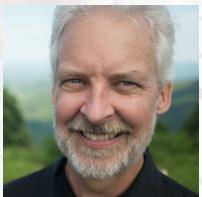


# Ray for NLP



**Dean Wampler**

Principal Software Engineer  
Domino Data Lab (formerly Anyscale)

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## System-of-Record for Enterprise Data Science Teams

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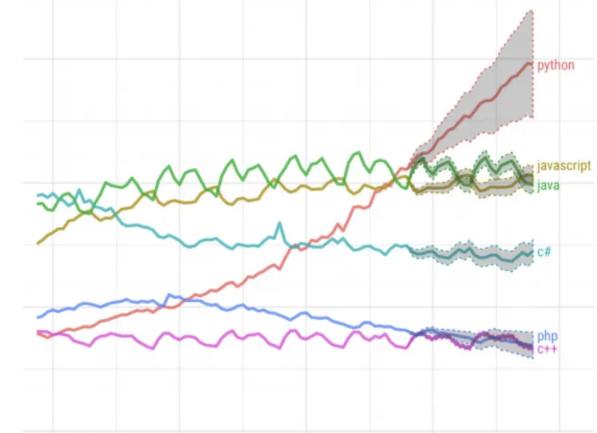
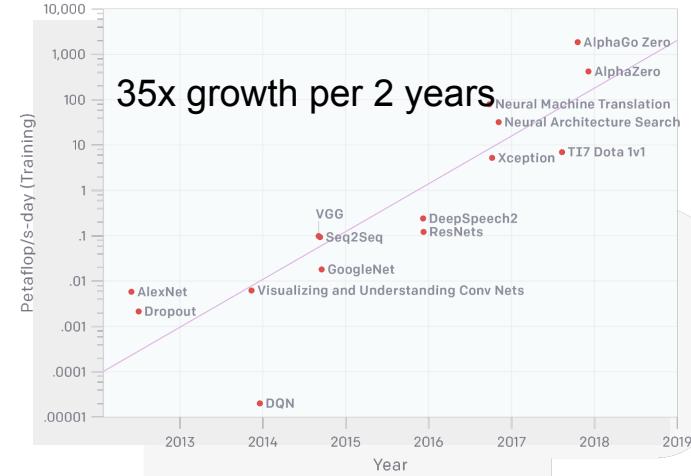
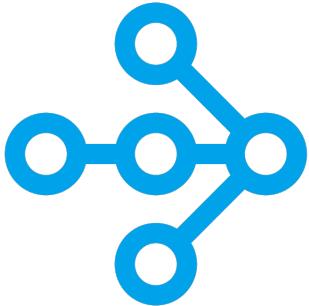
Make data science teams more productive and collaborative, and manage their work more efficiently.

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# Why Ray

- Model sizes and compute requirements are growing rapidly.
- Python is the dominant data science programming language.
- [ray.io](https://ray.io)

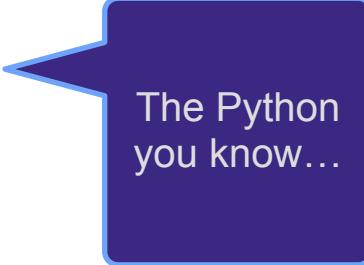


# How to scale Python in N easy steps!

```
def make_array(...):  
    a = ... # Construct a NumPy array  
    return a
```

```
def add_arrays(a, b):  
    return np.add(a, b)
```

...



The Python  
you know...

# How to scale Python in N easy steps!

```
@ray.remote  
def make_array(...):  
    a = ... # Construct a NumPy array  
    return a
```

```
@ray.remote  
def add_arrays(a, b):  
    return np.add(a, b)
```

...

Turn a  
function into  
a task.

