

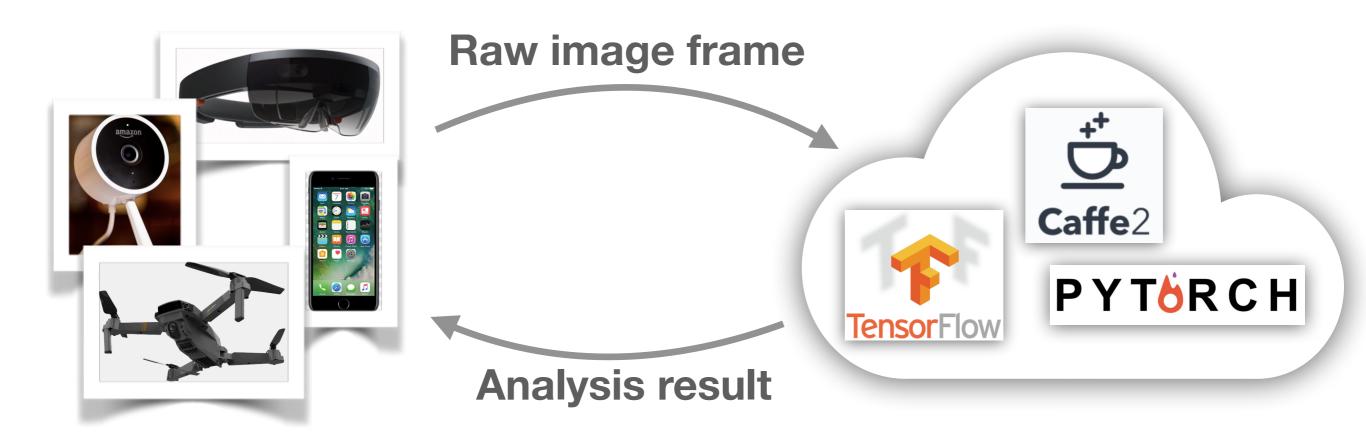
Couper: DNN Model Slicing for Video Analytics Containers at the Edge

Ke-Jou (Carol) Hsu

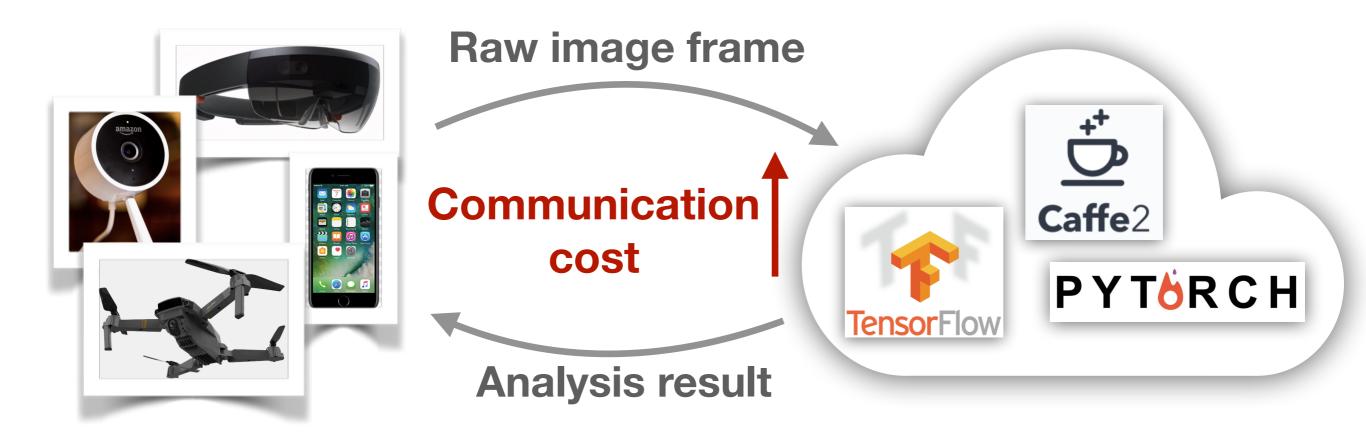
Ketan Bhardwaj

Ada Gavrilovska

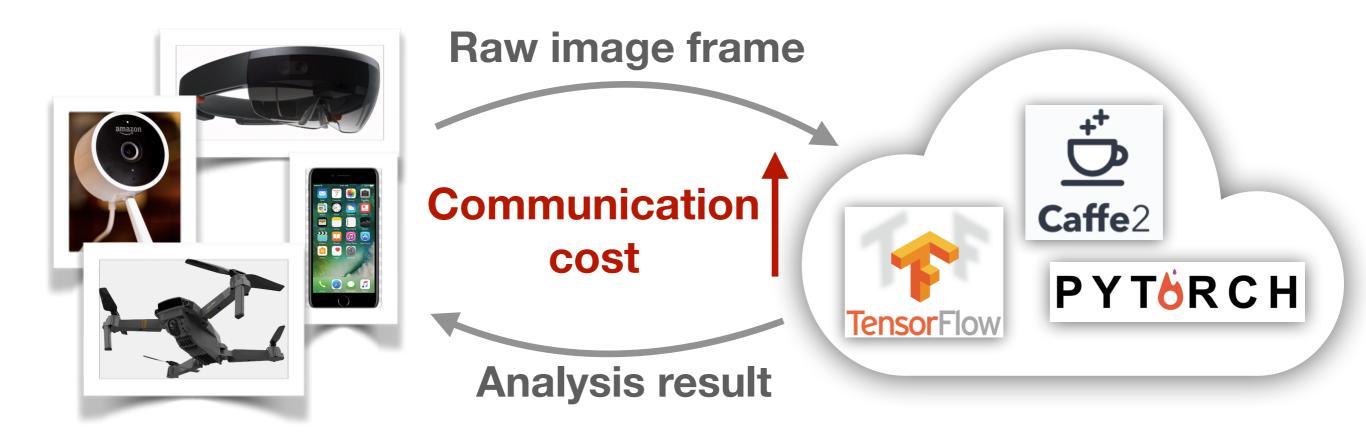
Video analytics applications are in high demand



Video analytics applications are in high demand

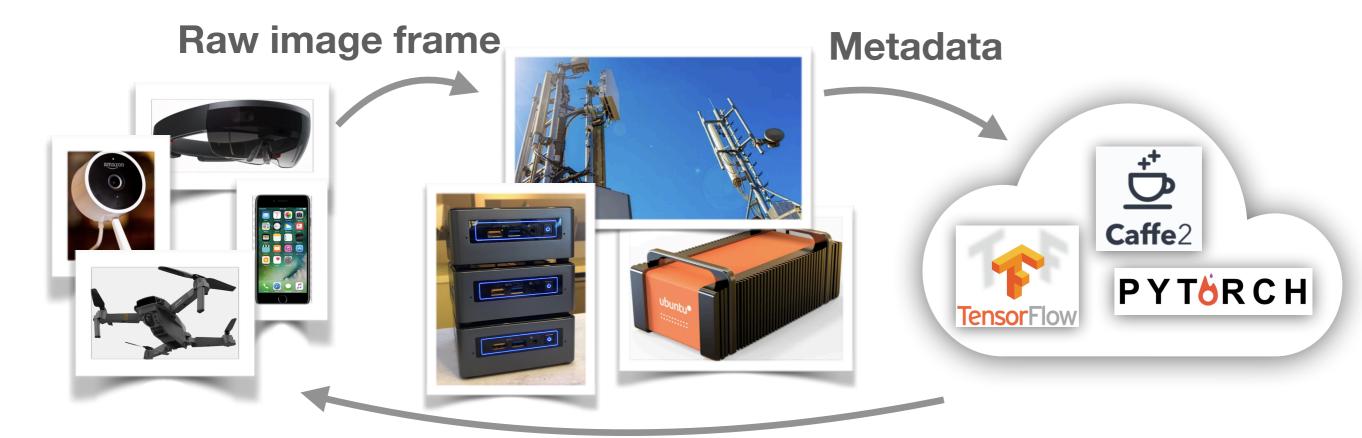


Video analytics applications are in high demand



Video analytics application may face great **performance degradation** because of its **data-intensive** and **latency-sensitive** workload

Edge's proximity benefit can help!



Analysis result

Edge computing brings benefits:

- Higher computing resource than client
- Reduce communication cost, lower processing latencies, higher processing rates, ...
- Flexible service deployment

Deep neural network (DNN)

Deep neural network (DNN)

High accuracy and famous

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High accuracy and famous

Computation-intensive workload

Deep neural network (DNN)

High accuracy and famous Computation-intensive workload

Model	VGG 16	MobileNet V2 1.4	ResNet V2 50	Inception V3	Inception ResNet V2	NASNet 331	PNASNet 331
Released Time	2014 Sep	2018 Jan	2016 Jul	2016 Jul	2016 Aug	2018 Apr	2018 Jul
Top-1 Accuracy	71.5	74.9	75.6	78.0	80.4	82.7	82.9
# Operators	54	155	205	788	871	1265	939

Accuracy increases, so does model complexity

Deep neural network (DNN)



 Google, Cliff Young (Linley processor conference 2018)

Deep neural network (DNN)



Google, Cliff Young (Linley processor conference 2018)

Single type of device cannot fit **every DNN**, more accurate DNNs require more resource

Deep neural network (DNN)

Client -> Edge -> Cloud

Deep neural network (DNN)

Client -> Edge -> Cloud





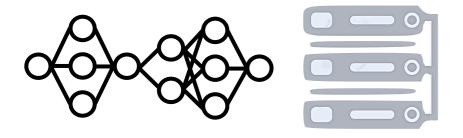




If edge cannot run whole DNN:



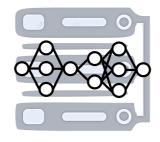
If edge cannot run whole DNN:



Optimize DNN for edge



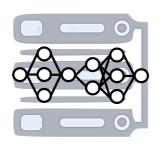
If edge cannot run whole DNN:



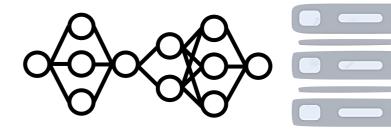
Optimize DNN for edge



If edge cannot run whole DNN:



or

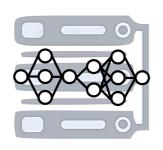


Optimize DNN for edge

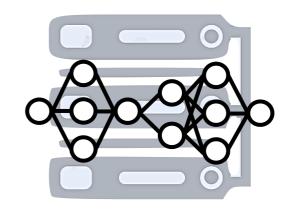
Bring specific edge for DNN



If edge cannot run whole DNN:



or

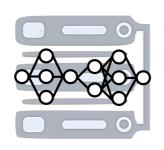


Optimize DNN for edge

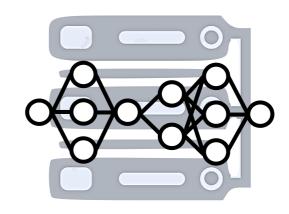
Bring specific edge for DNN



If edge cannot run whole DNN:



or



Optimize DNN for edge

Bring specific edge for DNN

These two methods are relatively **time- and money-consuming** and turns to be **impractical** for

rapid growth of DNNs and diverse and shared edge environment

Problem Statement

This is a multi-dimensional problem:

- 1. Heterogeneous computing resource on client-edge-cloud.
- 2. Various compute-intensive DNN models
- 3. No single deployment meets users' expectation forever

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Given a DNN and an edge,

How can we deploy the model with good performance?

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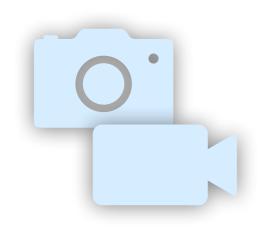
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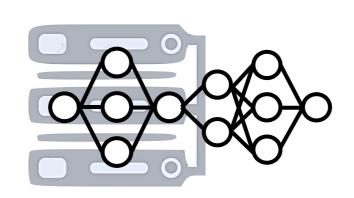
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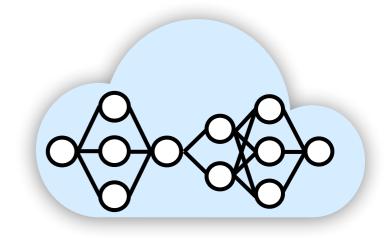
How can we deploy the model with good performance?

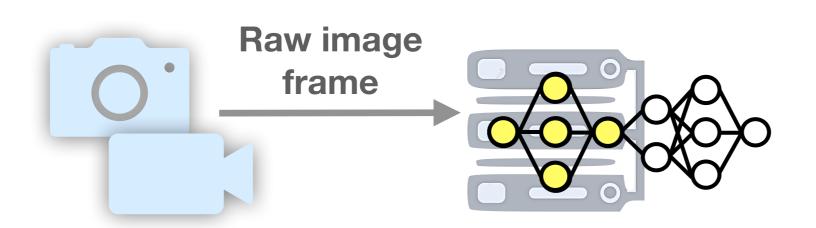
Couper: a general edge system

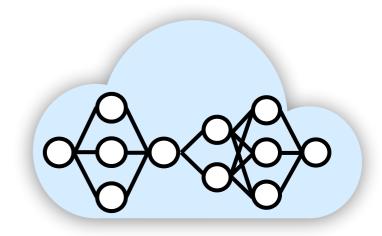
finding(and deploying) a good DNN deployment for you!

