aws re: Invent

AIM412-R1

Deep learning applications using PyTorch, featuring Freshworks

Kris Skrinak

PSA, Global Machine Learning Segment Lead Amazon Web Services

Michael Suo

Software Engineer PyTorch

Tarkeshwar Thakur

VP Engineering Freshworks





The broadest and most complete set of machine learning capabilities

VISION SPEECH PERSONALIZATION FORECASTING CONTACT CENTERS TEXT SEARCH FRAUD DEVELOPMENT **300** -@ Ø 4 8 MAI SERVICES Amazon Amazon Amazon Amazon Amazon Contact Amazon Amazon Amazon Amazon Amazon Rekognition Polly Transcribe Comprehend Textract Lex Personalize Forecast Fraud Detector CodeGuru Lens Kendra + Medical + Medical Amazon Connect SageMaker Studio IDE AMAZON **Ground Truth** NEW! SageMaker Model SageMaker SAGEMAKER SageMaker Model SageMaker Model SageMaker SageMaker data labelling Marketplace Notebooks Debugger algorithms Experiments training tuning Autopilot Model Monitor Neo hosting ML FRAMEWORKS NEW! Deep Learning **GPUs and** Elastic & INFRASTRUCTURE O PyTorch TensorFlow Inferentia **FPGA** AMIs & Containers **CPUs** Inference

The deep learning Amazon machine image (AMI)

With Amazon Elastic Inference

	Deep Learning AMI (Ubuntu 16.04)	Pricing Details			
aws	AWS Deep Learning AMI are built and optimized for building, training, debugging, and serving deep learning models in EC2 with popular frameworks such as TensorFlow, MXNet, PyTorch, Chainer, Keras, and more. Deep learning frameworks are installed in Conda environments to provide a reliable and isolated environment for practitioners. The AWS Deep More info	Hourly Fees			
		Instance Type	Software	EC2	Total
		t2.small	\$0.00	\$0.023	\$0.023/hr
		t2.medium	\$0.00	\$0.046	\$0.046/hr
		t2.large	\$0.00	\$0.093	\$0.093/hr
		t2.xlarge	\$0.00	\$0.186	\$0.186/hr
		t2.2xlarge	\$0.00	\$0.371	\$0.371/hr
Product Details		t3.small	\$0.00	\$0.021	\$0.021/hr
D.,	Amazon Web Services	t3.medium	\$0.00	\$0.042	\$0.042/hr
•		t3.large	\$0.00	\$0.083	\$0.083/hr
Customer Rating	***** (9)	t3.xlarge	\$0.00	\$0.166	\$0.166/hr
Latest Version	Linux/Unix, Ubuntu 16.04	t3.2xlarge	\$0.00	\$0.333	\$0.333/hr
Base Operating System		m5a.large	\$0.00	\$0.086	\$0.086/hr
•	64-bit (x86) Amazon Machine Image (AMI)	m5a.xlarge	\$0.00	\$0.172	\$0.172/hr
•	End User License Agreement	m5a.2xlarge	\$0.00	\$0.344	\$0.344/hr
	11/14/17	m5a.4xlarge	\$0.00	\$0.688	\$0.688/hr
AWS Services Required	Amazon EC2, Amazon EBS	m5a.12xlarge	\$0.00	\$2.064	\$2.064/hr
Highlights		m5a.24xlarge	\$0.00	\$4.128	\$4.128/hr
Used Ubuntu 16.04 as base		m5d.large	\$0.00	\$0.113	\$0.113/hr

