Introducción a Machine Learning con AWS.

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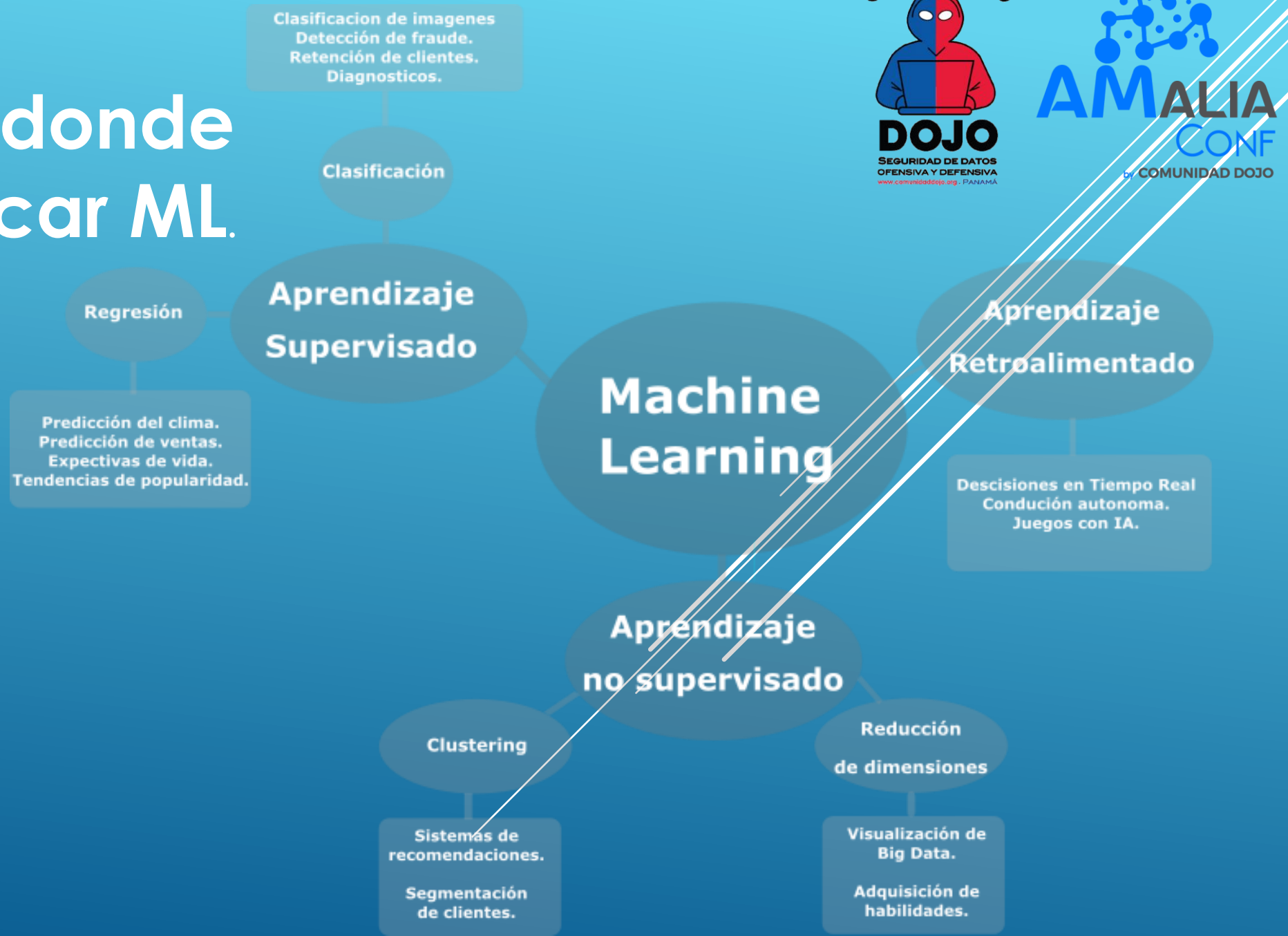
¿QUE ES MACHINE LEARNING?

Es la rama del campo de la inteligencia Artificial, que busca como dotar a las maquinas de capacidad de aprendizaje.

¿CÓMO APRENDEN LAS MAQUINAS?

Escenarios donde puedo aplicar ML.



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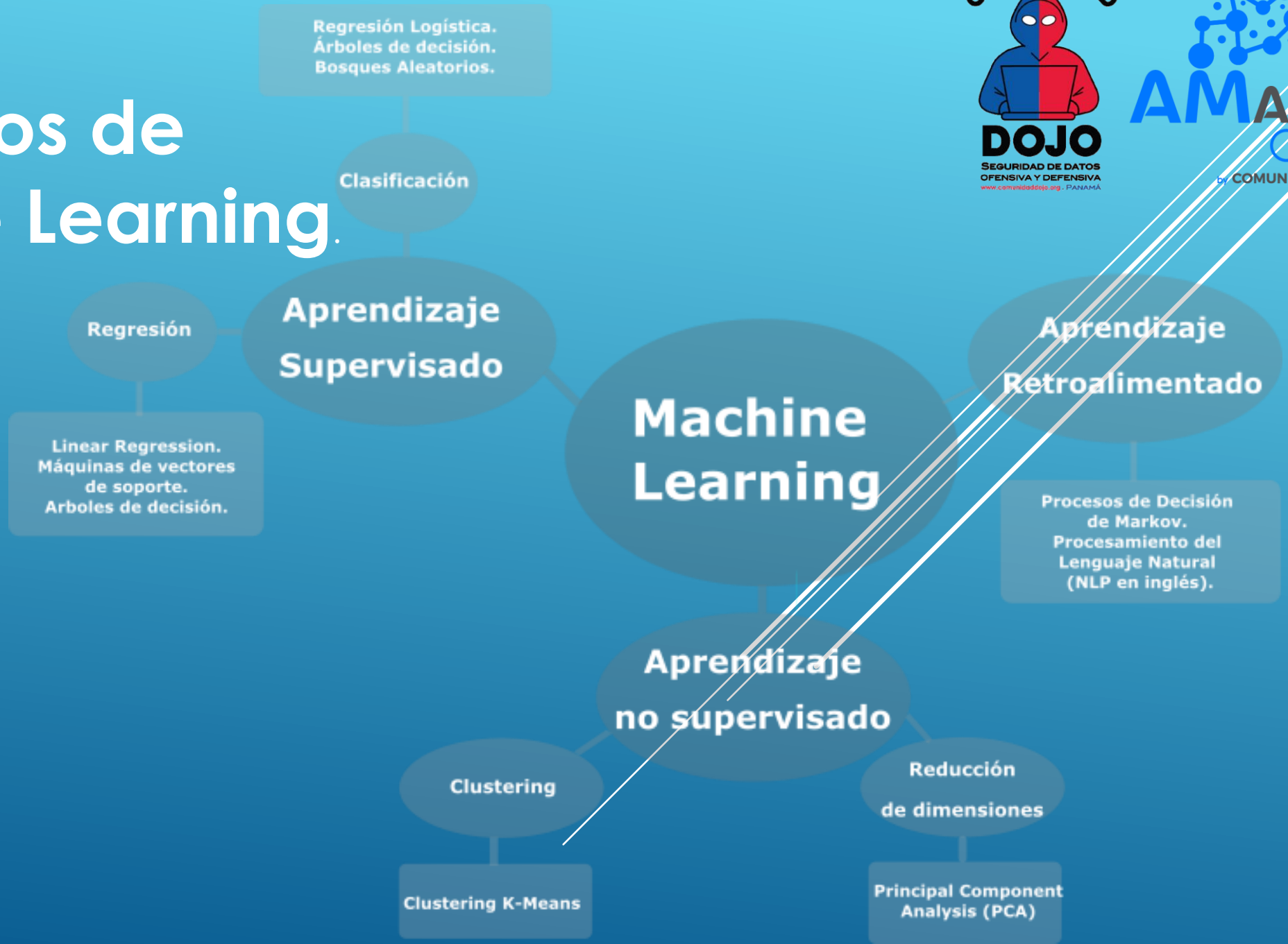
Algoritmos de Machine Learning.