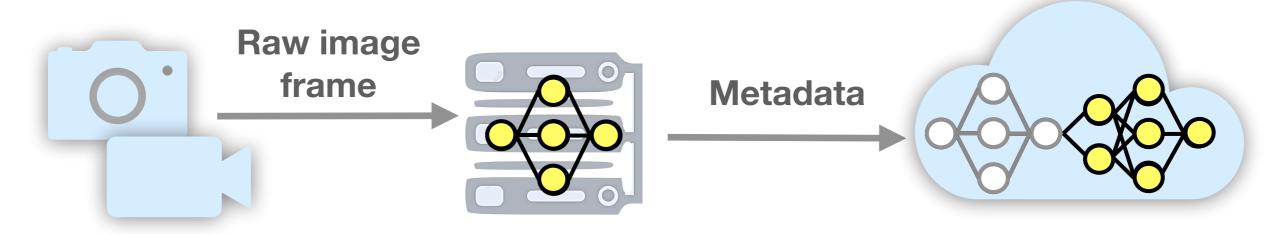


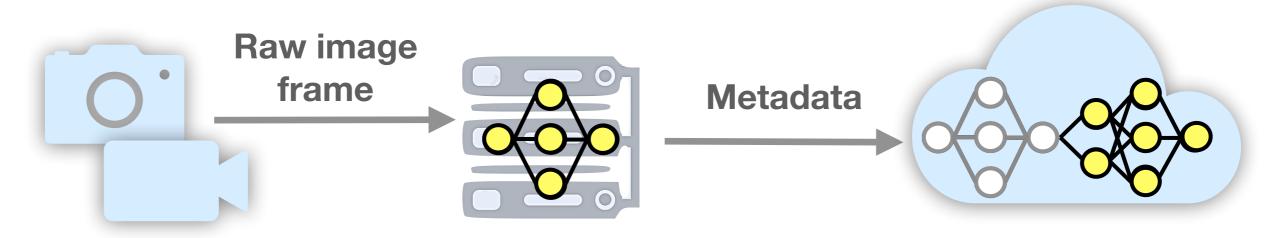


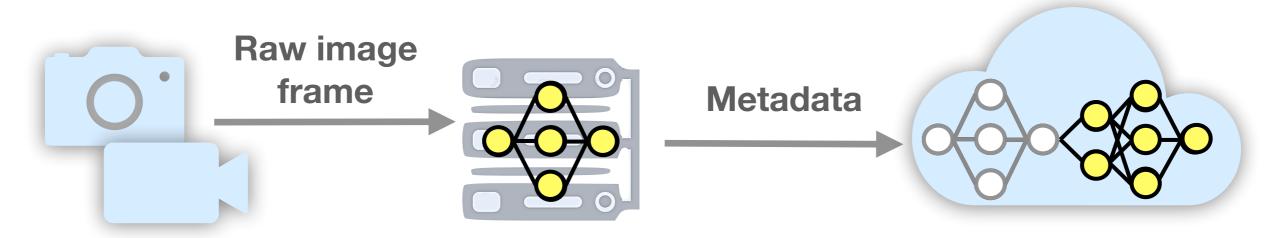






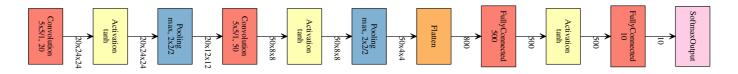


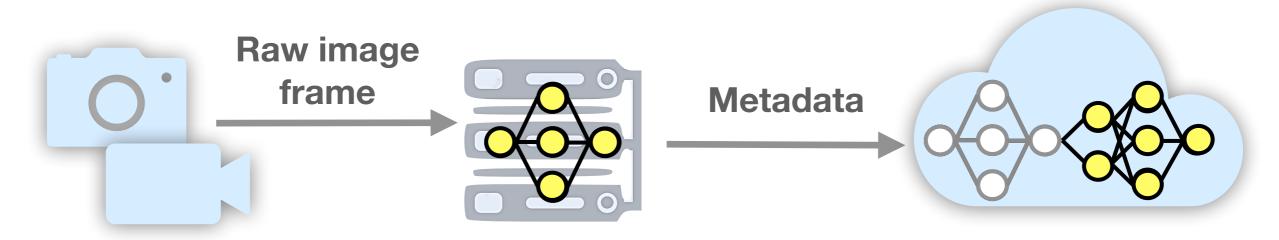


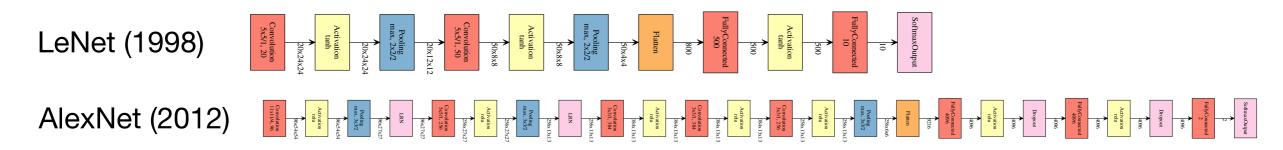


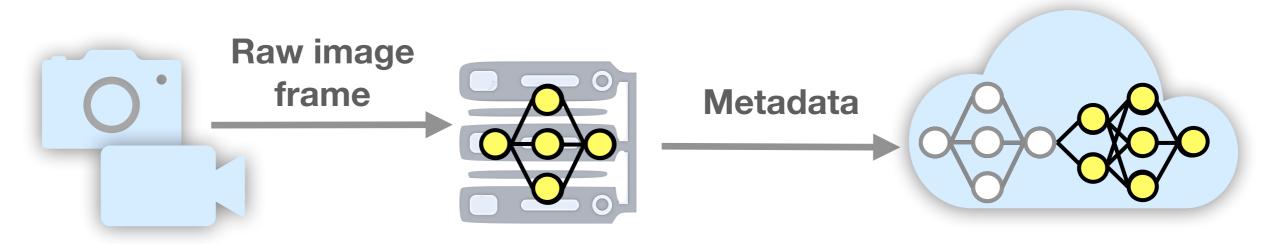
How do we decide the slicing point?

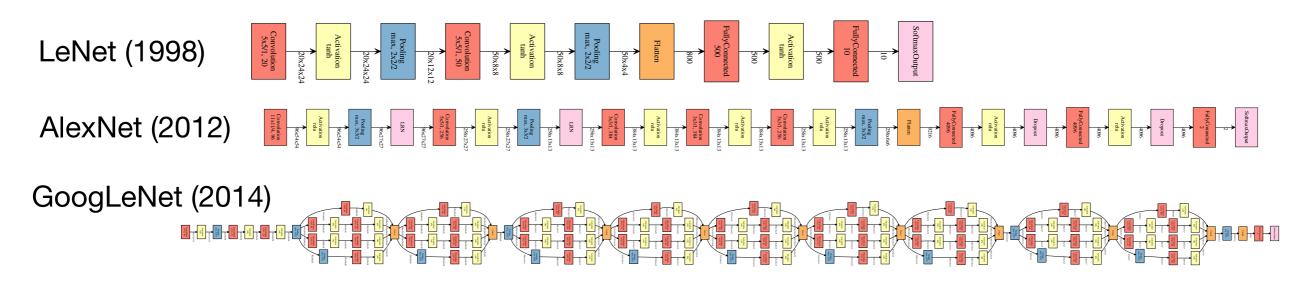
LeNet (1998)

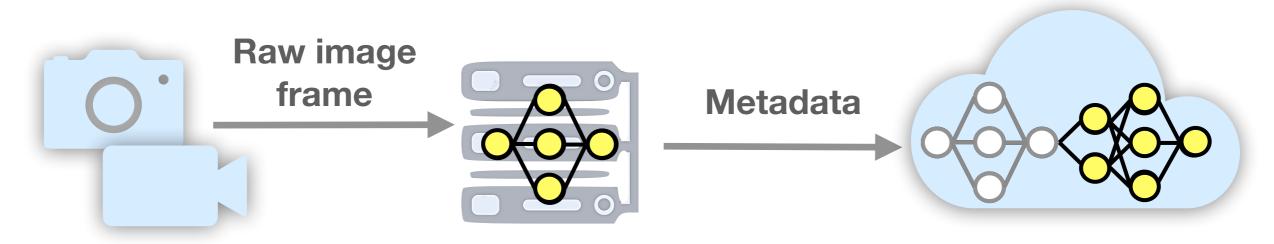


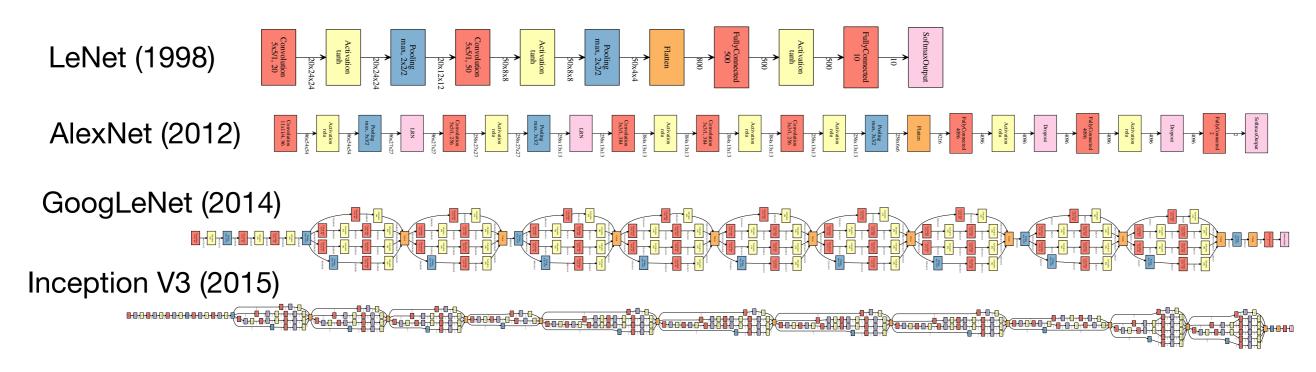


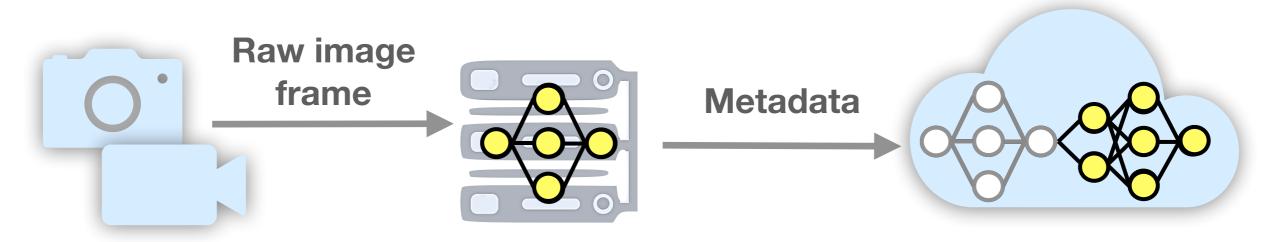


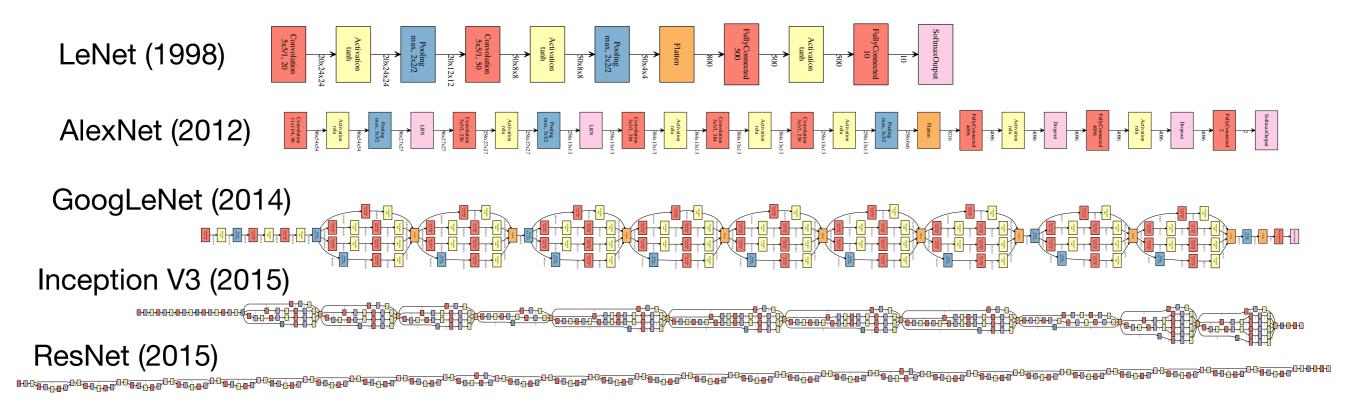


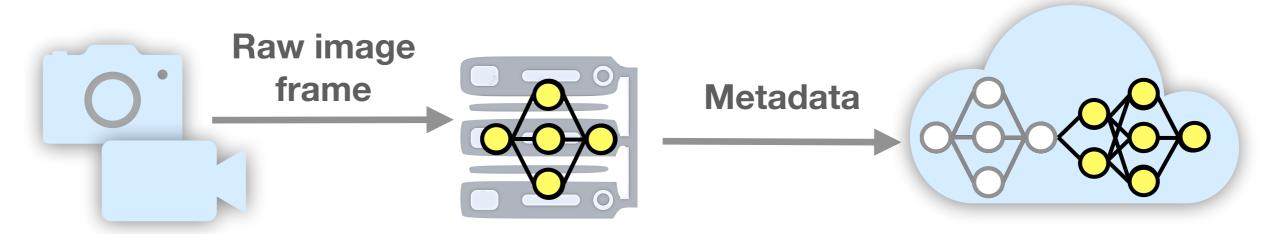








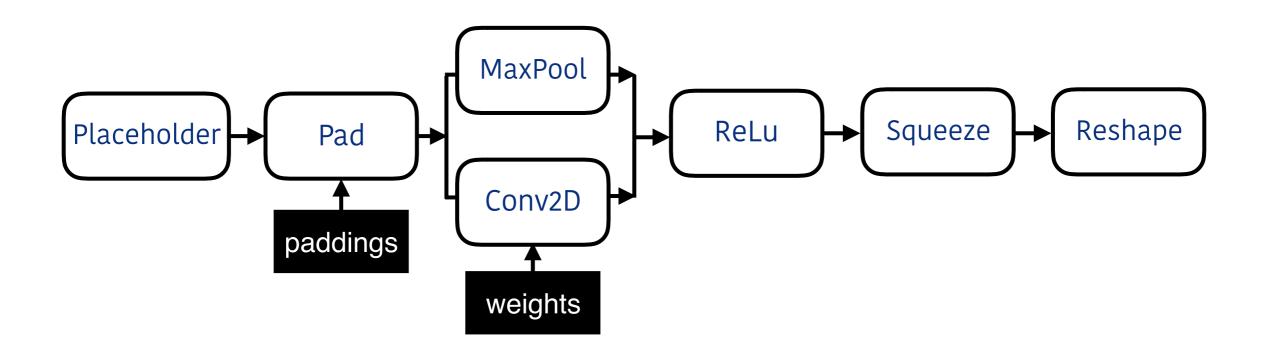




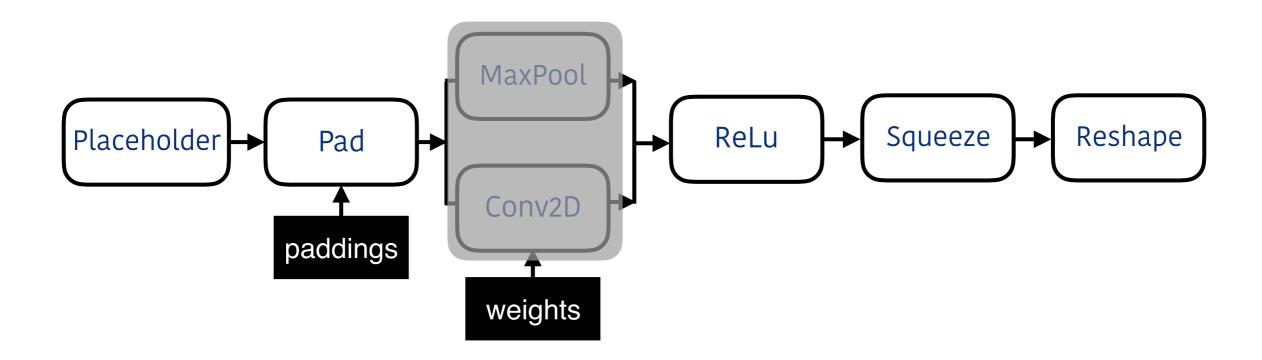
How do we decide the partition point?

- 1. Filter out splittable candidates in DNN
- 2. Pick up a right one among the candidates

