

Early exits and Split computing

MSDNet, SPINN

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1 Multi-Scale Dense Networks

- Context
- Problem Setup
- MSDNet's Architecture
- Testing and Results

2 Synergistic Progressive Inference of Neural Networks

- Context
- SPINN's Architecture
- Evaluations

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- State of the art incentivize resource-hungry models
- Two type of images:
 - "Easy" images, need smaller models for classification
 - "Hard" images, need to go through bigger models



So how do we compromise between those type of image for classification?

Two setting for computational constraints:

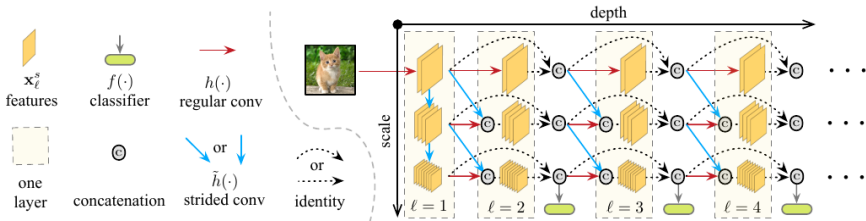
- **Anytime prediction** : finite and nondeterministic computational budget $B > 0$ for each images to be classified
- **Budgeted batch classification** : finite computational budget $B > 0$ for a set of D_{test} exemples. Here the model decide how much to spend on each images.



Two reasons why intermediate early exits hurt performance of DNN :

- 1 **The lack of coarse-level features**
 - Solution : **Multi-scale feature maps**
- 2 **Early classifiers interfere with later classifiers**
 - Solution : **Dense connectivity**

MSDNet - Architecture



Exit condition :

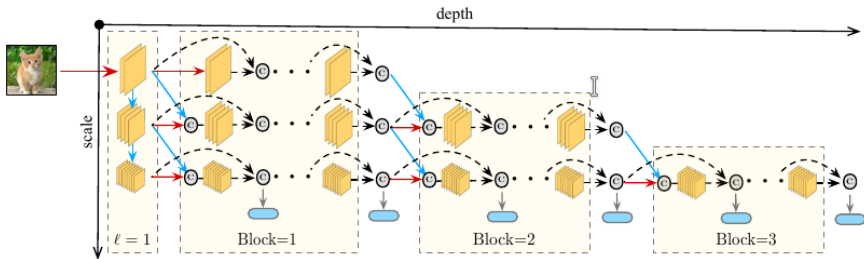
We have $q_k = z(1 - q)^{k-1}q$ with z such that $\sum_k p(q_k) = 1$

We solve for q : $|D_{test}| \sum_k q_k C_k \leq B$

We determine the threshold θ_k on a validation set such that $|D_{test}|q_k$ samples exit at the k_{th} exit.

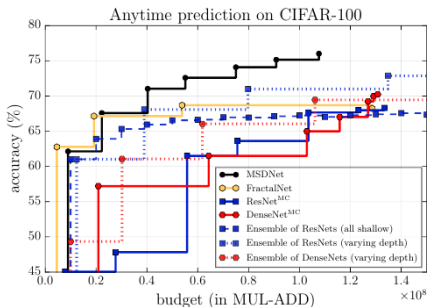
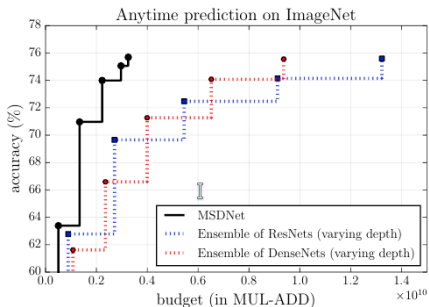


MSDNet - Network reduction



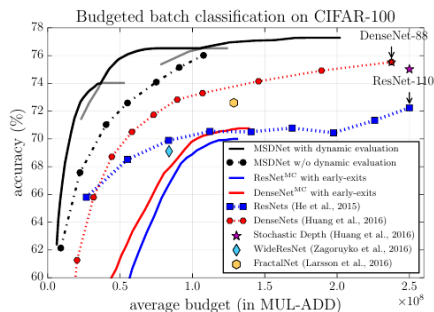
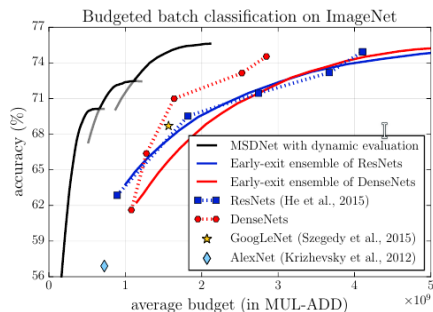
MSDNet - Testing and Results

Anytime prediction:



MSDNet - Testing and Results

Budgeted batch classification:



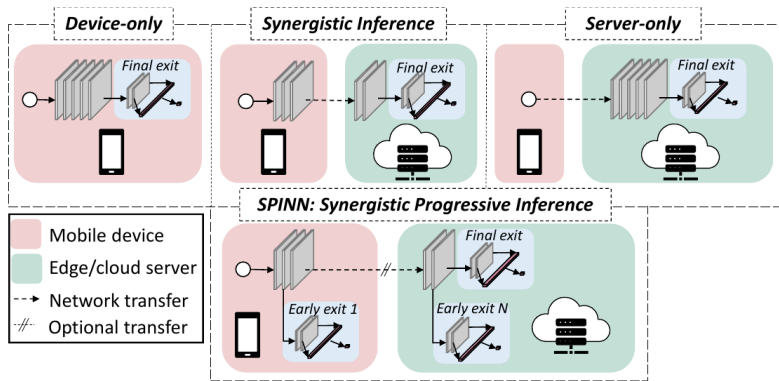
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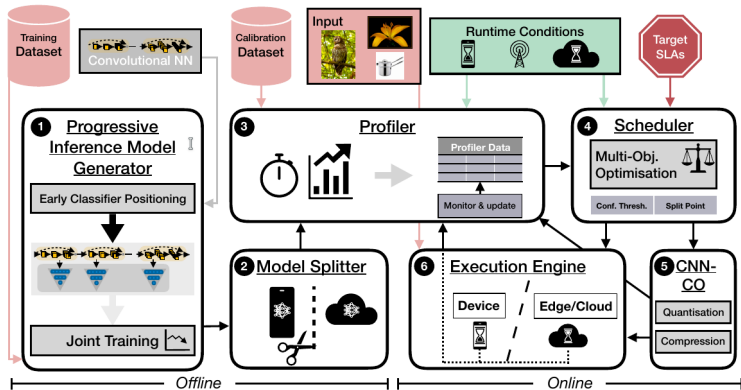
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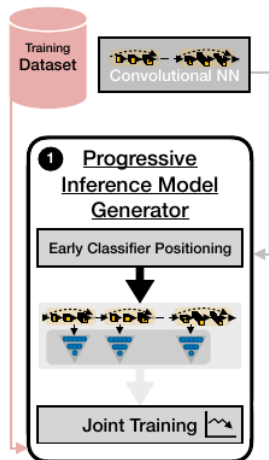
SPINN - Context



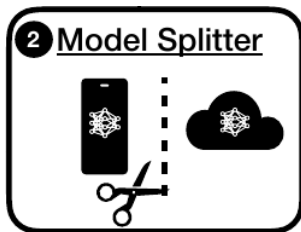
SPINN - Architecture



SPINN - Progressive inference model generator



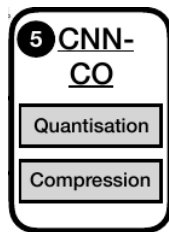
- 6 early exits place equidistantly (15%, 30%, ..., 90%)
- training end to end or fine tuning on classifier with frozen backbone if pretrained
- $$\text{softmax}(z)_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$$
$$\text{arg}_i \{ \max_i \{ \text{softmax}_i \} > \text{thr}_{\text{conf}} \}$$
$$j \in \text{classifier} \{ \max_i \{ \text{softmax}_i^j \} \}$$



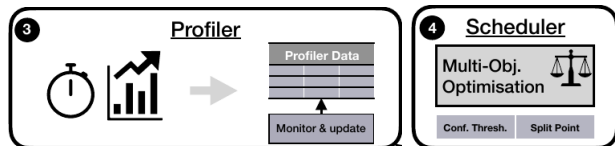
Input: Trained model

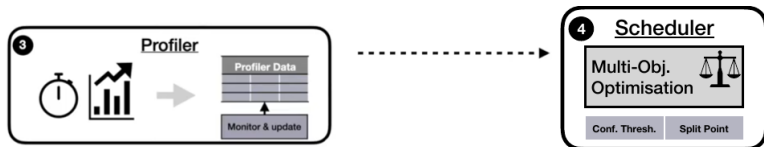
Output: Split point candidates

Split at ReLU activation for better packing.



- Lossy 8 bit Compression
- Bit Shuffling
- LZ4 Compressions





Offline component :

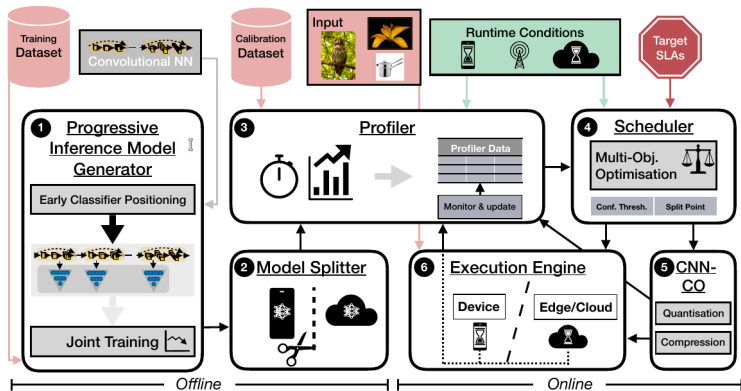
- Device-agnostic:
 - Accuracy per exit
 - Size of data to be transmitted
- Device-specific:
 - Latency

