Fraud Detection Using Machine Learning

AWS Implementation Guide

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Contents

About This Guide

This implementation guide discusses architectural considerations and configuration steps for deploying Fraud Detection Using Machine Learning on the Amazon Web Services (AWS) Cloud. It includes links to a AWS CloudFormation template that launches and configures the AWS services required to deploy this solution using AWS best practices for security and availability.

The guide is intended for developers and data scientists who have practical experience with machine learning and architecting on the AWS Cloud.

Overview

Fraud is an ongoing problem that can cost businesses billions of dollars annually and damage customer trust. Many companies use a rule-based approach to detect fraudulent activity where fraud patterns are defined as rules. But, implementing and maintaining rules can be a complex, time-consuming process because fraud is constantly evolving, rules require fraud patterns to be known, and rules can lead to false positives or false negatives.

Machine learning (ML) can provide a more flexible approach to fraud detection. ML models do not use pre-defined rules to determine whether activity is fraudulent. Instead, ML models are trained to recognize fraud patterns in datasets, and the models are self-learning which enables them to adapt to new, unknown fraud patterns.

Amazon SageMaker is a fully managed service that enables developers and data scientists to quickly and easily build, train, and deploy machine learning models at any scale. Amazon SageMaker removes the barriers that typically slow down developers who want to use machine learning. This ability makes Amazon SageMaker applicable for a variety of use cases, including fraud detection.

To help customers more easily leverage Amazon SageMaker for real-time fraud detection, AWS offers the Fraud Detection Using Machine Learning solution. This solution automates the detection of potentially fraudulent activity, and flags that activity for review. The solution also includes an example dataset but you can modify the solution to work with any dataset.

Cost

You are responsible for the cost of the AWS services used while running this solution. As of the date of publication, the one-time cost to train the solution's ML model in the US East (N. Virginia) Region is **$0.50** for the Amazon SageMaker ml.c4.large instance. The cost to process transactions using the example dataset is approximately **$0.30 per hour**. Prices are subject to change. For full details, see the pricing webpage for each AWS service you will be using in this solution.

Architecture Overview

Deploying this solution builds the following environment in the AWS Cloud.

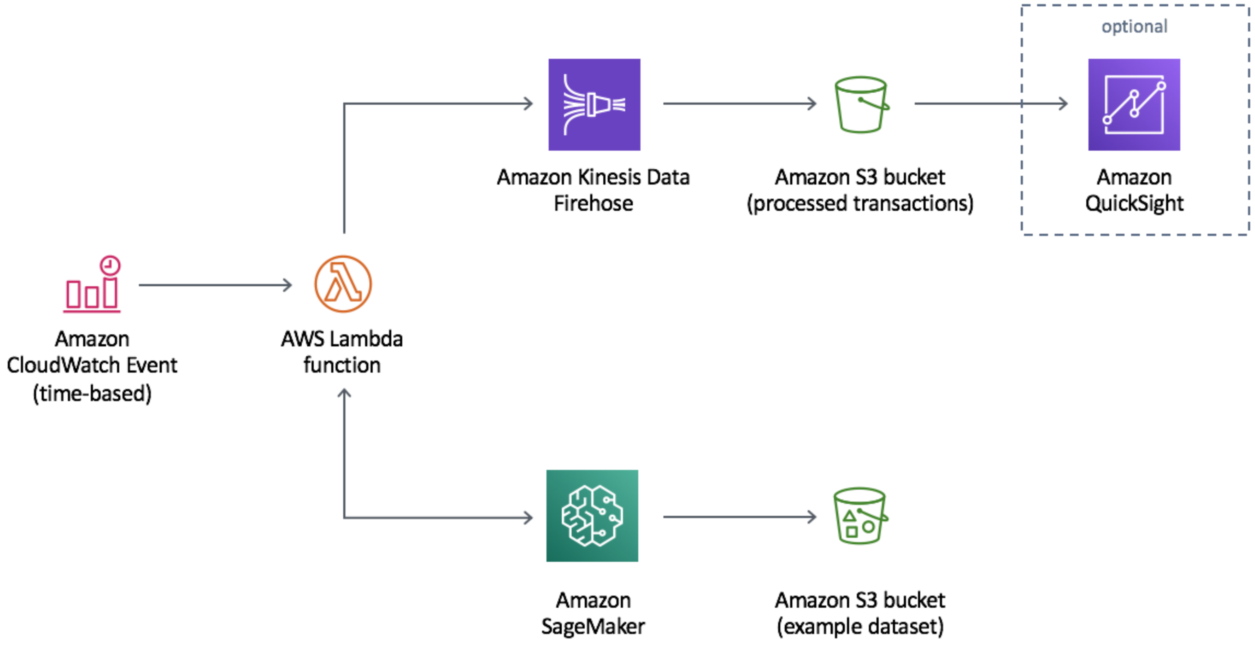

optional
Amazon Kinesis Data Firehose
Amazon S3 bucket (processed transactions)
Amazon QuickSight
Amazon CloudWatch Event (time-based)
AWS Lambda function
Amazon SageMaker
Amazon S3 bucket (example dataset)

Figure 1: Fraud Detection Using Machine Learning architecture on AWS

The AWS CloudFormation template deploys an example dataset of credit card transactions contained in an Amazon Simple Storage Service (Amazon S3) bucket and an Amazon SageMaker endpoint with an ML model that will be trained on the dataset.

