

## TVM @ Microsoft

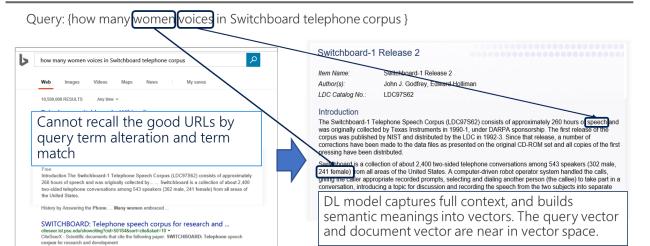
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Microsoft AI and Research

## Deep Learning at Microsoft

### Web Search

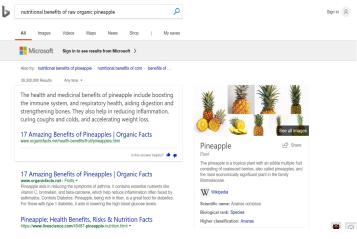


### Conversational Search

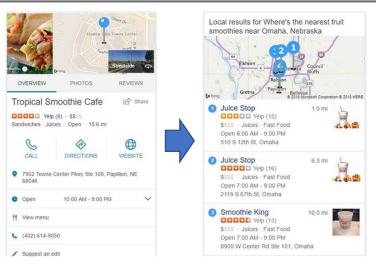
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In most browsers, press Ctrl+Shift+Del or Ctrl+Shift+Fn+Del or

### QnA at Web Scale



### **Entity Search**

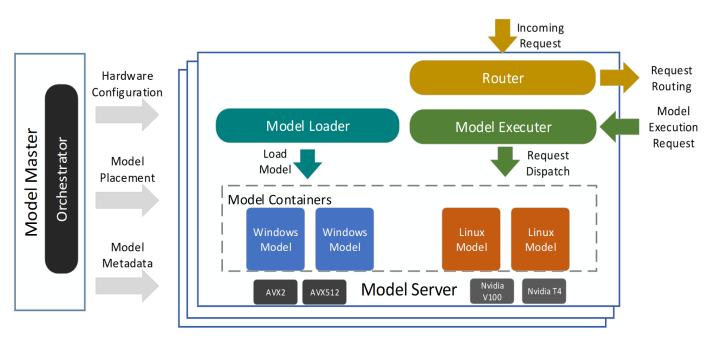


### **Grammar Checking**

abc	Add comma after introductory element
if ut	50,
1	Ignore Once
X	Cut
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1 6	Paste
s PA	Paste Text Only
d	Set Proofing Language
el⊟	Start New List
1	Continue Numbering
X Z	Set Numbering Value

# **Deep Learning Inference Service**

- Serves Bing, Office, and Cortana
- Large scale
  - Millions of model inferences per second
  - Hundreds of models
  - Tens of thousands of servers
  - Forty data centers worldwide
- Variety of serving requirements
  - TensorFlow, PyTorch
  - Windows, Linux
  - CPU, GPU
- Strict latency requirements
  - Often single-digit milliseconds



# Model Optimization Example

- Large-scale BERT<sup>1</sup> for Bing web ranking
  - 1 million queries per second
- TensorFlow latency and throughput were unacceptable
- Hand-optimized BERT on V100 GPU
- 800x throughput increase
- Millions of dollars saved
- Over a month of dev time
- Blog post
  - <u>https://azure.microsoft.com/en-us/blog/bing-delivers-its-largest-improvement-in-search-experience-using-azure-gpus/</u>

1. Devlin et. al., "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding", https://arxiv.org/pdf/1810.04805.pdf

## Model Optimization Challenges

- Existing DL frameworks don't fit our requirements
- Challenges
  - Reducing latency to a scenario-acceptable number
  - Supporting advanced models at large scale while saving cost
  - Agility to bring new optimization techniques into production
- We need new solutions to ship new and exciting models

# Model Optimization Solutions

### **Custom Optimizations**

- Rewrite models with high • performance C++ library
- Customized serving runtime and ٠ performance tuning
- Example: DeepCPU, DeepGPU, ٠ TensorRT

Low latency and high throughput

Best utilization of hardware

ow agility.

