

Conviva Unified Framework (CUF) for Real Time, Near Real Time and Offline Analysis of Video Streaming With Spark and Databricks

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CONVIVA®



SPARK SUMMIT 2016
DATA SCIENCE AND ENGINEERING AT SCALE
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is a video experience management platform that maximizes viewer engagement



Unleashing the Power of OTT



- Video streaming over the internet (OTT) is growing rapidly
- Major industry shifts in the last couple of years
 - HBO Now
 - ESPN/SlingTV
 - Verizon Go90
 - Facebook, Twitter
 - Amazon Prime Video

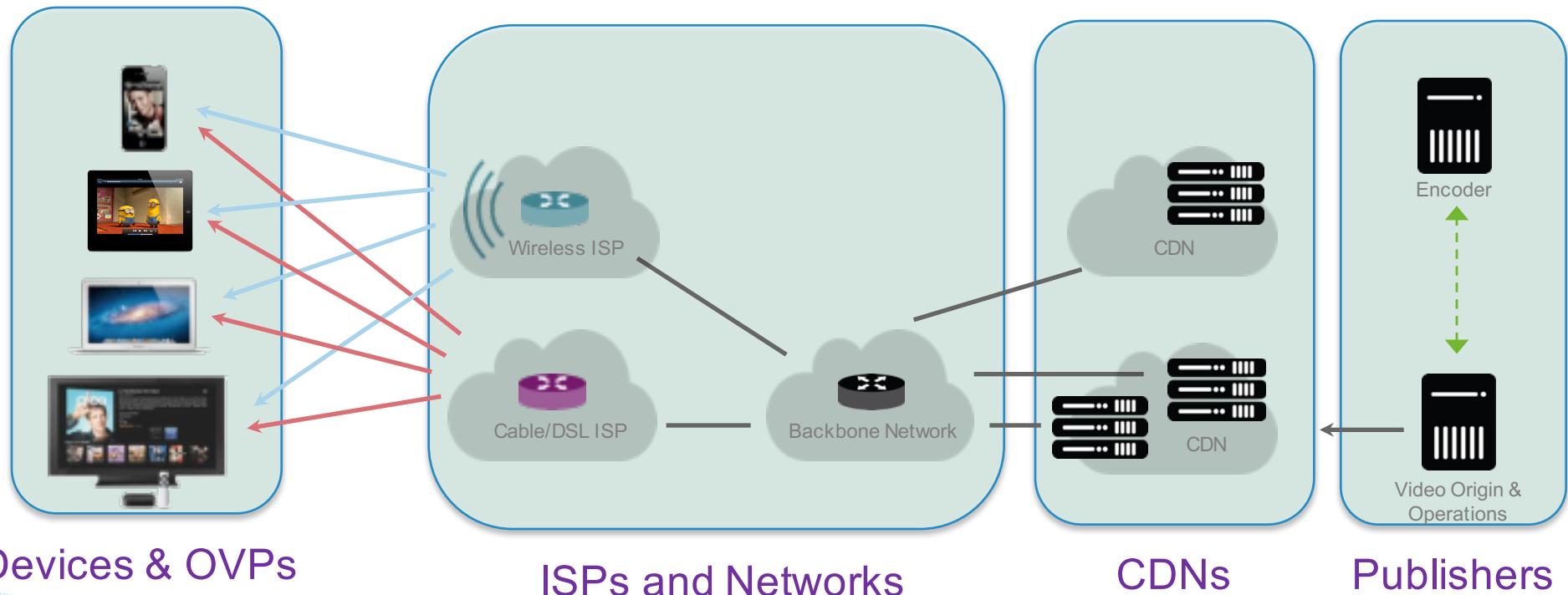
**Online Video – A Hugely Important Application
“Big Bang” Moment is Unfolding – Right Now**



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Internet Video Streaming is Hard

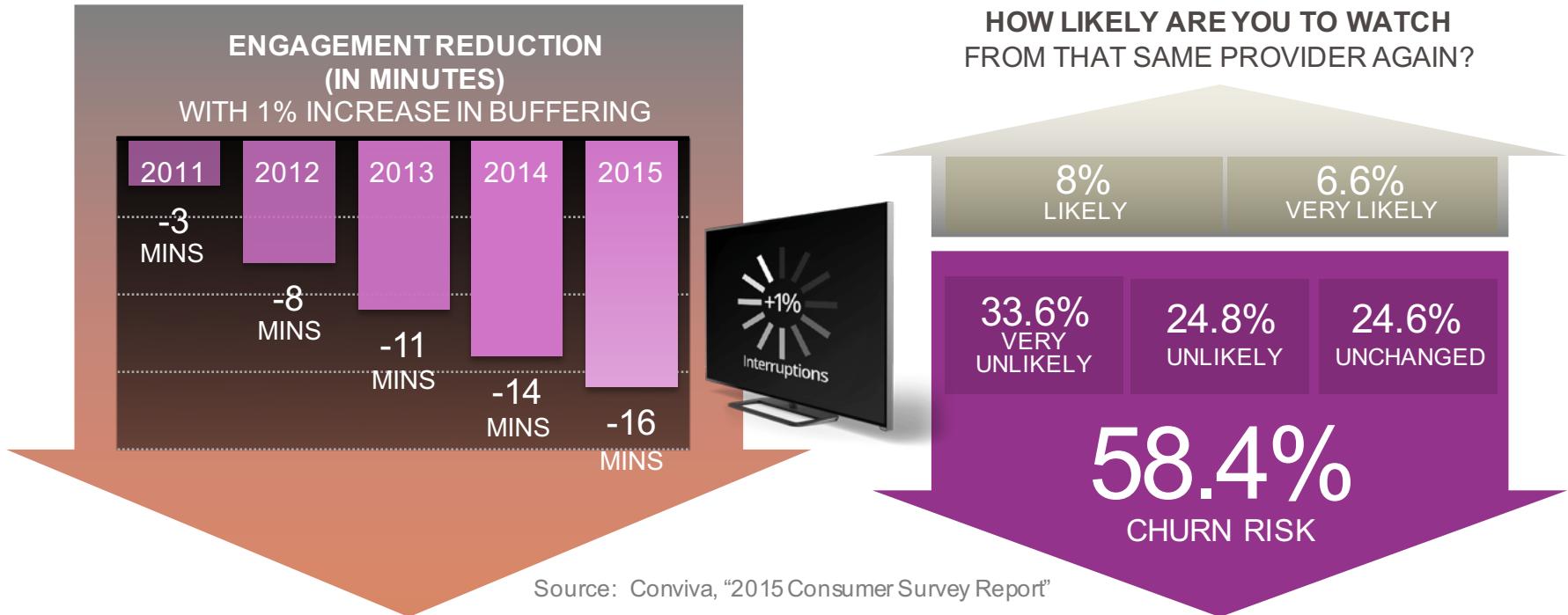
Many parties, many paths but no E2E owner