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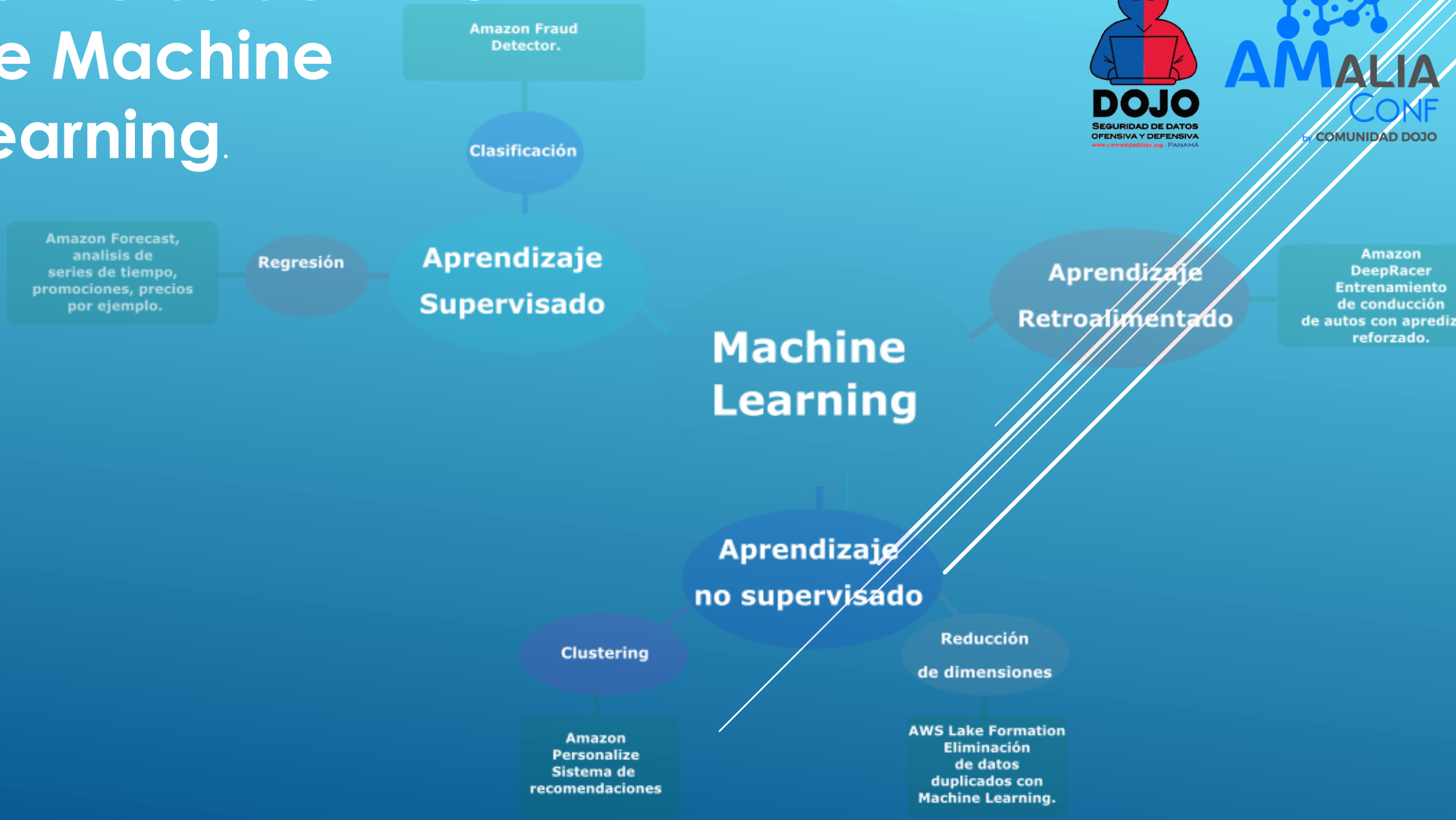
Servicios de AWS de Machine Learning.



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Proceso de despliegue de un Proyecto de Machine Learning

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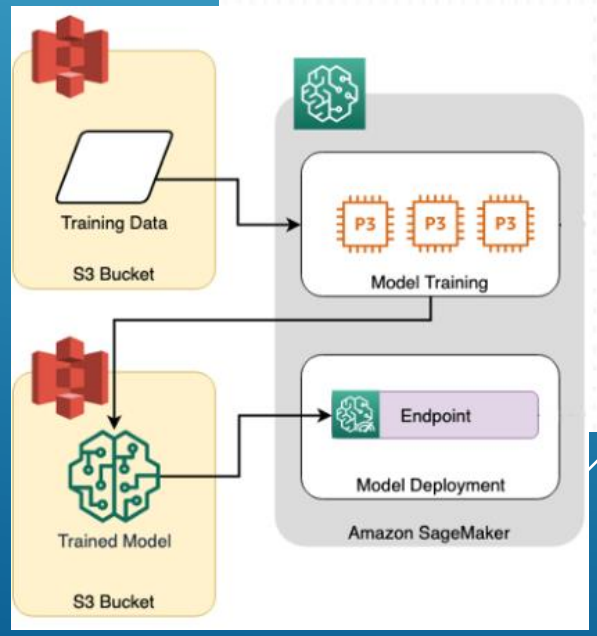
Servicios disponibles:

- Data Labeling.
- Model Building.
- Training
- Tunning and Deployment.



Etiquete	Creación	Entrene y ajuste	Implemente y administre
Amazon SageMaker Ground Truth Build and manage training data sets	**Amazon SageMaker Studio** Integrated development environment (IDE) for machine learning		
	Amazon SageMaker Autopilot Automatically build and train models		**Amazon SageMaker Model Monitor** Automatically detect concept drift
	Amazon SageMaker Notebooks One-click notebooks with elastic compute	**Amazon SageMaker Experiments** Capture, organize, and search every step	**Amazon SageMaker Neo** Train once, deploy anywhere
	AWS Marketplace Pre-built algorithms and models	**Amazon SageMaker Debugger** Debug and profile training runs	**Amazon Augmented AI** Add human review of model predictions
		Automatic Model Tuning One-click hyperparameter optimization	

