

Real-time Machine Learning with Redis-ML and Apache Spark

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Agenda

- Intro to Redis and Redis Labs 5 min
- Using Redis-ML for Model Serving why and how 10 min
- Building a recommendation system using Spark-ML and Redis-ML 10 min
- QA



Redis Labs – Home of Redis



The commercial company behind Open Source Redis

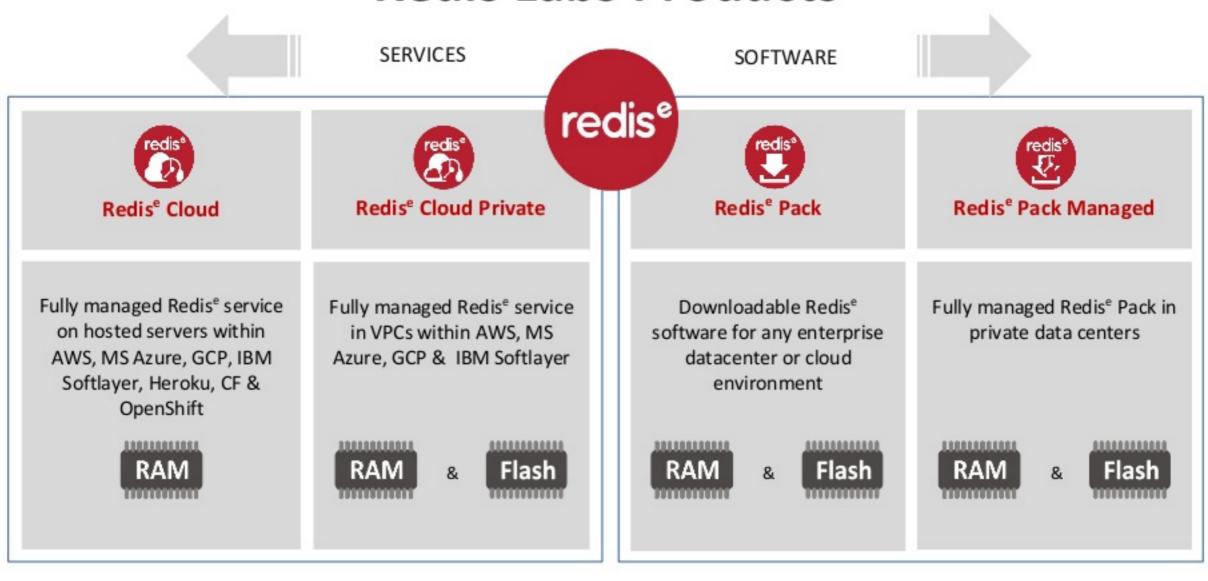


Provider of the Redis Enterprise (Redis^e) technology, platform and products



Founded in 2011 HQ in Mountain View CA, R&D center in Tel-Aviv IL

Redis Labs Products





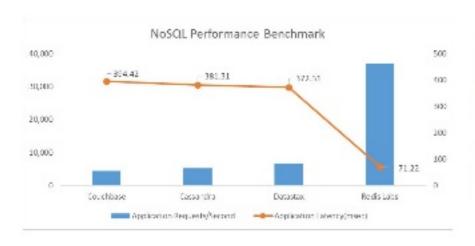
A Brief Overview of Redis

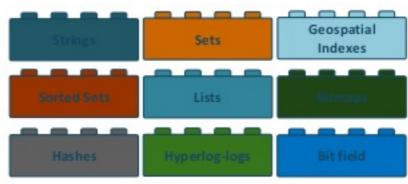
- Started in 2009 by Salvatore Sanfilippo
- Most popular KV store
- In memory disk backed
- Notable Users:
 - Twitter, Netflix, Uber, Groupon, Twitch
 - Many, many more...