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QoE is Critical to Engagement

For both – Video and Advertisement business



Viewers are expecting TV like quality and better



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Experience Matters!!

Must solve for **EXPERIENCE** and **ENGAGEMENT**

Success is more than just great content...

Experience impacts engagement

Competition for eyeballs increasing...

Internet of Content > Traditional TV viewing

TV revenues are up for grabs...

Internet offers SVOD, AVOD, PPV &

"Unbundled choices"

OR ELSE All bets are off!



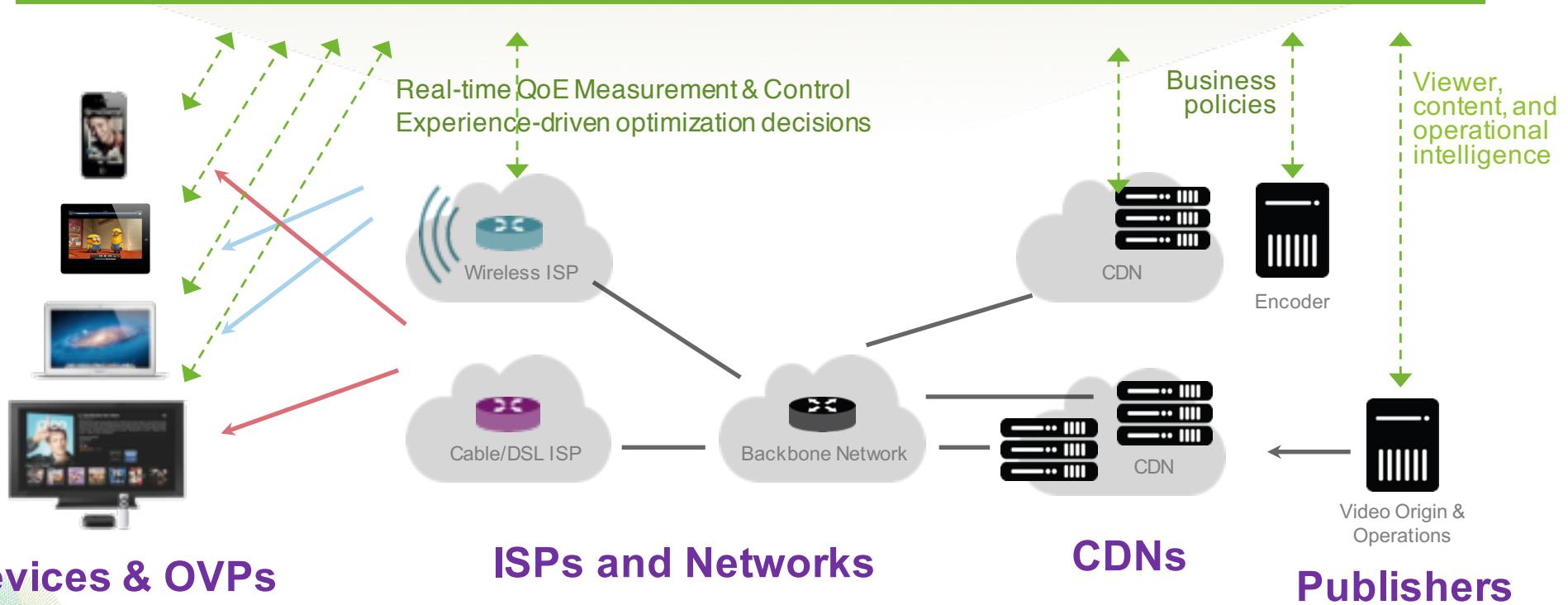
Publishers and Service Providers cannot lose touch with viewers' experience



