

Hybrid Networks

Improving Deep Learning Networks via
Integrating two views of Images

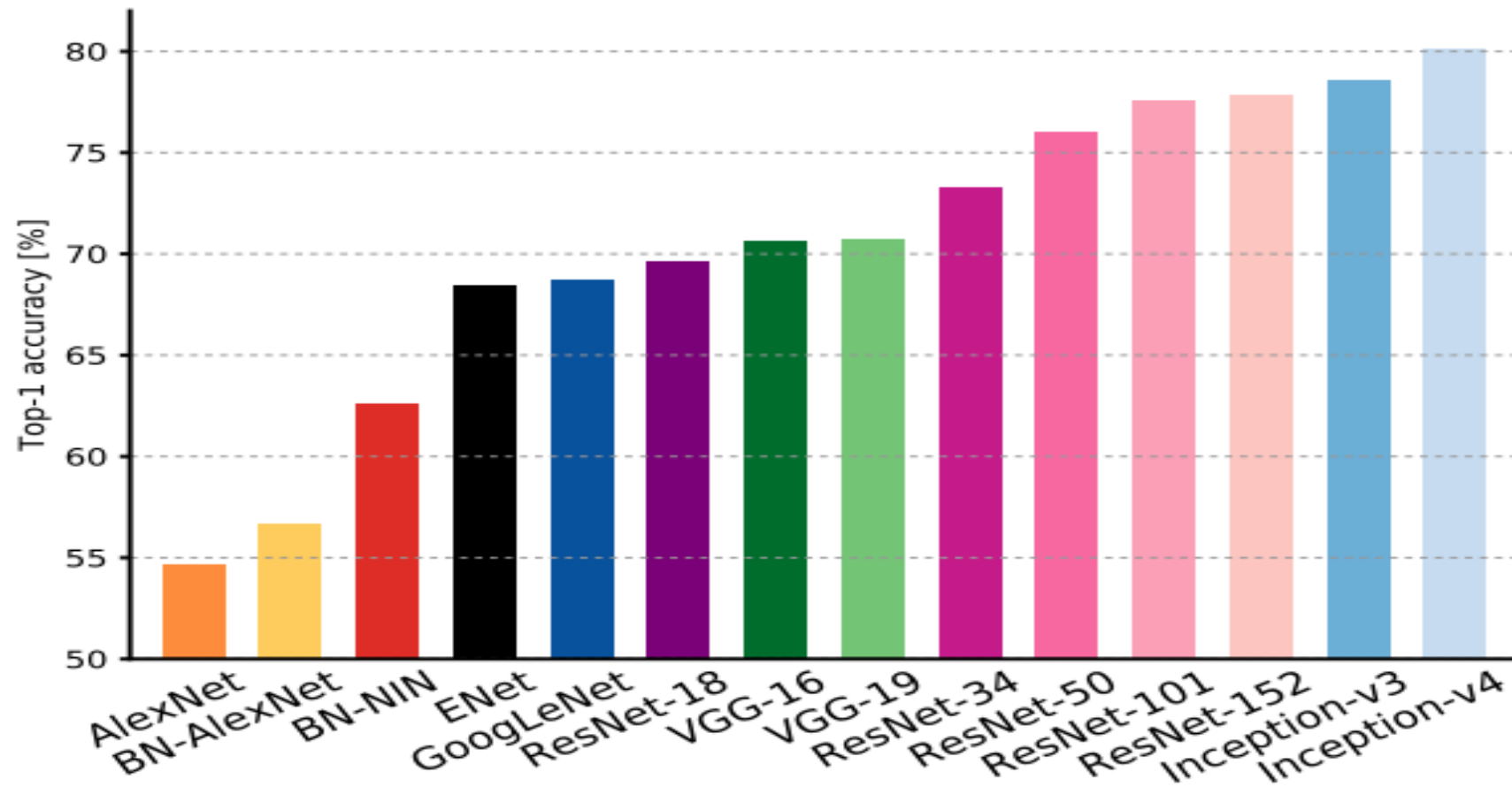
Sunny Verma^{1,2}, Chen Wang², Liming Zhu², and Wei Liu¹

1: Advanced Analytics Institute, University of Technology, Sydney, Australia

2: Architecture and Analytics Platforms, CSIRO, Data61

Motivations

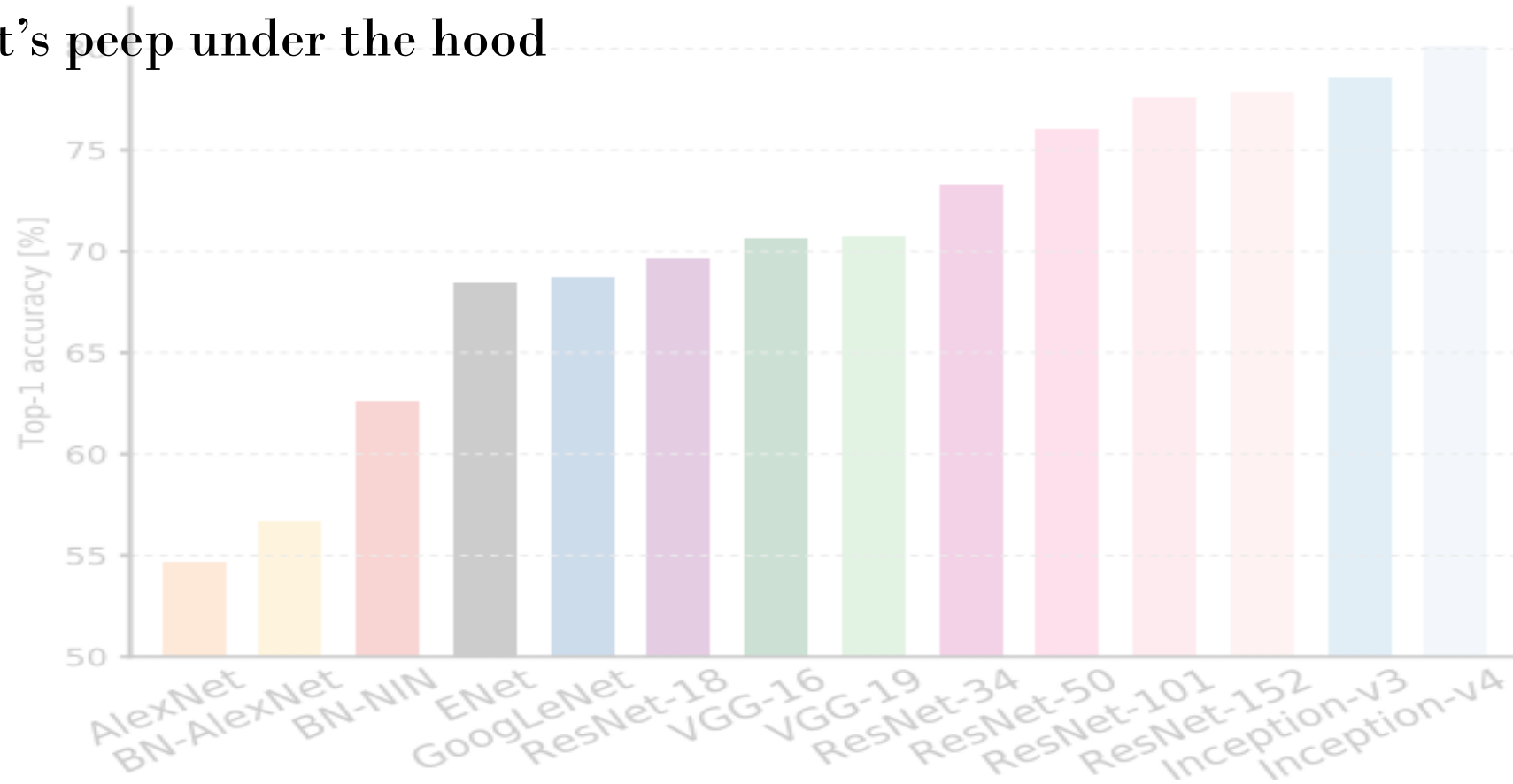
Deep Models have advanced image recognition field substantially



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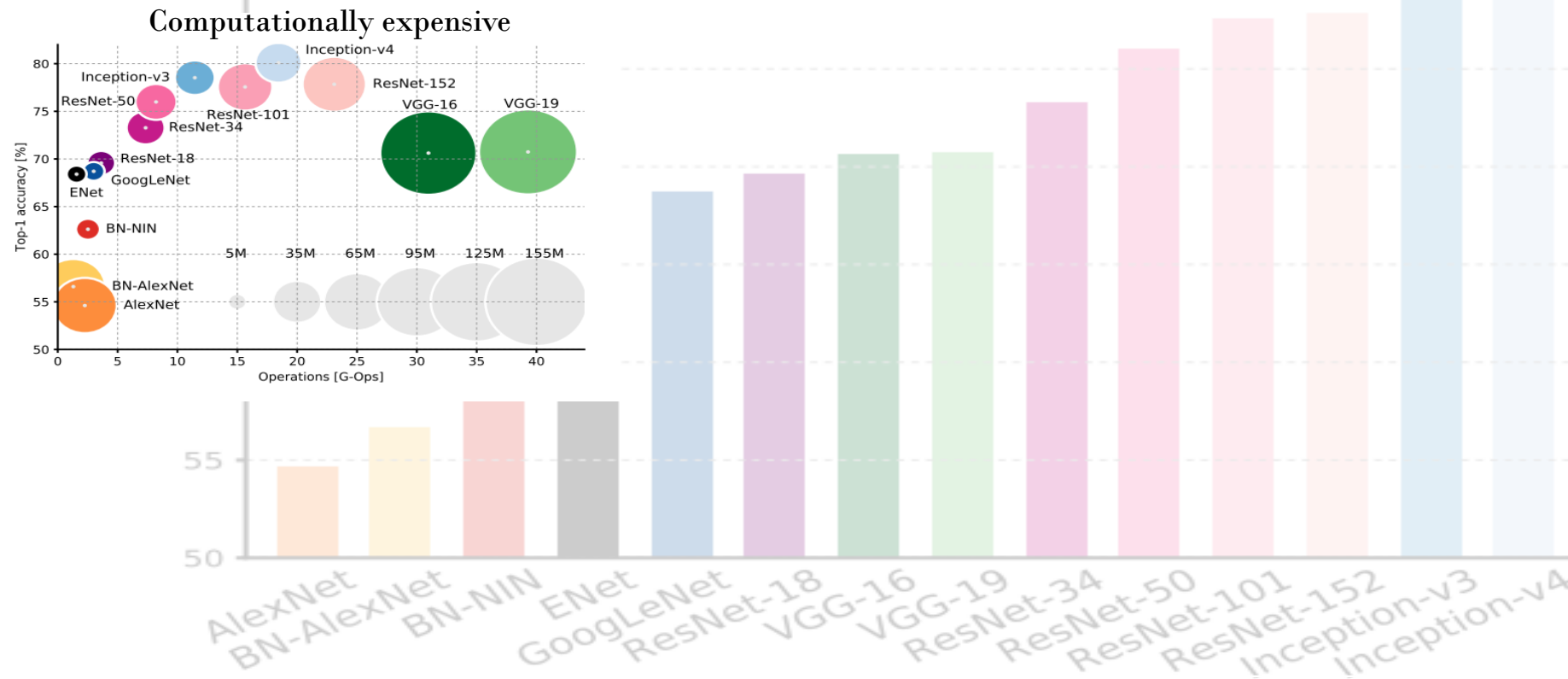
- Let's peep under the hood



