CS4225
AY24/25 SEM 1
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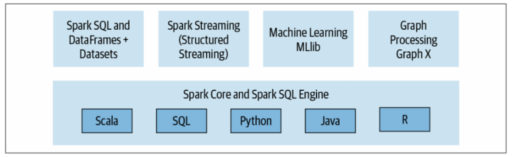
Apache Spark

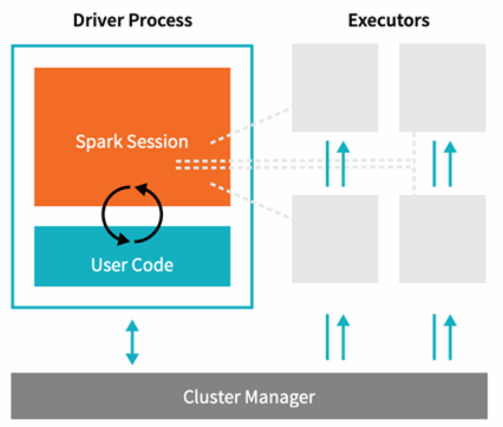
Hadoop vs Spark

- **Hadoop**: Disk-based, MapReduce, HDFS. Not suitable for iterative algorithms as it incurs network and disk I/O overhead for intermediate data.
- **Spark**: In-memory, DAG, RDDs. In the event memory is insufficient, Spark spills data from memory to disk.

Spark Architecture and APIs



Spark SQL and DataFrames + Datasets
Spark Streaming (Structured Streaming)
Machine Learning MLlib
Graph Processing Graph X
Spark Core and Spark SQL Engine
Scala
SQL
Python
Java
R



- **Driver Process**: Manages the execution of the Spark job. Responds to user inputs. Distribute work to the executors.
- **Cluster Manager**: Manages the resources of the cluster. Eg. YARN, Mesos, Kubernetes.
- **Worker Node**: Runs the executors.
- **Executor**: Runs tasks and keeps data in memory or disk storage across them.
- **RDDs**: Resilient Distributed Datasets. A collection of JVM objects. Functional operators (map, filter, etc) are applied to RDDs to transform them.
- **DataFrames**: A distributed collection of data organized into named columns. Similar to a table in a relational database. Expression-based transformation operations. Logical plans and optimisers.
- **Datasets**: A distributed collection of data with a known schema. Combines the benefits of RDDs and DataFrames. Internally rows, externally JVM objects. Typs safe and fast.

RDDs

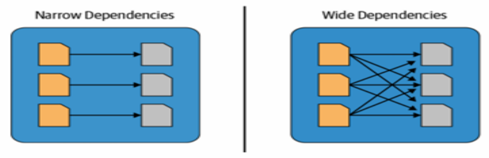
- **Resilient Distributed Datasets**
- Fault-tolerant collection of elements that can be operated on in parallel
- Immutable, partitioned collection of records
- Distributed across a cluster of machines.

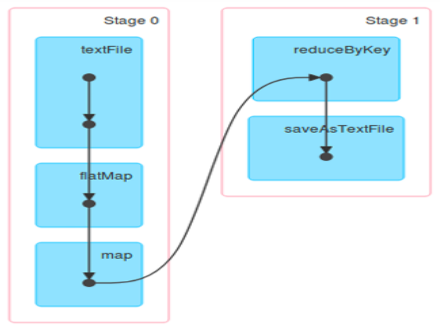
Transformations and Actions

- Transformations are operations that create a new RDD from an existing one.
- Lazy evaluation: Transformations are not executed immediately. They are only executed when an action is called. This allows Spark to optimise the execution plan.
- Example: `map`, `filter`, `flatMap`, `groupByKey`, `reduceByKey`, `join`, `order`, `select`
- Actions are operations that return a value to the driver program after running a computation on the dataset.
- Example: `collect`, `count`, `reduce`, `saveAsTextFile`, `foreach`, `take`, `show`
- Execution of transformations and actions are executed in parallel accross different worker machines as RDDs are distributed across different worker machines. Results are returned to the driver program in the final step.
- Caching: Persisting RDDs in memory across operations. Useful for iterative algorithms.
- `cache()` is a transformation that persists the RDD in memory.
- `persist(options)` is an action that allows for more control over the persistence of the RDD.
- `unpersist()` is an action that removes the RDD from memory.
- We should cache RDDs that are used multiple times in the computation or when it is expensive to recompute the RDD.
- If we did not cache the RDD, Spark will recompute the RDD each time it is used in an action.
- When worker nodes have insufficient memory, Spark may evict LRU RDDs from memory to disk.