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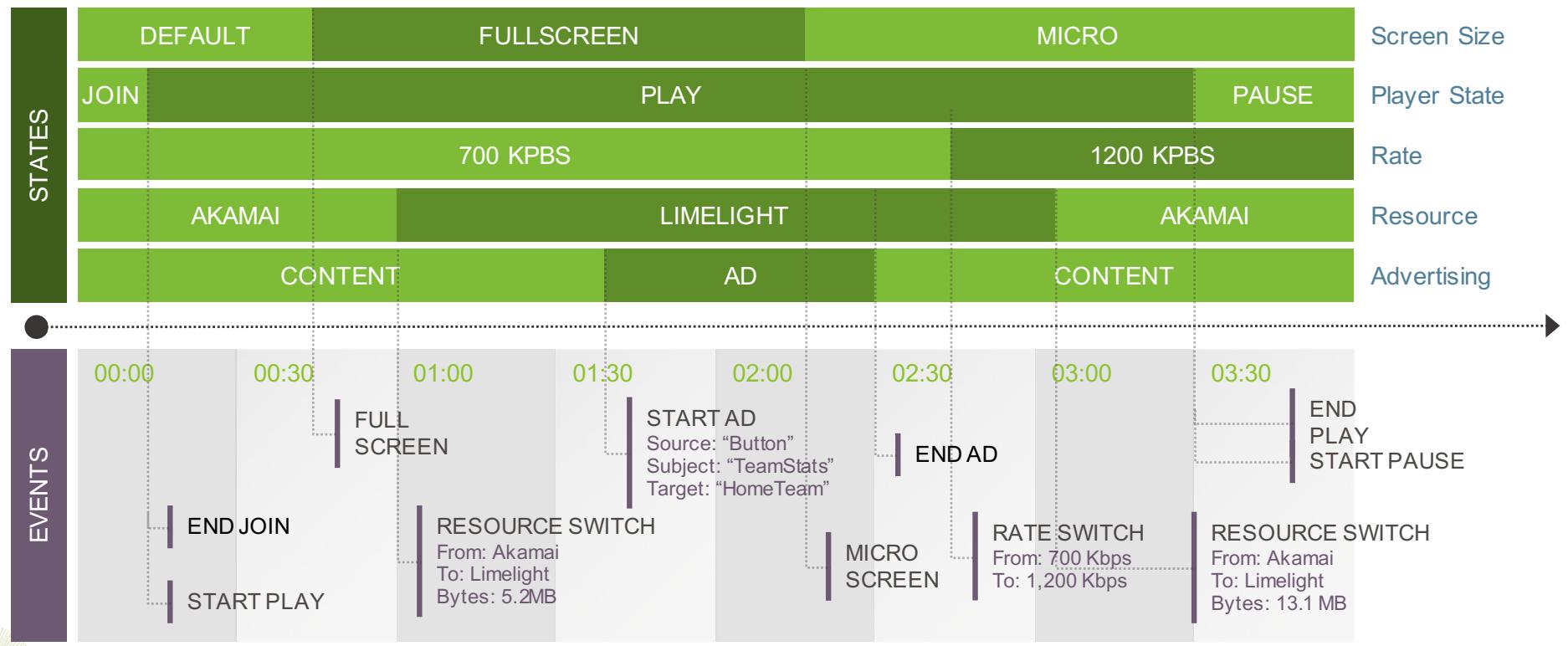
RIVA

CONVIVA EXPERIENCE MANAGEMENT PLATFORM



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Granular Dataset Indexed by Rich Metadata



Scale of Deployment

AVOD

2

SVOD

Infra

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Scale of Deployment



50B+
Streams
/Year



1B+
Devices
/Year



180+
Countries



3M
Events
/Sec



All
Global
CDNs



275
US
ISPs

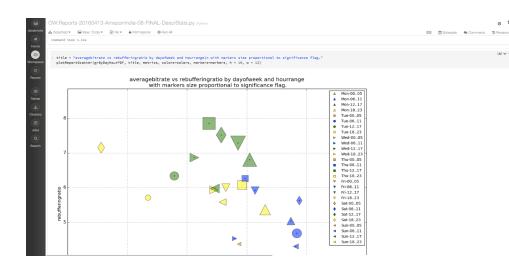
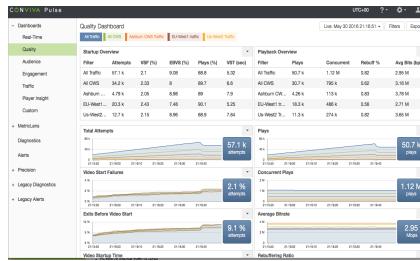


500+
Types of
Video Players



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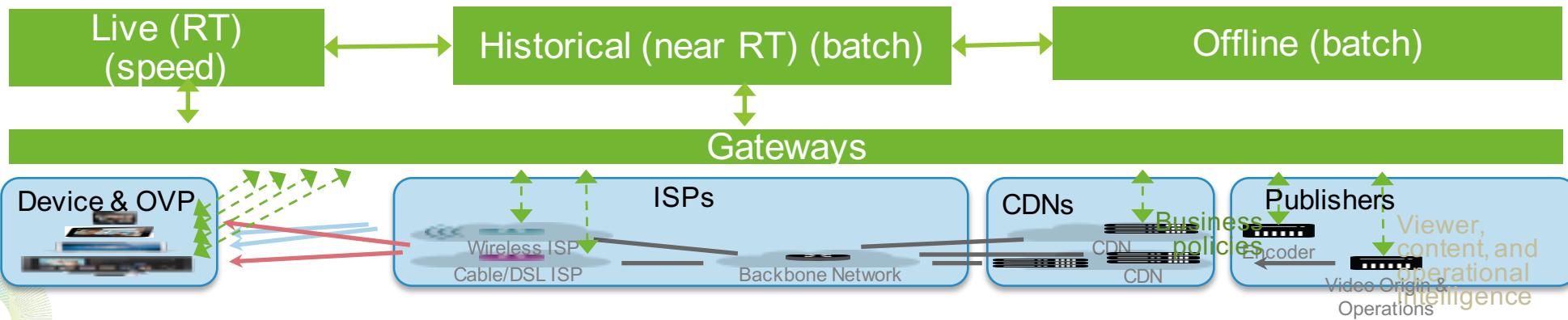
Use Cases requiring 3 Stacks



