Real-Time twitter Sentiment Analysis System

CSYE7200 Team 5

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Outline

- Project Overview
- Project Web UI
- Project Implementation
  - Data Ingestion
  - Data Processing and Storage
  - AWS Deploy
- Project Summary

Project Overview

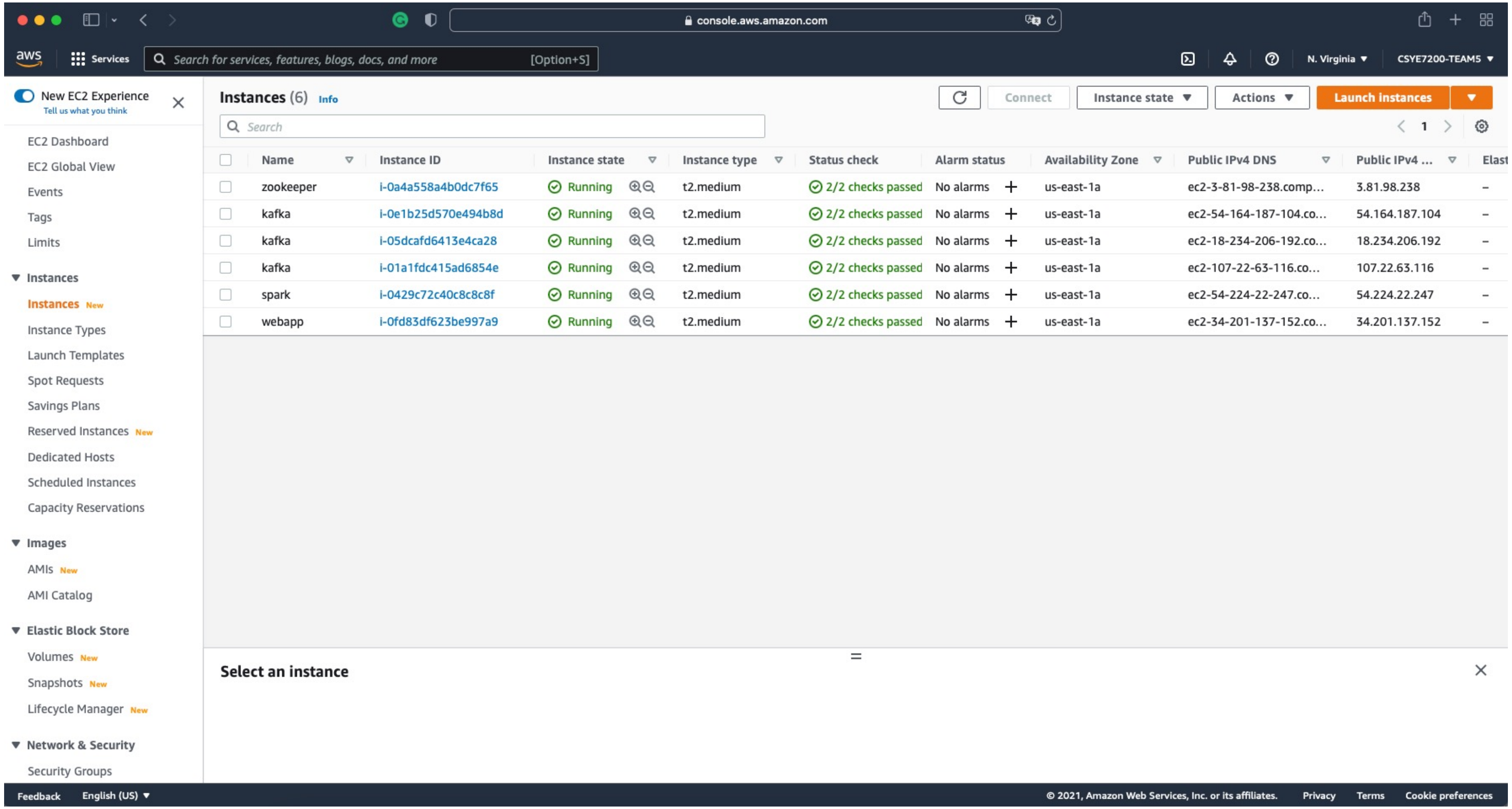
Project Overview

This real-time sentiment analysis system will achieve the sentiment analysis for the streaming tweets which are related to the input keyword by users and will show the sentiment analysis results in the visualization chart as the feedback to the user.

This system consists of data ingestion module, data processing and storage module, web UI and this system will be deployed on the cloud.

Project Web UI

Project Web UI
AWS Server

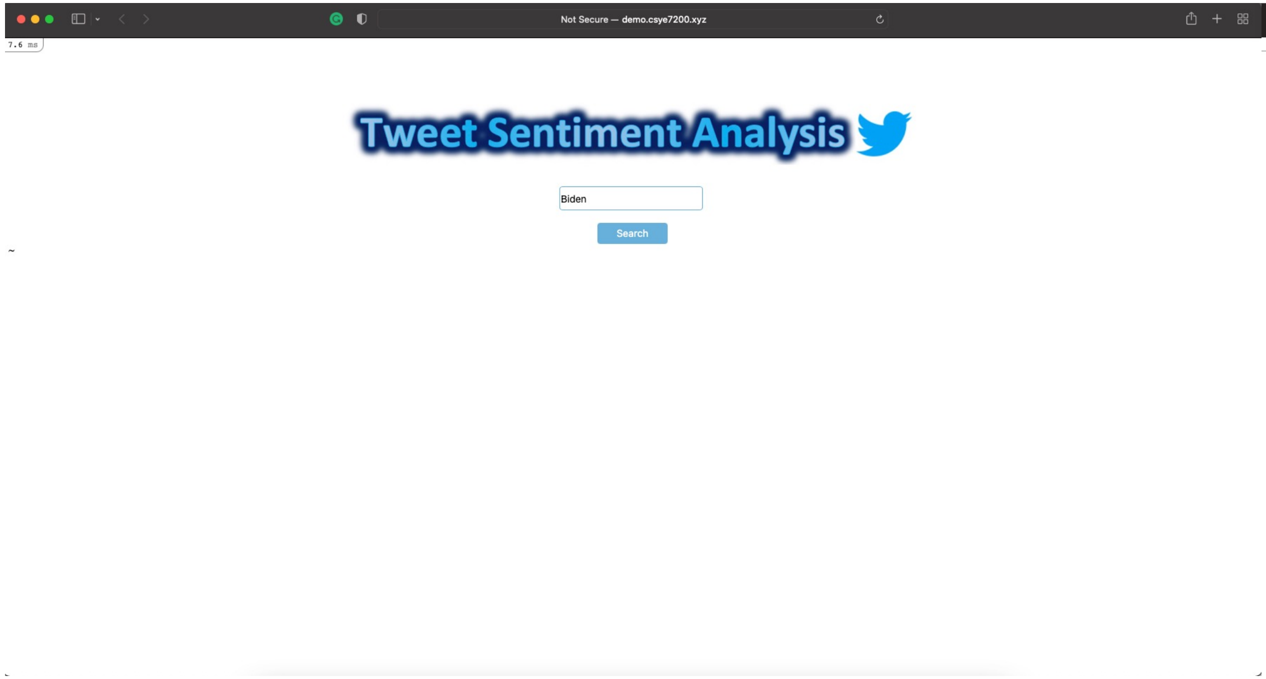


Instances (6) Info

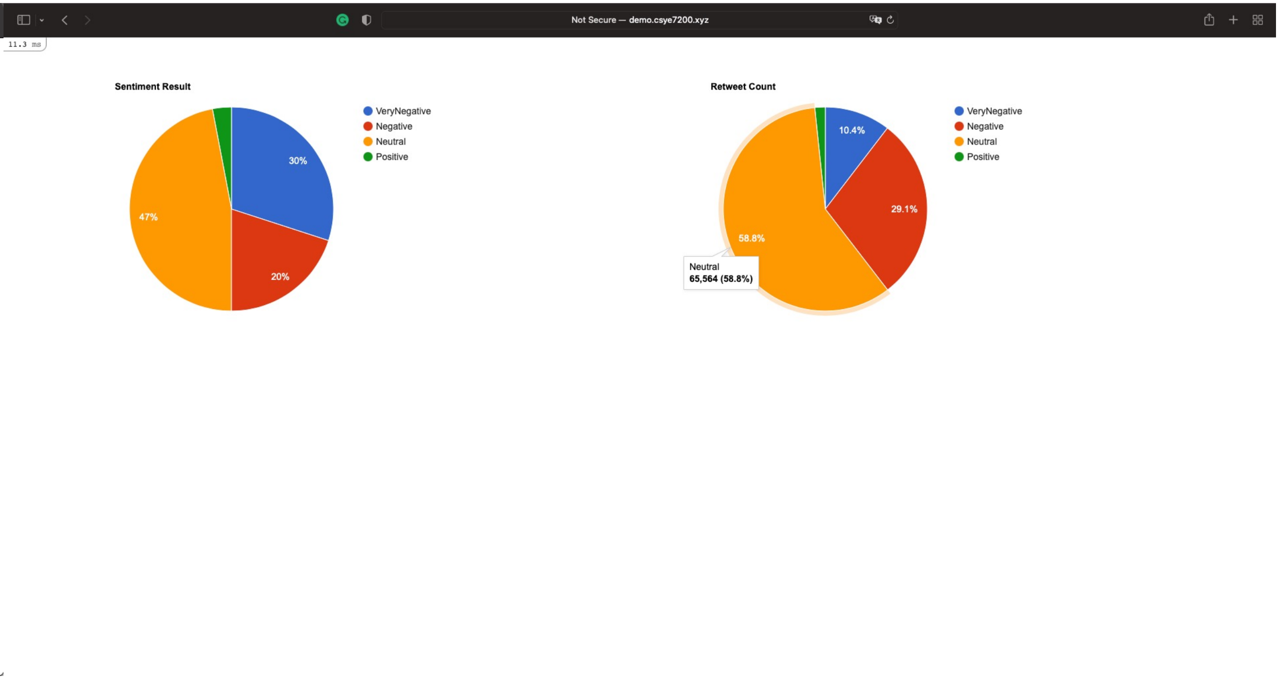
□	Name	Instance ID	Instance state	Instance type	Status check	Alarm status	Availability Zone	Public IPv4 DNS	Public IPv4 ...	Elast
□	zookeeper	i-0a4a558a4b0dc7f65	✓ Running	t2.medium	✓ 2/2 checks passed	No alarms +	us-east-1a	ec2-3-81-98-238.comp...	3.81.98.238	–
□	kafka	i-0e1b25d570e494b8d	✓ Running	t2.medium	✓ 2/2 checks passed	No alarms +	us-east-1a	ec2-54-164-187-104.co...	54.164.187.104	–
□	kafka	i-05dcafd6413e4ca28	✓ Running	t2.medium	✓ 2/2 checks passed	No alarms +	us-east-1a	ec2-18-234-206-192.co...	18.234.206.192	–
□	kafka	i-01a1fdc415ad6854e	✓ Running	t2.medium	✓ 2/2 checks passed	No alarms +	us-east-1a	ec2-107-22-63-116.co...	107.22.63.116	–
□	spark	i-0429c72c40c8c8c8f	✓ Running	t2.medium	✓ 2/2 checks passed	No alarms +	us-east-1a	ec2-54-224-22-247.co...	54.224.22.247	–
□	webapp	i-0fd83df623be997a9	✓ Running	t2.medium	✓ 2/2 checks passed	No alarms +	us-east-1a	ec2-34-201-137-152.co...	34.201.137.152	–