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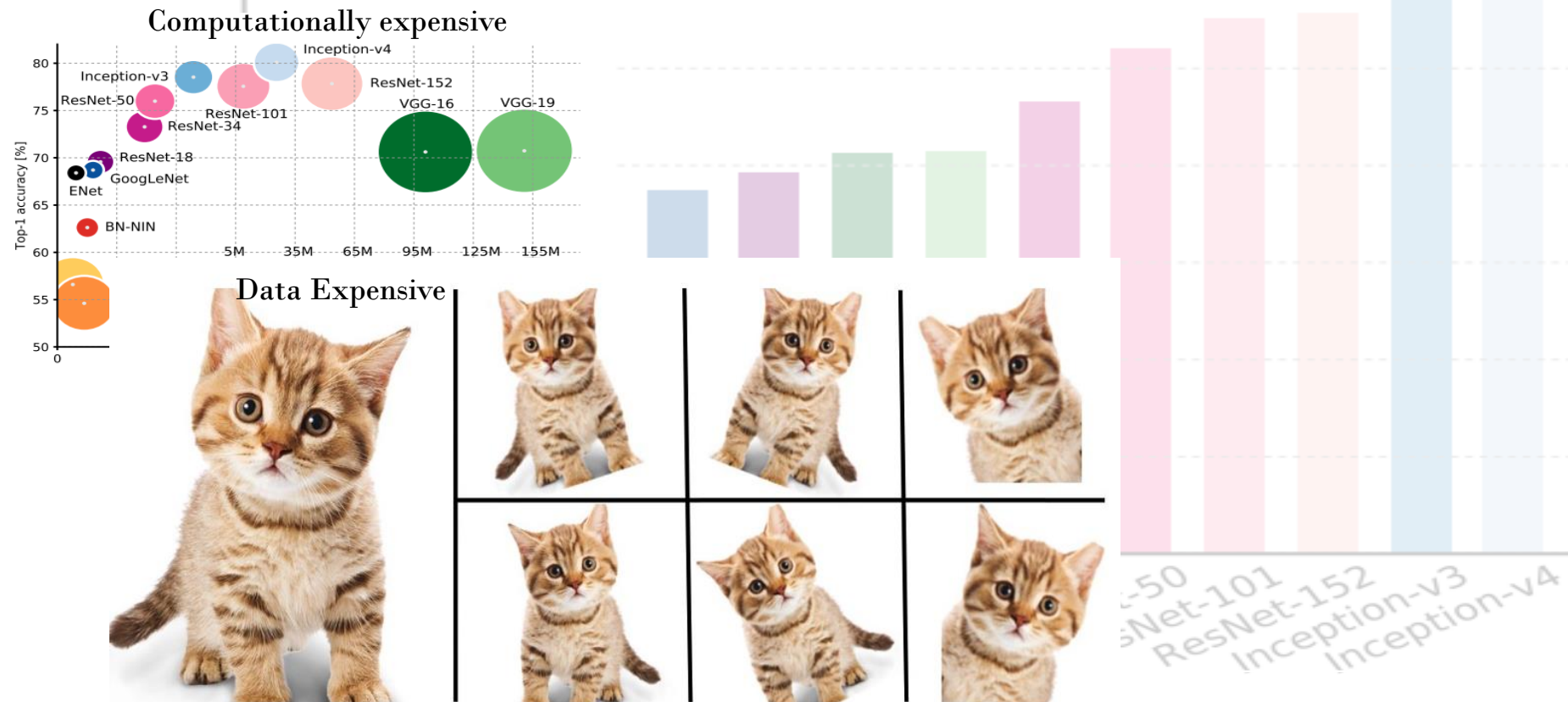
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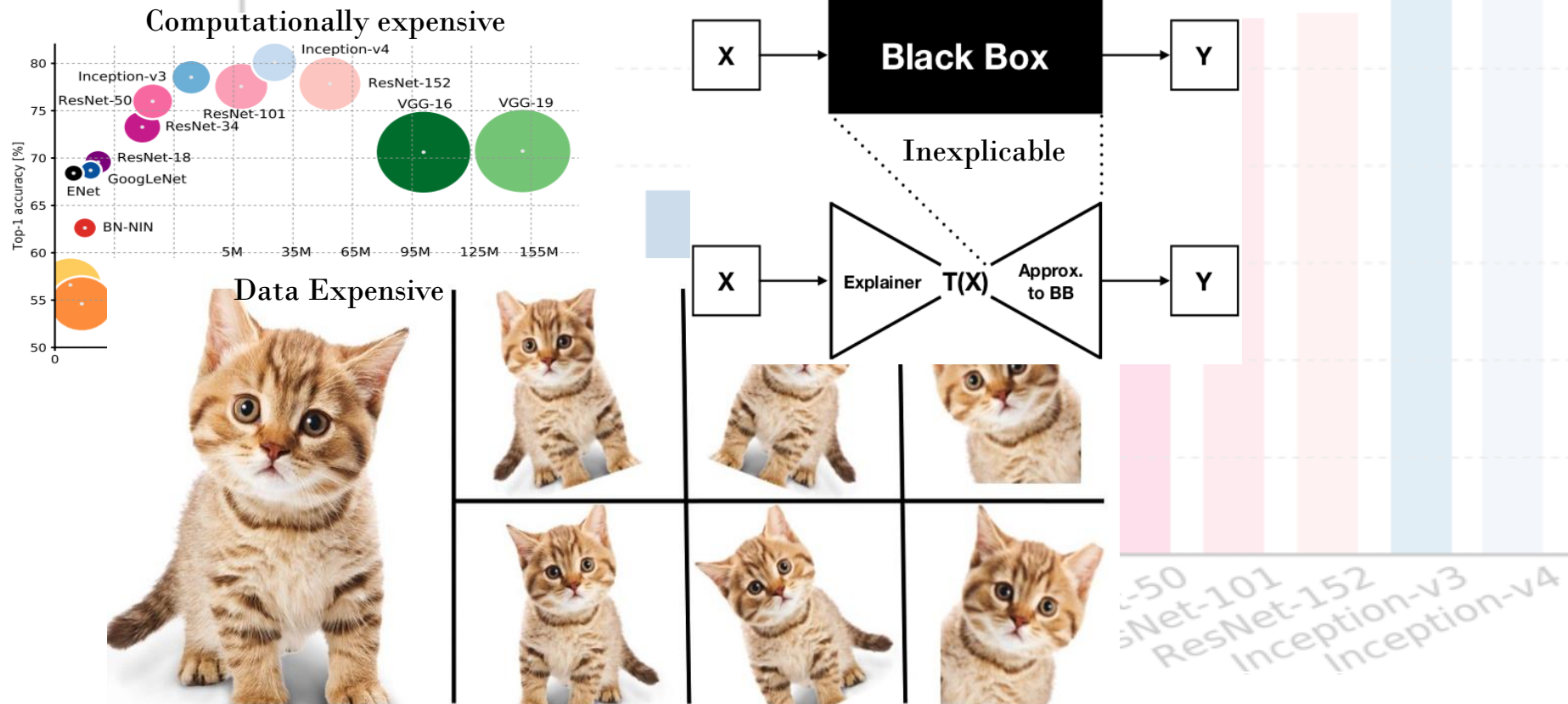
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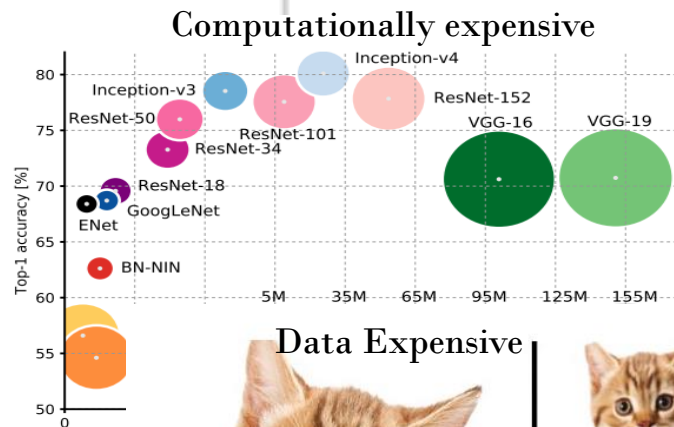
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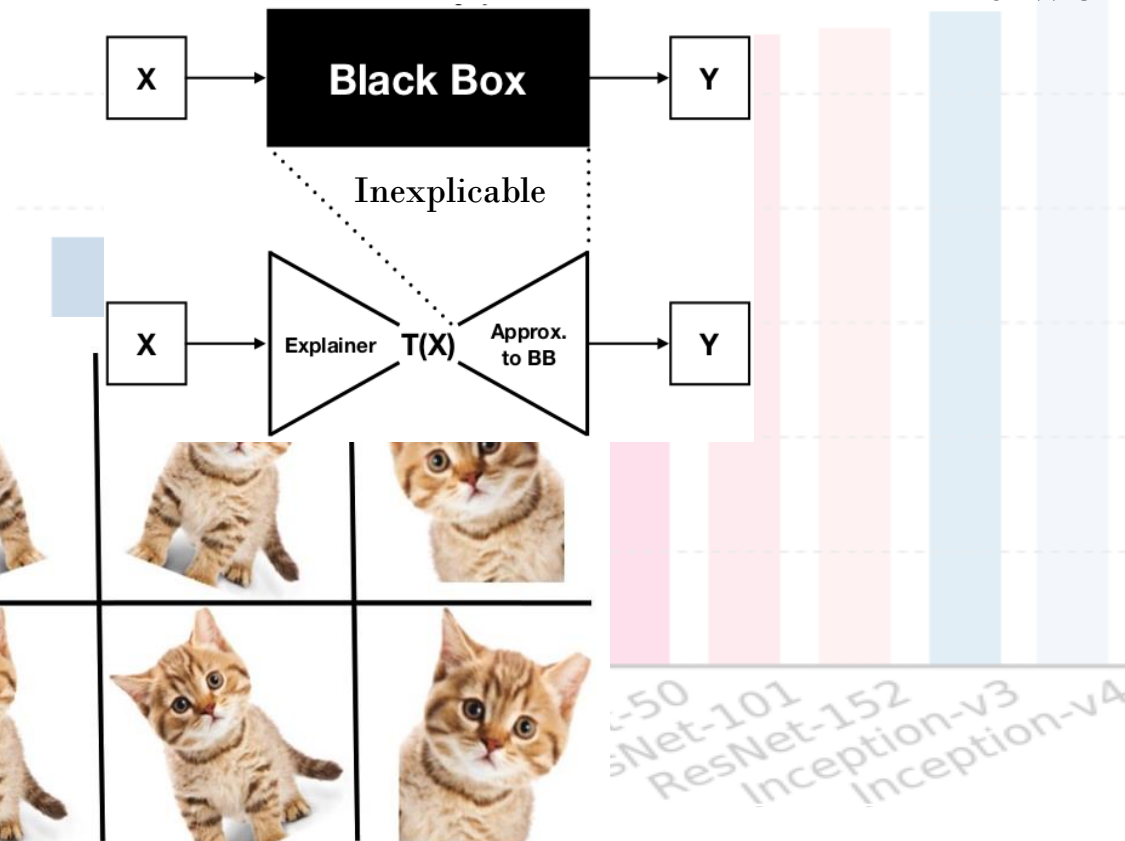
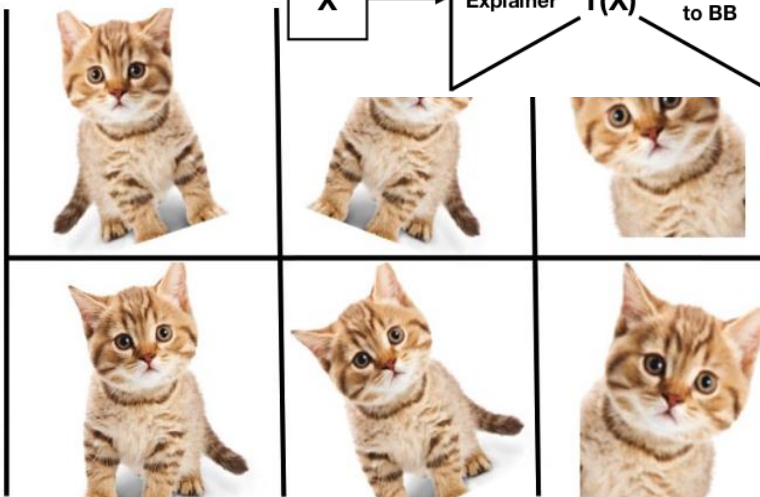
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Data Expensive

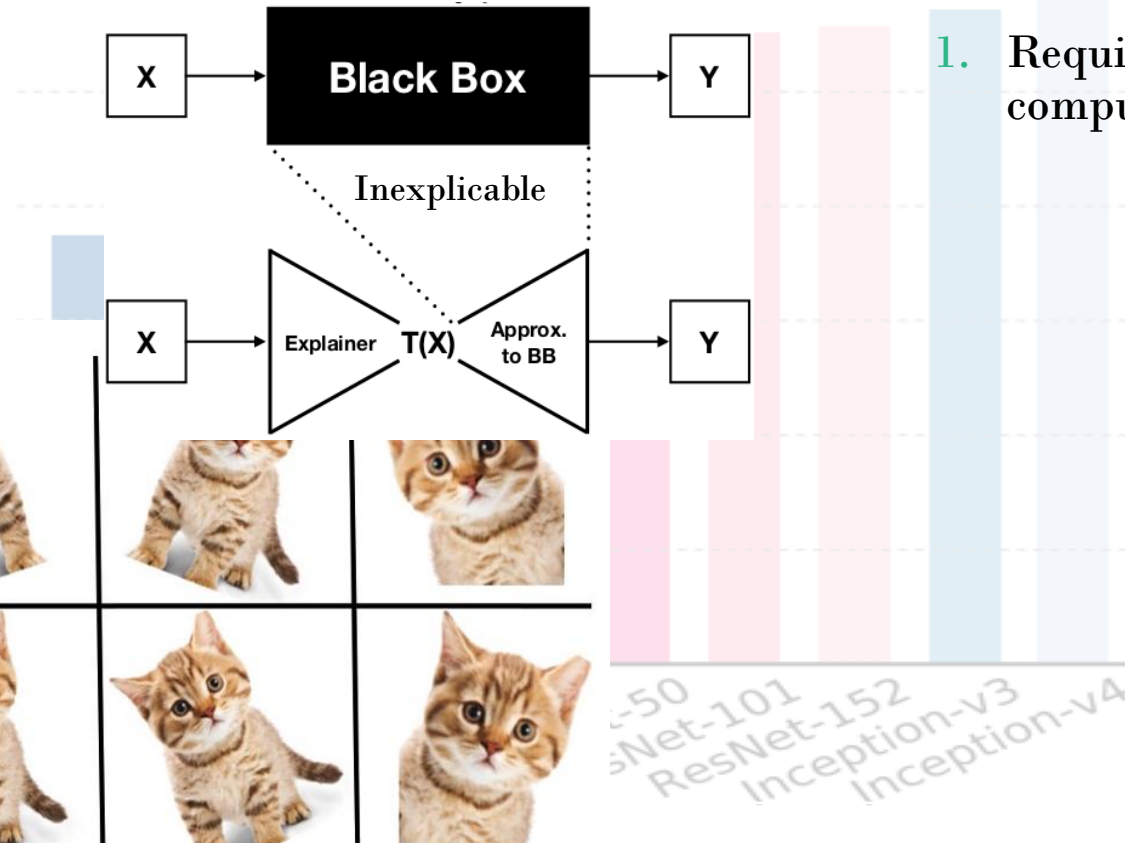
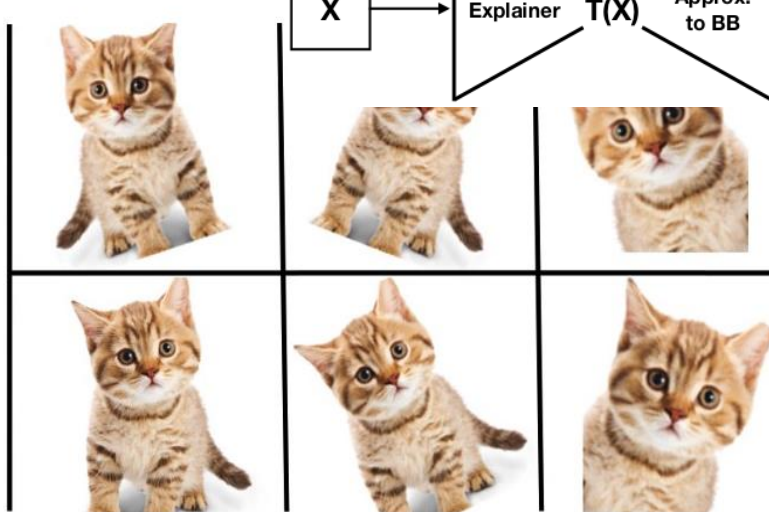
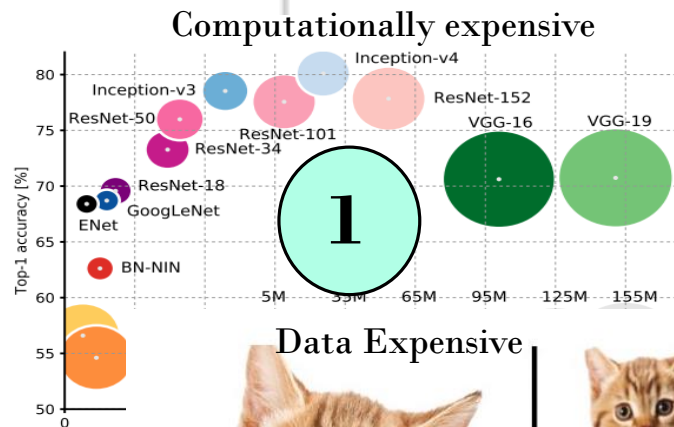


- This work

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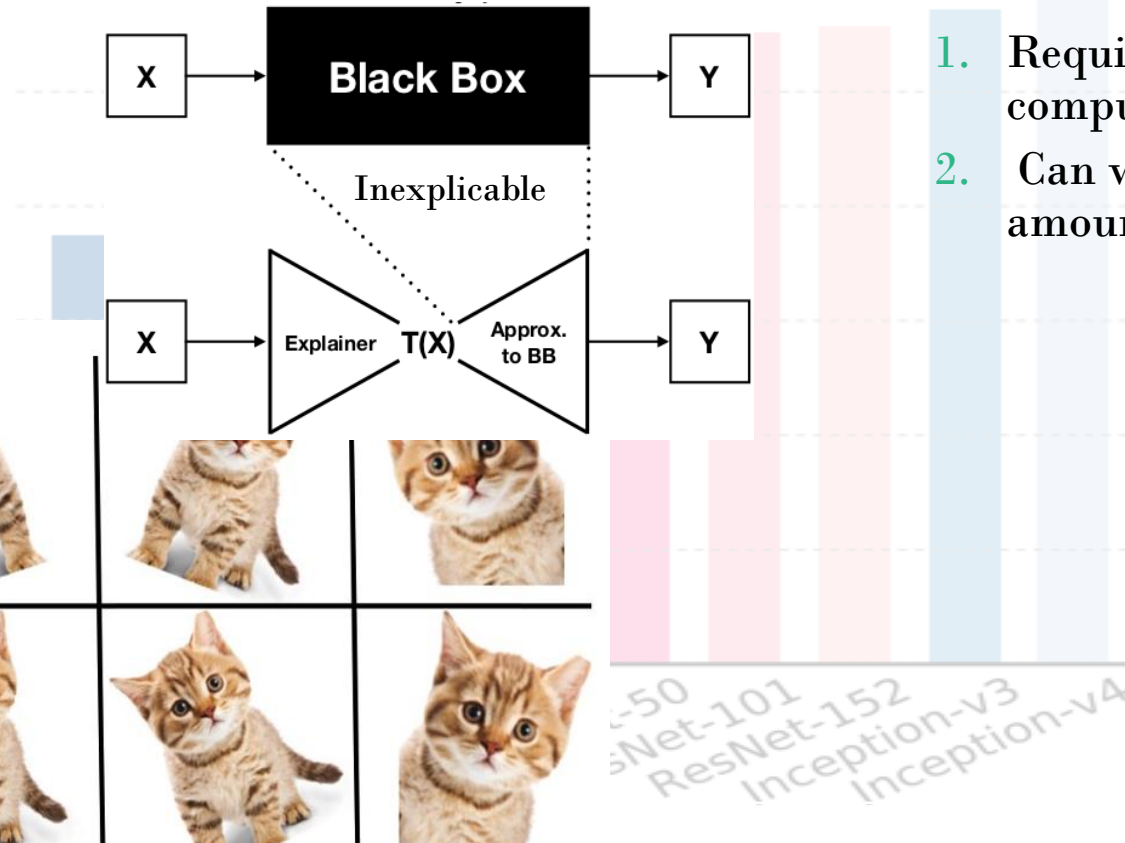
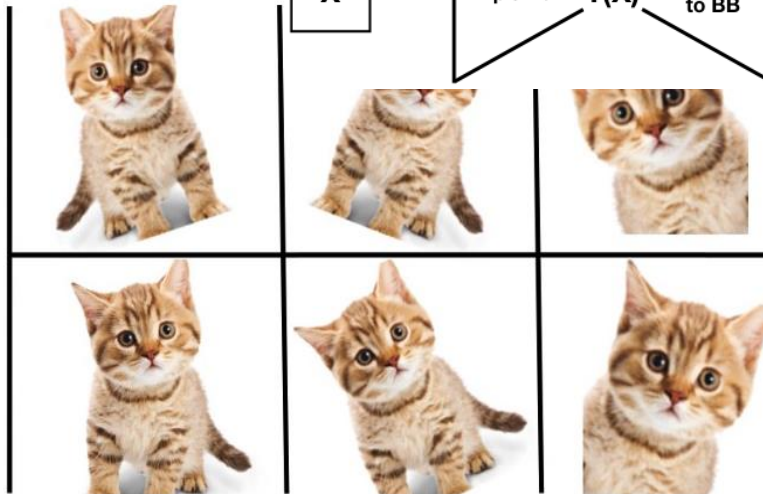
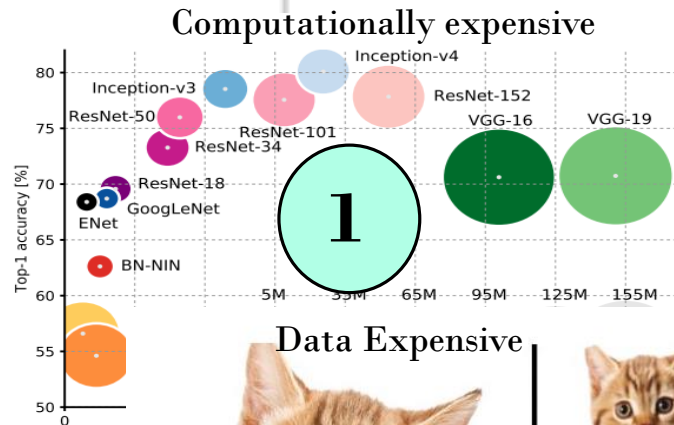
- This work

- Requires significantly less computational resources.