The solution also deploys an Amazon CloudWatch Events rule that is configured to run every minute. The rule is configured to trigger an AWS Lambda function that processes transactions from the example dataset and invoke the Amazon SageMaker endpoint which predicts whether those transactions are fraudulent based on the trained ML model. An Amazon Kinesis Data Firehose delivery stream loads the processed transactions into another Amazon S3 bucket for storage.

Once the transactions have been loaded into Amazon S3, you can use analytics tools and services, including Amazon QuickSight, for visualization, reporting, ad-hoc queries, and more detailed analysis. For customers who want to use Amazon QuickSight to visualize the processed transactions, see Appendix A.

By default, the solution is configured to process transactions from the example dataset. To use your own dataset, you must modify the solution. For more information, see Customization.

Solution Components

Amazon SageMaker

Fraud Detection Using Machine Learning uses an Amazon SageMaker notebook instance, which is a fully managed machine learning (ML) Amazon Elastic Compute Cloud (Amazon EC2) compute instance that runs the solution's Jupyter notebook. The notebook is used to train and deploy the solution's ML model. For more information on notebook instances, see Use Notebook Instances in the *Amazon SageMaker Developer Guide*.

Algorithm

Amazon SageMaker provides several built-in machine learning algorithms that you can use for a variety of problem types. This solution leverages the built-in Linear Learner Algorithm, an algorithm used for solving either classification or regression problems, to provide a scalable linear regression model. For more information, see How Linear Learner Works in the *Amazon SageMaker Developer Guide*.

Dataset

Fraud Detection Using Machine Learning contains a publicly available anonymized credit card transaction dataset that is used to train the solution's machine learning (ML) model. The dataset was collected and analyzed during a research collaboration of Worldline and the Machine Learning Group of Université Libre de Bruxelles on big data mining and fraud detection. The dataset consists of anonymized credit card transactions over a two-day period in 2013 by European card holders. Because the dataset is derived from real data, the distribution of fraud is low compared to legitimate transactions. Fraudulent transactions make up 0.172% of the total transactions. For more information, see Appendix B.

Considerations

Customization

By default, Fraud Detection Using Machine Learning uses a credit card fraud dataset to train the machine learning (ML) model. However, you can customize the solution to use your own dataset. To train the model on your own dataset, you must modify the included notebook to point the model to your dataset. You must also modify the solution's AWS Lambda function to process your events.

We also recommend replacing the solution's Amazon CloudWatch Events rule that triggers the Lambda function with an Amazon API Gateway endpoint that is externally invoked by a transaction or event from your existing business infrastructure.

Regional Deployment

Fraud Detection Using Machine Learning uses Amazon SageMaker and Amazon Kinesis Data Firehose which are currently available in specific AWS Regions only. Therefore, you must launch this solution in a region where these services are available.[1]

AWS CloudFormation Template

This solution uses AWS CloudFormation to automate the deployment of the Fraud Detection Using Machine Learning solution on the AWS Cloud. It includes the following CloudFormation template, which you can download before deployment:

View template

fraud-detection-using-machine-learning.template: Use this template to launch the solution and all associated components. The default configuration deploys an Amazon CloudWatch Events rule, an AWS Lambda function, an Amazon SageMaker endpoint, an Amazon Kinesis Data Firehose delivery stream, and Amazon Simple Storage Service (Amazon S3) buckets, but you can also customize the template based on your specific needs.

Automated Deployment

Before you launch the automated deployment, please review the considerations discussed in this guide. Follow the step-by-step instructions in this section to configure and deploy Fraud Detection Using Machine Learning into your account.

Time to deploy: Approximately five minutes

What We'll Cover

The procedure for deploying this architecture on AWS consists of the following steps. For detailed instructions, follow the links for each step.

Step 1. Launch the Stack

- Launch the AWS CloudFormation template into your AWS account.

[1] For the most current service availability by region, see https://aws.amazon.com/about-aws/global-infrastructure/regional-product-services/

- Enter values for required parameters: **Stack Name**, **Model and Data Bucket Name**, **Results Bucket Name**
- Review the other template parameters, and adjust if necessary.

