

COM203

Using IaC with Terraform to provision big data platform on Amazon EMR

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Agenda

- Architecture Big Data Platform
- GitOps Flow
- Demo (Deploy Amazon EMR Cluster)



Abstract

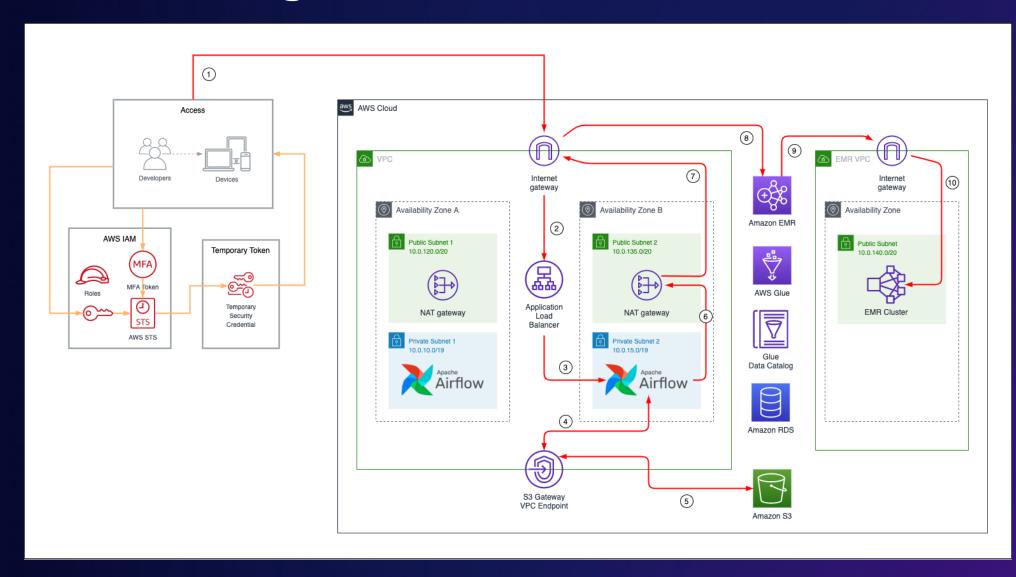
USING IAC WITH TERRAFORM TO PROVISION BIG DATA PLATFORM ON AMAZON EMR

- Training multiple Machine Learning (ML) Models in a serial mode can be challenging, timeconsuming, and ineffective. Parallel modelling provides tremendous benefits in building a variety of
 models by speeding up the process through parallelisation so the model building process becomes
 more efficient.
- Solve the problem of training multiple ML models by using Spark Panda's UDF (a Python library for building ML models) inside Amazon EMR cluster
- Provision Amazon EMR cluster using Terraform as an Infrastructure-as-Code tool

