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Roll No.: 1801CS16 CS555 Chandrawanshi 25 Nov 2021

Q.1) ⇒ a) a-iii, b-iv, c-ii, d-i

Q.2) → c) Basically Available Soft-state Eventual

Q.3) ⇒ a) i, ii, iii

Q.4) → a) Cassandra is a NoSQL database and RDBMS uses SQL for querying and maintaining the database

Q.5) ⇒ c) Partition Tolerance.

Q.6) ⇒ a) Record at a time

Q.7) ⇒ d) All of the above.

Q.8) ⇒ a) MapReduce, HDFS.

Q.9) → b) Property.

Q.10) ⇒ b) The location details of where the first whole record in a block begins and the last whole record in the block ends

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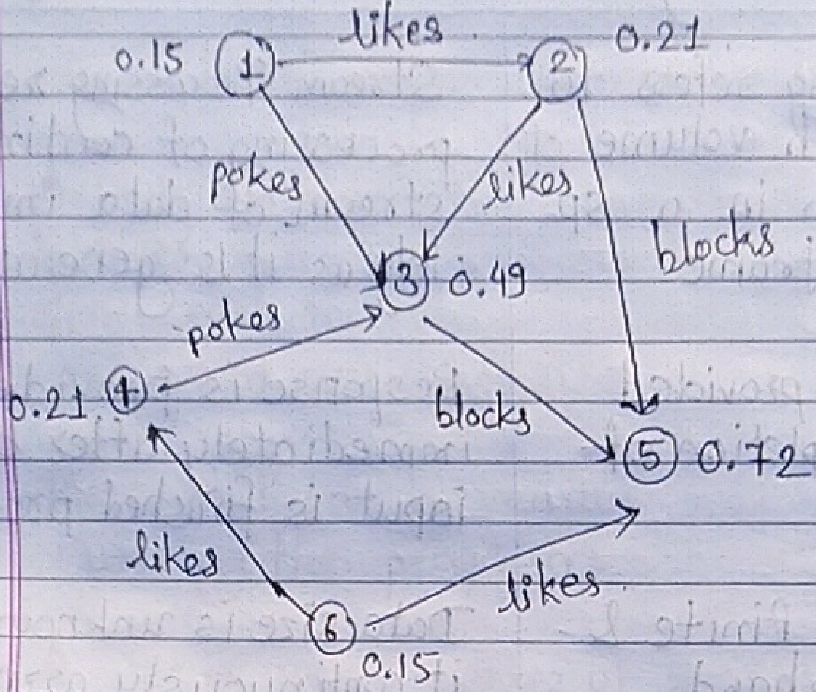
Q.11) → Given, Graph



Graph Object :

Vertices RDD	
ID	Attr
1	0.15
2	0.21
3	0.49
4	0.21
5	0.72
6	0.15

Edges RDD		
Src	Dest	Attr
1	2	likes
1	3	pokes
2	3	likes
2	5	blocks
3	5	blocks
4	3	pokes
6	4	likes
6	5	likes