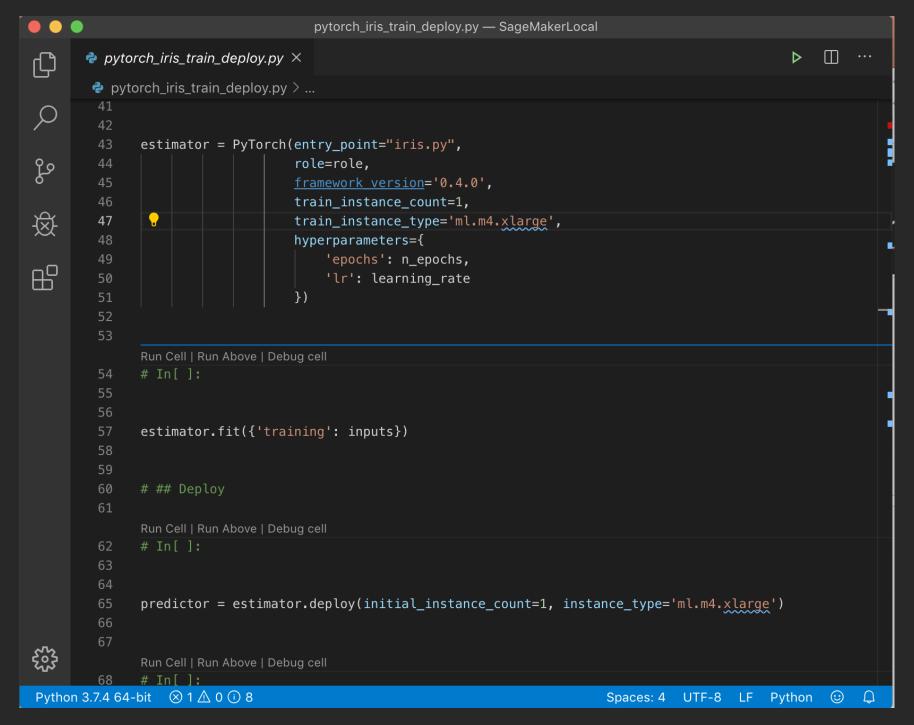
Training with PyTorch estimators

```
import os
import subprocess
instance type = 'local'
if subprocess.call('nvidia-smi') == 0:
    ## Set type to GPU if one is present
    instance type = 'local gpu'
print("Instance type = " + instance type)
from sagemaker.estimator import Estimator
hyperparameters = { 'epochs': 1}
estimator = Estimator(role=role,
                      train instance count=1,
                      train instance type=instance type,
                      image name='pytorch-extending-our-containers-cifar10-example:latest',
                      hyperparameters=hyperparameters)
estimator.fit('file:///tmp/pytorch-example/cifar-10-data')
predictor = estimator.deploy(1, instance type)
```