Motivations

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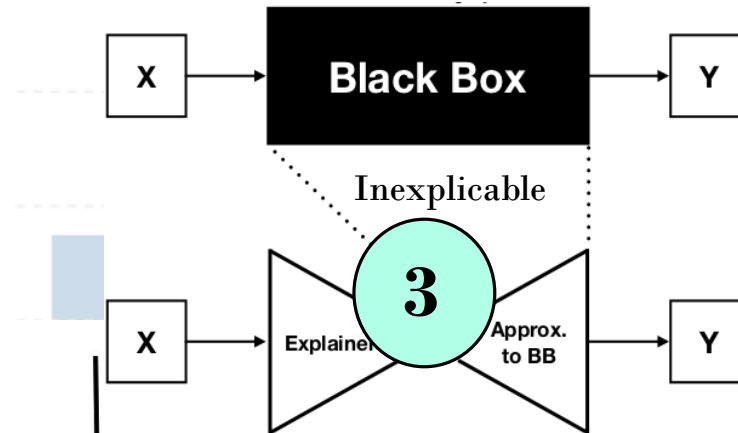
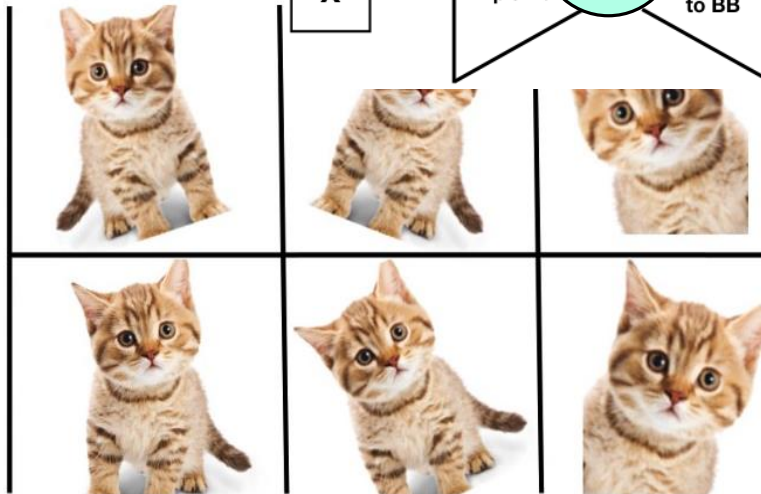
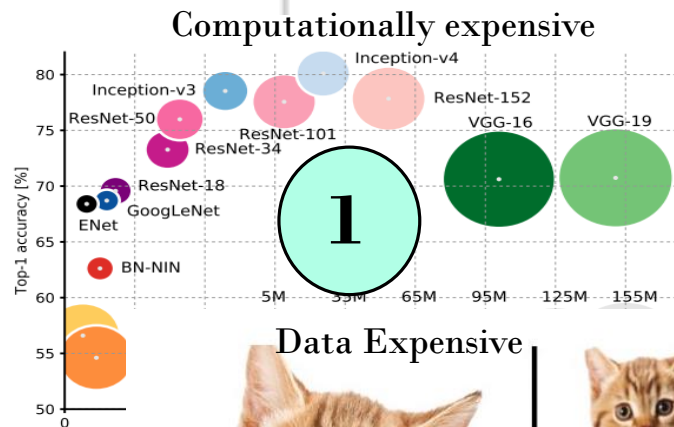
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Motivations

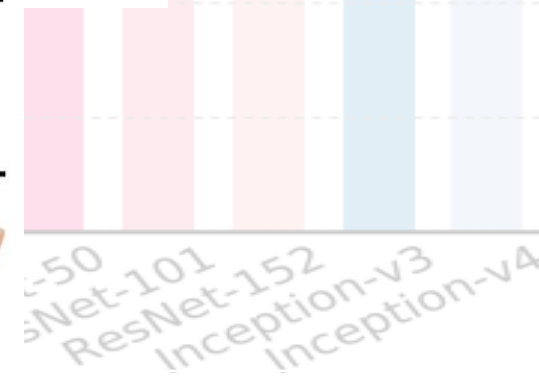
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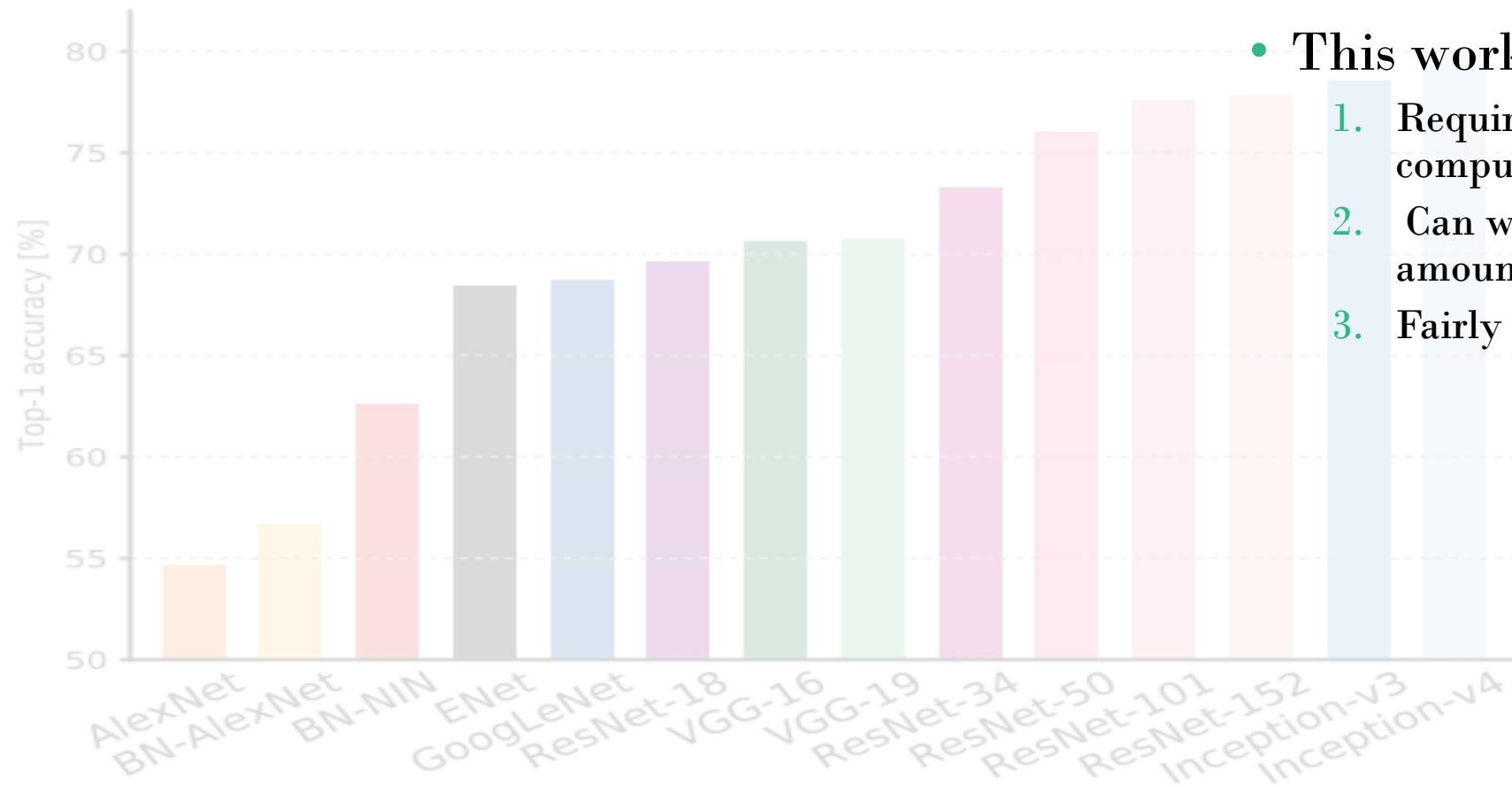
- This work

- Requires significantly less computational resources.
- Can work with available amount of data.
- Fairly Interpretable



Challenges

Deep Models have advanced image recognition field substantially

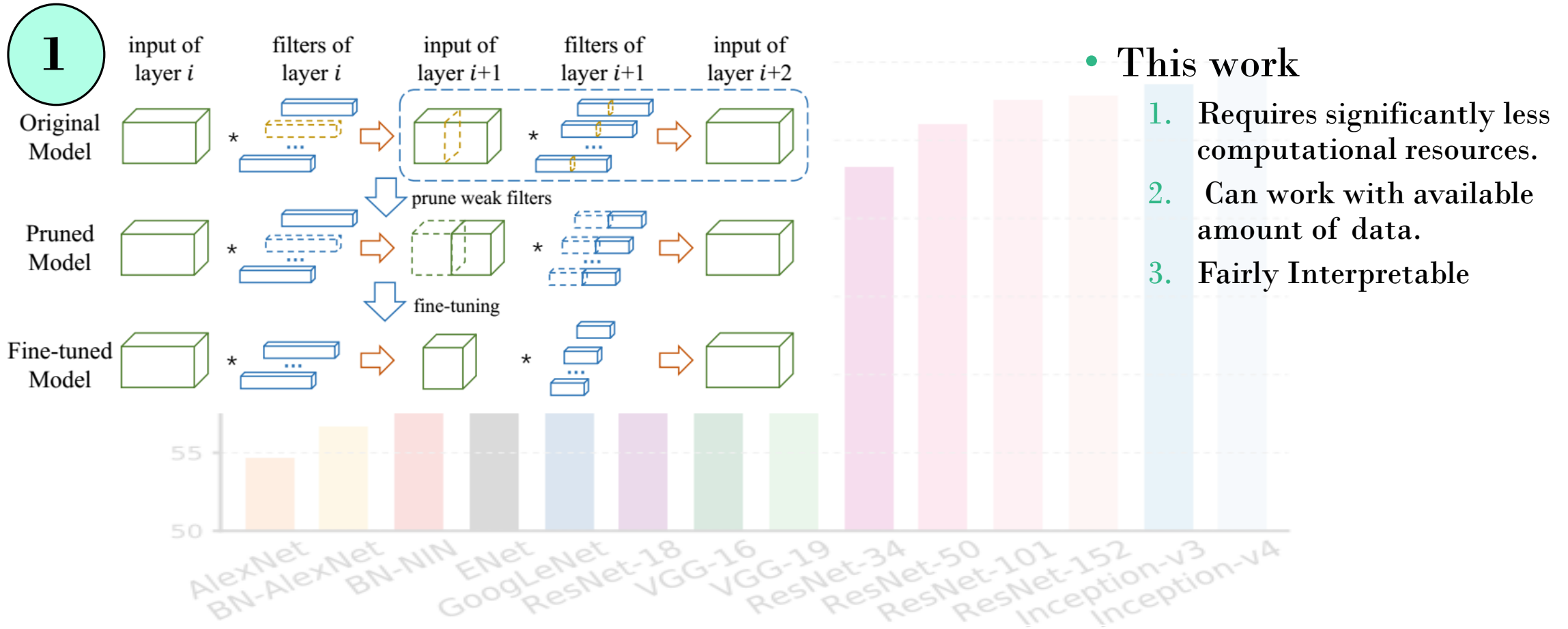


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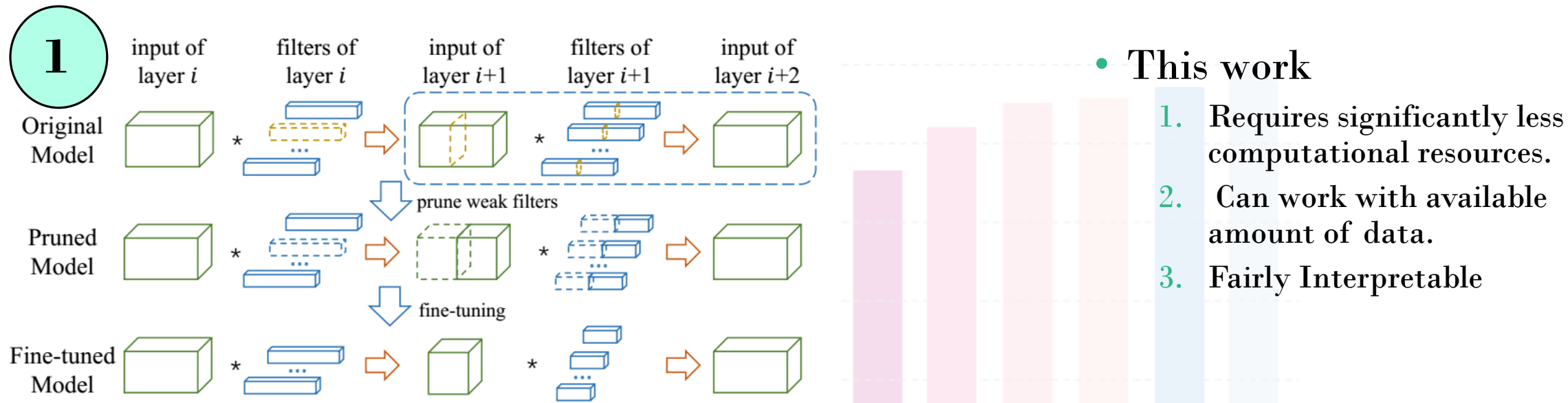
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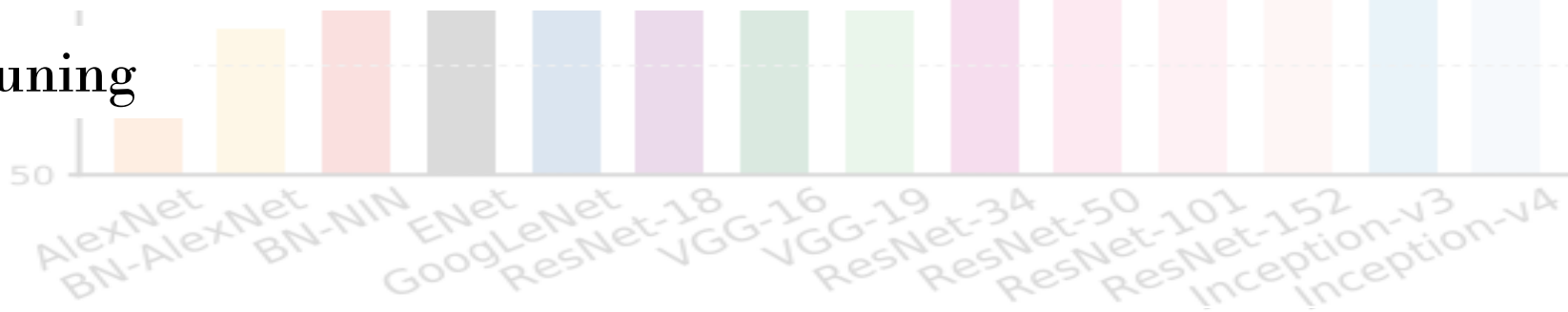