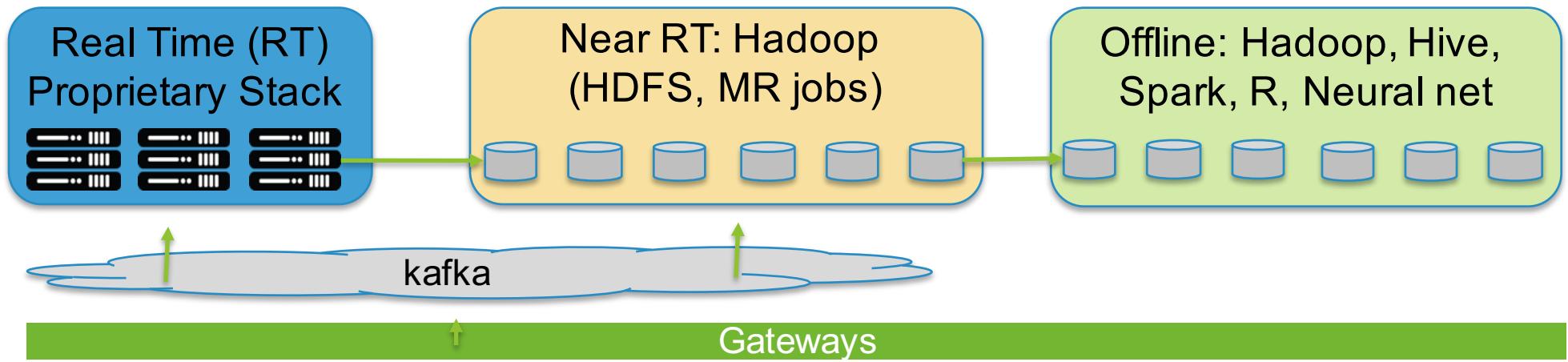
- Real time metrics
- Real time alerts
- Real time optimization

- Near real time metrics
- Historical trending
- Benchmarking

- In depth & ad hoc analysis
- Data exploration
- ML model training



Old Architecture



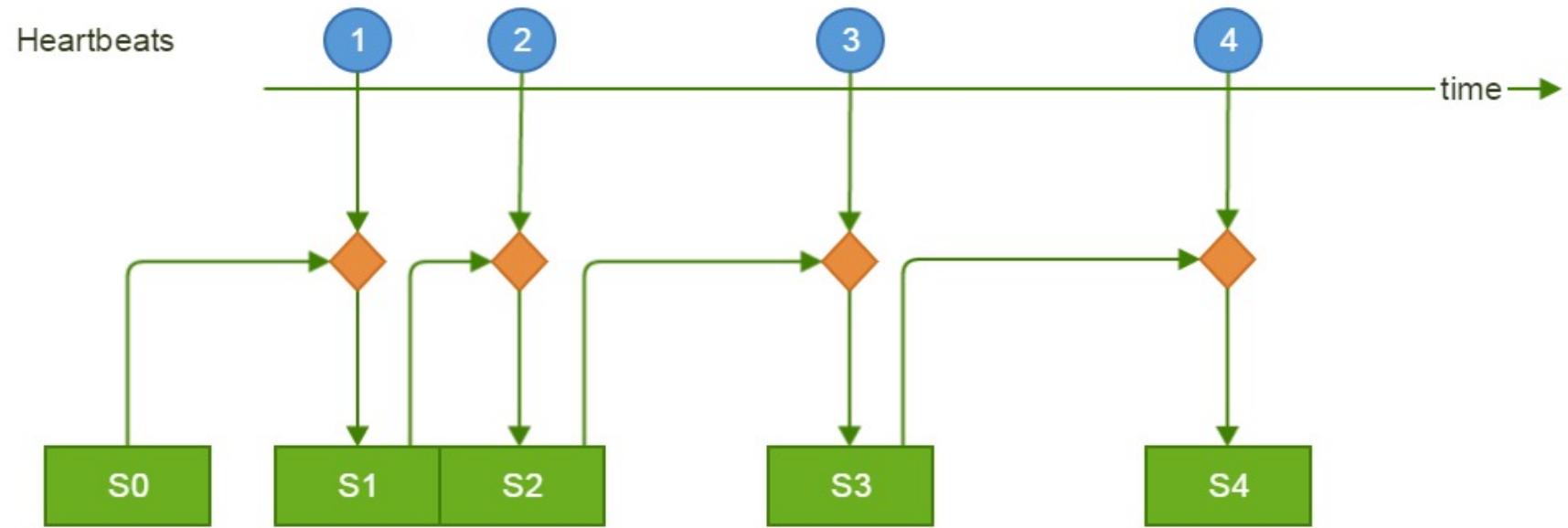
- RT and near RT stacks get input from Kafka independently
- RT and near RT run independently (except some RT results saved to HDFS for some near RT calculation)
- Offline gets data from near RT Hadoop, with additional calculation specifics to offline analysis.
- Hive/Spark/R/NeuralNet etc. are used for various offline tasks

Major Issues with old stack

- **Code discrepancy among all 3 separate stacks**
 - RT: Pure updating model vs near RT: batch model
 - Offline: separate Hive layer; can have different calculation logic scattered in hive queries. (some standard UDFs/UDAFs help to certain extend)
- **A very complex and vulnerable RT stack**
 - Tricky thread locking
 - Mutable objects
 - Fixed data flow, specific delicate data partition, load balance.
- **Metric discrepancies cross all 3 stacks**
- **Different stacks also incur a lot of overhead of development, deployment**

