From
"All-At-Once, Once-A-Day"
To
"A-Little-Each-Time, All-The-Time"

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#SAISExp5

OLX Group and its Data Platform

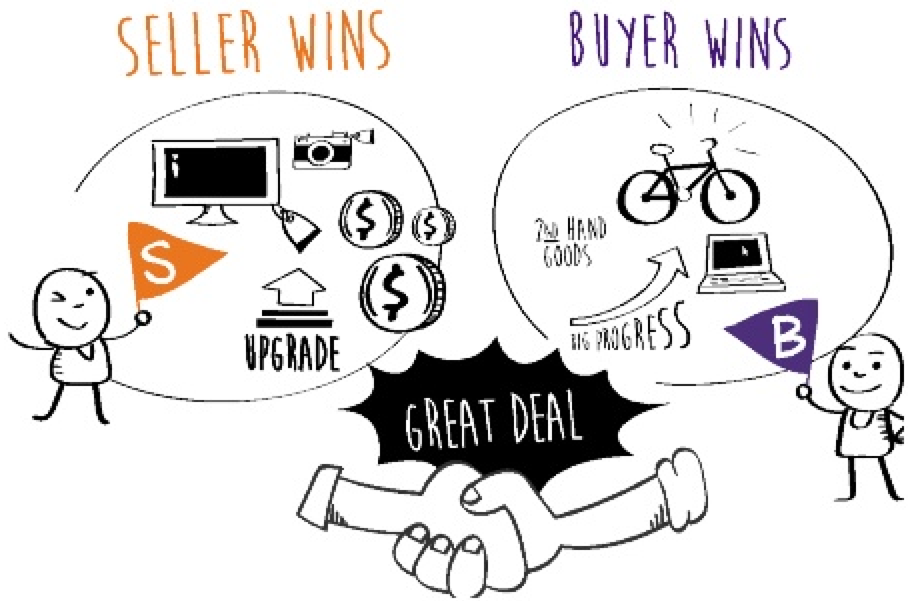
Users Communication and Lifecycle Management

Near-Time Data Engineering with Spark

Takeaways & Questions

Our Mission

we fuel local economies
by making it
super easy
for anyone to
buy or sell
almost anything
through our platforms