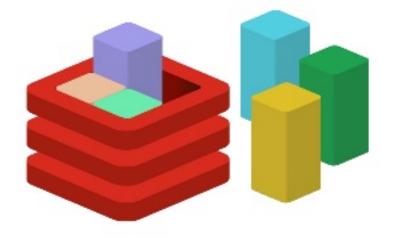




Redis Main Differentiations







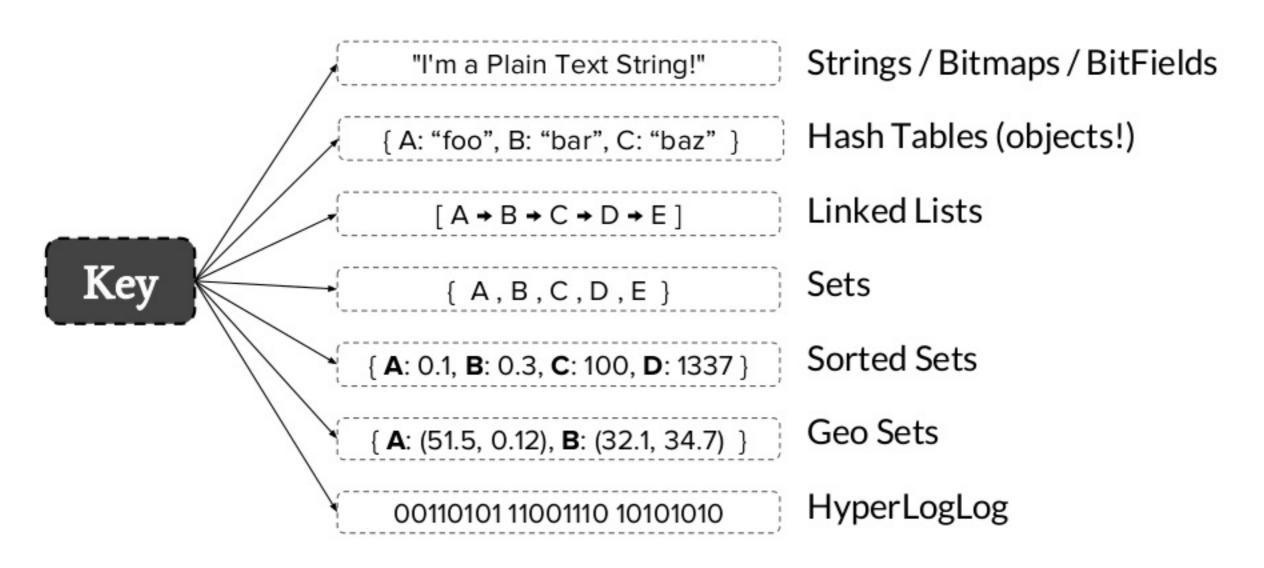
Performance

Simplicity (through Data Structures)

Extensibility (through Redis Modules)



A Quick Recap of Redis





Simple Redis Example (string, hash)

```
127.0.0.1:6379> SET spark summit
OK
127.0.0.1:6379> GET spark
"summit"
127.0.0.1:6379> HMSET spark hash org apache version 2.1.1
OK
127.0.0.1:6379> HGET spark hash version
"2.1.1"
127.0.0.1:6379> HGETALL spark hash
1) "org"
2) "apache"
3) "version"
4) "2.1.1"
```



Another Simple Redis Example (sorted set)

```
127.0.0.1:6379> zadd my_sorted_set 1 foo
(integer) 1
127.0.0.1:6379> zadd my sorted set 5 bar
(integer) 1
127.0.0.1:6379> zadd my sorted set 3 baz
(integer) 1
127.0.0.1:6379> ZRANGE my_sorted_set 0 2
1) "foo"
2) "baz"
3) "bar"
127.0.0.1:6379>
```



What Modules Actually Are

- Dynamic libraries loaded to redis
- Written in C/C++
- Use a C ABI/API isolating redis internals
- Use existing or add new data-structures
- Near Zero latency access to data





Modules: A Revolutionary Approach

Adapt your database to your data, not the other way around

Neural Redis

Simple Neural Network Native to Redis

ReJSON

JSON Engine on Redis.

