Hugging Face + Ray AIR: Scaling Transformers

Jules S. Damji, Antoni Baum
Anyscale, Ray Team
Data Council 2023, Austin, TX

RAY

A Quick Poll ....

Who we are ....

Jules S. Damji

- Dev Adv @ Anyscale, Databricks & Hortonworks
- SWE at
  - Sun Microsystems,
  - Netscape,
  - @Home
  - Opsware/LoudCloud,
  - VeriSign,

Antoni Baum

- Software Engineer at Anyscale
- On Libraries Team
  - AIR, Train, Tune
- Open source enthusiast!

RAY

anyscale

Who we are: Original creators of Ray, a unified framework for scalable computing

What we do: Scalable compute for AI/ML and Python

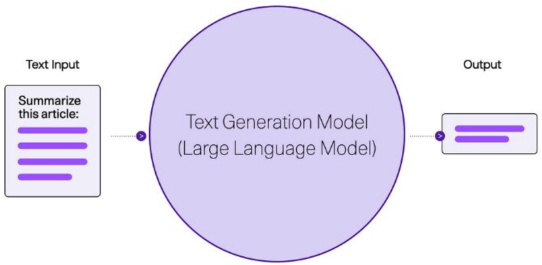
Why we do it: Scaling is a necessity, scaling is hard; make distributed computing easy and simple for everyone

Agenda

1. State of ML and AI today …
2. Hugging Face for cutting edge ML
3. Distributed training is a necessity
4. 🤗 + Ray AIR = easy distributed training
5. Deep Dive into Ray AIR Trainer
6. Demo

State of ML and AI today ....

Text Generation: Software that generates coherent human language



Text generation models are a central pillar of Generative AI.

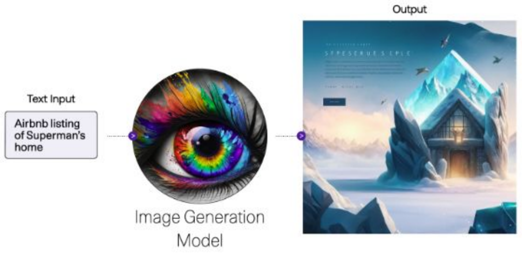
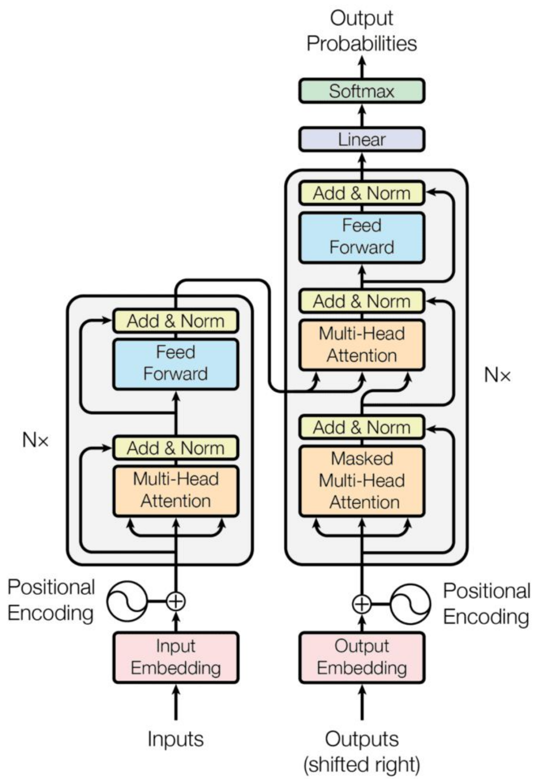


Image generation models create (often astounding) images guided by text prompts.

- Deep Learning + Transformers are the SOTA
- Impressive foundational & LLM models (e.g., GPT-3, DALL-E, ChaptGPT, Stability, etc)
- Generative AI
  - Text classification, sentiment analysis
  - Toxicity, entity recognition, language translation,
  - Sentence completion, text-2-image generation, q & a etc

What are Transformers?

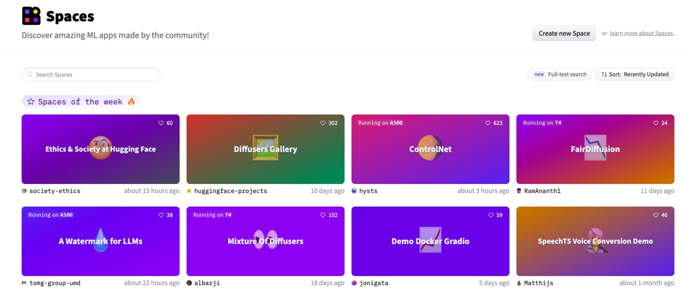
- Attention Is All You Need (circa 2017, Vaswani et al)
- Deep Neural Networks
  - Encoders
  - Attention heads
  - Decorders
  - Attention heads
- Final layers
  - Linear & Softmax

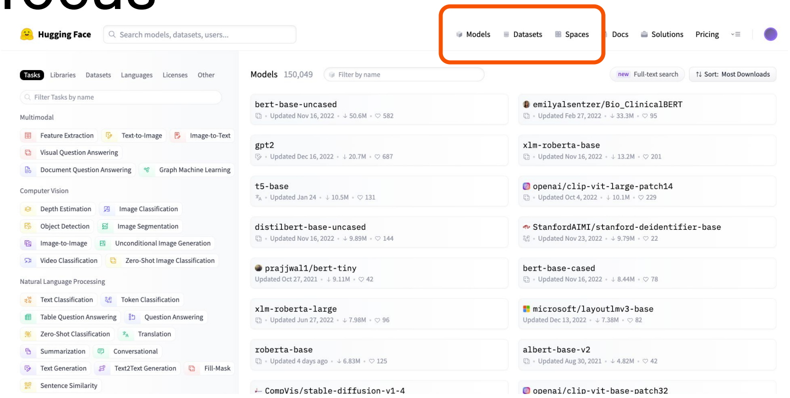


Transformers for SOTA ML/AI

Simple, robust and powerful

- Library for Python developers
- Provides an opinionated, high level API
- Mostly focused on NLP
- Multiple LLM models (GPT, BERT, etc.)
- Huge community & social focus