Online component :

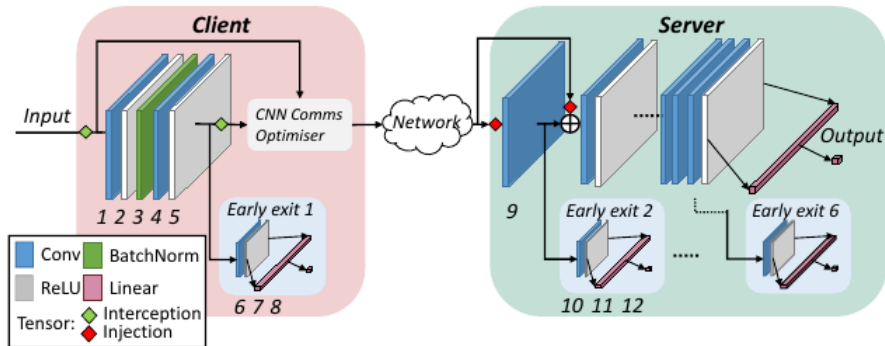
- Runtime conditions
- Runtime monitoring

- Removes infeasible points
- Ranks and select best design
- Tunes early exit confidence threshold

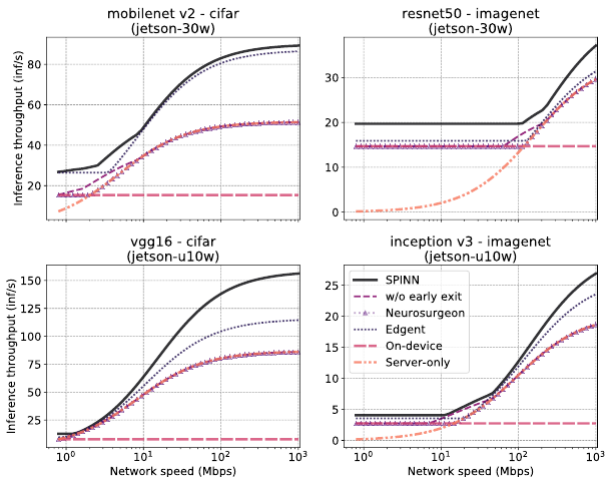
SPINN - Execution



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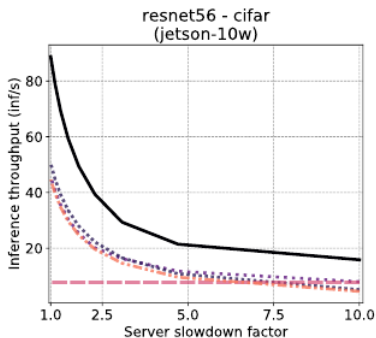


SPINN - Evaluations

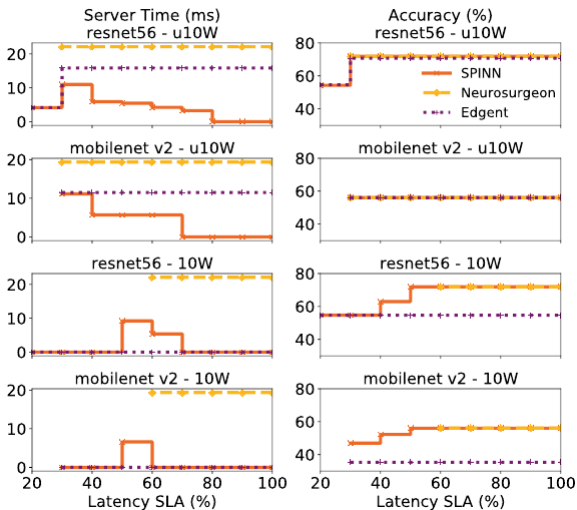


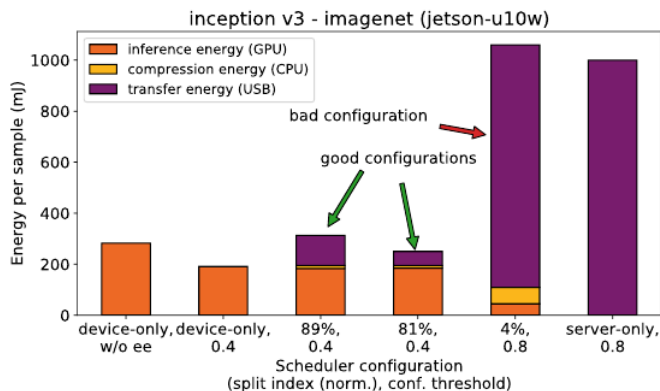
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SPINN - Evaluations



SPINN - Evaluations





SPINN delivers a progressive inference network, that is scalable to **environment conditions** and **app-specific performance goals**:

- **Delivers higher performance** than state of the art,
- Doesn't sacrifices on **accuracy**.