Select an instance

Project Web UI Screen Shot



Biden



Project Web UI URL

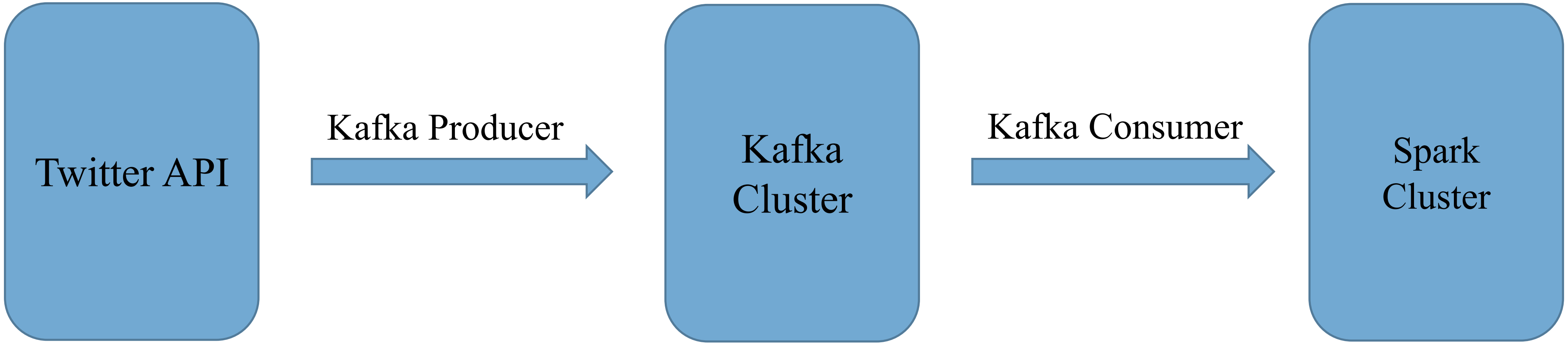
AWS Services：
https://console.aws.amazon.com/ec2/v2/home?region=us-east-1 - Instances:

Web UI URL：

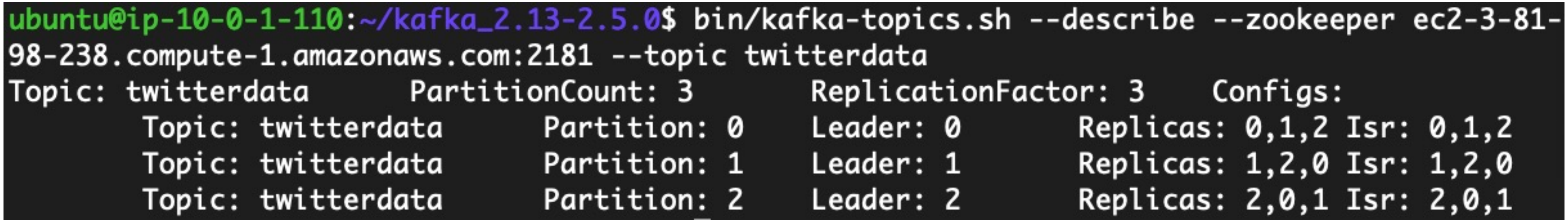
demo.csye7200.xyz

Implementation: Data Ingestion

Implementation: Data Ingestion workflow



Implementation: Data Ingestion
Kafka



```
ubuntu@ip-10-0-1-110:~/kafka_2.13-2.5.0$ bin/kafka-topics.sh --describe --zookeeper ec2-3-81-
98-238.compute-1.amazonaws.com:2181 --topic twitterdata
Topic: twitterdata      PartitionCount: 3       ReplicationFactor: 3    Configs:
        Topic: twitterdata      Partition: 0    Leader: 0       Replicas: 0,1,2 Isr: 0,1,2
        Topic: twitterdata      Partition: 1    Leader: 1       Replicas: 1,2,0 Isr: 1,2,0
        Topic: twitterdata      Partition: 2    Leader: 2       Replicas: 2,0,1 Isr: 2,0,1
```

