Building a Modern Big Data & Advanced Analytics Pipeline

(Ideas for building UDAP)





- Emerging technology firm focused on helping enterprises build breakthrough software solutions
- Building software solutions powered by disruptive enterprise software trends
 - -Machine learning and data science
 - -Cyber-security
 - -Enterprise IOT
 - -Powered by Cloud and Mobile
- · Bringing innovation from startups and academic institutions to the enterprise
- Award winning agencies: Inc 500, American Business Awards, International Business Awards

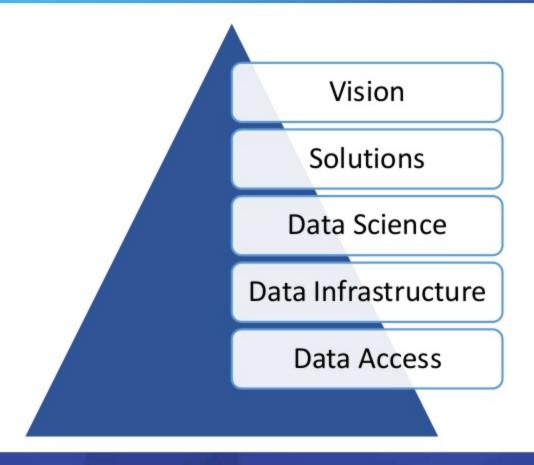
Agenda

- The principles of big data and advanced analytics pipelines
- Some inspiration
- Capabilities
- · Building a big data and advanced analytics pipeline



The principles of an enterprise big data infrastructure

Data Needs



There are only a few technology choices....



Big Data Landscape 2016 **Analytics**





Some inspiration....

Netflix

Data Access

Data Fetching:

Falcor(https://github.com/Ne tflix/falcor)

Data Streaming: Apache Kafka (http://kafka.apache.org/)

Federated Job Execution

Engine:

Genie(https://github.com/Net flix/genie)

Data Infrastructure

Data Lakes: Apache Hadoop (http://hadoop.apache.org/)

Data Compute: Apache Spark

SQL Querying: Presto (https://prestodb.io/)

Data Discovery : Metacat

Data Science

Multidimensional analysis: Druid (http://druid.io/)

Data Visualization: Sting

Machine learning: Scikitlearn(http://scikitlearn.org/stable/)

Tools & Solutions

Netflix big data portal

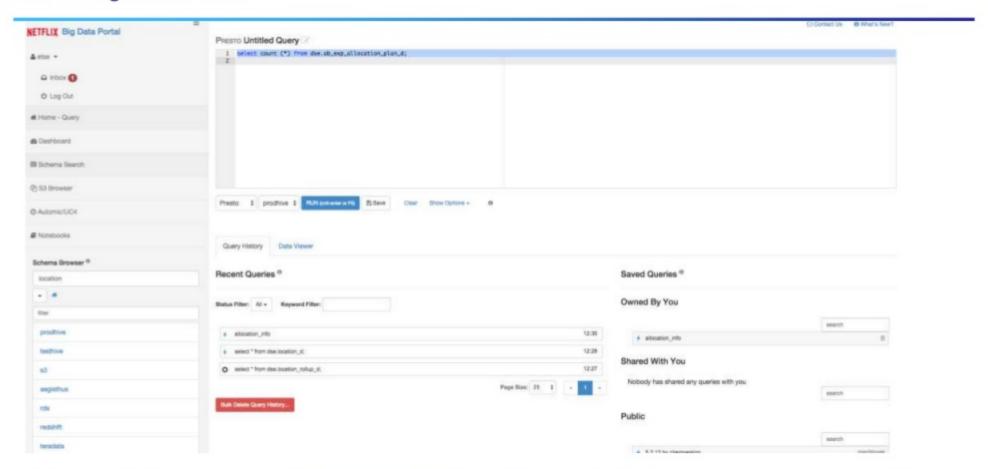
Hadoop Search:

Inviso(https://github.com/Net flix/inviso)

Workflow visualization (https://github.com/Netflix/Lipstick)

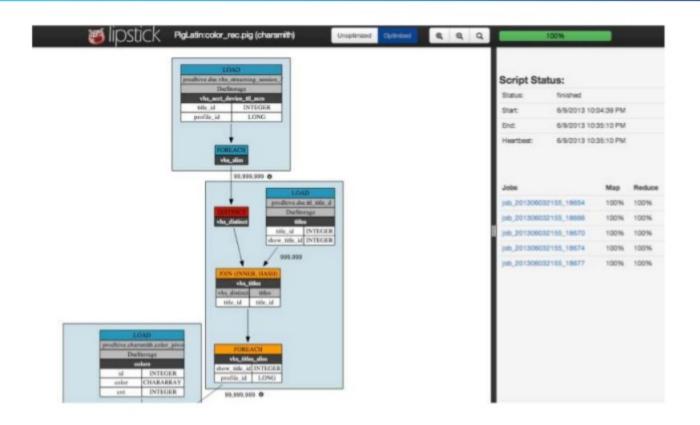


Netflix Big Data Portal



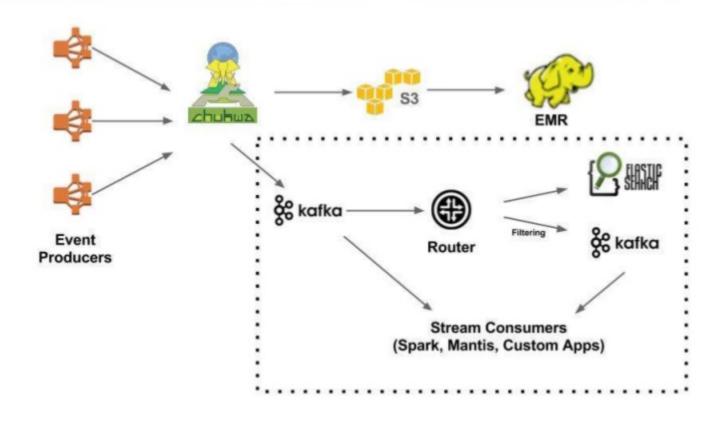


Netflix Lipstick





Netflix Data Pipeline



Data Access

Data Fetching:

GraphQL(https://facebook.git hub.io/react/blog/2015/05/0 1/graphql-introduction.html)

Data Streaming: Apache Kafka (http://kafka.apache.org/)

Data Infrastructure

Data Lakes: Apache Hadoop (http://hadoop.apache.org/)

Data Compute: Apache Spark

SQL Aggregation: Apache Crunch(https://crunch.apache.org/)

Fast Data Access: Apache Cassandra(<u>http://cassandra.apache.org/</u>)

Workflow Manager :Luigi(https://github.com/spo tify/luigi)

Data Transformation: Apache Falcon(http://hortonworks.co m/hadoop/falcon/)

Data Science

Data Visualization: Sting

Machine learning: Spark MLib(http://scikit-learn.org/stable/)

Data Discovery: Raynor

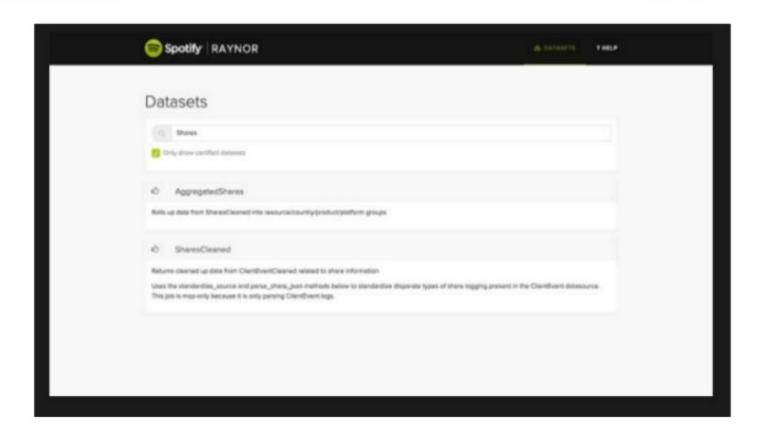
Tools & Solutions

Hadoop Search: Inviso(https://gith

Inviso(https://github.com/Net flix/inviso)