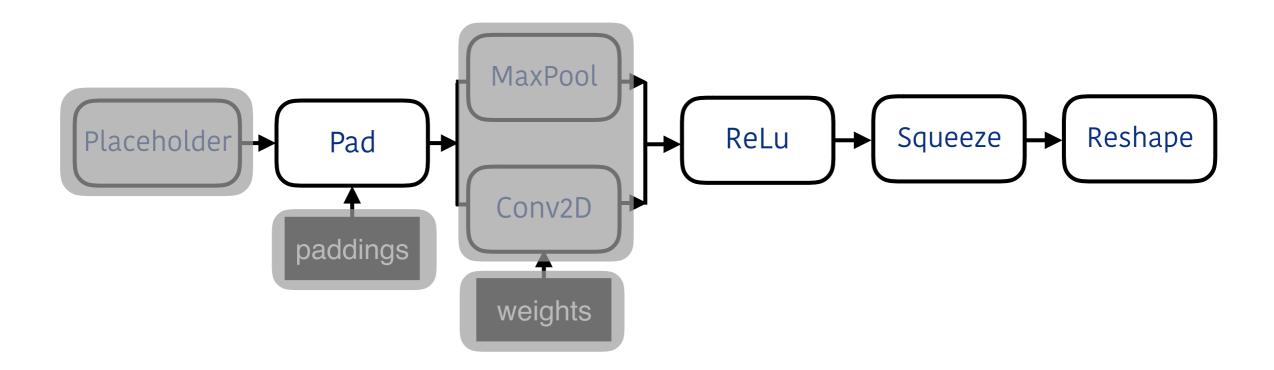
Listing splicing candidates



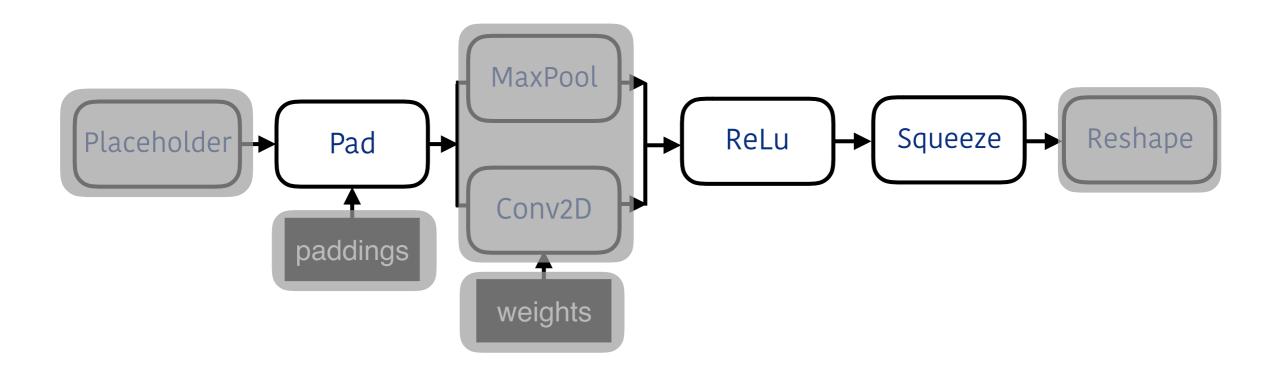
Listing splicing candidates



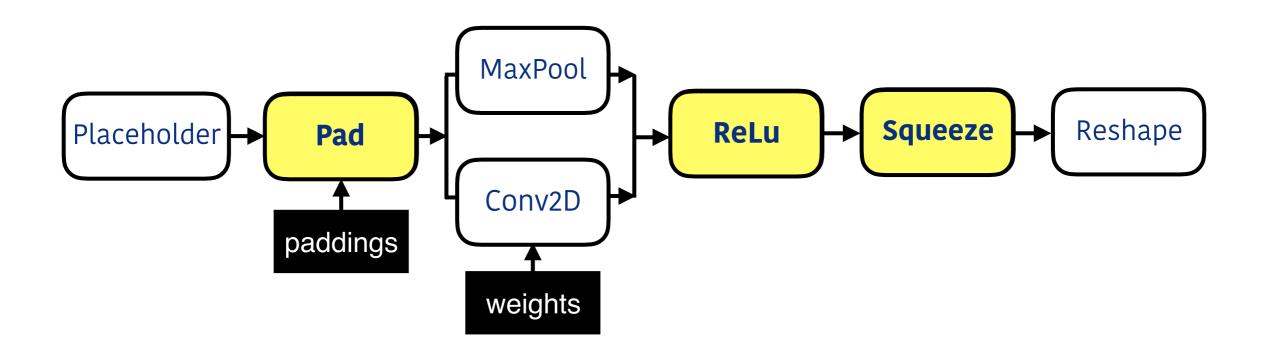
Multi-parallel path



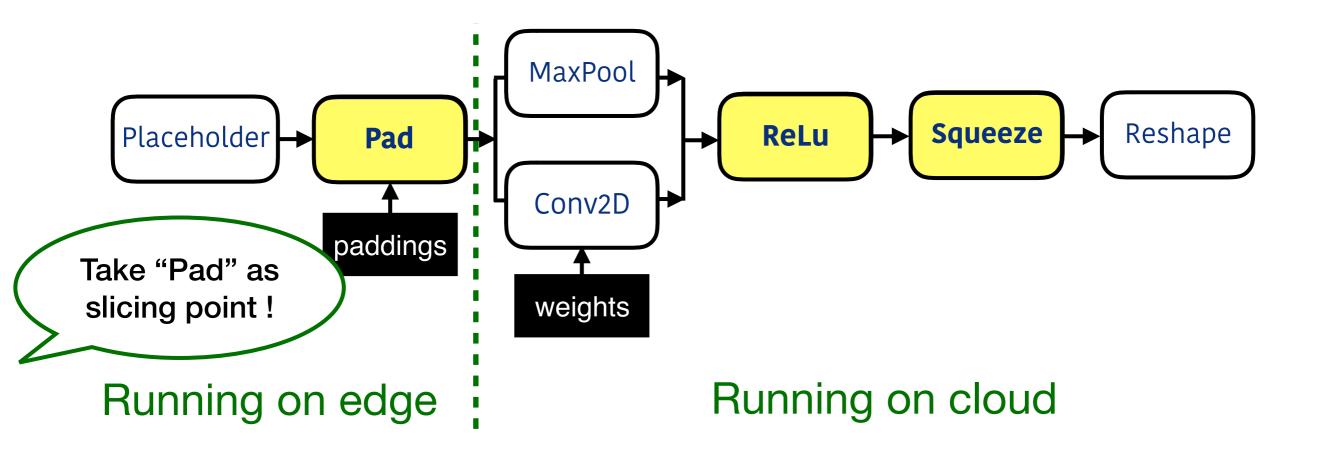
- Multi-parallel path
- X Constant or reading operator



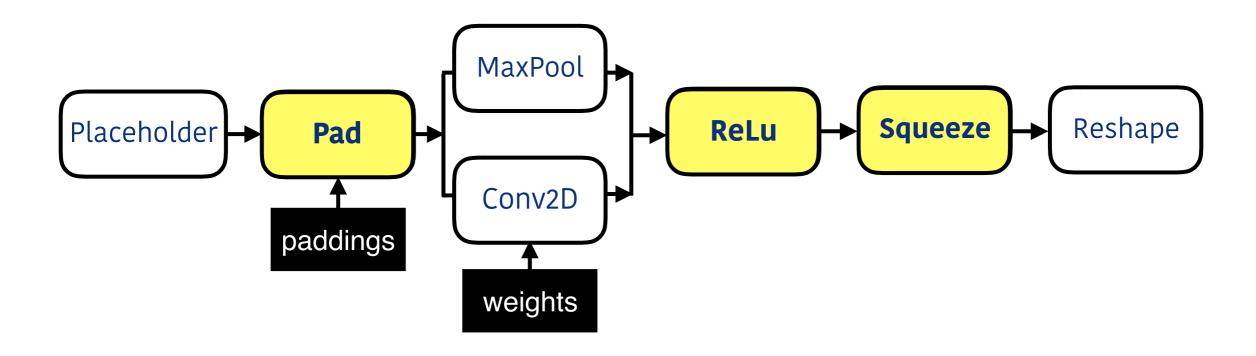
- Multi-parallel path
- X Constant or reading operator
- Last operator

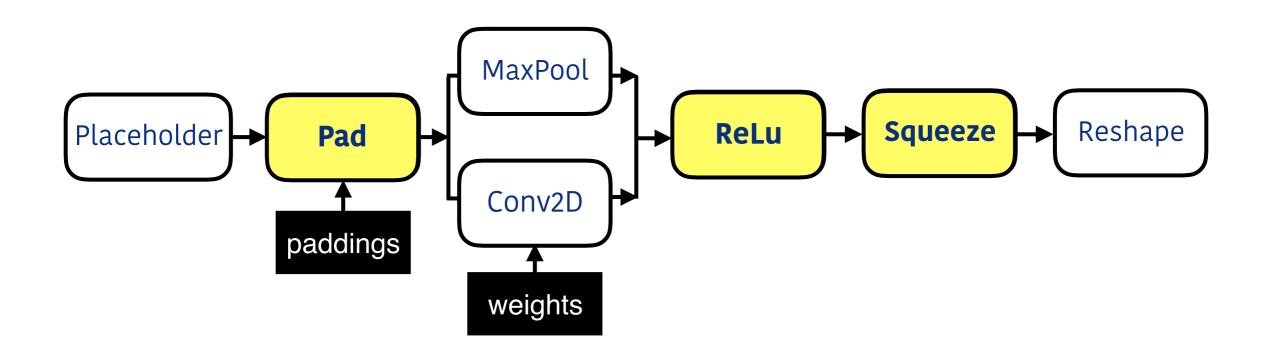


- Multi-parallel path
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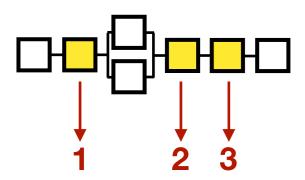
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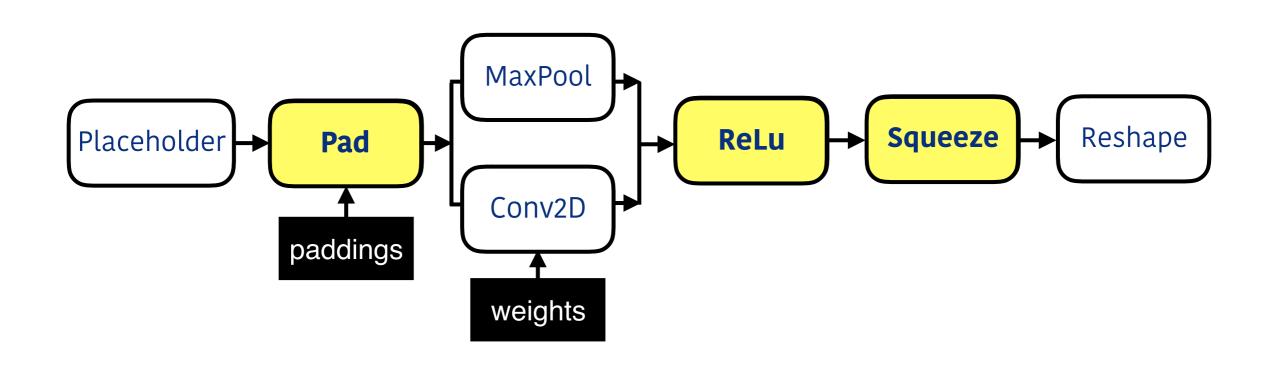




Strongman

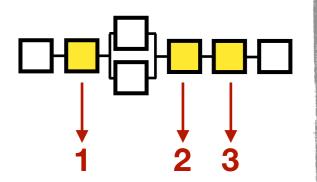
Evaluate every candidate





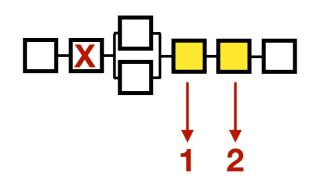
Strongman

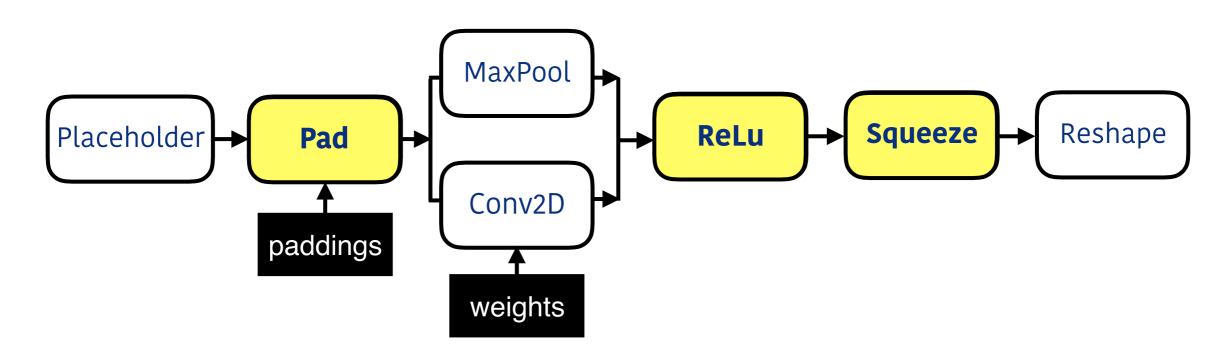
Evaluate every candidate

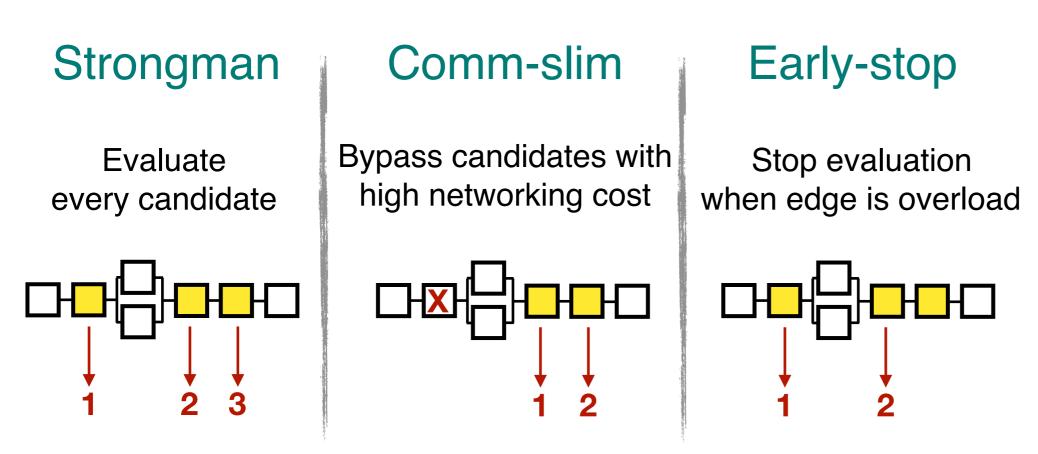


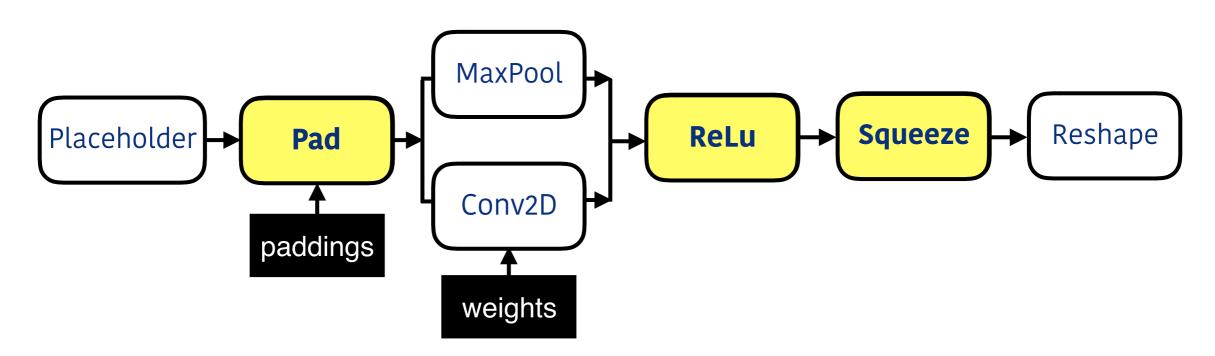
Comm-slim

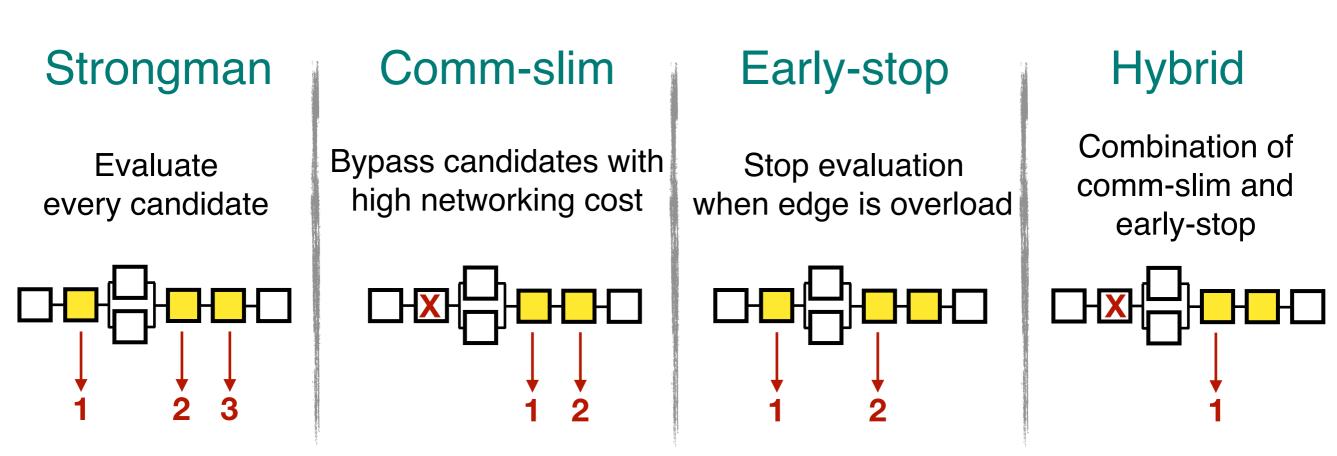
Bypass candidates with high networking cost