Kafka topic: twitterdata

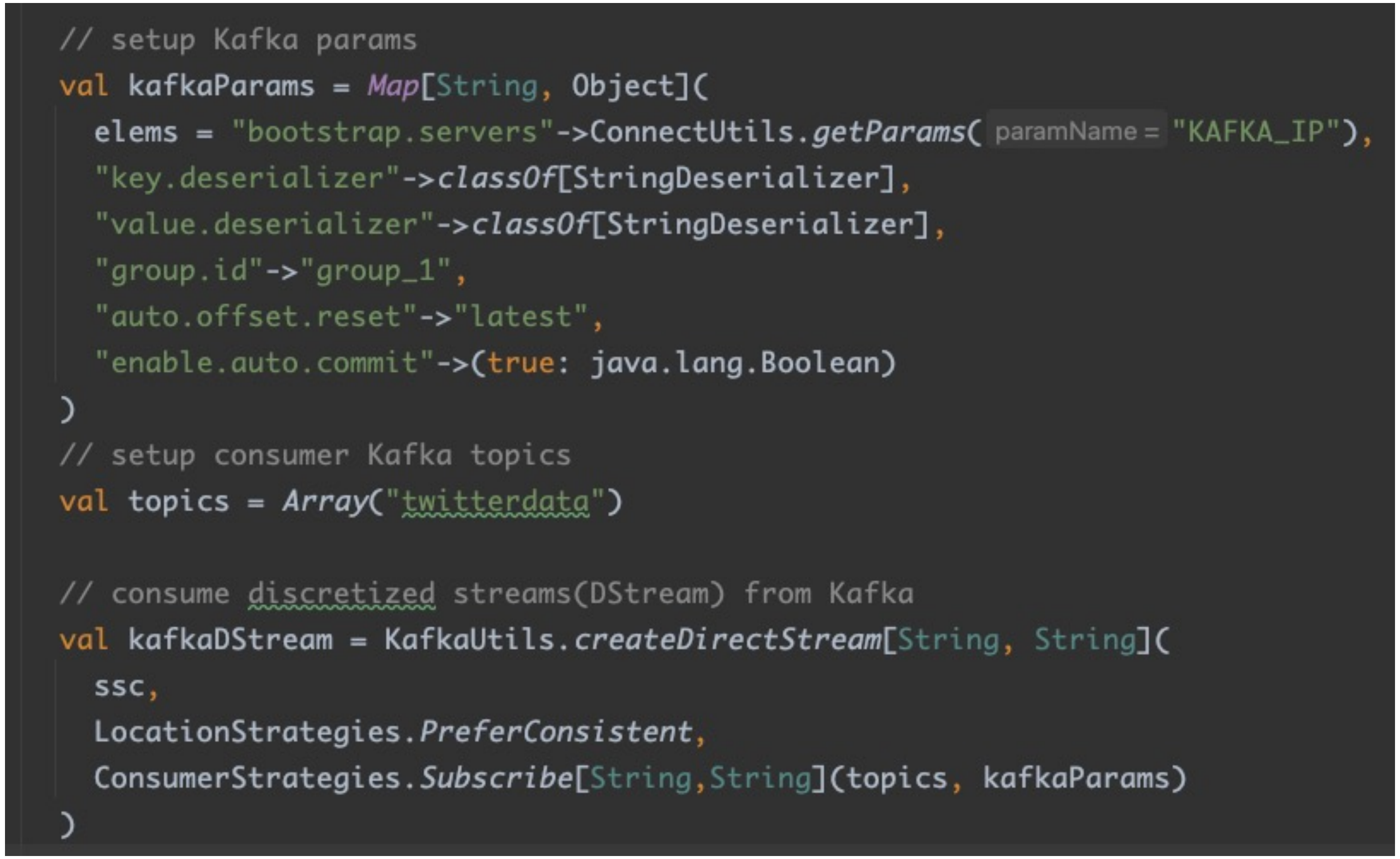
Broker count: 3

Partition count: 3 higher parallelism, higher throughput

Replication count: 3

Implementation: Data Ingestion
Kafka

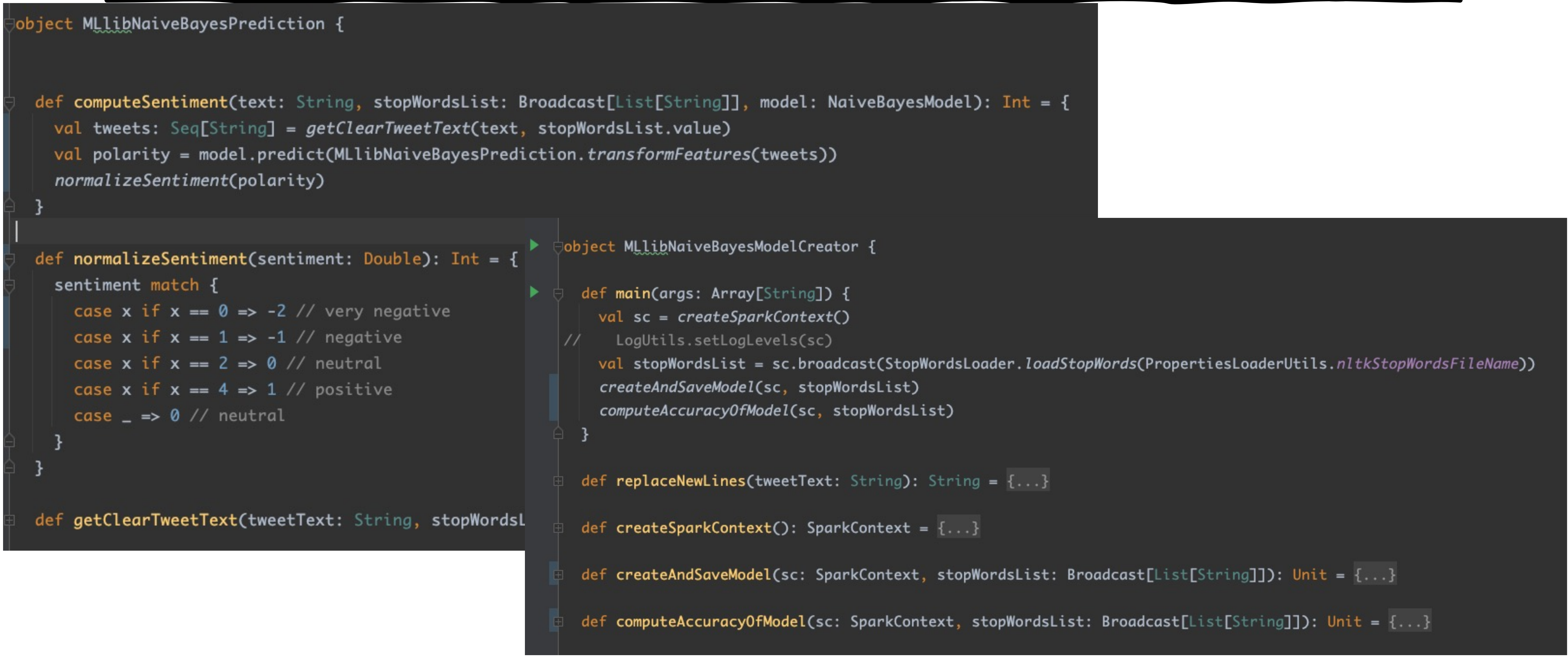
Kafka consumer connects with Spark Streaming



```
// setup Kafka params
val kafkaParams = Map[String, Object](
  elems = "bootstrap.servers"->ConnectUtils.getParams( paramName = "KAFKA_IP"),
  "key.deserializer"->classOf[StringDeserializer],
  "value.deserializer"->classOf[StringDeserializer],
  "group.id"->"group_1",
  "auto.offset.reset"->"latest",
  "enable.auto.commit"->(true: java.lang.Boolean)
)
// setup consumer Kafka topics
val topics = Array("twitterdata")

// consume discretized streams(DStream) from Kafka
val kafkaDStream = KafkaUtils.createDirectStream[String, String](
  ssc,
  LocationStrategies.PreferConsistent,
  ConsumerStrategies.Subscribe[String,String](topics, kafkaParams)
)
```

Implementation: Data Processing

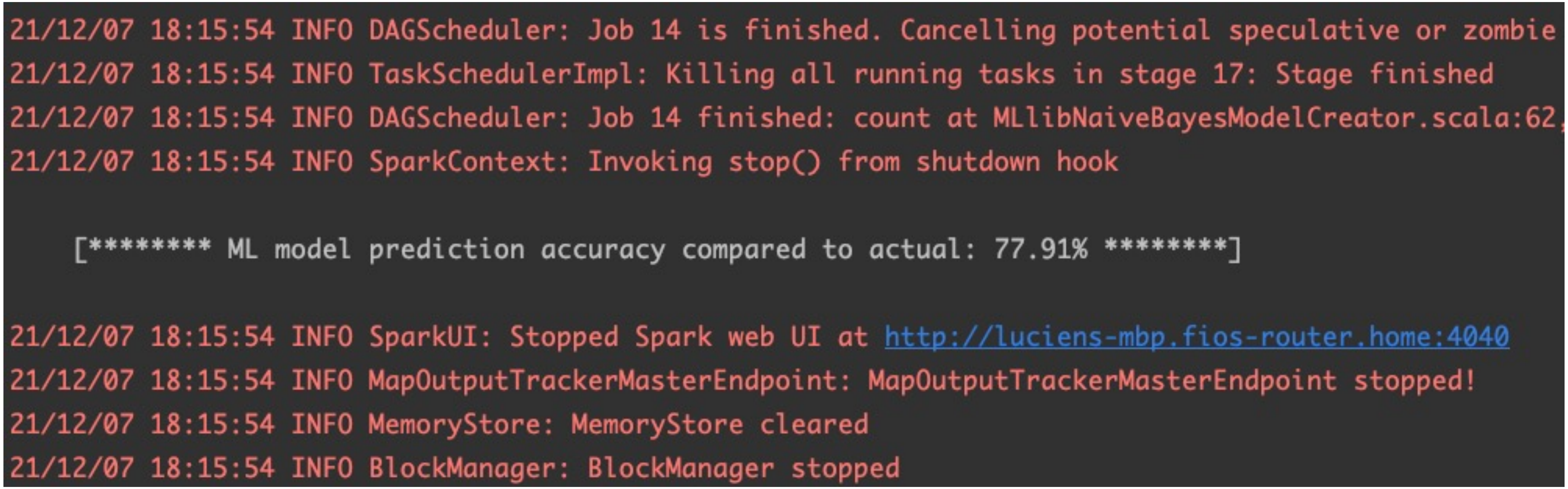
Implementation: Data Processing Spark MLlib



```scala
object MLlibNaiveBayesPrediction {


  def computeSentiment(text: String, stopWordsList: Broadcast[List[String]], model: NaiveBayesModel): Int = {
    val tweets: Seq[String] = getClearTweetText(text, stopWordsList.value)
    val polarity = model.predict(MLlibNaiveBayesPrediction.transformFeatures(tweets))
    normalizeSentiment(polarity)
  }

  def normalizeSentiment(sentiment: Double): Int = {
    sentiment match {
      case x if x == 0 => -2 // very negative
      case x if x == 1 => -1 // negative
      case x if x == 2 => 0 // neutral
      case x if x == 4 => 1 // positive
      case _ => 0 // neutral
    }
  }

  def getClearTweetText(tweetText: String, stopWordsL
```

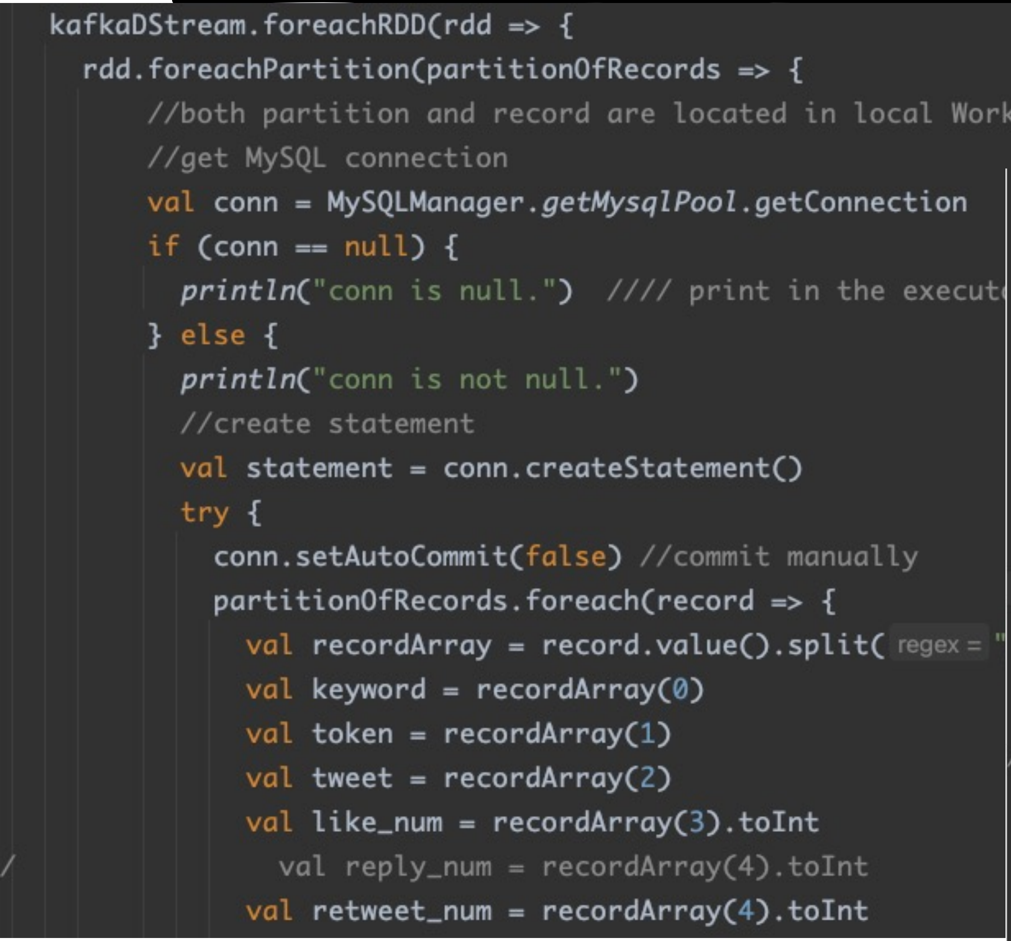
```scala
object MLlibNaiveBayesModelCreator {

  def main(args: Array[String]) {
    val sc = createSparkContext()
//    LogUtils.setLogLevels(sc)
    val stopWordsList = sc.broadcast(StopWordsLoader.loadStopWords(PropertiesLoaderUtils.nltkStopWordsFileName))
    createAndSaveModel(sc, stopWordsList)
    computeAccuracyOfModel(sc, stopWordsList)
  }

  def replaceNewLines(tweetText: String): String = {...}

  def createSparkContext(): SparkContext = {...}

  def createAndSaveModel(sc: SparkContext, stopWordsList: Broadcast[List[String]]): Unit = {...}

  def computeAccuracyOfModel(sc: SparkContext, stopWordsList: Broadcast[List[String]]): Unit = {...}
```