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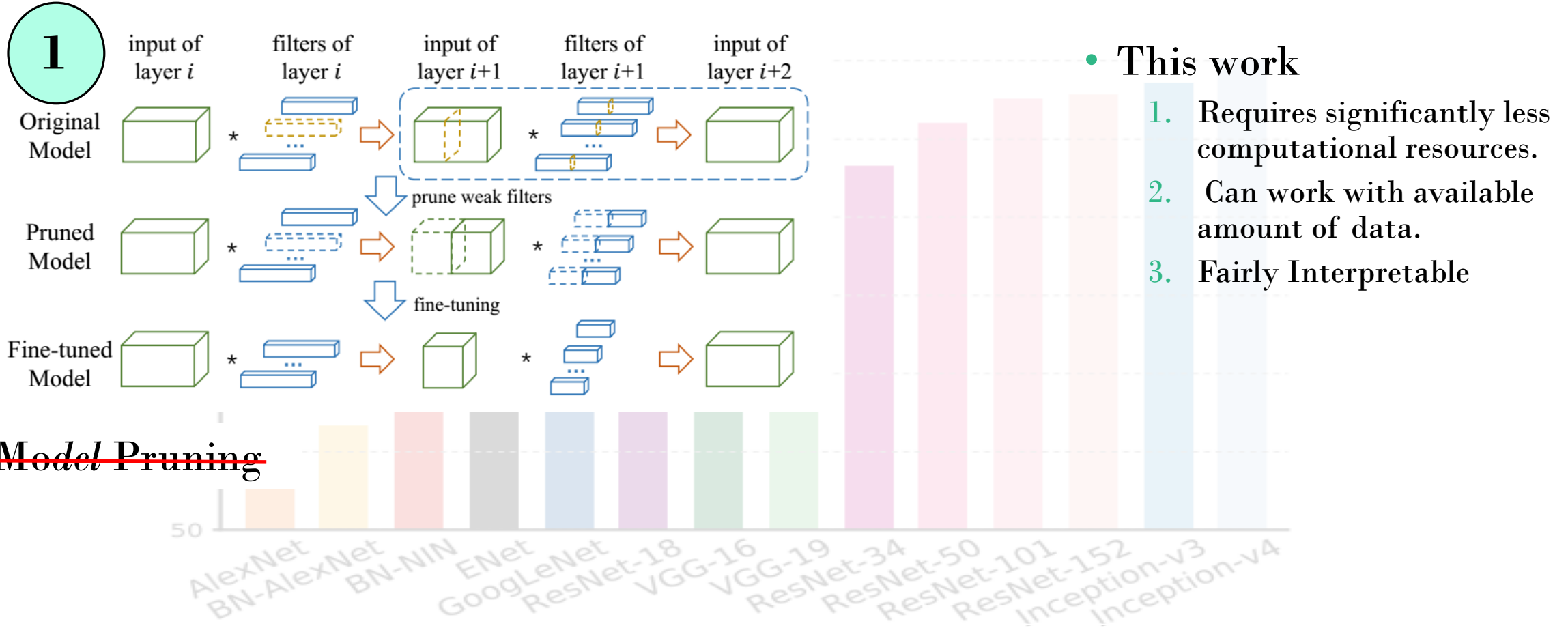


Model Pruning



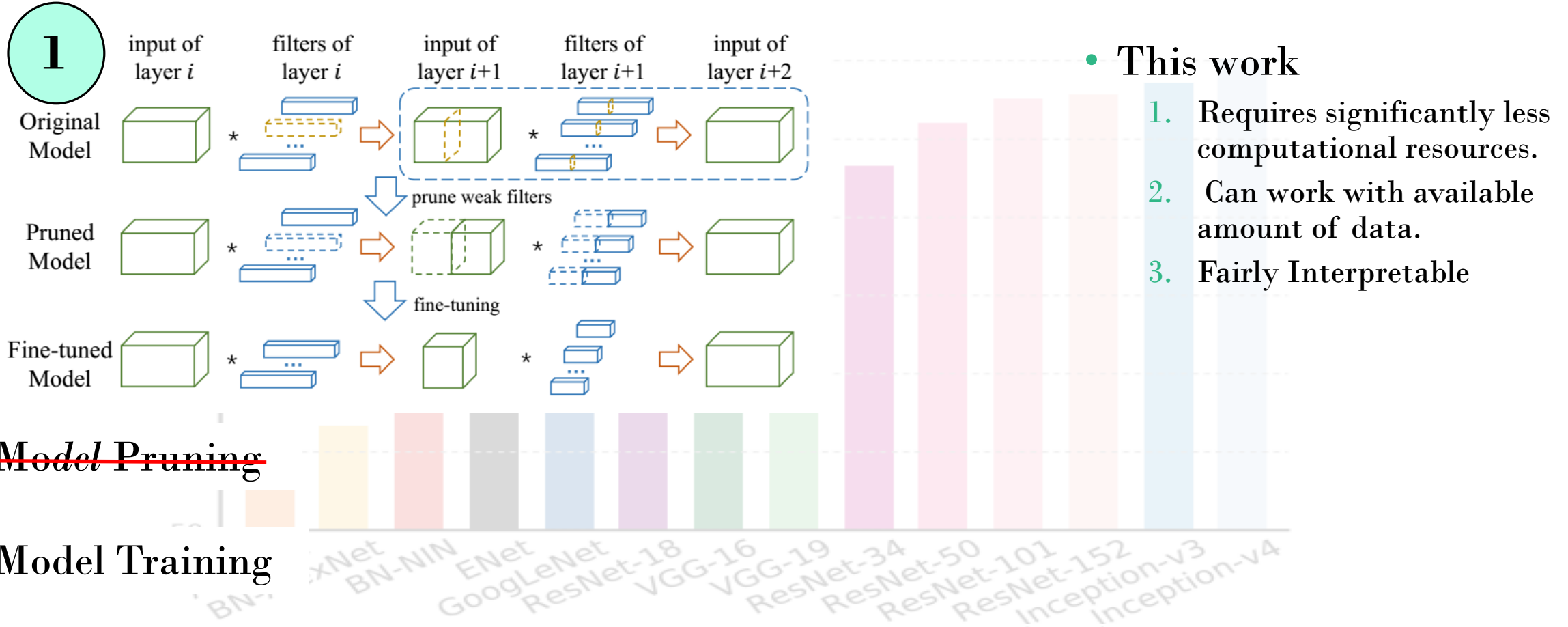
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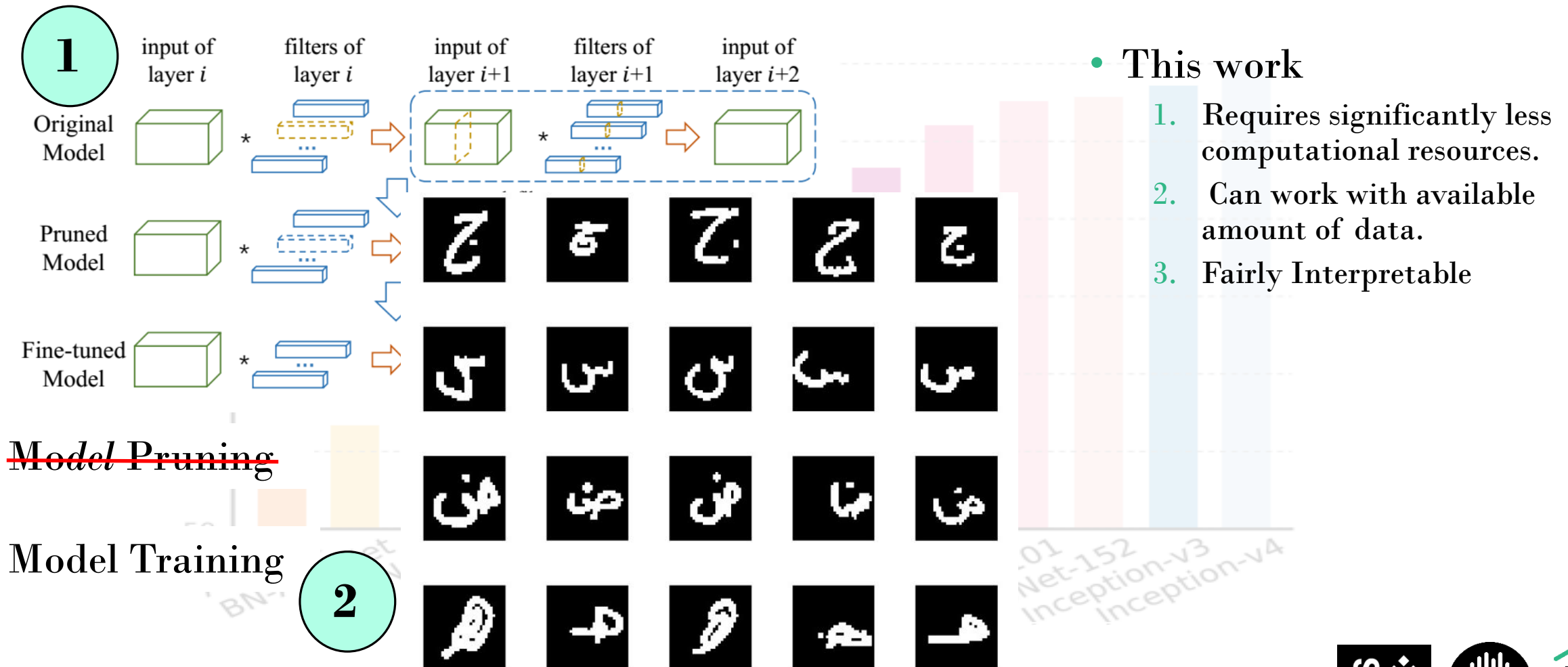
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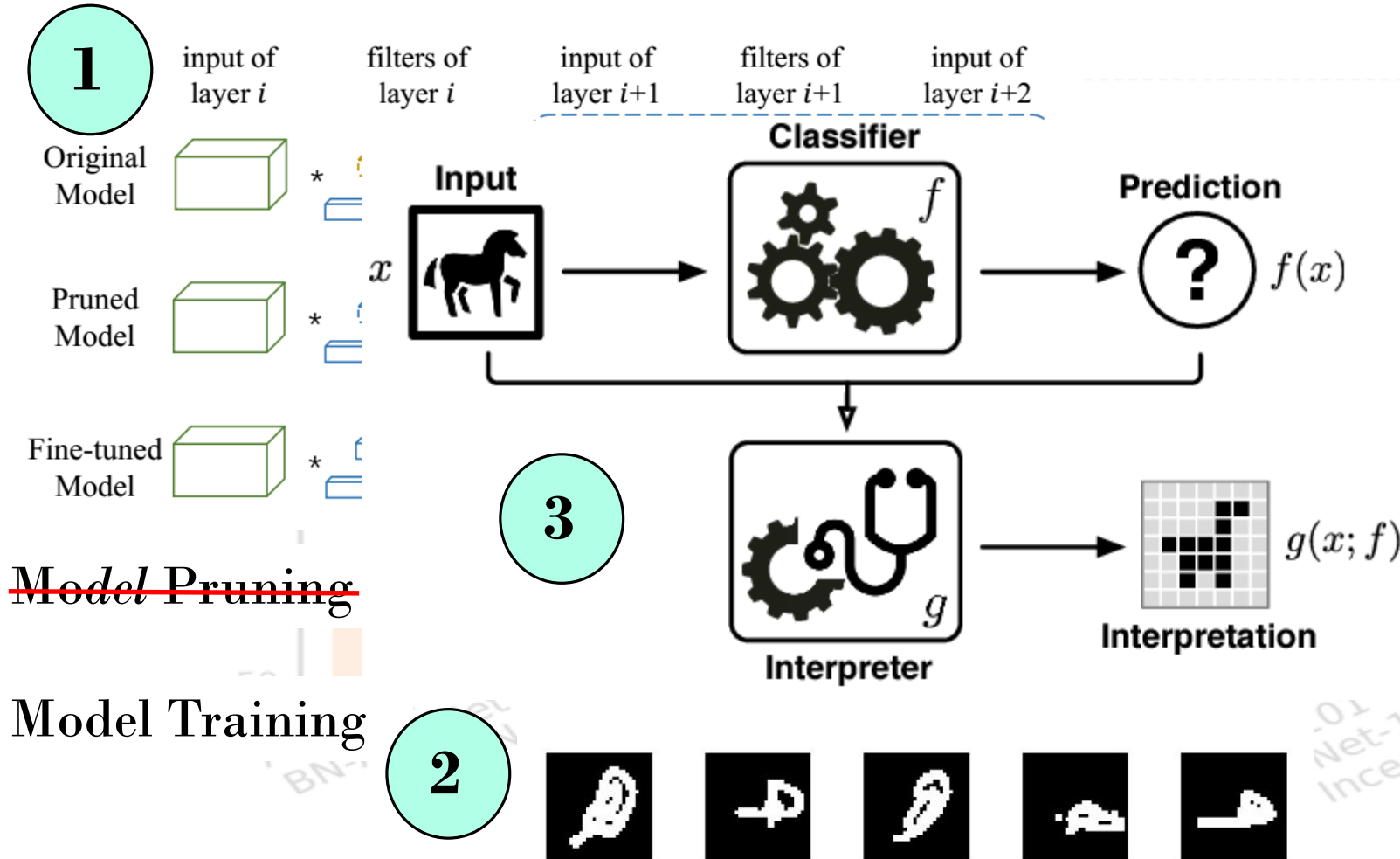
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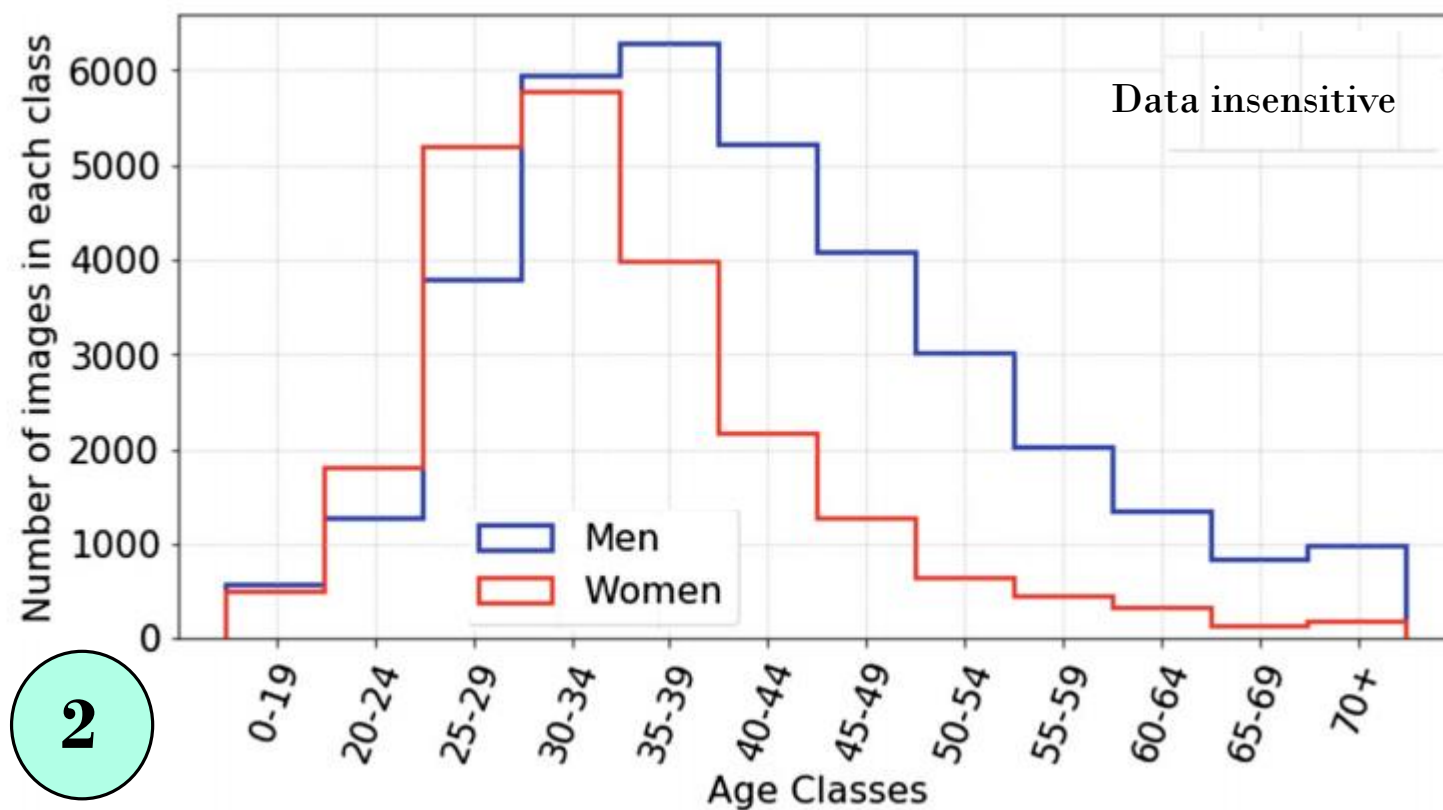
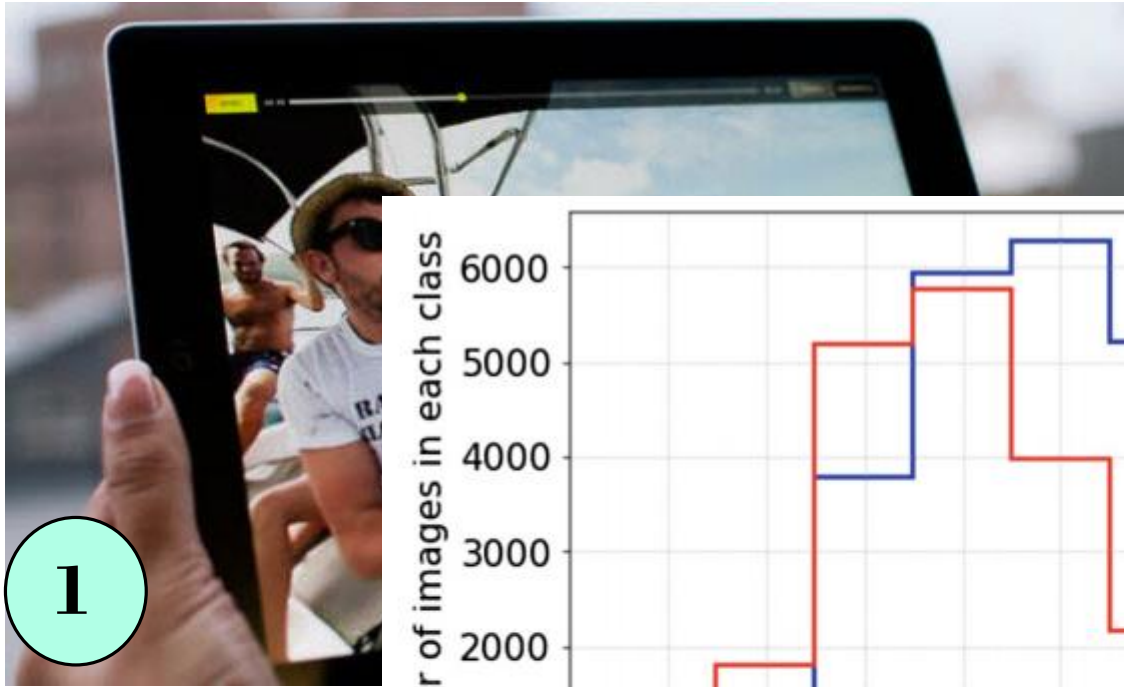
Importance