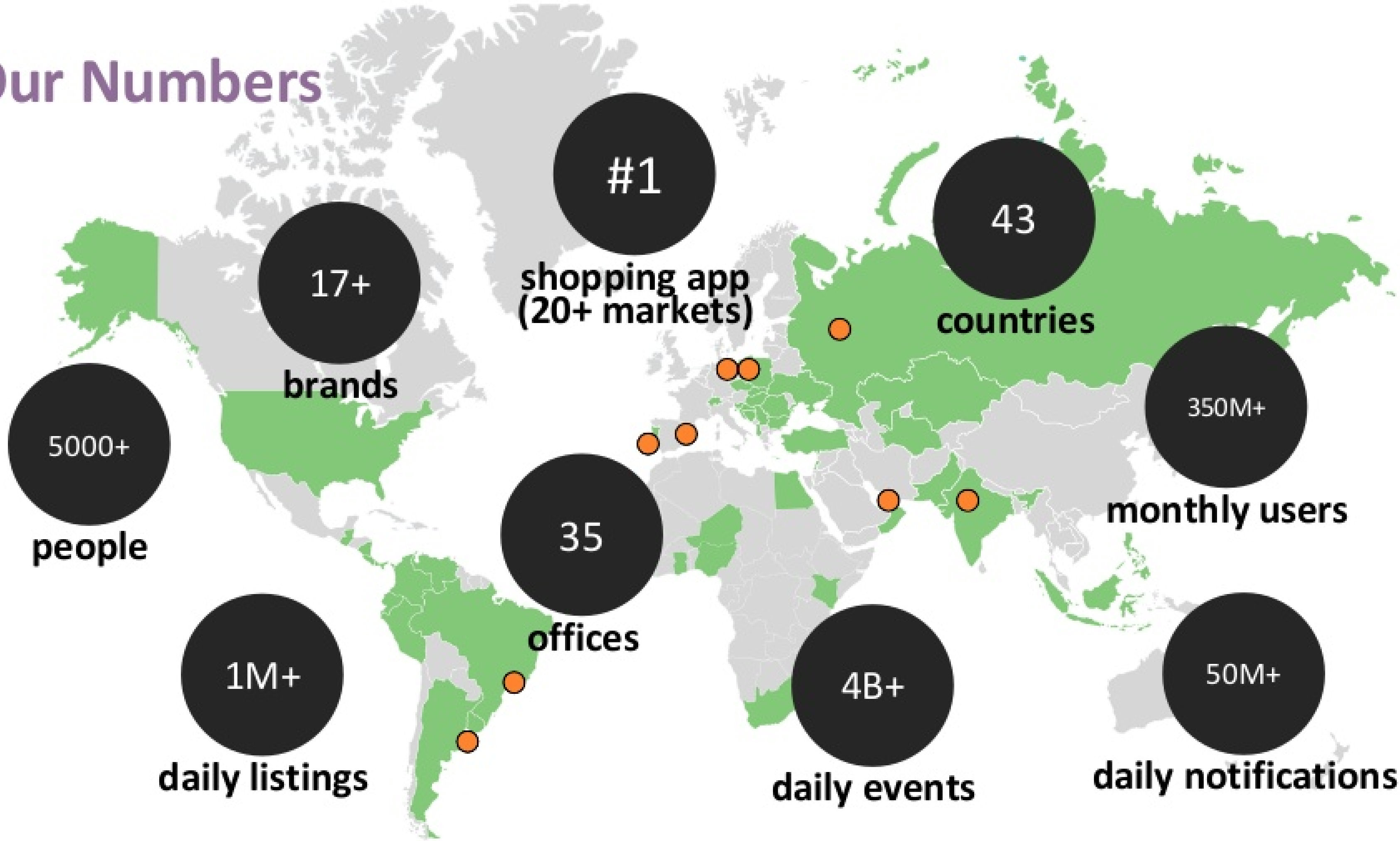
Who We Are

OLX GROUP

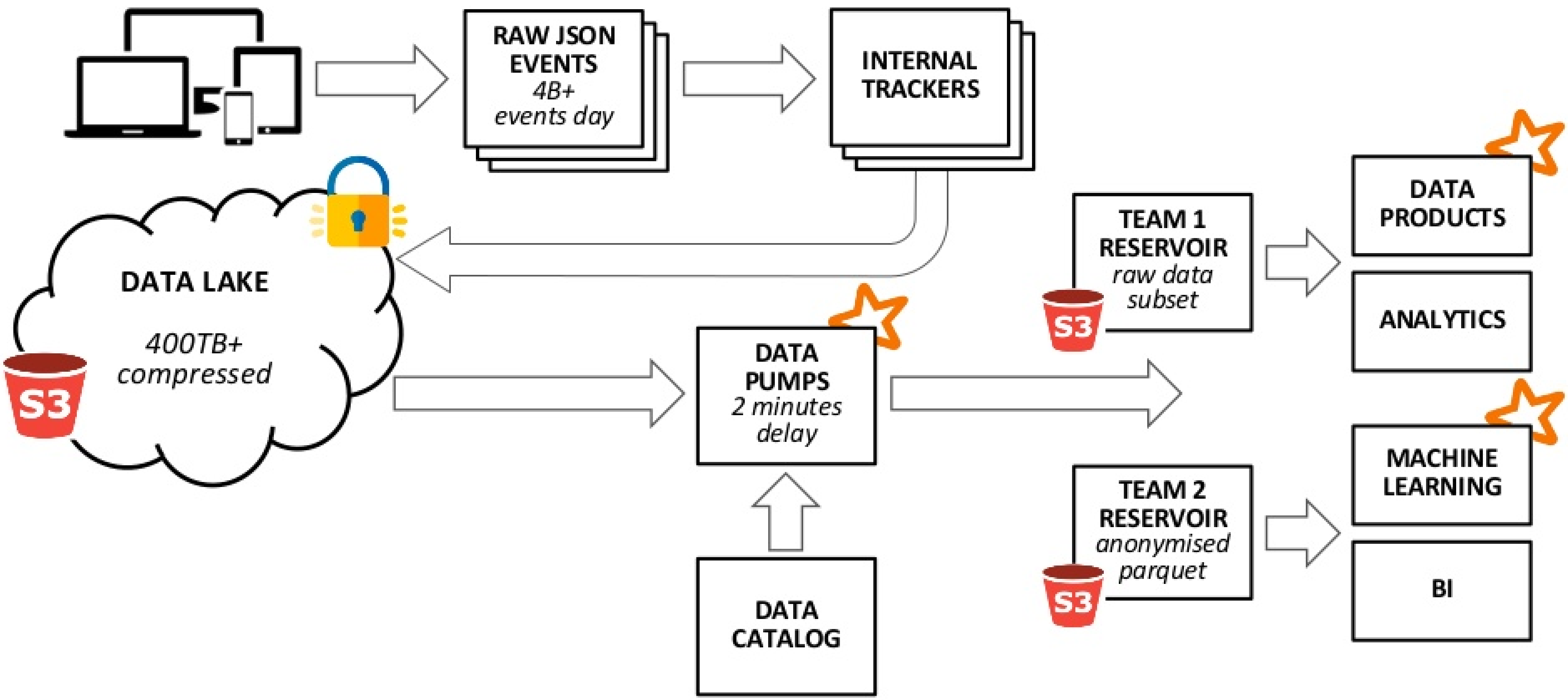
NASPERS

we operate a network of
market-leading trading platforms
in over **40 countries**
that are used by more than
350 million people every month
to **buy and sell** almost anything

Our Numbers


#1
shopping app
(20+ markets)
17+
brands
43
countries
5000+
people
350M+
monthly users
35
offices
1M+
daily listings
4B+
daily events
50M+
daily notifications

Data Platform Overview



Users Communication Team

"optimize and deliver all OLX Group end-user communication"

Transactional	Marketing	Lifecycle (CLM)
standard messages produced due to day-to-day interactions	one-off messages sent to advertise specific initiatives	messages crafted to influence customers journey positively
(reset password, post approved, new follower, ...)	*(happy holidays, get the new OLX app, ...)*	*(we miss you, we picked this item just for you, ...)*

