AMPS-Inf: Automatic Model Partitioning for Serverless Inference with Cost Efficiency

Jananie Jarachanthan*, Li Chen*, Fei Xu†, Bo Li‡

*University of Louisiana at Lafayette, †East China Normal University, ‡Hong Kong University of Science and Technology
Serverless Computing

- Serverless computing provides an abstraction over complex operations and programming of servers.
- Serverless computing becomes increasingly popular due to its auto-scaling and pay-per-use natures.

![AWS Lambda](logo.png)  ![Google Cloud Functions](logo.png)  ![Azure Functions](logo.png)
Serverless Computing

- Serverless applications.
  - Real-time video encoding: ExCamera\(^1\)
  - Interactive data analytics: Locus\(^2\), PyWren\(^3\)
  - Web applications
  - Machine learning: Cirrus\(^4\), SIREN\(^5\)

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\(^1\) Encoding, Fast and Slow: Low-Latency Video Processing Using Thousands of Tiny Threads, NSDI’17.
\(^2\) Shuffling, Fast and Slow: Scalable Analytics on Serverless Infrastructure, NSDI’19.
\(^3\) Occupy the Cloud: Distributed Computing for the 99%, SoCC’17.
\(^4\) Cirrus: a Serverless Framework for End-to-end ML Workflows, SoCC ’19.
Serverless Machine Learning

• How can machine learning applications exploit serverless computing?

"Serverless Inference?"

Challenges

• Faster growth of the size and complexity of advanced neural network models.

<table>
<thead>
<tr>
<th>Neural network models</th>
<th>Model size</th>
<th>Deployment size</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet50</td>
<td>98MB</td>
<td>267MB</td>
</tr>
<tr>
<td>InceptionV3</td>
<td>92MB</td>
<td>261MB</td>
</tr>
</tbody>
</table>

ResNet50 model has 25,636,712 parameters and its size is $(25,636,712 \times 4)/1024/1024 \approx 98MB$. Deployment size = Keras dependencies (169 MB) + Model size
Serverless Machine Learning

• How can machine learning applications exploit serverless computing?

"Serverless Inference?"

Challenges

• Minimization of the billing cost without violating a pre-defined Service Level Objective or SLO in term of query response time.
Serverless Inference

Partition the Model

• How to split the complex computation graph?
  *How to find specific partition among a gigantic number of possible ones?*
• How to coordinate the partitions?
  *How to coordinate intermediate outputs?*
• Which function resource type to specify for each partition?
  *How to choose from a large resource configuration space?*

"End-to-end query response time and the total billing cost"
Serverless Inference

Partition the Model

• How to split the complex computation graph?
  
  How to find specific partition among a gigantic number of possible ones?

• How to coordinate the partitions?
  
  How to coordinate intermediate outputs?

• Which function resource type to specify for each partition?
  
  How to choose from a large resource configuration space?

AMPS-Inf
Serverless Inference

Motivating experiments

• Deployment and Configuration:
  o Lambda function with the serving code (e.g., Python).
  o Model weights (.h5).
  o Associated ML dependency libraries (e.g., Keras).
  o ML model to be inferenced (.YAML).
  o Resource configurations (e.g., the allocated memory block).
Serverless Inference

Motivating experiments

- Inference of pre-trained Keras MobileNet (<250MB).
- Inference of pre-trained Keras ResNet50 (>250MB).

- Sage 1: Jupyter Notebook instance.
- Sage 2: Hosting instance.
Serverless Inference

Motivating experiments

• Inference of pre-trained Keras MobileNet (<250MB).

Inference with one lambda.

<table>
<thead>
<tr>
<th>Lambda settings</th>
<th>SageMaker settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input .pkl image</td>
<td>Same image (jpg)</td>
</tr>
<tr>
<td>Model YAML</td>
<td>JSON</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Memory (MB)</th>
<th>512</th>
<th>1024</th>
<th>1536</th>
<th>2048</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time (s)</td>
<td>22.03</td>
<td>10.65</td>
<td>7.52</td>
<td>6.38</td>
</tr>
<tr>
<td>Cost ($)</td>
<td>0.00018</td>
<td>0.00017</td>
<td>0.00019</td>
<td>0.00021</td>
</tr>
</tbody>
</table>
Serverless Inference

Motivating experiments

• Inference of pre-trained Keras MobileNet (<250MB).
• Inference of pre-trained Keras ResNet50 (>250MB).

Inference across lambdas

<table>
<thead>
<tr>
<th>Settings</th>
<th>Sage 1</th>
<th>Sage 2</th>
<th>Lam. 512MB</th>
<th>Lam. 1024MB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time (s)</td>
<td>33.346</td>
<td>484.509</td>
<td>47.078</td>
<td>21.799</td>
</tr>
<tr>
<td>Cost ($)</td>
<td>0.014</td>
<td>0.056</td>
<td>0.0017</td>
<td>0.0011</td>
</tr>
</tbody>
</table>

Completion time and cost of ResNet50 serving (one image) in different settings.
Serverless Inference Model For Cost-efficiency And Timely Response

• Consider a pre-trained neural network model with $Y$ layers.
• There is $N$ complete set of possible model partition combinations.
• Given a particular partitioning $g \in N$, we specify $k$, $k \leq K$ lambdas to be coordinated for model serving.
• $K$ is the limit on the maximum number of lambdas that can be requested.
• The number of layers in the partition that the $i$-th lambda ($i \in \{1,2,\ldots,k\}$) will be allocated is represented by an integer variable $y^g_i$.
• Each lambda’s memory allocation can be any from $L$ memory blocks.
• When $i$-th lambda is allocated with the $j$-th type of memory ($j \in \{1,2,\ldots,L\}$), binary variable denotes $x^g_{j,i}$ the memory allocation.
Serverless Inference Model For Cost-efficiency And Timely Response

• The completion time of $i^{th}$ lambda consists of computation time and data transfer time.