Implementation: Data Processing Spark MLlib

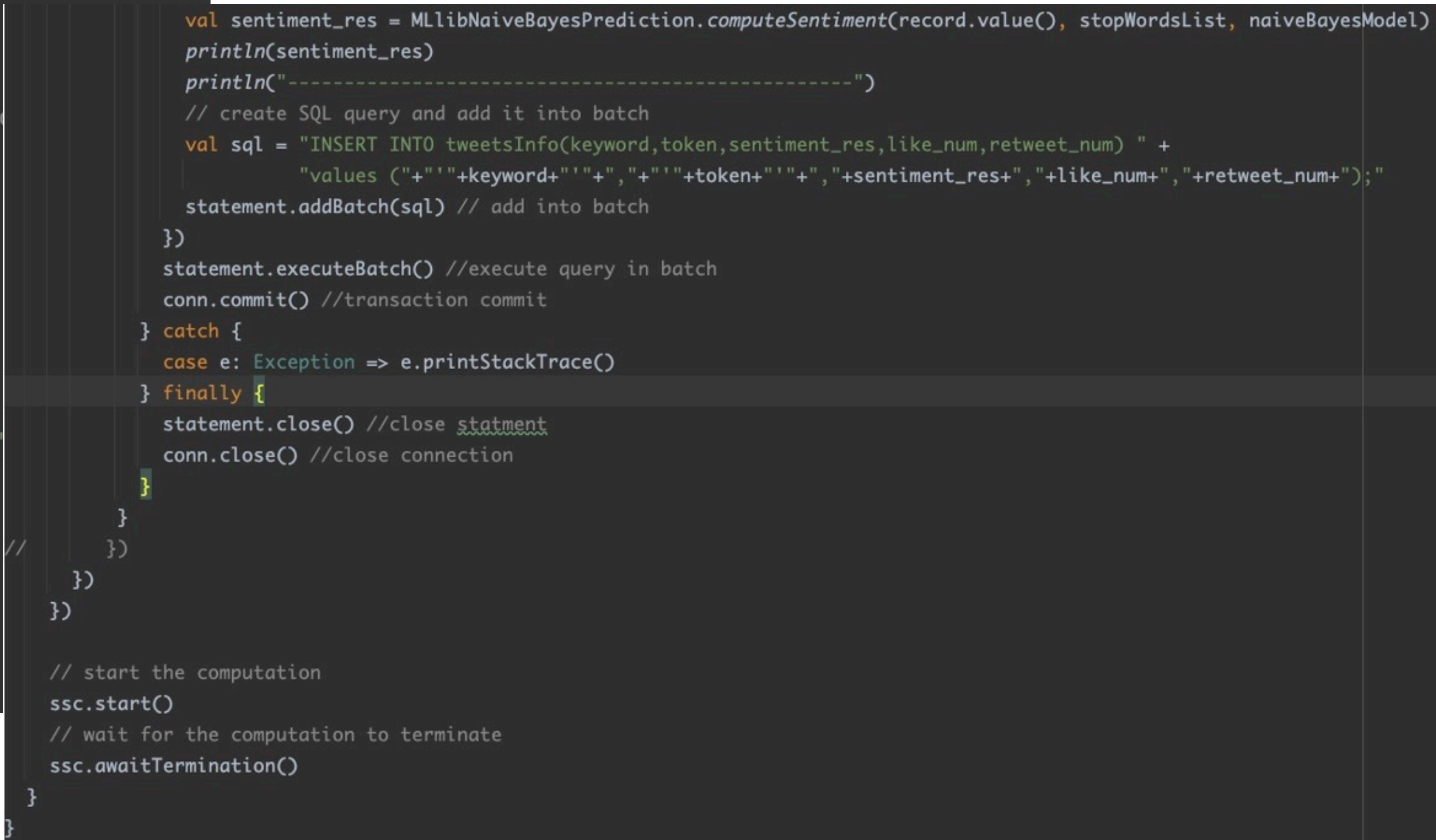


```
21/12/07 18:15:54 INFO DAGScheduler: Job 14 is finished. Cancelling potential speculative or zombie
21/12/07 18:15:54 INFO TaskSchedulerImpl: Killing all running tasks in stage 17: Stage finished
21/12/07 18:15:54 INFO DAGScheduler: Job 14 finished: count at MLlibNaiveBayesModelCreator.scala:62,
21/12/07 18:15:54 INFO SparkContext: Invoking stop() from shutdown hook

    [******** ML model prediction accuracy compared to actual: 77.91% ********]

21/12/07 18:15:54 INFO SparkUI: Stopped Spark web UI at http://luciens-mbp.fios-router.home:4040
21/12/07 18:15:54 INFO MapOutputTrackerMasterEndpoint: MapOutputTrackerMasterEndpoint stopped!
21/12/07 18:15:54 INFO MemoryStore: MemoryStore cleared
21/12/07 18:15:54 INFO BlockManager: BlockManager stopped
```

Implementation: Data Processing
Spark Streaming



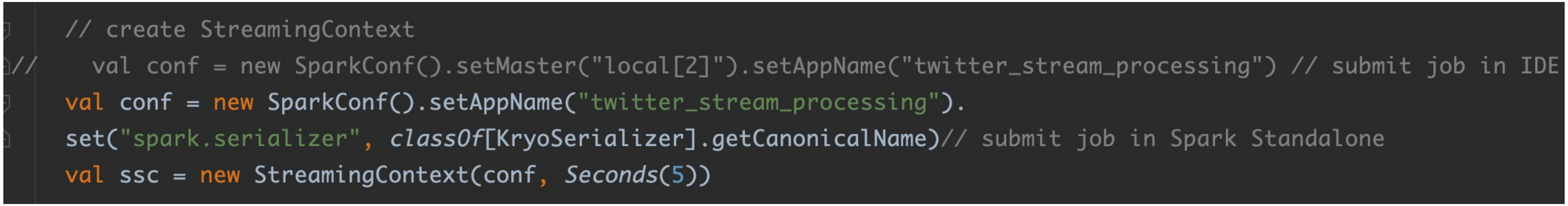
```
kafkaDStream.foreachRDD(rdd => {
  rdd.foreachPartition(partitionOfRecords => {
      //both partition and record are located in local Worker
      //get MySQL connection
      val conn = MySQLManager.getMysqlPool.getConnection
      if (conn == null) {
        println("conn is null.")  //// print in the execut
      } else {
        println("conn is not null.")
        //create statement
        val statement = conn.createStatement()
        try {
          conn.setAutoCommit(false) //commit manually
          partitionOfRecords.foreach(record => {
            val recordArray = record.value().split( regex = "
            val keyword = recordArray(0)
            val token = recordArray(1)
            val tweet = recordArray(2)
            val like_num = recordArray(3).toInt
/             val reply_num = recordArray(4).toInt
            val retweet_num = recordArray(4).toInt
```



```
            val sentiment_res = MLlibNaiveBayesPrediction.computeSentiment(record.value(), stopWordsList, naiveBayesModel)
            println(sentiment_res)
            println("----------------------------------------------")
            // create SQL query and add it into batch
            val sql = "INSERT INTO tweetsInfo(keyword,token,sentiment_res,like_num,retweet_num) " +
                      "values ("+"'"+keyword+"'"+","+"'"+token+"'"+","+sentiment_res+","+like_num+","+retweet_num+");"
            statement.addBatch(sql) // add into batch
          })
          statement.executeBatch() //execute query in batch
          conn.commit() //transaction commit
        } catch {
          case e: Exception => e.printStackTrace()
        } finally {
          statement.close() //close statment
          conn.close() //close connection
        }
      }
//    })
    })
  })

  // start the computation
  ssc.start()
  // wait for the computation to terminate
  ssc.awaitTermination()
}
}
```

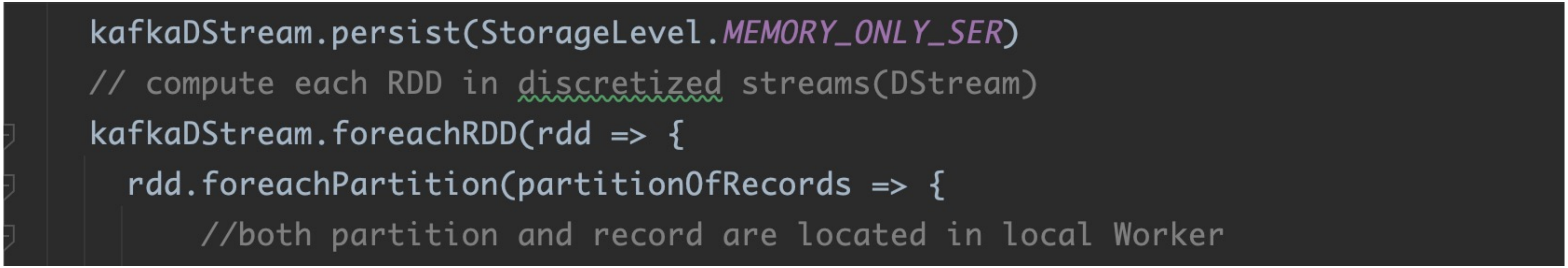
Implementation: Data Processing Optimization

Kryo Serializer instead of default Java Serializer



```
  // create StreamingContext
//   val conf = new SparkConf().setMaster("local[2]").setAppName("twitter_stream_processing") // submit job in IDE
  val conf = new SparkConf().setAppName("twitter_stream_processing").
  set("spark.serializer", classOf[KryoSerializer].getCanonicalName)// submit job in Spark Standalone
  val ssc = new StreamingContext(conf, Seconds(5))
```