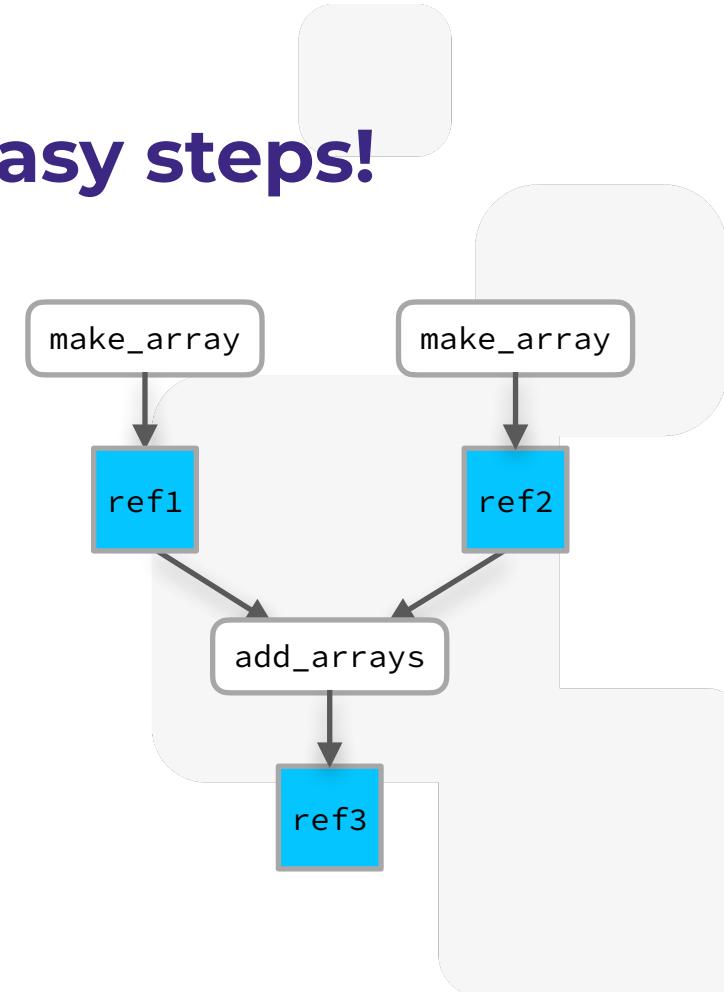
# for completeness, start with:

```
import ray  
import numpy as np  
  
ray.init(...)
```

# How to scale Python in N easy steps!

```
...  
ref1 = make_array.remote(...)  
ref2 = make_array.remote(...)  
ref3 = add_arrays.remote(ref1, ref2)
```

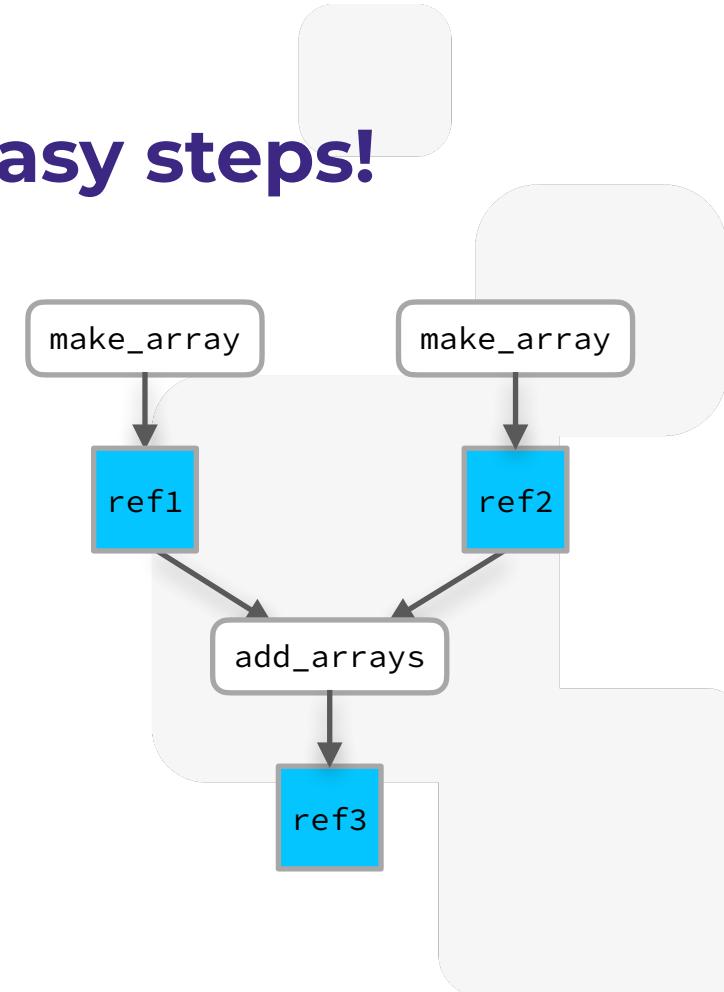
Start a task  
with remote.