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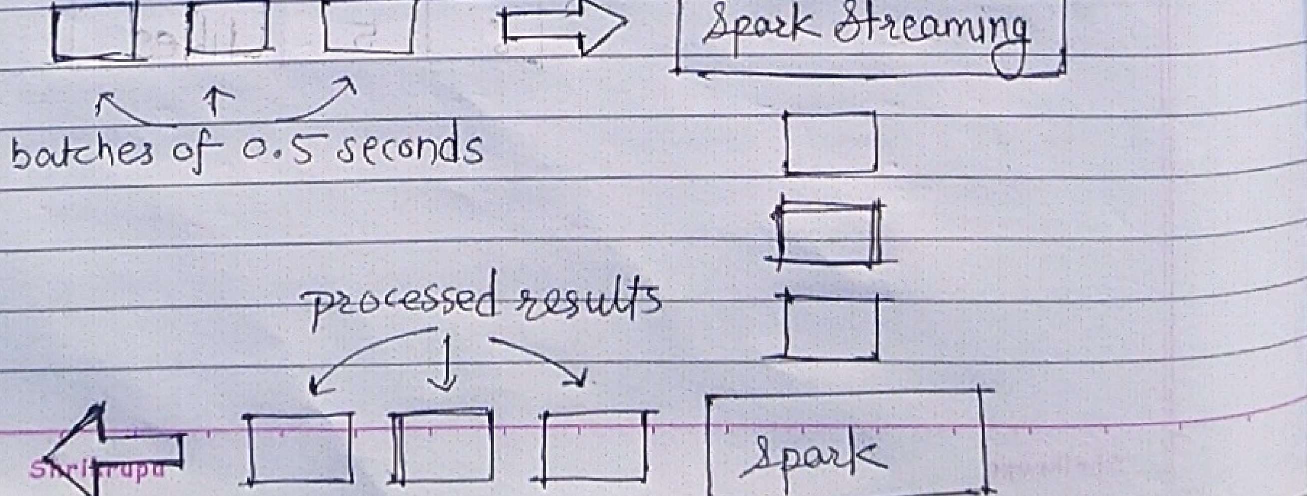
Q 12) ⇒

Batch Processing	Stream Processing.
a) Batch processing refers to processing high volume of data in batch in a specified time frame.	Stream Processing refers to processing of continuous stream of data immediately as it is generated.
b) The response is provided after job completion of all the data.	Response is provided immediately after one input is finished processing
c) Data size is finite & known beforehand	Data size is unknown & it continuously arrives.

In discretized stream operations, the streaming data is chunked into small batches & each batch is treated as RDD & process them using RDD operations & finally the processed results of the RDD operations are returned in batches.

For example we get a stream of tweets from Twitter API. They can be chunked into batches every 0.5 seconds & these batches can be stored as RDDs & further processed



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Q.13) ⇒ Given,
Total no of mappers = a
Total no. of Reducers = b

A mapreduce job with a mappers and b reducers involves upto $a * b$ distinct copy operations since each mapper may have intermediate output going to every reducer.

There will be b output files generated after running the program.

As there are c number of unique words.
Each of the b files will contain exactly $\frac{c}{b}$ <key, value> pairs.

⇒ Total pairs $= \frac{c}{b} \times b = c$

Eg. In a word count example, a<key, value> pair is obtained from every word found. If we have 100 words, then 100 <key, value> pairs will be generated from the mappers to the reducers.

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Q14) → **Benefits of spark over mapreduce :**

i) Spark is easy to program whereas mapreduce requires lot of hand coding.
ii) Spark has interactive mode while mapreduce doesn't
iii) Spark executes batch processing jobs much faster (about 10 to 100 times) than map reduce.
iv) Spark uses an abstraction called RDD which in turn makes Spark feature rich.
v) Spark has lower latency as it caches partial/complete results accross distributed nodes on the other hand map reduce is completely disk-based.

How SparkSQL is different from HQL & SQL :

SparkSQL is basically a special component on the spark core engine that supports SQL and HQL without changing any syntax. It basically blurs the line between RDDs and relational tables.

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Q.15) →

Spark's library for machine learning (ML) is called MLib. It is heavily based on scikit-learn's ideas on pipelines. In this library to create a ML model the basic concepts are :

Data Frame :- This ML API uses DataFrama from Spark SQL as on ML dataset, which can hold a variety of Data Types.

Transformer :- A Transformer is an algorithm that can transform one dataframe into another dataframe.

Estimator :- An Estimator is an algorithm which can be fit on a data frame to produce a transformer.

Pipeline : A pipeline chains multiple transformers and estimators together to specify ML workflow.

Parameter : All transformers & estimators share a common API for specifying parameters.