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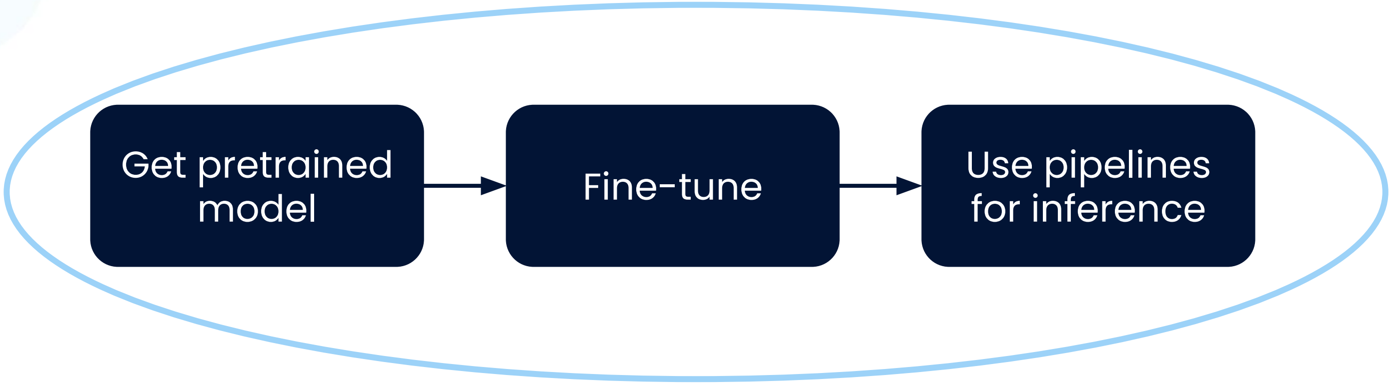
How 🤗 makes ML/AI easier …

- Abstract DL complexities with simple flow
- Increase developer velocity
- Huge 🤗 Hub to choose from

Simple flow & abstraction



How 🤗 makes ML/AI easier …

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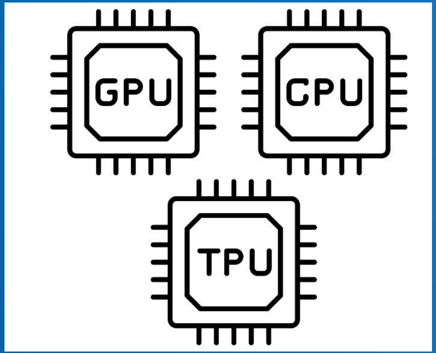
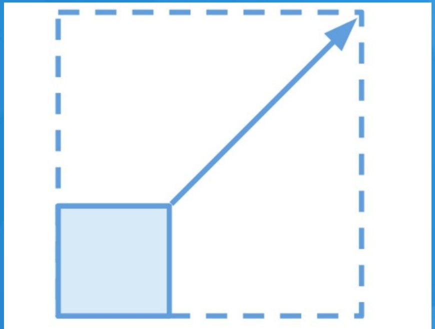
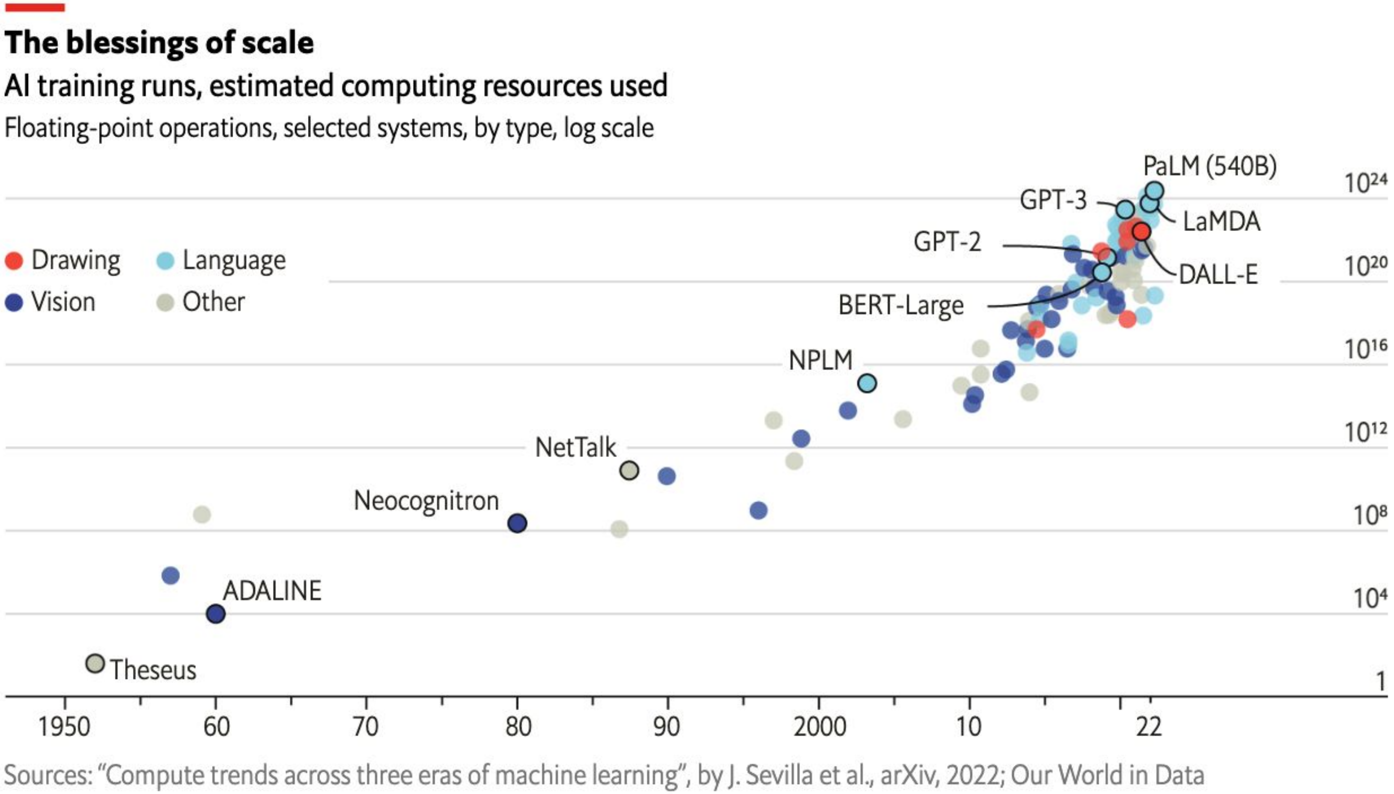
```
from transformers import AutoModelForSequenceClassification, TrainingArguments, Trainer
from datasets import laod_dataset

dataset = load_dataset("yelp_review_full")
train_dataset, eval_dataset = dataset["train"], dataset["test"]
model = AutoModelForSequenceClassification.from_pretrained("bert-base-cased", num_labels=5)
training_args = TrainingArguments(f"{model_checkpoint}-yelp", evaluation_strategy="epoch")
trainer = Trainer(model=model, args=training_args, train_dataset=train_dataset, eval_dataset=eval_dataset)
trainer.train()
```