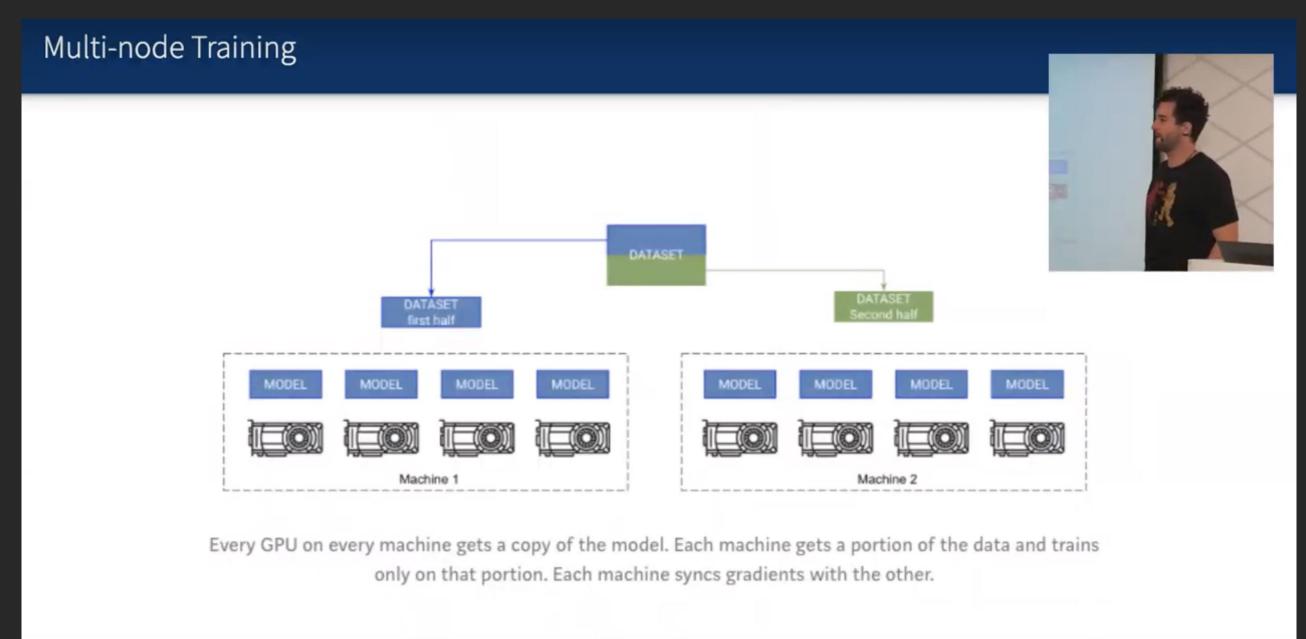
Deploying PyTorch at scale with Amazon SageMaker

```
from sagemaker.estimator import Estimator
hyperparameters = { 'epochs': 1}
instance type = 'ml.m4.xlarge'
estimator = Estimator(role=role,
                      train instance count=1,
                      train_instance_type=instance_type,
                      image name=ecr image,
                      hyperparameters=hyperparameters)
estimator.fit(data location)
predictor = estimator.deploy(1, instance type)
# get some test images
dataiter = iter(testloader)
images, labels = dataiter.next()
# print images
imshow(torchvision.utils.make grid(images))
print('GroundTruth: ', ' '.join('%4s' % classes[labels[j]] for j in range(4)))
predictor.accept = 'application/json'
predictor.content type = 'application/json'
predictor.serializer = json serializer
predictor.deserializer = json deserializer
outputs = predictor.predict(images.numpy())
_, predicted = torch.max(torch.from numpy(np.array(outputs)), 1)
print('Predicted: ', ' '.join('%4s' % classes[predicted[j]]
                              for j in range(4)))
```

PyTorch in Amazon SageMaker Local



PyTorch Lightning on AWS



Latest on PyTorch

Michael Suo Software Engineer PyTorch





What is PyTorch?



An open source deep learning platform

GPU-enabled Tensors with behaviour similar to NumPy

What is PyTorch?

Graphs are defined dynamically, as they are executed in Python

Fast tape-based autograd

A graph is created on the fly





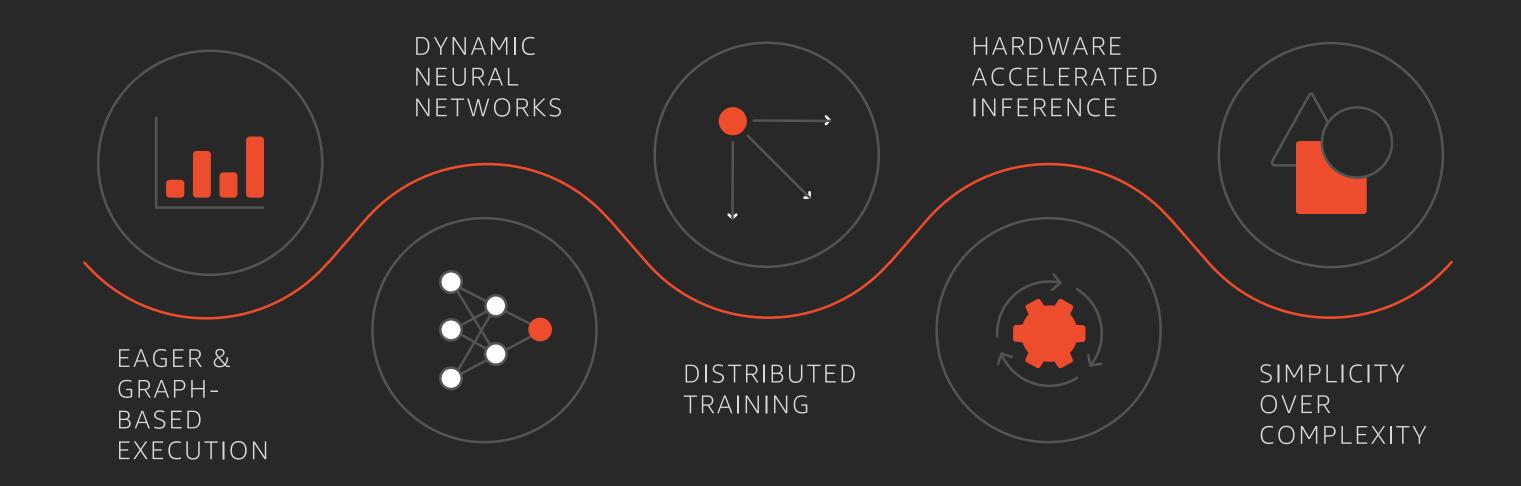




```
W_h = torch.randn(20, 20, requires_grad=True)
W_x = torch.randn(20, 10, requires_grad=True)
x = torch.randn(1, 10)
prev h = torch.randn(1, 20)
```