Raynor





LinkedIn

Data Access

Data Streaming: Apache Kafka (http://kafka.apache.org/)

Data Fetching:

GraphQL(https://facebook.git hub.io/react/blog/2015/05/0 1/graphql-introduction.html)

Data Infrastructure

Data Lakes: Apache Hadoop (http://hadoop.apache.org/)

Data Compute: Apache Spark(<u>http://www.project-voldemort.com/voldemort/</u>)

Fast Data Access:

Voldemort(http://cassandra.a pache.org/)

Stream Analytics: Apache Samza(http://samza.apache.org/)

Real Time Search : Zoie (http://javasoze.github.io/zoie/)

Data Science

Multidimensional analysis: Druid (http://druid.io/)

Data Visualization: Sting

Machine learning: Scikitlearn(http://scikitlearn.org/stable/)

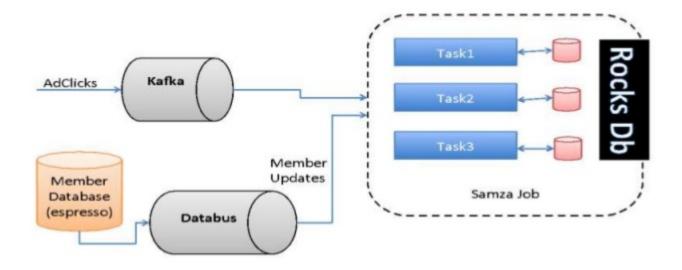
Data Discovery: Raynor

Tools & Solutions

Hadoop Search: Inviso(<u>https://github.com/Netflix/inviso</u>)

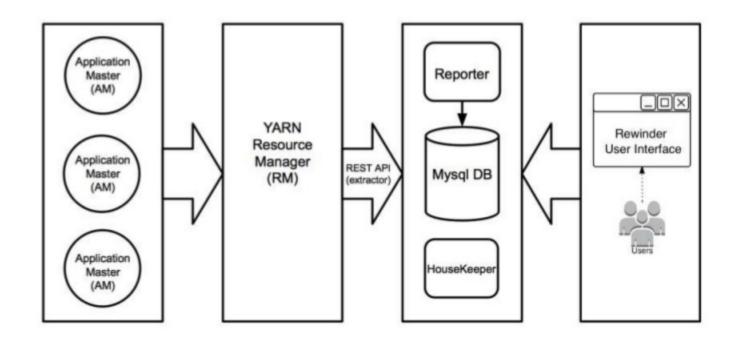


LinkedIn Stream Data Processing





LinkedIn Rewinder



Goldman Sachs

Data Access

Data Fetching:

GraphQL(https://facebook.git hub.io/react/blog/2015/05/0 1/graphql-introduction.html

Data Streaming: Apache Kafka (http://kafka.apache.org/)

Data Infrastructure

Data Lakes: Apache Hadoop/HBase

(http://hadoop.apache.org/)

Data Compute: Apache Spark

Data Transformation: Apache Pig(http://hortonworks.com/ hadoop/falcon/)

Stream Analytics: Apache

Storm

(http://storm.apache.org/)

Data Science

Multidimensional analysis: Druid (http://druid.io/)

Data Visualization: Sting

Machine learning: Spark MLib(http://scikitlearn.org/stable/)