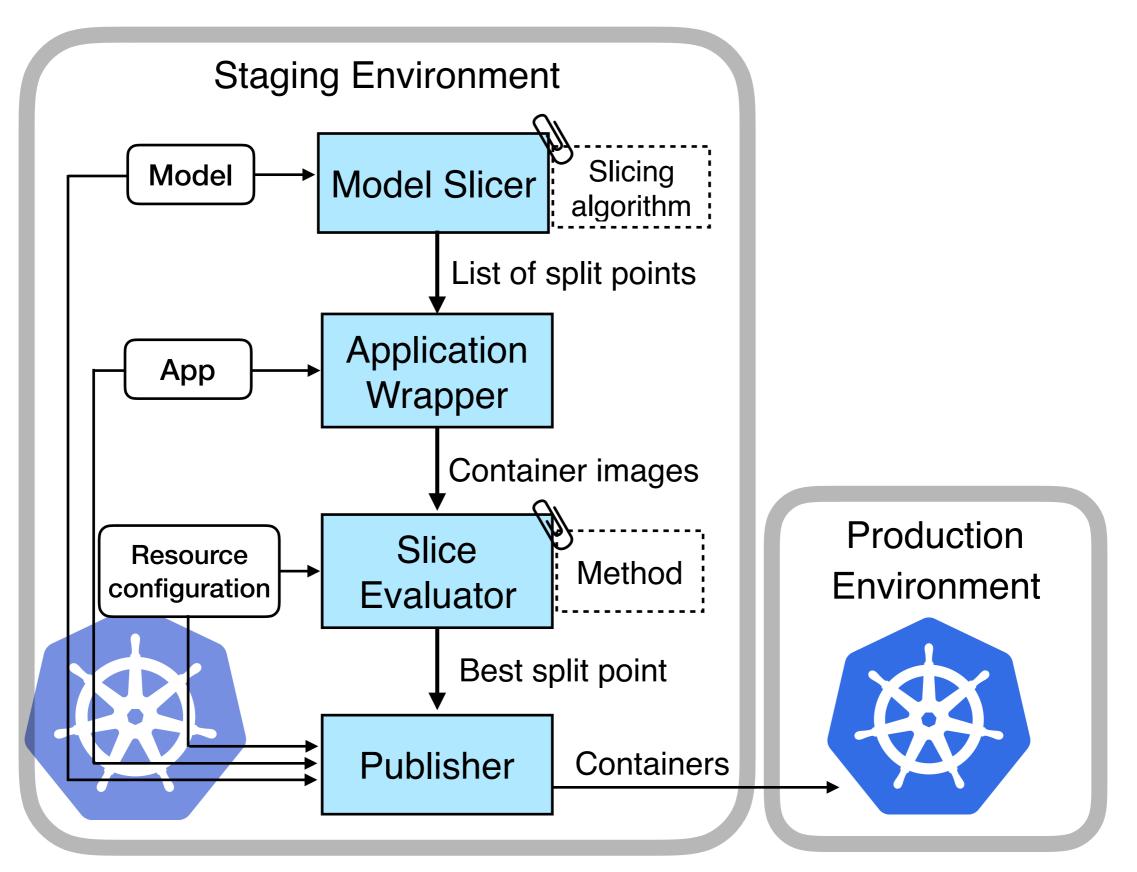


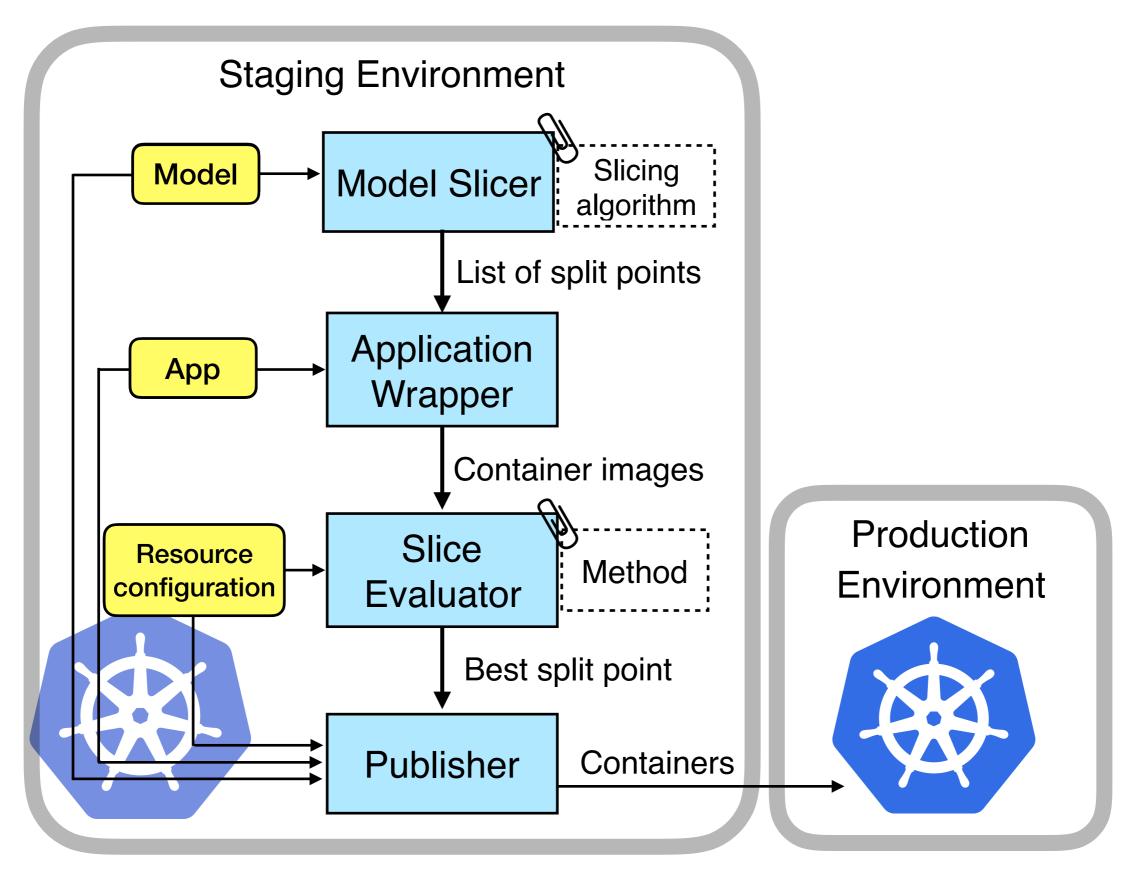


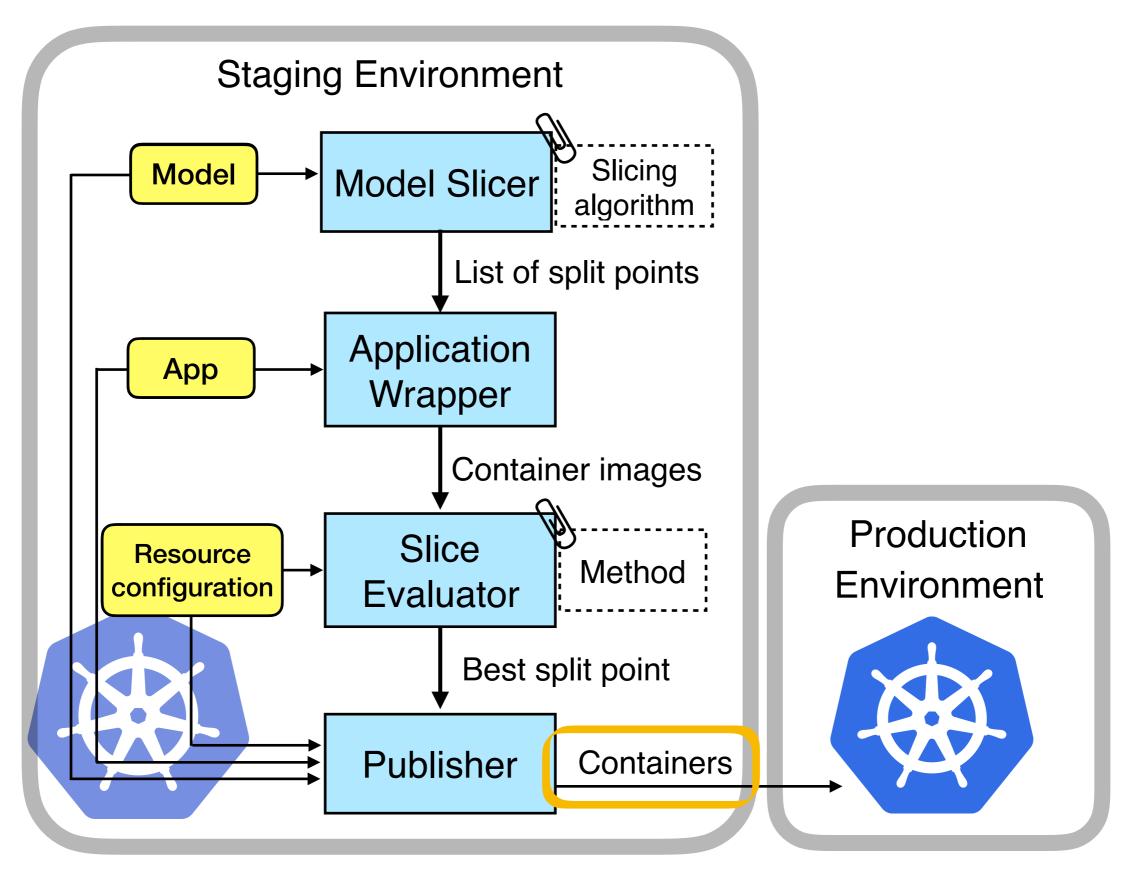


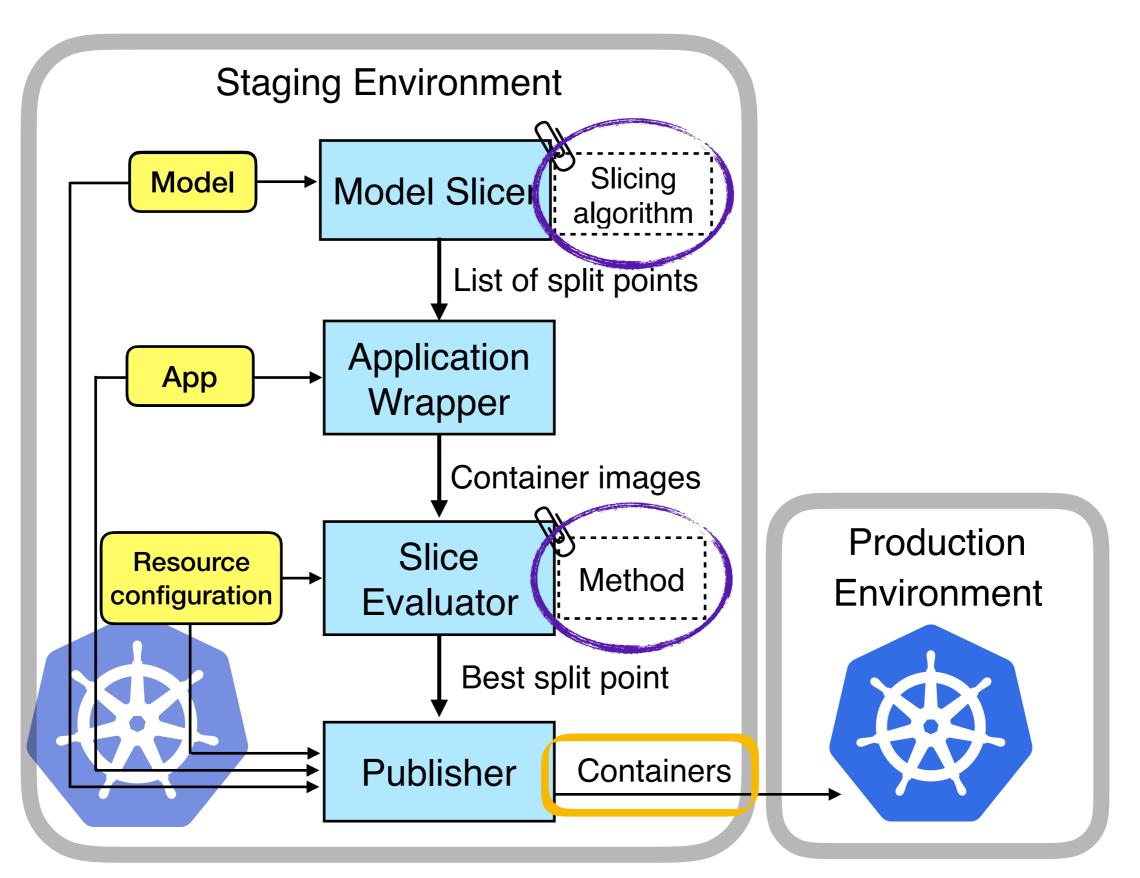


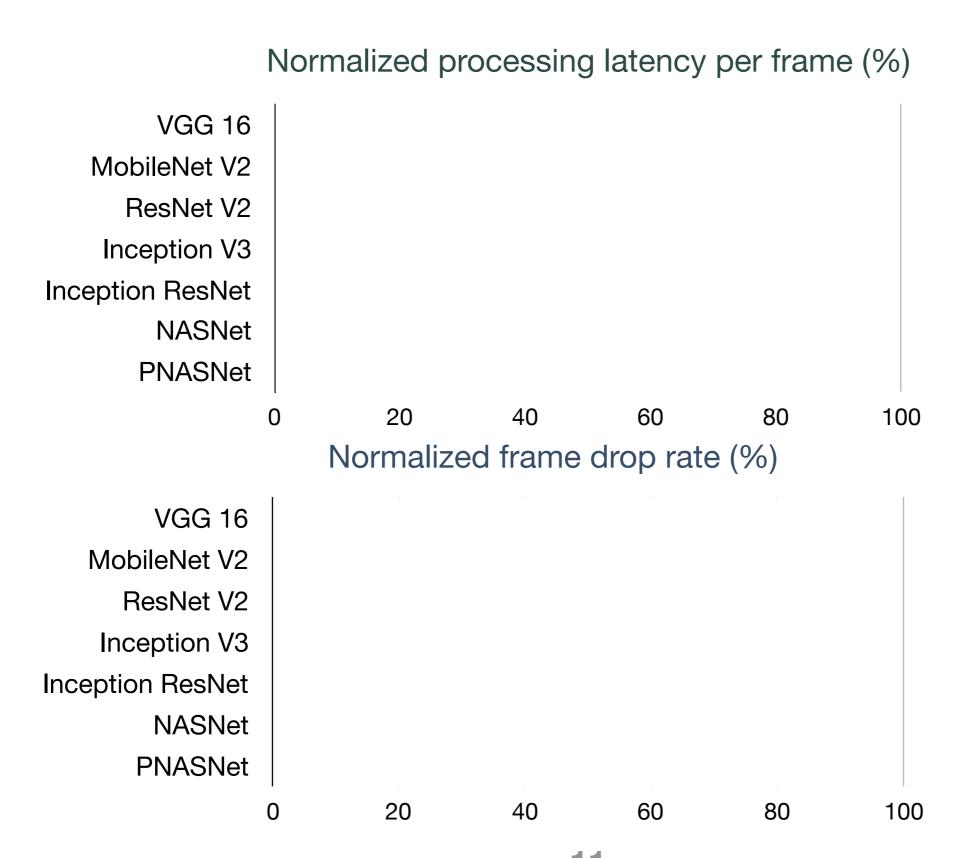






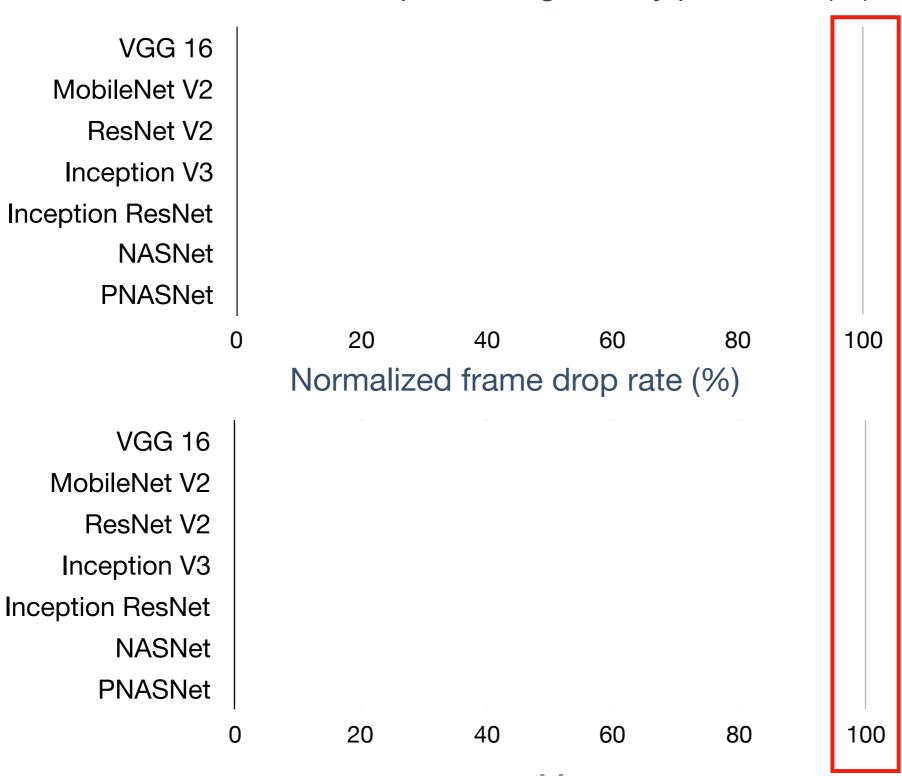


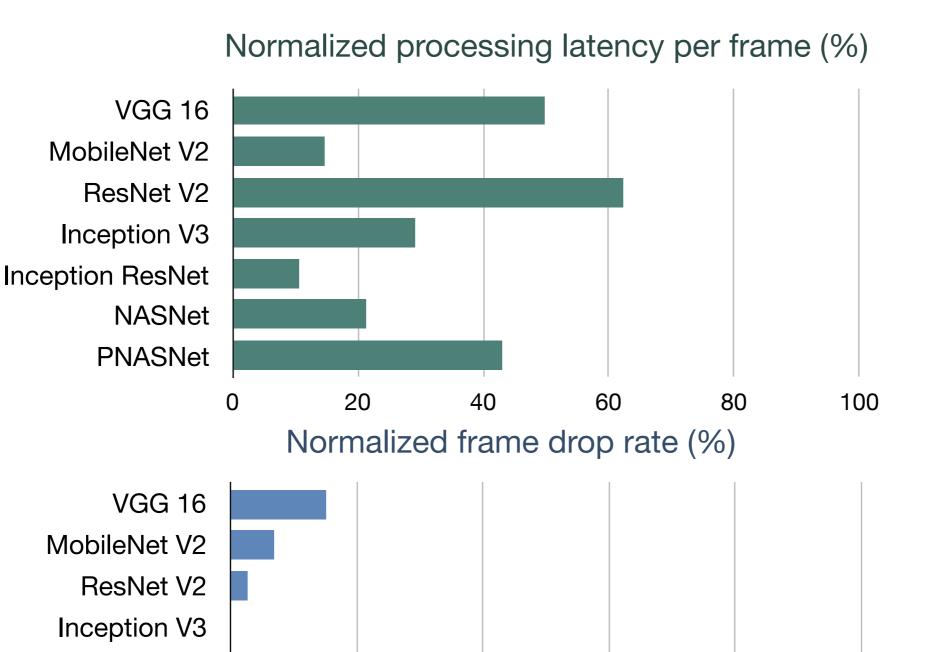




placing all DNN inference on cloud

Normalized processing latency per frame (%)





