RUNNING EMERGING AI APPLICATIONS ON BIG DATA PLATFORMS WITH RAY ON APACHE SPARK

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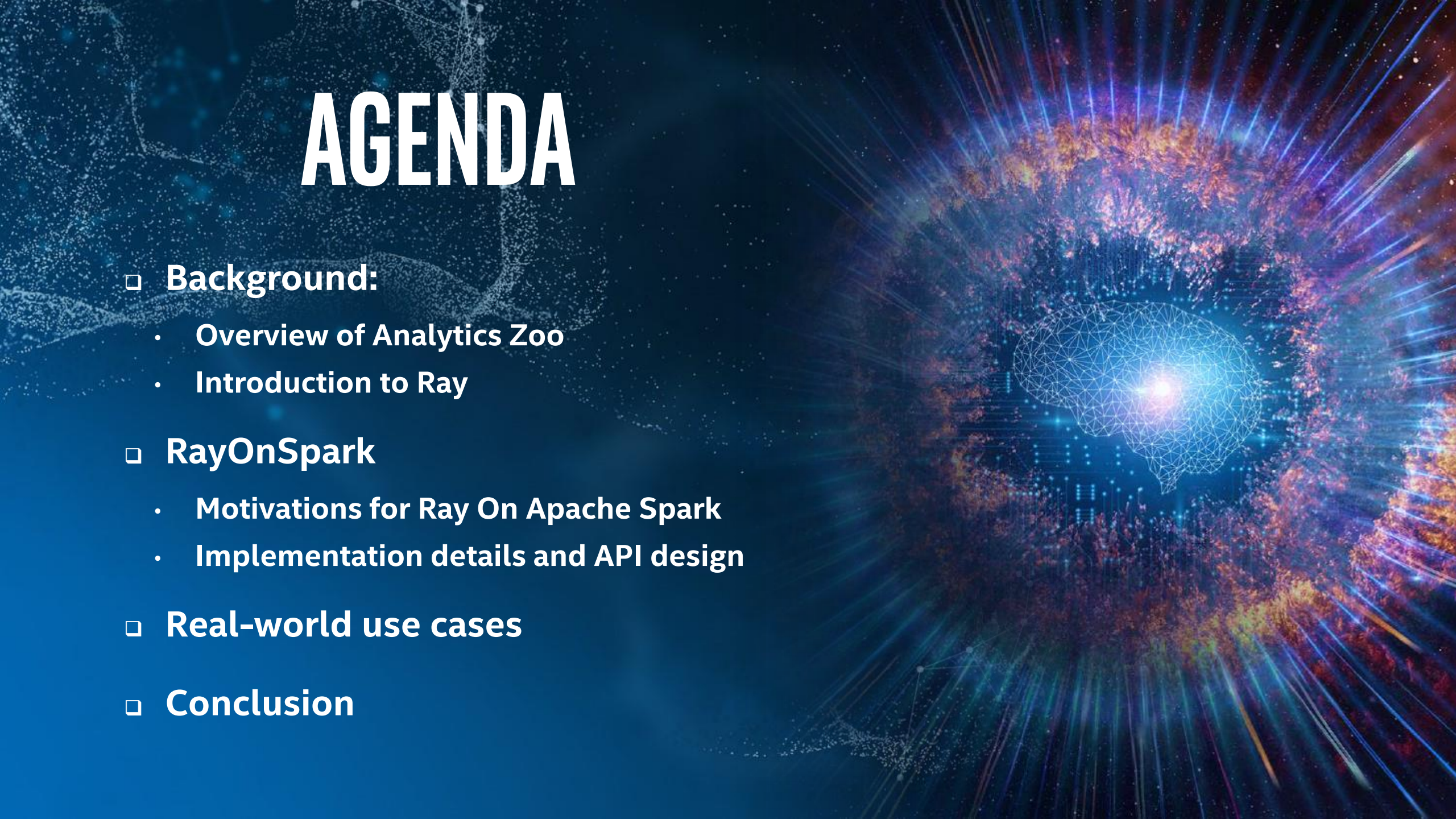
AGENDA

- Background:
  - Overview of Analytics Zoo
  - Introduction to Ray
- RayOnSpark
  - Motivations for Ray On Apache Spark
  - Implementation details and API design
- Real-world use cases
- Conclusion