Step 2. Run the Notebook

- Run the Jupyter Notebook to train the ML model.

Step 3. Enable the CloudWatch Events Rule

- Enable the Amazon CloudWatch Events rule.

Step 4. Verify the Lambda Function Is Processing Transactions

- Verify that the AWS Lambda function is processing transactions.

Step 1. Launch the Stack

This automated AWS CloudFormation template deploys Fraud Detection Using Machine Learning on the AWS Cloud.

> **Note**: You are responsible for the cost of the AWS services used while running this solution. See the Cost section for more details. For full details, see the pricing webpage for each AWS service you will be using in this solution.

1. Log in to the AWS Management Console and click the button to the right to launch the `fraud-detection-using-machine-learning` AWS CloudFormation template.

   Launch Solution

   You can also download the template as a starting point for your own implementation.

2. The template is launched in the US East (N. Virginia) Region by default. To launch the solution in a different AWS Region, use the region selector in the console navigation bar.

   > **Note**: This solution uses the Amazon SageMaker and Amazon Kinesis Data Firehose services, which are currently available in specific AWS Regions only. Therefore, you must launch this solution in an AWS Region where these services are available. For the most current availability by region, see AWS service offerings by region.

3. On the **Select Template** page, verify that you selected the correct template and choose **Next**.

4. On the **Specify Details** page, assign a name to your solution stack.

5. Under **Parameters**, review the parameters for the template and modify them as necessary.

   This solution uses the following default values.

Parameter	Default	Description
Amazon S3 Bucket Configuration		
Model and Data Bucket Name	*<Requires input>*	Specify a name for a solution-created Amazon S3 bucket where Amazon SageMaker model and training data will be stored
Results Bucket Name	*<Requires input>*	Specify a name for a solution-created S3 bucket where processed events will be stored
Amazon Kinesis Firehose Configuration		
Kinesis Firehose S3 Prefix	`fraud-detection/firehose/`	The Kinesis Data Firehose prefix for the delivery of processed events

6. Choose **Next.**
7. On the **Options** page, choose **Next**.
8. On the **Review** page, review and confirm the settings. Be sure to check the box acknowledging that the template will create AWS Identity and Access Management (IAM) resources.
9. Choose **Create** to deploy the stack.

   You can view the status of the stack in the AWS CloudFormation Console in the **Status** column. You should see a status of CREATE_COMPLETE in approximately five minutes.

> **Important:** If you delete the solution stack, you must manually delete the Amazon SageMaker endpoint (`fraud_detection_endpoint`).

Step 2. Run the Notebook

1. Navigate to the Amazon SageMaker console.
2. In the navigation pane, select **Notebook instances**.
3. Select **FraudDetectionNotebookInstance**.

   The notebook instance should already be running.
4. Select **Open Jupyter**.
5. In the Jupyter notebook interface, open the `sagemaker_fraud_detection.ipynb` file.
6. In the **Cell** dropdown menu, select **Run All** to run the file.

Step 3. Enable the CloudWatch Events Rule

1. Navigate to the AWS Lambda console.
2. In the navigation pane, select **Functions**.

3. Select the `fraud_detection_event_processor` Lambda function.
4. In the diagram in the **Designer** tab, select **CloudWatch Events**.
5. In the **CloudWatch Events** tab, select `<stackname>-ScheduleRule-<id>`.
6. Select **Actions** > **Enable**.
7. Select **Enable**.

Step 4. Verify the Lambda Function Is Processing Transactions

1. Navigate to the AWS Lambda console.
2. In the navigation pane, select **Functions**.
3. Select the `fraud_detection_event_processor` Lambda function.
4. Select **Monitoring** and verify that the **Invocations** graph shows activity.

   After a few minutes, check the results Amazon S3 bucket for processed transactions.

Security

When you build systems on AWS infrastructure, security responsibilities are shared between you and AWS. This shared model can reduce your operational burden as AWS operates, manages, and controls the components from the host operating system and virtualization layer down to the physical security of the facilities in which the services operate. For more information about security on AWS, visit the AWS Security Center.

Amazon Kinesis Data Firehose

By default, the solution’s Amazon Kinesis Data Firehose delivery stream is not encrypted because its destination bucket is encrypted. If you customize the solution to use your own dataset, we recommend encrypting the delivery stream using server-side encryption. For more information, see Using Server-Side Encryption with Amazon Kinesis Data Firehose in the *Amazon Kinesis Data Firehose Developer Guide*.

Additional Resources

AWS services

- Amazon SageMaker
- AWS Lambda
- Amazon CloudWatch Events
- Amazon Kinesis Data Firehose
- Amazon Simple Storage Service
- Amazon QuickSight
- AWS CloudFormation

Appendix A: Data Visualization

You can visualize the transactions this solution processes using Amazon QuickSight or your own visualization tools. Use the following procedure to configure Amazon QuickSight.

