Scaling to a million ML models using Kubernetes, Apache Spark and Apache Arrow

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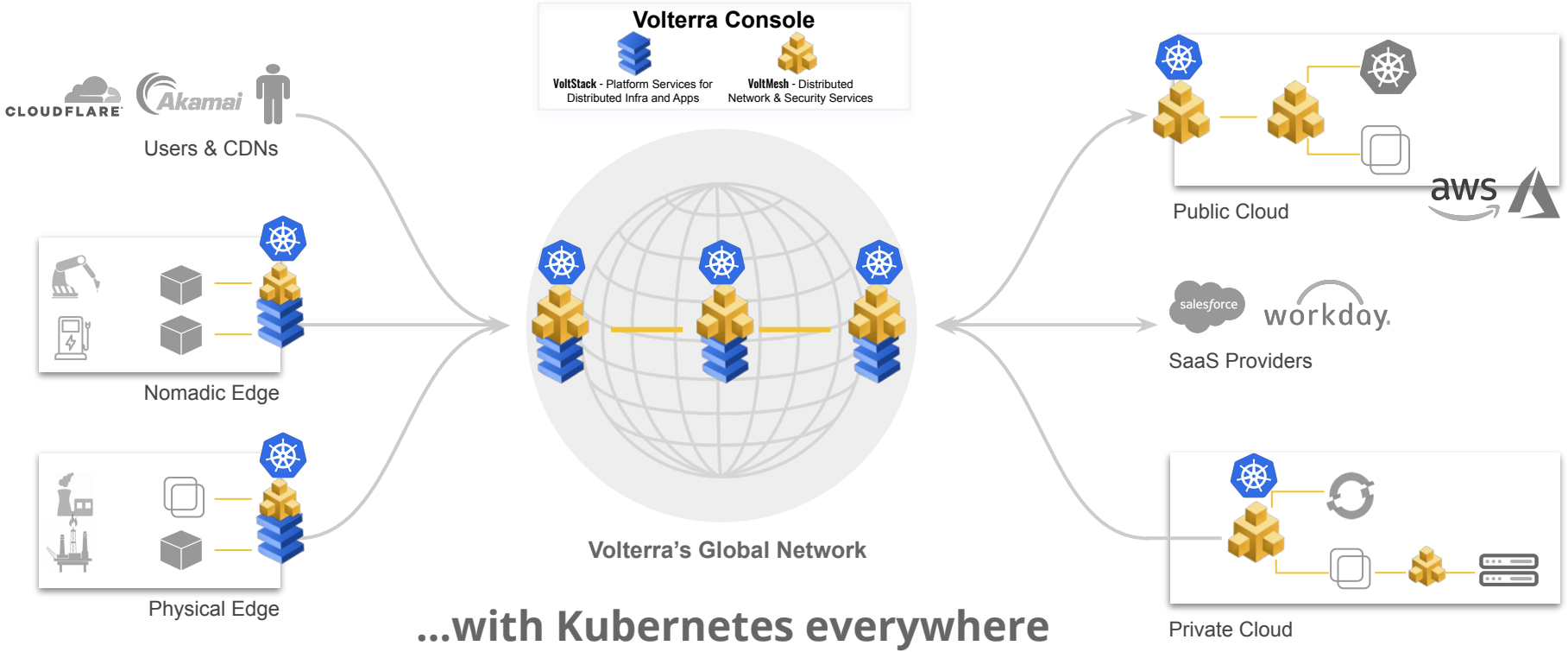
Enable a Distributed Cloud for Everyone, Everywhere

Agenda

- Overview
- Volterra ML Functions & Model Explosion
- ML Infrastructure Evolution Journey
- Model Scaling Challenges

