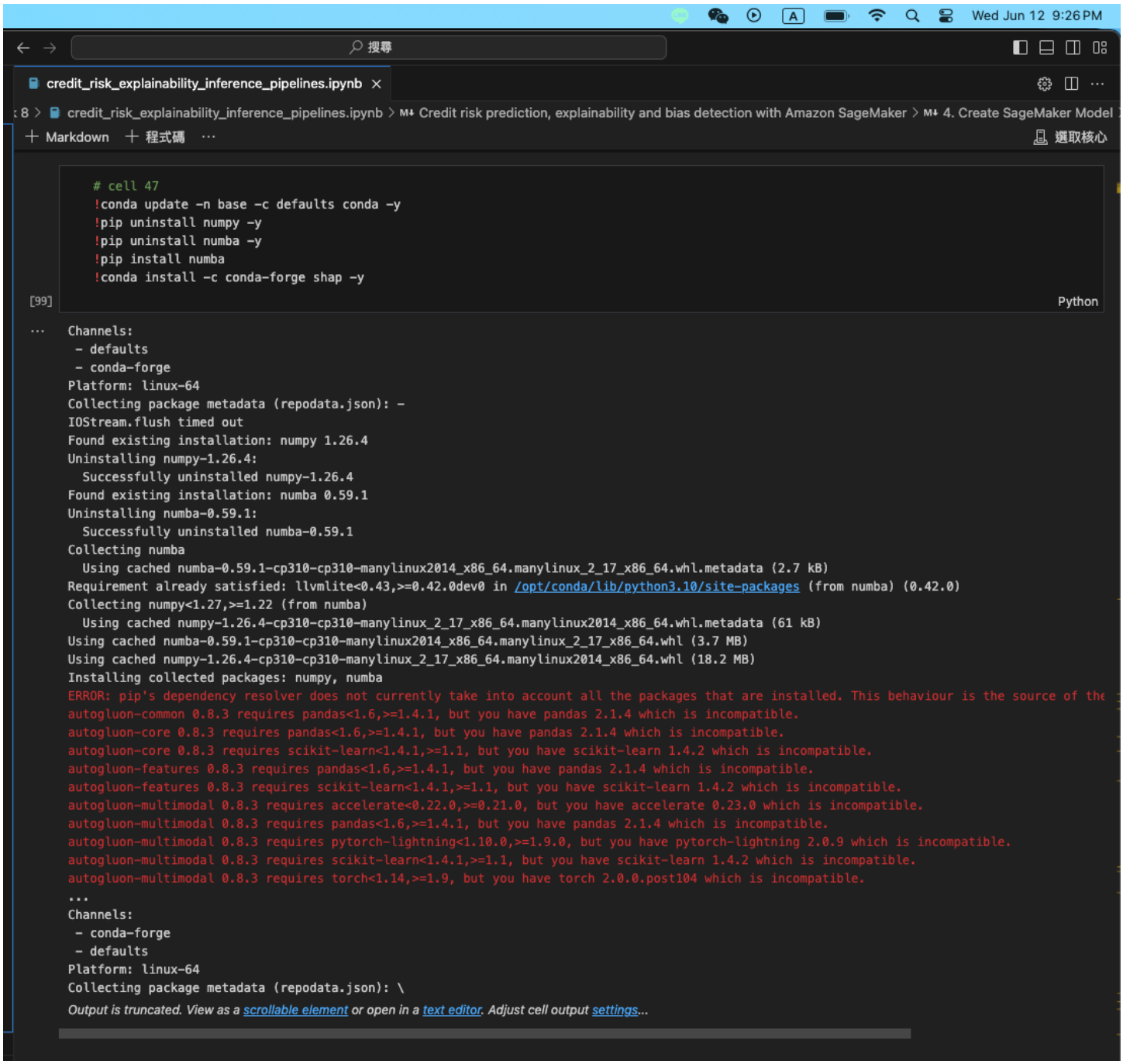
Step 27:
Convert the probability score to a binary value(1/0), based on a threshold(0.5), where probability scores greater than 0.5 are positive outcomes (good credit) and lesser are negative outcomes (bad credit)



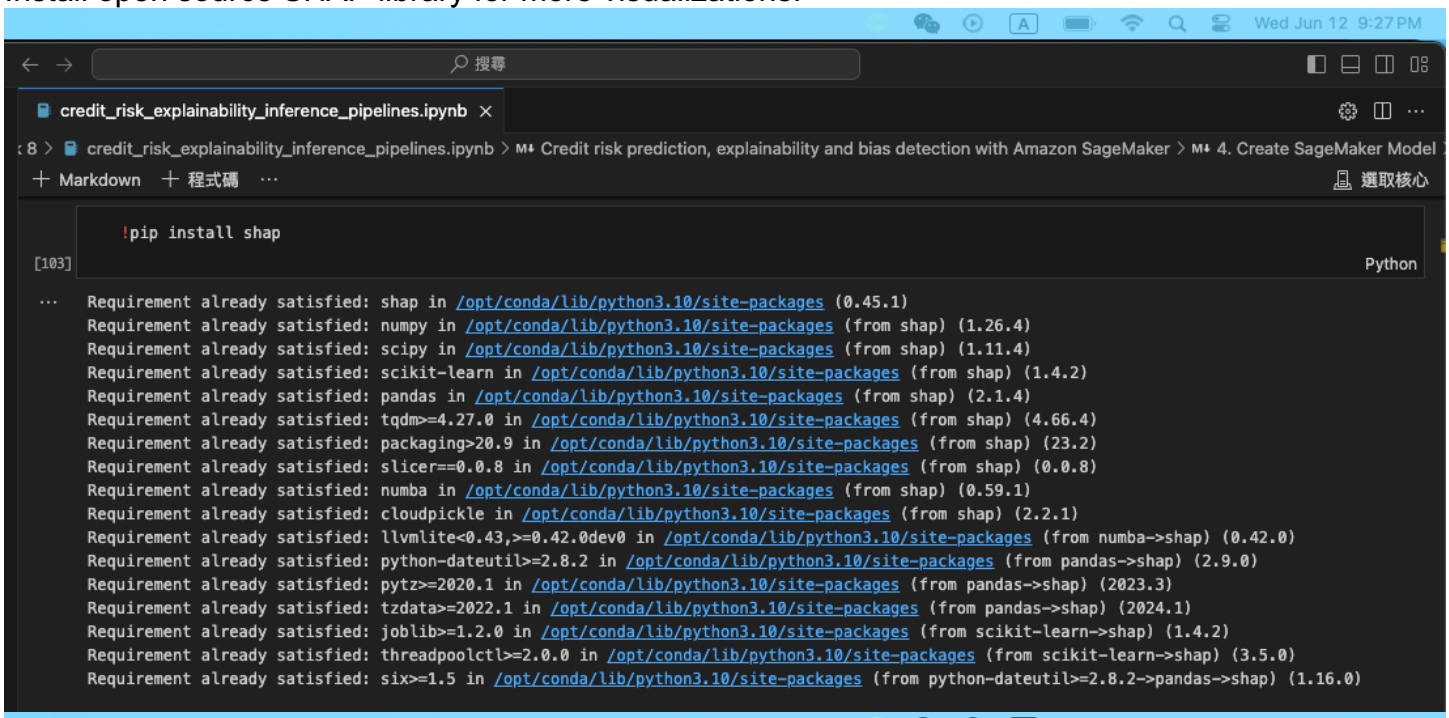
Step 28:
Filter for bad credit predictions only