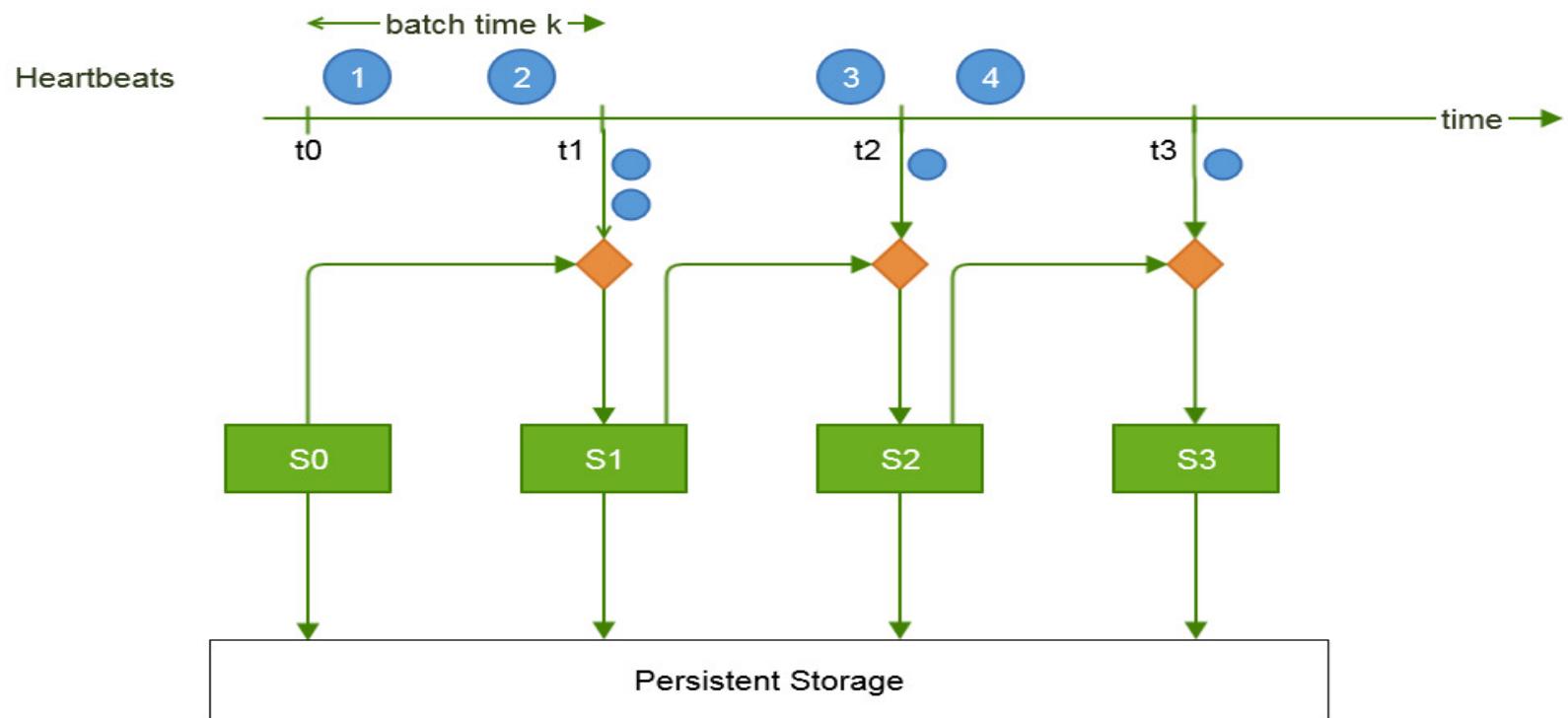


Proprietary Real Time Stack



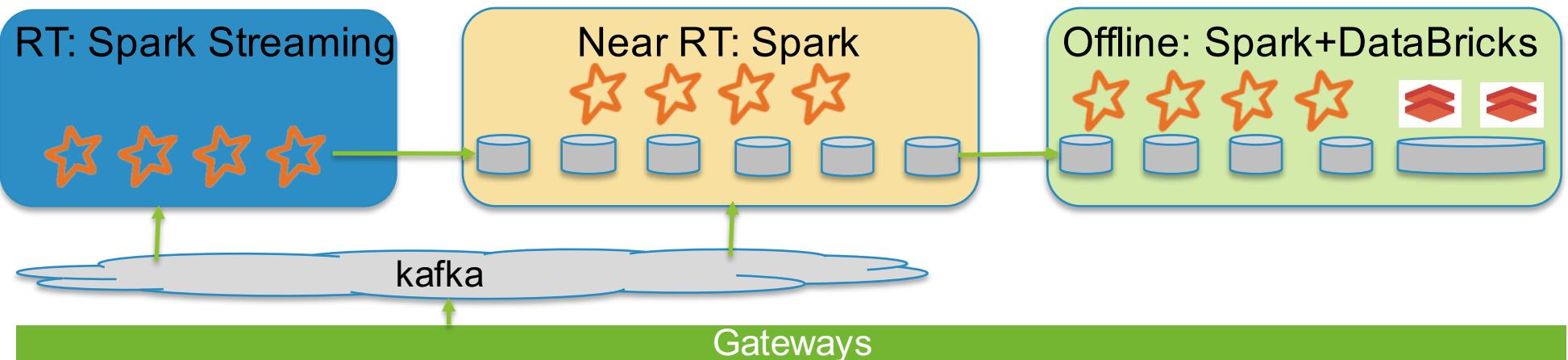
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Hadoop Batch Based Near RT Stack