Data Discovery: Custom data catalog

Tools & Solutions

Secure data exchange: Symphony

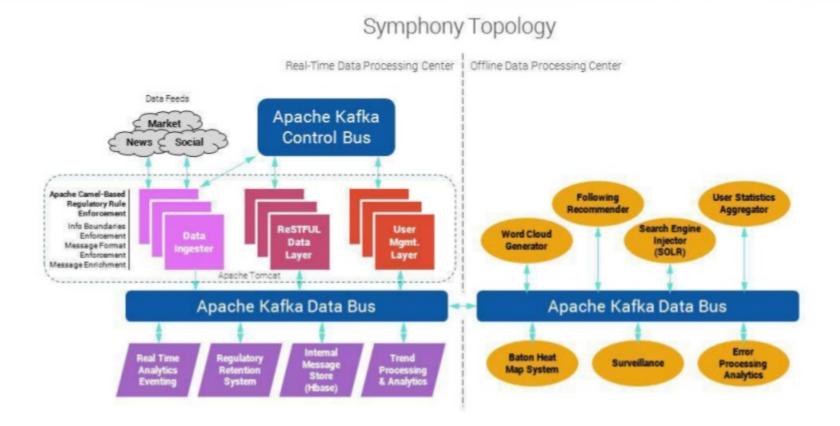
(http://www.goldmansachs.co m/what-we-

do/engineering/see-our-

work/inside-symphony.html)



Goldman Sachs Data Exchange Architecture





Capabilities of a big data pipeline

Data Access....



Goals

- Provide the foundation for data collection and data ingestion methods at an enterprise scale
- Support different data collection models in a consistent architecture
- Incorporate and remove data sources without impacting the overall infrastructure



Foundational Capabilities

- · On-demand data access
- · Batch data access
- Stream data access
- Data transformation



On-Demand Data Access

Best Practices

- Enable standard data access protocols for line of business systems
- Empower client applications with data querying capabilities
- Provide data access infrastructure building blocks such as caching across business data sources

- GraphQL(https://facebook.github.io/react/blog/2015/05/01/graphql-introduction.html)
- Odata(<u>http://odata.org</u>)
- Falcor (http://netflix.github.io/falcor/)



Batch Data Access

Best Practices

- Enable agile ETL models
- Support federated job processing

- Genie(<u>https://github.com/Netflix/genie</u>)
- Luigi(<u>https://github.com/spotify/luigi</u>)
- Apache
 Pig(<u>https://pig.apache.org/</u>)

Stream Data Access

Best Practices

- Enable streaming data from line of business systems
- Provide the infrastructure to incorporate new data sources such as sensors, web streams etc
- Provide a consistent model for data integration between line of business systems

- Apache
 Kafka(<u>http://kafka.apache.org/</u>
)
- RabbitMQ(<u>https://www.rabbitmq.com/</u>)
- ZeroMQ(http://zeromq.org/)
- Many others....



Data Virtualization

Best Practices

- Enable federated aggregation of disparate data sources
- Focus on small data sources
- Enable standard protocols to access the federated data sources

- Denodo(<u>http://www.denodo.co</u> <u>m/en</u>)
- JBoss Data
 Virtualization(<u>http://www.jbosss.org/products/datavirt/overview/</u>)



Data Infrastructure....



Goals

- Store heterogeneous business data at scale
- Provide consistent models to aggregate and compose data sources from different data sources
- Manage and curate business data sources
- Discover and consume data available in your organization



Foundational Capabilities

- · Data lakes
- Data quality
- · Data discovery
- Data transformation

Data Lakes

Best Practices

- Focus on complementing and expanding our data warehouse capabilities
- Optimize the data lake to incorporate heterogeneous data sources
- Support multiple data ingestion models
- Consider a hybrid cloud strategy (pilot vs. production)

- Hadoop(<u>http://hadoop.apache.org/</u>)
- Hive(<u>https://hive.apache.org/</u>)
- Hbase(<u>https://hbase.apache.org/</u>)
- Spark(<u>http://spark.apache.org/</u>)
- Greenplum(<u>http://greenplum.org/</u>)
- Many others....