• The monetary cost incurred by the lambda depends on the execution time, price of its allocated memory, S3 storage cost, cost of Get and Put request from S3, and the lambda invocation cost.

\[
\begin{align*}
\min_{x,y} & \quad S_{i,j}^g \\
\text{s.t.} & \quad y_i^g e_i^g + D + F \leq A \quad \text{Deployment size} \\
& \quad y_i^g z_i^g + p_i^g \leq J \quad \text{Temporary storage size} \\
& \quad y_i^g \leq \left\lceil Y/k \right\rceil \quad \text{Number of neural network layers per partition} \\
& \quad 1 + \left\lceil \left( \sum_{j \in L} x_{j,i}^g z_i^g \right) + D + F - M \right\rceil / \beta \right\rceil \leq j \quad \text{Number of memory blocks} \\
& \quad x_{j,i}^g \in \{0, 1\}
\end{align*}
\]

It is a mixed-integer quadratic programming (MIQP) and can be solved by any MIQP solver.
Architecture overview of AMPS-Inf
Architecture overview of AMPS-Inf

Pre-trained Model

Optimizer

 Output

 Coordinator

 n-deployment packages

User

①

②

③

ZIP

ZIP

ZIP

= Function + Weights (.h5)

Output = Best configuration (Partitions, Lambdas' memories)
Architecture overview of AMPS-Inf

User ① Pre-trained Model

Optimizer ② Output

Coordinator

n-YAMLs, Dependencies ④

n-deployment packages

Deploy ④
Architecture overview of AMPS-Inf

1. User
2. Pre-trained Model
3. Optimizer
4. Coordinator
5. Output
6. n-deployment packages
7. Execute
8. Deploy
9. n-Lambdas
10. n-YAMLs, Dependencies

AMPS-Inf
Architecture overview of AMPS-Inf

1. User
2. Pre-trained Model
3. Optimizer
4. Coordinator
5. n-deployment packages
6. n-Lambdas
7. Predictions

AMPS-Inf

AWS

= Function + Weights (.h5)

Output = Best configuration (Partitions, Lambdas' memories)
Performance Evaluation

Experimental setups

• Input of AMPS-Inf: .pkl single image, YAML pre-trained model and weights (.h5).

• AMPS-Inf settings: AWS Lambda, AWS S3

<table>
<thead>
<tr>
<th>Comparison with</th>
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<th>Platform</th>
<th>Input</th>
<th>Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon Sage Maker</td>
<td>Sage 1</td>
<td>Instance-based notebook (ml.t2.medium)</td>
<td>Model (JSON), Weights (.h5), Single image</td>
<td>MobileNet, ResNet50, InceptionV3, Xception</td>
</tr>
<tr>
<td></td>
<td>Sage 2</td>
<td>Instance-based notebook (ml.t2.medium), hosting instance (ml.m4.xlarge), AWS S3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Performance Evaluation

Small model (MobileNet inference)

The time for loading model and weights

The time for prediction

<table>
<thead>
<tr>
<th>Model</th>
<th>AMPS-Inf</th>
<th>Sage 1</th>
<th>Sage 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet50</td>
<td>463.48</td>
<td>462.30</td>
<td>401.78</td>
</tr>
<tr>
<td>Inception-V3</td>
<td>462.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Xception</td>
<td>401.78</td>
<td></td>
<td></td>
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The overall time spent for deployment and prediction in Sage 2
Performance Evaluation

Comparison with SageMaker for one image request:

- Cost reduction of AMPS-Inf for ResNet50, Inception-v3, and Xception by 92.85%, 98.67%, and 96.29%, respectively, when compared to Sage 1.
- In comparison with Sage 2, AMPS-Inf achieves cost reduction of 98.18%, 99.33%, and 98.02%, respectively, for the three models.
Performance Evaluation

Experimental setups

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<tr>
<td></td>
<td>Heuristic baseline</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Optimal baseline</td>
<td></td>
<td></td>
<td></td>
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![Graph showing completion time and cost for different models and settings.](image)
Performance Evaluation

Experimental setups

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Performance Evaluation

Experimental setups

AMPS-Inf : Two lambdas/partitions per batch.

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AMPS-Inf

• To address the challenges on splitting model and coordinating partitions, and to hide these complexities from users, we design and implement AMPS-Inf, an automated framework for serverless machine learning inference towards cost-efficiency and timely-response.

• AMPS-Inf is evaluated with four pre-trained models, in comparison with Amazon SageMaker and three different baselines.

• AMPS-Inf outperformed the state-of-the-art in cost and performance.

• AMPS-Inf extended for the batch inference and compared with an existing work BATCH.

• Results demonstrate that AMPS-Inf, by finding the best configuration of lambda resource type and model partitions, achieves cost saving of up to 98% without degrading the response time performance.
AMPS-Inf's future

• Extend to other platforms.
• Extend the design for batch inference serving at a very large scale.
• Evaluate AMPS-Inf for the models in other frameworks such as Tensorflow, PyTorch, and etc.
• Quantize weights for models with complex single layer.