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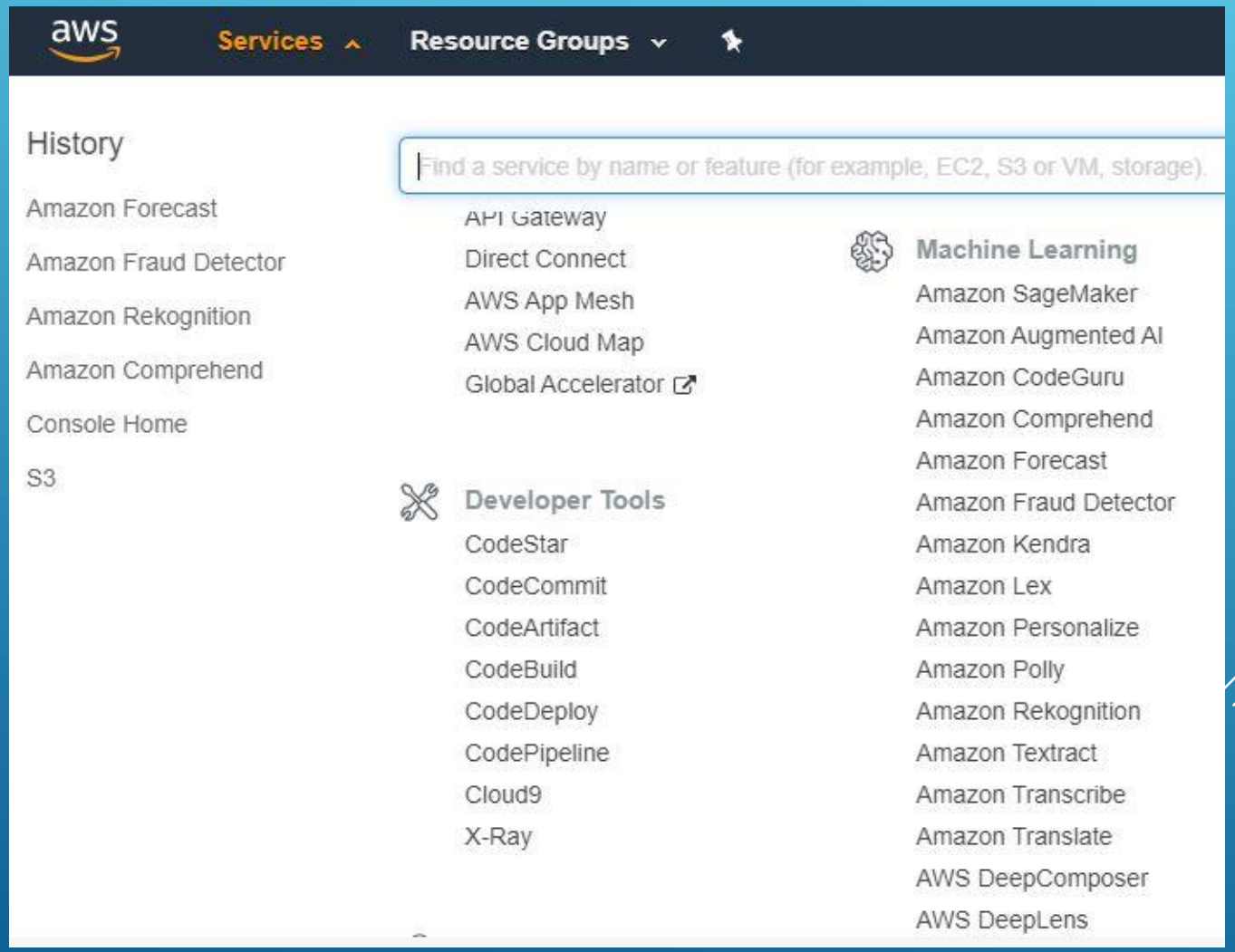
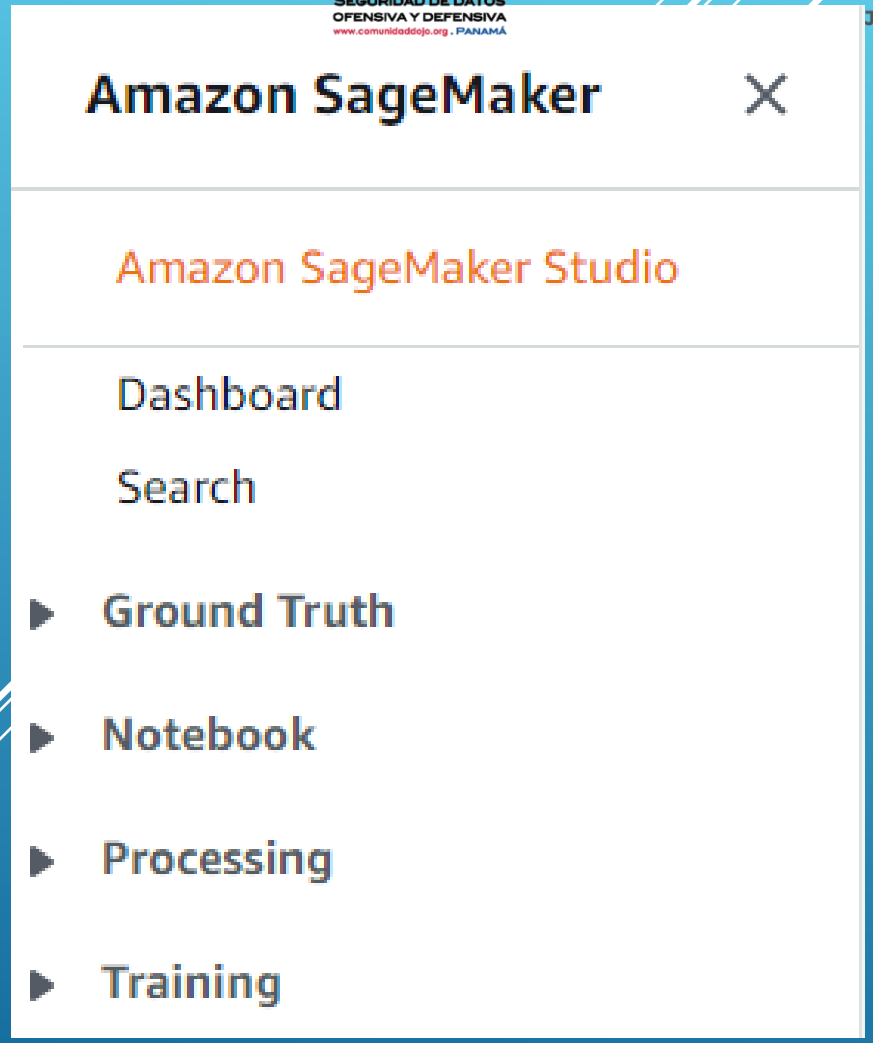

aws
Services
Resource Groups
History
Amazon Forecast
Amazon Fraud Detector
Amazon Rekognition
Amazon Comprehend
Console Home
S3
Find a service by name or feature (for example, EC2, S3 or VM, storage).
API Gateway
Direct Connect
AWS App Mesh
AWS Cloud Map
Global Accelerator
Developer Tools
CodeStar
CodeCommit
CodeArtifact
CodeBuild
CodeDeploy
CodePipeline
Cloud9
X-Ray
Machine Learning
Amazon SageMaker
Amazon Augmented AI
Amazon CodeGuru
Amazon Comprehend
Amazon Forecast
Amazon Fraud Detector
Amazon Kendra
Amazon Lex
Amazon Personalize
Amazon Polly
Amazon Rekognition
Amazon Textract
Amazon Transcribe
Amazon Translate
AWS DeepComposer
AWS DeepLens


Amazon SageMaker
Amazon SageMaker Studio
Dashboard
Search
Ground Truth
Notebook
Processing
Training

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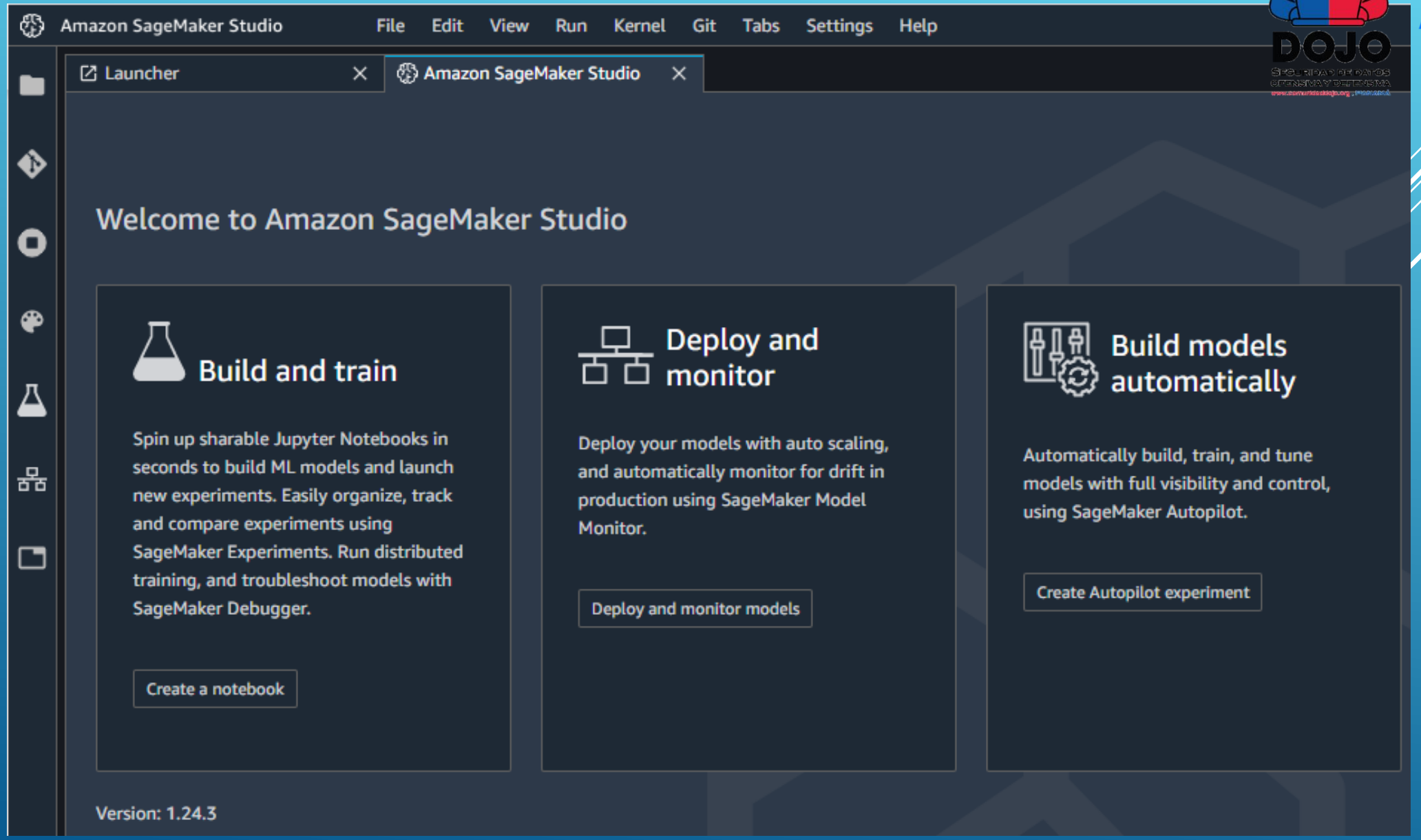