What is PyTorch?







NEW CORE FRAMEWORK FEATURES



NEW LIBRARIES



NEW FRAMEWORKS



PYTORCH MOBILE

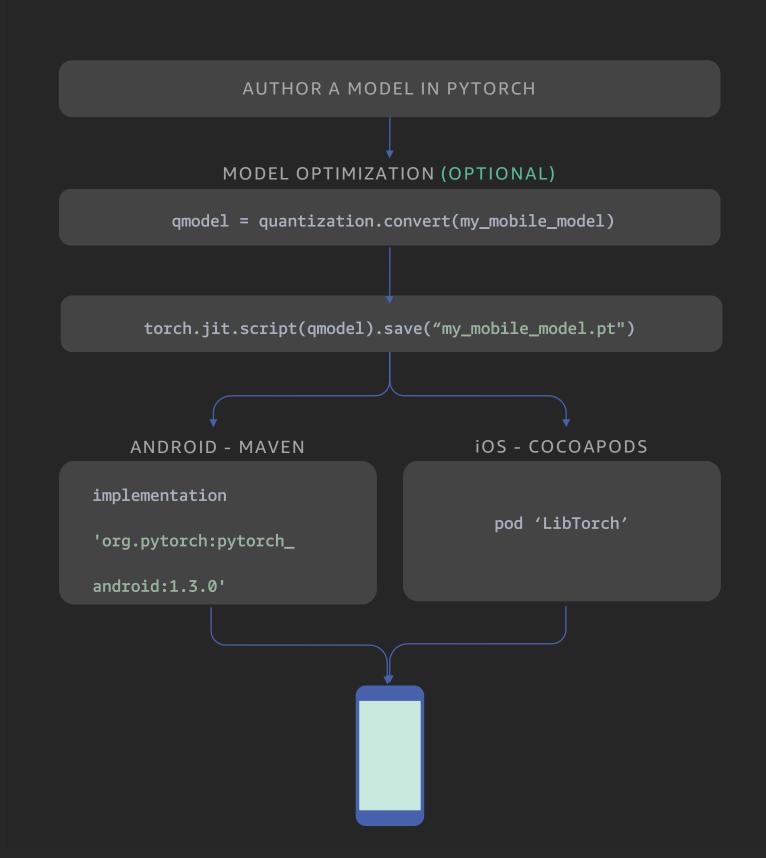
EXPERIMENTAL

End-to-end workflows for mobile in iOS and Android:

• No separate runtime to export

COMING SOON

- Build-level optimization and selective compilation
- Whole program optimization with link time optimization





QUANTIZATION

EXPERIMENTAL

- Neural networks inference is expensive
- IoT and mobile devices have limited resources
- Quantizing models enables efficient inference at scale

LESS MEMORY USAGE

```
2-4X

SPEEDUPS IN COMPUTE
```

```
model = ResNet50()
model.load_state_dict(torch.load("model.pt"))
qmodel = quantization.prepare(
         model, {"": quantization.default_qconfig})
qmodel.eval()
for batch, target in data_loader:
     model(batch)
qmodel = quantization.convert(qmodel)
```