WE BUILT VOLTERRA

...to distribute cloud services wherever your apps & data need them



...with Kubernetes everywhere

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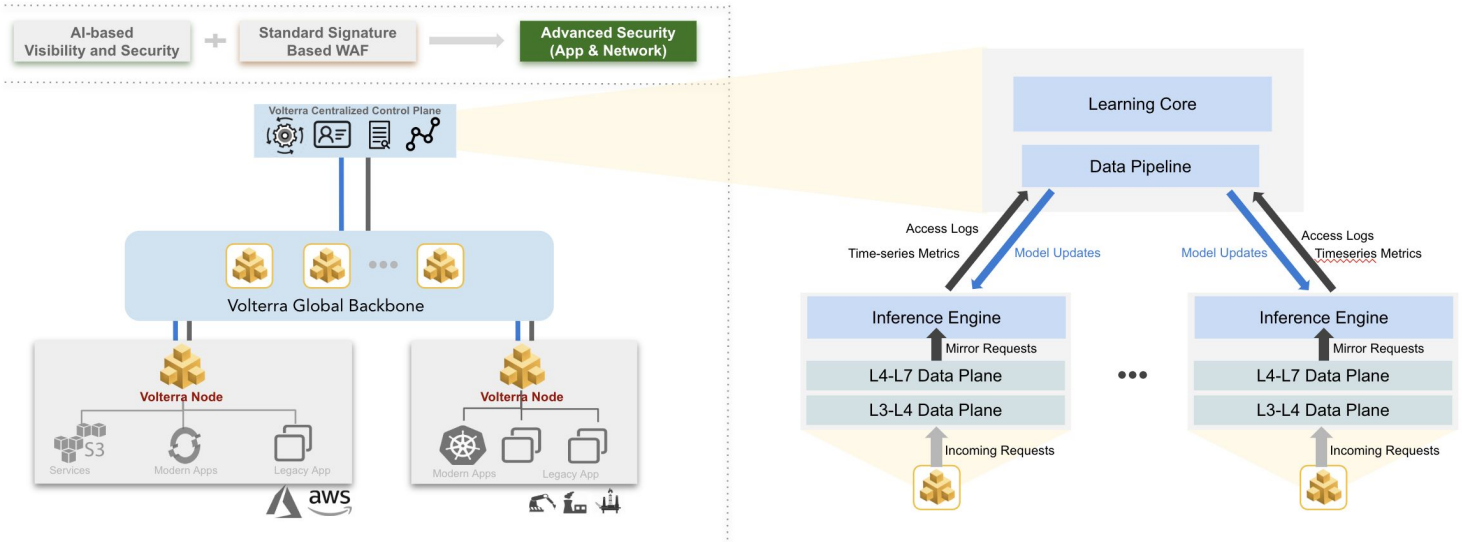
VoltMesh - Application Security



VoltMesh - Application Security

- Rule-based WAFs
- Application DoS & BOT Detection
- Application Anomaly Detection
- Time-series Anomaly Detection
- API Endpoint Markup
- API Behavioral Analysis & Anomalies