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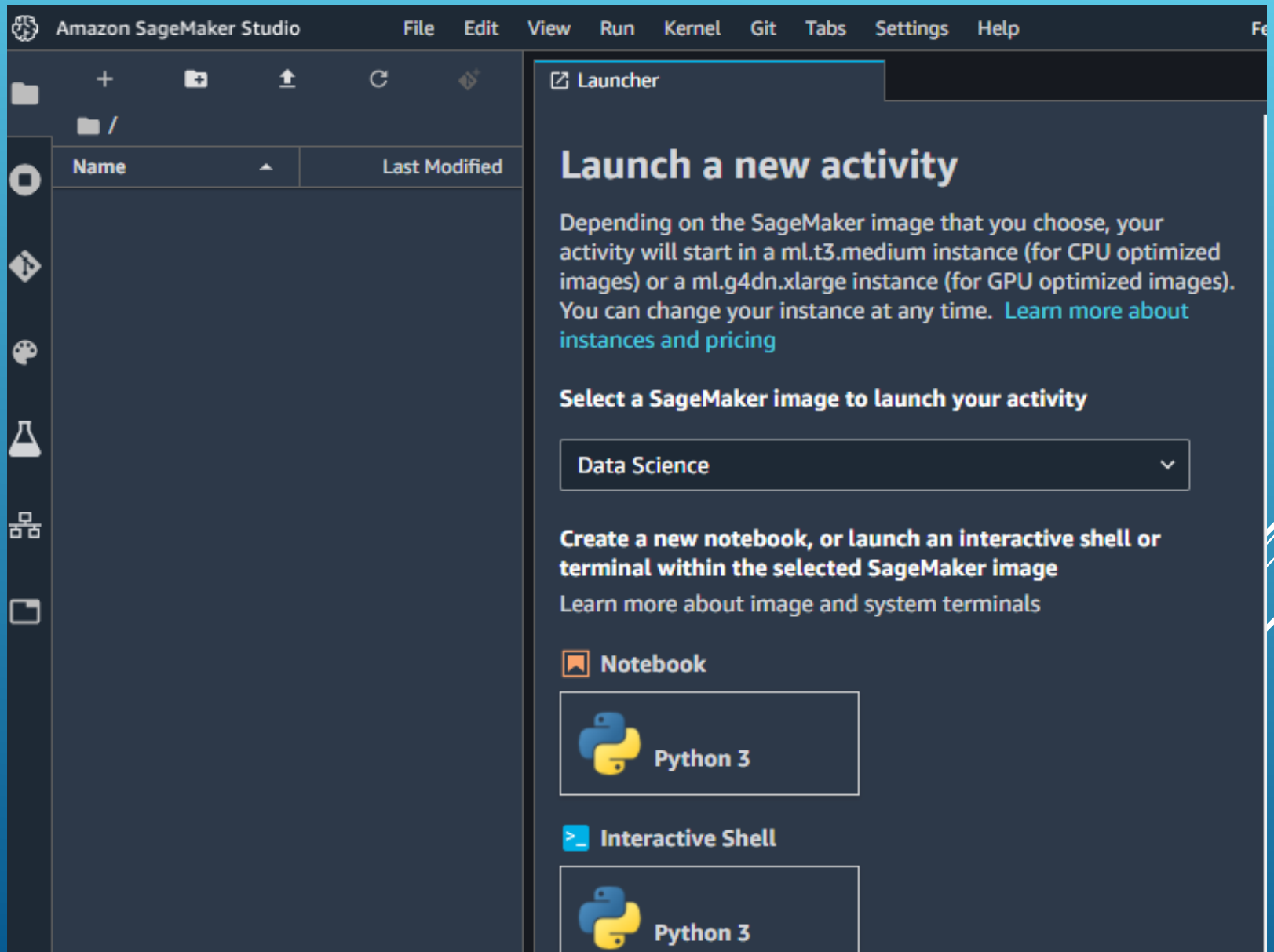

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Importación de las librerías.

```
[61]: #Preparación de datos
      import os
      import pandas as pd
      from sklearn.model_selection import train_test_split
      from sklearn.preprocessing import OrdinalEncoder
      import sagemaker
      # Modelado
      from sklearn.svm import SVC
      from sklearn.tree import DecisionTreeClassifier
      from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
      from sklearn.neighbors import KNeighborsClassifier
      #Prueba Inferencia.
      import boto3
      import pandas as pd
```

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Lectura de datos.

Descarga y Lectura del dataset

[38]:
```
#%%sh
#wget -N -P data http://archive.ics.uci.edu/ml/machine-learning-databases/00222/bank.zip
#unzip data/bank.zip -d data
```

Verificamos la ruta de trabajo para los datos.

[39]:
```
pwd
```

[39]:
```
'/root/sagemaker-studio-demo'
```

Hacemos una ispección de los datos.

[119]:
```
DATA_PATH = '/root/sagemaker-studio-demo/bank/data/'
df = pd.read_csv(DATA_PATH+'bank-full.csv', sep=';')
df
```

[119]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no

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Lectura de datos.

```
[65]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        45211 non-null  int64
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64
 12  campaign   45211 non-null  int64
 13  pdays      45211 non-null  int64
 14  previous   45211 non-null  int64
 15  poutcome   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

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Adecuación de los datos.

Separamos el dataset en el grupo de entrenamiento y test

[25]:
```
train, test = train_test_split(data, test_size=0.2)
```

```
Guardamos los datos en csv para el entrenamiento y validación posterior.
```

[27]:
```
train_file = DATA_PATH+'bank-train.csv'
pd.DataFrame.from_records(train).to_csv(train_file, index=False, header=True, sep=',')

test_file = DATA_PATH+'bank-test.csv'
pd.DataFrame.from_records(test).to_csv(test_file, index=False, header=True, sep=',')
```

Subimos el dataset para entrenamiento al bucket de S3

[30]:
```
session = sagemaker.Session()
uri = session.upload_data(path=train_file, key_prefix='bank')
```

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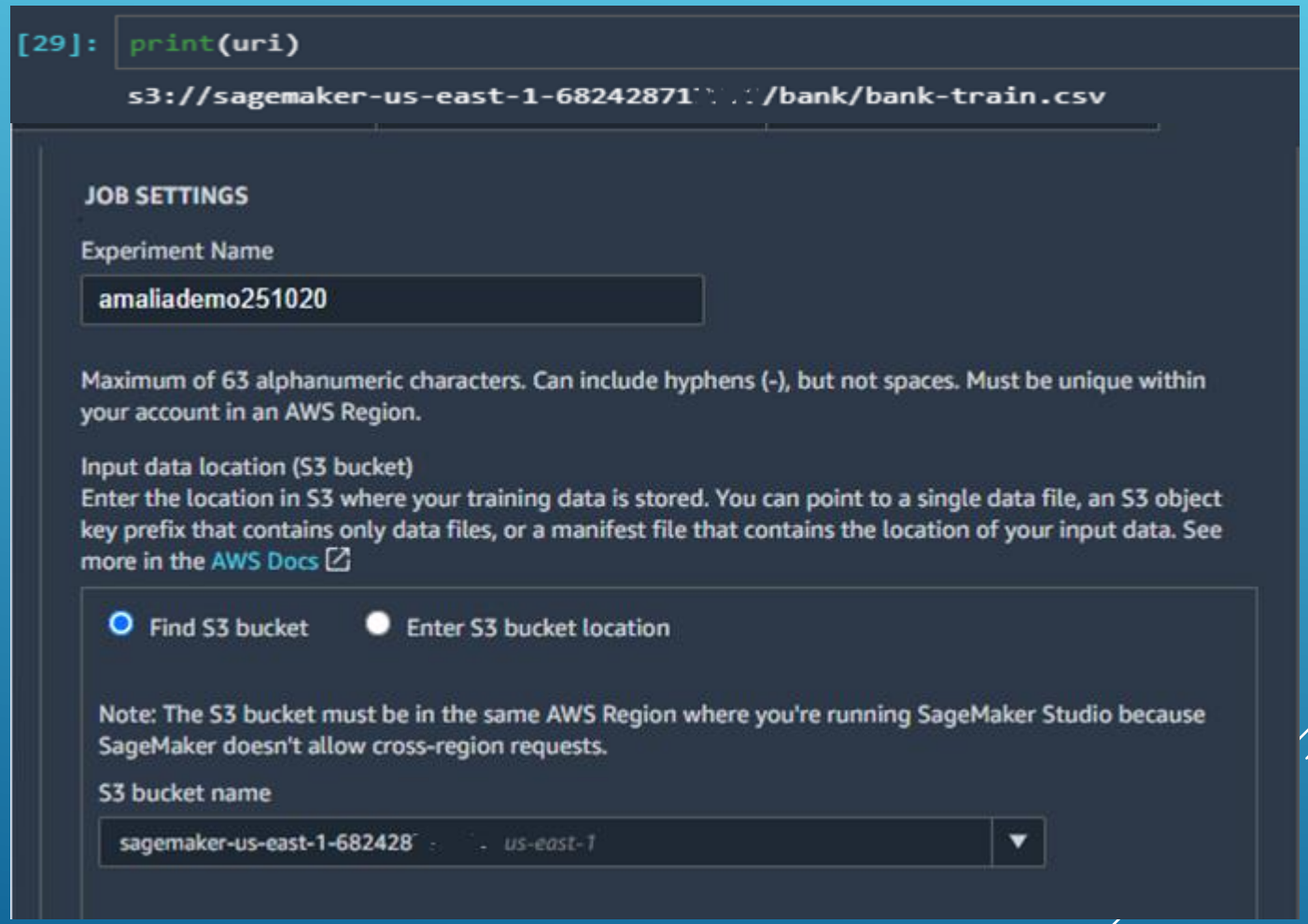
Creamos el experimiento con autopilot.



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Creamos el experimiento con autopilot.