Architecture Big Data Platform



Architecture Big Data Platform



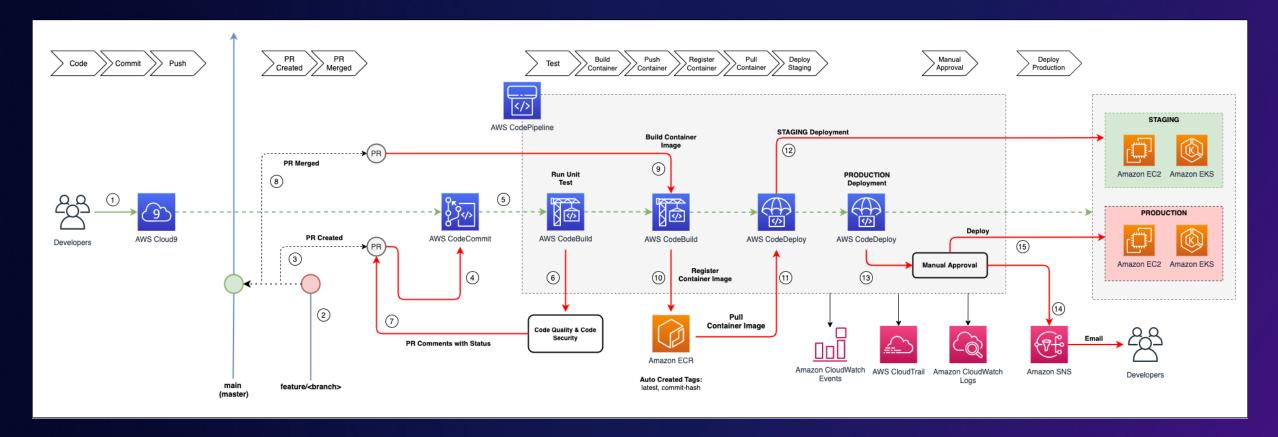




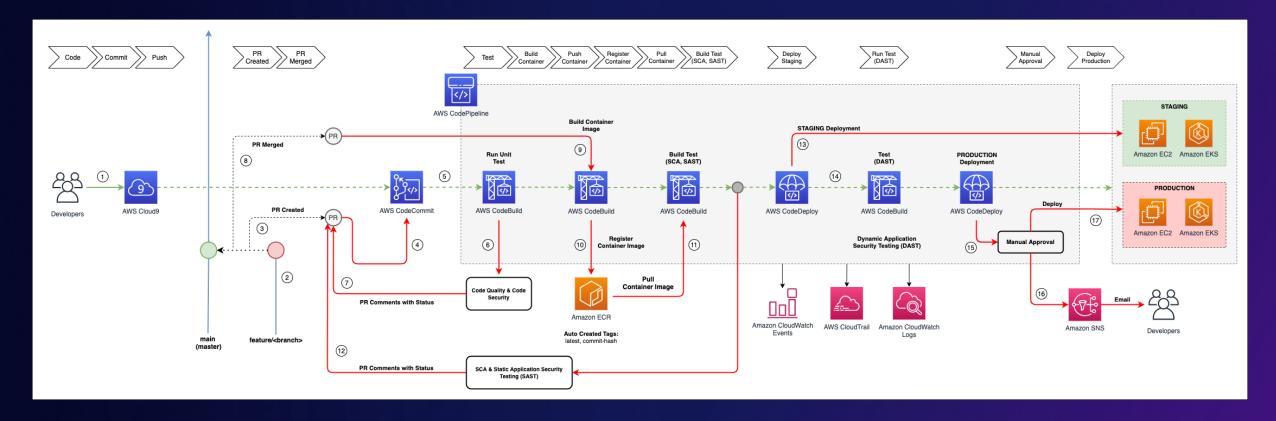
- GitOps Flow
- CI/CD Pipeline Deployment



GITOPS FLOW

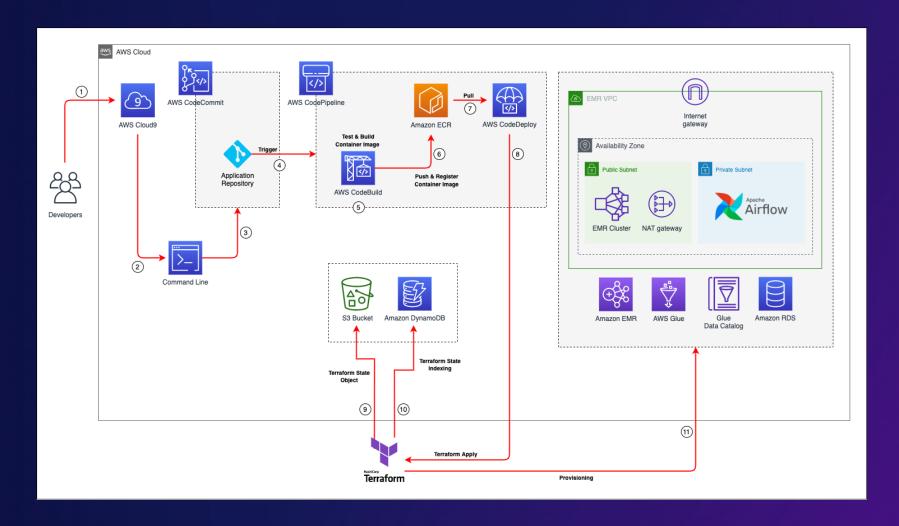


GITOPS DEVSECOPS FLOW



CI/CD PIPELINE DEPLOYMENT

Workflow of CI/CD pipeline in provisioning Amazon EMR Cluster Terraform



Demo



- Preparations
- Deploy Amazon EMR
- Bootstrap Script & Terraform Stack
- Running Spark Job