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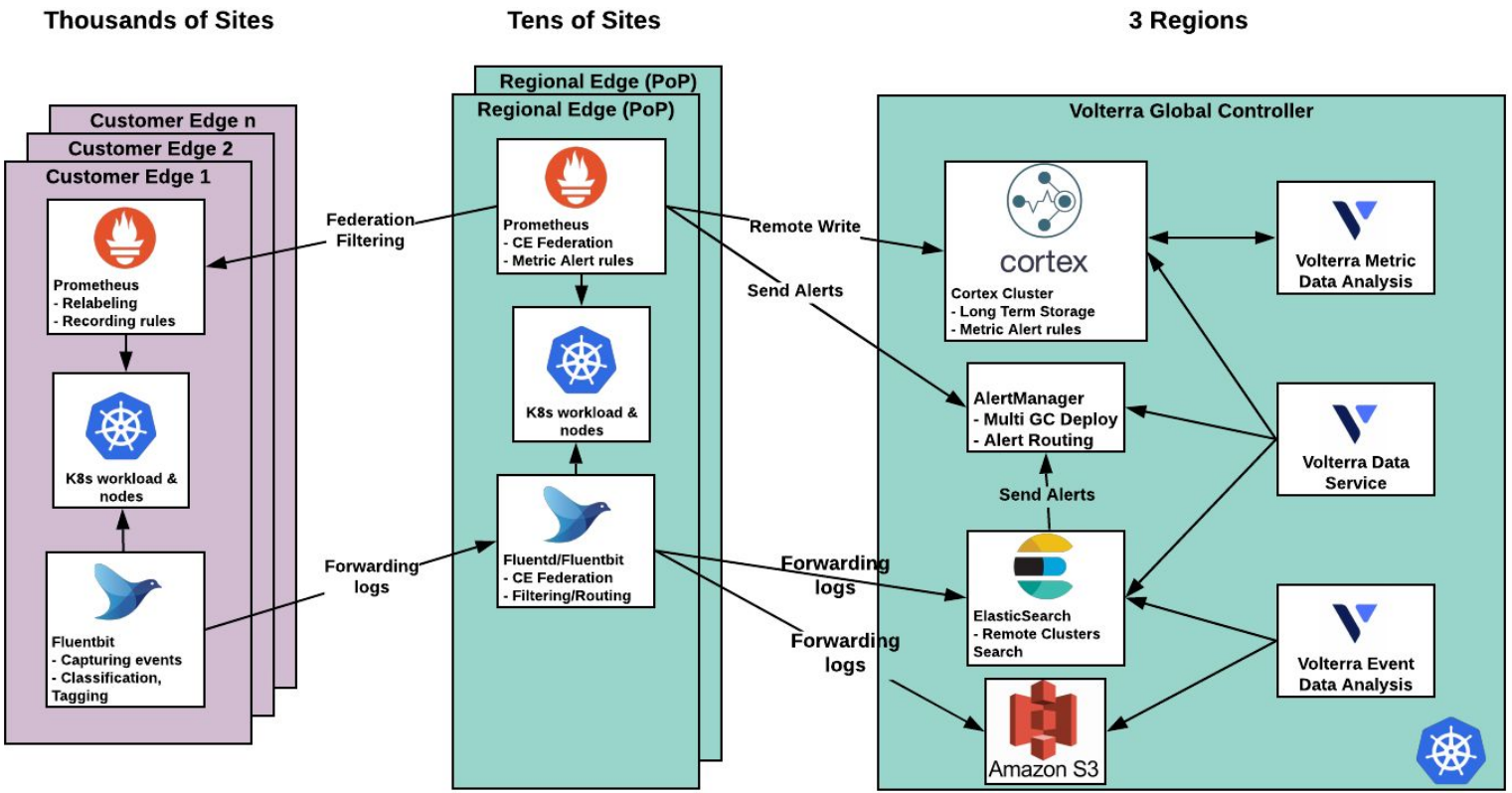
Volterra Metrics and Logging infrastructure