Pre-released

Rate Limiter

Based on Generic Cell Rate Algorithm (GCRA)

Redis-ML

Machine Learning Model Serving

Time Series

Time series values aggregation in Redis

Crypto Engine Wrapper

Secure way to store data in Redis via encrypt/decrypt with various Themis primitives

RediSearch

Full Text Search Engine in Redis

Graph

Graph database on Redis based on Cypher language

Secondary Index/RQL

Indexing + SQL -like syntax for querying indexes. Pre-released

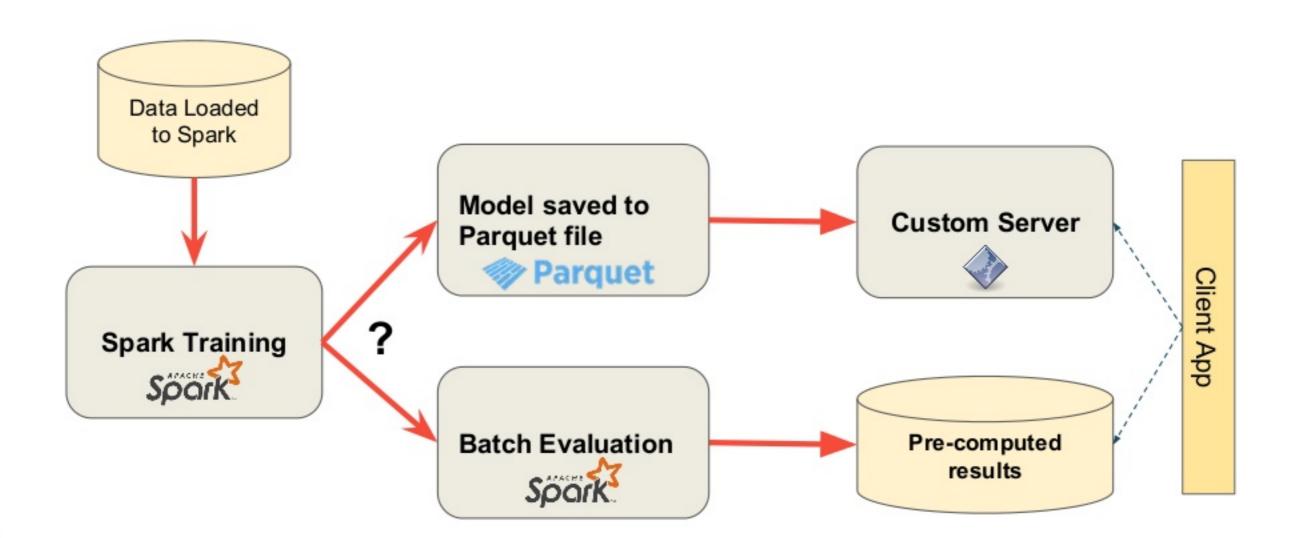




Redis ML

Machine Learning Model Server

Spark-ML End-to-End Flow



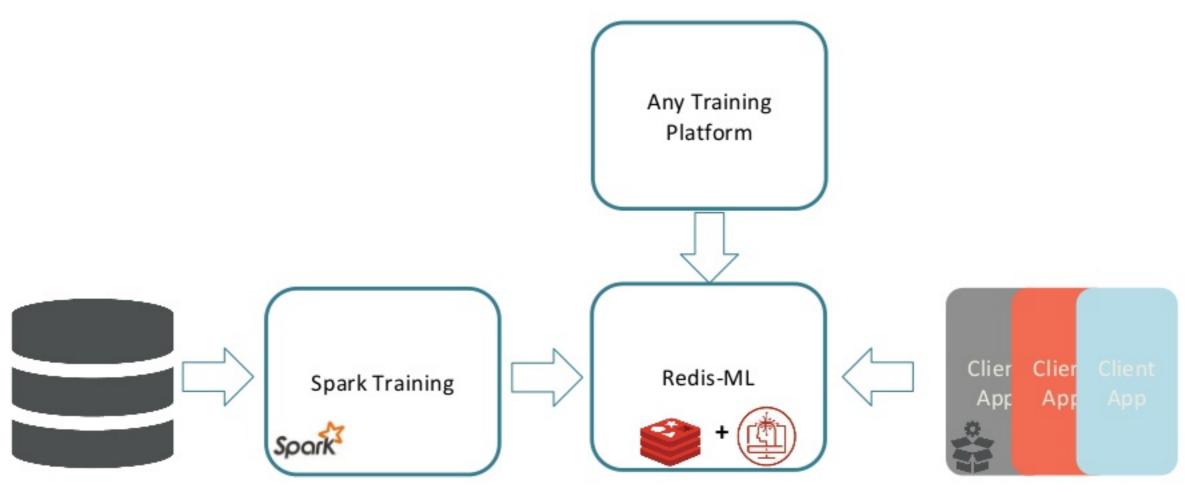


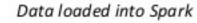
ML Models Serving Challenges

- Models are becoming bigger and more complex
- Can be challenging to deploy & serve