Directed Acyclic Graph (DAG)

- A DAG is a graph with directed edges and no cycles.
- In Spark, the DAG is a logical representation of the computation.
- Transformations construct the DAG; actions execute the DAG.
- Spark optimises the DAG by combining operations and minimising data shuffling.
- Narrow dependencies: Each partition of the parent RDD is used by at most one partition of the child RDD. Example: `map`, `filter`, `flatMap`, `contains`
- Wide dependencies: Each partition of the parent RDD may be used by multiple partitions of the child RDD. Example: `groupByKey`, `join`, `reduceByKey`, `sortByKey`, `orderByKey`
- In the DAG, consecutive narrow transformations are combined into a single stage and executed on the same machines. Wide transformations are separated into different stages.
- Across stages, data is shuffled across the network, which involves writing intermediate data to disk.
- Spark tries to minimise the number of stages and the amount of data shuffled.
- **Lineage**: The sequence of transformations that lead to an RDD.
- If a worker node fails, Spark can recompute the lost partitions of an RDD using the lineage. Note: we only need to recompute the lost partitions, not the entire RDD.





DataFrames

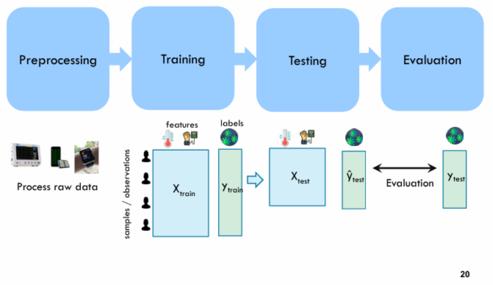
- A distributed collection of data organised into named columns.
- Similar to a table in a relational database.
- Easier to use than RDDs as it has a higher-level API.
- All Dataframe operations are still ultimately compiled down to RDD operation by Spark.
- Generally, transformation functions take in either strings or column objects.
- Transformations are still lazyly evaluated.

Spark SQL

- Spark SQL is a module for working with structured data.
- It provides a programming abstraction called DataFrames and can also act as a distributed SQL query engine.
- Spark SQL provides a domain-specific language for working with structured data.
- It allows running SQL queries on existing RDDs and DataFrames.
- Catalyst optimiser is the Spark SQL query optimiser. It takes a computational query and converts it into an optimised logical plan. Four Phases: Analysis, Logical Optimisation, Physical Planning, Code Generation (Project Tungsten).
- Multiple physical plans can be generated for a single logical plan. The optimiser chooses the best physical plan based on cost estimation.
- Project Tungsten is the Spark SQL execution engine. It aims to improve performance by optimising memory usage and CPU utilisation.
- Tungsten optimises memory usage by using binary processing, cache-aware computation, and code generation.
- **Unified API**: Spark SQL can be used with Java, Scala, Python, SQL, and R. It has one engine for all types of data processing.