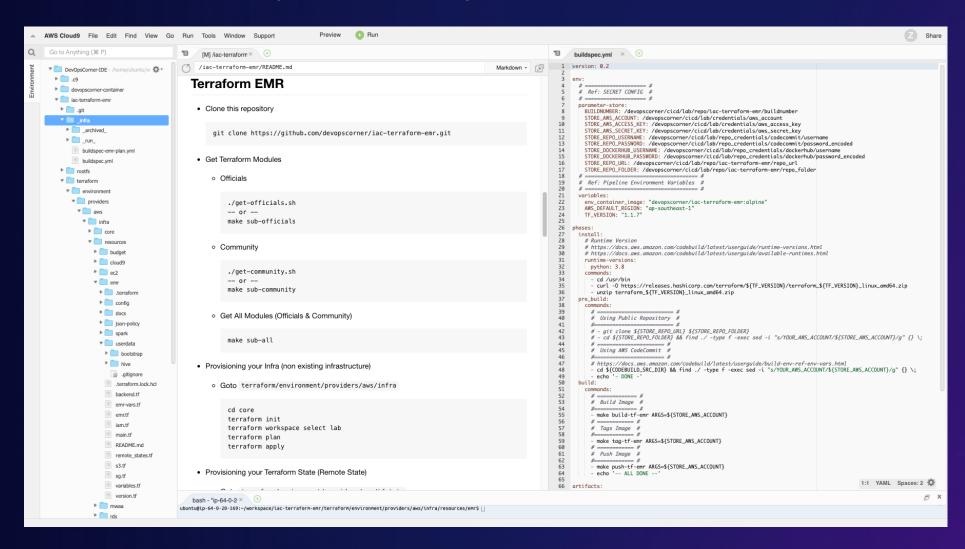


PREPARATIONS

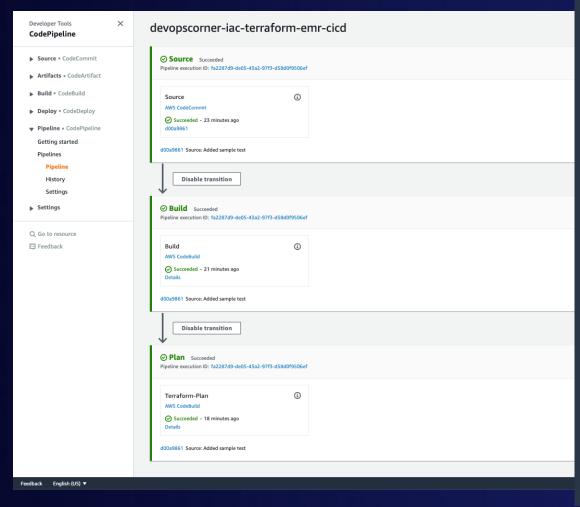
- IAM Role, Policy (AssumeRole)
- Infrastructure
 - VPC, Subnet, NAT, Internet-Gateway, DNS
- S3 Bucket
 - Bucket for Terraform State
 - Bucket for EMR Bootstrap & EMR Configuration
- DynamoDB
 - Indexing Terraform State
- Database (RDS) optional



DEPLOY AMAZON EMR - BUILDSPEC (AWS CODEBUILD)