- Do not scale well, speed and size
- Can be very expensive



A Simpler Machine Learning Lifecycle





Model is saved in Redis-ML

Serving Client





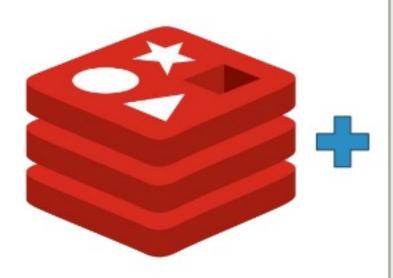
Redis-ML – ML Serving Engine

- Store training output as "hot model"
- Perform evaluation directly in Redis
- Enjoy the performance, scalability and HA of Redis





Redis-ML



ML Models

Tree Ensembles

Linear Regression

Logistic Regression

Matrix + Vector Operations

More to come...



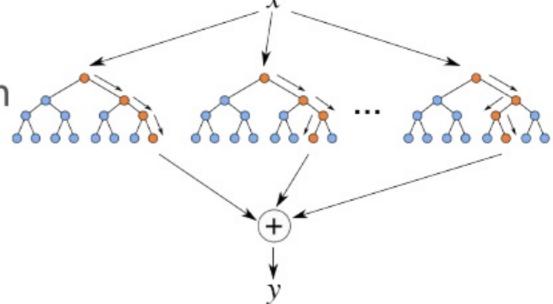
Random Forest Model

A collection of decision trees

Supports classification & regression



- Categorical (e.g. day == "Sunday")
- Numerical (e.g. age < 43)





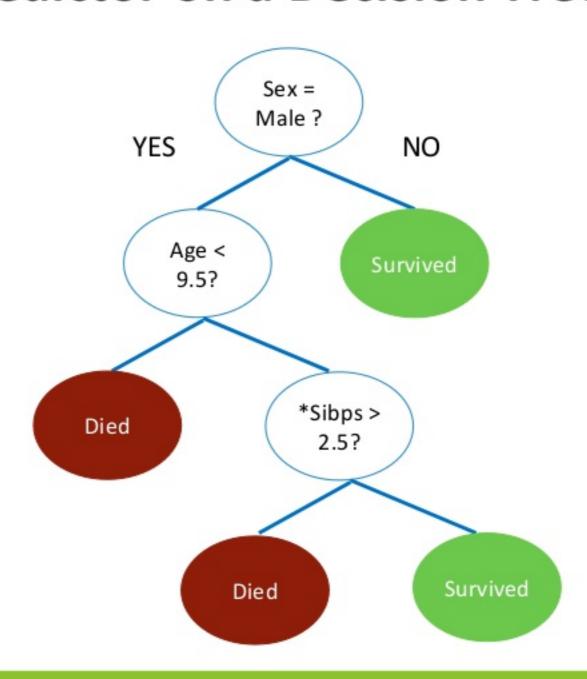
Decision is taken by the majority of decision trees