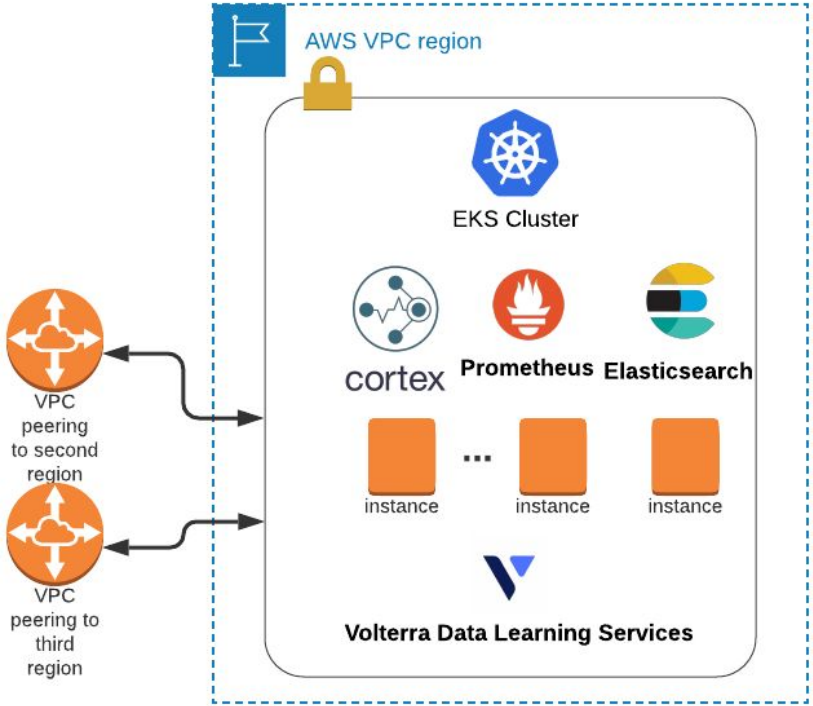


Volterra ML Model Explosion and Scaling

- Volterra ML models has to be done across several dimensions: Application, API, Virtual Host, Source, Destination etc
- This leads to large cardinality of models for each ML module
- We need to scale as we deploy more complex applications in several locations
- Our ML models was running on a single instance in a serialized manner; one after the other
- The training of all models simultaneously took very long. This alone can cause a scenario that once a model was ready and deployed it was already obsolete

Where We Started

- Single Kubernetes cluster with continuous static running learning jobs
- Inefficient CPU and RAM usage
- Resizing to bigger and bigger VM flavors
- Managing scaling to multiple instances
- Autoscaling processing and memory
- Handling very large dataset ingestion and training



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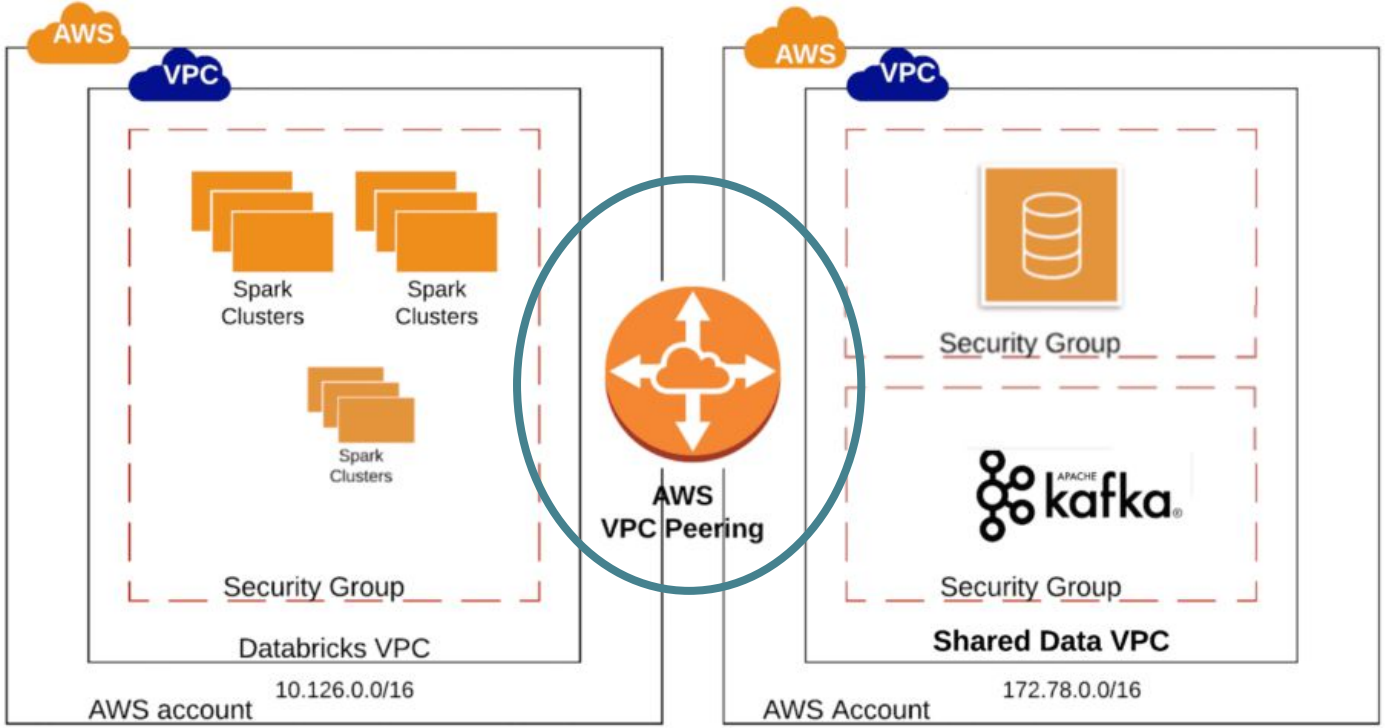
What Would Be an Ideal Solution?