DEPLOY AMAZON EMR - AWS DEVELOPER TOOLS



```
+.[*m .[*m.[*mprotocol.[*m.[*m
+.[*m .[*m.[*msecurity_group_id.[*m.[*m
+.[*m .[*m.[*mself.[*m.[*m
                                                                                                                                                          = "tcp"
                                                                                                                                                         = (known after apply)
                             +·[*m·[*m·[*msource_security_group_id·[*m·[*m = (known after apply)
+·[*m·[*m·[*mto_port·[*m·[*m = 9443
                             +-[*m -[*m-[*mtype-[*m-[*m
                                                                                                                                                          = "inaress"
                  # random_pet.this.[*m will be created.[*m.[*m
               ·[*m +·[*m·[*m resource "random_pet" "this" {
                             +-[*m·[*mid·[*m·[*m = (known after apply)
+-[*m·[*m·[*mlength·[*m·[*m = 2
                            +-[*m -[*m-[*mseparator-[*m-[*m = "-"
                  # module.s3_bucket.data.aws_iam_policy_document.combined[*].[*m will be read during apply
                  # (config refers to values not yet known) · [*m · [*m
                ·[*m <=·[*m·[*m data "aws_iam_policy_document" "combined" {
                            +·[*m ·[*m·[*mid·[*m·[*m
+·[*m ·[*m·[*mjson·[*m·[*m
                                                                                                                                                      = (known after apply)
                                                                                                                                                      = (known after apply)
                              +\cdot[*m \cdot [*m \cdot [*
                  # module.s3_bucket.aws_s3_bucket_ownership_controls.this[*].[*m will be created.[*m.[*m
                ·[*m +·[*m·[*m resource "aws_s3_bucket_ownership_controls" "this" {
                             +-[*m -[*mbucket-[*m-[*m = (known after apply)
+-[*m -[*m-[*mid-[*m-[*m = (known after apply)
                                       + · [*m · [*m · [*mobject_ownership · [*m · [*m = "BucketOwnerPreferred"
                  # module.s3_bucket.aws_s3_bucket_policy.this[*].[*m will be created.[*m.[*m
               ·[*m +·[*m·[*m resource "aws_s3_bucket_policy" "this" {
                             +-[*m -[*m-[*m-[*m = "devopscorner-emr"
+-[*m -[*m-[*mid-[*m-[*m = (known after apply)
                              +·[*m ·[*m·[*mpolicy·[*m·[*m = (known after apply)
               # module.s3_bucket.aws_s3_bucket_public_access_block.this[*].[*m will be created.[*m.[*m
.[*m +-[*m resource "aws_s3_bucket_public_access_block" "this" {
                             +-[*m -[*m-[*mblock_public_acls-[*m-[*m = true
+-[*m -[*m-[*mblock_public_policy-[*m-[*m = true
                              +-[*m -[*m-[*mbucket-[*m-[*m
                                                                                                                                                      = (known after apply)
                             +.[*m ·[*m·[*mid·[*m·[*m
+.[*m ·[*m·[*mignore_public_acls·[*m·[*m
                                                                                                                                                      = (known after apply)
                              +-[*m -[*m-[*mrestrict_public_buckets-[*m-[*m = true
                ·[*mPlan:·[*m 2* to add, * to change, * to destroy.
1818 ---
1820 Note: You didn't use the -out option to save this plan, so Terraform can't
 1821 guarantee to take exactly these actions if you run "terraform apply" now.
1823 [Container] 2*22/*3/*9 23:29:24 Phase complete: BUILD State: SUCCEEDED
 1824 [Container] 2*22/*3/*9 23:29:24 Phase context status code: Message:
 1826 [Container] 2*22/*3/*9 23:29:24 Phase complete: POST_BUILD State: SUCCEEDED
1827 [Container] 2*22/*3/*9 23:29:24 Phase context status code: Message:
 1828 [Container] 2*22/*3/*9 23:29:24 Phase complete: UPLOAD_ARTIFACTS State: SUCCEEDED
1829 [Container] 2*22/*3/*9 23:29:24 Phase context status code: Message:
```