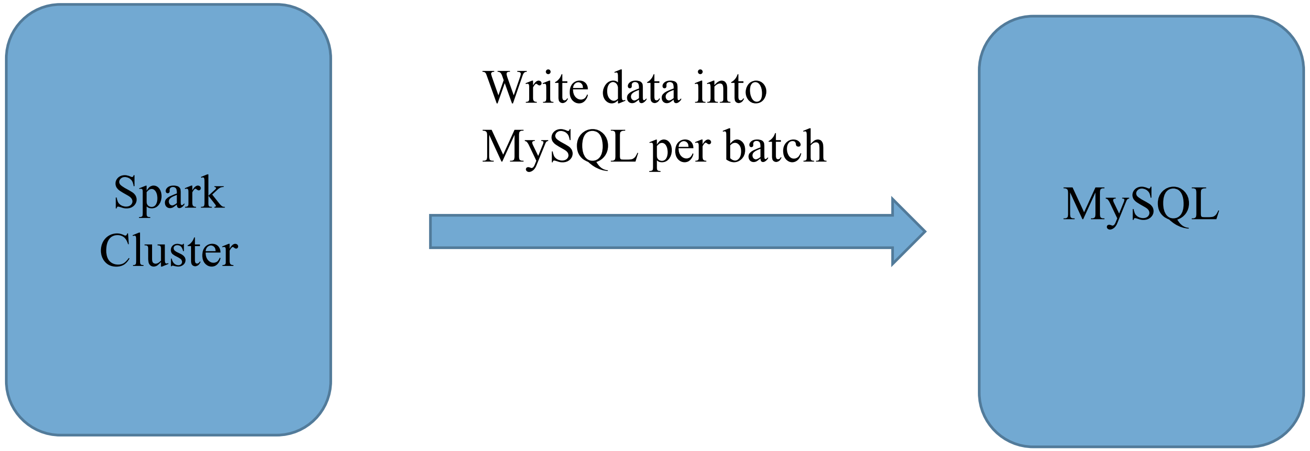
DStream Cache and serialization



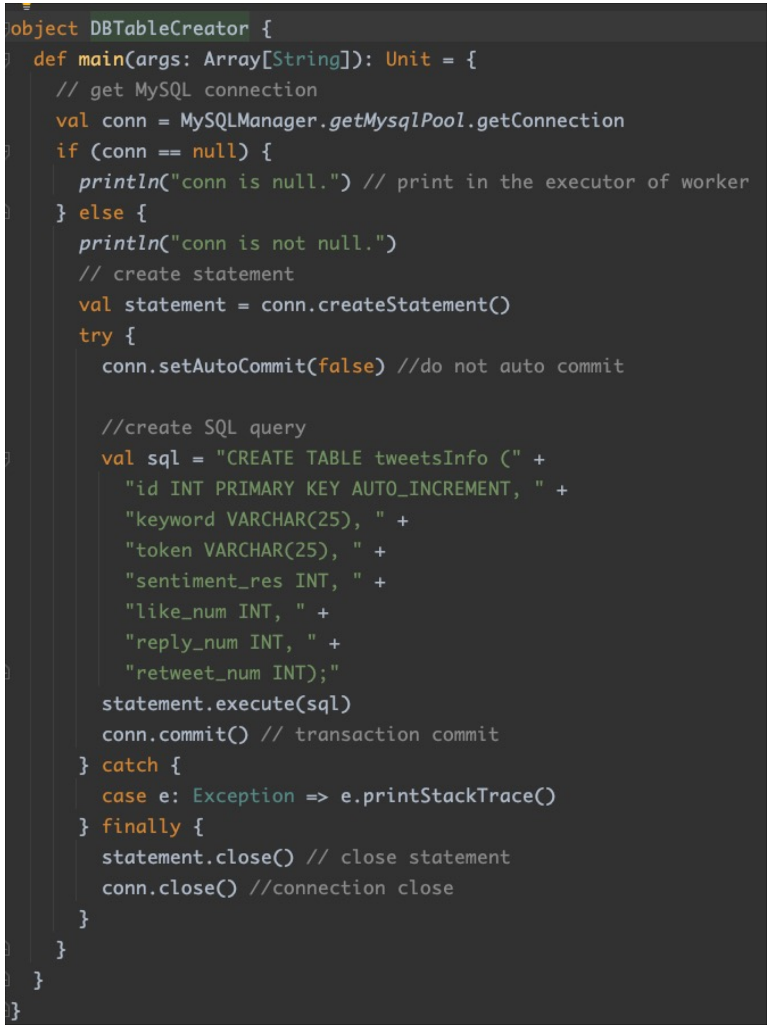
```
kafkaDStream.persist(StorageLevel.MEMORY_ONLY_SER)
// compute each RDD in discretized streams(DStream)
kafkaDStream.foreachRDD(rdd => {
  rdd.foreachPartition(partitionOfRecords => {
      //both partition and record are located in local Worker
```