```
[65]: df.info()

16  y          45211 non-null  object
```

For more information on the format of a manifest file, please see the AWS Docs

Target attribute name
The target attribute is the attribute in your dataset that you want Amazon SageMaker Autopilot to make predictions for.

16

The attribute name is case-sensitive and must match exactly the name in your input dataset

Output data location (S3 bucket)
Enter the location in S3 where you want to store the output.

Find S3 bucket Enter S3 bucket location

Note: The S3 bucket must be in the same AWS Region where you're running SageMaker Studio because SageMaker doesn't allow cross-region requests.

S3 bucket name

sagemaker-us-east-1-6824287 us-east-1

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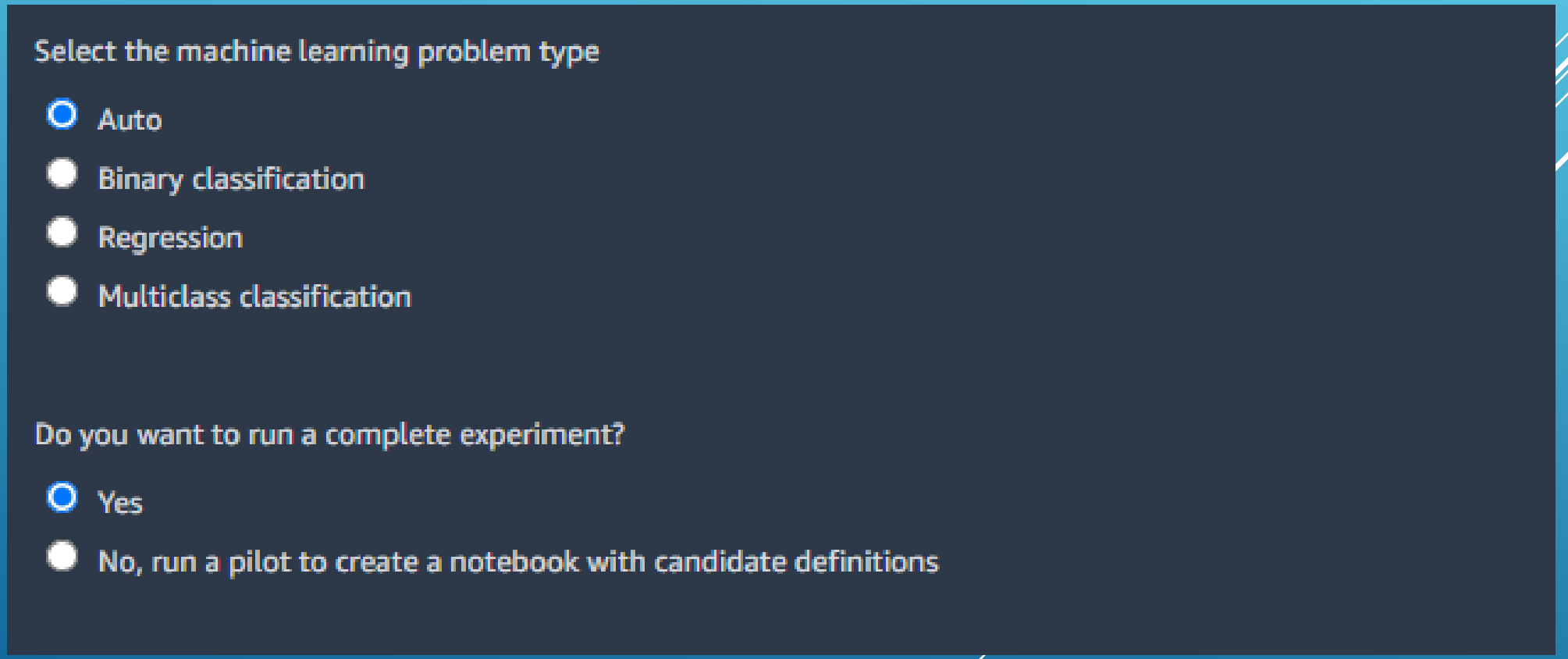
. Seleccionamos el tipo de entrenamiento.



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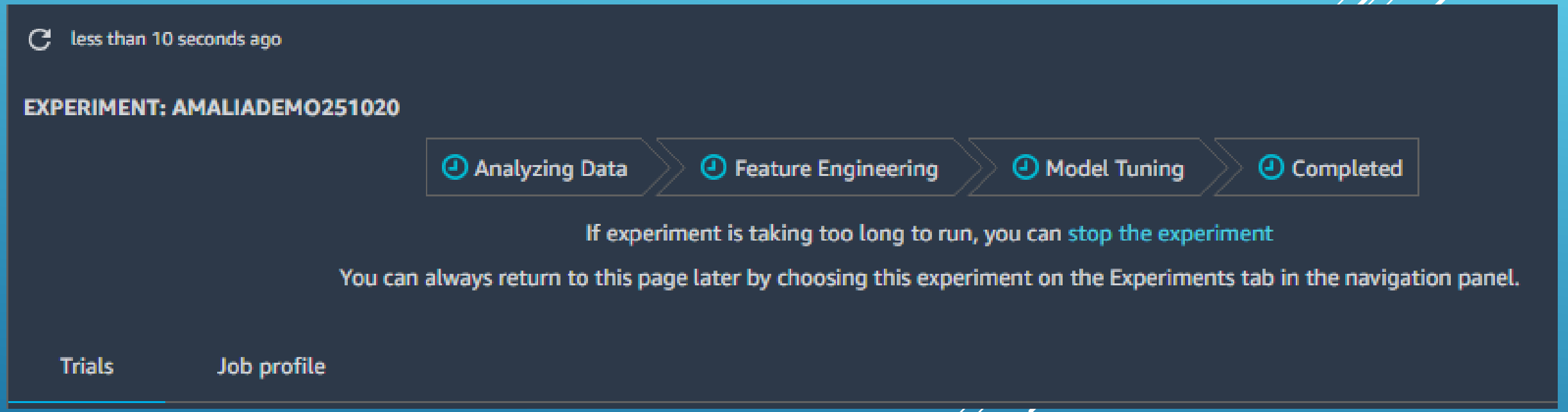
. Esperamos a que se autoejecuten las etapas del entrenamiento.



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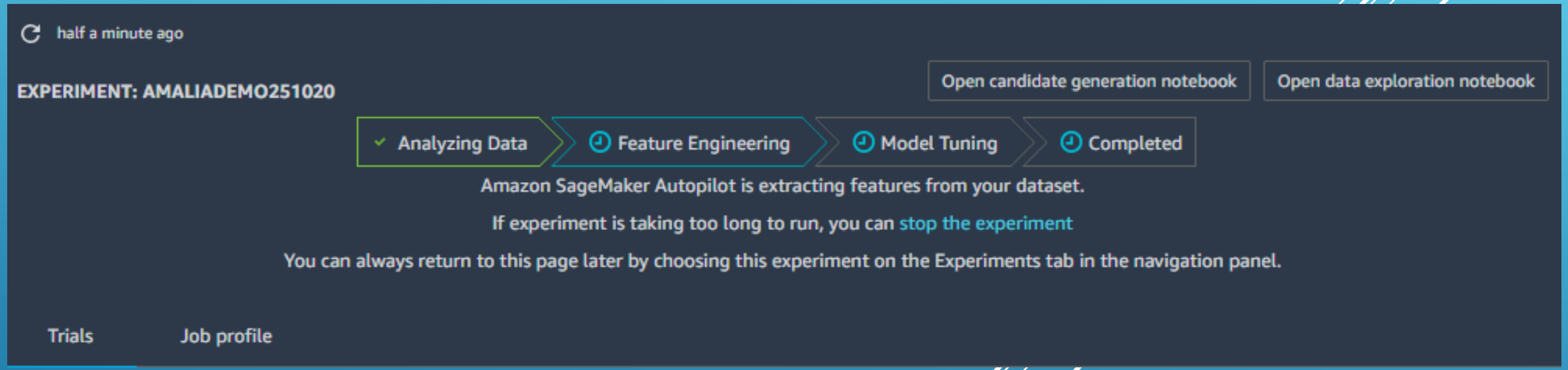
. Esperamos a que se autoejecuten las etapas del entrenamiento.



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Notebook generado.

Open data exploration notebook

1. Understand how the job analyzed features to select the candidate pipelines.
2. Modify and improve the generated AutoML pipelines using knowledge that you have about the dataset.

We read `36168` rows from the training dataset. The dataset has `17` columns and the column named `16` is used as the target column. This is identified as a `BinaryClassification` problem. Here are **2** examples of labels: `['1.0', '0.0']`.