NAMED TENSORS

EXPERIMENTAL

- Enables cleaner, better code with more expressivity tensors are manipulated based on names
- Code becomes self-documenting by adding names to tensor dimensions
- Prevent silent user errors through runtime checking of names

```
# Tensor[N, C, H, W]
images = torch.randn(32, 3, 56, 56)
images.sum(dim=1)
images.select(dim=1, index=0)
```

Today we name and access dimensions by comment

```
NCHW = ['N', 'C', 'H', 'W']
images = torch.randn(32, 3, 56, 56, names=NCHW)
images.sum('C')
images.select('C', 0)
```

But naming explicitly leads to more readable and maintainable code



TORCHSCRIPT

A static, high-performance subset of Python.

- 1. Prototype your model with PyTorch
- Control flow is preserved
- 3. First-class support for lists, dictionaries, etc.

```
import torch
class MyModule(torch.nn.Module):
    def __init__(self, N, M, state: List[Tensor]):
       super(MyModule, self).__init__()
       self.weight = torch.nn.Parameter(torch.rand(N, M))
       self.state = state
    def forward(self, input):
       self.state.append(input)
       if input.sum() > 0:
            output = self.weight.mv(input)
       else:
            output = self.weight + input
       return output
# Compile the model code to a static representation
my_module = MyModule(3, 4, [torch.rand(3, 4)])
my_script_module = torch.jit.script(my_module)
# Save the compiled code and model data
# so it can be loaded elsewhere
my_script_module.save("my_script_module.pt")
```



PYTORCH JIT

An optimizing just-in-time compiler for PyTorch programs.

- 1. Lightweight, thread-safe interpreter
- 2. Easy to write custom transformations
- 3. Not just for inference! Autodiff support

```
graph(%self : ClassType<MyModule>,
      %input.1 : Tensor):
 %16 : int = prim::Constant[value=1]()
 %6 : None = prim::Constant()
 %8 : int = prim::Constant[value=0]()
 %2 : Tensor[] = prim::GetAttr[name="state"](%self)
 %4 : Tensor[] = aten::append(%2, %input.1)
 %7 : Tensor = aten::sum(%input.1, %6)
 %9 : Tensor = aten::gt(%7, %8)
 %10 : bool = aten::Bool(%9)
 %output : Tensor = prim::If(%10)
    block0():
      %11 : Tensor = prim::GetAttr[name="weight"](%self)
      %output.1 : Tensor = aten::mv(%11, %input.1)
      -> (%output.1)
    block1():
      %14 : Tensor = prim::GetAttr[name="weight"](%self)
      %output.2 : Tensor = aten::add(%14, %input.1, %16)
      -> (%output.2)
 return (%output)
```





NEW CORE FRAMEWORK FEATURES



NEW LIBRARIES



NEW FRAMEWORKS



CRYPTEN

A platform for research in machine learning using secure-computation techniques

KEY FEATURES:

- Tensors and CrypTensors coexist and can be mixed and matched
- Uses standard eager execution no compilers! Easy debugging and learning
- Support for secure multi-party computation (MPC)
- Homomorphic encryption (FHE) (COMING)
- Trusted execution environments (COMING)

```
import crypten
import torch
crypten.init()
x = torch.tensor([1.0, 2.0, 3.0])
x_enc = crypten.cryptensor(x)
x_dec = x_enc.get_plain_text()
assert torch.all_close(x_dec, x)
y_enc = crypten.cryptensor([2.0, 3.0, 4.0])
xy_{enc} = x_{enc} + y_{enc}
xy_dec = xy_enc.get_plain_text()
assert torch.all_close(xy_dec, x + y) # this passes!
z = torch.tensor([4.0, 5.0, 6.0])
xz_{enc} = x_{enc} + z
xz_dec = xz_enc.get_plain_text()
assert torch.all_close(xz_dec, x + z) # this passes!
```

