EECS E6893 Big Data Analytics
HW3: Twitter data analysis with Spark Streaming

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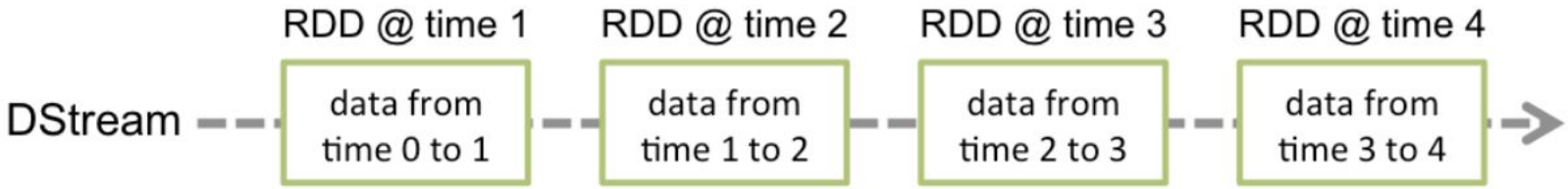
Spark Streaming

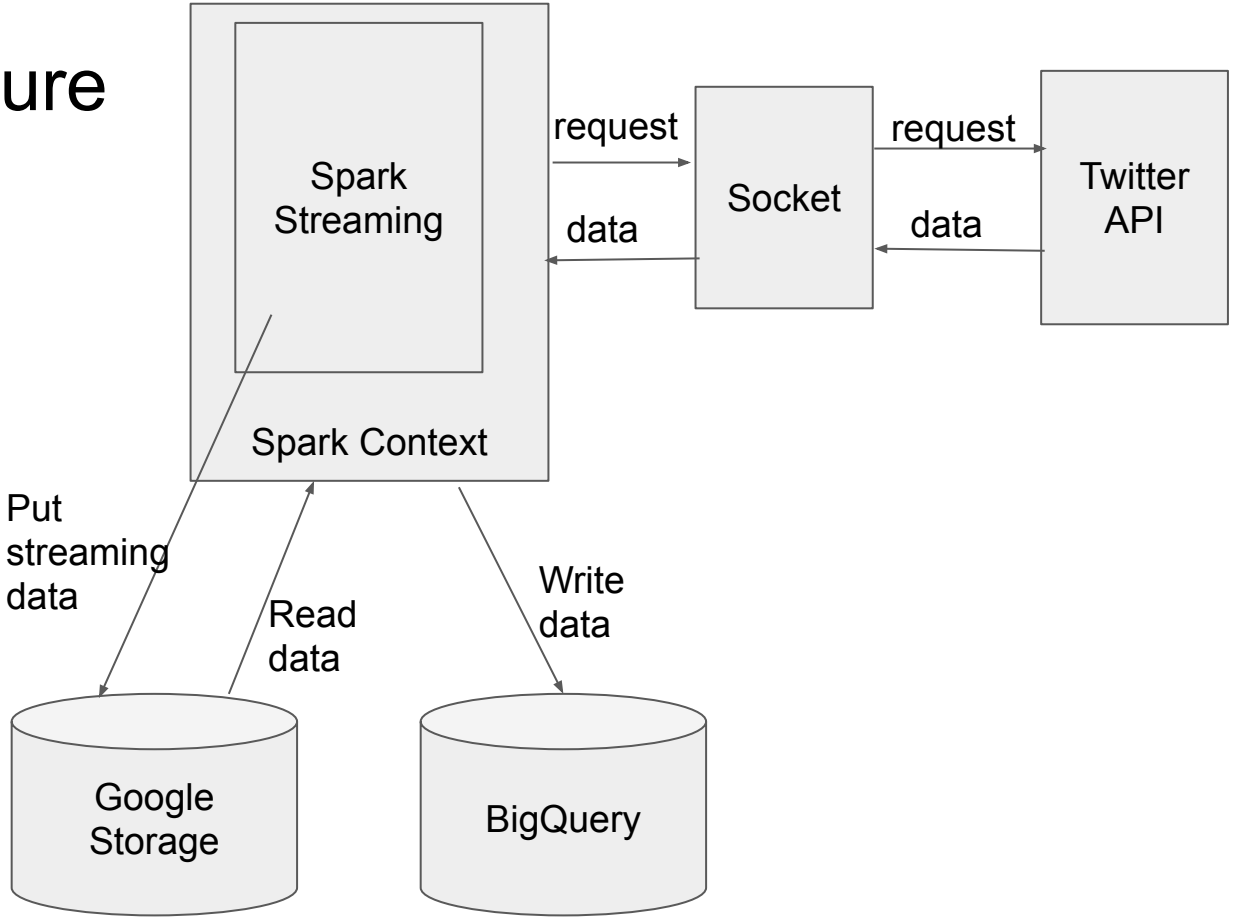
https://spark.apache.org/docs/latest/streaming-programming-guide.html