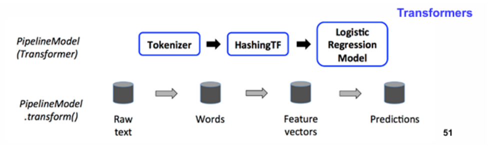
Machine Learning with Spark

Typical Machine Learning Pipeline



- Data Quality: Missing values (impute, drop, add column indicating it is missing or not)
- Categorical Encoding: Convert categorical variables to numerical variables. Numerical values are often assigned in a way that represents the ordinal relationship between the categories or inherent order among the categories.
- One Hot Encoding: Convert categorical variables to binary vectors. Each category is represented by a binary vector. Useful when there is no ordinal relationship between the categories, and to ensure that the categorical variable does not imply any numerical relationship.
- Normalization: Scale the features to a standard range. Useful for algorithms that are sensitive to the scale of the input features. Example: clipping, log transform, standard scalerm, min-max scaler.
- Logistic Regression: A linear model for binary classification. It models the probability that the output is 1 given the input features. Ultilses the sigmoid function. $\sigma(x) = \frac{1}{1+e^{-x}}$
- $\hat{y} = \sigma(x \cdot w + b)$
- Cross Entroypy Loss: Measures the difference between two probability distributions. It is used as the loss function for logistic regression. $L(y, \hat{y}) = -y\log(\hat{y}) - (1-y)\log(1-\hat{y})$
- Gradient Descent: An optimisation algorithm that minimises the loss function. It iteratively updates the weights and biases in the direction of the negative gradient of the loss function.
- $w_{t+1} = w_t - \alpha \nabla_w L(w_t)$
- Evaluation Metrics: Accuracy, Precision, Recall, F1 Score, ROC Curve, AUC.
- Accuracy: $\frac{TP+TN}{TP+TN+FP+FN}$
- Precision: $\frac{TP}{TP+FP}$
- Recall: $\frac{TP}{TP+FN}$
- F1 Score: $2 \times \frac{Precision \times Recall}{Precision + Recall}$
- Errors: Mean Squared Error, Mean Absolute Error, Root Mean Squared Error.
- Mean Squared Error: $\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
- Mean Absolute Error: $\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$
- Root Mean Squared Error: $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
- R Squared Value (0 to 1): Measures the proportion of the variance in the dependent variable that is predictable from the independent variable. The higher the better.

Pipelines


Transformers
PipelineModel (Transformer)
Tokenizer
HashingTF
Logistic Regression Model
PipelineModel .transform()
Raw text
Words
Feature vectors
Predictions
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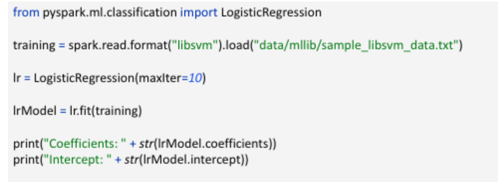
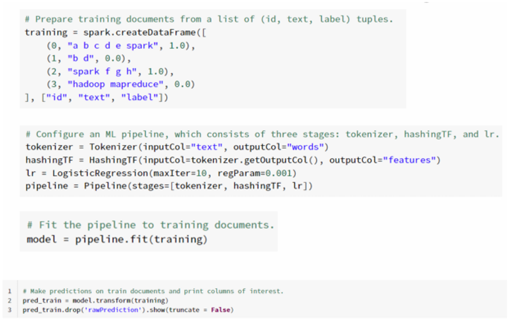
- Benefits: Better code reuse, Easier to perform cross validation, Easier to tune hyperparameters, Easier to productionise the model.
- Transformers are the building blocks of a pipeline.
- A transformer has a transform() method that takes in a DataFrame and returns a new DataFrame.
- Example: VectorAssembler, StringIndexer, OneHotEncoder, StandardScaler, LogisticRegression
- Generally, these transformers output a new DataFrame which append their result to the original DataFrame.
- A fitted model (e.g LogisticRegressionModel) is also a transformer. It transforms Dataframe by adding a prediction column.
- Estimators is an algorithm that takes in data, and outputs a fitted model. Example: A learnign algorithm like LogisticRegression can be fit to data, producing the trained logistic regression model.
- Estimators have a `fit()` method that takes in a DataFrame and returns a Transformer.



```
from pyspark.ml.classification import LogisticRegression

training = spark.read.format("libsvm").load("data/mllib/sample_libsvm_data.txt")

lr = LogisticRegression(maxIter=10)

lrModel = lr.fit(training)

print("Coefficients: " + str(lrModel.coefficients))
print("Intercept: " + str(lrModel.intercept))
```

- Pipelines are a sequence of stages. Each stage is either a Transformer or an Estimator.
- Pipeline itself is an Estimator. It has a `fit()` method that takes in a DataFrame and returns a PipelineModel.
- When `fit()` is called on a Pipeline, the stages are executed in order. For Transformers, the `transform()` method is called. For Estimators, the `fit()` method is called.
- The output of `Pipeline.fii()` is a PipelineModel, which is a Transformer, and consists of a series of Transformers.
- The `transform()` method of the PipelineModel applies the fitted model to the input DataFrame.