Suggested Action Items

- Verify the number of unique values of a feature is expected with respect to domain knowledge. If it differs, one explanation could be multiple encodings of a value. For example `US` and `U.S.` will count as two different words. You could correct the error at the data source or pre-process your dataset in your S3 bucket.

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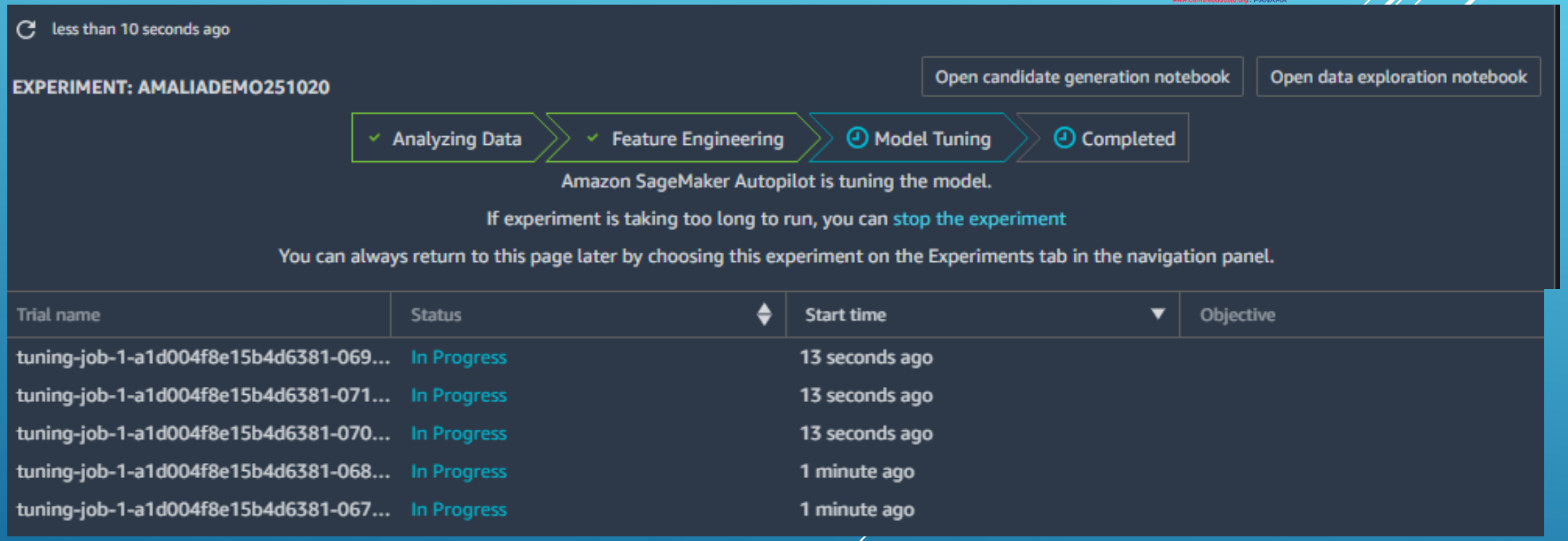
Esperamos a que se autoejecuten las etapas del entrenamiento.



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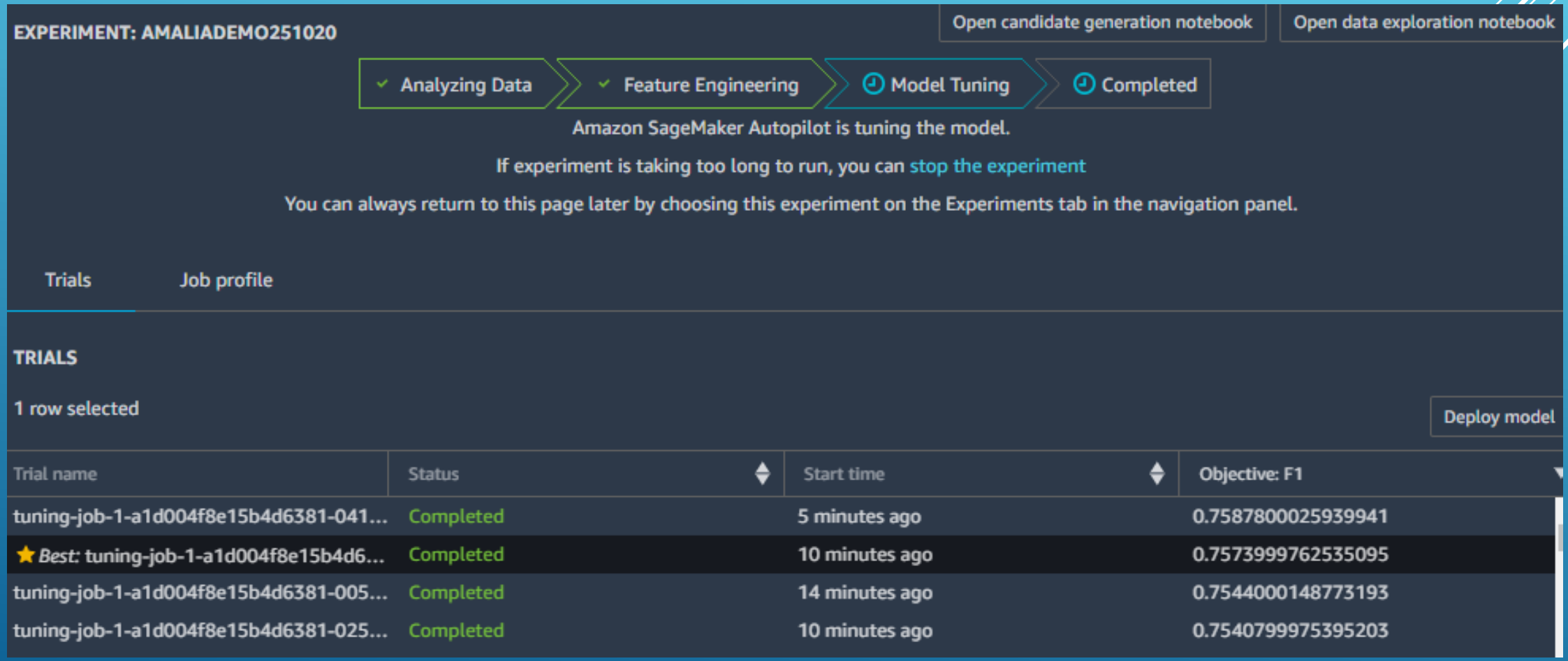
. Análisis de modelo.



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Notebook open candidate .

.

The AutoML recommendation job has recommended the following hyperparameters, objectives and accuracy metrics for the algorithm and problem type:

[ ]:
```
ALGORITHM_OBJECTIVE_METRICS = {
    'xgboost': 'validation:f1',
    'linear-learner': 'validation:binary_f_beta',
}

STATIC_HYPERPARAMETERS = {
    'xgboost': {
        'objective': 'binary:logistic',
        'save_model_on_termination': 'true',
        'scale_pos_weight': 7.524157435776573,
    },
    'linear-learner': {
        'predictor_type': 'binary_classifier',
        'loss': 'logistic',
        'mini_batch_size': 800,
        'binary_classifier_model_selection_criteria': 'loss_function',
        'num_models': 1,
        'positive_example_weight_mult': 7.524157435776573,
    },
}
```

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Notebook open candidate .