Titanic Survival Predictor on a Decision Tree

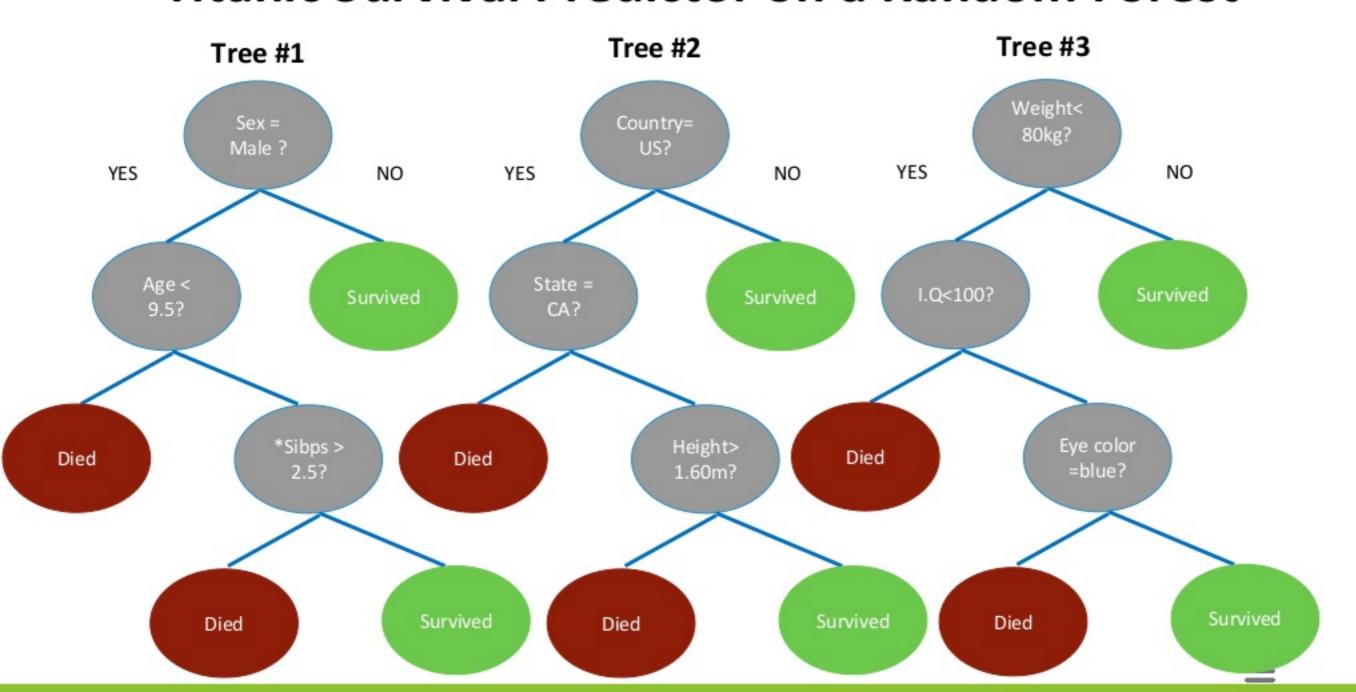


*Sibps = siblings + spouses





Titanic Survival Predictor on a Random Forest



Would John Survive The Titanic

John's features:

{male, 34, married + 2, US, CA, 1.78m, 78kg, 110iq, blue eyes}

- Tree#1 Survived
- Tree#2 Failed
- Tree#3 Survived
- Random forest decision Survived