AI ON BIG DATA

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BigDL

Distributed, High-Performance

Deep Learning Framework

for Apache Spark*

https://github.com/intel-analytics/bigdl

ANALYTICS ZOO

Unified Analytics + AI Platform

for TensorFlow*, PyTorch*, Keras*, BigDL, Ray* and Apache Spark*

https://github.com/intel-analytics/analytics-zoo

ACCELERATING DATA ANALYTICS + AI SOLUTIONS AT SCALE

ANALYTICS ZOO

Unified Data Analytics and AI Platform for distributed TensorFlow, Keras and PyTorch on Apache Spark/Flink & Ray

Models & Algorithms

- Recommendation
- Time Series
- Computer Vision
- NLP

Automated ML Workflow

- AutoML for Time Series
- Automatic Cluster Serving

Integrated Analytics & AI Pipelines

- Distributed TensorFlow & PyTorch on Spark
- RayOnSpark
- Spark Dataframes & ML Pipelines for DL
- InferenceModel

Compute Environment

- Laptop
- K8s Cluster
- Hadoop Cluster
- Spark Cluster

- DL Frameworks (TF/PyTorch/OpenVINO/…)
- Distributed Analytics (Spark/Flink/Ray/…)
- Python Libraries (Numpy/Pandas/sklearn/…)

Powered by oneAPI

https://github.com/intel-analytics/analytics-zoo

UNIFIED DATA ANALYTICS AND AI PLATFORM

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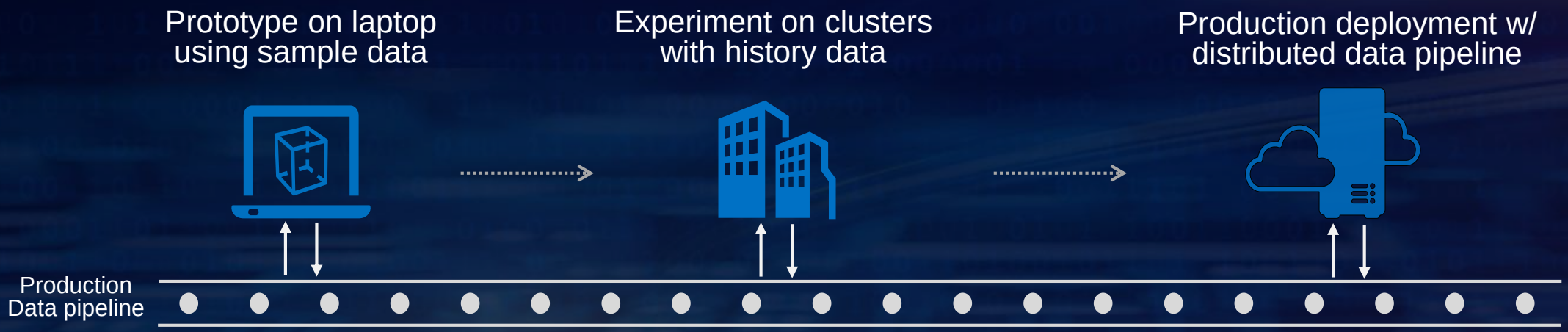
Seamless Scaling from Laptop to Distributed Big Data Clusters



- Easily prototype end-to-end pipelines that apply AI models to big data.
- "Zero" code change from laptop to distributed cluster.
- Seamlessly deployed on production Hadoop/K8s clusters.
- Automate the process of applying machine learning to big data.

RAY

Ray is a fast and simple framework for building and running distributed applications.