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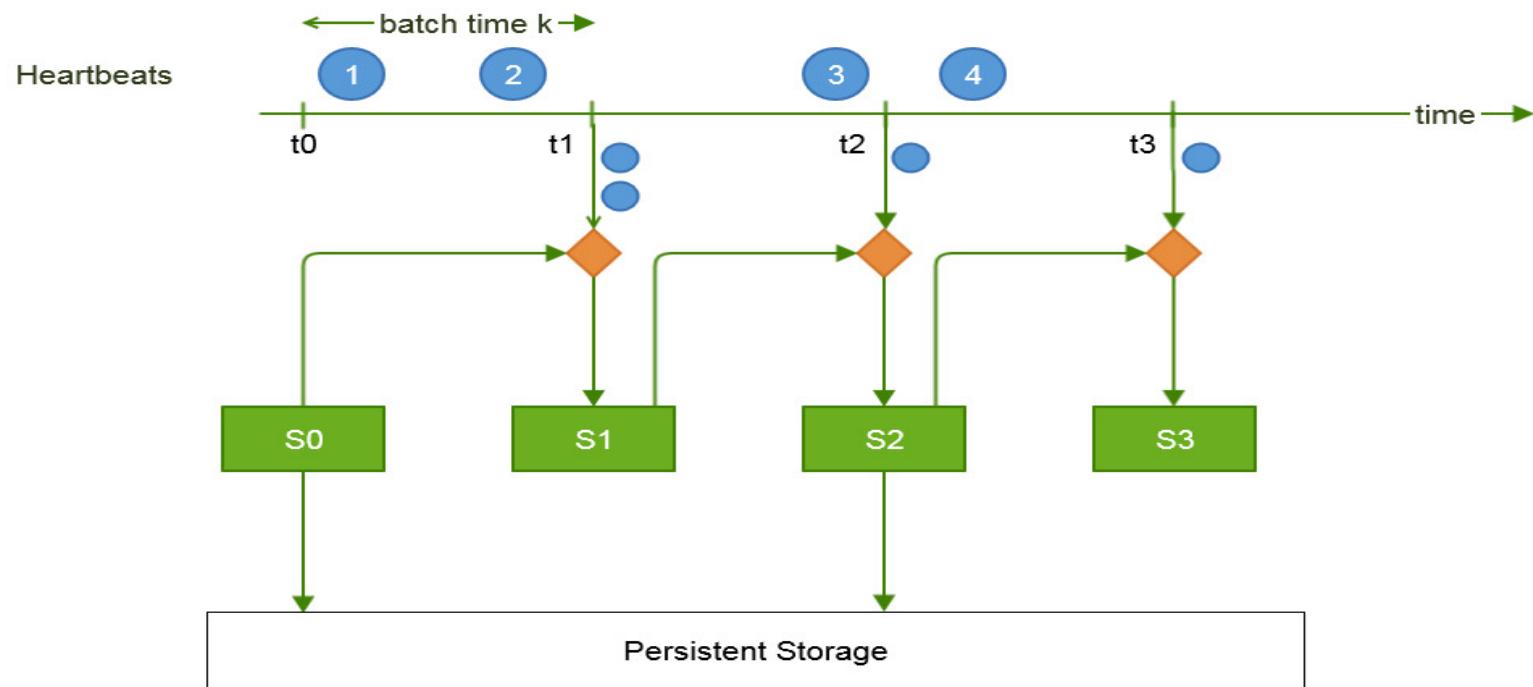
New Architecture



- All Converging to Spark based Technology.
- Max. sharing of code cross all 3 stacks
- Offline: with better cluster management (Databricks), running over many on-demand clusters instead of one pre-built



Unified Stack



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Unified Stack High Level Code

```
val rawlogs = (DStream from rawlogs)
```

```
val ssMapped = rawlogs.transform {  
    (map function)  
}
```

```
val ssReduced = ssMapped.updateStateByKey {  
    (reduce/update function)  
}
```

```
(every n batches)  
saveToStorage(ssReduced)
```



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updateStateByKey, mapWithState

- Acts as the ‘reduce’ phase of the computation
- Helps maintain the evolving state shown earlier
- The performance of updateStateByKey is proportional to the size of the state instead of the size of the batch data
- In Spark 1.6, will be replaced in our workflow by mapWithState, which only updates as needed



Deployment

- RT portion In production environment for ~5 months
- Backward compatible migration first, major improvements later
- Performance tuning is important
- For RT: Checkpointing, reliability vs performance



Importance of the Offline Stack

- For data centric companies, most important innovations are happening with exploring and learning through the big data
- Speed and efficiency of offline data analysis and learning is the key to the success
- Data and Insights accessible to many internal organizations besides data scientists (customer support, SE, PM,...) is extremely important for the overall success



What's Important to Data Scientists

- Efficient access to all the data
- Can work independently with all the resources needed.
- Can work with the teams (internally and with other teams)
- Interactivity for data exploration
- Easy to use, powerful data visualization
- Machine learning tools



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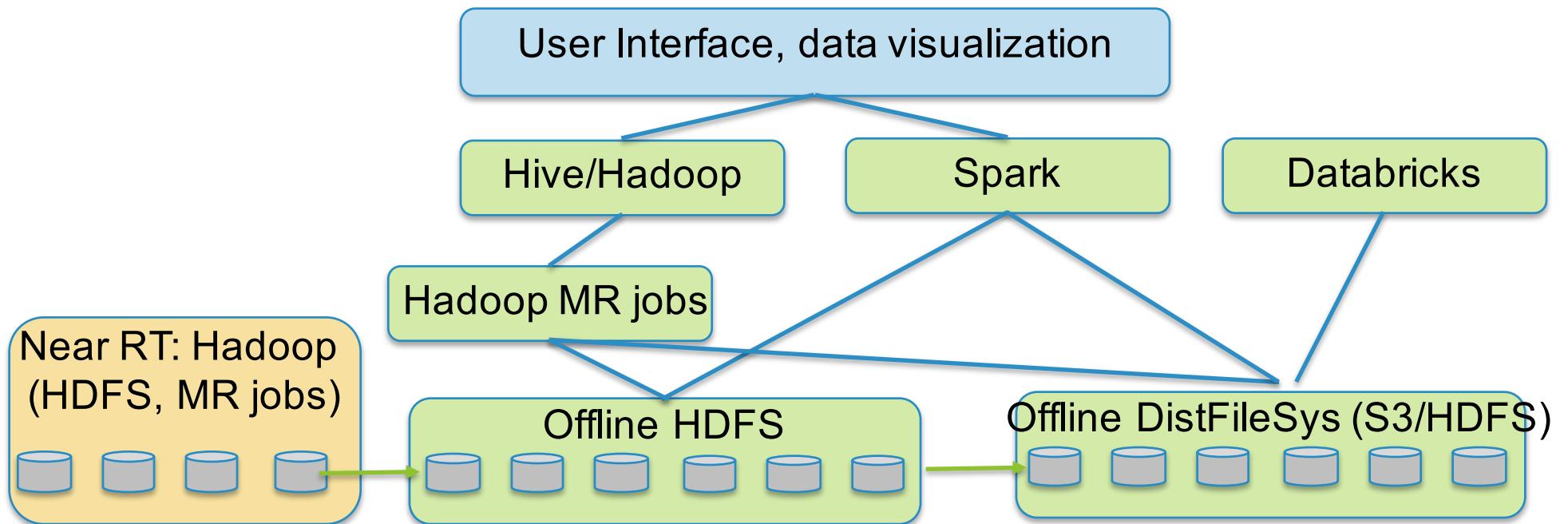
What's Important to Data Scientists