SOTA models need loads of compute!





Blessings of scale ….



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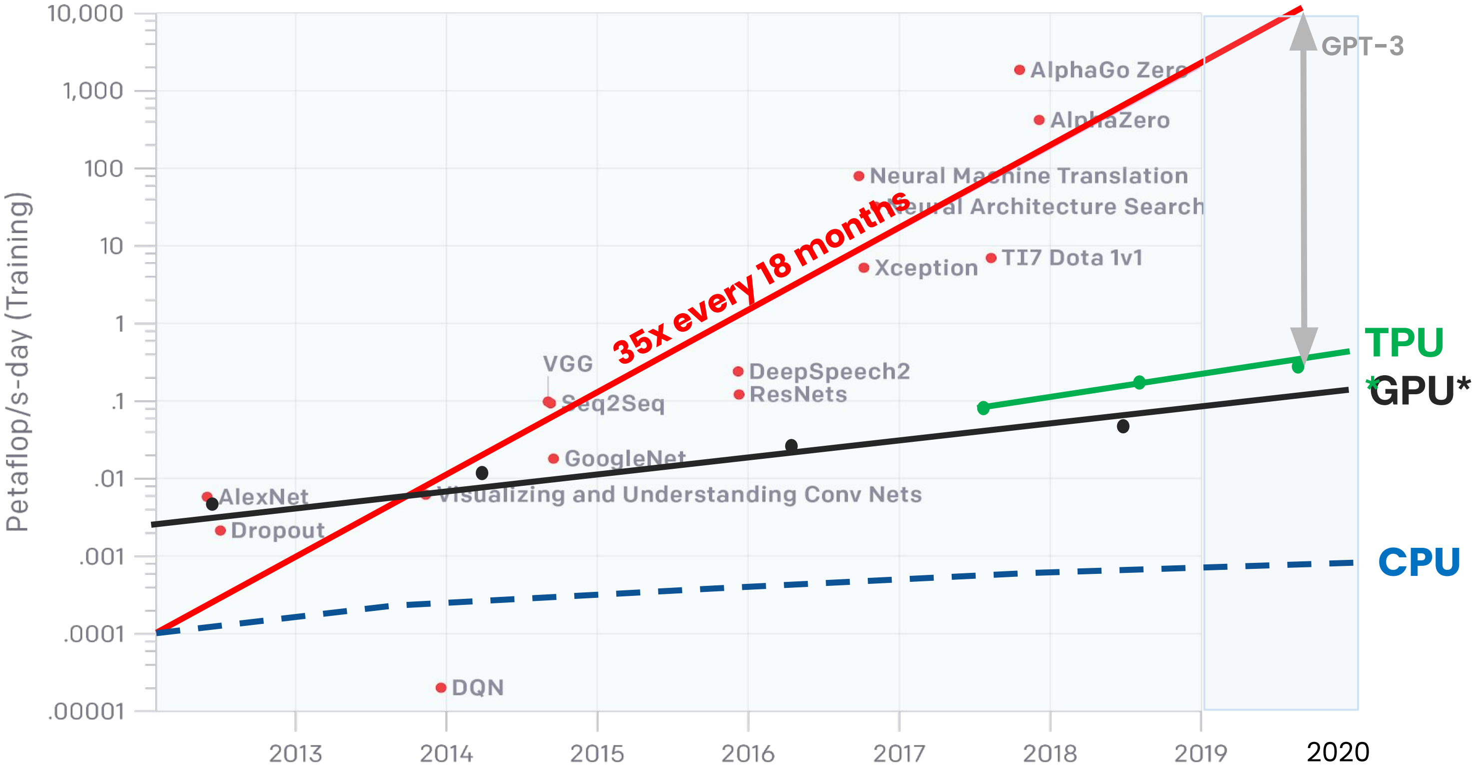
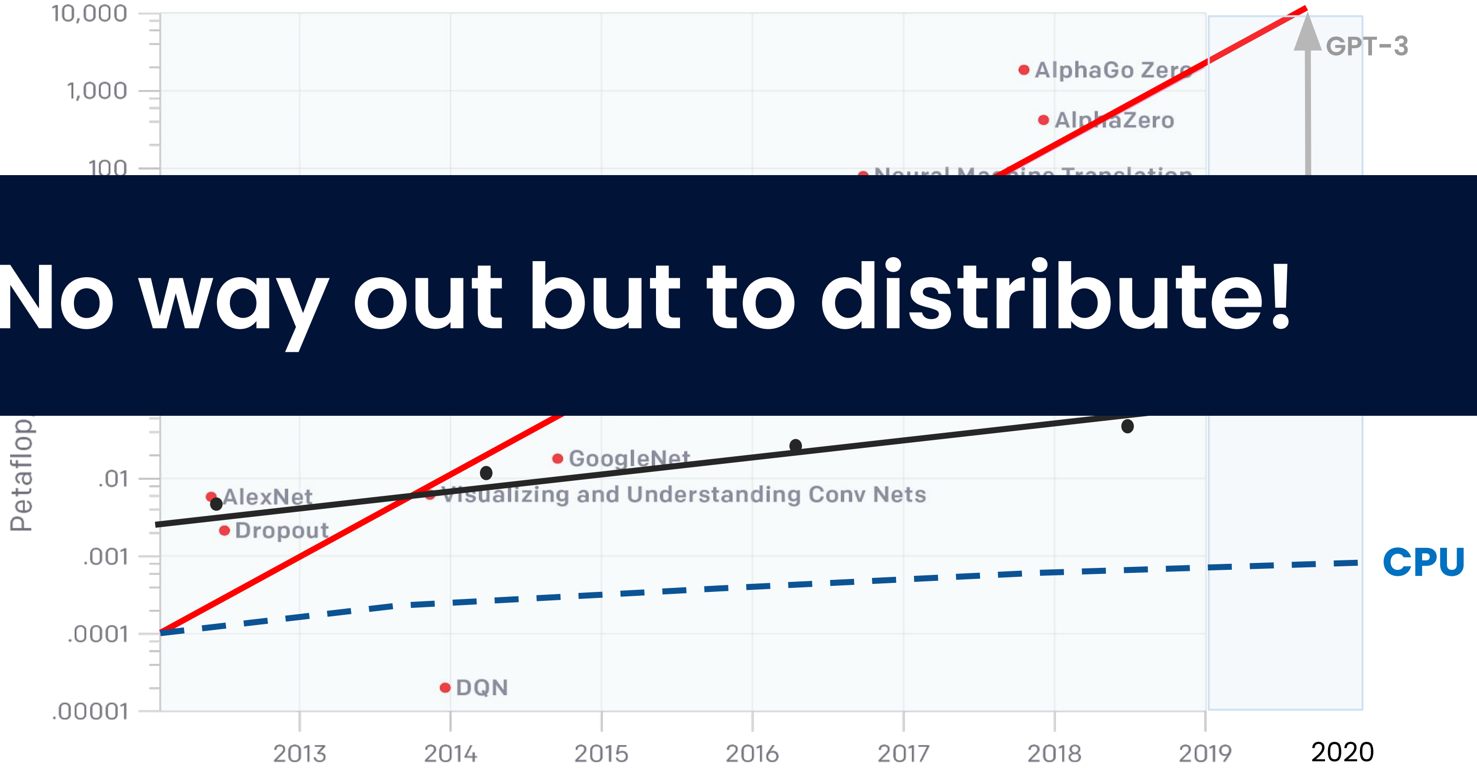
Compute - supply demand problem



https://openai.com/blog/ai-and-compute/

Specialized hardware is not enough



No way out but to distribute!

https://openai.com/blog/ai-and-compute/

We have to go distributed

New problems!