Customers Lifecycle Management

70%

of mobile APPs users are lost after 3 days

40%

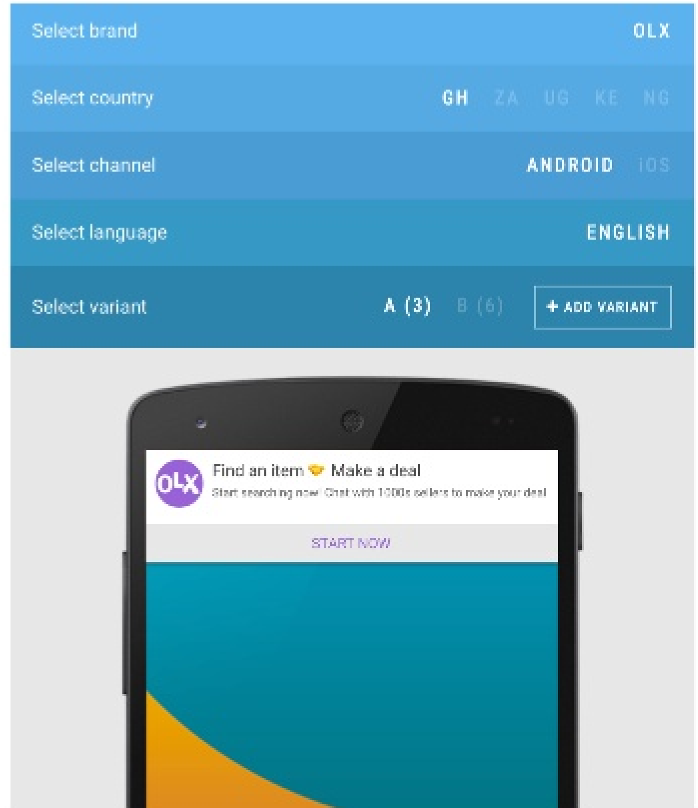
increase in Daily Active Users

15%

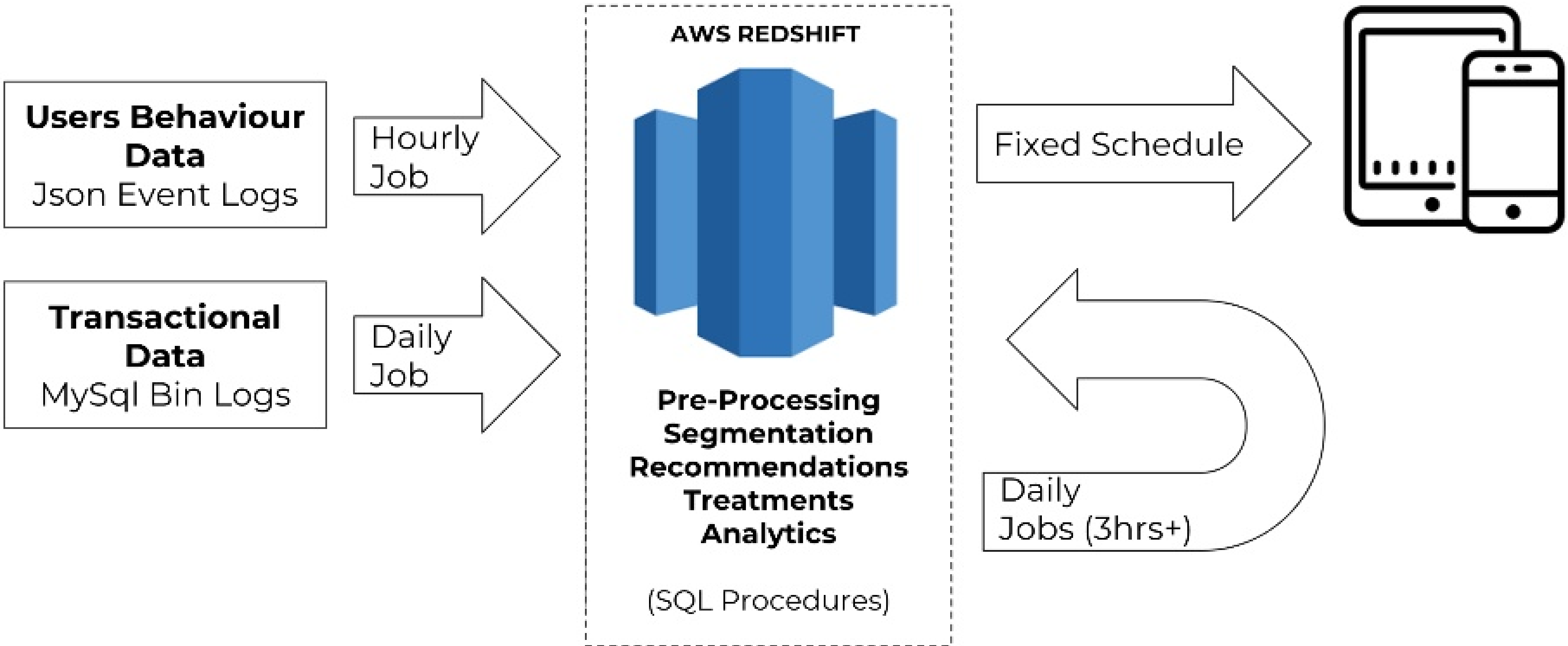
contribution to Value Added Services purchase

CLM Services Ecosystem

- Segmentation
- Recommendations
- User-Devices Mapping
- Live / Control Group Bucketing
- Audience Generation
- Treatments Definition (A/B Testing)
- Messages Prioritization
- Frequency Capping
- Scheduling
- Analytics