# How to scale Python in N easy steps!

```
...  
ref1 = make_array.remote(...)  
ref2 = make_array.remote(...)  
ref3 = add_arrays.remote(ref1, ref2)  
array = ray.get(ref3)
```

Fetch the  
computed  
value



# How to scale Python in N easy steps!

...

```
ref1 = make_array.remote(...)  
ref2 = make_array.remote(...)  
ref3 = add_arrays.remote(ref1, ref2)  
array = ray.get(ref3)
```

Ray handles  
cluster  
scheduling,  
async  
computing

No need to  
call ray.get()  
for these  
first!

# How to scale Python in N easy steps!

...

```
ref1 = make_array.remote(...)  
ref2 = make_array.remote(...)  
ref3 = add_arrays.remote(ref1, ref2)  
array = ray.get(ref3)
```

What about  
Distributed  
state??

# How to scale Python in N easy steps!

...

```
ref1 = make_array.remote(...)  
ref2 = make_array.remote(...)  
ref3 = add_arrays.remote(ref1, ref2)  
array = ray.get(ref3)
```

The Python  
classes you  
love

```
class Counter(object):  
    def __init__(self):  
        self.value = 0  
    def increment(self):  
        self.value += 1  
    return self.value
```

# How to scale Python in N easy steps!

```
...  
ref1 = make_array.remote(...)  
ref2 = make_array.remote(...)  
ref3 = add_arrays.remote(ref1, ref2)  
array = ray.get(ref3)
```

From class to  
“actor”

```
@ray.remote  
class Counter(object):  
    def __init__(self):  
        self.value = 0  
    def increment(self):  
        self.value += 1  
        return self.value  
    def get_count(self):  
        return self.value
```

Must add a  
getter  
method

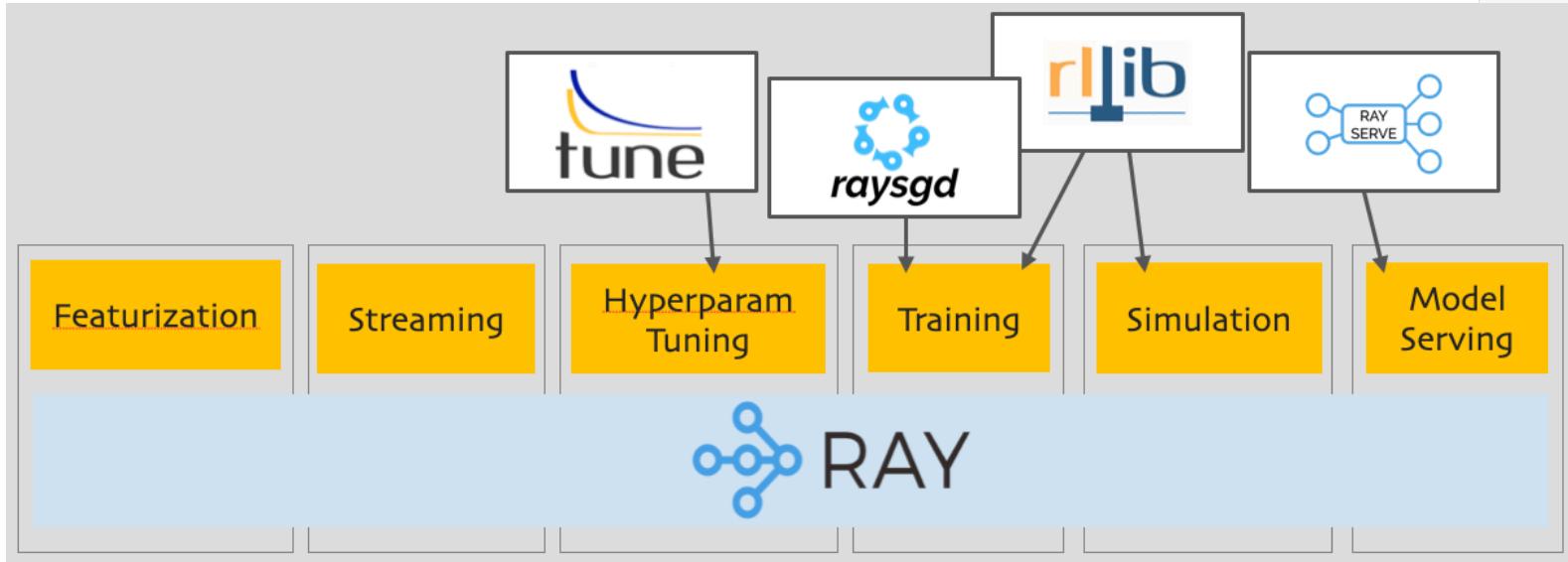
# How to scale Python in N easy steps!

```
...  
ref1 = make_array.remote(...)  
ref2 = make_array.remote(...)  
ref3 = add_arrays.remote(ref1, ref2)  
array = ray.get(ref3)
```

```
...  
c = Counter.remote()  
ref4 = c.increment.remote()  
ref5 = c.increment.remote()  
ray.get([ref4, ref5]) # [1, 2]
```