Implementation: Data Storage

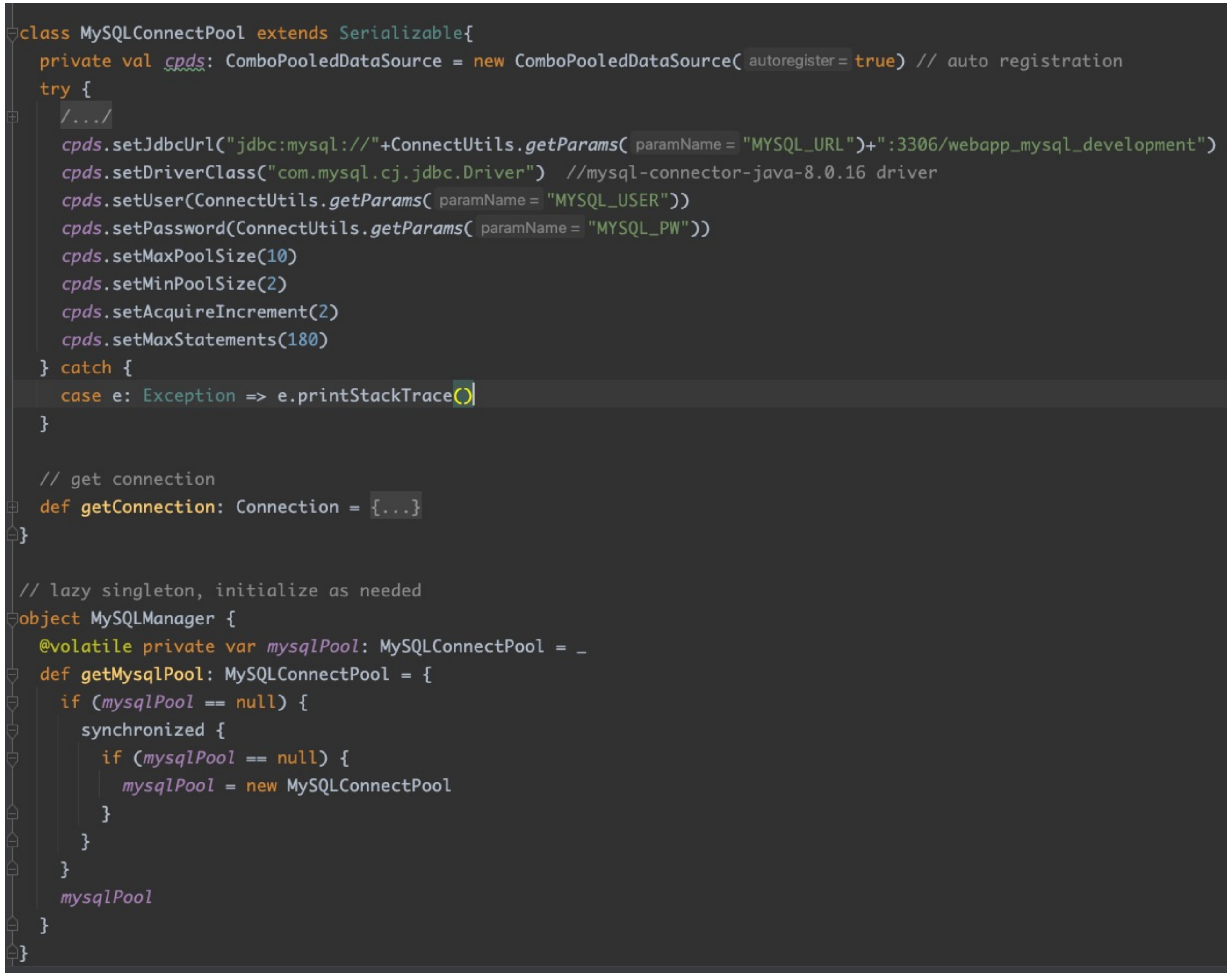
Implementation: Data Storage MySQL



Implementation: Data Storage
MySQL

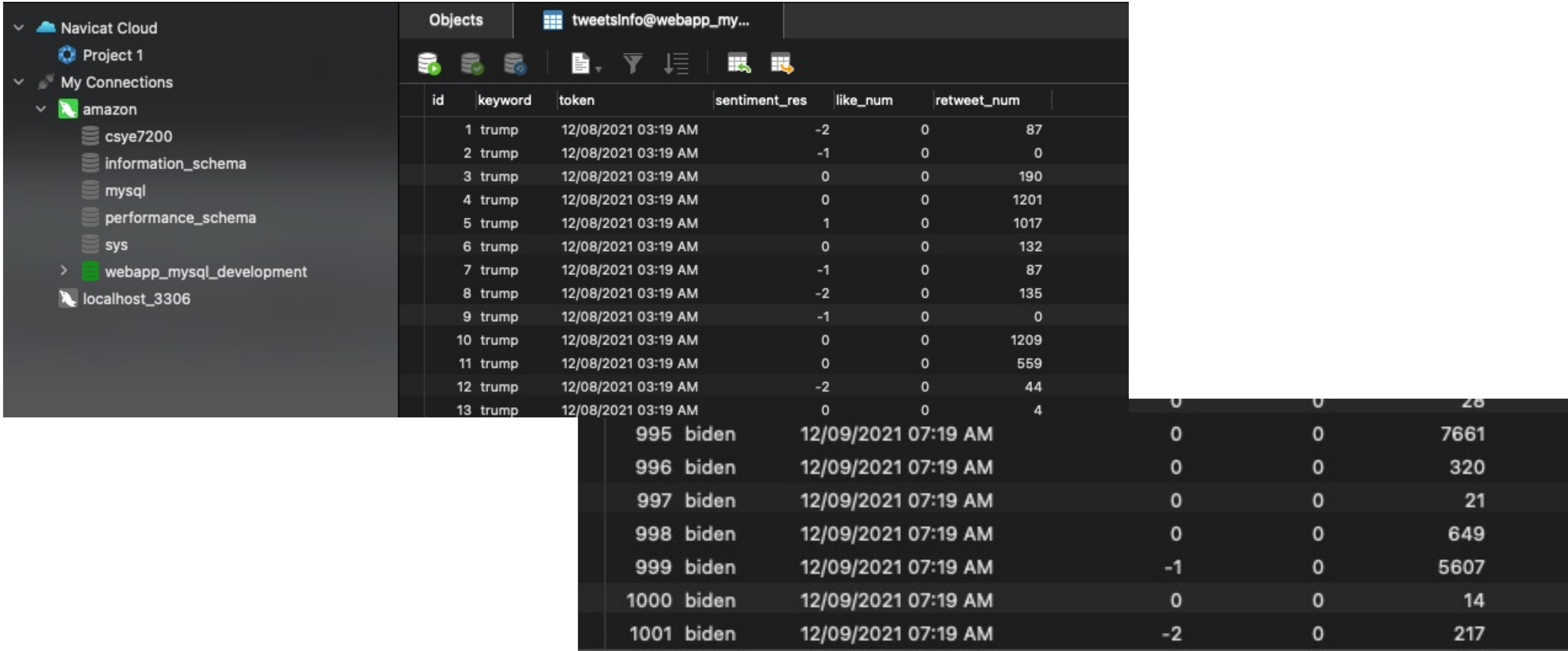


```
object DBTableCreator {
  def main(args: Array[String]): Unit = {
    // get MySQL connection
    val conn = MySQLManager.getMysqlPool.getConnection
    if (conn == null) {
      println("conn is null.") // print in the executor of worker
    } else {
      println("conn is not null.")
      // create statement
      val statement = conn.createStatement()
      try {
        conn.setAutoCommit(false) //do not auto commit

        //create SQL query
        val sql = "CREATE TABLE tweetsInfo (" +
          "id INT PRIMARY KEY AUTO_INCREMENT, " +
          "keyword VARCHAR(25), " +
          "token VARCHAR(25), " +
          "sentiment_res INT, " +
          "like_num INT, " +
          "reply_num INT, " +
          "retweet_num INT);"
        statement.execute(sql)
        conn.commit() // transaction commit
      } catch {
        case e: Exception => e.printStackTrace()
      } finally {
        statement.close() // close statement
        conn.close() //connection close
      }
    }
  }
}
```



```
class MySQLConnectPool extends Serializable{
  private val cpds: ComboPooledDataSource = new ComboPooledDataSource( autoregister = true) // auto registration
  try {
    /.../
    cpds.setJdbcUrl("jdbc:mysql://"+ConnectUtils.getParams( paramName = "MYSQL_URL")+":3306/webapp_mysql_development")
    cpds.setDriverClass("com.mysql.cj.jdbc.Driver")  //mysql-connector-java-8.0.16 driver
    cpds.setUser(ConnectUtils.getParams( paramName = "MYSQL_USER"))
    cpds.setPassword(ConnectUtils.getParams( paramName = "MYSQL_PW"))
    cpds.setMaxPoolSize(10)
    cpds.setMinPoolSize(2)
    cpds.setAcquireIncrement(2)
    cpds.setMaxStatements(180)
  } catch {
    case e: Exception => e.printStackTrace()
  }

  // get connection
  def getConnection: Connection = {...}
}

// lazy singleton, initialize as needed
object MySQLManager {
  @volatile private var mysqlPool: MySQLConnectPool = _
  def getMysqlPool: MySQLConnectPool = {
    if (mysqlPool == null) {
      synchronized {
        if (mysqlPool == null) {
          mysqlPool = new MySQLConnectPool
        }
      }
    }
    mysqlPool
  }
}
```

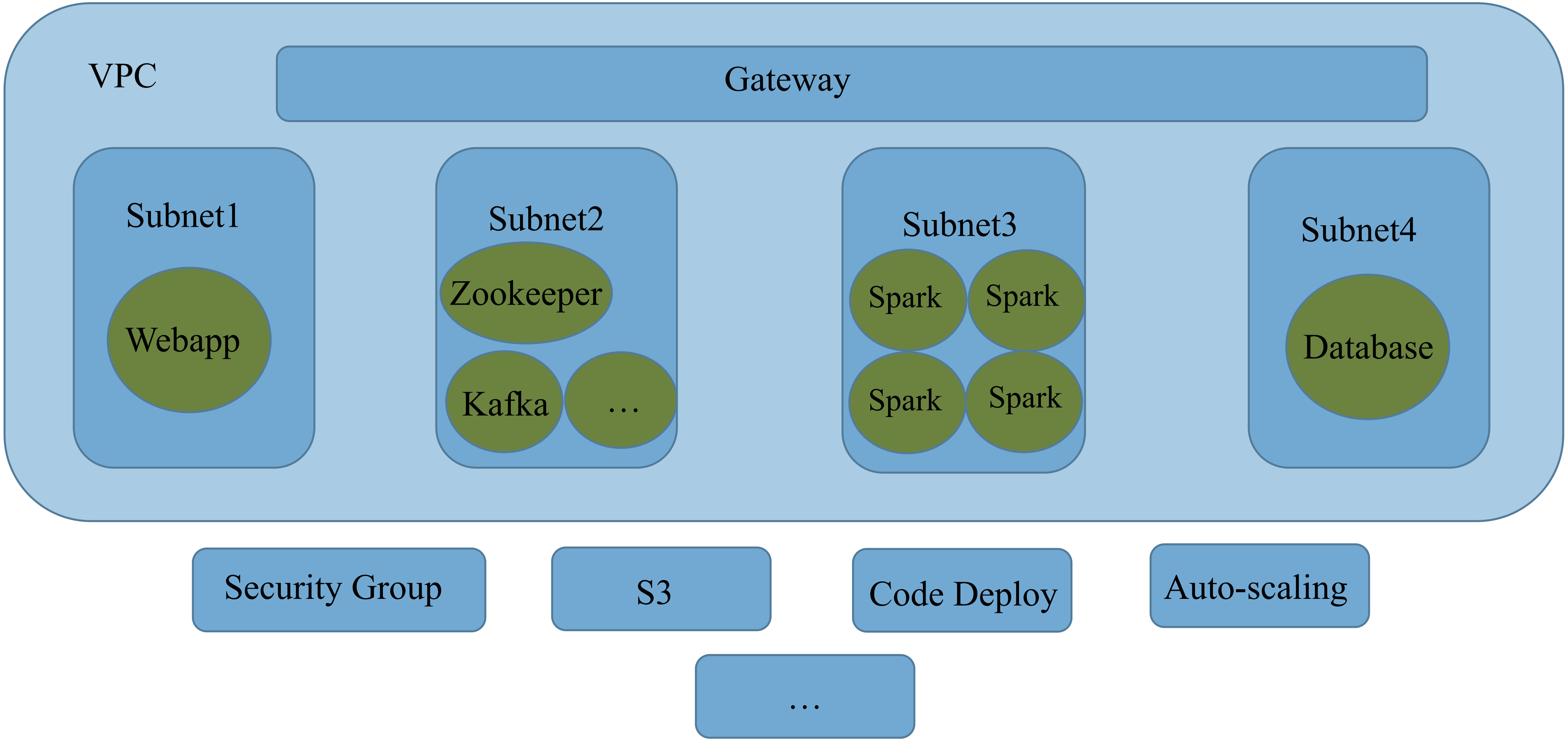
Implementation: Data Storage
MySQL



id	keyword	token	sentiment_res	like_num	retweet_num
1	trump	12/08/2021 03:19 AM	-2	0	87
2	trump	12/08/2021 03:19 AM	-1	0	0
3	trump	12/08/2021 03:19 AM	0	0	190
4	trump	12/08/2021 03:19 AM	0	0	1201
5	trump	12/08/2021 03:19 AM	1	0	1017
6	trump	12/08/2021 03:19 AM	0	0	132
7	trump	12/08/2021 03:19 AM	-1	0	87
8	trump	12/08/2021 03:19 AM	-2	0	135
9	trump	12/08/2021 03:19 AM	-1	0	0
10	trump	12/08/2021 03:19 AM	0	0	1209
11	trump	12/08/2021 03:19 AM	0	0	559
12	trump	12/08/2021 03:19 AM	-2	0	44
13	trump	12/08/2021 03:19 AM	0	0	4
			0	0	28
995	biden	12/09/2021 07:19 AM	0	0	7661
996	biden	12/09/2021 07:19 AM	0	0	320
997	biden	12/09/2021 07:19 AM	0	0	21
998	biden	12/09/2021 07:19 AM	0	0	649
999	biden	12/09/2021 07:19 AM	-1	0	5607
1000	biden	12/09/2021 07:19 AM	0	0	14
1001	biden	12/09/2021 07:19 AM	-2	0	217