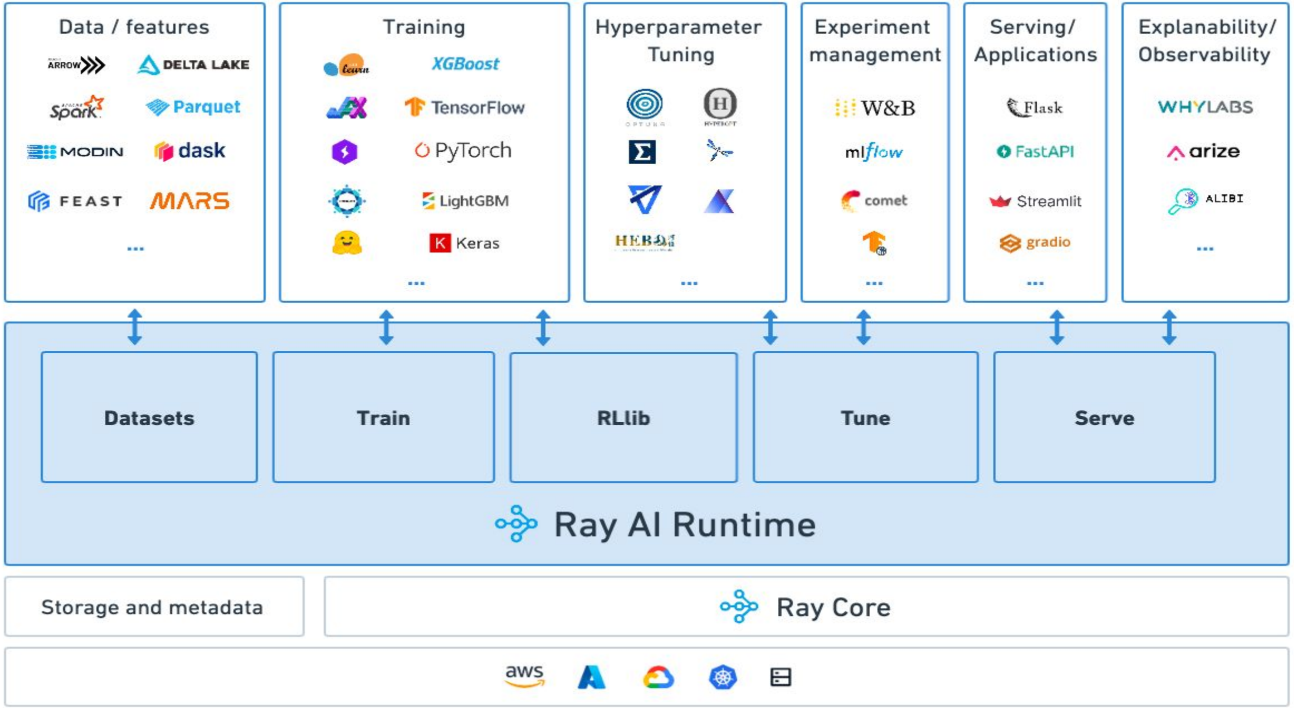
- Slow Developer velocity
- Managing complex infrastructure
- Keeping end-to-end ML pipelines scalable

Solution is Ray AIR

Ray AI Runtime (AIR) is a scalable, unified toolkit for both data scientists and software engineers.

Ray AIR provides a flexible, pythonic framework for each step of the ML workflow.

The Ray AI Runtime (Ray AIR)



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When to use Ray AIR

Scale a single type of workload

Scale end-to-end ML applications

Run ecosystem libraries using a unified API

Build a custom ML platform

Why use Ray & Ray AIR

Efficient data layer and distributed object store

Python-based API

Robust scheduling and resource management

Build a top Ray:

- Compute strata Infrastructure
- Addresses challenges of distributed computing!

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Combining Hugging Face and Ray AIR

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Ray AIR's 🤗 Trainer: API

```
def trainer_init_per_worker(train_dataset, eval_dataset, **config):
    # HF code goes here
    return transformers.Trainer(...)
scaling_config = ScalingConfig(num_workers=3, use_gpu=True)
trainer = HuggingFaceTrainer(
    trainer_init_per_worker=trainer_init_per_worker,
    scaling_config=scaling_config,
    datasets={"train": ray_train_ds, "evaluation": ray_evaluation_ds},
)
result = trainer.fit()
```

1. Use existing HF code in a function
2. Provide `ScalingConfig` & other Ray AIR configs if needed
3. Initialize the `HuggingFaceTrainer` with Ray Datasets
4. Fit the trainer
5. Inspect the results

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Ray AIR's 🤗 Trainer Implementation

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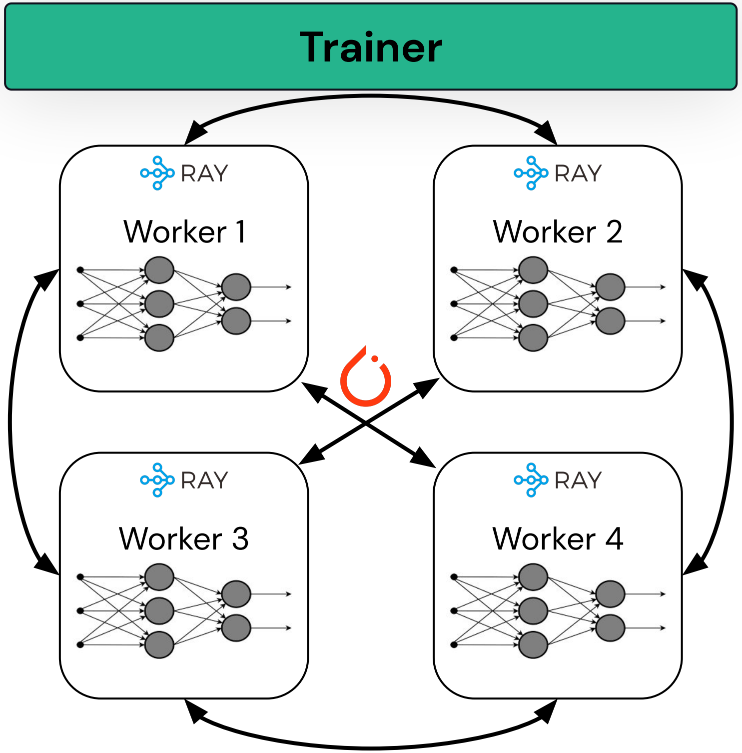
Ray AIR's 🤗 Trainer: Implementation