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Q.16) ⇒

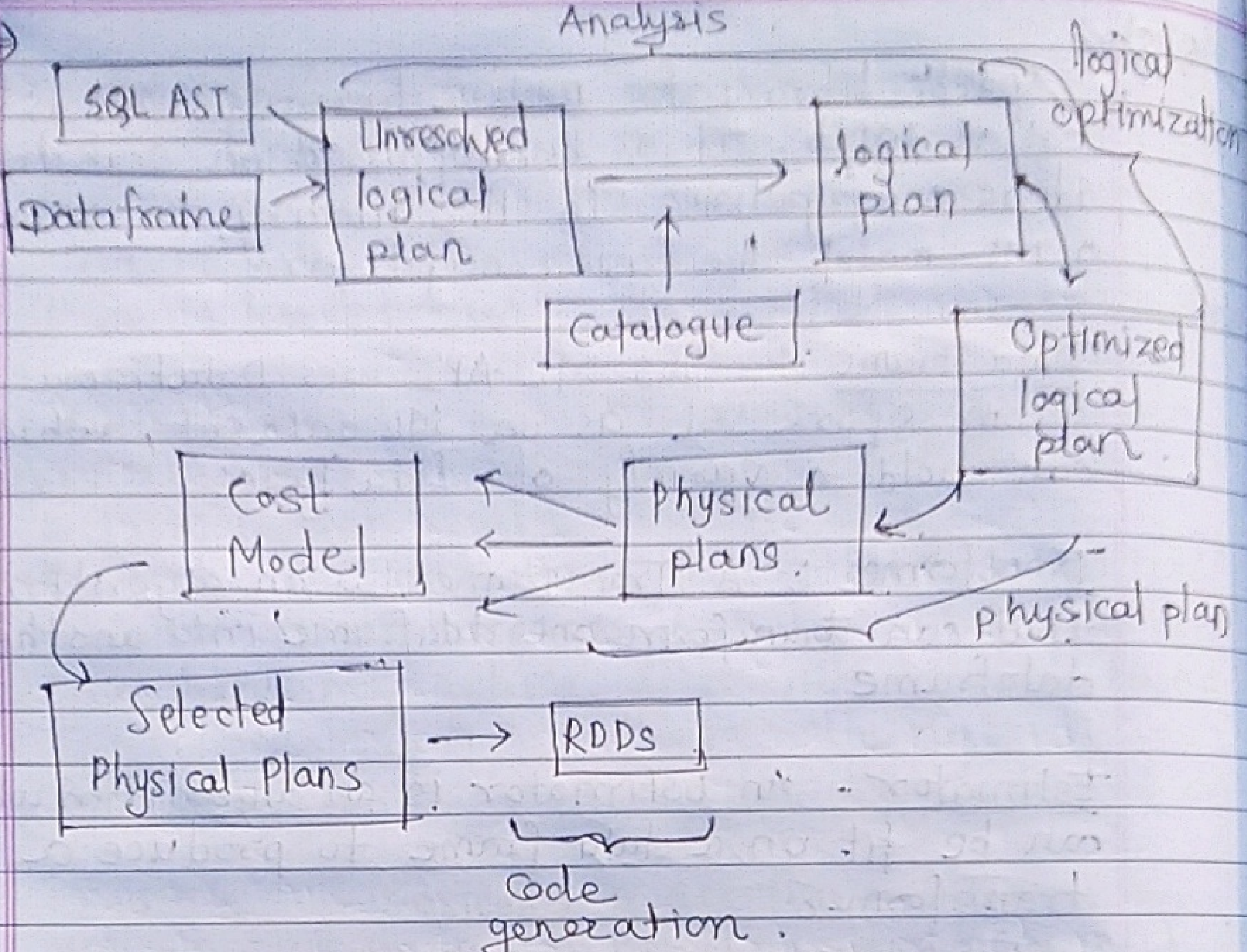

Fig. optimization/execution pipeline for dataframes & SQL.

Dataframes and SQL share the same optimization execution pipeline. Actually, dataframes are tied to spark SQL. Datafram API provides interface & DSL (domain specific lang.) to interact with data. Spark SQL allows manipulation of distributed data similar to SQL. For Dataframe API it assumes a table-like structure similar to SparkSQL. Dataframe is a size-mutable, heterogenous tabular data structure. It is built on top of Spark RDD API. It allows faster execution.