60

80

100

40

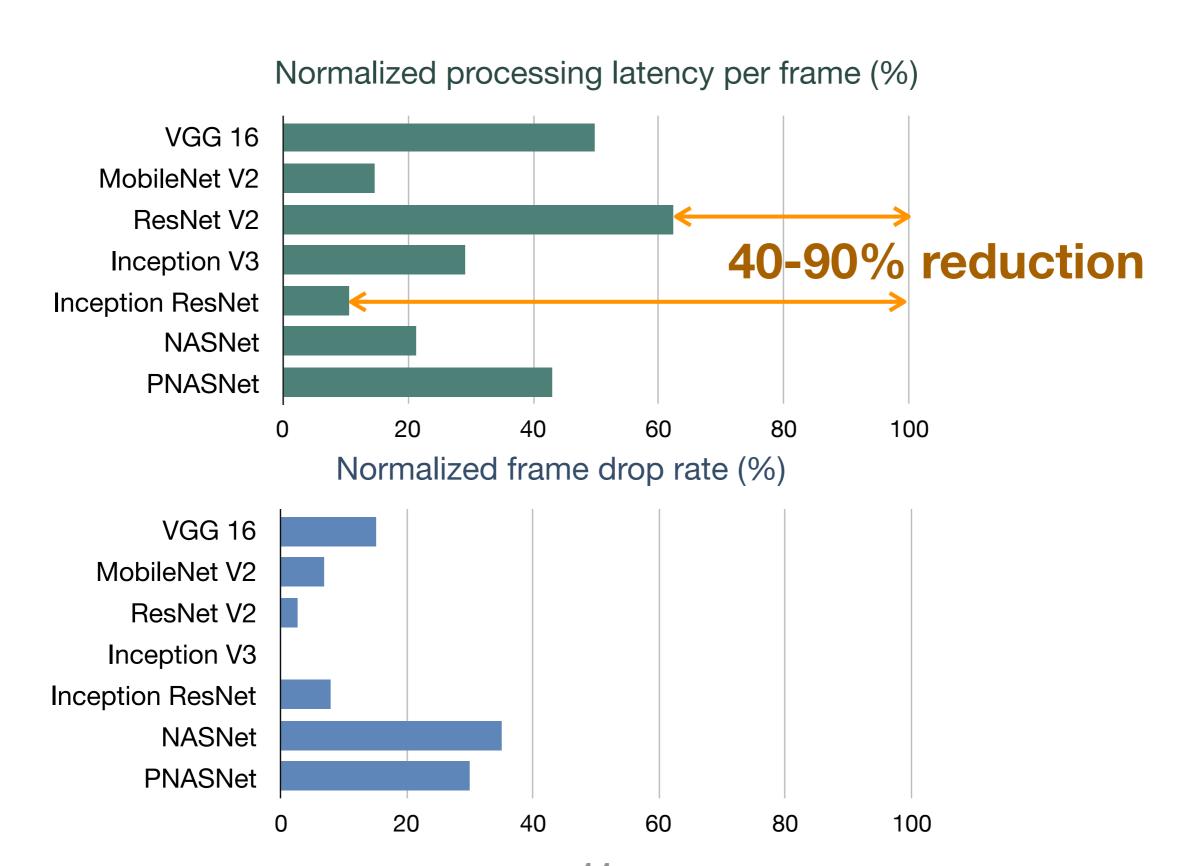
20

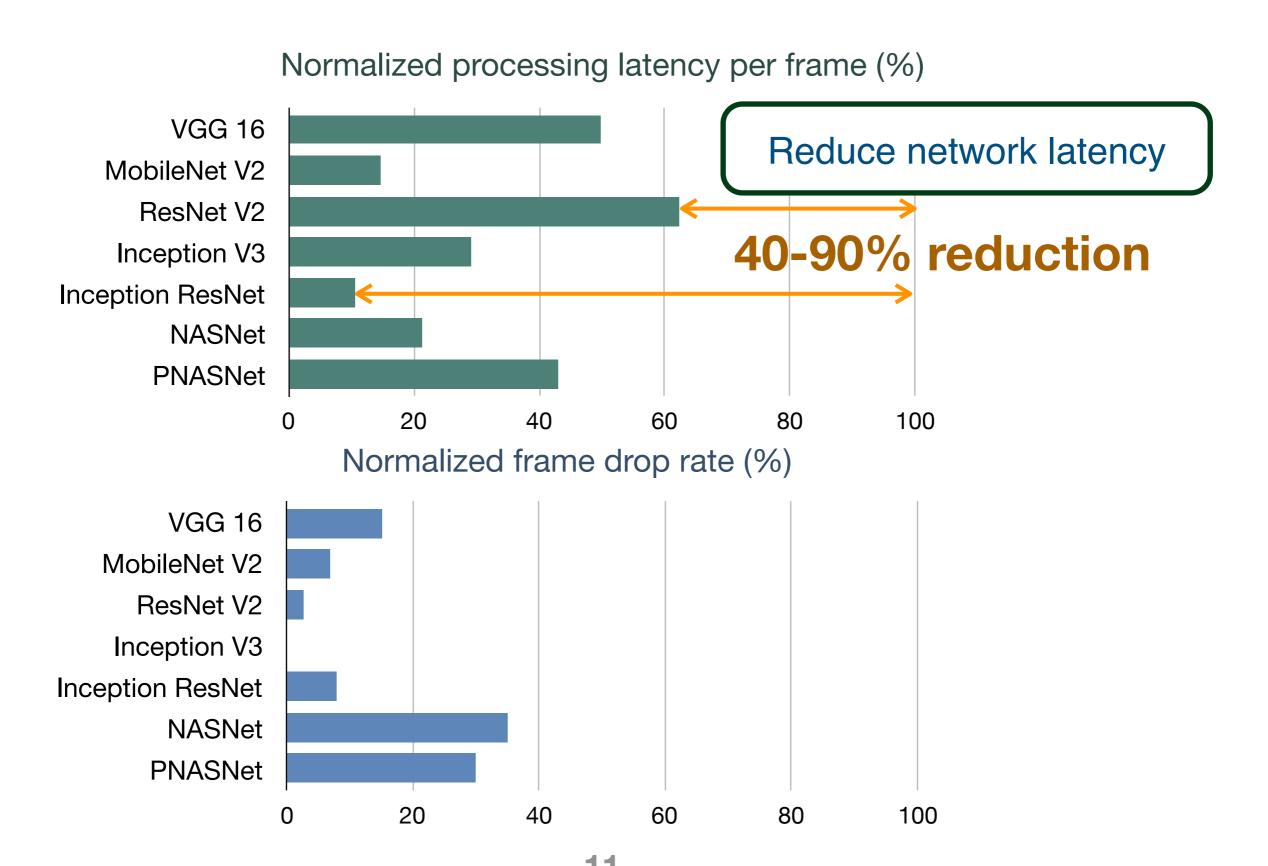
Inception ResNet

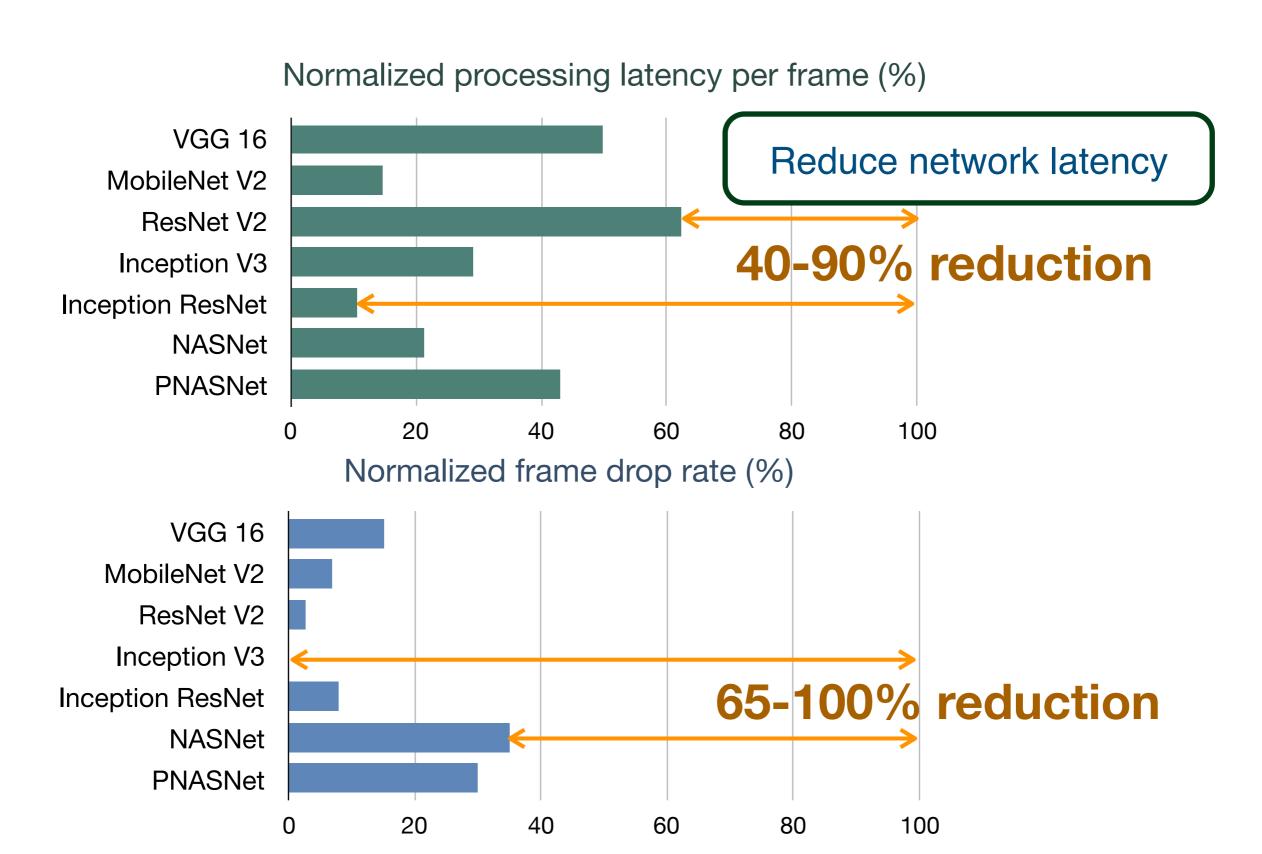
NASNet

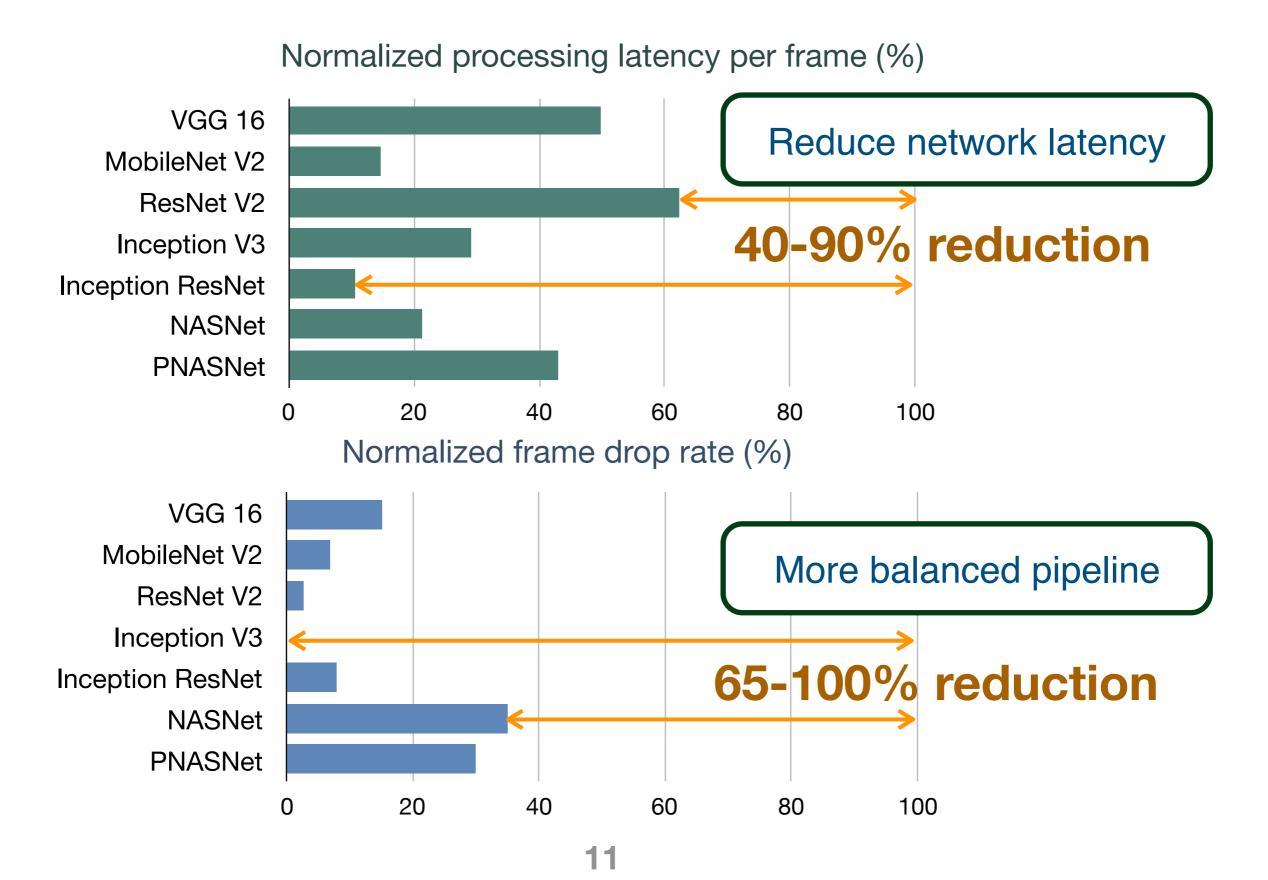
PNASNet

0









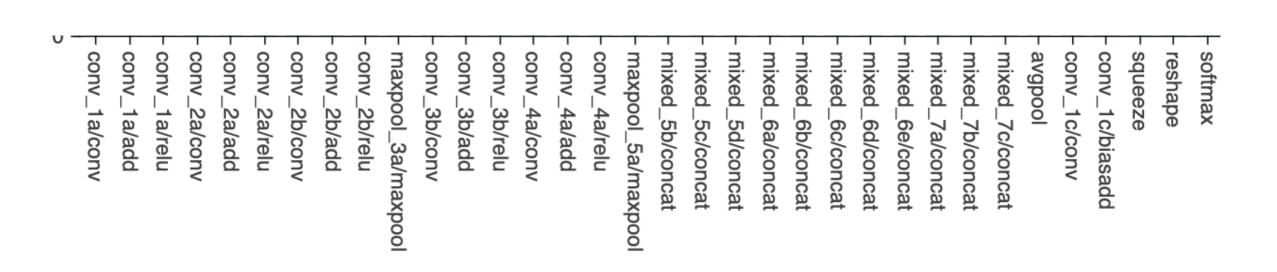
Model	# Onergton	Method		
Model	# Operator	Strongman 34	Hybrid	
Inception V3	788	34	2	