Implementation: AWS Deploy

Implementation: AWS Deploy Cloud



VPC

Gateway

Subnet1

Webapp

Subnet2

Zookeeper

Kafka

…

Subnet3

Spark

Spark

Spark

Spark

Subnet4

Database

Security Group

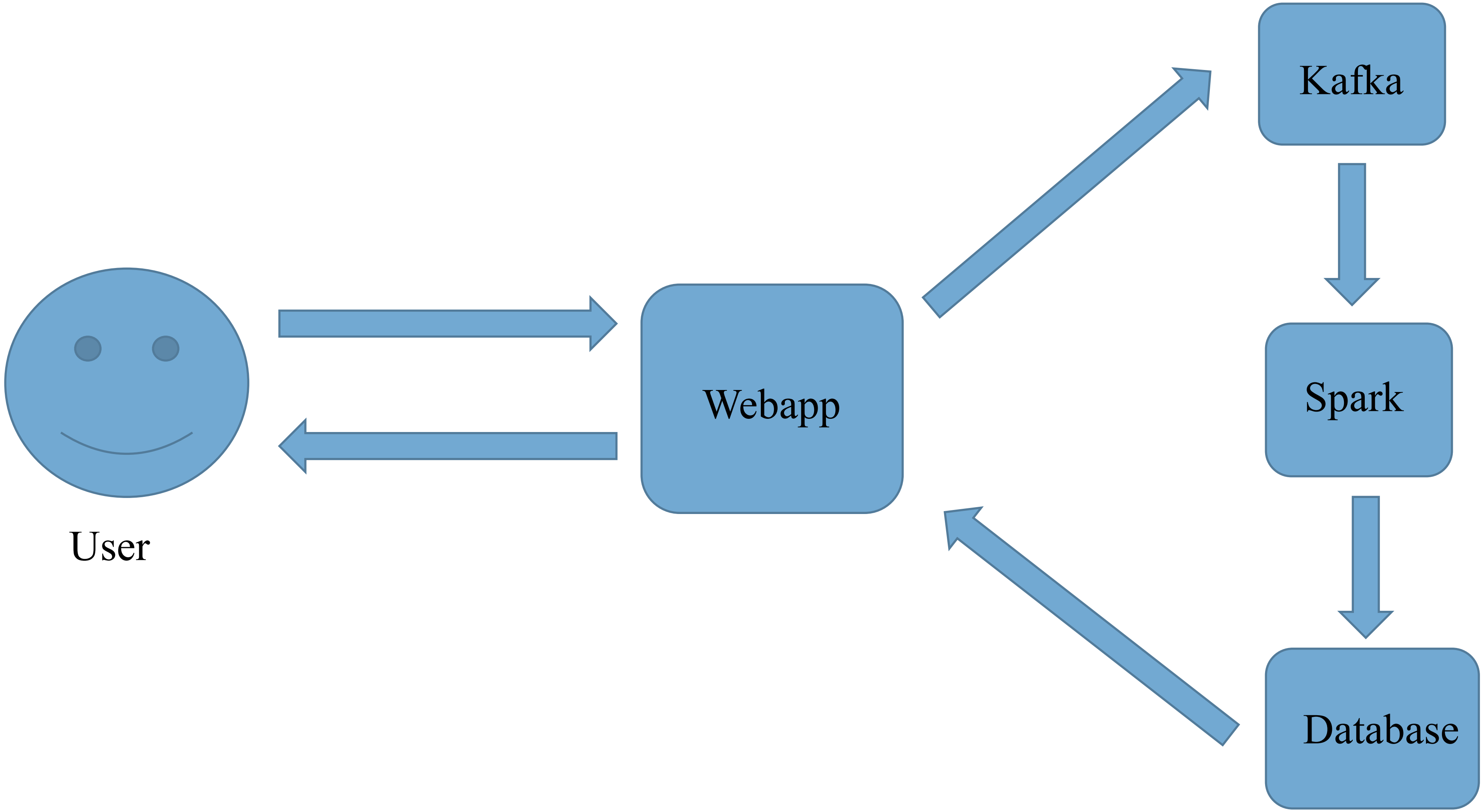
S3

Code Deploy

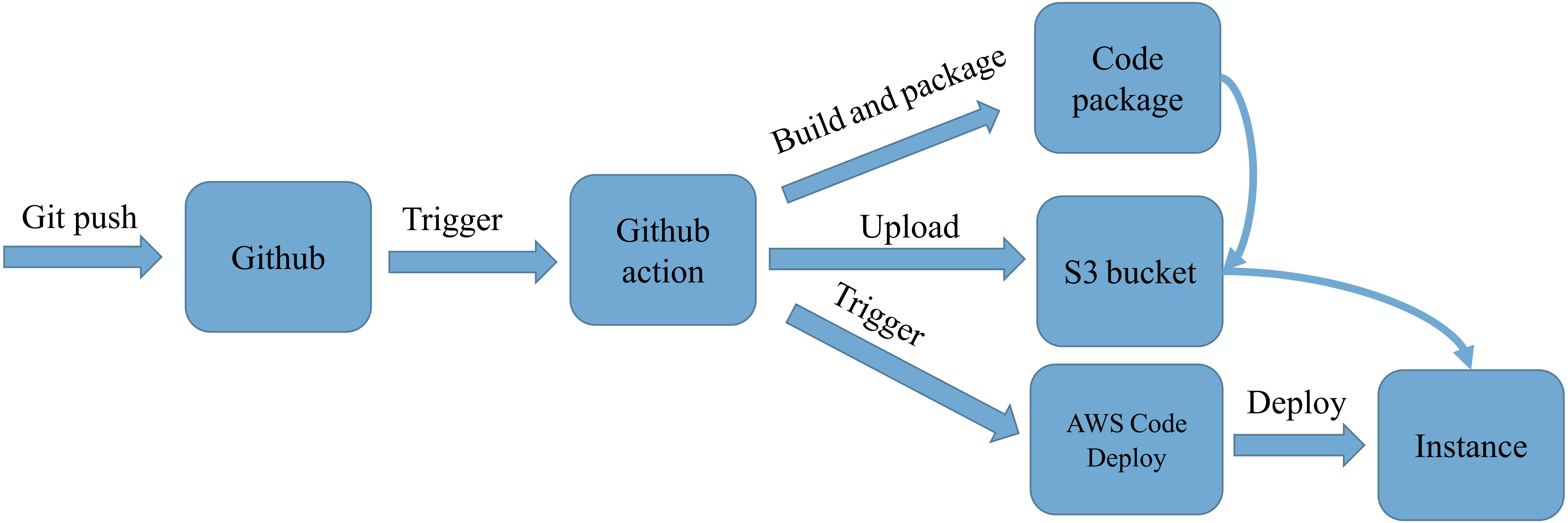
Auto-scaling

…

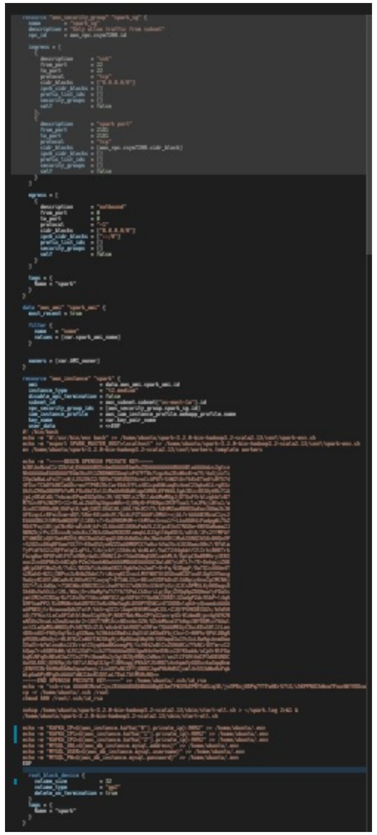
Implementation: AWS Deploy Workflow



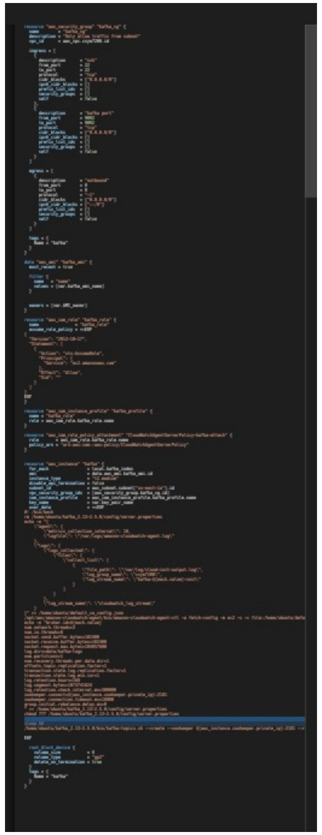
Implementation: AWS Deploy
Continuous Integration and Code Deployment / CICD



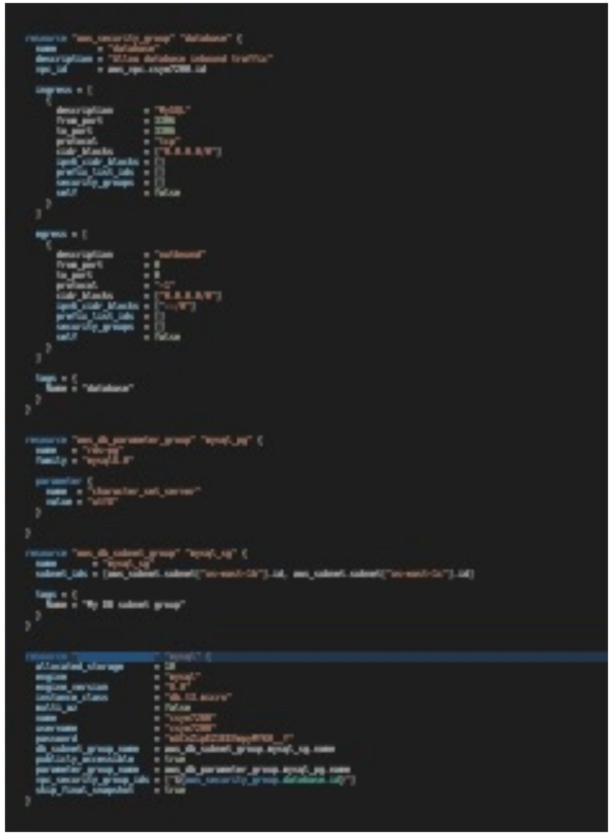
Implementation: AWS Deploy Terraform



```
resource "aws_security_group" "spark_sg" {
  name        = "spark_sg"
  description = "Only allow traffic from subnet"
  vpc_id      = aws_vpc.csye7200.id

  ingress = [
    {
      description      = "ssh"
      from_port        = 22
      to_port          = 22
      protocol         = "tcp"
      cidr_blocks      = ["0.0.0.0/0"]
      ipv6_cidr_blocks = []
      prefix_list_ids  = []
      security_groups  = []
      self             = false
    },
    {
      description      = "spark port"
      from_port        = 2181
      to_port          = 2181
      protocol         = "tcp"
      cidr_blocks      = [aws_vpc.csye7200.cidr_block]
      ipv6_cidr_blocks = []
      prefix_list_ids  = []
      security_groups  = []
      self             = false
    }
  ]

  egress = [
    {
      description      = "outbound"
      from_port        = 0
      to_port          = 0
      protocol         = "-1"
      cidr_blocks      = ["0.0.0.0/0"]
      ipv6_cidr_blocks = ["::/0"]
      prefix_list_ids  = []
      security_groups  = []
      self             = false
    }
  ]

  tags = {
    Name = "spark"
  }
}

data "aws_ami" "spark_ami" {
  most_recent = true

  filter {
    name   = "name"
    values = [var.spark_ami_name]
  }

  owners = [var.AMI_owner]
}

resource "aws_instance" "spark" {
  [illegible]
```

