

Secure and efficient deep learning everywhere

Octomizer Outline

Who we are (recap)

Deployment pain

The vision

The Octomizer: TVM for everyone







Drive TVM adoption

.....

Core infrastructure and improvements

Expand the set of users who can deploy ML models: Services, automation, and integrations

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deployment of ML models in

the edge and the cloud

OctoML



Founding Team - The Octonauts



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40+ years of combined experience in computer systems design and machine learning











Deployment Pain/Complexity

- Model ingestion
- Performance estimation and comparison
 - Cartesian product of models, frameworks, and hardware
- Optimization
 - o 00, O1, O2
 - Target settings: march, mtune, mcpu
 - Size reductions
 - Quantization, pruning, distillation
- Custom operators (scheduling, cross hardware support)
- Lack of portability / varying coverage across frameworks
- Model integration
 - Output portability
 - Packaging (Android APK, iOS ipa, Python wheel, Maven artifact, etc)



Deep learning deployment should be easy. For *everyone*.

TVM is core to making that happen.

... but it's only the first (important!) step



The Machine Learning Lifecycle







Model optimization \longrightarrow De

- Quantization
- Custom kernels
- Framework modifications
- Hardware vendor partnerships

- Deployment
 - Packaging
 - Binary size
 - Integration
 - Build chain setup





Edge/embedded inference





Octomizer: deep learning optimization as a service



Optimize over multiple clouds for training and inference at scale.

Better latency, lower OP ex.

Optimize for edge deployment. Longer battery life, smaller form factor, lower part cost, etc.

Demo (frontend and optimization)

- Simple, easy to use Python API
 - pip install octomizer
 - export OCTOML_ACCESS_TOKEN= ...

```
import octomizer
model = octomizer.upload(model, params, 'resnet-18')
job = model.start job('autotvm', { # also 'onnxrt' etc...
   'hardware': 'gcp/<instance_type>',
   'TVM_NUM_THREADS': 1,
   'tvm hash': '...'
})
while job.get_status().status \neq 'COMPLETE':
   sleep(1)
model.download_pkg("base_model", 'python') # Package with default schedules
model.download_pkg("optimized_model", 'python', job)
```



Octomizer optimization



- Code generation of operator library
 - Auto-tuning per hardware target, operator, and operator parameters
- Hardware targets supported:
 - GCP cloud instances
 - ARM A class CPU/GPU
 - ARM M class microcontrollers
- On the roadmap:
 - AWS and Azure cloud instances
 - Quantization
 - Hardware-aware architecture search
 - Compression/distillation





Demo (visualization)





Octomizer under the hood

- Entire stack designed for easy, cross-cloud and private cloud/on-prem deployment
- Consists of:
 - Kubernetes
 - Kustomize for declarative deployments
 - Rust + Actix-web for robust, safe and simple deployments
 - Only external service dependency is an object store
 - Support for TVM RPC Trackers for external device management/execution
- OctoML hosted Octomizer today supports
 - GCP cloud instances
 - ARM A class CPU/GPU
 - ARM M class microcontrollers
 - More to come...









Stay tuned through twitter (@octoml) or email.

Reach out if you have use cases to share: jknight@octoml.ai

Looking for private beta partners.

<u>We are hiring</u> see <u>octoml.ai</u> for more details!