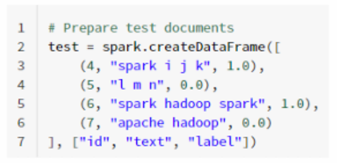


```
# Prepare training documents from a list of (id, text, label) tuples.
training = spark.createDataFrame([
    (0, "a b c d e spark", 1.0),
    (1, "b d", 0.0),
    (2, "spark f g h", 1.0),
    (3, "hadoop mapreduce", 0.0)
], ["id", "text", "label"])
```

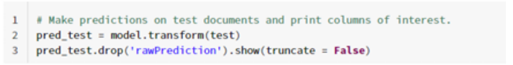
```
# Configure an ML pipeline, which consists of three stages: tokenizer, hashingTF, and lr.
tokenizer = Tokenizer(inputCol="text", outputCol="words")
hashingTF = HashingTF(inputCol=tokenizer.getOutputCol(), outputCol="features")
lr = LogisticRegression(maxIter=10, regParam=0.001)
pipeline = Pipeline(stages=[tokenizer, hashingTF, lr])
```

```
# Fit the pipeline to training documents.
model = pipeline.fit(training)
```

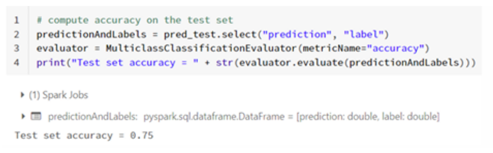
```
# Make predictions on train documents and print columns of interest.
pred_train = model.transform(training)
pred_train.drop('rawPrediction').show(truncate = False)
```



```
# Prepare test documents
test = spark.createDataFrame([
    (4, "spark i j k", 1.0),
    (5, "l m n", 0.0),
    (6, "spark hadoop spark", 1.0),
    (7, "apache hadoop", 0.0)
], ["id", "text", "label"])
```



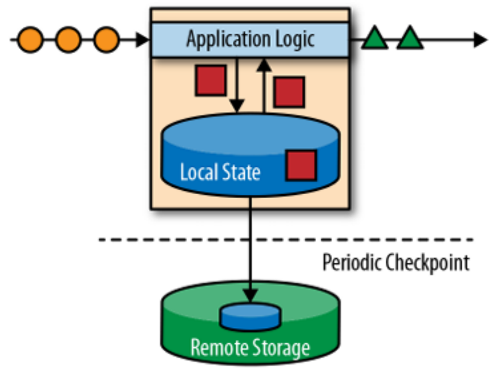
```
# Make predictions on test documents and print columns of interest.
pred_test = model.transform(test)
pred_test.drop('rawPrediction').show(truncate = False)
```



```
# compute accuracy on the test set
predictionAndLabels = pred_test.select("prediction", "label")
evaluator = MulticlassClassificationEvaluator(metricName="accuracy")
print("Test set accuracy = " + str(evaluator.evaluate(predictionAndLabels)))
```

```
▸ (1) Spark Jobs
▸ predictionAndLabels:  pyspark.sql.dataframe.DataFrame = [prediction: double, label: double]
Test set accuracy = 0.75
```

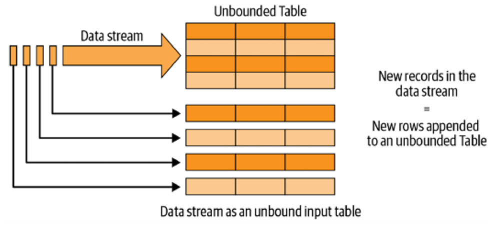
Stream Processing



Goal: Process data in real-time as it is generated. State can be stored and accessed in many different places including program variables, local files, or embedded/external databases.