- Re-use of existing production logic/code when applicable
- Easy transfer of work into production
- Integrated environments with engineering discipline
 - Code management and version control
 - Design and code reviews

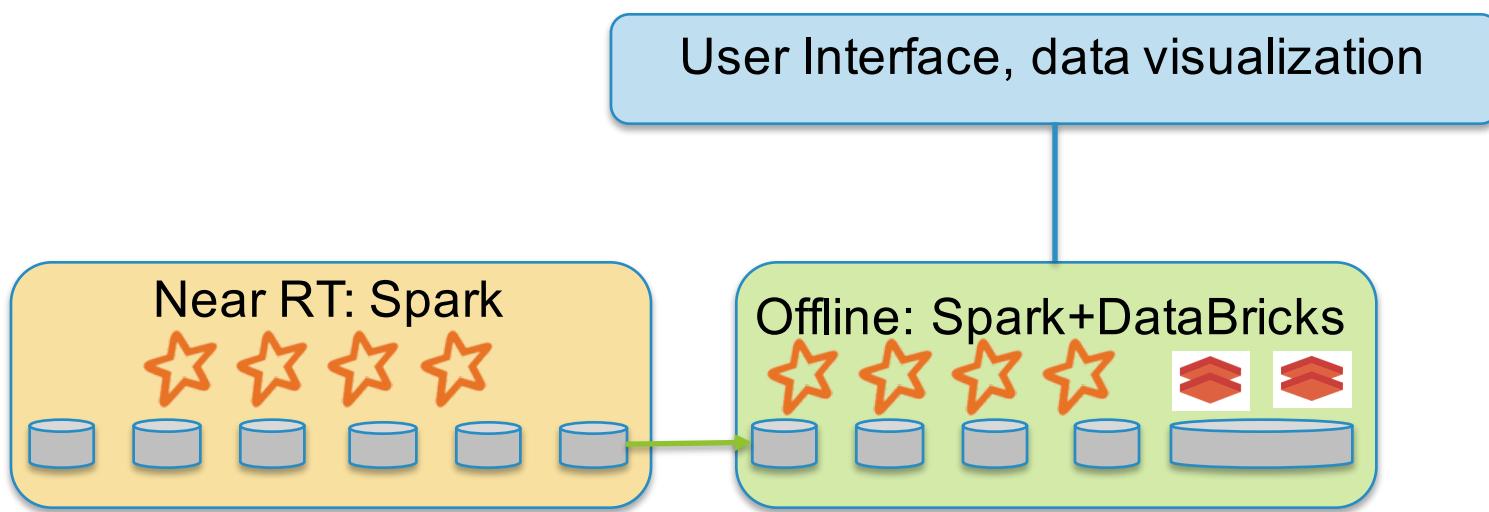


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Old Architecture



New Architecture



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Benefits of Databricks

- Cluster management:
 - Instead of one shared cluster, everyone can launch/manage his/her own clusters
- Interactive environments
 - Notebook environment is very convenient and powerful
- Easy to share/working together
 - Sharing notebooks are easy (with permission control)
- Data visualization
 - Good visualization tools: matplotlib, ggplot inside R
- Reasonably good machine learning tools
 - MLLib, R, other packages (H2O)



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Benefits of Databricks

- Same code can potentially be moved to other stacks and production
- New features built faster here:
 - Harder to change production environment
 - New features developed, tested and deployed faster
- Huge efficiency gain for the data science team
- Production issue debugging also using Databricks with big efficiency gain



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ML Example: Long Term Retention

- Long Term Retention Analysis
 - Months/years of data: many billions of views, many millions of subscribers per publisher/service provider.
 - Determining appropriate time interval for subscriber history and for subscriber abandonment.
 - Finding best features for predictive model.
 - Handling categorical features with too many possible values.



