Data Analytics Pipeline for Historical Taxi Data

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Overview

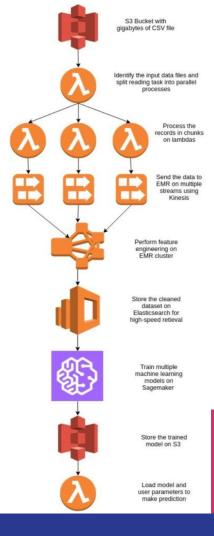
- Historical data of NYC-TLC
- Big data volume
- Predicting taxi fare and journey time
- Scalability and fault tolerance

Tools and technologies

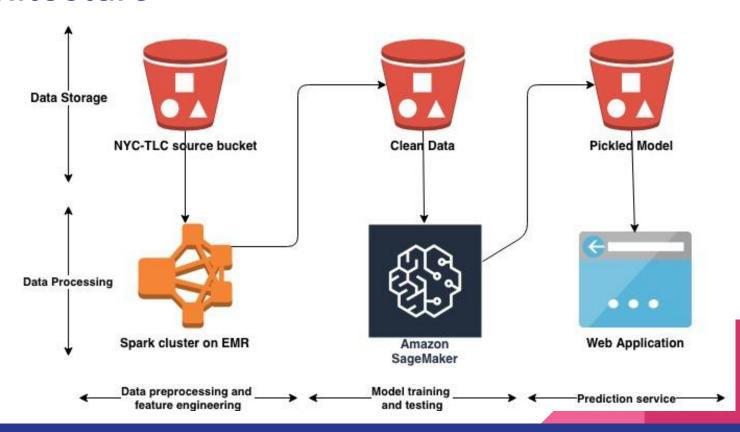
- Amazon Web Services
 - Elastic map reduce EMR
 - Spark
 - Sagemaker
 - o S3
- Jupyter Notebooks
- Python Flask

Approach

- Initial approach
 - Lambda architecture
- Why we moved away?
 - Over engineered solution
 - AWS is inherently well integrated
 - Complexity
 - Cost
- Final solution
 - Dropped speed layer
 - Batch processing and serving layer

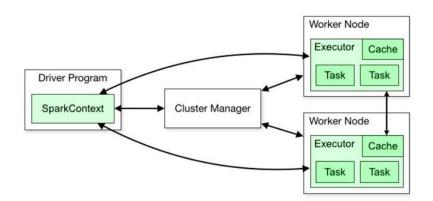


Architecture



Spark

- 3 node cluster
- Two approaches to parallelization
 - Split the file
 - Serial code was a bottleneck
 - Lots of Disk IO
 - Pandas is in-memory
 - Max input file size is 2 GB
 - Each worker instance has 16 GB RAM and 8 cores

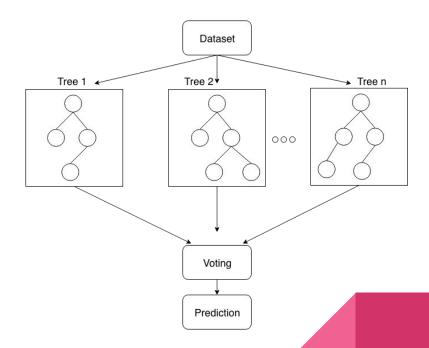


Data Preprocessing

- Cleaning the data
 - Attribute selection
 - Data validation
 - Invalid fare
 - Invalid date
 - Missing values
- Feature Engineering
 - Zipcode
 - Trip Frequency

Data modelling and machine learning

- Sagemaker
 - Random Forest
 - K-mean clustering
 - XgBoost



Performance

- Data preprocessing
 - Serial processing time ~46 hours
 - Parallel processing
 - 2 * m4.xlarge instance
 - 16 cores
 - duration ~ 3 hours
 - Linear scaleup (16 * 3 ~= 46)
- Data modelling
 - Used inbuilt parallelisation provided by ML algorithms
 - o m4.2xlarge instance 32 GB RAM



Challenges

- Design choices
 - Lambda or batch only processing
 - Chunking file or not for parallelism
- Data preprocessing
 - Selecting attributes
 - Storage cost
- Integrating various components

Future Scope

- Stream processing instead of batch processing
 - Use Kafka
- Automating the manual steps

Conclusion

- Built a data analytics pipeline
- Batch processing of over 100 million records
- Trained machine learning models
- Built a web application to query
- All in 100 bucks!

Questions?