```
[ ]: from sagemaker.parameter import CategoricalParameter, ContinuousParameter, IntegerParameter

ALGORITHM_TUNABLE_HYPERPARAMETER_RANGES = {
    'xgboost': {
        'num_round': IntegerParameter(2, 1024, scaling_type='Logarithmic'),
        'max_depth': IntegerParameter(2, 8, scaling_type='Logarithmic'),
        'eta': ContinuousParameter(1e-3, 1.0, scaling_type='Logarithmic'),
        'gamma': ContinuousParameter(1e-6, 64.0, scaling_type='Logarithmic'),
        'min_child_weight': ContinuousParameter(1e-6, 32.0, scaling_type='Logarithmic'),
        'subsample': ContinuousParameter(0.5, 1.0, scaling_type='Linear'),
        'colsample_bytree': ContinuousParameter(0.3, 1.0, scaling_type='Linear'),
        'lambda': ContinuousParameter(1e-6, 2.0, scaling_type='Logarithmic'),
        'alpha': ContinuousParameter(1e-6, 2.0, scaling_type='Logarithmic'),
    },
    'linear-learner': {
        'wd': ContinuousParameter(1e-7, 1.0, scaling_type='Logarithmic'),
        'l1': ContinuousParameter(1e-7, 1.0, scaling_type='Logarithmic'),
        'learning_rate': ContinuousParameter(1e-5, 1.0, scaling_type='Logarithmic'),
    },
}
```

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Notebook open candidate .

.

Finally, deploy the model to SageMaker to make it functional.

```
pipeline_model.deploy(initial_instance_count=1,
                      instance_type='ml.m5.2xlarge',
                      endpoint_name=pipeline_model.name,
                      wait=True)
```

Congratulations! Now you could visit the sagemaker endpoint console page to find the deployed endpoint (it'll take a few minutes to be in service).

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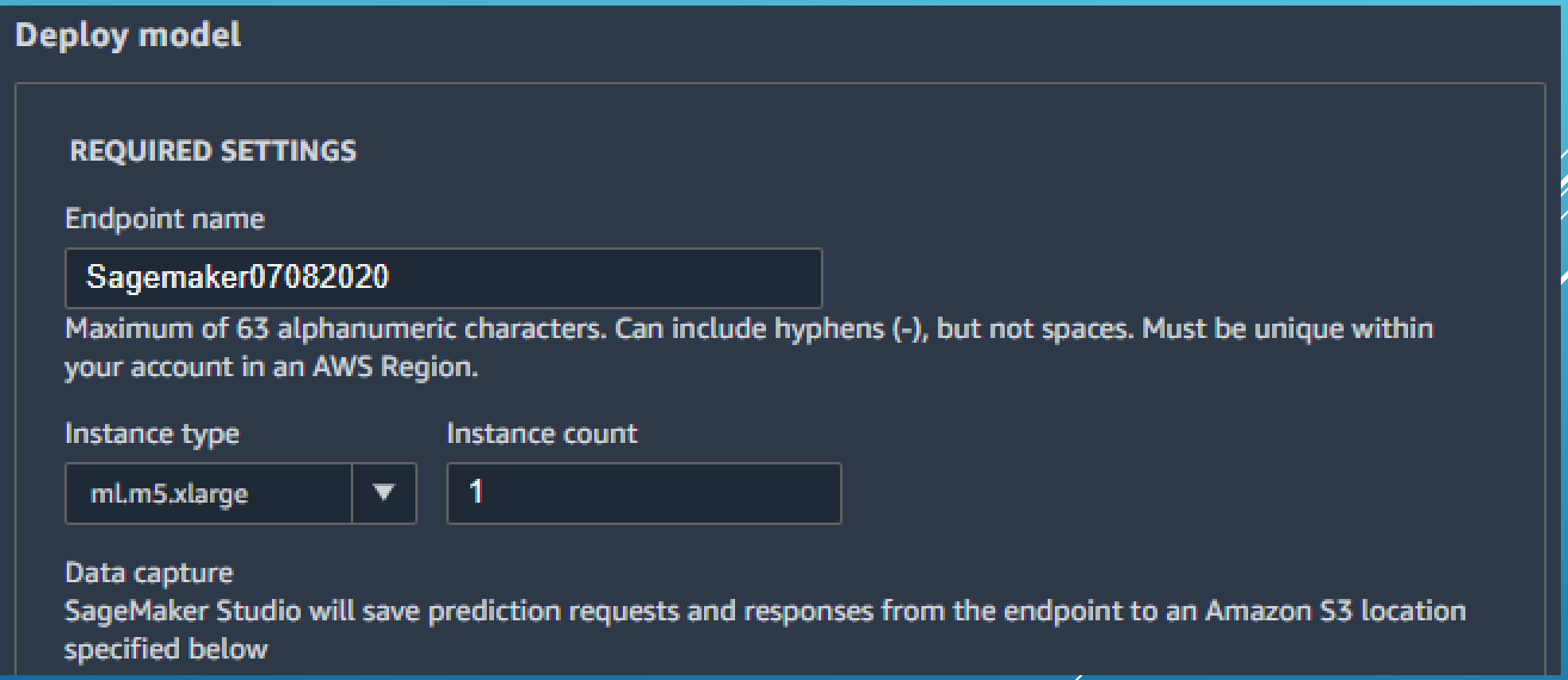
. Hacemos el despliegue de end point.



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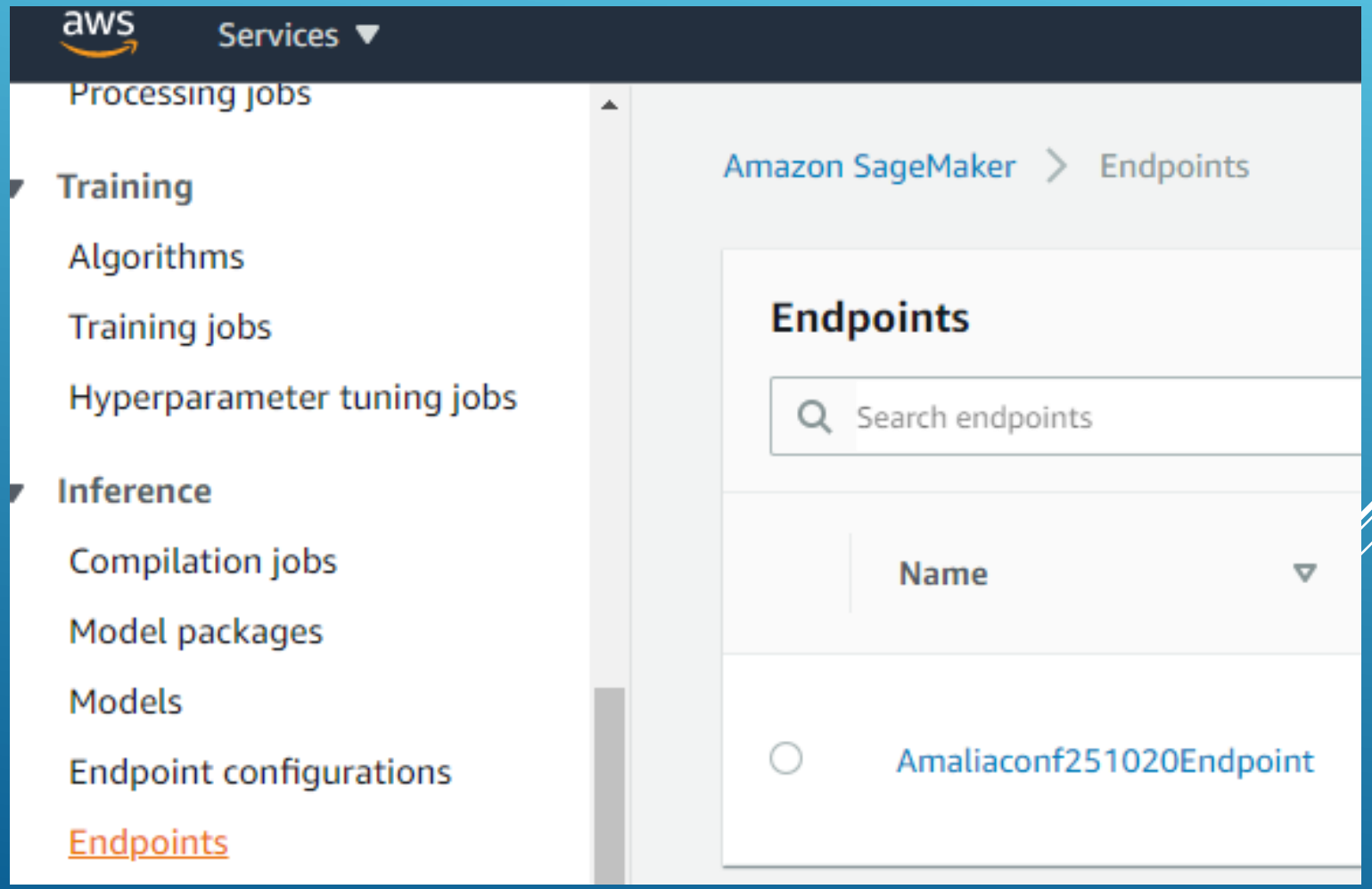
. Verificamos el despliegue del endpoint.



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Hacemos la prueba de inferencia.

Prueba de Inferencia.

[13]:
```
sm = boto3.Session().client('runtime.sagemaker')
```

[14]:
```
def infer(endpoint, input_data):
    response = sm.invoke_endpoint(EndpointName=endpoint, ContentType='text/csv', Accept='text/csv', Body=input_data)
    prediction = response['Body'].read().decode("utf-8")
    return prediction
```

[19]:
```
endpoint = 'Amaliaconf251020Endpoint'
data = '17.0,1.0,1.0,1.0,0.0,916.0,1.0,0.0,0.0,8.0,5.0,279.0,0.0,0.0,0.0,0.0,3.0'

prediction = infer(endpoint, data)
print(prediction[0])
```

```
0
```

[20]:
```
if prediction[0] == '0':
    print('No se recomienda ofertarle el servicio')
else:
    print('Se recomienda ofertarle el servicio')
```