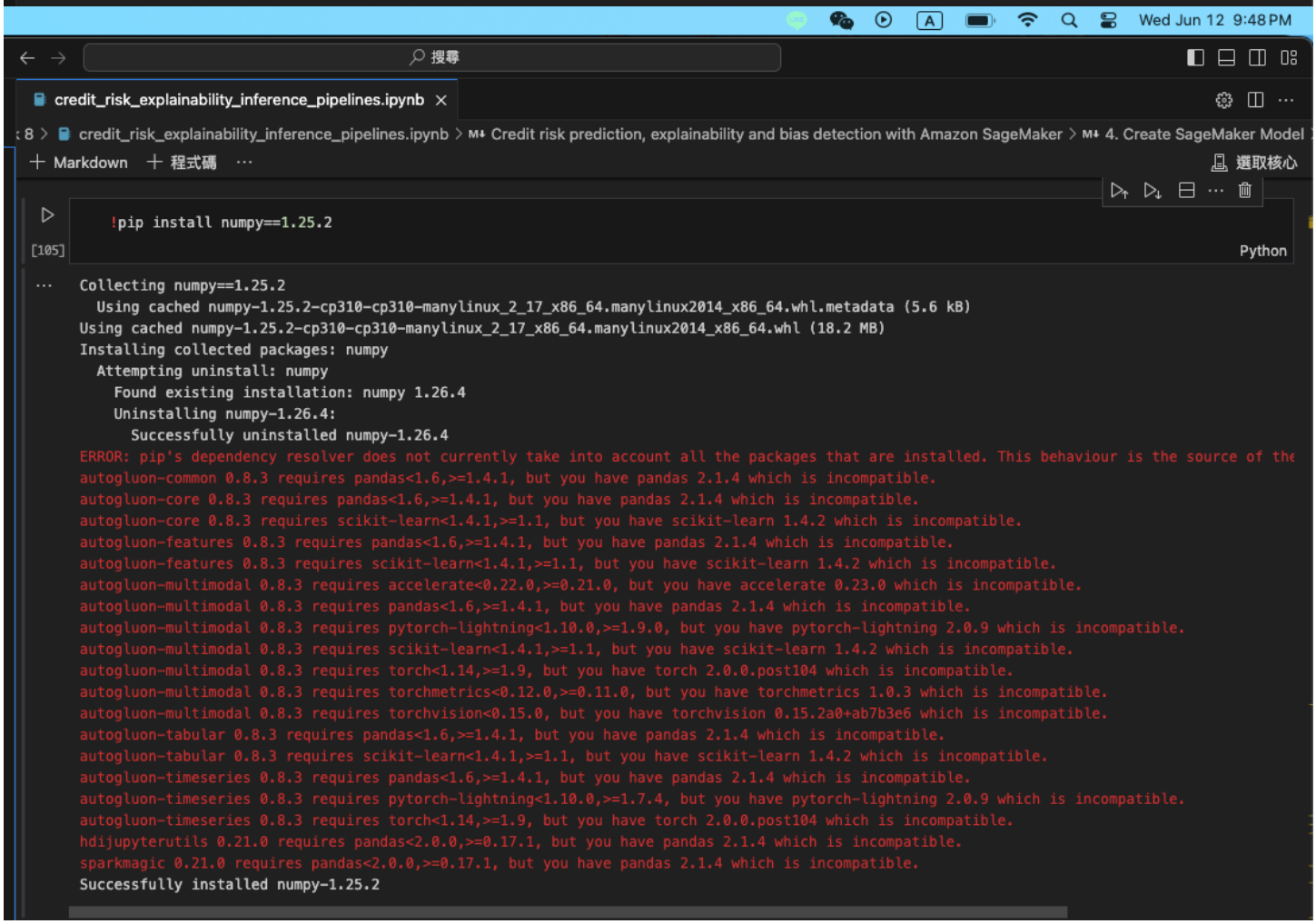


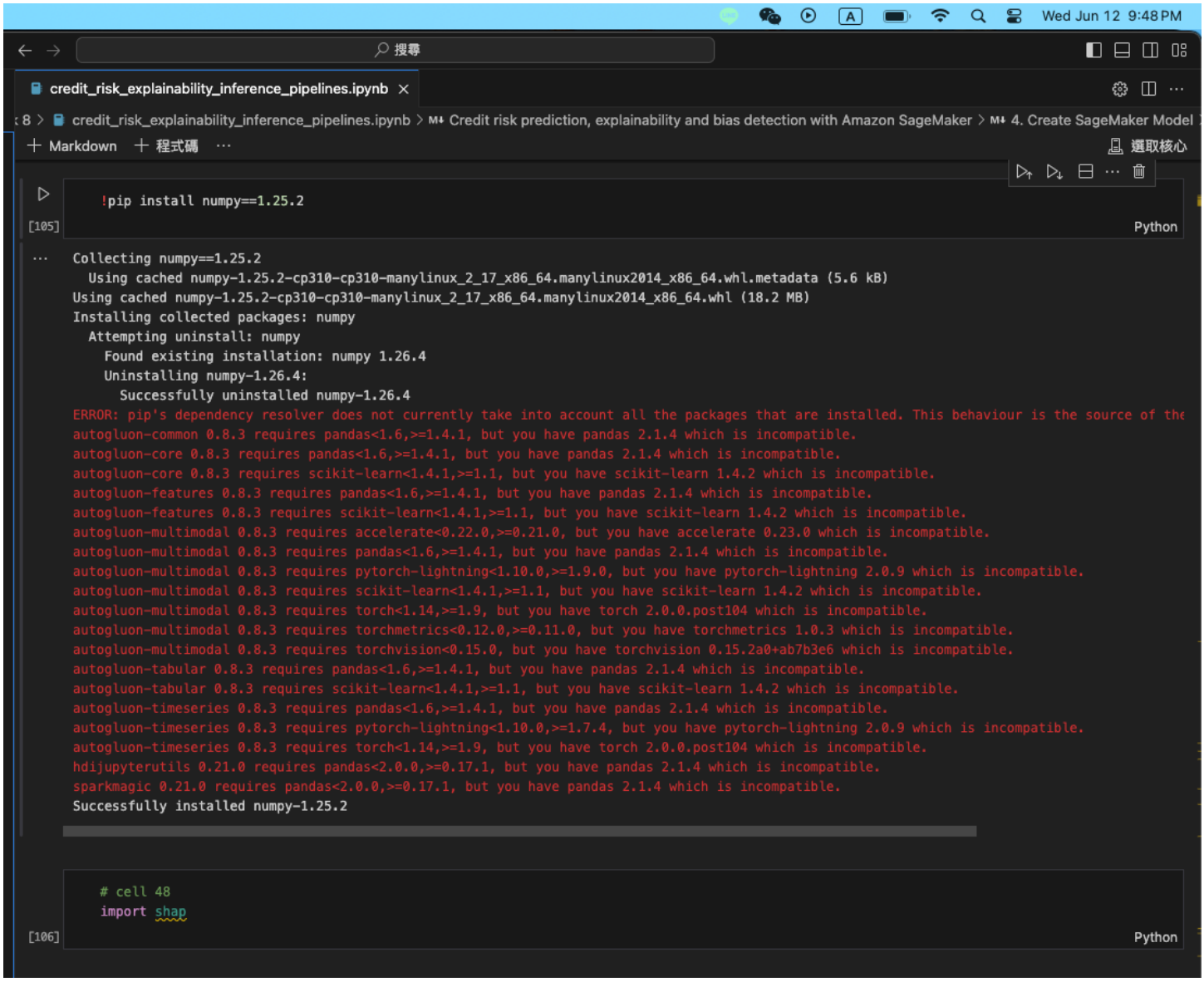
Step 29:
Create SHAP plots to understand how much different features contributed to a specific negative outcome



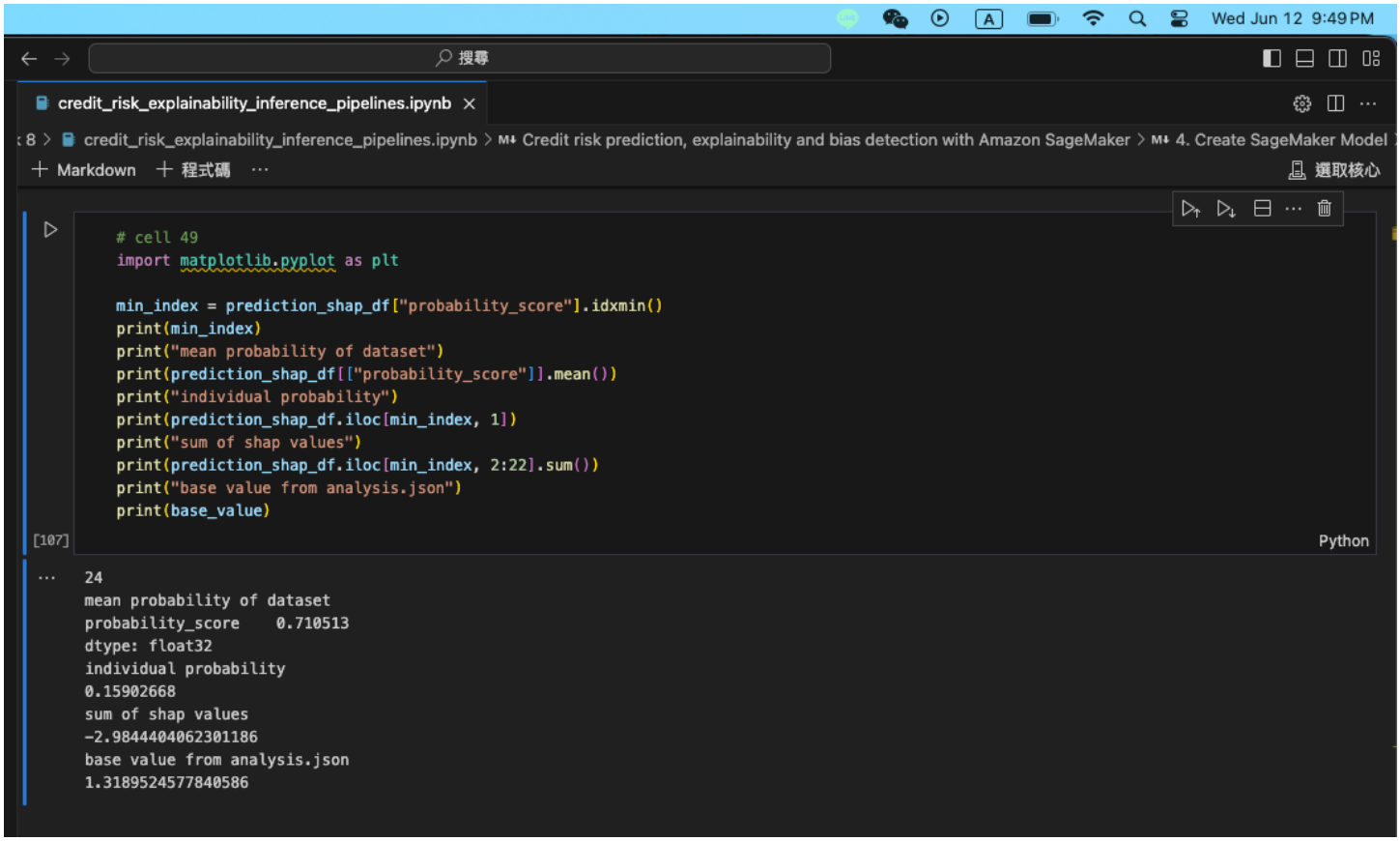
Step 30:
Install open source SHAP library for more visualizations.



