Comparing Scaled-YOLOv4 & YOLOv7

TensorFlow Model Garden

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Outline

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d. Scaled-YOLOv4 aims to find a method for *synergistic compound scaling* (translation: $\pm$ stages) based on design requirements for object-detection based tasks.

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Both Scaled-YOLOv4 and YOLOv7 build upon neural scaling as a method for improving inference speed and accuracy.

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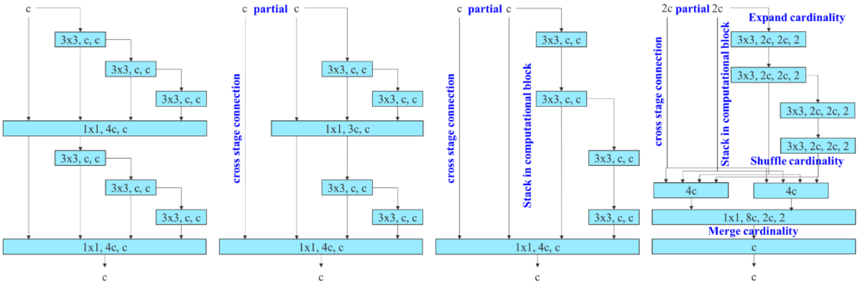
1. Overview
2. Architecture

Comparing Architectures



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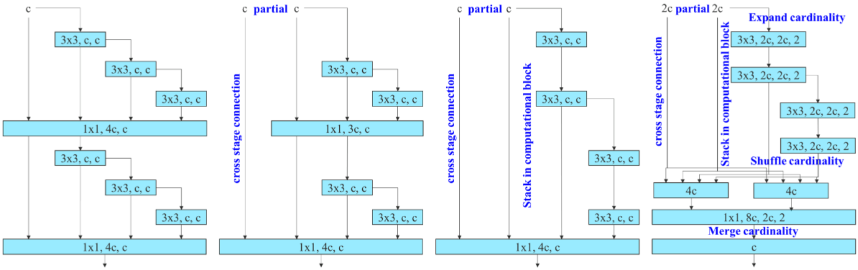

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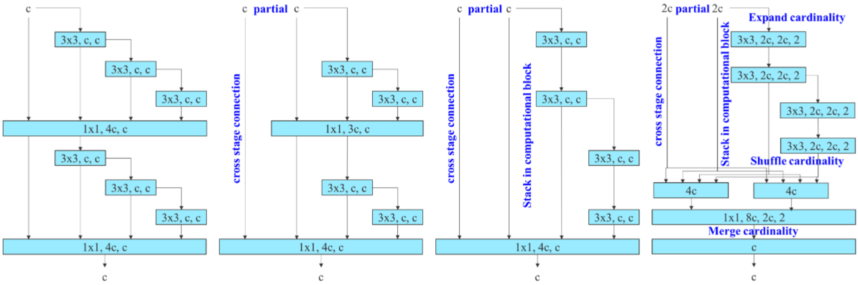

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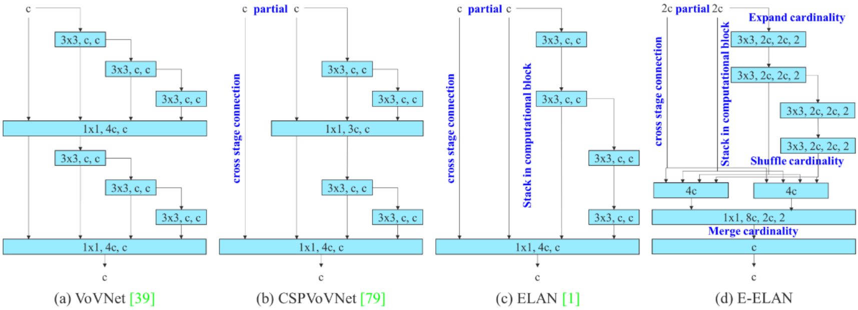

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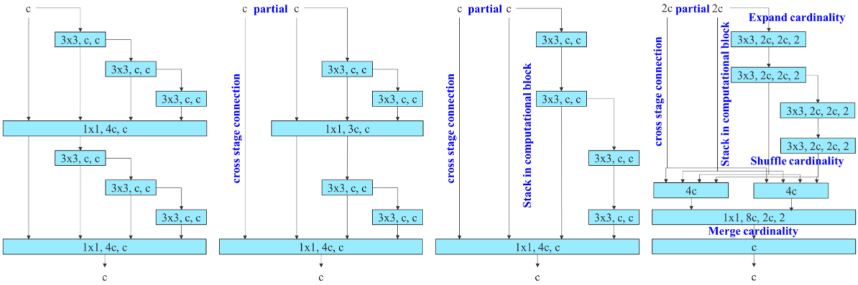

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- **E-ELAN:** Group convolution to increase cardinality.

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   - The lead head has a relatively strong learning capability; the auxilliary head eases it so that it can focus on learning residual information.

Thank you!

That's all I've got; have an awesome rest of your day!