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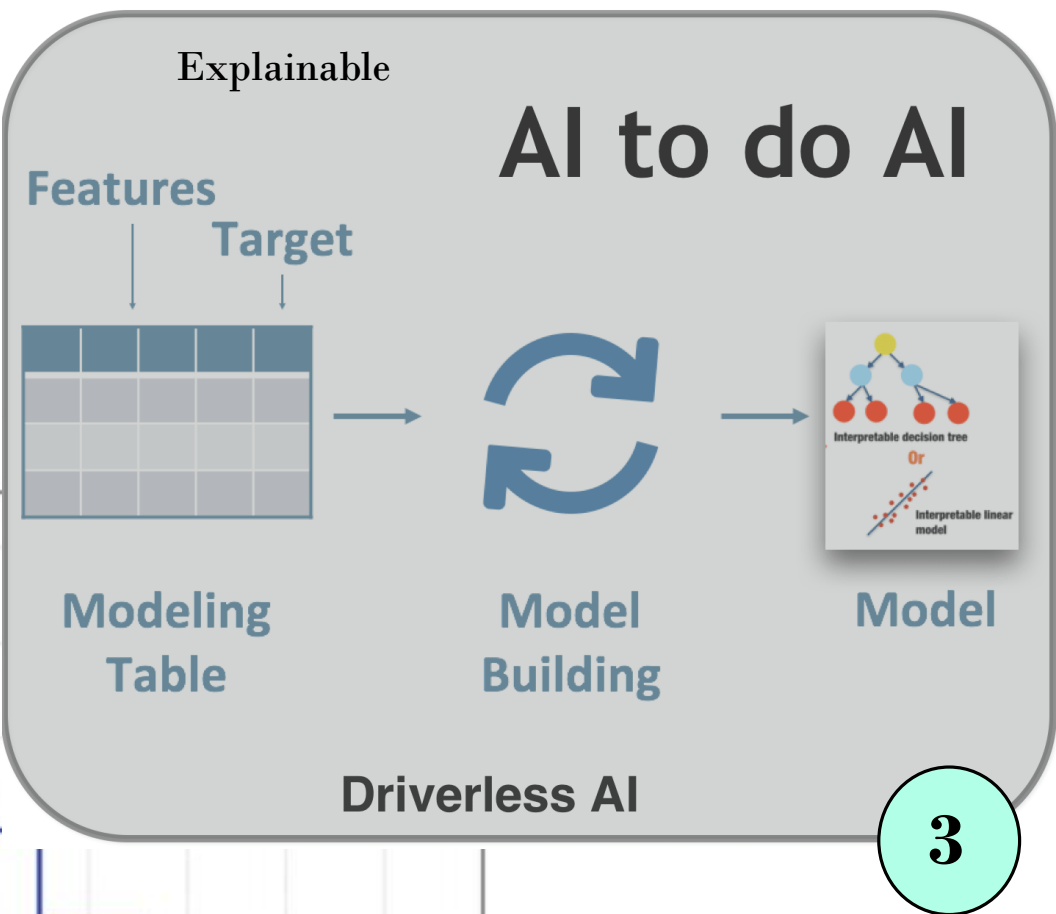
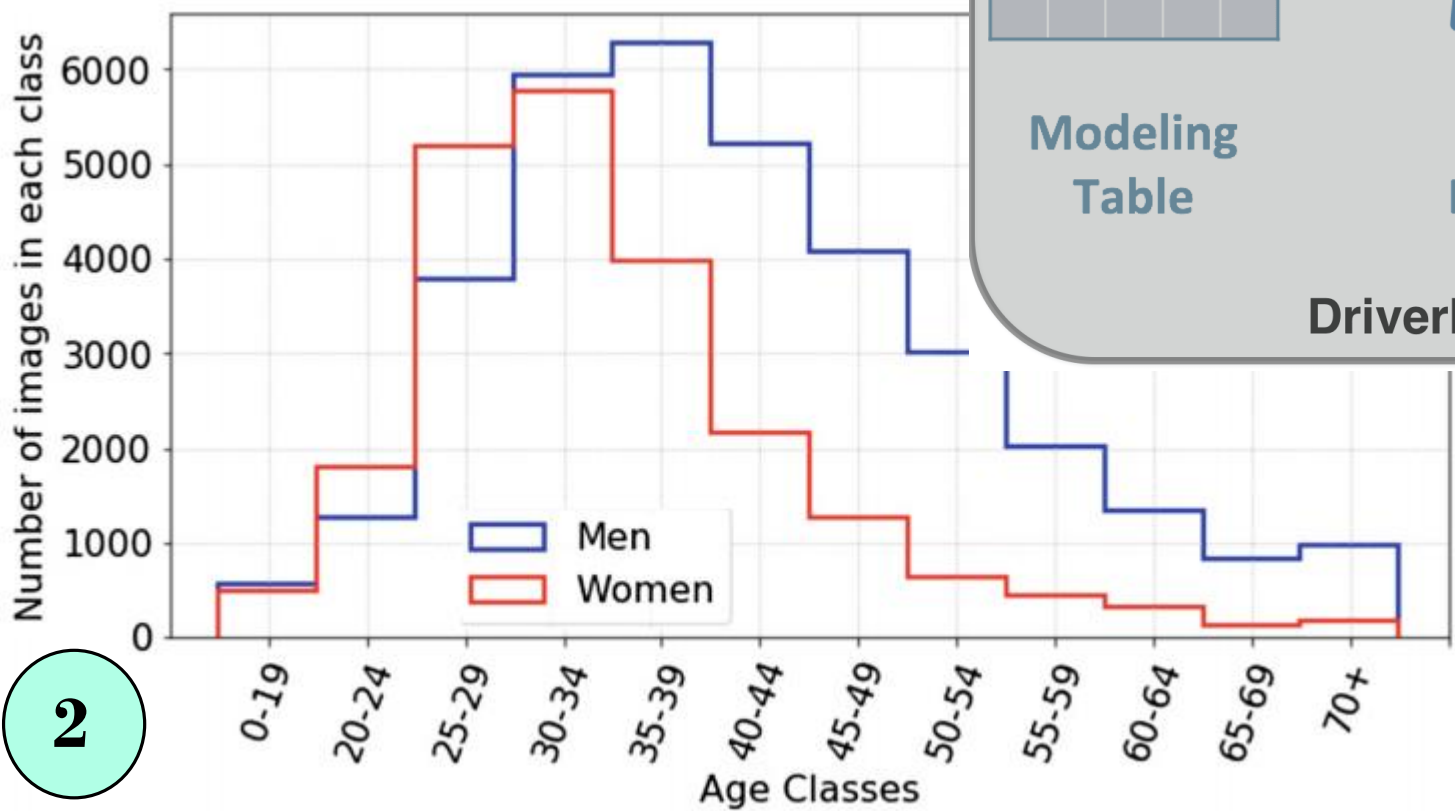
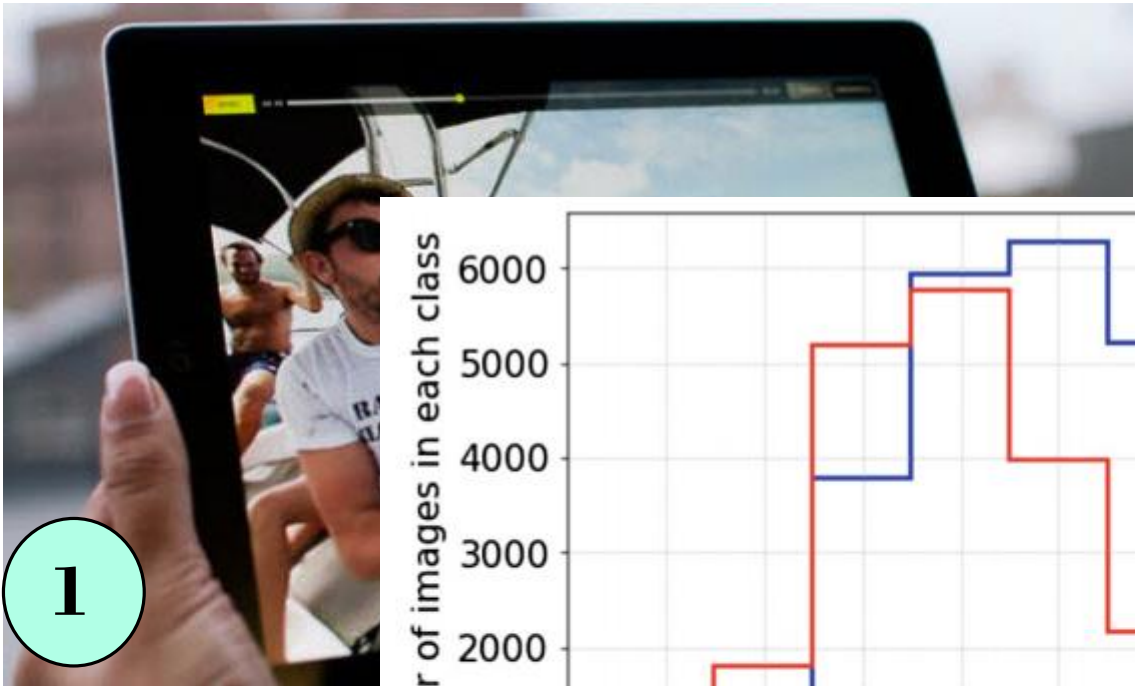
Environment Independent