- Run several models in parallel with high performance
- Autoscale with increasing number of applications. Seamlessly handle varying levels of scale per customer.
- Optimize CPU Resources, Cost effective
- Automation with CI/CD, Minimize Infrastructure Management
- Secure and Seamless Data Ingestion

⇒ End-to-end integration of existing Kubernetes infra with Spark Scaling and Parallelization (Databricks)

Standard Databricks Integration



Databricks requires VPC Peering, which opens new security concerns…

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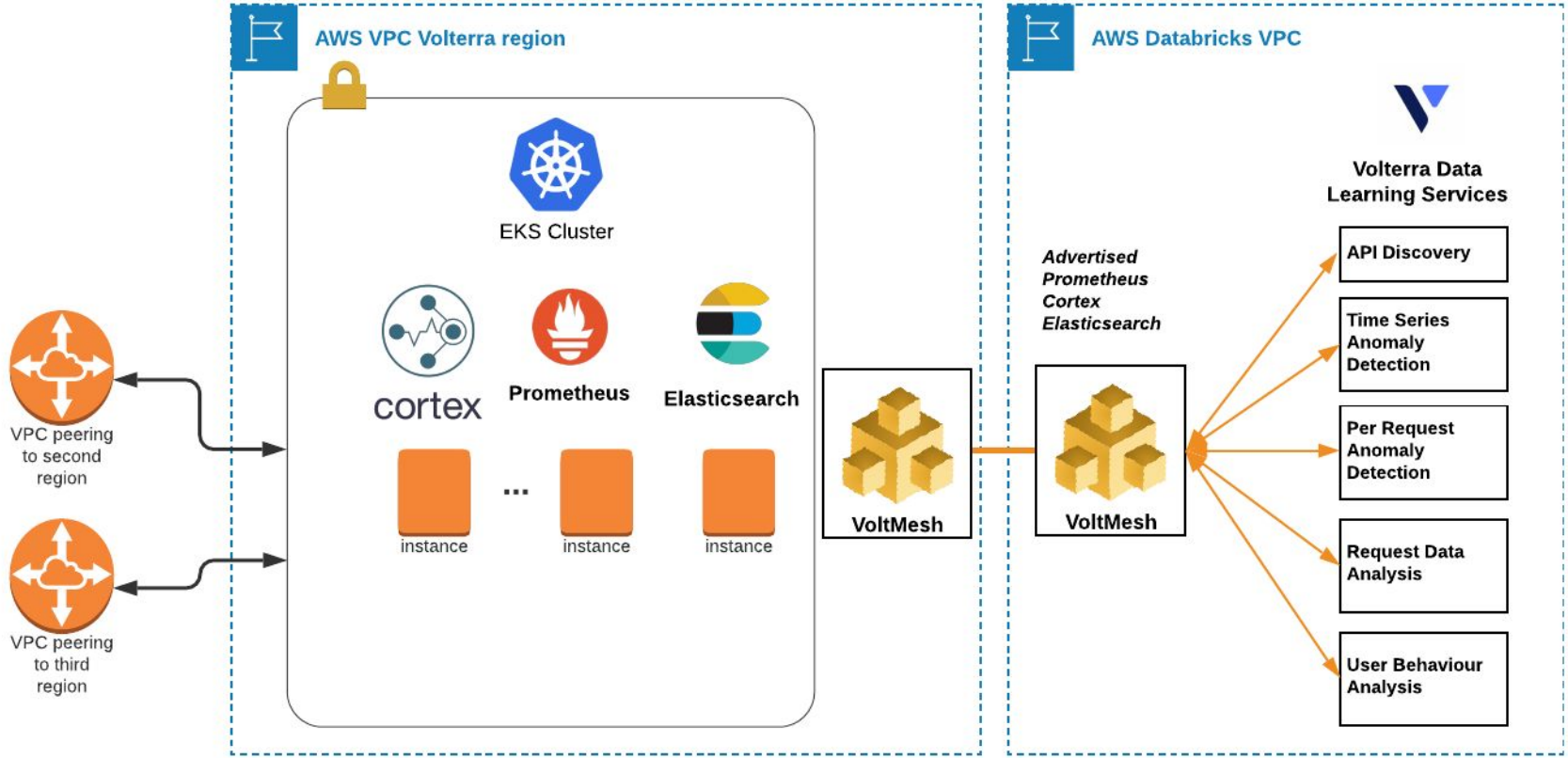
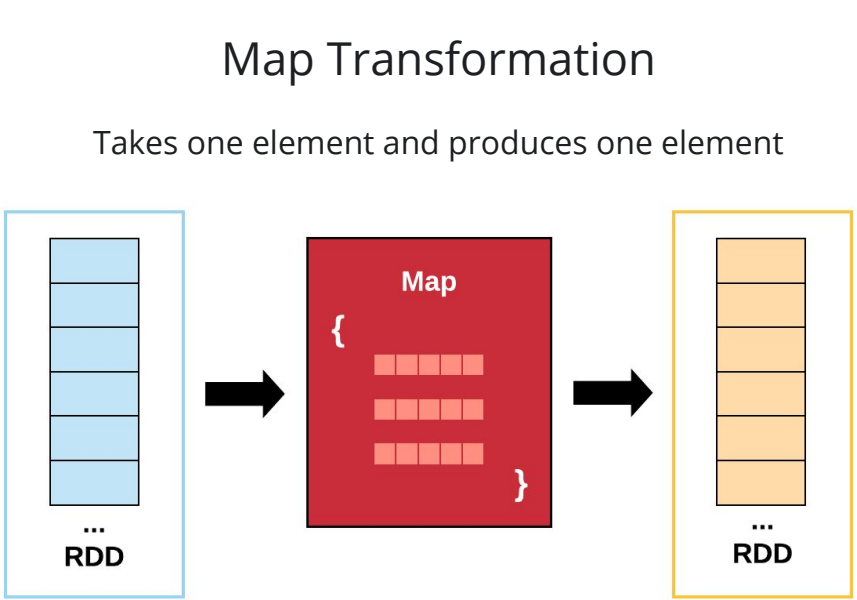
Final Design Using VoltMesh Secure Ingress GW