Forest Data Type Example

```
> MODULE LOAD "./redis-ml.so"
OK
> ML.FOREST.ADD myforest 0 . CATEGORIC sex "male" .L LEAF 1 .R LEAF 0
OK
> ML.FOREST.RUN myforest sex:male
"1"
> ML.FOREST.RUN myforest sex:no_thanx
"0"
```



Using Redis-ML With Spark

```
scala > import com.redislabs.client.redisml.MLClient
       import com.redislabs.provider.redis.ml.Forest
scala>
scala> val jedis = new Jedis("localhost")
scala> val rfModel = pipelineModel.stages.last.asInstanceOf[RandomForest]
// Create a new forest instance
scala > val f = new Forest (rfModel.trees)
// Load the model to redis
scala> f.loadToRedis ("forest-test", "localhost")
// Classify a feature vector
scala > jedis.getClient.sendCommand (MLClient.ModuleCommand.FOREST RUN,
"forest-test", makeInputString(0))
scala > jedis.getClient.getStatusCodeReply
res53: String = 1
```



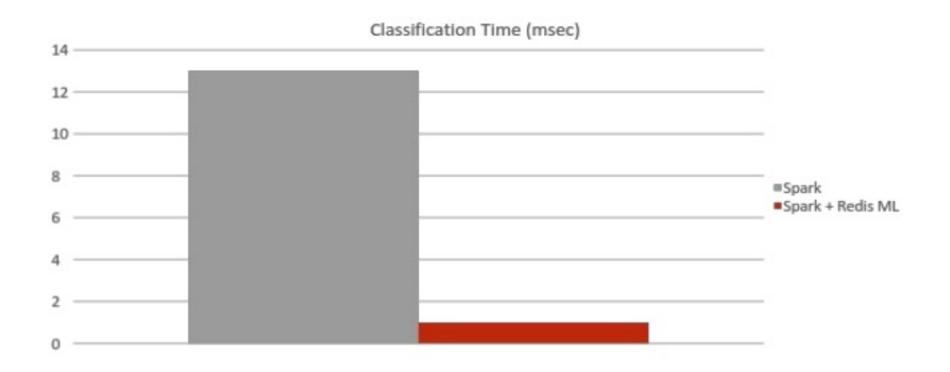
Real World Challenge

- Ad serving company
- Need to serve 20,000 ads/sec @ 50msec data-center latency
- Runs 1k campaigns → 1K random forest
- Each forest has 15K trees
- On average each tree has 7 levels (depth)
- Would require < 1000 x c4.8xlarge