- Distributed Data Parallel/FSDP training on a Ray Cluster
  - Takes advantage of PyTorch DDP & Hugging Face support for it
- Runs user-defined Hugging Face code without any changes
- Automatically converts Ray Datasets to format expected by Hugging Face
- Built-in logging & monitoring
- Upcoming: Separate `AccelerateTrainer` for lower level code with 🤗 Accelerate

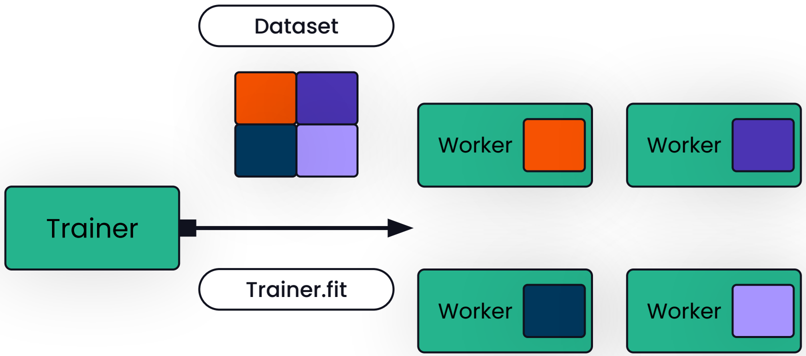
Ray AIR's 🤗 Trainer: Parallelization

- PyTorch DDP on a Ray Cluster
  - FSDP, DeepSpeed are also supported
- Abstracts away infrastructure
- Supports both CPU and GPU workers



Ray AIR's 🤗 Trainer: Data ingest

- Ray AIR uses Ray Datasets as a common data format
- Easily read from disk/cloud, or from other formats
- Fully distributed
- Can handle data too big to fit on one node or even the entire cluster



Ray AIR's 🤗 Trainer: Preprocessors

- Ray AIR provides out-of-box preprocessors for common ML tasks
- You can also write your own UDFs to map-apply
- Automatically applied during training and inference

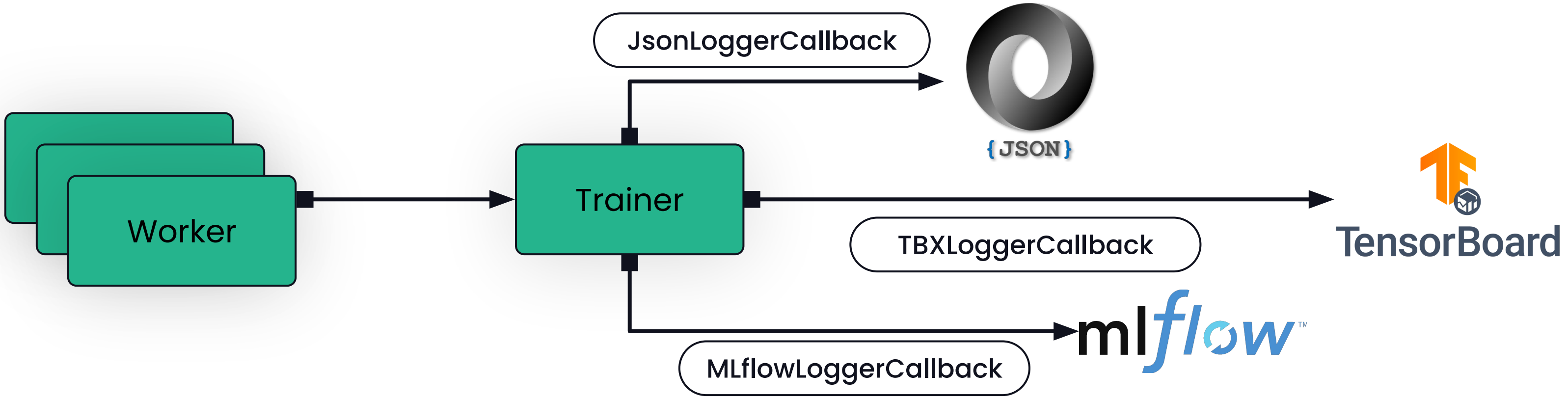
```
from ray.train.huggingface import HuggingFaceTrainer
from ray.data.preprocessors import BatchMapper
from transformers import AutoTokenizer

def tokenize_function(df):
    tokenizer = AutoTokenizer.from_pretrained("sgugger/gpt2-like-tokenizer")
    return tokenizer(df["text"])

batch_tokenizer = BatchMapper(tokenize_function)
trainer = HuggingFaceTrainer(
    trainer_init_per_worker=train_function,
    scaling_config=ScalingConfig(num_workers=num_workers, use_gpu=use_gpu),
    datasets={"train": ray_train, "evaluation": ray_validation},
    preprocessor=batch_tokenizer,
)
```

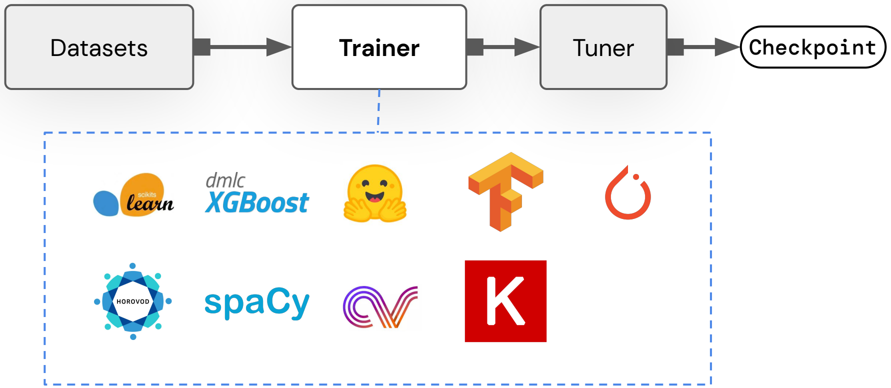
Ray AIR's 🤗 Trainer: Logging & Monitoring