Dstream



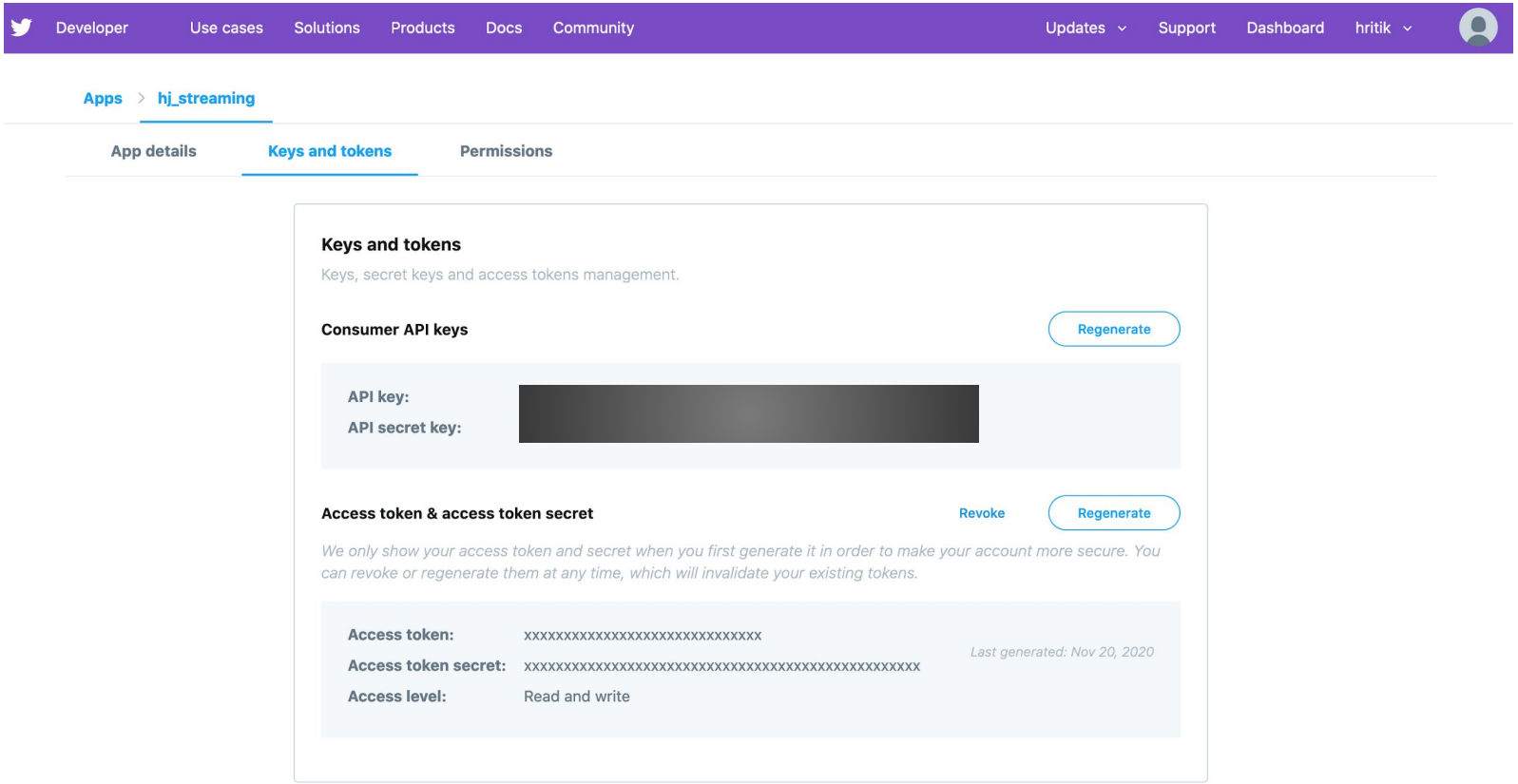
- A basic abstraction provided by Spark Streaming
- Represents a continuous stream of data
- Contains a continuous series of RDDs at different time

Architecture



Register on Twitter Apps (Do this ASAP)

https://developer.twitter.com/en/apply-for-access.html



Register on Twitter Apps (Do this ASAP)

↓

https://developer.twitter.com/en/apply-for-access.html

```
# credentials
# TODO: replace with your own credentials
ACCESS_TOKEN = ''      # your access token
ACCESS_SECRET = ''     # your access token secret
CONSUMER_KEY = ''      # your API key
CONSUMER_SECRET = ''   # your API secret key
```

Socket

Using TCP source -- need to provide IP and Port for the client to connect

```
class twitter_client:
    def __init__(self, TCP_IP, TCP_PORT):
      self.s = s = socket.socket(socket.AF_INET, socket.SOCK_STREAM)
      self.s.bind((TCP_IP, TCP_PORT))

    def run_client(self, tags):
      try:
        self.s.listen(1)
        while True:
          print("Waiting for TCP connection...")
          conn, addr = self.s.accept()
          print("Connected... Starting getting tweets.")
          sendData(conn,tags)
          conn.close()
      except KeyboardInterrupt:
        exit
```

Spark Streaming

```
if __name__ == '__main__':
    # Spark settings
    conf = SparkConf()
    conf.setMaster('local[2]')
    conf.setAppName("TwitterStreamApp")

    # create spark context with the above configuration
    sc = SparkContext(conf=conf)
    sc.setLogLevel("ERROR")

    # create sql context, used for saving rdd
    sql_context = SQLContext(sc)

    # create the Streaming Context from the above spark context with batch interval size 5 seconds
    ssc = StreamingContext(sc, 5)
    # setting a checkpoint to allow RDD recovery
    ssc.checkpoint("~/checkpoint_TwitterApp")

    # read data from port 9001
    dataStream = ssc.socketTextStream("localhost",9001)
    dataStream.pprint()
```

Create a local StreamingContext with two working threads and batch interval of 5 second.