Former "Batch" Approach



From

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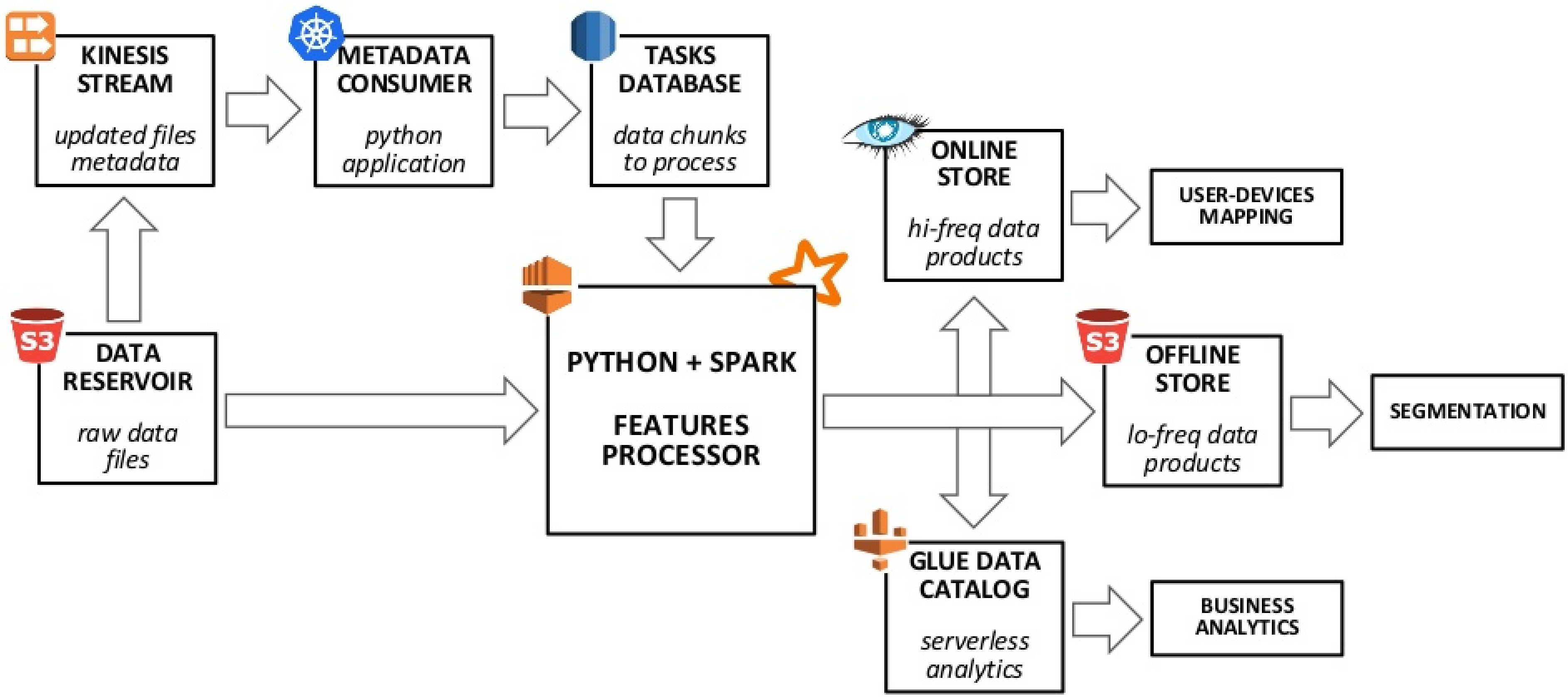
To

“A-Little-Each-Time, All-The-Time”