Same idioms

# But you may never use the Ray API...



[ray.io](http://ray.io)

@deanwampler

# But you may never use the Ray API...



[huggingface.co](https://huggingface.co)

# Hugging Face Transformers

Since NLP model training is \$\$\$\$\$, it's easier to use **transfer learning:**

- Start with a pre-trained model
- Add a few more layers
- Train for a few epochs for a particular application
- Profit?



# Transformers

[github.com/huggingface/transformers](https://github.com/huggingface/transformers)

# Hugging Face Transformers

Well, hyper-parameter tuning is also expensive and it can be tricky.

- Avoiding local minima: [arxiv.org/abs/1811.01088](https://arxiv.org/abs/1811.01088)
- High variance in results common: [github.com/pytorch/  
fairseq/blob/master/examples roberta/wsc](https://github.com/pytorch/fairseq/blob/master/examples roberta/wsc)



# Transformers

[github.com/huggingface/transformers](https://github.com/huggingface/transformers)

credit: Thomas Wolf, *Transfer Learning in NLP: Concepts, Tools & Trends* (Ray Summit 2020)

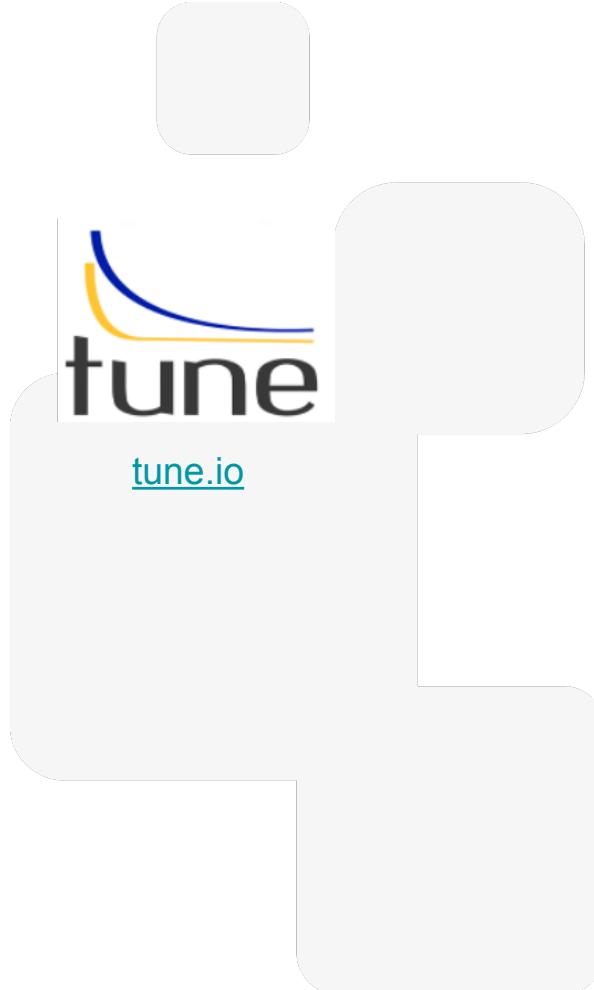
# Hugging Face Transformers

Using [Ray Tune](#) You can get 1.5% better results using *Bayesian Optimization*, 5% better using *Population-Based Training* for the same compute resources.