Create stream from TCP socket IP localhost and Port 9001

Spark Streaming

```
ssc.start()
time.sleep(STREAMTIME)
ssc.stop(stopSparkContext=False, stopGraceFully=True)
```

```
STREAMTIME = 600          # time that the streaming process runs
```

Start streaming context

Stop after 600 seconds (You can set STREAMTIME to a smaller value at first)

Save results to BigQuery

Start streaming

1. Run twitterHTTPClient.py
2. Run sparkStreaming.py

You can test sparkStreaming.py multiple times and leave twitterHTTPClient.py running

Stop twitterHTTPClient.py (on job page of the cluster or use gcloud command)

Task1: hashtagCount

```python
def hashtagCount(words):
    """
    Calculate the accumulated hashtags count sum from the beginning of the stream
    and sort it by descending order of the count.
    Ignore case sensitivity when counting the hashtags:
        "#Ab" and "#ab" is considered to be a same hashtag
    You have to:
    1. Filter out the word that is hashtags.
       Hashtag usually start with "#" and followed by a serious of alphanumeric
    2. map (hashtag) to (hashtag, 1)
    3. sum the count of current DStream state and previous state
    4. transform unordered DStream to a ordered Dstream
    Hints:
        you may use regular expression to filter the words
        You can take a look at updateStateByKey and transform transformations
    Args:
        dstream(DStream): stream of real time tweets
    Returns:
        DStream Object with inner structure (hashtag, count)
    """

    # TODO: insert your code here
    pass
```

Task2: wordCount

```
WORD = ['data', 'spark', 'ai', 'movie', 'good']     #the words you should filter and do word count

# Helper functions
```

```
def wordCount(words):
    """
    Calculte the count of 5 sepcial words for every 60 seconds (window no overlap)
    You can choose your own words.
    Your should:
    1. filter the words
    2. count the word during a special window size
    3. add a time related mark to the output of each window, ex: a datetime type
    Hints:
        You can take a look at reduceByKeyAndWindow transformation
        Dstream is a serious of rdd, each RDD in a DStream contains data from a certain interval
        You may want to take a look of transform transformation of DStream when trying to add a time
    Args:
        dstream(DStream): stream of real time tweets
    Returns:
        DStream Object with inner structure (word, (count, time))
    """

    # TODO: insert your code here
    pass
```

Task3: Save results

Create a dataset:

bq mk <Dataset name>

Replace with your own bucket and dataset name:

```
# global variables
bucket = ""    # TODO : replace with your own bucket name
output_directory_hashtags = 'gs://{}/hadoop/tmp/bigquery/pyspark_output/hashtagsCount'.format(bucket)
output_directory_wordcount = 'gs://{}/hadoop/tmp/bigquery/pyspark_output/wordcount'.format(bucket)

# output table and columns name
output_dataset = ''                    #the name of your dataset in BigQuery
output_table_hashtags = 'hashtags'
columns_name_hashtags = ['hashtags', 'count']
output_table_wordcount = 'wordcount'
columns_name_wordcount = ['word', 'count', 'timestamp']
```

Task3: Save results

```
# save hashtags count and word count to google storage
# used to save to google BigQuery
# You should:
#   1. topTags: only save the last DStream
#   2. wordCount: save each DStream
# Hints:
#   1. You can take a look at foreachRDD transformation
#   2. You may want to use helper function saveToStorage
# TODO: insert your code here
```

Sample Results

hashtags

Schema Details Preview

Row	count	hashtags
1	25	#valimai
2	14	#ai
3	11	#isapafeelgoodweekend
4	8	#isapawithfeelings
5	7	#วาร์ปสิวะ
6	7	#thalaajith
7	6	#warpsiwax
8	5	#mainemendoza
9	5	#jojorabbit
10	4	#bigdata
11	4	#uncen

wordcount

Schema Details Preview

Row	time	count	word
1	2019-10-18 23:30:10 UTC	2	ai
2	2019-10-18 23:30:50 UTC	2	ai
3	2019-10-18 23:31:30 UTC	3	ai
4	2019-10-18 23:31:50 UTC	5	ai
5	2019-10-18 23:31:10 UTC	8	ai
6	2019-10-18 23:30:30 UTC	10	ai
7	2019-10-18 23:30:10 UTC	1	data
8	2019-10-18 23:31:50 UTC	1	data
9	2019-10-18 23:30:50 UTC	1	data
10	2019-10-18 23:31:10 UTC	2	data
11	2019-10-18 23:31:30 UTC	2	good

Reference

https://spark.apache.org/docs/latest/streaming-programming-guide.html