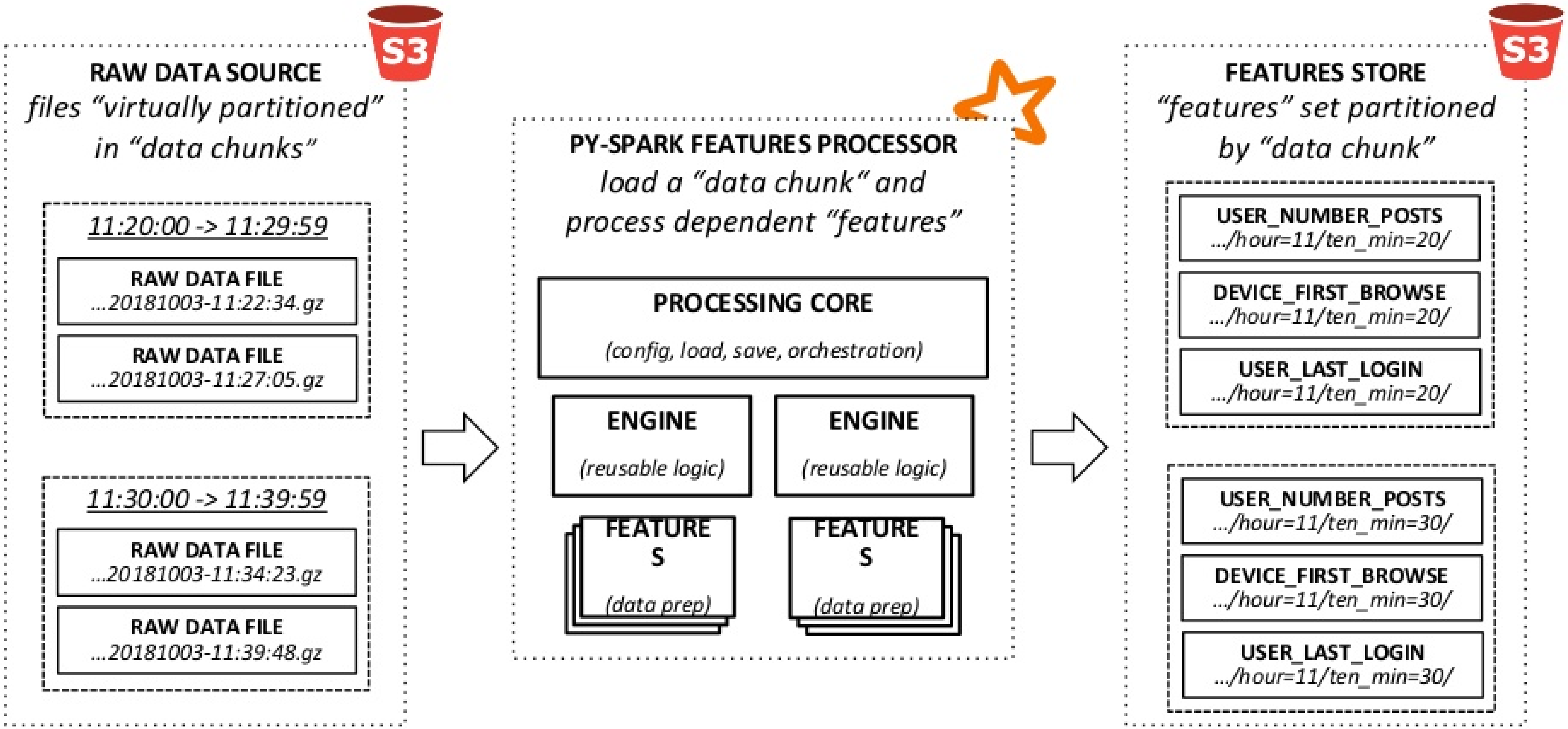
New “Near-Time” Approach

- **Near-Time** - Produce and send messages within 10 minutes after a set of events happened
- **Open** - Give our users freedom to be more creative and experiment more
- **Reliable** - Powered by technologies that make it easy to apply engineering best practices
- **Flexible** - Adapt to Big Data challenges easily

Near-Time Data Processing with Spark (Platform)



Near-Time Data Processing with Spark (Data Flow)



Data Chunks Metadata Example

kinesis stream metadata (raw data files paths)

```
s3://raw-data-reservoir/in/horizontals/olx/android/2018/08/01/201808-01-104234.gz
s3://raw-data-reservoir/in/horizontals/olx/android/2018/08/01/201808-01-104400.gz
s3://raw-data-reservoir/in/horizontals/olx/android/2018/08/01/201808-01-104954.gz

s3://raw-data-reservoir/in/horizontals/olx/android/2018/08/01/201808-01-105403.gz
s3://raw-data-reservoir/in/horizontals/olx/android/2018/08/01/201808-01-105744.gz
s3://raw-data-reservoir/in/horizontals/olx/android/2018/08/01/201808-01-105923.gz
```

tasks database records (data chunks to process)

```
     source_bucket        |         file_path          |     data_chunk      |    ts_to_process
--------------------------+----------------------------+---------------------+-------------------
 s3://raw-data-reservoir | in/horizontals/olx/android/ | 2018-08-01 10:40:00 | 2018-08-01 10:53:00

 s3://raw-data-reservoir | in/horizontals/olx/android/ | 2018-08-01 10:50:00 | 2018-08-01 11:03:00
```