Deploy Amazon EMR

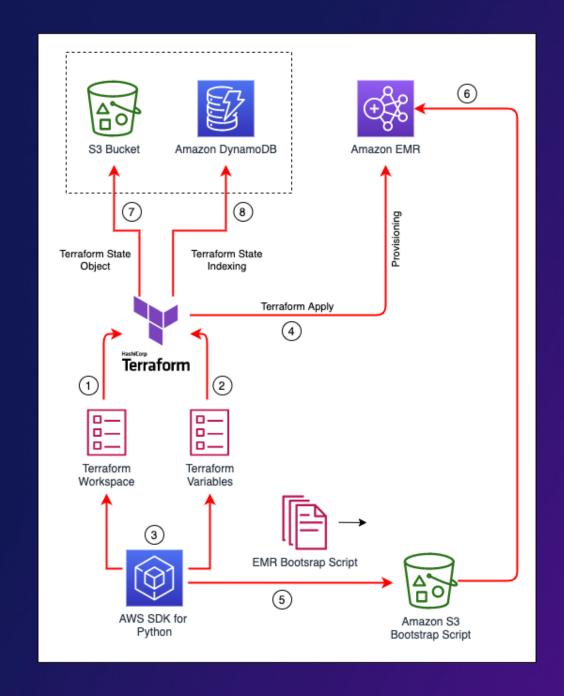
(ETA: 30 minutes)



BOOTSTRAP SCRIPT & TERRAFORM STACK

Bootstrap script including:

- IAM (Role & Policy)
- Provisioning Master, Core & Task Instance Fleet
- Instance Type Provisioning
- Volume (EBS) Size Instance
- Hadoop Debugging
- Autoscaling
- Monitoring & Log



Run Spark Jobs



RUNNING SPARK JOB - SERIAL MODEL

```
e serial_model.py 9+ ×
                                                                                            serial_model.py 9+ X
Users > dwidenni > Desktop > ₱ serial_model.py > ♦ train_model
                                                                                            Users > dwidenni > Desktop > 🧓 serial_model.py > ...
  1 def train model(train ds):
                                                                                             38 partition_column = ["asset_type"]
          X = train ds[feature column]
                                                                                              39 target_column = ['status']
          y = train_ds[target_column]
          X_train, X_test, y_train, y_test = train_test_split(
                                                                                                  train_ratio = 0.7
                                                                                                  partition_list = list(df[partition_column].unique())
              train_size=train_ratio,
                                                                                             44 base model = tree.DecisionTreeClassifier()
              random_state=42
          base_model.fit(X_train, y_train)
                                                                                         48 training_result = pd.DataFrame()
                                                                                             49 for partition in partition list:
          y_pred_test = base_model.predict(X_test)
                                                                                                      sub_df = df.loc[df[partition_column]==partition]
                                                                                                      model_training = train_model(sub_df)
          accuracy_test = metrics.accuracy_score(y_test, y_pred_test).tolist()
                                                                                                      training_result = pd.concat([training_result, model_training])
          f1_test = metrics.f1_score(y_test, y_pred_test, average='weighted').
          precision_test = metrics.precision_score(y_test, y_pred_test,
                                             average='weighted').tolist()
           recall_test = metrics.recall_score(y_test, y_pred_test,
                                       average='weighted').tolist()
          model_results_test = pd.DataFrame(
              [[idx, accuracy_test, f1_test, precision_test, recall_test]],
              columns=["id", "accuracy", "weighted_f1", "weightedPrecision",
              "weightedRecall"])
          filename = 'finalized model {}.sav'.format(idx)
          joblib.dump(base_model, filename)
          return model_results_test
 35  df = pd.read_csv('activity_analytics.csv')
 38 partition_column = ["asset_type"]
 39 target_column = ['status']
 41 train_ratio = 0.7
  42 partition list = list(df[partition column].unique())
```