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99% reduction

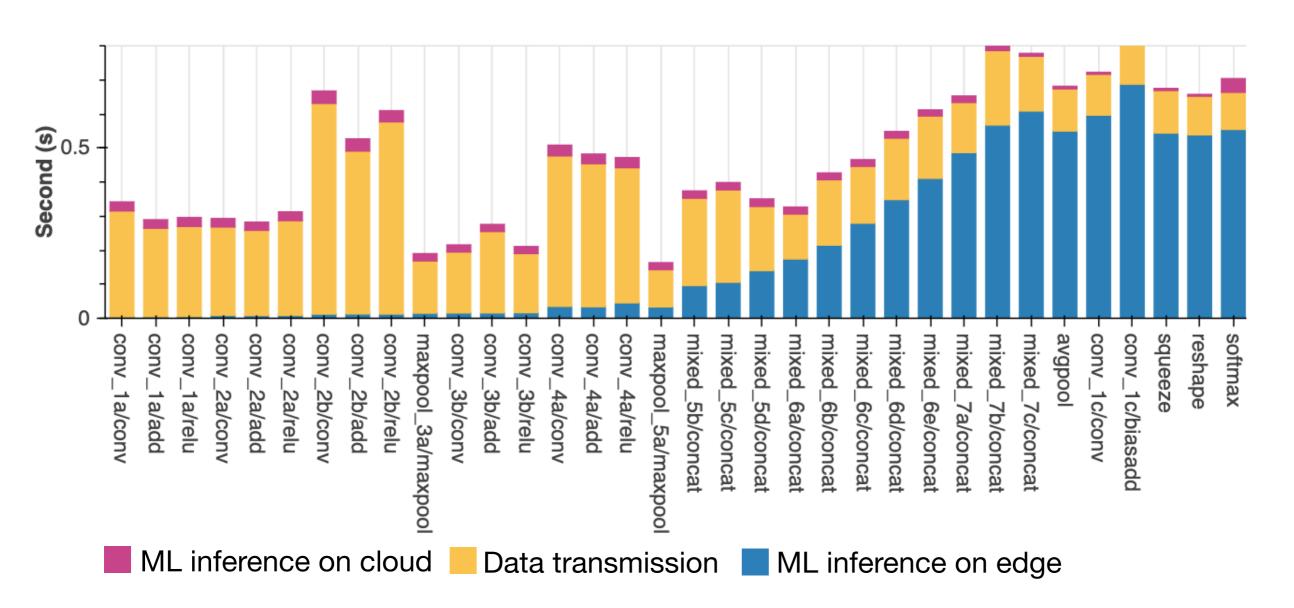
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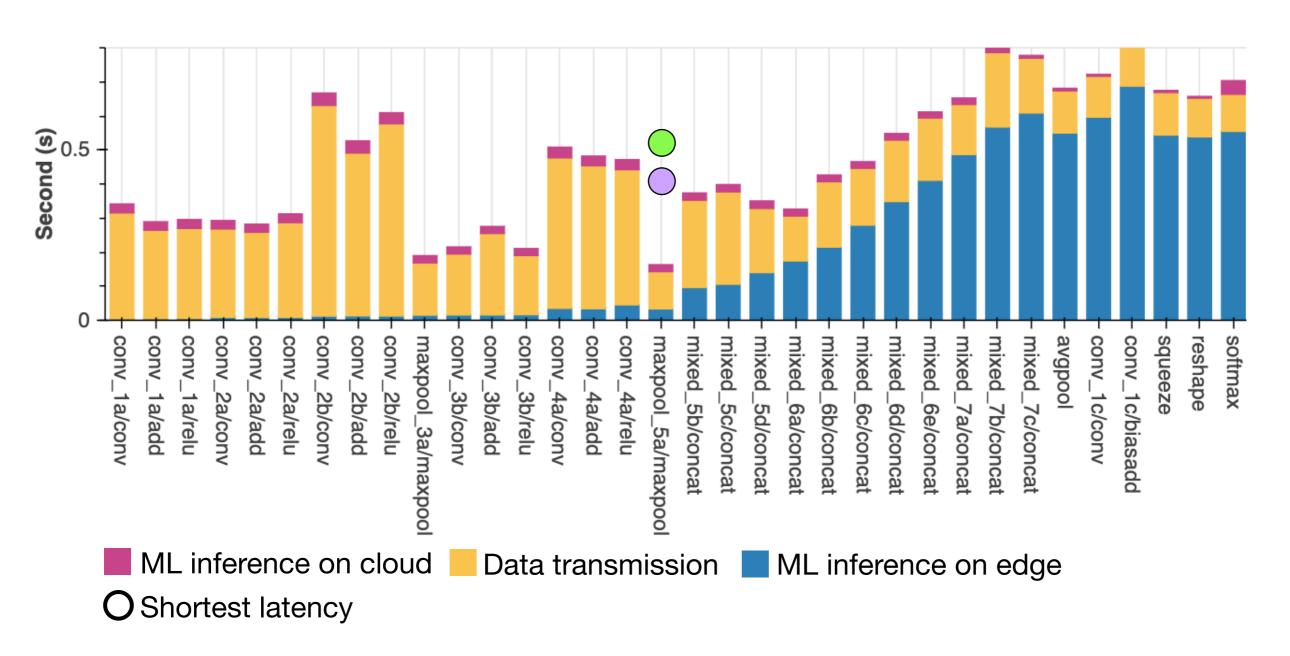


Strongman method tests 34 slicing candidates

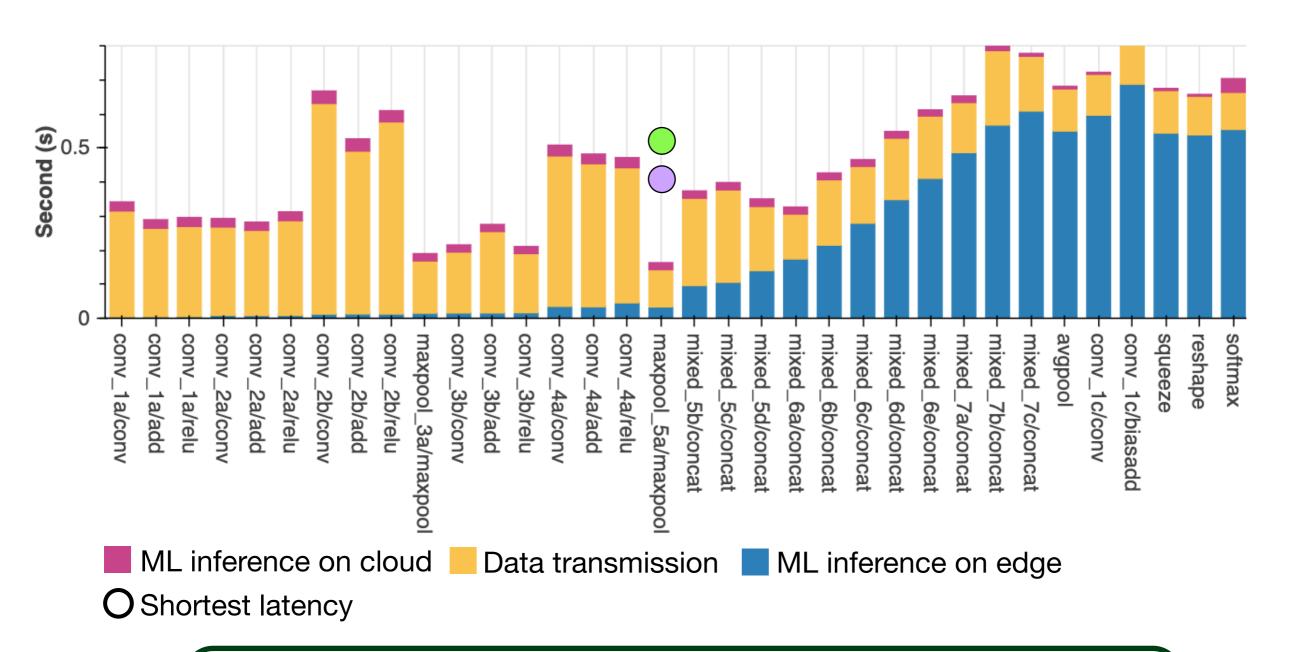
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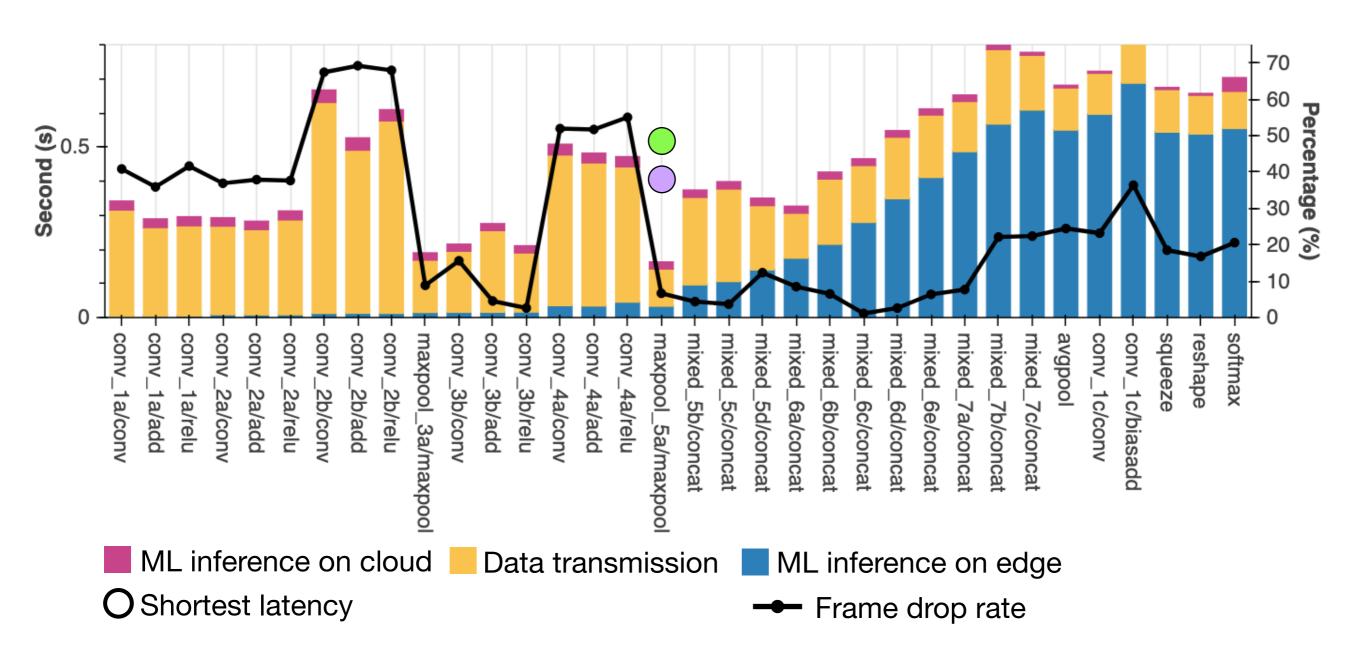


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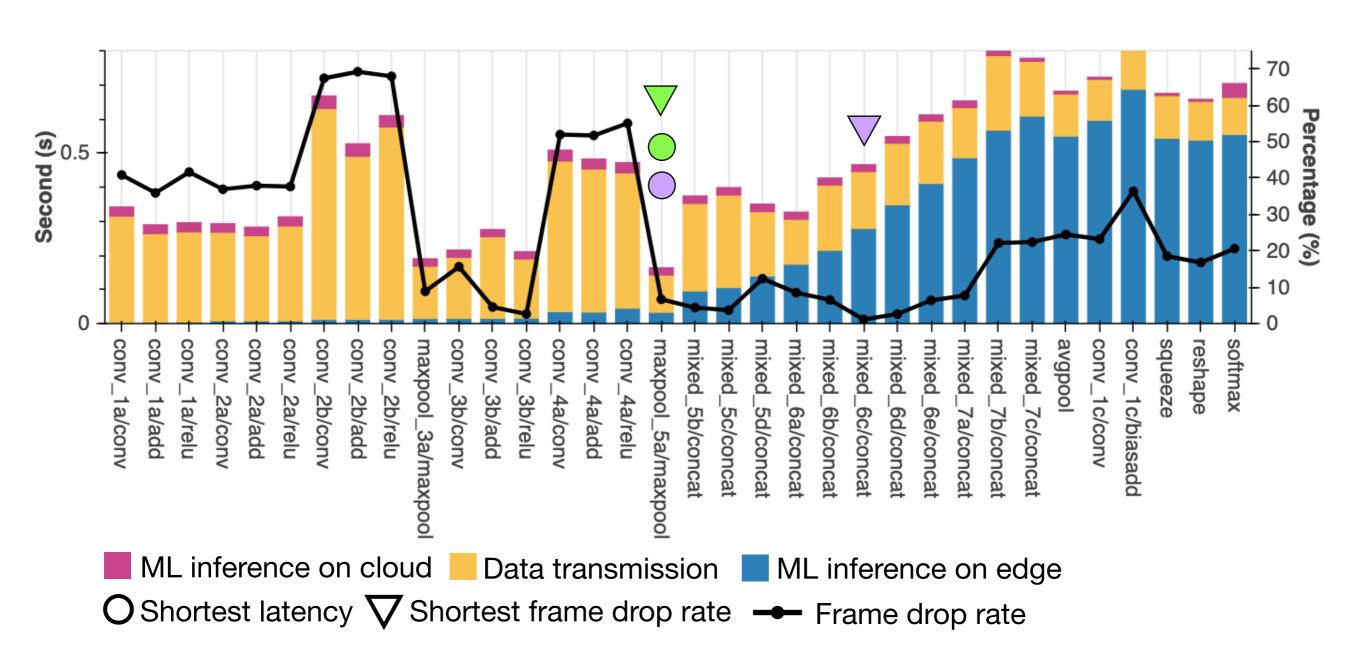


Hybrid method can find the same slicing deployment with much smaller problem space