Importance

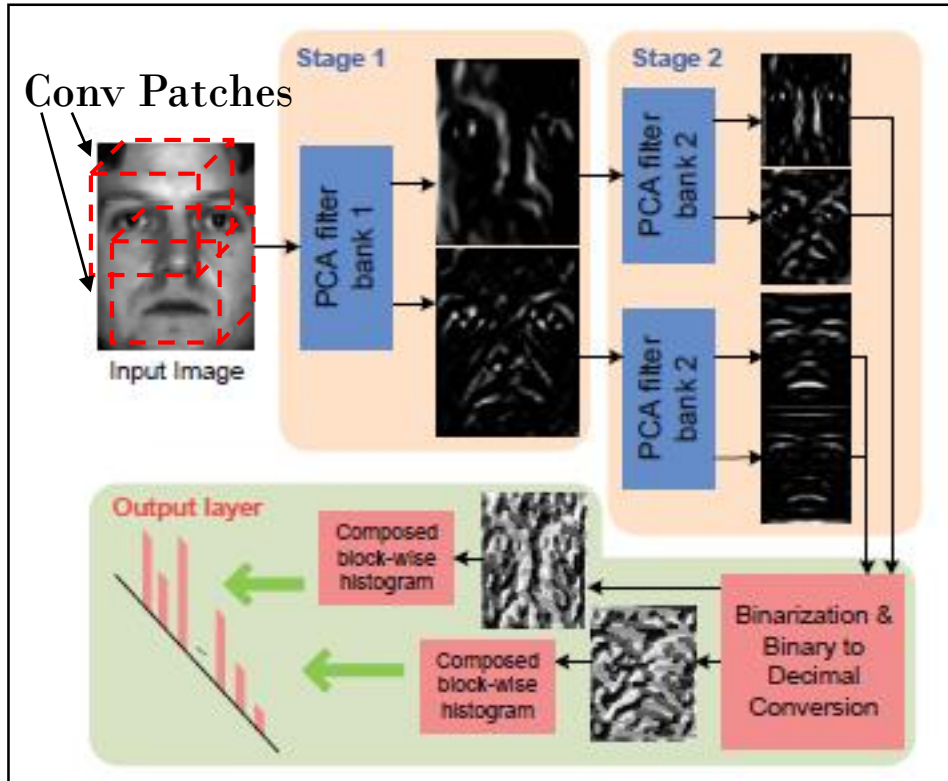


Importance



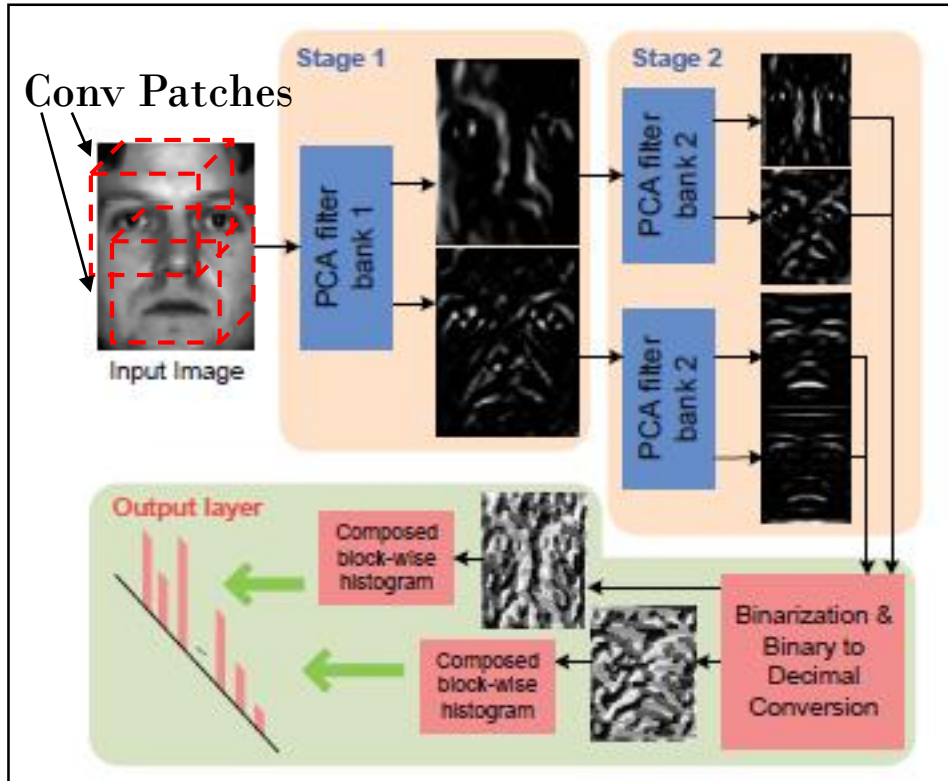
Existing Solution

PCANet



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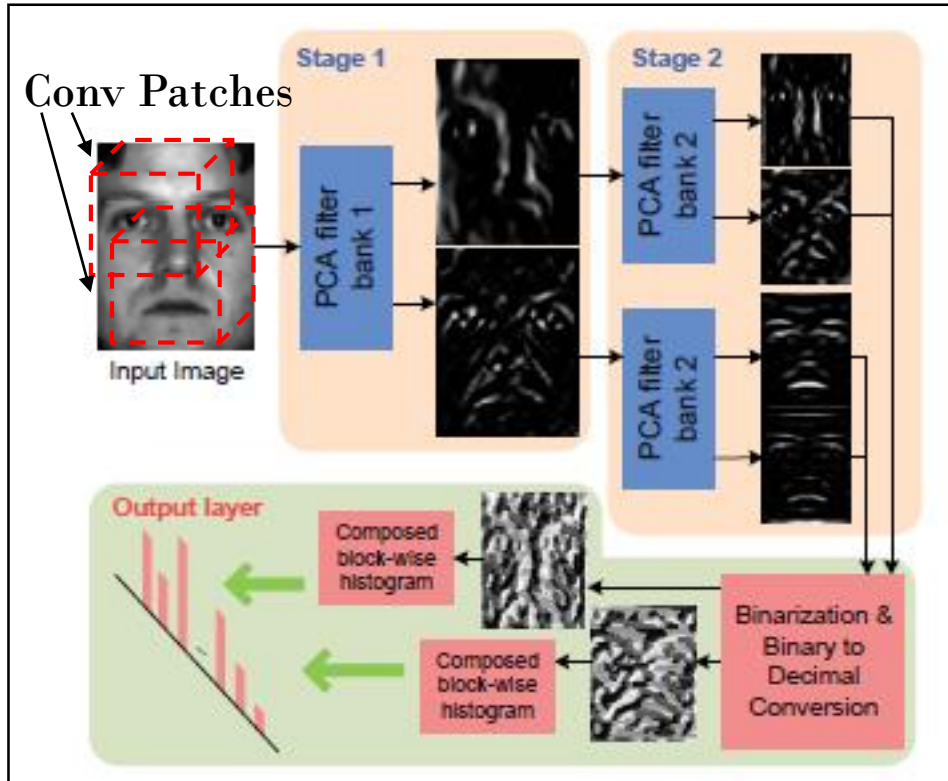


- Advantages

1. Light Weight Deep Network.
2. Acceptable performance with less data.
3. Unsupervised feature extractor
 - Less sensitive to data perturbation

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PCANet

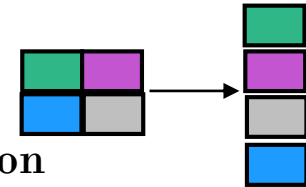


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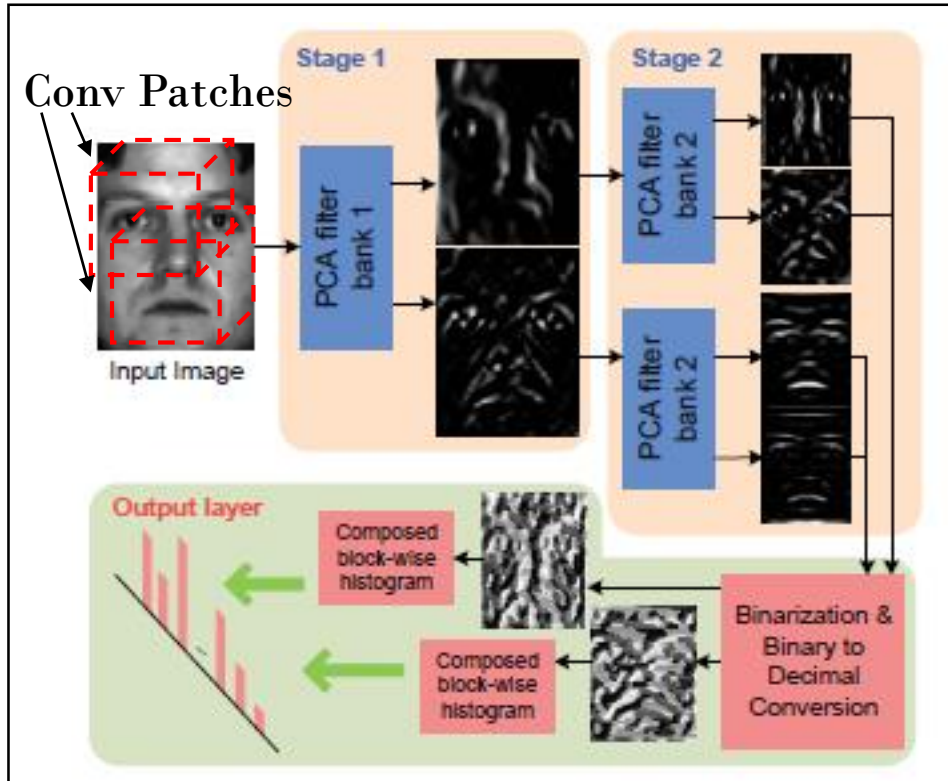
- Drawbacks

1. Vectorizes each patch
 - Destroys spatial information



Existing Solution

PCANet

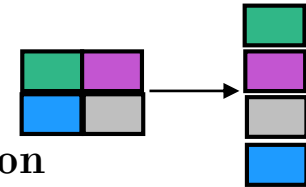


- Advantages

1. Light Weight Deep Network.
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- Drawbacks

1. Vectorizes each patch
 - Destroys spatial information
2. Patch matrix becomes tall/wide.
 - Requires more computational resources
 - Better algorithms

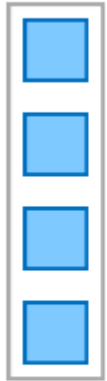


Tensor Network, Preliminaries

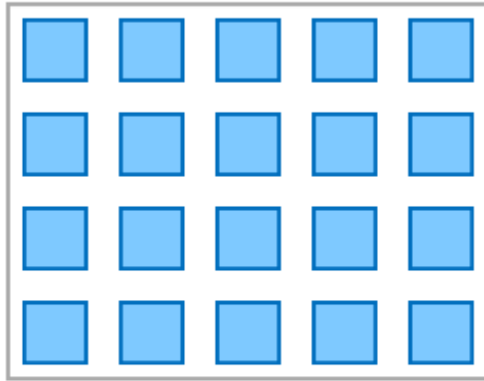
Scalar



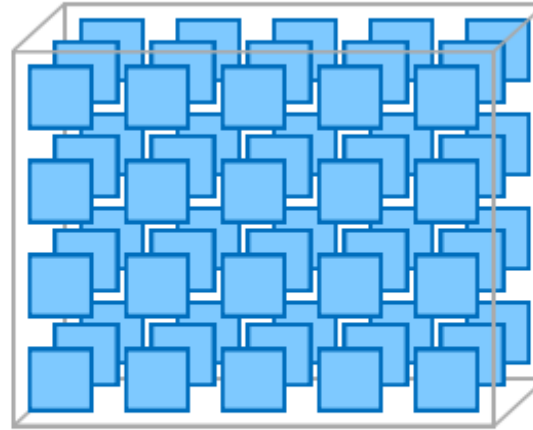
Vector



Matrix

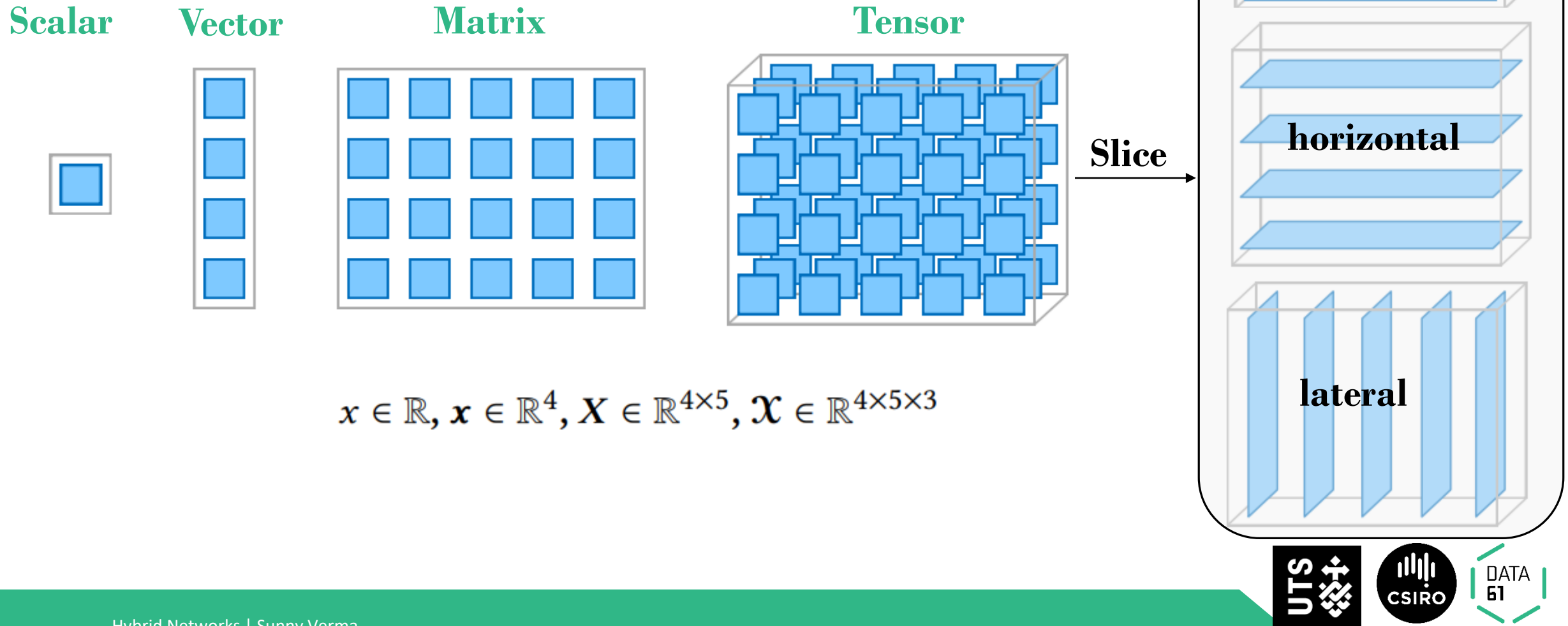


Tensor



$$x \in \mathbb{R}, \mathbf{x} \in \mathbb{R}^4, \mathbf{X} \in \mathbb{R}^{4 \times 5}, \mathcal{X} \in \mathbb{R}^{4 \times 5 \times 3}$$

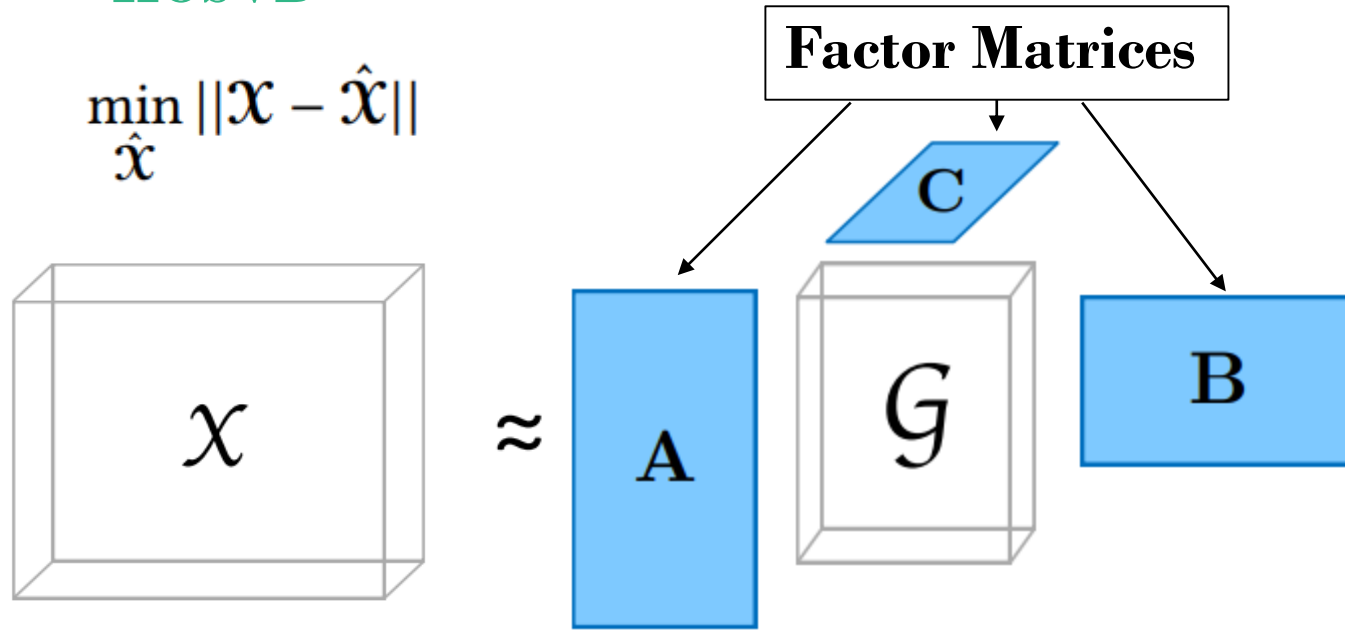
Tensor Network, Preliminaries



TDNet

HOSVD

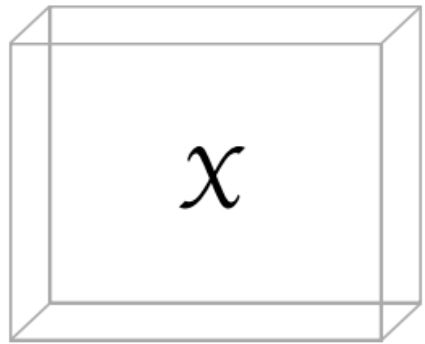
$$\min_{\hat{\mathcal{X}}} ||\mathcal{X} - \hat{\mathcal{X}}||$$