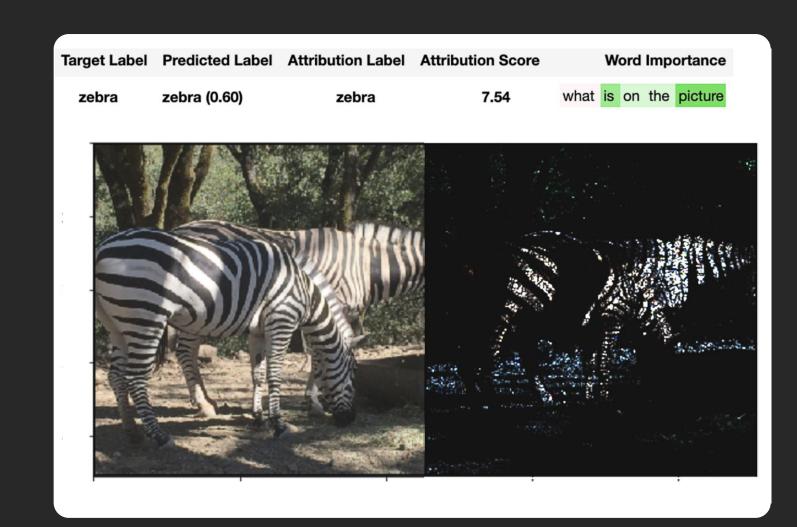


CAPTUM

Model interpretability library for PyTorch

SUPPORT FOR ATTRIBUTION ALGORITHMS TO INTERPRET:

- Output predictions with respect to inputs
- Output predictions with respect to layers
- Neurons with respect to inputs
- Currently provides gradient-based approaches (e.g., Integrated Gradients)



Text contributions: 7.54

Image contributions: 11.19

Total contributions: 18.73





NEW CORE FRAMEWORK FEATURES



NEW LIBRARIES



NEW FRAMEWORKS



DETECTRON2

- Support for the latest models and new tasks
- Increased flexibility to aid computer vision research
- Improvements in maintainability and scalability to support production use cases



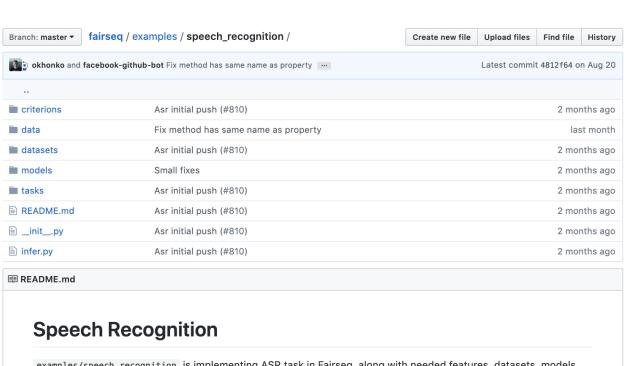


SPEECH EXTENSIONS TO FAIRSEQ

Now supports end-to-end learning for speech recognition

NEW FEATURES INCLUDE:

- Attention-based and CTC-based approaches
- Transformer-based ASR models
- Integration of the Wav2Letter++ decoder into Fairseq
- Compatible with torchaudio and Kaldi for feature extraction



examples/speech_recognition is implementing ASR task in Fairseq, along with needed features, datasets, models and loss functions to train and infer model described in Transformers with convolutional context for ASR (Abdelrahman Mohamed et al., 2019).

Additional dependencies

On top of main fairseq dependencies there are couple more additional requirements.

- 1. Please follow the instructions to install torchaudio. This is required to compute audio fbank features.
- Sclite is used to measure WER. Sclite can be downloaded and installed from source from sctk package here.Training and inference doesn't require Sclite dependency.

Preparing librispeech data

./examples/speech_recognition/datasets/prepare-librispeech.sh \$DIR_TO_SAVE_RAW_DATA \$DIR_FOR_PREPROCESSED_

Training librispeech data

python train.py \$DIR_FOR_PREPROCESSED_DATA --save-dir \$MODEL_PATH --max-epoch 80 --task speech_recognition

Inference for librispeech

Resources



PyTorch.org



Youtube.com/pytorch



Twitter.com/pytorch



Facebook.com/pytorch



Medium.com/pytorch

Freshworks

Tarkeshwar Thakur

VP Engineering Freshworks





We build business software

that enables our customers to deliver moments of wow

Our scale

150,000+ Global customers

3 Million+
Support tickets per day

375,000 Active support agents



To consider

Diversity

Customers in insurance, finance, travel, logistics, etc.