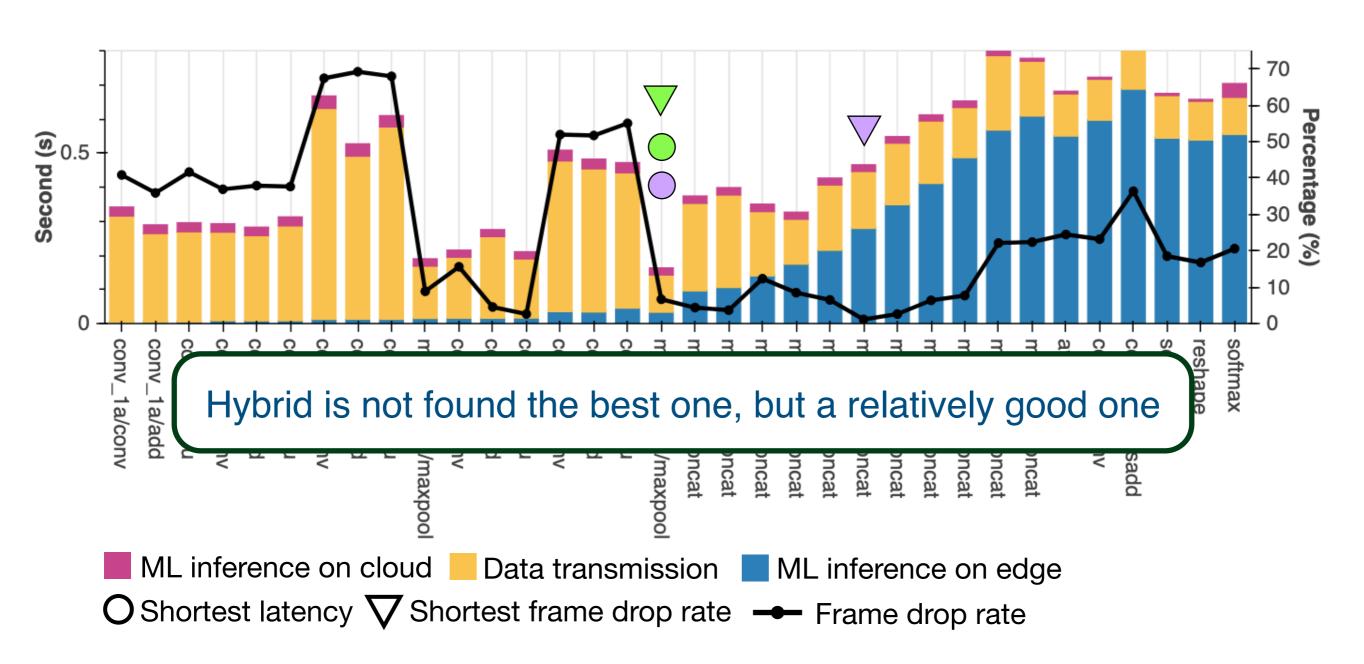
Model	# Operator	Method	
Model	# Operator	Strongman	Hybrid
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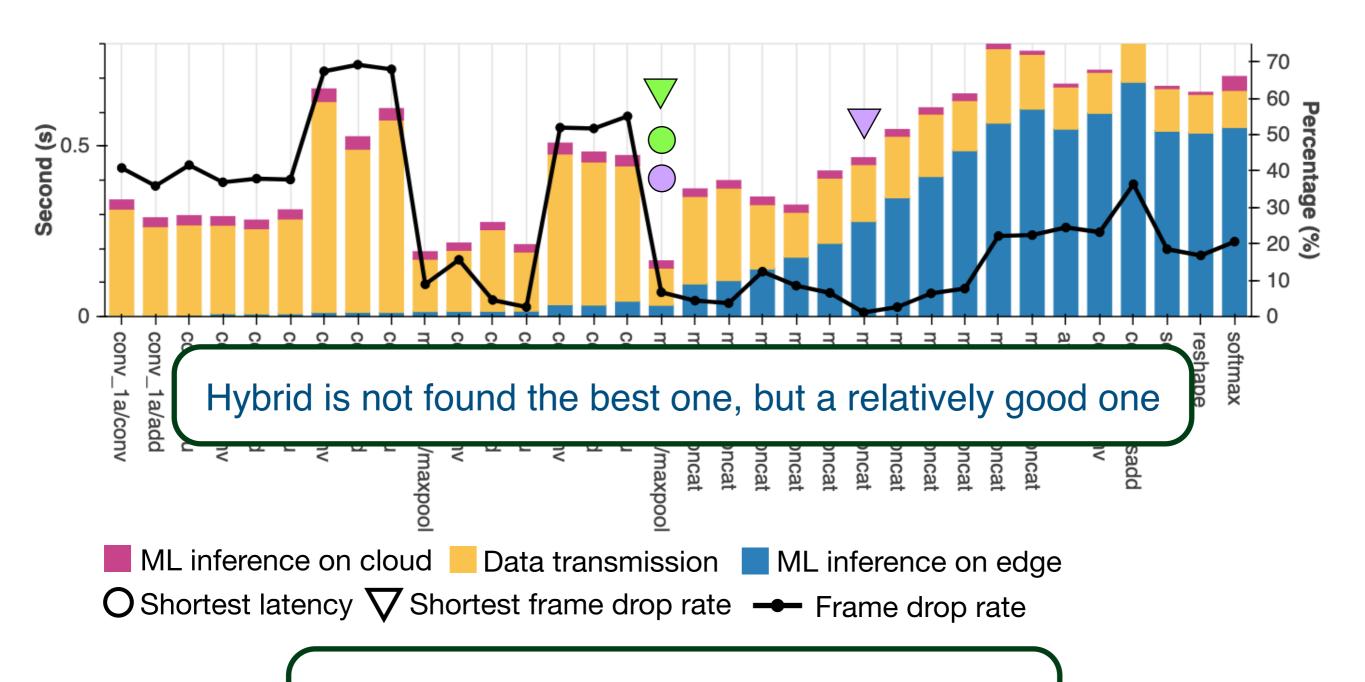
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Model	# Operator	Metl	nod
Model	# Operator	Strongman I	Hybrid
Inception V3	788	34	2



Not single slicing deployment for all SLAs

Couper contribution

Improve DNN inference on various metrics:

Achieved up to 90% improvement on processing latency and 100% improvement on processing quality.

- Rapid to find solution:
 Reduced 99% problem space for searching best deployment.
- Flexible to different DNN inference service:
 Supported pluggable slicing algorithm and evaluating method.
- Compatible with contemporary software stack:
 Deployed with container orchestration, Kubernetes.

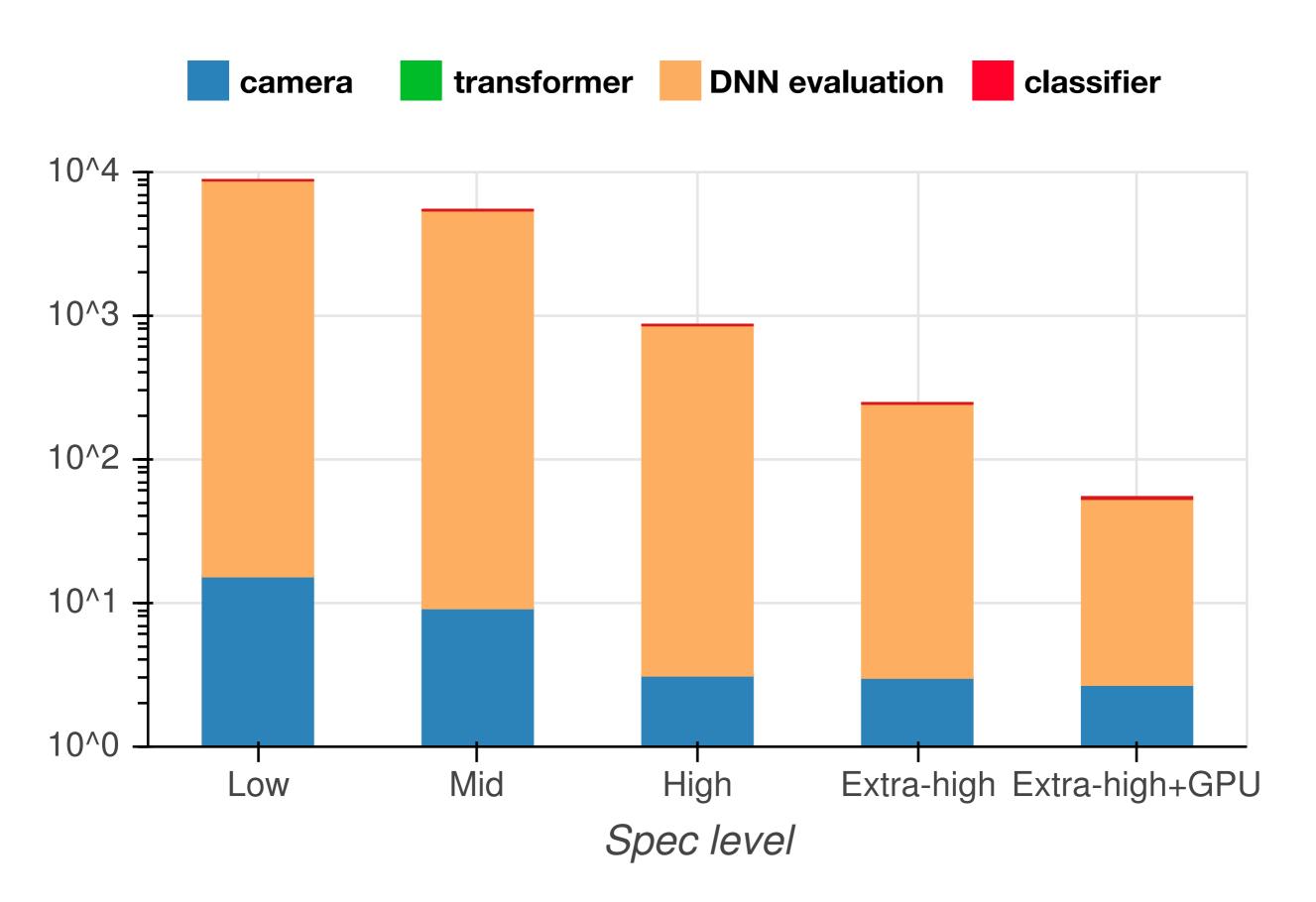
Thanks for your attention!







Running PNASNet on different edge



Here comes Couper!

This is a multi-dimensional problem:

- 1. Heterogeneous computing resource between client, edge and cloud.
- 2. Various compute-intensive DNN models
- => slicing the DNN to fit the edge resource

Here comes Couper!

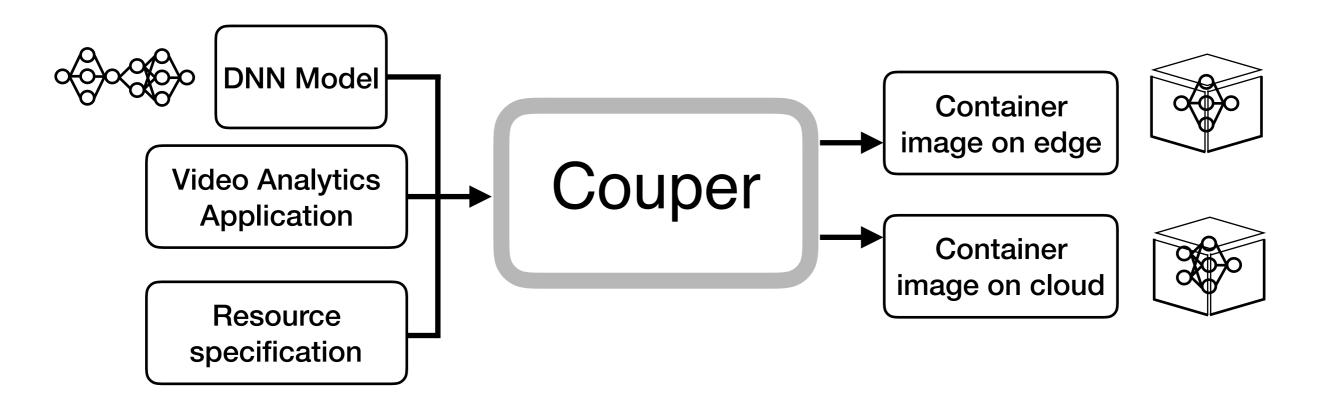
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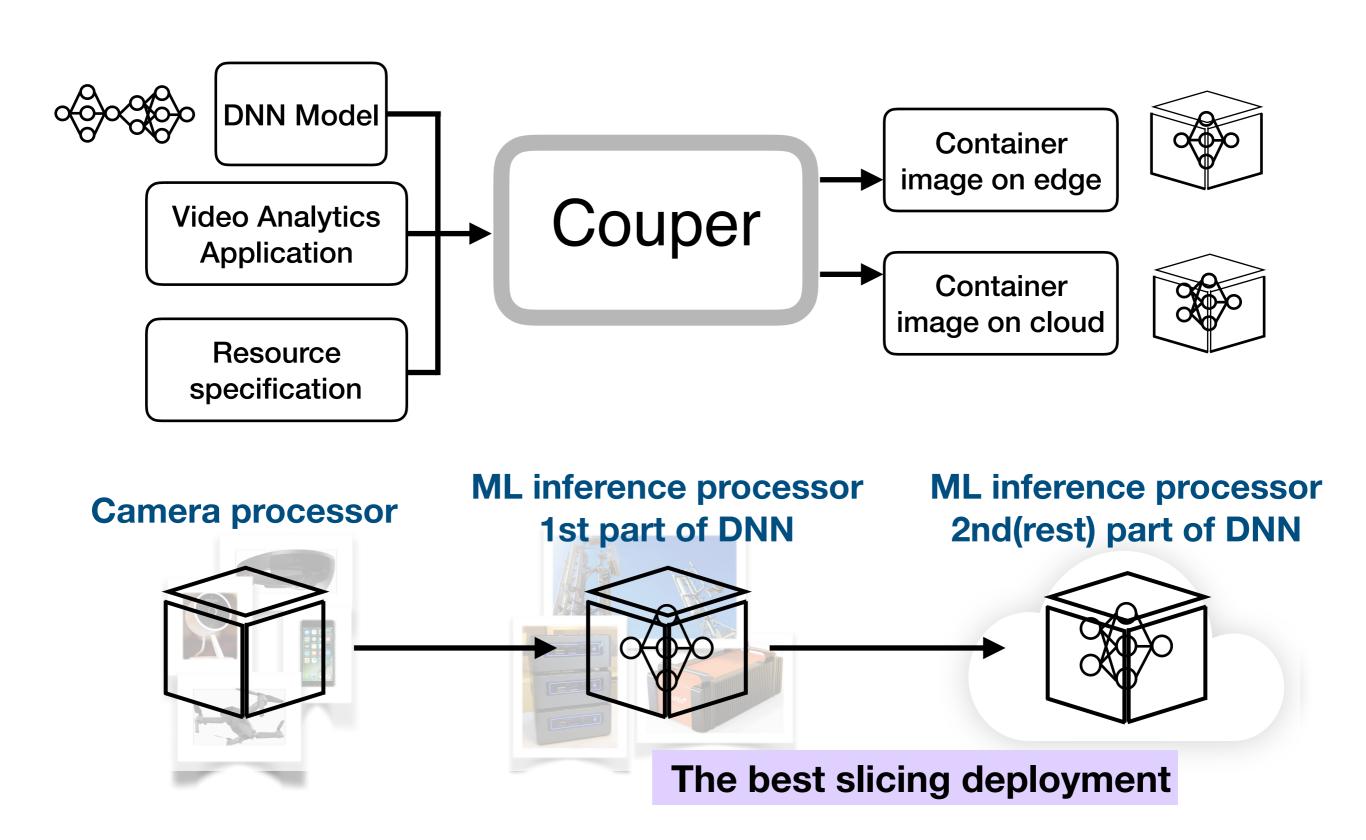
=> slicing the DNN to fit the edge resource

	Neurosurgeon (ASPLOS'17)	DDNN (ICDCS'17)	Edge-host partitioning of DNN (AVSS'18)	Couper
Edge involved?				
Generic slicing method?				
Verified by production DNN?				
Supporting different tenancies?				

Couper Introduction



Couper Introduction



Goals:

- How Couper improves performance?
- How Couper reduces problem space and saves evaluation time?
- Why Couper supports different evaluating methods?