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Q.17) ⇒

Benefits of using GraphX algorithm over a dataset

Relationship between data can be seen everywhere in real world. Graph analytics can make sense of these connections to derive some incredible outputs and to provide more insights that can't be seen with naked eye.

Algos. & their benefits :

1) Page Rank : Measure the importance of each vertex in a graph. eg. In case of flights, if a city has high number of incoming & outgoi-ng flights it might be of more importance.

2) Connected Component : Gives all the connected components and also labels each with an ID. This mechanism can be used in friend recomm-endation system on social networking sites.

3) Triangle Counting :- Used in social network analysis spam detection and link recomm-endation system.

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Q.18) ⇒

Cassandra :- It is a free open-source, distributed wide-column store, NoSQL database management system. designed to handle large amounts of data across many commodity servers, providing high availability with no single point of failure.

Advantages :

* Highly Scalable
* High Availability through data replication at different location and on different data centres.
* High fault tolerance through replication & distributed arch.
* High Performance along with hybrid cloud support.

Cassandra Write :

- clients sends write to one coordinator node in cluster
- Coordinator uses partitioner to send query to all replica nodes responsible for key.
- When X replicas respond coordinators sends ACK to client. If any replica is down, write is done to all others and write is kept locally till the down replic restarts. Buffering done in case all are down.
- On receiving a write
  - → log it in disk commit log
  - → make changes to apt. memtable.
- If memtable is full, flush to disk.

→ DataFile : An SSTable - list of key, value pairs (sorted by key)

→ IndexFile : An SSTable of pairs.

→ A bloom filer for efficient search

→ SSTables are immutable.

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Q.19) →

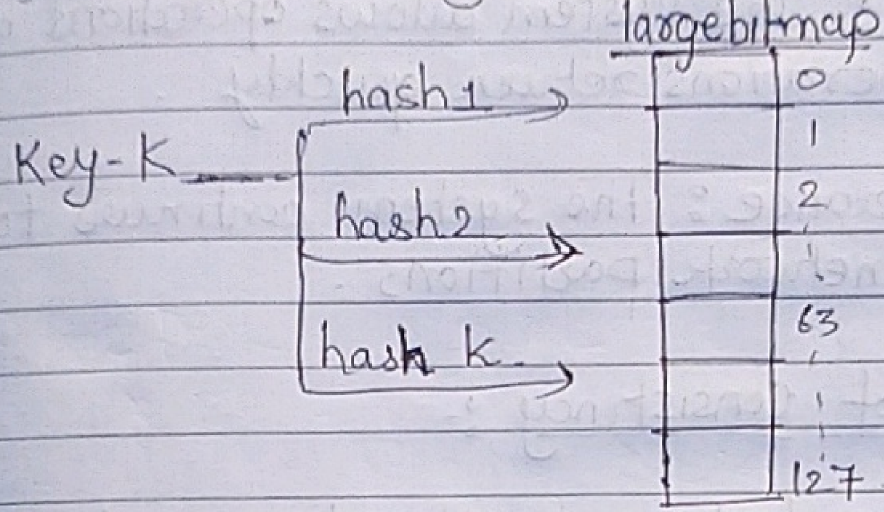
Bloom Filter

i) Compact way of representing a set of items.

ii) Checking for existence is cheap.

iii) Some probability of false positives. (An item not in set may show as present in set).

iv) No False negatives.



On insert
set all hashed bits.

For check
if set
return true
else
return false

Compaction: Data updates accumulate over time and SS Table and logs need to be compacted.

- The process of compaction merges SSTables. ie. by merging updates for a key.
- Run periodically and locally at each server.

Deletion: Don't delete them right away

- Add a tombstone to the log.
- Eventually, when compaction encounters tombstone it will delete them.

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Q.29 ⇒ <u>CAP Theorem</u> :- In a distributed system you can satisfy atmost 2 out of 3 granularities:

1. <u>Consistency</u> : All nodes see same data at any time or reads return latest written values by any client.