Tucker Decomposition

TDNet

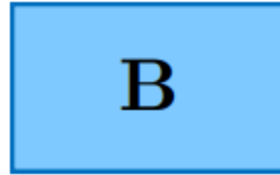
$$\min_{\hat{\mathcal{X}}} ||\mathcal{X} - \hat{\mathcal{X}}||$$



\approx



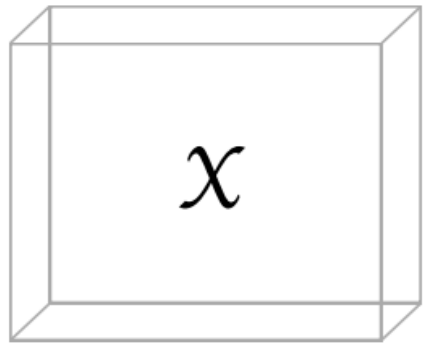
Factor Matrices



Proposed LoMOI

TDNet

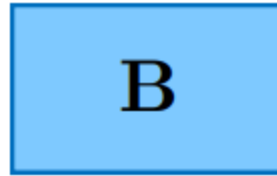
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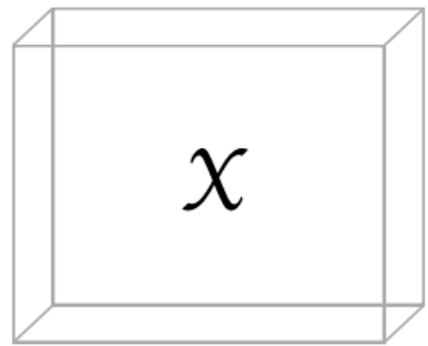


- Learns from minutiae view of the data.
- Preserves spatial structure in the data

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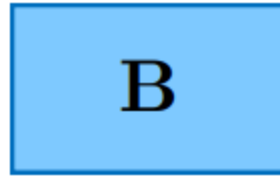
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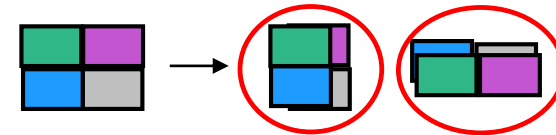
\approx



Factor Matrices



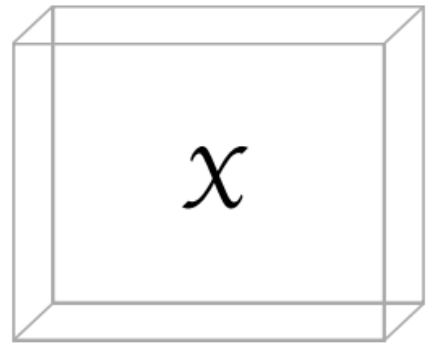
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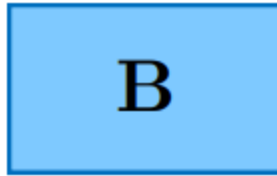
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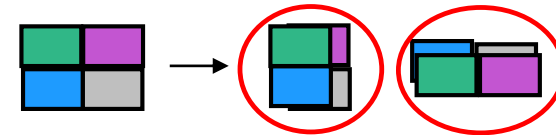


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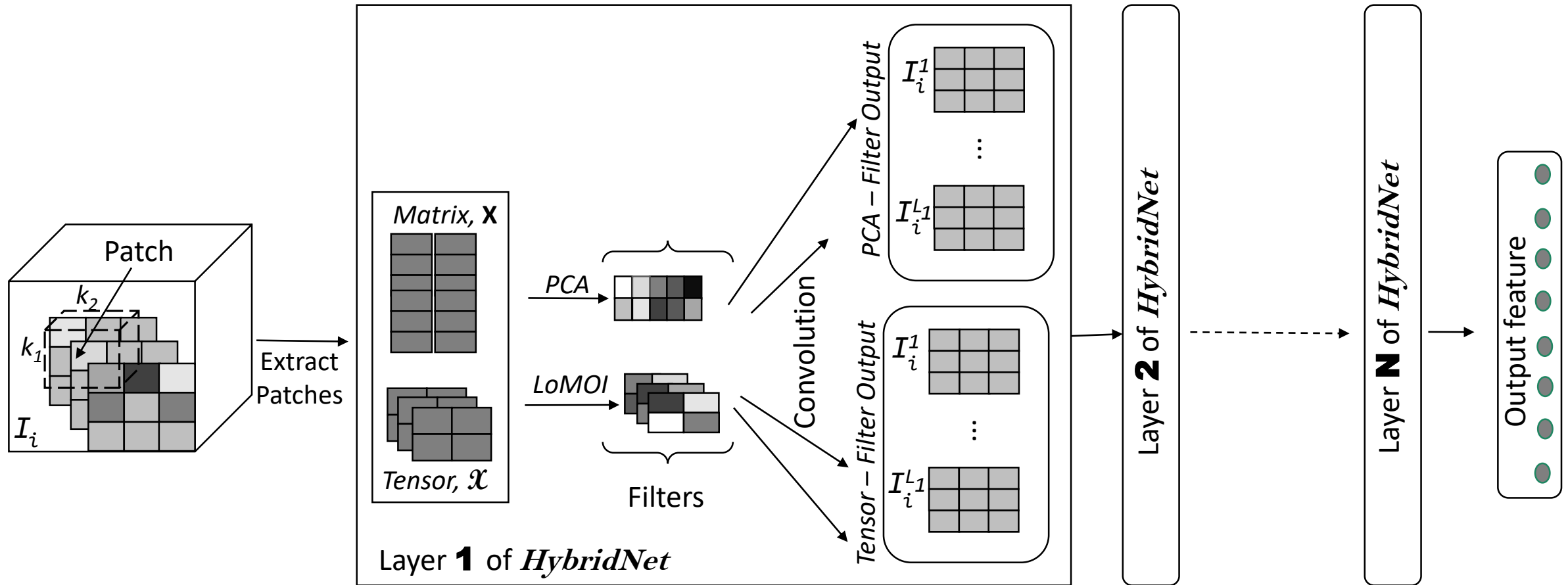
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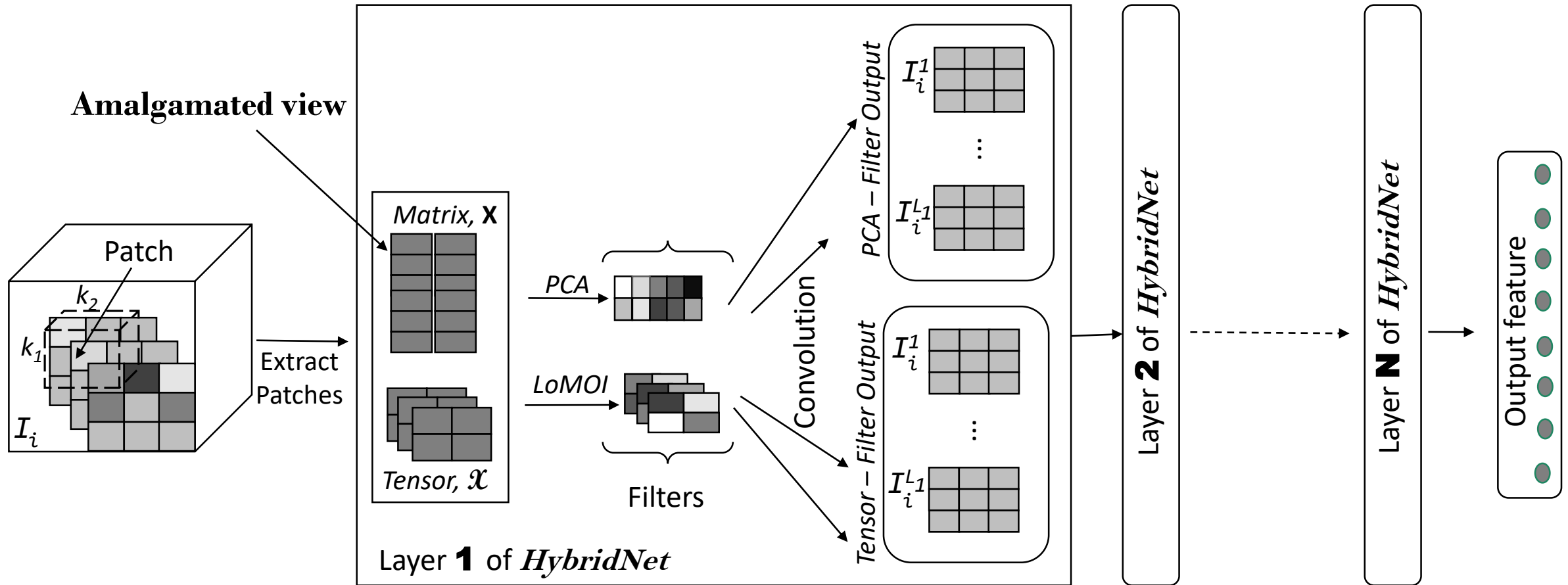


- Computationally less expensive than PCA.
- Captures variations in each mode independently.

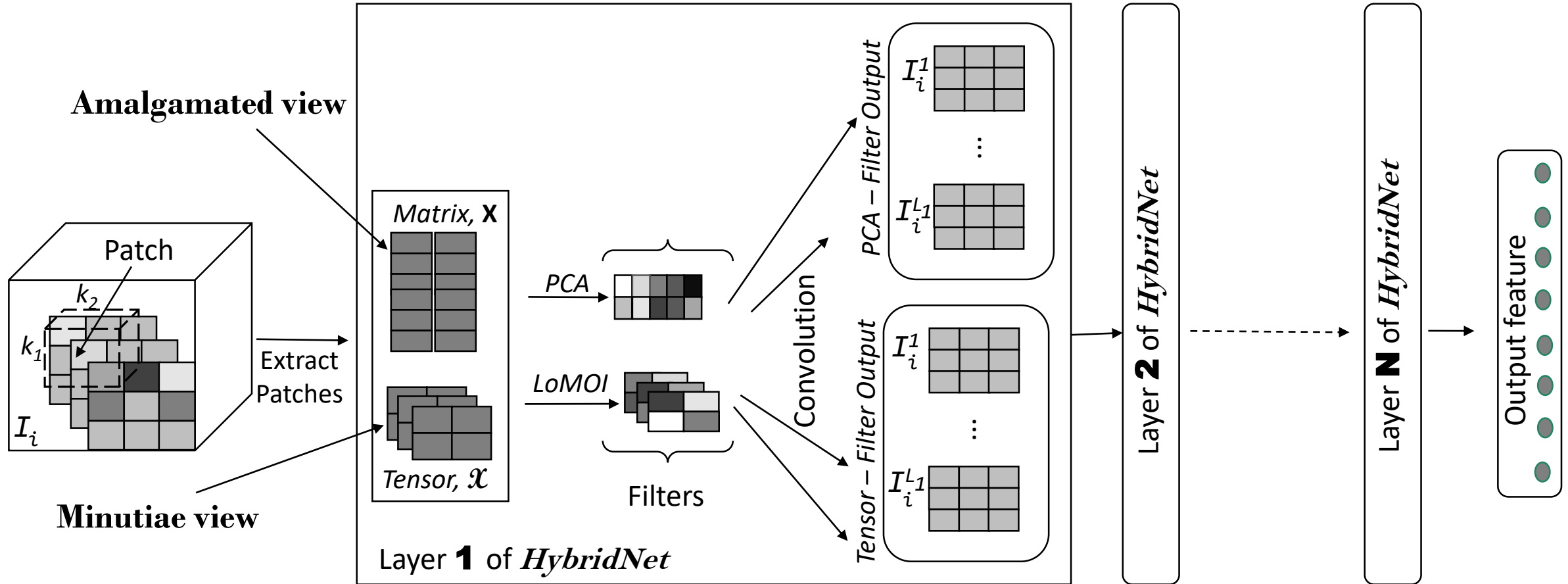
Hybrid Networks



Hybrid Networks

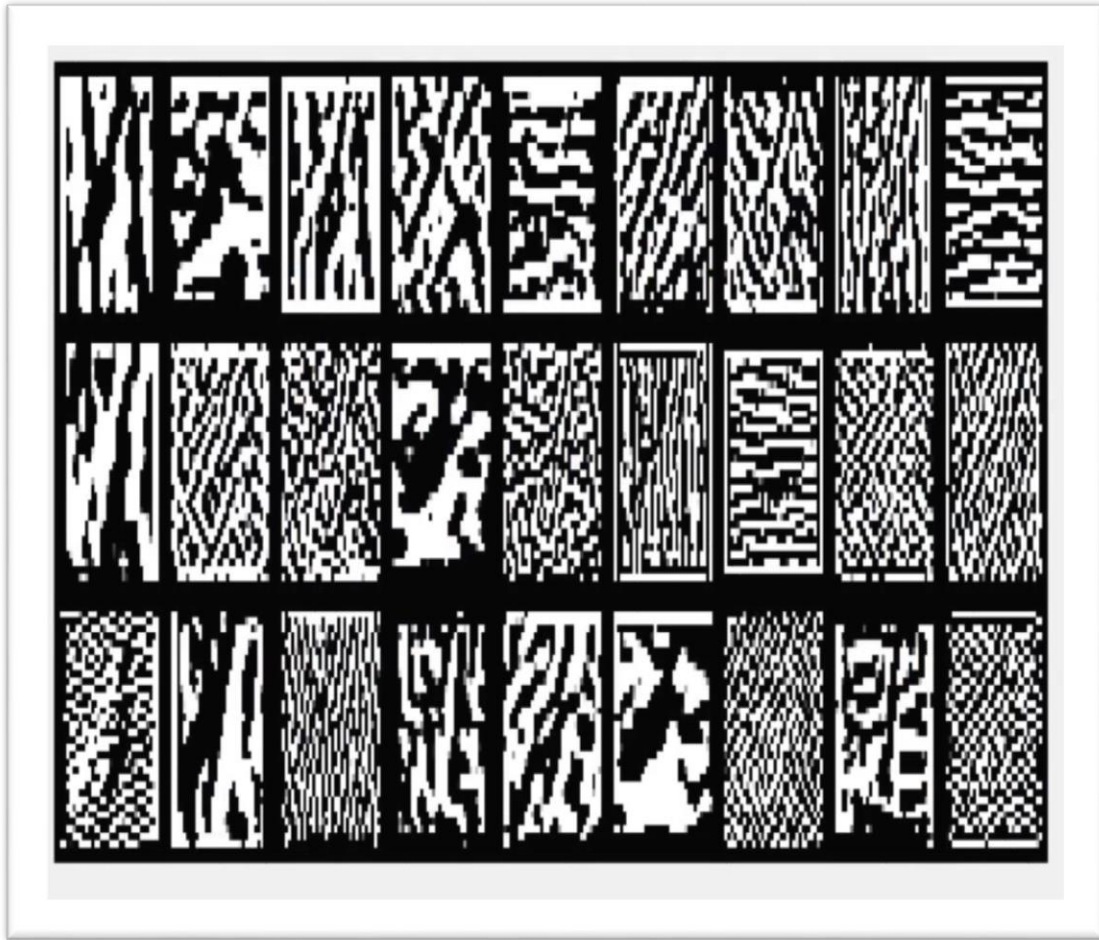


Hybrid Networks



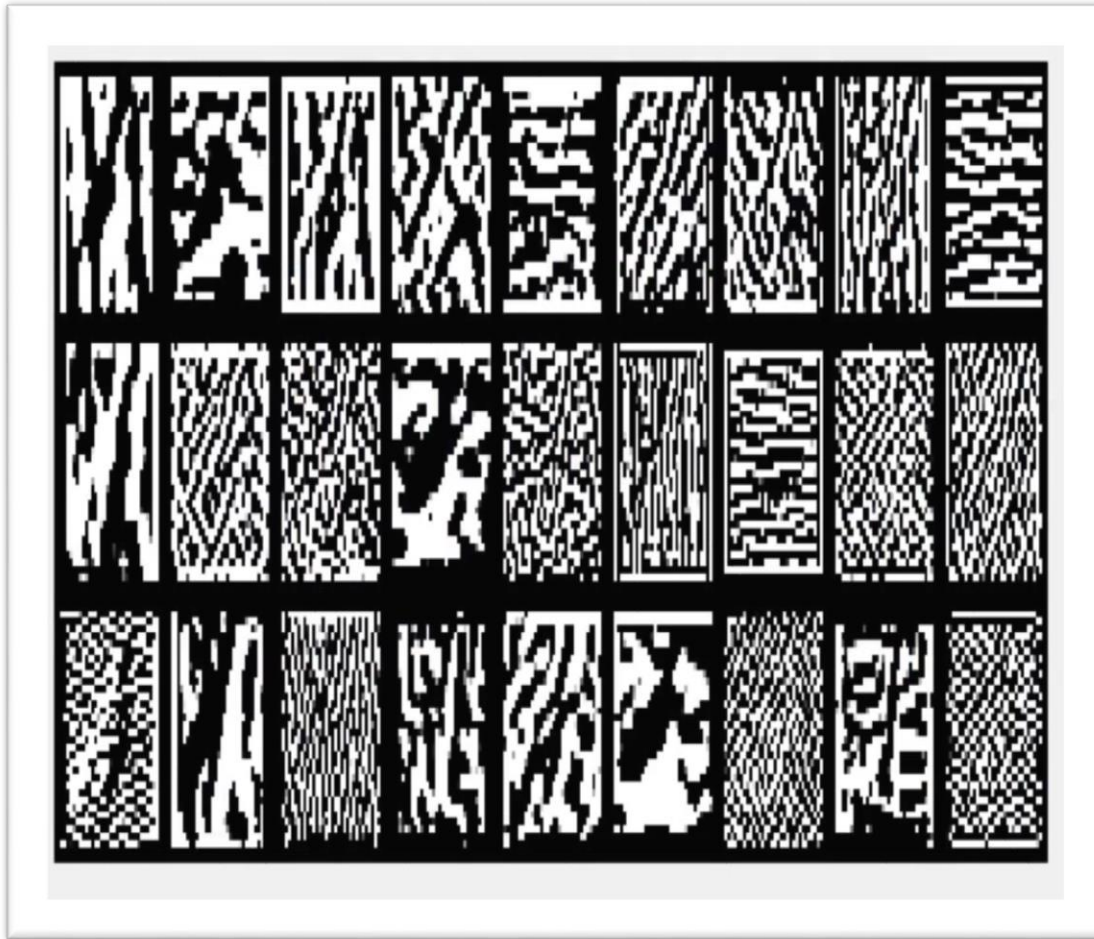
Output from the first layer in Hybrid Networks