Uniqueness

Each customer has unique vocabulary, jargon, technical terms

Security

Need to keep customer information private and secure, no sharing

Meet Jonathan

System admin

Problem statement

Routing

Who is the best person to solve the customer's problem?

Categorization

What kind of issue is it?

Prioritization

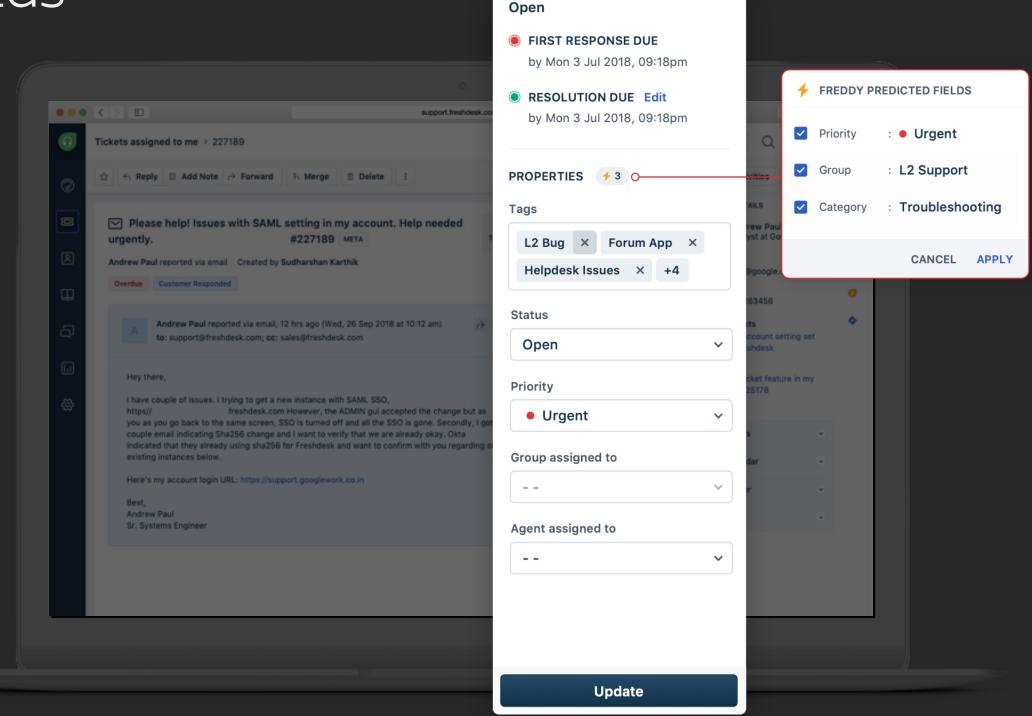
How urgent is the issue?



The Goal

Reduce ticket assignment and resolution times Improve triage and set context for agents

Ticket fields



What we needed

Build text classification models

Use ticket text and subject to predict fields

Quick, accurate, and small models

Chose Facebook's fastText & PyTorch: high accuracy, quick modeling times, quantization, extensibility