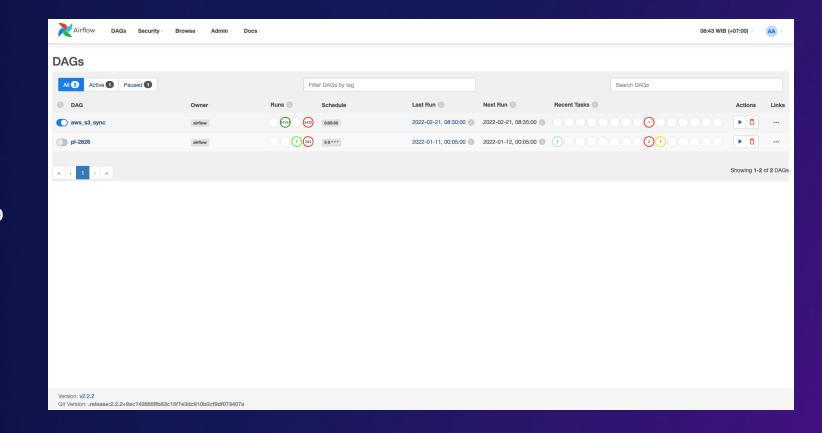
RUNNING SPARK JOB - PARALLEL MODEL

```
🌏 paralel_model.py 9+ 🗵
Users > dwidenni > Desktop > ₱ paralel_model.py > ♦ train_model > ₱ f1_test
                                                                                          Users > dwidenni > Desktop > 🔁 paralel_model.py > .
  base model = tree.DecisionTreeClassifier()
  2 schema = StructType([
        StructField("id", StringType()),
                                                                                           45 spark = SparkSession.builder \
         StructField("accuracy", FloatType()),
                                                                                                 .appName("parallel_model_training") \
         StructField("weighted_f1", FloatType()),
          StructField("weightedPrecision", FloatType()),
          StructField("weightedRecall", FloatType())
                                                                                       49 df = spark.read.options(header='True', inferSchema='True')\
                                                                                                    .csv('activity_analytics.csv')
                                                                                       53 partition_column = ["asset_type"]
 12 @pandas_udf(schema, PandasUDFType.GROUPED_MAP)
 13 def train model(train ds):
                                                                                       55 feature_column = ["avg_","max_","min_","stddev_","rng_"]
                                                                                                train ratio = 0.7
         X = train_ds[feature_column]
         v = train ds[target column]
         X_train, X_test, y_train, y_test = train_test_split(
                                                                                       partition_result = df.groupBy(partition_column).apply(
                                                                                                    train model
                                                                                                    ).toPandas()
          base_model.fit(X_train, y_train)
          y_pred_test = base_model.predict(X_test)
          accuracy_test = metrics.accuracy_score(y_test, y_pred_test).tolist()
          f1_test = metrics.f1_score(y_test, y_pred_test, average='weighted').
          precision_test = metrics.precision_score(y_test, y_pred_test,
                                            average='weighted').tolist()
          recall_test = metrics.recall_score(y_test, y_pred_test,
                                      average='weighted').tolist()
          model_results_test = pd.DataFrame(
             [[idx, accuracy_test, f1_test, precision_test, recall_test]],
              columns=["id", "accuracy", "weighted_f1", "weightedPrecision",
              "weightedRecall"])
          filename = 'finalized_model_{}.sav'.format(idx)
          joblib.dump(base model, filename)
          return model_results_test
```



RUNNING SPARK JOB - AIRFLOW MONITORING WORKFLOW

- Airflow is a useful tool to monitor workflow as Directed Acyclic Graphs (DAGs) of tasks
- The scheduler for automation pipeline and monitoring Spark job (python script) will be running under Airflow



References



References

Resources	Links
Docker Container CI/CD	https://github.com/devopscorner/devopscorner-container
User Data Installer Scripts	https://github.com/devopscorner/scripts
IaC Terraform EMR	https://github.com/devopscorner/iac-terraform-emr
Big Data and Machine Learning	https://devopscorner.id/category/machine-learning/
How to Efficiently Train Multiple ML Models on a Spark Cluster	https://medium.com/zebrax/how-to-efficiently-train-multiple-ml-models-on-a-spark-cluster-7d84512d36f0



Thank you!

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