- All Hugging Face metrics are reported every epoch
- Use Ray AIR callbacks for Tensorboard, MLflow, Weights & Biases, Comet, etc.
- Inspect Result after training



Ray AIR's 🤗 Trainer: Checkpointing

- Automatic, configurable checkpointing
- Resume training from `Checkpoint` object
- Enables spot instance usage
- Use the `Checkpoint` for inference & serving



🤗 training workflow

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training_args = TrainingArguments(f"{model_checkpoint}-yelp",
evaluation_strategy="epoch")

trainer = Trainer(model=model, args=training_args, train_dataset=train_dataset,
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trainer.train()
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🤗 training workflow, distributed with Ray AIR

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    scaling_config=ScalingConfig(num_workers=3, use_gpu=True),
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)
```

🤗 training workflow, distributed with Ray AIR

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)
result = trainer.fit()
```

🤗 training workflow, distributed with Ray AIR

Ray Datasets ingest

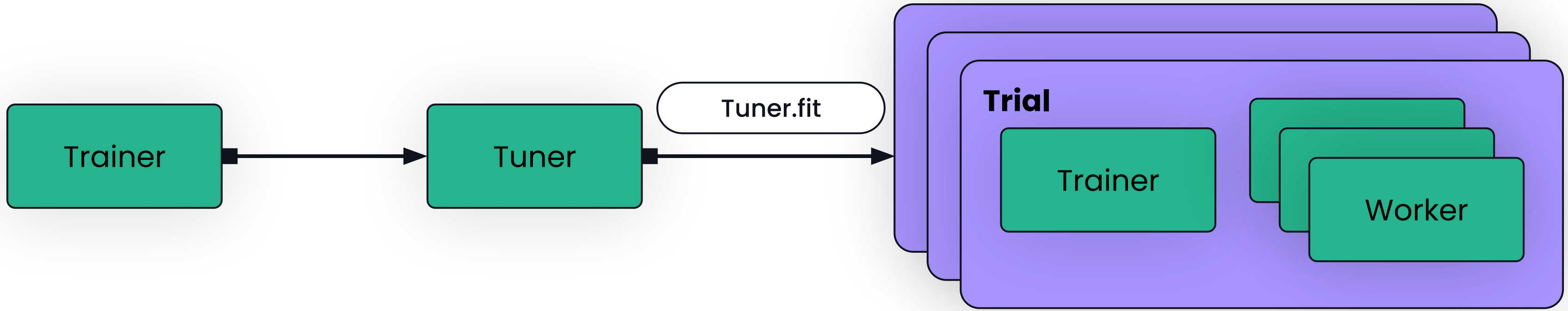
Use existing 🤗 code

Integrate with the rest of Ray AIR

Hyperparameter tuning with Ray AIR

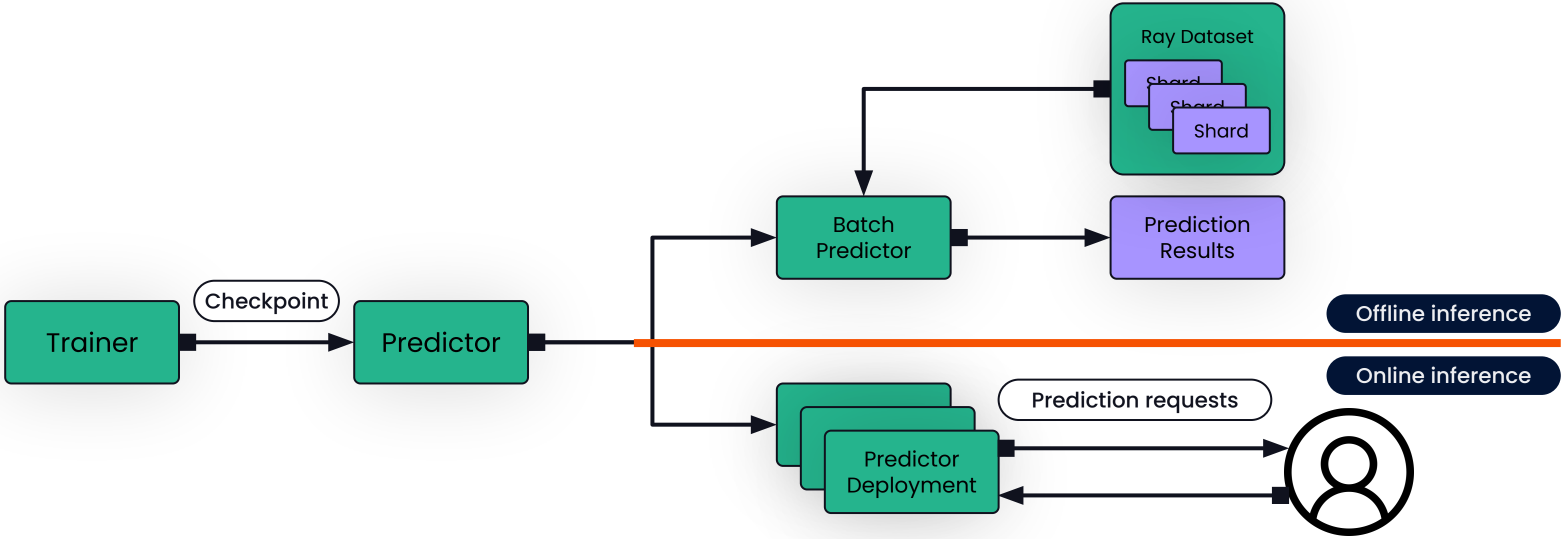
Launch a SOTA distributed hyperparam search in 2 lines of code!

```
trainer = HuggingFaceTrainer(...)
tuner = Tuner(trainer, param_space={"batch_size": tune.grid_search([1, 2, 3])})
results = tuner.fit()
```