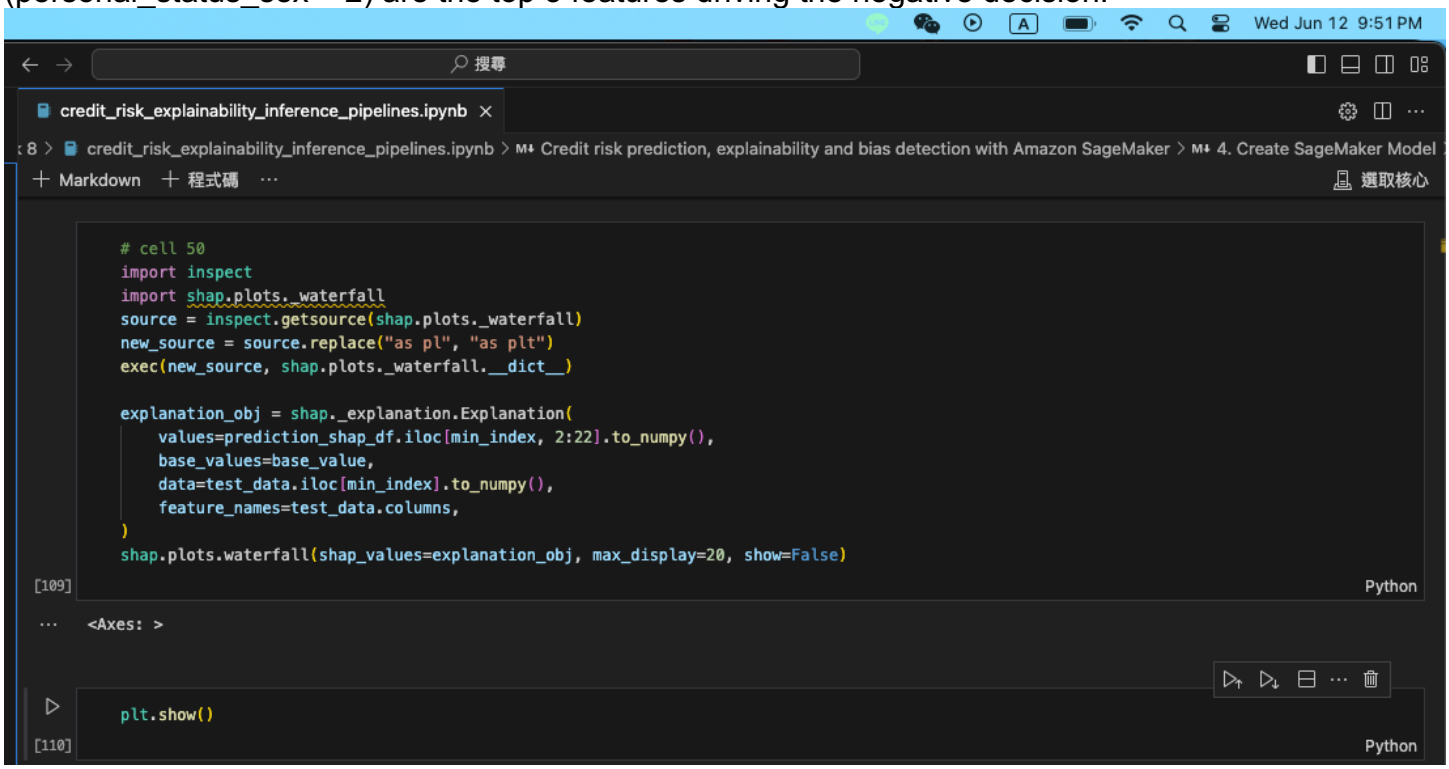


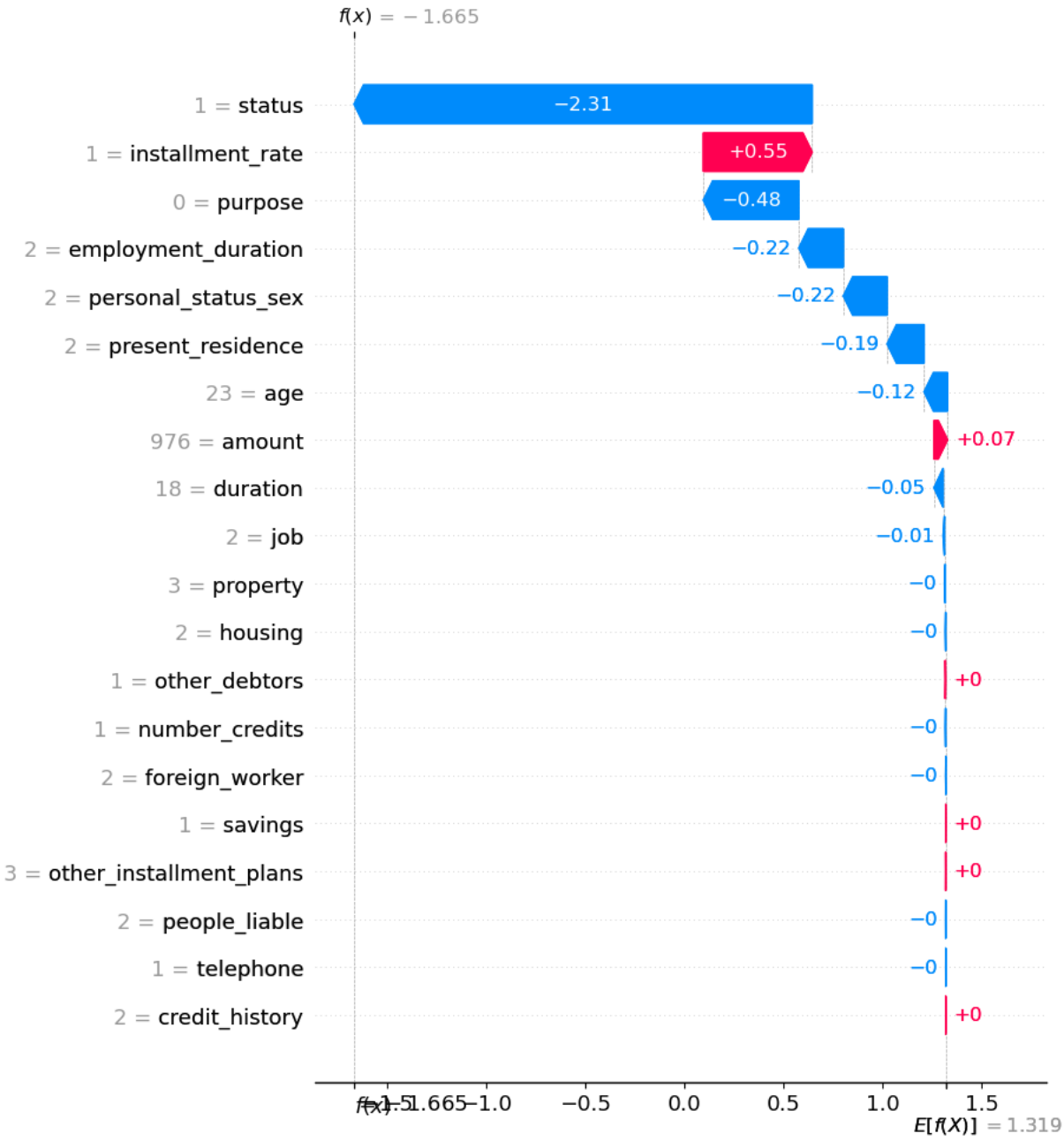


Step 31:
SHAP explanation plot for a single bad credit ensemble prediction instance.

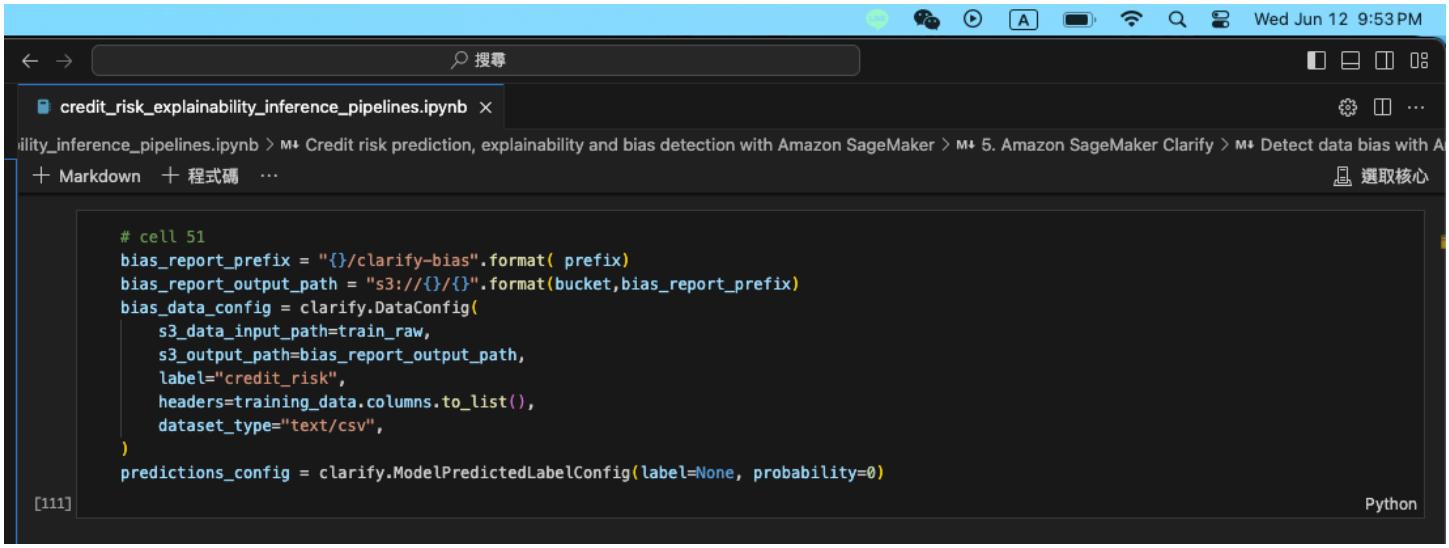


Step 32:
Example 'bad credit' prediction SHAP values, the input features (status = 1) , (purpose = 0) and (personal_status_sex = 2) are the top 3 features driving the negative decision.