1. Open a text editor and copy the following code.

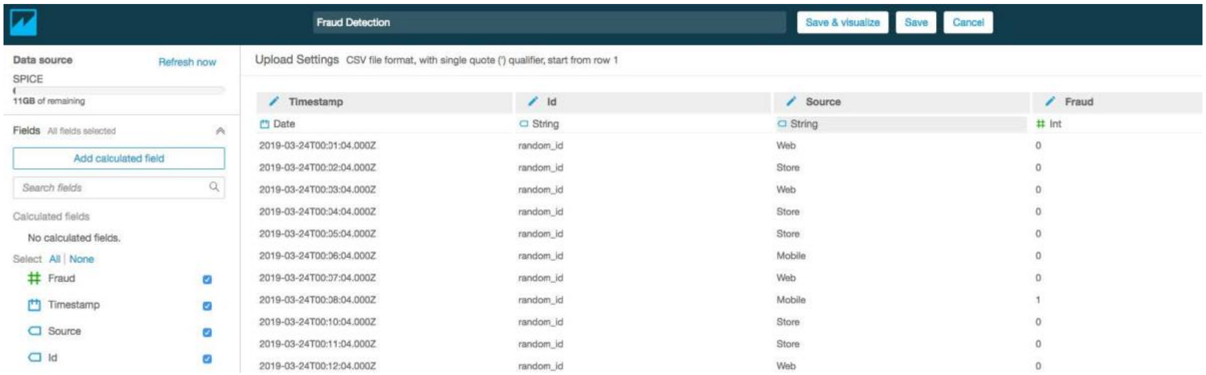
```
{
   "fileLocations": [
       {
                "URIPrefixes": [
                        "https://s3-us-east-1.amazonaws.com/bucket-
name/"
               ]
        }
   ],
   "globalUploadSettings": {
           "format": "CSV",
           "delimiter": ",",
           "textqualifier": "'",
           "containsHeader": "false"
   }
}
```

2. Modify the `URIPrefixes` URL.
   - Modify the region name to match the region where you deployed the solution, if necessary.
   - Modify the Amazon S3 bucket name to match the name you specified for **Results Bucket Name** AWS CloudFormation template parameter during deployment.
3. Save the following code as `manifest.json`.
4. Navigate to the Amazon QuickSight console.

5. Select **Manage Data**.
6. Select **New data set**.
7. Select **S3**.
8. For **Data source name**, enter a name. For example, `fraud_detection_events`.
9. For **Upload a manifest file**, select the **Upload** radio button and click the folder icon. Navigate to the `manifest.json` file you saved earlier.
10. Select **Connect**.

    After a few minutes, a success message should appear that shows that the S3 data imported into the Amazon QuickSight in-memory calculation engine (SPICE). SPICE acts as a cache for the data stored in your data source. For more information, see SPICE in the *Amazon QuickSight User Guide*.

11. When the **Finish data set creation** window appears, select **Edit/Preview data**.
12. On the **Edit** page, change the column headers to more meaningful names. For example, `Timestamp`, `ID`, `Source`, and `Fraud`.



Upload Settings CSV file format, with single quote (') qualifier, start from row 1

Timestamp	Id	Source	Fraud
Date	String	String	Int
2019-03-24T00:01:04.000Z	random_id	Web	0
2019-03-24T00:02:04.000Z	random_id	Store	0
2019-03-24T00:03:04.000Z	random_id	Web	0
2019-03-24T00:04:04.000Z	random_id	Store	0
2019-03-24T00:05:04.000Z	random_id	Store	0
2019-03-24T00:06:04.000Z	random_id	Mobile	0
2019-03-24T00:07:04.000Z	random_id	Web	0
2019-03-24T00:08:04.000Z	random_id	Mobile	1
2019-03-24T00:10:04.000Z	random_id	Store	0
2019-03-24T00:11:04.000Z	random_id	Store	0
2019-03-24T00:12:04.000Z	random_id	Web	0

Figure 2: Amazon QuickSight SPICE dataset

13. Select **Save & Visualize**.

    Now, you can create graphical representations of your data. For more information, see Working with Amazon QuickSight Visuals in the *Amazon QuickSight User Guide*.

Appendix B: Acknowledgements

Fraud Detection Using Machine Learning contains a publicly available anonymized credit card transaction dataset that was collected and analyzed during a research collaboration of Worldline and the Machine Learning Group of Université Libre de Bruxelles on big data mining and fraud detection. For more details on current and past fraud detection projects, see ResearchGate and DEFEATFRAUD.

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Source Code

You can visit our GitHub repository to download the templates and scripts for this solution, and to share your customizations with others.

Document Revisions

Date	Change	In sections
May 2019	Initial publication	--

Notices

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