Inference & Serving with Ray AIR

- Pass the Checkpoint obtained after the end of the training to a `HuggingFacePredictor` for scalable offline & online inference!
- Uses 🤗 Pipelines under the hood
  - Get same output as with vanilla 🤗, but in Ray Dataset format



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- Uses 🤗 Pipelines under the hood
  - Get same output as with vanilla 🤗, but in Ray Dataset format

```
tokenizer = AutoTokenizer.from_pretrained("sgugger/gpt2-like-tokenizer")
prompt = ["My text: Complete me..."]
predictor = BatchPredictor.from_checkpoint(
    results.checkpoint,
    HuggingFacePredictor,
    task="text-generation",
    tokenizer=tokenizer,
)
data = ray.data.from_pandas(pd.DataFrame(prompt, columns=["prompt"]))
prediction = predictor.predict(data, num_gpus_per_worker=1)
```

Demo

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GPT-J-6B Fine-Tuning with Ray AIR and DeepSpeed

In this example, we will showcase how to use the Ray AIR for **GPT-J fine-tuning**. GPT-J is a GPT-2-like causal language model trained on the Pile dataset. This particular model has 6 billion parameters. For more information on GPT-J, click here.

We will use Ray AIR (with the 🤗 Transformers integration) and a pretrained model from Hugging Face hub. Note that you can easily adapt this example to use other similar models.

This example focuses more on the performance and distributed computing aspects of Ray AIR. If you are looking for a more beginner friendly introduction to Ray AIR 🤗 Transformers integration, see {doc}`this example </ray-air/examples/huggingface_text_classification>`.

It is highly recommended to read Ray AIR Key Concepts and Ray Data Key Concepts before starting this example.

`In order to run this example, make sure your Ray cluster has access to at least one GPU with 16 or more GBs of memory. The amount of memory needed will depend on the model. This notebook is being tested with 16 g4dn.4xlarge instances.`

In this notebook, we will:

1. Set up Ray
2. Load the dataset
3. Preprocess the dataset with Ray AIR
4. Run the training with Ray AIR
5. Generate text from prompt with Ray AIR

Uncomment and run the following line in order to install all the necessary dependencies (this notebook is being tested with `transformers==4.26.0`):

```
#! pip install "datasets" "evaluate" "accelerate>=0.16.0" "transformers>=4.26.0" "torch>=1.12.0" "deepspeed"
```

```
import numpy as np
import pandas as pd
import os
```

Try it out now!

https://docs.ray.io/en/master/ray-air/examples/gptj_deepspeed_fine_tuning.html

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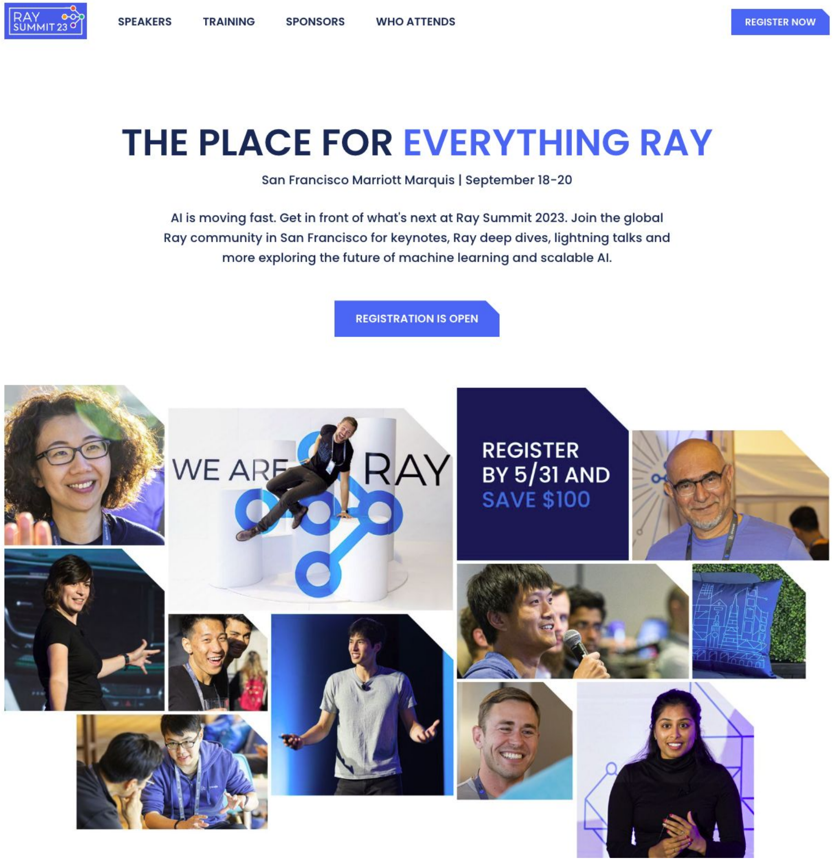

https://bit.ly/raysummit2023

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Thank you!

Q & A

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Antoni Baum, antoni@anyscale.com,

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