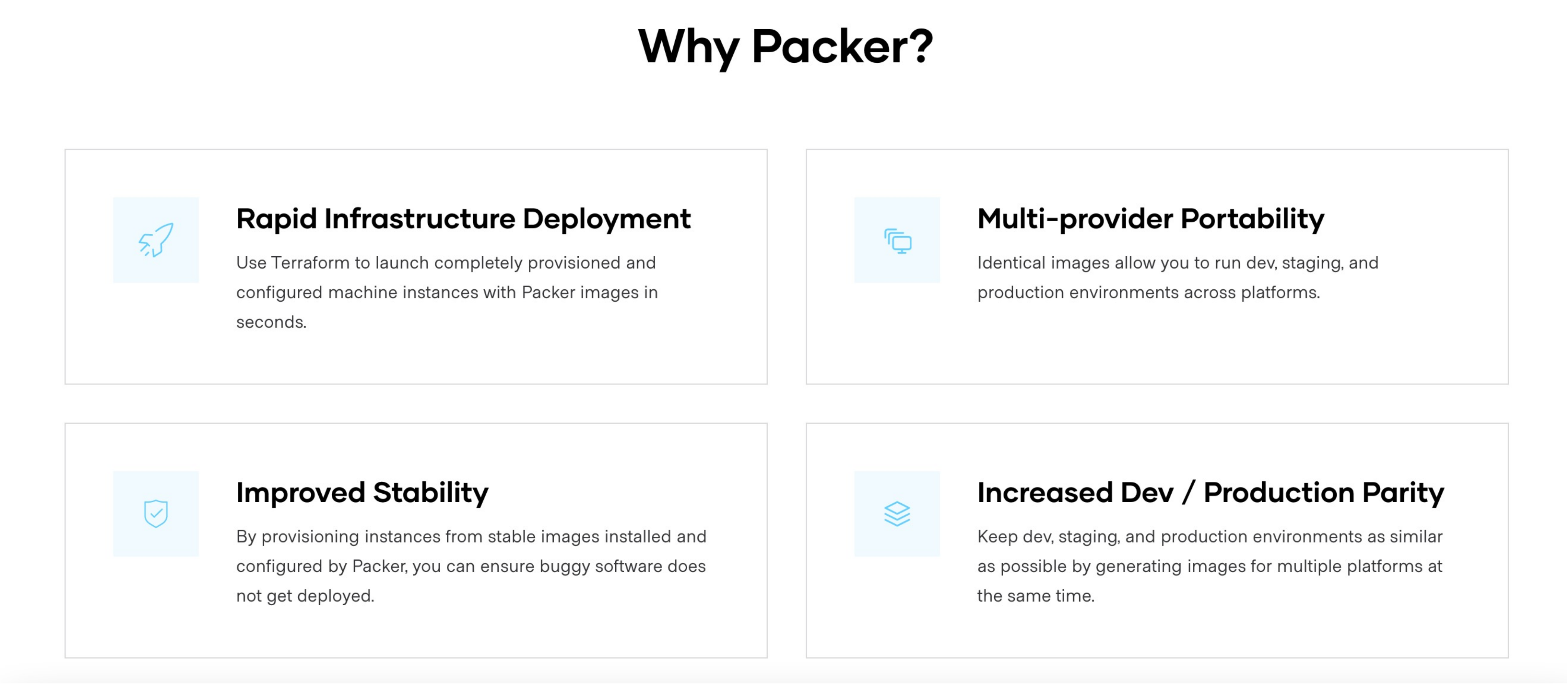


```
resource "aws_security_group" "kafka_sg" {
  name        = "kafka_sg"
  description = "Only allow traffic from subnet"
  vpc_id      = aws_vpc.csye7200.id

  [illegible]
```



```
resource "aws_security_group" "database" {
  name        = "database"
  description = "Allow database inbound traffic"
  vpc_id      = aws_vpc.csye7200.id

  ingress = [
    {
      description      = "MySQL"
      from_port        = 3306
      to_port          = 3306
      protocol         = "tcp"
      cidr_blocks      = ["0.0.0.0/0"]
      ipv6_cidr_blocks = []
      prefix_list_ids  = []
      security_groups  = []
      self             = false
    }
  ]

  egress = [
    {
      description      = "outbound"
      from_port        = 0
      to_port          = 0
      protocol         = "-1"
      cidr_blocks      = ["0.0.0.0/0"]
      ipv6_cidr_blocks = ["::/0"]
      prefix_list_ids  = []
      security_groups  = []
      self             = false
    }
  ]

  tags = {
    Name = "database"
  }
}


resource "aws_db_parameter_group" "mysql_pg" {
  name   = "rds-pg"
  family = "mysql8.0"

  parameter {
    name  = "character_set_server"
    value = "utf8"
  }

}

resource "aws_db_subnet_group" "mysql_sg" {
  name       = "mysql_sg"
  subnet_ids = [aws_subnet.subnet["us-east-1b"].id, aws_subnet.subnet["us-east-1a"].id]

  tags = {
    Name = "My DB subnet group"
  }
}


resource "[illegible]" "mysql" {
  allocated_storage      = 10
  engine                 = "mysql"
  engine_version         = "8.0"
  instance_class         = "db.t3.micro"
  multi_az               = false
  name                   = "csye7200"
  username               = "csye7200"
  password               = "[illegible]"
  db_subnet_group_name   = aws_db_subnet_group.mysql_sg.name
  publicly_accessible    = true
  parameter_group_name   = aws_db_parameter_group.mysql_pg.name
  vpc_security_group_ids = ["${aws_security_group.database.id}"]
  skip_final_snapshot    = true
}
```

Implementation: AWS Deploy Packer



Why Packer?

Rapid Infrastructure Deployment

Use Terraform to launch completely provisioned and configured machine instances with Packer images in seconds.

Multi-provider Portability

Identical images allow you to run dev, staging, and production environments across platforms.

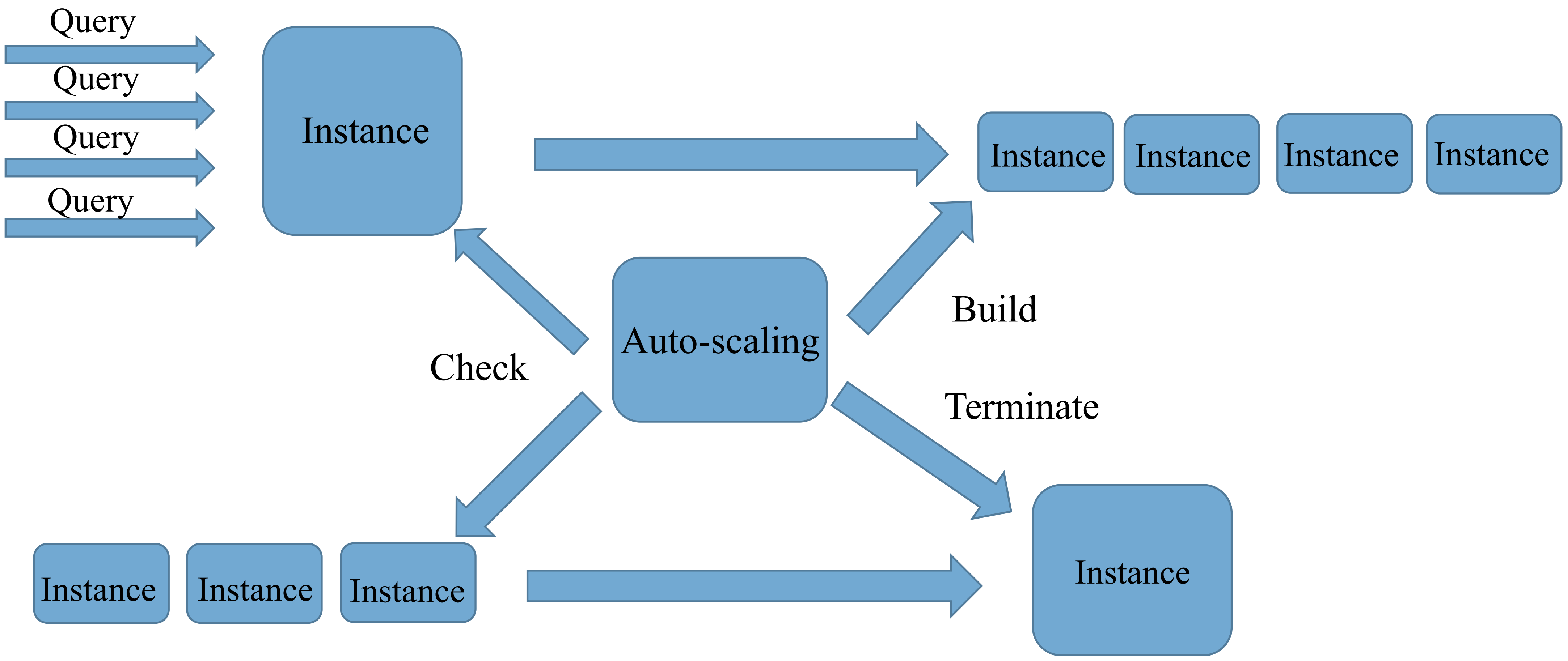
Improved Stability

By provisioning instances from stable images installed and configured by Packer, you can ensure buggy software does not get deployed.

Increased Dev / Production Parity

Keep dev, staging, and production environments as similar as possible by generating images for multiple platforms at the same time.

Implementation: AWS Deploy Auto-Scaling



Summary

Summary
Acceptance Criteria

1. This system can ingest the relative streaming tweets from Twitter according to the input keywords by user. Shown in Web UI and Data ingestion part

2. This system can process about 150 tweets for every query and perform the sentiment analysis for these real-time tweets in the seconds. Shown in Spark Streaming and MySQL part

3. This system will be expected to achieve 70% sentiment analysis accuracy.

Shown in Spark MLlib part

4. This system will show the sentiment analysis results in the visualization chart as the feedback to the user. Shown in Web UI part

5. This system will be deployed on AWS. Shown in AWS deploy part

Summary
Conclusion

By completing the project, we know how to design and build the big data system. We have a deeper understanding of big data frameworks, tools and cloud computing. Most importantly, we will achieve good, practical, working knowledge of Scala.

Thank You!