Data Quality

Best Practices

- Avoid traditional data quality methodologies
- Leverage machine learning to streamline data quality rules
- Leverage modern data quality platforms
- Crowsourced vs. centralized data quality models

- Trifacta(http://trifacta.com)
- Tamr(<u>http://tamr.com</u>)
- Alation(<u>https://alation.com/</u>)
- Paxata(http://www.paxata.com/)



Data Discovery

Best Practices

- Master management solutions don't work with modern data sources
- Promote crow-sourced vs. centralized data publishing
- Focus on user experience
- Consider build vs. buy options

- Tamr(http://tamr.com)
- Custom solutions...
- Spotify Raynor
- Netflix big data portal



Data Transformations

Best Practices

- Enable programmable ETLs
- Support data transformations for both batch and real time data sources
- Agility over robustness

- Apache
 Pig(<u>https://pig.apache.org/</u>)
- Streamsets(<u>https://streamsets.</u>
 <u>com/</u>)
- Apache Spark (http://spark.apache.org/)



Data Science....



Goals

- Discover insights of business data sources
- Integrate machine learning capabilities as part of the enterprise data pipeline
- Provide the foundation for predictive analytic capabilities across the enterprise
- Enable programmatic execution of machine learning models



Foundational Capabilities

- Data visualization & self-service BI
- · Predictive analytics
- Stream analytics
- · Proactive analytics

Data Visualization and Self-Service BI

Best Practices

- Access business data sources from mainstream data visualization tools like Excel, Tableau, QlickView, Datameer, etc.
- Publish data visualizations so that they can be discovered by other information workers
- Embed visualization as part of existing line of business solutions

- Tableau(<u>http://www.tableau.com/</u>)
- PowerBI(<u>https://powerbi.microsoft.com/en-us/</u>)
- Datameer(<u>http://www.datameer.com/</u>
)
- QlikView(<u>http://www.qlik.com/</u>)
- Visualization libraries
-

Predictive Analytics

Best Practices

- Implement the tools and frameworks to author machine learning models using business data sources
- Expose predictive models via programmable APIs
- Provide the infrastructure to test, train and evaluate machine learning models

- Spark
 Mlib(<u>http://spark.apache.org/docs/latest/mllib-guide.html</u>)
- Scikit-Learn(<u>http://scikit-learn.org/</u>)
- Dato(<u>https://dato.com/</u>)
- H20.ai(<u>http://www.h20.ai/</u>)
-



Stream Analytics

Best Practices

- Aggregate data real time from diverse data sources
- Model static queries over dynamic streams of data
- Create simulations and replays of real data streams

- Apache Storm(<u>http://storm.apache.org/</u>)
- Spark Streaming
 (http://spark.apache.org/streaming/
- Apache Samza(<u>http://samza.apache.org/</u>)
-

Proactive Analytics

Best Practices

- Automate actions based on the output of predictive models
- Use programmatic models to script proactive analytics business rules
- Continuously test and validate proactive rules

- Spark
 Mlib(<u>http://spark.apache.org/d</u>
 ocs/latest/mllib-guide.html)
- Scikit-Learn(<u>http://scikit-learn.org/</u>)



Solutions....



Enterprise Data Solutions

- Leverage a consistent data pipeline as part of all solutions
- Empower different teams to contribute to different aspects of the big data pipeline
- Keep track of key metrics about the big data pipeline such as time to deliver solutions, data volume over time, data quality metrics, etc



Some Examples

- · Data discovery
- Data quality
- Data testing tools
- ..