2. <u>Availability</u> : The system allows operations all the time and operations return quickly.

3. <u>Partition Tolerance</u> : The system continues to work in spite of network partitions.

<u>Importance of Consistency</u> :-

When we access our bank or investment account via multiple clients we want update done from one to be visible to other. When thousands of customers ae looking to book a flight all updates by any client should be accessible to others.

<u>Importance of Availability</u> :

→ A 500 ms increase in latency at Amazon.com or Google.com can cause 20% drop in revenue.
→ At amazon each added ms of latency will result in \$6M yearly loss.
→ SLAs written by providers predominantly deal with latencies faced by clients.

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Importance of partition tolerance :-

→ Partitions can happen across data centers when the connections are lost.
→ partitions can also occurs within a datacenter due to rack switch outage (one possibility)

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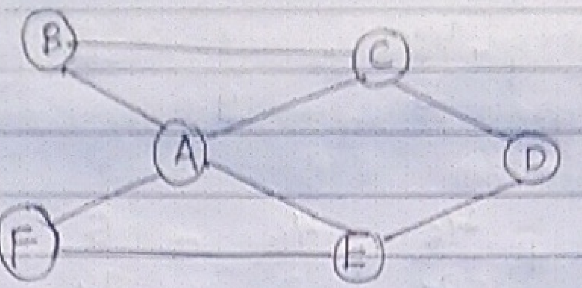
Q.1) ⇒



(a) Partition

A-B B-C A-C | A-E A-F E-F | C-D D-E.

Cut vertex A, E.

Vertex Table.

1,A
2,B
3,C
4,D
5,E
6,F

Edge Table.

mirror cache: 1, 2, 3	1-2
	2-3
	1-3
mirror cache: 1, 5, 6	1-5
	5-6
	1-6
mirror cache: 3, 4, 5	3-4
	4-5

Edge Triplets.

1-2, (1,A), (2,B)
2-3, (2,B), (3,C)
1-3, (1,A), (3,C)
1-5, (1,A), (5,E)
1-6, (1,A), (6,F)
5-6, (5,E), (6,F)
3-4, (3,C), (4,D)
4-5, (4,D), (5,E)

(b) Iteration 1

$$A = \frac{1/6}{2} + \frac{1/6}{3} + \frac{1/6}{3} + \frac{1/6}{2} = \frac{5}{18}$$

$$B = \frac{1/6}{4} + \frac{1/6}{3} = \frac{7}{72}$$

$$C = \frac{1/6}{4} + \frac{1/6}{2} + \frac{1/6}{2} = \frac{5}{24}$$

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$$D = \frac{1/6}{3} + \frac{1/6}{3} = \frac{1}{9}$$

$$E = \frac{1/6}{4} + \frac{1/6}{2} + \frac{1/6}{2} = \frac{5}{24}$$

$$F = \frac{1/6}{4} + \frac{1/6}{3} = \frac{7}{72}$$

Iteration 2

$$A = \frac{5/24}{3} + \frac{7/72}{2} + \frac{7/72}{2} + \frac{5/24}{3} = 0.2361$$

$$B = \frac{5/18}{4} + \frac{5/24}{3} = 0.1388$$

$$C = \frac{5/18}{4} + \frac{7/72}{2} + \frac{1/9}{2} = 0.1736$$

$$D = \frac{5/24}{3} + \frac{5/24}{3} = 0.1388$$

$$E = \frac{5/18}{4} + \frac{1/9}{2} + \frac{7/72}{2} = 0.1736$$

$$F = \frac{5/18}{4} + \frac{5/24}{3} = 0.1388$$

Vertex / PageRank	A	B	C	D	E	F
→	0.2361	0.1388	0.1736	0.1388	0.1736	0.1388

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(C)
(i) ⇒ Array(Edge(5,4,3784), Edge(6,5,3711))
i.e. All the results whose distance is greater than 2500 and top 2 in descending order

(ii) ⇒ ((1,JFK),(2,LAX), 2475)
((5,DFW),(4,HNL), 3784)
((6,OGG),(5,DFW), 3711)
((2,LAX),(3,MIA), 2342)
((6,OGG),(2,LAX), 2486)
((4,HNL),(1,JFK), 2556)

i.e. The graph in form of edge triplets

(iii) ⇒ Distance 3784 from DFW to HNL
Distance 3711 from OGG to DFW
Distance 2556 from HNL to JFK
Distance 2486 from OGG to LAX
Distance 2475 from JFK to LAX
Distance 2342 from LAX to MIA.

i.e. Sort all results in descending order and then output acc. to the given format.