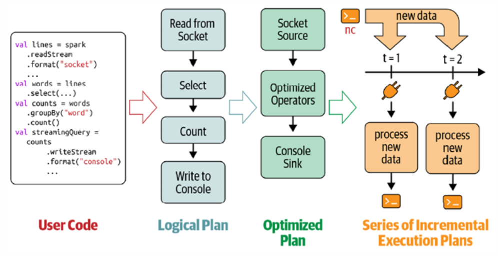
Micro-Batch Stream Processing

- Spark Structured Streaming uses a micro-batch processing model.
- Data from the input stream is divided into micro batches, each of which will be processed in the Spark cluster in a distributed manner.
- Small deterministic tasks generate the output of each micro-batch. Time is divided into small intervals, and data is processed in each interval.
- Advantages: quick; recover from failures efficently; deterministic nature ensures end-to-end exactly-once processing.
- Disadvantages: latency (cannot handle millisecond); micro-batch size affects latency and throughput; micro-batch processing can be less efficient than true stream processing.
- It is sufficient for most use cases.
- In Spark Structured Streaming, the input data is treated as an unbounded table.


Unbounded Table
Data stream
New records in the data stream = New rows appended to an unbounded Table
Data stream as an unbound input table

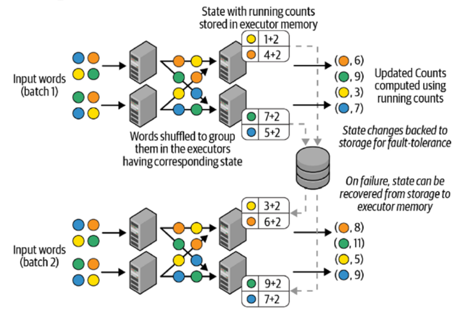
- Five Steps to Define Steaming Query:
  1. Define the input source.
  2. Transform Data.
  3. Define output sink and output mode.
  4. Specifying processing details. (Triggering details, checkpointing, etc)
  5. Start the query.

Incremental execution of streaming queries



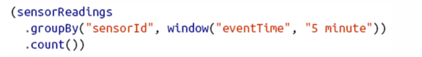
```
val lines = spark
  .readStream
  .format("socket")
  ...
val words = lines
  .select(...)
val counts = words
  .groupBy("word")
  .count()
val streamingQuery =
  counts
      .writeStream
      .format("console")
      ...
```

Distributed state management in Structured Streaming

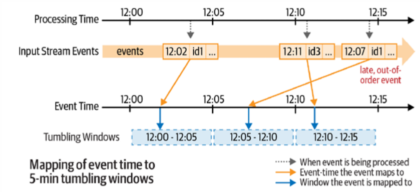

State with running counts stored in executor memory
Input words (batch 1)
Input words (batch 2)
Words shuffled to group them in the executors having corresponding state
Updated Counts computed using running counts
State changes backed to storage for fault-tolerance
On failure, state can be recovered from storage to executor memory
1+2
4+2
7+2
5+2
3+2
6+2
9+2
7+2
(●, 6)
(●, 9)
(●, 3)
(●, 7)
(●, 8)
(●, 11)
(●, 5)
(●, 9)

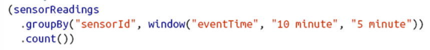
Data Transformation

- **Stateless Transformations:**
  - Process each row individually without needing information from previous rows
  - Projection operations: `select()`, `explode()`, `map()`, `flatMap()`
  - Selection operations: `filter()`, `where()`
- **Stateful Transformations:**
  - Process each row based on information from previous rows.
  - Example: `DataFrame.groupBy().count()`
  - In every micro-batch, the incremental plan adds the count of new records to the previous count generated by the previous micro-batch
  - The state is maintained in the memory of the Spark executors and is checkpointed to the configured location to tolerate failures.
- **Stateful Streaming Aggregations:**
  - **Aggregations not based on time windows:**
    - Global aggregations: `groupBy().count()`
    - Grouped aggregations: `groupBy("sensorId").mean("value")`
    - Supported aggregations: `count()`, `sum()`, `avg()`, `min()`, `max()`, `countDistinct()`, `collect_set()`, `approx_count_distinct()`
  - Processing Time: The time at which the data is processed by the system. (Not deterministic, susceptible to system delays)
  - Event Time: The time at which the event occurred in the real world. (Deterministic)
  - Event time decouples the processing speeed from the results. An event time window computation will yield the same result regardless of the processing time.
  - Watermark: A threshold that determines how late the data can be in event time. Data that arrives later than the watermark is considered late data.
  - **Aggregations with Event-Time Windows:**
    - Example: `sensorReadings.groupBy("sensorId", window("eventTime", windowLength, shiftAmt)).count()`