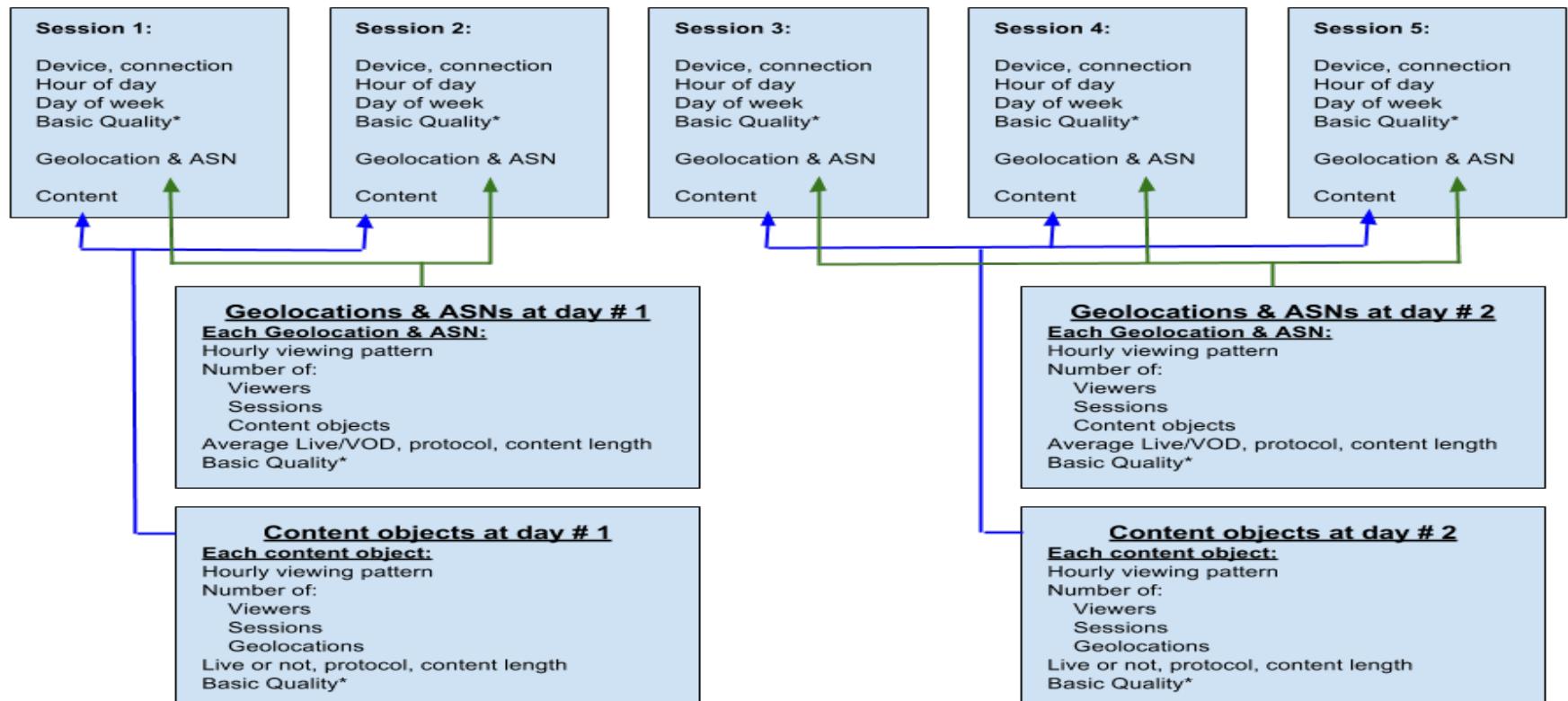
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Characterization of Categorical Features

- One-hot encoding:
 - Some categorical features (e.g. Device) with dense limited values
- Some features have too many sparse categorical values
 - City & ASN
 - Video Content
- Aggregated features of many months of subscriber behavior:
 - All content that the subscriber watched
 - all Geolocations from which the viewer watched



Geolocation & Day



(*) **Basic Quality:** Failed/not, Start-time, Buffering, Bit-rate

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Work Flow Inside Databricks

- Create dataframes with features for each geo x day, content x day
- For each subscriber history, for each video session, replace geo and content with features of geo x day, content x day for that day
- Aggregate each subscriber history to obtain final features
- All done inside Databricks environment. Highly iterative process: especially related to feature design and extractions (many interactions)
- Use Spark MLlib, various models, such as Gradient Boosted Tree Regression
- User visualization inside Databricks



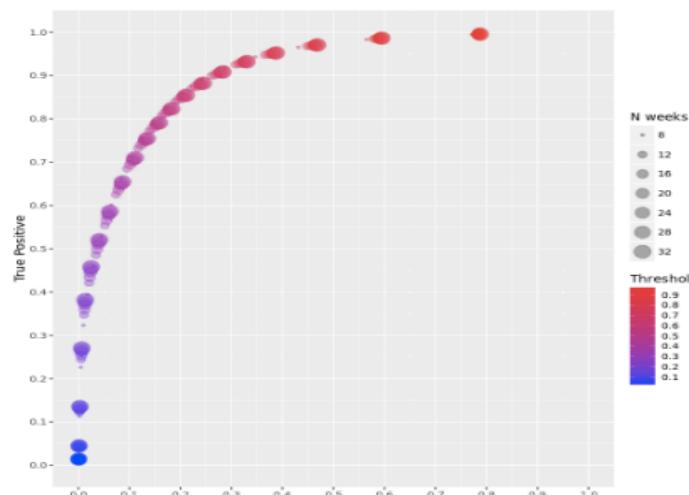
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Sample Results

Common ROC (churn) representation

```
> ggplot(dfrROC,aes(x=dfrROCS$FalsePositiveChurn, y=dfrROCS$Selectivity)) +  
  geom_point(alpha=0.3, aes(size=dfrROCS$targ, color=dfrROCS$tP)) +  
  scale_size_continuous(name="N weeks", breaks=c(8,12,16,20,24,28,32), labels=c("8","12","16","20","24","28","32")) +  
  scale_color_gradient(name="Threshold", low="blue", high="red", breaks=c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9), labels=c("0.1","0.2","0.3","0.4","0.5","0.6","0.7","0.8","0.9")) +  
  ggtitle(expression(atop("ROC. Model is trained on 8 weeks history to predict next 8 weeks inactivity",  
    atop("The model is applied 8 weeks later. The prediction is compared with N weeks inactivity.","")))) +  
  labs(x="False Positive",y="True Positive") +  
  coord_cartesian(xlim=c(0,1), ylim=c(0,1)) +  
  scale_x_continuous(breaks=c(0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1)) + scale_y_continuous(breaks=c(0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1))
```

ROC. Model is trained on 8 weeks history to predict next 8 weeks inactivity
The model is applied 8 weeks later. The prediction is compared with N weeks inactivity.



Much More Work Ahead

- Improve the real time performance, trading off latency vs metrics accuracy/failure handling.
- <100ms real time processing and response still need more work.
- Making sure modular design for all the logics so that it can be shared cross all 3 stacks wherever possible
- More exciting and challenge works ...



We Are Hiring

<http://www.conviva.com/our-team/careers/>

THANK YOU.

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