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Q.22) → wSpec1 sees the table as sorted by date & partitioned by name & window size is 3 (row between (-1, 1))

ie.

Name	Date	Amount	Moving Avg.
Alice	2021-05-01	50	$(50+45)/2 = 47.5$
Alice	2021-05-03	45	$(45+50+55)/3 = 50$
Alice	2021-05-04	55	$(45+55)/2 = 50$
Bob	2021-05-01	25	$(25+29)/2 = 27$
Bob	2021-05-04	29	$(29+25+27)/3 = 27$
Bob	2021-05-06	27	$(27+29)/2 = 28$.

Since, window size is 3, so for the current row, a row before and a row after is considered having same name (due to partition).

Q.23) ⇒ MLib is a ML library that contains various ML algos. These include:
- correlation & hypothesis testing
- classification
- regression

ML Components :-

Algorithms : Classification, regression, clustering, collaborative filter.

Pipeline : Constructing, Evaluating, tuning, persistance

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Featurization : extraction , transformation

Utilities : linear Algebra, Statistics .

* End-to-end machine learning pipeline pseudo-code for temp. forecast of a given building :

```
{
 rawdata = spark.read ("x.csv")
 func addcol (ColumnName : String):
     Dataframe => Dataframe = df
     => df.add column (ColumnName).

 vectorizer = VectorAssembler(inputCols = cols,
          OutputCols = "Features")

 Classify = < Model's Code >

 Pipeline = new Pipeline().setStages( Array(
          addcol, vectorizer, Classify))

 Model = pipeline.fit(rawdata) . } .
```

Info/Columns in data :

- Date
- Time .
- TargetTemp
- ActualTemp
- System
- SystemAge
- BuildingID .

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Q.24) → We will use inception V3 model combined with multinomial logistic regression in Spark to build our model.

Steps:

- Load the image to spark dataframe, we manually load each image into spark dataframe with a Target column.
- Split the dataset randomly in 8:2 ratio for training & testing resp.
- For training we will combine inception V3 model and logistic regression in spark.
- The DeepImageFeaturizer automatically peels off the last layer of a pre-trained neural network & uses the output from all the previous layers as features for the logistic regression algorithm.

Pseudo Code:

```
# Create a Spark Session
spark = sparksession.builder.appName ('Digit Recog')
        getorCreate () .

# load image
zero = ImageSchema.readImages ("0"). withColumn ("label", lit(0))
one = ImageSchema.readImages ("1") withColumn ("label", lit(1))
- - - - - -
- - - - - -
nine = ImageSchema.readImages ("9") withColumn ("label", lit(9))
```

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dataframes = [zero, one, two, three , four, five,
six, seven, eight, nine].

# merge dataframe.
df = reduce (lambda first, second : first.union(second), data)

repartion, df = df.repartion(200)
test, train split, train, test = df.randomSplit ([0.8, 0.2], 42)

# Training
featurizer = DeepImageFeaturizer (inputCol = "image",
outputCol = "features",
modelName = "InceptionV3")

# used as a multi-class classifier.
lr = LogisticRegression (maxIter = 5, regParam = 0.03,
elasticNetParam = 0.5, labelCol = "label")

define a pipeline model

sparkdn = Pipeline (stages = [featurizer, lr])
spark_model = sparkdn.fit (train)
# start fitting or training.

After training, model can be evaluated using
F1-score, Precision, Recall, Accuracy on
Testset.