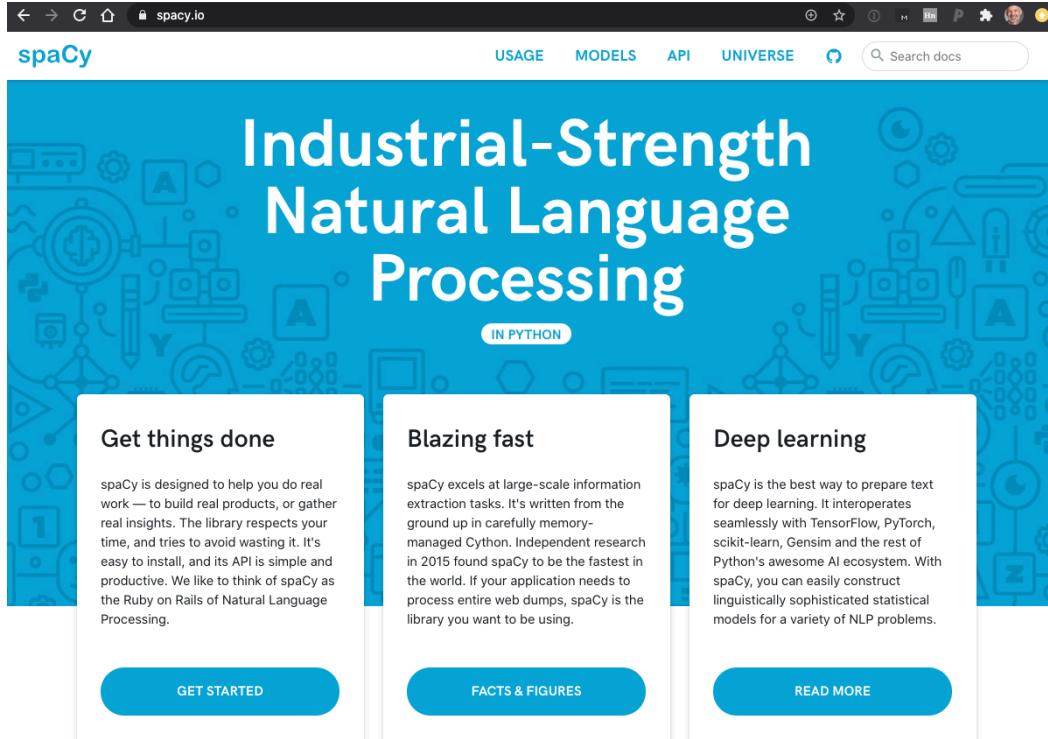
- See this [blog post](#) ([Ray blog](#) on Medium)

Hyper-parameters:

- learning rate
- weight decay
- # of epochs
- per-GPU batch size



# But you may never use the Ray API...



[spacy.io](https://spacy.io)

# spaCy v3

spaCy v3 release will introduce a new integration with Ray, which will bring effortless parallel and distributed training to spaCy.

- [github.com/explosion/spacy-ray](https://github.com/explosion/spacy-ray)
- Matthew Honnibal, [Why spaCy Is Going with Ray](#) (Ray Summit 2020)



# spaCy v3

```
$ python -m spacy train ...
```

```
$ pip install spacy-ray  
$ python -m spacy ray train --n-workers 2 ...
```

```
# “spacy ray pretrain” and “spacy ray parse”  
# are planned.
```