Faster model build times

Initial pipeline took 24–30 hours to build 35K models on a Spark cluster

Amazon SageMaker + PyTorch

Time taken to build 30k models significantly reduced from 24 hours to 60 minutes

Why PyTorch

Hassle-free transition

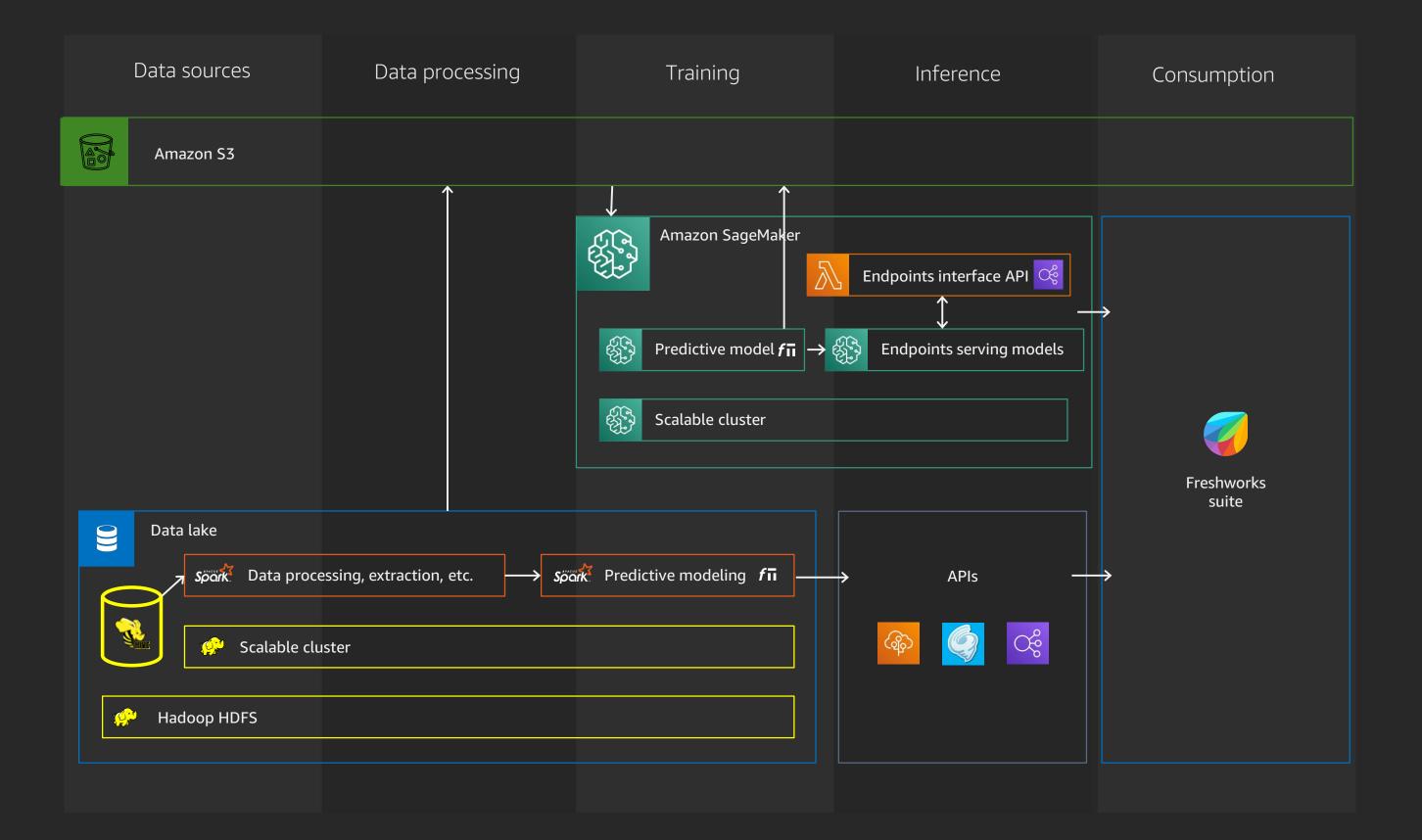
Transition from custom pipeline -> PyTorch containers on Amazon SageMaker was seamless

Extensibility to deeper networks

Wanted to experiment with modern deep learning architectures for embeddings & classifiers in PyTorch

Quantization, interpretability, and combining classifiers

Focus on smaller models, explaining predictions, and building multi-head/multi-label classifiers



Learn ML with AWS Training and Certification

The same training that our own developers use, now available on demand



Role-based ML learning paths for developers, data scientists, data platform engineers, and business decision makers



70+ free digital ML courses from AWS experts let you learn from real-world challenges tackled at AWS



Validate expertise with the **AWS Certified Machine Learning - Specialty** exam

Visit https://aws.training/machinelearning



Thank you!

Tarkeshwar Thakur tarkeshwar.thakur@freshworks.com







Please complete the session survey in the mobile app.