Processed Features Data Example

```
parquet-tools head ../features_store/user_numb_posts/year=2018/month=08/day=01/hour=09/ten_mins=30/

id = c360f89568
country = gh
brand = olx
actions_count = 1

id = 8fe540bb38
country = za
brand = olx
actions_count = 3


parquet-tools head ../features_store/user_last_login/year=2018/month=08/day=01/hour=10/ten_mins=10/

id = 0947a3e926
country = cz
brand = letgo
last_action_timestamp = 1533118630

id = ff3ca262b3
country = ke
brand = olx
last_action_timestamp = 1533118751
```

Features Code Example (Data Preparation)

```
class FeatureDeviceLastBrowse(EngineLastActionTime):

    def _preprocess_engine_input_data(self):
        engine_input_data = self._source_data_frame

        # pre-process source data
        engine_input_data = \
            engine_input_data\
                .withColumn('device_id', clean_str('device_id'))\
                .withColumn('country', clean_str('country'))\
                .withColumn('brand', clean_str('brand'))\

        # filter data relevant to features
        events = ['app_open', 'view_listings', 'view_item',
                  'search_start', 'chat_inbox', 'on_resume']

        engine_input_data = \
            engine_input_data\
                .filter(filter_col('event_name', events))

        # expose columns engine requires
        engine_input_data = \
            engine_input_data\
                .select('device_id','country','brand','timestamp'

        return engine_input_data
```

```
class FeatureUserLastLogin(EngineLastActionTime):

    def _preprocess_engine_input_data(self):
        engine_input_data = self._source_data_frame

        # pre-process source data
        engine_input_data = \
            engine_input_data\
                .withColumn('user_id', clean_str('user_id'))\
                .withColumn('country', clean_str('country'))\
                .withColumn('brand', clean_str('brand'))\

        # filter data relevant to features
        events = ['login_sign_in_complete']

        engine_input_data = \
            engine_input_data \
                .filter(filter_col('event_name', events))

        # expose columns engine requires
        engine_input_data = \
            engine_input_data\
                .select('user_id','country','brand','timestamp')

        return engine_input_data
```

Engines Code Example (Data Transformation)

```
class EngineLastActionTime(ProcessingCore):

    # define input schema (raw data from feature)
    def _engine_input_data_schema(self):
        return StructType([
                StructField('id', StringType(), True),
                StructField('country', StringType(), True),
                StructField('brand', StringType(), True),
                StructField('timestamp', IntegerType(), True)
        ])

    # define logic transformation (input -> output)
    def _engine_transform(self, df):
        df = df.groupBy('id', 'country', 'brand')\
               .agg(F.max('timestamp'))

        return df

    # define output schema (transformed data to save)
    def _engine_output_data_schema(self):
        return StructType([
                StructField('id', StringType(), True),
                StructField('country', StringType(), True),
                StructField('brand', StringType(), True),
                StructField('last_action_ts', IntegerType(), True)
        ])
```

Data Product Example (Serverless Analytics)

New query 1 +

```sql
select
  brand, country, count(distinct(id)) cnt
from
  features_store.device_last_browse
where
  year='2018' and month ='09' and day = '20'
group by 1, 2
order by 3 desc
```

Run query | Save as | Create view from query | (Run time: 6.65 seconds, Data scanned: 58.35MB)

Use Ctrl + Enter to run query, Ctrl + Space to autocomplete | Format query | Clear

Results

	brand	country	cnt
1	letgo	cz	893241
2	olx	za	761791
3	olx	ke	271683

Spark Environment

- **PySpark 2.3.0** : Python3 + Spark SQL + Dataframes
- **AWS EMR 5.15** (Yarn) : r5.xlarge instances
  1 Master + 1 Core + N Task (SPOT)
- **Deployment Mode :** Client
- **Scheduler Mode** : Fair
- **Features Stores : Offline** S3 (Parquet) – **Online** Cassandra
- **CI / CD** : GitLab Pipeline (RPM Packaging)

Takeaways

- Goodbye Schedulers, **Welcome Events**!
- Raw data is messy and unpredictable. **Constantly (re)processing small chunks of data** helps with accuracy and consistency
- **Separation of storage and compute** helps to optimize resources and allows scalability on-the-cheap
- Python + Spark : **Software + Data + Science engineered together** for effective big data processing

THANK YOU! Questions?

GET IN TOUCH WITH US!

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