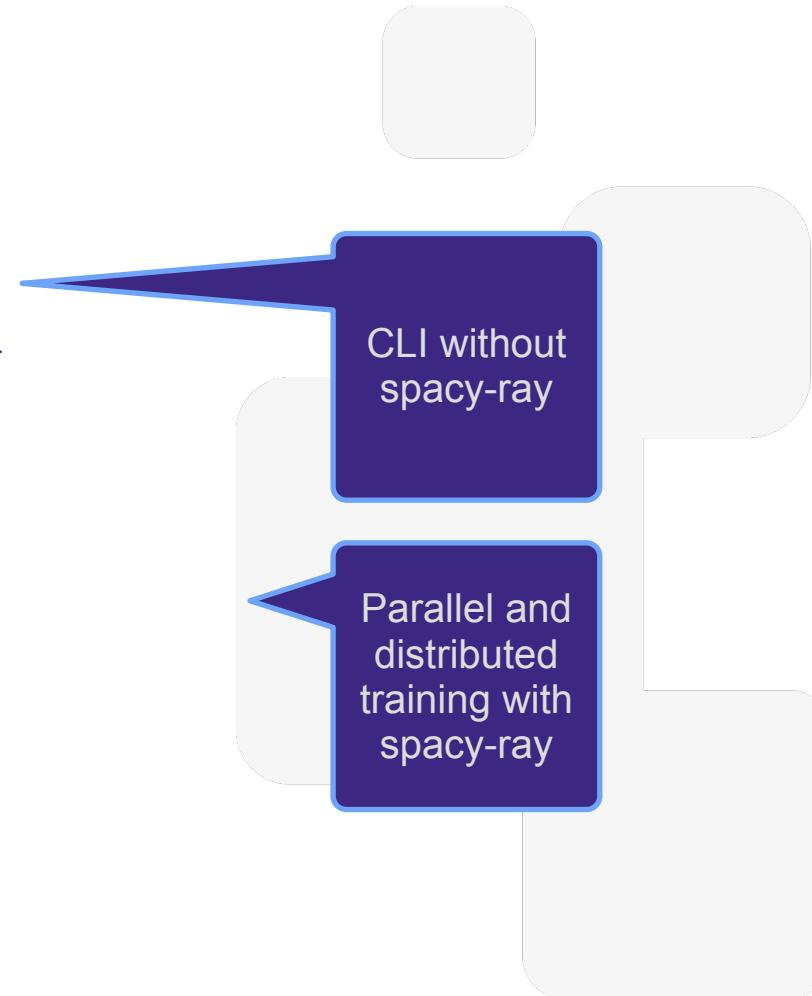
CLI without  
spacy-ray

Parallel and  
distributed  
training with  
spacy-ray

# spaCy v3

spaCy v3 includes changes to the data model and some pipeline improvements. The Ray support is not a lot of code:

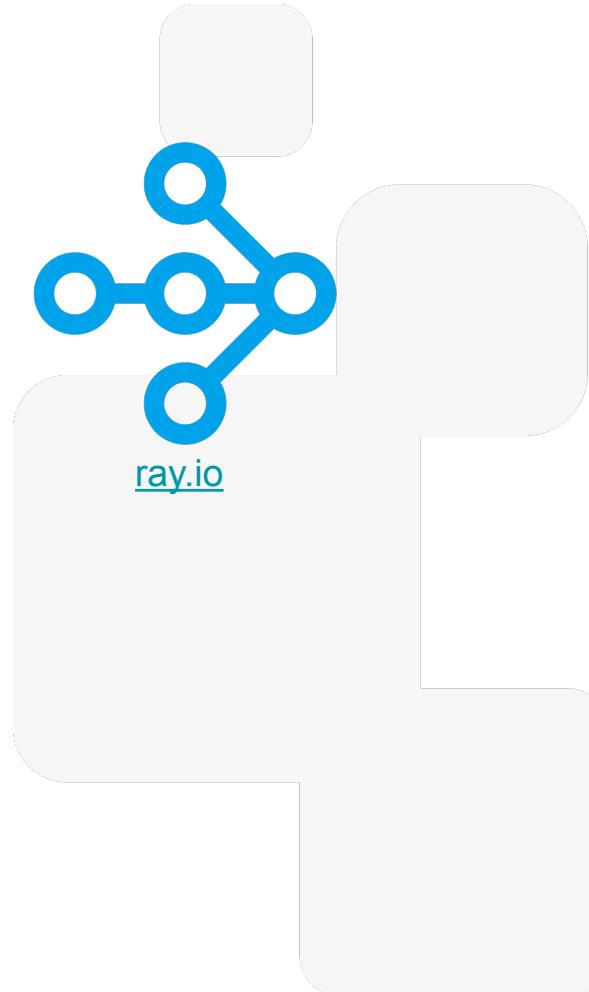
- Shard parameters into distributed state with Ray actors.
- Train on local shard.
- Asynchronously receive updates from other actors.
- Merge updates.
- Repeat...



# Your uses of Ray for NLP?

Ray's flexible task model can be used for coarse- and fine-grained computation. The actor model makes "sharded", distributed state intuitive to manage. So, use it for:

- Tokenization and other data prep
- Distributed training: Ray Tune and [Ray SGD](#) for easier distributed TensorFlow and PyTorch
- Simple, scalable model serving with [Ray Serve](#)



# Ray in NLP

The creators of Hugging Face and spaCy and the how they use Ray. See the [Anyscale blog](#) and [YouTube channel](#).



[raysummit.org](http://raysummit.org)

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**Thanks for listening!**

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- [@deanwampler](https://twitter.com/deanwampler)



# Title



@deanwampler