Redis ML with Spark ML 40x Faster

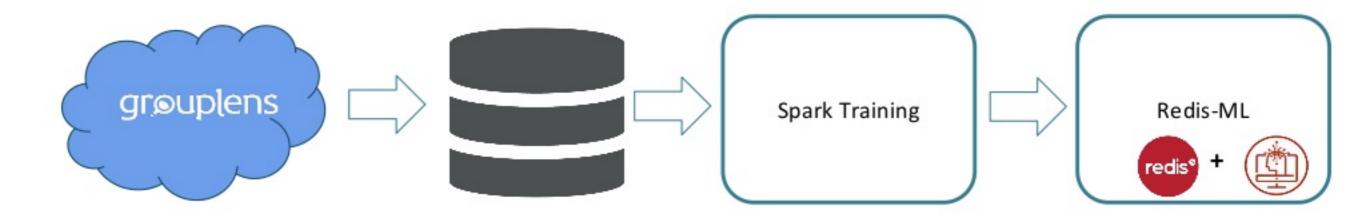
Classification Time Over Spark





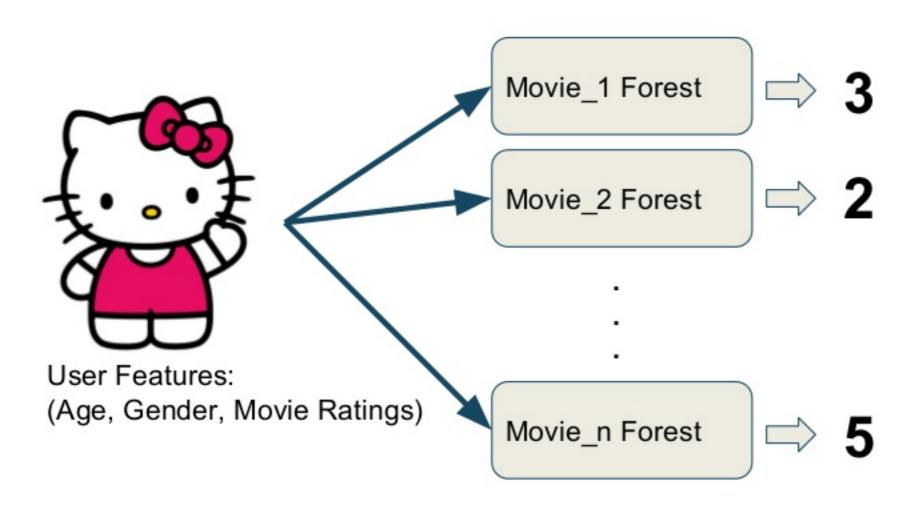
Real World Example: Movie Recommendation System

Overview





Concept: One Forest For Each Movie





The Tools

Transform:





Classify:





Containers:





Using the Dockers

```
$ docker pull shaynativ/redis-ml
$ docker run --net=host shaynativ/redis-ml &
$ docker pull shaynativ/spark-redis-ml
$ docker run --net=host shaynativ/spark-redis-ml
```



Step 1: Get The Data

- Download and extract the <u>MovieLens 100K Dataset</u>
- The data is organized in separate files:
 - Ratings: user id | item id | rating (1-5) | timestamp
 - Item (movie) info: movie id | genre info fields (1/0)
 - User info: user id | age | gender | occupation
- Our classifier should return the expected rating (from 1 to 5) a user would give the movie in question



Step 2: Transform

- The training data for each movie should contain 1 line per user:
 - class (rating from 1 to 5 the user gave to this movie)
 - user info (age, gender, occupation)
 - user ratings of other movies (movie_id:rating ...)
 - user genre rating averages (genre:avg_score ...)
- Run gen_data.py to transform the files to the desired format

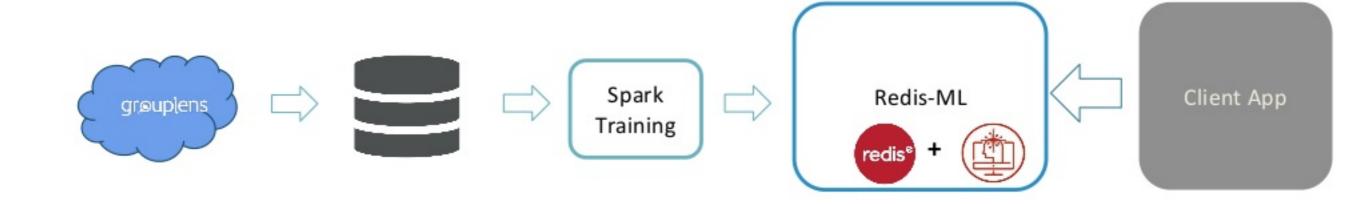


Step3: Train and Load to Redis

```
// Create a new forest instance
val rf = new
RandomForestClassifier().setFeatureSubsetStrategy("auto").setLabelCol("indexedLabel").setFeat
uresCol("indexedFeatures").setNumTrees(500)
// Train model
val model = pipeline.fit(trainingData)
val rfModel = model.stages(2).asInstanceOf[RandomForestClassificationModel]
// Load the model to redis
val f = new Forest(rfModel.trees)
f.loadToRedis("movie-10", "127.0.0.1")
```