- Ray Core provides easy Python interface for parallelism by using remote functions and actors.

```python
import ray
ray.init()

@ray.remote(num_cpus, …)
def f(x):
    return x * x

# Executed in parallel
ray.get([f.remote(i) for i in range(5)])
```

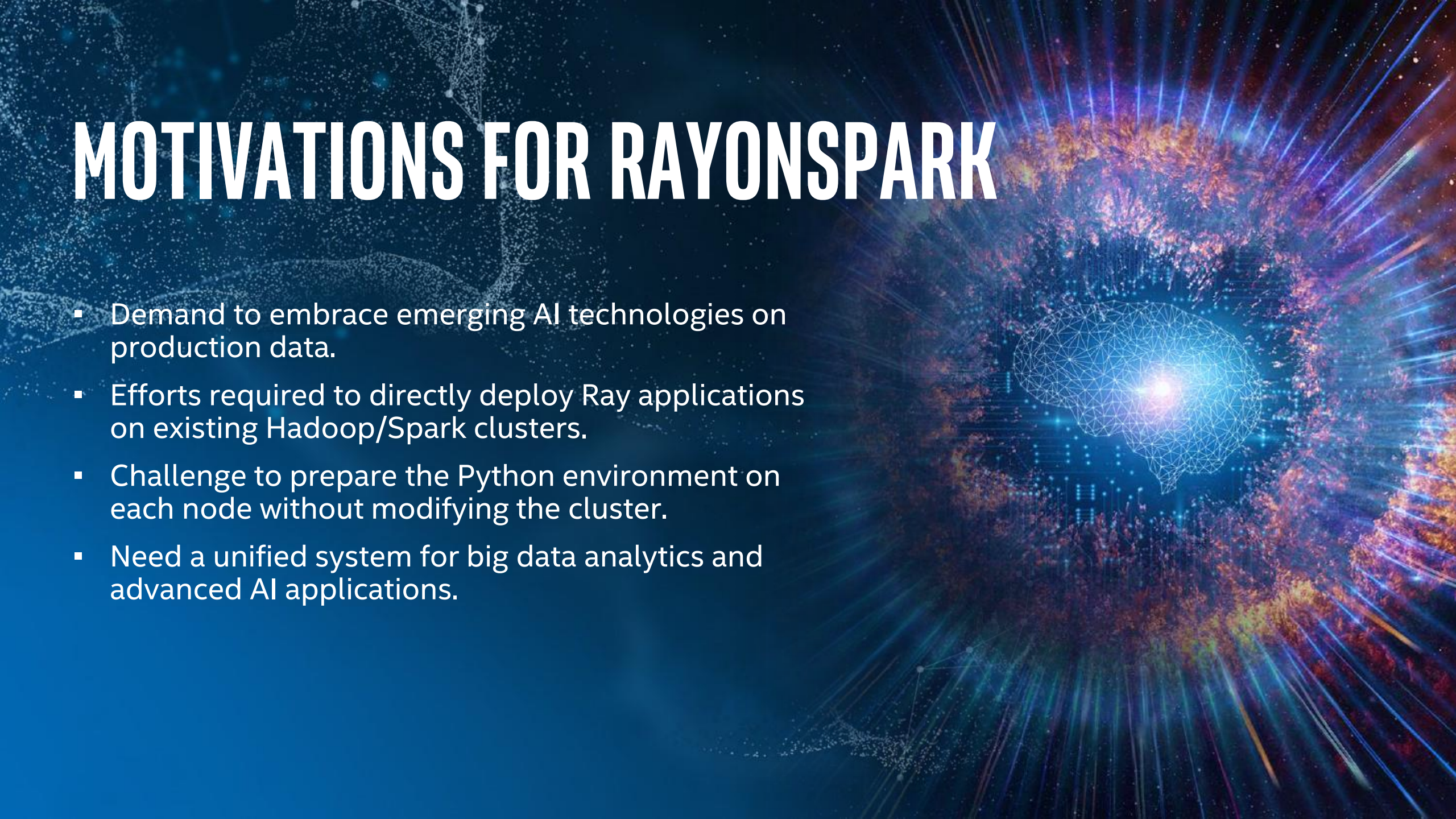
```python
@ray.remote(num_cpus, …)
class Counter(object):
    def __init__(self):
        self.n = 0
    def increment(self):
        self.n += 1
        return self.n

counters = [Counter.remote() for i in range(5)]
# Executed in parallel
ray.get([c.increment.remote() for c in counters])
```

RAY

Ray is packaged with several high-level libraries to accelerate machine learning workloads.