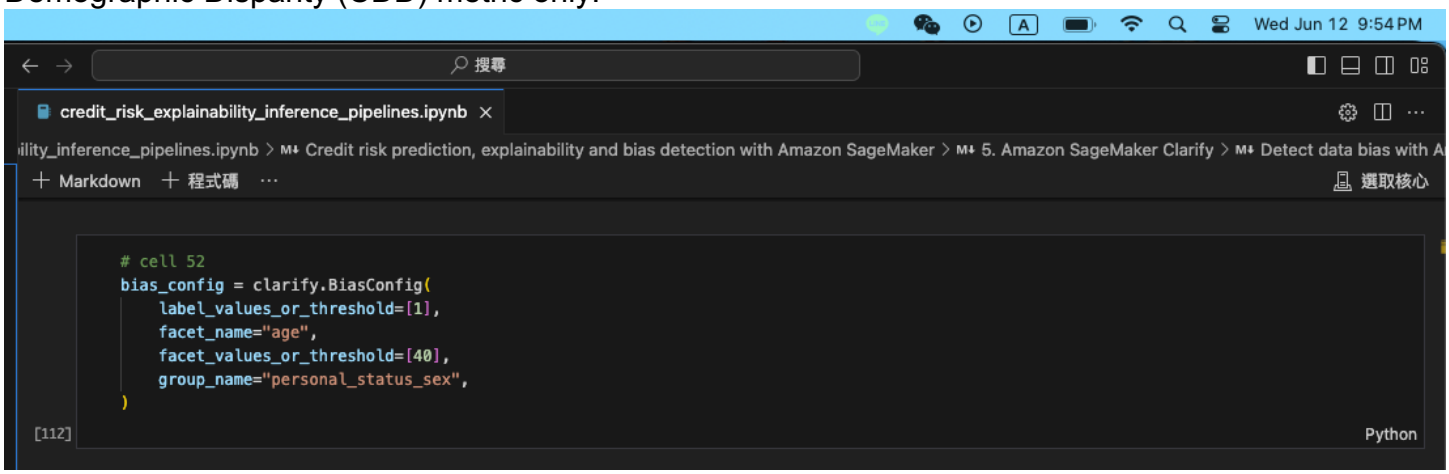


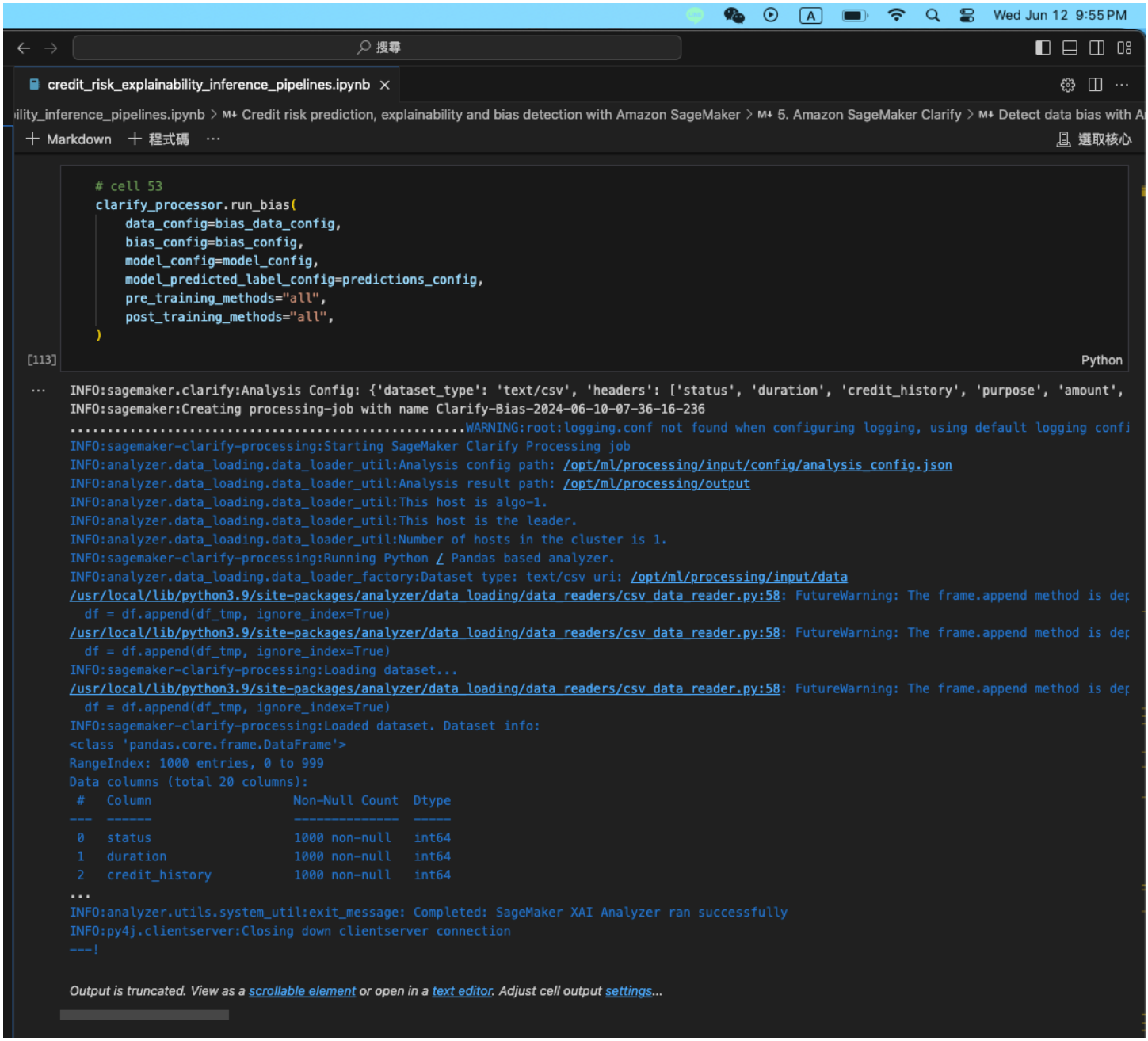
Step 33:
Specify where to find the input dataset, where to store the output, the target column (label), the header names, and the dataset type.



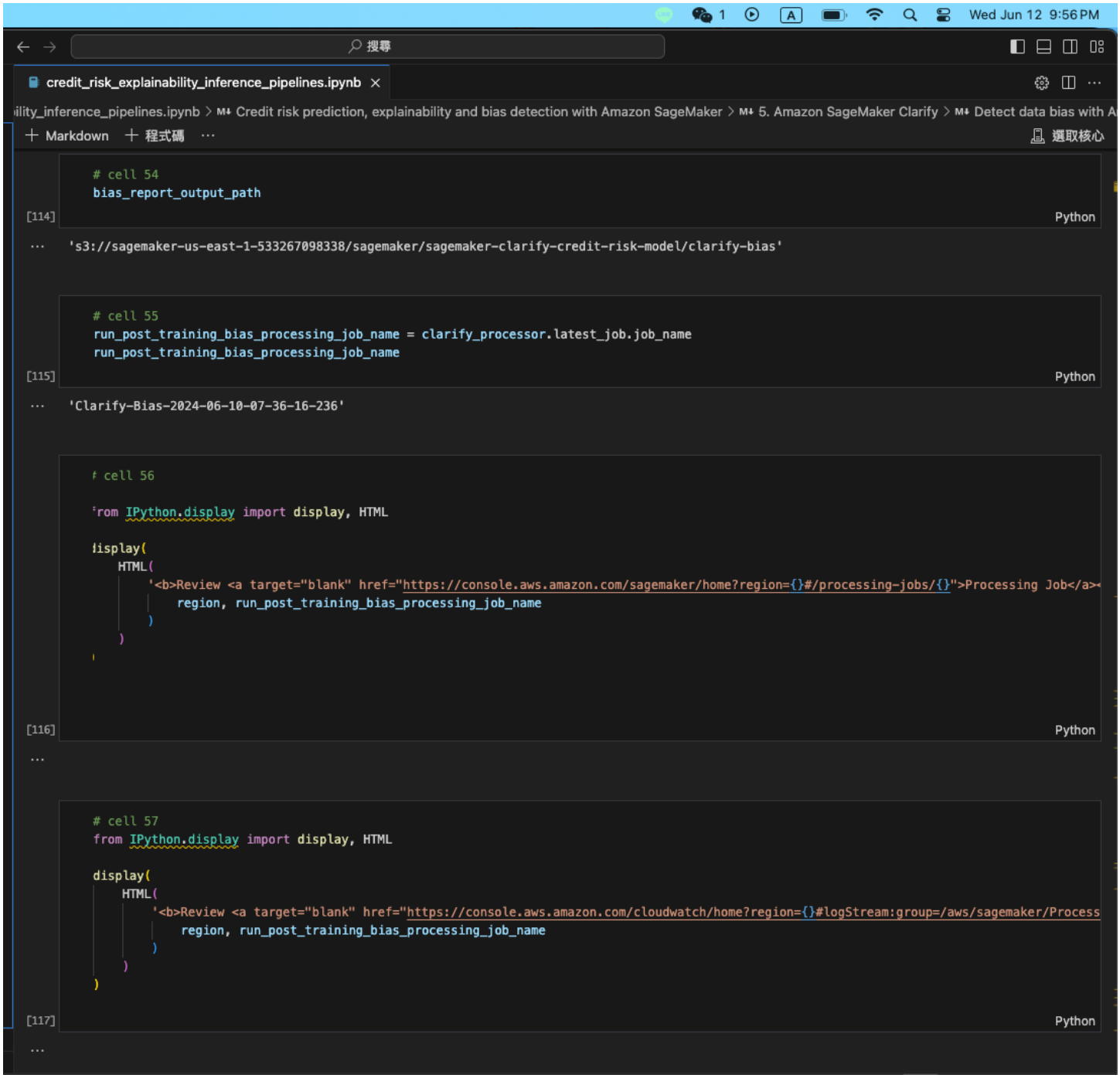
Step 34:

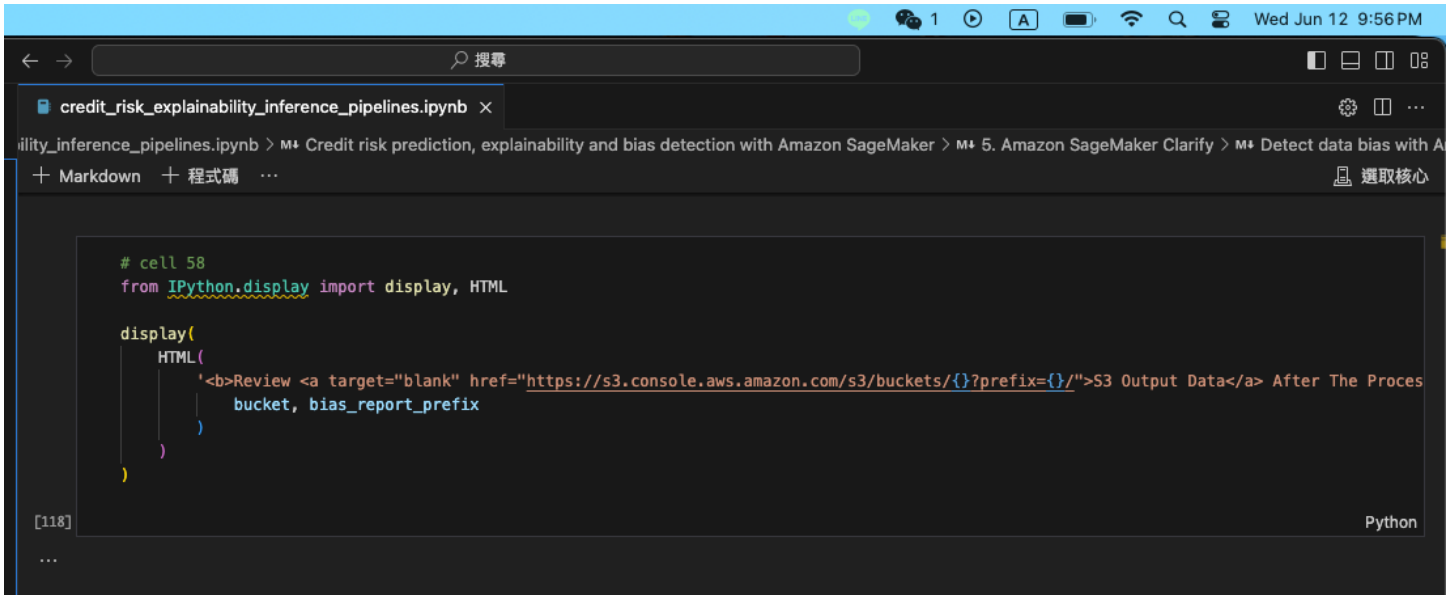
The group 'personal_status_sex' is used to form subgroups for the measurement of Conditional Demographic Disparity (CDD) metric only.



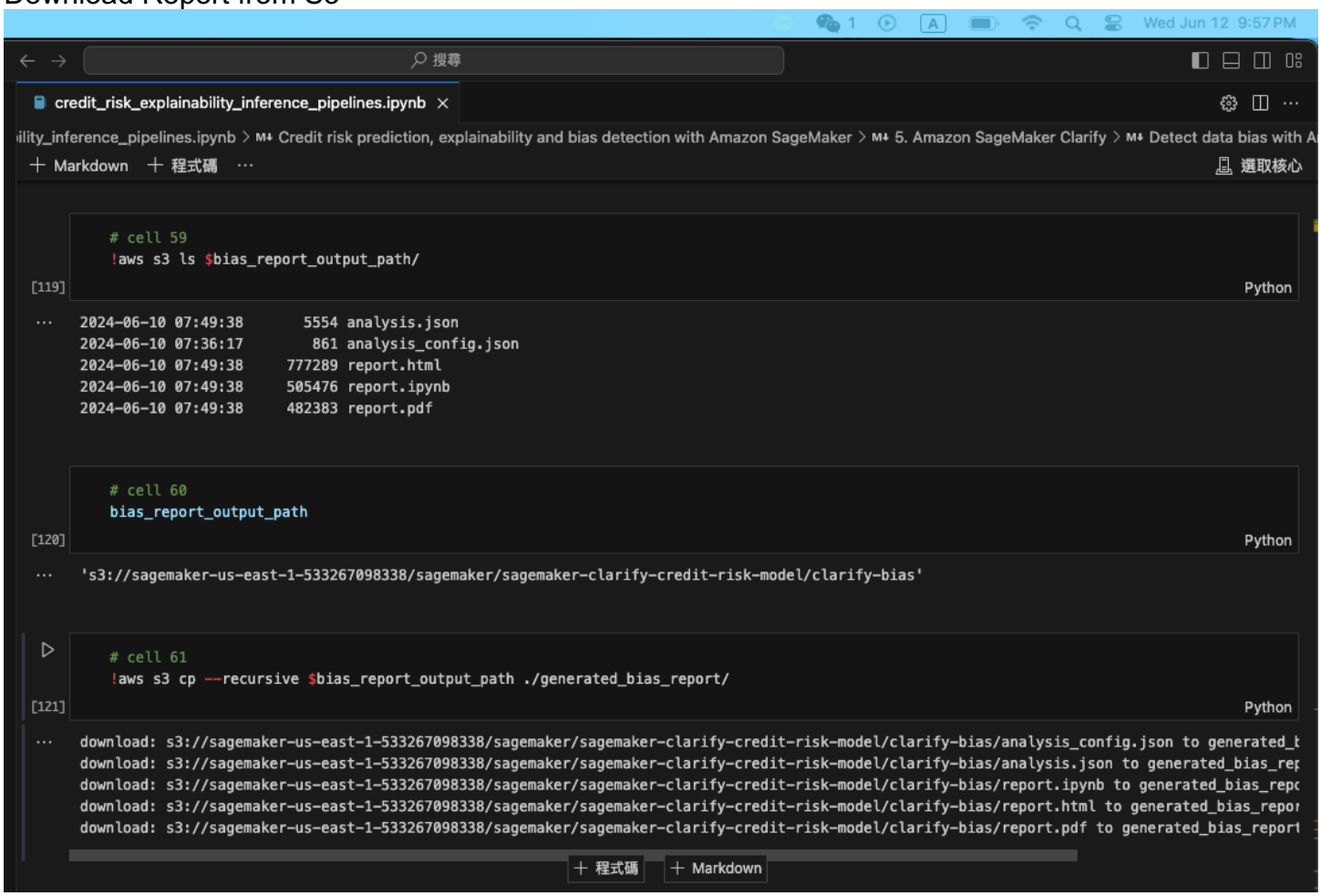


Step 35:
Viewing the Bias detection Report

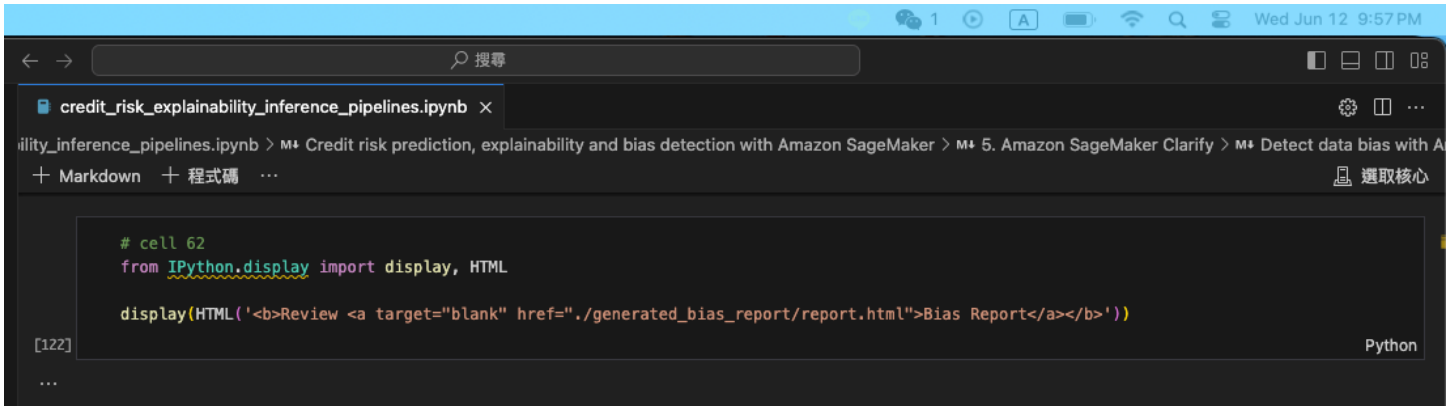

Wed Jun 12 9:56 PM
搜尋
credit_risk_explainability_inference_pipelines.ipynb
ility_inference_pipelines.ipynb > Credit risk prediction, explainability and bias detection with Amazon SageMaker > 5. Amazon SageMaker Clarify > Detect data bias with A
Markdown
程式碼
選取核心
cell 54
bias_report_output_path
[114]
Python
's3://sagemaker-us-east-1-533267098338/sagemaker/sagemaker-clarify-credit-risk-model/clarify-bias'
# cell 55
run_post_training_bias_processing_job_name = clarify_processor.latest_job.job_name
run_post_training_bias_processing_job_name
[115]
Python
'Clarify-Bias-2024-06-10-07-36-16-236'
# cell 56
from IPython.display import display, HTML
display(
HTML(
'<b>Review Processing Job
region, run_post_training_bias_processing_job_name
)
)
[116]
Python
# cell 57
from IPython.display import display, HTML
display(
HTML(
'<b>Review <a target="blank" href="https://console.aws.amazon.com/cloudwatch/home?region={}#logStream:group=/aws/sagemaker/Process
region, run_post_training_bias_processing_job_name
)
)
)
[117]
Python