Step 3: Execute in Redis





Python Client Example

```
>> import redis
>> config = {"host":"localhost", "port":6379}
>> r = redis.StrictRedis(**config)
>> user profile = r.get("user shay profile")
>> print(user profile)
12:1.0,13:1.0,14:3.0,15:1.0,17:1.0,18:1.0,19:1.0,20:1.0,23:1.0,24:5.0,1.0,115:1.0,116:2.
0,117:2.0,119:1.0,120:4.0,121:2.0,122:2.0,
1360:1.0,1361:1.0,1362:1.0,
1701:6.0,1799:435.0,1801:0.2,1802:0.11,1803:0.04,1812:0.04,1813:0.07,1814:0.24,1815:0.09
,1816:0.32,1817:0.06
>> r.execute_command("ML.FOREST.RUN", "movie-10", user_profile)
131
```



Redis CLI Example

```
>keys *
127.0.0.1:6379> KEYS *
1) "movie-5"
2) "movie-1"
  . . . . . . . .
 8) "movie-6"
 9) "movie-4"
10) "movie-10"
11) "user 1 profile"
>ML.FOREST.RUN movie-10
12:1.0,13:1.0,,332:3.0,333:1.0,334:1.0,335:2.0,336:1.0,357:2.0,358:1.0,359:1.0,362:1.0,367:1.
. . . . . . . .
,410:3.0,411:2.0,412:2.0,423:1.0,454:1.0,455:1.0,456:1.0,457:3.0,458:1.0,459:1.0,470:1"
"3"
```



Performance

```
Redis time: 0.635129ms, res=3
Spark time: 46.657662ms, res=3.0
Redis time: 0.644444ms, res=3
Spark time: 49.028983ms, res=3.0
Classification averages:
redis: 0.9401250000000001 ms
spark: 58.01970206666667 ms
ratio: 61.71488053893542
diffs: 0.0
```



Getting Actual Recommendations - Python Script

```
import operator
r = redis.StrictRedis(**config)
user profile = r.get("user-1-profile")
results = {}
for i in range(1, 11):
```



Getting Actual Recommendations - Results

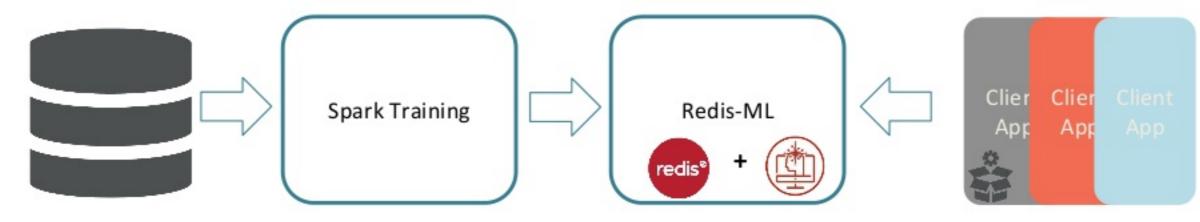
```
$ ./classify_user.py 1
Movies sorted by scores:
movie-4:3
movie-3:2
movie-6:2
movie-7:2
movie-8:2
movie-9:2
movie-1:1
movie-2:1
movie-5:1
movie-10:0
Recommended movie for user 1: movie-4
```



Summary

- Train with Spark, Serve with Redis
- 97% resource cost serving
- Simplify ML lifecycle

- Redis^e (Cloud or Pack):
 - -Scaling, HA, Performance
 - –PAYG cost optimized
 - –Ease of use
 - —Supported by the teams who created Spark and Redis





Resources

- Redis-ML: https://github.com/RedisLabsModules/redis-ml
- Spark-Redis-ML: https://github.com/RedisLabs/spark-redis-ml
- Databricks Notebook: http://bit.ly/sparkredisml
- Dockers: https://hub.docker.com/r/shaynativ/redis-ml/
 - https://hub.docker.com/r/shaynativ/spark-redis-ml/



Q&A





Thank You.

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