PCANet

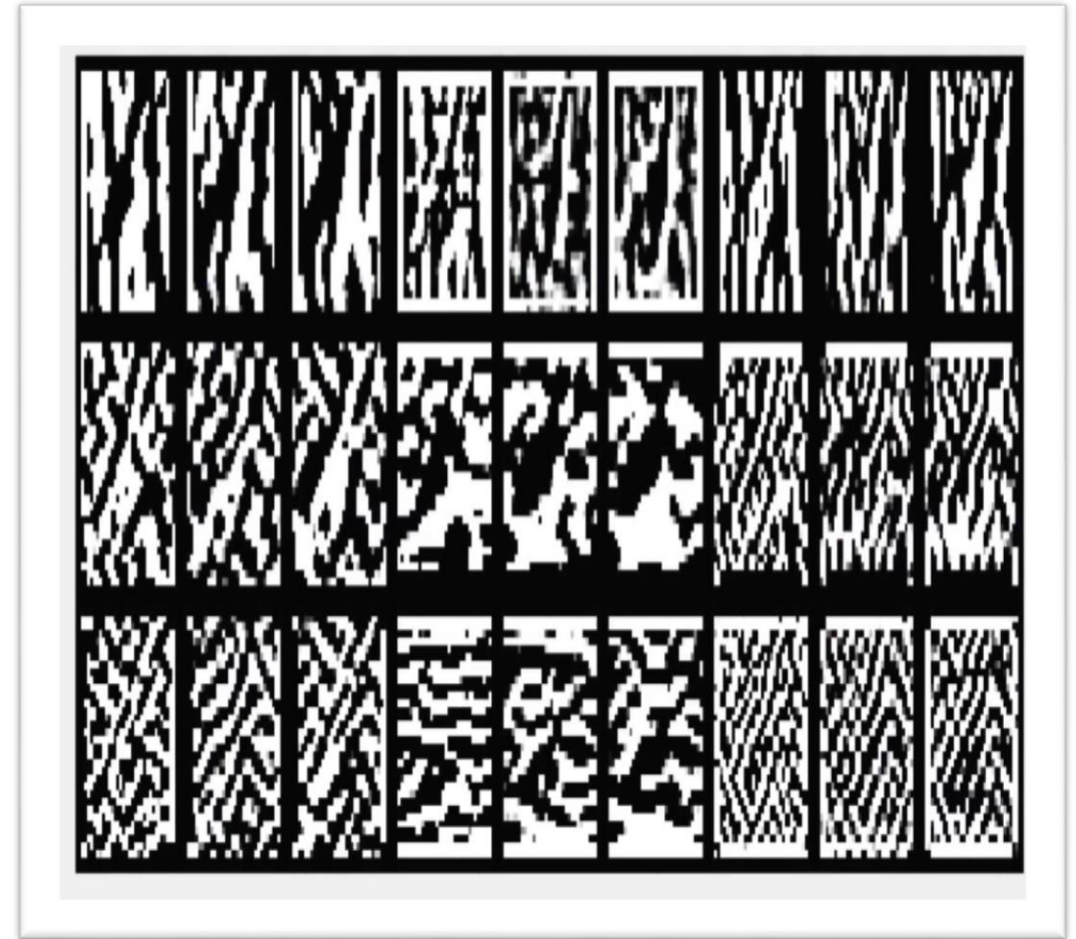


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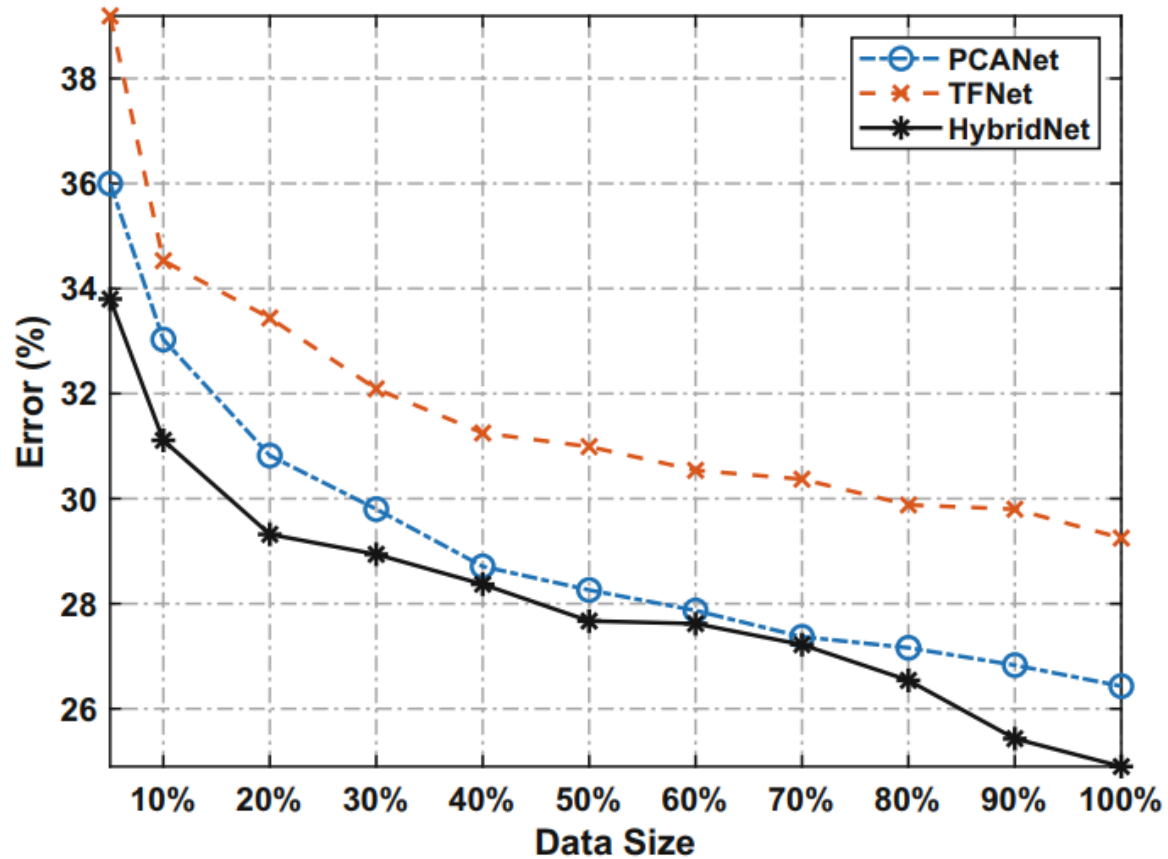


TensorNet



Results

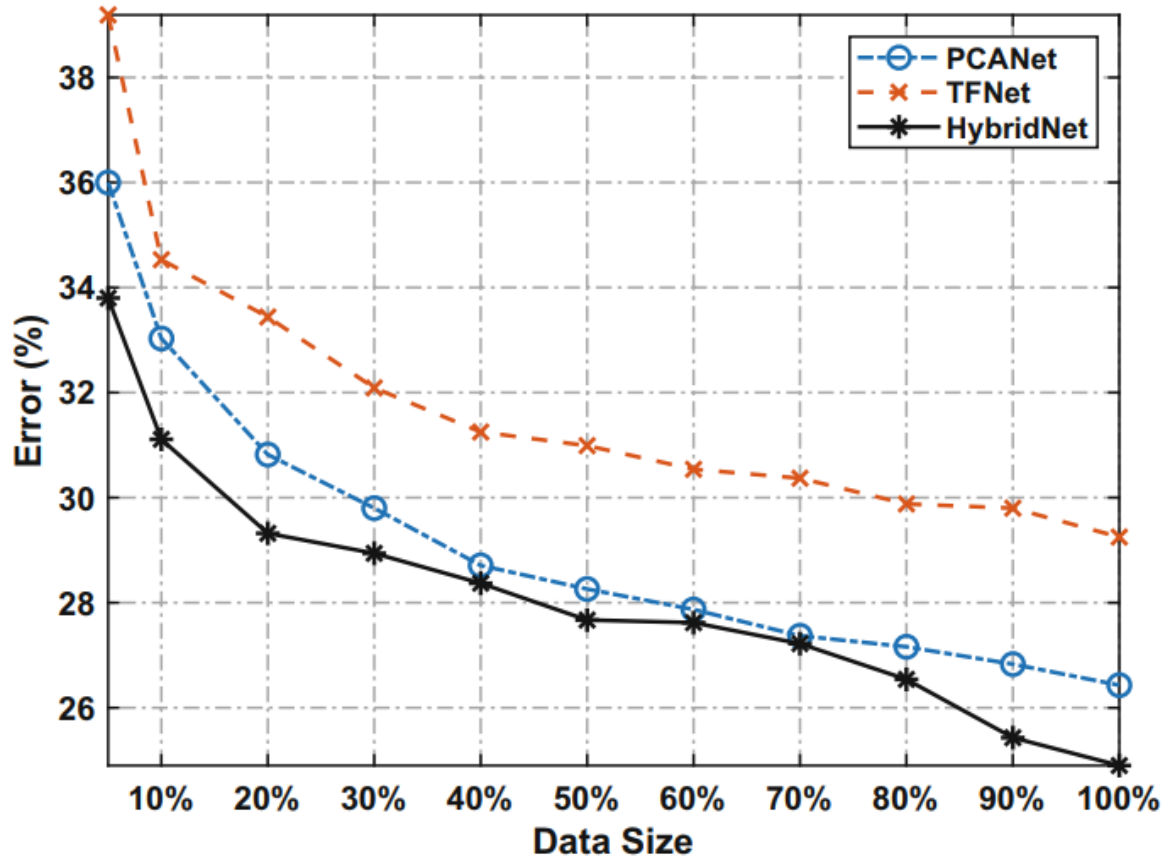
PCANet



CIFAR 10

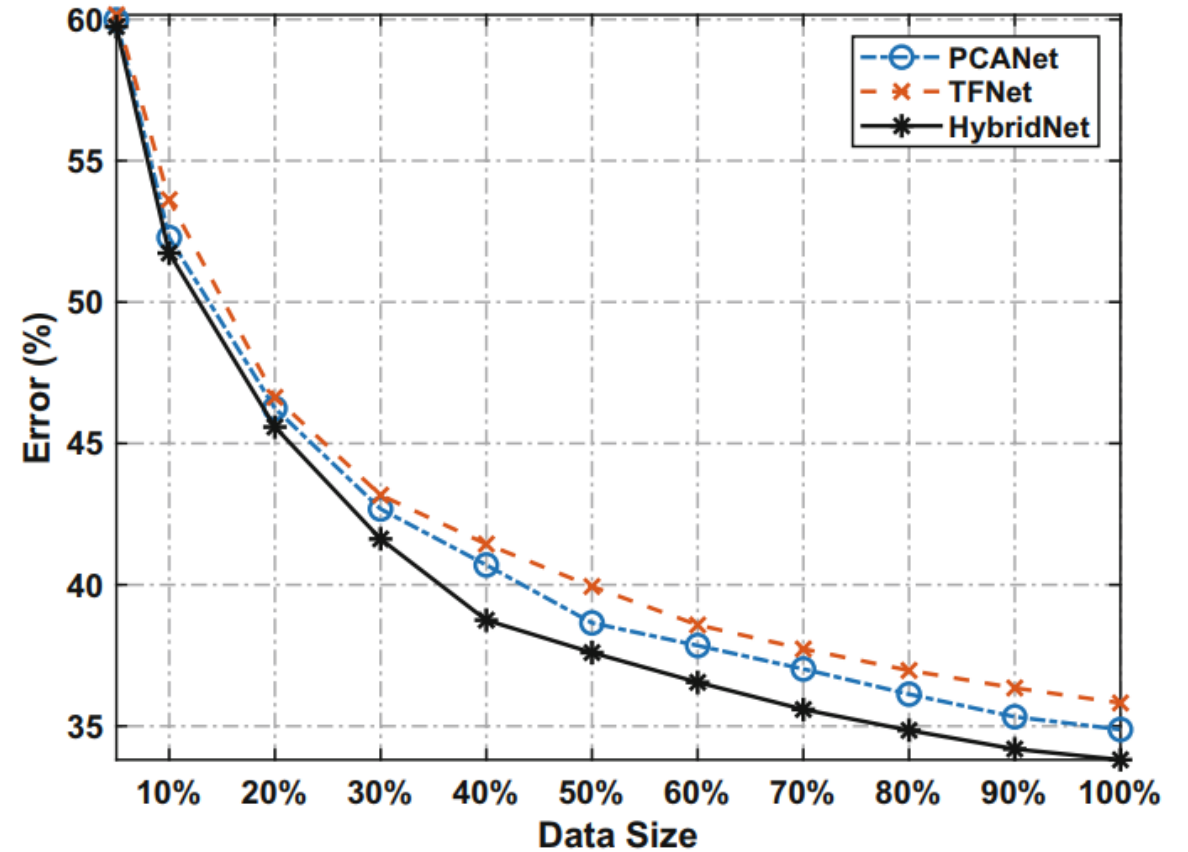
Results

PCANet



CIFAR 10

TensorNet



MNIST bg-img-rot

Contributions

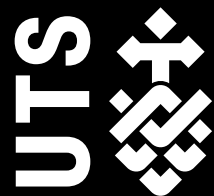
- Contributions and findings
 - Both the amalgamated view and minutiae view of the data are individually insufficient.
 - To preserve the spatial information in the data TDNet is introduced.
 - HDNet is proposed to learn from both the views of the data.

Contributions, Conclusions

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 - To preserve the spatial information in the data TDNet is introduced.
 - HDNet is proposed to learn from both the views of the data.
- Advantages and Limitations
 - Light Weight deep architecture which is unsupervised, fast, and less insensitive to noisy labels
 - Extremely challenging datasets might require more layers and non-linearities.

Contributions, Conclusions, and Future Works

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- Future Works
 - Introduce fusion layer to combine the two networks.
 - Introduction mechanisms to handle rotations in the images.



THANK YOU

Sunny Verma