```
No se recomienda ofertarle el servicio
```

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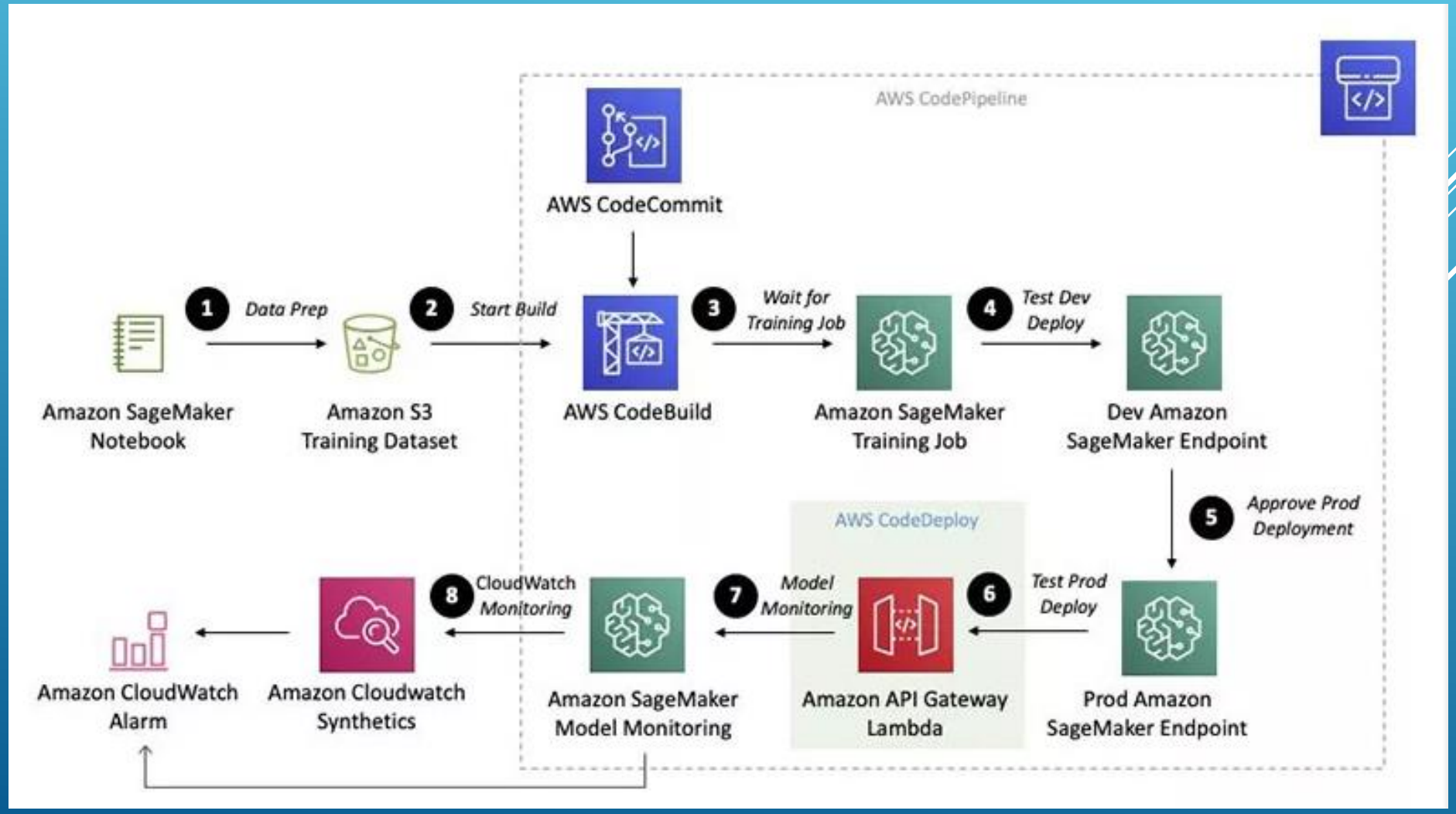
. Siguiente paso el monitoreo del endpoint.



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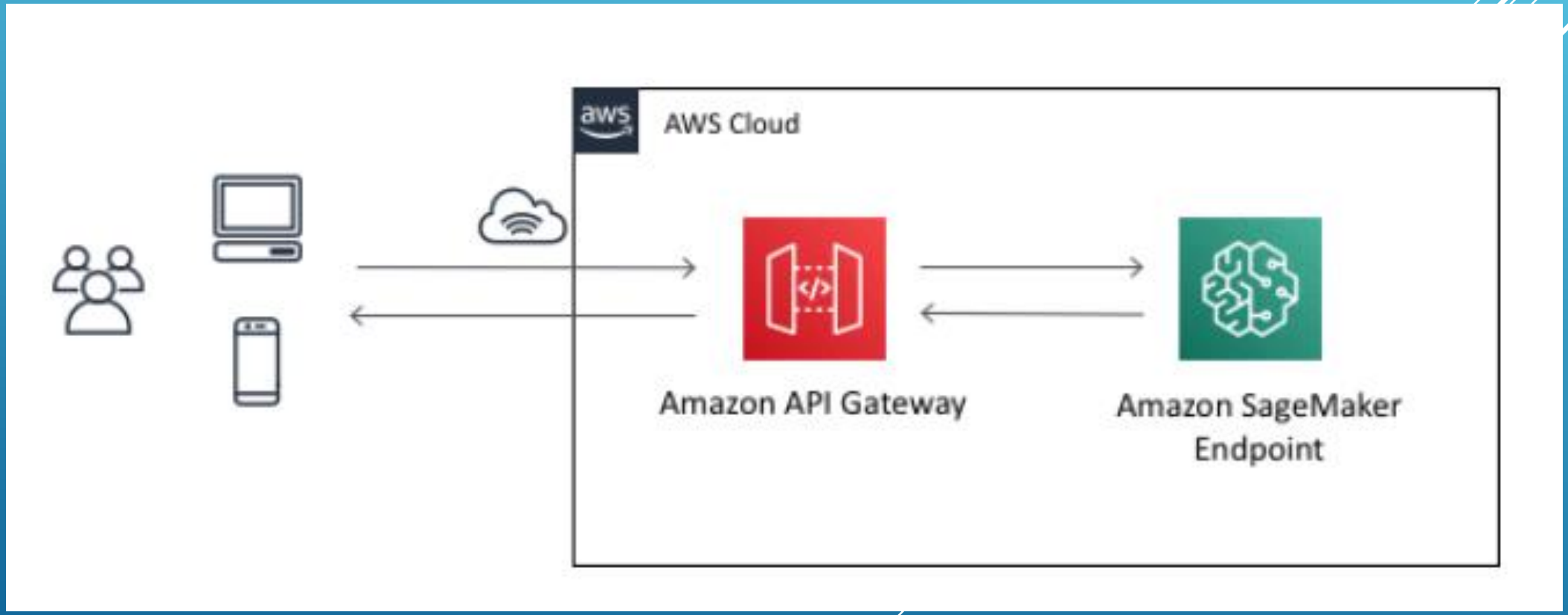
Como ultimo paso es interactuar con el endpoint y nuestras aplicaciones.



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- Documentación

Ejemplos AWS Sagemaker

https://aws.amazon.com/es/sagemaker/getting-started/

https://github.com/vascencio/amaliaconf

GRACIAS.

Victor Ascencio | 25 de Octubre 2020

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