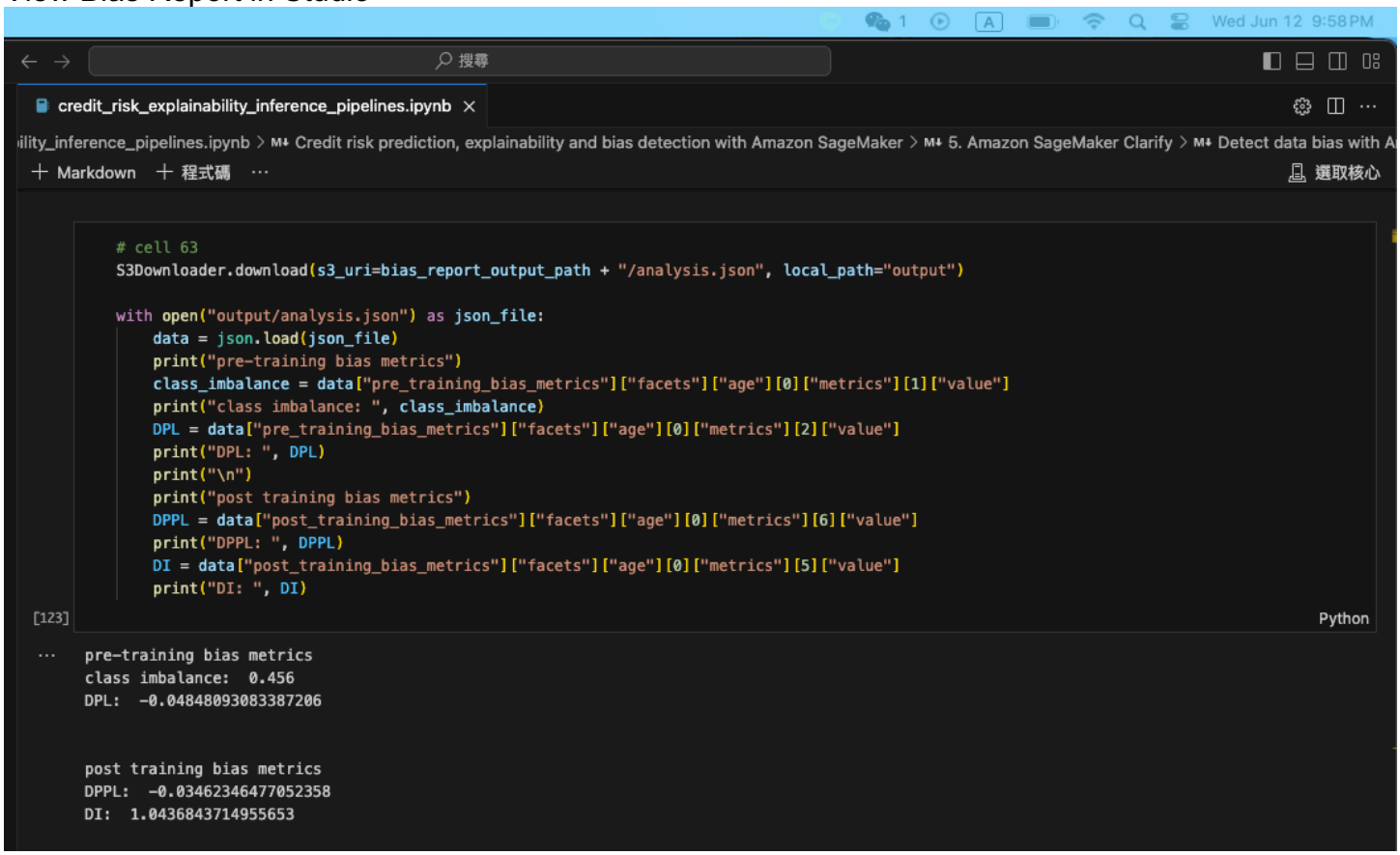
Step 36:
Download Report from S3



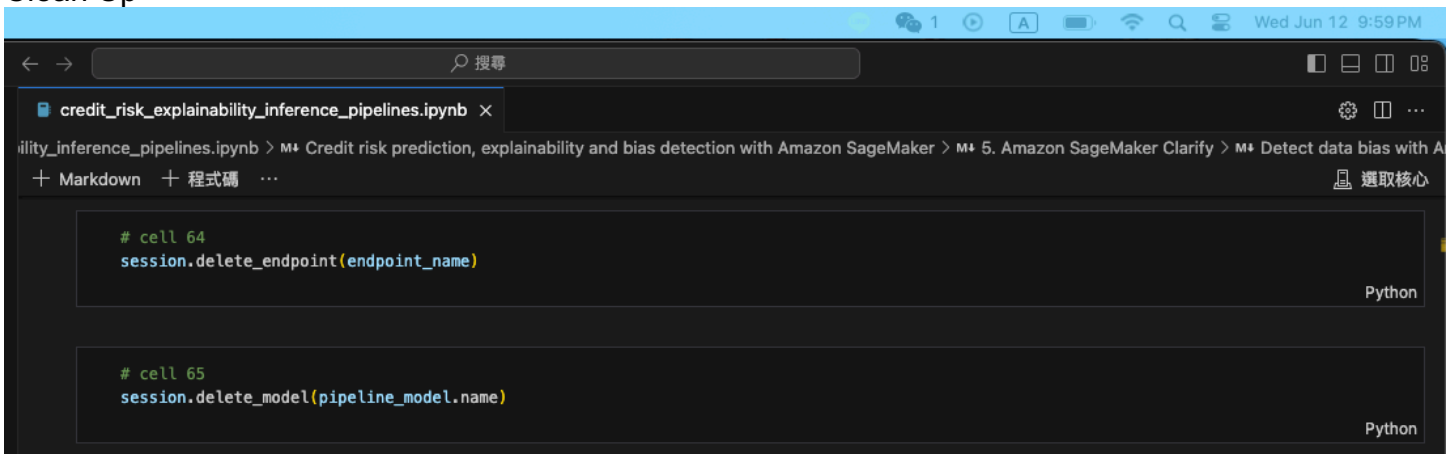
Step 37:
View the bias report pdf that contains the pre-training bias and post-training bias metrics.



Step 38:
View Bias Report in Studio



Step 39:
Clean Up



Analysis Report

Global dataset report

This report is the output of the Amazon SageMaker Clarify analysis. The report is split into following parts:

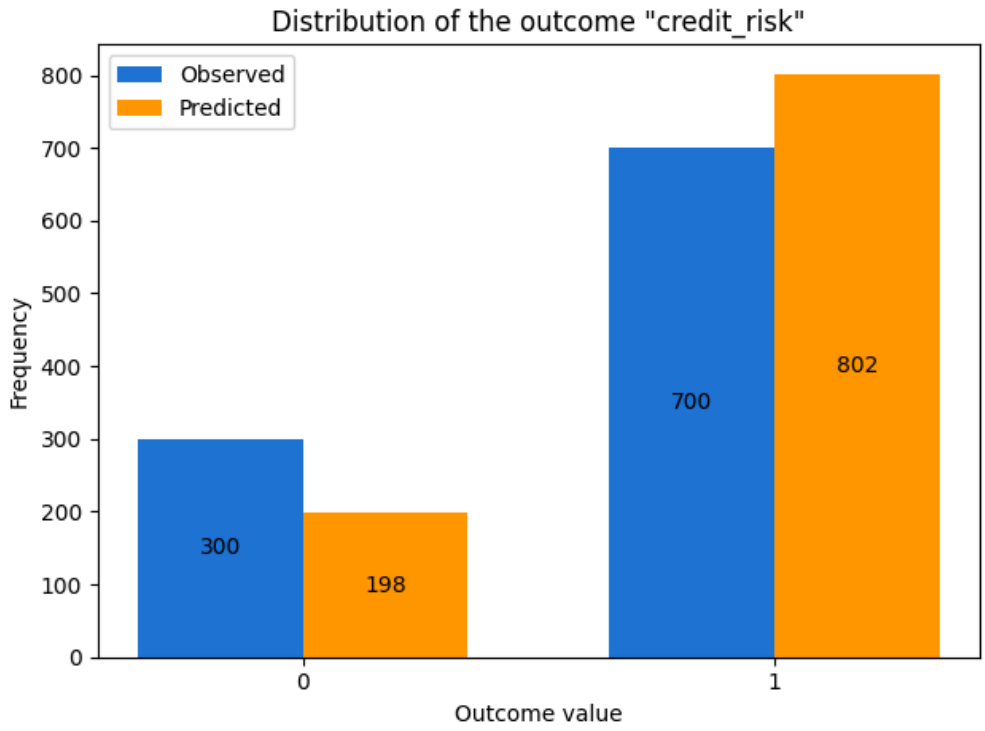
1. Analysis configuration
2. High level model performance
3. Pretraining bias metrics
4. Posttraining bias metrics

Analysis Configuration

Bias analysis requires you to configure the outcome label column, the facet and optionally a group variable. Generating explanations requires you to configure the outcome label. You configured the analysis with the following variables. The complete analysis configuration is appended at the end.