- Tune: Scalable Experiment Execution and Hyperparameter Tuning
- RLlib: Scalable Reinforcement Learning
- RaySGD: Distributed Training Wrappers
- https://github.com/ray-project/ray/

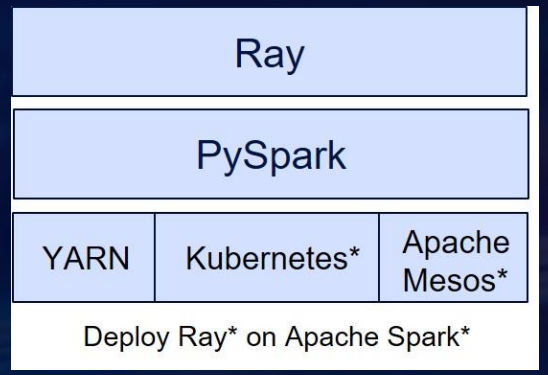
MOTIVATIONS FOR RAYONSPARK



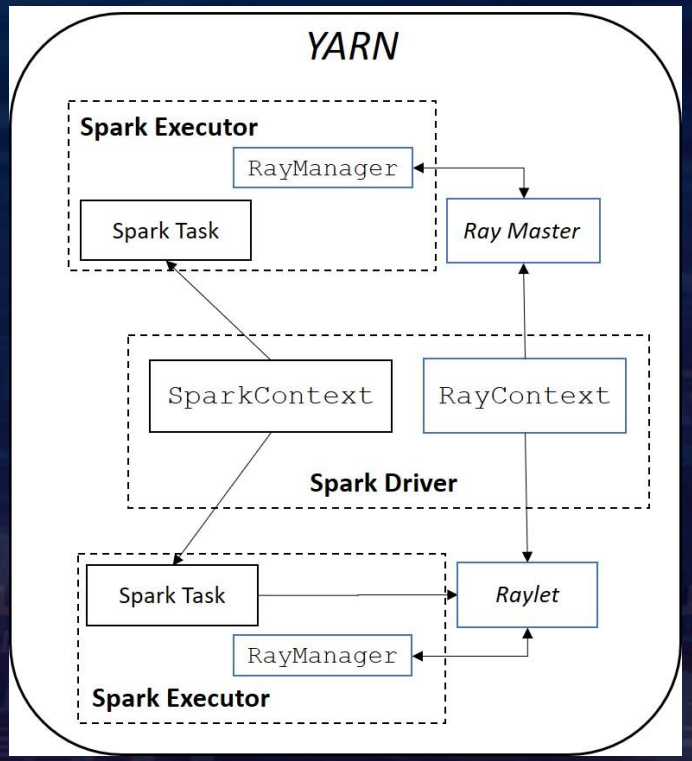
- Demand to embrace emerging AI technologies on production data.
- Efforts required to directly deploy Ray applications on existing Hadoop/Spark clusters.
- Challenge to prepare the Python environment on each node without modifying the cluster.
- Need a unified system for big data analytics and advanced AI applications.

IMPLEMENTATION OF RAYONSPARK

RayOnSpark allows Ray applications to seamlessly integrate into Spark data processing pipelines.



- Leverage conda-pack and Spark for runtime Python package distribution.
- *RayContext* on Spark driver launches Ray across the cluster.
- Ray processes exist alongside Spark executors.
- For each Spark executor, a Ray Manager is created to manage Ray processes.
- Able to run in-memory Spark RDDs or DataFrames in Ray applications.



Launch Ray* on Apache Spark*

RAYONSPARK API

Three-step programming with minimum code changes:

- Initiate or use an existing *SparkContext*.
- Initiate *RayContext*.
- Shut down *SparkContext* and *RayContext* after tasks finish.

More instructions at: https://analytics-zoo.github.io/master/#ProgrammingGuide/rayonspark/

```
import ray
from zoo import init_spark_on_yarn
from zoo.ray import RayContext
```

RayOnSpark code

```
sc = init_spark_on_yarn(hadoop_conf, conda_name,
num_executors, executor_cores,…)
ray_ctx = RayContext(sc, object_store_memory,…)
ray_ctx.init()
```

Pure Ray code

```
@ray.remote
class Counter(object):
      def __init__(self):
          self.n = 0
      def increment(self):
          self.n += 1
          return self.n
counters = [Counter.remote() for i in range(5)]
ray.get([c.increment.remote() for c in counters])
```

```
ray_ctx.stop()
sc.stop()
```

USE CASES OF RAYONSPARK

- Scalable AutoML for time series prediction.
  - Automate the feature generation, model selection and hyperparameter tuning processes.
  - See more at: https://github.com/intel-analytics/analytics-zoo/tree/master/pyzoo/zoo/automl.