Hardware specification of experiments:

Davias	CPU Freq	CPU	RAM	CDU	RTT (ms)	
Device	(GHz)	proc	(GB)	GPU	client	cloud
Client device	2.0	2	1			
Low-end edge	2.0	4	16	NT/A	1	65
Mid-end edge	3.1	8	32	N/A	15	50
High-end edge	3.1	16	64		25	42
Cloud server	3.1	48	96	2 Nvidia P100		

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More powerful edge is further from client

The original layers of DNN and the # evaluation candidates

Model	# Lavan	Method					
Model	# Layer	Strongman	Comm-slim	Hybrid			
VGG 16	54	52	20	1			
MobileNet V2 1.4	158	155	132	3			
ResNet V2 50	205	34	15	1			
Inception V3	788	34	15	2			
Inception ResNet V2	871	106	28	3			
NASNet 331	1265	7	3	1			
PNASNet 331	939	7	3	1			

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NASNet 331	1265		7		3		1	
PNASNet 331	939		7		3		1	
					•		1	_

Up to 98% evaluation time reduction

Hugely reduce problem space(split point candidates) by methods

Next Step

Couper Enhancement:

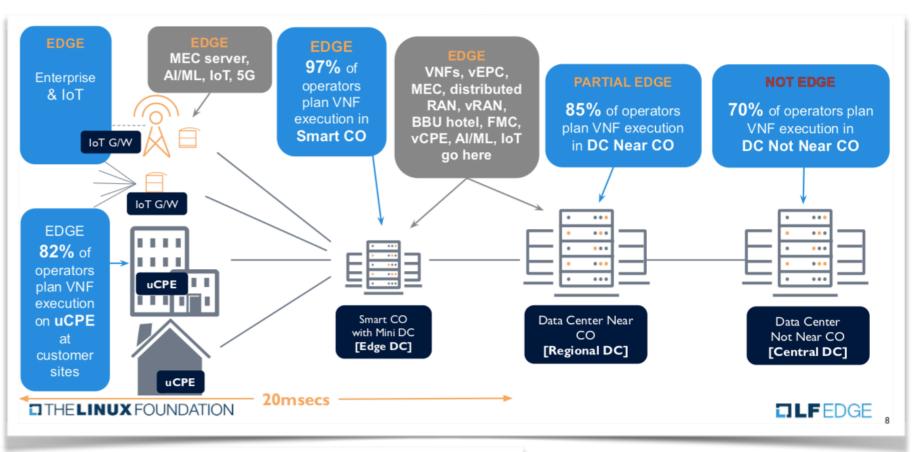
Working with different DNN model, application, and framework (i.e. Yolov3 with object detection)

Collaborate with edge software stack:

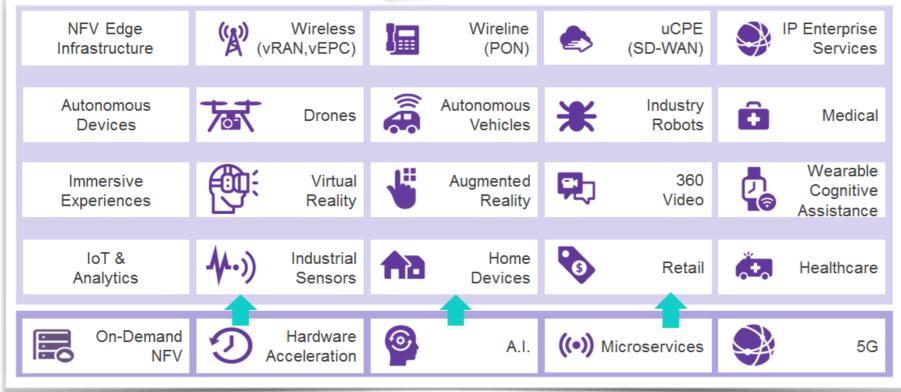
Evaluating 5G environment, edge infrastructure (i.e. Akraino), and supporting software (i.e. NFV techniques)

Multi-tenancy with different workloads:

Evaluating on the compute and network interference/overhead while sharing resource with other services

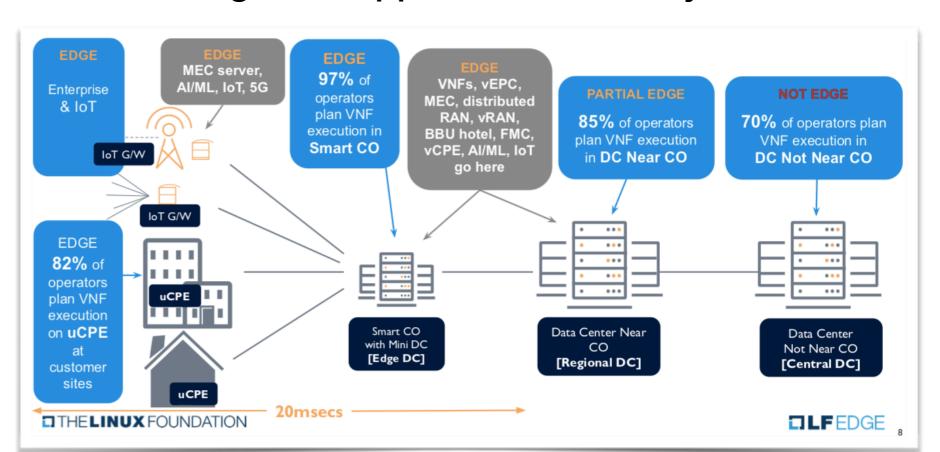


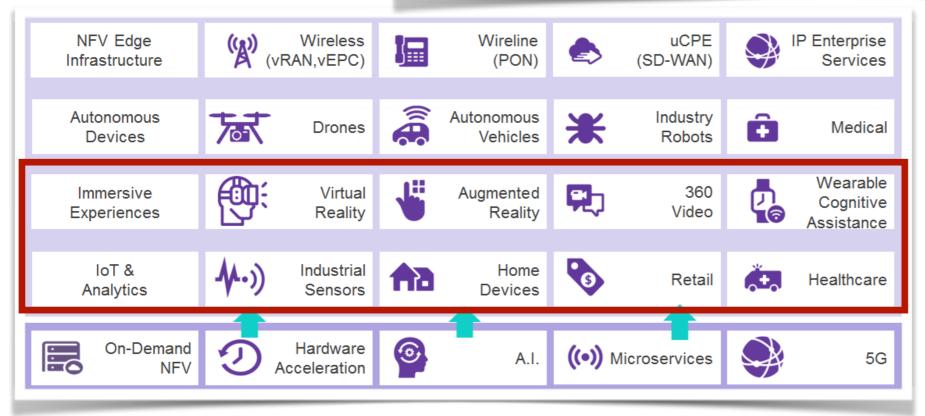
(backup page)



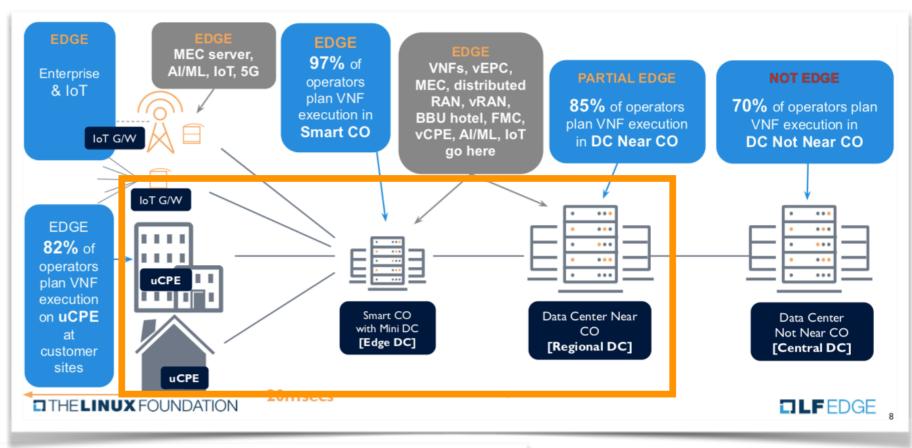
❖ Linux Foundation Edge, Akraino — emerging technology and edge coverage

Edge resources are diverse and target to support multi-tenancy (backup page)

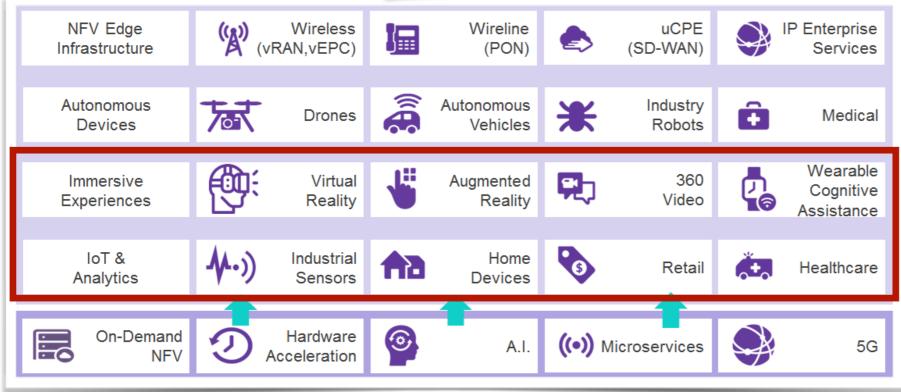




Linux Foundation Edge, Akraino — emerging technology and edge coverage

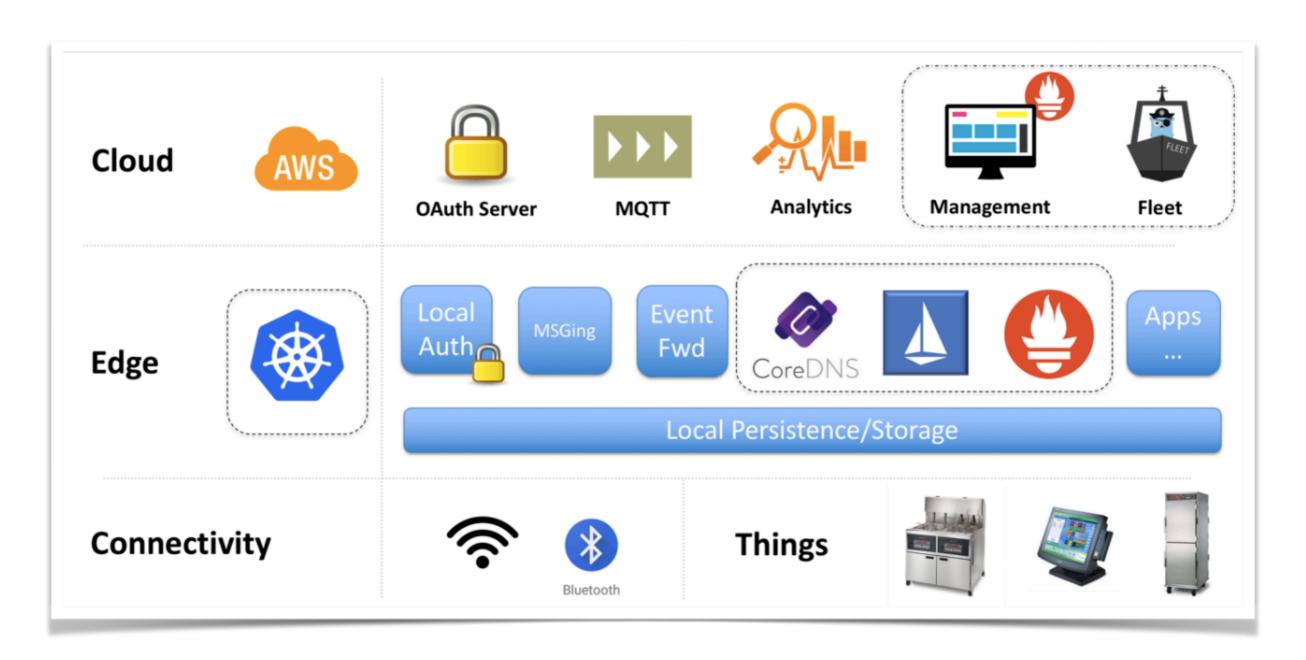


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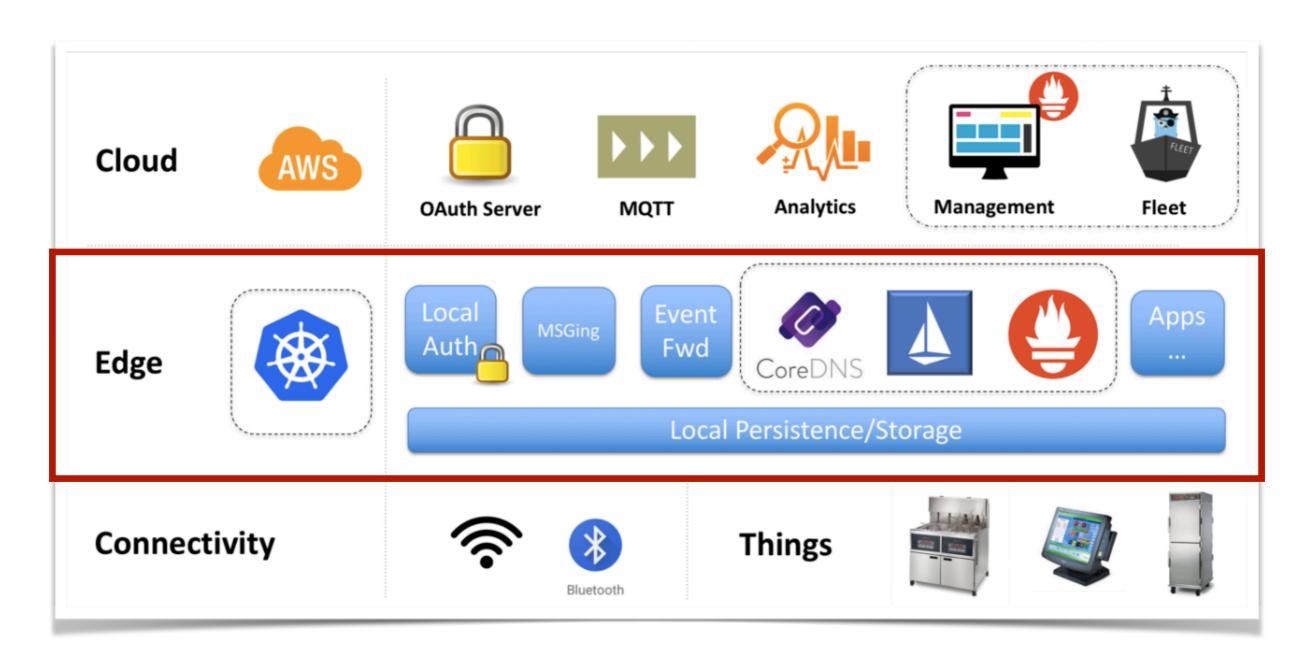
❖ Linux Foundation Edge, Akraino — emerging technology and edge coverage

Even in specific edge device owned by certain company, need to support multiple services



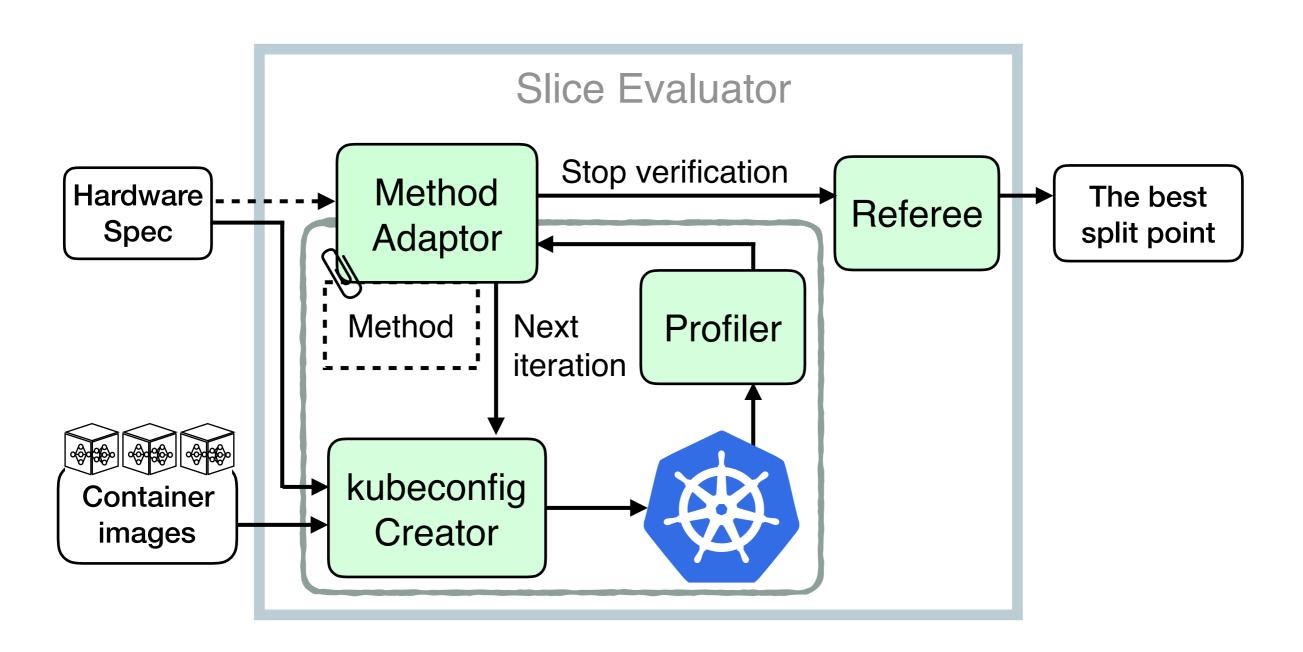
Chick-fil-A, Edge computing architecture overview

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Chick-fil-A, Edge computing architecture overview

Couper Introduction



Goals:

- How Couper improves performance?
- How Couper reduces problem space and saves evaluation time?
- Why Couper supports different evaluating methods?

Hardware specification of experiments:

Davias	CPU Freq	CPU	RAM	CDU	RTT (ms)	
Device	(GHz)	proc	(GB)	GPU	client	cloud
Client device	2.0	2	1			
Low-end edge	2.0	4	16	NT/A	1	65
Mid-end edge	3.1	8	32	N/A	15	50
High-end edge	3.1	16	64		25	42
Super-high-end edge	3.1	16	64	1 Nvidia P100	25	42
Cloud server	3.1	48	96	2 Nvidia P100		

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More powerful edge is further from client

Evaluation

Real evaluation time in minutes across models and edge devices, the hybrid method comes out decision more faster than strongman

Model	Inception V3	Inception ResNet V2	PNASNet 331
The evaluation time of Strongman	> 30	≈ 120	≈ 10
Low-end edge	1	1	1
Mid-end edge	2	3	1
High-end edge	10	16	1