Model Parallelization Approach 1

Create Spark Dataframe of Model Keys and use *map/collect* to apply the Model Function in Parallel



Spark provides a *resilient distributed dataset* (RDD), that can be operated on in parallel
RDDs transformations: *map*
RDD action: *collect*

```
def outer_func(key_tuples, var1, var2):
  # Build Pandas Dataframe from keys
  pd_df = pd.DataFrame.from_records(key_tuples)
  # Build the Spark Dataframe from Pandas
  spark_df = spark.createDataFrame(pd_df)
  # Model Function inside an Outer Function
  def my_func(pd_frame):
    key1 = pd_frame['key1']
    key2 = pd_frame['key2']
    return model_func(key1, key2, var1, var2))
  results = spark_df.rdd.map(my_func).collect()
```

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Model Parallelization Approach 2

Use Pandas UDFs with Apache Arrow

Pandas UDFs allow not only to scale out their workloads, but also to leverage the Pandas APIs in Apache Spark.

The user-defined functions are executed by:

- Apache Arrow, to exchange data directly between JVM and Python driver/executors with near-zero (de)serialization cost.
- The Pandas UDFs work with Pandas APIs inside the function and Apache Arrow for exchanging data.
- It allows vectorized operations that can increase performance up to 100x, compared to row-at-a-time Python UDFs.
- Grouped Map Pandas UDFs: split a Spark DataFrame into groups based on the conditions specified in the group by operator, applies a UDF (pandas.DataFrame > pandas.DataFrame) to each group, combines and returns the results as a new Spark DataFrame.

Apache Arrow

Being columnar in memory, Apache Arrow manages memory more efficiently than row storage and takes advantage of modern CPU and GPU.

	session_id	timestamp	source_ip
Row 1	1331246660	3/8/2012 2:44PM	99.155.155.225
Row 2	1331246351	3/8/2012 2:38PM	65.87.165.114
Row 3	1331244570	3/8/2012 2:09PM	71.10.106.181
Row 4	1331261196	3/8/2012 6:46PM	76.102.156.138

Traditional Memory Buffer

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	3/8/2012 2:44PM
	99.155.155.225
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Arrow Memory Buffer

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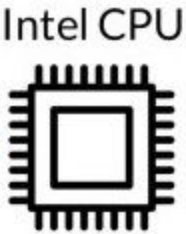

Arrow leverages the data parallelism (SIMD) in modern Intel CPUs:

```
SELECT * FROM clickstream WHERE
session_id = 1331246351
```

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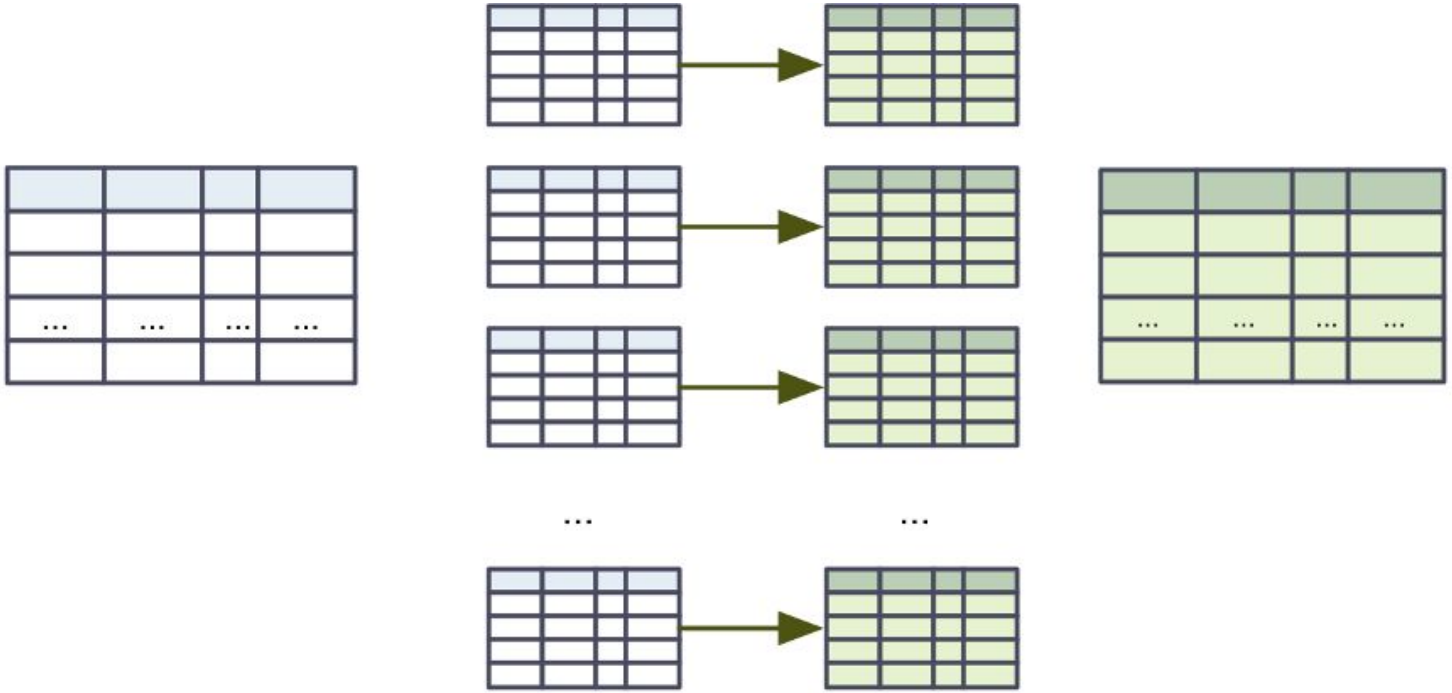
Grouped Map Pandas UDF