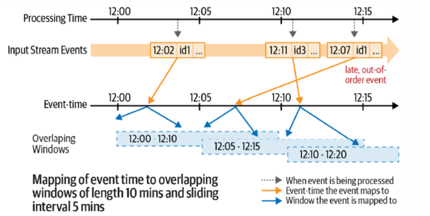


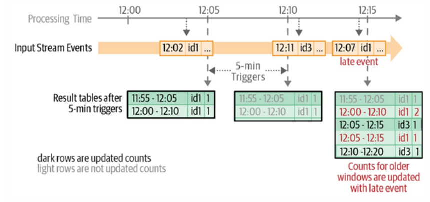
```
(sensorReadings
  .groupBy("sensorId", window("eventTime", "5 minute"))
  .count())
```





```
(sensorReadings
  .groupBy("sensorId", window("eventTime", "10 minute", "5 minute"))
  .count())
```

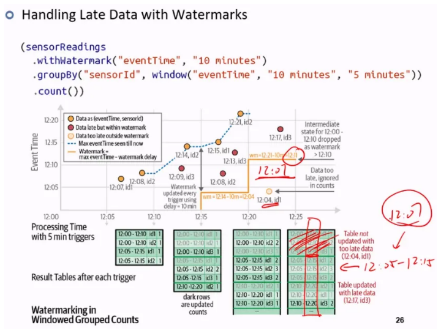



Processing Time
12:00
12:05
12:10
12:15
Input Stream Events
12:02 id1 ...
12:11 id3 ...
12:07 id1 ...
late event
5-min Triggers
Result tables after 5-min triggers
dark rows are updated counts
light rows are not updated counts
Counts for older windows are updated with late event

11:55 - 12:05	id1	1
12:00 - 12:10	id1	1

11:55 - 12:05	id1	1
12:00 - 12:10	id1	1

11:55 - 12:05	id1	1
12:00 - 12:10	id1	2
12:05 - 12:15	id3	1
12:05 - 12:15	id1	1
12:10 -12:20	id3	1



- Handling Late Data with Watermarks

```
(sensorReadings
  .withWatermark("eventTime", "10 minutes")
  .groupBy("sensorId", window("eventTime", "10 minutes", "5 minutes"))
  .count())
```

Data as (eventTime, sensorId)
Data late but within watermark
Data too late outside watermark
Max eventTime seen till now
Watermark = max eventTime - watermark delay
Event Time
12:20
12:15
12:10
12:05
12:07, id1
12:08, id2
12:14, id2
12:09, id3
12:15, id1
12:13, id3
12:08, id2
12:21, id2
12:17, id3
12:04, id1
Watermark updated every trigger using delay = 10 min
wm = 12:14 - 10m = 12:04
wm = 12:21 - 10m = 12:11
12:07
Intermediate state for 12:00 - 12:10 dropped as watermark > 12:10
Data too late, ignored in counts
12:00
12:05
12:10
12:15
12:20
12:25
Processing Time with 5 min triggers
Result Tables after each trigger
dark rows are updated counts
Table not updated with too late data (12:04, id1)
12:07
← 12:05 – 12:15
Table updated with late data (12:17, id3)
Watermarking in Windowed Grouped Counts
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- Take the latest **event time** and minus the watermark time. Let go of the rows in the result window with end interval time lower than calculated time.
- Watermark just determines which window records in the table to drop off. If it was not dropped, it may still be updated even though the late data event time is before the watermark time.
- Data with event time of 12:07 is still updated as the event window [12:05 — 12:15] is not dropped as the window end interval time is not before the watermark time.
- **Performance Tuning:**
  - Cluster resource provisioning appropriately to run 24/7
  - Number of partitions for shuffles to be set much lower than batch queries
  - Setting source rate limits for stability
  - Multiple streaming queries in the same Spark application
  - Tuning Spark SQL Engine