Other Interesting Capabilities

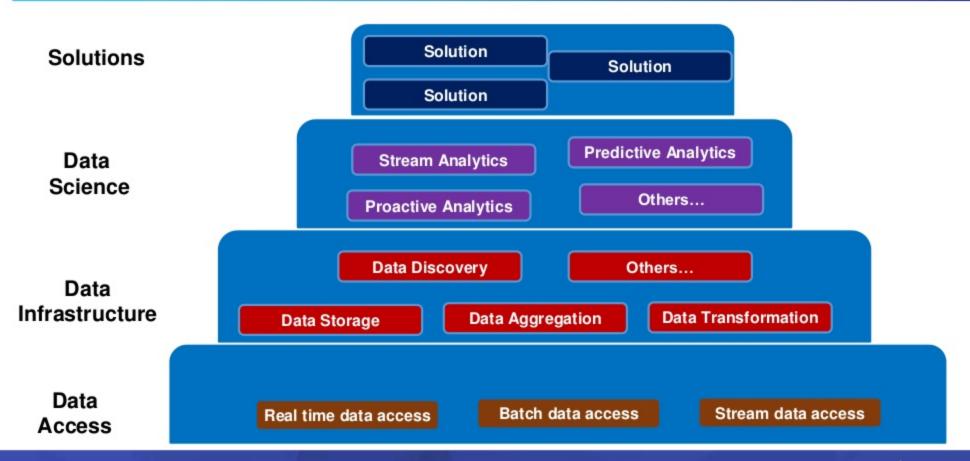
- Mobile analytics
- Embedded analytics capabilities (ex: Salesforce Wave, Workday)
- Aggregation with external sources
- · Video & image analytics
- Deep learning

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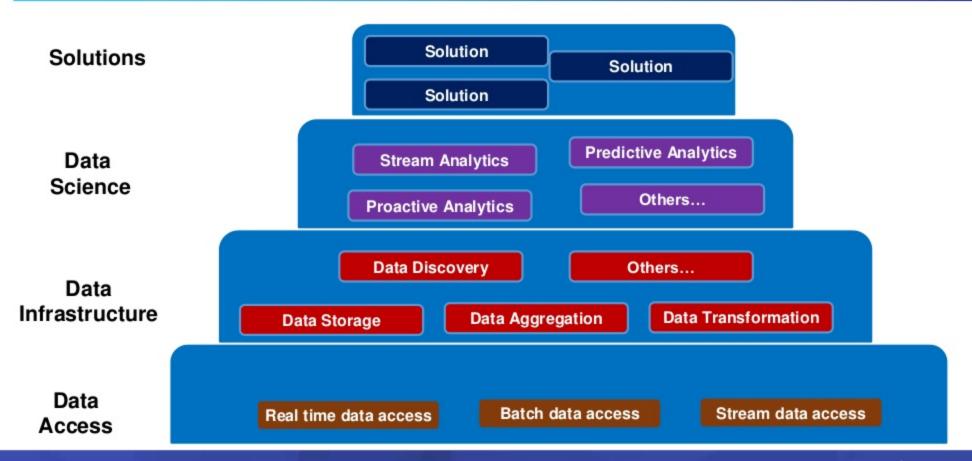
Building a big data and advanced analytics pipeline

Infrastructure-Driven





Domain-Driven





Infrastructure-Drives vs. Domain-Driven Approaches

Infrastructure-Driven

- Lead by the architecture team
- Military discipline
- Commitment from business stakeholders

Domain-Driven

- Federated data teams
- Rapid releases
- Pervasive communications



Some General Rules

- Establish a vision across all levels of the data pipeline
- You can't buy everything...Is likely you will build custom data infrastructure building blocks
- Deliver infrastructure and functional capabilities incrementally
- Establish a data innovation group responsible for piloting infrastructure capabilities ahead of production schedules
- Encourage adoption even in early stages
- Iterate



Summary

- Big data and advanced analytics pipelines are based on 4 fundamental elements: data access, data infrastructure, data science, data solutions....
- A lot of inspiration can be learned from the big data solutions built by lead internet vendors
- Establish a common vision and mission
- Start small....iterate....



Thanks

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