Original data frame

Split
(the data frame in in-memory manageable chunks)

Apply
(the transformation to each chunk independently)

Combine
(each chunk back into a data frame)

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Grouped Map Pandas UDF

```
# define schema for what the pandas udf will return
schema = StructType([StructField('group_id', IntegerType()),
StructField('model_str', StringType())])

@pandas_udf(schema, functionType=PandasUDFType.GROUPED_MAP)
def train_model(df_pandas):
    # get the value of this group id
    group_id = df_pandas['group_id'].iloc[0]
    # get features and label for all training instances in this group
    X = df_pandas[['my_feature_1', 'my_feature_2']]
    Y = df_pandas['my_label']
    # train this model
    model = RandomForestRegressor()
    model.fit(X,Y)
    # get a string representation of our trained model to store
    model_str = pickle.dumps(model)
    # build the DataFrame to return
    df_to_return = pd.DataFrame([group_id, model_str],
    columns = ['group_id', 'model_str'])
    return df_to_return

spark.conf.set("spark.sql.execution.arrow.enabled", "true")
df_sp = spark.createDataFrame(df_pd)
results = df_sp.groupBy('group_id').apply(train_model)
res_pd = results.toPandas()
```

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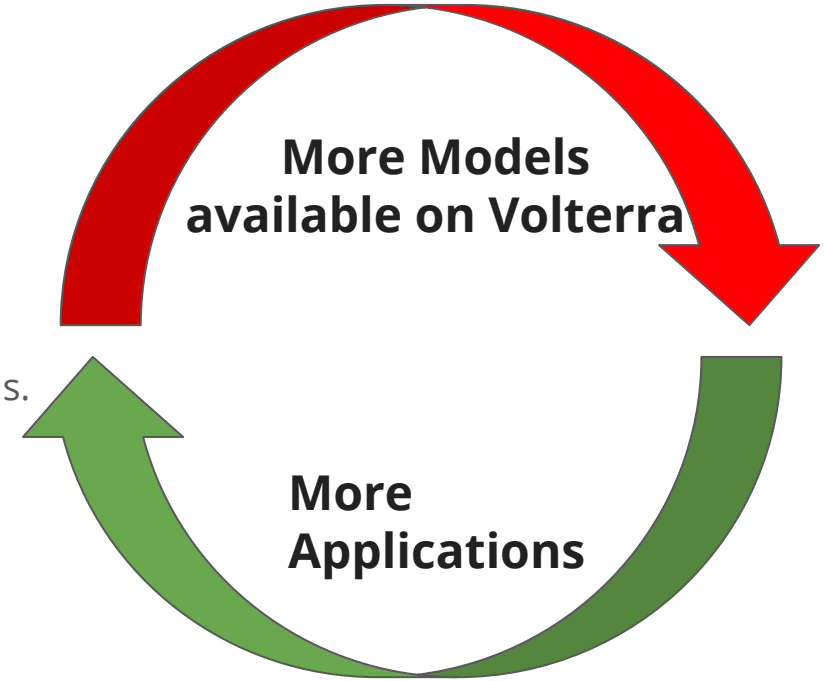
Conclusion

- **Goal: Add new models and scale with growing customers/applications**
  - End to End Automation, Security and CI/CD
- **Features**
  - Microservice architecture
    - Embedded Spark
  - Provide platform to seamlessly add new models.
  - Minimize resource costs
  - Extend to Spark Streaming for near real-time applications



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