- Data parallel pre-processing and distributed training pipeline of deep neural networks.
  - Use PySpark or Ray for parallel data loading and processing.
  - Use RayOnSpark to implement thin wrappers to automatically setup distributed environment.
  - Run distributed training with either framework native modules or Horovod (from Uber) as the backend.
  - Users only need to write the training script on the single node and make minimum code changes to achieve distributed training.

PROJECT ORCA

Easily scaling out AI pipelines.

- https://github.com/intel-analytics/analytics-zoo/tree/master/pyzoo/zoo/orca

- *Project Orca* allows you to easily scale out your single node Python notebook across large clusters, by providing:
  - Data-parallel preprocessing for Python AI (supporting common Python libraries such as Pandas, Numpy, PIL, TensorFlow Dataset, PyTorch DataLoader, etc.)
  - Sklearn-style APIs for transparently distributed training and inference (supporting TensorFlow, PyTorch, Keras, MXNet, Horovod, etc.)

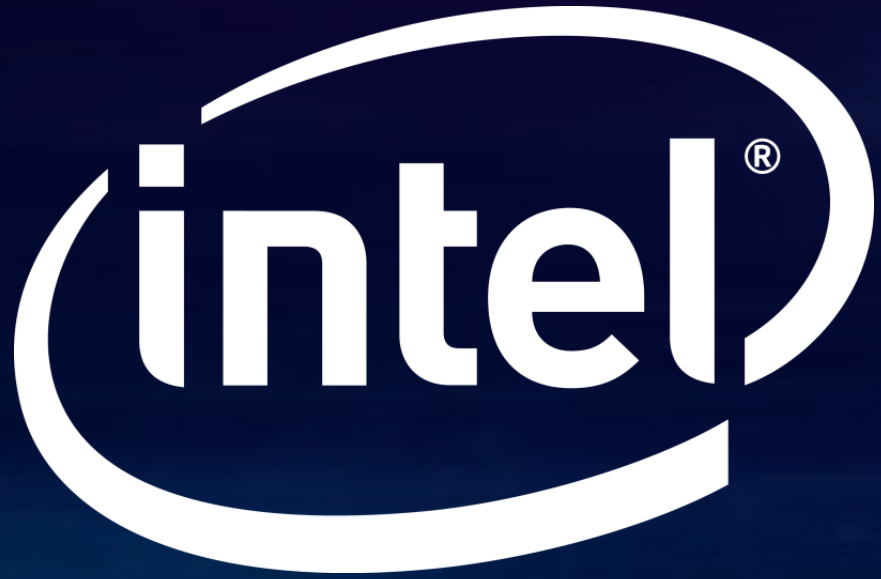
RECOMMENDATION SYSTEM AT

- Burger King performs Spark ETL tasks first, followed by distributed MXNet training.
- Similar to RaySGD, we implement a lightweight shim layer around native MXNet modules for easy deployment on YARN cluster.
- The entire pipeline runs on a single cluster. No extra data transfer needed.
- Check our blog at: https://medium.com/riselab/context-aware-fast-food-recommendation-at-burger-king-with-rayonspark-2e7a6009dd2d

```
from zoo.orca.learn.mxnet import Estimator

mxnet_estimator = Estimator(train_config, model, loss, metrics,
                            num_workers, num_servers)

mxnet_estimator.fit(data=train_rdd, validation_data=val_rdd,
                    epochs=…, batch_size=…)
```

CONCLUSION

- RayOnSpark: Running Emerging AI Applications on Big Data Clusters with Ray and Analytics Zoo https://medium.com/riselab/rayonspark-running-emerging-ai-applications-on-big-data-clusters-with-ray-and-analytics-zoo-923e0136ed6a
- More information for Analytics Zoo at:
  - https://github.com/intel-analytics/analytics-zoo
  - https://analytics-zoo.github.io/
- We are working on full support and more out-of-box solutions for scaling Python AI pipelines based on Ray and Spark in Project Orca.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