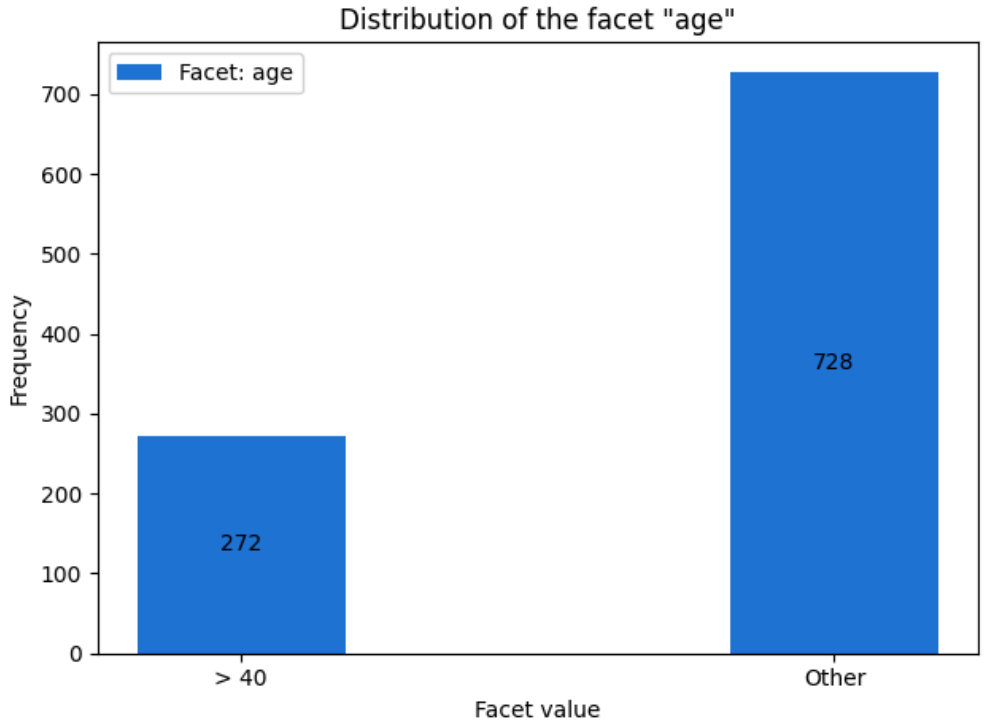
Outcome label: You chose the column `credit_risk` in the input data as the outcome label. Bias metric computation requires designating the positive outcome. You chose `credit_risk = 1` as the positive outcome. `credit_risk` consisted of values `[0, 1]` .

The figure below shows the distribution of values of `credit_risk` .



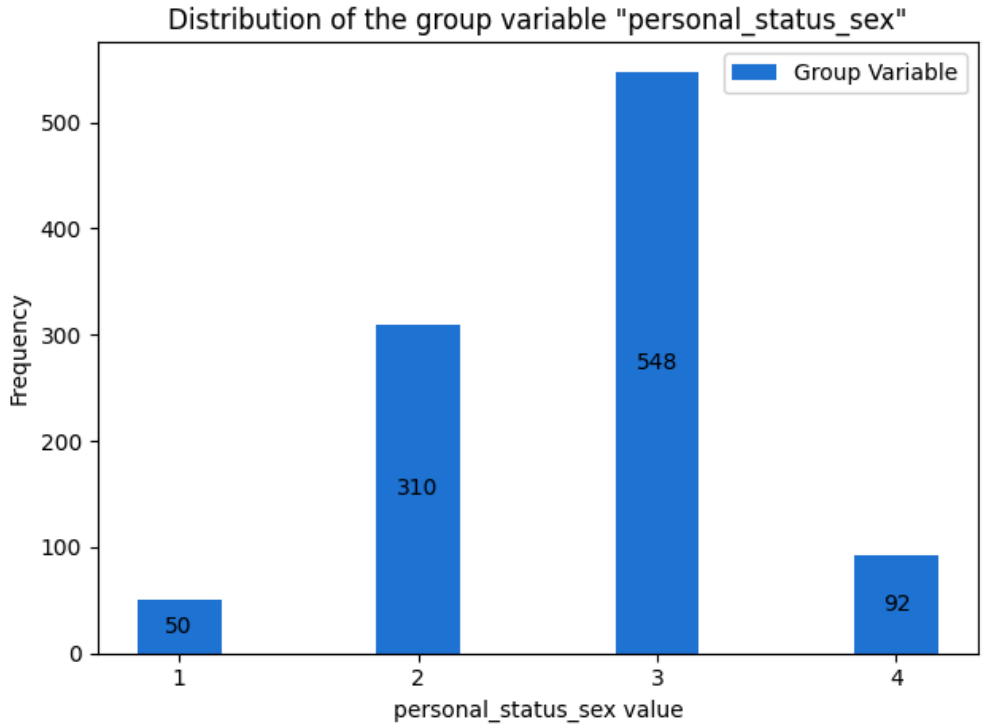
Facet: You chose the column `age` in the input data as the facet. `age` varied between `19.00` and `75.00` . Bias metrics were computed by comparing the inputs `age > 40` with all other inputs.

The figure below shows the distribution of values of `age` .



Group variable: Some bias metrics require an additional grouping variable. You chose `personal_status_sex` as the grouping variable.

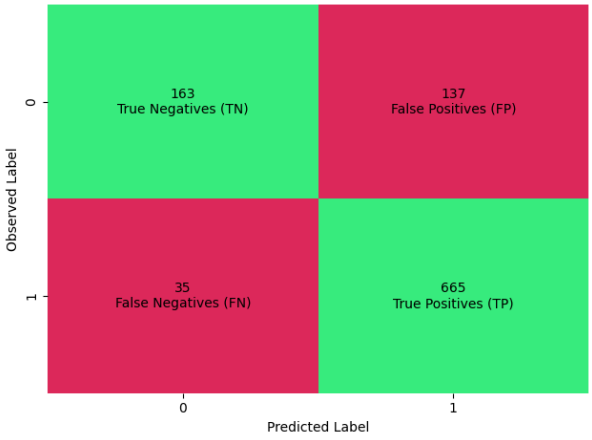
The figure below shows the distribution of values of `personal_status_sex` .



High level model performance

Input data points can be divided into different categories based on their observed and predicted label. For instance, a False Negative (FN) is an input with a positive observed label (`credit_risk = 1`) but negative predicted label (`credit_risk != 1`). A True Negative (TN) is an input whose observed and predicted labels are both negative. True Positives (TP) and False Positives (FP) are defined similarly.

Based on the model predictions, the inputs can be divided into different categories as:

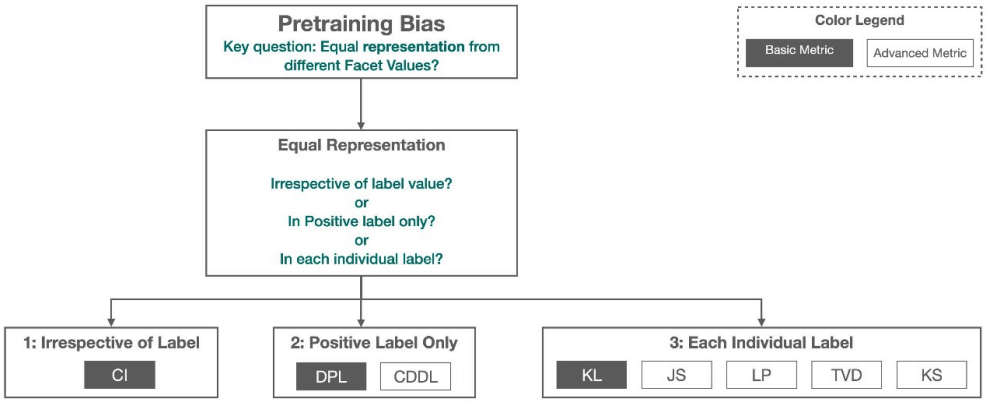


Here are metrics showing the model performance.

Metric	Description	Value
Accuracy	Proportion of inputs assigned the correct predicted label by the model.	0.828
Proportion of Positive Predictions in Labels	Proportion of input assigned in positive predicted label.	0.802
Proportion of Negative Predictions in Labels	Proportion of input assigned the negative predicted label.	0.198
True Positive Rate / Recall	Proportion of inputs with positive observed label correctly assigned the positive predicted label.	0.950
True Negative Rate / Specificity	Proportion of inputs with negative observed label correctly assigned the negative predicted label.	0.543
Acceptance Rate / Precision	Proportion of inputs with positive predicted label that actually have a positive observed label.	0.829
Rejection Rate	Proportion of inputs with negative predicted label that actually have a negative observed label.	0.823
Conditional Acceptance	Ratio between the positive observed labels and positive predicted labels.	0.873
Conditional Rejection	Ratio between the negative observed labels and negative predicted labels.	1.515
F1 Score	Harmonic mean of precision and recall.	0.885

Pre-training Bias Metrics

Pretraining bias metrics measure imbalances in facet value representation in the training data. Imbalances can be measured across different dimensions. For instance, you could focus imbalances within the inputs with positive observed label only. The figure below shows how different pretraining bias metrics focus on different dimensions. For a detailed description of these dimensions, see Learn How Amazon SageMaker Clarify Helps Detect Bias (https://aws.amazon.com/blogs/machine-learning/learn-how-amazon-sagemaker-clarify-helps-detect-bias/).

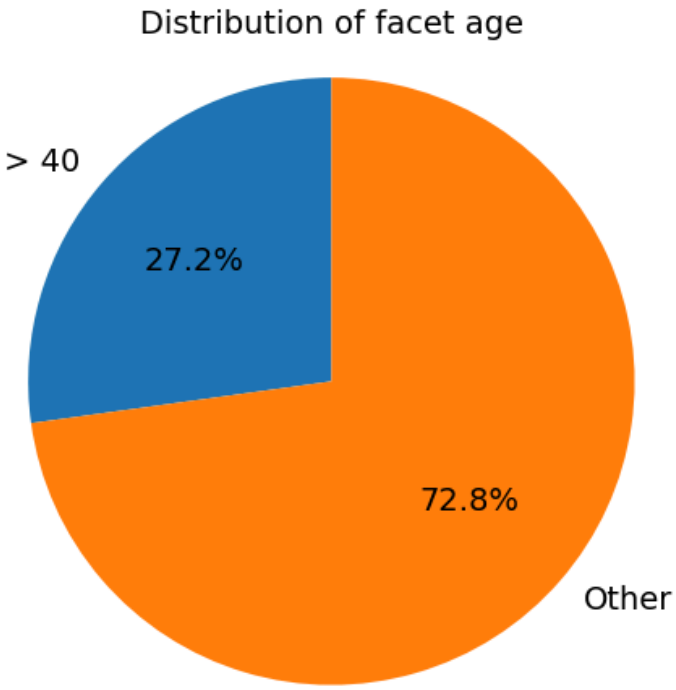


The metric values along with an informal description of what they mean are shown below. For mathematical formulas and examples, see the [Measure Pretraining Bias] (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-measure-data-bias.html) section of the AWS documentation.