### Framework Integration

- Integrate custom ops with existing frameworks (e.g., TF, PyTorch)
- Replace nodes in model graphs and leverage existing framework serving engine
- Example: Customized TensorFlow, WinML
  - Less development work
- Decent latency improvement

Suboptimal performance

### Compiler

- Graph-level optimizations •
- Optimized code generation •
- Cross-platform, cross-device •

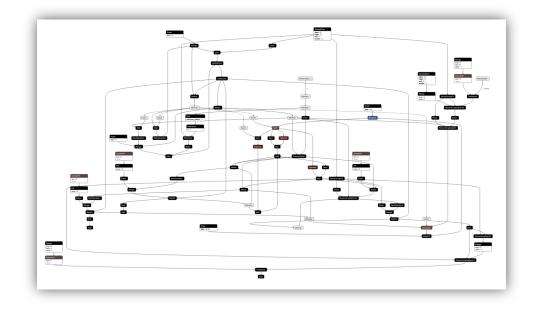
Can we achieve low latency, high throughput, and high agility?

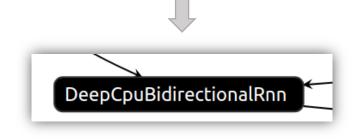
# Case-Study 1: Query Understanding for Bing

- Generate query encoding for ranking
- Model: CNN embedding + LSTM + scoring function
- Latency SLA: 35ms
- TensorFlow: 112ms on CPU
- TVM + Custom RNN: 34ms on CPU

# A Hybrid Approach: TVM + DeepCPU

- DeepCPU<sup>1</sup> is plugged in as TVM external library
  - Automatically identify high-level TF constructs
    - Utilize TensorFlow scopes
    - Identify single- and bi-directional LSTMs
  - Rewrite Relay graph
    - Replace subgraph with a custom op node
  - 63ms -> 15ms
- CNN and the rest of graph are optimized and auto-tuned by TVM
  - 49ms -> 19ms (2.5 times speedup)
- 1. "DeepCPU: Serving RNN-based Deep Learning Models 10x Faster", Zhang et. al. USENIX ATC 2018



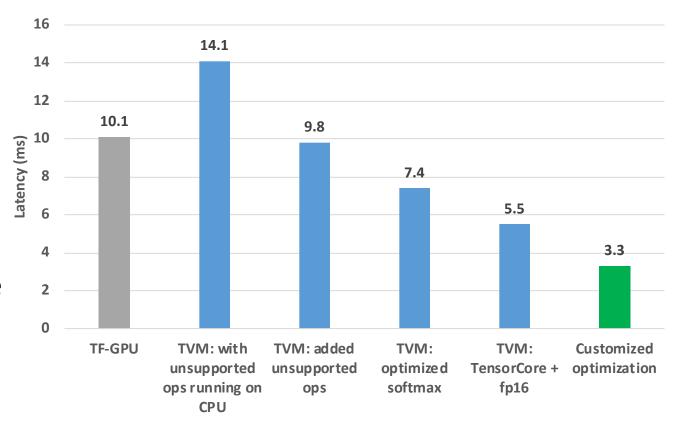


## Case-Study 2: Azure QnA Maker Service

- Azure cognitive service that creates question-and-answer bots
- Model: Distilled BERT
- Latency SLA: 10ms
- TensorFlow: 73ms on CPU, 10.1ms on GPU
- TVM + our improvements: 28ms on CPU, 5.5ms on GPU

## Optimizing BERT with TVM on GPU

- New operators
  - OneHot, Erf, BatchMatMul with
    > 3 dimensions
- New softmax schedule tailored for large-vocabulary projection
- Adding support for half-precision and extended GEMM on TensorCore
- Still a gap with hand-tuned version but decent speedup over TF-GPU (46% improvement)



### On Nvidia V100

## Contributions to TVM

- CombineParallelDense IR pass
- Operators for TensorFlow and ONNX frontends
- Improve softmax compute and CPU schedule
  - Auto-tune softmax schedule
  - > 80% improvement on 16 cores
- Fix schedule\_extern to prevent fusion of external ops
  - ~50% improvement when using external libraries on CPU
- Support MKL and cuBLAS for BatchMatMul
- Windows support and fixes

### We're hiring!

# Our Experience with TVM

- Vibrant, supportive, and open community
- Developer-friendly
- Emphasis on innovating and experimenting with new techniques
- Performance improvement over popular DL frameworks
- Several models shipped to production
- We are looking forward to contributing and trying new features from the community!
  - Dynamic shapes, TensorFlow dynamic RNN, bring-your-own-codegen

## Thank you!