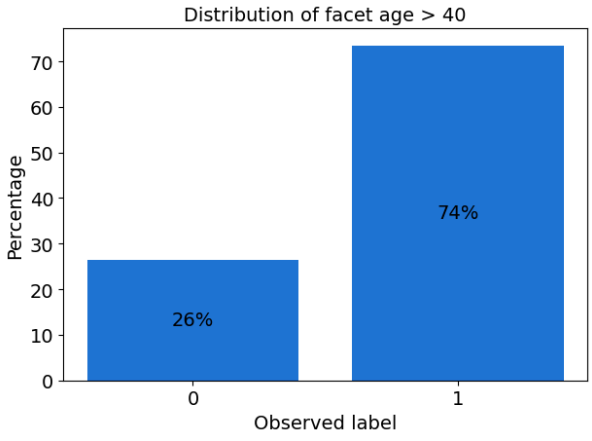
We computed the bias metrics for the label `credit_risk` using label value(s)/threshold `credit_risk = 1` for the following facets:

- Facet column: **age**

The pie chart shows the distribution of facet column `age` in your data.



The bar plot(s) below show the distribution of facet column `age` in your data.

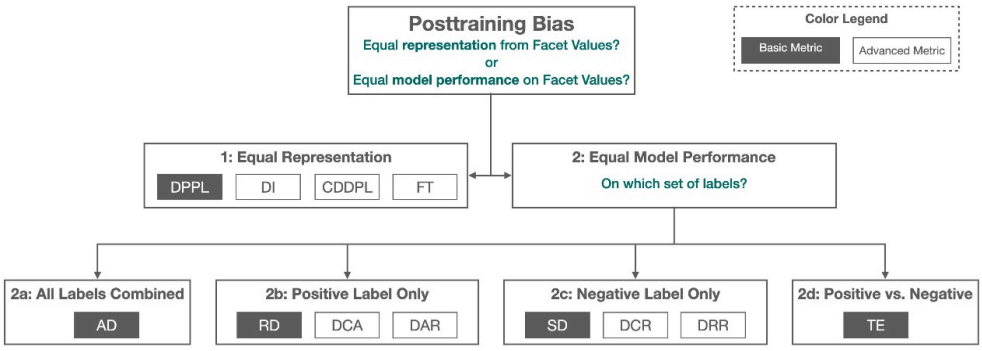


Facet Value(s)/Threshold: `age > 40`

Metric	Description	Value
Conditional Demographic Disparity in Labels (CDDL) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-data-bias-metric-cddl.html)	Measures maximum divergence between the observed label distributions for facet values `age > 40` and rest of the inputs in the dataset.	-0.035
Class Imbalance (CI) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-bias-metric-class-imbalance.html)	Measures the imbalance in the number of inputs with facet values `age > 40` and rest of the inputs.	0.456
Difference in Proportions of Labels (DPL) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-data-bias-metric-kl-divergence.html)	Measures the imbalance of positive observed labels between facet values `age > 40` and rest of the inputs.	-0.048
Jensen-Shannon Divergence (JS) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-data-bias-metric-jensen-shannon-divergence.html)	Measures how much the observed label distributions of facet values `age > 40` and rest of the inputs diverge from each other entropically.	0.001
Kullback-Leibler Divergence (KL) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-data-bias-metric-cddl.html)	Measures how much the observed label distributions of facet values `age > 40` and rest of the inputs diverge from each other entropically.	0.006
Kolmogorov-Smirnov (KS) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-data-bias-metric-kolmogorov-smirnov.html)	Measures maximum divergence between the observed label distributions for facet values `age > 40` and rest of the inputs in the dataset.	0.048
Lp-norm (LP) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-data-bias-metric-lp-norm.html)	Measures a p-norm difference between the observed label distributions associated with facet values `age > 40` rest of the inputs in the dataset.	0.069
Total Variation Distance (TVD) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-data-bias-metric-total-variation-distance.html)	Measures half of the L1-norm difference between the observed label distributions associated with facet values `age > 40` and rest of the inputs in the dataset.	0.048

Post-training Bias Metrics

Posttraining bias metrics measure imbalances in model predictions across different inputs. The figure below shows how different posttraining metrics target different types of imbalances over inputs. For a detailed description of these types, see [Learn How Amazon SageMaker Clarify Helps Detect Bias (https://aws.amazon.com/blogs/machine-learning/learn-how-amazon-sagemaker-clarify-helps-detect-bias/)](https://aws.amazon.com/blogs/machine-learning/learn-how-amazon-sagemaker-clarify-helps-detect-bias/).

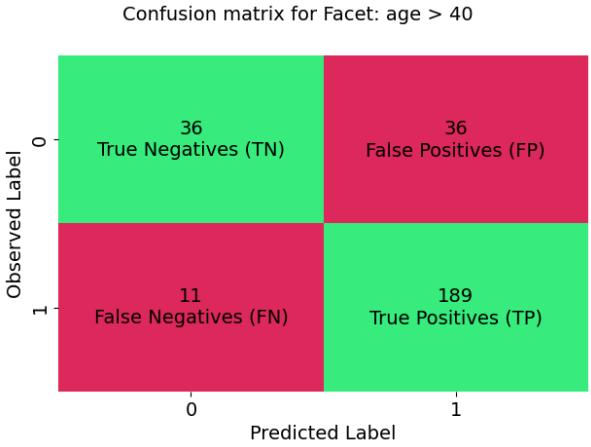


Bias can also result form imbalances in the model outcomes even when the facet value is not considered. The metric computing these imbalances is GE. The metric values along with an informal description of what they mean are shown below. For mathematical formulas and examples, see the [Measure Posttraining Data and Model Bias](https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-measure-post-training-bias.html) section of the AWS documentation.

We computed the bias metrics for the label `credit_risk` using label value(s)/threshold `credit_risk = 1` for the following facets:

- Facet column: **age**

Facet Value(s)/Threshold: `age > 40`



Metric	Description	Value
Accuracy Difference (AD) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-ad.html)	Measures the difference between the prediction accuracy for facet values `age > 40` and rest of the inputs.	0.001
Conditional Demographic Disparity in Predicted Labels (CDDPL) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-dppl.html)	Measures the disparity of predicted labels between facet values `age > 40` and rest of the inputs as a whole, but also by subgroups dictated by Age.	-0.020
Difference in Acceptance Rates (DAR) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-dcr.html)	Measures the difference in the ratios of the observed positive outcomes (TP) to the predicted positives (TP + FP) between facet values `age > 40` and rest of the inputs.	-0.015
Difference in Conditional Acceptance (DCAcc) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-dca.html)	Compares the observed labels to the labels predicted by the model. Assesses whether this is the same across facet values `age > 40` and rest of the inputs for predicted positive outcomes (acceptances).	-0.022
Difference in Conditional Rejection (DCR) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-dcr.html)	Compares the observed labels to the labels predicted by the model and assesses whether this is the same across facet values `age > 40` and rest of the inputs for negative outcomes (rejections).	0.022
Disparate Impact (DI) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-di.html)	Measures the ratio of proportions of the predicted labels for facet values `age > 40` and rest of the inputs.	1.044
Difference in Positive Proportions in Predicted Labels (DPPL) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-dppl.html)	Measures the difference in the proportion of positive predictions between facet values `age > 40` and rest of the inputs.	-0.035
Difference in Rejection Rates (DRR) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-drr.html)	Measures the difference in the ratios of the observed negative outcomes (TN) to the predicted negatives (TN + FN) between facet values `age > 40` and rest of the inputs.	-0.075
Counterfactual Fliptest (FT) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-ft.html)	Examines each input with facet value `age > 40` and assesses whether similar members from rest of the inputs have different model predictions.	-0.107
Generalized entropy (GE) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-ge.html)	Measures the inequality in benefits b assigned to each input by the model predictions.	0.067
Recall Difference (RD) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-rd.html)	Measures the difference between the recall, aka true positive rate, of the model for facet values `age > 40` and rest of the inputs.	0.007
Specificity difference (SD) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-sd.html)	Measures the difference between the specificity, aka true negative rate, of the model for facet values `age > 40` and rest of the inputs.	-0.057
Treatment Equality (TE) (https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-post-training-bias-metric-te.html)	Measures the difference in the ratio of false positives to false negatives between facet values `age > 40` and rest of the inputs.	0.068

Appendix: Analysis Configuration Parameters

```
{
    "dataset_type": "text/csv",
    "headers": [
        "status",
        "duration",
        "credit_history",
        "purpose",
        "amount",
        "savings",
        "employment_duration",
        "installment_rate",
        "personal_status_sex",
        "other_debtors",
        "present_residence",
        "property",
        "age",
        "other_installment_plans",
        "housing",
        "number_credits",
        "job",
        "people_liable",
        "telephone",
        "foreign_worker",
        "credit_risk"
    ],
    "label": "credit_risk",
    "label_values_or_threshold": [
        1
    ],
    "facet": [
        {
            "name_or_index": "age",
            "value_or_threshold": [
                40
            ]
        }
    ],
    "group_variable": "personal_status_sex",
    "methods": {
        "report": {
            "name": "report",
            "title": "Analysis Report"
        },
        "pre_training_bias": {
            "methods": "all"
        },
        "post_training_bias": {
            "methods": "all"
        }
    },
    "predictor": {
```

```
            "model_name": "credit-risk-inference-pipeline-1717999879",
            "instance_type": "ml.c5.xlarge",
            "initial_instance_count": 1,
            "accept_type": "text/csv",
            "probability": 0
        }
    }
```